Course: ENSF 611 – Fall 2022
Lab #: 0
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lab0-pandas-auto_mpg

September 25, 2022

1 Pandas

As described at https://pandas.pydata.org > pandas is an open source, BSD-licensed library providing high-performance, easy-to-use data structures and data analysis tools for the Python programming language.

1.1 Resources

1. Ch 5-6 in Python for Data Analysis, 2nd Ed, Wes McKinney (UCalgary library and https://github.com/wesm/pydata-book)
2. Ch 3 in Python Data Science Handbook, Jake VanderPlas (Ucalgary library and https://github.com/jakevdp/PythonDataScienceHandbook)

Let's explore some of the features.

First, import Pandas, and Numpy as a good companion.

[1]:
```
import numpy as np
import pandas as pd
```

1.2 Create pandas DataFrames

There are several ways to create Pandas DataFrames, most notably from reading a csv (comma separated values file). DataFrames are 'spreadsheets' in Python. We will often use `df` as a variable name for a DataFrame.

If data is not stored in a file, a DataFrame can be created from a dictionary of lists

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada', 'Nevada'],
             'year': [2000, 2001, 2002, 2001, 2002, 2003],
             'pop': [1.5, 1.7, 3.6, 2.4, 2.9, 3.2]}
frame = pd.DataFrame(data)
```

where dictionary keys become column headers.

An alternative is to create from a numpy array and set column headers seperatly:

[2]:
```
# From a numpy array
df = pd.DataFrame( np.arange(20).reshape(5,4), columns=['alpha', 'beta',␣
 ↪'gamma', 'delta'])
df
```

[2]:

	alpha	beta	gamma	delta
0	0	1	2	3
1	4	5	6	7
2	8	9	10	11
3	12	13	14	15
4	16	17	18	19

[3]:
```python
# checking its type
type(df)
```

[3]:
```
pandas.core.frame.DataFrame
```

1.3 Indexing

Accessing data in Dataframes is done by rows and columns, either index or label based.

[4]:
```python
# select a column
df['alpha']
```

[4]:
```
0     0
1     4
2     8
3    12
4    16
Name: alpha, dtype: int32
```

[5]:
```python
# select two columns
df[['alpha', 'gamma']]
```

[5]:

	alpha	gamma
0	0	2
1	4	6
2	8	10
3	12	14
4	16	18

[6]:
```python
# select rows
df.iloc[:2]
```

[6]:

	alpha	beta	gamma	delta
0	0	1	2	3
1	4	5	6	7

[7]:
```python
# select rows and columns
df.iloc[:2, :2]
```

[7]:

	alpha	beta
0	0	1

```
1       4     5
```

[8]:
```python
# select rows and columns, mixed
df.loc[:2, ['alpha', 'beta']]
```

[8]:

	alpha	beta
0	0	1
1	4	5
2	8	9

1.4 DataFrame math

Similar to Numpy, DataFrames support direct math

[9]:
```python
# direct math
df2 = (9/5) * df + 32
df2
```

[9]:

	alpha	beta	gamma	delta
0	32.0	33.8	35.6	37.4
1	39.2	41.0	42.8	44.6
2	46.4	48.2	50.0	51.8
3	53.6	55.4	57.2	59.0
4	60.8	62.6	64.4	66.2

[10]:
```python
# add two dataframes of same shape
df + df2
```

[10]:

	alpha	beta	gamma	delta
0	32.0	34.8	37.6	40.4
1	43.2	46.0	48.8	51.6
2	54.4	57.2	60.0	62.8
3	65.6	68.4	71.2	74.0
4	76.8	79.6	82.4	85.2

[11]:
```python
# map a function to each column
f = lambda x: x.max() - x.min()

df.apply(f)
```

[11]:
```
alpha    16
beta     16
gamma    16
delta    16
dtype: int64
```

1.5 DataFrame manipulation

Adding and deleting columns, as well as changing entries is similar to Python dictionaries.

Note that most DataFrame methods do not change the DataFrame directly, but return a new DataFrame. It is always good to check how the method you are invoking behaves.

[12]:
```
# add a column
df['epsilon'] = ['low', 'medium', 'low', 'high', 'high']
df
```

[12]:
```
   alpha  beta  gamma  delta epsilon
0      0     1      2      3     low
1      4     5      6      7  medium
2      8     9     10     11     low
3     12    13     14     15    high
4     16    17     18     19    high
```

[13]:
```
# What is the size?
df.shape
```

[13]:
```
(5, 5)
```

[15]:
```
# delete column
df_dropped = df.drop(columns=['gamma'])
df_dropped
```

[15]:
```
   alpha  beta  delta epsilon
0      0     1      3     low
1      4     5      7  medium
2      8     9     11     low
3     12    13     15    high
4     16    17     19    high
```

[16]:
```
# the original dataframe is unaffected
df
```

[16]:
```
   alpha  beta  gamma  delta epsilon
0      0     1      2      3     low
1      4     5      6      7  medium
2      8     9     10     11     low
3     12    13     14     15    high
4     16    17     18     19    high
```

Let's create a copy and assign new values to the first column:

[17]:
```
df_copy = df.copy()
df_copy['alpha'] = 20
print(df)
print(df_copy)
```

```
   alpha  beta  gamma  delta epsilon
0      0     1      2      3     low
```

```
1      4     5      6      7  medium
2      8     9     10     11     low
3     12    13     14     15    high
4     16    17     18     19    high
   alpha  beta  gamma  delta epsilon
0     20     1      2      3     low
1     20     5      6      7  medium
2     20     9     10     11     low
3     20    13     14     15    high
4     20    17     18     19    high
```

DataFrames can be sorted by column:

[18]:
```
# sorting values
df.sort_values(by='epsilon')
```

[18]:
```
   alpha  beta  gamma  delta epsilon
3     12    13     14     15    high
4     16    17     18     19    high
0      0     1      2      3     low
2      8     9     10     11     low
1      4     5      6      7  medium
```

1.6 Load data from file

Most often data will come from somewhere, often csv files, and using `pd.read_csv()` will allow smooth creation of DataFrames.

Let's load that same heart-attack.csv that we used in Numpy before:

[2]:
```
data = pd.read_csv('auto-mpg.data.csv')
```

After loading data, it is good practice to check what we have. Usually, the sequences is: 1. Check dimension 2. Peek at the first rows 3. Get info on data types and missing values 4. Summarize columns

[3]:
```
# Check dimension (rows, columns)
data.shape
```

[3]:
```
(398, 9)
```

[4]:
```
# Peek at the first rows
data.head()
```

[4]:
```
    mpg  cylinders  displacement horsepower  weight  acceleration  model year  \
0  18.0          8         307.0        130    3504          12.0          70
1  15.0          8         350.0        165    3693          11.5          70
2  18.0          8         318.0        150    3436          11.0          70
3  16.0          8         304.0        150    3433          12.0          70
4  17.0          8         302.0        140    3449          10.5          70
```

```
   origin                  car name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
```

[5]:
```
# Column names are
data.columns
```

[5]:
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model year', 'origin', 'car name'],
      dtype='object')
```

[6]:
```
# Get info on data types and missing values
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    398 non-null    object
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64
 7   origin        398 non-null    int64
 8   car name      398 non-null    object
dtypes: float64(3), int64(4), object(2)
memory usage: 28.1+ KB
```

1.7 Summarize values

What is the mean, std, min, max in each column?

[7]:
```
data.mean()
```

```
C:\Users\Ardit\AppData\Local\Temp\ipykernel_11480\531903386.py:1: FutureWarning:
Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None')
is deprecated; in a future version this will raise TypeError.  Select only valid
columns before calling the reduction.
  data.mean()
```

[7]:
```
mpg               23.514573
cylinders          5.454774
```

```
displacement     193.425879
weight          2970.424623
acceleration      15.568090
model year        76.010050
origin             1.572864
dtype: float64
```

[8]:
```
# where are the other columns? Check data types
data.dtypes
```

[8]:
```
mpg             float64
cylinders         int64
displacement    float64
horsepower       object
weight            int64
acceleration    float64
model year        int64
origin            int64
car name         object
dtype: object
```

Notice that many columns are of type object, which is not a number. Maybe this has to do with missing values? We know from peeking at the first rows that there are '?' values in there. Let's replace these with the string NaN for not-a-number.

[9]:
```
# replace '?' with 'NaN'
data = data.replace({'?': 'NaN'})
data.head()
```

[9]:
```
    mpg  cylinders  displacement horsepower  weight  acceleration  model year  \
0  18.0          8         307.0        130    3504          12.0          70
1  15.0          8         350.0        165    3693          11.5          70
2  18.0          8         318.0        150    3436          11.0          70
3  16.0          8         304.0        150    3433          12.0          70
4  17.0          8         302.0        140    3449          10.5          70

   origin                   car name
0       1  chevrolet chevelle malibu
1       1          buick skylark 320
2       1         plymouth satellite
3       1              amc rebel sst
4       1                ford torino
```

Pandas knows that 'NaN' probably means that numbers are missing. Now we can convert the data type from object to float

[10]:
```
# convert dtypes
data.iloc[:, :8] = data.iloc[:, :8].astype('float')
```

```
data.dtypes
```

[10]:
```
mpg             float64
cylinders       float64
displacement    float64
horsepower      float64
weight          float64
acceleration    float64
model year      float64
origin          float64
car name         object
dtype: object
```

We could have loaded the data with the `na_values` argument to indicate that '?' means missing number:

[11]:
```
data = pd.read_csv('auto-mpg.data.csv', na_values='?')
data.dtypes
```

[11]:
```
mpg             float64
cylinders         int64
displacement    float64
horsepower      float64
weight            int64
acceleration    float64
model year        int64
origin            int64
car name         object
dtype: object
```

This worked nicely. Now we can describe all columns, meaning printing basic statistics. Note that by default Pandas ignores NaN, whereas Numpy does not.

[12]:
```
data.describe() # ignores NaN
```

[12]:
```
              mpg   cylinders  displacement  horsepower       weight  \
count  398.000000  398.000000    398.000000  392.000000   398.000000
mean    23.514573    5.454774    193.425879  104.469388  2970.424623
std      7.815984    1.701004    104.269838   38.491160   846.841774
min      9.000000    3.000000     68.000000   46.000000  1613.000000
25%     17.500000    4.000000    104.250000   75.000000  2223.750000
50%     23.000000    4.000000    148.500000   93.500000  2803.500000
75%     29.000000    8.000000    262.000000  126.000000  3608.000000
max     46.600000    8.000000    455.000000  230.000000  5140.000000

       acceleration  model year      origin
count    398.000000  398.000000  398.000000
mean      15.568090   76.010050    1.572864
```

```
std        2.757689    3.697627    0.802055
min        8.000000   70.000000    1.000000
25%       13.825000   73.000000    1.000000
50%       15.500000   76.000000    1.000000
75%       17.175000   79.000000    2.000000
max       24.800000   82.000000    3.000000
```

We could be interested by these statistics in each of the origins. To get these, we first group values by origin, then ask for the description. We will only look at mpg for clarity

[13]:
```python
data.groupby(by='origin').describe().mpg
```

[13]:
```
        count       mean       std   min   25%   50%    75%   max
origin
1       249.0  20.083534  6.402892   9.0  15.0  18.5  24.00  39.0
2        70.0  27.891429  6.723930  16.2  24.0  26.5  30.65  44.3
3        79.0  30.450633  6.090048  18.0  25.7  31.6  34.05  46.6
```

1.8 Find NaNs

How many NaNs in each column?

We can ask which entries are null, which produces a boolean array

[14]:
```python
data.isnull()
```

[14]:
```
       mpg  cylinders  displacement  horsepower  weight  acceleration  \
0    False      False         False       False   False         False
1    False      False         False       False   False         False
2    False      False         False       False   False         False
3    False      False         False       False   False         False
4    False      False         False       False   False         False
..     …          …            …           …       …             …
393  False      False         False       False   False         False
394  False      False         False       False   False         False
395  False      False         False       False   False         False
396  False      False         False       False   False         False
397  False      False         False       False   False         False

     model year  origin  car name
0         False   False     False
1         False   False     False
2         False   False     False
3         False   False     False
4         False   False     False
..          …       …        …
393       False   False     False
394       False   False     False
395       False   False     False
```

```
396       False   False     False
397       False   False     False

[398 rows x 9 columns]
```

Applying `sum()` to this boolean array will count the number of `True` values in each column

[15]:
```
data.isnull().sum()
```

[15]:
```
mpg             0
cylinders       0
displacement    0
horsepower      6
weight          0
acceleration    0
model year      0
origin          0
car name        0
dtype: int64
```

We get complementary information from `info()`

[16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   mpg           398 non-null    float64
 1   cylinders     398 non-null    int64
 2   displacement  398 non-null    float64
 3   horsepower    392 non-null    float64
 4   weight        398 non-null    int64
 5   acceleration  398 non-null    float64
 6   model year    398 non-null    int64
 7   origin        398 non-null    int64
 8   car name      398 non-null    object
dtypes: float64(4), int64(4), object(1)
memory usage: 28.1+ KB
```

We can fill (replace) these missing values, for example with the minimum value in each column

[17]:
```
data.fillna(data.min()).describe()
```

[17]:
```
              mpg   cylinders  displacement  horsepower       weight  \
count  398.000000  398.000000    398.000000  398.000000   398.000000
mean    23.514573    5.454774    193.425879  103.587940  2970.424623
std      7.815984    1.701004    104.269838   38.859575   846.841774
```

```
min      9.000000    3.000000     68.000000   46.000000  1613.000000
25%     17.500000    4.000000    104.250000   75.000000  2223.750000
50%     23.000000    4.000000    148.500000   92.000000  2803.500000
75%     29.000000    8.000000    262.000000  125.000000  3608.000000
max     46.600000    8.000000    455.000000  230.000000  5140.000000

       acceleration  model year      origin
count    398.000000  398.000000  398.000000
mean      15.568090   76.010050    1.572864
std        2.757689    3.697627    0.802055
min        8.000000   70.000000    1.000000
25%       13.825000   73.000000    1.000000
50%       15.500000   76.000000    1.000000
75%       17.175000   79.000000    2.000000
max       24.800000   82.000000    3.000000
```

1.9 Count unique values (a histogram)

We finish off, with our good friend the histogram

[18]:
```
data['mpg'].value_counts()
```

[18]:
```
13.0    20
14.0    19
18.0    17
15.0    16
26.0    14
        ..
31.9     1
16.9     1
18.2     1
22.3     1
44.0     1
Name: mpg, Length: 129, dtype: int64
```

[ ]:
```

```

lab0-visualization-auto_mpg

September 25, 2022

1 Visualization

1.1 Topics

1. Matplotlib core framework
2. Pandas plot()
3. Seaborn statistical visualization
4. (not covered) Grammar of graphics (ggplot2 see plotnine)
5. (not covered) Interactive plotting

1.2 Resources

1. Ch 9 in Python for Data Analysis, 2nd Ed, Wes McKinney (UCalgary library and https://github.com/wesm/pydata-book)
2. Ch 4 in Python Data Science Handbook, Jake VanderPlas (Ucalgary library and https://github.com/jakevdp/PythonDataScienceHandbook)
3. Fundamentals of Data Visualization, Claus O. Wilke (Ucalgary library and https://serialmentor.com/dataviz/index.html)
4. Overview by Jake VanderPlas https://www.youtube.com/watch?v=FytuB8nFHPQ

1.3 Matplotlib

> Matplotlib is a Python 2D plotting library which produces publication quality figures
> in a variety of hardcopy formats and interactive environments across platforms.
> Matplotlib tries to make easy things easy and hard things possible.
> For simple plotting the pyplot module provides a MATLAB-like interface

https://matplotlib.org

Importing matplotlib looks like this

[1]:
```
%matplotlib inline

import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
```

1.3.1 Two interfaces

There are two ways to interact with Matplot lib: a Matlab style and an object oriented style interface.

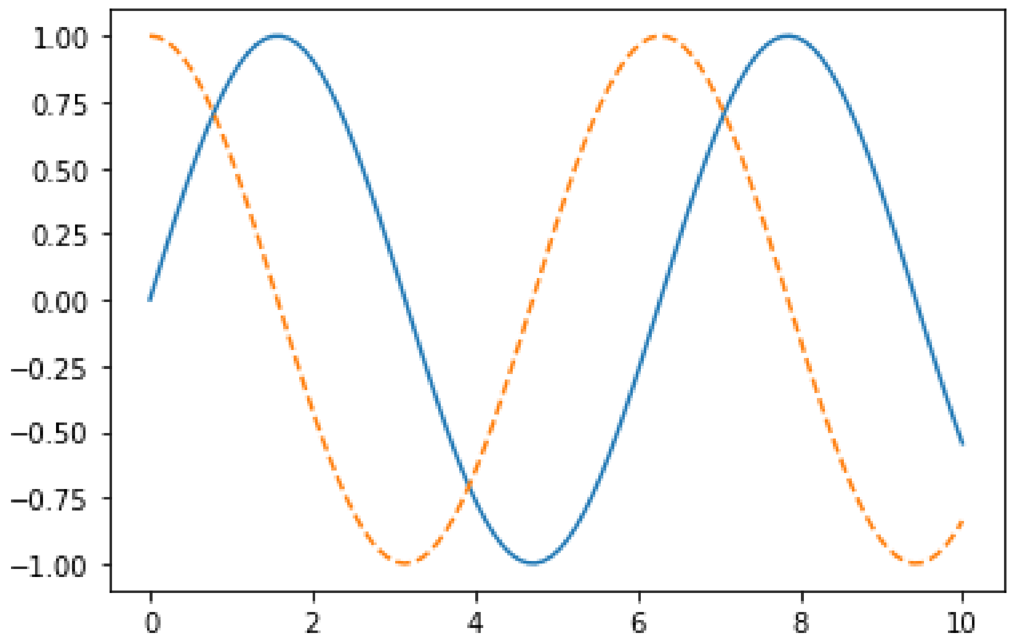
See Ch 4 in Python Data Science Handbook, Jake VanderPlas

- Two Interfaces for the Price of One, pp. 222
- Matplotlib Gotchas, pp. 232

1.3.2 Matlab style interface

[2]:
```
x = np.linspace(0, 10, 100)

plt.plot(x, np.sin(x), '-')
plt.plot(x, np.cos(x), '--');
```

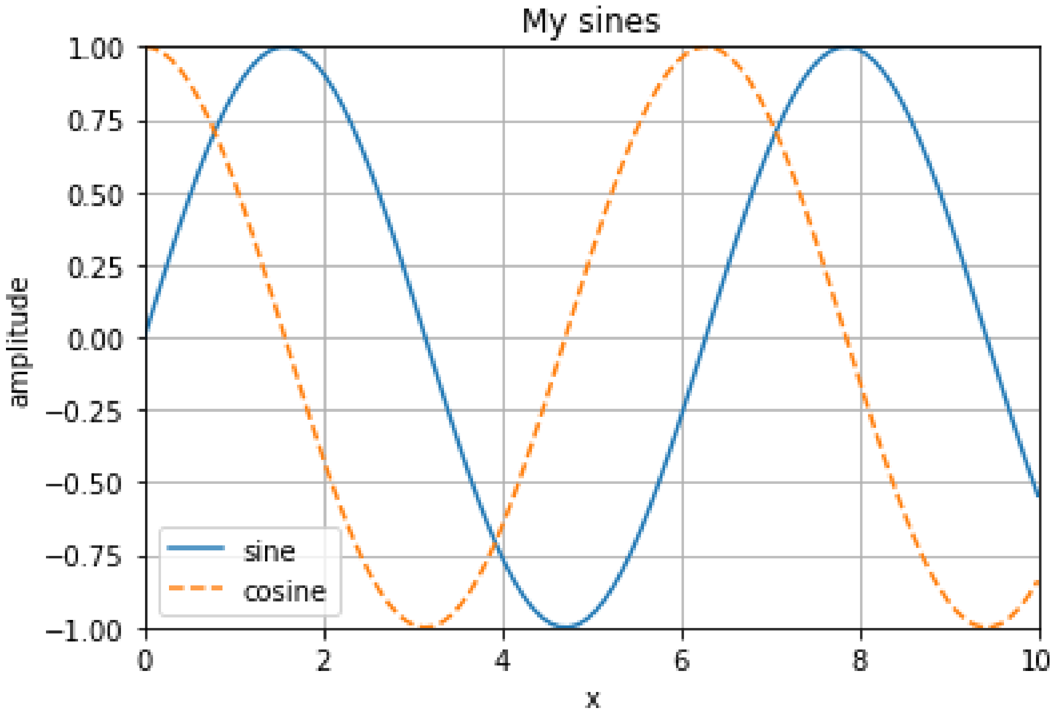


Adding decorations to the plot is done by repeatatly calling functions on the imported `plt` module. All calls within the cell will be applied to the current figure and axes.

[3]:
```
plt.plot(x, np.sin(x), '-', label='sine')
plt.plot(x, np.cos(x), '--', label ='cosine')

plt.xlim([0, 10])
plt.ylim([-1, 1])
plt.xlabel('x')
plt.ylabel('amplitude')
plt.title('My sines')
```

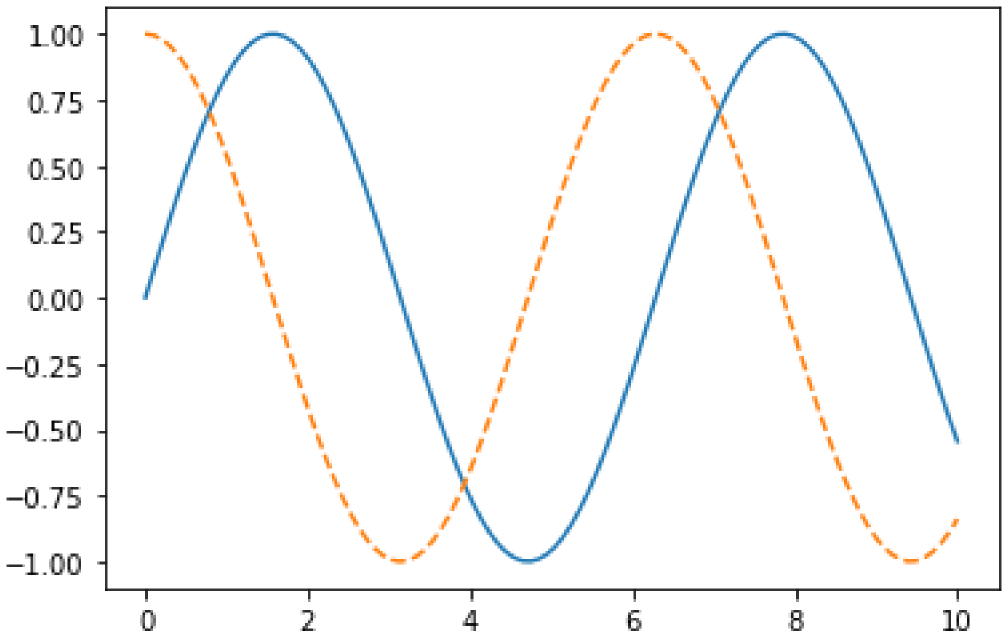
```
plt.grid()
plt.legend();
```



1.3.3 Object oriented interface

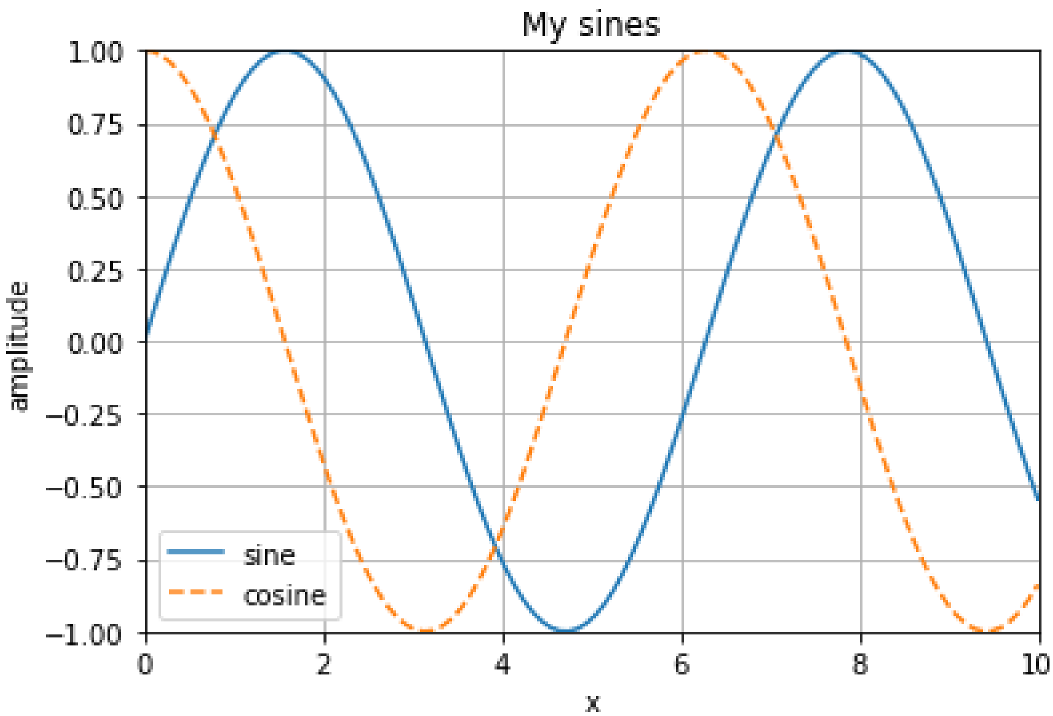
With this interface, you first create a figure and an axes object, then call their methods to change the plot.

[4]:
```
fig = plt.figure()
ax = plt.axes()
ax.plot(x, np.sin(x), '-')
ax.plot(x, np.cos(x), '--');
```



[5]:
```
fig = plt.figure()
ax = plt.axes()
ax.plot(x, np.sin(x), '-', label='sine')
ax.plot(x, np.cos(x), '--', label ='cosine')

ax.set(xlim=[0, 10], ylim=[-1, 1],
       xlabel='x', ylabel='amplitude',
       title='My sines');
ax.grid()
ax.legend();
```



1.3.4 Save to file

With the figure object at hand, we can save to file

[6]:
```
fig.savefig('sines.pdf')
```

[7]:
```
ls *.pdf
```

```
 Volume in drive C has no label.
 Volume Serial Number is 94FF-36B3

 Directory of C:\Users\Ardit\OneDrive - University of Calgary\ENSF
611\ensf611-labs\lab0

2022-09-25  07:29 PM          (73,893) Lab0_ababoci.pdf
2022-09-25  07:26 PM            66,030 lab0-pandas-auto_mpg.pdf
2022-09-25  07:32 PM            13,528 sines.pdf
               3 File(s)        153,451 bytes
               0 Dir(s)  745,490,845,696 bytes free
```

1.4 Plotting with pandas

We use the standard convention for referencing the matplotlib API … We provide the basics in pandas to easily create decent looking plots.

https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html

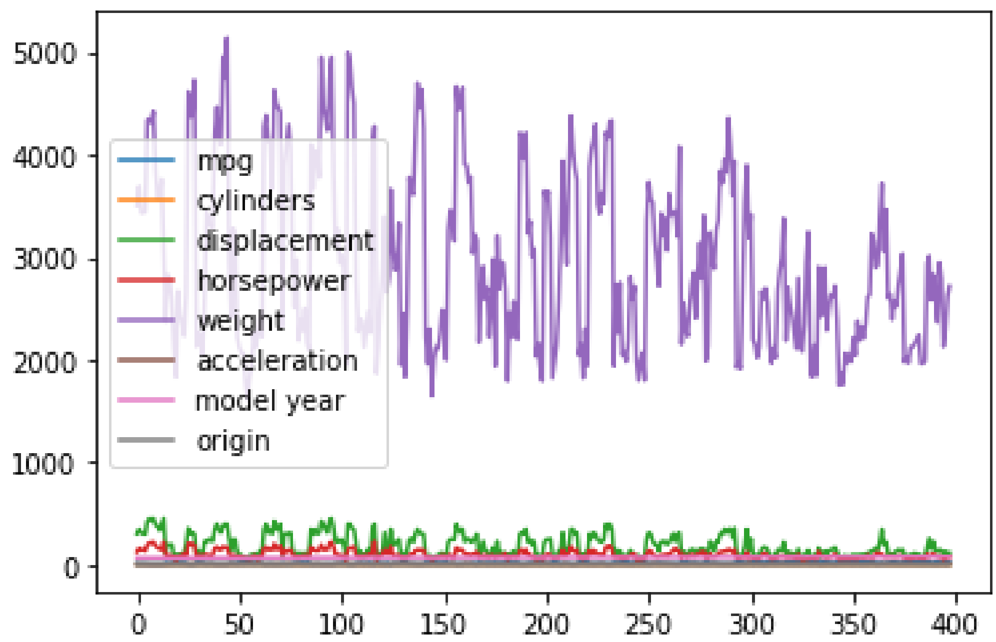
Let's load the auto-mpg dataset

[6]:
```
data = pd.read_csv('auto-mpg.data.csv', na_values='?')
```

Plotting all columns, works, but does not provide a lot of insight.

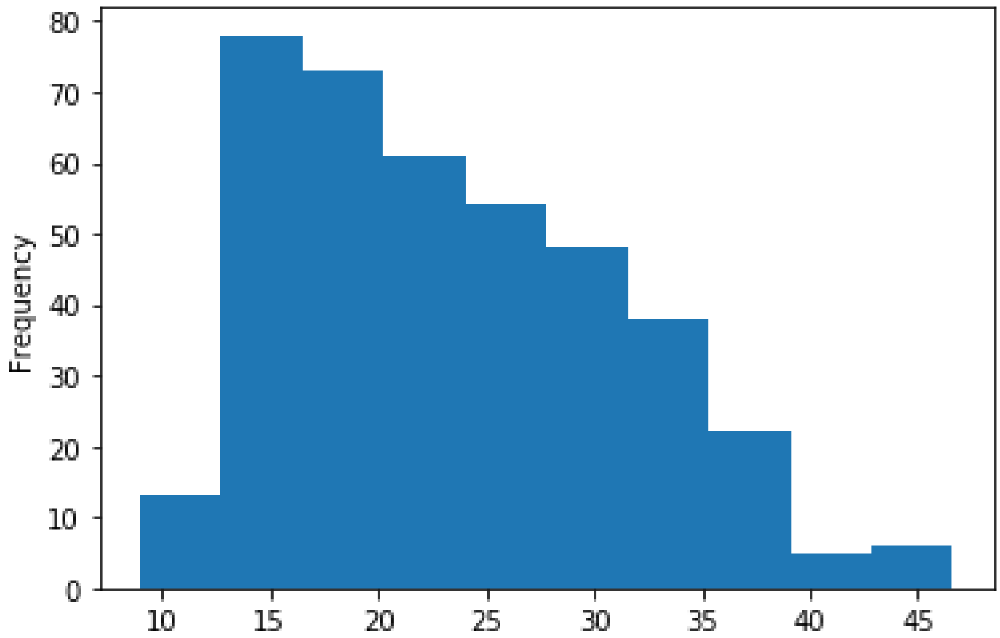
[7]:
```
data.plot()
```

[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1631df5d288>



Let's look at the mpg distribution (a histogram)

[8]:
```
data['mpg'].plot.hist();
```



How many samples do we have in each origin?

[9]:
```
data.origin.value_counts()
```

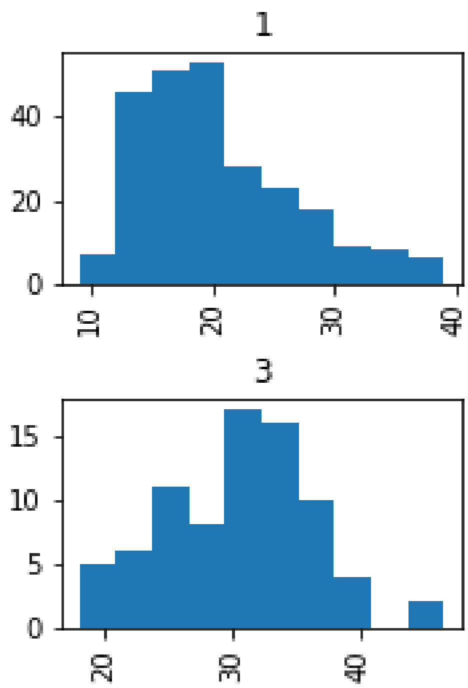
[9]:
```
1    249
3     79
2     70
Name: origin, dtype: int64
```

Notice that we accessed the origin column with dot notation. This can be done whenever the column name is 'nice' enough to be a python variable name.

Do we have similar mpgs in each origin?
Plotting three histograms for each origin side beside directly form the dataframe:

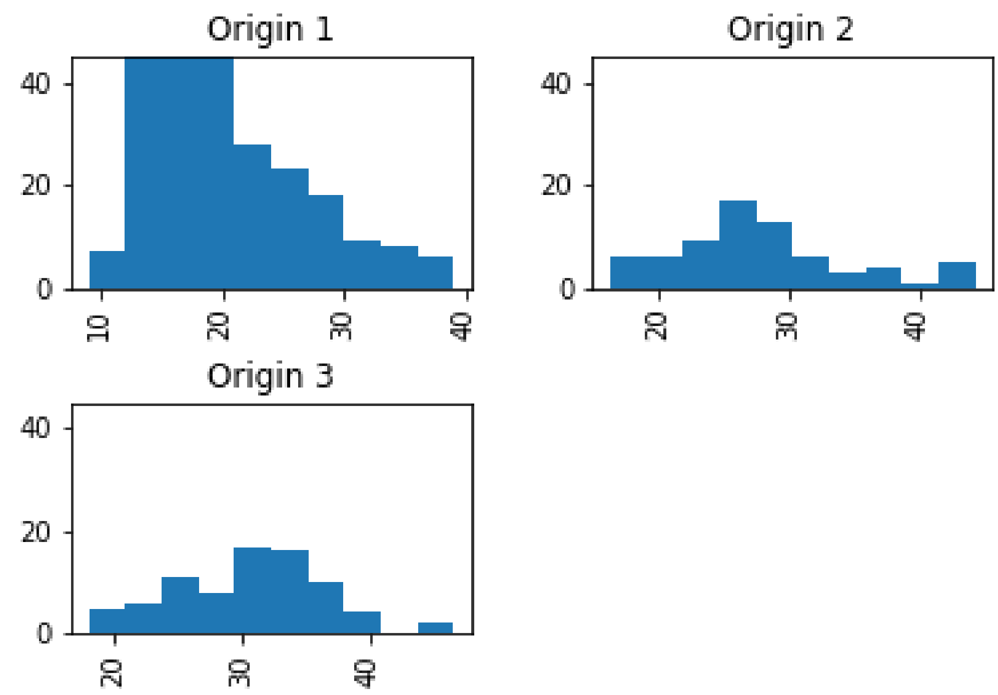
[10]:
```
axs = data.hist(column='mpg', by='origin')
print(axs)
```

```
[[<matplotlib.axes._subplots.AxesSubplot object at 0x000001631F0EAE88>
  <matplotlib.axes._subplots.AxesSubplot object at 0x000001631F13B4C8>]
 [<matplotlib.axes._subplots.AxesSubplot object at 0x000001631F16D708>
  <matplotlib.axes._subplots.AxesSubplot object at 0x000001631F1A2AC8>]]
```



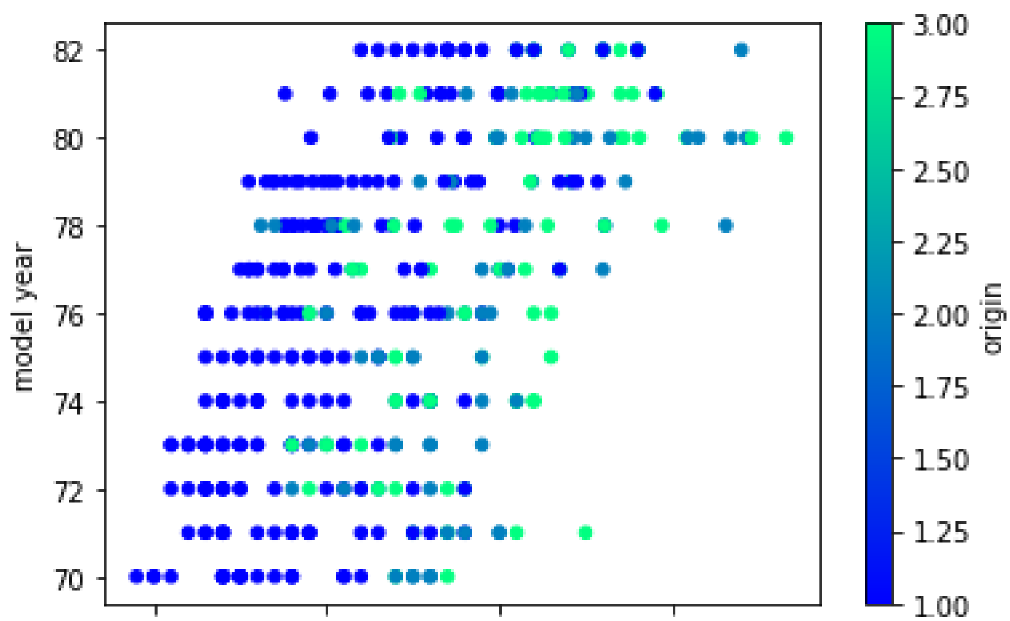
To format this plot, we can work on the axes (array) that is returned by the plot call. We use Matplotlib object oriented interface methods to do this

[11]:
```
axs = data.hist(column='mpg', by='origin')
axs[0][0].set(title='Origin 1', ylim=[0, 45])
axs[0][1].set(title='Origin 2', ylim=[0, 45])
axs[1][0].set(title='Origin 3', ylim=[0, 45]);
```



Is mpg and model year correlated? Maybe it is different for the different origins?
Let's have a look with a scatter plot.

[12]:
```
data.plot.scatter('mpg', 'model year', c='origin', colormap='winter');
```

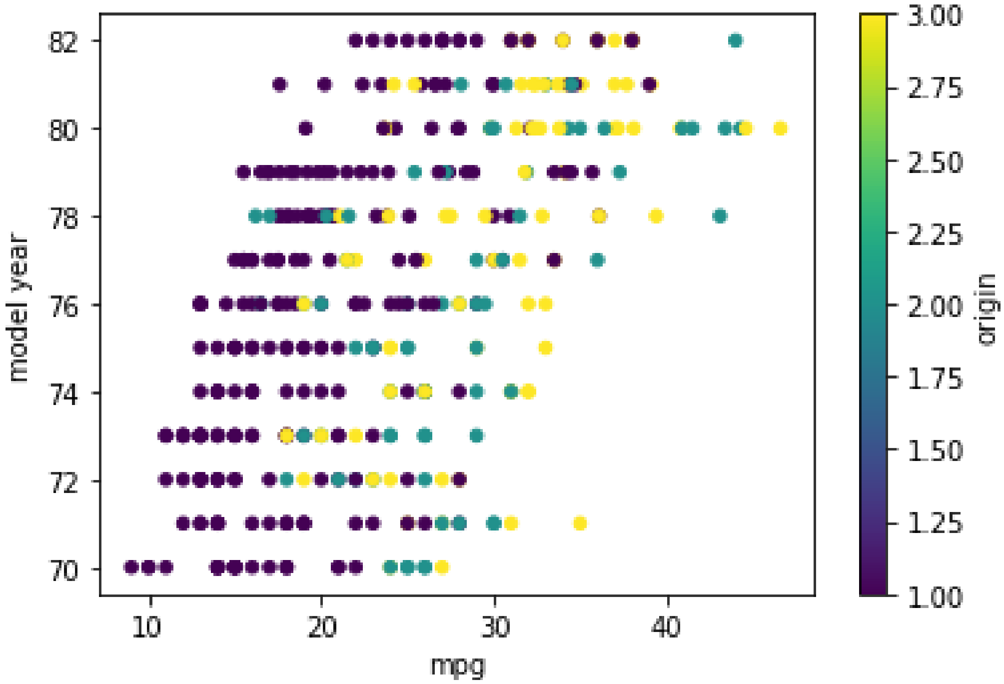


According to:
https://stackoverflow.com/questions/43578976/pandas-missing-x-tick-labels

the missing x-labels are a pandas bug.

Workaraound is to create axes prior to calling plot

[13]:
```
fig, ax = plt.subplots()
data.plot.scatter('mpg', 'model year', c='origin', colormap='viridis', ax=ax);
```

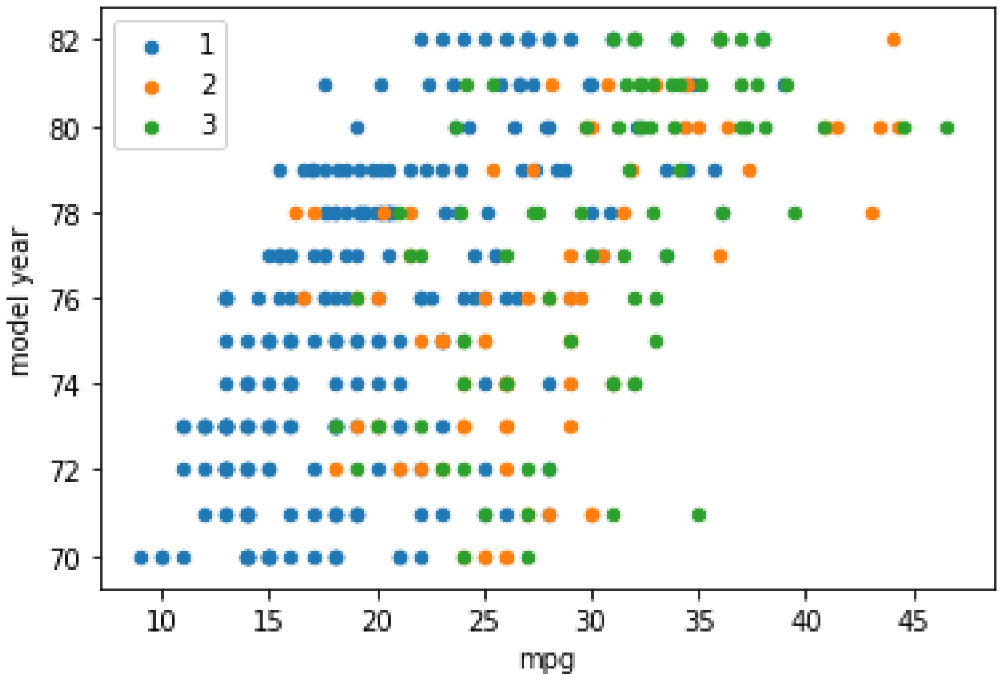


It is a bit annoying that there is a colorbar, we know origin is categorical.

One way to avoid the colorbar is to loop over the categories and assign colors based on the category.

See: https://stackoverflow.com/questions/26139423/plot-different-color-for-different-categorical-levels-using-matplotlib

[14]:
```
colors = {1: 'tab:blue', 2: 'tab:orange', 3: 'tab:green'}
fig, ax = plt.subplots()
for key, group in data.groupby(by='origin'):
    group.plot.scatter('mpg', 'model year', c=colors[key], label=key, ax=ax);
```



1.5 Seaborn

> Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.

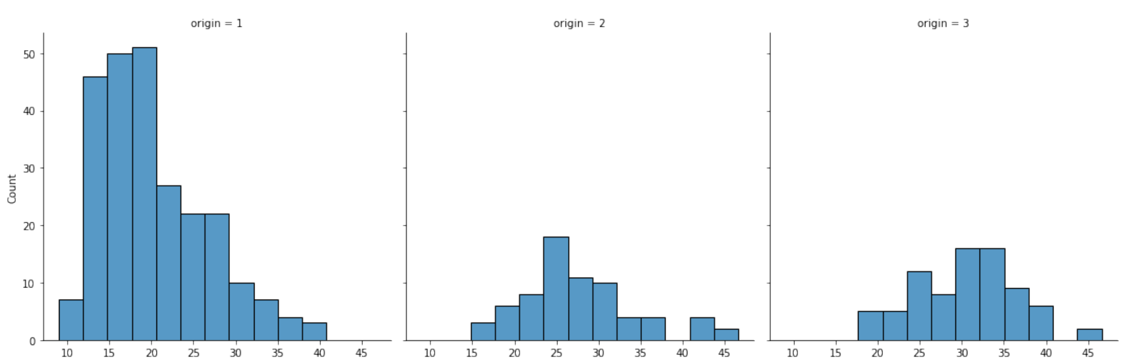
http://seaborn.pydata.org/index.html

Seaborn is usually imported as `sns`

[15]:
```
import seaborn as sns
```

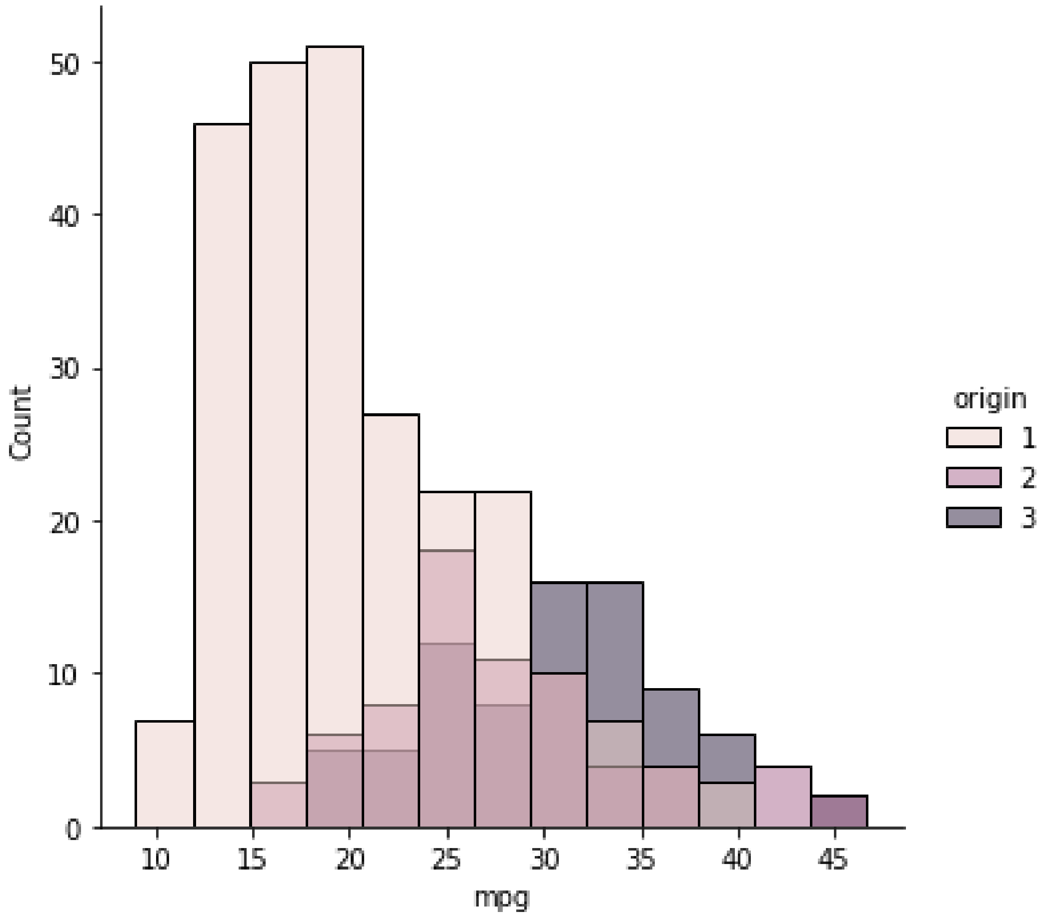
Let's re-create the histograms by origin with seaborn with the figure level `displot()` function.

[16]:
```
# Use origin to split mpg into columns
sns.displot(x='mpg', col='origin', data=data);
```



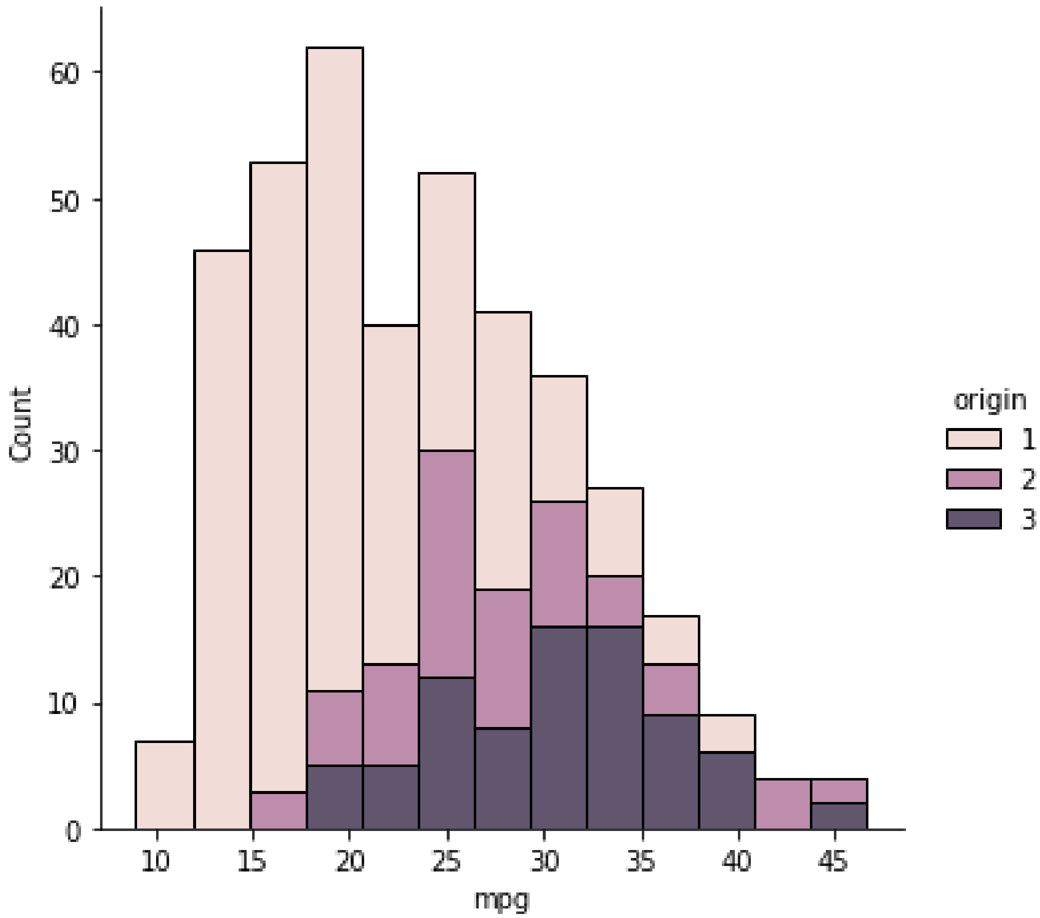
We can display the counts in the same plot, one on top of the other.

[17]:
```
# Use origin to color (hue) in the same plot
sns.displot(x='mpg', hue='origin', data=data);
```



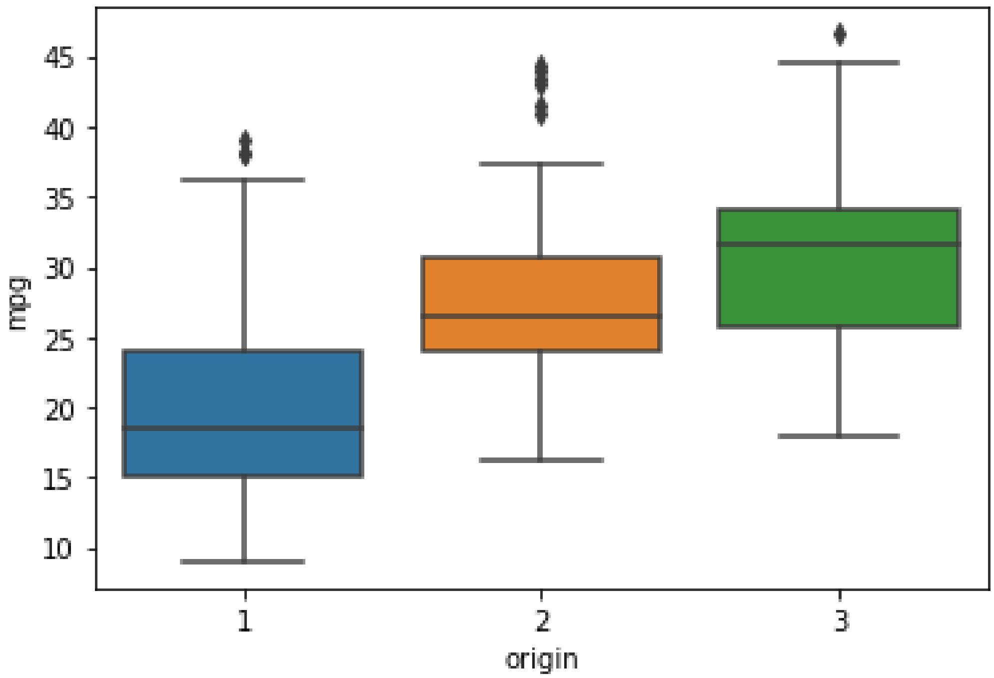
To have an idea of the split between origin, we can stack the counts, adding up to total.

[18]:
```
sns.displot(x='mpg', hue='origin', data=data, multiple='stack');
```



We can look at the differences in origins with a boxplot too

[19]:
```
sns.boxplot(x='origin', y='mpg', data=data);
```

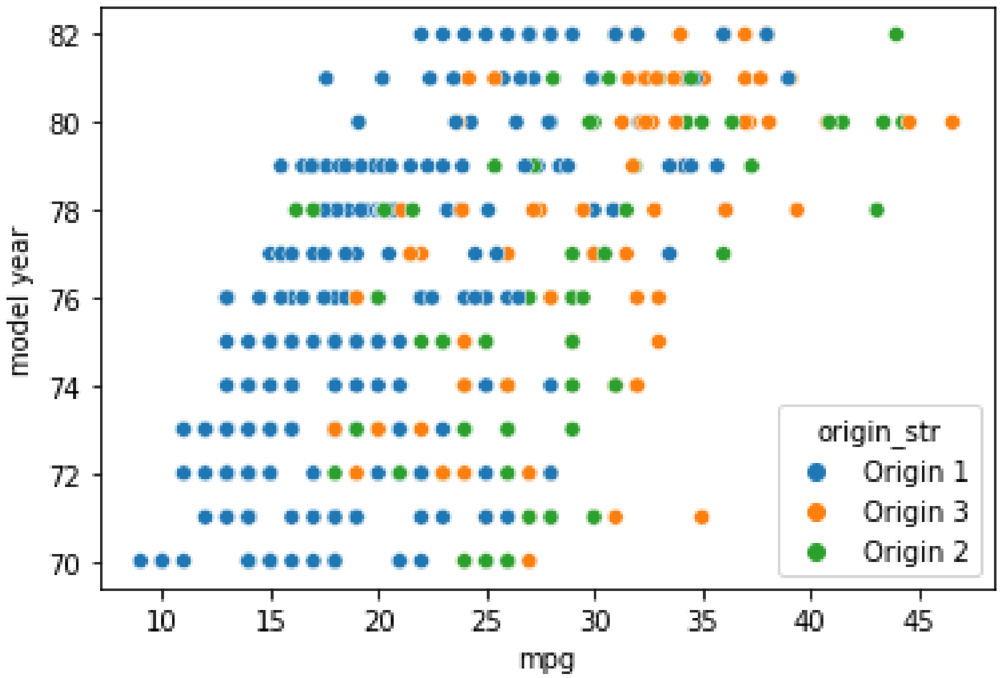


Let's re-create the scatter plot to see if mpg and model year are correlated by origin.

To make the legend show strings we will create a origin string column with strings naming the origins rather than 0 and 1.

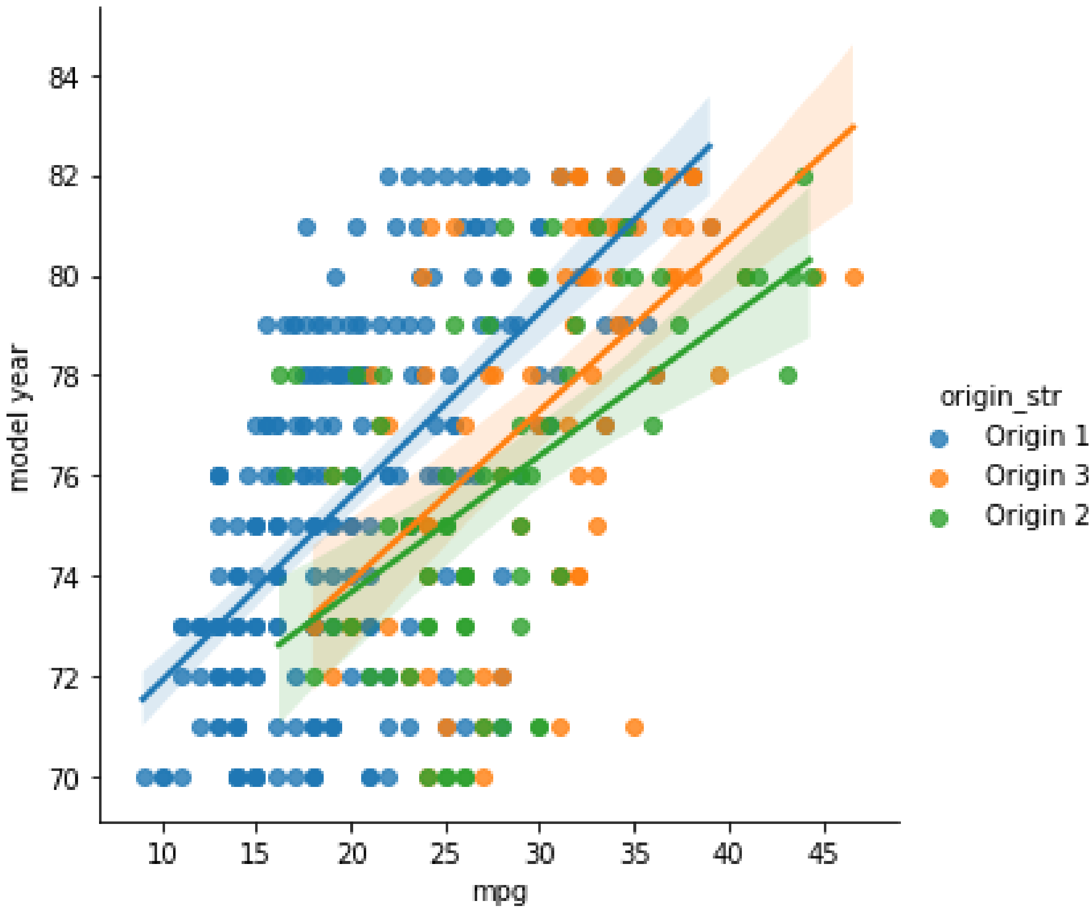
[20]:
```
data['origin_str'] = data['origin'].replace([1, 2, 3], ['Origin 1', 'Origin 2',␣
 ↪'Origin 3'])
```

[21]:
```
ax = sns.scatterplot(x='mpg', y='model year', data=data, hue='origin_str')
```



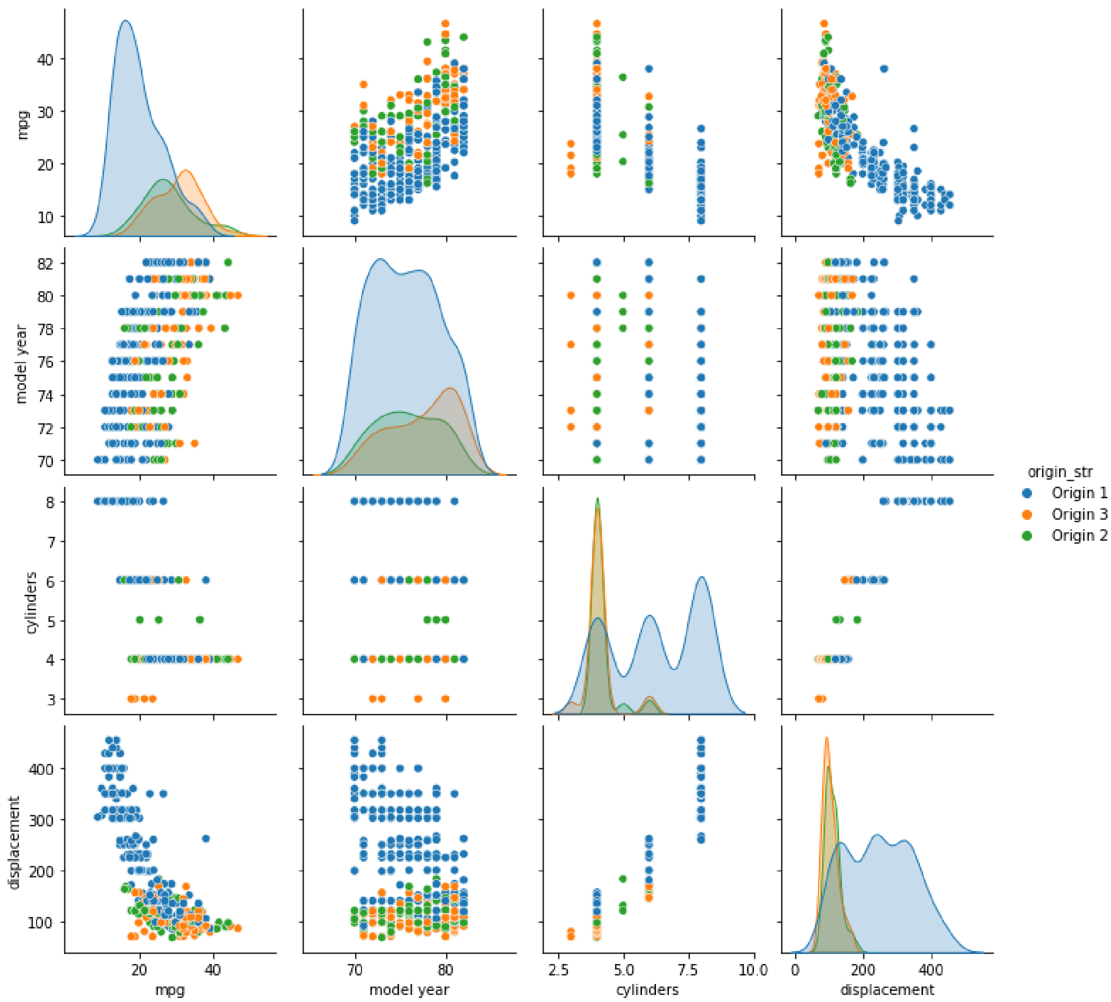
Adding a regression line helps with visualizing the relationship

[22]:
```
ax = sns.lmplot(x='mpg', y='model year', data=data, hue='origin_str')
```



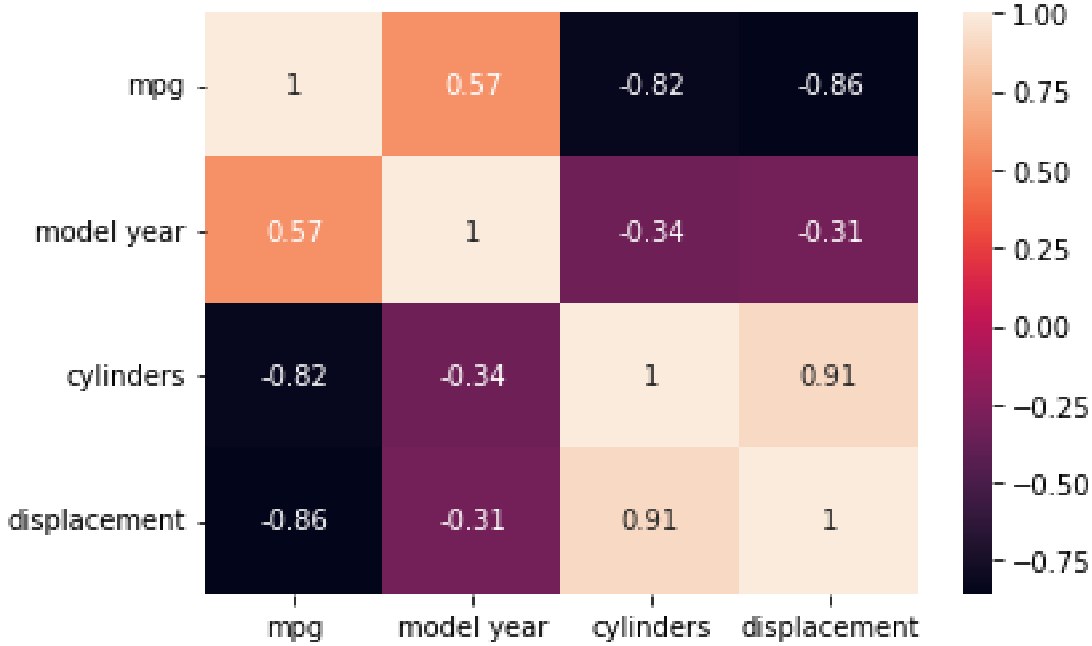
Maybe there are other correlations in the data set. Pairplot is a great way to get an overview

[23]:
```
sns.pairplot(data, vars=['mpg', 'model year', 'cylinders', 'displacement'],␣
↪hue='origin_str');
```



As an alternative, we can visualize the correlation matrix as a heatmap

[24]:
```
g = sns.heatmap(data[['mpg', 'model year', 'cylinders', 'displacement']].
 ↪corr(method='spearman'),
              annot=True)
```



There are nice tutorials on the Seaborn website, be sure to check these out.

```
[ ]:
```