

CREDIT SCORE CLASSIFICATION

April 30, 2023

1 Problem Statement :-) Credit Score Classification: Case Study

Description :-) The credit score of a person determines the creditworthiness of the person. It helps financial companies determine if you can repay the loan or credit you are applying for.

1.0.1 1. Importing Necessary Libraries

```
[1]: import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio
import matplotlib.pyplot as plt
```

2 2. Data Set Information

1. ID: Unique ID of the record
2. Customer_ID: Unique ID of the customer
3. Month: Month of the year
4. Name: The name of the person
5. Age: The age of the person
6. SSN: Social Security Number of the person
7. Occupation: The occupation of the person
8. Annual_Income: The Annual Income of the person
9. Monthly_Inhand_Salary: Monthly in-hand salary of the person
10. Num_Bank_Accounts: The number of bank accounts of the person
11. Num_Credit_Card: Number of credit cards the person is having
12. Interest_Rate: The interest rate on the credit card of the person
13. Num_of_Loan: The number of loans taken by the person from the bank
14. Type_of_Loan: The types of loans taken by the person from the bank
15. Delay_from_due_date: The average number of days delayed by the person from the date of payment
16. Num_of_Delayed_Payment: Number of payments delayed by the person
17. Changed_Credit_Card: The percentage change in the credit card limit of the person
18. Num_Credit_Inquiries: The number of credit card inquiries by the person
19. Credit_Mix: Classification of Credit Mix of the customer

20. Outstanding_Debt: The outstanding balance of the person
21. Credit_Utilization_Ratio: The credit utilization ratio of the credit card of the customer
22. Credit_History_Age: The age of the credit history of the person
23. Payment_of_Min_Amount: Yes if the person paid the minimum amount to be paid only, otherwise no.
24. Total_EMI_per_month: The total EMI per month of the person
25. Amount_invested_monthly: The monthly amount invested by the person
26. Payment_Behaviour: The payment behaviour of the person
27. Monthly_Balance: The monthly balance left in the account of the person
28. Credit_Score: The credit score of the person

- The Credit_Score column is the target variable in this problem. You are required to find relationships based on how banks classify credit scores and train a model to classify the credit score of a person.

2.0.1 2.1 Reading Dataset

```
[2]: data=pd.read_csv("train.csv")
data.head()
```

```
[2]:
```

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	\
0	5634	3392	1	Aaron Maashoh	23.0	821000265.0	Scientist	
1	5635	3392	2	Aaron Maashoh	23.0	821000265.0	Scientist	
2	5636	3392	3	Aaron Maashoh	23.0	821000265.0	Scientist	
3	5637	3392	4	Aaron Maashoh	23.0	821000265.0	Scientist	
4	5638	3392	5	Aaron Maashoh	23.0	821000265.0	Scientist	

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Credit_Mix	\
0	19114.12	1824.843333	3.0	...	Good	
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	809.98	26.822620	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	No	49.574949	21.46538	
2	No	49.574949	21.46538	
3	No	49.574949	21.46538	
4	No	49.574949	21.46538	

	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	331.209863	Good
3	Low_spent_Small_value_payments	223.451310	Good
4	High_spent_Medium_value_payments	341.489231	Good

[5 rows x 28 columns]

- Let's have a look at the information about the columns in the dataset:

```
[3]: data.shape
```

```
[3]: (100000, 28)
```

- The DataSet Contain Observation => 100000 , Feature => 28

```
[4]: 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)
memory usage: 21.4+ MB

```

- Some Feature is Object and some numeric

[5]: data.describe()

```

[5]:
count      ID      Customer_ID      Month      Age \
count  100000.000000  100000.000000  100000.000000  100000.000000
mean    80631.500000   25982.666640    4.500000    33.316340
std     43301.486619   14340.543051    2.291299    10.764812
min      5634.000000    1006.000000    1.000000    14.000000
25%     43132.750000   13664.500000    2.750000    24.000000
50%     80631.500000   25777.000000    4.500000    33.000000
75%    118130.250000   38385.000000    6.250000    42.000000
max    155629.000000   50999.000000    8.000000    56.000000

count      SSN Annual_Income Monthly_Inhand_Salary  Num_Bank_Accounts \
count  1.000000e+05  100000.000000    100000.000000    100000.000000
mean    5.004617e+08   50505.123449    4197.270835      5.368820
std     2.908267e+08   38299.422093    3186.432497      2.593314
min     8.134900e+04    7005.930000     303.645417      0.000000
25%     2.451686e+08   19342.972500    1626.594167      3.000000
50%     5.006886e+08   36999.705000    3095.905000      5.000000
75%     7.560027e+08   71683.470000    5957.715000      7.000000
max     9.999934e+08  179987.280000   15204.633333     11.000000

count      Num_Credit_Card Interest_Rate  ... Delay_from_due_date  \
count  100000.000000  100000.000000  ...    100000.000000
mean      5.533570    14.53208  ...      21.08141
std       2.067098     8.74133  ...      14.80456
min        0.000000     1.00000  ...       0.00000
25%        4.000000     7.00000  ...      10.00000
50%        5.000000    13.00000  ...      18.00000
75%        7.000000    20.00000  ...      28.00000
max       11.000000    34.00000  ...      62.00000

count      Num_of_Delayed_Payment Changed_Credit_Limit  Num_Credit_Inquiries  \
count  100000.000000    100000.000000    100000.000000
mean      13.313120     10.470323      5.798250
std       6.237166      6.609481      3.867826
min        0.000000      0.500000      0.000000
25%        9.000000      5.380000      3.000000
50%       14.000000      9.400000      5.000000

```

75%	18.000000	14.850000	8.000000
max	25.000000	29.980000	17.000000

	Outstanding_Debt	Credit_Utilization_Ratio	Credit_History_Age \
count	100000.000000	100000.000000	100000.000000
mean	1426.220376	32.285173	221.220460
std	1155.129026	5.116875	99.680716
min	0.230000	20.000000	1.000000
25%	566.072500	28.052567	144.000000
50%	1166.155000	32.305784	219.000000
75%	1945.962500	36.496663	302.000000
max	4998.070000	50.000000	404.000000

	Total_EMI_per_month	Amount_invested_monthly	Monthly_Balance
count	100000.000000	100000.000000	100000.000000
mean	107.699208	55.101315	392.697586
std	132.267056	39.006932	201.652719
min	0.000000	0.000000	0.007760
25%	29.268886	27.959111	267.615983
50%	66.462304	45.156550	333.865366
75%	147.392573	71.295797	463.215683
max	1779.103254	434.191089	1183.930696

[8 rows x 21 columns]

3. Handling Null Value

[6]: data.isnull()

[6]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation \
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
...
99995	False	False	False	False	False	False	False
99996	False	False	False	False	False	False	False
99997	False	False	False	False	False	False	False
99998	False	False	False	False	False	False	False
99999	False	False	False	False	False	False	False

	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts ... \
0	False	False	False ...
1	False	False	False ...
2	False	False	False ...

3	False	False	False	...
4	False	False	False	...
...
99995	False	False	False	...
99996	False	False	False	...
99997	False	False	False	...
99998	False	False	False	...
99999	False	False	False	...

	Credit_Mix	Outstanding_Debt	Credit_Utilization_Ratio	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
...	
99995	False	False	False	
99996	False	False	False	
99997	False	False	False	
99998	False	False	False	
99999	False	False	False	

	Credit_History_Age	Payment_of_Min_Amount	Total_EMI_per_month	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
...	
99995	False	False	False	
99996	False	False	False	
99997	False	False	False	
99998	False	False	False	
99999	False	False	False	

	Amount_invested_monthly	Payment_Behaviour	Monthly_Balance	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
...	
99995	False	False	False	
99996	False	False	False	
99997	False	False	False	
99998	False	False	False	
99999	False	False	False	

	Credit_Score
0	False
1	False
2	False
3	False
4	False
...	...
99995	False
99996	False
99997	False
99998	False
99999	False

[100000 rows x 28 columns]

```
[7]: data.isnull().sum()
```

```
[7]: 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
```

The dataset doesn't have any null values.
at the Credit_Score column values:

As this dataset is labelled, let's have a look

```
[8]: data['Credit_Score'].value_counts()
```

```
[8]: Standard      53174  
     Poor         28998  
     Good         17828  
     Name: Credit_Score, dtype: int64
```

4. Data Exploration

- The dataset has many features that can train a Machine Learning model for credit score classification. Let's explore all the features one by one.

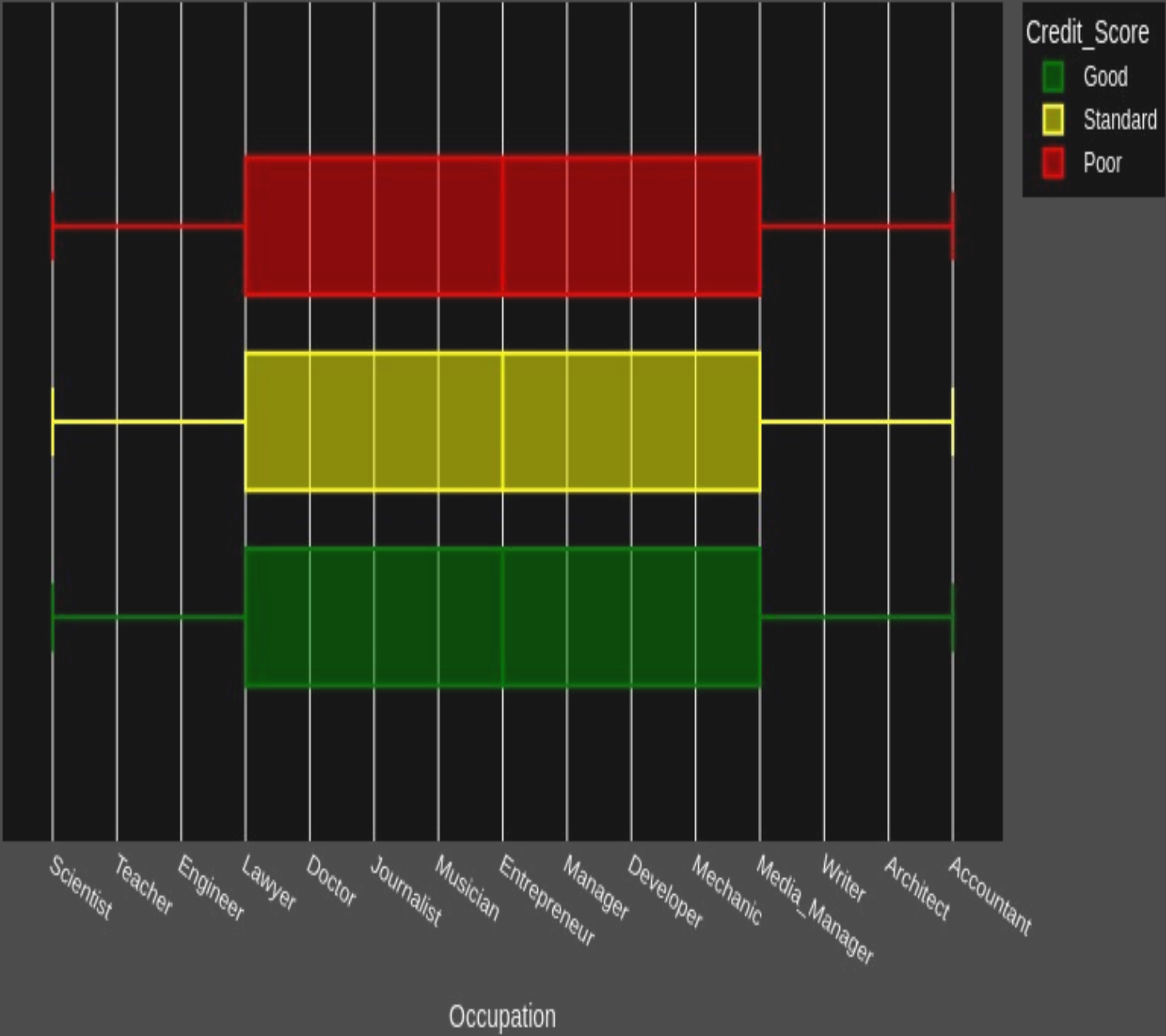
```
[9]: data.columns.unique()
```

```
[9]: 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')
```

```
[10]: fig=px.box(data,x='Occupation',  
                color='Credit_Score',  
                color_discrete_map={'Poor':'red',  
                                    'Standard':'yellow',  
                                    'Good':'green'})  
  
fig.update_layout(  
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark gray  
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a dark gray  
    font_color='white',  
    title={'text':'Credit score Based On Occupation','font_color':'red'})  
fig.show()
```

- There's not much difference in the credit scores of all occupations mentioned in the data.
Now let's explore whether the Annual Income of the person impacts your credit scores or not:

Credit score Based On Occupation

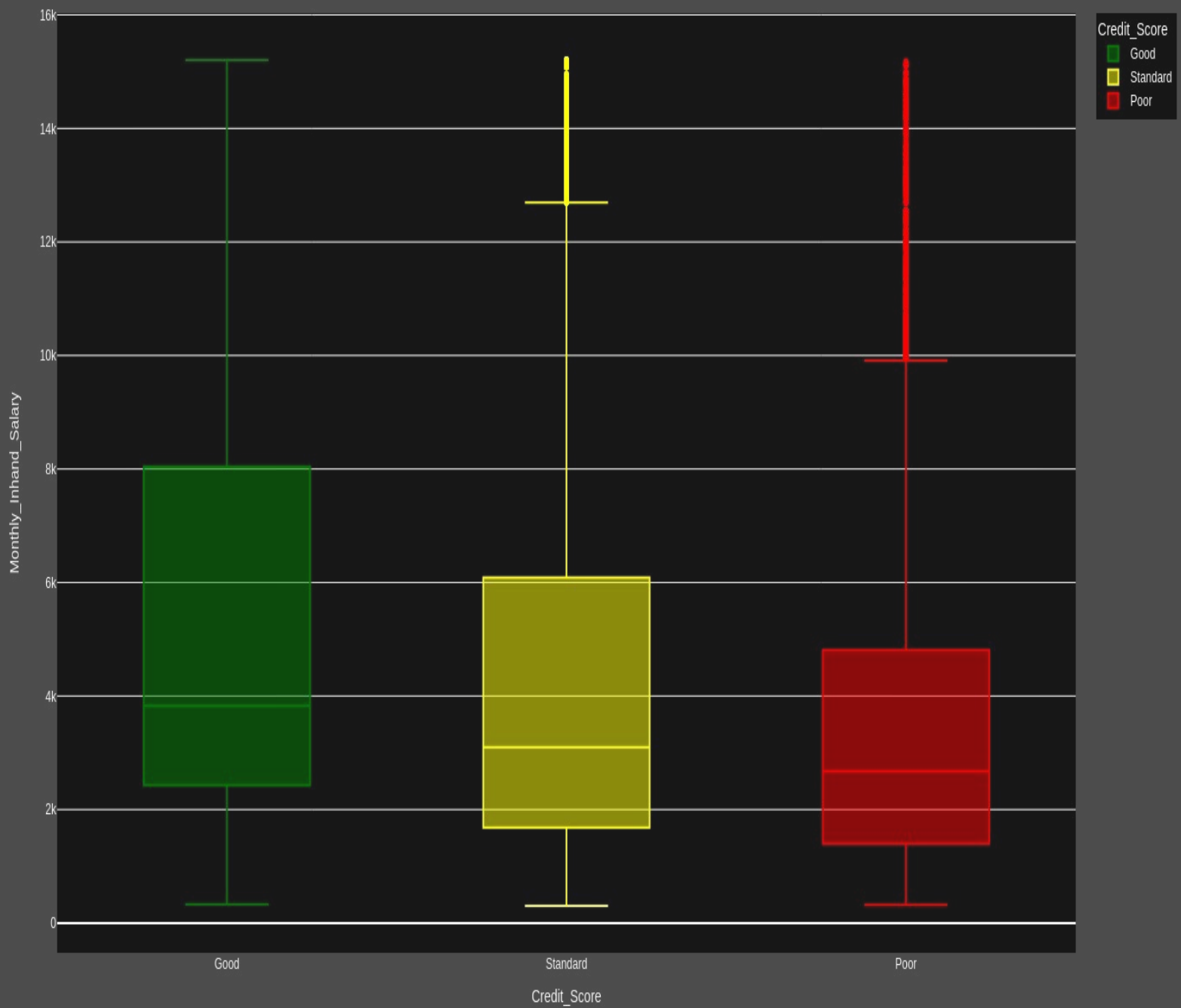


```
[11]: fig=px.box(data,
                x='Credit_Score',
                y='Annual_Income',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                    'Standard':'yellow',
                                    'Good':'green'},
                )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Occupation','font_color':'red'},
    width=1400,
    height=900
)
fig.show()
```

- According to the above visualization, the more you earn annually, the better your credit score is.
- Now let's explore whether the monthly in-hand salary impacts credit scores or not

```
[12]: fig=px.box(data,
                x='Credit_Score',
                y='Monthly_Inhand_Salary',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                    'Standard':'yellow',
                                    'Good':'green'},
                )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Monthly Inhand Salary ','font_color':
    'red'},
    width=1400,
    height=900
)
fig.show()
```

Credit score Based On Monthly Inhand Salary



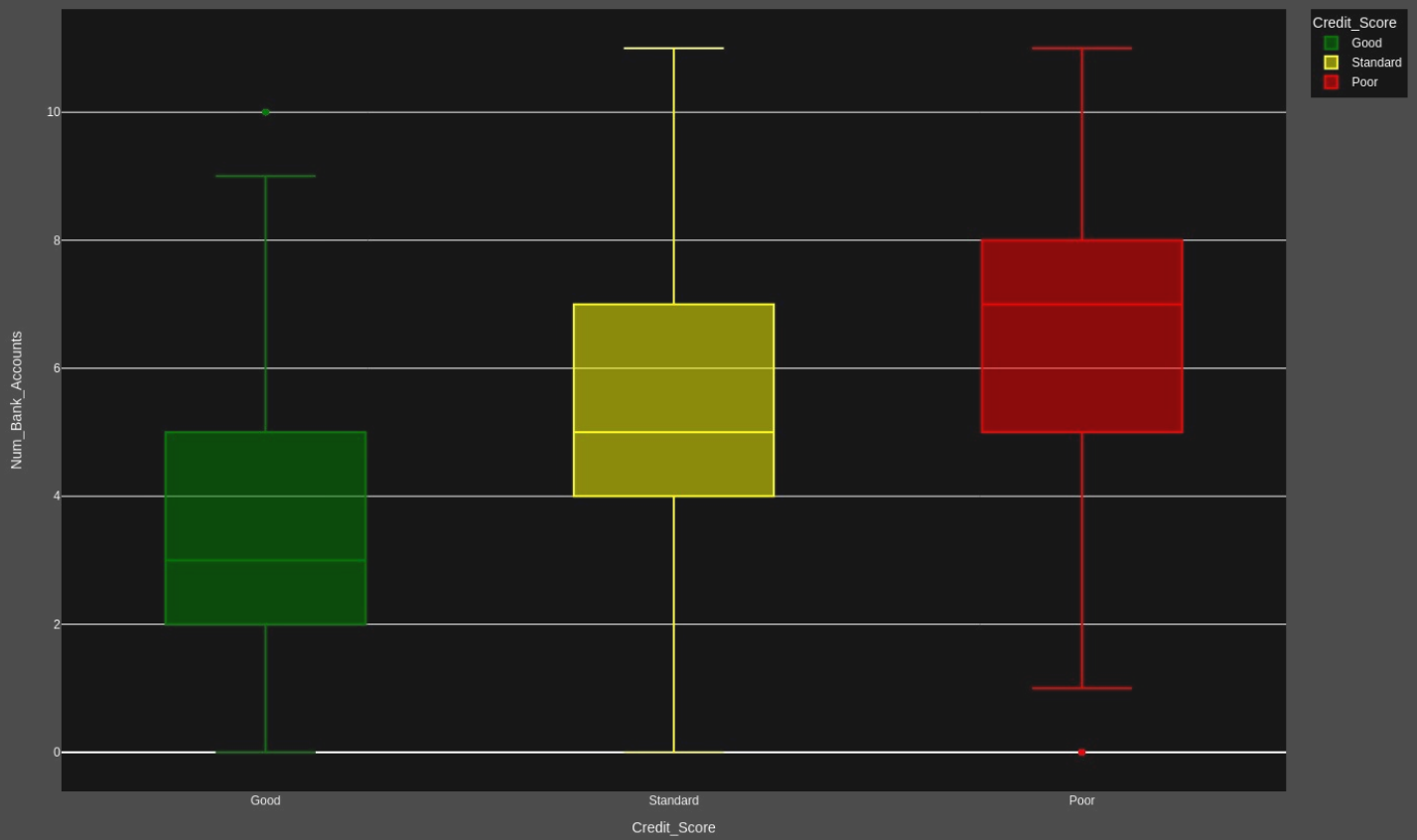
- Like annual income, the more monthly in-hand salary you earn, the better your credit score will become.
- Now let's see if having more bank accounts impacts credit scores or not

```
[13]: fig=px.box(data,
                x='Credit_Score',
                y='Num_Bank_Accounts',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                    'Standard':'yellow',
                                    'Good':'green'},
                )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Number of Bank Accounts ','font_color':
    'red'},
    width=1400,
    height=900
)
fig.show()
```

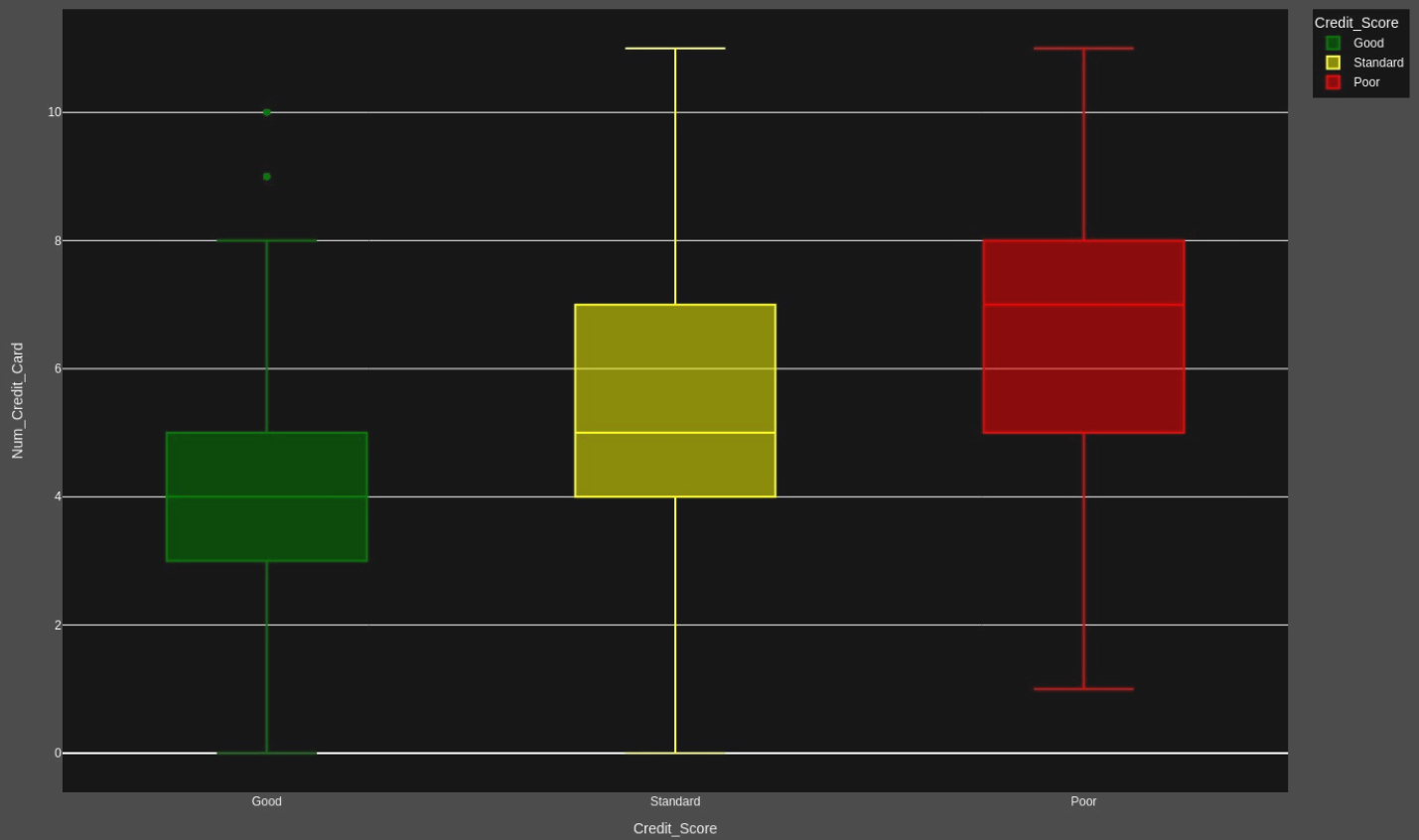
- Maintaining more than five accounts is not good for having a good credit score.
- A person should have 2 – 3 bank accounts only. So having more bank accounts doesn't positively impact credit scores.
- Now let's see the impact on credit scores based on the number of credit cards you have:

```
[14]: fig=px.box(data,
                x='Credit_Score',
                y='Num_Credit_Card',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                    'Standard':'yellow',
                                    'Good':'green'},
                )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
```

Credit score Based On Number of Bank Accounts



Credit score Based On Number Of Credit Card



```

        title={'text':'Credit score Based On Number Of Credit Card','font_color':
'red'},
        width=1400,
        height=900
    )
    fig.show()

```

- Just like the number of bank accounts, having more credit cards will not positively impact your credit scores.
- Having 3 – 5 credit cards is good for your credit score.
- Now let's see the impact on credit scores based on how much average interest you pay on loans and EMIs:

```

[15]: fig=px.box(data,
                x='Credit_Score',
                y='Interest_Rate',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                   'Standard':'yellow',
                                   'Good':'green'},
                )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark_
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a_
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Average Interest rates','font_color':
'red'},
    width=1400,
    height=900
)
fig.show()

```

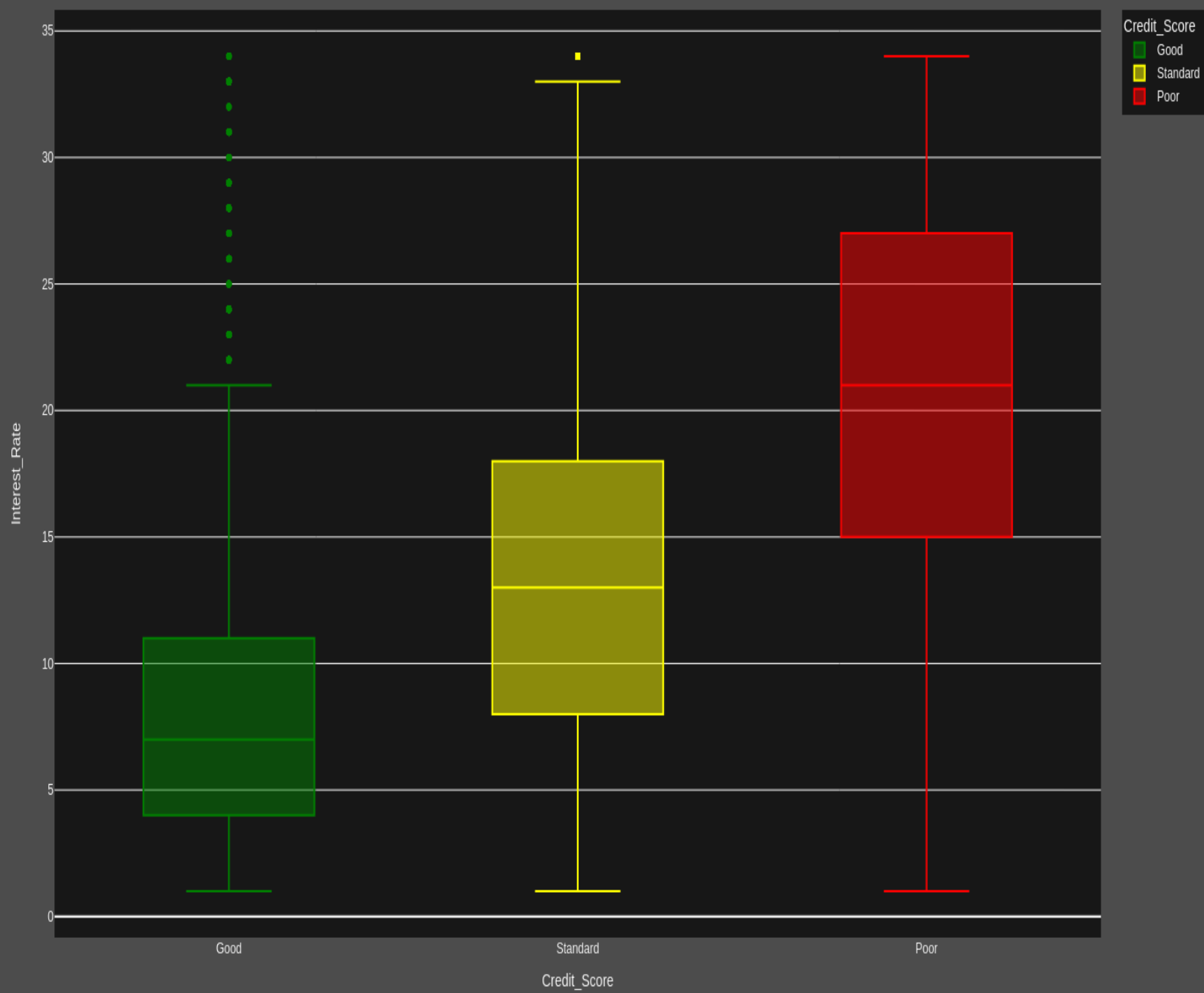
- If the average interest rate is 4 – 11%, the credit score is good.
- Having an average interest rate of more than 15% is bad for your credit scores.
- Now let's see how many loans you can take at a time for a good credit score:

```

[16]: fig=px.box(data,
                x='Credit_Score',
                y='Num_of_Loan',
                color='Credit_Score',
                color_discrete_map={'Poor':'red',
                                   'Standard':'yellow',
                                   'Good':'green'},
                )

```

Credit score Based On Average Interest rates



```

fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Number Of Loan','font_color':'red'},
    width=1400,
    height=900
)
fig.show()

```

- To have a good credit score, you should not take more than 1 – 3 loans at a time.
- Having more than three loans at a time will negatively impact your credit scores.
- Now let's see if delaying payments on the due date impacts your credit scores or not:

```

[17]: fig=px.box(data,
    x='Credit_Score',
    y='Delay_from_due_date',
    color='Credit_Score',
    color_discrete_map={'Poor':'red',
                        'Standard':'yellow',
                        'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Average Number of Days Delayed For
    Credit Crad Payments ','font_color':'red'},
    width=1400,
    height=900
)
fig.show()

```

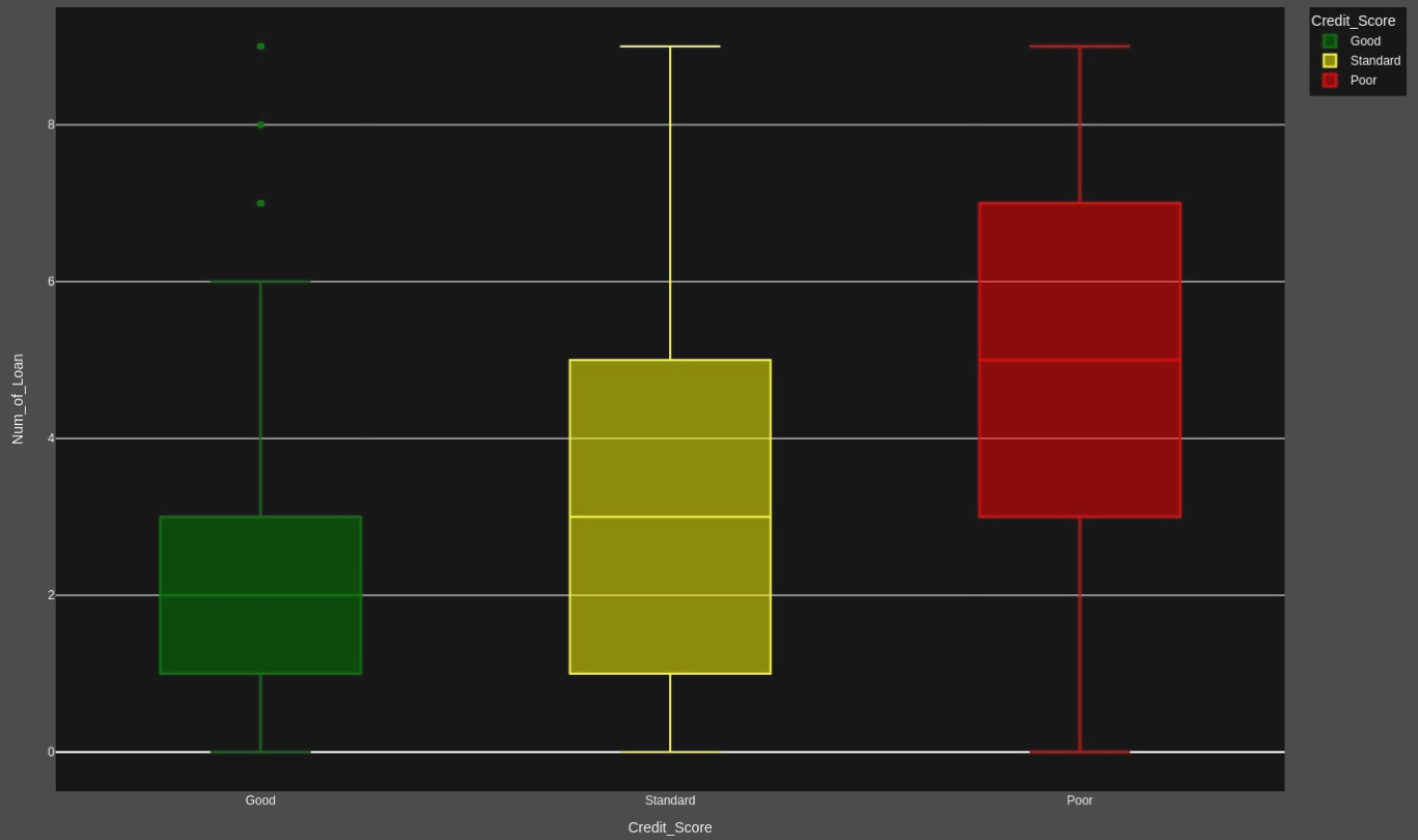
- So you can delay your credit card payment 5 – 14 days from the due date.
- Delaying your payments for more than 17 days from the due date will impact your credit scores negatively.
- Now let's have a look at if frequently delaying payments will impact credit scores or not:

```

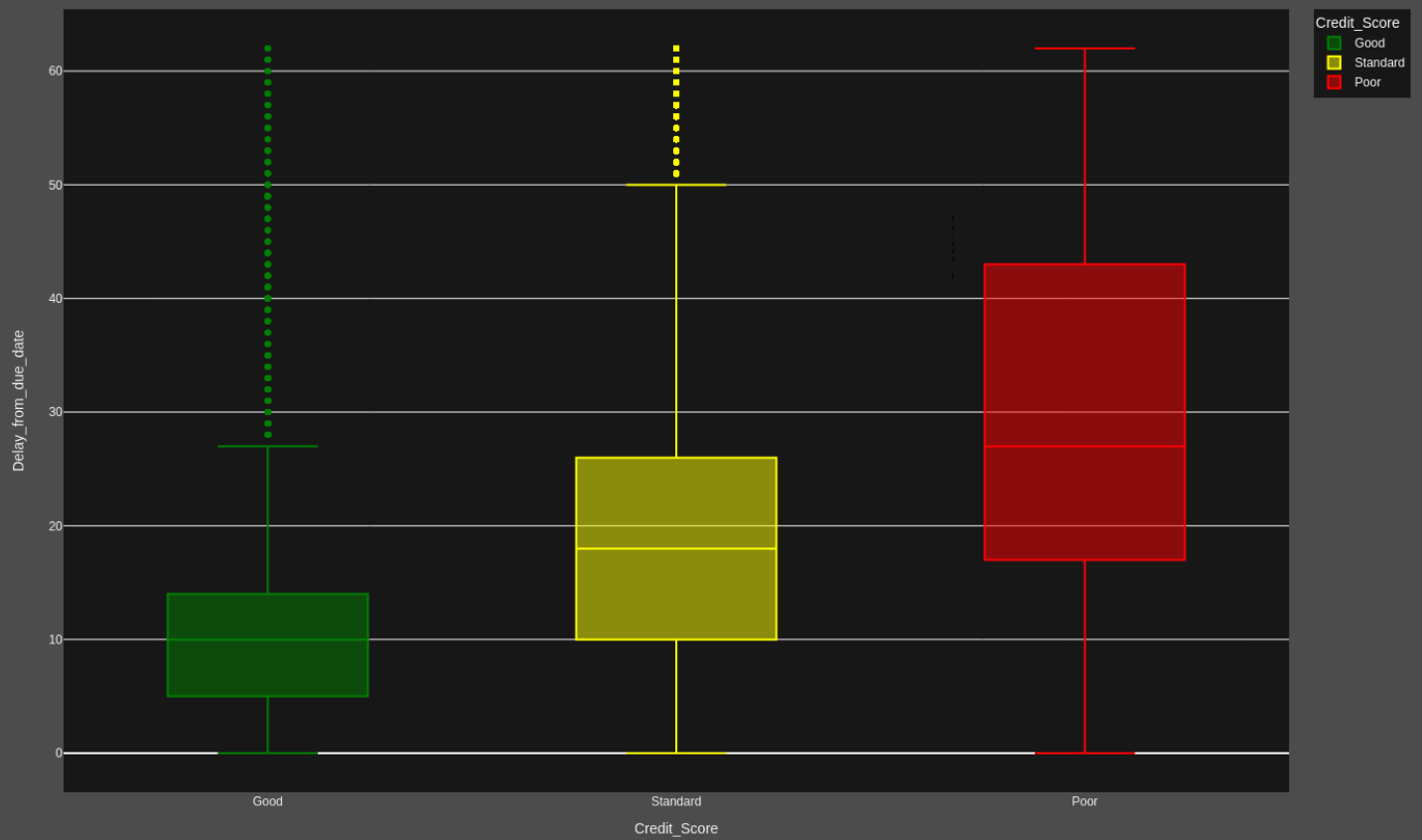
[18]: fig=px.box(data,
    x='Credit_Score',
    y='Num_of_Delayed_Payment',

```


Credit score Based On Number Of Loan



Credit score Based On Average Number of Days Delayed For Credit Card Payments



```

        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                            'Standard':'yellow',
                            'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Average Number of Delayed
    Payments','font_color':'red'},
    width=1400,
    height=900
)
fig.show()

```

- So delaying 4 – 12 payments from the due date will not affect your credit scores.
- But delaying more than 12 payments from the due date will affect your credit scores negatively.
- Now let's see if having more debt will affect credit scores or not:

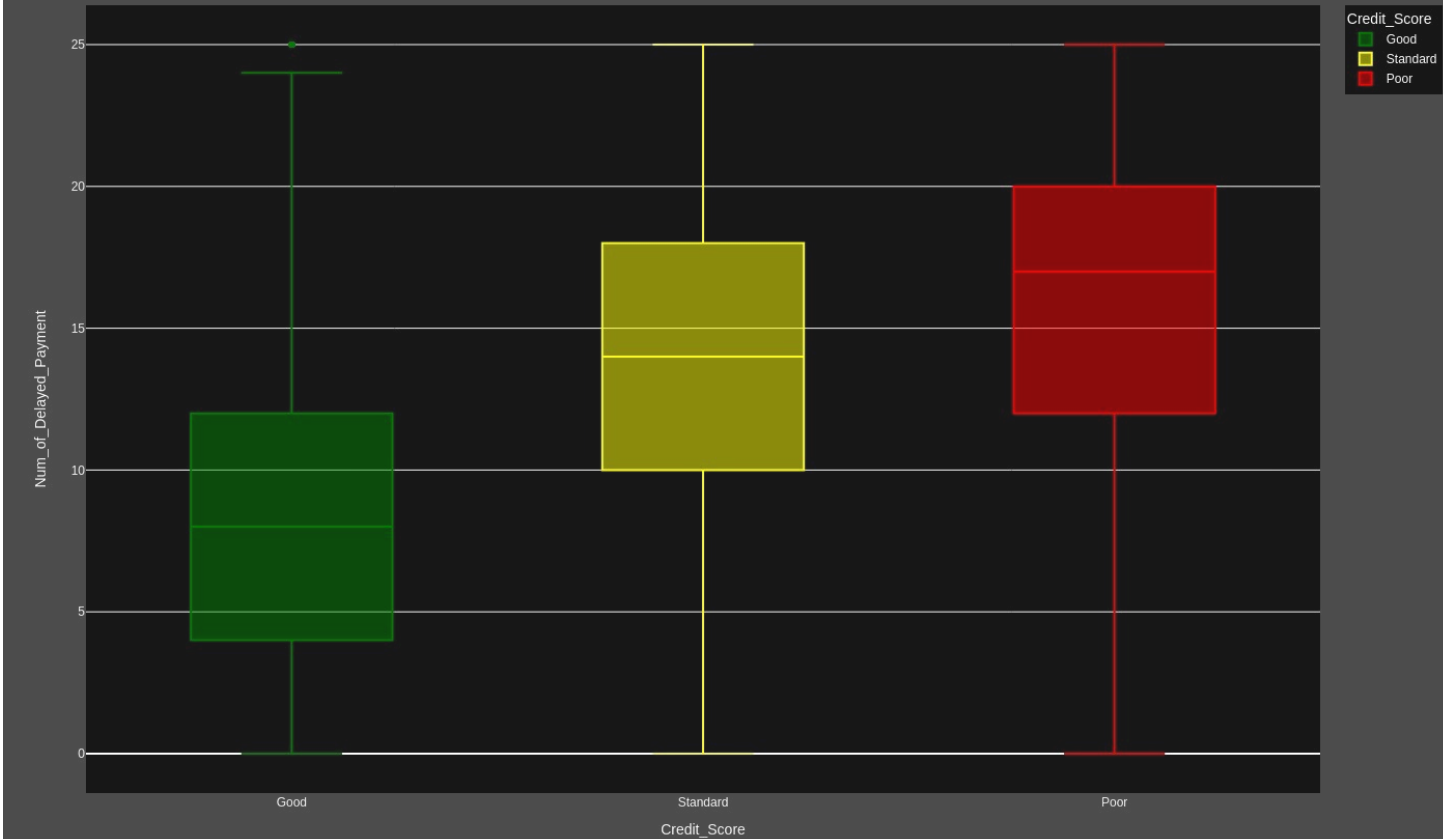
```

[19]: fig=px.box(data,
        x='Credit_Score',
        y='Outstanding_Debt',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                            'Standard':'yellow',
                            'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark
    gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a
    dark gray
    font_color='white',
    title={'text':'Credit score Based On Outstanding Debt','font_color':'red'},
    width=1400,
    height=900
)
fig.show()

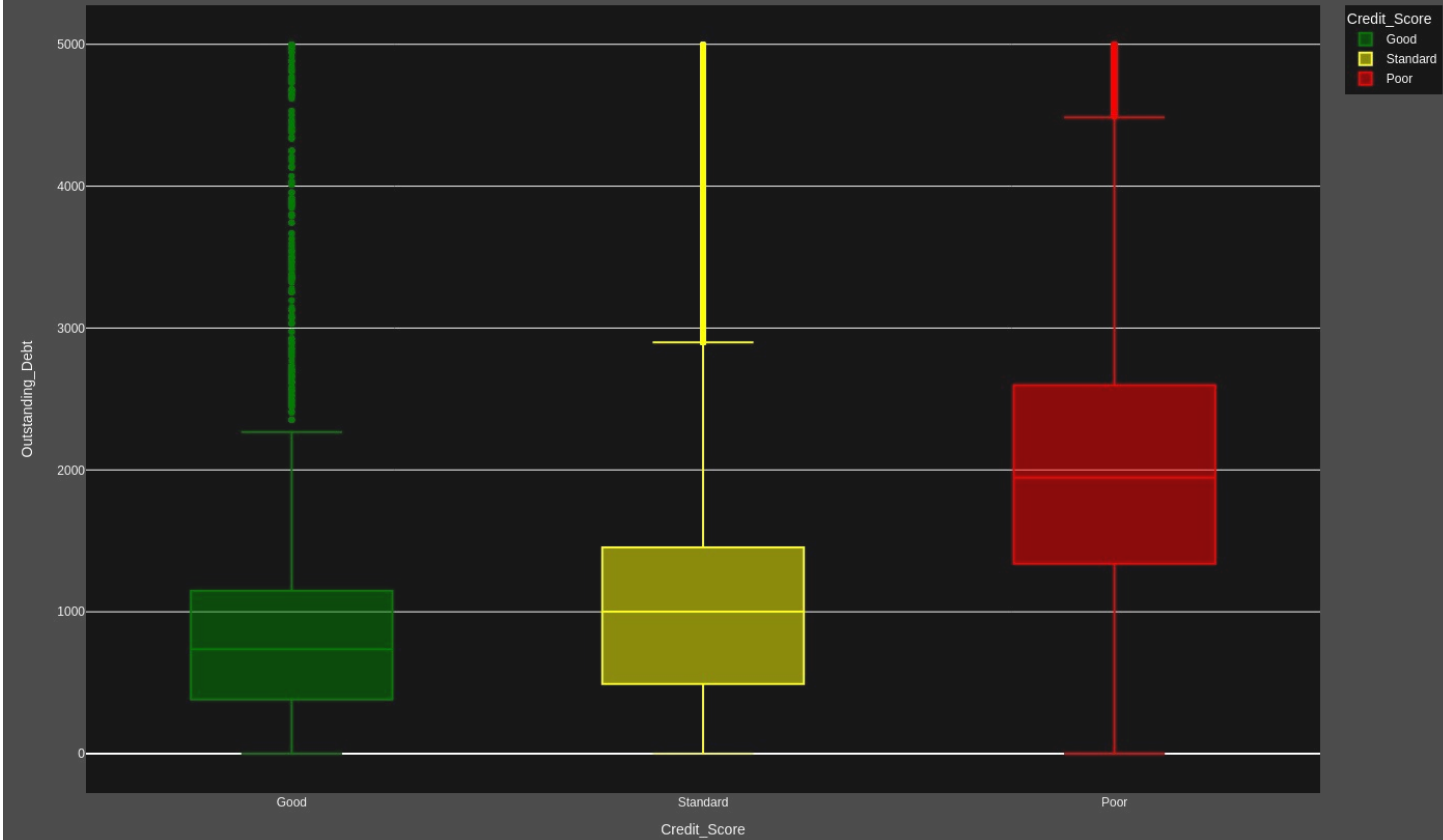
```

- An outstanding debt of \$380 – \$1150 will not affect your credit scores.
- But always having a debt of more than \$1338 will affect your credit scores nega-

Credit score Based On Average Number of Delayed Payments



Credit score Based On Outstanding Debt



tively.

- Now let's see if having a high credit utilization ratio will affect credit scores or not:

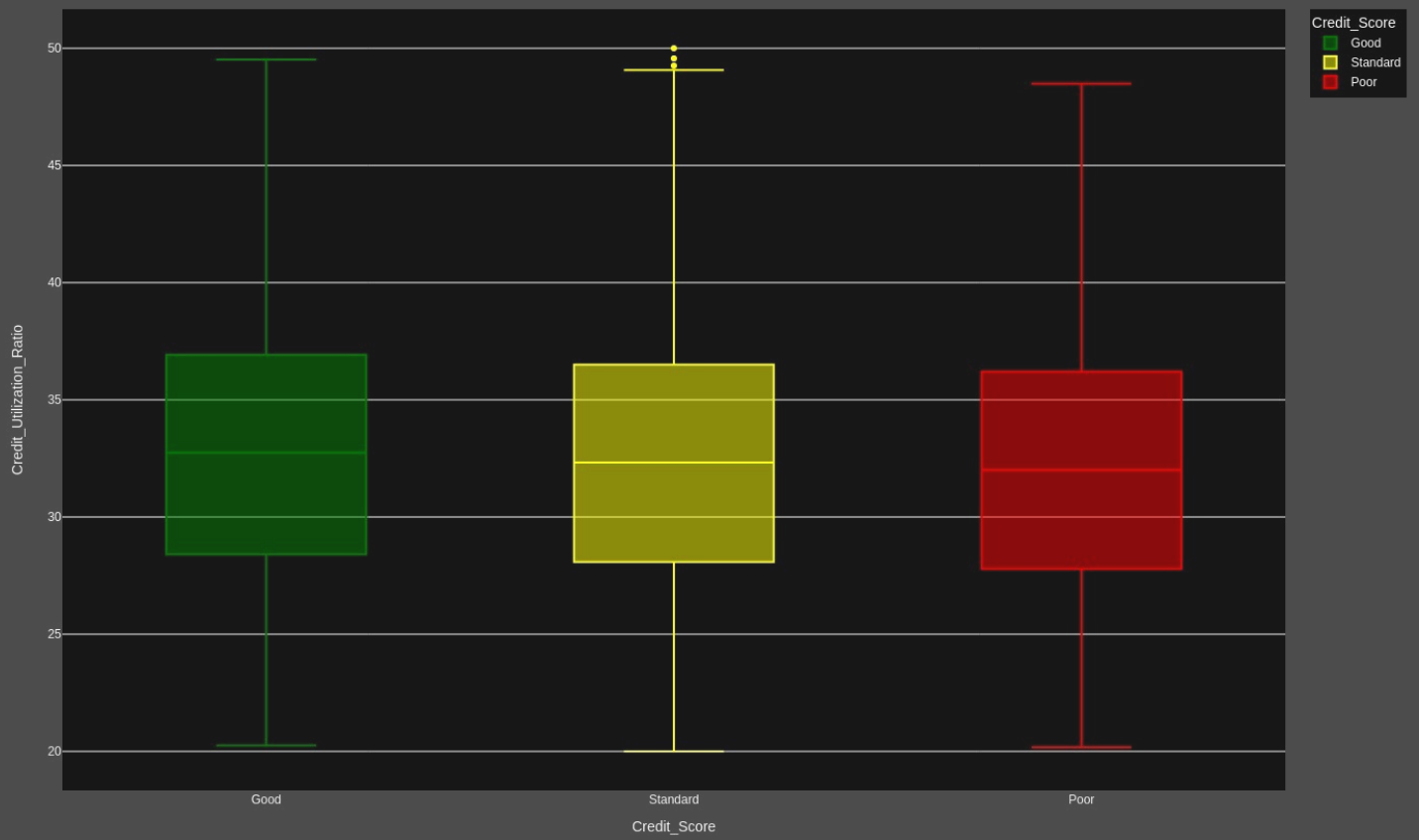
```
[20]: fig=px.box(data,
        x='Credit_Score',
        y='Credit_Utilization_Ratio',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                             'Standard':'yellow',
                             'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a dark gray
    font_color='white',
    title={'text':'Credit score Based On Credit Utilization Ratio',
           'font_color':'red'},
    width=1400,
    height=900
)
fig.show()
```

- Credit utilization ratio means your total debt divided by your total available credit.
- According to the above figure, your credit utilization ratio doesn't affect your credit scores.
- Now let's see how the credit history age of a person affects credit scores:

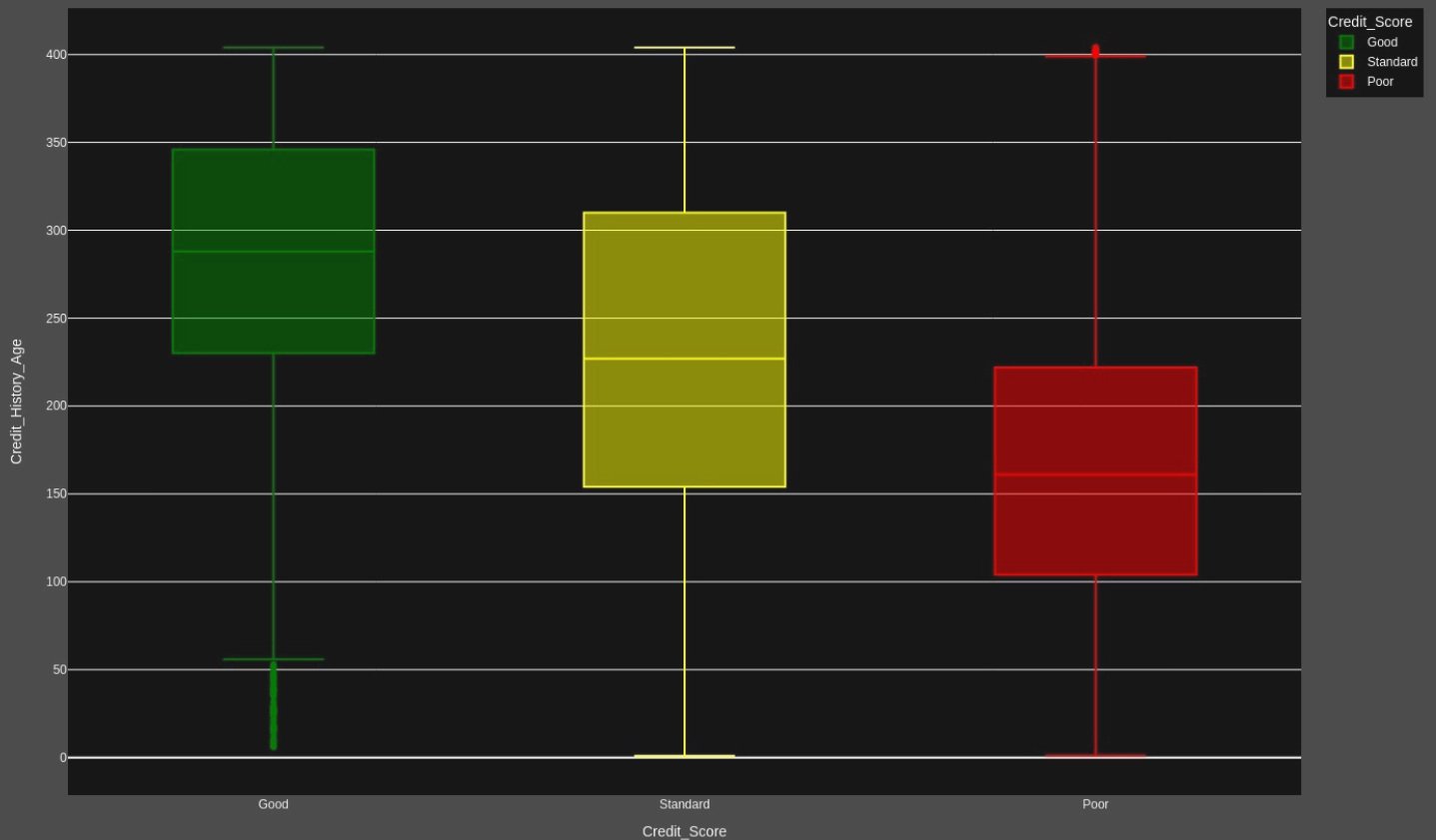
```
[21]: fig=px.box(data,
        x='Credit_Score',
        y='Credit_History_Age',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                             'Standard':'yellow',
                             'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a dark gray
    font_color='white',

```

Credit score Based On Credit Utilization Ratio



Credit score Based On Credit History Age



```

        title={'text':'Credit score Based On Credit History Age','font_color':
'red'},
        width=1400,
        height=900
    )
    fig.show()

```

So, having a long credit history results in better credit scores.
EMIs you can have in a month for a good credit score:

* Now let's see how many

```

[22]: fig=px.box(data,
        x='Credit_Score',
        y='Total_EMI_per_month',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                             'Standard':'yellow',
                             'Good':'green'},
    )
    fig.update_traces(quartilemethod='exclusive')
    fig.update_layout(
        plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark_
        gray
        paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a_
        dark gray
        font_color='white',
        title={'text':'Credit score Based On Total EMI Per Month','font_color':
'red'},
        width=1400,
        height=900
    )
    fig.show()

```

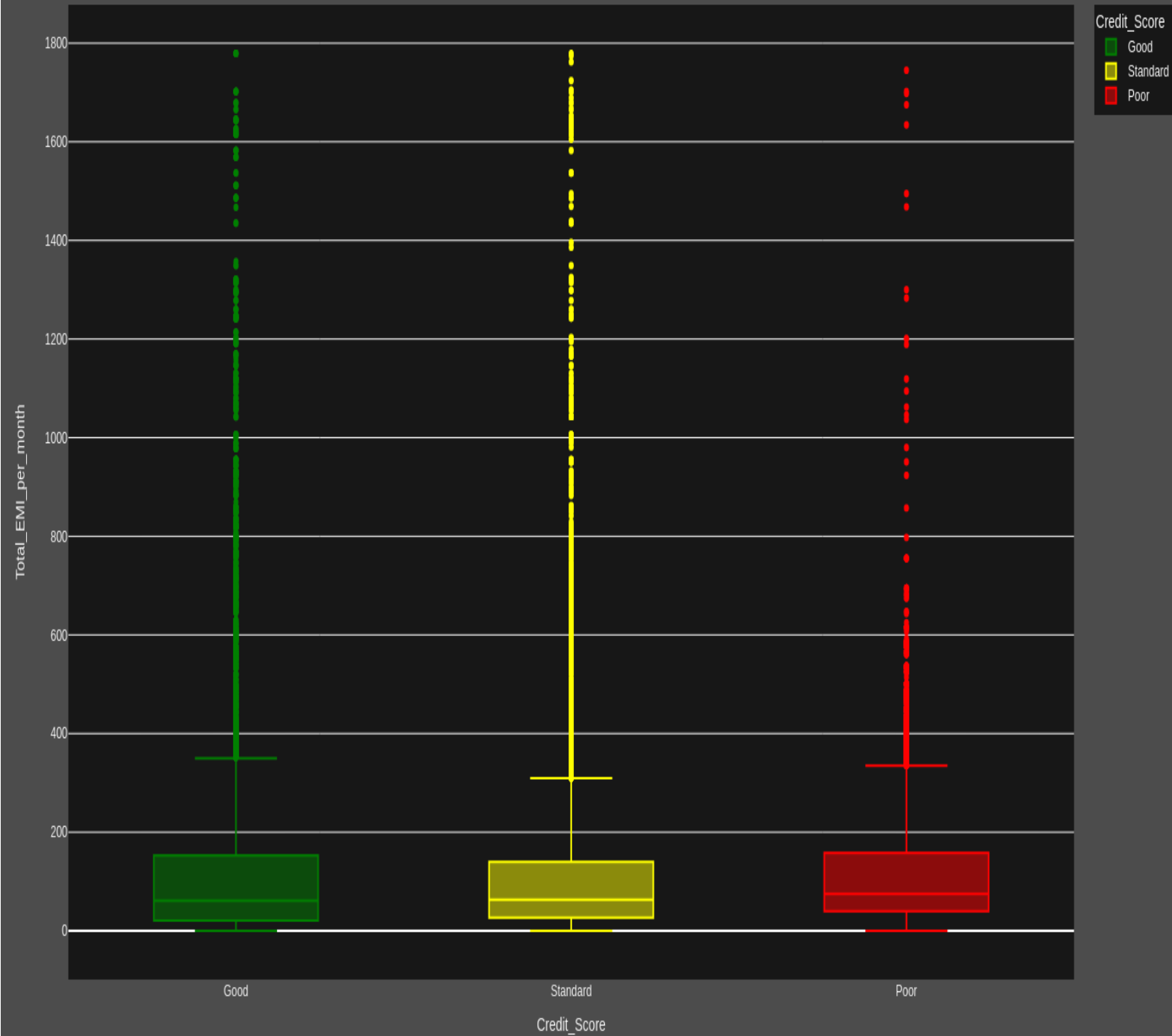
- The number of EMIs you are paying in a month doesn't affect much on credit scores.
- Now let's see if your monthly investments affect your credit scores or not:

```

[23]: fig=px.box(data,
        x='Credit_Score',
        y='Amount_invested_monthly',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                             'Standard':'yellow',
                             'Good':'green'},
    )
    fig.update_traces(quartilemethod='exclusive')
    fig.update_layout(

```

Credit score Based On Total EMI Per Month



```

    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark_
gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a_
dark gray
    font_color='white',
    title={'text':'Credit score Based On Amount Invested Monthly','font_color':
'red'},
    width=1400,
    height=900
)
fig.show()

```

- The amount of money you invest monthly doesn't affect your credit scores a lot.
- Now let's see if having a low amount at the end of the month affects credit scores or not:

```

[24]: fig=px.box(data,
        x='Credit_Score',
        y='Monthly_Balance',
        color='Credit_Score',
        color_discrete_map={'Poor':'red',
                             'Standard':'yellow',
                             'Good':'green'},
    )
fig.update_traces(quartilemethod='exclusive')
fig.update_layout(
    plot_bgcolor='rgba(0,0,0,0.7)', # sets the plot background color to a dark_
gray
    paper_bgcolor='rgba(0,0,0,0.7)', # sets the paper background color to a_
dark gray
    font_color='white',
    title={'text':'Credit score Based On Monthly Balance Left','font_color':
'red'},
    width=1400,
    height=900
)
fig.show()

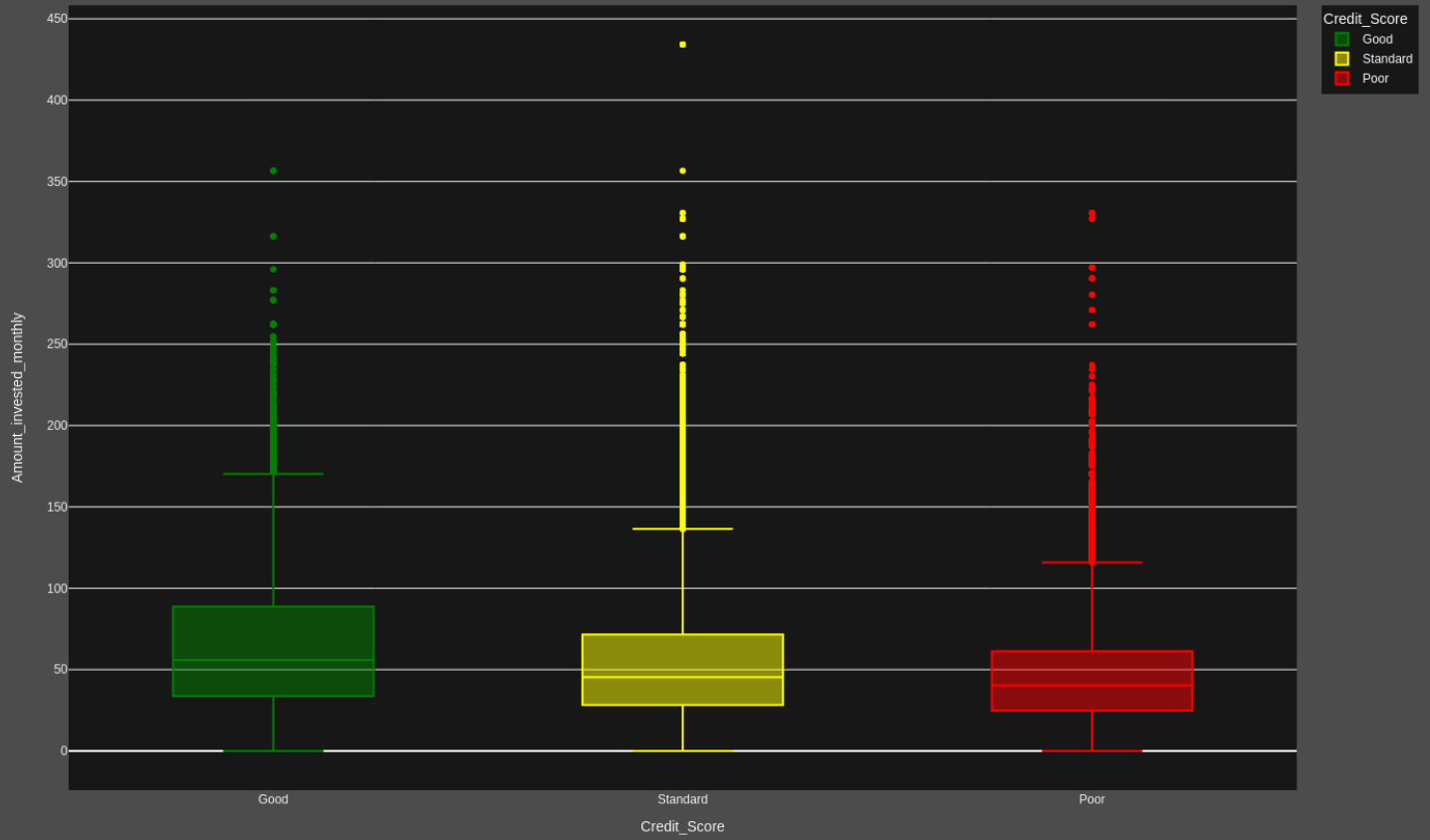
```

So, having a high monthly balance in your account at the end of the month is good for your credit scores. * A monthly balance of less than \$250 is bad for credit scores.

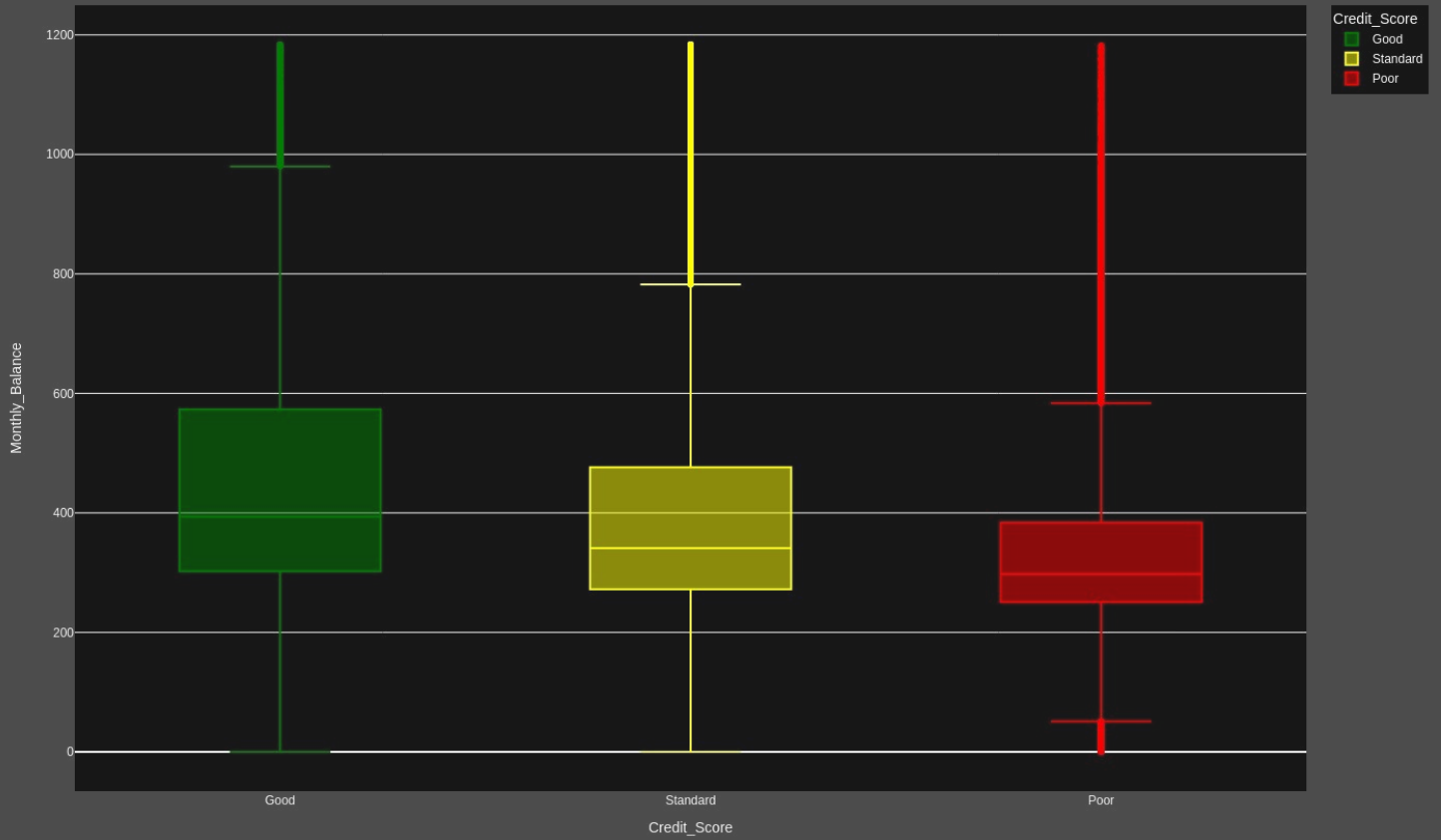
4.0.1 Credit Score Classification Model

- One more important feature (Credit Mix) in the dataset is valuable for determining credit scores.
- The credit mix feature tells about the types of credits and loans you have taken.
- As the Credit_Mix column is categorical, I will transform it into a numerical feature so that we can use it to train a Machine Learning model for the task of

Credit score Based On Amount Invested Monthly



Credit score Based On Monthly Balance Left



credit score classification:

```
[25]: data['Credit_Mix']=data['Credit_Mix'].map({"Standard":1,"Good":2,"Bad":0})
```

- Now I will split the data into features and labels by selecting the features we found important for our model:

```
[26]: from sklearn.model_selection import train_test_split
```

- Making Dependent and Independent Feature

```
[27]: # Independent Feature
x = np.array(data[["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"]])
# dependent Features
y = np.array(data["Credit_Score"])
```

```
[28]: x_train, x_test, y_train, y_test = train_test_split(x, y,
                                                         test_size=0.33,
                                                         random_state=42)
```

```
[29]: from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(x_train, y_train)
```

```
[29]: RandomForestClassifier()
```

- Now, let's make predictions from our model by giving inputs to our model according to the features we used to train the model:

```
[30]: 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: 3) : ")
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, l]])
print("Predicted Credit Score = ", model.predict(features))
```

Credit Score Prediction :
Annual Income: 19114.12
Monthly Inhand Salary: 1824.6
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: 3) : 3
Outstanding Debt: 250
Credit History Age: 200
Monthly Balance: 310
Predicted Credit Score = ['Good']

•

5 Summary

Classifying customers based on their credit scores helps banks and credit card companies immediately to issue loans to customers with good creditworthiness. A person with a good credit score will get loans from any bank and financial institution. I hope you liked this article on Credit Score Classification with Machine Learning using Python. Feel free to ask valuable questions in the comments section below.

6 Reference

- [DataSet Link \(Click Me\)](#)
- [Aman Kharwal \(medium.com\)](#)

```
<h2 style='padding: 20px;
        color:red;
        text-align:center;'>
    END OF THE PROJECT !
</h2>
</div>
```

```
<h2 style='padding: 20px;
        color:GREEN;
```

```
        text-align:center;'>  
    THANK YOU !  
</h2>  
</div>
```

