In [171…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [172…
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

In [173…
```
%matplotlib inline
```

In [174…
```
df = pd.read_csv('HW2.csv')
df.head()
```

```
/var/folders/qs/5vt90tvd159ctgq252mwn07r0000gn/T/ipykernel_92460/3949404760.py:1: DtypeWarning: Columns (26) have mixed types. Specify dtype option on import or set low_memory=False.
  df = pd.read_csv('HW2.csv')
```

Out[174]:

	ID	Customer_ID	Month	Name	Age	SSN	Occupation	Annual_Income	Monthly_Inhand_Salary	Num_Bank_Accounts
0	0x1602	CUS_0xd40	January	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3
1	0x1603	CUS_0xd40	February	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3
2	0x1604	CUS_0xd40	March	Aaron Maashoh	-500	821-00-0265	Scientist	19114.12	NaN	3
3	0x1605	CUS_0xd40	April	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	NaN	3
4	0x1606	CUS_0xd40	May	Aaron Maashoh	23	821-00-0265	Scientist	19114.12	1824.843333	3

5 rows × 28 columns

In [175…
```
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
```

In [176…

```
df2 = df[[column for column in df if df[column].count()/len(df) >= 0.3]]
del df2['ID']
print("List of dropped columns:", end=" ")
for c in df.columns:
    if c not in df2.columns:
        print(c, end = ', ')
print('\n')
df = df2
```

```
List of dropped columns: ID,
```

In [177…

```python
print(df.isnull().values.any())
print(df.shape)
```

```
True
(100000, 27)
```

In [178…

```python
print(df.isnull().sum())
```

```
Customer_ID                     0
Month                           0
Name                         9985
Age                             0
SSN                             0
Occupation                      0
Annual_Income                   0
Monthly_Inhand_Salary       15002
Num_Bank_Accounts               0
Num_Credit_Card                 0
Interest_Rate                   0
Num_of_Loan                     0
Type_of_Loan                11408
Delay_from_due_date             0
Num_of_Delayed_Payment       7002
Changed_Credit_Limit            0
Num_Credit_Inquiries         1965
Credit_Mix                      0
Outstanding_Debt                0
Credit_Utilization_Ratio        0
Credit_History_Age           9030
Payment_of_Min_Amount           0
Total_EMI_per_month             0
Amount_invested_monthly      4479
Payment_Behaviour               0
Monthly_Balance              1200
Credit_Score                    0
dtype: int64
```

In [179…

```python
df.dropna(inplace=True)
```

Since the frequency of missing values are not too significant, we can decide to drop the null values and still be able to find some insights.

In [180…

```
for col in df:
    print(df[col].describe())
    print("\n")
```

```
count          53049
unique         11071
top        CUS_0x533b
freq               8
Name: Customer_ID, dtype: object


count       53049
unique          8
top       January
freq         6744
Name: Month, dtype: object


count      53049
unique      9168
top       Stevex
freq          30
Name: Name, dtype: object


count     53049
unique     1057
top          38
freq       1567
Name: Age, dtype: object


count         53049
unique        11064
top       #F%$D@*&8
freq           2971
Name: SSN, dtype: object


count       53049
unique         16
top       _______
freq         3727
Name: Occupation, dtype: object


count        53049
unique       14707
top       20867.67
```

```
freq            11
Name: Annual_Income, dtype: object


count    53049.000000
mean      4024.502617
std       3094.967739
min        303.645417
25%       1575.345833
50%       2991.016667
75%       5712.553333
max      15204.633333
Name: Monthly_Inhand_Salary, dtype: float64


count    53049.000000
mean        16.842806
std        115.605025
min         -1.000000
25%          4.000000
50%          6.000000
75%          8.000000
max       1798.000000
Name: Num_Bank_Accounts, dtype: float64


count    53049.000000
mean        22.787253
std        129.339640
min          0.000000
25%          4.000000
50%          6.000000
75%          7.000000
max       1499.000000
Name: Num_Credit_Card, dtype: float64


count    53049.000000
mean        76.272352
std        479.226709
min          1.000000
25%          8.000000
50%         15.000000
75%         22.000000
max       5797.000000
```

```
Name: Interest_Rate, dtype: float64


count     53049
unique      249
top           3
freq       8644
Name: Num_of_Loan, dtype: object


count             53049
unique             6259
top       Not Specified
freq                874
Name: Type_of_Loan, dtype: object


count    53049.000000
mean        21.994119
std         15.220406
min         -5.000000
25%         10.000000
50%         19.000000
75%         29.000000
max         67.000000
Name: Delay_from_due_date, dtype: float64


count     53049
unique      470
top          19
freq       3169
Name: Num_of_Delayed_Payment, dtype: object


count     53049
unique     3975
top           _
freq       1102
Name: Changed_Credit_Limit, dtype: object


count    53049.000000
mean        27.062866
std        187.185825
```

```
min          0.000000
25%          3.000000
50%          6.000000
75%          9.000000
max       2594.000000
Name: Num_Credit_Inquiries, dtype: float64


count        53049
unique           4
top       Standard
freq         19418
Name: Credit_Mix, dtype: object


count      53049
unique     11407
top       1151.7
freq          16
Name: Outstanding_Debt, dtype: object


count    53049.000000
mean        32.219031
std          5.057398
min         20.881250
25%         28.046338
50%         32.251786
75%         36.408991
max         49.564519
Name: Credit_Utilization_Ratio, dtype: float64


count                      53049
unique                       404
top       18 Years and 2 Months
freq                         257
Name: Credit_History_Age, dtype: object


count     53049
unique        3
top         Yes
freq      29670
Name: Payment_of_Min_Amount, dtype: object
```

```
count    53049.000000
mean      1445.924761
std       8407.429893
min          4.462837
25%         41.244418
50%         78.418272
75%        169.286269
max      82331.000000
Name: Total_EMI_per_month, dtype: float64


count         53049
unique        50540
top       __10000__
freq           2402
Name: Amount_invested_monthly, dtype: object


count                            53049
unique                               7
top       Low_spent_Small_value_payments
freq                             13581
Name: Payment_Behaviour, dtype: object


count                               53049
unique                              53044
top       __-333333333333333333333333333__
freq                                    6
Name: Monthly_Balance, dtype: object


count        53049
unique           3
top       Standard
freq         27951
Name: Credit_Score, dtype: object
```

In [181…

```
df = df[~df['Occupation'].str.contains("_")]
df = df[df['Num_Bank_Accounts']>0]
df = df[df['Delay_from_due_date']>0]
```

```
df = df[~df['Age'].astype(str).str.contains('_')]
df = df[df['Age'].astype(int)>0]
df = df[df['Age'].astype(int)<100]
df = df[~df['Amount_invested_monthly'].astype(str).str.contains('_')]
df = df[~df['Monthly_Balance'].astype(str).str.contains('_')]
df = df[~df['Changed_Credit_Limit'].astype(str).str.contains('_')]
df = df[~df['SSN'].astype(str).str.contains('#F%')]
df = df[~df['Num_of_Loan'].astype(str).str.contains('_')]
df = df[df['Num_of_Loan'].astype(int)>0]
df = df[~df['Credit_Mix'].astype(str).str.contains('_')]
df = df[~df['Payment_Behaviour'].astype(str).str.contains('!@')]
df = df[df['Changed_Credit_Limit'].astype(float)>0]
df = df[df['Num_Credit_Inquiries'].astype(int)<40]
df = df[df['Num_Credit_Inquiries'].astype(int)>0]
df = df[df['Num_of_Loan'].astype(int)<40]
df = df[df['Num_Bank_Accounts']<20]
df = df[df['Num_Credit_Card']<20]
df = df[df['Num_Credit_Card']>0]
df = df[df['Interest_Rate']<100]
df = df[df['Total_EMI_per_month']<2000.0]
df = df[~df['Num_of_Delayed_Payment'].astype(str).str.contains('_')]
df = df[df['Num_of_Delayed_Payment'].astype(int)<100]
df = df[~df['Annual_Income'].astype(str).str.contains('_')]
df = df[~df['Outstanding_Debt'].astype(str).str.contains('_')]
df = df[df['Annual_Income'].astype(float)<600000.0]
```

In [182…

```
df['Changed_Credit_Limit'] = df['Changed_Credit_Limit'].astype(float).round(3)
df['Total_EMI_per_month'] = df['Total_EMI_per_month'].round(3)
df['Credit_Utilization_Ratio'] = df['Credit_Utilization_Ratio'].round(3)
df['Amount_invested_monthly'] = df['Amount_invested_monthly'].astype(float).round(3)
df['Monthly_Balance'] = df['Monthly_Balance'].astype(float).round(3)
df['Monthly_Inhand_Salary'] = df['Monthly_Inhand_Salary'].round(3)
df['Annual_Income'] = df['Annual_Income'].astype(float).round(3)
```

In [183…

```
'''
Now let's change the data type from object to int/float for the columns:
int--
Age
Num_of_Loan
Delay_from_due_date

float--
Outstanding_Debt
'''
```

