Loan_Data_Study

April 14, 2023

#

Kaggle's Loan Dataset

####

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###

Data Dictionary

Gender: Female/Male/Nan Married: Yes/No Dependents: 0, 1, 2, 3+ (to be recoded) Education: Graduate/Not Graduate Self_Employed: Whether an applicant is self-employeed Applicant_Income: Amount of applicant income Coapplicant_Income: Amount of co-applicant income Loan_Amount: Amount of loan Term: Length of the loan Credit_History: Whether the applicant has credit history Area: Urban, Semiurban and Rural #### Imports

[31]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import pandas as pd
```

[32]:
```
%load_ext autoreload
%autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

[33]:
```
loans= pd.read_csv('loan_train.csv')
loans
```

[33]:
```
     Gender Married Dependents     Education Self_Employed  Applicant_Income  \
0      Male      No          0      Graduate            No            584900
1      Male     Yes          1      Graduate            No            458300
2      Male     Yes          0      Graduate           Yes            300000
3      Male     Yes          0  Not Graduate            No            258300
4      Male      No          0      Graduate            No            600000
..      …       …          …             …             …                 …
609  Female      No          0      Graduate            No            290000
610    Male     Yes         3+      Graduate            No            410600
```

```
611    Male     Yes          1      Graduate            No           807200
612    Male     Yes          2      Graduate            No           758300
613  Female      No          0      Graduate           Yes           458300

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area Status
0                   0.0     15000000  360.0             1.0      Urban      Y
1              150800.0     12800000  360.0             1.0      Rural      N
2                   0.0      6600000  360.0             1.0      Urban      Y
3              235800.0     12000000  360.0             1.0      Urban      Y
4                   0.0     14100000  360.0             1.0      Urban      Y
..                  …            …     …              …        …     …
609                 0.0      7100000  360.0             1.0      Rural      Y
610                 0.0      4000000  180.0             1.0      Rural      Y
611             24000.0     25300000  360.0             1.0      Urban      Y
612                 0.0     18700000  360.0             1.0      Urban      Y
613                 0.0     13300000  360.0             0.0  Semiurban      N

[614 rows x 12 columns]
```

[34]:
```
loans.describe()
```

[34]:
```
       Applicant_Income  Coapplicant_Income   Loan_Amount       Term  \
count      6.140000e+02        6.140000e+02  6.140000e+02  600.00000
mean       5.403459e+05        1.621246e+05  1.414104e+07  342.00000
std        6.109042e+05        2.926248e+05  8.815682e+06   65.12041
min        1.500000e+04        0.000000e+00  0.000000e+00   12.00000
25%        2.877500e+05        0.000000e+00  9.800000e+06  360.00000
50%        3.812500e+05        1.188500e+05  1.250000e+07  360.00000
75%        5.795000e+05        2.297250e+05  1.647500e+07  360.00000
max        8.100000e+06        4.166700e+06  7.000000e+07  480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[35]:
```
loans.columns
```

[35]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'Applicant_Income', 'Coapplicant_Income', 'Loan_Amount', 'Term',
       'Credit_History', 'Area', 'Status'],
      dtype='object')
```

[36]:

```
loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Gender              601 non-null    object
 1   Married             611 non-null    object
 2   Dependents          599 non-null    object
 3   Education           614 non-null    object
 4   Self_Employed       582 non-null    object
 5   Applicant_Income    614 non-null    int64
 6   Coapplicant_Income  614 non-null    float64
 7   Loan_Amount         614 non-null    int64
 8   Term                600 non-null    float64
 9   Credit_History      564 non-null    float64
 10  Area                614 non-null    object
 11  Status              614 non-null    object
dtypes: float64(3), int64(2), object(7)
memory usage: 57.7+ KB
```

[37]:

```
val_cols=['Gender', 'Married', 'Dependents', 'Education',␣
 ↪'Self_Employed','Term',
        'Credit_History', 'Area', 'Status']
```

[38]:

```
for col in val_cols:
    print(loans[col].value_counts())
    print("{} empty cells".format(loans[col].isna().sum()))
```

```
Male      489
Female    112
Name: Gender, dtype: int64
13 empty cells
Yes    398
No     213
Name: Married, dtype: int64
3 empty cells
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
15 empty cells
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
0 empty cells
```

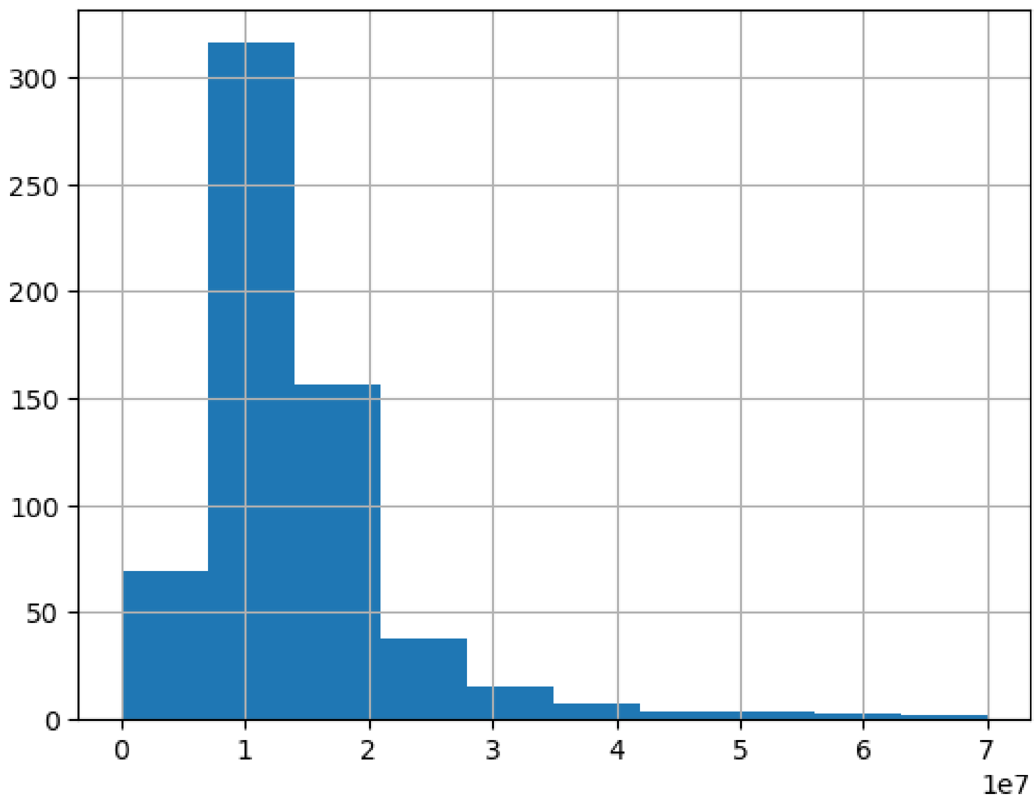
```
No     500
Yes     82
Name: Self_Employed, dtype: int64
32 empty cells
360.0    512
180.0     44
480.0     15
300.0     13
240.0      4
84.0       4
120.0      3
60.0       2
36.0       2
12.0       1
Name: Term, dtype: int64
14 empty cells
1.0    475
0.0     89
Name: Credit_History, dtype: int64
50 empty cells
Semiurban    233
Urban        202
Rural        179
Name: Area, dtype: int64
0 empty cells
Y    422
N    192
Name: Status, dtype: int64
0 empty cells
```

