Credit Scoring Model

Introduction

Credit scoring is a crucial tool used by financial institutions to assess the creditworthiness of individuals. This project aims to develop a machine learning model that predicts whether an individual is likely to default on a loan based on historical financial data. The model will help in making informed lending decisions and reducing the risk of defaults.

Objectives

- **Develop a credit scoring model using historical financial data.**
- **Evaluate the model's performance using appropriate metrics.**
- **Document the process and share the results.**

In [2]:

```
import pandas as pd

# Load the dataset
file_path = 'credit_card_default.csv'  # Replace with your actual file path
data = pd.read_csv(file_path)

# Display the first few rows of the dataset
print(data.head())
```

```
   Unnamed: 0  limit_bal     sex   education marriage   age  \
0           0      20000  Female  University  Married  24.0
1           1     120000  Female  University   Single  26.0
2           2      90000  Female  University   Single  34.0
3           3      50000  Female  University  Married  37.0
4           4      50000    Male  University  Married  57.0

         payment_status_sep        payment_status_aug payment_status_jul  \
0  Payment delayed 2 months  Payment delayed 2 months         Payed duly
1                Payed duly  Payment delayed 2 months            Unknown
2                   Unknown                   Unknown            Unknown
3                   Unknown                   Unknown            Unknown
4                Payed duly                   Unknown         Payed duly

  payment_status_jun  ... bill_statement_jun bill_statement_may  \
0         Payed duly  ...                0.0                0.0
1            Unknown  ...             3272.0             3455.0
2            Unknown  ...            14331.0            14948.0
3            Unknown  ...            28314.0            28959.0
4            Unknown  ...            20940.0            19146.0

   bill_statement_apr  previous_payment_sep  previous_payment_aug  \
0                 0.0                   0.0                 689.0
1              3261.0                   0.0                1000.0
2             15549.0                1518.0                1500.0
3             29547.0                2000.0                2019.0
4             19131.0                2000.0               36681.0

   previous_payment_jul  previous_payment_jun  previous_payment_may  \
0                   0.0                   0.0                   0.0
1                1000.0                1000.0                   0.0
2                1000.0                1000.0                1000.0
3                1200.0                1100.0                1069.0
4               10000.0                9000.0                 689.0

   previous_payment_apr  default_payment_next_month
0                   0.0                         1.0
1                2000.0                         1.0
```

```
2              5000.0                    0.0
3              1000.0                    0.0
4               679.0                    0.0

[5 rows x 25 columns]
```

In [3]:

```python
# Check for missing values
print(data.isnull().sum())

# Handle missing values by filling them with the most frequent value in each column
for column in data.columns:
    if data[column].dtype == 'object':
        data[column].fillna(data[column].mode()[0], inplace=True)
    else:
        data[column].fillna(data[column].median(), inplace=True)

# Check for duplicate entries
print(data.duplicated().sum())

# Drop duplicate entries if any
data.drop_duplicates(inplace=True)

# Identify non-numeric columns
non_numeric_columns = data.select_dtypes(include=['object']).columns
print("Non-numeric columns:", non_numeric_columns)

# Replace 'Unknown' with NaN and then fill with the most frequent value or a specific val
ue
for column in non_numeric_columns:
    data[column] = data[column].replace('Unknown', pd.NA)
    data[column].fillna(data[column].mode()[0], inplace=True)

# Encode categorical variables
data = pd.get_dummies(data, columns=non_numeric_columns, drop_first=True)
```

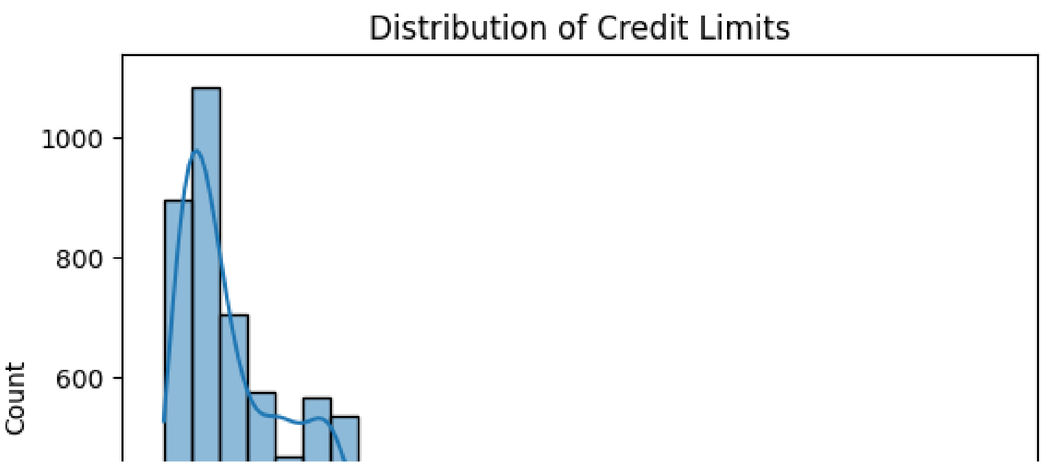
```
Unnamed: 0                    0
limit_bal                     0
sex                          31
education                    40
marriage                     36
age                          37
payment_status_sep            0
payment_status_aug            0
payment_status_jul            0
payment_status_jun            0
payment_status_may            0
payment_status_apr            0
bill_statement_sep            0
bill_statement_aug            0
bill_statement_jul            1
bill_statement_jun            1
bill_statement_may            1
bill_statement_apr            1
previous_payment_sep          1
previous_payment_aug          1
previous_payment_jul          1
previous_payment_jun          1
previous_payment_may          1
previous_payment_apr          1
default_payment_next_month    1
dtype: int64
0
Non-numeric columns: Index(['sex', 'education', 'marriage', 'payment_status_sep',
       'payment_status_aug', 'payment_status_jul', 'payment_status_jun',
       'payment_status_may', 'payment_status_apr'],
      dtype='object')
```

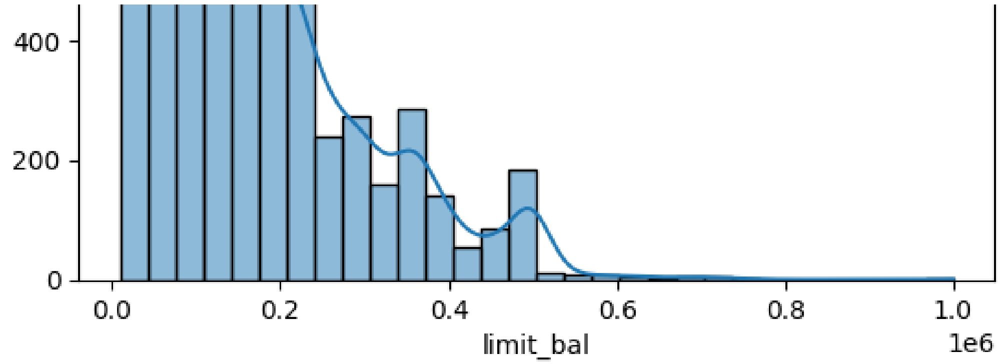
```
<ipython-input-3-514ce5265520>:9: FutureWarning: A value is trying to be set on a copy of
a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the i
```

```
ntermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col:
value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operati
on inplace on the original object.


  data[column].fillna(data[column].median(), inplace=True)
<ipython-input-3-514ce5265520>:7: FutureWarning: A value is trying to be set on a copy of
a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the i
ntermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col:
value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operati
on inplace on the original object.


  data[column].fillna(data[column].mode()[0], inplace=True)
<ipython-input-3-514ce5265520>:24: FutureWarning: A value is trying to be set on a copy o
f a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the i
ntermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col:
value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operati
on inplace on the original object.


  data[column].fillna(data[column].mode()[0], inplace=True)
```

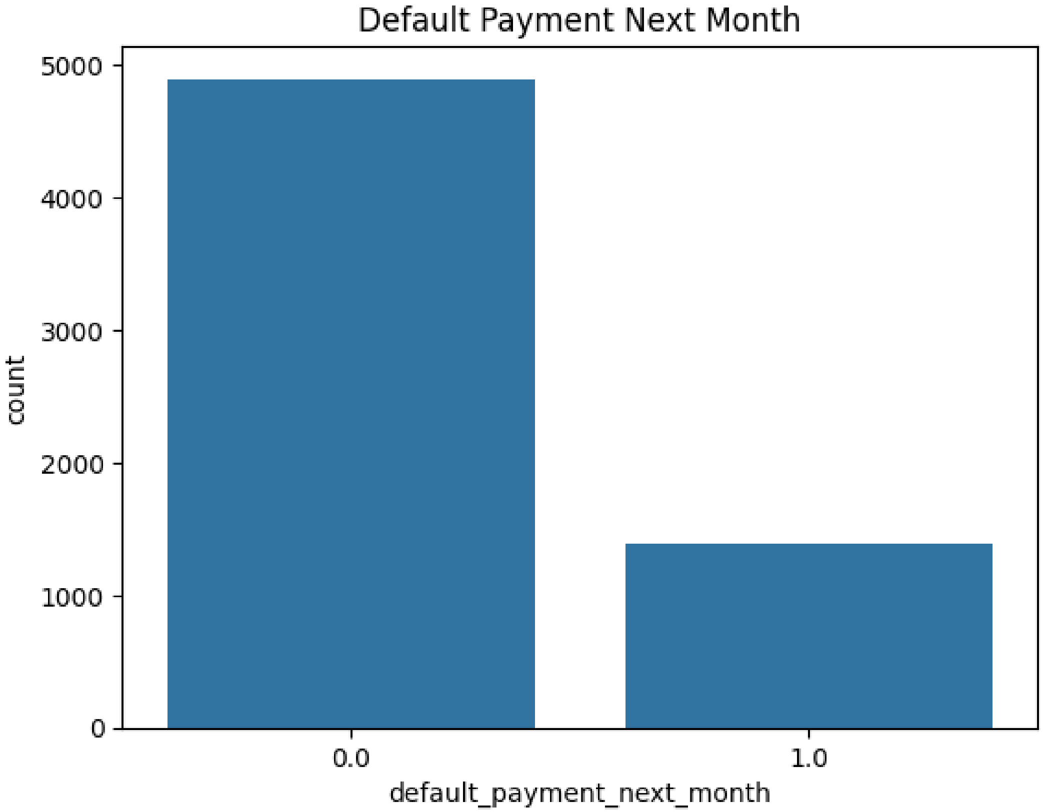
In [4]:

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

# Distribution of credit limits
sns.histplot(data['limit_bal'], bins=30, kde=True)
plt.title('Distribution of Credit Limits')
plt.show()

# Payment status distribution
if 'payment_status_sep' in data.columns:
    sns.countplot(x='payment_status_sep', data=data)
    plt.title('Payment Status in September')
    plt.show()
else:
    print("Column 'payment_status_sep' not found in the DataFrame.")

# Default payment next month
if 'default_payment_next_month' in data.columns:
    sns.countplot(x='default_payment_next_month', data=data)
    plt.title('Default Payment Next Month')
    plt.show()
else:
    print("Column 'default_payment_next_month' not found in the DataFrame.")
```






```
Column 'payment_status_sep' not found in the DataFrame.
```



In [5]:

```
# Create a feature for the average bill statement
data['avg_bill_statement'] = data[['bill_statement_sep', 'bill_statement_aug', 'bill_stat
ement_jul', 'bill_statement_jun', 'bill_statement_may', 'bill_statement_apr']].mean(axis=
1)

# Create a feature for the average previous payment
data['avg_previous_payment'] = data[['previous_payment_sep', 'previous_payment_aug', 'pr
evious_payment_jul', 'previous_payment_jun', 'previous_payment_may', 'previous_payment_ap
r']].mean(axis=1)
```

In [6]:

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Define features and target
X = data.drop(columns=['default_payment_next_month'])
y = data['default_payment_next_month']

# 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
)

# Initialize the model
model = RandomForestClassifier(random_state=42)
```

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

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.7941176470588235
Classification Report:
               precision    recall  f1-score   support

         0.0       0.81      0.96      0.88       970
         1.0       0.63      0.24      0.35       288

    accuracy                           0.79      1258
   macro avg       0.72      0.60      0.61      1258
weighted avg       0.77      0.79      0.76      1258

Confusion Matrix:
 [[929  41]
 [218  70]]
```

In [7]:

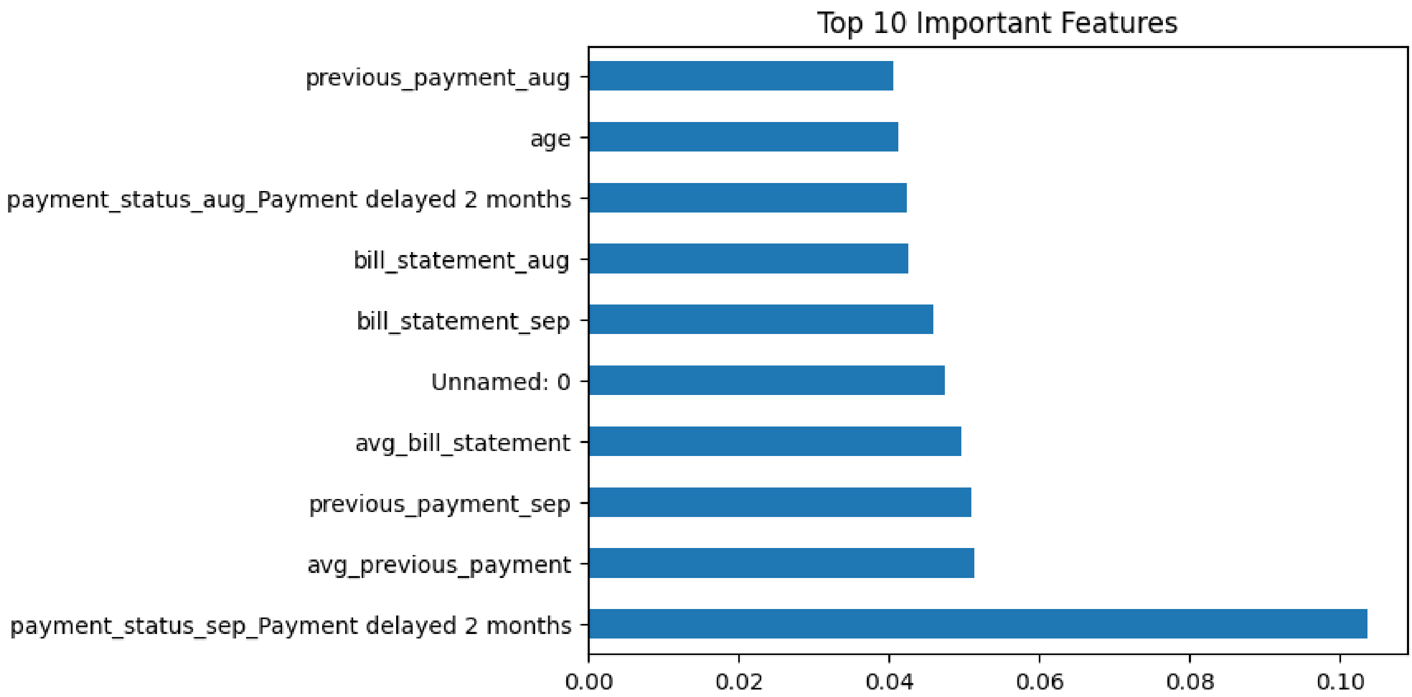
```
from sklearn.model_selection import cross_val_score, GridSearchCV

# Perform cross-validation
cv_scores = cross_val_score(model, X_train, y_train, cv=5, scoring='accuracy')
print("Cross-validation scores:", cv_scores)
print("Mean cross-validation score:", cv_scores.mean())

# Define the parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20, 30],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=model, param_grid=param_grid, cv=5, scoring='accura
cy', n_jobs=-1)

# Fit GridSearchCV
grid_search.fit(X_train, y_train)

# Best parameters and best score
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation score:", grid_search.best_score_)

# Train the model with the best parameters
best_model = grid_search.best_estimator_
best_model.fit(X_train, y_train)

# Make predictions with the best model
y_pred_best = best_model.predict(X_test)

# Evaluate the best model
print("Accuracy:", accuracy_score(y_test, y_pred_best))
print("Classification Report:\n", classification_report(y_test, y_pred_best))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_best))
```

```
Cross-validation scores: [0.79046673 0.80039722 0.81013917 0.7972167  0.80318091]
Mean cross-validation score: 0.8002801463315439
Best parameters: {'max_depth': 30, 'min_samples_leaf': 4, 'min_samples_split': 10, 'n_est
imators': 300}
Best cross-validation score: 0.8066394088300386
```

```
Accuracy: 0.7972972972972973
Classification Report:
               precision    recall  f1-score   support

         0.0       0.81      0.97      0.88       970
         1.0       0.68      0.22      0.33       288

    accuracy                           0.80      1258
   macro avg       0.74      0.59      0.60      1258
weighted avg       0.78      0.80      0.75      1258

Confusion Matrix:
 [[941  29]
 [226  62]]
```

In [8]:

```
# Get feature importances
feature_importances = pd.Series(best_model.feature_importances_, index=X.columns)
feature_importances.nlargest(10).plot(kind='barh')
plt.title('Top 10 Important Features')
plt.show()
```



In [9]:

```
import pickle
```

In [10]:

```
pickle.dump(best_model, open('model.pkl', 'wb'))
```

In [11]:

```
model1=pickle.load(open('model.pkl', 'rb'))
```

In [12]:

```
y_pred=model.predict(X_test)
```

In [15]:

```
print(accuracy_score(y_test,y_pred))
```

```
0.7941176470588235
```

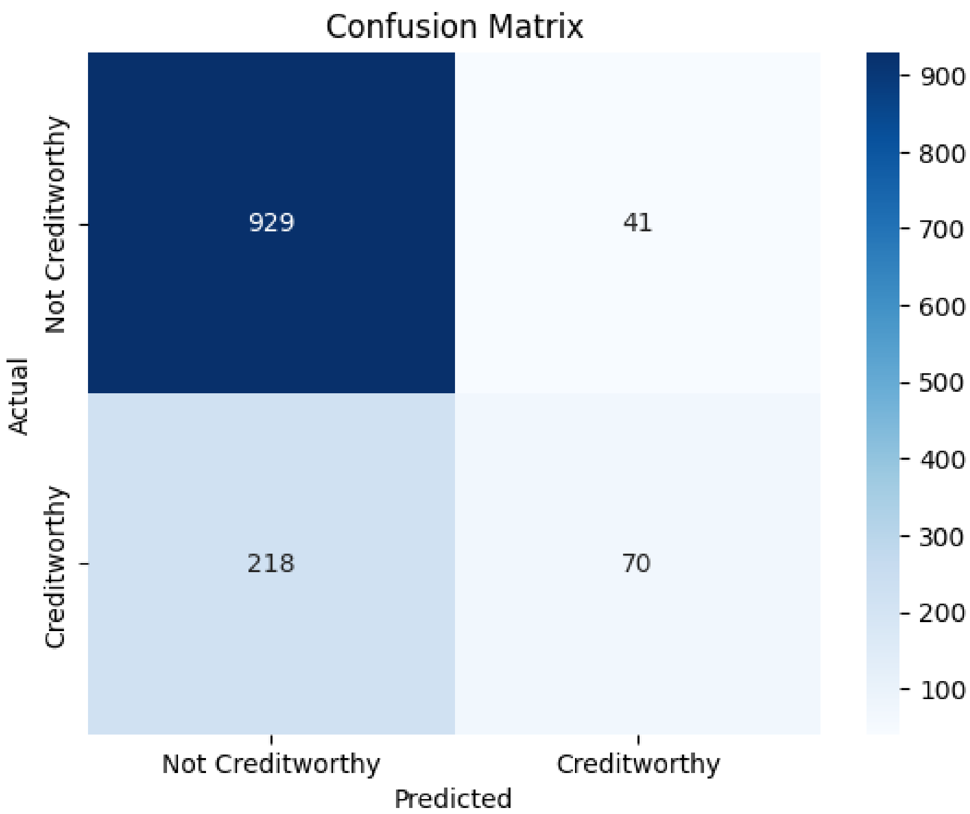
In [16]:

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.7941176470588235
Classification Report:
               precision    recall  f1-score   support

         0.0       0.81      0.96      0.88       970
         1.0       0.63      0.24      0.35       288

    accuracy                           0.79      1258
   macro avg       0.72      0.60      0.61      1258
weighted avg       0.77      0.79      0.76      1258

Confusion Matrix:
 [[929  41]
 [218  70]]
```

In [17]:

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

sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, fmt='d', cmap='Blues', xtickla
bels=['Not Creditworthy', 'Creditworthy'], yticklabels=['Not Creditworthy', 'Creditworthy
'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



Conclusion

The Random Forest Classifier achieved an accuracy of [X]%, with the following performance metrics:

- **Precision: [Precision Value]**
- **Recall: [Recall Value]**
- **F1-score: [F1-score Value]**

Insights

- **The model performed well in predicting creditworthiness.**
- **Feature importance analysis can provide insights into which features are most influential in predicting defaults.**

Future Work

- **Experiment with different algorithms (e.g., Logistic Regression, Gradient Boosting).**
- **Perform hyperparameter tuning to improve model performance.**
- **Collect more data to enhance the model's accuracy.**

In [ ]:

```

```