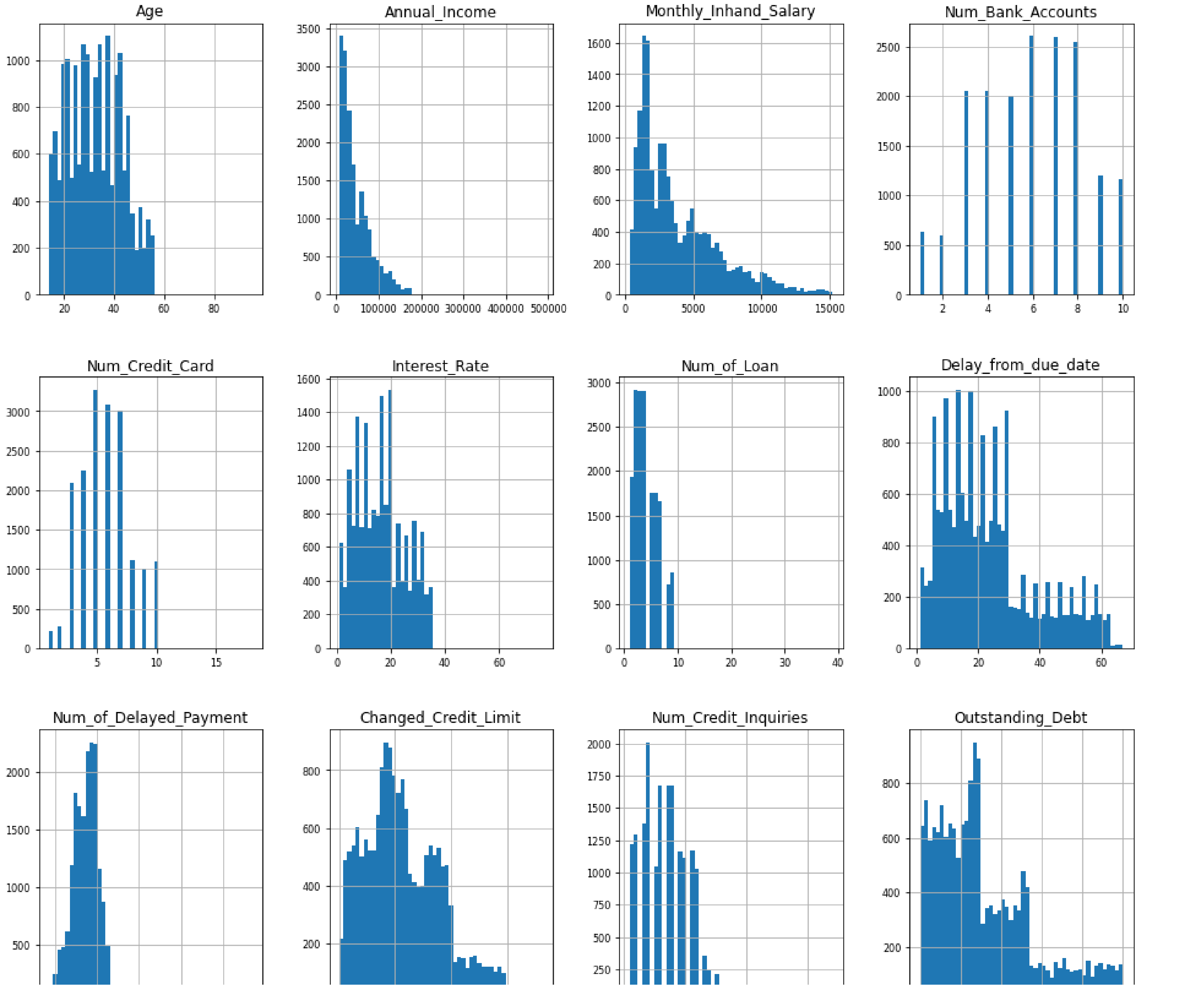
```
df['Age'] = df['Age'].astype('int64')
df['Num_of_Loan'] = df['Num_of_Loan'].astype('int64')
df['Delay_from_due_date'] = df['Delay_from_due_date'].astype('int64')
df['Num_of_Delayed_Payment'] = df['Num_of_Delayed_Payment'].astype('int64')
df['Outstanding_Debt'] = df['Outstanding_Debt'].astype('float64')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17431 entries, 9 to 99991
Data columns (total 27 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Customer_ID               17431 non-null  object 
 1   Month                     17431 non-null  object 
 2   Name                      17431 non-null  object 
 3   Age                       17431 non-null  int64  
 4   SSN                       17431 non-null  object 
 5   Occupation                17431 non-null  object 
 6   Annual_Income             17431 non-null  float64
 7   Monthly_Inhand_Salary     17431 non-null  float64
 8   Num_Bank_Accounts         17431 non-null  int64  
 9   Num_Credit_Card           17431 non-null  int64  
 10  Interest_Rate             17431 non-null  int64  
 11  Num_of_Loan               17431 non-null  int64  
 12  Type_of_Loan              17431 non-null  object 
 13  Delay_from_due_date       17431 non-null  int64  
 14  Num_of_Delayed_Payment    17431 non-null  int64  
 15  Changed_Credit_Limit      17431 non-null  float64
 16  Num_Credit_Inquiries      17431 non-null  float64
 17  Credit_Mix                17431 non-null  object 
 18  Outstanding_Debt          17431 non-null  float64
 19  Credit_Utilization_Ratio  17431 non-null  float64
 20  Credit_History_Age        17431 non-null  object 
 21  Payment_of_Min_Amount     17431 non-null  object 
 22  Total_EMI_per_month       17431 non-null  float64
 23  Amount_invested_monthly   17431 non-null  float64
 24  Payment_Behaviour         17431 non-null  object 
 25  Monthly_Balance           17431 non-null  float64
 26  Credit_Score              17431 non-null  object 
dtypes: float64(9), int64(7), object(11)
memory usage: 3.7+ MB
```

