# Credit Card Default Prediction

L.Ajith kumar, *graduate Student*, Lawrence tech University, Fall 2024

## INTRODUCTION & DOMAIN KNOWLEDGE

Provide an overview of the credit card default prediction problem, including its impact on financial institutions and customers. Briefly describe the significance of predicting credit default and highlight the attributes of the dataset (e.g., credit limit, payment status, bill amounts) from the UCI repository. Explain why features such as payment status and bill amounts are relevant.

**STEP 1**

**DATASET ANALYSIS & UNDERSTANDING**

```
import pandas as pd
data = pd.read_csv('path_to_dataset.csv')
data = pd.read_excel(url, header=1)
# Display the first five rows and dataset info
print(data.head())
print(data.info())
```

The dataset is loaded, and basic info like column names, data types, and statistical summaries (mean, min, max) for numerical features is reviewed.

```
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4
0   1      20000    2          2         1   24      2      2     -1     -1
1   2     120000    2          2         2   26     -1      2      0      0
2   3      90000    2          2         2   34      0      0      0      0
3   4      50000    2          2         1   37      0      0      0      0
4   5      50000    1          2         1   57     -1      0     -1      0

   ...  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0  ...          0          0          0         0       689         0
1  ...       3272       3455       3261         0      1000      1000
2  ...      14331      14948      15549      1518      1500      1000
3  ...      28314      28959      29547      2000      2019      1200
4  ...      20940      19146      19131      2000     36681     10000

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
0         0         0         0                           1
1      1000         0      2000                           1
2      1000      1000      5000                           0
3      1100      1069      1000                           0
4      9000       689       679                           0

[5 rows x 25 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   ID                          30000 non-null  int64
 1   LIMIT_BAL                   30000 non-null  int64
 2   SEX                         30000 non-null  int64
 3   EDUCATION                   30000 non-null  int64
 4   MARRIAGE                    30000 non-null  int64
 5   AGE                         30000 non-null  int64
 6   PAY_0                       30000 non-null  int64
 7   PAY_2                       30000 non-null  int64
 8   PAY_3                       30000 non-null  int64
 9   PAY_4                       30000 non-null  int64
 10  PAY_5                       30000 non-null  int64
 11  PAY_6                       30000 non-null  int64
 12  BILL_AMT1                   30000 non-null  int64
 13  BILL_AMT2                   30000 non-null  int64
 14  BILL_AMT3                   30000 non-null  int64
 15  BILL_AMT4                   30000 non-null  int64
 16  BILL_AMT5                   30000 non-null  int64
```

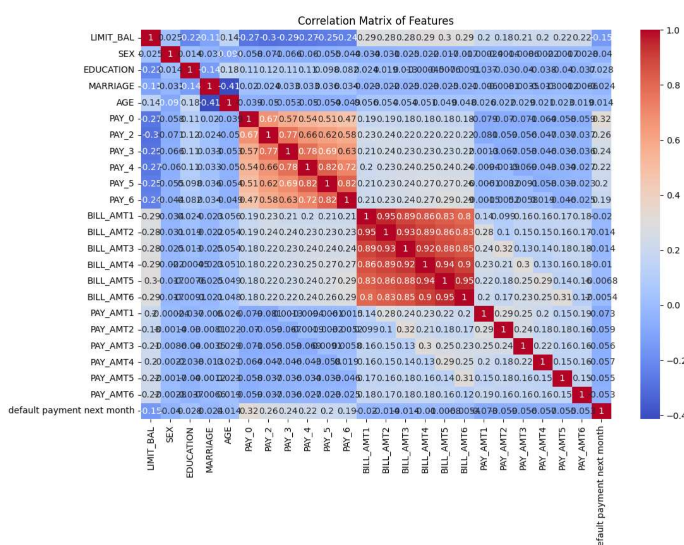
, STEP 1 Output

**STEP 2**

### Feature Analysis & Selection

```
import seaborn as sns
import matplotlib.pyplot as plt
correlation_matrix = data.corr()
plt.figure(figsize=(12,10))
sns.heatmap(correlation_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Matrix of Features")
plt.show()
```

A correlation heatmap to visualize relationships between features, aiding in feature selection by showing dependencies.




