analysis

October 4, 2024

[40]:
```
import pandas as pd # for data science
import numpy as np  # linear algebra library
import matplotlib.pyplot as plt # plotting library
import datetime as dt
# import stats functions
from scipy import stats
# normal continuous random variable
from scipy.stats import norm
from statsmodels.tsa.holtwinters import ExponentialSmoothing # for future␣
↪forcasting
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans # for clustering
from scipy.cluster.hierarchy import dendrogram, linkage, fcluster # for␣
↪hierarchy clustering
from sklearn.metrics import mean_absolute_error, r2_score
import warnings

# Suppress all warnings
warnings.filterwarnings("ignore")
```

[3]:
```
# Read in Data file using the URL
retail_data = pd.read_csv('https://archive.ics.uci.edu/static/public/352/data.
↪csv')

data = pd.DataFrame(retail_data)

# Displaying all the columns (variables) from the dataset
variables = data.columns.tolist()
print(variables)

# Clean the data by removing missing values from each column for analysis␣
↪accuracy
df = data.dropna(subset=variables)
```

```
['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
'UnitPrice', 'CustomerID', 'Country']
```

[4]:
```
# Descriptive Statistics
# Display the first few rows of the DataFrame
df.head()
```

[4]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

      InvoiceDate  UnitPrice  CustomerID         Country
0  12/1/2010 8:26       2.55     17850.0  United Kingdom
1  12/1/2010 8:26       3.39     17850.0  United Kingdom
2  12/1/2010 8:26       2.75     17850.0  United Kingdom
3  12/1/2010 8:26       3.39     17850.0  United Kingdom
4  12/1/2010 8:26       3.39     17850.0  United Kingdom
```

[5]:
```
# View last few rows
df.tail()
```

[5]:
```
       InvoiceNo StockCode                      Description  Quantity  \
541904    581587     22613       PACK OF 20 SPACEBOY NAPKINS        12
541905    581587     22899      CHILDREN'S APRON DOLLY GIRL          6
541906    581587     23254     CHILDRENS CUTLERY DOLLY GIRL          4
541907    581587     23255  CHILDRENS CUTLERY CIRCUS PARADE          4
541908    581587     22138     BAKING SET 9 PIECE RETROSPOT          3

            InvoiceDate  UnitPrice  CustomerID Country
541904  12/9/2011 12:50       0.85     12680.0  France
541905  12/9/2011 12:50       2.10     12680.0  France
541906  12/9/2011 12:50       4.15     12680.0  France
541907  12/9/2011 12:50       4.15     12680.0  France
541908  12/9/2011 12:50       4.95     12680.0  France
```

[6]:
```
# Check datatypes
df.dtypes
```

[6]:
```
InvoiceNo       object
StockCode       object
Description     object
Quantity         int64
InvoiceDate     object
UnitPrice      float64
CustomerID     float64
Country         object
dtype: object
```

[7]:
```python
# Data Cleaning
# Convert 'InvoiceDate' to datetime format
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])

# Add a 'TotalSales' column: Quantity * UnitPrice
df['TotalSales'] = df['Quantity'] * df['UnitPrice']

# Extract only United Kingdom retail data for analysis
uk_data = df[df['Country'] == 'United Kingdom']
uk_data.tail()
```

[7]:
```
       InvoiceNo StockCode                          Description  Quantity  \
541889    581585     22466       FAIRY TALE COTTAGE NIGHT LIGHT        12
541890    581586     22061  LARGE CAKE STAND  HANGING STRAWBERY         8
541891    581586     23275     SET OF 3 HANGING OWLS OLLIE BEAK        24
541892    581586     21217        RED RETROSPOT ROUND CAKE TINS        24
541893    581586     20685                 DOORMAT RED RETROSPOT        10

