

▼ Importing Libraries

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from xgboost import XGBClassifier
import plotly.express as px
import xgboost as xgb
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score

import warnings

warnings.filterwarnings("ignore", category=ImportWarning, module='specific_module')
# Code that might trigger the warning for specific_module
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

▼ Importing dataset

```
# Load your dataset
import pandas as pd
df = pd.read_csv('/content/drive/MyDrive/Credit Card Score/Credit-Score-Data.csv')
df
```

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	I
0	5634	3392	1	Aaron Maashoh	23	821000265	Scientist	19114.12	
1	5635	3392	2	Aaron Maashoh	23	821000265	Scientist	19114.12	
2	5636	3392	3	Aaron Maashoh	23	821000265	Scientist	19114.12	
3	5637	3392	4	Aaron Maashoh	23	821000265	Scientist	19114.12	
4	5638	3392	5	Aaron Maashoh	23	821000265	Scientist	19114.12	
...
99995	155625	37932	4	Nicks	25	78735990	Mechanic	39628.99	
99996	155626	37932	5	Nicks	25	78735990	Mechanic	39628.99	
99997	155627	37932	6	Nicks	25	78735990	Mechanic	39628.99	
99998	155628	37932	7	Nicks	25	78735990	Mechanic	39628.99	
99999	155629	37932	8	Nicks	25	78735990	Mechanic	39628.99	

100000 rows × 28 columns

```
df.shape
```

(100000, 28)

✓ Data pre-processing

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 28 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   ID                                    100000 non-null  int64
1   Customer_ID                          100000 non-null  int64
2   Month                                100000 non-null  int64
3   Name                                  100000 non-null  object
4   Age                                    100000 non-null  int64
5   SSN                                    100000 non-null  int64
6   Occupation                            100000 non-null  object
7   Annual_Income                         100000 non-null  float64
8   Monthly_Inhand_Salary                 100000 non-null  float64
9   Num_Bank_Accounts                     100000 non-null  int64
10  Num_Credit_Card                        100000 non-null  int64
11  Interest_Rate                          100000 non-null  int64
12  Num_of_Loan                            100000 non-null  int64
13  Type_of_Loan                           100000 non-null  object
14  Delay_from_due_date                    100000 non-null  int64
15  Num_of_Delayed_Payment                 100000 non-null  int64
16  Changed_Credit_Limit                   100000 non-null  float64
17  Num_Credit_Inquiries                   100000 non-null  int64
18  Credit_Mix                             100000 non-null  object
19  Outstanding_Debt                       100000 non-null  float64
20  Credit_Utilization_Ratio               100000 non-null  float64
21  Credit_History_Age                     100000 non-null  int64
22  Payment_of_Min_Amount                  100000 non-null  object
23  Total_EMI_per_month                    100000 non-null  float64
24  Amount_invested_monthly                100000 non-null  float64
25  Payment_Behaviour                       100000 non-null  object
26  Monthly_Balance                        100000 non-null  float64
27  Credit_Score                           100000 non-null  object
dtypes: float64(8), int64(13), object(7)
memory usage: 21.4+ MB
```

```
df.columns
```

```
Index(['ID', 'Customer_ID', 'Month', 'Name', 'Age', 'SSN', 'Occupation',
       'Annual_Income', 'Monthly_Inhand_Salary', 'Num_Bank_Accounts',
       'Num_Credit_Card', 'Interest_Rate', 'Num_of_Loan', 'Type_of_Loan',
       'Delay_from_due_date', 'Num_of_Delayed_Payment', 'Changed_Credit_Limit',
       'Num_Credit_Inquiries', 'Credit_Mix', 'Outstanding_Debt',
       'Credit_Utilization_Ratio', 'Credit_History_Age',
       'Payment_of_Min_Amount', 'Total_EMI_per_month',
       'Amount_invested_monthly', 'Payment_Behaviour', 'Monthly_Balance',
       'Credit_Score'],
      dtype='object')
```

