```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import sys
# modify "customized_path_to_homework", path of folder in drive, where you uploaded your homework
customized_path_to_homework = "/content/drive/MyDrive/Colab Notebooks/assignment_3/dataset"
sys.path.append(customized_path_to_homework)
```

```
import os, sys
import pandas as pd
import numpy as np
import matplotlib.mlab as mlab
import matplotlib.pyplot as plt
import datetime
sys.path.insert(0,'../')
%load_ext autoreload
%autoreload 2
# import warnings filter
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

```
dt_training = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/assignment_3/dataset/adult.data')
# sneak peak in the data
dt_training.head(1)
```

	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=5(
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=5(

```
dt_training.columns = ['age','workclass','fnlwgt','education','education-num','marital-status','occupation','relationship','race','sex','capi
dt_training.head(1)
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capita lo
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	

```
dt_test = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/assignment_3/dataset/adult.test',header=None, skiprows=[0])
# sneak peak in the data
dt_test.head(3)
```

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K.
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K.
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K.

```
dt_test.columns = ['age','workclass','fnlwgt','education','education-num','marital-status','occupation','relationship','race','sex','capital-
dt_training.replace([np.inf, -np.inf], np.nan,inplace=True)
dt_test.replace([np.inf, -np.inf], np.nan,inplace=True)
```

```
dt_training.shape
dt_training.head(10)
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	cap
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	
2	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	
3	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	
4	37	Private	284582	Masters	14	Married-civ-spouse	Exec-managerial	Wife	White	Female	0	
5	49	Private	160187	9th	5	Married-spouse-absent	Other-service	Not-in-family	Black	Female	0	
6	52	Self-emp-not-inc	209642	HS-grad	9	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	
7	31	Private	45781	Masters	14	Never-married	Prof-specialty	Not-in-family	White	Female	14084	
8	42	Private	159449	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	5178	
9	37	Private	280464	Some-college	10	Married-civ-spouse	Exec-managerial	Husband	Black	Male	0	

```
dt_test.shape
dt_test.head(10)
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capi
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	
5	34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	
6	29	?	227026	HS-grad	9	Never-married	?	Unmarried	Black	Male	0	
7	63	Self-emp-not-inc	104626	Prof-school	15	Married-civ-spouse	Prof-specialty	Husband	White	Male	3103	
8	24	Private	369667	Some-college	10	Never-married	Other-service	Unmarried	White	Female	0	
9	55	Private	104996	7th-8th	4	Married-civ-spouse	Craft-repair	Husband	White	Male	0	

```
categorical_variables = [var for var in dt_training.columns if dt_training[var].dtype=='O']
print(categorical_variables)
```

```
['workclass', 'education', 'marital-status', 'occupation', 'relationship', 'race', 'sex', 'native-country', 'class']
```

```
dt_training[categorical_variables].isnull().sum()
```

```
workclass         0
education         0
marital-status    0
occupation        0
relationship      0
race              0
sex               0
native-country    0
class             0
dtype: int64
```

```
dt_training.workclass.value_counts()
```

```
 Private             22696
 Self-emp-not-inc     2541
 Local-gov            2093
 ?                    1836
 State-gov            1297
 Self-emp-inc         1116
 Federal-gov           960
 Without-pay            14
 Never-worked            7
Name: workclass, dtype: int64
```

```
dt_training['workclass'].replace('?', np.NaN, inplace=True)
dt_test['workclass'].replace('?', np.NaN, inplace=True)

dt_training['occupation'].replace('?', np.NaN, inplace=True)
dt_test['occupation'].replace('?', np.NaN, inplace=True)

dt_training['native-country'].replace('?', np.NaN, inplace=True)
dt_test['native-country'].replace('?', np.NaN, inplace=True)

dt_training['class'].replace('<=50K', '<=50K.', inplace=True)
dt_training['class'].replace('>50K', '>50K.', inplace=True)
```

```
numerical = [var for var in dt_training.columns if dt_training[var].dtype!='O']
```

```
dt_training[numerical].isnull().sum()
```

```
age               0
fnlwgt            0
education-num     0
capital-gain      0
capital-loss      0
hours-per-week    0
dtype: int64
```

```
#Initializing X_train,y_train,X_test,y_test

X_train= dt_training.drop(['class'], axis=1)
y_train = dt_training['class']
X_test = dt_test.drop(['class'], axis=1)
y_test = dt_test['class']
```

```
X_train.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain
0	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0
1	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0

```
X_train.shape, X_test.shape
```

```
((32560, 14), (16281, 14))
```

```
#Replacing NA with frequent values
for df2 in [X_train, X_test]:
  df2['workclass'].fillna(X_train['workclass'].mode()[0], inplace=True)
  df2['occupation'].fillna(X_train['occupation'].mode()[0], inplace=True)
  df2['native-country'].fillna(X_train['native-country'].mode()[0], inplace=True)
```

```
X_test.isnull().sum()
```

```
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
dtype: int64
```

```
pip install scikit-learn
```

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.2.2)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.3)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.2.0)
```

```
from sklearn.preprocessing import LabelEncoder
categorical_variables = [var for var in X_train.columns if X_train[var].dtype=='O']
print(categorical_variables)
```

```
['workclass', 'education', 'marital-status', 'occupation', 'relationship', 'race', 'sex', 'native-country']
```

```
# Encode categorical features as a one-hot numeric array using LabelEncoder.
labelencoder = LabelEncoder()
X_train["workclass"]= labelencoder.fit_transform(X_train["workclass"])
X_train["education"]= labelencoder.fit_transform(X_train["education"])
X_train["marital-status"]= labelencoder.fit_transform(X_train["marital-status"])
X_train["occupation"]= labelencoder.fit_transform(X_train["occupation"])
X_train["relationship"]= labelencoder.fit_transform(X_train["relationship"])
X_train["race"]= labelencoder.fit_transform(X_train["race"])
X_train["sex"]= labelencoder.fit_transform(X_train["sex"])
X_train["native-country"]= labelencoder.fit_transform(X_train["native-country"])
X_test["workclass"]= labelencoder.fit_transform(X_test["workclass"])
X_test["education"]= labelencoder.fit_transform(X_test["education"])
X_test["marital-status"]= labelencoder.fit_transform(X_test["marital-status"])
X_test["occupation"]= labelencoder.fit_transform(X_test["occupation"])
X_test["relationship"]= labelencoder.fit_transform(X_test["relationship"])
X_test["race"]= labelencoder.fit_transform(X_test["race"])
X_test["sex"]= labelencoder.fit_transform(X_test["sex"])
X_test["native-country"]= labelencoder.fit_transform(X_test["native-country"])
```

```
X_train
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss
0	50	6	83311	9	13	2	4	0	4	1	0	0
1	38	4	215646	11	9	0	6	1	4	1	0	0
2	53	4	234721	1	7	2	6	0	2	1	0	0
3	28	4	338409	9	13	2	10	5	2	0	0	0
4	37	4	284582	12	14	2	4	5	4	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
32555	27	4	257302	7	12	2	13	5	4	0	0	0
32556	40	4	154374	11	9	2	7	0	4	1	0	0
32557	58	4	151910	11	9	6	1	4	4	0	0	0
32558	22	4	201490	11	9	4	1	3	4	1	0	0
32559	52	5	287927	11	9	2	4	5	4	0	15024	0

```
X_test
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss
0	25	4	226802	1	7	4	7	3	2	1	0	0
1	38	4	89814	11	9	2	5	0	4	1	0	0
2	28	2	336951	7	12	2	11	0	4	1	0	0
3	44	4	160323	15	10	2	7	0	2	1	7688	0
4	18	0	103497	15	10	4	0	3	4	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...
16276	39	4	215419	9	13	0	10	1	4	0	0	0
16277	64	0	321403	11	9	6	0	2	2	1	0	0
16278	38	4	374983	9	13	2	10	0	4	1	0	0
16279	44	4	83891	9	13	0	1	3	1	1	5455	0
16280	35	5	182148	9	13	2	4	0	4	1	0	0