               InvoiceDate  UnitPrice  CustomerID         Country  TotalSales
541889 2011-12-09 12:31:00       1.95     15804.0  United Kingdom        23.4
541890 2011-12-09 12:49:00       2.95     13113.0  United Kingdom        23.6
541891 2011-12-09 12:49:00       1.25     13113.0  United Kingdom        30.0
541892 2011-12-09 12:49:00       8.95     13113.0  United Kingdom       214.8
541893 2011-12-09 12:49:00       7.08     13113.0  United Kingdom        70.8
```

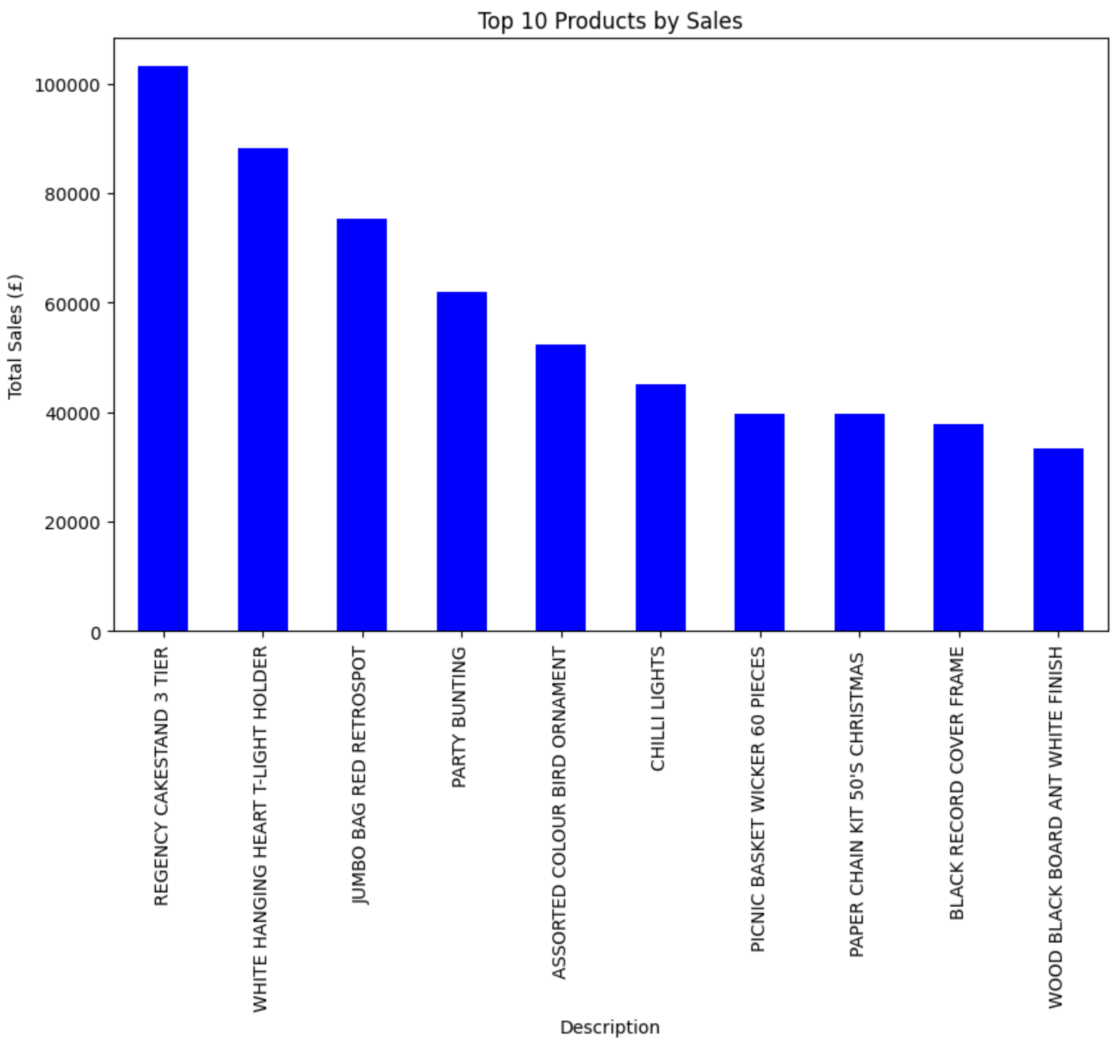
[8]:
```python
# Data Analysis
# Sales Analysis
# Dtermine the total Sales
total_sales = uk_data['TotalSales'].sum()
print(f"Total Sales in UK: £{total_sales:.2f}")

# Average Sales per Transaction by invoiceNo
average_sales = uk_data.groupby('InvoiceNo')['TotalSales'].mean().mean()
print(f"Average Sales per Transaction: £{average_sales:.2f}")
```

