Midterm Skills Exam: Data Wrangling and Analysis

CPE311 - Computational Thinking with Python

Name: Dela Cruz, Gabrielle

Section: CPE22S3

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Submitted to: Engr. Roman M. Richard

Link to Colab: https://colab.research.google.com/drive/1fq6mNUxo11dSaHQC1DUNm2uip5LTMC-M?usp=sharing

```
!pip install ucimlrepo
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.7-py3-none-any.whl (8.0 kB)
Requirement already satisfied: pandas>=1.0.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: certifi>=2020.12.5 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/di
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (f
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.7
```

```
from ucimlrepo import fetch_ucirepo

census_income = fetch_ucirepo(id=20)
x = census_income.data.features
y = census_income.data.targets

print(census_income.metadata)
print(census_income.variables)
```

```
{'uci_id': 20, 'name': 'Census Income', 'repository_url': 'https://archive.ics.uci.ed
             name     role  ... units missing_values
0             age  Feature  ...  None             no
1       workclass  Feature  ...  None            yes
2          fnlwgt  Feature  ...  None             no
3       education  Feature  ...  None             no
4   education-num  Feature  ...  None             no
5  marital-status  Feature  ...  None             no
```

```
6      occupation  Feature  ...  None         yes
7    relationship  Feature  ...  None          no
8            race  Feature  ...  None          no
9             sex  Feature  ...  None          no
10   capital-gain  Feature  ...  None          no
11   capital-loss  Feature  ...  None          no
12 hours-per-week  Feature  ...  None          no
13 native-country  Feature  ...  None         yes
14         income   Target  ...  None          no

[15 rows x 7 columns]
```

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

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relations
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-fa
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husb
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-fa
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husb
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	W
...	...	...	...	...	...	...	...	
48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-fa
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-rela
48839	38	Private	374983	Bachelors	13	Married-civ-spouse	Prof-specialty	Husb

Next steps: Generate code with x View recommended plots

```
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: Generate code with y | View recommended plots

```
concatCensus = pd.concat([x, y], axis=1)
concatCensus
```

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relations
0	39	State-gov	77516	Bachelors	13	Never-married	Adm-clerical	Not-in-fai
1	50	Self-emp-not-inc	83311	Bachelors	13	Married-civ-spouse	Exec-managerial	Husb:
2	38	Private	215646	HS-grad	9	Divorced	Handlers-cleaners	Not-in-fai
3	53	Private	234721	11th	7	Married-civ-spouse	Handlers-cleaners	Husb:
4	28	Private	338409	Bachelors	13	Married-civ-spouse	Prof-specialty	V
...	...	...	...	...	...	...	...	

48837	39	Private	215419	Bachelors	13	Divorced	Prof-specialty	Not-in-fai
48838	64	NaN	321403	HS-grad	9	Widowed	NaN	Other-rela
48839	38	Private	374983	Bachelors	13	Married-civ-spouse	Prof-specialty	Husb
48840	44	Private	83891	Bachelors	13	Divorced	Adm-clerical	Own-c

Next steps: Generate code with concatCensus | View recommended plots

```
# Removing duplicate rows for cleaner data presentation.
concatCensus.drop_duplicates(inplace=True)

# Getting to know the Dtype and column names of data.
concatCensus.info()
```

```
<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
```

```
# Determining works/occupations in the dataset.
concatCensus.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)
```

```
# Determining workclasses in the dataset.
concatCensus.workclass.unique()
```

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

```
# Determining workers employed in native-country column in the dataset.
concatCensus['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)
```

```
# Getting to know the number of employed in the occupations column.
concatCensus.occupation.value_counts()
```

```
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
```

```
# Getting to know the number of employed in native-country column.
concatCensus['native-country'].value_counts()
```

```
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
```

```
# Converting categorical to numerical data and adding a dictionary to corresponding educa
education = dict(zip(concatCensus.education, concatCensus['education-num']))
concatCensus.drop(columns=['education'], inplace=True)
concatCensus
```

	age	workclass	fnlwgt	education-num	marital-status	occupation	relationship	race
0	39	State-gov	77516	13	Never-married	Adm-clerical	Not-in-family	White
1	50	Self-emp-not-inc	83311	13	Married-civ-spouse	Exec-managerial	Husband	White
2	38	Private	215646	9	Divorced	Handlers-cleaners	Not-in-family	White

3	53	Private	234721	7	Married-civ-spouse	Handlers-cleaners	Husband	Black
4	28	Private	338409	13	Married-civ-spouse	Prof-specialty	Wife	Black
...	...	...	...	...	...	...	...	..
48837	39	Private	215419	13	Divorced	Prof-specialty	Not-in-family	White
48838	64	NaN	321403	9	Widowed	NaN	Other-relative	Black
48839	38	Private	374983	13	Married-civ-spouse	Prof-specialty	Husband	White

Asian-

Next steps: Generate code with concatCensus | View recommended plots

```
# Getting to know the totals of degrees of education.
education
```

```
{'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}
```

```
columns = ['workclass', 'marital-status', 'occupation', 'relationship', 'race', 'sex', 'nat
uniqueValues = []

for column in columns:
  uniqueValues.append(concatCensus[column].unique().tolist())
uniqueValues
```

```
[['State-gov',
  'Self-emp-not-inc',
  'Private',
```

```
 'Federal-gov',
 'Local-gov',
 '?',
 'Self-emp-inc',
 'Without-pay',
 'Never-worked',
 nan],
['Never-married',
 'Married-civ-spouse',
 'Divorced',
 'Married-spouse-absent',
 'Separated',
 'Married-AF-spouse',
 'Widowed'],
['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],
['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',
```

```
# Creating results dictionaries for further reference
results = []

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

results
```

```
[{'State-gov': 1,
  'Self-emp-not-inc': 2,
  'Private': 3,
  'Federal-gov': 4,
  'Local-gov': 5,
  '?': 6,
  'Self-emp-inc': 7,
  'Without-pay': 8,
  'Never-worked': 9,
  nan: 10},
 {'Never-married': 1,
  'Married-civ-spouse': 2,
  'Divorced': 3,
  'Married-spouse-absent': 4,
  'Separated': 5,
  'Married-AF-spouse': 6,
  'Widowed': 7},
 {'Adm-clerical': 1,
  'Exec-managerial': 2,
  'Handlers-cleaners': 3,
  'Prof-specialty': 4,
  'Other-service': 5,
  'Sales': 6,
  'Craft-repair': 7,
  'Transport-moving': 8,
  'Farming-fishing': 9,
  'Machine-op-inspct': 10,
  'Tech-support': 11,
  '?': 12,
  'Protective-serv': 13,
  'Armed-Forces': 14,
  'Priv-house-serv': 15,
  nan: 16},
 {'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}
```

```
  'Other': 5},
 {'Male': 1, 'Female': 2},
 {'United-States': 1,
  'Cuba': 2,
  'Jamaica': 3,
  'India': 4,
  '?': 5,
  'Mexico': 6,
  'South': 7,
  'Puerto-Rico': 8,
  'Honduras': 9,
  'England': 10,
  'Canada': 11,
  'Germany': 12,
  'Iran': 13,
```

```
# Mapping the categorical data to numerical values.
for column in range(len(columns)):
  concatCensus.replace(results[column], inplace=True)
concatCensus
```

	age	workclass	fnlwgt	education-num	marital-status	occupation	relationship	race
0	39	1.0	77516	13	1	1	1	1
1	50	2.0	83311	13	2	2	2	1
2	38	3.0	215646	9	3	3	1	1
3	53	3.0	234721	7	2	3	2	2
4	28	3.0	338409	13	2	4	3	2
...	...	...	...	...	...	...	...	...
48837	39	3.0	215419	13	3	4	1	1
48838	64	10.0	321403	9	7	10	6	2
48839	38	3.0	374983	13	2	4	2	1
48840	44	3.0	83891	13	3	1	4	3
48841	35	7.0	182148	13	2	2	2	1

48813 rows × 14 columns

Next steps: Generate code with concatCensus | View recommended plots

```
concatCensus.describe()
```

	age	workclass	fnlwgt	education-num	marital-status	occupati
count	48813.000000	48813.000000	4.881300e+04	48813.000000	48813.000000	48813.0000

mean	38.647348	3.390695	1.896679e+05	10.078688	2.084322	5.4215
std	13.709005	1.501250	1.056062e+05	2.570257	1.257648	3.0924
min	17.000000	1.000000	1.228500e+04	1.000000	1.000000	1.0000
25%	28.000000	3.000000	1.175550e+05	9.000000	1.000000	3.0000
50%	37.000000	3.000000	1.781400e+05	10.000000	2.000000	5.0000
75%	48.000000	3.000000	2.376200e+05	12.000000	2.000000	7.0000
max	90.000000	10.000000	1.490400e+06	16.000000	7.000000	15.0000

```
maleCensus = concatCensus.query('sex == 1')
femaleCensus = concatCensus.query('sex == 2')
lessthanCensus = concatCensus.query('income == 1')
morethanCensus = concatCensus.query('income == 2')

# Getting the average census for males of the dataset.
maleCensus.mean()
```

```
age                   39.497594
workclass              3.362447
fnlwgt            191738.905795
education-num         10.095492
marital-status         1.928320
occupation             5.816984
relationship           2.262389
race                   1.191107
sex                    1.000000
capital-gain        1326.980509
capital-loss         100.468174
hours-per-week        42.419264
native-country         2.312617
income                 1.969262
dtype: float64
```

```
femaleCensus.mean()
```

```
age                   36.932827
workclass              3.447658
fnlwgt            185491.732172
education-num         10.044803
marital-status         2.398900
occupation             4.624027
relationship           3.096898
race                   1.279137
sex                    2.000000
capital-gain         581.085156
capital-loss          61.513472
hours-per-week        36.403720
```

```
native-country        2.313991
income                1.779199
dtype: float64
```

```
lessthanCensus.mean()
```

```
age                   36.787392
workclass              3.277674
fnlwgt            190345.926796
education-num          9.596081
marital-status         2.082557
occupation             5.464167
relationship           2.681756
race                   1.245688
sex                    1.388007
capital-gain         148.884970
capital-loss          53.190258
hours-per-week        38.842862
native-country         2.386954
income                 1.000000
dtype: float64
```

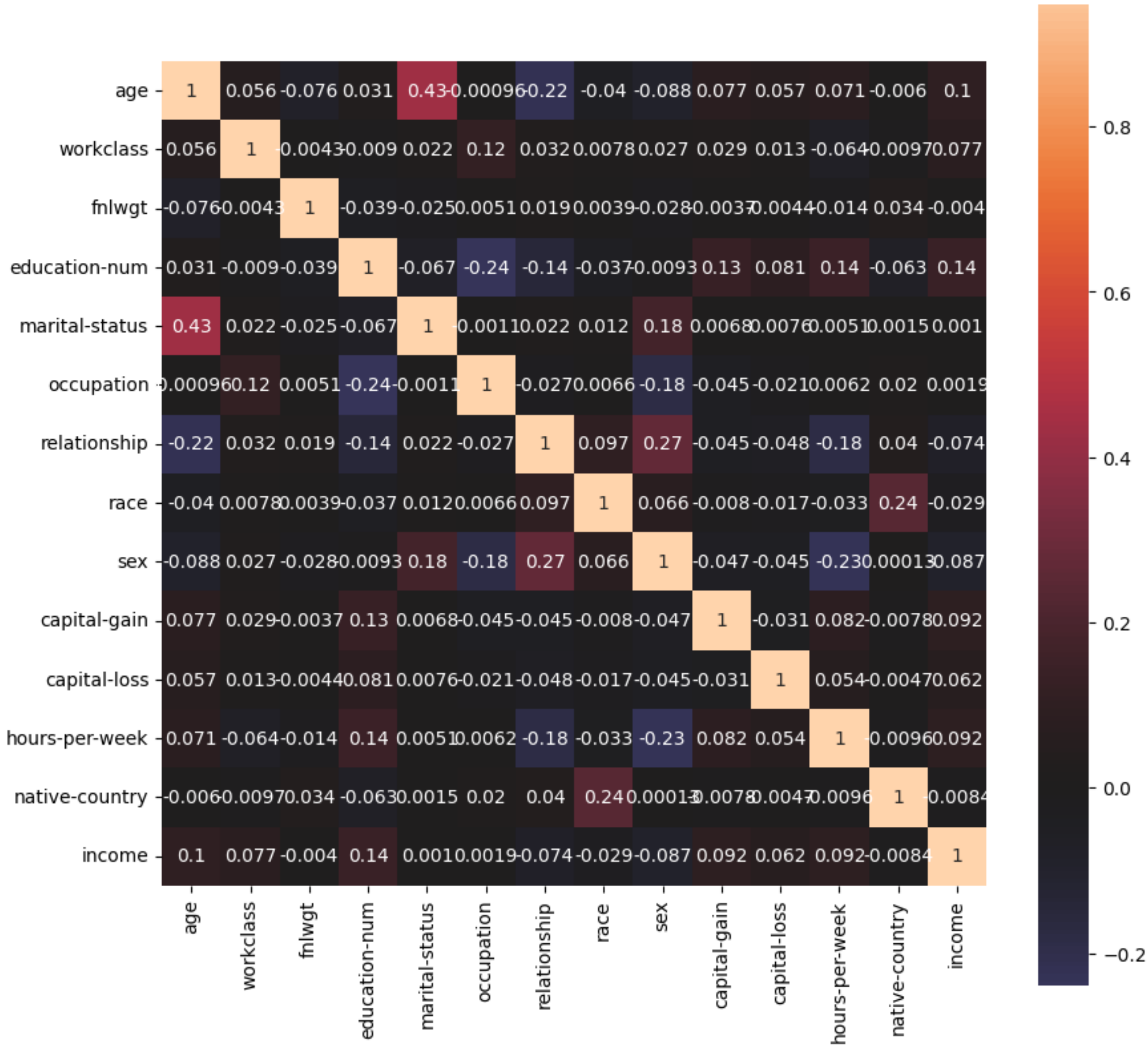
```
morethanCensus.mean()
```

```
age                   44.250925
workclass              3.412808
fnlwgt            188000.480674
education-num         11.612195
marital-status         2.089680
occupation             4.890292
relationship           2.105243
race                   1.146320
sex                    1.150402
capital-gain        4007.164562
capital-loss         195.051282
hours-per-week        45.473402
native-country         2.054089
income                 2.000000
dtype: float64
```

Using Matplotlib for Data Visualization

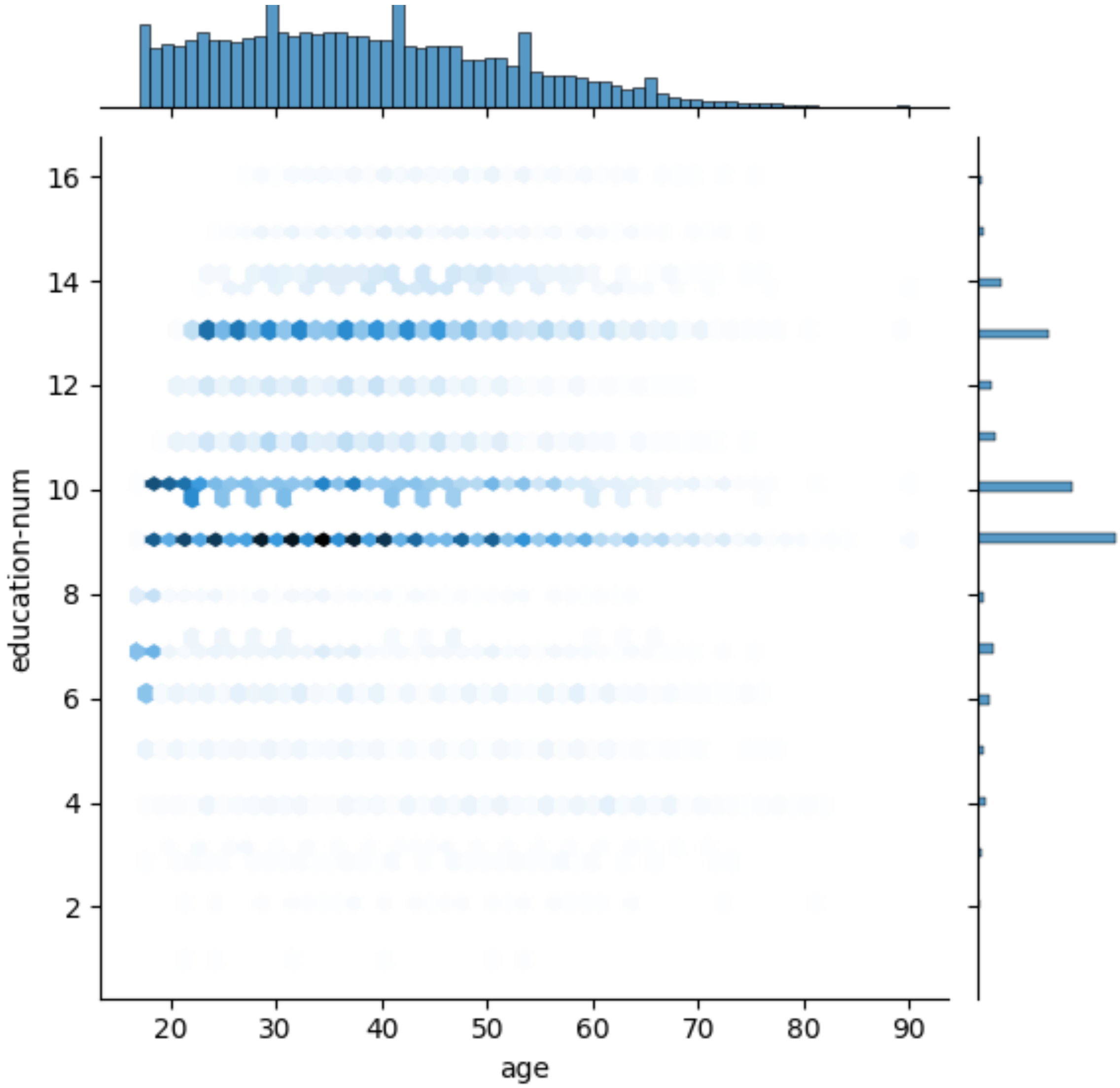
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10,10))
sns.heatmap(concatCensus.sort_index().corr(), annot=True, center=0, square=True)
```

```
<Axes: >
```



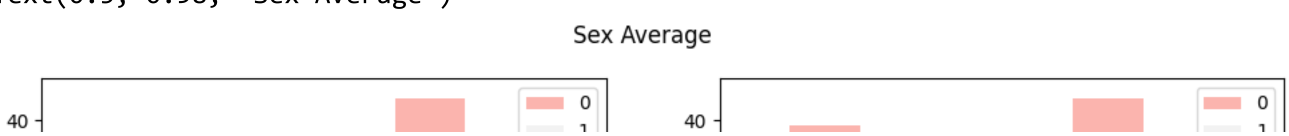
```
# Graphing the categorical data by by a jointplot in Seaborn -- relation of age and hours p
sns.jointplot(x='age', y='education-num', data=concatCensus, kind='hex')
```

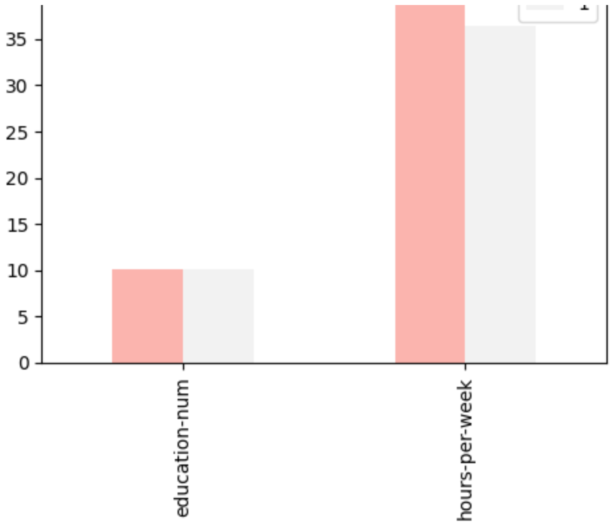
```
<seaborn.axisgrid.JointGrid at 0x78ae239be770>
```

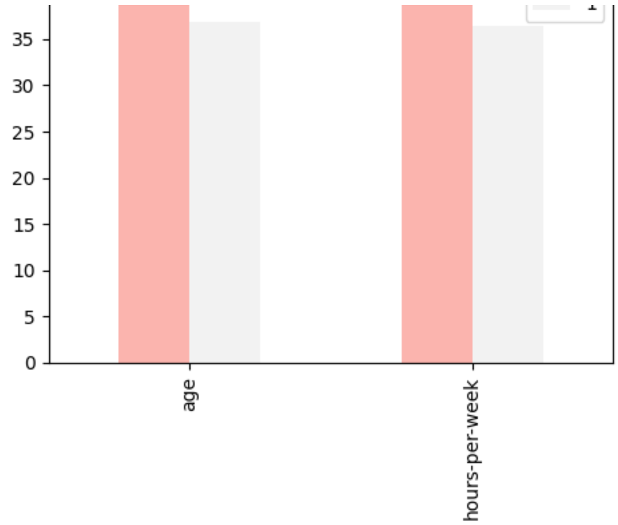



```
# Creating a bar graph that shows the relationship between sex average.
a = maleCensus.agg({'age': 'mean', 'education-num': 'mean', 'hours-per-week': 'mean'})
b = femaleCensus.agg({'age': 'mean', 'education-num': 'mean', 'hours-per-week': 'mean'})

sexCensus = pd.concat([a,b], axis = 1)
lowValues = sexCensus.iloc[[1,2 ]]
highValues = sexCensus.iloc[[0,2]]

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

lowValues.plot(kind='bar', cmap='Pastel1', ax=ax_low)
highValues.plot(kind='bar', cmap='Pastel1', ax=ax_high)

fig.suptitle('Sex Average')
```

```
Text(0.5, 0.98, 'Sex Average')
```

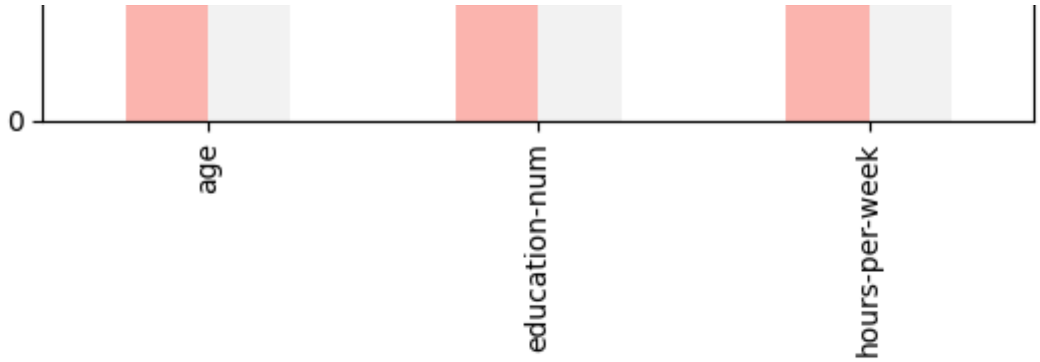







```
# Creating a bar graph for Average Income
c = lessthanCensus.agg({'age': 'mean', 'education-num': 'mean', 'hours-per-week': 'mean'}
d = morethanCensus.agg({'age': 'mean', 'education-num': 'mean', 'hours-per-week': 'mean'}

averageIncome = pd.concat([c,d], axis = 1)
averageIncome.plot(kind='bar', cmap='Pastel1', title='Average Income')
```

```
<Axes: title={'center': 'Average Income'}>
```


0
age
education-num
hours-per-week