Credit Scoring and Segmentation with Python

Credit scoring and segmentation are pivotal processes in evaluating the creditworthiness of individuals or businesses, vital for informed decision-making in financial institutions. This article delves into the intricacies of these processes, offering a step-by-step guide using Python.

Understanding Credit Scoring and Segmentation: At its core, credit scoring and segmentation involve assessing borrowers' credit profiles to determine their likelihood of repaying debts. This begins with gathering pertinent data such as payment history, credit utilization, and credit mix. Sophisticated algorithms then analyze this data to generate numerical credit scores, reflecting borrowers' creditworthiness.

The Importance of Segmentation: Segmenting customers based on their credit scores is crucial for effective risk management. By categorizing customers into different risk tiers, financial institutions can tailor loan approvals, interest rates, and credit limits accordingly. This strategic segmentation optimizes lending portfolios and minimizes the risk of defaults.

Steps to Credit Scoring and Segmentation: To further elaborate on the steps outlined in the article, we can provide additional details and context for each stage of the credit scoring and segmentation process.

1. **Data Collection and Organization:**
    - Emphasize the importance of collecting comprehensive and accurate data to ensure the reliability of credit assessments.
    - Discuss various sources of data, including credit reports, financial statements, and transaction history, highlighting the need for data privacy and compliance with regulatory standards.
    - Mention data preprocessing techniques such as data cleaning, normalization, and feature engineering to prepare the dataset for analysis.
2. **Algorithmic Analysis:**
    - Explore different types of algorithms commonly used in credit scoring, such as logistic regression, decision trees, and ensemble methods like random forests and gradient boosting.
    - Explain the concept of model training and validation, including techniques like cross-validation and hyperparameter tuning to optimize model performance.
    - Address challenges such as class imbalance and overfitting, and discuss strategies to mitigate these issues in credit scoring models.
3. **Segmentation:**
    - Introduce the concept of segmentation thresholds and discuss various approaches for determining optimal cutoff points, such as ROC analysis and business rule optimization.
    - Highlight the importance of interpretability and explainability in segmentation models, especially in regulated industries where transparency is essential.
    - Discuss advanced segmentation techniques, including clustering algorithms like K-means and hierarchical clustering, for identifying nuanced patterns in credit profiles.

Additionally, we can provide practical examples and case studies to illustrate how credit scoring and segmentation techniques are applied in real-world scenarios. This could involve analyzing sample datasets, discussing industry best practices, and showcasing successful implementations of credit risk management strategies.

On each step of the credit scoring and segmentation process, readers can gain a deeper understanding of the methodologies and considerations involved in assessing creditworthiness

and managing credit risk effectively.

In [1]:
```
import pandas as pd
import plotly.graph_objects as go
import plotly.express as px
import plotly.io as pio
pio.templates.default = "plotly_white"

data = pd.read_csv("C:/Users/anike/OneDrive/Desktop/Projects/Machine Learning/Credit S
print(data.head())
```

```
   Age  Gender Marital Status Education Level Employment Status  \
0   60    Male        Married          Master          Employed
1   25    Male        Married     High School        Unemployed
2   30  Female         Single          Master          Employed
3   58  Female        Married             PhD        Unemployed
4   32    Male        Married        Bachelor     Self-Employed

   Credit Utilization Ratio  Payment History  Number of Credit Accounts  \
0                      0.22           2685.0                          2
1                      0.20           2371.0                          9
2                      0.22           2771.0                          6
3                      0.12           1371.0                          2
4                      0.99            828.0                          2

   Loan Amount  Interest Rate  Loan Term   Type of Loan
0      4675000           2.65         48  Personal Loan
1      3619000           5.19         60      Auto Loan
2       957000           2.76         12      Auto Loan
3      4731000           6.57         60      Auto Loan
4      3289000           6.28         36  Personal Loan
```

Key Features in Credit Scoring Data

In the realm of credit scoring, each feature within the dataset holds significance, reflecting various aspects of an individual's financial profile. Here's an in-depth exploration of the key features:

1. **Age: Unveiling Financial Maturity**
   - Insight: Analyzing age provides insights into financial habits, stability, and earning potential, vital for assessing creditworthiness.
2. **Gender: Navigating Ethical Considerations**
   - Insight: While gender is included, ethical dilemmas emerge when considering its use, highlighting the need for fair and unbiased credit evaluation practices.
3. **Marital Status: Reflecting Financial Commitments**
   - Insight: Marital status offers clues to shared financial obligations and stability, influencing credit risk assessments.
4. **Education Level: Assessing Financial Literacy**
   - Insight: Higher education levels often correlate with better financial understanding and earning potential, shaping creditworthiness.
5. **Employment Status: Indicator of Repayment Capacity**
   - Insight: Employment status plays a pivotal role in evaluating an individual's ability to meet financial obligations, affecting credit risk assessments.
6. **Credit Utilization Ratio: Balancing Credit Management**
   - Insight: The ratio of credit used to available credit reflects financial discipline and influences credit scores.
7. **Payment History: Foundation of Creditworthiness**
   - Insight: Timely payments establish reliability, while late payments or defaults signal risk, shaping credit scores significantly.
8. **Number of Credit Accounts: Gauge of Credit Behavior**

- Insight: The count of active credit accounts provides insights into credit behavior and management, impacting creditworthiness.

9. **Loan Amount: Quantifying Financial Obligations**
    - Insight: The monetary value of loans indicates the level of financial obligations and repayment capacity.
10. **Interest Rate: Impact on Borrowing Costs**
    - Insight: Interest rates directly affect borrowing costs, influencing affordability and financial strain.
11. **Loan Term: Duration of Financial Commitment**
    - Insight: The duration of loans affects repayment schedules and overall financial commitments, guiding credit risk assessments.
12. **Type of Loan: Diverse Borrowing Purposes**
    - Insight: Loan types, such as personal or auto loans, offer insights into borrowing purposes and associated risk profiles.

Understanding the nuances of these features is essential for crafting robust credit scoring models and making informed lending decisions, ensuring fair and transparent practices in the financial landscape.

In [2]:
```
print(data.describe())
print(data.head())
```

```
               Age  Credit Utilization Ratio  Payment History  \
count  1000.000000               1000.000000      1000.000000
mean     42.702000                  0.509950      1452.814000
std      13.266771                  0.291057       827.934146
min      20.000000                  0.000000         0.000000
25%      31.000000                  0.250000       763.750000
50%      42.000000                  0.530000      1428.000000
75%      54.000000                  0.750000      2142.000000
max      65.000000                  1.000000      2857.000000

       Number of Credit Accounts   Loan Amount  Interest Rate    Loan Term
count                1000.000000  1.000000e+03    1000.000000  1000.000000
mean                    5.580000  2.471401e+06      10.686600    37.128000
std                     2.933634  1.387047e+06       5.479058    17.436274
min                     1.000000  1.080000e+05       1.010000    12.000000
25%                     3.000000  1.298000e+06       6.022500    24.000000
50%                     6.000000  2.437500e+06      10.705000    36.000000
75%                     8.000000  3.653250e+06      15.440000    48.000000
max                    10.000000  4.996000e+06      19.990000    60.000000
   Age  Gender Marital Status Education Level Employment Status  \
0   60    Male        Married          Master          Employed
1   25    Male        Married     High School        Unemployed
2   30  Female         Single          Master          Employed
3   58  Female        Married             PhD        Unemployed
4   32    Male        Married        Bachelor     Self-Employed

   Credit Utilization Ratio  Payment History  Number of Credit Accounts  \
0                      0.22           2685.0                          2
1                      0.20           2371.0                          9
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3                      0.12           1371.0                          2
4                      0.99            828.0                          2

   Loan Amount  Interest Rate  Loan Term   Type of Loan
0      4675000           2.65         48  Personal Loan
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2       957000           2.76         12      Auto Loan
3      4731000           6.57         60      Auto Loan
4      3289000           6.28         36  Personal Loan
```
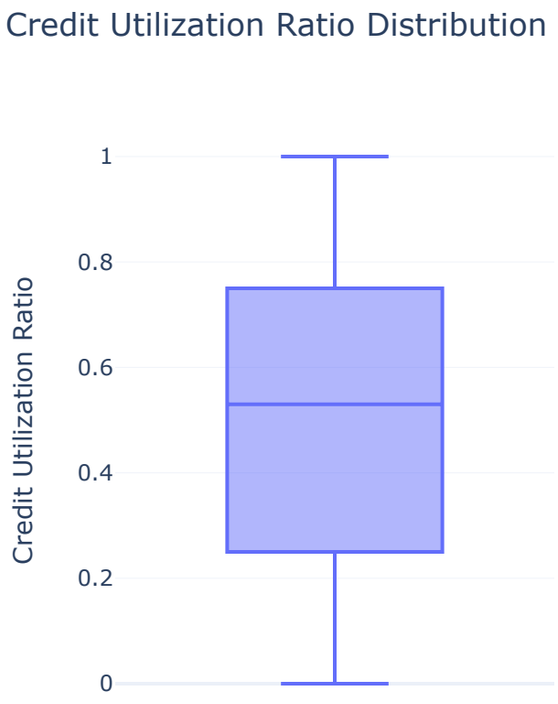

Distribution of the credit utilization ratio in the data

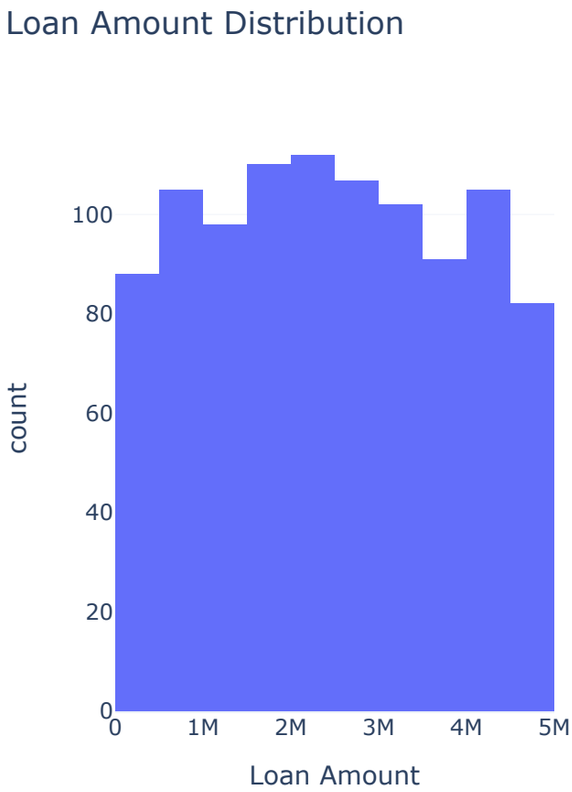
In [3]:
```
credit_utilization_fig = px.box(data, y='Credit Utilization Ratio',
                                title='Credit Utilization Ratio Distribution',
                                height = 500,
```

```
                                width = 400)
credit_utilization_fig.show()
```



Distribution of the loan amount in the data

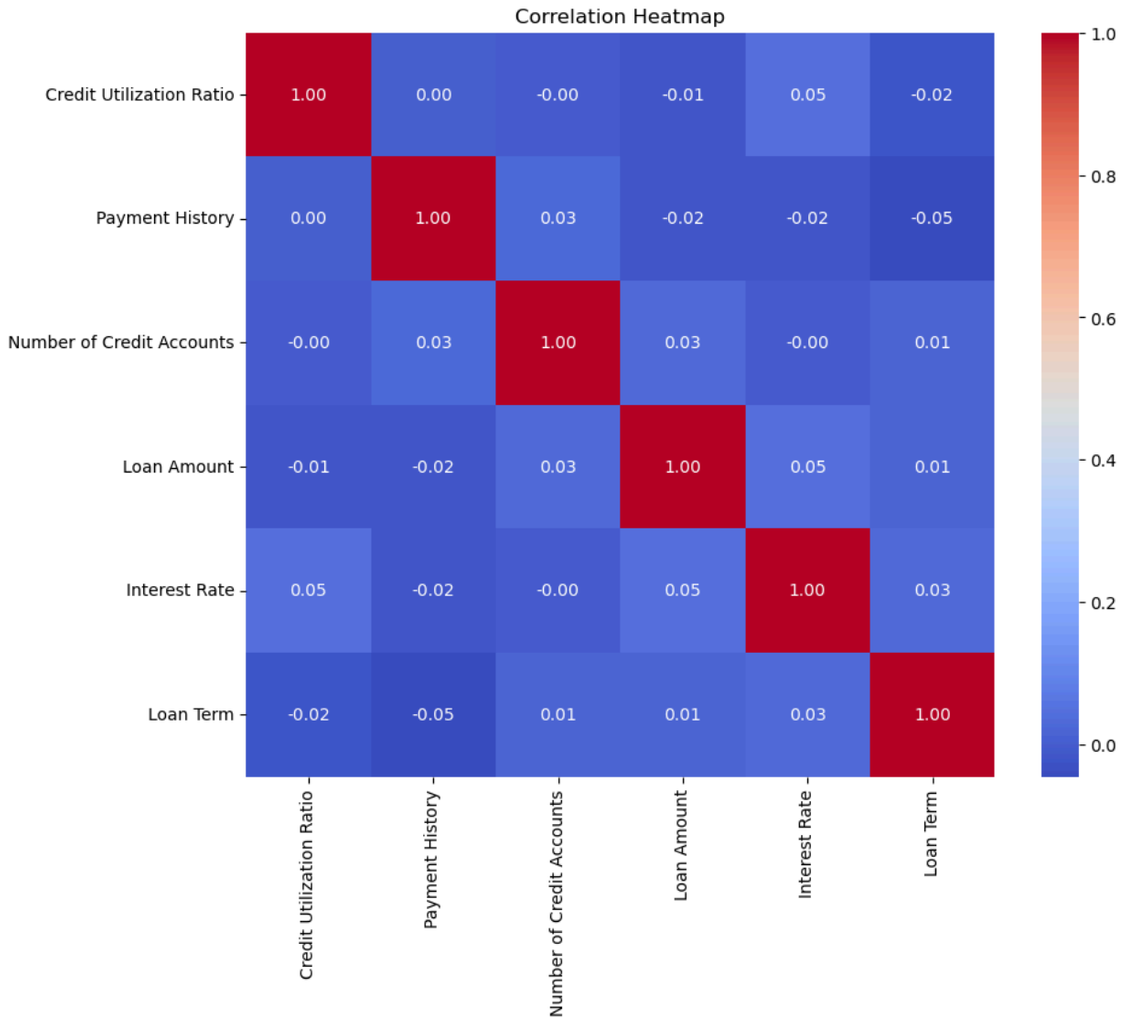
In [4]:
```
loan_amount_fig = px.histogram(data, x='Loan Amount',
                               nbins=20,
                               title='Loan Amount Distribution',
                               height = 500,
                               width = 400)
loan_amount_fig.show()
```



The correlation matrix

Visualizing the correlation matrix using a heatmap makes it easier to interpret the results. In the heatmap, each cell is color-coded based on the correlation coefficient, with warmer colors (e.g., red) indicating positive correlation and cooler colors (e.g., blue) indicating negative correlation. Annotations within the heatmap display the correlation coefficients for better interpretation. This visualization helps identify patterns and relationships between features in the dataset, guiding further analysis and modeling decisions.

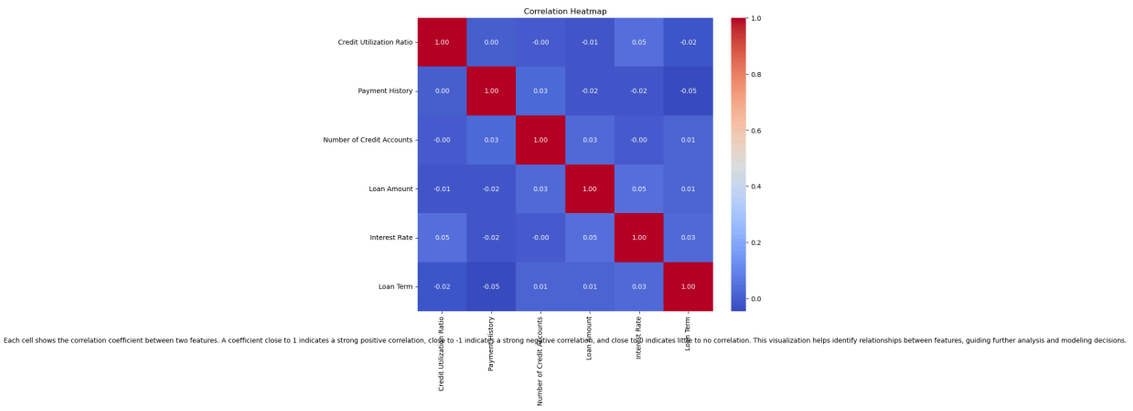
In [5]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select numeric columns for correlation analysis
numeric_df = data[['Credit Utilization Ratio', 'Payment History', 'Number of Credit Ac
                   'Loan Amount', 'Interest Rate', 'Loan Term']]

# Compute the correlation matrix
correlation_matrix = numeric_df.corr()

# Create a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



An enhanced version of the code above.

In this version, I've added a text annotation at the bottom of the plot to provide an explanation of the correlation heatmap. This explanation helps interpret the heatmap by describing the meaning of correlation coefficients and how they influence the relationships between features. This additional information enhances the understanding of the visualization and its implications for analyzing the dataset. Adjust the position and formatting of the text according to your preference.

In [6]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select numeric columns for correlation analysis
numeric_df = data[['Credit Utilization Ratio', 'Payment History', 'Number of Credit Ac
                   'Loan Amount', 'Interest Rate', 'Loan Term']]

# Compute the correlation matrix
correlation_matrix = numeric_df.corr()

# Create a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')

# Add explanation
plt.text(0.5, -0.1, "Each cell shows the correlation coefficient between two features.
A coefficient close to 1 indicates a strong positive correlation, close to -1 indicate
strong negative correlation, and close to 0 indicates little to no correlation. \
This visualization helps identify relationships between features, guiding further anal
         horizontalalignment='center', verticalalignment='center', transform=plt.gca()

plt.show()
```



Implementing the FICO Credit Scoring Model

In the absence of credit scores within the dataset, it becomes imperative to employ established methodologies for credit assessment. The FICO scoring model stands as a prominent choice, widely embraced within the industry for its robustness and reliability.

Understanding FICO Credit Scoring: The FICO scoring model encompasses a systematic approach to evaluating creditworthiness, leveraging a series of variables and calculations. By comprehending its methodology, one can effectively implement this model to derive credit scores for individuals.

Key Steps in FICO Credit Scoring:

1. **Variable Selection**:
   - Identify essential variables crucial for credit assessment, including payment history, credit utilization, and length of credit history.
2. **Weight Assignment**:
   - Assign appropriate weights to each variable, reflecting their significance in predicting credit risk.
3. **Normalization of Values**:
   - Normalize variable values to ensure standardized comparison across different metrics, facilitating accurate assessment.
4. **Component Score Calculation**:
   - Compute component scores for each variable by applying assigned weights to normalized values.
5. **Aggregation of Scores**:

- Summate component scores to derive the total credit score, providing a comprehensive evaluation of creditworthiness.

6. **Adjustments for Specific Factors**:
   - Make necessary adjustments to the total score to accommodate specific circumstances or behaviors impacting credit risk.
7. **Establishment of Score Ranges**:
   - Define distinct score ranges to categorize individuals into various risk categories, aiding in decision-making processes.
8. **Testing and Validation**:
   - Validate the scoring model's efficacy through rigorous testing and analysis, ensuring reliability and predictive accuracy.

Implementation of FICO Scoring Model: Utilizing the outlined steps, one can effectively implement the FICO scoring model to calculate credit scores, thereby facilitating informed decision-making within the financial domain.

By elucidating the intricacies of the FICO credit scoring model, this guide empowers individuals to navigate the credit assessment process with confidence and precision.

In [7]:
```
# Define the mapping for categorical features
education_level_mapping = {'High School': 1, 'Bachelor': 2, 'Master': 3, 'PhD': 4}
employment_status_mapping = {'Unemployed': 0, 'Employed': 1, 'Self-Employed': 2}

# Apply mapping to categorical features
data['Education Level'] = data['Education Level'].map(education_level_mapping)
data['Employment Status'] = data['Employment Status'].map(employment_status_mapping)

# Calculate credit scores using the complete FICO formula
credit_scores = []

for index, row in data.iterrows():
    payment_history = row['Payment History']
    credit_utilization_ratio = row['Credit Utilization Ratio']
    number_of_credit_accounts = row['Number of Credit Accounts']
    education_level = row['Education Level']
    employment_status = row['Employment Status']

    # Apply the FICO formula to calculate the credit score
    credit_score = (payment_history * 0.35) + (credit_utilization_ratio * 0.30) + (num
    credit_scores.append(credit_score)

# Add the credit scores as a new column to the DataFrame
data['Credit Score'] = credit_scores

print(data.head())
```

```
   Age  Gender Marital Status  Education Level  Employment Status  \
0   60    Male        Married                3                  1
1   25    Male        Married                1                  0
2   30  Female         Single                3                  1
3   58  Female        Married                4                  0
4   32    Male        Married                2                  2

   Credit Utilization Ratio  Payment History  Number of Credit Accounts  \
0                      0.22           2685.0                          2
1                      0.20           2371.0                          9
2                      0.22           2771.0                          6
3                      0.12           1371.0                          2
4                      0.99            828.0                          2

   Loan Amount  Interest Rate  Loan Term   Type of Loan  Credit Score
0      4675000           2.65         48  Personal Loan       940.516
1      3619000           5.19         60      Auto Loan       831.360
2       957000           2.76         12      Auto Loan       971.216
3      4731000           6.57         60      Auto Loan       480.586
4      3289000           6.28         36  Personal Loan       290.797
```

Below is a breakdown of how the code functions:

1. **Mapping Categorical Features**: Initially, the code defines mappings for two categorical features: "Education Level" and "Employment Status". These mappings assign numerical values to different categories within each feature. For instance, "High School" is mapped to 1, "Bachelor" to 2, "Master" to 3, and "PhD" to 4 for the "Education Level" feature. Similarly, "Unemployed" is mapped to 0, "Employed" to 1, and "Self-Employed" to 2 for the "Employment Status" feature.

2. **Applying Mappings**: The code then applies these mappings to the corresponding columns in the DataFrame. This transformation converts the categorical values of "Education Level" and "Employment Status" into their respective numerical representations.

3. **Iterating Through Rows**: Next, the code iterates over each row of the DataFrame to calculate the credit scores for each individual. It retrieves the values of relevant features such as **"Payment History"**, **"Credit Utilization Ratio"**, **"Number of Credit Accounts"**, **"Education Level"**, and **"Employment Status"** from each row.

4. **Calculating Credit Scores**: Within the iteration, the FICO formula is applied to compute the credit score for each individual. This formula incorporates weighted values assigned to the aforementioned features: **35% weight for "Payment History"**, **30% weight for "Credit Utilization Ratio"**, **15% weight for "Number of Credit Accounts"**, **10% weight for "Education Level"**, and **10% weight for "Employment Status"**. The calculated credit score is then stored in a list named "credit_scores".

By executing these steps, the code systematically calculates credit scores for individuals based on their respective financial and demographic attributes.

Segmenting Customers with KMeans Clustering.

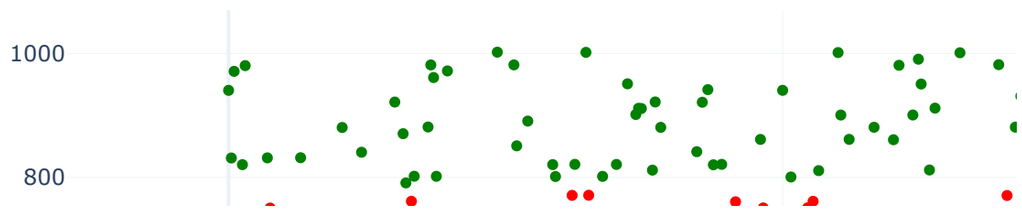
1. **Data Preparation**: Ensure credit scores are included or calculated.
2. **Feature Selection**: Choose relevant attributes for segmentation.
3. **Normalization**: Scale features for clustering.
4. **KMeans Clustering**: Apply KMeans algorithm.
5. **Model Training**: Train KMeans on data.
6. **Cluster Assignment**: Assign customers to clusters.
7. **Interpretation**: Analyze cluster characteristics.
8. **Visualization**: Visualize clusters for insights.
9. **Evaluation**: Assess segmentation quality.
10. **Application**: Tailor strategies to customer segments.

In [8]:
```
from sklearn.cluster import KMeans

X = data[['Credit Score']]
kmeans = KMeans(n_clusters=4, n_init=10, random_state=42)
kmeans.fit(X)
data['Segment'] = kmeans.labels_
```

```
C:\Users\anike\anaconda3\ana\lib\site-packages\sklearn\cluster\_kmeans.py:1436: UserW
arning:

KMeans is known to have a memory leak on Windows with MKL, when there are less chunks
than available threads. You can avoid it by setting the environment variable OMP_NUM_
THREADS=4.
```

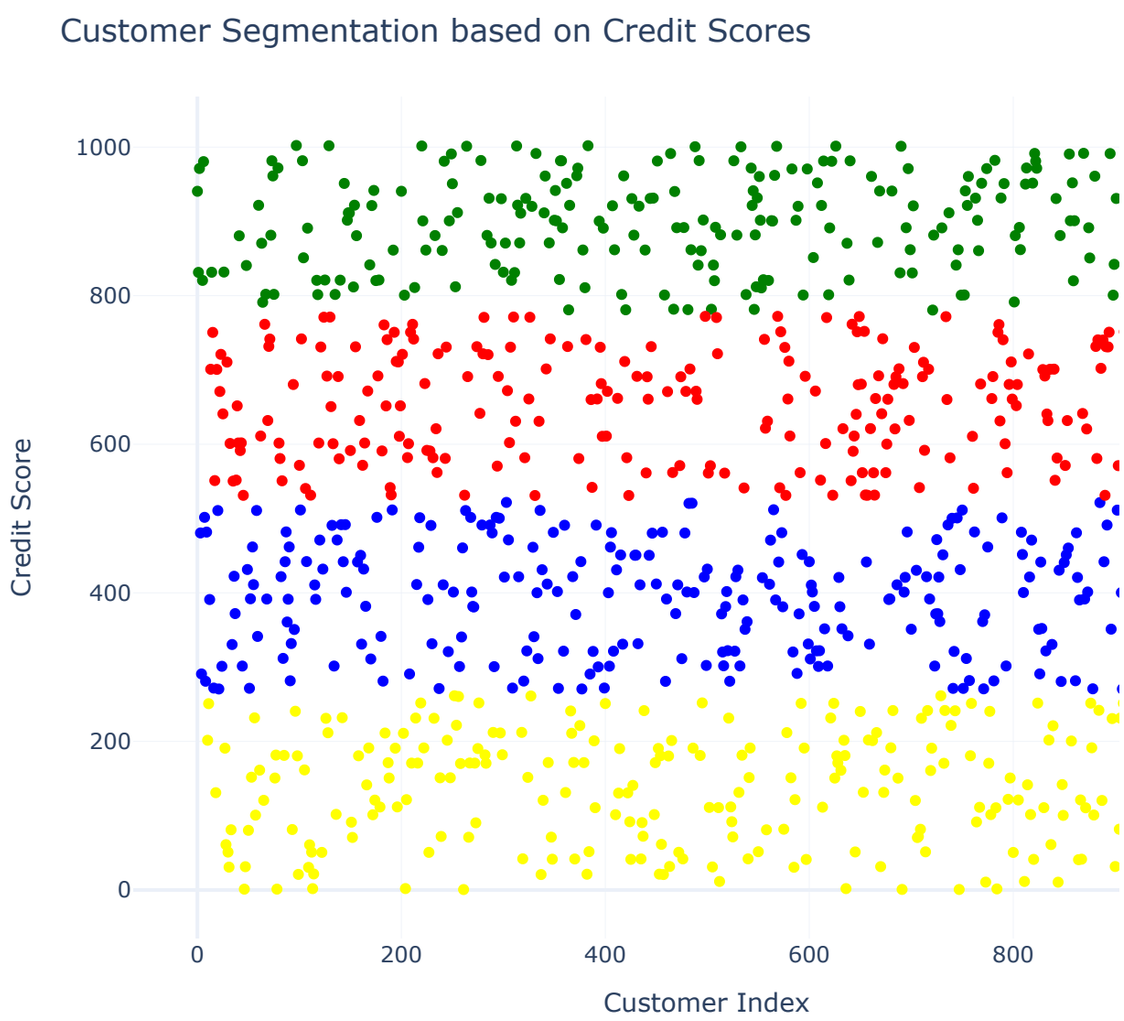
In [9]:
```
# Convert the 'Segment' column to category data type
data['Segment'] = data['Segment'].astype('category')

# Visualize the segments using Plotly
fig = px.scatter(data, x=data.index, y='Credit Score', color='Segment',
                 color_discrete_sequence=['green', 'blue', 'yellow', 'red'])
fig.update_layout(
    xaxis_title='Customer Index',
    yaxis_title='Credit Score',
    title='Customer Segmentation based on Credit Scores'
```

```
)
fig.show()
```

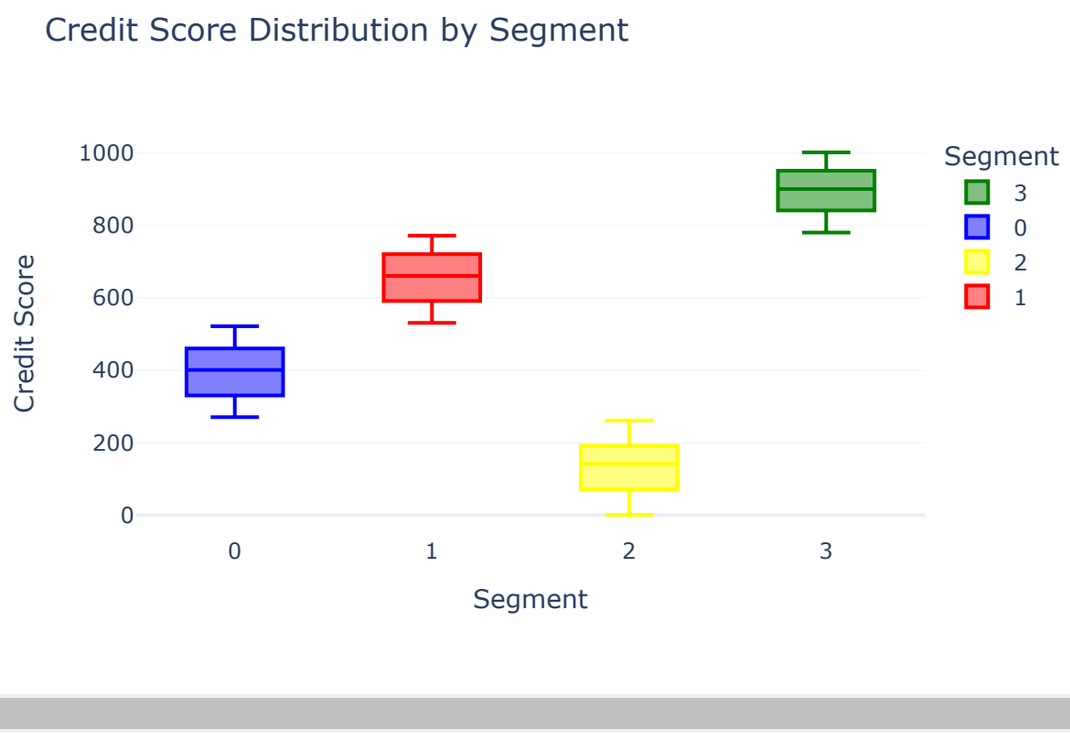


In [10]:

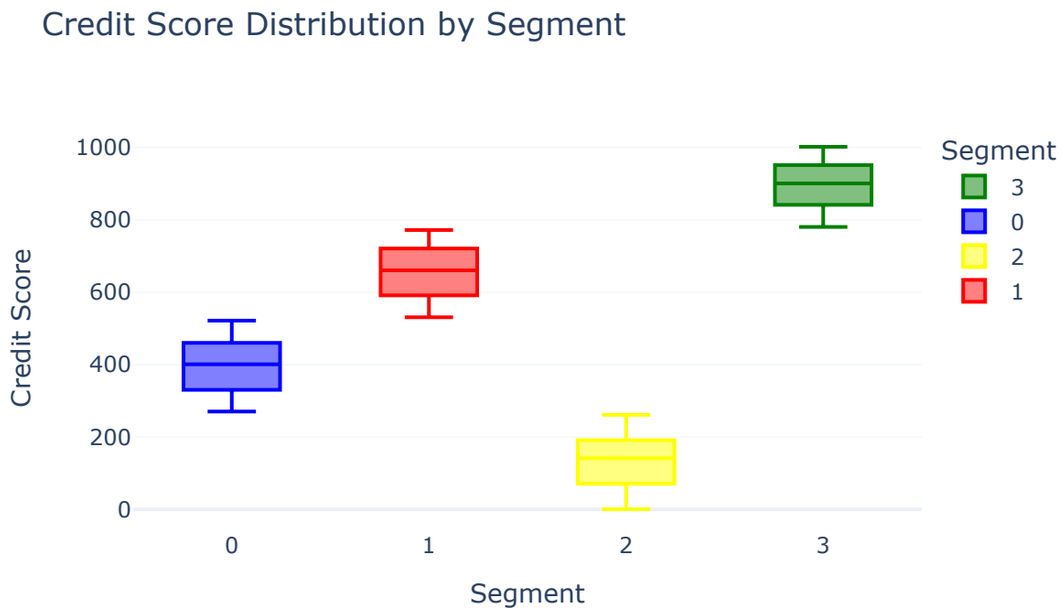
```
# Convert the 'Segment' column to category data type
data['Segment'] = data['Segment'].astype('category')

# Visualize the segments using Plotly Scatter Plot
import plotly.express as px

# Plot 1: Scatter plot of Credit Scores by Segment
fig1 = px.scatter(data, x=data.index, y='Credit Score', color='Segment',
                  color_discrete_sequence=['green', 'blue', 'yellow', 'red'])
fig1.update_layout(
    xaxis_title='Customer Index',
    yaxis_title='Credit Score',
    title='Customer Segmentation based on Credit Scores',
    width=800,  # Medium size
    height=600  # Medium size
)
fig1.show()
```



In [11]:
```
# Plot 2: Box plot of Credit Scores by Segment
fig2 = px.box(data, x='Segment', y='Credit Score', color='Segment',
              color_discrete_sequence=['green', 'blue', 'yellow', 'red'],
              title='Credit Score Distribution by Segment')
fig2.update_layout(
    xaxis_title='Segment',
    yaxis_title='Credit Score',
    width=600,  # Medium size
    height=400  # Medium size
)
fig2.show()
```



In [12]:
```
# Plot 2: Box plot of Credit Scores by Segment
fig2 = px.box(data, x='Segment', y='Credit Score', color='Segment',
              color_discrete_sequence=['green', 'blue', 'yellow', 'red'],
              title='Credit Score Distribution by Segment')
fig2.update_layout(
    xaxis_title='Segment',
    yaxis_title='Credit Score',
    width=600,  # Medium size
    height=400  # Medium size
)
fig2.show()
```



We initiate by converting the **'Segment'** column to a categorical data type using the **astype()** method. This ensures efficient storage and computation for **categorical** data.

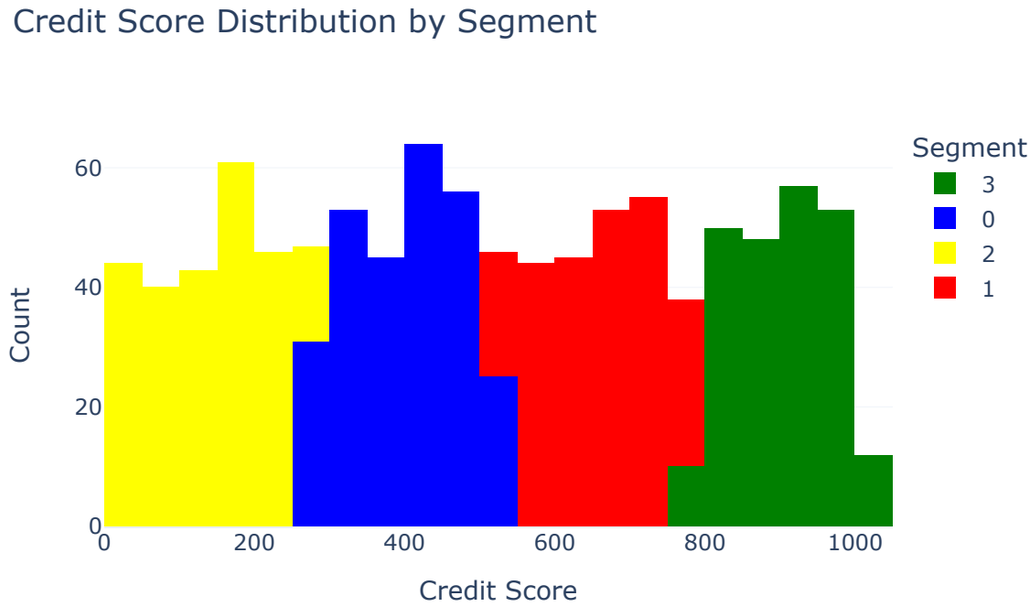
Visualization 1 (Scatter Plot): Utilizing Plotly Express, we craft a scatter plot revealing the **distribution** of **credit scores** among different **customer segments**. Each data point represents a customer, colored according to their **segment**.

Visualization 2 (Box Plot): Employing a **box plot**, we provide a succinct summary of the **credit score distribution** for each **segment**. This visualization aids in understanding the **central tendency** and **spread** of credit scores within each segment.

Visualization 3 (Bar Plot): Lastly, we depict the **distribution** of **segments** using a **bar plot**. This visualization showcases the **count** of **customers** in each **segment**, offering insight into the size of each segment relative to others.

These visualizations offer a comprehensive understanding of **customer segmentation** based on **credit scores**, facilitating **strategic decision-making** and **targeted marketing efforts**.

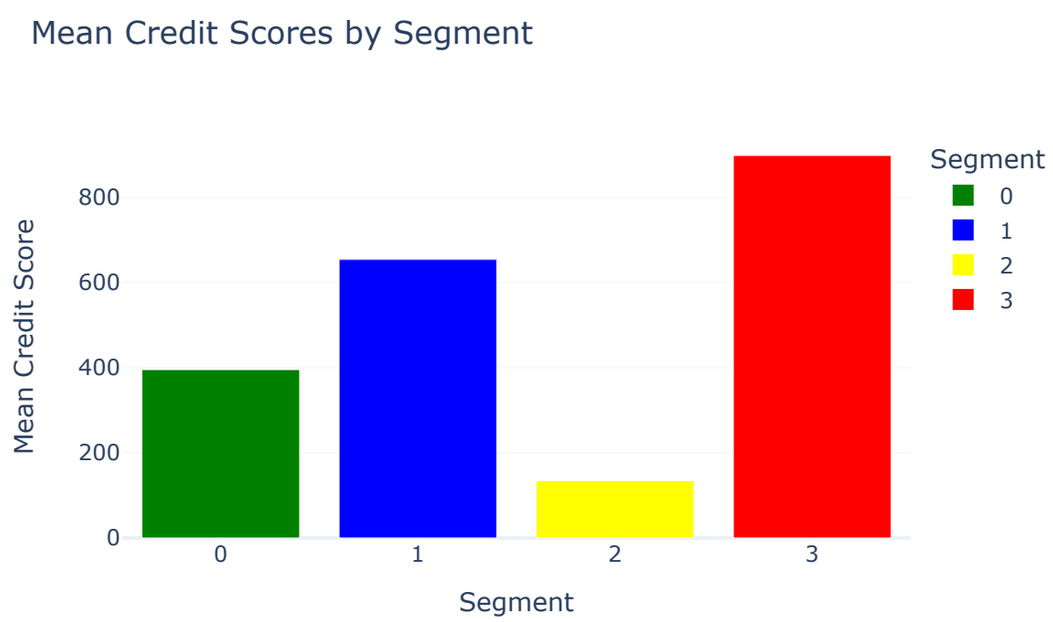
In [13]:
```
# Plot 4: Histogram of Credit Scores
fig4 = px.histogram(data, x='Credit Score', color='Segment',
                    color_discrete_sequence=['green', 'blue', 'yellow', 'red'],
                    title='Credit Score Distribution by Segment')
fig4.update_layout(
    xaxis_title='Credit Score',
    yaxis_title='Count',
    width=600,  # Medium size
    height=400  # Medium size
)
fig4.show()
```



In [14]:
```
# Plot 5: Pie Chart of Segment Proportions
segment_proportions = data['Segment'].value_counts(normalize=True).reset_index()
segment_proportions.columns = ['Segment', 'Proportion']
fig5 = px.pie(segment_proportions, values='Proportion', names='Segment',
              title='Segment Proportions')
fig5.show()
```

In [15]:
```
# Plot 6: Bar Plot of Mean Credit Scores by Segment
mean_credit_scores = data.groupby('Segment')['Credit Score'].mean().reset_index()
fig6 = px.bar(mean_credit_scores, x='Segment', y='Credit Score',
              color='Segment', color_discrete_sequence=['green', 'blue', 'yellow', '
              title='Mean Credit Scores by Segment')
fig6.update_layout(
    xaxis_title='Segment',
    yaxis_title='Mean Credit Score',
    width=600,  # Medium size
    height=400  # Medium size
```

```
)
fig6.show()
```



Visualization 4 (Histogram of Credit Scores):

- This histogram showcases the **distribution** of **credit scores** within each **customer segment**.
- By observing the distribution of credit scores, we can discern patterns such as skewness, central tendency, and variability within each segment.
- A histogram is particularly useful for visualizing the spread of credit scores and identifying any potential outliers or concentration of scores within specific ranges.

Visualization 5 (Pie Chart of Segment Proportions):

- The pie chart presents the **proportional representation** of each **customer segment** relative to the total customer base.
- Each segment is represented by a slice of the pie, with the size of each slice indicating the proportion of customers belonging to that segment.
- This visualization offers a quick and intuitive overview of segment sizes, allowing for easy comparison of segment proportions without delving into absolute counts.

Visualization 6 (Bar Plot of Mean Credit Scores by Segment):

- This bar plot illustrates the **mean credit score** for each **customer segment**, providing insights into the average creditworthiness of customers within each segment.
- By comparing mean credit scores across segments, we can identify segments with higher or lower average credit scores, which can inform strategic decision-making regarding marketing strategies or product offerings.
- This visualization facilitates a comparative analysis of creditworthiness among segments, highlighting potential areas for targeted interventions or improvements.

Together, these additional visualizations complement the existing scatter plot, box plot, and bar plot by offering deeper insights into the distribution, proportionality, and average creditworthiness of customer segments. They provide a comprehensive understanding of segment characteristics and aid in formulating informed strategies for customer segmentation and targeting within the financial landscape.

Summary

Credit scoring and segmentation are crucial processes in the financial domain, facilitating informed decision-making for lenders and financial institutions. In this comprehensive guide, we explored the intricate methodologies and techniques involved in credit scoring and segmentation using Python.

Understanding Credit Scoring and Segmentation: We began by elucidating the core concepts of credit scoring and segmentation, emphasizing the significance of assessing borrowers' credit profiles to determine their creditworthiness. By gathering pertinent data such as payment history, credit utilization, and credit mix, sophisticated algorithms generate numerical credit scores, providing insights into borrowers' ability to repay debts.

Importance of Segmentation: Segmenting customers based on their credit scores enables effective risk management and tailored lending strategies. By categorizing customers into different risk tiers, financial institutions can optimize loan approvals, interest rates, and credit limits, mitigating the risk of defaults and enhancing portfolio management.

Steps to Credit Scoring and Segmentation: We delved into the step-by-step process of credit scoring and segmentation, emphasizing data collection, algorithmic analysis, and segmentation techniques. Through meticulous data preprocessing, algorithm selection, and segmentation threshold determination, financial institutions can derive actionable insights to drive strategic decision-making.

Visualizing Credit Data: Using Plotly and Matplotlib, we visualized key aspects of credit data, including the distribution of credit utilization ratios, loan amounts, and correlation matrices. These visualizations provided insights into the relationships between credit features, guiding further analysis and modeling decisions.

Implementing the FICO Credit Scoring Model: In the absence of credit scores in the dataset, we demonstrated how to implement the FICO scoring model to calculate credit scores for individuals. By applying the FICO formula and assigning weights to relevant features, we derived comprehensive credit scores to aid in credit risk assessment.

Segmenting Customers with KMeans Clustering: Utilizing KMeans clustering, we segmented customers based on their credit scores, facilitating targeted marketing efforts and personalized lending strategies. Through visualizations such as scatter plots, box plots, and bar plots, we gained insights into segment characteristics and proportions, guiding strategic decision-making.

Conclusion: Mastering credit scoring and segmentation is paramount for financial institutions seeking to mitigate credit risk and optimize lending strategies. By leveraging Python and understanding the intricacies of these processes, institutions can make data-driven decisions that bolster their financial health and resilience in an ever-evolving market landscape.

Through this guide, readers gain a comprehensive understanding of credit scoring and segmentation methodologies, empowering them to navigate the complexities of credit assessment with confidence and precision in the dynamic financial landscape.