Adults_StoryTelling

August 6, 2024

1 Data Story Telling

In this exercise, I will make a data story a compelling story about a dataset of adults income compared to different demografics, social or economical factors. The information collected includes data on age, gender, country of origin, marital status, housing conditions, marriage, education, employment, etc.

This project is designed for technical audience.

The overall structure of this study will be divided in 3 blocks: 1) Investigation Questions 2) Trends or patterns identified 3) Results of visualizations and conclusions

Some of the investigation questions could be:

- Does the data set include Interesting insights?
- What patters do I see with Histograms, Bar-graphs, Scatter plots, time series.
- Can I see visual comparisson between groups?
- Looking at the plots, what are some insights I can make?
- Is there a hypothesis I can - and should - investigate further?
- What other questions are the insights leading me to ask?

1.0.1 Hypothesis testing:

1) There is a significant gap of income by geneder.
2) There is a significant gap by racial condition.

1.1 Attributes Description

From Kaggle I obtained these Data Dictionary:

https://www.kaggle.com/code/jieyima/income-classification-model

1.1.1 1. Categorical Attributes

- **workclass**: (categorical) Private, Self-emp-not-inc, Self-emp-inc, Federal-gov, Local-gov, State-gov, Without-pay, Never-worked.
  - Individual work category
- **education**: (categorical) Bachelors, Some-college, 11th, HS-grad, Prof-school, Assoc-acdm, Assoc-voc, 9th, 7th-8th, 12th, Masters, 1st-4th, 10th, Doctorate, 5th-6th, Preschool.
  - Individual's highest education degree
- **marital-status**: (categorical) Married-civ-spouse, Divorced, Never-married, Separated, Widowed, Married-spouse-absent, Married-AF-spouse.

- Individual marital status
- **occupation**: (categorical) Tech-support, Craft-repair, Other-service, Sales, Exec-managerial, Prof-specialty, Handlers-cleaners, Machine-op-inspct, Adm-clerical, Farming-fishing, Transport-moving, Priv-house-serv, Protective-serv, Armed-Forces.
  - Individual's occupation
- **relationship**: (categorical) Wife, Own-child, Husband, Not-in-family, Other-relative, Unmarried.
  - Individual's relation in a family
- **race**: (categorical) White, Asian-Pac-Islander, Amer-Indian-Eskimo, Other, Black.
  - Race of Individual
- **Gender**: (categorical) Female, Male.
  - Gender of Individual
- **native-country**: (categorical) United-States, Cambodia, England, Puerto-Rico, Canada, Germany, Outlying-US(Guam-USVI-etc), India, Japan, Greece, South, China, Cuba, Iran, Honduras, Philippines, Italy, Poland, Jamaica, Vietnam, Mexico, Portugal, Ireland, France, Dominican-Republic, Laos, Ecuador, Taiwan, Haiti, Columbia, Hungary, Guatemala, Nicaragua, Scotland, Thailand, Yugoslavia, El-Salvador, Trinadad&Tobago, Peru, Hong, Holand-Netherlands.
  - Individual's native country

1.1.2 2. Continuous Attributes

- **age**: continuous.
  - Age of an individual
- **education-num**: number of education years, continuous.
  - Individual's years of receiving education
- **fnlwgt**: final weight, continuous.
  - The weights on the CPS files are controlled to independent estimates of the civilian noninstitutional population of the US. These are prepared monthly for us by Population Division here at the Census Bureau.
- **capital-gain**: continuous.
  - Capital gains
- **capital-loss**: continuous.
  - Capital losses
- **hours-per-week**: continuous.
  - Individual's working hours per week

[156]:
```python
#Import the libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import sklearn
```

[157]:
```python
# Numeric Df
df_num = df.select_dtypes(include=['number'])

# Categorical Df
```

```python
df_cat = df.select_dtypes(include=['object', 'category'])

# Include income in both dataframes as this is the response variable
df_num['income'] = df['income']
df_cat['income'] = df['income']
```

[158]:
```python
#Read the adult.csv dataset
df= pd.read_csv('adult.csv')
df.head()
```

[158]:
```
   age  workclass  fnlwgt     education  educational-num      marital-status  \
0   25    Private  226802          11th                7       Never-married
1   38    Private   89814       HS-grad                9  Married-civ-spouse
2   28  Local-gov  336951    Assoc-acdm               12  Married-civ-spouse
3   44    Private  160323  Some-college               10  Married-civ-spouse
4   18          ?  103497  Some-college               10       Never-married

          occupation relationship   race  gender  capital-gain  capital-loss  \
0  Machine-op-inspct    Own-child  Black    Male             0             0
1    Farming-fishing      Husband  White    Male             0             0
2    Protective-serv      Husband  White    Male             0             0
3  Machine-op-inspct      Husband  Black    Male          7688             0
4                  ?    Own-child  White  Female             0             0

   hours-per-week native-country income
0              40  United-States  <=50K
1              50  United-States  <=50K
2              40  United-States   >50K
3              40  United-States   >50K
4              30  United-States  <=50K
```

[159]:
```python
df.shape
```

[159]: (48842, 15)

[160]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   age              48842 non-null  int64
 1   workclass        48842 non-null  object
 2   fnlwgt           48842 non-null  int64
 3   education        48842 non-null  object
 4   educational-num  48842 non-null  int64
 5   marital-status   48842 non-null  object
```

```
 6   occupation       48842 non-null  object
 7   relationship     48842 non-null  object
 8   race             48842 non-null  object
 9   gender           48842 non-null  object
 10  capital-gain     48842 non-null  int64
 11  capital-loss     48842 non-null  int64
 12  hours-per-week   48842 non-null  int64
 13  native-country   48842 non-null  object
 14  income           48842 non-null  object
dtypes: int64(6), object(9)
memory usage: 5.6+ MB
```

[161]:
```
df.isnull().sum()
```

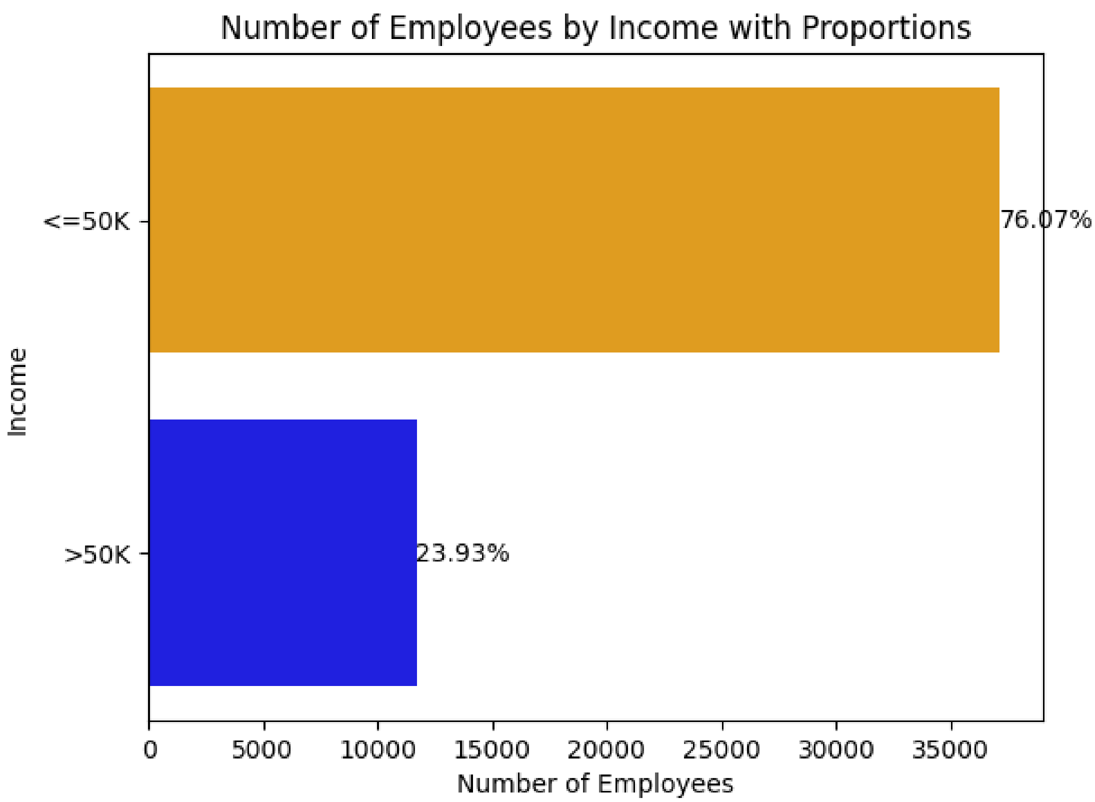
[161]:
```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country     0
income             0
dtype: int64
```

[162]:
```
# IT seems that income only has two values, either <=50K or >50K. Let's check␣
↪the unique values in the income column
df['income'].unique()
```

[162]:
```
array(['<=50K', '>50K'], dtype=object)
```

[163]:
```
# Calculate the proportions
income_counts = df['income'].value_counts()
income_proportions = df['income'].value_counts(normalize=True)

# Develop the horizontal bar plot
colors = ['orange', 'blue']
ax = sns.countplot(y='income', data=df, palette=colors, hue='income',␣
↪dodge=False, legend=False)

# Add the proportions to the plot
for p, proportion in zip(ax.patches, income_proportions):
```

```
    width = p.get_width()
    plt.text(width + 2000, p.get_y() + p.get_height() / 2, f'{proportion:.2%}',␣
↪ha='center', va='center')

plt.xlabel('Number of Employees')
plt.ylabel('Income')
plt.title('Number of Employees by Income with Proportions')
plt.show()
```



[164]:
```
#Identiy the didfferent edducation categories
df['education'].unique()
```

[164]:
```
array(['11th', 'HS-grad', 'Assoc-acdm', 'Some-college', '10th',
       'Prof-school', '7th-8th', 'Bachelors', 'Masters', 'Doctorate',
       '5th-6th', 'Assoc-voc', '9th', '12th', '1st-4th', 'Preschool'],
      dtype=object)
```

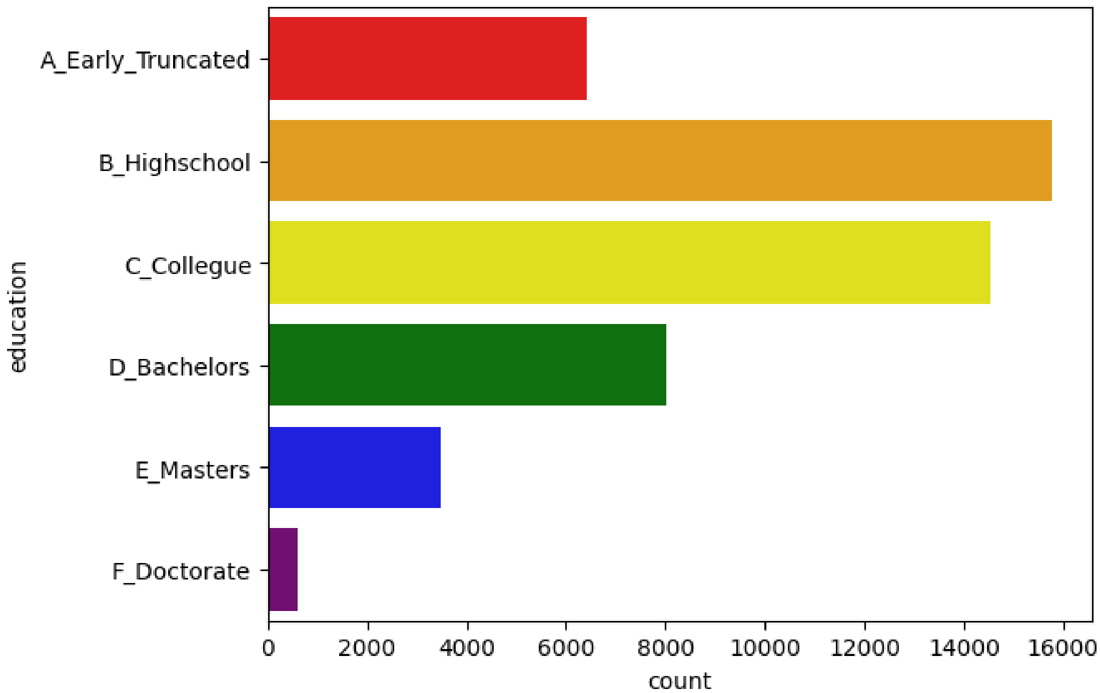
1.1.3 It looks that the employees with an income >50k is 3 times higher:

[165]:
```
education_mapping = {
    'Preschool': 'A_Early_Truncated',
    '10th': 'A_Early_Truncated',
    '11th': 'A_Early_Truncated',
    '12th': 'A_Early_Truncated',
    '1st-4th': 'A_Early_Truncated',
    '5th-6th': 'A_Early_Truncated',
    '7th-8th': 'A_Early_Truncated',
    '9th': 'A_Early_Truncated',
    'HS-grad': 'B_Highschool',
    'Some-college': 'C_Collegue',
    'Assoc-acdm': 'C_Collegue',
    'Assoc-voc': 'C_Collegue',
    'Bachelors': 'D_Bachelors',
    'Masters': 'E_Masters',
    'Prof-school': 'E_Masters',
    'Doctorate': 'F_Doctorate',

}

df['education'] = df['education'].replace(education_mapping)
```

[166]:
```
# Define the order of the education categories
education_order = [
    'A_Early_Truncated',
    'B_Highschool',
    'C_Collegue',
    'D_Bachelors',
    'E_Masters',
    'F_Doctorate'
]

# Reorder
df['education'] = pd.Categorical(df['education'], categories=education_order,␣
 ↪ordered=True)

# Plot the countplot with different colors per category
colors = ['red', 'orange', 'yellow', 'green', 'blue', 'purple']
ax = sns.countplot(y='education', data=df, palette=colors,␣
 ↪order=education_order)
```

```
/var/folders/tt/4rw4wd117d5_9ss8qs8210jw0000gn/T/ipykernel_5773/4208264815.py:16
: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
```

```
effect.

  ax = sns.countplot(y='education', data=df, palette=colors,
order=education_order)
```



[167]:
```python
# Review all the possible categories of marital status
df['marital-status'].unique()
```

[167]:
```
array(['Never-married', 'Married-civ-spouse', 'Widowed', 'Divorced',
       'Separated', 'Married-spouse-absent', 'Married-AF-spouse'],
      dtype=object)
```

[168]:
```python
# Merge all types of married in only one category "Married"
married_mapping = {
    'Married-civ-spouse': 'Married',
    'Married-spouse-absent': 'Married',
    'Married-AF-spouse': 'Married',
}

df['marital-status'] = df['marital-status'].replace(married_mapping)
```

[169]:
```python
df['marital-status'].unique()
```

[169]: array(['Never-married', 'Married', 'Widowed', 'Divorced', 'Separated'],
      dtype=object)

[170]:
```
# Review the categories of Workclass
df['workclass'].unique()
```

[170]:
```
array(['Private', 'Local-gov', '?', 'Self-emp-not-inc', 'Federal-gov',
       'State-gov', 'Self-emp-inc', 'Without-pay', 'Never-worked'],
      dtype=object)
```

[171]:
```
# Review the categories of Occupation
df['occupation'].unique()
```

[171]:
```
array(['Machine-op-inspct', 'Farming-fishing', 'Protective-serv', '?',
       'Other-service', 'Prof-specialty', 'Craft-repair', 'Adm-clerical',
       'Exec-managerial', 'Tech-support', 'Sales', 'Priv-house-serv',
       'Transport-moving', 'Handlers-cleaners', 'Armed-Forces'],
      dtype=object)
```

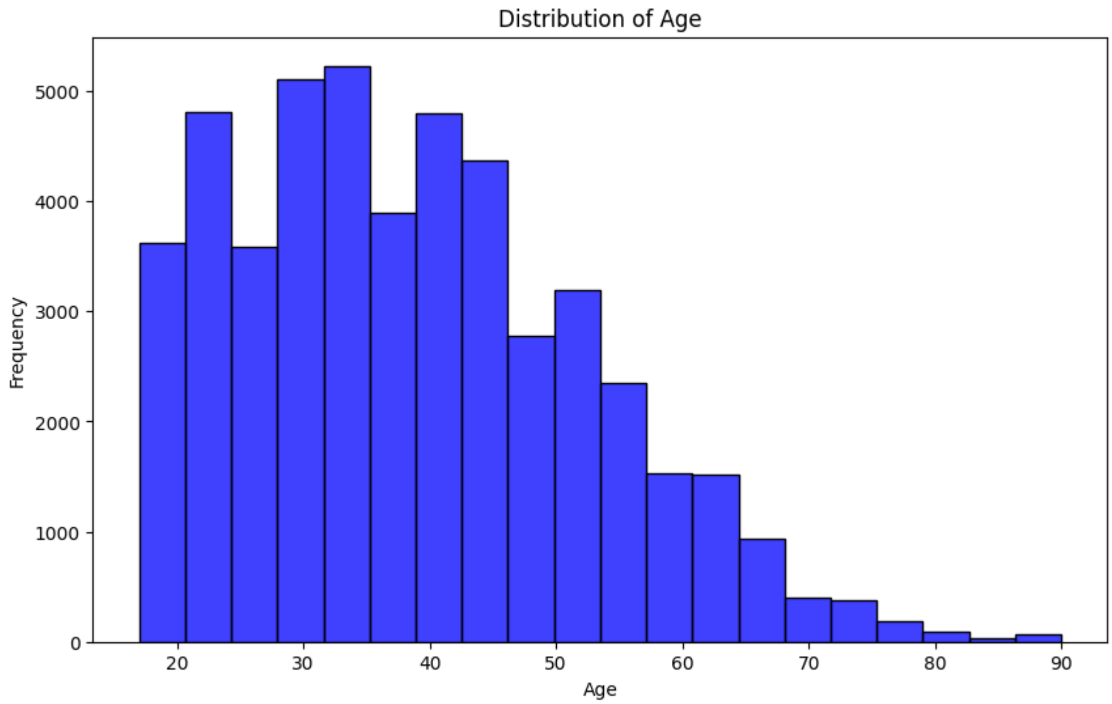
[172]:
```
# Review the categories of Relationship
df['relationship'].unique()
```

[172]:
```
array(['Own-child', 'Husband', 'Not-in-family', 'Unmarried', 'Wife',
       'Other-relative'], dtype=object)
```

[173]:
```
# Review the categories of Age
df['age'].unique()
```

[173]:
```
array([25, 38, 28, 44, 18, 34, 29, 63, 24, 55, 65, 36, 26, 58, 48, 43, 20,
       37, 40, 72, 45, 22, 23, 54, 32, 46, 56, 17, 39, 52, 21, 42, 33, 30,
       47, 41, 19, 69, 50, 31, 59, 49, 51, 27, 57, 61, 64, 79, 73, 53, 77,
       80, 62, 35, 68, 66, 75, 60, 67, 71, 70, 90, 81, 74, 78, 82, 83, 85,
       76, 84, 89, 88, 87, 86])
```

[174]:
```
#Plot the ages
plt.figure(figsize=(10, 6))
sns.histplot(df['age'], bins=20, color='blue')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```



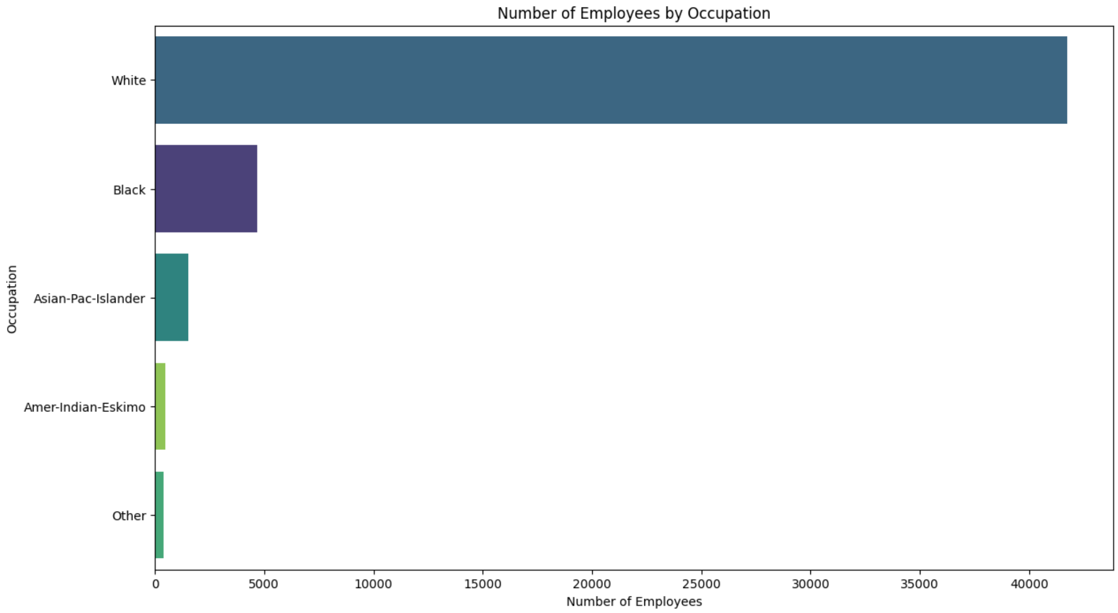
[175]:
```
df.columns
```

[175]:
```
Index(['age', 'workclass', 'fnlwgt', 'education', 'educational-num',
       'marital-status', 'occupation', 'relationship', 'race', 'gender',
       'capital-gain', 'capital-loss', 'hours-per-week', 'native-country',
       'income'],
      dtype='object')
```

[176]:
```
# Review the categories of Race
df['race'].unique()
```

[176]:
```
array(['Black', 'White', 'Asian-Pac-Islander', 'Other',
       'Amer-Indian-Eskimo'], dtype=object)
```

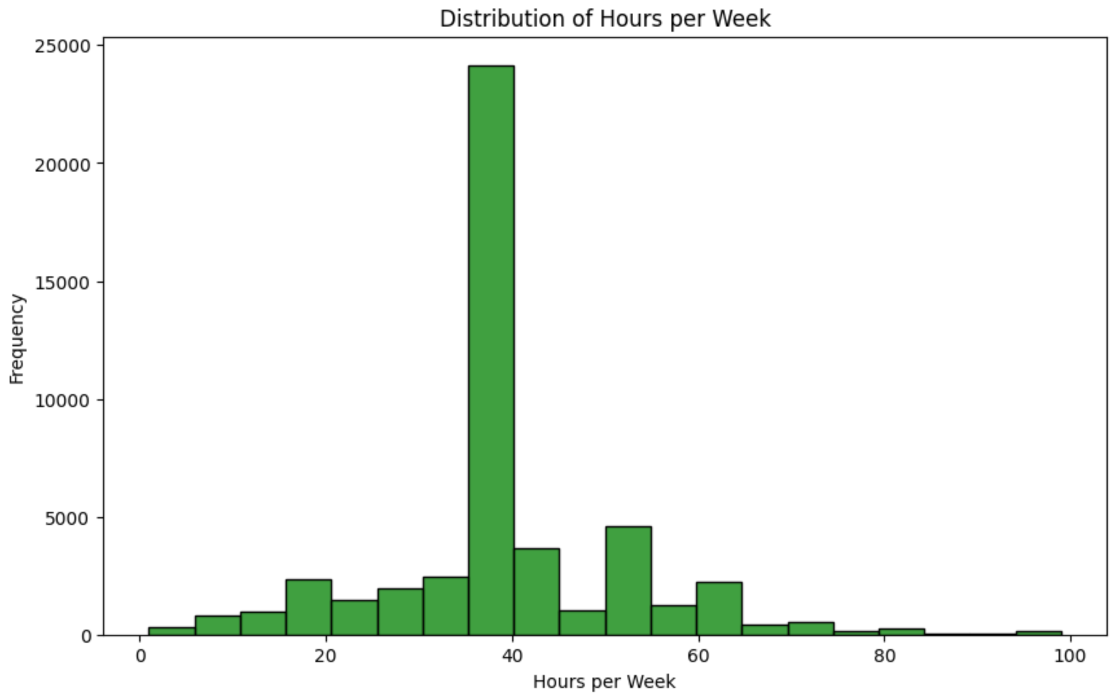
[177]:
```
#Plot the countplot of the individuals by race
plt.figure(figsize=(14, 8))
ax = sns.countplot(y='race', data=df, palette='viridis', order=df['race'].
 ↪value_counts().index, hue='race', dodge=False, legend=False)
plt.title('Number of Employees by Occupation')
plt.xlabel('Number of Employees')
plt.ylabel('Occupation')
plt.show()
```



[178]:
```
#Review the unique categories of hours per week
df['hours-per-week'].unique()
```

[178]:
```
array([40, 50, 30, 32, 10, 39, 35, 48, 25, 20, 45, 47,  6, 43, 90, 54, 60,
       38, 36, 18, 24, 44, 56, 28, 16, 41, 22, 55, 14, 33, 37,  8, 12, 70,
       15, 75, 52, 84, 42, 80, 68, 99, 65,  5, 17, 72, 53, 29, 96, 21, 46,
        3,  1, 23, 49, 67, 76,  7,  2, 58, 26, 34,  4, 51, 78, 63, 31, 92,
       77, 27, 85, 13, 19, 98, 62, 66, 57, 11, 86, 59,  9, 64, 73, 61, 88,
       79, 89, 74, 69, 87, 97, 94, 82, 91, 81, 95])
```

[179]:
```
#Plot the distribution of hours per week
plt.figure(figsize=(10, 6))
sns.histplot(df['hours-per-week'], bins=20, color='green')
plt.title('Distribution of Hours per Week')
plt.xlabel('Hours per Week')
plt.ylabel('Frequency')
plt.show()
```



[180]:
```
df.info()
```

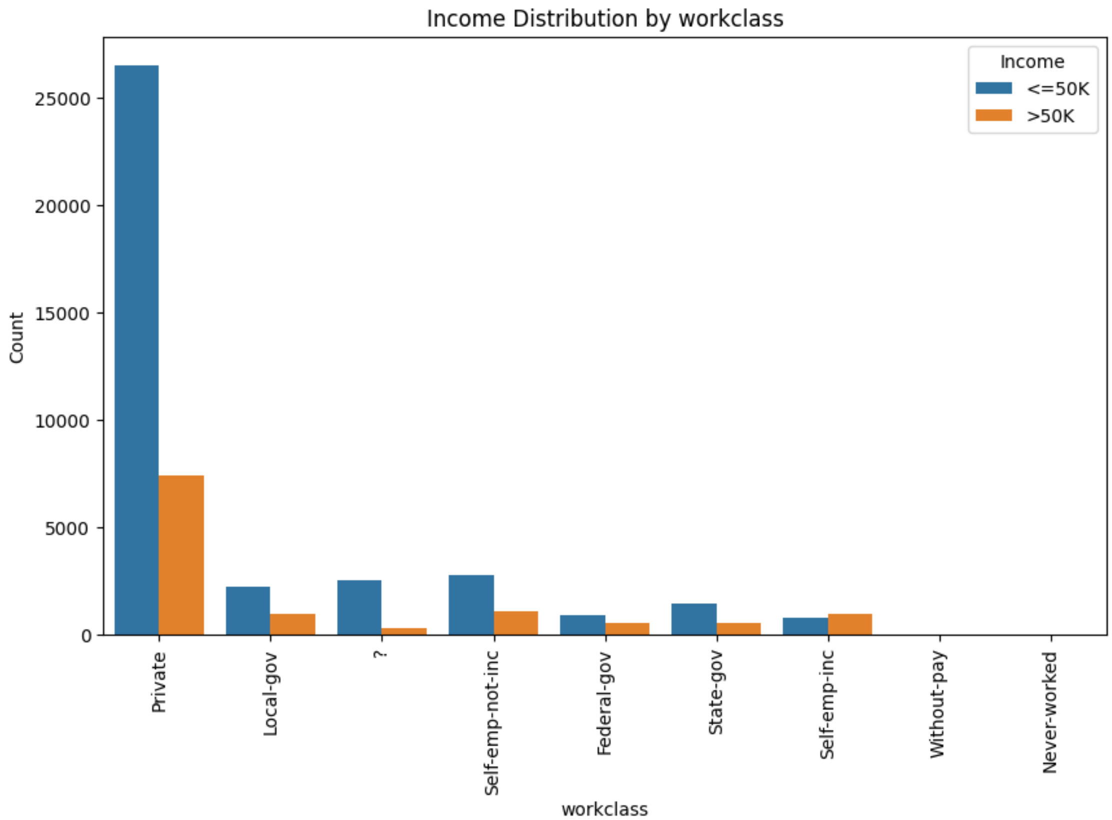
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   age               48842 non-null  int64
 1   workclass         48842 non-null  object
 2   fnlwgt            48842 non-null  int64
 3   education         48842 non-null  category
 4   educational-num   48842 non-null  int64
 5   marital-status    48842 non-null  object
 6   occupation        48842 non-null  object
 7   relationship      48842 non-null  object
 8   race              48842 non-null  object
 9   gender            48842 non-null  object
 10  capital-gain      48842 non-null  int64
 11  capital-loss      48842 non-null  int64
 12  hours-per-week    48842 non-null  int64
 13  native-country    48842 non-null  object
 14  income            48842 non-null  object
dtypes: category(1), int64(6), object(8)
memory usage: 5.3+ MB
```

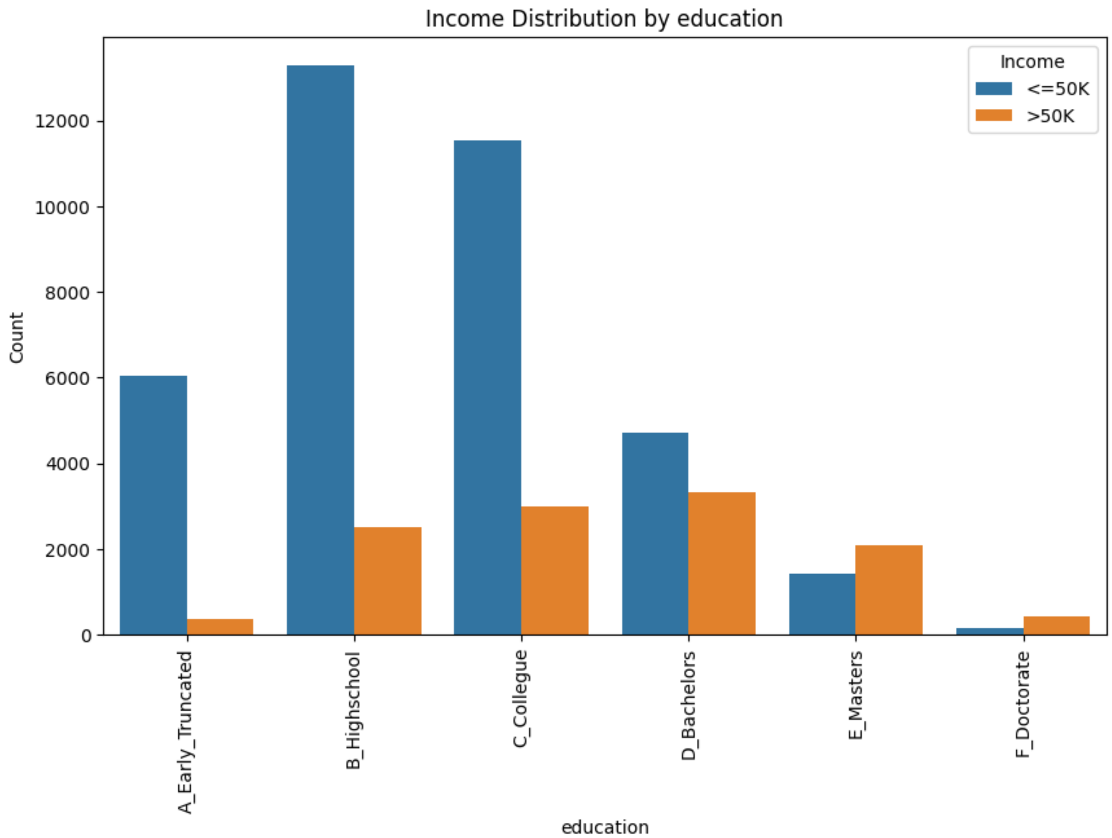
Separate numeric and Categorical Features in 2 dataframes:

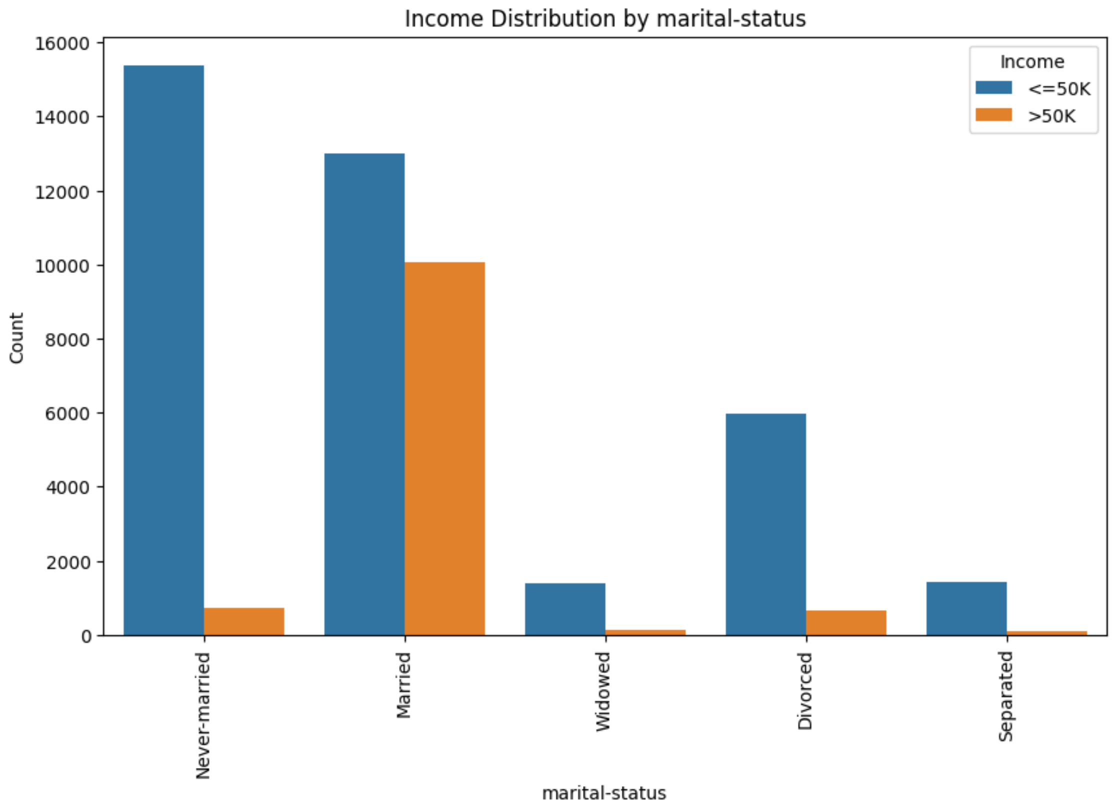
[181]:
```python
# Numeric Df
df_num = df.select_dtypes(include=['number'])

# Categorical Df
df_cat = df.select_dtypes(include=['object', 'category'])

# Include income in both dataframes as this is the response variable
df_num['income'] = df['income']
df_cat['income'] = df['income']
```

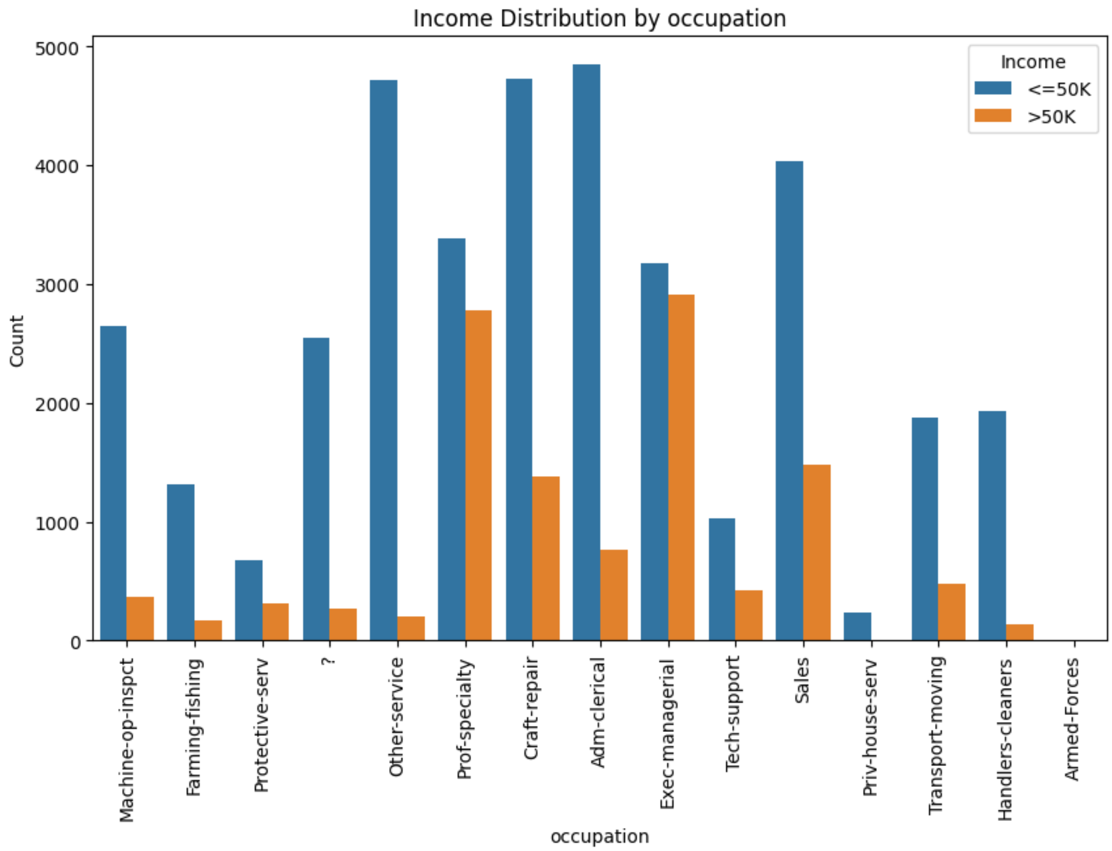
1.2 Categorical Analysis

[182]:
```python
# Lista de columnas categóricas
categorical_features = ['workclass', 'education', 'marital-status',␣
 ↪'occupation', 'relationship', 'race', 'gender']

# Crear gráficos de barras para cada feature categórico
for feature in categorical_features:
    plt.figure(figsize=(10, 6))
    sns.countplot(data=df_cat, x=feature, hue='income')
    plt.title(f'Income Distribution by {feature}')
    plt.xlabel(feature)
    plt.ylabel('Count')
    plt.xticks(rotation=90)
    plt.legend(title='Income')
    plt.show()
```

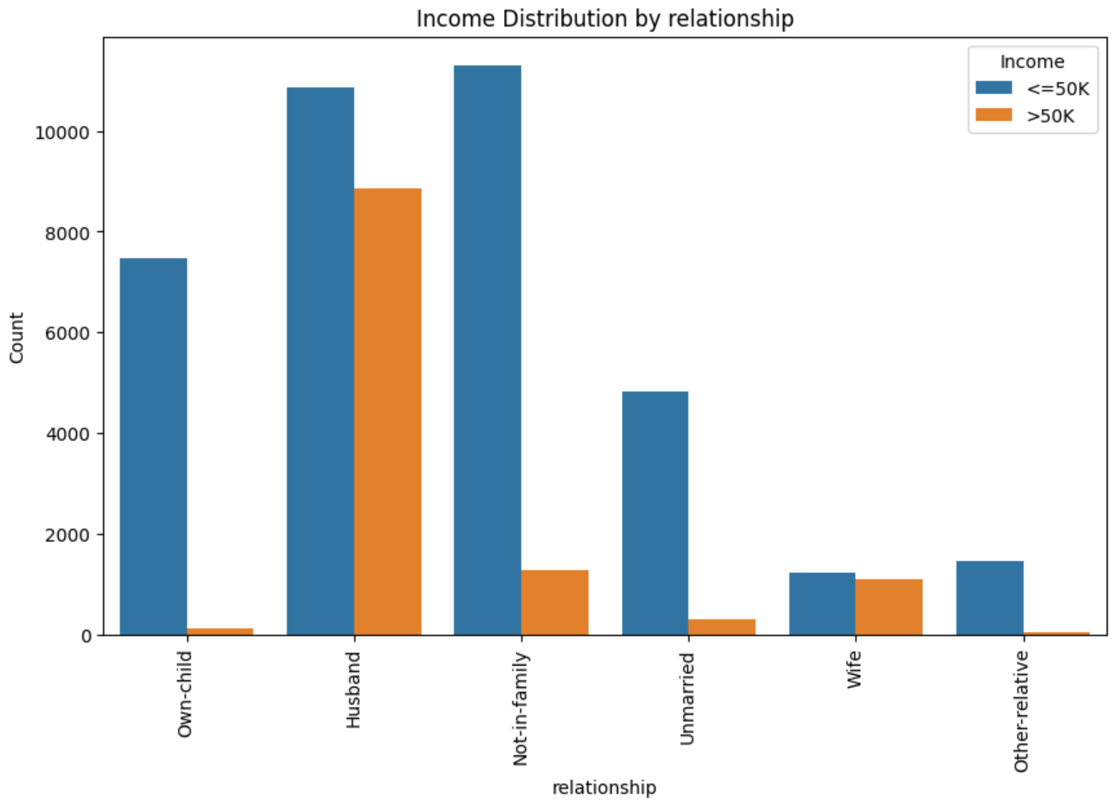

Income Distribution by workclass
Income
<=50K
>50K
Count
25000
20000
15000
10000
5000
0
Private
Local-gov
?
Self-emp-not-inc
Federal-gov
State-gov
Self-emp-inc
Without-pay
Never-worked
workclass

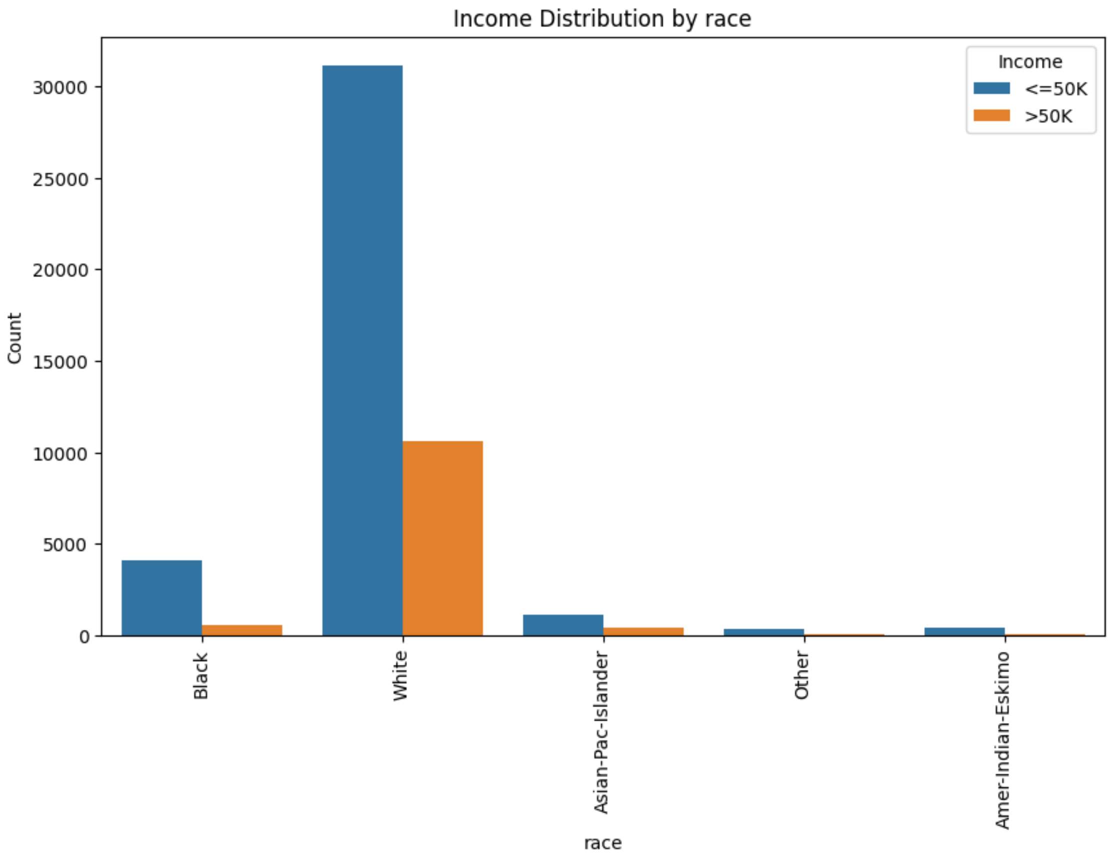

Income Distribution by education
Income
<=50K
>50K
Count
12000
10000
8000
6000
4000
2000
0
A_Early_Truncated
B_Highschool
C_Collegue
D_Bachelors
E_Masters
F_Doctorate
education

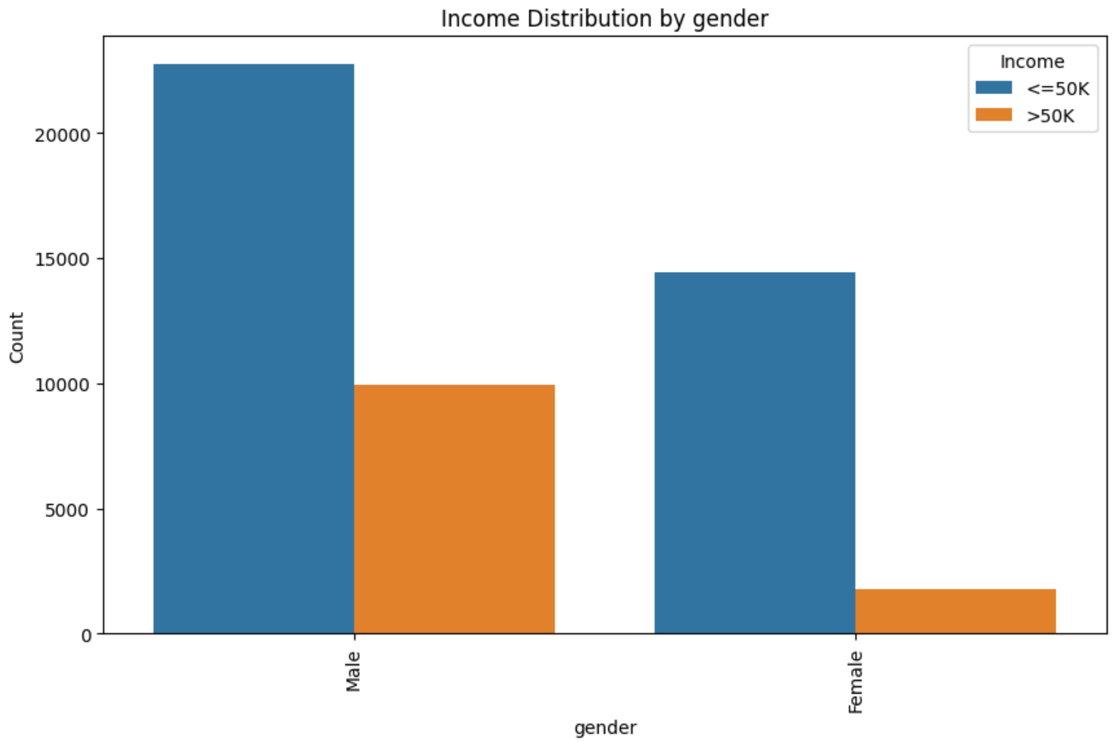

Income Distribution by marital-status
Income
<=50K
>50K
Count
16000
14000
12000
10000
8000
6000
4000
2000
0
Never-married
Married
Widowed
Divorced
Separated
marital-status



Income Distribution by occupation
Income
<=50K
>50K
Count
5000
4000
3000
2000
1000
0
Machine-op-inspct
Farming-fishing
Protective-serv
?
Other-service
Prof-specialty
Craft-repair
Adm-clerical
Exec-managerial
Tech-support
Sales
Priv-house-serv
Transport-moving
Handlers-cleaners
Armed-Forces
occupation


Income Distribution by relationship
Income
<=50K
>50K
Count
10000
8000
6000
4000
2000
0
Own-child
Husband
Not-in-family
Unmarried
Wife
Other-relative
relationship


Income Distribution by race
Income
<=50K
>50K
Count
30000
25000
20000
15000
10000
5000
0
Black
White
Asian-Pac-Islander
Other
Amer-Indian-Eskimo
race



1.3 Conclusions of Categorical Visualizations:

From the categorical Features I can identify some preliminary patterns:

1) Self employment income seems to have a higher proportion of >50k income.
2) Masters and Doctorate have a proportion of >50k Income higher than the rest of the education levels.
3) For some reason Married individuals seem to have a higher proportion of >50k Income
4) Exec-Managerial is the category with the highest proportion of >50k
5) Husband and Wife Relationship Status also confirm #3 insight.
6) White race has the highest >50k Income proportion.
7) Male Gender shows a higher proportion of >50k Income.

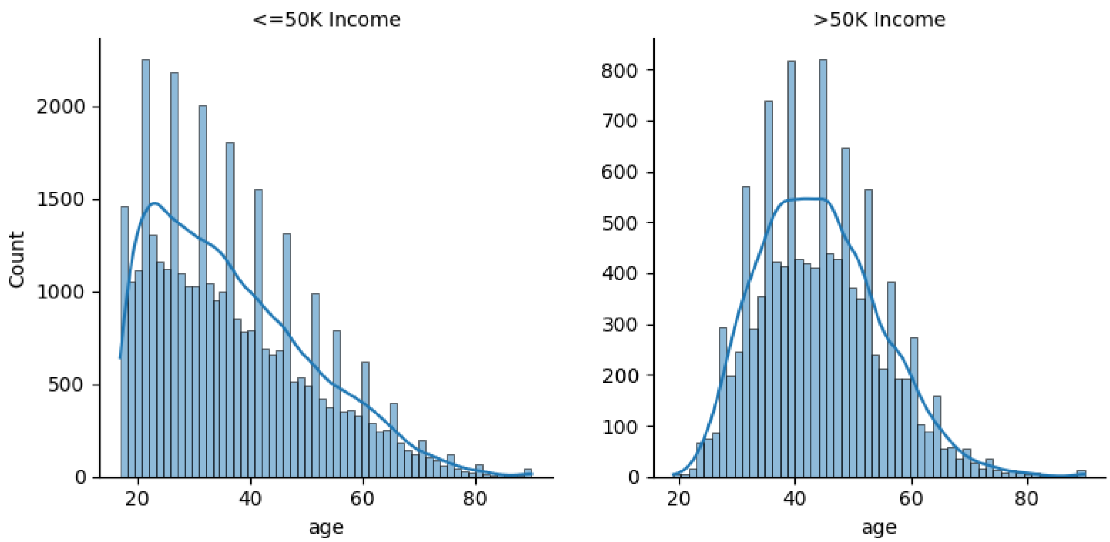
1.4 Numerical Analysis

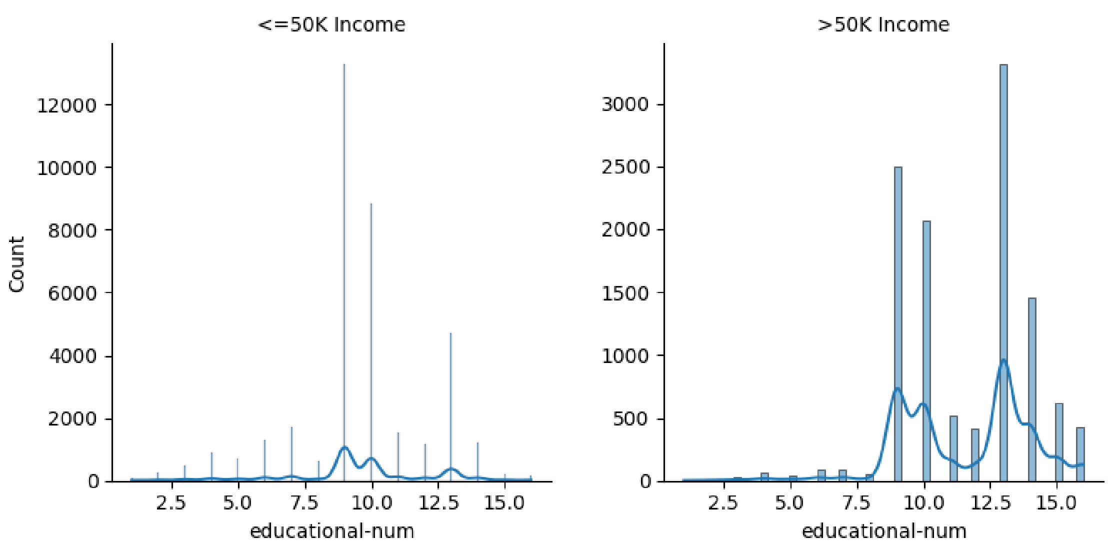
[183]:
```
df_num.columns
```

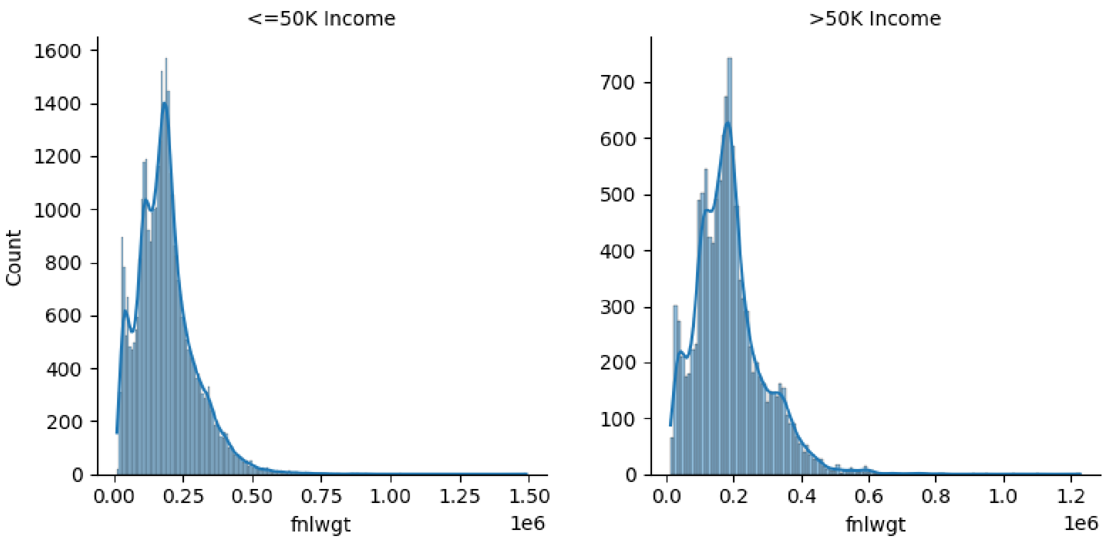
[183]:
```
Index(['age', 'fnlwgt', 'educational-num', 'capital-gain', 'capital-loss',
       'hours-per-week', 'income'],
      dtype='object')
```

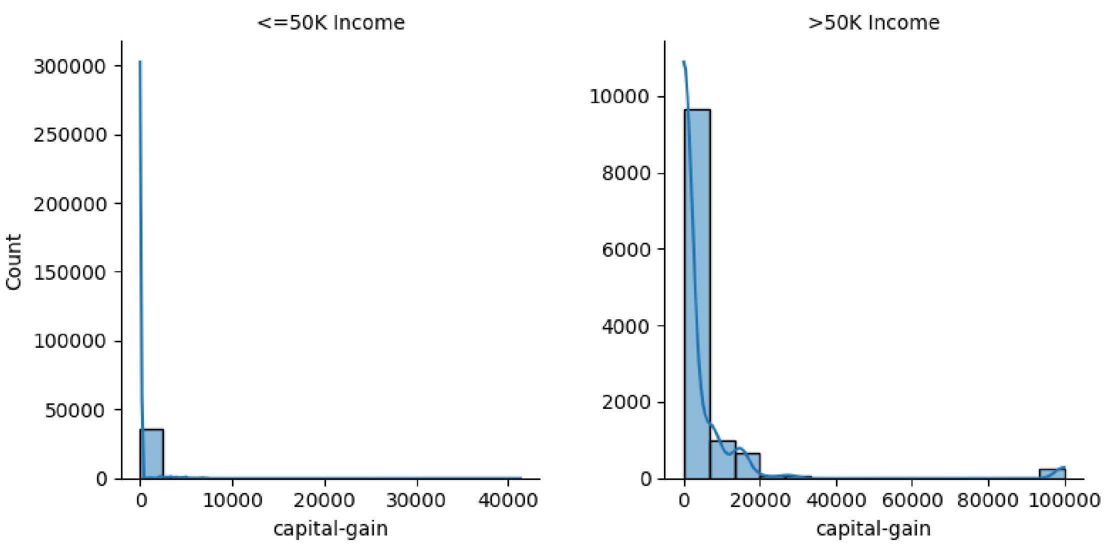
[184]:
```python
continuous_features = ['age', 'educational-num', 'fnlwgt', 'capital-gain', 'capital-loss', 'hours-per-week']
```

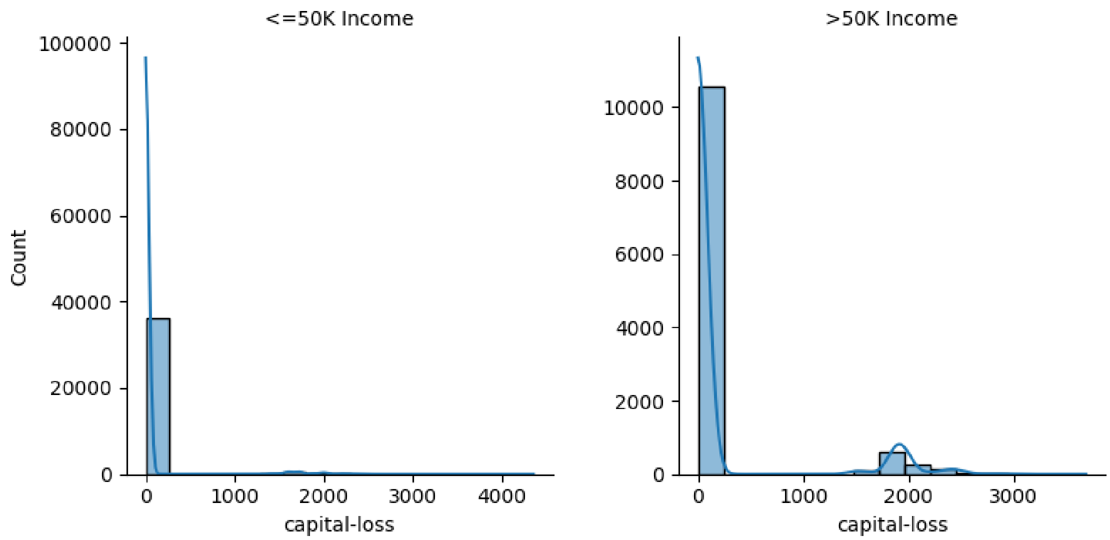
[185]:
```python
for feature in continuous_features:
    g = sns.FacetGrid(df, col='income', col_wrap=2, height=4, sharex=False, sharey=False)
    g.map_dataframe(sns.histplot, x=feature, kde=True)
    g.set_titles("{col_name} Income")
    g.set_axis_labels(feature, 'Count')
    plt.show()
```

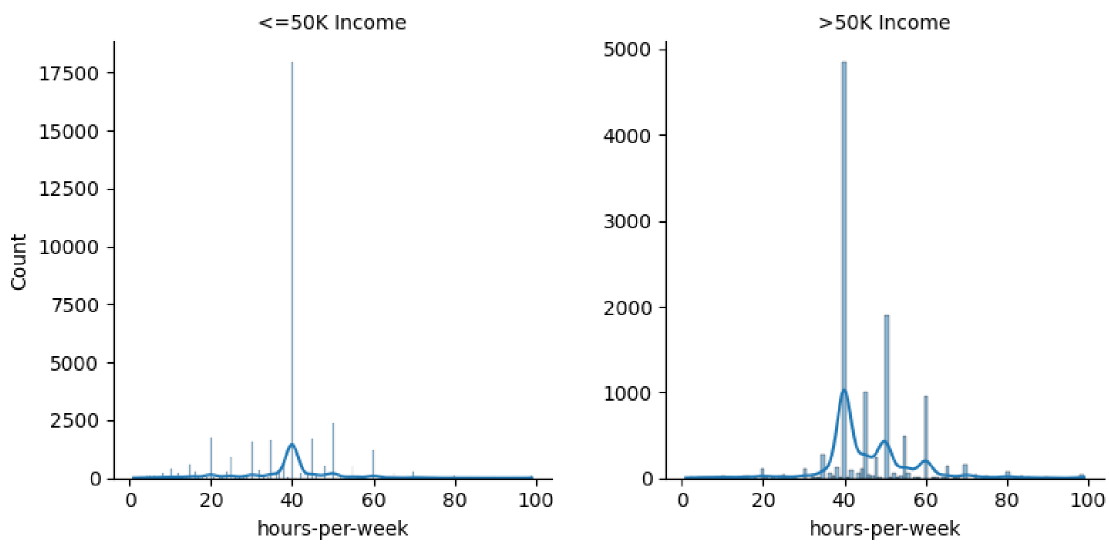





<=50K Income
>50K Income
Count
fnlwgt
1e6
fnlwgt
1e6


<=50K Income
>50K Income
Count
capital-gain
capital-gain



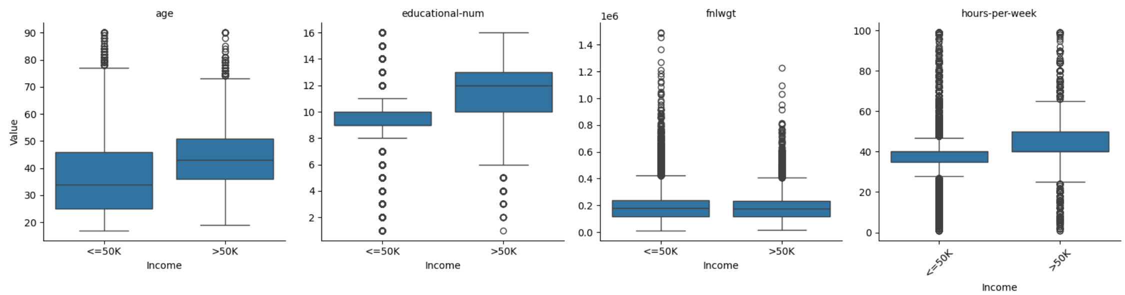


Capital Loss and Capital Gain have a very large spread, so I will not consider them in the boxplots!

[186]:

```
# Choose and melt the Interesting numerical features:

continuous_features = ['age', 'educational-num', 'fnlwgt', 'hours-per-week']
df_melted = pd.melt(df, id_vars='income', value_vars=continuous_features,
    var_name='feature', value_name='value')

# Create a facegrid with boxplot graphics:
```

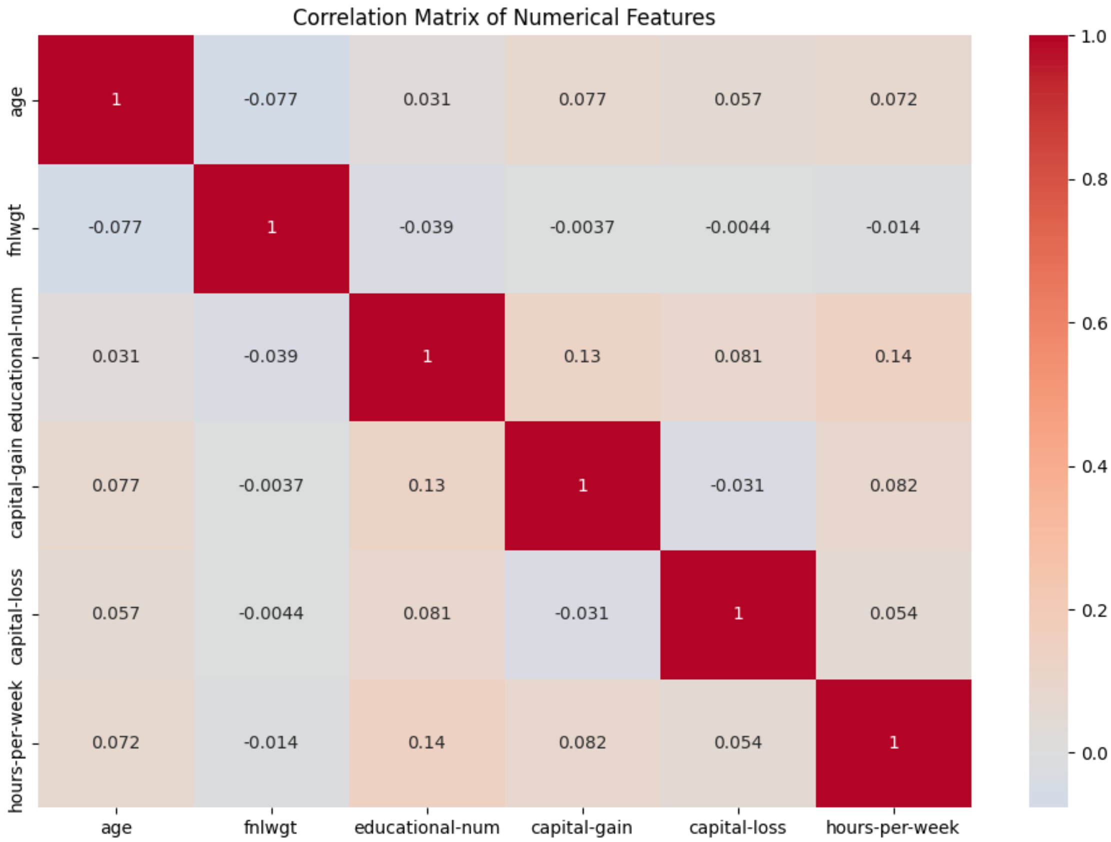
```
g = sns.FacetGrid(df_melted, col='feature', col_wrap=4, height=4, sharey=False)
g.map(sns.boxplot, 'income', 'value', order=df['income'].unique())
g.set_titles("{col_name}")
g.set_axis_labels('Income', 'Value')
plt.xticks(rotation=45)
plt.show()
```



1.5 Conclusions on the numerical variables

Income in general looks higher with: 1) More Senior employees 2) More Educated Employees 3) Workers that dedicate more hours per week to work.

[191]:
```
# Correlation matrix between the numerical features, exclusing the income (as␣
↪this is the response variable)
df_num_no_income = df_num.drop(columns='income')

correlation_matrix = df_num_no_income.corr()

# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



No pattern or correlation can be found between the numerical variables!

2 Answers to the Investigation Questions

2.0.1 1. Does the data set include interesting insights?

Yes, the dataset provides several interesting insights. For example, it reveals significant differences in income based on education level, marital status, gender, and occupation. Higher education levels such as Masters and Doctorate are associated with higher income, and certain occupations like executive managerial roles have a higher proportion of individuals earning more than $50K.

2.0.2 2. What patterns do I see with histograms, bar-graphs, scatter plots, time series?

- **Histograms**: Show the distribution of continuous variables like age, education years, and hours worked per week. I see some features like Capital Gain and Capital Loss which have a very large spread and don't show an evident pattern.
- **Bar-graphs**: Reveal the count of individuals within each category of a categorical variable, such as education level, work class, and marital status. They highlight that married individuals and those in executive managerial positions tend to have higher incomes.
- **Scatter plots**: This graph helps to identify relationships between two continuous variables,

however this was not used in this study as all the numerical variables didn't seem to be correlated.

2.0.3 3. Can I see visual comparison between groups?

Yes, visual comparisons between groups are evident: - **Box plots**: Show the distribution of income across different education levels or occupations. - **Facet grids**: Display histograms or scatter plots for different income levels or genders, allowing a comparison across multiple groups. - **Grouped bar charts**: Highlight differences in income distribution among various categories, such as marital status and race.

2.0.4 4. Looking at the plots, what are some insights I can make?

Some key insights from the plots include: - Individuals with higher education levels tend to earn more. - Certain occupations, such as executive managerial roles, have a higher proportion of high-income earners. - Married individuals generally have higher incomes compared to unmarried ones. - There are significant income disparities based on gender and race, with males and White individuals having higher proportions of >$50K income.

2.0.5 5. Is there a hypothesis I can - and should - investigate further?

Yes, several hypotheses can be investigated further: - The impact of higher education levels on income. - The significant income differences across various occupations. - The reasons behind the effect of marital status on income levels. - Gender and race disparities in income and their underlying causes.

2.0.6 6. What other questions are the insights leading me to ask?

Based on the insights, additional questions could include: - What specific factors within education and occupation contribute most to higher income? - How do other demographic factors, such as region and work hours, influence income? - Are there interactions between variables (e.g., does the impact of education on income vary by gender or race)? - How does the income distribution vary across different geographic locations?

2.1 Hypothesis testing:

1) There is a significant gap of income by gender: ### YES
2) There is a significant gap by racial condition. ### YES

[1]:
```
#Export this notebook as PDF for the final submission
!jupyter nbconvert --to pdf "Exploratory Data Analysis.ipynb"
```

```
[NbConvertApp] WARNING | pattern 'Exploratory Data Analysis.ipynb' matched no
files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
```

```
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and
include the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=
--ClearOutputPreprocessor.enabled=True]
--coalesce-streams
```

```
    Coalesce consecutive stdout and stderr outputs into one stream (within each
cell).
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=
--CoalesceStreamsPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True
--TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True
--TemplateExporter.exclude_input=True
--TemplateExporter.exclude_input_prompt=True]
--allow-chromium-download
    Whether to allow downloading chromium if no suitable version is found on the
system.
    Equivalent to: [--WebPDFExporter.allow_chromium_download=True]
--disable-chromium-sandbox
    Disable chromium security sandbox when converting to PDF..
    Equivalent to: [--WebPDFExporter.disable_sandbox=True]
--show-input
    Shows code input. This flag is only useful for dejavu users.
    Equivalent to: [--TemplateExporter.exclude_input=False]
--embed-images
    Embed the images as base64 dataurls in the output. This flag is only useful
for the HTML/WebPDF/Slides exports.
    Equivalent to: [--HTMLExporter.embed_images=True]
--sanitize-html
    Whether the HTML in Markdown cells and cell outputs should be sanitized..
    Equivalent to: [--HTMLExporter.sanitize_html=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL']
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook',
'pdf', 'python', 'qtpdf', 'qtpng', 'rst', 'script', 'slides', 'webpdf']
            or a dotted object name that represents the import path for an
            ``Exporter`` class
```

```
    Default: ''
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_name]
--template-file=<Unicode>
    Name of the template file to use
    Default: None
    Equivalent to: [--TemplateExporter.template_file]
--theme=<Unicode>
    Template specific theme(e.g. the name of a JupyterLab CSS theme distributed
    as prebuilt extension for the lab template)
    Default: 'light'
    Equivalent to: [--HTMLExporter.theme]
--sanitize_html=<Bool>
    Whether the HTML in Markdown cells and cell outputs should be sanitized.This
    should be set to True by nbviewer or similar tools.
    Default: False
    Equivalent to: [--HTMLExporter.sanitize_html]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    Overwrite base name use for output files.
                Supports pattern replacements '{notebook_name}'.
    Default: '{notebook_name}'
    Equivalent to: [--NbConvertApp.output_base]
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each notebook.
To recover
                                  previous default behaviour (outputting to the
current
                                  working directory) use . as the flag value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url pointing to a
copy
```

```
            of reveal.js.
            For speaker notes to work, this must be a relative path to a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of the
            current directory (from which the server is run).
            See the usage documentation
            (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-
html-slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb --to html

            Options include ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'qtpdf', 'qtpng', 'rst', 'script', 'slides',
'webpdf'].

            > jupyter nbconvert --to latex mynotebook.ipynb

            Both HTML and LaTeX support multiple output templates. LaTeX
includes
            'base', 'article' and 'report'.  HTML includes 'basic', 'lab' and
            'classic'. You can specify the flavor of the format used.

            > jupyter nbconvert --to html --template lab mynotebook.ipynb

            You can also pipe the output to stdout, rather than a file

            > jupyter nbconvert mynotebook.ipynb --stdout

            PDF is generated via latex

            > jupyter nbconvert mynotebook.ipynb --to pdf

            You can get (and serve) a Reveal.js-powered slideshow
```

```
            > jupyter nbconvert myslides.ipynb --to slides --post serve

            Multiple notebooks can be given at the command line in a couple of
            different ways:

            > jupyter nbconvert notebook*.ipynb
            > jupyter nbconvert notebook1.ipynb notebook2.ipynb

            or you can specify the notebooks list in a config file, containing::

                c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

            > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```