EDA on census income dataset

[2]:
```python
import pandas as pd
import seaborn as sns
from matplotlib import pyplot as plt
```

[3]:
```python
df = pd.read_csv(r'C:\Users\Fatman\Documents\adult.data.csv')
```

[4]:
```python
df
```

[4]:
```
       age         workclass  fnlwgt   education  education-num  \
0       39         State-gov   77516   Bachelors             13
1       50  Self-emp-not-inc   83311   Bachelors             13
2       38           Private  215646     HS-grad              9
3       53           Private  234721        11th              7
4       28           Private  338409   Bachelors             13
…     …                  …     …           …            …
32556   27           Private  257302  Assoc-acdm             12
32557   40           Private  154374     HS-grad              9
32558   58           Private  151910     HS-grad              9
32559   22           Private  201490     HS-grad              9
32560   52      Self-emp-inc  287927     HS-grad              9

           marital-status         occupation   relationship   race     sex  \
0           Never-married       Adm-clerical  Not-in-family  White    Male
1      Married-civ-spouse    Exec-managerial        Husband  White    Male
2                Divorced  Handlers-cleaners  Not-in-family  White    Male
3      Married-civ-spouse  Handlers-cleaners        Husband  Black    Male
4      Married-civ-spouse     Prof-specialty           Wife  Black  Female
…                     …                  …            …     …     …
32556  Married-civ-spouse       Tech-support           Wife  White  Female
32557  Married-civ-spouse  Machine-op-inspct        Husband  White    Male
32558             Widowed       Adm-clerical      Unmarried  White  Female
32559       Never-married       Adm-clerical      Own-child  White    Male
32560  Married-civ-spouse    Exec-managerial           Wife  White  Female

       capital-gain  capital-loss  hours-per-week native-country salary
0              2174             0              40  United-States  <=50K
1                 0             0              13  United-States  <=50K
2                 0             0              40  United-States  <=50K
```

```
3                 0           0            40  United-States  <=50K
4                 0           0            40           Cuba  <=50K
…             …           …            …        …      …
32556             0           0            38  United-States  <=50K
32557             0           0            40  United-States   >50K
32558             0           0            40  United-States  <=50K
32559             0           0            20  United-States  <=50K
32560         15024           0            40  United-States   >50K

[32561 rows x 15 columns]
```

[5]:
```python
df.shape
```

[5]:
```
(32561, 15)
```

[6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32561 entries, 0 to 32560
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             32561 non-null  int64
 1   workclass       32561 non-null  object
 2   fnlwgt          32561 non-null  int64
 3   education       32561 non-null  object
 4   education-num   32561 non-null  int64
 5   marital-status  32561 non-null  object
 6   occupation      32561 non-null  object
 7   relationship    32561 non-null  object
 8   race            32561 non-null  object
 9   sex             32561 non-null  object
 10  capital-gain    32561 non-null  int64
 11  capital-loss    32561 non-null  int64
 12  hours-per-week  32561 non-null  int64
 13  native-country  32561 non-null  object
 14  salary          32561 non-null  object
dtypes: int64(6), object(9)
memory usage: 3.7+ MB
```

[7]:
```python
df.describe()
```

[7]:
```
                age        fnlwgt  education-num  capital-gain  capital-loss  \
count  32561.000000  3.256100e+04   32561.000000  32561.000000  32561.000000
mean      38.581647  1.897784e+05      10.080679   1077.648844     87.303830
std       13.640433  1.055500e+05       2.572720   7385.292085    402.960219
min       17.000000  1.228500e+04       1.000000      0.000000      0.000000
25%       28.000000  1.178270e+05       9.000000      0.000000      0.000000
```

```
50%        37.000000  1.783560e+05       10.000000       0.000000       0.000000
75%        48.000000  2.370510e+05       12.000000       0.000000       0.000000
max        90.000000  1.484705e+06       16.000000   99999.000000    4356.000000

       hours-per-week
count    32561.000000
mean        40.437456
std         12.347429
min          1.000000
25%         40.000000
50%         40.000000
75%         45.000000
max         99.000000
```

1. How many men and women (sex feature) are represented in this dataset?

[8]:
```python
df['sex'].value_counts()
```

[8]:
```
sex
Male      21790
Female    10771
Name: count, dtype: int64
```

2. What is the average age (age feature) of women?

[9]:
```python
filt = (df['sex'] == 'Female')
avg_a_f = df.loc[filt, 'age'].mean()
print(f"The average age of women is {round(avg_a_f)}.")
```

```
The average age of women is 37.
```

3. What is the percentage of German citizens (native-country feature)?

[10]:
```python
filt = df['native-country'] == 'Germany'
p_of_g = df.loc[filt, 'native-country'].count() / df.shape[0]
print(f"The percentage of German citizens is {p_of_g}.")
```

```
The percentage of German citizens is 0.004207487485028101.
```

4-5. What are mean value and standard deviation of the age of those who receive more than 50K per year (salary feature) and those who receive less than 50K per year?

[11]:
```python
# Approach 1:

s1 = df.loc[df['salary'] == '>50K', 'age']
s2 = df.loc[df['salary'] == '<=50K', 'age']
print(f"The mean value and standard deviation of the age of those who receive more than 50K per year(rich) is {round(s1.mean())} and {round(s1.std())}.")
print(f"The mean value and standard deviation of the age of those who receive less than 50K per year(poor) is {round(s2.mean())} and {round(s2.std())}.")
```

```
The mean value and standard deviation of the age of those who receive more than
50K per year(rich) is 44 and 11.
The mean value and standard deviation of the age of those who receive less than
50K per year(poor) is 37 and 14.
```

[12]:
```python
# Approach 2:

sal_group = df.groupby('salary')[ 'age'].agg(['mean', 'std'])
sal_group
```

[12]:

salary	mean	std
<=50K	36.783738	14.020088
>50K	44.249841	10.519028

6. Is it true that people who earn more than 50K have at least high school education? (education – Bachelors, Prof-school, Assoc-acdm, Assoc-voc, Masters or Doctorate feature)

[13]:
```python
filt = (df['salary'] == '>50K')
print(df.loc[filt, 'education'].unique())
print("\nNo, it's not true that people who earn more than 50K have at least␣
↪high school education.")
```

```
['HS-grad' 'Masters' 'Bachelors' 'Some-college' 'Assoc-voc' 'Doctorate'
 'Prof-school' 'Assoc-acdm' '7th-8th' '12th' '10th' '11th' '9th' '5th-6th'
 '1st-4th']

No, it's not true that people who earn more than 50K have at least high school
education.
```

7. Display age statistics for each race (race feature) and each gender (sex feature). Use groupby() and describe(). Find the maximum age of men of Amer-Indian-Eskimo race.

[14]:
```python
grp_r_s = df.groupby(['race', 'sex'])
grp_r_s['age'].describe()
```

[14]:

race	sex	count	mean	std	min	25%	50%	\
Amer-Indian-Eskimo	Female	119.0	37.117647	13.114991	17.0	27.0	36.0	
	Male	192.0	37.208333	12.049563	17.0	28.0	35.0	
Asian-Pac-Islander	Female	346.0	35.089595	12.300845	17.0	25.0	33.0	
	Male	693.0	39.073593	12.883944	18.0	29.0	37.0	
Black	Female	1555.0	37.854019	12.637197	17.0	28.0	37.0	
	Male	1569.0	37.682600	12.882612	17.0	27.0	36.0	
Other	Female	109.0	31.678899	11.631599	17.0	23.0	29.0	
	Male	162.0	34.654321	11.355531	17.0	26.0	32.0	
White	Female	8642.0	36.811618	14.329093	17.0	25.0	35.0	
	Male	19174.0	39.652498	13.436029	17.0	29.0	38.0	

```
                                 75%   max
race               sex
Amer-Indian-Eskimo Female  46.00  80.0
                   Male    45.00  82.0
Asian-Pac-Islander Female  43.75  75.0
                   Male    46.00  90.0
Black              Female  46.00  90.0
                   Male    46.00  90.0
Other              Female  39.00  74.0
                   Male    42.00  77.0
White              Female  46.00  90.0
                   Male    49.00  90.0
```

[15]:
```python
max_age = grp_r_s.get_group(('Amer-Indian-Eskimo', 'Male'))['age'].max()
print(f"The maximum age of men of Amer-Indian-Eskimo race is {round(max_age)}.")
```

```
The maximum age of men of Amer-Indian-Eskimo race is 82.
```

8. Among whom is the proportion of those who earn a lot (>50K) greater: married or single men (marital-status feature)? Consider as married those who have a marital-status starting with Married (Married-civ-spouse, Married-spouse-absent or Married-AF-spouse), the rest are considered bachelors.

[16]:
```python
# Married men

filt = (df['sex'] == 'Male') & (df['marital-status'].str.startswith('Married'))
df[filt]['salary'].value_counts(normalize = True)
```

[16]:
```
salary
<=50K    0.559486
>50K     0.440514
Name: proportion, dtype: float64
```

[17]:
```python
# Single men

filt = (df['sex'] == 'Male') & ~(df['marital-status'].str.startswith('Married'))
df[filt]['salary'].value_counts(normalize = True)
```

[17]:
```
salary
<=50K    0.915505
>50K     0.084495
Name: proportion, dtype: float64
```

9. What is the maximum number of hours a person works per week (hours-per-week feature)? How many people work such a number of hours and what is the percentage of those who earn a lot among them?

[18]:
```python
max_load = df['hours-per-week'].max()
#df['hours-per-week'].value_counts()
```

```
print(f"Maximum number of hours a person works per week is {max_load}.")
```

```
Maximum number of hours a person works per week is 99.
```

[19]:
```
num_workaholics = df[df['hours-per-week'] == filt].shape[0]
print(f"Number of people that work such a number of hours is {num_workaholics}.
↪")
```

```
Number of people that work such a number of hours is 4.
```

[20]:
```
filter1 = (df['hours-per-week'] == df['hours-per-week'].max())
who_work_for_max_hperw = df.loc[filter1].shape[0]
```

[21]:
```
filter2 = (df['hours-per-week'] == df['hours-per-week'].max()) & (df['salary']␣
↪== '>50K')
who_work_for_max_hperw_with_hs = df.loc[filter2].shape[0]
```

[22]:
```
calc = who_work_for_max_hperw_with_hs / who_work_for_max_hperw * 100
print(f"Percentage of people who work for maximum no.of weeks with higher␣
↪salary is {round(calc)}%.")
```

```
Percentage of people who work for maximum no.of weeks with higher salary is 29%.
```

10. Count the average time of work (hours-per-week) for those who earn a little and a lot (salary) for each country (native-country). What will these be for Japan?

[23]:
```
grp_n_s = df.groupby(['native-country', 'salary'])['hours-per-week'].mean()
grp_n_s
```

[23]:
```
native-country  salary
?               <=50K     40.164760
                >50K      45.547945
Cambodia        <=50K     41.416667
                >50K      40.000000
Canada          <=50K     37.914634
                            …
United-States   >50K      45.505369
Vietnam         <=50K     37.193548
                >50K      39.200000
Yugoslavia      <=50K     41.600000
                >50K      49.500000
Name: hours-per-week, Length: 82, dtype: float64
```

[24]:
```
grp_n_s['Japan']
```

[24]:
```
salary
<=50K    41.000000
>50K     47.958333
Name: hours-per-week, dtype: float64
```

[25]:
```python
print(f"Average time of work (hours-per-week) for those who earn a little in Japan is {grp_n_s['Japan'][0]}.")
print(f"Average time of work (hours-per-week) for those who earn a lot in Japan is {grp_n_s['Japan'][1]}.")
```

```
Average time of work (hours-per-week) for those who earn a little in Japan is
41.0.
Average time of work (hours-per-week) for those who earn a lot in Japan is
47.958333333333336.
```

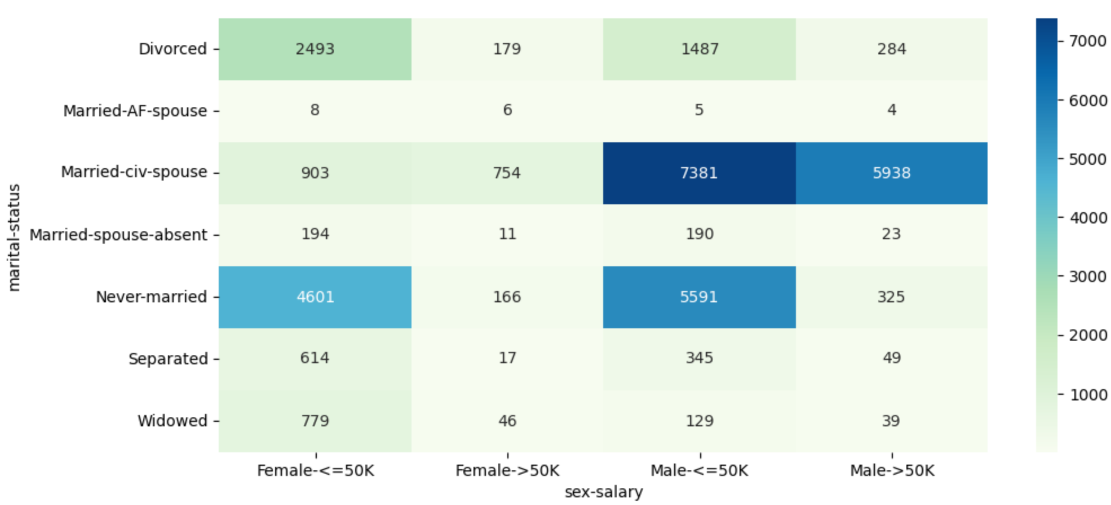
1. How does the salary distribution differ between different marital statuses?

[26]:
```python
pivot_table_df = df.pivot_table(index='marital-status', columns=['sex', 'salary'], aggfunc='size', fill_value=0)
print(pivot_table_df)
```

```
sex                    Female       Male
salary                  <=50K >50K <=50K  >50K
marital-status
Divorced                 2493  179  1487   284
Married-AF-spouse           8    6     5     4
Married-civ-spouse        903  754  7381  5938
Married-spouse-absent     194   11   190    23
Never-married            4601  166  5591   325
Separated                 614   17   345    49
Widowed                   779   46   129    39
```

[33]:
```python
plt.figure(figsize=(11, 5))
sns.heatmap(pivot_table_df, cmap="GnBu", annot = True, fmt = ".0f")
```

[33]: `<Axes: xlabel='sex-salary', ylabel='marital-status'>`



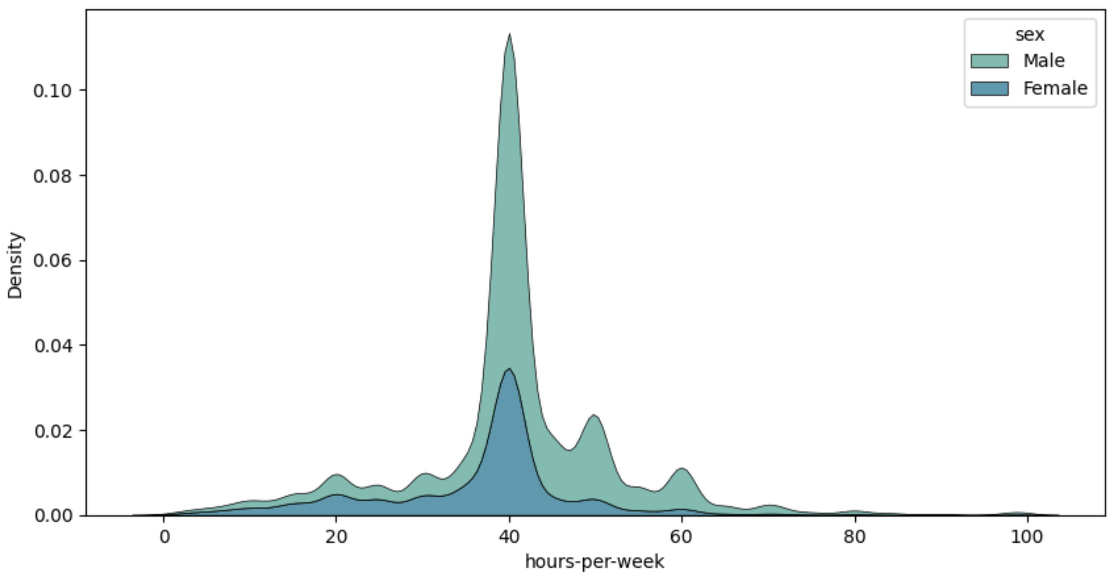
Heatmap of Marital Status vs Sex and Salary: This heatmap shows the count of records for each combination of marital-status, sex, and salary. The color intensity in the heatmap represents the count of records. Darker colors represent higher counts.

[ ]:

2. Create two kdeplots of the hours-per-week feature for each gender on the same chart.

[36]:
```python
plt.figure(figsize=(10, 5))
sns.kdeplot(data = df, x="hours-per-week", hue = 'sex', multiple = 'stack',␣
  ↪alpha=.7, linewidth = 0.5, palette = 'crest')
```

[36]: <Axes: xlabel='hours-per-week', ylabel='Density'>



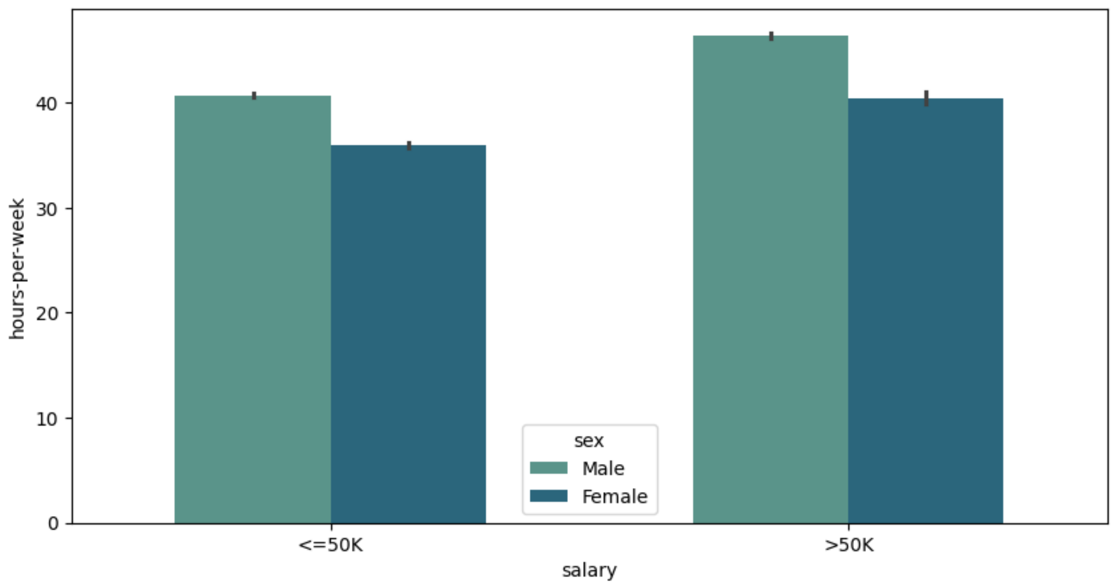
KDE Plot of Hours per Week by Sex: This plot shows the distribution of hours-per-week for each sex. The KDE (Kernel Density Estimate) plot is a way to estimate the probability density function of a continuous random variable. It uses a Gaussian kernel to estimate the PDF. In this plot, the sex is differentiated by color.

[ ]:

3. How does the average hours worked per week vary between genders for each salary level?

[37]:
```python
plt.figure(figsize=(10,5))
sns.barplot(data = df, x = 'salary', y = 'hours-per-week', hue = "sex", width =␣
  ↪0.6, palette = "crest")
```

[37]: <Axes: xlabel='salary', ylabel='hours-per-week'>



Bar Plot of Salary vs Hours per Week by Sex: This bar plot shows the average hours-per-week for each salary level, differentiated by sex. The height of the bar represents the average hours-per-week.

[ ]:

```

```

[30]:

```
4. How does the count of records vary with different combinations of age and␣
↪hours worked per week?
```

Object `week` not found.

[38]:

```
# Define bins for 'age' and 'hours-per-week'
plt.figure(figsize=(11,5))
bins_age = pd.cut(df['age'], bins=range(0, 100, 10))
# bins_age_as_strings = bins_age.astype(str).str.replace(r'[\(\]]' , ' ', regex␣
↪= True).replace(r'[\,]' , ' -', regex = True)
bins_hours_per_week = pd.cut(df['hours-per-week'], bins=range(0, 100, 10))
heatmap_data = pd.crosstab(bins_age, bins_hours_per_week)

sns.heatmap(heatmap_data, cmap='crest', annot = True, fmt=".0f")
```

[38]: <Axes: xlabel='hours-per-week', ylabel='age'>

Heatmap of Age vs Hours per Week: This heatmap shows the count of records for each combination of age and hours-per-week bins. The age and hours-per-week are divided into bins of size 10. The color intensity in the heatmap represents the count of records. Darker colors represent higher counts.

[ ]:

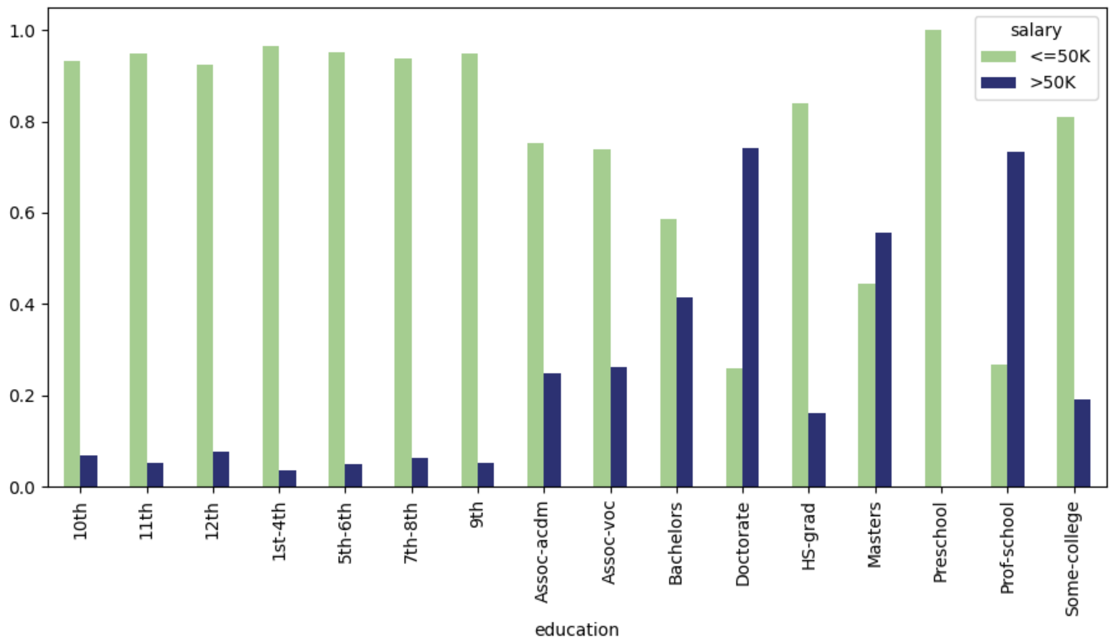
```

```

5. How does the proportion of salary levels vary within each education group?

[40]:

```
fig, ax = plt.subplots(figsize=(11, 5))
df.groupby(['education'])['salary'].value_counts(normalize=True).unstack().
  ↪plot(kind='bar', cmap = "crest", ax=ax)
plt.show()
```



Bar Plot of Education vs Salary: This bar plot shows the proportion of each salary level within each education group. The height of the bar represents the proportion of salary.