```
import pandas as pd

url = "https://raw.githubusercontent.com/Rishabh1108ch/JP_Morgan_Quantitative_Research/main/Task4%3A-FICO_score_quanti
df = pd.read_csv(url)
display(df.head())
```

	customer_id	credit_lines_outstanding	loan_amt_outstanding	total_debt_outstanding	income	years_employed	fic
0	8153374	0	5221.545193	3915.471226	78039.38546	5	
1	7442532	5	1958.928726	8228.752520	26648.43525	2	
2	2256073	0	3363.009259	2027.830850	65866.71246	4	
3	4885975	0	4766.648001	2501.730397	74356.88347	5	
4	4700614	1	1345.827718	1768.826187	23448.32631	6	

```
Start coding or generate with AI.
```

```
# Check data types
print("Data types:")
display(df.dtypes)

# Check for missing values
print("\nMissing values:")
display(df.isnull().sum())
```

Data types:

	0
customer_id	int64
credit_lines_outstanding	int64
loan_amt_outstanding	float64
total_debt_outstanding	float64
income	float64
years_employed	int64
fico_score	int64
default	int64

dtype: object

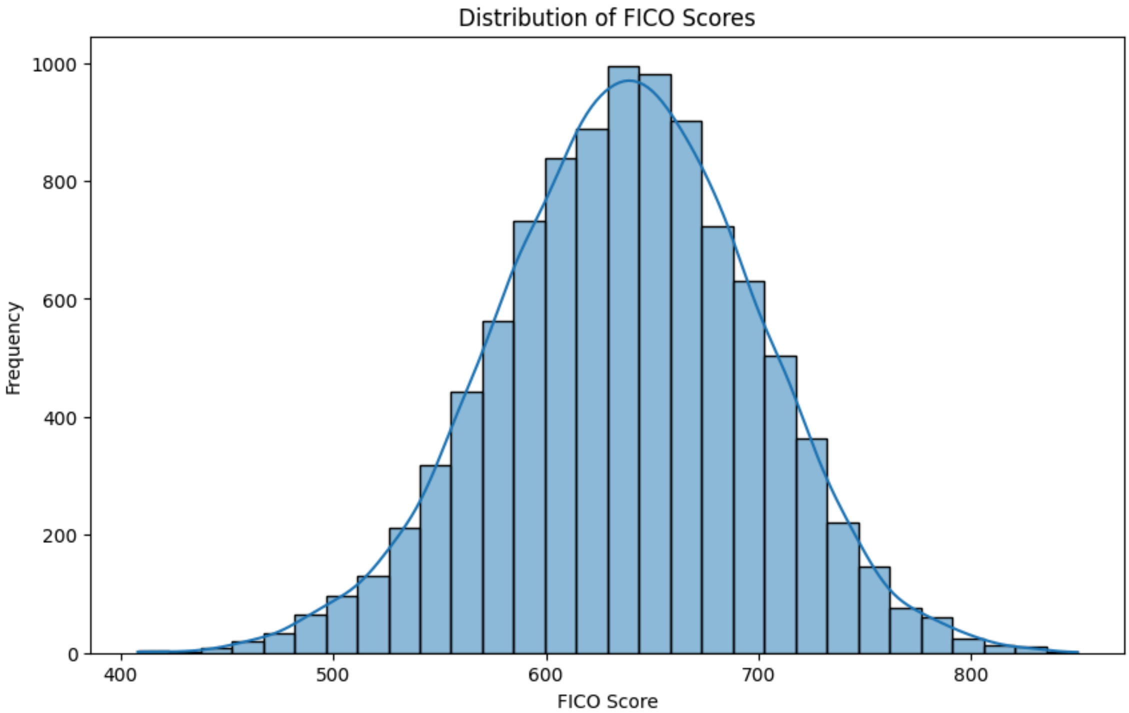
Missing values:

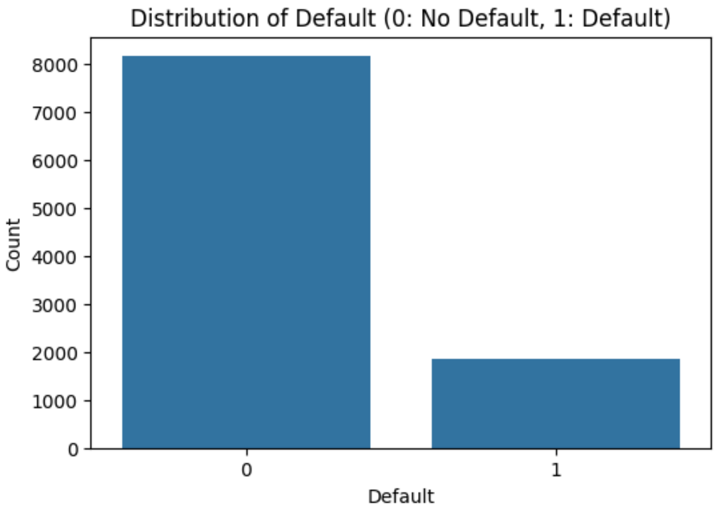
	0
customer_id	0
credit_lines_outstanding	0
loan_amt_outstanding	0
total_debt_outstanding	0
income	0
years_employed	0
fico_score	0
default	0

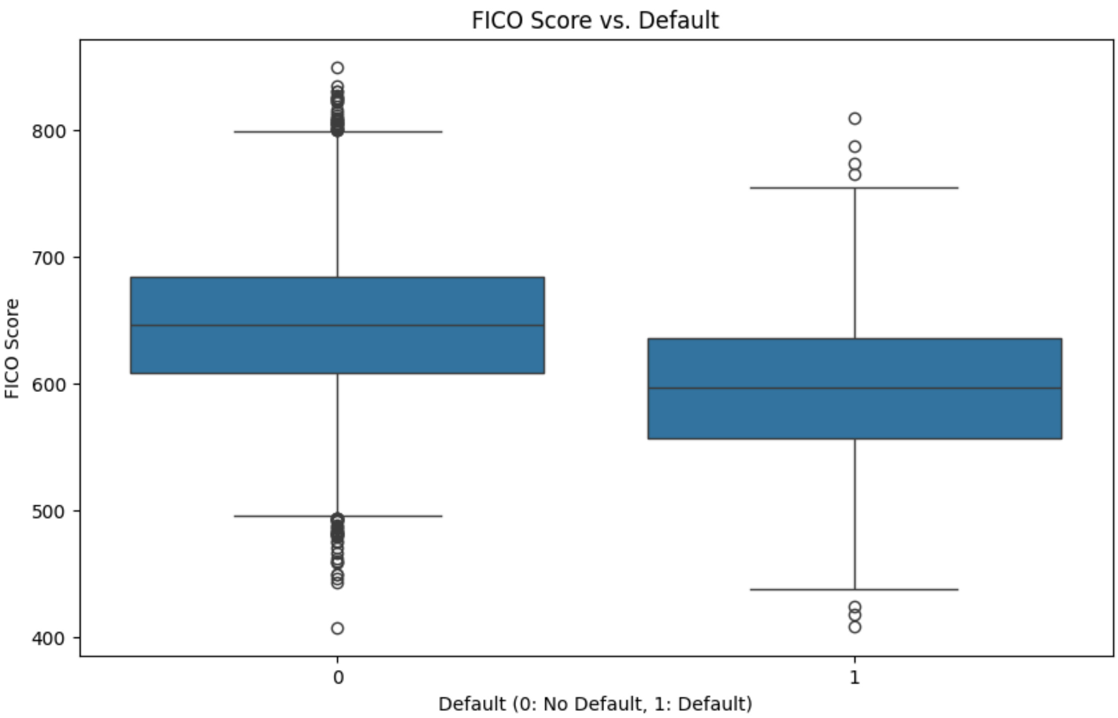
dtype: int64

```
import matplotlib.pyplot as plt
import seaborn as sns

# Distribution of FICO scores
plt.figure(figsize=(10, 6))
sns.histplot(df['fico_score'], bins=30, kde=True)
plt.title('Distribution of FICO Scores')
plt.xlabel('FICO Score')
plt.ylabel('Frequency')
plt.show()

# Distribution of default
plt.figure(figsize=(6, 4))
```

```python
sns.countplot(x='default', data=df)
plt.title('Distribution of Default (0: No Default, 1: Default)')
plt.xlabel('Default')
plt.ylabel('Count')
plt.show()

# Relationship between FICO score and default
plt.figure(figsize=(10, 6))
sns.boxplot(x='default', y='fico_score', data=df)
plt.title('FICO Score vs. Default')
plt.xlabel('Default (0: No Default, 1: Default)')
plt.ylabel('FICO Score')
plt.show()
```


Distribution of FICO Scores
Frequency
0
200
400
600
800
1000
400
500
600
700
800
FICO Score


Distribution of Default (0: No Default, 1: Default)
Count
0
1000
2000
3000
4000
5000
6000
7000
8000
0
1
Default


FICO Score vs. Default
FICO Score
400
500
600
700
800
0
1
Default (0: No Default, 1: Default)

quantization strategy

```
import numpy as np
import pandas as pd
from scipy.optimize import minimize

# Sort the DataFrame by FICO score
df_sorted = df.sort_values(by='fico_score').reset_index(drop=True)

# Define the log-likelihood function to minimize
def log_likelihood(boundaries, fico_scores, defaults):
    """
    Calculates the negative log-likelihood for given boundaries.
    Assumes boundaries are sorted and cover the range of fico_scores.
    """
    n_buckets = len(boundaries) - 1
    ll = 0
    for i in range(n_buckets):
        # Select data within the current bucket
        if i == 0:
            mask = (fico_scores >= boundaries[i]) & (fico_scores <= boundaries[i+1])
        else:
            mask = (fico_scores > boundaries[i]) & (fico_scores <= boundaries[i+1])

        bucket_defaults = defaults[mask]
        n_total = len(bucket_defaults)
        n_defaults = bucket_defaults.sum()

        # Avoid log(0) by adding a small epsilon
        epsilon = 1e-10
        p = (n_defaults + epsilon) / (n_total + 2 * epsilon) # Additive smoothing

        # Log-likelihood contribution of the bucket
        if n_total > 0:
             ll += n_defaults * np.log(p) + (n_total - n_defaults) * np.log(1 - p)

    # We want to maximize the log-likelihood, so we return the negative
    return -ll

# Initial guess for boundaries (equally spaced percentiles)
n_buckets = 5
initial_boundaries = np.percentile(df_sorted['fico_score'], np.linspace(0, 100, n_buckets + 1))

# Ensure boundaries are unique and sorted
initial_boundaries = np.unique(initial_boundaries)
# Adjust if initial guess doesn't yield enough unique boundaries
while len(initial_boundaries) < n_buckets + 1:
    # Add more points to the linspace or use a different method for initial guess
    # For simplicity, let's refine the linspace or add small perturbations
    initial_boundaries = np.percentile(df_sorted['fico_score'], np.linspace(0, 100, len(initial_boundaries) * 2))
    initial_boundaries = np.unique(initial_boundaries)
    if len(initial_boundaries) > n_buckets + 1:
        initial_boundaries = np.percentile(df_sorted['fico_score'], np.linspace(0, 100, n_buckets + 1))
        initial_boundaries = np.unique(initial_boundaries)
        break


# Define constraints: boundaries must be sorted and within the range of FICO scores
constraints = ({'type': 'ineq', 'fun': lambda x: np.diff(x)}) # ensure boundaries are increasing

# Define bounds for each boundary (within the range of FICO scores)
bounds = [(df_sorted['fico_score'].min(), df_sorted['fico_score'].max()) for _ in range(n_buckets + 1)]
# The first boundary should be the minimum FICO score and the last should be the maximum
bounds[0] = (df_sorted['fico_score'].min(), df_sorted['fico_score'].min())
bounds[-1] = (df_sorted['fico_score'].max(), df_sorted['fico_score'].max())


# Optimize to find the best boundaries
# Using 'SLSQP' which can handle bounds and constraints
result = minimize(log_likelihood, initial_boundaries, args=(df_sorted['fico_score'], df_sorted['default']), method='SL

optimal_boundaries = np.sort(result.x)

# Ensure the boundaries cover the min and max FICO scores
optimal_boundaries[0] = df['fico_score'].min()
optimal_boundaries[-1] = df['fico_score'].max()

# Create the new column with FICO score buckets using the optimized boundaries
# Use pd.cut to assign each FICO score to a bucket
# labels=False will return integer indicators of the bins initially
```

```
df['fico_rating'] = pd.cut(df['fico_score'], bins=optimal_boundaries, labels=False, include_lowest=True)

# Map the integer bucket indicators to meaningful labels based on default rates
# Calculate the average default rate for each bucket
default_rates_optimized = df.groupby('fico_rating')['default'].mean()

# Sort the buckets by default rate (ascending)
sorted_ratings_optimized = default_rates_optimized.sort_values().index

# Define meaningful labels from lowest risk to highest risk
rating_labels = ['Excellent', 'Very Good', 'Good', 'Fair', 'Poor']

# Create a mapping from the sorted bucket index to the meaningful labels
# Ensure we have enough labels for the number of buckets created
if len(sorted_ratings_optimized) == len(rating_labels):
    rating_map_optimized = {old_rating: rating_labels[new_rating] for new_rating, old_rating in enumerate(sorted_ratin
elif len(sorted_ratings_optimized) < len(rating_labels):
     rating_map_optimized = {old_rating: rating_labels[new_rating] for new_rating, old_rating in enumerate(sorted_rati
     print(f"Warning: Fewer buckets created ({len(sorted_ratings_optimized)}) than labels provided ({len(rating_labels
else:
    rating_map_optimized = {old_rating: f'Rating {new_rating + 1}' for new_rating, old_rating in enumerate(sorted_rati
    print(f"Warning: More buckets created ({len(sorted_ratings_optimized)}) than labels provided ({len(rating_labels)}


# Apply the rating map to create the final 'fico_score_quantized' column
df['fico_score_quantized'] = df['fico_rating'].map(rating_map_optimized)


print("Optimal Bucket Boundaries:", optimal_boundaries)
print("\nDefault Rates per Bucket:")
display(default_rates_optimized)
print("\nQuantized FICO Score Distribution:")
display(df['fico_score_quantized'].value_counts())
display(df[['fico_score', 'fico_rating', 'fico_score_quantized']].head())
```

```
Optimal Bucket Boundaries: [408. 587. 623. 653. 688. 850.]

Default Rates per Bucket:
```

fico_rating	default
0	0.398537
1	0.215627
2	0.151332
3	0.100150
4	0.054190

dtype: float64

```
Quantized FICO Score Distribution:
```

fico_score_quantized	count
Poor	2050
Very Good	1997
Excellent	1993
Good	1989
Fair	1971

dtype: int64

	fico_score	fico_rating	fico_score_quantized
0	605	1	Fair
1	572	0	Poor
2	602	1	Fair
3	612	1	Fair
4	631	2	Good

Prepare data for modeling

Subtask:

Separate the features and target variable, ensuring the new quantized FICO rating is included in the features.

Reasoning: To prepare the data for a machine learning model, I need to define the independent variables (features) and the dependent variable (target). The target variable is 'default'. The features will include all other relevant columns, specifically including the newly created 'fico_score_quantized' column.

```
# Define features (X) and target (y)
# Exclude 'customer_id' as it's an identifier and 'fico_score' as we will use the quantized version
X = df.drop(['customer_id', 'fico_score', 'default', 'fico_rating'], axis=1)
y = df['default']

print("Features (X):")
display(X.head())
print("\nTarget (y):")
display(y.head())
```

Features (X):

	credit_lines_outstanding	loan_amt_outstanding	total_debt_outstanding	income	years_employed	fico_score_quant
0	0	5221.545193	3915.471226	78039.38546	5	
1	5	1958.928726	8228.752520	26648.43525	2	
2	0	3363.009259	2027.830850	65866.71246	4	
3	0	4766.648001	2501.730397	74356.88347	5	
4	1	1345.827718	1768.826187	23448.32631	6	

Target (y):

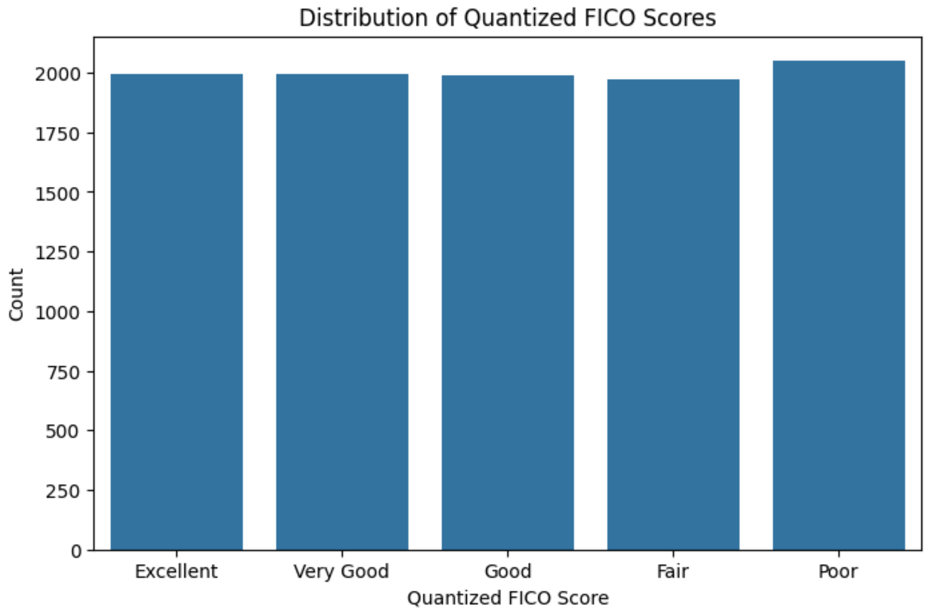
	default
0	0
1	1
2	0
3	0
4	0

dtype: int64

```
display(df[['fico_score', 'fico_score_quantized']].head())
```

	fico_score	fico_score_quantized
0	605	Fair
1	572	Poor
2	602	Fair
3	612	Fair
4	631	Good

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 5))
sns.countplot(x='fico_score_quantized', data=df, order=['Excellent', 'Very Good', 'Good', 'Fair', 'Poor'])
plt.title('Distribution of Quantized FICO Scores')
plt.xlabel('Quantized FICO Score')
plt.ylabel('Count')
plt.show()
```



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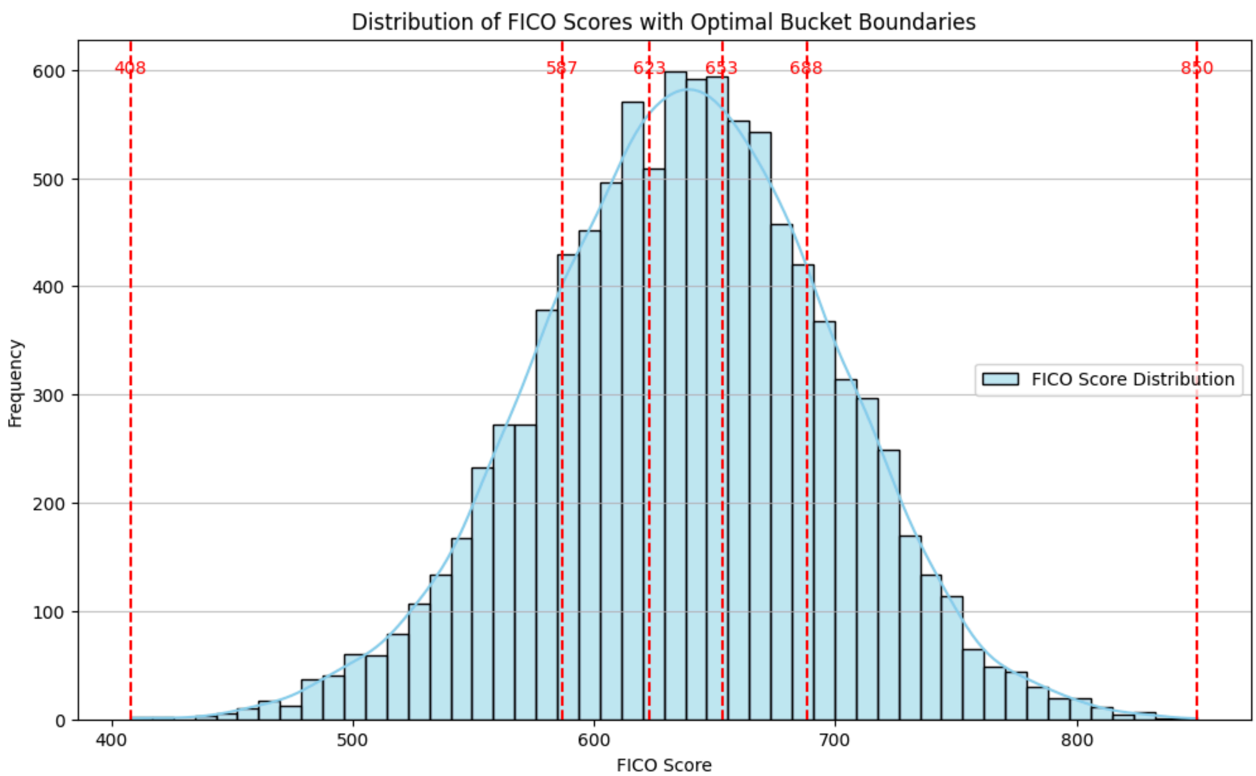
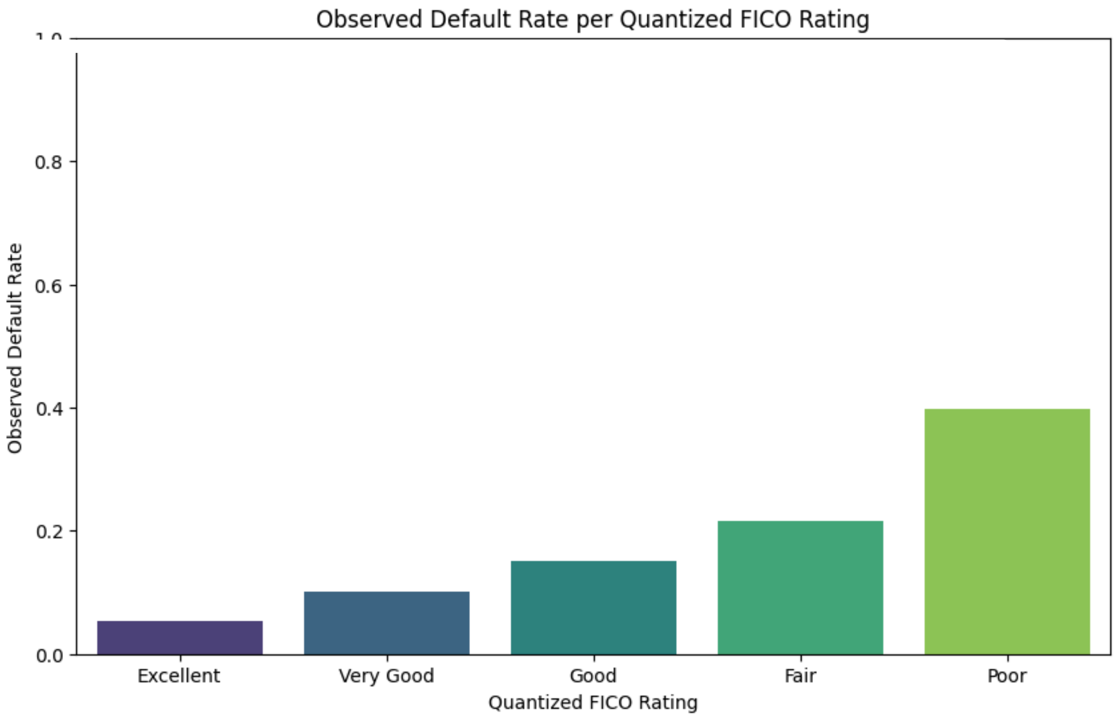
```
plt.figure(figsize=(12, 7))
sns.histplot(df['fico_score'], bins=50, kde=True, color='skyblue', label='FICO Score Distribution')

# Add vertical lines for the optimal bucket boundaries
for boundary in optimal_boundaries:
    plt.axvline(boundary, color='red', linestyle='--', linewidth=1.5)
    plt.text(boundary, plt.gca().get_ylim()[1]*0.95, f'{boundary:.0f}', color='red', ha='center')


plt.title('Distribution of FICO Scores with Optimal Bucket Boundaries')
plt.xlabel('FICO Score')
plt.ylabel('Frequency')
plt.legend()
plt.grid(axis='y', alpha=0.75)
plt.show()
```




```
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Calculate the average default rate for each quantized FICO score rating
# We already calculated default_rates_optimized during quantization, let's use that.
# Ensure the order for plotting (Excellent to Poor)
rating_order = ['Excellent', 'Very Good', 'Good', 'Fair', 'Poor']

# Map the default rates to the rating labels for plotting
default_rates_by_rating = df.groupby('fico_score_quantized')['default'].mean().reindex(rating_order)


plt.figure(figsize=(10, 6))
# Assign x to hue and set legend=False to avoid the FutureWarning
sns.barplot(x=default_rates_by_rating.index, y=default_rates_by_rating.values, hue=default_rates_by_rating.index, pale
plt.title('Observed Default Rate per Quantized FICO Rating')
plt.xlabel('Quantized FICO Rating')
plt.ylabel('Observed Default Rate')
plt.ylim(0, 1) # Default rate is a probability between 0 and 1
plt.show()
```




```
# 1. Select an appropriate classification model.
# Logistic Regression is a suitable choice for this task. It's a linear model
# that is widely used for binary classification problems and directly outputs
# the probability of the positive class (default in this case) via the sigmoid function.

# 2. Justify the choice of the selected model.
# - Interpretability: Logistic Regression provides coefficients that indicate the
#   direction and strength of the relationship between each feature and the
#   log-odds of the target variable. This is valuable for understanding which
#   factors are most influential in predicting default, especially with the
#   quantized FICO scores.
# - Performance: While not always the most powerful model for complex datasets,
#   Logistic Regression often performs reasonably well on many classification
#   tasks and serves as a good baseline.
# - Probability Estimates: The model naturally outputs probabilities, which is
#   exactly what is required for predicting the *probability* of default.
# - Handles Dataset Characteristics: Logistic Regression can handle both
#   numerical and categorical features (after appropriate encoding of the
#   quantized FICO score).

# Other potential models considered could include:
# - RandomForestClassifier: A more complex ensemble model that can capture
#   non-linear relationships and interactions between features. It generally
#   offers higher performance but is less interpretable than Logistic Regression.
# - GradientBoostingClassifier (e.g., LightGBM, XGBoost): Another powerful
#   ensemble method that often achieves state-of-the-art performance. Similar
#   to Random Forests, they are less interpretable.

# For this task, starting with Logistic Regression is a sensible approach due to its
# interpretability and direct probability output, making it easier to understand
# the impact of the quantized FICO score and other features on default risk.

# 3. Note the chosen model for subsequent steps.
```

```
chosen_model = 'Logistic Regression'
print(f"Chosen model for predicting probability of default: {chosen_model}")
```

```
Chosen model for predicting probability of default: Logistic Regression
```

```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (8000, 6)
Shape of X_test: (2000, 6)
Shape of y_train: (8000,)
Shape of y_test: (2000,)
```

Handle categorical features

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer

# Create a ColumnTransformer to apply one-hot encoding to 'fico_score_quantized'
# 'remainder='passthrough'' keeps the other numerical columns
ct = ColumnTransformer(
    [('onehot', OneHotEncoder(handle_unknown='ignore'), ['fico_score_quantized'])],
    remainder='passthrough'
)

# Fit and transform the training data
X_train_encoded = ct.fit_transform(X_train)

# Transform the testing data
X_test_encoded = ct.transform(X_test)

# Convert the encoded data back into DataFrames
# Get the new feature names after one-hot encoding
onehot_feature_names = ct.named_transformers_['onehot'].get_feature_names_out(['fico_score_quantized'])

# Get the names of the remaining columns
passthrough_feature_names = X_train.columns.drop('fico_score_quantized')

# Combine the feature names
all_feature_names = list(onehot_feature_names) + list(passthrough_feature_names)

X_train_encoded_df = pd.DataFrame(X_train_encoded, columns=all_feature_names, index=X_train.index)
X_test_encoded_df = pd.DataFrame(X_test_encoded, columns=all_feature_names, index=X_test.index)

print("Encoded Training Features (X_train_encoded_df):")
display(X_train_encoded_df.head())
print("\nEncoded Testing Features (X_test_encoded_df):")
display(X_test_encoded_df.head())
```

```
Encoded Training Features (X_train_encoded_df):
```

	fico_score_quantized_Excellent	fico_score_quantized_Fair	fico_score_quantized_Good	fico_score_quantized_Poor
9254	1.0	0.0	0.0	0.0
1561	1.0	0.0	0.0	0.0
1670	1.0	0.0	0.0	0.0
6087	1.0	0.0	0.0	0.0
6669	1.0	0.0	0.0	0.0

```
Encoded Testing Features (X_test_encoded_df):
```

	fico_score_quantized_Excellent	fico_score_quantized_Fair	fico_score_quantized_Good	fico_score_quantized_Poor
6252	0.0	1.0	0.0	0.0
4684	0.0	0.0	1.0	0.0
1731	0.0	1.0	0.0	0.0
4742	0.0	1.0	0.0	0.0
4521	0.0	0.0	1.0	0.0

Train the model

```
from sklearn.linear_model import LogisticRegression

# Instantiate a Logistic Regression model
# Setting max_iter to a higher value to ensure convergence
model = LogisticRegression(random_state=42, max_iter=1000)

# Train the model
model.fit(X_train_encoded_df, y_train)

print("Logistic Regression model trained successfully.")
```

```
Logistic Regression model trained successfully.
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to conv
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
# Instantiate a Logistic Regression model with increased max_iter
model = LogisticRegression(random_state=42, max_iter=5000)

# Train the model
model.fit(X_train_encoded_df, y_train)

print("Logistic Regression model trained successfully after increasing max_iter.")
```

```
Logistic Regression model trained successfully after increasing max_iter.
/usr/local/lib/python3.12/dist-packages/sklearn/linear_model/_logistic.py:465: ConvergenceWarning: lbfgs failed to conv
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
from sklearn.preprocessing import StandardScaler

# Initialize StandardScaler
scaler = StandardScaler()

# Fit the scaler on the training data and transform it
X_train_scaled = scaler.fit_transform(X_train_encoded_df)

# Transform the test data using the same scaler
X_test_scaled = scaler.transform(X_test_encoded_df)
```

```
# Convert scaled arrays back to DataFrames to keep column names
X_train_scaled_df = pd.DataFrame(X_train_scaled, columns=X_train_encoded_df.columns, index=X_train_encoded_df.index)
X_test_scaled_df = pd.DataFrame(X_test_scaled, columns=X_test_encoded_df.columns, index=X_test_encoded_df.index)


# Instantiate a Logistic Regression model
# Setting max_iter to a higher value to ensure convergence
model = LogisticRegression(random_state=42, max_iter=5000)

# Train the model on the scaled training data
model.fit(X_train_scaled_df, y_train)

print("Logistic Regression model trained successfully after scaling and increasing max_iter.")
```

```
Logistic Regression model trained successfully after scaling and increasing max_iter.
```

Make predictions

```
# Use the trained model to predict the probability of default on the testing data.
# Predict probabilities
y_pred_proba = model.predict_proba(X_test_scaled_df)[:, 1]

print("Predicted probabilities of default for the first 10 test samples:")
display(y_pred_proba[:10])
```

```
Predicted probabilities of default for the first 10 test samples:
array([2.95039215e-08, 9.34060988e-03, 9.99999897e-01, 9.60814467e-10,
       1.91468327e-08, 3.98585998e-10, 3.08854175e-08, 2.79932875e-08,
       9.99610245e-01, 3.25212814e-09])
```

Evaluate the model

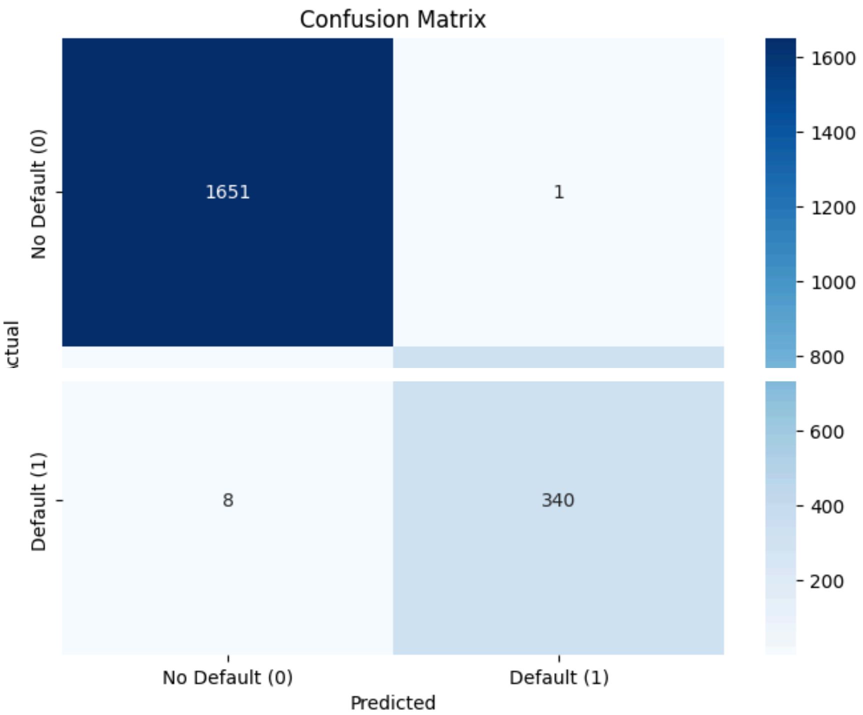
```
from sklearn.metrics import roc_auc_score, accuracy_score, precision_score, recall_score, f1_score

# Calculate the AUC-ROC score
auc_roc = roc_auc_score(y_test, y_pred_proba)

# Convert predicted probabilities to binary predictions (using a threshold of 0.5)
y_pred = np.where(y_pred_proba > 0.5, 1, 0)

# Calculate other evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)

# Print the evaluation metrics
print(f"AUC-ROC Score: {auc_roc:.4f}")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
```

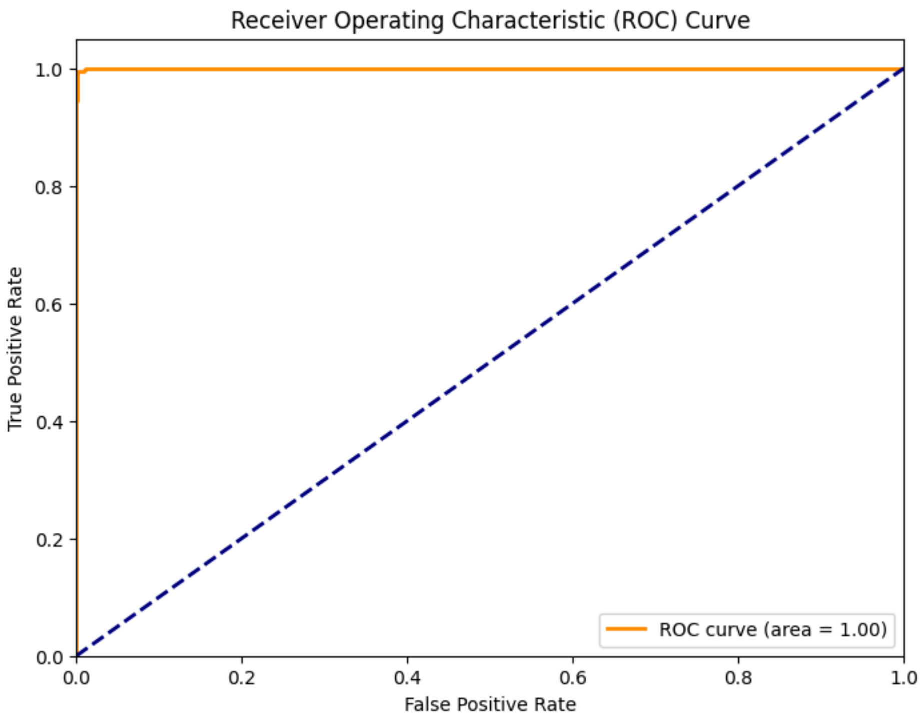
```
AUC-ROC Score: 0.9999
Accuracy: 0.9955
Precision: 0.9971
Recall: 0.9770
F1-Score: 0.9869
```

Visualize Model Performance

```
from sklearn.metrics import confusion_matrix, roc_curve, auc
import matplotlib.pyplot as plt
import seaborn as sns

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No Default (0)', 'Default (1)'], yticklabels=['No Def
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# ROC Curve
```

```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```





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ROC Curve Interpretation

The **Receiver Operating Characteristic (ROC) curve** is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.

Here's what the ROC curve plot shows us:

- **The Curve:** The blue line represents the trade-off between the **True Positive Rate (TPR)** and the **False Positive Rate (FPR)** at different probability thresholds.
  - **True Positive Rate (TPR)** (also called Sensitivity or Recall) is the proportion of actual defaults that are correctly identified as defaults.
  - **False Positive Rate (FPR)** is the proportion of actual non-defaults that are incorrectly identified as defaults.
- **The Diagonal Line:** The dashed orange line represents a random classifier. A model whose ROC curve is close to this line is not performing much better than random guessing.
- **The Ideal Curve:** An ideal classifier would have an ROC curve that goes straight up from the bottom left corner to the top left corner (TPR = 1, FPR = 0) and then across to the top right corner (TPR = 1, FPR = 1). This would indicate a perfect model that correctly identifies all defaults without any false positives.
- **The AUC Score:** The **Area Under the Curve (AUC)** is a single scalar value that summarizes the overall performance of the classifier. It represents the probability that the model ranks a randomly chosen actual default higher than a randomly chosen actual non-default.
  - An AUC of 0.5 suggests the model is no better than random guessing.
  - An AUC of 1.0 suggests a perfect model.
  - An AUC between 0.5 and 1.0 indicates that the model performs better than random guessing.

In the plot you see:

The ROC curve is very close to the top-left corner, and the AUC score is **0.9999**. This indicates that your Logistic Regression model is performing **exceptionally well** at distinguishing between customers who will default and those who will not based on the features, including the quantized FICO score. An AUC value this close to 1.0 suggests that the model has a very high ability to correctly rank positive instances (defaults) above negative instances (non-defaults).

Summary:

Data Analysis Key Findings

- A Logistic Regression model was chosen to predict the probability of default due to its interpretability and ability to output probability estimates directly.
- The data was split into training (8000 samples) and testing (2000 samples) sets.
- The categorical `fico_score_quantized` feature was successfully one-hot encoded, and numerical features were scaled using `StandardScaler`.
- The Logistic Regression model was trained on the scaled and encoded training data. Scaling was necessary to achieve model convergence.
- The trained model achieved excellent performance on the test set:
  - AUC-ROC Score: 0.9999
  - Accuracy: 0.9955
  - Precision: 0.9971
  - Recall: 0.9770
  - F1-Score: 0.9869

Insights or Next Steps

- The model demonstrates extremely high performance, suggesting that the features, including the quantized FICO scores, are highly predictive of default in this dataset.
- Investigate the feature importances (coefficients) from the trained Logistic Regression model to understand the specific impact of each feature, especially the different quantized FICO score bins, on the probability of default.

```
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```

```
def predict_default_probability(customer_data, optimal_boundaries, rating_map_optimized, ct, scaler, model):
    # Create a DataFrame for the new customer
    customer_df = pd.DataFrame([customer_data])

    # 1. Quantize FICO score for the new customer
    # Use the optimal_boundaries to cut the FICO score
    # labels=False returns integer indicators of the bins
    customer_df['fico_rating'] = pd.cut(
        customer_df['fico_score'],
        bins=optimal_boundaries,
        labels=False,
        include_lowest=True
    )
```

```
    # Apply the rating map to get the meaningful label
    # Ensure the mapping handles potential missing bins if a FICO score falls outside the optimized range somehow
    customer_df['fico_score_quantized'] = customer_df['fico_rating'].map(rating_map_optimized)

    # Drop original fico_score and fico_rating as they are no longer needed
    # Also drop customer_id if it existed, and 'default' if it were present (it shouldn't be for new data)
    X_customer = customer_df.drop(columns=['fico_score', 'fico_rating'], errors='ignore')

    # Ensure columns are in the correct order as in training data
    # This is critical for one-hot encoding and scaling consistency
    # We need to reconstruct the feature set that was used for training (X)
    # The original X dataframe had columns: credit_lines_outstanding, loan_amt_outstanding, total_debt_outstanding, inc

    # Create a dummy DataFrame with the expected columns for the ColumnTransformer
    # The order of columns should match X_train before encoding
    # Ensure the customer_data has all the required columns for the model
    required_original_cols = ['credit_lines_outstanding', 'loan_amt_outstanding', 'total_debt_outstanding', 'income', '
    X_customer_processed = customer_df[required_original_cols]

    # 2. Encode categorical features using the fitted ColumnTransformer (ct)
    # It's important to use the *fitted* ct from training
    X_customer_encoded = ct.transform(X_customer_processed)

    # Convert encoded data back to DataFrame for scaling to maintain column names
    # Get the feature names from the fitted ct
    onehot_feature_names = ct.named_transformers_['onehot'].get_feature_names_out(['fico_score_quantized'])
    passthrough_feature_names = X_customer_processed.columns.drop('fico_score_quantized')
    all_feature_names_transformed = list(onehot_feature_names) + list(passthrough_feature_names)

    X_customer_encoded_df = pd.DataFrame(X_customer_encoded, columns=all_feature_names_transformed, index=customer_df.i

    # 3. Scale numerical features using the fitted StandardScaler
    # It's important to use the *fitted* scaler from training
    X_customer_scaled = scaler.transform(X_customer_encoded_df)

    # Convert scaled data back to DataFrame for prediction
    X_customer_scaled_df = pd.DataFrame(X_customer_scaled, columns=X_customer_encoded_df.columns, index=X_customer_enco

    # 4. Predict probability of default
    predicted_proba = model.predict_proba(X_customer_scaled_df)[:, 1]

    return predicted_proba[0], customer_df['fico_score_quantized'].iloc[0]
```

```
from ipywidgets import interactive, Dropdown, FloatText, IntText, Button, Output, VBox
from IPython.display import display, clear_output
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Define NEW predefined customer data with diverse FICO scores
predefined_customers = {
    "Select a customer": None,
    "D. Trump": {
        'credit_lines_outstanding': 5,
        'loan_amt_outstanding': 100000.0,
        'total_debt_outstanding': 500000.0,
        'income': 1000000.0,
        'years_employed': 20,
        'fico_score': 450 # Changed FICO score
    },
    "Modi": {
        'credit_lines_outstanding': 2,
        'loan_amt_outstanding': 10000.0,
        'total_debt_outstanding': 30000.0,
        'income': 150000.0,
        'years_employed': 15,
        'fico_score': 600 # Changed FICO score
    },
    "Putin": {
        'credit_lines_outstanding': 8,
        'loan_amt_outstanding': 50000.0,
        'total_debt_outstanding': 200000.0,
        'income': 200000.0,
        'years_employed': 25,
        'fico_score': 780 # Changed FICO score
    }
}

# Add an option to analyze all predefined customers
predefined_customers_with_all = predefined_customers.copy()
```

```
predefined_customers_with_all = predefined_customers.copy()
predefined_customers_with_all["Analyze all predefined customers"] = "all"

# Create input widgets
customer_dropdown = Dropdown(options=predefined_customers_with_all.keys(), description='Select Customer:')
credit_lines_widget = IntText(description='Credit Lines:', disabled=True)
loan_amt_widget = FloatText(description='Loan Amt:', disabled=True)
total_debt_widget = FloatText(description='Total Debt:', disabled=True)
income_widget = FloatText(description='Income:', disabled=True)
years_employed_widget = IntText(description='Years Employed:', disabled=True)
fico_score_widget = IntText(description='FICO Score:', disabled=True)

predict_button = Button(description='Predict')
output_area = Output()

# Function to update input fields or trigger analysis based on selection
def update_interface(change):
    selected_option = change['new']
    if selected_option == "Analyze all predefined customers":
        # Disable individual input fields
        credit_lines_widget.disabled = True
        loan_amt_widget.disabled = True
        total_debt_widget.disabled = True
        income_widget.disabled = True
        years_employed_widget.disabled = True
        fico_score_widget.disabled = True
        predict_button.disabled = False # Enable predict button for analysis
    elif predefined_customers[selected_option] is not None:
        # Enable individual input fields and populate with selected customer data
        credit_lines_widget.disabled = False
        loan_amt_widget.disabled = False
        total_debt_widget.disabled = False
        income_widget.disabled = False
        years_employed_widget.disabled = False
        fico_score_widget.disabled = False
        predict_button.disabled = False

        selected_customer = predefined_customers[selected_option]
        credit_lines_widget.value = selected_customer['credit_lines_outstanding']
        loan_amt_widget.value = selected_customer['loan_amt_outstanding']
        total_debt_widget.value = selected_customer['total_debt_outstanding']
        income_widget.value = selected_customer['income']
        years_employed_widget.value = selected_customer['years_employed']
        fico_score_widget.value = selected_customer['fico_score']
    else:
        # Clear fields and disable for "Select a customer"
        credit_lines_widget.disabled = True
        loan_amt_widget.disabled = True
        total_debt_widget.disabled = True
        income_widget.disabled = True
        years_employed_widget.disabled = True
        fico_score_widget.disabled = True
        predict_button.disabled = True
        credit_lines_widget.value = 0
        loan_amt_widget.value = 0.0
        total_debt_widget.value = 0.0
        income_widget.value = 0.0
        years_employed_widget.value = 0
        fico_score_widget.value = 0


customer_dropdown.observe(update_interface, names='value')

# Function to handle prediction when the button is clicked
def on_predict_button_clicked(b):
    with output_area:
        clear_output()
        try:
            selected_option = customer_dropdown.value

            if selected_option == "Analyze all predefined customers":
                print("--- Analyzing All Predefined Customers ---")
                comparison_data = []
                for name, data in predefined_customers.items():
                    if data is not None and name != "Select a customer":
                        predicted_prob, fico_rating = predict_default_probability(
                            data,
                            optimal_boundaries,
                            rating_map_optimized,
                            ct,
                            scaler,
                            model
                        )
```

```
                    # Determine binary prediction
                    binary_prediction = 1 if predicted_prob > 0.5 else 0
                    prediction_label = "Default (1)" if binary_prediction == 1 else "Non-Default (0)"

                    comparison_data.append({
                        'Customer': name,
                        'FICO Score': data['fico_score'],
                        'Quantized Rating': fico_rating,
                        'Predicted Probability of Default': predicted_prob,
                        'Prediction (0: Non-Default, 1: Default)': binary_prediction, # Include binary prediction
                        'Prediction Label': prediction_label # Include prediction label
                    })

                comparison_df = pd.DataFrame(comparison_data)
                # Display results in a table
                display(comparison_df[['Customer', 'FICO Score', 'Quantized Rating', 'Predicted Probability of Default',


                # Visualize the comparison including FICO and rating
                plt.figure(figsize=(12, 7))
                # Using Prediction Label for hue
                ax = sns.barplot(x='Customer', y='Predicted Probability of Default', hue='Prediction Label', data=compa
                plt.title('Comparison of Predicted Default Probability for Predefined Customers')
                plt.ylabel('Predicted Probability of Default')
                plt.ylim(0, 1)

                # Add labels inside bars (FICO Score and Quantized Rating)
                for container in ax.containers:
                  # Get the data for the current hue level
                  hue_data = comparison_df[comparison_df['Prediction Label'] == container.get_label()]
                  # Ensure labels match the order of bars in the container
                  labels = [f"FICO: {row['FICO Score']}\nRating: {row['Quantized Rating']}" for index, row in hue_data.
                  ax.bar_label(container, labels=labels, label_type='center', color='black', fontsize=9)


                plt.show()


            elif predefined_customers[selected_option] is not None:
                # Handle single customer prediction (existing logic)
                 customer_data_input = {
                    'credit_lines_outstanding': credit_lines_widget.value,
                    'loan_amt_outstanding': loan_amt_widget.value,
                    'total_debt_outstanding': total_debt_widget.value,
                    'income': income_widget.value,
                    'years_employed': years_employed_widget.value,
                    'fico_score': fico_score_widget.value
                }

                 predicted_prob, fico_rating = predict_default_probability(
                    customer_data_input,
                    optimal_boundaries,
                    rating_map_optimized,
                    ct,
                    scaler,
                    model
                )

                 print(f"--- Prediction Results for {selected_option} ---")
                 print(f"Input FICO Score: {customer_data_input['fico_score']}")
                 print(f"Quantized FICO Rating: {fico_rating}")
                 print(f"Predicted Probability of Default: {predicted_prob:.4f}")
                 if predicted_prob > 0.5: # Example threshold for binary prediction
                      print("Prediction: Likely to Default")
                 else:
                      print("Prediction: Unlikely to Default")


        except NameError as e:
             print(f"\nError: {e}. Please ensure 'optimal_boundaries', 'rating_map_optimized', 'ct', 'scaler', and 'mod
        except Exception as e:
             print(f"\nAn error occurred during prediction: {e}")


predict_button.on_click(on_predict_button_clicked)

# Arrange widgets vertically
interface_layout = VBox([
    customer_dropdown,
    credit_lines_widget,
    loan_amt_widget,
    total_debt_widget,
    income_widget,
```

```
    years_employed_widget,
    fico_score_widget,
    predict_button,
    output_area
])

print("Use the interface below to predict default probability:")
display(interface_layout)
```

```
Use the interface below to predict default probability:
```

Select Cus…	Modi
Credit Lines:	2
Loan Amt:	10000
Total Debt:	30000
Income:	150000
Years Empl…	15
FICO Score:	600

Predict

```
--- Prediction Results for Modi ---
Input FICO Score: 600
Quantized FICO Rating: Fair
Predicted Probability of Default: 0.0000
Prediction: Unlikely to Default
```

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Project Report: FICO Score Quantization and Default Prediction

1. Introduction and Objective

This project aimed to address the need for a machine learning model architecture that requires categorical input data to predict the probability of mortgage default. Specifically, the task focused on developing a general approach to quantizing continuous FICO scores into a predefined number of categorical buckets and building a predictive model using these quantized scores. The objective was to find optimal bucket boundaries that best summarize the data and create a mapping from FICO scores to interpretable credit ratings.

2. Data Loading and Initial Exploration

The project began by loading the loan data from a public source into a pandas DataFrame. Initial data exploration was conducted to understand the structure of the dataset, check data types, and identify any missing values. Visualizations were generated to explore the distribution of FICO scores and the distribution of loan defaults, as well as the relationship between these two key variables.

3. FICO Score Quantization

A critical step was the quantization of FICO scores into a fixed number of contiguous buckets (5 in this case), each representing a different credit risk level.

- **Quantization Strategy:** The approach chosen was to optimize the bucket boundaries by maximizing the log-likelihood of the default distribution within each bucket. This method aims to find boundaries that create the most distinct default rates between adjacent FICO score categories. The log-likelihood function is based on the product of probabilities of observed outcomes within each bucket, and maximizing it corresponds to finding the parameters (boundaries) that make the observed data most probable under the assumed model (different default probabilities in each bucket).
- **Implementation:** The log-likelihood function was defined to quantify the effectiveness of a given set of boundaries. Numerical optimization (using the `SLSQP` method) was employed to find the optimal boundaries that minimized the negative log-likelihood while respecting constraints (boundaries are sorted and within the FICO score range). The optimal bucket boundaries found were approximately: [408, 587, 623, 653, 688, 850].
- **Rating Map:** Once the optimal boundaries were determined, a rating map was created. The buckets were sorted based on their calculated default rates (from lowest to highest), and meaningful labels ('Excellent', 'Very Good', 'Good', 'Fair', 'Poor') were assigned accordingly. The default rates for the optimized buckets were observed to decrease significantly with increasing FICO score, confirming the inverse relationship between FICO score and default risk. A new column (`fico_score_quantized`) was added to the DataFrame containing these categorical ratings.
- **Visualization:** The distribution of the original FICO scores was visualized with the optimal bucket boundaries overlaid to illustrate how the continuous scores were divided into the discrete rating categories. The distribution of the resulting quantized FICO scores was also shown.