DATA FEATURES

1 credit. policy it is ‘1’ if the customer meets the credit underwriting criteria of LendingClub.com, and ‘0’ otherwise

2 purpose The purpose of the loan (takes values "credit_card", "debt_consolidation", "educational", "major_purchase", "small_business", and "all other").

3 int.rate The interest rate of the loan, proportionate to the amount of riskiness (a rate of 11% would be stored as 0.11). E.g. - Borrowers judged by LendingClub.com to be riskier, are assigned higher interest rates

4 installment The monthly installments that a borrower owes to the lending company, if the loan is funded.

5 log.annual.inc The natural log of the self-reported annual income of the borrower.

6 di The debt-to-income ratio of the borrower (amount of debt divided by annual income).

7 fico The FICO credit score of the borrower. (FICO is a credit bureau similar to RBI for banks)

8 days.with.cr.line The number of days the borrower has had a credit line.

9 vol. bal The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle)

10 vol. util The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available).

11 in. last.6 months The borrower's number of inquiries by creditors in the last 6 months.

12 delinq.2yrs The number of times the borrower had been 30+ days past due on a payment in the past 2 years.

13 pub.rec The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

14 not. fully.paid (Target) Whether a borrower will fully pay off the loan or not.

In [1]:
```
import os
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

Firstly this is a SUPERVISED Learning Task

In [3]:
```
df=pd.read_csv("C:/Users/srial/Downloads/Dataset (4).csv")
df
```

Out[3]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.
...	...	...	...	...	...	...	...	
9573	0	all_other	0.1461	344.76	12.180755	10.39	672	10474.
9574	0	all_other	0.1253	257.70	11.141862	0.21	722	4380.
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	687	3450.
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	692	1800.
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	732	4740.

In [20]:
```
pd.crosstab(df['not.fully.paid'],df['credit.policy'])
```

Out[20]:

credit.policy	0	1
not.fully.paid		
0	1349	6696
1	519	1014

In [21]:
```
pd.crosstab(df['not.fully.paid'],df['credit.policy'],normalize=True)
```

Out[21]:

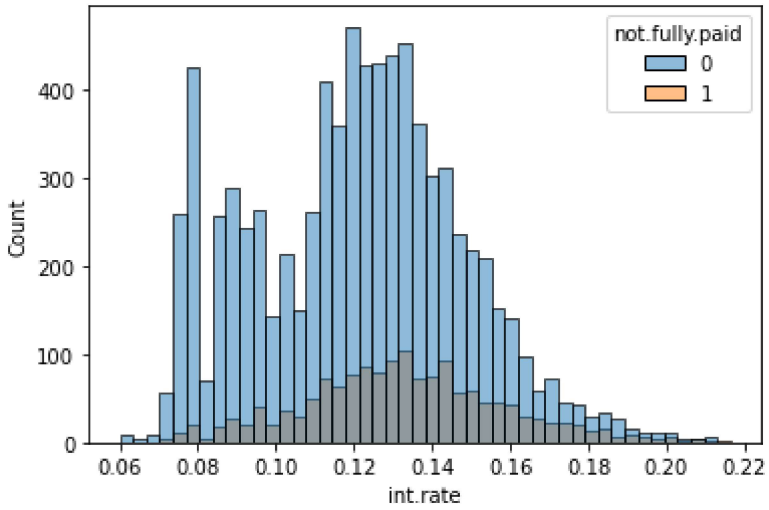
credit.policy	0	1
not.fully.paid		
0	0.140844	0.699102
1	0.054187	0.105868

In [ ]:
```

```

In [22]:
```
sns.histplot(x='int.rate',hue='not.fully.paid',data=df)
```

Out[22]:
```
<AxesSubplot:xlabel='int.rate', ylabel='Count'>
```



we interpret that people who didn't meet the credit policy members are not have high rate of not paying loan fully

In [23]:
```
df['not.fully.paid'].value_counts()
```

Out[23]:
```
0    8045
1    1533
Name: not.fully.paid, dtype: int64
```

from target variable we clearly say that this is classification problem

In [24]:
```
df.shape
```

Out[24]:
```
(9578, 14)
```

In [25]:
```
df.columns
```

Out[25]:
```
Index(['credit.policy', 'purpose', 'int.rate', 'installment', 'log.annual.inc',
       'dti', 'fico', 'days.with.cr.line', 'revol.bal', 'revol.util',
       'inq.last.6mths', 'delinq.2yrs', 'pub.rec', 'not.fully.paid'],
      dtype='object')
```

Data exploring

In [26]:
```
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
```

we have only one categorical variable...(purpose)

Null values

In [27]:
```
df.isnull().sum()
```

Out[27]:
```
credit.policy        0
purpose              0
int.rate             0
installment          0
log.annual.inc       0
dti                  0
fico                 0
days.with.cr.line    0
revol.bal            0
revol.util           0
inq.last.6mths       0
delinq.2yrs          0
pub.rec              0
not.fully.paid       0
dtype: int64
```

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unique values

In [28]:
```
for i in df.columns:
    print(i,'-----',round((df[i].nunique()/df.shape[0])*100,3))
```

```
credit.policy ----- 0.021
purpose ----- 0.073
int.rate ----- 2.6
installment ----- 49.99
log.annual.inc ----- 20.745
dti ----- 26.404
fico ----- 0.459
days.with.cr.line ----- 28.054
revol.bal ----- 82.157
revol.util ----- 10.806
inq.last.6mths ----- 0.292
delinq.2yrs ----- 0.115
pub.rec ----- 0.063
not.fully.paid ----- 0.021
```

duplicates

In [29]:
```
df.duplicated().sum()
```

Out[29]:
```
0
```

categorical variable

In [30]:
```
df['purpose'].value_counts()
```

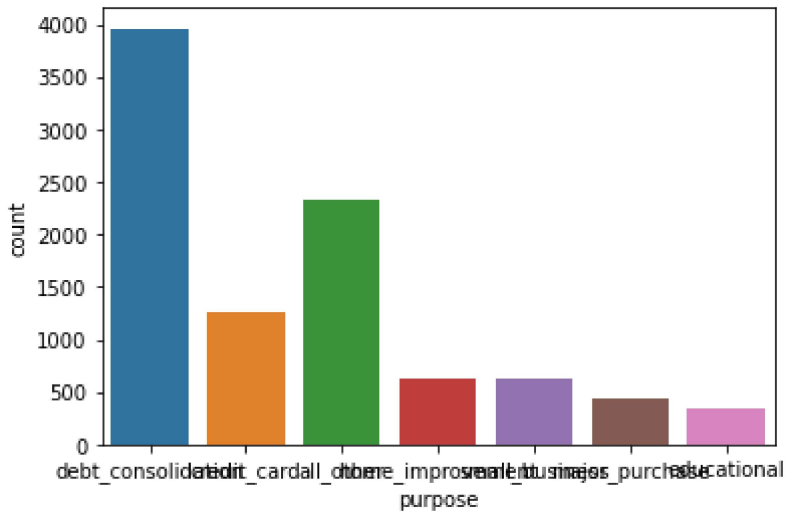
Out[30]:
```
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: purpose, dtype: int64
```

In [31]:
```
###debt_consolidtaion candidates are more('for clearing debts')
```

In [7]:
```
sns.countplot(df['purpose']);
plt.figure(figsize=(35,5))
```

```
C:\Users\srial\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWar
ning: Pass the following variable as a keyword arg: x. From version 0.12, the o
nly valid positional argument will be `data`, and passing other arguments witho
ut an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[7]:
```
<Figure size 2520x360 with 0 Axes>
```




```
<Figure size 2520x360 with 0 Axes>
```

In [33]:
```
df.describe(include='O')
```

Out[33]:

	purpose
count	9578
unique	7
top	debt_consolidation
freq	3957

numerical variables

In [34]:
```
df.describe(percentiles=[0.2,0.85,0.95,0.99])
```

Out[34]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.c
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.0
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.7
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.9
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.9
20%	1.000000	0.096300	143.384000	10.463103	5.930000	677.000000	2504.0
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.9
85%	1.000000	0.149600	534.410000	11.512925	20.554500	752.000000	6967.2
95%	1.000000	0.167000	756.265500	11.918391	23.650000	782.000000	9329.9
99%	1.000000	0.188600	870.390000	12.484574	26.242300	802.000000	12930.0
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.9

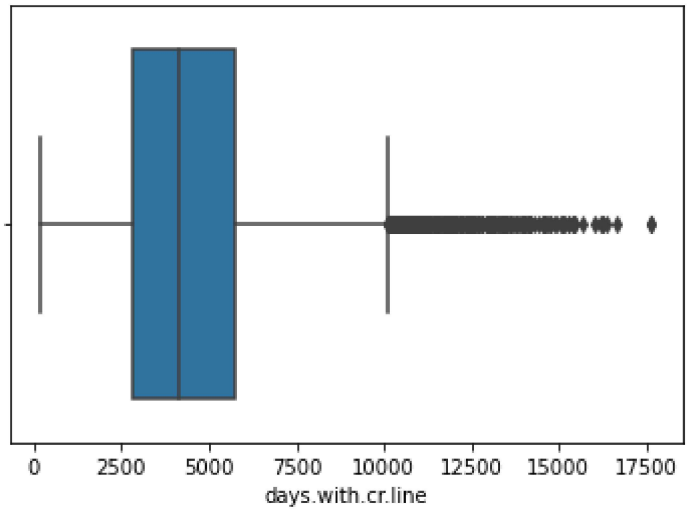
In [35]:
```
df['days.with.cr.line'].describe()
```

Out[35]:
```
count     9578.000000
mean      4560.767197
std       2496.930377
min        178.958333
25%       2820.000000
50%       4139.958333
75%       5730.000000
max      17639.958330
Name: days.with.cr.line, dtype: float64
```

In [36]:
```
import warnings
warnings.filterwarnings(action='ignore')
```

In [37]:
```
sns.boxplot(df['days.with.cr.line'])
```

Out[37]:
```
<AxesSubplot:xlabel='days.with.cr.line'>
```



In [38]:
```
q1=df['days.with.cr.line'].quantile(0.25)
q3=df['days.with.cr.line'].quantile(0.75)
iqr=q3-q1
iqr
```

Out[38]:
```
2910.0
```

In [39]:
```
ll=q1-3*iqr
ul=q3+3*iqr
ll,ul
```

Out[39]:
```
(-5910.0, 14460.0)
```

by extreme outliers

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exploring each variable(univariate)

In [40]:
```
df
```

Out[40]:

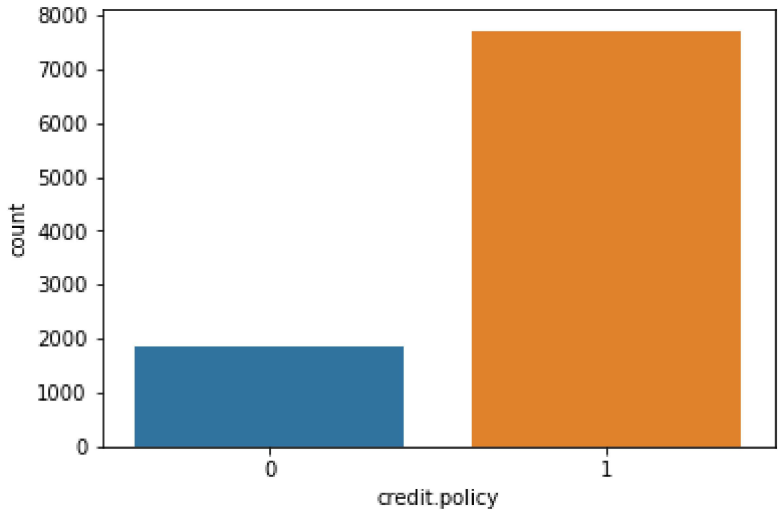
	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.l
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000
...	...	...	...	...	...	...	...	...
9573	0	all_other	0.1461	344.76	12.180755	10.39	672	10474.000
9574	0	all_other	0.1253	257.70	11.141862	0.21	722	4380.000
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	687	3450.041
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	692	1800.000
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	732	4740.000

9578 rows × 14 columns

###credit policy

In [41]:
```
sns.countplot(df['credit.policy'])
```

Out[41]:
```
<AxesSubplot:xlabel='credit.policy', ylabel='count'>
```



In [42]:
```
df['credit.policy'].value_counts()
```

Out[42]:
```
1    7710
0    1868
Name: credit.policy, dtype: int64
```

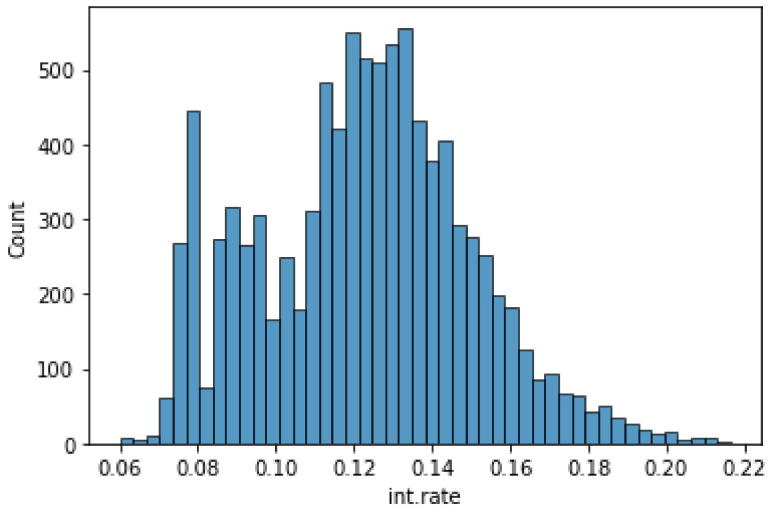
(int.rate)

In [43]:
```
df['int.rate'].value_counts()
```

Out[43]:
```
0.1253    354
0.0894    299
0.1183    243
0.1218    215
0.0963    210
          ...
0.1756      1
0.1741      1
0.1772      1
0.1746      1
0.1941      1
Name: int.rate, Length: 249, dtype: int64
```

In [44]:
```
sns.histplot(df['int.rate'])
```

Out[44]:
```
<AxesSubplot:xlabel='int.rate', ylabel='Count'>
```

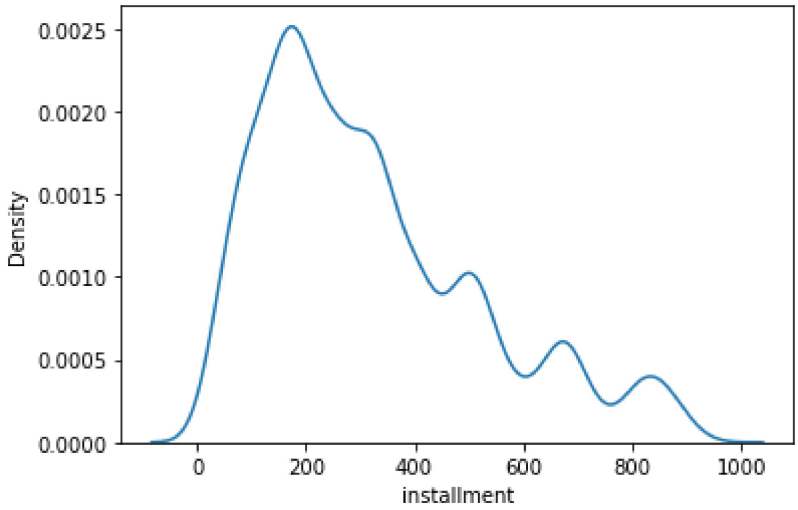


In [45]:
```
###MORE MEMBERS HAVE INTEREST RATE FROM 0.12 PAISA TO 0.15 PAISA
```

installment

In [46]:
```
sns.kdeplot(df['installment'])
```

Out[46]:
```
<AxesSubplot:xlabel='installment', ylabel='Density'>
```

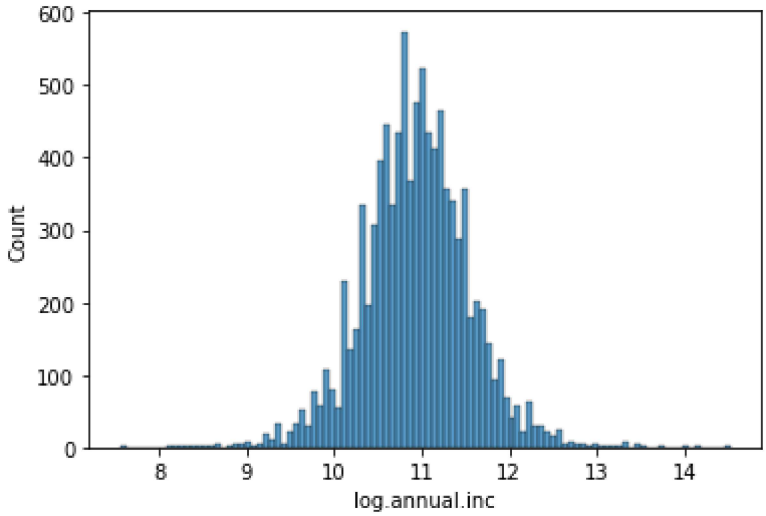


In [47]:
```
###most customers have paying installments from 100 to 400
```

log.annual.inc

In [48]:
```
sns.histplot(df['log.annual.inc'])
```

Out[48]:
```
<AxesSubplot:xlabel='log.annual.inc', ylabel='Count'>
```

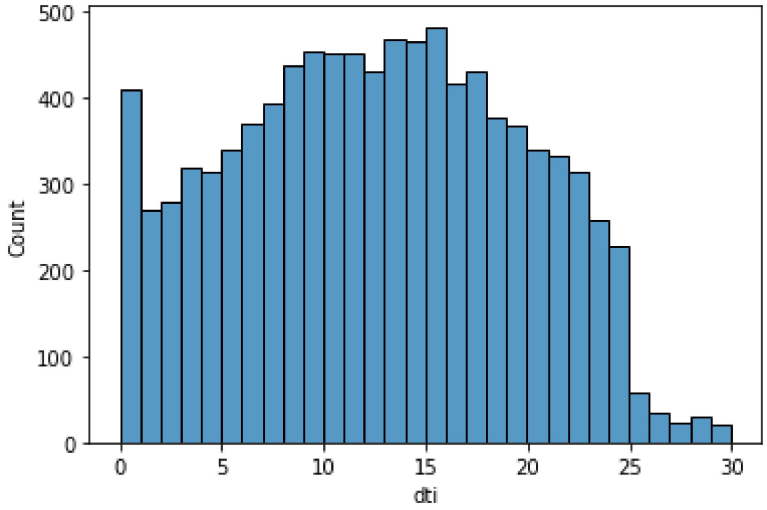


In [49]:
```
### mostly members annual income is from 10 to 12
```

debt/income

In [50]:
```
sns.histplot(df['dti'])
```

Out[50]:
```
<AxesSubplot:xlabel='dti', ylabel='Count'>
```

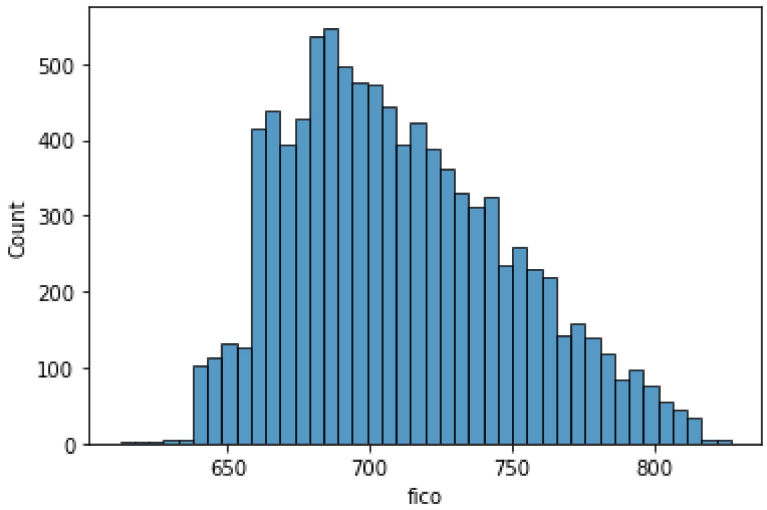


In [51]:
```
## example for if a person has 10000 debt then lets assuume his annual income wil
## members have d/i ratio ranging from 1 to 30
```

fico(credit score)

In [52]:
```
sns.histplot(df['fico'])
```

Out[52]:
```
<AxesSubplot:xlabel='fico', ylabel='Count'>
```



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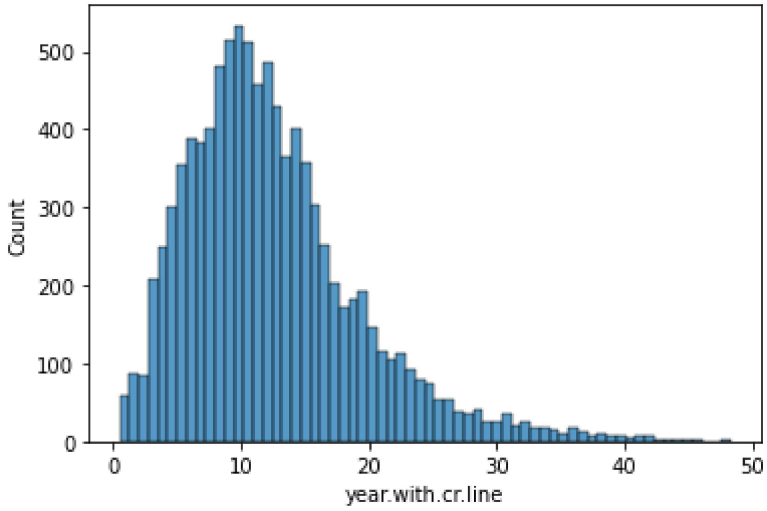
days.with.credit.line

In [53]:
```
df['year.with.cr.line']=df['days.with.cr.line']/365
###converting days into years
df.drop(labels=['days.with.cr.line'],axis=1,inplace=True)
##dropping the days.with.cr.line
```

In [54]:
```
sns.histplot(df['year.with.cr.line'])
```

Out[54]: <AxesSubplot:xlabel='year.with.cr.line', ylabel='Count'>

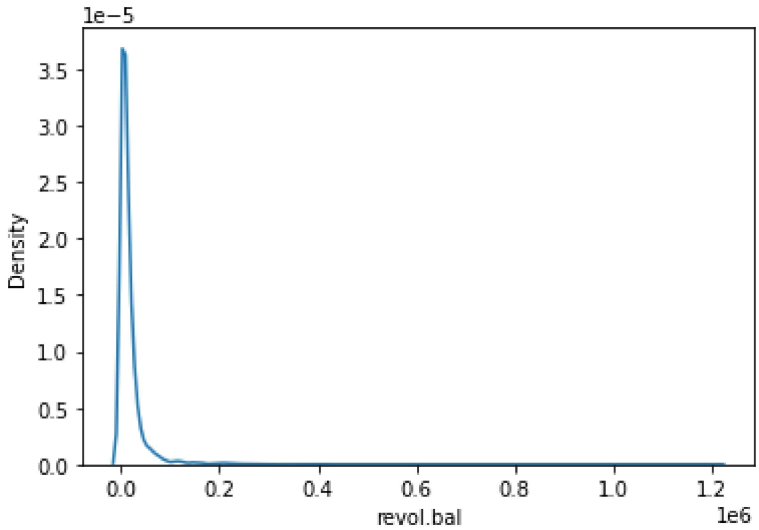


In [55]:
```
###most members repayment years  is from 0-20
```

revol.bal

In [56]:
```
sns.kdeplot(df['revol.bal'])
```

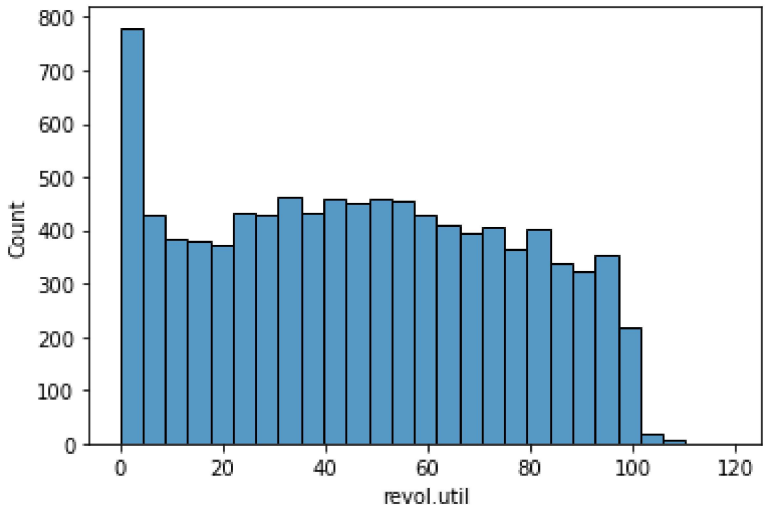
Out[56]: <AxesSubplot:xlabel='revol.bal', ylabel='Density'>



revol.util

In [57]:
```
sns.histplot(df['revol.util'])
```

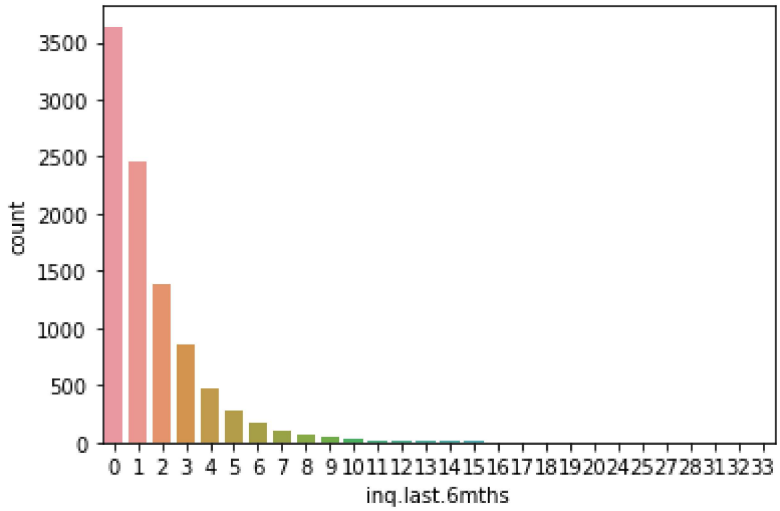
Out[57]:
```
<AxesSubplot:xlabel='revol.util', ylabel='Count'>
```



inq.last.6mths

In [58]:
```
sns.countplot(df['inq.last.6mths'])
```

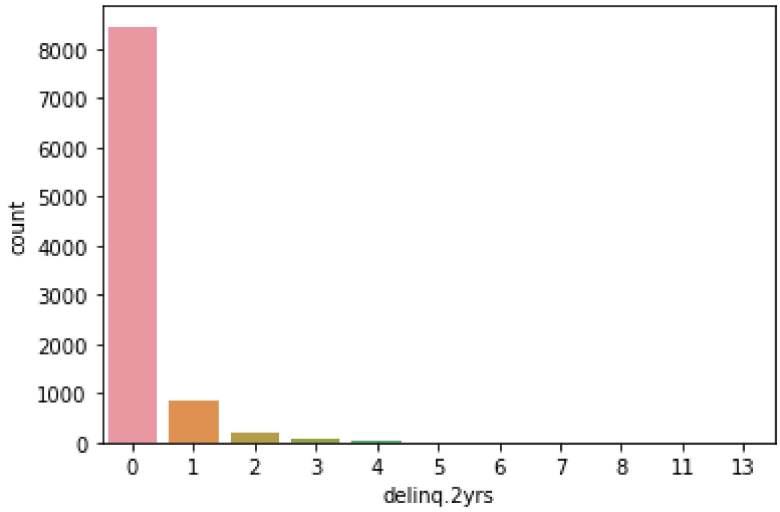
Out[58]:
```
<AxesSubplot:xlabel='inq.last.6mths', ylabel='count'>
```



delinq.2yrs

In [59]:
```
sns.countplot(df['delinq.2yrs'])
```

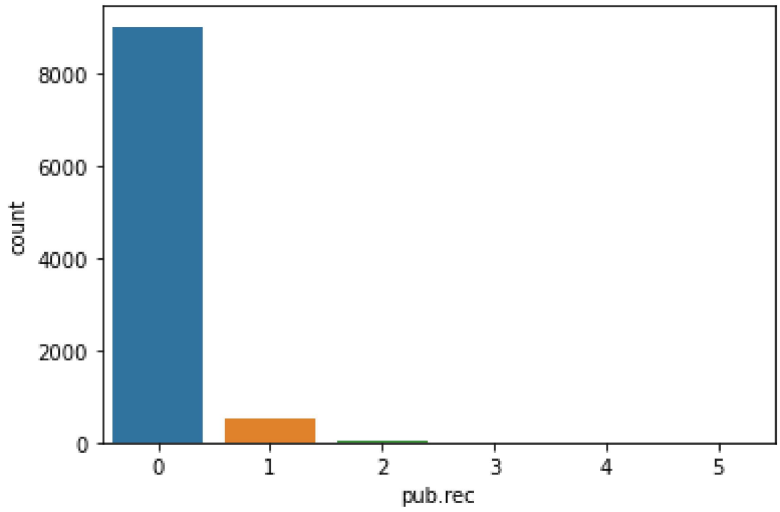
Out[59]:
```
<AxesSubplot:xlabel='delinq.2yrs', ylabel='count'>
```



pub.rec

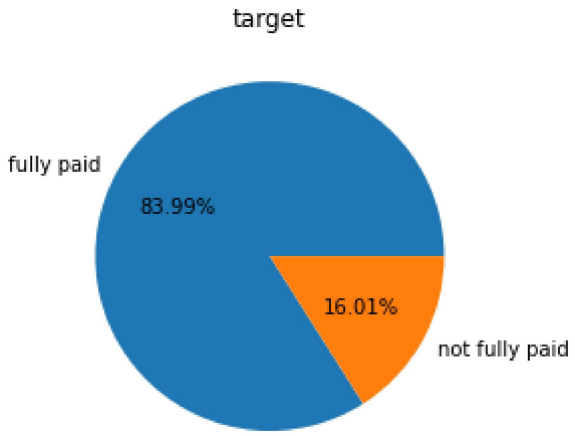
In [60]:
```
sns.countplot(df['pub.rec'])
```

Out[60]:
```
<AxesSubplot:xlabel='pub.rec', ylabel='count'>
```

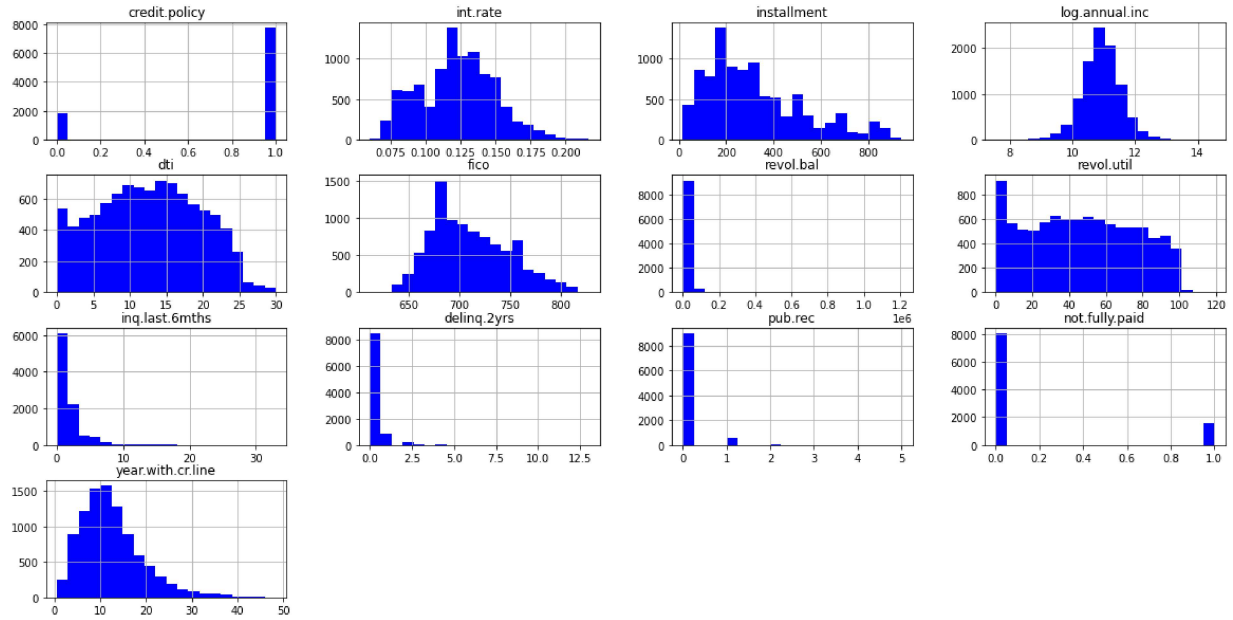


target one

In [61]:



In [62]:
```
df.hist(bins = 20, figsize = (20,10), color = 'b');
```



lets our asses begin....

firstly rename the names

In [63]:
```
df.columns
```

Out[63]:
```
Index(['credit.policy', 'purpose', 'int.rate', 'installment', 'log.annual.inc',
       'dti', 'fico', 'revol.bal', 'revol.util', 'inq.last.6mths',
       'delinq.2yrs', 'pub.rec', 'not.fully.paid', 'year.with.cr.line'],
      dtype='object')
```

In [64]:
```
df1=df.rename(columns={'int.rate':'interestrate','log.annual.inc':'annual income'
```

In [65]:
```
df1
```

Out[65]:

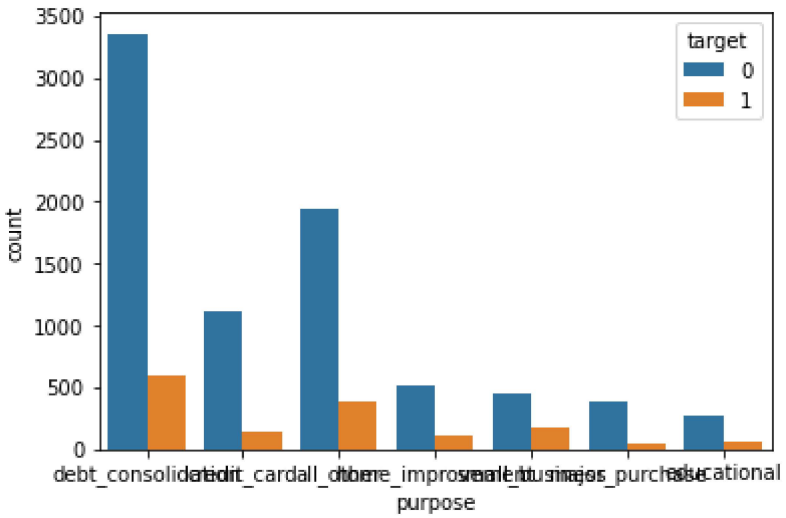
	credit.policy	purpose	interestrate	installment	annual income	debts/income	creditscor
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	73
1	1	credit_card	0.1071	228.22	11.082143	14.29	70
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	68
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	71
4	1	credit_card	0.1426	102.92	11.299732	14.97	66
...	...	...	...	...	...	...	...
9573	0	all_other	0.1461	344.76	12.180755	10.39	67
9574	0	all_other	0.1253	257.70	11.141862	0.21	72
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	68
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	69
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	73

9578 rows × 14 columns

Bivariate Analysis

In [66]:
```
sns.countplot(x=df1['purpose'],hue=df1['target'],orient='horizantal')
```

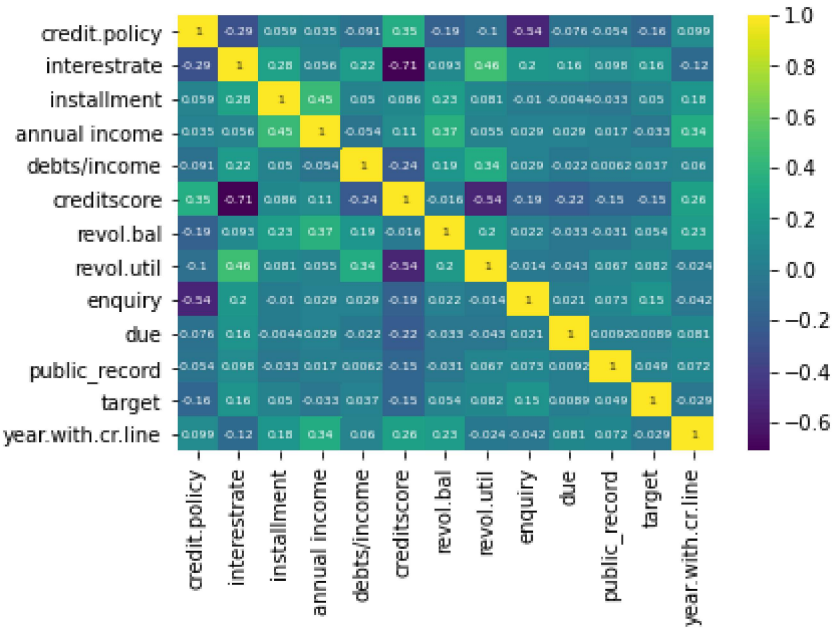
Out[66]:
```
<AxesSubplot:xlabel='purpose', ylabel='count'>
```



relation plot(corr)

In [67]:
```
sns.heatmap(df1.corr(),cmap='viridis',annot=True,annot_kws={"size":6})
plt.figure(figsize=(13,24))
```

Out[67]:
```
<Figure size 936x1728 with 0 Axes>
```

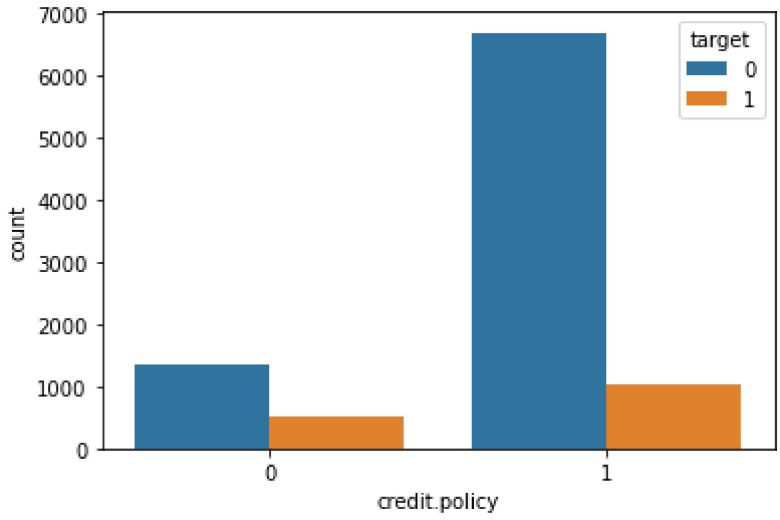



```
<Figure size 936x1728 with 0 Axes>
```

In [68]:
```
##we noticed some relation between  interest rate and credit score(0.71)
```

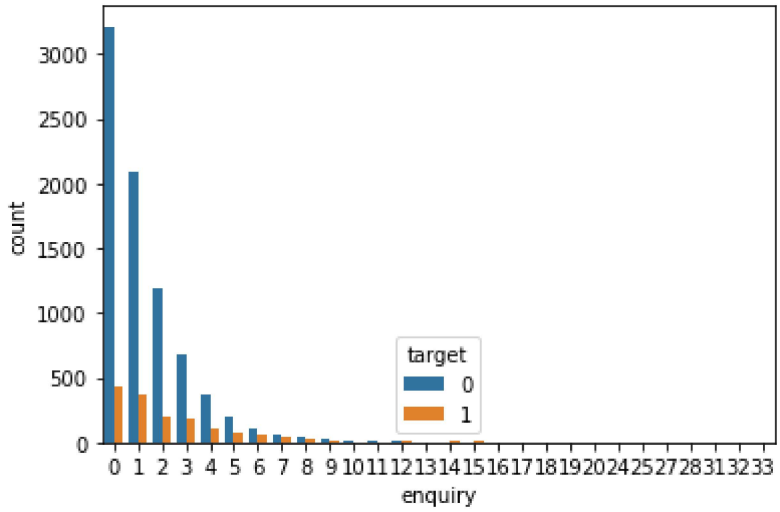
In [69]:
```
sns.countplot(x=df1['credit.policy'],hue=df1['target'])
```

Out[69]:
```
<AxesSubplot:xlabel='credit.policy', ylabel='count'>
```



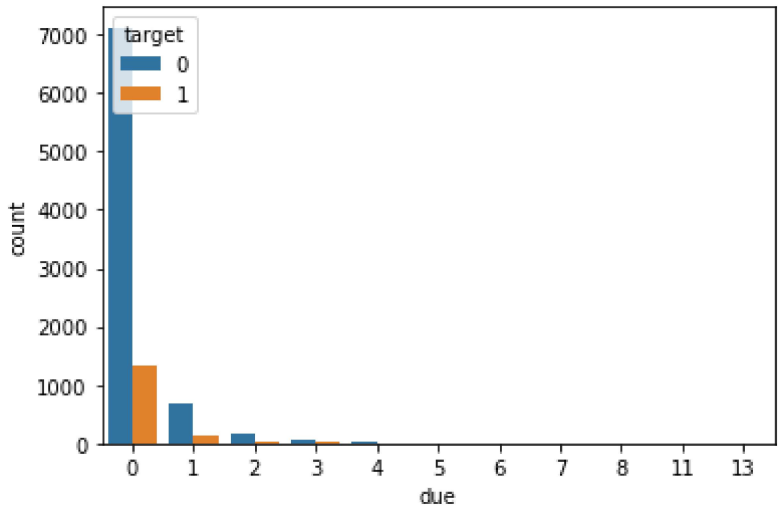
In [70]:
```
sns.countplot(x=df1['enquiry'],hue=df1['target'])
```

Out[70]: <AxesSubplot:xlabel='enquiry', ylabel='count'>



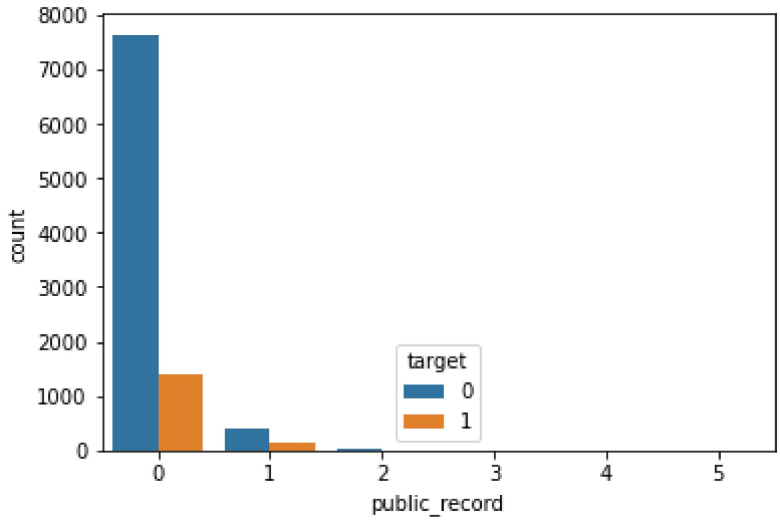
In [71]:
```
sns.countplot(x=df1['due'],hue=df1['target'])
```

Out[71]: <AxesSubplot:xlabel='due', ylabel='count'>



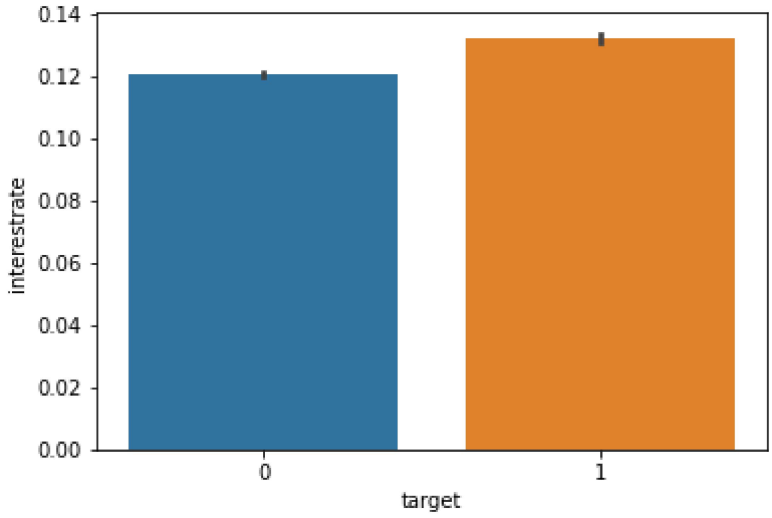
In [72]:
```
sns.countplot(x=df1['public_record'],hue=df1['target'])
```

Out[72]: <AxesSubplot:xlabel='public_record', ylabel='count'>



In [73]:
```
sns.barplot(y=df1['interestrate'],x=df1['target'])
```

Out[73]: <AxesSubplot:xlabel='target', ylabel='interestrate'>



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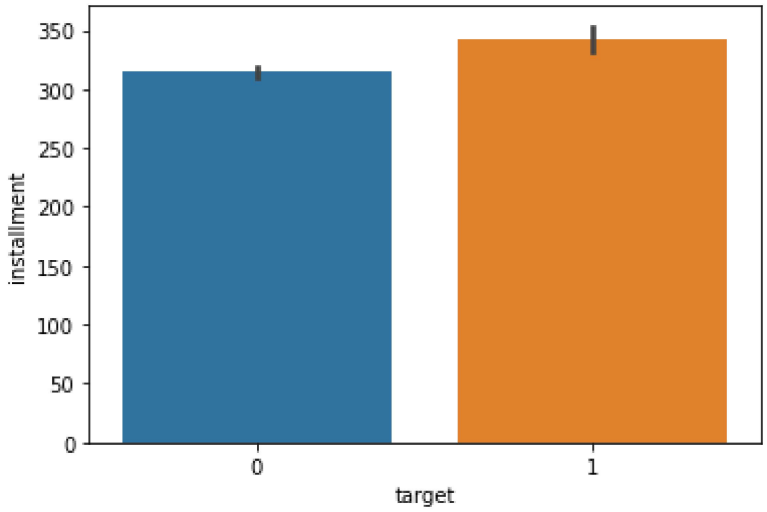
In [74]:
```
sns.barplot(y=df1['installment'],x=df1['target'])
```

Out[74]:
```
<AxesSubplot:xlabel='target', ylabel='installment'>
```



frequency for purposes

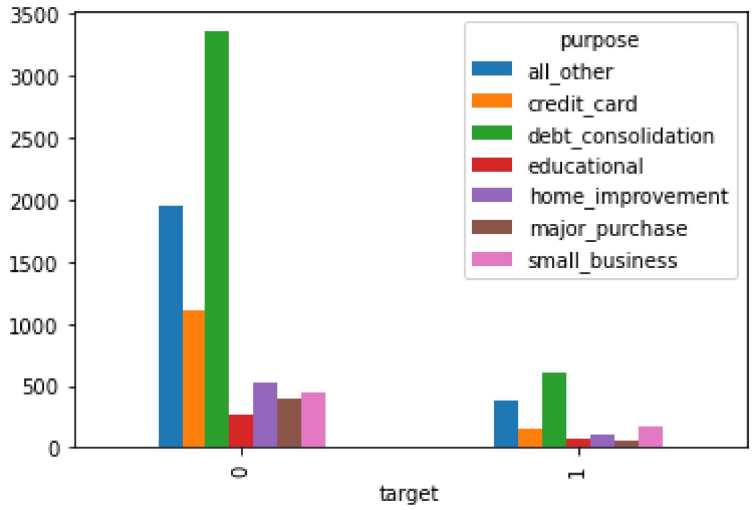
In [75]:
```
pd.crosstab(df1.target, df1.purpose)
```

Out[75]:

purpose	all_other	credit_card	debt_consolidation	educational	home_improvement	major_purchas
target						
0	1944	1116	3354	274	522	38
1	387	146	603	69	107	4

In [76]:
```
pd.crosstab(df1.target, df1.purpose).plot(kind='bar')
```

Out[76]: <AxesSubplot:xlabel='target'>



debt consolidations

In [ ]:
```
```

In [77]:
```
df1
```

Out[77]:

	credit.policy	purpose	interestrate	installment	annual income	debts/income	creditscor
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	73
1	1	credit_card	0.1071	228.22	11.082143	14.29	70
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	68
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	71
4	1	credit_card	0.1426	102.92	11.299732	14.97	66
...	...	...	...	...	...	...	.
9573	0	all_other	0.1461	344.76	12.180755	10.39	67
9574	0	all_other	0.1253	257.70	11.141862	0.21	72
9575	0	debt_consolidation	0.1071	97.81	10.596635	13.09	68
9576	0	home_improvement	0.1600	351.58	10.819778	19.18	69
9577	0	debt_consolidation	0.1392	853.43	11.264464	16.28	73

9578 rows × 14 columns

In [78]:
```
import hvplot.pandas
```

In [79]:
```
df1.hvplot.hist(y='interestrate', by='target', alpha=0.3)
```

Out[79]:

less interest guys have cleared their loans

In [80]:
```
df1.hvplot.hist(y='annual income', by='target', bins=50, alpha=0.3)
```

Out[80]:

In [ ]:
```

```

In [81]:
```
df1.hvplot.hist(y='creditscore', by='target', bins=50, alpha=0.3)
```

Out[81]:

we seethat high credit score members have fully paid

In [82]:
```
df1.hvplot.hist(y='debts/income', by='target', bins=50, alpha=0.3)
```

Out[82]:

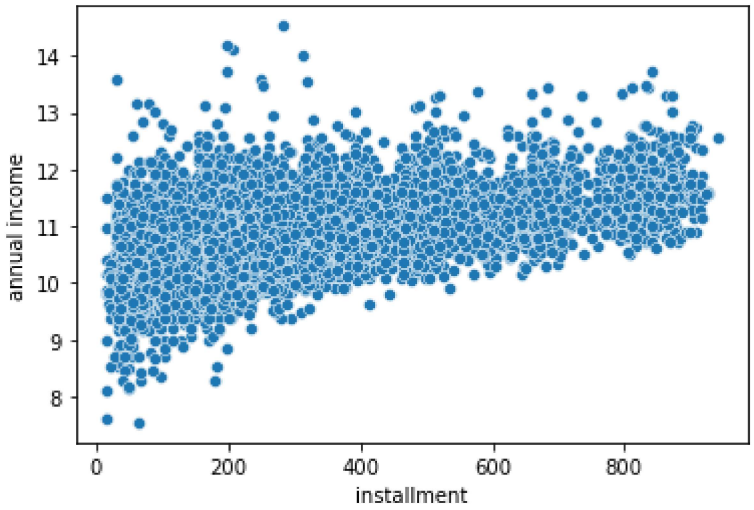
d/i ratio will always be low for repaying

In [83]:
```
df1.hvplot.hist(y='revol.bal', by='target', bins=50, alpha=0.3)
```

Out[83]:

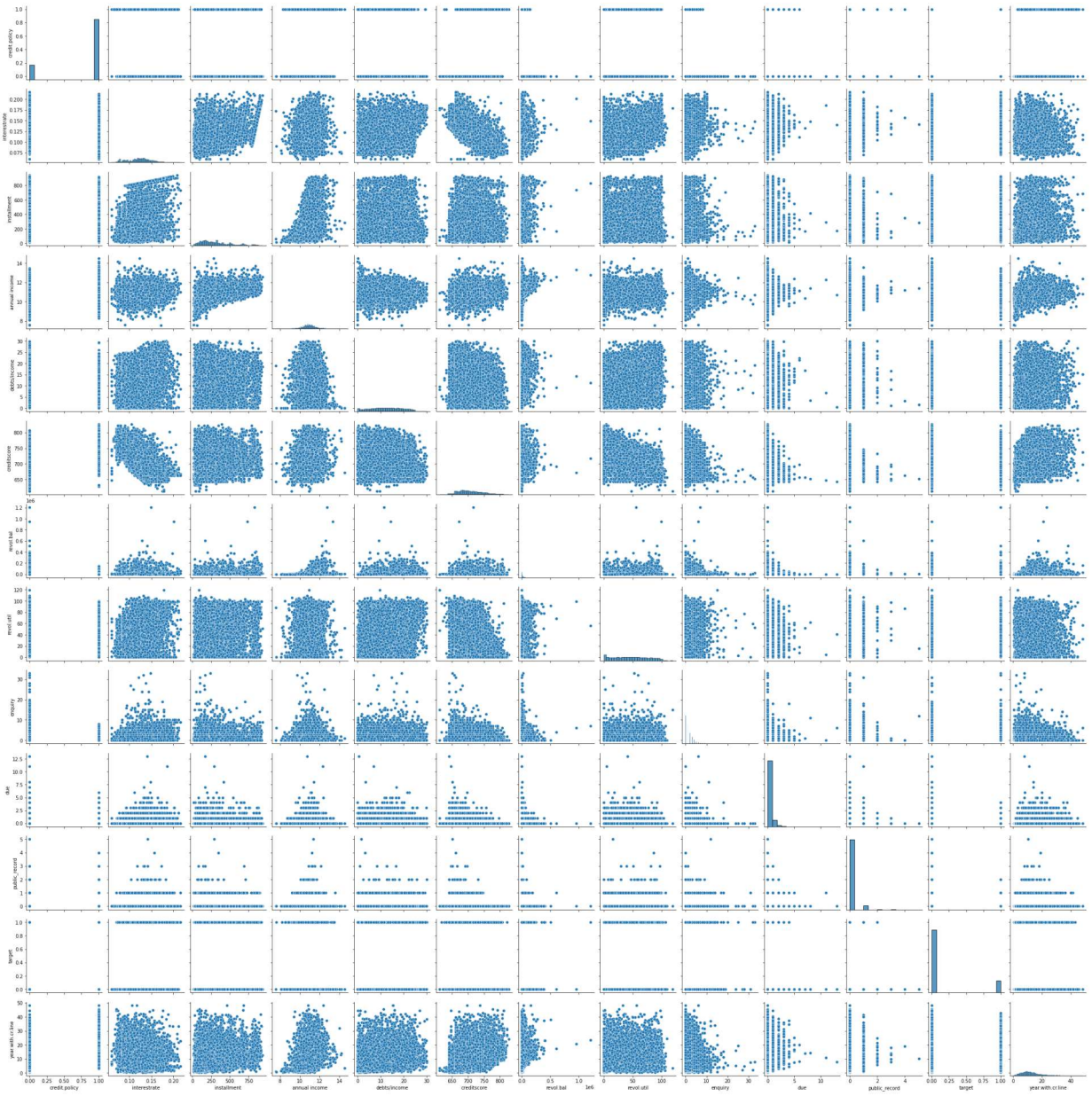
In [84]:
```
sns.scatterplot(x='installment',y='annual income',data=df1)
```

Out[84]:
```
<AxesSubplot:xlabel='installment', ylabel='annual income'>
```



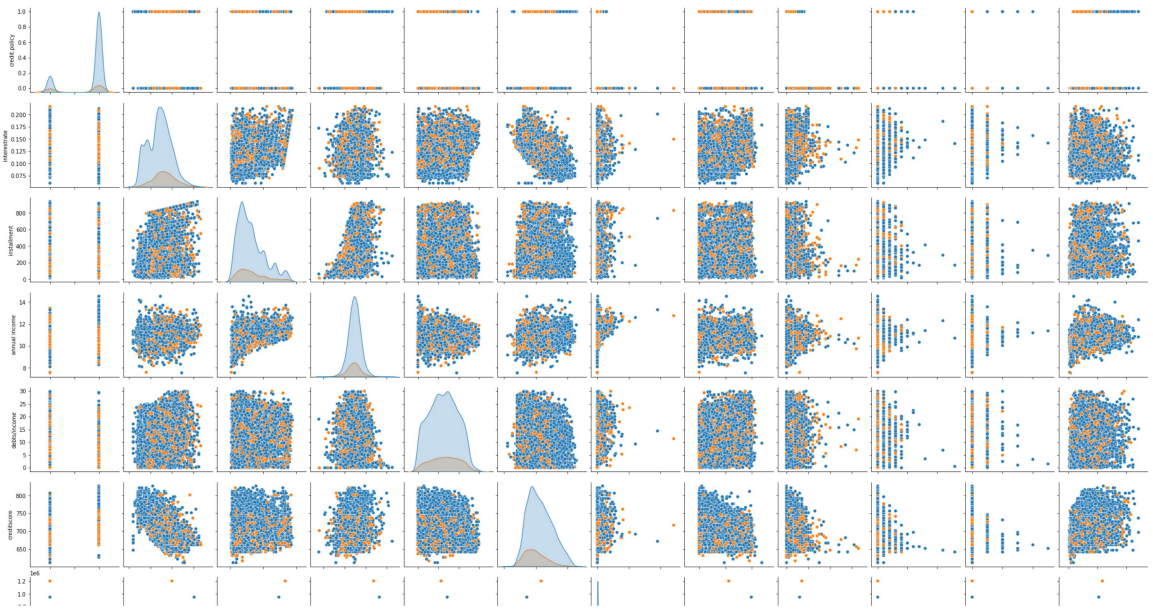
In [85]:
```
sns.pairplot(df1)
```

Out[85]:
```
<seaborn.axisgrid.PairGrid at 0x1f8fb9bcf70>
```



In [86]:
```
sns.pairplot(df1,hue='target')
```

Out[86]:
```
<seaborn.axisgrid.PairGrid at 0x1f88020d220>
```



In [ ]:
```

```

In [ ]:
```

```

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spltiing the data for modelling

In [87]:
```
from sklearn.model_selection import train_test_split
x=df1.drop(['target'],axis=1)
y=df1['target']
```

In [88]:
```
df['purpose'].value_counts()
```

Out[88]:
```
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: purpose, dtype: int64
```

firstly we see that our categorical variable is nominal one ...then we apply

1.pd.get dummies 2.one hot encoding

encode the training dataset

In [89]:
```
 x_encoded_s=pd.get_dummies(x,columns=['purpose'],drop_first=True)
x_encoded_s
```

Out[89]:

	credit.policy	interestrate	installment	annual income	debts/income	creditscore	revol.bal	revol.u
0	1	0.1189	829.10	11.350407	19.48	737	28854	52
1	1	0.1071	228.22	11.082143	14.29	707	33623	76
2	1	0.1357	366.86	10.373491	11.63	682	3511	25
3	1	0.1008	162.34	11.350407	8.10	712	33667	73
4	1	0.1426	102.92	11.299732	14.97	667	4740	39
...	...	...	...	...	...	...	...	
9573	0	0.1461	344.76	12.180755	10.39	672	215372	82
9574	0	0.1253	257.70	11.141862	0.21	722	184	1
9575	0	0.1071	97.81	10.596635	13.09	687	10036	82
9576	0	0.1600	351.58	10.819778	19.18	692	0	3
9577	0	0.1392	853.43	11.264464	16.28	732	37879	57

9578 rows × 18 columns

we use pd.get_dummies

we also convert the categorical to count stats as per becase we have different values in categorical

In [ ]:
```
```

In [94]:
```
from sklearn.ensemble import ExtraTreesClassifier
mo=ExtraTreesClassifier()
mo.fit(x_encoded_s,y)
print(mo.feature_importances_)
```

```
[0.02160234 0.10542818 0.10346293 0.10291493 0.09945324 0.09613961
 0.10094005 0.10207646 0.07192656 0.02764373 0.01531394 0.10086054
 0.00666715 0.01493909 0.00693782 0.00874019 0.00623567 0.00871757]
```

In [95]:
```
xtrain,xtest,ytrain,ytest=train_test_split(x_encoded_s,y,test_size=0.25)
```

model selection

In [96]:
```
from sklearn import tree
model=tree.DecisionTreeClassifier( criterion='gini')
```

In [126]:
```
model.fit(xtrain,ytrain)
```

Out[126]:
```
DecisionTreeClassifier()
```

In [98]:
```
model.score(xtest,ytest)
```

Out[98]:
```
0.7419624217118997
```

In [99]:
```
model.score(xtrain,ytrain)
```

Out[99]:
```
1.0
```

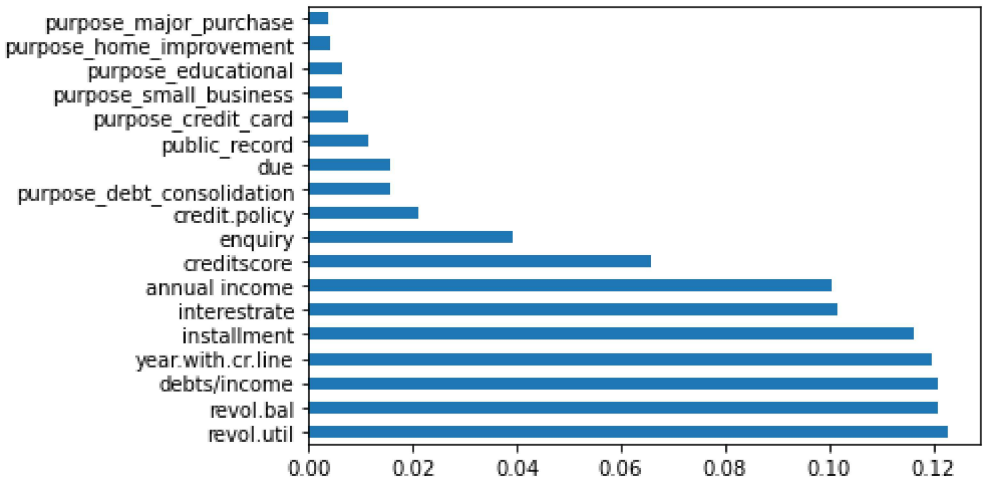
these are the important features or variable of the dataset

In [100]:
```
print(model.feature_importances_)
```

```
[0.02126267 0.10152835 0.11628112 0.10048087 0.12075118 0.06596796
 0.12082604 0.12292463 0.0390066  0.01549304 0.01146959 0.11968715
 0.00759706 0.01574614 0.00650699 0.00418759 0.00367542 0.00660759]
```

In [103]:
```
feature_importance=pd.Series(model.feature_importances_,index=x_encoded_s.columns
feature_importance.nlargest(19).plot(kind='barh')
plt.show
```

Out[103]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```

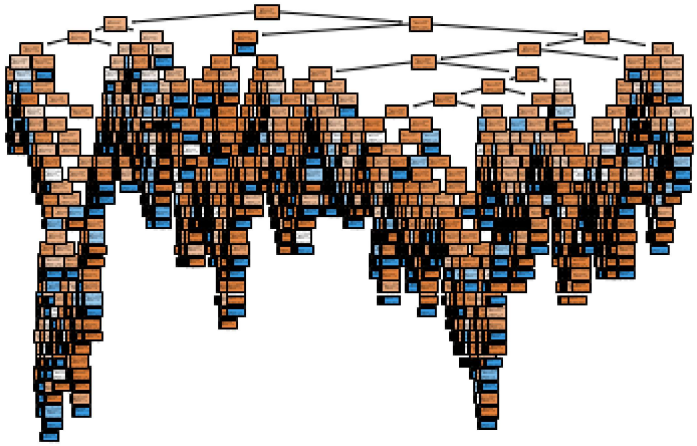


In [106]:
```
from sklearn.model_selection import cross_val_score
c=cross_val_score(model,x_encoded_s,y,cv=10)
c.mean()
```

Out[106]:
```
0.7100320024083612
```

In [ ]:

In [107]:
```
tree.plot_tree(model,filled=True,);
```



train

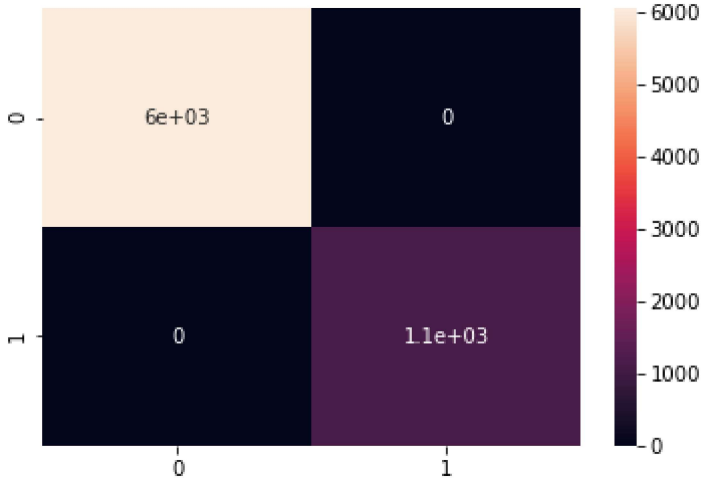
In [108]:
```
y_pred_train=model.predict(xtrain)
```

In [140]:
```
from sklearn.metrics import classification_report,confusion_matrix,roc_auc_score,
cm_train=confusion_matrix(ytrain,y_pred_train)
cm_train
```

Out[140]:
```
array([[6043,    0],
       [   0, 1140]], dtype=int64)
```

In [110]:
```
sns.heatmap(cm_train,annot=True)
```

Out[110]:
```
<AxesSubplot:>
```



In [111]:
```
b=classification_report(ytrain,y_pred_train)
print(b)
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6043
           1       1.00      1.00      1.00      1140

    accuracy                           1.00      7183
   macro avg       1.00      1.00      1.00      7183
weighted avg       1.00      1.00      1.00      7183
```

test

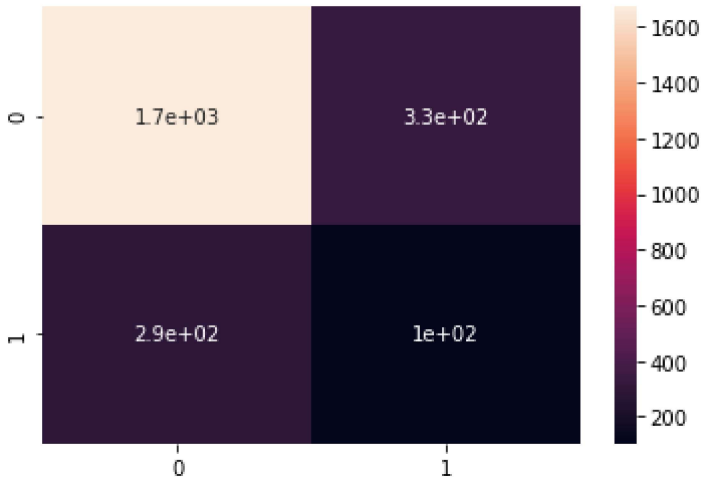
In [112]:
```
from sklearn.metrics import classification_report,confusion_matrix,roc_auc_score
y_pred=model.predict(xtest)
```

In [113]:
```
cm=confusion_matrix(ytest,y_pred)
cm
```

Out[113]:
```
array([[1673,  329],
       [ 289,  104]], dtype=int64)
```

In [114]:
```
sns.heatmap(cm,annot=True)
```

Out[114]:
```
<AxesSubplot:>
```



In [115]:
```
b=classification_report(ytest,y_pred)
print(b)
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.84      2002
           1       0.24      0.26      0.25       393

    accuracy                           0.74      2395
   macro avg       0.55      0.55      0.55      2395
weighted avg       0.75      0.74      0.75      2395
```

predict_probability

In [137]:
```
p_p=model.predict_proba(xtest)
au=p_p[:,1]##positive prediction
print(p_p[:,0])
A=p_p
y_pred_r=model.predict(xtest)
y_pred_r
```

```
[1. 1. 1. ... 1. 1. 1.]
```

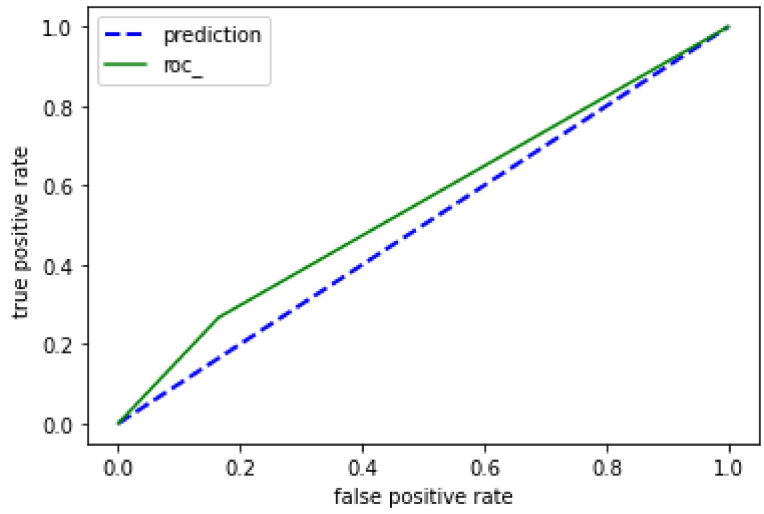
Out[137]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [128]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_curve
```

AUC CURVE

In [131]:
```
fpr,tpr,thresholds =roc_curve(ytest,au)
```

In [132]:
```
fpr,tpr,thresholds =roc_curve(ytest,au)
plt.plot([0,1],[0,1],color='blue',label='prediction',linewidth=2,linestyle='--')
plt.xlabel('false positive rate')
plt.plot(fpr,tpr ,color='green',label='roc_')
plt.xlabel('false positive rate')
plt.ylabel('true positive rate ')
plt.legend()
plt.show()
```



In [134]:
```
print(roc_auc_score(ytest,au))
```

```
0.5511702038419596
```

In [141]:
```
def evaluate_preds(ytest, y_pred_r):
    """
    Performs evaluation comparison on y_true labels vs. y_pred labels.
    """
    accuracy = accuracy_score(ytest, y_pred_r)
    precision = precision_score(ytest, y_pred_r)
    recall = recall_score(ytest, y_pred_r)
    f1 = f1_score(ytest, y_pred_r)
    metric_dict = {"accuracy": round(accuracy, 2),
                   "precision": round(precision, 2),
                   "recall": round(recall, 2),
                   "f1": round(f1, 2)}
    print(f"Acc: {accuracy * 100:.2f}%")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
    print(f"F1 score: {f1:.2f}")

    return metric_dict
```

In [142]:
```
base_model = evaluate_preds(ytest, y_pred_r)
```

```
Acc: 74.20%
Precision: 0.24
Recall: 0.27
F1 score: 0.25
```

we seeeethat data is unbalanced

to get rid of unbalanced data

In [143]:
```
from imblearn import over_sampling,under_sampling
from imblearn.over_sampling import RandomOverSampler
```

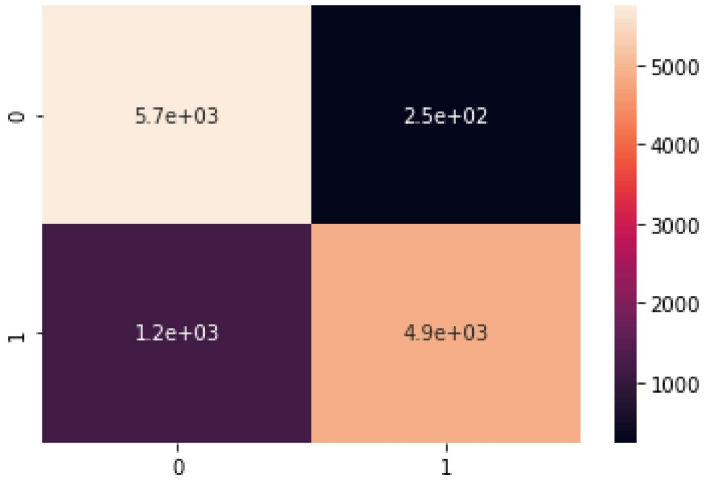
In [145]:
```
ros=RandomOverSampler( random_state=23)
x_rs,y_rs=ros.fit_resample(x_encoded_s,y)
x_train,x_test,y_train,y_test=train_test_split(x_rs,y_rs,test_size=0.25)
y_pred_train_rs=model.predict(x_train)
```

In [146]:
```
cm_rs=confusion_matrix(y_train,y_pred_train_rs)
cm_rs
```

Out[146]:
```
array([[5746,  246],
       [1179, 4896]], dtype=int64)
```

In [147]:
```
sns.heatmap(cm_rs,annot=True)
```

Out[147]:
```
<AxesSubplot:>
```



In [148]:
```
y_pred_train_rs=model.predict(x_train)
c=classification_report(y_train,y_pred_train_rs)
print(c)
```

```
              precision    recall  f1-score   support

           0       0.83      0.96      0.89      5992
           1       0.95      0.81      0.87      6075

    accuracy                           0.88     12067
   macro avg       0.89      0.88      0.88     12067
weighted avg       0.89      0.88      0.88     12067
```

In [ ]:
```

```

test

In [149]:
```
y_pred_rs=model.predict(x_test)
c=classification_report(y_test,y_pred_rs)
print(c)
```

```
              precision    recall  f1-score   support

           0       0.84      0.96      0.89      2053
           1       0.95      0.81      0.87      1970

    accuracy                           0.88      4023
   macro avg       0.89      0.88      0.88      4023
weighted avg       0.89      0.88      0.88      4023
```

In [150]:
```
cm_rs=confusion_matrix(y_test,y_pred_rs)
cm_rs
```

Out[150]:
```
array([[1969,   84],
       [ 383, 1587]], dtype=int64)
```

now these are to be balanced

In [ ]:
```

```

for incresing the precision ,recall we prune the tree

post pruning

In [151]:
```
model=tree.DecisionTreeClassifier(ccp_alpha=0.0)
###its defualt is o for giving better alpha our model should be increased
###firstly we take best alpha value
```

In [152]:
```
path=model.cost_complexity_pruning_path(x_train,y_train)
path
ccp_alphas=path.ccp_alphas
ccp_alphas;
```

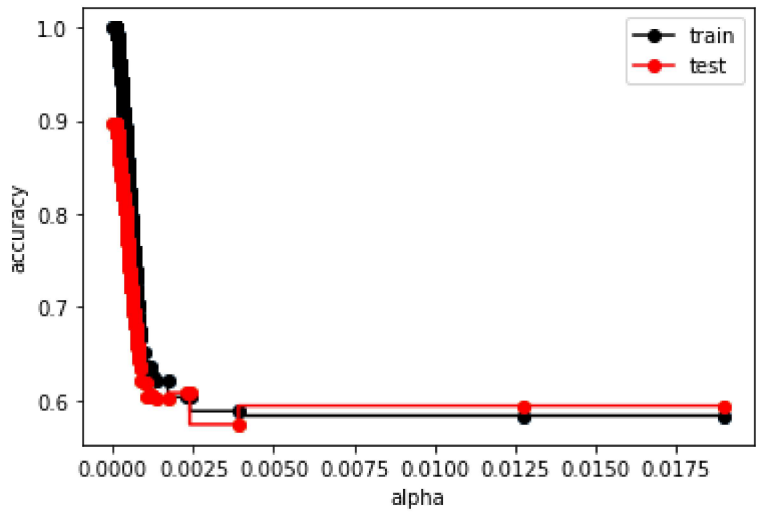
In [153]:
```
l=[]
for k in ccp_alphas:
    model_p=tree.DecisionTreeClassifier(ccp_alpha=k,random_state=0)
    model_p.fit(x_train,y_train)
    l.append(model_p)### we are taking alpha for every in decision tree
```

In [154]:
```
test_scores=[model_p.score(x_test,y_test) for model_p in l]
test_scores;
```

In [155]:
```
train_scores=[model_p.score(x_train,y_train) for model_p in l]
train_scores;
```

In [156]:
```

plt.scatter(ccp_alphas,train_scores)
plt.scatter(ccp_alphas,test_scores)
plt.plot(ccp_alphas,train_scores,color='black',marker='o',label='train',drawstyle
plt.plot(ccp_alphas,test_scores,color='red',marker='o',label='test',drawstyle='st
plt.xlabel('alpha')
plt.ylabel('accuracy')
plt.legend()
plt.subplots
plt.show()
```



In [157]:
```
after_p=tree.DecisionTreeClassifier(ccp_alpha=0.0001)
after_p.fit(x_train,y_train)
```

Out[157]:
```
DecisionTreeClassifier(ccp_alpha=0.0001)
```

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train

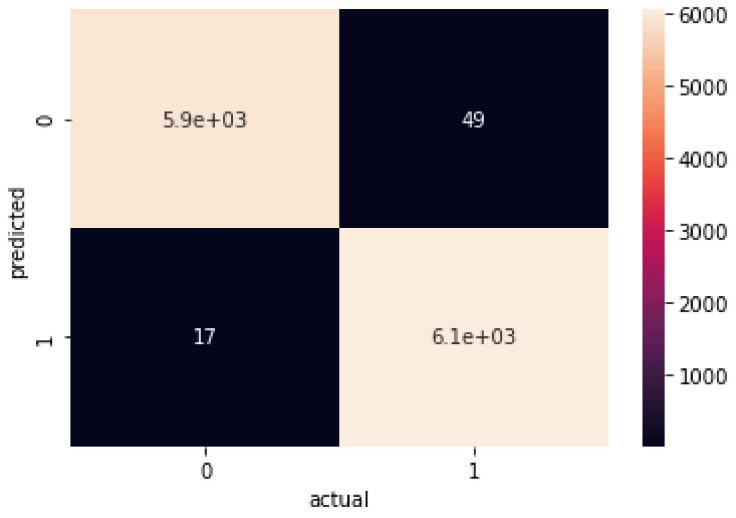
In [158]:
```
y_pred_ap=after_p.predict(x_train)
y_pred_ap
b=classification_report(y_train,y_pred_ap)
print(b)
```

```
              precision    recall  f1-score   support

           0       1.00      0.99      0.99      5992
           1       0.99      1.00      0.99      6075

    accuracy                           0.99     12067
   macro avg       0.99      0.99      0.99     12067
weighted avg       0.99      0.99      0.99     12067
```

In [159]:
```
m=confusion_matrix(y_train,y_pred_ap)
print(m)
sns.heatmap(m, annot=True,robust=True)
plt.xlabel('actual')
plt.ylabel('predicted')
```

```
[[5943   49]
 [  17 6058]]
```

Out[159]:
```
Text(33.0, 0.5, 'predicted')
```



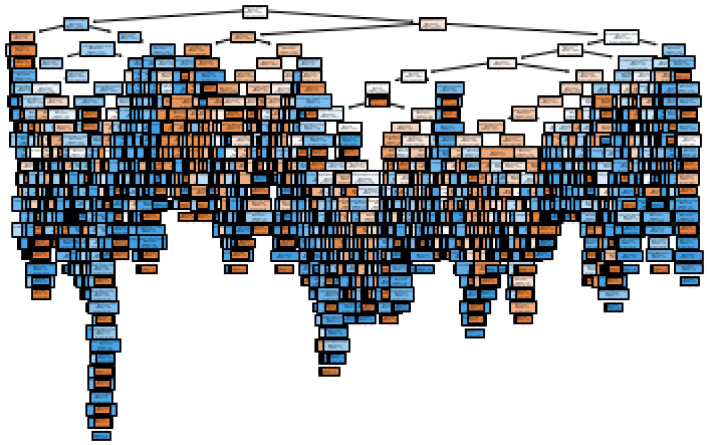
test

In [160]:
```
y_pred_ap=after_p.predict(x_test)
y_pred_ap
b=classification_report(y_test,y_pred_ap)
print(b)
```

```
              precision    recall  f1-score   support

           0       0.98      0.80      0.88      2053
           1       0.82      0.98      0.89      1970

    accuracy                           0.89      4023
   macro avg       0.90      0.89      0.89      4023
weighted avg       0.90      0.89      0.89      4023
```

In [ ]:
```
#### its lesss complex than before
```

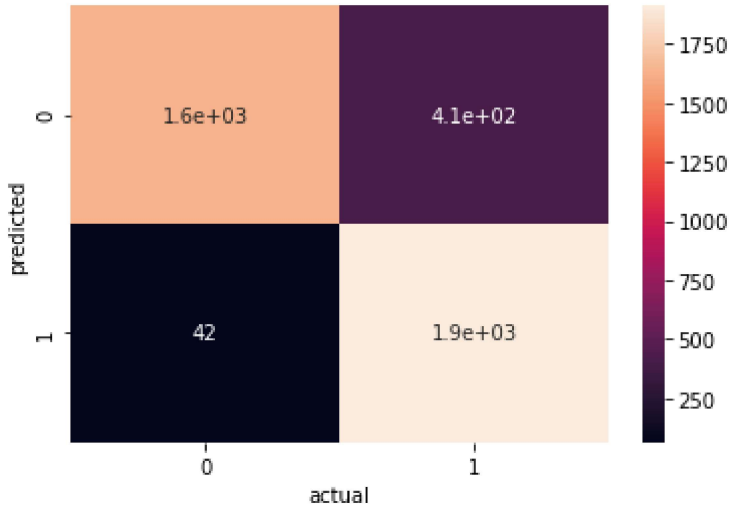
In [162]:
```
tree.plot_tree(after_p,filled=True,feature_names=x_encoded_s.columns);
```



In [163]:
```
m=confusion_matrix(y_test,y_pred_ap)
print(m)
sns.heatmap(m, annot=True,robust=True)
plt.xlabel('actual')
plt.ylabel('predicted')
```

```
[[1639  414]
 [  42 1928]]
```

Out[163]: Text(33.0, 0.5, 'predicted')



In [164]:
```
#tp=1607
#tn=1924
#fp=437
#fn=54
```

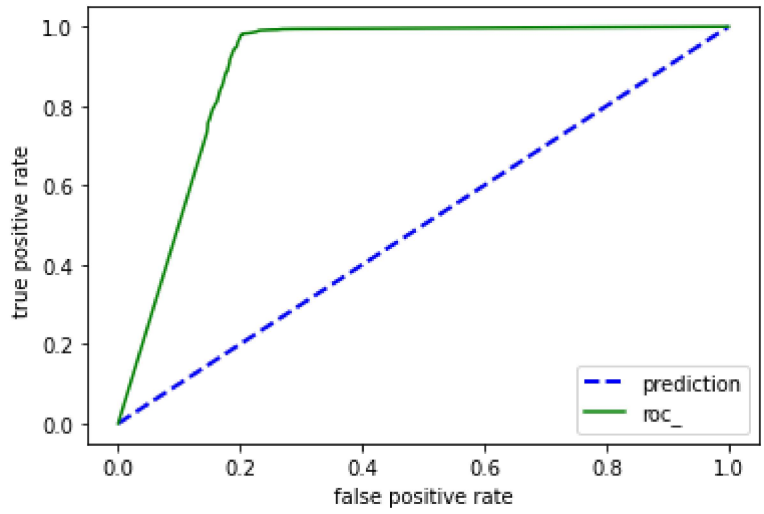
ROC-AUC CURVE

In [165]:
```
from sklearn.metrics import roc_curve,auc
from sklearn.metrics import roc_curve
y_pred_roc=after_p.predict_proba(x_test)
y_pred_roc_pos=y_pred_roc[:,1]##taking positive probabilities
y_pred_roc_pos
```

Out[165]:
```
array([0.        , 0.96774194, 1.        , ..., 1.        , 1.        ,
       0.        ])
```

In [166]:
```
fpr,tpr,thresholds =roc_curve(y_test,y_pred_roc_pos)
```

In [167]:
```
fpr,tpr,thresholds =roc_curve(y_test,y_pred_roc_pos)
plt.plot([0,1],[0,1],color='blue',label='prediction',linewidth=2,linestyle='--')
plt.xlabel('false positive rate')
plt.plot(fpr,tpr ,color='green',label='roc_')
plt.xlabel('false positive rate')
plt.ylabel('true positive rate ')
plt.legend()
plt.show()
```



In [168]:
```
from sklearn.metrics import  roc_auc_score,auc
print(roc_auc_score(y_test,y_pred_roc_pos))
print(auc(fpr,tpr))
```

```
0.8975430285257923
0.8975430285257923
```

In [169]:
```
###larger area means better model(area under curve)
```

In [173]:
```
def evaluate_preds(y_test, y_pred_ap):
    """
    Performs evaluation comparison on y_true labels vs. y_pred labels.
    """
    accuracy = accuracy_score(y_test, y_pred_ap)
    precision = precision_score(y_test, y_pred_ap)
    recall = recall_score(y_test, y_pred_ap)
    f1 = f1_score(y_test, y_pred_ap)
    metric_dict = {"accuracy": round(accuracy, 2),
                   "precision": round(precision, 2),
                   "recall": round(recall, 2),
                   "f1": round(f1, 2)}
    print(f"Acc: {accuracy * 100:.2f}%")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
    print(f"F1 score: {f1:.2f}")

    return metric_dict
```

In [175]:
```
post_pruning_model = evaluate_preds(y_test, y_pred_ap)
```

```
Acc: 88.67%
Precision: 0.82
Recall: 0.98
F1 score: 0.89
```

now we can seethat precision ,recall increases some what.....

again prune the tree using hyperparameters

pruning

In [176]:
```
from sklearn.model_selection import GridSearchCV
model_grid=tree.DecisionTreeClassifier(ccp_alpha=0.0001)
grid={'max_depth':range(1,12), 'min_samples_leaf':range(1,15),'min_samples_split'
gs=GridSearchCV(model_grid,grid,cv=5)
```

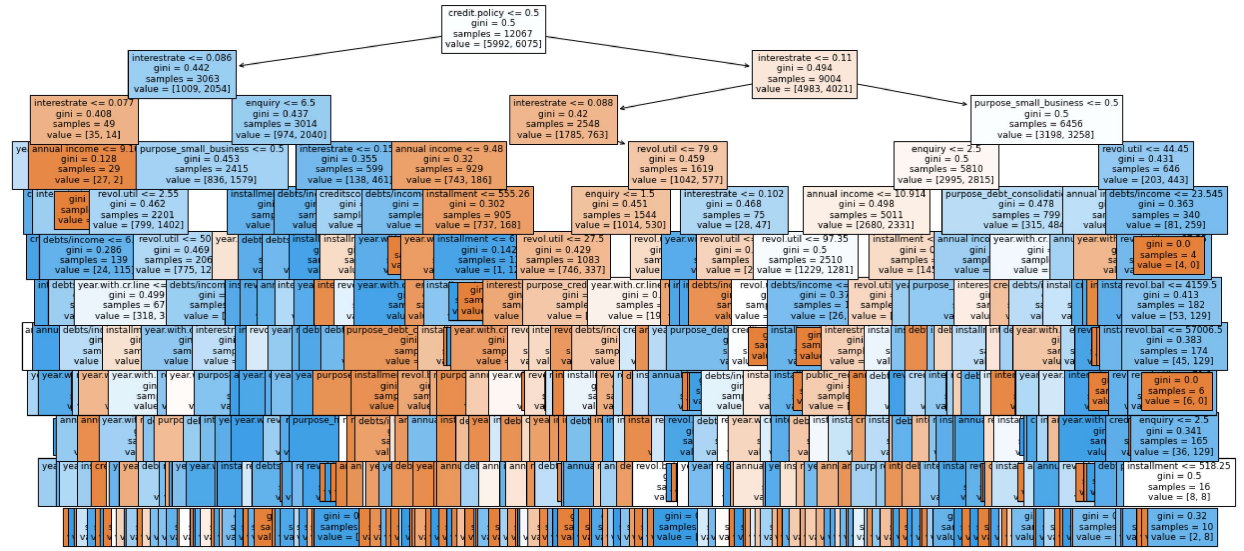
In [177]:
```
gs.fit(x_train,y_train)
```

Out[177]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(ccp_alpha=0.0001),
             param_grid={'max_depth': range(1, 12),
                         'min_samples_leaf': range(1, 15),
                         'min_samples_split': range(2, 5)})
```

In [178]:
```
gs.best_params_
```

Out[178]:
```
{'max_depth': 11, 'min_samples_leaf': 1, 'min_samples_split': 3}
```

In [180]:
```
model_grid_best=tree.DecisionTreeClassifier(ccp_alpha=0.0001,max_depth=11, min_sa
model_grid_best.fit(x_train,y_train)
fig, axe = plt.subplots(figsize=(20,10))
tree.plot_tree(model_grid_best, filled=True,feature_names=x_encoded_s.columns,ax=
```



In [181]:
```
model_grid_best.score(x_train,y_train)
```

Out[181]:
```
0.7627413607358913
```

In [182]:
```
model_grid_best.score(x_test,y_test)
```

Out[182]:
```
0.6982351478995774
```

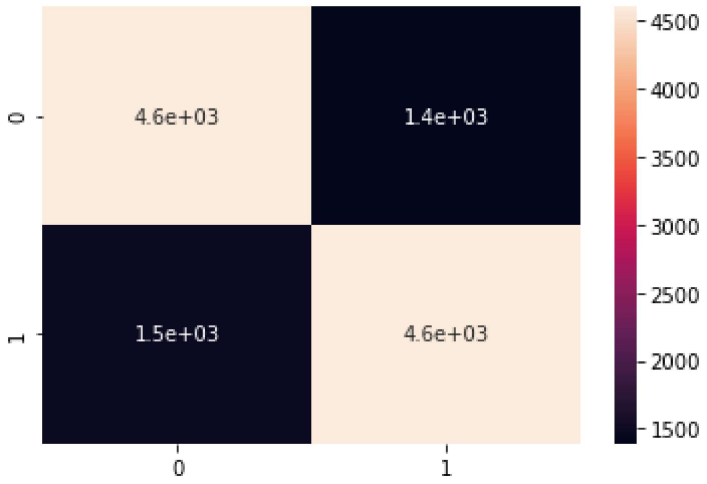
train

In [183]:
```
y_pred_g_train=model_grid_best.predict(x_train)
print(classification_report(y_train,y_pred_g_train))
```

```
              precision    recall  f1-score   support

           0       0.76      0.77      0.76      5992
           1       0.77      0.76      0.76      6075

    accuracy                           0.76     12067
   macro avg       0.76      0.76      0.76     12067
weighted avg       0.76      0.76      0.76     12067
```

In [184]:
```
sns.heatmap(confusion_matrix(y_train,y_pred_g_train),annot=True)
a_train=confusion_matrix(y_train,y_pred_g_train)
print(a_train)
```

```
[[4601 1391]
 [1472 4603]]
```



In [ ]:
```
```

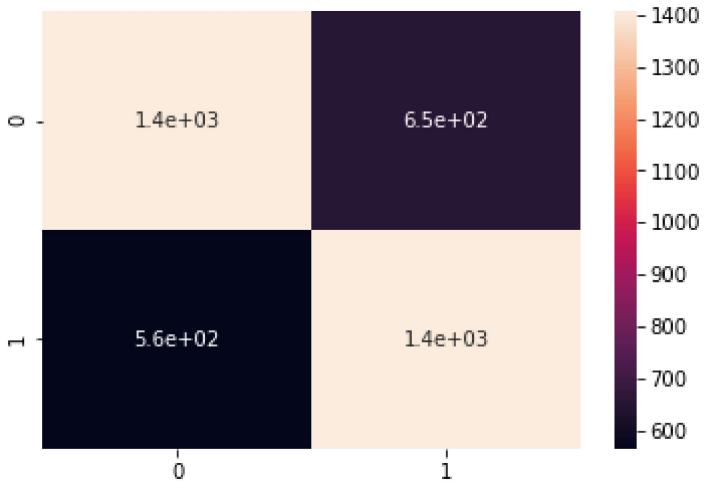
test

In [185]:
```
y_pred_g=model_grid_best.predict(x_test)
print(classification_report(y_test,y_pred_g))
```

```
              precision    recall  f1-score   support

           0       0.71      0.68      0.70      2053
           1       0.68      0.71      0.70      1970

    accuracy                           0.70      4023
   macro avg       0.70      0.70      0.70      4023
weighted avg       0.70      0.70      0.70      4023
```

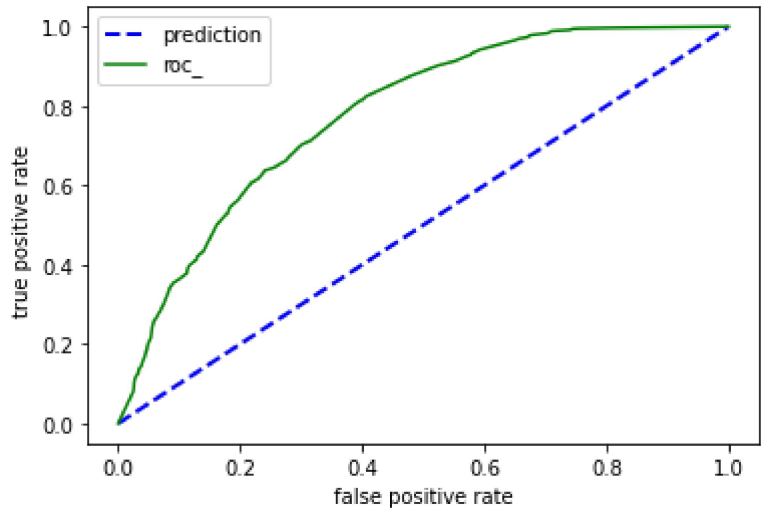
In [186]:
```
sns.heatmap(confusion_matrix(y_test,y_pred_g),annot=True)
a=confusion_matrix(y_test,y_pred_g)
print(a)
```

```
[[1403  650]
 [ 564 1406]]
```



In [187]:
```
y_pred_roc=model_grid_best.predict_proba(x_test)
y_pred_roc_pos=y_pred_roc[:,1]##taking positive probabilities
y_pred_roc_pos
fpr,tpr,thresholds =roc_curve(y_test,y_pred_roc_pos)
```

In [188]:
```
fpr,tpr,thresholds =roc_curve(y_test,y_pred_roc_pos)
plt.plot([0,1],[0,1],color='blue',label='prediction',linewidth=2,linestyle='--')
plt.xlabel('false positive rate')
plt.plot(fpr,tpr ,color='green',label='roc_')
plt.xlabel('false positive rate')
plt.ylabel('true positive rate ')
plt.legend()
plt.show()
```



In [189]:
```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,y_pred_roc_pos)
```

Out[189]:
```
0.7785784576736781
```

In [192]:
```
def evaluate_preds(y_test, y_pred_g):
    """
    Performs evaluation comparison on y_true labels vs. y_pred labels.
    """
    accuracy = accuracy_score(y_test, y_pred_g)
    precision = precision_score(y_test, y_pred_g)
    recall = recall_score(y_test, y_pred_g)
    f1 = f1_score(y_test, y_pred_g)
    metric_dict = {"accuracy": round(accuracy, 2),
                   "precision": round(precision, 2),
                   "recall": round(recall, 2),
                   "f1": round(f1, 2)}
    print(f"Acc: {accuracy * 100:.2f}%")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
    print(f"F1 score: {f1:.2f}")

    return metric_dict
```

In [229]:
```
prune_model_grid= evaluate_preds(y_test, y_pred_g)
```

```
Acc: 69.82%
Precision: 0.68
Recall: 0.71
F1 score: 0.70
```

we check some models then we got some results .....

In [ ]:

In [ ]:

In [ ]:
```
df1
```

comaparing our models (plot)

try subsetting the target and show.....

apply binning in showing the debts/income,interest rate,

Type *Markdown* and LaTeX: α^2

feature engineering

creating bins

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concorodance test results

rank ordering test results.....

writing scripts for the given questions clearly

m

modelling with some important variables

In [196]:
```
x_encoded_upd=x_encoded_s.drop(['purpose_credit_card','purpose_debt_consolidation
y=df1['target']
```

In [197]:
```
x_encoded_upd
```

Out[197]:

	interestrate	installment	annual income	debts/income	creditscore	revol.bal	revol.util	public_rec
0	0.1189	829.10	11.350407	19.48	737	28854	52.1	
1	0.1071	228.22	11.082143	14.29	707	33623	76.7	
2	0.1357	366.86	10.373491	11.63	682	3511	25.6	
3	0.1008	162.34	11.350407	8.10	712	33667	73.2	
4	0.1426	102.92	11.299732	14.97	667	4740	39.5	
...	...	...	...	...	...	...	...	
9573	0.1461	344.76	12.180755	10.39	672	215372	82.1	
9574	0.1253	257.70	11.141862	0.21	722	184	1.1	
9575	0.1071	97.81	10.596635	13.09	687	10036	82.9	
9576	0.1600	351.58	10.819778	19.18	692	0	3.2	
9577	0.1392	853.43	11.264464	16.28	732	37879	57.0	

9578 rows × 9 columns

In [198]:
```
X_train,X_test,Y_train,Y_test=train_test_split(x_encoded_upd,y,test_size=0.25)
```

In [199]:
```
from sklearn import tree
model_upd_d=tree.DecisionTreeClassifier( criterion='gini')
```

In [200]:
```
model_upd_d.fit(X_train,Y_train)
```

Out[200]:
```
DecisionTreeClassifier()
```

In [201]:
```
model_upd_d.score(X_test,Y_test)
```

Out[201]:
```
0.7306889352818372
```

In [202]:
```
model_upd_d.score(X_train,Y_train)
```

Out[202]:
```
1.0
```

In [203]:
```
y_pred_upd=model_upd_d.predict(X_test)
s=classification_report(Y_test,y_pred_upd)
print(s)
```

```
              precision    recall  f1-score   support

           0       0.84      0.83      0.84      2003
           1       0.20      0.21      0.20       392

    accuracy                           0.73      2395
   macro avg       0.52      0.52      0.52      2395
weighted avg       0.74      0.73      0.73      2395
```

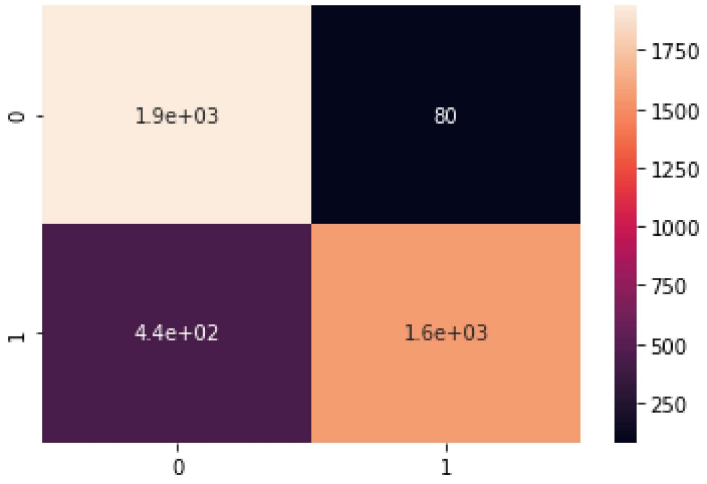
In [204]:
```
ros=RandomOverSampler( random_state=23)
x_rs_upd,y_rs_upd=ros.fit_resample(x_encoded_upd,y)
x_train_upd,x_test_upd,y_train_upd,y_test_upd=train_test_split(x_rs_upd,y_rs_upd,
y_pred_rs_upd=model_upd_d.predict(x_test_upd)
```

In [205]:
```
s_upd=classification_report(y_test_upd,y_pred_rs_upd)
print(s_upd)
```

```
              precision    recall  f1-score   support

           0       0.82      0.96      0.88      2019
           1       0.95      0.78      0.86      2004

    accuracy                           0.87      4023
   macro avg       0.88      0.87      0.87      4023
weighted avg       0.88      0.87      0.87      4023
```

In [206]:
```
sns.heatmap(confusion_matrix(y_test_upd,y_pred_rs_upd),annot=True)
s_s=confusion_matrix(y_test_upd,y_pred_rs_upd)
print(s_s)
```

```
[[1939   80]
 [ 436 1568]]
```



In [209]:
```
tree.plot_tree(model_upd_d,filled=True)
```

Out[209]:
```
[Text(0.3753065079911161, 0.9848484848484849, 'X[0] <= 0.093\ngini = 0.267\ns
amples = 7183\nvalue = [6042, 1141]'),
 Text(0.05245684330868697, 0.9545454545454546, 'X[2] <= 9.258\ngini = 0.103\n
samples = 1267\nvalue = [1198, 69]'),
 Text(0.030088131198093702, 0.9242424242424242, 'X[1] <= 84.64\ngini = 0.486
\nsamples = 12\nvalue = [7, 5]'),
 Text(0.02784542874163367, 0.8939393939393939, 'X[1] <= 52.665\ngini = 0.444
\nsamples = 6\nvalue = [2, 4]'),
 Text(0.026724077513403652, 0.8636363636363636, 'X[8] <= 1.108\ngini = 0.444
\nsamples = 3\nvalue = [2, 1]'),
 Text(0.025602726285173634, 0.8333333333333334, 'gini = 0.0\nsamples = 1\nval
ue = [0, 1]'),
 Text(0.02784542874163367, 0.8333333333333334, 'gini = 0.0\nsamples = 2\nvalu
e = [2, 0]'),
 Text(0.028966779969863687, 0.8636363636363636, 'gini = 0.0\nsamples = 3\nval
ue = [0, 3]'),
 Text(0.032330833654553734, 0.8939393939393939, 'X[2] <= 8.843\ngini = 0.278
\nsamples = 6\nvalue = [5, 1]'),
 Text(0.03120948242632372, 0.8636363636363636, 'gini = 0.0\nsamples = 1\nvalu
```

see above how decision tree is splitiing

TUNING USING RANDOMISED SEARCH CV

In [210]:
```
m=tree.DecisionTreeClassifier(criterion='gini')
rs_rf = RandomizedSearchCV(m,
                           param_distributions=grid,
                           cv=5,
                           n_iter=20,
                           verbose=True)
```

```
<IPython.core.display.Javascript object>
```

In [211]:
```
rs_rf
```

Out[211]:
```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_iter=20,
                   param_distributions={'max_depth': range(1, 12),
                                        'min_samples_leaf': range(1, 15),
                                        'min_samples_split': range(2, 5)},
                   verbose=True)
```

In [212]:
```
rs_rf.fit(x_train,y_train)
```

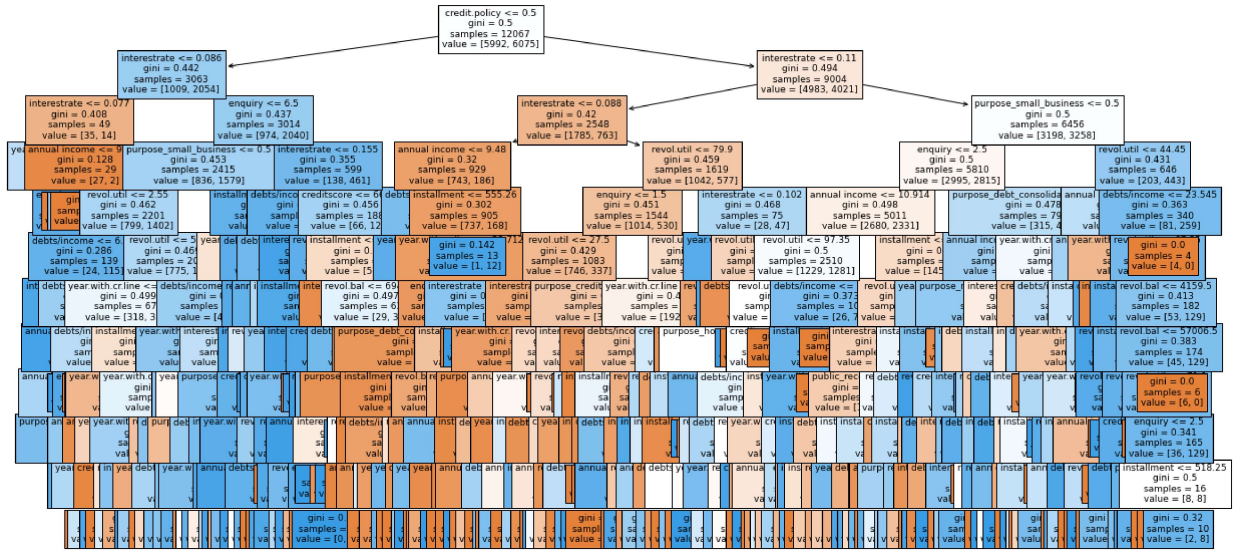
```
Fitting 5 folds for each of 20 candidates, totalling 100 fits
```

Out[212]:
```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_iter=20,
                   param_distributions={'max_depth': range(1, 12),
                                        'min_samples_leaf': range(1, 15),
                                        'min_samples_split': range(2, 5)},
                   verbose=True)
```

In [213]:
```
rs_rf.best_params_
```

Out[213]:
```
{'min_samples_split': 3, 'min_samples_leaf': 5, 'max_depth': 10}
```

In [215]:
```
model_grid_rcv=tree.DecisionTreeClassifier(ccp_alpha=0.0001,max_depth=11, min_sam
model_grid_rcv.fit(x_train,y_train)
fig, axe = plt.subplots(figsize=(20,10))
tree.plot_tree(model_grid_rcv, filled=True,feature_names=x_encoded_s.columns,ax=a
```



In [216]:
```
model_grid_rcv.score(x_train,y_train)
```

Out[216]:
```
0.7604209828457777
```

In [217]:
```
model_grid_rcv.score(x_test,y_test)
```

Out[217]:
```
0.6967437235893612
```

train

In [218]:
```
y_pred_rcv_train=model_grid_rcv.predict(x_train)
```

In [219]:
```
y_pred_g_train=model_grid_best.predict(x_train)
print(classification_report(y_train,y_pred_rcv_train))
```

```
              precision    recall  f1-score   support

           0       0.76      0.76      0.76      5992
           1       0.76      0.76      0.76      6075

    accuracy                           0.76     12067
   macro avg       0.76      0.76      0.76     12067
weighted avg       0.76      0.76      0.76     12067
```

test

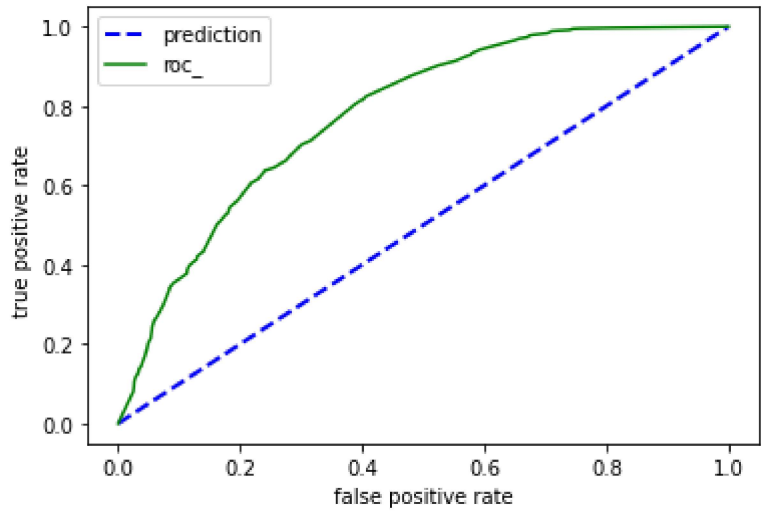
In [220]:
```
y_pred_rcv_test=model_grid_rcv.predict(x_test)
print(classification_report(y_test,y_pred_rcv_test))
```

```
              precision    recall  f1-score   support

           0       0.71      0.68      0.70      2053
           1       0.68      0.71      0.70      1970

    accuracy                           0.70      4023
   macro avg       0.70      0.70      0.70      4023
weighted avg       0.70      0.70      0.70      4023
```

In [221]:
```
y_pred_rcv=model_grid_rcv.predict_proba(x_test)
y_pred_rcv_pos=y_pred_roc[:,1]##taking positive probabilities
y_pred_rcv_pos
fpr,tpr,thresholds =roc_curve(y_test,y_pred_rcv_pos)
```

In [222]:
```
fpr,tpr,thresholds =roc_curve(y_test,y_pred_rcv_pos)
```

In [223]:
```
fpr,tpr,thresholds =roc_curve(y_test,y_pred_rcv_pos)
plt.plot([0,1],[0,1],color='blue',label='prediction',linewidth=2,linestyle='--')
plt.xlabel('false positive rate')
plt.plot(fpr,tpr ,color='green',label='roc_')
plt.xlabel('false positive rate')
plt.ylabel('true positive rate ')
plt.legend()
plt.show()
```



In [224]:
```
roc_auc_score(y_test,y_pred_rcv_test)
```

Out[224]: 0.6971071182199629

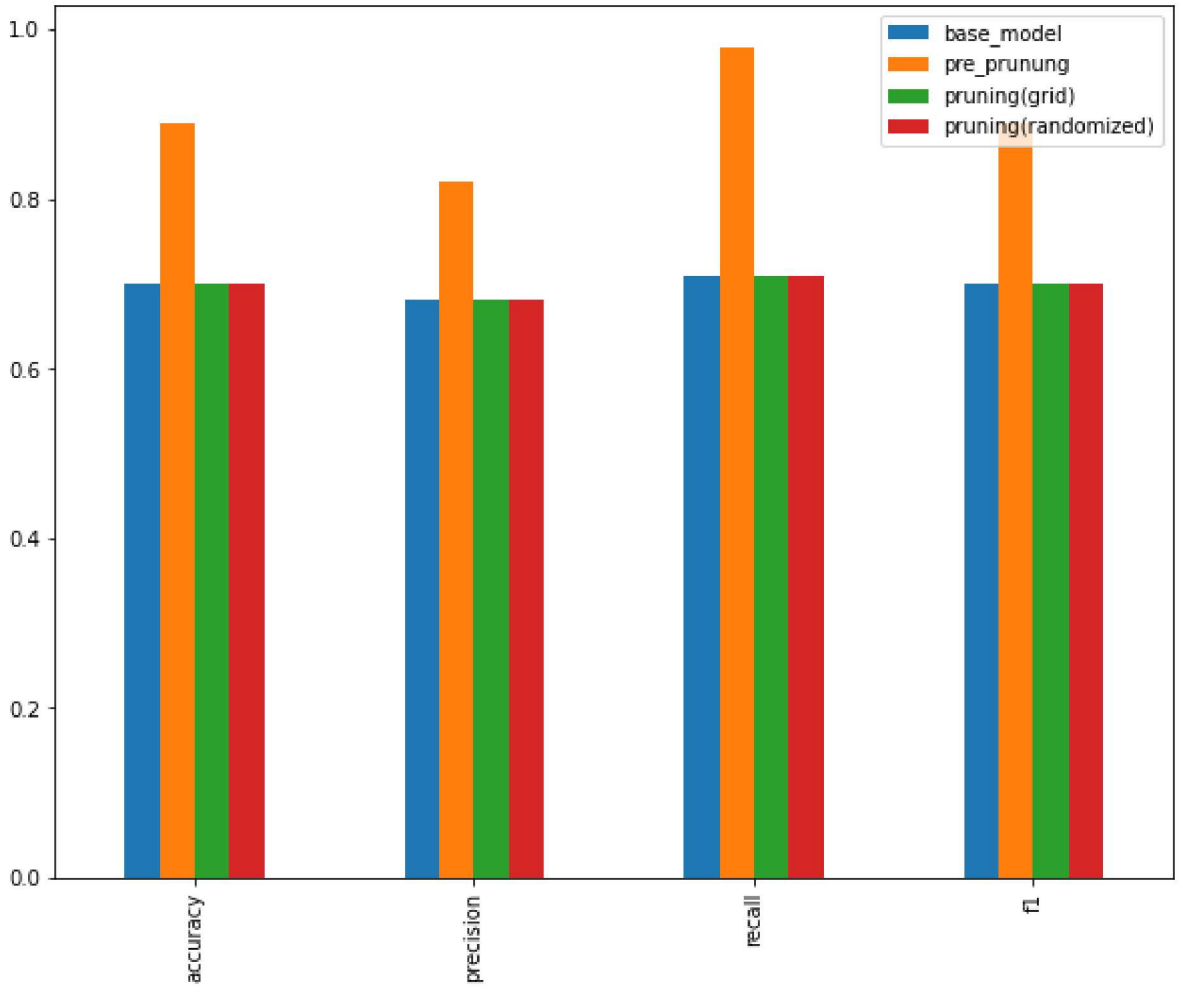
In [226]:
```
def evaluate_preds(y_test, y_pred_rcv_test):
    """
    Performs evaluation comparison on y_true labels vs. y_pred labels.
    """
    accuracy = accuracy_score(y_test, y_pred_rcv_test)
    precision = precision_score(y_test, y_pred_rcv_test)
    recall = recall_score(y_test, y_pred_rcv_test)
    f1 = f1_score(y_test, y_pred_rcv_test)
    metric_dict = {"accuracy": round(accuracy, 2),
                   "precision": round(precision, 2),
                   "recall": round(recall, 2),
                   "f1": round(f1, 2)}
    print(f"Acc: {accuracy * 100:.2f}%")
    print(f"Precision: {precision:.2f}")
    print(f"Recall: {recall:.2f}")
    print(f"F1 score: {f1:.2f}")

    return metric_dict
```

In [232]:
```
prune_model_randomized = evaluate_preds(y_test, y_pred_rcv_test)
```

```
Acc: 69.67%
Precision: 0.68
Recall: 0.71
F1 score: 0.70
```

comparing metrics on different models

In [233]:
```
compare_metrics = pd.DataFrame({"base_model": base_model,
                                "pre_prunung": post_pruning_model,
                                "pruning(grid)": prune_model_grid,
                               'pruning(randomized)':prune_model_randomized})
compare_metrics.plot.bar(figsize=(10, 8));
```



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