In [227]: import pandas as pd import numpy as np import seaborn as sns import matplotlib.pyplot as plt from sklearn.preprocessing import LabelEncoder from sklearn.model_selection import train_test_split from sklearn.linear_model import LogisticRegression from sklearn.naive_bayes import GaussianNB,MultinomialNB from sklearn.neighbors import KNeighborsClassifier from sklearn.metrics import classification_report

In [182]: sv('/home/hemang/TE/sem2/DSBDAL Practical/DSBDALExam DataSets/Adult/adult.csv')

Out[182]:

	39	State- gov	77516	Bachelors	13	Never- married	Adm- clerical	Not-in- family	White	Male	2174	0	40
0	50	Self- emp- not-inc	83311	Bachelors	13	Married- civ- spouse	Exec- managerial	Husband	White	Male	0	0	13
1	38	Private	215646	HS-grad	9	Divorced	Handlers- cleaners	Not-in- family	White	Male	0	0	40
2	53	Private	234721	11th	7	Married- civ- spouse	Handlers- cleaners	Husband	Black	Male	0	0	40
3	28	Private	338409	Bachelors	13	Married- civ- spouse	Prof- specialty	Wife	Black	Female	0	0	40
4	37	Private	284582	Masters	14	Married- civ- spouse	Exec- managerial	Wife	White	Female	0	0	40
										•••			
32555	27	Private	257302	Assoc- acdm	12	Married- civ- spouse	Tech- support	Wife	White	Female	0	0	38
32556	40	Private	154374	HS-grad	9	Married- civ- spouse	Machine- op-inspct	Husband	White	Male	0	0	40
32557	58	Private	151910	HS-grad	9	Widowed	Adm- clerical	Unmarried	White	Female	0	0	40
32558	22	Private	201490	HS-grad	9	Never- married	Adm- clerical	Own-child	White	Male	0	0	20
32559	52	Self- emp- inc	287927	HS-grad	9	Married- civ- spouse	Exec- managerial	Wife	White	Female	15024	0	40

32560 rows × 15 columns

4

```
In [183]: df.columns = ['age','workclass','fnlwgt','education','education-num','marital-s
df
```

Out[183]:

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

32560 rows × 15 columns

```
In [184]: df.isnull().sum()
```

Out[184]: age

0 workclass 0 fnlwgt 0 0 education education-num 0 marital-status 0 occupation 0 relationship 0 0 race 0 sex capital-gain 0 capital-loss 0 hours-per-week 0 native-country 0 salary 0 dtype: int64

In [185]: df.shape

Out[185]: (32560, 15)

In [186]: df.dropna(inplace=True)

df.replace('?',pd.NA,inplace=True)

d1

Out[186]:

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

32560 rows × 15 columns

In [187]: df['age'].fillna(method='ffill',inplace=True)
df

Out[187]:

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

32560 rows × 15 columns

 \triangleleft

In [188]: df[df['age'] < 40]

Out[188]:

	age	workclass	fnlwgt	education	education- num	marital- status	occupation	relationship	race	sex
1	38	Private	215646	HS-grad	9	Divorced	Handlers- cleaners	Not-in-family	White	Male
3	28	Private	338409	Bachelors	13	Married- civ- spouse	Prof- specialty	Wife	Black	Female
4	37	Private	284582	Masters	14	Married- civ- spouse	Exec- managerial	Wife	White	Female
7	31	Private	45781	Masters	14	Never- married	Prof- specialty	Not-in-family	White	Female
9	37	Private	280464	Some- college	10	Married- civ- spouse	Exec- managerial	Husband	Black	Male
32550	32	Private	34066	10th	6	Married- civ- spouse	Handlers- cleaners	Husband	Amer- Indian- Eskimo	Male
32552	32	Private	116138	Masters	14	Never- married	Tech- support	Not-in-family	Asian- Pac- Islander	Male
32554	22	Private	310152	Some- college	10	Never- married	Protective- serv	Not-in-family	White	Male
32555	27	Private	257302	Assoc- acdm	12	Married- civ- spouse	Tech- support	Wife	White	Female
32558	22	Private	201490	HS-grad	9	Never- married	Adm- clerical	Own-child	White	Male
18323	rows	× 15 columı	ns							

In [189]: df['sex'].value_counts()

Name: sex, dtype: int64

In [190]: df.dtypes

Out[190]: age int64 workclass object

fnlwgt int64 education object education-num int64 marital-status object occupation object relationship object race object object sex capital-gain int64 capital-loss int64 hours-per-week int64 native-country object salary object

dtype: object

```
In [191]: # from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['sex'] = le.fit_transform(df['sex'])
df['salary'] = le.fit_transform(df['salary'])
df
```

Out[191]:

	age	workclass	fnlwgt	education	education- num	marital- status	occupation	relationship	race	sex	capi g
0	50	Self-emp- not-inc	83311	Bachelors	13	Married- civ- spouse	Exec- managerial	Husband	White	1	
1	38	Private	215646	HS-grad	9	Divorced	Handlers- cleaners	Not-in-family	White	1	
2	53	Private	234721	11th	7	Married- civ- spouse	Handlers- cleaners	Husband	Black	1	
3	28	Private	338409	Bachelors	13	Married- civ- spouse	Prof- specialty	Wife	Black	0	
4	37	Private	284582	Masters	14	Married- civ- spouse	Exec- managerial	Wife	White	0	
32555	27	Private	257302	Assoc- acdm	12	Married- civ- spouse	Tech- support	Wife	White	0	
32556	40	Private	154374	HS-grad	9	Married- civ- spouse	Machine- op-inspct	Husband	White	1	
32557	58	Private	151910	HS-grad	9	Widowed	Adm- clerical	Unmarried	White	0	
32558	22	Private	201490	HS-grad	9	Never- married	Adm- clerical	Own-child	White	1	
32559	52	Self-emp- inc	287927	HS-grad	9	Married- civ- spouse	Exec- managerial	Wife	White	0	150
22502		v 15 aaluma									

32560 rows × 15 columns

In [192]: df['salary'].value_counts()

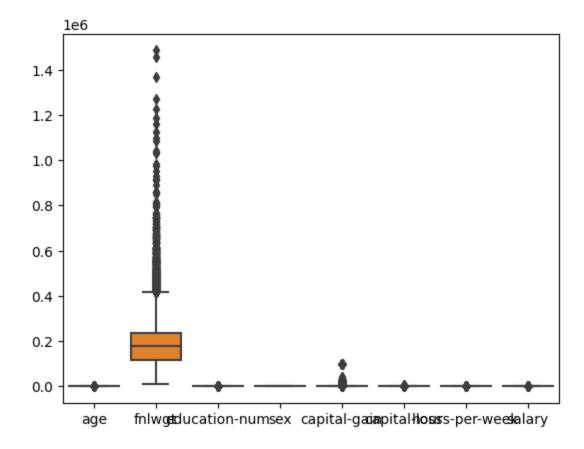
Out[192]: 0 24719 1 7841

Name: salary, dtype: int64

In [193]: df.dtypes Out[193]: age int64 workclass object fnlwgt int64 education object education-num int64 marital-status object occupation object relationship object object race int64 sex capital-gain int64 capital-loss int64 hours-per-week int64 native-country object salary int64 dtype: object

In [194]: sns.boxplot(df)

Out[194]: <AxesSubplot: >



```
In [195]: sns.boxplot(df['age'])
```

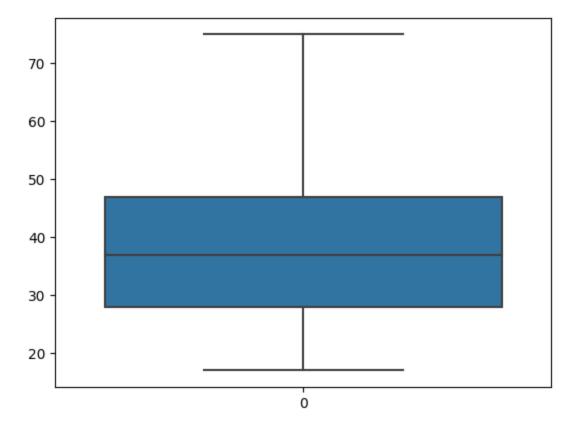
Out[195]: <AxesSubplot: >

```
In [198]: # outliers(df['age'])
    Q3,Q1 = np.percentile(df['age'],[75,25])
    IQR = Q3-Q1
    lower = Q1-1.5*IQR
    upper = Q3 + 1.5*IQR

def2 = df[(df['age']>=lower ) & (df['age'] <=upper)]
    df = def2y</pre>
```

```
In [201]: sns.boxplot(df['age'])
```

Out[201]: <AxesSubplot: >



In [205]: df.reset_index()
df

Out[205]:

ıcation	education- num	marital- status	occupation	relationship	race	sex	capital- gain	capital- loss	hours- per- week	native- country	salary
chelors	13	Married- civ- spouse	Exec- managerial	Husband	White	1	0	0	13	United- States	0
IS-grad	9	Divorced	Handlers- cleaners	Not-in-family	White	1	0	0	40	United- States	0
11th	7	Married- civ- spouse	Handlers- cleaners	Husband	Black	1	0	0	40	United- States	0
chelors	13	Married- civ- spouse	Prof- specialty	Wife	Black	0	0	0	40	Cuba	0
/lasters	14	Married- civ- spouse	Exec- managerial	Wife	White	0	0	0	40	United- States	0
Assoc- acdm	12	Married- civ- spouse	Tech- support	Wife	White	0	0	0	38	United- States	0
IS-grad	9	Married- civ- spouse	Machine- op-inspct	Husband	White	1	0	0	40	United- States	1
IS-grad	9	Widowed	Adm- clerical	Unmarried	White	0	0	0	40	United- States	0
IS-grad	9	Never- married	Adm- clerical	Own-child	White	1	0	0	20	United- States	0
IS-grad	9	Married- civ- spouse	Exec- managerial	Wife	White	0	15024	0	40	United- States	1

4

```
In [207]: | def2 = df[['age', 'education-num', 'capital-gain']]
Out[207]:
                 age education-num capital-gain
               0
                  50
                               13
                                          0
                                9
                                          0
               1
                   38
               2
                                7
                                          0
                  53
                  28
               3
                               13
                                          0
               4
                   37
                               14
                                          0
            32555
                   27
                               12
                                          0
            32556
                                9
                                          0
                  40
            32557
                   58
                                9
                                          0
            32558
                   22
                                9
                                          0
            32559
                                       15024
                  52
                                9
           32319 rows × 3 columns
In [2111]: x = def2
           y = df['salary']
In [209]: xtrain,xtest,ytrain,ytest = train test split(x,y,test size=0.2)
In [221]: reg = LogisticRegression()
           reg.fit(x,y)
           ypred = reg.predict(xtest)
In [223]: |mul = MultinomialNB()
           mul.fit(x,y)
           ypred2 = mul.predict(xtest)
In [225]: knn = KNeighborsClassifier()
           knn.fit(x,y)
           ypred3 = knn.predict(xtest)
In [229]: print(classification report(ypred,ytest))
```

recall f1-score

0.88

0.46

0.81

0.67

0.83

0.82

0.71

0.77

0.81

support

5726

6464

6464

6464

738

precision

0.96

0.34

0.65

0.89

0

1

accuracy

macro avg

weighted avg

```
In [230]: print(classification_report(ypred2,ytest))
                        precision
                                      recall f1-score
                                                         support
                     0
                                        0.79
                                                  0.87
                             0.96
                                                            5924
                     1
                             0.21
                                        0.62
                                                  0.32
                                                             540
                                                  0.78
                                                            6464
              accuracy
                             0.59
             macro avg
                                        0.71
                                                  0.59
                                                            6464
                                                  0.82
          weighted avg
                             0.90
                                        0.78
                                                            6464
In [231]: print(classification report(ypred3,ytest))
                        precision
                                      recall f1-score
                                                         support
                     0
                                        0.85
                             0.91
                                                  0.88
                                                            5268
                                                  0.55
                     1
                             0.48
                                        0.63
                                                            1196
              accuracy
                                                  0.81
                                                            6464
             macro avg
                             0.70
                                        0.74
                                                  0.71
                                                            6464
          weighted avg
                             0.83
                                        0.81
                                                  0.82
                                                            6464
 In [ ]:
```