Exploratory data analysis with pandas in python, part 2

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github.com/brown-ccv/dscov_data_science

https://ccv-research.jupyter.brown.edu/

Overview of part 1

- read in csv, excel, and sql data into a pandas data frame
- filter rows in various ways
- select columns
- merge and append data frames

Learning objectives for today

By the end of this talk, you will be able to

- visualize one column (continuous or categorical data)
- visualize column pairs (all variations of continuous and categorical columns)
- visualize multiple columns simultaneously

Dataset of the day

Adult dataset, see [here (https://archive.ics.uci.edu/ml/datasets/Adult)](https://archive.ics.uci.edu/ml/datasets/Adult)

Packages of the day

matplotlib and pandas

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Let's load the data first!

In [59]:
```
import pandas as pd
import numpy as np
import matplotlib
from matplotlib import pylab as plt
df = pd.read_csv('data/adult_data.csv')
print(df.dtypes)
```

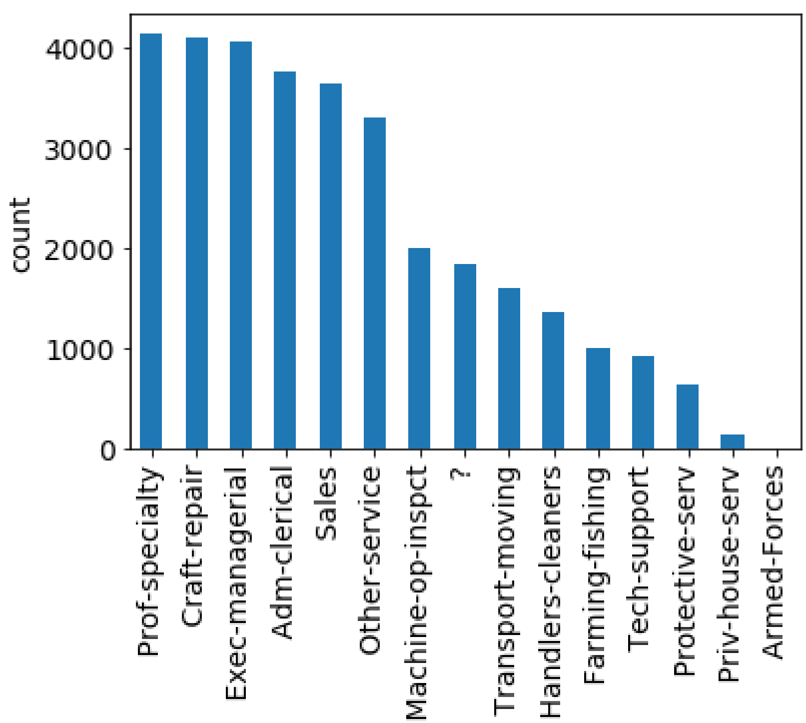
```
age                int64
workclass         object
fnlwgt             int64
education         object
education-num      int64
marital-status    object
occupation        object
relationship      object
race              object
sex               object
capital-gain       int64
capital-loss       int64
hours-per-week     int64
native-country    object
gross-income      object
dtype: object
```

Column is categorical

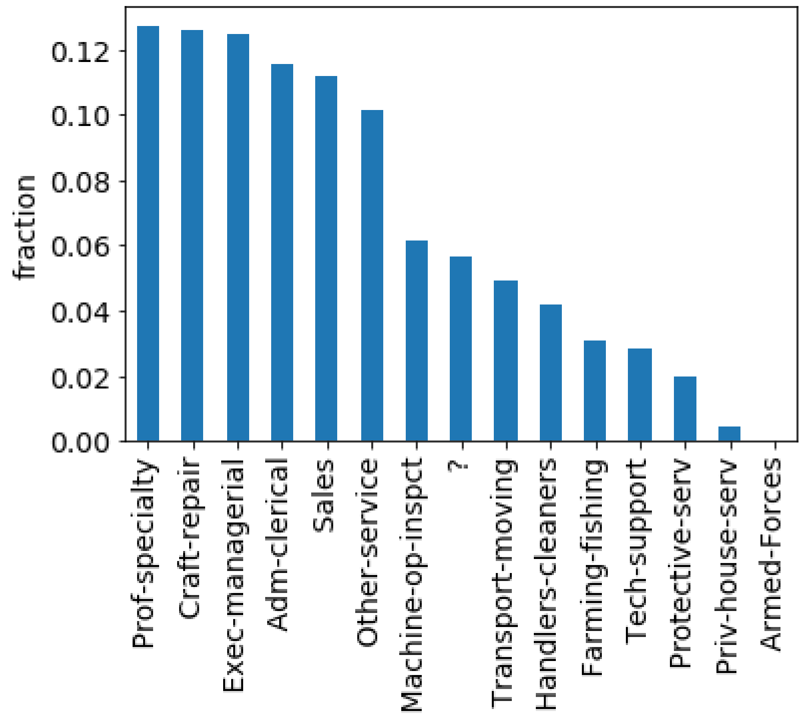
In [60]:
```python
print(df['occupation'].value_counts())
```

```
 Prof-specialty        4140
 Craft-repair          4099
 Exec-managerial       4066
 Adm-clerical          3770
 Sales                 3650
 Other-service         3295
 Machine-op-inspct     2002
 ?                     1843
 Transport-moving      1597
 Handlers-cleaners     1370
 Farming-fishing        994
 Tech-support           928
 Protective-serv        649
 Priv-house-serv        149
 Armed-Forces             9
Name: occupation, dtype: int64
```

In [61]:
```python
pd.value_counts(df['occupation']).plot.bar()
plt.ylabel('count')
plt.show()
```



In [62]:
```python
pd.value_counts(df['occupation'],normalize=True).plot.bar()
plt.ylabel('fraction')
plt.show()
```

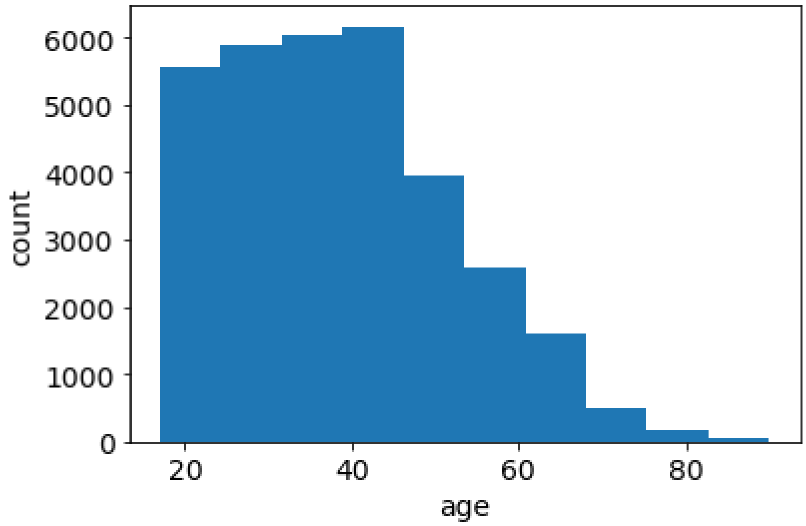


Column is continuous

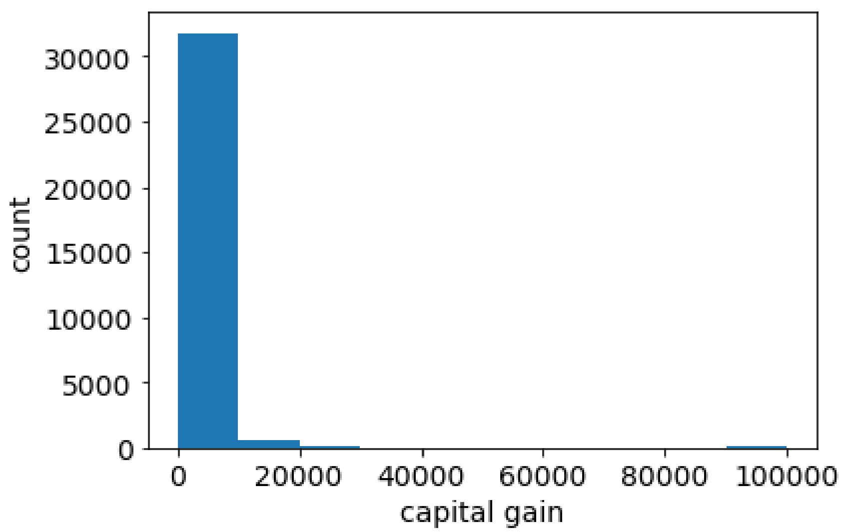
In [63]:
```python
print(df['age'].describe())
```

```
count    32561.000000
mean        38.581647
std         13.640433
min         17.000000
25%         28.000000
50%         37.000000
75%         48.000000
max         90.000000
Name: age, dtype: float64
```

In [76]:
```
df['age'].plot.hist() # bins = int(np.sqrt(df['age'].count())) # bins =
 df['age'].nunique()
plt.xlabel('age')
plt.ylabel('count')
plt.show()
```



In [78]:
```
df['capital-gain'].plot.hist() # log=True, bins = np.logspace(np.log10
(1),np.log10(np.max(df['capital-gain'])),50)
#plt.semilogx()
plt.xlabel('capital gain')
plt.ylabel('count')
plt.show()
```



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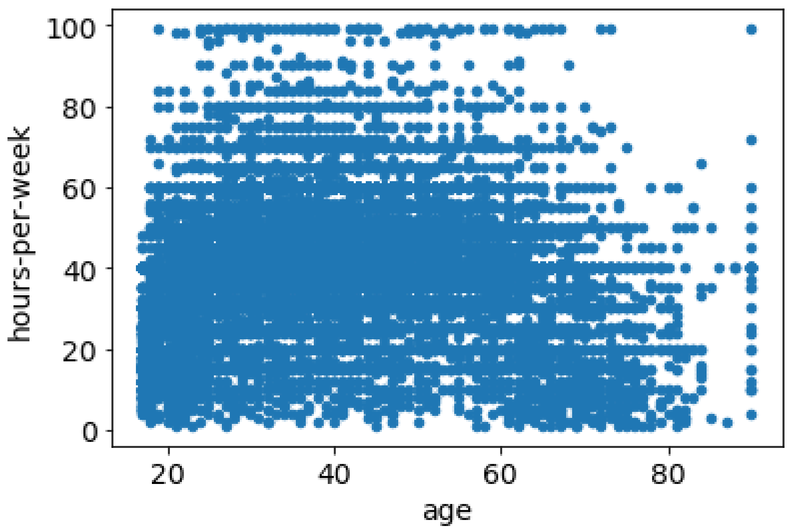
Overview

Visualization types	column continuous	column categorical
column continuous	scatter plot, heatmap	category-specific histograms, box plot, violin plot
column categorical	category-specific histograms, box plot, violin plot	stacked bar plot

Continuous vs. continuous columns

- scatter plot

In [66]:
```
df.plot.scatter('age','hours-per-week')
plt.show()
```

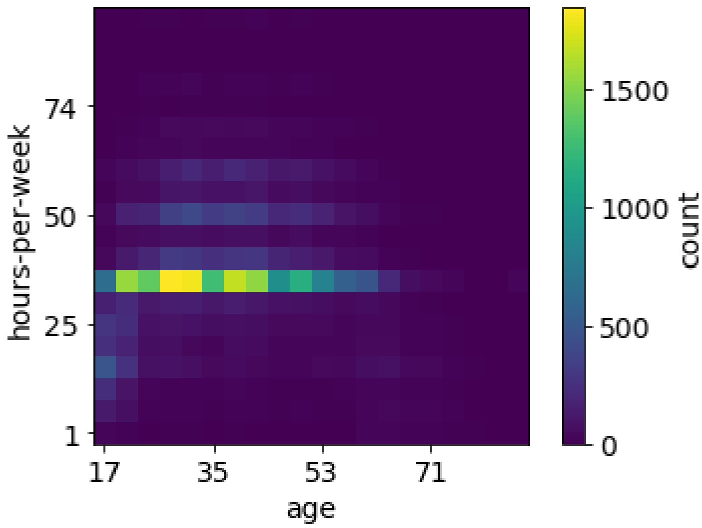


Continuous vs. continuous columns

- heatmap

In [67]:
```
nbins = 20

heatmap, xedges, yedges = np.histogram2d(df['age'], df['hours-per-week'
], bins=nbins)
extent = [xedges[0], xedges[-1], yedges[0], yedges[-1]]
```

```
In [68]: plt.imshow(heatmap.T, origin='lower') # use log count
plt.xlabel('age')
plt.ylabel('hours-per-week')
plt.xticks(np.arange(nbins)[::int(nbins/4)],xedges[::int(nbins/4)].astyp
e(int))
plt.yticks(np.arange(nbins)[::int(nbins/4)],yedges[::int(nbins/4)].astyp
e(int))
plt.colorbar(label='count')
plt.show()
```



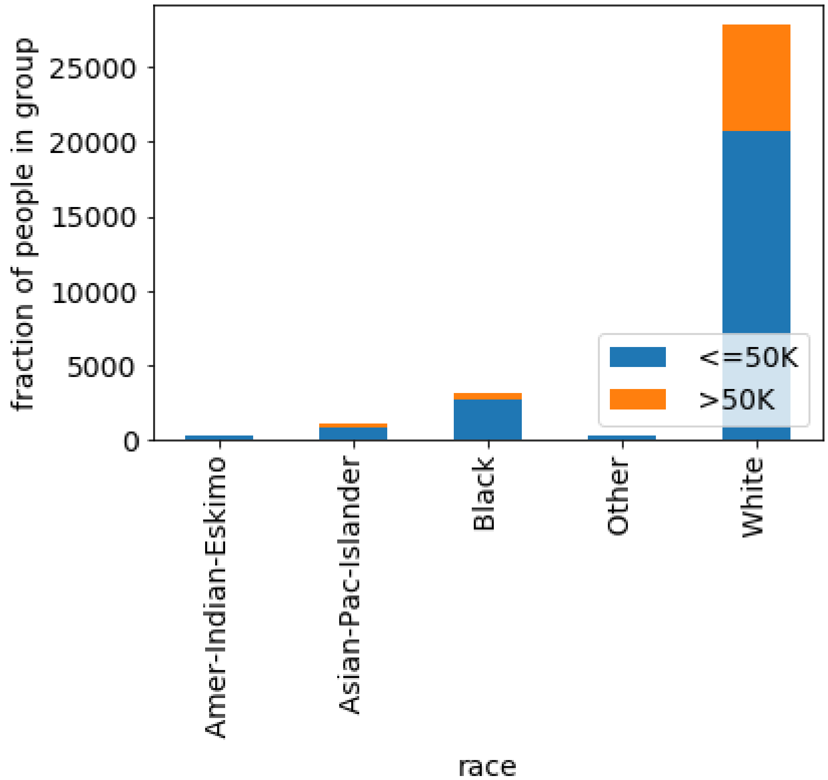
Categorical vs. categorical columns

- stacked bar plot

```
In [69]: count_matrix = df.groupby(['race', 'gross-income']).size().unstack()
print(count_matrix)

#count_matrix_norm = count_matrix.div(count_matrix.sum(axis=1),axis=0)
#print(count_matrix_norm)
```

```
gross-income           <=50K   >50K
race
 Amer-Indian-Eskimo      275     36
 Asian-Pac-Islander      763    276
 Black                  2737    387
 Other                   246     25
 White                 20699   7117
```

In [70]:
```
count_matrix.plot(kind='bar', stacked=True)
plt.ylabel('fraction of people in group')
plt.legend(loc=4)
plt.show()
```

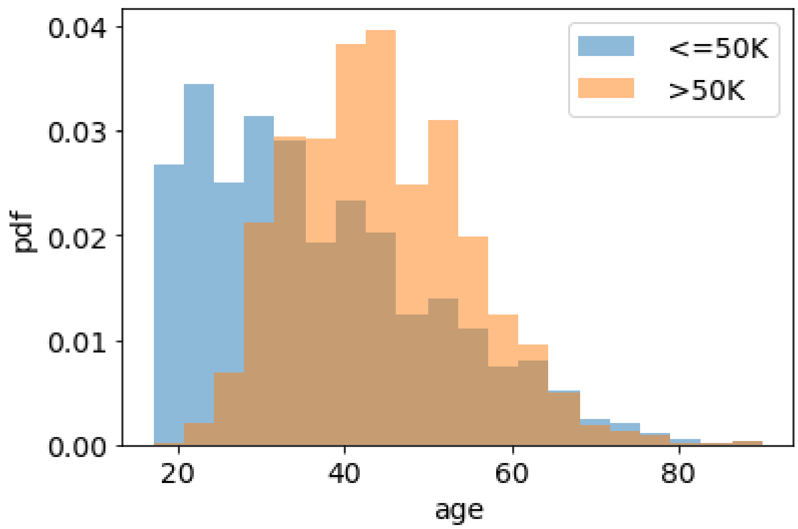


Continuous vs. categorical columns

- category-specific histograms

In [71]:

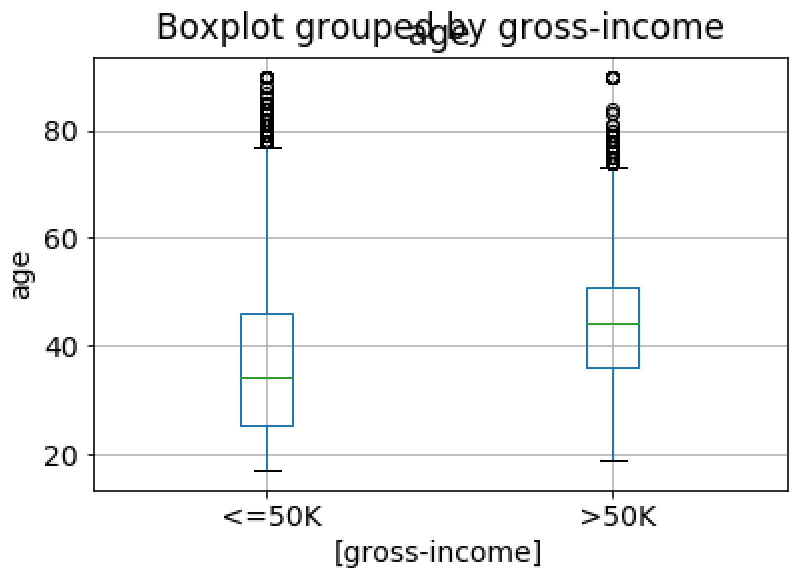
```
import matplotlib
from matplotlib import pylab as plt

categories = df['gross-income'].unique()
bin_range = (df['age'].min(),df['age'].max())

for c in categories:
    plt.hist(df[df['gross-income']==c]['age'],alpha=0.5,label=c,range=bin_range,bins=20,density=True)
plt.legend()
plt.ylabel('pdf')
plt.xlabel('age')
plt.show()
```



Continuous vs. categorical columns

- box plot

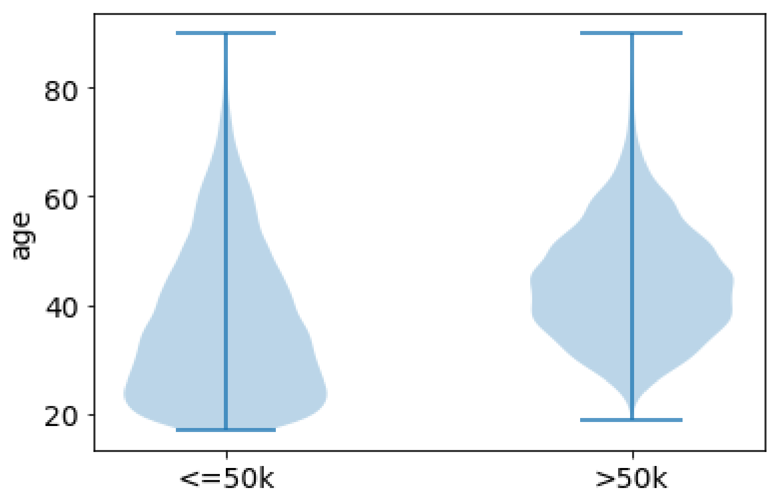
In [72]:
```
df[['age','gross-income']].boxplot(by='gross-income')
plt.ylabel('age')
plt.show()
```



Continuous vs. categorical columns

- violin plot

In [73]:
```
dataset = [df[df['gross-income']==' <=50K']['age'].values,
           df[df['gross-income']==' >50K']['age'].values]

plt.violinplot(dataset = dataset)
plt.xticks([1,2],['<=50k','>50k'])
plt.ylabel('age')
plt.show()
```



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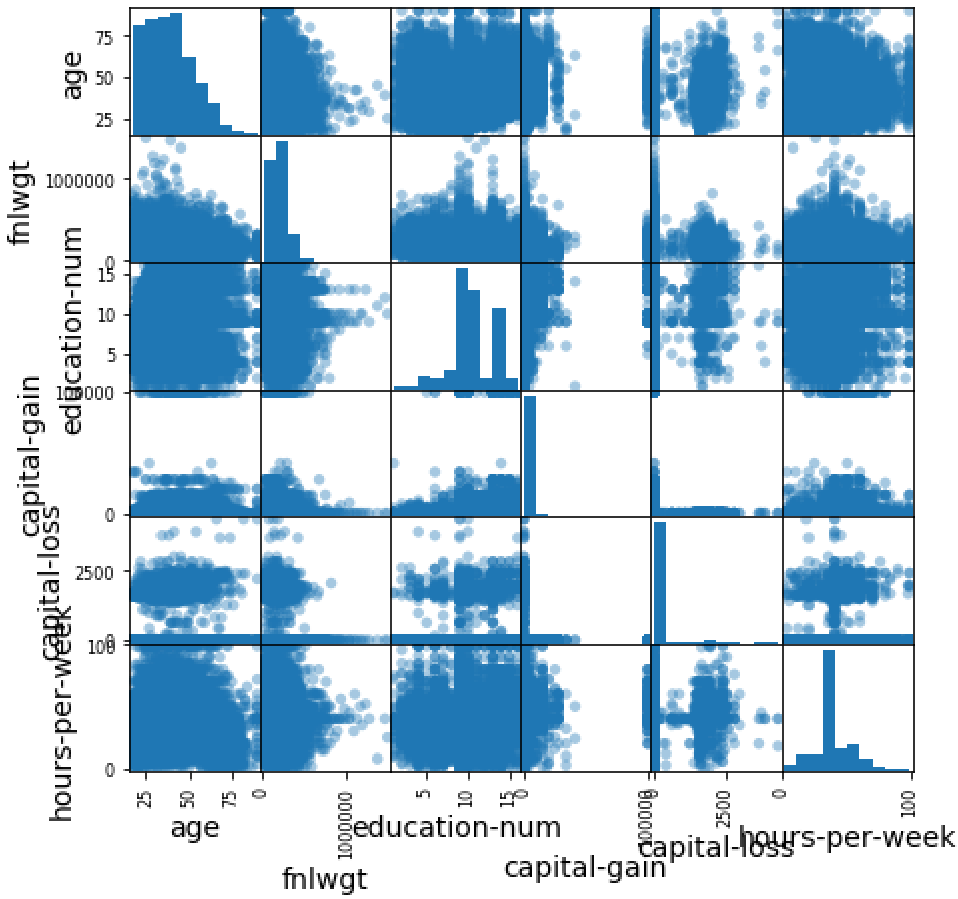
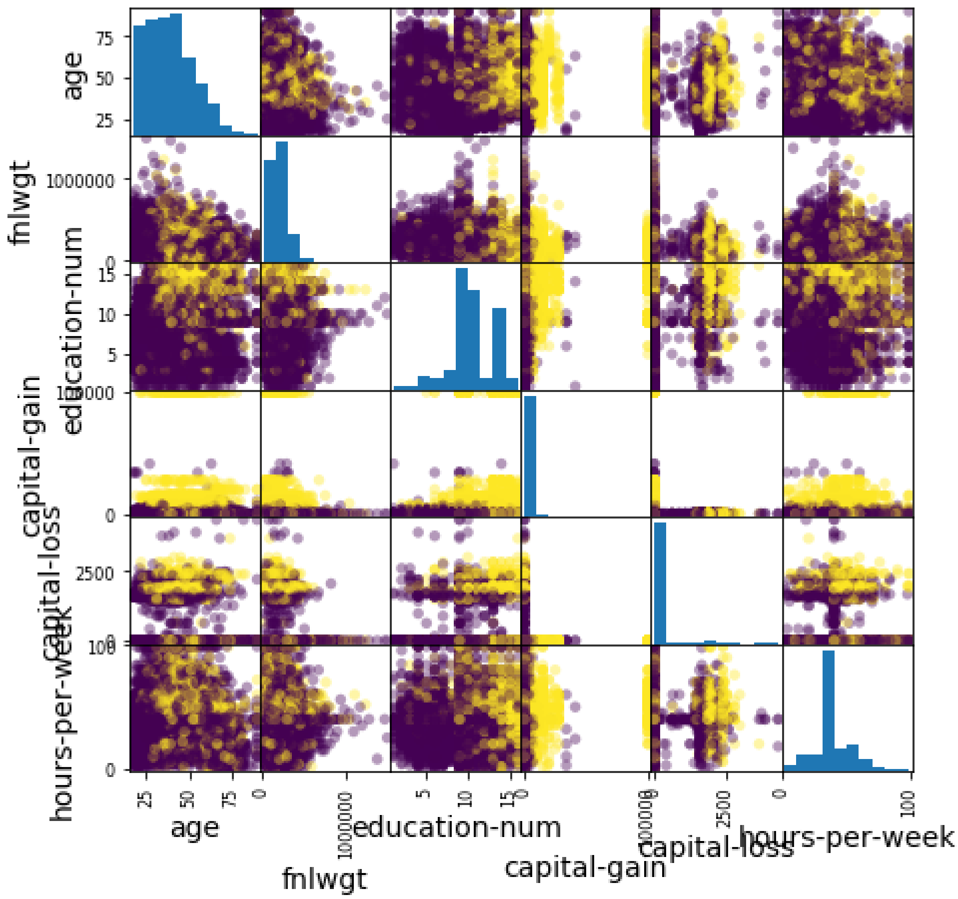
Scatter matrix

In [74]:
```
pd.plotting.scatter_matrix(df.select_dtypes(int), figsize=(7, 7), marker
='o',hist_kwds={'bins': 10},
                           s=30, alpha=.4)
plt.show()
```



In [75]:
```
pd.plotting.scatter_matrix(df.select_dtypes(int), figsize=(7, 7),c = pd.
get_dummies(df['gross-income']).iloc[:,1],
                                marker='o',hist_kwds={'bins': 10}, s=30, alph
a=.4)
plt.show()
```



By now, you can

- visualize one column (continuous or categorical data)
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- visualize multiple columns simultaneously