```
Total Sales in UK: £6767873.39
Average Sales per Transaction: £34.16
```

[33]:
```python
# determine the top 10 Products by Sales
top_products = uk_data.groupby('Description')['TotalSales'].sum().
 ↪sort_values(ascending=False).head(10)
print("Top 10 Products by Total Sales:")
print(top_products)

# Distribution of top 10 product sales
plt.figure(figsize=(10,6))
top_products.plot(kind='bar', color='blue')
plt.title('Top 10 Products by Sales')
```

```
plt.ylabel('Total Sales (£)')
plt.xticks(rotation=90)
plt.show()
```

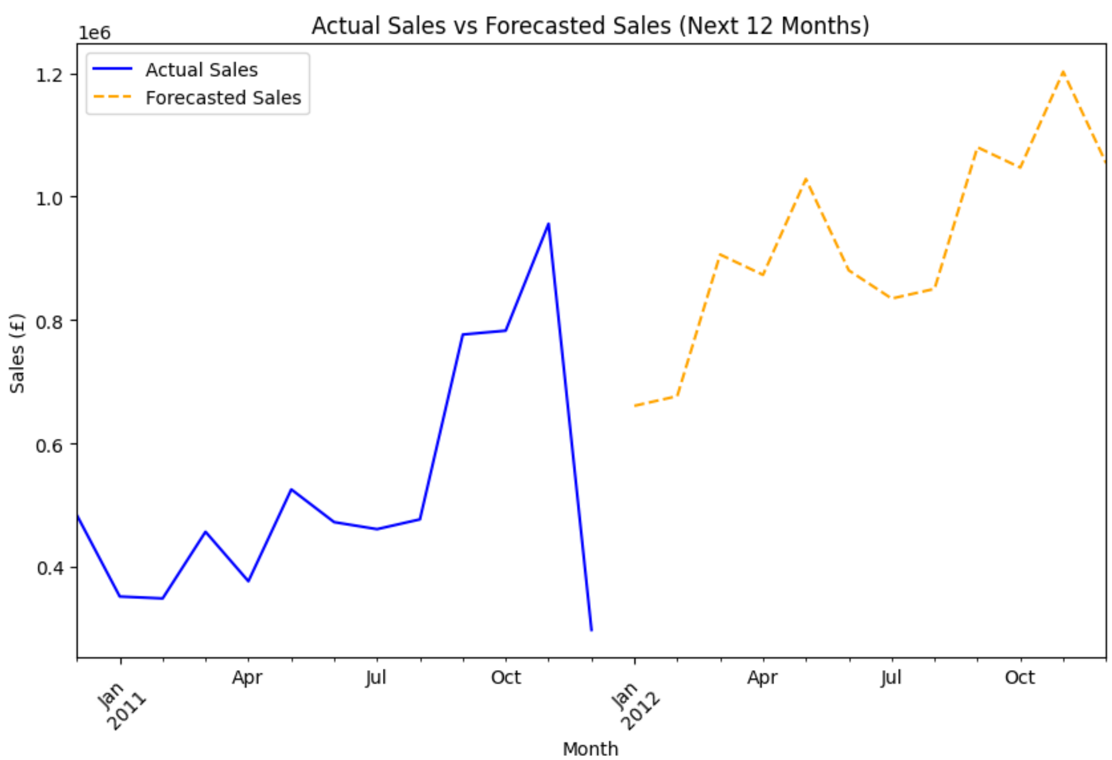
```
Top 10 Products by Total Sales:
Description
REGENCY CAKESTAND 3 TIER              103122.85
WHITE HANGING HEART T-LIGHT HOLDER     88313.95
JUMBO BAG RED RETROSPOT                75416.67
PARTY BUNTING                          61952.58
ASSORTED COLOUR BIRD ORNAMENT          52314.87
CHILLI LIGHTS                          45155.61
PICNIC BASKET WICKER 60 PIECES         39619.50
PAPER CHAIN KIT 50'S CHRISTMAS         39596.73
BLACK RECORD COVER FRAME               37799.42
WOOD BLACK BOARD ANT WHITE FINISH      33408.76
Name: TotalSales, dtype: float64
```



[22]:
```
# Time-Series Analysis
# Total sales by Date (day) ignoring time
# sales_by_date = uk_data.groupby(uk_data['InvoiceDate'].dt.date)['TotalSales'].
↪sum()

# Group sales by month
monthly_sales = uk_data.groupby(uk_data['InvoiceDate'].dt.
↪to_period('M'))['TotalSales'].sum()
# Fit a Time-Series Model (Holt-Winters Exponential Smoothing)
model = ExponentialSmoothing(monthly_sales, trend='add', seasonal='add',␣
↪seasonal_periods=6)
fitted_model = model.fit()

# Make Predictions - Forecast sales for the next 12 months
forecast = fitted_model.forecast(12)

# Create a DataFrame for the forecasted period
forecast_df = pd.DataFrame(forecast, columns=['ForecastedSales'])
forecast_df = forecast_df['ForecastedSales'].apply(lambda x: f"{x:.2f}")
# Combine actual and forecasted data into one table
combined_sales = pd.concat([monthly_sales, forecast_df], axis=1)

# Display the combined table
print(combined_sales)

# Plot Actual Sales and Forecasted Sales
plt.figure(figsize=(10,6))
monthly_sales.plot(kind='line', label='Actual Sales', color='blue')
forecast.plot(kind='line', label='Forecasted Sales', color='orange',␣
↪linestyle='--')
plt.title('Actual Sales vs Forecasted Sales (Next 12 Months)')
plt.xlabel('Month')
plt.ylabel('Sales (£)')
plt.legend()
plt.xticks(rotation=45)
plt.show()

# Print the forecasted values
#print(forecast)
```

```
         TotalSales ForecastedSales
2010-12  483799.740             NaN
2011-01  351981.280             NaN
2011-02  348853.630             NaN
2011-03  456917.870             NaN
```

```
2011-04  376744.411            NaN
2011-05  525573.350            NaN
2011-06  472509.250            NaN
2011-07  461147.601            NaN
2011-08  477008.410            NaN
2011-09  776529.842            NaN
2011-10  782777.880            NaN
2011-11  956109.660            NaN
2011-12  297920.470            NaN
2012-01         NaN      660994.93
2012-02         NaN      676656.92
2012-03         NaN      906173.73
2012-04         NaN      873185.58
2012-05         NaN     1028587.85
2012-06         NaN      880533.20
2012-07         NaN      834841.36
2012-08         NaN      850503.35
2012-09         NaN     1080020.16
2012-10         NaN     1047032.01
2012-11         NaN     1202434.27
2012-12         NaN     1054379.63
```



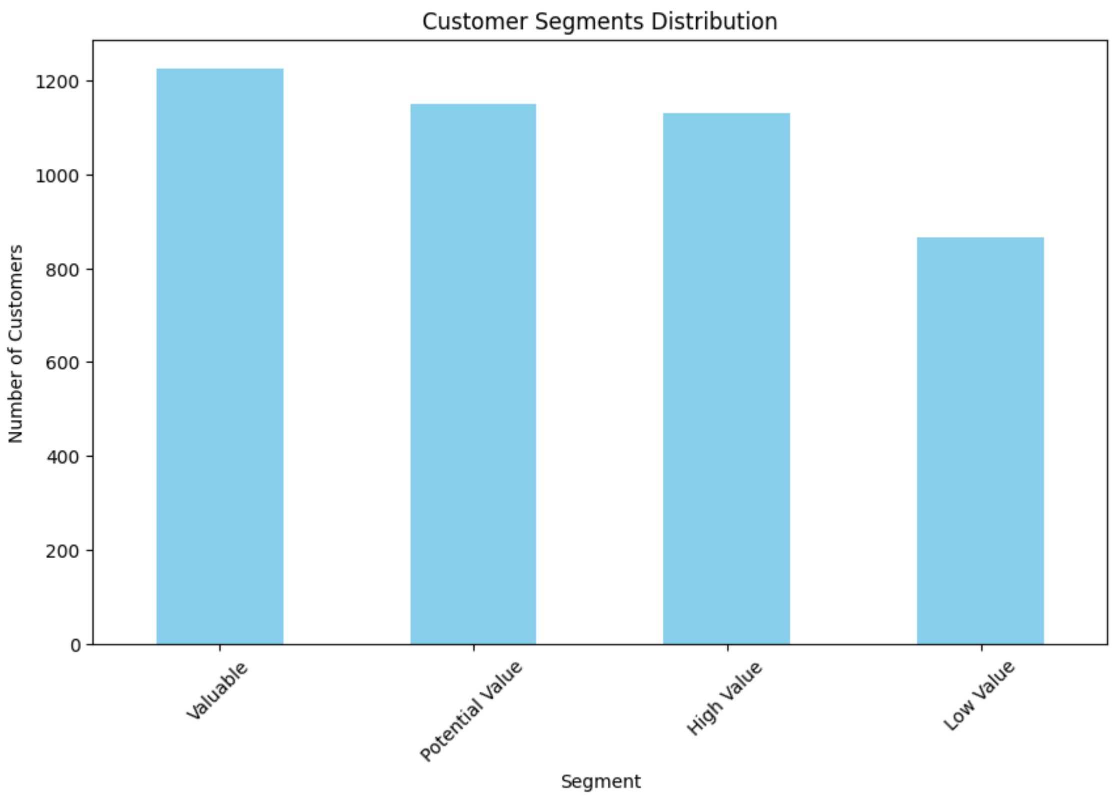
[34]:
```
## RFM Analysis

# Today is set as the maximum InvoiceDate + 1 day to calculate recency
today = df['InvoiceDate'].max() + dt.timedelta(days=1)

# Calculate RFM Metrics for each customer
rfm = df.groupby('CustomerID').agg({
    'InvoiceDate': lambda x: (today - x.max()).days,  # Recency
    'InvoiceNo': 'count',  # Frequency
    'TotalSales': 'sum'  # Monetary
})

# Rename columns
rfm.columns = ['Recency', 'Frequency', 'Monetary']

# Assign RFM scores by ranking customers
rfm['R_rank'] = pd.qcut(rfm['Recency'], 4, labels=[4, 3, 2, 1])  # Quartiles␣
↪for recency
rfm['F_rank'] = pd.qcut(rfm['Frequency'].rank(method='first'), 4, labels=[1, 2,␣
↪3, 4])  # Quartiles for frequency
rfm['M_rank'] = pd.qcut(rfm['Monetary'], 4, labels=[1, 2, 3, 4])  # Quartiles␣
↪for monetary

# Create an overall RFM score
rfm['RFM_Score'] = rfm['R_rank'].astype(str) + rfm['F_rank'].astype(str) +␣
↪rfm['M_rank'].astype(str)

# Analyze the segments based on RFM scores to determine top customers,␣
↪potential loyalists, etc.
rfm['Segment'] = pd.cut(rfm['RFM_Score'].astype(int), bins=[0, 123, 234, 344,␣
↪444], labels=['Low Value', 'Potential Value', 'Valuable', 'High Value'])

# Show the RFM table and segments
rfm.head()
```

[34]:
```
            Recency  Frequency  Monetary R_rank F_rank M_rank RFM_Score  \
CustomerID
12346.0         326          2      0.00      1      1      1       111
12347.0           2        182   4310.00      4      4      4       444
12348.0          75         31   1797.24      2      2      4       224
12349.0          19         73   1757.55      3      3      4       334
12350.0         310         17    334.40      1      1      2       112

                Segment
CustomerID
12346.0       Low Value
12347.0      High Value
```

```
12348.0     Potential Value
12349.0           Valuable
12350.0          Low Value
```

[61]:

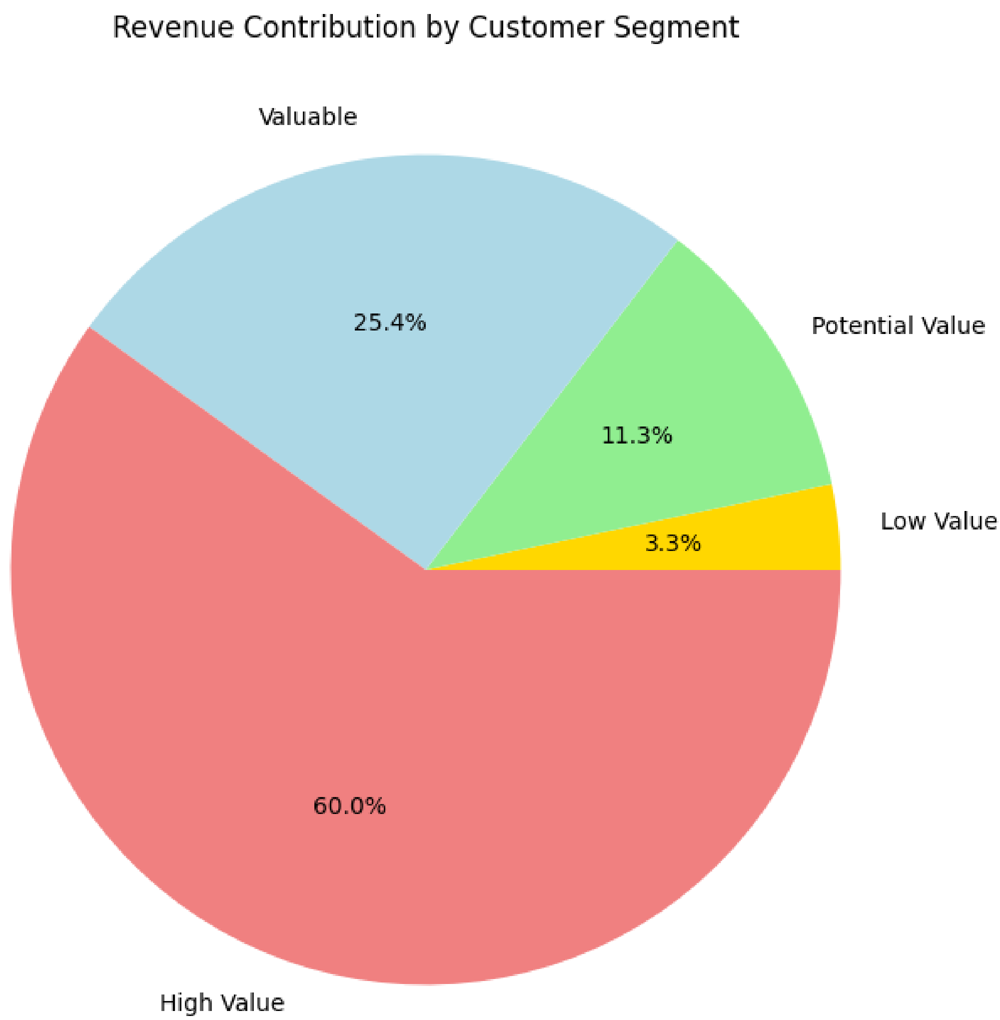
```
# Count the number of customers in each segment
segment_counts = rfm['Segment'].value_counts()

# Plot a bar chart
plt.figure(figsize=(10,6))
segment_counts.plot(kind='bar', color='skyblue')
plt.title('Customer Segments Distribution')
plt.xlabel('Segment')
plt.ylabel('Number of Customers')
plt.xticks(rotation=45)
plt.show()
```



[62]:

```
# Calculate the total revenue contributed by each segment
segment_revenue = rfm.groupby('Segment')['Monetary'].sum()

# Plot a pie chart
plt.figure(figsize=(8,8))
```

```
segment_revenue.plot(kind='pie', autopct='%1.1f%%', colors=['gold',
↪'lightgreen', 'lightblue', 'lightcoral'])
plt.title('Revenue Contribution by Customer Segment')
plt.ylabel('')  # Hide y-label
plt.show()
```



[67]:
```
# Sort customers by RFM score to identify top customers
top_customers = rfm.sort_values(by='RFM_Score', ascending=False).head(10)

# Display top 10 customers
top_customers
```

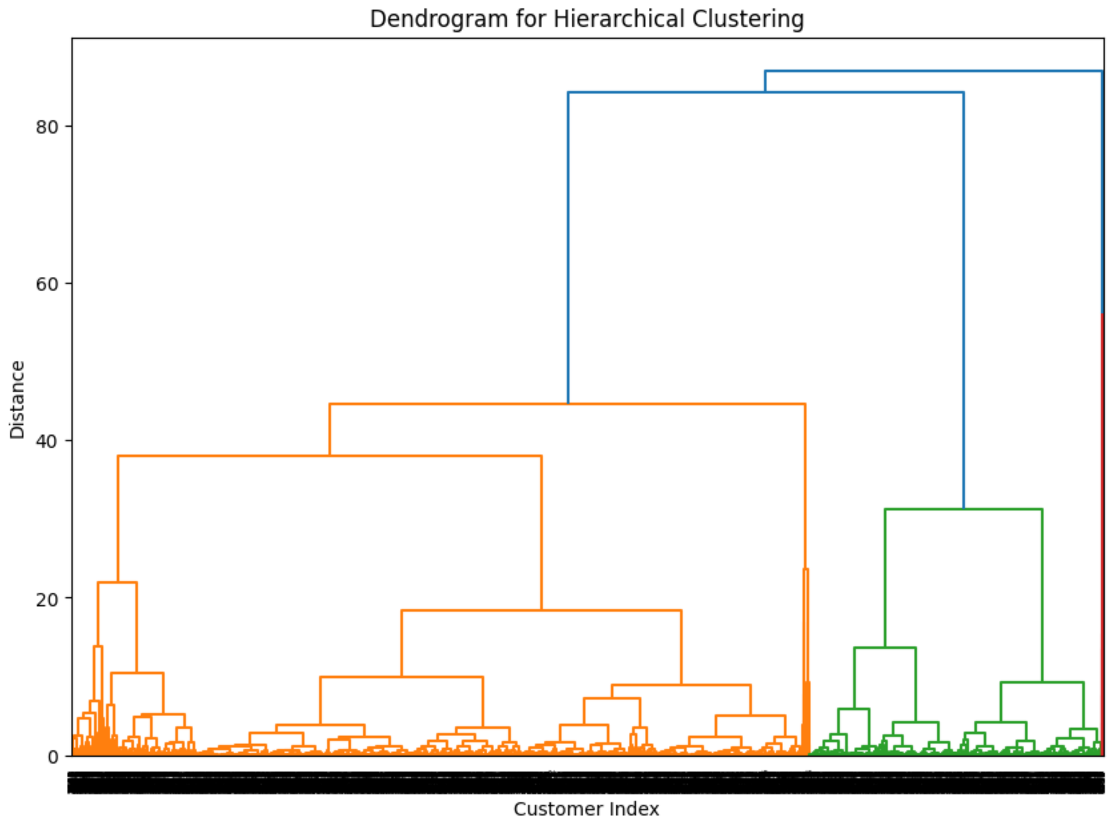
[67]:

```
              Recency  Frequency  Monetary R_rank F_rank M_rank RFM_Score  \
CustomerID
13854.0             9        114   8025.02      4      4      4       444
16525.0             2        200  11895.57      4      4      4       444
14243.0             9        148   2535.88      4      4      4       444
16458.0             3        202   3482.74      4      4      4       444
12901.0             9        125  16293.10      4      4      4       444
17677.0             2        321  16219.22      4      4      4       444
16474.0             7        368   1811.47      4      4      4       444
14217.0             2        107   1925.36      4      4      4       444
14215.0            12        109   1777.92      4      4      4       444
17675.0             1        721  20098.10      4      4      4       444

                 Segment
CustomerID
13854.0       High Value
16525.0       High Value
14243.0       High Value
16458.0       High Value
12901.0       High Value
17677.0       High Value
16474.0       High Value
14217.0       High Value
14215.0       High Value
17675.0       High Value
```

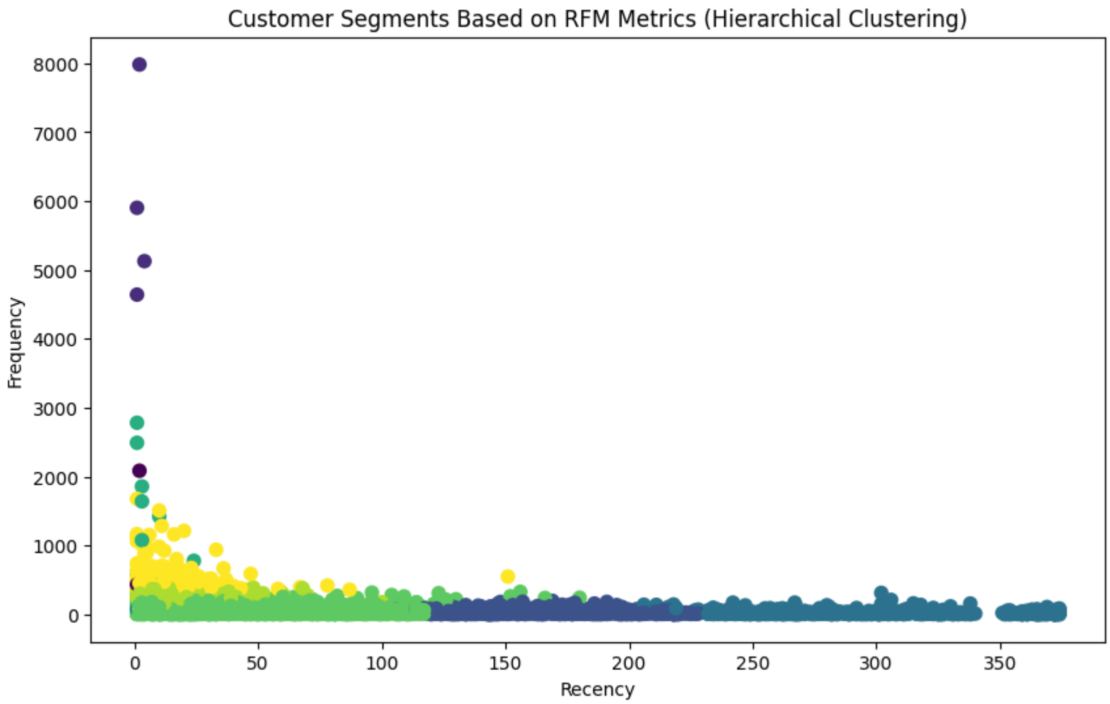
[45]:

```python
## Using clustering model to determine the RFM of customer groups
rfm = rfm[['Recency', 'Frequency', 'Monetary']]

scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm)
# Step 3: Perform hierarchical clustering using the 'ward' method (or␣
↪'complete', 'average')
linked = linkage(rfm_scaled, method='ward')

# Plot the dendrogram to visualize the clustering hierarchy
plt.figure(figsize=(10, 7))
dendrogram(linked,
           orientation='top',
           distance_sort='descending',
           show_leaf_counts=True)
plt.title('Dendrogram for Hierarchical Clustering')
plt.xlabel('Customer Index')
plt.ylabel('Distance')
plt.show()
```

```
# Choose the number of clusters by cutting the dendrogram at an appropriate␣
↪level
distance_threshold = 20  # adjust this based dendrogram. the higher the number␣
↪the lesser the number of clusters
rfm['Cluster'] = fcluster(linked, distance_threshold, criterion='distance')


# Step 6: Analyze the clusters
# Grouping customers by clusters and calculating the average RFM values for␣
↪each cluster
cluster_summary = rfm.groupby('Cluster').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': 'mean',
    'Cluster': 'count'
}).rename(columns={'Cluster': 'Customer Count'})

# Display the cluster summary
print(cluster_summary)

# Step 7: Visualize the clusters (optional: Recency vs. Frequency)
plt.figure(figsize=(10, 6))
plt.scatter(rfm['Recency'], rfm['Frequency'], c=rfm['Cluster'], cmap='viridis',␣
↪marker='o', s=50)
plt.title('Customer Segments Based on RFM Metrics (Hierarchical Clustering)')
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.show()
```



	Recency	Frequency	Monetary	Customer Count
Cluster				
1	3.666667	956.333333	241136.560000	3
2	2.000000	5914.000000	64776.602500	4
3	169.586319	33.923453	593.782427	614
4	296.179200	24.744000	395.939474	625
5	8.450000	289.850000	39145.576500	20
6	6.428571	1720.571429	72088.068571	7
7	40.687451	59.877241	993.429000	2566
8	16.688442	233.520101	4977.057236	398
9	14.170370	589.503704	6577.552148	135


Customer Segments Based on RFM Metrics (Hierarchical Clustering)
8000
7000
6000
5000
4000
3000
2000
1000
0
Frequency
0
50
100
150
200
250
300
350
Recency