16281 rows × 14 columns

```
y_train
```

```
0        <=50K
1        <=50K
2        <=50K
3        <=50K
4        <=50K
         ...
32555    <=50K
32556     >50K
32557    <=50K
32558    <=50K
32559     >50K
Name: class, Length: 32560, dtype: object
```

```
#normalizing the features
cols = dt_training.columns.drop('class')
from sklearn.preprocessing import RobustScaler

scaler = RobustScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country'],
      dtype='object')
```

```
X_train = pd.DataFrame(X_train, columns=[cols])
X_test = pd.DataFrame(X_test, columns=[cols])
```

```
X_train.head()
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss
0	0.65	2.0	-0.797262	-0.666667	1.000000	0.0	-0.428571	-0.333333	0.0	0.0	0.0	0.0
1	0.05	0.0	0.312717	0.000000	-0.333333	-1.0	-0.142857	0.000000	0.0	0.0	0.0	0.0
2	0.80	0.0	0.472711	-3.333333	-1.000000	0.0	-0.142857	-0.333333	-2.0	0.0	0.0	0.0
3	-0.45	0.0	1.342409	-0.666667	1.000000	0.0	0.428571	1.333333	-2.0	-1.0	0.0	0.0
4	0.00	0.0	0.890927	0.333333	1.333333	0.0	-0.428571	1.333333	0.0	-1.0	0.0	0.0

Exploratory Data Analysis

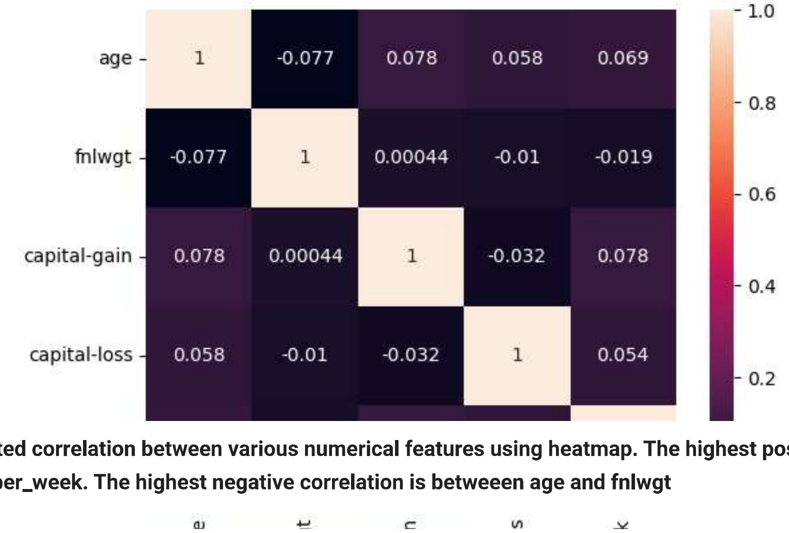
```
import matplotlib.pylab as plt
import seaborn as sns
dt_training_data1= dt_training.dropna(axis=0)
pd.crosstab(dt_training_data1['occupation'], dt_training_data1['class'], margins=True)
```

class	<=50K	>50K	All
occupation			
?	1652	191	1843
Adm-clerical	3262	507	3769
Armed-Forces	8	1	9
Craft-repair	3170	929	4099
Exec-managerial	2098	1968	4066
Farming-fishing	879	115	994
Handlers-cleaners	1284	86	1370
Machine-op-inspct	1752	250	2002
Other-service	3158	137	3295
Priv-house-serv	148	1	149
Prof-specialty	2281	1859	4140
Protective-serv	438	211	649
Sales	2667	983	3650
Tech-support	645	283	928
Transport-moving	1277	320	1597
All	24719	7841	32560

Generated Cross tab comparision between Income and Occupation. The highest number of people getting more than 50K are from Exec_managerial position. The highest number of people getting less than 50K are from craft-repair position.

```
variable = ["age","fnlwgt","capital-gain","capital-loss","hours-per-week"]
corr = dt_training_data1[variable].corr()# plot the heatmap
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, annot=True, cmap=None)
```

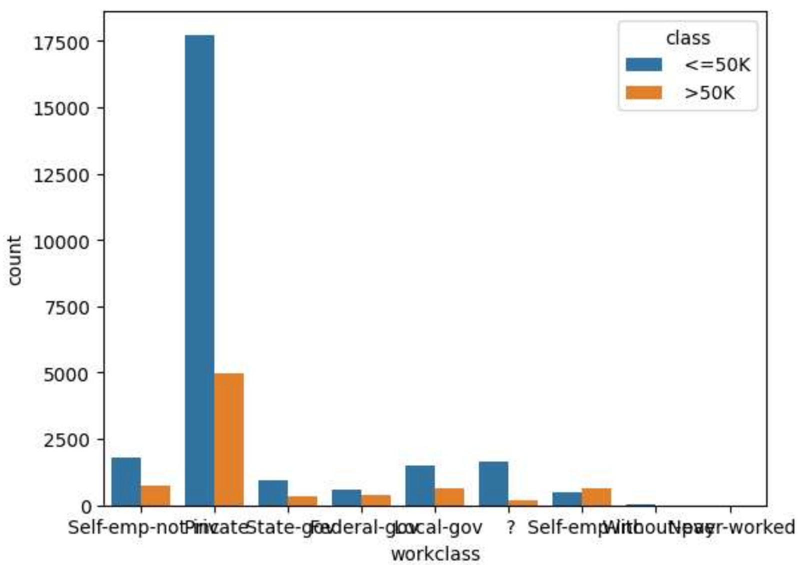
```
<Axes: >
```



Generated correlation between various numerical features using heatmap. The highest positive correlation is between age and hours_per_week. The highest negative correlation is betweeen age and fnlwgt

```
sns.countplot(x='workclass', hue='class', data=dt_training_data1)
```

```
<Axes: xlabel='workclass', ylabel='count'>
```



Created a countplot with workclass. Private class are high in numbers

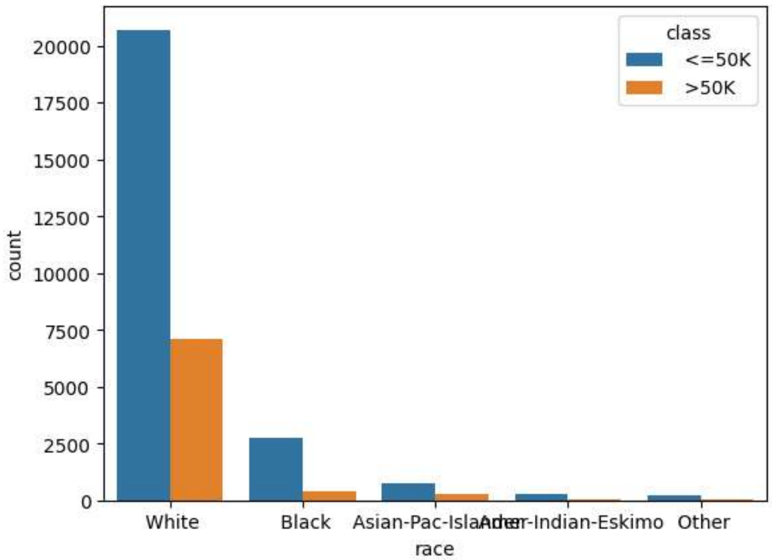
```
dt_training_data1['age'].plot(kind='hist', bins=20, figsize=(12,6), facecolor='steelblue',zorder=2, rwidth=0.9)
```

```
<Axes: ylabel='Frequency'>
```

Histogram is generated on age features. People with ages between 30-35 are considered more compared to other ages.

```
sns.countplot(x='race', hue='class', data=dt_training_data1,zorder=2)
```

```
<Axes: xlabel='race', ylabel='count'>
```



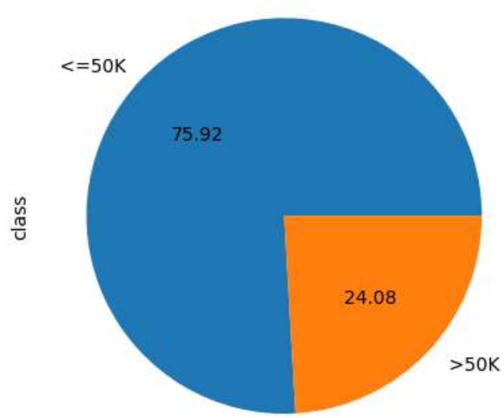
Countplot is created for race. White people are considered more in the dataset

```
pd.crosstab(dt_training_data1['education'], dt_training_data1['class'], margins=True)
```

class	<=50K	>50K	All
education			
10th	871	62	933
11th	1115	60	1175
12th	400	33	433
1st-4th	162	6	168
5th-6th	317	16	333
7th-8th	606	40	646
9th	487	27	514
Assoc-acdm	802	265	1067
Assoc-voc	1021	361	1382
Bachelors	3133	2221	5354
Doctorate	107	306	413
HS-grad	8826	1675	10501
Masters	764	959	1723
Preschool	51	0	51
Prof-school	153	423	576
Some-college	5904	1387	7291
All	24719	7841	32560

Cross tab is created between Education and the Income. People who did prof-school has more 50k Income percentage compared to other Education

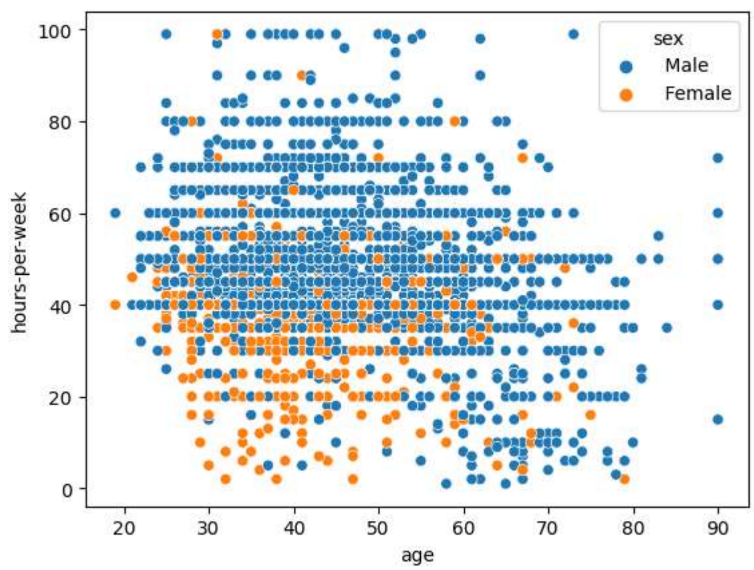
```
dt_training_data1['class'].value_counts().plot(kind="pie", autopct="%.2f")
plt.show()
```



Percentage of Income considered is given in a pie chart. People with <=50K is considered more with people >50K

```
Income_greater_50K = dt_training_data1[dt_training_data1["class"] == " >50K"]
sns.scatterplot( x=Income_greater_50K["age"], y=Income_greater_50K["hours-per-week"], hue=Income_greater_50K['sex'])
```

```
<Axes: xlabel='age', ylabel='hours-per-week'>
```



Scatterplot is considered between Age and hours_per_week for people earning more than 50k. The plot is dense beween the age 30-40 and between hours_per week 40-60. As per the plot, male is getting more than 50k compared to female

Machine Learning Models

Gaussian Naive Bayes classifier

```
# train a Gaussian Naive Bayes classifier on the training set
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
```

```
# instantiate the model
gnb = GaussianNB()
#5-fold cross validation
scores = cross_val_score(gnb, X_train, y_train, cv = 5, scoring='accuracy')
print('5 Cross validation score of GaussianNB model:{}'.format(scores))
print(" ")

# fit the model
gnb.fit(X_train, y_train)
print(" ")
y_pred1 = gnb.predict(X_train)
print(" ")
y_pred = gnb.predict(X_test)


print('Model accuracy score of GaussianNB model: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
print('Training accuracy score of GaussianNB model: {0:0.4f}'. format(accuracy_score(y_train, y_pred1)))
print('The Classification Report of GaussianNB model\n\n'+(classification_report(y_test, y_pred)))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell
  and should_run_async(code)
5 Cross validation score of GaussianNB model:[0.79867936 0.79576167 0.80113636 0.79422604 0.80558968]



Model accuracy score of GaussianNB model: 0.0000
Training accuracy score of GaussianNB model: 0.7990
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
The Classification Report of GaussianNB model

              precision    recall  f1-score   support

       <=50K       0.00      0.00      0.00       0.0
      <=50K.       0.00      0.00      0.00   12435.0
        >50K       0.00      0.00      0.00       0.0
       >50K.       0.00      0.00      0.00    3846.0

    accuracy                           0.00   16281.0
   macro avg       0.00      0.00      0.00   16281.0
weighted avg       0.00      0.00      0.00   16281.0

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
```

```
# train a DecisionTreeClassifier on the training set

from sklearn.tree import DecisionTreeClassifier

# instantiate the model

clf = DecisionTreeClassifier()

#5-fold cross validation
scores = cross_val_score(clf, X_train, y_train, cv = 5, scoring='accuracy')
print('5 Cross validation score of DecisionTreeClassifier model:{}'.format(scores))

# fit the model
clf.fit(X_train, y_train)
y_pred1 = clf.predict(X_train)
y_pred = clf.predict(X_test)

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
print('Training accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred1)))
print('The Classification Report of DecisionTreeClassification model\n\n'+classification_report(y_test, y_pred))
```

```
<frozen importlib._bootstrap>:914: ImportWarning: _PyDriveImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _OpenCVImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _BokehImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _AltairImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: APICoreClientInfoImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _PyDriveImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _OpenCVImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _BokehImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _AltairImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: APICoreClientInfoImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _PyDriveImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _OpenCVImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _BokehImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _AltairImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: APICoreClientInfoImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _PyDriveImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _OpenCVImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _BokehImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _AltairImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: APICoreClientInfoImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _PyDriveImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _OpenCVImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _BokehImportHook.find_spec() not found; falling back to find_module()
<frozen importlib._bootstrap>:914: ImportWarning: _AltairImportHook.find_spec() not found; falling back to find_module()
5 Cross validation score of DecisionTreeClassifier model:[0.80773956 0.8022113  0.80666462 0.81342138 0.80605037]
Model accuracy score: 0.0000
Training accuracy score: 1.0000
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are i
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
The Classification Report of DecisionTreeClassification model

              precision    recall  f1-score   support

        <=50K       0.00      0.00      0.00       0.0
       <=50K.       0.00      0.00      0.00   12435.0
         >50K       0.00      0.00      0.00       0.0
        >50K.       0.00      0.00      0.00    3846.0

     accuracy                           0.00   16281.0
    macro avg       0.00      0.00      0.00   16281.0
 weighted avg       0.00      0.00      0.00   16281.0

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are i
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-
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/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are i
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
```

```
# train a LogisticRegression on the training set

from sklearn.linear_model import LogisticRegression

# instantiate the model

lr= LogisticRegression( solver='lbfgs',max_iter = 700)

#5-fold cross validation
scores = cross_val_score(lr, X_train, y_train, cv = 5, scoring='accuracy')
print('5 Cross validation score of Logistic Regression model:{}'.format(scores))

# fit the model
lr.fit(X_train, y_train)
y_pred1 = lr.predict(X_train)
y_pred = lr.predict(X_test)

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))
print('Training accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred1)))
print('The Classification Report of Logistic Regression model\n\n'+classification_report(y_test, y_pred))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell
  and should_run_async(code)
5 Cross validation score of Logistic Regression model:[0.82463145 0.82340295 0.82708845 0.82555283 0.82662776]
Model accuracy score: 0.0000
Training accuracy score: 0.8255
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
The Classification Report of Logistic Regression model

              precision    recall  f1-score   support

       <=50K       0.00      0.00      0.00       0.0
      <=50K.       0.00      0.00      0.00   12435.0
        >50K       0.00      0.00      0.00       0.0
       >50K.       0.00      0.00      0.00    3846.0

    accuracy                           0.00   16281.0
   macro avg       0.00      0.00      0.00   16281.0
weighted avg       0.00      0.00      0.00   16281.0

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Precision and F-score are ill-
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning: Recall and F-score are ill-def
  _warn_prf(average, modifier, msg_start, len(result))
```

We can find that the DecisionTreeClassifier overfits as the training accuracy is 1.000. In order to tackle this, we can change the max_depth..

The LogicalRegression performs well compared to other ml models as it has more accuracy score. Decision Tree outperforms other ml models if we set max_depth to 5 as it avoids overfitting. Gaussian NB considers all features to be conditionally independent and thats the reason for its underperformance