Lending_loan_project

March 25, 2023

[1]:
```
# import library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
print('All libray imported')
```

```
All libray imported
```

[2]:
```
# load the dataset
df=pd.read_csv('loan_data.csv')
```

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

[3]:
```
   credit.policy             purpose  int.rate  installment  log.annual.inc  \
0              1  debt_consolidation    0.1189       829.10       11.350407
1              1         credit_card    0.1071       228.22       11.082143
2              1  debt_consolidation    0.1357       366.86       10.373491
3              1  debt_consolidation    0.1008       162.34       11.350407
4              1         credit_card    0.1426       102.92       11.299732

     dti  fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths  \
0  19.48   737        5639.958333      28854        52.1               0
1  14.29   707        2760.000000      33623        76.7               0
2  11.63   682        4710.000000       3511        25.6               1
3   8.10   712        2699.958333      33667        73.2               1
4  14.97   667        4066.000000       4740        39.5               0

   delinq.2yrs  pub.rec  not.fully.paid
0            0        0               0
1            0        0               0
2            0        0               0
3            0        0               0
4            1        0               0
```

[4]:
```
df.shape
```

[4]:
```
(9578, 14)
```

[5]:
```python
df.describe()
```

[5]:

	credit.policy	int.rate	installment	log.annual.inc	dti
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679
std	0.396245	0.026847	207.071301	0.614813	6.883970
min	0.000000	0.060000	15.670000	7.547502	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500
50%	1.000000	0.122100	268.950000	10.928884	12.665000
75%	1.000000	0.140700	432.762500	11.291293	17.950000
max	1.000000	0.216400	940.140000	14.528354	29.960000

	fico	days.with.cr.line	revol.bal	revol.util
count	9578.000000	9578.000000	9.578000e+03	9578.000000
mean	710.846314	4560.767197	1.691396e+04	46.799236
std	37.970537	2496.930377	3.375619e+04	29.014417
min	612.000000	178.958333	0.000000e+00	0.000000
25%	682.000000	2820.000000	3.187000e+03	22.600000
50%	707.000000	4139.958333	8.596000e+03	46.300000
75%	737.000000	5730.000000	1.824950e+04	70.900000
max	827.000000	17639.958330	1.207359e+06	119.000000

	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000
mean	1.577469	0.163708	0.062122	0.160054
std	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000
75%	2.000000	0.000000	0.000000	0.000000
max	33.000000	13.000000	5.000000	1.000000

[6]:
```python
# missing value
df.isnull().sum()
```

[6]:
```
credit.policy        0
purpose              0
int.rate             0
installment          0
log.annual.inc       0
dti                  0
fico                 0
days.with.cr.line    0
revol.bal            0
revol.util           0
inq.last.6mths       0
delinq.2yrs          0
```

```
pub.rec             0
not.fully.paid      0
dtype: int64
```

There is no null values in the dataset

[7]:
```
df['not.fully.paid'].value_counts()
```

[7]:
```
0    8045
1    1533
Name: not.fully.paid, dtype: int64
```

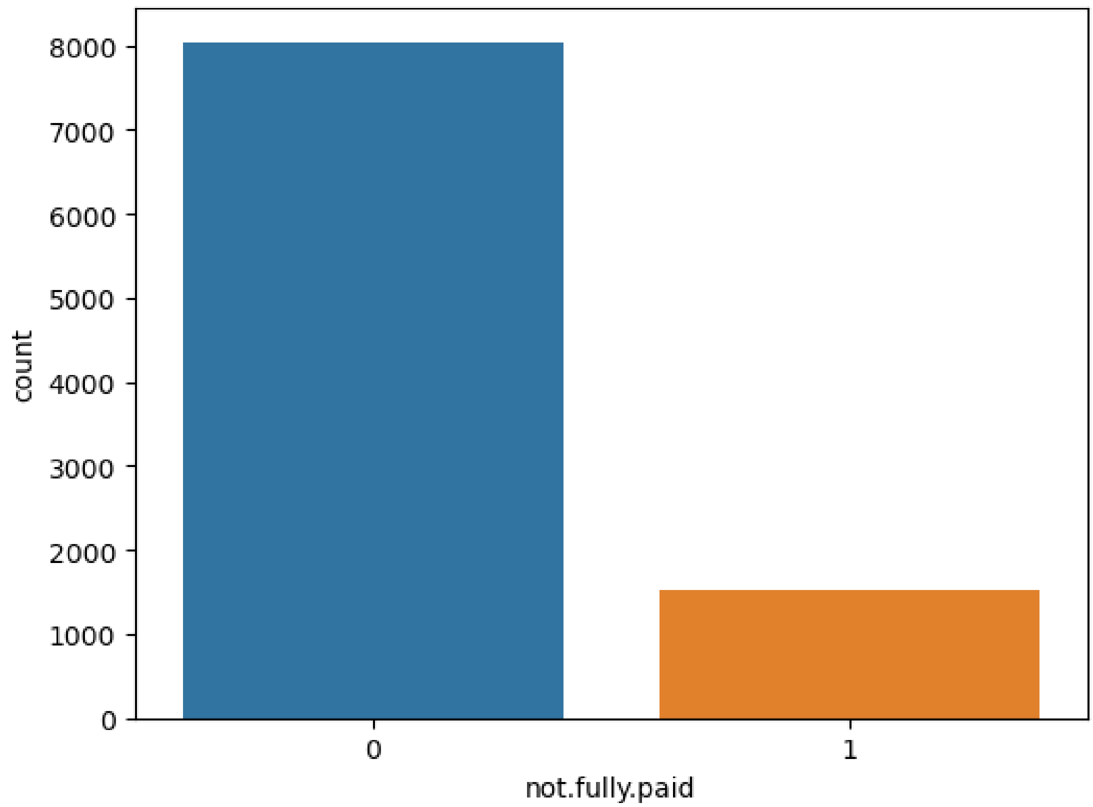
We can see that the dataset is imbalanced