[39]:
```
for col in loans.loc[:,~(loans.columns.isin(val_cols))].columns:
    print("{} has {} empty cells".format(col,loans[col].isna().sum()))
```

```
Applicant_Income has 0 empty cells
Coapplicant_Income has 0 empty cells
Loan_Amount has 0 empty cells
```

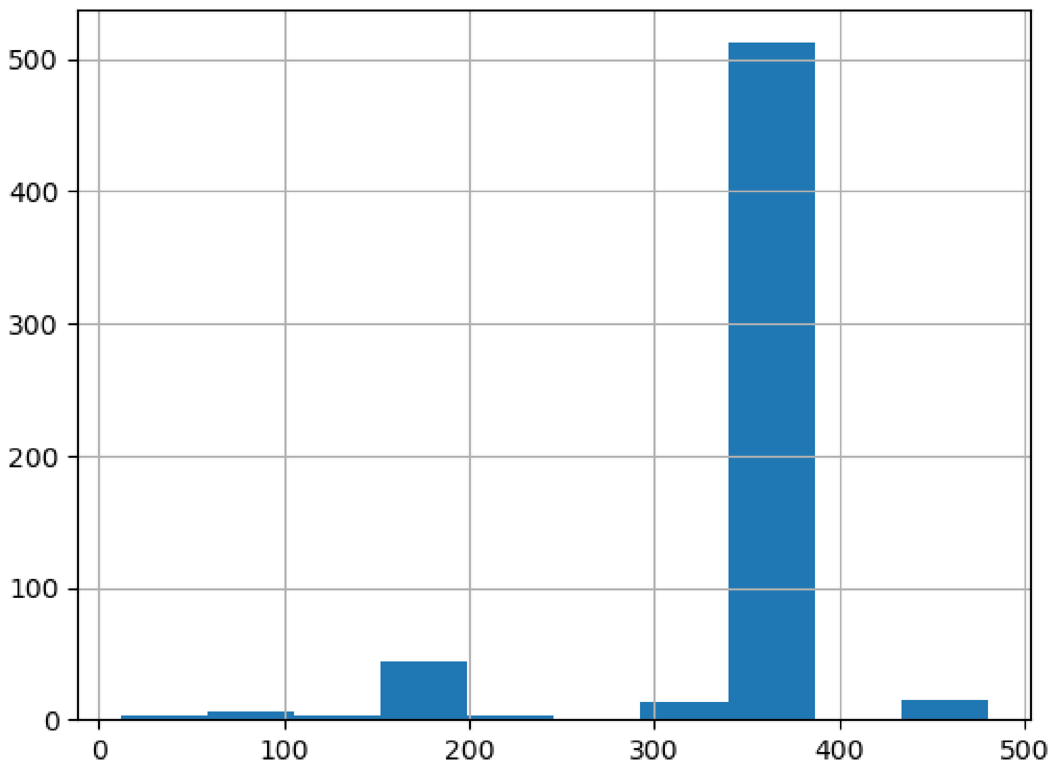
[40]:
```
loans["Loan_Amount"].hist()
```

