House Loan Data Analysis

May 30, 2023

1 House Loan Data Analysis

1.0.1 Course-end Project 1

1.1 DESCRIPTION

For safe and secure lending experience, it's important to analyze the past data. In this project, you have to build a deep learning model to predict the chance of default for future loans using the historical data. As you will see, this dataset is highly imbalanced and includes a lot of features that make this problem more challenging.

Objective: Create a model that predicts whether or not an applicant will be able to repay a loan using historical data.

Domain: Finance

Analysis to be done: Perform data preprocessing and build a deep learning prediction model.

Steps to be done: Load the dataset that is given to you

Check for null values in the dataset

Print percentage of default to payer of the dataset for the TARGET column

Balance the dataset if the data is imbalanced

Plot the balanced data or imbalanced data

Encode the columns that is required for the model

Calculate Sensitivity as a metrice

Calculate area under receiver operating characteristics curve

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[2]:
```python
# Task 1
df = pd.read_csv("loan_data_.csv")
df
```

[2]:
```
        SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0           100002       1         Cash loans           M            N
1           100003       0         Cash loans           F            N
2           100004       0    Revolving loans           M            Y
3           100006       0         Cash loans           F            N
4           100007       0         Cash loans           M            N
…              …     …                …           …            …
307506      456251       0         Cash loans           M            N
307507      456252       0         Cash loans           F            N
307508      456253       0         Cash loans           F            N
307509      456254       1         Cash loans           F            N
307510      456255       0         Cash loans           F            N

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                    Y             0          202500.0    406597.5
1                    N             0          270000.0   1293502.5
2                    Y             0           67500.0    135000.0
3                    Y             0          135000.0    312682.5
4                    Y             0          121500.0    513000.0
…                  …           …               …         …
307506               N             0          157500.0    254700.0
307507               Y             0           72000.0    269550.0
307508               Y             0          153000.0    677664.0
307509               Y             0          171000.0    370107.0
307510               N             0          157500.0    675000.0

        AMT_ANNUITY  …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20  \
0           24700.5  …                 0                0                0
1           35698.5  …                 0                0                0
2            6750.0  …                 0                0                0
3           29686.5  …                 0                0                0
4           21865.5  …                 0                0                0
…               …  …               …              …              …
307506      27558.0  …                 0                0                0
307507      12001.5  …                 0                0                0
307508      29979.0  …                 0                0                0
307509      20205.0  …                 0                0                0
307510      49117.5  …                 0                0                0

       FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                     0                        0.0                       0.0
1                     0                        0.0                       0.0
2                     0                        0.0                       0.0
```

```
3                 0                        NaN                        NaN
4                 0                        0.0                        0.0
…               …                        …                        …
307506            0                        NaN                        NaN
307507            0                        NaN                        NaN
307508            0                        1.0                        0.0
307509            0                        0.0                        0.0
307510            0                        0.0                        0.0

        AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                              0.0                        0.0
1                              0.0                        0.0
2                              0.0                        0.0
3                              NaN                        NaN
4                              0.0                        0.0
…                            …                        …
307506                         NaN                        NaN
307507                         NaN                        NaN
307508                         0.0                        1.0
307509                         0.0                        0.0
307510                         0.0                        2.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                             0.0                         1.0
1                             0.0                         0.0
2                             0.0                         0.0
3                             NaN                         NaN
4                             0.0                         0.0
…                           …                         …
307506                        NaN                         NaN
307507                        NaN                         NaN
307508                        0.0                         1.0
307509                        0.0                         0.0
307510                        0.0                         1.0

[307511 rows x 122 columns]
```

[3]:
```
df.describe()
```

[3]:
```
          SK_ID_CURR         TARGET   CNT_CHILDREN  AMT_INCOME_TOTAL  \
count  307511.000000  307511.000000  307511.000000      3.075110e+05
mean   278180.518577       0.080729       0.417052      1.687979e+05
std    102790.175348       0.272419       0.722121      2.371231e+05
min    100002.000000       0.000000       0.000000      2.565000e+04
25%    189145.500000       0.000000       0.000000      1.125000e+05
50%    278202.000000       0.000000       0.000000      1.471500e+05
75%    367142.500000       0.000000       1.000000      2.025000e+05
```

```
max    456255.000000       1.000000      19.000000      1.170000e+08

         AMT_CREDIT    AMT_ANNUITY  AMT_GOODS_PRICE  \
count  3.075110e+05  307499.000000     3.072330e+05
mean   5.990260e+05   27108.573909     5.383962e+05
std    4.024908e+05   14493.737315     3.694465e+05
min    4.500000e+04    1615.500000     4.050000e+04
25%    2.700000e+05   16524.000000     2.385000e+05
50%    5.135310e+05   24903.000000     4.500000e+05
75%    8.086500e+05   34596.000000     6.795000e+05
max    4.050000e+06  258025.500000     4.050000e+06

       REGION_POPULATION_RELATIVE     DAYS_BIRTH  DAYS_EMPLOYED  …  \
count               307511.000000  307511.000000  307511.000000  …
mean                     0.020868  -16036.995067   63815.045904  …
std                      0.013831    4363.988632  141275.766519  …
min                      0.000290  -25229.000000  -17912.000000  …
25%                      0.010006  -19682.000000   -2760.000000  …
50%                      0.018850  -15750.000000   -1213.000000  …
75%                      0.028663  -12413.000000    -289.000000  …
max                      0.072508   -7489.000000  365243.000000  …

       FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  \
count     307511.000000     307511.000000     307511.000000     307511.000000
mean           0.008130          0.000595          0.000507          0.000335
std            0.089798          0.024387          0.022518          0.018299
min            0.000000          0.000000          0.000000          0.000000
25%            0.000000          0.000000          0.000000          0.000000
50%            0.000000          0.000000          0.000000          0.000000
75%            0.000000          0.000000          0.000000          0.000000
max            1.000000          1.000000          1.000000          1.000000

       AMT_REQ_CREDIT_BUREAU_HOUR  AMT_REQ_CREDIT_BUREAU_DAY  \
count               265992.000000              265992.000000
mean                     0.006402                   0.007000
std                      0.083849                   0.110757
min                      0.000000                   0.000000
25%                      0.000000                   0.000000
50%                      0.000000                   0.000000
75%                      0.000000                   0.000000
max                      4.000000                   9.000000

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
count               265992.000000              265992.000000
mean                     0.034362                   0.267395
std                      0.204685                   0.916002
min                      0.000000                   0.000000
```

```
25%                      0.000000                     0.000000
50%                      0.000000                     0.000000
75%                      0.000000                     0.000000
max                      8.000000                    27.000000

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
count              265992.000000               265992.000000
mean                    0.265474                    1.899974
std                     0.794056                    1.869295
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    1.000000
75%                     0.000000                    3.000000
max                   261.000000                   25.000000

[8 rows x 106 columns]
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 307511 entries, 0 to 307510
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 286.2+ MB
```

[5]:
```
type(df)
```

[5]:
```
pandas.core.frame.DataFrame
```

[6]:
```
df.columns
```

[6]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL',
       'AMT_CREDIT', 'AMT_ANNUITY',
       …
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=122)
```

[7]:
```
df.head()
```

[7]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
```

```
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          202500.0    406597.5      24700.5
1               N             0          270000.0   1293502.5      35698.5
2               Y             0           67500.0    135000.0       6750.0
3               Y             0          135000.0    312682.5      29686.5
4               Y             0          121500.0    513000.0      21865.5

   …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20 FLAG_DOCUMENT_21  \
0  …                 0                0                0                0
1  …                 0                0                0                0
2  …                 0                0                0                0
3  …                 0                0                0                0
4  …                 0                0                0                0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                        0.0
1                        0.0                        0.0
2                        0.0                        0.0
3                        NaN                        NaN
4                        0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0

   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]
```

[8]:
```
# Task2
df.isnull()
```

[8]:
```
        SK_ID_CURR  TARGET  NAME_CONTRACT_TYPE  CODE_GENDER  FLAG_OWN_CAR  \
0            False   False               False        False         False
1            False   False               False        False         False
```

```
2            False   False               False        False          False
3            False   False               False        False          False
4            False   False               False        False          False
…            …     …                 …          …           …
307506       False   False               False        False          False
307507       False   False               False        False          False
307508       False   False               False        False          False
307509       False   False               False        False          False
307510       False   False               False        False          False

        FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
0                 False         False             False       False
1                 False         False             False       False
2                 False         False             False       False
3                 False         False             False       False
4                 False         False             False       False
…                 …           …                 …         …
307506            False         False             False       False
307507            False         False             False       False
307508            False         False             False       False
307509            False         False             False       False
307510            False         False             False       False

        AMT_ANNUITY  …  FLAG_DOCUMENT_18  FLAG_DOCUMENT_19  \
0             False  …             False             False
1             False  …             False             False
2             False  …             False             False
3             False  …             False             False
4             False  …             False             False
…             …  …               …                 …
307506        False  …             False             False
307507        False  …             False             False
307508        False  …             False             False
307509        False  …             False             False
307510        False  …             False             False

        FLAG_DOCUMENT_20  FLAG_DOCUMENT_21  AMT_REQ_CREDIT_BUREAU_HOUR  \
0                  False             False                       False
1                  False             False                       False
2                  False             False                       False
3                  False             False                        True
4                  False             False                       False
…                  …               …                         …
307506             False             False                        True
307507             False             False                        True
307508             False             False                       False
307509             False             False                       False
```

```
307510             False              False                           False

        AMT_REQ_CREDIT_BUREAU_DAY  AMT_REQ_CREDIT_BUREAU_WEEK  \
0                           False                       False
1                           False                       False
2                           False                       False
3                            True                        True
4                           False                       False
…                             …                          …
307506                       True                        True
307507                       True                        True
307508                      False                       False
307509                      False                       False
307510                      False                       False

        AMT_REQ_CREDIT_BUREAU_MON  AMT_REQ_CREDIT_BUREAU_QRT  \
0                           False                      False
1                           False                      False
2                           False                      False
3                            True                       True
4                           False                      False
…                             …                         …
307506                       True                       True
307507                       True                       True
307508                      False                      False
307509                      False                      False
307510                      False                      False

        AMT_REQ_CREDIT_BUREAU_YEAR
0                            False
1                            False
2                            False
3                             True
4                            False
…                              …
307506                        True
307507                        True
307508                       False
307509                       False
307510                       False

[307511 rows x 122 columns]
```

[9]:
```
df.isnull().sum()
```

[9]:
```
SK_ID_CURR                         0
TARGET                             0
```

```
NAME_CONTRACT_TYPE                 0
CODE_GENDER                        0
FLAG_OWN_CAR                       0
                                 …
AMT_REQ_CREDIT_BUREAU_DAY      41519
AMT_REQ_CREDIT_BUREAU_WEEK     41519
AMT_REQ_CREDIT_BUREAU_MON      41519
AMT_REQ_CREDIT_BUREAU_QRT      41519
AMT_REQ_CREDIT_BUREAU_YEAR     41519
Length: 122, dtype: int64
```

[10]:
```
df.head()
```

[10]:
```
   SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
0      100002       1         Cash loans           M            N
1      100003       0         Cash loans           F            N
2      100004       0    Revolving loans           M            Y
3      100006       0         Cash loans           F            N
4      100007       0         Cash loans           M            N

  FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  AMT_ANNUITY  \
0               Y             0          202500.0    406597.5      24700.5
1               N             0          270000.0   1293502.5      35698.5
2               Y             0           67500.0    135000.0       6750.0
3               Y             0          135000.0    312682.5      29686.5
4               Y             0          121500.0    513000.0      21865.5

   …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20 FLAG_DOCUMENT_21  \
0  …                 0                0                0                0
1  …                 0                0                0                0
2  …                 0                0                0                0
3  …                 0                0                0                0
4  …                 0                0                0                0

  AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
0                        0.0                       0.0
1                        0.0                       0.0
2                        0.0                       0.0
3                        NaN                       NaN
4                        0.0                       0.0

   AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
0                         0.0                        0.0
1                         0.0                        0.0
2                         0.0                        0.0
3                         NaN                        NaN
4                         0.0                        0.0
```

```
   AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
0                        0.0                         1.0
1                        0.0                         0.0
2                        0.0                         0.0
3                        NaN                         NaN
4                        0.0                         0.0

[5 rows x 122 columns]
```

[11]:
```
 #Task 3
defaulters=(df.TARGET==1).sum()
payers=(df.TARGET==0).sum()
print((defaulters/payers)*100)
```

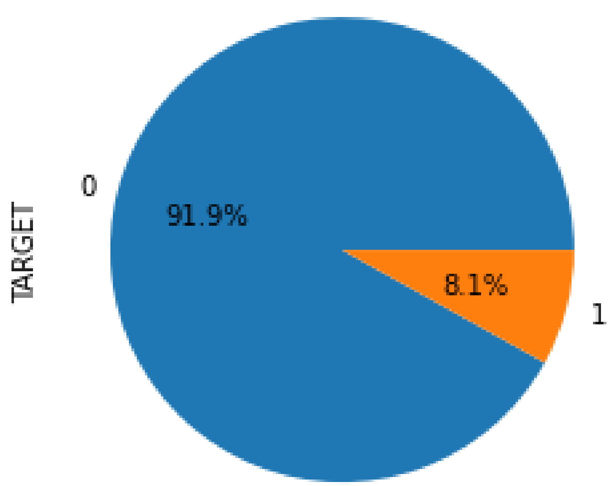
```
8.781828601345662
```

[12]:
```
without_id=[column for column in df.columns if column!='SK_ID_CURR']

#check for duplicate values
na=df[df.duplicated(subset=without_id,keep=False)]
print("Duplicates are: ",na.shape[0])
```

```
Duplicates are:  0
```

[13]:
```
df.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%')
```

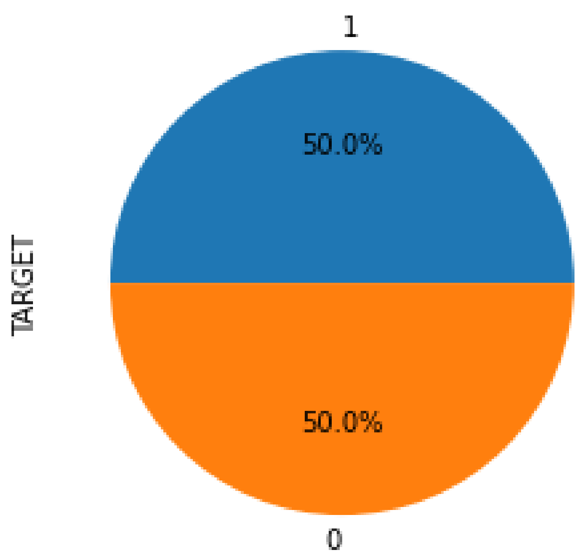
[13]: <AxesSubplot:ylabel='TARGET'>



[14]:
```
import matplotlib as plt
```

[15]:
```
shuffled_data=df.sample(frac=1,random_state=3)
unpaid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==1]
paid_home_loan=shuffled_data.loc[shuffled_data['TARGET']==0].
 ↪sample(n=24825,random_state=69)
normalised_df=pd.concat([unpaid_home_loan,paid_home_loan])
normalised_df.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

[15]:
```
<AxesSubplot:ylabel='TARGET'>
```



[16]:
```
import tensorflow as tf
```

[17]:
```
normalised_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49650 entries, 207339 to 121862
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 46.6+ MB
```

[18]:
```
normalised_df.head()
```

[18]:
```
        SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
207339      340318       1         Cash loans           F            N
8756        110186       1         Cash loans           M            Y
```

```
230344      366811       1         Cash loans           F            N
178329      306645       1         Cash loans           M            Y
55586       164407       1         Cash loans           M            N

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
207339               N             0          112500.0    405000.0
8756                 N             0          135000.0    544491.0
230344               Y             0          112500.0    225000.0
178329               Y             0          157500.0    595273.5
55586                N             0          157500.0    521451.0

        AMT_ANNUITY  …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20  \
207339      21969.0  …                 0                0                0
8756        17563.5  …                 0                0                0
230344      17905.5  …                 0                0                0
178329      29083.5  …                 0                0                0
55586       35406.0  …                 0                0                0

       FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
207339                0                        0.0                       0.0
8756                  0                        0.0                       0.0
230344                0                        NaN                       NaN
178329                0                        NaN                       NaN
55586                 0                        0.0                       0.0

        AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
207339                         0.0                        0.0
8756                           0.0                        0.0
230344                         NaN                        NaN
178329                         NaN                        NaN
55586                          0.0                        0.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
207339                        0.0                         3.0
8756                          0.0                         0.0
230344                        NaN                         NaN
178329                        NaN                         NaN
55586                         0.0                         1.0

[5 rows x 122 columns]
```

[19]:
```
normalised_df.dropna(axis=0)
normalised_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49650 entries, 207339 to 121862
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
```

```
dtypes: float64(65), int64(41), object(16)
memory usage: 46.6+ MB
```

[20]:
```
normalised_df.isnull().sum()
```

[20]:
```
SK_ID_CURR                    0
TARGET                        0
NAME_CONTRACT_TYPE            0
CODE_GENDER                   0
FLAG_OWN_CAR                  0
                           …
AMT_REQ_CREDIT_BUREAU_DAY    7648
AMT_REQ_CREDIT_BUREAU_WEEK   7648
AMT_REQ_CREDIT_BUREAU_MON    7648
AMT_REQ_CREDIT_BUREAU_QRT    7648
AMT_REQ_CREDIT_BUREAU_YEAR   7648
Length: 122, dtype: int64
```

[21]:
```
print(pd.unique(normalised_df.AMT_REQ_CREDIT_BUREAU_DAY))
print(pd.unique(normalised_df.AMT_REQ_CREDIT_BUREAU_WEEK))
print(pd.unique(normalised_df.AMT_REQ_CREDIT_BUREAU_MON))
print(pd.unique(normalised_df.AMT_REQ_CREDIT_BUREAU_QRT))
print(pd.unique(normalised_df.AMT_REQ_CREDIT_BUREAU_YEAR))
```

