adult-income-dataset-intel-5

July 8, 2024

0.0.1 Loading Necessary Libraries

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.linear_model import LogisticRegression



# Warning Filter
import warnings
warnings.filterwarnings('ignore')
```

0.0.2 Loading Dataset

[2]:
```python
df = pd.read_csv('/content/adult.csv')
df.head(10)
```

[2]:
```
   age         workclass  fnlwgt     education  educational-num  \
0   25           Private  226802          11th                7
1   38           Private   89814       HS-grad                9
2   28         Local-gov  336951    Assoc-acdm               12
3   44           Private  160323  Some-college               10
4   18                 ?  103497  Some-college               10
5   34           Private  198693          10th                6
6   29                 ?  227026       HS-grad                9
7   63  Self-emp-not-inc  104626   Prof-school               15
8   24           Private  369667  Some-college               10
9   55           Private  104996       7th-8th                4

       marital-status         occupation relationship   race  gender  \
0       Never-married  Machine-op-inspct    Own-child  Black    Male
1  Married-civ-spouse    Farming-fishing      Husband  White    Male
2  Married-civ-spouse    Protective-serv      Husband  White    Male
3  Married-civ-spouse  Machine-op-inspct      Husband  Black    Male
4       Never-married                  ?    Own-child  White  Female
```

```
5       Never-married      Other-service  Not-in-family  White    Male
6       Never-married                  ?      Unmarried  Black    Male
7  Married-civ-spouse     Prof-specialty        Husband  White    Male
8       Never-married      Other-service      Unmarried  White  Female
9  Married-civ-spouse       Craft-repair        Husband  White    Male

   capital-gain  capital-loss  hours-per-week native-country income
0             0             0              40  United-States  <=50K
1             0             0              50  United-States  <=50K
2             0             0              40  United-States   >50K
3          7688             0              40  United-States   >50K
4             0             0              30  United-States  <=50K
5             0             0              30  United-States  <=50K
6             0             0              40  United-States  <=50K
7          3103             0              32  United-States   >50K
8             0             0              40  United-States  <=50K
9             0             0              10  United-States  <=50K
```

0.0.3 Learning More about Dataset

[3]:
```python
df.columns
```

[3]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income'],
      dtype='object')
```

[4]:
```python
df.shape
```

[4]:
```
(48842, 15)
```

[5]:
```python
df.dtypes
```

[5]:
```
age                 int64
workclass          object
fnlwgt              int64
education          object
educational-num     int64
marital-status     object
occupation         object
relationship       object
race               object
gender             object
capital-gain        int64
capital-loss        int64
hours-per-week      int64
```

```
native-country     object
income             object
dtype: object
```

[6]:
```
df.isnull().sum()
```

[6]:
```
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
```

[7]:
```
df.nunique()
```

[7]:
```
age                   74
workclass              9
fnlwgt             28523
education             16
educational-num       16
marital-status         7
occupation            15
relationship           6
race                   5
gender                 2
capital-gain         123
capital-loss          99
hours-per-week        96
native-country        42
income                 2
dtype: int64
```

[8]:
```
df.describe().T
```

[8]:
```
                   count           mean            std      min       25%  \
age              48842.0      38.643585      13.710510     17.0      28.0
fnlwgt           48842.0  189664.134597  105604.025423  12285.0  117550.5
```

```
educational-num  48842.0     10.078089     2.570973     1.0       9.0
capital-gain     48842.0   1079.067626  7452.019058     0.0       0.0
capital-loss     48842.0     87.502314   403.004552     0.0       0.0
hours-per-week   48842.0     40.422382    12.391444     1.0      40.0

                      50%       75%        max
age                  37.0      48.0       90.0
fnlwgt           178144.5  237642.0  1490400.0
educational-num      10.0      12.0       16.0
capital-gain          0.0       0.0    99999.0
capital-loss          0.0       0.0     4356.0
hours-per-week       40.0      45.0       99.0
```

0.0.4 Value Count Function

[9]:
```python
df['workclass'].value_counts() #fillna
```

[9]:
```
workclass
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: count, dtype: int64
```

[10]:
```python
df['occupation'].value_counts() #fillna
```

[10]:
```
occupation
Prof-specialty       6172
Craft-repair         6112
Exec-managerial      6086
Adm-clerical         5611
Sales                5504
Other-service        4923
Machine-op-inspct    3022
?                    2809
Transport-moving     2355
Handlers-cleaners    2072
Farming-fishing      1490
Tech-support         1446
Protective-serv       983
Priv-house-serv       242
Armed-Forces           15
```

```
Name: count, dtype: int64
```

[11]:
```python
df['native-country'].value_counts() #fillna
```

[11]:
```
native-country
United-States                 43832
Mexico                          951
?                               857
Philippines                     295
Germany                         206
Puerto-Rico                     184
Canada                          182
El-Salvador                     155
India                           151
Cuba                            138
England                         127
China                           122
South                           115
Jamaica                         106
Italy                           105
Dominican-Republic              103
Japan                            92
Guatemala                        88
Poland                           87
Vietnam                          86
Columbia                         85
Haiti                            75
Portugal                         67
Taiwan                           65
Iran                             59
Greece                           49
Nicaragua                        49
Peru                             46
Ecuador                          45
France                           38
Ireland                          37
Hong                             30
Thailand                         30
Cambodia                         28
Trinadad&Tobago                  27
Laos                             23
Yugoslavia                       23
Outlying-US(Guam-USVI-etc)       23
Scotland                         21
Honduras                         20
Hungary                          19
Holand-Netherlands                1
```

```
Name: count, dtype: int64
```

[12]:
```python
df['income'].value_counts() #0,1
```

[12]:
```
income
<=50K    37155
>50K     11687
Name: count, dtype: int64
```

[13]:
```python
df['marital-status'].value_counts()
```

[13]:
```
marital-status
Married-civ-spouse       22379
Never-married            16117
Divorced                  6633
Separated                 1530
Widowed                   1518
Married-spouse-absent      628
Married-AF-spouse           37
Name: count, dtype: int64
```

[14]:
```python
df['gender'].value_counts()
```

[14]:
```
gender
Male      32650
Female    16192
Name: count, dtype: int64
```

[15]:
```python
df['race'].value_counts()
```

[15]:
```
race
White                 41762
Black                  4685
Asian-Pac-Islander     1519
Amer-Indian-Eskimo      470
Other                   406
Name: count, dtype: int64
```

0.0.5 Removing rows with ? Values

[16]:
```python
# Replacing ? with NaN
df['workclass'] = df['workclass'].replace('?', np.nan)
df['occupation'] = df['occupation'].replace('?', np.nan)
df['native-country'] = df['native-country'].replace('?', np.nan)

# Drop rows with any NaN values
df = df.dropna()
```

```python
# Check the shape of the DataFrame
df.shape

df2=df.copy()
```

0.0.6 Feature Engineering

[17]:
```python
# For Education
df.education = df.education.
 ↪replace(['Preschool','1st-4th','5th-6th','7th-8th','9th','10th','11th','12th'],'School')
df.education = df.education.replace('HS-grad','High School')
df.education = df.education.
 ↪replace(['Assoc-voc','Assoc-acdm','Prof-school','Some-college'],'Higher-Education')
df.education = df.education.replace('Bachelors','Under-Grad')
df.education = df.education.replace('Masters','Graduation')
df.education = df.education.replace('Doctorate','Doc')
```

[18]:
```python
# For Marital status
df['marital-status'] = df['marital-status'].
 ↪replace(['Married-civ-spouse','Married-AF-spouse'],'Married')
df['marital-status'] = df['marital-status'].
 ↪replace(['Never-married'],'Unmarried')
df['marital-status'] = df['marital-status'].
 ↪replace(['Divorced','Separated','Widowed','Married-spouse-absent'],'Single')
```

[19]:
```python
# For Income
df['income'] = df['income'].replace({'<=50K': 0, '>50K': 1})
```

[20]:
```python
df
```

[20]:
```
       age     workclass  fnlwgt         education  educational-num  \
0       25       Private  226802            School                7
1       38       Private   89814       High School                9
2       28     Local-gov  336951  Higher-Education               12
3       44       Private  160323  Higher-Education               10
5       34       Private  198693            School                6
…     …            …       …                …               …
48837   27       Private  257302  Higher-Education               12
48838   40       Private  154374       High School                9
48839   58       Private  151910       High School                9
48840   22       Private  201490       High School                9
48841   52  Self-emp-inc  287927       High School                9

      marital-status         occupation   relationship   race  gender  \
0          Unmarried  Machine-op-inspct      Own-child  Black    Male
```

```
1           Married    Farming-fishing        Husband  White    Male
2           Married    Protective-serv        Husband  White    Male
3           Married  Machine-op-inspct        Husband  Black    Male
5         Unmarried      Other-service  Not-in-family  White    Male
…               …                  …            …     …     …
48837       Married       Tech-support           Wife  White  Female
48838       Married  Machine-op-inspct        Husband  White    Male
48839        Single       Adm-clerical      Unmarried  White  Female
48840     Unmarried       Adm-clerical      Own-child  White    Male
48841       Married    Exec-managerial           Wife  White  Female

       capital-gain  capital-loss  hours-per-week native-country  income
0                 0             0              40  United-States       0
1                 0             0              50  United-States       0
2                 0             0              40  United-States       1
3              7688             0              40  United-States       1
5                 0             0              30  United-States       0
…               …             …               …            …     …
48837             0             0              38  United-States       0
48838             0             0              40  United-States       1
48839             0             0              40  United-States       0
48840             0             0              20  United-States       0
48841         15024             0              40  United-States       1

[45222 rows x 15 columns]
```

[21]:
```
df2
```

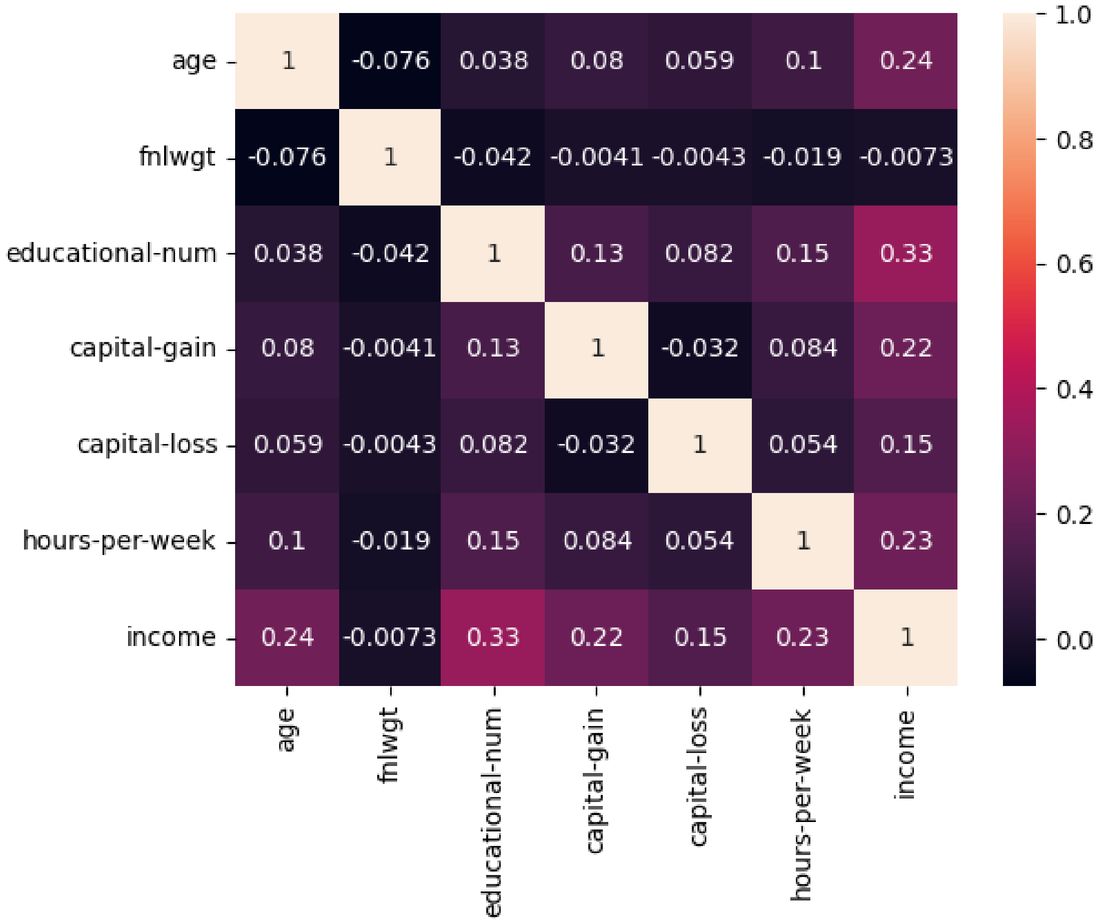
[21]:
```
       age     workclass  fnlwgt     education  educational-num  \
0       25       Private  226802          11th                7
1       38       Private   89814       HS-grad                9
2       28     Local-gov  336951    Assoc-acdm               12
3       44       Private  160323  Some-college               10
5       34       Private  198693          10th                6
…     …             …       …             …               …
48837   27       Private  257302    Assoc-acdm               12
48838   40       Private  154374       HS-grad                9
48839   58       Private  151910       HS-grad                9
48840   22       Private  201490       HS-grad                9
48841   52  Self-emp-inc  287927       HS-grad                9

           marital-status         occupation   relationship   race  gender  \
0           Never-married  Machine-op-inspct      Own-child  Black    Male
1      Married-civ-spouse    Farming-fishing        Husband  White    Male
2      Married-civ-spouse    Protective-serv        Husband  White    Male
3      Married-civ-spouse  Machine-op-inspct        Husband  Black    Male
5           Never-married      Other-service  Not-in-family  White    Male
```

```
…                       …                 …          …       …
48837  Married-civ-spouse       Tech-support           Wife  White  Female
48838  Married-civ-spouse  Machine-op-inspct        Husband  White    Male
48839             Widowed       Adm-clerical      Unmarried  White  Female
48840       Never-married       Adm-clerical      Own-child  White    Male
48841  Married-civ-spouse    Exec-managerial           Wife  White  Female

       capital-gain  capital-loss  hours-per-week native-country income
0                 0             0              40  United-States  <=50K
1                 0             0              50  United-States  <=50K
2                 0             0              40  United-States   >50K
3              7688             0              40  United-States   >50K
5                 0             0              30  United-States  <=50K
…               …             …               …            …      …
48837             0             0              38  United-States  <=50K
48838             0             0              40  United-States   >50K
48839             0             0              40  United-States  <=50K
48840             0             0              20  United-States  <=50K
48841         15024             0              40  United-States   >50K

[45222 rows x 15 columns]
```

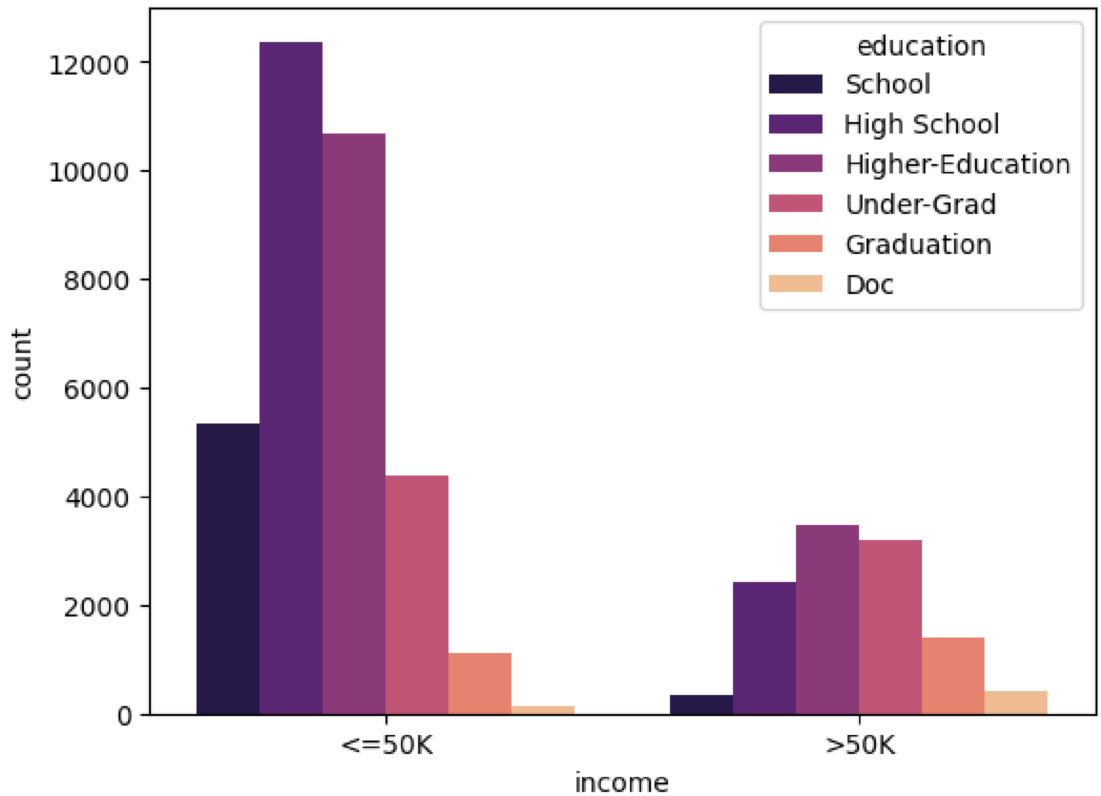
0.1 2. df2= Pre Column Reductions (Used in Plots)

0.1.1 Some Graphs and Plots

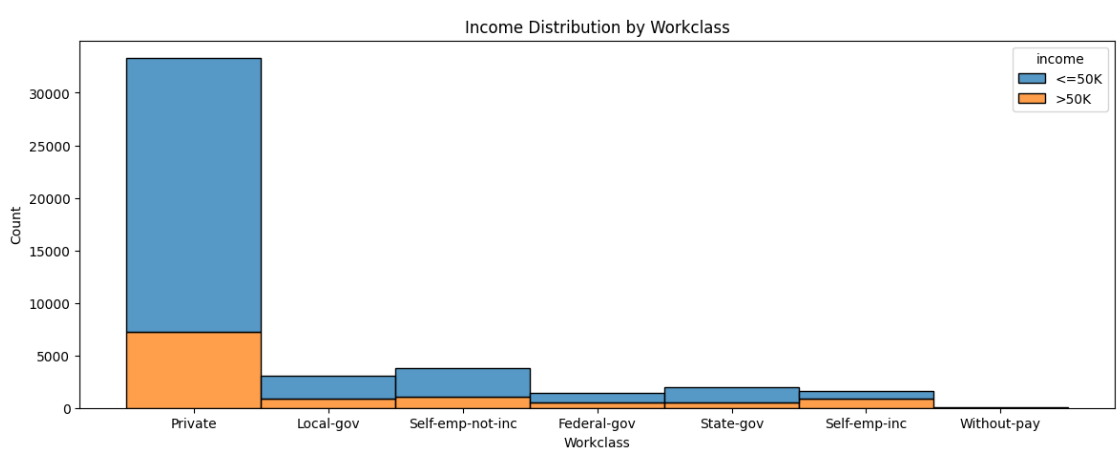
[22]:
```python
# Select only numeric columns
numeric_df = df.select_dtypes(include=['number'])

# Calculate the correlation matrix for numeric columns
correlation_matrix = numeric_df.corr()

# Display the heatmap
sns.heatmap(correlation_matrix, annot=True);
```



[23]:
```
# @title Income with Education
sns.countplot(x=df2['income'],palette='magma',hue='education',data=df);
```

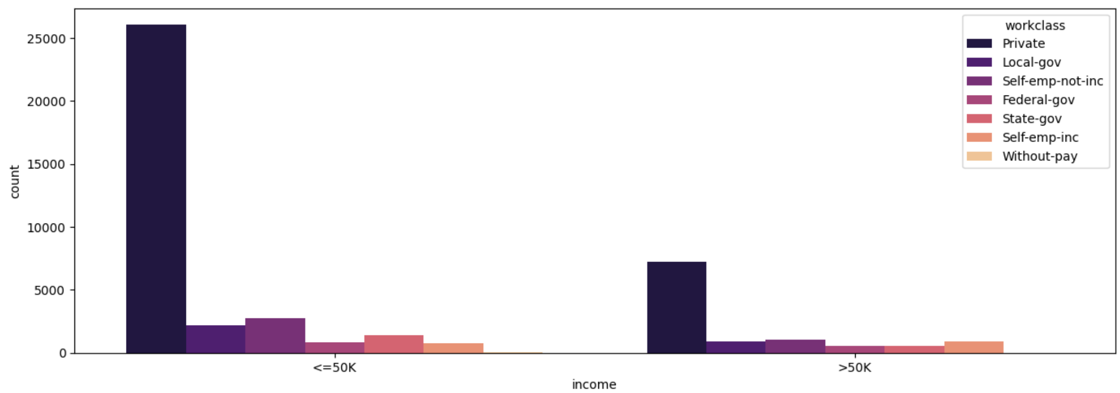



```
[24]: # @title Income Distribution by Workclass
plt.figure(figsize=(14,5))
sns.histplot(data=df2, x="workclass", hue="income",multiple="stack")
plt.title("Income Distribution by Workclass")
plt.xlabel("Workclass")
plt.ylabel("Count")
plt.show()
print(df2['workclass'].unique())
```

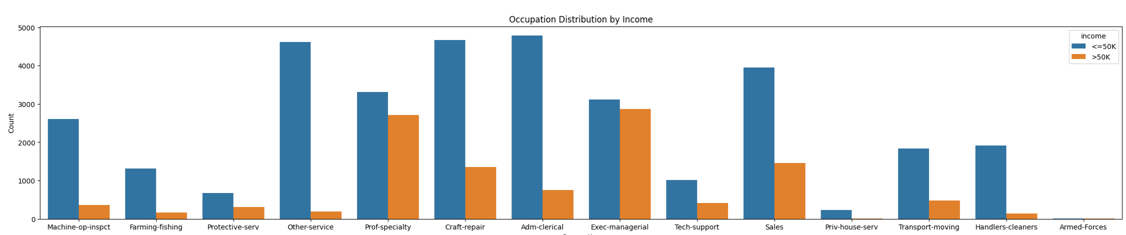


```
['Private' 'Local-gov' 'Self-emp-not-inc' 'Federal-gov' 'State-gov'
 'Self-emp-inc' 'Without-pay']
```

[25]:
```
# @title  Income Distribution by Workclass
plt.figure(figsize = (15,5))
sns.countplot(data = df2, x = 'income',palette='magma', hue = 'workclass');
```

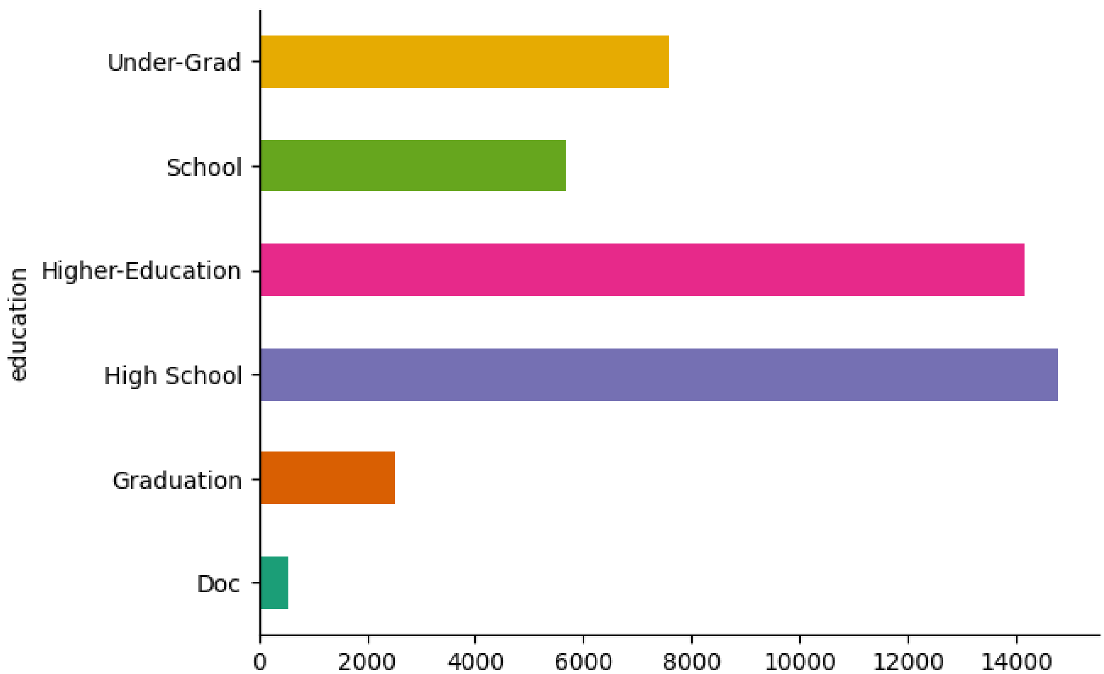


[26]:
```
# @title Occupation Distribution by Income
plt.figure(figsize=(28,5))
sns.countplot(data=df2, x="occupation", hue="income")
plt.title("Occupation Distribution by Income")
plt.xlabel("Occupation")
plt.ylabel("Count")
plt.show()
print(df2['occupation'].unique())
```

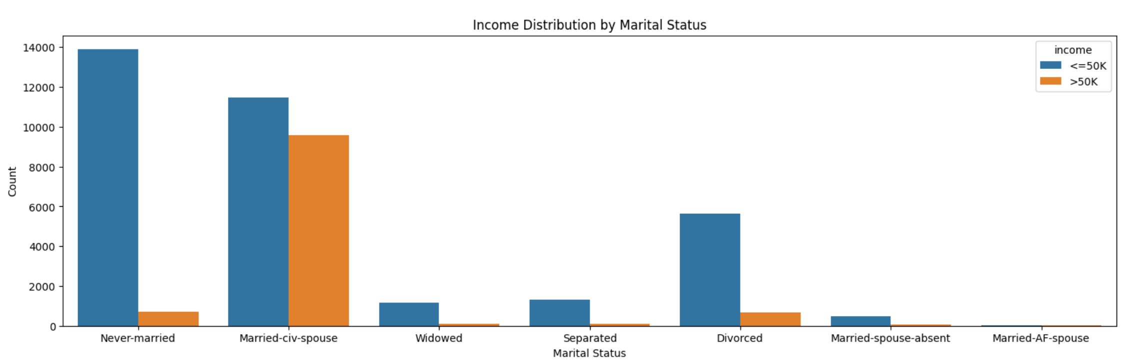



```
['Machine-op-inspct' 'Farming-fishing' 'Protective-serv' 'Other-service'
 'Prof-specialty' 'Craft-repair' 'Adm-clerical' 'Exec-managerial'
 'Tech-support' 'Sales' 'Priv-house-serv' 'Transport-moving'
 'Handlers-cleaners' 'Armed-Forces']
```

[27]:
```
# @title Education Graph 2
df.groupby('education').size().plot(kind='barh', color=sns.palettes.
 ↪mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

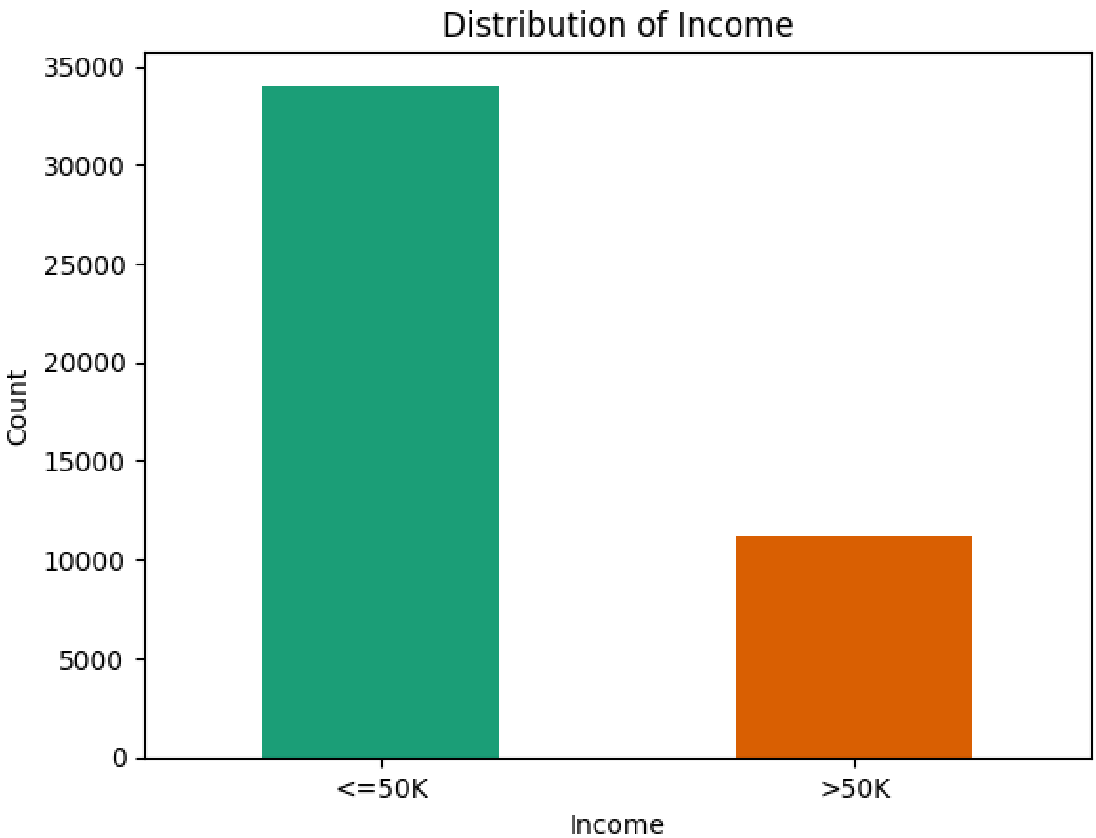


[28]:
```
# @title Income Distribution by Marital Status
plt.figure(figsize=(18,5))
sns.countplot(data=df2, x="marital-status", hue="income")
plt.title("Income Distribution by Marital Status")
plt.xlabel("Marital Status")
plt.ylabel("Count")
plt.show()
print(df2['marital-status'].unique())
```



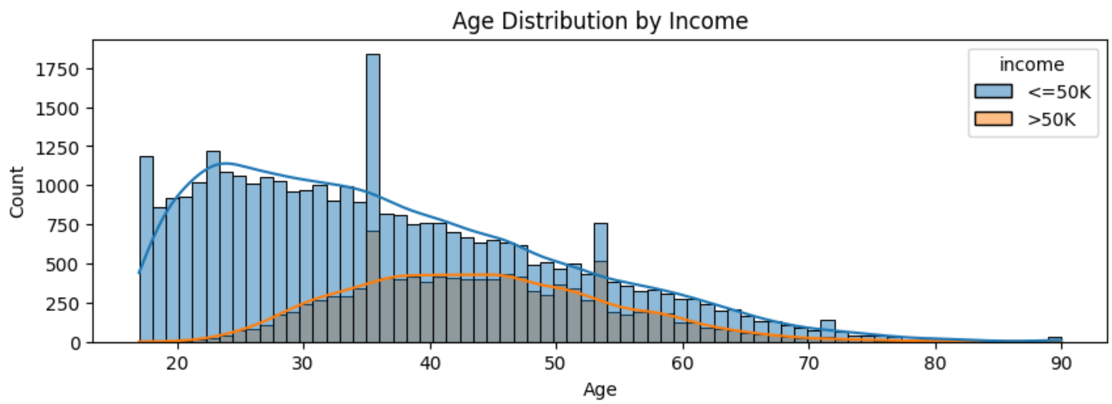
```
['Never-married' 'Married-civ-spouse' 'Widowed' 'Separated' 'Divorced'
 'Married-spouse-absent' 'Married-AF-spouse']
```

[29]:
```
# @title Income Graph
#df2 for income plots
df2['income'].value_counts().plot(kind='bar', color=sns.color_palette('Dark2'))
plt.title('Distribution of Income')
plt.xlabel('Income')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```



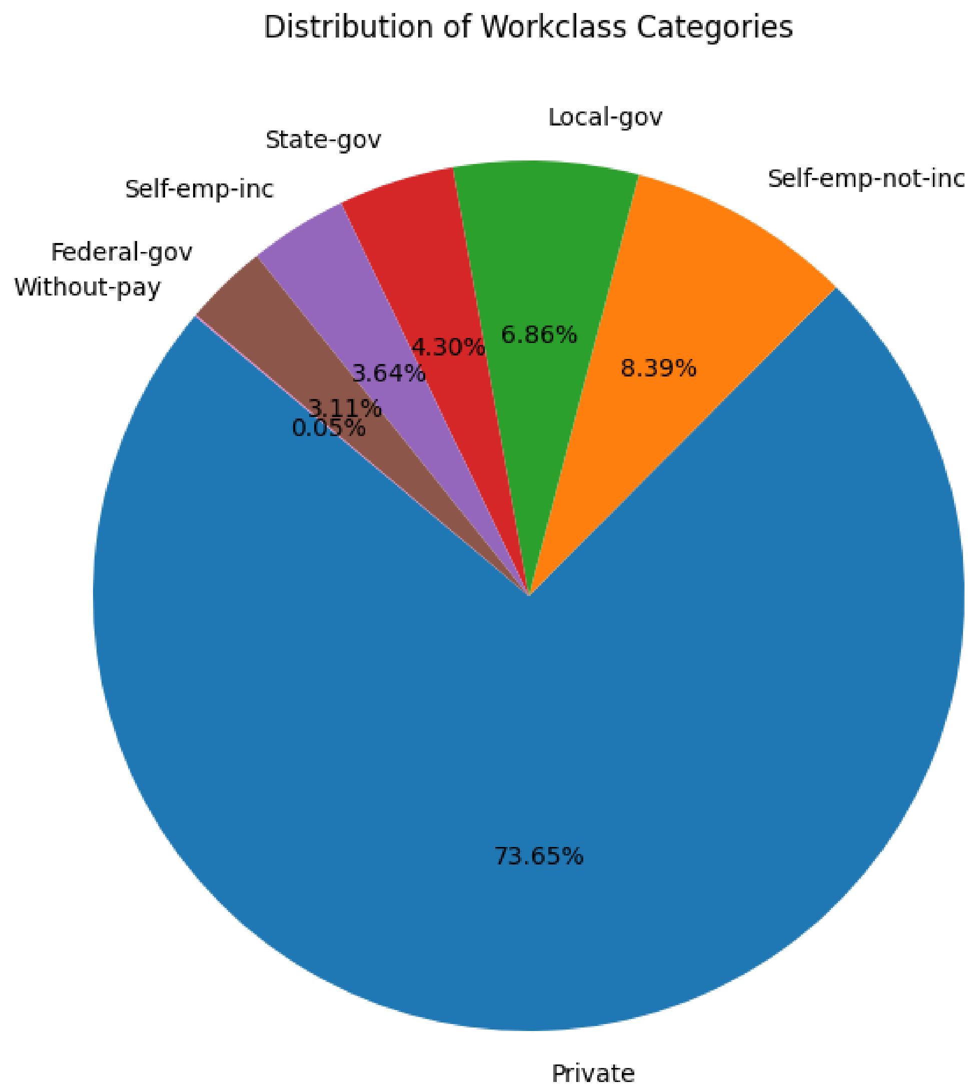
[30]:
```
# @title Age Distribution by Income

# Plot the histogram with a custom hue using Seaborn
plt.figure(figsize=(10, 3))
sns.histplot(data=df2, x="age", hue="income", kde=True, multiple="layer")
plt.title("Age Distribution by Income")
```

```
plt.xlabel("Age")
plt.ylabel("Count")
plt.show()

# Get the sorted unique ages
unique_age = df2['age'].unique()
sorted_age = np.sort(unique_age)
print(sorted_age)
```




```
[17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40
 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64
 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88
 89 90]
```

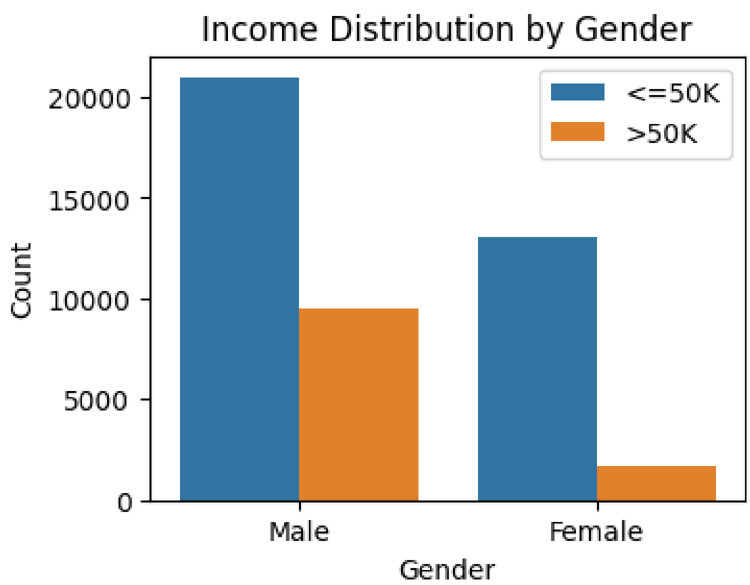
[31]:
```
# @title Distribution of Workclass Categories
workclass_counts = df2['workclass'].value_counts()
labels = workclass_counts.index
sizes = workclass_counts.values
plt.figure(figsize=(8,14))
plt.pie(sizes,labels=labels, autopct='%1.2f%%', startangle=140)
plt.title("Distribution of Workclass Categories")
plt.show()
print(df2['workclass'].unique())
```




```
['Private' 'Local-gov' 'Self-emp-not-inc' 'Federal-gov' 'State-gov'
 'Self-emp-inc' 'Without-pay']
```

[32]:

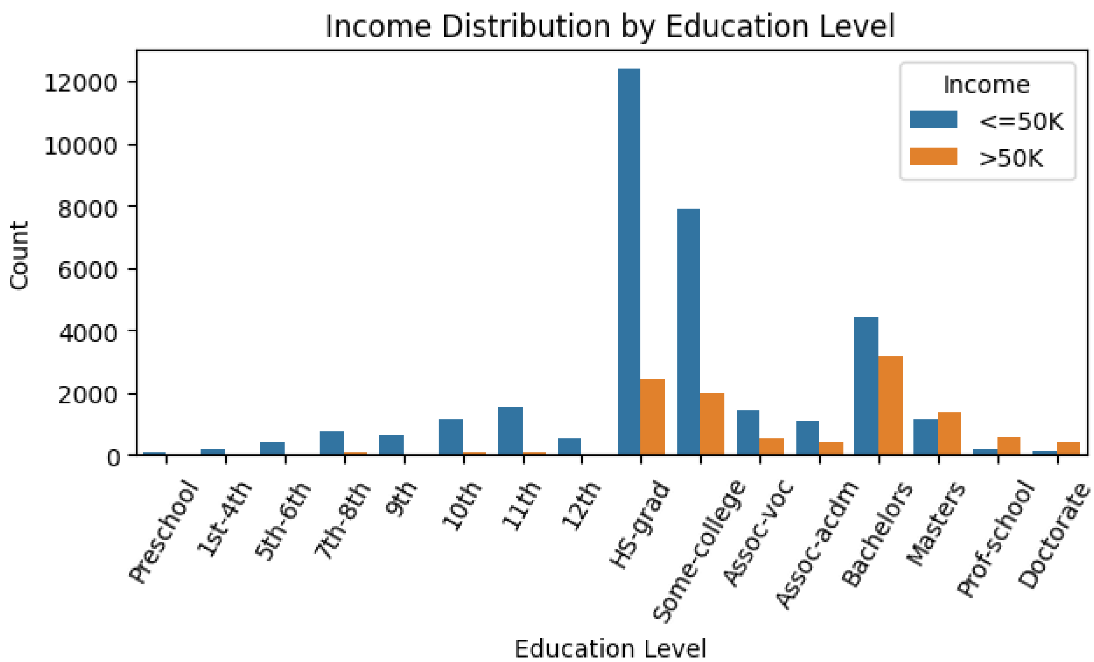
```
# @title Income Distribution by Gender
plt.figure(figsize=(4,3))
sns.countplot(data=df2,x="gender",hue="income")
plt.title("Income Distribution by Gender")
plt.xlabel("Gender")
plt.ylabel("Count")
plt.legend()
plt.show()
print(df2['gender'].unique())
```



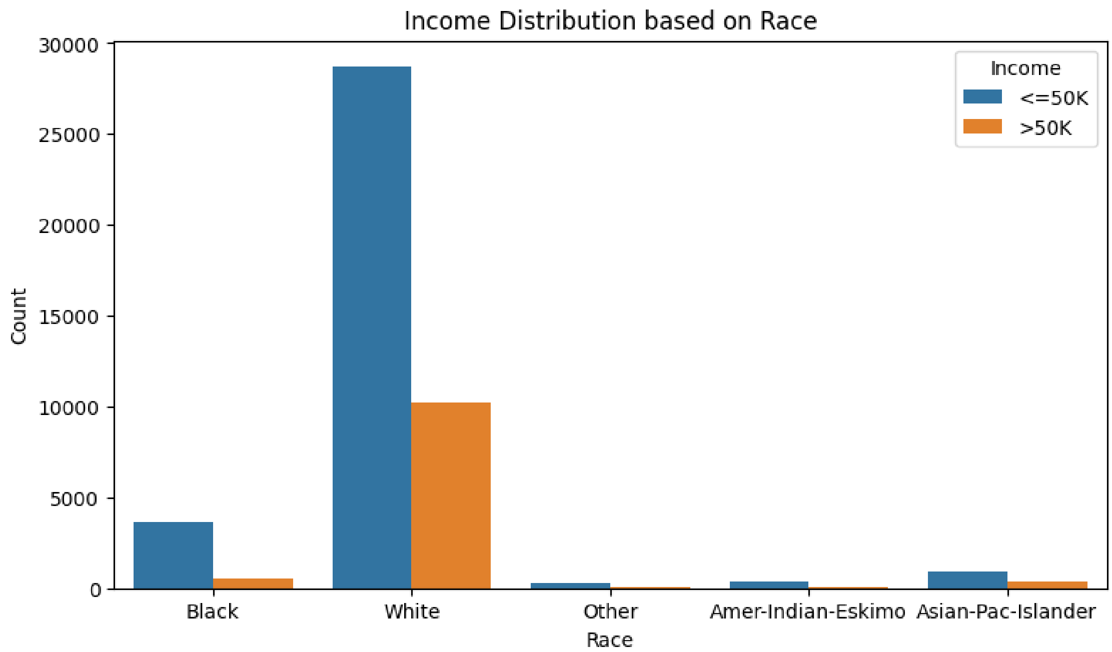

```
['Male' 'Female']
```

[33]:

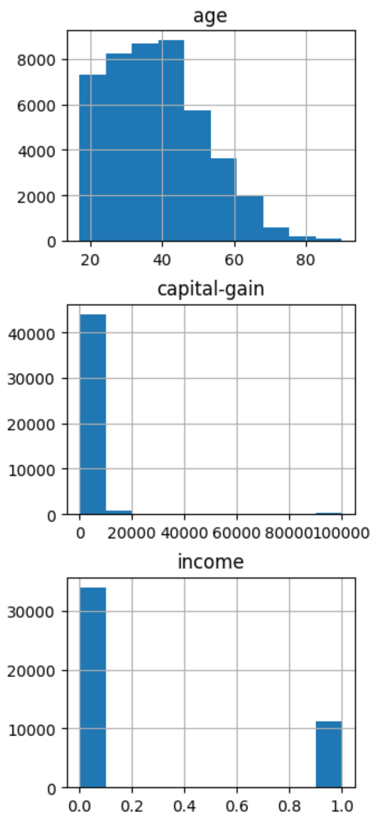
```
# @title Income Distribution by Education
education_order = df2.sort_values('educational-num')['education'].unique()
plt.figure(figsize=(7,3))
sns.countplot(data=df2,x="education",hue="income",order=education_order)
plt.title("Income Distribution by Education Level")
plt.xlabel("Education Level")
plt.ylabel("Count")
plt.xticks(rotation=60)
plt.legend(title="Income")
plt.show()
```



[36]:
```python
# @title Income Distribution based on Race
plt.figure(figsize=(9, 5))
sns.countplot(data=df2, x="race", hue="income")
plt.title("Income Distribution based on Race")
plt.xlabel("Race")
plt.ylabel("Count")
plt.legend(title="Income")
plt.show()
```

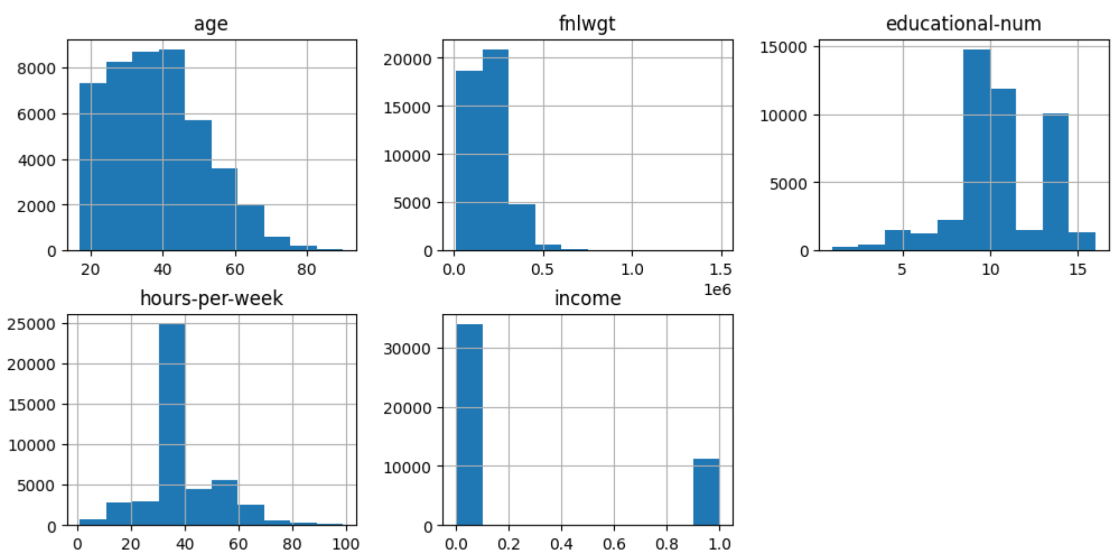


[37]:
```
# @title Histogram
df.hist(figsize=(12,12), layout=(4,3), sharex=False);
# Noticeable that most of the data of capital gain and loss is 0 so dropping␣
↪them
df.drop(['capital-gain', 'capital-loss'], axis=1, inplace=True)
```

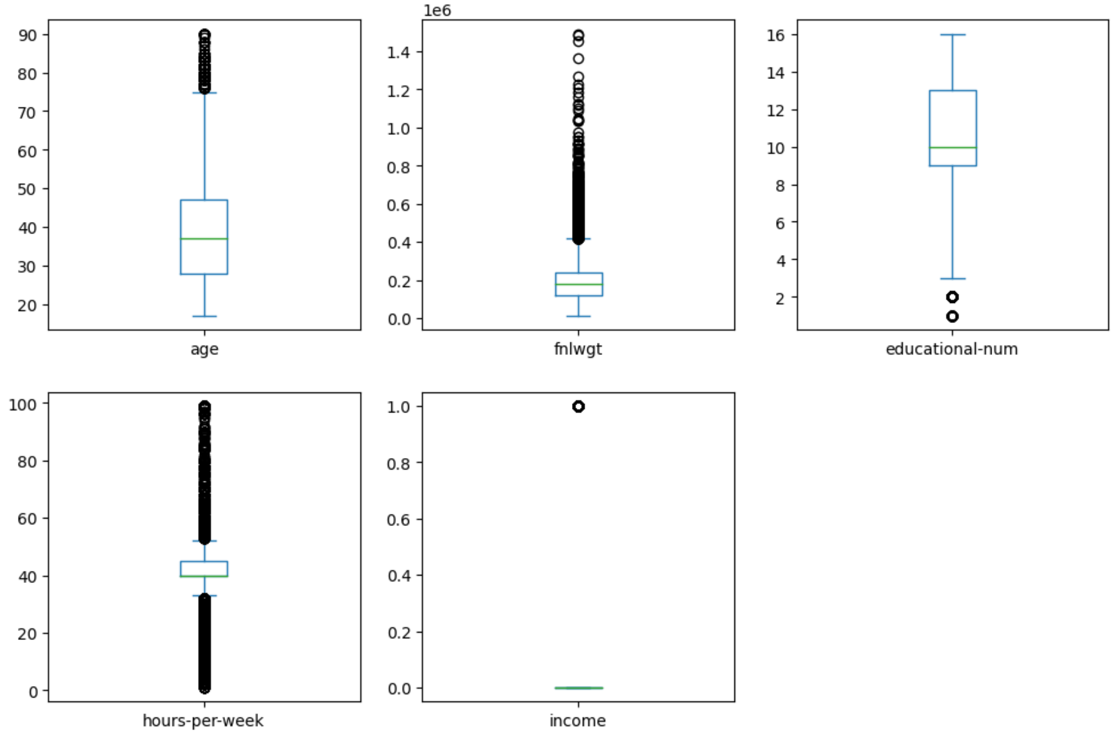


[38]:

```
# @title After Dropping capital gain, loss
df.hist(figsize=(12,12), layout=(4,3), sharex=False);
```



[39]:
```python
# @title Boxplot for checking Outliers

df.plot(kind='box',figsize=(12,12),layout=(3,3),sharex=False,subplots=True);
```



[40]:
```python
# To find out the Categorical dataset

categorical_df = df.select_dtypes(object)
categorical_df
```

[40]:
```
          workclass         education marital-status         occupation  \
0           Private            School      Unarried  Machine-op-inspct
1           Private       High School        Married    Farming-fishing
2         Local-gov  Higher-Education        Married    Protective-serv
3           Private  Higher-Education        Married  Machine-op-inspct
5           Private            School      Unarried      Other-service
…               …                …              …                 …
48837       Private  Higher-Education        Married       Tech-support
48838       Private       High School        Married  Machine-op-inspct
48839       Private       High School         Single       Adm-clerical
48840       Private       High School      Unarried       Adm-clerical
48841  Self-emp-inc       High School        Married    Exec-managerial

        relationship   race   gender native-country
```

```
0          Own-child  Black    Male  United-States
1            Husband  White    Male  United-States
2            Husband  White    Male  United-States
3            Husband  Black    Male  United-States
5      Not-in-family  White    Male  United-States
…                …     …       …               …
48837           Wife  White  Female  United-States
48838        Husband  White    Male  United-States
48839      Unmarried  White  Female  United-States
48840      Own-child  White    Male  United-States
48841           Wife  White  Female  United-States

[45222 rows x 8 columns]
```

[41]:
```python
#Checking nan values
df.isna().sum()
```

[41]:
```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

[42]:
```python
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
# One-hot encoding categorical variables
df = pd.get_dummies(df, columns=['education', 'marital-status', 'race',␣
↪'gender', 'relationship', 'occupation', 'workclass', 'native-country'])

# Splitting the dataset into features and target variable
X = df.drop('income', axis=1)
y = df['income']

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Scaling the features
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Prediction Models

[43]:
```
# @title K-Nearest Neighbours

from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, accuracy_score



# Fitting the KNN model
knn = KNeighborsClassifier(n_neighbors=5)  # You can tune n_neighbors
knn.fit(X_train, y_train)

# Predicting the test set results
y_pred_knn = knn.predict(X_test)

# Making the Confusion Matrix
cm_knn = confusion_matrix(y_test, y_pred_knn)
print("KNN Confusion Matrix:")
print(cm_knn)

# Calculating the accuracy score
accuracy_knn = accuracy_score(y_test, y_pred_knn)
print('KNN Accuracy:', accuracy_knn)

# Calculating the accuracy score using the confusion matrix
accuracy_from_cm_knn = (cm_knn[0, 0] + cm_knn[1, 1]) / cm_knn.sum()
print('KNN Accuracy from Confusion Matrix:', accuracy_from_cm_knn)
```

```
KNN Confusion Matrix:
[[6097  745]
 [ 949 1254]]
KNN Accuracy: 0.8127142067440575
KNN Accuracy from Confusion Matrix: 0.8127142067440575
```

[44]:
```
# @title Decision Tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, accuracy_score



# Fitting the Decision Tree model
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
```

```python
# Predicting the test set results
y_pred_dt = dt.predict(X_test)

# Making the Confusion Matrix
cm_dt = confusion_matrix(y_test, y_pred_dt)
print("Decision Tree Confusion Matrix:")
print(cm_dt)

# Calculating the accuracy score
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print('Decision Tree Accuracy:', accuracy_dt)

# Calculating the accuracy score using the confusion matrix
accuracy_from_cm_dt = (cm_dt[0, 0] + cm_dt[1, 1]) / cm_dt.sum()
print('Decision Tree Accuracy from Confusion Matrix:', accuracy_from_cm_dt)
```

```
Decision Tree Confusion Matrix:
[[5786 1056]
 [1018 1185]]
Decision Tree Accuracy: 0.770702045328911
Decision Tree Accuracy from Confusion Matrix: 0.770702045328911
```

[45]:
```python
# @title Random Forest
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score

# Fitting the Random Forest model
rf = RandomForestClassifier()
rf.fit(X_train, y_train)

# Predicting the test set results
y_pred_rf = rf.predict(X_test)

# Making the Confusion Matrix
cm_rf = confusion_matrix(y_test, y_pred_rf)
print("Random Forest Confusion Matrix:")
print(cm_rf)

# Calculating the accuracy score
accuracy_rf = accuracy_score(y_test, y_pred_rf)
print('Random Forest Accuracy:', accuracy_rf)

# Calculating the accuracy score using the confusion matrix
accuracy_from_cm_rf = (cm_rf[0, 0] + cm_rf[1, 1]) / cm_rf.sum()
print('Random Forest Accuracy from Confusion Matrix:', accuracy_from_cm_rf)
```

```
Random Forest Confusion Matrix:
[[6219  623]
```

```
 [ 968 1235]]
Random Forest Accuracy: 0.8241017136539525
Random Forest Accuracy from Confusion Matrix: 0.8241017136539525
```

[46]:
```python
# @title Logistic Regression
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, accuracy_score

# Fitting the Logistic Regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

# Predicting the test set results
y_pred_logreg = logreg.predict(X_test)

# Making the Confusion Matrix
cm_logreg = confusion_matrix(y_test, y_pred_logreg)
print("Logistic Regression Confusion Matrix:")
print(cm_logreg)

# Calculating the accuracy score using the accuracy_score function
accuracy_logreg = accuracy_score(y_test, y_pred_logreg)
print('Logistic Regression Accuracy:', accuracy_logreg)

# Calculating the accuracy score using the confusion matrix
accuracy_from_cm_logreg = (cm_logreg[0, 0] + cm_logreg[1, 1]) / cm_logreg.sum()
print('Logistic Regression Accuracy from Confusion Matrix:',␣
 ↪accuracy_from_cm_logreg)
```

```
Logistic Regression Confusion Matrix:
[[6305  537]
 [ 972 1231]]
Logistic Regression Accuracy: 0.833167495854063
Logistic Regression Accuracy from Confusion Matrix: 0.833167495854063
```

[47]:
```python
# @title Accuracy Check

# Summary of Accuracy Scores

print('K Nearest Neighbour Accuracy:', accuracy_from_cm_knn)
print('Decision Tree Accuracy:', accuracy_from_cm_dt)
print('Random Forest Accuracy:', accuracy_from_cm_rf)
print('Logistic Regression Accuracy:', accuracy_from_cm_logreg)
```

```
K Nearest Neighbour Accuracy: 0.8127142067440575
Decision Tree Accuracy: 0.770702045328911
Random Forest Accuracy: 0.8241017136539525
Logistic Regression Accuracy: 0.833167495854063
```