In [184…

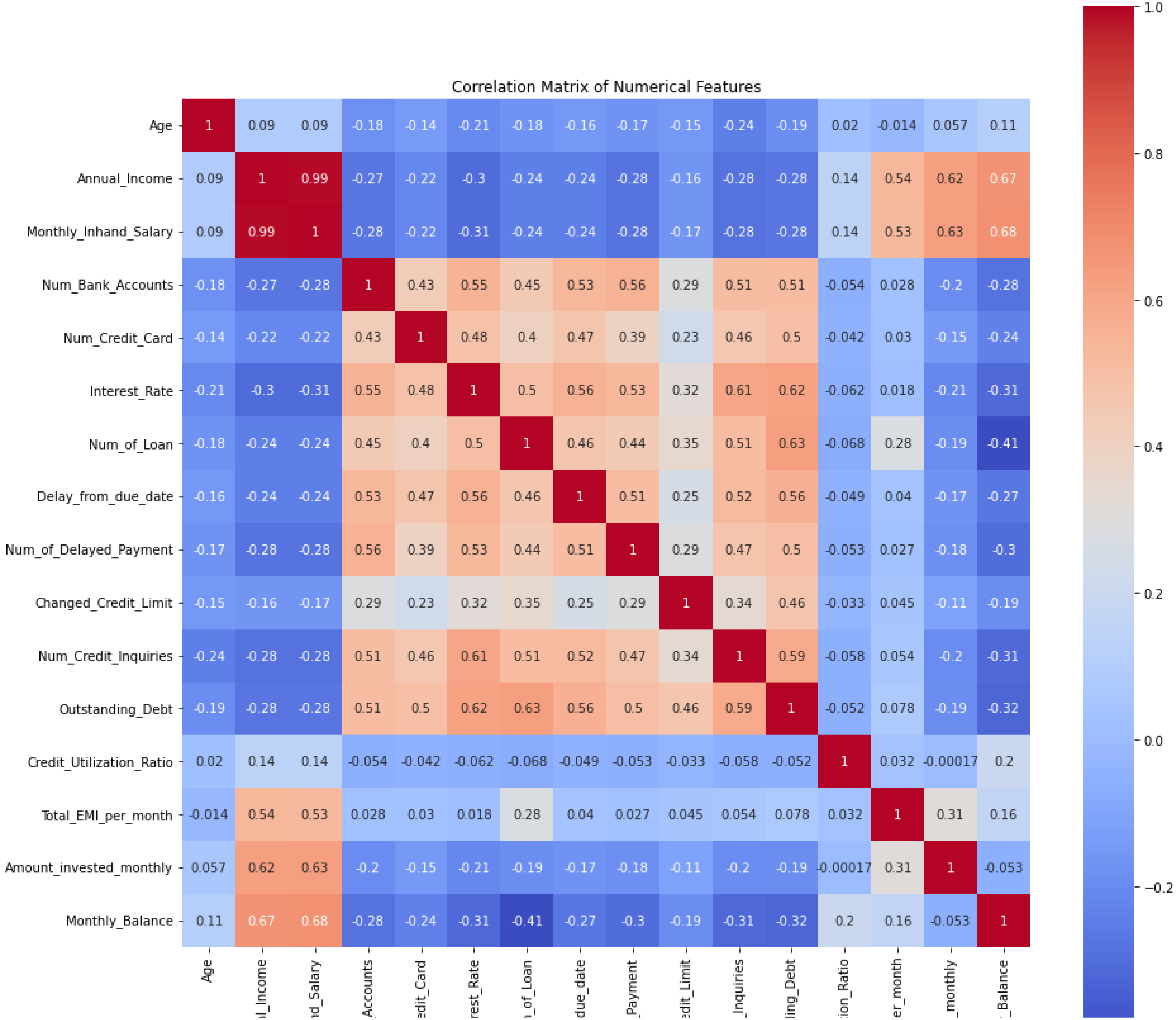
```
df_num = df.select_dtypes(include=['int64', 'float64'])
df_num.hist(figsize=(16,20), bins=50, xlabelsize=8, ylabelsize=8)
```

Out[184]:
```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'Annual_Income'}>,
        <AxesSubplot:title={'center':'Monthly_Inhand_Salary'}>,
        <AxesSubplot:title={'center':'Num_Bank_Accounts'}>],
       [<AxesSubplot:title={'center':'Num_Credit_Card'}>,
        <AxesSubplot:title={'center':'Interest_Rate'}>,
        <AxesSubplot:title={'center':'Num_of_Loan'}>,
        <AxesSubplot:title={'center':'Delay_from_due_date'}>],
       [<AxesSubplot:title={'center':'Num_of_Delayed_Payment'}>,
        <AxesSubplot:title={'center':'Changed_Credit_Limit'}>,
        <AxesSubplot:title={'center':'Num_Credit_Inquiries'}>,
        <AxesSubplot:title={'center':'Outstanding_Debt'}>],
       [<AxesSubplot:title={'center':'Credit_Utilization_Ratio'}>,
        <AxesSubplot:title={'center':'Total_EMI_per_month'}>,
        <AxesSubplot:title={'center':'Amount_invested_monthly'}>,
        <AxesSubplot:title={'center':'Monthly_Balance'}>]], dtype=object)
```


Age
Annual_Income
Monthly_Inhand_Salary
Num_Bank_Accounts
Num_Credit_Card
Interest_Rate
Num_of_Loan
Delay_from_due_date
Num_of_Delayed_Payment
Changed_Credit_Limit
Num_Credit_Inquiries
Outstanding_Debt

In [185…

```
corr_matrix = df_num.corr()
plt.figure(figsize=(15,15))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', square=True)
plt.title("Correlation Matrix of Numerical Features")
plt.show()
```


Correlation Matrix of Numerical Features
Age 1 0.09 0.09 -0.18 -0.14 -0.21 -0.18 -0.16 -0.17 -0.15 -0.24 -0.19 0.02 -0.014 0.057 0.11
Annual_Income 0.09 1 0.99 -0.27 -0.22 -0.3 -0.24 -0.24 -0.28 -0.16 -0.28 -0.28 0.14 0.54 0.62 0.67
Monthly_Inhand_Salary 0.09 0.99 1 -0.28 -0.22 -0.31 -0.24 -0.24 -0.28 -0.17 -0.28 -0.28 0.14 0.53 0.63 0.68
Num_Bank_Accounts -0.18 -0.27 -0.28 1 0.43 0.55 0.45 0.53 0.56 0.29 0.51 0.51 -0.054 0.028 -0.2 -0.28
Num_Credit_Card -0.14 -0.22 -0.22 0.43 1 0.48 0.4 0.47 0.39 0.23 0.46 0.5 -0.042 0.03 -0.15 -0.24
Interest_Rate -0.21 -0.3 -0.31 0.55 0.48 1 0.5 0.56 0.53 0.32 0.61 0.62 -0.062 0.018 -0.21 -0.31
Num_of_Loan -0.18 -0.24 -0.24 0.45 0.4 0.5 1 0.46 0.44 0.35 0.51 0.63 -0.068 0.28 -0.19 -0.41
Delay_from_due_date -0.16 -0.24 -0.24 0.53 0.47 0.56 0.46 1 0.51 0.25 0.52 0.56 -0.049 0.04 -0.17 -0.27
Num_of_Delayed_Payment -0.17 -0.28 -0.28 0.56 0.39 0.53 0.44 0.51 1 0.29 0.47 0.5 -0.053 0.027 -0.18 -0.3
Changed_Credit_Limit -0.15 -0.16 -0.17 0.29 0.23 0.32 0.35 0.25 0.29 1 0.34 0.46 -0.033 0.045 -0.11 -0.19
Num_Credit_Inquiries -0.24 -0.28 -0.28 0.51 0.46 0.61 0.51 0.52 0.47 0.34 1 0.59 -0.058 0.054 -0.2 -0.31
Outstanding_Debt -0.19 -0.28 -0.28 0.51 0.5 0.62 0.63 0.56 0.5 0.46 0.59 1 -0.052 0.078 -0.19 -0.32
Credit_Utilization_Ratio 0.02 0.14 0.14 -0.054 -0.042 -0.062 -0.068 -0.049 -0.053 -0.033 -0.058 -0.052 1 0.032 -0.00017 0.2
Total_EMI_per_month -0.014 0.54 0.53 0.028 0.03 0.018 0.28 0.04 0.027 0.045 0.054 0.078 0.032 1 0.31 0.16
Amount_invested_monthly 0.057 0.62 0.63 -0.2 -0.15 -0.21 -0.19 -0.17 -0.18 -0.11 -0.2 -0.19 -0.00017 0.31 1 -0.053
Monthly_Balance 0.11 0.67 0.68 -0.28 -0.24 -0.31 -0.41 -0.27 -0.3 -0.19 -0.31 -0.32 0.2 0.16 -0.053 1
Age
l_Income
d_Salary
Accounts
edit_Card
rest_Rate
_of_Loan
due_date
Payment
edit_Limit
Inquiries
ing_Debt
ion_Ratio
er_month
monthly
_Balance
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

Given the strong correlation between "Annual_Income" and "Monthly_Inhand_Salary", it is advisable to drop one of the variables. In this case, I will remove "Annual_Income" as the distribution of "Monthly_Inhand_Salary" appears to be more balanced.

In [186…

```
df.drop(columns=['Annual_Income'], inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 17431 entries, 9 to 99991
Data columns (total 26 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Customer_ID               17431 non-null  object 
 1   Month                     17431 non-null  object 
 2   Name                      17431 non-null  object 
 3   Age                       17431 non-null  int64  
 4   SSN                       17431 non-null  object 
 5   Occupation                17431 non-null  object 
 6   Monthly_Inhand_Salary     17431 non-null  float64
 7   Num_Bank_Accounts         17431 non-null  int64  
 8   Num_Credit_Card           17431 non-null  int64  
 9   Interest_Rate             17431 non-null  int64  
 10  Num_of_Loan               17431 non-null  int64  
 11  Type_of_Loan              17431 non-null  object 
 12  Delay_from_due_date       17431 non-null  int64  
 13  Num_of_Delayed_Payment    17431 non-null  int64  
 14  Changed_Credit_Limit      17431 non-null  float64
 15  Num_Credit_Inquiries      17431 non-null  float64
 16  Credit_Mix                17431 non-null  object 
 17  Outstanding_Debt          17431 non-null  float64
 18  Credit_Utilization_Ratio  17431 non-null  float64
 19  Credit_History_Age        17431 non-null  object 
 20  Payment_of_Min_Amount     17431 non-null  object 
 21  Total_EMI_per_month       17431 non-null  float64
 22  Amount_invested_monthly   17431 non-null  float64
 23  Payment_Behaviour         17431 non-null  object 
 24  Monthly_Balance           17431 non-null  float64
 25  Credit_Score              17431 non-null  object 
dtypes: float64(8), int64(7), object(11)
memory usage: 3.6+ MB
```

In [187…

```
df.shape
```

Out[187]:

```
(17431, 26)
```

In [189…

```
ohe_features = ['Customer_ID',
                'Month',
                'Name',
                'SSN',
                'Occupation'
                ]
```

```
te_features = [ 'Type_of_Loan',
                'Credit_Mix',
                'Credit_History_Age',
                'Payment_of_Min_Amount',
                'Payment_Behaviour',
                ]

num_features = ['Age',
                'Monthly_Balance',
                'Amount_invested_monthly',
                'Outstanding_Debt',
                'Changed_Credit_Limit',
                'Num_of_Delayed_Payment',
                'Monthly_Inhand_Salary',
                'Num_Bank_Accounts',
                'Num_Credit_Card',
                'Interest_Rate',
                'Num_of_Loan',
                'Delay_from_due_date',
                'Num_Credit_Inquiries',
                'Credit_Utilization_Ratio',
                'Total_EMI_per_month']

feature_names = ohe_features + te_features + num_features
```

In [188…

```
# Encode non-numeric values
categorical_cols = ['Credit_Score'] + ohe_features + te_features
for col in categorical_cols:
    if df[col].dtype == 'object':
        df[col] = df[col].astype('category').cat.codes
```

```
Customer_ID                 0
Month                       0
Name                        0
Age                         0
SSN                         0
Occupation                  0
Monthly_Inhand_Salary       0
Num_Bank_Accounts           0
Num_Credit_Card             0
Interest_Rate               0
Num_of_Loan                 0
Type_of_Loan                0
Delay_from_due_date         0
Num_of_Delayed_Payment      0
Changed_Credit_Limit        0
Num_Credit_Inquiries        0
Credit_Mix                  0
Outstanding_Debt            0
Credit_Utilization_Ratio    0
Credit_History_Age          0
Payment_of_Min_Amount       0
Total_EMI_per_month         0
Amount_invested_monthly     0
Payment_Behaviour           0
Monthly_Balance             0
Credit_Score                0
dtype: int64
```

In [196…

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, OrdinalEncoder
from sklearn.compose import make_column_transformer
from category_encoders import TargetEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import make_pipeline


X_dev, X_test, y_dev, y_test = train_test_split(df[feature_names], df[['Credit_Score']], stratify=df[['Credit_
X_train, X_val, y_train, y_val = train_test_split(X_dev, y_dev, stratify=y_dev, test_size=0.2, random_state=4

lg = LogisticRegression(multi_class='multinomial', solver='lbfgs', max_iter=1000)
preprocess = make_column_transformer((StandardScaler(), num_features),
```

```
                                    (OneHotEncoder(handle_unknown='ignore'), ohe_features),
                                     (TargetEncoder(handle_unknown='ignore'), te_features),
                                     remainder='passthrough')
pipe = make_pipeline(preprocess, GridSearchCV(lg,
                                             param_grid={},
                                             return_train_score=True))

pipe.fit(X_train, y_train)
grid_search_results = pipe.named_steps['gridsearchcv']
print(f"Best train score: ", grid_search_results.best_score_)
print(f"Best train alpha: ", grid_search_results.best_params_)
print(f"Test score:", pipe.score(X_dev, y_dev))
```

```
Warning: No categorical columns found. Calling 'transform' will only return input data.
```

```
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,
), for example using ravel().
  y = column_or_1d(y, warn=True)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_logistic.py:814: ConvergenceW
arning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993: DataConversionWarn
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    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993: DataConversionWarn
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), for example using ravel().
  y = column_or_1d(y, warn=True)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_logistic.py:814: ConvergenceW
arning: lbfgs failed to converge (status=1):
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993: DataConversionWarn
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), for example using ravel().
  y = column_or_1d(y, warn=True)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_logistic.py:814: ConvergenceW
arning: lbfgs failed to converge (status=1):
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/validation.py:993: DataConversionWarn
ing: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,
), for example using ravel().
  y = column_or_1d(y, warn=True)
Best train score:  0.6649036306588973
Best train alpha:  {}
Test score: 0.6645152036718301
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/linear_model/_logistic.py:814: ConvergenceW
arning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

During the model development phase, a validation dataset is used to improve the performance of a model by evaluating its performance on a subset of the original data that is held out during training. This dataset is used to fine-tune the model's hyperparameters and select the best performing model. While the validation dataset is helpful in improving the model's performance during training, it should not be used to obtain a final estimate of the model's performance on new, unseen data. Instead, a separate test dataset should be used for this purpose to ensure an unbiased estimate of the model's performance.

In [192…

```
y_pred = pipe.predict(X_val)
val_acc = accuracy_score(y_val, y_pred)
val_report = classification_report(y_val, y_pred)
print("Validation accuracy:", val_acc)
print("Validation classification report:", val_report)
```

```
Validation accuracy: 0.6457511652922194
Validation classification report:               precision    recall  f1-score   support

           0       0.56      0.46      0.51       373
           1       0.67      0.54      0.60       945
           2       0.65      0.76      0.70      1471

    accuracy                           0.65      2789
   macro avg       0.63      0.59      0.60      2789
weighted avg       0.65      0.65      0.64      2789
```

In [193…

```
y_pred = pipe.predict(X_test)
test_acc = accuracy_score(y_test, y_pred)
test_report = classification_report(y_test, y_pred)
print("Test accuracy:", test_acc)
print("Test classification report:", test_report)
```

```
Test accuracy: 0.6498422712933754
Test classification report:               precision    recall  f1-score   support

           0       0.56      0.46      0.51       467
           1       0.67      0.55      0.61      1181
           2       0.66      0.76      0.70      1839

    accuracy                           0.65      3487
   macro avg       0.63      0.59      0.61      3487
weighted avg       0.65      0.65      0.64      3487
```

Based on the classification report, the model has an overall test accuracy of 0.65, meaning it correctly predicted 65% of the samples in the test set.

The precision for class 0 is 0.56, meaning that out of all the samples the model predicted to be in class 0, only 56% of them are actually in class 0. The recall for class 0 is 0.46, meaning that out of all the samples in class 0, the model correctly predicted 46% of them. The F1-score for class 0 is 0.51, which is the harmonic mean of precision and recall.

Similarly, for class 1, the precision is 0.67, the recall is 0.55, and the F1-score is 0.61. For class 2, the precision is 0.66, the recall is 0.76, and the F1-score is 0.70.

The macro-average F1-score is 0.61, which is the average of the F1-scores for all three classes. The weighted-average F1-score is 0.64, which takes into account the imbalance in the number of samples in each class. Overall, the model performs reasonably well but may need further improvements, especially for predicting class 0.

CART has several benefits, such as producing easily interpretable decision trees, processing both numerical and categorical data for classification and regression, and handling missing data through exclusion during tree construction. However, the algorithm is susceptible to overfitting when the tree grows too deep or when the stopping criterion is not optimized.

In [204…

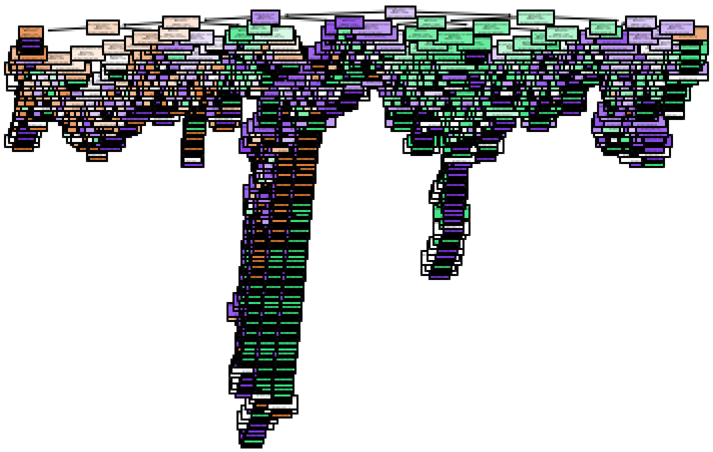
```
from sklearn.tree import DecisionTreeClassifier, plot_tree

dtc = DecisionTreeClassifier(random_state=82)
preprocess = make_column_transformer((StandardScaler(), num_features),
                                    (OneHotEncoder(handle_unknown='ignore'), ohe_features),
                                     (TargetEncoder(handle_unknown='ignore'), te_features),
                                     remainder='passthrough')
pipe = make_pipeline(preprocess, GridSearchCV(dtc,
                                             param_grid={},
                                             return_train_score=True))

pipe.fit(X_train, y_train)
grid_search_results = pipe.named_steps['gridsearchcv']
print(f"Best train score: ", grid_search_results.best_score_)
print(f"Best train alpha: ", grid_search_results.best_params_)
print(f"Test score:", pipe.score(X_dev, y_dev))
```

```
Warning: No categorical columns found. Calling 'transform' will only return input data.
Best train score:  0.6893769610040341
Best train alpha:  {}
Test score: 0.9386115892139989
```

In [205…

```
best_tree = grid_search_results.best_estimator_
ohe_feature_names = preprocess.named_transformers_['onehotencoder'].get_feature_names()
te_feature_names = preprocess.named_transformers_['targetencoder'].get_feature_names()
feature_names = num_features + ohe_feature_names.tolist() + te_feature_names
visual_tree = plot_tree(best_tree, feature_names=feature_names, filled=True)
plt.show()
```

```
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Fun
ction get_feature_names is deprecated; get_feature_names is deprecated in 1.0 and will be removed in 1.2. Ple
ase use get_feature_names_out instead.
  warnings.warn(msg, category=FutureWarning)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/category_encoders/utils.py:360: FutureWarning: `get
_feature_names` is deprecated in all of sklearn. Use `get_feature_names_out` instead.
  warnings.warn("`get_feature_names` is deprecated in all of sklearn. Use `get_feature_names_out` instead.",
```



In [206…

```
test_accuracies = []

for i in range(30):
    dtc = DecisionTreeClassifier(random_state=i)
    preprocess = make_column_transformer((StandardScaler(), num_features),
                                         (OneHotEncoder(handle_unknown='ignore'), ohe_features),
                                         (TargetEncoder(handle_unknown='ignore'), te_features),
                                         remainder='passthrough')
    pipe = make_pipeline(preprocess, GridSearchCV(dtc,
                                                  param_grid={},
                                                  return_train_score=True))
    pipe.fit(X_train, y_train)
    test_accuracy = pipe.score(X_dev, y_dev)
    test_accuracies.append(test_accuracy)
    print(f"Run {i}: test score = {test_accuracy}")

test_accuracies = np.array(test_accuracies)
mean_accuracy = np.mean(test_accuracies)
std_accuracy = np.std(test_accuracies)

print(f"Average accuracy: {mean_accuracy}")
print(f"Standard deviation: {std_accuracy}")
```

```
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 0: test score = 0.9403327596098681
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 1: test score = 0.9395438898450946
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 2: test score = 0.9389701663798049
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 3: test score = 0.9389701663798049
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 4: test score = 0.9398307515777395
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 5: test score = 0.9386833046471601
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 6: test score = 0.9386833046471601
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 7: test score = 0.9397590361445783
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 8: test score = 0.9400458978772231
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 9: test score = 0.9388984509466437
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 10: test score = 0.9399024670109007
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 11: test score = 0.9394004589787722
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 12: test score = 0.9396873207114171
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 13: test score = 0.9395438898450946
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 14: test score = 0.9398307515777395
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 15: test score = 0.9403327596098681
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 16: test score = 0.9391135972461274
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 17: test score = 0.9381095811818704
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 18: test score = 0.9391853126792886
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 19: test score = 0.9399024670109007
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 20: test score = 0.9390418818129661
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 21: test score = 0.9399024670109007
Warning: No categorical columns found. Calling 'transform' will only return input data.
```

```
Run 22: test score = 0.9392570281124498
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 23: test score = 0.9397590361445783
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 24: test score = 0.9386833046471601
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 25: test score = 0.9388984509466437
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 26: test score = 0.9392570281124498
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 27: test score = 0.9405479059093517
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 28: test score = 0.939328743545611
Warning: No categorical columns found. Calling 'transform' will only return input data.
Run 29: test score = 0.9401893287435457
Average accuracy: 0.9394530502964239
Standard deviation: 0.0005745993187061979
```

Both bagging and random forests are powerful ensemble learning techniques that utilize multiple decision trees to enhance model performance. Bagging generates independent bootstrap samples of the training data, and fits a decision tree to each sample, with predictions being aggregated across all trees in the ensemble. On the other hand, random forests use a specific type of bagging, where each decision tree is trained on a random subset of features, reducing the risk of overfitting and increasing generalization performance. Random forests also employ feature bagging, or random subspace method, to add more randomness to the model, and further reduce overfitting. Overall, random forests are a more sophisticated approach than bagging for boosting model performance.

Feature subsampling, a key technique in random forest models, trains each decision tree on a random subset of features, reducing correlation between trees, avoiding overfitting, and increasing model performance. By enabling the model to focus on the most important features while ignoring the noise, this technique is efficient in handling high-dimensional and complex data.

In [203…

```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(random_state=0)
param_grid = {}
pipe = make_pipeline(preprocess, GridSearchCV(rfc,
                                              param_grid = param_grid,
                                              return_train_score=True))
pipe.fit(X_train, y_train)
grid_search_results = pipe.named_steps['gridsearchcv']
print(f"Best train score: ", grid_search_results.best_score_)
```

```
print(f"Best train alpha: ", grid_search_results.best_params_)
print(f"Test score:", pipe.score(X_dev, y_dev))
```

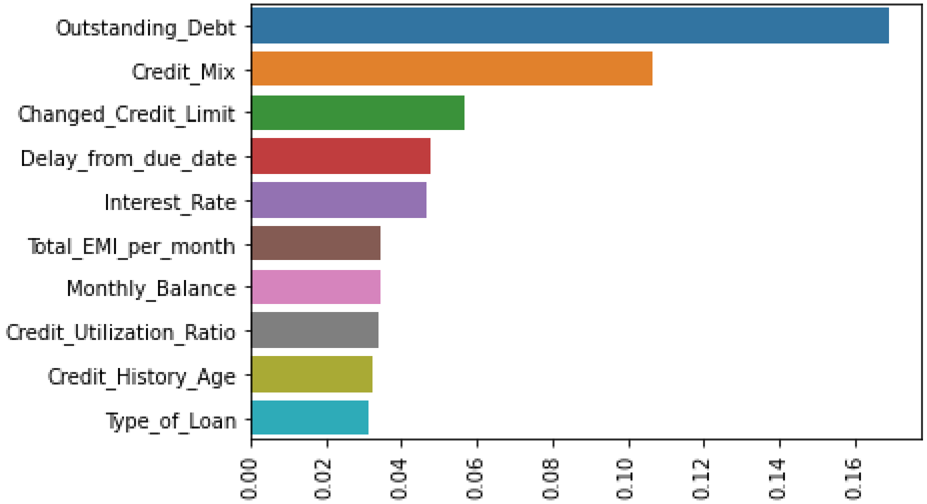
```
Warning: No categorical columns found. Calling 'transform' will only return input data.
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_validation.py:680: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_validation.py:680: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_validation.py:680: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_validation.py:680: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_validation.py:680: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/sklearn/model_selection/_search.py:926: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().
  self.best_estimator_.fit(X, y, **fit_params)
Best train score:  0.7367099955177051
Best train alpha:  {}
Test score: 0.9491537578886976
```

Random forest had a higher train/test score than those of decision tree classifiers and logistic regression models. The results of this evaluation indicate that the random forest model outperformed the other two models in terms of its train/test score. This suggests that the random forest algorithm was better able to capture the underlying patterns and relationships within the data and make more accurate predictions than the decision tree classifiers and logistic regression models.

In [207…

```
rf = grid_search_results.best_estimator_
feat_imps = zip(feature_names, rf.feature_importances_)
feats, imps = zip(*(sorted(list(filter(lambda x: x[1] != 0, feat_imps)), key=lambda x:x[1], reverse=True)))
ax = sns.barplot(list(imps[:10]), list(feats[:10]))
ax.tick_params(axis='x', rotation=90)
```

```
/Users/jasonjin/opt/anaconda3/lib/python3.9/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



In [ ]:

In [ ]: