Loading libraries

In [103…

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder
```

Step 1: Load the dataset

In [104…

```
# Define column names for the dataset
columns = ['age', 'workclass', 'fnlwgt', 'education', 'education_num', 'mari
# Load training and test data
train_data = pd.read_csv('adult.data', names=columns, sep=r',\s', engine='py
test_data = pd.read_csv('adult.test', names=columns, sep=r',\s', engine='pyt
```

Step 2: Output the structure of the dataset

In [105…

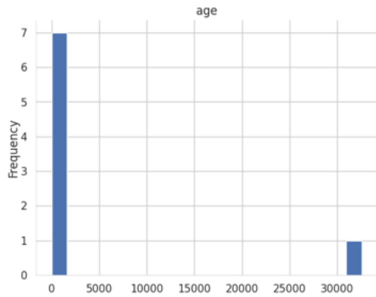
```
print("Train Data Structure:")
print(train_data.info())
train_data.head()
train_data.describe()
```

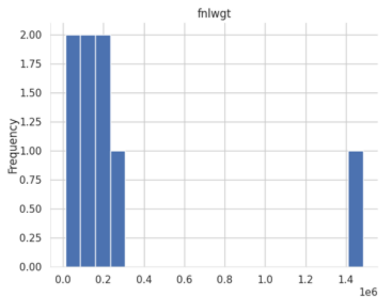
```
Train Data Structure:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32561 non-null  int64 
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64 
 3   education       32561 non-null  object
 4   education_num   32561 non-null  int64 
 5   marital_status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital_gain    32561 non-null  int64 
 11  capital_loss    32561 non-null  int64 
 12  hours_per_week  32561 non-null  int64 
 13  country         32561 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
None
```

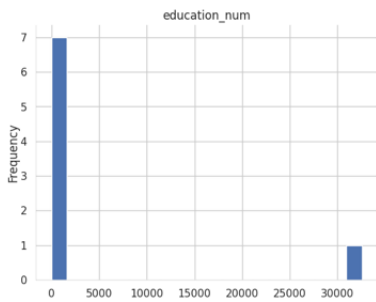
Out[105…

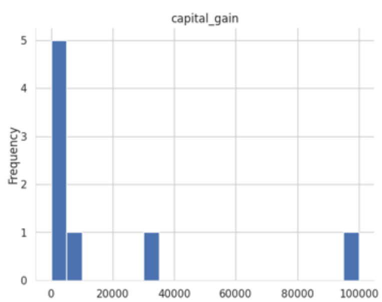
	age	fnlwgt	education_num	capital_gain	capital_loss	ho
count	32561.000000	3.256100e+04	32561.000000	32561.000000	32561.000000	
mean	38.581647	1.897784e+05	10.080679	1077.648844	87.303830	
std	13.640433	1.055500e+05	2.572720	7385.292085	402.960219	
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	
25%	28.000000	1.178270e+05	9.000000	0.000000	0.000000	
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	

Distributions

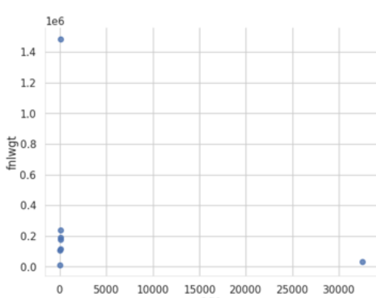


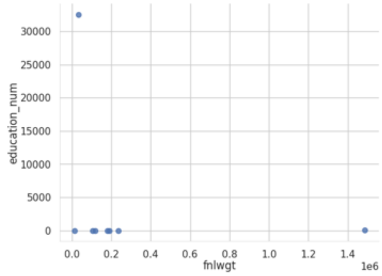


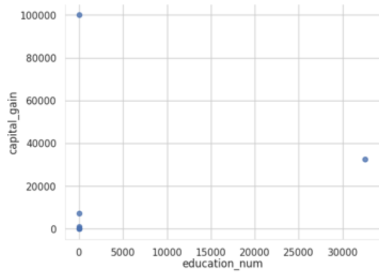


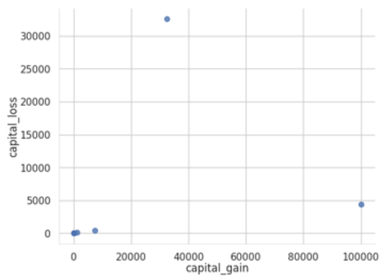


2-d distributions

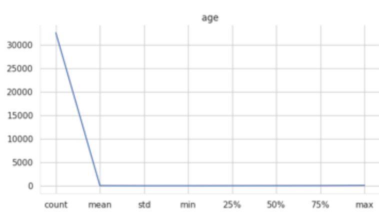


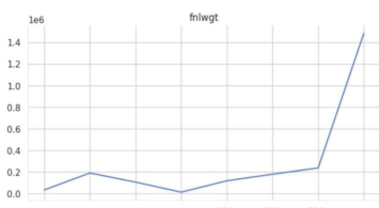

education_num
fnlwgt
1e6
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4
0 5000 10000 15000 20000 25000 30000

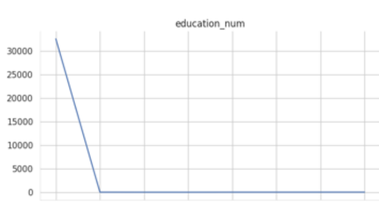

capital_gain
education_num
0 5000 10000 15000 20000 25000 30000
0 20000 40000 60000 80000 100000

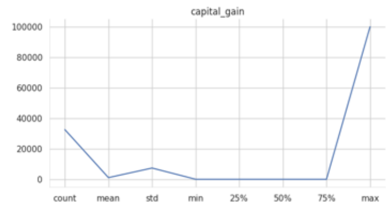

capital_loss
capital_gain
0 20000 40000 60000 80000 100000
0 5000 10000 15000 20000 25000 30000

Values


age
count mean std min 25% 50% 75% max
0 5000 10000 15000 20000 25000 30000


fnlwgt
1e6
0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4
count mean std min 25% 50% 75% max


education_num
count mean std min 25% 50% 75% max
0 5000 10000 15000 20000 25000 30000



In [106…

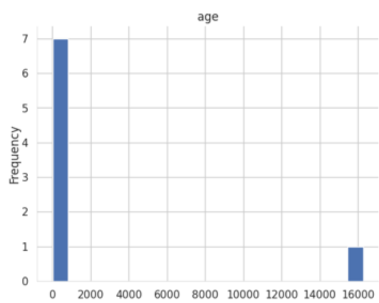
```
print("Test Data Structure:")
print(test_data.info())
test_data.head()
test_data.describe()
```

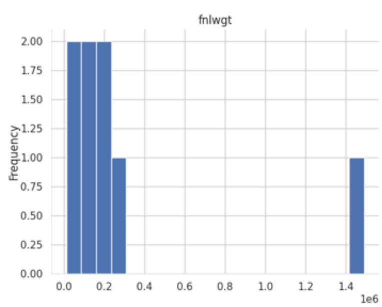
```
Test Data Structure:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16281 entries, 0 to 16280
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             16281 non-null  int64 
 1   workclass       16281 non-null  object
 2   fnlwgt          16281 non-null  int64 
 3   education       16281 non-null  object
 4   education_num   16281 non-null  int64 
 5   marital_status  16281 non-null  object
 6   occupation      16281 non-null  object
 7   relationship    16281 non-null  object
 8   race            16281 non-null  object
 9   sex             16281 non-null  object
 10  capital_gain    16281 non-null  int64 
 11  capital_loss    16281 non-null  int64 
 12  hours_per_week  16281 non-null  int64 
 13  country         16281 non-null  object
 14  income          16281 non-null  object
dtypes: int64(6), object(9)
memory usage: 1.9+ MB
None
```

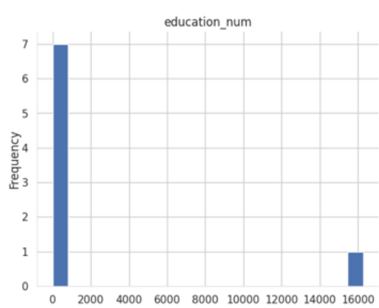
Out[106…

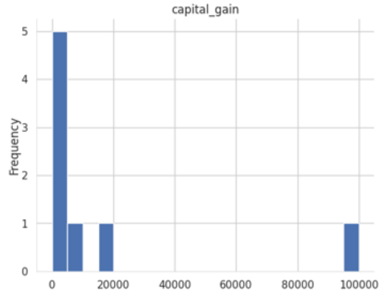
	age	fnlwgt	education_num	capital_gain	capital_loss	ho
count	16281.000000	1.628100e+04	16281.000000	16281.000000	16281.000000	
mean	38.767459	1.894357e+05	10.072907	1081.905104	87.899269	
std	13.849187	1.057149e+05	2.567545	7583.935968	403.105286	
min	17.000000	1.349200e+04	1.000000	0.000000	0.000000	
25%	28.000000	1.167360e+05	9.000000	0.000000	0.000000	
50%	37.000000	1.778310e+05	10.000000	0.000000	0.000000	
75%	48.000000	2.383840e+05	12.000000	0.000000	0.000000	
max	90.000000	1.490400e+06	16.000000	99999.000000	3770.000000	

Distributions

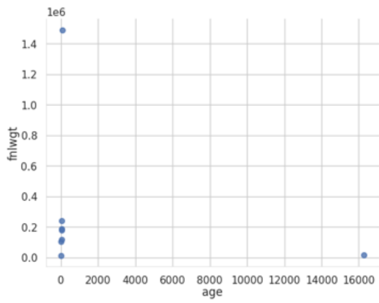


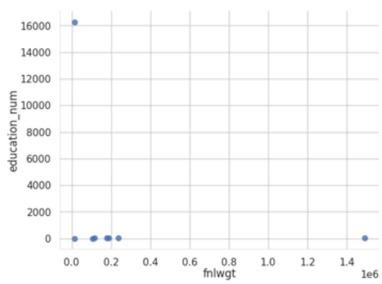


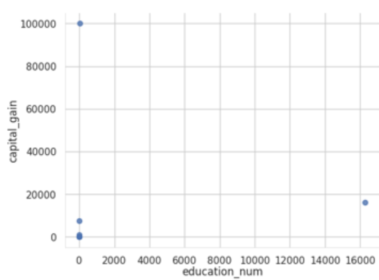


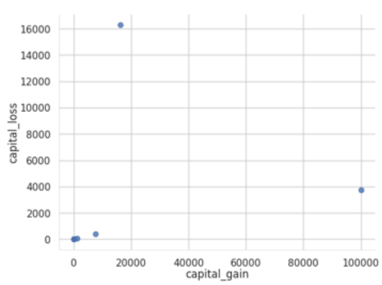


2-d distributions

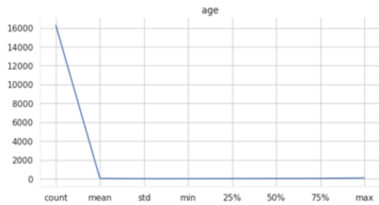


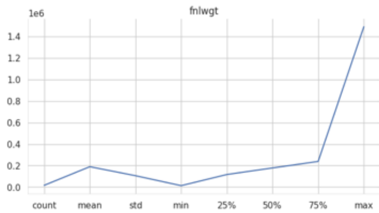


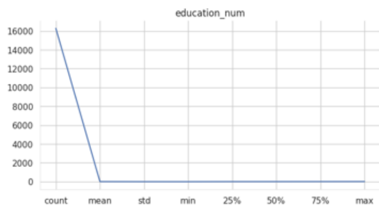


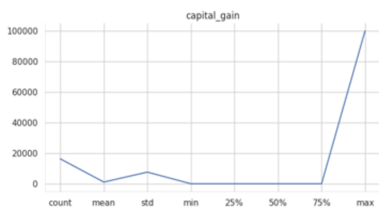


Values









Step 3: Clean the dataset, handle the missing values and encode the categorical values

In [107…

```
# Replace "?" with NaN for missing values
train_data.replace('?', pd.NA, inplace=True)
test_data.replace('?', pd.NA, inplace=True)

# Handle missing values by dropping rows with NaN
train_data.dropna(inplace=True)
test_data.dropna(inplace=True)

# Modifying 'income' column to remove periods
train_data['income'] = train_data['income'].str.strip()
test_data['income'] = test_data['income'].str.replace(r'\.', '', regex=True)

# Encode categorical features
categorical_columns = ['workclass', 'education', 'marital_status', 'occupati
                       'race', 'sex', 'country', 'income']
label_enc = LabelEncoder()
for i in categorical_columns:
```

```
    train_data[i] = label_enc.fit_transform(train_data[i].astype(str))
    test_data[i] = label_enc.transform(test_data[i].astype(str))
```

In [110…

```
# Check the cleaned data
print("\nCleaned Train Data:")
train_data.head()
```

```
Cleaned Train Data:
```

Out[110…

	age	workclass	fnlwgt	education	education_num	marital_status	occupation	re
0	39	5	77516	9	13	4	0	
1	50	4	83311	9	13	2	3	
2	38	2	215646	11	9	0	5	
3	53	2	234721	1	7	2	5	
4	28	2	338409	9	13	2	9	

In [111…

```
print("\nCleaned Test Data:")
test_data.head()
```

```
Cleaned Test Data:
```

Out[111…

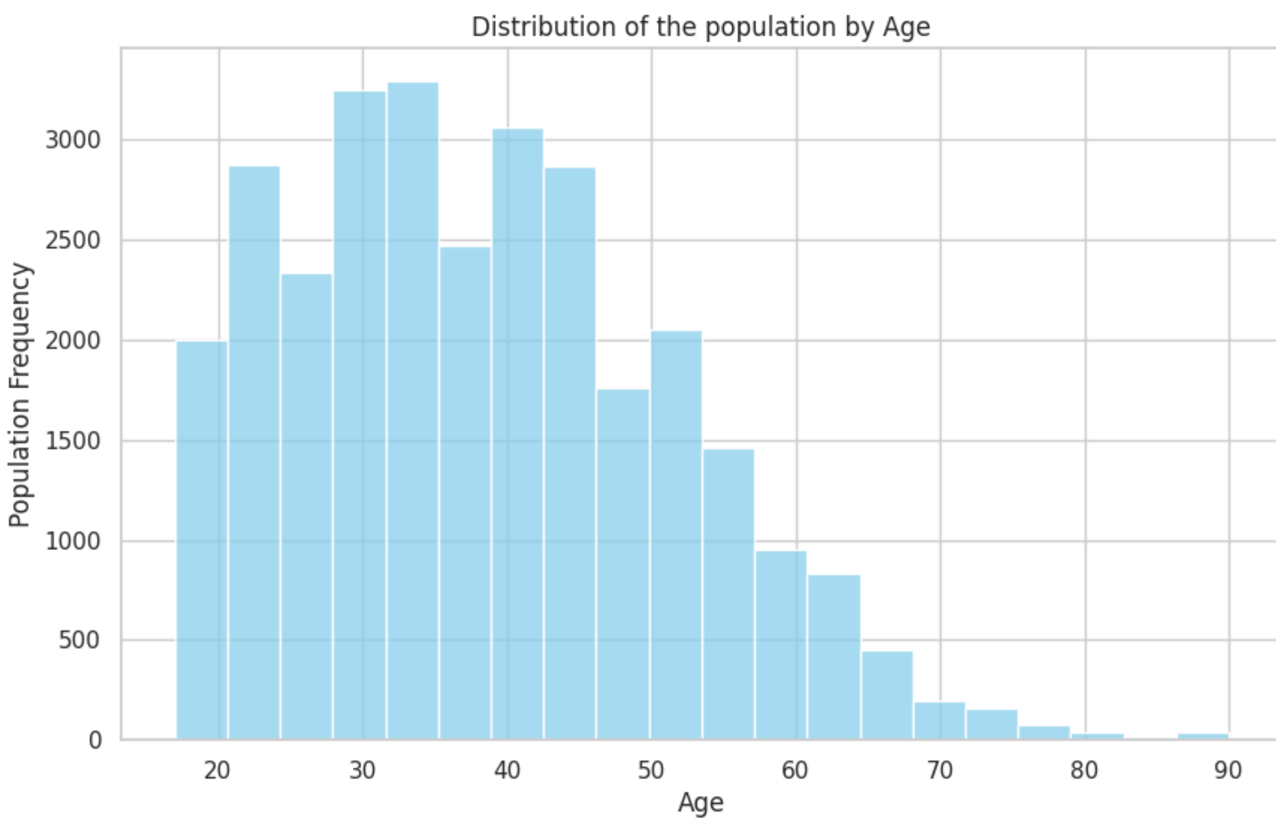
	age	workclass	fnlwgt	education	education_num	marital_status	occupation	re
0	25	2	226802	1	7	4	6	
1	38	2	89814	11	9	2	4	
2	28	1	336951	7	12	2	10	
3	44	2	160323	15	10	2	6	
5	34	2	198693	0	6	4	7	

Step 4: Explore the data (Visualizations)

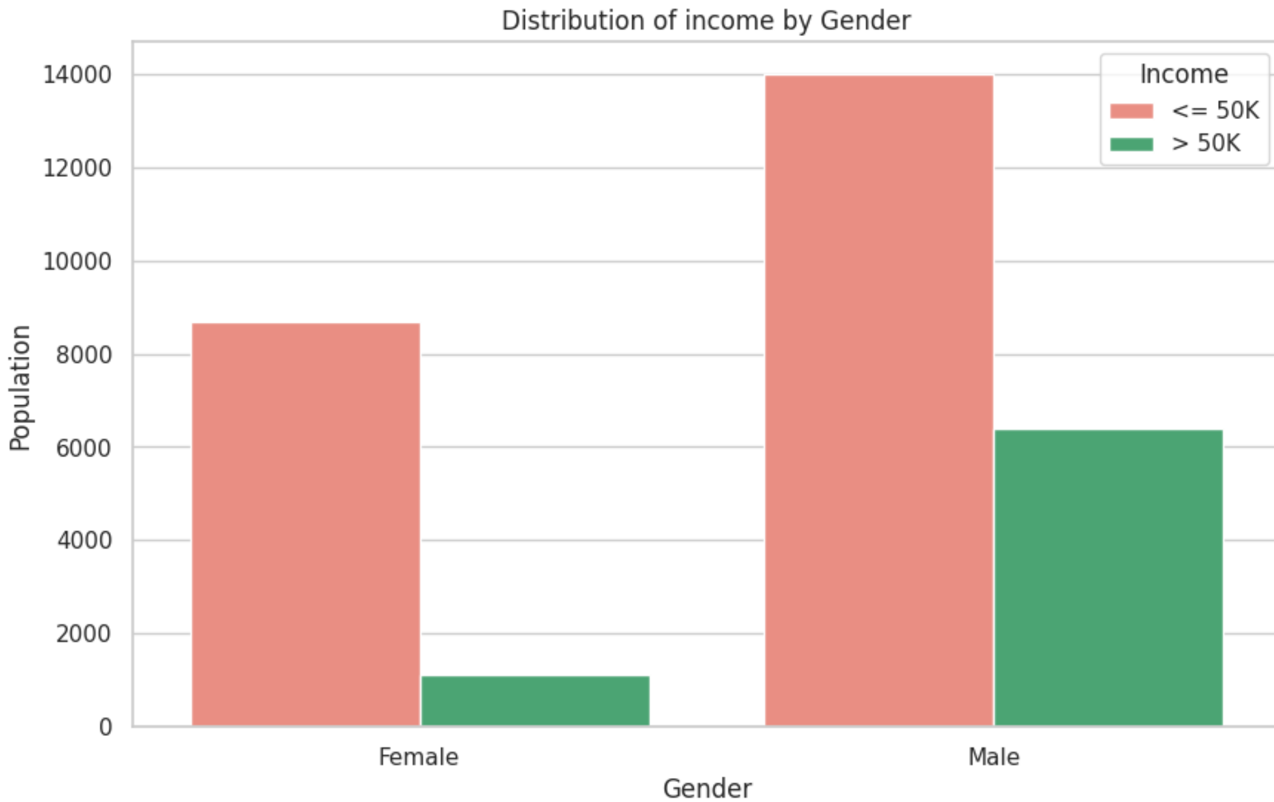
In [112…

```
# 1. Distribution of Age in the Dataset
plt.figure(figsize=(10, 6))
sns.histplot(train_data['age'], bins=20, color='skyblue')
plt.title('Distribution of the population by Age')
plt.xlabel('Age')
plt.ylabel('Population Frequency')
plt.show()

# 2. Distribution of Income by Gender
```

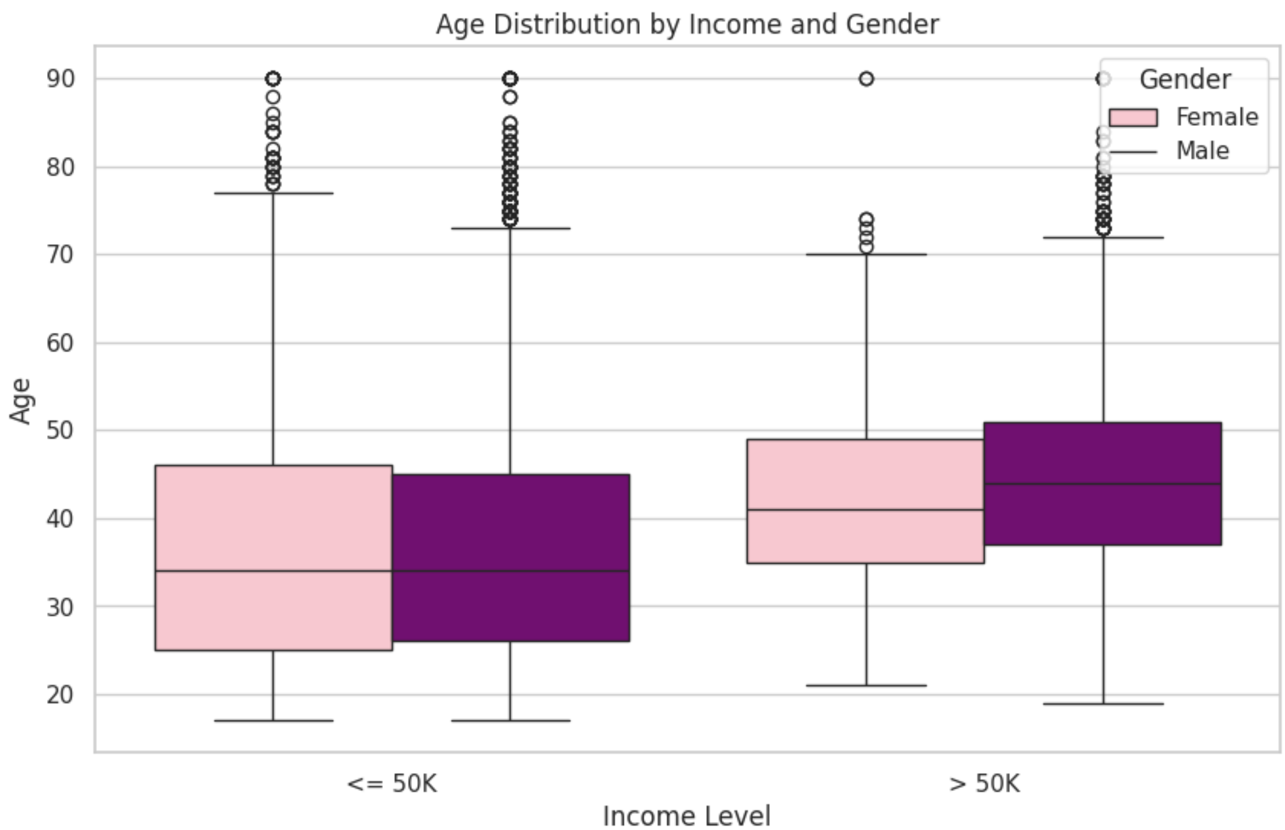
```
plt.figure(figsize=(10, 6))
sns.countplot(x='sex', hue='income', data=train_data, palette=['salmon', 'me
plt.title('Distribution of income by Gender')
plt.xlabel('Gender')
plt.ylabel('Population')
plt.xticks([0, 1], ['Female', 'Male'])
plt.legend(title="Income", labels=['<= 50K', '> 50K'])
plt.show()

# 3. Box Plot of Age by Income and Gender
plt.figure(figsize=(10, 6))
sns.boxplot(x='income', y='age', hue='sex', data=train_data, palette=['pink'
plt.title('Age Distribution by Income and Gender')
plt.xlabel('Income Level')
plt.ylabel('Age')
plt.xticks([0, 1], ['<= 50K', '> 50K'])
plt.legend(title='Gender', labels=['Female', 'Male'], loc='upper right')
plt.show()
```



```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tu
ple to get_group in a future version of pandas. Pass `(name,)` instead of `n
ame` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tu
ple to get_group in a future version of pandas. Pass `(name,)` instead of `n
ame` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
```



```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tu
ple to get_group in a future version of pandas. Pass `(name,)` instead of `n
ame` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640: FutureWa
rning: SeriesGroupBy.grouper is deprecated and will be removed in a future v
ersion of pandas.
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning:
When grouping with a length-1 list-like, you will need to pass a length-1 tu
ple to get_group in a future version of pandas. Pass `(name,)` instead of `n
ame` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py:640: FutureWa
rning: SeriesGroupBy.grouper is deprecated and will be removed in a future v
ersion of pandas.
  positions = grouped.grouper.result_index.to_numpy(dtype=float)
```



Step 5: Apply predictive modeling

In [113…

```
# Split features and target variable
X_train = train_data.drop('income', axis=1)
Y_train = train_data['income']
```

```
X_test = test_data.drop('income', axis=1)
Y_test = test_data['income']

# Train a Random Forest classifier
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, Y_train)

# Predict on the test set
Y_predicted = clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(Y_test, Y_predicted)
print(f"Test Accuracy whether an individual earns more than $50K a year: {ac
```

```
Test Accuracy whether an individual earns more than $50K a year: 85.08%
```