House Loan Analysis

December 21, 2021

[1]:
```python
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O
```

[2]:
```python
import pandas as pd
import sklearn
import numpy as np
import matplotlib.pyplot as plt
import os
import warnings
import seaborn as sns
```

[4]:
```python
from sklearn.preprocessing import OneHotEncoder
from sklearn.datasets import make_blobs
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.svm import LinearSVC
from sklearn.metrics import roc_auc_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_auc_score
```

[5]:
```python
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.linear_model import SGDClassifier
import plotly.offline as py
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode, iplot
from sklearn.model_selection import train_test_split
```

[6]:
```python
house_loan=pd.read_csv('loan_data.csv')
```

[7]:
```python
house_loan.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              0.0              0.0
1  …               0.0              0.0              0.0              0.0
2  …               0.0              0.0              0.0              0.0
3  …               0.0              0.0              0.0              0.0
4  …               0.0              0.0              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]
```

[9]:
```
house_loan.describe()
```

[9]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	\
count	23282.000000	23282.000000	23282.000000	2.328200e+04	
mean	113570.719440	0.079804	0.416373	1.733403e+05	
std	7830.755945	0.270996	0.719606	7.720617e+05	
min	100002.000000	0.000000	0.000000	2.565000e+04	
25%	106808.250000	0.000000	0.000000	1.125000e+05	
50%	113562.500000	0.000000	0.000000	1.464750e+05	
75%	120362.750000	0.000000	1.000000	2.025000e+05	
max	127085.000000	1.000000	8.000000	1.170000e+08	

	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	\
count	2.328200e+04	23282.000000	2.326400e+04	
mean	6.002050e+05	27134.236535	5.395397e+05	
std	4.022264e+05	14607.498468	3.698661e+05	
min	4.500000e+04	2052.000000	4.500000e+04	
25%	2.700000e+05	16456.500000	2.385000e+05	
50%	5.160690e+05	24986.250000	4.500000e+05	
75%	8.100000e+05	34720.875000	6.795000e+05	
max	4.050000e+06	258025.500000	4.050000e+06	

	REGION_POPULATION_RELATIVE	DAYS_BIRTH	DAYS_EMPLOYED	…	\
count	23282.000000	23282.000000	23282.000000	…	
mean	0.020731	-16010.774805	62798.682459	…	
std	0.013776	4351.106672	140445.941033	…	
min	0.000533	-25182.000000	-16365.000000	…	
25%	0.010006	-19618.750000	-2789.000000	…	
50%	0.018850	-15748.500000	-1232.000000	…	
75%	0.028663	-12361.000000	-294.000000	…	
max	0.072508	-7680.000000	365243.000000	…	

	FLAG_DOCUMENT_18	FLAG_DOCUMENT_19	FLAG_DOCUMENT_20	FLAG_DOCUMENT_21	\
count	23281.000000	23281.000000	23281.000000	23281.000000	
mean	0.007818	0.000644	0.000558	0.000515	
std	0.088072	0.025375	0.023624	0.022698	
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	20168.000000	20168.000000	
mean	0.007388	0.007586	
std	0.087357	0.113509	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.000000	0.000000	

```
75%                    0.000000                    0.000000
max                    2.000000                    5.000000

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
count                20168.000000                20168.000000
mean                     0.032576                    0.275932
std                      0.196866                    0.955535
min                      0.000000                    0.000000
25%                      0.000000                    0.000000
50%                      0.000000                    0.000000
75%                      0.000000                    0.000000
max                      5.000000                   24.000000

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
count               20168.000000                20168.000000
mean                    0.263288                    1.888388
std                     0.613881                    1.864287
min                     0.000000                    0.000000
25%                     0.000000                    0.000000
50%                     0.000000                    1.000000
75%                     0.000000                    3.000000
max                     8.000000                   25.000000

[8 rows x 106 columns]
```

[10]:
```
house_loan.columns
```

[10]:
```
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)
```

[11]:
```
house_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23282 entries, 0 to 23281
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(100), int64(6), object(16)
memory usage: 21.7+ MB
```

[13]:
```
house_loan.isnull().sum()
```

[13]:
```
SK_ID_CURR                     0
TARGET                         0
NAME_CONTRACT_TYPE             0
CODE_GENDER                    0
FLAG_OWN_CAR                   0
                            …
AMT_REQ_CREDIT_BUREAU_DAY   3114
AMT_REQ_CREDIT_BUREAU_WEEK  3114
AMT_REQ_CREDIT_BUREAU_MON   3114
AMT_REQ_CREDIT_BUREAU_QRT   3114
AMT_REQ_CREDIT_BUREAU_YEAR  3114
Length: 122, dtype: int64
```

[14]:
```python
defaulters=(house_loan.TARGET==1).sum()
payers=(house_loan.TARGET==0).sum()
print((defaulters/payers)*100)
```

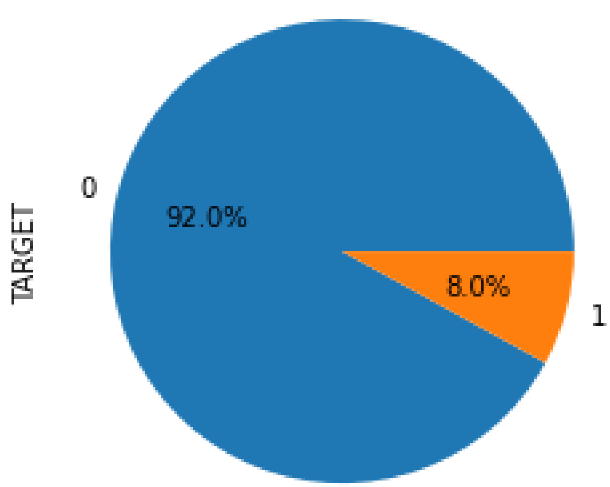
```
8.672516803584765
```

[15]:
```python
without_id=[column for column in house_loan.columns if column!='SK_ID_CURR']

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

```
Duplicates are:  0
```

[16]:
```python
house_loan.TARGET.value_counts().plot(kind='pie',autopct='%1.1f%%')
```

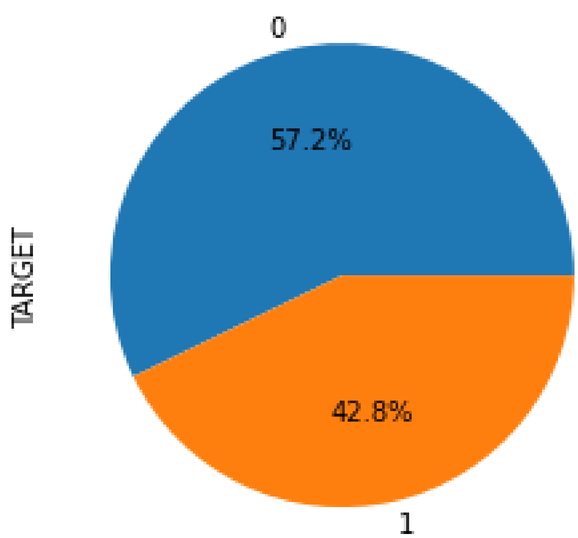
[16]:
```
<AxesSubplot:ylabel='TARGET'>
```



[17]:
```python
import matplotlib as plt
```

[18]:
```python
shuffled_data=house_loan.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=2482,random_state=69)
normalised_home_loan=pd.concat([unpaid_home_loan,paid_home_loan])
normalised_home_loan.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

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



[19]:
```python
import tensorflow as tf
```

[20]:
```python
normalised_home_loan.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4340 entries, 15136 to 3579
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(100), int64(6), object(16)
memory usage: 4.1+ MB
```

[21]:
```python
normalised_home_loan.head
```

```
[21]: <bound method NDFrame.head of         SK_ID_CURR  TARGET NAME_CONTRACT_TYPE
CODE_GENDER FLAG_OWN_CAR  \
15136       117678       1    Revolving loans           F            N
3422        103996       1         Cash loans           M            Y
17567       120489       1         Cash loans           M            Y
5764        106741       1         Cash loans           M            N
5577        106530       1         Cash loans           F            N
…              …     …                …         …         …
6137        107172       0    Revolving loans           M            N
18615       121710       0         Cash loans           F            N
7154        108325       0         Cash loans           F            N
6823        107956       0         Cash loans           F            N
3579        104182       0         Cash loans           F            N

      FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
15136               Y             2           76500.0    225000.0
3422                Y             0          103500.0    438493.5
17567               Y             2          315000.0    335592.0
5764                Y             0          144000.0    306000.0
5577                Y             0          157500.0    540000.0
…                 …           …                 …          …
6137                Y             1          315000.0    675000.0
18615               Y             1          112500.0    743031.0
7154                Y             0          180000.0    594121.5
6823                Y             0          103500.0    263686.5
3579                N             0          111640.5    312768.0

       AMT_ANNUITY  …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20  \
15136      11250.0  …               0.0              0.0              0.0
3422       26626.5  …               0.0              0.0              0.0
17567      26644.5  …               0.0              0.0              0.0
5764       16600.5  …               0.0              0.0              0.0
5577       26109.0  …               0.0              0.0              0.0
…              …  …              …                …                …
6137       33750.0  …               0.0              0.0              0.0
18615      39717.0  …               0.0              0.0              0.0
7154       26167.5  …               0.0              0.0              0.0
6823       17298.0  …               0.0              0.0              0.0
3579       20353.5  …               0.0              0.0              0.0

      FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
15136              0.0                        0.0                       0.0
3422               0.0                        0.0                       0.0
17567              0.0                        0.0                       0.0
5764               0.0                        NaN                       NaN
5577               0.0                        0.0                       0.0
…                 …                        …                       …
```

```
6137                  0.0                        0.0                        0.0
18615                 0.0                        0.0                        0.0
7154                  0.0                        0.0                        0.0
6823                  0.0                        0.0                        0.0
3579                  0.0                        0.0                        0.0

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
15136                         0.0                        0.0
3422                          0.0                        0.0
17567                         0.0                        0.0
5764                          NaN                        NaN
5577                          0.0                        0.0
…                             …                          …
6137                          0.0                        1.0
18615                         0.0                        0.0
7154                          0.0                        0.0
6823                          0.0                        0.0
3579                          0.0                        0.0

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
15136                        0.0                         3.0
3422                         2.0                         1.0
17567                        1.0                         5.0
5764                         NaN                         NaN
5577                         0.0                         0.0
…                            …                           …
6137                         0.0                         0.0
18615                        0.0                         3.0
7154                         0.0                         1.0
6823                         0.0                         0.0
3579                         0.0                         0.0

[4340 rows x 122 columns]>
```

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

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4340 entries, 15136 to 3579
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(100), int64(6), object(16)
memory usage: 4.1+ MB
```

[23]:
```
normalised_home_loan.isnull().sum()
```

[23]:
```
SK_ID_CURR                      0
TARGET                          0
```

```
NAME_CONTRACT_TYPE              0
CODE_GENDER                     0
FLAG_OWN_CAR                    0
                               …
AMT_REQ_CREDIT_BUREAU_DAY     658
AMT_REQ_CREDIT_BUREAU_WEEK    658
AMT_REQ_CREDIT_BUREAU_MON     658
AMT_REQ_CREDIT_BUREAU_QRT     658
AMT_REQ_CREDIT_BUREAU_YEAR    658
Length: 122, dtype: int64
```

[24]:
```
#print(normalised_home_loan.apply())
```

[25]:
```
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_DAY))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_WEEK))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_MON))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_QRT))
print(pd.unique(normalised_home_loan.AMT_REQ_CREDIT_BUREAU_YEAR))
```

```
[ 0. nan  1.  2.  5.]
[ 0. nan  1.  2.  5.]
[ 0. nan  1.  2.  7.  5.  3.  6.  4.  9. 10.  8. 13. 16. 12.]
[ 0.  2.  1. nan  3.  4.  6.  5.]
[ 3.  1.  5. nan  0.  4.  2.  9.  6.  7.  8. 11. 16. 10.]
```

[26]:
```
normalised_home_loan.dropna(axis=0)
```

[26]:
```
       SK_ID_CURR  TARGET NAME_CONTRACT_TYPE CODE_GENDER FLAG_OWN_CAR  \
4448       105200       1         Cash loans           M            Y
11552      113461       1         Cash loans           F            Y
21432      124969       1         Cash loans           F            Y
17128      119978       1         Cash loans           F            Y
7064       108227       1         Cash loans           F            Y
…             …     …               …         …          …
15436      118014       0         Cash loans           F            Y
18326      121377       0         Cash loans           M            Y
3378       103946       0         Cash loans           M            Y
19438      122670       0         Cash loans           M            Y
11363      113233       0         Cash loans           F            Y

      FLAG_OWN_REALTY  CNT_CHILDREN  AMT_INCOME_TOTAL  AMT_CREDIT  \
4448                N             2          157500.0    732834.0
11552               N             0          202500.0    502497.0
21432               Y             1          202500.0    450000.0
17128               Y             1          135000.0    550980.0
7064                N             2          126000.0    432661.5
…                …           …                …          …
```

```
15436              Y            0         360000.0    473760.0
18326              Y            0         270000.0    900000.0
3378               Y            0         166500.0    888840.0
19438              N            0         270000.0    785398.5
11363              N            2         270000.0   2013840.0

       AMT_ANNUITY  …  FLAG_DOCUMENT_18 FLAG_DOCUMENT_19 FLAG_DOCUMENT_20  \
4448       46962.0  …               0.0              0.0              0.0
11552      36562.5  …               0.0              0.0              0.0
21432      32742.0  …               0.0              0.0              0.0
17128      33835.5  …               0.0              0.0              0.0
7064       22653.0  …               0.0              0.0              0.0
…              …  …               …              …              …
15436      51021.0  …               0.0              0.0              0.0
18326      29034.0  …               0.0              0.0              0.0
3378       32053.5  …               0.0              0.0              0.0
19438      30042.0  …               0.0              0.0              0.0
11363      55377.0  …               0.0              0.0              0.0

      FLAG_DOCUMENT_21 AMT_REQ_CREDIT_BUREAU_HOUR AMT_REQ_CREDIT_BUREAU_DAY  \
4448               0.0                        0.0                       0.0
11552              0.0                        0.0                       0.0
21432              0.0                        0.0                       0.0
17128              0.0                        0.0                       0.0
7064               0.0                        0.0                       0.0
…                …                        …                       …
15436              0.0                        0.0                       0.0
18326              0.0                        0.0                       0.0
3378               0.0                        0.0                       0.0
19438              0.0                        0.0                       0.0
11363              0.0                        0.0                       0.0

       AMT_REQ_CREDIT_BUREAU_WEEK  AMT_REQ_CREDIT_BUREAU_MON  \
4448                          0.0                        1.0
11552                         0.0                        1.0
21432                         0.0                        0.0
17128                         0.0                        1.0
7064                          0.0                        2.0
…                           …                        …
15436                         0.0                        0.0
18326                         0.0                        8.0
3378                          0.0                        0.0
19438                         0.0                        0.0
11363                         0.0                        0.0

       AMT_REQ_CREDIT_BUREAU_QRT  AMT_REQ_CREDIT_BUREAU_YEAR
4448                         3.0                         4.0
```

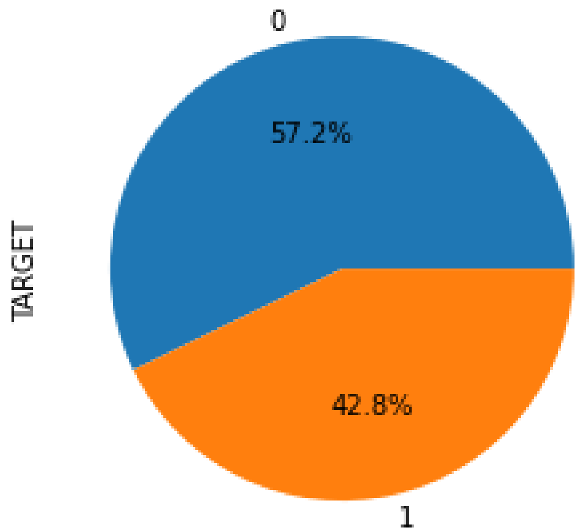
```
11552                       0.0                         2.0
21432                       0.0                         0.0
17128                       0.0                         2.0
7064                        0.0                         0.0
…                         …                         …
15436                       0.0                         0.0
18326                       0.0                         0.0
3378                        0.0                         0.0
19438                       0.0                         0.0
11363                       0.0                         0.0

[98 rows x 122 columns]
```

[27]:
```
print(normalised_home_loan.info())
print(normalised_home_loan.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4340 entries, 15136 to 3579
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(100), int64(6), object(16)
memory usage: 4.1+ MB
None
SK_ID_CURR                      0
TARGET                          0
NAME_CONTRACT_TYPE              0
CODE_GENDER                     0
FLAG_OWN_CAR                    0
                              …
AMT_REQ_CREDIT_BUREAU_DAY     658
AMT_REQ_CREDIT_BUREAU_WEEK    658
AMT_REQ_CREDIT_BUREAU_MON     658
AMT_REQ_CREDIT_BUREAU_QRT     658
AMT_REQ_CREDIT_BUREAU_YEAR    658
Length: 122, dtype: int64
```

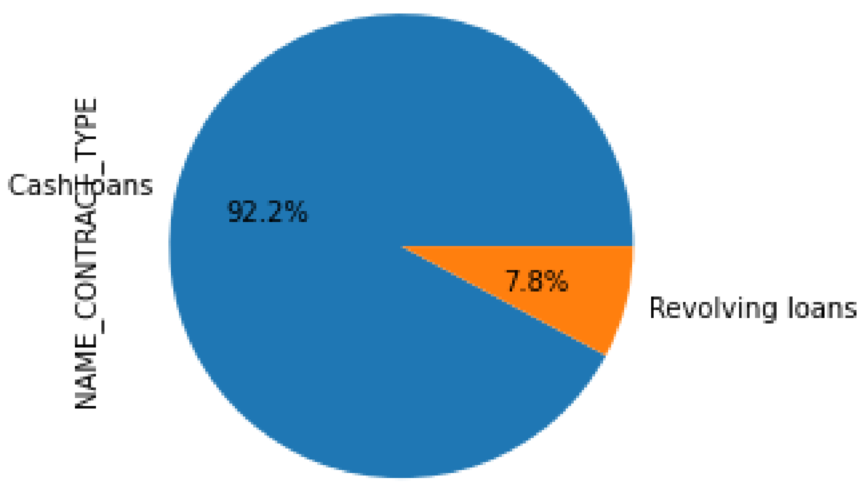
[28]:
```
normalised_home_loan.TARGET.value_counts().plot(kind='pie',autopct="%1.1f%%")
```

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



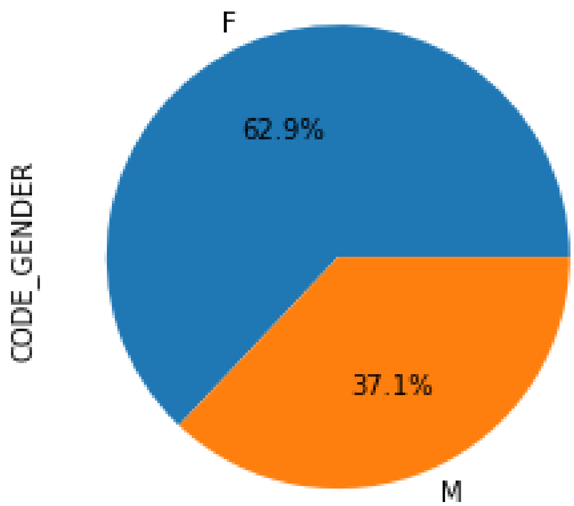

```
[29]: normalised_home_loan.NAME_CONTRACT_TYPE.value_counts().
       ↪plot(kind='pie',autopct="%1.1f%%")
      #high amount of cash loans
```

```
[29]: <AxesSubplot:ylabel='NAME_CONTRACT_TYPE'>
```



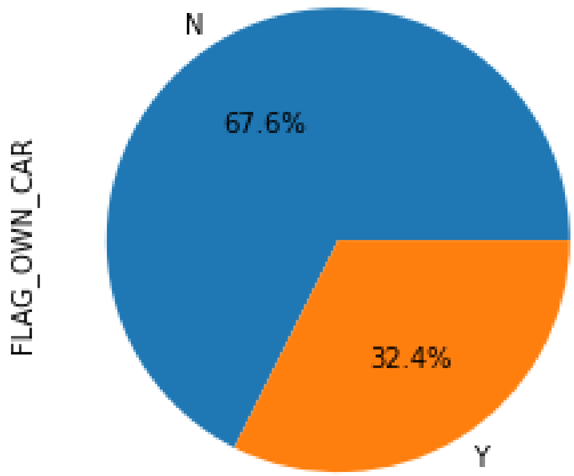
[30]:
```
normalised_home_loan.CODE_GENDER.value_counts().plot(kind='pie',autopct="%1.
↪1f%%")
#roughly equal amount
```

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



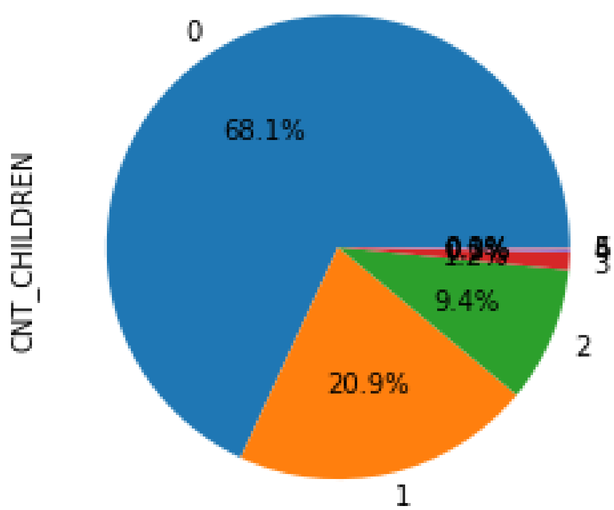
[31]:
```
normalised_home_loan.FLAG_OWN_CAR.value_counts().plot(kind='pie',autopct="%1.
↪1f%%")
```

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



[32]:
```
normalised_home_loan.CNT_CHILDREN.value_counts().plot(kind='pie',autopct="%1.
↪1f%%")
```

[32]: <AxesSubplot:ylabel='CNT_CHILDREN'>



[35]:
```
pip install lightgbm
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting lightgbm
  Downloading lightgbm-3.3.1-py3-none-manylinux1_x86_64.whl (2.0 MB)
     |                 | 2.0 MB 8.8 MB/s eta 0:00:01
Requirement already satisfied: wheel in /usr/local/lib/python3.7/site-
packages (from lightgbm) (0.34.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/site-packages
(from lightgbm) (1.4.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/site-packages
(from lightgbm) (1.18.2)
Requirement already satisfied: scikit-learn!=0.22.0 in
/usr/local/lib/python3.7/site-packages (from lightgbm) (0.24.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/site-packages (from scikit-learn!=0.22.0->lightgbm)
(2.2.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/site-
packages (from scikit-learn!=0.22.0->lightgbm) (0.14.1)
Installing collected packages: lightgbm
Successfully installed lightgbm-3.3.1
WARNING: You are using pip version 20.3.3; however, version 21.3.1 is
available.
You should consider upgrading via the '/usr/local/bin/python3.7 -m pip install
--upgrade pip' command.
Note: you may need to restart the kernel to use updated packages.
```

[36]:

```
init_notebook_mode(connected=True)
import cufflinks as cf
cf.go_offline()
import pickle
import gc
import lightgbm as lgb
warnings.filterwarnings('ignore')
%matplotlib inline
```

[38]:

```
#!pip install chart_studio


cf.set_config_file(theme='polar')

normalised_home_loan[normalised_home_loan['AMT_INCOME_TOTAL'] <␣
 ↪2000000]['AMT_INCOME_TOTAL'].iplot(kind='histogram', bins=100,
   xTitle = 'Total Income', yTitle ='Count of applicants',
             title='Distribution of AMT_INCOME_TOTAL')
```

[39]:
```
(normalised_home_loan[normalised_home_loan['AMT_INCOME_TOTAL']>1000000]['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['AMT_INCOME_TOTAL'] >␣
 ↪1000000])*100
```

[39]:
```
0    66.666667
1    33.333333
Name: TARGET, dtype: float64
```

[40]:
```
#print((normalised_home_loan[normalised_home_loan['CNT_CHILDREN']>1]['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['CNT_CHILDREN'] > 2])*100)
print((normalised_home_loan[normalised_home_loan['CNT_CHILDREN']>2]['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['CNT_CHILDREN'] > 2])*100)
print((normalised_home_loan[normalised_home_loan['CNT_CHILDREN']>5]['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['CNT_CHILDREN'] > 5])*100)
#as number of children is increasing lone defaulters are increasing
```

```
1    55.882353
0    44.117647
Name: TARGET, dtype: float64
0    100.0
Name: TARGET, dtype: float64
```

[41]:
```
print((normalised_home_loan[normalised_home_loan['FLAG_OWN_CAR']=='N']['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['FLAG_OWN_CAR'] =='N'])*100)
print((normalised_home_loan[normalised_home_loan['FLAG_OWN_CAR']=='Y']['TARGET'].
 ↪value_counts())/
 ↪len(normalised_home_loan[normalised_home_loan['FLAG_OWN_CAR'] =='Y'])*100)

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

```
0    56.646217
1    43.353783
Name: TARGET, dtype: float64
0    58.321479
1    41.678521
Name: TARGET, dtype: float64
```

[42]:
```
print((normalised_home_loan[normalised_home_loan['CODE_GENDER']=='M']['TARGET'].
 ↪value_counts())/len(normalised_home_loan[normalised_home_loan['CODE_GENDER']␣
 ↪=='M'])*100)
```

```
print((normalised_home_loan[normalised_home_loan['CODE_GENDER']=='F']['TARGET'].
    ↪value_counts())/len(normalised_home_loan[normalised_home_loan['CODE_GENDER']␣
    ↪=='F'])*100)

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

```
0    50.124378
1    49.875622
Name: TARGET, dtype: float64
0    61.346999
1    38.653001
Name: TARGET, dtype: float64
```

[43]:
```
print((normalised_home_loan[normalised_home_loan['NAME_CONTRACT_TYPE']=='Cash␣
    ↪loans']['TARGET'].value_counts())/
    ↪len(normalised_home_loan[normalised_home_loan['NAME_CONTRACT_TYPE']=='Cash␣
    ↪loans'])*100)
print((normalised_home_loan[normalised_home_loan['NAME_CONTRACT_TYPE']=='Revolving␣
    ↪loans']['TARGET'].value_counts())/
    ↪len(normalised_home_loan[normalised_home_loan['NAME_CONTRACT_TYPE']=='Revolving␣
    ↪loans'])*100)

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

```
0    55.986003
1    44.013997
Name: TARGET, dtype: float64
0    71.386431
1    28.613569
Name: TARGET, dtype: float64
```

[44]:
```
normalised_home_loan=normalised_home_loan.sample(frac=1,random_state=5)
```

[45]:
```
from sklearn.preprocessing import OrdinalEncoder

ordenc=OrdinalEncoder()
normalised_home_loan['NAME_CONTRACT_TYPE_CODE']=ordenc.
    ↪fit_transform(normalised_home_loan[['NAME_CONTRACT_TYPE']])
print(normalised_home_loan[['NAME_CONTRACT_TYPE','NAME_CONTRACT_TYPE_CODE']].
    ↪head(20))
print(normalised_home_loan['NAME_CONTRACT_TYPE_CODE'].value_counts())
```

```
      NAME_CONTRACT_TYPE  NAME_CONTRACT_TYPE_CODE
2282          Cash loans                      0.0
21488         Cash loans                      0.0
5623          Cash loans                      0.0
7255          Cash loans                      0.0
```

```
1248          Cash loans                      0.0
451      Revolving loans                      1.0
14868         Cash loans                      0.0
3485          Cash loans                      0.0
9180          Cash loans                      0.0
4898          Cash loans                      0.0
4128          Cash loans                      0.0
22749         Cash loans                      0.0
16041         Cash loans                      0.0
22629         Cash loans                      0.0
67       Revolving loans                      1.0
8350          Cash loans                      0.0
3113          Cash loans                      0.0
16487         Cash loans                      0.0
17207         Cash loans                      0.0
21916         Cash loans                      0.0
0.0    4001
1.0     339
Name: NAME_CONTRACT_TYPE_CODE, dtype: int64
```

[46]:
```
normalised_home_loan['CODE_GENDER_CODE']=ordenc.
 ↪fit_transform(normalised_home_loan[['CODE_GENDER']])
print(normalised_home_loan[['CODE_GENDER','CODE_GENDER_CODE']].head(20))
print(normalised_home_loan['CODE_GENDER_CODE'].value_counts())
```

```
      CODE_GENDER  CODE_GENDER_CODE
2282            M               1.0
21488           F               0.0
5623            M               1.0
7255            F               0.0
1248            F               0.0
451             F               0.0
14868           F               0.0
3485            M               1.0
9180            F               0.0
4898            F               0.0
4128            M               1.0
22749           F               0.0
16041           F               0.0
22629           F               0.0
67              M               1.0
8350            F               0.0
3113            F               0.0
16487           F               0.0
17207           M               1.0
21916           F               0.0
0.0    2732
1.0    1608
```

```
Name: CODE_GENDER_CODE, dtype: int64
```

[48]:

```
#2 other values in code_gender
normalised_home_loan.loc[normalised_home_loan['CODE_GENDER_CODE']==2]
```

[48]:

```
Empty DataFrame
Columns: [SK_ID_CURR, TARGET, NAME_CONTRACT_TYPE, CODE_GENDER, FLAG_OWN_CAR,
FLAG_OWN_REALTY, CNT_CHILDREN, AMT_INCOME_TOTAL, AMT_CREDIT, AMT_ANNUITY,
AMT_GOODS_PRICE, NAME_TYPE_SUITE, NAME_INCOME_TYPE, NAME_EDUCATION_TYPE,
NAME_FAMILY_STATUS, NAME_HOUSING_TYPE, REGION_POPULATION_RELATIVE, DAYS_BIRTH,
DAYS_EMPLOYED, DAYS_REGISTRATION, DAYS_ID_PUBLISH, OWN_CAR_AGE, FLAG_MOBIL,
FLAG_EMP_PHONE, FLAG_WORK_PHONE, FLAG_CONT_MOBILE, FLAG_PHONE, FLAG_EMAIL,
OCCUPATION_TYPE, CNT_FAM_MEMBERS, REGION_RATING_CLIENT,
REGION_RATING_CLIENT_W_CITY, WEEKDAY_APPR_PROCESS_START,
HOUR_APPR_PROCESS_START, REG_REGION_NOT_LIVE_REGION, REG_REGION_NOT_WORK_REGION,
LIVE_REGION_NOT_WORK_REGION, REG_CITY_NOT_LIVE_CITY, REG_CITY_NOT_WORK_CITY,
LIVE_CITY_NOT_WORK_CITY, ORGANIZATION_TYPE, EXT_SOURCE_1, EXT_SOURCE_2,
EXT_SOURCE_3, APARTMENTS_AVG, BASEMENTAREA_AVG, YEARS_BEGINEXPLUATATION_AVG,
YEARS_BUILD_AVG, COMMONAREA_AVG, ELEVATORS_AVG, ENTRANCES_AVG, FLOORSMAX_AVG,
FLOORSMIN_AVG, LANDAREA_AVG, LIVINGAPARTMENTS_AVG, LIVINGAREA_AVG,
NONLIVINGAPARTMENTS_AVG, NONLIVINGAREA_AVG, APARTMENTS_MODE, BASEMENTAREA_MODE,
YEARS_BEGINEXPLUATATION_MODE, YEARS_BUILD_MODE, COMMONAREA_MODE, ELEVATORS_MODE,
ENTRANCES_MODE, FLOORSMAX_MODE, FLOORSMIN_MODE, LANDAREA_MODE,
LIVINGAPARTMENTS_MODE, LIVINGAREA_MODE, NONLIVINGAPARTMENTS_MODE,
NONLIVINGAREA_MODE, APARTMENTS_MEDI, BASEMENTAREA_MEDI,
YEARS_BEGINEXPLUATATION_MEDI, YEARS_BUILD_MEDI, COMMONAREA_MEDI, ELEVATORS_MEDI,
ENTRANCES_MEDI, FLOORSMAX_MEDI, FLOORSMIN_MEDI, LANDAREA_MEDI,
LIVINGAPARTMENTS_MEDI, LIVINGAREA_MEDI, NONLIVINGAPARTMENTS_MEDI,
NONLIVINGAREA_MEDI, FONDKAPREMONT_MODE, HOUSETYPE_MODE, TOTALAREA_MODE,
WALLSMATERIAL_MODE, EMERGENCYSTATE_MODE, OBS_30_CNT_SOCIAL_CIRCLE,
DEF_30_CNT_SOCIAL_CIRCLE, OBS_60_CNT_SOCIAL_CIRCLE, DEF_60_CNT_SOCIAL_CIRCLE,
DAYS_LAST_PHONE_CHANGE, FLAG_DOCUMENT_2, FLAG_DOCUMENT_3, FLAG_DOCUMENT_4,
FLAG_DOCUMENT_5, …]
Index: []

[0 rows x 124 columns]
```

[49]:

```
normalised_home_loan['FLAG_OWN_CAR_CODE']=ordenc.
 ↪fit_transform(normalised_home_loan[['FLAG_OWN_CAR']])
print(normalised_home_loan[['FLAG_OWN_CAR','FLAG_OWN_CAR_CODE']].head(20))
print(normalised_home_loan['FLAG_OWN_CAR_CODE'].value_counts())
```

```
      FLAG_OWN_CAR  FLAG_OWN_CAR_CODE
2282             Y                1.0
21488            N                0.0
5623             Y                1.0
7255             N                0.0
1248             Y                1.0
```

```
451              N              0.0
14868            N              0.0
3485             N              0.0
9180             N              0.0
4898             Y              1.0
4128             Y              1.0
22749            N              0.0
16041            Y              1.0
22629            N              0.0
67               N              0.0
8350             Y              1.0
3113             N              0.0
16487            Y              1.0
17207            Y              1.0
21916            N              0.0
0.0    2934
1.0    1406
Name: FLAG_OWN_CAR_CODE, dtype: int64
```

[50]:
```
normalised_home_loan['CNT_CHILDREN_CODE']=ordenc.
 ↪fit_transform(normalised_home_loan[['CNT_CHILDREN']])
print(normalised_home_loan[['CNT_CHILDREN_CODE','CNT_CHILDREN']].head(20))
print(normalised_home_loan['CNT_CHILDREN_CODE'].value_counts())
```

```
       CNT_CHILDREN_CODE  CNT_CHILDREN
2282                 0.0             0
21488                0.0             0
5623                 0.0             0
7255                 0.0             0
1248                 1.0             1
451                  0.0             0
14868                0.0             0
3485                 0.0             0
9180                 0.0             0
4898                 0.0             0
4128                 0.0             0
22749                0.0             0
16041                0.0             0
22629                1.0             1
67                   0.0             0
8350                 2.0             2
3113                 0.0             0
16487                0.0             0
17207                1.0             1
21916                0.0             0
0.0    2955
1.0     908
2.0     409
```

```
3.0      53
4.0      11
5.0       3
6.0       1
Name: CNT_CHILDREN_CODE, dtype: int64
```

[51]:
```
normalised_home_loan=normalised_home_loan.sample(frac=1,random_state=45)
```

[52]:
```
normalised_home_loan['TARGET'].value_counts()
```

[52]:
```
0    2482
1    1858
Name: TARGET, dtype: int64
```

[53]:
```
y=normalised_home_loan.TARGET
```

[54]:
```
normalised_home_loan_features=['SK_ID_CURR','NAME_CONTRACT_TYPE_CODE','CNT_CHILDREN_CODE','FLA
```

[55]:
```
from sklearn.model_selection import train_test_split
```

[56]:
```
X=normalised_home_loan[normalised_home_loan_features]
```

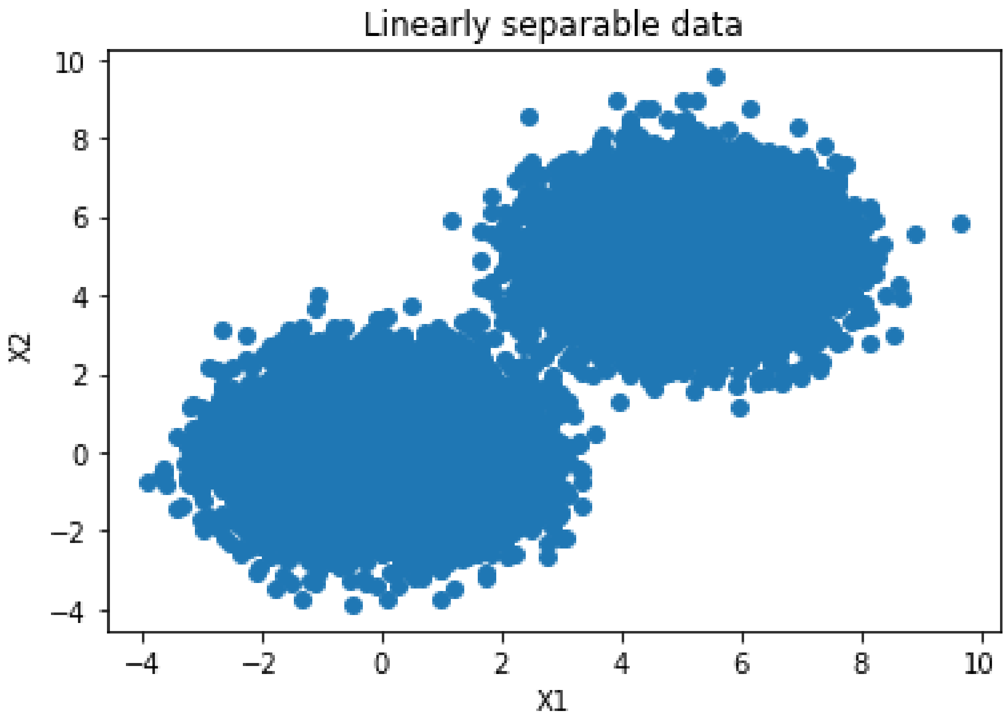
[57]:
```
blobs_random_seed = 42
centers = [(0,0), (5,5)]
cluster_std = 1
frac_test_split = 0.33
num_features_for_samples = 2
num_samples_total = 49650
```

[58]:
```
# 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)
```

[59]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

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

[60]:
```
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()
```

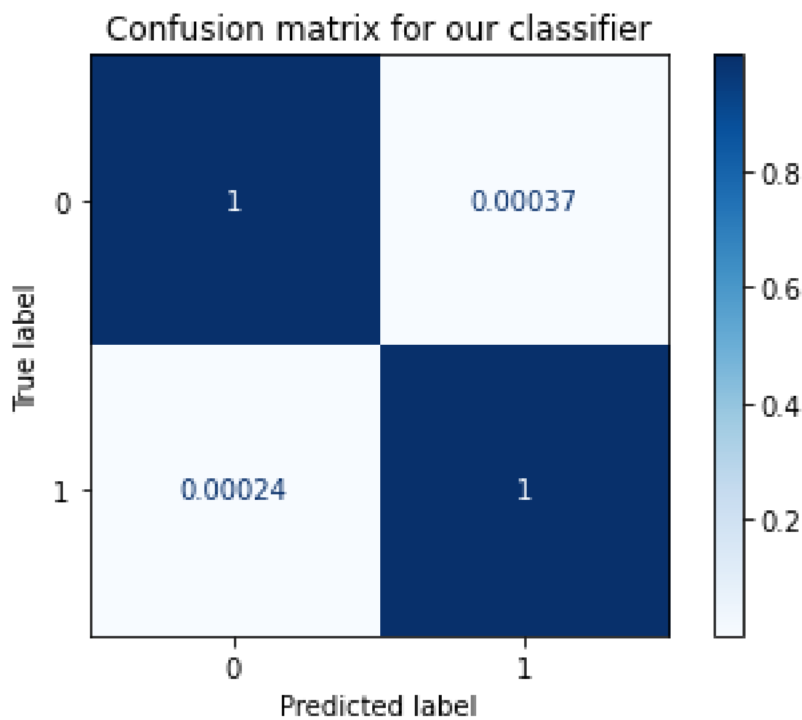


[61]:
```
from sklearn import svm
from sklearn.metrics import plot_confusion_matrix
```

[62]:
```
clf=svm.SVC(kernel='linear')
```

[63]:
```
clf=clf.fit(X_train,y_train)
```

[64]:
```
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()
```

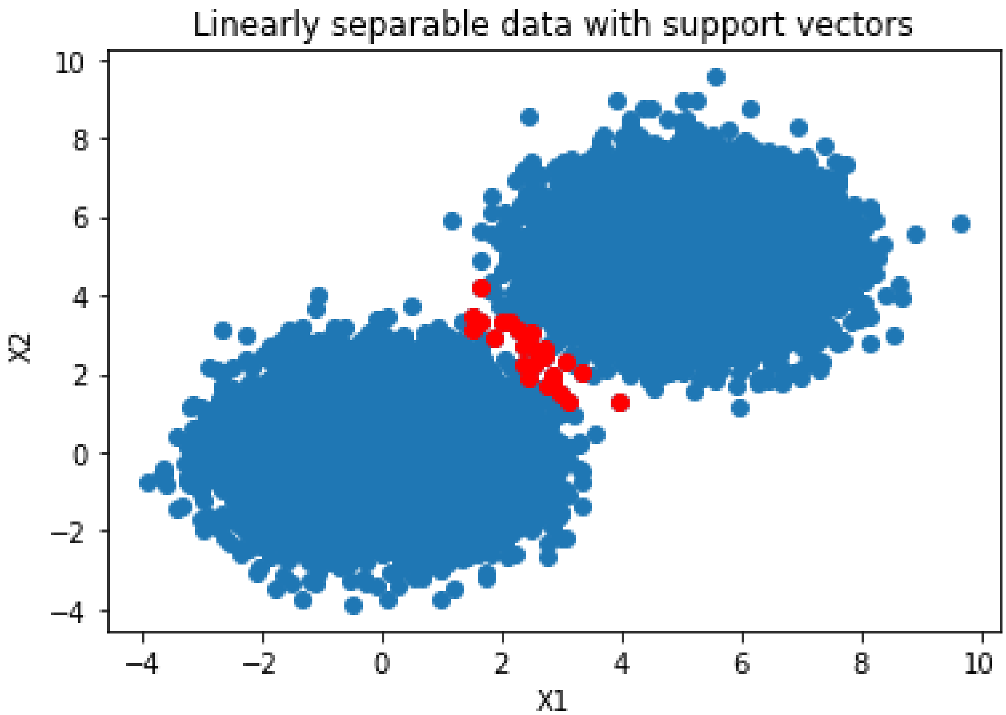


[65]:
```
from sklearn.metrics import precision_score, recall_score,f1_score
```

[66]:
```
print(precision_score(y_test, predictions))
print(recall_score(y_test, predictions))
print(f1_score(y_test,predictions,average=None))
```

```
0.9996342801414116
0.9997561570348695
[0.99969447 0.99969521]
```

[67]:
```
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()
```

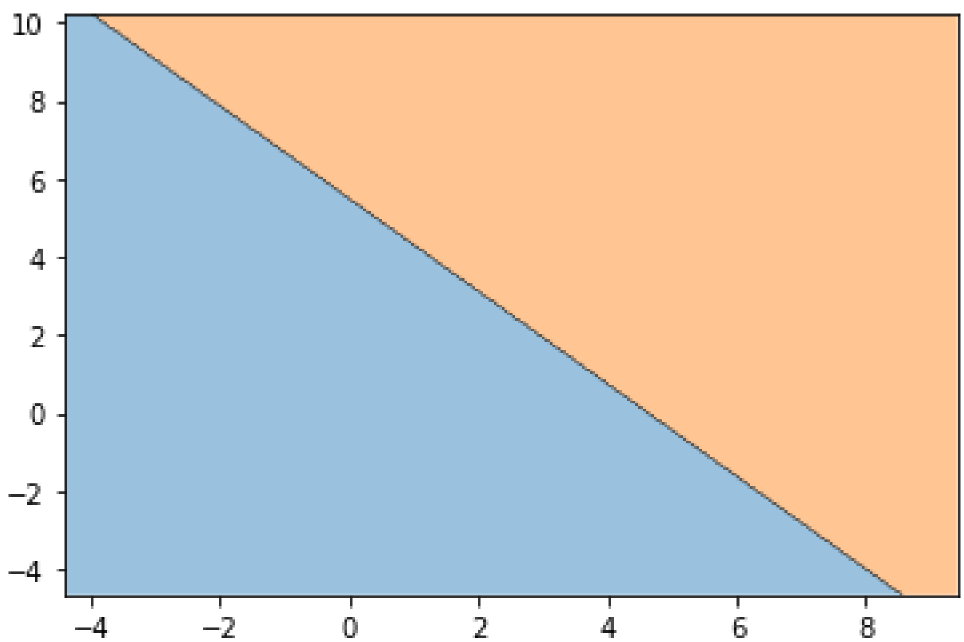


[68]:
```
from mlxtend.plotting import plot_decision_regions
```

[70]:
```
plot_decision_regions(X_test, y_test, clf=clf, legend=2)
```

```
   ␣
↪---------------------------------------------------------------------------

       TypeError                                 Traceback (most recent call␣
↪last)

       <ipython-input-70-93f94d0acd5e> in <module>
   ----> 1 plot_decision_regions(X_test, y_test, clf=clf, legend=2)


       /usr/local/lib/python3.7/site-packages/mlxtend/plotting/decision_regions.
↪py in plot_decision_regions(X, y, clf, feature_index, filler_feature_values,␣
↪filler_feature_ranges, ax, X_highlight, res, zoom_factor, legend, hide_spines,␣
↪markers, colors, scatter_kwargs, contourf_kwargs, scatter_highlight_kwargs)
       247                        antialiased=True)
       248
   --> 249     ax.axis(xmin=xx.min(), xmax=xx.max(), y_min=yy.min(), y_max=yy.
↪max())
```

```
    250
    251     # Scatter training data samples


    /usr/local/lib/python3.7/site-packages/matplotlib/axes/_base.py in␣
↪axis(self, emit, *args, **kwargs)
   1816             self.set_ylim(ymin, ymax, emit=emit, auto=yauto)
   1817         if kwargs:
-> 1818             raise TypeError(f"axis() got an unexpected keyword␣
↪argument "
   1819                             f"'{next(iter(kwargs))}'")
   1820         return (*self.get_xlim(), *self.get_ylim())


    TypeError: axis() got an unexpected keyword argument 'y_min'
```



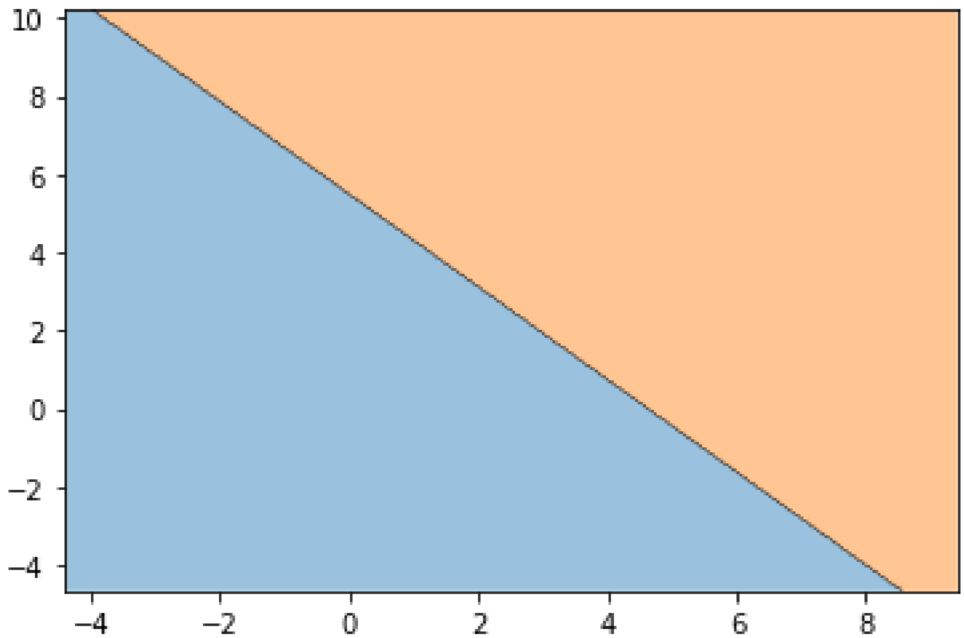
[73]:
```
plt.pyplot.show()
```

[74]:
```
import matplotlib.pyplot as plt
from mlxtend.plotting import plot_decision_regions

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn import datasets
import numpy as np
```

[75]:

```
plot_decision_regions(X_test, y_test, clf=clf, legend=2)
plt.pyplot.show()
```

```
␣
↪---------------------------------------------------------------------------

    TypeError                                 Traceback (most recent call␣
↪last)

    <ipython-input-75-ead453bdfdbf> in <module>
  ----> 1 plot_decision_regions(X_test, y_test, clf=clf, legend=2)
        2 plt.pyplot.show()


    /usr/local/lib/python3.7/site-packages/mlxtend/plotting/decision_regions.
↪py in plot_decision_regions(X, y, clf, feature_index, filler_feature_values,␣
↪filler_feature_ranges, ax, X_highlight, res, zoom_factor, legend, hide_spines,␣
↪markers, colors, scatter_kwargs, contourf_kwargs, scatter_highlight_kwargs)
    247                  antialiased=True)
    248
  --> 249     ax.axis(xmin=xx.min(), xmax=xx.max(), y_min=yy.min(), y_max=yy.
↪max())
    250
    251     # Scatter training data samples


    /usr/local/lib/python3.7/site-packages/matplotlib/axes/_base.py in␣
↪axis(self, emit, *args, **kwargs)
   1816             self.set_ylim(ymin, ymax, emit=emit, auto=yauto)
   1817         if kwargs:
  -> 1818             raise TypeError(f"axis() got an unexpected keyword␣
↪argument "
   1819                             f"'{next(iter(kwargs))}'")
   1820         return (*self.get_xlim(), *self.get_ylim())


    TypeError: axis() got an unexpected keyword argument 'y_min'
```


10
8
6
4
2
0
−2
−4
−4
−2
0
2
4
6
8

```
[ ]:
```