Credit_Risk_Analysis

December 10, 2023

1 End to End Data Mining Project

1.1 Classification Problem: to analyse a loan data set for credit risk analysis

Target variable: default (index)

- a) Discover and visualise the data
- b) Prepare the data for ML
- c) Select and train models
- d) Fine-tune the models
- e) Evaluate outcomes

2 Discover and visualise the data

Dataset: Loan data set for credit risk analysis (https://www.kaggle.com/datasets/rameshmehta/credit-risk-analysis)

Moreover, the dataset is very unbalanced, with approximately 6 % of loans considered as defaulted. This dataset has different types of features such as categorical, numeric & date.

2.1 Uploading and reading the data

Indented block

[ ]:
```
import pandas as pd
import csv

from google.colab import drive
drive.mount('/content/drive')

path = "/content/drive/MyDrive/dataset/data.csv"
df =  pd.read_csv(path)

df.head(10)
```

```
Mounted at /content/drive
```

```
<ipython-input-1-e91b16405913>:8: DtypeWarning: Columns (17,45,53) have mixed
types. Specify dtype option on import or set low_memory=False.
  df =  pd.read_csv(path)
```

[ ]:

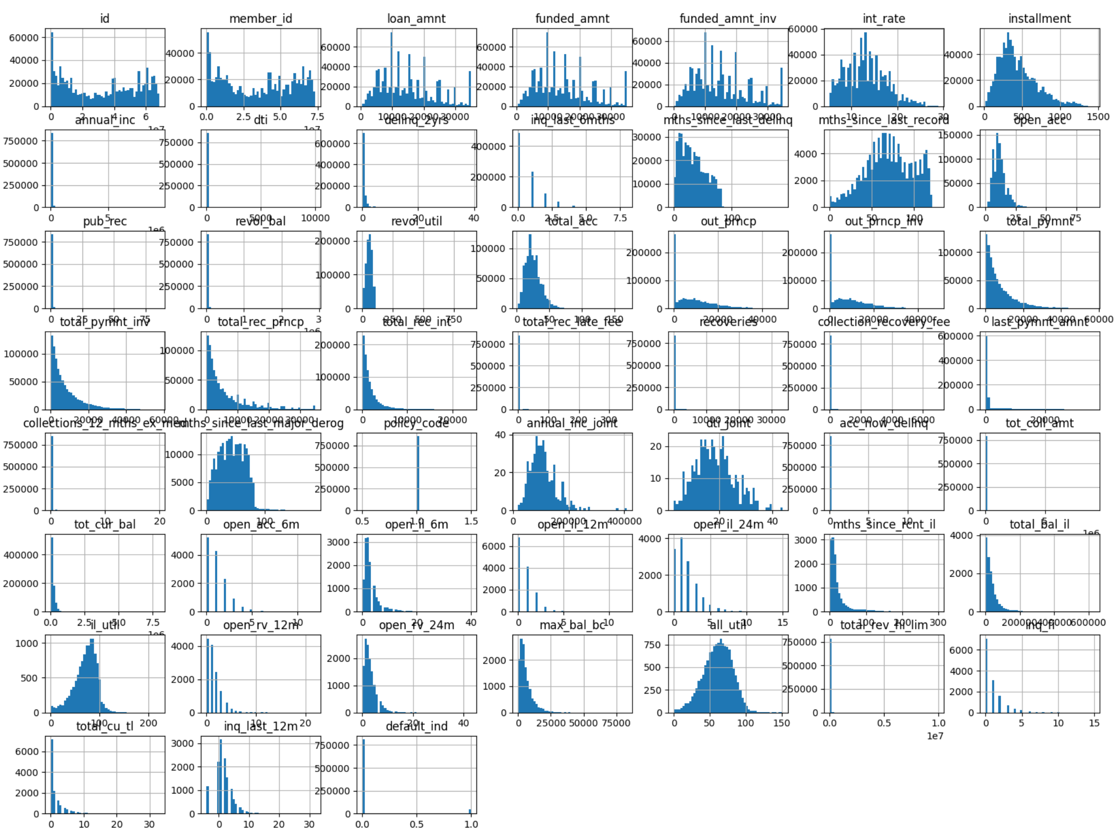
```
        id  member_id  loan_amnt  funded_amnt  funded_amnt_inv        term  \
0  1077501    1296599       5000         5000           4975.0   36 months
1  1077430    1314167       2500         2500           2500.0   60 months
2  1077175    1313524       2400         2400           2400.0   36 months
3  1076863    1277178      10000        10000          10000.0   36 months
4  1075358    1311748       3000         3000           3000.0   60 months
5  1075269    1311441       5000         5000           5000.0   36 months
6  1069639    1304742       7000         7000           7000.0   60 months
7  1072053    1288686       3000         3000           3000.0   36 months
8  1071795    1306957       5600         5600           5600.0   60 months
9  1071570    1306721       5375         5375           5350.0   60 months

   int_rate  installment grade sub_grade  … il_util open_rv_12m open_rv_24m  \
0     10.65       162.87     B        B2  …     NaN         NaN         NaN
1     15.27        59.83     C        C4  …     NaN         NaN         NaN
2     15.96        84.33     C        C5  …     NaN         NaN         NaN
3     13.49       339.31     C        C1  …     NaN         NaN         NaN
4     12.69        67.79     B        B5  …     NaN         NaN         NaN
5      7.90       156.46     A        A4  …     NaN         NaN         NaN
6     15.96       170.08     C        C5  …     NaN         NaN         NaN
7     18.64       109.43     E        E1  …     NaN         NaN         NaN
8     21.28       152.39     F        F2  …     NaN         NaN         NaN
9     12.69       121.45     B        B5  …     NaN         NaN         NaN

   max_bal_bc all_util total_rev_hi_lim inq_fi total_cu_tl inq_last_12m  \
0         NaN      NaN              NaN    NaN         NaN          NaN
1         NaN      NaN              NaN    NaN         NaN          NaN
2         NaN      NaN              NaN    NaN         NaN          NaN
3         NaN      NaN              NaN    NaN         NaN          NaN
4         NaN      NaN              NaN    NaN         NaN          NaN
5         NaN      NaN              NaN    NaN         NaN          NaN
6         NaN      NaN              NaN    NaN         NaN          NaN
7         NaN      NaN              NaN    NaN         NaN          NaN
8         NaN      NaN              NaN    NaN         NaN          NaN
9         NaN      NaN              NaN    NaN         NaN          NaN

  default_ind
0           0
1           1
2           0
3           0
4           0
5           0
```

```
6              0
7              0
8              1
9              1

[10 rows x 73 columns]
```

2.2 Exploratory Visualisations

2.2.1 Histograms

[ ]:
```python
%matplotlib inline
import matplotlib.pyplot as plt

# Plot the histograms for attributes
df.hist(bins = 50, figsize = (20, 15))
plt.show()
```



2.2.2 Interpretation

To start off, the x-axis represents the range of values for each attribute and is divided into bins that represents a specific range of values. The y-axis represents the frequency of values within each bin. It shows how many data points fall within the corresponding range of values on the x-axis.

1) Shape of histograms

Symmetric Distribution: The histogram is roughly symmetrical around a central value which indicates a normal distribution. This means that the data points are evenly distributed around the mean, and there are approximately an equal number of data points on both sides of the central value. From the result shown above, an example is all_util.

Skewed Distribution: The histogram is skewed to the left or right. A left-skewed (negative-skewed) distribution indicates that the majority of the data points are on the right side. A right-skewed (positive-skewed) distribution indicates that the majority of the data points are on the left side. An example of this is total_pymnt.

2) Central Tendency: The central tendency of the data can be estimated from the histogram. For a symmetric distribution, the peak of the histogram corresponds to the mean, median, and mode, which are all the same in a normal distribution. For skewed distributions, these measures may differ.

3) Spread: The spread or variability of the data can be observed by looking at the width of the histogram. A wider histogram indicates higher variability, whereas a narrower histogram indicates lower variability. For example, the attribute max_bal_bc has a higher variability than all_util.

