ML_Finance_HW2

February 23, 2023

0.0.1 • Goal: Learn and use different models to solve a multi-class classification problem.

0.0.2 • Background: This data collects personal information of clients. The management wants to build an intelligent system to segregate the people into credit score brackets to reduce the manual efforts

0.0.3 • Author: Dhyey Dharmendrakumar Mavani

[1]:
```python
# checking the current working directory access
import os
print(os.getcwd())
```

```
/Users/dhyeymavani/Library/CloudStorage/GoogleDrive-dmavani25@amherst.edu/My
Drive/Columbia VUS/SPRING2023/MATH GR 5430 MACHINE LEARNING FOR
FINANCE/ML_Finance_HW2
```

1 1. Setup and Data Fetching (5 points)

[2]:
```python
# importing the data from the given csv (with cols separated by ";")
import pandas as pd
import numpy as np
client_data = pd.read_csv("./HW2.csv")
client_data
```

```
/var/folders/rb/x4vhwjb16wj764ztdb96gnlh0000gn/T/ipykernel_27457/3103777598.py:4
: DtypeWarning: Columns (26) have mixed types. Specify dtype option on import or
set low_memory=False.
  client_data = pd.read_csv("./HW2.csv")
```

[2]:
```
            ID Customer_ID     Month           Name   Age          SSN  \
0       0x1602   CUS_0xd40   January  Aaron Maashoh    23  821-00-0265
1       0x1603   CUS_0xd40  February  Aaron Maashoh    23  821-00-0265
2       0x1604   CUS_0xd40     March  Aaron Maashoh  -500  821-00-0265
3       0x1605   CUS_0xd40     April  Aaron Maashoh    23  821-00-0265
4       0x1606   CUS_0xd40       May  Aaron Maashoh    23  821-00-0265
…          …          …        …              …     …           …
99995  0x25fe9  CUS_0x942c     April          Nicks    25  078-73-5990
```

```
99996  0x25fea  CUS_0x942c       May         Nicks    25  078-73-5990
99997  0x25feb  CUS_0x942c      June         Nicks    25  078-73-5990
99998  0x25fec  CUS_0x942c      July         Nicks    25  078-73-5990
99999  0x25fed  CUS_0x942c    August         Nicks    25  078-73-5990

      Occupation Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  …  \
0      Scientist      19114.12            1824.843333                  3  …
1      Scientist      19114.12                    NaN                  3  …
2      Scientist      19114.12                    NaN                  3  …
3      Scientist      19114.12                    NaN                  3  …
4      Scientist      19114.12            1824.843333                  3  …
…            …           …                    …                  …   …
99995   Mechanic      39628.99            3359.415833                  4  …
99996   Mechanic      39628.99            3359.415833                  4  …
99997   Mechanic      39628.99            3359.415833                  4  …
99998   Mechanic      39628.99            3359.415833                  4  …
99999   Mechanic     39628.99_            3359.415833                  4  …

       Credit_Mix  Outstanding_Debt Credit_Utilization_Ratio  \
0               _            809.98                26.822620
1            Good            809.98                31.944960
2            Good            809.98                28.609352
3            Good            809.98                31.377862
4            Good            809.98                24.797347
…           …                …                       …
99995           _            502.38                34.663572
99996           _            502.38                40.565631
99997        Good            502.38                41.255522
99998        Good            502.38                33.638208
99999        Good            502.38                34.192463

           Credit_History_Age  Payment_of_Min_Amount Total_EMI_per_month  \
0       22 Years and 1 Months                     No           49.574949
1                         NaN                     No           49.574949
2       22 Years and 3 Months                     No           49.574949
3       22 Years and 4 Months                     No           49.574949
4       22 Years and 5 Months                     No           49.574949
…                         …                     …                 …
99995   31 Years and 6 Months                     No           35.104023
99996   31 Years and 7 Months                     No           35.104023
99997   31 Years and 8 Months                     No           35.104023
99998   31 Years and 9 Months                     No           35.104023
99999  31 Years and 10 Months                     No           35.104023

      Amount_invested_monthly                 Payment_Behaviour  \
0           80.41529543900253  High_spent_Small_value_payments
1          118.28022162236736   Low_spent_Large_value_payments
```

```
2              81.699521264648   Low_spent_Medium_value_payments
3             199.4580743910713    Low_spent_Small_value_payments
4            41.420153086217326  High_spent_Medium_value_payments
…                           …                                 …
99995         60.97133255718485   High_spent_Large_value_payments
99996         54.18595028760385  High_spent_Medium_value_payments
99997         24.02847744864441   High_spent_Large_value_payments
99998        251.67258219721603    Low_spent_Large_value_payments
99999         167.1638651610451                            !@9#%8

          Monthly_Balance Credit_Score
0      312.49408867943663         Good
1      284.62916249607184         Good
2       331.2098628537912         Good
3      223.45130972736786         Good
4      341.48923103222177         Good
…                     …          …
99995          479.866228         Poor
99996           496.65161         Poor
99997          516.809083         Poor
99998          319.164979     Standard
99999          393.673696         Poor

[100000 rows x 28 columns]
```

2 2. Exploratory Data Analysis (20 points)

- **Data cleaning: Some features have missing or invalid values. Choose the way you see as appropriate to clean the dataframe so that there are no missing or invalid values.**

[3]:
```python
client_data_after_dropping_nas = client_data.dropna()
client_data_after_dropping_nas.reset_index(inplace = True)

for i in range(len(client_data_after_dropping_nas['Age'])):
    alpha_num_str = client_data_after_dropping_nas['Age'][i]
    num_str = '' .join((z for z in alpha_num_str if z.isdigit()))
    client_data_after_dropping_nas.iat[i, 5] = num_str

client_data_after_dropping_nas["Age"] = client_data_after_dropping_nas["Age"].
 ↪astype(int)
temp_age_filtered_client_data =␣
 ↪client_data_after_dropping_nas[client_data_after_dropping_nas['Age'] < 100]
age_filtered_client_data =␣
 ↪temp_age_filtered_client_data[temp_age_filtered_client_data['Age'] > 0]

occupation_filtered_client_data =␣
 ↪age_filtered_client_data[age_filtered_client_data['Occupation'] != "_______"]
```

```
del occupation_filtered_client_data['index']

occupation_filtered_client_data = occupation_filtered_client_data.reset_index()

for i in range(len(occupation_filtered_client_data['Annual_Income'])):
    alpha_num_str = occupation_filtered_client_data['Annual_Income'][i]
    num_str = '' .join((z for z in alpha_num_str if (z.isdigit() or z == ".")))
    head, sep, tail = num_str.partition('.')
    occupation_filtered_client_data.iat[i, 8] = head

occupation_filtered_client_data['Annual_Income'] = occupation_filtered_client_data['Annual_Income'].astype(int)

del occupation_filtered_client_data['index']

occupation_filtered_client_data = occupation_filtered_client_data.reset_index()

for i in range(len(occupation_filtered_client_data['Num_of_Loan'])):
    alpha_num_str = occupation_filtered_client_data['Num_of_Loan'][i]
    num_str = '' .join((z for z in alpha_num_str if (z.isdigit())))
    head, sep, tail = num_str.partition('_')
    occupation_filtered_client_data.iat[i, 13] = num_str

occupation_filtered_client_data["Num_of_Loan"] = occupation_filtered_client_data["Num_of_Loan"].astype(int)

loan_filtered_client_data = occupation_filtered_client_data[occupation_filtered_client_data["Num_of_Loan"] >= 0]
loan_filtered_client_data = loan_filtered_client_data[loan_filtered_client_data["Num_of_Loan"] <= 10]

bank_acc_filtered_client_data = loan_filtered_client_data[loan_filtered_client_data["Num_Bank_Accounts"] >= 0]
bank_acc_filtered_client_data = bank_acc_filtered_client_data[bank_acc_filtered_client_data["Num_Bank_Accounts"] <= 10]

credit_card_filtered_client_data = bank_acc_filtered_client_data[bank_acc_filtered_client_data["Num_Credit_Card"] >= 0]
credit_card_filtered_client_data = credit_card_filtered_client_data[credit_card_filtered_client_data["Num_Credit_Card"] <= 10]
```

```python
interest_filtered_client_data = credit_card_filtered_client_data[credit_card_filtered_client_data["Interest_Rate"] >= 0]
interest_filtered_client_data = interest_filtered_client_data[interest_filtered_client_data["Interest_Rate"] <= 35]

delay_filtered_client_data = interest_filtered_client_data[interest_filtered_client_data["Delay_from_due_date"] >= 0]
delay_filtered_client_data = delay_filtered_client_data[delay_filtered_client_data["Delay_from_due_date"] <= 65]

del delay_filtered_client_data['index']

delay_filtered_client_data = delay_filtered_client_data.reset_index()

for i in range(len(delay_filtered_client_data["Num_of_Delayed_Payment"])):
    alpha_num_str = delay_filtered_client_data["Num_of_Delayed_Payment"][i]
    num_str = '' .join((z for z in alpha_num_str if (z.isdigit())))
    head, sep, tail = num_str.partition('_')
    delay_filtered_client_data.iat[i, 16] = head

delay_filtered_client_data["Num_of_Delayed_Payment"] = delay_filtered_client_data["Num_of_Delayed_Payment"].astype(int)

delayed_pay_filtered_client_data = delay_filtered_client_data[delay_filtered_client_data["Num_of_Delayed_Payment"] >= 0]
delayed_pay_filtered_client_data = delayed_pay_filtered_client_data[delayed_pay_filtered_client_data["Num_of_Delayed_Payment"] <= 25]

del delayed_pay_filtered_client_data['index']

delayed_pay_filtered_client_data = delayed_pay_filtered_client_data.reset_index()
delayed_pay_filtered_client_data.replace("_", np.nan, inplace=True)
delayed_pay_filtered_client_data.dropna(inplace=True)

delayed_pay_filtered_client_data["Changed_Credit_Limit"] = delayed_pay_filtered_client_data["Changed_Credit_Limit"].astype(float)
```

```python
cred_inq_filtered_client_data = delayed_pay_filtered_client_data[delayed_pay_filtered_client_data["Num_Credit_Inquiries"] >= 0]
cred_inq_filtered_client_data = cred_inq_filtered_client_data[cred_inq_filtered_client_data["Num_Credit_Inquiries"] <= 25]

credit_mix_filtered_client_data = cred_inq_filtered_client_data[cred_inq_filtered_client_data['Credit_Mix'] != "_"]

del credit_mix_filtered_client_data['index']

credit_mix_filtered_client_data = credit_mix_filtered_client_data.reset_index()

for i in range(len(credit_mix_filtered_client_data['Outstanding_Debt'])):
    alpha_num_str = credit_mix_filtered_client_data['Outstanding_Debt'][i]
    num_str = '' .join((z for z in alpha_num_str if (z.isdigit() or z == ".")))
    head, sep, tail = num_str.partition('_')
    credit_mix_filtered_client_data.iat[i, 20] = head

credit_mix_filtered_client_data['Outstanding_Debt'] = credit_mix_filtered_client_data['Outstanding_Debt'].astype(float)

del credit_mix_filtered_client_data['index']

credit_mix_filtered_client_data = credit_mix_filtered_client_data.reset_index()

for i in range(len(credit_mix_filtered_client_data['Credit_History_Age'])):
    alpha_num_str = credit_mix_filtered_client_data['Credit_History_Age'][i]
    res = [float(i) for i in alpha_num_str.split() if i.isdigit()]
    y, m = res
    age = (y + m/12)
    credit_mix_filtered_client_data.iat[i, 22] = age

credit_mix_filtered_client_data['Credit_History_Age'] = credit_mix_filtered_client_data['Credit_History_Age'].astype(float)

credit_mix_filtered_client_data.replace("NM", np.nan, inplace=True)
credit_mix_filtered_client_data.dropna(inplace=True)

credit_mix_filtered_client_data.replace("__10000__", "10000.00", inplace=True)
credit_mix_filtered_client_data['Amount_invested_monthly'] = credit_mix_filtered_client_data['Amount_invested_monthly'].astype(float)

credit_mix_filtered_client_data.replace("!@9#%8", np.nan, inplace=True)
```

```
credit_mix_filtered_client_data.dropna(inplace=True)

credit_mix_filtered_client_data.replace("__-333333333333333333333333333__", np.
↪nan, inplace=True)
credit_mix_filtered_client_data.dropna(inplace=True)
credit_mix_filtered_client_data['Monthly_Balance'] =␣
↪credit_mix_filtered_client_data['Monthly_Balance'].astype(float)

cleaned_client_data = credit_mix_filtered_client_data.copy()

del cleaned_client_data['index']

cleaned_client_data = cleaned_client_data.reset_index()

del cleaned_client_data['index']

cleaned_client_data
```

```
/var/folders/rb/x4vhwjb16wj764ztdb96gnlh0000gn/T/ipykernel_27457/3187363897.py:9
: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  client_data_after_dropping_nas["Age"] =
client_data_after_dropping_nas["Age"].astype(int)
```

[3]:

```
              ID Customer_ID     Month              Name  Age          SSN  \
0         0x1608    CUS_0xd40      July     Aaron Maashoh   23  821-00-0265
1         0x160f   CUS_0x21b1  February  Rick Rothackerj   28  004-07-5839
2         0x1612   CUS_0x21b1       May  Rick Rothackerj   28  004-07-5839
3         0x1613   CUS_0x21b1      June  Rick Rothackerj   28  004-07-5839
4         0x1615   CUS_0x21b1    August  Rick Rothackerj   28  004-07-5839
…            …          …         …                …   …            …
26523  0x25fb6   CUS_0x372c   January  Lucia Mutikanik   18  340-85-7301
26524  0x25fce   CUS_0xaf61   January   Chris Wickhamm   49  133-16-7738
26525  0x25fcf   CUS_0xaf61  February   Chris Wickhamm   49  133-16-7738
26526  0x25fdb   CUS_0x8600  February   Sarah McBridec   28  031-35-0942
26527  0x25fe1   CUS_0x8600    August   Sarah McBridec   29  031-35-0942

      Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0      Scientist          19114            1824.843333                  3
1        Teacher          34847            3037.986667                  2
2        Teacher          34847            3037.986667                  2
3        Teacher          34847            3037.986667                  2
4        Teacher          34847            3037.986667                  2
```

```
…          …          …                …               …
26523     Lawyer       42903          3468.315833                 0
26524     Writer       37188          3097.008333                 1
26525     Writer       37188          3097.008333                 1
26526  Architect       20002          1929.906667                10
26527  Architect       20002          1929.906667                10

       …  Credit_Mix  Outstanding_Debt  Credit_Utilization_Ratio  \
0      …        Good            809.98                 22.537593
1      …        Good            605.03                 38.550848
2      …        Good            605.03                 34.977895
3      …        Good            605.03                 33.381010
4      …        Good            605.03                 32.933856
…    …          …                 …                         …
26523  …        Good           1079.48                 27.289440
26524  …        Good            620.64                 39.080823
26525  …        Good            620.64                 32.803431
26526  …         Bad           3571.70                 39.772607
26527  …         Bad           3571.70                 37.140784

      Credit_History_Age  Payment_of_Min_Amount  Total_EMI_per_month  \
0              22.583333                     No            49.574949
1              26.666667                     No            18.816215
2              26.916667                     No            18.816215
3              27.000000                     No            18.816215
4              27.166667                     No            18.816215
…                  …                      …                   …
26523          28.083333                     No         50894.000000
26524          29.750000                     No            84.205949
26525          29.833333                     No            84.205949
26526           5.750000                    Yes         12112.000000
26527           6.250000                    Yes            60.964772

       Amount_invested_monthly                Payment_Behaviour  \
0                   178.344067   Low_spent_Small_value_payments
1                    40.391238  High_spent_Large_value_payments
2                   130.115420   Low_spent_Small_value_payments
3                    43.477190  High_spent_Large_value_payments
4                   218.904344   Low_spent_Small_value_payments
…                        …                               …
26523                78.514945  High_spent_Small_value_payments
26524               223.875018   Low_spent_Small_value_payments
26525                70.869970  High_spent_Large_value_payments
26526               148.275233   Low_spent_Small_value_payments
26527                34.662906  High_spent_Large_value_payments

      Monthly_Balance  Credit_Score
```

```
0          244.565317          Good
1          484.591214          Good
2          444.867032          Good
3          481.505262          Good
4          356.078109          Good
…                …           …
26523      493.341182          Good
26524      291.619866          Good
26525      394.624914          Good
26526      273.750662          Poor
26527      337.362988      Standard

[26528 rows x 28 columns]
```

[4]:
```
cleaned_client_data.to_csv("clean_client_data.csv")
```

Columns in the cleaned data:

- 'Unnamed: 0'
- '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'

[5]:
```python
data = pd.read_csv("./clean_client_data.csv")
del data["Unnamed: 0"]
data
```

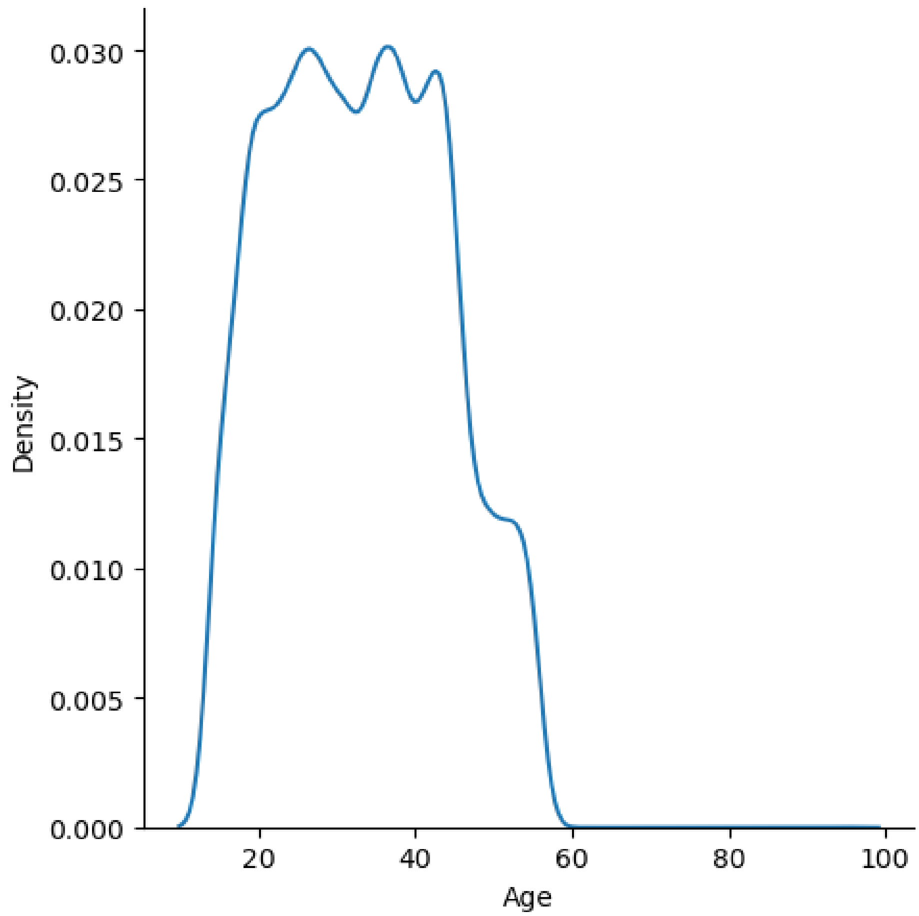
[5]:
```
              ID Customer_ID     Month              Name  Age          SSN  \
0         0x1608   CUS_0xd40      July    Aaron Maashoh   23  821-00-0265
1         0x160f  CUS_0x21b1  February  Rick Rothackerj   28  004-07-5839
2         0x1612  CUS_0x21b1       May  Rick Rothackerj   28  004-07-5839
3         0x1613  CUS_0x21b1      June  Rick Rothackerj   28  004-07-5839
4         0x1615  CUS_0x21b1    August  Rick Rothackerj   28  004-07-5839
…            …          …         …              …   …            …
26523    0x25fb6  CUS_0x372c   January  Lucia Mutikanik   18  340-85-7301
26524    0x25fce  CUS_0xaf61   January   Chris Wickhamm   49  133-16-7738
26525    0x25fcf  CUS_0xaf61  February   Chris Wickhamm   49  133-16-7738
26526    0x25fdb  CUS_0x8600  February   Sarah McBridec   28  031-35-0942
26527    0x25fe1  CUS_0x8600    August   Sarah McBridec   29  031-35-0942

      Occupation  Annual_Income  Monthly_Inhand_Salary  Num_Bank_Accounts  \
0      Scientist          19114            1824.843333                  3
1        Teacher          34847            3037.986667                  2
2        Teacher          34847            3037.986667                  2
3        Teacher          34847            3037.986667                  2
4        Teacher          34847            3037.986667                  2
…            …              …                    …                 …
26523     Lawyer          42903            3468.315833                  0
26524     Writer          37188            3097.008333                  1
26525     Writer          37188            3097.008333                  1
26526  Architect          20002            1929.906667                 10
26527  Architect          20002            1929.906667                 10

       …  Credit_Mix  Outstanding_Debt  Credit_Utilization_Ratio  \
0      …        Good            809.98                 22.537593
1      …        Good            605.03                 38.550848
2      …        Good            605.03                 34.977895
3      …        Good            605.03                 33.381010
4      …        Good            605.03                 32.933856
…    …         …                …                      …
26523  …        Good           1079.48                 27.289440
26524  …        Good            620.64                 39.080823
26525  …        Good            620.64                 32.803431
26526  …         Bad           3571.70                 39.772607
26527  …         Bad           3571.70                 37.140784

      Credit_History_Age  Payment_of_Min_Amount  Total_EMI_per_month  \
0              22.583333                     No            49.574949
1              26.666667                     No            18.816215
2              26.916667                     No            18.816215
```

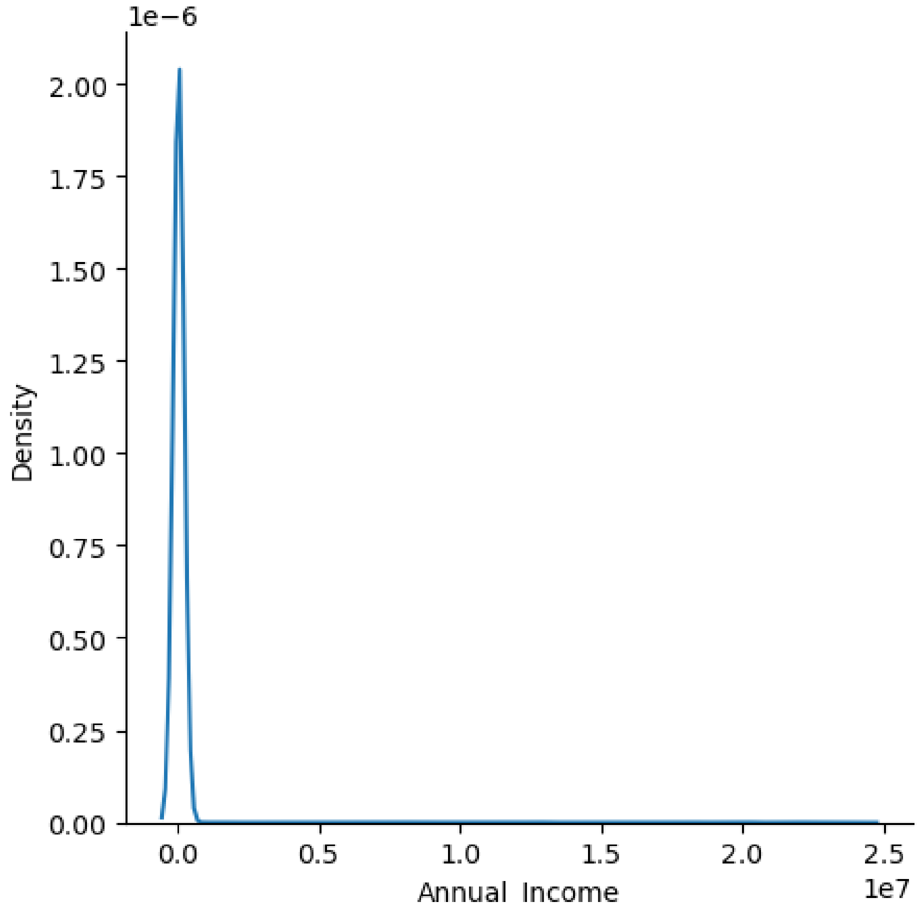
```
3             27.000000                  No          18.816215
4             27.166667                  No          18.816215
…                   …               …                   …
26523         28.083333                  No       50894.000000
26524         29.750000                  No          84.205949
26525         29.833333                  No          84.205949
26526          5.750000                 Yes       12112.000000
26527          6.250000                 Yes          60.964772

       Amount_invested_monthly                Payment_Behaviour  \
0                   178.344067   Low_spent_Small_value_payments
1                    40.391238  High_spent_Large_value_payments
2                   130.115420   Low_spent_Small_value_payments
3                    43.477190  High_spent_Large_value_payments
4                   218.904344   Low_spent_Small_value_payments
…                         …                              …
26523                78.514945  High_spent_Small_value_payments
26524               223.875018   Low_spent_Small_value_payments
26525                70.869970  High_spent_Large_value_payments
26526               148.275233   Low_spent_Small_value_payments
26527                34.662906  High_spent_Large_value_payments

      Monthly_Balance  Credit_Score
0          244.565317          Good
1          484.591214          Good
2          444.867032          Good
3          481.505262          Good
4          356.078109          Good
…                 …            …
26523      493.341182          Good
26524      291.619866          Good
26525      394.624914          Good
26526      273.750662          Poor
26527      337.362988      Standard

[26528 rows x 28 columns]
```

- **Plot the distributions of two numerical features of your choice. What do you discover about those variables?**

[6]:
```python
import seaborn as sns
sns.displot(data, x="Age", kind="kde")
sns.displot(data, x="Annual_Income", kind="kde")
```

[6]:
```
<seaborn.axisgrid.FacetGrid at 0x7fef9c445d60>
```

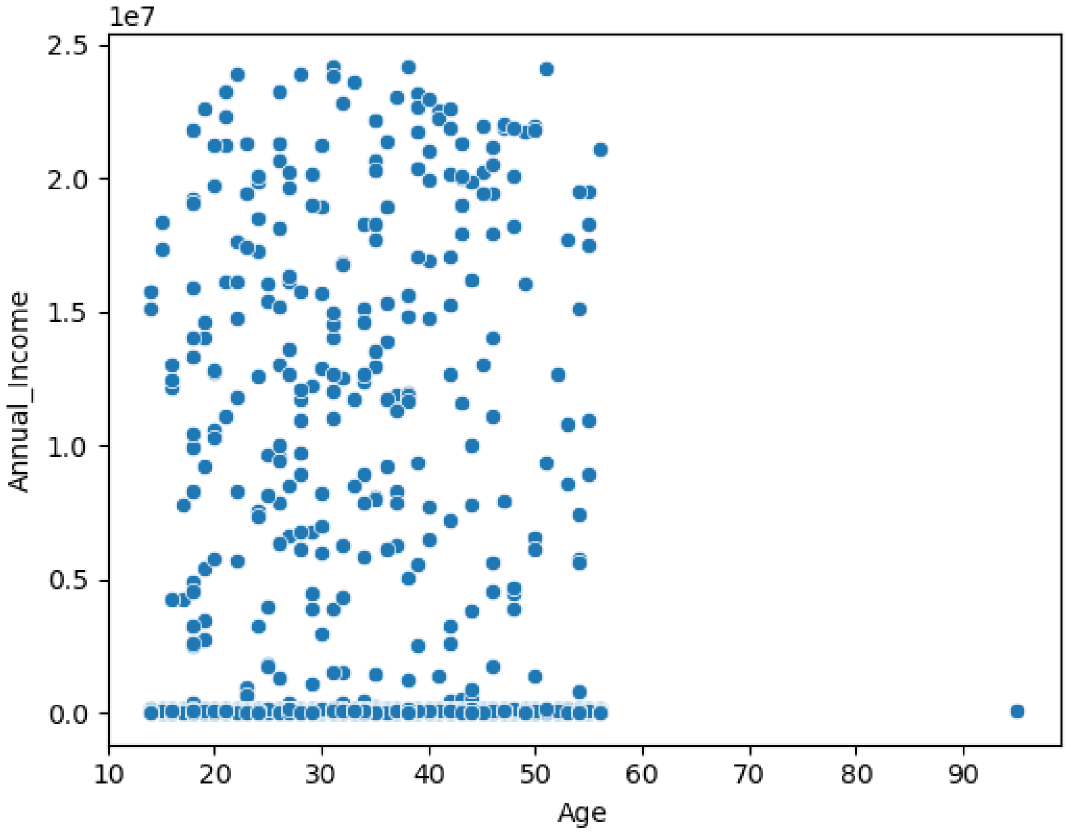

0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
20
40
60
80
100
Age



We have chosen here to plot the density distributions of numeric variables age and annual income in our filtered dataset. We can see that both the distributions are right-skewed, while that of annual income is more so. Furthermore, we can see that the age with most density is around three peaks at 25, 38 and 42 approximately, while the density of annual income variable peaks when annual income takes a value of 0.05*10^7 (around 50,000). We can also see that age mostly lies between 10 to 60, while campaign values mostly lie between 0 to 1,000,000.

[36]:
```
sns.scatterplot(data=data, x="Age", y="Annual_Income")
```

[36]: <AxesSubplot: xlabel='Age', ylabel='Annual_Income'>



Furthermore, on plotting the numeric variables of interest as a scatterplot with annual income on the y-axis and age on x-axis as shown above, we can see that annual income has almost the same seemingly random variation among different ages from 15 to 60 with most people in the low annual income range.

- **Plot the correlation matrix of all numeric features. What do you discover?**

[7]:
```
data.corr()
```

[7]:
```
                            Age  Annual_Income  Monthly_Inhand_Salary  \
Age                    1.000000       0.009402               0.085716
Annual_Income          0.009402       1.000000               0.035314
Monthly_Inhand_Salary  0.085716       0.035314               1.000000
Num_Bank_Accounts     -0.191913      -0.008823              -0.281451
Num_Credit_Card       -0.150085      -0.004909              -0.222464
Interest_Rate         -0.217417      -0.019732              -0.308845
Num_of_Loan           -0.196767      -0.002397              -0.249267
Delay_from_due_date   -0.170238      -0.011910              -0.246699
Num_of_Delayed_Payment -0.182203     -0.004452              -0.282958
Changed_Credit_Limit  -0.154947      -0.008059              -0.173013
Num_Credit_Inquiries  -0.243182      -0.013630              -0.285780
```

```
Outstanding_Debt          -0.200344      -0.008690                 -0.277441
Credit_Utilization_Ratio   0.022428       0.009059                  0.159732
Credit_History_Age         0.232788       0.003094                  0.283447
Total_EMI_per_month        0.000514      -0.010581                  0.010987
Amount_invested_monthly   -0.004075      -0.000604                  0.049266
Monthly_Balance            0.108362       0.020047                  0.680436

                          Num_Bank_Accounts  Num_Credit_Card  Interest_Rate  \
Age                               -0.191913        -0.150085      -0.217417
Annual_Income                     -0.008823        -0.004909      -0.019732
Monthly_Inhand_Salary             -0.281451        -0.222464      -0.308845
Num_Bank_Accounts                  1.000000         0.440339       0.579838
Num_Credit_Card                    0.440339         1.000000       0.499532
Interest_Rate                      0.579838         0.499532       1.000000
Num_of_Loan                        0.469219         0.417180       0.539941
Delay_from_due_date                0.556531         0.481129       0.584251
Num_of_Delayed_Payment             0.595783         0.413135       0.561430
Changed_Credit_Limit               0.323093         0.245925       0.355906
Num_Credit_Inquiries               0.526000         0.468567       0.633609
Outstanding_Debt                   0.515963         0.498871       0.633570
Credit_Utilization_Ratio          -0.060204        -0.048869      -0.066029
Credit_History_Age                -0.487774        -0.419828      -0.576757
Total_EMI_per_month                0.005370        -0.001450       0.003615
Amount_invested_monthly           -0.013920        -0.001580      -0.010806
Monthly_Balance                   -0.284251        -0.235929      -0.318435

                          Num_of_Loan  Delay_from_due_date  \
Age                         -0.196767            -0.170238
Annual_Income               -0.002397            -0.011910
Monthly_Inhand_Salary       -0.249267            -0.246699
Num_Bank_Accounts            0.469219             0.556531
Num_Credit_Card              0.417180             0.481129
Interest_Rate                0.539941             0.584251
Num_of_Loan                  1.000000             0.490506
Delay_from_due_date          0.490506             1.000000
Num_of_Delayed_Payment       0.463587             0.537229
Changed_Credit_Limit         0.367170             0.286690
Num_Credit_Inquiries         0.544718             0.539331
Outstanding_Debt             0.640329             0.578490
Credit_Utilization_Ratio    -0.077027            -0.054367
Credit_History_Age          -0.596080            -0.487857
Total_EMI_per_month         -0.000914            -0.005720
Amount_invested_monthly     -0.019284            -0.004256
Monthly_Balance             -0.406558            -0.267302

                          Num_of_Delayed_Payment  Changed_Credit_Limit  \
Age                                    -0.182203             -0.154947
```

```
Annual_Income                            -0.004452             -0.008059
Monthly_Inhand_Salary                    -0.282958             -0.173013
Num_Bank_Accounts                         0.595783              0.323093
Num_Credit_Card                           0.413135              0.245925
Interest_Rate                             0.561430              0.355906
Num_of_Loan                               0.463587              0.367170
Delay_from_due_date                       0.537229              0.286690
Num_of_Delayed_Payment                    1.000000              0.315604
Changed_Credit_Limit                      0.315604              1.000000
Num_Credit_Inquiries                      0.497532              0.368664
Outstanding_Debt                          0.505241              0.464225
Credit_Utilization_Ratio                 -0.062507             -0.038766
Credit_History_Age                       -0.481429             -0.425295
Total_EMI_per_month                      -0.007373              0.001202
Amount_invested_monthly                  -0.024517             -0.007301
Monthly_Balance                          -0.294056             -0.195844

                          Num_Credit_Inquiries  Outstanding_Debt  \
Age                                  -0.243182         -0.200344
Annual_Income                        -0.013630         -0.008690
Monthly_Inhand_Salary                -0.285780         -0.277441
Num_Bank_Accounts                     0.526000          0.515963
Num_Credit_Card                       0.468567          0.498871
Interest_Rate                         0.633609          0.633570
Num_of_Loan                           0.544718          0.640329
Delay_from_due_date                   0.539331          0.578490
Num_of_Delayed_Payment                0.497532          0.505241
Changed_Credit_Limit                  0.368664          0.464225
Num_Credit_Inquiries                  1.000000          0.597826
Outstanding_Debt                      0.597826          1.000000
Credit_Utilization_Ratio             -0.066738         -0.058116
Credit_History_Age                   -0.603835         -0.632136
Total_EMI_per_month                  -0.005862         -0.001622
Amount_invested_monthly              -0.009351         -0.012362
Monthly_Balance                      -0.311252         -0.316415

                          Credit_Utilization_Ratio  Credit_History_Age  \
Age                                       0.022428            0.232788
Annual_Income                             0.009059            0.003094
Monthly_Inhand_Salary                     0.159732            0.283447
Num_Bank_Accounts                        -0.060204           -0.487774
Num_Credit_Card                          -0.048869           -0.419828
Interest_Rate                            -0.066029           -0.576757
Num_of_Loan                              -0.077027           -0.596080
Delay_from_due_date                      -0.054367           -0.487857
Num_of_Delayed_Payment                   -0.062507           -0.481429
Changed_Credit_Limit                     -0.038766           -0.425295
```

```
Num_Credit_Inquiries                    -0.066738            -0.603835
Outstanding_Debt                        -0.058116            -0.632136
Credit_Utilization_Ratio                 1.000000             0.058006
Credit_History_Age                       0.058006             1.000000
Total_EMI_per_month                      0.000988             0.004571
Amount_invested_monthly                  0.014140             0.012146
Monthly_Balance                          0.216091             0.326325

                          Total_EMI_per_month  Amount_invested_monthly  \
Age                                  0.000514                -0.004075
Annual_Income                       -0.010581                -0.000604
Monthly_Inhand_Salary                0.010987                 0.049266
Num_Bank_Accounts                    0.005370                -0.013920
Num_Credit_Card                     -0.001450                -0.001580
Interest_Rate                        0.003615                -0.010806
Num_of_Loan                         -0.000914                -0.019284
Delay_from_due_date                 -0.005720                -0.004256
Num_of_Delayed_Payment              -0.007373                -0.024517
Changed_Credit_Limit                 0.001202                -0.007301
Num_Credit_Inquiries                -0.005862                -0.009351
Outstanding_Debt                    -0.001622                -0.012362
Credit_Utilization_Ratio             0.000988                 0.014140
Credit_History_Age                   0.004571                 0.012146
Total_EMI_per_month                  1.000000                 0.001333
Amount_invested_monthly              0.001333                 1.000000
Monthly_Balance                      0.003377                -0.008427

                          Monthly_Balance
Age                              0.108362
Annual_Income                    0.020047
Monthly_Inhand_Salary            0.680436
Num_Bank_Accounts               -0.284251
Num_Credit_Card                 -0.235929
Interest_Rate                   -0.318435
Num_of_Loan                     -0.406558
Delay_from_due_date             -0.267302
Num_of_Delayed_Payment          -0.294056
Changed_Credit_Limit            -0.195844
Num_Credit_Inquiries            -0.311252
Outstanding_Debt                -0.316415
Credit_Utilization_Ratio         0.216091
Credit_History_Age               0.326325
Total_EMI_per_month              0.003377
Amount_invested_monthly         -0.008427
Monthly_Balance                  1.000000
```

We can see that some of the correlations are unusually high, for example, 0.680436 (close to or greater than 0.6) between monthly balance and monthly inhand salary. This might be causing multi-collinearity issues down the line. Some of the solutions which we can employ in this case range from removing the highly correlated independent variables to introducing a linear combination of the highly correlated independent variables instead of having them individually present as columns. I am deleting the column for monthly balance below to resolve this issue.

[8]:
```
del data["Monthly_Balance"]

'''
We also delete the identifying information such as SSN, ID, Customer_ID, and␣
↪Name
before converting our categorical variables to numerical encoding because we␣
↪don't
want these columns to be encoded as this might cause overfitting and it might␣
↪lead
to non-convergence issues with our model because each observation will take on␣
↪a
different value and number of categories will be very close to the total number␣
↪of
observations.
'''
del data["SSN"]
del data["ID"]
del data["Customer_ID"]
del data["Name"]

data
```

[8]:
```
          Month  Age  Occupation  Annual_Income  Monthly_Inhand_Salary  \
0          July   23  Scientist           19114            1824.843333
1      February   28    Teacher           34847            3037.986667
2           May   28    Teacher           34847            3037.986667
3          June   28    Teacher           34847            3037.986667
4        August   28    Teacher           34847            3037.986667
…             …    …          …               …                      …
26523   January   18     Lawyer           42903            3468.315833
26524   January   49     Writer           37188            3097.008333
26525  February   49     Writer           37188            3097.008333
26526  February   28  Architect           20002            1929.906667
26527    August   29  Architect           20002            1929.906667

       Num_Bank_Accounts  Num_Credit_Card  Interest_Rate  Num_of_Loan  \
0                      3                4              3            4
1                      2                4              6            1
2                      2                4              6            1
3                      2                4              6            1
4                      2                4              6            1
```

```
…                    …              …             …           …
26523                0              4             6             1
26524                1              4             5             3
26525                1              4             5             3
26526               10              8            29             5
26527               10              8            29             5

                                              Type_of_Loan  …  \
0      Auto Loan, Credit-Builder Loan, Personal Loan,…  …
1                                   Credit-Builder Loan  …
2                                   Credit-Builder Loan  …
3                                   Credit-Builder Loan  …
4                                   Credit-Builder Loan  …
…                                                   …  …
26523                                     Not Specified  …
26524  Home Equity Loan, Mortgage Loan, and Student Loan  …
26525  Home Equity Loan, Mortgage Loan, and Student Loan  …
26526  Personal Loan, Auto Loan, Mortgage Loan, Stude…  …
26527  Personal Loan, Auto Loan, Mortgage Loan, Stude…  …

       Num_Credit_Inquiries  Credit_Mix  Outstanding_Debt  \
0                       4.0        Good            809.98
1                       2.0        Good            605.03
2                       2.0        Good            605.03
3                       2.0        Good            605.03
4                       2.0        Good            605.03
…                       …          …              …
26523                   1.0        Good           1079.48
26524                   3.0        Good            620.64
26525                   3.0        Good            620.64
26526                   9.0         Bad           3571.70
26527                   9.0         Bad           3571.70

       Credit_Utilization_Ratio Credit_History_Age  Payment_of_Min_Amount  \
0                     22.537593          22.583333                     No
1                     38.550848          26.666667                     No
2                     34.977895          26.916667                     No
3                     33.381010          27.000000                     No
4                     32.933856          27.166667                     No
…                           …               …                  …
26523                 27.289440          28.083333                     No
26524                 39.080823          29.750000                     No
26525                 32.803431          29.833333                     No
26526                 39.772607           5.750000                    Yes
26527                 37.140784           6.250000                    Yes

       Total_EMI_per_month  Amount_invested_monthly  \
```

```
0              49.574949          178.344067
1              18.816215           40.391238
2              18.816215          130.115420
3              18.816215           43.477190
4              18.816215          218.904344
…                   …                 …
26523       50894.000000           78.514945
26524          84.205949          223.875018
26525          84.205949           70.869970
26526       12112.000000          148.275233
26527          60.964772           34.662906

                    Payment_Behaviour  Credit_Score
0       Low_spent_Small_value_payments          Good
1      High_spent_Large_value_payments          Good
2       Low_spent_Small_value_payments          Good
3      High_spent_Large_value_payments          Good
4       Low_spent_Small_value_payments          Good
…                                  …           …
26523  High_spent_Small_value_payments          Good
26524   Low_spent_Small_value_payments          Good
26525  High_spent_Large_value_payments          Good
26526   Low_spent_Small_value_payments          Poor
26527  High_spent_Large_value_payments      Standard

[26528 rows x 23 columns]
```

- **Appropriately encode all categorical features in the dataframe**

[9]:
```
data.dtypes
```

[9]:
```
Month                        object
Age                           int64
Occupation                   object
Annual_Income                 int64
Monthly_Inhand_Salary       float64
Num_Bank_Accounts             int64
Num_Credit_Card               int64
Interest_Rate                 int64
Num_of_Loan                   int64
Type_of_Loan                 object
Delay_from_due_date           int64
Num_of_Delayed_Payment        int64
Changed_Credit_Limit        float64
Num_Credit_Inquiries        float64
Credit_Mix                   object
Outstanding_Debt            float64
```

```
Credit_Utilization_Ratio    float64
Credit_History_Age          float64
Payment_of_Min_Amount        object
Total_EMI_per_month         float64
Amount_invested_monthly     float64
Payment_Behaviour            object
Credit_Score                 object
dtype: object
```

[10]:
```python
from sklearn.preprocessing import LabelEncoder

# get the categorical columns
cat_cols = data.select_dtypes(include=['object']).columns

# create the label encoder object
label_encoder = LabelEncoder()

# apply label encoding to each categorical column
data[cat_cols] = data[cat_cols].apply(lambda col: label_encoder.
 ↪fit_transform(col))

# print the encoded dataframe
data
```

[10]:
```
       Month  Age  Occupation  Annual_Income  Monthly_Inhand_Salary  \
0          4   23          12          19114            1824.843333
1          2   28          13          34847            3037.986667
2          7   28          13          34847            3037.986667
3          5   28          13          34847            3037.986667
4          1   28          13          34847            3037.986667
…          …  …           …              …                      …
26523      3   18           7          42903            3468.315833
26524      3   49          14          37188            3097.008333
26525      2   49          14          37188            3097.008333
26526      2   28           1          20002            1929.906667
26527      1   29           1          20002            1929.906667

       Num_Bank_Accounts  Num_Credit_Card  Interest_Rate  Num_of_Loan  \
0                      3                4              3            4
1                      2                4              6            1
2                      2                4              6            1
3                      2                4              6            1
4                      2                4              6            1
…                    …              …              …           …
26523                  0                4              6            1
26524                  1                4              5            3
26525                  1                4              5            3
```

```
26526                 10                8             29             5
26527                 10                8             29             5

       Type_of_Loan  …  Num_Credit_Inquiries  Credit_Mix  Outstanding_Debt  \
0               119  …                   4.0           1            809.98
1               649  …                   2.0           1            605.03
2               649  …                   2.0           1            605.03
3               649  …                   2.0           1            605.03
4               649  …                   2.0           1            605.03
…               …  …                   …          …               …
26523          3257  …                   1.0           1           1079.48
26524          2335  …                   3.0           1            620.64
26525          2335  …                   3.0           1            620.64
26526          4636  …                   9.0           0           3571.70
26527          4636  …                   9.0           0           3571.70

       Credit_Utilization_Ratio  Credit_History_Age  Payment_of_Min_Amount  \
0                     22.537593           22.583333                      0
1                     38.550848           26.666667                      0
2                     34.977895           26.916667                      0
3                     33.381010           27.000000                      0
4                     32.933856           27.166667                      0
…                           …                 …                    …
26523                 27.289440           28.083333                      0
26524                 39.080823           29.750000                      0
26525                 32.803431           29.833333                      0
26526                 39.772607            5.750000                      1
26527                 37.140784            6.250000                      1

       Total_EMI_per_month  Amount_invested_monthly  Payment_Behaviour  \
0                49.574949               178.344067                  5
1                18.816215                40.391238                  0
2                18.816215               130.115420                  5
3                18.816215                43.477190                  0
4                18.816215               218.904344                  5
…                      …                      …                …
26523         50894.000000                78.514945                  2
26524            84.205949               223.875018                  5
26525            84.205949                70.869970                  0
26526         12112.000000               148.275233                  5
26527            60.964772                34.662906                  0

       Credit_Score
0                 0
1                 0
2                 0
3                 0
```

```
4                   0
…               …
26523               0
26524               0
26525               0
26526               1
26527               2

[26528 rows x 23 columns]
```

[11]:
```
data.dtypes
```

[11]:
```
Month                        int64
Age                          int64
Occupation                   int64
Annual_Income                int64
Monthly_Inhand_Salary      float64
Num_Bank_Accounts            int64
Num_Credit_Card              int64
Interest_Rate                int64
Num_of_Loan                  int64
Type_of_Loan                 int64
Delay_from_due_date          int64
Num_of_Delayed_Payment       int64
Changed_Credit_Limit       float64
Num_Credit_Inquiries       float64
Credit_Mix                   int64
Outstanding_Debt           float64
Credit_Utilization_Ratio   float64
Credit_History_Age         float64
Payment_of_Min_Amount        int64
Total_EMI_per_month        float64
Amount_invested_monthly    float64
Payment_Behaviour            int64
Credit_Score                 int64
dtype: object
```

3 3. Logistic Regression (20 points)

- **What is the use of validation dataset in machine learning?** The validation dataset is a subset of the original dataset that is used to evaluate the performance of a model during training and to select the best hyperparameters.

During the training phase of a machine learning model, the model is trained on a training dataset, and its performance is evaluated on a validation dataset. The goal is to optimize the model's performance on the validation dataset while preventing overfitting to the training dataset. Overfitting occurs when the model learns the noise or the specifics of the training dataset too well, resulting in poor generalization to new, unseen data.

The validation dataset is used to tune the hyperparameters of the model, such as the learning rate, the number of layers, the number of hidden units, etc. Hyperparameters are model parameters that are not learned during training and must be set before training the model. By evaluating the model's performance on the validation dataset for different hyperparameter values, we can select the best hyperparameters that optimize the model's performance.

The main advantage of using a validation dataset is that it provides an unbiased estimate of the model's performance on unseen data. This estimate can be used to compare different models or to select the best hyperparameters for a given model. Without a validation dataset, it is difficult to estimate the model's performance on unseen data accurately, and we risk overfitting the model to the training data.

To summarize, the validation dataset is used in machine learning to:

- Evaluate the performance of the model during training
- Prevent overfitting of the model to the training data
- Tune the hyperparameters of the model
- Provide an unbiased estimate of the model's performance on unseen data.

- **Make an appropriate split of the data train, validation, test and fit a multi-class logistic regression model using the Scikit-learn library.**

[22]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import pandas as pd

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(data.drop('Credit_Score',␣
↪axis=1), data['Credit_Score'], test_size=0.2, random_state=8990)

# Split the training data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.
↪2, random_state=8990)

# Fit the multi-class logistic regression model
clf = LogisticRegression(multi_class='multinomial', solver='lbfgs',␣
↪max_iter=10000)
clf.fit(X_train, y_train)

# Predict the classes of the validation set
y_val_pred = clf.predict(X_val)

# Calculate the validation set accuracy
val_accuracy = accuracy_score(y_val, y_val_pred)

# Predict the classes of the test set
y_test_pred = clf.predict(X_test)
```

```python
# Calculate the test set accuracy
test_accuracy = accuracy_score(y_test, y_test_pred)

print(f"Validation set accuracy: {val_accuracy:.3f}")
print(f"Test set accuracy: {test_accuracy:.3f}")
```

```
Validation set accuracy: 0.554
Test set accuracy: 0.543
```

- **Print the classification report of the model. What do you find in the report?**

[23]:
```python
from sklearn.metrics import classification_report

logistic_model_classification_report = classification_report(y_test,␣
↪y_test_pred)

print(logistic_model_classification_report)
```

```
              precision    recall  f1-score   support

           0       0.35      0.01      0.02       854
           1       0.51      0.35      0.42      1626
           2       0.55      0.81      0.66      2826

    accuracy                           0.54      5306
   macro avg       0.47      0.39      0.36      5306
weighted avg       0.51      0.54      0.48      5306
```

This classification report is for a logistic regression model, which has been used to classify data into three classes (0, 1, and 2).

The report shows various metrics that evaluate the performance of the model. Here is a brief explanation of each metric:

- ***Precision:*** Precision measures the proportion of true positives (correctly predicted instances of a class) among the instances that the model predicted as positive. In this report, the precision for class 0 is very low at 0.35, indicating that the model has a high number of false positives for this class. The precision for class 1 and 2 are 0.51 and 0.55, respectively, indicating that the model is better at predicting these classes.
- ***Recall:*** Recall measures the proportion of true positives among the instances that actually belong to a class. In this report, the recall for class 0 is very low at 0.01, indicating that the model is not good at identifying instances of this class. The recall for class 1 and 2 are 0.35 and 0.81, respectively, indicating that the model is better at identifying these classes.
- ***F1-score:*** F1-score is a weighted average of precision and recall that takes into account both metrics. It is a good metric for evaluating the overall performance of a model. In this report, the F1-score for class 0 is very low at 0.02, indicating that the model is not good at predicting

this class. The F1-scores for class 1 and 2 are 0.42 and 0.66, respectively, indicating that the model is better at predicting these classes.

- ***Support:*** Support indicates the number of instances of each class in the test set.
- ***Accuracy:*** Accuracy measures the proportion of correctly classified instances among all instances. In this report, the overall accuracy of the model is 0.54, indicating that the model is correct in its prediction for 54% of instances.
- ***Macro average:*** Macro average calculates the average metric score across all classes, giving equal weight to each class. In this report, the macro average F1-score is 0.36, indicating that the overall performance of the model is not very good.
- ***Weighted average:*** Weighted average calculates the average metric score across all classes, weighting each class by its support. In this report, the weighted average F1-score is 0.48, which is slightly better than the macro average F1-score but still indicates that the model's performance is not very good.

Overall, this classification report suggests that the logistic regression model is not very accurate at predicting class 0, and performs better at predicting classes 1 and 2. The overall performance of the model is also not very good, with a low macro average F1-score and accuracy of 54%.

4 4. Decision Tree and Bagging (30 points)

- **Describe the algorithm CART. What are the advantages and disadvantages of CART?** CART (Classification And Regression Trees) is a decision tree algorithm used for both classification and regression tasks. The algorithm works by recursively splitting the data into two subsets, based on a single feature at a time, until the subsets are as homogeneous as possible in terms of the target variable.

Here are the main steps of the CART algorithm:

1. Select the feature that provides the best split. The feature with the highest information gain (for classification) or the highest reduction in variance (for regression) is chosen as the splitting feature.
2. Split the data into two subsets based on the chosen feature. The subsets are chosen such that each subset is as pure as possible with respect to the target variable.
3. Repeat steps 1 and 2 for each subset, until a stopping criterion is met. The stopping criterion could be a maximum depth of the tree, a minimum number of samples per leaf, or a minimum improvement in impurity.
4. Create a tree by assigning a label or value to each leaf node, based on the majority class (for classification) or the mean value (for regression) of the samples in the leaf node.

Advantages of CART:

1. CART is a simple and interpretable algorithm. The resulting decision tree can be easily visualized and understood, which is useful for explaining the reasoning behind the model's predictions.
2. CART can handle a mix of categorical and continuous features, making it versatile and applicable to a wide range of problems.

3. CART is a non-parametric algorithm, which means that it does not make any assumptions about the distribution of the data. This makes it useful when the data does not follow a specific distribution.

4. CART can handle missing values and outliers by using surrogate splits, which improve the robustness of the model.

Disadvantages of CART:

1. CART is prone to overfitting the data, which means that it can learn the noise or specific features of the training data too well, resulting in poor generalization to new, unseen data.

2. CART is sensitive to small variations in the data and can produce different trees for different splits, which makes the model less stable and harder to interpret.

3. CART is a greedy algorithm, which means that it makes the best split at each step without considering the overall structure of the tree. This can lead to suboptimal solutions.

4. CART can be biased towards features with many categories, as they can dominate the splitting process and result in an unbalanced tree.

Overall, CART is a powerful algorithm that can be used for a wide range of problems. However, to avoid overfitting and improve the performance of the model, it is important to tune the hyperparameters of the algorithm and use techniques such as pruning, regularization, and ensemble methods.

- **Implement DecisionTreeClassifier from the sklearn library to train one decision tree. You can evaluate the accuracy of the validation set to tune model parameters. You should only evaluate your final accuracy on the test dataset.**

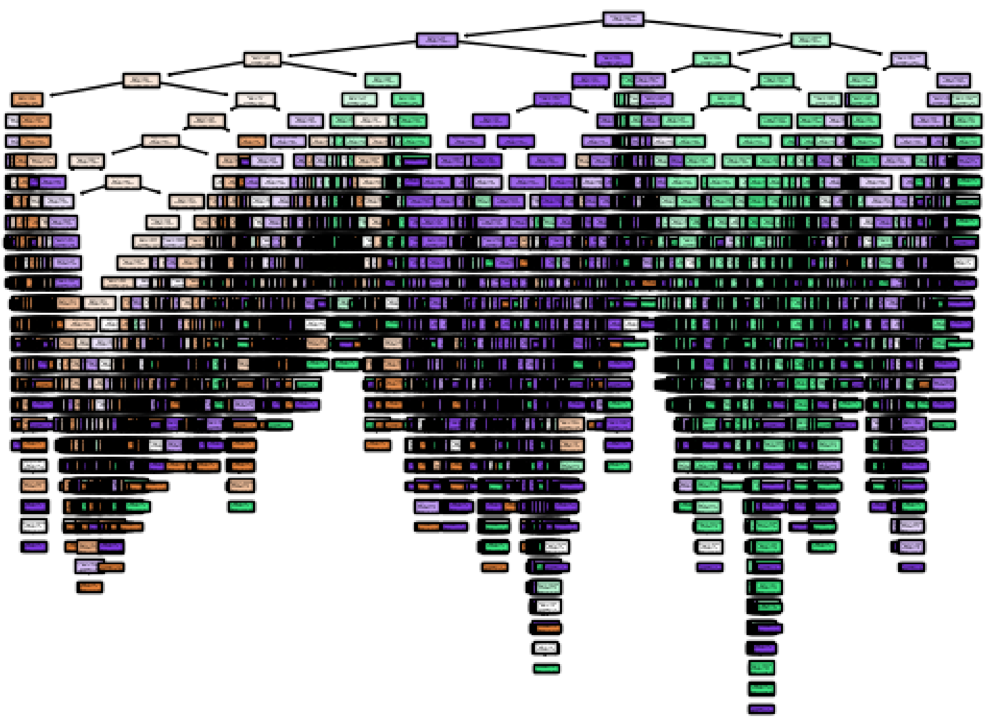
[24]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Split data into train, validation, and test sets
train_data, test_data, train_labels, test_labels = train_test_split(data.
 ↪drop('Credit_Score', axis=1), data['Credit_Score'], test_size=0.2,␣
 ↪random_state=8990)
train_data, val_data, train_labels, val_labels = train_test_split(train_data,␣
 ↪train_labels, test_size=0.2, random_state=8990)

# Train a decision tree classifier on the training data
clf = DecisionTreeClassifier()
clf.fit(train_data, train_labels)

# Evaluate the accuracy on the validation set to tune model parameters
val_pred = clf.predict(val_data)
val_acc = accuracy_score(val_labels, val_pred)
print("Validation accuracy:", val_acc)

# Evaluate the accuracy on the test set
```

```
test_pred = clf.predict(test_data)
test_acc = accuracy_score(test_labels, test_pred)
print("Test accuracy:", test_acc)
```

```
Validation accuracy: 0.6525323910482921
Test accuracy: 0.6515265736901621
```

- **Use sklearn's sklearn.tree.plot tree method and matplotlib to visualize your classification tree.**

[25]:
```
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

# Visualize the decision tree
plt.figure()
plot_tree(clf, filled=True)
plt.show()
```



- **Use 30 different random seeds to train 30 identical decision trees and record the test accuracies. Calculate and report the average accuracy and standard deviation across the 30 runs. What do you find using this bagging method?**

[26]:
```
import numpy as np
```

```python
# Define a function to train a decision tree using a given random seed
def train_decision_tree(seed, train_data, train_labels, test_data, test_labels):
    clf = DecisionTreeClassifier(random_state=seed)
    clf.fit(train_data, train_labels)
    test_pred = clf.predict(test_data)
    test_acc = accuracy_score(test_labels, test_pred)
    return test_acc

# Split data into train and test sets
train_data, test_data, train_labels, test_labels = train_test_split(data.
 ↪drop('Credit_Score', axis=1), data['Credit_Score'], test_size=0.2,␣
 ↪random_state=8990)

# Train 30 decision trees with different random seeds and record the test␣
 ↪accuracies
test_accs = []
for seed in range(30):
    test_acc = train_decision_tree(seed, train_data, train_labels, test_data,␣
 ↪test_labels)
    test_accs.append(test_acc)

# Calculate and report the average accuracy and standard deviation across the␣
 ↪30 runs
avg_acc = np.mean(test_accs)
std_dev = np.std(test_accs)
print("Average accuracy:", avg_acc)
print("Standard deviation:", std_dev)
```

```
Average accuracy: 0.6578967206935545
Standard deviation: 0.0030367385530887395
```

Bagging, or bootstrap aggregation, is a technique that involves training multiple models on different subsets of the training data and combining their predictions to obtain a final prediction. In this case, we are training identical decision trees on different subsets of the data by using different random seeds, and averaging their test accuracies to obtain an estimate of the overall accuracy of the model.

By using this bagging method, we can obtain a more robust estimate of the accuracy of the model, and reduce the impact of random variations in the data or the training process. The standard deviation across the 30 runs can give us an idea of the level of variability in the accuracy estimates, and help us assess the reliability of the model.

In this case specifically, we found that the standard deviation is very low and the average accuracy is close to the accuracy we obtained in the first run in the part before this.

5 5. Random Forest (25 points)

• **What is the difference between bagging and random forest?** Bagging and random forests are both ensemble learning techniques that combine the predictions of multiple decision trees to improve the accuracy and robustness of the model. However, there are some differences between these two methods:

- ***Sampling method:*** Bagging and random forests use different sampling methods to generate the training sets for the individual decision trees. Bagging samples the training data with replacement to create multiple subsets, each of which is used to train a decision tree. Random forests also sample the features used to split the nodes of each decision tree, in addition to sampling the training data.
- ***Decision tree construction:*** Bagging and random forests use different techniques for constructing the individual decision trees. Bagging uses a standard decision tree algorithm, such as CART or ID3, to build each tree independently. Random forests use a modified version of the decision tree algorithm, where only a random subset of features is considered for each split, rather than all features.
- ***Prediction aggregation:*** Bagging and random forests use different methods for aggregating the predictions of the individual decision trees. Bagging usually takes a simple average of the predictions of all decision trees to generate the final prediction. Random forests use a majority vote or weighted average of the predictions, where the weight of each tree depends on its accuracy.
- ***Performance:*** Random forests tend to perform better than bagging, especially for high-dimensional datasets with many features, because they can reduce the variance and overfitting of the individual decision trees. Random forests also provide an estimate of the importance of each feature, which can be useful for feature selection and interpretation.

In summary, both bagging and random forests are powerful ensemble learning techniques that can improve the accuracy and robustness of decision tree models. However, random forests add an additional layer of randomness by sampling the features used to split the nodes, which can further reduce the variance and overfitting of the individual trees, and provide better performance for high-dimensional datasets.

• **Why is it important for individual estimators in the random forest to have access to only a subset of all features?** In random forests, it is important for individual estimators (i.e., decision trees) to have access to only a subset of all features for several reasons:

- ***Reduces correlation:*** When decision trees are trained on all features, they tend to be highly correlated and make similar predictions, which can lead to overfitting and reduced performance. By limiting the number of features available to each tree, random forests can reduce the correlation between the trees and improve the diversity of the ensemble.
- ***Reduces overfitting:*** When there are many features in the dataset, individual trees can easily overfit the training data and perform poorly on unseen data. By using a random subset of features for each tree, random forests can reduce the overfitting and improve the generalization performance of the ensemble.
- ***Faster training:*** When there are many features in the dataset, training decision trees on all features can be computationally expensive and time-consuming. By using a random subset

of features for each tree, random forests can reduce the training time and make the algorithm more scalable.

- ***Feature importance:*** Random forests can also provide an estimate of the importance of each feature in the dataset, based on how often they are used to split the nodes of the individual trees. By identifying the most important features, random forests can help with feature selection and interpretation, and improve the understanding of the underlying data.

In summary, limiting the number of features available to each decision tree in random forests can improve the diversity, generalization performance, training time, and interpretability of the ensemble, making it a powerful and widely used machine learning technique.

- **Implement a random forest classifier to solve the classification problem again.**

[27]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data.drop('Credit_Score',␣
↪axis=1), data['Credit_Score'], test_size=0.2, random_state=8990)

# Initialize the random forest classifier
rfc = RandomForestClassifier(n_estimators=100, max_features='sqrt',␣
↪random_state=8990)

# Fit the classifier to the training data
rfc.fit(X_train, y_train)

# Make predictions on the test data
y_pred = rfc.predict(X_test)

# Evaluate the accuracy of the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.7664907651715039
```

- **Compare and contrast models from Section 3, 4 and 5.** Logistic regression, decision tree, and random forest are all popular machine learning algorithms used for classification tasks. Here are some key differences between these models:

- ***Model complexity:*** Logistic regression is a linear model that tries to find a linear boundary between classes, while decision trees and random forests can model more complex nonlinear boundaries. Random forests are a type of ensemble learning method that combines multiple decision trees, which can improve the accuracy and reduce overfitting compared to a single decision tree.

- ***Interpretability:*** Logistic regression is a simple and interpretable model that can provide coefficients that indicate the importance of each feature. Decision trees can also provide insights into the decision-making process by showing the split points for each feature. However, random forests can be more difficult to interpret due to the large number of trees and the ensemble nature of the model.

- ***Robustness to noise:*** Decision trees are susceptible to overfitting and can be sensitive to small changes in the training data. Random forests can reduce overfitting and improve generalization performance by using a subset of features and a bootstrap sampling technique. Logistic regression can also be susceptible to overfitting, but can be more robust to noisy features.
- ***Scalability:*** Logistic regression is a relatively fast and scalable algorithm, especially when the number of features is small. Decision trees and random forests can be slower and more computationally intensive, especially when the number of features and trees is large.

In terms of performance, the best algorithm depends on the specific dataset and problem at hand. Logistic regression can be effective when the relationship between the features and target is linear, while decision trees and random forests can handle more complex relationships. Random forests can often provide the highest accuracy and are robust to overfitting, but can be more difficult to interpret and slower to train.

In summary, logistic regression, decision tree, and random forest are all useful algorithms for classification tasks, but differ in terms of model complexity, interpretability, robustness to noise, and scalability. It is important to experiment with different algorithms and evaluate their performance on the specific dataset to determine the best model for the task at hand.

In this specific case, we can see that the Random Forests model gives us the highest accuracy of around 0.76. We also note that the accuracy of random forest model is almost 0.2 greater than that of logistic regression and almost 0.10 more than that obtained with the decision trees and bagging method.