Problem Statement

- Over the years, the company has collected basic bank details and gathered a lot of credit-related information. The management wants to build an intelligent system to segregate the people into credit score brackets to reduce the manual efforts.

Data Description

- Data has 2 Files Train Data and Test Data. Train data has 28 Columns and Test data has 27 Columns
- Columns:-
    - **ID**: Represents a unique identification of an entry
    - **Customer ID**: Represents a unique identification of a person
    - **Month**: Represents the month of the year
    - **Name**: Represents the name of a person
    - **Age**: Represents the age of the person
    - **SSN**: Represents the social security number of a person
    - **Occupation**: Represents the occupation of the person
    - **Annual_Income**: Represents the annual income of the person
    - **Monthly_Inhand_Salary**: Represents the monthly base salary of a person
    - **Num_Bank_Accounts**: Represents the number of bank accounts a person holds
    - **Num_Credit_Card**: Represents the number of other credit cards held by a person
    - **Interest_Rate**: Represents the interest rate on credit card
    - **Num_of_Loan**: Represents the number of loans taken from the bank
    - **Type_of_Loan**: Represents the types of loan taken by a person
    - **Delay_from_due_date**: Represents the average number of days delayed from the payment date
    - **Num_of_Delayed_Payment**: Represents the average number of payments delayed by a person
    - **Changed_Credit_Limit**: Represents the percentage change in credit card limit
    - **Num_Credit_Inquiries**: Represents the number of credit card inquiries
    - **Credit_Mix**: Represents the classification of the mix of credits
    - **Outstanding_Debt**: Represents the remaining debt to be paid (in USD)
    - **Credit_Utilization_Ratio**: Represents the utilization ratio of credit card
    - **Credit_History_Age**: Represents the age of credit history of the person
    - **Payment_of_Min_Amount**: Represents whether only the minimum amount was paid by the person
    - **Total_EMI_per_month**: Represents the Equated Monthly Installments payments (in USD)
    - **Amount_invested_monthly**: Represents the monthly amount invested by the customer (in USD)
    - **Payment_Behaviour**: Represents the payment behavior of the customer (in USD)
    - **Monthly_Balance**: Represents the monthly balance amount of the customer (in USD)
    - **Credit_Score**: Represents the bracket of credit score (Poor, Standard, Good)

Importing Libraries

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.model_selection import GridSearchCV, train_test_split, cross_val_score, StratifiedKFold
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
```

In [2]:

```
df = pd.read_csv("train.csv", sep = "," , encoding = 'utf-8')
test = pd.read_csv("test.csv", sep = "," , encoding = 'utf-8')
```

In [3]:

```
df.head()
```

Out[3]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Credit_Mix	Outstanding_Debt	Credit_Utilization
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	_	809.98	26.8
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	Good	809.98	31.9
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	NaN	3	...	Good	809.98	28.6
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3	...	Good	809.98	31.3
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	Good	809.98	24.7

5 rows × 28 columns

In [4]:
```
test.head()
```

Out[4]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	...	Num_Credit_Inquiries	Credit_Mix	Outstandin
0	0x160a	CUS_0xd40	September	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3	...	2022.0	Good	
1	0x160b	CUS_0xd40	October	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	1824.843333	3	...	4.0	Good	
2	0x160c	CUS_0xd40	November	Aaron Maashoh	24	821-00-0265	Scientist	19114.12	1824.843333	3	...	4.0	Good	
3	0x160d	CUS_0xd40	December	Aaron Maashoh	24_	821-00-0265	Scientist	19114.12	NaN	3	...	4.0	Good	
4	0x1616	CUS_0x21b1	September	Rick Rothackerj	28	004-07-5839	_______	34847.84	3037.986667	2	...	5.0	Good	

5 rows × 27 columns

In [5]:
```
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  object 
 1   Customer_ID               100000 non-null  object 
 2   Month                     100000 non-null  object 
 3   Name                      90015 non-null   object 
 4   Age                       100000 non-null  object 
 5   SSN                       100000 non-null  object 
 6   Occupation                100000 non-null  object 
 7   Annual_Income             100000 non-null  object 
 8   Monthly_Inhand_Salary     84998 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  object 
 13  Type_of_Loan              88592 non-null   object 
 14  Delay_from_due_date       100000 non-null  int64  
 15  Num_of_Delayed_Payment    92998 non-null   object 
 16  Changed_Credit_Limit      100000 non-null  object 
 17  Num_Credit_Inquiries      98035 non-null   float64
 18  Credit_Mix                100000 non-null  object 
 19  Outstanding_Debt          100000 non-null  object 
 20  Credit_Utilization_Ratio  100000 non-null  float64
 21  Credit_History_Age        90970 non-null   object 
 22  Payment_of_Min_Amount     100000 non-null  object 
 23  Total_EMI_per_month       100000 non-null  float64
 24  Amount_invested_monthly   95521 non-null   object 
 25  Payment_Behaviour         100000 non-null  object 
 26  Monthly_Balance           98800 non-null   object 
 27  Credit_Score              100000 non-null  object 
dtypes: float64(4), int64(4), object(20)
memory usage: 21.4+ MB
```

Data Cleaning & Preprocessing

In [6]:
```
def filling_na(df, column, type_=None):
    """
    This fucntion for filling null values to work with the data properly
    Parameters:
    df: DataFrame to fill the na with
    column: column which will fill the value in it
    type_: type of data needed be filled

    """
    np.random.seed(7)
    if type_ == "num":
        filling_list = df[column].dropna()
        df[column] = df[column].fillna(pd.Series(np.random.choice(filling_list, size=len(df.index))))

    else:
        filling_list = df[column].dropna().unique()
        df[column] = df[column].fillna(pd.Series(np.random.choice(filling_list, size=len(df.index))))
    return df[column]
```

In [7]:

```
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
Monthly_Inhand_Salary	84998.0	4194.170850	3183.686167	303.645417	1625.568229	3093.745000	5957.448333	15204.633333
Num_Bank_Accounts	100000.0	17.091280	117.404834	-1.000000	3.000000	6.000000	7.000000	1798.000000
Num_Credit_Card	100000.0	22.474430	129.057410	0.000000	4.000000	5.000000	7.000000	1499.000000
Interest_Rate	100000.0	72.466040	466.422621	1.000000	8.000000	13.000000	20.000000	5797.000000
Delay_from_due_date	100000.0	21.068780	14.860104	-5.000000	10.000000	18.000000	28.000000	67.000000
Num_Credit_Inquiries	98035.0	27.754251	193.177339	0.000000	3.000000	6.000000	9.000000	2597.000000
Credit_Utilization_Ratio	100000.0	32.285173	5.116875	20.000000	28.052567	32.305784	36.496663	50.000000
Total_EMI_per_month	100000.0	1403.118217	8306.041270	0.000000	30.306660	69.249473	161.224249	82331.000000

In [8]:

```
df.describe(include='O').T
```

Out[8]:

	count	unique	top	freq
ID	100000	100000	0x1602	1
Customer_ID	100000	12500	CUS_0xd40	8
Month	100000	8	January	12500
Name	90015	10139	Langep	44
Age	100000	1788	38	2833
SSN	100000	12501	#F%$D@*&8	5572
Occupation	100000	16	_______	7062
Annual_Income	100000	18940	36585.12	16
Num_of_Loan	100000	434	3	14386
Type_of_Loan	88592	6260	Not Specified	1408
Num_of_Delayed_Payment	92998	749	19	5327
Changed_Credit_Limit	100000	4384	_	2091
Credit_Mix	100000	4	Standard	36479
Outstanding_Debt	100000	13178	1360.45	24
Credit_History_Age	90970	404	15 Years and 11 Months	446
Payment_of_Min_Amount	100000	3	Yes	52326
Amount_invested_monthly	95521	91049	__10000__	4305
Payment_Behaviour	100000	7	Low_spent_Small_value_payments	25513
Monthly_Balance	98800	98792	__-333333333333333333333333333__	9
Credit_Score	100000	3	Standard	53174

In [9]:

```
df["Amount_invested_monthly"] = df["Amount_invested_monthly"].replace("__10000__", 10000.00)
df["Amount_invested_monthly"] = df["Amount_invested_monthly"].astype("float64")
df["Amount_invested_monthly"].dtype
```

Out[9]:

```
dtype('float64')
```

In [10]:

```
df["Monthly_Balance"] = df["Monthly_Balance"].replace("__-333333333333333333333333333__", 0)
df["Monthly_Balance"] = df["Monthly_Balance"].astype("float64")
df["Monthly_Balance"].dtype
```

Out[10]:

```
dtype('float64')
```

In [11]:

```
df["Num_of_Delayed_Payment"] = df["Num_of_Delayed_Payment"].str.replace(r'_$',"", regex=True)
df["Num_of_Delayed_Payment"] = df["Num_of_Delayed_Payment"].astype("float64")
df["Num_of_Delayed_Payment"].dtype
```

Out[11]:

```
dtype('float64')
```

In [12]:

```
df["Annual_Income"] = df["Annual_Income"].str.replace(r'_$',"", regex=True)
df["Annual_Income"] = df["Annual_Income"].astype("float64")
df["Annual_Income"].dtype
```

Out[12]:

```
dtype('float64')
```

In [13]:

```
df["Age"] = df["Age"].str.replace(r'_$',"", regex=True)
df["Age"] = df["Age"].astype("int64")
```

```
df["Age"].dtype
```

Out[13]:

```
dtype('int64')
```

In [14]:

```
df["Outstanding_Debt"] = df["Outstanding_Debt"].str.replace(r'_$',"", regex=True)
df["Outstanding_Debt"] = df["Outstanding_Debt"].astype("float64")
df["Outstanding_Debt"].dtype
```

Out[14]:

```
dtype('float64')
```

In [15]:

```
df["Occupation"] = df["Occupation"].replace("_______",np.nan)
```

In [16]:

```
df["Credit_History_Age_#Year"] = df["Credit_History_Age"].str.split(" ", expand=True)[0]
df["Credit_History_Age_#Month"] = df["Credit_History_Age"].str.split(" ", expand=True)[3]
```

In [17]:

```
df["Payment_Behaviour"] = df["Payment_Behaviour"].replace("!@9#%8","Medium_spent_Medium_value_payments")
```

In [18]:

```
df.Age.replace(-500, np.median(df.Age), inplace=True)
for i in df.Age.values:
    if i > 118:
        df.Age.replace(i, np.median(df.Age), inplace=True)
```

In [19]:

```
df["Num_of_Loan"] = df["Num_of_Loan"].str.replace(r'_$',"", regex=True)
df["Num_of_Loan"] = df["Num_of_Loan"].astype("int64")
df["Num_of_Loan"].dtype
```

Out[19]:

```
dtype('int64')
```

In [20]:

```
df["Credit_Mix"] = df["Credit_Mix"].replace("_", "Don't Have")
```

In [21]:

```
df["Changed_Credit_Limit"] = df["Changed_Credit_Limit"].replace("_", 0)
df["Changed_Credit_Limit"] = df["Changed_Credit_Limit"].astype("float64")
```

In [22]:

```
df.Num_of_Loan.replace(-100, np.median(df.Num_of_Loan), inplace=True)
for i in df.Num_of_Loan.values:
    if i > 10:
        df.Num_of_Loan.replace(i, np.median(df.Num_of_Loan), inplace=True)
```

In [23]:

```
df["Interest_Rate"] = df["Interest_Rate"].astype("float64")
df["Interest_Rate"] = df["Interest_Rate"]/100
```

In [24]:

```
for i in df.Interest_Rate:
    if i > 20:
        df.Interest_Rate.replace(i, np.median(df.Interest_Rate), inplace=True)
```

In [25]:

```
for i in df.Num_Bank_Accounts:
    if i > 100:
        df.Num_Bank_Accounts.replace(i, np.median(df.Num_Bank_Accounts), inplace=True)
```

In [26]:

```
for i in df.Num_Credit_Card:
    if i > 50:
        df.Num_Credit_Card.replace(i, np.median(df.Num_Credit_Card), inplace=True)
```

In [27]:

```
df["Monthly_Inhand_Salary"] = filling_na(df, "Monthly_Inhand_Salary", "num")
df["Num_Credit_Inquiries"] = filling_na(df, "Num_Credit_Inquiries", "num")
df["Amount_invested_monthly"] = filling_na(df, "Amount_invested_monthly", "num")
df["Num_of_Delayed_Payment"] = filling_na(df, "Num_of_Delayed_Payment", "num")
df["Monthly_Balance"] = filling_na(df, "Monthly_Balance", "num")
df["Credit_History_Age_#Year"] = filling_na(df, "Credit_History_Age_#Year", "num")
df["Credit_History_Age_#Month"] = filling_na(df, "Credit_History_Age_#Month", "num")
df["Type_of_Loan"] = filling_na(df, "Type_of_Loan")
df["Credit_History_Age"] = filling_na(df, "Credit_History_Age")
df["Occupation"] = filling_na(df, "Occupation")
```

In [28]:

```
df["Credit_History_Age_#Year"] = df["Credit_History_Age_#Year"].astype("int64")
df["Credit_History_Age_#Month"] = df["Credit_History_Age_#Month"].astype("int64")
df["Credit_History_Age_#Month"] = round(df["Credit_History_Age_#Month"] / 12, 2)
df["Credit_History_Age_In_Years"] = df["Credit_History_Age_#Year"] + df["Credit_History_Age_#Month"]
```

In [29]:

```
df.drop_duplicates(subset="ID", inplace=True)
df.drop(["Name", "Credit_History_Age", "Credit_History_Age_#Year", "Credit_History_Age_#Month", "ID", "Customer_ID","SSN"], axis=1, inplace=True)
```

In [30]:

```
df.Type_of_Loan = df.Type_of_Loan.str.replace("and", "")
df.Type_of_Loan = df.Type_of_Loan.str.replace(" ", "")

cat_values=[]
loan_cat = df.Type_of_Loan.unique()
for i in loan_cat:
    for j in i.split(","):
        cat_values.append(j)

loan_types = set([x.strip(' ') for x in set(cat_values)])
loan_types = list(loan_types)
loan_types
```

Out[30]:
```
['AutoLoan',
 'DebtConsolidationLoan',
 'StudentLoan',
 'MortgageLoan',
 'PaydayLoan',
 'HomeEquityLoan',
 'NotSpecified',
 'Credit-BuilderLoan',
 'PersonalLoan']
```

In [31]:
```
df.head()
```

Out[31]:

	Month	Age	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts	Num_Credit_Card	Interest_Rate	Num_of_Loan	Type_of_Loan	...	Credit_
0	January	23	Scientist	19114.12	1824.843333	3	4	0.03	4	AutoLoan,Credit-BuilderLoan,PersonalLoan,HomeE...	...	Don't H
1	February	23	Scientist	19114.12	1082.203750	3	4	0.03	4	AutoLoan,Credit-BuilderLoan,PersonalLoan,HomeE...	...	G
2	March	33	Scientist	19114.12	2686.018333	3	4	0.03	4	AutoLoan,Credit-BuilderLoan,PersonalLoan,HomeE...	...	G
3	April	23	Scientist	19114.12	2201.945833	3	4	0.03	4	AutoLoan,Credit-BuilderLoan,PersonalLoan,HomeE...	...	G
4	May	23	Scientist	19114.12	1824.843333	3	4	0.03	4	AutoLoan,Credit-BuilderLoan,PersonalLoan,HomeE...	...	G

5 rows × 24 columns

In [32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100000 entries, 0 to 99999
Data columns (total 24 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   Month                     100000 non-null  object 
 1   Age                       100000 non-null  int64  
 2   Occupation                100000 non-null  object 
 3   Annual_Income             100000 non-null  float64
 4   Monthly_Inhand_Salary     100000 non-null  float64
 5   Num_Bank_Accounts         100000 non-null  int64  
 6   Num_Credit_Card           100000 non-null  int64  
 7   Interest_Rate             100000 non-null  float64
 8   Num_of_Loan               100000 non-null  int64  
 9   Type_of_Loan              100000 non-null  object 
 10  Delay_from_due_date       100000 non-null  int64  
 11  Num_of_Delayed_Payment    100000 non-null  float64
 12  Changed_Credit_Limit      100000 non-null  float64
 13  Num_Credit_Inquiries      100000 non-null  float64
 14  Credit_Mix                100000 non-null  object 
 15  Outstanding_Debt          100000 non-null  float64
 16  Credit_Utilization_Ratio  100000 non-null  float64
 17  Payment_of_Min_Amount     100000 non-null  object 
 18  Total_EMI_per_month       100000 non-null  float64
 19  Amount_invested_monthly   100000 non-null  float64
 20  Payment_Behaviour         100000 non-null  object 
 21  Monthly_Balance           100000 non-null  float64
 22  Credit_Score              100000 non-null  object 
 23  Credit_History_Age_In_Years  100000 non-null  float64
dtypes: float64(12), int64(5), object(7)
memory usage: 19.1+ MB
```

In [33]:
```
df.describe().T
```

Out[33]:

	count	mean	std	min	25%	50%	75%	max
Age	100000.0	33.318990	1.064554e+01	14.000000	25.000000	33.000000	41.000000	1.180000e+02
Annual_Income	100000.0	176415.701298	1.429618e+06	7005.930000	19457.500000	37578.610000	72790.920000	2.419806e+07
Monthly_Inhand_Salary	100000.0	4193.254053	3.184554e+03	303.645417	1625.485208	3089.424167	5964.883333	1.520463e+04
Num_Bank_Accounts	100000.0	5.410010	2.951401e+00	-1.000000	3.000000	6.000000	7.000000	1.000000e+02
Num_Credit_Card	100000.0	5.536430	2.151232e+00	0.000000	4.000000	5.000000	7.000000	5.000000e+01
Interest_Rate	100000.0	0.214428	9.483375e-01	0.010000	0.080000	0.130000	0.200000	1.999000e+01
Num_of_Loan	100000.0	3.510550	2.395985e+00	0.000000	2.000000	3.000000	5.000000	9.000000e+00
Delay_from_due_date	100000.0	21.068780	1.486010e+01	-5.000000	10.000000	18.000000	28.000000	6.700000e+01
Num_of_Delayed_Payment	100000.0	30.669270	2.240522e+02	-3.000000	9.000000	14.000000	18.000000	4.397000e+03
Changed_Credit_Limit	100000.0	10.171791	6.880628e+00	-6.490000	4.970000	9.250000	14.660000	3.697000e+01
Num_Credit_Inquiries	100000.0	27.797390	1.934427e+02	0.000000	3.000000	6.000000	9.000000	2.597000e+03
Outstanding_Debt	100000.0	1426.220376	1.155129e+03	0.230000	566.072500	1166.155000	1945.962500	4.998070e+03
Credit_Utilization_Ratio	100000.0	32.285173	5.116875e+00	20.000000	28.052567	32.305784	36.496663	5.000000e+01
Total_EMI_per_month	100000.0	1403.118217	8.306041e+03	0.000000	30.306660	69.249473	161.224249	8.233100e+04
Amount_invested_monthly	100000.0	638.632192	2.046581e+03	0.000000	74.569477	135.771365	265.460971	1.000000e+04
Monthly_Balance	100000.0	402.471604	2.139575e+02	0.000000	270.057822	336.649353	470.176839	1.602041e+03
Credit_History_Age_In_Years	100000.0	18.437997	8.306417e+00	0.080000	12.080000	18.330000	25.170000	3.367000e+01

In [34]:

```
df.describe(include='O').T
```

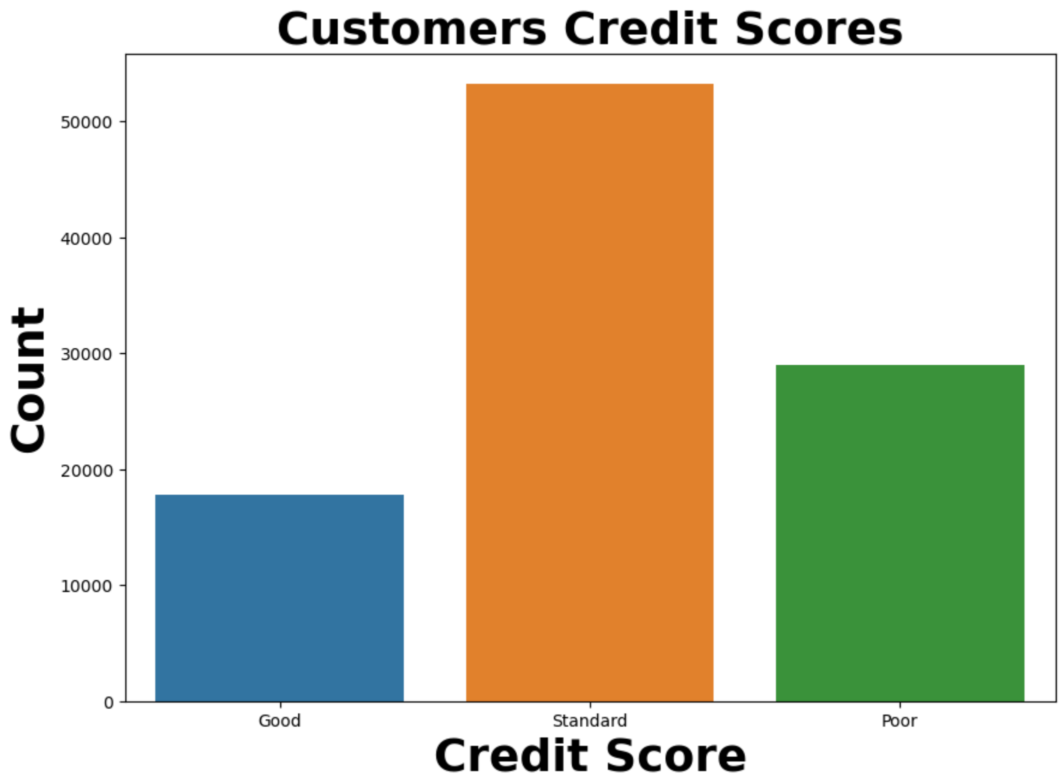
Out[34]:

	count	unique	top	freq
Month	100000	8	January	12500
Occupation	100000	15	Lawyer	7093
Type_of_Loan	100000	6260	NotSpecified	1409
Credit_Mix	100000	4	Standard	36479
Payment_of_Min_Amount	100000	3	Yes	52326
Payment_Behaviour	100000	7	Low_spent_Small_value_payments	25513
Credit_Score	100000	3	Standard	53174

Exploratory Data Analysis

In [35]:

```
plt.figure(figsize=(10,7))
sns.countplot(data = df, x="Credit_Score")
plt.title("Customers Credit Scores", size=27,fontweight="bold")
plt.xlabel("Credit Score", size=27,fontweight="bold")
plt.ylabel("Count", size=27,fontweight="bold")
plt.show()
```

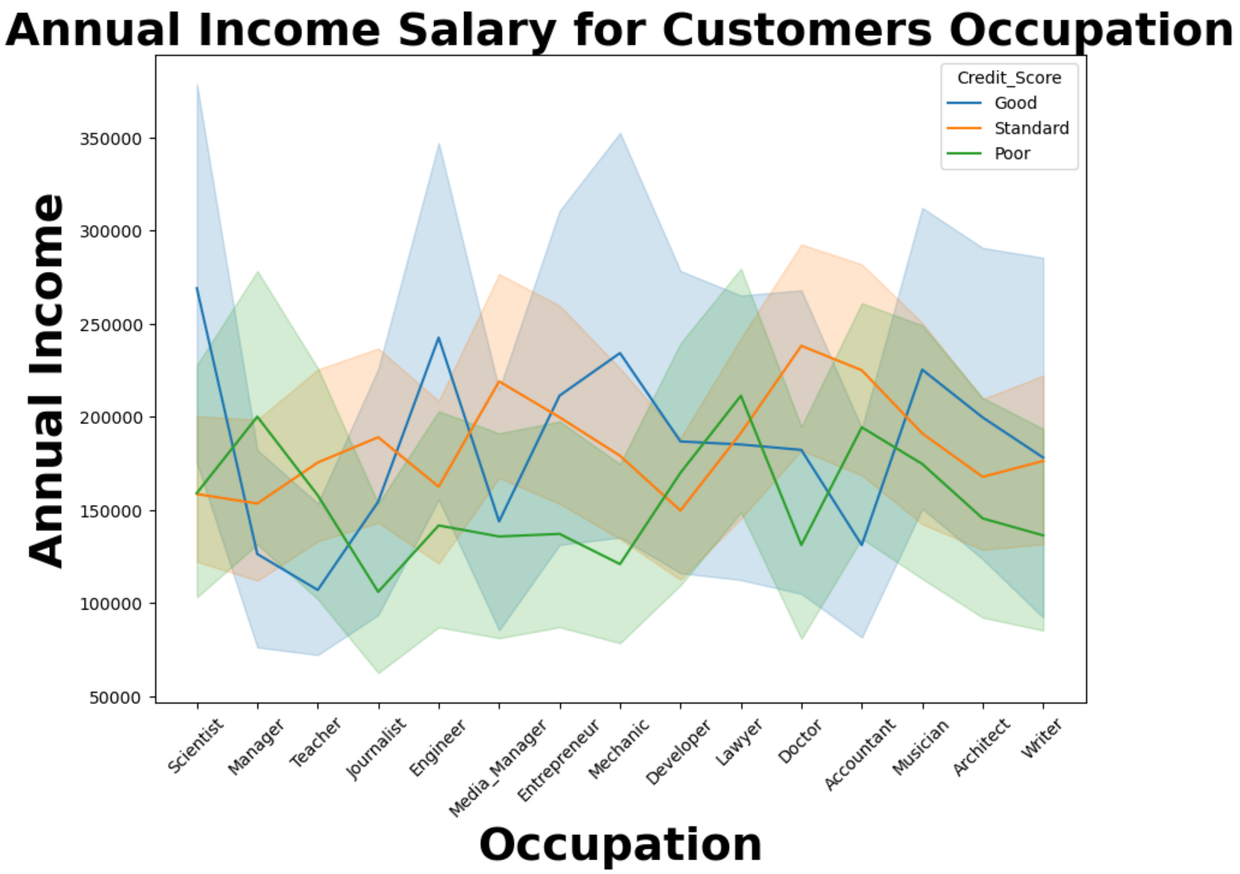


Comment:

- Most people fill in the standard category

In [36]:

