In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
```

In [2]:
```
train = pd.read_csv('adult.data.csv')
test = pd.read_csv('adult.test.csv')
```

In [3]:
```
print(train)
```

```
       age          workclass  fnlwgt    education  education-num  \
0       39          State-gov   77516    Bachelors             13
1       50   Self-emp-not-inc   83311    Bachelors             13
2       38            Private  215646      HS-grad              9
3       53            Private  234721         11th              7
4       28            Private  338409    Bachelors             13
...    ...                ...     ...          ...            ...
32556   27            Private  257302   Assoc-acdm             12
32557   40            Private  154374      HS-grad              9
32558   58            Private  151910      HS-grad              9
32559   22            Private  201490      HS-grad              9
32560   52       Self-emp-inc  287927      HS-grad              9

            marital-status          occupation    relationship    race  \
0            Never-married        Adm-clerical   Not-in-family   White
1       Married-civ-spouse     Exec-managerial         Husband   White
2                 Divorced   Handlers-cleaners   Not-in-family   White
3       Married-civ-spouse   Handlers-cleaners         Husband   Black
4       Married-civ-spouse      Prof-specialty            Wife   Black
...                    ...                 ...             ...     ...
32556   Married-civ-spouse        Tech-support            Wife   White
32557   Married-civ-spouse   Machine-op-inspct         Husband   White
32558              Widowed        Adm-clerical       Unmarried   White
32559        Never-married        Adm-clerical       Own-child   White
32560   Married-civ-spouse     Exec-managerial            Wife   White

           sex  capital-gain  capital-loss  hours-per-week  native-country  \
0         Male          2174             0              40   United-States
1         Male             0             0              13   United-States
2         Male             0             0              40   United-States
3         Male             0             0              40   United-States
4       Female             0             0              40            Cuba
...        ...           ...           ...             ...             ...
32556   Female             0             0              38   United-States
32557     Male             0             0              40   United-States
32558   Female             0             0              40   United-States
32559     Male             0             0              20   United-States
32560   Female         15024             0              40   United-States

       income
0       <=50K
1       <=50K
2       <=50K
3       <=50K
4       <=50K
...       ...
32556   <=50K
32557    >50K
32558   <=50K
32559   <=50K
32560    >50K

[32561 rows x 15 columns]
```

In [4]:
```
train.replace(' ?',np.nan,inplace=True)
```

In [5]:
```
train=train.dropna()
```

In [6]:
```
train
```

Out[6]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife
...	...	...	...	...	...	...	...	...
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife

30162 rows × 15 columns

In [7]:
```
test.replace(' ?',np.nan,inplace=True)
test=test.dropna()
test
```

Out[7]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black
5	34	Private	10th	6	Never-married	Other-service	Not-in-family	White
...	...	...	...	...	...	...	...	...
16275	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White
16276	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White
16278	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White
16279	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander
16280	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White

15060 rows × 14 columns

In [8]:
```
del train["fnlwgt"]
```

In [9]:
```
train
```

Out[9]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black
...	...	...	...	...	...	...	...	...
32556	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White
32557	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White
32558	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White
32559	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White
32560	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White

30162 rows × 14 columns

In [10]:
```
df=pd.concat([train,test])
```

In [11]:
```
df
```

Out[11]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black
...	...	...	...	...	...	...	...	...
16275	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White
16276	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White
16278	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White
16279	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander
16280	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White

45222 rows × 14 columns

In [12]:
```
print('Number of training data: ', len(train))
print('Number of training data: ', len(test))
```

```
Number of training data:  30162
Number of training data:  15060
```

In [13]:
```
df.info
```

Out[13]:
```
<bound method DataFrame.info of        age          workclass   education  educati
on-num       marital-status  \
0       39          State-gov   Bachelors             13        Never-married
1       50   Self-emp-not-inc   Bachelors             13   Married-civ-spouse
2       38            Private     HS-grad              9             Divorced
3       53            Private        11th              7   Married-civ-spouse
4       28            Private   Bachelors             13   Married-civ-spouse
...    ...                ...         ...            ...                  ...
16275   33            Private   Bachelors             13        Never-married
16276   39            Private   Bachelors             13             Divorced
16278   38            Private   Bachelors             13   Married-civ-spouse
16279   44            Private   Bachelors             13             Divorced
16280   35       Self-emp-inc   Bachelors             13   Married-civ-spouse

                occupation    relationship                 race      sex  \
0            Adm-clerical   Not-in-family                White     Male
1          Exec-managerial         Husband                White     Male
2        Handlers-cleaners   Not-in-family                White     Male
3        Handlers-cleaners         Husband                Black     Male
4           Prof-specialty            Wife                Black   Female
...                    ...             ...                  ...      ...
16275       Prof-specialty       Own-child                White     Male
16276       Prof-specialty   Not-in-family                White   Female
16278       Prof-specialty         Husband                White     Male
16279         Adm-clerical       Own-child   Asian-Pac-Islander     Male
16280      Exec-managerial         Husband                White     Male

       capital-gain  capital-loss  hours-per-week  native-country  income
0              2174             0              40   United-States   <=50K
1                 0             0              13   United-States   <=50K
2                 0             0              40   United-States   <=50K
3                 0             0              40   United-States   <=50K
4                 0             0              40            Cuba   <=50K
...             ...           ...             ...             ...     ...
16275             0             0              40   United-States   <=50K
16276             0             0              36   United-States   <=50K
16278             0             0              50   United-States   <=50K
16279          5455             0              40   United-States   <=50K
16280             0             0              60   United-States    >50K

[45222 rows x 14 columns]>
```

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 45222 entries, 0 to 16280
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             45222 non-null  int64 
 1   workclass       45222 non-null  object
 2   education       45222 non-null  object
 3   education-num   45222 non-null  int64 
 4   marital-status  45222 non-null  object
 5   occupation      45222 non-null  object
 6   relationship    45222 non-null  object
 7   race            45222 non-null  object
 8   sex             45222 non-null  object
 9   capital-gain    45222 non-null  int64 
 10  capital-loss    45222 non-null  int64 
 11  hours-per-week  45222 non-null  int64 
 12  native-country  45222 non-null  object
 13  income          45222 non-null  object
dtypes: int64(5), object(9)
memory usage: 5.2+ MB
```

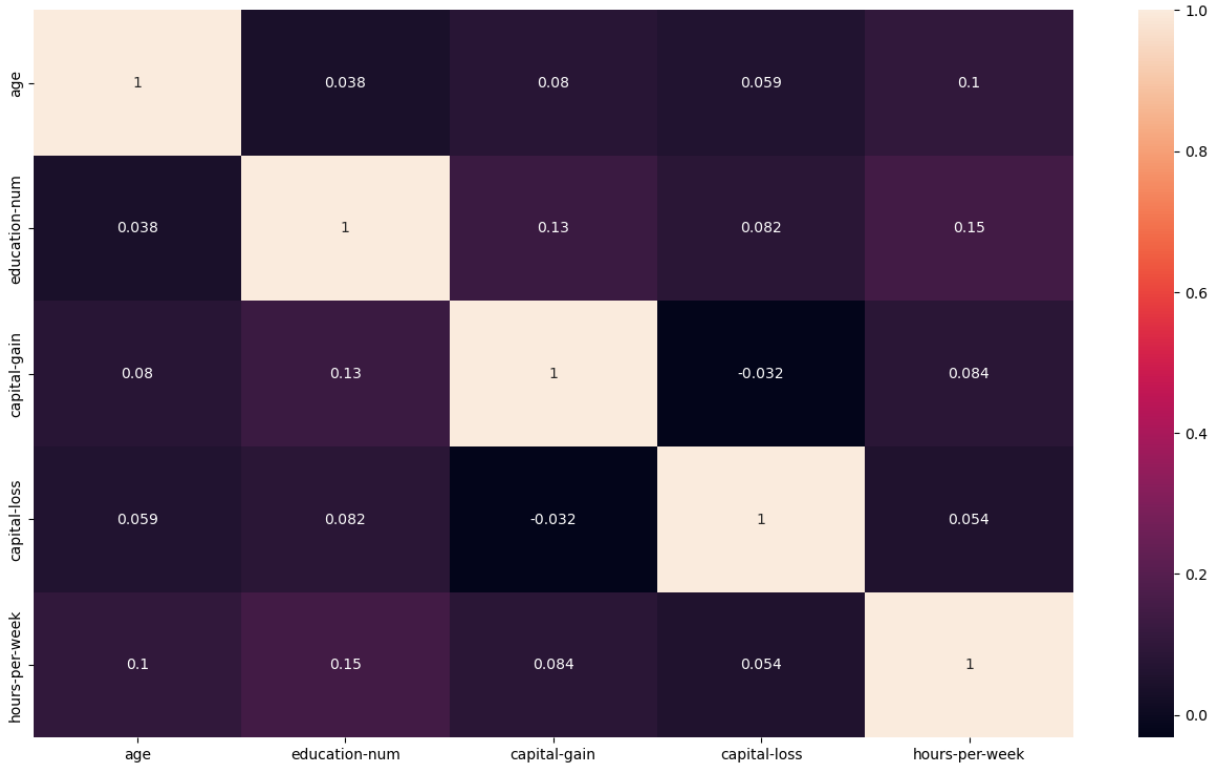
In [15]:
```
pip install seaborn --upgrade
```

```
Requirement already satisfied: seaborn in d:\app\anaconda\lib\site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in d:\app\anaconda\lib\site-pack
ages (from seaborn) (1.24.3)
Requirement already satisfied: pandas>=1.2 in d:\app\anaconda\lib\site-packages (fro
m seaborn) (2.1.4)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in d:\app\anaconda\lib\site-p
ackages (from seaborn) (3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in d:\app\anaconda\lib\site-packages
(from matplotlib!=3.6.1,>=3.4->seaborn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in d:\app\anaconda\lib\site-packages (fr
om matplotlib!=3.6.1,>=3.4->seaborn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in d:\app\anaconda\lib\site-package
s (from matplotlib!=3.6.1,>=3.4->seaborn) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\app\anaconda\lib\site-package
s (from matplotlib!=3.6.1,>=3.4->seaborn) (1.4.4)
Requirement already satisfied: packaging>=20.0 in d:\app\anaconda\lib\site-packages
(from matplotlib!=3.6.1,>=3.4->seaborn) (23.1)
Requirement already satisfied: pillow>=6.2.0 in d:\app\anaconda\lib\site-packages (f
rom matplotlib!=3.6.1,>=3.4->seaborn) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in d:\app\anaconda\lib\site-packages
(from matplotlib!=3.6.1,>=3.4->seaborn) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in d:\app\anaconda\lib\site-pack
ages (from matplotlib!=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in d:\app\anaconda\lib\site-packages (fr
om pandas>=1.2->seaborn) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in d:\app\anaconda\lib\site-packages
(from pandas>=1.2->seaborn) (2023.3)
Requirement already satisfied: six>=1.5 in d:\app\anaconda\lib\site-packages (from p
ython-dateutil>=2.7->matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [16]:
```
df2 = df.select_dtypes(include=['int64'])
plt.figure(figsize=(16,9))
```

```
sns.heatmap(df2.corr(method='pearson'),annot=True)
```

Out[16]: <Axes: >



In [17]:
```
feature = df.drop('income',axis=1)
label = df['income']
```

In [18]:
```
feature.select_dtypes(exclude=['int64']).columns
```

Out[18]:
```
Index(['workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country'],
      dtype='object')
```

In [19]:
```
feature_onehot = pd.get_dummies(feature,columns=feature.select_dtypes(exclude=['int
feature_onehot
```

Out[19]:

	age	education-num	capital-gain	capital-loss	hours-per-week	workclass_Federal-gov	workclass_Local-gov	workclass_Private	worl Self
0	39	13	2174	0	40	False	False	False	
1	50	13	0	0	13	False	False	False	
2	38	9	0	0	40	False	False	True	
3	53	7	0	0	40	False	False	True	
4	28	13	0	0	40	False	False	True	
...	...	...	...	...	...	...	...	...	
16275	33	13	0	0	40	False	False	True	
16276	39	13	0	0	36	False	False	True	
16278	38	13	0	0	50	False	False	True	
16279	44	13	5455	0	40	False	False	True	
16280	35	13	0	0	60	False	False	False	

45222 rows × 103 columns

In [20]:
```
x_train = feature_onehot[:30162]
x_test = feature_onehot[30162:]
y_train=label[:30162]
y_test=label[30162:]
```

In [21]:
```
clf = tree.DecisionTreeClassifier(criterion="entropy",random_state=0)
clf.fit(x_train,y_train)
```

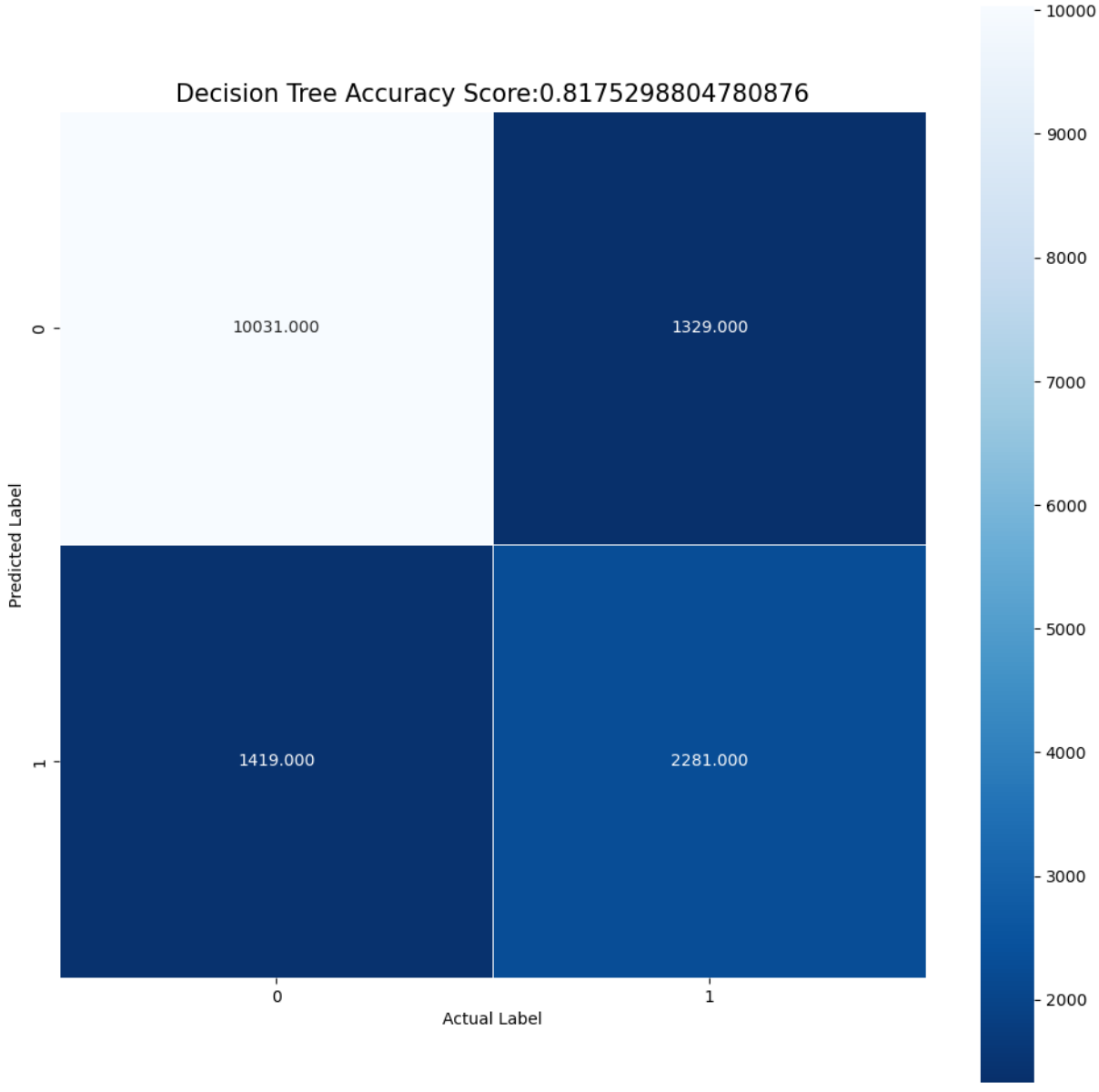
Out[21]:
```
▾ DecisionTreeClassifier

