# classification-using-random-forest

# June 16, 2024

```
[26]: import pandas as pd
      import numpy as np
      import plotly.express as px
      import plotly.graph_objects as go
      import plotly.io as pio
      pio.templates.default = "plotly_white"
[27]: data = pd.read_csv("C:/Users/suova/OneDrive/Desktop/Credit Score Data/train.
       ⇔csv")
      print(data.head())
          ID
              Customer_ID
                            Month
                                             Name
                                                    Age
                                                                 SSN Occupation \
     0
       5634
                      3392
                                   Aaron Maashoh 23.0
                                                         821000265.0 Scientist
        5635
                      3392
                                2 Aaron Maashoh 23.0
                                                         821000265.0
                                                                      Scientist
       5636
                      3392
                                3 Aaron Maashoh 23.0
                                                         821000265.0
                                                                      Scientist
     3
       5637
                      3392
                                4 Aaron Maashoh 23.0
                                                         821000265.0
                                                                      Scientist
        5638
                      3392
                                5 Aaron Maashoh 23.0
                                                         821000265.0
                                                                      Scientist
        Annual_Income
                       Monthly_Inhand_Salary
                                               Num_Bank_Accounts
                                                                      Credit_Mix
              19114.12
                                                                             Good
     0
                                  1824.843333
                                                              3.0
     1
              19114.12
                                  1824.843333
                                                              3.0 ...
                                                                             Good
     2
              19114.12
                                  1824.843333
                                                              3.0 ...
                                                                             Good
     3
              19114.12
                                  1824.843333
                                                              3.0 ...
                                                                             Good
     4
              19114.12
                                  1824.843333
                                                              3.0 ...
                                                                             Good
        Outstanding Debt
                           Credit_Utilization_Ratio Credit_History_Age
     0
                                          26.822620
                   809.98
                                                                  265.0
     1
                   809.98
                                          31.944960
                                                                  266.0
     2
                   809.98
                                          28.609352
                                                                  267.0
     3
                   809.98
                                          31.377862
                                                                  268.0
     4
                   809.98
                                          24.797347
                                                                  269.0
        Payment_of_Min_Amount
                                Total_EMI_per_month
                                                      Amount_invested_monthly
     0
                            No
                                          49.574949
                                                                     21.46538
     1
                                          49.574949
                                                                     21.46538
                            No
     2
                            No
                                          49.574949
                                                                     21.46538
     3
                            No
                                          49.574949
                                                                     21.46538
     4
                                          49.574949
                                                                     21.46538
                            No
```

```
Payment_Behaviour Monthly_Balance Credit_Score
0
   High_spent_Small_value_payments
                                         312.494089
                                                             Good
1
    Low_spent_Large_value_payments
                                         284.629162
                                                             Good
2
   Low_spent_Medium_value_payments
                                                             Good
                                         331.209863
    Low_spent_Small_value_payments
                                                             Good
                                         223.451310
4 High_spent_Medium_value_payments
                                                             Good
                                         341.489231
```

[5 rows x 28 columns]

# [28]: print(data.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	float64
5	SSN	100000 non-null	float64
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	float64
10	Num_Credit_Card	100000 non-null	float64
11	Interest_Rate	100000 non-null	float64
12	Num_of_Loan	100000 non-null	float64
13	Type_of_Loan	100000 non-null	object
14	Delay_from_due_date	100000 non-null	float64
15	Num_of_Delayed_Payment	100000 non-null	float64
16	Changed_Credit_Limit	100000 non-null	float64
17	Num_Credit_Inquiries	100000 non-null	float64
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	float64
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: $float64(18)$ $int64(3)$ $object(7)$			

 ${\tt dtypes: float64(18), int64(3), object(7)}$ 

memory usage: 21.4+ MB

None

```
[29]: print(data.isnull().sum())
     ID
                                   0
     Customer_ID
                                   0
                                   0
     Month
     Name
                                   0
                                   0
     Age
     SSN
                                   0
     Occupation
                                   0
     Annual_Income
     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
                                   0
     Outstanding_Debt
     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
[30]: data["Credit_Score"].value_counts()
[30]: Standard
                  53174
      Poor
                  28998
      Good
                  17828
      Name: Credit_Score, dtype: int64
[31]: fig = px.box(data,
                    x="Occupation",
                    color="Credit_Score",
                    title="Credit Scores Based on Occupation",
                    color_discrete_map={'Poor':'red',
                                         'Standard': 'yellow',
                                         'Good':'green'})
      fig.show()
```

### Credit Scores Based on Occupation



## Credit Scores Based on Annual Income



# fig.show()

### Credit Scores Based on Monthly Inhand Salary



# Credit Scores Based on Number of Bank Accounts



```
'Good':'green'})
fig.update_traces(quartilemethod="exclusive")
fig.show()
```

#### Credit Scores Based on Number of Credit cards



### Credit Scores Based on the Average Interest rates



Credit Scores Based on Number of Loans Taken by the Person



Credit Scores Based on Average Number of Days Delayed for Credit card Payments



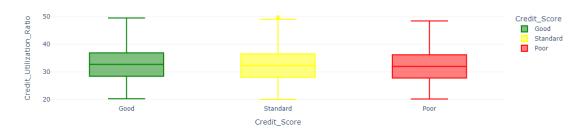
Credit Scores Based on Number of Delayed Payments



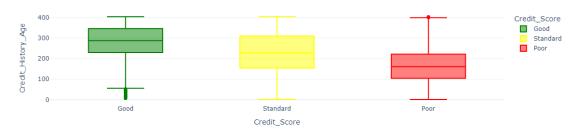
Credit Scores Based on Outstanding Debt



### Credit Scores Based on Credit Utilization Ratio



Credit Scores Based on Credit History Age



Credit Scores Based on Total Number of EMIs per Month



Credit Scores Based on Amount Invested Monthly



Credit Scores Based on Monthly Balance Left



C:\Users\suova\AppData\Local\Temp\ipykernel\_6664\2049170333.py:6:

## DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to  $(n_{samples})$ , for example using ravel().

# [48]: RandomForestClassifier()

Credit Score Prediction:

```
[49]: #Accuracy of the model from sklearn.metrics import accuracy_score,precision_score,recall_score print(accuracy_score(ytest, model.predict(xtest)))
```

0.807

```
[50]: print("Credit Score Prediction : ")
    a = float(input("Annual Income: "))
    b = float(input("Monthly Inhand Salary: "))
    c = float(input("Number of Bank Accounts: "))
    d = float(input("Number of Credit cards: "))
    e = float(input("Interest rate: "))
    f = float(input("Number of Loans: "))
    g = float(input("Average number of days delayed by the person: "))
    h = float(input("Number of delayed payments: "))
    i = input("Credit Mix (Bad: 0, Standard: 1, Good: 2) : ")
    j = float(input("Outstanding Debt: "))
    k = float(input("Credit History Age: "))
    l = float(input("Monthly Balance: "))

features = np.array([[a, b, c, d, e, f, g, h, i, j, k, 1]])
    print("Predicted Credit Score = ", model.predict(features))
```

```
Annual Income: 19114.12
Monthly Inhand Salary: 1824.8433
Number of Bank Accounts: 2
Number of Credit cards: 2
Interest rate: 9
Number of Loans: 2
Average number of days delayed by the person: 12
Number of delayed payments: 3
Credit Mix (Bad: 0, Standard: 1, Good: 2): 2
Outstanding Debt: 250
Credit History Age: 200
Monthly Balance: 310
Predicted Credit Score = ['Good']
```

Annual Income: 19114.12 Monthly Inhand Salary: 1824.843333 Number of Bank Accounts: 2 Number of Credit cards: 2 Interest rate: 9 Number of Loans: 2 Average number of days delayed

by the person: 12 Number of delayed payments: 3 Credit Mix (Bad: 0, Standard: 1, Good: 2): 2 Outstanding Debt: 250 Credit History Age: 200 Monthly Balance: 310 Predicted Credit Score = ['Good']

Credit Score Prediction: Annual Income: 350000 Monthly Inhand Salary: 18000 Number of Bank Accounts: 8 Number of Credit cards: 5 Interest rate: 9 Number of Loans: 9 Average number of days delayed by the person: 234 Number of delayed payments: 13 Credit Mix (Bad: 0, Standard: 1, Good: 2): 0 Outstanding Debt: 789 Credit History Age: 123 Monthly Balance: 567 Predicted Credit Score = ['Standard']

Credit Score Prediction: Annual Income: 34081.38 Monthly Inhand Salary: 2611.115 Number of Bank Accounts: 8 Number of Credit cards: 7 Interest rate: 15 Number of Loans: 3 Average number of days delayed by the person: 30 Number of delayed payments: 14 Credit Mix (Bad: 0, Standard: 1, Good: 2): 1 Outstanding Debt: 1704.18 Credit History Age: 176 Monthly Balance: 392.19 Predicted Credit Score = ['Poor']

[]: