Experiment No. 4
Apply Random Forest Algorithm on Adult Census Income Dataset and analyze the performance of the model
Date of Performance:
Date of Submission:

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

Objective: Able to perform various feature engineering tasks, apply Random Forest Algorithm on the given dataset and maximize the accuracy, Precision, Recall, F1 score.

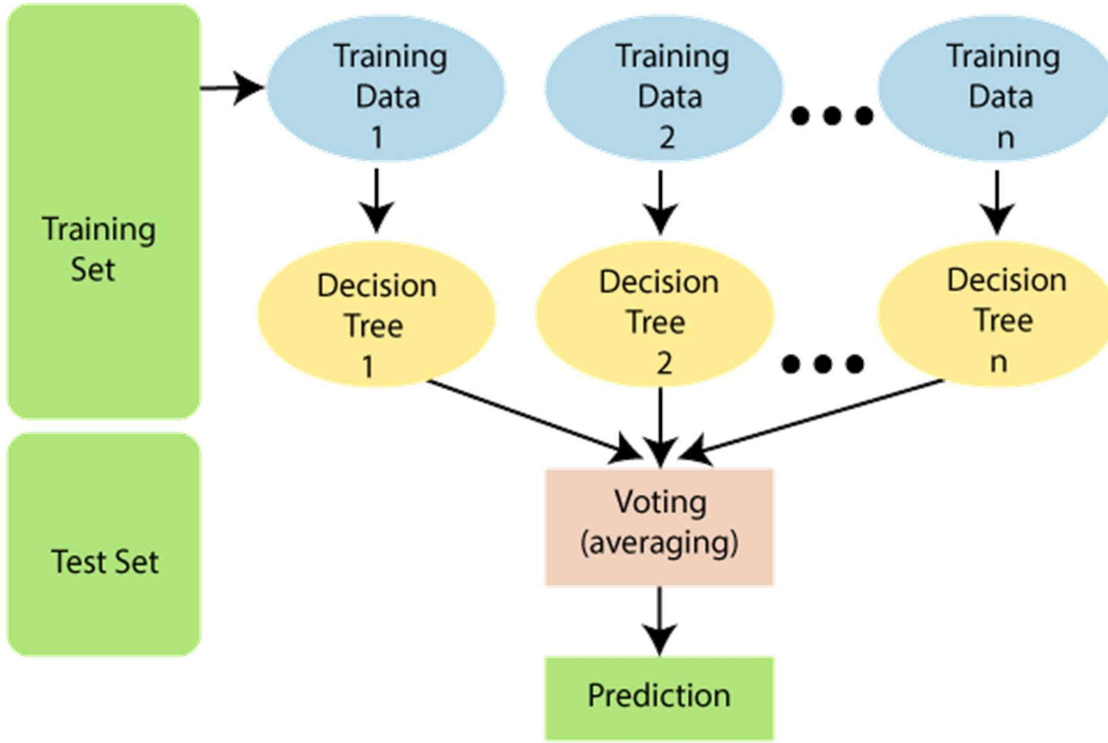
Theory:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:



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. The correlation heat map of the dataset reveals significant positive correlations between education level and income, suggesting that higher education is associated with higher earnings. The heat map provides a quick and informative overview of the dataset's feature relationships, which can guide the feature engineering process and help in building more accurate predictive models.

2. Accuracy , confusion matrix, precision, recall and F1 score are checked by considering entropy as criterion and entropy not as criterion. When all above parameter where checked by considering entropy : Accuracy = 78% , precision=85% , recall= 87% and F1 score = 86% . When all above parameter where checked without considering entropy : Accuracy = 82% , precision=83% , recall= 95% and F1 score = 89% .

```
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_new=df
```

```python
df.shape
```

```
(48842, 15)
```

Data Preprocessing

```python
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
```

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

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

```python
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
```

```python
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
```

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

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

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

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

```
52
```

```python
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
```

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

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

```
Private             33307
Self-emp-not-inc     3796
Local-gov            3100
State-gov            1946
```

```
Self-emp-inc         1646
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
```

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

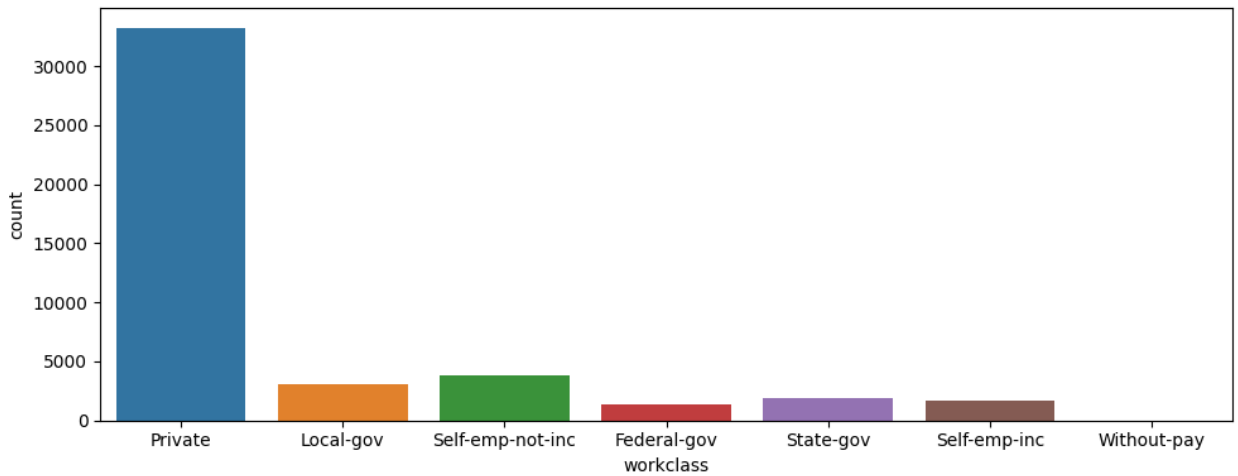
```python
df.head()
```

```
   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
```

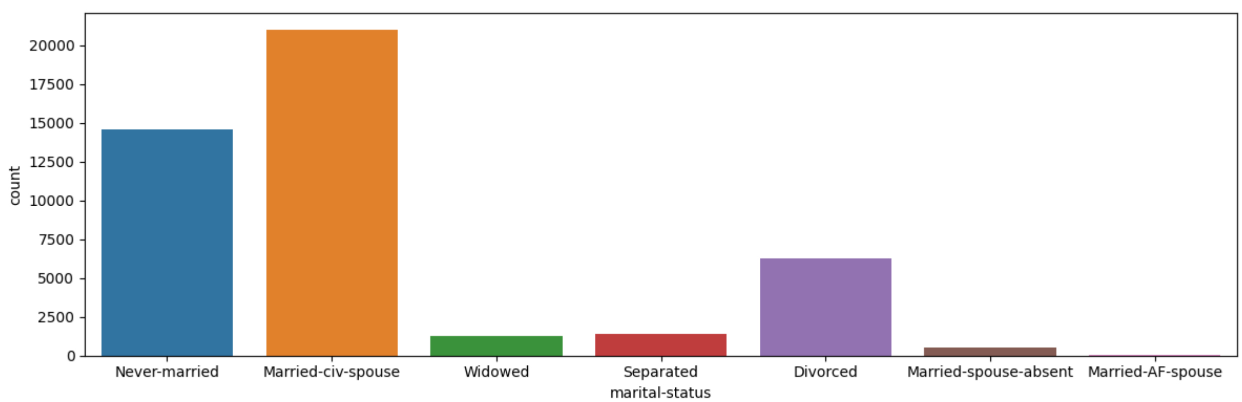
```python
df.shape
```

```
(45175, 11)
```

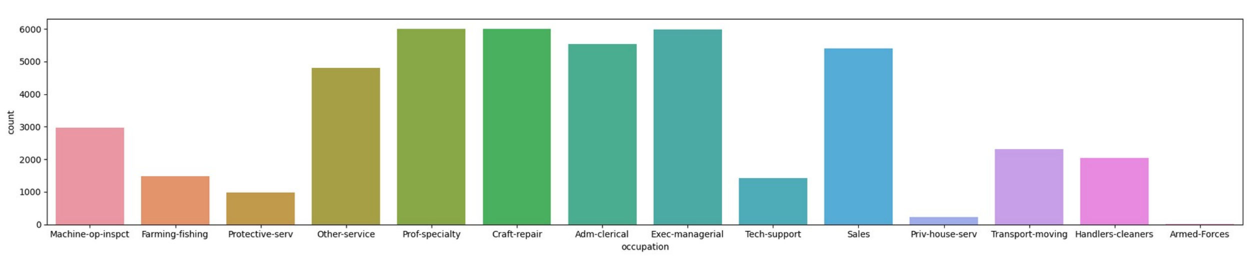
```python
plt.figure(figsize=(10, 4))
sns.countplot(df , x='workclass' )
plt.tight_layout()
```



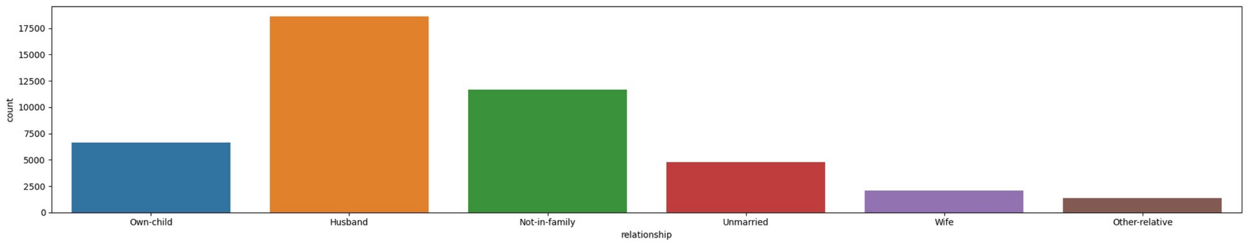

```
plt.figure(figsize=(12, 4))
sns.countplot(df , x='marital-status' )
plt.tight_layout()
```



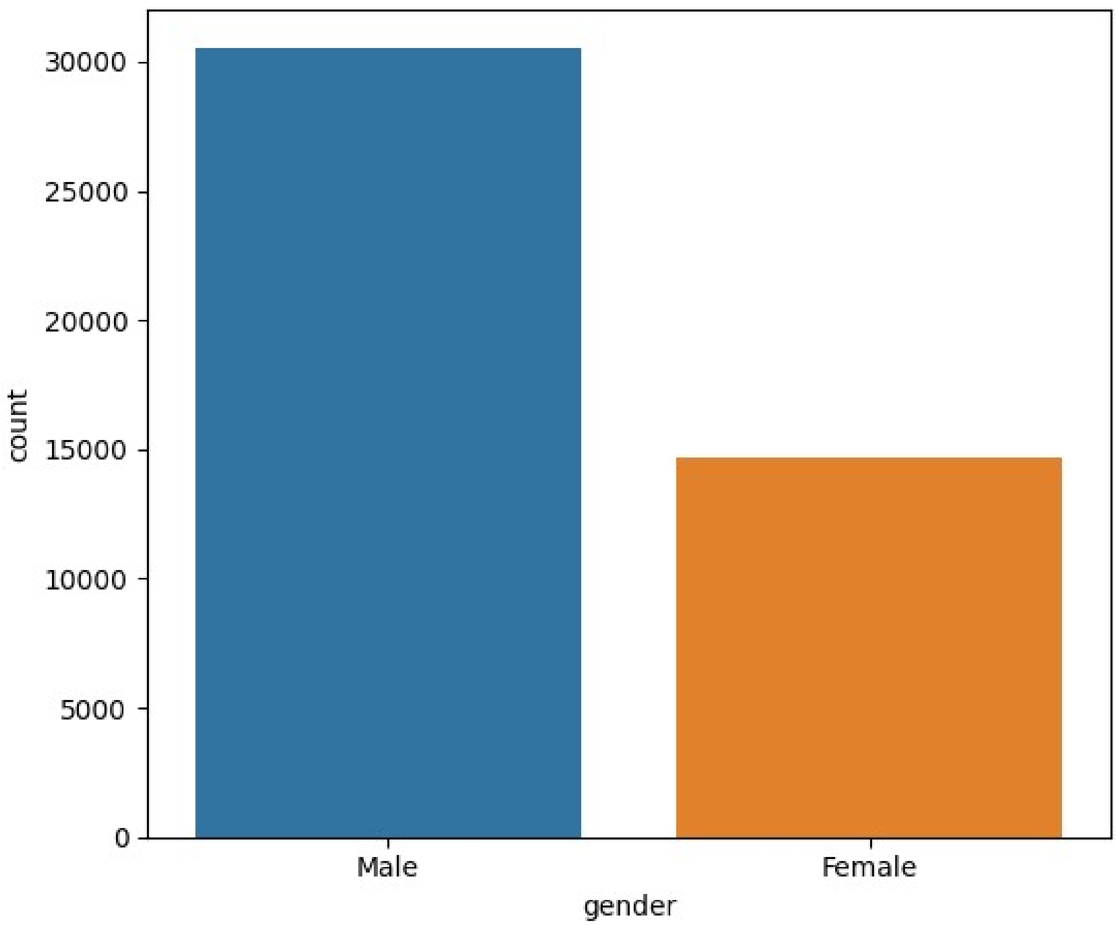

```
plt.figure(figsize=(20, 4))
sns.countplot(df , x='occupation' )
plt.tight_layout()
```



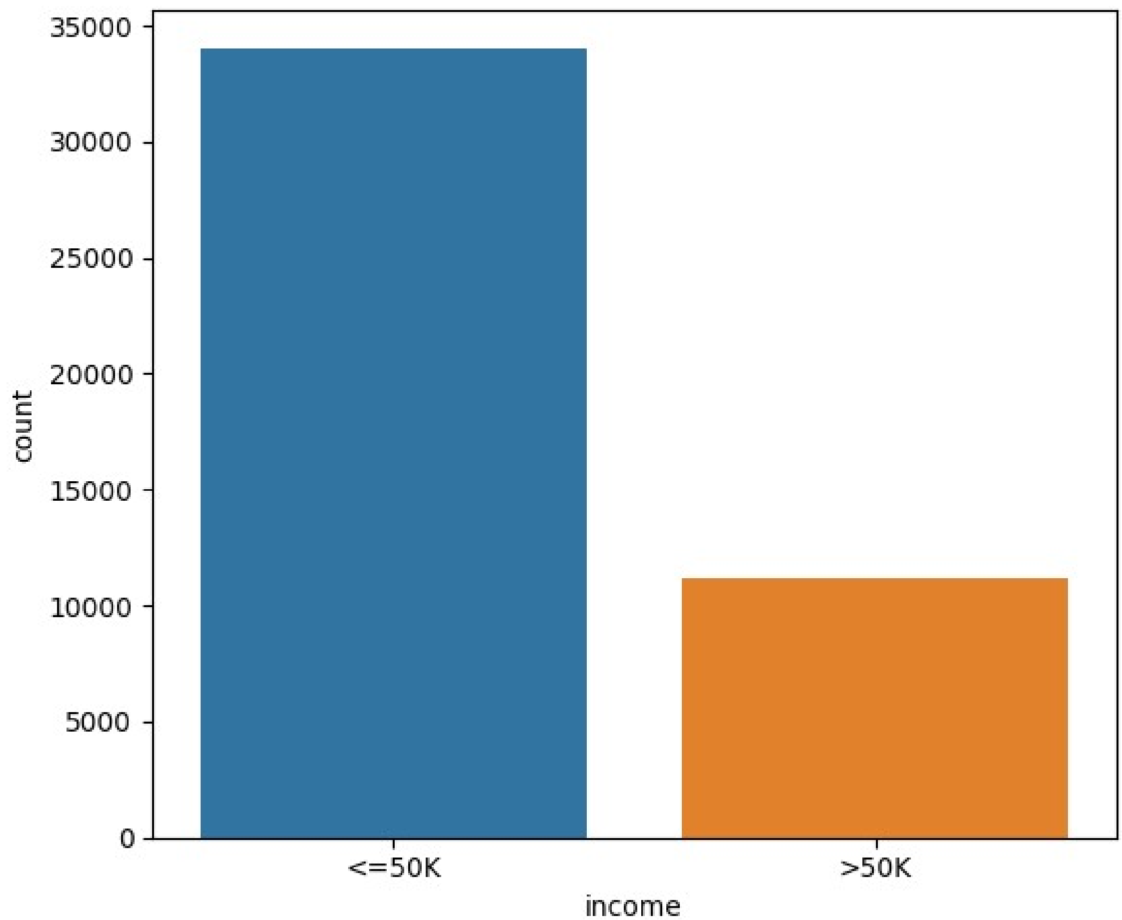

```
plt.figure(figsize=(20, 4))
sns.countplot(df , x='relationship')
plt.tight_layout()
```




```
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()
```



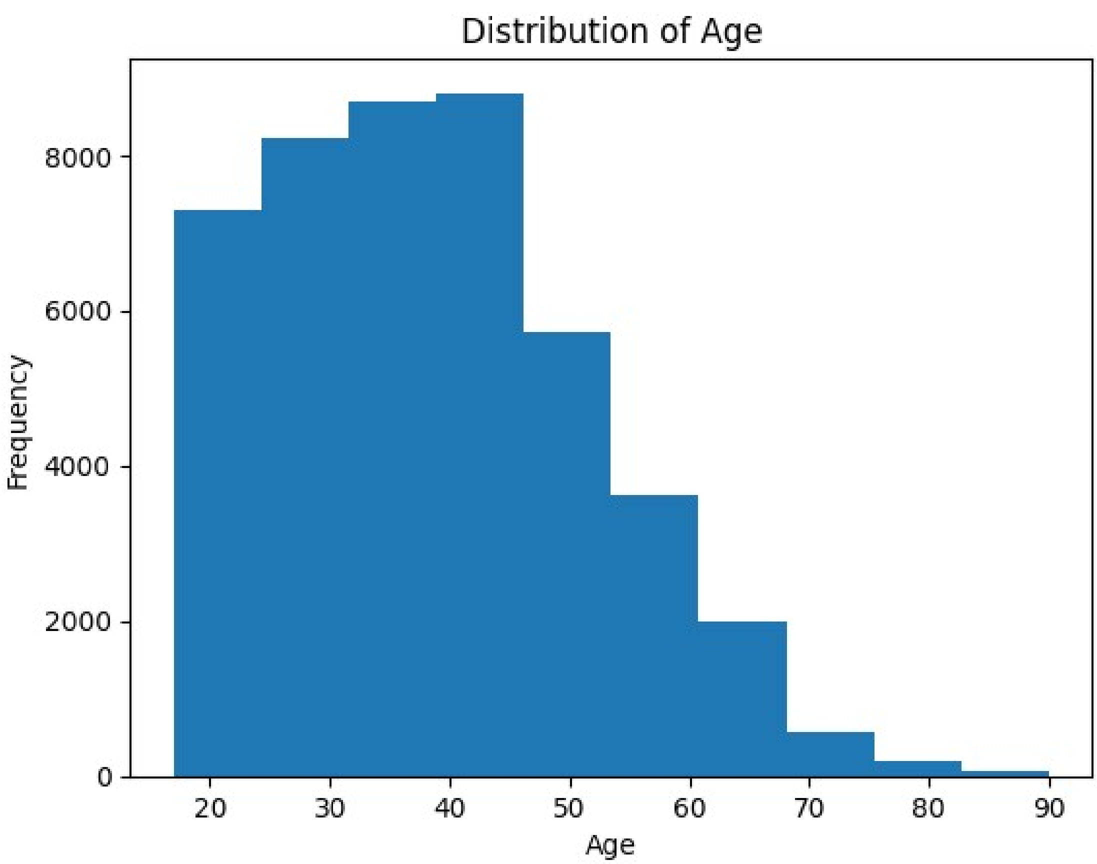

```
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()

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  
```

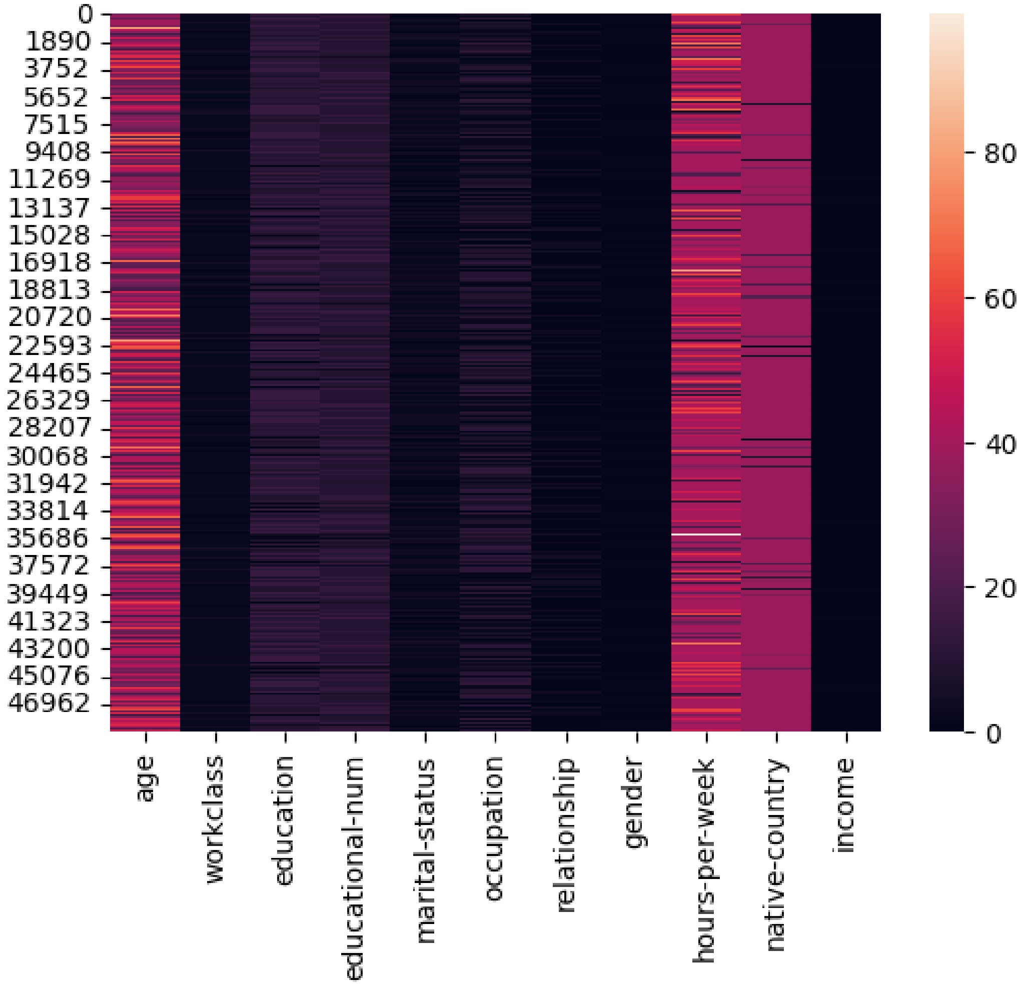
```python
df['income'] = df['income'].astype('category')
```

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

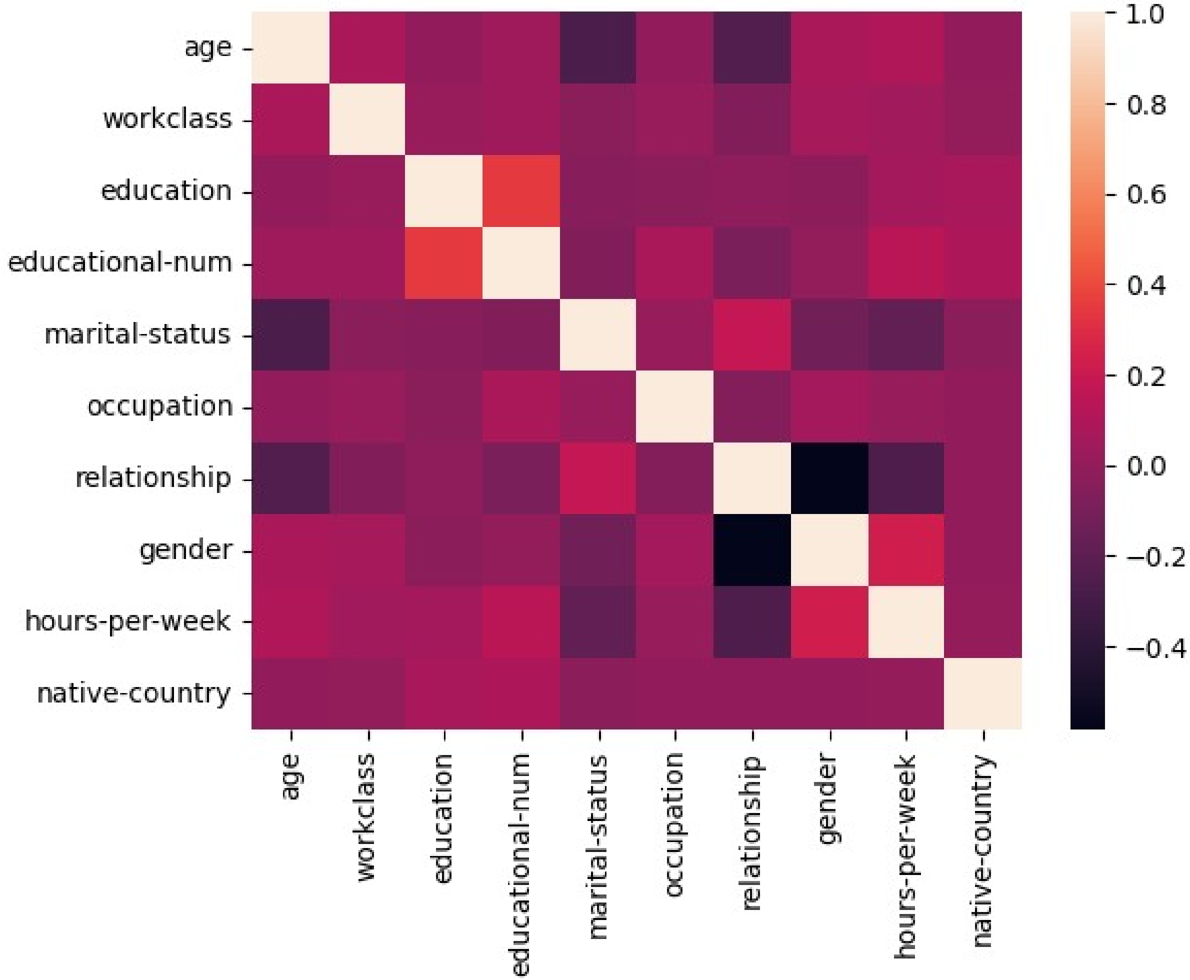
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 45175 entries, 0 to 48841
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype   
---  ------           --------------  -----   
 0   age              45175 non-null  int64   
 1   workclass        45175 non-null  int64   
 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
```

```python
sns.heatmap(df)
```

```
<Axes: >
```




```
sns.heatmap(df.corr())

<ipython-input-79-aa4f4450a243>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  sns.heatmap(df.corr())

<Axes: >
```




```
rdf.corr()['age']
```

```
<ipython-input-40-4fe920abfb17>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it
will default to False. Select only valid columns or specify the value
of numeric_only to silence this warning.
  df.corr()['age']
```

```
age                1.000000
workclass          0.085825
education         -0.003706
educational-num    0.037269
marital-status    -0.271265
occupation        -0.004511
relationship      -0.247572
gender             0.081920
hours-per-week     0.101604
native-country    -0.003645
Name: age, dtype: float64
```

#Train Test Split

```
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      0.95      0.89     10175
           1       0.72      0.42      0.53      3378

    accuracy                           0.82     13553
   macro avg       0.78      0.68      0.71     13553
weighted avg       0.80      0.82      0.80     13553


print(confusion_matrix(y_test,y_pred_default))
```

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

Decision tree with criterion : entropy

```
sc=DecisionTreeClassifier(criterion='entropy' ,  random_state=20)
sc.fit(X_train , y_train)
```

```
DecisionTreeClassifier(criterion='entropy', random_state=20)
```

```
predictions=sc.predict(X_test)
```

```
print(confusion_matrix(y_test , predictions))
```

```
[[8859 1316]
 [1602 1776]]
```