```
[ 0. nan  1.  2.  4.  3.  9.]
[ 0. nan  1.  2.  4.  3.  5.  6.]
[ 0. nan  1.  3.  5.  9.  2.  6.  8.  4. 11. 12.  7. 13. 10. 17. 15. 14.
 16. 18. 27.]
[ 0. nan  2.  3.  1.  4.  5.  6. 19.  7.]
[ 3.  0. nan  1.  5.  4.  2.  6.  7.  8.  9. 10. 14. 13. 12. 11. 22. 16.
 23. 17.]
```

[22]:
```
normalised_df.dropna(axis=0)
```

[22]:
```
        SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
279124      423360       1         Cash loans           M            Y
216116      350411       1         Cash loans           M            Y
133687      255050       1         Cash loans           M            Y
4159        104863       1         Cash loans           M            Y
208602      341779       1         Cash loans           F            Y
…              …      …                …           …          …
108677      226053       0         Cash loans           M            Y
258603      399273       0    Revolving loans           M            Y
51880       160079       0         Cash loans           M            Y
282820      427561       0         Cash loans           F            Y
207101      340051       0    Revolving loans           F            Y

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
```

```
279124                N             1          157500.0   1125000.0
216116                N             0          112500.0    225000.0
133687                N             1          337500.0    704844.0
4159                  N             0          265500.0    521280.0
208602                Y             1          247500.0    544491.0
…                …           …                …         …
108677                Y             0          135000.0    679500.0
258603                Y             1          450000.0    180000.0
51880                 Y             0          202500.0    750649.5
282820                N             0          270000.0   1800000.0
207101                Y             0          103500.0    315000.0

        AMT_ANNUITY  …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20  \
279124      33025.5  …                 0                0                0
216116      25447.5  …                 0                0                0
133687      26977.5  …                 0                0                0
4159        28408.5  …                 0                0                0
208602      17694.0  …                 0                0                0
…                …  …               …               …               …
108677      36333.0  …                 0                0                0
258603       9000.0  …                 0                0                0
51880       53514.0  …                 0                0                0
282820      62568.0  …                 0                0                0
207101      15750.0  …                 0                0                0

       FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
279124                0                        0.0                       0.0
216116                0                        0.0                       0.0
133687                0                        0.0                       0.0
4159                  0                        0.0                       0.0
208602                0                        0.0                       0.0
…                    …                         …                        …
108677                0                        0.0                       0.0
258603                0                        0.0                       0.0
51880                 0                        0.0                       0.0
282820                0                        0.0                       0.0
207101                0                        0.0                       0.0

        AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
279124                         0.0                        0.0
216116                         1.0                        1.0
133687                         0.0                        0.0
4159                           0.0                        0.0
208602                         0.0                        0.0
…                             …                         …
108677                         0.0                        0.0
258603                         0.0                        0.0
```

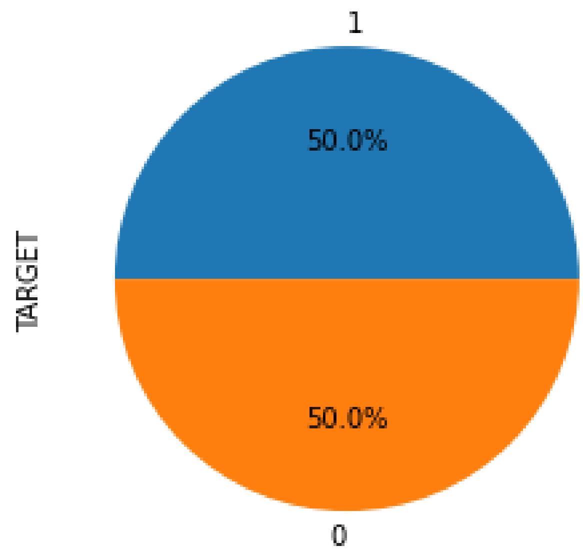
```
51880                          0.0                           0.0
282820                         0.0                           1.0
207101                         0.0                           1.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
279124                        0.0                         1.0
216116                        0.0                         1.0
133687                        2.0                         2.0
4159                          0.0                         2.0
208602                        0.0                         2.0
…                            …                           …
108677                        0.0                         0.0
258603                        0.0                         1.0
51880                         1.0                         3.0
282820                        0.0                         1.0
207101                        1.0                         5.0

[1230 rows x 122 columns]
```

[23]:
```
print(normalised_df.info())
print(normalised_df.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49650 entries, 207339 to 121862
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(65), int64(41), object(16)
memory usage: 46.6+ MB
None
SK_ID_CURR                       0
TARGET                           0
NAME_CONTRACT_TYPE               0
CODE_GENDER                      0
FLAG_OWN_CAR                     0
                              …
AMT_REQ_CREDIT_BUREAU_DAY     7648
AMT_REQ_CREDIT_BUREAU_WEEK    7648
AMT_REQ_CREDIT_BUREAU_MON     7648
AMT_REQ_CREDIT_BUREAU_QRT     7648
AMT_REQ_CREDIT_BUREAU_YEAR    7648
Length: 122, dtype: int64
```

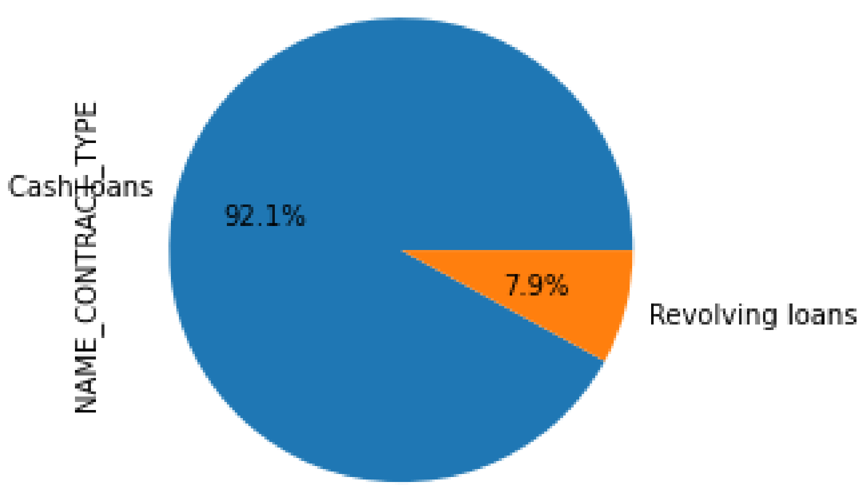
[24]:
```
normalised_df.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

[24]:
```
<AxesSubplot:ylabel='TARGET'>
```



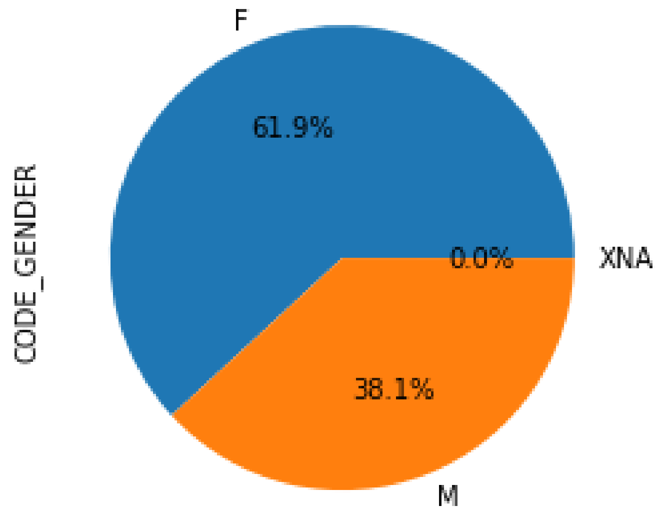
[25]:
```
normalised_df.NAME_CONTRACT_TYPE.value_counts().plot(kind='pie',autopct="%1.
↪1f%%")
```

[25]: <AxesSubplot:ylabel='NAME_CONTRACT_TYPE'>



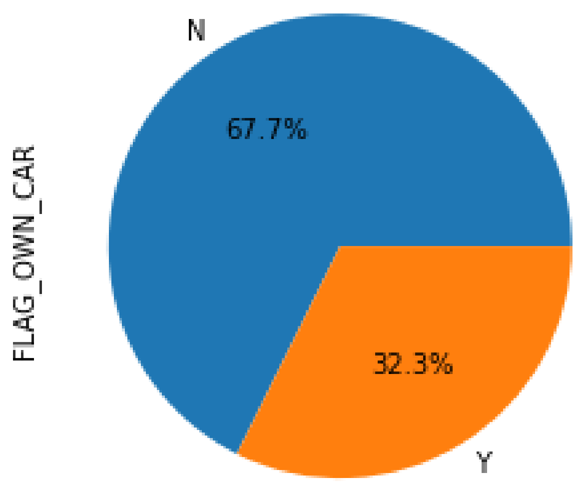
[26]:
```
normalised_df.CODE_GENDER.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

[26]: <AxesSubplot:ylabel='CODE_GENDER'>



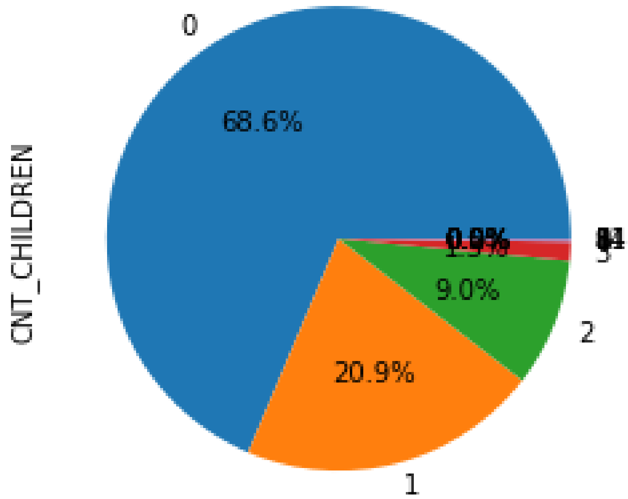
[27]:
```
normalised_df.FLAG_OWN_CAR.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

[27]: <AxesSubplot:ylabel='FLAG_OWN_CAR'>



[28]:
```
normalised_df.CNT_CHILDREN.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

[28]:
```
<AxesSubplot:ylabel='CNT_CHILDREN'>
```



[29]:
```python
print((normalised_df[normalised_df['AMT_INCOME_TOTAL']>1000000]['TARGET'].value_counts())/len(normalised_df[normalised_df['AMT_INCOME_TOTAL'] > 1000000])*100)
```

```
0    64.864865
1    35.135135
Name: TARGET, dtype: float64
```

[30]:
```python
print((normalised_df[normalised_df['CNT_CHILDREN']>2]['TARGET'].value_counts())/len(normalised_df[normalised_df['CNT_CHILDREN'] > 2])*100)
print((normalised_df[normalised_df['CNT_CHILDREN']>5]['TARGET'].value_counts())/len(normalised_df[normalised_df['CNT_CHILDREN'] > 5])*100)
#as number of children is increasing lone defaulters are increasing
```

```
1    57.047872
0    42.952128
Name: TARGET, dtype: float64
1    81.818182
0    18.181818
Name: TARGET, dtype: float64
```

[31]:
```python
print((normalised_df[normalised_df['FLAG_OWN_CAR']=='N']['TARGET'].value_counts())/len(normalised_df[normalised_df['FLAG_OWN_CAR'] =='N'])*100)
print((normalised_df[normalised_df['FLAG_OWN_CAR']=='Y']['TARGET'].value_counts())/len(normalised_df[normalised_df['FLAG_OWN_CAR'] =='Y'])*100)
```

```
#people with own cars are slighlty more likely to repay back the loan
```

```
1    51.350064
0    48.649936
Name: TARGET, dtype: float64
0    52.823962
1    47.176038
Name: TARGET, dtype: float64
```

[32]:
```
print((normalised_df[normalised_df['CODE_GENDER']=='M']['TARGET'].
 ↪value_counts())/len(normalised_df[normalised_df['CODE_GENDER'] =='M'])*100)
print((normalised_df[normalised_df['CODE_GENDER']=='F']['TARGET'].
 ↪value_counts())/len(normalised_df[normalised_df['CODE_GENDER'] =='F'])*100)

#men more likely to default in payment of loans
```

```
1    56.280372
0    43.719628
Name: TARGET, dtype: float64
0    53.867691
1    46.132309
Name: TARGET, dtype: float64
```

[33]:
```
print((normalised_df[normalised_df['NAME_CONTRACT_TYPE']=='Cash␣
 ↪loans']['TARGET'].value_counts())/
 ↪len(normalised_df[normalised_df['NAME_CONTRACT_TYPE']=='Cash loans'])*100)
print((normalised_df[normalised_df['NAME_CONTRACT_TYPE']=='Revolving␣
 ↪loans']['TARGET'].value_counts())/
 ↪len(normalised_df[normalised_df['NAME_CONTRACT_TYPE']=='Revolving␣
 ↪loans'])*100)

#cash loans have a higher percent of defaulters
```

```
1    50.802923
0    49.197077
Name: TARGET, dtype: float64
0    59.309995
1    40.690005
Name: TARGET, dtype: float64
```

[34]:
```
normalised_df=normalised_df.sample(frac=1,random_state=5)
```

[35]:
```
from sklearn.preprocessing import OrdinalEncoder

ordenc=OrdinalEncoder()
normalised_df['NAME_CONTRACT_TYPE_CODE']=ordenc.
 ↪fit_transform(normalised_df[['NAME_CONTRACT_TYPE']])
```

```
print(normalised_df[['NAME_CONTRACT_TYPE','NAME_CONTRACT_TYPE_CODE']].head(10))
print(normalised_df['NAME_CONTRACT_TYPE_CODE'].value_counts())
```

```
       NAME_CONTRACT_TYPE  NAME_CONTRACT_TYPE_CODE
302218         Cash loans                      0.0
167526         Cash loans                      0.0
159305         Cash loans                      0.0
275427         Cash loans                      0.0
8837           Cash loans                      0.0
192094         Cash loans                      0.0
235115    Revolving loans                      1.0
79051          Cash loans                      0.0
123267    Revolving loans                      1.0
5517           Cash loans                      0.0
0.0    45708
1.0     3942
Name: NAME_CONTRACT_TYPE_CODE, dtype: int64
```

[36]:
```
normalised_df['CODE_GENDER_CODE']=ordenc.
 ↪fit_transform(normalised_df[['CODE_GENDER']])
print(normalised_df[['CODE_GENDER','CODE_GENDER_CODE']].head(10))
print(normalised_df['CODE_GENDER_CODE'].value_counts())
```

```
       CODE_GENDER  CODE_GENDER_CODE
302218           M               1.0
167526           F               0.0
159305           M               1.0
275427           F               0.0
8837             M               1.0
192094           M               1.0
235115           F               0.0
79051            F               0.0
123267           M               1.0
5517             F               0.0
0.0    30716
1.0    18932
2.0        2
Name: CODE_GENDER_CODE, dtype: int64
```

[37]:
```
# 2 other values in code_gender
normalised_df.loc[normalised_df['CODE_GENDER_CODE']==2]
```

[37]:
```
        SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
83382       196708       0    Revolving loans         XNA            N
189640      319880       0    Revolving loans         XNA            Y

       FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
```

```
83382                Y              1          135000.0    405000.0
189640               Y              0          247500.0    540000.0

        AMT_ANNUITY  …  FLAG_DOCUMENT_20 FLAG_DOCUMENT_21  \
83382       20250.0  …                 0                0
189640      27000.0  …                 0                0

       AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
83382                         0.0                       0.0
189640                        0.0                       0.0

       AMT_REQ_CREDIT_BUREAU_WEEK AMT_REQ_CREDIT_BUREAU_MON  \
83382                         0.0                       0.0
189640                        0.0                       0.0

        AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR  \
83382                         0.0                         3.0
189640                        1.0                         6.0

        NAME_CONTRACT_TYPE_CODE  CODE_GENDER_CODE
83382                       1.0               2.0
189640                      1.0               2.0

[2 rows x 124 columns]
```

[38]:
```
normalised_df['FLAG_OWN_CAR_CODE']=ordenc.
 ↪fit_transform(normalised_df[['FLAG_OWN_CAR']])
print(normalised_df[['FLAG_OWN_CAR','FLAG_OWN_CAR_CODE']].head(10))
print(normalised_df['FLAG_OWN_CAR_CODE'].value_counts())
```

```
       FLAG_OWN_CAR  FLAG_OWN_CAR_CODE
302218            N                0.0
167526            N                0.0
159305            N                0.0
275427            N                0.0
8837              N                0.0
192094            N                0.0
235115            N                0.0
79051             N                0.0
123267            N                0.0
5517              N                0.0
0.0    33591
1.0    16059
Name: FLAG_OWN_CAR_CODE, dtype: int64
```

[39]:
```
normalised_df['CNT_CHILDREN_CODE']=ordenc.
 ↪fit_transform(normalised_df[['CNT_CHILDREN']])
```

```
print(normalised_df[['CNT_CHILDREN_CODE','CNT_CHILDREN']].head(10))
print(normalised_df['CNT_CHILDREN_CODE'].value_counts())
```

```
        CNT_CHILDREN_CODE  CNT_CHILDREN
302218                0.0             0
167526                0.0             0
159305                2.0             2
275427                0.0             0
8837                  0.0             0
192094                0.0             0
235115                0.0             0
79051                 0.0             0
123267                1.0             1
5517                  0.0             0
0.0     34073
1.0     10381
2.0      4444
3.0       642
4.0        89
5.0        10
6.0         6
8.0         2
7.0         1
10.0        1
9.0         1
Name: CNT_CHILDREN_CODE, dtype: int64
```

[40]:
```
normalised_df=normalised_df.sample(frac=1,random_state=45)
```

[41]:
```
normalised_df['TARGET'].value_counts()
```

[41]:
```
1    24825
0    24825
Name: TARGET, dtype: int64
```

[42]:
```
y=normalised_df.TARGET
```

[43]:
```
normalised_df_features=['SK_ID_CURR','NAME_CONTRACT_TYPE_CODE','CNT_CHILDREN_CODE','FLAG_OWN_C
```

[44]:
```
from sklearn.model_selection import train_test_split
```

[45]:
```
X=normalised_df[normalised_df_features]
```

[46]:
```
from sklearn.datasets import make_blobs
```

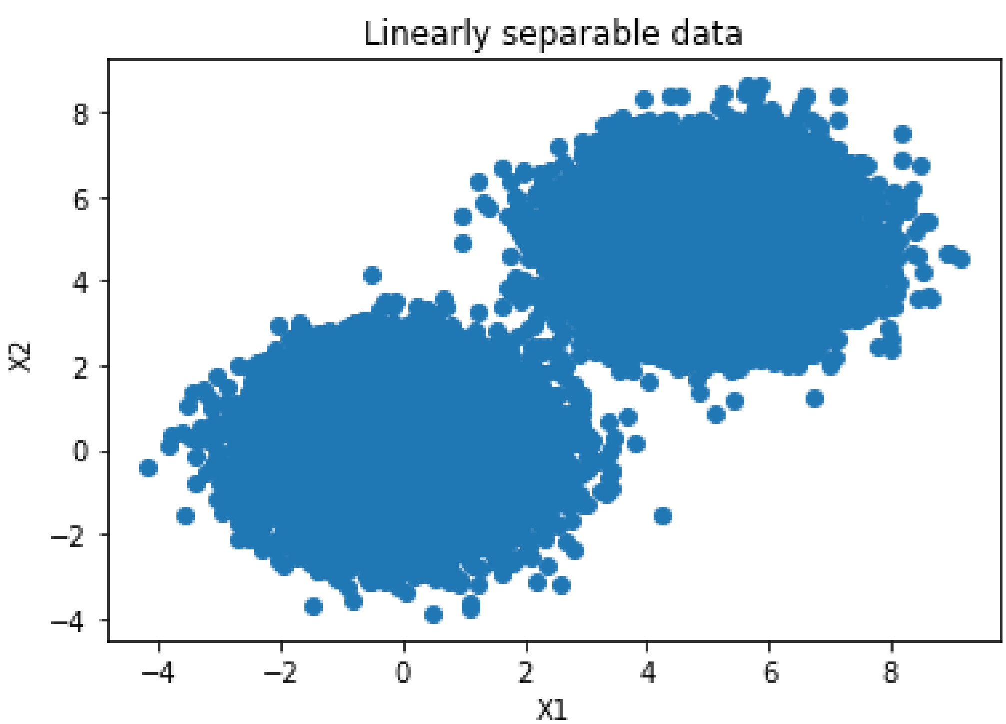
[47]:
```
blobs_random_seed = 42
centers = [(0,0), (5,5)]
```

```
cluster_std = 1
frac_test_split = 0.33
num_features_for_samples = 2
num_samples_total = 49650

# Generate data
inputs, targets = make_blobs (n_samples = num_samples_total, centers = centers,␣
↪n_features = num_features_for_samples, cluster_std = cluster_std)

X_train,X_test,y_train,y_test=train_test_split(inputs,targets,test_size=0.
↪33,random_state=45)
```

[48]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(33265, 2) (16385, 2) (33265,) (16385,)
```

[49]:
```
plt.pyplot.scatter(X_train[:,0], X_train[:,1])
plt.pyplot.title('Linearly separable data')
plt.pyplot.xlabel('X1')
plt.pyplot.ylabel('X2')
plt.pyplot.show()
```

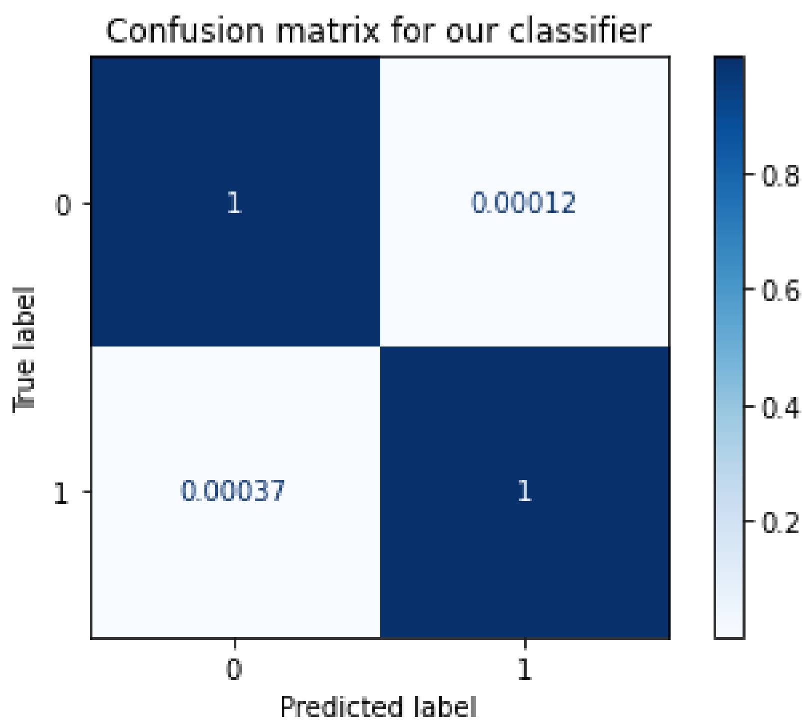


[50]:
```
from sklearn import svm
from sklearn.metrics import plot_confusion_matrix
```

[51]:
```
clf=svm.SVC(kernel='linear')
clf=clf.fit(X_train,y_train)
```

[52]:
```
predictions = clf.predict(X_test)

# Generate confusion matrix
matrix = plot_confusion_matrix(clf, X_test, y_test,
                                 cmap=plt.cm.Blues,
                                 normalize='true')
plt.pyplot.title('Confusion matrix for our classifier')
plt.pyplot.show(matrix)
plt.pyplot.show()
```

```
/usr/local/lib/python3.7/site-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```

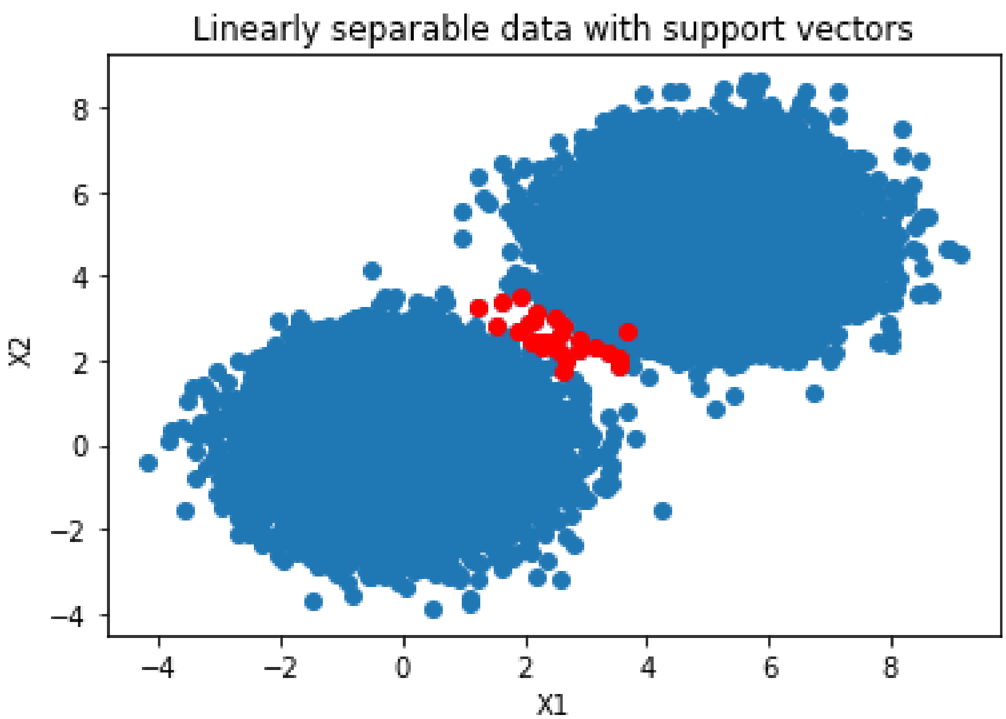


[53]:
```
from sklearn.metrics import precision_score, recall_score,f1_score
```

[54]:
```
print(precision_score(y_test, predictions))
print(recall_score(y_test, predictions))
print(f1_score(y_test,predictions,average=None))
```

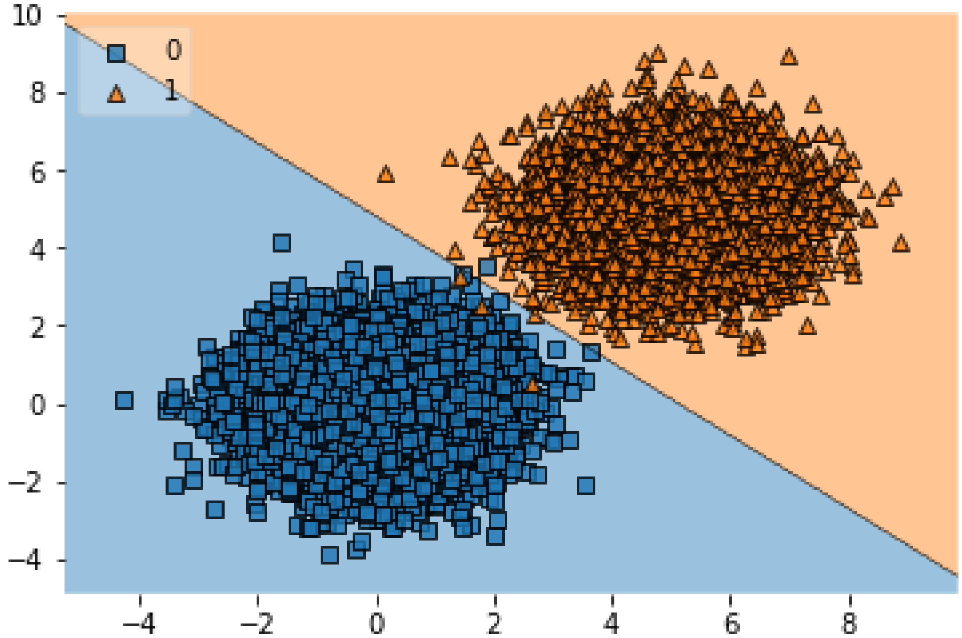
```
0.9998773908778813
0.9996322628095121
[0.99975693 0.99975481]
```

[55]:
```
support_vectors = clf.support_vectors_

# Visualize support vectors
plt.pyplot.scatter(X_train[:,0], X_train[:,1])
plt.pyplot.scatter(support_vectors[:,0], support_vectors[:,1], color='red')
plt.pyplot.title('Linearly separable data with support vectors')
plt.pyplot.xlabel('X1')
plt.pyplot.ylabel('X2')
plt.pyplot.show()
```



[56]:
```
from mlxtend.plotting import plot_decision_regions
```

[57]:
```
plot_decision_regions(X_test, y_test, clf=clf,legend=2)
plt.pyplot.show()
```



2 Thank you