0.1 Exploratory data analysis of different factors of the dataset.

[8]:
```
df.dtypes
```

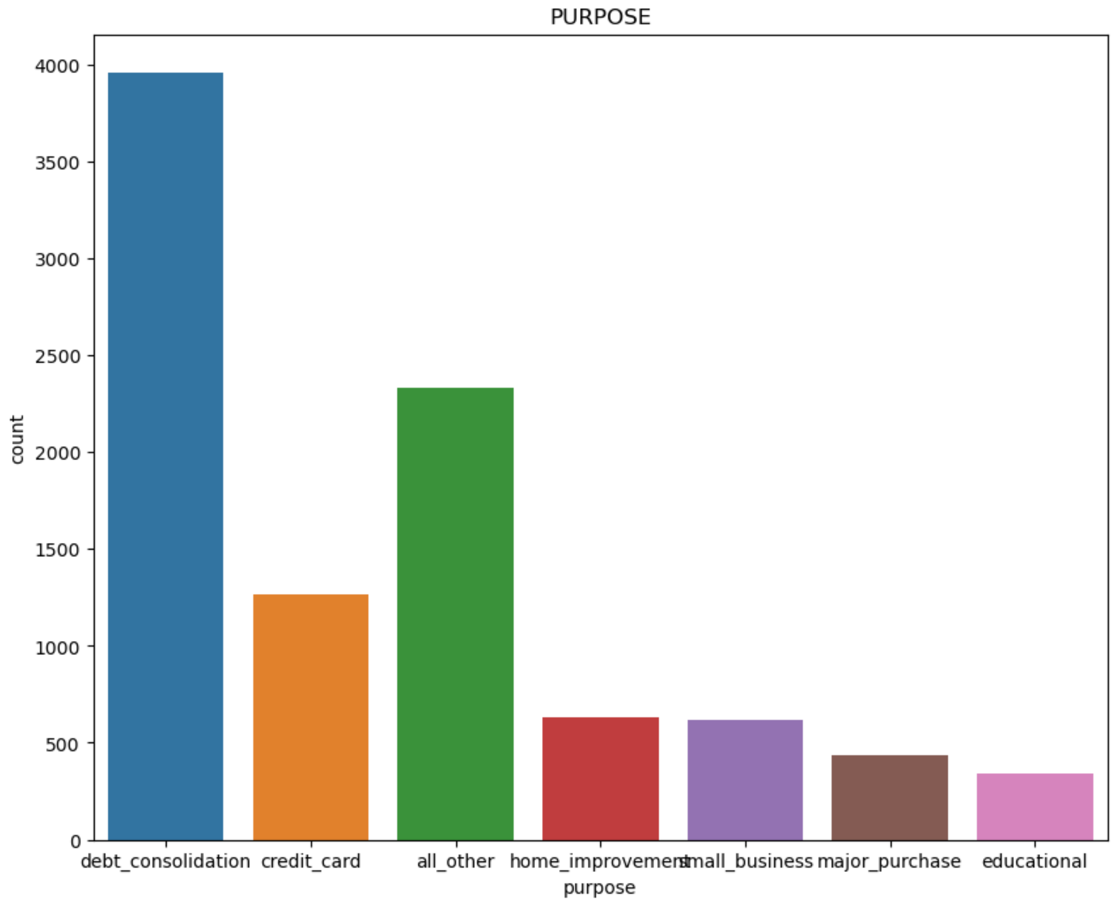
[8]:
```
credit.policy          int64
purpose               object
int.rate             float64
installment          float64
log.annual.inc       float64
dti                  float64
fico                   int64
days.with.cr.line    float64
revol.bal              int64
revol.util           float64
inq.last.6mths         int64
delinq.2yrs            int64
pub.rec                int64
not.fully.paid         int64
dtype: object
```

[9]:
```
sns.countplot(x=df['not.fully.paid'])
plt.show()
```

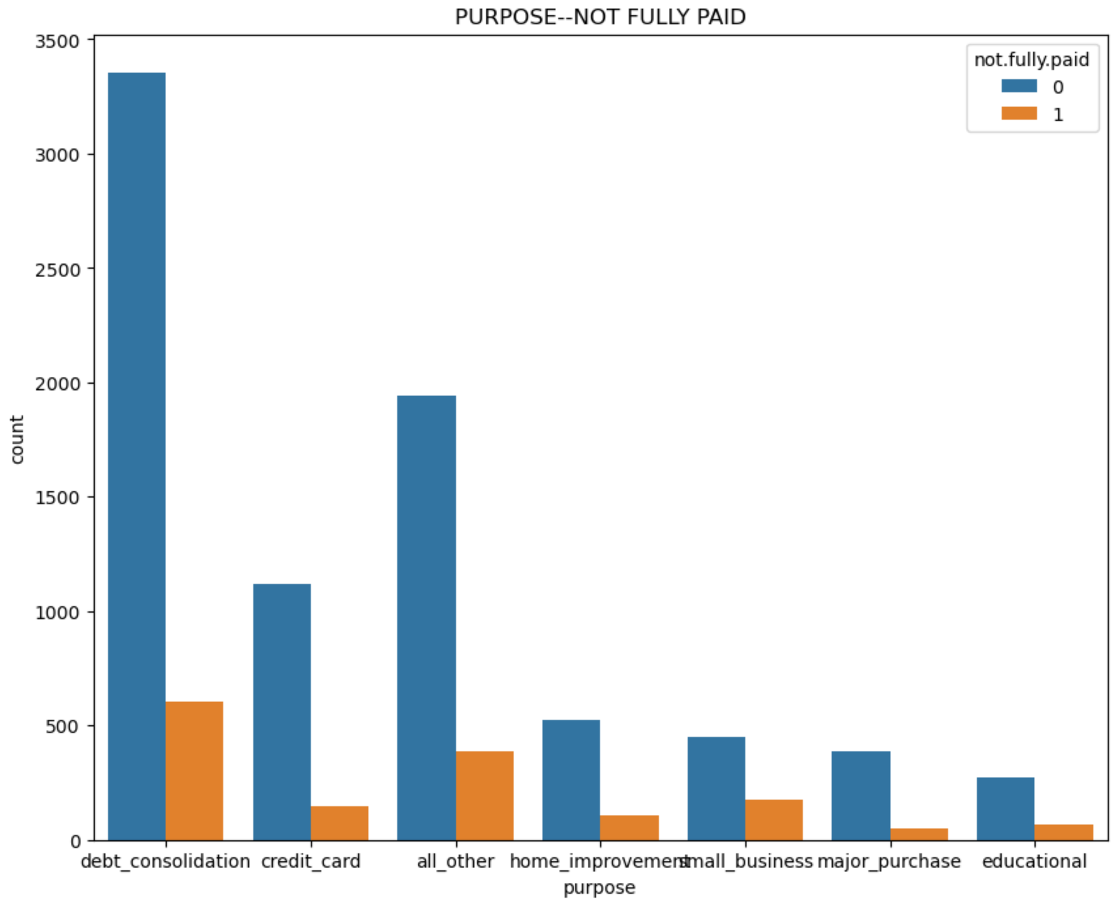


[10]:

