Project (Supervised Machine Learning)

HR Analytics - Job changing prediction

In [133]:

```
#importing the libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [134]:

```
# call csv file and convert it to dataframe using Pandas function
```

In [135]:

```
df=pd.read_csv("aug_train.csv")
```

In [136]:

```
# .head() will give the first 5 rows of the dataset by default

df.head()
```

Out[136]:

	enrollee_id	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_s
0	8949	city_103	0.920	Male	Has relevent experience	no_enrollment	Graduate	STEM	>20	N
1	29725	city_40	0.776	Male	No relevent experience	no_enrollment	Graduate	STEM	15	50
2	11561	city_21	0.624	NaN	No relevent experience	Full time course	Graduate	STEM	5	N
3	33241	city_115	0.789	NaN	No relevent experience	NaN	Graduate	Business Degree	<1	N
4	666	city_162	0.767	Male	Has relevent experience	no_enrollment	Masters	STEM	>20	50

In [137]:

```
# dtypes will tell the data types of each column

df.dtypes
```

Out[137]:

```
enrollee_id                 int64
city                       object
city_development_index    float64
gender                     object
relevent_experience        object
enrolled_university        object
education_level            object
major_discipline           object
experience                 object
company_size               object
company_type               object
last_new_job               object
training_hours              int64
target                    float64
dtype: object
```

In [138]:

```
# .info() will give basic info about the dataset

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 19158 entries, 0 to 19157
Data columns (total 14 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   enrollee_id             19158 non-null  int64  
 1   city                    19158 non-null  object 
 2   city_development_index  19158 non-null  float64
 3   gender                  14650 non-null  object 
 4   relevent_experience     19158 non-null  object 
 5   enrolled_university     18772 non-null  object 
 6   education_level         18698 non-null  object 
 7   major_discipline        16345 non-null  object 
 8   experience              19093 non-null  object 
 9   company_size            13220 non-null  object 
 10  company_type            13018 non-null  object 
 11  last_new_job            18735 non-null  object 
 12  training_hours          19158 non-null  int64  
 13  target                  19158 non-null  float64
dtypes: float64(2), int64(2), object(10)
memory usage: 2.0+ MB
```

In [139]:

```
# .shape will give number of rows and columns respectively

df.shape
```

Out[139]:

```
(19158, 14)
```

Data cleaning & EDA process

In [140]:

```
# Using other pandas Functions like .isnull().sum(), .value_counts()
# Find out messy or Null values.
```

In [141]:

```
# isnull().sum() gives the count of null values present in each column

df.isnull().sum()
```

Out[141]:

```
enrollee_id                  0
city                         0
city_development_index       0
gender                    4508
relevent_experience          0
enrolled_university        386
education_level            460
major_discipline          2813
experience                  65
company_size              5938
company_type              6140
last_new_job               423
training_hours               0
target                       0
dtype: int64
```

In [142]:

```
# value_counts() returns object containing counts of unique values

df['enrollee_id'].value_counts()
```

Out[142]:

```
8949     1
10660    1
30726    1
18507    1
31273    1
        ..
11547    1
32067    1
14356    1
18051    1
23834    1
Name: enrollee_id, Length: 19158, dtype: int64
```

In [143]:

```
# column 'enrollee_id' contains all unique values so, drop that column

del df["enrollee_id"]
```

In [144]:

```
df['city'].value_counts()
```

Out[144]:

```
city_103    4355
city_21     2702
city_16     1533
city_114    1336
city_160     845
            ...
city_129       3
city_111       3
city_121       3
city_140       1
city_171       1
Name: city, Length: 123, dtype: int64
```

In [145]:

```
df['city_development_index'].value_counts()
```

Out[145]:

```
0.920    5200
0.624    2702
0.910    1533
0.926    1336
0.698     683
         ...
0.649       4
0.807       4
0.781       3
0.625       3
0.664       1
Name: city_development_index, Length: 93, dtype: int64
```

In [146]:

```
# column 'gender' contains 23% null values and it is categorical data so, fill it by mode

df['gender'].value_counts()
```

Out[146]:

```
Male      13221
Female     1238
Other       191
Name: gender, dtype: int64
```

In [147]:

```
df.gender.replace(np.nan,'Male',inplace=True)
```

In [148]:

```
df['gender'].value_counts()
```

Out[148]:

```
Male      17729
Female     1238
Other       191
Name: gender, dtype: int64
```

In [149]:

```
df['relevent_experience'].value_counts()
```

Out[149]:

```
Has relevent experience    13792
No relevent experience      5366
Name: relevent_experience, dtype: int64
```

In [150]:

```
df['enrolled_university'].value_counts()
```

Out[150]:

```
no_enrollment       13817
Full time course     3757
Part time course     1198
Name: enrolled_university, dtype: int64
```

In [151]:

```
df['education_level'].value_counts()
```

Out[151]:

```
Graduate          11598
Masters            4361
High School        2017
Phd                 414
Primary School      308
Name: education_level, dtype: int64
```

In [152]:

```
# column 'major_discipline' contains 18% null values and it is categorical data so, fill it by mode

df['major_discipline'].value_counts()
```

Out[152]:

```
STEM               14492
Humanities           669
Other                381
Business Degree      327
Arts                 253
No Major             223
Name: major_discipline, dtype: int64
```

In [153]:

```
df.major_discipline.replace(np.nan,'STEM',inplace=True)
```

In [154]:

```
df['major_discipline'].value_counts()
```

Out[154]:

```
STEM               17305
Humanities           669
Other                381
Business Degree      327
Arts                 253
No Major             223
Name: major_discipline, dtype: int64
```

In [155]:

```
df['experience'].value_counts()
```

Out[155]:

```
>20    3286
5      1430
4      1403
3      1354
6      1216
2      1127
7      1028
10      985
9       980
8       802
15      686
11      664
14      586
1       549
<1      522
16      508
12      494
13      399
17      342
19      304
18      280
20      148
Name: experience, dtype: int64
```

In [156]:

```
# column 'company_size' contains 29% null values and it is categorical data so, fill it by mode

df['company_size'].value_counts()
```

Out[156]:

```
50-99        3083
100-500      2571
10000+       2019
10/49        1471
1000-4999    1328
<10          1308
500-999       877
5000-9999     563
Name: company_size, dtype: int64
```

In [157]:

```
df.company_size.replace(np.nan,'50-99',inplace=True)
```

In [158]:

```
df['company_size'].value_counts()
```

Out[158]:

```
50-99        9021
100-500      2571
10000+       2019
10/49        1471
1000-4999    1328
<10          1308
500-999       877
5000-9999     563
Name: company_size, dtype: int64
```

In [159]:

```
# column 'company_type' contains 29% null values and it is categorical data so, fill it by mode

df['company_type'].value_counts()
```

Out[159]:

```
Pvt Ltd                9817
Funded Startup         1001
Public Sector           955
Early Stage Startup     603
NGO                     521
Other                   121
Name: company_type, dtype: int64
```

In [160]:

```
df.company_type.replace(np.nan,'Pvt Ltd',inplace=True)
```

In [161]:

```
df['company_type'].value_counts()
```

Out[161]:

```
Pvt Ltd                15957
Funded Startup          1001
Public Sector            955
Early Stage Startup      603
NGO                      521
Other                    121
Name: company_type, dtype: int64
```

In [162]:

```
df['last_new_job'].value_counts()
```

Out[162]:

```
1        8040
>4       3290
2        2900
never    2452
4        1029
3        1024
Name: last_new_job, dtype: int64
```

In [163]:

```
df['training_hours'].value_counts()
```

Out[163]:

```
28     329
12     292
18     291
22     282
50     279
      ...
266      6
234      5
272      5
286      5
238      4
Name: training_hours, Length: 241, dtype: int64
```

In [164]:

```
df['target'].value_counts()
```

Out[164]:

```
0.0    14381
1.0     4777
Name: target, dtype: int64
```

In [165]:

```
df.isnull().sum()
```

Out[165]:

```
city                        0
city_development_index      0
gender                      0
relevent_experience         0
enrolled_university       386
education_level           460
major_discipline            0
experience                 65
company_size                0
company_type                0
last_new_job              423
training_hours              0
target                      0
dtype: int64
```

In [166]:

```
# remaining columns contain less than 3% null values so, drop that using dropna function

df.dropna(inplace=True)
```

In [167]:

```
df.isnull().sum()
```

Out[167]:

```
city                      0
city_development_index    0
gender                    0
relevent_experience       0
enrolled_university       0
education_level           0
major_discipline          0
experience                0
company_size              0
company_type              0
last_new_job              0
training_hours            0
target                    0
dtype: int64
```

In [168]:

```
df.shape
```

Out[168]:

```
(18014, 13)
```

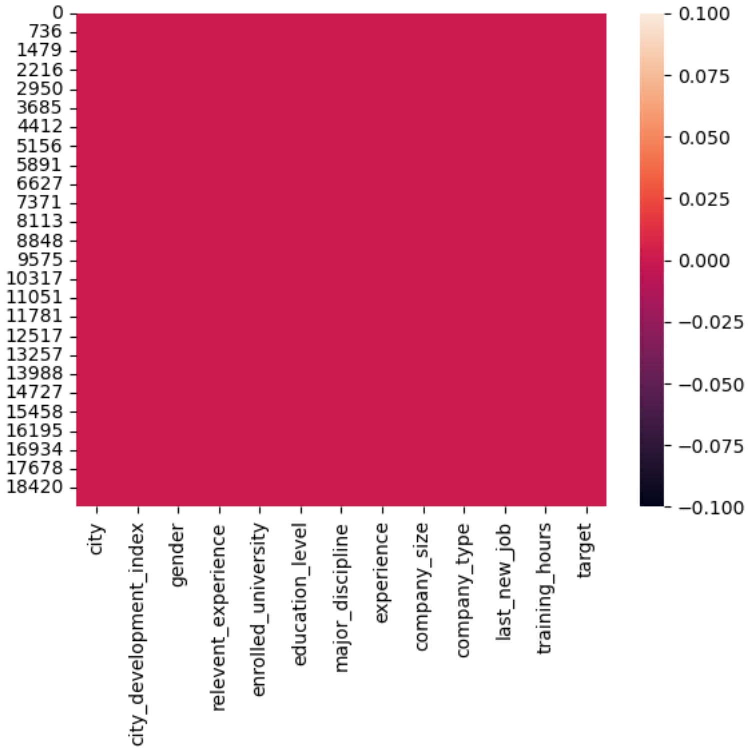
In [169]:

```
# plot heatmap to find null values present in the dataframe

sns.heatmap(df.isnull())
```

Out[169]:

```
<AxesSubplot:>
```



split data into numerical column and categorical column

In [170]:

```
numcol=[]
for i in df.dtypes.index:
    if df.dtypes[i]!='object':
        numcol.append(i)
numcol
```

Out[170]:

```
['city_development_index', 'training_hours', 'target']
```

In [171]:

```
len(numcol)
```

Out[171]:

```
3
```

In [172]:

```
catcol=[]
for i in df.dtypes.index:
    if df.dtypes[i]=='object':
        catcol.append(i)
catcol
```

Out[172]:

```
['city',
 'gender',
 'relevent_experience',
 'enrolled_university',
 'education_level',
 'major_discipline',
 'experience',
 'company_size',
 'company_type',
 'last_new_job']
```

In [173]:

```
# Using OrdinalEncoder convert our categorical columns into numerical column
```

In [174]:

```
from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder()
df[catcol]=oe.fit_transform(df[catcol])
```

In [175]:

```
numcol=[]
for i in df.dtypes.index:
    if df.dtypes[i]!='object':
        numcol.append(i)
numcol
```

Out[175]:

```
['city',
 'city_development_index',
 'gender',
 'relevent_experience',
 'enrolled_university',
 'education_level',
 'major_discipline',
 'experience',
 'company_size',
 'company_type',
 'last_new_job',
 'training_hours',
 'target']
```

In [176]:

```
len(numcol)
```

Out[176]:

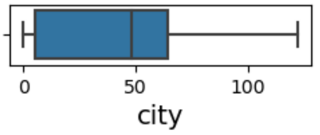
```
13
```

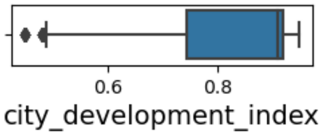
In [177]:

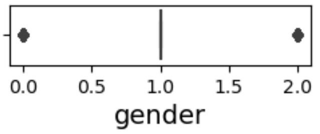
```
# Plot Boxplot for numerical columns to find outliers present
```

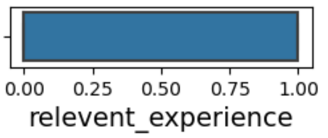
In [178]:

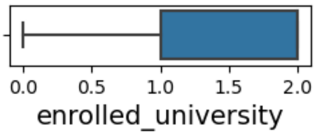
```
plt.figure()
plotn=1
for i in numcol:
    if plotn<=13:
        ax=plt.subplot(7,2,plotn)
        sns.boxplot(df[i])
        plt.xlabel(i,fontsize=14)
        plotn=plotn+1
        plt.show()
```

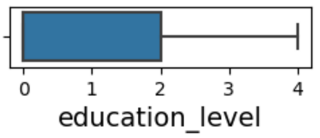


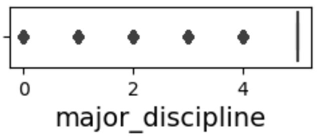


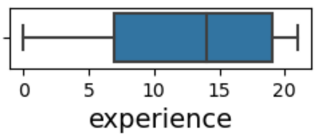


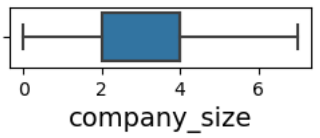


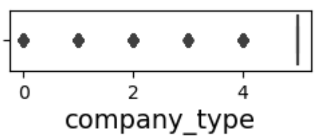


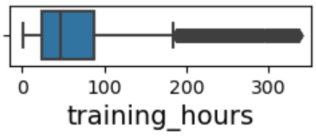


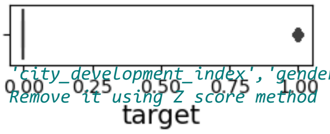













```
# 'city_development_index','gender','major_discipline','company_type','training_hours' columns contain outliers so,
# Remove it using Z score method
features=df[[
 'city_development_index',
 'gender',
 'major_discipline',
 'company_type',
 'training_hours']]
```

In [180]:

```
from scipy.stats import zscore
z=abs(zscore(features))
```

In [181]:

```
z
```

Out[181]:

	city_development_index	gender	major_discipline	company_type	training_hours
0	0.722878	0.211859	0.302358	0.397819	0.488663
1	0.456367	0.211859	0.302358	0.397819	0.305505
2	1.701127	0.211859	0.302358	0.397819	0.293920
4	0.530070	0.211859	0.302358	2.667981	0.954882
5	0.554638	0.211859	0.302358	0.397819	0.688471
...	...	...	...	...	...
19153	0.378931	0.211859	2.795276	0.397819	0.388759
19154	0.722878	0.211859	0.302358	0.397819	0.222252
19155	0.722878	0.211859	0.302358	0.397819	0.355457
19156	0.243448	0.211859	0.302358	0.397819	0.527030

In [182]:

```
len(numcol)
```

Out[182]:

```
13
```

In [183]:

```
df
```

Out[183]:

	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_size	compa
0	5.0	0.920	1.0	0.0	2.0	0.0	5.0	21.0	4.0	
1	77.0	0.776	1.0	1.0	2.0	0.0	5.0	6.0	4.0	
2	64.0	0.624	1.0	1.0	0.0	0.0	5.0	15.0	4.0	
4	50.0	0.767	1.0	0.0	2.0	2.0	5.0	21.0	4.0	
5	57.0	0.764	1.0	0.0	1.0	0.0	5.0	2.0	4.0	
...	...	...	...	...	...	...	...	...	...	
19153	55.0	0.878	1.0	1.0	2.0	0.0	2.0	5.0	4.0	
19154	5.0	0.920	1.0	0.0	2.0	0.0	5.0	5.0	4.0	
19155	5.0	0.920	1.0	0.0	2.0	0.0	5.0	21.0	4.0	
19156	94.0	0.802	1.0	0.0	2.0	1.0	5.0	20.0	5.0	
19157	95.0	0.855	1.0	1.0	2.0	4.0	5.0	11.0	4.0	

18014 rows × 13 columns

In [184]:

```
newdf=df[(z<3).all(axis=1)]
newdf
```

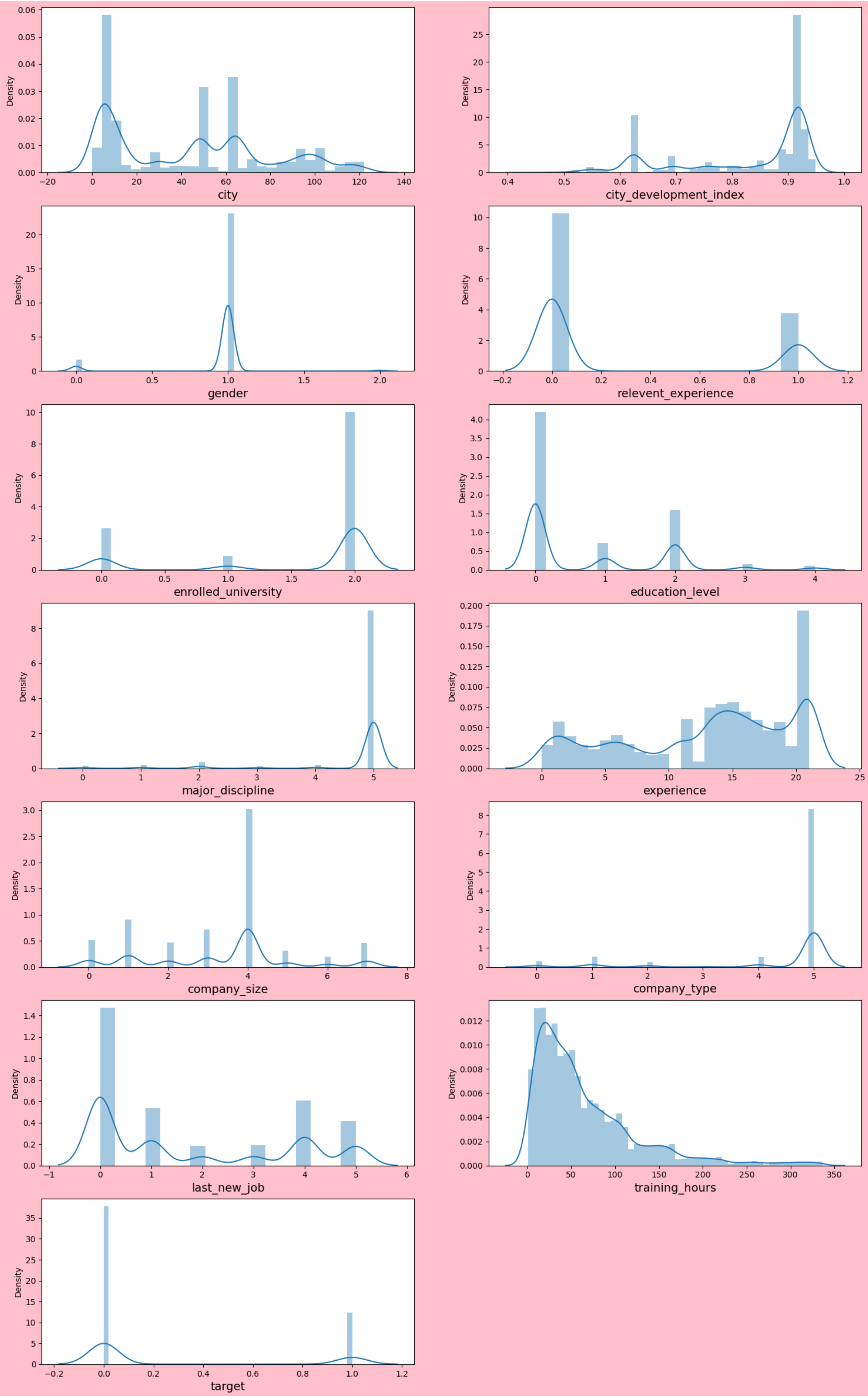
Out[184]:

	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_size	compa
0	5.0	0.920	1.0	0.0	2.0	0.0	5.0	21.0	4.0	
1	77.0	0.776	1.0	1.0	2.0	0.0	5.0	6.0	4.0	
2	64.0	0.624	1.0	1.0	0.0	0.0	5.0	15.0	4.0	
4	50.0	0.767	1.0	0.0	2.0	2.0	5.0	21.0	4.0	
5	57.0	0.764	1.0	0.0	1.0	0.0	5.0	2.0	4.0	
...	...	...	...	...	...	...	...	...	...	
19153	55.0	0.878	1.0	1.0	2.0	0.0	2.0	5.0	4.0	
19154	5.0	0.920	1.0	0.0	2.0	0.0	5.0	5.0	4.0	
19155	5.0	0.920	1.0	0.0	2.0	0.0	5.0	21.0	4.0	
19156	94.0	0.802	1.0	0.0	2.0	1.0	5.0	20.0	5.0	
19157	95.0	0.855	1.0	1.0	2.0	4.0	5.0	11.0	4.0	

15241 rows × 13 columns

In [185]:

```
plt.figure(figsize=(18,30),facecolor='pink')
plotn=1
for i in numcol:
    if plotn<=13:
        ax=plt.subplot(7,2,plotn)
        sns.distplot(df[i])
        plt.xlabel(i,fontsize=14)
        plotn=plotn+1
```


Density
city
Density
city_development_index
Density
gender
Density
relevent_experience
Density
enrolled_university
Density
education_level
Density
major_discipline
Density
experience
Density
company_size
Density
company_type
Density
last_new_job
Density
training_hours
Density
target

In [186]:

```
# find the skewness present in each column

newdf.skew()
```

Out[186]:

```
city                      0.392934
city_development_index   -1.009967
gender                    0.000000
relevent_experience       1.053978
enrolled_university      -1.269671
education_level           1.141437
major_discipline         -4.240788
experience               -0.506145
company_size             -0.133202
company_type             -2.884169
last_new_job              0.506748
training_hours            1.265576
target                    1.183469
dtype: float64
```

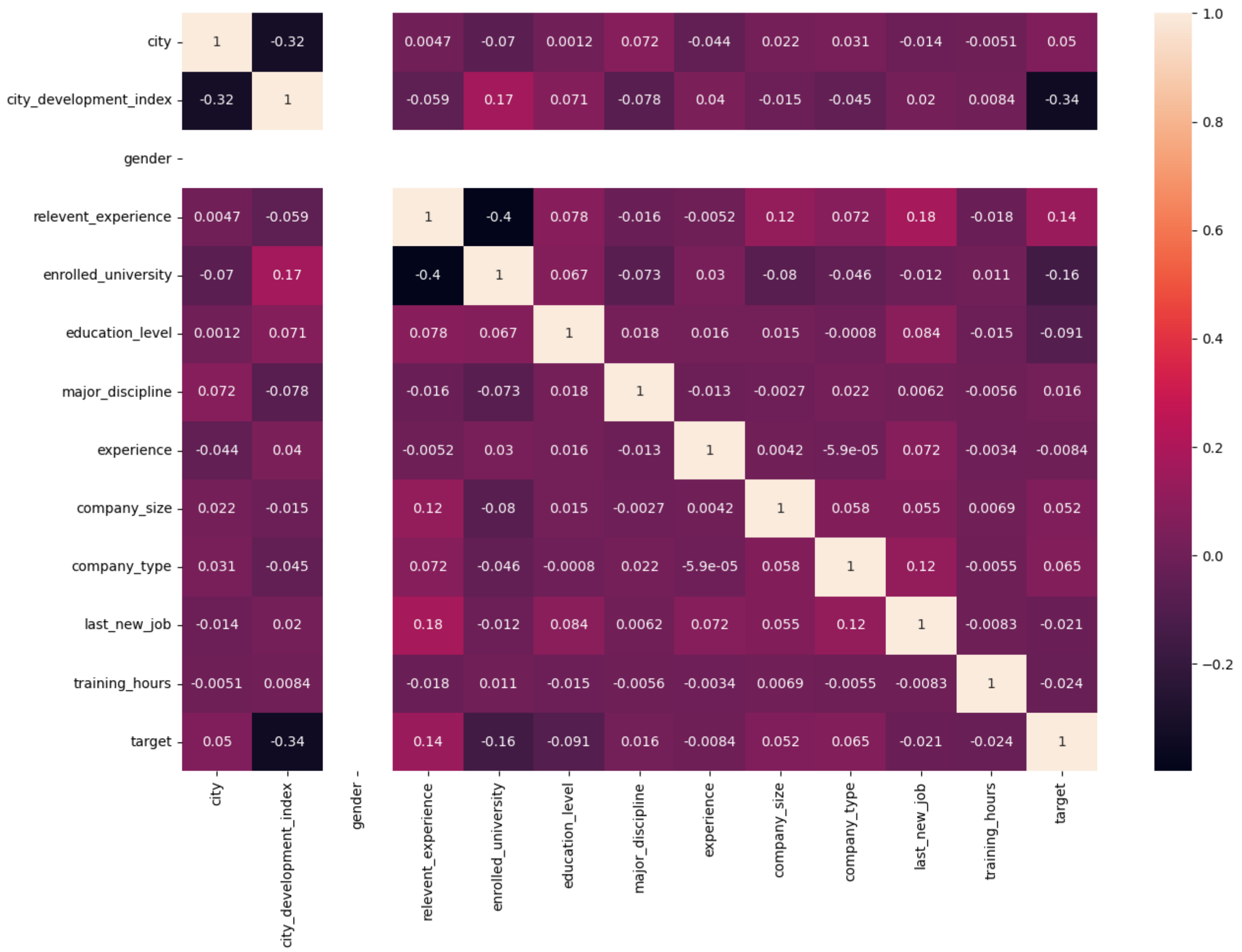
In [187]:

```
# by plotting heatmap find the corelation of target and features

plt.figure(figsize=(15,10))
sns.heatmap(newdf.corr(),annot=True)
```

Out[187]:

```
<AxesSubplot:>
```



In [188]:

```
newdf.skew()
```

Out[188]:

```
city                       0.392934
city_development_index    -1.009967
gender                     0.000000
relevent_experience        1.053978
enrolled_university       -1.269671
education_level            1.141437
major_discipline          -4.240788
experience                -0.506145
company_size              -0.133202
company_type              -2.884169
last_new_job               0.506748
training_hours             1.265576
target                     1.183469
dtype: float64
```

In [189]:

```
# using PowerTransformer remove the skewness from the columns

ske=['city_development_index','relevent_experience','enrolled_university','education_level','major_discipline','company_type','training_ho
from sklearn.preprocessing import PowerTransformer
pt=PowerTransformer(method='yeo-johnson')
newdf[ske]=pt.fit_transform(newdf[ske].values)
```

In [190]:

```
newdf.skew()
```

Out[190]:

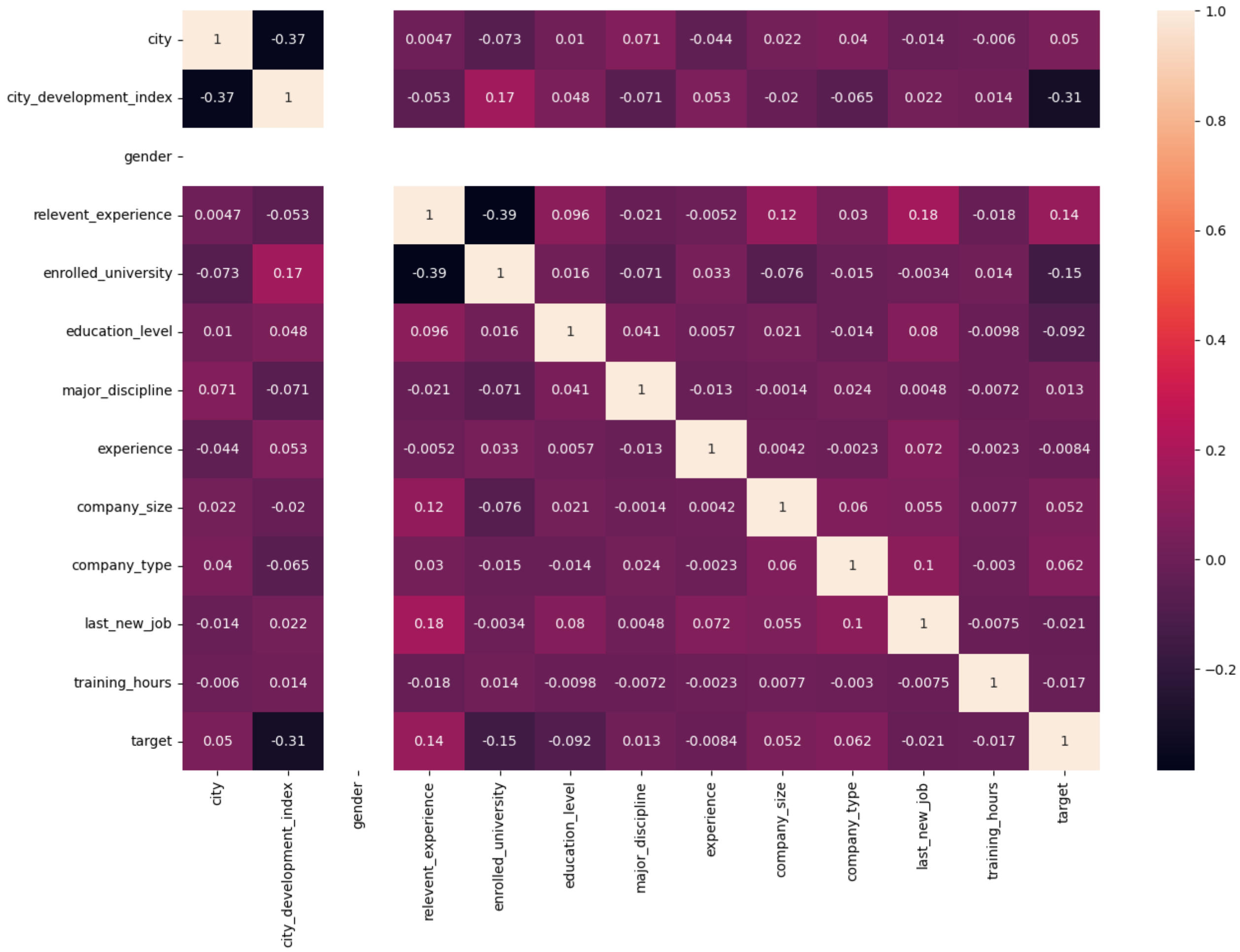
```
city                       0.392934
city_development_index    -0.578227
gender                     0.000000
relevent_experience        1.053978
enrolled_university       -1.119472
education_level            0.526783
major_discipline          -3.533052
experience                -0.506145
company_size              -0.133202
company_type              -2.140145
last_new_job               0.506748
training_hours            -0.038330
target                     1.183469
dtype: float64
```

In [191]:

```
plt.figure(figsize=(15,10))
sns.heatmap(newdf.corr(),annot=True)
```

Out[191]:

```
<AxesSubplot:>
```



In [192]:

```
# split our features and target in x and y respectively

x = newdf.iloc[:,:-1]
x
```

Out[192]:

	city	city_development_index	gender	relevent_experience	enrolled_university	education_level	major_discipline	experience	company_size	compa
0	5.0	0.824465	1.0	-0.603400	0.593154	-0.783349	0.263427	21.0	4.0	C
1	77.0	-0.896247	1.0	1.657274	0.593154	-0.783349	0.263427	6.0	4.0	C
2	64.0	-1.539893	1.0	1.657274	-1.790745	-0.783349	0.263427	15.0	4.0	C
4	50.0	-0.957226	1.0	-0.603400	0.593154	1.355215	0.263427	21.0	4.0	-2
5	57.0	-0.976701	1.0	-0.603400	-1.257944	-0.783349	0.263427	2.0	4.0	C
...	...	...	...	...	...	...	...	...	...	
19153	55.0	0.141141	1.0	1.657274	0.593154	-0.783349	-3.799967	5.0	4.0	C
19154	5.0	0.824465	1.0	-0.603400	0.593154	-0.783349	0.263427	5.0	4.0	C
19155	5.0	0.824465	1.0	-0.603400	0.593154	-0.783349	0.263427	21.0	4.0	C
19156	94.0	-0.696705	1.0	-0.603400	0.593154	0.936905	0.263427	20.0	5.0	C
19157	95.0	-0.159486	1.0	1.657274	0.593154	1.617743	0.263427	11.0	4.0	C

15241 rows × 12 columns

In [193]:

```
y = newdf.iloc[:,-1]
y
```

Out[193]:

```
0        1.0
1        0.0
2        0.0
4        0.0
5        1.0
        ...
19153    1.0
19154    1.0
19155    0.0
19156    0.0
19157    0.0
Name: target, Length: 15241, dtype: float64
```

In [194]:

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
xscaled=sc.fit_transform(x)
xscaled
```

Out[194]:

```
array([[-1.1093143 ,  0.8244648 ,  0.        , ...,  0.3974375 ,
        -0.93128936, -0.24866313],
       [ 0.92006722, -0.89624695,  0.        , ...,  0.3974375 ,
         1.14011509,  0.0426654 ],
       [ 0.55365111, -1.53989266,  0.        , ...,  0.3974375 ,
         1.6579662 ,  0.72532224],
       ...,
       [-1.1093143 ,  0.8244648 ,  0.        , ...,  0.3974375 ,
         0.62226398, -0.03105416],
       [ 1.39922674, -0.69670461,  0.        , ...,  0.3974375 ,
        -0.41343825,  0.92780978],
       [ 1.4274126 , -0.15948638,  0.        , ...,  0.3974375 ,
        -0.93128936,  1.29442076]])
```

In [195]:

```
# split the data for training and testing
```

In [196]:

```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(xscaled,y,test_size=0.30,random_state=1)
```

In [197]:

```
from sklearn.metrics import classification_report,accuracy_score
```

In [198]:

```
def mymodel(model):
    model.fit(xtrain,ytrain)
    ypred=model.predict(xtest)

    train=model.score(xtrain,ytrain)
    test=model.score(xtest,ytest)

    print(f"Training Accuracy : {train}\nTesting Accuracy : {test}")
    print(classification_report(ytest,ypred))
    return model
```

Apply LogisticRegression() and find out accuracy

from sklearn.linear_model import LogisticRegression

In [199]:

```
lr=mymodel(LogisticRegression())
```

```
Training Accuracy : 0.7695913010873641
Testing Accuracy : 0.76186310955609
              precision    recall  f1-score   support

         0.0       0.78      0.95      0.86      3428
         1.0       0.57      0.20      0.30      1145

    accuracy                           0.76      4573
   macro avg       0.68      0.57      0.58      4573
weighted avg       0.73      0.76      0.72      4573
```

In [200]:

```
lr=LogisticRegression()
lr.fit(xtrain,ytrain)
ypred=lr.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [201]:

```
from sklearn.model_selection import cross_val_score
ac=ac
print(ac)
cv_score=(cross_val_score(lr,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is",difference)
```

```
0.76186310955609

 Cross validation Score: 0.7647792959956752

 R2 Score - Cross Validation score is -0.0029161864395851333
```

Apply KNeighborsClassifier and find out accuracy

In [202]:

```
from sklearn.neighbors import KNeighborsClassifier
```

In [203]:

```
knn=mymodel(KNeighborsClassifier(n_neighbors=5))
```

```
Training Accuracy : 0.8189913760779902
Testing Accuracy : 0.7430570741307676
              precision    recall  f1-score   support

         0.0       0.80      0.87      0.84      3428
         1.0       0.48      0.35      0.41      1145

    accuracy                           0.74      4573
   macro avg       0.64      0.61      0.62      4573
weighted avg       0.72      0.74      0.73      4573
```

In [204]:

```
knn=KNeighborsClassifier()
knn.fit(xtrain,ytrain)
ypred=knn.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [205]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(knn,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7430570741307676

 Cross validation Score: 0.7489004828397762

 R2 Score - Cross Validation score is -0.0058434087090085685
```

Apply DecisionTreeClassifier and find out accuracy

In [206]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [207]:

```
dtc = mymodel(DecisionTreeClassifier())
```

```
Training Accuracy : 0.9970003749531309
Testing Accuracy : 0.7074130767548655
              precision    recall  f1-score   support

         0.0       0.81      0.80      0.80      3428
         1.0       0.42      0.44      0.43      1145

    accuracy                           0.71      4573
   macro avg       0.61      0.62      0.62      4573
weighted avg       0.71      0.71      0.71      4573
```

In [208]:

```
dtc=DecisionTreeClassifier()
dtc.fit(xtrain,ytrain)
ypred=dtc.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [209]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(dtc,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7041329542969604

 Cross validation Score: 0.7044156726227523

 R2 Score - Cross Validation score is -0.0002827183257918531
```

Apply SVM algorithm and find out Accuracy

In [210]:

```
from sklearn.svm import LinearSVC
from sklearn.svm import SVC

# Hard margin
linsvc=mymodel(LinearSVC(random_state=1))
```

```
Training Accuracy : 0.7679977502812149
Testing Accuracy : 0.7616444347255631
              precision    recall  f1-score   support

         0.0       0.77      0.96      0.86      3428
         1.0       0.59      0.15      0.24      1145

    accuracy                           0.76      4573
   macro avg       0.68      0.56      0.55      4573
weighted avg       0.73      0.76      0.70      4573
```

In [211]:

```
linsvc=LinearSVC()
linsvc.fit(xtrain,ytrain)
ypred=dtc.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [212]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(linsvc,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7041329542969604

 Cross validation Score: 0.6258202852964141

 R2 Score - Cross Validation score is 0.07831266900054634
```

In [213]:

```
# soft margin

linSVC=mymodel(LinearSVC(random_state=1,C=0.8))
```

```
Training Accuracy : 0.7679977502812149
Testing Accuracy : 0.7616444347255631
              precision    recall  f1-score   support

         0.0       0.77      0.96      0.86      3428
         1.0       0.59      0.15      0.24      1145

    accuracy                           0.76      4573
   macro avg       0.68      0.56      0.55      4573
weighted avg       0.73      0.76      0.70      4573
```

In [214]:

```
linSVC=LinearSVC(random_state=1,C=0.8)
linSVC.fit(xtrain,ytrain)
ypred=dtc.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [215]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(linSVC,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7041329542969604

 Cross validation Score: 0.6460790035715853

 R2 Score - Cross Validation score is 0.058053950725375114
```

Apply all Naive Bayes algorithm to find Accuracy

MultinomialNB,BernoulliNB,GaussianNB

In [216]:

```
from sklearn.naive_bayes import MultinomialNB,BernoulliNB,GaussianNB
```

In [217]:

```
bnb=mymodel(BernoulliNB())
```

```
Training Accuracy : 0.7559055118110236
Testing Accuracy : 0.7502733435381588
              precision    recall  f1-score   support

         0.0       0.78      0.92      0.85      3428
         1.0       0.50      0.23      0.31      1145

    accuracy                           0.75      4573
   macro avg       0.64      0.58      0.58      4573
weighted avg       0.71      0.75      0.71      4573
```

In [218]:

```
bnb.fit(xtrain,ytrain)
ypred=bnb.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [219]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(bnb,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7502733435381588

 Cross validation Score: 0.7498197851539465

 R2 Score - Cross Validation score is 0.00045355838421223815
```

In [220]:

```
gnb=mymodel(GaussianNB())
```

```
Training Accuracy : 0.7488751406074241
Testing Accuracy : 0.7502733435381588
              precision    recall  f1-score   support

         0.0       0.82      0.86      0.84      3428
         1.0       0.50      0.43      0.46      1145

    accuracy                           0.75      4573
   macro avg       0.66      0.64      0.65      4573
weighted avg       0.74      0.75      0.74      4573
```

In [221]:

```
gnb.fit(xtrain,ytrain)
ypred=gnb.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [222]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(gnb,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7502733435381588

 Cross validation Score: 0.7466701573339738

 R2 Score - Cross Validation score is 0.0036031862041849827
```

Apply all Boosting algorithms to find Accuracy

GradientBoostingClassifier , XGBClassifier ,AdaBoostClassifier

In [223]:

```
from sklearn.ensemble import GradientBoostingClassifier

gbr=mymodel(GradientBoostingClassifier(n_estimators=2))
```

```
Training Accuracy : 0.7567491563554556
Testing Accuracy : 0.7496173190465777
              precision    recall  f1-score   support

         0.0       0.75      1.00      0.86      3428
         1.0       0.00      0.00      0.00      1145

    accuracy                           0.75      4573
   macro avg       0.37      0.50      0.43      4573
weighted avg       0.56      0.75      0.64      4573
```

In [224]:

```
gbr.fit(xtrain,ytrain)
ypred=gbr.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [225]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(gbr,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7496173190465777

 Cross validation Score: 0.7546092733816603

 R2 Score - Cross Validation score is -0.0049919543350825935
```

In [226]:

```
from xgboost import XGBClassifier

xgb=mymodel(XGBClassifier(random_state=1,reg_alpha=1))
```

```
Training Accuracy : 0.8872328458942632
Testing Accuracy : 0.7692980537940083
              precision    recall  f1-score   support

         0.0       0.82      0.89      0.85      3428
         1.0       0.55      0.40      0.46      1145

    accuracy                           0.77      4573
   macro avg       0.69      0.65      0.66      4573
weighted avg       0.75      0.77      0.76      4573
```

In [227]:

```
xgb.fit(xtrain,ytrain)
ypred=xgb.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [228]:

```
ac=ac

print(ac)
cv_score=(cross_val_score(xgb,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7692980537940083

 Cross validation Score: 0.7747519301969839

 R2 Score - Cross Validation score is -0.005453876402975566
```

In [229]:

```
from sklearn.ensemble import AdaBoostClassifier

adb=mymodel(AdaBoostClassifier(random_state=1))
```

```
Training Accuracy : 0.7818710161229846
Testing Accuracy : 0.7817625191340477
              precision    recall  f1-score   support

         0.0       0.81      0.93      0.86      3428
         1.0       0.62      0.33      0.43      1145

    accuracy                           0.78      4573
   macro avg       0.71      0.63      0.65      4573
weighted avg       0.76      0.78      0.76      4573
```

In [230]:

```
adb.fit(xtrain,ytrain)
ypred=adb.predict(xtest)
ac=accuracy_score(ytest,ypred)
cr=classification_report(ytest,ypred)
```

In [231]:

```
ac=ac
print(ac)
cv_score=(cross_val_score(adb,x,y,cv=5).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.7817625191340477

 Cross validation Score: 0.7795420210059836

 R2 Score - Cross Validation score is 0.00222049812806413
```

In [232]:

```
067,0.7067,0.7067,0.7502,0.7502,0.7496,0.7692,0.7817],'CV Score':[0.7647,0.7489,0.7058,0.6961,0.6460,0.7498,0.7466,0.7546,0.7747,0.7795]}
```

In [233]:

```
D=pd.DataFrame(d)
D
```

Out[233]:

	Accuracy	CV Score
0	0.7618	0.7647
1	0.7430	0.7489
2	0.7067	0.7058
3	0.7067	0.6961
4	0.7067	0.6460
5	0.7502	0.7498
6	0.7502	0.7466
7	0.7496	0.7546
8	0.7692	0.7747
9	0.7817	0.7795

In [234]:

```
D['Difference']=(D['Accuracy']-D['CV Score'])
```

In [235]:

```
D
```

Out[235]:

	Accuracy	CV Score	Difference
0	0.7618	0.7647	-0.0029
1	0.7430	0.7489	-0.0059
2	0.7067	0.7058	0.0009
3	0.7067	0.6961	0.0106
4	0.7067	0.6460	0.0607
5	0.7502	0.7498	0.0004
6	0.7502	0.7466	0.0036
7	0.7496	0.7546	-0.0050
8	0.7692	0.7747	-0.0055
9	0.7817	0.7795	0.0022

```
Here we got less difference in KNeighborsClassifier i.e.-0.0059
```

```
So Moving towards hyperparameter Tunning of KNeighborsClassifier
```

In [236]:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
```

In [237]:

```
grid_params = { 'n_neighbors' : [5,7,9,11,13,15],
               'weights' : ['uniform','distance'],
               'metric' : ['minkowski','euclidean','manhattan']}
```

In [238]:

```
gs = GridSearchCV(KNeighborsClassifier(), grid_params, verbose = 1, cv=3, n_jobs = -1)
```

In [239]:

```
gs.fit(xtrain,ytrain)
print(gs.best_estimator_)
```

```
Fitting 3 folds for each of 36 candidates, totalling 108 fits
KNeighborsClassifier(metric='manhattan', n_neighbors=15)
```

In [240]:

```
gs.best_score_
```

Out[240]:

```
0.7639670041244845
```

In [241]:

```
ypred=gs.predict(xtest)
print(ypred)
```

```
[0. 0. 0. ... 1. 0. 0.]
```

In [242]:

```
from sklearn.metrics import accuracy_score
print(accuracy_score(ytest, ypred), ": is the accuracy score")
```

```
0.759457686420293 : is the accuracy score
```

In [243]:

```
from sklearn.model_selection import cross_val_score
ac=accuracy_score(ytest,ypred)
print(ac)
cv_score=(cross_val_score(gs,x,y,cv=3).mean())
print("\n Cross validation Score:",cv_score)

#Difference of R2 score minus CV score

difference=ac-cv_score
print("\n R2 Score - Cross Validation score is", difference)
```

```
0.759457686420293
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Fitting 3 folds for each of 36 candidates, totalling 108 fits
Fitting 3 folds for each of 36 candidates, totalling 108 fits

 Cross validation Score: 0.7655669492799327

 R2 Score - Cross Validation score is -0.0061092628596397525
```

In [244]:

```
print('Model accuracy: ',np.mean(scores))
```

```
Model accuracy:  0.7635323831487283
```