```
#Checking for null values
```

```
df.isna().sum()
```

```
ID                                0
Customer_ID                       0
Month                              0
Name                               0
Age                                0
SSN                                0
Occupation                         0
Annual_Income                      0
Monthly_Inhand_Salary              0
Num_Bank_Accounts                  0
Num_Credit_Card                    0
Interest_Rate                      0
Num_of_Loan                        0
Type_of_Loan                       0
Delay_from_due_date                0
Num_of_Delayed_Payment              0
Changed_Credit_Limit               0
Num_Credit_Inquiries               0
Credit_Mix                         0
Outstanding_Debt                   0
Credit_Utilization_Ratio           0
Credit_History_Age                 0
Payment_of_Min_Amount              0
```

```
Total_EMI_per_month      0
Amount_invested_monthly  0
Payment_Behaviour        0
Monthly_Balance          0
Credit_Score             0
dtype: int64
```

```
#Checking for duplicated
df.duplicated().sum()
```

```
0
```

```
# Value count for each value
```

```
for i in df.columns:
```

```
    print(i, '\n', df[i].value_counts())
```

```
    print('-'*90)
```

```
Total_EMI_per_month
0.000000      10985
49.574949         8
46.354927         8
68.686857         8
137.778067         8
```

```
...
```

```
841.840387         1
82.544594          1
57.268474          1
144.179455         1
859.516628         1
```

```
Name: Total_EMI_per_month, Length: 11890, dtype: int64
```

```
-----
Amount_invested_monthly
```

```
0.000000      1920
110.634894         8
14.954207         8
82.215338         8
37.771077         8
```

```
...
```

```
58.064394         8
132.912602         8
83.539607         8
33.925532         8
24.028477         8
```

```
Name: Amount_invested_monthly, Length: 12261, dtype: int64
```

```
-----
Payment_Behaviour
```

```
Low_spent_Small_value_payments      28616
High_spent_Medium_value_payments    19738
High_spent_Large_value_payments     14726
Low_spent_Medium_value_payments     14399
High_spent_Small_value_payments     11764
Low_spent_Large_value_payments       10757
```

```
Name: Payment_Behaviour, dtype: int64
```

```
-----
Monthly_Balance
```

```
236.241829         8
1183.930696         8
235.451585         7
281.207616         7
1040.212843         7
```

```
..
```

```
469.067198         1
645.980641         1
463.759938         1
623.262089         1
393.673696         1
```

```
Name: Monthly_Balance, Length: 98492, dtype: int64
```

```
-----
Credit_Score
```

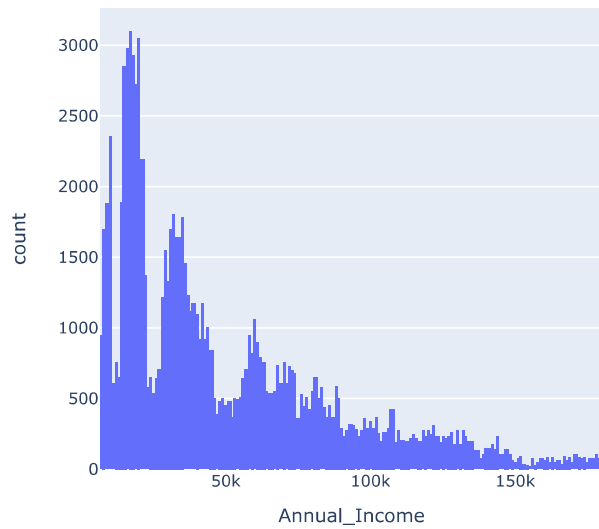
```
Standard      53174
Poor          28998
Good          17828
```

```
Name: Credit_Score, dtype: int64
```

EDA

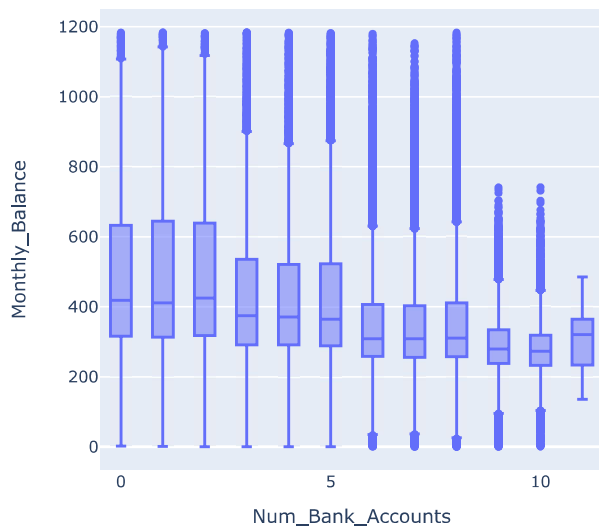
```
Income = px.histogram(df, x='Annual_Income', title='Distribution of Annual Income')
Income.show()
```

Distribution of Annual Income



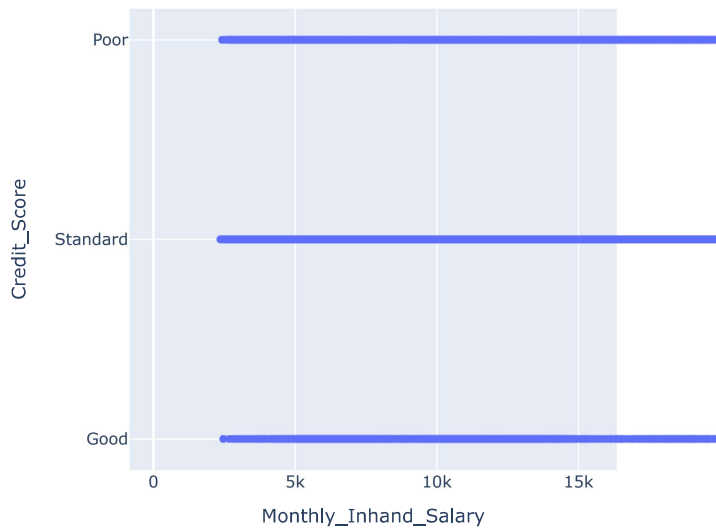
```
Mon_balance = px.box(df, x='Num_Bank_Accounts', y='Monthly_Balance', title='Monthly Balance by Number of Bank Accounts')
Mon_balance.show()
```

Monthly Balance by Number of Bank Accounts



```
score = px.scatter(df, x='Monthly_Inhand_Salary', y='Credit_Score', title='Monthly Inhand Salary vs. Credit Score')
score.show()
```

Monthly Inhand Salary vs. Credit Score



✓ Label encoder

```
# Encode categorical variables
label_encoders = {}
for column in df.select_dtypes(include=['object']).columns:
    label_encoders[column] = LabelEncoder()
    df[column] = label_encoders[column].fit_transform(df[column])
```

```
# Define features and target variable
# Sample data (replace with your actual data)
X = df[["Annual_Income", "Monthly_Inhand_Salary",
        "Num_Bank_Accounts", "Num_Credit_Card",
        "Interest_Rate", "Num_of_Loan",
        "Delay_from_due_date", "Num_of_Delayed_Payment",
        "Credit_Mix", "Outstanding_Debt",
        "Credit_History_Age", "Monthly_Balance"]]
y = df["Credit_Score"]
```

```
# Split the dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

y

```
0      0
1      0
2      0
3      0
4      0
..
99995  1
99996  1
99997  1
99998  2
99999  1
Name: Credit_Score, Length: 100000, dtype: int64
```

✓ Logistic Regression

```
# Initialize and train the Logistic Regression model
lr = LogisticRegression()
lr.fit(X_train, y_train)

# Make predictions and calculate accuracy
y_pred_lr = lr.predict(X_test)
accuracy_lr = accuracy_score(y_test, y_pred_lr)

print(f"Logistic Regression Accuracy: {accuracy_lr}")
```

Logistic Regression Accuracy: 0.5479
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning:

lbfgs failed to converge (status=1):
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

▼ Decision Tree

```
# Initialize and train the Decision Tree model
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)

# Make predictions and calculate accuracy
y_pred_dt = dt.predict(X_test)
accuracy_dt = accuracy_score(y_test, y_pred_dt)

print(f"Decision Tree Accuracy: {accuracy_dt}")
```