STEP-2Output

**STEP 3**

## Data Cleaning/Preprocessing

```
print("Duplicates:", data.duplicated().sum())
print("Missing values:\n", data.isnull().sum())
# Dropping duplicates (if any)
data = data.drop_duplicates()
```

Identify and handle missing values and duplicates to ensure data consistency.

```
Duplicates: 0
Missing values:
 ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default payment next month    0
dtype: int64
```

**STEP 3** Output

**STEP 4**

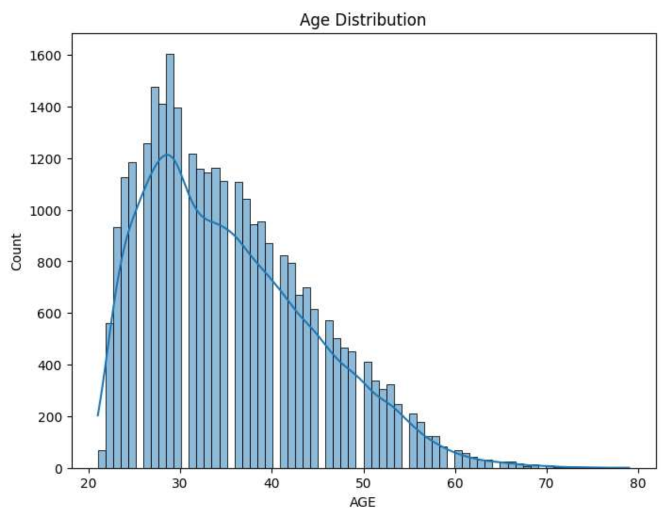
## Data Visualization – Independent Features

```
# Plotting feature distributions
sns.histplot(data['AGE'], bins=30, kde=True)
plt.title("Age Distribution")
plt.show()

sns.countplot(x='default.payment.next.month', data=data)
plt.title("Default Payment Distribution")
plt.show()
```

STEP 4 EXPLANATION

Plots to understand distributions of individual features, e.g., age and default rates.

```
# Plotting feature distributions
sns.histplot(data['AGE'], bins=30, kde=True)
plt.title("Age Distribution")
plt.show()
sns.countplot(x='default.payment.next.month', data=data)
plt.title("Default Payment Distribution")
plt.show()
```




