Scaler_Project8_LoanTap

September 11, 2022

[1092]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
import warnings
warnings.filterwarnings('ignore')
```

[1093]:
```
df = pd.read_csv('logistic_regression.txt')
```

Data dictionary:

loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

term : The number of payments on the loan. Values are in months and can be either 36 or 60.

int_rate : Interest Rate on the loan

installment : The monthly payment owed by the borrower if the loan originates.

grade : LoanTap assigned loan grade

sub_grade : LoanTap assigned loan subgrade

emp_title :The job title supplied by the Borrower when applying for the loan.

emp_length : Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.

home_ownership : The home ownership status provided by the borrower during registration or obtained from the credit report.

annual_inc : The self-reported annual income provided by the borrower during registration.

verification_status : Indicates if income was verified by LoanTap, not verified, or if the income source was verified

issue_d : The month which the loan was funded

loan_status : Current status of the loan - Target Variable

purpose : A category provided by the borrower for the loan request.

title : The loan title provided by the borrower dti : A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower's self-reported monthly income.

earliest_cr_line :The month the borrower's earliest reported credit line was opened

open_acc : The number of open credit lines in the borrower's credit file.

pub_rec : Number of derogatory public records

revol_bal : Total credit revolving balance

revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

total_acc : The total number of credit lines currently in the borrower's credit file

initial_list_status : The initial listing status of the loan. Possible values are – W, F

application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers

mort_acc : Number of mortgage accounts.

pub_rec_bankruptcies : Number of public record bankruptcies

Address: Address of the individual

[1094]:
```
df.head()
```

[1094]:
```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5

                 emp_title emp_length home_ownership  annual_inc  …  \
0                Marketing  10+ years           RENT    117000.0  …
1          Credit analyst     4 years       MORTGAGE     65000.0  …
2             Statistician   < 1 year           RENT     43057.0  …
3          Client Advocate    6 years           RENT     54000.0  …
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0  …

  open_acc pub_rec revol_bal revol_util total_acc  initial_list_status  \
0     16.0     0.0   36369.0       41.8      25.0                    w
1     17.0     0.0   20131.0       53.3      27.0                    f
2     13.0     0.0   11987.0       92.2      26.0                    f
3      6.0     0.0    5472.0       21.5      13.0                    f
4     13.0     0.0   24584.0       69.8      43.0                    f

  application_type  mort_acc  pub_rec_bankruptcies  \
0       INDIVIDUAL       0.0                   0.0
```

```
1       INDIVIDUAL       3.0                    0.0
2       INDIVIDUAL       0.0                    0.0
3       INDIVIDUAL       0.0                    0.0
4       INDIVIDUAL       1.0                    0.0

                                              address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650

[5 rows x 27 columns]
```

[1095]:
```
df.shape
```

[1095]:
```
(396030, 27)
```

[1096]:
```
df.columns
```

[1096]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'loan_status', 'purpose', 'title',
       'dti', 'earliest_cr_line', 'open_acc', 'pub_rec', 'revol_bal',
       'revol_util', 'total_acc', 'initial_list_status', 'application_type',
       'mort_acc', 'pub_rec_bankruptcies', 'address'],
      dtype='object')
```

[1097]:
```
df.describe().T
```

[1097]:
```
                         count          mean           std     min       25%  \
loan_amnt             396030.0  14113.888089   8357.441341  500.00   8000.00
int_rate              396030.0     13.639400      4.472157    5.32     10.49
installment           396030.0    431.849698    250.727790   16.08    250.33
annual_inc            396030.0  74203.175798  61637.621158    0.00  45000.00
dti                   396030.0     17.379514     18.019092    0.00     11.28
open_acc              396030.0     11.311153      5.137649    0.00      8.00
pub_rec               396030.0      0.178191      0.530671    0.00      0.00
revol_bal             396030.0  15844.539853  20591.836109    0.00   6025.00
revol_util            395754.0     53.791749     24.452193    0.00     35.80
total_acc             396030.0     25.414744     11.886991    2.00     17.00
mort_acc              358235.0      1.813991      2.147930    0.00      0.00
pub_rec_bankruptcies  395495.0      0.121648      0.356174    0.00      0.00

                           50%       75%       max
loan_amnt             12000.00  20000.00  40000.00
int_rate                 13.33     16.49     30.99
```

```
installment             375.43    567.30     1533.81
annual_inc            64000.00  90000.00  8706582.00
dti                      16.91     22.98     9999.00
open_acc                 10.00     14.00       90.00
pub_rec                   0.00      0.00       86.00
revol_bal             11181.00  19620.00  1743266.00
revol_util               54.80     72.90      892.30
total_acc                24.00     32.00      151.00
mort_acc                  1.00      3.00       34.00
pub_rec_bankruptcies      0.00      0.00        8.00
```

[1098]:

```python
df.describe(exclude=np.number).T
```

[1098]:

	count	unique	top	freq
term	396030	2	36 months	302005
grade	396030	7	B	116018
sub_grade	396030	35	B3	26655
emp_title	373103	173105	Teacher	4389
emp_length	377729	11	10+ years	126041
home_ownership	396030	6	MORTGAGE	198348
verification_status	396030	3	Verified	139563
issue_d	396030	115	Oct-2014	14846
loan_status	396030	2	Fully Paid	318357
purpose	396030	14	debt_consolidation	234507
title	394275	48817	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
initial_list_status	396030	2	f	238066
application_type	396030	3	INDIVIDUAL	395319
address	396030	393700	USCGC Smith\r\nFPO AE 70466	8

[1099]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object
 5   sub_grade             396030 non-null  object
 6   emp_title             373103 non-null  object
 7   emp_length            377729 non-null  object
 8   home_ownership        396030 non-null  object
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object
```

```
 11  issue_d               396030 non-null  object
 12  loan_status           396030 non-null  object
 13  purpose               396030 non-null  object
 14  title                 394275 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object
 23  application_type      396030 non-null  object
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

Train-validation-test split to avoid data leakage

[1100]:
```
from sklearn.model_selection import train_test_split
```

[1101]:
```
# Defining x and y variables
x = df.drop('loan_status', axis = 1)
y = df['loan_status']
```

[1102]:
```
# Splitting test data from original data set
x_traincv, x_test, y_traincv, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=42)
# Splitting validation data from train data set
x_train, x_val, y_train, y_val = train_test_split(x_traincv, y_traincv,␣
 ↪test_size=0.25, random_state=42)
```

[1103]:
```
#Lets combine x and y for now to do EDA
x_train['loan_status'] = y_train.values
x_test['loan_status'] = y_test.values
x_val['loan_status'] = y_val.values
```

0.0.1 EDA and Feature engineering

[1104]:
```
#Lets combine x_train and y_train for now to do EDA
x_train['loan_status'] = y_train.values
```

[1105]:
```
x_train.head(3)
```

[1105]:
```
        loan_amnt        term  int_rate  installment grade sub_grade  \
249928     7200.0   36 months     17.57       258.75     D        D4
```

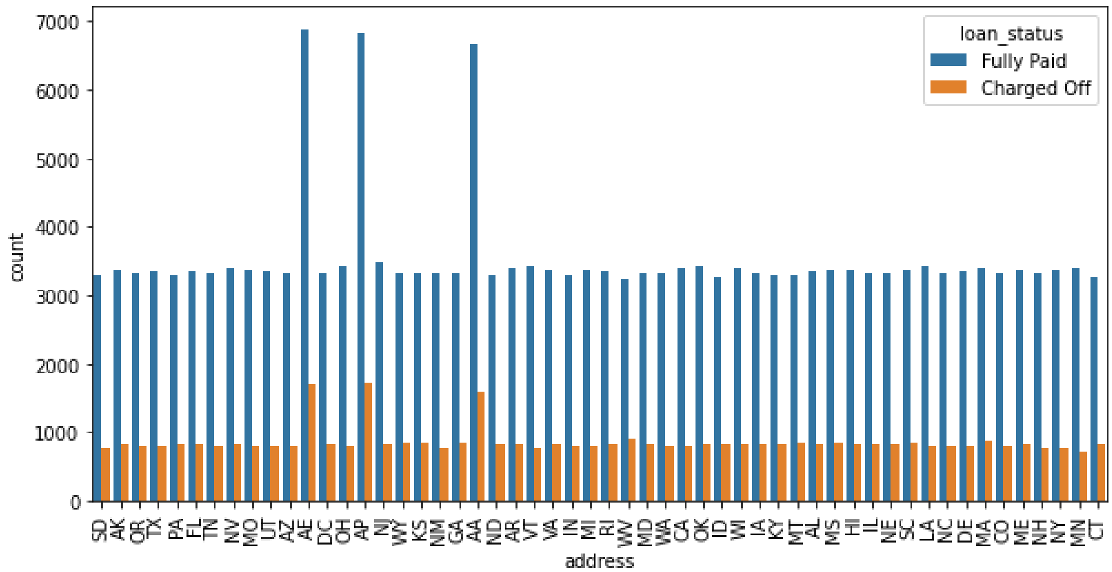
```
279578    10000.0   36 months     11.99       332.10     B         B5
163928    14000.0   36 months      6.62       429.86     A         A2

                          emp_title emp_length home_ownership  annual_inc  \
249928  Accounts Payable Specialist   < 1 year       MORTGAGE     28800.0
279578                      Teacher  10+ years       MORTGAGE     56000.0
163928                 McKinney ISD  10+ years       MORTGAGE     50000.0

        … pub_rec revol_bal revol_util total_acc  initial_list_status  \
249928  …     1.0    2759.0       35.8      16.0                    w
279578  …     0.0   13838.0       76.0      31.0                    f
163928  …     0.0    6474.0        8.5      40.0                    f

       application_type  mort_acc  pub_rec_bankruptcies  \
249928       INDIVIDUAL       2.0                   1.0
279578       INDIVIDUAL       0.0                   0.0
163928       INDIVIDUAL       3.0                   0.0

                                                  address  loan_status
249928       1349 Parker Street\r\nRandolphside, SD 29597   Fully Paid
279578  22542 Micheal Island Suite 019\r\nTuckermouth,…  Charged Off
163928        957 Angela Squares\r\nStevenmouth, OR 30723   Fully Paid

[3 rows x 27 columns]
```

[1106]:

```
x_train['address'] = x_train['address'].apply(lambda x : x[-8:-6])
```

[1107]:

```
plt.figure(figsize=(10,5))
sns.countplot(x_train['address'], hue = x_train['loan_status'])
plt.xticks(rotation = '90')
plt.show()
```



[1108]:
```
#dropping address column as it has almost no effect with the target variable.
x_train.drop('address', axis = 1,inplace=True)
x_val.drop('address', axis = 1,inplace=True)
x_test.drop('address', axis = 1,inplace=True)
```

Univariate analyis

[1109]:
```
cont_features = x_train.describe().columns
cont_features
```

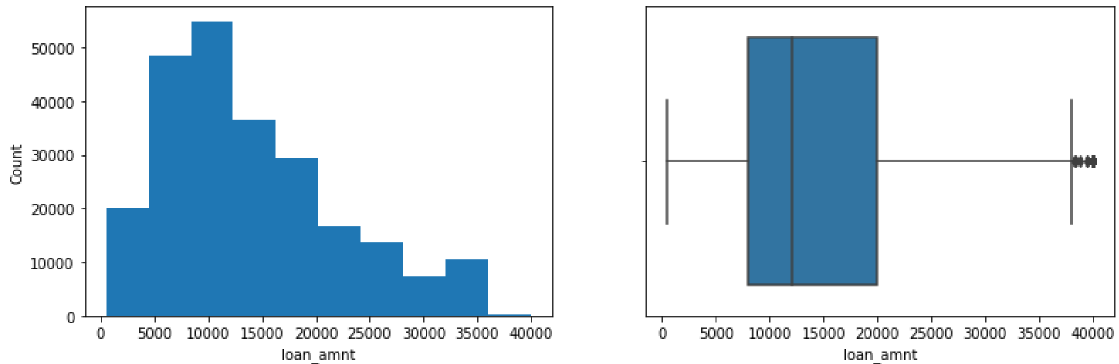
[1109]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti', 'open_acc',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'mort_acc',
       'pub_rec_bankruptcies'],
      dtype='object')
```

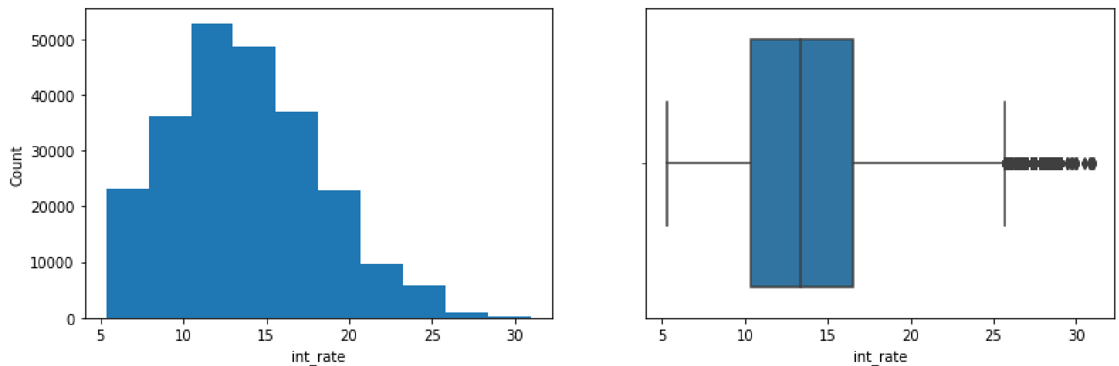
[1110]:
```
# Deleting 'pub_rec_bankruptcies', 'mort_acc',  'pub_rec' from cont_features as␣
 ↪they appear to be categorical
cont_features = np.delete(cont_features, [-1,-2,-6])
cont_features
```

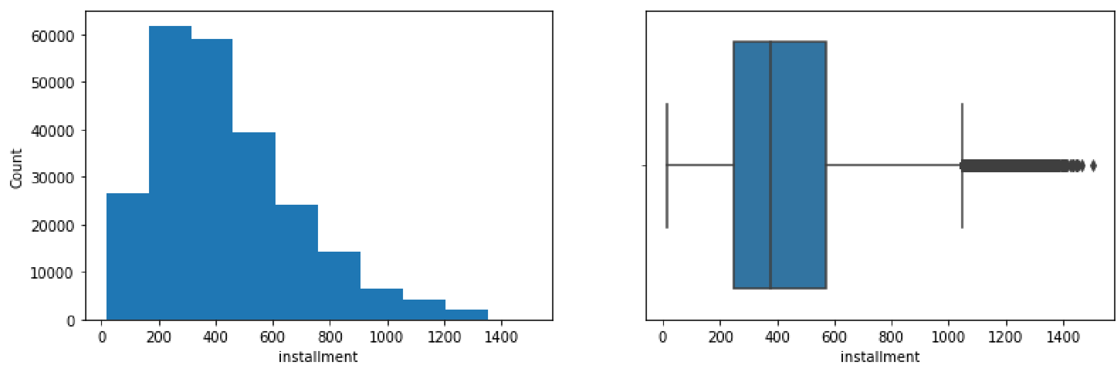
[1110]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti', 'open_acc',
       'revol_bal', 'revol_util', 'total_acc'],
      dtype='object')
```

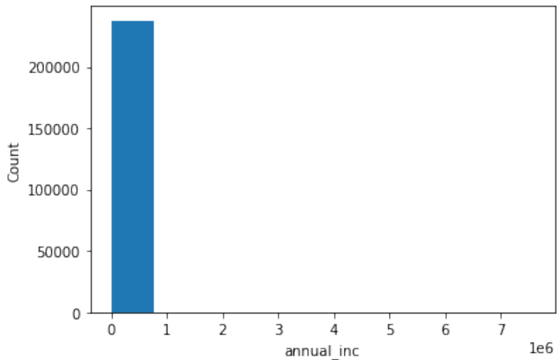
[1111]:
```
for cont_var in cont_features:
    plt.figure(figsize=(13,4))
    plt.subplot(1, 2, 1)
    plt.hist(x_train[cont_var], histtype = 'stepfilled')
```

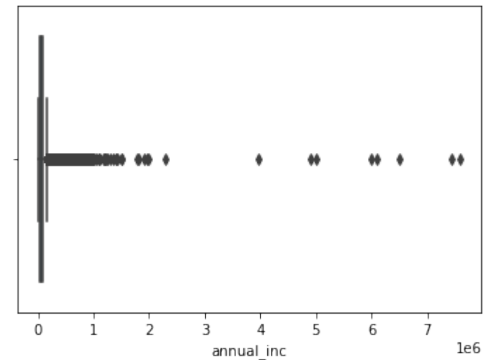
```
    plt.xlabel(cont_var)
    plt.ylabel('Count')
    plt.subplot(1, 2, 2)
    sns.boxplot(x_train[cont_var])
plt.show()
```

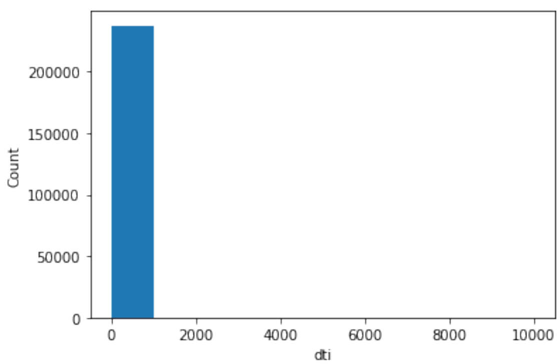


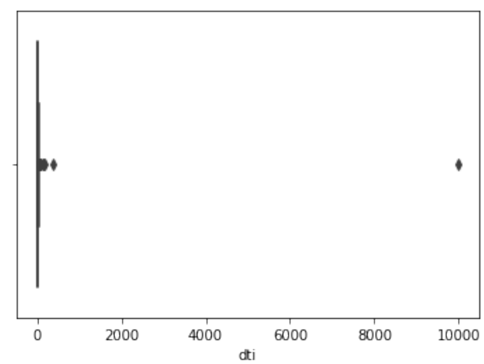


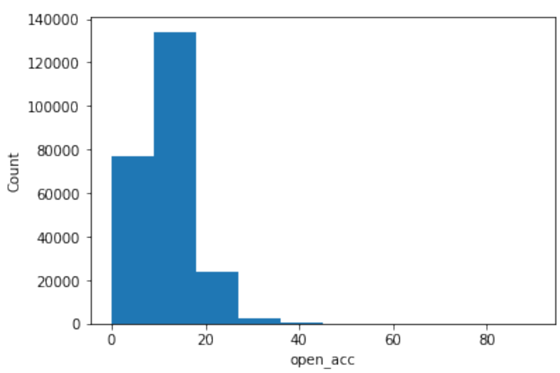


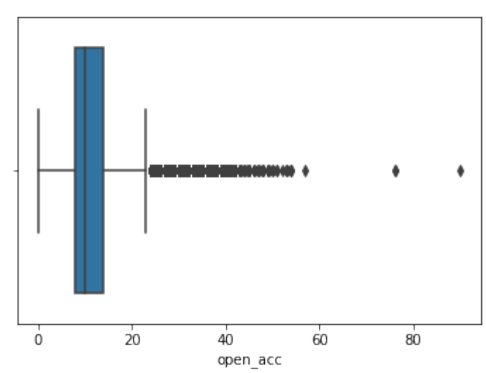

Count
annual_inc
1e6

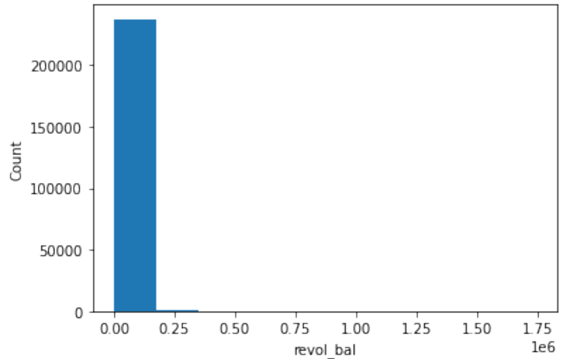

annual_inc
1e6

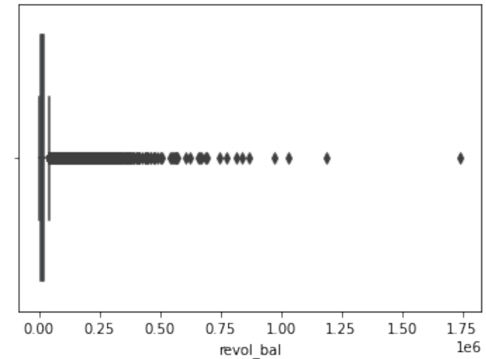

Count
dti

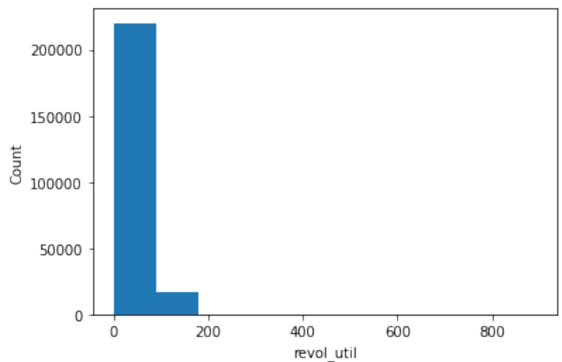

dti

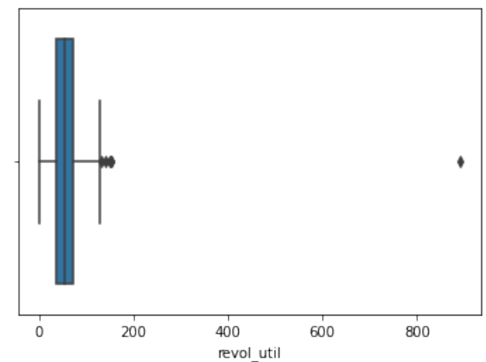

Count
open_acc

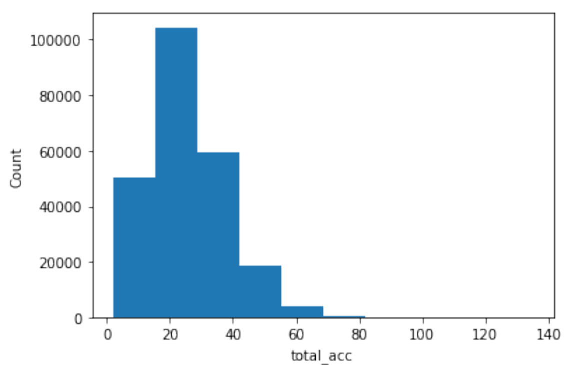

open_acc

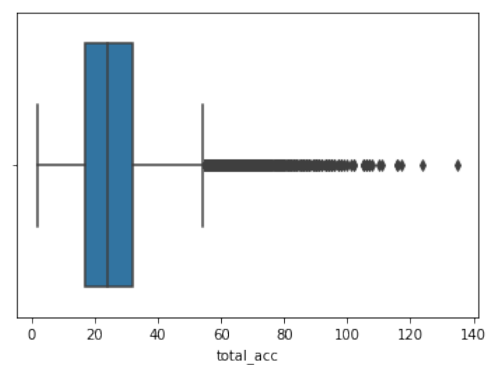










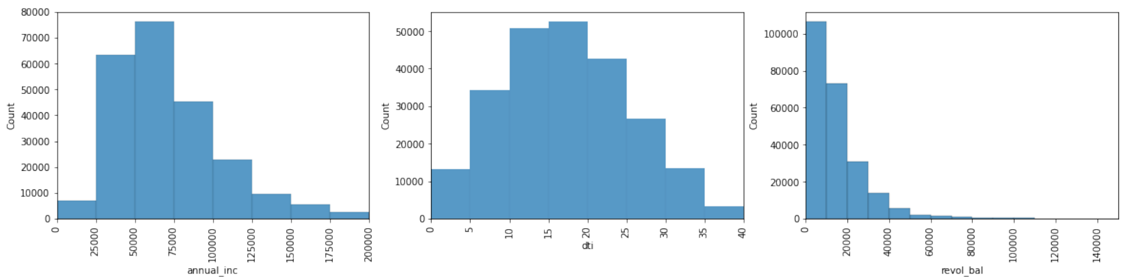


Inference from the above graphs

- We can see that almost all the continuos features from the above plots are skewed to the right.
- Since they are skewed, the features contain outliers which need to be treated.
- Will provide the buisness insights and recommendations in the text editor.

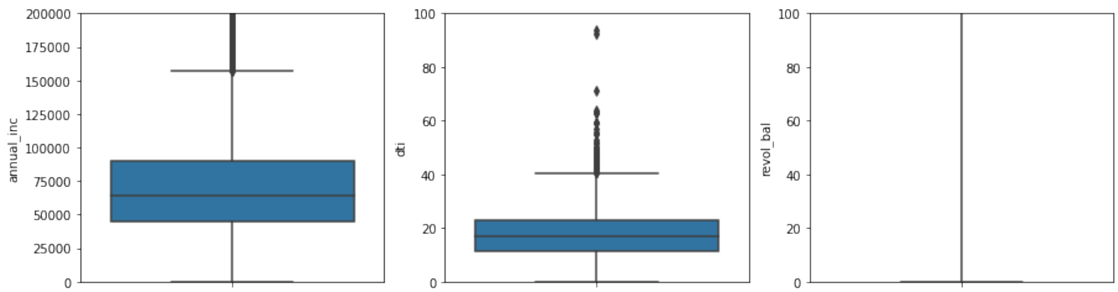
[1112]:

```
# Plotting for some cont_features individually again as scaling was not properly done above due to so many outliers.
plt.figure(figsize=(20,4))
plt.subplot(1,3,1)
sns.histplot(x_train['annual_inc'], binwidth=25000)
plt.xlim(0, 0.2*10**6)
plt.xticks(rotation='90')
plt.subplot(1,3,2)
sns.histplot(x_train['dti'], binwidth=5)
plt.xlim(0, 40)
plt.xticks(rotation='90')
plt.subplot(1,3,3)
sns.histplot(x_train['revol_bal'], binwidth=10000)
plt.xlim(0,0.15*10**6)
plt.xticks(rotation='90')
plt.show()
```



[1113]:

```
plt.figure(figsize=(15,4))
plt.subplot(1,3,1)
sns.boxplot(y = x_train['annual_inc'])
plt.ylim(0, 0.2*10**6)
plt.subplot(1,3,2)
sns.boxplot(y = x_train['dti'])
plt.ylim(0, 100)
plt.subplot(1,3,3)
sns.boxplot(y = x_train['revol_bal'])
plt.ylim(0, 100)
plt.show()
```



[1114]:
```
# purpose and title features appear to be same. Hence, dropping title feature
x_train.drop('title',axis = 1, inplace=True)
x_val.drop('title',axis = 1, inplace=True)
x_test.drop('title',axis = 1, inplace=True)
```

[1115]:
```
cat_features = np.array(x_train.describe(exclude=np.number).columns)
cat_features
```

[1115]:
```
array(['term', 'grade', 'sub_grade', 'emp_title', 'emp_length',
       'home_ownership', 'verification_status', 'issue_d', 'purpose',
       'earliest_cr_line', 'initial_list_status', 'application_type',
       'loan_status'], dtype=object)
```

[1116]:
```
# Removing date_time and 'emp_title' features.
cat_features = np.delete(cat_features, [3,7,9])
```

[1117]:
```
# Adding 'pub_rec_bankruptcies', 'mort_acc',  'pub_rec' to cat_features as they␣
 ↪appear to be categorical
cat_features = np.append(cat_features, ['pub_rec', 'mort_acc',␣
 ↪'pub_rec_bankruptcies'])
cat_features
```

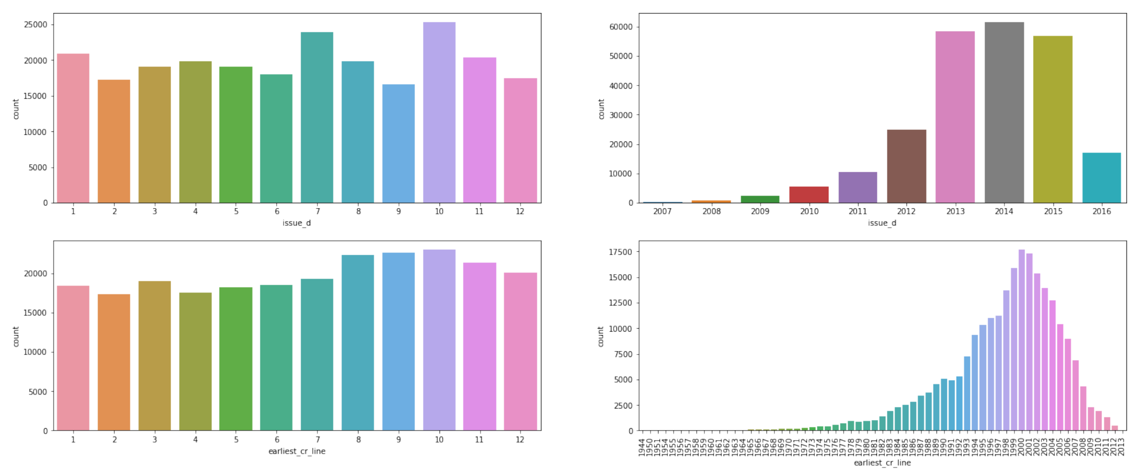
[1117]:
```
array(['term', 'grade', 'sub_grade', 'emp_length', 'home_ownership',
       'verification_status', 'purpose', 'initial_list_status',
       'application_type', 'loan_status', 'pub_rec', 'mort_acc',
       'pub_rec_bankruptcies'], dtype=object)
```

[1118]:
```
i = 1
plt.figure(figsize=(25,65))
for cat_var in cat_features:
    plt.subplot(5,3,i)
    sns.countplot(x_train[cat_var])
    plt.xticks(rotation=90)
    i += 1
plt.show()
```


count
term
36 months
60 months
grade
D
B
A
E
C
F
G
sub_grade
emp_length
< 1 year
10+ years
2 years
8 years
6 years
3 years
1 year
7 years
4 years
5 years
9 years
home_ownership
MORTGAGE
OWN
RENT
OTHER
NONE
ANY
verification_status
Source Verified
Not Verified
Verified
purpose
debt_consolidation
other
major_purchase
home_improvement
car
small_business
credit_card
moving
vacation
medical
wedding
house
educational
renewable_energy
initial_list_status
w
f
application_type
INDIVIDUAL
DIRECT_PAY
JOINT
loan_status
Fully Paid
Charged Off
pub_rec
mort_acc
pub_rec_bankruptcies

[1119]:
```python
# Lets now convert issue_d and earliest_cr_line features to date_time dtype
for vals in [x_train, x_test, x_val]:
    vals['issue_d'] = pd.to_datetime(vals['issue_d'])
    vals['earliest_cr_line'] = pd.to_datetime(vals['earliest_cr_line'])
```

[1120]:
```python
plt.figure(figsize=(25,10))
plt.subplot(221)
sns.countplot(x_train['issue_d'].dt.month)
plt.subplot(222)
sns.countplot(x_train['issue_d'].dt.year)
plt.subplot(223)
sns.countplot(x_train['earliest_cr_line'].dt.month)
plt.subplot(224)
sns.countplot(x_train['earliest_cr_line'].dt.year)
plt.xticks(rotation='90')
plt.show()
```



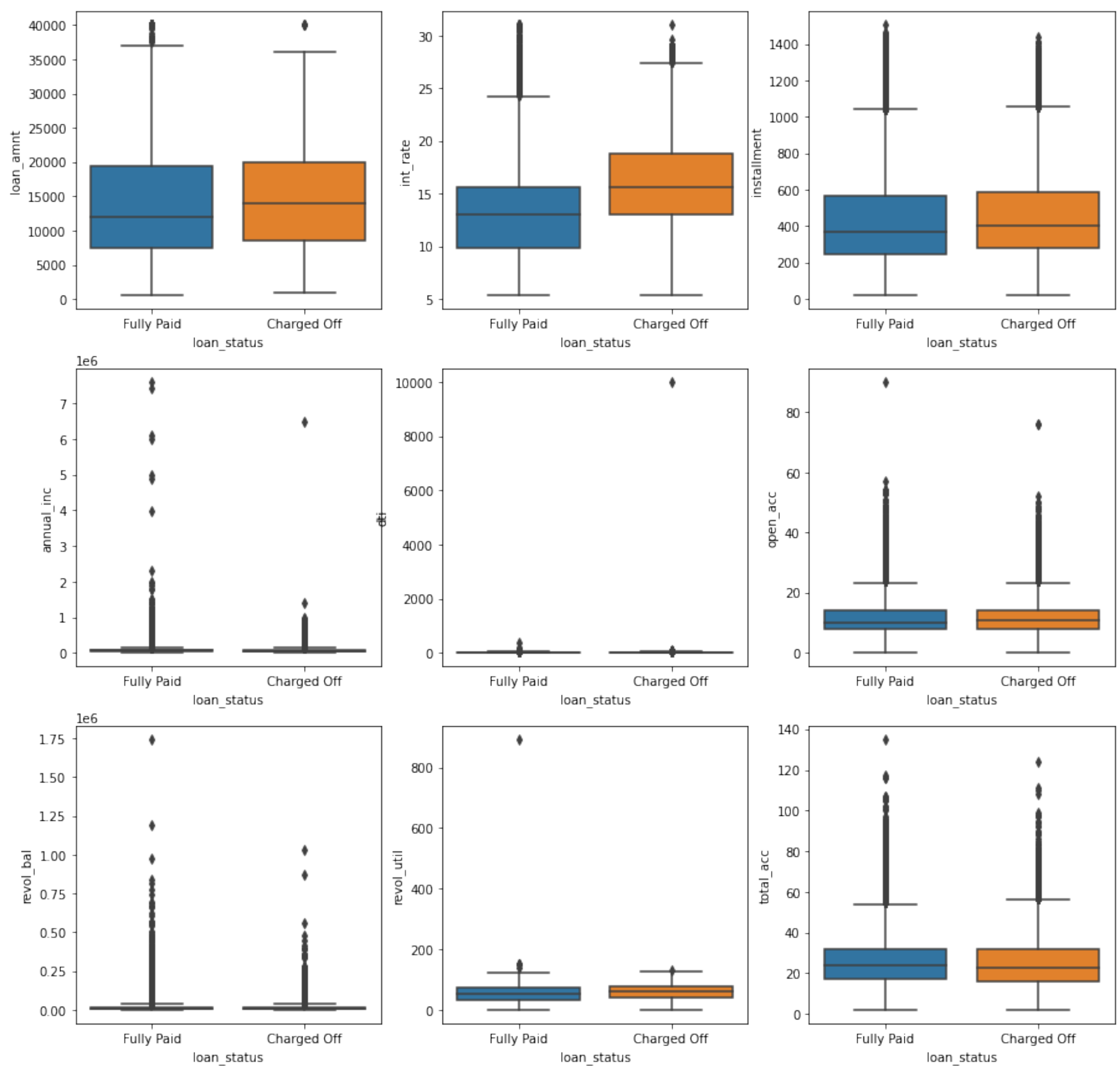
[1121]:
```python
# Since emp_title' feature has a lot of categories, i'll just go with the top␣
 ↪value_counts()
x_train['emp_title'].value_counts()[:10]
```

[1121]:
```
Teacher              2684
Manager              2524
Registered Nurse     1134
RN                   1114
Supervisor           1105
Sales                 988
Project Manager       909
```

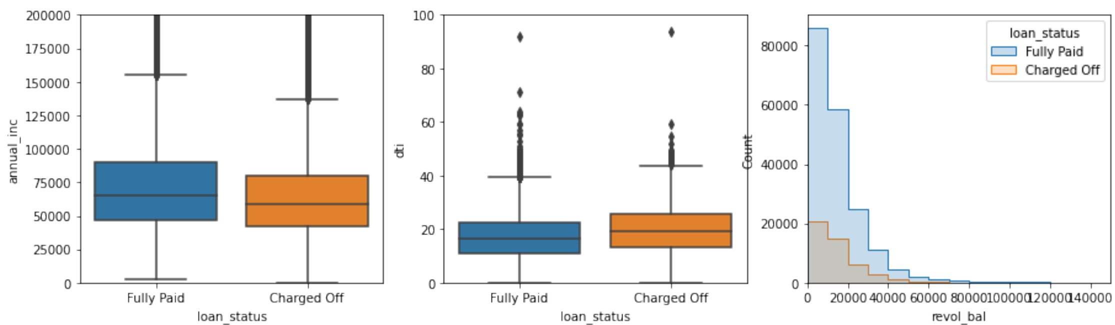
```
Owner                    868
Driver                   814
Office Manager           707
Name: emp_title, dtype: int64
```

Multivariate analyis (predictors vs target variable)

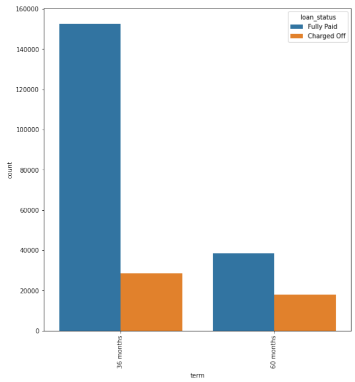
[1122]:
```python
i = 1
plt.figure(figsize=(15,15))
for cols in cont_features:
    plt.subplot(3,3,i)
    sns.boxplot(y=x_train[cols], x = x_train['loan_status'])
    i += 1
plt.show()
```

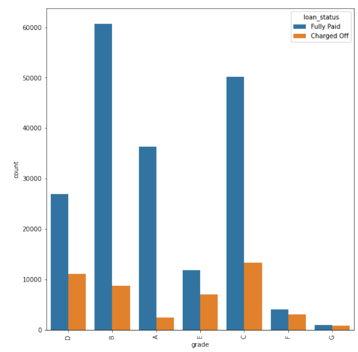


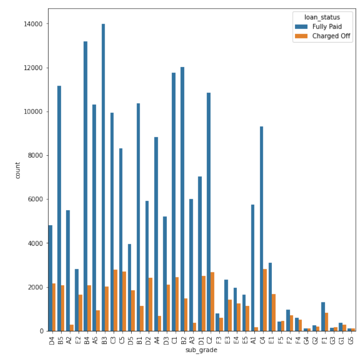
[1123]:
```
# Plotting for some cont_features individually again as scaling was not␣
↪properly done above due to so many outliers.
plt.figure(figsize=(15,4))
plt.subplot(1,3,1)
sns.boxplot(y=x_train['annual_inc'], x = x_train['loan_status'])
plt.ylim(0, 0.2*10**6)
plt.subplot(1,3,2)
sns.boxplot(y=x_train['dti'], x = x_train['loan_status'])
plt.ylim(0, 100)
plt.subplot(1,3,3)
sns.histplot(x = x_train['revol_bal'], binwidth=10000, hue =␣
↪x_train['loan_status'], element="step")
plt.xlim(0,0.15*10**6)
plt.show()
```

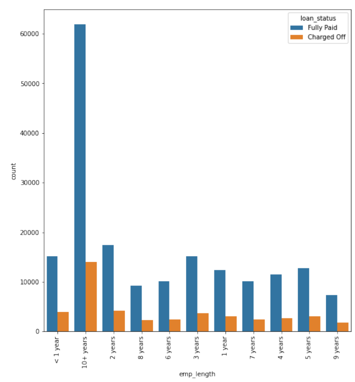


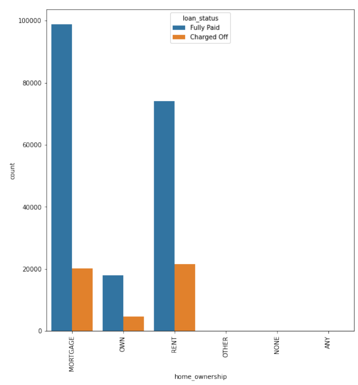
[1124]:
```
plt.figure(figsize=(30,55))
for cat_var in enumerate(cat_features):
    plt.subplot(5,3,cat_var[0]+1)
    sns.countplot(x = x_train[cat_var[1]], hue = x_train['loan_status'])
    plt.xticks(rotation='90')
plt.show()
```

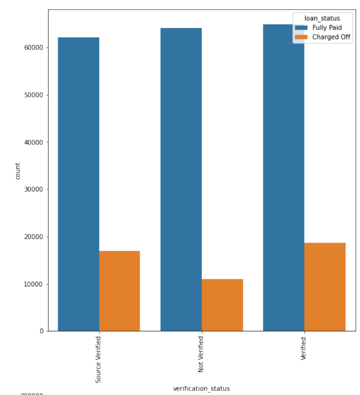

loan_status
Fully Paid
Charged Off
count
36 months
60 months
term

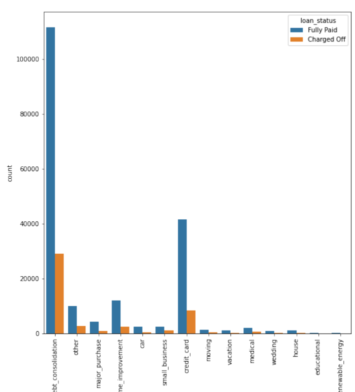

loan_status
Fully Paid
Charged Off
count
D
B
A
E
C
F
G
grade

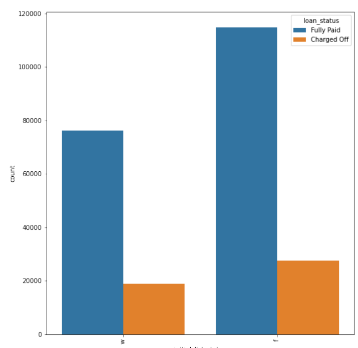

loan_status
Fully Paid
Charged Off
count
sub_grade

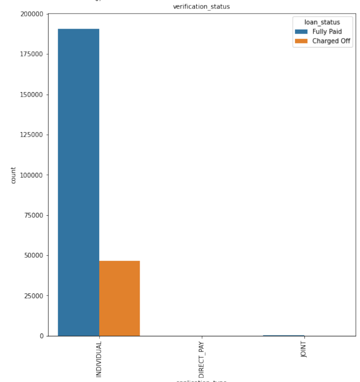

loan_status
Fully Paid
Charged Off
count
< 1 year
10+ years
2 years
8 years
6 years
3 years
1 year
7 years
4 years
5 years
9 years
emp_length

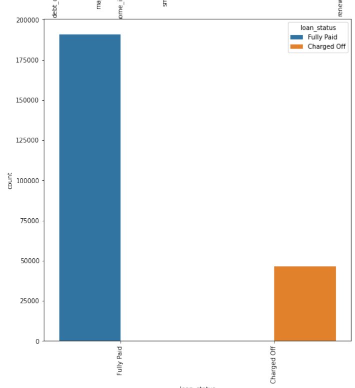

loan_status
Fully Paid
Charged Off
count
MORTGAGE
OWN
RENT
OTHER
NONE
ANY
home_ownership

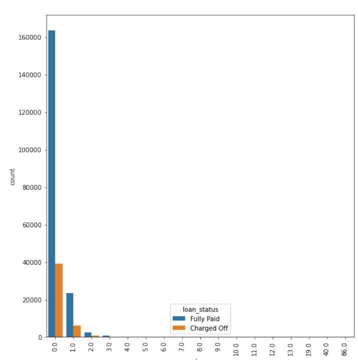

loan_status
Fully Paid
Charged Off
count
Source Verified
Not Verified
Verified
verification_status

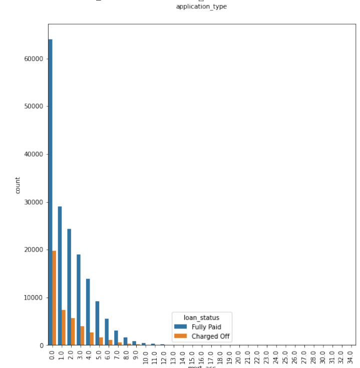

loan_status
Fully Paid
Charged Off
count
debt_consolidation
other
major_purchase
home_improvement
car
small_business
credit_card
moving
vacation
medical
wedding
house
educational
renewable_energy

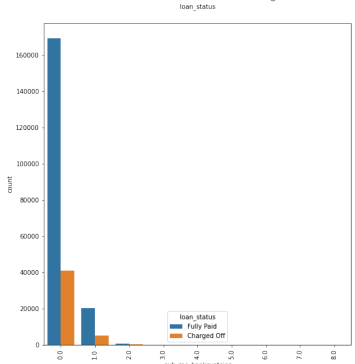

loan_status
Fully Paid
Charged Off
count
w
f
initial_list_status


loan_status
Fully Paid
Charged Off
count
INDIVIDUAL
DIRECT_PAY
JOINT
application_type


loan_status
Fully Paid
Charged Off
count
Fully Paid
Charged Off
loan_status

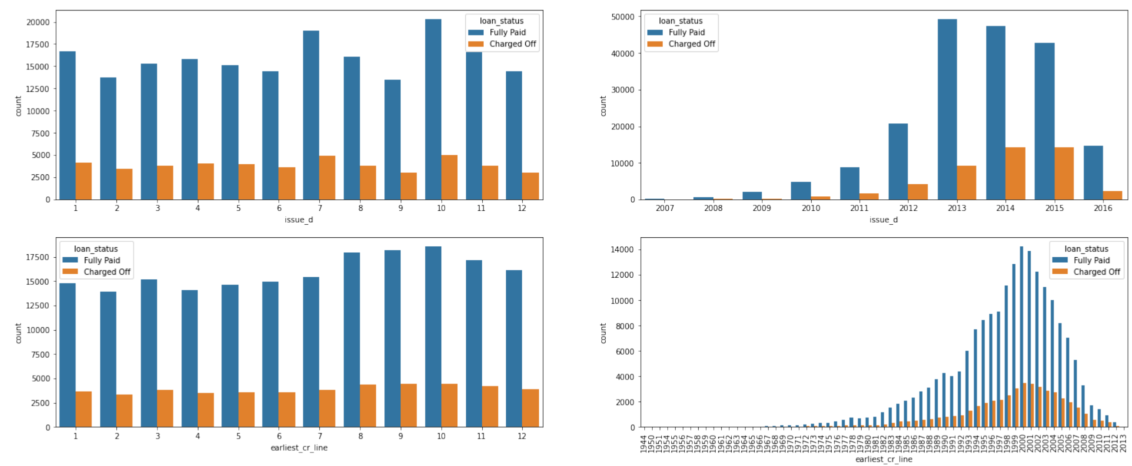

loan_status
Fully Paid
Charged Off
count
pub_rec


loan_status
Fully Paid
Charged Off
count
mort_acc


loan_status
Fully Paid
Charged Off
count
pub_rec_bankruptcies

[1125]:

```
plt.figure(figsize=(25,10))
plt.subplot(221)
sns.countplot(x = x_train['issue_d'].dt.month, hue = x_train['loan_status'])
plt.subplot(222)
sns.countplot(x = x_train['issue_d'].dt.year, hue = x_train['loan_status'])
plt.subplot(223)
sns.countplot(x = x_train['earliest_cr_line'].dt.month, hue = x_train['loan_status'])
plt.subplot(224)
sns.countplot(x = x_train['earliest_cr_line'].dt.year, hue = x_train['loan_status'])
plt.xticks(rotation='90')
plt.show()
```



[1126]:

```
# Since emp_title' feature has a lot of categories, i'll just go with the top value_counts()
print(x_train[x_train['loan_status'] == 'Charged Off']['emp_title'].value_counts()[:5],
x_train[x_train['loan_status'] == 'Fully Paid']['emp_title'].value_counts()[:5])
```

```
Manager              552
Teacher              516
Owner                271
Sales                232
Registered Nurse     229
Name: emp_title, dtype: int64 Teacher              2168
Manager              1972
Registered Nurse      905
RN                    896
```

```
Supervisor           879
Name: emp_title, dtype: int64
```

0.0.2 Feature Encoding and engineering

[1127]:
```
x_train['term'].unique()
```

[1127]:
```
array([' 36 months', ' 60 months'], dtype=object)
```

[1128]:
```
# replacing term with 0's and 1's
x_train['term'].replace({' 36 months':0, ' 60 months': 1}, inplace = True)
x_test['term'].replace({' 36 months':0, ' 60 months': 1}, inplace = True)
x_val['term'].replace({' 36 months':0, ' 60 months': 1}, inplace = True)
```

[1129]:
```
x_train['grade'].unique()
```

[1129]:
```
array(['D', 'B', 'A', 'E', 'C', 'F', 'G'], dtype=object)
```

[1130]:
```
# Considering A as the best grade.
x_train['grade'].replace({'A':6, 'B':5, 'C':4, 'D':3, 'E':2, 'F':1, 'G':0},␣
 ↪inplace = True)
x_test['grade'].replace({'A':6, 'B':5, 'C':4, 'D':3, 'E':2, 'F':1, 'G':0},␣
 ↪inplace = True)
x_val['grade'].replace({'A':6, 'B':5, 'C':4, 'D':3, 'E':2, 'F':1, 'G':0},␣
 ↪inplace = True)
```

[1131]:
```
# Considering A1 as the best sub-grade. Each grade has 5 subgrades
x_train['sub_grade'].unique(), len(x_val['sub_grade'].unique())
```

[1131]:
```
(array(['D4', 'B5', 'A2', 'E2', 'B4', 'A5', 'B3', 'C3', 'C5', 'D5', 'B1',
        'D2', 'A4', 'D3', 'C1', 'B2', 'A3', 'D1', 'C2', 'F3', 'E3', 'E4',
        'E5', 'A1', 'C4', 'E1', 'F5', 'F2', 'F4', 'G4', 'G2', 'F1', 'G3',
        'G1', 'G5'], dtype=object),
 35)
```

[1132]:
```
sub_grades = 34
for i in ['A', 'B', 'C', 'D', 'E', 'F', 'G']:
    for j in range(1,6):
        x_train['sub_grade'].replace(f'{i}{j}', sub_grades, inplace = True)
        x_test['sub_grade'].replace(f'{i}{j}', sub_grades, inplace = True)
        x_val['sub_grade'].replace(f'{i}{j}', sub_grades, inplace = True)
        sub_grades -= 1
```

[1133]:
```
x_train['loan_status'].unique()
```

[1133]:
```
array(['Fully Paid', 'Charged Off'], dtype=object)
```

[1134]:
```
x_train['loan_status'].replace({'Charged Off':0, 'Fully Paid': 1}, inplace =␣
↪True)
x_test['loan_status'].replace({'Charged Off':0, 'Fully Paid': 1}, inplace =␣
↪True)
x_val['loan_status'].replace({'Charged Off':0, 'Fully Paid': 1}, inplace = True)
```

[1135]:
```
# emp_length is an ordinal categorical variable from <1year to 10+years
x_train['emp_length'].unique()
```

[1135]:
```
array(['< 1 year', '10+ years', '2 years', '8 years', '6 years',
       '3 years', nan, '1 year', '7 years', '4 years', '5 years',
       '9 years'], dtype=object)
```

[1136]:
```
emp_lengths = np.sort(np.delete(x_train['emp_length'].unique(), [0, 1, 6]))
```

[1137]:
```
for data in [x_train, x_test, x_val]:
    data['emp_length'].replace({'< 1 year': 0, '10+ years':10}, inplace = True)
    for i in range(len(emp_lengths)):
        data['emp_length'].replace(emp_lengths[i], i+1, inplace = True)
```

[1138]:
```
# As there are many categories, lets perform target encoding instead of one-hot
x_train['purpose'].unique(), x_train['emp_title'].unique()
```

[1138]:
```
(array(['debt_consolidation', 'other', 'major_purchase',
        'home_improvement', 'car', 'small_business', 'credit_card',
        'moving', 'vacation', 'medical', 'wedding', 'house', 'educational',
        'renewable_energy'], dtype=object),
 array(['Accounts Payable Specialist', 'Teacher', 'McKinney ISD', …,
        'operator machine cnc', 'Lombardo Bros. Masonry,LLC',
        'Travel Counselor - TLS'], dtype=object))
```

[1139]:
```
# Since there are too many features aleady, I'll go with target encoding again
x_train['home_ownership'].unique(), x_train['verification_status'].unique(),␣
↪x_train['application_type'].unique()
```

[1139]:
```
(array(['MORTGAGE', 'OWN', 'RENT', 'OTHER', 'NONE', 'ANY'], dtype=object),
 array(['Source Verified', 'Not Verified', 'Verified'], dtype=object),
 array(['INDIVIDUAL', 'DIRECT_PAY', 'JOINT'], dtype=object))
```

[1140]:
```
# adding all the features which needs to be target encoded to a list
target_encode_features = ['purpose', 'emp_title', 'home_ownership',␣
↪'verification_status', 'application_type']
```

[1141]:
```
import category_encoders as ce
```

[1142]:
```
y_val.shape, x_val.shape, y_val.shape, x_val.shape
```

[1142]:
```
((79206,), (79206, 25), (79206,), (79206, 25))
```

[1143]:
```
for fea in target_encode_features:
    x_train[fea] = ce.TargetEncoder().
↪fit_transform(x_train[fea],x_train['loan_status'])
    x_val[fea] = ce.TargetEncoder().
↪fit_transform(x_val[fea],x_val['loan_status'])
    x_test[fea] = ce.TargetEncoder().
↪fit_transform(x_test[fea],x_test['loan_status'])
```

[1144]:
```
x_train['initial_list_status'].unique()
```

[1144]:
```
array(['w', 'f'], dtype=object)
```

[1145]:
```
# Label encoding
x_train['initial_list_status'].replace({'w':0,'f':1}, inplace = True)
x_test['initial_list_status'].replace({'w':0,'f':1}, inplace = True)
x_val['initial_list_status'].replace({'w':0,'f':1}, inplace = True)
```

[1146]:
```
# Encoding date_time features
for data_sets in [x_train, x_test, x_val]:
    data_sets['issue_yr'] = data_sets['issue_d'].dt.year
    data_sets['issue_mo'] = data_sets['issue_d'].dt.month
    data_sets['earliest_cr_line_yr'] = data_sets['earliest_cr_line'].dt.year
    data_sets['earliest_cr_line_mo'] = data_sets['earliest_cr_line'].dt.month

    data_sets.drop(['issue_d', 'earliest_cr_line'], axis = 1, inplace=True)
```

[1147]:
```
x_train['pub_rec'].unique(), x_train['mort_acc'].unique(),␣
↪x_train['pub_rec_bankruptcies'].unique()
```

[1147]:
```
(array([ 1.,  0.,  4.,  3.,  2.,  5.,  6.,  8.,  7., 13., 12., 11.,  9.,
        19., 10., 86., 40.]),
 array([ 2.,  0.,  3.,  1., nan,  5., 16.,  6.,  4.,  9.,  7., 10., 11.,
        13.,  8., 12., 22., 15., 24., 18., 14., 20., 27., 17., 19., 23.,
        25., 31., 21., 26., 34., 28., 32., 30.]),
 array([ 1.,  0.,  2.,  4., nan,  3.,  6.,  5.,  8.,  7.]))
```

[1148]:
```
# Creating flags and changing the values greater than one to one in the columns␣
↪'pub_rec', 'mort_acc' and 'pub_rec_bankruptcies'
def func(x):
    if x > 1:
        return 1
    elif x < 1:
        return 0
for data_sets in [x_train, x_test, x_val]:
    data_sets['pub_rec'] = data_sets['pub_rec'].apply(func)
    data_sets['mort_acc'] = data_sets['mort_acc'].apply(func)
```

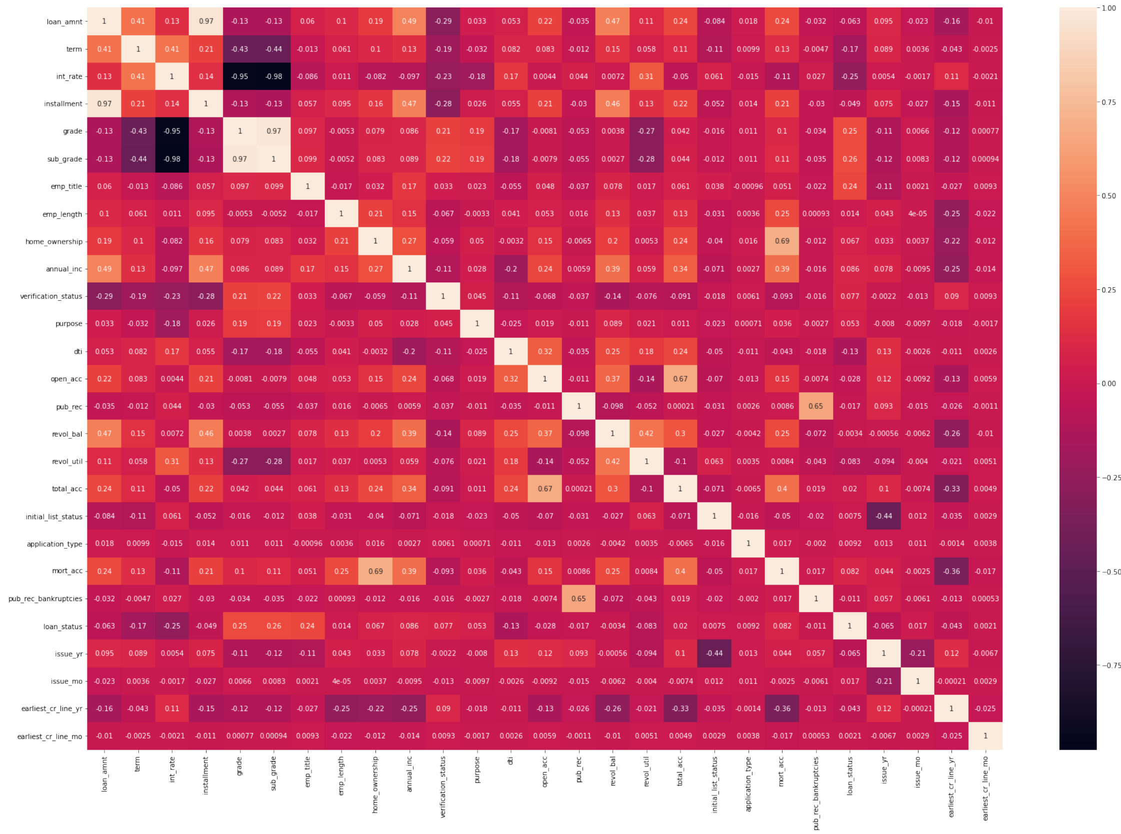
```
    data_sets['pub_rec_bankruptcies'] = data_sets['pub_rec_bankruptcies'].
↪apply(func)
```

[1149]:
```
# All features have been converted to int or float data type
x_val.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 79206 entries, 85557 to 109034
Data columns (total 27 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   loan_amnt             79206 non-null  float64
 1   term                  79206 non-null  int64
 2   int_rate              79206 non-null  float64
 3   installment           79206 non-null  float64
 4   grade                 79206 non-null  int64
 5   sub_grade             79206 non-null  int64
 6   emp_title             79206 non-null  float64
 7   emp_length            75488 non-null  float64
 8   home_ownership        79206 non-null  float64
 9   annual_inc            79206 non-null  float64
 10  verification_status   79206 non-null  float64
 11  purpose               79206 non-null  float64
 12  dti                   79206 non-null  float64
 13  open_acc              79206 non-null  float64
 14  pub_rec               69331 non-null  float64
 15  revol_bal             79206 non-null  float64
 16  revol_util            79147 non-null  float64
 17  total_acc             79206 non-null  float64
 18  initial_list_status   79206 non-null  int64
 19  application_type      79206 non-null  float64
 20  mort_acc              59582 non-null  float64
 21  pub_rec_bankruptcies  70609 non-null  float64
 22  loan_status           79206 non-null  int64
 23  issue_yr              79206 non-null  int64
 24  issue_mo              79206 non-null  int64
 25  earliest_cr_line_yr   79206 non-null  int64
 26  earliest_cr_line_mo   79206 non-null  int64
dtypes: float64(18), int64(9)
memory usage: 16.9 MB
```

[1150]:
```
# Going for spearman correlation
spearman_corr = x_train.corr(method='spearman')
```

[1151]:
```
plt.figure(figsize=(30,20))
sns.heatmap(spearman_corr, annot=True)
plt.show()
```



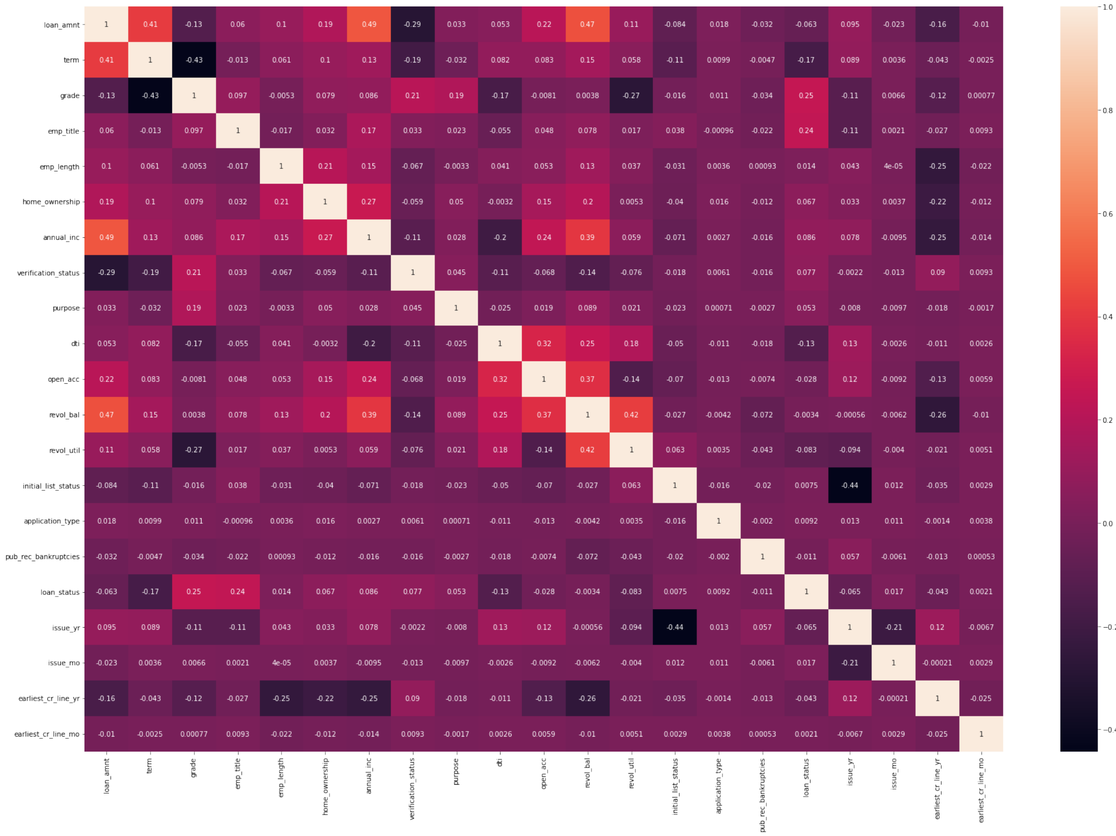
[1152]:
```
x_train['emp_length'].unique()
```

[1152]:
```
array([ 0., 10.,  2.,  8.,  6.,  3., nan,  1.,  7.,  4.,  5.,  9.])
```

[1153]:
```
# Lets drop some columns which has high correlation with each other.
for data_sets in [x_train, x_test, x_val]:
    data_sets.drop('int_rate', axis=1, inplace=True) # int_rate has high␣
 ↪negative correlation with grade and subgrade
    data_sets.drop('sub_grade', axis=1, inplace=True) # grade has high positive␣
 ↪correlation with subgrade
    data_sets.drop('mort_acc', axis=1, inplace=True) #mort_acc has high␣
 ↪positive correlation with pub_rec_bankruptcies
    data_sets.drop('pub_rec', axis=1, inplace=True) #pub_rec has high positive␣
 ↪correlation with pub_rec_bankruptcies and mort_acc
    data_sets.drop('total_acc', axis=1, inplace=True) #total_acc and open_acc␣
 ↪has high positive correlation among each other
    data_sets.drop('installment', axis=1, inplace=True) # installment and␣
 ↪loan_amnt has high positive correlation among each other
```

[1154]:

```
# Going for spearman correlation.
spearman_corr = x_train.corr(method='spearman')
plt.figure(figsize=(30,20))
sns.heatmap(spearman_corr, annot=True)
plt.show()
```



Missing Value Treatment

[1155]:

```
x_train.isnull().sum()/x_train.shape[0]*100
```

[1155]:

```
loan_amnt              0.000000
term                   0.000000
grade                  0.000000
emp_title              0.000000
emp_length             4.575411
home_ownership         0.000000
annual_inc             0.000000
verification_status    0.000000
purpose                0.000000
dti                    0.000000
open_acc               0.000000
```

```
revol_bal                0.000000
revol_util               0.071123
initial_list_status      0.000000
application_type         0.000000
pub_rec_bankruptcies    10.878805
loan_status              0.000000
issue_yr                 0.000000
issue_mo                 0.000000
earliest_cr_line_yr      0.000000
earliest_cr_line_mo      0.000000
dtype: float64
```

[1156]:

```
#Missing values in revol_util and pub_rec_bankruptcies are very less. Hence we␣
↪can drop the null value rows
x_train.dropna(subset=['revol_util'], inplace = True)
x_test.dropna(subset=['revol_util'],inplace = True)
x_val.dropna(subset=['revol_util'],inplace = True)
```

[1157]:

```
for data_sets in [x_train, x_test, x_val]:
    data_sets['emp_length'].fillna(value = data_sets['emp_length'].mode()[0],␣
↪inplace = True)
    data_sets['pub_rec_bankruptcies'].fillna(value =␣
↪data_sets['pub_rec_bankruptcies'].mode()[0], inplace = True)
```

[1158]:

```
# No missing values found
x_train.isnull().sum()/x_train.shape[0]*100
```

[1158]:

```
loan_amnt               0.0
term                    0.0
grade                   0.0
emp_title               0.0
emp_length              0.0
home_ownership          0.0
annual_inc              0.0
verification_status     0.0
purpose                 0.0
dti                     0.0
open_acc                0.0
revol_bal               0.0
revol_util              0.0
initial_list_status     0.0
application_type        0.0
pub_rec_bankruptcies    0.0
loan_status             0.0
issue_yr                0.0
issue_mo                0.0
earliest_cr_line_yr     0.0
```

```
earliest_cr_line_mo     0.0
dtype: float64
```

[1159]:
```
x_val.isnull().sum()/x_train.shape[0]*100
```

[1159]:
```
loan_amnt               0.0
term                    0.0
grade                   0.0
emp_title               0.0
emp_length              0.0
home_ownership          0.0
annual_inc              0.0
verification_status     0.0
purpose                 0.0
dti                     0.0
open_acc                0.0
revol_bal               0.0
revol_util              0.0
initial_list_status     0.0
application_type        0.0
pub_rec_bankruptcies    0.0
loan_status             0.0
issue_yr                0.0
issue_mo                0.0
earliest_cr_line_yr     0.0
earliest_cr_line_mo     0.0
dtype: float64
```

Outlier Treatment using IQR method

[1160]:
```
cont_features
```

[1160]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti', 'open_acc',
       'revol_bal', 'revol_util', 'total_acc'],
      dtype='object')
```

[1161]:
```
#Will be using IQR method to treat the outliers present in the continuos␣
↪variables
cont_features = cont_features.delete([1,2,-1])
```

[1162]:
```
def IQR(col):
    Q3 = np.percentile(col, 75)
    Q1 = np.percentile(col, 25)
    iqr = Q3-Q1
    upper_lmt = Q3+1.5*iqr
    lower_lmt = Q1-1.5*iqr
    return lower_lmt, upper_lmt
```

[1163]:
```
for cont_var in cont_features:
    x_train =␣
  ↪x_train[(x_train[cont_var]>=IQR(x_train[cont_var])[0])&(x_train[cont_var]<=IQR(x_train[cont
```

Duplicates treatment

[1164]:
```
# No duplicates found
x_train.duplicated().value_counts()
```

[1164]:
```
False    210605
dtype: int64
```

Imbalance check

[1165]:
```
# We can see that there is a huge imbalance of classes. Will be using weighted␣
  ↪balancing method while model training
y_train.value_counts()
```

[1165]:
```
Fully Paid     191038
Charged Off     46580
Name: loan_status, dtype: int64
```

Training a Logistic regression model

[1166]:
```
# Removing target variable from all the 3 data sets and creating target␣
  ↪variable y columns again
y_train = x_train['loan_status']
x_train = x_train.drop('loan_status', axis = 1)
y_test = x_test['loan_status']
x_test = x_test.drop('loan_status', axis = 1)
y_val = x_val['loan_status']
x_val = x_val.drop('loan_status', axis = 1)
```

[1167]:
```
from sklearn.pipeline import make_pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import MinMaxScaler
```

Defining type1 and type 2 error before modelling

- 1 - Fully paid, 0 - Charged off
- type1 error (False postive) : Model has falsely predicted that an individual will fully the loan amount.
- type2 error (False negative) : Model has falsely predicted that an individual will be charged off.
- Will be tuning my model based on precision score which controls false positives. Would not want to increase line of credit for non creditworthy individuals

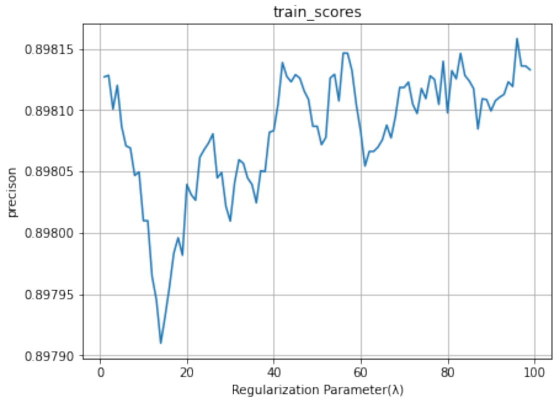
[1168]:
```
from sklearn.metrics import precision_score, PrecisionRecallDisplay,␣
  ↪RocCurveDisplay, recall_score, ConfusionMatrixDisplay
```

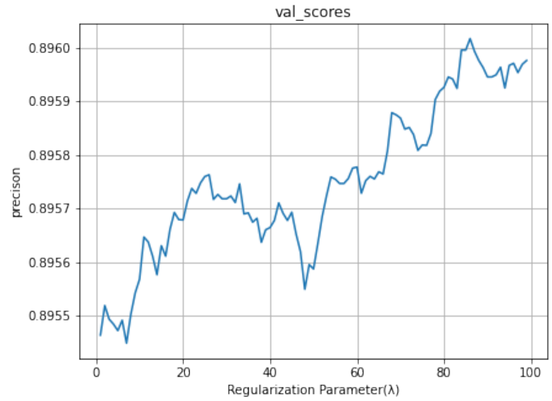
[1169]:

```
# Creating a pipeline which does scaling first and then trains a model. Will be using ridge regularisation to avoid overfit.
# Hyperparameter C(1/ ) is decided based on the best score on validation data.
train_scores = []
val_scores = []
for lmda in np.arange(1, 100, 1): # range of values of Lambda
    #Creating a pipeline
    pipeline = make_pipeline(MinMaxScaler(), LogisticRegression(penalty='l2', C=1/lmda, class_weight={1:1, 0:(191038/46580)}))

    pipeline.fit(x_train, y_train) #Training model

    train_pred = pipeline.predict(x_train) #Predicting train values

    train_scores.append(precision_score(y_train, train_pred)) #Getting precision score for train data set.

    val_pred = pipeline.predict(x_val) #Predicting validation values

    val_scores.append(precision_score(y_val, val_pred)) #Getting precision score for validation data set.
```

[1170]:

```
plt.figure(figsize=(15,5))
plt.subplot(1,2,1)
sns.lineplot(np.arange(1, 100, 1), train_scores)
plt.xlabel("Regularization Parameter( )")
plt.ylabel("precison")
plt.title("train_scores")
plt.grid()
plt.subplot(1,2,2)
sns.lineplot(np.arange(1, 100, 1), val_scores)
plt.xlabel("Regularization Parameter( )")
plt.ylabel("precison")
plt.title("val_scores")
plt.grid()
plt.show()
```





[1171]:
```
# The best value of lambda for the highest precision score came out to be 86 or␣
↪c 1/86.
np.argmax(val_scores)+1, max(val_scores)
```

[1171]: (86, 0.8960167552263119)

[1172]:
```
best_pipeline = make_pipeline(MinMaxScaler(), LogisticRegression(penalty='l2', ␣
↪C=1/86, class_weight={1:1, 0:(191038/46580)}))
best_pipeline.fit(x_train, y_train)
train_predictions = best_pipeline.predict(x_train)
test_predictions = best_pipeline.predict(x_test)
precision_score(y_train, train_predictions), precision_score(y_test,␣
↪test_predictions)
```

[1172]: (0.8981176523546226, 0.8946739534974829)

0.894 is our score on test data set using best_pipeline model.

Feature weights and its importance

[1173]:
```
best_pipeline[1].coef_[0]
```

[1173]:
```
array([-0.56716216, -0.45385136,  1.9311417 ,  6.34746557,  0.04413189,
        0.80269123,  0.89436773,  0.1239122 ,  0.36733854, -0.77087636,
       -0.45718063,  0.34891655, -0.71654255, -0.05511867,  0.13668311,
       -0.09724329, -0.08157176,  0.12887524,  0.03707136,  0.02736661])
```

[1177]:
```
weights_x_train = pd.DataFrame(data = {'features' : x_train.columns, 'weights' :
↪ best_pipeline[1].coef_[0]})
weights_x_train.sort_values(by = 'weights', key = abs)
# We have so many columns with negligible weightage. emp_title has an insane␣
↪upper hand as compared to other columns
```

[1177]:

```
                  features   weights
19   earliest_cr_line_mo  0.027367
18   earliest_cr_line_yr  0.037071
4             emp_length  0.044132
13   initial_list_status -0.055119
16               issue_yr -0.081572
15  pub_rec_bankruptcies -0.097243
7    verification_status  0.123912
17              issue_mo  0.128875
14      application_type  0.136683
11             revol_bal  0.348917
8                purpose  0.367339
1                   term -0.453851
10              open_acc -0.457181
0              loan_amnt -0.567162
12            revol_util -0.716543
9                    dti -0.770876
5         home_ownership  0.802691
6             annual_inc  0.894368
2                  grade  1.931142
3              emp_title  6.347466
```

[1178]:

```
ordered_features = np.array(weights_x_train.sort_values(by = 'weights', key =␣
↪abs)['features'])
```

[1179]:

```
ordered_features
```

[1179]:

```
array(['earliest_cr_line_mo', 'earliest_cr_line_yr', 'emp_length',
       'initial_list_status', 'issue_yr', 'pub_rec_bankruptcies',
       'verification_status', 'issue_mo', 'application_type', 'revol_bal',
       'purpose', 'term', 'open_acc', 'loan_amnt', 'revol_util', 'dti',
       'home_ownership', 'annual_inc', 'grade', 'emp_title'], dtype=object)
```

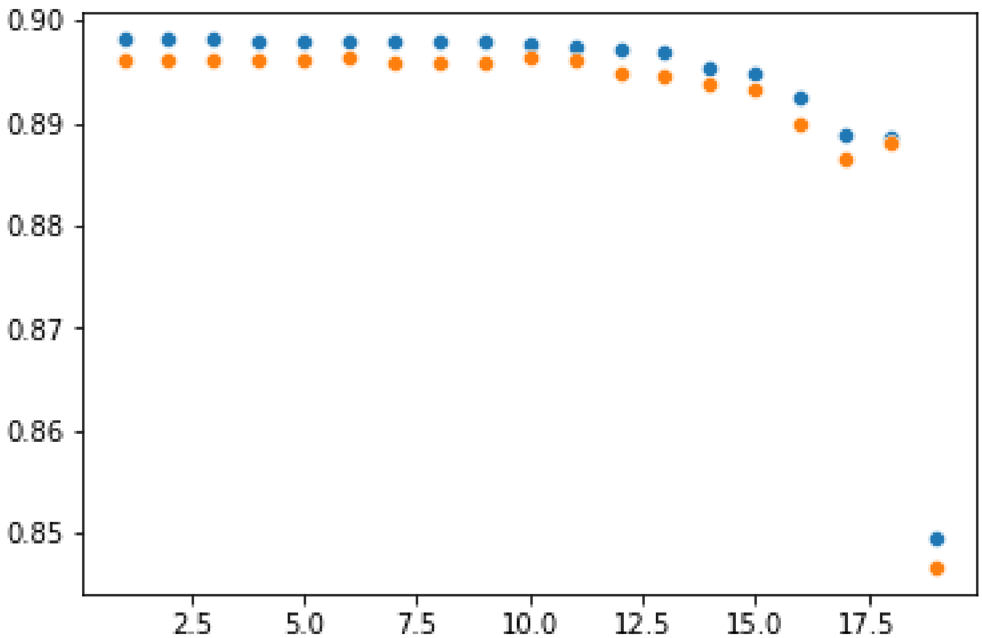
[1180]:

```
# Dropping features from train and val data set in the order from␣
↪ordered_features to see if there is any change in score.
# Lesser the better
_train_scores = []
_val_scores = []
for i in range(1,len(ordered_features)):
    new_pipeline = make_pipeline(MinMaxScaler(),␣
↪LogisticRegression(penalty='l2',  C=1/86, class_weight={1:1, 0:(191038/
↪46580)}))
    new_x_train = x_train.drop(ordered_features[:i], axis = 1)
    new_x_val = x_val.drop(ordered_features[:i], axis = 1)
    new_pipeline.fit(new_x_train, y_train)
    _train_scores.append(precision_score(y_train, new_pipeline.
↪predict(new_x_train)))
```

```
    _val_scores.append(precision_score(y_val, new_pipeline.predict(new_x_val)))
```

[1181]:
```
sns.scatterplot(x = np.arange(1,len(ordered_features),1),y = _train_scores)
sns.scatterplot(x = np.arange(1,len(ordered_features),1),y = _val_scores)
```

[1181]:
```
<AxesSubplot:>
```



[1182]:
```
_val_scores
```

[1182]:
```
[0.8959920888837182,
 0.8960676335996277,
 0.896020016292331,
 0.8961406501385955,
 0.8961560082966639,
 0.8962522054404095,
 0.8957554388887813,
 0.895750576472184,
 0.8957751937984496,
 0.8965060053033848,
 0.8961175645123568,
 0.8949014516700107,
 0.8946285445530973,
 0.8938879623270872,
 0.8932501905897531,
 0.8898572618286754,
```

```
 0.8864615617204626,
 0.8880314055917273,
 0.8467054908485857]
```

[1183]:
```python
# We'll keep 0.88 as the threshold and remove all the features from the until␣
↪our validation scores drops below 0.88
_val_scores[-2:]
# Just with the features grade and emp_title we can achieve a score of 0.89 on␣
↪validation data set. Eventhough this is a very
# good score, i'll still go with annual_inc, dti, home_ownership, grade and␣
↪emp_title as per the business domain.
```

[1183]: `[0.8880314055917273, 0.8467054908485857]`

[1184]:
```python
# changing x_train and x_test again and training a new model with fewer features
x_train = x_train[['annual_inc','dti', 'home_ownership', 'grade', 'emp_title']]
x_test = x_test[['annual_inc','dti', 'home_ownership', 'grade', 'emp_title']]
best_new_pipeline = make_pipeline(MinMaxScaler(),␣
↪LogisticRegression(penalty='l2',  C=0.1, class_weight={1:1,0:(191038/
↪46580)}))
best_new_pipeline.fit(x_train, y_train)
train_predictions = best_new_pipeline.predict(x_train)
test_predictions = best_new_pipeline.predict(x_test)
precision_score(y_train, train_predictions), precision_score(y_test,␣
↪test_predictions), recall_score(y_test, test_predictions)
```

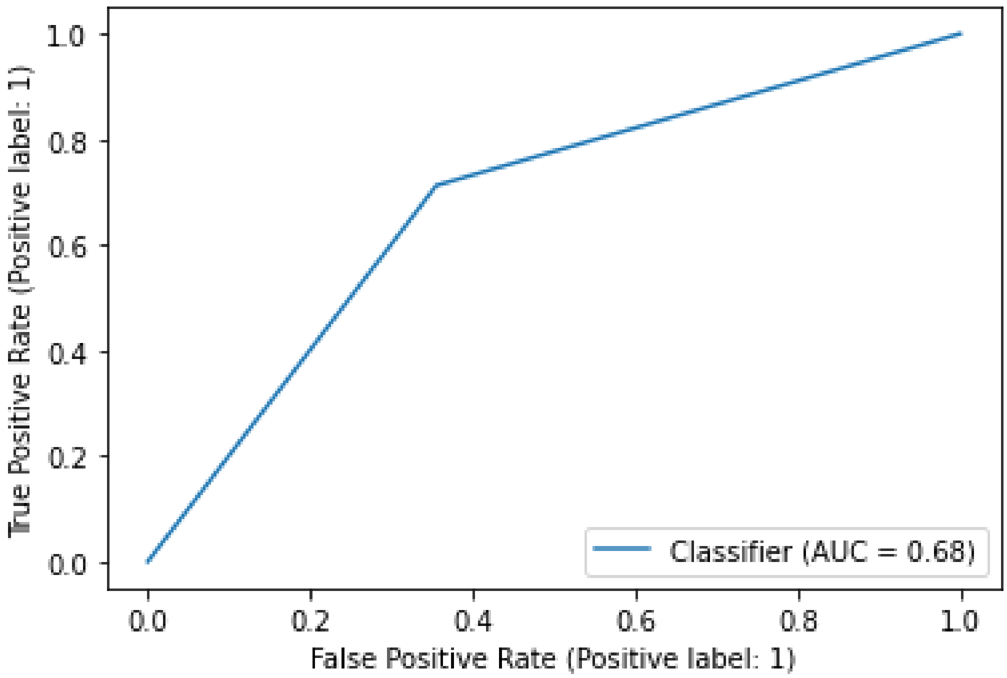
[1184]: `(0.894733676200788, 0.8912444933920705, 0.7126031920748487)`

best_new_pipeline is the optimised model with fewer features. Model with a test precision score of 0.891 is ready for deployment

ROC, PRC and Confusion matrix

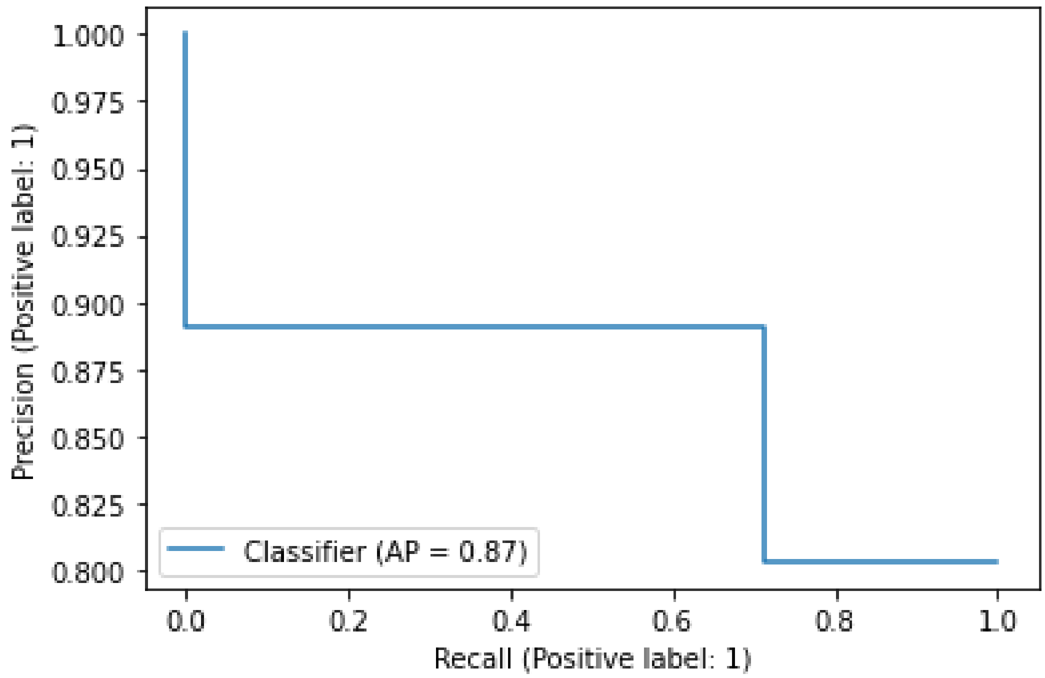
[1186]:
```python
# Auc = 0.68 which is better than the random model(0.5 AUC), but not the best␣
↪obviously. It might be because of 2 reasons.
# 1. y_test data is highly imbalanced. Due to this AUC-ROC doesn't work.
# 2. We built our model only trying to decrease our false positives. But, TPR␣
↪which is recall also includes false negatives
# which we did not take into our account.
RocCurveDisplay.from_predictions(y_test, test_predictions)
```

[1186]: `<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x28b04937d00>`



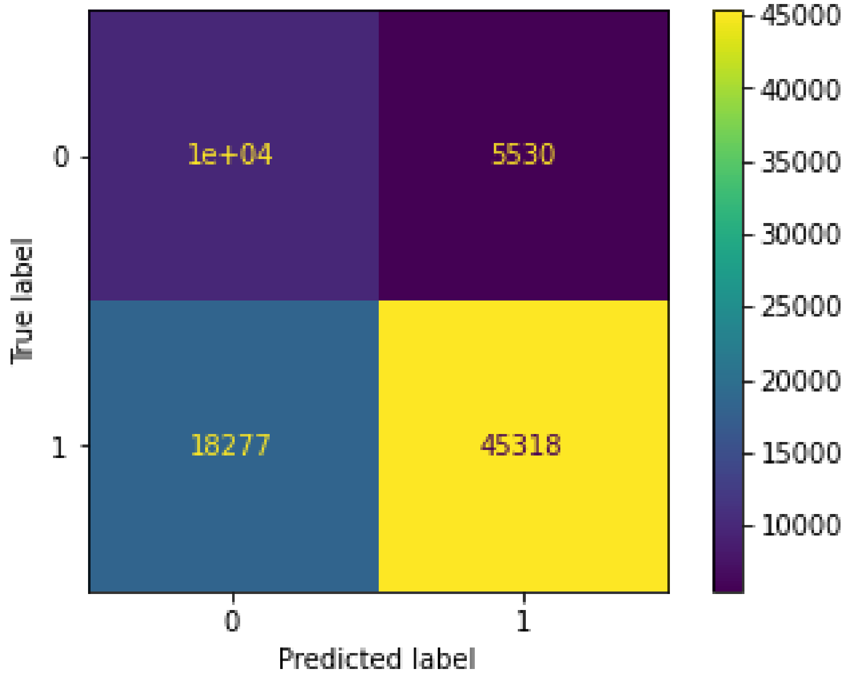
[1187]:
```
#PRC works even if there is an unbalance. AUC was found to be 0.87 across all
↪the thresholds which was very good.
PrecisionRecallDisplay.from_predictions(y_test, test_predictions)
```

[1187]:
```
<sklearn.metrics._plot.precision_recall_curve.PrecisionRecallDisplay at
0x28aa2140dc0>
```



[1188]:
```
# We can see that our type2 error is very high as compared to type 1 error. We␣
↪might lose good customers, but will not be at
# a loss by giving loans to non credit worthy customers
ConfusionMatrixDisplay.from_predictions(y_test, test_predictions)
```

[1188]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x28b1e8d7160>


1e+04
5530
18277
45318
0
1
True label
0
1
Predicted label
45000
40000
35000
30000
25000
20000
15000
10000

```
[ ]:
```