about all the feautures description

age: the age of an individual

● workclass: a general term to represent the employment status of an individual ○ Private, Selfempnotinc, Selfempinc, Federalgov, Localgov, Stategov, Withoutpay, Neverworked.

● fnlwgt: final weight. In other words, this is the number of people the census believes the entry represents..

● education: the highest level of education achieved by an individual. ○ Bachelors, Somecollege, 11th, HSgrad, Profschool, Assocacdm, Assocvoc, 9th, 7th8th, 12th, Masters, 1st4th, 10th, Doctorate, 5th6th, Preschool.

● maritalstatus: marital status of an individual. Marriedcivspouse corresponds to a civilian spouse while MarriedAFspouse is a spouse in the Armed Forces ○ Marriedcivspouse, Divorced, Nevermarried, Separated, Widowed, Marriedspouseabsent, MarriedAFspouse.

● occupation: the general type of occupation of an individual ○ Techsupport, Craftrepair, Otherservice, Sales, Execmanagerial, Profspecialty, Handlerscleaners, Machineopinspct, Admclerical, Farmingfishing, Transportmoving, Privhouseserv, Protectiveserv, ArmedForces.

● relationship: represents what this individual is relative to others. For example an individual could be a Husband. Each entry only has one relationship attribute and is somewhat redundant with marital status. We might not make use of this attribute at all ○ Wife, Ownchild, Husband, Notinfamily, Otherrelative, Unmarried.

● race: Descriptions of an individual's race ○ White, AsianPacIslander, AmerIndianEskimo, Other, Black.

● sex: the biological sex of the individual ○ Male, Female

● capitalgain: capital gains for an individual ○ Integer greater than or equal to 0

● capitalloss: capital loss for an individual ○ Integer greater than or equal to 0

● hoursperweek: the hours an individual has reported to work per week ○ continuous.

● nativecountry: country of origin for an individual ○ UnitedStates, Cambodia, England, PuertoRico, Canada, Germany, OutlyingUS(Guam-USVIetc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, DominicanRepublic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, HolandNetherlands.

● the label or our target: whether or not an individual makes more than $50,000 annually. ○ <=50k, >50k

• Project Description:

Problem statement: Create a classification model to predict whether a person makes over $50k a year

importing dataframe

importing crucial libraries

In [162…

```
import os
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [163…

```
os.chdir(r'C:\Users\63094\Downloads\hero wired\datacsv')
os.listdir();
df=pd.read_csv('adult.csv')
df
```

Out[163…

	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	United-States	<=50K

...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=50K
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

32560 rows × 15 columns

In [164…

```
df.head(10)
```

Out[164…

	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	United-States	<=50K
5	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	16	Jamaica	<=50K
6	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	United-States	>50K
7	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50	United-States	>50K
8	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	40	United-States	>50K
9	37	Private	280464	Some-college	10	Married-civ-spouse	Exec-managerial	Husband	Black	Male	0	0	80	United-States	>50K

firstly we rename the column names

In [165…

```
df= df.rename({'39':'age',' State-gov':'workclass',' 77516':'fnlwgt',
                         ' Bachelors':'Education',
                        ' 13':'education_num',
                        ' Adm-clerical':'occupation',
                         ' Never-married':'marital_status',
                        ' Not-in-family':'relationship',
                         ' White':'race',
                         ' Male':'sex',
                         ' 2174':'capital_gain',
                        ' 0':'capital_loss',
                         ' 40':'hours_per_week',
                         ' United-States':'native_country',
                         ' <=50K':'Target'},axis=1)
```

In [166…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32560 entries, 0 to 32559
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32560 non-null  int64 
 1   workclass       32560 non-null  object
 2   fnlwgt          32560 non-null  int64 
 3   Education       32560 non-null  object
 4   education_num   32560 non-null  int64 
 5   marital_status  32560 non-null  object
 6   occupation      32560 non-null  object
 7   relationship    32560 non-null  object
 8   race            32560 non-null  object
```

```
 9   sex             32560 non-null  object
 10  capital_gain    32560 non-null  int64
 11  capital_loss    32560 non-null  int64
 12  hours_per_week  32560 non-null  int64
 13  native_country  32560 non-null  object
 14  Target          32560 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [167…

```
df
```

Out[167…

	age	workclass	fnlwgt	Education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	h
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	

32560 rows × 15 columns

finally,we rename the columns with meaningful names based on the rowinformation

In [168…

```
df.tail(10)
```

Out[168…

	age	workclass	fnlwgt	Education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss
32550	32	Private	34066	10th	6	Married-civ-spouse	Handlers-cleaners	Husband	Amer-Indian-Eskimo	Male	0	0
32551	43	Private	84661	Assoc-voc	11	Married-civ-spouse	Sales	Husband	White	Male	0	0
32552	32	Private	116138	Masters	14	Never-married	Tech-support	Not-in-family	Asian-Pac-Islander	Male	0	0
32553	53	Private	321865	Masters	14	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0
32554	22	Private	310152	Some-college	10	Never-married	Protective-serv	Not-in-family	White	Male	0	0
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0

null values

In [169…
```
df.isnull().sum()
```

Out[169…
```
age               0
workclass         0
fnlwgt            0
Education         0
education_num     0
marital_status    0
occupation        0
relationship      0
race              0
sex               0
capital_gain      0
capital_loss      0
hours_per_week    0
native_country    0
Target            0
dtype: int64
```

In [170…
```
## we have no null values
```

duplicates

In [171…
```
df.duplicated().sum()
```

Out[171… 24

we have 24 duplictes lets drop

In [172…
```
df.drop_duplicates(inplace=True)
```

In [173…
```
df
```

Out[173…

	age	workclass	fnlwgt	Education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	h
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	

32536 rows × 15 columns

In [174…
```
df.shape
```

Out[174… (32536, 15)

In [175…
```
df.columns
```

Out[175…
```
Index(['age', 'workclass', 'fnlwgt', 'Education', 'education_num',
       'marital_status', 'occupation', 'relationship', 'race', 'sex',
       'capital_gain', 'capital_loss', 'hours_per_week', 'native_country',
       'Target'],
      dtype='object')
```

unique values in the dataframe

In [176…
```
for i in  df.columns:
    print(i,'-----',df[i].nunique())
```

```
age ----- 73
workclass ----- 9
fnlwgt ----- 21647
Education ----- 16
education_num ----- 16
marital_status ----- 7
occupation ----- 15
relationship ----- 6
race ----- 5
sex ----- 2
capital_gain ----- 119
capital_loss ----- 92
hours_per_week ----- 94
native_country ----- 42
Target ----- 2
```

categorical values

In [177…
```
df.describe(include='object')
```

Out[177…

	workclass	Education	marital_status	occupation	relationship	race	sex	native_country	Target
count	32536	32536	32536	32536	32536	32536	32536	32536	32536
unique	9	16	7	15	6	5	2	42	2
top	Private	HS-grad	Married-civ-spouse	Prof-specialty	Husband	White	Male	United-States	<=50K
freq	22673	10494	14970	4136	13187	27794	21774	29152	24697

numerical values

In [178…
```
df.describe()
```

Out[178…

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
count	32536.000000	3.253600e+04	32536.000000	32536.000000	32536.000000	32536.000000
mean	38.585536	1.897843e+05	10.081725	1078.410069	87.370912	40.440343
std	13.638193	1.055563e+05	2.571622	7388.068465	403.107737	12.347079
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178315e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.369932e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

In [179…
```
df
```

Out[179…

	age	workclass	fnlwgt	Education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	h
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	

1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0

32536 rows × 15 columns

univariate analysis

In [180…

```
df
```

Out[180…

	age	workclass	fnlwgt	Education	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	h
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	
32556	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	
32557	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	
32558	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	
32559	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	

32536 rows × 15 columns

In [181…

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

Out[181…

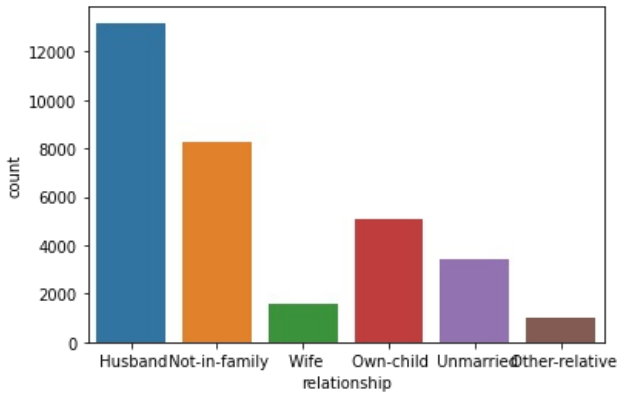
```
Private             22673
Self-emp-not-inc     2540
Local-gov            2093
?                    1836
State-gov            1297
Self-emp-inc         1116
Federal-gov           960
Without-pay            14
Never-worked            7
Name: workclass, dtype: int64
```

In [182…

```
sns.countplot(df['relationship'])
```

```
C:\Users\63094\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

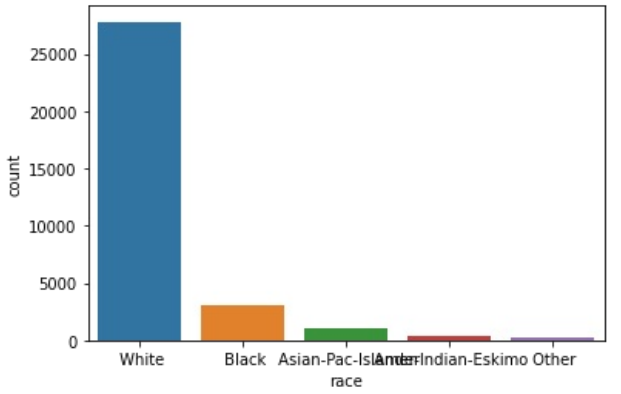
Out[182… <AxesSubplot:xlabel='relationship', ylabel='count'>



In [183…
```
sns.countplot(df['race'])
```

```
C:\Users\63094\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

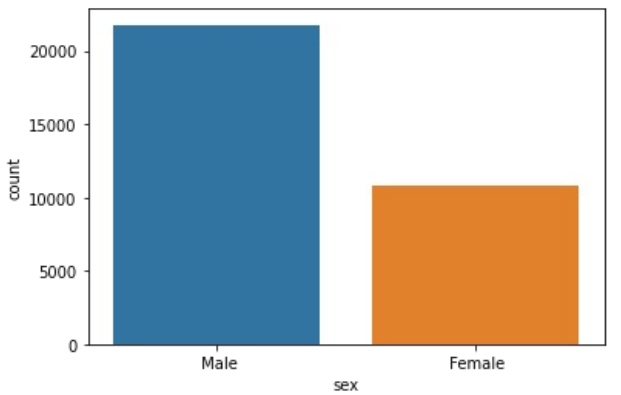
Out[183… <AxesSubplot:xlabel='race', ylabel='count'>



In [184…
```
sns.countplot(df['sex'])
```

```
C:\Users\63094\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

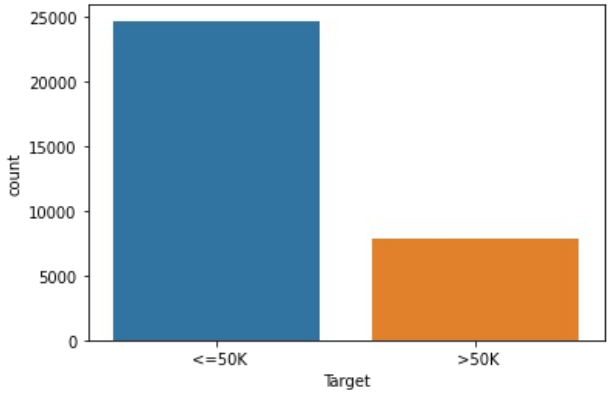
Out[184… <AxesSubplot:xlabel='sex', ylabel='count'>



In [185…
```
sns.countplot(df['Target'])
```

```
C:\Users\63094\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable
as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other argu
ments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[185… <AxesSubplot:xlabel='Target', ylabel='count'>

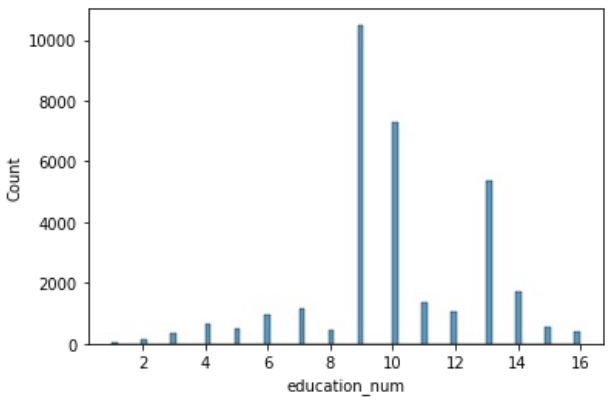


In [186…
```
df['Education'].value_counts()
```

Out[186…
```
 HS-grad         10494
 Some-college     7282
 Bachelors        5352
 Masters          1722
 Assoc-voc        1382
 11th             1175
 Assoc-acdm       1067
 10th              933
 7th-8th           645
 Prof-school       576
 9th               514
 12th              433
 Doctorate         413
 5th-6th           332
 1st-4th           166
 Preschool          50
Name: Education, dtype: int64
```

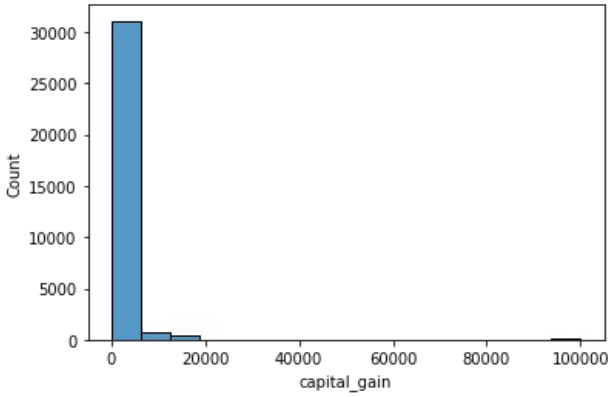
In [187…
```
sns.histplot(df['education_num'])
```

Out[187… <AxesSubplot:xlabel='education_num', ylabel='Count'>



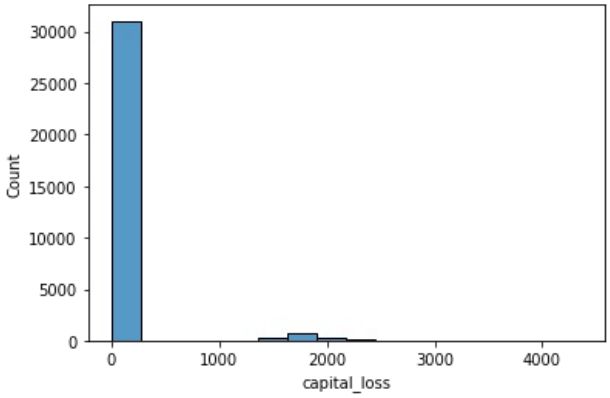
In [188…
```
sns.histplot(df['capital_gain'])
```

Out[188… <AxesSubplot:xlabel='capital_gain', ylabel='Count'>



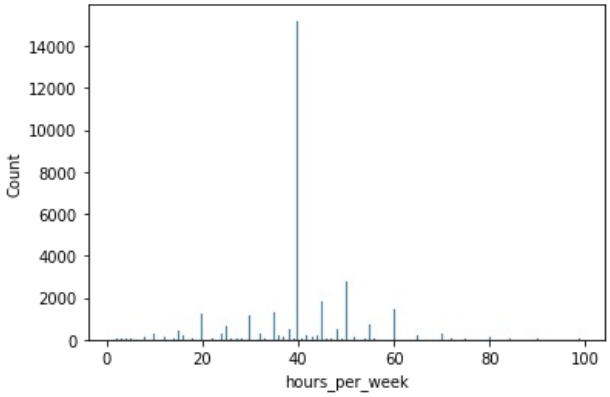
In [189…
```
sns.histplot(df['capital_loss'])
```

Out[189… <AxesSubplot:xlabel='capital_loss', ylabel='Count'>



In [190…
```
sns.histplot(df['hours_per_week'])
```

Out[190… <AxesSubplot:xlabel='hours_per_week', ylabel='Count'>



In [191…
```
df['occupation'].value_counts()
```

Out[191…
```
Prof-specialty       4136
Craft-repair         4094
Exec-managerial      4065
Adm-clerical         3767
Sales                3650
Other-service        3291
Machine-op-inspct    2000
?                    1843
Transport-moving     1597
Handlers-cleaners    1369
Farming-fishing       992
Tech-support          927
Protective-serv       649
Priv-house-serv       147
```

```
 Armed-Forces            9
Name: occupation, dtype: int64
```

In [192…
```
df['occupation'].fillna(value = 'Prof-specialty', inplace = True)
```

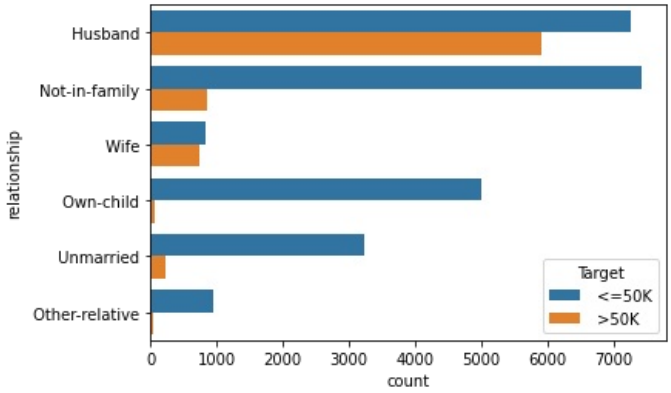
In [193…
```
df['occupation'].value_counts()
```

Out[193…
```
 Prof-specialty       4136
 Craft-repair         4094
 Exec-managerial      4065
 Adm-clerical         3767
 Sales                3650
 Other-service        3291
 Machine-op-inspct    2000
 ?                    1843
 Transport-moving     1597
 Handlers-cleaners    1369
 Farming-fishing       992
 Tech-support          927
 Protective-serv       649
 Priv-house-serv       147
 Armed-Forces            9
Name: occupation, dtype: int64
```

bivarient analysis based on target

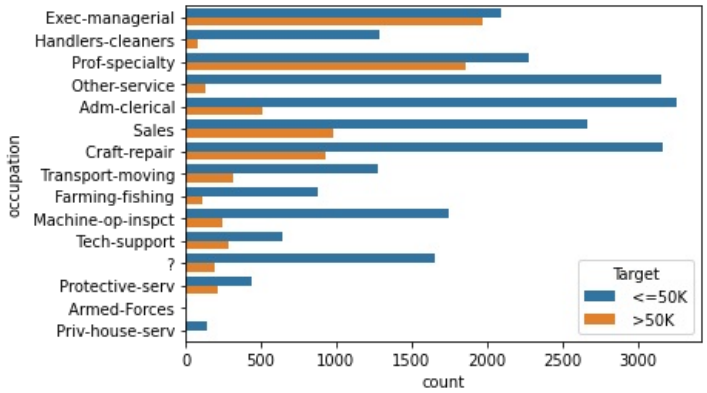
In [194…
```
sns.countplot(hue=df['Target'],y=df['relationship'])
```

Out[194… <AxesSubplot:xlabel='count', ylabel='relationship'>



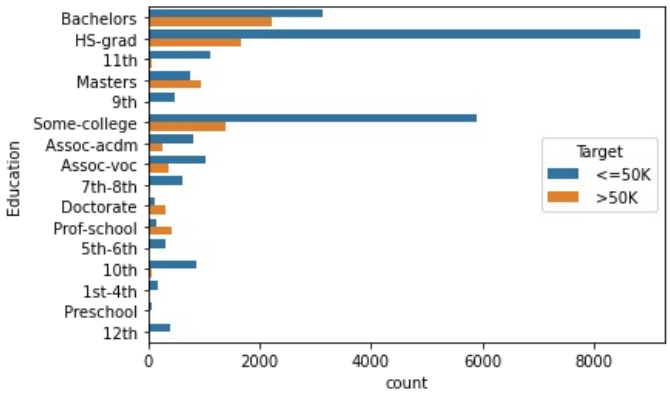
In [195…
```
sns.countplot(hue=df['Target'],y=df['occupation'])
```

Out[195… <AxesSubplot:xlabel='count', ylabel='occupation'>



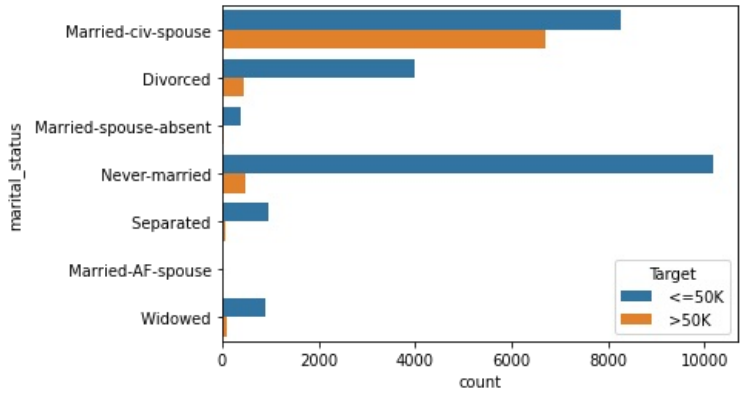
In [196…
```
sns.countplot(hue=df['Target'],y=df['Education'])
```

Out[196… <AxesSubplot:xlabel='count', ylabel='Education'>



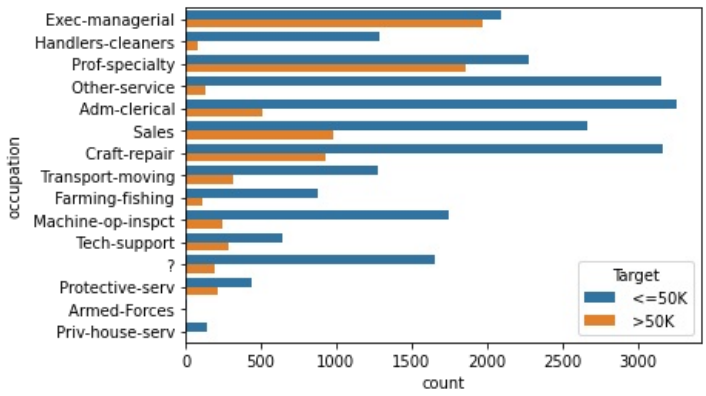
In [197…
```
sns.countplot(hue=df['Target'],y=df['marital_status'])
```

Out[197… <AxesSubplot:xlabel='count', ylabel='marital_status'>



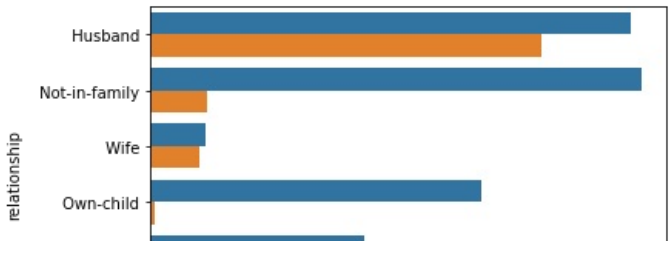
In [198…
```
sns.countplot(hue=df['Target'],y=df['occupation'])
```

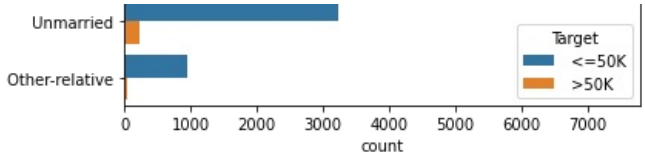
Out[198… <AxesSubplot:xlabel='count', ylabel='occupation'>



In [199…
```
sns.countplot(hue=df['Target'],y=df['relationship'])
```

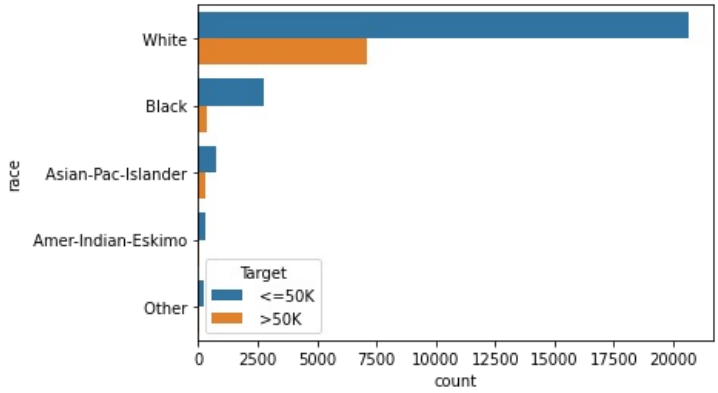
Out[199… <AxesSubplot:xlabel='count', ylabel='relationship'>





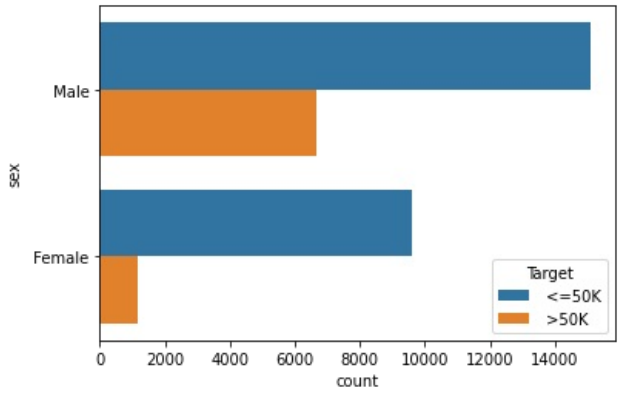
In [200…
```
sns.countplot(hue=df['Target'],y=df['race'])
```

Out[200… <AxesSubplot:xlabel='count', ylabel='race'>



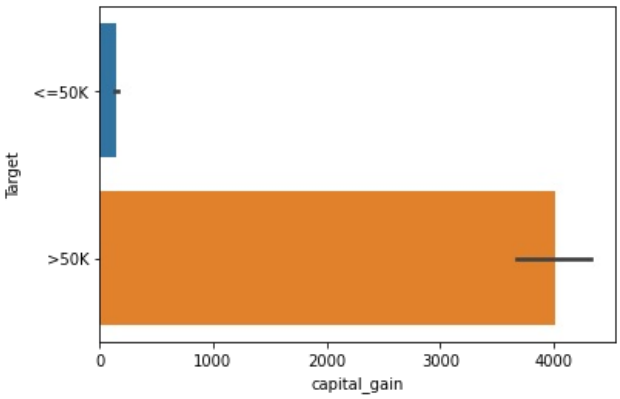
In [201…
```
sns.countplot(hue=df['Target'],y=df['sex'])
```

Out[201… <AxesSubplot:xlabel='count', ylabel='sex'>



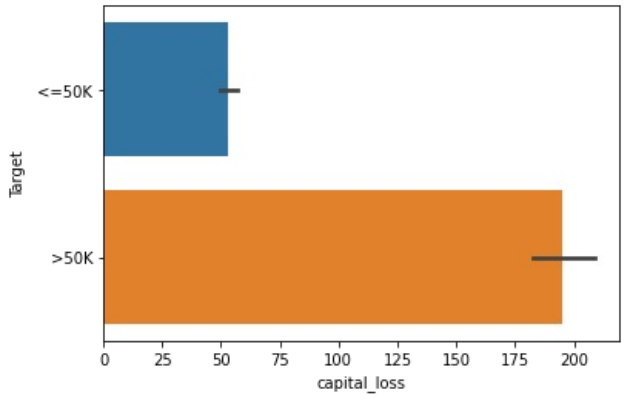
In [202…
```
sns.barplot(x=df['capital_gain'],y=df['Target'])
```

Out[202… <AxesSubplot:xlabel='capital_gain', ylabel='Target'>



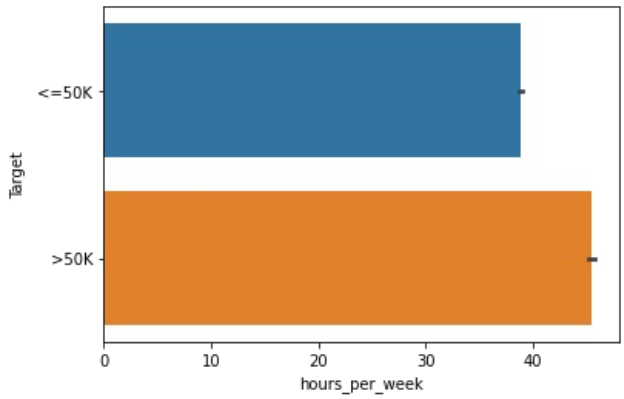
In [203…
```
sns.barplot(x=df['capital_loss'],y=df['Target'])
```

Out[203… <AxesSubplot:xlabel='capital_loss', ylabel='Target'>



In [204…
```
sns.barplot(x=df['hours_per_week'],y=df['Target'])
```

Out[204…
```
<AxesSubplot:xlabel='hours_per_week', ylabel='Target'>
```



we draw the bivarient analysis and we see some insighths by these diagrams

In [205…
```
from sklearn.model_selection import train_test_split
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

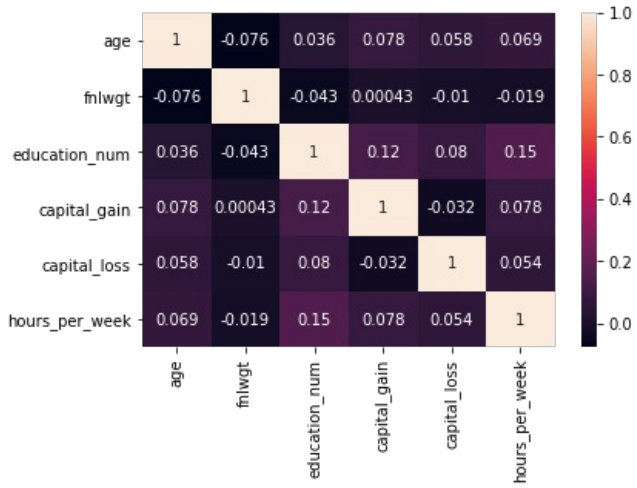
In [206…
```
df.corr()
```

Out[206…

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
age	1.000000	-0.076448	0.036224	0.077676	0.057745	0.068515
fnlwgt	-0.076448	1.000000	-0.043353	0.000433	-0.010267	-0.018900
education_num	0.036224	-0.043353	1.000000	0.122661	0.079901	0.148426
capital_gain	0.077676	0.000433	0.122661	1.000000	-0.031638	0.078408
capital_loss	0.057745	-0.010267	0.079901	-0.031638	1.000000	0.054229
hours_per_week	0.068515	-0.018900	0.148426	0.078408	0.054229	1.000000

In [207…
```
sns.heatmap(df.corr(),annot=True)
```

Out[207…
```
<AxesSubplot:>
```



dropping un relevent or unused columns

In [208…
```
df.drop(labels=['Education','fnlwgt'],axis=1,inplace=True)
```

In [209…
```
df
```

Out[209…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	nativ
0	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Ur
1	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Ur
2	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Ur
3	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
4	37	Private	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	Ur
...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	Private	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	Ur
32556	40	Private	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	Ur
32557	58	Private	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	Ur
32558	22	Private	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	Ur
32559	52	Self-emp-inc	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	Ur

32536 rows × 13 columns

In [210…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32536 entries, 0 to 32559
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32536 non-null  int64 
 1   workclass       32536 non-null  object
 2   education_num   32536 non-null  int64 
 3   marital_status  32536 non-null  object
 4   occupation      32536 non-null  object
 5   relationship    32536 non-null  object
 6   race            32536 non-null  object
 7   sex             32536 non-null  object
 8   capital_gain    32536 non-null  int64 
 9   capital_loss    32536 non-null  int64 
 10  hours_per_week  32536 non-null  int64 
```

```
 11  native_country  32536 non-null  object
 12  Target          32536 non-null  object
dtypes: int64(5), object(8)
memory usage: 3.5+ MB
```

In [211…

