Topic: Machine Learning Domain: Data Science Industry: Banking and Finance Technology: Python,Pandas,NumPy,Matplotlib,Scikit-learn Problem Topic: Credit Fraud Detection Date of Assignment : 28th March 2023 Submission Deadline: 28th March 2023 Introduction to Problem Statement Imagine you work for a consumer finance company which specializes in lending various types of loans to urban customers. When the company receives a loan application, the company has to make a decision for loan approval based on the applicant’s profile. Two types of risks are associated with the bank’s decision: ● If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company ● If the applicant is not likely to repay the loan, i.e. he/she is likely to default, then approving the loan may lead to a financial loss for the company The data given below contains the information about past loan applicants and whether they ‘defaulted’ or not. The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc. In this case study, you will use EDA to understand how consumer attributes and loan attributes influence the tendency of default. When a person applies for a loan, there are two types of decisions that could be taken by the company: ● Loan accepted: If the company approves the loan, there are 3 possible scenarios described below: ● Fully paid: Applicant has fully paid the loan (the principal and the interest rate) ● Current: Applicant is in the process of paying the installments, i.e. the tenure of the loan is not yet completed. These candidates are not labeled as 'defaulted'. ● Charged-off: Applicant has not paid the installments in due time for a long period of time, i.e. he/she has defaulted on the loan ● Loan rejected: The company had rejected the loan (because the candidate does not meet their requirements etc.). Since the loan was rejected, there is no transactional history of those applicants with the company and so this data is not available with the company (and thus in this dataset) Business Objectives This company is the largest online loan marketplace, facilitating personal loans, business loans, and financing of medical procedures. Borrowers can easily access lower interest rate loans through a fast-online interface. Like most other lending companies, lending loans to ‘risky’ applicants is the largest source of financial loss (called credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed. In other words, borrowers who default cause the largest amount of loss to the lenders. In this case, the customers labeled as 'charged-off' are the 'defaulters'. If one is able to identify these risky loan applicants, then such loans can be reduced thereby cutting down the amount of credit loss. Identification of such applicants using EDA is the aim of this case study. In other words, the company wants to understand the driving factors (or driver variables) behind loan default, i.e. the variables which are strong indicators of default. The company can utilize this knowledge for its portfolio and risk assessment. Results Expected ● Write all your code in one well-commented Python file; briefly mention the insights and observations from the analysis. ● Explain the results of univariate, bivariate analysis etc. in business terms. ● Include visualizations and summarize the most important results. ● Form narrative questions from the dataset? Try to answer those questions with supportive visualizations? ● For this you can perform univariate as well as bivariate analysis. ● After the numerical analysis is done, create a hypothesis. ● Then to support your hypothesis, perform the visual exploration to identify trends and support your hypothesis. ● Build an appropriate machine learning model that can help the stakeholders in making the decision of accepting or rejecting the loan application faster and with confidence. ● Test your model by dividing the dataset into a 70:30 ratio for training and testing. ● Print all the parameters used for evaluating your model. ● Discuss what steps you have used to avoid overfitting/underfitting the model. Dataset link: [https://drive.google.com/file/d/15LErgl6CqWvKoEsscePF6Krb3uI_-3au/view?usp=sharing (https://drive.google.com/file/d/15LErgl6CqWvKoEsscePF6Krb3uI_-3au/view?usp=sharing)](https://drive.google.com/file/d/15LErgl6CqWvKoEsscePF6Krb3uI_-3au/view?usp=sharing)

In [264]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
```

In [265]:
```
df=pd.read_csv("C:\\Users\\N CH SHANMUKHA\\Downloads\\loan.csv")
df
```

```
C:\Users\N CH SHANMUKHA\anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3146: DtypeWarning: Columns (47)
have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[265]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g_dpd_24m
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	NaN
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	NaN
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	NaN
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	NaN
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	A	A4	...	NaN
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	C	C1	...	NaN
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	A	A4	...	NaN
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	A	A2	...	NaN
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	E	E2	...	NaN

39717 rows × 111 columns

Data Prepreocessing

In [266]:
```
x=list(df.columns)
```

In [267]:
```
d=[]
for i in x:
    if (df[i].isnull().sum() > 39717*0.75) or df[i].astype(object).describe().unique()[1]==1:
        d.append(i)
df.drop(columns=d,inplace=True)
df
```

Out[267]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	total_pymnt_inv	total_
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	B	B2	...	5833.84	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	C	C4	...	1008.71	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	C	C5	...	3005.67	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	C	C1	...	12231.89	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	B	B5	...	3513.33	
...	...	...	...	...	...	...	...	...	...	...	...	...	
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	A	A4	...	1213.88	
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	C	C1	...	1020.51	
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	A	A4	...	1397.12	
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	A	A2	...	672.66	
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	E	E2	...	980.83	

39717 rows × 46 columns

In the above snippet we are removing the attributes / features those who are having null values more than 75% data and also those columns/features/attributes those have a single repeating value in its entire column.

In [268]:
```
df.duplicated().sum()
```

Out[268]: 0

The above snippet will check for any duplicate values.

so 0 at the output implies that we dont have any duplicate records.

In [269]:
```
df.columns
```

Out[269]:
```
Index(['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_inv',
       'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title',
       'emp_length', 'home_ownership', 'annual_inc', 'verification_status',
       'issue_d', 'loan_status', 'url', 'desc', 'purpose', 'title', 'zip_code',
       'addr_state', 'dti', 'delinq_2yrs', 'earliest_cr_line',
       'inq_last_6mths', 'mths_since_last_delinq', 'open_acc', 'pub_rec',
       'revol_bal', 'revol_util', 'total_acc', 'out_prncp', 'out_prncp_inv',
       'total_pymnt', 'total_pymnt_inv', 'total_rec_prncp', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'last_pymnt_d', 'last_pymnt_amnt', 'last_credit_pull_d',
       'pub_rec_bankruptcies'],
      dtype='object')
```

EDA

In [270]:
```
df.drop(columns=['id', 'member_id'],inplace=True)
```

as id and member_id dont have any importance we have removed that

In [271]:
```
df['total_rec_late_fee'].astype(object).describe()
```

Out[271]:
```
count     39717.0
unique     1356.0
top           0.0
freq      37671.0
Name: total_rec_late_fee, dtype: float64
```

In [272]:
```
df['int_rate']=df['int_rate'].str[0:-2].astype(float)  # extracted the first two elements as it implies the number
```

In [273]:
```
for i in list(df.columns):
    print(df[i].describe())
```

```
50%           0.000000
75%           0.000000
max        6311.470000
Name: out_prncp, dtype: float64
count     39717.000000
mean         50.989768
std         373.824457
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max        6307.370000
Name: out_prncp_inv, dtype: float64
count     39717.000000
mean      12153.596544
std        9042.040766
min           0.000000
25%        5576.930000
50%        9899.640319
75%       16534.433040
```

Feature engineering and feature Selection

In [274]:
```
df['desc']=df['desc'].str.len()
```

the above will replace the value with its length although we can use nlp here to gain more accuracy but instead we use its length

In [275]:
```
df.drop(columns=['url'],inplace=True)  ## not required for our model
```

In [276]:
```
df.drop(columns=['title'],inplace=True)  ## As it has more number of unique values we droped the column
```

In [277]:
```
list(df['zip_code'])
```

```
 '104xx',
 '950xx',
 '329xx',
 '226xx',
 '226xx',
 '992xx',
 '614xx',
 '802xx',
 '902xx',
 '672xx',
 '083xx',
 '100xx',
 '770xx',
 '787xx',
 '926xx',
 '931xx',
 '860xx',
 '712xx',
 '060xx',
```

In [278]:
```
df.drop(columns=['zip_code'],inplace=True)
```

In [279]:
```
df['earliest_cr_line']
```

Out[279]:
```
0        Jan-85
1        Apr-99
2        Nov-01
3        Feb-96
4        Jan-96
          ...
39712    Nov-90
39713    Dec-86
39714    Oct-98
39715    Nov-88
39716    Oct-03
Name: earliest_cr_line, Length: 39717, dtype: object
```

In [280]:
```
df['earliest_cr_line']=df['earliest_cr_line'].str[-2:].astype(float)
```

In the above code we extracted last two elements where it represents the year and thus we converted into number/ int

In [281]:
```
df['defaulted']=(df['loan_status']=='Charged Off').astype(int)  ## Setting the target column
```

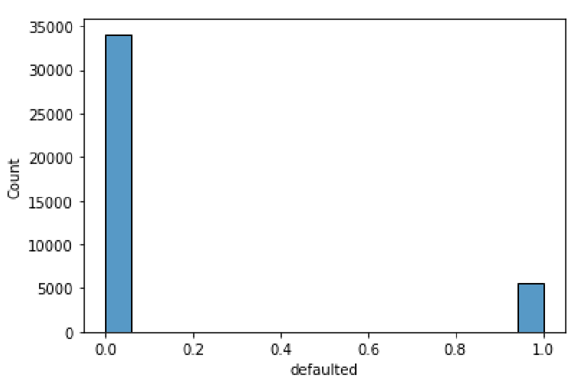
In [282]:
```
df['loan_status'],df['defaulted']
```

Out[282]:
```
(0         Fully Paid
 1        Charged Off
 2         Fully Paid
 3         Fully Paid
 4            Current
             ...
 39712     Fully Paid
 39713     Fully Paid
 39714     Fully Paid
 39715     Fully Paid
 39716     Fully Paid
 Name: loan_status, Length: 39717, dtype: object,
 0        0
 1        1
 2        0
 3        0
 4        0
         ..
 39712    0
 39713    0
 39714    0
 39715    0
 39716    0
 Name: defaulted, Length: 39717, dtype: int32)
```

Checking for data imbalnce

In [283]:
```
sns.histplot(df['defaulted'])
```

Out[283]:
```
<AxesSubplot:xlabel='defaulted', ylabel='Count'>
```



as we can see that the data is imbalanced and thus we require to resample the data

so we have four options for that

1. under sampling majority (random)(duplicating)

1. over sampling minority (random)(duplicating)

1. under sampling majority (with slight manupulation)

1. over sampling minority (with slight manupulation)

as we know that we have a huge data so we can go for under sampling , if our data would be minimal then we can go for over sampling for minority class.

How to Balance Data With the Imbalanced-Learn Python Module? A number of more sophisticated resampling techniques have been proposed in the scientific literature.

For example, we can cluster the records of the majority class and do the under-sampling by removing records from each cluster, thus seeking to preserve information. In over-sampling, instead of creating exact copies of the minority class records, we can introduce small variations into those copies, creating more diverse synthetic samples.

Let’s apply some of these resampling techniques using the Python library imbalanced-learn. It is compatible with scikit-learn and is part of scikit-learn-contrib projects.

import imblearn 3. Random Under-Sampling With Imblearn You may have heard about pandas, numpy, matplotlib, etc. while learning data science. But there is another library: imblearn, which is used to sample imbalanced datasets and improve your model performance.

RandomUnderSampler is a fast and easy way to balance the data by randomly selecting a subset of data for the targeted classes. Under-sample the majority class(es) by randomly picking samples with or without replacement.

import library

from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler(random_state=42, replacement=True)# fit predictor and target variable x_rus, y_rus = rus.fit_resample(x, y)

print('original dataset shape:', Counter(y)) print('Resample dataset shape', Counter(y_rus)) Image for post

In [284]:
```
x=df.drop(columns=['defaulted','loan_status'])
x
```

Out[284]:

	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	...	total_pymnt_inv
0	5000	5000	4975.0	36 months	10.6	162.87	B	B2	NaN	10+ years	...	5833.84
1	2500	2500	2500.0	60 months	15.2	59.83	C	C4	Ryder	< 1 year	...	1008.71
2	2400	2400	2400.0	36 months	15.9	84.33	C	C5	NaN	10+ years	...	3005.67
3	10000	10000	10000.0	36 months	13.4	339.31	C	C1	AIR RESOURCES BOARD	10+ years	...	12231.89
4	3000	3000	3000.0	60 months	12.6	67.79	B	B5	University Medical Group	1 year	...	3513.33
...	...	...	...	...	...	...	...	...	...	...	...	...
39712	2500	2500	1075.0	36 months	8.0	78.42	A	A4	FiSite Research	4 years	...	1213.88
39713	8500	8500	875.0	36 months	10.2	275.38	C	C1	Squarewave Solutions, Ltd.	3 years	...	1020.51
39714	5000	5000	1325.0	36 months	8.0	156.84	A	A4	NaN	< 1 year	...	1397.12
39715	5000	5000	650.0	36 months	7.4	155.38	A	A2	NaN	< 1 year	...	672.66
39716	7500	7500	800.0	36 months	13.7	255.43	E	E2	Evergreen Center	< 1 year	...	980.83

39717 rows × 40 columns

In [285]:
```
y=df['defaulted']
```

In [286]:
```
from imblearn.under_sampling import RandomUnderSampler

rus = RandomUnderSampler(random_state=42, replacement=True)# fit predictor and target variable
x_rus, y_rus = rus.fit_resample(x, y)

print('original dataset shape:', y.shape)
print('Resample dataset shape', y_rus.shape)
```

```
original dataset shape: (39717,)
Resample dataset shape (11254,)
```

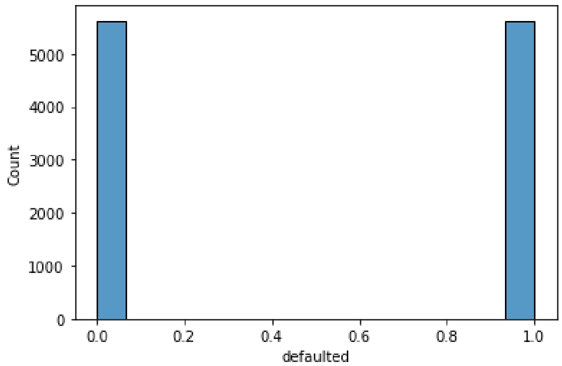
The above code is under sampling the majority class so that there will be a class balance so our model can be performed well.

In [287]:
```
y_rus.astype(object).describe()
```

Out[287]:
```
count     11254
unique        2
top           1
freq       5627
Name: defaulted, dtype: int64
```

In [288]:
```
sns.histplot(y_rus)
```

Out[288]: <AxesSubplot:xlabel='defaulted', ylabel='Count'>



now it seems to be balanced

In [289]:
```
x_rus
```

Out[289]:

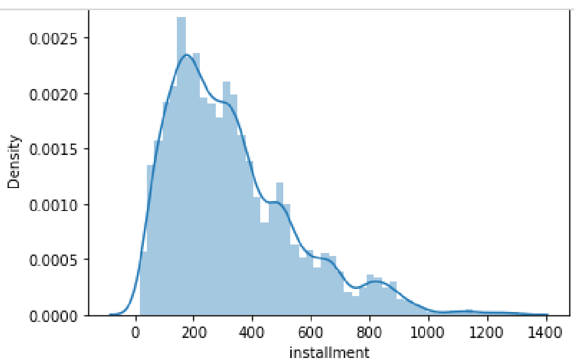
	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	...	total_pymnt_in
0	16000	16000	16000.0	36 months	13.0	539.57	C	C2	National Radio Astronomy Observatory	< 1 year	...	19305.9
1	25000	25000	24975.0	60 months	14.6	590.17	C	C3	sonoma county water agency	4 years	...	28911.6
2	5000	5000	5000.0	36 months	16.4	177.00	D	D3	SCG Communications LLC	3 years	...	6371.8
3	10000	10000	9975.0	36 months	7.5	311.11	A	A3	Allan hanley	6 years	...	11171.8
4	9000	9000	9000.0	60 months	11.1	196.18	B	B5	Brooklyn Sports Club	< 1 year	...	11770.4
...	...	...	...	...	...	...	...	...	...	...	...	..
11249	2500	2500	675.0	36 months	12.8	84.00	D	D4	Nebraska Occupational Therapy	< 1 year	...	599.2
11250	2500	2500	825.0	36 months	9.6	80.26	B	B4	AMZ Marketing	< 1 year	...	688.3
11251	6500	6500	225.0	36 months	15.0	225.37	F	F1	Universal Advertising	9 years	...	139.4
11252	1000	1000	950.0	36 months	10.5	32.55	C	C2	Invision Power Services	2 years	...	668.8
11253	20000	20000	2800.0	36 months	13.4	678.08	E	E1	Auto motors of miami	6 years	...	2845.8

11254 rows × 40 columns

In [290]:
```
cols=list(x.columns)
cols
```

Out[290]:
```
['loan_amnt',
 'funded_amnt',
 'funded_amnt_inv',
 'term',
 'int_rate',
 'installment',
 'grade',
 'sub_grade',
 'emp_title',
 'emp_length',
 'home_ownership',
 'annual_inc',
 'verification_status',
 'issue_d',
 'desc',
 'purpose',
 'addr_state',
 'dti',
 'delinq_2yrs',
 'earliest_cr_line',
 'inq_last_6mths',
 'mths_since_last_delinq',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 'out_prncp',
 'out_prncp_inv',
 'total_pymnt',
 'total_pymnt_inv',
 'total_rec_prncp',
 'total_rec_int',
 'total_rec_late_fee',
 'recoveries',
 'collection_recovery_fee',
 'last_pymnt_d',
 'last_pymnt_amnt',
 'last_credit_pull_d',
 'pub_rec_bankruptcies']
```

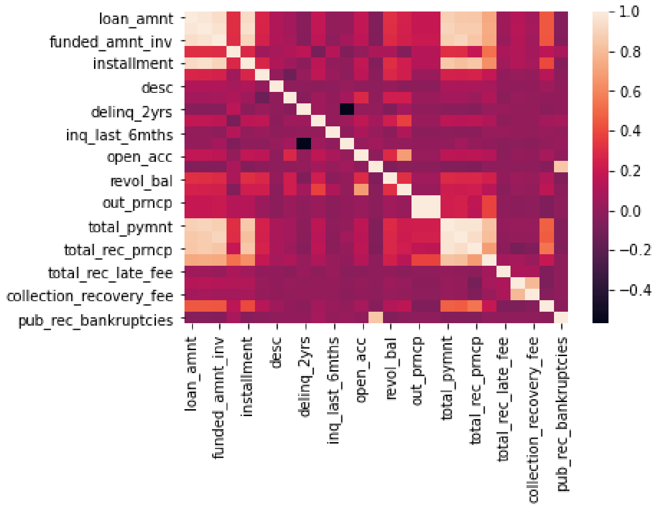
In [291]:
```
for i in cols:
    if x_rus[i].dtype!='O':
        sns.distplot(x_rus[i])
        plt.show()
```




```
C:\Users\N CH SHANMUKHA\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

In [292]:
```python
plt.Figure(figsize=(15,15))
sns.heatmap(x.corr())
```

Out[292]: <AxesSubplot:>



Removing highly co-related features

In [293]:
```python
x_rus.drop(columns=['funded_amnt','funded_amnt_inv'],inplace=True)
```

In [294]:
```
x_rus.corr()
```

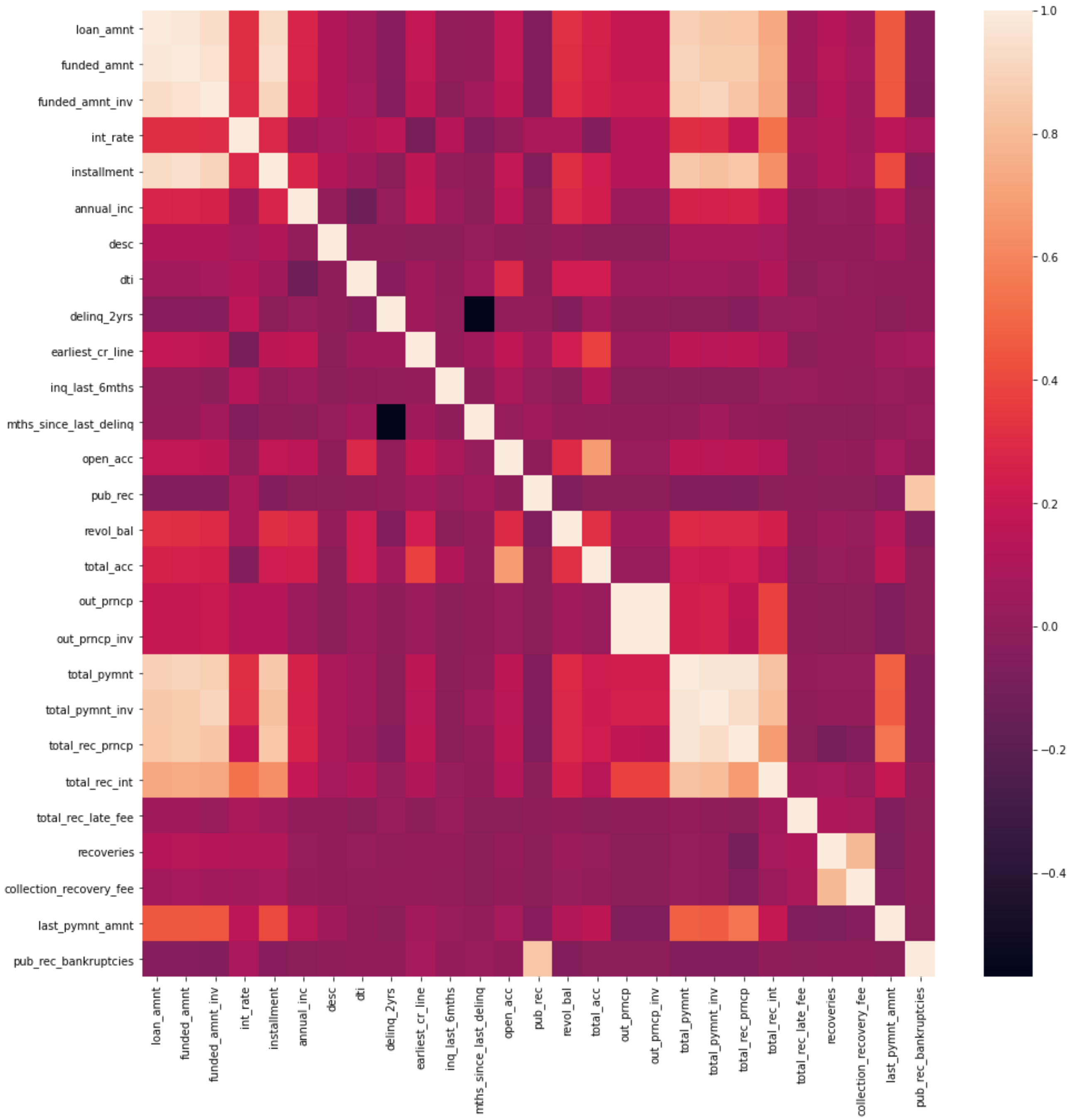
Out[294]:

	loan_amnt	int_rate	installment	annual_inc	desc	dti	delinq_2yrs	earliest_cr_line	inq_last_6mths	mths_sinc
loan_amnt	1.000000	0.338163	0.925773	0.359422	0.122730	0.064195	-0.023754	0.196097	0.015360	
int_rate	0.338163	1.000000	0.306985	0.090615	0.075780	0.092431	0.142722	-0.058817	0.114374	
installment	0.925773	0.306985	1.000000	0.364192	0.115640	0.046236	-0.008448	0.173638	0.022488	
annual_inc	0.359422	0.090615	0.364192	1.000000	0.044399	-0.122178	0.028987	0.225795	0.031661	
desc	0.122730	0.075780	0.115640	0.044399	1.000000	-0.007357	-0.011871	0.014592	-0.019988	
dti	0.064195	0.092431	0.046236	-0.122178	-0.007357	1.000000	-0.052450	0.052590	-0.014496	
delinq_2yrs	-0.023754	0.142722	-0.008448	0.028987	-0.011871	-0.052450	1.000000	0.049088	-0.002149	
earliest_cr_line	0.196097	-0.058817	0.173638	0.225795	0.014592	0.052590	0.049088	1.000000	0.037534	
inq_last_6mths	0.015360	0.114374	0.022488	0.031661	-0.019988	-0.014496	-0.002149	0.037534	1.000000	
mths_since_last_delinq	0.007615	-0.041795	-0.004622	-0.031056	0.008911	0.074177	-0.575744	0.056870	-0.007823	
open_acc	0.178716	0.021388	0.178815	0.214280	-0.003313	0.298595	-0.009396	0.163902	0.090672	
pub_rec	-0.051449	0.097949	-0.049267	-0.019534	0.014577	0.002091	0.005103	0.080858	0.019475	
revol_bal	0.310835	0.085494	0.302038	0.380359	0.031380	0.223427	-0.062757	0.250086	-0.013462	
total_acc	0.262700	-0.032076	0.242573	0.304081	-0.008372	0.246580	0.061027	0.369311	0.111528	
out_prncp	0.138120	0.070268	0.090790	0.044660	0.002985	0.030130	-0.021178	0.025262	-0.030364	
out_prncp_inv	0.138026	0.070295	0.090725	0.044520	0.002910	0.030089	-0.021156	0.025178	-0.030237	
total_pymnt	0.743681	0.207183	0.737505	0.323962	0.088817	0.035884	-0.024831	0.157391	-0.042300	
total_pymnt_inv	0.711741	0.208834	0.696216	0.307370	0.088241	0.042392	-0.030475	0.142443	-0.056553	
total_rec_prncp	0.633850	0.040772	0.661598	0.302545	0.079336	0.005726	-0.039638	0.148240	-0.058443	
total_rec_int	0.717161	0.494107	0.635402	0.258774	0.086350	0.086989	0.009989	0.122141	0.002425	
total_rec_late_fee	0.074678	0.098672	0.094787	0.030246	-0.007898	-0.019279	0.025606	0.004477	0.042009	
recoveries	0.236583	0.177951	0.215815	0.073700	0.006876	0.035273	0.019713	0.036615	0.015623	
collection_recovery_fee	0.124425	0.092084	0.135871	0.050338	0.003010	0.013422	0.023726	0.028023	0.011054	
last_pymnt_amnt	0.321842	0.043035	0.306348	0.160883	0.042098	-0.016672	-0.013004	0.073030	-0.024958	
pub_rec_bankruptcies	-0.029117	0.092006	-0.030192	-0.013008	0.016238	0.012614	0.002685	0.085700	0.018730	

25 rows × 25 columns

In [295]:
```
plt.figure(figsize=(16, 16))
sns.heatmap(x.corr())
```