[40]: `<matplotlib.axes._subplots.AxesSubplot at 0x16596413970>`



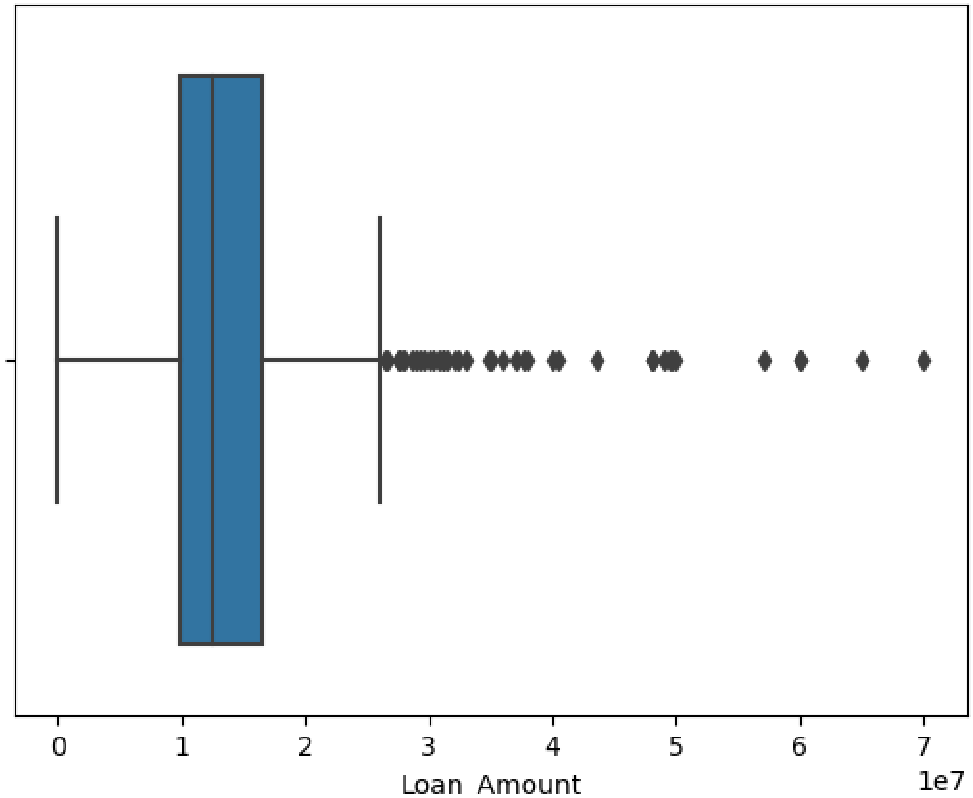
[41]:
```
loans["Term"].hist()
```

[41]: <matplotlib.axes._subplots.AxesSubplot at 0x1659b546f40>



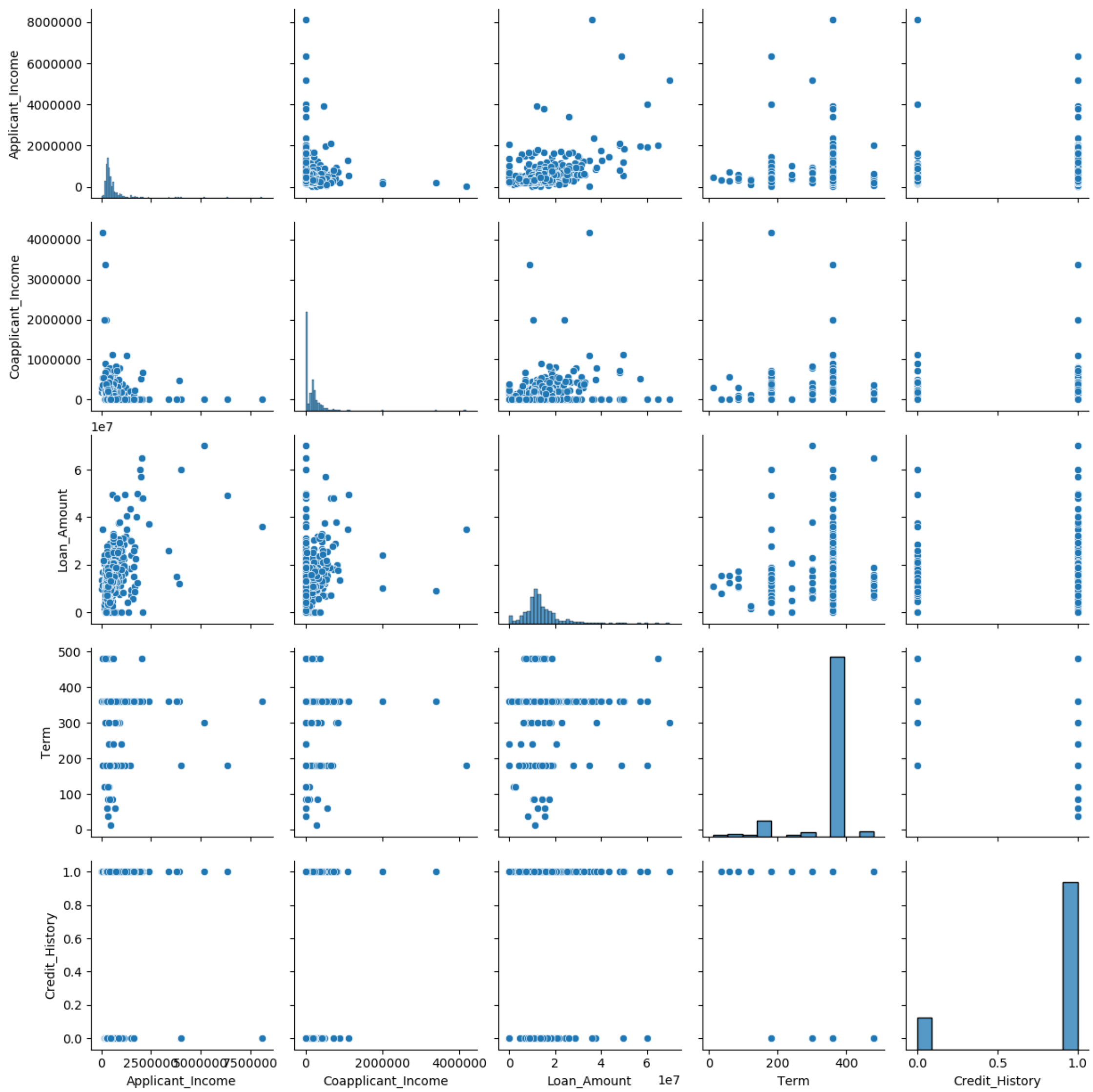
[42]:
```
sns.boxplot(data=loans,x="Loan_Amount", hue="Gender")
```

[42]: <matplotlib.axes._subplots.AxesSubplot at 0x1659b592430>



[43]:
```
sns.pairplot(loans)
```

[43]: <seaborn.axisgrid.PairGrid at 0x165986ea3d0>



[44]:
```
loans[loans["Gender"].isna()]
```

[44]:
```
    Gender Married Dependents     Education Self_Employed  Applicant_Income  \
23     NaN     Yes          2  Not Graduate            No            336500
126    NaN     Yes         3+      Graduate            No           2380300
171    NaN     Yes         3+      Graduate            No           5176300
188    NaN     Yes          0      Graduate           Yes             67400
314    NaN     Yes          0      Graduate            No            247300
334    NaN     Yes          1      Graduate           Yes            983300
460    NaN     Yes          0      Graduate           Yes            208300
467    NaN     Yes          0      Graduate            No           1669200
477    NaN     Yes          2      Graduate            No            287300
507    NaN      No          0      Graduate            No            358300
```

```
576     NaN      Yes           0      Graduate             No             308700
588     NaN       No           0      Graduate             No             475000
592     NaN       No          3+      Graduate            Yes             935700

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area Status
23             191700.0     11200000  360.0             0.0      Rural      N
126                 0.0     37000000  360.0             1.0      Rural      Y
171                 0.0     70000000  300.0             1.0      Urban      Y
188            529600.0     16800000  360.0             1.0      Rural      Y
314            184300.0     15900000  360.0             1.0      Rural      N
334            183300.0     18200000  180.0             1.0      Urban      Y
460            408300.0     16000000  360.0             NaN  Semiurban      Y
467                 0.0     11000000  360.0             1.0  Semiurban      Y
477            187200.0     13200000  360.0             0.0  Semiurban      N
507                 0.0      9600000  360.0             1.0      Urban      N
576            221000.0     13600000  360.0             0.0  Semiurban      N
588                 0.0      9400000  360.0             1.0  Semiurban      Y
592                 0.0     29200000  360.0             1.0  Semiurban      Y
```

[45]:
```python
loans[loans["Married"].isna()]
```

[45]:
```
     Gender Married Dependents Education Self_Employed  Applicant_Income  \
104    Male     NaN        NaN  Graduate            No            381600
228    Male     NaN        NaN  Graduate            No            475800
435  Female     NaN        NaN  Graduate            No           1004700

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area Status
104             75400.0     16000000  360.0             1.0      Urban      Y
228                 0.0     15800000  480.0             1.0  Semiurban      Y
435                 0.0            0  240.0             1.0  Semiurban      Y
```

[46]:
```python
loans[loans["Dependents"].isna()]
```

[46]:
```
     Gender Married Dependents     Education Self_Employed  Applicant_Income  \
102    Male     Yes        NaN      Graduate            No           1365000
104    Male     NaN        NaN      Graduate            No            381600
120    Male     Yes        NaN      Graduate            No            566700
226    Male     Yes        NaN  Not Graduate           Yes            473500
228    Male     NaN        NaN      Graduate            No            475800
293  Female      No        NaN      Graduate            No            541700
301    Male     Yes        NaN  Not Graduate            No            287500
332    Male      No        NaN      Graduate            No            283300
335    Male     Yes        NaN      Graduate           Yes            550300
346    Male     Yes        NaN  Not Graduate            No            352300
355  Female      No        NaN      Graduate            No            381300
435  Female     NaN        NaN      Graduate            No           1004700
517    Male     Yes        NaN  Not Graduate            No            307400
```

```
571    Male     Yes         NaN      Graduate            No           511600
597    Male      No         NaN      Graduate            No           298700

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area Status
102                 0.0            0  360.0             1.0      Urban      Y
104             75400.0     16000000  360.0             1.0      Urban      Y
120            266700.0     18000000  360.0             1.0      Rural      Y
226                 0.0     13800000  360.0             1.0      Urban      N
228                 0.0     15800000  480.0             1.0  Semiurban      Y
293                 0.0     14300000  480.0             0.0      Urban      N
301            175000.0     10500000  360.0             1.0  Semiurban      Y
332                 0.0      7100000  360.0             1.0      Urban      Y
335            449000.0      7000000    NaN             1.0  Semiurban      Y
346            323000.0     15200000  360.0             0.0      Rural      N
355                 0.0     11600000  180.0             1.0      Urban      Y
435                 0.0            0  240.0             1.0  Semiurban      Y
517            180000.0     12300000  360.0             0.0  Semiurban      N
571            145100.0     16500000  360.0             0.0      Urban      N
597                 0.0      8800000  360.0             0.0  Semiurban      N
```

[47]:
```
loans[["Gender","Education"]].value_counts()
```

[47]:
```
Gender  Education
Male    Graduate        376
        Not Graduate    113
Female  Graduate         92
        Not Graduate     20
dtype: int64
```

[48]:
```
loans["Status"]= loans["Status"].replace(["Y","N"],[1,0])
loans
```

[48]:
```
     Gender Married Dependents     Education Self_Employed  Applicant_Income  \
0      Male      No          0      Graduate            No            584900
1      Male     Yes          1      Graduate            No            458300
2      Male     Yes          0      Graduate           Yes            300000
3      Male     Yes          0  Not Graduate            No            258300
4      Male      No          0      Graduate            No            600000
..      …       …          …           …            …                …
609  Female      No          0      Graduate            No            290000
610    Male     Yes         3+      Graduate            No            410600
611    Male     Yes          1      Graduate            No            807200
612    Male     Yes          2      Graduate            No            758300
613  Female      No          0      Graduate           Yes            458300

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area  Status
0                   0.0     15000000  360.0             1.0      Urban       1
```

```
1           150800.0    12800000  360.0              1.0     Rural      0
2                0.0     6600000  360.0              1.0     Urban      1
3           235800.0    12000000  360.0              1.0     Urban      1
4                0.0    14100000  360.0              1.0     Urban      1
..               …           …      …                  …        …       …
609              0.0     7100000  360.0              1.0     Rural      1
610              0.0     4000000  180.0              1.0     Rural      1
611          24000.0    25300000  360.0              1.0     Urban      1
612              0.0    18700000  360.0              1.0     Urban      1
613              0.0    13300000  360.0              0.0  Semiurban     0

[614 rows x 12 columns]
```

[49]:
```python
recode_dict={"Gender":{'Male':"1", 'Female':"0", np.nan:"0"},
                "Married":{'Yes':"1",'No':"0",np.nan:"0"},
                                "Dependents":{"3+":"4",np.nan:"2" },#average␣
↪number of children per family is 2
                "Education":{"Graduate":"1", "Not Graduate":"0"},
                                "Self_Employed":{"Yes":"1","No": "0",np.nan:
↪"1"},
                                "Term":{np.nan:360},
                                "Credit_History":{np.nan:"0"}
                }
```

[50]:
```python
for key in recode_dict.keys():
    for llave, values in recode_dict[key].items():
        loans[key] = loans[key].replace(llave,values)
```

[51]:
```python
loans
```

[51]:
```
    Gender Married Dependents Education Self_Employed  Applicant_Income  \
0        1       0          0         1             0            584900
1        1       1          1         1             0            458300
2        1       1          0         1             1            300000
3        1       1          0         0             0            258300
4        1       0          0         1             0            600000
..     …       …          …         …             …                 …
609      0       0          0         1             0            290000
610      1       1          4         1             0            410600
611      1       1          1         1             0            807200
612      1       1          2         1             0            758300
613      0       0          0         1             1            458300

     Coapplicant_Income  Loan_Amount   Term Credit_History       Area  Status
0                   0.0     15000000  360.0            1.0      Urban       1
1              150800.0     12800000  360.0            1.0      Rural       0
2                   0.0      6600000  360.0            1.0      Urban       1
```

```
3           235800.0    12000000   360.0           1.0      Urban       1
4                0.0    14100000   360.0           1.0      Urban       1
..               ...         ...     ...           ...        ...
609              0.0     7100000   360.0           1.0      Rural       1
610              0.0     4000000   180.0           1.0      Rural       1
611          24000.0    25300000   360.0           1.0      Urban       1
612              0.0    18700000   360.0           1.0      Urban       1
613              0.0    13300000   360.0           0.0  Semiurban       0

[614 rows x 12 columns]
```

[52]:

```
loans.isna().sum()
```

[52]:

```
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
Applicant_Income     0
Coapplicant_Income   0
Loan_Amount          0
Term                 0
Credit_History       0
Area                 0
Status               0
dtype: int64
```

[53]:

```
loan_t = pd.read_csv('loan_test.csv')
loan_t
```

[53]:

```
    Gender Married Dependents     Education Self_Employed  Applicant_Income  \
0     Male     Yes          0      Graduate            No            572000
1     Male     Yes          1      Graduate            No            307600
2     Male     Yes          2      Graduate            No            500000
3     Male     Yes          2      Graduate            No            234000
4     Male      No          0  Not Graduate            No            327600
..     ...     ...        ...           ...           ...               ...
362   Male     Yes         3+  Not Graduate           Yes            400900
363   Male     Yes          0      Graduate            No            415800
364   Male      No          0      Graduate            No            325000
365   Male     Yes          0      Graduate            No            500000
366   Male      No          0      Graduate           Yes            920000

     Coapplicant_Income  Loan_Amount   Term  Credit_History       Area
0                     0     11000000  360.0             1.0      Urban
1                150000     12600000  360.0             1.0      Urban
2                180000     20800000  360.0             1.0      Urban
```

```
3              254600    10000000   360.0              NaN       Urban
4                   0     7800000   360.0              1.0       Urban
..                …            …        …         …       …
362            177700    11300000   360.0              1.0       Urban
363             70900    11500000   360.0              1.0       Urban
364            199300    12600000   360.0              NaN   Semiurban
365            239300    15800000   360.0              1.0       Rural
366                 0     9800000   180.0              1.0       Rural

[367 rows x 11 columns]
```

[54]:
```python
loan_t.isna().sum()
```

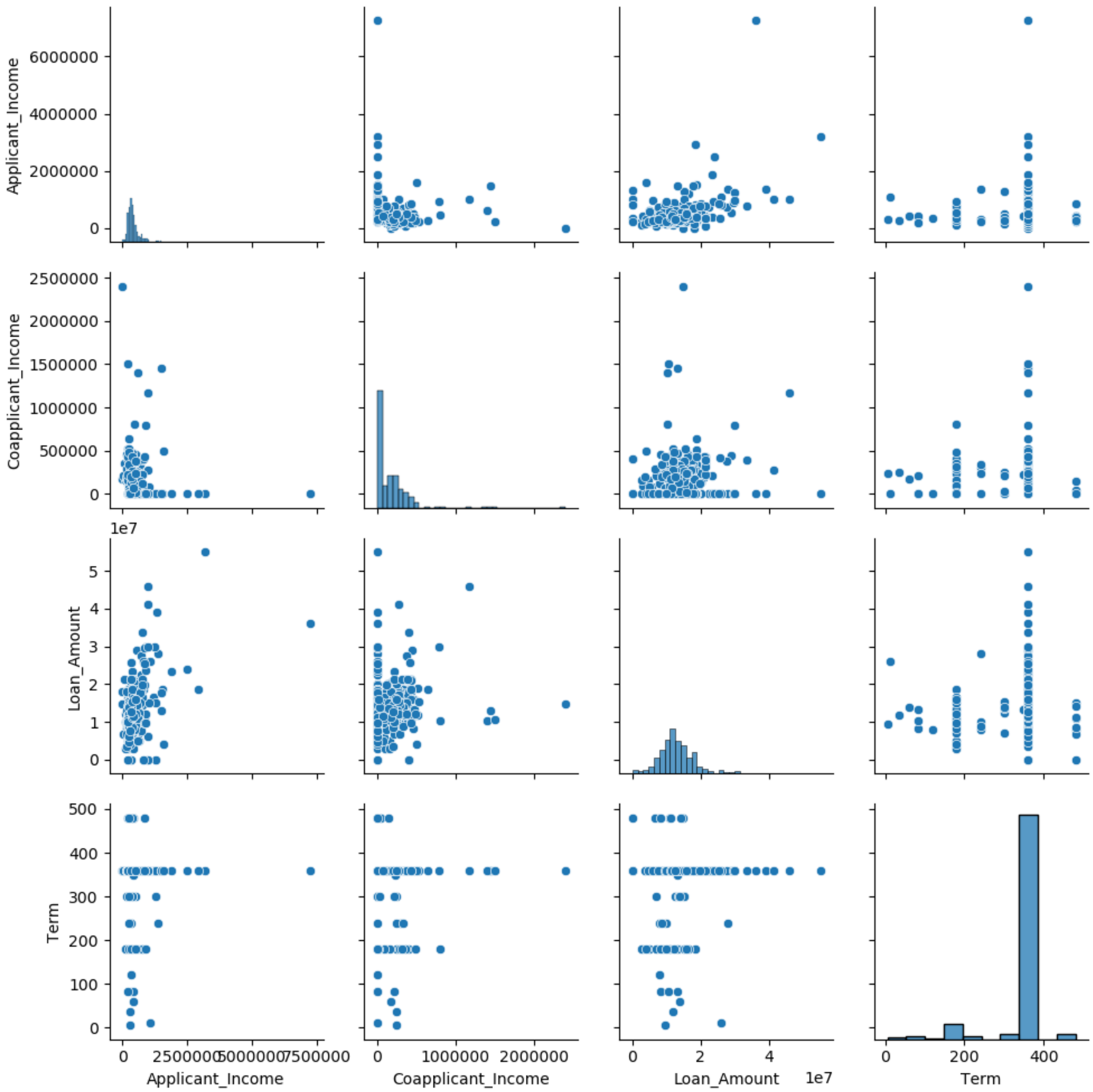
[54]:
```
Gender                11
Married                0
Dependents            10
Education              0
Self_Employed         23
Applicant_Income       0
Coapplicant_Income     0
Loan_Amount            0
Term                   6
Credit_History        29
Area                   0
dtype: int64
```

[55]:
```python
for key in recode_dict.keys():
    for llave, values in recode_dict[key].items():
        loan_t[key] = loan_t[key].replace(llave,values)
```

[56]:
```python
loan_t.describe()
```

[56]:
```
       Applicant_Income  Coapplicant_Income   Loan_Amount        Term
count      3.670000e+02        3.670000e+02  3.670000e+02  367.000000
mean       4.805599e+05        1.569578e+05  1.342779e+07  342.822888
std        4.910685e+05        2.334232e+05  6.296143e+06   64.658402
min        0.000000e+00        0.000000e+00  0.000000e+00    6.000000
25%        2.864000e+05        0.000000e+00  1.000000e+07  360.000000
50%        3.786000e+05        1.025000e+05  1.250000e+07  360.000000
75%        5.060000e+05        2.430500e+05  1.575000e+07  360.000000
max        7.252900e+06        2.400000e+06  5.500000e+07  480.000000
```

[57]:
```python
sns.pairplot(loan_t)
plt.show()
```



[58]:
```
loans_C= loans.copy(deep=True)
```

[59]:
```
loan_t = pd.get_dummies(loan_t, columns=["Area"], prefix="Area",␣
↪prefix_sep="_", drop_first=True)
loans = pd.get_dummies(loans, columns=["Area"], prefix="Area", prefix_sep="_",␣
↪drop_first=True)
```

[60]:
```
clms= ["Gender","Married", "Dependents",␣
↪"Education","Self_Employed","Area_Semiurban","Area_Urban"]
for col in clms:
    loans[col].astype(int)
    loan_t[col].astype(int)
```

[61]:
```
loans
```

[61]:
```
     Gender Married Dependents Education Self_Employed  Applicant_Income  \
0         1       0          0         1             0            584900
1         1       1          1         1             0            458300
2         1       1          0         1             1            300000
3         1       1          0         0             0            258300
4         1       0          0         1             0            600000
..      …      …        …        …            …                …
609       0       0          0         1             0            290000
610       1       1          4         1             0            410600
611       1       1          1         1             0            807200
612       1       1          2         1             0            758300
613       0       0          0         1             1            458300

     Coapplicant_Income  Loan_Amount   Term Credit_History  Status  \
0                   0.0     15000000  360.0            1.0       1
1              150800.0     12800000  360.0            1.0       0
2                   0.0      6600000  360.0            1.0       1
3              235800.0     12000000  360.0            1.0       1
4                   0.0     14100000  360.0            1.0       1
..                  …         …    …            …     …
609                 0.0      7100000  360.0            1.0       1
610                 0.0      4000000  180.0            1.0       1
611             24000.0     25300000  360.0            1.0       1
612                 0.0     18700000  360.0            1.0       1
613                 0.0     13300000  360.0            0.0       0

     Area_Semiurban  Area_Urban
0                 0           1
1                 0           0
2                 0           1
3                 0           1
4                 0           1
..              …          …
609               0           0
610               0           0
611               0           1
612               0           1
613               1           0

[614 rows x 13 columns]
```

[62]:
```
loan_t
```

[62]:
```
     Gender Married Dependents Education Self_Employed  Applicant_Income  \
0         1       1          0         1             0            572000
```

```
1        1       1          1          1             0             307600
2        1       1          2          1             0             500000
3        1       1          2          1             0             234000
4        1       0          0          0             0             327600
..     ...     ...        ...        ...           ...                ...
362      1       1          4          0             1             400900
363      1       1          0          1             0             415800
364      1       0          0          1             0             325000
365      1       1          0          1             0             500000
366      1       0          0          1             1             920000

     Coapplicant_Income  Loan_Amount   Term Credit_History  Area_Semiurban  \
0                     0     11000000  360.0            1.0               0
1                150000     12600000  360.0            1.0               0
2                180000     20800000  360.0            1.0               0
3                254600     10000000  360.0              0               0
4                     0      7800000  360.0            1.0               0
..                  ...          ...    ...            ...             ...
362              177700     11300000  360.0            1.0               0
363               70900     11500000  360.0            1.0               0
364              199300     12600000  360.0              0               1
365              239300     15800000  360.0            1.0               0
366                   0      9800000  180.0            1.0               0

     Area_Urban
0             1
1             1
2             1
3             1
4             1
..          ...
362           1
363           1
364           0
365           0
366           0

[367 rows x 12 columns]
```

0.1 Linear Regression

[63]:
```
train_y= loans["Status"]
trainX=loans.loc[:,~loans.columns.isin(["Status"])]
from sklearn.linear_model import LinearRegression
model= LinearRegression()
model.fit(trainX, train_y)
coeff_df = pd.DataFrame(model.coef_,trainX.columns,columns=['Coefficient'])
```

[64]:
```python
print(model.intercept_)
coeff_df
```

0.2381053915970613

[64]:

	Coefficient
Gender	-3.411145e-03
Married	1.004201e-01
Dependents	-7.153846e-03
Education	5.834911e-02
Self_Employed	1.530687e-02
Applicant_Income	-2.281071e-08
Coapplicant_Income	-7.925575e-08
Loan_Amount	5.603476e-10
Term	-1.915369e-04
Credit_History	4.682007e-01
Area_Semiurban	1.312022e-01
Area_Urban	4.700892e-02

[65]:
```python
test_X=loan_t
y_pred = model.predict(test_X)
```

[66]:
```python
loan_tc_lin= loan_t.copy(deep=True)
loan_tc_lin['Status'] = y_pred
```

[67]:
```python
loan_tc_lin[loan_tc_lin["Status"] > .65].shape
```

[67]: (271, 13)

[68]:
```python
loan_tc_lin.describe()
```

[68]:

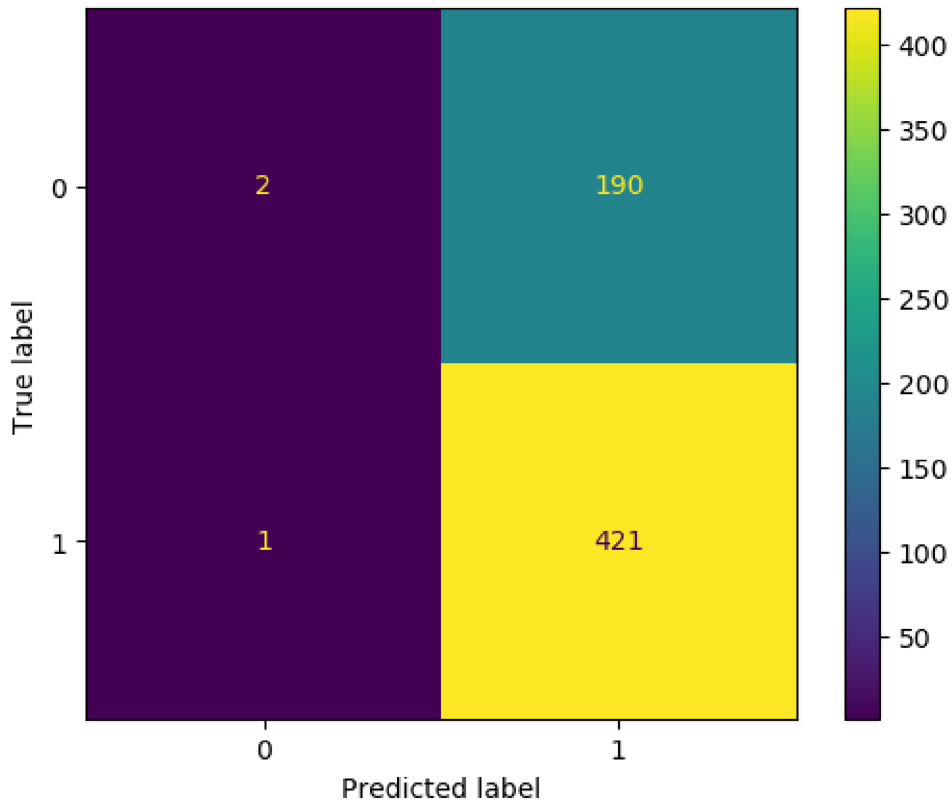
	Applicant_Income	Coapplicant_Income	Loan_Amount	Term \
count	3.670000e+02	3.670000e+02	3.670000e+02	367.000000
mean	4.805599e+05	1.569578e+05	1.342779e+07	342.822888
std	4.910685e+05	2.334232e+05	6.296143e+06	64.658402
min	0.000000e+00	0.000000e+00	0.000000e+00	6.000000
25%	2.864000e+05	0.000000e+00	1.000000e+07	360.000000
50%	3.786000e+05	1.025000e+05	1.250000e+07	360.000000
75%	5.060000e+05	2.430500e+05	1.575000e+07	360.000000
max	7.252900e+06	2.400000e+06	5.500000e+07	480.000000

	Area_Semiurban	Area_Urban	Status
count	367.000000	367.000000	367.000000
mean	0.316076	0.381471	0.673555
std	0.465578	0.486411	0.217928
min	0.000000	0.000000	0.042169
25%	0.000000	0.000000	0.625886
50%	0.000000	0.000000	0.757887

75%	1.000000	1.000000	0.819488
max	1.000000	1.000000	0.946153

0.2 Logistic Regression

[98]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
log_mod= LogisticRegression()
log_mod.fit(trainX, train_y)
train_pred = log_mod.predict(trainX)
cm_log= confusion_matrix(train_y,train_pred)
ConfusionMatrixDisplay(confusion_matrix=cm_log, display_labels=log_mod.
 ↪classes_).plot()
plt.show()
```



[70]:
```
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
 ↪f1_score, classification_report
print("Accuracy:",accuracy_score(train_y, train_pred))
print("precision score: ", precision_score(train_y,train_pred))
print("recall score: ", recall_score(train_y,train_pred))
```

```
print("f1-score: ", f1_score(train_y,train_pred))
```

```
Accuracy: 0.6889250814332247
precision score:  0.6890343698854338
recall score:  0.9976303317535545
f1-score:  0.8151016456921589
```

[71]:
```
loan_T_log = loan_t.copy(deep=True)
loan_T_log["Status"] = log_mod.predict(test_X)
print(loan_T_log["Status"].value_counts())
loan_T_log[loan_T_log["Status"]==0]
```

```
1    366
0      1
Name: Status, dtype: int64
```

[71]:
```
     Gender  Married  Dependents  Education  Self_Employed  Applicant_Income  \
325       1        0           0          1              0            287500

     Coapplicant_Income  Loan_Amount  Term  Credit_History  Area_Semiurban  \
325              241600      9500000   6.0             0.0               1

     Area_Urban  Status
325           0       0
```

##

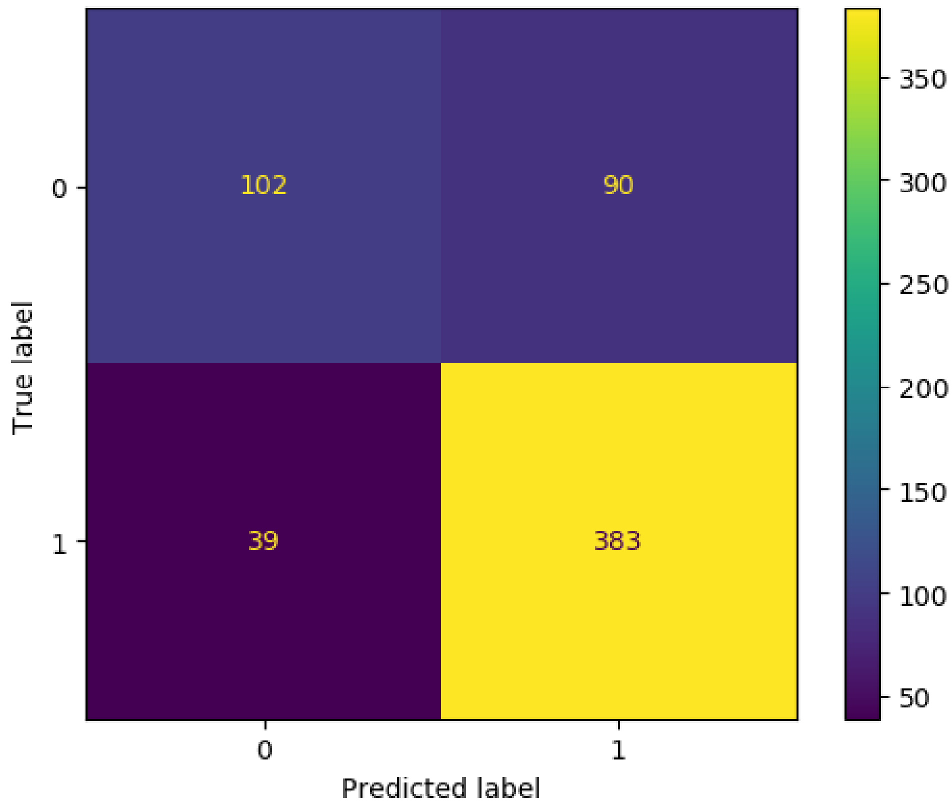
Decision Trees

[88]:
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(max_depth =4, random_state= 1)
dt.fit(trainX,train_y)
```

[88]:
```
DecisionTreeClassifier(max_depth=4, random_state=1)
```

[99]:
```
pred_dt= dt.predict(trainX)
print("Accuracy:",accuracy_score(train_y, pred_dt))
print("precision score: ", precision_score(train_y,pred_dt))
print("recall score: ", recall_score(train_y,pred_dt))
print("f1-score: ", f1_score(train_y,pred_dt))
cm_dt= confusion_matrix(train_y,pred_dt)
ConfusionMatrixDisplay(confusion_matrix=cm_dt, display_labels=dt.classes_).
  ↪plot()
plt.show()
```

```
Accuracy: 0.7899022801302932
precision score:  0.8097251585623678
recall score:  0.9075829383886256
f1-score:  0.8558659217877094
```



[92]:
```
loan_T_dt = loan_t.copy(deep=True)
loan_T_dt["Status"] = dt.predict(test_X)
print(loan_T_dt["Status"].value_counts())
loan_T_dt[loan_T_dt["Status"]==0]
```

```
1    279
0     88
Name: Status, dtype: int64
```

[92]:

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	\
3	1	1	2	1	0	234000	
7	1	1	2	0	0	388100	
12	1	0	4	1	0	416600	
13	1	1	2	1	1	1217300	
26	1	1	2	1	0	436300	
..	…	…	…	…	…	…	
346	1	1	0	1	0	339100	
354	1	1	4	0	0	531600	
358	1	1	2	0	0	313200	
360	0	1	0	1	0	855000	
364	1	0	0	1	0	325000	

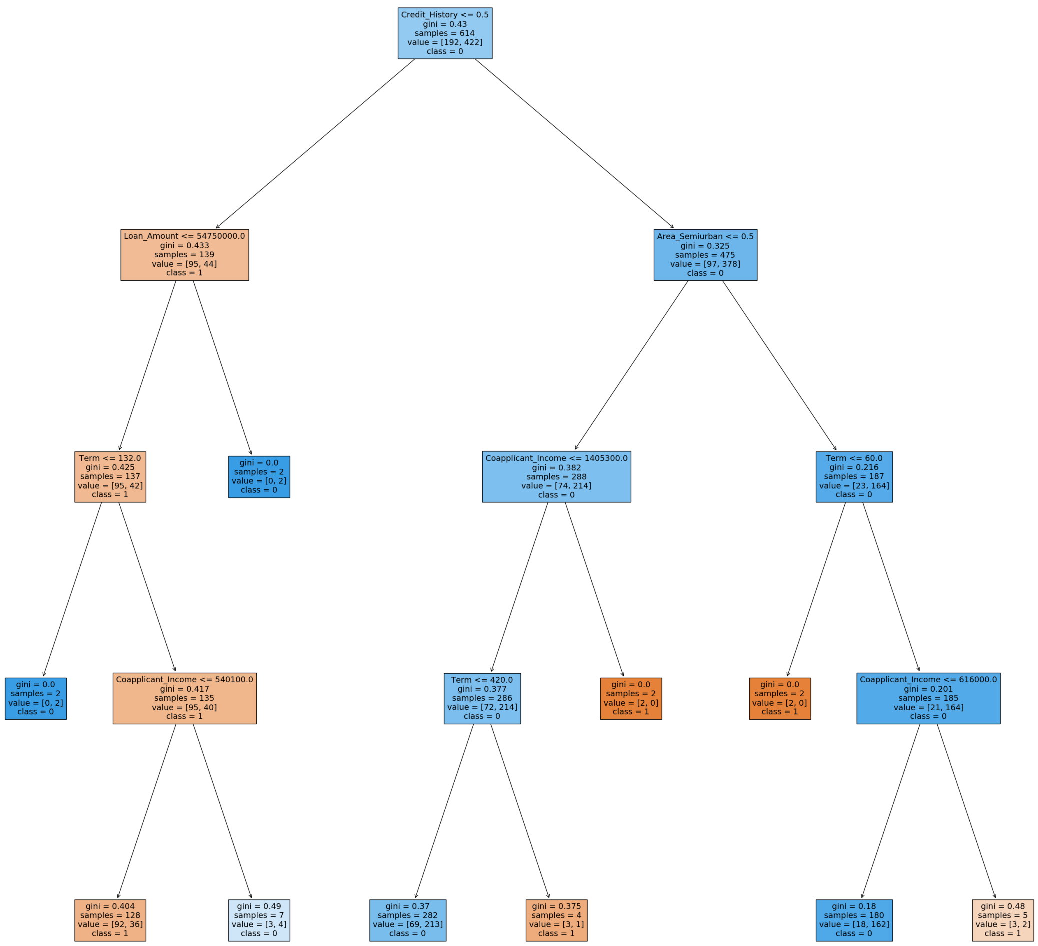
```
     Coapplicant_Income  Loan_Amount   Term Credit_History  Area_Semiurban  \
3                254600     10000000  360.0              0               0
7                     0     14700000  360.0            0.0               0
12                    0      4000000  180.0              0               0
13                    0     16600000  360.0            0.0               1
26               125000     14000000  360.0              0               0
..                  …          …     …             …            …
346              196600     13300000  360.0            0.0               0
354               18700     15800000  180.0            0.0               1
358                   0      7600000  360.0              0               0
360              425500      9600000  360.0              0               0
364              199300     12600000  360.0              0               1

     Area_Urban  Status
3             1       0
7             0       0
12            1       0
13            0       0
26            1       0
..          …     …
346           0       0
354           0       0
358           0       0
360           1       0
364           0       0

[88 rows x 13 columns]
```

[91]:
```python
imptcs = pd.DataFrame(dt.feature_importances_,trainX.columns)
imptcs
```

[91]:

	0
Gender	0.000000
Married	0.000000
Dependents	0.000000
Education	0.000000
Self_Employed	0.000000
Applicant_Income	0.000000
Coapplicant_Income	0.084653
Loan_Amount	0.027793
Term	0.103738
Credit_History	0.724166
Area_Semiurban	0.059650
Area_Urban	0.000000

```
[90]: from sklearn.tree import plot_tree
fig= plt.figure(figsize=(35,35))
_ = plot_tree(dt, feature_names=trainX.columns, class_names=train_y.astype(str),filled=True)
```

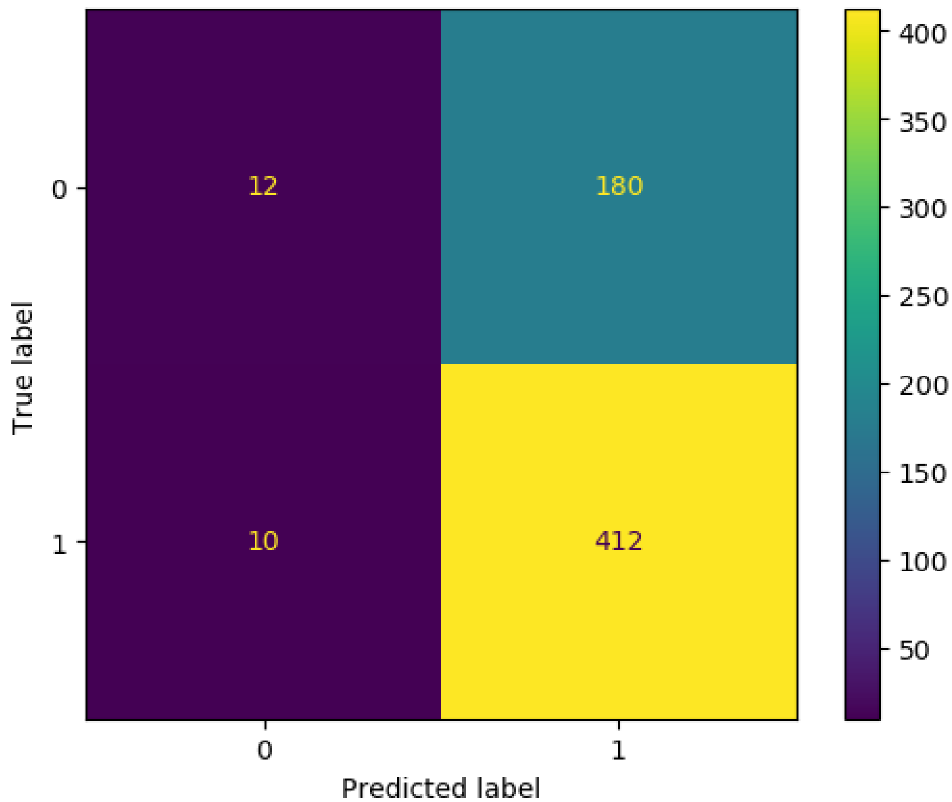


According to the decision tree, the most important factor was the applicant's credit history, which accounts for 72.4% of the variabiliy of the dataset. The next determining factor was the term of the loan, followed by co-applicant income. Gender, marital status, family size, education, self-employment, and, surprisingly, applicant income did not play a part in the decision to grant a loan.

##

Neural Net

[95]:
```
from sklearn.neural_network import MLPClassifier
nn= MLPClassifier()
nn.fit(trainX,train_y)
pred_nn= nn.predict(trainX)
cm_nn= confusion_matrix(train_y,pred_nn,labels=nn.classes_)
ConfusionMatrixDisplay(confusion_matrix=cm_nn, display_labels=nn.classes_).
 ↪plot()
plt.show()
```



[96]:
```
print("Accuracy:",accuracy_score(train_y, pred_nn))
print("precision score: ", precision_score(train_y,pred_nn))
print("recall score: ", recall_score(train_y,pred_nn))
print("f1-score: ", f1_score(train_y,pred_nn))
```

```
Accuracy: 0.6905537459283387
precision score:  0.6959459459459459
recall score:  0.976303317535545
f1-score:  0.8126232741617356
```