Python for Remote Sensing Applications in Earth Science, Part 1:
Jupyter Notebooks and Plotting

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Code, data, and installation guide http://www.rebekahesmaili.com/workshop.html

1 Introduction

1.1 Why Python?

Pros

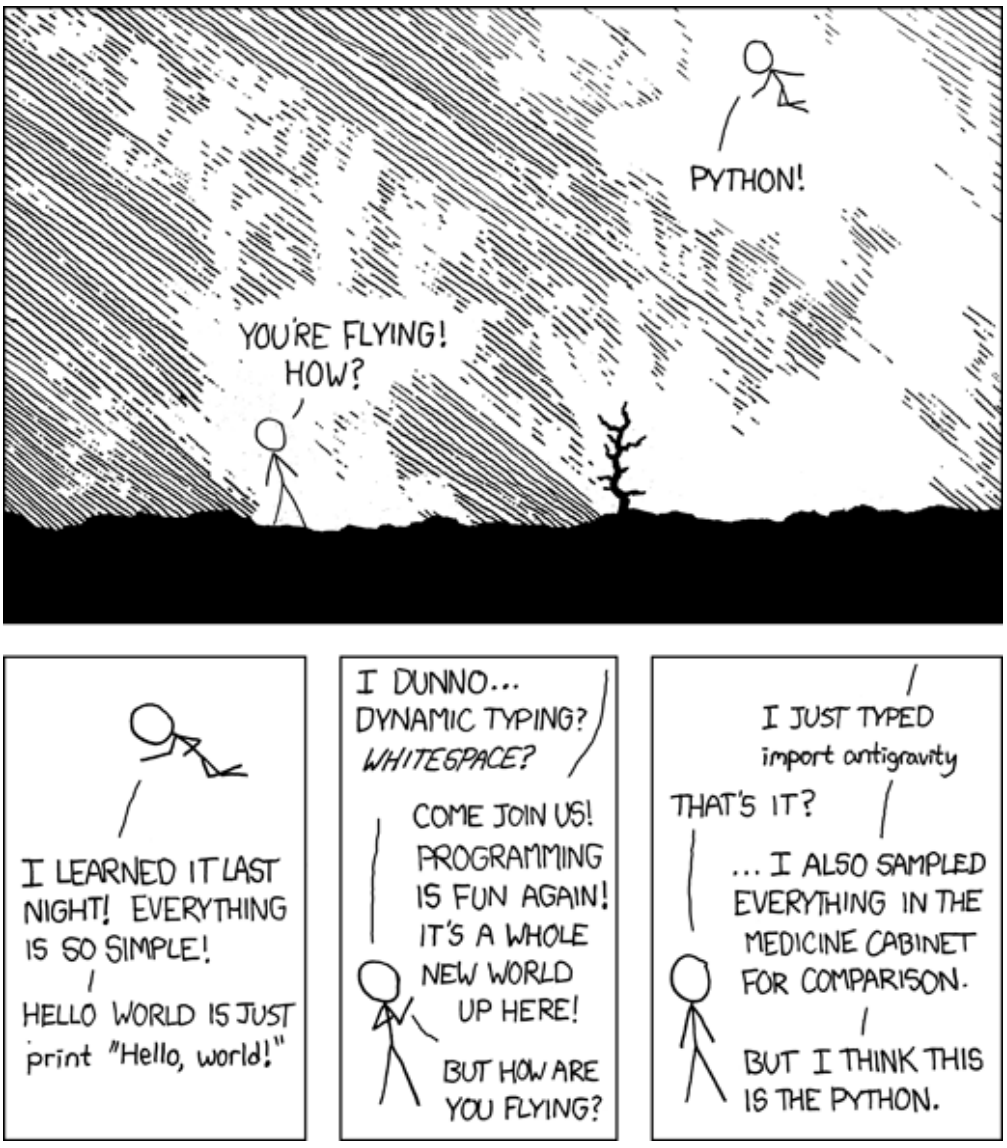
- General-purpose, cross-platform
- Free and open source
- Reasonably easy to learn, good statistical and visualization packages/modules
- Forces good syntax
- Reads satellite data formats like HDF, NetCDF, GRIB

Cons

- Performance penalties for interpretted languages
- Packages are a "black box" and can be discontinued

1.2 Objective

- You won't learn how to code in Python
- You will learn to:
  - Read/write ascii data


PYTHON!
YOU'RE FLYING! HOW?
I LEARNED IT LAST NIGHT! EVERYTHING IS SO SIMPLE!
HELLO WORLD IS JUST print "Hello, world!"
I DUNNO... DYNAMIC TYPING? WHITESPACE?
COME JOIN US! PROGRAMMING IS FUN AGAIN! IT'S A WHOLE NEW WORLD UP HERE!
BUT HOW ARE YOU FLYING?
I JUST TYPED import antigravity
THAT'S IT?
... I ALSO SAMPLED EVERYTHING IN THE MEDICINE CABINET FOR COMPARISON.
BUT I THINK THIS IS THE PYTHON.

  - Basic plotting and visualization
  - Saving files and data
- By the end of this class, you should be able to **analyze and visualize satellite datasets.**

Python is an interpretted language, so you as minimum you need to have Python on your computer.

1.3 What is Anaconda?

- Anaconda is a package manager
- Comes bundled with Python, a lot of useful scientific/mathematical packages, and development environments.
- Easiest place to start if you new

1.4 Development environments

- Spyder: most Matlab-like
- Jupyter notebooks: web based. Similar to Mathematica, runs code inline
- Text editor + run with command line for scripting

1.5 Launching Jupyter Notebook

1.5.1 Linux/Mac

- Open terminal, **cd to the directory where you have your notebooks and data**, and type:

```
jupyter notebook
```

1.5.2 Windows

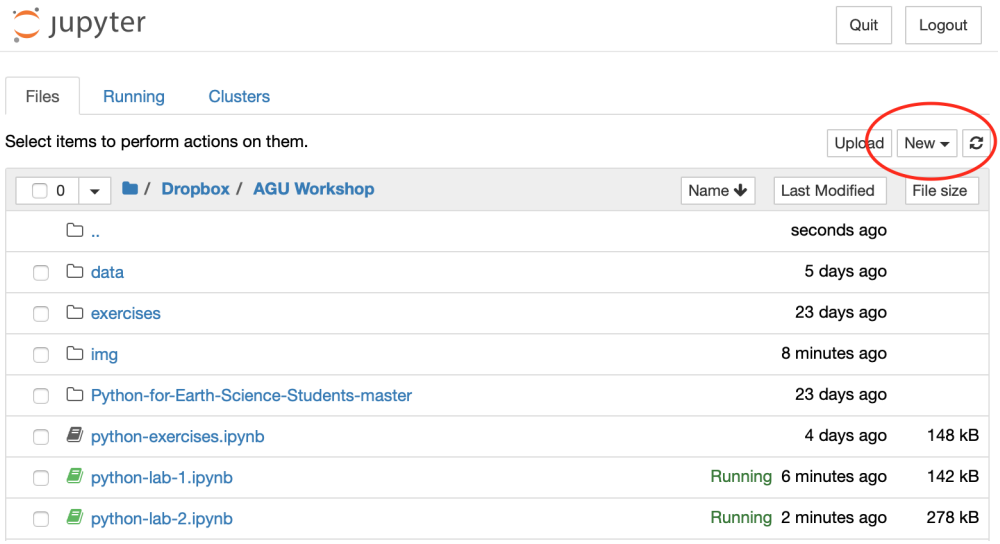
- Start $\rightarrow$ Anaconda3 $\rightarrow$ Jupyter Notebook

1.6 Jupyter Home Screen

- This will launch your default web browser with a local webserver that displays the contents of the directory that you're working in.
- Note: in all the examples, the path assumed that jupyter is launched from the notebook directory. You will need to change the path to point to your data if this is different.
- Click on New on the top right.

Exercise 1: Set-up your environment and create a notebook

- For your opertating system, launch Jupyter Notebooks
- Create a new notebook
- Change the name from "untitled" to something better
- Save in the **same directory as the data folder** that we provided (or move the data directory to the same place at the file because we'll need it later!).



2 Very basic python commands

```
In [19]: # This is a comment
         print("hello world")
```

```
hello world
```

```
In [20]: # This is an array
         a = [1,2,3,4,5,6]
```

```
In [21]: # This will show me the array
         print(a)
```

```
[1, 2, 3, 4, 5, 6]
```

```
In [22]: # So will this test
         a
```

```
Out[22]: [1, 2, 3, 4, 5, 6]
```

```
In [23]: # Is this what you expected to happen?
         a*2
```

```
Out[23]: [1, 2, 3, 4, 5, 6, 1, 2, 3, 4, 5, 6]
```

- Math didn't "happen" because it was a list, not a number array or matrix.
- Need to use an additional package to do matrix operations

2.1 Importing Packages

Packages give us additional functionality, saving us the trouble of writing procedures ourselves. There are ~6000 packages in the conda-forge repository alone!

Today we'll discuss:

- NumPy Fast mathematical operations on large datasets.
- Pandas Encapsulation of data, easy read/write of ascii data. Builds extra functionality on top of NumPy.
- Matplotlib Primarily python plotting/visualization package. You can generate plots, histograms, scatterplots, etc., with just a few lines of code.
- Cartopy Package designed for geospatial data processing in order to produce maps and other geospatial data analyses.

```
In [24]: import numpy as np
```

2.1.1 NumPy

- Defining Arrays
- Array operations

```
In [25]: # Convert a to a numpy array
         a = np.array(a)

         # Now that a is a numpy array, multiply each element x2
         a*2
```

```
Out[25]: array([ 2,  4,  6,  8, 10, 12])
```

```
In [26]: b = a.reshape(3,2)

         # Sum vertically downwards across rows (axis 0)
         b.sum(axis=0)
```

```
Out[26]: array([ 9, 12])
```

```
In [27]: # Get the minimum horizontally across columns (axis 1)
         b.max(axis=0)
```

```
Out[27]: array([5, 6])
```

```
In [28]: # Boolean operations
         b>1
```

```
Out[28]: array([[False,  True],
                [ True,  True],
                [ True,  True]])
```

For more examples, work through the: Numpy Quickstart

2.1.2 Pandas

- A library that helps encapsulate data
- Comparable to data frames in R, structures in IDL, namespaces in C++ and modern Fortran

Pros:

- You can name columns and refence by labels instead of indices like in numpy arrays
- This also makes performing group operations easier and more readable

Cons:

- Pandas is a wrapper for NumPy, so there is some efficiency overhead
- NumPy arrays are better for referencing datasets > 2D

```
In [29]: import pandas as pd
```

3 Working with Data

3.1 Case Study: 2018 California Camp Fire from Space

- A forest fire began on **Nov 8, 2018** and burned for 17 days had burned over a 621 km^2 area.
- Caused by very low regional humidity due to strong gusting wind events and very dry surface
- The smoke from the fire also had an impact on regional air quality.
- We'll look at satellite observations from JPSS show the **fire location** and the impact of the California wildfires had on **gases** like CO, Ozone, and **Aerosol Optical Depth (AOD)**.

3.2 Emmitted gases (carbon monoxide, ozone) and environment (water vaper)

- Providing an ascii file that extracts key variables from the NUCAPS sounding dataset
- Atmospheric sounding/profiling is a measurement of vertical distribution of physical properties of the atmospheric column such as pressure, temperature, liquid water content, ozone concentration, pollution, and other properties.
- Remote sensing soundings generally use passive infrared and microwave radiometers
- More information: https://www.star.nesdis.noaa.gov/jpss/soundings.php

```
In [30]: # Import dataset containing trace gases at 850mb and 500mb pressure levels.
         fname = 'data/campfire-gases-2018-11.csv'
         gases = pd.read_csv(fname)
```

Note: If you are getting errors!
Check the path in the home tab in your browser, it must be relative to the where jupyter was initially launched.

```
In [31]: # Show column names
         list(gases)
```

```
Out[31]: ['Latitude',
          'Longitude',
          'Time',
          'H2O_MR_500mb',
          'H2O_MR_850mb',
          'CO_MR_500mb',
          'CO_MR_850mb',
          'O3_MR_500mb',
          'O3_MR_850mb',
          'CH4_MR_500mb',
          'CH4_MR_850mb',
          'N2O_MR_500mb',
          'N2O_MR_850mb',
          'CO2_500mb',
          'CO2_850mb',
          'datetime']
```

Exercise 2: Import an ascii file

- From the data folder, import the a dataset "VIIRSNDE_global2018312.v1.0.txt" which is a dataset containing the global location of fires for Nov 8, 2018.
- Use the pandas read_csv command. Assign it to a variable.
  - HINT: You might need to check out the file path with respect to your notebook location.
- What are the column names?

```
In [32]: # SOLUTION
         fname = 'data/VIIRSNDE_global2018312.v1.0.txt'
         fires = pd.read_csv(fname)
```

3.2.1 Basic Plotting with MatplotLib

Common (simple) tasks in Earth science...

- Time series
- Computing dataset mean
- Creating maps

```
In [33]: # Matplotlib
         from matplotlib import pyplot as plt

         # Options to print figures into notebook/increase size
         # Only necessary for jupyter notebooks
         %matplotlib inline
         plt.rcParams['figure.figsize'] = [12, 6]
         plt.rcParams.update({'font.size': 16})
```

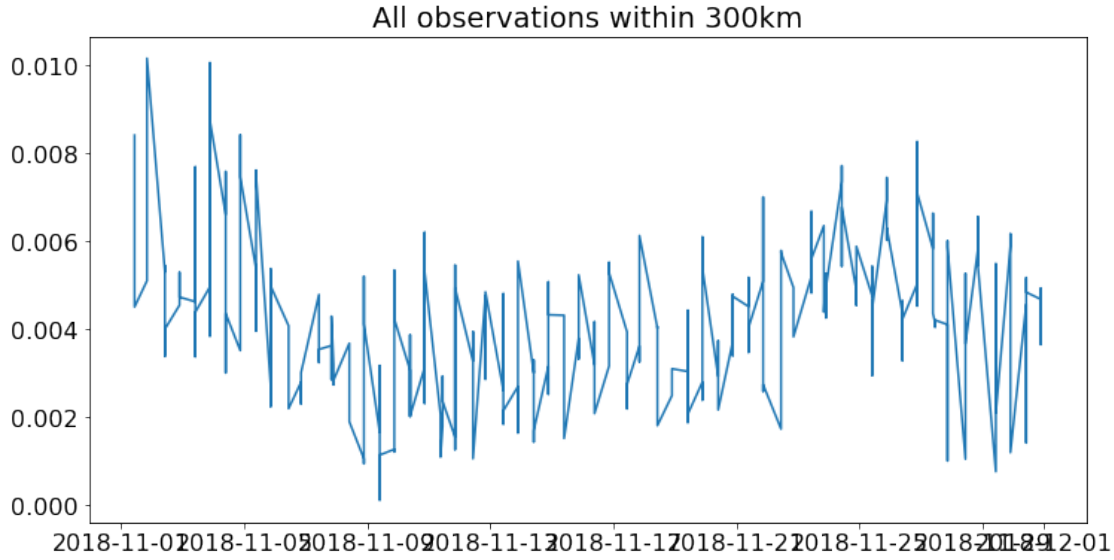
Time series data Need to tell python the date strings in the file are dates/times.

```
In [34]: # Convert the string dates and times to date format (Note: \ continues to new line)
         fmt = '%Y-%m-%d %H:%M:%S'
         gases['datetime'] = pd.to_datetime(gases['datetime'], format=fmt)
```

Plotting a single variable

- Add the data using plt.plot('X Column Name', 'Y Column Name')

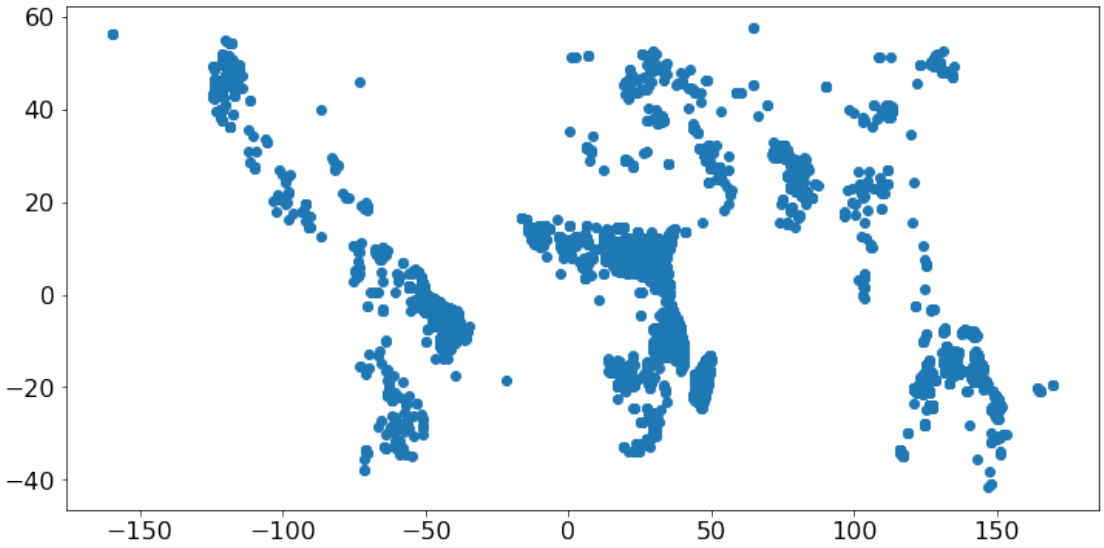
```
In [35]: plt.plot(gases['datetime'], gases['H2O_MR_850mb'])
         plt.title('All observations within 300km')
         #plt.xticks(rotation=35)
         plt.show()
```



Exercise 3
??? = Fill in the blank!
Create a scatter plot

- Import time series data from VIIRSNDE_global2018312.v1.0.txt from Exercise 2.
- Use the ???.scatter(???, ???) to create a plot mapping the latitude/longitude location of fires.

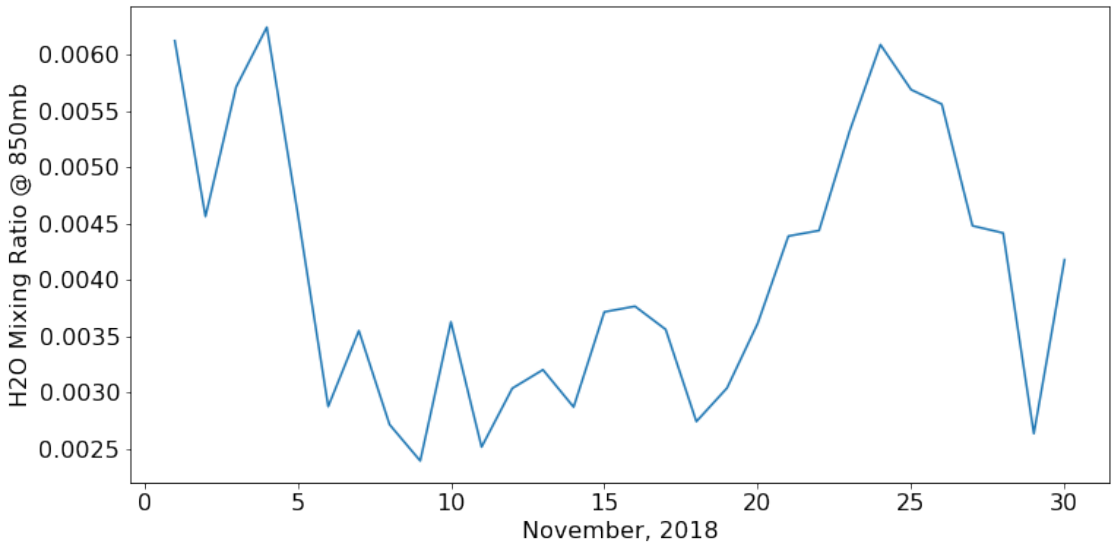
```
In [37]: # SOLUTION
         plt.scatter(fires.Lon, fires.Lat)
         plt.show()
```



3.2.2 Computing basic statistics

There are multiple observations per day in the gases plot - might be useful to only look at daily avergae. * In pandas, the 'groupby' command passes the column name to perform an operation on. * Chain another command telling it what operation to person (e.g. mean, standard deviation, or your own defined function)

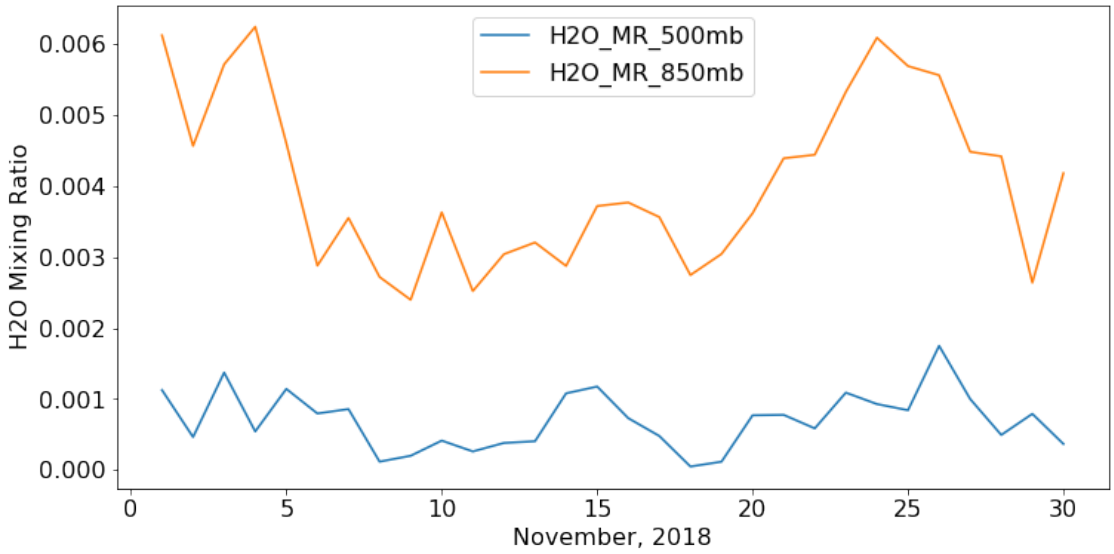
```
In [38]: dailyAvg = gases.groupby(gases.datetime.dt.day).mean()

In [39]: plt.plot(dailyAvg.index, dailyAvg['H2O_MR_850mb'])
         #plt.scatter(dailyAvg.index, dailyAvg['H2O_MR_850mb'])

         plt.xlabel("November, 2018")
         plt.ylabel("H2O Mixing Ratio @ 850mb")

         plt.show()
```



Adding data to an existing plot

- Call plt.plot() and fill in the x and y variables for EACH line/data series on the plot
- Add in any aesthetics, such as rotating the axes, labels, and adding a legend
- Show the plot using plt.show()

```
In [40]: plt.plot(dailyAvg.index, dailyAvg['H2O_MR_500mb'])
         plt.plot(dailyAvg.index, dailyAvg['H2O_MR_850mb'])

         plt.xlabel("November, 2018")
         plt.ylabel("H2O Mixing Ratio")

         plt.legend()
         plt.show()
```



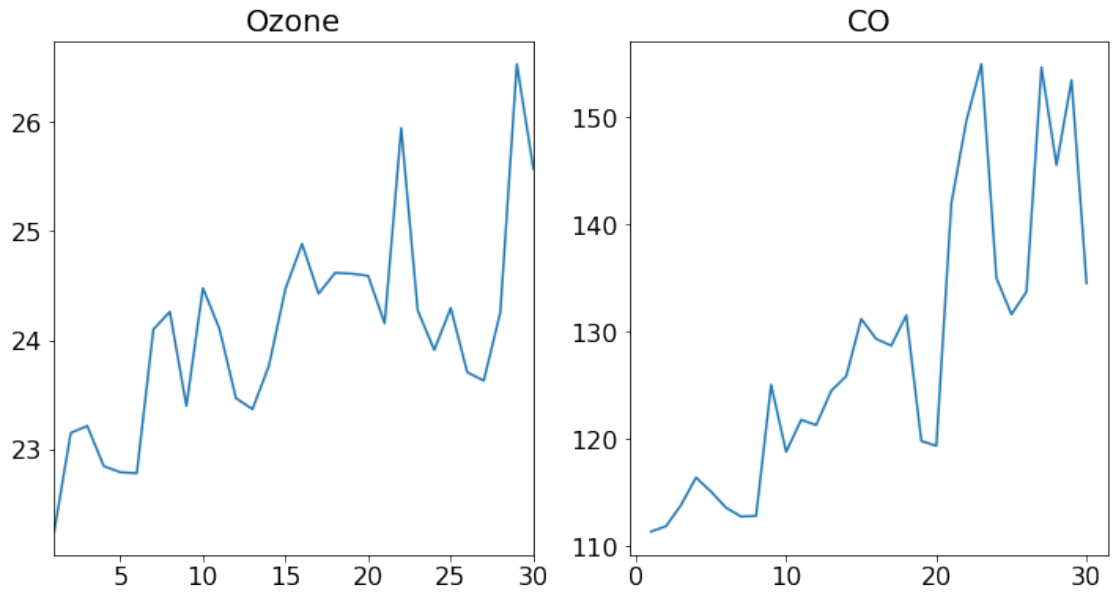
Plotting two side-by-side plots

- Before writing your plt.plot code, add: plt.subplot(**row number** , **column number** , **position of the plot**)
- Call plt.plot() and fill in the x and y variables for the first line/data series on the plot
- Call plt.sunplot again, increment the position of plot number
- Add in any aesthetics, such as rotating the axes, labels, and adding a legend
- Show the plot using plt.show()

Example:

- plt.subplot(2,1,1) places the plot in the first position of a two row, one column stack of plots.
- plt.subplot(1,2,2) places the plot in the second position of a two column, one row of plots next to each other.

```
In [41]: plt.subplot(1,2,1)
         plt.plot(dailyAvg.index, dailyAvg.O3_MR_850mb)
         plt.title('Ozone')
         plt.xlim(1, 30)
         #plt.legend()

         plt.subplot(1,2,2)
         plt.plot(dailyAvg.index, dailyAvg.CO_MR_850mb)
         plt.title('CO')
         plt.show()
```



3.2.3 Creating maps from data

In exercise 3, we made a scatterplot showing where the fires are but wouldn't it be nice to see that on a map? Basic maps only require a few extra lines of code.

3.3 Cartopy

- Cartopy is not included in Anaconda, need to install yourself.

Open the terminal (Mac/Linix) or Anaconda Prompt (Windows) and type:

```
conda install -c conda-forge cartopy
```

- Rather than import all of Cartopy, we just want the projection classes to pair with matplot lib.
- More map projections.

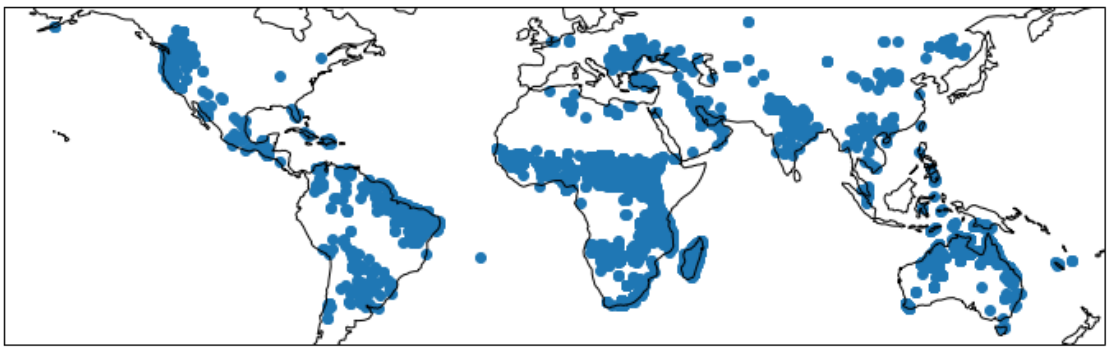
```
In [42]: from cartopy import crs as ccrs
```

```
In [43]: # In case you haven't imported it yet...we need it now!
         fires = pd.read_csv("data/VIIRSNDE_global2018312.v1.0.txt")
         fires.head()
```

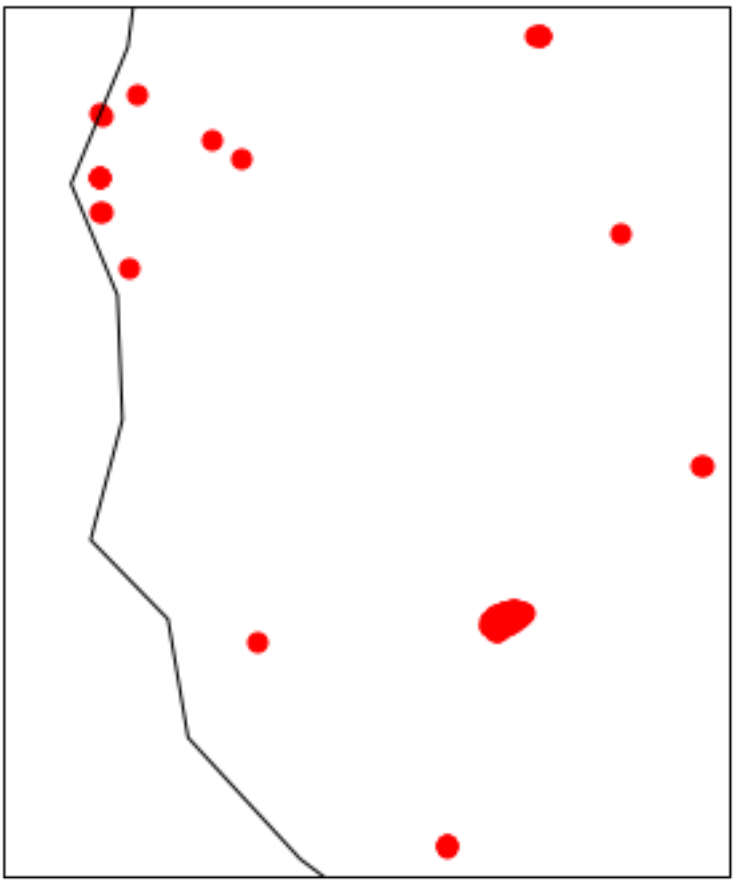
```
Out[43]:          Lon        Lat  Mask  Conf  brt_t13(K)    frp(MW)  line  sample  Sat  \
         0  27.110006  30.769241     8    52  302.877533   5.814295   242    1735  NDE
         1  26.083252  30.534357     9   100  332.959717  24.340988   301    1620  NDE
         2  34.865997  28.162659     8    38  301.165985   6.107953   396    2589  NDE
         3  34.872623  28.161121     8    71  307.277985   9.287819   396    2590  NDE
```

```
4  34.865070  28.158880     8    39  301.227783    6.001442   402    2590  NDE

   YearDay  Hour
0  2018312     1
1  2018312     1
2  2018312     1
3  2018312     1
4  2018312     1
```

In [44]:
```
ax=plt.axes(projection=ccrs.PlateCarree())
ax.coastlines()
plt.scatter(fires['Lon'], fires['Lat'])
plt.show()
```



In [45]:
```
ax=plt.axes(projection=ccrs.PlateCarree())
ax.coastlines()
plt.scatter(fires['Lon'], fires['Lat'], color='red', s=50)
plt.xlim(-125, -120)
plt.ylim(38, 44)
plt.show()
```



3.3.1 Aerosol Optical Depth (AOD)

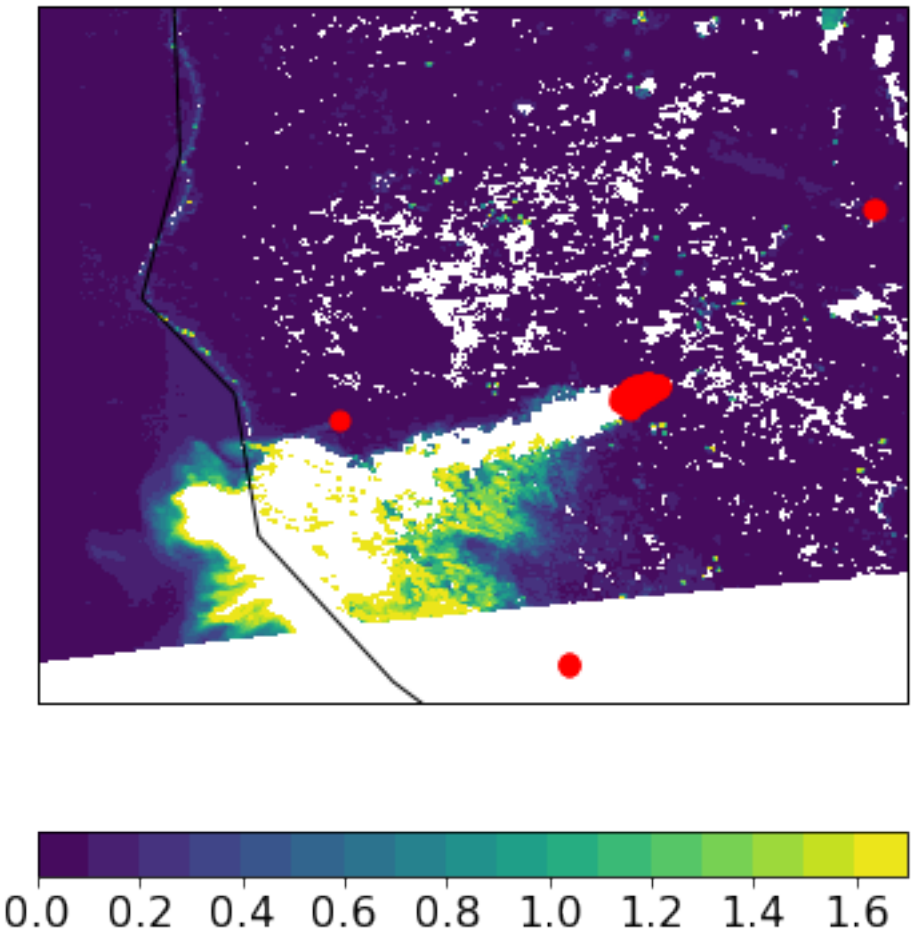
- Aerosols are particles suspended in the atmosphere, including dust, sea salt, volcanic ash, smoke, and pollution.
- AOD is a unitless measure of the amount of aerosols in the atmosphere.
- Low values indicate clear air, high values indicate lots of particles
- Measurements are obtained from the VIIRS instrument on the Suomi-NPP satellite.
- Data are stored in **netCDF** or **HDF format**
- More information: https://www.star.nesdis.noaa.gov/jpss/aerosols.php

3.3.2 netCDF Primer

- Hosted by the Unidata program at the University Corporation for Atmospheric Research (UCAR)
- NetCDF (Network Common Data Form) a set of software libraries and self-describing, machine-independent data formats
- Support the creation, access, and sharing of array-oriented scientific data

NOTE: We'll cover this more in more detail in the next workshop session!

```
In [46]: from netCDF4 import Dataset

In [47]: fname='data/JRR-AOD_v1r2_npp_s201811082130296_e201811082131537_c201811082228260.nc'
         file_id_NPP = Dataset(fname)

In [48]: aod = file_id_NPP.variables['AOD550'][:,:]
         lat = file_id_NPP.variables['Latitude'][:,:]
         lon = file_id_NPP.variables['Longitude'][:,:]

In [49]: # Scaling the data from 0-1.8.
         levs = np.arange(0, 1.8, 0.1)
         img_proj = ccrs.PlateCarree()

In [54]: # Using cartopy, create the map projection and plot the data
         ax = plt.axes(projection=img_proj)
         ax.coastlines()

         # Can change color scheme using the get_cmap command
         x1 = plt.contourf(lon, lat, aod, levs, transform=img_proj)
         plt.colorbar(x1, orientation="horizontal", fraction=0.05)
         plt.scatter(fires['Lon'], fires['Lat'], color='red', s=50)

         # To zoom in on data:
         plt.xlim(-125, -120)
         plt.ylim(38, 42)
         plt.show()
```



3.3.3 Saving

- You can right click and save on images
- Add **plt.savefig('pick_a_filename')**.
  - e.g. plt.savefig('CampFire.png')
  - NOTE: if you plt.show() BEFORE saving, nothing saves!
- Variables can be saved using **variablename.to_csv('filename.csv')**
  - e.g. DailyAvg.savefig('DailyAvgGases_Nov2018.csv')
- You also specify a path (e.g. /location/to/directory/), otherwise the save is in the directory that you launched jupyter notebook.

3.4 Resources

3.4.1 In-person through UMD/McKeldin Research Commons

- Data Science Workshop Series

- All Workshops
- Statistical Consulting Service

3.4.2 Online tutorials

- Some (free!) ways to learn:
  - CS Dojo Youtube series for absolute beginners
  - Automate Boring Stuff
  - Codeacademy
  - Local Meetups

3.5 Datasets

Searchable satellite data:

- NOAA CLASS Comprehensive Large Array-data Stewardship System (CLASS) is an electronic library of NOAA environmental data.
- NASA MIRDOR is an electronic library of NASA environmental data. Most NASA satellite data are stored here.
- NASA Langley Atmospheric Science Data Center (ASDC) Distributed Active Archive Center (DAAC). Aerosols, clouds, radiation, and field campaign data.
- EUMETSAT

Other channels:

- Amazon Web Services has GOES-16 radiance, Landsat, MODIS, and more
- python-AWIPS Has a good repository of atmospheric datasets
- Python Satellite Data Analysis Toolkit (pysat) Can pull space science related datasets (e.g. COSMIC-1)