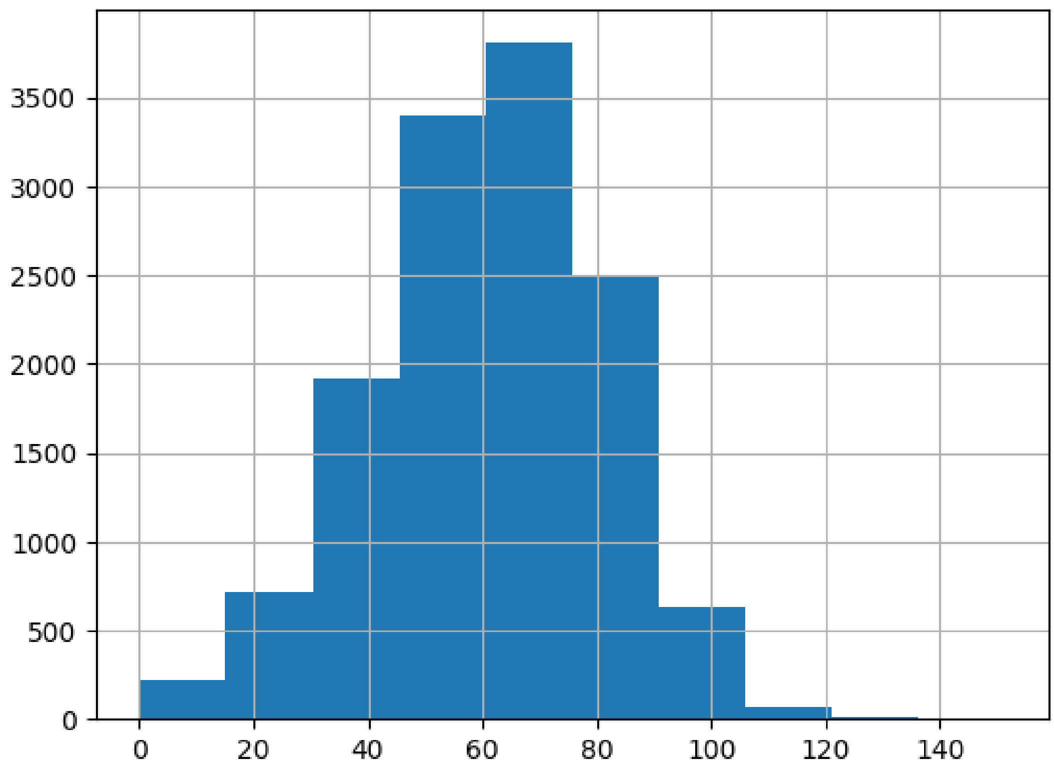
4) Outliers: Outliers, which are extreme values in the data, can also be identified from the histogram. Outliers are data points that lie far away from the bulk of the data and may appear as isolated bars far from the main distribution. For example, it is observed that there are outliers in the histogram of annual_inc_joint.

5) Multimodal Distribution: If there are multiple peaks in the histogram, it suggests a multimodal distribution, indicating that the data may have multiple distinct groups or categories.

2.2.3 Symmetric distribution example

[ ]:
```
df['all_util'].hist()
```

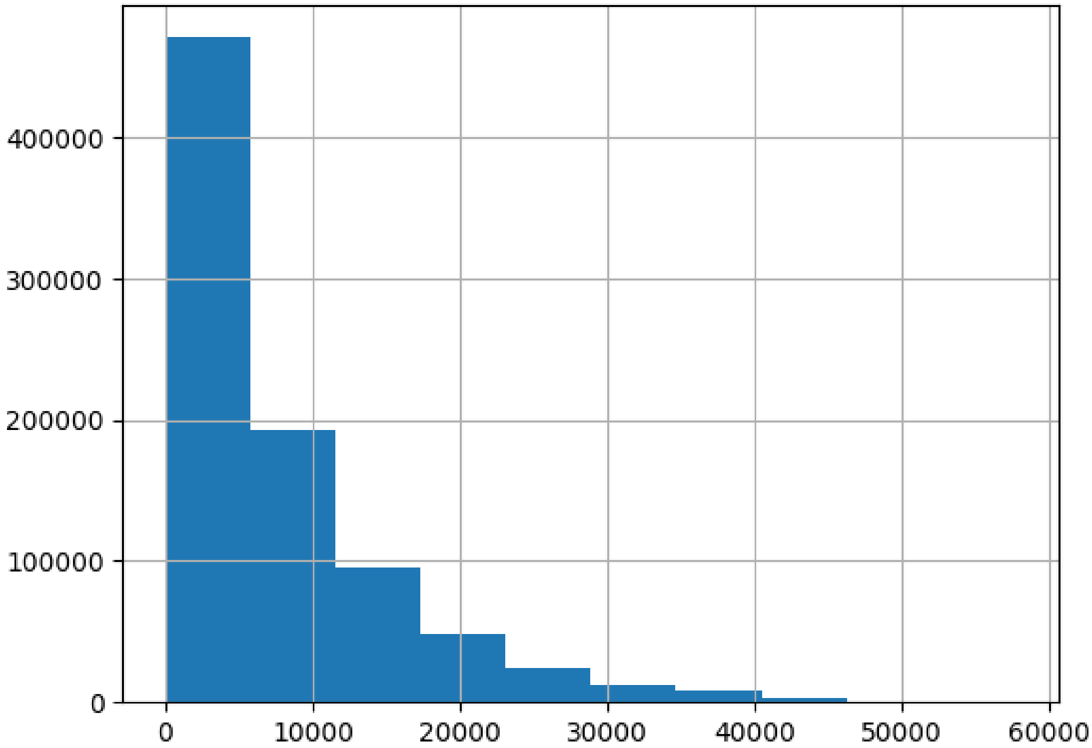
[ ]:
```
<Axes: >
```



2.2.4 Skewed distribution example

[ ]:
```
df['total_pymnt'].hist()
```

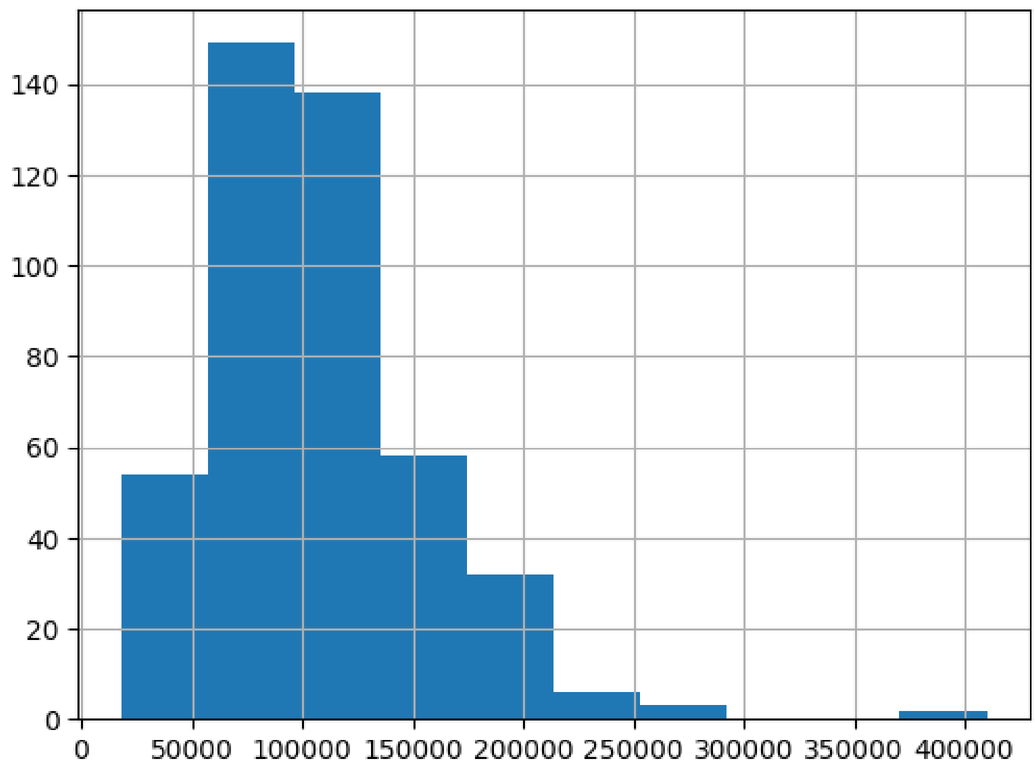
[ ]: <Axes: >



2.2.5 Outliers example

[ ]:
```
df['annual_inc_joint'].hist()
```

[ ]: <Axes: >



#Prepare the data for machine learning algorithms

2.3 Check for duplicate rows

[ ]:
```
# Check if there is any duplicate rows and drop them
df = df.drop_duplicates(subset = None, keep = 'first', inplace = False)
print(f"Number of duplicate rows: {df.duplicated().sum()}")
df
```

```
Number of duplicate rows: 0
```

[ ]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	\
0	1077501	1296599	5000	5000	4975.0	
1	1077430	1314167	2500	2500	2500.0	
2	1077175	1313524	2400	2400	2400.0	
3	1076863	1277178	10000	10000	10000.0	
4	1075358	1311748	3000	3000	3000.0	
…	…	…	…	…	…	
855964	36371250	39102635	10000	10000	10000.0	
855965	36441262	39152692	24000	24000	24000.0	
855966	36271333	38982739	13000	13000	13000.0	
855967	36490806	39222577	12000	12000	12000.0	

```
855968  36271262   38982659      20000        20000          20000.0

              term  int_rate  installment grade sub_grade  … il_util  \
0        36 months     10.65       162.87     B        B2  …     NaN
1        60 months     15.27        59.83     C        C4  …     NaN
2        36 months     15.96        84.33     C        C5  …     NaN
3        36 months     13.49       339.31     C        C1  …     NaN
4        60 months     12.69        67.79     B        B5  …     NaN
…              …        …           …   …         …  …       …
855964   36 months     11.99       332.10     B        B5  …     NaN
855965   36 months     11.99       797.03     B        B5  …     NaN
855966   60 months     15.99       316.07     D        D2  …     NaN
855967   60 months     19.99       317.86     E        E3  …     NaN
855968   36 months     11.99       664.20     B        B5  …     NaN

       open_rv_12m open_rv_24m  max_bal_bc all_util total_rev_hi_lim inq_fi  \
0              NaN         NaN         NaN      NaN              NaN    NaN
1              NaN         NaN         NaN      NaN              NaN    NaN
2              NaN         NaN         NaN      NaN              NaN    NaN
3              NaN         NaN         NaN      NaN              NaN    NaN
4              NaN         NaN         NaN      NaN              NaN    NaN
…              …          …          …        …              …     …
855964         NaN         NaN         NaN      NaN          17100.0    NaN
855965         NaN         NaN         NaN      NaN          10200.0    NaN
855966         NaN         NaN         NaN      NaN          18000.0    NaN
855967         NaN         NaN         NaN      NaN          27000.0    NaN
855968         NaN         NaN         NaN      NaN          41700.0    NaN

       total_cu_tl inq_last_12m default_ind
0              NaN          NaN           0
1              NaN          NaN           1
2              NaN          NaN           0
3              NaN          NaN           0
4              NaN          NaN           0
…              …           …          …
855964         NaN          NaN           0
855965         NaN          NaN           0
855966         NaN          NaN           0
855967         NaN          NaN           0
855968         NaN          NaN           0

[855969 rows x 73 columns]
```

Based on the result above, there is no duplicate row.

2.4 First review of columns to be removed

Based on the dictionary provided, they are some attributes that are not relevant to predicting the loan default and will be removed.

```
[ ]: # First review of columns to be removed (data that serve little meanings)
unhelpColumns =␣
  ↪['id','member_id','grade','emp_title','desc','title','zip_code','verification_status_joint']
df.drop(unhelpColumns, axis=1, inplace=True)
```

2.5 Refine attributes

Convert date object columns to useful information of float type

```
[ ]: # Find the neighbor index where new derived columns will be inserted
target_index = df.columns.get_loc('issue_d')

# Insert the new column (pymnt_gap) beside the specific column
df.insert(target_index + 1, 'pymnt_gap', '')

# Insert the new column (pymnt_duration) beside the specific column
df.insert(target_index + 1, 'pymnt_duration', '')

# Insert the new column (credit_hist) beside the specific column
df.insert(target_index + 1, 'credit_hist', '')
```

```
[ ]: # Convert the object-type columns to datetime type
df['issue_d'] = pd.to_datetime(df['issue_d'])
df['last_pymnt_d'] = pd.to_datetime(df['last_pymnt_d'])
df['next_pymnt_d'] = pd.to_datetime(df['next_pymnt_d'])
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'])


# Update pymnt_duration: How long payment has been ongoing in days
df['pymnt_duration'] = (df['last_pymnt_d'] - df['issue_d']).dt.days

# Update pymnt_gap: What is the duration from previous payment to next payment␣
  ↪in days
df['pymnt_gap'] = (df['next_pymnt_d'] - df['last_pymnt_d']).dt.days

# Update credit_hist: The Earliest activation of credit account to when loan␣
  ↪issued
df['credit_hist'] = (df['issue_d'] - df['earliest_cr_line']).dt.days
```

```
[ ]: # Once the dates have been used, remove them

# Second review of unhelpful columns to be removed (dates)
```

```
dateColumns =␣
 ↪['issue_d','earliest_cr_line','last_pymnt_d','next_pymnt_d','last_credit_pull_d']
df.drop(dateColumns, axis=1, inplace=True)
```

Convert some object columns into float columns via numeric extraction

```
[ ]: # Extract numbers in object columns & convert to float
import pandas as pd

# Update column emp_length
df['emp_length'] = df['emp_length'].str.extract('(\d+)', expand=False).
 ↪astype(float)

# Update column term
df['term'] = df['term'].str.extract('(\d+)', expand=False).astype(float)
```

2.6 Encoding categorical columns

```
[ ]: # Get the list of integer & float columns (excluding the last column)
obj_columns = df.select_dtypes(include='object').columns.tolist()
df[obj_columns].head(3)
```

```
[ ]:   sub_grade home_ownership verification_status pymnt_plan         purpose  \
0        B2           RENT            Verified          n     credit_card
1        C4           RENT     Source Verified          n             car
2        C5           RENT        Not Verified          n  small_business

  addr_state initial_list_status application_type
0         AZ                   f       INDIVIDUAL
1         GA                   f       INDIVIDUAL
2         IL                   f       INDIVIDUAL
```

```
[ ]: # Identify the categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns
categorical_columns
```

```
[ ]: Index(['sub_grade', 'home_ownership', 'verification_status', 'pymnt_plan',
       'purpose', 'addr_state', 'initial_list_status', 'application_type'],
      dtype='object')
```

2.6.1 Label encoding

To calculate the correlations, categorical columns need to be converted to numerical columns in the first place.

In the list above, label encoding should be applied to sub_grade as it represents an ordinal relationship among the sub-grades (eg. A1<A2<A3). Label encoding will preserve this order while

converting them to numerical values. One-hot encoding will be applied to other attributes as they are nominal and do not have an inherent order.

