CSC110Y1-F Fall 2020 - Fundamentals of Computer Science 1
Course Project Proposal

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1. Part 1

An interactive report of the effect of Amazon rainforest's area on the local annual precipitation and CO_2 emission (with python prime shipping).

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2. Part 2

Research Question: **To what extent do the changes in the Amazon rainforest's area affect the local annual precipitation and CO_2 emission?**

During our initial research on topics related to climate change, we found that the South American rainforest contributes 20% (Thomas, 2020) of the oxygen produced by photosynthesis on land, while the Amazon rainforest is responsible for 10% of the current greenhouse gas emissions (Melillo et al., y 20). This information was surprising to us since 20% of photosynthesis implies a lot of conversion from carbon dioxide, which is a greenhouse gas, to oxygen, whereas the 10% contribution to greenhouse gas seems to contradict that information. Due to this contradiction, we were curious about whether tree populations actually help control the climate. After some research, we learned that the effect of trees on climate change is more complex than we originally thought. There are many factors to consider, such as the carbon dioxide to oxygen conversion, the tendency to trap heat due to their dark color, reaction to form methane and ozone, and political movements revolving around tree plantations (Marshall, y 26). This led us into choosing an empirical approach —we wanted to directly observe the relationship between the change of tree population and climate change. We chose to focus our data on the Amazon rainforest not only because it is the largest rainforest on Earth (World Wildlife Fund., 2013), but also because there have been several pieces of evidence that show that the Amazon rainforest has been suffering from deforestation recently. Although there might be other underlying factors causing the changes in precipitation and CO_2 emission, it is still worth considering that over $700,000km^2$ $(270,000mi^2)$ of Amazon rainforest had been lost since 1970, reducing its size to 80.7% of its original size, in 2018 (Butler, ry 4); There have been more than 40,000 fires in the rainforest in 2019 (Government of Brazil., er 4); and that forest exploitation in Amazon has risen for 14 consecutive months in June 2020 (Reuters, 2020). With these major pieces of evidence of deforestation correlating to the change in global and local climate, we believe that it is a relevant topic to contemporary society that should not be ignored.

3. Part 3

- **TRMM (TMPA/3B43) Rainfall Estimate L3 1 month 0.25 degree x 0.25 degree V7 (TRMM_3B43)**

  This is a rainfall estimate dataset made by NASA.
  we have download the data for reviewers:

  https://sudo.fit/3B43_rainfall.zip

  If you want to download by yourself, the link is here:
  https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary

- **annual CO2 emissions by region**

  This is a CO2 emissions data provided by "our world in data".
  The link is here:
  https://ourworldindata.org/grapher/annual-co-emissions-by-region

- **Deforestation Figures for the Amazon**

  This is a deforestation data provided by "mongabay".
  The link is here
  https://rainforests.mongabay.com/amazon/deforestation_calculations.html

4. Part 4

PROCESSING INPUT DATA

In the input part, we first start the deserialization by creating a class called `Climate` with public attribute `name`, `year` and `value` to maintain the entire input data section can be saved in the same format for later analysing with data from different types (e.g. HDF and CSV).

In our own method `precipitation_read_hdf`, we first processed the input selected latitude and longitude of the top left endpoint and bottom right endpoint of the rectangular region in the global map. Since the NASA data is stored as longitude and latitude every 0.25 degrees. The longitude is recorded as 1440 points, while the latitude NASA only stores from 50 degrees north to 50 degrees south i.e. 400 points(NASA, 2020). We used the knowledge of linear algebra to change the basis and represent the input endpoint latitudes and longitudes with the new basis. Then we import `os` library to visit all the HDF file in the folder path by method `os.listdir` to get a list of all HDF file name(Python Software Foundation, 2020b). To read HDF file, we import a new library called `pyhdf`. This library helps to get access to the precipitation dataset from NASA since NASA use HDF to save all the satellite data. We mainly use `SD` and `SDC` class in `pyhdf.SD` module since `SD` helps to open a HDF file and return SD Instance and `SDC` is used to call `SDC.READ` method to use **read only mode** with HDF file(Open source community, 2020). We also use `numpy` library to deal with array transpose with imported dataset (Numpy community, 2020).

In our own function `precipitation_read_csv` and `deforestation_read_csv`, we only import `csv`, we use `DictReader` to get the header of the CSV file(Python Software Foundation, 2020a). Then the corresponding value in the CSV will be read through `for loop` and in each loop iteration create a `Climate` instance and stored in a list.

We include a function `get_data()` to give the example location of the file saved and the endpoints we select. This function also returns a list contains all three type of data(Co2emission/Precipitation/Deforestation).

Function `save_data_as_csv` is a serialization process. We transform `Climate` class into a CSV file that is being merged and updated. And then in the analysis process, the merged data can be simply used by function `read_data_from_csv` which is also a deserialization process.

ANALYSIS DESCRIPTION.

For this project, we use smooth polynomial fitting to relate two of the variables in our `nested list`. Now, although there exist readily available functions that would do the same in the module `numpy` (SciPy community, e 29), we try implementing our own functions for the same, to test our learning from the course.

We split the mathematical algorithm for this problem using top-down design. The most important part of the data analysis section is the PolynomialRegression custom class that we have defined, which, when initializing a variable of this class, takes in a dictionary with the name of the independent variable as the key, and its corresponding value in the dictionary as the list of all its values, and also, a corresponding dictionary for the dependent variable, and also a specified degree for the polynomial, and the level of precision expected. The initializer then calls upon a function that we designed using the ordinary least squares method to create a list of coefficients for the polynomial function that has the least variance with respect to the input data. Note that this list is implemented in terms of ascending order of power, to favour the implementation of the other methods in this class that analyze how well this polynomial represents the data (i.e., a measure of the accuracy of this polynomial). We defined the method `__call__` to allow the polynomial to defined as a callable, i.e., if `poly` is a variable of type PolynomialRegression, we we can simply evaluate `poly` at a value `x` by calling `poly(x)`.

We first have the method `r_squared` to calculate the coefficient of determination for this polynomial. We also have `extreme_absolute_error` to return the maximum and minimum absolute difference between the polynomial's value and a particular value in the input data. Then, we have the additional methods `covariance_with_polynomial` and `correlation_of_data` as additional measure of accuracy.

The other part in this section of the project is defining our own functions to handle the matrices involved in such a computation. We tried defining our own functions for these operations as much as possible, and while these implementations are not as efficient as possible, they serve our purposes quite well. For one, any improvement will be rather negligible as the degrees we consider are rather small, so the matrix size doesn't change rapidly; and also, optimizing the algorithm would lead to reducing the running time by only a few milliseconds, which is not our main priority in this code. However, iif we wished to optimize these functions, we could either choose to use the `matmul()` function in the `numpy` module, or we could choose to implement parts of the matrix multiplication with dot products by using `numpy.dot()` function from the `numpy` module to improve the process.

We have the functions `make_matrix` and `find_coefficients` which are perhaps the most important functions in this part. The former initializes the matrix X, and the latter solves the matrix equation $\vec{y} = X\vec{\beta} + \epsilon$ for β, where X represents the matrix of powers of x created from the input data, $\vec{y}$ represents the values of y in the input data, and $\vec{\beta}$ is the estimated coefficients vector, while $\vec{\epsilon}$ consists of the random errors at each of the points (i.e., the difference between the polynomial evaluated at the point and the actual y-value). Since we could not find any efficient way to create an algorithm to compute the inverses (we haven't really covered any such 'efficient' algorithm in either MAT223 or MAT240), we made use of `numpy`'s built-in function called `numpy.linalg.inv()` along with a type conversion method `tolist()` that converts objects of type array (a data class in `numpy`) to a nested list format.

Finally, we added a method in the PolynomialRegression class to allow for plotting the graph of the polynomial and a scatter plot of the data, using the functions `numpy.linspace` and `matplotlib.pyplot`, and specifying our own customizations to the graph.

INTERACTIVE PART

Our program also includes an interactive text-based model because the graphing library we use does not allow us to search for specific values. We thought that a text-based output would be more appropriate if the user is looking for the coefficient of determination, or the rate of change at a specific data point, because the graphical representation of those values would not be useful to the user.

The interactive model first calls `prompt_independent` and `prompt_dependent` to get the desired independent and dependent variables for our calculation. Note that the possible independent variables are CO_2 and forest area, and the possible dependent variables are CO_2 and precipitation. Therefore, if CO_2 is chosen as the independent variable, our program would not prompt the user for the dependent variable.

After selecting the variables and finishing the calculation, the interactive model uses a while loop with a condition that is always True. This allows the user to be prompted as many times as they wish. Inside of the while loop, we prompt the user again for the values they want to look up using `prompt_y` and `prompt_x`, which each has a while loop inside that iterates until the user input is valid.

After obtaining the variables to look for, the program would iterate through every value in the list of values the user is searching for. For example, if the user wants to find the forest cover when the year is 2000, the program would iterate through the list of years. If any of the values *is close* (using `math.isclose()`) to the expected value, in this case, 2000, we take the dependent value (forest cover) with the same index in the list of dependent values. To do so, we need a list of value for each variable, and the index of each value in the list must match the other. This is achieved using the function `get_output_data()`, which retrieves the required values we need from `PolynomialRegression` and `get_data`.

Technical requirement:

The Annual total CO_2 emissions dataset we have is a CSV file. In order to parse it easily, We decide to use pandas for CSV file reading.

Pandas is a python library written for data manipulation and analysis. (Pandas Development Team., 2020) In particular, it offers data structures and operations for manipulating numerical tables and time series.

Specific, we will use the function `read_csv`". This function has many parameters available for us, but we will only use `filepath_or_buffer` parameter. It takes a valid string path, which is the path to our CSV file.

This function will return a class - Pandas DataFrame that contains the data of the CSV file. Pandas DataFrame is easier for calculating dataset thanks to its various built-in functions. This way, we can access each cell of the CSV file for our later research.

5. Part 5

Special instruction for pyhdf: You can't install pyhdf directly using pip. Please follow the following instructions:

https://fhs.github.io/pyhdf/install.html

The most important part is to make sure HDF4 libraries or include files reside in directories that are searched by default on your system (in the PATH). Actuall, you can install pypdf using pip if HDF4 libraries is already in your PATH.

If you don't want to install pyhdf, you can just read from our parsed data (dataset.csv). In this case, please use read_data_from_csv in get_data_nohdf.py. It will return a list contains Climate classes, which we will use later in the data analysis.

TRMM (TMPA/3B43) Rainfall Estimate L3 1 month 0.25 degree x 0.25 degree V7 (TRMM_3B43)

We have downloaded and uploaded on one of our members' server. It is nearly 1G. Here is the link:

http://sudo.fit/3B43_rainfall.zip

If you decide to download by yourself, please follow the instruction provided by NASA:

https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary

Please unzip it into a folder called 3B43_rainfall.

Annual total CO2 emissions, by world region

Their website provided the option to download them as csv.

https://ourworldindata.org/grapher/annual-co-emissions-by-region

It is called "annual-co-emissions-by-region.csv" in MarkUs. You can manually do it, too.

Deforestation Figures for the Amazon

The original form is here:

https://rainforests.mongabay.com/amazon/deforestation_calculations.html

We have changed this into csv manually. It is called "deforestation.csv" in markus. You can manually do it, too.

Pre-processing of the datasets

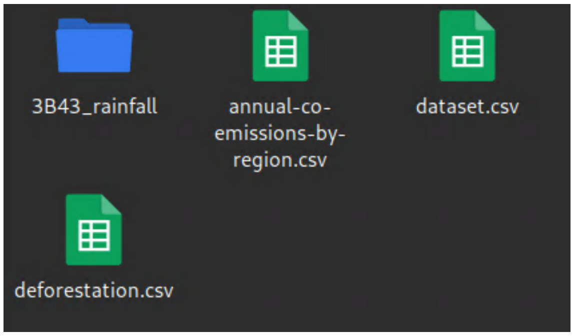
All the data are saved into a class called Climate. It have 3 valuables: name, year and value.

We serialize our data. They are saved in dataset.csv. To transform the raw dataset into the serialized data, please using get_data.py and call save_data_as_csv(get_data(), "dataset.csv").

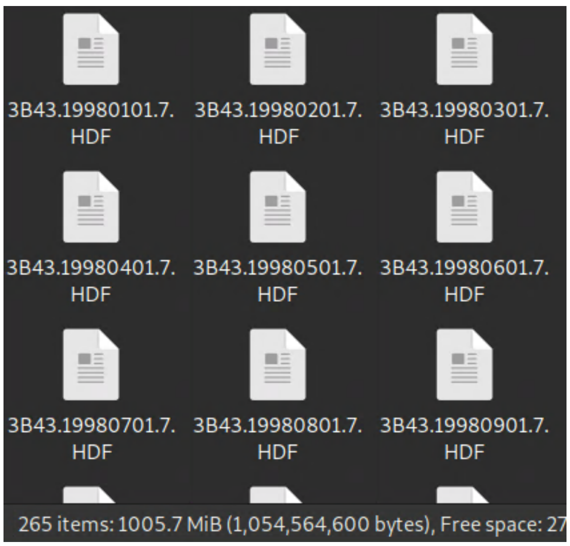
If you want to deserialize from transformed dataset, please using

read_data_from_csv("dataset.csv") in get_data_nohdf.py

After download, please put all the data file into ./data/3B43_rainfall. The final data folder should looks like:



inside ./data/3B43_rainfall should looks like:



Getting output

Run `main.py`. The console will prompt you for the independent variable to use for the calculation. You can either choose '`forest cover`' or '`CO2`'. If you choose '`CO2`', the only dependent variable is '`precipitation`', so the program will not prompt you for the dependent variable. However, if you choose '`forest cover`', the program will prompt you again for the dependent variable, which could either be '`CO2`' or '`precipitation`'.

After choosing the variables, the program will start asking you for a variable you want to search for, and the value of another variable where you want it. For example, if you want to search for the value of forest cover at the year of 2000, input forest cover for the first prompt, and year=2000 for the second prompt. We've also provided an example when prompting you, so hopefully it is clear.

When you are done with the text-based report, just press ctrl + C on windows or cmd + C on mac to kill the process, which an interactive graph will appear (it might appear in the background so check other windows). You can use the magnifying glass and select a portion to zoom in on, or the 4-directional arrow symbol to move the graph.

6. Part 6

In the input part, our original plan was to grab and parse the data directly from the website via a python program and store it in a file. At the time we didn't have a firm idea of the format of the storage. And we found that one of the datasets was so small that we didn't think it was necessary to write long code to grab this little bit of data. We stored the deforestation data as CSV files by manual processing. Another thing we did not expect is that the rainfall data is not divided by country, but by latitude and longitude. Also this dataset has the most special storage type. So we first need to find a python library that can open this type of file and process the corresponding data type `ndarray` that it outputs(Numpy community, 2020). Second, we needed to process the selected area. We chose to pick the top-left endpoint and the bottom-right endpoint of the rectangular region of the Amazon directly from the map. The rest of the input part procedure followed the original design in our proposal.

For the data analysis part of this project, we initially planned on using an approach that was quite similar to the calculus 'way' of constructing the polynomial regression (hereby shortened to simply 'polyreg') model. For instance, in the project proposal, we mentioned that we would first construct a trivial initial candidate polynomial (we were, of course, referring to the linear regression model from Assignment 1, when we said trivial, since it has the right 'shape' but nor the right degree), which would then use to find the sum of the squares of the perpendicular distance from each of the points to the polynomial. We had also mentioned that we would then minimize this sum by using the simplex algorithm.

However, we later found out that coding the simplex algorithm and modifying it to fit this task was not a manageable feat, as there so many degrees of freedom for this problem that we simply could not write an efficient piece of code to work in all cases.

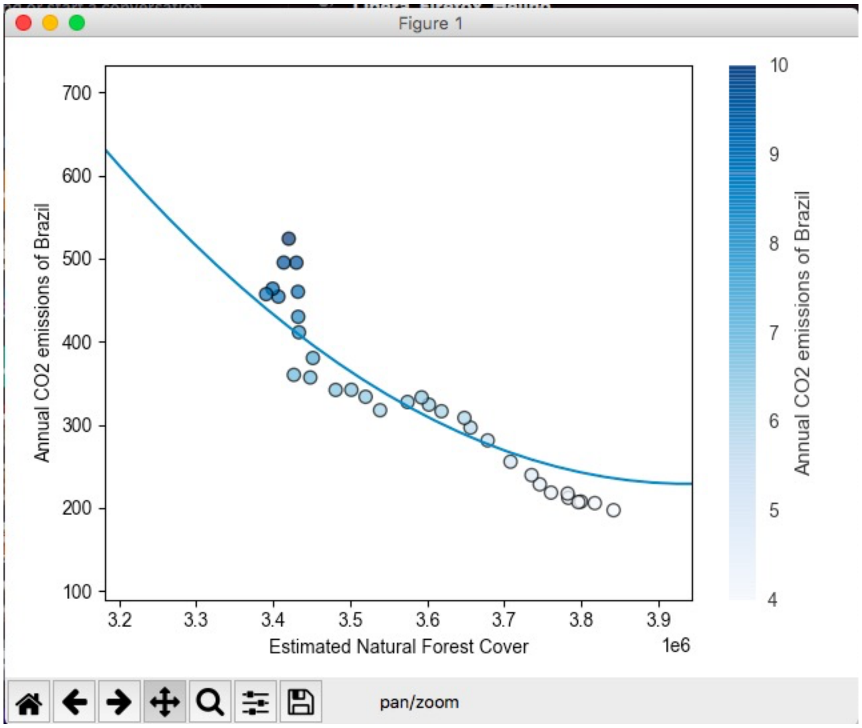
As such, we switched our approach to the more 'linear algebra way' of solving this task, by using matrices instead. We made good use of the Gauss-Markov theorem (Frank Wood, 2011), and applied it to the ordinary least squares method (Gordon Anderson, 2009) to arrive at a relatively straightforward, already well-established, and mathematically proven approach that was more guaranteed to offer a good estimate for the polynomial model.

Because of the limited data size, we've also decided that extrapolation would not be appropriate, as the given inputs are not enough to make an accurate enough prediction.

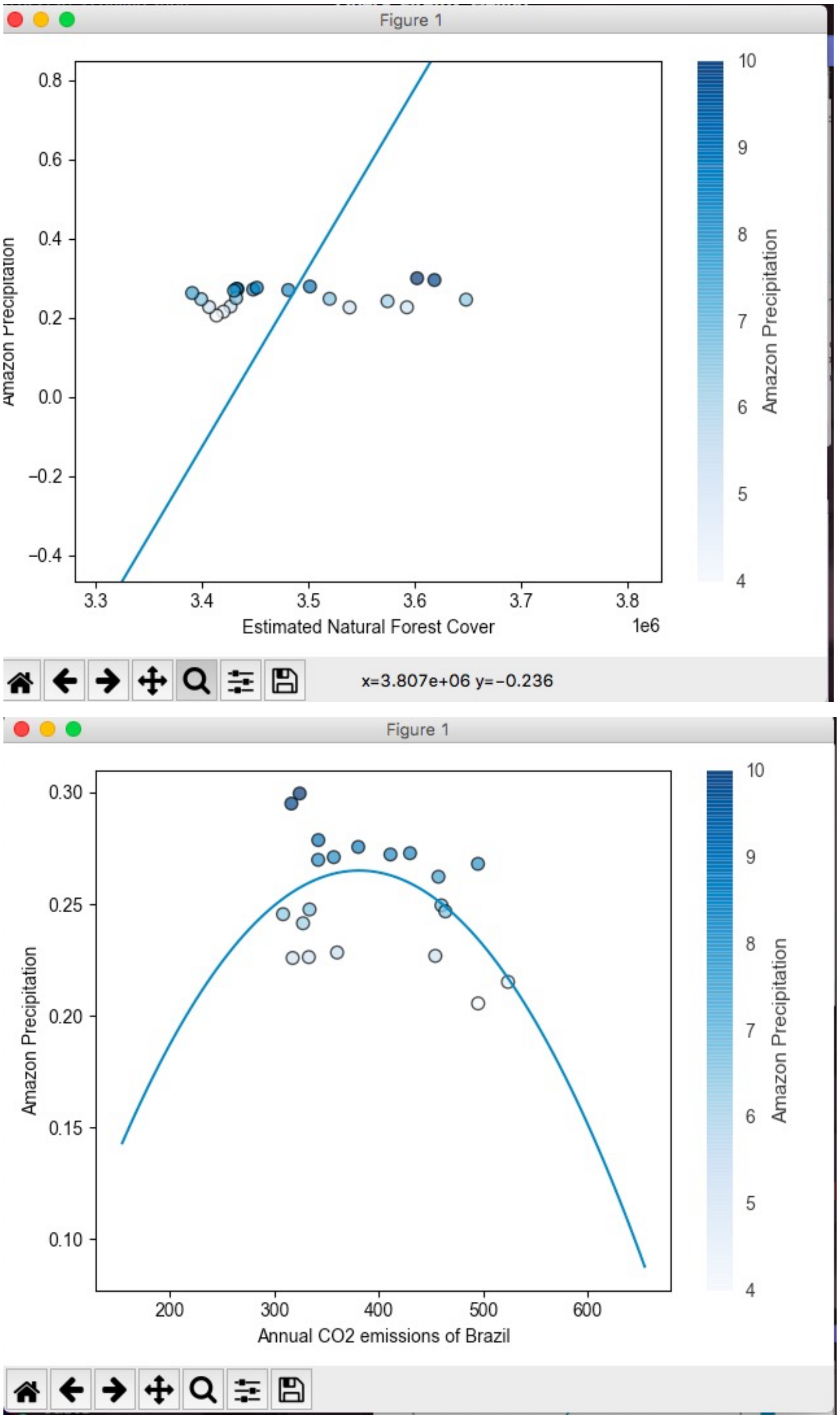
Furthermore, we decided to remove the trivia log in our interactive model after analyzing the data and finding out that there is not much trivia. However, we also added more features in the interactive model to balance this decrease in feature. For example, we added the flexibility for the user to choose which independent and dependent variable they wish to use for the calculation. We also added more values for the user to look up, namely the absolute error of the regression line at each x value.

7. Part 7

Do the results of your computational exploration help answer this question?



The coefficient of determinant (r^2) of the regression line in the graph above suggests that the Estimated Natural Forest Cover has a fairly close relationship with Annual CO2 emissions of Brazil. As the forest area increases, the annual CO2 emission decreases logarithmically. This suggests that forestation does help reducing CO2 on a local level. However, this relationship could also be falsely induced by modernization in the Brazil forests. The decrease in forest cover could be caused by the use of tree-cutting machines, and could lead to more factories in the forest — both are factors that contribute to CO2 emission. Although we cannot assume that the emission of CO2 is directly affected by the forest area, our analysis helps us conclude that there exists a logarithmic relationship between the two variables. Whether this relationship is direct or indirect, manipulating the forest cover has statistically show its effect on CO2 emission.



On the other hand, the Precipitation did not show a strong enough relationship with neither Estimated Natural Forest Cover nor Annual CO2 emissions of Brazil, which suggests that the impact of forest cover on precipitation is negligible with the presence of other factors.

Furthermore, although we did not have enough data points to conduct a justified extrapolation, with polynomial regression models, one must be careful when extrapolating from the available data. As we saw with the case for some of the polynomials we encountered when testing with randomly generated data points, the behaviour of the polynomial strayed away from the general trend as we moved away from the region of the original data.

As such, while the polynomial model certainly proved helpful for observing whether there exists any nonlinear trend in the data, we must bear in mind that this is not the only form of regressional analysis possible. In particular, we might also be motivated to test out our hypothesis with exponential models (especially as we have an estimate of whether the trend will be increasing or decreasing) since, then, the direction of change of the model is the same throughout. However, the main drawback behind these models (which is also the reason why we didn't use them) is that they're relatively more 'rigid' and thus have less flexibility in their application. Furthermore, for higher values of extrapolation, the exponential model would usually overestimate the behaviour of the data by quite a large amount.

Finally, we wish to address the issue of the way in which numpy calculates (or rather, 'approximates' is a better word) the inverse of a matrix. Since computers cannot accurately have a sense of fractions or irrationals, neither can they accurately handle polynomials, when we call upon the `matrix_inverse_numpy` function, this means that the computer is prone to floating point error at each step in the calculation. However, since the values we were dealing differed by quite a large margin (for instance, forest cover was of the order of 10^6, while precipitation was of the order of 10^{-1}), this meant that the resulting polynomials weren't as accurate as they would have been if we opted for a more manual approach of calculation, due to possible errors in the approximations used in the function `matrix_inverse_numpy`. To fix this, we might consider the 'relative polynomial regression model', i.e., consider the values relative to the maximum of the values, and effectively, 'scale' the range and domain of the polynomial to simply $[0, 1]$, which has the outcome of a better approximation of a trend but a more indirect polynomial equation relating the two variables.

What limitations did you encounter, with the datasets you found, the algorithms and libraries you used, or other obstacles?

The first obstacle we encountered was data downloading. NASA remove the FTP support a few years ago, so we had to download it using wget with login credentials, which required Linux background. Since some members in the team were interested in the Linux system, we decided to spend more time searching for ways to retrieve the data rather than moving on to another dataset. With some perseverance, we overcame this obstacle by splitting the team into groups that each retrieved a different data. This boosted our efficiency because one group was looking for a backup data in case we failed to download the NASA one at the end, while the other group was enriching themselves with relevant knowledge on data retrieval. As a success, we were able to download the data from NASA smoothly.

Another significant obstacle we faced was the unity of data structure among the group. For people spending more time with calculation, the Polynomial class we created ourselves was better to work with. However, it was quite different to know what the original data structure we downloaded, and from what the data should look like at the end. We resolved this conflict by creating a public interface first, that is, Climate class. We all agreed on using this public interface, so we can easily integrate with other's code. Also, we don't need to wait until others finish before we begin our job, because we can expect the result class of our partners' code.

What are some next steps for further exploration?

After learning that forest cover is logarithmically related to CO2 emission on a local level, we are curious about the reason. Although it makes sense that CO2 emission decreases as forest cover increases due to photosynthesis, the logarithmacity is not explained. We want to look further into into this by investigating forest of different sizes and examining the change in CO2 emission as a correlated effect of the change of forest size. Moreover, we are interested in applying this knowledge in our society. For example, knowing that the emission of CO2 decreases logarithmically, should we encourage urban tree plantation as opposed to forestation, since increasing the forest size of the smaller forests yields as greater rate of change? Or maybe it is only logarithmic within the data we analyzed, and it shows a different trend on smaller forests so forestation is still more effective than urban tree planation in terms of decreasing CO2.

Nevertheless, our current findings suggests that we can at least focus on going in the direction of encouraging tree plantation and preventing deforestation, before investigating which is more efficient for the climate in our future exploration.

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