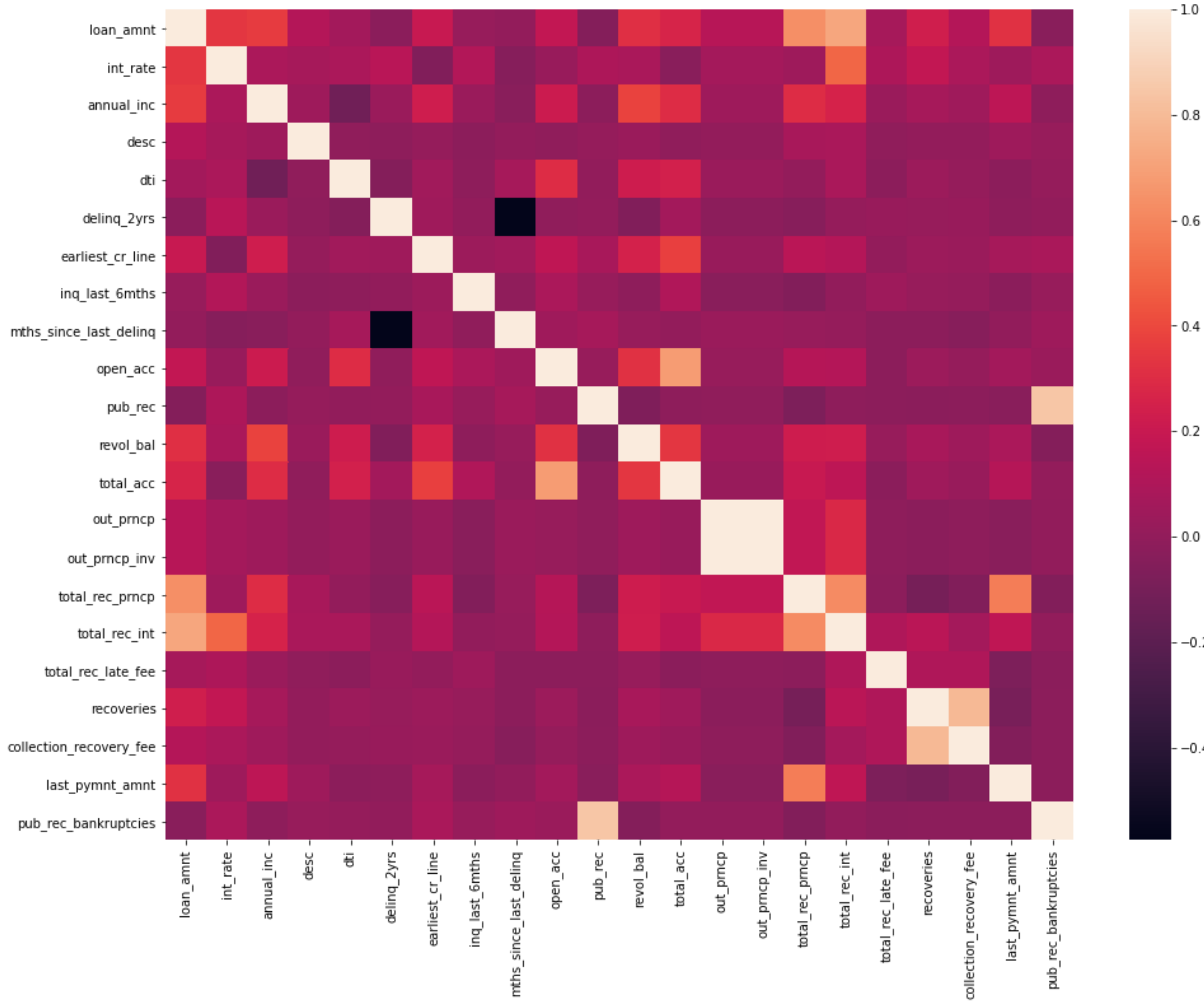
Out[295]: <AxesSubplot:>



In [296]:
```
x_rus.drop(columns=['installment','total_pymnt','total_pymnt_inv',],inplace=True)
```

In [297]:
```python
plt.figure(figsize=(16, 12))
sns.heatmap(x_rus.corr())
```

Out[297]: <AxesSubplot:>



In [298]:
```python
x_rus.drop(columns=['out_prncp_inv'],inplace=True)
```

In [299]:
```python
cols=list(x_rus.columns)
```

In [300]:
```python
d=[]
for i in cols:
    if x_rus[i].dtype == 'O':
        if len(x_rus[i].unique()) >=100:
            d.append(i)
d
```

Out[300]: ['emp_title', 'revol_util', 'last_pymnt_d']

the above code will find the columns whose having unique values greater than 100 so that we can remove them further

In [301]:
```python
x_rus['revol_util']=x_rus['revol_util'].str[0:-2]                    # removing last element
```

In [302]:
```python
x_rus['revol_util']=x_rus['revol_util'].replace(to_replace=['','0']).astype(float)  ## replacing empty character with
```

In [303]:
```python
x_rus['last_pymnt_d']=x_rus['last_pymnt_d'].str[-2:].astype(float)   # extracting last two elements
```

In [304]:
```
x_rus['earliest_cr_line']
```

Out[304]:
```
0        97.0
1        97.0
2        74.0
3         5.0
4        87.0
         ... 
11249    92.0
11250    94.0
11251    90.0
11252     4.0
11253    96.0
Name: earliest_cr_line, Length: 11254, dtype: float64
```

In [305]:
```
def year(x):
    if x>50:
        return 100-x
    else:
        return -x
```

The above code will be applied the feature so that it can find duration (last payment date - earliest credit line)

In [306]:
```
x_rus['earliest_cr_line']=x_rus['earliest_cr_line'].apply(year)
```

In [307]:
```
x_rus['duration']=x_rus['earliest_cr_line']+x_rus['last_pymnt_d']
```

In [308]:
```
x_rus.drop(columns=['last_pymnt_d','earliest_cr_line'],inplace=True)  ## drop these unwanted columns
```

In [309]:
```
cols=list(x_rus.columns)
for i in cols:
    print(i,x_rus[i].isnull().sum())
```

```
loan_amnt 0
term 0
int_rate 0
grade 0
sub_grade 0
emp_title 819
emp_length 370
home_ownership 0
annual_inc 0
verification_status 0
issue_d 0
desc 3649
purpose 0
addr_state 0
dti 0
delinq_2yrs 0
inq_last_6mths 0
mths_since_last_delinq 7145
open_acc 0
pub_rec 0
revol_bal 0
revol_util 19
total_acc 0
out_prncp 0
total_rec_prncp 0
total_rec_int 0
total_rec_late_fee 0
recoveries 0
collection_recovery_fee 0
last_pymnt_amnt 0
last_credit_pull_d 1
pub_rec_bankruptcies 217
duration 71
```

the above code will check for null values

In [310]:
```
x_rus['desc']=x_rus['desc'].fillna(0)
```

In [311]:
```
x_rus.drop(columns=['mths_since_last_delinq','emp_title'],inplace=True)
```

In [312]:
```
cols=list(x_rus.columns)
for i in cols:
    if x_rus[i].dtype=='O':
        print(i,x_rus[i].nunique())
```

```
term 2
grade 7
sub_grade 35
emp_length 11
home_ownership 5
verification_status 3
issue_d 54
purpose 14
addr_state 48
last_credit_pull_d 95
```

In [313]:
```
x_rus.drop(columns=['last_credit_pull_d'],inplace=True)
```

In [314]:
```
cols=list(x_rus.columns)
for i in cols:
    print(i,x_rus[i].dtype,x_rus[i].isnull().sum(),sep='     ')
```

```
loan_amnt     int64     0
term     object     0
int_rate     float64     0
grade     object     0
sub_grade     object     0
emp_length     object     370
home_ownership     object     0
annual_inc     float64     0
verification_status     object     0
issue_d     object     0
desc     float64     0
purpose     object     0
addr_state     object     0
dti     float64     0
delinq_2yrs     int64     0
inq_last_6mths     int64     0
open_acc     int64     0
pub_rec     int64     0
revol_bal     int64     0
revol_util     float64     19
total_acc     int64     0
out_prncp     float64     0
total_rec_prncp     float64     0
total_rec_int     float64     0
total_rec_late_fee     float64     0
recoveries     float64     0
collection_recovery_fee     float64     0
last_pymnt_amnt     float64     0
pub_rec_bankruptcies     float64     217
duration     float64     71
```

In [315]:
```
x_rus['emp_length']=x_rus['emp_length'].fillna(x_rus['emp_length'].describe()[2])
```

In [316]:
```
x_rus['revol_util']=x_rus['revol_util'].fillna(x_rus['revol_util'].mean())
```

In [317]:
```
x_rus['pub_rec_bankruptcies']=x_rus['pub_rec_bankruptcies'].fillna(x_rus['pub_rec_bankruptcies'].mean())
```

In [318]:
```
x_rus['duration']=x_rus['duration'].fillna(x_rus['duration'].mean())
```

In [319]:
```
cols=list(x_rus.columns)
for i in cols:
    print(i,x_rus[i].dtype,x_rus[i].isnull().sum(),sep='     ')
```

```
loan_amnt     int64     0
term     object     0
int_rate     float64     0
grade     object     0
sub_grade     object     0
emp_length     object     0
home_ownership     object     0
annual_inc     float64     0
verification_status     object     0
issue_d     object     0
desc     float64     0
purpose     object     0
addr_state     object     0
dti     float64     0
delinq_2yrs     int64     0
inq_last_6mths     int64     0
open_acc     int64     0
pub_rec     int64     0
revol_bal     int64     0
revol_util     float64     0
total_acc     int64     0
out_prncp     float64     0
total_rec_prncp     float64     0
total_rec_int     float64     0
total_rec_late_fee     float64     0
recoveries     float64     0
collection_recovery_fee     float64     0
last_pymnt_amnt     float64     0
pub_rec_bankruptcies     float64     0
duration     float64     0
```

In [320]:
```
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import OrdinalEncoder
```

In [321]:
```
l=[]
for i in cols:
    if x_rus[i].dtype=='O':
        l.append(i)
l
```

Out[321]:
```
['term',
 'grade',
 'sub_grade',
 'emp_length',
 'home_ownership',
 'verification_status',
 'issue_d',
 'purpose',
 'addr_state']
```

In [322]:
```python
ohe = OneHotEncoder(drop='first',sparse=True)
df1 = ohe.fit_transform(x_rus[l])
df1 = pd.DataFrame(df1.toarray())
df1
```

```
C:\Users\N CH SHANMUKHA\anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:868: FutureWarning: `sparse` w
as renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you leave
`sparse` to its default value.
  warnings.warn(
```

Out[322]:

	0	1	2	3	4	5	6	7	8	9	...	160	161	162	163	164	165	166	167	168	169
0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
1	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
11249	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11250	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11251	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11252	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0
11253	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

11254 rows × 170 columns

In [323]:
```python
x_rus.shape
```

Out[323]: (11254, 30)

In [324]:
```python
x_rus.drop(columns=l,inplace=True)
```

In [325]:
```python
x_rus=pd.concat([x_rus,df1],axis=1)
x_rus
```

Out[325]:

	loan_amnt	int_rate	annual_inc	desc	dti	delinq_2yrs	inq_last_6mths	open_acc	pub_rec	revol_bal	...	160	161	162	163	164	16
0	16000	13.0	65000.0	83.0	4.23	0	1	3	0	7634	...	0.0	0.0	0.0	0.0	1.0	0.
1	25000	14.6	106000.0	0.0	7.15	0	2	9	0	29579	...	0.0	0.0	0.0	0.0	0.0	0.
2	5000	16.4	60000.0	52.0	24.50	0	2	11	0	35018	...	0.0	0.0	0.0	0.0	0.0	0.
3	10000	7.5	30000.0	293.0	4.04	0	1	8	0	4905	...	0.0	0.0	0.0	0.0	0.0	0.
4	9000	11.1	105000.0	0.0	12.13	0	0	8	0	26541	...	0.0	0.0	0.0	0.0	0.0	0.
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
11249	2500	12.8	32000.0	75.0	20.00	0	1	11	0	3408	...	0.0	0.0	0.0	0.0	0.0	0.
11250	2500	9.6	75000.0	37.0	20.00	0	3	9	0	269	...	0.0	0.0	0.0	0.0	0.0	0.
11251	6500	15.0	213000.0	1002.0	6.45	0	0	11	0	56411	...	0.0	0.0	0.0	0.0	0.0	0.
11252	1000	10.5	33990.0	207.0	14.47	0	1	9	0	4485	...	0.0	0.0	0.0	0.0	1.0	0.
11253	20000	13.4	145000.0	11.0	10.15	0	0	17	0	41674	...	0.0	0.0	0.0	0.0	0.0	0.

11254 rows × 191 columns

In [326]:
```python
x_rus.columns = x_rus.columns.astype(str)
```

In [327]:
```python
from sklearn.preprocessing import StandardScaler
scaler =  StandardScaler()
scaler.fit(x_rus)
x = scaler.transform(x_rus)
x
```

Out[327]:
```
array([[ 0.56504861,  0.07443684, -0.01671238, ..., -0.10293816,
        -0.05972411, -0.03889549],
       [ 1.71852604,  0.49467183,  0.84720819, ..., -0.10293816,
        -0.05972411, -0.03889549],
       [-0.84475715,  0.96743619, -0.12206855, ..., -0.10293816,
        -0.05972411, -0.03889549],
       ...,
       [-0.65251091,  0.59973057,  3.10183017, ..., -0.10293816,
        -0.05972411, -0.03889549],
       [-1.35741379, -0.58218033, -0.67013133, ..., -0.10293816,
        -0.05972411, -0.03889549],
       [ 1.07770524,  0.17949559,  1.6689863 , ..., -0.10293816,
        -0.05972411, -0.03889549]])
```

In [328]:
```python
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y_rus, test_size=0.30, random_state=32)
```

In [329]:
```python
from sklearn.tree import DecisionTreeClassifier
dtree_model = DecisionTreeClassifier().fit(x_train, y_train)
dtree_predictions = dtree_model.predict(x_test)
```

In [330]:
```python
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, dtree_predictions)
cm
```

Out[330]:
```
array([[1605,   43],
       [  42, 1687]], dtype=int64)
```

In [331]:
```python
from sklearn.metrics import accuracy_score
accuracy_score(y_test,dtree_predictions)
```

Out[331]:
```
0.9748297305300563
```

In [332]:
```python
from sklearn.metrics import f1_score
f1_score(y_test, dtree_predictions)
```

Out[332]:
```
0.9754264238219139
```

In [333]:
```python
from sklearn.metrics import recall_score
dtree_recall=recall_score(y_test,dtree_predictions)
dtree_recall
```

Out[333]:
```
0.9757085020242915
```

In [334]:
```python
from sklearn.naive_bayes import GaussianNB
gnb = GaussianNB().fit(x_train, y_train)
gnb_predictions = gnb.predict(x_test)
gnb_predictions
```

Out[334]:
```
array([1, 0, 0, ..., 1, 1, 1])
```

In [335]:
```python
train_acc=gnb.predict(x_train)
accuracy_score(y_train,train_acc)
```

Out[335]:
```
0.7463501332994795
```

In [336]:
```python
recall=recall_score(y_test,gnb_predictions)
recall
```

Out[336]:
```
0.9676113360323887
```

In [337]:
```
from sklearn.ensemble import RandomForestClassifier
classifier = RandomForestClassifier(n_estimators = 15, criterion = 'gini', random_state = 40)
classifier.fit(x_train, y_train)
```

Out[337]:
```
RandomForestClassifier
RandomForestClassifier(n_estimators=15, random_state=40)
```

In [338]:
```
rfc_predictions=classifier.predict(x_test)
rfc_predictions
```

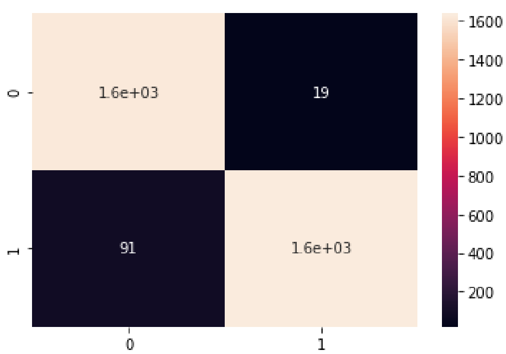
Out[338]: `array([1, 0, 0, ..., 0, 1, 0])`

In [339]:
```
train_acc=classifier.predict(x_train)
accuracy_score(y_train,train_acc)
```

Out[339]: `0.9993652405738225`

In [340]:
```
print(sns.heatmap((confusion_matrix(y_test, rfc_predictions)),annot=True))
```

```
AxesSubplot(0.125,0.125;0.62x0.755)
```



In [341]:
```
recall=recall_score(y_test,rfc_predictions)
recall
```

Out[341]: `0.9473684210526315`

In [342]:
```
f1_score(y_test,rfc_predictions)
```

Out[342]: `0.96751329001772`

Considering the above accuracy scores of the above algorithms it seems to be random forest is giving the best results among others so we are saving the model which used random forest.

Saving The Model

In [343]:
```
import pickle
pickle.dump(classifier, open('model2.pkl', 'wb'))
pickled_model = pickle.load(open('model2.pkl', 'rb'))
pickled_model.predict(x_test)
```

Out[343]: `array([1, 0, 0, ..., 0, 1, 0])`

In [ ]:
```

```