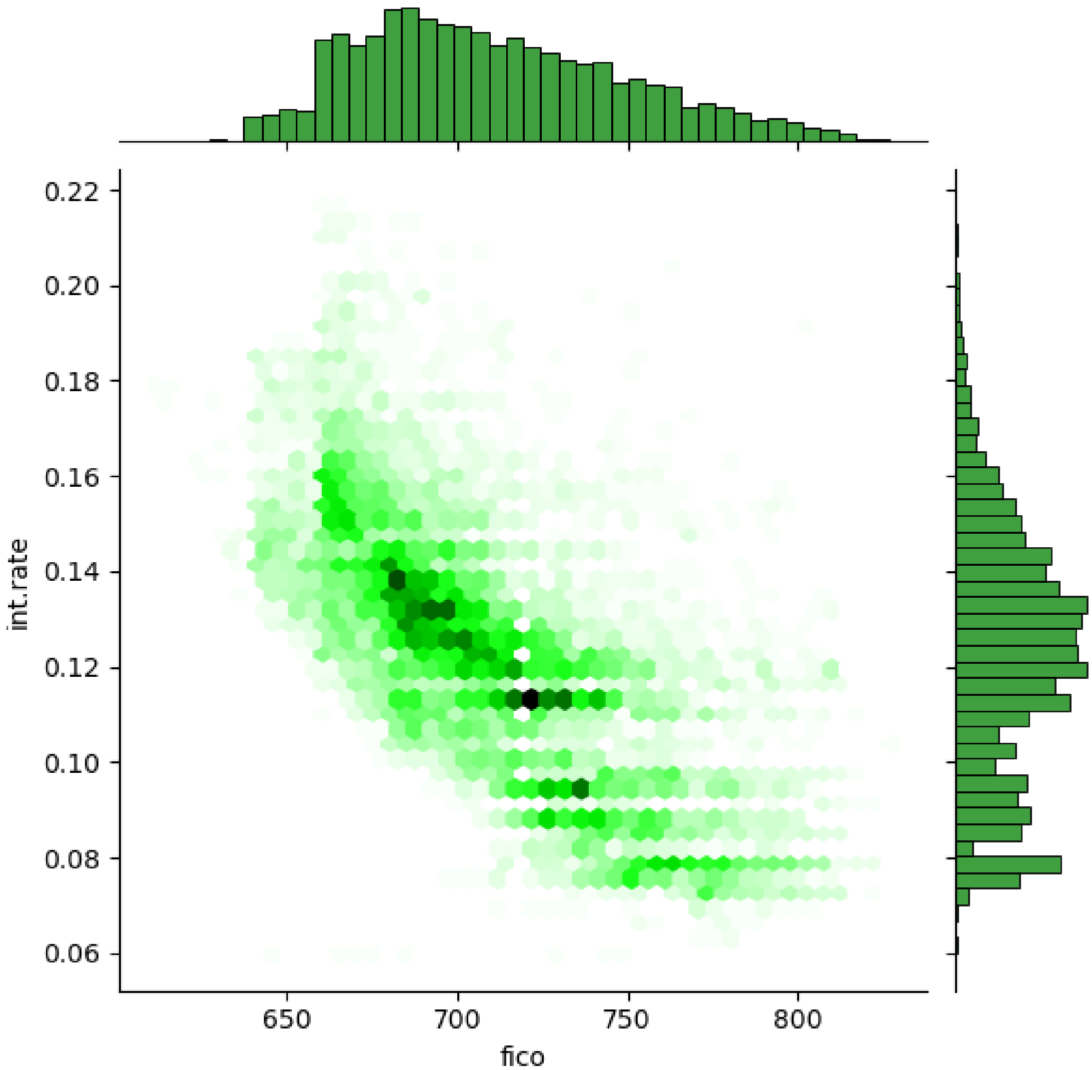
```
plt.figure(figsize=(10,8))
sns.countplot(x=df['purpose'])
plt.title('PURPOSE')
plt.show()
```



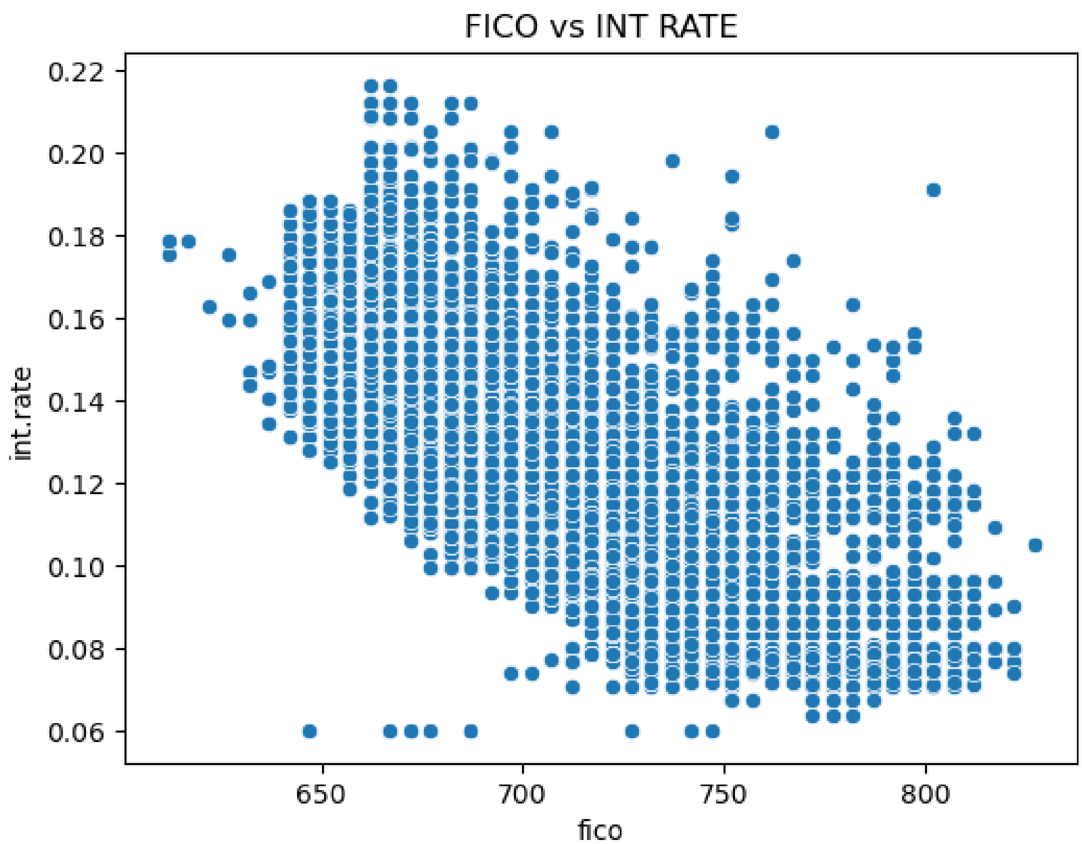
[11]:
```
plt.figure(figsize=(10,8))
sns.countplot(x='purpose',hue='not.fully.paid',data=df)
plt.title('PURPOSE--NOT FULLY PAID')
plt.show()
```



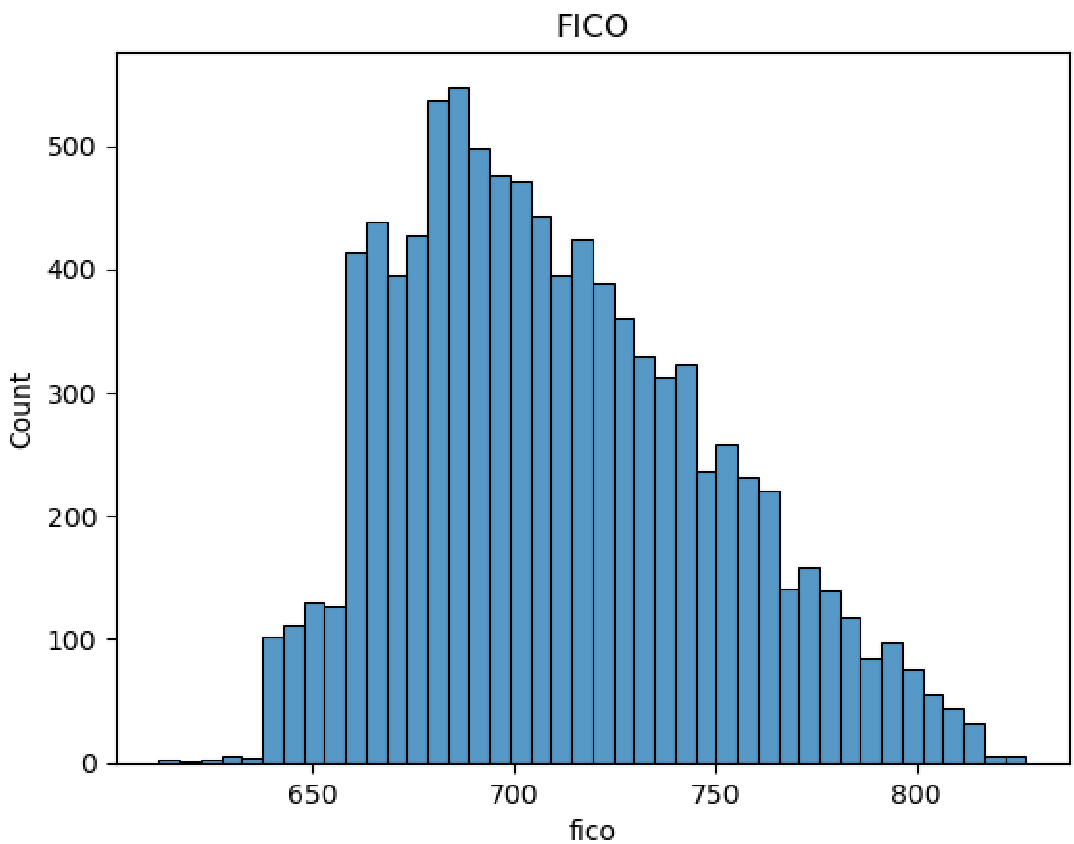
[13]:
```
sns.jointplot(x='fico',y='int.rate',data=df,kind='hex',color='g')
plt.show()
```



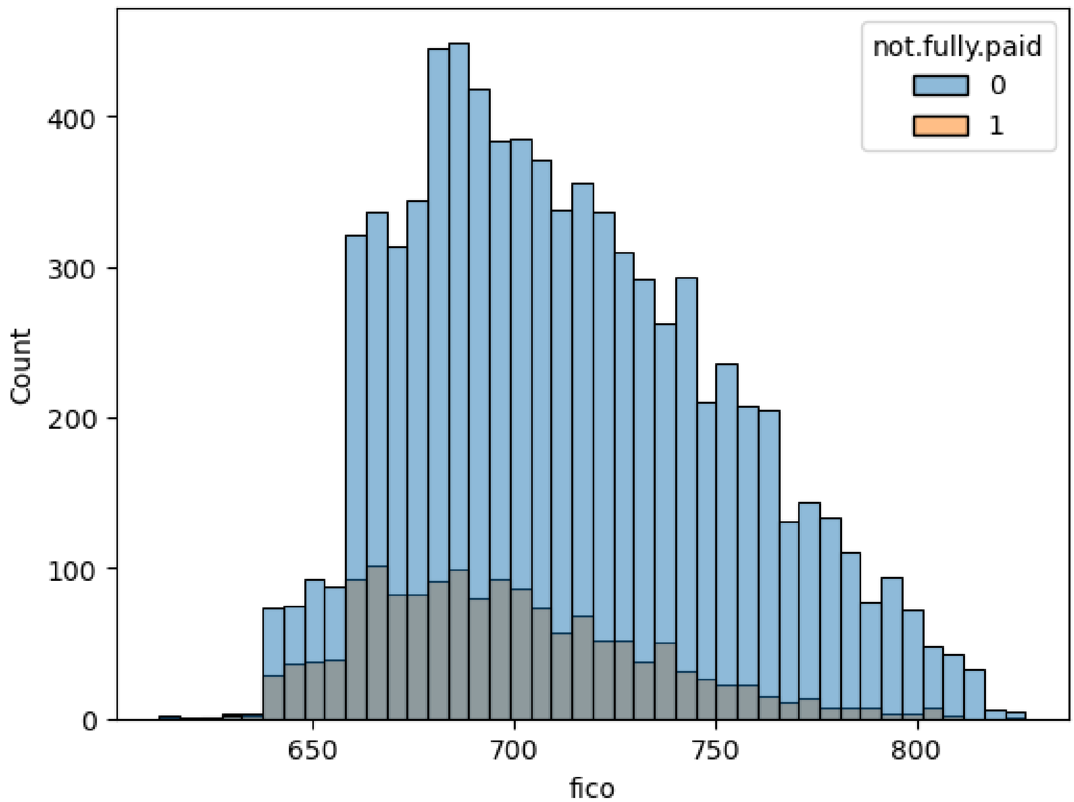
[14]:
```
sns.scatterplot(x='fico',y='int.rate',data=df)
plt.title('FICO vs INT RATE')
plt.show()
```



[15]:
```
sns.histplot(df['fico'])
plt.title('FICO')
plt.show()
```



[16]:
```
sns.histplot(x='fico',hue='not.fully.paid',data=df)
plt.show()
```



Feature Transformation

Transform categorical values into numerical values (discrete)

[17]:
```
# handle imbalanced dataset
df['not.fully.paid'].value_counts()
```

[17]:
```
0    8045
1    1533
Name: not.fully.paid, dtype: int64
```

[18]:
```
not_fully_paid_0=df[df['not.fully.paid']==0]
not_fully_paid_1=df[df['not.fully.paid']==1]
```

[19]:
```
not_fully_paid_0.shape
```

[19]:
```
(8045, 14)
```

[20]:
```
not_fully_paid_1.shape
```

[20]:
```
(1533, 14)
```

[21]:
```python
# resample
from sklearn.utils import resample
df_minor_upsample=resample(not_fully_paid_1,replace=True,n_samples=8045)
```

[22]:
```python
new_df=pd.concat([not_fully_paid_0,df_minor_upsample])
```

[23]:
```python
# shuffle
from sklearn.utils import shuffle
new_df=shuffle(new_df)
```

[24]:
```python
new_df['not.fully.paid'].value_counts()
```

[24]:
```
1    8045
0    8045
Name: not.fully.paid, dtype: int64
```

[25]:
```python
new_df.shape
```

[25]:
```
(16090, 14)
```

[26]:
```python
new_df.dtypes
```

[26]:
```
credit.policy          int64
purpose               object
int.rate             float64
installment          float64
log.annual.inc       float64
dti                  float64
fico                   int64
days.with.cr.line    float64
revol.bal              int64
revol.util           float64
inq.last.6mths         int64
delinq.2yrs            int64
pub.rec                int64
not.fully.paid         int64
dtype: object
```

[27]:
```python
# convert purpose into num data
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
```

[28]:
```python
for i in new_df.columns:
    if new_df[i].dtypes=='object':
        new_df[i]=le.fit_transform(new_df[i])
```

[29]:
```python
new_df.dtypes
```

[29]:
```
credit.policy           int64
purpose                 int32
int.rate              float64
installment           float64
log.annual.inc        float64
dti                   float64
fico                    int64
days.with.cr.line     float64
revol.bal               int64
revol.util            float64
inq.last.6mths          int64
delinq.2yrs             int64
pub.rec                 int64
not.fully.paid          int64
dtype: object
```

0.1.1 Additional Feature Engineering

You will check the correlation between features and will drop those features which have a strong correlation

This will help reduce the number of features and will leave you with the most relevant features

[30]:
```
new_df.corr()
```

[30]:
```
                   credit.policy   purpose  int.rate  installment  \
credit.policy           1.000000  0.001142 -0.295701     0.055276
purpose                 0.001142  1.000000  0.149777     0.202076
int.rate               -0.295701  0.149777  1.000000     0.274894
installment             0.055276  0.202076  0.274894     1.000000
log.annual.inc          0.016821  0.115126  0.089838     0.474987
dti                    -0.090337 -0.051584  0.206692     0.021452
fico                    0.371511  0.072352 -0.678889     0.113061
days.with.cr.line       0.092346  0.047141 -0.107275     0.174885
revol.bal              -0.185985  0.062379  0.083167     0.244972
revol.util             -0.091225 -0.076654  0.414681     0.048772
inq.last.6mths         -0.551733  0.052115  0.195930    -0.008373
delinq.2yrs            -0.055858  0.004895  0.137808    -0.002184
pub.rec                -0.058386  0.009387  0.117686    -0.014899
not.fully.paid         -0.197173  0.062396  0.222356     0.075112

                   log.annual.inc       dti      fico  days.with.cr.line  \
credit.policy            0.016821 -0.090337  0.371511           0.092346
purpose                  0.115126 -0.051584  0.072352           0.047141
int.rate                 0.089838  0.206692 -0.678889          -0.107275
```

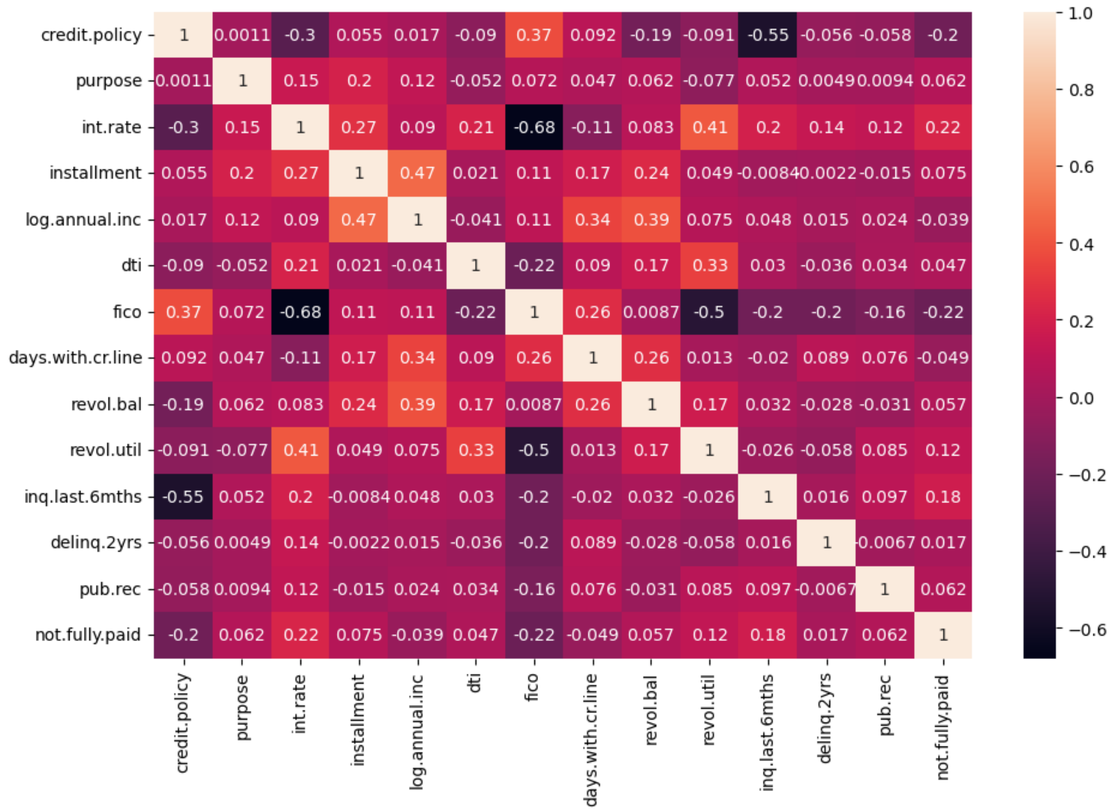
```
installment           0.474987  0.021452  0.113061           0.174885
log.annual.inc        1.000000 -0.040918  0.105130           0.343448
dti                  -0.040918  1.000000 -0.219243           0.090496
fico                  0.105130 -0.219243  1.000000           0.256211
days.with.cr.line     0.343448  0.090496  0.256211           1.000000
revol.bal             0.386005  0.166552  0.008684           0.260577
revol.util            0.075082  0.325346 -0.499926           0.012919
inq.last.6mths        0.048183  0.030226 -0.195416          -0.020169
delinq.2yrs           0.014727 -0.035742 -0.199436           0.089317
pub.rec               0.023778  0.034298 -0.157073           0.075621
not.fully.paid       -0.038936  0.046921 -0.215887          -0.049048

                   revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
credit.policy      -0.185985   -0.091225       -0.551733    -0.055858
purpose             0.062379   -0.076654        0.052115     0.004895
int.rate            0.083167    0.414681        0.195930     0.137808
installment         0.244972    0.048772       -0.008373    -0.002184
log.annual.inc      0.386005    0.075082        0.048183     0.014727
dti                 0.166552    0.325346        0.030226    -0.035742
fico                0.008684   -0.499926       -0.195416    -0.199436
days.with.cr.line   0.260577    0.012919       -0.020169     0.089317
revol.bal           1.000000    0.168770        0.032100    -0.027557
revol.util          0.168770    1.000000       -0.026466    -0.057753
inq.last.6mths      0.032100   -0.026466        1.000000     0.015911
delinq.2yrs        -0.027557   -0.057753        0.015911     1.000000
pub.rec            -0.031355    0.084822        0.097453    -0.006730
not.fully.paid      0.056760    0.116037        0.175923     0.016787

                    pub.rec  not.fully.paid
credit.policy     -0.058386       -0.197173
purpose            0.009387        0.062396
int.rate           0.117686        0.222356
installment       -0.014899        0.075112
log.annual.inc     0.023778       -0.038936
dti                0.034298        0.046921
fico              -0.157073       -0.215887
days.with.cr.line  0.075621       -0.049048
revol.bal         -0.031355        0.056760
revol.util         0.084822        0.116037
inq.last.6mths     0.097453        0.175923
delinq.2yrs       -0.006730        0.016787
pub.rec            1.000000        0.062179
not.fully.paid     0.062179        1.000000
```

[31]:
```
plt.figure(figsize=(11,7))
sns.heatmap(new_df.corr(),annot=True)
```

[31]: <Axes: >



[32]:
```python
# see the sorted results
new_df.corr().abs()['not.fully.paid'].sort_values(ascending=False)
```

[32]:
```
not.fully.paid       1.000000
int.rate             0.222356
fico                 0.215887
credit.policy        0.197173
inq.last.6mths       0.175923
revol.util           0.116037
installment          0.075112
purpose              0.062396
pub.rec              0.062179
revol.bal            0.056760
days.with.cr.line    0.049048
dti                  0.046921
log.annual.inc       0.038936
delinq.2yrs          0.016787
Name: not.fully.paid, dtype: float64
```

[33]:
```
new_df.columns
```

[33]:
```
Index(['credit.policy', 'purpose', 'int.rate', 'installment', 'log.annual.inc',
       'dti', 'fico', 'days.with.cr.line', 'revol.bal', 'revol.util',
       'inq.last.6mths', 'delinq.2yrs', 'pub.rec', 'not.fully.paid'],
      dtype='object')
```

[34]:
```
# Taking the column with top correlation
X=new_df[['credit.policy','purpose', 'int.rate', 'installment','fico','revol.
 ↪bal','revol.util','inq.last.6mths','pub.rec']]
```

[35]:
```
X.shape
```

[35]:
```
(16090, 9)
```

[36]:
```
#Lets put the target variable to y
y=new_df['not.fully.paid']
```

[37]:
```
# Create train set & test set
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=.2,random_state=42)
```

[38]:
```
X_train.shape
```

[38]:
```
(12872, 9)
```

[39]:
```
X_test.shape
```

[39]:
```
(3218, 9)
```

[40]:
```
X_train
```

[40]:
```
      credit.policy  purpose  int.rate  installment  fico  revol.bal  \
9218              0        2    0.1426       343.06   687      28282
6190              1        2    0.1322       243.37   682      23079
6671              1        2    0.1357       271.75   697       6382
3983              1        0    0.1221       266.52   717       6883
9375              0        2    0.1148       403.87   727     256757
…                …        …       …           …     …         …
4574              1        3    0.1322       338.01   692       2263
2651              1        6    0.1189       530.63   757      29204
2547              1        1    0.1379       272.61   682       9287
5910              1        0    0.0774       168.59   747       2534
1737              1        1    0.0963       102.71   712       7572

      revol.util  inq.last.6mths  pub.rec
9218        85.4               5        0
```

```
6190        74.9               0        0
6671        74.2               1        0
3983        65.6               0        0
9375        82.7               0        0
…          …             …      …
4574        17.7               0        0
2651        51.9               2        0
2547        61.9               1        0
5910        22.2               2        0
1737        17.1               2        0

[12872 rows x 9 columns]
```

[41]:
```
# Apply scaling
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
```

[42]:
```
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
```

0.2 Create a deep learning model using Keras with Tensorflow backend

[43]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

[44]:
```
# create the architecture
# 2 ANN layer
model=Sequential()
model.add(Dense(19,activation='relu',input_shape=[9]))
model.add(Dropout(0.20))


model.add(Dense(10,activation='relu'))
model.add(Dropout(0.20))

# output layer
model.add(Dense(1,activation='sigmoid'))
```

[45]:
```
model.summary()
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 19)                190
```

```
 dropout (Dropout)           (None, 19)                0

 dense_1 (Dense)             (None, 10)                200

 dropout_1 (Dropout)         (None, 10)                0

 dense_2 (Dense)             (None, 1)                 11

=================================================================
Total params: 401
Trainable params: 401
Non-trainable params: 0
_________________________________________________________________
```

[46]:
```
# compile the model
model.compile(loss='binary_crossentropy',optimizer='adam',metrics=['accuracy'])
```

[47]:
```
early_stop=EarlyStopping(monitor='val_loss',min_delta=0.
 ↪001,mode='min',patience=10,verbose=1)
```

[48]:
```
model.fit(X_train,y_train,
          epochs=50,
          batch_size=256,
          validation_data=(X_test,y_test),
          callbacks=[early_stop])
```

```
Epoch 1/50
51/51 [==============================] - 2s 11ms/step - loss: 0.7052 - accuracy:
0.5597 - val_loss: 0.6643 - val_accuracy: 0.6016
Epoch 2/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6789 - accuracy:
0.5762 - val_loss: 0.6580 - val_accuracy: 0.6041
Epoch 3/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6672 - accuracy:
0.5926 - val_loss: 0.6559 - val_accuracy: 0.6081
Epoch 4/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6627 - accuracy:
0.6018 - val_loss: 0.6547 - val_accuracy: 0.6053
Epoch 5/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6623 - accuracy:
0.6016 - val_loss: 0.6544 - val_accuracy: 0.6053
Epoch 6/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6584 - accuracy:
0.6035 - val_loss: 0.6534 - val_accuracy: 0.6025
Epoch 7/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6551 - accuracy:
0.6050 - val_loss: 0.6524 - val_accuracy: 0.6041
```

```
Epoch 8/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6566 - accuracy:
0.6060 - val_loss: 0.6517 - val_accuracy: 0.6010
Epoch 9/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6528 - accuracy:
0.6052 - val_loss: 0.6509 - val_accuracy: 0.5998
Epoch 10/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6528 - accuracy:
0.6113 - val_loss: 0.6505 - val_accuracy: 0.6022
Epoch 11/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6517 - accuracy:
0.6087 - val_loss: 0.6500 - val_accuracy: 0.6010
Epoch 12/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6514 - accuracy:
0.6080 - val_loss: 0.6496 - val_accuracy: 0.6053
Epoch 13/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6505 - accuracy:
0.6078 - val_loss: 0.6493 - val_accuracy: 0.6078
Epoch 14/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6498 - accuracy:
0.6130 - val_loss: 0.6487 - val_accuracy: 0.6081
Epoch 15/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6486 - accuracy:
0.6193 - val_loss: 0.6485 - val_accuracy: 0.6069
Epoch 16/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6478 - accuracy:
0.6159 - val_loss: 0.6478 - val_accuracy: 0.6128
Epoch 17/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6468 - accuracy:
0.6165 - val_loss: 0.6473 - val_accuracy: 0.6122
Epoch 18/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6472 - accuracy:
0.6189 - val_loss: 0.6473 - val_accuracy: 0.6066
Epoch 19/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6453 - accuracy:
0.6220 - val_loss: 0.6467 - val_accuracy: 0.6128
Epoch 20/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6469 - accuracy:
0.6182 - val_loss: 0.6467 - val_accuracy: 0.6140
Epoch 21/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6465 - accuracy:
0.6212 - val_loss: 0.6462 - val_accuracy: 0.6116
Epoch 22/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6461 - accuracy:
0.6156 - val_loss: 0.6462 - val_accuracy: 0.6156
Epoch 23/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6461 - accuracy:
0.6206 - val_loss: 0.6462 - val_accuracy: 0.6147
```

```
Epoch 24/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6427 - accuracy:
0.6214 - val_loss: 0.6458 - val_accuracy: 0.6187
Epoch 25/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6444 - accuracy:
0.6227 - val_loss: 0.6457 - val_accuracy: 0.6178
Epoch 26/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6433 - accuracy:
0.6237 - val_loss: 0.6457 - val_accuracy: 0.6184
Epoch 27/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6448 - accuracy:
0.6234 - val_loss: 0.6454 - val_accuracy: 0.6187
Epoch 28/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6442 - accuracy:
0.6244 - val_loss: 0.6456 - val_accuracy: 0.6187
Epoch 29/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6438 - accuracy:
0.6193 - val_loss: 0.6448 - val_accuracy: 0.6200
Epoch 30/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6433 - accuracy:
0.6271 - val_loss: 0.6450 - val_accuracy: 0.6203
Epoch 31/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6442 - accuracy:
0.6208 - val_loss: 0.6448 - val_accuracy: 0.6193
Epoch 32/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6430 - accuracy:
0.6226 - val_loss: 0.6449 - val_accuracy: 0.6209
Epoch 33/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6436 - accuracy:
0.6231 - val_loss: 0.6446 - val_accuracy: 0.6209
Epoch 34/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6413 - accuracy:
0.6234 - val_loss: 0.6442 - val_accuracy: 0.6187
Epoch 35/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6410 - accuracy:
0.6241 - val_loss: 0.6446 - val_accuracy: 0.6218
Epoch 36/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6425 - accuracy:
0.6235 - val_loss: 0.6447 - val_accuracy: 0.6227
Epoch 37/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6441 - accuracy:
0.6216 - val_loss: 0.6448 - val_accuracy: 0.6224
Epoch 38/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6410 - accuracy:
0.6262 - val_loss: 0.6445 - val_accuracy: 0.6221
Epoch 39/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6424 - accuracy:
0.6257 - val_loss: 0.6444 - val_accuracy: 0.6234
```

```
Epoch 39: early stopping
```

