AMULYA REDDY DATLA
CSE 574
PROJECT-1
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```
#Ignore the warnings if any
import warnings
warnings.filterwarnings('ignore')
```

The above code snippet ignores all the warnings that might occur while running the code

```
#Import all the necessary libraries
import pandas as pd
import numpy as np
from IPython.display import Image, display
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

The above code snippet imports all the required libraries

```
#Setting the option to display maximum number of columns and rows
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

The above code snippet sets the option to visialize maximum number of columns and rows

1. Load the dataset (Points: 5)

```
#Load the dataset
columns=["age","workclass","fnlwgt","education","education-
num","marital-
status","occupation","relationship","race","sex","capital-
```

```
gain","capital-loss","hours-per-week","native-country","income"]
file_path = r"C:\Users\L E N O V O\Desktop\ML\Project_1_python\
dataset_adult\adult.data"
df = pd.read_csv(file_path, names=columns,sep=",\
s*",engine="python",na_values="?")
```

The above code loads a CSV dataset named "adult.data" into a pandas DataFrame, specifying column names, using comma-space as the separator and handling "?" as missing values

2. Output the structure of the dataset (Points: 10)

```
#Display few tuples of the dataset
df.head()

   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

       marital-status         occupation   relationship   race     sex
\
0       Never-married       Adm-clerical  Not-in-family  White    Male

1  Married-civ-spouse    Exec-managerial        Husband  White    Male

2            Divorced  Handlers-cleaners  Not-in-family  White    Male

3  Married-civ-spouse  Handlers-cleaners        Husband  Black    Male

4  Married-civ-spouse     Prof-specialty           Wife  Black  Female


   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

#Display the column names of the data
df.columns

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')
```

```
#Display the information of dataset
df.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       30725 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      30718 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  31978 non-null  object
 14  income          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB

#Describe the statistical characteristics of the dataset
df.describe()

                age        fnlwgt  education-num  capital-gain
capital-loss  \
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

       hours-per-week
count    32561.000000
```

```
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000

#Display datatype of values in each column
print(df.dtypes)

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

#Display the shape of the dataset
print("Shape of the dataset is",df.shape)

Shape of the dataset is (32561, 15)
```

The above commands display a sample of the data, list column names, summarize data types and missing values, provide descriptive statistics for numerical columns, and show the overall dimensions of the dataset. All these together offer a comprehensive initial overview of the structure and content of the dataset.

3. Clean the dataset, handle the missing values and encode the categorical values (Points: 15)

```
#Display the number of null values in the data before cleaning
print(df.isnull().sum())

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
```

```
#Data cleaning step to remove duplicates
df.drop_duplicates(inplace=True)

#Handling missing values
categorical_columns=df.select_dtypes(include=['object']).columns
numerical_columns=df.select_dtypes(include=['int64','float64']).column
s
print("Categorical columns in the dataset are:",categorical_columns)
print("Numerical columns in the dataset are:",numerical_columns)
for col in categorical_columns:
    df[col].fillna(df[col].mode()[0],inplace=True)
for col in numerical_columns:
    df[col].fillna(df[col].mean,inplace=True)
```

```
Categorical columns in the dataset are: Index(['workclass',
'education', 'marital-status', 'occupation',
       'relationship', 'race', 'sex', 'native-country', 'income'],
      dtype='object')
Numerical columns in the dataset are: Index(['age', 'fnlwgt',
'education-num', 'capital-gain', 'capital-loss',
       'hours-per-week'],
      dtype='object')
```

```
#Display number of unique values for each categorical columns
distinct_values = df[categorical_columns].nunique()
print(distinct_values)
```

```
workclass          8
education         16
marital-status     7
occupation        14
relationship       6
race               5
sex                2
native-country    41
income             2
dtype: int64
```

```
#Displaying number of null values after data cleaning
print(df.isnull().sum())
```

```
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
```

A comprehensive data cleaning process is formed by the above collective steps, through which data quality issues, such as missing values and duplicates, are identified and quantified. Redundant entries are removed, and missing data is handled appropriately, with categorical gaps being filled by the mode and numerical gaps by the mean. Insights into the structure of categorical data are provided through unique value counts. The effectiveness of the cleaning is verified by a final check for remaining null values. Consequently, the dataset is rendered more suitable for further analysis or modeling, and the risk of inaccurate results or misleading insights is minimized.

```
#Label encoding of categorical features
encoding_maps = []
for col in categorical_columns:
    unique_values = df[col].unique()
    value_to_number = {value: number for number, value in
enumerate(unique_values, start=1)}
    df[col] = df[col].map(value_to_number)
    encoding_maps.append({
        'column': col,
        'mapping': value_to_number
    })
k={}
for encoding in encoding_maps:
    k[encoding['column']]=encoding['mapping']
    print(encoding['column'],k[encoding['column']])
```

```
workclass {'State-gov': 1, 'Self-emp-not-inc': 2, 'Private': 3,
'Federal-gov': 4, 'Local-gov': 5, 'Self-emp-inc': 6, 'Without-pay': 7,
'Never-worked': 8}
education {'Bachelors': 1, 'HS-grad': 2, '11th': 3, 'Masters': 4,
'9th': 5, 'Some-college': 6, 'Assoc-acdm': 7, 'Assoc-voc': 8, '7th-
8th': 9, 'Doctorate': 10, 'Prof-school': 11, '5th-6th': 12, '10th':
13, '1st-4th': 14, 'Preschool': 15, '12th': 16}
```

```
marital-status {'Never-married': 1, 'Married-civ-spouse': 2,
'Divorced': 3, 'Married-spouse-absent': 4, 'Separated': 5, 'Married-
AF-spouse': 6, 'Widowed': 7}
occupation {'Adm-clerical': 1, 'Exec-managerial': 2, 'Handlers-
cleaners': 3, 'Prof-specialty': 4, 'Other-service': 5, 'Sales': 6,
'Craft-repair': 7, 'Transport-moving': 8, 'Farming-fishing': 9,
'Machine-op-inspct': 10, 'Tech-support': 11, 'Protective-serv': 12,
'Armed-Forces': 13, 'Priv-house-serv': 14}
relationship {'Not-in-family': 1, 'Husband': 2, 'Wife': 3, 'Own-
child': 4, 'Unmarried': 5, 'Other-relative': 6}
race {'White': 1, 'Black': 2, 'Asian-Pac-Islander': 3, 'Amer-Indian-
Eskimo': 4, 'Other': 5}
sex {'Male': 1, 'Female': 2}
native-country {'United-States': 1, 'Cuba': 2, 'Jamaica': 3, 'India':
4, 'Mexico': 5, 'South': 6, 'Puerto-Rico': 7, 'Honduras': 8,
'England': 9, 'Canada': 10, 'Germany': 11, 'Iran': 12, 'Philippines':
13, 'Italy': 14, 'Poland': 15, 'Columbia': 16, 'Cambodia': 17,
'Thailand': 18, 'Ecuador': 19, 'Laos': 20, 'Taiwan': 21, 'Haiti': 22,
'Portugal': 23, 'Dominican-Republic': 24, 'El-Salvador': 25, 'France':
26, 'Guatemala': 27, 'China': 28, 'Japan': 29, 'Yugoslavia': 30,
'Peru': 31, 'Outlying-US(Guam-USVI-etc)': 32, 'Scotland': 33,
'Trinadad&Tobago': 34, 'Greece': 35, 'Nicaragua': 36, 'Vietnam': 37,
'Hong': 38, 'Ireland': 39, 'Hungary': 40, 'Holand-Netherlands': 41}
income {'<=50K': 1, '>50K': 2}
```

The above code snippet performs label encoding on categorical features within a dataset by iterating through each categorical column and creating a unique mapping of categorical values to numerical labels. The original categorical values in the dataframe are replaced with their corresponding numerical labels, and these mappings are stored in a list called 'encoding_maps' for future reference.

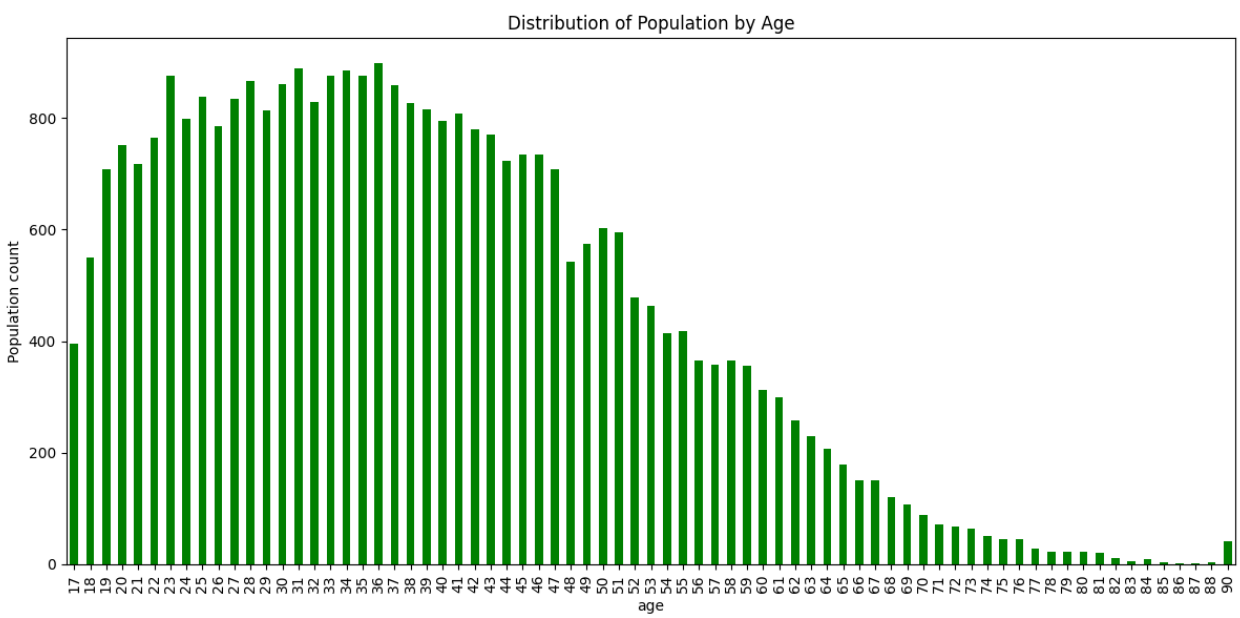
```
#Displaying shape of the data frame and few tuples after data cleaning
and encoding
print(df.shape)
df.head()

(32537, 15)

   age  workclass  fnlwgt  education  education-num  marital-status  \
0   39          1   77516          1             13               1
1   50          2   83311          1             13               2
2   38          3  215646          2              9               3
3   53          3  234721          3              7               2
4   28          3  338409          1             13               2

   occupation  relationship  race  sex  capital-gain  capital-loss  \
0           1             1     1    1          2174             0
1           2             2     1    1             0             0
2           3             1     1    1             0             0
```

```
3            3             2      2    1              0              0
4            4             3      2    2              0              0

   hours-per-week  native-country  income
0              40               1       1
1              13               1       1
2              40               1       1
3              40               1       1
4              40               2       1
```

The above code snippet displays the shape and few tuples of the data after performing the data cleaning and encoding.

4.Explore the data to understand better, for example, draw a bar plot to identify the distribution of the population in the dataset by age, followed by distribution of income by gender. (Points: 20)

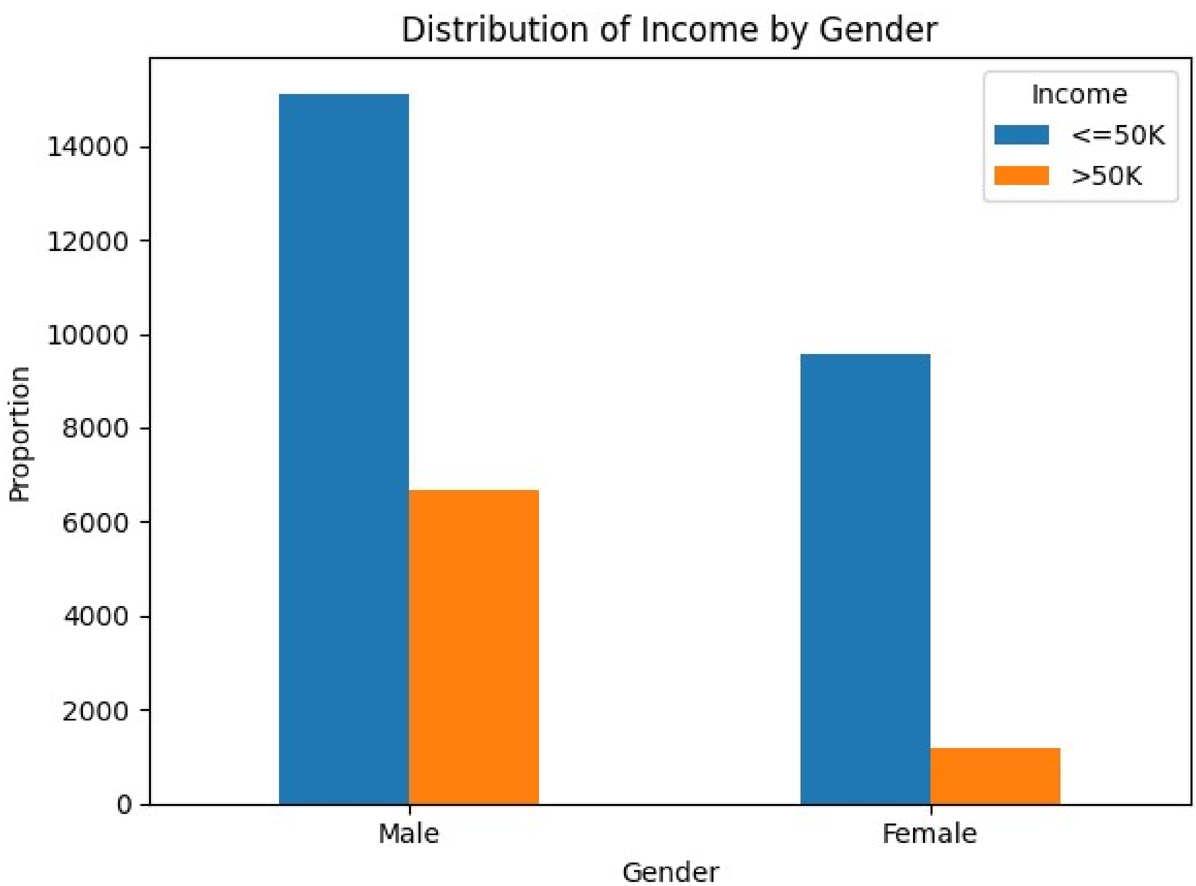
```
#Barplot for distribution of population by age
plt.figure(figsize=(12, 6))
df['age'].value_counts().sort_index().plot(kind='bar',color='green')
plt.title('Distribution of Population by Age')
plt.xlabel('age')
plt.ylabel('Population count')
plt.tight_layout()
plt.show()
```



The above bar plot is showing the distribution of population by age. Each bar represents the population count for a specific age, with ages on the x-axis and population count on the y-axis. The bars are colored green. The chart is titled "Distribution of Population by Age," and it appears to have a peak in the younger age groups, gradually declining as age increases. The layout is adjusted for clarity, with labels for both axes

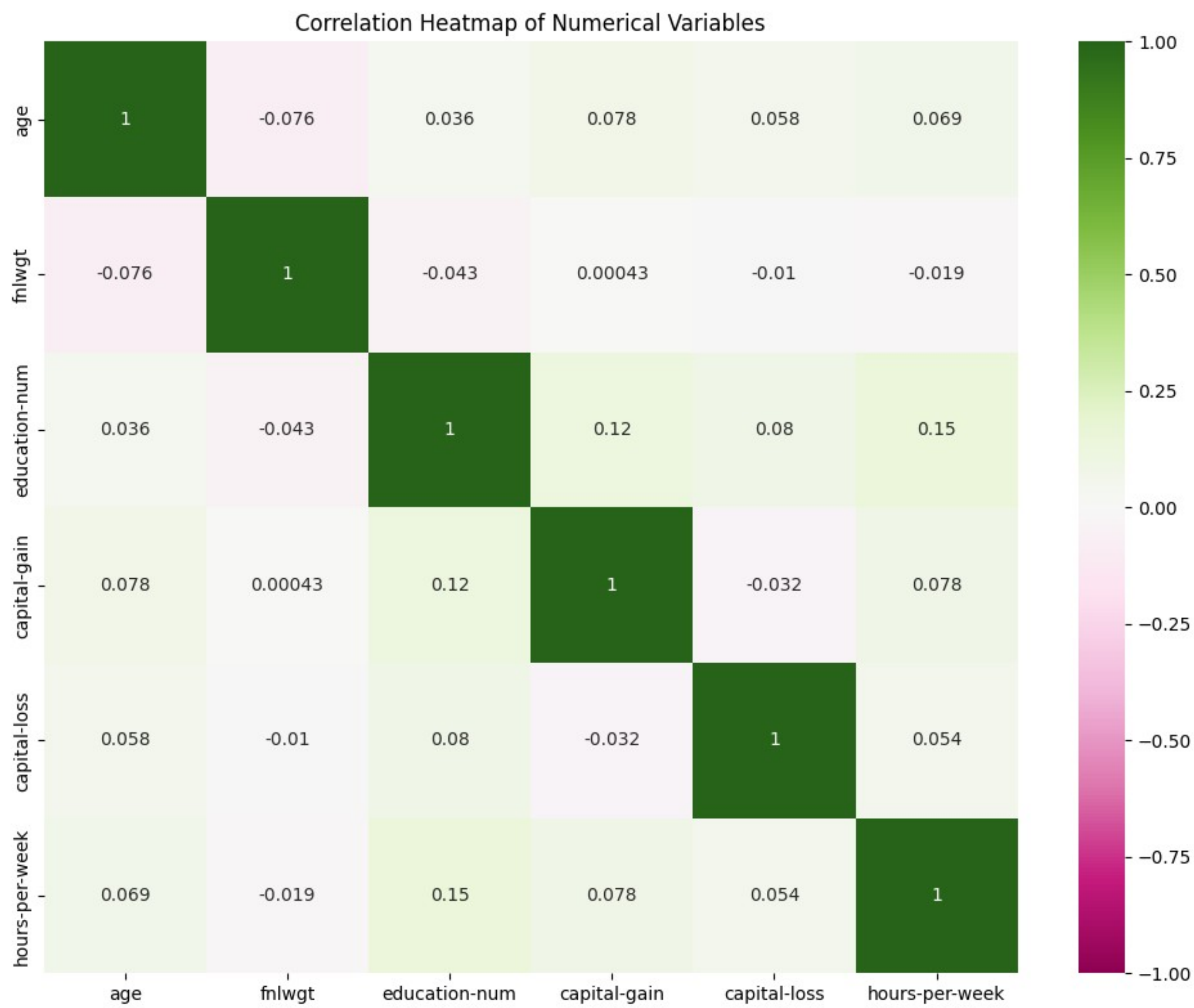
```
# Barplot for distribution of income by gender
print(k['income'],k['sex'])
plt.figure(figsize=(12, 6))
income_by_gender = df.groupby(['sex', 'income']).size().unstack()
income_by_gender.plot(kind='bar')
plt.title('Distribution of Income by Gender')
plt.xlabel('Gender')
plt.ylabel('Proportion')
plt.xticks([0, 1], ['Male', 'Female'],rotation=0)
plt.legend(title='Income',labels=['<=50K', '>50K'])
plt.tight_layout()
plt.show()
```

```
{'<=50K': 1, '>50K': 2} {'Male': 1, 'Female': 2}

<Figure size 1200x600 with 0 Axes>
```



The above bar plot illustrates the distribution of income by gender. It shows that a larger number of males earn both <=50K and >50K compared to females. For both genders, the majority fall into the <=50K category, but the disparity is more pronounced among females, with a smaller proportion earning >50K. This plot highlights a gender gap in higher income brackets.

```
#Correlation matrix for all the numerical columns
correlation_matrix = df[numerical_columns].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='PiYG', vmin=-1,
vmax=1, center=0)
plt.title('Correlation Heatmap of Numerical Variables')
plt.tight_layout()
plt.show()
```



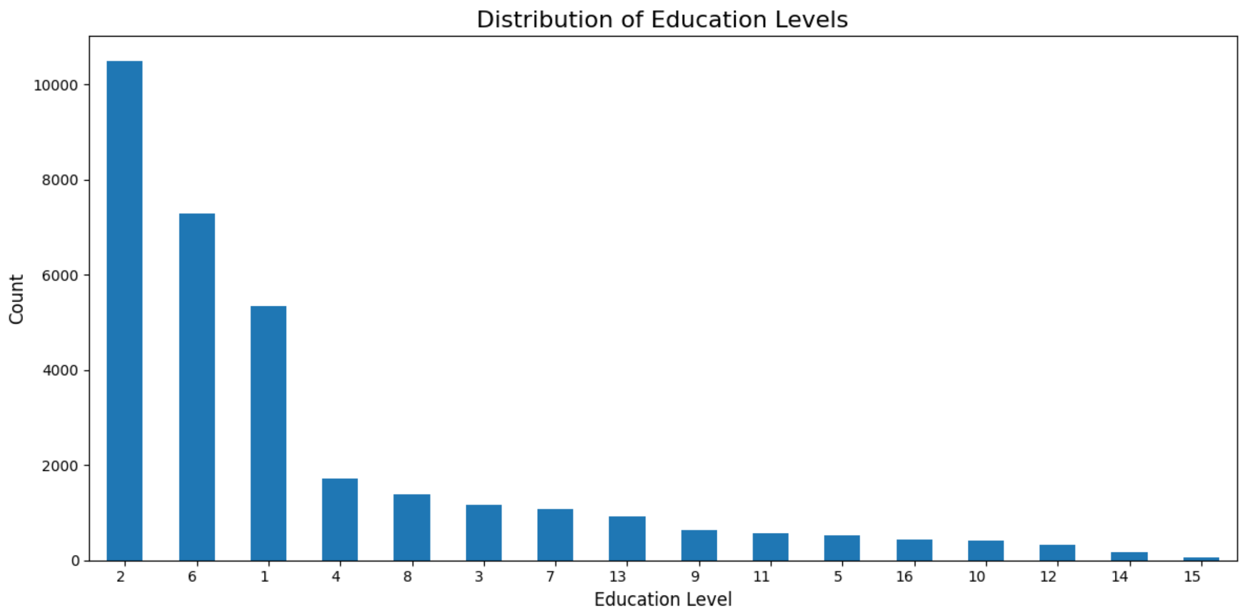
The above correlation heatmap shows the relationships between numerical features, with colors indicating the strength and direction of correlations. Most variables exhibit weak correlations, as reflected by the light colors.

```
#Display of correlation matrix
print(df[numerical_columns].corr())
```

```
                      age    fnlwgt  education-num  capital-gain
capital-loss  \
age             1.000000 -0.076447       0.036224      0.077676
0.057745
fnlwgt         -0.076447  1.000000      -0.043388      0.000429      -
0.010260
education-num   0.036224 -0.043388       1.000000      0.122664
0.079892
capital-gain    0.077676  0.000429       0.122664      1.000000      -
0.031639
capital-loss    0.057745 -0.010260       0.079892     -0.031639
1.000000
hours-per-week  0.068515 -0.018898       0.148422      0.078408
0.054229

                hours-per-week
age                   0.068515
fnlwgt               -0.018898
education-num         0.148422
capital-gain          0.078408
capital-loss          0.054229
hours-per-week        1.000000
```

The above code snippet calculates and displays the correlation matrix for the numerical columns in the DataFrame. The resulting correlation matrix shows the relationships between numerical features.

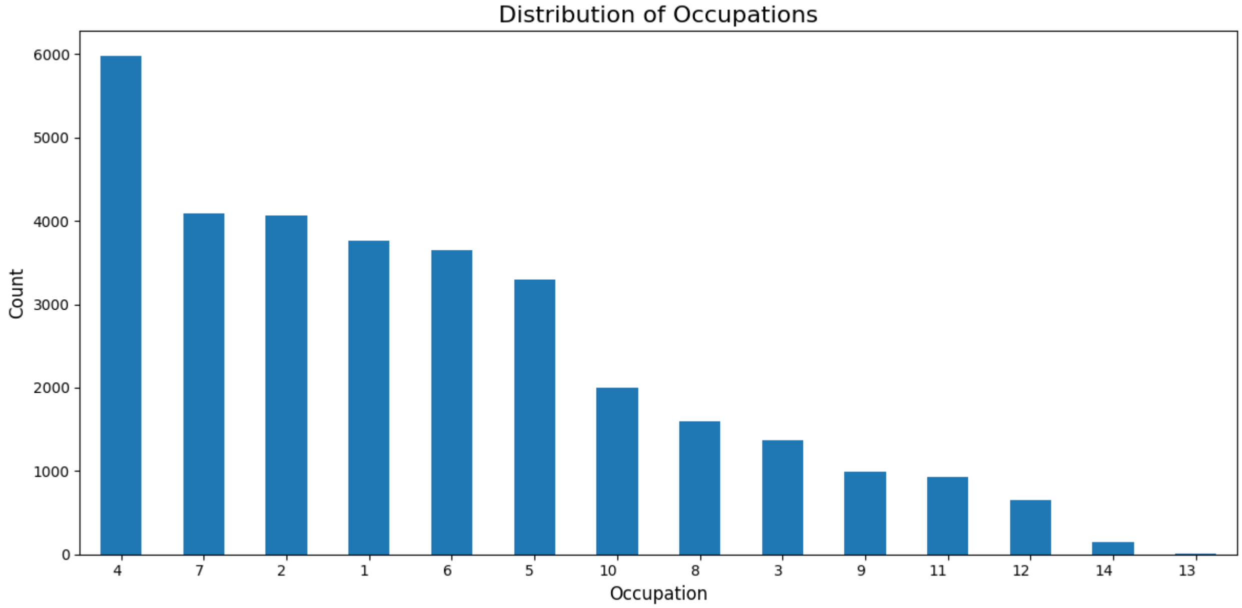
```
# Distribution of education levels
print(k['education'])
plt.figure(figsize=(12, 6))
education_counts =
df['education'].value_counts().sort_values(ascending=False)
education_counts.plot(kind='bar')
plt.title('Distribution of Education Levels', fontsize=16)
plt.xlabel('Education Level', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=0, ha='right')
plt.tight_layout()
plt.show()

{'Bachelors': 1, 'HS-grad': 2, '11th': 3, 'Masters': 4, '9th': 5,
'Some-college': 6, 'Assoc-acdm': 7, 'Assoc-voc': 8, '7th-8th': 9,
'Doctorate': 10, 'Prof-school': 11, '5th-6th': 12, '10th': 13, '1st-
4th': 14, 'Preschool': 15, '12th': 16}
```



The above bar chart shows the distribution of education levels. Most individuals fall into the education levels of HS-grad, Some-college and Bachelors with the highest counts. The education level Preschool is the least. The x-axis lists education levels, and the y-axis shows the count of individuals.

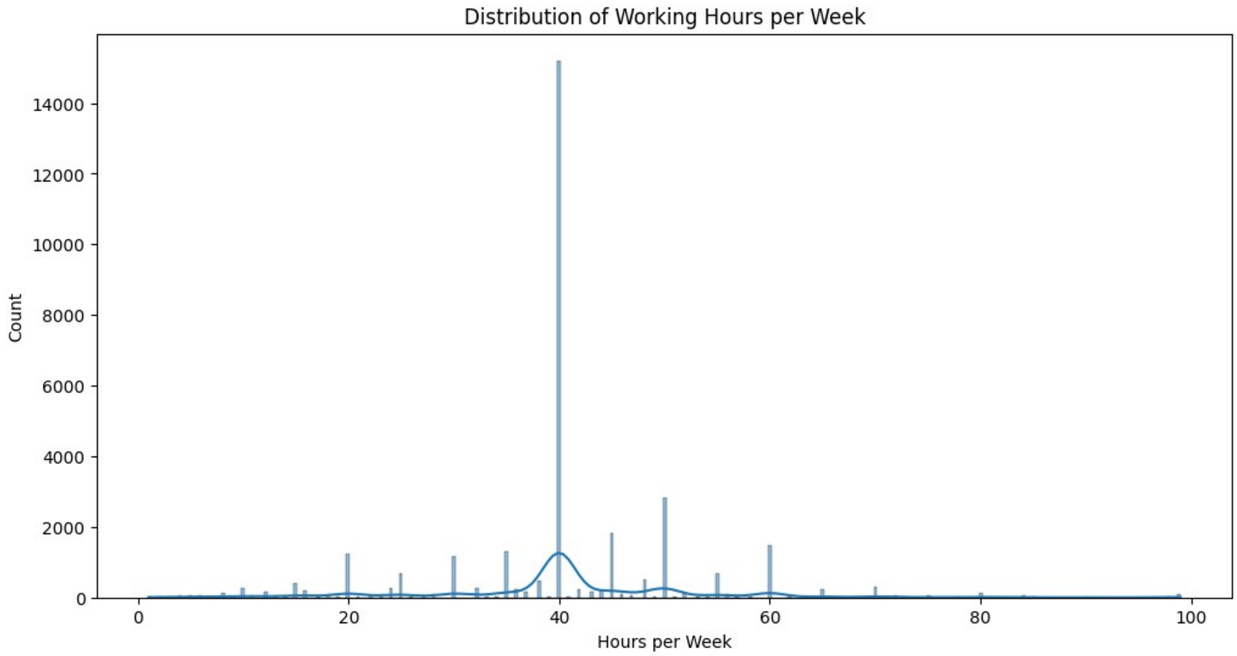
```
# Distribution of occupations
print(k['occupation'])
plt.figure(figsize=(12, 6))
occupation_counts =
df['occupation'].value_counts().sort_values(ascending=False)
occupation_counts.plot(kind='bar')
plt.title('Distribution of Occupations', fontsize=16)
plt.xlabel('Occupation', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.xticks(rotation=0, ha='right')
plt.tight_layout()
plt.show()
```

```
{'Adm-clerical': 1, 'Exec-managerial': 2, 'Handlers-cleaners': 3,
'Prof-specialty': 4, 'Other-service': 5, 'Sales': 6, 'Craft-repair':
7, 'Transport-moving': 8, 'Farming-fishing': 9, 'Machine-op-inspct':
10, 'Tech-support': 11, 'Protective-serv': 12, 'Armed-Forces': 13,
'Priv-house-serv': 14}
```



The above bar chart shows the distribution of Occupations. Occupation of Prof-specialty has the highest count of individuals. Occupations Craft-repair, Exec-managerial and Adm-clerical have reasonably good count of individuals.The occupation of Armed-Forces is the least. The x-axis lists Occupations, and the y-axis shows the count of individuals.

```
#Distribution of Working Hours per Week
plt.figure(figsize=(12, 6))
sns.histplot(df['hours-per-week'], kde=True)
plt.title('Distribution of Working Hours per Week')
plt.xlabel('Hours per Week')
plt.show()
```

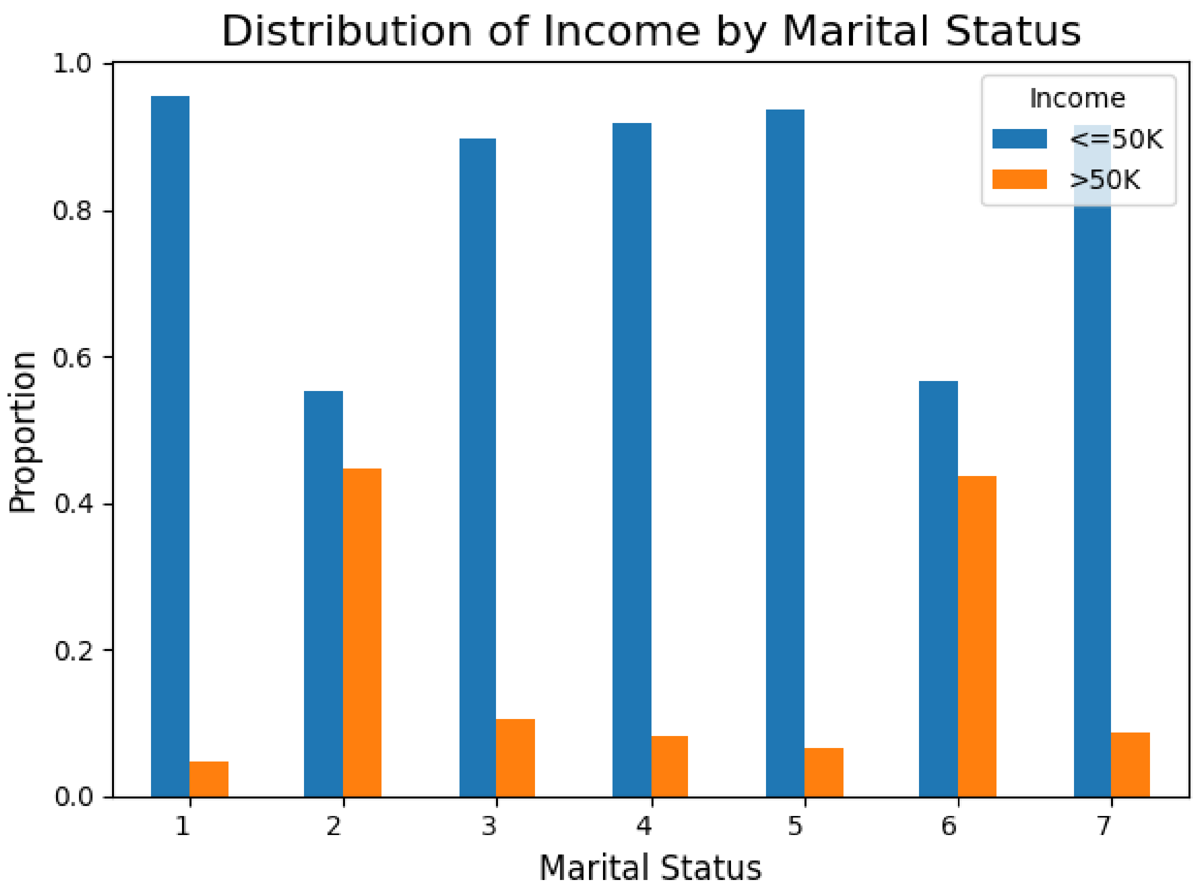


The above plot shows the distribution of working hours per week, with a sharp peak around 40 hours. The x-axis represents hours worked, and the y-axis shows the count of individuals. A density curve overlays the histogram to highlight the distribution pattern.

```
#Distribution of Income by Marital Status
print(k['marital-status'],k['income'])
plt.figure(figsize=(12, 6))
income_by_marital = df.groupby('marital-status')
['income'].value_counts(normalize=True).unstack()
income_by_marital.plot(kind='bar', stacked=False)
plt.title('Distribution of Income by Marital Status', fontsize=16)
plt.xlabel('Marital Status', fontsize=12)
plt.ylabel('Proportion', fontsize=12)
plt.legend(title='Income', labels=['<=50K', '>50K'])
plt.xticks(rotation=0, ha='right')
plt.tight_layout()
plt.show()
```

```
{'Never-married': 1, 'Married-civ-spouse': 2, 'Divorced': 3, 'Married-
spouse-absent': 4, 'Separated': 5, 'Married-AF-spouse': 6, 'Widowed':
7} {'<=50K': 1, '>50K': 2}
```

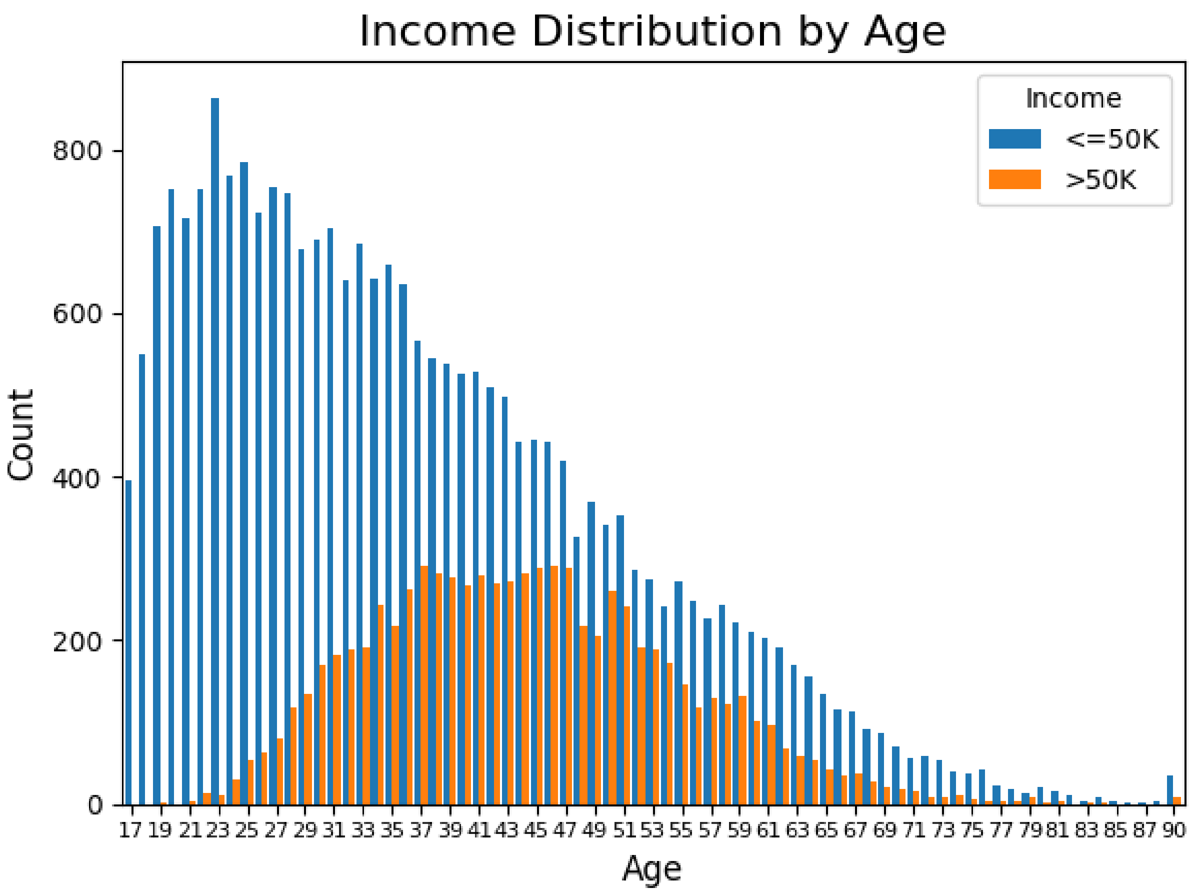
```
<Figure size 1200x600 with 0 Axes>
```



The above bar chart shows the distribution of income by marital status. Each marital status category is represented on the x-axis, with proportions of income levels (<=50K and >50K) on the y-axis. Blue bars indicate lower income, while orange bars indicate higher income. Most categories have a higher proportion of individuals earning <=50K.

```
#Distribution of income by age
income_by_age = df.groupby(['age', 'income']).size().unstack()
income_by_age.columns = ['<=50K', '>50K']
plt.figure(figsize=(25, 10))
income_by_age.plot(kind='bar', stacked=False, width=0.9)
plt.title('Income Distribution by Age', fontsize=16)
plt.xlabel('Age', fontsize=12)
plt.ylabel('Count', fontsize=12)
plt.legend(title='Income')
plt.xticks(range(0, len(income_by_age), 2), income_by_age.index[::2],
rotation=0, fontsize=8)
plt.tight_layout()
plt.show()
```

```
<Figure size 2500x1000 with 0 Axes>
```

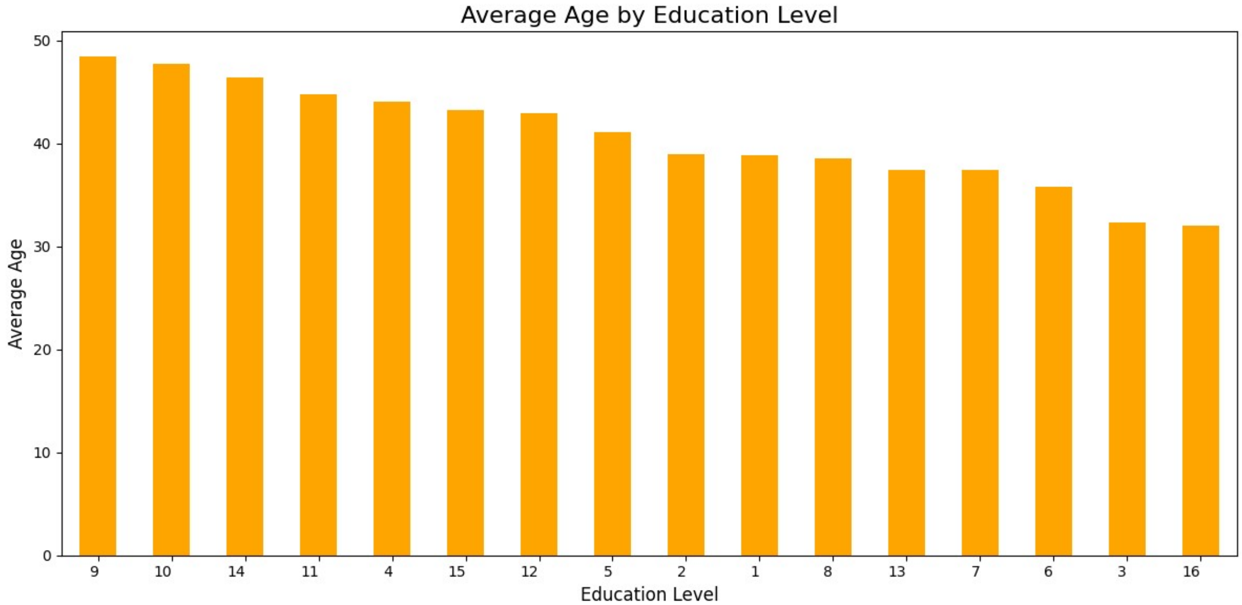


The bar chart illustrates income distribution by age. The x-axis represents age groups, while the y-axis shows the count of individuals. Two income categories (<=50K and >50K) are displayed with different colors. The chart reveals that younger age groups have a higher count of individuals earning <=50K, with the distribution tapering off as age increases. The individuals within 37-39 and 47-49 are more likely to have earnings >50K.

```
#Distribution of average Age by Education Level
print(k['education'])
avg_age_by_education = df.groupby('education')
['age'].mean().sort_values(ascending=False)
plt.figure(figsize=(12, 6))
avg_age_by_education.plot(kind='bar', color='orange')
plt.title('Average Age by Education Level', fontsize=16)
plt.xlabel('Education Level', fontsize=12)
plt.ylabel('Average Age', fontsize=12)
plt.xticks(rotation=0, ha='right')
plt.tight_layout()
plt.show()
```

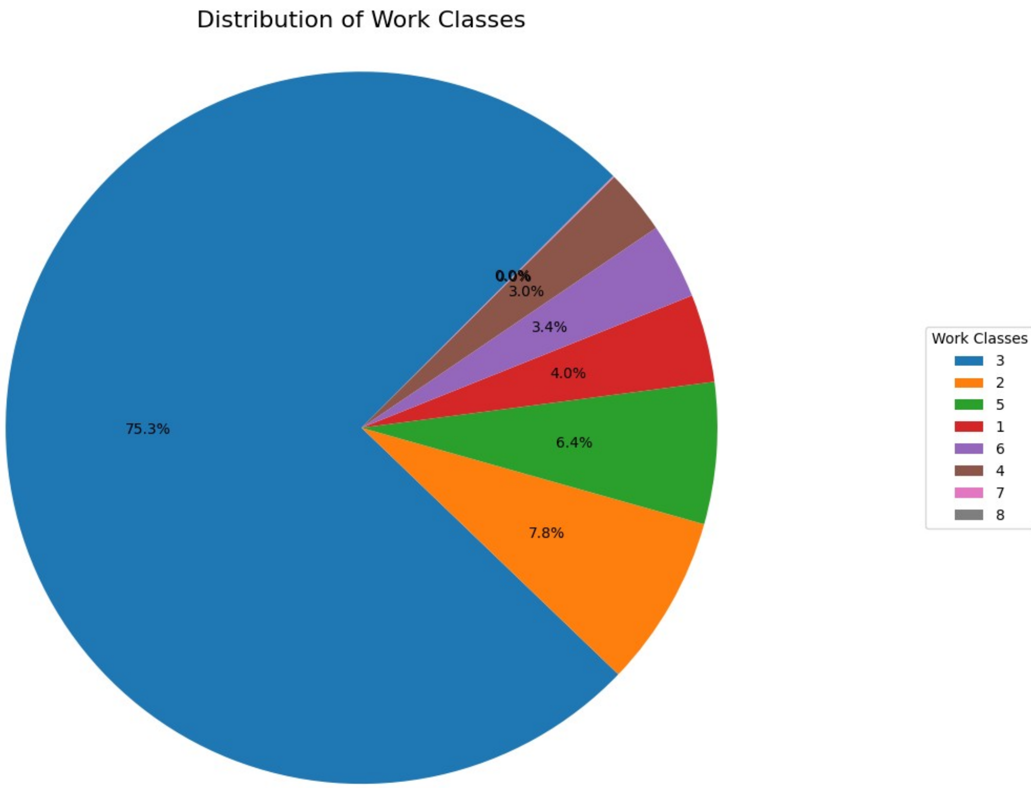
```
{'Bachelors': 1, 'HS-grad': 2, '11th': 3, 'Masters': 4, '9th': 5,
'Some-college': 6, 'Assoc-acdm': 7, 'Assoc-voc': 8, '7th-8th': 9,
```

```
'Doctorate': 10, 'Prof-school': 11, '5th-6th': 12, '10th': 13, '1st-4th': 14, 'Preschool': 15, '12th': 16}
```



The above bar chart displays the average age by education level. The x-axis represents different education levels, while the y-axis shows the average age of individuals within each level. The bars are colored orange, and the chart indicates that higher education levels are associated with older average ages. The title and axis labels provide clear context for the data presented.

```
#Distribution of Work Classes
print(k['workclass'])
workclass_counts = df['workclass'].value_counts()
plt.figure(figsize=(12, 8))
patches, texts, autotexts = plt.pie(workclass_counts.values,
autopct='%1.1f%%', startangle=45)
plt.title('Distribution of Work Classes', fontsize=16)
plt.axis('equal')
plt.legend(patches, workclass_counts.index, title="Work Classes",
loc="center left", bbox_to_anchor=(1, 0.5))
plt.tight_layout()
plt.show()

{'State-gov': 1, 'Self-emp-not-inc': 2, 'Private': 3, 'Federal-gov': 4, 'Local-gov': 5, 'Self-emp-inc': 6, 'Without-pay': 7, 'Never-worked': 8}
```



The above pie chart displays the distribution of different work classes. The largest segment, comprising 75.3%, belongs to "Private" workclass. Other notable segments include "Self-emp-not-inc" at 7.8% and "Local-gov" at 6.4%. Smaller segments range from 0% to 4%. The chart is visually balanced with a legend indicating the work class numbers and their corresponding colors.

5) Apply predictive modeling to the data to predict whether an individual earns more than $5π0K a year. (Points: 30)

```
#Preparing the target and the features in training dataset
y_train = df['income']
X_train = df.drop(['income'], axis=1)

# Training the models
models = {
    'Logistic Regression': LogisticRegression(random_state=42),
    'Random Forest': RandomForestClassifier(random_state=42),
    'SVM': SVC(random_state=42),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(random_state=42),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB(),
    'AdaBoost': AdaBoostClassifier(random_state=42),
    'Extra Trees': ExtraTreesClassifier(random_state=42),
    }
```

```
for name, model in models.items():
    model.fit(X_train, y_train)
    print(f"\n{name} trained.")
```

```
Logistic Regression trained.

Random Forest trained.

SVM trained.

Decision Tree trained.

Gradient Boosting trained.

K-Nearest Neighbors trained.

Naive Bayes trained.

AdaBoost trained.

Extra Trees trained.
```

The above code snippet prepares the training data by separating the target variable ('income') from the features. It initializes a dictionary of various classification models, including Logistic Regression, Random Forest, SVM, Decision Tree, Gradient Boosting, K-Nearest Neighbors, Naive Bayes, AdaBoost, and Extra Trees. The code then iterates through the dictionary, fitting each model to the training data (X_train and y_train) and printing a message upon successful training. This allows for the simultaneous training of multiple models for subsequent performance comparison in the machine learning pipeline.

```
#loading test data
file_path = r"C:\Users\L E N O V O\Desktop\ML\Project_1_python\
dataset_adult\adult.test"
df_test = pd.read_csv(file_path, names=columns, sep=",\s*",
engine="python", na_values="?")
df_test = df_test[1:]
df_test=df_test.dropna()
df_test[numerical_columns] =
df_test[numerical_columns].apply(pd.to_numeric, downcast="integer")
df_test['income'] = df_test['income'].str.replace('.', '',
regex=False)
df_test.head()
```

```
   age  workclass  fnlwgt     education  education-num      marital-
status  \
1   25    Private  226802          11th              7        Never-
married
2   38    Private   89814       HS-grad              9  Married-civ-
spouse
```

```
3   28  Local-gov  336951    Assoc-acdm             12  Married-civ-
spouse
4   44    Private  160323  Some-college             10  Married-civ-
spouse
6   34    Private  198693          10th              6       Never-
married

          occupation   relationship   race   sex  capital-gain
capital-loss  \
1  Machine-op-inspct      Own-child  Black  Male             0
0
2    Farming-fishing        Husband  White  Male             0
0
3    Protective-serv        Husband  White  Male             0
0
4  Machine-op-inspct        Husband  Black  Male          7688
0
6      Other-service  Not-in-family  White  Male             0
0

   hours-per-week native-country income
1              40  United-States  <=50K
2              50  United-States  <=50K
3              40  United-States   >50K
4              40  United-States   >50K
6              30  United-States  <=50K

#encoding
for col in categorical_columns:
    df_test[col] = df_test[col].map(k[col])

#Getting target and features for test data
y_test = df_test['income']
X_test = df_test.drop(['income'], axis=1)
```

The above few snippets of code reads the test data from a CSV file, preprocesses it by handling missing values and data types, encodes categorical features using the same mapping as the training data, and separates the target variable ('income') from the features. The result is a prepared test dataset (X_test and y_test) ready for model evaluation

```
# Accuracies of various models
for name, model in models.items():
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"\n{name} Accuracy: {accuracy*100:.4f}")
    print(classification_report(y_test, y_pred))


Logistic Regression Accuracy: 79.3559
              precision    recall  f1-score   support
```

```
           1       0.80      0.96      0.88     11360
           2       0.71      0.27      0.39      3700

    accuracy                           0.79     15060
   macro avg       0.76      0.62      0.63     15060
weighted avg       0.78      0.79      0.76     15060


Random Forest Accuracy: 84.9402
              precision    recall  f1-score   support

           1       0.88      0.93      0.90     11360
           2       0.73      0.61      0.67      3700

    accuracy                           0.85     15060
   macro avg       0.81      0.77      0.78     15060
weighted avg       0.84      0.85      0.84     15060


SVM Accuracy: 79.1169
              precision    recall  f1-score   support

           1       0.78      1.00      0.88     11360
           2       0.96      0.16      0.27      3700

    accuracy                           0.79     15060
   macro avg       0.87      0.58      0.57     15060
weighted avg       0.83      0.79      0.73     15060


Decision Tree Accuracy: 80.7902
              precision    recall  f1-score   support

           1       0.88      0.87      0.87     11360
           2       0.61      0.62      0.61      3700

    accuracy                           0.81     15060
   macro avg       0.74      0.75      0.74     15060
weighted avg       0.81      0.81      0.81     15060


Gradient Boosting Accuracy: 86.2218
              precision    recall  f1-score   support

           1       0.88      0.95      0.91     11360
           2       0.79      0.59      0.68      3700

    accuracy                           0.86     15060
   macro avg       0.84      0.77      0.80     15060
weighted avg       0.86      0.86      0.85     15060
```

```
K-Nearest Neighbors Accuracy: 76.9920
              precision    recall  f1-score   support

           1       0.81      0.92      0.86     11360
           2       0.55      0.32      0.41      3700

    accuracy                           0.77     15060
   macro avg       0.68      0.62      0.63     15060
weighted avg       0.74      0.77      0.75     15060


Naive Bayes Accuracy: 78.8911
              precision    recall  f1-score   support

           1       0.81      0.95      0.87     11360
           2       0.65      0.31      0.42      3700

    accuracy                           0.79     15060
   macro avg       0.73      0.63      0.64     15060
weighted avg       0.77      0.79      0.76     15060


AdaBoost Accuracy: 85.3785
              precision    recall  f1-score   support

           1       0.88      0.94      0.91     11360
           2       0.76      0.59      0.67      3700

    accuracy                           0.85     15060
   macro avg       0.82      0.77      0.79     15060
weighted avg       0.85      0.85      0.85     15060


Extra Trees Accuracy: 83.7915
              precision    recall  f1-score   support

           1       0.88      0.91      0.89     11360
           2       0.69      0.61      0.65      3700

    accuracy                           0.84     15060
   macro avg       0.79      0.76      0.77     15060
weighted avg       0.83      0.84      0.83     15060
```

This code snippet evaluates the performance of selected machine learning models on the test dataset. It predicts outcomes using each model on the test data (X_test) and calculates accuracy by comparing predictions to the actual values (y_test). The accuracy is printed as a percentage for each model, along with a classification report that includes metrics like precision, recall, and F1-score, enabling a detailed comparison of model performances.

Conclusion: Based on the model accuracies, Gradient Boosting model achieved the highest accuracy at 86.22%, making it the best-performing model for this dataset. AdaBoost and Random Forest also performed well, with accuracies of 85.38% and 84.94% respectively. Extra Trees and Decision Tree showed moderate performance, with accuracies of 83.79% and 80.79%. Logistic Regression and SVM had similar accuracies, around 79%. Naive Bayes and K-Nearest Neighbors had the lowest accuracies, at 78.89% and 76.99%. Overall, ensemble methods like Gradient Boosting and AdaBoost provided superior accuracy compared to other models.

6) In conclusion, prepare a project report with the code to show the diagrams and output generated and submit a poster using the template provided. Use creativity to represent the results in the poster format. In your poster, you need to cite the dataset as "Becker, B. & Kohavi, R. (1996). Adult [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C5XW20."(Points: 20)

```
image_path = r'C:\Users\L E N O V O\Desktop\ML\Project_1_python\Poster.jpg'
display(Image(filename=image_path))
```

AMULYA REDDY DATLA

UB Person number: 50560100

Introduction:

This project aims to analyze the adult census bureau dataset to predict individuals with income '>50K' to achieve an accuracy of 85% or higher. Key tasks include data cleaning, exploratory data analysis, model development and performance evaluation.

Methods:

In this project data cleaning steps are performed after loading the dataset to make the exploratory data analysis clear. Dropping of the duplicate entries is done to eliminate redundancy. Handling null values is done by imputing categorical features with mode and numerical features with mean. Label encoding is done to all the categorical features.

Data Analysis:

In the comprehensive exploratory data analysis (EDA), examination of various demographic and socioeconomic factors to uncover valuable insights is done. Visualization of the distribution of the population by age and income by gender, revealed key trends and potential disparities.

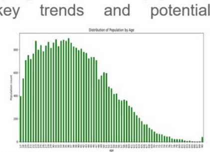


Figure 1

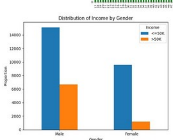


Figure 2

Correlation matrix and heatmap are generated to highlight significant relationships among the numerical variables. The plots obtained aided in understanding the relations carefully.

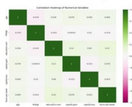


Figure 3

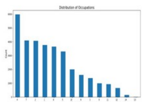


Figure 4

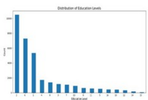


Figure 5

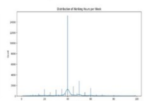


Figure 6

Additionally, the average age by educational level was analyzed, uncovering patterns in educational attainment. This thorough exploratory data analysis has laid a robust foundation for understanding the complex interplay of these factors within the dataset, paving the way for more in-depth analysis and insights.

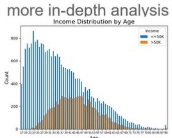


Figure 7

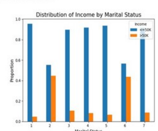


Figure 8

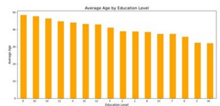


Figure 9

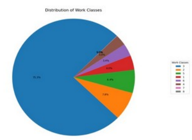


Figure 10

The figures represent the plots that serve as a foundation for further analysis and understanding of the patterns in the data.

Model Training and Prediction:

In this phase of the study, a diverse array of machine learning models was employed to predict income levels based on the features of the dataset. The models included Logistic Regression, Random Forest, Support Vector Machine(SVM), Decision Tree, Gradient Boosting, K-Nearest Neighbors, Naive Bayes, AdaBoost, and Extra Trees. Each model was systematically trained on the preprocessed dataset, utilizing various algorithmic approaches to capture different aspects of the underlying patterns in data. This selection of models allows for a robust evaluation of predictive performance across different machine learning paradigms, ensuring a thorough exploration of the predictive potential in a dataset.

Results:

The results of accuracy scores and additional classification metrics are obtained and ranking of the models based on their accuracy is as below.

1)Gradient Boosting: 86.2218%

2)AdaBoost: 85.3785%

3)Random Forest: 84.9402%

4)Extra Trees: 83.7915%

5)Decision Tree: 80.7902%

6)Logistic Regression: 79.3559%

7)SVM: 79.1169%

8)Naïve Bayes: 78.8911%

9)K-Nearest Neighbours: 76.9920%

Conclusion

In conclusion, the Gradient Boosting classifier performed the best overall for predicting the '>50K' income class, followed closely by Random Forest and AdaBoost. These ensemble methods demonstrated a good balance between precision and recall making them effective choices for this income prediction task.

References

1. Becker, B. & Kohavi, R. (1996). Adult [Dataset]. UCI Machine Learning Repository.

2.https://doi.org/10.24432/C5XW20