Lab 6: Data Analysis & Pre-Processing

For this lab, you will experiment with Python, NumPy and Pandas in order to perform some basic data preprocessing and exploratory tasks. You must only use Python, NumPy, Pandas & Matplotlib to perform the tasks for this lab.

Importing Libraries

Here are the following libraries to be imported as part of the requirements of the lab:

- **Pandas:** Pandas is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series.
- **NumPy:** NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays.
- **Matplotlib:** Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits.

In [1]:
```
# importing different libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

Part 1: Using Pandas DataFrame, Statistics & `describe()`

Be sure to do the following in order to complete part one completely:

- ☒Download the data set adult-modified.csv and load it into a appropriate data structure such as the Pandas DataFrame.
- ☒Explore the general characteristics of the data as a whole: examine the means, standard deviations, and other statistics associated with the numeric attributes.
- ☒Use `describe()` and frequencies associated with categorical attributes

Creating a DataFrane

Here, we create a DataFrame from the .csv file and then print out the details of that DataFrame

In [2]:
```
## taking the .csv file in and converting into a Pandas DataFrame
read_data = pd.read_csv("adult-modified.csv")

## printing out the DataFrame for viewing and understanding
read_data
```

Out[2]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
...	...	...	...	...	...	...	...	...
9407	38	Private	10	Married	White	Male	60	>50K
9408	25	Private	9	Single	White	Female	8	<=50K
9409	21	Private	10	Single	Black	Male	40	<=50K
9410	38	Private	2	Married	White	Male	53	<=50K
9411	39	Private	10	Single	White	Female	40	<=50K

9412 rows × 8 columns

Collecting all Integer Columns

We create a list ofall the column headings that contain integer values only

In [3]:
```
# collecting all the columns that have integer data values
integer_columns = ['age', 'education', 'hours-per-week']
```

Calculating the Mean, Median & Standard Deviation using `.mean()`, `.median()` and `std()`

We calculate the mean of all the integer columns by using the `mean()` function and then print out the mean of each column

In [4]:
```
# calculating the mean of different integer columns
mean_data = read_data[integer_columns].mean().round(2)
mean_data.to_frame(name="mean")
```

Out[4]:

	mean
age	38.36
education	10.13
hours-per-week	41.08

In [5]:
```
# calculating the median of different integer columns
median_data = read_data[integer_columns].median().round(2)
median_data.to_frame(name="median")
```

Out[5]:

	median
age	37.0
education	10.0
hours-per-week	40.0

In [6]:
```
# calculating the standard deviation of different integer columns
standard_deviation_data = read_data[integer_columns].std().round(2)
standard_deviation_data.to_frame(name="standard deviation")
```

Out[6]:

	standard deviation
age	12.96
education	2.54
hours-per-week	11.88

Using `.describe()` to caluclate the frequencies of columns with categorical attributes

Here, we perform different operations on columns that contain non-numerical data

In [7]:
```
# summarizing the data
summary_data = read_data[['workclass', 'marital-status', 'race', 'sex', 'income']].describe()
summary_data
```

Out[7]:

	workclass	marital-status	race	sex	income
count	9412	9412	9412	9412	9412
unique	3	2	5	2	2
top	Private	Married	White	Male	<=50K
freq	6947	4737	8062	6383	7093

Part 2: Visualizing Numerical Data into Different Types of Graphs

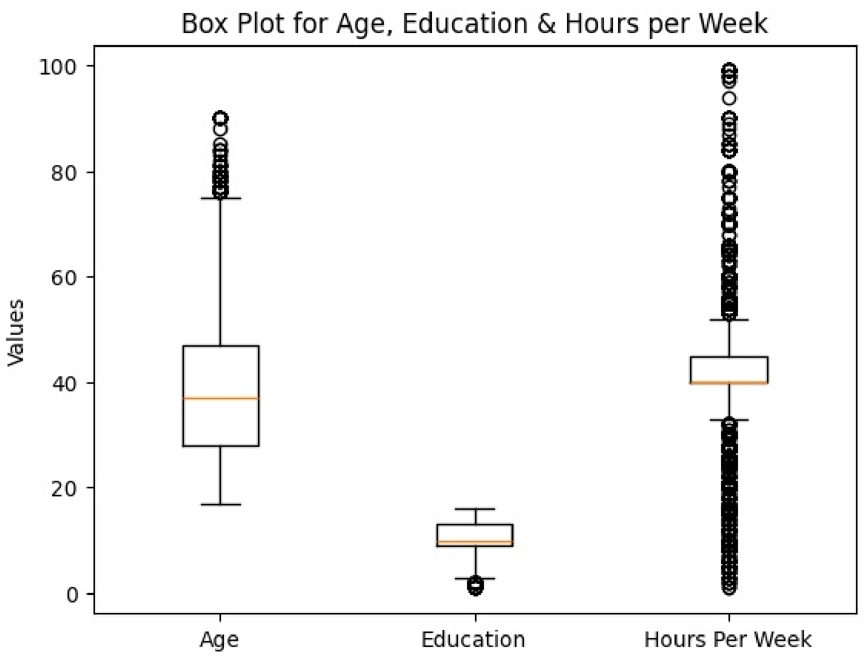
Be sure to do the following in order to complete part two completely:

- ☒For the three numeric attributes (age, hours-per-week, education), display box plots that show the overall dispersion and skew in these variables.
- ☒Next, create histograms for these three variables showing the overall data distribution in each.
- ☒Finally, display a scatter plot of age (x-axis) vs. hours per week (y-axis)

Displaying Box Plots

Here, we create box plots for columns that have numerical data in order to display the overall dispersion and skew in the variables

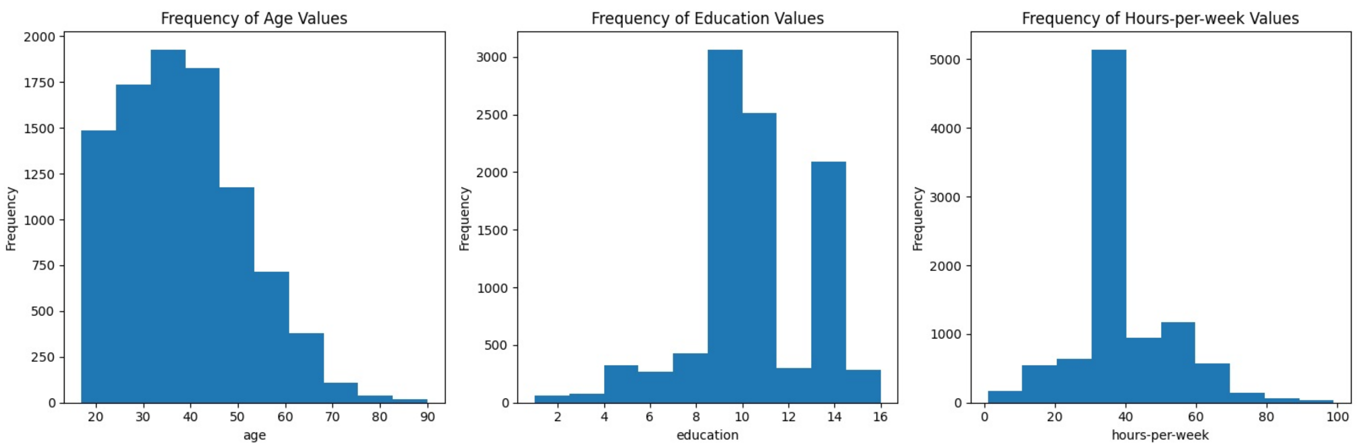
In [8]:
```
# displaying box plot for columns that have numerical data
plt.boxplot([read_data['age'], read_data['education'], read_data['hours-per-week']], labels=['Age', 'Education'
plt.ylabel('Values')
plt.title('Box Plot for Age, Education & Hours per Week')
plt.show()
```



Displaying Histograms

Here, we create histograms for columns that have numerical data in order to display the overall distribution of data in each column.

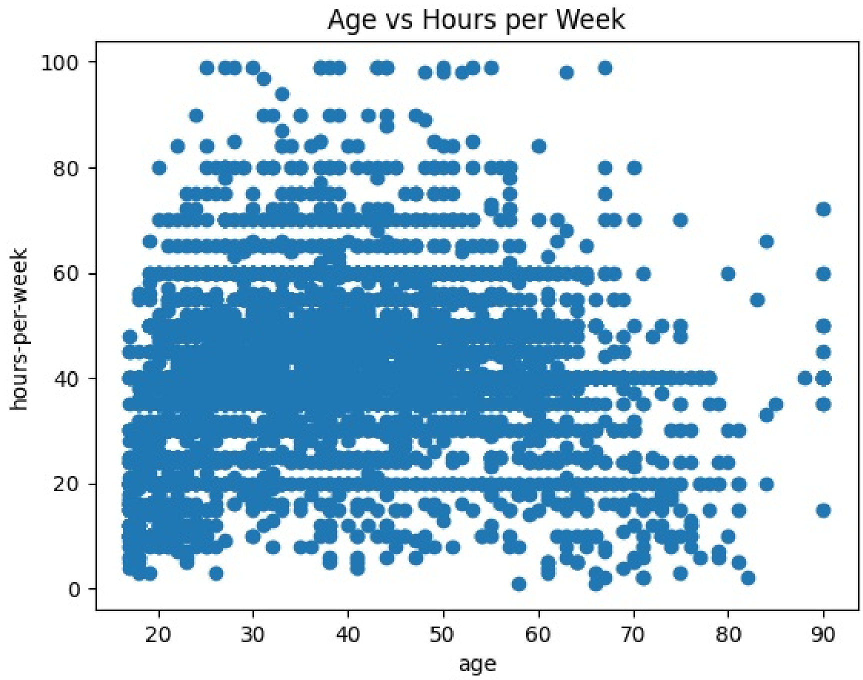
In [9]:
```
# displaying histograms of multiple columns

histogram_columns = ['age', 'education', 'hours-per-week']

figure, axes = plt.subplots(1, len(histogram_columns), figsize=(15, 5))  # Adjust figsize for better visualizat


for i, column in enumerate(histogram_columns):
    axes[i].hist(read_data[column])  # Adjust bins and color as needed
    axes[i].set_xlabel(column)
    axes[i].set_ylabel("Frequency")
    axes[i].set_title(f"Frequency of {column.capitalize()} Values")

plt.tight_layout()
plt.show()

# plt.hist(read_data['age'])
# plt.xlabel("Age Values")
# plt.ylabel("Frequency")
# plt.title("Frequency of Age Values")
# plt.show()
```



Displaying Scatter Plot

Lastly, we create a scatter plot where we plot the age (x-axis) against the hours per week (y-axis)

In [10]:
```
# displaying the scatter plot
plt.scatter(read_data['age'], read_data['hours-per-week'])
plt.xlabel('age')
plt.ylabel('hours-per-week')
plt.title('Age vs Hours per Week')
plt.show()
```



Part 3: Creating Bar Charts of Categorical Data

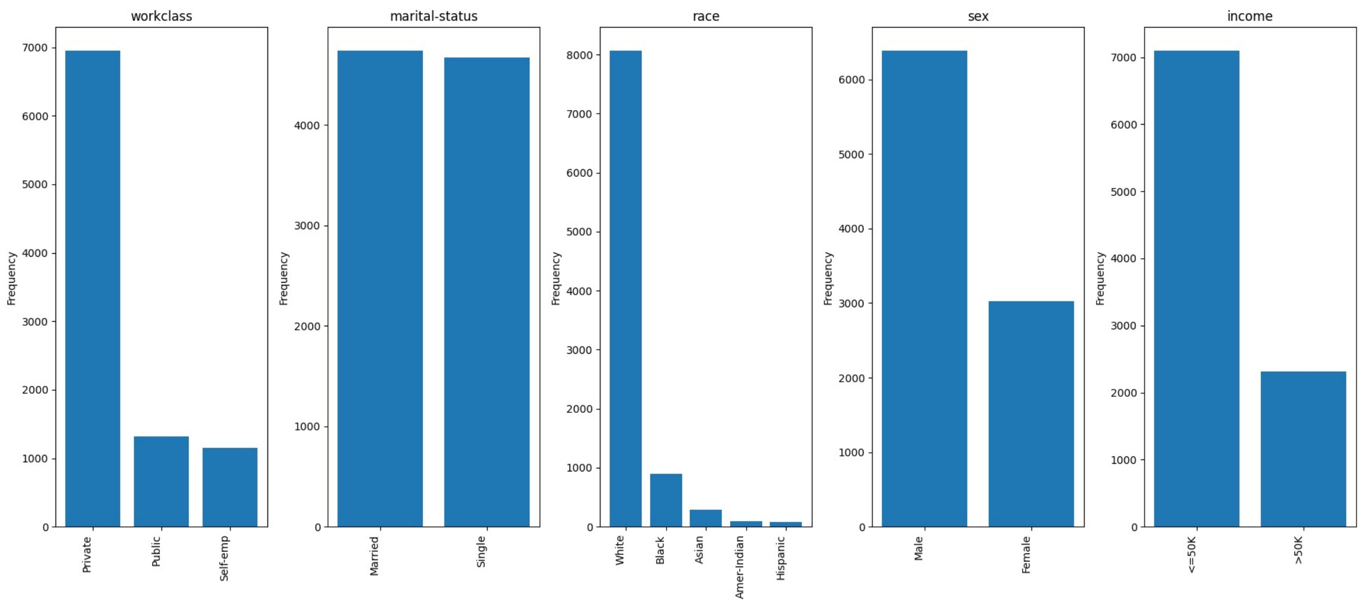
Be sure to do the following in order to complete part three:

- ☒For the remaining categorical attributes, create bar charts that show the distribution of category frequencies. (e.g. married vs single, private vs public, self-employed;).
- ☒Be sure to use bar charts in a single figure as shown below

Displaying Distribution of Category Frequencies

We create a bar chart of different categorical columns within the data set that shows the distribution of category frequencies

In [11]:
```
# displaying the distribution of category frequencies
column_names = ['workclass', 'marital-status', 'race', 'sex', 'income']

figure, axes = plt.subplots(1, len(column_names), figsize=(18,8))

for i, column in enumerate(column_names):
    unique_count = read_data[column].value_counts()
    axes[i].bar(unique_count.index, unique_count.values)
    axes[i].set_xticks(range(len(unique_count.index)))
    axes[i].set_ylabel("Frequency")
    axes[i].set_title(f"{column}")

    plt.setp(axes[i].get_xticklabels(), rotation=90, ha="right")

plt.tight_layout()
plt.show()
```



Part 4: Cross Tabulation of Data

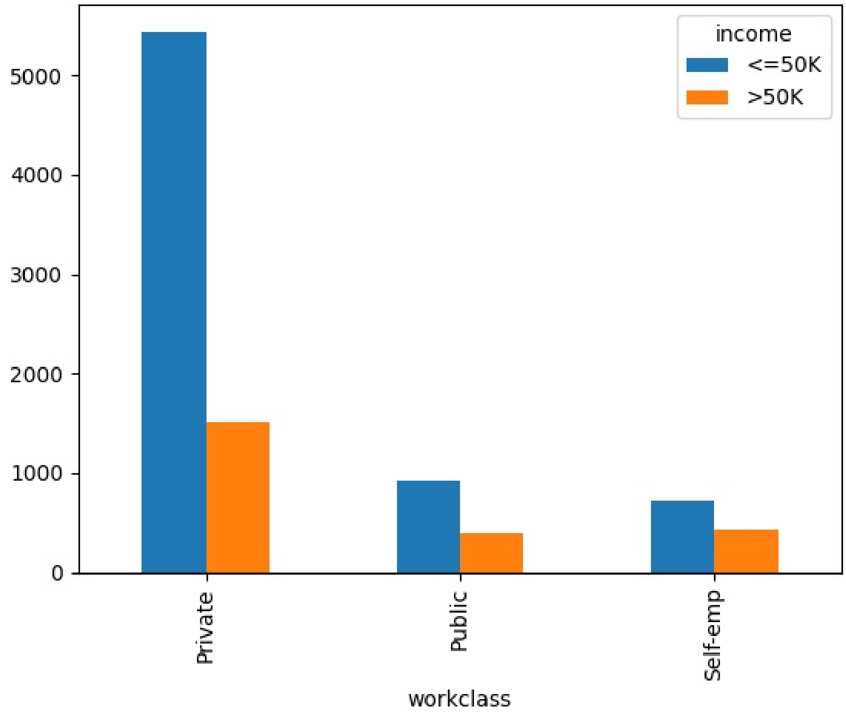
Be sure to do the following in order to complete part four:

- ☒Perform cross-tabulations of each of the work class and race attributes with the income attribute.
- ☒Show the resulting cross-tables as well as bar charts to visualize the relationships between these pairs of attributes.
- ☒In the case of race vs income cross tab, create another chart comparing the percentages of each race category that fall in low income group

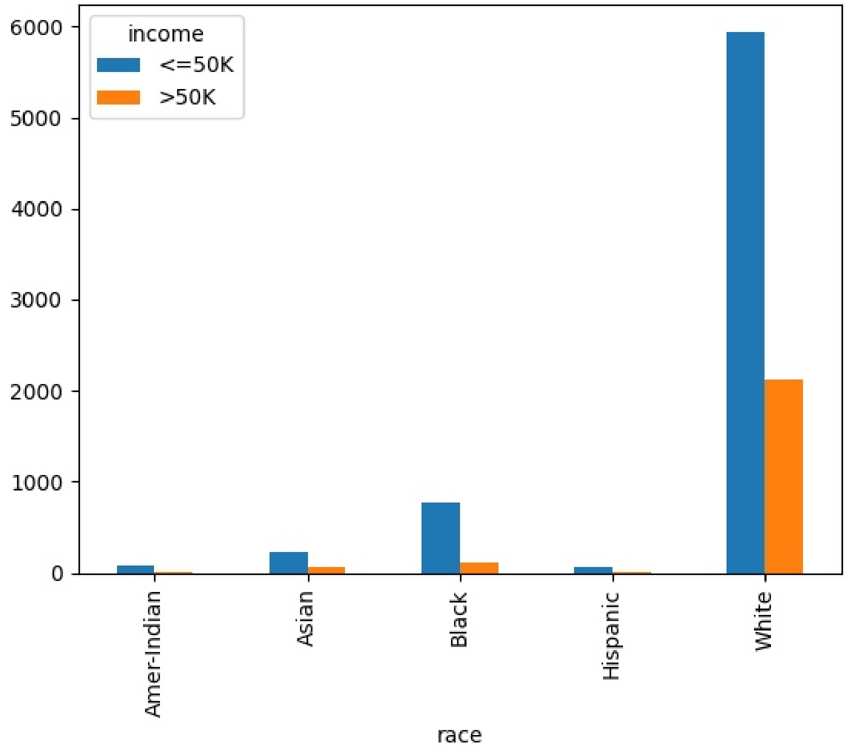
Cross Tabulation between Work, Race & Income

Here, we perform cross tabulation of data between the workclass and the income column, as well as the race and the income column

In [12]:
```
# cross tabulation between work class and income attribute
work_race_grouped = pd.crosstab(read_data['workclass'], read_data['income'])
work_race_grouped.plot(kind="bar")
plt.show()
```



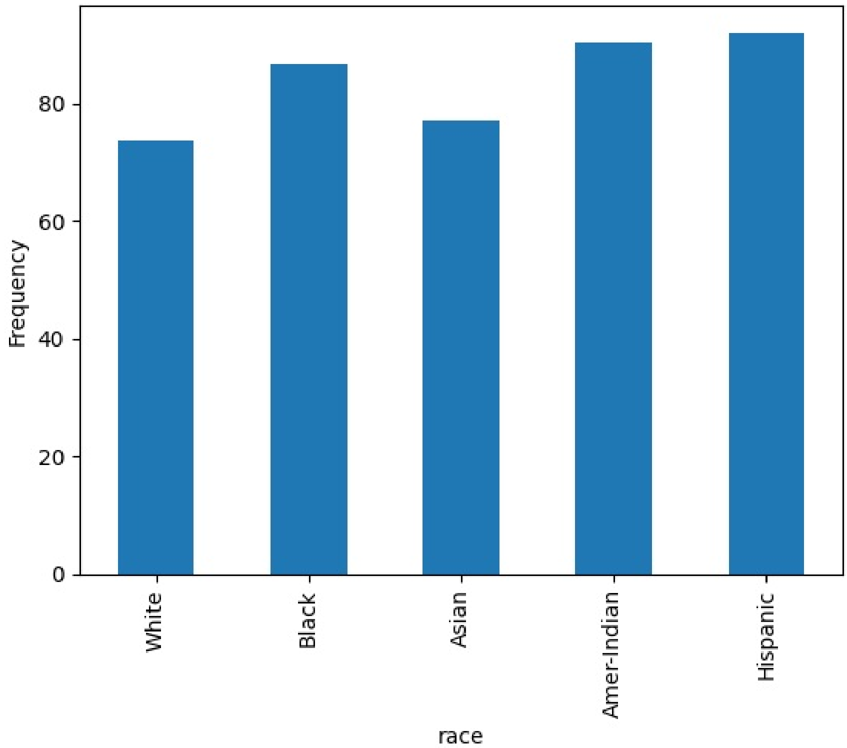
In [13]:
```
# cross tabulation between race attribute and income attribute
work_race_grouped = pd.crosstab(read_data['race'], read_data['income'])
work_race_grouped.plot(kind="bar")
plt.show()
```



Comparison of Percentages of each Low Income Race Group

Now, we compare the percentages of each low income race group within the given dataset that we've been provided with.

In [14]:
```
# comparing percentages of each low income race group
low_income = read_data[read_data['income'] =='<=50K']
low_race = low_income['race'].value_counts()
total_race = read_data['race'].value_counts()
calculated_percentage = (low_race / total_race) * 100
calculated_percentage.plot(kind='bar')
plt.ylabel('Frequency')
plt.show()
```



Part 5: Comparision and Analysis

Be sure to do the following in order to complete part five:

- ☒Compare and contrast the characteristics of the low income and high income categories across the different attributes.
- ☒Consider creating separate subsets of the data based on the income categories and then characterizing each subset by observing

summary statistics for each group across different variables.

- ☒Discuss observations focusing on unique characteristics that distinguish among the two groups.

Creating Subsets of Data

Here, we focus on creating subsets of data based off of income for each different attributes

In [15]:
```
# creating high income and low income category subsets of data
low_income_category = read_data[read_data['income'] == "<=50K"]
high_income_category = read_data[read_data['income'] == ">50K"]
```

Summary Statistics

Next, we characterize each subset by checking the summary statistics for each group across different column headings

In [16]:
```
# displaying the low income statistics
low_income_statistics = low_income_category.describe()
low_income_statistics
```

Out[16]:

	age	education	hours-per-week
count	7093.000000	7093.000000	7093.000000
mean	36.635979	9.646976	39.567038
std	13.339117	2.397358	11.868506
min	17.000000	1.000000	1.000000
25%	26.000000	9.000000	38.000000
50%	35.000000	9.000000	40.000000
75%	45.000000	10.000000	40.000000
max	90.000000	16.000000	99.000000

In [17]:
```
# displaying the high income statistics
high_income_statistics = high_income_category.describe()
high_income_statistics
```

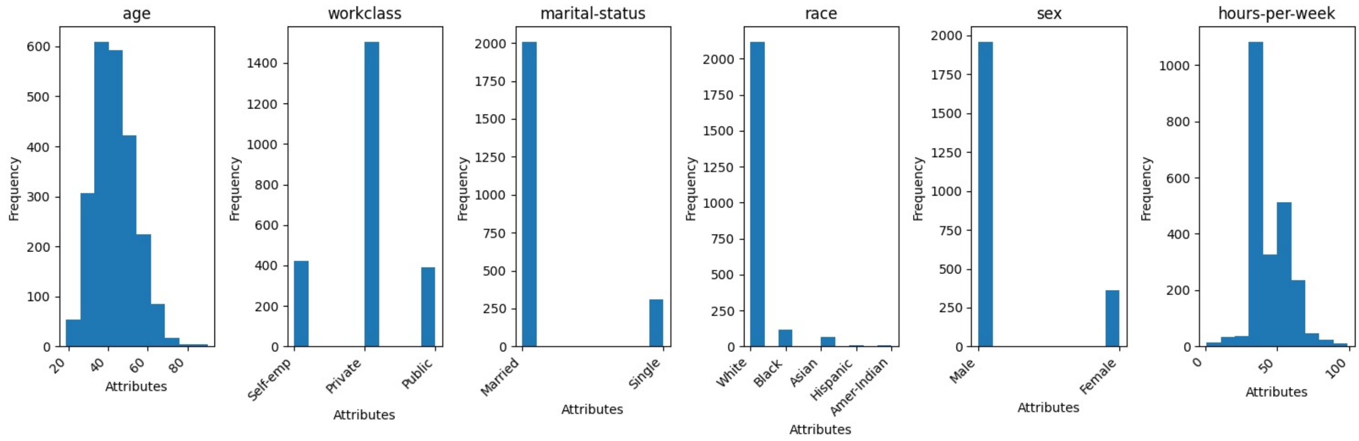
Out[17]:

	age	education	hours-per-week
count	2319.000000	2319.000000	2319.000000
mean	43.622251	11.588185	45.708495
std	10.047667	2.410764	10.678794
min	19.000000	2.000000	1.000000
25%	36.000000	9.000000	40.000000
50%	43.000000	12.000000	40.000000
75%	50.000000	13.000000	50.000000
max	90.000000	16.000000	99.000000

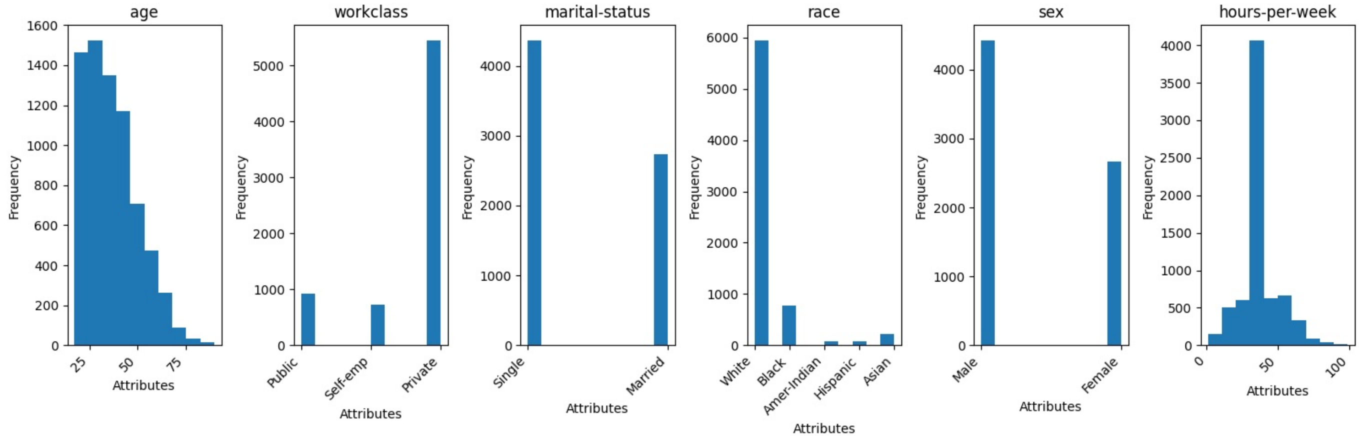
Visualizing Data for Low Income & High Income

Next, we visualize the data for the low income and high income categories and see the visual difference between them

In [18]:
```
# visualizing the high income data subset using matplotlib
column_list = ['age', 'workclass', 'marital-status', 'race', 'sex', 'hours-per-week']
column_length = len(column_list)

figure, axes = plt.subplots(1, column_length, figsize=(15, 5), sharey=False)

for i, column in enumerate(column_list):
    axes[i].hist(high_income_category[column])
    axes[i].set_xlabel("Attributes")
    axes[i].set_ylabel("Frequency")
    axes[i].set_title(f"{column}")

    plt.setp(axes[i].get_xticklabels(), rotation=45, ha="right")

plt.tight_layout()
plt.show()
```




```
In [19]: # visualizing the low income data subset using matplotlib
column_list = ['age', 'workclass', 'marital-status', 'race', 'sex', 'hours-per-week']
column_length = len(column_list)

figure, axes = plt.subplots(1, column_length, figsize=(15, 5), sharey=False)

for i, column in enumerate(column_list):
    axes[i].hist(low_income_category[column])
    axes[i].set_xlabel("Attributes")
    axes[i].set_ylabel("Frequency")
    axes[i].set_title(f"{column}")

    plt.setp(axes[i].get_xticklabels(), rotation=45, ha="right")

plt.tight_layout()
plt.show()
```



Observations into Statistics

Lastly, we check the unique characteristics that help to distinguish between the two groups of incomes

Observation: from this data, we can see the following observations:

- It is seen that people at the age of 50 have the highest income compared to toher age groups
- Private employees tend to have the highest income compared to self-employed and public employees
- Married people have a higher income than single people and this would make sense as there are two people contributing to the household
- Males tend to have a higher income than females and there are people who are willing to work 50 hours per week to make that high income

Part 6: One Hot Encoding

Be sure to do the following in order to complete part six:

- ☒Convert the data into the standard spreadsheet format. Note that this requires converting each categorical attribute into multiple binary attributes
- ☒The numeric attributes should remain unchanged
- ☒Save the data in a new DataFrame and show the top 10 rows in the new DataFrame. Save the new table into a local file called `adult_numeric.csv`

```
In [20]: # performing one hot encoding
```

```
encoded_data = pd.get_dummies(read_data, columns=["workclass", "marital-status", "race", "sex", "income"], drop_
```

Showing Top 10 Rows

In order to show the top 10 rows of a Pandas DataFrame, what we can use is the `.head()` method, with a given parameter that shows the exact number of the top ten rows.

In [21]:
```
# showing the top ten rows using .head()
encoded_data.head(10)
```

Out[21]:

	age	education	hours-per-week	workclass_Public	workclass_Self-emp	marital-status_Single	race_Asian	race_Black	race_Hispanic	race_White	s
0	39	13	40	True	False	True	False	False	False	True	
1	50	13	13	False	True	False	False	False	False	True	
2	38	9	40	False	False	True	False	False	False	True	
3	53	7	40	False	False	False	False	True	False	False	
4	28	13	40	False	False	False	False	True	False	False	
5	37	14	40	False	False	False	False	False	False	True	
6	49	5	16	False	False	False	False	True	False	False	
7	52	9	45	False	True	False	False	False	False	True	
8	31	14	50	False	False	True	False	False	False	True	
9	42	13	40	False	False	False	False	False	False	True	

Saving the Data

Lastly, we can save the Pandas DataFrame in a `.csv` file, which can then be saved with a given filename

In [22]:
```
# saving thhe data as a .csv file
encoded_data.to_csv('adult_numeric.csv', index=False)
```

Part 7: Correlation Analysis

Be sure to do the following in order to complete part seven:

- ☒Using the numeric dataset with dummy variables, perform basic correlation analysis among the attributes and construct a complex correlation matrix
- ☒Use the correlation matrix to display the decreasing order of correlations, all attributes and their correlations to education
- ☒Repeat to display correlations with attribute income <=50K . Briefly discuss general observations about sample of adult population based on this correlation analysis.

Constructing a Complex Correlation Matrix

Using the numeric dataset we have produced, we will now construct a complex correlation matrix for analytical purposes

In [23]:
```
# creating a correlation matrix, and displaying the correlation matrix
new_data = pd.read_csv("adult_numeric.csv")
new_data['income_<50K'] = ~new_data['income_>50K']
new_data
```

Out[23]:

	age	education	hours-per-week	workclass_Public	workclass_Self-emp	marital-status_Single	race_Asian	race_Black	race_Hispanic	race_White
0	39	13	40	True	False	True	False	False	False	True
1	50	13	13	False	True	False	False	False	False	True
2	38	9	40	False	False	True	False	False	False	True
3	53	7	40	False	False	False	False	True	False	False
4	28	13	40	False	False	False	False	True	False	False
...	...	...	...	...	...	...	...	...	...	...
9407	38	10	60	False	False	False	False	False	False	True
9408	25	9	8	False	False	True	False	False	False	True
9409	21	10	40	False	False	True	False	True	False	False
9410	38	2	53	False	False	False	False	False	False	True
9411	39	10	40	False	False	True	False	False	False	True

9412 rows × 13 columns

In [24]:

```
# correlating the matrix and displaying it
correlation_matrix = new_data.corr()
correlation_matrix
```

Out[24]:

	age	education	hours-per-week	workclass_Public	workclass_Self-emp	marital-status_Single	race_Asian	race_Black	race_
age	1.000000	0.034733	0.103170	0.080254	0.187633	-0.381168	-0.008097	-0.008668	-
education	0.034733	1.000000	0.141730	0.154462	0.044472	-0.050627	0.057360	-0.069029	-
hours-per-week	0.103170	0.141730	1.000000	-0.021407	0.154025	-0.183944	0.000550	-0.071442	
workclass_Public	0.080254	0.154462	-0.021407	1.000000	-0.150335	0.002351	0.012883	0.070250	-
workclass_Self-emp	0.187633	0.044472	0.154025	-0.150335	1.000000	-0.165075	0.006576	-0.080694	-
marital-status_Single	-0.381168	-0.050627	-0.183944	0.002351	-0.165075	1.000000	-0.017852	0.104427	-
race_Asian	-0.008097	0.057360	0.000550	0.012883	0.006576	-0.017852	1.000000	-0.057795	-
race_Black	-0.008668	-0.069029	-0.071442	0.070250	-0.080694	0.104427	-0.057795	1.000000	-
race_Hispanic	-0.031973	-0.044845	0.011964	-0.018927	-0.011495	-0.000605	-0.016009	-0.028999	
race_White	0.022413	0.051765	0.055561	-0.066491	0.071008	-0.082114	-0.436496	-0.790710	-
sex_Male	0.071804	0.008180	0.221588	-0.045338	0.145559	-0.357736	-0.001773	-0.106323	-
income_>50K	0.232261	0.329066	0.222686	0.047981	0.105593	-0.414173	-0.006693	-0.084836	-
income_<50K	-0.232261	-0.329066	-0.222686	-0.047981	-0.105593	0.414173	0.006693	0.084836	

Attributes and Correlation to Education

We now use the correlation matrix to correlate the attributes with education in a decreasing order. This can be used for analytical purposes.

In [25]:

```
# correlation between income_>50K and other attributes
education_correlation = correlation_matrix['education'].sort_values(ascending=False)
education_correlation
```

Out[25]:

```
education                 1.000000
income_>50K               0.329066
workclass_Public          0.154462
hours-per-week            0.141730
race_Asian                0.057360
race_White                0.051765
workclass_Self-emp        0.044472
age                       0.034733
sex_Male                  0.008180
race_Hispanic            -0.044845
marital-status_Single    -0.050627
race_Black               -0.069029
income_<50K              -0.329066
Name: education, dtype: float64
```

In [26]:
```python
# correlation between income_<50K and other attributes
income_correlation = correlation_matrix['income_<50K'].sort_values(ascending=False)
income_correlation
```

Out[26]:
```
income_<50K             1.000000
marital-status_Single   0.414173
race_Black              0.084836
race_Hispanic           0.034607
race_Asian              0.006693
workclass_Public       -0.047981
race_White             -0.092589
workclass_Self-emp     -0.105593
sex_Male               -0.203886
hours-per-week         -0.222686
age                    -0.232261
education              -0.329066
income_>50K            -1.000000
Name: income_<50K, dtype: float64
```

General Observations

Lastly, discuss the general observations about a sample adult population based off of the correlation analysis

Observation: from the observation, we can see the following things:

- when it comes to correlation between education and other attributes, the three leading attributes are income being greater than 50K, where the adult works in a public job, and the hours per week they work
- when it comes to correlation between income being less than 50K and other attributes, the three leading attributes are single adults, who are black or hispanic

Part 8: Discretizing Attributes

Be sure to do the following in order to complete eight:

- ☒Discretize the age attribute into three categories, which can correspond to “young”, “mid-age” and “old”
- ☒Don’t change the original age attribute or add the discretized age to the table
- ☒Create a new DataFrame with the numeric and the discretized age attributes as two columns and display the top ten rows of the new DataFrame

Discretizing Attributes

Here, we discretize the age attributes by having it to corresponding it to three different categories, which gives a further insight into the data. To accomplish this, we can use bins to define age ranges and then use `cut()` to discretize the age column.

In [27]:
```python
# categorizing the attributes
bins = [0, 23, 50, 100]
labels = ['young', 'mid-age', 'old']

new_data['categorized_age'] = pd.cut(new_data['age'], bins=bins, labels=labels, right=False)
age_df = new_data[['age', 'categorized_age']]
age_df.head(10)
```

Out[27]:

	age	categorized_age
0	39	mid-age
1	50	old
2	38	mid-age
3	53	old
4	28	mid-age
5	37	mid-age
6	49	mid-age
7	52	old
8	31	mid-age
9	42	mid-age

Part 9: Min-Max Normalization

- ☒Use min-max normalization to transform the values of the attribute “hours per week” within the range 0 to 1.

- ☒Perform z-score normalization to standardize the values of all numeric attributes (age, hours per week and education). This should be performed on all three attributes at the same time instead of one by one.
- ☒Show the top ten rows of the three versions of the hours per week attribute (original, normalized and standardized), side by side in a new DataFrame.

Min-Max Normalization

First up, we perform min-max normalization in order to convert the values of the column named "hours per week". For every feature, the minimum value of that feature get transformed into a 0, the maximum value gets transformed into a 1, and any other value becomes a decimal between 0 and 1.

In [28]:
```
# min-max normalization
min_max_columns = ['age', 'education', 'hours-per-week']
minimum_hours = new_data[min_max_columns].min()
maximum_hours = new_data[min_max_columns].max()
min_max_df = (new_data[min_max_columns] / minimum_hours) / (maximum_hours - minimum_hours)
min_max_df
```

Out[28]:

	age	education	hours-per-week
0	0.031426	0.866667	0.408163
1	0.040290	0.866667	0.132653
2	0.030620	0.600000	0.408163
3	0.042707	0.466667	0.408163
4	0.022562	0.866667	0.408163
...	...	...	...
9407	0.030620	0.666667	0.612245
9408	0.020145	0.600000	0.081633
9409	0.016922	0.666667	0.408163
9410	0.030620	0.133333	0.540816
9411	0.031426	0.666667	0.408163

9412 rows × 3 columns

Z-Score Normalization

Next up, we perform the z-score normalization to standardize all numeric attributes. We use z-score as a strategy of normlaizing data that avoids the outlier issue. We use the value of the mean and standard deviation of the feature.

In [29]:
```
# z-score normalization
z_columns = ['age', 'education', 'hours-per-week']
mean_data = new_data[z_columns].mean()
std_data = new_data[z_columns].std()
z_df = (new_data[z_columns] - mean_data) / std_data
z_df
```

Out[29]:

	age	education	hours-per-week
0	0.049582	1.130842	-0.090892
1	0.898208	1.130842	-2.362742
2	-0.027566	-0.442649	-0.090892
3	1.129651	-1.229394	-0.090892
4	-0.799044	1.130842	-0.090892
...	...	...	...
9407	-0.027566	-0.049276	1.591959
9408	-1.030487	-0.442649	-2.783455
9409	-1.339078	-0.049276	-0.090892
9410	-0.027566	-3.196258	1.002961
9411	0.049582	-0.049276	-0.090892

9412 rows × 3 columns

Combining DataFrames

To show all the DataFrames together, we combine the min-max normalization DataFrame with the Z-score normalization

In [30]:

```
# combining the DataFrames together
final_df = pd.concat([min_max_df, z_df], axis=1)
final_df
```

Out[30]:

	age	education	hours-per-week	age	education	hours-per-week
0	0.031426	0.866667	0.408163	0.049582	1.130842	-0.090892
1	0.040290	0.866667	0.132653	0.898208	1.130842	-2.362742
2	0.030620	0.600000	0.408163	-0.027566	-0.442649	-0.090892
3	0.042707	0.466667	0.408163	1.129651	-1.229394	-0.090892
4	0.022562	0.866667	0.408163	-0.799044	1.130842	-0.090892
...	...	...	...	...	...	...
9407	0.030620	0.666667	0.612245	-0.027566	-0.049276	1.591959
9408	0.020145	0.600000	0.081633	-1.030487	-0.442649	-2.783455
9409	0.016922	0.666667	0.408163	-1.339078	-0.049276	-0.090892
9410	0.030620	0.133333	0.540816	-0.027566	-3.196258	1.002961
9411	0.031426	0.666667	0.408163	0.049582	-0.049276	-0.090892

9412 rows × 6 columns

Part 10: Pandas and Missing Values

Download a modified version of the data that contains missing values, and perform the following:

- ☒Using Pandas, determine all the attributes with missing values and the number of missing values for each attribute
- ☒Show all instances in the data that contain a missing value
- ☒Fill the missing values for all numeric attributes using the mean value for the attribute
- ☒After filling in the missing numeric values, drop all rows where a categorical attribute contains a missing value
- ☒Show that the final resulting table doesn't contain missing values

Loading up the `.csv` File

Here, we use `read_csv()` to load up the file that we want to view. This requires a string parameter to be passed in in order to locate the file

In [31]:

```
# opening up the .csv file
missing_data = pd.read_csv('adult-modified-missing-vals.csv')
missing_data
```

Out[31]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
...	...	...	...	...	...	...	...	...
9995	38	Private	10	Married	White	Male	60	>50K
9996	25	Private	9	Single	White	Female	8	<=50K
9997	21	Private	10	Single	Black	Male	40	<=50K
9998	?	Private	2	Married	White	Male	53	<=50K
9999	39	Private	10	Single	White	Female	40	<=50K

10000 rows × 8 columns

Determining Missing Values

To find missing values, we use `isnull()` along with the `sum()` to find out how many missing values there are for each attribute. Before we do that, we need to replace each mention of "?" with a null variable.

In [32]:
```python
# replacing the ? with NaN
missing_data.replace("?", np.nan, inplace=True)
missing_data
```

Out[32]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
...	...	...	...	...	...	...	...	...
9995	38	Private	10	Married	White	Male	60	>50K
9996	25	Private	9	Single	White	Female	8	<=50K
9997	21	Private	10	Single	Black	Male	40	<=50K
9998	NaN	Private	2	Married	White	Male	53	<=50K
9999	39	Private	10	Single	White	Female	40	<=50K

10000 rows × 8 columns

In [33]:
```python
# determining the attributes with missing values, and how many of them are missing attributes
missing_columns = missing_data.isnull().sum()
missing_columns
```

Out[33]:
```
age               198
workclass         588
education           0
marital-status      0
race                0
sex                 0
hours-per-week      0
income              0
dtype: int64
```

Missing Value Instances

Next, we find rows of data that contain any missing values

In [34]:
```python
# instances in the data that contains a missing value
missing_instances = missing_data[missing_data.isnull().any(axis=1)]
missing_instances
```

Out[34]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
19	NaN	Self-emp	14	Single	White	Female	45	>50K
27	NaN	NaN	10	Married	Asian	Male	60	>50K
40	NaN	Private	5	Married	White	Male	43	<=50K
61	32	NaN	4	Married	White	Male	40	<=50K
65	NaN	Private	9	Married	White	Male	40	<=50K
...	...	...	...	...	...	...	...	...
9965	NaN	Private	10	Married	Amer-Indian	Female	40	<=50K
9966	NaN	Private	13	Married	White	Male	50	>50K
9987	67	NaN	4	Married	White	Male	40	<=50K
9993	NaN	Private	9	Married	White	Female	15	<=50K
9998	NaN	Private	2	Married	White	Male	53	<=50K

777 rows × 8 columns

Replacing Missing Values with Mean

Next up, we replace every single missing value in DataFrame with the means of the columns

In [35]:
```python
# replacing missing values with the mean of the columns
mean_data = read_data['age'].mean()
missing_data['age'] = missing_data['age'].fillna(mean_data)
missing_data
```

Out[35]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
...	...	...	...	...	...	...	...	...
9995	38	Private	10	Married	White	Male	60	>50K
9996	25	Private	9	Single	White	Female	8	<=50K
9997	21	Private	10	Single	Black	Male	40	<=50K
9998	38.35731	Private	2	Married	White	Male	53	<=50K
9999	39	Private	10	Single	White	Female	40	<=50K

10000 rows × 8 columns

In [36]:

```
# removing any rows with NaN
missing_data = missing_data.dropna()
missing_data
```

Out[36]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
...	...	...	...	...	...	...	...	...
9995	38	Private	10	Married	White	Male	60	>50K
9996	25	Private	9	Single	White	Female	8	<=50K
9997	21	Private	10	Single	Black	Male	40	<=50K
9998	38.35731	Private	2	Married	White	Male	53	<=50K
9999	39	Private	10	Single	White	Female	40	<=50K

9412 rows × 8 columns

Displaying the First Ten Rows

Lastly, we are displaying the first tewenty rows of the dataset or pandas DataFrame

In [37]:

```
missing_data.head(20)
```

Out[37]:

	age	workclass	education	marital-status	race	sex	hours-per-week	income
0	39	Public	13	Single	White	Male	40	<=50K
1	50	Self-emp	13	Married	White	Male	13	<=50K
2	38	Private	9	Single	White	Male	40	<=50K
3	53	Private	7	Married	Black	Male	40	<=50K
4	28	Private	13	Married	Black	Female	40	<=50K
5	37	Private	14	Married	White	Female	40	<=50K
6	49	Private	5	Married	Black	Female	16	<=50K
7	52	Self-emp	9	Married	White	Male	45	>50K
8	31	Private	14	Single	White	Female	50	>50K
9	42	Private	13	Married	White	Male	40	>50K
10	37	Private	10	Married	Black	Male	80	>50K
11	30	Public	13	Married	Asian	Male	40	>50K
12	23	Private	13	Single	White	Female	30	<=50K
13	32	Private	12	Single	Black	Male	50	<=50K
14	40	Private	11	Married	Asian	Male	40	>50K
15	34	Private	4	Married	Amer-Indian	Male	45	<=50K
16	25	Self-emp	9	Single	White	Male	35	<=50K
17	32	Private	9	Single	White	Male	40	<=50K
18	38	Private	7	Married	White	Male	50	<=50K
19	38.35731	Self-emp	14	Single	White	Female	45	>50K