DecisionTreeClassifier(criterion='entropy', random_state=0)
```

In [22]:
```
tree_pred = clf.predict(x_test)

tree_score = metrics.accuracy_score(y_test,tree_pred)
print("Accruracy:",tree_score)
print("Report:",metrics.classification_report(y_test,tree_pred))
```

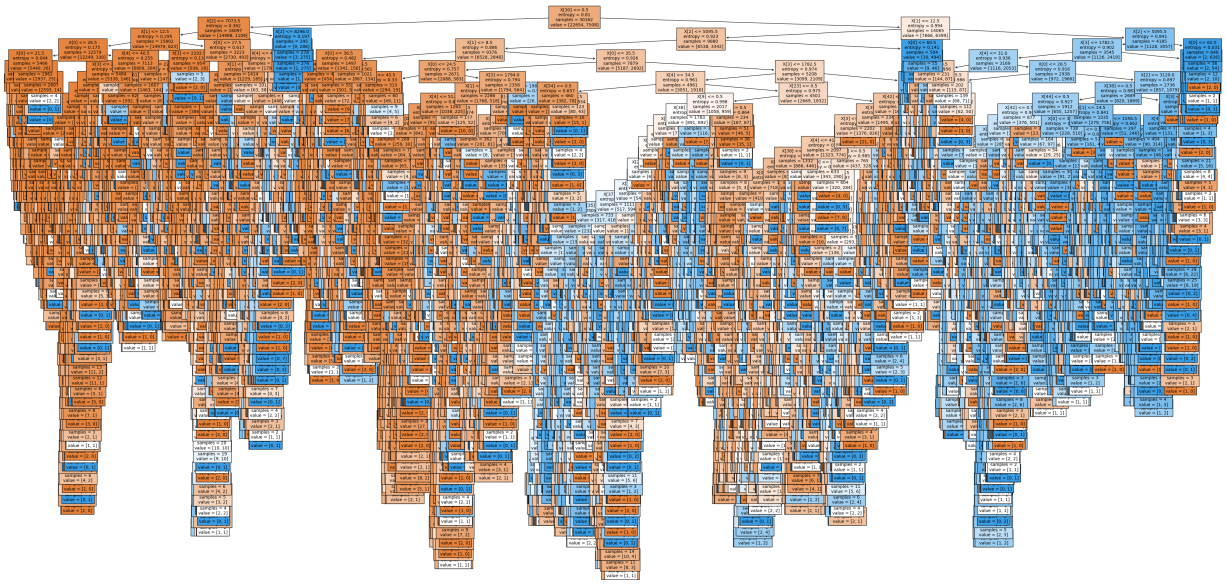
```
Accruracy: 0.8175298804780876
Report:               precision    recall  f1-score   support

       <=50K       0.88      0.88      0.88     11360
        >50K       0.63      0.62      0.62      3700

    accuracy                           0.82     15060
   macro avg       0.75      0.75      0.75     15060
weighted avg       0.82      0.82      0.82     15060
```

In [23]:
```
tree_cm = metrics.confusion_matrix(y_test,tree_pred)
```

In [24]:
```
plt.figure(figsize=(12,12))
sns.heatmap(tree_cm,annot=True, fmt=".3f",linewidth=.5,square=True,cmap='Blues_r');
plt.xlabel('Actual Label');
plt.ylabel('Predicted Label');
title ='Decision Tree Accuracy Score:{0}'.format(tree_score)
plt.title(title,size=15);
```



In [25]:
```
fig, ax = plt.subplots(figsize=(50,24))
tree.plot_tree(clf,filled=True,fontsize=10)
plt.savefig('decision_tree',dpi=100)
plt.show()
```



In [26]:
```
clf = tree.DecisionTreeClassifier(criterion="gini",random_state=0)
clf.fit(x_train,y_train)
```

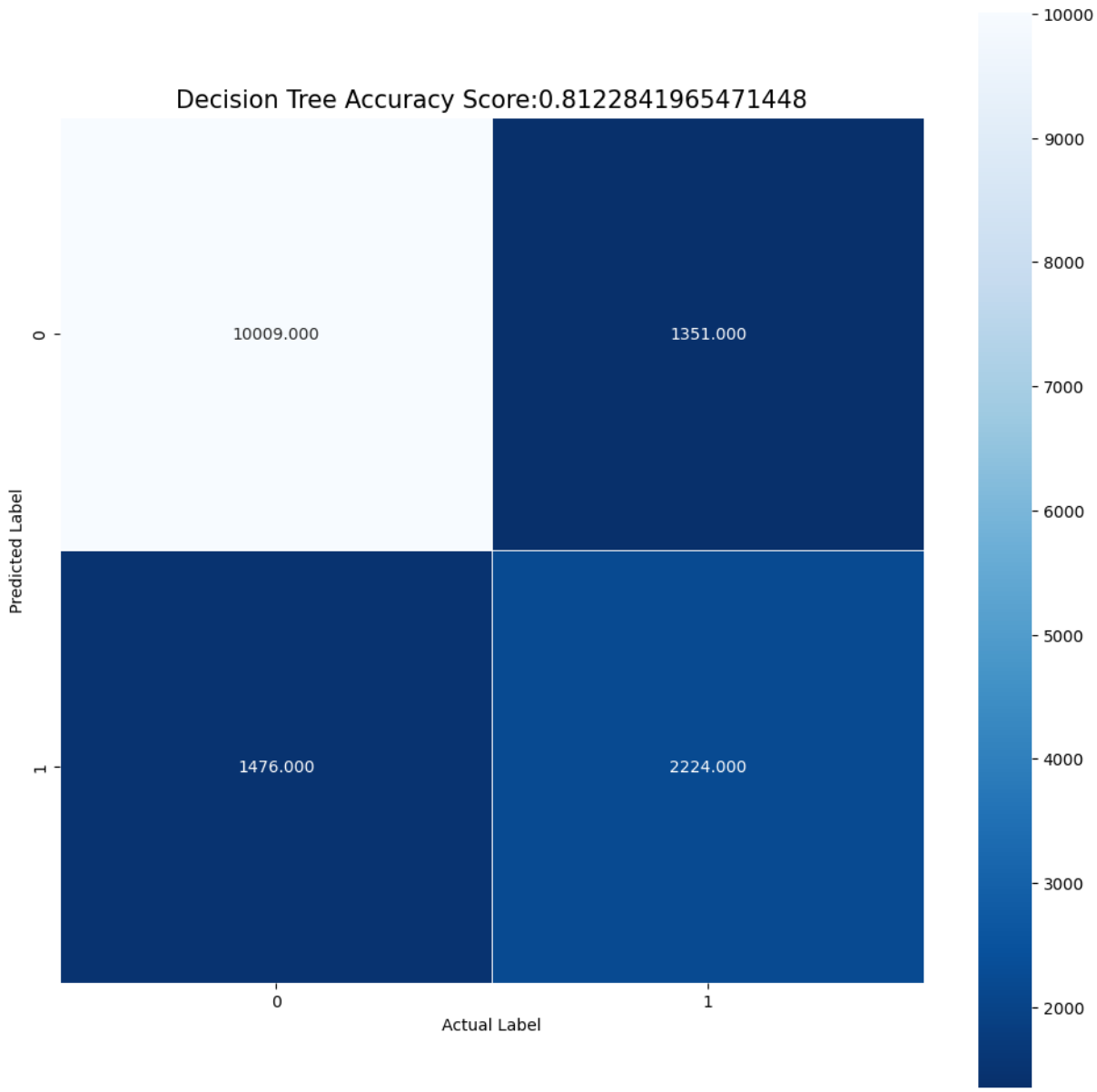
Out[26]:
```
▾          DecisionTreeClassifier

DecisionTreeClassifier(random_state=0)
```

In [27]:
```
tree_pred = clf.predict(x_test)
tree_score = metrics.accuracy_score(y_test,tree_pred)
print("Accruracy:",tree_score)
print("Report:",metrics.classification_report(y_test,tree_pred))
```

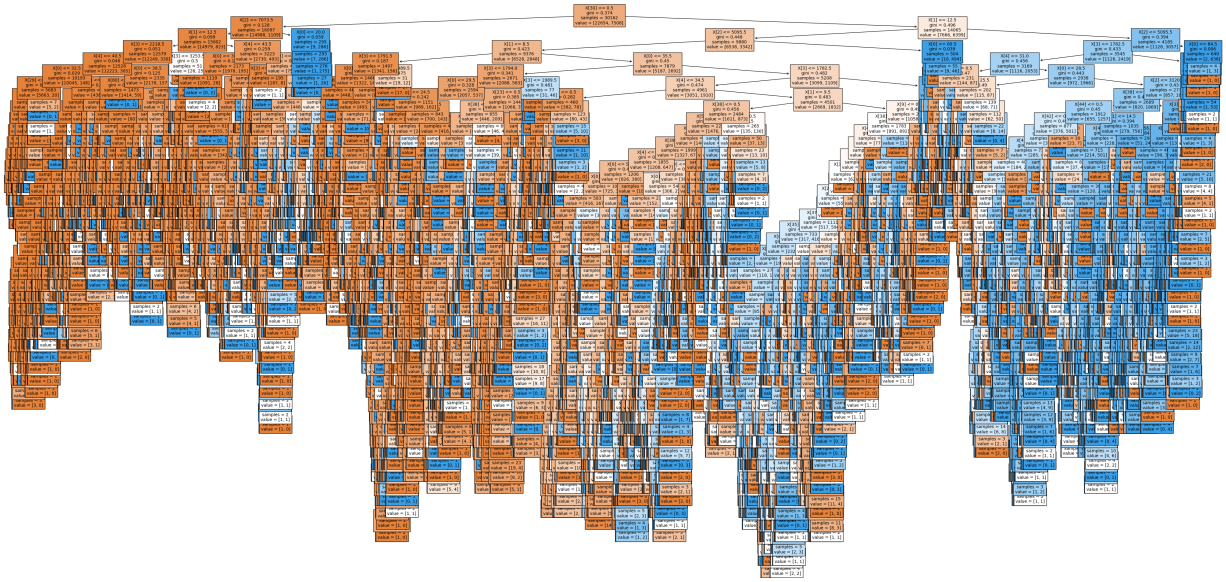
```
Accruracy: 0.8122841965471448
Report:                precision    recall  f1-score   support

         <=50K       0.87      0.88      0.88     11360
          >50K       0.62      0.60      0.61      3700

      accuracy                           0.81     15060
     macro avg       0.75      0.74      0.74     15060
  weighted avg       0.81      0.81      0.81     15060
```

In [28]:
```
tree_cm = metrics.confusion_matrix(y_test,tree_pred)
```

In [29]:
```
plt.figure(figsize=(12,12))
sns.heatmap(tree_cm,annot=True, fmt=".3f",linewidth=.5,square=True,cmap='Blues_r');
plt.xlabel('Actual Label');
plt.ylabel('Predicted Label');
title ='Decision Tree Accuracy Score:{0}'.format(tree_score)
plt.title(title,size=15);
```



In [30]:
```
fig, ax = plt.subplots(figsize=(50,24))
tree.plot_tree(clf,filled=True,fontsize=10)
plt.savefig('decision_tree',dpi=100)
plt.show()
```



In [31]:
```
gnb = GaussianNB()
```

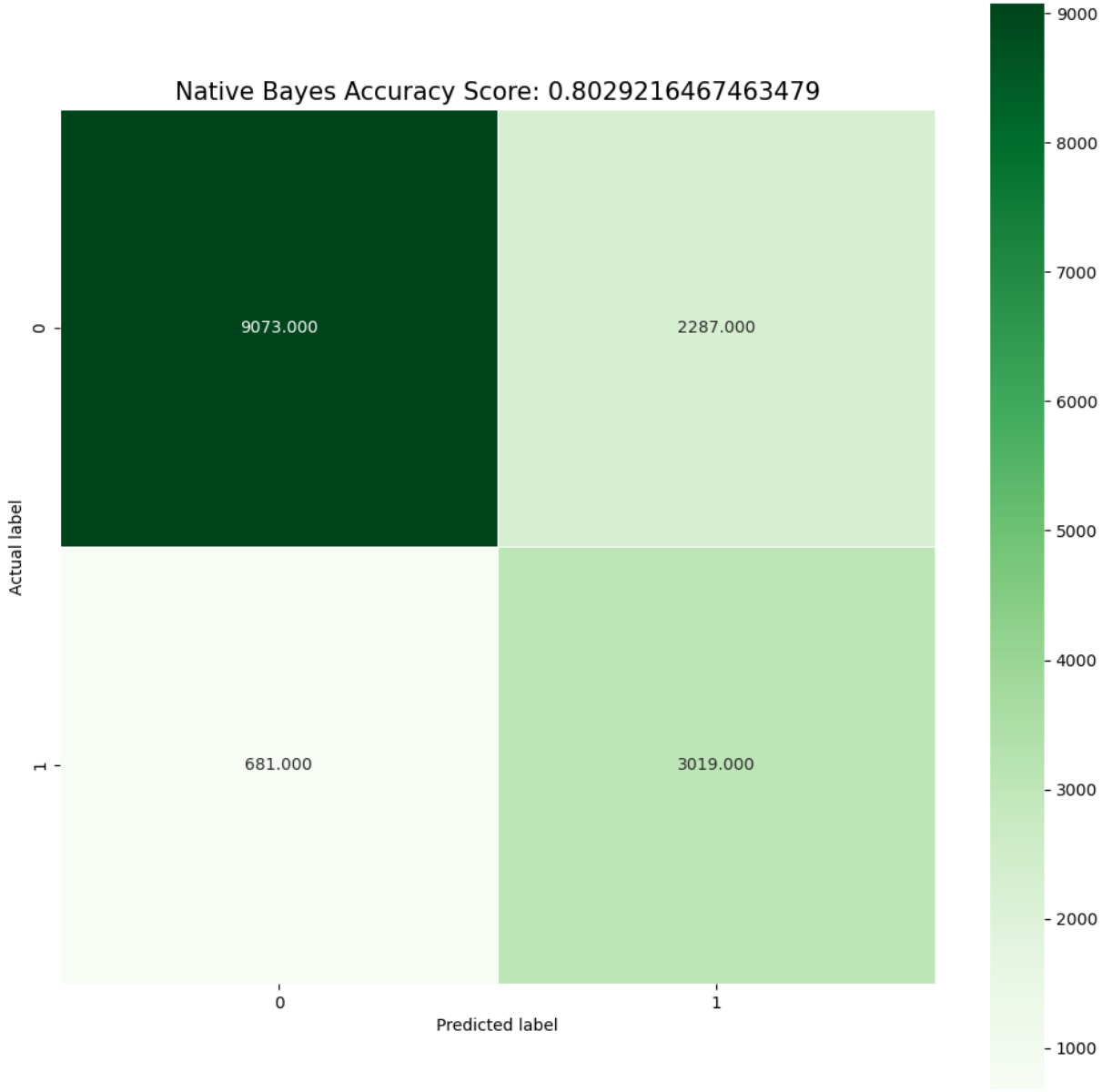
In [33]:
```
bayes_pred = gnb.fit(x_train, y_train).predict(x_test)
```

In [34]:
```
bayes_score = metrics.accuracy_score(y_test, bayes_pred)
```

In [35]:
```
print("Accuracy: ", bayes_score)
print("Report: ", metrics.classification_report(y_test, bayes_pred))
```

```
Accuracy:  0.8029216467463479
Report:                precision    recall  f1-score   support

         <=50K       0.93      0.80      0.86     11360
          >50K       0.57      0.82      0.67      3700

      accuracy                           0.80     15060
     macro avg       0.75      0.81      0.76     15060
  weighted avg       0.84      0.80      0.81     15060
```

In [36]:
```
bayes_cm = metrics.confusion_matrix(y_test, bayes_pred)
plt.figure(figsize=(12,12))
sns.heatmap(bayes_cm,annot=True, fmt=".3f",linewidth=.5,square=True,cmap='Greens');
plt.ylabel('Actual label');
plt.xlabel('Predicted label');
title = 'Native Bayes Accuracy Score: {0}'.format(bayes_score)
plt.title(title, size=15);
```



10 So sánh kết quả của các mô hình trên.

Dựa vào mô hình ta có độ chính xác của các thuật toán lần lượt là:

- Thuật toán cây ID3 với 81.753%
- Thuật toán Naive Bayes với 80.292%
- Thuật toán cây CART với 81.228%

Vậy đối với mô hình này sử dụng thuật toán cây quyết định ID3 cho ra độ chính xác cao nhất

Còn nếu xét trên từng lớp

- với số lớp <= 50k ID3: 0.88, CART: 0.88, Naive: 0.86

Cả ba thuật toán cho ra độ chính xác khá cao

- với số lớp > 50k ID3: 0.62, CART: 0.61, Naive: 0.67

Cả ba thuật toán vẫn chưa cho ra được sự chính xác cao