In [35]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("adult.csv")
df.head(5)
```

Out[2]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	ra
0	90	?	77053	HS-grad	9	Widowed	?	Not-in-family	Wh
1	82	Private	132870	HS-grad	9	Widowed	Exec-managerial	Not-in-family	Wh
2	66	?	186061	Some-college	10	Widowed	?	Unmarried	Bla
3	54	Private	140359	7th-8th	4	Divorced	Machine-op-inspct	Unmarried	Wh
4	41	Private	264663	Some-college	10	Separated	Prof-specialty	Own-child	Wh

In [3]:
```
df.shape
```

Out[3]:
```
(32561, 15)
```

In [4]:
```
df.dtypes
```

Out[4]:
```
age                int64
workclass         object
fnlwgt             int64
education         object
education.num      int64
marital.status    object
occupation        object
relationship      object
race              object
sex               object
capital.gain       int64
capital.loss       int64
hours.per.week     int64
native.country    object
income            object
dtype: object
```

In [5]:
```
df.describe
```

Out[5]:
```
<bound method NDFrame.describe of        age workclass  fnlwgt     educ
ation  education.num      marital.status  \
0       90         ?   77053       HS-grad              9              W
idowed
1       82   Private  132870       HS-grad              9              W
idowed
2       66         ?  186061  Some-college             10              W
idowed
3       54   Private  140359       7th-8th              4             Di
vorced
4       41   Private  264663  Some-college             10            Sep
arated
...    ...       ...     ...           ...            ...
...
32556   22   Private  310152  Some-college             10        Never-m
arried
32557   27   Private  257302    Assoc-acdm             12  Married-civ-
spouse
32558   40   Private  154374       HS-grad              9  Married-civ-
spouse
32559   58   Private  151910       HS-grad              9              W
idowed
32560   22   Private  201490       HS-grad              9        Never-m
arried

              occupation   relationship   race     sex  capital.gain  \
0                      ?  Not-in-family  White  Female             0
1        Exec-managerial  Not-in-family  White  Female             0
2                      ?      Unmarried  Black  Female             0
3      Machine-op-inspct      Unmarried  White  Female             0
4         Prof-specialty      Own-child  White  Female             0
...                  ...            ...    ...     ...           ...
32556    Protective-serv  Not-in-family  White    Male             0
32557       Tech-support           Wife  White  Female             0
32558  Machine-op-inspct        Husband  White    Male             0
32559       Adm-clerical      Unmarried  White  Female             0
32560       Adm-clerical      Own-child  White    Male             0

       capital.loss  hours.per.week native.country income
0              4356              40  United-States  <=50K
1              4356              18  United-States  <=50K
2              4356              40  United-States  <=50K
3              3900              40  United-States  <=50K
4              3900              40  United-States  <=50K
...             ...             ...            ...    ...
32556             0              40  United-States  <=50K
32557             0              38  United-States  <=50K
32558             0              40  United-States   >50K
32559             0              40  United-States  <=50K
32560             0              20  United-States  <=50K

[32561 rows x 15 columns]>
```

In [6]:
```
df = df.replace('?', np.NaN)
df.head
```

Out[6]:
```
<bound method NDFrame.head of        age workclass  fnlwgt     educatio
n  education.num      marital.status  \
0       90       NaN   77053       HS-grad             9             W
idowed
1       82   Private  132870       HS-grad             9             W
idowed
2       66       NaN  186061  Some-college            10             W
idowed
3       54   Private  140359       7th-8th             4            Di
vorced
4       41   Private  264663  Some-college            10           Sep
arated
...    ...       ...     ...           ...           ...
...
32556   22   Private  310152  Some-college            10        Never-m
arried
32557   27   Private  257302    Assoc-acdm            12  Married-civ-
spouse
32558   40   Private  154374       HS-grad             9  Married-civ-
spouse
32559   58   Private  151910       HS-grad             9             W
idowed
32560   22   Private  201490       HS-grad             9        Never-m
arried

              occupation   relationship   race     sex  capital.gain  \
0                    NaN  Not-in-family  White  Female             0
1        Exec-managerial  Not-in-family  White  Female             0
2                    NaN      Unmarried  Black  Female             0
3      Machine-op-inspct      Unmarried  White  Female             0
4         Prof-specialty      Own-child  White  Female             0
...                  ...            ...    ...     ...           ...
32556    Protective-serv  Not-in-family  White    Male             0
32557       Tech-support           Wife  White  Female             0
32558  Machine-op-inspct        Husband  White    Male             0
32559       Adm-clerical      Unmarried  White  Female             0
32560       Adm-clerical      Own-child  White    Male             0

       capital.loss  hours.per.week native.country income
0              4356              40  United-States  <=50K
1              4356              18  United-States  <=50K
2              4356              40  United-States  <=50K
3              3900              40  United-States  <=50K
4              3900              40  United-States  <=50K
...             ...             ...            ...    ...
32556             0              40  United-States  <=50K
32557             0              38  United-States  <=50K
32558             0              40  United-States   >50K
32559             0              40  United-States  <=50K
32560             0              20  United-States  <=50K

[32561 rows x 15 columns]>
```

In [7]:
```
df.isna().sum()
```

Out[7]:
```
age                  0
workclass         1836
fnlwgt               0
education            0
education.num        0
marital.status       0
occupation        1843
relationship         0
race                 0
sex                  0
capital.gain         0
capital.loss         0
hours.per.week       0
native.country     583
income               0
dtype: int64
```

In [8]:
```
df["workclass"].mode()[0]
```

Out[8]:
```
'Private'
```

In [9]:
```
df["occupation"].mode()[0]
```

Out[9]:
```
'Prof-specialty'
```

In [10]:
```
df["native.country"].mode()[0]
```

Out[10]:
```
'United-States'
```

In [11]:
```
df["workclass"].fillna(df["workclass"].mode()[0], inplace=True)
df["occupation"].fillna(df["occupation"].mode()[0], inplace=True)
df["native.country"].fillna(df["native.country"].mode()[0], inplace=True

df["workclass"].describe()
```

Out[11]:
```
count       32561
unique          8
top       Private
freq        24532
Name: workclass, dtype: object
```

In [12]:
```
df.describe
```

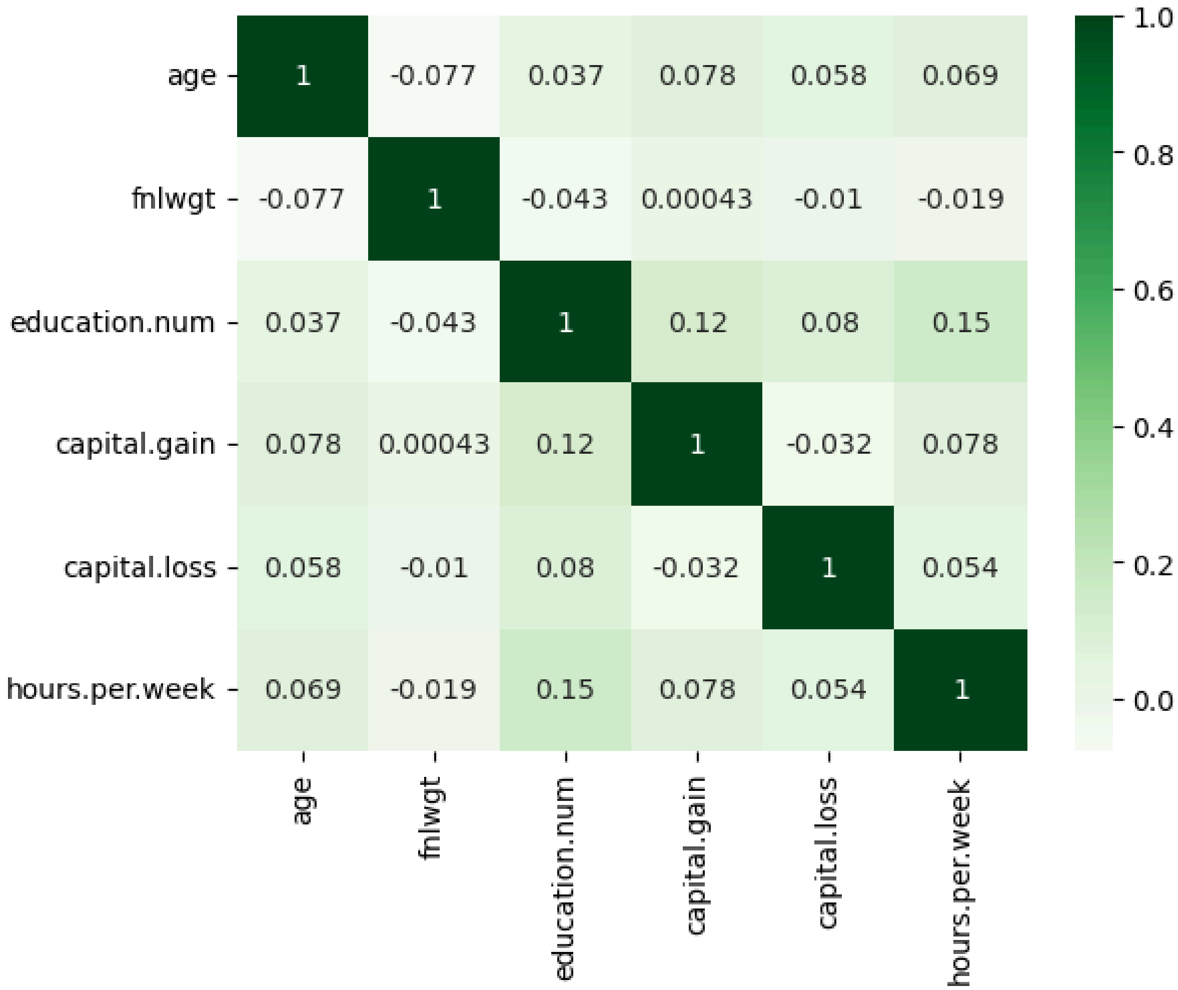
Out[12]:
```
<bound method NDFrame.describe of        age workclass  fnlwgt     educ
ation  education.num      marital.status  \
0       90   Private   77053       HS-grad              9             W
idowed
1       82   Private  132870       HS-grad              9             W
idowed
2       66   Private  186061  Some-college             10             W
idowed
3       54   Private  140359       7th-8th              4            Di
vorced
4       41   Private  264663  Some-college             10           Sep
arated
...    ...       ...     ...           ...            ...
...
32556   22   Private  310152  Some-college             10       Never-m
arried
32557   27   Private  257302    Assoc-acdm             12  Married-civ-
spouse
32558   40   Private  154374       HS-grad              9  Married-civ-
spouse
32559   58   Private  151910       HS-grad              9             W
idowed
32560   22   Private  201490       HS-grad              9       Never-m
arried

              occupation   relationship   race     sex  capital.gain  \
0         Prof-specialty  Not-in-family  White  Female             0
1        Exec-managerial  Not-in-family  White  Female             0
2         Prof-specialty      Unmarried  Black  Female             0
3      Machine-op-inspct      Unmarried  White  Female             0
4         Prof-specialty      Own-child  White  Female             0
...                  ...            ...    ...     ...           ...
32556    Protective-serv  Not-in-family  White    Male             0
32557       Tech-support           Wife  White  Female             0
32558  Machine-op-inspct        Husband  White    Male             0
32559       Adm-clerical      Unmarried  White  Female             0
32560       Adm-clerical      Own-child  White    Male             0

       capital.loss  hours.per.week native.country income
0              4356              40  United-States  <=50K
1              4356              18  United-States  <=50K
2              4356              40  United-States  <=50K
3              3900              40  United-States  <=50K
4              3900              40  United-States  <=50K
...             ...             ...            ...    ...
32556             0              40  United-States  <=50K
32557             0              38  United-States  <=50K
32558             0              40  United-States   >50K
32559             0              40  United-States  <=50K
32560             0              20  United-States  <=50K

[32561 rows x 15 columns]>
```

In [13]:
```
df.isna().sum()
```

Out[13]:
```
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
income            0
dtype: int64
```

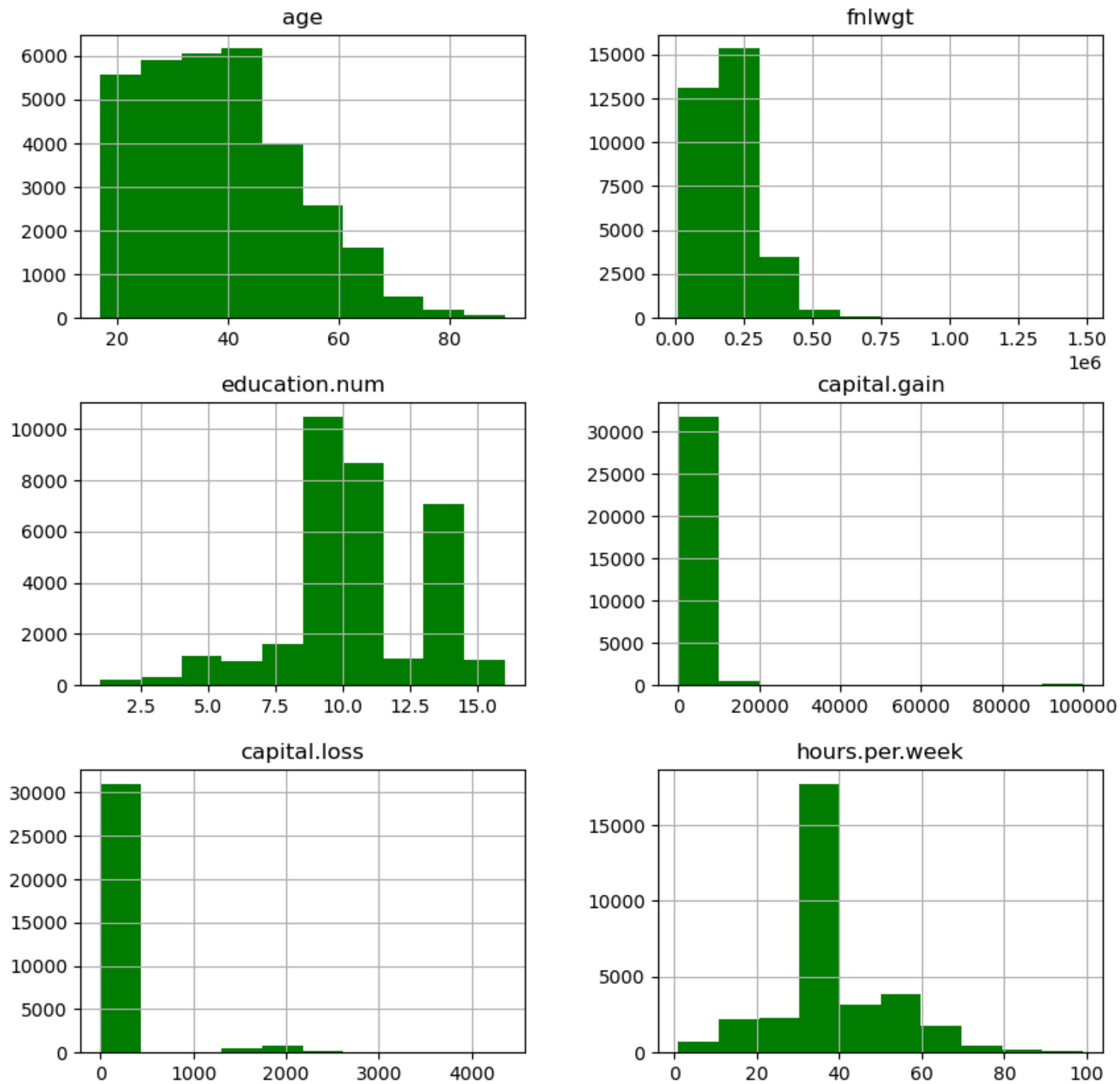
In [14]:
```
sns.heatmap(df.corr(),cmap = 'Greens',annot = True)
```

Out[14]: <AxesSubplot:>

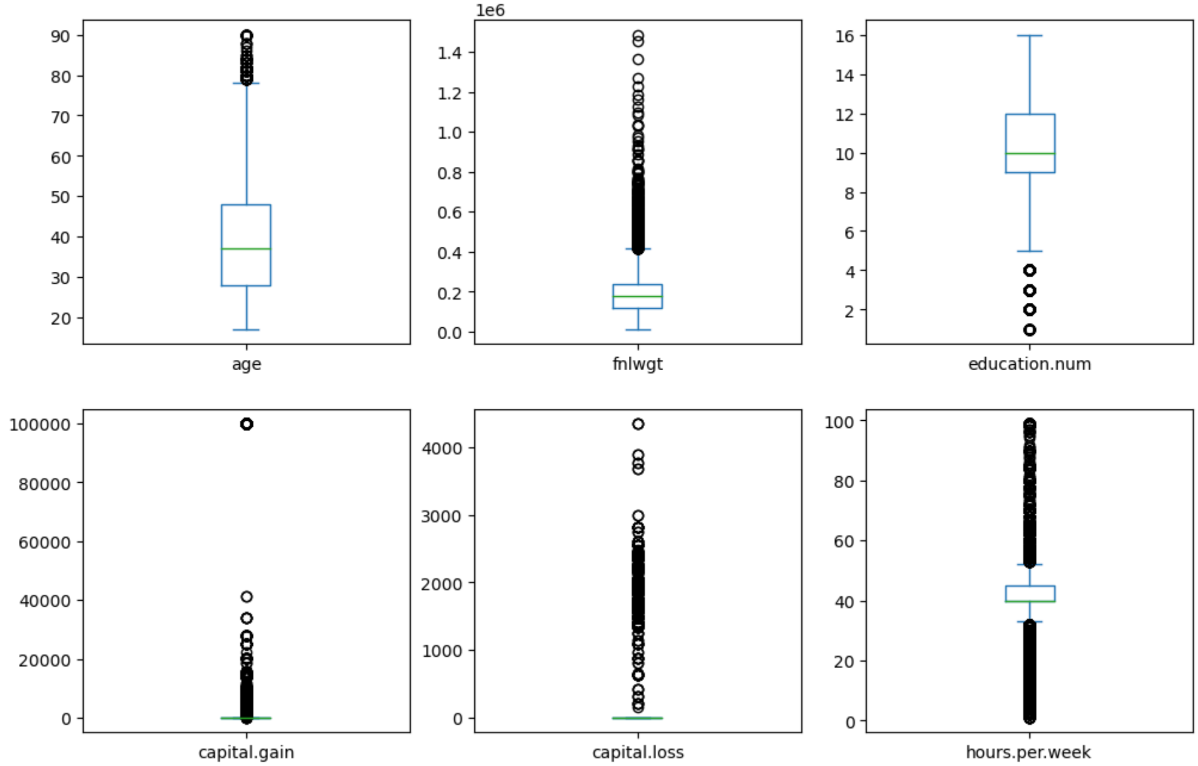


In [15]:
```
df.hist(figsize = (10,10), color = "Green")
```

Out[15]:
```
array([[<AxesSubplot:title={'center':'age'}>,
        <AxesSubplot:title={'center':'fnlwgt'}>],
       [<AxesSubplot:title={'center':'education.num'}>,
        <AxesSubplot:title={'center':'capital.gain'}>],
       [<AxesSubplot:title={'center':'capital.loss'}>,
        <AxesSubplot:title={'center':'hours.per.week'}>]], dtype=objec
t)
```



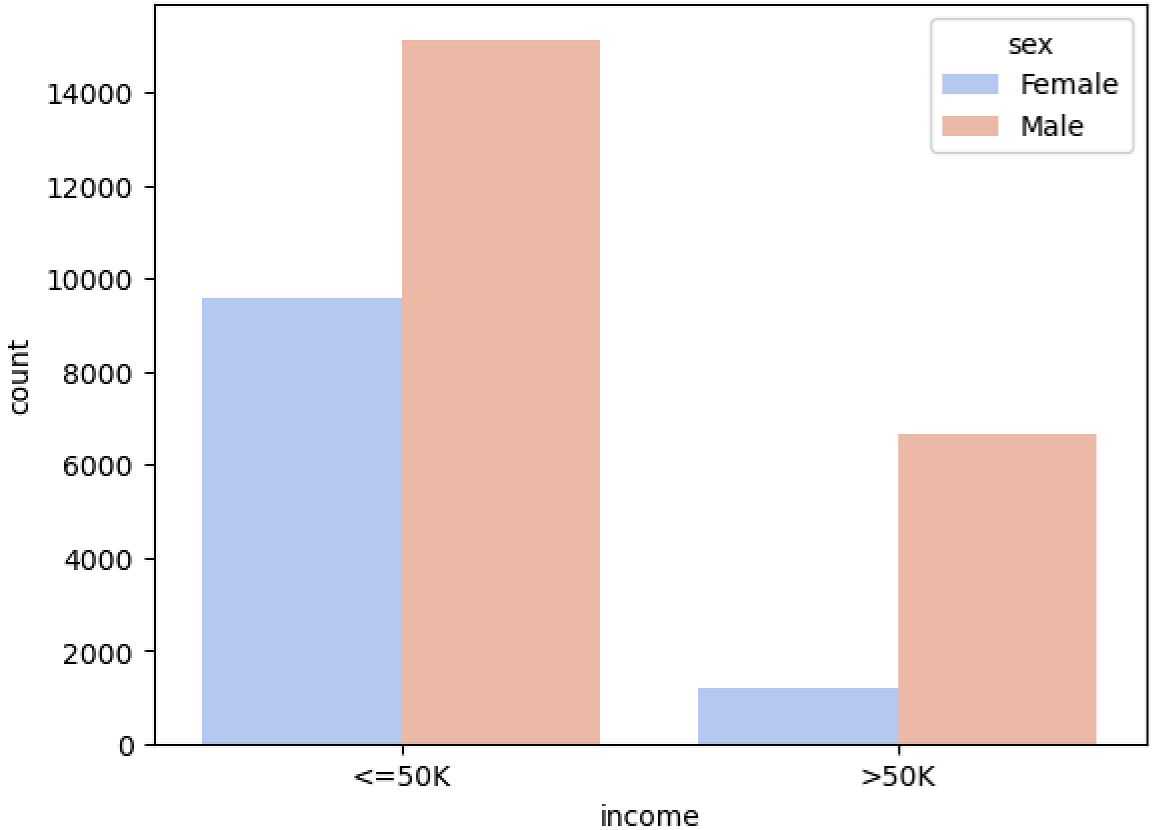
In [16]:
```
df.plot(kind = 'box', figsize = (12,12), layout = (3,3), sharex = False,
```



In [18]:
```
df['income'].value_counts()
```

Out[18]:
```
<=50K    24720
>50K      7841
Name: income, dtype: int64
```

In [19]:
```
sns.countplot(df['income'], palette='coolwarm', hue='sex', data=df);
```



In [20]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler,OneHotEncoder

num_col = ['age', 'fnlwgt','education.num','capital.gain','capital.loss'
df.num = df[num_col]
df.num
```

Out[20]:

	age	fnlwgt	education.num	capital.gain	capital.loss	hours.per.week
0	90	77053	9	0	4356	40
1	82	132870	9	0	4356	18
2	66	186061	10	0	4356	40
3	54	140359	4	0	3900	40
4	41	264663	10	0	3900	40
...	...	...	...	...	...	...
32556	22	310152	10	0	0	40
32557	27	257302	12	0	0	38
32558	40	154374	9	0	0	40
32559	58	151910	9	0	0	40
32560	22	201490	9	0	0	20

32561 rows × 6 columns

PCA

In [21]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components=3)
pca.fit_transform(df.num)
```

Out[21]:
```
array([[-1.12725567e+05, -1.08159367e+03,  4.26250405e+03],
       [-5.69085666e+04, -1.08329643e+03,  4.26463275e+03],
       [-3.71756658e+03, -1.08491460e+03,  4.26671954e+03],
       ...,
       [-3.54043958e+04, -1.07641859e+03, -9.05501713e+01],
       [-3.78683960e+04, -1.07634102e+03, -9.06102320e+01],
       [ 1.17116044e+04, -1.07785772e+03, -8.87784724e+01]])
```

In [22]:
```
print(pca.components_)
print(sum(pca.explained_variance_ratio_))
```

```
[[-9.90507714e-06  9.99999999e-01 -1.05283840e-06  3.03678811e-05
  -3.91389877e-05 -2.19555372e-06]
 [ 1.43514070e-04 -3.04337871e-05  4.27228452e-05  9.99998483e-01
  -1.72989546e-03  1.31095844e-04]
 [ 2.01710563e-03  3.91106215e-05  5.32933664e-04  1.72935042e-03
   9.99994820e-01  1.73646184e-03]]
0.999999969574739
```

In [23]:
```
pca.explained_variance_ratio_
```

Out[23]:
```
array([9.95113642e-01, 4.87183949e-03, 1.44878108e-05])
```

In [24]:
```
X= df.drop(['income'], axis=1)
y = df['income']
```

In [25]:
```
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

In [26]:
```
df2= df.copy()
df2= df2.apply(LabelEncoder().fit_transform)
df2.head()
```

Out[26]:

	age	workclass	fnlwgt	education	education.num	marital.status	occupation	relationship	race
0	72	3	2649	11	8	6	9	1	4
1	65	3	6514	11	8	6	3	1	4
2	49	3	11175	15	9	6	9	4	2
3	37	3	7009	5	3	0	6	4	4
4	24	3	16850	15	9	5	9	3	4

In [27]:
```
ss= StandardScaler().fit(df2.drop('income', axis=1))
```

In [28]:
```
X= ss.transform(df2.drop('income', axis=1))
y= df['income']
```

In [29]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
```

Logistic Regression

In [30]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

lr = LogisticRegression()

model = lr.fit(X_train, y_train)
prediction = model.predict(X_test)

print("Accuracy on training data: {:,.3f}".format(lr.score(X_train, y_tra
print("Accuracy on test data: {:,.3f}".format(lr.score(X_test, y_test)))
```

```
Accuracy on training data: 0.824
Accuracy on test data: 0.823
```

Random Forest Classifier

In [34]:
```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier()

model1 = rfc.fit(X_train, y_train)
prediction1 = model1.predict(X_test)

print("Accuracy on training data: {:,.3f}".format(rfc.score(X_train, y_t
print("Accuracy on test data: {:,.3f}".format(rfc.score(X_test, y_test))
```

```
Accuracy on training data: 1.000
Accuracy on test data: 0.854
```