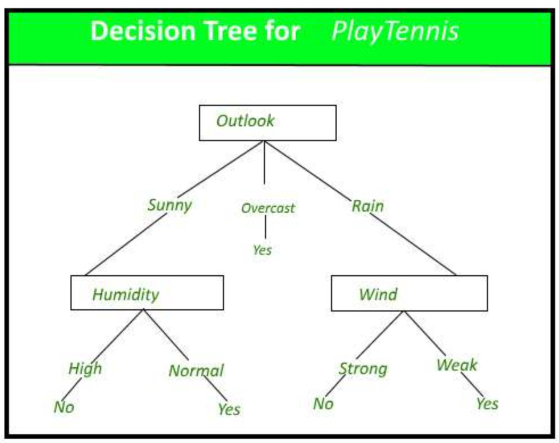
Experiment No. 3
Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

Aim: Apply Decision Tree Algorithm on Adult Census Income Dataset and analyze the performance of the model.

Objective: To perform various feature engineering tasks, apply Decision Tree Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score. Improve the performance by performing different data engineering and feature engineering tasks.

Theory:

Decision Tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.



Dataset:

Predict whether income exceeds $50K/yr based on census data. Also known as "Adult" dataset.

Attribute Information:

Listing of attributes:

>50K, <=50K.

age: continuous.

workclass: Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.

fnlwgt: continuous.

education: Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.

education-num: continuous.

marital-status: Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

occupation: Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.

relationship: Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.

race: White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.

sex: Female, Male.

capital-gain: continuous.

capital-loss: continuous.

hours-per-week: continuous.

native-country: United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.

Conclusion:

1. All the categorical attributes were converted into numerical values for purpose of simplicity by using label encoding.This transformation assigns a unique numerical label to each category within a feature. While label encoding simplifies the data representation, it's important to note that it might introduce ordinal relationships between categories that don't exist.
2. The accuracy of the model is 81% , precision is 83% , recall is 94% and F1 score is 89% . Based on the confusion matrix it can observed that the Type I error is 540 and Type II error is 1955.

```
from google.colab import drive

# Mount Google Drive
drive.mount('/content/drive')

Mounted at /content/drive

import pandas as pd
import numpy as np
import seaborn  as sns
import matplotlib.pyplot as plt

df=pd.read_csv("/content/drive/MyDrive/dataset/adult.csv")

df.head()

   age  workclass  fnlwgt     education  educational-num      marital-
status  \
0   25    Private  226802          11th                7       Never-
married
1   38    Private   89814       HS-grad                9  Married-civ-
spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-
spouse
3   44    Private  160323  Some-college               10  Married-civ-
spouse
4   18          ?  103497  Some-college               10       Never-
married

          occupation relationship   race  gender  capital-gain
capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0
0
1    Farming-fishing      Husband  White    Male             0
0
2    Protective-serv      Husband  White    Male             0
0
3  Machine-op-inspct      Husband  Black    Male          7688
0
4                  ?    Own-child  White  Female             0
0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K

df.shape
```

```
(48842, 15)
```

Data Preprocessing

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

```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

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

```
array(['Private', 'Local-gov', '?', 'Self-emp-not-inc', 'Federal-gov',
       'State-gov', 'Self-emp-inc', 'Without-pay', 'Never-worked'],
      dtype=object)
```

```
df.describe()
```

```
                age        fnlwgt  educational-num  capital-gain  \
count  48842.000000  4.884200e+04     48842.000000  48842.000000
mean      38.643585  1.896641e+05        10.078089   1079.067626
std       13.710510  1.056040e+05         2.570973   7452.019058
min       17.000000  1.228500e+04         1.000000      0.000000
25%       28.000000  1.175505e+05         9.000000      0.000000
50%       37.000000  1.781445e+05        10.000000      0.000000
75%       48.000000  2.376420e+05        12.000000      0.000000
max       90.000000  1.490400e+06        16.000000  99999.000000

       capital-loss  hours-per-week
count  48842.000000    48842.000000
mean      87.502314       40.422382
std      403.004552       12.391444
min        0.000000        1.000000
25%        0.000000       40.000000
50%        0.000000       40.000000
75%        0.000000       45.000000
max     4356.000000       99.000000
```

```python
df['capital-gain'].unique()
```

```
array([    0,  7688,  3103,  6418,  7298,  3908, 14084,  5178, 15024,
       99999,  2597,  2907,  4650,  6497,  1055,  5013, 27828,  4934,
        4064,  3674,  2174, 10605,  3418,   114,  2580,  3411,  4508,
        4386,  8614, 13550,  6849,  2463,  3137,  2885,  2964,  1471,
       10566,  2354,  1424,  1455,  3325,  4416, 25236,   594,  2105,
        4787,  2829,   401,  4865,  1264,  1506, 10520,  3464,  2653,
       20051,  4101,  1797,  2407,  3471,  1086,  1848, 14344,  1151,
        2993,  2290, 15020,  9386,  2202,  3818,  2176,  5455, 11678,
        7978,  7262,  6514, 41310,  3456,  7430,  2414,  2062, 34095,
        1831,  6723,  5060, 15831,  2977,  2346,  3273,  2329,  9562,
        2635,  4931,  1731,  6097,   914,  7896,  5556,  1409,  3781,
        3942,  2538,  3887, 25124,  7443,  5721,  1173,  4687,  6612,
        6767,  2961,   991,  2036,  2936,  2050,  1111,  2228, 22040,
        3432,  6360,  2009,  1639, 18481,  2387])
```

```python
df['capital-gain'].nunique()
```

```
123
```

```python
df['capital-gain'].value_counts()
```

```
0        44807
15024      513
7688       410
7298       364
99999      244
         ...  
1111         1
7262         1
22040        1
1639         1
2387         1
Name: capital-gain, Length: 123, dtype: int64
```

```python
df['capital-loss'].value_counts()
```

```
0       46560
1902      304
1977      253
1887      233
2415       72
        ...  
2465        1
2080        1
155         1
1911        1
2201        1
Name: capital-loss, Length: 99, dtype: int64
```

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

```
203488    21
190290    19
120277    19
125892    18
126569    18
          ..
188488     1
285290     1
293579     1
114874     1
257302     1
Name: fnlwgt, Length: 28523, dtype: int64
```

```
df['race'].unique()
```

```
array(['Black', 'White', 'Asian-Pac-Islander', 'Other',
       'Amer-Indian-Eskimo'], dtype=object)
```

Drop columns fnlwgt , race , capital-gain , capital-loss

```
df.duplicated().sum()
```

```
47
```

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

```
Private             33906
Self-emp-not-inc     3862
Local-gov            3136
?                    2799
State-gov            1981
Self-emp-inc         1695
Federal-gov          1432
Without-pay            21
Never-worked           10
Name: workclass, dtype: int64
```

```
df.replace('?',np.nan,inplace = True)
df.dropna(inplace=True)
```

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

```
Private             33262
Self-emp-not-inc     3795
Local-gov            3100
State-gov            1946
Self-emp-inc         1645
Federal-gov          1406
```

```
Without-pay             21
Name: workclass, dtype: int64
```

```
df.shape
```

```
(45222, 15)
```

```
df=df.drop_duplicates()
```

```
df.shape
```

```
(45175, 15)
```

```
df.head()
```

```
   age  workclass  fnlwgt     education  educational-num      marital-
status  \
0   25    Private  226802          11th                7       Never-
married
1   38    Private   89814       HS-grad                9  Married-civ-
spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-
spouse
3   44    Private  160323  Some-college               10  Married-civ-
spouse
5   34    Private  198693          10th                6       Never-
married

          occupation   relationship   race gender  capital-gain
capital-loss  \
0  Machine-op-inspct      Own-child  Black   Male             0
0
1    Farming-fishing        Husband  White   Male             0
0
2    Protective-serv        Husband  White   Male             0
0
3  Machine-op-inspct        Husband  Black   Male          7688
0
5      Other-service  Not-in-family  White   Male             0
0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
5              30  United-States  <=50K
```

```
df.drop(['fnlwgt','race','capital-gain','capital-
loss'],axis=1,inplace=True)
```

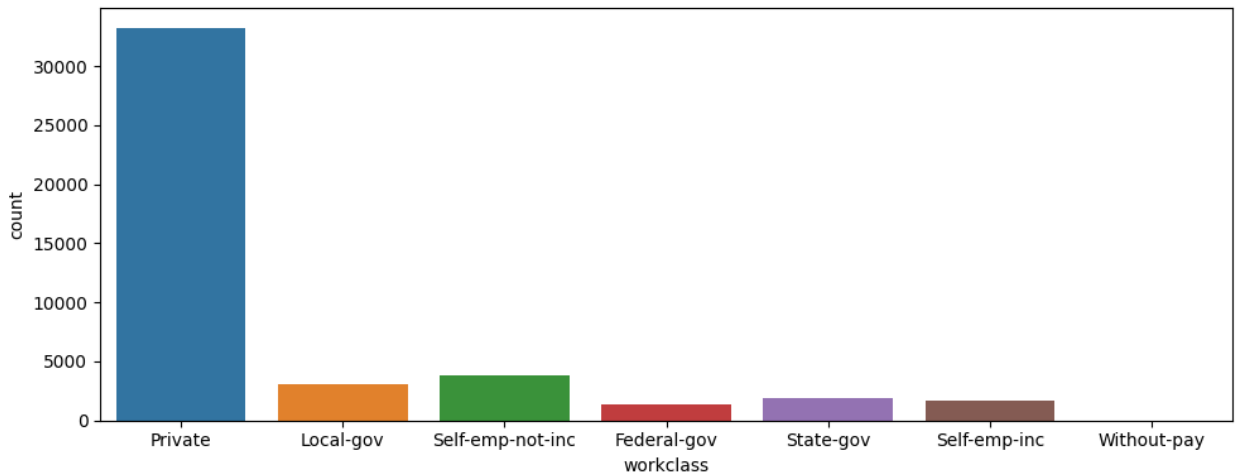
```
df.head()
```

```
   age  workclass     education  educational-num      marital-
status  \
0   25    Private          11th                7       Never-married

1   38    Private       HS-grad                9  Married-civ-spouse

2   28  Local-gov    Assoc-acdm               12  Married-civ-spouse

3   44    Private  Some-college               10  Married-civ-spouse

5   34    Private          10th                6       Never-married


          occupation   relationship gender  hours-per-week native-
country  \
0  Machine-op-inspct      Own-child   Male              40  United-
States
1    Farming-fishing        Husband   Male              50  United-
States
2    Protective-serv        Husband   Male              40  United-
States
3  Machine-op-inspct        Husband   Male              40  United-
States
5      Other-service  Not-in-family   Male              30  United-
States

  income
0  <=50K
1  <=50K
2   >50K
3   >50K
5  <=50K
```

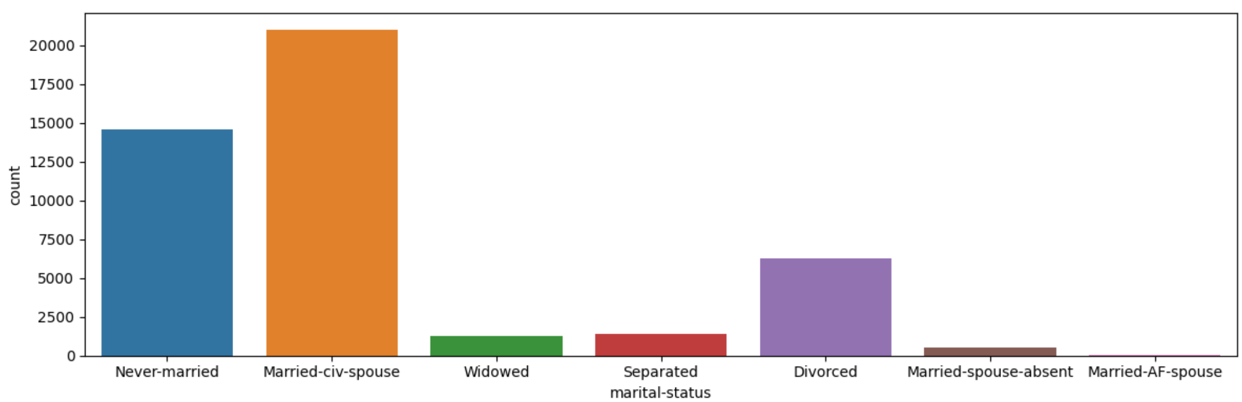
```
df.shape
```

```
(45175, 11)
```

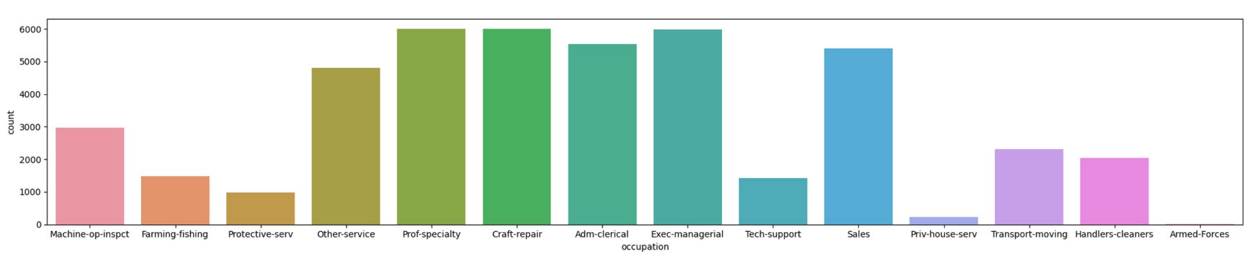
```
plt.figure(figsize=(10, 4))
sns.countplot(df , x='workclass' )
plt.tight_layout()
```



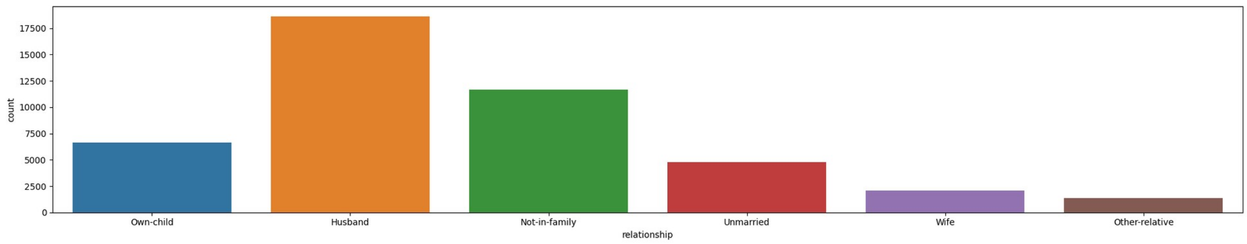

```
plt.figure(figsize=(12, 4))
sns.countplot(df , x='marital-status' )
plt.tight_layout()
```



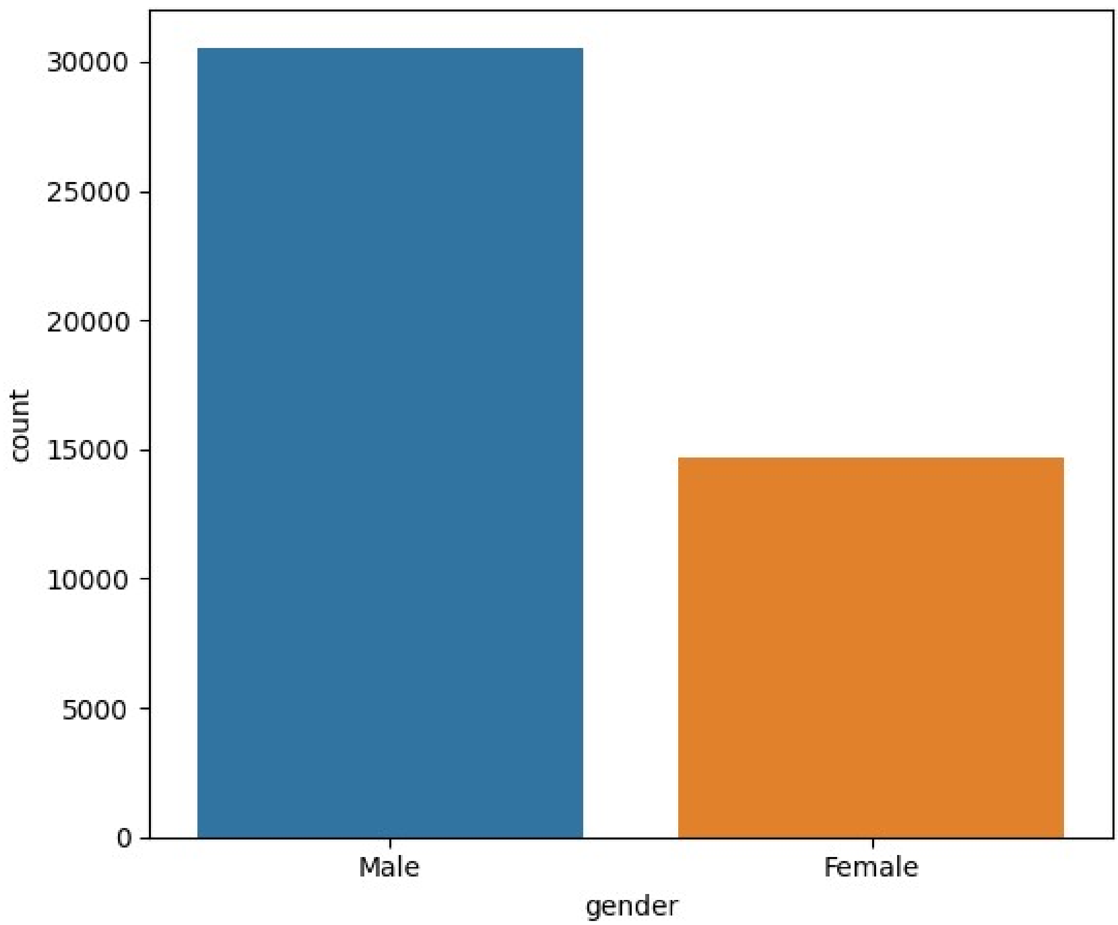

```
plt.figure(figsize=(20, 4))
sns.countplot(df , x='occupation' )
plt.tight_layout()
```



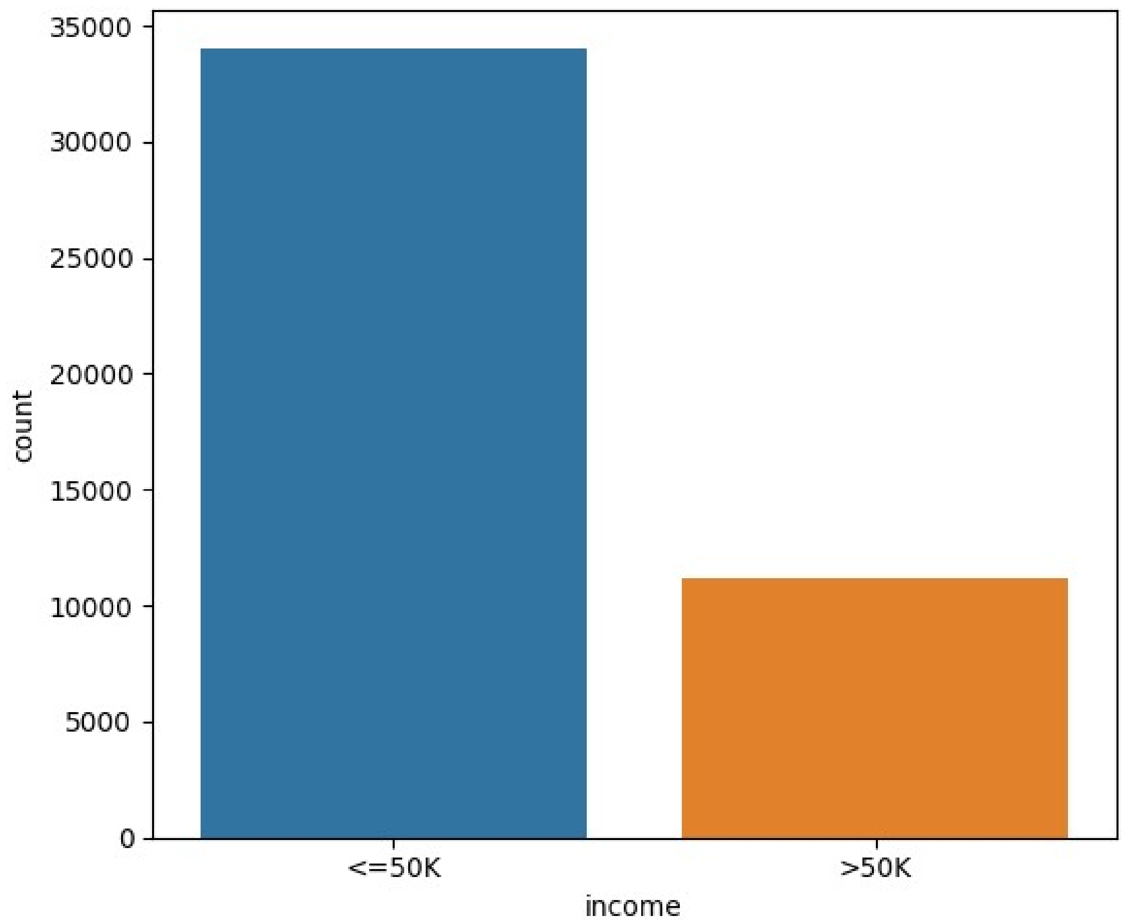

```
plt.figure(figsize=(20, 4))
sns.countplot(df , x='relationship')
plt.tight_layout()
```




```
plt.figure(figsize=(6, 5))
sns.countplot(df , x='gender')
plt.tight_layout()
```




```
plt.figure(figsize=(6, 5))
sns.countplot(df , x='income')
plt.tight_layout()
```

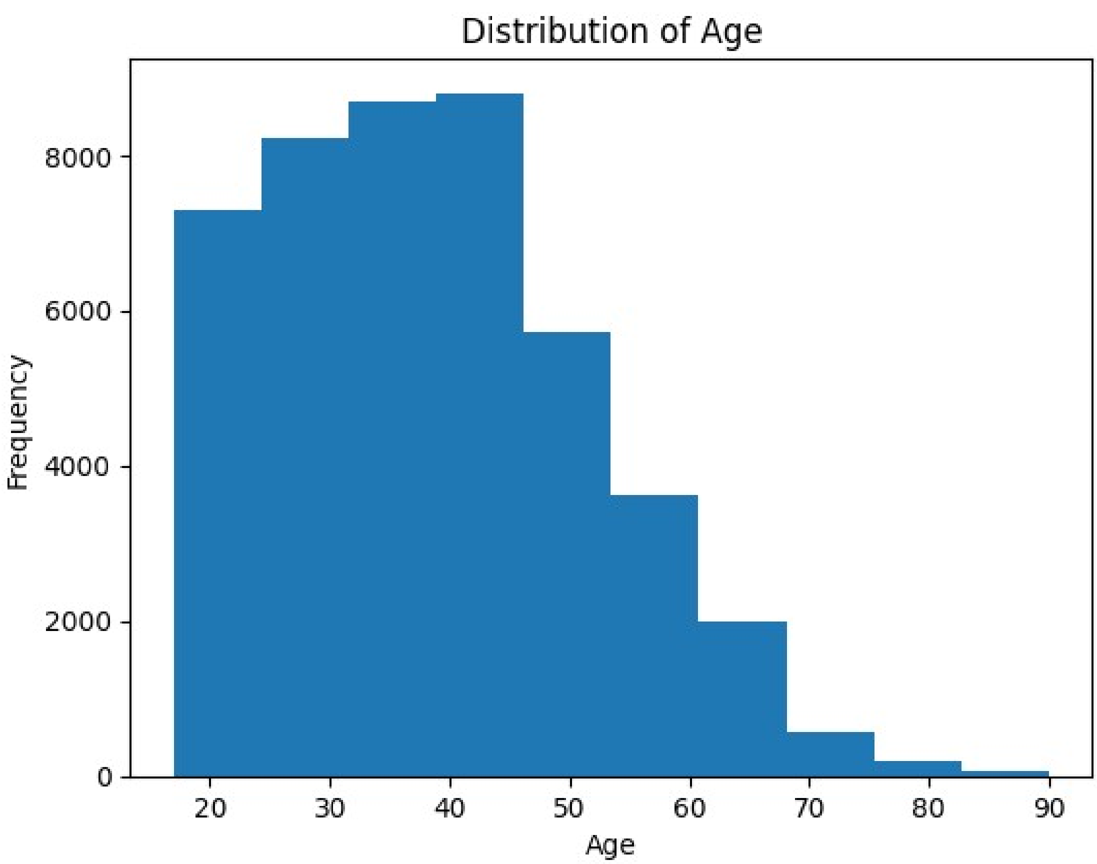



```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()

df['workclass'] = label_encoder.fit_transform(df['workclass'])
df['marital-status'] = label_encoder.fit_transform(df['marital-
status'])
df['occupation'] = label_encoder.fit_transform(df['occupation'])
df['relationship'] = label_encoder.fit_transform(df['relationship'])
df['gender'] = label_encoder.fit_transform(df['gender'])
df['native-country'] = label_encoder.fit_transform(df['native-
country'])
df['income'] = label_encoder.fit_transform(df['income'])

df['education'] = label_encoder.fit_transform(df['education'])

df.head()

   age  workclass  education  educational-num  marital-status
occupation  \
0   25          2          1                7               4
6
1   38          2         11                9               2
```

```
4
2   28           1          7                12               2
10
3   44           2         15                10               2
6
5   34           2          0                 6               4
7

   relationship  gender  hours-per-week  native-country  income
0             3       1              40              38       0
1             0       1              50              38       0
2             0       1              40              38       1
3             0       1              40              38       1
5             1       1              30              38       0
```

```python
plt.hist(df['age'])
# add labels and title
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Distribution of Age')
```

```
Text(0.5, 1.0, 'Distribution of Age')
```



```python
df.head()
```

```
   age  workclass  education  educational-num  marital-status
occupation  \
0   25          2          1                7               4
6
1   38          2         11                9               2
4
2   28          1          7               12               2
10
3   44          2         15               10               2
6
5   34          2          0                6               4
7

   relationship  gender  hours-per-week  native-country  income
0             3       1              40              38       0
1             0       1              50              38       0
2             0       1              40              38       1
3             0       1              40              38       1
5             1       1              30              38       0
```

```python
df['income'] = df['income'].astype('category')
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45175 entries, 0 to 48841
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              45175 non-null  int64
 1   workclass        45175 non-null  int64
 2   education        45175 non-null  int64
 3   educational-num  45175 non-null  int64
 4   marital-status   45175 non-null  int64
 5   occupation       45175 non-null  int64
 6   relationship     45175 non-null  int64
 7   gender           45175 non-null  int64
 8   hours-per-week   45175 non-null  int64
 9   native-country   45175 non-null  int64
 10  income           45175 non-null  category
dtypes: category(1), int64(10)
memory usage: 3.8 MB
```

#Train Test Split

```python
from sklearn.model_selection import train_test_split
```

```
# Putting independent variables/features to X
X = df.drop('income',axis=1)

# Putting response/dependent variable/feature to y
y = df['income']

X.head()

   age  workclass  education  educational-num  marital-status
occupation  \
0   25          2          1                7               4
6
1   38          2         11                9               2
4
2   28          1          7               12               2
10
3   44          2         15               10               2
6
5   34          2          0                6               4
7

   relationship  gender  hours-per-week  native-country
0             3       1              40              38
1             0       1              50              38
2             0       1              40              38
3             0       1              40              38
5             1       1              30              38

y.head()

0    0
1    0
2    1
3    1
5    0
Name: income, dtype: category
Categories (2, int64): [0, 1]

X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.30,random_state=101)

X_train.head()

       age  workclass  education  educational-num  marital-status
occupation  \
47222   34          2         11                9               2
9
48391   33          2         11                9               0
2
30359   64          0         11                9               2
9
```

```
22468   33          2          0                6               4
5
21211   34          1          6                5               4
7

       relationship  gender  hours-per-week  native-country
47222             0       1              60              29
48391             1       1              60              38
30359             0       1               8              38
22468             4       1              40              38
21211             3       1              40              38
```

Import model

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

Training model

```
dt_default = DecisionTreeClassifier(max_depth=5)
dt_default.fit(X_train,y_train)

DecisionTreeClassifier(max_depth=5)
```

Checking Accuracy

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

y_pred_default = dt_default.predict(X_test)

print(classification_report(y_test,y_pred_default))

              precision    recall  f1-score   support

           0       0.83      0.94      0.89     10237
           1       0.71      0.41      0.52      3316

    accuracy                           0.81     13553
   macro avg       0.77      0.68      0.70     13553
weighted avg       0.80      0.81      0.80     13553


print(confusion_matrix(y_test,y_pred_default))

[[9635  540]
 [1955 1423]]
```