UCI Adult Income Dataset - Exploratory and Descriptive Analysis

In this notebook, we carry out an in-depth exploratory and descriptive analysis of the UCI Adult Income Dataset, a widely used dataset for income prediction tasks based on individual demographic and employment attributes.

This phase of analysis is essential for uncovering patterns, detecting potential biases, and gaining intuition about the dataset's structure before applying any modelling procedures. We examine the distribution of key numerical and categorical variables, investigate relationships between demographic features and income levels, and use visualizations to summarize insights. Particular focus is placed on income disparities across **age groups**, **geographical regions**, **races**, and **education-occupation combinations**, helping lay a solid foundation for downstream modeling and policy-relevant interpretation.

We begin our analysis by importing the core Python libraries required for **data handling**, **numerical computation**, **visualization**, and **directory management**:

- `pandas`: Enables efficient manipulation, filtering, and aggregation of structured tabular data, forming the backbone of our analysis pipeline.
- `numpy`: Provides support for fast numerical operations, array-based computation, and statistical routines.
- `os`: Facilitates interaction with the file system, allowing us to construct flexible and portable directory paths for data and output management.
- `plotly.express`: A high-level graphing library that enables the creation of interactive, publication-quality visualizations, which we use extensively to uncover patterns and present insights throughout the notebook.

```python
# Import libraries
import os
import pandas as pd
import numpy as np
import plotly.express as px
```

Define and Create Directory Paths

To ensure reproducibility and organized storage, we programmatically create directories if they don't already exist for:

- **raw data**
- **processed data**
- **results**
- **documentation**

These directories will store intermediate and final outputs for reproducibility.

```
# Get working directory
current_dir = os.getcwd()

# Go one directory up to the root directory
project_root_dir = os.path.dirname(current_dir)

# Define paths to the data folder
data_dir = os.path.join(project_root_dir, 'data')
raw_dir = os.path.join(data_dir, 'raw')
processed_dir = os.path.join(data_dir, 'processed')

# Define paths to results folder
results_dir = os.path.join(project_root_dir, 'results')

# Define paths to docs folder
docs_dir = os.path.join(project_root_dir, 'docs')

# Create directories if they do not exist
os.makedirs(raw_dir, exist_ok = True)
os.makedirs(processed_dir, exist_ok = True)
os.makedirs(results_dir, exist_ok = True)
os.makedirs(docs_dir, exist_ok = True)
```

Loading the Cleaned Dataset

We load the cleaned version of the UCI Adult Income Dataset from the processed data directory into a Pandas DataFrame. The `head(10)` function shows the first ten records, giving a glimpse into the data columns such as `age`, `workclass`, `education_num`, etc.

```
adult_data_filename = os.path.join(processed_dir, "adult_cleaned.csv")
adult_df = pd.read_csv(adult_data_filename)
adult_df.head(10)
```

	age	workclass	fnlwgt	education_num	marital_status	relationship	race	sex	capital_gain	capit
0	39	government	77516	13	single	single	white	male	2	
1	50	self-employed	83311	13	married	male spouse	white	male	0	
2	38	private	215646	9	divorced or separated	single	white	male	0	
3	53	private	234721	7	married	male spouse	black	male	0	
4	28	private	338409	13	married	female spouse	black	female	0	
5	37	private	284582	14	married	female spouse	white	female	0	
6	49	private	160187	5	divorced or separated	single	black	female	0	
7	52	self-employed	209642	9	married	male spouse	white	male	0	
8	31	private	45781	14	single	single	white	female	1	
9	42	private	159449	13	married	male spouse	white	male	5	

Dataset Dimensions and Data Types

Here, we examine the structure of the dataset:

- There are *32,513* entries and *16* variables.
- The dataset includes both **numerical** (e.g., `age`, `hours_per_week`) and **categorical** variables (e.g., `sex`, `education_level`).

Understanding data types and null entries is essential before proceeding with analysis.

```
adult_df.shape
```

```
(32513, 16)
```

```
adult_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32513 entries, 0 to 32512
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   age                 32513 non-null  int64
 1   workclass           32513 non-null  object
```

```
 2   fnlwgt              32513 non-null  int64
 3   education_num       32513 non-null  int64
 4   marital_status      32513 non-null  object
 5   relationship        32513 non-null  object
 6   race                32513 non-null  object
 7   sex                 32513 non-null  object
 8   capital_gain        32513 non-null  int64
 9   capital_loss        32513 non-null  int64
 10  hours_per_week      32513 non-null  int64
 11  income              32513 non-null  object
 12  education_level     32513 non-null  object
 13  occupation_grouped  32513 non-null  object
 14  native_region       32513 non-null  object
 15  age_group           32513 non-null  object
dtypes: int64(6), object(10)
memory usage: 4.0+ MB
```

Summary Statistics: Numerical Variables

```
adult_df.describe()
```

	age	fnlwgt	education_num	capital_gain	capital_loss	hours_per_week
count	32513.000000	3.251300e+04	32513.000000	32513.000000	32513.000000	32513.000000
mean	38.590256	1.897942e+05	10.081629	1079.239812	87.432719	40.440962
std	13.638932	1.055788e+05	2.572015	7390.625650	403.243596	12.350184
min	17.000000	1.228500e+04	1.000000	0.000000	0.000000	1.000000
25%	28.000000	1.178330e+05	9.000000	0.000000	0.000000	40.000000
50%	37.000000	1.783560e+05	10.000000	0.000000	0.000000	40.000000
75%	48.000000	2.370510e+05	12.000000	0.000000	0.000000	45.000000
max	90.000000	1.484705e+06	16.000000	99999.000000	4356.000000	99.000000

This summary provides a snapshot of key distribution characteristics. We see that:

- Age ranges from 17 to 90, with a mean of 38.6 years. It is slightly right-skewed (positively skewed). While the average age is approximately 38.6 years, an examination of the percentiles reveals that the majority of individuals are clustered in the younger to middle-age range, with fewer observations in the older age brackets. This skewed age distribution might suggest labor force participation is concentrated in specific age groups, which could reflect broader demographic or economic realities.

- Capital gains/losses are highly skewed, with most values at 0 (the 75th percentile is 0). This indicates that a small number of individuals report very large gains or losses, especially evident in the capital gain variable which reaches up to $99,999. These variables act as proxies for wealth-related income that goes beyond regular wages or salaries. Individuals with non-zero values for capital gains or losses often represent a distinct socioeconomic subset of the population — typically more financially literate, or with access to investment assets. The stark inequality in their distributions mirrors real-world disparities in asset ownership and investment returns.
- The dataset has individuals working anywhere from 1 to 99 hours per week, with a median of 40. This aligns with the standard full-time work week in many countries (8 hours per day for 5 working days). The mean is slightly above that at 40.4 hours, suggesting a mild right skew, with a small subset of individuals working significantly longer hours. The mode is also 40, further reinforcing the prevalence of full-time work. A non-trivial number of individuals report working very few hours, possibly due to part-time work, unemployment, or semi-retirement. On the other extreme, some report working more than 45 hours per week, which may indicate multiple jobs, weekend-work, self-employment, or informal labor, and could reflect socio economic necessity.

Summary Statistics: Categorical Variables

```
adult_df.describe(include='object')
```

	workclass	marital_status	relationship	race	sex	income	education_level	occupation_grouped	na
count	32513	32513	32513	32513	32513	32513	32513	32513	
unique	6	4	5	5	2	2	7	5	
top	private	married	male spouse	white	male	<=50k	high school graduate	white co	
freq	22650	14984	13178	27771	21758	24677	10484	16532	

```
# if you want the percentage
adult_df['workclass'].value_counts(normalize=True)
```

```
workclass
private          0.696644
government       0.133793
self-employed    0.112447
unknown          0.056470
voluntary        0.000431
unemployed       0.000215
Name: proportion, dtype: float64
```

```python
adult_df['marital_status'].value_counts(normalize=True)
```

```
marital_status
married                  0.460862
single                   0.327684
divorced or separated    0.180912
widowed                  0.030542
Name: proportion, dtype: float64
```

```python
adult_df['relationship'].value_counts(normalize=True)
```

```
relationship
male spouse          0.405315
single               0.360686
child                0.155599
female spouse        0.048227
extended relative    0.030173
Name: proportion, dtype: float64
```

```python
adult_df['race'].value_counts(normalize=True)
```

```
race
white                        0.854151
black                        0.096023
asian or pacific islander    0.031926
american indian or eskimo    0.009565
other                        0.008335
Name: proportion, dtype: float64
```

```python
adult_df['sex'].value_counts(normalize=True)
```

```
sex
male      0.669209
female    0.330791
Name: proportion, dtype: float64
```

```python
adult_df['education_level'].value_counts(normalize=True)
```

```
education_level
high school graduate    0.322456
tertiary                0.247809
some college            0.223787
secondary               0.093932
associate               0.075324
primary                 0.035155
preschool               0.001538
Name: proportion, dtype: float64
```

```
adult_df['occupation_grouped'].value_counts(normalize=True)
```

```
occupation_grouped
white collar    0.508474
blue collar     0.308861
service         0.125704
unknown         0.056685
military        0.000277
Name: proportion, dtype: float64
```

```
adult_df['native_region'].value_counts(normalize=True)
```

```
native_region
north america      0.923261
asia               0.020638
other              0.017870
central america    0.016117
europe             0.016024
south america      0.006090
Name: proportion, dtype: float64
```

```
adult_df['age_group'].value_counts(normalize=True)
```

```
age_group
26-35    0.261465
36-45    0.246086
46-60    0.224156
18-25    0.167533
61-75    0.064313
<18      0.029065
76+      0.007382
Name: proportion, dtype: float64
```

`workclass`

The private sector dominates, employing ~69.7% of the population. The government sector (13.4%) and self-employment (11.2%) also make up substantial portions of the workforce. A small fraction is labeled as "unknown" (5.6%), which may correspond to missing or ambiguous data entries. Tiny proportions are voluntary (0.04%) or unemployed (0.02%), possibly underreported or underrepresented in the sample.

`marital_status`

Married individuals make up the largest group (46.1%), followed by those who are single (32.8%) and divorced or separated (18.1%). Widowed individuals represent a small minority (~3.1%).

`relationship`

The majority are labeled as "male spouse" (40.5%) or "single" (36.1%). Smaller categories include children (15.6%), female spouses (4.8%), and extended relatives (3.0%). The dominance of `male spouse` reflects the dataset's gendered structure and may point to traditional family roles. The relative scarcity of "female spouse" roles suggests potential gender imbalances in how income-earning is reported within households.

`race`

The dataset is overwhelmingly composed of White individuals (~85.4%). Other racial groups include Black (9.6%), Asian or Pacific Islander (3.2%), American Indian or Eskimo (1.0%), and Other (0.8%). The racial imbalance limits the generalizability of models trained on this data. Smaller racial groups may suffer from limited statistical power, affecting fairness and performance in predictive modeling.

`sex`

Males constitute 66.9% of the dataset, with females making up the remaining 33.1%. This male-skewed distribution could be due to sampling (e.g., primary earners in households), workforce participation patterns, or reporting biases.

`education_level`

Secondary-school graduates form the largest educational group (~32%), highlighting the central role of high school completion in the labor force. Tertiary education holders — those with university or equivalent degrees — account for nearly 25% of the population, representing a substantial segment with advanced qualifications. A notable 22.4% have attended some college without necessarily earning a degree, suggesting that partial post-secondary education is common, yet may not always translate into formal certification. The remaining 20% are distributed among those with only secondary education (9.4%), associate degrees (7.5%), primary school (3.5%), and a very small group with only preschool education (0.15%). It is ecident that the education distribution is skewed toward mid- to high-level education, with relatively few individuals having only basic schooling. This reflects a dataset that largely captures working-age adults in formal labor, which may underrepresent the least-educated populations.

`occupation_grouped`

White-collar occupations are the most prevalent (~51%), followed by blue-collar, service, and unknown. Smaller categories include military, which is marginal. Essentially, slightly over half of individuals in the dataset work in professional, managerial, sales, clerical, or tech-support roles. This suggests the dataset is heavily weighted toward professional and administrative occupations. Nearly a third of the population works in manual labor or skilled trade positions (craft, transport, machine operation, farming, etc.). This indicates a significant segment engaged in physically intensive or technical labor.

`native_region`

The vast majority of individuals are from North America (~92.3%). Smaller proportions are from Central America, Asia, Europe, South America, and a generic Other category. The heavy concentration of North American individuals reflects the U.S. focus of the dataset.

`age_group`

The largest groups are 26–35 and 36–45, followed by 46–60. These three age groups represent about 73% of the dataset. Very few individuals are under 18 or above 75, consistent with the dataset's focus on the working-age population.

Income Distribution

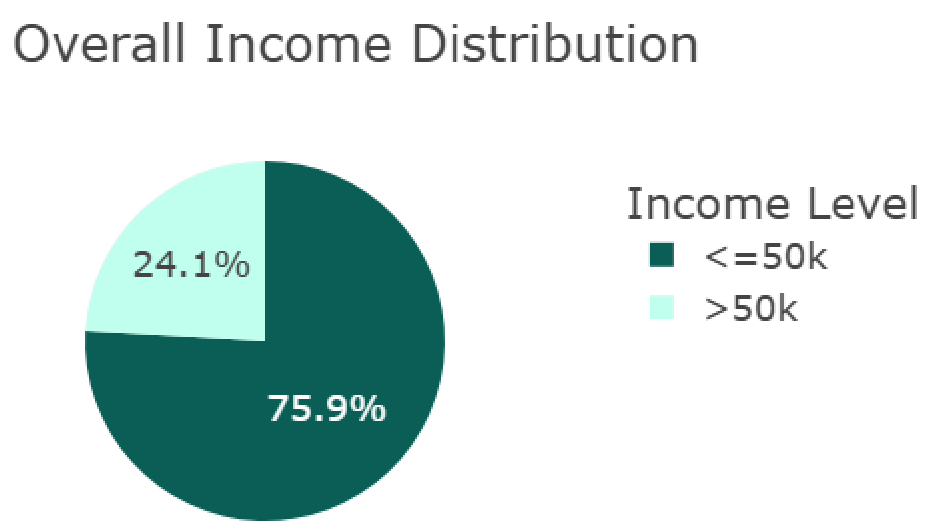
Given that `income` is the target variable, most of the analysis hereafter will be based on it. We first of all examine the income distribution in the dataset.

```
adult_df_income = adult_df.groupby('income').size().reset_index(name='total')
adult_df_income
```

	income	total
0	<=50k	24677
1	>50k	7836

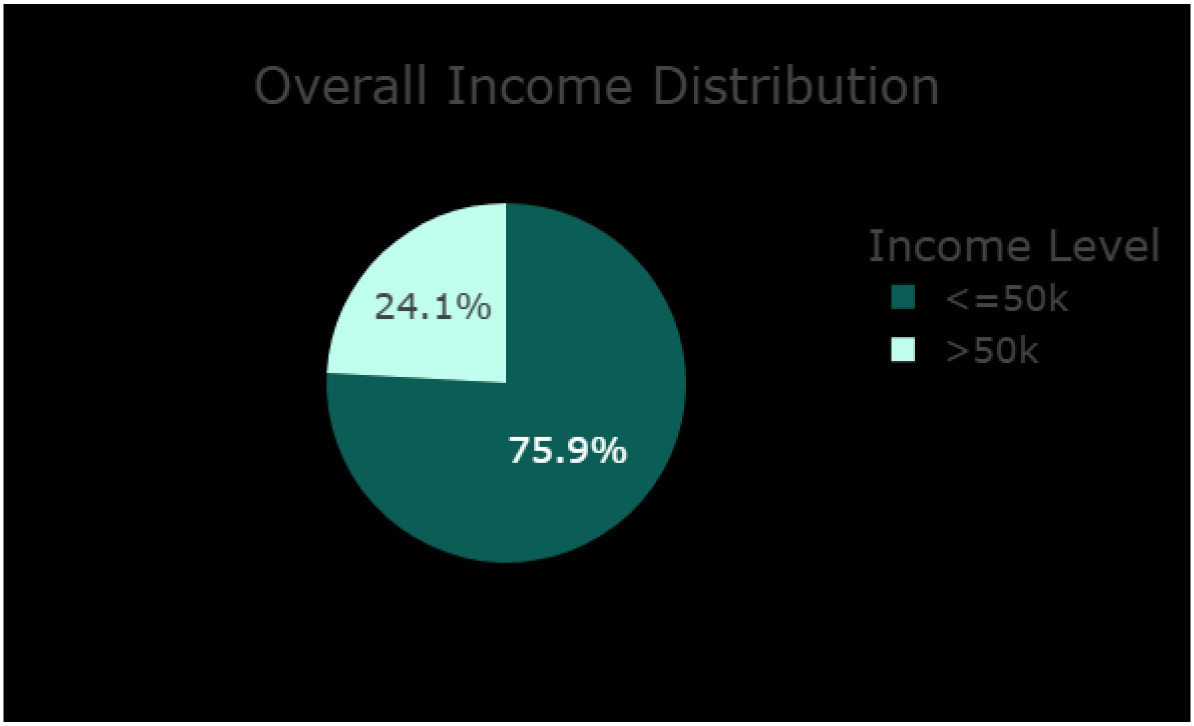
```
fig = px.pie(
    adult_df_income,
    names='income',
    values='total',
    title='Overall Income Distribution',
```

```
    color_discrete_sequence=['#0b5e55', '#c0ffee']
)

fig.update_layout(
    template='presentation',
    legend_title=dict(text='Income Level'),
    paper_bgcolor='white',
    plot_bgcolor='white'
)

fig.show()

# Save the image and HTML
fig.write_image(os.path.join(results_dir, 'income_distribution_pie_chart.jpg'))
fig.write_image(os.path.join(results_dir, 'income_distribution_pie_chart.png'))
fig.write_html(os.path.join(results_dir, 'income_distribution_pie_chart.html'))
```




```
fig = px.pie(adult_df_income, names='income', values='total', title='Overall Income Distribu
fig.update_layout(template='presentation', legend_title=dict(text='Income Level'), paper_bgc
fig.show()
fig.write_image(os.path.join(results_dir, 'income_distribution_pie_chart.jpg'))
```

```
fig.write_image(os.path.join(results_dir, 'income_distribution_pie_chart.png'))
fig.write_html(os.path.join(results_dir, 'income_distribution_pie_chart.html'))
```



This pie chart visualizes the overall income split: 76% of individuals earn 50K, while 24% earn >50K. This means that nearly 3 out of 4 individuals fall into the lower income bracket (<=50K). This shows that there is a significant imbalance.

Income by Age Group

```
adult_df_income_age = adult_df.groupby(['age_group', 'income']).size().reset_index(name='tota
adult_df_income_age
```

	age_group	income	total_by_age
0	18-25	<=50k	5333
1	18-25	>50k	114
2	26-35	<=50k	6910
3	26-35	>50k	1591
4	36-45	<=50k	5230

	age_group	income	total_by_age
5	36-45	>50k	2771
6	46-60	<=50k	4479
7	46-60	>50k	2809
8	61-75	<=50k	1580
9	61-75	>50k	511
10	76+	<=50k	200
11	76+	>50k	40
12	<18	<=50k	945

```
total_per_group = adult_df_income_age.groupby('age_group').size()
total_per_group
```

```
age_group
18-25    2
26-35    2
36-45    2
46-60    2
61-75    2
76+      2
<18      1
dtype: int64
```

```
total_per_group = adult_df_income_age.groupby('age_group')['total_by_age'].transform('sum')
total_per_group
```

```
0     5447
1     5447
2     8501
3     8501
4     8001
5     8001
6     7288
7     7288
8     2091
9     2091
10     240
11     240
12     945
Name: total_by_age, dtype: int64
```