```
plt.figure(figsize=(10,7))
sns.lineplot(data=df, x="Occupation", y="Annual_Income", hue="Credit_Score")
plt.xticks(rotation=45)
plt.title("Annual Income Salary for Customers Occupation", size=27,fontweight="bold")
plt.xlabel("Occupation", size=27,fontweight="bold")
plt.ylabel("Annual Income", size=27,fontweight="bold")
plt.show()
```

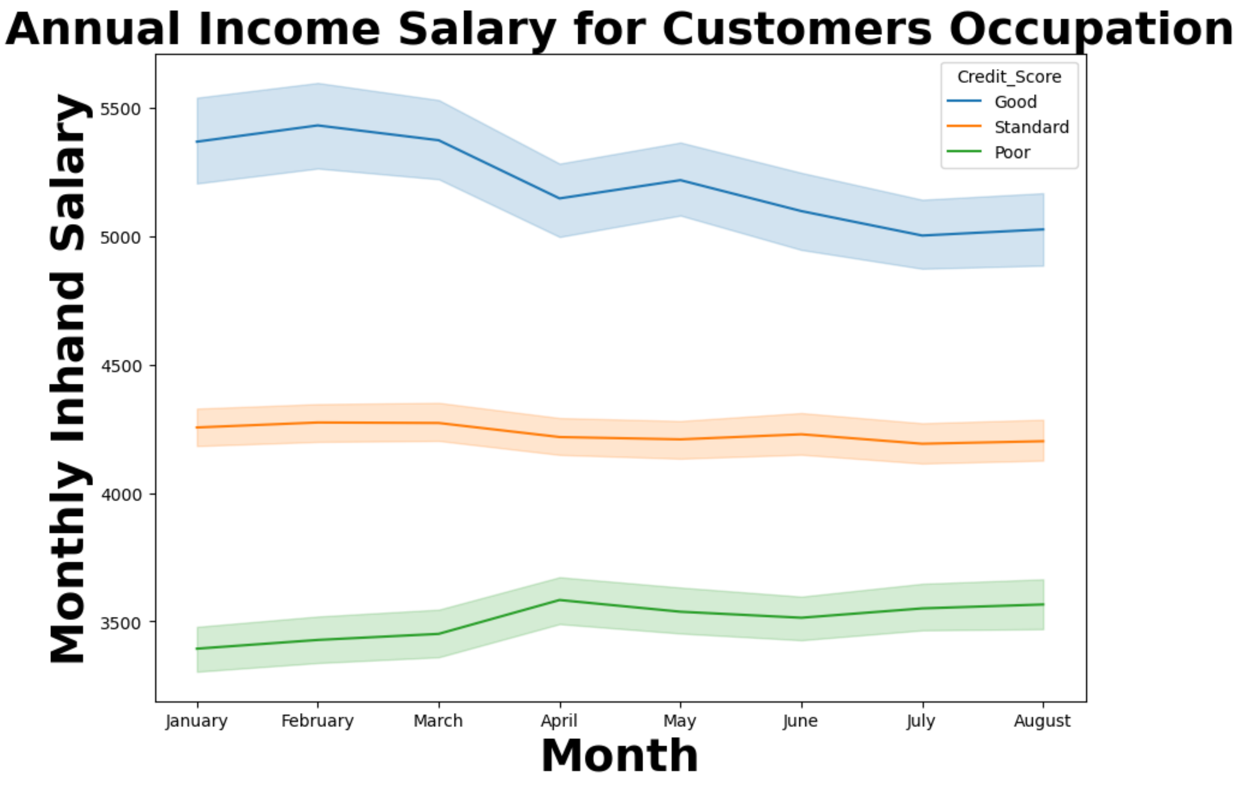


Comment:

- The Annual Income of the Cutomers doesn't affect on the credit score as we see that the variance on the annual income and the people can still have a good credit score whether the cutomer has a 100000 USD or 250000 USD Annually

In [37]:

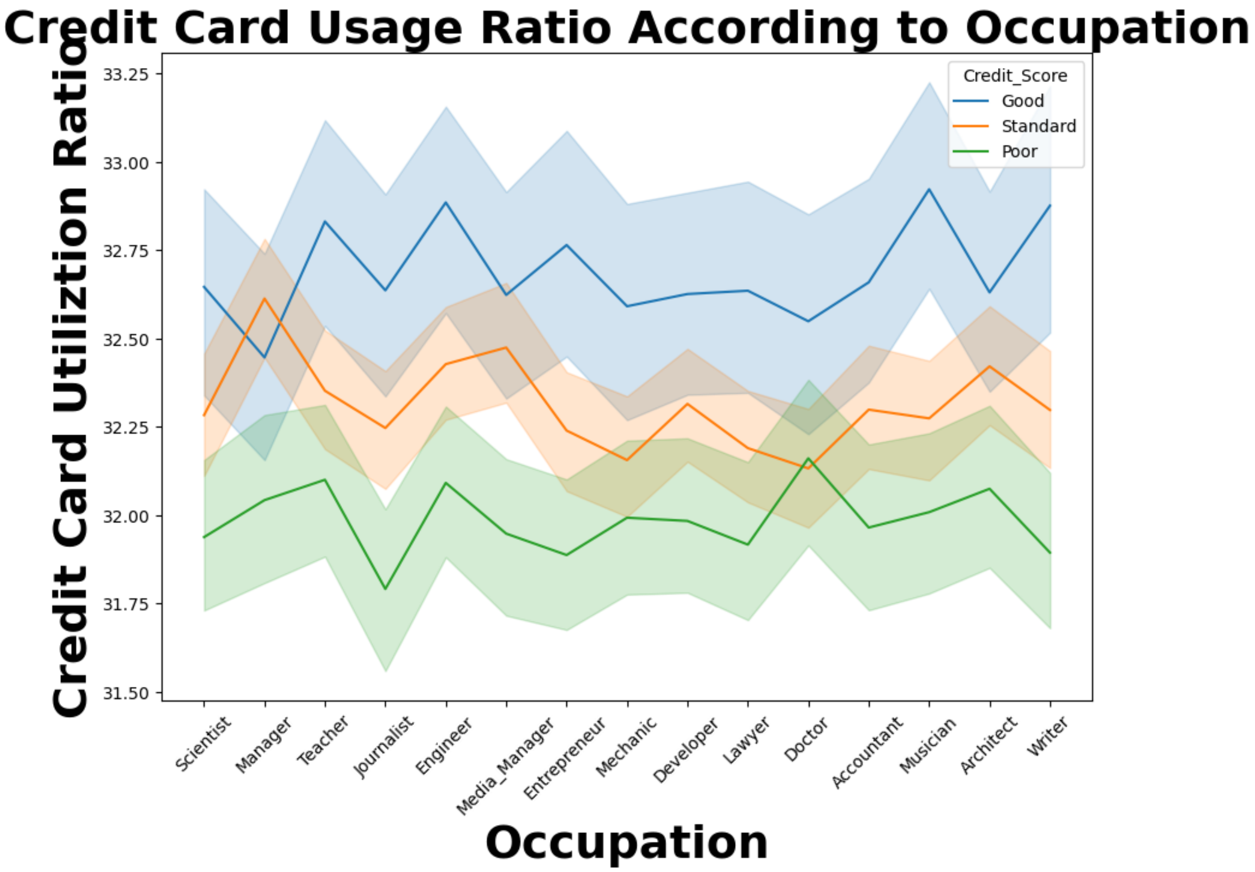
```
plt.figure(figsize=(10,7))
sns.lineplot(data=df, x="Month", y="Monthly_Inhand_Salary", hue="Credit_Score")
plt.title("Annual Income Salary for Customers Occupation", size=27,fontweight="bold")
plt.xlabel("Month", size=27,fontweight="bold")
plt.ylabel("Monthly Inhand Salary", size=27,fontweight="bold")
plt.show()
```



Comment:

- People who has a high inhand monthly salary have a good credit score and who has a low inhand salary has a low credit score

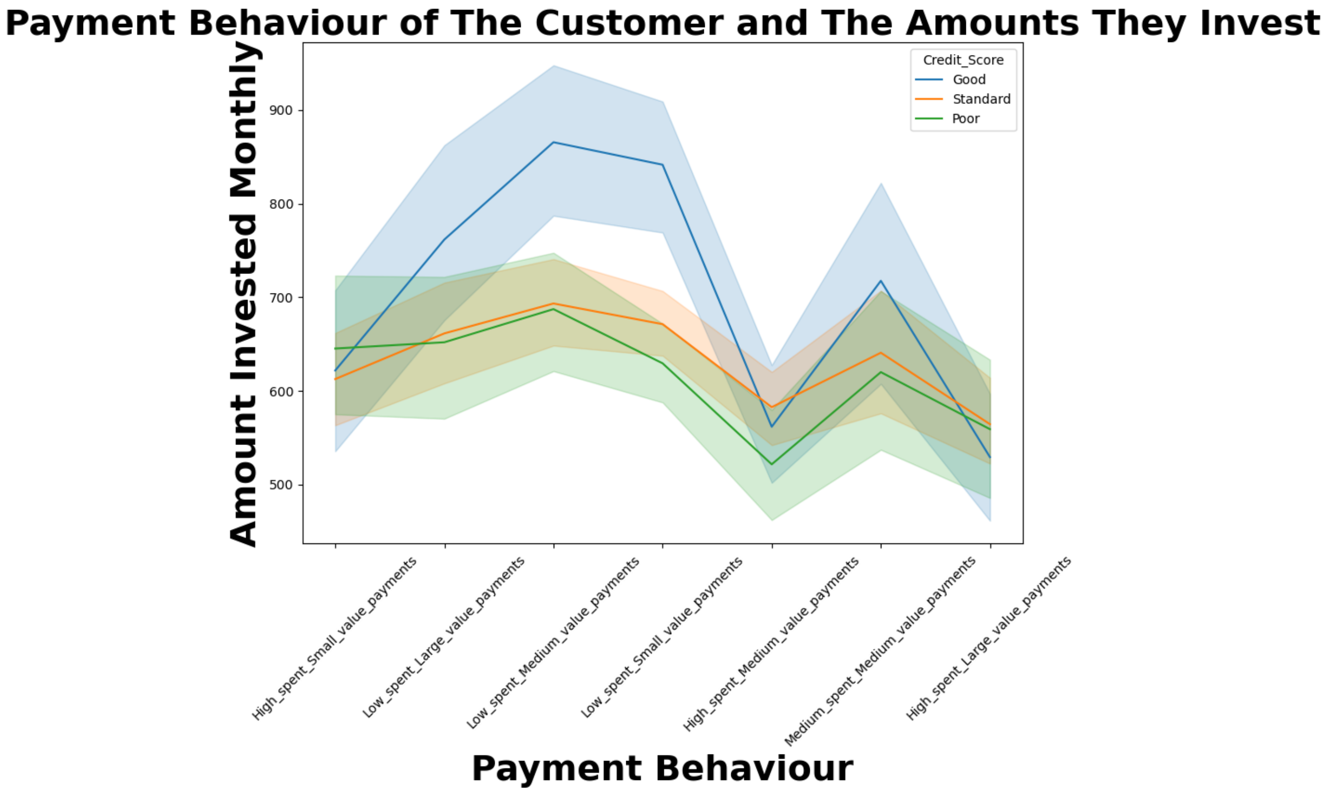
In [38]:
```
plt.figure(figsize=(10,7))
sns.lineplot(data=df, x="Occupation", y="Credit_Utilization_Ratio", hue="Credit_Score")
plt.xticks(rotation=45)
plt.title("Credit Card Usage Ratio According to Occupation", size=27,fontweight="bold")
plt.xlabel("Occupation", size=27,fontweight="bold")
plt.ylabel("Credit Card Utiliztion Ratio", size=27,fontweight="bold")
plt.show()
```



Comment:

- More the People use the credit card it makes the credit score much better

In [39]:
```
plt.figure(figsize=(10,7))
sns.lineplot(data=df, x="Payment_Behaviour", y="Amount_invested_monthly", hue="Credit_Score")
plt.xticks(rotation=45)
plt.title("Payment Behaviour of The Customer and The Amounts They Invest", size=27,fontweight="bold")
plt.xlabel("Payment Behaviour", size=27,fontweight="bold")
plt.ylabel("Amount Invested Monthly", size=27,fontweight="bold")
plt.show()
```

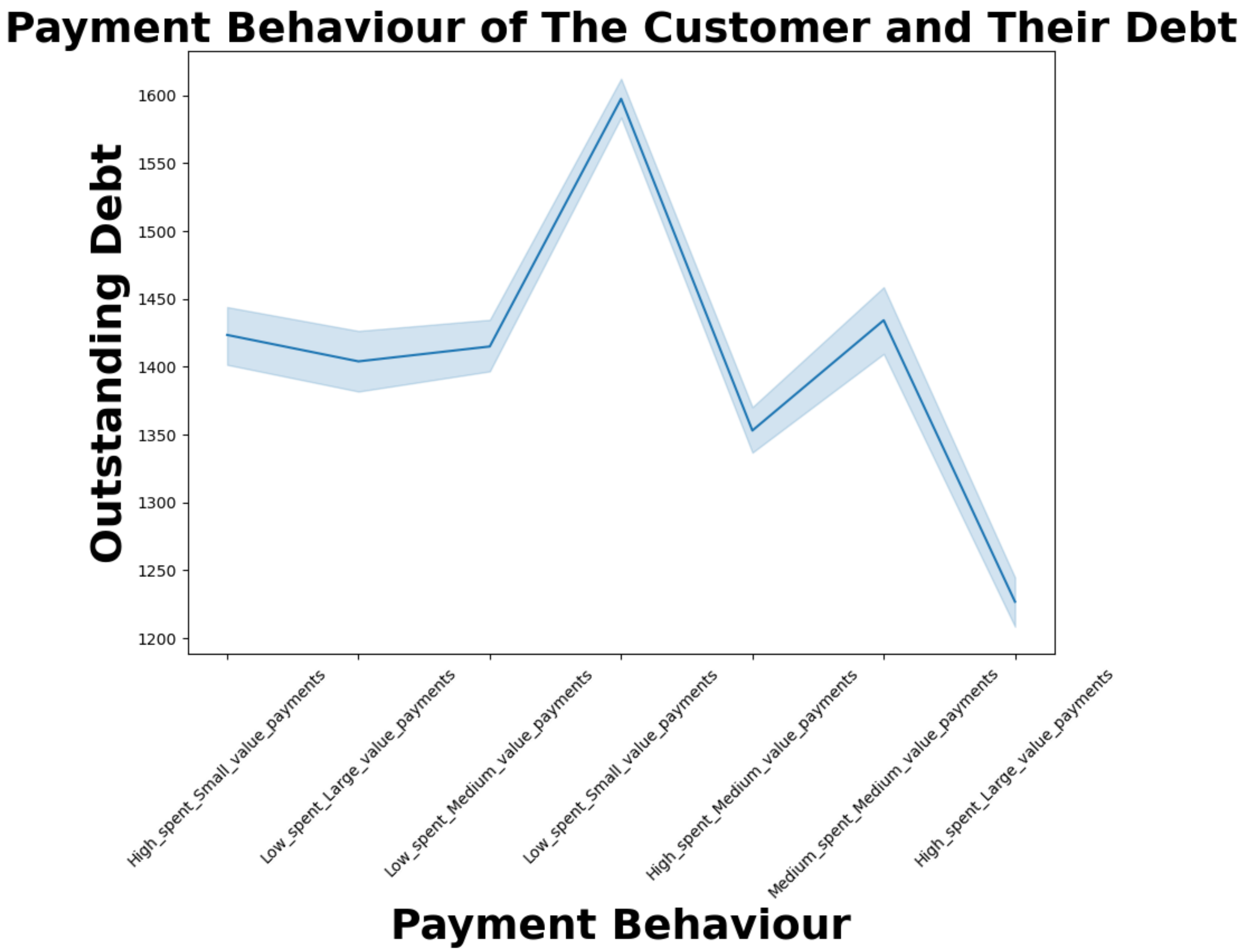


Comment:

- Most People who invest between **700 to 800 USD** of their money have a good Credit Score and most people who have a standard credit score invest between **600 to 700 USD** per Month

In [40]:

```
plt.figure(figsize=(10,7))
sns.lineplot(data=df, x="Payment_Behaviour", y="Outstanding_Debt")
plt.xticks(rotation=45)
plt.title("Payment Behaviour of The Customer and Their Debt", size=27,fontweight="bold")
plt.xlabel("Payment Behaviour", size=27,fontweight="bold")
plt.ylabel("Outstanding Debt", size=27,fontweight="bold")
plt.show()
```

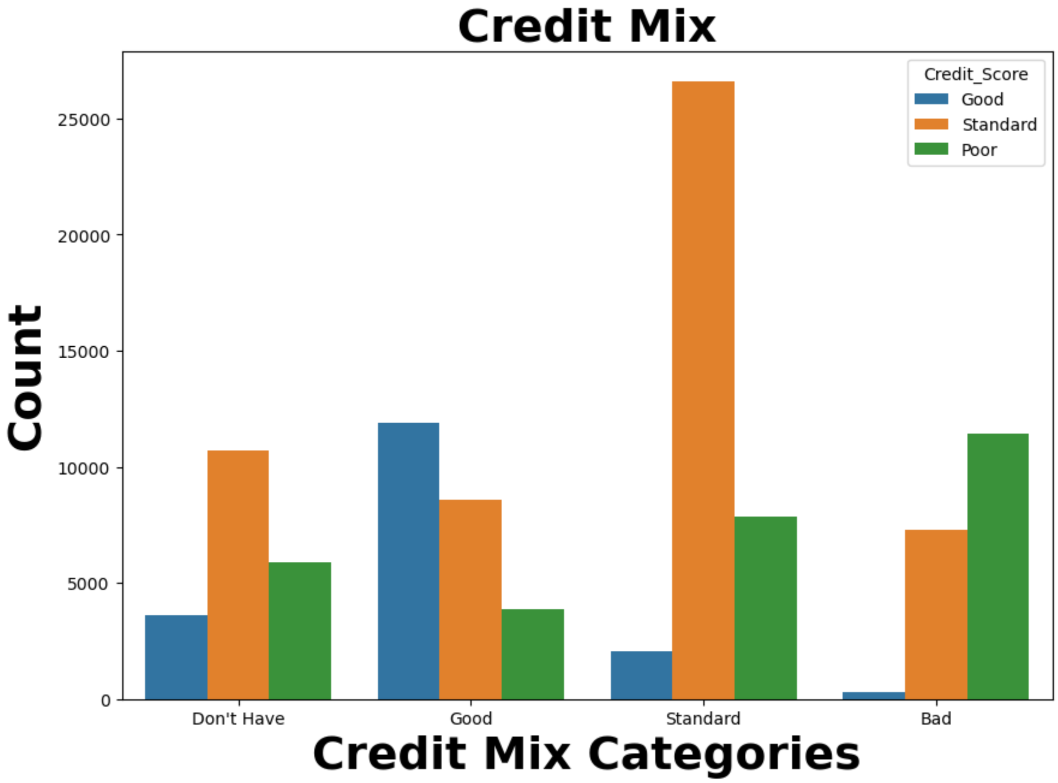


Comment:

- People who don't use the credit card so much but also pay small portion of the credit card has the majority on the outstanding debt **(Low_spent_Small_value_payments)** and the Category after that which has the 2nd most outstanding debt the people who **(Medium_spent_Medium_value_payments)**.
- The people who have the least outstanding debt are **Hight_spent_High_value_payments**.

In [41]:

```
plt.figure(figsize=(10,7))
sns.countplot(data=df, x="Credit_Mix", hue="Credit_Score")
#plt.xticks(rotation=45)
plt.title("Credit Mix", size=27,fontweight="bold")
plt.xlabel("Credit Mix Categories", size=27,fontweight="bold")
plt.ylabel("Count", size=27,fontweight="bold")
plt.show()
```

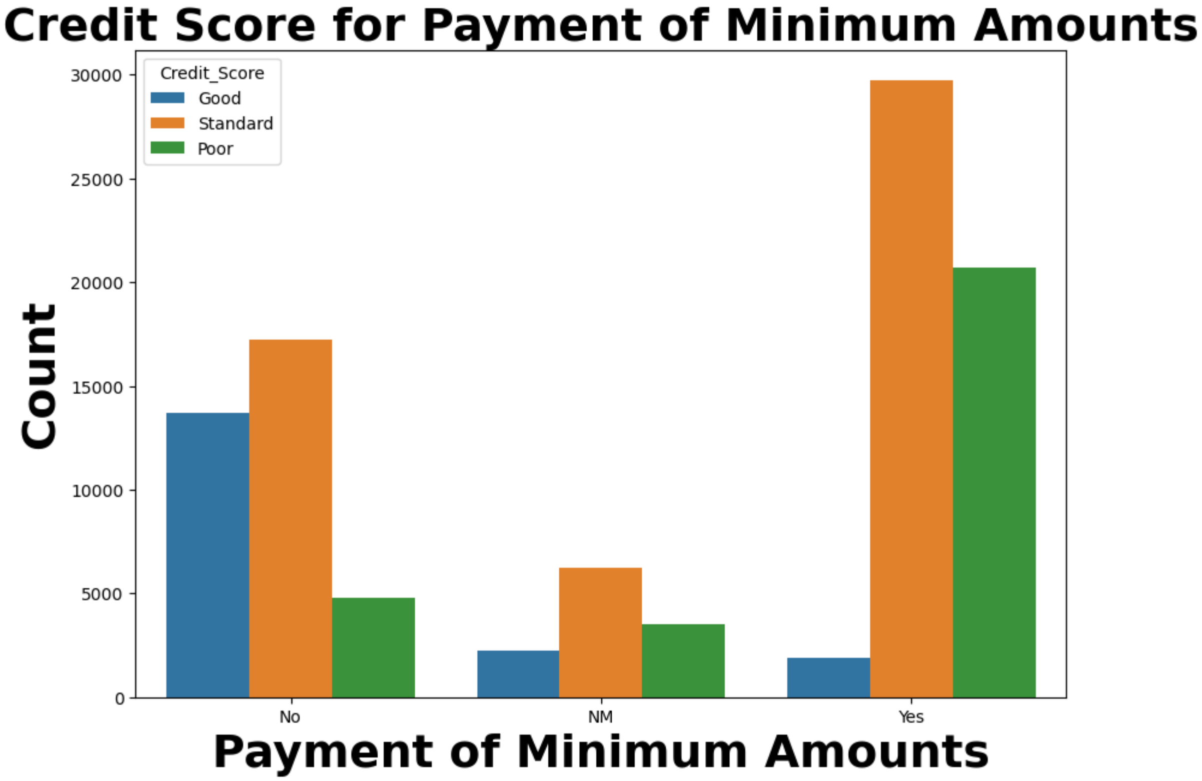


Comment:

- People who don't have a credit mix most of them has a Standard Credit score and the 2nd most category has a bad credit Score.
- People who have a good credit mix most of them have a good credit score and the 2nd most category has a standard credit score.
- People who have astandard mix most of them has a standard credit score and the 2nd most category have a bad credit score.
- People who have a bad credit mix most of the has a bad credit score and the 2nd most category have a standard credit score.

In [42]:

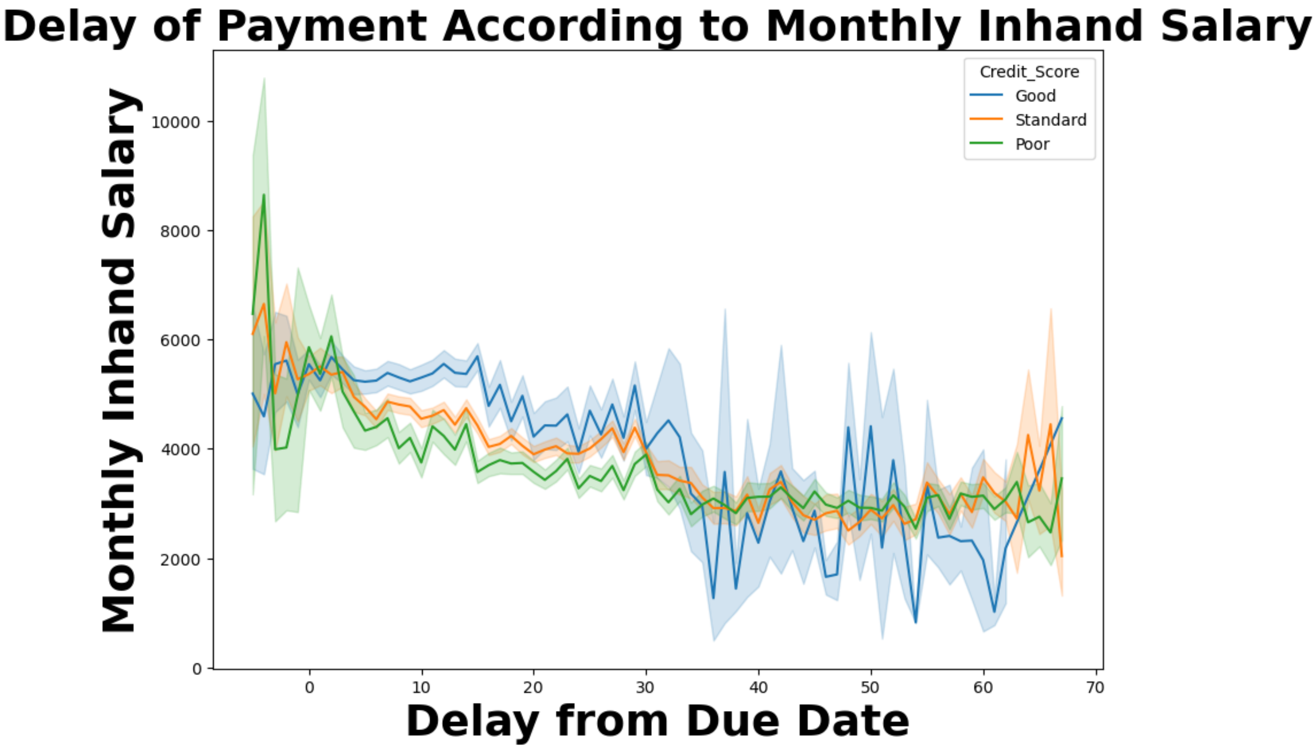
```
plt.figure(figsize=(10,7))
sns.countplot(data = df, x = 'Payment_of_Min_Amount',hue="Credit_Score")
plt.title("Credit Score for Payment of Minimum Amounts", size=27,fontweight="bold")
plt.xlabel("Payment of Minimum Amounts", size=27,fontweight="bold")
plt.ylabel("Count", size=27,fontweight="bold")
plt.show()
```



Comment:

- Customers who pay the minimum amounts has a poor credit score which but the people who don't pay the minimum amounts has a good credit score more than the others which mean that there are a lot of people who stay in debt for a long time as they don't pay the all amounts and they pay part of it which made an insterest on them.

In [43]:
```
plt.figure(figsize=(10,7))
sns.lineplot(data = df, x = 'Delay_from_due_date', y = 'Monthly_Inhand_Salary', hue="Credit_Score")
plt.title("Delay of Payment According to Monthly Inhand Salary", size=27,fontweight="bold")
plt.xlabel("Delay from Due Date", size=27,fontweight="bold")
plt.ylabel("Monthly Inhand Salary", size=27,fontweight="bold")
plt.show()
```



Comment:

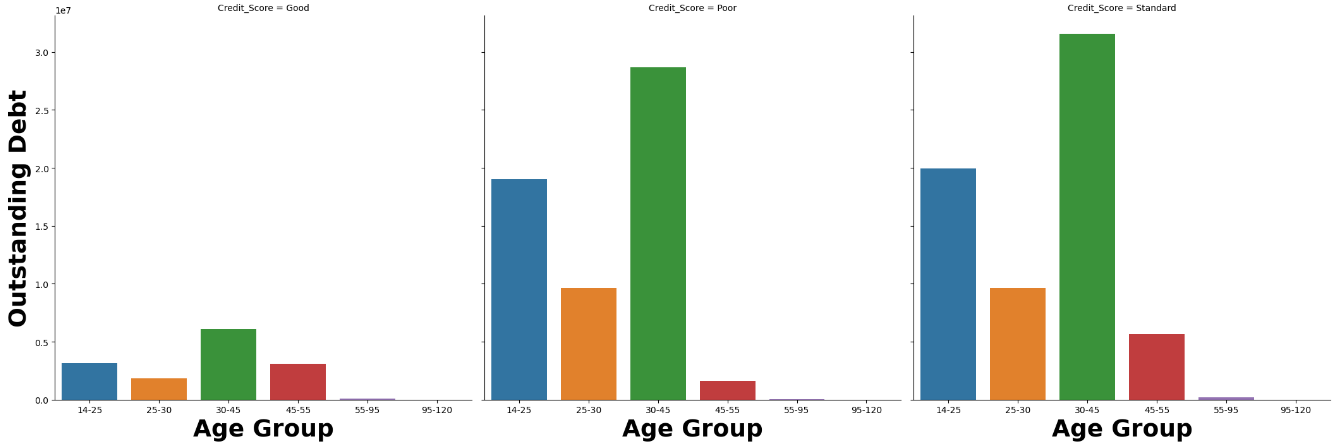
- More the Customer has less Monthly inhand Salary more he where Delayed from Due Date but at the same time, There are peole who delayed from the due date but also have a good credit score.

In [44]:
```
df["Age_Group"] = pd.cut(df.Age, bins=[14,25,30,45,55,95,120], labels=["14-25", "25-30", "30-45", "45-55", "55-95", "95-120"])
age_groups = df.groupby(["Age_Group", "Credit_Score"])["Outstanding_Debt","Annual_Income","Num_Bank_Accounts", "Num_Credit_Card"].sum().reset_index()
age_groups
```

Out[44]:

	Age_Group	Credit_Score	Outstanding_Debt	Annual_Income	Num_Bank_Accounts	Num_Credit_Card
0	14-25	Good	3137180.79	6.649730e+08	13799	15490
1	14-25	Poor	19005227.84	1.430461e+09	59369	58506
2	14-25	Standard	19952090.01	2.223223e+09	79088	77066
3	25-30	Good	1825730.64	3.288637e+08	7940	9083
4	25-30	Poor	9617599.66	7.935326e+08	29979	29512
5	25-30	Standard	9651424.60	1.372142e+09	41370	40866
6	30-45	Good	6071054.67	1.351365e+09	25420	30938
7	30-45	Poor	28685654.13	1.908736e+09	89952	89917
8	30-45	Standard	31548539.35	4.717357e+09	130148	129358
9	45-55	Good	3116857.45	9.038921e+08	14801	18157
10	45-55	Poor	1596323.10	3.177945e+08	6558	9072
11	45-55	Standard	5631458.47	1.331342e+09	33128	36221
12	55-95	Good	96907.67	4.656179e+07	356	480
13	55-95	Poor	52396.44	2.750242e+06	156	280
14	55-95	Standard	178580.28	7.886179e+07	943	1007
15	95-120	Good	1137.57	6.412913e+04	7	12
16	95-120	Poor	4100.65	1.159066e+05	18	22
17	95-120	Standard	5851.26	2.418140e+05	17	19

In [45]:
```
g = sns.catplot(data=age_groups, x="Age_Group", y="Outstanding_Debt", height=7, aspect=1, col="Credit_Score", kind="bar", ci=None)
g.set_axis_labels( "Age Group", "Outstanding Debt", size=27,fontweight="bold")
plt.show()
```

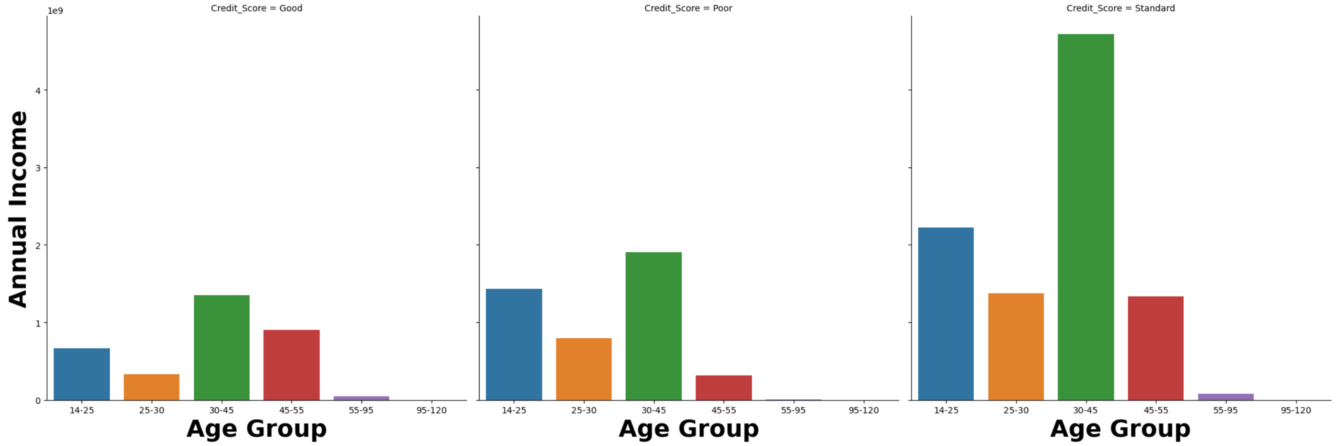


Comment:

- Customers Between age of 30 and 45 the most category who have a lot of outstanding debts which mean that people in their youth age have a high purchase power and Cutomers between 45 to 55 their outstaning debt is less than young people.

In [46]:

```
g = sns.catplot(data=age_groups, x="Age_Group", y="Annual_Income", height=7, aspect=1, col="Credit_Score", kind="bar", ci=None)
g.set_axis_labels( "Age Group", "Annual Income", size=27,fontweight="bold")
plt.show()
```

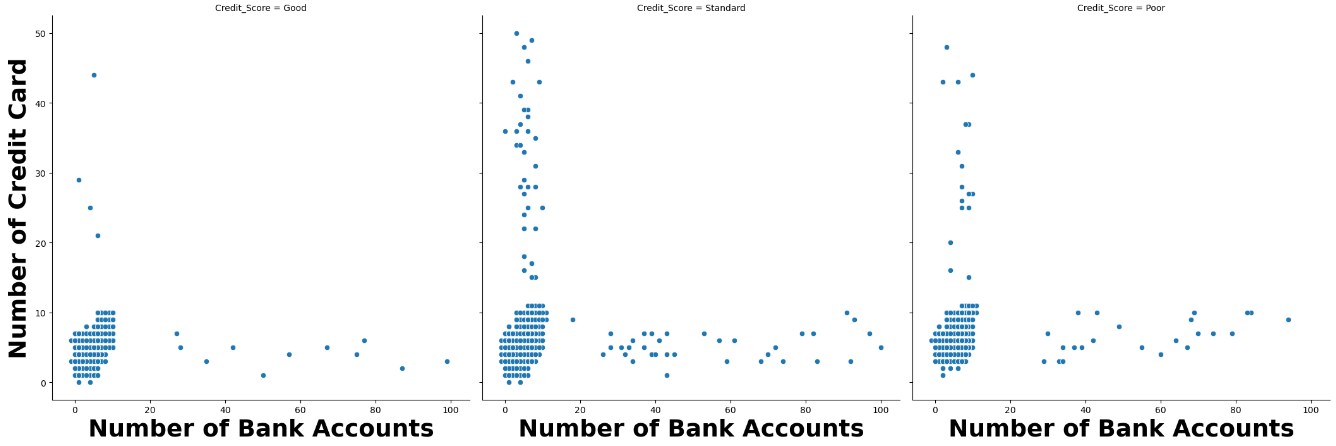


Comment:

- Customers between age 30 and 45 has the most Annual Income and the 2nd more group age are customers between 14 and 25 which mean not people from 25 and 30 which indicate that there are people who can make money in a young age more than the old people but as the same time as indication that the 2 largest Categories most of their credit score are Standard or Poor but the as for the people between 45 and 55 have more good credit score than the young people from 14 to 25

In [47]:

```
g = sns.relplot(data=df, x="Num_Bank_Accounts", y="Num_Credit_Card", col="Credit_Score", height=7, aspect=1)
g.set_axis_labels( "Number of Bank Accounts", "Number of Credit Card", size=27,fontweight="bold")
plt.show()
```



Comment:

- Most peopel have Accounts from 0 to 10 Accounts and the number of credit cards also from 0 to 10 which mean each account has at least one credit card

Prepare Data for Modeling

In [48]:

```
df["AutoLoan"] = 0
df["Credit-BuilderLoan"] = 0
df["DebtConsolidationLoan"] = 0
df["HomeEquityLoan"] = 0
df["MortgageLoan"] = 0
df["NotSpecified"] = 0
df["PaydayLoan"] = 0
df["PersonalLoan"] = 0
df["StudentLoan"] = 0
index = 0
for i in df.Type_of_Loan:
    for j in i.split(','):
        df[j][index] = 1
    index+=1
```

In [49]:

```
le = LabelEncoder()
df.Credit_Mix = le.fit_transform(df.Credit_Mix)
df.Credit_Mix.value_counts()
```

Out[49]:

```
3    36479
2    24337
1    20195
0    18989
Name: Credit_Mix, dtype: int64
```

In [50]:

```
le = LabelEncoder()
df.Payment_of_Min_Amount = le.fit_transform(df.Payment_of_Min_Amount)
df.Payment_of_Min_Amount.value_counts()
```

Out[50]:

```
2    52326
1    35667
0    12007
Name: Payment_of_Min_Amount, dtype: int64
```

In [51]:

```
le = LabelEncoder()
df.Payment_Behaviour = le.fit_transform(df.Payment_Behaviour)
df.Payment_Behaviour.value_counts()
```

Out[51]:

```
5    25513
1    17540
4    13861
0    13721
2    11340
3    10425
6     7600
Name: Payment_Behaviour, dtype: int64
```

In [52]:

```
le = LabelEncoder()
df.Credit_Score = le.fit_transform(df.Credit_Score)
df.Credit_Score.value_counts()
```

Out[52]:

```
2    53174
1    28998
0    17828
Name: Credit_Score, dtype: int64
```

In [53]:

```
x = df.drop(["Month", "Age", "Occupation", "Type_of_Loan", "Credit_Score", "Age_Group"], axis=1).values
y = df["Credit_Score"].values
```

Modeling

In [54]:

```
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size=0.2,random_state=77)
```

In [55]:

```
xgbc = xgb.XGBClassifier()
```

In [56]:

```
param_grid = {"classifier__max_depth": [3,5,7,9,11], "classifier__learning_rate": [0.1, 0.4, 0.5, 0.6, 0.7], "classifier__n_estimators": [100, 200, 300, 40
```

In [57]:

```
param = {"max_depth": [3,5,7,9,11], "learning_rate": [0.1, 0.4, 0.5], "n_estimators": [100, 200, 300, 400], "eta": [0.01, 0.05, 0.12], "subsample": [0.5, 0
```

In [58]:

```
param_grid
```

Out[58]:

```
{'classifier__max_depth': [3, 5, 7, 9, 11],
 'classifier__learning_rate': [0.1, 0.4, 0.5, 0.6, 0.7],
 'classifier__n_estimators': [100, 200, 300, 400],
 'classifier__eta': [0.01, 0.05, 0.12, 0.2, 0.3],
 'classifier__subsample': [0.5, 0.6, 0.7, 0.8, 1]}
```

In [59]:

```
pipe = Pipeline([
    ["smote", SMOTE(random_state=77)],
    ["scaler", StandardScaler()],
    ["reducer", PCA()],
    ["classifier", XGBClassifier()]
])

stratified_kfold = StratifiedKFold(n_splits=10, shuffle=True, random_state=77)
```

max_depth=5, learning_rate=0.1, n_estimators=300, eta=0.01, subsample=0.7

In [60]:

```
grid_search = GridSearchCV(
    estimator=pipe,
    param_grid=param_grid,
    scoring="accuracy",
    n_jobs=-1,
    cv=stratified_kfold)
```

In [ ]:

```
grid_search.fit(xtrain, ytrain)
```