## *RFM Analysis using Python*

I'll start the task of RFM Analysis by importing the necessary Python libraries and the dataset:

```
import pandas as pd
import plotly.express as px
import plotly.io as pio
import plotly.graph_objects as go
pio.templates.default = "plotly_white"

data = pd.read_csv("/content/rfm_data.csv")
print(data.head())
```

```
   CustomerID PurchaseDate  TransactionAmount ProductInformation  OrderID  \
0        8814   2023-04-11             943.31          Product C   890075
1        2188   2023-04-11             463.70          Product A   176819
2        4608   2023-04-11              80.28          Product A   340062
3        2559   2023-04-11             221.29          Product A   239145
4        9482   2023-04-11             739.56          Product A   194545

   Location
0     Tokyo
1    London
2  New York
3    London
4     Paris
```

## Calculating RFM Values

I'll now calculate the Recency, Frequency, and Monetary values of the customers to move further:

```
from datetime import datetime

# Convert 'PurchaseDate' to datetime
data['PurchaseDate'] = pd.to_datetime(data['PurchaseDate'])

# Calculate Recency
data['Recency'] = (datetime.now().date() - data['PurchaseDate'].dt.date).dt.days

# Calculate Frequency
frequency_data = data.groupby('CustomerID')['OrderID'].count().reset_index()
frequency_data.rename(columns={'OrderID': 'Frequency'}, inplace=True)
data = data.merge(frequency_data, on='CustomerID', how='left')

# Calculate Monetary Value
monetary_data = data.groupby('CustomerID')['TransactionAmount'].sum().reset_index()
monetary_data.rename(columns={'TransactionAmount': 'MonetaryValue'}, inplace=True)
data = data.merge(monetary_data, on='CustomerID', how='left')
```

To calculate recency, we subtracted the purchase date from the current date and extracted the number of days using the datetime.now().date() function. It gives us the number of days since the customer's last purchase, representing their recency value.

After that, we calculated the frequency for each customer. We grouped the data by 'CustomerID' and counted the number of unique 'OrderID' values to determine the number of purchases made by each customer. It gives us the frequency value, representing the total number of purchases made by each customer.

Finally, we calculated the monetary value for each customer. We grouped the data by 'CustomerID' and summed the 'TransactionAmount' values to calculate the total amount spent by each customer. It gives us the monetary value, representing the total monetary contribution of each customer.

By performing these calculations, we now have the necessary RFM values (recency, frequency, monetary value) for each customer, which are important indicators for understanding customer behaviour and segmentation in RFM analysis.

Let's have a look at the resulting data before moving forward:

```
print(data.head())
```

```
   CustomerID PurchaseDate  TransactionAmount ProductInformation  OrderID  \
0        8814   2023-04-11             943.31          Product C   890075
1        2188   2023-04-11             463.70          Product A   176819
```

```
   2        4608   2023-04-11             80.28          Product A   340062
   3        2559   2023-04-11            221.29          Product A   239145
   4        9482   2023-04-11            739.56          Product A   194545

      Location  Recency  Frequency  MonetaryValue
   0     Tokyo      203          1         943.31
   1    London      203          1         463.70
   2  New York      203          1          80.28
   3    London      203          1         221.29
   4     Paris      203          1         739.56
```

## Calculating RFM Scores

Now let’s calculate the recency, frequency, and monetary scores:

```
# Define scoring criteria for each RFM value
recency_scores = [5, 4, 3, 2, 1]  # Higher score for lower recency (more recent)
frequency_scores = [1, 2, 3, 4, 5]  # Higher score for higher frequency
monetary_scores = [1, 2, 3, 4, 5]  # Higher score for higher monetary value

# Calculate RFM scores
data['RecencyScore'] = pd.cut(data['Recency'], bins=5, labels=recency_scores)
data['FrequencyScore'] = pd.cut(data['Frequency'], bins=5, labels=frequency_scores)
data['MonetaryScore'] = pd.cut(data['MonetaryValue'], bins=5, labels=monetary_scores)
```

We assigned scores from 5 to 1 to calculate the recency score, where a higher score indicates a more recent purchase. It means that customers who have purchased more recently will receive higher recency scores.

We assigned scores from 1 to 5 to calculate the frequency score, where a higher score indicates a higher purchase frequency. Customers who made more frequent purchases will receive higher frequency scores.

To calculate the monetary score, we assigned scores from 1 to 5, where a higher score indicates a higher amount spent by the customer.