[48]: <keras.callbacks.History at 0x21cb28ecf10>

[49]:
```python
history=model.fit(X_train,y_train,
          epochs=50,
          batch_size=256,
          validation_data=(X_test,y_test))
```

```
Epoch 1/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6411 - accuracy:
0.6262 - val_loss: 0.6445 - val_accuracy: 0.6249
Epoch 2/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6397 - accuracy:
0.6288 - val_loss: 0.6445 - val_accuracy: 0.6277
Epoch 3/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6404 - accuracy:
0.6242 - val_loss: 0.6442 - val_accuracy: 0.6271
Epoch 4/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6406 - accuracy:
0.6207 - val_loss: 0.6441 - val_accuracy: 0.6259
Epoch 5/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6408 - accuracy:
0.6262 - val_loss: 0.6443 - val_accuracy: 0.6240
Epoch 6/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6408 - accuracy:
0.6252 - val_loss: 0.6442 - val_accuracy: 0.6203
Epoch 7/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6404 - accuracy:
0.6235 - val_loss: 0.6442 - val_accuracy: 0.6221
Epoch 8/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6402 - accuracy:
0.6227 - val_loss: 0.6443 - val_accuracy: 0.6252
Epoch 9/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6409 - accuracy:
0.6268 - val_loss: 0.6442 - val_accuracy: 0.6246
Epoch 10/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6384 - accuracy:
0.6254 - val_loss: 0.6442 - val_accuracy: 0.6234
Epoch 11/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6396 - accuracy:
0.6280 - val_loss: 0.6441 - val_accuracy: 0.6271
Epoch 12/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6388 - accuracy:
0.6283 - val_loss: 0.6440 - val_accuracy: 0.6240
Epoch 13/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6406 - accuracy:
0.6258 - val_loss: 0.6443 - val_accuracy: 0.6221
```

```
Epoch 14/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6390 - accuracy:
0.6226 - val_loss: 0.6443 - val_accuracy: 0.6268
Epoch 15/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6383 - accuracy:
0.6248 - val_loss: 0.6443 - val_accuracy: 0.6237
Epoch 16/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6382 - accuracy:
0.6254 - val_loss: 0.6442 - val_accuracy: 0.6212
Epoch 17/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6393 - accuracy:
0.6314 - val_loss: 0.6446 - val_accuracy: 0.6218
Epoch 18/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6386 - accuracy:
0.6281 - val_loss: 0.6443 - val_accuracy: 0.6227
Epoch 19/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6382 - accuracy:
0.6253 - val_loss: 0.6442 - val_accuracy: 0.6255
Epoch 20/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6396 - accuracy:
0.6246 - val_loss: 0.6443 - val_accuracy: 0.6203
Epoch 21/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6397 - accuracy:
0.6273 - val_loss: 0.6440 - val_accuracy: 0.6224
Epoch 22/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6381 - accuracy:
0.6290 - val_loss: 0.6439 - val_accuracy: 0.6259
Epoch 23/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6384 - accuracy:
0.6297 - val_loss: 0.6440 - val_accuracy: 0.6224
Epoch 24/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6394 - accuracy:
0.6263 - val_loss: 0.6435 - val_accuracy: 0.6255
Epoch 25/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6368 - accuracy:
0.6280 - val_loss: 0.6439 - val_accuracy: 0.6234
Epoch 26/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6373 - accuracy:
0.6277 - val_loss: 0.6437 - val_accuracy: 0.6234
Epoch 27/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6384 - accuracy:
0.6290 - val_loss: 0.6439 - val_accuracy: 0.6221
Epoch 28/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6387 - accuracy:
0.6294 - val_loss: 0.6437 - val_accuracy: 0.6221
Epoch 29/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6370 - accuracy:
0.6325 - val_loss: 0.6439 - val_accuracy: 0.6224
```

```
Epoch 30/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6380 - accuracy:
0.6319 - val_loss: 0.6438 - val_accuracy: 0.6231
Epoch 31/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6383 - accuracy:
0.6294 - val_loss: 0.6438 - val_accuracy: 0.6206
Epoch 32/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6362 - accuracy:
0.6285 - val_loss: 0.6434 - val_accuracy: 0.6240
Epoch 33/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6356 - accuracy:
0.6328 - val_loss: 0.6440 - val_accuracy: 0.6212
Epoch 34/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6353 - accuracy:
0.6288 - val_loss: 0.6434 - val_accuracy: 0.6187
Epoch 35/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6382 - accuracy:
0.6307 - val_loss: 0.6433 - val_accuracy: 0.6209
Epoch 36/50
51/51 [==============================] - 0s 3ms/step - loss: 0.6363 - accuracy:
0.6224 - val_loss: 0.6434 - val_accuracy: 0.6218
Epoch 37/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6377 - accuracy:
0.6252 - val_loss: 0.6433 - val_accuracy: 0.6231
Epoch 38/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6376 - accuracy:
0.6255 - val_loss: 0.6431 - val_accuracy: 0.6231
Epoch 39/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6359 - accuracy:
0.6300 - val_loss: 0.6432 - val_accuracy: 0.6234
Epoch 40/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6363 - accuracy:
0.6273 - val_loss: 0.6431 - val_accuracy: 0.6243
Epoch 41/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6356 - accuracy:
0.6244 - val_loss: 0.6428 - val_accuracy: 0.6259
Epoch 42/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6356 - accuracy:
0.6321 - val_loss: 0.6427 - val_accuracy: 0.6231
Epoch 43/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6358 - accuracy:
0.6281 - val_loss: 0.6432 - val_accuracy: 0.6234
Epoch 44/50
51/51 [==============================] - 0s 4ms/step - loss: 0.6360 - accuracy:
0.6326 - val_loss: 0.6430 - val_accuracy: 0.6246
Epoch 45/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6355 - accuracy:
0.6321 - val_loss: 0.6429 - val_accuracy: 0.6249
```

```
Epoch 46/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6359 - accuracy:
0.6286 - val_loss: 0.6434 - val_accuracy: 0.6249
Epoch 47/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6354 - accuracy:
0.6294 - val_loss: 0.6432 - val_accuracy: 0.6221
Epoch 48/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6366 - accuracy:
0.6311 - val_loss: 0.6430 - val_accuracy: 0.6243
Epoch 49/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6345 - accuracy:
0.6287 - val_loss: 0.6430 - val_accuracy: 0.6265
Epoch 50/50
51/51 [==============================] - 0s 5ms/step - loss: 0.6355 - accuracy:
0.6304 - val_loss: 0.6429 - val_accuracy: 0.6246
```

[50]:
```
model.evaluate(X_test,y_test)
```

```
101/101 [==============================] - 0s 2ms/step - loss: 0.6429 -
accuracy: 0.6246
```

[50]:
```
[0.6428872346878052, 0.6246115565299988]
```

[51]:
```
y_pred=model.predict(X_test)
```

```
101/101 [==============================] - 0s 1ms/step
```

[52]:
```
y_pred
```

[52]:
```
array([[0.5871634 ],
       [0.5871743 ],
       [0.60559916],
       …,
       [0.3994345 ],
       [0.4221612 ],
       [0.5309749 ]], dtype=float32)
```

[53]:
```
predictions=(y_pred>0.5).astype('int')
```

[54]:
```
predictions
```

[54]:
```
array([[1],
       [1],
       [1],
       …,
       [0],
       [0],
       [1]])
```

[55]:
```
y_test
```

[55]:
```
329     0
5316    1
2767    1
2665    1
587     0
       ..
4852    1
7991    1
2253    0
600     1
679     1
Name: not.fully.paid, Length: 3218, dtype: int64
```

[56]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
accuracy_score(predictions,y_test)
```

[56]:
```
0.6246115599751398
```

[57]:
```
print(classification_report(predictions,y_test))
```

```
              precision    recall  f1-score   support

           0       0.64      0.62      0.63      1659
           1       0.61      0.63      0.62      1559

    accuracy                           0.62      3218
   macro avg       0.62      0.62      0.62      3218
weighted avg       0.63      0.62      0.62      3218
```

[58]:
```
model.save('loan_default1.h5')
```