Lecture 9: numpy, scipy and matplotlib
Some examples adapted from A. Tewari
Reminder!

If you don’t already have a Flux/Fladoop username, request one promptly!

Make sure you can ssh to Fladoop: [http://arc-ts.umich.edu/hadoop-user-guide/](http://arc-ts.umich.edu/hadoop-user-guide/)

**UNIX/Linux/MacOS:** you should be all set!

**Windows:**

install PuTTY:


and you may also want cygwin [https://www.cygwin.com/](https://www.cygwin.com/)

You also probably want to set up VPN to access Flux from off-campus:

[http://its.umich.edu/enterprise/wifi-networks/vpn](http://its.umich.edu/enterprise/wifi-networks/vpn)
Numerical computing in Python: **numpy**

One of a few increasingly-popular, free competitors to **MATLAB**

Numpy quickstart guide: [https://docs.scipy.org/doc/numpy-dev/user/quickstart.html](https://docs.scipy.org/doc/numpy-dev/user/quickstart.html)

For **MATLAB** fans:
[https://docs.scipy.org/doc/numpy-dev/user/numpy-for-matlab-users.html](https://docs.scipy.org/doc/numpy-dev/user/numpy-for-matlab-users.html)

Closely related package **scipy** is for optimization
See [https://docs.scipy.org/doc/](https://docs.scipy.org/doc/)
Installing packages

So far, we have only used built-in modules

But there are many modules/packages that do not come preinstalled

Ways to install packages:

At the conda prompt or in terminal: conda install numpy
https://conda.io/docs/user-guide/tasks/manage-pkgs.html

Using pip (recommended): pip install numpy

Using UNIX/Linux package manager (not recommended)

From source (not recommended)
Installing packages with `pip`

The above command installs the package `beautifulsoup4`. We will use that later in the semester. To install `numpy`, type the same command, but use `numpy` in place of `beautifulsoup4`.

If you have both Python 2 and Python 3 installed, make sure you specify which one you want to install in!
numpy data types

Five basic numerical data types:

- boolean (bool)
- integer (int)
- unsigned integer (uint)
- floating point (float)
- complex (complex)

Many more complicated data types are available, e.g., each of the numerical types can vary in how many bits it uses.

https://docs.scipy.org/doc/numpy/user/basics.types.html

import ... as ... lets us import a package and give it a shorter name.

Note that this is not the same as a Python int.
Numpy data types

32-bit and 64-bit representations are distinct!

Data type followed by underscore uses the default number of bits. This default varies by system.

As a rule, it’s best never to check for equality of floats. Instead, check whether they are within some error tolerance of one another.
numpy.array: numpy’s version of Python array (i.e., list)

Can be created from a Python list...

```
1 np.array([1, 2, 3], dtype='uint')
array([1, 2, 3], dtype=uint64)
```

...by “shaping” an array...

```
1 np.zeros((2, 3))
array([[0., 0., 0.],
       [0., 0., 0.]])
```

...by “ranges”...

```
1 np.arange(2, 3, 0.1, dtype='float')
array([2. , 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 2.8, 2.9])
```

...or reading directly from a file

see https://docs.scipy.org/doc/numpy/user/basics.creation.html
**numpy** allows arrays of arbitrary dimension (tensors)

1-dimensional arrays:

```python
1 x = np.arange(12)  # x=[1,2,...,12]
2 x
array([ 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11])
```

2-dimensional arrays (matrices):

```python
1 x.shape = (3,4)  # now x is a 3-by-4 matrix
2 x  # observe that shape fills the new matrix by row.
array([[ 0, 1, 2, 3],
       [ 4, 5, 6, 7],
       [ 8, 9, 10, 11]])
```

3-dimensional arrays (“3-tensor”):

```python
1 x.shape = (2,3,2)
2 x  # now x is a 2-by-3-by-2 "cube" of numbers
array([[[ 0, 1],
       [ 2, 3],
       [ 4, 5]],
       [[[ 6, 7],
          [ 8, 9],
          [10, 11]]]])
```
More on `numpy.arange` creation

`np.arange(x)`: array version of Python’s `range(x)`, like \([0, 1, 2, \ldots, x-1]\)

`np.arange(x, y)`: array version of `range(x, y)`, like \([x, x+1, \ldots, y-1]\)

`np.arange(x, y, z)`: array of elements \([x, y)\) in `z`-size increments.

Related useful functions, that give better/clearer control of start/endpoints and allow for multidimensional arrays:

https://docs.scipy.org/doc/numpy/reference/generated/numpy.linspace.html
https://docs.scipy.org/doc/numpy/reference/generated/numpy.ogrid.html
More on `numpy.arange` creation

`np.arange(x)`: array version of Python’s `range(x)`, like `[0, 1, 2, ..., x-1]`

`np.arange(x, y)`: array version of `range(x, y)`, like `[x, x+1, ..., y-1]`

`np.arange(x, y, z)`: array of elements `[x, y)` in `z`-size increments.

```
np.arange(10)
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

```
np.arange(5, 10)
array([5, 6, 7, 8, 9])
```

```
np.arange(0, 1, 0.1)
array([ 0.,  0.1,  0.2,  0.3,  0.4,  0.5,  0.6,  0.7,  0.8,  0.9])
```
numpy array indexing is highly expressive

Not very relevant to us right now...

...but this will come up again in a few weeks when we cover TensorFlow
More array indexing

Numpy allows MATLAB/R-like indexing by Booleans

```python
1 x = np.arange(10)
2 x[x>7]
array([8, 9])

1 x[(x>7) or (x<2)]
```

```
ValueError: The truth value of an array with more than one element is ambiguous. Use a.any() or a.all()
```

Believe it or not, this error is by design! The designers of `numpy` were concerned about ambiguities in Boolean vector operations, so they split the two operations into two separate methods, `x.any()` and `x.all()`
More array indexing

From the documentation:
When the index consists of as many integer arrays as the array being indexed has dimensions, the indexing is straight forward, but different from slicing. Advanced indexes always are broadcast and iterated as one.

https://docs.scipy.org/doc/numpy/reference/arrays.indexing.html#integer-array-indexing

If we specify fewer than the number of indices, numpy assumes we mean: in the remaining indices.

Warning: if you’re used to MATLAB or R, this behavior will seem weird to you.
**Boolean operations:** `np.any()`, `np.all()`

```
x = np.arange(10)
x.all(x>7)
False

np.any(x>7)
True

np.any([x>7,x<2])
True

np.any([x>7,x<2], axis=1)
array([ True,  True], dtype=bool)

np.any([x>7,x<2], axis=0)
array([ True,  True, False, False, False, False, False, False, False,  True,  True], dtype=bool)
```

Just like the `any` and `all` functions in Python proper.

The `axis` argument picks which axis along which to perform the Boolean operation. If left unspecified, it treats the array as a single vector.

Setting `axis` to be the first (i.e., 0-th) axis yields the entrywise behavior we wanted.
Boolean operations: `np.logical_and()`

`numpy` also has built-in Boolean vector operations, which are simpler/clearer at the cost of the expressiveness of `np.any()`, `np.all()`.

```python
1  x = np.arange(10)
2  x[np.logical_and(x>3,x<7)]

array([4, 5, 6])
```

```python
1  np.logical_or(x<3,x>7)

array([ True,  True,  True, False, False, False, False, False, False,  True,  True], dtype=bool)
```

```python
1  x[np.logical_xor(x>3,x<7)]

array([0, 1, 2, 3, 7, 8, 9])
```

```python
1  x[np.logical_not(x>3)]

array([0, 1, 2, 3])
```

This is an example of a `numpy` “universal function” (ufunc), which we'll discuss more in a few slides.
Random numbers in `numpy`

`np.random` contains methods for generating random numbers

```python
# Example usage

1  np.random.random((2,3))
array([[ 0.61420793,  0.46363275,  0.22880783],
       [ 0.24268979,  0.13462754,  0.6026283 ]])

1  np.random.normal(0,1,20)
array([ 1.31323138,  0.76807767,  1.92180038, -0.34121468,  0.72572401,
       1.0273551, -0.78435871,  0.42732636,  1.05947171,  0.23042635,
       0.3951938,  0.3595342,  0.14710555,  0.42279814,  0.84381846,
       1.06495165, -1.51074354, -0.16419861,  2.89275956, -1.18501386])

1  np.random.uniform(0,1,(2,4))
array([[ 0.08399452,  0.03934797,  0.3603464 ,  0.66361677],
       [ 0.33499095,  0.29427732,  0.14963153,  0.87892145]])
```

Lots more distributions:

https://docs.scipy.org/doc/numpy/reference/routines.random.html#distributions
np.random.choice(): random samples from data

np.random.choice(x, [size, replace, p])

Generates a sample of size elements from the array x, drawn with (replace=True) or without (replace=False) replacement, with element probabilities given by vector p.

```python
x = np.arange(1,11)
for i in range(5):
    print np.random.choice(x,5,False,x/float(sum(x)))
```

```bash
[ 1 5 10 7 6]
[8 5 9 2 6]
[ 9 6 3 8 10]
[ 7 9 10 5 6]
[8 5 6 9 1]
```
shuffle() vs permutation()

np.random.shuffle(x)
randomly permutes entries of \( x \) in place
so \( x \) itself is changed by this operation!

np.random.permutation(x)
returns a random permutation of \( x \)
and \( x \) remains unchanged.
Statistics in `numpy`

`numpy` implements all the standard statistics functions you’ve come to expect.

```python
1  x = np.random.normal(0,1,100)
2  np.mean(x), np.median(x), np.std(x)
```

```
(-0.062724875643358866, -0.05261873350441526, 1.0556291754262765)
```

```python
1  np.min(x), np.max(x), np.ptp(x)  # ptp gets max-min
```

```
(-3.1029568746428113, 1.9628924810049164, 5.0658493556477282)
```

```python
1  np.std(x), np.var(x)
```

```
(1.0556291754262765, 1.1143529560111607)
```
Statistics in **numpy** (cont’d)

Numpy deals with NaNs more gracefully than MATLAB/R:

```python
1 x[5] = np.nan
2 np.mean(x)
```

```
nan
```

```python
1 np.nanmin(x), np.nanmax(x), np.nanstd(x), np.nanvar(x)
```

```
(-3.1029568746428113,
 1.9628924810049164,
 1.0439479158102707,
 1.0898272509246081)
```

For more statistical functions, see:

Probability and statistics in \texttt{scipy}

(Among) all the distributions you could possibly ever want:

https://docs.scipy.org/doc/scipy/reference/stats.html#continuous-distributions
https://docs.scipy.org/doc/scipy/reference/stats.html#multivariate-distributions
https://docs.scipy.org/doc/scipy/reference/stats.html#discrete-distributions

More statistical functions (moments, kurtosis, statistical tests):

https://docs.scipy.org/doc/scipy/reference/stats.html#statistical-functions

\begin{verbatim}
import scipy.stats
x = np.random.normal(0, 1, 20)
scipy.stats.kstest(x, 'norm')
\end{verbatim}

KstestResult(statistic=0.23182037538316391, pvalue=0.19897055187485568)

Scipy is a distinct Python package, part of the \texttt{numpy} ecosystem.
Matrix-vector operations in `numpy`

Trying to multiply two arrays, and you get broadcast behavior, *not* a matrix-vector product.

Broadcast multiplication still requires that dimensions agree and all that.
Matrix-vector operations in **numpy**

Create a numpy matrix from a numpy array. Can also create matrices from strings with MATLAB-like syntax. See documentation:

```
A = np.matrix(np.reshape(np.arange(1,13),(3,4)))
```

```
matrix([[ 1,  2,  3,  4],
         [ 5,  6,  7,  8],
         [ 9, 10, 11, 12]])
```

```
x = np.ones((4,1))
A*x
```

```
matrix([[ 10.],
         [ 26.],
         [ 42.]])
```

```
y = np.ones((1,3))
y*A
```

```
matrix([[ 15.,  18.,  21.,  24.]])
```

Now matrix-vector and vector-matrix multiplication work as we want.

numpy/scipy universal functions (ufuncs)

From the documentation:
A universal function (or ufunc for short) is a function that operates on ndarrays in an element-by-element fashion, supporting array broadcasting, type casting, and several other standard features. That is, a ufunc is a “vectorized” wrapper for a function that takes a fixed number of scalar inputs and produces a fixed number of scalar outputs.
https://docs.scipy.org/doc/numpy/reference/ufuncs.html

So ufuncs are vectorized operations, just like in R and MATLAB
ufuncs in action

List comprehensions are great, but they’re not well-suited to numerical computing.

```python
x = range(10)
x**2
```

```
TypeError: unsupported operand type(s) for ** or pow(): 'list' and 'int'
```

```python
[x**2 for x in np.arange(10)]
```

[0, 1, 4, 9, 16, 25, 36, 49, 64, 81]

Unlike Python lists, numpy arrays support vectorized operations.
Sorting with `numpy/scipy`

ASCII rears its head—capital letters are “earlier” than all lower-case by default.

Sorting is along the “last” axis by default. Note contrast with `np.any()`. To treat the array as a single vector, `axis` must be set to `None`.

Original array is unchanged by use of `np.sort()`, like Python’s built-in `sorted()`.
A cautionary note

`numpy/scipy` have several similarly-named functions with different behaviors!

Example: `np.amax`, `np.ndarray.max`, `np.maximum`

The best way to avoid these confusions is to
1) Read the documentation carefully
2) Test your code!
Plotting with `matplotlib`

`matplotlib` is a plotting library for use in Python.

Similar to R’s `ggplot2` and MATLAB’s plotting functions.

For MATLAB fans, `matplotlib.pyplot` implements MATLAB-like plotting:

[http://matplotlib.org/users/pyplot_tutorial.html](http://matplotlib.org/users/pyplot_tutorial.html)

Sample plots with code:

[http://matplotlib.org/tutorials/introductory/sample_plots.html](http://matplotlib.org/tutorials/introductory/sample_plots.html)
Basic plotting: `matplotlib.pyplot.plot`

`matplotlib.pyplot.plot(x, y)` plots $y$ as a function of $x$.

`matplotlib.pyplot(t)` sets x-axis to `np.arange(len(t))`. 

```python
import matplotlib as mp
import matplotlib.pyplot as plt
%matplotlib inline
x = np.arange(0, 5, 0.1, dtype='float')
_ = plt.plot(x**2)
```
Basic plotting: `matplotlib.pyplot.plot`

Jupyter “magic” command to make images appear in-line.

Reminder: Python `'_'_` is a placeholder, similar to MATLAB `'~'`. Tells Python to treat this like variable assignment, but don’t store result anywhere.
Customizing plots

```python
1  x = np.arange(0, 5, 0.25, dtype='float')
2  _ = plt.plot(x**2, ':ro')
```

Second argument to `pyplot.plot` specifies line type, line color, and marker type. Specify broader array of colors, line weights, markers, etc., using long-hand arguments.
Customizing plots

Long form of the command on the previous slide. Same plot!

A full list of the long-form arguments available to `pyplot.plot` are available in the table titled “Here are the available Line2D properties.”: [http://matplotlib.org/users/pyplot_tutorial.html](http://matplotlib.org/users/pyplot_tutorial.html)
Multiple lines in a single plot

```python
1 t = np.arange(0., 5., 0.2)
2 # plt.plot(xvals, y1vals, traits1, y2vals, traits2, ... )
3 _ = plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
```

**Note:** more complicated specification of individual lines can be achieved by adding them to the plot one at a time.
Multiple lines in a single plot: long form

```python
1 t = np.arange(0., 5., 0.2)
2 plt.grid()
3 plt.plot(t, t, 'r--')
4 plt.plot(t, t**2, 'bs')
5 plt.plot(t, t**3, 'g^')
6 _ = plt.show()
```

`plt.grid` turns grid lines on/off.

**Note:** same plot as previous slide, but specifying one line at a time so we could, if we wanted, use more complicated line attributes.
Titles and axis labels

```
import numpy as np
import matplotlib.pyplot as plt

t = np.arange(0., 5., 0.2)
plt.grid()
plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
plt.title('Profits as a function of goats')
plt.xlabel('Goats')
plt.ylabel('Profits')
plt.show()
```

Specifying titles and axis labels couldn’t be more straight-forward.
Titles and axis labels

```python
import numpy as np
import matplotlib.pyplot as plt

t = np.arange(0., 5., 0.2)
plt.title('Title text', fontsize=18)
plt.xlabel('x axis', fontsize=14)
plt.ylabel('y axis', fontsize=14)
_ = plt.plot(t, t, 'r--', t, t**2, 'bs', t, t**3, 'g^')
plt.show()
```
Legends

```python
plt.xlabel("\$n\$", fontsize=16)  # set the axes labels
plt.ylabel("\$f(n)\$", fontsize=16)
plt.title("Different growth behaviors")  # set the plot title
plt.plot(t, t, '-ob', label='linear, \$f(n)=n\$')
plt.plot(t, t**2, ':^r', label='quadratic, \$f(n)=n^2\$')
plt.plot(t, t**3, '-sg', label='cubic, \$f(n)=n^3\$')
_ = plt.legend(loc='best')  # places legend at best location
```

Can use LaTeX in labels, titles, etc.

`pyplot.legend` generates legend based on label arguments passed to `pyplot.plot`. `loc='best'` tells `pyplot` to place the legend where it thinks is best.
Annotating figures

```
1 t = np.arange(0.0, 5.0, 0.01)
2 s = np.cos(2*np.pi*t)  # np.pi is 3.14159...
3 plt.plot(t, s, lw=2)  # plot the cosine.
4 # Annotate the figure with an arrow and text.
5 _ = plt.annotate('local max', xy=(2, 1), xytext=(3, 1.5),
6     fontsize=14,
7     arrowprops=dict(facecolor='black', shrink=0.02))
```

Specify text coordinates and coordinates of the arrowhead using the coordinates of the plot itself. This is pleasantly different from many other plotting packages, which require specifying coordinates in pixels!
Plotting histograms: `pyplot.hist()`

```python
mu, sigma = 100, 15
x = np.random.normal(mu, sigma, 10000)
# hist( data, nbins, ...)
(n, bins, patches) = plt.hist(x, 50, normed=1, facecolor='teal')
```
Plotting histograms: `pyplot.hist()`

```python
(n, bins, patches) = plt.hist(x, 50, normed=0, facecolor='teal')
```

Bin counts. Note that if `normed=1`, then these will be proportions between 0 and 1 instead of counts.
Bar plots

```
bar(x, height, *, align='center', **kwargs)
```

```
t = np.arange(10)
s = np.random.normal(1, 1, 10)
_ = plt.bar(t, s, align='center')
```

Full set of available arguments to `bar(...)` can be found at
http://matplotlib.org/api/_as_gen/matplotlib.pyplot.bar.html#matplotlib.pyplot.bar

Horizontal analogue given by `barh`
http://matplotlib.org/api/_as_gen/matplotlib.pyplot.barh.html#matplotlib.pyplot.barh
Tick labels

```python
import string

t = np.arange(10)
s = np.random.normal(1,1,10)
mylabels = list(string.ascii_lowercase[0:len(t)])
_= plt.bar(t, s, tick_label=mylabels, align='center')
```

Can specify what the x-axis tick labels should be by using the `tick_label` argument to plot functions.
Box & whisker plots

```python
K = 12; n = 25
draws = np.zeros((n, K))
means = np.zeros((n, 1))
for k in range(K):
    mu = np.sin(2 * np.pi * k / K)
    draws[:, k] = np.random.normal(mu, 1, n)
_ = plt.boxplot(draws, labels=list('JFMAMJJASOND'))
```

`plt.boxplot(x, ...) : x is the data. Many more optional arguments are available, most to do with how to compute medians, confidence intervals, whiskers, etc. See http://matplotlib.org/api/_as_gen/matplotlib.pyplot.boxplot.html#matplotlib.pyplot.boxplot`
Pie Charts

Don’t use pie charts!

A table is nearly always better than a dumb pie chart; the only worse design than a pie chart is several of them, for then the viewer is asked to compare quantities located in spatial disarray both within and between charts [...] Given their low [information] density and failure to order numbers along a visual dimension, pie charts should never be used.

Edward Tufte  
*The Visual Display of Quantitative Information*

But if you must…

```python
pyplot.pie(x, ...)
```

[link](http://matplotlib.org/api/_as_gen/matplotlib.pyplot.pie.html#matplotlib.pyplot.pie)
Heatmaps and tiling

```python
n=20
x = np.arange(1,n+1)
M = x*np.reshape(x,(n,1))
_ = plt.imshow(M)
```

`imshow` is matplotlib analogue of MATLAB’s `imagesc`, R’s `image`. Lots of optional extra arguments for changing scale, color scheme, etc. See documentation: https://matplotlib.org/api/pyplot_api.html#matplotlib.pyplot.imshow
These three lines create an object, `mvn1`, representing a multivariate normal distribution.
Drawing contours

```
mu = np.array([0.5, 0.5])
Sigma = np.array([[0.1, 0.05], [0.05, 0.1]])
mvnl = scipy.stats.multivariate_normal(mu, Sigma)
x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y
_ = plt.contour(x, y, mvnl.pdf(pos))
```
Drawing contours

Here, \texttt{mgrid} generates a grid of \((x,y)\) pairs, so this line actually generates a 100-by-100 grid of \((x,y)\) coordinates, hence the tuple assignment.

```
1 mu=np.array([0.5, 0.5])
2 Sigma=np.array([[0.1, 0.05],[0.05, 0.1]])
3 mvn1 = scipy.stats.multivariate_normal(mu, Sigma)
4 x, y = np.mgrid[0:1:.01, 0:1:.01]
5 pos = np.empty(x.shape + (2,))
6 pos[:, :, 0] = x; pos[:, :, 1] = y
7 _ = plt.contour(x, y, mvn1.pdf(pos))
```
Drawing contours

```python
mu = np.array([0.5, 0.5])
Sigma = np.array([[0.1, 0.05], [0.05, 0.1]])
mvn1 = scipy.stats.multivariate_normal(mu, Sigma)
x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y
_plt.contour(x, y, mvn1.pdf(pos))
```

The `pos` array is a 3-dimensional array. Like a box of numbers. We're going to plot a surface, but at each `(x,y)` coordinate, the surface value depends on both `x` and `y`. 
The reason for building `pos` the way we did is apparent if we read the documentation for `scipy.stats.(dist).pdf`.
Drawing contours

```python
mu=np.array([0.5,0.5])
Sigma=np.array([[0.1,0.05],[0.05,0.1]])
mvnl = scipy.stats.multivariate_normal(mu,Sigma)
x, y = np.mgrid[0:1:.01, 0:1:.01]
pos = np.empty(x.shape + (2,))
pos[:, :, 0] = x; pos[:, :, 1] = y
_ = plt.contour(x, y, mvnl.pdf(pos))
```

`matplotlib.contour` takes a set of x coordinates, a set of y coordinates, and an array of their corresponding values.

`matplotlib.contour` offers plenty of optional arguments for changing color schemes, spacing of contour lines, etc. [https://matplotlib.org/api/contour_api.html](https://matplotlib.org/api/contour_api.html)
Subplots

```python
subplot(nrows, ncols, plot_number)
```

**Shorthand:** `subplot(XYZ)`

- Makes an $X$-by-$Y$ plot
- Picks out the $Z$-th plot
- Counting in row-major order

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`tight_layout()` automatically tries to clean things up so that subplots don’t overlap. Without this command in this example, the labels “sqrt” and “logarithmic” overlap with the x-axis tick labels in the first row.
Specifying axis ranges

plt.ylim([lower,upper]) sets y-axis limits

plt.xlim([lower,upper]) for x-axis

For-loop goes through all of the subplots and sets their y-axis limits
Nonlinear axes

Scale the axes with `plt.xscale` and `plt.yscale`

Built-in scales:
- Linear (`'linear'`)
- Log (`'log'`)
- Symmetric log (`'symlog'`)
- Logit (`'logit'`)

Can also specify customized scales: [https://matplotlib.org/devel/add_new_projection.html#adding-new-scales](https://matplotlib.org/devel/add_new_projection.html#adding-new-scales)
Saving images

plt.savefig(filename) will try to automatically figure out what file type you want based on the file extension.

Can make it explicit using plt.savefig('filename', format='fmt')

Options for specifying resolution, padding, etc: https://matplotlib.org/api/_as_gen/matplotlib.pyplot.savefig.html
Animations

`matplotlib.animate` package generates animations

I won’t require you to make any, but they’re fun to play around with (and they can be a great visualization tool)

The details are a bit tricky, so I recommend starting by looking at some of the example animations here: [http://matplotlib.org/api/animation_api.html#examples](http://matplotlib.org/api/animation_api.html#examples)