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```
!pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.6-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.6
```

```
from ucimlrepo import fetch_ucirepo

# fetch dataset
census_income = fetch_ucirepo(id=20)

# data (as pandas dataframes)
X = census_income.data.features
y = census_income.data.targets

# metadata
print(census_income.metadata)

# variable information
print(census_income.variables)
```

```
{'uci_id': 20, 'name': 'Census Income', 'repository_url': 'https://archive.ics.uci.edu/dataset/20/census+income', 'data_url': 'https://archive.ics.uci.edu/static/public/20/data.csv', 'abstract': 'Predict whether income excee
              name     role         type      demographic  \
0              age  Feature      Integer              Age
1        workclass  Feature  Categorical           Income
2           fnlwgt  Feature      Integer             None
3        education  Feature  Categorical  Education Level
4    education-num  Feature      Integer  Education Level
5   marital-status  Feature  Categorical            Other
6       occupation  Feature  Categorical            Other
7     relationship  Feature  Categorical            Other
8             race  Feature  Categorical             Race
9              sex  Feature       Binary              Sex
10    capital-gain  Feature      Integer             None
11    capital-loss  Feature      Integer             None
12  hours-per-week  Feature      Integer             None
13  native-country  Feature  Categorical            Other
14          income   Target       Binary           Income

                                          description units missing_values
0                                                 N/A  None             no
1   Private, Self-emp-not-inc, Self-emp-inc, Feder...  None            yes
2                                                None  None             no
3    Bachelors, Some-college, 11th, HS-grad, Prof-...  None             no
4                                                None  None             no
5   Married-civ-spouse, Divorced, Never-married, S...  None             no
6   Tech-support, Craft-repair, Other-service, Sal...  None            yes
7   Wife, Own-child, Husband, Not-in-family, Other...  None             no
8   White, Asian-Pac-Islander, Amer-Indian-Eskimo,...  None             no
9                                       Female, Male.  None             no
10                                               None  None             no
11                                               None  None             no
```

```
12                                           None  None            no
13  United-States, Cambodia, England, Puerto-Rico,...  None           yes
14                                     >50K, <=50K.  None            no
```

```
import pandas as pd
import numpy as np
```

```
X
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	0	0	36	United-States
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-relative	Black	Male	0	0	40	United-

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```
y
```

	income
0	<=50K
1	<=50K
2	<=50K
3	<=50K
4	<=50K
...	...
48837	<=50K.
48838	<=50K.
48839	<=50K.
48840	<=50K.
48841	>50K.

48842 rows × 1 columns

Next steps: View recommended plots

```
merged_census = pd.concat([X, y], axis = 1)
merged_census
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Divorced	Prof-	Not-in-family	White	Female	0	0	36	United-	<=50K

Next steps: View recommended plots

```
# checks for duplicates
```

```
# checks for duplicates
merged_census[merged_census.duplicated()].shape[0]
```

```
29
```

```
# removes duplicate rows
merged_census.drop_duplicates(inplace=True)
```

```
merged_census.info()
# it can be noticed that workclass, occupation, and native-country has missing data
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 48813 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             48813 non-null  int64 
 1   workclass       47850 non-null  object
 2   fnlwgt          48813 non-null  int64 
 3   education       48813 non-null  object
 4   education-num   48813 non-null  int64 
 5   marital-status  48813 non-null  object
 6   occupation      47847 non-null  object
 7   relationship    48813 non-null  object
 8   race            48813 non-null  object
 9   sex             48813 non-null  object
 10  capital-gain    48813 non-null  int64 
 11  capital-loss    48813 non-null  int64 
 12  hours-per-week  48813 non-null  int64 
 13  native-country  48539 non-null  object
 14  income          48813 non-null  object
dtypes: int64(6), object(9)
memory usage: 6.0+ MB
```

```
# working with workclass first
merged_census.workclass.unique()
# it can be noticed that there are 2 missing values (? and NaN)
```

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

```
# checking the frequency of the unique values
merged_census.workclass.value_counts()
# as Private is the most frequent, it would be more appropriate
# to change the missing values to Private in order for there to be
# less significant skewing of data
```

```
workclass
Private             33879
Self-emp-not-inc     3861
Local-gov            3136
State-gov            1981
?                    1836
Self-emp-inc         1694
Federal-gov          1432
```

```
Without-pay           21
Never-worked          10
Name: count, dtype: int64
```

```
merged_census.workclass.fillna('Private', inplace=True)
merged_census.workclass.replace('?', 'Private', inplace=True)
merged_census
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Divorced	Prof-	Not-in-family	White	Female	0	0	36	United-	<=50K

Next steps: View recommended plots

```
merged_census.workclass.unique()
```

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

```
# working with occupation
merged_census.occupation.unique()
```

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

```
merged_census.occupation.value_counts()
# as the data is more evenly distributed, I decided to use forward fill
```

```
occupation
Prof-specialty       6167
```

```
Craft-repair         6107
Exec-managerial      6084
Adm-clerical         5608
Sales                5504
Other-service        4919
Machine-op-inspct    3019
Transport-moving     2355
Handlers-cleaners    2071
?                    1843
Farming-fishing      1487
Tech-support         1445
Protective-serv       983
Priv-house-serv       240
Armed-Forces           15
Name: count, dtype: int64
```

```
merged_census.occupation.fillna(method='ffill', inplace=True)
```

```
merged_census.occupation.replace('?', method='ffill', inplace=True)
merged_census
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Divorced	Prof-	Not-in-family	White	Female	0	0	36	United-	<=50K

Next steps: View recommended plots

```
# working with native-country
merged_census['native-country'].unique()
```

```
array(['United-States', 'Cuba', 'Jamaica', 'India', '?', 'Mexico',
       'South', 'Puerto-Rico', 'Honduras', 'England', 'Canada', 'Germany',
       'Iran', 'Philippines', 'Italy', 'Poland', 'Columbia', 'Cambodia',
       'Thailand', 'Ecuador', 'Laos', 'Taiwan', 'Haiti', 'Portugal',
       'Dominican-Republic', 'El-Salvador', 'France', 'Guatemala',
       'China', 'Japan', 'Yugoslavia', 'Peru',
```

```
           'Outlying-US(Guam-USVI-etc)', 'Scotland', 'Trinadad&Tobago',
           'Greece', 'Nicaragua', 'Vietnam', 'Hong', 'Ireland', 'Hungary',
           'Holand-Netherlands', nan], dtype=object)
```

```
merged_census['native-country'].value_counts()
# as United-States is the most frequent,
# it is more appropriate to change the missing values
# to the United-States
```

```
native-country
United-States                 43810
Mexico                          947
?                               582
Philippines                     295
Germany                         206
Puerto-Rico                     184
Canada                          182
El-Salvador                     155
India                           151
Cuba                            138
England                         127
China                           122
South                           115
Jamaica                         106
Italy                           105
Dominican-Republic              103
Japan                            92
Poland                           87
Guatemala                        86
Vietnam                          86
Columbia                         85
Haiti                            75
Portugal                         67
Taiwan                           65
Iran                             59
Greece                           49
Nicaragua                        49
Peru                             46
Ecuador                          45
France                           38
Ireland                          37
Hong                             30
Thailand                         30
Cambodia                         28
Trinadad&Tobago                  27
Laos                             23
Yugoslavia                       23
Outlying-US(Guam-USVI-etc)       23
Scotland                         21
Honduras                         20
Hungary                          19
Holand-Netherlands                1
Name: count, dtype: int64
```

```
merged_census['native-country'].fillna('United-States', inplace=True)
merged_census['native-country'].replace('?', 'United-States', inplace=True)
merged_census
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex	capital-gain	capital-loss	hours-per-week	native-country	income
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	2174	0	40	United-States	<=50K
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	0	0	13	United-States	<=50K
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	0	0	40	United-States	<=50K
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	0	0	40	United-States	<=50K
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	0	0	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	215419	Bachelors	13	Divorced	Prof-	Not-in-family	White	Female	0	0	36	United-	<=50K

Next steps: View recommended plots

```
# it can be noticed that in income, the values are in the wrong format
merged_census.income.unique()
```

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

```
# replacing the values to be more uniform
merged_census.income.replace('<=50K.', '<=50K', inplace=True)
merged_census.income.replace('>50K.', '>50K', inplace=True)
```

```
merged_census.income.unique()
```

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

```
merged_census.info()
# all missing data are handled
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 48813 entries, 0 to 48841
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   age             48813 non-null  int64 
 1   workclass       48813 non-null  object
 2   fnlwgt          48813 non-null  int64 
 3   education       48813 non-null  object
 4   education-num   48813 non-null  int64 
 5   marital-status  48813 non-null  object
 6   occupation      48813 non-null  object
```

```
 7   relationship    48813 non-null  object
 8   race            48813 non-null  object
 9   sex             48813 non-null  object
 10  capital-gain    48813 non-null  int64
 11  capital-loss    48813 non-null  int64
 12  hours-per-week  48813 non-null  int64
 13  native-country  48813 non-null  object
 14  income          48813 non-null  object
dtypes: int64(6), object(9)
memory usage: 6.0+ MB
```

```
# as for now, I don't have any use for fnlwgt, capital-gain, and capital-loss,
# I decided to drop them
merged_census.drop(columns=['fnlwgt', 'capital-gain', 'capital-loss'], inplace=True)
merged_census
```

	age	workclass	education	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	native-country	income
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	Not-in-family	White	Male	40	United-States	<=50K
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	13	United-States	<=50K
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	40	United-States	<=50K
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40	United-States	<=50K
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	Bachelors	13	Divorced	Prof-specialty	Not-in-family	White	Female	36	United-States	<=50K
48838	64	Private	HS-grad	9	Widowed	Prof-specialty	Other-relative	Black	Male	40	United-States	<=50K
48839	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	50	United-States	<=50K

Next steps: View recommended plots

```
# converting the categorical data into numerical data
# as there is already education-num, which represents the education numerically
# we can already drop the education column
# but I want to have a dictionary of the corresponding values of the education

education_map = dict(zip(merged_census.education, merged_census['education-num']))

merged_census.drop(columns=['education'], inplace=True)
merged_census
```

	age	workclass	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	native-country	income
0	39	State-gov	13	Never-married	Adm-clerical	Not-in-family	White	Male	40	United-States	<=50K
1	50	Self-emp-not-inc	13	Married-civ-spouse	Exec-managerial	Husband	White	Male	13	United-States	<=50K
2	38	Private	9	Divorced	Handlers-cleaners	Not-in-family	White	Male	40	United-States	<=50K
3	53	Private	7	Married-civ-spouse	Handlers-cleaners	Husband	Black	Male	40	United-States	<=50K
4	28	Private	13	Married-civ-spouse	Prof-specialty	Wife	Black	Female	40	Cuba	<=50K
...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	13	Divorced	Prof-specialty	Not-in-family	White	Female	36	United-States	<=50K
48838	64	Private	9	Widowed	Prof-specialty	Other-relative	Black	Male	40	United-States	<=50K
48839	38	Private	13	Married-civ-spouse	Prof-specialty	Husband	White	Male	50	United-States	<=50K

Next steps: View recommended plots

```
education_map
```

```
{'Bachelors': 13,
 'HS-grad': 9,
 '11th': 7,
 'Masters': 14,
 '9th': 5,
 'Some-college': 10,
 'Assoc-acdm': 12,
 'Assoc-voc': 11,
 '7th-8th': 4,
 'Doctorate': 16,
 'Prof-school': 15,
 '5th-6th': 3,
 '10th': 6,
 '1st-4th': 2,
 'Preschool': 1,
 '12th': 8}
```

```
# getting the unique values
columns = [
    'workclass', 'marital-status', 'occupation', 'relationship', 'race', 'sex', 'native-country', 'income'
] # columns to get the unique values
unique_values = []

# gets the unique values of a column and appends it to the unique_values list
for column in columns:
  unique_values.append(merged_census[column].unique().tolist())
unique_values
```

```
 'Sales',
 'Craft-repair',
 'Transport-moving',
 'Farming-fishing',
 'Machine-op-inspct',
 'Tech-support',
 'Protective-serv',
 'Armed-Forces',
 'Priv-house-serv'],
['Not-in-family',
 'Husband',
 'Wife',
 'Own-child',
 'Unmarried',
 'Other-relative'],
['White', 'Black', 'Asian-Pac-Islander', 'Amer-Indian-Eskimo', 'Other'],
['Male', 'Female'],
['United-States',
 'Cuba',
 'Jamaica',
 'India',
 'Mexico',
 'South',
 'Puerto-Rico',
 'Honduras',
 'England',
 'Canada',
 'Germany',
 'Iran',
 'Philippines',
 'Italy',
 'Poland',
 'Columbia',
 'Cambodia',
 'Thailand',
 'Ecuador',
 'Laos',
 'Taiwan',
 'Haiti',
 'Portugal',
 'Dominican-Republic',
 'El-Salvador',
 'France',
 'Guatemala',
 'China',
 'Japan',
 'Yugoslavia',
 'Peru',
 'Outlying-US(Guam-USVI-etc)',
 'Scotland',
 'Trinadad&Tobago',
 'Greece',
 'Nicaragua',
 'Vietnam',
 'Hong',
 'Ireland',
 'Hungary',
 'Holand-Netherlands'],
['<=50K', '>50K']]
```

```
# creates the dictionaries
result_dicts = [] # stores the results here

for data in unique_values:
  keys = [i for i in data]
  values = [i for i in range(1, len(data)+1)]
  result_dicts.append({keys[i] : values[i] for i in range(len(values))})
result_dicts
```

```
  'Machine-op-inspct': 10,
  'Tech-support': 11,
  'Protective-serv': 12,
  'Armed-Forces': 13,
  'Priv-house-serv': 14},
 {'Not-in-family': 1,
  'Husband': 2,
  'Wife': 3,
  'Own-child': 4,
  'Unmarried': 5,
  'Other-relative': 6},
 {'White': 1,
  'Black': 2,
  'Asian-Pac-Islander': 3,
  'Amer-Indian-Eskimo': 4,
  'Other': 5},
 {'Male': 1, 'Female': 2},
 {'United-States': 1,
  'Cuba': 2,
  'Jamaica': 3,
  'India': 4,
  'Mexico': 5,
  'South': 6,
  'Puerto-Rico': 7,
  'Honduras': 8,
  'England': 9,
```

```
 'Greece': 35,
 'Nicaragua': 36,
 'Vietnam': 37,
 'Hong': 38,
 'Ireland': 39,
 'Hungary': 40,
 'Holand-Netherlands': 41},
{'<=50K': 1, '>50K': 2}]
```

```
# maps the categorical data to their numerical counterparts
for column in range(len(columns)):
  merged_census.replace(result_dicts[column], inplace=True)

merged_census
```

	age	workclass	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	native-country	income
0	39	1	13	1	1	1	1	1	40	1	1
1	50	2	13	2	2	2	1	1	13	1	1
2	38	3	9	3	3	1	1	1	40	1	1
3	53	3	7	2	3	2	2	1	40	1	1
4	28	3	13	2	4	3	2	2	40	2	1
...	...	...	...	...	...	...	...	...	...	...	...
48837	39	3	13	3	4	1	1	2	36	1	1
48838	64	3	9	7	4	6	2	1	40	1	1
48839	38	3	13	2	4	2	1	1	50	1	1
48840	44	3	13	3	1	4	3	1	40	1	1
48841	35	6	13	2	2	2	1	1	60	1	2

48813 rows × 11 columns

Next steps: View recommended plots

```
merged_census.describe()
```

	age	workclass	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	native-country	income
count	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000	48813.000000
mean	38.647348	3.104419	10.078688	2.084322	5.276484	2.539037	1.220290	1.331510	40.425051	2.126073	1.239383
std	13.709005	0.917171	2.570257	1.257648	3.044477	1.440102	0.625738	0.470761	12.390954	4.782588	0.426711
min	17.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
25%	28.000000	3.000000	9.000000	1.000000	2.000000	1.000000	1.000000	1.000000	40.000000	1.000000	1.000000
50%	37.000000	3.000000	10.000000	2.000000	5.000000	2.000000	1.000000	1.000000	40.000000	1.000000	1.000000
75%	48.000000	3.000000	12.000000	2.000000	7.000000	4.000000	1.000000	2.000000	45.000000	1.000000	1.000000

```
# comparing easy to distinguish categories (sex and income)
male_census = merged_census.query('sex == 1')
female_census = merged_census.query('sex == 2')
less_than_census = merged_census.query('income == 1')
more_than_census = merged_census.query('income == 2')
```

```
male_census.mean()
```

```
age               39.497594
workclass          3.110570
education-num     10.095492
marital-status     1.928320
occupation         5.687383
relationship       2.262389
race               1.191107
sex                1.000000
hours-per-week    42.419264
native-country     2.118262
income             1.303883
dtype: float64
```

```
female_census.mean()
```

```
age               36.932827
workclass          3.092016
education-num     10.044803
marital-status     2.398900
occupation         4.447905
relationship       3.096898
race               1.279137
sex                2.000000
hours-per-week    36.403720
native-country     2.141824
income             1.109319
dtype: float64
```

```
# on average, men are reported to be older than women
# men have also received slightly higher education than women
```

```
# men also work longer per week than women
# and men earn more than women
# women on the other hand are in their later stage of relationships compared to men
```

```
less_than_census.mean()
```

```
age               36.875916
workclass          3.053787
education-num      9.598901
marital-status     2.082660
occupation         5.412734
relationship       2.677063
race               1.242512
sex                1.388198
hours-per-week    38.842599
native-country     2.191419
income             1.000000
dtype: float64
```

```
more_than_census.mean()
```

```
age               44.275909
workclass          3.265297
education-num     11.603166
marital-status     2.089602
occupation         4.843560
relationship       2.100471
race               1.149679
sex                1.151391
hours-per-week    45.453145
native-country     1.918442
income             2.000000
dtype: float64
```

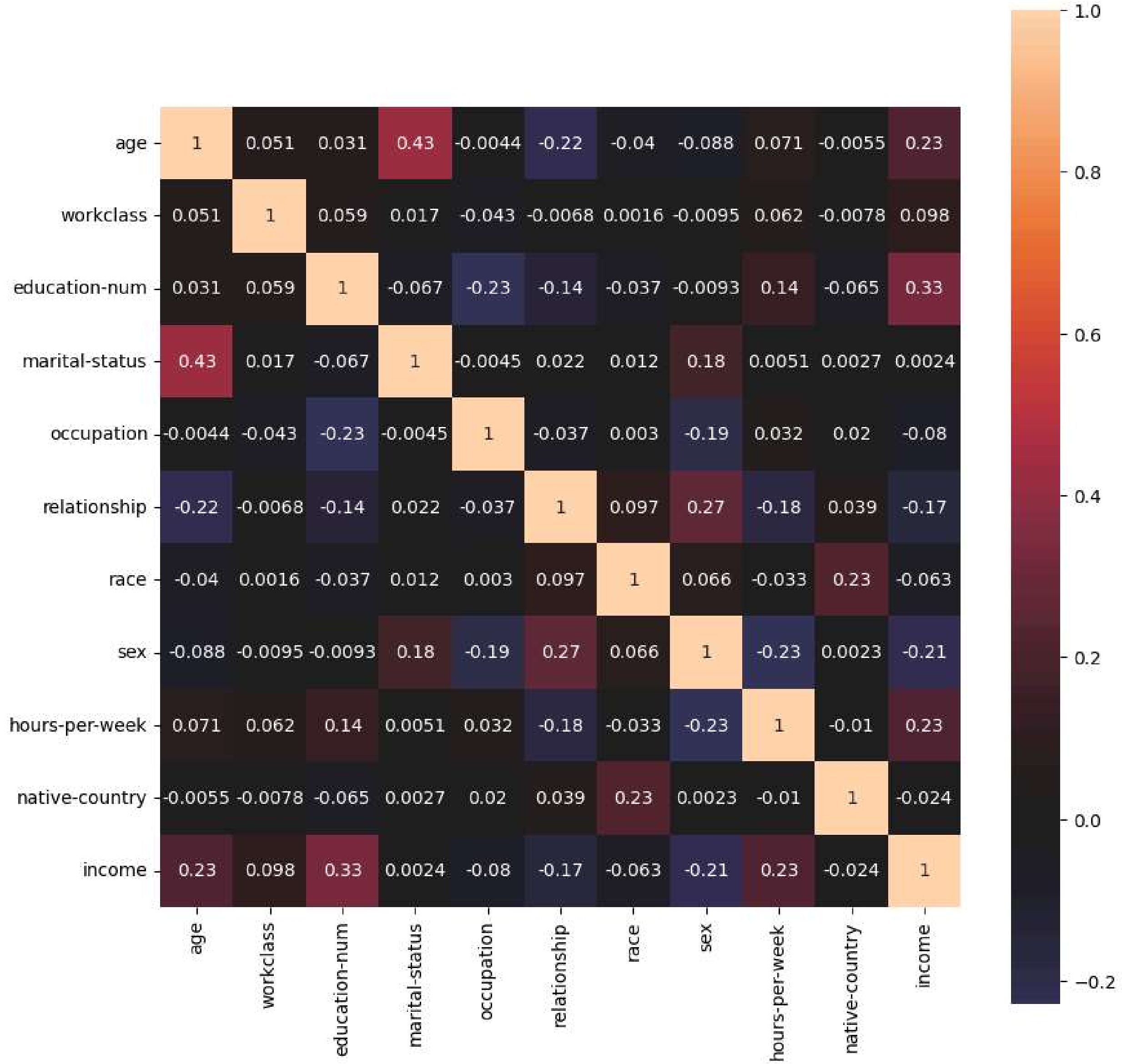
```
# on average, people who earn more are older
# they also have higher educational attainment
# they also work longer hours
```

Plotting

```
%matplotlib inline
import matplotlib.pyplot as plt
```

```
import seaborn as sns
plt.figure(figsize=(10,10))
sns.heatmap(
    merged_census.sort_index().corr(),
    annot=True, center=0, square=True
)
# it can be noticed that there are notable correlations
# with marital status and age, education and income,
# race and native country, and hours per week and income
```

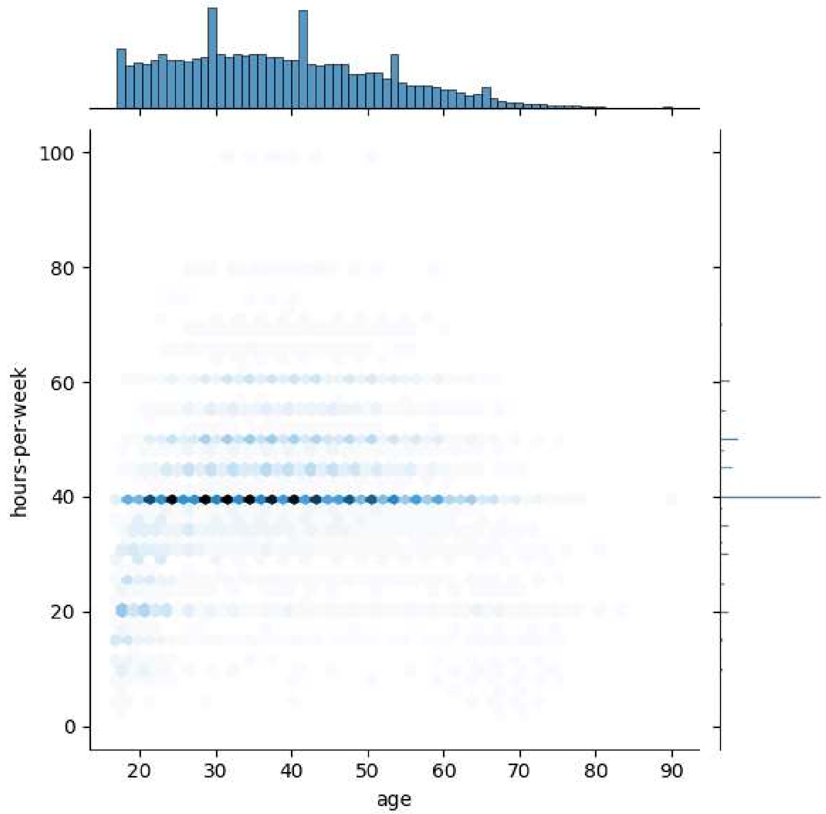
<Axes: >




```
# as both age and hours-per-week are the only datapoints left that are non-categorical,
# I decided to graph them
sns.jointplot(
  x='age',
  y='hours-per-week',
  kind='hex', # hex plot
  data=merged_census
)
```

```
# it can then be noticed that there is a lot of people working 40 hours per week
```

    <seaborn.axisgrid.JointGrid at 0x79e88a809b40>



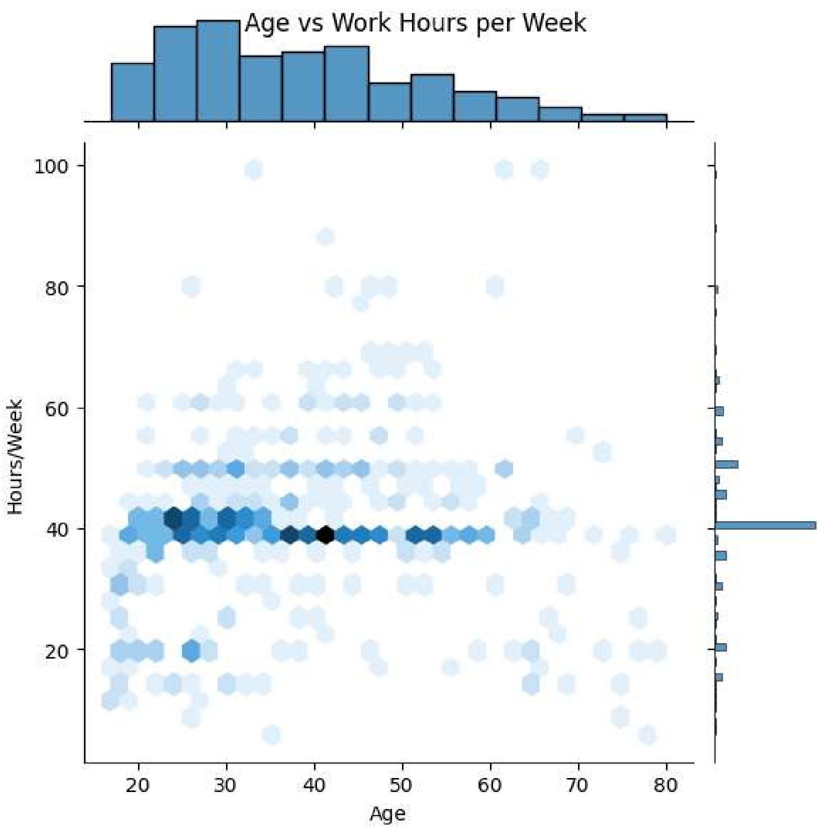

```
# however, the data looks too small,
# therefore I decided to get a sample of 500
census_sample = merged_census.sample(n=500, random_state=0)
census_sample
```

	age	workclass	education-num	marital-status	occupation	relationship	race	sex	hours-per-week	native-country	income
2293	52	3	10	2	7	2	1	1	40	1	2
7348	25	1	10	2	5	3	1	2	15	1	1
40927	28	3	9	2	7	2	1	1	40	1	2
22311	19	3	9	1	5	4	2	2	40	1	1
44795	29	3	4	2	7	2	1	1	40	23	2
...	...	...	...	...	...	...	...	...	...	...	...
24803	18	3	9	1	1	4	1	2	20	1	1
13739	21	3	10	1	6	4	2	2	20	1	1
43071	32	2	9	2	7	2	1	1	32	1	1
28013	19	3	10	1	2	4	1	2	40	1	1
1433	18	3	10	1	6	4	1	2	15	1	1

500 rows × 11 columns

Next steps: View recommended plots

```
sns.jointplot(
  x='age',
  y='hours-per-week',
  kind='hex', # hex plot
  data=census_sample,
)
plt.xlabel('Age')
plt.ylabel('Hours/Week')
plt.suptitle('Age vs Work Hours per Week')
# it can be seen that most of the data is at around
# age 20-50 and are working 20-60 hours per week
plt.savefig('age_hours-week.png')
```




```
a = male_census.agg({
    'age' : 'mean',
    'education-num' : 'mean',
    'hours-per-week' : 'mean',
    'income' : 'mean',
    'marital-status' : 'mean'
})
a
```

```
age               39.497594
education-num     10.095492
hours-per-week    42.419264
income             1.303883
marital-status     1.928320
dtype: float64
```

```
b = female_census.agg({
    'age' : 'mean',
    'education-num' : 'mean',
    'hours-per-week' : 'mean',
    'income' : 'mean',
    'marital-status' : 'mean'
})
b
```

```
age               36.932827
education-num     10.044803
hours-per-week    36.403720
income             1.109319
marital-status     2.398900
dtype: float64
```

```
by_sex_census = pd.concat([a, b], axis = 1)
by_sex_census
```

	0	1
age	39.497594	36.932827
education-num	10.095492	10.044803
hours-per-week	42.419264	36.403720
income	1.303883	1.109319
marital-status	1.928320	2.398900

Next steps: View recommended plots

```
by_sex_census.rename(columns={0 : 'male', 1 : 'female'}, inplace=True)
by_sex_census.index=['Age', 'Education', 'Hours/Week', 'Income', 'Marital Status']
by_sex_census
```

	male	female
Age	39.497594	36.932827
Education	10.095492	10.044803
Hours/Week	42.419264	36.403720
Income	1.303883	1.109319
Marital Status	1.928320	2.398900

Next steps: View recommended plots

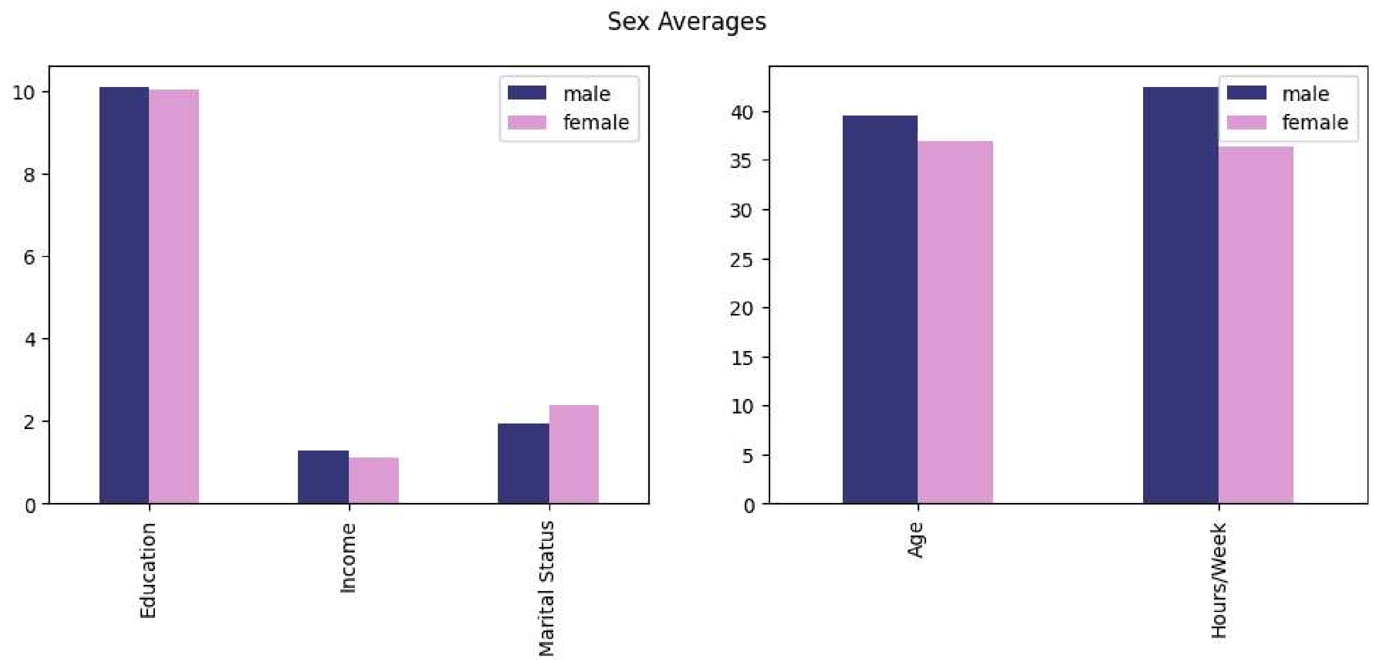
```
# creating the bar plot
low_values = by_sex_census.iloc[[1,3,4]]
high_values = by_sex_census.iloc[[0,2]]

fig, (ax_low, ax_high) = plt.subplots(1, 2, figsize=(12, 4))

low_values.plot(
    kind='bar',
    cmap='tab20b',
    ax=ax_low
)

high_values.plot(
    kind='bar',
    cmap='tab20b',
    ax=ax_high
)
fig.suptitle('Sex Averages')

plt.savefig('sex_average.png')
```




```
c = less_than_census.agg({
    'age' : 'mean',
    'education-num' : 'mean',
    'hours-per-week' : 'mean',
})
c
```

```
age              36.875916
education-num     9.598901
hours-per-week   38.842599
dtype: float64
```

```
d = more_than_census.agg({
    'age' : 'mean',
    'education-num' : 'mean',
    'hours-per-week' : 'mean',
})
d
```

```
age              44.275909
education-num    11.603166
hours-per-week   45.453145
dtype: float64
```

```
by_income_census = pd.concat([c, d], axis = 1)
by_income_census
```

	0	1
age	36.875916	44.275909
education-num	9.598901	11.603166
hours-per-week	38.842599	45.453145

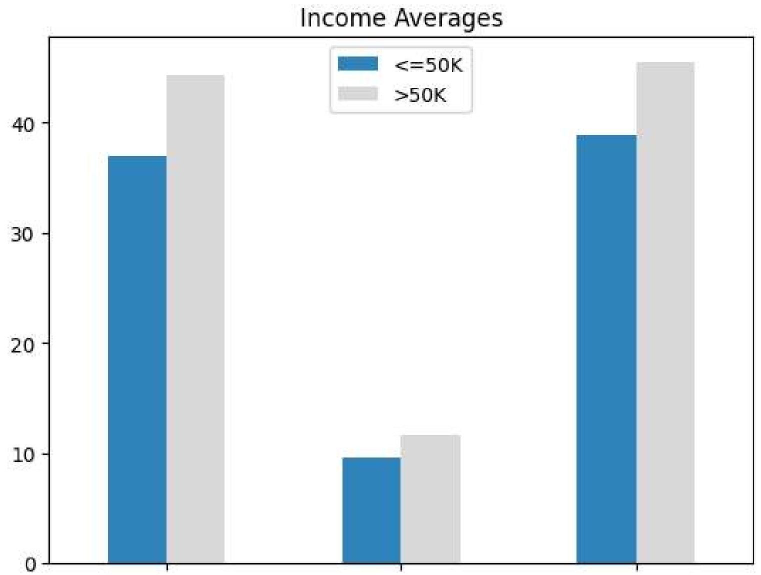
Next steps: View recommended plots

```
by_income_census.rename(columns={0 : '<=50K', 1 : '>50K'}, inplace=True)
by_income_census.index = ['Age', 'Education', 'Hours/Week']
by_income_census
```

	<=50K	>50K
Age	36.875916	44.275909
Education	9.598901	11.603166
Hours/Week	38.842599	45.453145

Next steps: View recommended plots

```
# creating the bar plot
by_income_census.plot(
    kind='bar',
    cmap = 'tab20c',
    title = 'Income Averages'
)
plt.savefig('income_average.png')
```


Income Averages
<=50K
>50K
0
10
20
30
40