MCIS6273 Data Mining (Prof. Maull) / Spring 2024 / HW1

Points Possible	Due Date	Time Commitment (estimated)
20	Wednesday February 28 @ Midnight	*up to* 20 hours

- **GRADING:** Grading will be aligned with the completeness of the objectives.
- **INDEPENDENT WORK:** Copying, cheating, plagiarism and academic dishonesty *are not tolerated* by University or course policy. Please see the syllabus for the full departmental and University statement on the academic code of honor.

OBJECTIVES

- Perfom basic data engineering in Python using OpenAQ weather data
- Perfom basic data analysis in Python using OpenAQ weather data

WHAT TO TURN IN

You are being encouraged to turn the assignment in using the provided Jupyter Notebook. To do so, make a directory in your Lab environment called `homework/hw0`. Put all of your files in that directory. Then zip or tar that directory, rename it with your name as the first part of the filename (e.g. `maull_hw0_files.zip`, `maull_hw0_files.tar.gz`), then download it to your local machine, then upload the `.zip` to Blackboard.

If you do not know how to do this, please ask, or visit one of the many tutorials out there on the basics of using zip in Linux.

If you choose not to use the provided notebook, you will still need to turn in a `.ipynb` Jupyter Notebook and corresponding files according to the instructions in this homework.

ASSIGNMENT TASKS

(30%) Perfom basic data engineering in Python using OpenAQ weather data

Like last homework, you will continue your practice of data engineering to prepare data for analysis.

This time, we will get important data from an API by combining other data sources together for a single purpose.

You are aware that there are many airports in the US – and in this assignment, we will get the latitude and longitude coordinates of over 60 major airports and perform and important query against an API to find the nearest air quality stations to those airports.

In effect, we will have the API perform a *nearest neighbor* lookup for us and from that, we will build a dataset that we can use to visualize the airports and the stations around those airports.

The power of open data cannot be over-emphasized in this part of the assignment, since without it, we would not be able to perform these actions so efficiently, but furthermore, we would not be able to get to the *important* questions so quickly.

You will not need an API key for the OpenAQ API. The service is FREE, but I will ask that you put a 1-2 second pause (what I call a *be nice* pause) between each call. While the API and service is FREE, running it is not.

Learn more about OpenAQ here:

- https://openaq.org

They aggregate *global* air quality data and need continued support to keep operations running smooth and to bring this amazing service to anyone on the planet Earth with an Internet connection.

Find out how to make a donation to support their server, data storage and development costs here:

- https://secure.givelively.org/donate/openaq-inc/

Your code must be implemented in Jupyter as a notebook – you will be required to turn in a `.ipynb` file.

§ Task: Use Python to make HTTP/API calls to obtain and prepare data.

The first order of business will require you to obtain the list of all US airports from this comprehensive site:

- https://data.humdata.org/dataset/ourairports-usa

The direct link to this file is here:

- https://ourairports.com/countries/US/airports.hxl

and you can call `pd.read_csv()` directly on it to pull the data into a DataFrame!

Perform the following:

- store the entire DataFrame in a `csv` file and name it: `all_us_airports.csv`
- make sure the data is clean – that is you may notice some non useful data that made it when you call for the file; remove that non useful row

§ Task: Filter data to a subset for further use.

Now that you have a useful file, we will want to filter it further so we can restrict it to just the data we are interested in.

Specifically, we want only the large airports (or those designated as such) and we don't need all the extra columns.

Load your `all_us_airports.csv` and do some filtering as such:

- produce a new reference file with just the airports of `large_airport` type, and
  - there should only be 67
  - name the file `large_us_airports.csv`
  - filter this data to only include the following relevant columns: `name`, `latitude_deg`, `longitude_deg`, `iata_code`

§ Task: Plot the data using Folium

The interactive capabilities of Jupyter are one of the main reasons we use it and you will now see why!

We will use a library called `folium` to display an interactive map of all the airports in our `large_us_airports.csv` file.

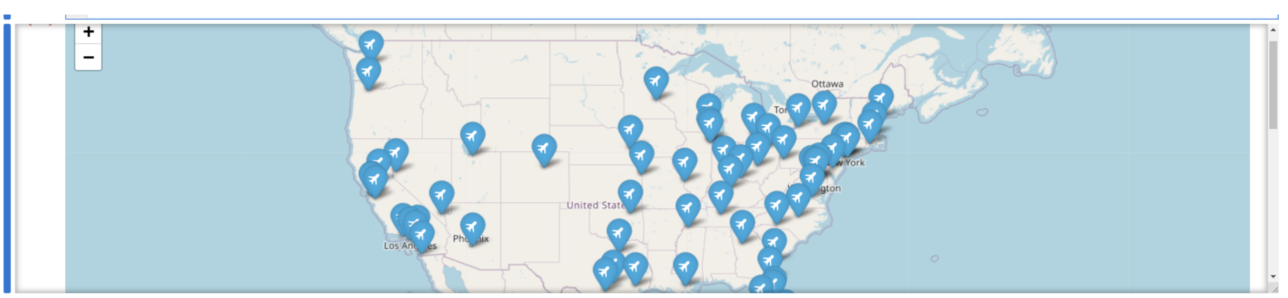
You should learn about folium here:

- https://python-visualization.github.io/folium/latest/

In this part, you will create a map of the airports from the previous part.

Do not overthink this – it will be a few lines of code to load the data, loop over it, pull the lat/lon of each airport and then display the map. PLay with the provided demos in the folium documentation.

Your map should include the airport icon in the pin and the contents of the pin should be the airport name and iata code in parethesis, for example, `Denver International Airport (DEN)`.



You can find out how to put a different icon in the pin from this documentation: folium Icon documentation

§ Task: Obtain a dataset from OpenAQ

In this part, will do a small subset of the work required to build the dataset for the next part. Lucky for us, I have already pulled the data for the part after this so you don't have to.

You will call OpenAQ API for the follow:

1. obtain PM2.5 data only
2. obtain a single day of data for June 6, 2023
3. the data will be for all sensors within 7.5km of downtown Detroit

- the lat/lon for downtown Detroit is: **42.33143000,-83.04575000**

You will need to make sure you understand the documentation at OpenAQ. Here is the best starting point to obtain data from the endpoint:

- https://openaq.org/developers/platform-overview/
- https://docs.openaq.org/docs/introduction

This will provide information about the specific call to get the data:

- `/measurements` endpoint: https://docs.openaq.org/reference/measurements_get_v2_measurements_get

§ Task: Transform, filter and store the OpenAQ data as CSV

After you've obtained the data, you will need make the data a little more useful as a single file. The JSON is very valuable, but let's assume we do not need all of it (as is often the case). So we're going to filter and restrict the data to just what we think we might need later.

Beware, assuming what you "need later" can be tricky and it is always a good idea to keep the original data payloads (the JSON directly from OpenAQ) as a receipt of how your filtered data was brewed.

Once you pull the data into a DataFrame, you'll notice a lot of data are actually JSON (unless you use the more advanced functions of `read_json`). You will also notice there are fields we might likely not need (i.e. `isAnalysis`, `isMobile`, etc), again with the caveat that we don't really *know* what we don't need, but we have some ideas about what we *do* need.

Transform

1. convert the `coordinates` field to two fields: `sensor_lat` and `sensor_lon` which break out the `coordinates->latitude` and `coordinates->longitude` correspondingly
   - you will find `DataFrame.apply()` to be exceedingly useful for this
2. convert the `date` field to a single value using the `date->local` and make sure that value is a `datetime64`.
   - you will need to carefully study `pd.to_datetime()` documentation
   - the new date field will be called `local_time`, once converted, you will not need the original `date` field

Filter

1. reduce the DataFrame to include only the fields: `locationId`, `location`, `entity`, `parameter`, `value`, `sensor_lat`, and `sensor_lon`, `local_time`
2. restrict manufacturer to the subset: `Governmental Organization` and `Community Organization`

Store

1. with the final transformed and filtered DataFrame:
   - store it to a file called `20230606_detroit_downtown_7_5km_aq.csv`
   - the file should have the columns `locationId`, `location`, `entity`, `parameter`, `value`, `local_time`, `sensor_lat`, and `sensor_lon`
   - the file will have over six thousand lines in it

(35%) Perfom basic data analysis in Python using OpenAQ weather data

Now that we have some sample data (stations within 7.5km of downtown Detroit on June 6, 2023) we are going to look at air quality on that day using the core statistical tools we have learned about thus far.

You may remember from the news last year, there was a significant wildfire in Canada which produced a long-lasting plume of smoke over centeral and eastern North America and the United States for some time June.

This fire rose to importance because it underscored the significance of smoke and particulate pollution on respiratory health, raising awareness about the importance of air quality monitoring and perhaps exposing some of the inadequacies of such monitoring not only in our country, but globally.

Because OpenAQ has many (hudreds of) millions of datapoints, including those from PM2.5 air quality sensors, air quality around the time of this fire was being carefully monitored. This data collection and open platform is the reason we can explore it further in this assignment.

We will also notice that the sensors in OpenAQ data include government "reference" sensors, like those used and managed by the US EPA (Environmental Protection Agengy) for official data, as well as those providing data from "community" sensors made by companies like Purple Air.

It will be noted, we are restricting our view to this short window of time to keep the computational burden on the cloud servers lower. A larger dataset in the would help provide more robust confidence of our analysis in this the assignment.

§ Task: Load your Detroit data and answer the following questions

1. What is the mean and median PM2.5 reading over all sensors?
2. What is the standard deviation?
3. Which `location_id` recorded the highest PM2.5? What was the reading?
4. What is the ratio of `Community Organization` to `Governmental Organization` entity type?
5. How many unique sensor stations are in the data (use `sensorId`)?
6. What is the station density per km?
7. What is the daily mean, median, min, max, 75% and standard deviation separately for all `Community Organization` and `Government Organization` sensors in the data (that is group each separately and report the statistics being asked)?
8. What is your opinion of the differences in the statistics? Comment specifically about the mean and 75%.

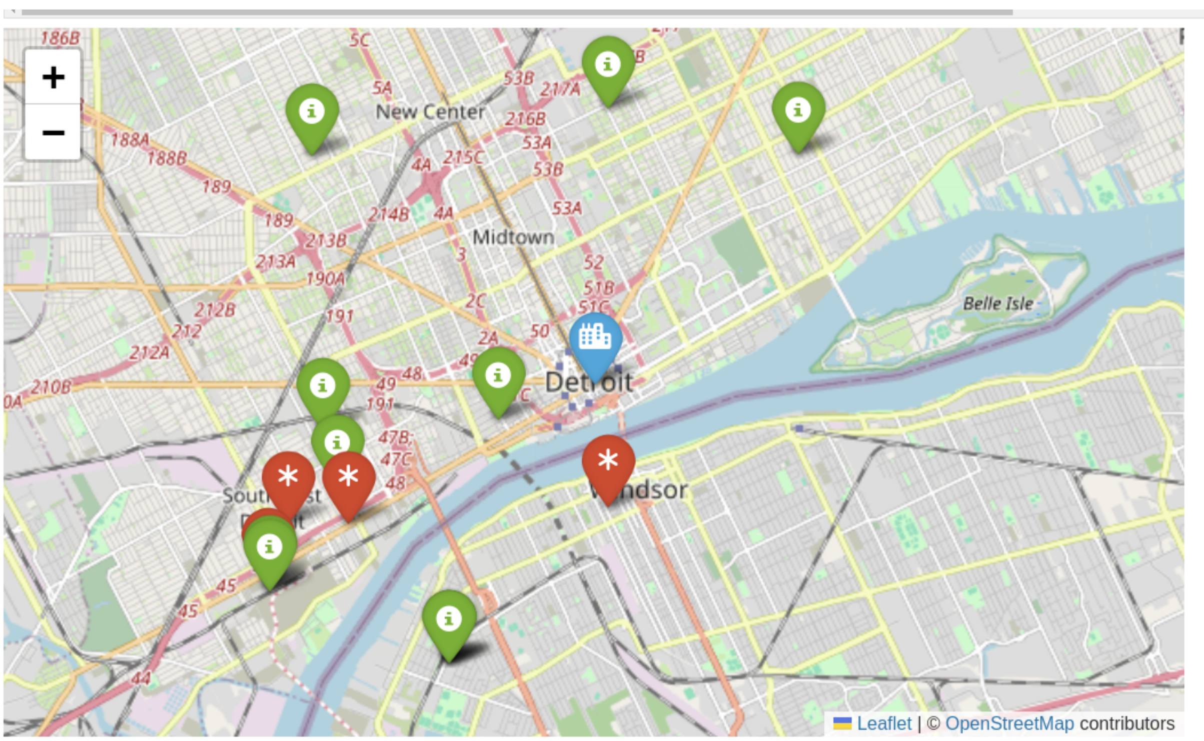
§ Task: Build a map of the stations

Use the folium library to build the map:

1. Put the pin for downtown Detroit in default blue with the "city" icon
   - you will use Font Awesome and add the parameter `prefix=fa` to the build your icon, see the folium icon documentation for more information
2. Put the community sensors on the map with green pins and the default info ("i") icon
3. Put the government sensors on the map with red pins and the default asterisk ("*") icon

Your map should look something like this:

[91]:



§ Task: Explore hourly averages for the day

1. What are the average readings for each of the 6 hour blocks 12am-6am, 6am-noon, noon-6pm and 6pm-11:59pm?
2. Compare and contrast these readings – make a comment about their differences.

3. Plot the hourly averages for the day using line plots (see `DataFrame.plot()`).
   - label the plot "Hourly PM2.5 Averages for June 6, 2023 (Detroit, MI)"
   - the x-axis should be the hour (0..23)
   - the y-axis should be the PM2.5 value
4. Plot the hourly averages of the *government* and *community* sensors on the same plot. The government averages will be in blue, community in orange, the x and y axes the same as the previous plot.

§ Task: Determine if the sensor means for the day are different, and if that difference is *statistically significant*.

We know that the government sensors are intended to be ground truth and thus if the community sensors' values are similar to the government sensors, then we can have more confidence that their data can be trusted.

One way to do this is to use statistical tests to determine if given a sample of data from each sensor, that they are statistically "the same". We do not intent that they are the actual same value, but that they are *statistically* the same – that their differences are not *meaningful* or "significant" or "statistically significant".

We will not delve into the depths of statistics here, other than to say that if two data sample can be compared and we want to know, perhaps, if the same sensor produced the data, with the assumption that the sensors were calibrated and deemed in working order.

The goal then of a statistical test would be, perhaps to take the means of the two samples, compare them *statistically* and determine if there is a significant probability that the means of the two groups are *statistically* the "same".

One such test we will use is called the t-test (aka "Students t-test"). This test takes two data samples, statistically compares them and gives us another statistic and a p-value that give us a probability that the statistic is equal to or more extreme than the sample due to random chance alone. You may have heard of the "null hypothesis", which states that there is no difference between the two sample statistics (e.g. sample means). If we *reject* or more appropriately *fail to accept* the null hypothesis, we say that we have confidence the sample differences are not due to chance alone and that there *may* be a true difference, which could be explained by something other than chance.

The p-value puts a probability on that chance, and while p-values have undergone a lot of controversy in recent decades, they still relay useful information when stated properly. They can put us in the ballpark of meaningful statistical analyses, but they often are misused to mean that *rejection of null hypothesis* means **acceptance** that the alternative hypothesis is true, which is not at all the case!

There is an excellent library in Python called `scipy` which provides many statistical tools for use in cases where Pandas or SciKit-Learn do not. SciPy provides an independent t-test which we can use to determine if the means of these two sensors for this day are the same or if their differences are statistically significant.

You can learn more about t-tests for significance:

- https://www.ncbi.nlm.nih.gov/books/NBK553048/
- https://www.stat.cmu.edu/%7Ehseltman/309/Book/chapter6.pdf
- https://bookdown.org/introrbook/intro2r/t-test.html
- https://stats.libretexts.org/Bookshelves/Applied_Statistics/Biological_Statistics_(McDonald)

What our aim will be is to build the case that the non-government sensors appear to be producing values as good as the government one's.

But wait! We *assume* that the government sensors are ground truth and thus correct. We assume that the community sensors are calibrated and can produce values as good as the government one's. What if these assumptions are unfounded? During this analysis, you will see if these and other assumptions may require further investigation.

Before we get started, you will already realize there are many more datapoints across more community sensors than government sensors. This imbalance must be taken into account. You will only have 95 data points for the government sensors and many thousands of data points from non-government (community) sensors.

1. In this first task, build a dataset with 95 data points sampled from 100 random draws of data from the community sensors:

- an easy way to do this is with the `DataFrame.sample()`, with `95` as the parameter
- you can then loop 100 times and average over all those loops
- you may want to just concatenate the 100 draws to a 100 column by 95 rows DataFrame and compute the `mean()`, but there are other ways

2. What are the descriptive statistics of your sample and the government data?
3. Compare and contrast, bring attention to the mean, 75% and standard deviations.
4. Run a test for normality on the two samples using `scipy.stats.normaltest()`.

- Can you *fail to reject the null hypothesis* (that the samples are drawn from normal distributions) at $\alpha < 0.05$?

5. Run a Barlett test for equal variances (also known as *homoscedasticity*).

- Can you *fail to reject the null hypothesis* (that the samples have equal variances) at $\alpha < 0.05$?

6. Run the independent t-test, and use the result in the parameter `equal_var=`. That is if you fail to reject the null hypothesis from Bartlett's then `equal_var=True`.

- Can you *fail to reject the null hypothesis* (that the means of two independent samples have identical average expected values) at $\alpha < 0.001$? (Notice we have raised the bar for statistical significance!)

§ Task: Reflect on the Detroit air quaity data of June 6, 2023 from each of the sensor types in the data

Going back to the original datasets (including all data points for community sensors), comment on the following:

- What is your reaction to the statement: *Community sensors picked up the poor air quality of the Canadian fires better than Government sensors*.
  - use evidence to support your reaction
  - take into account things like density in your reaction
- What is your reaction to the statement: *There need to be more community sensors deployed in downtown Detroit*.
  - use data and evidence in your reaction
  - make note of other data points you might need to more thoughtfully react to the statement

§ Task: Complete the online HW1 assessment.

Once you are done with the coding part of the assignment, you will need to complete the online assessment for the final **4 points of your grade** for this assignment.

§ Task: BONUS

You can earn up to 5 points extra for this part of the assignment.

1. build the OpenAQ dataset for 2023 for JFK airport in New York City
   - stations must be with 7.5km of the airport
   - date ranges must be May 1, 2023 to August 31, 2023
2. analyze the data and answer the questions
   - compare June 6 in your dataset with the Detroit dataset
   - comment on their similarities and differences both in terms of sensor density and intensity of PM2.5 on that day