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.
3) Income could be modeled with some usually known features like: age, gender, region, education.

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

[157]:
```
# 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']
```

[158]:
```
#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]:
```
df.shape
```

[159]:
```
(48842, 15)
```

[160]:
```
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()
```

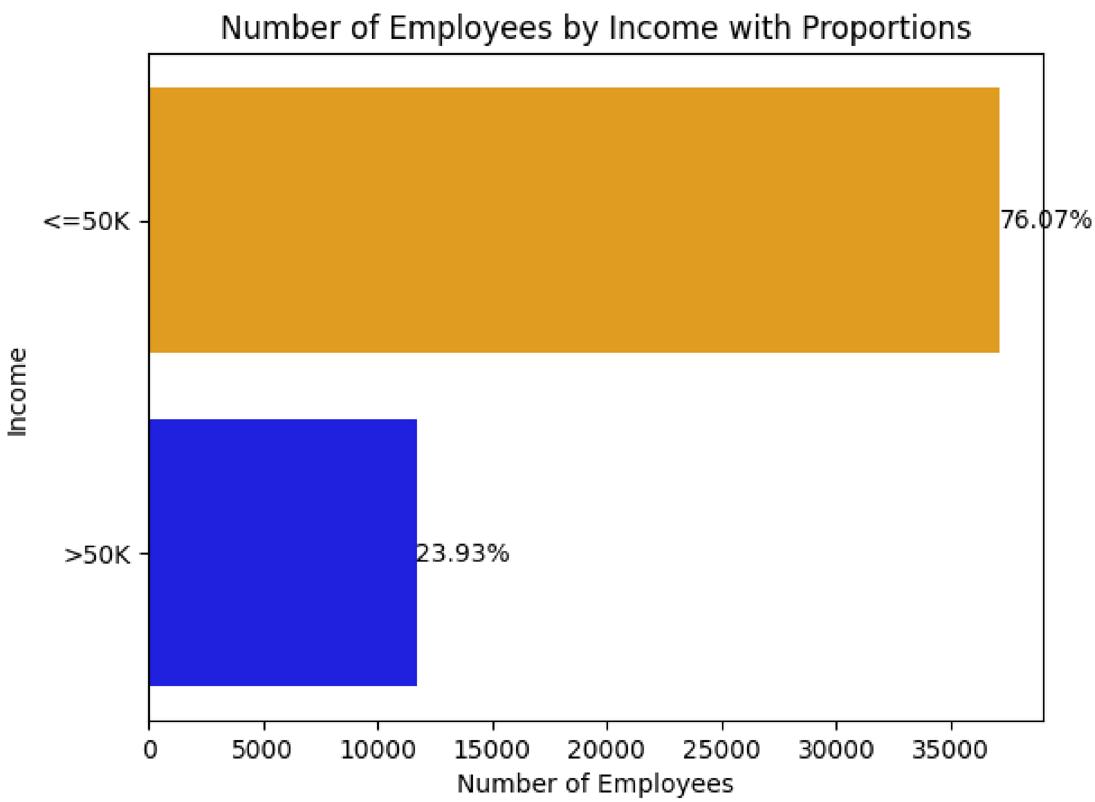
[161]:
```
age                0
workclass          0
fnlwgt             0
education          0
educational-num    0
marital-status     0
occupation         0
relationship       0
race               0
gender             0
capital-gain       0
capital-loss       0
hours-per-week     0
native-country  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

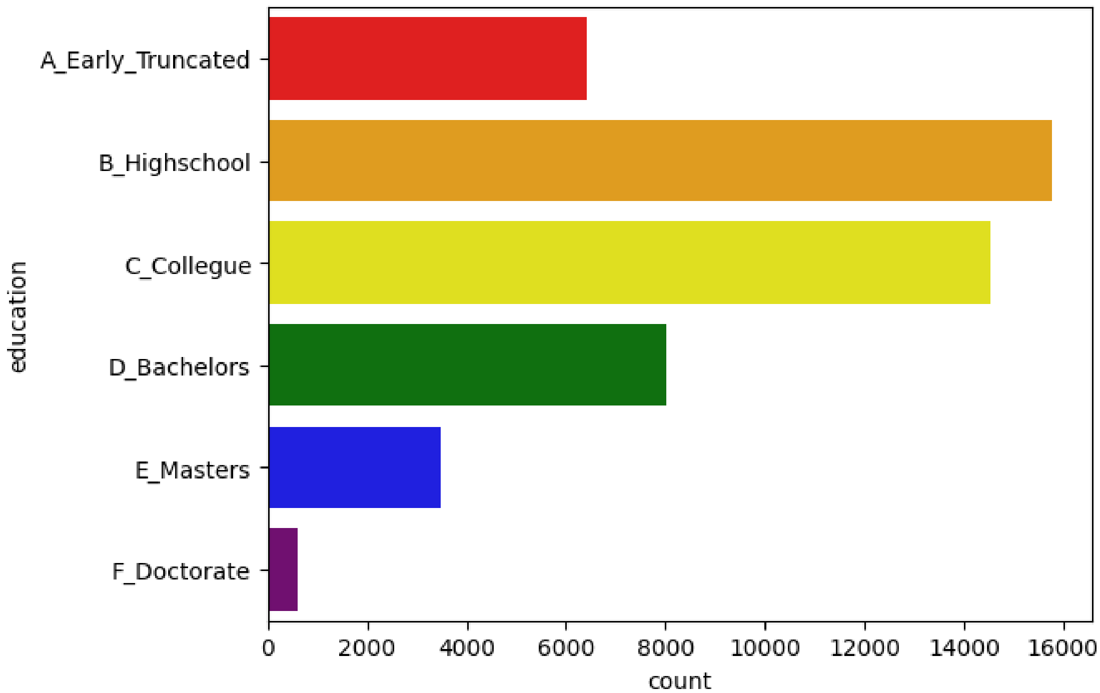
1.1.3 It looks that the employees with an income >50k is 3 times higher:

[165]:
```python
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]:
```python
# 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)
```

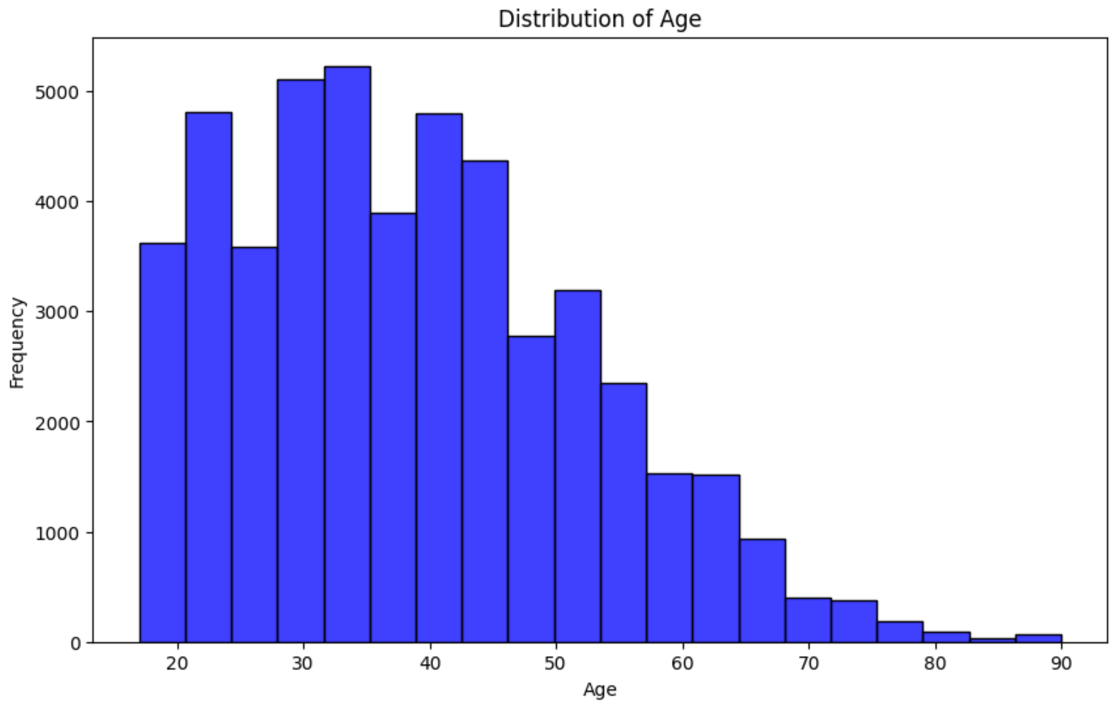
[172]:
```
# Review the categories of Relationship
df['relationship'].unique()
```

[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()
```



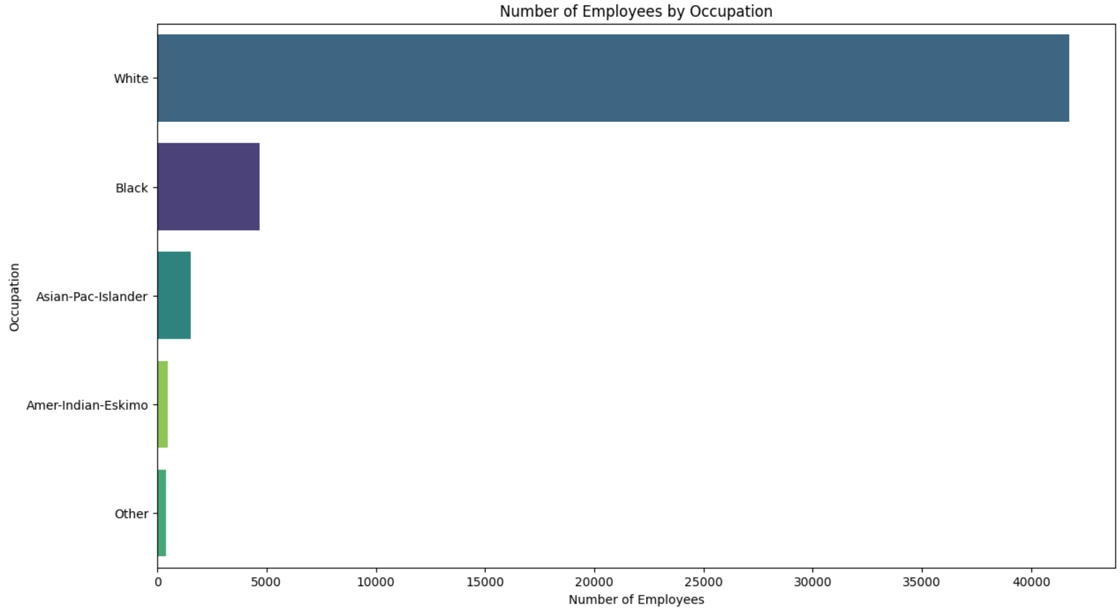
[175]:
```
df.columns
```

[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)
```

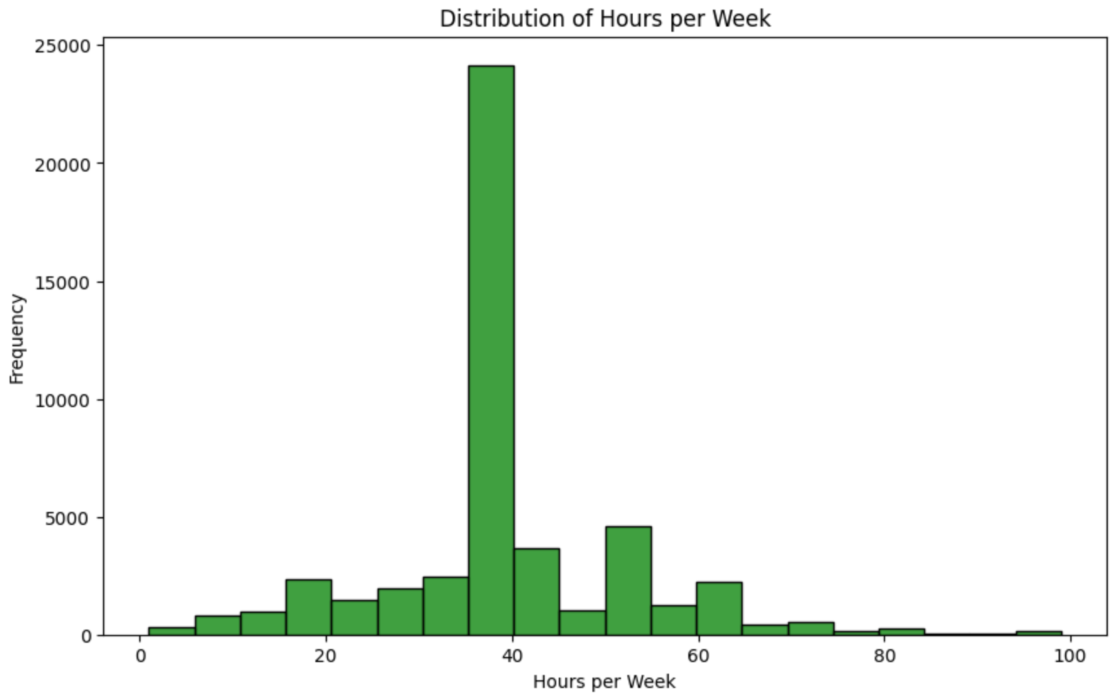
[177]:
```
#Plot the countplot of the individuals by race
plt.figure(figsize=(14, 8))
ax = sns.countplot(y='race', data=df, palette='viridis', order=df['race'].
 ↪value_counts().index, hue='race', dodge=False, legend=False)
plt.title('Number of Employees by Occupation')
plt.xlabel('Number of Employees')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



[178]:
```python
#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]:
```python
#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()
```

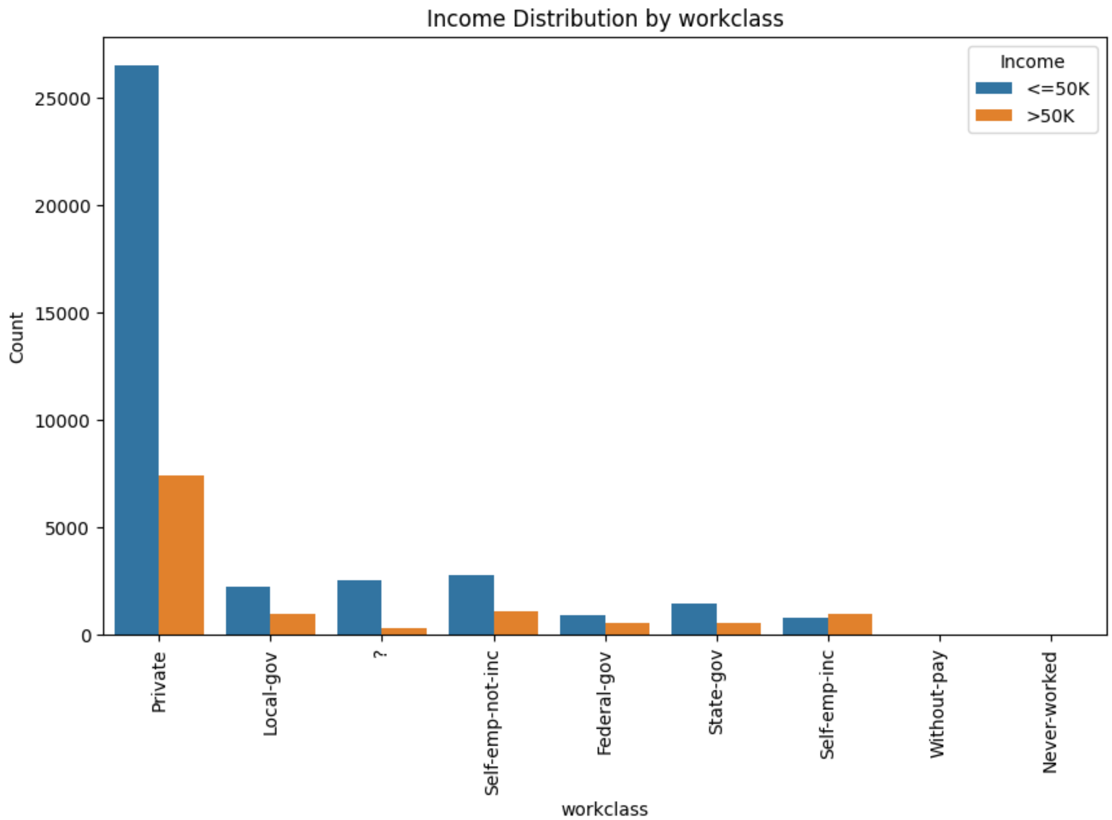
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   age               48842 non-null  int64
 1   workclass         48842 non-null  object
 2   fnlwgt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

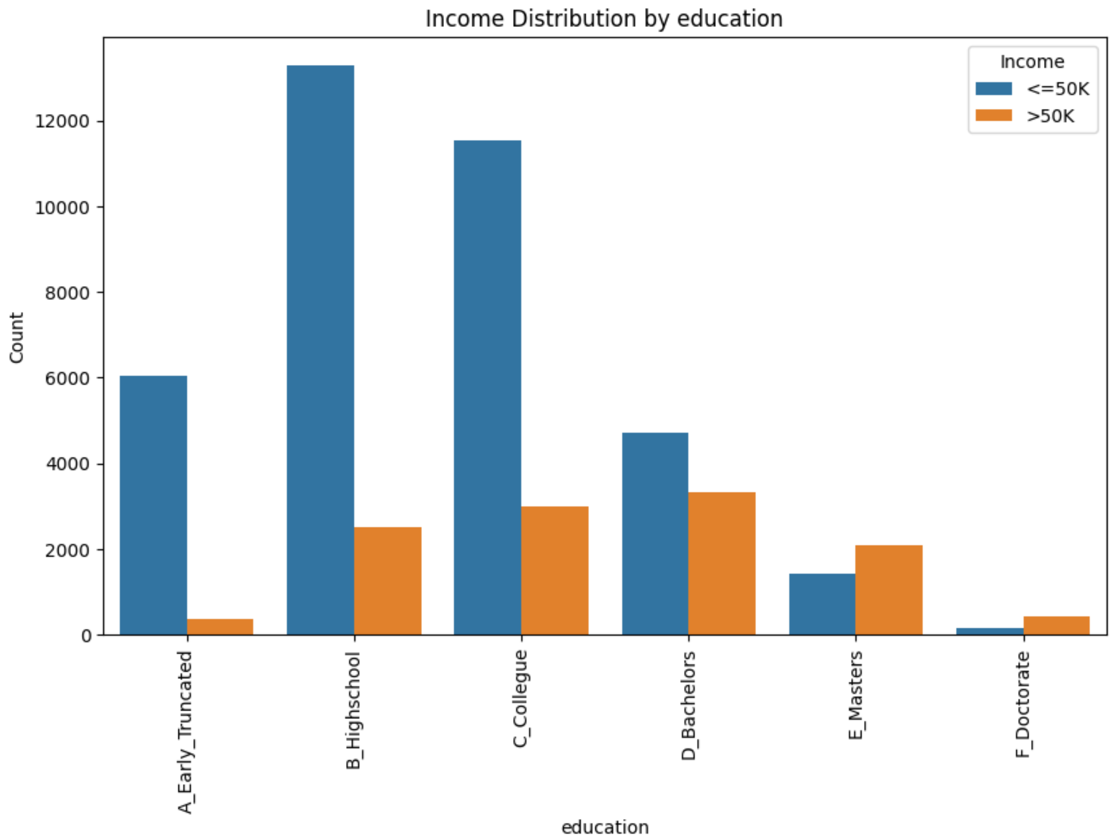
Separate numeric and Categorical Features in 2 dataframes:

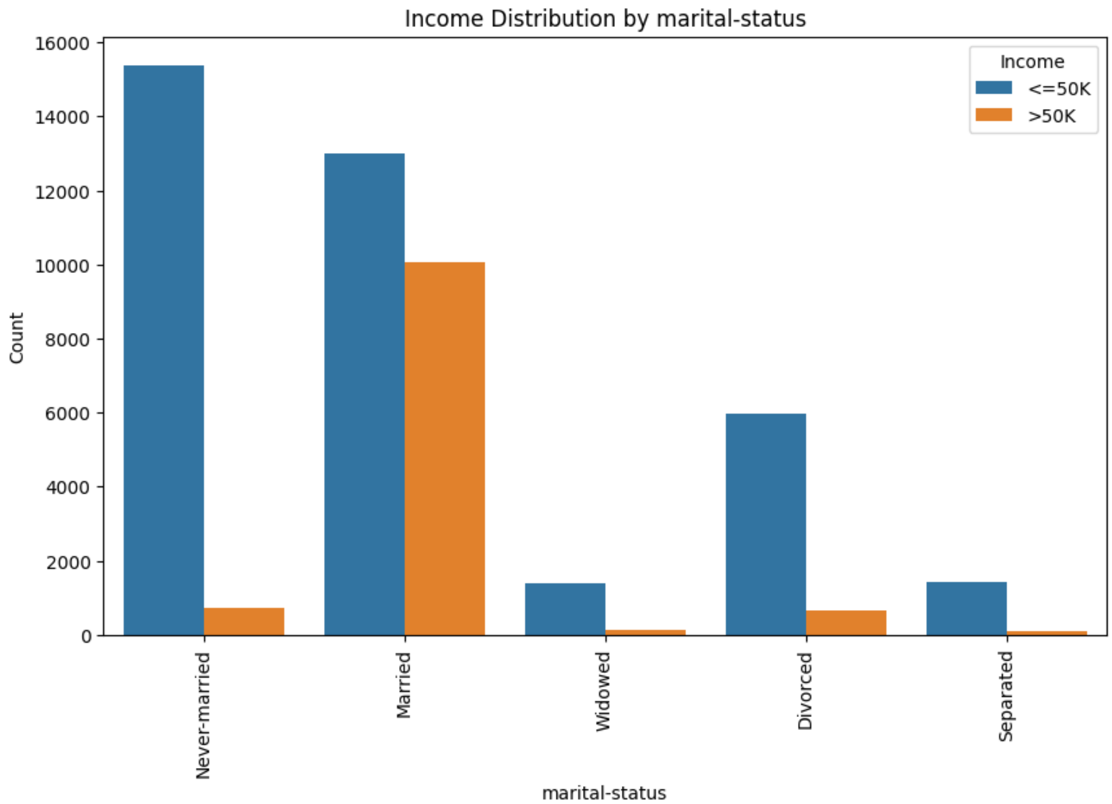
[181]:
```
# Numeric Df
df_num = df.select_dtypes(include=['number'])

# 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']
```

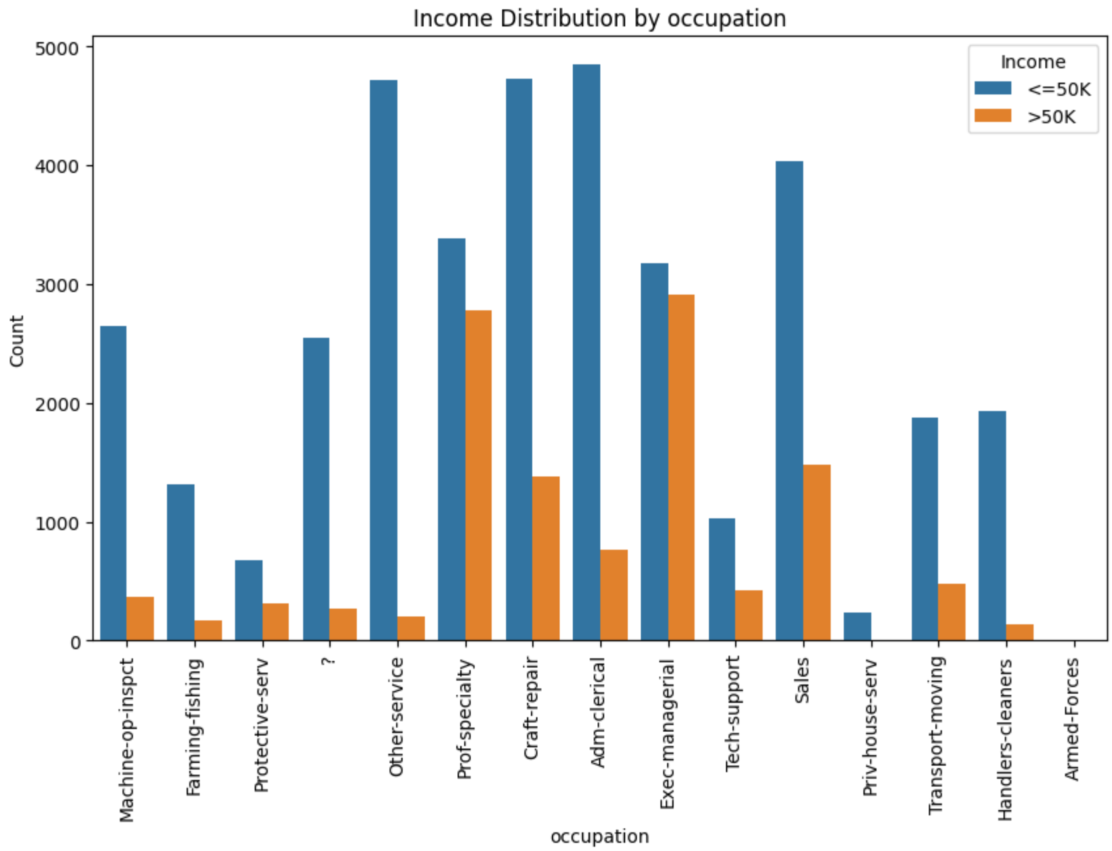
1.2 Categorical Analysis

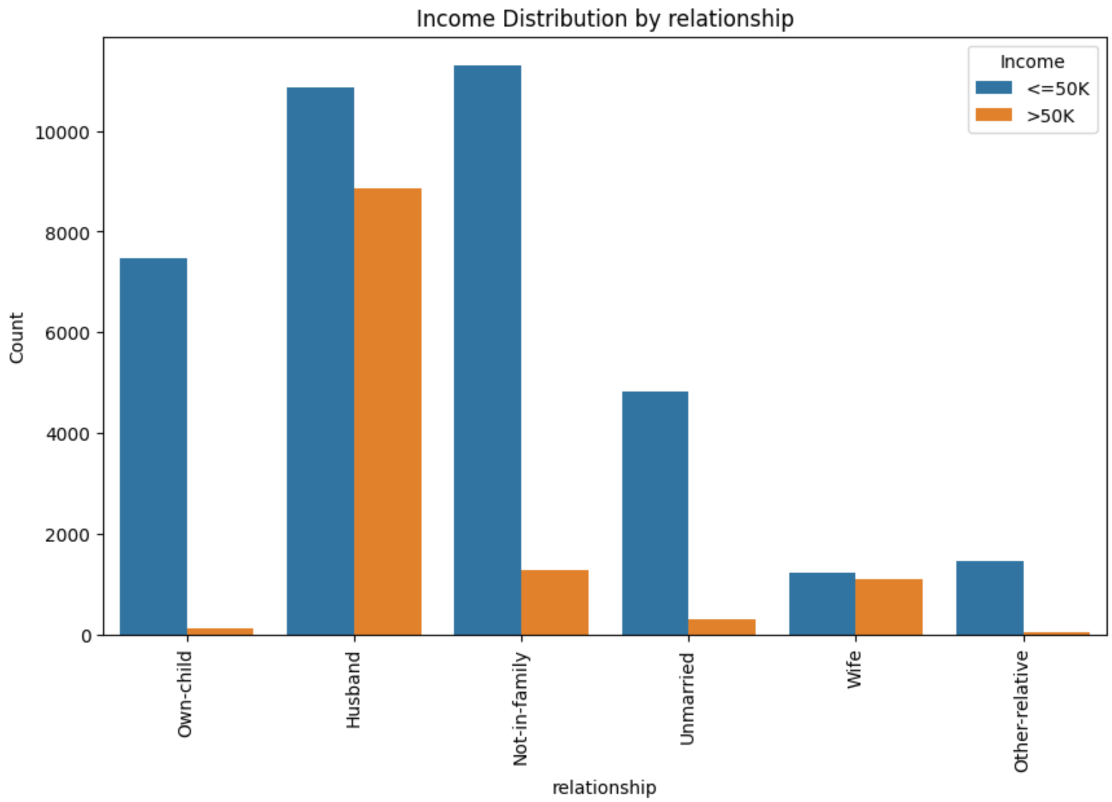
[182]:
```
# Lista de columnas categóricas
categorical_features = ['workclass', 'education', 'marital-status',␣
↪'occupation', 'relationship', 'race', 'gender']

# 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()
```

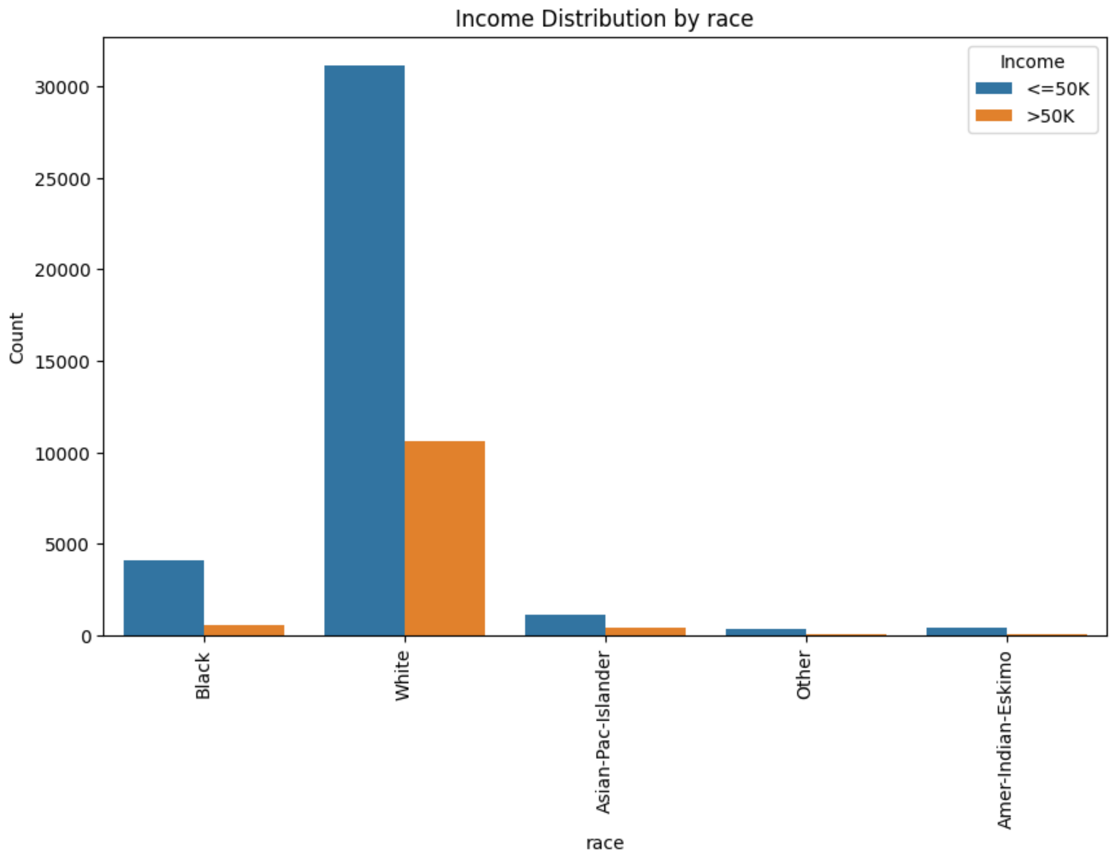

Income Distribution by workclass
Income
<=50K
>50K
Count
25000
20000
15000
10000
5000
0
Private
Local-gov
?
Self-emp-not-inc
Federal-gov
State-gov
Self-emp-inc
Without-pay
Never-worked
workclass

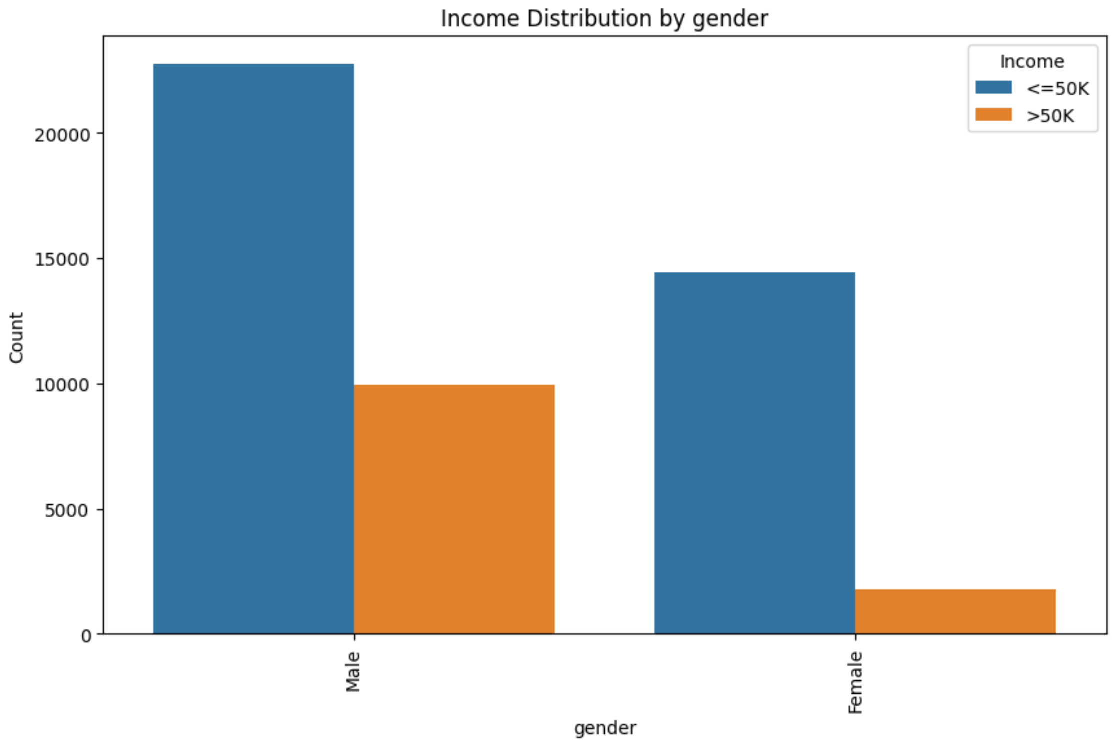

Income Distribution by education
Income
<=50K
>50K
Count
0
2000
4000
6000
8000
10000
12000
A_Early_Truncated
B_Highschool
C_Collegue
D_Bachelors
E_Masters
F_Doctorate
education


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
0
1000
2000
3000
4000
5000
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
0
2000
4000
6000
8000
10000
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.

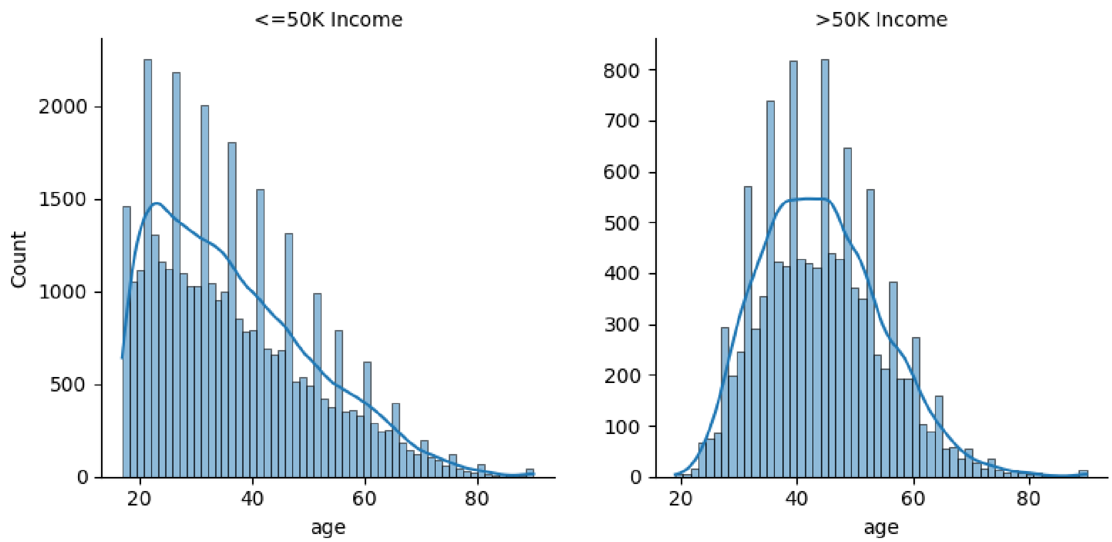
1.4 Numerical Analysis

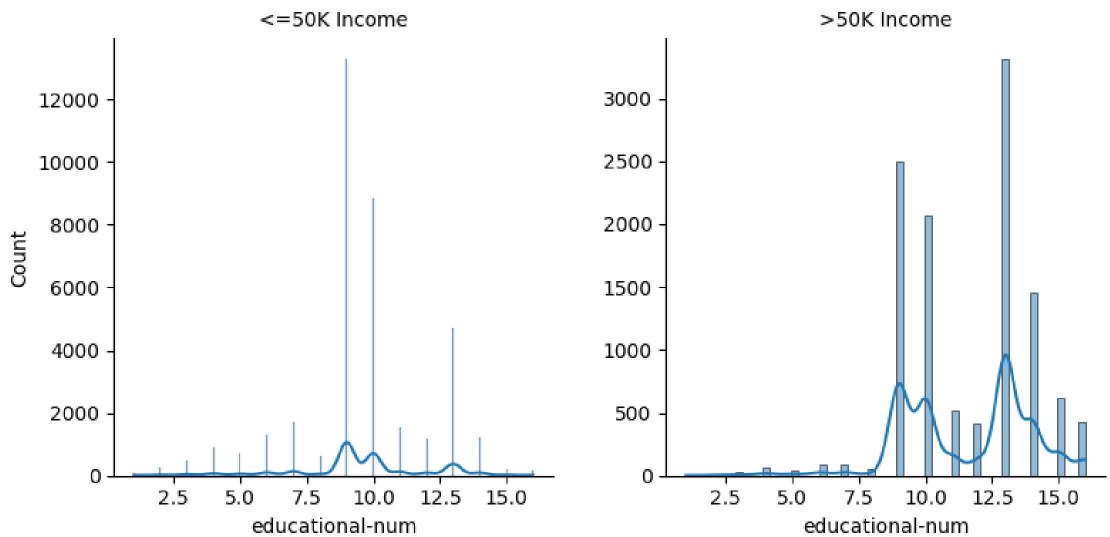
[183]:
```
df_num.columns
```

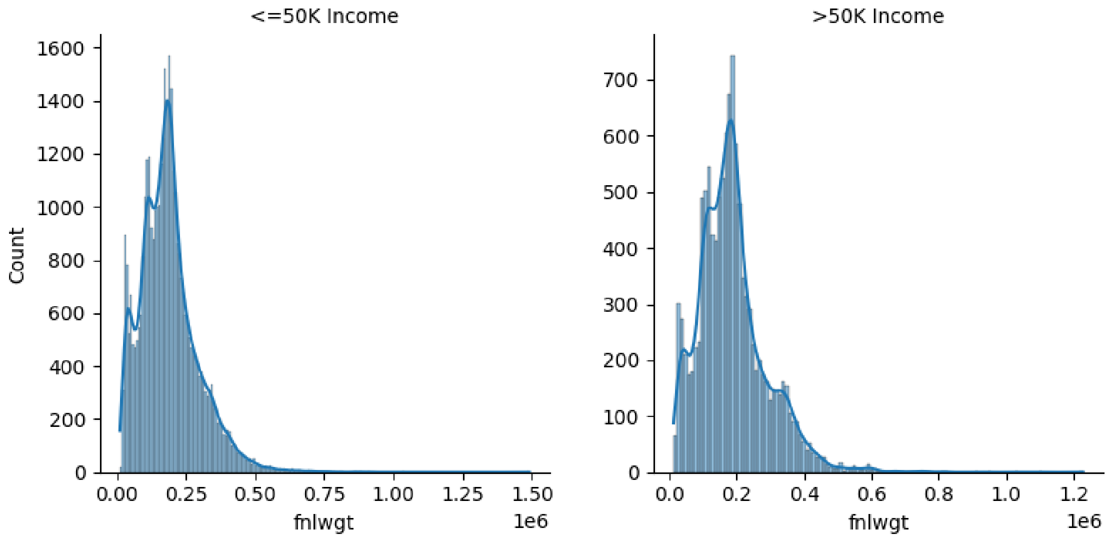
[183]:
```
Index(['age', 'fnlwgt', 'educational-num', 'capital-gain', 'capital-loss',
       'hours-per-week', 'income'],
      dtype='object')
```

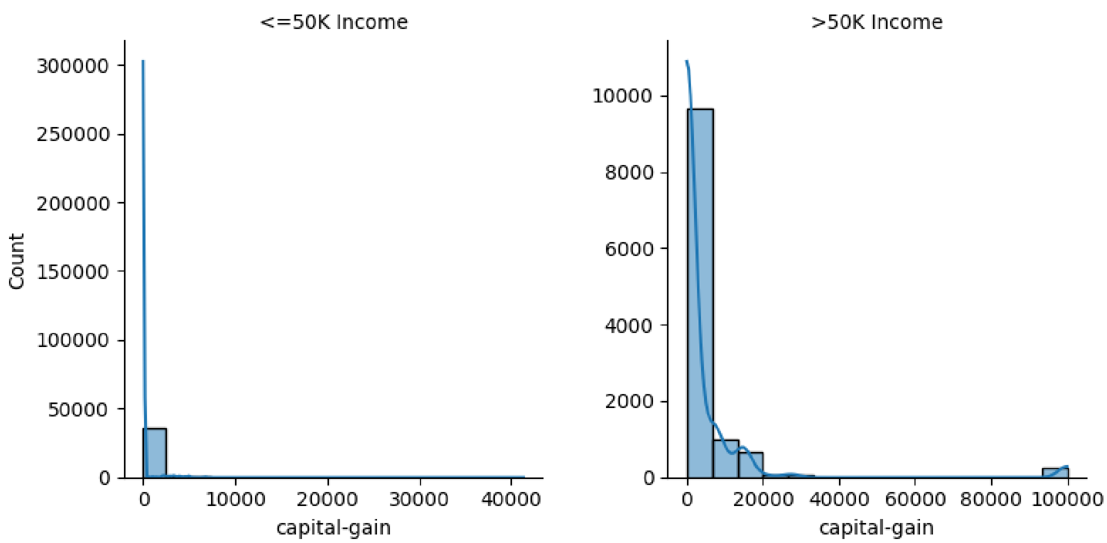
[184]:
```
continuous_features = ['age', 'educational-num', 'fnlwgt', 'capital-gain',␣
↪'capital-loss', 'hours-per-week']
```

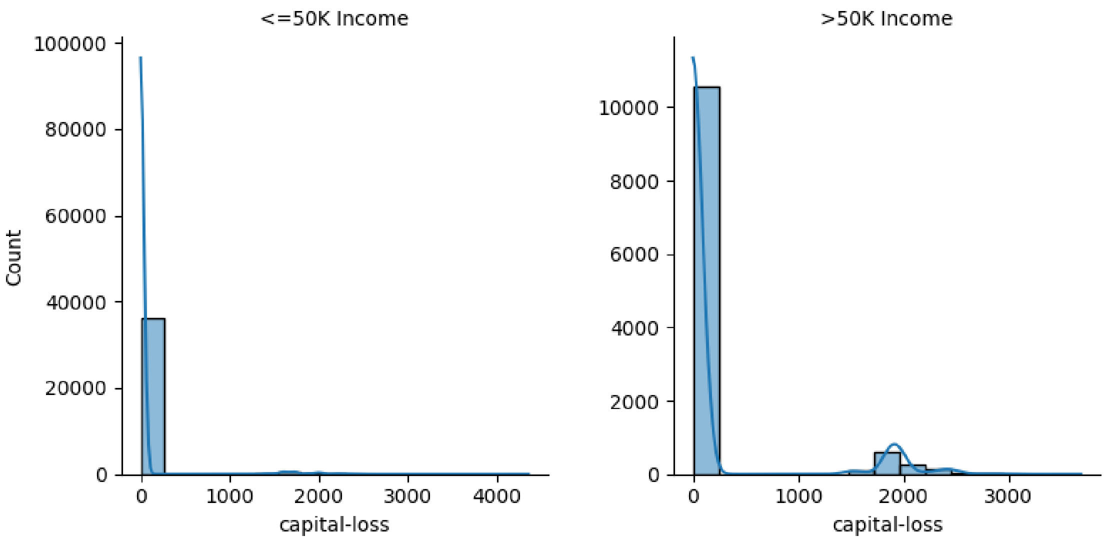
[185]:
```
for feature in continuous_features:
    g = sns.FacetGrid(df, col='income', col_wrap=2, height=4, sharex=False,␣
↪sharey=False)
    g.map_dataframe(sns.histplot, x=feature, kde=True)
    g.set_titles("{col_name} Income")
    g.set_axis_labels(feature, 'Count')
    plt.show()
```

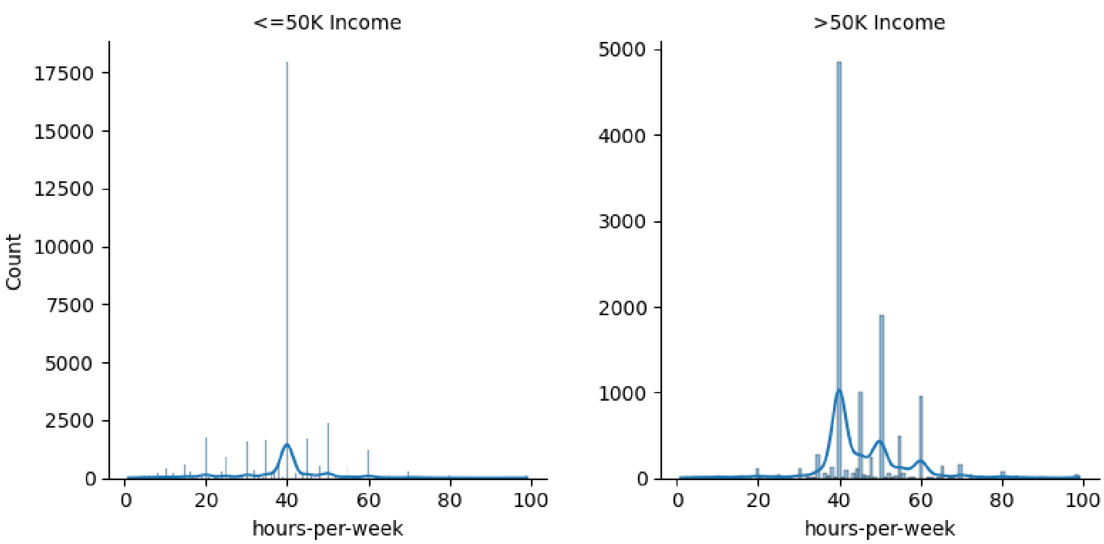





<=50K Income
>50K Income
Count
fnlwgt
1e6
0.00 0.25 0.50 0.75 1.00 1.25 1.50
0.0 0.2 0.4 0.6 0.8 1.0 1.2
0 200 400 600 800 1000 1200 1400 1600
0 100 200 300 400 500 600 700


<=50K Income
>50K Income
Count
capital-gain
0 10000 20000 30000 40000
0 20000 40000 60000 80000 100000
0 50000 100000 150000 200000 250000 300000
0 2000 4000 6000 8000 10000

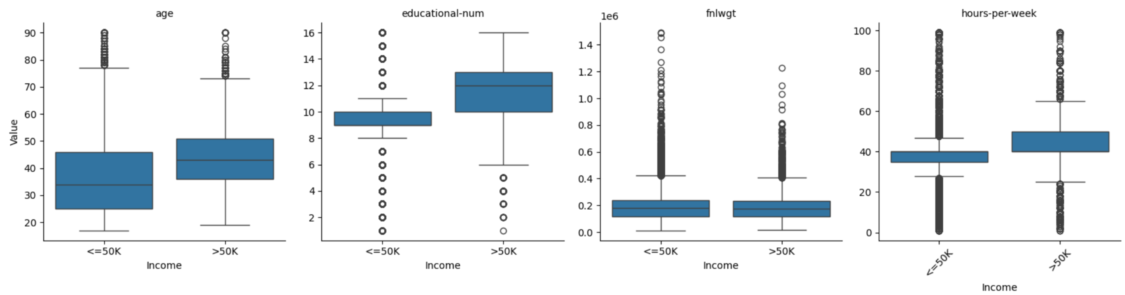




Capital Loss and Capital Gain have a very large spread, so I will not consider them in the boxplots!

[186]:
```python
# 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:
```

```python
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.

[ ]:
```python
#Export this notebook to pdf
```