PG AIML- Deep Learning with Tensorflow and Keras

Course-End Project Problem Statement

simplilearn

Get Certified. Get Ahead.

Course-End Project: Lending Club Loan Data Analysis

Problem statement:

For companies like Lending Club correctly predicting whether or not a loan will be a default is very important. In this project, using the historical data from 2007 to 2015, you have to build a deep learning model to predict the chance of default for future loans. As you will see later this dataset is highly imbalanced and includes a lot of features that makes this problem more challenging.

Dataset description:

Dataset name: **loan_data.csv**

- **credit.policy:** 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise.
- **purpose:** The purpose of the loan (takes values "credit_card", "debt_consolidation", "educational", "major_purchase", "small_business", and "all_other").
- **int.rate:** The interest rate of the loan, as a proportion (a rate of 11% would be stored as 0.11). Borrowers judged by LendingClub.com to be more risky are assigned higher interest rates.
- **installment:** The monthly installments owed by the borrower if the loan is funded.
- **log.annual.inc:** The natural log of the self-reported annual income of the borrower.
- **dti:** The debt-to-income ratio of the borrower (amount of debt divided by annual income).
- **fico:** The FICO credit score of the borrower.
- **days.with.cr.line:** The number of days the borrower has had a credit line.
- **revol.bal:** The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle).
- **revol.util:** The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available).
- **inq.last.6mths:** The borrower's number of inquiries by creditors in the last 6 months.
- **delinq.2yrs:** The number of times the borrower had been 30+ days past due on a payment in the past 2 years.
- **pub.rec:** The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

Task to be performed:

Perform exploratory data analysis and feature engineering and then apply feature engineering. Follow up with a deep learning model to predict whether or not the loan will be default using the historical data.

Tasks:

1. Feature Transformation
   - Transform categorical values into numerical values (discrete)
2. Exploratory data analysis of different factors of the dataset.
3. 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
4. Modeling
   - After applying EDA and feature engineering, you are now ready to build the predictive models
   - In this part, you will create a deep learning model using Keras with Tensorflow backend

Solution :

1. Feature Transformation
   - Transform categorical values into numerical values (discrete)

Import libraries and read file

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

import tensorflow
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Input
from  sklearn.metrics  import  confusion_matrix,  accuracy_score  ,
classification_report

import warnings
warnings.filterwarnings('ignore')
```

```
#reading the data set
data = pd.read_csv("C:/Users/david/Desktop/personal/AI/course-4_PC AIML - Deep Learning/project/1596018188_datasets (1)/loan_data.csv")
data.head()
```

```
df.head()
```

```
#reading the data set
data = pd.read_csv("C:/Users/david/Desktop/personal/AI/course-4_PC AIML - Deep Learning/project/1596018188_datasets (1)/loan_data
data.head()
```

	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.f
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	

```
# Transform categorical values into numerical values (discrete)

df= pd.get_dummies(data, columns = ["purpose"])
df.head()
```

```
df= pd.get_dummies(data, columns = ["purpose"])
df.head()
```

	credit.policy	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	purpose_
0	1	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0	
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0	
2	1	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0	
3	1	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0	
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0	

2. Exploratory data analysis of different factors of the dataset.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 20 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   credit.policy               9578 non-null   int64
 1   int.rate                    9578 non-null   float64
 2   installment                 9578 non-null   float64
 3   log.annual.inc              9578 non-null   float64
 4   dti                         9578 non-null   float64
 5   fico                        9578 non-null   int64
 6   days.with.cr.line           9578 non-null   float64
 7   revol.bal                   9578 non-null   int64
 8   revol.util                  9578 non-null   float64
 9   inq.last.6mths              9578 non-null   int64
 10  delinq.2yrs                 9578 non-null   int64
 11  pub.rec                     9578 non-null   int64
 12  not.fully.paid              9578 non-null   int64
 13  purpose_all_other           9578 non-null   uint8
 14  purpose_credit_card         9578 non-null   uint8
 15  purpose_debt_consolidation  9578 non-null   uint8
 16  purpose_educational         9578 non-null   uint8
 17  purpose_home_improvement    9578 non-null   uint8
 18  purpose_major_purchase      9578 non-null   uint8
 19  purpose_small_business      9578 non-null   uint8
dtypes: float64(6), int64(7), uint8(7)
memory usage: 1.0 MB
```

df.shape

```
df.shape
```

```
(9578, 20)
```

df.describe().T

```
]: df.describe().T
```

]:

	count	mean	std	min	25%	50%	75%	max
credit.policy	9578.0	0.804970	0.396245	0.000000	1.000000	1.000000	1.000000	1.000000e+00
int.rate	9578.0	0.122640	0.026847	0.060000	0.103900	0.122100	0.140700	2.164000e-01
installment	9578.0	319.089413	207.071301	15.670000	163.770000	268.950000	432.762500	9.401400e+02
log.annual.inc	9578.0	10.932117	0.614813	7.547502	10.558414	10.928884	11.291293	1.452835e+01
dti	9578.0	12.606679	6.883970	0.000000	7.212500	12.665000	17.950000	2.996000e+01
fico	9578.0	710.846314	37.970537	612.000000	682.000000	707.000000	737.000000	8.270000e+02
days.with.cr.line	9578.0	4560.767197	2496.930377	178.958333	2820.000000	4139.958333	5730.000000	1.763996e+04
revol.bal	9578.0	16913.963876	33756.189557	0.000000	3187.000000	8596.000000	18249.500000	1.207359e+06
revol.util	9578.0	46.799236	29.014417	0.000000	22.600000	46.300000	70.900000	1.190000e+02
inq.last.6mths	9578.0	1.577469	2.200245	0.000000	0.000000	1.000000	2.000000	3.300000e+01
delinq.2yrs	9578.0	0.163708	0.546215	0.000000	0.000000	0.000000	0.000000	1.300000e+01
pub.rec	9578.0	0.062122	0.262126	0.000000	0.000000	0.000000	0.000000	5.000000e+00
not.fully.paid	9578.0	0.160054	0.366676	0.000000	0.000000	0.000000	0.000000	1.000000e+00
purpose_all_other	9578.0	0.243370	0.429139	0.000000	0.000000	0.000000	0.000000	1.000000e+00
purpose_credit_card	9578.0	0.131760	0.338248	0.000000	0.000000	0.000000	0.000000	1.000000e+00
purpose_debt_consolidation	9578.0	0.413134	0.492422	0.000000	0.000000	0.000000	1.000000	1.000000e+00