To calculate RFM scores, we used the pd.cut() function to divide recency, frequency, and monetary values into bins. We define 5 bins for each value and assign the corresponding scores to each bin.

```
# Convert RFM scores to numeric type
data['RecencyScore'] = data['RecencyScore'].astype(int)
data['FrequencyScore'] = data['FrequencyScore'].astype(int)
data['MonetaryScore'] = data['MonetaryScore'].astype(int)
```

RFM Value Segmentation

Now let’s calculate the final RFM score and the value segment according to the scores:

```
# Calculate RFM score by combining the individual scores
data['RFM_Score'] = data['RecencyScore'] + data['FrequencyScore'] + data['MonetaryScore']

# Create RFM segments based on the RFM score
segment_labels = ['Low-Value', 'Mid-Value', 'High-Value']
data['Value Segment'] = pd.qcut(data['RFM_Score'], q=3, labels=segment_labels)
```

To calculate the RFM score, we add the scores obtained for recency, frequency and monetary value. For example, if a customer has a recency score of 3, a frequency score of 4, and a monetary score of 5, their RFM score will be 12.

After calculating the RFM scores, we created RFM segments based on the scores. We divided RFM scores into three segments, namely “Low-Value”, “Mid-Value”, and “High-Value”. Segmentation is done using the pd.qcut() function, which evenly distributes scores between segments.

Now let’s have a look at the resulting data:

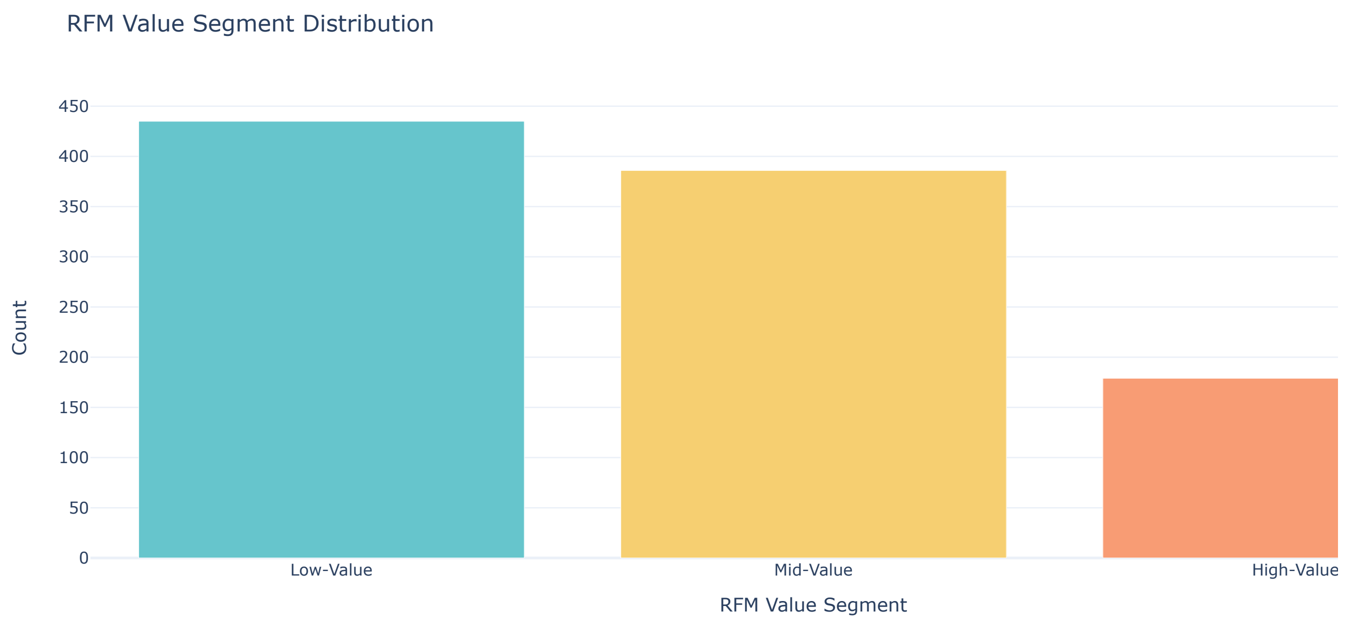
```
print(data.head())
```

```
      CustomerID PurchaseDate  TransactionAmount ProductInformation  OrderID  \
   0        8814   2023-04-11             943.31          Product C   890075
   1        2188   2023-04-11             463.70          Product A   176819
   2        4608   2023-04-11              80.28          Product A   340062
   3        2559   2023-04-11             221.29          Product A   239145
   4        9482   2023-04-11             739.56          Product A   194545

      Location  Recency  Frequency  MonetaryValue  RecencyScore  FrequencyScore  \
```

```
0      Tokyo      203          1         943.31            1               1
1     London      203          1         463.70            1               1
2   New York      203          1          80.28            1               1
3     London      203          1         221.29            1               1
4      Paris      203          1         739.56            1               1

   MonetaryScore  RFM_Score Value Segment
0              2          4     Low-Value
1              1          3     Low-Value
2              1          3     Low-Value
3              1          3     Low-Value
4              2          4     Low-Value
```

Now let's have a look at the segment distribution:

```
# RFM Segment Distribution
segment_counts = data['Value Segment'].value_counts().reset_index()
segment_counts.columns = ['Value Segment', 'Count']

pastel_colors = px.colors.qualitative.Pastel

# Create the bar chart
fig_segment_dist = px.bar(segment_counts, x='Value Segment', y='Count',
                          color='Value Segment', color_discrete_sequence=pastel_colors,
                          title='RFM Value Segment Distribution')

# Update the layout
fig_segment_dist.update_layout(xaxis_title='RFM Value Segment',
                              yaxis_title='Count',
                              showlegend=False)

# Show the figure
fig_segment_dist.show()
```




## RFM Customer Segments

The above segments that we calculated are RFM value segments. Now we'll calculate RFM customer segments. The RFM value segment represents the categorization of customers based on their RFM scores into groups such as "low value", "medium value", and "high value". These segments are determined by dividing RFM scores into distinct ranges or groups, allowing for a more granular analysis of overall customer RFM characteristics. The RFM value segment helps us understand the relative value of customers in terms of recency, frequency, and monetary aspects.

Now let's create and analyze RFM Customer Segments that are broader classifications based on the RFM scores. These segments, such as "Champions", "Potential Loyalists", and "Can't Lose" provide a more strategic perspective on customer behaviour and characteristics in terms of recency, frequency, and monetary aspects. Here's how to create the RFM customer segments:

```
# Create a new column for RFM Customer Segments
data['RFM Customer Segments'] = ''

# Assign RFM segments based on the RFM score
data.loc[data['RFM_Score'] >= 9, 'RFM Customer Segments'] = 'Champions'
data.loc[(data['RFM_Score'] >= 6) & (data['RFM_Score'] < 9), 'RFM Customer Segments'] = 'Potential Loyalists'
data.loc[(data['RFM_Score'] >= 5) & (data['RFM_Score'] < 6), 'RFM Customer Segments'] = 'At Risk Customers'
data.loc[(data['RFM_Score'] >= 4) & (data['RFM_Score'] < 5), 'RFM Customer Segments'] = "Can't Lose"
data.loc[(data['RFM_Score'] >= 3) & (data['RFM_Score'] < 4), 'RFM Customer Segments'] = "Lost"

# Print the updated data with RFM segments
print(data[['CustomerID', 'RFM Customer Segments']])
```

```
     CustomerID RFM Customer Segments
0          8814            Can't Lose
1          2188                  Lost
2          4608                  Lost
3          2559                  Lost
4          9482            Can't Lose
..          ...                   ...
995        2970   Potential Loyalists
996        6669   Potential Loyalists
997        8836   Potential Loyalists
998        1440   Potential Loyalists
999        4759   Potential Loyalists

[1000 rows x 2 columns]
```

In the above code, we are assigning RFM segments to customers based on their RFM scores and then creating a new column called “RFM Customer Segments” in the data.

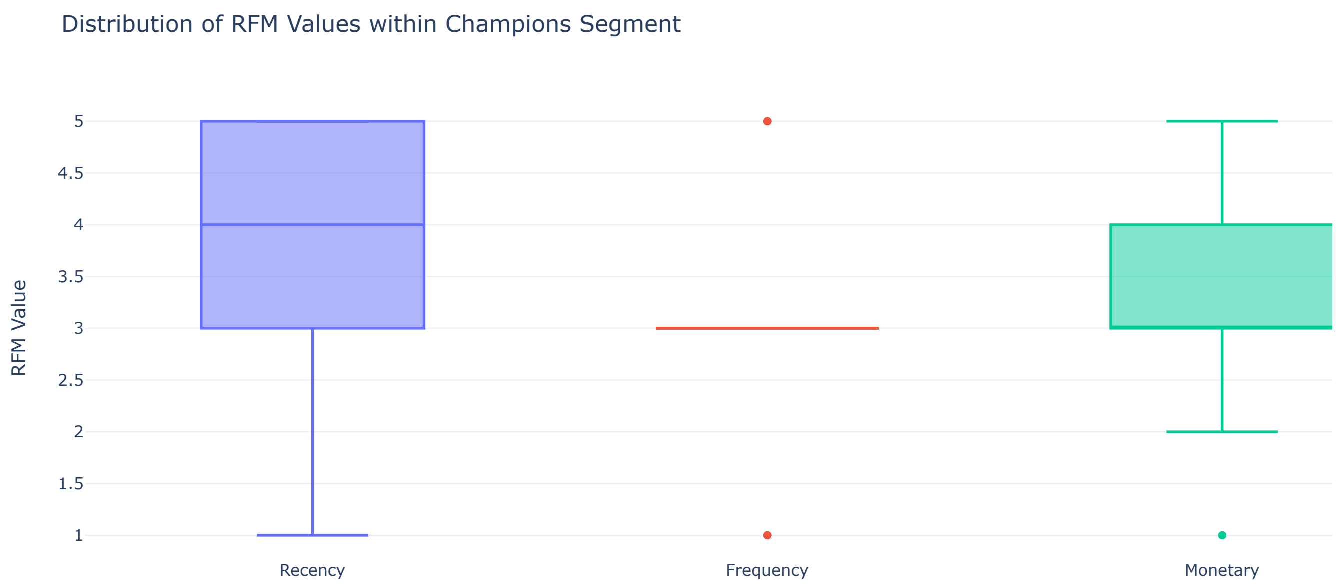
## RFM Analysis

Now let’s analyze the distribution of customers across different RFM customer segments within each value segment:

```
segment_product_counts = data.groupby(['Value Segment', 'RFM Customer Segments']).size().reset_index(name='Count')

segment_product_counts = segment_product_counts.sort_values('Count', ascending=False)

fig_treemap_segment_product = px.treemap(segment_product_counts,
                                         path=['Value Segment', 'RFM Customer Segments'],
                                         values='Count',
                                         color='Value Segment', color_discrete_sequence=px.colors.qualitative.Pastel,
                                         title='RFM Customer Segments by Value')
fig_treemap_segment_product.show()
```


Now let’s analyze the distribution of RFM values within the Champions segment:

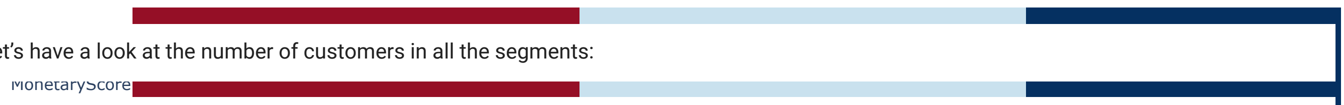
```
# Filter the data to include only the customers in the Champions segment
champions_segment = data[data['RFM Customer Segments'] == 'Champions']

fig = go.Figure()
fig.add_trace(go.Box(y=champions_segment['RecencyScore'], name='Recency'))
fig.add_trace(go.Box(y=champions_segment['FrequencyScore'], name='Frequency'))
fig.add_trace(go.Box(y=champions_segment['MonetaryScore'], name='Monetary'))

fig.update_layout(title='Distribution of RFM Values within Champions Segment',
                  yaxis_title='RFM Value',
                  showlegend=True)

fig.show()
```




Now let's analyze the correlation of the recency, frequency, and monetary scores within the champions segment:

```
correlation_matrix = champions_segment[['RecencyScore', 'FrequencyScore', 'MonetaryScore']].corr()

# Visualize the correlation matrix using a heatmap
fig_heatmap = go.Figure(data=go.Heatmap(
                   z=correlation_matrix.values,
                   x=correlation_matrix.columns,
                   y=correlation_matrix.columns,
                   colorscale='RdBu',
                   colorbar=dict(title='Correlation')))

fig_heatmap.update_layout(title='Correlation Matrix of RFM Values within Champions Segment')

fig_heatmap.show()
```

Correlation Matrix of RFM Values within Champions Segment




Now let’s have a look at the number of customers in all the segments:

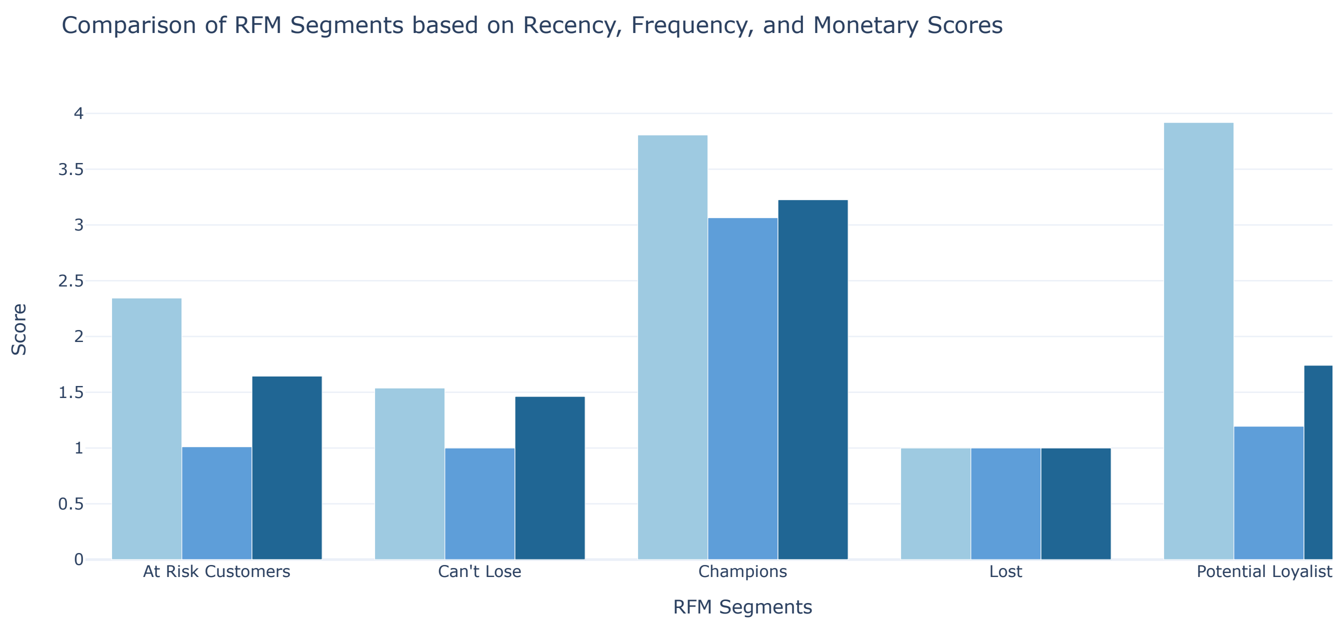
```
import plotly.colors

pastel_colors = plotly.colors.qualitative.Pastel

segment_counts = data['RFM Customer Segments'].value_counts()

# Create a bar chart to compare segment counts
fig = go.Figure(data=[go.Bar(x=segment_counts.index, y=segment_counts.values,
                            marker=dict(color=pastel_colors))])

# Set the color of the Champions segment as a different color
champions_color = 'rgb(158, 202, 225)'
fig.update_traces(marker_color=[champions_color if segment == 'Champions' else pastel_colors[i]
                                for i, segment in enumerate(segment_counts.index)],
                  marker_line_color='rgb(8, 48, 107)',
                  marker_line_width=1.5, opacity=0.6)

# Update the layout
fig.update_layout(title='Comparison of RFM Segments',
                  xaxis_title='RFM Segments',
                  yaxis_title='Number of Customers',
                  showlegend=False)

fig.show()
```


Now let’s have a look at the recency, frequency, and monetary scores of all the segments:

```
# Calculate the average Recency, Frequency, and Monetary scores for each segment
segment_scores = data.groupby('RFM Customer Segments')['RecencyScore', 'FrequencyScore', 'MonetaryScore'].mean().reset_index()

# Create a grouped bar chart to compare segment scores
fig = go.Figure()

# Add bars for Recency score
fig.add_trace(go.Bar(
    x=segment_scores['RFM Customer Segments'],
    y=segment_scores['RecencyScore'],
    name='Recency Score',
    marker_color='rgb(158,202,225)'
))

# Add bars for Frequency score
```

```
fig.add_trace(go.Bar(
    x=segment_scores['RFM Customer Segments'],
    y=segment_scores['FrequencyScore'],
    name='Frequency Score',
    marker_color='rgb(94,158,217)'
))

# Add bars for Monetary score
fig.add_trace(go.Bar(
    x=segment_scores['RFM Customer Segments'],
    y=segment_scores['MonetaryScore'],
    name='Monetary Score',
    marker_color='rgb(32,102,148)'
))

# Update the layout
fig.update_layout(
    title='Comparison of RFM Segments based on Recency, Frequency, and Monetary Scores',
    xaxis_title='RFM Segments',
    yaxis_title='Score',
    barmode='group',
    showlegend=True
)

fig.show()
```

```
<ipython-input-14-cb2923398eb1>:2: FutureWarning:

Indexing with multiple keys (implicitly converted to a tuple of keys) will be deprecated, use a list instead.
```




## Summary

RFM Analysis is used to understand and segment customers based on their buying behaviour. RFM stands for recency, frequency, and monetary value, which are three key metrics that provide information about customer engagement, loyalty, and value to a business.