```
df.replace({' ?':np.nan},inplace=True)
```

In [212…

```
df.head(30)
```

Out[212…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native
0	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Unit
1	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Unit
2	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Unit
3	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
4	37	Private	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	Unit
5	49	Private	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	16	
6	52	Self-emp-not-inc	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	Unit
7	31	Private	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	0	50	Unit
8	42	Private	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	40	Unit
9	37	Private	10	Married-civ-spouse	Exec-managerial	Husband	Black	Male	0	0	80	Unit
10	30	State-gov	13	Married-civ-spouse	Prof-specialty	Husband	Asian-Pac-Islander	Male	0	0	40	
11	23	Private	13	Never-married	Adm-clerical	Own-child	White	Female	0	0	30	Unit
12	32	Private	12	Never-married	Sales	Not-in-family	Black	Male	0	0	50	Unit
13	40	Private	11	Married-civ-spouse	Craft-repair	Husband	Asian-Pac-Islander	Male	0	0	40	
14	34	Private	4	Married-civ-spouse	Transport-moving	Husband	Amer-Indian-Eskimo	Male	0	0	45	
15	25	Self-emp-not-inc	9	Never-married	Farming-fishing	Own-child	White	Male	0	0	35	Unit
16	32	Private	9	Never-married	Machine-op-inspct	Unmarried	White	Male	0	0	40	Unit
17	38	Private	7	Married-civ-spouse	Sales	Husband	White	Male	0	0	50	Unit
18	43	Self-emp-not-inc	14	Divorced	Exec-managerial	Unmarried	White	Female	0	0	45	Unit
19	40	Private	16	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	60	Unit
20	54	Private	9	Separated	Other-service	Unmarried	Black	Female	0	0	20	Unit
21	35	Federal-gov	5	Married-civ-spouse	Farming-fishing	Husband	Black	Male	0	0	40	Unit
22	43	Private	7	Married-civ-spouse	Transport-moving	Husband	White	Male	0	2042	40	Unit
23	59	Private	9	Divorced	Tech-support	Unmarried	White	Female	0	0	40	Unit
24	56	Local-gov	13	Married-civ-spouse	Tech-support	Husband	White	Male	0	0	40	Unit
25	19	Private	9	Never-married	Craft-repair	Own-child	White	Male	0	0	40	Unit
26	54	NaN	10	Married-civ-spouse	NaN	Husband	Asian-Pac-Islander	Male	0	0	60	
27	39	Private	9	Divorced	Exec-managerial	Not-in-family	White	Male	0	0	80	Unit

28	49	Private	9	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0	40	Unit
29	23	Local-gov	12	Never-married	Protective-serv	Not-in-family	White	Male	0	0	52	Unit

now its filled with nan values

In [213…
```
df.isnull().sum()
```

Out[213…
```
age                0
workclass       1836
education_num      0
marital_status     0
occupation      1843
relationship       0
race               0
sex                0
capital_gain       0
capital_loss       0
hours_per_week     0
native_country   582
Target             0
dtype: int64
```

then it shows null values

In [214…
```
df.fillna(method='ffill',inplace=True)
```

In [215…
```
df.isnull().sum()
```

Out[215…
```
age              0
workclass        0
education_num    0
marital_status   0
occupation       0
relationship     0
race             0
sex              0
capital_gain     0
capital_loss     0
hours_per_week   0
native_country   0
Target           0
dtype: int64
```

we fill the null values with ffill method

In [216…
```
df.head(60)
```

Out[216…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native
0	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Unit
1	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Unit
2	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Unit
3	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	
4	37	Private	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	0	40	Unit
5	49	Private	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	0	16	
6	52	Self-emp-not-inc	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	45	Unit
7	31	Private	14	Never-married	Prof-	Not-in-family	White	Female	14084	0	50	Unit

					specialty							
8	42	Private	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	0	40	Unit
9	37	Private	10	Married-civ-spouse	Exec-managerial	Husband	Black	Male	0	0	80	Unit
10	30	State-gov	13	Married-civ-spouse	Prof-specialty	Husband	Asian-Pac-Islander	Male	0	0	40	
11	23	Private	13	Never-married	Adm-clerical	Own-child	White	Female	0	0	30	Unit
12	32	Private	12	Never-married	Sales	Not-in-family	Black	Male	0	0	50	Unit
13	40	Private	11	Married-civ-spouse	Craft-repair	Husband	Asian-Pac-Islander	Male	0	0	40	Unit
14	34	Private	4	Married-civ-spouse	Transport-moving	Husband	Amer-Indian-Eskimo	Male	0	0	45	
15	25	Self-emp-not-inc	9	Never-married	Farming-fishing	Own-child	White	Male	0	0	35	Unit
16	32	Private	9	Never-married	Machine-op-inspct	Unmarried	White	Male	0	0	40	Unit
17	38	Private	7	Married-civ-spouse	Sales	Husband	White	Male	0	0	50	Unit
18	43	Self-emp-not-inc	14	Divorced	Exec-managerial	Unmarried	White	Female	0	0	45	Unit
19	40	Private	16	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	60	Unit
20	54	Private	9	Separated	Other-service	Unmarried	Black	Female	0	0	20	Unit
21	35	Federal-gov	5	Married-civ-spouse	Farming-fishing	Husband	Black	Male	0	0	40	Unit
22	43	Private	7	Married-civ-spouse	Transport-moving	Husband	White	Male	0	2042	40	Unit
23	59	Private	9	Divorced	Tech-support	Unmarried	White	Female	0	0	40	Unit
24	56	Local-gov	13	Married-civ-spouse	Tech-support	Husband	White	Male	0	0	40	Unit
25	19	Private	9	Never-married	Craft-repair	Own-child	White	Male	0	0	40	Unit
26	54	Private	10	Married-civ-spouse	Craft-repair	Husband	Asian-Pac-Islander	Male	0	0	60	
27	39	Private	9	Divorced	Exec-managerial	Not-in-family	White	Male	0	0	80	Unit
28	49	Private	9	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0	40	Unit
29	23	Local-gov	12	Never-married	Protective-serv	Not-in-family	White	Male	0	0	52	Unit
30	20	Private	10	Never-married	Sales	Own-child	Black	Male	0	0	44	Unit
31	45	Private	13	Divorced	Exec-managerial	Own-child	White	Male	0	1408	40	Unit
32	30	Federal-gov	10	Married-civ-spouse	Adm-clerical	Own-child	White	Male	0	0	40	Unit
33	22	State-gov	10	Married-civ-spouse	Other-service	Husband	Black	Male	0	0	15	Unit
34	48	Private	7	Never-married	Machine-op-inspct	Unmarried	White	Male	0	0	40	Pu
35	21	Private	10	Never-married	Machine-op-inspct	Own-child	White	Male	0	0	40	Unit
36	19	Private	9	Married-AF-spouse	Adm-clerical	Wife	White	Female	0	0	25	Unit
37	31	Private	10	Married-civ-spouse	Sales	Husband	White	Male	0	0	38	Unit
38	48	Self-emp-not-inc	12	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	40	Unit
39	31	Private	5	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	43	Unit
40	53	Self-emp-not-inc	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	40	Unit
41	24	Private	13	Married-civ-spouse	Tech-support	Husband	White	Male	0	0	50	Unit
42	49	Private	9	Separated	Adm-	Unmarried	White	Female	0	0	40	Unit

					clerical							
43	25	Private	9	Never-married	Handlers-cleaners	Not-in-family	White	Male	0	0	35	Unit
44	57	Federal-gov	13	Married-civ-spouse	Prof-specialty	Husband	Black	Male	0	0	40	Unit
45	53	Private	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	38	Unit
46	44	Private	14	Divorced	Exec-managerial	Unmarried	White	Female	0	0	40	Unit
47	41	State-gov	11	Married-civ-spouse	Craft-repair	Husband	White	Male	0	0	40	Unit
48	29	Private	11	Never-married	Prof-specialty	Not-in-family	White	Male	0	0	43	Unit
49	25	Private	10	Married-civ-spouse	Exec-managerial	Wife	Other	Female	0	0	40	Unit
50	18	Private	9	Never-married	Other-service	Own-child	White	Female	0	0	30	Unit
51	47	Private	15	Married-civ-spouse	Prof-specialty	Wife	White	Female	0	1902	60	
52	50	Federal-gov	13	Divorced	Exec-managerial	Not-in-family	White	Male	0	0	55	Unit
53	47	Self-emp-inc	9	Divorced	Exec-managerial	Not-in-family	White	Male	0	0	60	Unit
54	43	Private	10	Married-civ-spouse	Tech-support	Husband	White	Male	0	0	40	Unit
55	46	Private	3	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	
56	35	Private	11	Married-civ-spouse	Other-service	Husband	White	Male	0	0	40	Pu
57	41	Private	9	Married-civ-spouse	Adm-clerical	Husband	White	Male	0	0	48	Unit
58	30	Private	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	5013	0	40	Unit
59	30	Private	13	Married-civ-spouse	Sales	Husband	White	Male	2407	0	40	Unit

no we see there are no ? marks in data every thing will be filled

Split data into training and testing data

In [217…
```
from sklearn.model_selection import train_test_split
```

In [218…
```
from sklearn.preprocessing import LabelEncoder
e=LabelEncoder()
df['workclass']=e.fit_transform(df['workclass'])
df['marital_status']=e.fit_transform(df['marital_status'])
df['occupation']=e.fit_transform(df['occupation'])
df['relationship']=e.fit_transform(df['relationship'])
df['race']=e.fit_transform(df['race'])
df['sex']=e.fit_transform(df['sex'])
df['native_country']=e.fit_transform(df['native_country'])
df['Target']=e.fit_transform(df['Target'])
```

In [219…
```
df
```

Out[219…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_c
0	50	5	13	2	3	0	4	1	0	0	13	
1	38	3	9	0	5	1	4	1	0	0	40	
2	53	3	7	2	5	0	2	1	0	0	40	
3	28	3	13	2	9	5	2	0	0	0	40	
4	37	3	14	2	3	5	4	0	0	0	40	
...	...	...	...	...	...	...	...	...	...	...	...	
32555	27	3	12	2	12	5	4	0	0	0	38	
32556	40	3	9	2	6	0	4	1	0	0	40	

32557	58	3	9	6	0	4	4	0	0	0	40
32558	22	3	9	4	0	3	4	1	0	0	20
32559	52	4	9	2	3	5	4	0	15024	0	40

32536 rows × 13 columns

it would be converted into the numrical values

In [220…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32536 entries, 0 to 32559
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32536 non-null  int64
 1   workclass       32536 non-null  int32
 2   education_num   32536 non-null  int64
 3   marital_status  32536 non-null  int32
 4   occupation      32536 non-null  int32
 5   relationship    32536 non-null  int32
 6   race            32536 non-null  int32
 7   sex             32536 non-null  int32
 8   capital_gain    32536 non-null  int64
 9   capital_loss    32536 non-null  int64
 10  hours_per_week  32536 non-null  int64
 11  native_country  32536 non-null  int32
 12  Target          32536 non-null  int32
dtypes: int32(8), int64(5)
memory usage: 2.5 MB
```

In [221…

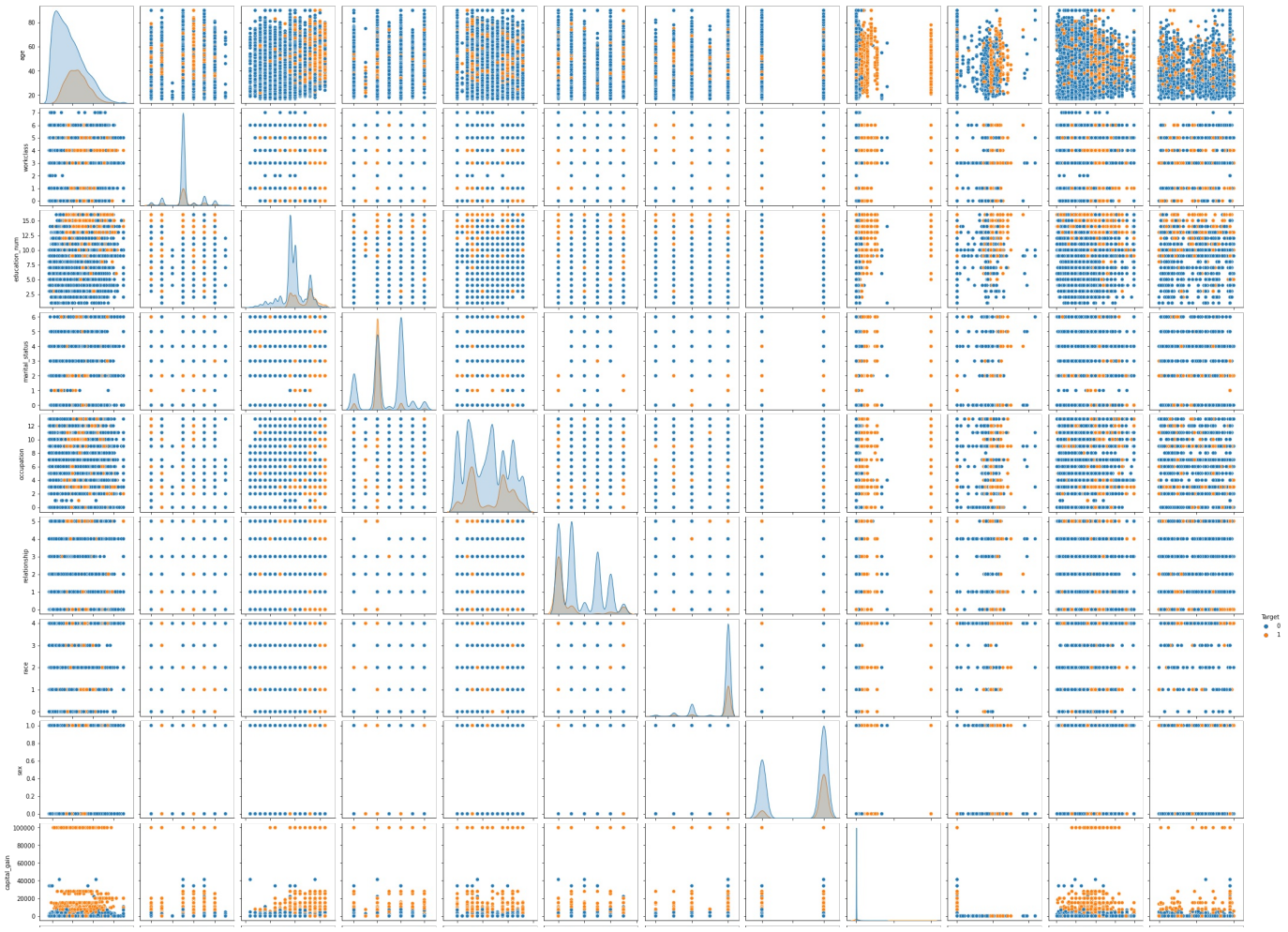
```
#0---->=50K,1---->>50K
```

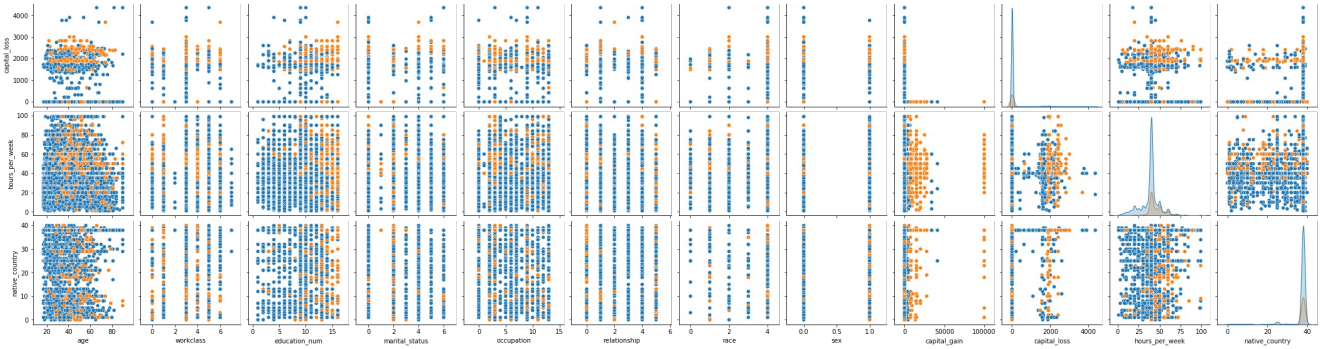
In [222…

```
sns.pairplot(df,hue='Target')
```

Out[222…

```
<seaborn.axisgrid.PairGrid at 0x1c604d0d280>
```





from these we say how we separable based on the target and how to classify the data

In [223…
```
x=df.drop('Target',axis=1)
y=df['Target']
```

In [224…
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=42)
```

In [225…
```
x_train
```

Out[225…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_c
16060	30	3	9	4	2	1	4	1	0	0	40	
18119	20	3	10	4	5	3	4	1	0	0	25	
18753	25	3	9	4	2	1	4	1	0	0	35	
20534	35	1	9	2	10	0	2	1	7298	0	35	
4585	21	3	9	4	0	1	4	0	0	0	35	
...	...	...	...	...	...	...	...	...	...	...	...	
29823	18	3	9	4	5	3	2	1	0	0	40	
5392	29	6	11	4	12	1	4	0	0	1590	64	
860	43	3	9	2	4	0	4	1	0	0	40	
15801	44	1	10	0	3	1	4	1	0	0	50	
23669	26	3	10	4	5	3	4	1	0	0	12	

21799 rows × 12 columns

In [226…
```
y
```

Out[226…
```
0        0
1        0
2        0
3        0
4        0
       ..
32555    0
32556    1
32557    0
32558    0
32559    1
Name: Target, Length: 32536, dtype: int32
```

In [227…
```
df['Target'].value_counts()
```

Out[227…
```
0    24697
1     7839
Name: Target, dtype: int64
```

we seethat imbalance in the data son we balance the daat using smote from imblearn.....

In [228…
```
from imblearn.over_sampling import SMOTE
smote=SMOTE(random_state = 101)
x_oversample, y_oversample = smote.fit_resample(x, y)
```

In [229…
```
x_train, x_test, y_train, y_test = train_test_split(x_oversample, y_oversample, test_size=0.33, random_state=42)
```

In [230…
```
y_oversample.value_counts()
```

Out[230…
```
0    24697
1    24697
Name: Target, dtype: int64
```

now see we balance the data by oversampling

now apply the model

In [231…
```
from sklearn import tree
from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
d=tree.DecisionTreeClassifier()
d.fit(x_train,y_train)
```

Out[231…
```
DecisionTreeClassifier()
```

In [232…
```
d.score(x_test,y_test)
```

Out[232…
```
0.8492730507330839
```

In [233…
```
x_test
```

Out[233…

	age	workclass	education_num	marital_status	occupation	relationship	race	sex	capital_gain	capital_loss	hours_per_week	native_c
4057	46	3	12	2	2	0	4	1	0	0	40	
31167	21	3	10	4	12	3	4	1	0	0	35	
22806	20	3	10	4	7	3	4	1	0	0	20	
14572	26	1	13	4	3	3	4	1	0	0	44	
11478	38	3	11	2	7	0	4	1	0	0	40	
...	...	...	...	...	...	...	...	...	...	...	...	
20723	24	3	12	2	0	5	4	0	0	0	40	
30256	38	3	9	5	13	4	2	0	0	0	30	
24889	45	3	9	2	13	0	4	1	0	0	40	
38431	42	3	14	2	7	1	4	0	0	1902	60	
22914	74	5	9	6	4	1	4	0	0	0	14	

16301 rows × 12 columns

In [234…
```
y_pred_train=d.predict(x_train)
y_pred_test=d.predict(x_test)
```

In [235…
```
y_pred_train
```

Out[235…
```
array([0, 1, 0, ..., 1, 0, 0])
```

train data

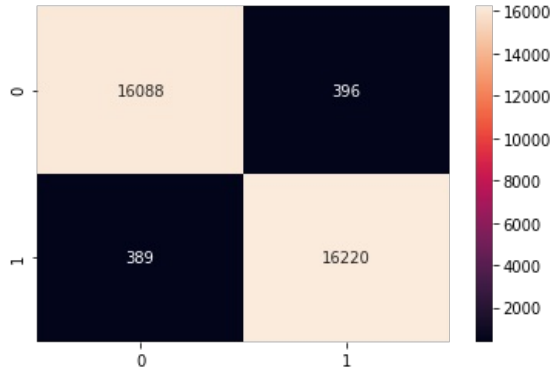
In [236…
```
print(classification_report(y_train,y_pred_train))
```

```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98     16484
           1       0.98      0.98      0.98     16609

    accuracy                           0.98     33093
   macro avg       0.98      0.98      0.98     33093
weighted avg       0.98      0.98      0.98     33093
```

In [237…
```
a=confusion_matrix(y_train,y_pred_train)
sns.heatmap(a,annot=True,fmt='g')
```

Out[237… <AxesSubplot:>



In [238…
```
ac=accuracy_score(y_train,y_pred_train)
ac
```

Out[238… 0.9762789713836763

mis classification/

In [239…
```
1-ac
```

Out[239… 0.023721028616323747

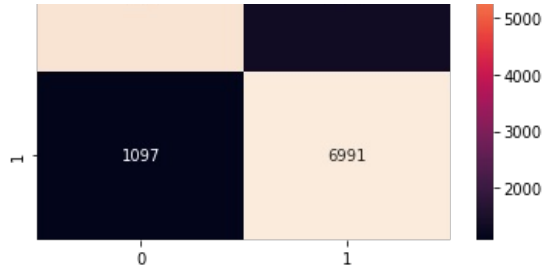
test data

In [240…
```
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.86      0.83      0.85      8213
           1       0.84      0.86      0.85      8088

    accuracy                           0.85     16301
   macro avg       0.85      0.85      0.85     16301
weighted avg       0.85      0.85      0.85     16301
```

In [241…
```
b=confusion_matrix(y_test,y_pred_test)
sns.heatmap(b,annot=True,fmt='g')
```

Out[241… <AxesSubplot:>



mis classification

In [242…
```
ac=accuracy_score(y_test,y_pred_test)
1-ac
```

Out[242… 0.1507269492669161

accuracy---85%

Random forest classifier

In [243…
```
from sklearn.ensemble import RandomForestClassifier
r=RandomForestClassifier()
r.fit(x_train,y_train)
r.score(x_test,y_test)
```

Out[243… 0.8842402306606957

In [244…
```
y_pred_train=r.predict(x_train)
y_pred_test=r.predict(x_test)
```

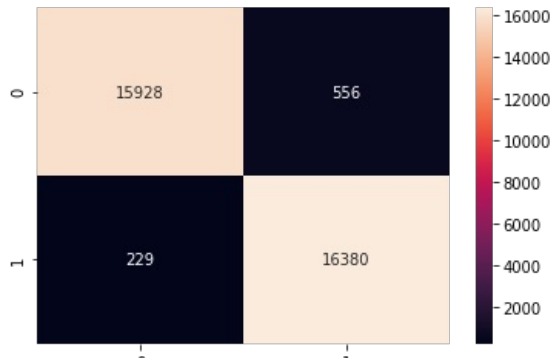
train

In [245…
```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.99      0.97      0.98     16484
           1       0.97      0.99      0.98     16609

    accuracy                           0.98     33093
   macro avg       0.98      0.98      0.98     33093
weighted avg       0.98      0.98      0.98     33093
```

In [246…
```
a=confusion_matrix(y_train,y_pred_train)
sns.heatmap(a,annot=True,fmt='g')
```

Out[246… <AxesSubplot:>



```
0                1
```

In [ ]:

In [247…
```
ac=accuracy_score(y_train,y_pred_train)
ac
```

Out[247… 0.9762789713836763

In [248…
```
1-ac
```

Out[248… 0.023721028616323747

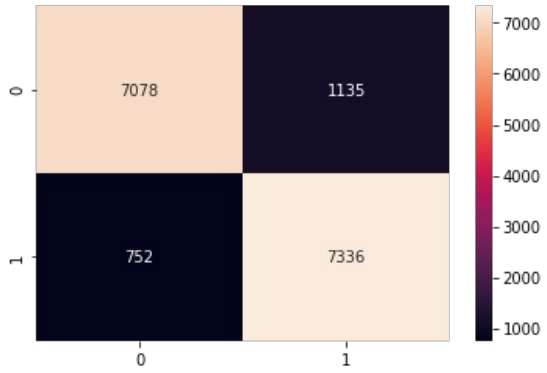
test

In [249…
```
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.90      0.86      0.88      8213
           1       0.87      0.91      0.89      8088

    accuracy                           0.88     16301
   macro avg       0.88      0.88      0.88     16301
weighted avg       0.89      0.88      0.88     16301
```

In [250…
```
a=confusion_matrix(y_test,y_pred_test)
sns.heatmap(a,annot=True,fmt='g')
```

Out[250… <AxesSubplot:>



In [251…
```
ac=accuracy_score(y_test,y_pred_test)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.8842402306606957
mis-classify% ---- 0.11575976933930432
```

Logistic Regression

In [252…
```
from sklearn.linear_model import LogisticRegression
l=LogisticRegression()
l.fit(x_train,y_train)
l.score(x_test,y_test)
```

```
C:\Users\63094\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs faile
d to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[252… 0.7498926446230293

In [253…
```
y_pred_train=l.predict(x_train)
y_pred_test=l.predict(x_test)
```

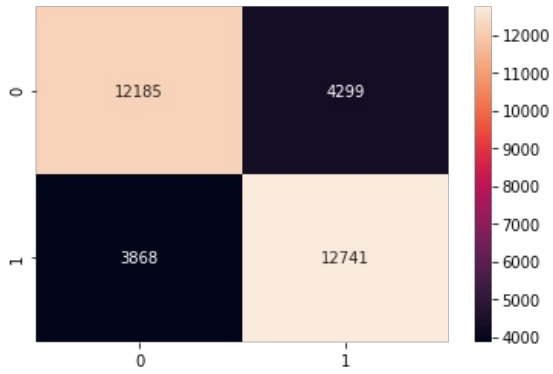
train

In [254…
```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.76      0.74      0.75     16484
           1       0.75      0.77      0.76     16609

    accuracy                           0.75     33093
   macro avg       0.75      0.75      0.75     33093
weighted avg       0.75      0.75      0.75     33093
```

In [255…
```
a=confusion_matrix(y_train,y_pred_train)
sns.heatmap(a,annot=True,fmt='g')
```

Out[255… <AxesSubplot:>



In [256…
```
ac=accuracy_score(y_train,y_pred_train)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.7532106487776872
mis-classify% ---- 0.24678935122231282
```

test

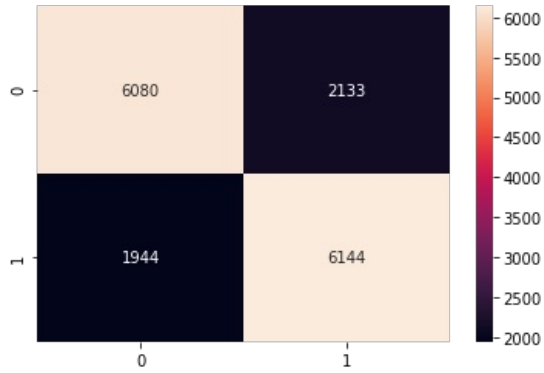
In [257…
```
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.76      0.74      0.75      8213
           1       0.74      0.76      0.75      8088

    accuracy                           0.75     16301
```

```
   macro avg       0.75      0.75      0.75     16301
weighted avg       0.75      0.75      0.75     16301
```

In [258…
```
a=confusion_matrix(y_test,y_pred_test)
sns.heatmap(a,annot=True,fmt='g')
```

Out[258… <AxesSubplot:>



In [259…
```
ac=accuracy_score(y_test,y_pred_test)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.7498926446230293
mis-classify% ---- 0.2501073553769707
```

KNN classifier

In [260…
```
from sklearn.neighbors import KNeighborsClassifier
```

In [261…
```
k=KNeighborsClassifier()
k.fit(x_train,y_train)
k.score(x_test,y_test)
```

Out[261… 0.85037727746764

In [262…
```
y_pred_train=k.predict(x_train)
y_pred_test=k.predict(x_test)
```

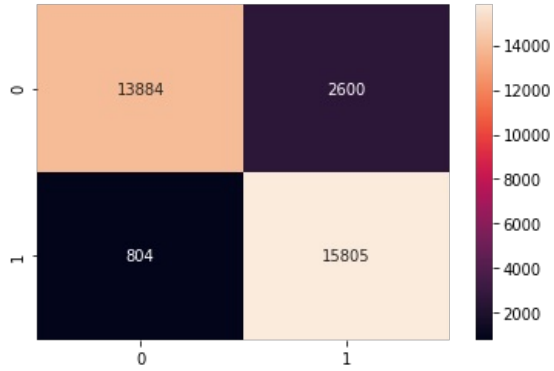
train

In [263…
```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.95      0.84      0.89     16484
           1       0.86      0.95      0.90     16609

    accuracy                           0.90     33093
   macro avg       0.90      0.90      0.90     33093
weighted avg       0.90      0.90      0.90     33093
```

In [264…
```
a=confusion_matrix(y_train,y_pred_train)
sns.heatmap(a,annot=True,fmt='g')
```

Out[264… <AxesSubplot:>



In [265…

```
ac=accuracy_score(y_train,y_pred_train)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.8971383676306167
mis-classify% ---- 0.10286163236938328
```

test

In [266…

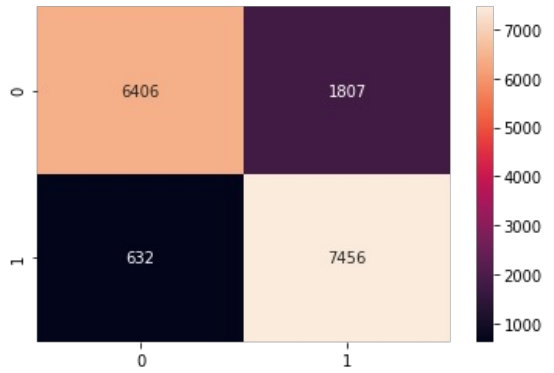
```
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.91      0.78      0.84      8213
           1       0.80      0.92      0.86      8088

    accuracy                           0.85     16301
   macro avg       0.86      0.85      0.85     16301
weighted avg       0.86      0.85      0.85     16301
```

In [267…

```
a=confusion_matrix(y_test,y_pred_test)
sns.heatmap(a,annot=True,fmt='g')
```

Out[267… <AxesSubplot:>



In [268…

```
ac=accuracy_score(y_test,y_pred_test)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.85037727746764
mis-classify% ---- 0.14962272253235998
```

SVC Classifier (with linear kernel)

In [ ]:

In [269…
```
from sklearn import svm
clf=svm.SVC()
```

In [270…
```
clf.fit(x_train,y_train)
```

Out[270… SVC()

In [271…
```
y_pred_train=clf.predict(x_train)
y_pred_test=clf.predict(x_test)
```

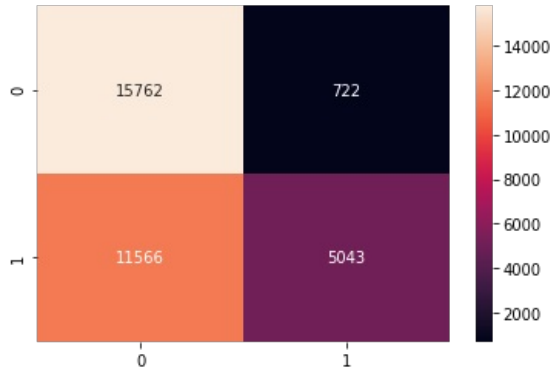
train

In [272…
```
print(classification_report(y_train,y_pred_train))
```

```
              precision    recall  f1-score   support

           0       0.58      0.96      0.72     16484
           1       0.87      0.30      0.45     16609

    accuracy                           0.63     33093
   macro avg       0.73      0.63      0.59     33093
weighted avg       0.73      0.63      0.58     33093
```

In [273…
```
a=confusion_matrix(y_train,y_pred_train)
sns.heatmap(a,annot=True,fmt='g')
```

Out[273… <AxesSubplot:>



In [274…
```
ac=accuracy_score(y_train,y_pred_train)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.6286828030096999
mis-classify% ---- 0.3713171969903001
```

test

print(classification_report(y_test,y_pred_test))

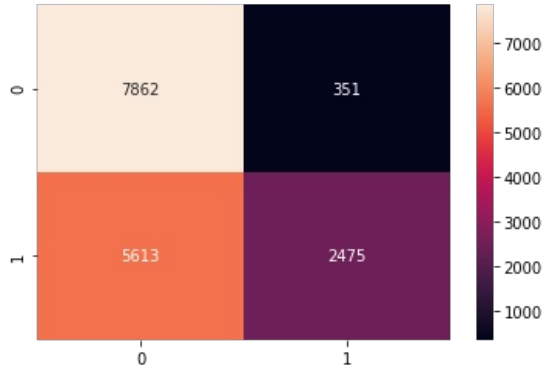
In [275…
```
print(classification_report(y_test,y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.58      0.96      0.73      8213
           1       0.88      0.31      0.45      8088

    accuracy                           0.63     16301
   macro avg       0.73      0.63      0.59     16301
```

```
weighted avg       0.73      0.63      0.59     16301
```

In [276…
```
a=confusion_matrix(y_test,y_pred_test)
sns.heatmap(a,annot=True,fmt='g')
```

Out[276… <AxesSubplot:>



In [277…
```
ac=accuracy_score(y_test,y_pred_test)
print(ac)
print('mis-classify%','----',1-ac)
```

```
0.634132875283725
mis-classify% ---- 0.365867124716275
```

finally, we say that random forest classifier gives the best accuracy and give the best predictions.....

In [ ]:

In [ ]: