Lending Club Loan Data Analysis

```
# import libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, BatchNormalization, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.metrics import confusion_matrix, auc, roc_curve

import warnings
warnings.filterwarnings('ignore')

# Get dataset
loan_df = pd.read_csv('loan_data.csv')
loan_df.head()
```

```
   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
```

```
loan_df.info()
```

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

As we can see here, there is no NaN value in any column.

```
loan_df.shape
```

```
(9578, 14)
```

From data, we can say, we have few categorical columns like credit.policy, purpose and columns with limited range of values like inq.last.6mths, delinq.2yrs, pub.rec and not.fully.paid.

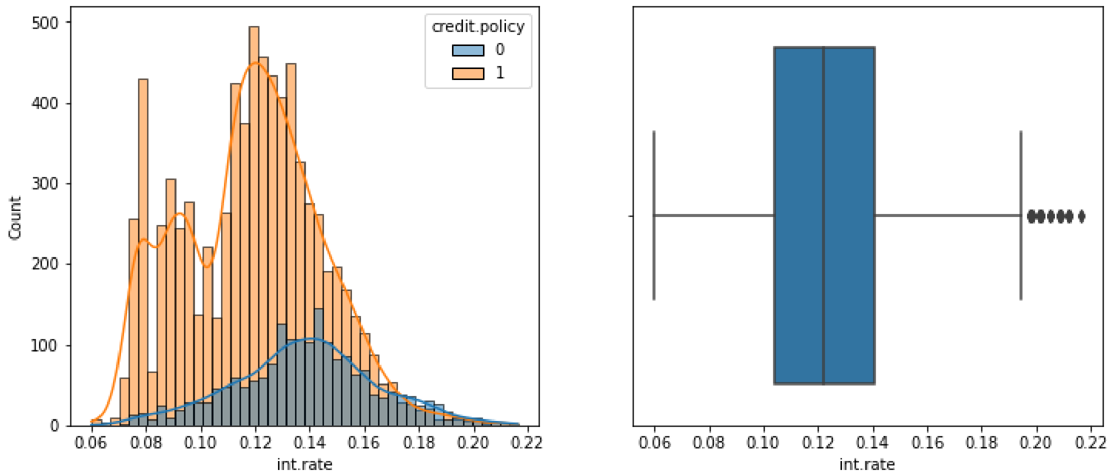
```
loan_df.describe()
```

```
       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
```

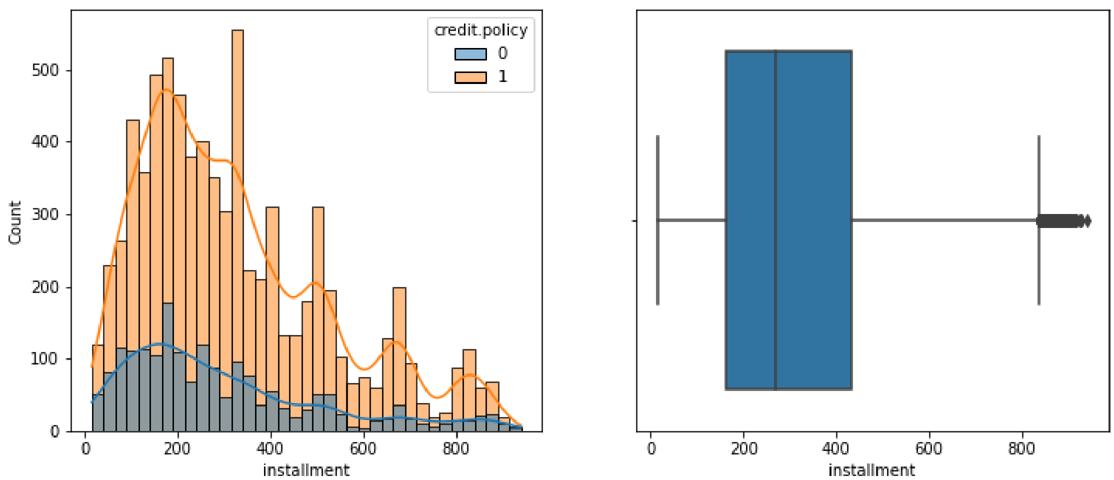
```
25%         1.000000     0.103900   163.770000       10.558414
7.212500
50%         1.000000     0.122100   268.950000       10.928884
12.665000
75%         1.000000     0.140700   432.762500       11.291293
17.950000
max         1.000000     0.216400   940.140000       14.528354
29.960000

              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
```

EDA Of numeric data

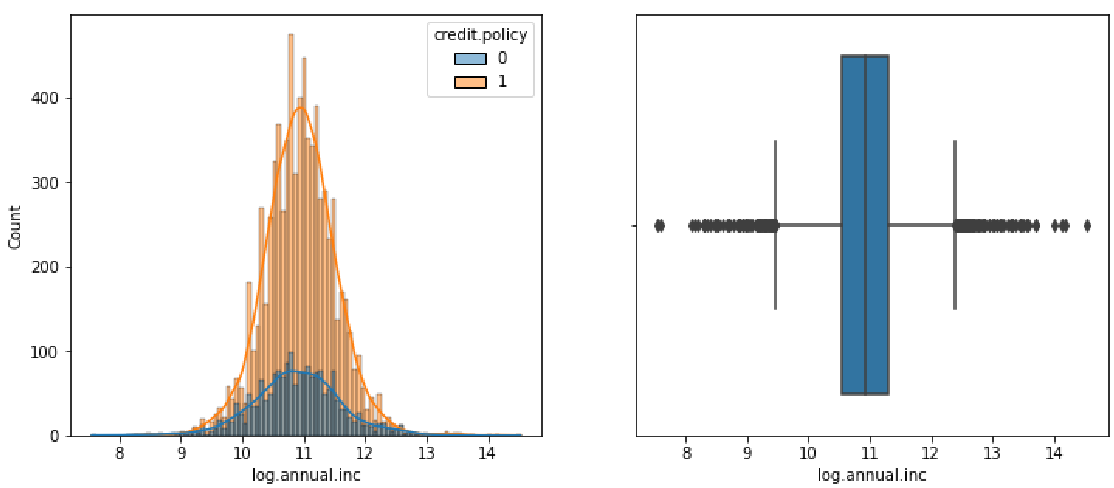
```python
def hist_box_plot(col):
    plt.figure(figsize=(12, 5))
    plt.subplot(1,2,1)
    sns.histplot(data=loan_df, x= col, hue='credit.policy', kde=True)
    plt.subplot(1,2,2)
    sns.boxplot(loan_df[col])
    plt.show()

def box_plot(df, col):
    sns.boxplot(df[col])
    plt.show()

hist_box_plot('int.rate')
```



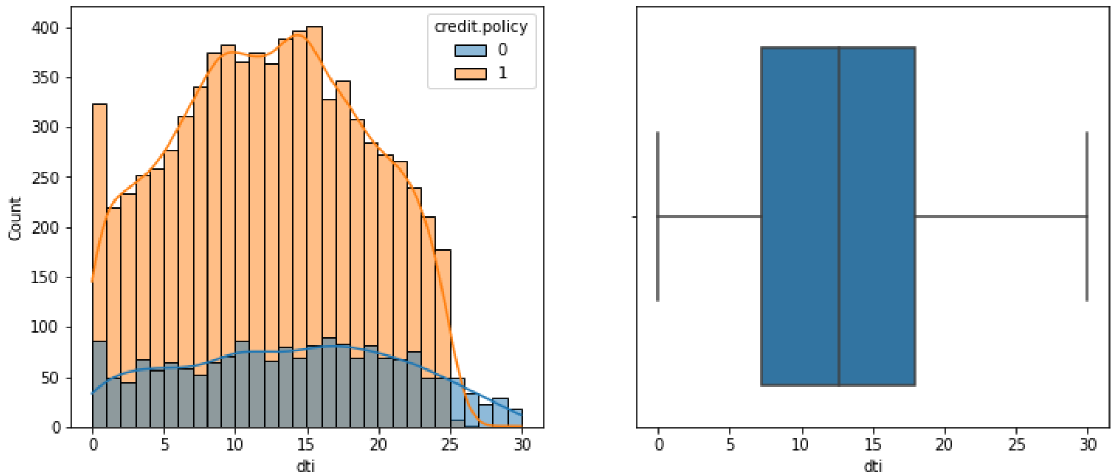

```
hist_box_plot('installment')
```



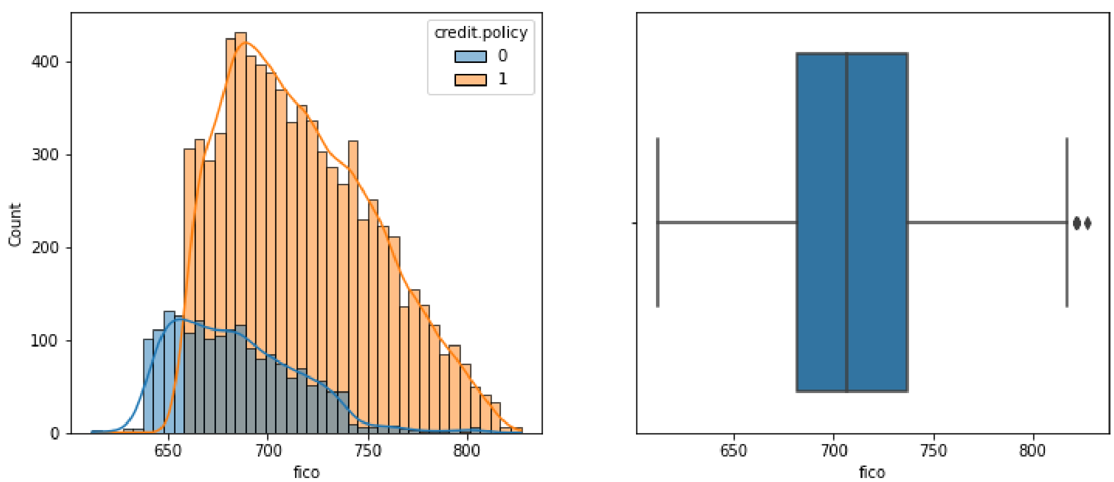

```
hist_box_plot('log.annual.inc')
```



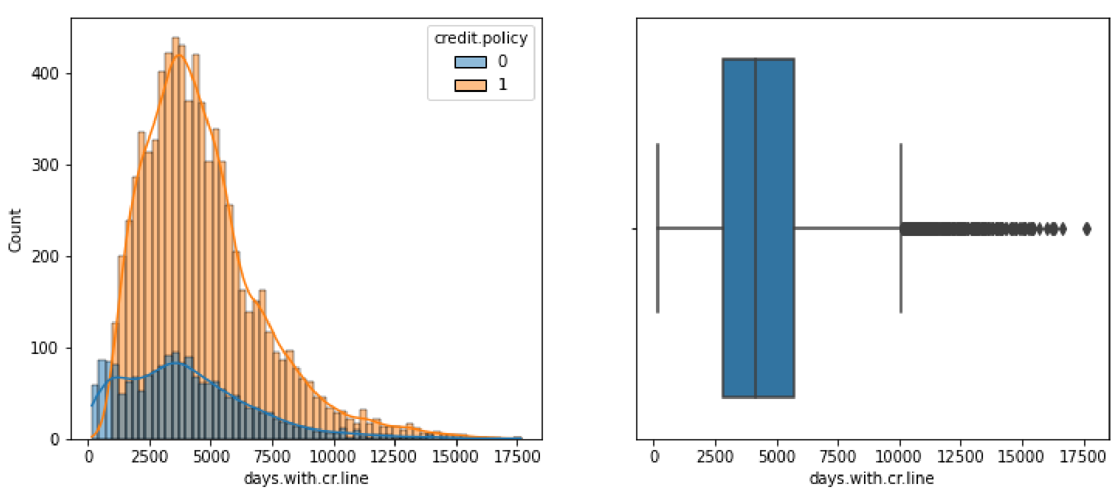

```
hist_box_plot('dti')
```



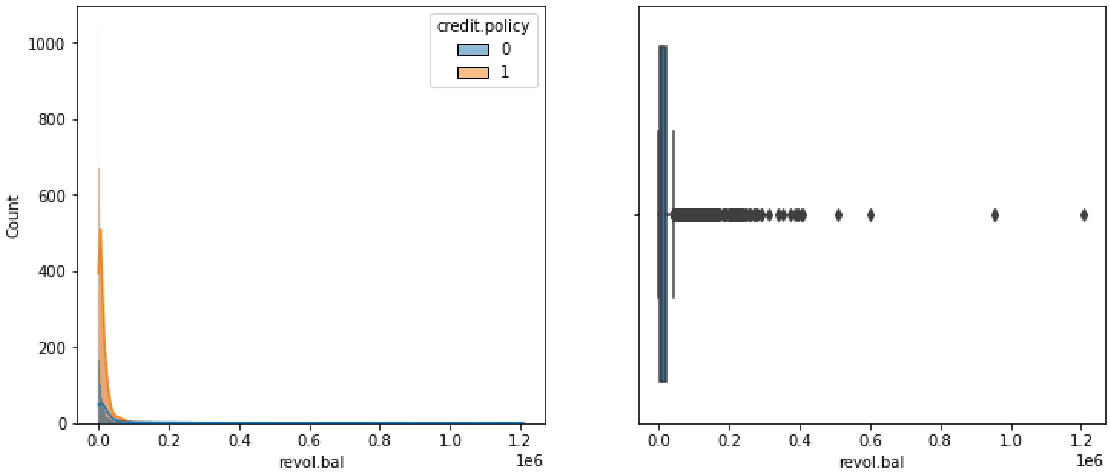

```
hist_box_plot('fico')
```



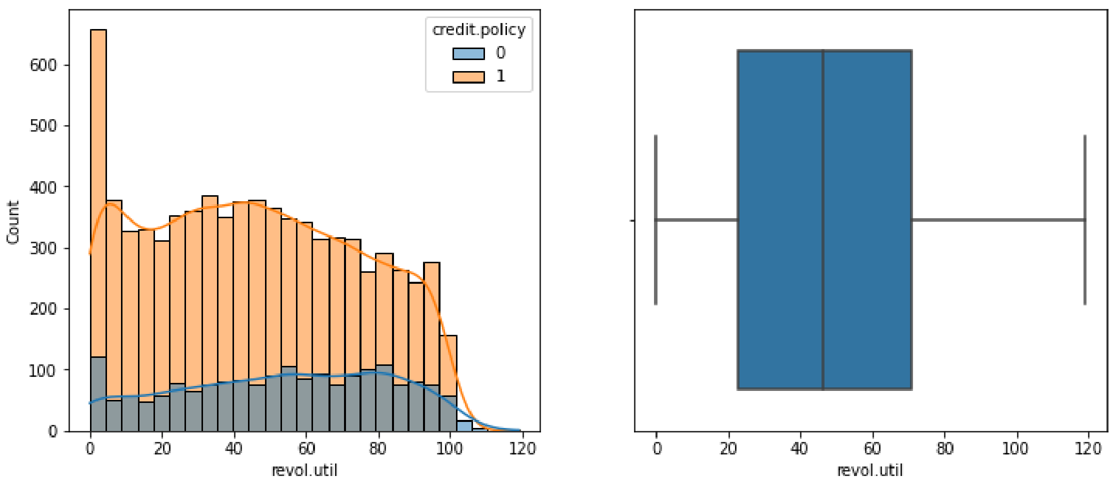

```
hist_box_plot('days.with.cr.line')
```




```
hist_box_plot('revol.bal')
```




```
hist_box_plot('revol.util')
```



We are getting sensible distribution plots for the numeric values. Also for customer meeting credit criteria, all the numeric column values are high.

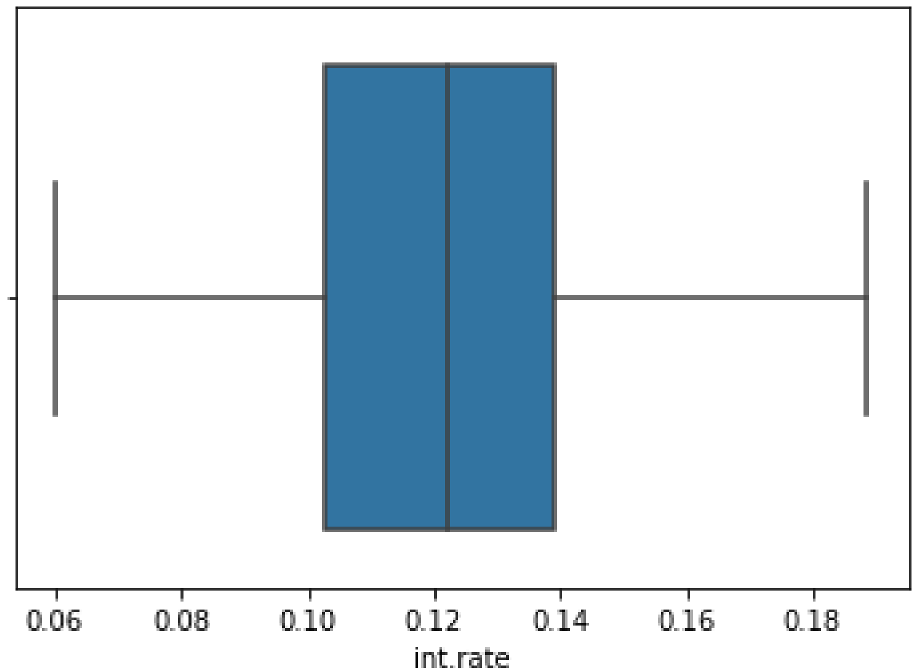
We can remove the outlier by considering minimum data loss (max 5% data loss).

```
loan_df[loan_df['int.rate'] < 0.19].shape[0]/ loan_df.shape[0] * 100
```

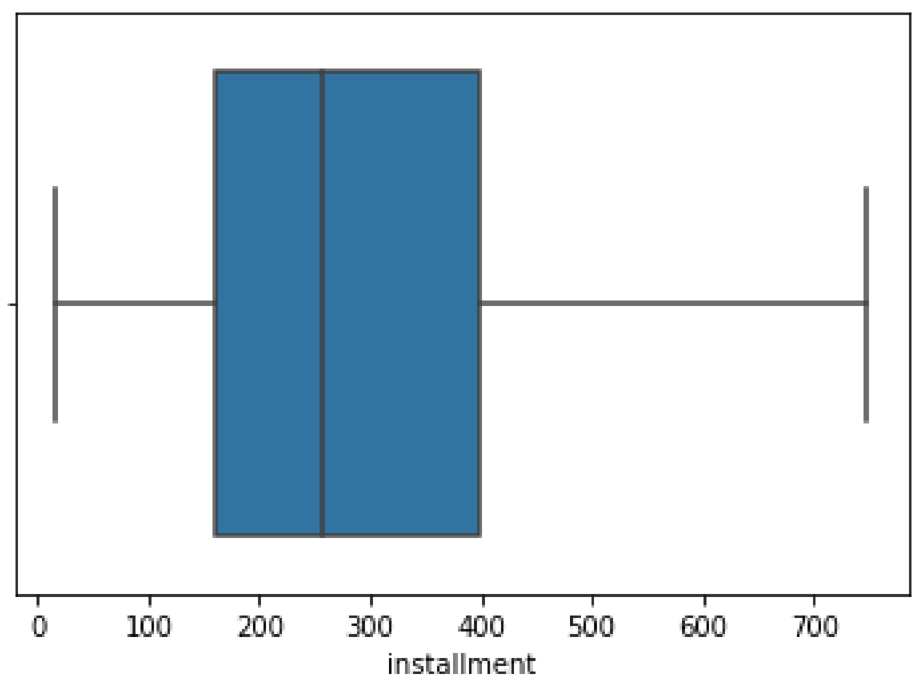
```
99.01858425558572
```

```
filter_loan_df = loan_df[loan_df['int.rate'] < 0.19]
```

```
box_plot(filter_loan_df, 'int.rate')
```



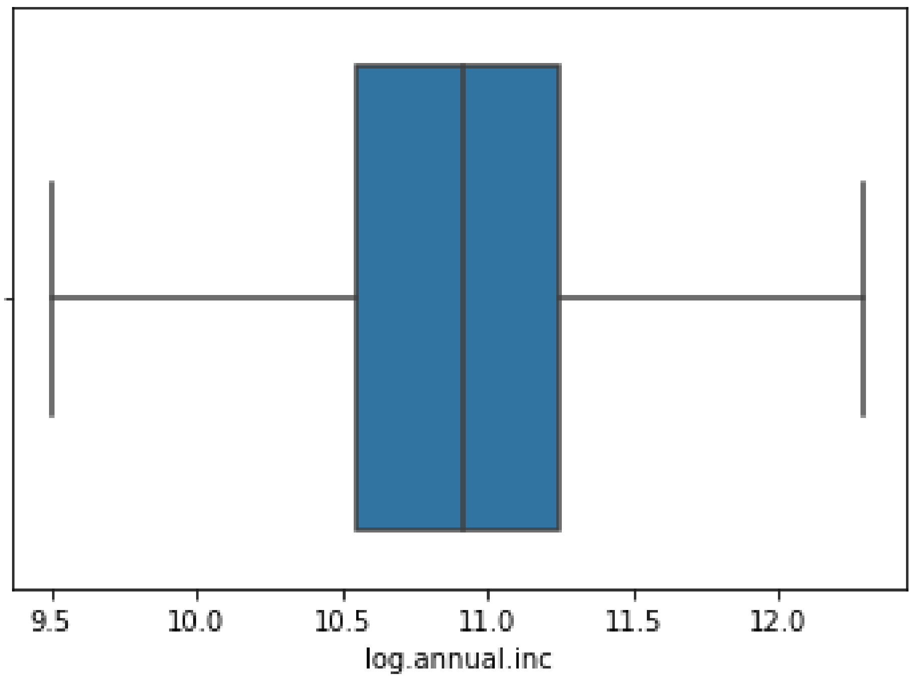

```
loan_df = filter_loan_df

loan_df[loan_df['installment'] < 750].shape[0]/ loan_df.shape[0] * 100

95.08646140868832

filter_loan_df = loan_df[loan_df['installment'] < 750]

box_plot(filter_loan_df, 'installment')
```



```
loan_df = filter_loan_df

loan_df[(loan_df['log.annual.inc'] > 9.5) & (loan_df['log.annual.inc']
< 12.3)].shape[0]/ loan_df.shape[0] * 100
```

```
97.26103348857839
```

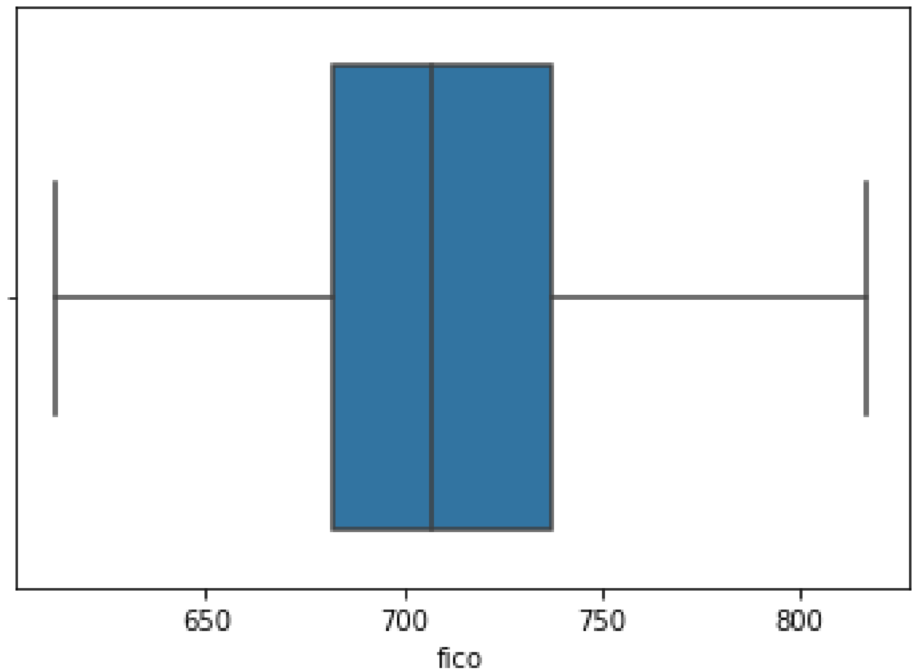
```
filter_loan_df = loan_df[(loan_df['log.annual.inc'] > 9.5) &
(loan_df['log.annual.inc'] < 12.3)]

box_plot(filter_loan_df, 'log.annual.inc')
```




```
loan_df = filter_loan_df

loan_df[loan_df['fico'] < 820].shape[0]/ loan_df.shape[0] * 100
```

```
99.94299395735948
```

```
filter_loan_df = loan_df[loan_df['fico'] < 820]

box_plot(filter_loan_df, 'fico')
```



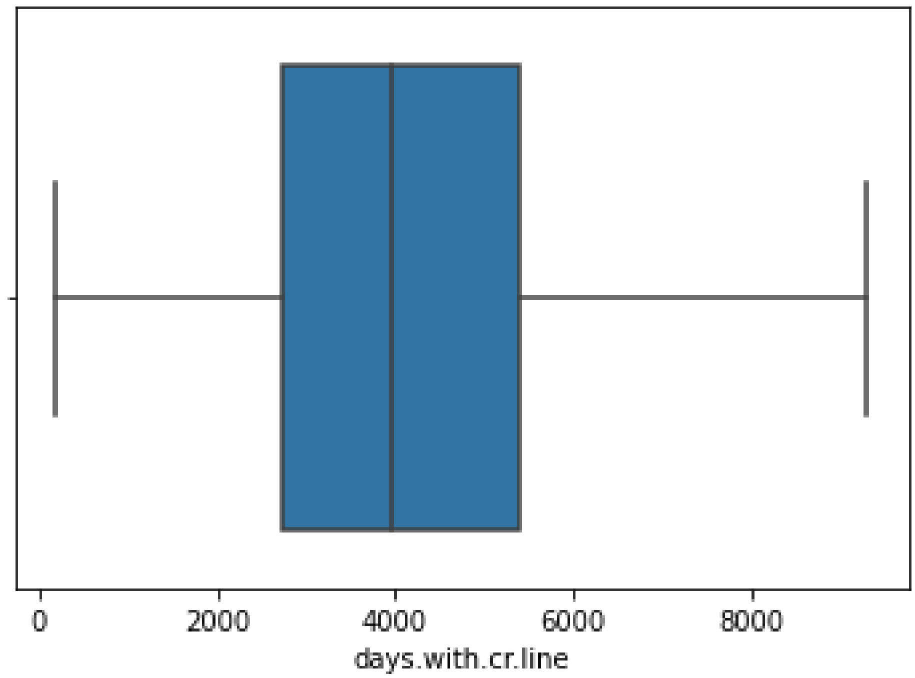

```
loan_df = filter_loan_df
```

```
loan_df[loan_df['days.with.cr.line'] < 9300].shape[0]/
loan_df.shape[0] * 100
```

```
95.25439196897102
```

```
filter_loan_df = loan_df[loan_df['days.with.cr.line'] < 9300]
```

```
box_plot(filter_loan_df, 'days.with.cr.line')
```




```
loan_df = filter_loan_df
```

```
loan_df[loan_df['revol.bal'] < 0.05].shape[0]/ loan_df.shape[0] * 100
```

```
3.1137724550898205
```

We cant remove the outlier here, number of outliers are so high.

Now lets check the shape.

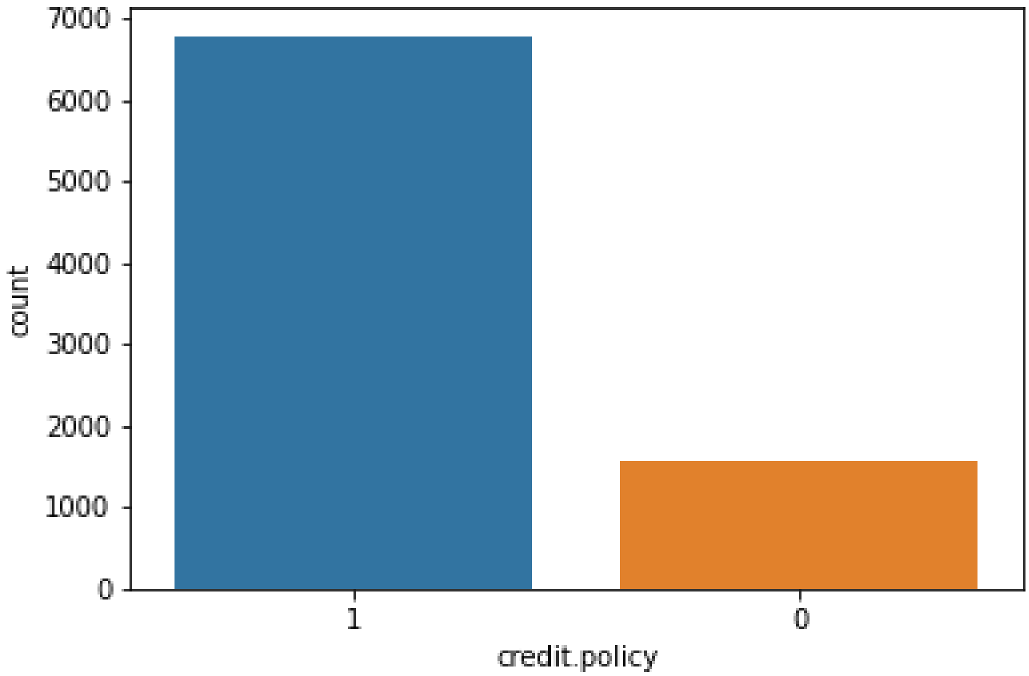
```
loan_df.shape
```

```
(8350, 14)
```

EDA on categorical data & numeric with limited number of values

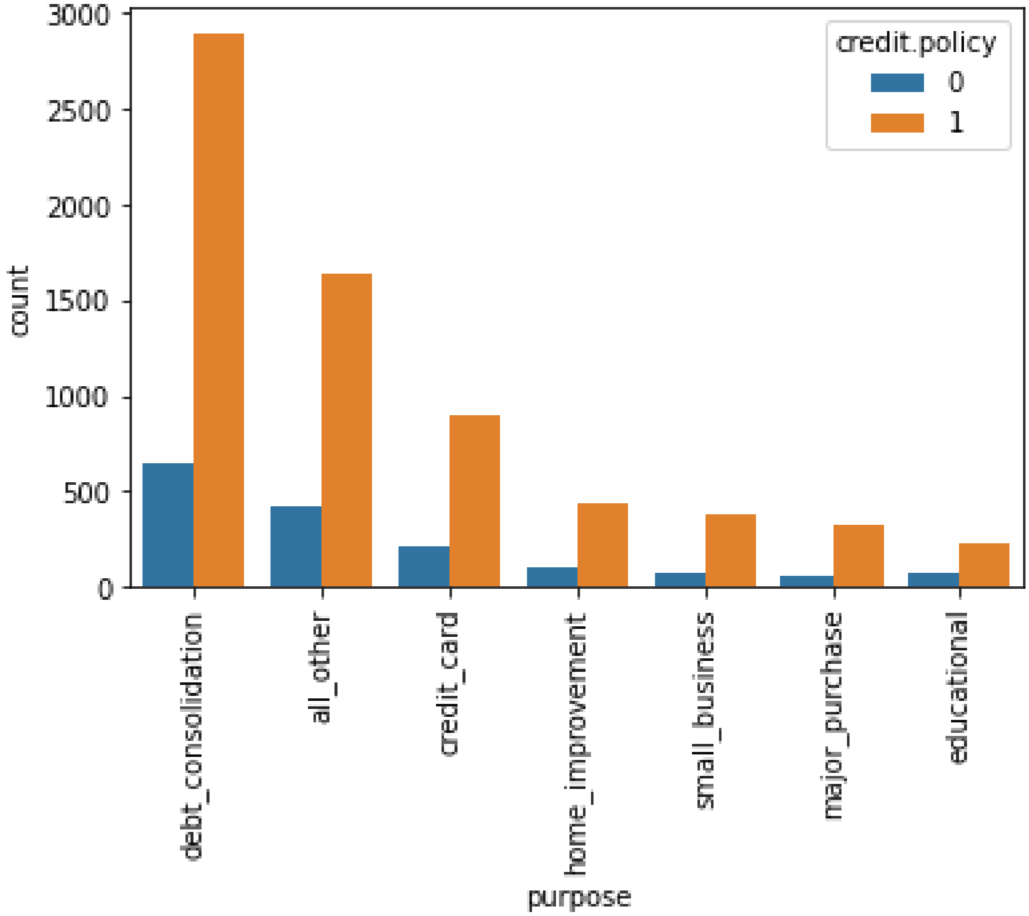
```
def count_plot(col, hue_val= None, rotate= False):
    sns.countplot(data= loan_df,
                  x= col,
                  hue= hue_val,
                  order = loan_df[col].value_counts().index)
    if rotate:
        plt.xticks(rotation=90)
```

```
count_plot('credit.policy')
```



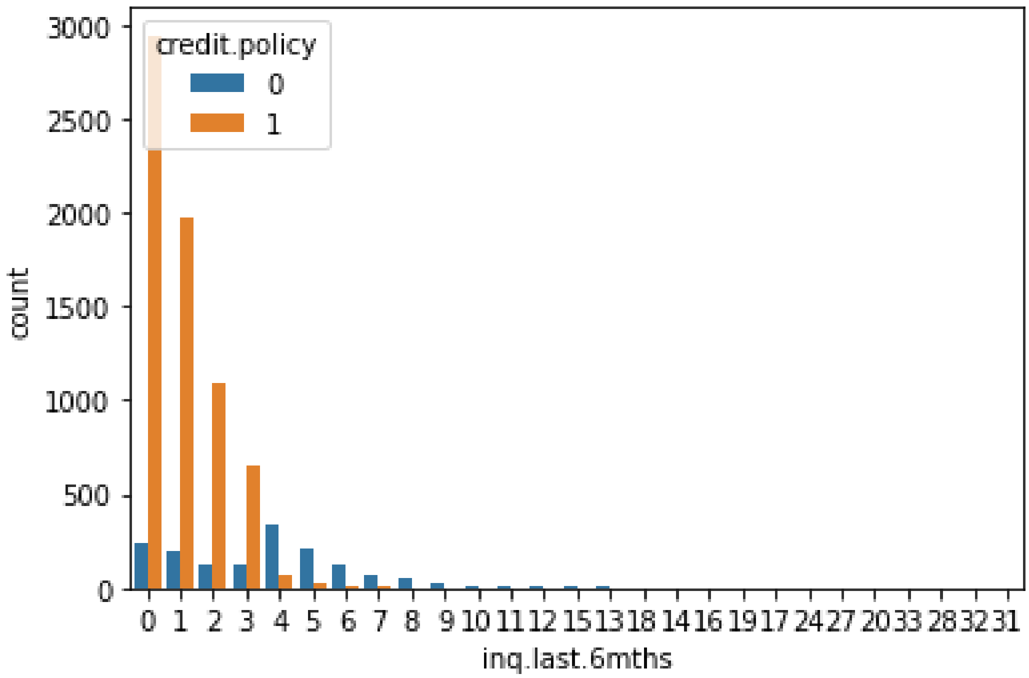
Its a imbalanced data.

```
count_plot('purpose', hue_val='credit.policy', rotate= True)
```



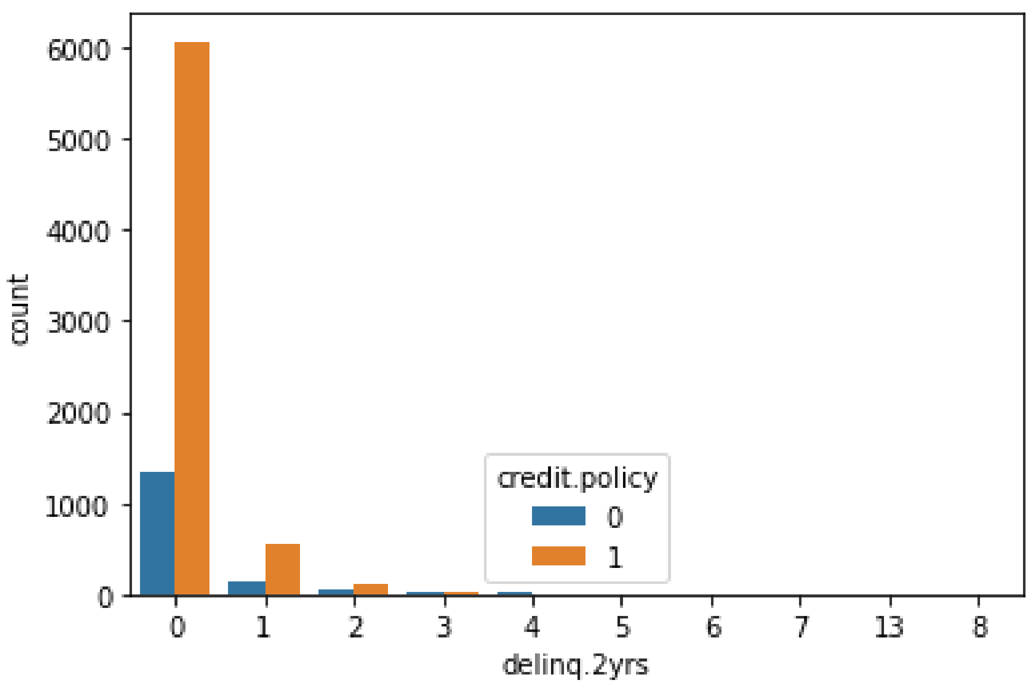
Most of the loans are applied for debt_consolidation where as educational loan count is minimum.

```
count_plot('inq.last.6mths', hue_val='credit.policy')
```



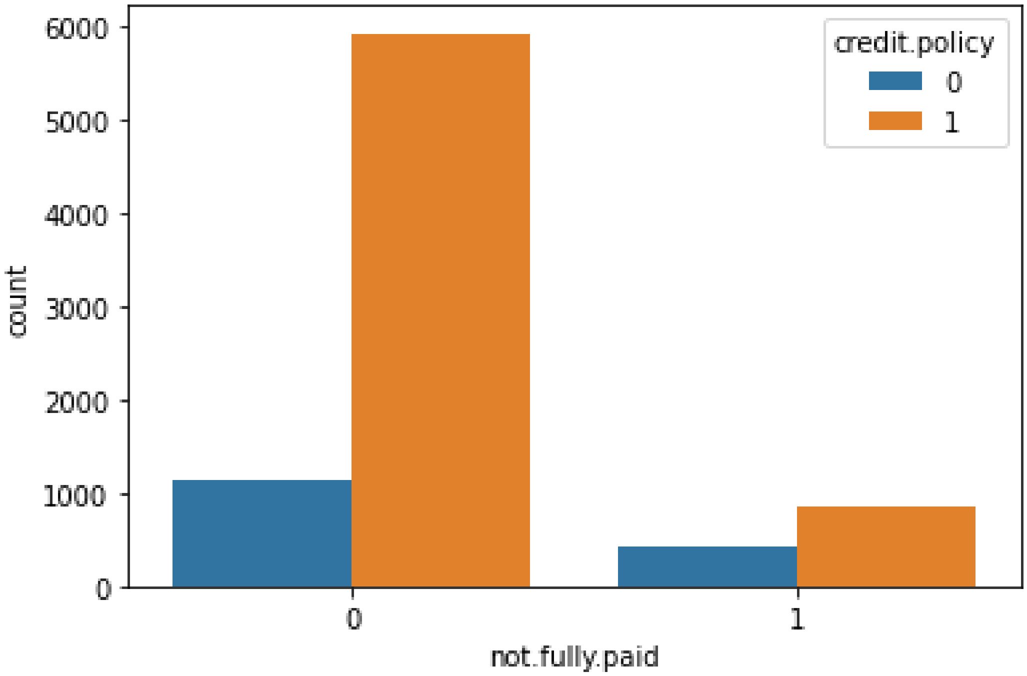
Most of the customers have 0-3 number of queries in last 6 months.

```
count_plot('delinq.2yrs', hue_val='credit.policy')
```



There are very few people with higher number of past dues.

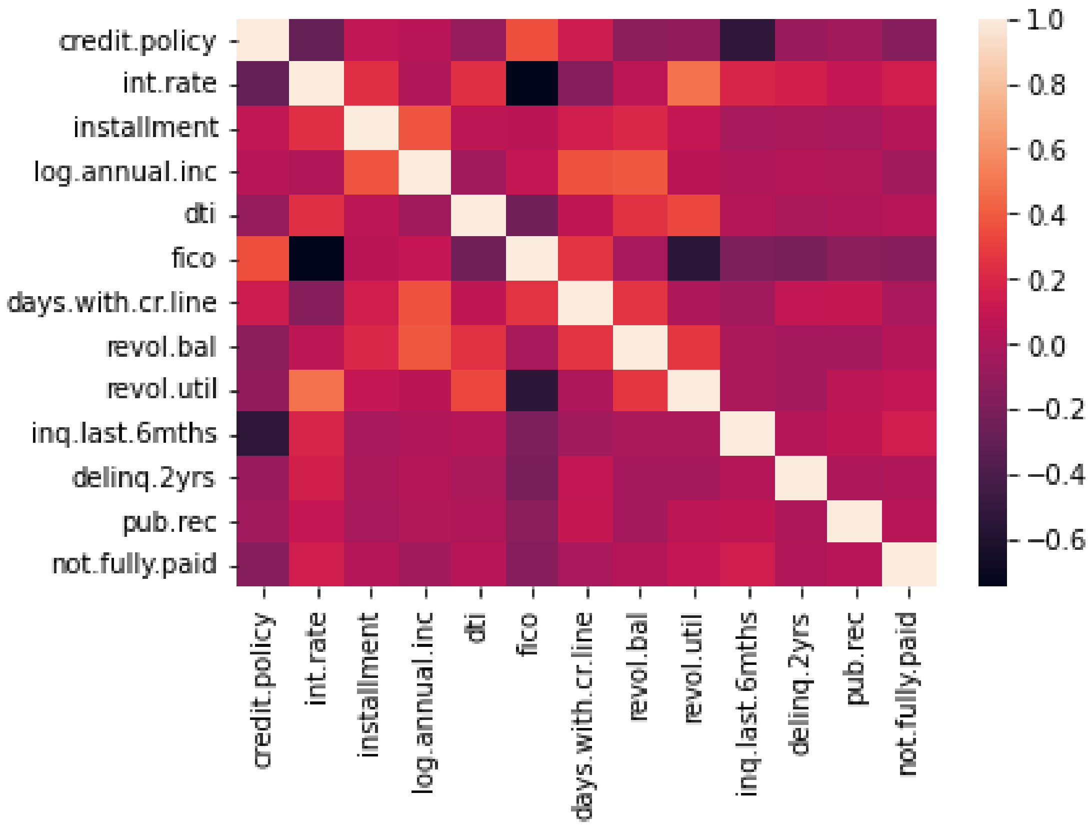
```
count_plot('not.fully.paid', hue_val='credit.policy')
```



There are many customers who have fully paid and are eligible for credit.

Additional Feature Engineering (Remove columns with high correlation if any with other feature columns)

```
loan_corr = loan_df.corr()

sns.heatmap(loan_corr)
plt.show()
```



There are many columns which are correlated with each other. As we have 13 feature columns and by looking at the column names, most of them are important features and impact the policy credit.

But we can filter out the columns with correlation among each other.

```
target_corr_cols =
loan_corr['credit.policy'].sort_values(ascending=False)
[1:].index.tolist()
target_corr_cols
```

```
['fico',
 'days.with.cr.line',
 'installment',
 'log.annual.inc',
 'pub.rec',
 'delinq.2yrs',
 'dti',
 'revol.util',
 'revol.bal',
 'not.fully.paid',
 'int.rate',
 'inq.last.6mths']
```

```
for col in target_corr_cols:
    corr_vals = loan_corr[col]
    corr_cols = corr_vals[corr_vals >= 0.6].index.tolist()
    print(col, corr_cols)
```

```
fico ['fico']
days.with.cr.line ['days.with.cr.line']
installment ['installment']
log.annual.inc ['log.annual.inc']
pub.rec ['pub.rec']
delinq.2yrs ['delinq.2yrs']
dti ['dti']
revol.util ['revol.util']
revol.bal ['revol.bal']
not.fully.paid ['not.fully.paid']
int.rate ['int.rate']
inq.last.6mths ['inq.last.6mths']
```

As we can see, we have set the high correlation lower limit as 0.6 and no columns are correlated with each other.

So we can use all the columns for modelling.

Now lets encode the purose column and get train and test dataset out of the loan_df.

Feature Transformation (Convert categorical values to numeric vectors)

```
loan_df_en = pd.get_dummies(data= loan_df, columns=['purpose'],
drop_first=True, dtype= 'int64')
```

```
loan_df_en.shape
```

```
(8350, 19)
```

```
loan_df_en.head()
```

```
   credit.policy  int.rate  installment  log.annual.inc    dti  
fico  \
1              1    0.1071       228.22       11.082143  14.29   707

2              1    0.1357       366.86       10.373491  11.63   682

3              1    0.1008       162.34       11.350407   8.10   712

4              1    0.1426       102.92       11.299732  14.97   667

5              1    0.0788       125.13       11.904968  16.98   727


   days.with.cr.line  revol.bal  revol.util  inq.last.6mths  
delinq.2yrs  \
1        2760.000000      33623        76.7               0
```

```
0
2        4710.000000       3511        25.6                1
0
3        2699.958333      33667        73.2                1
0
4        4066.000000       4740        39.5                0
1
5        6120.041667      50807        51.0                0
0

   pub.rec  not.fully.paid  purpose_credit_card
purpose_debt_consolidation  \
1        0               0                    1
0
2        0               0                    0
1
3        0               0                    0
1
4        0               0                    1
0
5        0               0                    1
0

   purpose_educational  purpose_home_improvement
purpose_major_purchase  \
1                    0                         0
0
2                    0                         0
0
3                    0                         0
0
4                    0                         0
0
5                    0                         0
0

   purpose_small_business
1                       0
2                       0
3                       0
4                       0
5                       0
```

```
loan_df_en.columns
```

```
Index(['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_credit_card', 'purpose_debt_consolidation',
```

```
        'purpose_educational', 'purpose_home_improvement',
        'purpose_major_purchase', 'purpose_small_business'],
      dtype='object')
```

Preprocessing steps for modelling

```
x = loan_df_en.drop(['credit.policy'], axis=1)
y = loan_df_en['credit.policy']

print(x.shape)
print(y.shape)
```

```
(8350, 18)
(8350,)
```

```
# train test split

x_train, x_test, y_train, y_test = train_test_split(x, y)

print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(6262, 18)
(2088, 18)
(6262,)
(2088,)
```

```
# Standardize the values

ss = StandardScaler()

x_train = ss.fit_transform(x_train)
x_test = ss.transform(x_test)
```

Deep Learning Model

```
model = Sequential()
model.add(Dense(128, activation= 'relu', input_shape=(18,),
                kernel_initializer='he_normal',
                kernel_regularizer='L2'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(64, activation= 'relu',
                kernel_initializer='he_normal',
                kernel_regularizer='L2'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(Dense(32, activation= 'relu',
                kernel_initializer='he_normal',
                kernel_regularizer='L2'))
model.add(BatchNormalization())
```

```
model.add(Dense(10, activation= 'relu',
                kernel_initializer='he_normal',
                kernel_regularizer='L2'))
model.add(Dense(1, activation= 'sigmoid',
               kernel_initializer='glorot_normal',
               kernel_regularizer='L2'))

model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               2432

 dropout (Dropout)           (None, 128)               0

 batch_normalization (BatchN  (None, 128)              512
 ormalization)

 dense_1 (Dense)             (None, 64)                8256

 dropout_1 (Dropout)         (None, 64)                0

 batch_normalization_1 (Batc  (None, 64)               256
 hNormalization)

 dense_2 (Dense)             (None, 32)                2080

 batch_normalization_2 (Batc  (None, 32)               128
 hNormalization)

 dense_3 (Dense)             (None, 10)                330

 dense_4 (Dense)             (None, 1)                 11

=================================================================
Total params: 14,005
Trainable params: 13,557
Non-trainable params: 448
_________________________________________________________________

model.compile(optimizer='adam',
                loss=tf.keras.losses.binary_crossentropy,
                metrics=[tf.keras.metrics.AUC()])

callback = EarlyStopping(monitor='val_loss', patience=5)

history = model.fit(
x_train, y_train,
validation_data=(x_test, y_test),
```

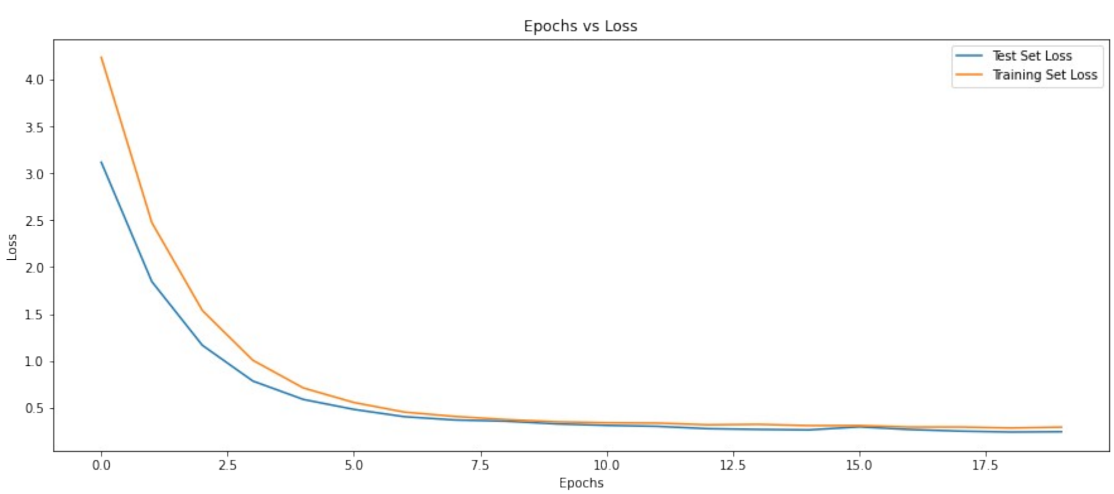
```
batch_size= 30,
epochs= 20,
verbose=1,
callbacks=[callback]
)

Epoch 1/20
209/209 [==============================] - 3s 5ms/step - loss: 4.2353
- auc: 0.6486 - val_loss: 3.1175 - val_auc: 0.8656
Epoch 2/20
209/209 [==============================] - 1s 4ms/step - loss: 2.4746
- auc: 0.8194 - val_loss: 1.8458 - val_auc: 0.9184
Epoch 3/20
209/209 [==============================] - 1s 5ms/step - loss: 1.5379
- auc: 0.8478 - val_loss: 1.1667 - val_auc: 0.9327
Epoch 4/20
209/209 [==============================] - 1s 5ms/step - loss: 1.0066
- auc: 0.8807 - val_loss: 0.7855 - val_auc: 0.9406
Epoch 5/20
209/209 [==============================] - 1s 5ms/step - loss: 0.7113
- auc: 0.8983 - val_loss: 0.5892 - val_auc: 0.9428
Epoch 6/20
209/209 [==============================] - 1s 4ms/step - loss: 0.5565
- auc: 0.9007 - val_loss: 0.4831 - val_auc: 0.9459
Epoch 7/20
209/209 [==============================] - 1s 4ms/step - loss: 0.4541
- auc: 0.9160 - val_loss: 0.4052 - val_auc: 0.9462
Epoch 8/20
209/209 [==============================] - 1s 5ms/step - loss: 0.4077
- auc: 0.9166 - val_loss: 0.3703 - val_auc: 0.9543
Epoch 9/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3748
- auc: 0.9210 - val_loss: 0.3576 - val_auc: 0.9552
Epoch 10/20
209/209 [==============================] - 1s 5ms/step - loss: 0.3508
- auc: 0.9292 - val_loss: 0.3290 - val_auc: 0.9511
Epoch 11/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3407
- auc: 0.9311 - val_loss: 0.3127 - val_auc: 0.9508
Epoch 12/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3374
- auc: 0.9289 - val_loss: 0.3027 - val_auc: 0.9581
Epoch 13/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3189
- auc: 0.9384 - val_loss: 0.2777 - val_auc: 0.9645
Epoch 14/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3238
- auc: 0.9337 - val_loss: 0.2697 - val_auc: 0.9662
Epoch 15/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3104
```

```
- auc: 0.9414 - val_loss: 0.2646 - val_auc: 0.9644
Epoch 16/20
209/209 [==============================] - 1s 4ms/step - loss: 0.3109
- auc: 0.9375 - val_loss: 0.2971 - val_auc: 0.9725
Epoch 17/20
209/209 [==============================] - 1s 3ms/step - loss: 0.2951
- auc: 0.9470 - val_loss: 0.2688 - val_auc: 0.9708
Epoch 18/20
209/209 [==============================] - 1s 3ms/step - loss: 0.2952
- auc: 0.9449 - val_loss: 0.2514 - val_auc: 0.9747
Epoch 19/20
209/209 [==============================] - 1s 3ms/step - loss: 0.2851
- auc: 0.9504 - val_loss: 0.2423 - val_auc: 0.9715
Epoch 20/20
209/209 [==============================] - 1s 3ms/step - loss: 0.2942
- auc: 0.9459 - val_loss: 0.2454 - val_auc: 0.9756
```

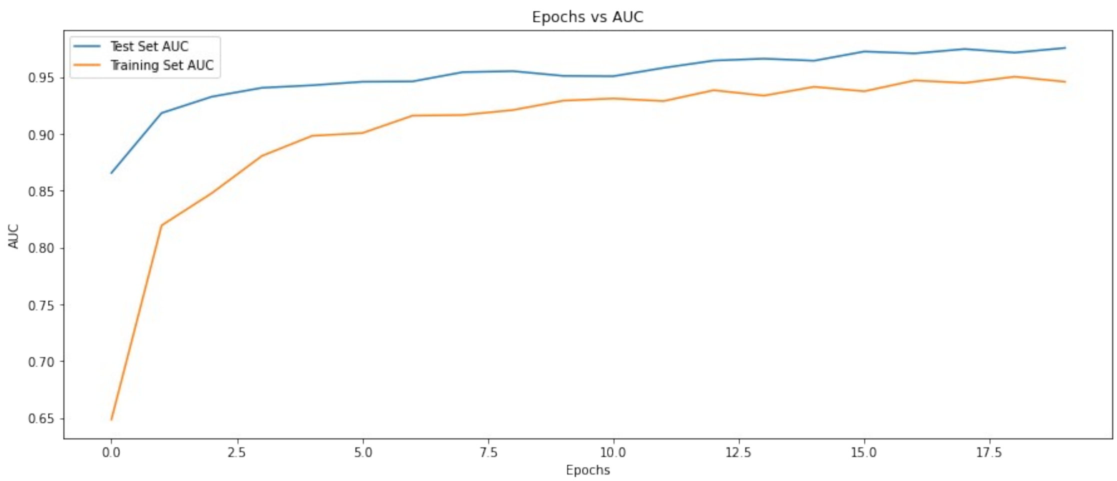
```
history = pd.DataFrame(history.history)
history.head()
```

	loss	auc	val_loss	val_auc
0	4.235277	0.648598	3.117543	0.865618
1	2.474607	0.819444	1.845755	0.918365
2	1.537950	0.847843	1.166706	0.932721
3	1.006636	0.880666	0.785537	0.940568
4	0.711283	0.898319	0.589222	0.942774

```
plt.figure(figsize = (15,6))
plt.plot(history.val_loss, label='Test Set Loss')
plt.plot(history.loss, label='Training Set Loss')
plt.title('Epochs vs Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



```
plt.figure(figsize = (15,6))
plt.plot(history.val_auc, label='Test Set AUC')
plt.plot(history.auc, label='Training Set AUC')
plt.title('Epochs vs AUC')
plt.xlabel('Epochs')
plt.ylabel('AUC')
plt.legend()
plt.show()
```




```
y_train_pred = model.predict(x_train)
cm1 = confusion_matrix(y_train, y_train_pred>0.5)
cm1
```

```
array([[ 847,  343],
       [  59, 5013]])
```

```
y_test_pred = model.predict(x_test)
cm2 = confusion_matrix(y_test, y_test_pred>0.5)
cm2
```

```
array([[ 256,  124],
       [  20, 1688]])
```

```
fpr_train, tpr_train, thresholds_train = roc_curve(y_train,
y_train_pred)
auc_score_train = auc(fpr_train, tpr_train)
print(auc_score_train)
```

```
0.9805026111390929
```

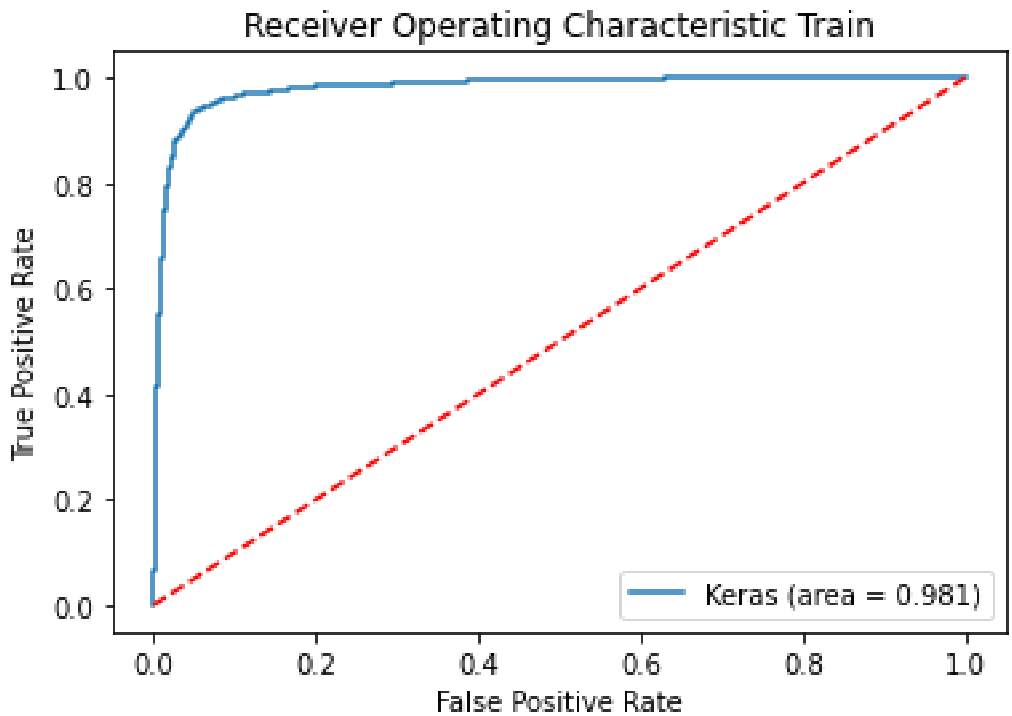
```
fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_test_pred)
auc_score_test = auc(fpr_test, tpr_test)
print(auc_score_test)
```

```
0.9757780722297548
```

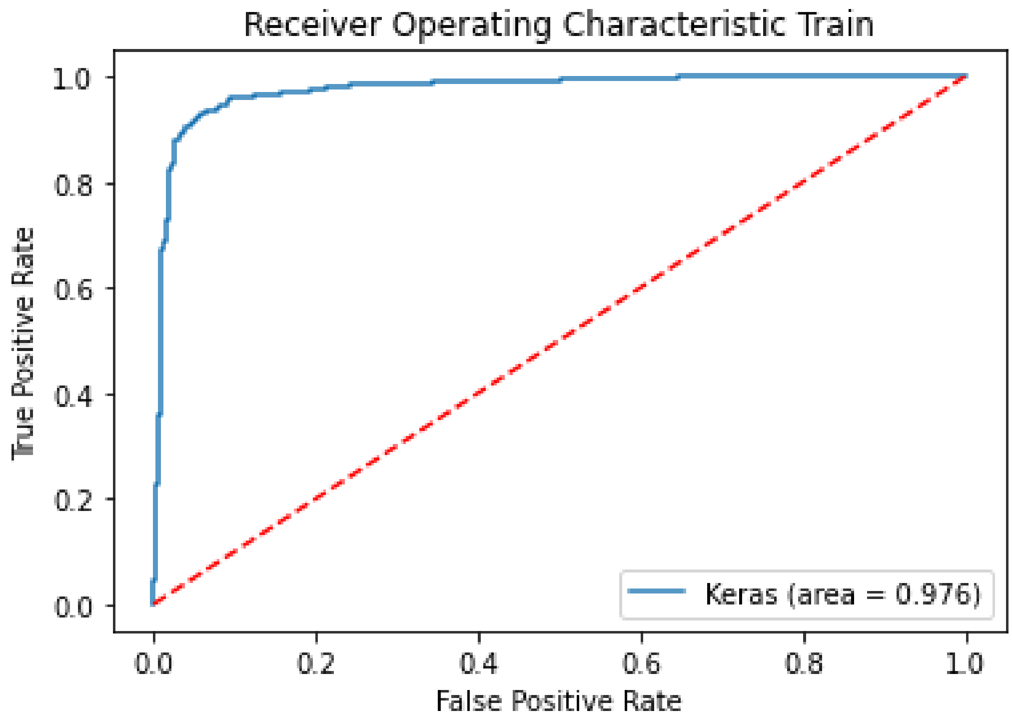
```
_, train_acc = model.evaluate(x_train, y_train, verbose=0)
_, test_acc = model.evaluate(x_test, y_test, verbose=0)
print('Train:{}%, Test: {} %'.format((train_acc*100), (test_acc*100)))
```

```
Train:98.04953336715698%, Test: 97.56362438201904 %
```

```
# Plot TPR FPR train
plt.title('Receiver Operating Characteristic Train')
plt.plot(fpr_train, tpr_train, label='Keras (area =
{:.3f})'.format(auc_score_train))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




```
# Plot TPR FPR test
plt.title('Receiver Operating Characteristic Train')
plt.plot(fpr_test, tpr_test, label='Keras (area =
{:.3f})'.format(auc_score_test))
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



We received good scores with this model and given data.