IMPORTING DATASET

```
# pip install ucimlrepo
```

```
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.
              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
```

SETUP

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
```

```
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

```
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

DATA CLEANING / WRANGLING

```
con_ci = pd.concat([X,y],axis=1) # concat X & y into a single dataframe
```

```
# remove certain columns for I don't intend to use it
del con_ci['fnlwgt']
del con_ci['relationship']
del con_ci['native-country']
```

```
con_ci
```

	age	workclass	education	education-num	marital-status	occupation	race	sex	capital-gain	capital-loss	hours-per-week	income
0	39	State-gov	Bachelors	13	Never-married	Adm-clerical	White	Male	2174	0	40	<=50K
1	50	Self-emp-not-inc	Bachelors	13	Married-civ-spouse	Exec-managerial	White	Male	0	0	13	<=50K
2	38	Private	HS-grad	9	Divorced	Handlers-cleaners	White	Male	0	0	40	<=50K
3	53	Private	11th	7	Married-civ-spouse	Handlers-cleaners	Black	Male	0	0	40	<=50K
4	28	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	Black	Female	0	0	40	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...
48837	39	Private	Bachelors	13	Divorced	Prof-specialty	White	Female	0	0	36	<=50K.
48838	64	NaN	HS-grad	9	Widowed	NaN	Black	Male	0	0	40	<=50K.
48839	38	Private	Bachelors	13	Married-civ-spouse	Prof-specialty	White	Male	0	0	50	<=50K.

```
for col in con_ci.columns:
  print(col,"\n", con_ci[col].unique())
```

```
age
 [39 50 38 53 28 37 49 52 31 42 30 23 32 40 34 25 43 54 35 59 56 19 20 45
 22 48 21 24 57 44 41 29 18 47 46 36 79 27 67 33 76 17 55 61 70 64 71 68
 66 51 58 26 60 90 75 65 77 62 63 80 72 74 69 73 81 78 88 82 83 84 85 86
 87 89]
workclass
 ['State-gov' 'Self-emp-not-inc' 'Private' 'Federal-gov' 'Local-gov' '?'
 'Self-emp-inc' 'Without-pay' 'Never-worked' nan]
education
 ['Bachelors' 'HS-grad' '11th' 'Masters' '9th' 'Some-college' 'Assoc-acdm'
 'Assoc-voc' '7th-8th' 'Doctorate' 'Prof-school' '5th-6th' '10th'
 '1st-4th' 'Preschool' '12th']
education-num
 [13  9  7 14  5 10 12 11  4 16 15  3  6  2  1  8]
marital-status
 ['Never-married' 'Married-civ-spouse' 'Divorced' 'Married-spouse-absent'
 'Separated' 'Married-AF-spouse' 'Widowed']
occupation
 ['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]
race
 ['White' 'Black' 'Asian-Pac-Islander' 'Amer-Indian-Eskimo' 'Other']
sex
 ['Male' 'Female']
capital-gain
 [ 2174     0 14084  5178  5013  2407 14344 15024  7688 34095  4064  4386
  7298  1409  3674  1055  3464  2050  2176   594 20051  6849  4101  1111
  8614  3411  2597 25236  4650  9386  2463  3103 10605  2964  3325  2580
  3471  4865 99999  6514  1471  2329  2105  2885 25124 10520  2202  2961
 27828  6767  2228  1506 13550  2635  5556  4787  3781  3137  3818  3942
   914   401  2829  2977  4934  2062  2354  5455 15020  1424  3273 22040
  4416  3908 10566   991  4931  1086  7430  6497   114  7896  2346  3418
  3432  2907  1151  2414  2290 15831 41310  4508  2538  3456  6418  1848
  3887  5721  9562  1455  2036  1831 11678  2936  2993  7443  6360  1797
  1173  4687  6723  2009  6097  2653  1639 18481  7978  2387  5060  1264
  7262  1731  6612]
capital-loss
 [   0 2042 1408 1902 1573 1887 1719 1762 1564 2179 1816 1980 1977 1876
```

```
 1340 2206 1741 1485 2339 2415 1380 1721 2051 2377 1669 2352 1672  653
 2392 1504 2001 1590 1651 1628 1848 1740 2002 1579 2258 1602  419 2547
 2174 2205 1726 2444 1138 2238  625  213 1539  880 1668 1092 1594 3004
 2231 1844  810 2824 2559 2057 1974  974 2149 1825 1735 1258 2129 2603
 2282  323 4356 2246 1617 1648 2489 3770 1755 3683 2267 2080 2457  155
 3900 2201 1944 2467 2163 2754 2472 1411 1429 3175 1510 1870 1911 2465
 1421]
hours-per-week
 [40 13 16 45 50 80 30 35 60 20 52 44 15 25 38 43 55 48 58 32 70  2 22 56
 41 28 36 24 46 42 12 65  1 10 34 75 98 33 54  8  6 64 19 18 72  5  9 47
 37 21 26 14  4 59  7 99 53 39 62 57 78 90 66 11 49 84  3 17 68 27 85 31
 51 77 63 23 87 88 73 89 97 94 29 96 67 82 86 91 81 76 92 61 74 95 79 69]
income
 ['<=50K' '>50K' '<=50K.' '>50K.']
```

```
con_ci.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48842 entries, 0 to 48841
Data columns (total 12 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   age             48842 non-null  int64
 1   workclass       47879 non-null  object
 2   education       48842 non-null  object
 3   education-num   48842 non-null  int64
 4   marital-status  48842 non-null  object
 5   occupation      47876 non-null  object
 6   race            48842 non-null  object
 7   sex             48842 non-null  object
 8   capital-gain    48842 non-null  int64
 9   capital-loss    48842 non-null  int64
 10  hours-per-week  48842 non-null  int64
 11  income          48842 non-null  object
dtypes: int64(5), object(7)
memory usage: 4.5+ MB
```

```
con_ci.replace({'?':'Other'},inplace=True) # change the "?" to Others
con_ci.replace('Other', inplace=True) # fill the null values with 'Others'
```

```
iu = {'<=50K.':'<=50K','>50K.':'>50K'}
con_ci.replace({'income':iu},inplace=True) # fix the income column
```

```
cci_std = con_ci.sort_values(by=['education-num', 'capital-gain', 'capital-loss', 'hours-per-week']) # sorting based on how I planned to visualize
```

```
cci_std
```

	age	workclass	education	education-num	marital-status	occupation	race	sex	capital-gain	capital-loss	hours-per-week	income
2884	71	Private	Preschool	1	Widowed	Craft-repair	Black	Male	0	0	10	<=50K
13248	68	Private	Preschool	1	Never-married	Machine-op-inspct	White	Male	0	0	10	<=50K
22167	39	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	12	<=50K
25113	23	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	15	<=50K
43338	53	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	15	<=50K
...	...	...	...	...	...	...	...	...	...	...	...	...
15279	52	Self-emp-inc	Doctorate	16	Married-civ-spouse	Prof-specialty	White	Male	99999	0	65	>50K
10964	56	Self-emp-inc	Doctorate	16	Married-civ-spouse	Prof-specialty	White	Male	99999	0	70	>50K
16740	41	Self-emp-inc	Doctorate	16	Married-civ-spouse	Prof-specialty	White	Male	99999	0	70	>50K
26825	49	Self-emp-not-	Doctorate	16	Never-married	Prof-specialty	White	Male	99999	0	70	>50K

```
cci_std['age-range'] = pd.cut(cci_std.age, bins=[0,10,20,30,40,50,60,70,80,90,100],
                              labels=['0-9', '10-19', '20-29', '30-39', '40-49',
                                      '50-59', '60-69', '70-79', '80-89', '90-100'])
cci_std # binning the age
```

	age	workclass	education	education-num	marital-status	occupation	race	sex	capital-gain	capital-loss	hours-per-week	income	age-range
2884	71	Private	Preschool	1	Widowed	Craft-repair	Black	Male	0	0	10	<=50K	70-79
13248	68	Private	Preschool	1	Never-married	Machine-op-inspct	White	Male	0	0	10	<=50K	60-69
22167	39	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	12	<=50K	30-39
25113	23	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	15	<=50K	20-29
43338	53	Private	Preschool	1	Never-married	Other-service	White	Female	0	0	15	<=50K	50-59
...	...	...	...	...	...	...	...	...	...	...	...	...	...
15279	52	Self-emp-inc	Doctorate	16	Married-civ-spouse	Prof-specialty	White	Male	99999	0	65	>50K	50-59
10964	56	Self-emp-inc	Doctorate	16	Married-civ-spouse	Prof-specialty	White	Male	99999	0	70	>50K	50-59
16740	41	Self-emp-inc	Doctorate	16	Married-civ-	Prof-specialty	White	Male	99999	0	70	>50K	40-49

```
for col in cci_std.columns:
  print(col,"\n", cci_std[col].unique())
```

```
age
 [71 68 39 23 53 54 40 31 42 34 21 47 30 65 63 24 41 37 51 20 25 19 28 35
 33 52 64 59 46 61 49 32 48 66 36 57 29 50 60 43 75 77 26 22 27 69 44 81
 74 80 67 78 56 45 55 62 72 58 38 73 90 76 84 70 82 17 18 88 79 83 89 87
 85 86]
workclass
 ['Private' nan 'State-gov' 'Local-gov' 'Self-emp-not-inc' 'Self-emp-inc'
 'Federal-gov' 'Without-pay' 'Never-worked']
education
 ['Preschool' '1st-4th' '5th-6th' '7th-8th' '9th' '10th' '11th' '12th'
 'HS-grad' 'Some-college' 'Assoc-voc' 'Assoc-acdm' 'Bachelors' 'Masters'
 'Prof-school' 'Doctorate']
education-num
 [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16]
marital-status
 ['Widowed' 'Never-married' 'Married-civ-spouse' 'Married-spouse-absent'
 'Separated' 'Divorced' 'Married-AF-spouse']
occupation
 ['Craft-repair' 'Machine-op-inspct' 'Other-service' nan 'Prof-specialty'
 'Handlers-cleaners' 'Adm-clerical' 'Farming-fishing' 'Sales'
 'Exec-managerial' 'Priv-house-serv' 'Transport-moving' 'Protective-serv'
 'Tech-support' 'Armed-Forces']
race
 ['Black' 'White' 'Amer-Indian-Eskimo' 'Asian-Pac-Islander']
sex
 ['Male' 'Female']
capital-gain
 [    0   594  4508 14344 41310  1086  2062  3674  3781  3908  3942  4386
  7688  1173  1797  2105  2176  2290  2346  2580  3103  3411  3464  4064
  4101  5178  6497  7298 99999   401  1264  1409  1848  2228  2407  2414
  2635  2653  2829  2885  2936  2961  2964  2977  3137  3456  3471  4865
  5013  6097  6418  6514 10566   114   914  1055  1111  1424  2050  2907
  2993  4650  5455  6849 10520  2538  2597  3273  3418  3818  4416  9386
 20051 34095  1151  1506  2174  2463  7430 10605 13550 14084 15024  1471
  2009 18481   991  1455  1731  1831  2036  2202  2329  2354  2387  3325
  3432  3887  4687  4787  4931  4934  5721  6360  6612  6723  6767  7443
  7896  8614  9562 11678 15831 22040 25124 27828  5060  5556  7262  7978
 15020 25236  1639]
capital-loss
 [   0 1672 1719 1602 1735 2042 2179 2603 1579 1628 1876 1887 1902 2001
 2002 2129 2267 2339  974 1408 1411 1590 1594 1651 1668 1977 2051 2057
 2149 2205 3175 3900  625 1617 1721 1848 2163 2231  155 1380 1485 1573
 1740 1741 1762 1980 2238 2559 3770  419  653  880 1258 1340 1870 2377
 2444 2754 2824 1564 2258  323  810 1092 1138 1429 1504 1510 1669 1726
 1816 1825 1974 2174 2206 2246 2282 2352 2392 2415 2457 2467 2472 2489
 3683 4356  213 1421 1539 1648 1844 1944 2547 3004 2465 2080 1755 1911
 2201]
hours-per-week
 [10 12 15 16 20 24 25 28 30 32 35 36 38 40 48 50 60 72 75  4  5 18 21 22
 34 37 43 44 45 52 53 54 55 56 65 66 70 77 85 96 67  3  6  8 14 19 33 42
 49 51 59 84 99  2  7 23 26 29 31 41 47 58 64 80 90 91 63 27 78  9 11 13
 39 46  1 17 68 88 76 98 57 62 69 73 81 82 86 87 89 94 95 97 79 61 74 92]
income
 ['<=50K' '>50K']
age-range
 ['70-79', '60-69', '30-39', '20-29', '50-59', '40-49', '10-19', '80-89']
Categories (10, object): ['0-9' < '10-19' < '20-29' < '30-39' ... '60-69' < '70-79' < '80-89' <
                          '90-100']
```

```
1 cci_std.dtypes
```

```
age                  int64
workclass           object
education           object
education-num        int64
marital-status      object
occupation          object
race                object
sex                 object
capital-gain         int64
capital-loss         int64
hours-per-week       int64
income              object
age-range         category
dtype: object
```

BASIC STATISTICS

```
1 cci_std.describe()
```

	age	education-num	capital-gain	capital-loss	hours-per-week
count	48842.000000	48842.000000	48842.000000	48842.000000	48842.000000
mean	38.643585	10.078089	1079.067626	87.502314	40.422382
std	13.710510	2.570973	7452.019058	403.004552	12.391444
min	17.000000	1.000000	0.000000	0.000000	1.000000
25%	28.000000	9.000000	0.000000	0.000000	40.000000
50%	37.000000	10.000000	0.000000	0.000000	40.000000
75%	48.000000	12.000000	0.000000	0.000000	45.000000
max	90.000000	16.000000	99999.000000	4356.000000	99.000000

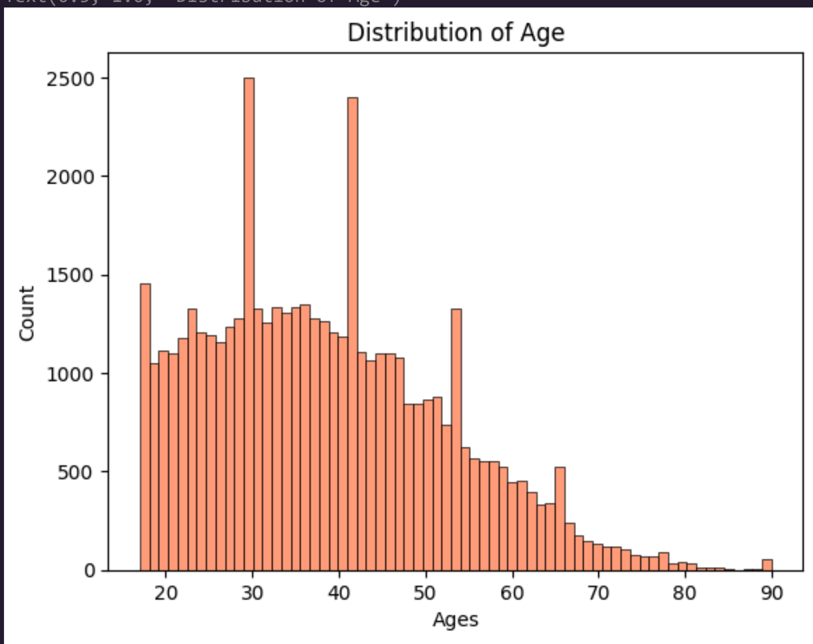
AGE

This plot shows the distribution of age of the sample.

the plot shows that the average age of the sample is starting around late 20's to early 40s.

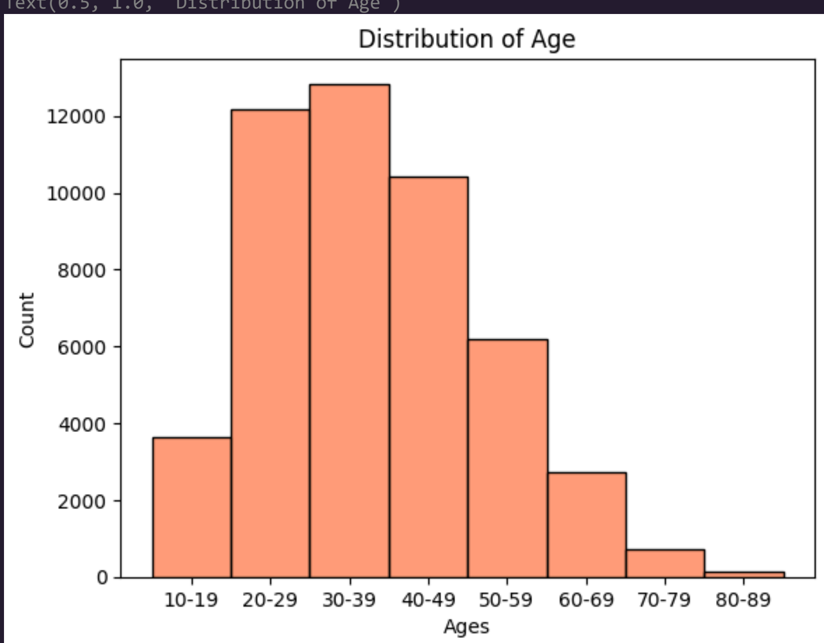
```python
sb.histplot(data=cci_std, x='age', color='coral')
plt.xlabel('Ages')
plt.ylabel('Count')
plt.title('Distribution of Age')
# more detailed
```

```
Text(0.5, 1.0, 'Distribution of Age')
```




```python
sb.histplot(data=cci_std, x='age-range', color='coral')
plt.xlabel('Ages')
plt.ylabel('Count')
plt.title('Distribution of Age')
# compact
```

```
Text(0.5, 1.0, 'Distribution of Age')
```



EDUCATION

This plot shows the education attained by the sample.

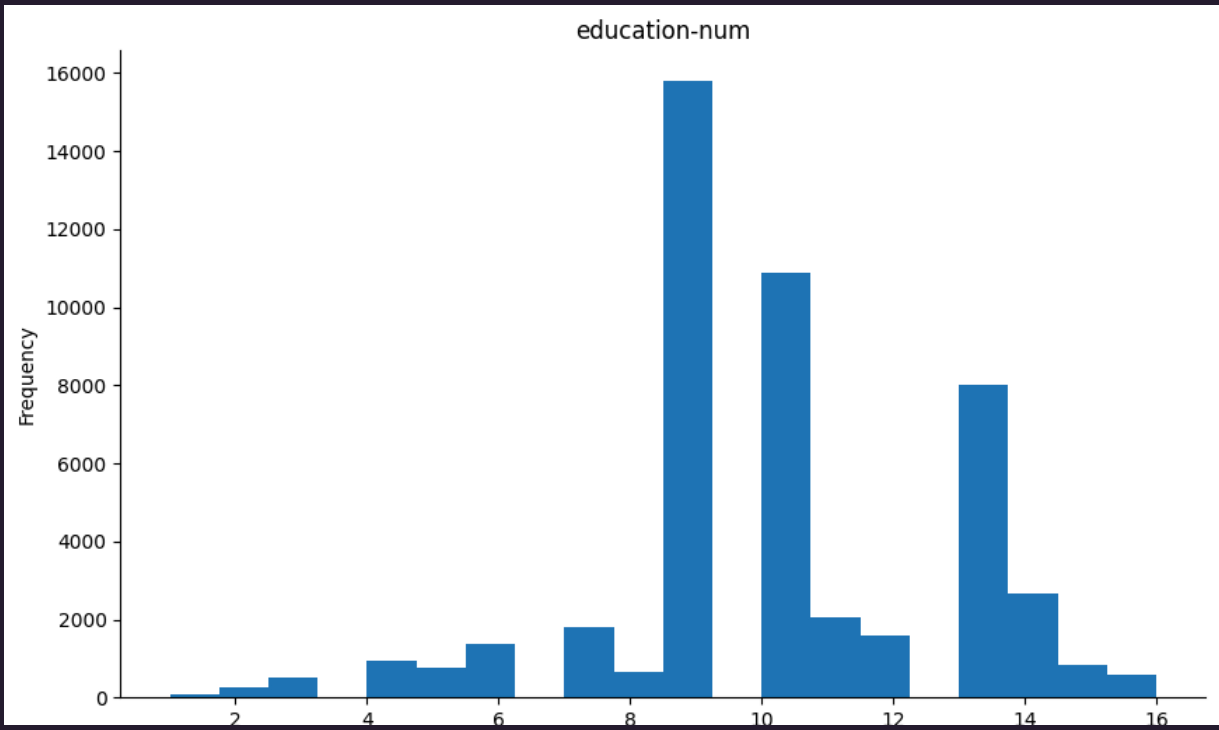
the plot shows that on average the education attained by the sample is around *HS Graduate* to *Some-Collage* and there are also noticeably some who pursued to get their *Bachelors*.

(for reference)

education and their corresponding education number :

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

```python
cci_std['education-num'].plot(kind='hist', bins=20, title='education-num', figsize=(10,6))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



MARITAL STATUS

This plot shows the marital status of the sample.

the plot shows that the most common marital statuses in the sample are *Married to a civillian spouse*, followed by *Never married*, and lastly *Divorced*

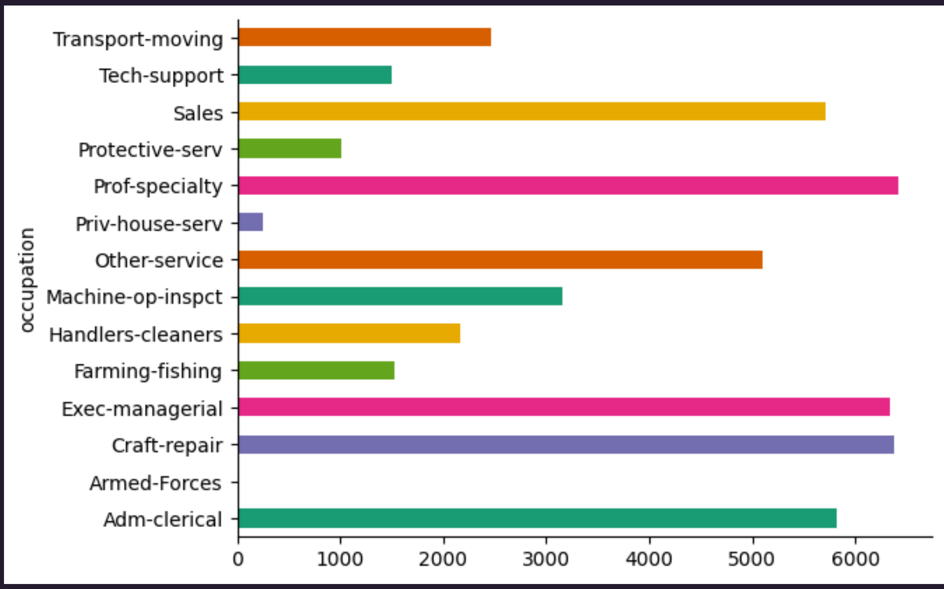
with some of the sample either *Widowed*, *Separated*, or *Married with absent spouse*, and with a very few of the sample that is *Married to a Spouse that is associated with the Armed Forces*.

```
cci_std.groupby('marital-status').size().plot(kind='barh', figsize=(10,6), color=sb.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

OCCUPATION

This plot shows the occupations of the sample.

```
cci_std.groupby('occupation').size().plot(kind='barh', color=sb.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```

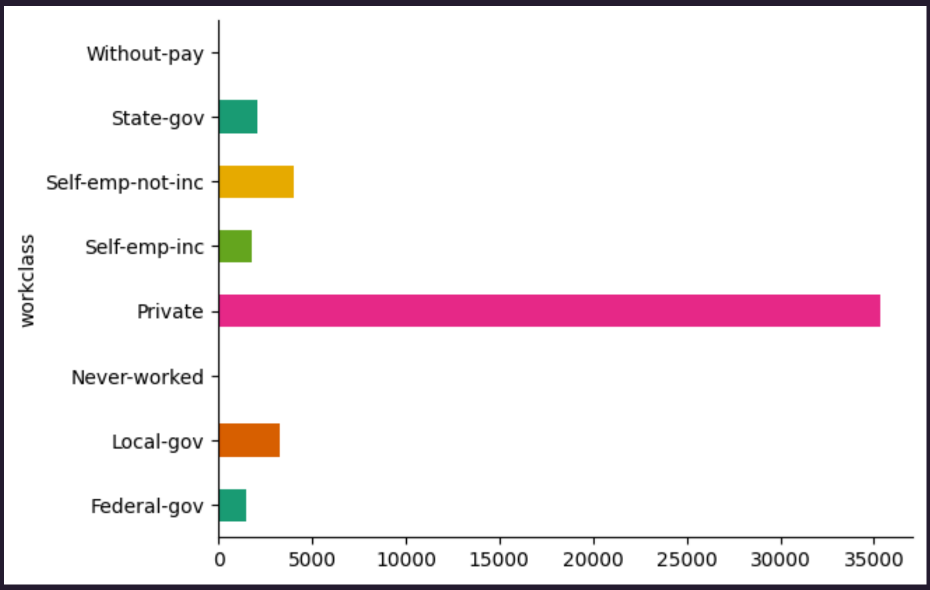


WORKCLASS

This plot shows the workclass of the sample.

the plot shows that a lot of them works in a private company or such, while there are a few who works at the government or is self employed.

```
cci_std.groupby('workclass').size().plot(kind='barh', color=sb.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



SEX & RACE

The following plots shows the Sex and Race distribution of the sample.

the top plot shows that more than 15000 identifies as Females representing one portion of the sample and double that size identifies as Males which is more than 35000 representing the other porTion of the sample.

the bottom plot shows that even though the Population where the sample is taken is in the US, there are some other races that works in the US, they are possibly immigrants that seeks better opportunity abroad.

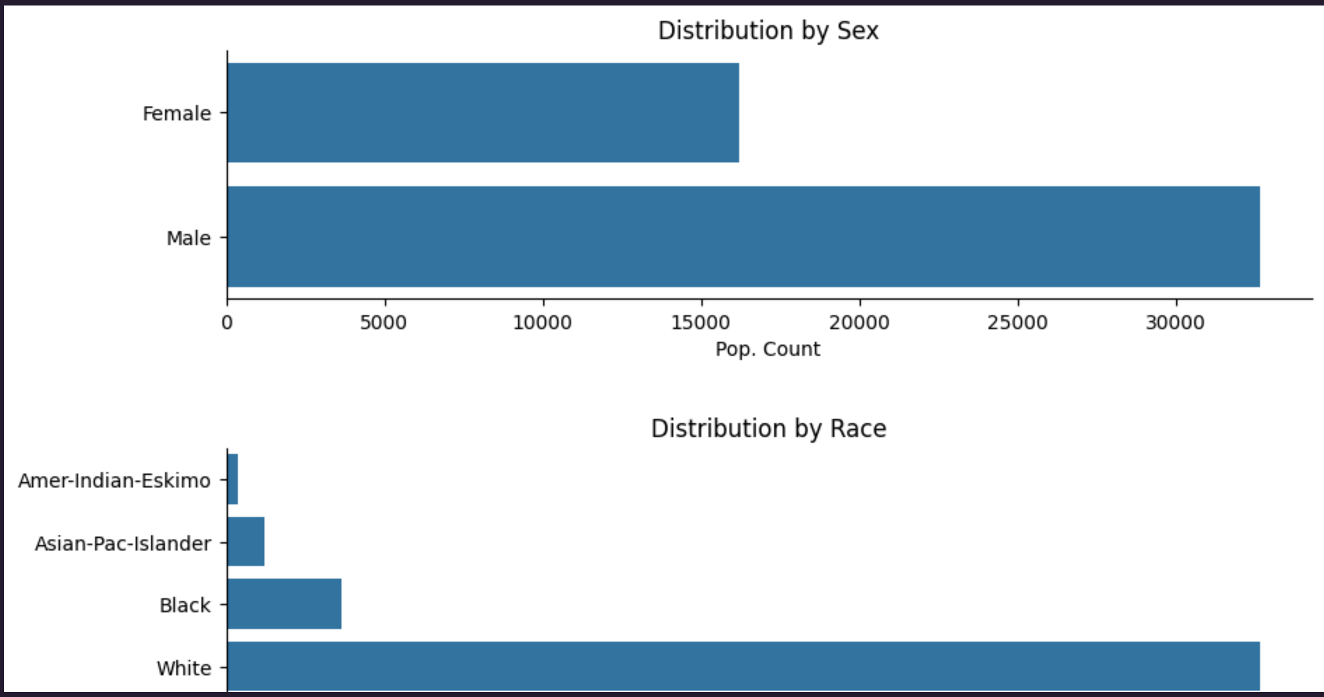
```
fig, axes = plt.subplots(nrows=2, sharex=False, figsize=(10,6))

# count by gender (top subplot)
sex_counts = cci_std.groupby('sex').size()
sb.barplot(ax=axes[0], x=sex_counts, y=sex_counts.index, orient='h')
axes[0].set_title('Distribution by Sex')
axes[0].spines[['top', 'right']].set_visible(False)
axes[0].set_xlabel('Pop. Count')
axes[0].set_ylabel('')

# count by race race (bottom subplot)
race_counts = cci_std.groupby('race').size()
sb.barplot(ax=axes[1], x=race_counts, y=race_counts.index, orient='h')
axes[1].set_title('Distribution by Race')
axes[1].spines[['top', 'right']].set_visible(False)
axes[1].set_xlabel('Pop. Count')
axes[1].set_ylabel('')

plt.subplots_adjust(hspace=0.6)

plt.show()
```

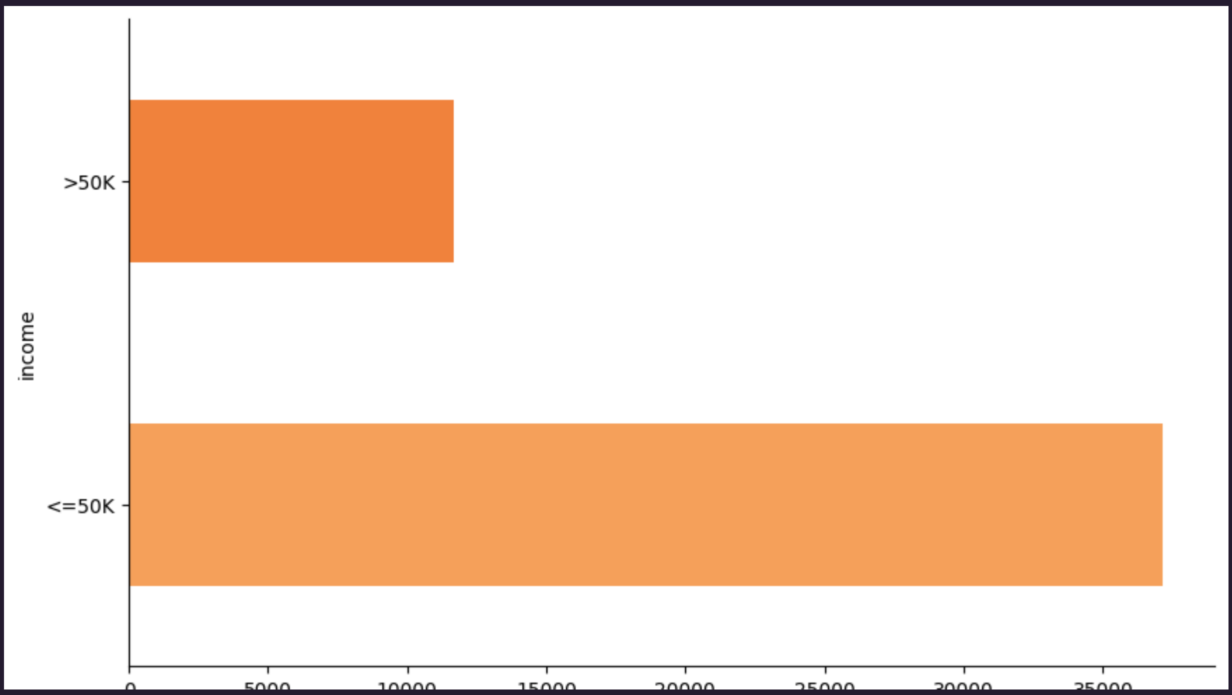


INCOME

The plot shows the income per year of the sample.

the plot shows that majority of the sample earns an income of less than 50K per year, and the others earn more than 50K per year

```
cci_std.groupby('income').size().plot(kind='barh', figsize=(10,6), color=sb.color_palette(palette='Oranges_d'))
plt.gca().spines[['top', 'right',]].set_visible(False)
```



CORRELATION ANALYSIS

CAPITAL GAIN/LOSS AND AGE

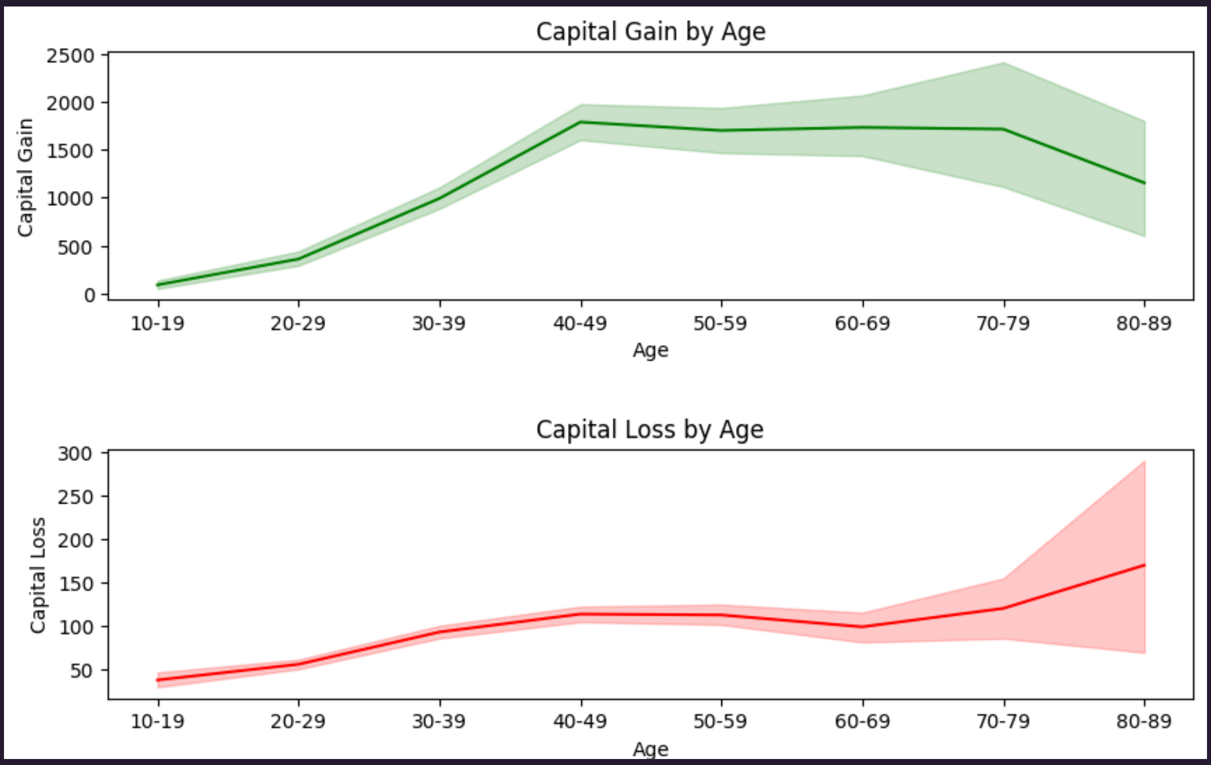
- the graphs shows the trend of capital gain and loss according to their age, the 2 are complementary; the capital gain/loss increases as the individual grows older.
- the data suggest that the sample tend to accumulate more capital gains (maybe from investment profits) as they grow older, specifically at around their 30s and peaks at their 40s, then it will stabilize and slowly decrease, this is probably because of having more time in their field therefore having higher income and better risk tolerance.
- capital loss seem to be noticably lower overall than capital gains, but they can always occur.

```
fig, axes = plt.subplots(nrows=2, sharex=False, figsize=(10,6))

sb.lineplot(x='age-range', y='capital-gain', data=cci_std, color='green', ax=axes[0])
axes[0].set_xlabel('Age')
axes[0].set_ylabel('Capital Gain')
axes[0].set_title('Capital Gain by Age')

sb.lineplot(x='age-range', y='capital-loss', data=cci_std, color='red', ax=axes[1])
axes[1].set_xlabel('Age')
axes[1].set_ylabel('Capital Loss')
axes[1].set_title('Capital Loss by Age')

plt.subplots_adjust(hspace=0.6)
plt.show()
```

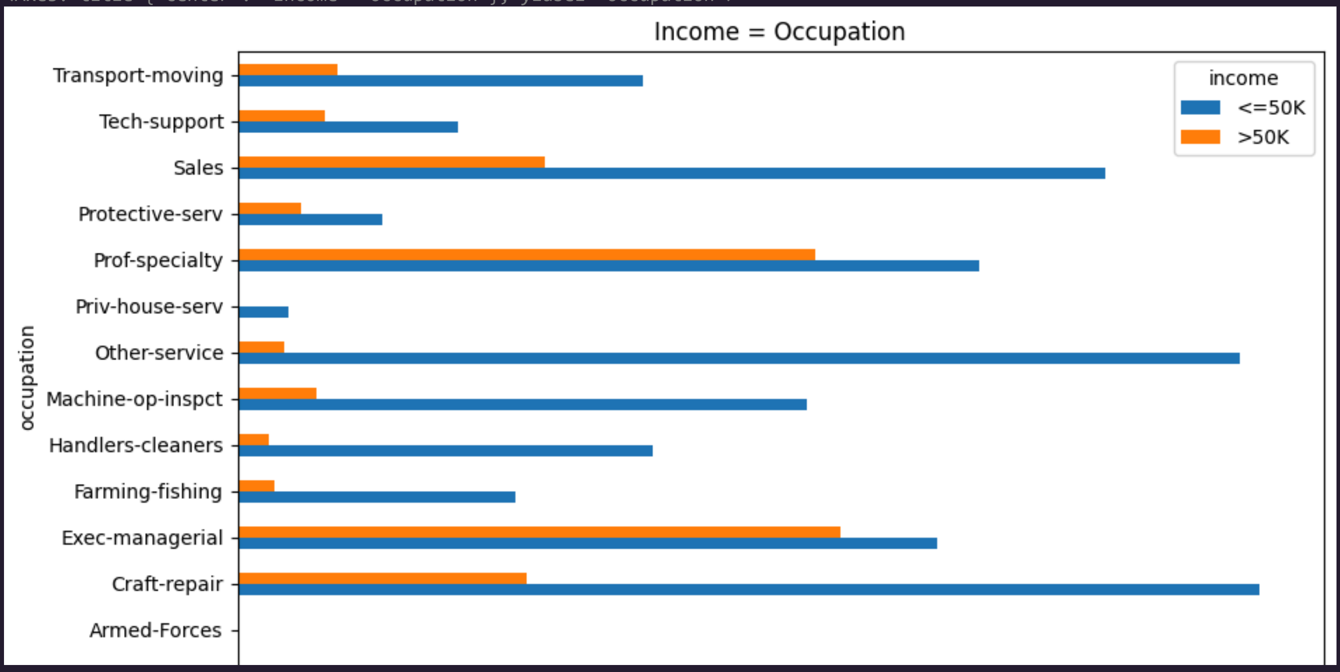


IS INCOME TIED TO THE OCCUPATION OF AN INDIVIDUAL

- the graph says a lot about it, with only 2 occupations that is close to each other when it comes to income (Exec-Manigerial & Prof-specialty), the rest shows that a lot of the individuals earns below 50K in these occupations and only some earns above 50K in that same occupations.
- the ones that earns above 50K in the jobs that the majority earns below 50K may be the ones that are the seasoned professionals, the ones that are in that job the longest and have a lot of experience hence the greater income.

```
oi = cci_std.groupby(['occupation','income']).size()
oi=oi.unstack()
oi.plot(kind='barh',title='Income = Occupation',figsize=(10,6))
```

```
<Axes: title={'center': 'Income = Occupation'}, ylabel='occupation'>
```



INCOME BASED ON THEIR WORK CLASS

- we can ignore without pay here because it's self explanatory.
- this shows the incomes based on Work Class, working in private seems to not have a benefit, looking at the other classes it's close to each other, there's a possibility to earn more than what they are currently earning.

```
wci = cci_std.groupby(['workclass','income']).size()
wci=wci.unstack()
wci.plot(kind = 'barh', grid = True, title = 'Income based on their Work Class',figsize=(10,6))
```

```
<Axes: title={'center': 'Income based on their Work Class'}, ylabel='workclass'>
```