RFM Analysis

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.

In [1]:
```
#Lets start the task of RFM Analysis by importing the necessary Python libraries
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("rfm_data.csv")
print(data.head())
```

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

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

Calculating RFM Values

In [2]:
```
from datetime import datetime
import pandas as pd

# Convert 'PurchaseDate' to datetime
data['PurchaseDate'] = pd.to_datetime(data['PurchaseDate'], format="%d-%m-%Y", e

# Check data type of 'PurchaseDate' column
if data['PurchaseDate'].dtype == 'datetime64[ns]':
    # Calculate Recency
    data['Recency'] = (datetime.now().date() - pd.DatetimeIndex(data['PurchaseDa
else:
    print("The 'PurchaseDate' column is not in the expected datetime format.")

# 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_inde
```

```
monetary_data.rename(columns={'TransactionAmount': 'MonetaryValue'}, inplace=Tru
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.

In [3]:
```
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 90 days 00:00:00          1         943.31  
1    London 90 days 00:00:00          1         463.70  
2  New York 90 days 00:00:00          1          80.28  
3    London 90 days 00:00:00          1         221.29  
4     Paris 90 days 00:00:00          1         739.56  
```

Calculating RFM Scores

In [4]:
```
#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_scor
data['MonetaryScore'] = pd.cut(data['MonetaryValue'], bins=5, labels=monetary_sc
```

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.

In [5]:
```
# 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

In [6]:
```
 #let’s calculate the final RFM score and the value segment according to the sco
    # Calculate RFM score by combining the individual scores
data['RFM_Score'] = data['RecencyScore'] + data['FrequencyScore'] + data['Moneta

# 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.

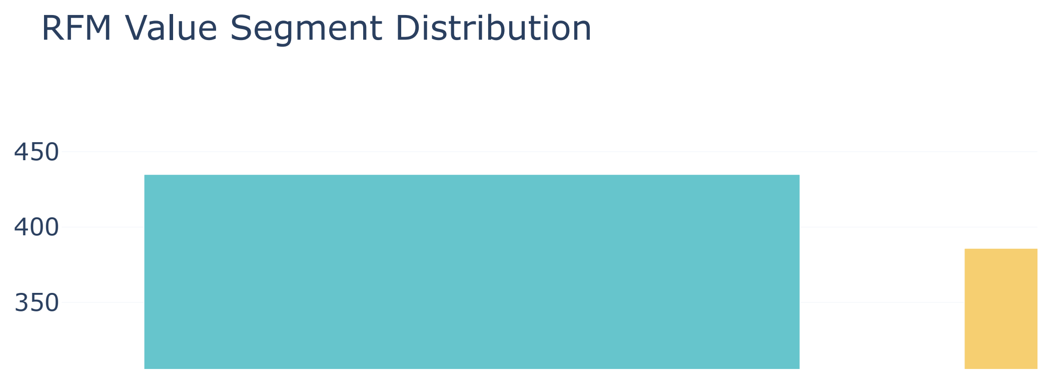
After calculating the RFM scores, we created RFM segments based on the scores. We divided RFM scores into three segments, namely “Low-Value”, “Mid-Value”, and “High-Value”. Segmentation is done using the pd.qcut() function, which evenly distributes scores between segments.

In [7]:
```
#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  \
0     Tokyo 90 days 00:00:00          1         943.31             1   
1    London 90 days 00:00:00          1         463.70             1   
2  New York 90 days 00:00:00          1          80.28             1   
3    London 90 days 00:00:00          1         221.29             1   
4     Paris 90 days 00:00:00          1         739.56             1   

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

In [8]:
```
#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_
```

```
                            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

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.

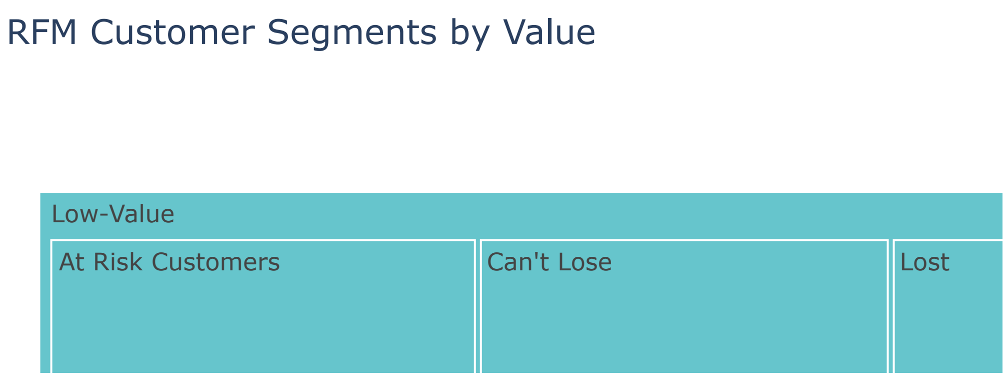
Now let's create and analyze RFM Customer Segments that are broader classifications based on the RFM scores. These segments, such as “Champions”, “Potential Loyalists”, and “Can't Lose” provide a more strategic perspective on customer behaviour and characteristics in terms of recency, frequency, and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

In [9]:
```
#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 Segme
data.loc[(data['RFM_Score'] >= 5) & (data['RFM_Score'] < 6), 'RFM Customer Segme
data.loc[(data['RFM_Score'] >= 4) & (data['RFM_Score'] < 5), 'RFM Customer Segme
data.loc[(data['RFM_Score'] >= 3) & (data['RFM_Score'] < 4), 'RFM Customer Segme

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

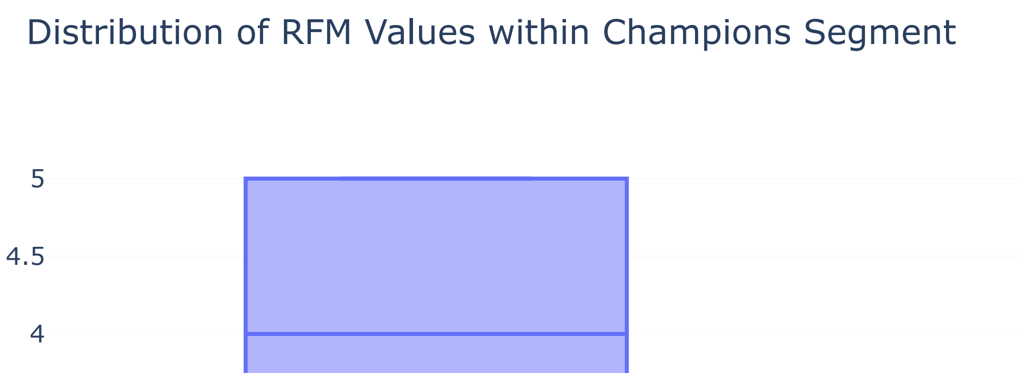
```
     CustomerID RFM Customer Segments
0          8814            Can't Lose
1          2188                  Lost
2          4608                  Lost
3          2559                  Lost
4          9482            Can't Lose
..          ...                   ...
995        2970   Potential Loyalists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

[1000 rows x 2 columns]
```

RFM Analysis

In [10]:
```
# let’s analyze the distribution of customers across different RFM customer segm
segment_product_counts = data.groupby(['Value Segment', 'RFM Customer Segments']

segment_product_counts = segment_product_counts.sort_values('Count', ascending=F

fig_treemap_segment_product = px.treemap(segment_product_counts,
                                         path=['Value Segment', 'RFM Customer Se
                                         values='Count',
                                         color='Value Segment', color_discrete_s
                                         title='RFM Customer Segments by Value')
fig_treemap_segment_product.show()
```

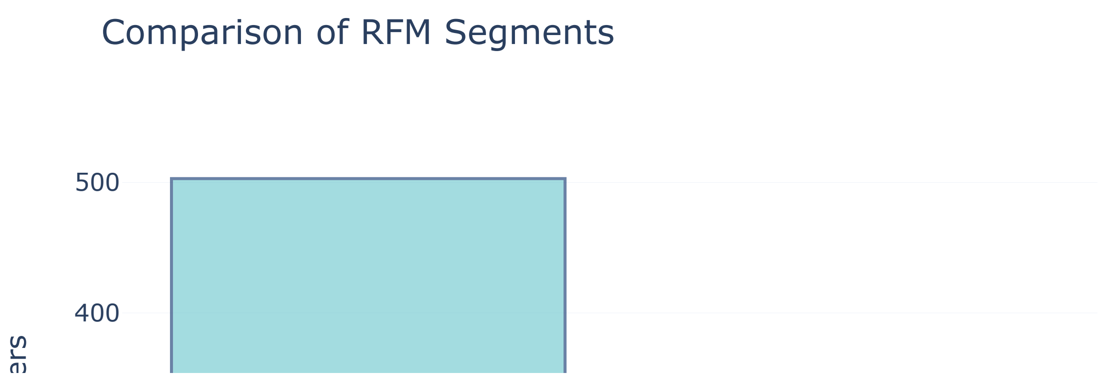


```
In [11]: #let’s analyze the distribution of RFM values within the Champions segment:
         # Filter the data to include only the customers in the Champions segment
         champions_segment = data[data['RFM Customer Segments'] == 'Champions']

         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()
```



In [12]:
```python
#let’s analyze the correlation of the recency, frequency, and monetary scores wi
correlation_matrix = champions_segment[['RecencyScore', 'FrequencyScore', 'Monet

# 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 Champic

fig_heatmap.show()
```

```
In [13]: #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 p
                                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()
```



```
In [14]: #Let’s have a look at the recency, frequency, and monetary scores of all the seg
# Calculate the average Recency, Frequency, and Monetary scores for each segment
segment_scores = data.groupby('RFM Customer Segments')[['RecencyScore', 'Frequer
# 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
    xaxis_title='RFM Segments',
    yaxis_title='Score',
    barmode='group',
    showlegend=True
)

fig.show()
```