# Predicting Income Class

1. Business Understanding - The objective of the exercise is to predict income of a citizen (below or above $50k) depending on factors presented.
2. Data Understanding - The data provided is in a csv file containing 32561 records from a census. There are unknown values in columns such as occupation and workclass. Exploratory analysis will be carried out in the notebook.
3. Data Preparation - Unknown records were handled by labelling as 'unknown' and assigned a numerical value.
4. Modelling - 8 models will be evaluated for this classification task. Training and test data will be split 70:30.
5. Evaluation - Each of the 8 models will be compared and evaluated
6. Deployment - This was not within the scope of this exercise

In [1]:
```
# Import relevant libraries


import pandas as pd
import numpy as np

#import pyplot and seaborn for visualization
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('ggplot')

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

In [2]:
```
# Load dataset

income_data = pd.read_csv(r"C:\Users\EZ FARMING\Desktop\Seun Personal Docs\DAT
income_data.head()
```

Out[2]:

| | age | workclass | fnlwgt | education | education-num | marital-status | occupation | relationship | race | s |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 39 | State-gov | 77516 | Bachelors | 13 | Never-married | Adm-clerical | Not-in-family | White | M |
| **1** | 50 | Self-emp-not-inc | 83311 | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | M |
| **2** | 38 | Private | 215646 | HS-grad | 9 | Divorced | Handlers-cleaners | Not-in-family | White | M |
| **3** | 53 | Private | 234721 | 11th | 7 | Married-civ-spouse | Handlers-cleaners | Husband | Black | M |
| **4** | 28 | Private | 338409 | Bachelors | 13 | Married-civ-spouse | Prof-specialty | Wife | Black | Fem |

## Data Inspection

In [3]:
```
# Get the shape of our dataset

income_data.shape
```

Out[3]: (32561, 15)

In [4]:
```
# Information about the columns

income_data.info()
```

```
<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   native-country  32561 non-null  object
 14   income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

In [5]:
```
income_data.isnull().sum()
```

Out[5]:
```
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 [6]:
```
# Check for duplicates

income_data.duplicated().sum()
```

Out[6]: 24

In [7]:
```
# There are 24 duplicates

# Let us proceed to drop the duplicated rows

income_data.drop_duplicates(inplace=True)
income_data.shape
```

Out[7]:
```
(32537, 15)
```

In [8]:
```
# notice some whitespaces in the column names

income_data.columns
```

Out[8]:
```
Index(['age', ' workclass', ' fnlwgt', ' education', ' education-num',
       ' marital-status', ' occupation', ' relationship', ' race', ' sex',
       ' capital-gain', ' capital-loss', ' hours-per-week', ' native-countr
y',
       ' income'],
      dtype='object')
```

In [9]:
```
# Remove the whitespaces in column names

income_data.columns = income_data.columns.str.lstrip()
income_data.columns
```

Out[9]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'education-num',
       'marital-status', 'occupation', 'relationship', 'race', 'sex',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income'],
      dtype='object')
```

In [10]:
```
# Let's drop the fnlwgt  column

income_data.drop(['fnlwgt'], axis=1, inplace=True)
income_data.head()
```

Out[10]:

| | age | workclass | education | education-num | marital-status | occupation | relationship | race | sex | capi g |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 39 | State-gov | Bachelors | 13 | Never-married | Adm-clerical | Not-in-family | White | Male | 2 |
| **1** | 50 | Self-emp-not-inc | Bachelors | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male | |
| **2** | 38 | Private | HS-grad | 9 | Divorced | Handlers-cleaners | Not-in-family | White | Male | |
| **3** | 53 | Private | 11th | 7 | Married-civ-spouse | Handlers-cleaners | Husband | Black | Male | |
| **4** | 28 | Private | Bachelors | 13 | Married-civ-spouse | Prof-specialty | Wife | Black | Female | |

In [11]:
```
# Print unique values in each column

for i in income_data.columns.tolist():
    print(i, '\n\n', income_data[i].unique())
    print('\n ----------------------------------------------------------------
```

```
age

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

 ----------------------------------------------------------------------------
----------------------------
workclass

 [' State-gov' ' Self-emp-not-inc' ' Private' ' Federal-gov' ' Local-gov'
 ' ?' ' Self-emp-inc' ' Without-pay' ' Never-worked']

 ----------------------------------------------------------------------------
----------------------------
education

 [' Bachelors' ' HS-grad' ' 11th' ' Masters' ' 9th' ' Some-college'
```

In [12]:
```
# We noticed ' ?' in workclass, occupation and native-country

# Let us replace the ' ?' with 'nan'
```

In [13]:
```
income_data[income_data == ' ?'] = np.nan
income_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32537 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32537 non-null  int64
 1   workclass       30701 non-null  object
 2   education       32537 non-null  object
 3   education-num   32537 non-null  int64
 4   marital-status  32537 non-null  object
 5   occupation      30694 non-null  object
 6   relationship    32537 non-null  object
 7   race            32537 non-null  object
 8   sex             32537 non-null  object
 9   capital-gain    32537 non-null  int64
 10  capital-loss    32537 non-null  int64
 11  hours-per-week  32537 non-null  int64
 12  native-country  31955 non-null  object
 13  income          32537 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.7+ MB
```

In [14]:
```
# Replace missing values with 'Unknown'

for col in ['workclass', 'occupation', 'native-country']:
    income_data[col].fillna('Unknown', inplace=True)
```

In [15]:
```
# Confirm the replacements

income_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 32537 entries, 0 to 32560
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             32537 non-null  int64 
 1   workclass       32537 non-null  object
 2   education       32537 non-null  object
 3   education-num   32537 non-null  int64 
 4   marital-status  32537 non-null  object
 5   occupation      32537 non-null  object
 6   relationship    32537 non-null  object
 7   race            32537 non-null  object
 8   sex             32537 non-null  object
 9   capital-gain    32537 non-null  int64 
 10  capital-loss    32537 non-null  int64 
 11  hours-per-week  32537 non-null  int64 
 12  native-country  32537 non-null  object
 13  income          32537 non-null  object
dtypes: int64(5), object(9)
memory usage: 3.7+ MB
```

In [16]:
```
income_data.describe(include='all').T
```

Out[16]:

| | count | unique | top | freq | mean | std | min | 25% | 50% | 75% |
|---|---|---|---|---|---|---|---|---|---|---|
| **age** | 32537.0 | NaN | NaN | NaN | 38.585549 | 13.637984 | 17.0 | 28.0 | 37.0 | 48.0 |
| **workclass** | 32537 | 9 | Private | 22673 | NaN | NaN | NaN | NaN | NaN | NaN |
| **education** | 32537 | 16 | HS-grad | 10494 | NaN | NaN | NaN | NaN | NaN | NaN |
| **education-num** | 32537.0 | NaN | NaN | NaN | 10.081815 | 2.571633 | 1.0 | 9.0 | 10.0 | 12.0 |
| **marital-status** | 32537 | 7 | Married-civ-spouse | 14970 | NaN | NaN | NaN | NaN | NaN | NaN |
| **occupation** | 32537 | 15 | Prof-specialty | 4136 | NaN | NaN | NaN | NaN | NaN | NaN |
| **relationship** | 32537 | 6 | Husband | 13187 | NaN | NaN | NaN | NaN | NaN | NaN |
| **race** | 32537 | 5 | White | 27795 | NaN | NaN | NaN | NaN | NaN | NaN |
| **sex** | 32537 | 2 | Male | 21775 | NaN | NaN | NaN | NaN | NaN | NaN |
| **capital-gain** | 32537.0 | NaN | NaN | NaN | 1078.443741 | 7387.957424 | 0.0 | 0.0 | 0.0 | 0.0 |
| **capital-loss** | 32537.0 | NaN | NaN | NaN | 87.368227 | 403.101833 | 0.0 | 0.0 | 0.0 | 0.0 |
| **hours-per-week** | 32537.0 | NaN | NaN | NaN | 40.440329 | 12.346889 | 1.0 | 40.0 | 40.0 | 45.0 |
| **native-country** | 32537 | 42 | United-States | 29153 | NaN | NaN | NaN | NaN | NaN | NaN |
| **income** | 32537 | 2 | <=50K | 24698 | NaN | NaN | NaN | NaN | NaN | NaN |

# EDA

## Income

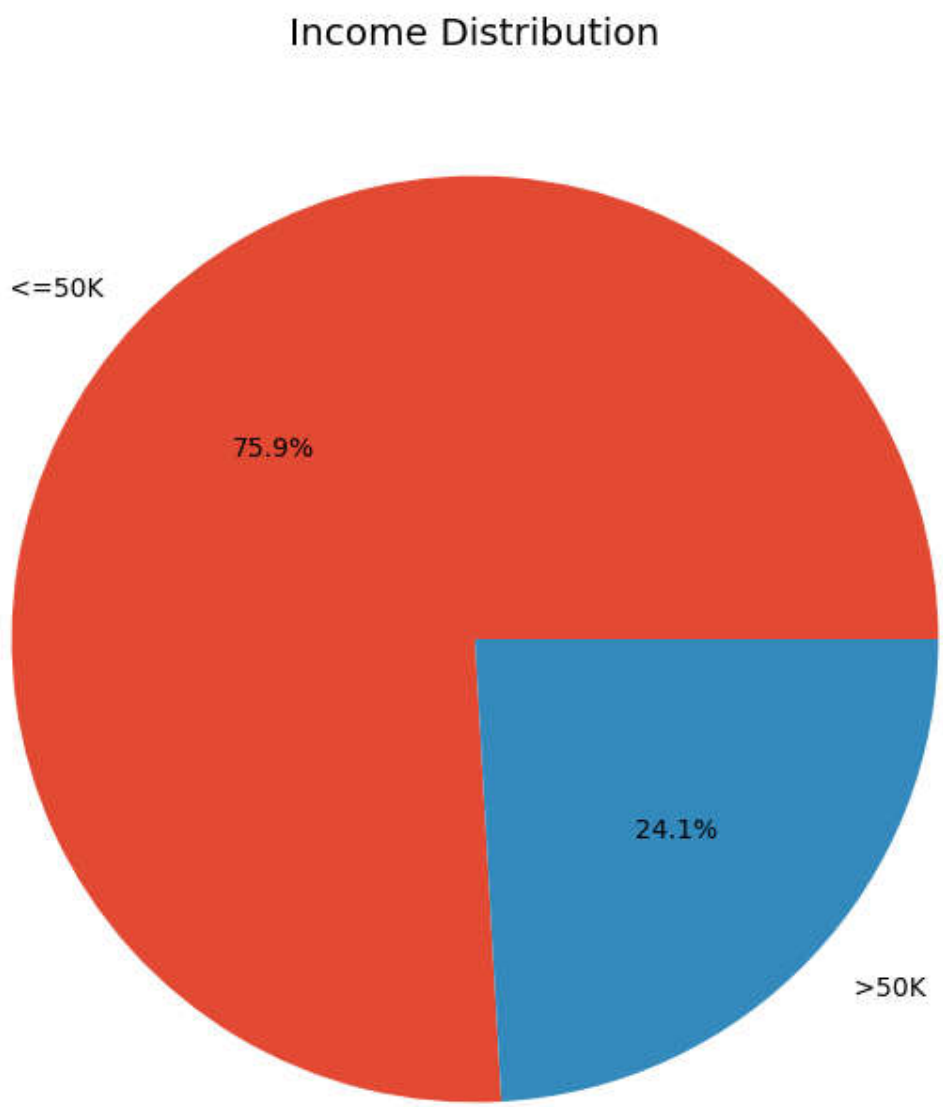
In [17]:
```
income_data['income'].value_counts()
```

Out[17]:
```
<=50K    24698
>50K      7839
Name: income, dtype: int64
```

In [18]:

```
income_counts = income_data['income'].value_counts()
plt.figure(figsize=(10,8))
plt.pie(income_counts, labels=income_counts.index, autopct='%1.1f%%')
plt.title('Income Distribution')
```

Out[18]: Text(0.5, 1.0, 'Income Distribution')

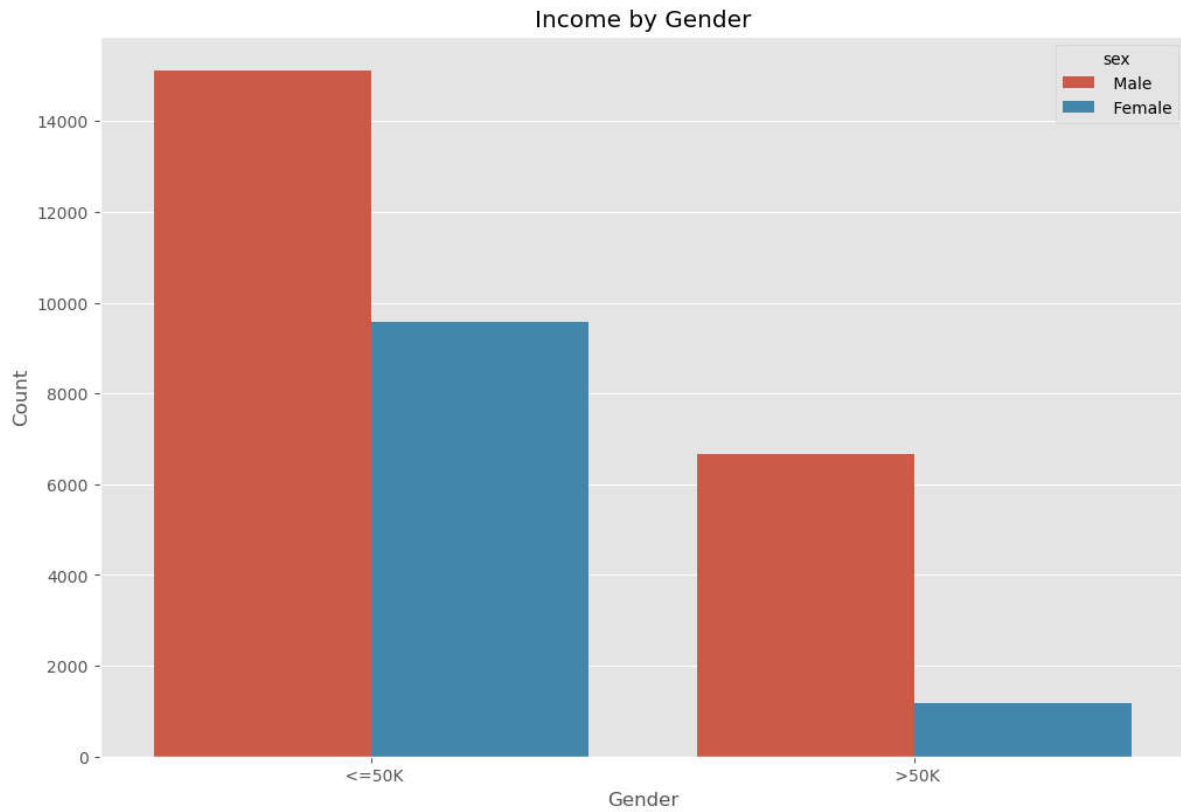



There are more persons earning below 50k US Dollars

In [19]:
```
# Income by Gender


plt.figure(figsize=(12,8))
plt.title('Income by Gender')
sns.countplot(x='income', data=income_data, hue='sex')
plt.xlabel('Gender')
plt.ylabel('Count')
```

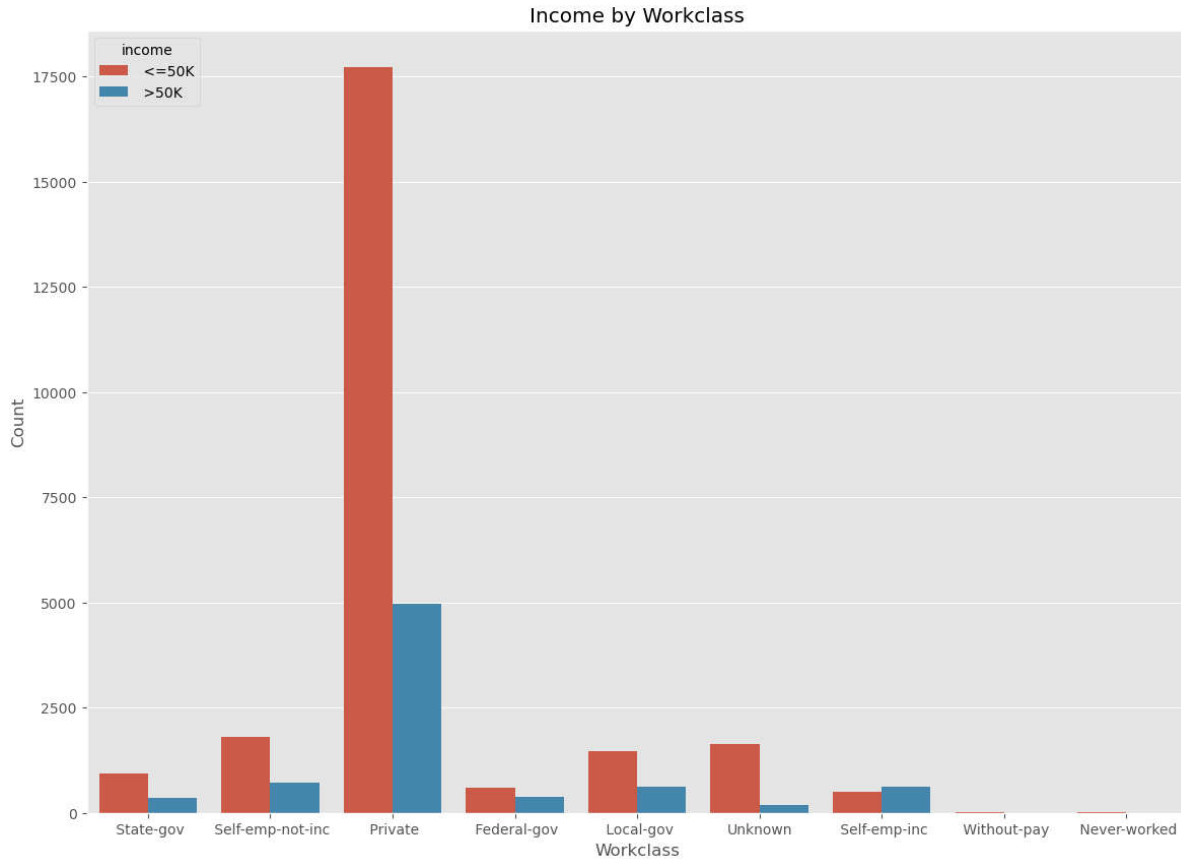
Out[19]: Text(0, 0.5, 'Count')




In total, the Male earn higher than the female. In the female category, those earning 50K and below are more than those earning more than 50k. In the male category also, those earning 50K and below are more than those earning more than 50k.

In [20]:
```
plt.figure(figsize=(14,10))
plt.title('Income by Workclass')
sns.countplot(x='workclass', data=income_data, hue='income')
plt.xlabel('Workclass')
plt.ylabel('Count')
```

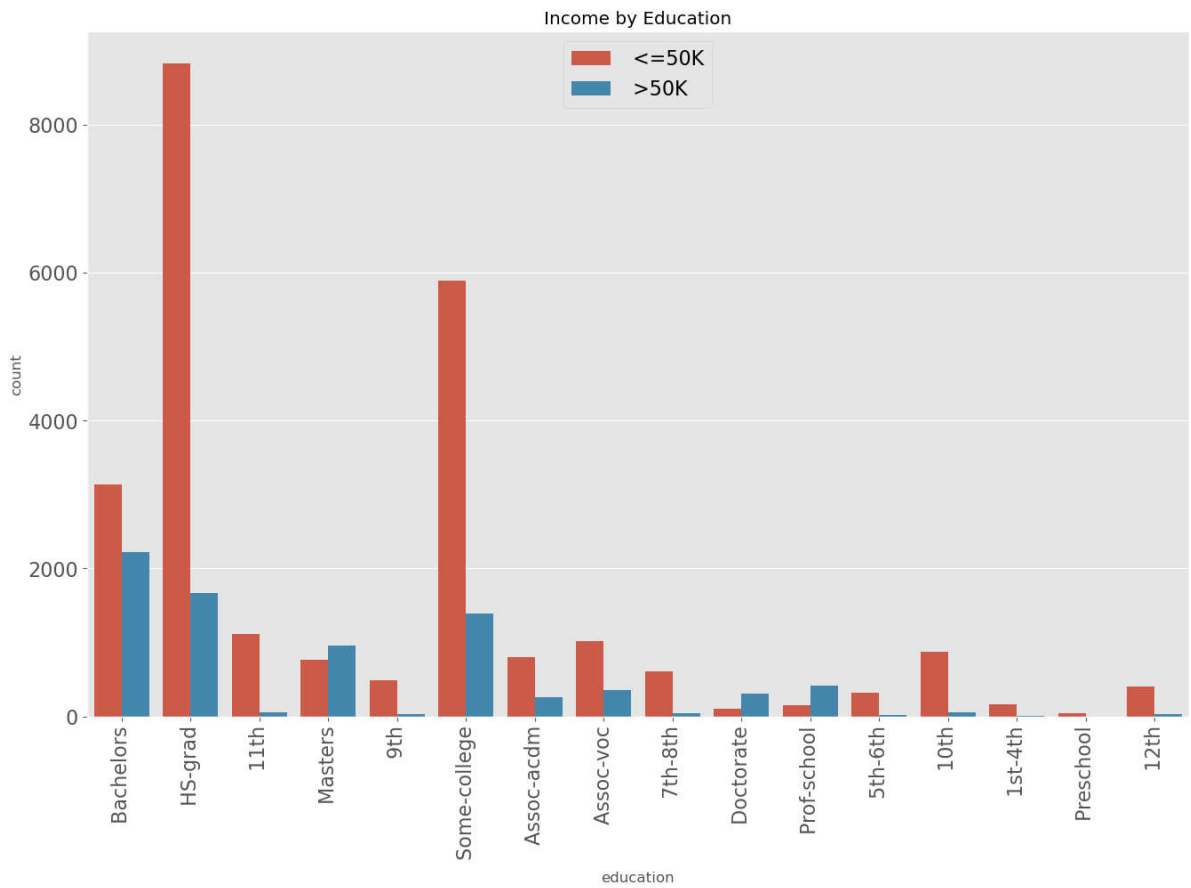
Out[20]: Text(0, 0.5, 'Count')




Most of the people belong to the Private workclass. Majority of the people earn less than or equal to 50k.

In [22]:
```
plt.figure(figsize=(16,10))
plt.title('Income by Education')
sns.countplot(x='education', data=income_data, hue='income')
plt.xticks(fontsize=16,rotation = 90)
plt.yticks(fontsize=16)
plt.legend(fontsize=16)
```

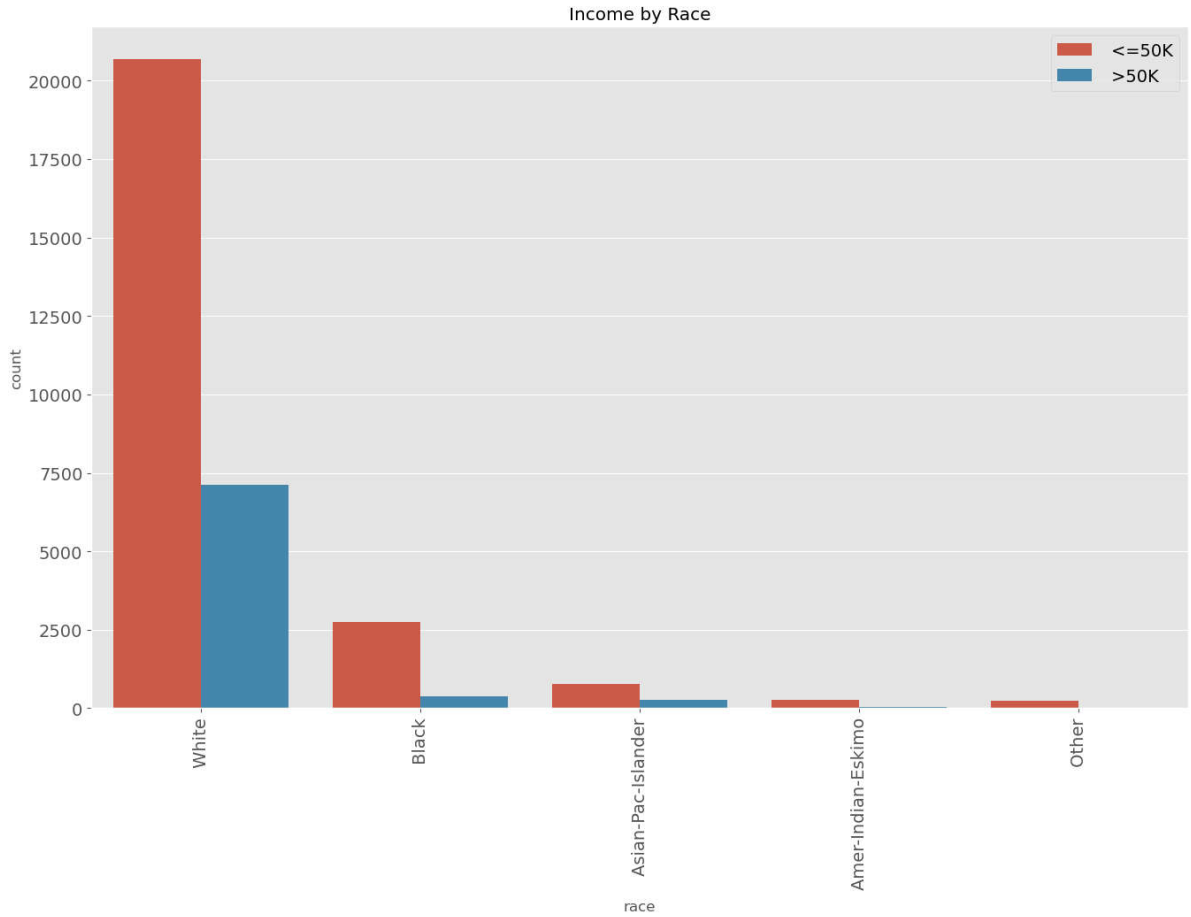
Out[22]:
```
<matplotlib.legend.Legend at 0x230846e5460>
```




The largest group of earners are the HS-grad, followed by some-college and then Bachelors. People earning higher than 50k are more than those earning below in categories like Masters, and doctorate, prof-school

In [23]:
```
plt.figure(figsize=(16,10))
plt.title('Income by Race')
sns.countplot(x='race', data=income_data, hue='income')
plt.xticks(fontsize=14,rotation = 90)
plt.yticks(fontsize=14)
plt.legend(fontsize=14)
```

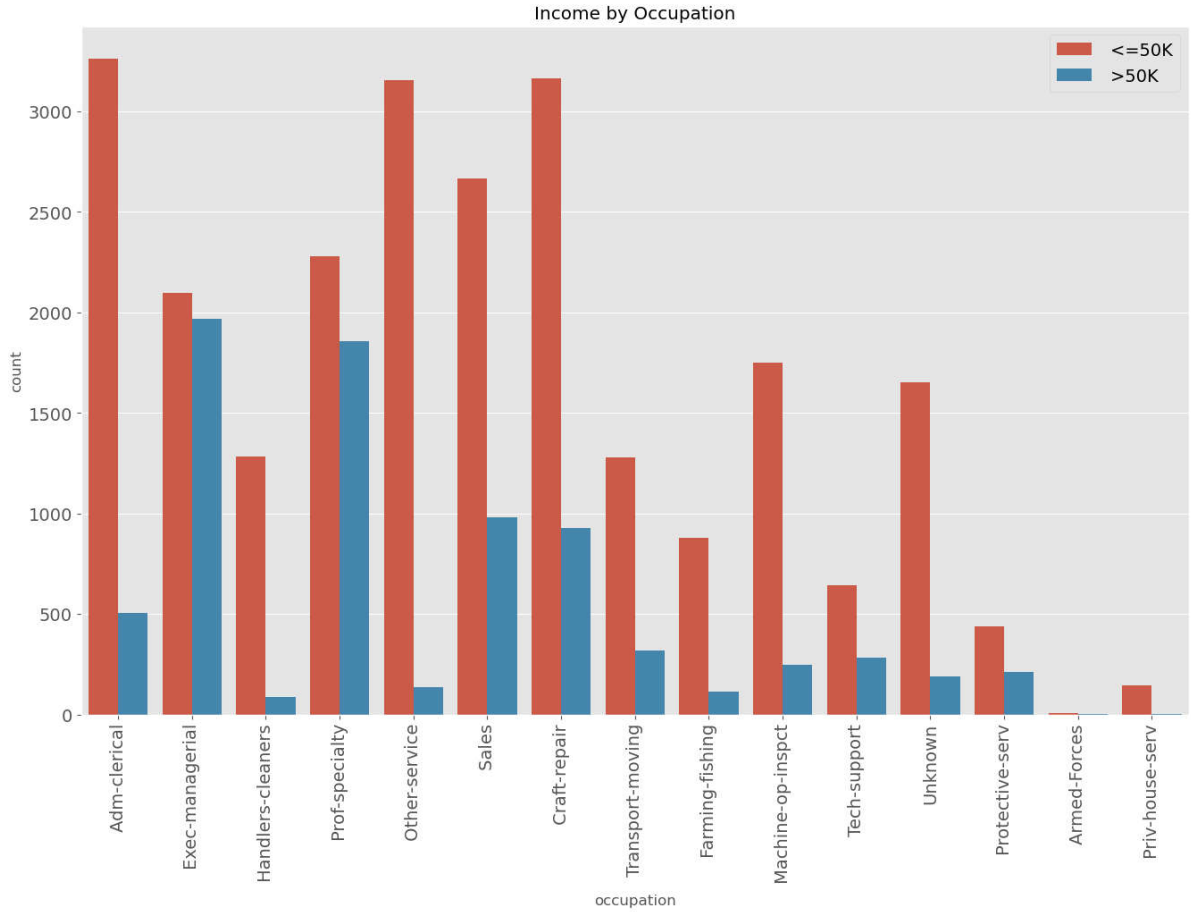
Out[23]:
```
<matplotlib.legend.Legend at 0x230847a6910>
```




Majority of the income earners are White, followed by Black.

In [24]:
```
plt.figure(figsize=(16,10))
plt.title('Income by Occupation')
sns.countplot(x='occupation', data=income_data, hue='income')
plt.xticks(fontsize=14,rotation = 90)
plt.yticks(fontsize=14)
plt.legend(fontsize=14)
```

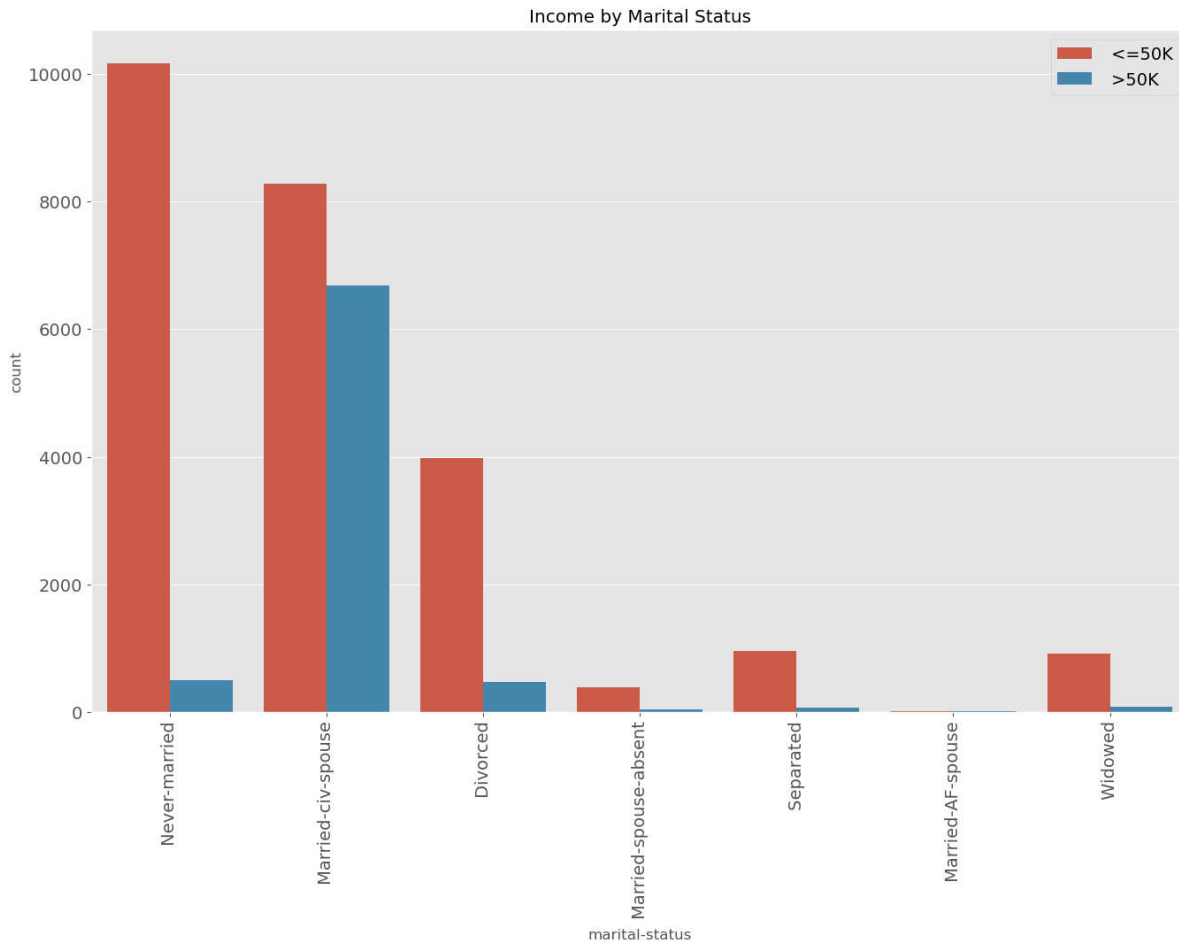
Out[24]:
```
<matplotlib.legend.Legend at 0x23084822f70>
```




The larger percentage of those that belong to the Exec-managerial, Prof-specialty and Protective-serv categories earn >50K.

In [25]:
```
plt.figure(figsize=(16,10))
plt.title('Income by Marital Status')
sns.countplot(x='marital-status', data=income_data, hue='income')
plt.xticks(fontsize=14,rotation = 90)
plt.yticks(fontsize=14)
plt.legend(fontsize=14)
```

Out[25]:
```
<matplotlib.legend.Legend at 0x230848e9760>
```



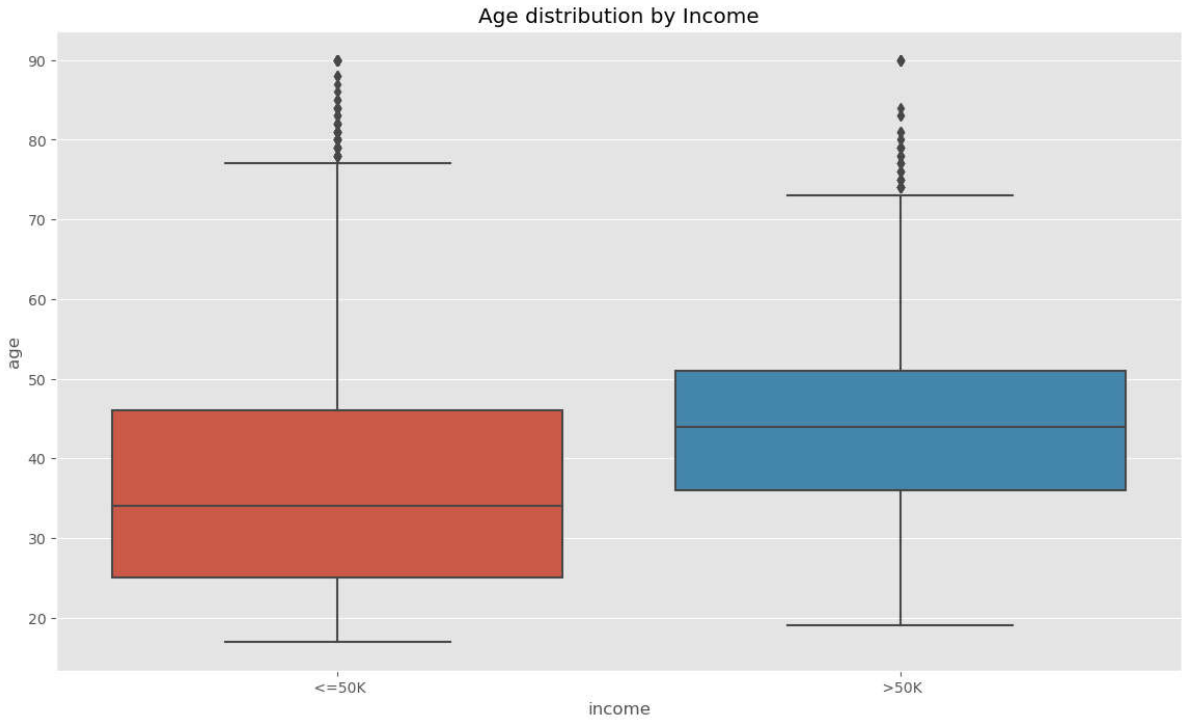

The largest count of income earners are Married-civ-spouse. The same group has the largest percentage of people earning >50k.

In [26]:

```
plt.figure(figsize=(14,8))

sns.boxplot(x='income', y='age', data=income_data)
plt.title('Age distribution by Income')
```

Out[26]: Text(0.5, 1.0, 'Age distribution by Income')




The median age of those with income <=50k is around 34 years, while those with income >50K is around 44 years. There are some outliers in the data.

## Data Pre-processing

In [27]:
```
# Let us transform income column into numerical attributes
# We will assign income <= 50k 0 and income > 50k 1


income_data['income'] = income_data['income'].map({' <=50K': 0, ' >50K': 1})
income_data['income']
```

Out[27]:
```
0        0
1        0
2        0
3        0
4        0
        ..
32556    0
32557    1
32558    0
32559    0
32560    1
Name: income, Length: 32537, dtype: int64
```

In [28]:
```
# Drop education column as it is similar to education-num column

income_data.drop(['education'], axis=1, inplace=True)
income_data.head()
```

Out[28]:

| | age | workclass | education-num | marital-status | occupation | relationship | race | sex | capital-gain | capital loss |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 39 | State-gov | 13 | Never-married | Adm-clerical | Not-in-family | White | Male | 2174 | ( |
| **1** | 50 | Self-emp-not-inc | 13 | Married-civ-spouse | Exec-managerial | Husband | White | Male | 0 | ( |
| **2** | 38 | Private | 9 | Divorced | Handlers-cleaners | Not-in-family | White | Male | 0 | ( |
| **3** | 53 | Private | 7 | Married-civ-spouse | Handlers-cleaners | Husband | Black | Male | 0 | ( |
| **4** | 28 | Private | 13 | Married-civ-spouse | Prof-specialty | Wife | Black | Female | 0 | ( |

In [29]:
```
categorical = []
numerical = []

for i in income_data.columns:
    if income_data[i].dtype=='O':
        categorical.append(i)
    else:
        numerical.append(i)

print(categorical, numerical, sep='\n\n\n')
```

```
['workclass', 'marital-status', 'occupation', 'relationship', 'race', 'sex',
'native-country']


['age', 'education-num', 'capital-gain', 'capital-loss', 'hours-per-week', 'i
ncome']
```

## Split the data

In [30]:
```
X = income_data.drop(['income'], axis=1)
y = income_data['income']
```

## Train-Test Split

In [31]:
```
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, ran

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(22775, 12)
(9762, 12)
(22775,)
(9762,)
```

## Encode the categorical variables

In [32]:
```
# Next, let us encode our categorical variables using one hot encoding

# Apply pd.get_dummies on training and test data

X_train = pd.get_dummies(X_train, columns=['workclass', 'marital-status', 'occ
X_test = pd.get_dummies(X_test, columns=['workclass', 'marital-status', 'occup

# Align the columns of the encoded test set with the columns of the encoded tr
X_test = X_test.reindex(columns=X_train.columns, fill_value=0)
```

In [33]:
```
display(X_train.head())
display(X_test.head())
```

| | age | education-num | capital-gain | capital-loss | hours-per-week | workclass_Federal-gov | workclass_Local-gov | workclass_Never-worked | workclass_Privat |
|---|---|---|---|---|---|---|---|---|---|
| **13011** | 36 | 13 | 0 | 0 | 40 | 0 | 0 | 0 | |
| **24494** | 30 | 10 | 0 | 0 | 40 | 0 | 0 | 0 | |
| **16923** | 41 | 11 | 7298 | 0 | 60 | 0 | 0 | 0 | |
| **25335** | 46 | 14 | 0 | 1977 | 60 | 0 | 0 | 0 | |
| **12363** | 37 | 11 | 0 | 0 | 40 | 0 | 1 | 0 | |

5 rows × 91 columns

| | age | education-num | capital-gain | capital-loss | hours-per-week | workclass_Federal-gov | workclass_Local-gov | workclass_Never-worked | workclass_Privat |
|---|---|---|---|---|---|---|---|---|---|
| **24188** | 50 | 10 | 0 | 0 | 40 | 0 | 0 | 0 | |
| **26471** | 25 | 9 | 0 | 0 | 45 | 0 | 0 | 0 | |
| **26843** | 47 | 9 | 0 | 1977 | 45 | 0 | 0 | 0 | |
| **8795** | 61 | 4 | 0 | 0 | 40 | 0 | 0 | 0 | |
| **27178** | 34 | 9 | 0 | 0 | 40 | 0 | 0 | 0 | |

5 rows × 91 columns

## Feature Scaling

In [34]:
```
# Robust Scaler is preferred here as it is more robust to outliers

from sklearn.preprocessing import RobustScaler

X_train[list(X_train.select_dtypes(exclude=['object']).columns)] = RobustScale
X_test[list(X_test.select_dtypes(exclude=['object']).columns)] = RobustScaler(


# scaler = RobustScaler()

# X_train = scaler.fit_transform(X_train)
# X_test = scaler.fit_transform(X_test)
```

In [35]:
```
display(X_train.head())
display(X_test.head())
```

| | age | education-num | capital-gain | capital-loss | hours-per-week | workclass_Federal-gov | workclass_Local-gov | workclass_Never-worked | workclas Priva |
|---|---|---|---|---|---|---|---|---|---|
| **13011** | -0.05 | 1.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ( |
| **24494** | -0.35 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ( |
| **16923** | 0.20 | 0.333333 | 7298.0 | 0.0 | 4.0 | 0.0 | 0.0 | 0.0 | ( |
| **25335** | 0.45 | 1.333333 | 0.0 | 1977.0 | 4.0 | 0.0 | 0.0 | 0.0 | -1 |
| **12363** | 0.00 | 0.333333 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 | 0.0 | -1 |

5 rows × 91 columns

| | age | education-num | capital-gain | capital-loss | hours-per-week | workclass_Federal-gov | workclass_Local-gov | workclass_Never-worked | workclas Priva |
|---|---|---|---|---|---|---|---|---|---|
| **24188** | 0.65 | 0.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ( |
| **26471** | -0.60 | -0.333333 | 0.0 | 0.0 | 1.0 | 0.0 | 0.0 | 0.0 | ( |
| **26843** | 0.50 | -0.333333 | 0.0 | 1977.0 | 1.0 | 0.0 | 0.0 | 0.0 | ( |
| **8795** | 1.20 | -2.000000 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | -1 |
| **27178** | -0.15 | -0.333333 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | ( |

5 rows × 91 columns

In [36]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(22775, 91)
(9762, 91)
```

In [ ]:
```

```

## Model Selection

In [37]:
```
!pip install xgboost
from sklearn.model_selection import  cross_val_score, cross_val_predict
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
import xgboost as xgb
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
from sklearn import tree
```

```
Requirement already satisfied: xgboost in c:\users\ez farming\anaconda\lib\si
te-packages (1.7.5)
Requirement already satisfied: scipy in c:\users\ez farming\anaconda\lib\site
-packages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\users\ez farming\anaconda\lib\site
-packages (from xgboost) (1.21.5)
```

In [38]:
```
classifiers = [
    (DecisionTreeClassifier(), "Decision Tree"),
    (KNeighborsClassifier(), "K-Nearest Neighbors"),
    (SVC(), "Support Vector Machine"),
    (LogisticRegression(), "Logistic Regression"),
    (RandomForestClassifier(), "Random Forest"),
    (GaussianNB(), "Naive Bayes"),
    (GradientBoostingClassifier(), "Gradient Boosting Machine"),
    (xgb.XGBClassifier(), "XGBoost")
]

# Iterate through the list of classifiers
for classifier, name in classifiers:
    # Train the classifier
    classifier.fit(X_train, y_train)

    # Predict on the test set
    y_pred = classifier.predict(X_test)

    # Print the classifier's name
    print("Classifier:", name)

    # Print the classification report
    print("\nClassification Report:\n")
    print(classification_report(y_test, y_pred))



    # Create Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    # Plotting the confusion matrix with colors
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, cmap="Blues", fmt="d", xticklabels=['<=50k','>
    plt.title(f"Confusion Matrix - {name}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    # Add a separator for clarity

    print("="*100)
    print('\n\n\n')
```

```
==============================================================================
=========================
```

In [41]:

```
metrics_df = pd.DataFrame(columns=['Model', 'Accuracy', 'Precision', 'Recall',


for classifier, name in classifiers:
    y_pred = classifier.predict(X_test)  # Replace X_test with your test data
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred, average='weighted')
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')
    metrics_df = metrics_df.append({'Model': name, 'Accuracy': accuracy, 'Prec
                                    'Recall': recall, 'F1-Score': f1}, ignore_
    metrics_df = metrics_df.sort_values(by='F1-Score', ascending=False)

display(metrics_df)
```

| | Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| **7** | XGBoost | 0.874616 | 0.870767 | 0.874616 | 0.871335 |
| **0** | Gradient Boosting Machine | 0.867957 | 0.863352 | 0.867957 | 0.861930 |
| **1** | K-Nearest Neighbors | 0.856894 | 0.853491 | 0.856894 | 0.854733 |
| **2** | Random Forest | 0.848392 | 0.843501 | 0.848392 | 0.844996 |
| **3** | Logistic Regression | 0.850748 | 0.844274 | 0.850748 | 0.844231 |
| **4** | Decision Tree | 0.816431 | 0.815976 | 0.816431 | 0.816200 |
| **5** | Naive Bayes | 0.783651 | 0.832494 | 0.783651 | 0.795729 |
| **6** | Support Vector Machine | 0.799939 | 0.791122 | 0.799939 | 0.764991 |

In [42]:

```
importances = classifier.feature_importances_

feature_names = X_train.columns  # Replace with the actual feature names or co
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importan
importance_df = importance_df.sort_values(by='Importance', ascending=False)
print(importance_df)
```

```
                              Feature  Importance
16  marital-status_ Married-civ-spouse    0.490016
2                        capital-gain    0.048139
39             relationship_ Own-child    0.040554
1                       education-num    0.035776
28           occupation_ Other-service    0.023070
..                                ...         ...
64            native-country_ Honduras    0.000000
63  native-country_ Holand-Netherlands    0.000000
62               native-country_ Haiti    0.000000
58              native-country_ France    0.000000
65                native-country_ Hong    0.000000

[91 rows x 2 columns]
```

In [ ]: