In [2]:
```
# Import các thư viện cần thiết
```

In [3]:
```
%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 [4]:
```
# Đọc dữ liệu
```

In [5]:
```
train = pd.read_csv('adult.data.csv')
test = pd.read_csv('adult.test.csv')
```

In [6]:
```
# Kiểm tra
```

In [7]:
```
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 [8]:
```
# Tiến hành tiền xử lý dữ liệu
# Xóa những dòng có chứa dữ liệu trống, biết rằng dữ liệu trống được ký hiệu bằng dấu '?'.
```

In [9]:
```
train.replace(' ?',np.nan,inplace=True)
```

In [10]:
```
train=train.dropna()
```

In [11]:
```
train
```

Out[11]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	nati coun
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	Unit Sta
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	Unit Sta
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	Unit Sta
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	Unit Sta
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	C
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
32556	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	Unit Sta
32557	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	Unit Sta
32558	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	Unit Sta
32559	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	Unit Sta
32560	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	Unit Sta

30162 rows × 15 columns

In [12]:
```
test.replace(' ?',np.nan,inplace=True)
test=test.dropna()
test
```

Out[12]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	inc
0	25	Private	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<
1	38	Private	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<
2	28	Local-gov	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	
3	44	Private	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	
5	34	Private	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
16275	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	40	United-States	<
16276	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	United-States	<
16278	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	United-States	<
16279	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	United-States	<
16280	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	United-States	

15060 rows × 14 columns

In [13]:
```
#  Xóa cột final weight ‘fnlwgt’ trong dữ liệu huấn luyện vì cột này không có trong dữ liệu kiểm thử
```

In [14]:
```
del train["fnlwgt"]
```

In [15]:
```
train
```

Out[15]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	inco
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
32556	27	Private	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=
32557	40	Private	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>
32558	58	Private	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=
32559	22	Private	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=
32560	52	Self-emp-inc	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>

30162 rows × 14 columns

In [16]:
```
# Nối dữ liệu huấn luyện và kiểm thử lại với nhau để phục vụ các bước tiếp theo
```

In [17]:
```
df=pd.concat([train,test])
```

In [18]:
```
# Kiểm tra
```

In [19]:
```
df
```

Out[19]:

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	inc
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
16275	33	Private	Bachelors	13	Never-married	Prof-specialty	Own-child	White	Male	0	0	40	United-States	<
16276	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	United-States	<
16278	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	0	0	50	United-States	<
16279	44	Private	Bachelors	13	Divorced	Adm-clerical	Own-child	Asian-Pac-Islander	Male	5455	0	40	United-States	<
16280	35	Self-emp-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	60	United-States	

45222 rows × 14 columns

In [20]:
```
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 [21]:
```
df.info
```

Out[21]:
```
<bound method DataFrame.info of        age          workclass   education  education-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 [22]:
```
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
```

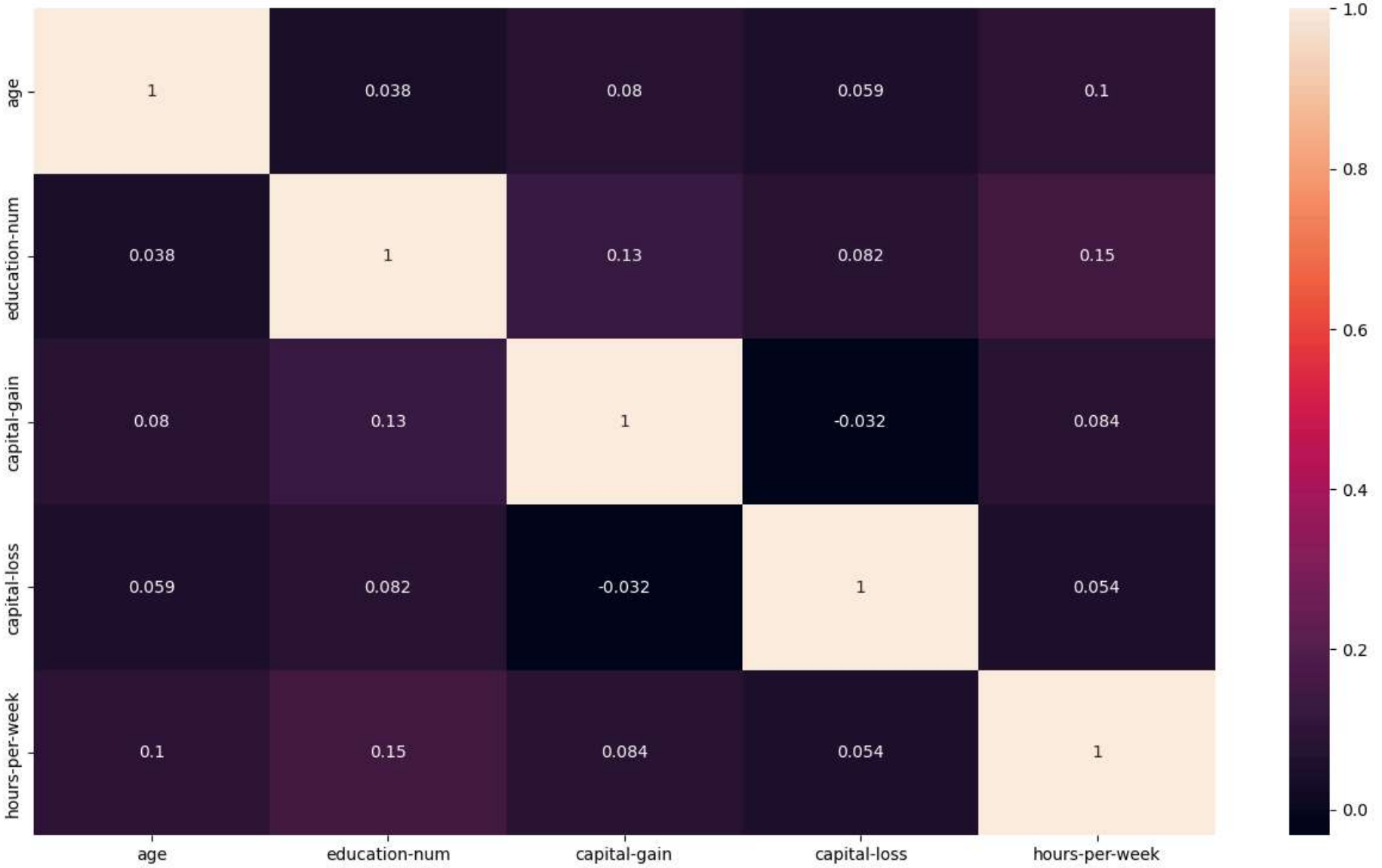
In [23]:
```
# Khảo sát độ tương đồng giữa các cột với nhau bằng công thức Pearson. Những cột nào có giá trị tương đồng cao thì hãy loại bỏ
```

In [24]:
```
pip install seaborn --upgrade
```

```
Requirement already satisfied: seaborn in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (0.13.2)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from seaborn)
(1.26.0)
Requirement already satisfied: pandas>=1.2 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from seaborn) (2.1.1)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from seaborn)
(3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.
6.1,>=3.4->seaborn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.6.1,>
=3.4->seaborn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.
6.1,>=3.4->seaborn) (4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.
6.1,>=3.4->seaborn) (1.4.4)
Requirement already satisfied: packaging>=20.0 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.6.
1,>=3.4->seaborn) (23.1)
Requirement already satisfied: pillow>=6.2.0 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.6.1,
>=3.4->seaborn) (10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!=3.
6.1,>=3.4->seaborn) (3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from matplotlib!
=3.6.1,>=3.4->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from pandas>=1.2->seabor
n) (2023.3.post1)
Requirement already satisfied: tzdata>=2022.1 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from pandas>=1.2->seab
orn) (2023.3)
Requirement already satisfied: six>=1.5 in c:\users\tento\anaconda3\envs\thktdl\lib\site-packages (from python-dateutil>=2.7->m
atplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [25]:
```
# pip install seaborn --upgrade
df2 = df.select_dtypes(include=['int64'])
plt.figure(figsize=(16,9))
sns.heatmap(df2.corr(method='pearson'),annot=True)
```

Out[25]:
```
<Axes: >
```



In [27]:
```
# Tách các cột dữ liệu thành hai phần, một phần chứa các thuộc tính bình thường, một phần chứa riêng thuộc tính quyết định
```

In [28]:
```
feature = df.drop('income',axis=1)
label = df['income']
```

In [33]:
```
# Chuyển đổi các cột không phải dạng số về dạng one-hot vector để phù hợp với đầu vào của thư viện
```

In [29]:
```
feature.select_dtypes(exclude=['int64']).columns
```

Out[29]:
```
Index(['workclass', 'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country'],
      dtype='object')
```

In [30]:
```
feature_onehot = pd.get_dummies(feature,columns=feature.select_dtypes(exclude=['int64']).columns)
feature_onehot
```

Out[30]:

	age	education-num	capital-gain	capital-loss	hours-per-week	workclass_Federal-gov	workclass_Local-gov	workclass_Private	workclass_Self-emp-inc	workclass_Self-emp-not-inc	...	native-country_Portugal	native-country_Puerto-Rico	na cou Sco
0	39	13	2174	0	40	False	False	False	False	False	...	False	False	
1	50	13	0	0	13	False	False	False	False	True	...	False	False	
2	38	9	0	0	40	False	False	True	False	False	...	False	False	
3	53	7	0	0	40	False	False	True	False	False	...	False	False	
4	28	13	0	0	40	False	False	True	False	False	...	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
16275	33	13	0	0	40	False	False	True	False	False	...	False	False	
16276	39	13	0	0	36	False	False	True	False	False	...	False	False	
16278	38	13	0	0	50	False	False	True	False	False	...	False	False	
16279	44	13	5455	0	40	False	False	True	False	False	...	False	False	
16280	35	13	0	0	60	False	False	False	True	False	...	False	False	

45222 rows × 103 columns

In [34]:
```
# Tách các dòng dữ liệu ra thành hai phần huấn luyện và kiểm thử như ban đầu
```

In [31]:
```
x_train = feature_onehot[:30162]
x_test = feature_onehot[30162:]
y_train=label[:30162]
y_test=label[30162:]
```

In [ ]:
```
# Xây dựng cây ID3 dựa trên dữ liệu huấn luyện và sau đó tiến hành kiểm thử kết quả của cây bằng ma trận nhầm lẫn. Biểu diễn c
```

In [35]:
```
clf = tree.DecisionTreeClassifier(criterion="entropy",random_state=0)
clf.fit(x_train,y_train)
```

Out[35]:
```
DecisionTreeClassifier
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

In [ ]:
```
# Sau khi xây dựng xong cây ID3, tiến hành áp dụng mô hình trên dữ liệu kiểm thử
```

In [36]:
```
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))
```

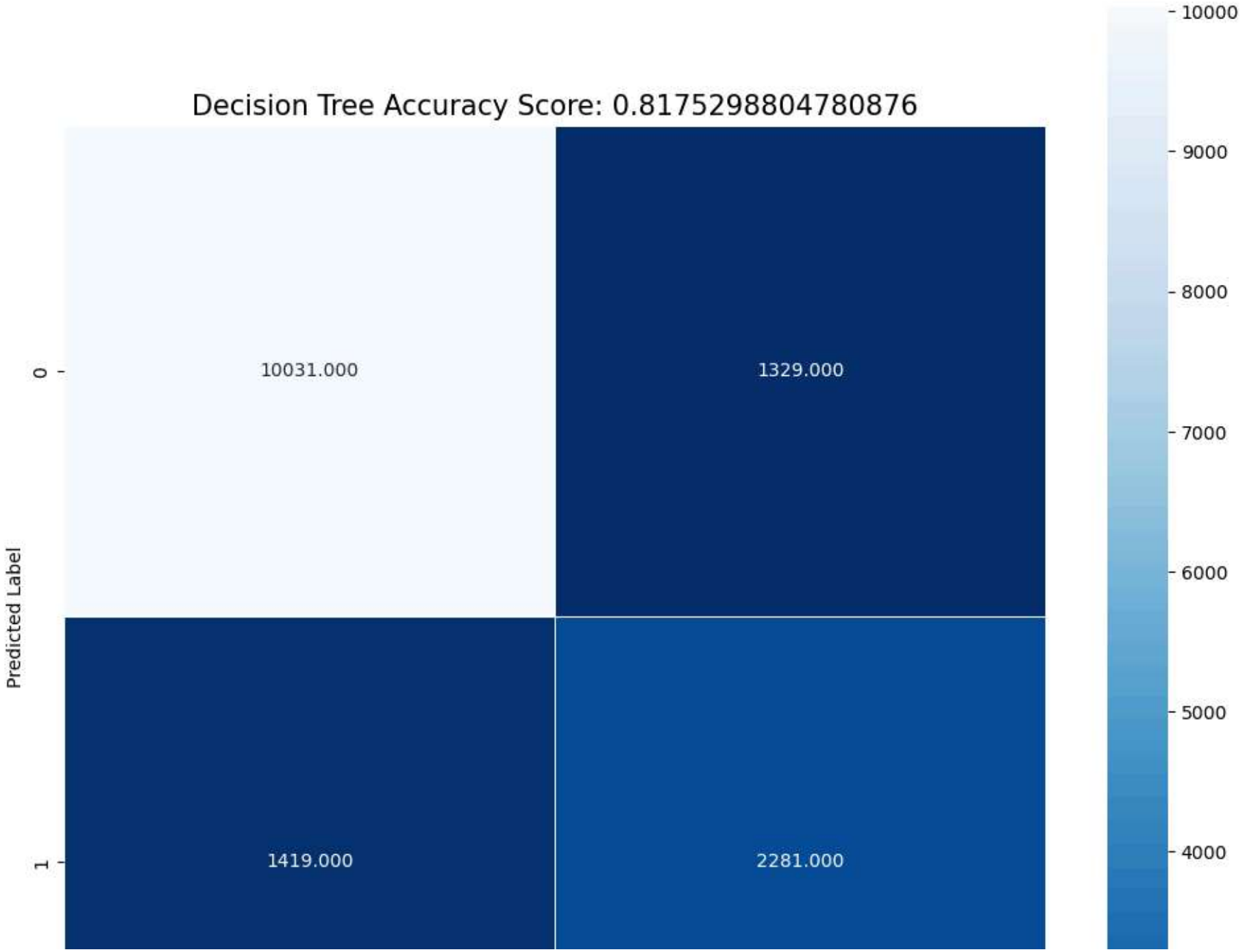
```
Accruracy: 0.8175298804780876
Report:               precision    recall  f1-score   support

       <=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 [ ]:
```
# tree_cm = metrics.confusion_matrix(y_test,tree_pred)
```

In [37]:
```
tree_cm = metrics.confusion_matrix(y_test,tree_pred)
```

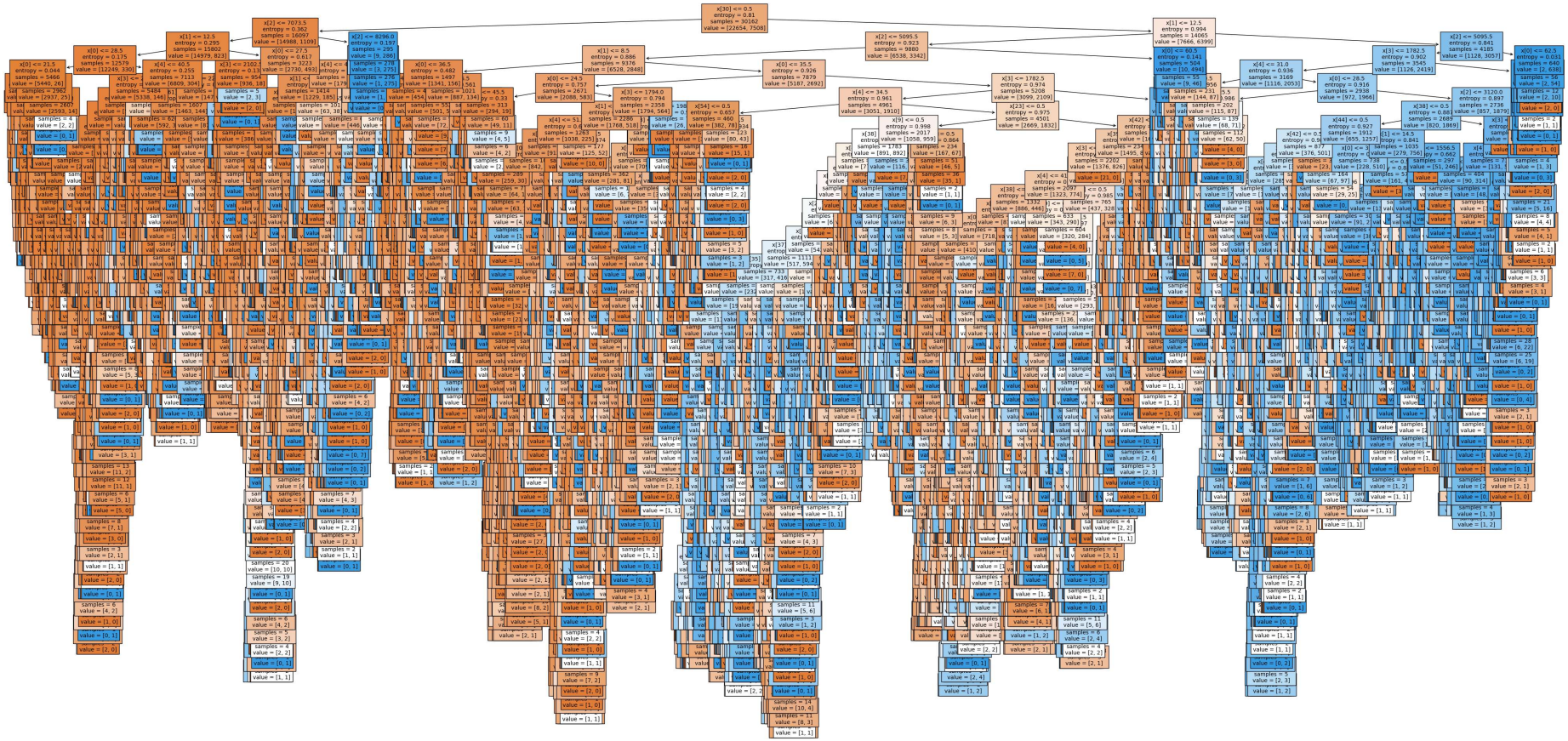
In [ ]:
```
# Biểu diễn lên đồ thị heatmap
```

In [39]:
```
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);
```


Decision Tree Accuracy Score: 0.8175298804780876
Predicted Label
0
1
10031.000
1329.000
1419.000
2281.000
10000
9000
8000
7000
6000
5000
4000

In [40]:
```
# Biểu diễn cây ID3
```

In [41]:
```
fig, ax = plt.subplots(figsize=(50,24))
tree.plot_tree(clf,filled=True,fontsize=10)
plt.savefig('decision_tree',dpi=100)
plt.show()
```



In [ ]:
```
#  thay thế giá trị criterion='gini'
```

In [42]:
```
clf = tree.DecisionTreeClassifier(criterion="gini",random_state=0)
clf.fit(x_train,y_train)
```

Out[42]:
```
DecisionTreeClassifier(random_state=0)
```

In [43]:
```
tree_pred = clf.predict(x_test)
tree_score = metrics.accuracy_score(y_test,tree_pred)
```

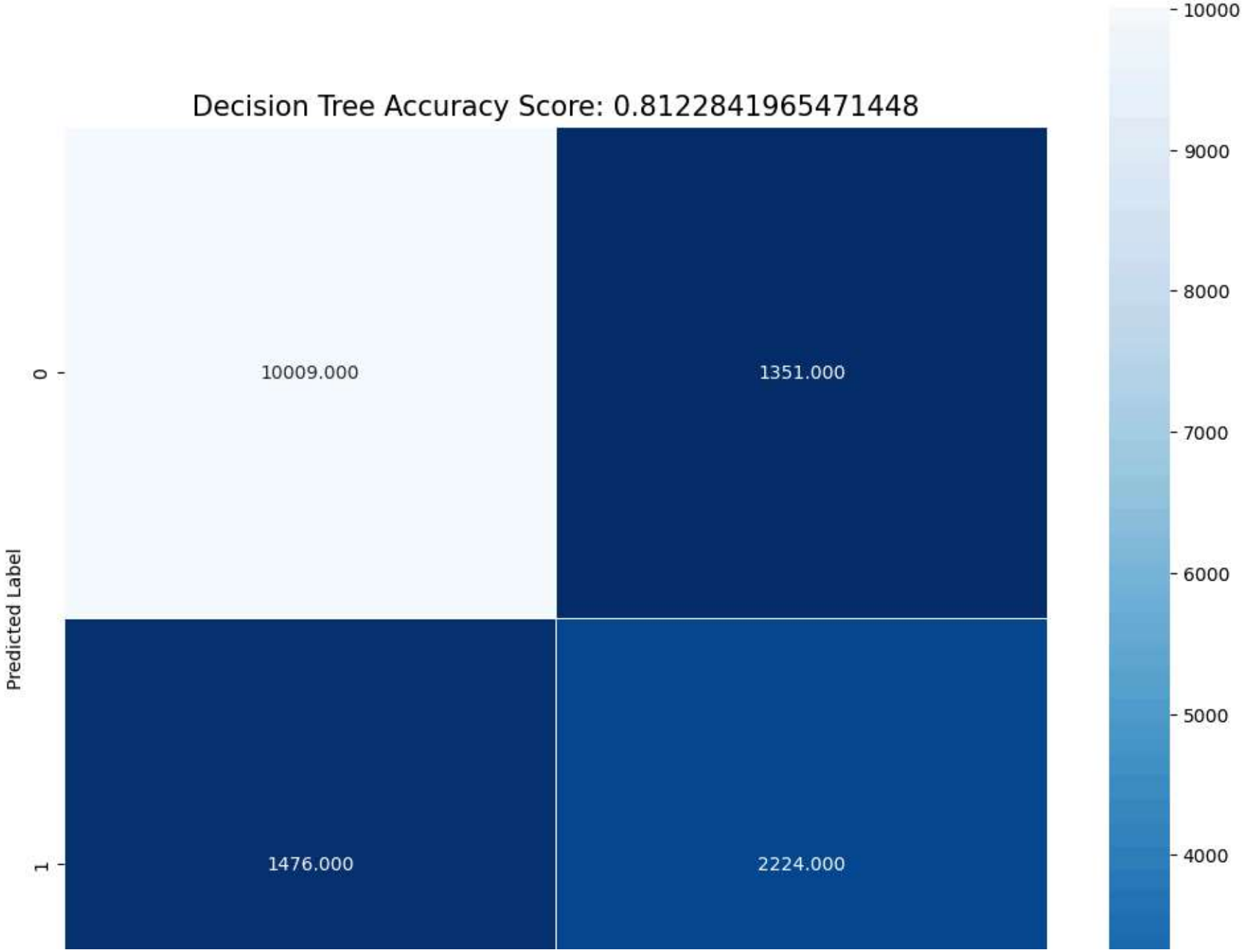
```
print("Accruracy:",tree_score)
print("Report:",metrics.classification_report(y_test,tree_pred))
```

```
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
```

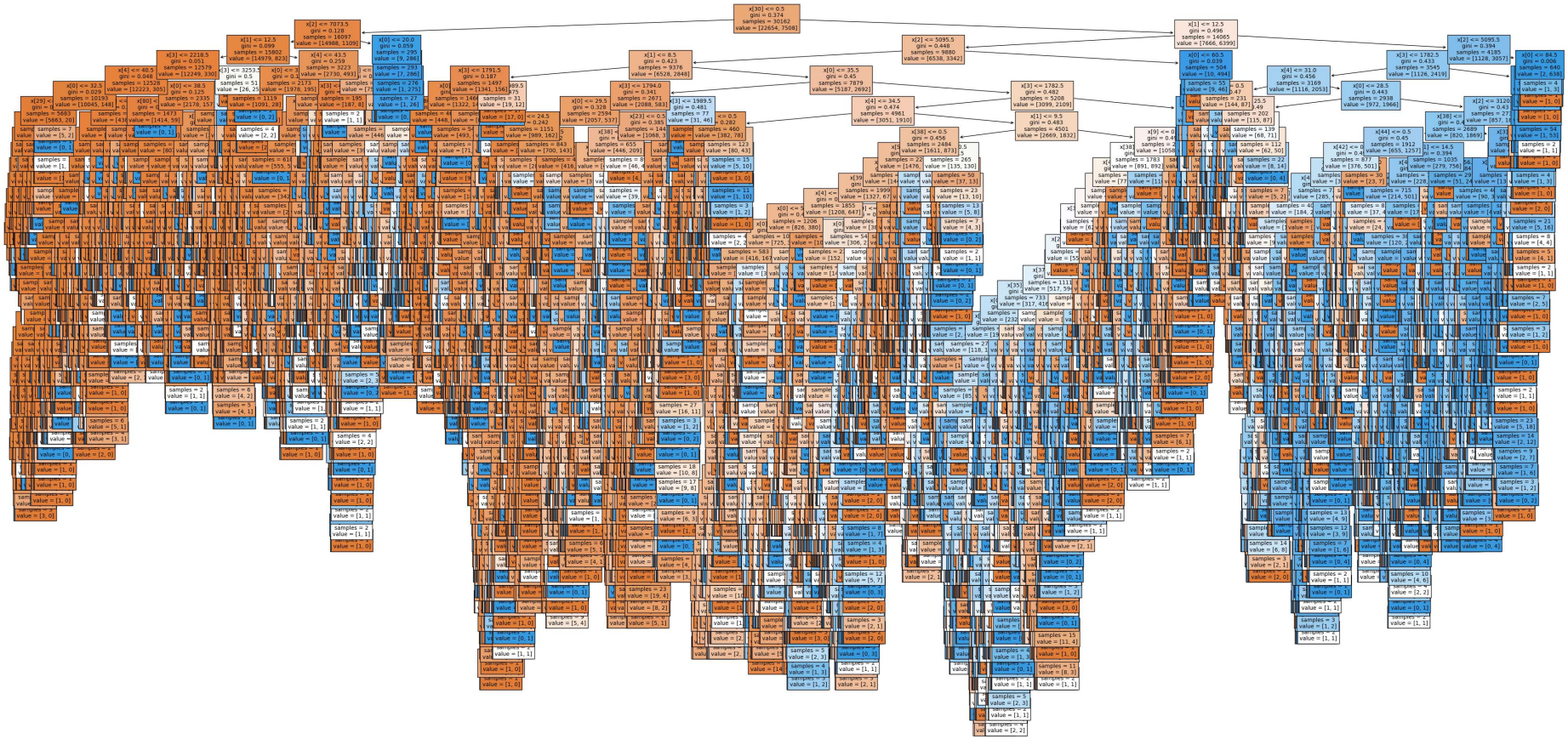
In [44]:
```
tree_cm = metrics.confusion_matrix(y_test,tree_pred)
```

In [45]:
```
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)
```

Out[45]:
```
Text(0.5, 1.0, 'Decision Tree Accuracy Score: 0.8122841965471448')
```


Decision Tree Accuracy Score: 0.8122841965471448
Predicted Label
0
1
10009.000
1351.000
1476.000
2224.000
10000
9000
8000
7000
6000
5000
4000

In [46]:
```
fig, ax = plt.subplots(figsize=(50,24))
tree.plot_tree(clf,filled=True,fontsize=10)
plt.savefig('decision_tree_gini',dpi=100)
plt.show()
```



In [ ]:
```
# Xây dựng mô hình phân lớp bằng thuật toán Naïve Bayes và kiểm tra kết quả đạt được
```

In [47]:
```
gnb = GaussianNB()
```

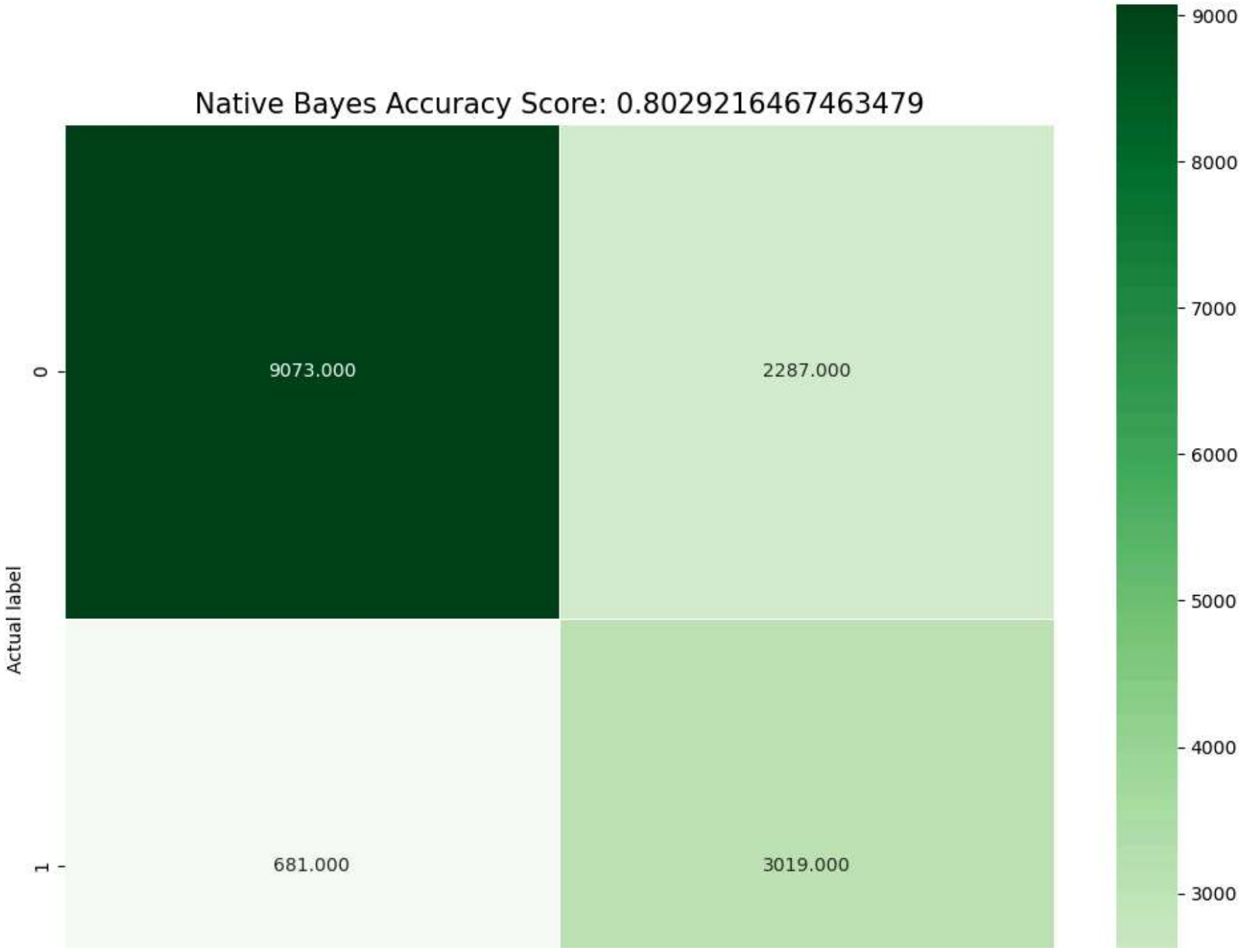
In [48]:
```
bayes_pred = gnb.fit(x_train, y_train).predict(x_test)
```

In [49]:
```
bayes_score = metrics.accuracy_score(y_test, bayes_pred)
```

In [50]:
```
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 [51]:
```
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);
```


Native Bayes Accuracy Score: 0.8029216467463479
Actual label
0
1
9073.000
2287.000
681.000
3019.000
9000
8000
7000
6000
5000
4000
3000

In [53]:
```
# 10. SO SÁNH KẾT QUẢ ĐẠT ĐƯỢC 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 caoược sự chí

# Kết quả này cho thấy rằng trong trường hợp này, dù ID3 có độ chính xác cao nhất trên toàn bộ tập dữ liệu, nhưng nó vẫn không
```

In [ ]:
```
```