In [339…
```
import pandas as pd
import numpy as np
import time
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.patches import Circle
from sklearn.model_selection import train_test_split, cross_val_score, GridS
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.metrics import accuracy_score, precision_score, recall_score, f
```

In [340…
```
application_record_df = pd.read_csv("./Resources/application_record.csv")
credit_record_df = pd.read_csv("./Resources/credit_record.csv")
```

In [341…
```
application_record_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 438557 entries, 0 to 438556
Data columns (total 18 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   ID                   438557 non-null  int64  
 1   CODE_GENDER          438557 non-null  object 
 2   FLAG_OWN_CAR         438557 non-null  object 
 3   FLAG_OWN_REALTY      438557 non-null  object 
 4   CNT_CHILDREN         438557 non-null  int64  
 5   AMT_INCOME_TOTAL     438557 non-null  float64
 6   NAME_INCOME_TYPE     438557 non-null  object 
 7   NAME_EDUCATION_TYPE  438557 non-null  object 
 8   NAME_FAMILY_STATUS   438557 non-null  object 
 9   NAME_HOUSING_TYPE    438557 non-null  object 
 10  DAYS_BIRTH           438557 non-null  int64  
 11  DAYS_EMPLOYED        438557 non-null  int64  
 12  FLAG_MOBIL           438557 non-null  int64  
 13  FLAG_WORK_PHONE      438557 non-null  int64  
 14  FLAG_PHONE           438557 non-null  int64  
 15  FLAG_EMAIL           438557 non-null  int64  
 16  OCCUPATION_TYPE      304354 non-null  object 
 17  CNT_FAM_MEMBERS      438557 non-null  float64
dtypes: float64(2), int64(8), object(8)
memory usage: 60.2+ MB
```

In [342…
```
credit_record_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 3 columns):
 #   Column          Non-Null Count    Dtype
---  ------          --------------    -----
 0   ID              1048575 non-null  int64
 1   MONTHS_BALANCE  1048575 non-null  int64
 2   STATUS          1048575 non-null  object
dtypes: int64(2), object(1)
memory usage: 24.0+ MB
```

In [343…

```
merged_df = pd.merge(application_record_df, credit_record_df, on='ID', how='

merged_df.describe()
```

Out[343…

	ID	CNT_CHILDREN	AMT_INCOME_TOTAL	DAYS_BIRTH	DAY
count	7.777150e+05	777715.000000	7.777150e+05	777715.000000	7
mean	5.078743e+06	0.428082	1.885348e+05	-16124.937046	
std	4.180442e+04	0.745755	1.016225e+05	4104.304018	1
min	5.008804e+06	0.000000	2.700000e+04	-25152.000000	
25%	5.044568e+06	0.000000	1.215000e+05	-19453.000000	
50%	5.069530e+06	0.000000	1.620000e+05	-15760.000000	
75%	5.115551e+06	1.000000	2.250000e+05	-12716.000000	
max	5.150487e+06	19.000000	1.575000e+06	-7489.000000	3

In [344…

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 777715 entries, 0 to 777714
Data columns (total 20 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   ID                   777715 non-null  int64  
 1   CODE_GENDER          777715 non-null  object 
 2   FLAG_OWN_CAR         777715 non-null  object 
 3   FLAG_OWN_REALTY      777715 non-null  object 
 4   CNT_CHILDREN         777715 non-null  int64  
 5   AMT_INCOME_TOTAL     777715 non-null  float64
 6   NAME_INCOME_TYPE     777715 non-null  object 
 7   NAME_EDUCATION_TYPE  777715 non-null  object 
 8   NAME_FAMILY_STATUS   777715 non-null  object 
 9   NAME_HOUSING_TYPE    777715 non-null  object 
 10  DAYS_BIRTH           777715 non-null  int64  
 11  DAYS_EMPLOYED        777715 non-null  int64  
 12  FLAG_MOBIL           777715 non-null  int64  
 13  FLAG_WORK_PHONE      777715 non-null  int64  
 14  FLAG_PHONE           777715 non-null  int64  
 15  FLAG_EMAIL           777715 non-null  int64  
 16  OCCUPATION_TYPE      537667 non-null  object 
 17  CNT_FAM_MEMBERS      777715 non-null  float64
 18  MONTHS_BALANCE       777715 non-null  int64  
 19  STATUS               777715 non-null  object 
dtypes: float64(2), int64(9), object(9)
memory usage: 118.7+ MB
```

In [345…

```
df = merged_df.copy()
#df.drop('MONTHS_BALANCE', axis=1, inplace=True)
df.head()
```

Out[345…

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDRE
0	5008804	M	Y	Y	
1	5008804	M	Y	Y	
2	5008804	M	Y	Y	
3	5008804	M	Y	Y	
4	5008804	M	Y	Y	

In [ ]:

```
```

In [346…

```
df['STATUS'].value_counts()
```

Out[346…
```
STATUS
C    329536
0    290654
X    145950
1      8747
5      1527
2       801
3       286
4       214
Name: count, dtype: int64
```

In [347…
```
# Filter DataFrame for clients with only 'C' and 'X' and '0' in their STATUS
cx0_clients = df[df['STATUS'].isin(['C', 'X', '0'])]

# Verify that these clients have only 'C' and 'X' in their STATUS by checkin
# This creates a boolean mask indicating whether each client only has 'C' an
cx0_mask = cx0_clients.groupby('ID')['STATUS'].transform(lambda x: set(x).is

# Apply mask
cx0_clients = cx0_clients[cx0_mask]
```

In [348…
```
cx0_clients['STATUS'].value_counts()
```

Out[348…
```
STATUS
C    329536
0    290654
X    145950
Name: count, dtype: int64
```

In [349…
```
# Now, filter out clients who do not have at least 6 months of 'MONTHS_BALAN
# We first calculate the max 'MONTHS_BALANCE' (absolute value) for each clie
max_months_balance = cx0_clients.groupby('ID')['MONTHS_BALANCE'].transform(l

# Apply the filter for at least 6 months
cx0_clients_filtered = cx0_clients[max_months_balance >= 6]

# Display the filtered DataFrame
cx0_clients_filtered
```

Out[349…

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
0	5008804	M	Y	Y	
1	5008804	M	Y	Y	
2	5008804	M	Y	Y	
3	5008804	M	Y	Y	
4	5008804	M	Y	Y	
...	...	...	...	...	
777708	5150337	M	N	Y	
777709	5150337	M	N	Y	
777710	5150337	M	N	Y	
777713	5150337	M	N	Y	
777714	5150337	M	N	Y	

751384 rows × 20 columns

In [350…

```
# Looking into one client
specific_user_data = cx0_clients_filtered[cx0_clients_filtered['ID'] == 5149
specific_user_data
```

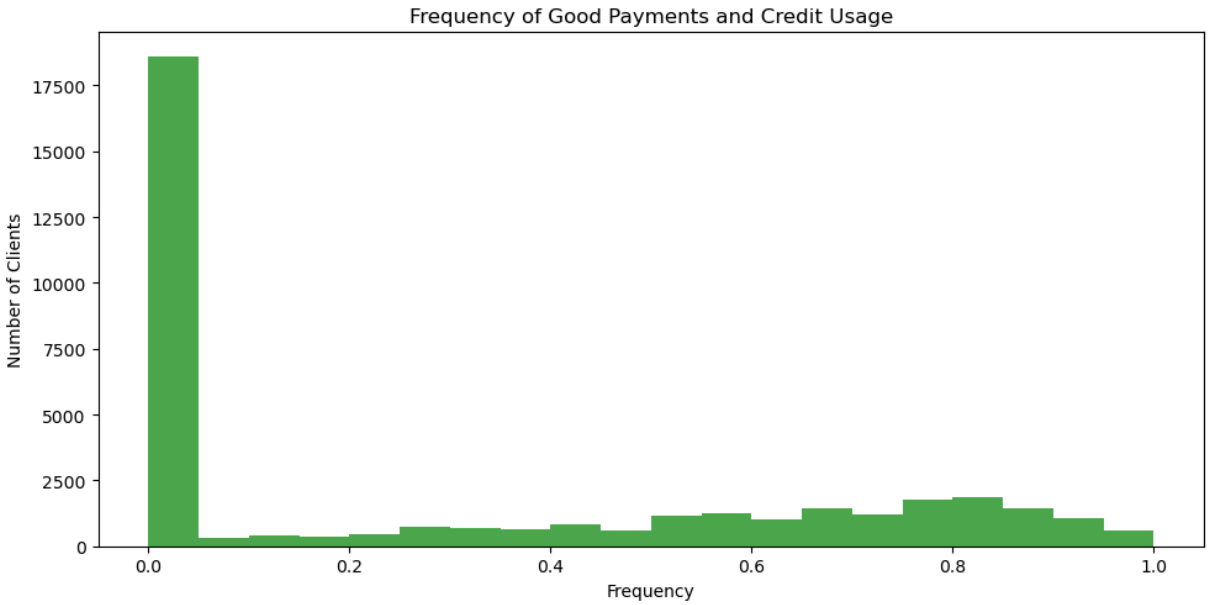
Out[350…

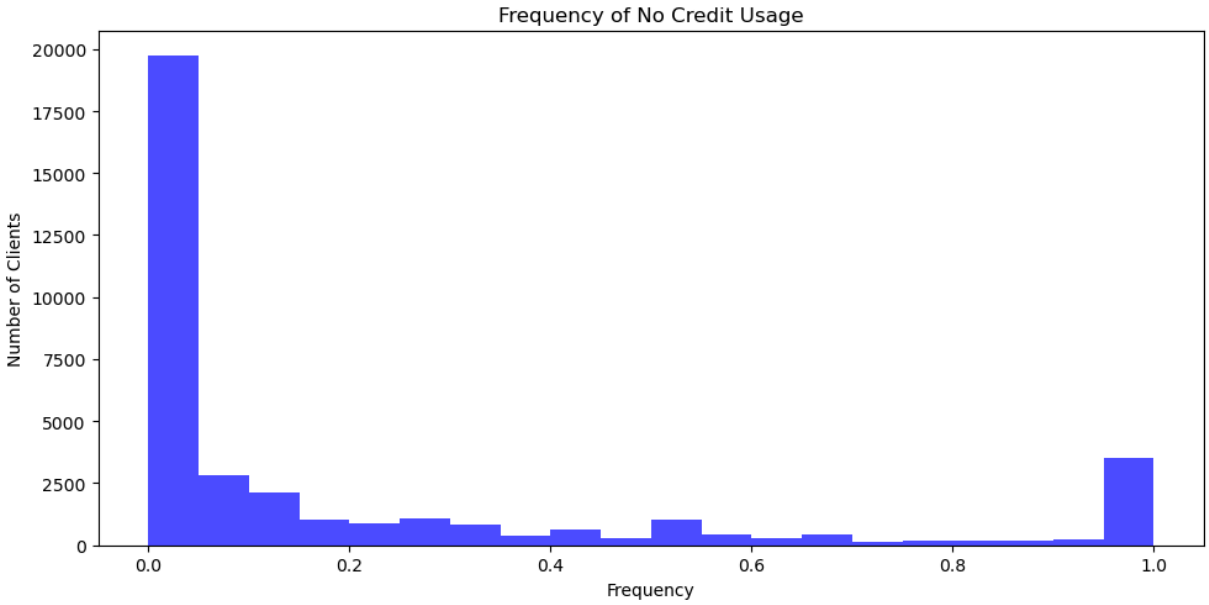
	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
777658	5149838	F	N	Y	
777659	5149838	F	N	Y	
777660	5149838	F	N	Y	
777661	5149838	F	N	Y	
777662	5149838	F	N	Y	
777663	5149838	F	N	Y	
777664	5149838	F	N	Y	
777665	5149838	F	N	Y	
777666	5149838	F	N	Y	
777667	5149838	F	N	Y	
777668	5149838	F	N	Y	
777669	5149838	F	N	Y	
777670	5149838	F	N	Y	
777671	5149838	F	N	Y	
777690	5149838	F	N	Y	

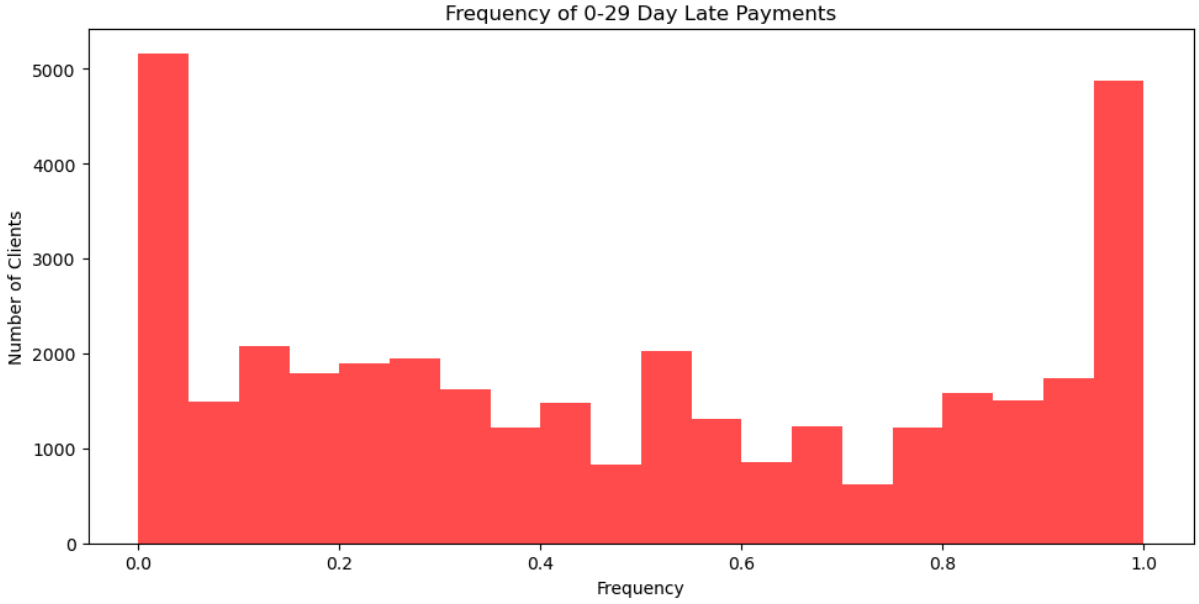
In [351…

```
# Calculate the count of 'C' and 'X' and '0'for each user
# Assuming 'df' is your merged DataFrame containing the 'STATUS' and 'ID' co
status_counts = df.groupby(['ID', 'STATUS']).size().unstack(fill_value=0)

# Calculate frequencies by dividing each status count by the total counts pe
status_frequencies = status_counts.div(status_counts.sum(axis=1), axis=0)


# Assuming status_frequencies contains the frequency of each status ('C', 'X
fig, axes = plt.subplots(3, 1, figsize=(10, 15))

if 'C' in status_frequencies.columns:
    axes[0].hist(status_frequencies['C'], bins=20, alpha=0.7, color='green')
    axes[0].set_title('Frequency of Good Payments and Credit Usage')
    axes[0].set_xlabel('Frequency')
    axes[0].set_ylabel('Number of Clients')

if 'X' in status_frequencies.columns:
    axes[1].hist(status_frequencies['X'], bins=20, alpha=0.7, color='blue')
    axes[1].set_title('Frequency of No Credit Usage')
    axes[1].set_xlabel('Frequency')
    axes[1].set_ylabel('Number of Clients')

if '0' in status_frequencies.columns:
    axes[2].hist(status_frequencies['0'], bins=20, alpha=0.7, color='red')
    axes[2].set_title('Frequency of 0-29 Day Late Payments')
    axes[2].set_xlabel('Frequency')
    axes[2].set_ylabel('Number of Clients')
```

```
plt.tight_layout()
plt.show()
```


Frequency of Good Payments and Credit Usage
Number of Clients
Frequency
0
2500
5000
7500
10000
12500
15000
17500
0.0
0.2
0.4
0.6
0.8
1.0


Frequency of No Credit Usage
Number of Clients
Frequency
0
2500
5000
7500
10000
12500
15000
17500
20000
0.0
0.2
0.4
0.6
0.8
1.0


Frequency of 0-29 Day Late Payments
Number of Clients
Frequency
0
1000
2000
3000
4000
5000
0.0
0.2
0.4
0.6
0.8
1.0

In [352…

```
# Calculate the frequency of each status for each user
status_frequency = cx0_clients_filtered.groupby('ID')['STATUS'].value_counts

# Calculate the average frequency of 'C' across all users who only have 'C',
average_c_frequency = status_frequency['C'].mean()

print(f"Average frequency of 'C' among CX0 users: {average_c_frequency}")
```

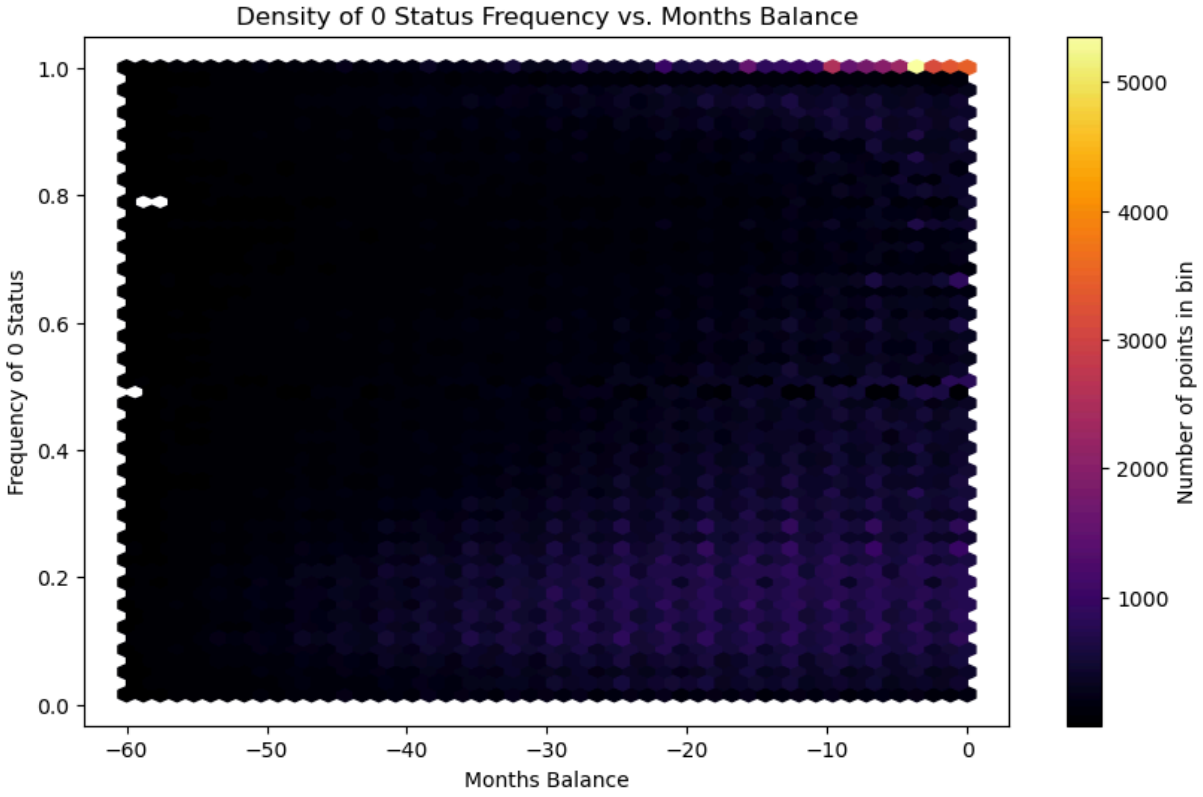
```
Average frequency of 'C' among CX0 users: 0.33666211822970865
```

In [353…

```
# Look into the frequency of '0' over the months the client has maintaind th

# Group by ID and calculate the frequency of each status
status_frequency = df.groupby('ID')['STATUS'].value_counts(normalize=True).u

# Now, merge this with the MONTHS_BALANCE information
merged_info = pd.merge(df[['ID', 'MONTHS_BALANCE']].drop_duplicates(), statu

# Filtering to include only rows where '0' status frequency is available
zero_frequency_data = merged_info[merged_info['0'] > 0]

plt.figure(figsize=(10, 6))

# Adjust the gridsize for finer or coarser hexagons, and set mincnt to 1 or
# The 'cmap' value is set to a palette that provides a good contrast, like '
# You can also try 'inferno', 'plasma', 'viridis', etc., for a more vivid co
plt.hexbin(zero_frequency_data['MONTHS_BALANCE'], zero_frequency_data['0'],
cb = plt.colorbar(label='Number of points in bin')

# Enhancing contrast and visibility
cb.set_label('Number of points in bin')
plt.xlabel('Months Balance')
plt.ylabel('Frequency of 0 Status')
plt.title('Density of 0 Status Frequency vs. Months Balance')

# Optionally, adjust the limits of the colorbar to make the color mapping mo
```

Out[353…

```
Text(0.5, 1.0, 'Density of 0 Status Frequency vs. Months Balance')
```



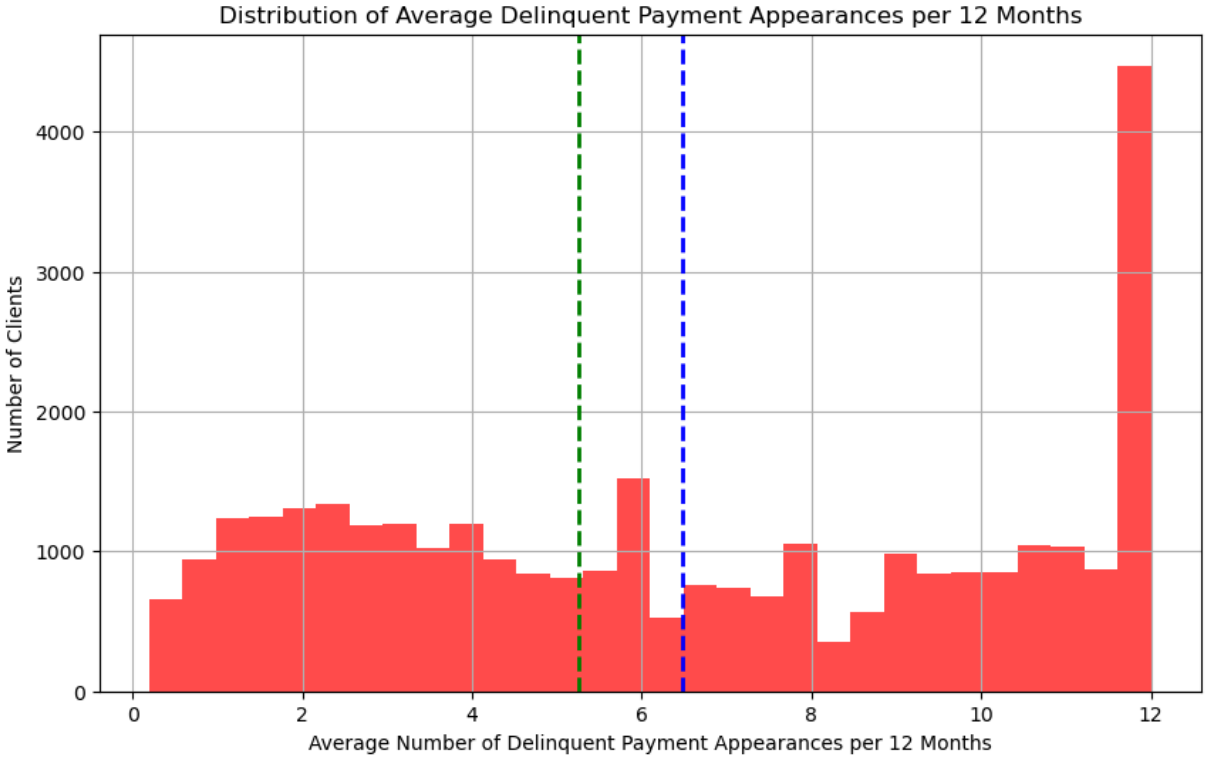
In [354…
```
# Step 1: Filter users with at least one '0' appearance
users_with_zero = df[df['STATUS'] == '0']['ID'].unique()

# Step 2 & 3: Calculate the number of '0' appearances and total months recor
zero_counts_per_user = df[df['ID'].isin(users_with_zero)].groupby('ID')['STA
total_months_per_user = df[df['ID'].isin(users_with_zero)].groupby('ID')['MO

# Step 4: Calculate average number of '0' appearances per 12 months
average_zeros_per_12_months = (zero_counts_per_user / total_months_per_user
average_zeros_per_12_months_half = average_zeros_per_12_months / 2
average_zeros_per_12_months_half_half = average_zeros_per_12_months_half / 2

# Printing the result
print(f"Average number of '0' appearances per 12 months for users with at le
```

```
Average number of '0' appearances per 12 months for users with at least one
'0': 6.471897774771895
```

In [355…
```
users_with_zero = df[df['STATUS'] == '0']
zero_counts = users_with_zero.groupby('ID')['STATUS'].count()
# Calculate the range of MONTHS_BALANCE for each user
months_range = df.groupby('ID')['MONTHS_BALANCE'].agg([min, max])
months_range['duration'] = months_range['max'] - months_range['min'] + 1

# Merge this information with zero_counts
average_zeros_per_year = pd.merge(zero_counts, months_range['duration'], on=

# Calculate the average number of '0' appearances per 12 months
average_zeros_per_year['avg_per_12_months'] = (average_zeros_per_year['STATU

plt.figure(figsize=(10, 6))
```

```
plt.axvline(x=average_zeros_per_12_months, color='b', linestyle='--', linewi
plt.axvline(x=target_average_zeros, color='g', linestyle='--', linewidth=2,

plt.hist(average_zeros_per_year['avg_per_12_months'], bins=30, alpha=0.7, co
plt.xlabel('Average Number of Delinquent Payment Appearances per 12 Months')
plt.ylabel('Number of Clients')
plt.title('Distribution of Average Delinquent Payment Appearances per 12 Mor
plt.grid(True)
plt.show()
```

```
/tmp/ipykernel_6453/3397970603.py:4: FutureWarning: The provided callable <b
uilt-in function min> is currently using SeriesGroupBy.min. In a future vers
ion of pandas, the provided callable will be used directly. To keep current
behavior pass the string "min" instead.
  months_range = df.groupby('ID')['MONTHS_BALANCE'].agg([min, max])
/tmp/ipykernel_6453/3397970603.py:4: FutureWarning: The provided callable <b
uilt-in function max> is currently using SeriesGroupBy.max. In a future vers
ion of pandas, the provided callable will be used directly. To keep current
behavior pass the string "max" instead.
  months_range = df.groupby('ID')['MONTHS_BALANCE'].agg([min, max])
```



In [356…
```
target_average_zeros = 5.25 # the chart below led me to select this value
```

In [357…
```
# Next up, setting the targets based on the conditions a client must meet
```

In [358…
```
df
```

Out[358…

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
0	5008804	M	Y	Y	
1	5008804	M	Y	Y	
2	5008804	M	Y	Y	
3	5008804	M	Y	Y	
4	5008804	M	Y	Y	
...	...	...	...	...	
777710	5150337	M	N	Y	
777711	5150337	M	N	Y	
777712	5150337	M	N	Y	
777713	5150337	M	N	Y	
777714	5150337	M	N	Y	

777715 rows × 20 columns

In [359…

```
df['Target'] = np.nan
df
```

Out[359…

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
0	5008804	M	Y	Y	
1	5008804	M	Y	Y	
2	5008804	M	Y	Y	
3	5008804	M	Y	Y	
4	5008804	M	Y	Y	
...	...	...	...	...	
777710	5150337	M	N	Y	
777711	5150337	M	N	Y	
777712	5150337	M	N	Y	
777713	5150337	M	N	Y	
777714	5150337	M	N	Y	

777715 rows × 21 columns

In [360…

```
# Setting target params

# Step 1: Calculate the number of '0' appearances and total months recorded
zero_counts_per_user = df[df['STATUS'] == '0'].groupby('ID')['STATUS'].apply
total_months_per_user = df.groupby('ID')['MONTHS_BALANCE'].nunique()

# Step 2: Calculate average number of '0' appearances per 12 months for each
average_zeros_per_12_months_per_user = zero_counts_per_user / total_months_p


# Group by 'ID' and check conditions
for id, group in df.groupby('ID'):
    # Initialize target as None
    target = None

    # Condition 1: Check if any status is not 'C' or 'X'
    if not all(group['STATUS'].isin(['C', 'X', '0'])):
        target = 0
    # Condition 2: Check for at least one 'MONTHS_BALANCE' >= 12 (in absolut
    elif not any(group['MONTHS_BALANCE'].abs() >= 6):
        target = 0

    elif average_zeros_per_12_months_per_user.get(id, 0) >= target_average_z
        target = 0
    # Condition 3: Calculate the average frequency of 'C' and compare to 56%
    else:
        c_frequency = (group['STATUS'] == 'C').mean() * 100
        target = 1 if c_frequency >= 30 else 0
```

```
    # Assign target value for the group
    df.loc[df['ID'] == id, 'Target'] = target

# Check if there are still any NaN values in 'Target'
nan_in_target = df['Target'].isna().sum()
print(f"NaN values in 'Target': {nan_in_target}")
```

```
NaN values in 'Target': 0
```

In [361…
```
frequncy = df['Target'].value_counts()
frequncy
```

Out[361…
```
Target
0.0    440195
1.0    337520
Name: count, dtype: int64
```

In [362…
```
training_df = df.copy()
```

In [363…
```
training_df
```

Out[363…

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CH
0	5008804	M	Y	Y	
1	5008804	M	Y	Y	
2	5008804	M	Y	Y	
3	5008804	M	Y	Y	
4	5008804	M	Y	Y	
...	...	...	...	...	
777710	5150337	M	N	Y	
777711	5150337	M	N	Y	
777712	5150337	M	N	Y	
777713	5150337	M	N	Y	
777714	5150337	M	N	Y	

777715 rows × 21 columns

In [364…
```
# Step 1: Prepare the data
# Exclude 'STATUS', 'MONTHS_BALANCE', and any other non-feature columns like
X = training_df.drop(['Target', 'STATUS', 'MONTHS_BALANCE', 'ID'], axis=1)
y = training_df['Target']
```

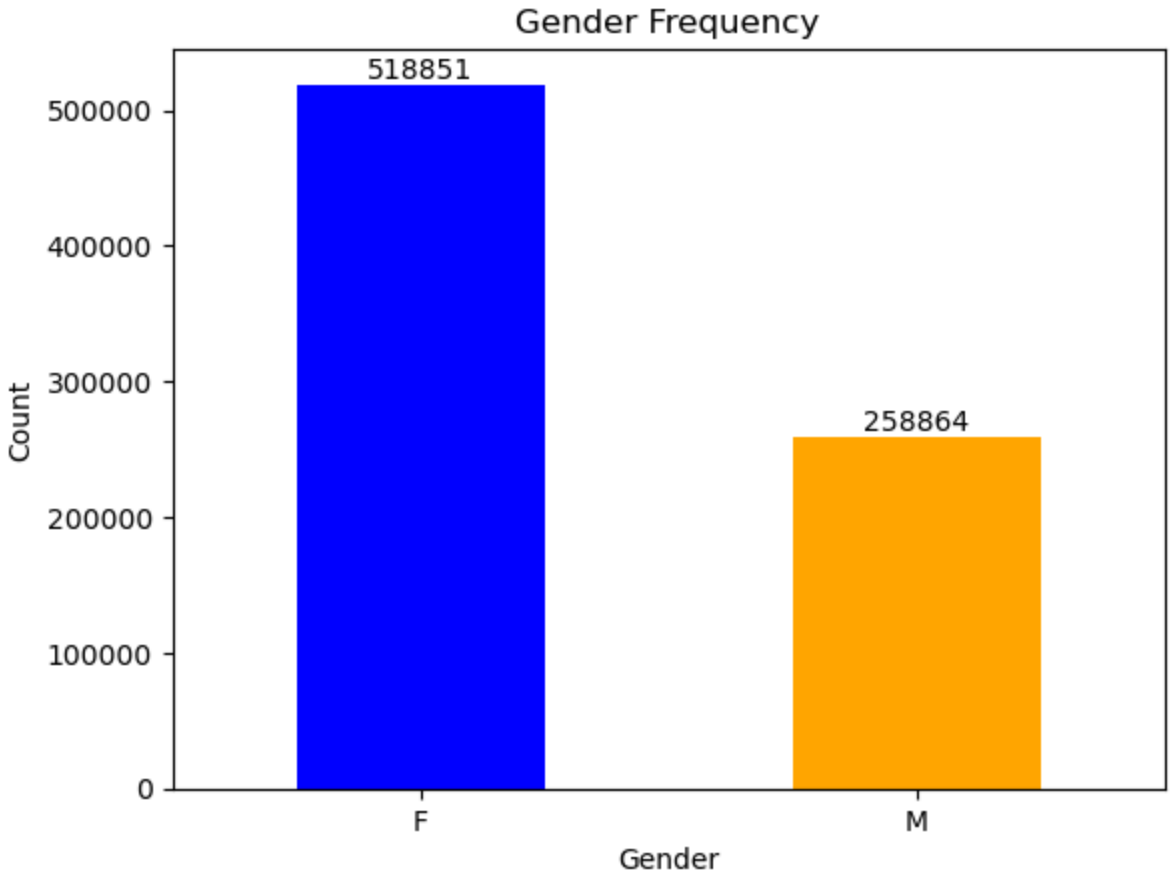
In [365…
```
# Double check y is accurate
y.value_counts()
```

Out[365…
```
Target
0.0    440195
1.0    337520
Name: count, dtype: int64
```

In [366…
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 777715 entries, 0 to 777714
Data columns (total 17 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   CODE_GENDER          777715 non-null  object 
 1   FLAG_OWN_CAR         777715 non-null  object 
 2   FLAG_OWN_REALTY      777715 non-null  object 
 3   CNT_CHILDREN         777715 non-null  int64  
 4   AMT_INCOME_TOTAL     777715 non-null  float64
 5   NAME_INCOME_TYPE     777715 non-null  object 
 6   NAME_EDUCATION_TYPE  777715 non-null  object 
 7   NAME_FAMILY_STATUS   777715 non-null  object 
 8   NAME_HOUSING_TYPE    777715 non-null  object 
 9   DAYS_BIRTH           777715 non-null  int64  
 10  DAYS_EMPLOYED        777715 non-null  int64  
 11  FLAG_MOBIL           777715 non-null  int64  
 12  FLAG_WORK_PHONE      777715 non-null  int64  
 13  FLAG_PHONE           777715 non-null  int64  
 14  FLAG_EMAIL           777715 non-null  int64  
 15  OCCUPATION_TYPE      537667 non-null  object 
 16  CNT_FAM_MEMBERS      777715 non-null  float64
dtypes: float64(2), int64(7), object(8)
memory usage: 100.9+ MB
```

In [367…
```
frequency = X['CODE_GENDER'].value_counts()
frequency.plot(kind='bar', color=['blue', 'orange'])

plt.title('Gender Frequency')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.xticks(rotation=0)  # Keep the gender labels horizontal for better reada

# Adding value labels above each bar
for index, value in enumerate(frequency):
    plt.text(index, value, str(value), ha='center', va='bottom')

plt.show()
```



In [368…
```
# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, ra
```

In [369…
```
X_train['CODE_GENDER'].value_counts()
```

Out[369…
```
CODE_GENDER
F    347434
M    173635
Name: count, dtype: int64
```

In [370…
```
X_test['CODE_GENDER'].value_counts()
```

Out[370…
```
CODE_GENDER
F    171417
M     85229
Name: count, dtype: int64
```

In [371…
```
y_train.value_counts()
```

Out[371…
```
Target
0.0    295101
1.0    225968
Name: count, dtype: int64
```

In [372…
```
y_test.value_counts()
```

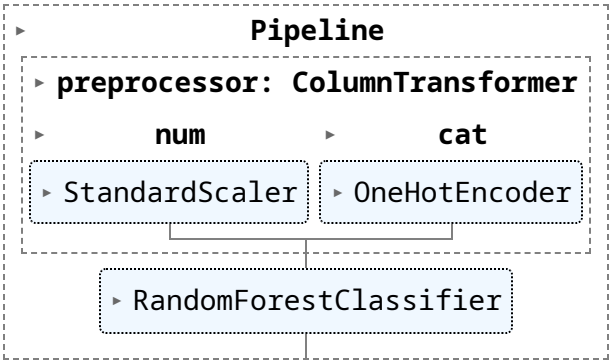
Out[372…
```
Target
0.0    145094
1.0    111552
Name: count, dtype: int64
```

In [373…
```
# Identify numerical and categorical columns (example placeholders)
numerical_cols = X_train.select_dtypes(include=['int64', 'float64']).columns
categorical_cols = X_train.select_dtypes(include=['object', 'category']).col
```

In [374…
```
# Step 2: Define preprocessing pipelines
numerical_transformer = StandardScaler()
categorical_transformer = OneHotEncoder(handle_unknown='ignore')

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_cols),
        ('cat', categorical_transformer, categorical_cols)
    ])
```

In [375…
```
# Step 3: Define the model
model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(class_weight='balanced', random_st
])

# Train the model
model.fit(X_train, y_train)
```

Out[375…



In [376…
```
# next, compare the default threshold to a modified threshold for tuning .
```

In [377…
```
y_pred = model.predict(X_test)
```

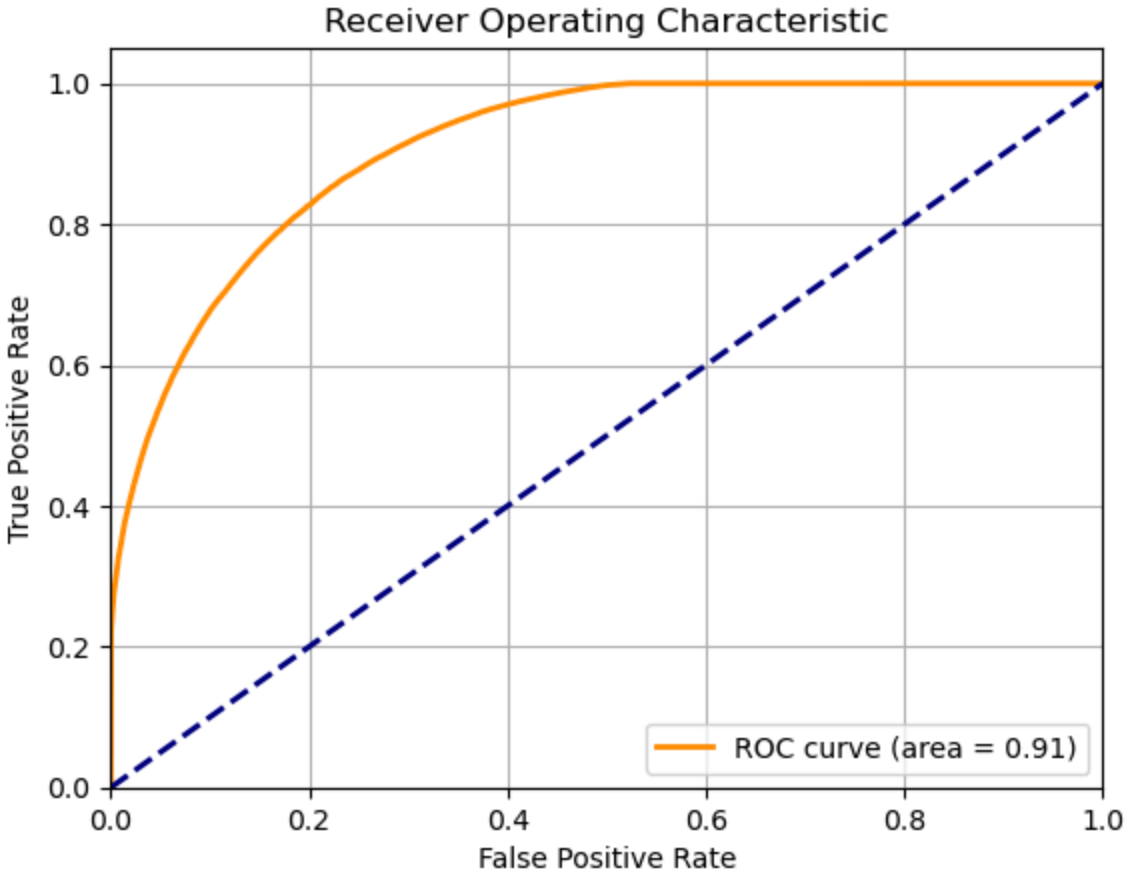
In [451…
```
# Tuning the decision threshold, the goal here is to reduce false negatives.
y_probs = model.predict_proba(X_test)[:, 1]
threshold = 0.545
y_pred_adjusted = (y_probs >= threshold).astype(int)
```

In [452…
```
y_probs.size
```

Out[452…
```
256646
```

In [453…

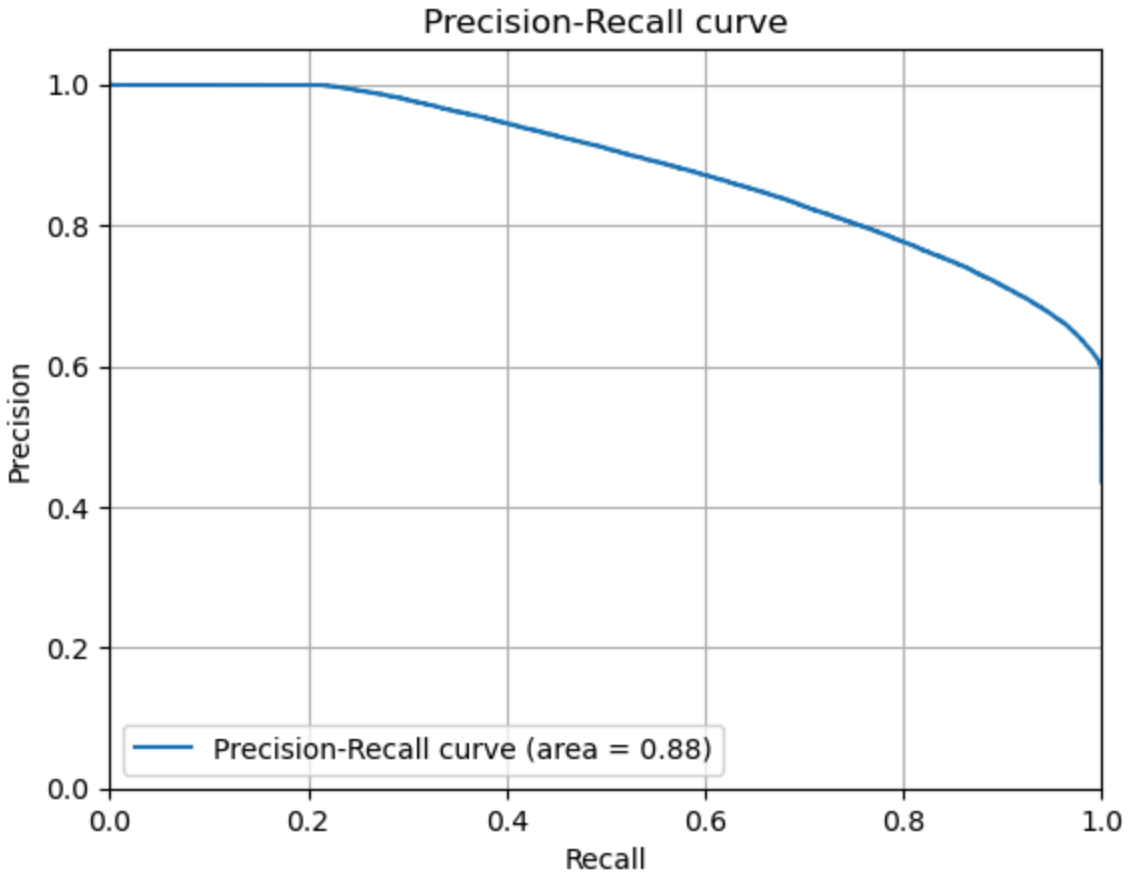
```
# Calculate TPR, FPR, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_probs)

# Calculate the area under the ROC curve
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure()
plt.grid(True)
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)
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')
plt.legend(loc='lower right')
plt.show()
```



In [454…

```
# Calculate precision and recall values
precision, recall, thresholds_pr = precision_recall_curve(y_test, y_probs)
average_precision = average_precision_score(y_test, y_probs)

# Plot Precision-Recall curve
plt.figure()
plt.grid(True)
plt.step(recall, precision, where='post', label='Precision-Recall curve (are
plt.xlabel('Recall')
```

```
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall curve')
plt.legend(loc='lower left')
plt.show()
```



In [455…
```
# Step 4: Evaluate the model
```

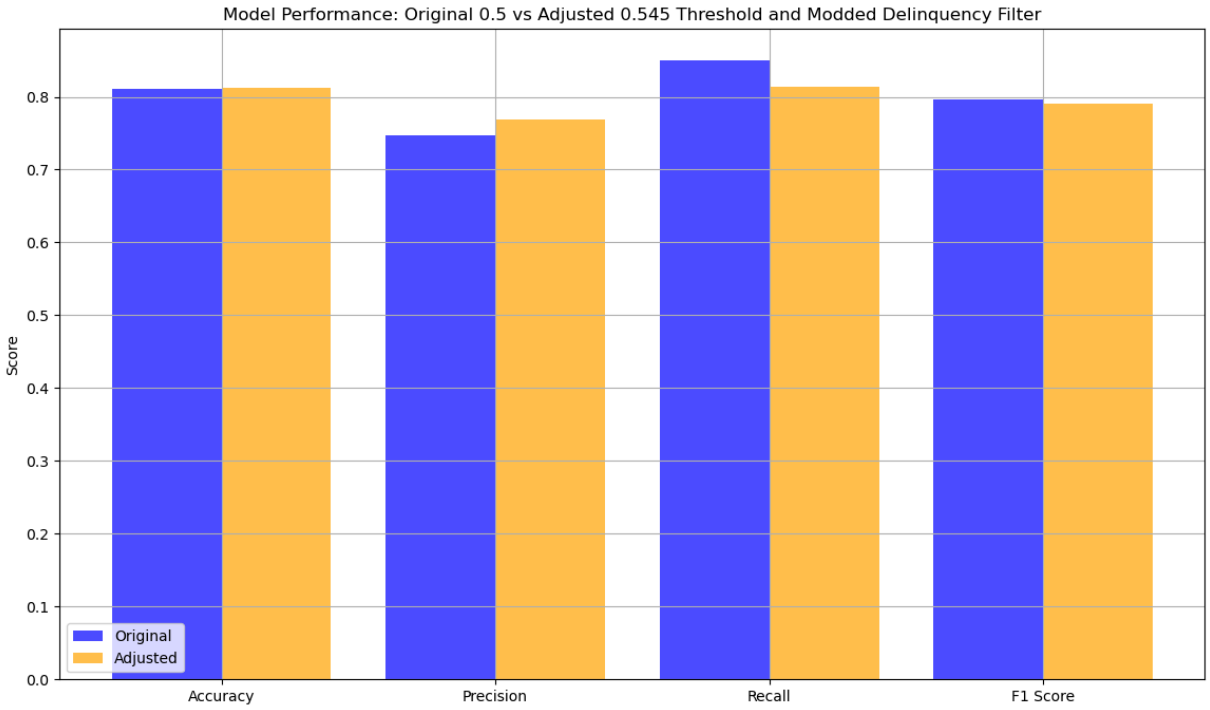
In [456…
```
# Original predictions metrics
accuracy_orig = accuracy_score(y_test, y_pred)
precision_orig = precision_score(y_test, y_pred)
recall_orig = recall_score(y_test, y_pred)
f1_orig = f1_score(y_test, y_pred)

# Adjusted predictions metrics
accuracy_adj = accuracy_score(y_test, y_pred_adjusted)
precision_adj = precision_score(y_test, y_pred_adjusted)
recall_adj = recall_score(y_test, y_pred_adjusted)
f1_adj = f1_score(y_test, y_pred_adjusted)


metrics_df = pd.DataFrame({
    'Metric': ['Accuracy', 'Precision', 'Recall', 'F1 Score'],
    'Original': [accuracy_orig, precision_orig, recall_orig, f1_orig],
    'Adjusted': [accuracy_adj, precision_adj, recall_adj, f1_adj]
})
```

```
print(metrics_df)
```

```
     Metric  Original  Adjusted
0  Accuracy  0.810322  0.812625
1  Precision  0.747715  0.768909
2     Recall  0.850617  0.813361
3   F1 Score  0.795853  0.790510
```

In [457…

```
# Data for plotting
metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
original_scores = [accuracy_orig, precision_orig, recall_orig, f1_orig]
adjusted_scores = [accuracy_adj, precision_adj, recall_adj, f1_adj]

# Setting up the matplotlib figure and axes
fig, ax = plt.subplots(figsize=(14, 8))

# Setting the positions and width for the bars
pos = list(range(len(original_scores)))
width = 0.4

# Plotting bars for original and adjusted scores
plt.bar(pos, original_scores, width, alpha=0.7, label='Original', color='blu
plt.bar([p + width for p in pos], adjusted_scores, width, alpha=0.7, label='

# Setting the y-axis label, chart title, and x-axis ticks
ax.set_ylabel('Score')
ax.set_title(f"Model Performance: Original 0.5 vs Adjusted {threshold} Thres
ax.set_xticks([p + 0.5 * width for p in pos])
ax.set_xticklabels(metrics)

# Adding the legend and grid
plt.legend(['Original', 'Adjusted'], loc='lower left')
plt.grid()

# Show the plot
plt.show()
```

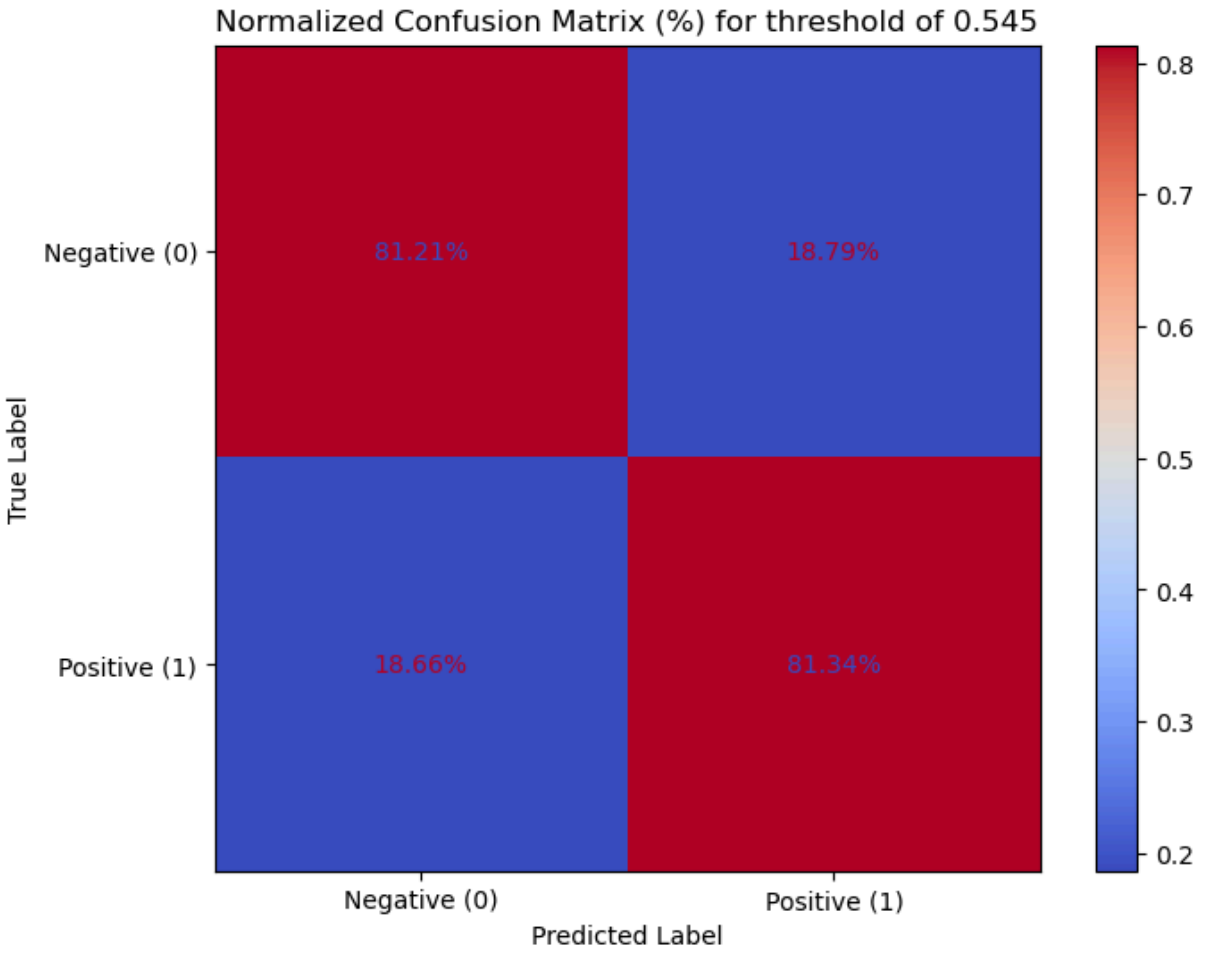


In [458…
```
# confusion_matrix

cm = confusion_matrix(y_test, y_pred_adjusted)

cm_normalized = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

# Convert to percentages
cm_percentage = cm_normalized * 100

cm_percentage
```

Out[458…
```
array([[81.20597682, 18.79402318],
       [18.66394148, 81.33605852]])
```

In [459…
```
from sklearn.metrics import ConfusionMatrixDisplay

labels = ['Negative (0)', 'Positive (1)']

# Normalize the confusion matrix to show percentages
cm_normalized = cm_percentage / 100

# Create a ConfusionMatrixDisplay instance with the normalized confusion mat
disp = ConfusionMatrixDisplay(confusion_matrix=cm_normalized, display_labels

# Plot the confusion matrix with percentages
fig, ax = plt.subplots(figsize=(8, 6))
disp.plot(cmap='coolwarm', ax=ax, values_format='.2%')  # Using percentage f

# Adding labels and title for clarity
ax.set_xlabel('Predicted Label')
ax.set_ylabel('True Label')
ax.set_title(f"Normalized Confusion Matrix (%) for threshold of {threshold}"
```

```
plt.show()
```



In [470…
```
import joblib
joblib.dump(model, 'random_forest_model_v2.joblib')
```

Out[470…
```
['random_forest_model_v2.joblib']
```

In [464…
```
# define a function to approve or decline a new applicant

def make_decision(new_applicant):
    # Ensure the new_applicant DataFrame aligns with the training data's exp
    # This includes proper handling of categorical and numerical features as

    # Directly apply the full preprocessing and prediction pipeline to the r
    # This approach ensures that new_applicant data is subjected to the same
    new_applicant_prediction = model.predict(new_applicant)
    print(new_applicant_prediction[0])

    if new_applicant_prediction[0] == 0.0:
        return 'Declined'
    else:
        return 'Approved'
```

In [465…
```
# Simulating a new applicant's data
new_applicant = pd.DataFrame([{
```

```
    "CODE_GENDER": "F",
    "FLAG_OWN_CAR": "Y",
    "FLAG_OWN_REALTY": "N",
    "CNT_CHILDREN": 0,
    "AMT_INCOME_TOTAL": 0.0,
    "NAME_INCOME_TYPE": "Working",
    "NAME_EDUCATION_TYPE": "Higher education",
    "NAME_FAMILY_STATUS": "Married",
    "NAME_HOUSING_TYPE": "With parents",
    "DAYS_BIRTH": -2000,
    "DAYS_EMPLOYED": -30,
    "FLAG_MOBIL": 1,
    "FLAG_WORK_PHONE": 0,
    "FLAG_PHONE": 1,
    "FLAG_EMAIL": 1,
    "OCCUPATION_TYPE": "Unemployed",
    "CNT_FAM_MEMBERS": 0.0,
}])
```

In [466…

```
# Process applicant

result = make_decision(new_applicant)

print(f"The application status is: {result}")
```

```
0.0
The application status is: Declined
```

In [467…

```
# Creating an applicant that should be approved

new_applicant_2 = pd.DataFrame([{
    "CODE_GENDER": "F",
    "FLAG_OWN_CAR": "N",
    "FLAG_OWN_REALTY": "Y",
    "CNT_CHILDREN": 0,
    "AMT_INCOME_TOTAL": 170000.0,
    "NAME_INCOME_TYPE": "Commercial associate",
    "NAME_EDUCATION_TYPE": "Secondary / secondary special",
    "NAME_FAMILY_STATUS": "Single / not married",
    "NAME_HOUSING_TYPE": "House / apartment",
    "DAYS_BIRTH": -19110,
    "DAYS_EMPLOYED": -3200,
    "FLAG_MOBIL": 1,
    "FLAG_WORK_PHONE": 0,
    "FLAG_PHONE": 1,
    "FLAG_EMAIL": 1,
    "OCCUPATION_TYPE": "Sales staff",
    "CNT_FAM_MEMBERS": 1.0,
}])
```

In [468…

```
# Process applicant

result = make_decision(new_applicant_2)

print(f"The application status is: {result}")
```

```
1.0
The application status is: Approved
```

In [ ]: