In [1]:
```
from matplotlib import pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
```

In [2]:
```
# SET THE RANDOM STATE
RANDOM_STATE = 0
```

1) Load the Data

In [3]:
```
data = pd.read_csv("data/cs-training.csv", index_col=0)

# Take a peak at the data
print(f"Num Entries: {data.shape[0]}")
print(f"Num Features: {data.shape[1]}")
display(data.head())
print(f"Features: {list(data.columns)}")
```

```
Num Entries: 150000
Num Features: 11
```

	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtRatio	MonthlyInco
1	1	0.766127	45	2	0.802982	912
2	0	0.957151	40	0	0.121876	260
3	0	0.658180	38	1	0.085113	304
4	0	0.233810	30	0	0.036050	330
5	0	0.907239	49	1	0.024926	6358

```
Features: ['SeriousDlqin2yrs', 'RevolvingUtilizationOfUnsecuredLines', 'age', 'NumberOfT
ime30-59DaysPastDueNotWorse', 'DebtRatio', 'MonthlyIncome', 'NumberOfOpenCreditLinesAndL
oans', 'NumberOfTimes90DaysLate', 'NumberRealEstateLoansOrLines', 'NumberOfTime60-89Days
PastDueNotWorse', 'NumberOfDependents']
```

2) Data Exploration

In [4]:
```
data.describe()
```

Out[4]:

	SeriousDlqin2yrs	RevolvingUtilizationOfUnsecuredLines	age	NumberOfTime30-59DaysPastDueNotWorse	DebtR
count	150000.000000	150000.000000	150000.000000	150000.000000	150000.000
mean	0.066840	6.048438	52.295207	0.421033	353.005
std	0.249746	249.755371	14.771866	4.192781	2037.818
min	0.000000	0.000000	0.000000	0.000000	0.000
25%	0.000000	0.029867	41.000000	0.000000	0.175
50%	0.000000	0.154181	52.000000	0.000000	0.366
75%	0.000000	0.559046	63.000000	0.000000	0.868
max	1.000000	50708.000000	109.000000	98.000000	329664.000

Label Balance Check

In [5]:
```
# Get a look at the number of examples in each label / clasification group
data.SeriousDlqin2yrs.value_counts()
```

Out[5]:
```
0    139974
1     10026
Name: SeriousDlqin2yrs, dtype: int64
```

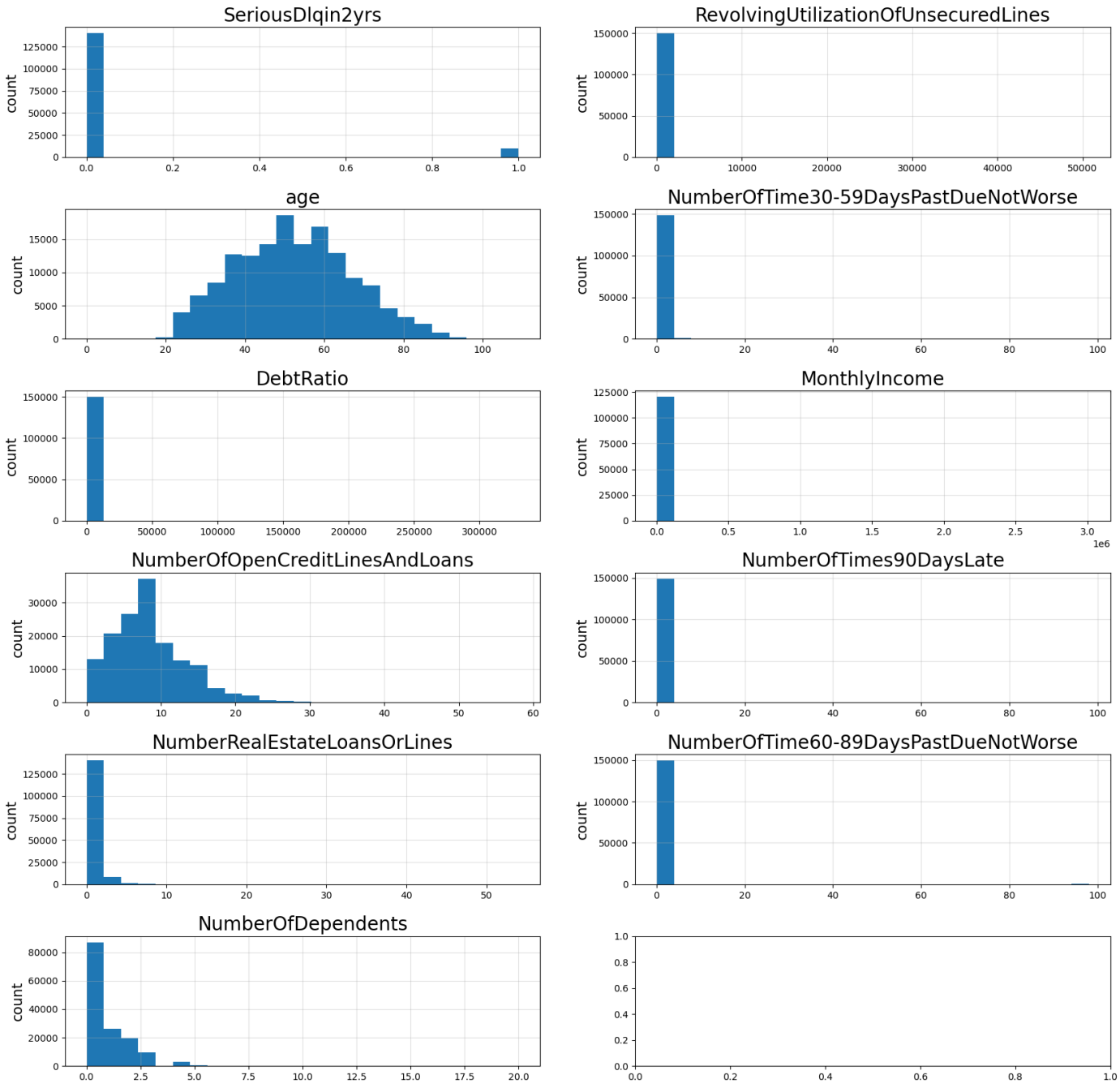
Looking at Missing Values

In [6]:
```
# Print out the number of missing values for each feature
data.isna().sum()
```

Out[6]:
```
SeriousDlqin2yrs                           0
RevolvingUtilizationOfUnsecuredLines       0
age                                        0
NumberOfTime30-59DaysPastDueNotWorse       0
DebtRatio                                  0
MonthlyIncome                          29731
NumberOfOpenCreditLinesAndLoans            0
NumberOfTimes90DaysLate                    0
NumberRealEstateLoansOrLines               0
NumberOfTime60-89DaysPastDueNotWorse       0
NumberOfDependents                      3924
dtype: int64
```

Visualizing the Distribution of Data for Each Feature

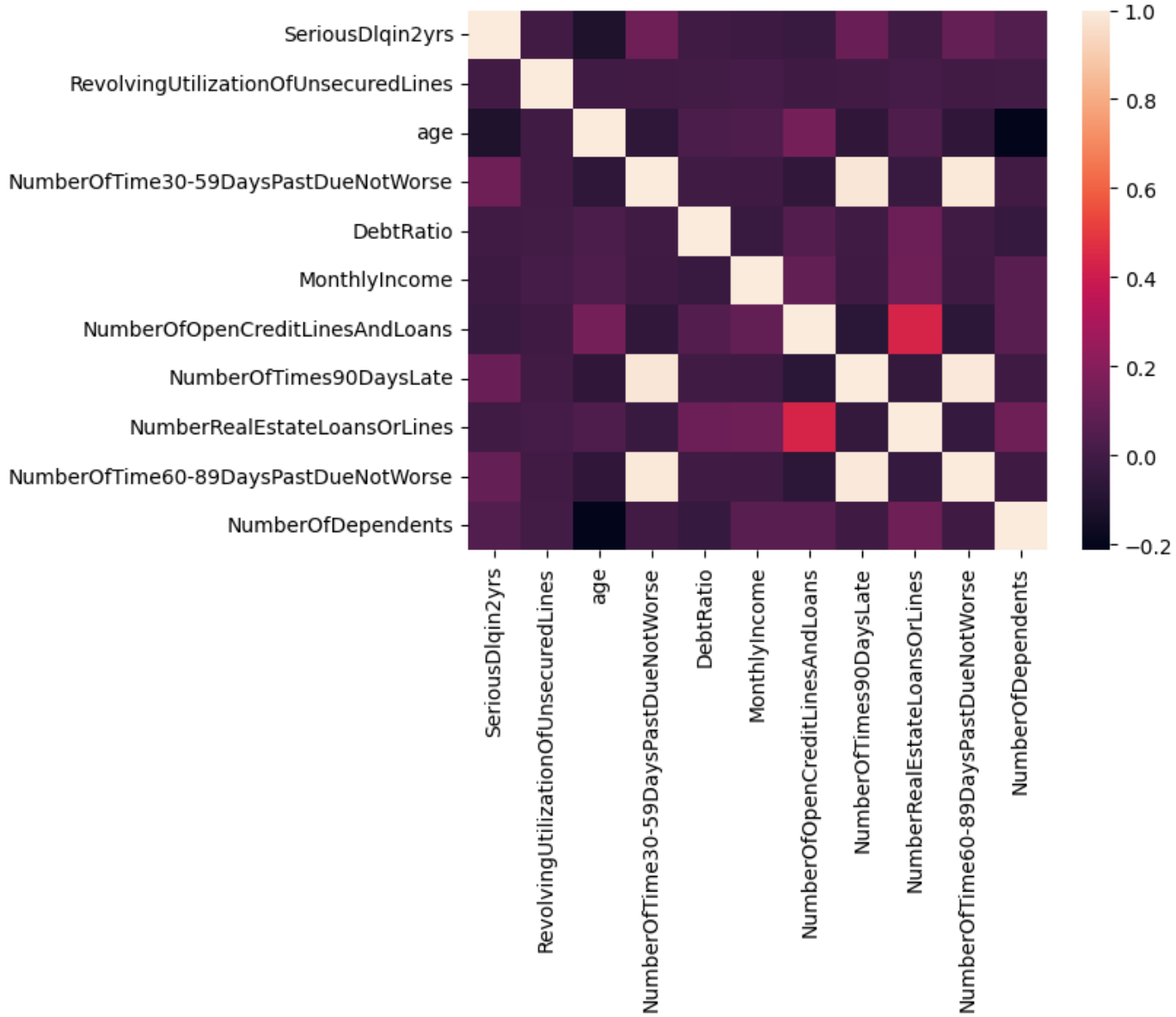
In [7]:
```
# Generate an Image to Visualize the distribution
fig, axs = plt.subplots(6, 2, figsize=(20,20))
plt.subplots_adjust(hspace=0.4, wspace=0.2)

# Go through each feature and custom make a histogram for it
for idx, col in enumerate(data.columns):
    fig_row, fig_col = idx//2, idx%2
    subplot = axs[fig_row, fig_col]
    subplot.hist(data[col], bins=25)
    subplot.set_title(col, fontsize=20)
    subplot.set_ylabel("count", fontsize=15)
    subplot.grid(alpha=0.4)
plt.savefig("initial_hist.png")
```



Looking at Correlation Between Features

In [8]:
```
# represent feature correlation matrix using a heatmap
corr = data.corr()

# plot the heatmap
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

Out[8]:
```
<AxesSubplot:>
```



3) Data Wrangling

Extract the Features and the labels from the dataset

In [9]:
```
X, y = data.iloc[:, 1:], data.iloc[:, 0]

print(f"Shape of X: {X.shape}")
print(F"Shape of y: {y.shape}")
```

```
Shape of X: (150000, 10)
Shape of y: (150000,)
```

Perform a statified shuffle split for splitting the taining and testing data

In [10]:
```
from sklearn.model_selection import StratifiedShuffleSplit

# Create an instance of Stratified Shuffle Split
stratified_split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=RANDOM

# Perform the stratified shuffle split
for train_index, test_index in stratified_split.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
```

```
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]

# Check the number of each type of label in the traning and test datasets
print(F"Delinquent Train: {y_train.sum()}")
print(F"Delinquent Test: {y_test.sum()}")
print()
print(f"Non-Delinquent Train: {(y_train==0).sum()}")
print(F"Non_Delinquent Test: {(y_test==0).sum()}")
```

```
Delinquent Train: 8021
Delinquent Test: 2005

Non-Delinquent Train: 111979
Non_Delinquent Test: 27995
```

Use an imputer to fill the missing values

In [11]:
```
from sklearn.impute import SimpleImputer

# Create Instance of Imputer using median strategy
imputer = SimpleImputer(strategy="median")

# Fit to the training data
imputer.fit(X_train)

# Save the index and columns before transformation
index = X_train.index
cols = X_train.columns

# Perform the Imputer Tansformation
X_train = imputer.transform(X_train)
X_train = pd.DataFrame(X_train, columns=cols,
                       index=index)

# Check that the missing values were filled
X_train.isna().sum()
```

Out[11]:
```
RevolvingUtilizationOfUnsecuredLines    0
age                                     0
NumberOfTime30-59DaysPastDueNotWorse    0
DebtRatio                               0
MonthlyIncome                           0
NumberOfOpenCreditLinesAndLoans         0
NumberOfTimes90DaysLate                 0
NumberRealEstateLoansOrLines            0
NumberOfTime60-89DaysPastDueNotWorse    0
NumberOfDependents                      0
dtype: int64
```

Balance the Labels by undersampling the Major Class

In [12]:
```
from sklearn.utils import resample
from sklearn.utils import shuffle

# Need to recombine the X_train and y_train for the down_sampling
train = X_train.copy()
train["SeriousDlqin2yrs"] = y_train

# Get the counts for the minor class
df_minor = train[train.SeriousDlqin2yrs == 1]
df_major = train[train.SeriousDlqin2yrs == 0]

# Let's downsample the major class
df_major_downsample = resample(df_major,
```

```
                                 replace=False,
                                 n_samples=df_minor.shape[0],
                                 random_state=RANDOM_STATE)

# Combine the two classes back together
df_downsample = pd.concat([df_major_downsample, df_minor])

# Check that the two labels are equal
print("Check for if the labels are balanced: ")
print(df_downsample.SeriousDlqin2yrs.value_counts())

# Shuffle the dataframe before splitting
shuffled = shuffle(df_downsample, random_state=RANDOM_STATE)

# Split the Downsampled data back into features & label
X_train_bal, y_train_bal = shuffled.iloc[:, :-1], shuffled["SeriousDlqin2yrs"]

# Check for proper splitting
print()
print(f"Shape of X: {X_train_bal.shape}")
print(f"Shape of y: {y_train_bal.shape}")
```

```
Check for if the labels are balanced:
0    8021
1    8021
Name: SeriousDlqin2yrs, dtype: int64

Shape of X: (16042, 10)
Shape of y: (16042,)
```

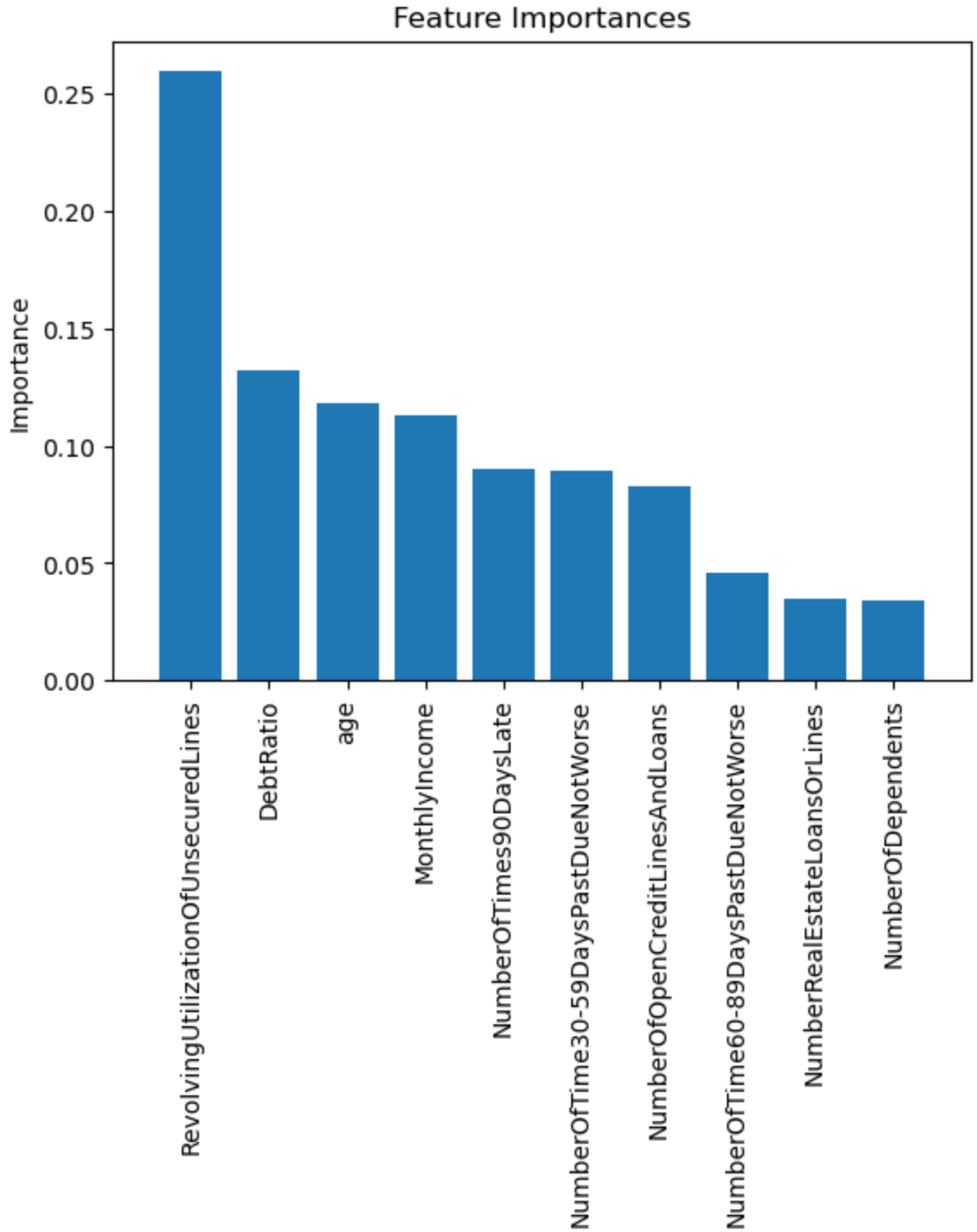
Looking at Feature Importances

In [13]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler


# Perform Standard Scaling
scaler = StandardScaler()
scaler.fit(X_train_bal)
X_scale = scaler.transform(X_train_bal)

# Fit a random forest model to find feature importances
feat_forest = RandomForestClassifier(n_estimators=500,
                                     random_state=RANDOM_STATE)
feat_forest.fit(X_scale, y_train_bal)
importances = feat_forest.feature_importances_

# Sort features in descending order of importance
# their indices are what should be sorted
indices = np.argsort(importances)[::-1]

# Define the features
features = X_train_bal.columns

# Print out feature importances
for f in range(X_scale.shape[1]):
    print("%2d) %-*s %f" % (f + 1, 30,
                            features[indices[f]],
                            importances[indices[f]]))


# Make a figure showing the importances
fig, axs = plt.subplots()
axs.bar(range(X_scale.shape[1]),
        importances[indices],
```

```
        align='center')
axs.set_xticks(range(X_scale.shape[1]),
           features[indices], rotation=90)
axs.set_xlim([-1, X_scale.shape[1]])
axs.set_title("Feature Importances")
axs.set_ylabel("Importance")
plt.show()
```

```
 1) RevolvingUtilizationOfUnsecuredLines 0.259576
 2) DebtRatio                            0.132057
 3) age                                  0.118252
 4) MonthlyIncome                        0.113137
 5) NumberOfTimes90DaysLate              0.090206
 6) NumberOfTime30-59DaysPastDueNotWorse 0.089476
 7) NumberOfOpenCreditLinesAndLoans      0.082814
 8) NumberOfTime60-89DaysPastDueNotWorse 0.045476
 9) NumberRealEstateLoansOrLines         0.035114
10) NumberOfDependents                   0.033892
```