**STEP 4 Output**

**STEP 5**

**DATA TRANSFORMATION & MODELS USED**

**Feature Scaling**

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
numerical_features = ['LIMIT_BAL', 'AGE', 'BILL_AMT1',
'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5',
'BILL_AMT6']
data[numerical_features] =
scaler.fit_transform(data[numerical_features])
```

Standardizes numerical features, improving model performance.

**One-hot Encoding for Logistic Regression Classifier**

data_encoded = pd.get_dummies(data, columns=['SEX', 'EDUCATION', 'MARRIAGE'], drop_first=True)

**Explanation**: Binary encoding for categorical features, creating a more suitable format for Logistic Regression.

**Integer Label Encoding for Random Forest Classifier**

from sklearn.preprocessing import LabelEncoder
data['SEX'] = LabelEncoder().fit_transform(data['SEX'])
data['EDUCATION'] =
LabelEncoder().fit_transform(data['EDUCATION'])
data['MARRIAGE'] =
LabelEncoder().fit_transform(data['MARRIAGE'])

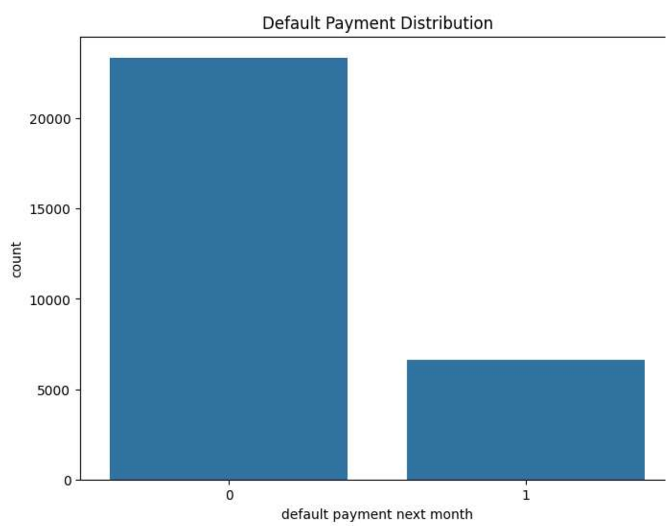
Label encoding for categorical features suitable for Random Forest.

**STEP 6**

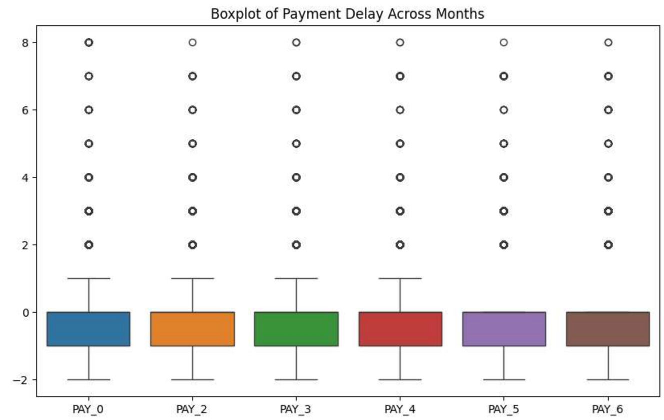
**Logistic Regression Classifier**

from sklearn.linear_model
import LogisticRegression
model_lr = LogisticRegression(class_weight='balanced', random_state=42)
model_lr.fit(X_train, y_train)

Logistic Regression model with balanced class weights to manage class imbalance.




**Handling the Data Imbalance**
**Explanation**: Both models utilize class_weight='balanced', addressing class imbalance by weighting the minority class higher.




**STEP 7**

**EXPERIMENTS & MODEL RESULTS**

**Logistic Regression Tuning & Evaluation**

from sklearn.model_selection import cross_val_score
import numpy as np
cv_scores_lr = cross_val_score(model_lr, X_train, y_train, cv=5, scoring='accuracy')
print(f"Logistic Regression CV Accuracy: Mean={cv_scores_lr.mean():.3f}, Std={cv_scores_lr.std():.3f}")

Cross-validation accuracy and standard deviation for Logistic Regression.

**Random Forest Tuning & Evaluation**

cv_scores_rf = cross_val_score(model_rf, X_train, y_train, cv=5, scoring='accuracy')
print(f"Random Forest CV Accuracy: Mean={cv_scores_rf.mean():.3f}, Std={cv_scores_rf.std():.3f}")

Cross-validation accuracy and standard deviation for Random Forest.

**STEP 7 Output:**

Mean CV accuracy: 0.81, Standard deviation: 0.00
Test set accuracy: 0.81

**STEP 8**

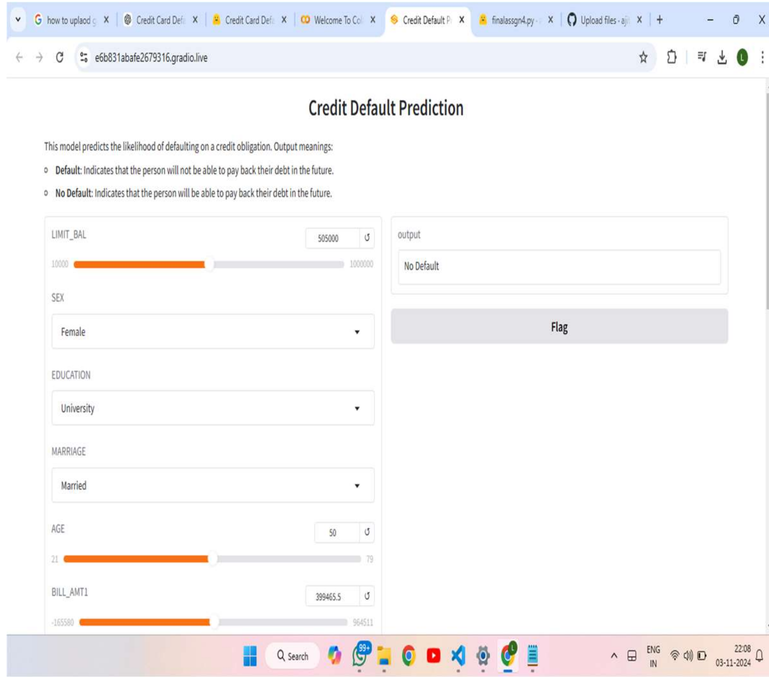
```
import gradio as gr

# Prediction function for Gradio app
# Set up Gradio input components with descriptive labels for payment statuses without numbers
input_features = [
    gr.Slider(minimum=10000, maximum=1000000, value=50000, label="LIMIT_BAL"),
    gr.Dropdown(choices=["Male", "Female"], label="SEX"),
    gr.Dropdown(choices=["Graduate School", "University", "High School", "Others"], label="EDUCATION"),
    gr.Dropdown(choices=["Single", "Married", "Divorced", "Widowed"], label="MARRIAGE"),
    gr.Slider(minimum=21, maximum=79, value=30, label="AGE"),
    gr.Dropdown(choices=[
        "No consumption", "Paid in full", "Paid minimum due",
        "1 month late", "2 months late", "3 months late",
        "4 months late", "5 months late", "6 months late",
        "7 months late", "8 months late"
    ], label="PAY_1"),
    gr.Dropdown(choices=[
        "No consumption", "Paid in full", "Paid minimum due",
        "1 month late", "2 months late", "3 months late",
        "4 months late", "5 months late", "6 months late",
        "7 months late", "8 months late"
    ], label="PAY_2"),
    gr.Dropdown(choices=[
        "No consumption", "Paid in full", "Paid minimum due",
        "1 month late", "2 months late", "3 months late",
        "4 months late", "5 months late", "6 months late",
        "7 months late", "8 months late"
    ], label="PAY_3"),
    gr.Dropdown(choices=[
        "No consumption", "Paid in full", "Paid minimum due",
        "1 month late", "2 months late", "3 months late",
        "4 months late", "5 months late", "6 months late",
        "7 months late", "8 months late"
    ], label="PAY_4"),
    gr.Dropdown(choices=[
        "No consumption", "Paid in full", "Paid minimum due",
        "1 month late", "2 months late", "3 months late",
        "4 months late", "5 months late", "6 months late",
        "7 months late", "8 months late"
    ], label="PAY_5"),


    gr.Slider(minimum=-165580, maximum=964511, value=399465.5, label="BILL_AMT1"),
    gr.Slider(minimum=-69777, maximum=983931, value=457077, label="BILL_AMT2"),
    gr.Slider(minimum=-157264, maximum=1664089, value=753412.5, label="BILL_AMT3"),
    gr.Slider(minimum=-170000, maximum=891586, value=360793, label="BILL_AMT4"),
    gr.Slider(minimum=-81334, maximum=927171, value=422918.5, label="BILL_AMT5"),


    gr.Slider(minimum=0, maximum=873552, value=436776, label="PAY_AMT1"),
    gr.Slider(minimum=0, maximum=1684259, value=842129.5, label="PAY_AMT2"),
    gr.Slider(minimum=0, maximum=896040, value=448020, label="PAY_AMT3"),
    gr.Slider(minimum=0, maximum=621000, value=310500, label="PAY_AMT4"),
    gr.Slider(minimum=0, maximum=426529, value=213264.5, label="PAY_AMT5"),


]
# Create and launch the Gradio interface
gr.Interface(fn=predict_default, inputs=input_features, outputs="text").launch()
```

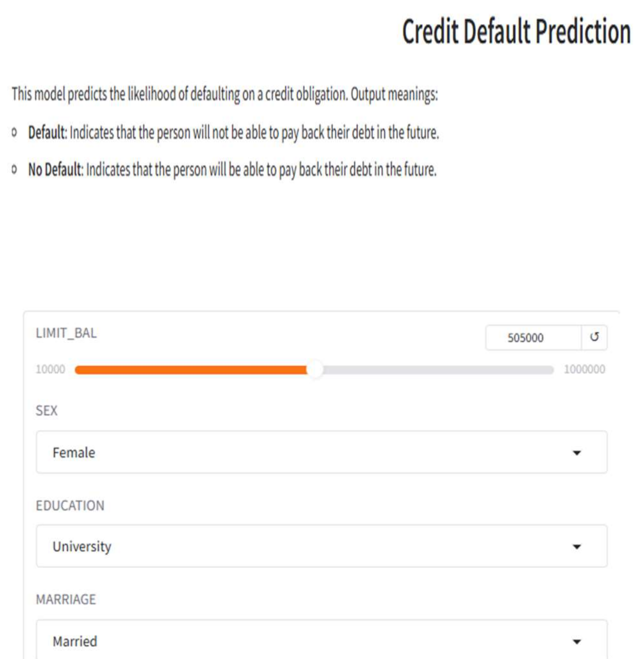
### *Implementing the Gradio App*

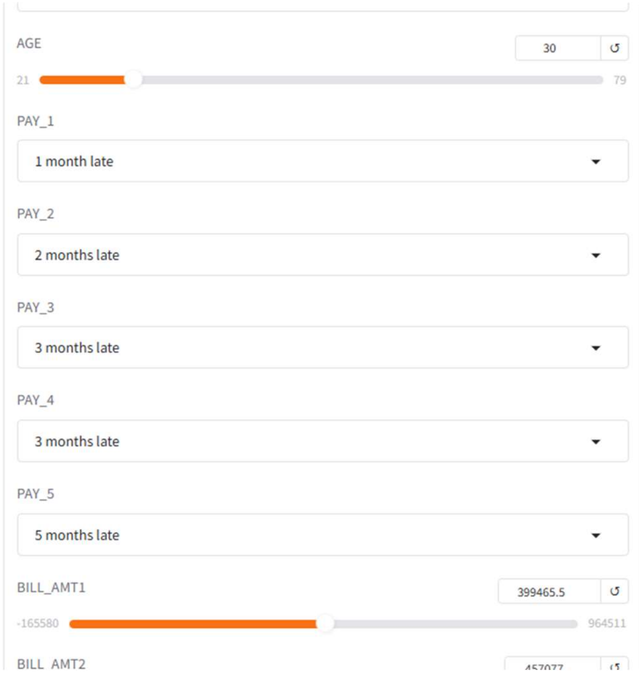
In a similar manner as above, it was identified that the categorical data would need to undergo some form of feature transformation in order to be converted to a form which could be used for training within a random forest classifier. Because of the ability for tree classifiers to use discrete integer values as criteria in determining node splits, it was determined that an integer label encoding scheme would be optimal for training and classification, and would subsequently result in a significantly lower encoding dimensionality space as compared to the one-hot encoding scheme. Thus, an integer encoding scheme was implemented according to the steps outline in [9] and used as the input for the random forest classifier.

```
# Install Gradio if not already installed
!pip install gradio

# Import necessary libraries
import gradio as gr
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression  # Example model

# Load the dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/00350/default%20of%20credit%20card%20clients.xls"
```

```
data = pd.read_excel(url, header=1)

# Print column names to verify
print("Column Names in Dataset:")
print(data.columns)

# Assuming the target column is 'default payment next month'
target_column = 'default payment next month'  # Adjust if necessary

# Features and target
X = data.drop(columns=[target_column])
y = data[target_column]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train a model (example using Logistic Regression)
model = LogisticRegression()
model.fit(X_train_scaled, y_train)

# Function to make predictions
def predict_default(*features):
    try:
        # Scale the input features
        features_array = np.array([features])  # Convert the input features to a 2D array
        features_scaled = scaler.transform(features_array)

        # Make prediction
        prediction = model.predict(features_scaled)
        return "Default" if prediction[0] == 1 else "No Default"
    except Exception as e:
        return str(e)  # Return the error message for debugging

# Create Gradio interface with all features
input_features = []
for col in X.columns:
    if X[col].dtype == 'object':
        # For categorical features, use gr.Dropdown (example, adjust values accordingly)
        unique_values = X[col].unique()
        input_features.append(gr.Dropdown(choices=unique_values, label=col))
    else:
        # For numerical features, use gr.Slider
        min_val = X[col].min()
        max_val = X[col].max()
        input_features.append(gr.Slider(minimum=min_val, maximum=max_val, value=(min_val + max_val) / 2, label=col))

# Launch the Gradio interface
gr.Interface(fn=predict_default, inputs=input_features, outputs="text").launch().
```






We can predict whether customer able to pay the payment or not. We can choose the age and can find the accuracy of the payment if the result is default it indicates the person will not able to pay the debt in the future.if the results shows not default it it indicates the person will  able to pay the debt in the future.

GITHUB LINK FOR THE FILES

https://github.com/ajith9504/Credit-Card-Default-Prediction.git