Predicting customer loan eligibility Using a Pipeline and a DecisionTreeClassifier

Dream Housing Finance company deals in all kinds of home loans. They have presence across all urban, semi urban and rural areas. Customer first applies for home loan and after that company validates the customer eligibility for loan.

Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have provided a dataset to identify the customers segments that are eligible for loan amount so that they can specifically target these customers.

```
In [370]: import numpy as np
import pandas as pd

loan_data = pd.read_csv('loan_data_set.csv')
print(loan_data.shape)
loan_data.head()

(614, 13)
```

Out[370]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	
4								•

Handling Missing Values

```
In [371]: #Explore the data for missing values
          loan_data.isnull().sum()
Out[371]: Loan ID
                                 0
          Gender
                                13
          Married
                                 3
                                15
          Dependents
          Education
                                 0
          Self Employed
                                32
          ApplicantIncome
                                 0
          CoapplicantIncome
                                 0
          LoanAmount
                                22
          Loan_Amount_Term
                                14
                                 50
          Credit History
          Property Area
                                 0
          Loan_Status
                                 0
          dtype: int64
In [372]: #Drop 13 rows with missing values in the gender column
          loan_data1 = loan_data[loan_data['Gender'].notna()]
          print(loan data1.shape)
          loan data1.isnull().sum()
          (601, 13)
Out[372]: Loan ID
                                 0
          Gender
                                 0
          Married
                                 3
                                15
          Dependents
          Education
                                 0
          Self Employed
                                 32
          ApplicantIncome
                                 0
          CoapplicantIncome
                                 0
          LoanAmount
                                22
          Loan_Amount_Term
                                14
                                49
          Credit_History
          Property Area
                                 0
          Loan Status
          dtype: int64
```

```
In [373]: #Fill missing values in 'Married' column with 'Yes' if loan value is equal or gre
m = loan_data1['Married'].isna()
loan_data1.loc[m, 'Married'] = np.where(loan_data1.loc[m, 'LoanAmount']>=153, 'Ye
loan_data1.isnull().sum()
```

c:\users\elijah\appdata\local\programs\python\python39\lib\site-packages\pandas
\core\indexing.py:1676: 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 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

self._setitem_single_column(ilocs[0], value, pi)

Out[373]: Loan_ID 0 Gender 0 Married 0 15 Dependents Education 0 Self Employed 32 ApplicantIncome 0 CoapplicantIncome 0 22 LoanAmount

Loan_Amount_Term 14
Credit_History 49
Property_Area 0
Loan Status 0

dtype: int64

```
In [374]: #Fill missing values in the numerical columns with the respective column means
          loan data2 = loan data1.fillna(loan data1.mean())
          #drop the remaining rows with missing values
          loan data2 = loan data2.dropna()
          #drop the loan ID column
          loan data3 = loan data2.drop('Loan ID', axis=1)
          print(loan data3.shape)
          loan data3.isnull().sum()
          (554, 12)
Out[374]: Gender
                                0
          Married
                                0
          Dependents
          Education
          Self Employed
                                0
          ApplicantIncome
          CoapplicantIncome
                                0
          LoanAmount
                                0
          Loan Amount Term
                                0
          Credit History
          Property Area
                                0
          Loan_Status
                                0
          dtype: int64
```

```
Data Preprocessing
In [375]: from sklearn.preprocessing import LabelEncoder
          #Do label encoding to the 'Dependents' categorical column(ordinal) and drop the d
          label enc = LabelEncoder()
          loan_data3['Dependents1'] = label_enc.fit_transform(loan_data3['Dependents'])
          loan data4 = loan data3.drop('Dependents', axis=1)
          #Split the data into X and y. Label encode y into a binary classification
          X = loan data4.drop('Loan Status', axis=1)
          y = loan_data4['Loan_Status']
          y = label enc.fit transform(y)
          #Split the dataset into train and test sets
          from sklearn.model selection import train test split
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_s
In [376]: #Create a column transformer to one-hot encode all other categorical features wit
          from sklearn.compose import make column transformer
          from sklearn.preprocessing import OneHotEncoder
          categorical columns = ['Gender', 'Married', 'Education', 'Self Employed', 'Proper
          col_trans = make_column_transformer((OneHotEncoder(drop='first', sparse=False),catering | sparse=False),catering |
```

```
In [377]: #Create a pipeline to preprocess(as above) the data then fit a classification mod
from sklearn.tree import DecisionTreeClassifier
from sklearn.pipeline import make_pipeline

svc_model = DecisionTreeClassifier(max_depth=3, min_samples_leaf = 30)
pipe = make_pipeline(col_trans, svc_model)

pipe.fit(X_train, y_train)
```

```
In [378]: #Since it is a classification task, we shall evaluate the model using the F1 Scor
from sklearn.metrics import f1_score, confusion_matrix

y_pred = pipe.predict(X_test)

print(f'F1-Score {round(f1_score(y_test, y_pred)*100,3)} %\n')
print('Confusion Matrix')
pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], margins=Tr
```

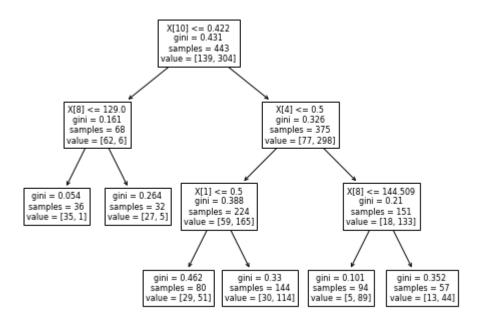
F1-Score 87.006 %

Confusion Matrix

Out[378]:

Predicted	0	1	All	
True				
0	11	22	33	
1	1	77	78	
ΔII	12	99	111	

In [379]: #Visualize the decision process using a tree from sklearn import tree import matplotlib.pyplot as plt plt.figure(figsize=(8,6)) tree.plot_tree(svc_model) plt.show()



```
In [380]: #We can also view the decision making process described using text
text_representation = tree.export_text(svc_model)
print(text_representation)
```

```
--- feature 10 <= 0.42
   |--- feature 8 <= 129.00
       |--- class: 0
    --- feature 8 > 129.00
       |--- class: 0
--- feature 10 > 0.42
   |--- feature 4 <= 0.50
        --- feature_1 <= 0.50
           |--- class: 1
        --- feature 1 > 0.50
           |--- class: 1
    --- feature 4 > 0.50
        --- feature 8 <= 144.51
           |--- class: 1
        --- feature 8 > 144.51
           |--- class: 1
```

In [381]: #Get some random sampled from the testing data to see the predictions
X_new = X_test.sample(5, random_state=4)
X_new

Out[381]:

	Gender	Married	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmoun
612	Male	Yes	Graduate	No	7583	0.0	187.
46	Male	Yes	Graduate	No	5649	0.0	44.
415	Female	No	Graduate	No	2995	0.0	60.
564	Male	Yes	Graduate	No	8799	0.0	258.
169	Male	Yes	Graduate	No	8000	0.0	200.
4							+

In [382]: pipe.predict(X_new)

Out[382]: array([1, 1, 1, 0, 1])