Decision Tree Accuracy: 0.76325

▼ Random forest

```
# Initialize and train the Random Forest model
rf = RandomForestClassifier()
rf.fit(X_train, y_train)

# Make predictions and calculate accuracy
y_pred_rf = rf.predict(X_test)
accuracy_rf = accuracy_score(y_test, y_pred_rf)

print(f"Random Forest Accuracy: {accuracy_rf}")
```

Random Forest Accuracy: 0.8137

▼ XG Boost

```
# Initialize and train the XGBoost model
xgb = XGBClassifier()
xgb.fit(X_train, y_train)

# Make predictions and calculate accuracy
y_pred_xgb = xgb.predict(X_test)
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)

print(f"XGBoost Accuracy: {accuracy_xgb}")
```

XGBoost Accuracy: 0.7645

▼ Comparing model

```
import plotly.graph_objects as go

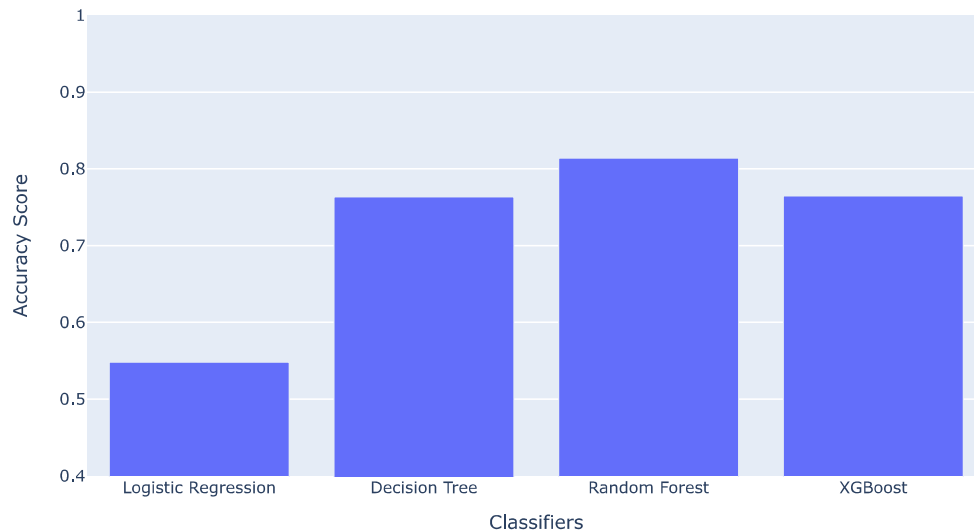
# Accuracy scores for each classifier
accuracies = {
    'Logistic Regression': accuracy_lr,
    'Decision Tree': accuracy_dt,
    'Random Forest': accuracy_rf,
    'XGBoost': accuracy_xgb
}

# Create a bar graph using Plotly
fig = go.Figure(data=[
    go.Bar(name='Accuracy', x=list(accuracies.keys()), y=list(accuracies.values()))
])

# Update the layout
fig.update_layout(title='Comparison of Model Accuracy Scores',
                  xaxis_title='Classifiers',
                  yaxis_title='Accuracy Score',
                  yaxis_range=[0.4, 1.0])

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

Comparison of Model Accuracy Scores



✓ New Data Predict

```
# Sample data for prediction
sample_data = pd.DataFrame({
    'Annual_Income': [20867.670],
    'Monthly_Inhand_Salary': [6769.130000],
    'Num_Bank_Accounts': [6],
    'Num_Credit_Card': [5],
    'Interest_Rate': [8],
    'Num_of_Loan': [3],
    'Delay_from_due_date': [15],
    'Num_of_Delayed_Payment': [19],
    'Credit_Mix': [2],
    'Outstanding_Debt': [1109.03],
    'Credit_History_Age': [190],
    'Monthly_Balance': [236.241829]
})

# Predict using the trained RandomForestClassifier model
predictions = rf.predict(sample_data)
```

```
# Map the predicted values to labels  
predicted_labels = [map_credit_mix(pred) for pred in predictions]
```

```
# Print the predicted labels  
print(predicted_labels)
```

 ['Good']