Pandas 4 (Visualization)

We have already seen some plotting methods in Pandas. In particular, we built bar plots using

> Series.plot(kind='bar')

In this lecture, we will consider more plotting options. Python's matplotlib module offers a broad range of plotting options, but we will focus on the pandas methods. Specifically, we will look at:

- Scatter plots,
- Line plots,
- Histograms, and
- Bar plots.

A lot of this is inspired by the visualization tutorial [here (https://github.com/ResearchComputing/Meetup-Fall-2013)](https://github.com/ResearchComputing/Meetup-Fall-2013).

In [1]:
```
from pandas import Series, DataFrame
import pandas as pd
%pylab inline = import pyplot
```

```
Populating the interactive namespace from numpy and matplotlib
```

Scatter plots

This is the easiest, and often the first plot we draw. The goal is to just see how two types of items are related. Let's see an example.

In [2]:
```
cars = pd.read_csv('Pandas_4_data/cars.csv').dropna()
cars[:5]
```

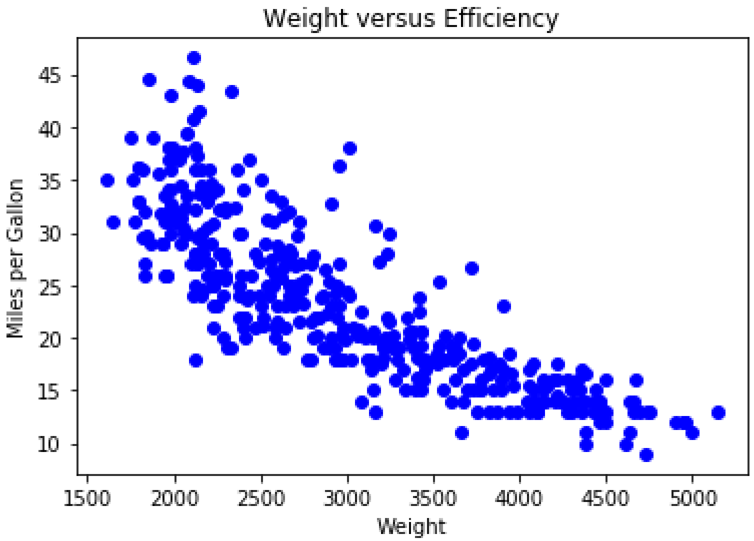
Out[2]:

	type	mpg	cyl	disp	hp	wt	speed	wt.1
0	AMC Ambassador Brougham	13.0	8	360.0	175.0	3821	11.0	73
1	AMC Ambassador DPL	15.0	8	390.0	190.0	3850	8.5	70
2	AMC Ambassador SST	17.0	8	304.0	150.0	3672	11.5	72
3	AMC Concord DL 6	20.2	6	232.0	90.0	3265	18.2	79
4	AMC Concord DL	18.1	6	258.0	120.0	3410	15.1	78

Is MPG related to weight?

x y 点

In [3]:
```
plot(cars['wt'], cars['mpg'], marker='o', color='blue', linestyle='None')
xlabel('Weight')
ylabel('Miles per Gallon')
title('Weight versus Efficiency')
show()
```
in Jupiter notebook, no need to call show()



Each point in the plot represents one particular car type. Clearly, increasing weight hurts MPG.

Let's look a little more closely at the plot() function

```
plot(cars['wt'], cars['mpg'], marker='o', color='blue', linestyle='None')
```

The first two arguments specify the x-axis and the y-axis, but what are the rest?

- marker='o' means we want each car to be plotted as a circle. We could alternately have chosen
  - marker='s' for square marks
  - marker='p' for pentagons 五边形
  - marker='.' for points
  - marker='^' for upward-pointing triangle, and on and on.

- color='blue' is pretty straightforward.

- linestyle='None' says we do not want consecutive cars to be connected by lines. In our case, the ordering of the cars doesn't matter; otherwise we could have chosen:
  - linestyle='-' for plain line
  - linestyle='--' for dashed line
  - linestyle='-.' for dotted-dashed line, and many others.

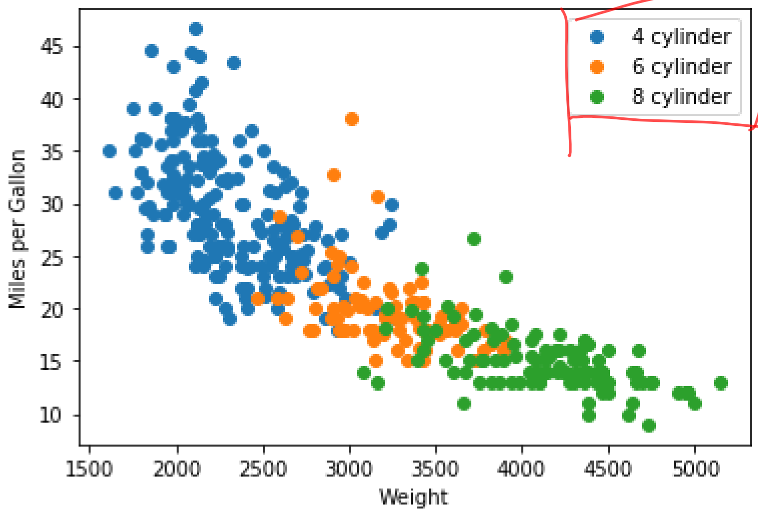
How are mpg, weight, and number of cylinders related?

Let us first group cars into 4-, 6-, and 8-cylinder ones.

In [4]:
```
c4 = cars[cars['cyl'] == 4]
c6 = cars[cars['cyl'] == 6]
c8 = cars[cars['cyl'] == 8]
```

One option would be to plot each individually, but we can also plot all of them together.

In [5]:
```
plot(c4['wt'], c4['mpg'], marker='o', linestyle='None', label='4 cylinder')
plot(c6['wt'], c6['mpg'], marker='o', linestyle='None', label='6 cylinder')
plot(c8['wt'], c8['mpg'], marker='o', linestyle='None', label='8 cylinder')
xlabel('Weight')
ylabel('Miles per Gallon')
legend(numpoints=1, loc='best')
show()
```



- So cars with more cylinders have higher weights and are less efficient (/shrug).
- Notice that we did not need to specify different colors in the calls to plot().
  - Python automatically cycles through a set of colors.

Suppose we really wanted to plot these three types of cars on three separate plots. How do we do it?

In [6]:

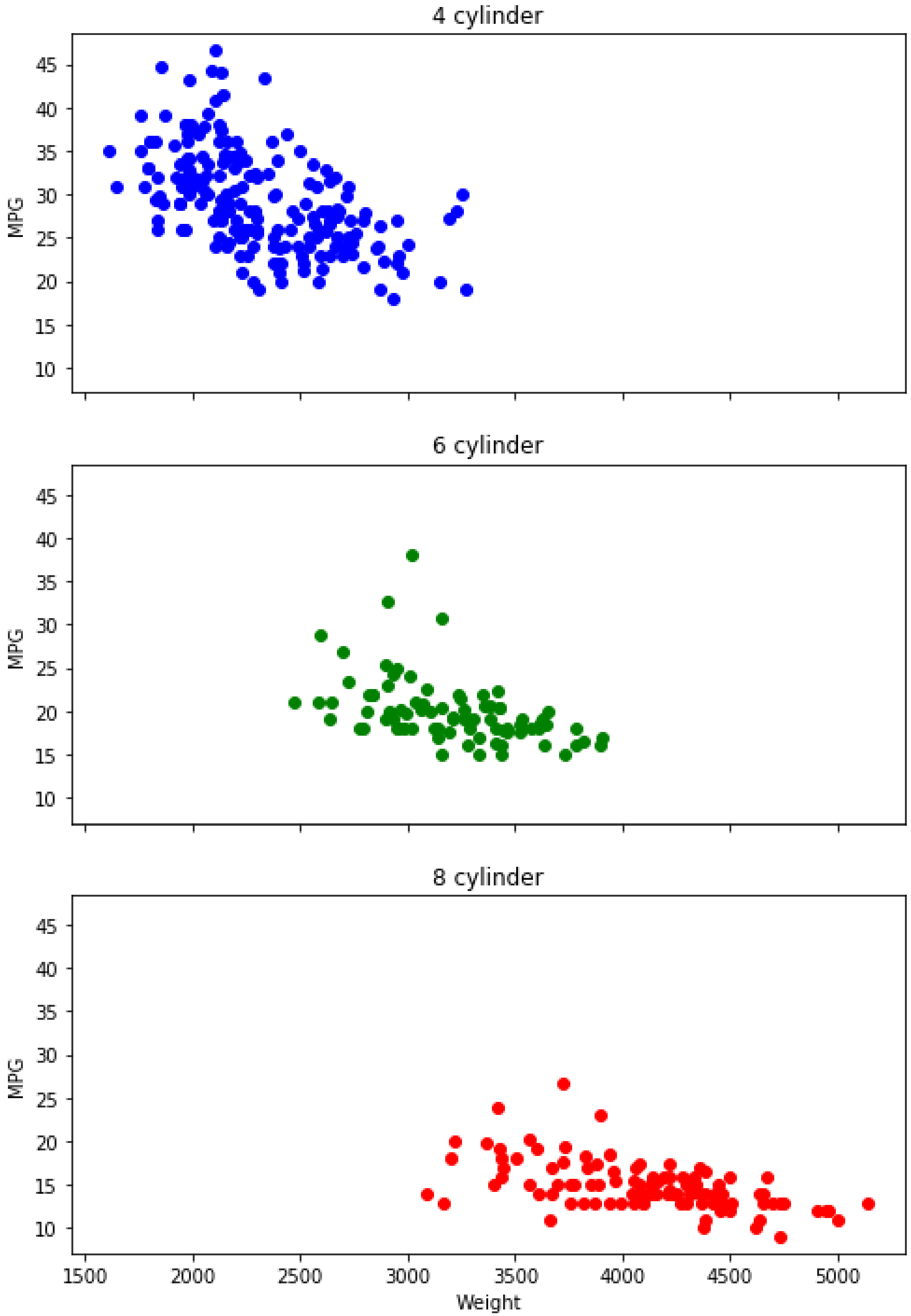
```
# First, create a blank figure and "axis" objects
fig, (ax1, ax2, ax3) = subplots(nrows=3,
                                ncols=1,
                                sharex=True,
                                sharey=True,
                                figsize=(8, 12))

# Each "axis" object corresponds to one subplot
# Fill in the subplots.
ax1.plot(c4['wt'], c4['mpg'], marker='o', color='blue', linestyle='None')
ax1.set_title('4 cylinder')
ax1.set_ylabel('MPG')

ax2.plot(c6['wt'], c6['mpg'], marker='o', color='green', linestyle='None')
ax2.set_title('6 cylinder')
ax2.set_ylabel('MPG')

ax3.plot(c8['wt'], c8['mpg'], marker='o', color='red', linestyle='None')
ax3.set_title('8 cylinder')
ax3.set_ylabel('MPG')
ax3.set_xlabel('Weight')

show()
```


4 cylinder
6 cylinder
8 cylinder
MPG
MPG
MPG
45
40
35
30
25
20
15
10
1500
2000
2500
3000
3500
4000
4500
5000
Weight

Let us understand this in more details.

```
fig, (ax1, ax2, ax3) = subplots(nrows=3,
                                ncols=1,
                                sharex=True,
                                sharey=True,
                                figsize=(8, 12))
```

- This creates an empty figure object called fig.

- Setting nrows=3 and ncols=1 means
  - this figure object will contain 3 subplots (assigned to ax1, ax2, and ax3)
  - laid out in 3 rows and 1 column (i.e., stacked on top of each other).

- sharex=True and sharey=True means
  - all three subplots will have the same range of x-values and y-values
  - so they will be aligned.

- figsize=(8, 12) says that the figure size will be 8 inches wide and 12 inches tall
  - This is something you must play with to see what works best.

Now we have an empty figure with space for three subplots. The subplot objects are ax1, ax2, and ax3, and we will "fill in" these subplots by calling plot() on these subplot objects.

```
ax1.plot(c4['wt'], c4['mpg'], marker='o', color='blue', linestyle='None')
ax1.set_title('4 cylinder')
ax1.set_ylabel('MPG')
```

1. First line is easy: we do our plot.
2. set_title and set_ylabel are obvious.

And finally:

```
Call the show() method
```

Line plots

Another common situation is plotting data over time. If each row in a DataFrame represents time, then there is a natural *ordering* of rows. In contrast, in scatter plots, there is no ordering between the DataFrame rows.

In [7]:

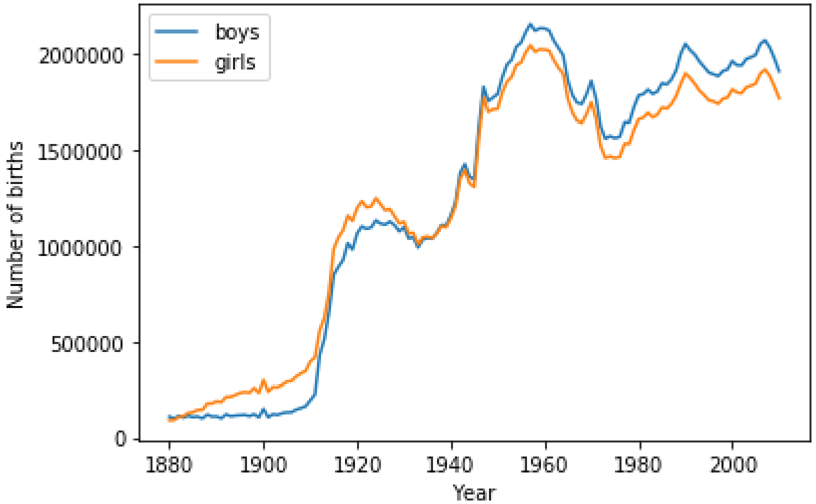
```
# This dataset contains the number of births of boys and girls
# from 1880-2008
births = pd.read_csv('Pandas_4_data/births.csv')
births[:5]
```

Out[7]:

	year	F	M
0	1880	90994.0	110492.0
1	1881	91955.0	100747.0
2	1882	107851.0	113687.0
3	1883	112322.0	104631.0
4	1884	129022.0	114445.0

How do the number of births vary over time?

In [8]:
```
plot(births['year'], births['M'], marker='None', linestyle='-', label='boys')
plot(births['year'], births['F'], marker='None', linestyle='-', label='girls')
xlabel('Year')
ylabel('Number of births')
legend(loc='best')
show()
```



Big jumps around 1920 (after WW I) and 1960 (baby boomers?)

Another line-plot sitation shows up when we do *regression*. Regression is the idea of fitting a line (or a curve) to a scatter-plot of data. We will see regression in more detail later in the course; for now, let's just use it.

Fit a line to the cars data.

In [9]:
```
# Regress the mpg values against the weight values
# We will see this in much more detail in a later lecture
import statsmodels.api as sm
from patsy import dmatrices
y, X = dmatrices('mpg ~ wt', cars, return_type='dataframe')
result = sm.OLS(y, X).fit()

slope = result.params['wt']
intercept = result.params['Intercept']
print('mpg = {:.4f} + {:.4f} * wt'.format(intercept, slope))
```

```
mpg = 46.2165 + -0.0076 * wt
```

We will discuss what slope and intercept mean in a later lecture. For now, just think of it as a prediction:

> If car weight is x, the regression predicts mpg = x * slope + intercept

So let's create a Series of regression predictions.

In [10]:
```
predicted = cars['wt'] * slope + intercept
regression_predictions = Series(predicted.values,
                                index=cars['wt'])
regression_predictions[:5]
```

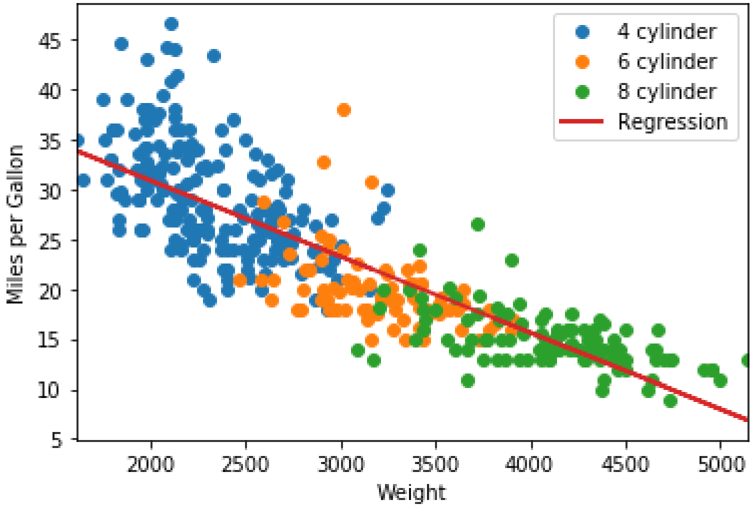
Out[10]:
```
wt
3821    16.996029
3850    16.774256
3672    18.135483
3265    21.247951
3410    20.139087
dtype: float64
```

Now, we can plot the predictions on the same plot as the actual cars.

In [11]:
```
# Repeating the earlier plot commands
plot(c4['wt'], c4['mpg'], marker='o', linestyle='None', label='4 cylinder')
plot(c6['wt'], c6['mpg'], marker='o', linestyle='None', label='6 cylinder')
plot(c8['wt'], c8['mpg'], marker='o', linestyle='None', label='8 cylinder')

# New plot command for the regression predictions
regression_predictions.plot(label='Regression', linewidth=2)

xlabel('Weight')
ylabel('Miles per Gallon')
legend(numpoints=1, loc='best')
show()
```



This example also demonstrates another way of plotting in pandas. Instead of saying:

```
plot(x, y)
```

we can say:

```
Series.plot()
```

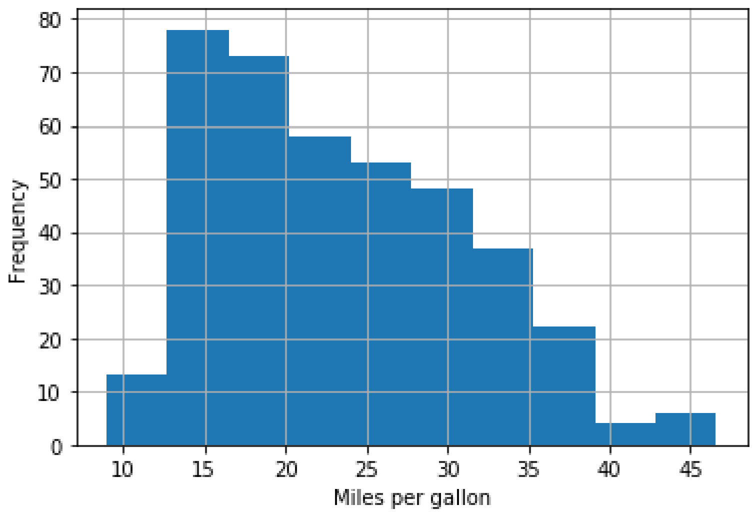
which is the same as:

```
plot(Series.index.values, Series.values)
```

Histograms

In [12]:
```
cars['mpg'].hist()
xlabel('Miles per gallon')
ylabel('Frequency')
```

Out[12]: Text(0, 0.5, 'Frequency')



> cars['mpg'].hist()

Let's go step-by-step through the histogram formation.

Step 1: Form the bins

- We take the cars['mpg'] Series, and then
- bin the MPGs into bins (by default, 10 bins) of equal-size.

Step 2: Assign cars to bins

Once we have the bins, we go down the list of MPGs in the cars['mpg'], and

- for each MPG, find the bin it falls into,
- and increase the count of that bin by 1.

Thus, the total count over all the bins is just the number of cars.

Step 3: Plot the bins

Finally, it plots the bins on the x-axis, and the count in each bin on the y-axis.

Compare histograms of mpg and speed

Is the MPG histogram "peaked" differently than the speed histogram? We can try to plot both histograms side-by-side and see if there are differences.

How will we do this?

- how many subplots?
- share the x-axis or the y-axis?

In [14]:

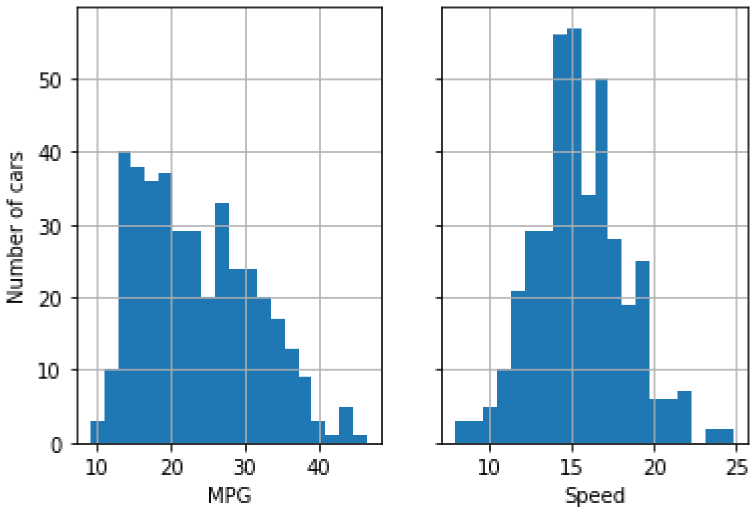
```
fig, (ax1, ax2) = subplots(nrows=1,
                           ncols=2,
                           sharey=True,
                           figsize=(6, 4))

# Plot the MPG histogram on the first subplot
cars['mpg'].hist(ax=ax1, bins=20)
ax1.set_xlabel('MPG')
ax1.set_ylabel('Number of cars')

# Plot the speed histogram on the second subplot
cars['speed'].hist(ax=ax2, bins=20)
ax2.set_xlabel('Speed')
```

Out[14]:

```
Text(0.5, 0, 'Speed')
```



Overall, most cars have MPG on the lower side (15-20 MPG), but speed is mostly around 15 mph. Perhaps for some cars, we get low MPG but not enough bang in terms of speed.

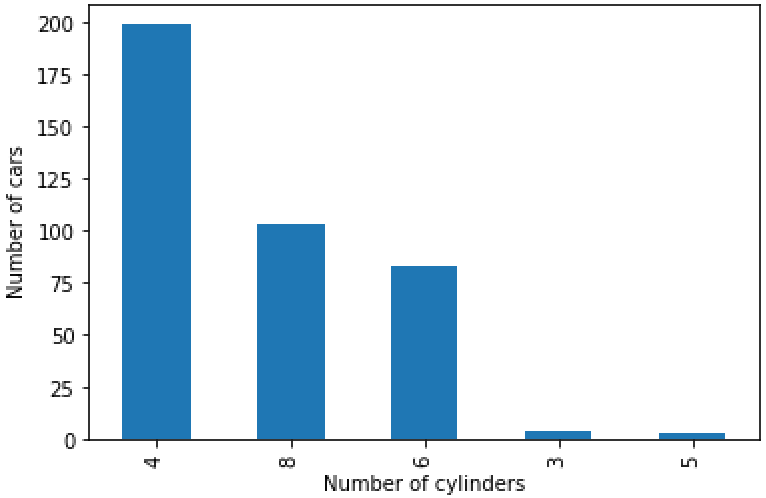
Bar plots

We've already met the bar plot in earlier lectures.

Example: Plot the number of cars with different number of cylinders.

In [15]:
```
cylinder_counts = cars['cyl'].value_counts()
cylinder_counts.plot(kind='bar')
xlabel('Number of cylinders')
ylabel('Number of cars')
```

Out[15]:
```
Text(0, 0.5, 'Number of cars')
```



Let us look at one interesting dataset: the top 1000 baby names in each year from 1880 onwards. We will explore several questions on this.

In [18]:
```
names = pd.read_csv('Pandas_4_data/baby-names-top1000.csv')
names[:5]
```

Out[18]:

	year	name	percent	sex
0	1880	John	0.081541	boy
1	1880	William	0.080511	boy
2	1880	James	0.050057	boy
3	1880	Charles	0.045167	boy
4	1880	George	0.043292	boy

In [19]:
```
names[-5:]  # last five
```

Out[19]:

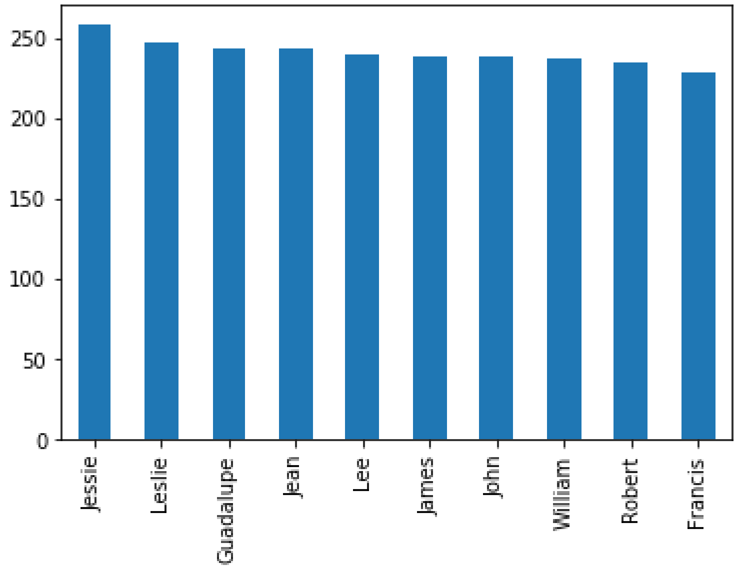
	year	name	percent	sex
257995	2008	Carleigh	0.000128	girl
257996	2008	Iyana	0.000128	girl
257997	2008	Kenley	0.000127	girl
257998	2008	Sloane	0.000127	girl
257999	2008	Elianna	0.000127	girl

Names from 1880 until 2008, so 129 years.

Which baby names are in the top-1000 list most often?

In [20]:
```
names['name'].value_counts()[:10].plot(kind='bar')
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1a8aaa23488>



Wait, what? There are only 129 years, so how can Jessie show up 250 times?

男的女的都有叫这个名字的

Let's find the most popular names for boys only.

In [21]:
```
common_boy_names = names[names['sex'] == 'boy']['name'].value_counts()
common_boy_names[:15]
```

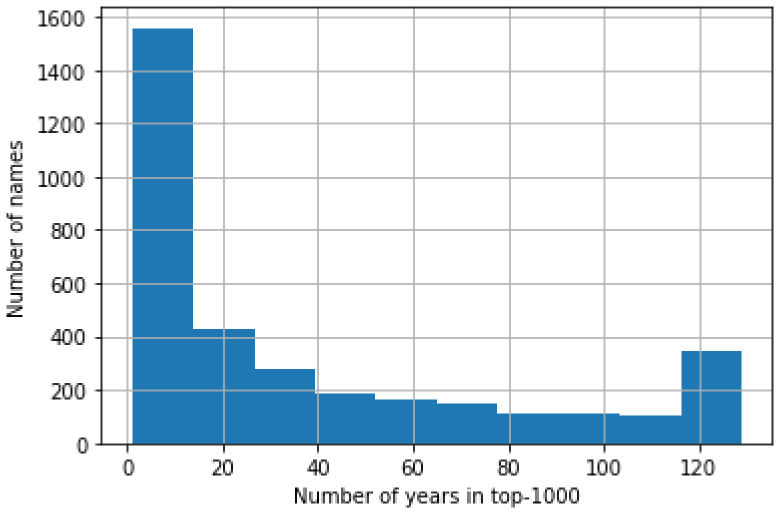
Out[21]:
```
Alfred      129
Lewis       129
John        129
Jack        129
Manuel      129
Gordon      129
Patrick     129
Felix       129
Wesley      129
August      129
Pedro       129
Avery       129
Emanuel     129
Alex        129
Arthur      129
Name: name, dtype: int64
```

Some names are evergreen...

How many names are super-popular, medium-popular, less-popular?

In [22]:
```
common_boy_names.hist()
xlabel('Number of years in top-1000')
ylabel('Number of names')
```

Out[22]:
```
Text(0, 0.5, 'Number of names')
```



There are two peaks: (a) almost unique names, and (b) evergreen names. However, there are very few names that *just* missed out on being evergreen. Let's see what these are.

In [23]:
```
common_boy_names[common_boy_names == 100]  # Common for 100 years, but not 129 years.
```

Out[23]:
```
Emery     100
Arturo    100
Sammy     100
Walker    100
Name: name, dtype: int64
```

Let's see how their popularity changed over time. But for that, we need the popularity timeline for these names.

How do we get a timeline for each name?

In [24]:
```
boy_names = names[names['sex'] == 'boy']
boy_names[:3]
```

Out[24]:

	year	name	percent	sex
0	1880	John	0.081541	boy
1	1880	William	0.080511	boy
2	1880	James	0.050057	boy

In [25]:

```
year_name_pivot = pd.pivot_table(boy_names,
                                 index='year',
                                 columns='name',
                                 values='percent')

year_name_pivot.iloc[:5, :5]
```

Out[25]:

name	Aaden	Aarav	Aaron	Ab	Abb
year					
1880	NaN	NaN	0.000861	0.000042	NaN
1881	NaN	NaN	0.000868	0.000037	NaN
1882	NaN	NaN	0.000697	0.000041	NaN
1883	NaN	NaN	0.000933	NaN	NaN
1884	NaN	NaN	0.000790	NaN	0.000041

In [26]:

```
# Let's fill in the missing values with 0
year_name_pivot = year_name_pivot.fillna(0)
```

In [27]:
```
year_name_pivot[['Sammy', 'Arturo', 'Emery', 'Walker']][:5]
```

Out[27]:

name	Sammy	Arturo	Emery	Walker
year				
1880	0.0	0.0	0.000439	0.000245
1881	0.0	0.0	0.000489	0.000231
1882	0.0	0.0	0.000434	0.000229
1883	0.0	0.0	0.000382	0.000178
1884	0.0	0.0	0.000415	0.000155

Now we can plot these timelines. That means four subplots. We could again do:

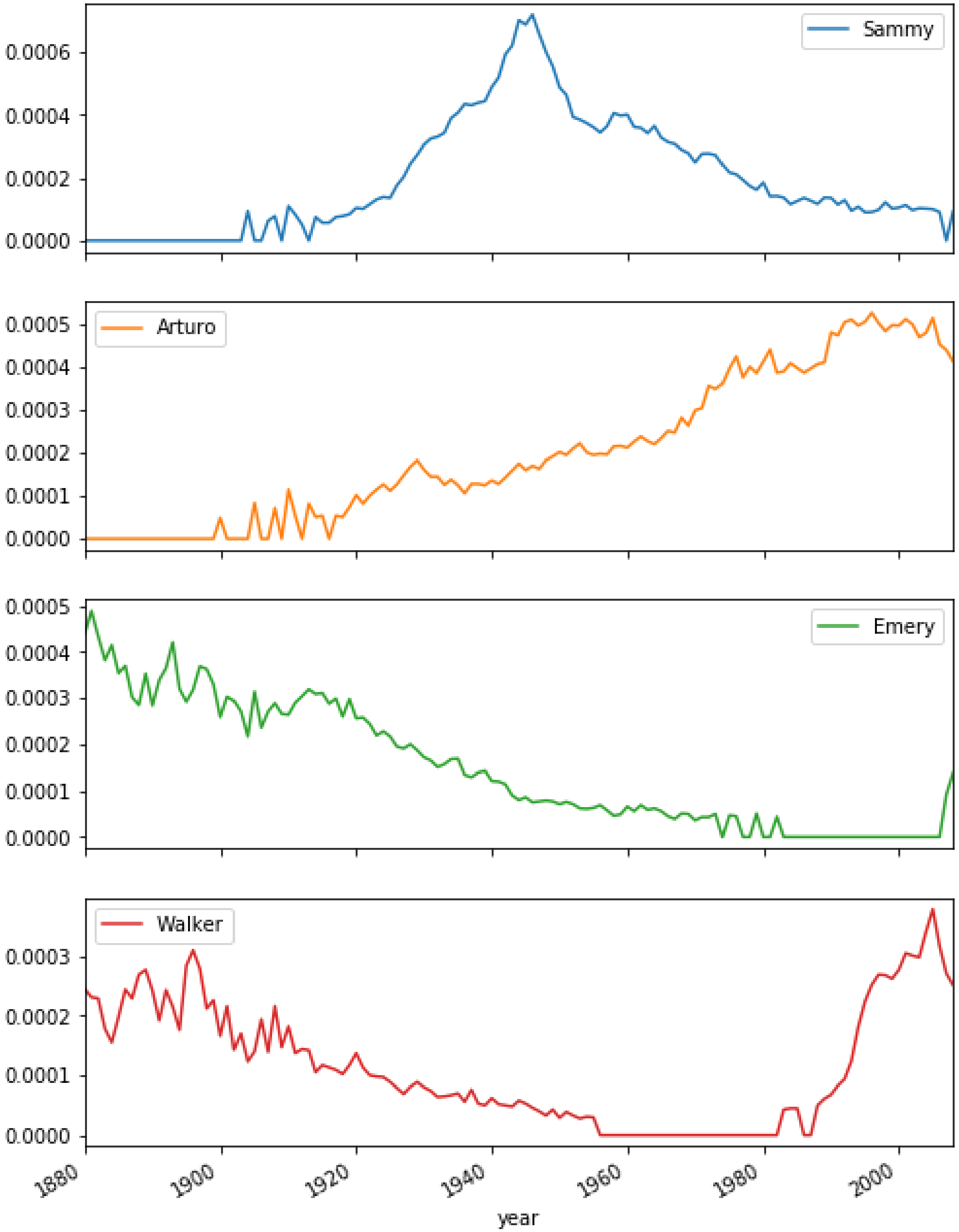
```
fig, (ax1, ax2, ax3, ax4) = subplots(nrows=4,
                                     ncols=1,
                                     sharex=True,
                                     sharey=True,
                                     figsize=(8, 12))

year_name_pivot['Sammy'].plot(ax=ax1)
year_name_pivot['Arturo'].plot(ax=ax2)
year_name_pivot['Emery'].plot(ax=ax3)
year_name_pivot['Walker'].plot(ax=ax4)
```

Instead, we use the fact that all of these are in a DataFrame, and pandas knows how to plot DataFrames nicely!

In [28]:
```
year_name_pivot[['Sammy', 'Arturo', 'Emery', 'Walker']].plot(subplots=True, figsize=(8, 12))
```

Out[28]:
```
array([<matplotlib.axes._subplots.AxesSubplot object at 0x000001A8AA8F8508>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x000001A8AAF9FAC8>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x000001A8AAD3F5C8>,
       <matplotlib.axes._subplots.AxesSubplot object at 0x000001A8AB0047C8>],
      dtype=object)
```



Find the names that were the most popular in at least one year.

In [29]:

```
name_year = year_name_pivot.T
top_names = name_year.idxmax()
top_names[:5]
```

Out[29]:

```
year
1880    John
1881    John
1882    John
1883    John
1884    John
dtype: object
```

In [30]:

```
top_names.value_counts()
```

Out[30]:

```
John       44
Michael    44
Robert     17
James      13
Jacob      10
David       1
dtype: int64
```

In [31]:
```
most_popular_names = top_names.value_counts().index.values
most_popular_names
```

Out[31]:
```
array(['John', 'Michael', 'Robert', 'James', 'Jacob', 'David'],
      dtype=object)
```

Let's plot the popularities of these 6 names from 1880 to present.

In [32]:
```
all_years = year_name_pivot.index.values

# Let's pick a manageable sample of years
sample_years = all_years[::10]  # one in 10 years.
sample_years
```

Out[32]:
```
array([1880, 1890, 1900, 1910, 1920, 1930, 1940, 1950, 1960, 1970, 1980,
       1990, 2000], dtype=int64)
```

In [33]:

```
# Create a DataFrame with just this information
df = year_name_pivot[most_popular_names].loc[sample_years]
df
```

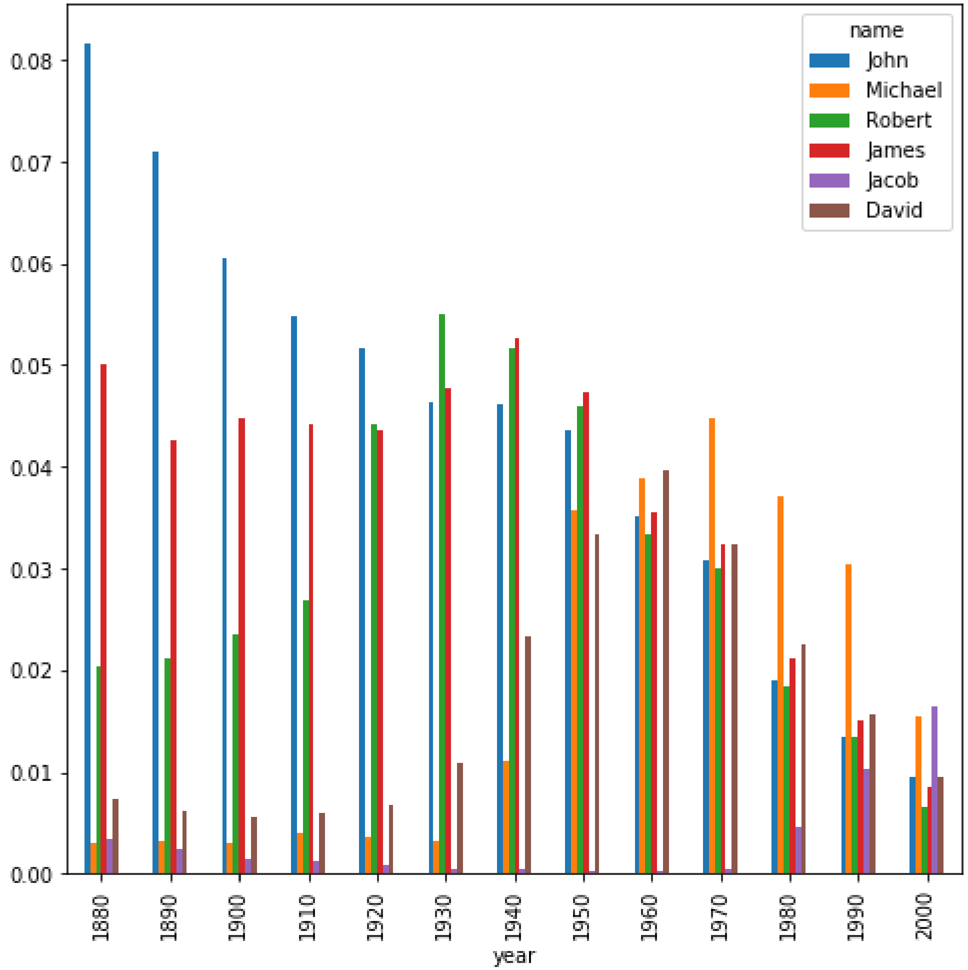
Out[33]:

name	John	Michael	Robert	James	Jacob	David
year						
1880	0.081541	0.002990	0.020404	0.050057	0.003412	0.007339
1890	0.071034	0.003300	0.021236	0.042580	0.002423	0.006107
1900	0.060619	0.003081	0.023608	0.044677	0.001436	0.005515
1910	0.054914	0.004049	0.026896	0.044092	0.001310	0.006034
1920	0.051710	0.003626	0.044224	0.043550	0.000952	0.006757
1930	0.046417	0.003136	0.055021	0.047781	0.000550	0.010864
1940	0.046173	0.011153	0.051586	0.052662	0.000434	0.023344
1950	0.043655	0.035810	0.045930	0.047336	0.000256	0.033382
1960	0.035145	0.038868	0.033415	0.035483	0.000227	0.039669
1970	0.030718	0.044784	0.030031	0.032425	0.000477	0.032416
1980	0.019018	0.037039	0.018475	0.021205	0.004593	0.022600
1990	0.013518	0.030358	0.013421	0.015042	0.010228	0.015684
2000	0.009617	0.015346	0.006577	0.008613	0.016514	0.009454

In [34]:

```
# Plot this as a bar plot
df.plot(kind='bar', figsize=(8, 8))
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1a8a78be688>



When we do

`Series.plot(kind='bar')`

it plots a normal bar plot. Instead, when we do

`DataFrame.plot(kind='bar')`

it plots each column (i.e., each Series) in the bar plot.

Doing plots with style

Sometimes you want funky. Just because.

In [35]:

```
# Redoing births over time, xkcd style
xkcd() # <-- Woo!

plot(births['year'], births['M'], marker='None', linestyle='-', label='boys')
plot(births['year'], births['F'], marker='None', linestyle='-', label='girls')
title('Births per year')
legend(loc='best')
show()
```