here categorical columns are : 'credit.policy','not.fully.paid','inq.last.6mths','delinq.2yrs' ,'pub.rec' ,'purpose_all_other', 'purpose_credit_card','purpose_debt_consolidation', 'purpose_educational','purpose_home_improvement', 'purpose_major_purchase','purpose_small_business'

checking if balanced or not :

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

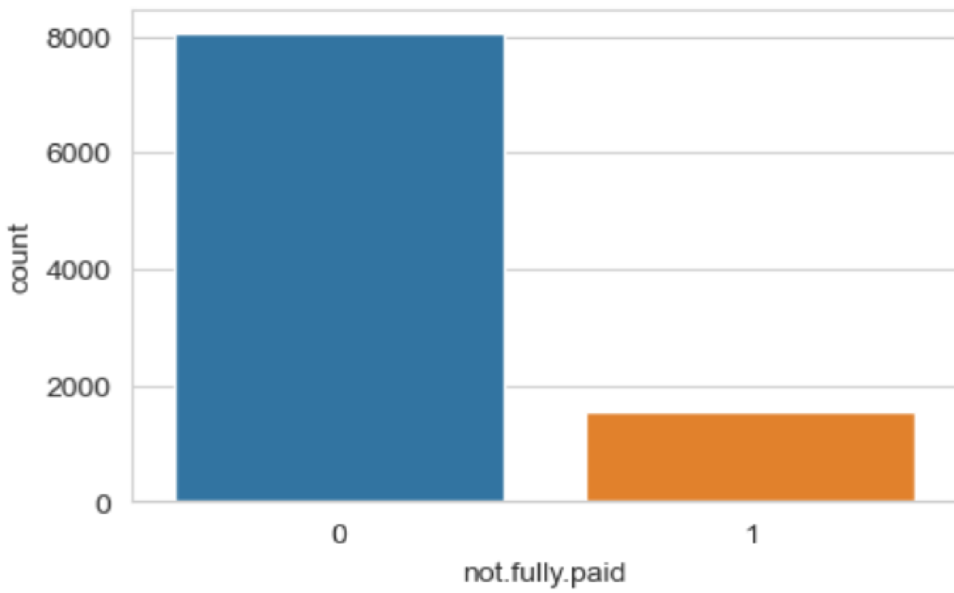
```
df['not.fully.paid'].value_counts()
```

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

```
plt.figure(figsize=(5,5))
sns.countplot(x='not.fully.paid',data=df)
```

```
plt.figure(figsize=(5,3))
sns.countplot(x='not.fully.paid',data=df)
```

```
<Axes: xlabel='not.fully.paid', ylabel='count'>
```



imbalanced class , we have more samples of fully paid borrowers versus not fully paid borrowers.

handling imbalanced dataset - using resample :

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

print('not_fully_paid_0', not_fully_paid_0.shape)
print('not_fully_paid_1', not_fully_paid_1.shape)
```

```
#handling imbalanced dataset - using resample

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

print('not_fully_paid_0', not_fully_paid_0.shape)
print('not_fully_paid_1', not_fully_paid_1.shape)
```

```
not_fully_paid_0 (8045, 20)
not_fully_paid_1 (1533, 20)
```

```
from sklearn.utils import resample
df_minority_upsampled = resample(not_fully_paid_1, replace =
True, n_samples = 8045)
df = pd.concat([not_fully_paid_0, df_minority_upsampled])

from sklearn.utils import shuffle
df = shuffle(df)

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

```
#imbalanced data handled
df['not.fully.paid'].value_counts()
```

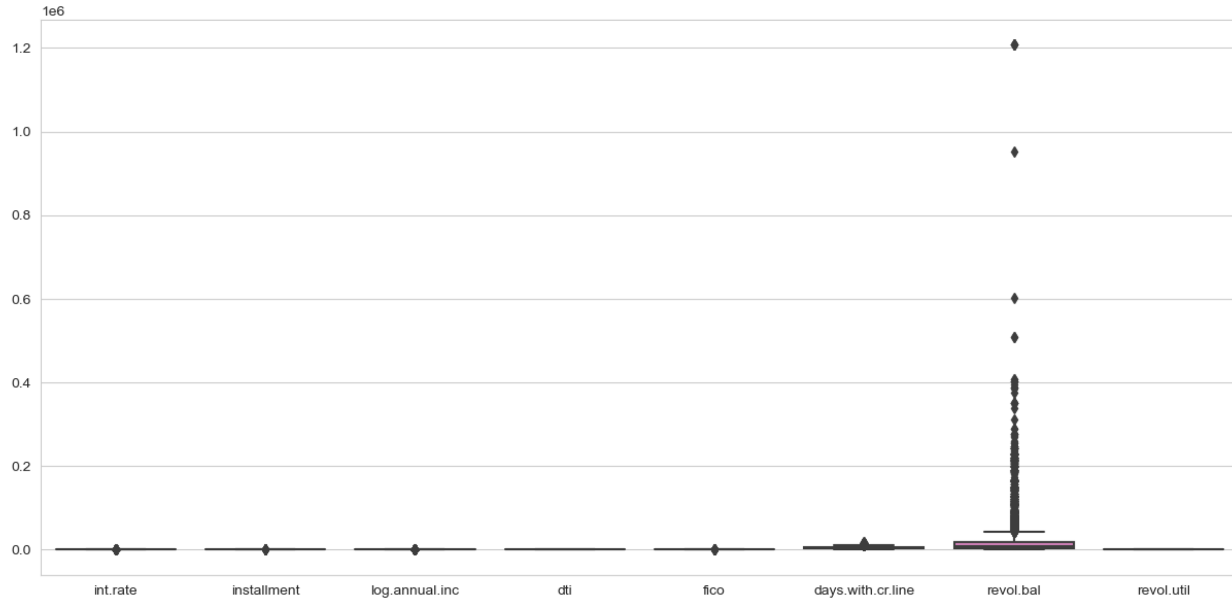
```
0    8045
1    8045
Name: not.fully.paid, dtype: int64
```

imbalanced data handled.

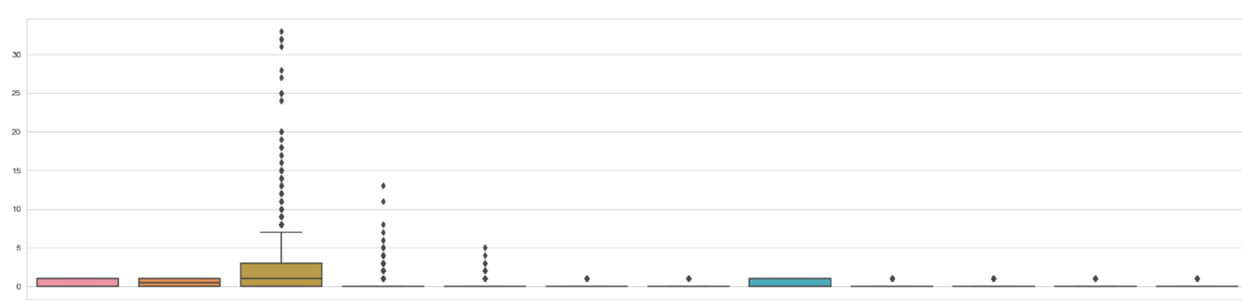
Is there any outliers ?

```
cols_1=['int.rate', 'installment', 'log.annual.inc',
'dti','fico', 'days.with.cr.line', 'revol.bal', 'revol.util']

sns.set_style('whitegrid')
```

```
plt.figure(figsize = (15,7))
sns.boxplot(data=df[cols_1])
```

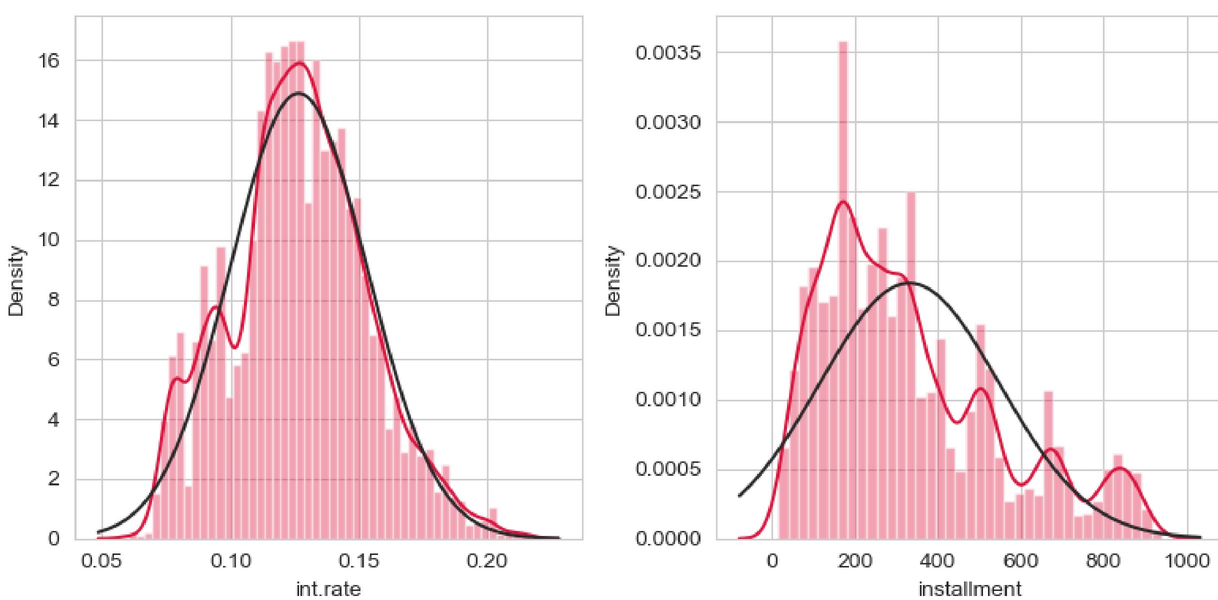


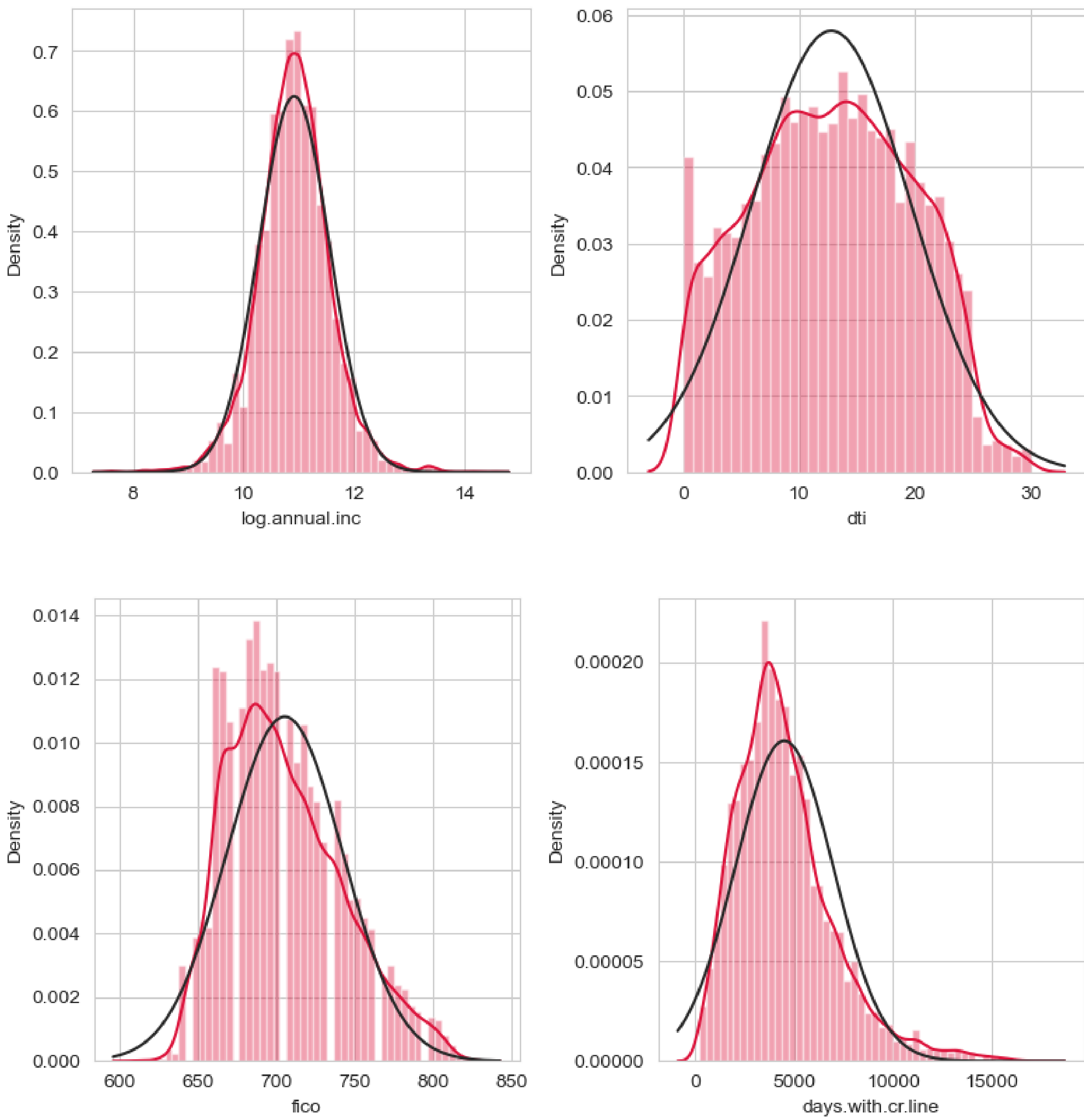

```
cols_2=['credit.policy','not.fully.paid','inq.last.6mths','delin
q.2yrs','pub.rec',
       'purpose_all_other', 'purpose_credit_card',
       'purpose_debt_consolidation', 'purpose_educational',
       'purpose_home_improvement', 'purpose_major_purchase',
       'purpose_small_business']

sns.set_style('whitegrid')
plt.figure(figsize = (26,6))
sns.boxplot(data=df[cols_2])
```

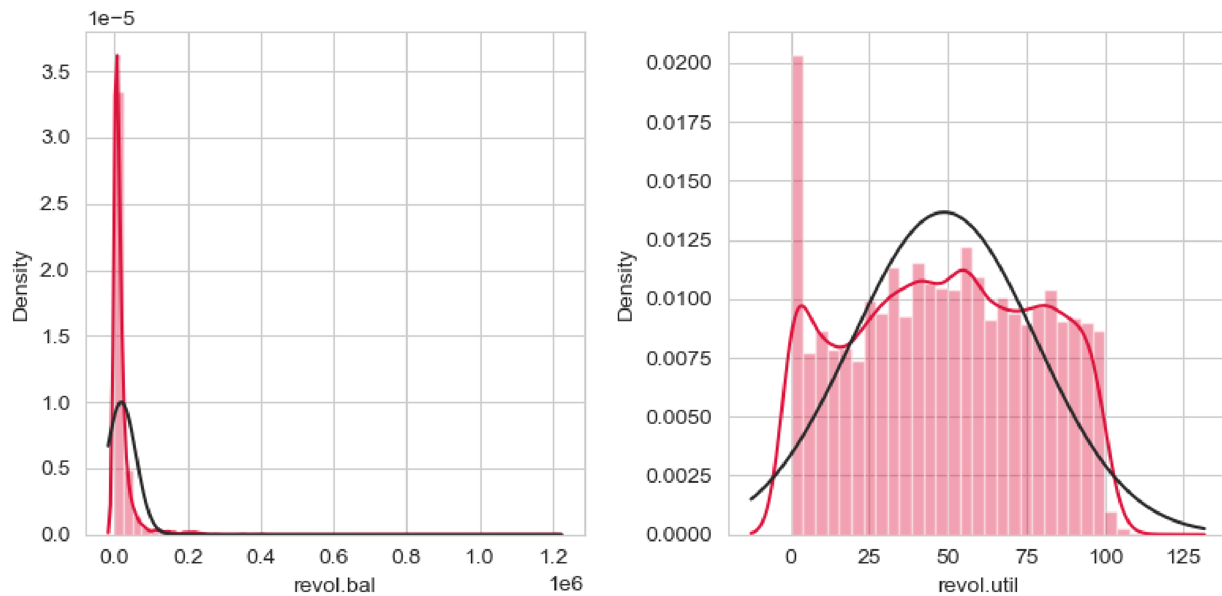


outliers are present in the dataset.

```
from scipy.stats import norm
import seaborn as sns
cols_1=['int.rate', 'installment', 'log.annual.inc',
'dti','fico', 'days.with.cr.line', 'revol.bal', 'revol.util']


for i in range(0,len(cols_1),2):
 plt.figure(figsize=(8,4))
 plt.subplot(121)
 sns.distplot(df[cols_1[i]], kde=True,fit = norm, color =
'crimson')
 plt.subplot(122)
 sns.distplot(df[cols_1[i+1]], kde=True,fit = norm, color =
'crimson')
 plt.tight_layout()
 plt.show()
```




Density
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
8
10
12
14
log.annual.inc
Density
0.06
0.05
0.04
0.03
0.02
0.01
0.00
0
10
20
30
dti
Density
0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
600
650
700
750
800
850
fico
Density
0.00020
0.00015
0.00010
0.00005
0.00000
0
5000
10000
15000
days.with.cr.line



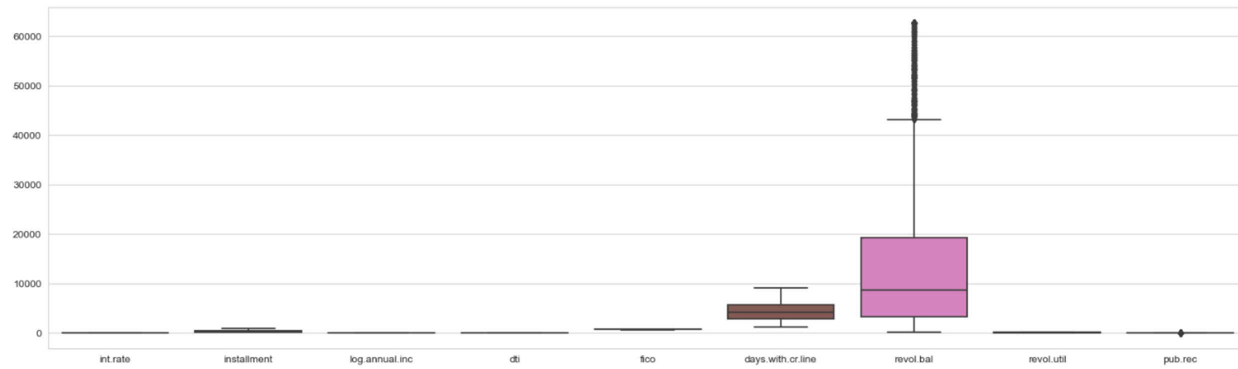
Handling outliers :

```
# Detect outliers in combined data set
def detect_outlier(feature):
    outliers = []
    data = df[feature]
    mean = np.mean(data)
    std =np.std(data)

    for y in data:
        z_score= (y - mean)/std
        if np.abs(z_score) > 3:
            outliers.append(y)
    print(f"\nOutlier caps for {feature}")
    print('  --95p: {:.1f} / {} values exceed
that'.format(data.quantile(.95),

len([i for i in data

if i > data.quantile(.95)])))
    print('  --3sd: {:.1f} / {} values exceed that'.format(mean
+ 3*(std), len(outliers)))
    print('  --99p: {:.1f} / {} values exceed
that'.format(data.quantile(.99),
```

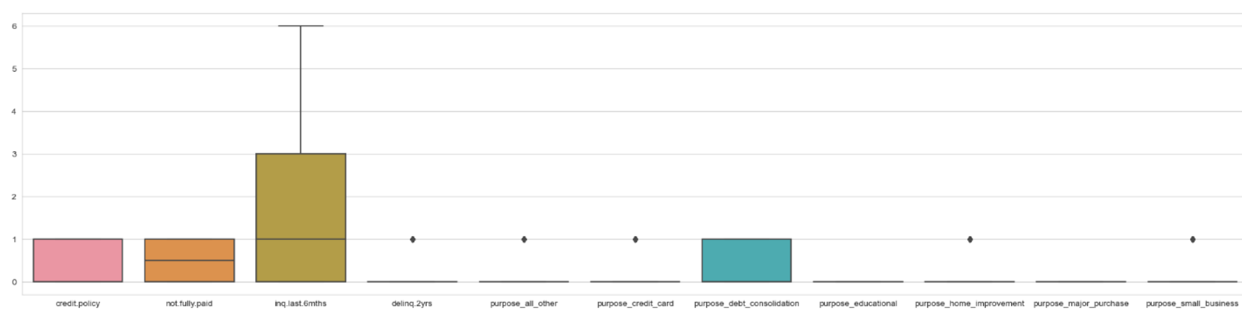
```
len([i for i in data

if i > data.quantile(.99)])))


# Determine what the upperbound should be for continuous
features in dataframe.
for feat in df:
    detect_outlier(feat)
```

```
Outlier caps for credit.policy
  --95p: 1.0 / 0 values exceed that
  --3sd: 2.1 / 0 values exceed that
  --99p: 1.0 / 0 values exceed that

Outlier caps for int.rate
  --95p: 0.2 / 805 values exceed that
  --3sd: 0.2 / 36 values exceed that
  --99p: 0.2 / 158 values exceed that

Outlier caps for installment
  --95p: 807.6 / 801 values exceed that
  --3sd: 983.4 / 0 values exceed that
  --99p: 878.9 / 157 values exceed that

Outlier caps for log.annual.inc
  --95p: 11.9 / 800 values exceed that
  --3sd: 12.8 / 168 values exceed that
  --99p: 12.6 / 156 values exceed that

Outlier caps for dti
  --95p: 23.8 / 800 values exceed that
  --3sd: 33.5 / 0 values exceed that
  --99p: 26.8 / 160 values exceed that

Outlier caps for fico
  --95p: 777.0 / 672 values exceed that
```

```
# Lower and Upper bounded outliers
for var in df:
    df[var].clip(lower = df[var].quantile(.05), upper =
df[var].quantile(0.95), inplace=True)


cols1 = ['int.rate', 'installment', 'log.annual.inc', 'dti',
       'fico', 'days.with.cr.line', 'revol.bal', 'revol.util',
'pub.rec']

sns.set_style('whitegrid')
plt.figure(figsize = (21,6))
sns.boxplot(data=df[cols1])
```




```
cols2=['credit.policy','not.fully.paid','inq.last.6mths','delinq
.2yrs',
       'purpose_all_other', 'purpose_credit_card',
       'purpose_debt_consolidation', 'purpose_educational',
       'purpose_home_improvement', 'purpose_major_purchase',
       'purpose_small_business']

sns.set_style('whitegrid')
plt.figure(figsize = (26,6))
sns.boxplot(data=df[cols2])
```



After capping off outliers, we can see that outliers are now elimited in the variables except revol.bal because it standard deviation is extremely high.

3. Additional Feature Engineering

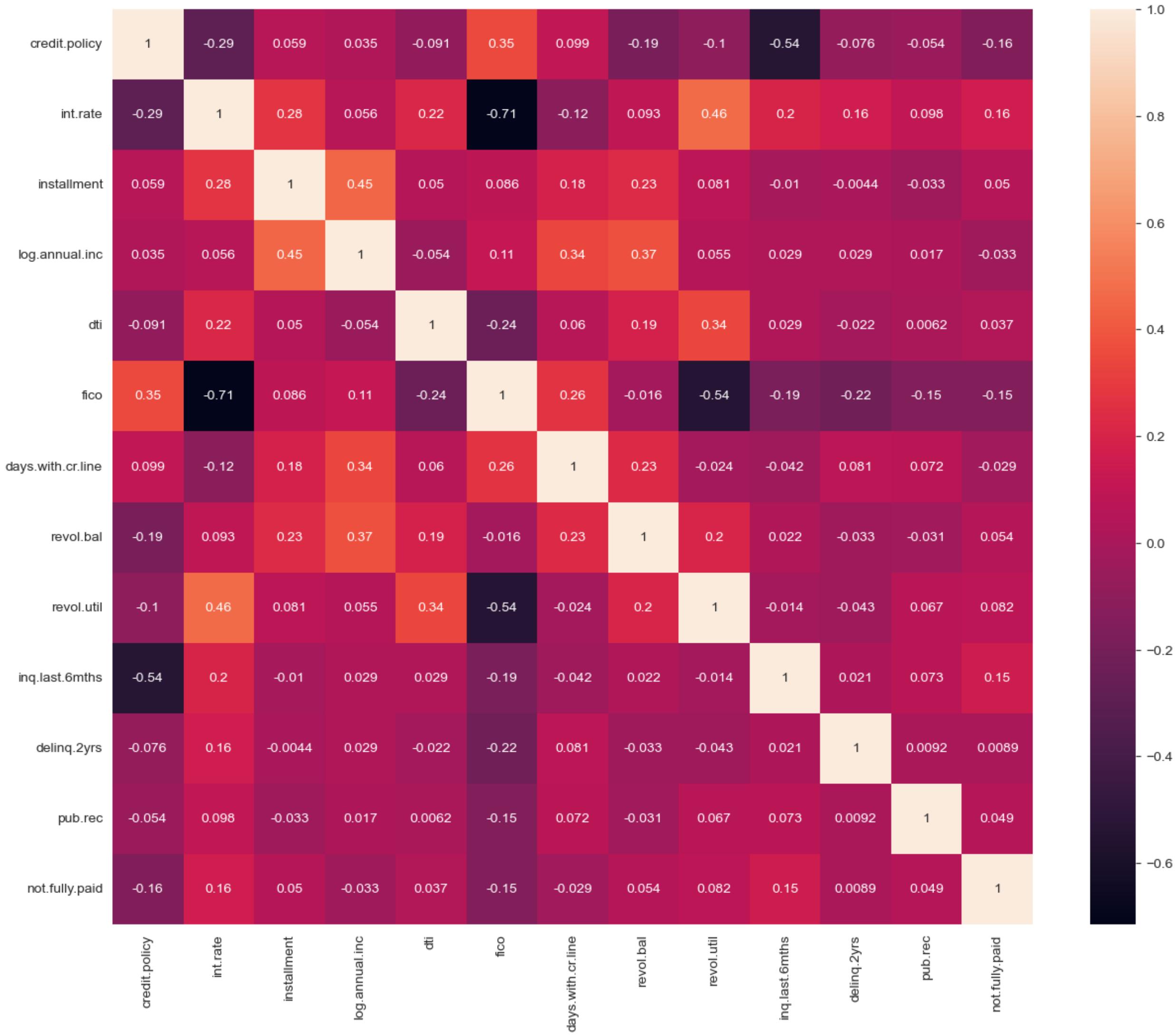
- You will check the correlation between features and will drop those features which have a strong correlation

```
df.corr()
```

```
df.corr()
```

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delin
credit.policy	1.000000	-0.282765	0.053693	0.019055	-0.072089	0.367873	0.086316	-0.096409	-0.084485	-0.584724	-0.0
int.rate	-0.282765	1.000000	0.259678	0.077954	0.197713	-0.702432	-0.111021	0.105973	0.427965	0.197232	0.1
installment	0.053693	0.259678	1.000000	0.477643	0.027296	0.112259	0.196378	0.327932	0.057627	-0.003825	0.0
log.annual.inc	0.019055	0.077954	0.477643	1.000000	-0.030829	0.105569	0.373146	0.496275	0.083805	0.031435	0.0
dti	-0.072089	0.197713	0.027296	-0.030829	1.000000	-0.208458	0.101486	0.294946	0.318520	0.017553	-0.0
fico	0.367873	-0.702432	0.112259	0.105569	-0.208458	1.000000	0.249862	-0.016108	-0.492924	-0.187073	-0.2
days.with.cr.line	0.086316	-0.111021	0.196378	0.373146	0.101486	0.249862	1.000000	0.342745	0.023656	-0.013847	0.0
revol.bal	-0.096409	0.105973	0.327932	0.496275	0.294946	-0.016108	0.342745	1.000000	0.346329	-0.005507	-0.0
revol.util	-0.084485	0.427965	0.057627	0.083805	0.318520	-0.492924	0.023656	0.346329	1.000000	-0.040142	-0.0
inq.last.6mths	-0.584724	0.197232	-0.003825	0.031435	0.017553	-0.187073	-0.013847	-0.005507	-0.040142	1.000000	-0.0
delinq.2yrs	-0.047963	0.164196	0.003193	0.015278	-0.021818	-0.229699	0.081987	-0.058498	-0.030781	-0.000095	1.0
pub.rec	-0.064586	0.102742	-0.028703	0.010706	0.030215	-0.162760	0.083195	-0.049377	0.080320	0.102095	-0.0
not.fully.paid	-0.193486	0.217160	0.078110	-0.044045	0.041874	-0.209217	-0.034872	0.054858	0.103689	0.190637	0.0
purpose_all_other	-0.025119	-0.120703	-0.205774	-0.084775	-0.124782	0.054284	-0.077735	-0.119198	-0.120135	0.009150	0.0
purpose_credit_card	0.012249	-0.043799	-0.000311	0.076602	0.078221	-0.007528	0.047579	0.115706	0.089308	-0.044536	-0.0
purpose_debt_consolidation	0.024277	0.089997	0.116552	-0.047857	0.181831	-0.140818	0.001324	0.047707	0.204263	-0.058960	-0.0

```
plt.figure(figsize = (15,12))
sns.heatmap(data = data.corr(), annot = True)
plt.show()
```



from the correlation heatmaps we can observe that no two features have positive corelation of more than 0.7 , so we will not remove any feature.

4. Modeling

- After applying EDA and feature engineering, you are now ready to build the predictive models
- In this part, you will create a deep learning model using Keras with Tensorflow backend

```
#Identify X and Y

X = df.drop("not.fully.paid", axis = 1)
```

```
y = df["not.fully.paid"]


# Split X and Y

X_train, X_test, y_train, y_test =
train_test_split(X,y,test_size = 0.10, stratify = y,
random_state = 987)
X_train, X_val, y_train, y_val =
train_test_split(X_train,y_train,test_size = 0.15, stratify =
y_train, random_state = 987)
print(X_train.shape,y_train.shape)
print(X_val.shape,y_val.shape)
print(X_test.shape,y_test.shape)


# feature scaling
scaler = StandardScaler()
X_train_scale = scaler.fit_transform(X_train)
X_val_scale = scaler.transform(X_val)
X_test_scale = scaler.transform(X_test)


# Lets build the Model
model = Sequential()
# No of Input will be == (total number of train examples , 8)
# where 8 = feature
model.add(Input(shape=(X_train_scale.shape[1],)))

# Hidden Layer 1
model.add(Dense(units=200,activation='relu'))
model.add(Dropout(0.2))
# Hidden Layer 2
model.add(Dense(units=200,activation='relu'))
model.add(Dropout(0.2))
# Hidden Layer 3
model.add(Dense(units=200,activation='relu'))
model.add(Dropout(0.2))

# Output Layer - this is a binary classification
model.add(Dense(units=1,activation='sigmoid'))
```

```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 200)               4000

 dropout (Dropout)           (None, 200)               0

 dense_1 (Dense)             (None, 200)               40200

 dropout_1 (Dropout)         (None, 200)               0

 dense_2 (Dense)             (None, 200)               40200

 dropout_2 (Dropout)         (None, 200)               0

 dense_3 (Dense)             (None, 1)                 201

=================================================================
Total params: 84601 (330.47 KB)
Trainable params: 84601 (330.47 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

```
model.compile(optimizer='adam',loss='binary_crossentropy',metric
s=['accuracy'])

history = model.fit(X_train_scale,y_train,
                    validation_data=(X_val_scale,
y_val),epochs=100,verbose=1)
```

```
history = model.fit(X_train_scale,y_train,
                    validation_data=(X_val_scale, y_val),epochs=100,verbose=1)
```

```
0.8923
Epoch 95/100
385/385 [==============================] - 2s 4ms/step - loss: 0.2043 - accuracy: 0.9170 - val_loss: 0.3175 - val_accuracy:
0.8790
Epoch 96/100
385/385 [==============================] - 2s 4ms/step - loss: 0.2034 - accuracy: 0.9180 - val_loss: 0.3220 - val_accuracy:
0.8840
Epoch 97/100
385/385 [==============================] - 2s 4ms/step - loss: 0.1912 - accuracy: 0.9231 - val_loss: 0.3263 - val_accuracy:
0.8873
Epoch 98/100
385/385 [==============================] - 2s 4ms/step - loss: 0.1941 - accuracy: 0.9211 - val_loss: 0.3277 - val_accuracy:
0.8808
Epoch 99/100
385/385 [==============================] - 2s 4ms/step - loss: 0.2003 - accuracy: 0.9207 - val_loss: 0.3371 - val_accuracy:
0.8813
Epoch 100/100
385/385 [==============================] - 2s 4ms/step - loss: 0.1973 - accuracy: 0.9183 - val_loss: 0.3008 - val_accuracy:
0.8942
```

```
X_train_pred= model.predict(X_train_scale)
X_test_pred=model.predict(X_test_scale)

cm = confusion_matrix(y_pred=X_train_pred > 0.5,y_true=y_train)
cm

cm = confusion_matrix(y_pred=X_test_pred > 0.5,y_true=y_test)
cm
```

```
X_train_pred= model.predict(X_train_scale)
X_test_pred=model.predict(X_test_scale)
```

```
385/385 [==============================] - 1s 2ms/step
51/51 [==============================] - 0s 2ms/step
```

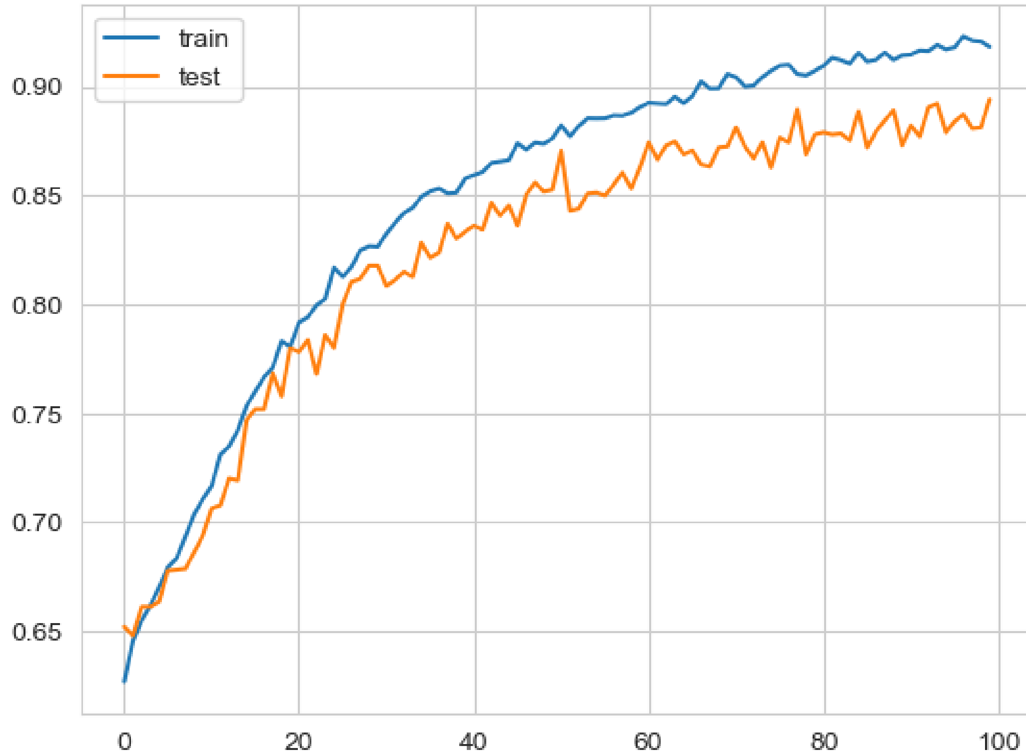
```
cm = confusion_matrix(y_pred=X_train_pred > 0.5,y_true=y_train)
cm
```

```
array([[6049,  105],
       [  41, 6113]], dtype=int64)
```

```
cm = confusion_matrix(y_pred=X_test_pred > 0.5,y_true=y_test)
cm
```

```
array([[658, 146],
       [ 26, 779]], dtype=int64)
```

```
from matplotlib import pyplot

pyplot.plot(history.history['accuracy'], label='train')
pyplot.plot(history.history['val_accuracy'], label='test')
pyplot.legend()
pyplot.show()
```




```
#training score
model.evaluate(X_train_scale,y_train)

#validatn score
model.evaluate(X_val_scale,y_val)

#testing score
model.evaluate(X_test_scale,y_test)
```

```
#training score
model.evaluate(X_train_scale,y_train)
```

```
385/385 [==============================] - 1s 2ms/step - loss: 0.0628 - accuracy: 0.9881
```

```
[0.0628020241856575, 0.9881377816200256]
```

```
#validatn score
model.evaluate(X_val_scale,y_val)
```

```
68/68 [==============================] - 0s 2ms/step - loss: 0.3008 - accuracy: 0.8942
```

```
[0.3008177578449249, 0.8941555619239807]
```

```
#testing score
model.evaluate(X_test_scale,y_test)
```

```
51/51 [==============================] - 0s 2ms/step - loss: 0.3353 - accuracy: 0.8931
```

```
[0.33529841899871826, 0.8931013345718384]
```

```
predictions =(model.predict(X_test_scale)>0.5)
predictions2 =(model.predict(X_val_scale)>0.5)

accuracy_score(y_test, predictions)

accuracy_score(y_val,predictions2)
```

```
predictions =(model.predict(X_test_scale)>0.5)
predictions2 =(model.predict(X_val_scale)>0.5)
```

```
51/51 [==============================] - 0s 2ms/step
68/68 [==============================] - 0s 2ms/step
```

```
accuracy_score(y_test, predictions)
```

```
0.8931013051584835
```

```
accuracy_score(y_val,predictions2)
```

```
0.8941555453290382
```

```
print(classification_report(y_test, predictions))

print(classification_report(y_val, predictions2))
```

```python
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.96      0.82      0.88       804
           1       0.84      0.97      0.90       805

    accuracy                           0.89      1609
   macro avg       0.90      0.89      0.89      1609
weighted avg       0.90      0.89      0.89      1609
```

```python
print(classification_report(y_val, predictions2))
```

```
              precision    recall  f1-score   support

           0       0.95      0.83      0.89      1087
           1       0.85      0.96      0.90      1086

    accuracy                           0.89      2173
   macro avg       0.90      0.89      0.89      2173
weighted avg       0.90      0.89      0.89      2173
```