Machine Learning Data Commons Web Portal

Developing a ML tutorial using a GECKO-A dataset



Omar Chaarawi, CU Boulder & SIParCS July 27, 2021



This material is based upon work supported by the National Center for Atmospheric Research, which is a major facility sponsored by the National Science Foundation under Cooperative Agreement No. 1852977.

Motivation

Previous tutorials developed:

- Artificial Intelligence for Earth Systems Science (AI4ESS) Summer School
- AMS ML Short Course

| + Code | + Tex | a copy to | Danie | | | | | | | | | / Editing | |
|--------|--|---|--|--|---|--|-----------------------------|-------------------------------|-------------|-------------|---------------------|-----------|--|
| 0 | | Time [5] 1 | Precursor [ug/m3] | Gas [ug/m3] | Aerosol [ug_m3] | temperature (K) | solar zemith angle (degree) | pre-existing aerosols (ug/m3) | o3 (ppb) | nox (ppb) | oh (10^6 molec/cm3) | | |
| 0 | count | 1.400000e+03 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | 1400.000000 | | |
| | mean | 2.160005e+05 | 0.003125 | 0.027601 | 0.032703 | 277.413314 | 44.923263 | 11.388653 | 75.422052 | 2.124920 | 5.493831 | | |
| | std | 2.329138e-10 | 0.002215 | 0.013710 | 0.020581 | 21.712817 | 26.064725 | 21.082845 | 43.495636 | 2.468413 | 2.582480 | | |
| | min | 2.160005e+05 | 0.001244 | 0.004393 | 0.001704 | 240.024774 | 0.018612 | 0.010031 | 1.017131 | 0.100186 | 1.011878 | | |
| | 25% | 2.160005e+05 | 0.001598 | 0.016943 | 0.015331 | 258.824046 | 22.235231 | 0.099235 | 36.417272 | 0.314910 | 3.231017 | | |
| | 50% | 2.160005e+05 | 0.002253 | 0.024975 | 0.028837 | 277.096217 | 44.858750 | 1.085965 | 76.044879 | 1.004467 | 5.479992 | | |
| | 75% | 2.160005e+05 | 0.003803 | 0.035183 | 0.048352 | 296.098148 | 68.039551 | 10.946353 | 112.534705 | 3.059370 | 7.758317 | | |
| | max | 2.160005e+05 | 0.012054 | 0.079415 | 0.086156 | 044 000547 | 00.050054 | | | | | | |
| | <pre># Spagh num_exps exps = plot_df fig, ax for i,1 for</pre> | etti plot ran piriments = 30 sorted(random = train.loc; = plt.subplo ab in euumra exp in exps: ax[i].plot(p | dom experiment tis sample(list(trais train['id'].isin() tts(],1, figsize=(tts(['Precursor [w lot_df[plot_df[']; | <pre>meseries s['id'].unique sxps)].reset_; 12,14)) p/m3]', 'Gas d'] == exp].ii</pre> | e()), num_expirim index(drop=True) [ug/m3]', 'Aeroso loc[1,0], plot_df | <pre>ald.B004/ ents)) 1 (og/m3)')): (plot_df['id'] =</pre> | * exp].iloc[:,i+1]} | 99.280288 | 149.927193 | 9.980638 | 9,999925 | | |
| | <pre># Spagh num_exp exps = plot_df fig, ax for i,1 for ax[ax[</pre> | etti plot ran siriments = 30 sorted(random = train.loc[:= plt.subplo ab in enuera exp in exps: ax[i].plot(p i].set_xlabel i].set_ylabel | <pre>dom experiment til .sample(list(train train['id'].imin() ts(3,1, figsize=(te(['Precursor [w lot_df[plot_df['ii ('Elapsed Time [s .(lab, fontsize=16)</pre> | <pre>neseries n['id'].uniqus sxps]].reset_] 12,14)) g/m3]', 'Gas d'] == exp].ii))</pre> | e()), num_expirim index(drop=True) [ug/m3]', 'Aeroso Loc[1,0], plot_df | <pre>antabasi ents)) [plot_df['id'] =</pre> | sidede4 | 99.290288 | 149.927193 | 9.960638 | 9.999025 | | |
| | Spagh num_exp exps = plot_df fig, ax for i,1 for ax[0.07 - [[[[[[[[[[[[] [] 0.03 - 0.03 - 0.03 - 0.03 - 0.03 - 0.03 - 0.03 - 0.03 - 0.04 - 0.05 - | etti plot rans irinenta = 10 sorted(randor = train.loef = plt.subplot ab in ecumerate ab in ecumerate ar(i).plot(p i).setylabel i).setylabel | dom experiment til .emple(list(trai) .trais['id'].isia(trais['id'].isia(trais['id'].isia(trais['id'].isia(trais['id'].isia(trais['id'].isia('id').isia('id' | <pre>sesseries ('id').emique sesseries ('id').emique y(n3)', 'Cas d'] == exp].i) </pre> | a()), num_expirim index(drop-True) (ug/m3)', 'Aeroso Loc[1,0], plot_df | <pre>sidested ents)) 1 (og/m1)')): [plot_df['id'] =</pre> | • emp).iloc(1,i+2)) | 60.20088 | 149.92/193 | 9.460438 | 9.99923 | | |