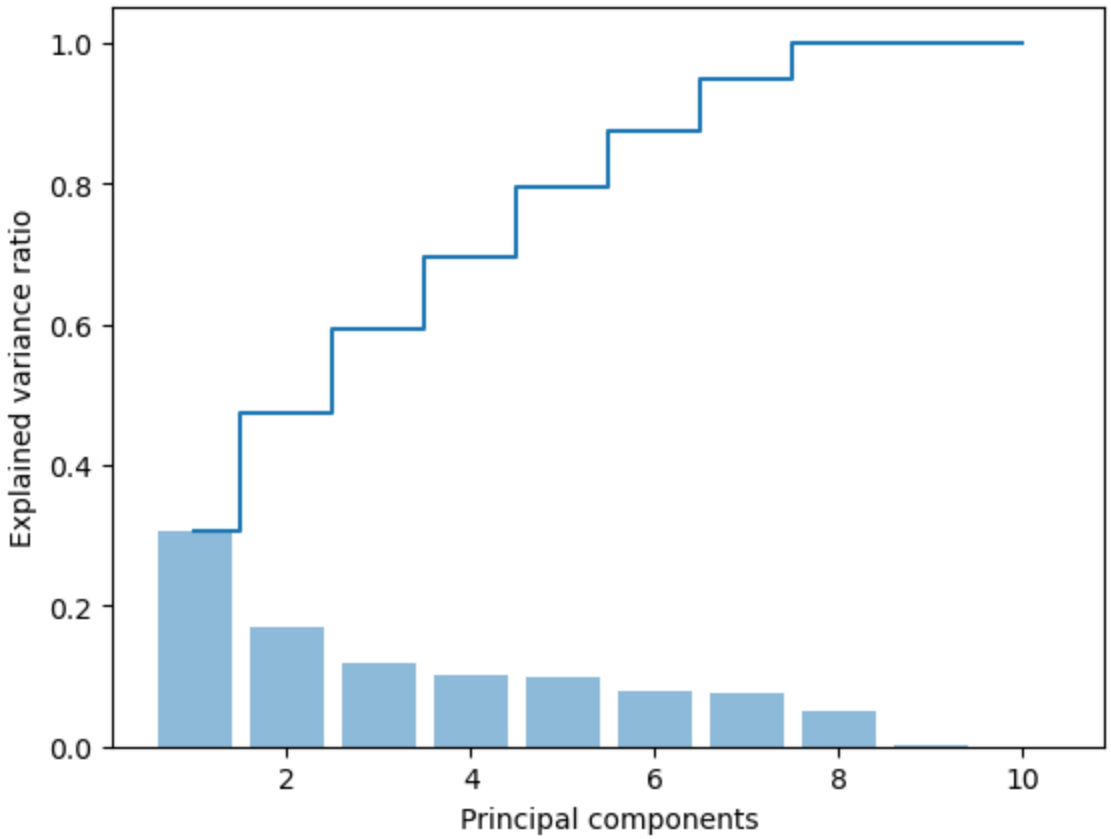


Peform Dimensionality Reduction

A) Principal Component Analysis

In [14]:
```
from sklearn.decomposition import PCA
from sklearn.pipeline import make_pipeline


# Scale the balanced label training set
scaler = StandardScaler()
scaler.fit(X_train_bal)
X_bal_scaled = scaler.transform(X_train_bal)

# Perform Principal Component Analysis
pca = PCA()
pca.fit(X_bal_scaled, y_train_bal)

# Calculate cumulative sum of EVR
cum_sum = np.cumsum(pca.explained_variance_ratio_)

# Plot the Explain Variance by # Principal Components
print(f"Explained Variance Ratio: \n{pca.explained_variance_ratio_}")
print(F"Cumulative Sum of EVR: \n {cum_sum}")
plt.bar(range(1, 11), pca.explained_variance_ratio_, alpha=0.5, align='center')
plt.step(range(1, 11), cum_sum, where='mid')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components')
plt.show()
```

```
Explained Variance Ratio:
[0.30587879 0.16867738 0.11931453 0.10115368 0.09935303 0.07923475
 0.07456405 0.05026824 0.00102548 0.00053007]
Cumulative Sum of EVR:
 [0.30587879 0.47455617 0.5938707  0.69502438 0.79437741 0.87361216
 0.94817621 0.99844445 0.99946993 1.        ]
```



In [15]:
```
# Set the Explained Variance Threshold required for
# determining number of principal components to use
THRESHOLD_EVR = 0.9
```

```
# Calculate num_components
n_components = np.argmax(cum_sum >= THRESHOLD_EVR) + 1
print(f"Number of Pricipal Components for PCA: {n_components}")

# Principal Component Analysis
pca = PCA(n_components=n_components)
X_train_bal_pca = pca.fit_transform(X_bal_scaled)

print(F"New shape of the data: {X_train_bal_pca.shape}")
```

```
Number of Pricipal Components for PCA: 7
New shape of the data: (16042, 7)
```

B) Linear Discriminant Analysis

In [16]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA

# Scale the balanced label training set
scaler = StandardScaler()
scaler.fit(X_train_bal)
X_bal_scaled = scaler.transform(X_train_bal)

# Perform Linear Discriminant Analysis
lda = LDA(n_components=1)
X_train_bal_lda = lda.fit_transform(X_bal_scaled, y_train_bal)
```

4) Building and Testing Models

In [17]:
```
# Define the number of trials to run
# when performing nested cross validation
NUM_TRIALS = 10
```

Nested Cross Validation Code to Assess Each Model Type to Determine which to move forward with

In [18]:
```
def perform_nested_CV(num_trials, model, p_grid, X, y):
    """
    Returns a list of the scores and plots the nested
    cross-validation scors for each trial.
    """
    # Make an array to store the socres
    nested_scores = np.zeros(num_trials)

    # Loop for each trial
    for i in range(num_trials):
        # Choose cross-validation techniques for the inner and outer loops,
        # independently of the dataset.
        # E.g "GroupKFold", "LeaveOneOut", "LeaveOneGroupOut", etc.
        inner_cv = KFold(n_splits=4, shuffle=True, random_state=i)
        outer_cv = KFold(n_splits=4, shuffle=True, random_state=i)

        # Perform parameter search for optimal model
        # on the inner CV
        clf = GridSearchCV(estimator=model,
                           param_grid=p_grid,
                           cv=inner_cv)

        # Perform outer CV to score the optimal model
        # found on the inner CV
```

```
        nested_score = cross_val_score(clf, X=X, y=y, cv=outer_cv)
        nested_scores[i] = nested_score.mean()

    return nested_scores

def plot_CV_scores(nested_scores):
    """
    Generates a figure that plots the nested_scores
    of the cross validations performed.
    """
    # Print the average across all of the nested scores
    print(f"Average CV Score: {np.mean(nested_scores)}")

    # Plot the scores for each of the nested CV
    # in nested scores file
    fig, axs = plt.subplots()
    axs.plot(nested_scores, color="b")
    axs.set_ylabel("Score")
    axs.set_xlabel("Trial #")
    axs.grid(alpha=0.4)
    return fig
```

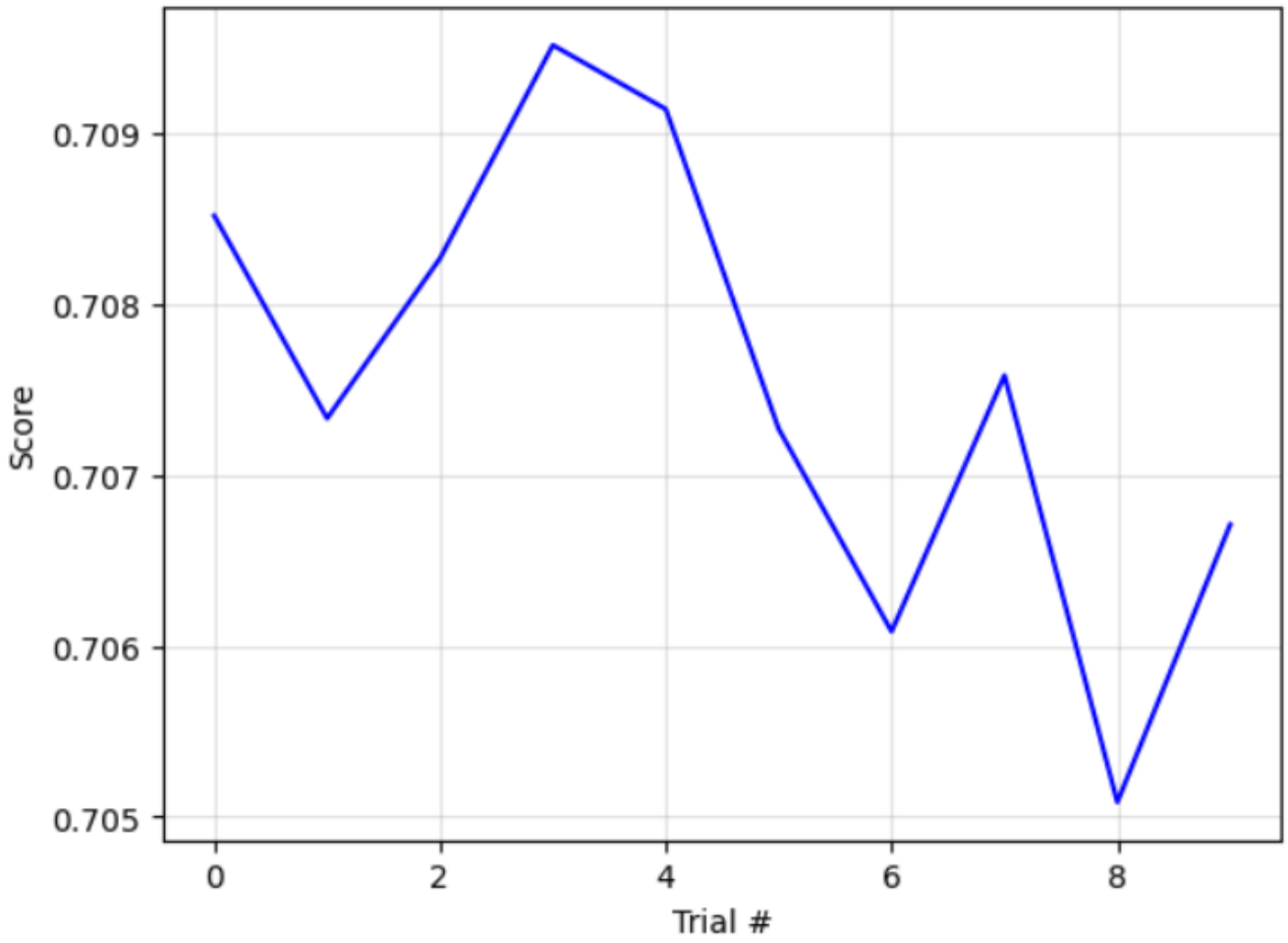
1) Logistic Regression Model - Nested CV - (Supervised)

Code is commented out because it takes a significant amount of time to run. The results can be visualized in the cell below the code.

In [19]:

```
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
from sklearn.linear_model import LogisticRegression

# # Set up possible values of parameters to optimize over
# p_grid = {"C": [1, 10, 100],
#           "solver": ["lbfgs", "liblinear"]}

# # Define the model
# lr = LogisticRegression(solver="liblinear")

# # Define the features and label
# # for nested CV
# X = X_train_bal_pca
# y = y_train_bal

# # Perform the nested CV
# nested_CV_scores = perform_nested_CV(NUM_TRIALS, lr, p_grid, X, y)
# plt.show(plot_CV_scores(nested_CV_scores))
```

```
Average CV Score: 0.70754917897229
```

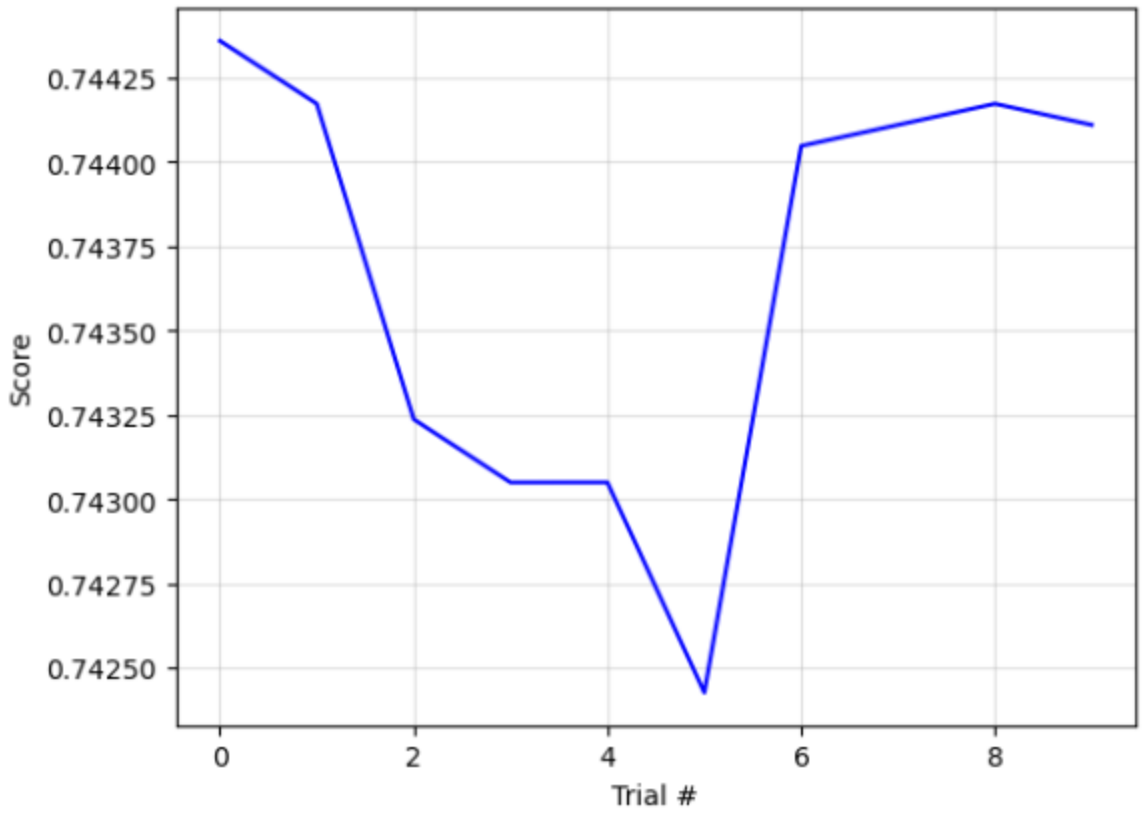


2) Support Vector Machine (SVM) - Nested CV - (Supervised)

Code is commented out because it takes a significant amount of time to run. The results can be visualized in the cell below the code.

In [20]:
```
from sklearn.model_selection import GridSearchCV, cross_val_score, KFold
from sklearn.svm import SVC

# # Set up possible values of parameters to optimize over
# p_grid = {"C": [1, 10],
#           "gamma": [.01, .1]}

# # Define the model
# svm = SVC(kernel="rbf")

# # Define the features and label
# # for nested CV
# X = X_train_bal_pca
# y = y_train_bal

# # Run the nested CV
# nested_CV_scores = perform_nested_CV(NUM_TRIALS, svm, p_grid, X, y)
# plt.show(plot_CV_scores(nested_CV_scores))
```

```
Average CV Score: 0.7436730257378245
```



3) K-Means Clustering - (Unsupervised)

A) Perform PCA Dimensionality Reduction to 2-D

In [21]:
```
# Principal Component Analysis for 2 Principal Components
pca_2 = PCA(n_components=2)
X_train_bal_pca_2 = pca_2.fit_transform(X_bal_scaled)

print(F"New shape of the data: {X_train_bal_pca_2.shape}")
print()

# Determine contribution of each feature to each principal component
dataset_pca_2 = pd.DataFrame(pca_2.components_, columns=cols, index=["PC_1", "PC_2"])

# Most Important Features for PC_1
print("Most Important Features for PC 1: ")
print(dataset_pca_2[abs(dataset_pca_2) > 0.3].iloc[0].dropna())
print()

# Most Important Features for PC_2
print("Most Important Features for PC 2: ")
print(dataset_pca_2[abs(dataset_pca_2) > 0.3].iloc[1].dropna())
print()
```

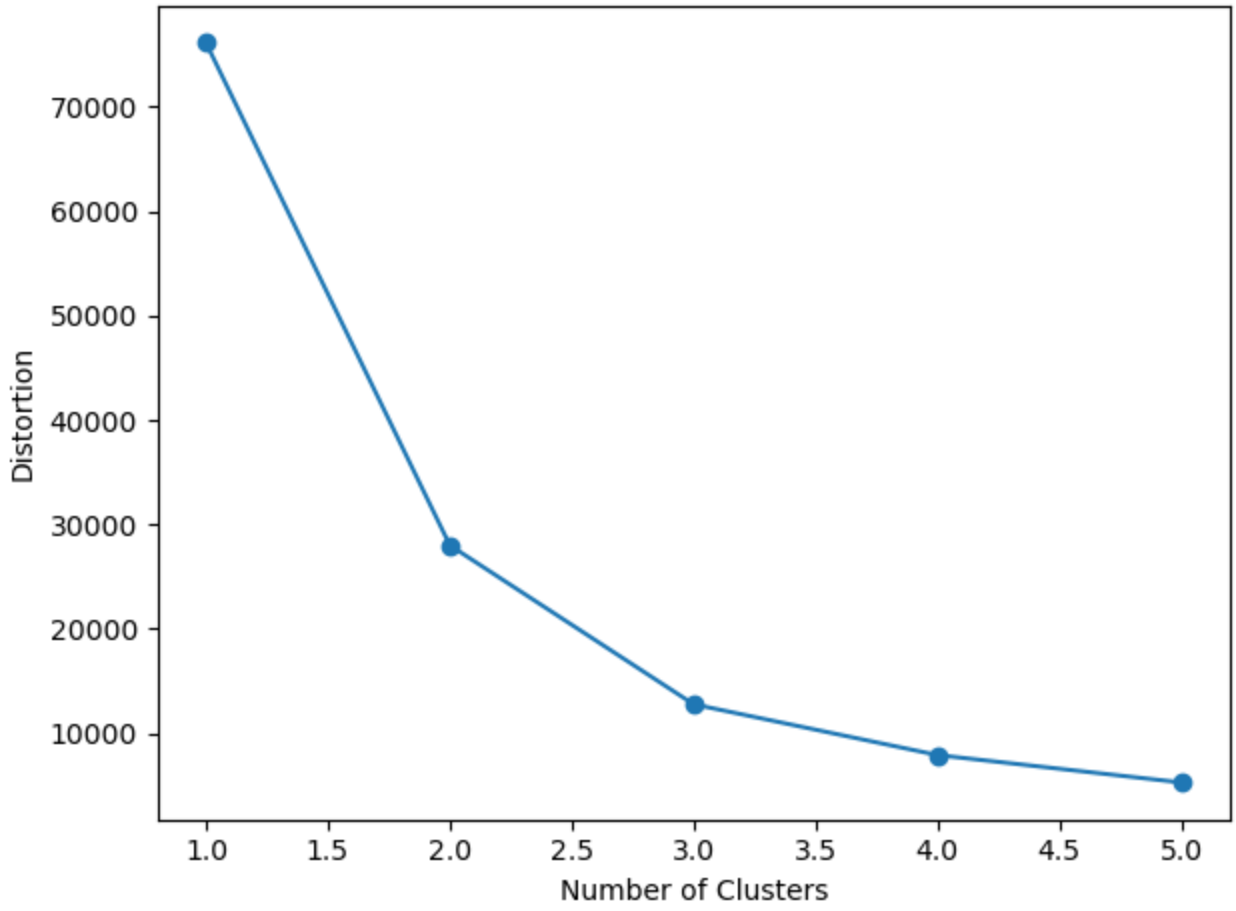
```
New shape of the data: (16042, 2)

Most Important Features for PC 1:
NumberOfTime30-59DaysPastDueNotWorse    0.560500
NumberOfTimes90DaysLate                 0.563166
NumberOfTime60-89DaysPastDueNotWorse    0.562465
Name: PC_1, dtype: float64

Most Important Features for PC 2:
MonthlyIncome                       0.443187
```

```
NumberOfOpenCreditLinesAndLoans    0.563457
NumberRealEstateLoansOrLines       0.592006
Name: PC_2, dtype: float64
```

B) Elbow Plot

In [22]:
```python
def elbow_plot(data):
    # Get the distortions for each cluster number
    distortions = []
    for i in range(1, 6):
        km = KMeans(n_clusters=i,
                init='k-means++',
                n_init=10,
                max_iter=300,
                random_state=0)
        km.fit(data)
        distortions.append(km.inertia_)

    # Make the figure
    fig, axs = plt.subplots()
    axs.plot(range(1, 6), distortions, marker="o")
    axs.set_xlabel("Number of Clusters")
    axs.set_ylabel("Distortion")
    plt.tight_layout()
    return fig
```

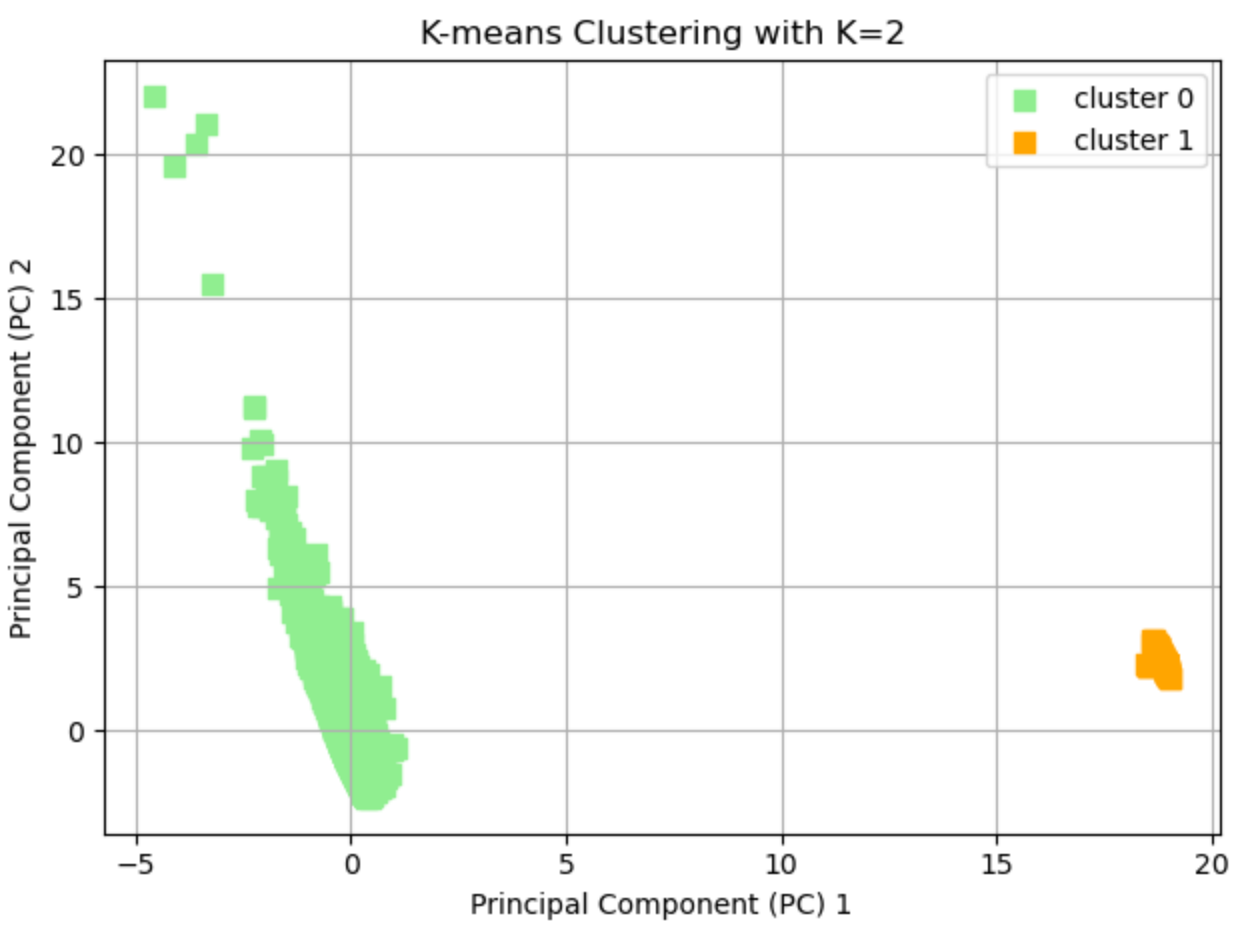
In [23]:
```python
from sklearn.cluster import KMeans

# Make an elbow plot
plt.show(elbow_plot(X_train_bal_pca_2))

# Based on the elbow plot, I would say that the
# ideal number of clusters is 2. After two clusters
# the distortion does not drastically decrease per cluster added.
```



C) Perform K-means Clustering

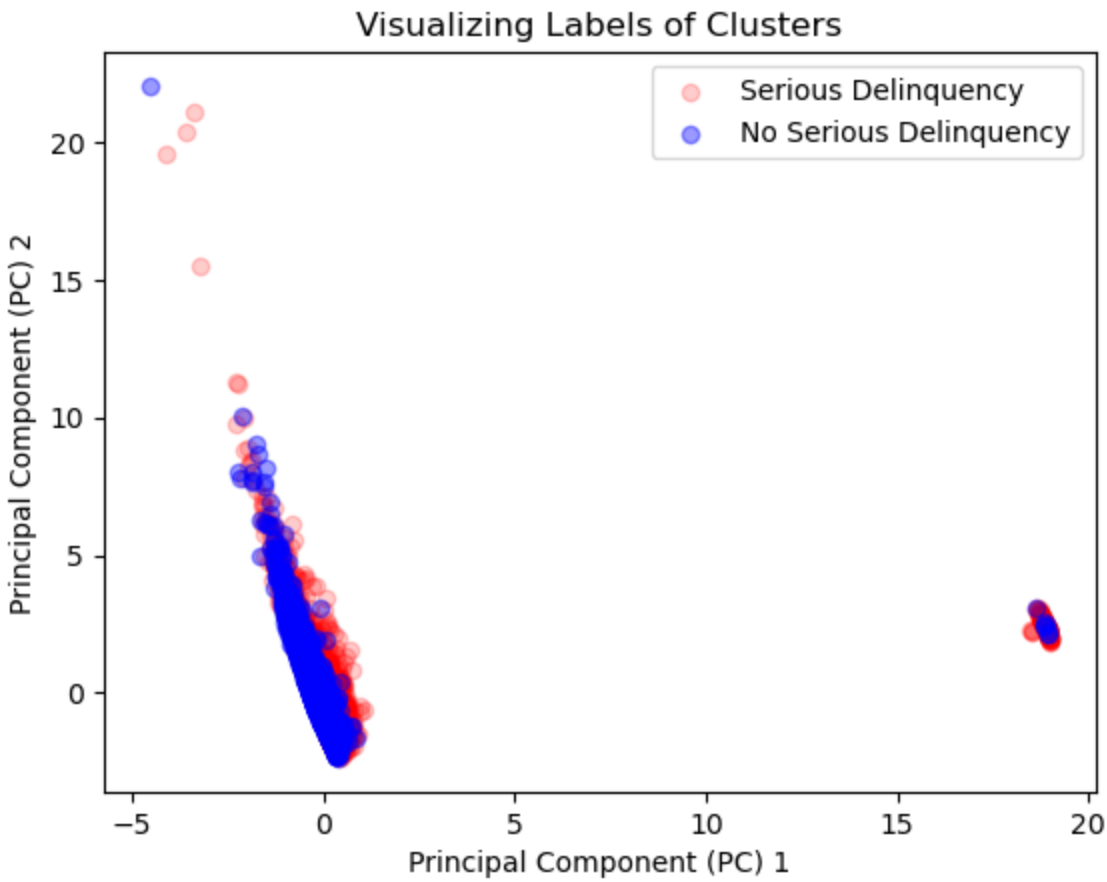
In [24]:

```
def print_cluster(model, n_clusters, X):
    y_km = model.fit_predict(X)
    color_list = ['lightgreen', 'orange', 'lightblue', 'red', 'yellow', 'brown', 'cyan']
    for i in range(n_clusters):
        plt.scatter(X[y_km == i, 0],
        X[y_km == i, 1],
        s=50,
        c=color_list[i],
        marker='s',
        label='cluster ' + str(i))
    plt.xlabel("Principal Component (PC) 1")
    plt.ylabel("Principal Component (PC) 2")
    plt.title(f"K-means Clustering with K={n_clusters}")
    plt.legend()
    plt.grid()
    plt.tight_layout()
    plt.show()

km = KMeans(n_clusters=2,
        init='k-means++',
        n_init=10,
        max_iter=300,
        tol=1e-04,
        random_state=0)

print_cluster(km, 2, X_train_bal_pca_2)
```



D) Analyze Labels in Clusters

In [25]:
```
fig, axs = plt.subplots()

axs.scatter(X_train_bal_pca_2[y_train_bal == 1, 0],
            X_train_bal_pca_2[y_train_bal == 1, 1],
            color="red",
            alpha=0.2,
            label="Serious Delinquency")

axs.scatter(X_train_bal_pca_2[y_train_bal == 0, 0],
            X_train_bal_pca_2[y_train_bal == 0, 1],
            color="blue",
            alpha=0.4,
           label="No Serious Delinquency")

axs.legend()
plt.xlabel("Principal Component (PC) 1")
plt.ylabel("Principal Component (PC) 2")
plt.title(f"Visualizing Labels of Clusters")
plt.show()
```

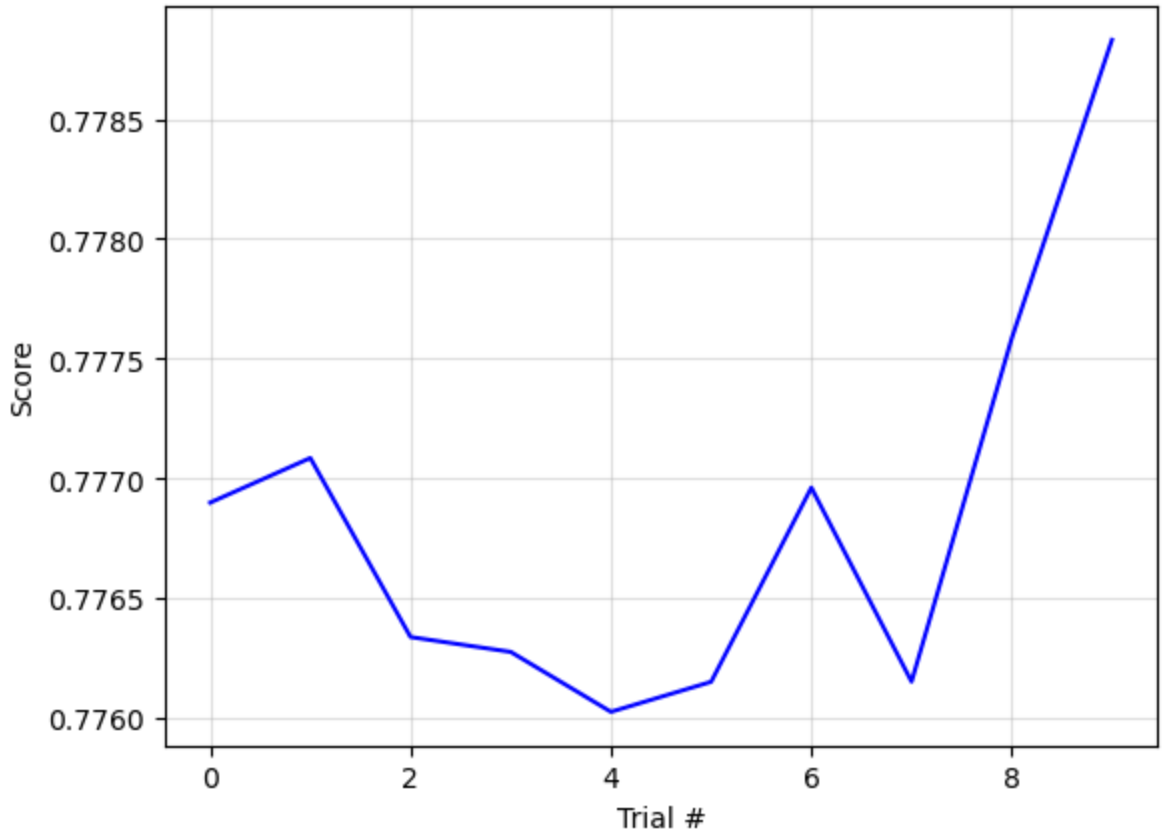


4) Random Forest - Nested CV - (Supervised)

Code is commented out because it takes a significant amount of time to run. The results can be visualized in the cell below the code.

In [26]:
```
from sklearn.ensemble import RandomForestClassifier

# # Set up possible values of parameters to optimize
# p_grid = {"max_depth": [4, 6, 8],
#           "min_samples_leaf": [30, 100]}

# # Create the random forest classifier
# rfc = RandomForestClassifier(n_estimators=10,
#                              criterion='gini',
#                              random_state=RANDOM_STATE)

# # Define the features and label
# # for nested CV
# X = X_train_bal
# y = y_train_bal

# # Run the nested CV
# nested_CV_scores = perform_nested_CV(10, rfc, p_grid, X, y)
# plt.show(plot_CV_scores(nested_CV_scores))
```

```
Average CV Score: 0.7768296427343508
```



5) Random Forest Classifier Hyperparameter Tuning

Code for Testing Parameter Values

In [27]:

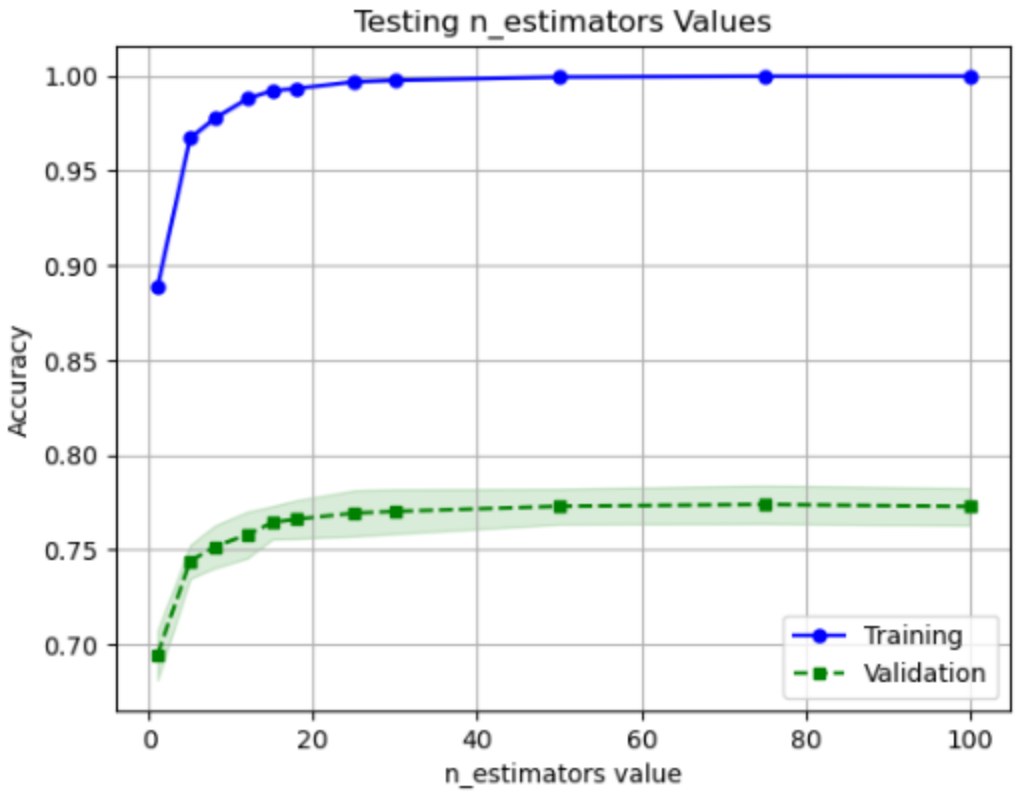
```
from sklearn.model_selection import validation_curve

def plot_scores(param_name, train_mean, train_std, test_mean, test_std):
    """
    Makes a plot of the parameter values and their
    corresponding training and testing accuracies.
    """
    fig, axs = plt.subplots()

    # Plot the accuracy values
    axs.plot(param_range, train_mean,
             color="blue",
             marker="o",
             markersize=5,
             label="Training")
    axs.plot(param_range,
             test_mean,
             color="green",
             linestyle="--",
             marker="s",
             markersize=5,
             label="Validation")

    # Plot the standard deviation range
    axs.fill_between(param_range,
                     train_mean + train_std,
```

```
                        train_mean - train_std,
                        alpha=0.15,
                        color="blue")
    axs.fill_between(param_range,
                        test_mean + test_std,
                        test_mean - test_std,
                        alpha=0.15,
                        color="green")

    # Make the formatting better
    axs.set_title(f"Testing {param_name} Values")
    axs.set_ylabel("Accuracy")
    axs.set_xlabel(f"{param_name} value")
    plt.grid(0.4)
    plt.legend()
    return fig

def run_param_test(model, param_name, param_range, X_train, y_train):
    """
    Perform a validation curve and plot the results.

    model: sklearn model to test
    param_name: string matching parameter to test for model
    param_lst: possible values for testing given parameter
    X_train: data to use to train and test the model
    y_train: labels for the data
    """
    # Run the validation curve
    train_scores, test_scores = validation_curve(estimator=model,
                                                 X=X_train,
                                                 y=y_train,
                                                 param_name=param_name,
                                                 param_range=param_range,
                                                 cv=10)
    # Calculate the mean and standard deivatins
    train_mean = np.mean(train_scores, axis=1)
    train_std = np.std(train_scores, axis=1)
    test_mean = np.mean(test_scores, axis=1)
    test_std = np.std(test_scores, axis=1)

    # Plot the results
    plt.show(plot_scores(param_name, train_mean, train_std, test_mean, test_std))

    # return dictionary
    return train_scores, test_scores
```

A) Testing N_Estimators

Code commented out since it takes a long time to run.

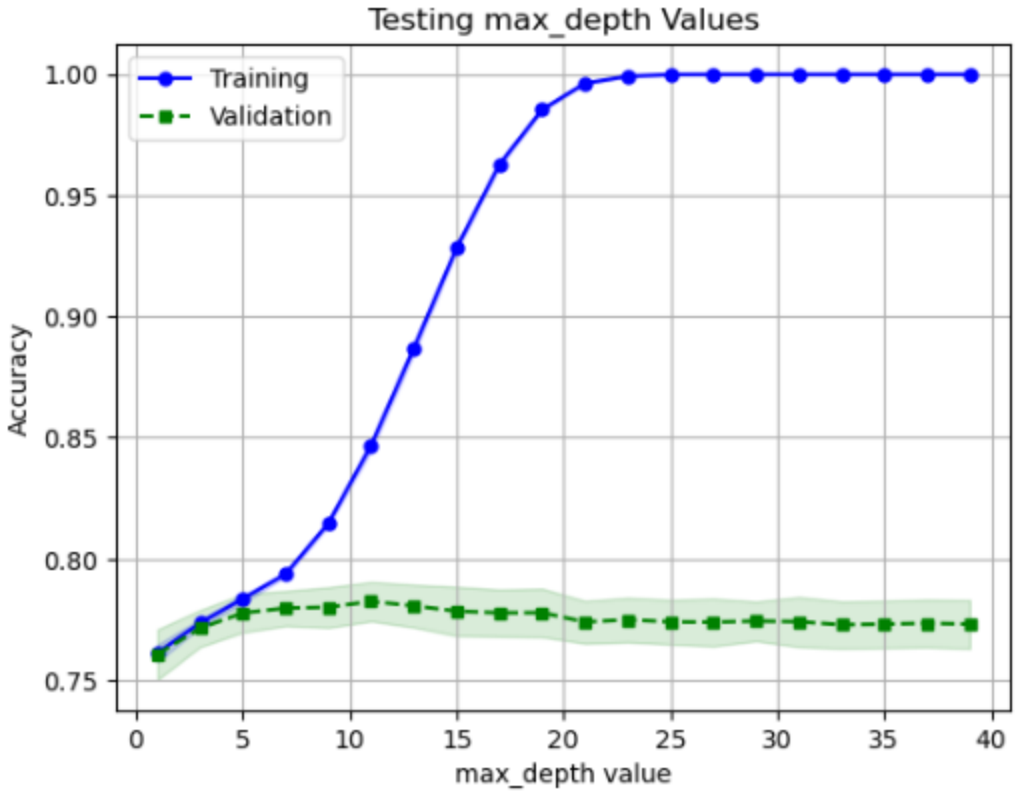
In [28]:
```
# # Define the model for testing
# rfc = RandomForestClassifier(criterion="gini",
#                              random_state=RANDOM_STATE)

# # Define the parameters for testing
# param_name = 'n_estimators'
# param_range = [1, 5, 8, 12, 15, 18, 25, 30, 50, 75, 100]

# # run the testing
# train_scores, test_scores = run_param_test(rfc, param_name, param_range, X_train_bal,
```



B) Testing Max Depth

Code commented out since it takes a long time to run.

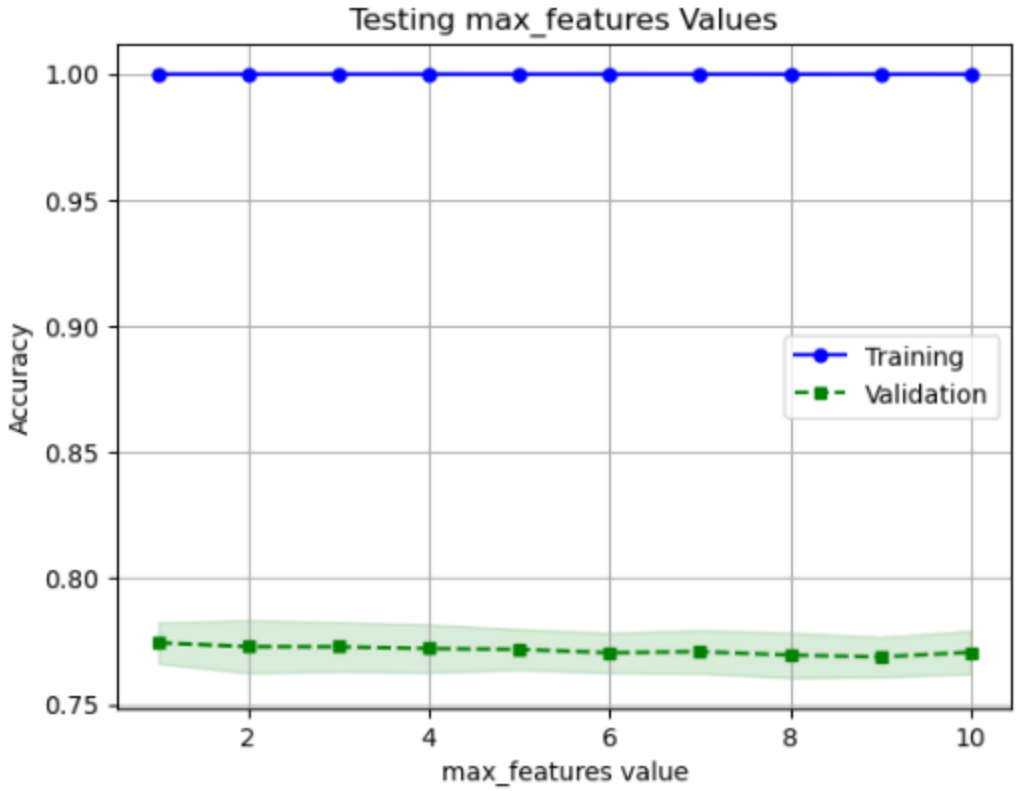
In [29]:
```
# # Define the model for testing
# rfc = RandomForestClassifier(criterion="gini",
#                              random_state=RANDOM_STATE)

# # Define the parameters for testing
# param_name = 'max_depth'
# param_range = range(1, 40, 2)

# # run the testing
# train_scores, test_scores = run_param_test(rfc, param_name, param_range, X_train_bal,
```



C) Testing Max Features

Code commented out since it takes a long time to run.

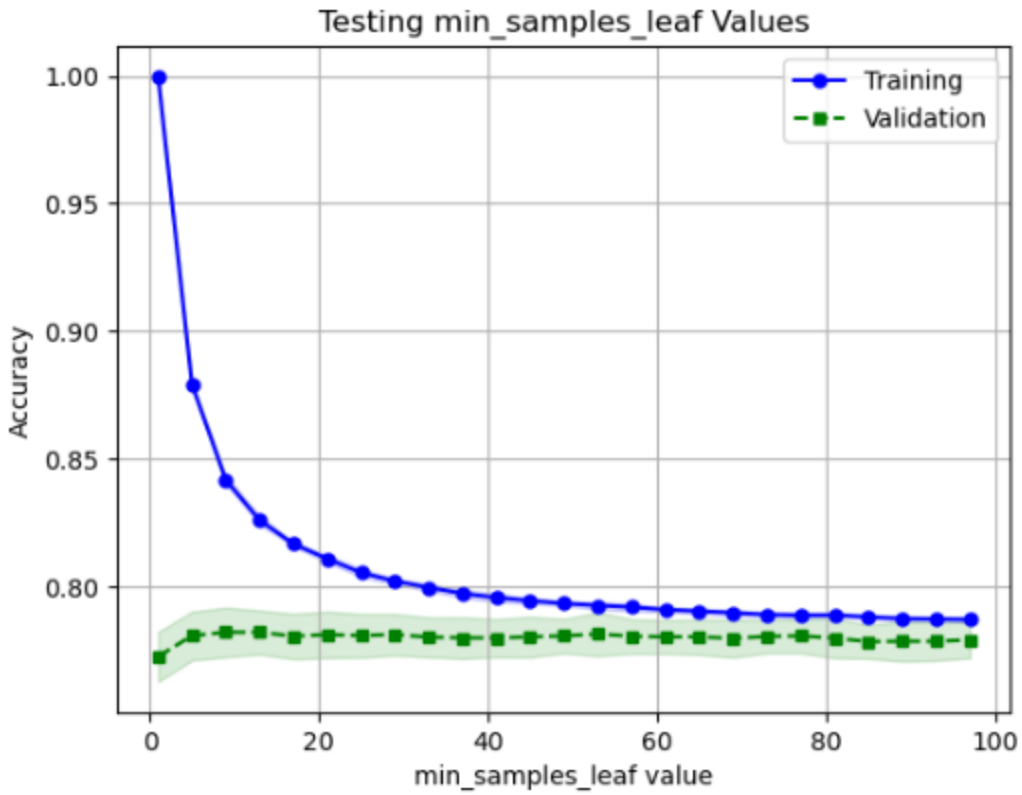
In [30]:
```
# # Define the model for testing
# rfc = RandomForestClassifier(criterion="gini",
#                              random_state=RANDOM_STATE)

# # Define the parameters for testing
# param_name = 'max_features'
# param_range = range(1, 11)

# # run the testing
# train_scores, test_scores = run_param_test(rfc, param_name, param_range, X_train_bal,
```



D) Testing Min Samples Leaf

Code commented out since it takes a long time to run.

In [31]:
```
# # Define the model for testing
# rfc = RandomForestClassifier(criterion="gini",
#                              random_state=RANDOM_STATE)

# # Define the parameters for testing
# param_name = 'min_samples_leaf'
# param_range = range(1, 100, 4)

# # run the testing
# train_scores, test_scores = run_param_test(rfc, param_name, param_range, X_train_bal,
```



E) Perform Randomized CV Search

In [32]:
```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint
from sklearn.ensemble import RandomForestClassifier

# Make the parameters to search
param_distribs = {'n_estimators': randint(low=15, high=25),
                  'max_features': randint(low=1, high=10),
                  'max_depth': randint(low=3, high=8),
                  'min_samples_leaf': randint(low=45, high=100)
                 }
# Define the model
rfc = RandomForestClassifier(criterion="gini",
                             random_state=RANDOM_STATE)
# Perform the randomized search
rnd_search = RandomizedSearchCV(rfc,
                                param_distributions=param_distribs,
                                n_iter=50,
                                cv=5,
                                scoring='accuracy',
                                random_state=RANDOM_STATE)
rnd_search.fit(X_train_bal, y_train_bal)
```

Out[32]:
```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(random_state=0),
                   n_iter=50,
                   param_distributions={'max_depth': <scipy.stats._distn_infrastructure.
rv_discrete_frozen object at 0x000002C37CF8E130>,
                                        'max_features': <scipy.stats._distn_infrastructu
re.rv_discrete_frozen object at 0x000002C37CF39EB0>,
                                        'min_samples_leaf': <scipy.stats._distn_infrastr
ucture.rv_discrete_frozen object at 0x000002C30827DF70>,
                                        'n_estimators': <scipy.stats._distn_infrastructu
re.rv_discrete_frozen object at 0x000002C37CF39DF0>},
                   random_state=0, scoring='accuracy')
```

In [33]:
```
print(f"Best Model Accuracy: {rnd_search.best_score_}")
```

```
print(f"Best Model Parameters: {rnd_search.best_params_}")
```

```
Best Model Accuracy: 0.7811989968985296
Best Model Parameters: {'max_depth': 7, 'max_features': 5, 'min_samples_leaf': 48, 'n_es
timators': 19}
```

In [34]:

```
# Collect the results
cvres = rnd_search.cv_results_

# Iterate through scores and params and add to results list
results = []
for mean_score, params in zip(cvres["mean_test_score"], cvres["params"]):
    results.append((mean_score, params))

# Print score and parameters in decreasing order of accuracy
results.sort(key=lambda x: -x[0])
for result in results:
    print(*result)
```

```
0.7811989968985296 {'max_depth': 7, 'max_features': 5, 'min_samples_leaf': 48, 'n_estima
tors': 19}
0.780824776637403 {'max_depth': 7, 'max_features': 6, 'min_samples_leaf': 45, 'n_estimat
ors': 18}
0.7803885036551655 {'max_depth': 7, 'max_features': 9, 'min_samples_leaf': 59, 'n_estima
tors': 19}
0.7800769966638407 {'max_depth': 7, 'max_features': 9, 'min_samples_leaf': 69, 'n_estima
tors': 18}
0.7797028346864219 {'max_depth': 6, 'max_features': 8, 'min_samples_leaf': 47, 'n_estima
tors': 24}
0.7796406265420898 {'max_depth': 7, 'max_features': 7, 'min_samples_leaf': 66, 'n_estima
tors': 22}
0.7792664645646713 {'max_depth': 7, 'max_features': 4, 'min_samples_leaf': 90, 'n_estima
tors': 21}
0.7792040038576044 {'max_depth': 6, 'max_features': 6, 'min_samples_leaf': 95, 'n_estima
tors': 19}
0.7788924774383765 {'max_depth': 6, 'max_features': 9, 'min_samples_leaf': 71, 'n_estima
tors': 17}
0.778767730875367 {'max_depth': 6, 'max_features': 6, 'min_samples_leaf': 57, 'n_estimat
ors': 24}
0.7785807178843169 {'max_depth': 6, 'max_features': 6, 'min_samples_leaf': 60, 'n_estima
tors': 15}
0.7784561461724312 {'max_depth': 6, 'max_features': 4, 'min_samples_leaf': 84, 'n_estima
tors': 24}
0.7784560101771125 {'max_depth': 6, 'max_features': 4, 'min_samples_leaf': 64, 'n_estima
tors': 22}
0.7784557187585726 {'max_depth': 5, 'max_features': 4, 'min_samples_leaf': 87, 'n_estima
tors': 21}
0.7783313996094214 {'max_depth': 6, 'max_features': 9, 'min_samples_leaf': 56, 'n_estima
tors': 17}
0.7783312441862 {'max_depth': 5, 'max_features': 5, 'min_samples_leaf': 56, 'n_estimator
s': 19}
0.7776455169337485 {'max_depth': 6, 'max_features': 8, 'min_samples_leaf': 60, 'n_estima
tors': 20}
0.7766482049783611 {'max_depth': 5, 'max_features': 4, 'min_samples_leaf': 65, 'n_estima
tors': 16}
0.776585705415489 {'max_depth': 5, 'max_features': 4, 'min_samples_leaf': 75, 'n_estimat
ors': 18}
0.7764613085547273 {'max_depth': 6, 'max_features': 2, 'min_samples_leaf': 85, 'n_estima
tors': 15}
0.7763989061313683 {'max_depth': 6, 'max_features': 3, 'min_samples_leaf': 73, 'n_estima
tors': 17}
0.7758377311628999 {'max_depth': 5, 'max_features': 4, 'min_samples_leaf': 69, 'n_estima
tors': 16}
0.7752770613199006 {'max_depth': 6, 'max_features': 3, 'min_samples_leaf': 72, 'n_estima
tors': 15}
0.7751521787615723 {'max_depth': 5, 'max_features': 9, 'min_samples_leaf': 99, 'n_estima
```

```
tors': 21}
0.7750896597707972 {'max_depth': 5, 'max_features': 4, 'min_samples_leaf': 75, 'n_estima
tors': 17}
0.7733448204045822 {'max_depth': 6, 'max_features': 1, 'min_samples_leaf': 76, 'n_estima
tors': 20}
0.7727837620035297 {'max_depth': 5, 'max_features': 2, 'min_samples_leaf': 81, 'n_estima
tors': 21}
0.7725967101566743 {'max_depth': 4, 'max_features': 9, 'min_samples_leaf': 46, 'n_estima
tors': 16}
0.7724722744401074 {'max_depth': 4, 'max_features': 2, 'min_samples_leaf': 76, 'n_estima
tors': 21}
0.7724721384447887 {'max_depth': 5, 'max_features': 1, 'min_samples_leaf': 84, 'n_estima
tors': 20}
0.77228528087696 {'max_depth': 6, 'max_features': 1, 'min_samples_leaf': 77, 'n_estimato
rs': 21}
0.7717240087689782 {'max_depth': 3, 'max_features': 2, 'min_samples_leaf': 54, 'n_estima
tors': 24}
0.7717240087689782 {'max_depth': 3, 'max_features': 2, 'min_samples_leaf': 50, 'n_estima
tors': 24}
0.7713499050752676 {'max_depth': 4, 'max_features': 9, 'min_samples_leaf': 61, 'n_estima
tors': 23}
0.7710386312187746 {'max_depth': 6, 'max_features': 1, 'min_samples_leaf': 85, 'n_estima
tors': 23}
0.7706642555344267 {'max_depth': 3, 'max_features': 2, 'min_samples_leaf': 82, 'n_estima
tors': 24}
0.7700410861285553 {'max_depth': 4, 'max_features': 1, 'min_samples_leaf': 55, 'n_estima
tors': 17}
0.7698538205747706 {'max_depth': 4, 'max_features': 4, 'min_samples_leaf': 83, 'n_estima
tors': 22}
0.7683577555021763 {'max_depth': 3, 'max_features': 5, 'min_samples_leaf': 68, 'n_estima
tors': 18}
0.7679838655153952 {'max_depth': 3, 'max_features': 5, 'min_samples_leaf': 48, 'n_estima
tors': 15}
0.7679836712363685 {'max_depth': 4, 'max_features': 1, 'min_samples_leaf': 99, 'n_estima
tors': 20}
0.7676721836729461 {'max_depth': 3, 'max_features': 5, 'min_samples_leaf': 62, 'n_estima
tors': 19}
0.7676720476776274 {'max_depth': 5, 'max_features': 1, 'min_samples_leaf': 74, 'n_estima
tors': 18}
0.7672983131140675 {'max_depth': 3, 'max_features': 5, 'min_samples_leaf': 96, 'n_estima
tors': 15}
0.7661138327444089 {'max_depth': 3, 'max_features': 2, 'min_samples_leaf': 95, 'n_estima
tors': 19}
0.7657399621855302 {'max_depth': 3, 'max_features': 1, 'min_samples_leaf': 81, 'n_estima
tors': 20}
0.7583215341204483 {'max_depth': 3, 'max_features': 9, 'min_samples_leaf': 57, 'n_estima
tors': 16}
0.758134482273593 {'max_depth': 3, 'max_features': 9, 'min_samples_leaf': 60, 'n_estimat
ors': 24}
0.7580721575618449 {'max_depth': 3, 'max_features': 9, 'min_samples_leaf': 58, 'n_estima
tors': 23}
0.7577604368635905 {'max_depth': 3, 'max_features': 7, 'min_samples_leaf': 64, 'n_estima
tors': 18}
```

6) Training Final Model Based on the Randomized Search

In [35]:
```
print(f"Best Model Parameters: {rnd_search.best_params_}")
```

```
Best Model Parameters: {'max_depth': 7, 'max_features': 5, 'min_samples_leaf': 48, 'n_es
timators': 19}
```

In [36]:
```
# Define the model
```

```
final_rfc = RandomForestClassifier(criterion="gini",
                                   max_depth=7,
                                   max_features=5,
                                   min_samples_leaf=48,
                                   n_estimators=19,
                                   random_state=RANDOM_STATE)

# Train the model on the entire training dataset
final_rfc.fit(X_train_bal, y_train_bal)
```

Out[36]:
```
RandomForestClassifier(max_depth=7, max_features=5, min_samples_leaf=48,
                       n_estimators=19, random_state=0)
```

7) Preparing Test Data And Testing Model for Accuracy

Preparing Test Data

In [37]:
```
# Check missing values before using the imputer
X_train.isna().sum()
```

Out[37]:
```
RevolvingUtilizationOfUnsecuredLines    0
age                                     0
NumberOfTime30-59DaysPastDueNotWorse    0
DebtRatio                               0
MonthlyIncome                           0
NumberOfOpenCreditLinesAndLoans         0
NumberOfTimes90DaysLate                 0
NumberRealEstateLoansOrLines            0
NumberOfTime60-89DaysPastDueNotWorse    0
NumberOfDependents                      0
dtype: int64
```

In [38]:
```
# Prepare the test data in the same manner as the training data

# Save the index and columns before transformation
index = X_test.index
cols = X_test.columns

# Fill the missing values with same values used in training set
X_test = imputer.transform(X_test)
X_test = pd.DataFrame(X_test,
                      columns=cols,
                      index=index)

# Check that the missing values were filled
X_test.isna().sum()
```

Out[38]:
```
RevolvingUtilizationOfUnsecuredLines    0
age                                     0
NumberOfTime30-59DaysPastDueNotWorse    0
DebtRatio                               0
MonthlyIncome                           0
NumberOfOpenCreditLinesAndLoans         0
NumberOfTimes90DaysLate                 0
NumberRealEstateLoansOrLines            0
NumberOfTime60-89DaysPastDueNotWorse    0
NumberOfDependents                      0
dtype: int64
```

Making Test Predictions and Assessing Accuracy

In [39]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score

# Make the predictions
y_pred = final_rfc.predict(X_test)

# Calculate probabilities for ROC curve
y_probs = final_rfc.predict_proba(X_test)[:, 1]
```

In [40]:
```
TN = np.sum((y_pred==0) & (y_test==0))
TP = np.sum((y_pred==1) & (y_test==1))
FP = np.sum((y_pred==1) & (y_test==0))
FN = np.sum((y_pred==0) & (y_test==1))

print(F"Number of Samples: {len(y_pred)}")
print(F"Number Positive: {np.sum(y_test==1)}")
print(F"Number Negative: {np.sum(y_test==0)}")
print("--------------------")

print(F"True Positive (TN): {TP}")
print(F"True Negative (TN): {TN}")
print(F"False Positive (TN): {FP}")
print(F"False Negative (TN): {FN}")
```

```
Number of Samples: 30000
Number Positive: 2005
Number Negative: 27995
--------------------
True Positive (TN): 1579
True Negative (TN): 21815
False Positive (TN): 6180
False Negative (TN): 426
```

In [41]:
```
# Score the predictions
accuracy = accuracy_score(y_test, y_pred)
precision = TP / (TP + FP)
recall = TP / (TP + FN)
f1 = (2*precision*recall) / (precision + recall)

print(f"Model Accuracy: {np.round(accuracy, 4)}")
print(F"Precision: {np.round(precision, 4)}")
print(f"Recall: {np.round(recall, 4)}")
print(f"F1 Score: {np.round(f1, 4)}")
```

```
Model Accuracy: 0.7798
Precision: 0.2035
Recall: 0.7875
F1 Score: 0.3234
```

In [42]:
```
from sklearn.metrics import roc_curve, roc_auc_score, auc

# Calculate the Area Under Curve (AUC)
fpr, tpr, thresholds = roc_curve(y_test, y_probs)
roc_auc = auc(fpr, tpr)
print("AUC:", roc_auc)

# Plot the ROC curve
fig, axs = plt.subplots()
axs.plot(fpr, tpr,
         color="orange",
         lw=2,
         label=f"Final Model (Area Under Curve = {np.round(roc_auc, 4)})")

axs.plot([0, 1], [0, 1],
         color="darkblue",
```

```
          lw=2,
          linestyle='--',
          label="Random Classifier")

axs.plot([0, 1], [1, 1],
          color="green",
          lw=2,
          linestyle='--',
          label="Perfect Classifier")
axs.plot([0, 0], [0, 1],
          color="green",
          lw=2,
          linestyle='--')

axs.set_xlim([-0.01, 1.0])
axs.set_ylim([0.0, 1.05])
axs.set_xlabel('False Positive Rate')
axs.set_ylabel('True Positive Rate')
axs.set_title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
AUC: 0.8607407004902461
```