Use label encoder to convert columns of objects to columns of floats

```
[ ]: import pandas as pd
     from sklearn.preprocessing import LabelEncoder

     # Assuming your DataFrame is named df

     # Create an instance of LabelEncoder
     label_encoder = LabelEncoder()

     # Apply label encoding to the specified columns

     df['sub_grade'] = label_encoder.fit_transform(df['sub_grade'])
     df['purpose'] = label_encoder.fit_transform(df['purpose'])
     df['addr_state'] = label_encoder.fit_transform(df['addr_state'])
```

2.6.2 One-hot encoding

Use hot encoder to convert columns of objects objects to columns of binary

```
[ ]: # Get the list of integer & float columns (excluding the last column)
     obj_columns = df.select_dtypes(include='object').columns.tolist()
     df[obj_columns].head(3)
```

```
[ ]:   home_ownership verification_status pymnt_plan initial_list_status  \
     0           RENT            Verified          n                   f
     1           RENT     Source Verified          n                   f
     2           RENT        Not Verified          n                   f

       application_type
     0       INDIVIDUAL
     1       INDIVIDUAL
     2       INDIVIDUAL
```

```
[ ]: import pandas as pd
     from sklearn.preprocessing import OneHotEncoder

     # Assuming your DataFrame is named df

     # Specify the columns to encode
     columns_to_encode = ['home_ownership', 'verification_status', 'pymnt_plan',␣
      ↪'initial_list_status', 'application_type']

     # Extract the columns to be encoded and reshape them to a 2D array
     columns_data = df[columns_to_encode].values
```

```python
# Create an instance of the OneHotEncoder
one_hot_encoder = OneHotEncoder()

# Apply one-hot encoding to the selected columns
encoded_data = one_hot_encoder.fit_transform(columns_data)

# Get the column names for the one-hot encoded features
feature_names = one_hot_encoder.get_feature_names_out(columns_to_encode)

# Create a DataFrame with the one-hot encoded columns
encoded_df = pd.DataFrame(encoded_data.toarray(), columns=feature_names)

# Drop the original columns from the DataFrame
df = df.drop(columns=columns_to_encode)

# Concatenate the original DataFrame with the one-hot encoded DataFrame
df_encoded = pd.concat([df, encoded_df], axis=1)
```

3 User Defined Feature

##Total Payment Ratio = total payment / loan amount

Indicates what proportion of the loan amount has been paid off so far

[ ]:
```python
def add_total_pymnt_ratio(df, flag):
    if flag:
        df['total_pymnt_ratio'] = df['total_pymnt'] / df['loan_amnt']
    return df

df_encoded = add_total_pymnt_ratio(df_encoded, True)
```

[ ]:
```python
# Rearrange df_encoded for default ind to be last column

columns = df_encoded.columns.tolist()
columns.remove('default_ind')
columns.append('default_ind')
df_encoded = df_encoded[columns]
```

3.1 Addressing missing values

Fill missing values with median and scale all values

[ ]:
```python
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer

# Get the list of integer & float columns (excluding the last column target)
```

```
num_columns = df_encoded.select_dtypes(include=['int64','float64']).columns.
 ↪tolist()[:-1]

# Create a subset of the DataFrame with the integer columns
X = df_encoded[num_columnas]

# Initialize the imputer with a strategy to fill missing values (e.g., using␣
 ↪median)
imputer = SimpleImputer(strategy='median')

# Impute missing values in the integer columns
X_imputed = imputer.fit_transform(X)

# Initialize the StandardScaler
scaler = StandardScaler()

# Scale the integer columns
scaled_values = scaler.fit_transform(X_imputed)

# Create a new DataFrame with the scaled values
df_scaled = pd.DataFrame(scaled_values, columns=X.columns)

# Assign the scaled values back to the original DataFrame, excluding the last␣
 ↪column
df_encoded[num_columns] = df_scaled
```

3.2 Filter by correlation to determine the attributes used to train models

Create and then sort columns by correlation to default_ind

[ ]:
```
# Calculate the correlation between numeric variables and the target variable
correlation_with_target = df_encoded.corrwith(df['default_ind'])

# Sort the correlation values in descending order (absolute values)
sorted_correlation = correlation_with_target.abs().sort_values(ascending=False)

# Print the sorted correlation values
# print(sorted_correlation)
```

[ ]:
```
# Show all rows
pd.set_option('display.max_rows',None)
print(sorted_correlation)
```

```
default_ind                        1.000000
recoveries                         0.475738
collection_recovery_fee            0.330764
out_prncp                          0.225960
```

out_prncp_inv	0.225959
int_rate	0.155037
total_rec_late_fee	0.140760
sub_grade	0.126923
initial_list_status_f	0.098812
initial_list_status_w	0.098812
total_rec_prncp	0.090336
last_pymnt_amnt	0.087217
pymnt_gap	0.084740
inq_last_6mths	0.074407
pymnt_duration	0.057103
total_pymnt_ratio	0.056362
verification_status_Verified	0.050291
credit_hist	0.046097
total_rec_int	0.046050
tot_cur_bal	0.045139
revol_util	0.044479
purpose	0.043574
total_pymnt_inv	0.040232
total_pymnt	0.039220
total_rev_hi_lim	0.037430
annual_inc	0.037066
home_ownership_RENT	0.035016
verification_status_Source Verified	0.032761
term	0.031378
home_ownership_MORTGAGE	0.030095
open_acc	0.021698
mths_since_last_record	0.021639
total_acc	0.021087
revol_bal	0.020696
pub_rec	0.019607
open_il_12m	0.018112
verification_status_Not Verified	0.016924
inq_fi	0.016437
total_cu_tl	0.014713
emp_length	0.013833
open_il_24m	0.010993
collections_12_mths_ex_med	0.010651
open_rv_24m	0.010228
mths_since_rcnt_il	0.009245
delinq_2yrs	0.009186
open_il_6m	0.008767
addr_state	0.008272
funded_amnt_inv	0.008209
total_bal_il	0.007836
max_bal_bc	0.007657
home_ownership_OTHER	0.007626
home_ownership_OWN	0.007489

```
open_rv_12m                        0.006937
mths_since_last_major_derog        0.006194
funded_amnt                        0.005797
application_type_INDIVIDUAL        0.005446
application_type_JOINT             0.005446
loan_amnt                          0.004907
installment                        0.004753
dti                                0.004429
il_util                            0.004211
home_ownership_NONE                0.003241
acc_now_delinq                     0.003116
tot_coll_amt                       0.002445
open_acc_6m                        0.001802
all_util                           0.001602
inq_last_12m                       0.001584
mths_since_last_delinq             0.001042
annual_inc_joint                   0.000832
pymnt_plan_n                       0.000579
pymnt_plan_y                       0.000579
dti_joint                          0.000459
home_ownership_ANY                 0.000449
policy_code                             NaN
dtype: float64
```

We filter out unecessary columns which are those attributes with absolute correlation lower than 0.01 and they will be removed.

[ ]:
```
correlation_threshold = 0.01
filtered_columns = df_encoded.columns[df_encoded.corr()['default_ind'].abs() >=␣
 ↪correlation_threshold]
```

[ ]:
```
processed_df = df_encoded[filtered_columns]
df = processed_df
```

3.3 Checking for attributes outliers

[ ]:
```
outliers = []
def outlierFinder(dataF, col):
    # Use Quatile 3 value to subtract Quatile 1 value to get interquatile range
    # The lower quartile, or first quartile (Q1), is the value under which 25% of␣
 ↪data
    # The upper quartile, or third quartile (Q3), is the value under which 75% of␣
 ↪data
    Q1 = np.percentile(np.array(dataF[col].tolist()), 25)
    Q3 = np.percentile(np.array(dataF[col].tolist()), 75)
    interquatileRange = Q3-Q1
```

```
    upperBound = Q3 + (3 * interquatileRange)
    lowerBound = Q1 - (3 * interquatileRange)

    count = 0

    for value in dataF[col].tolist():
      if((value <lowerBound ) |(value>upperBound)):
        # Increment the outliers count when the values fall outside of the interqu
        count+=1
    outliers.append(count)
    return lowerBound, upperBound, count
```

Finding outliers in columns of data type Sparse[uint8, 0] may not be meaningful because these columns typically represent categorical variables encoded using one-hot encoding. The Sparse[uint8, 0] data type is used to efficiently store binary data where most of the entries are zero. Thus, only the outliers of the integer and float attributes will be evaluated.

[ ]:
```
import numpy as np
# Select the numerical attributes
numerical_att = df.select_dtypes(include=['float64', 'int64'])
numerical_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 855969 entries, 0 to 855968
Data columns (total 43 columns):
 #   Column                                Non-Null Count   Dtype
---  ------                                --------------   -----
 0   term                                  855969 non-null  float64
 1   int_rate                              855969 non-null  float64
 2   sub_grade                             855969 non-null  float64
 3   emp_length                            855969 non-null  float64
 4   annual_inc                            855969 non-null  float64
 5   credit_hist                           855969 non-null  float64
 6   pymnt_duration                        855969 non-null  float64
 7   pymnt_gap                             855969 non-null  float64
 8   purpose                               855969 non-null  float64
 9   inq_last_6mths                        855969 non-null  float64
 10  mths_since_last_record                855969 non-null  float64
 11  open_acc                              855969 non-null  float64
 12  pub_rec                               855969 non-null  float64
 13  revol_bal                             855969 non-null  float64
 14  revol_util                            855969 non-null  float64
 15  total_acc                             855969 non-null  float64
 16  out_prncp                             855969 non-null  float64
 17  out_prncp_inv                         855969 non-null  float64
 18  total_pymnt                           855969 non-null  float64
 19  total_pymnt_inv                       855969 non-null  float64
 20  total_rec_prncp                       855969 non-null  float64
```

```
 21   total_rec_int                        855969 non-null  float64
 22   total_rec_late_fee                   855969 non-null  float64
 23   recoveries                           855969 non-null  float64
 24   collection_recovery_fee              855969 non-null  float64
 25   last_pymnt_amnt                      855969 non-null  float64
 26   collections_12_mths_ex_med           855969 non-null  float64
 27   tot_cur_bal                          855969 non-null  float64
 28   open_il_12m                          855969 non-null  float64
 29   open_il_24m                          855969 non-null  float64
 30   open_rv_24m                          855969 non-null  float64
 31   total_rev_hi_lim                     855969 non-null  float64
 32   inq_fi                               855969 non-null  float64
 33   total_cu_tl                          855969 non-null  float64
 34   home_ownership_MORTGAGE              855969 non-null  float64
 35   home_ownership_RENT                  855969 non-null  float64
 36   verification_status_Not Verified     855969 non-null  float64
 37   verification_status_Source Verified  855969 non-null  float64
 38   verification_status_Verified         855969 non-null  float64
 39   initial_list_status_f                855969 non-null  float64
 40   initial_list_status_w                855969 non-null  float64
 41   total_pymnt_ratio                    855969 non-null  float64
 42   default_ind                          855969 non-null  int64
dtypes: float64(42), int64(1)
memory usage: 287.3 MB
```

[ ]:
```
# Display the number of outliers of each attribute
for attribute in numerical_att:
  if(outlierFinder(df, attribute)[2] > 0):
    print(f'There is {outlierFinder(df, attribute)[2]} outliers in {attribute}')
```

```
There is 11687 outliers in annual_inc
There is 1743 outliers in credit_hist
There is 53 outliers in pymnt_duration
There is 168074 outliers in pymnt_gap
There is 350577 outliers in purpose
There is 13940 outliers in inq_last_6mths
There is 129393 outliers in mths_since_last_record
There is 3322 outliers in open_acc
There is 130514 outliers in pub_rec
There is 17586 outliers in revol_bal
There is 4 outliers in revol_util
There is 856 outliers in total_acc
There is 8079 outliers in total_pymnt
There is 8235 outliers in total_pymnt_inv
There is 13036 outliers in total_rec_prncp
There is 22622 outliers in total_rec_int
There is 9974 outliers in total_rec_late_fee
There is 24187 outliers in recoveries
```

```
There is 23035 outliers in collection_recovery_fee
There is 144596 outliers in last_pymnt_amnt
There is 11145 outliers in collections_12_mths_ex_med
There is 6660 outliers in tot_cur_bal
There is 6501 outliers in open_il_12m
There is 9251 outliers in open_il_24m
There is 10801 outliers in open_rv_24m
There is 19910 outliers in total_rev_hi_lim
There is 6212 outliers in inq_fi
There is 6157 outliers in total_cu_tl
There is 46467 outliers in default_ind
```

3.3.1 Find the attributes with the most outliers

[ ]:
```
# To remove outliers in the list
unique_outliers = frozenset(outliers)
total_outliers = 0
sorted_outliers = sorted(unique_outliers, reverse = True)

for outlier in unique_outliers:
 total_outliers += outlier

print("Total number of outliers: ", total_outliers)
# We arrange the outliers number in descending order
print("Outliers in descending orders: ", sorted_outliers)
```

```
Total number of outliers:  1204617
Outliers in descending orders:  [350577, 168074, 144596, 130514, 129393, 46467,
24187, 23035, 22622, 19910, 17586, 13940, 13036, 11687, 11145, 10801, 9974,
9251, 8235, 8079, 6660, 6501, 6212, 6157, 3322, 1743, 856, 53, 4, 0]
```

From the result shown above, the 3 attributes with the most outliers are purpose, pymnt__gap, and pymnt__amnt.

3.4 Scaling all processed data

[ ]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer

# Get the list of integer & float columns (excluding the last column target)
num_columns = df.select_dtypes(include=['int64','float64']).columns.tolist()[:
 ↪-1]

# Create a subset of the DataFrame with the integer columns
X = df[num_columns]

# Initialize the imputer with a strategy to fill missing values (e.g., using␣
 ↪mean)
```

```
imputer = SimpleImputer(strategy='median')

# Impute missing values in the integer columns
X_imputed = imputer.fit_transform(X)

# Initialize the StandardScaler
scaler = StandardScaler()

# Scale the integer columns
scaled_values = scaler.fit_transform(X_imputed)

# Create a new DataFrame with the scaled values
df_scaled = pd.DataFrame(scaled_values, columns=X.columns)

# Assign the scaled values back to the original DataFrame, excluding the last␣
↪column
df[num_columns] = df_scaled
```

```
<ipython-input-25-b676b087eb6a>:26: 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
  df[num_columns] = df_scaled
```

[ ]:
```
#df.to_csv('/content/drive/My Drive/mydata.csv', index=False) #midpoint export␣
↪to csv for future reference
```

3.5 Splitting data into test and train data

Training data: X_train, X_test Testing data: y_train, y_test

[ ]:
```
from sklearn.model_selection import StratifiedShuffleSplit

# Assuming 'default_ind' is the column representing your target variable
# Replace 'test_size' with the desired proportion for the test dataset (0.2 for␣
↪20%)

feature_columns = df.drop('default_ind', axis=1)  # Features (input data)
target_column = df['default_ind']  # Target variable (labels)

sss = StratifiedShuffleSplit(n_splits=4, test_size=0.2, random_state=42) #i␣
↪tried n =1, too high accuracy

for train_index, test_index in sss.split(feature_columns, target_column):
```

```
    X_train, X_test = feature_columns.iloc[train_index], feature_columns.
↪iloc[test_index]
    y_train, y_test = target_column.iloc[train_index], target_column.
↪iloc[test_index]
```

Stratified shuffle split seperates train and test data with a balanced number of cases in relation to the target variable. This gives us a balanced sample for Machine Learning.

3.6 SMOTE Implementation

Apply SMOTE to oversample the minority class in the training set

[ ]:
```
from imblearn.over_sampling import SMOTE

# Apply SMOTE to oversample the minority class in the training set
smote = SMOTE(random_state=42)
X_train, y_train = smote.fit_resample(X_train, y_train)
```

SMOTE synthesizes more cases of the minority class (cases where default is 1, 6% of total samples), so that training can be based on more balanced classes.

4 Select and train models

4.1 Model 1:

4.1.1 Linear Support Vector Classifier

Implement Training Model

[ ]:
```
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report, confusion_matrix

# Define the model
clf = LinearSVC(max_iter=5000)

# Train the model
clf.fit(X_train, y_train)

# Predict the response for test dataset
y_pred = clf.predict(X_test)

# Evaluating the Model
print(classification_report(y_test, y_pred))
```

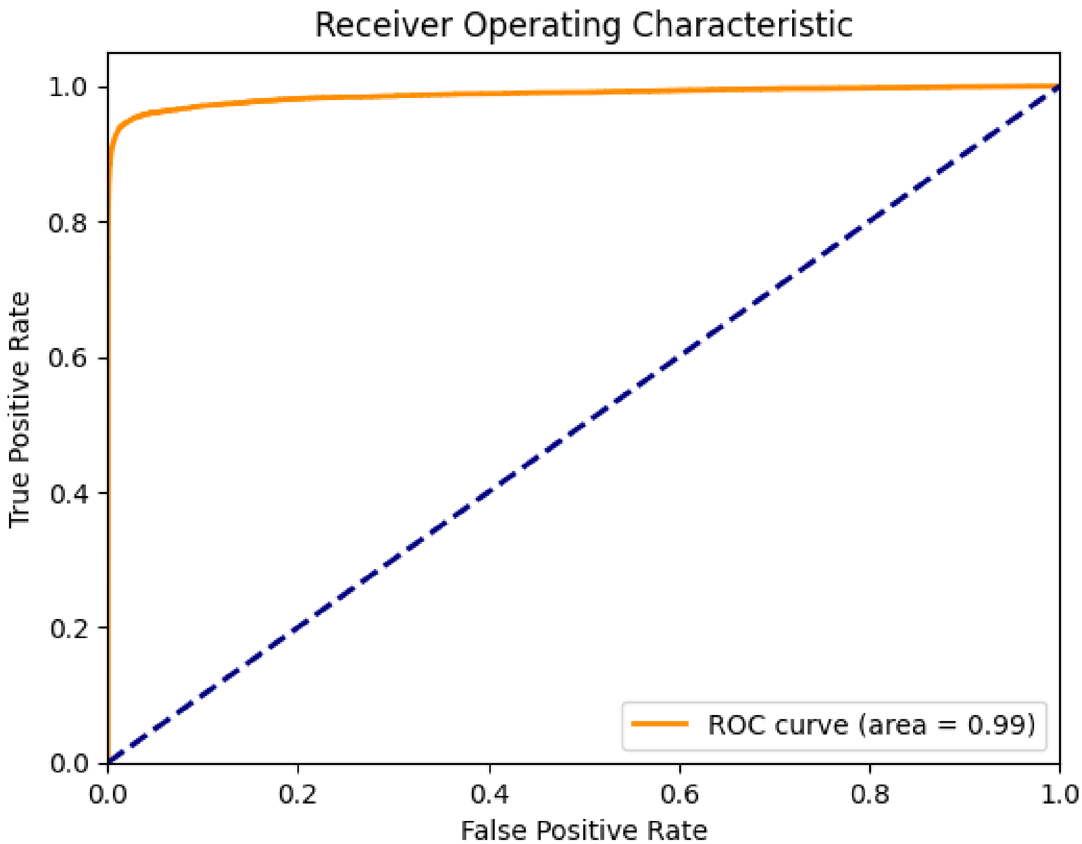
```
/usr/local/lib/python3.10/dist-packages/sklearn/svm/_base.py:1244:
ConvergenceWarning: Liblinear failed to converge, increase the number of
iterations.
  warnings.warn(
```

```
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    161901
           1       0.74      0.95      0.83      9293

    accuracy                           0.98    171194
   macro avg       0.87      0.96      0.91    171194
weighted avg       0.98      0.98      0.98    171194
```

Linear Support Vector Classifier

Visualise Training Model

[ ]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Compute decision function values for the samples in X_test
y_score = clf.decision_function(X_test)

# Compute the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_score)

# Compute the area under the ROC curve
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' %␣
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--') # Reference line␣
 ↪for random classifier
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```



Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

[ ]:
```
# import the confusion_matrix function
from sklearn.metrics import confusion_matrix

# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# print the confusion matrix
print(cm)

TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0]
TP = cm[1, 1]
```

```
[[158814   3087]
 [   507   8786]]
```

4.2 Model 2:

4.2.1 XG-Boost

Implement Training Model

[ ]:
```
import xgboost as xgb
from sklearn.model_selection import train_test_split

# Create a XGBoost classifier
model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')

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

# Predict the labels of the test set
y_pred = model.predict(X_test)

print(classification_report(y_test, y_pred))
```

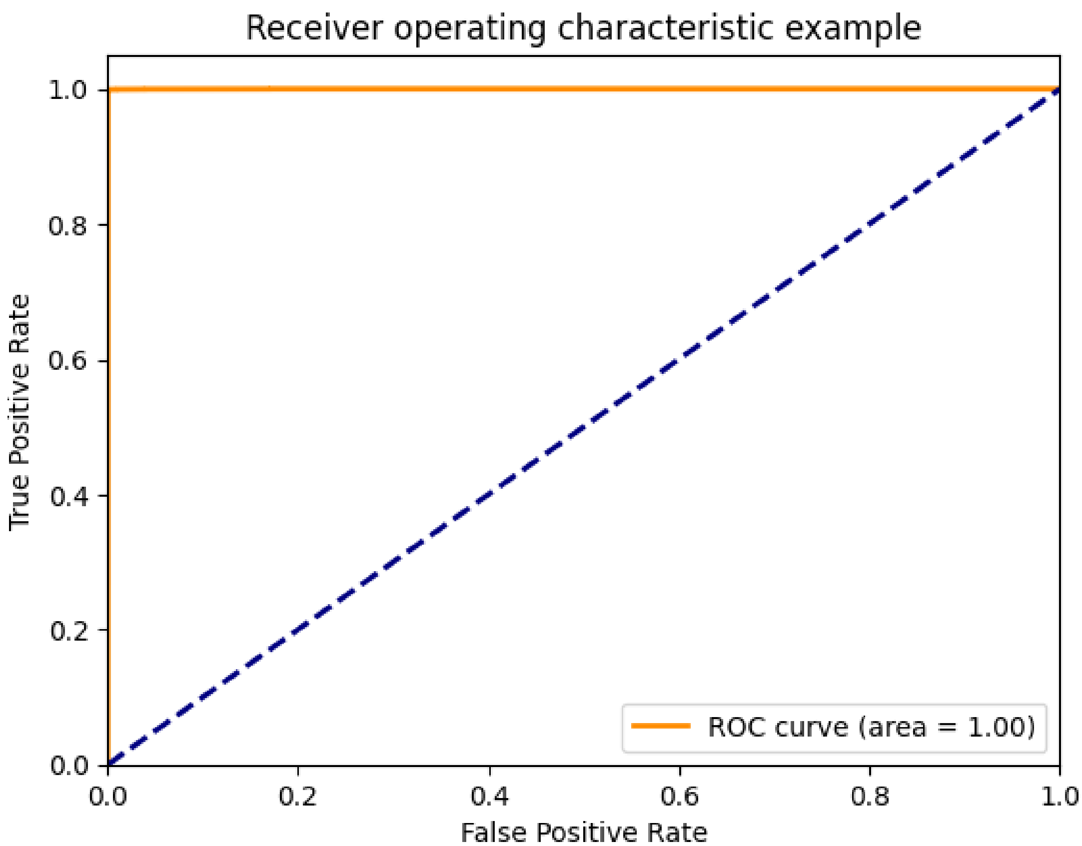
```
/usr/local/lib/python3.10/dist-packages/xgboost/sklearn.py:1395: UserWarning:
`use_label_encoder` is deprecated in 1.7.0.
  warnings.warn("`use_label_encoder` is deprecated in 1.7.0.")
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    161901
           1       1.00      1.00      1.00      9293

    accuracy                           1.00    171194
   macro avg       1.00      1.00      1.00    171194
weighted avg       1.00      1.00      1.00    171194
```

XG-Boost

Visualise Training Model

[ ]:
```
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

# Predict the probabilities of the positive class
y_pred_proba = model.predict_proba(X_test)[:, 1]

# Generate the ROC curve using the true labels and predicted probabilities
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
```

```
lw = 2
plt.plot(fpr, tpr, color='darkorange', lw=lw, label='ROC curve (area = %0.2f)'␣
 ↪% roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic example')
plt.legend(loc="lower right")
plt.show()
```



Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

[ ]:
```
from sklearn.metrics import confusion_matrix

print(confusion_matrix(y_test, y_pred))
```

```
[[161887     14]
```

```
 [    20   9273]]
```

4.3 Model 3:

4.3.1 Decision Tree

Implement Training Model

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Assuming X_train and X_test are DataFrames with the same columns after␣
 ↪one-hot encoding
classifier = DecisionTreeClassifier()
classifier.fit(X_train, y_train)

# Make predictions on the test data
y_predict = classifier.predict(X_test)

# Summary of the predictions made by the classifier
print(classification_report(y_test, y_predict))
print(confusion_matrix(y_test, y_predict))

# Accuracy score
print('accuracy is', accuracy_score(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    161901
           1       0.99      1.00      0.99      9293

    accuracy                           1.00    171194
   macro avg       1.00      1.00      1.00    171194
weighted avg       1.00      1.00      1.00    171194

[[161834     67]
 [    32   9261]]
accuracy is 0.9994217087047443
```

Decision Tree

Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

[ ]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# print the confusion matrix
```

```
print(cm)

TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0]
TP = cm[1, 1]
```

```
[[161887     14]
 [    20   9273]]
```

4.3.2 k-fold cross-validation

Based on the accuracy result in the previous session, the decision tree model has a very high accuracy of around 99%, which is in doubt to be a result of overfitting. Thus, we will check this overfitting by using k-fold cross-validation.

This technique involves splitting the data into k subsets (folds), training the model on k-1 subsets, and then evaluating it on the remaining fold. This process is repeated k times, with each subset acting as the test set once.

The output will show the accuracy of the model on each fold and the average accuracy over all folds. If the average accuracy is close to the accuracy on the training data, it indicates that the model is not overfitting and generalizes well to new data. However, if there is a significant drop in accuracy between training and validation, it may indicate overfitting.

[ ]:
```
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

# Create the decision tree classifier
classifier = DecisionTreeClassifier()

# Perform k-fold cross-validation with k=5 (you can change k as needed)
k = 5
scores = cross_val_score(classifier, X_train, y_train, cv=k, scoring='accuracy')

# Print the accuracy for each fold
print("Accuracy for each fold:", scores)

# Print the average accuracy over all folds
average_accuracy = scores.mean()
print("Average accuracy:", average_accuracy)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
```

```
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
```

```
Accuracy for each fold: [0.99901427 0.99881713 0.99894126 0.99897046 0.99899967]
Average accuracy: 0.99894855597459019
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
```

From the results shown above, the accuracy for each fold is highly similar to the average accuracy. Thus, this indicates that the model is not overfitting.

4.4 Model 4:

4.4.1 Random Forest

Implement Training Model

[ ]:
```python
from sklearn.ensemble import RandomForestClassifier

classifier = RandomForestClassifier(random_state=42)
```

```
classifier.fit(X_train, y_train)
y_predict = classifier.predict(X_test)

# Summary of the predictions made by the classifier
print(classification_report(y_test, y_predict))
print(confusion_matrix(y_test, y_predict))

# Accuracy score
print('Accuracy is',accuracy_score(y_predict,y_test))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    161901
           1       1.00      1.00      1.00      9293

    accuracy                           1.00    171194
   macro avg       1.00      1.00      1.00    171194
weighted avg       1.00      1.00      1.00    171194

[[161885     16]
 [    44   9249]]
Accuracy is 0.9996495204271177
```

Random Forest

Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

```
[ ]: # Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# print the confusion matrix
print(cm)

TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0]
TP = cm[1, 1]
```

```
[[161887     14]
 [    20   9273]]
```

4.4.2 k-fold cross-validation

```
[ ]: from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score

# Assuming you have X_train and Y_train as your training data
```

```python
# Create the Random Forest classifier
classifier = RandomForestClassifier()

# Perform k-fold cross-validation with k=5 (you can change k as needed)
k = 5
scores = cross_val_score(classifier, X_train, y_train, cv=k, scoring='accuracy')

# Print the accuracy for each fold
print("Accuracy for each fold:", scores)

# Print the average accuracy over all folds
average_accuracy = scores.mean()
print("Average accuracy:", average_accuracy)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/validation.py:768:
UserWarning: pandas.DataFrame with sparse columns found.It will be converted to
a dense numpy array.
  warnings.warn(
```

```
Accuracy for each fold: [0.99904348 0.99886824 0.99893396 0.99897046 0.99898507]
Average accuracy: 0.9989602424153918
```

From the results shown above, the accuracy for each fold is highly similar to the average accuracy. Thus, this indicates that the model is not overfitting.

4.5 Model 5:

4.5.1 Logistical Regression

Implement Training Model

```
[ ]: from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Create an instance of the logistic regression model
model = LogisticRegression(max_iter=1000)

# Fit the model to the resampled training data
model.fit(X_train, y_train)

# Make predictions on the scaled testing data
y_pred = model.predict(X_test)

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

# Print the classification report for more detailed evaluation
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9777036578384757
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.98      0.99    161901
           1       0.72      0.95      0.82      9293

    accuracy                           0.98    171194
   macro avg       0.86      0.96      0.91    171194
```

```
weighted avg       0.98      0.98      0.98    171194
```

Logistical Regression

Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

```
[ ]: # Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# print the confusion matrix
print(cm)

TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0]
TP = cm[1, 1]
```

```
[[158546   3355]
 [   462   8831]]
```

4.6 Model 6:

4.6.1 K Nearest Neighbours

Implement Training Model

```
[ ]: from sklearn.neighbors import KNeighborsClassifier

# Create an instance of the k-Nearest Neighbors (KNN) classifier
knn = KNeighborsClassifier(n_neighbors=5)  # You can set the number of␣
 ↪neighbors (k) based on your choice

# Fit the KNN classifier to the scaled training data
knn.fit(X_train, y_train)

# Make predictions on the scaled testing data
y_pred = knn.predict(X_test)

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

# Print the classification report and confusion matrix for more detailed␣
 ↪evaluation
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9587836022290501
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.96      0.98    161901
           1       0.58      0.88      0.70      9293

    accuracy                           0.96    171194
   macro avg       0.79      0.92      0.84    171194
weighted avg       0.97      0.96      0.96    171194
```

Logistical Regression

Printing of Confusion Matrix

[[true negatives, false positives], [false negatives, true positives]]

[ ]:
```
# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# print the confusion matrix
print(cm)

TN = cm[0, 0]
FP = cm[0, 1]
FN = cm[1, 0]
TP = cm[1, 1]
```

```
[[155949   5952]
 [  1104   8189]]
```

5 Fine-tune the models

5.1 K Nearest Neighbours

5.1.1 Adjustment of parameters (selection of value of k)

k = 50

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪accuracy_score

# Create an instance of the k-Nearest Neighbors (KNN) classifier
knn = KNeighborsClassifier(n_neighbors=50)  # You can set the number of␣
 ↪neighbors (k) based on your choice

# Fit the KNN classifier to the scaled training data
knn.fit(X_train, y_train)
```

```python
# Make predictions on the scaled testing data
y_pred = knn.predict(X_test)

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

# Print the classification report and confusion matrix for more detailed␣
↪evaluation
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.9264168136733764
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.93      0.96    161901
           1       0.42      0.94      0.58      9293

    accuracy                           0.93    171194
   macro avg       0.71      0.93      0.77    171194
weighted avg       0.96      0.93      0.94    171194
```

5.2 GridSearch for best K Value for KNN Model

[ ]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report

# Assuming 'X_train' and 'y_train' are your training data and labels
# Assuming 'X_test' and 'y_test' are your testing data and labels

# Create an instance of the KNN classifier
knn = KNeighborsClassifier()

# Define the hyperparameter grid to search
param_grid = {'n_neighbors': [1, 3, 5, 7, 10, 15, 20, 25, 50, 100, 200]}

# Create a GridSearchCV object and perform the search
grid_search = GridSearchCV(knn, param_grid, cv=5)  # 'cv' is the number of␣
↪cross-validation folds
grid_search.fit(X_train, y_train)

# Get the best hyperparameters and the corresponding model
best_k = grid_search.best_params_['n_neighbors']
```

```
best_knn_model = grid_search.best_estimator_

# Print the best k value
print("Best k:", best_k)

# Retrain the best model on the full training set
best_knn_model.fit(X_train, y_train)

# Make predictions on the test set using the best model
y_pred = best_knn_model.predict(X_test)

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

# Print the classification report and confusion matrix for more detailed
 ↪evaluation
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

Best k: 3

Accuracy: 0.9812318188721567

Classification Report:

```
           precision    recall  f1-score   support

        0       0.98      1.00      0.99    161901
        1       0.96      0.68      0.80      9293

accuracy                            0.98    171194
```

macro avg 0.97 0.84 0.89 171194

weighted avg 0.98 0.98 0.98 171194

Tuning of the KNN model improved precison, at the expense of recall, and gave an overall higher f1-score. However, for the cases of capturing all possible defualt cases, compromising recall score might not be a favorable outcome.

5.3 XG BOOST

XG BOOST CROSS VALIDATION TEST

[ ]:
```
import xgboost as xgb
from sklearn.model_selection import train_test_split

# Assuming processed_df is your DataFrame and 'default_ind' is the target
 ↪variable
X = processed_df.drop(columns='default_ind')
```

```python
y = processed_df['default_ind']

# convert the dataset into an optimized data structure that the model can use
dtrain = xgb.DMatrix(X, label=y)

# specify the hyperparameters
params = {
    'objective':'binary:logistic',
    'max_depth': 4,
    'alpha': 10,
    'learning_rate': 0.1,
    'n_estimators':100,
}

# Perform cross-validation: metrics to be monitored are logloss for binary␣
 ↪classification
cv_results = xgb.cv(
    dtrain=dtrain,
    params=params,
    nfold=5,
    num_boost_round=50,
    early_stopping_rounds=10,
    metrics="logloss",
    as_pandas=True,
    seed=123,
)

print(cv_results)
```

```
[14:45:37] WARNING: ../src/learner.cc:767:
Parameters: { "n_estimators" } are not used.

[14:45:42] WARNING: ../src/learner.cc:767:
Parameters: { "n_estimators" } are not used.

[14:45:46] WARNING: ../src/learner.cc:767:
Parameters: { "n_estimators" } are not used.

[14:45:49] WARNING: ../src/learner.cc:767:
Parameters: { "n_estimators" } are not used.

[14:45:55] WARNING: ../src/learner.cc:767:
Parameters: { "n_estimators" } are not used.

    train-logloss-mean  train-logloss-std  test-logloss-mean  test-logloss-std
0             0.602707           0.000015           0.602717          0.000044
1             0.528571           0.000026           0.528577          0.000077
```

2	0.466739	0.000068	0.466762	0.000162
3	0.414393	0.000111	0.414422	0.000256
4	0.369598	0.000033	0.369616	0.000145
5	0.330907	0.000025	0.330923	0.000158
6	0.297329	0.000153	0.297347	0.000141
7	0.268020	0.000027	0.268038	0.000151
8	0.242203	0.000035	0.242221	0.000124
9	0.219643	0.000030	0.219663	0.000142
10	0.199556	0.000033	0.199578	0.000122
11	0.181564	0.000429	0.181585	0.000356
12	0.164778	0.000340	0.164806	0.000280
13	0.149920	0.000267	0.149954	0.000220
14	0.136743	0.000209	0.136779	0.000180
15	0.125012	0.000168	0.125047	0.000151
16	0.114591	0.000066	0.114633	0.000122
17	0.105247	0.000072	0.105288	0.000129
18	0.096938	0.000097	0.096972	0.000149
19	0.089442	0.000083	0.089485	0.000109
20	0.082694	0.000061	0.082741	0.000118
21	0.076612	0.000042	0.076666	0.000120
22	0.070853	0.000060	0.070907	0.000109
23	0.065710	0.000098	0.065764	0.000129
24	0.061101	0.000098	0.061163	0.000113
25	0.056891	0.000064	0.056953	0.000109
26	0.053081	0.000061	0.053143	0.000117
27	0.049681	0.000055	0.049750	0.000116
28	0.046251	0.000249	0.046336	0.000270
29	0.043253	0.000087	0.043338	0.000129
30	0.040367	0.000115	0.040453	0.000169
31	0.037991	0.000087	0.038084	0.000116
32	0.035615	0.000077	0.035703	0.000205
33	0.033647	0.000137	0.033733	0.000264
34	0.031640	0.000180	0.031739	0.000282
35	0.029985	0.000046	0.030084	0.000170
36	0.028312	0.000169	0.028414	0.000239
37	0.026845	0.000118	0.026950	0.000151
38	0.025427	0.000060	0.025526	0.000211
39	0.024098	0.000190	0.024204	0.000244
40	0.023000	0.000093	0.023107	0.000196
41	0.021943	0.000101	0.022054	0.000135
42	0.020961	0.000054	0.021073	0.000224
43	0.020025	0.000116	0.020143	0.000258
44	0.019189	0.000098	0.019309	0.000250
45	0.018469	0.000125	0.018593	0.000296
46	0.017680	0.000172	0.017799	0.000323
47	0.017045	0.000092	0.017165	0.000221
48	0.016455	0.000162	0.016577	0.000255
49	0.015931	0.000180	0.016054	0.000291

##Linear Support Vector Classifier

```
[ ]: # Predict on the training set
y_train_pred = clf.predict(X_train)

# Evaluate the model's performance on the training set
print("Training Set Evaluation:")
print(classification_report(y_train, y_train_pred))

# Evaluate the model's performance on the test set
print("Test Set Evaluation:")
print(classification_report(y_test, y_pred))
```

```
Training Set Evaluation:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99    647711
           1       0.98      0.81      0.89     37064

    accuracy                           0.99    684775
   macro avg       0.98      0.90      0.94    684775
weighted avg       0.99      0.99      0.99    684775

Test Set Evaluation:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99    161791
           1       0.98      0.81      0.89      9403

    accuracy                           0.99    171194
   macro avg       0.98      0.91      0.94    171194
weighted avg       0.99      0.99      0.99    171194
```

6 Evaluate the outcomes

7 Comparison of Models' Performance

- Linear Support Vector
- XG Boost
- Decision Tree
- Random Forest
- Logistical Regression
- K Nearest Neighbours

```
[ ]: results = {
    'Linear SVM': {
```

```python
        'precision': 0.98,
        'recall': 0.81,
        'f1-score': 0.89
    },
    'XG Boost': {
        'precision': 1.00,
        'recall': 1.00,
        'f1-score': 1.00
    },
    'Decision Tree': {
        'precision': 0.99,
        'recall': 1.00,
        'f1-score': 0.99
    },
    'Random Forest': {
        'precision': 1.00,
        'recall': 1.00,
        'f1-score': 1.00
    },
    'Logistic Regression': {
        'precision': 0.72,
        'recall': 0.95,
        'f1-score': 0.82
    },
    'KNN': {
        'precision': 0.96,
        'recall': 0.68,
        'f1-score': 0.80
    },
}

# Print the updated dictionary
for model, metrics in results.items():
    print(f"{model}:")
    print(f"  Precision: {metrics['precision']}")
    print(f"  Recall: {metrics['recall']}")
    print(f"  F1-score: {metrics['f1-score']}")
    print()
```

```
Linear SVM:
  Precision: 0.98
  Recall: 0.81
  F1-score: 0.89

XG Boost:
  Precision: 1.0
  Recall: 1.0
```

```
  F1-score: 1.0

Decision Tree:
  Precision: 0.99
  Recall: 1.0
  F1-score: 0.99

Random Forest:
  Precision: 1.0
  Recall: 1.0
  F1-score: 1.0

Logistic Regression:
  Precision: 0.72
  Recall: 0.95
  F1-score: 0.82

KNN:
  Precision: 0.96
  Recall: 0.68
  F1-score: 0.8
```

Decision Tree, Random Forest and XG Boost (Which acts by grouping weaker decision trees to form strong decison trees) have the best results for this end to end project.

All three models revolve around a decision tree based model, and that seems to be the best fit for this set of loan data and classification problem.