AI4ESS Hackathon made use of GECKO-A data, but is not introductory level course

Goal: Combine principles of hackathon notebook and AMS ML Short course to develop introductory ML courses that utilize GECKO-A data





GECKO-A Data

GECKO-A is a hyper-explicit mechanism for determining quantities of chemical precursor present in the atmosphere

Quantities of chemical precursors play a role in climate through both direct and indirect radiation effects

Accurate predictions of aerosolized quantities of VOCs might improve climate prediction models, though GECKO-A is far too computationally expensive



ML Techniques could be used to create an emulator that would generate data close enough to explicit models that it would be useful in developing climate models



Suggested Layout for ML Tutorials

How would a ML scientist approach the GECKO-A emulator problem?

Notebook 1:

- Gathering Data
- **Preparing Data**

Notebook 2:

- Choosing a model ٠
- Training that model using our ٠ data

data for each feature distributed?

Notebook 3:

- Evaluating that model
- **Tuning parameters**

Notebook 4:

Predict ٠





Data Distributions



Tools of the trade are used to better distribute the data



Data Distributions



Log transform followed by a z-score standardization allows for a more normal distribution



PCA Visualization and Exploration



Correlation Matrix before PCA

Correlation Matrix of inverse transform after PCA

Shows the possibility for aggregation of some data (reduce dimension)



PCA Visualization and Exploration



Much of the information can be explained using only 10 principal components

Reasonable to aggregate some of the data. Summing was used in practice, but option to further explore PCA





Choosing a model



Linear Regression on unscaled data



Linear Regression on scaled data

- Different methods for scaling are discussed and their effect on building a model reflected through comparison
- Even minor improvements draw out major data incites
- Performing a log transform on some features allowed us to capture the diurnal signal of the data, which is not an easy task





Choosing a model



- Though linear models are often the easiest start with, they have limits
- May not be the best model for the problem at hand
- How do you show that you have exhausted a model



- Ridge regression at alpha=200
- Shows improvement in prediction of aerosol with only small cost in accuracy for other components

We have essentially exhausted a linear model and can move on to others



Choosing a model



The goal of the tutorial is to lead the user to a model that performs as well as the model developed by the AIML group

There is room for further exploration. The PCA route is still underdeveloped

Could a user improve the linear models using PCA to aggregate features, rather than summing the bins?



Future Direction

Finish and release tutorial

Tutorials will be released as a self-guided set of Jupyter Notebook tutorials with publicly available GECKO-A data.

Google Collab

Tutorials developed in Jupyter will be migrated to Google Collab and tested in that environment.

Test in an off-premises environment

The tutorials have so far been developed in NCAR's Casper supercomputer. Testing needs to be done to insure the tutorials remain accessible in a local environment.

Discontinuation of the "Iris" Dataset

The popular dataset is problematic because of historical reasons and does not make for an appropriate dataset for a tutorial. Examples using this dataset will be removed and replaced.





Acknowledgements

David John Gagne

John Schreck

The AIML group

SIParCS program

NCAR, UCAR



