Weather to Cosmic Rays: Machine Learning for Particle Flux

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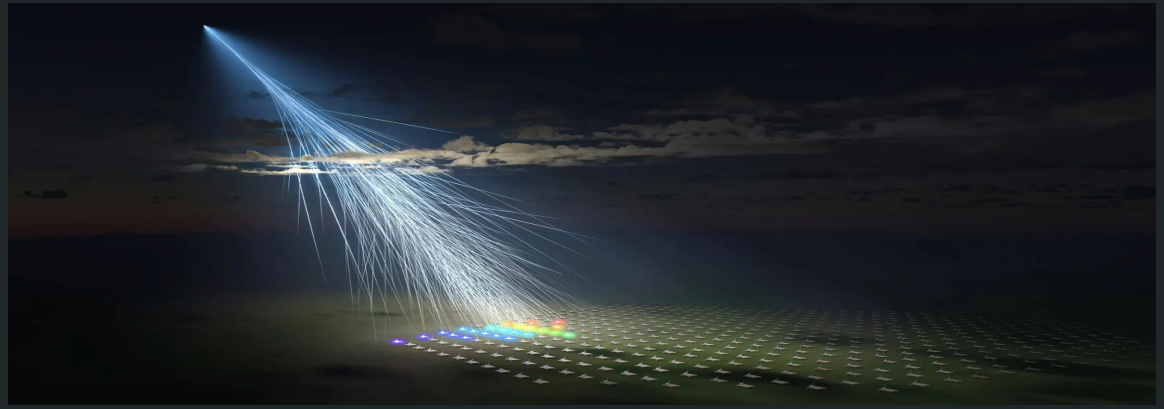
Presentation Outline



Introduction
Overview, Cosmic Rays, Pierre Auger Observatory

Methods
SHAP Feature Importance, Data, Preprocessing, Weather, Model

Results
Model Performance and SHAP Feature Importance

Conclusion
Outlook, Future Improvements

Figure 1: Particle Shower induced by Cosmic Ray [1]

Overview

- Use weather data from the Pierre Auger Observatory to predict cosmic ray count rates
- Understanding this relationship helps pick experiment site location, understand variations in cosmic ray data, and protect sensitive equipment from cosmic ray exposure
- Use SGDRegressor (linear), and a gradient boosted decision tree (non-linear)
- Verify our physics based understanding by investigating feature importance with SHAP (SHapley Additive exPlanations)
- Goal is to have a Mean Absolute Error < 15 counts per second

Cosmic Rays

- Energetic particles from outer space
- Can originate from the Sun, black holes, supernovae, and outside our galaxy
- Interactions with the atmosphere create showers of secondary particles (air showers)
- Secondary Showers are measured on the surface for insight into cosmic ray energy, however are subject to variations in the weather

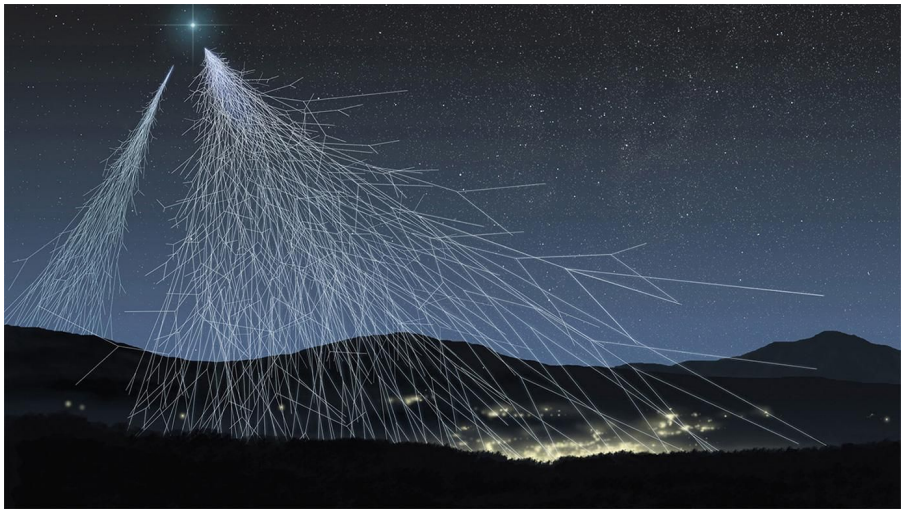


Figure 2: Particle Shower induced by Cosmic Ray [2]

Pierre Auger Observatory

- Cosmic Ray observatory located in Argentina
- 1660 Water tank detectors are spread out over 3000 km^2
- Detect particles on the surface of the earth
- Also have UV detectors that measure the brightness of UV light emitted from interactions in the atmosphere
- Pierre Auger has five different weather stations taking measurements on pressure, density, temperature

Figure 3: Water Detector at Pierre Auger [3]

Weather

- Different atmospheric variables affect the characteristics of an air shower
- While not a huge factor, variables can induce biases in measurements
- Pierre Auger already uses linear correction shown in eq 1, to account for variations in weather
- Our goal is to use ML Models to recreate this relationship leveraging the fact that this relationship exists

$$S(r_{\text{opt}}) = S_0 \left[1 + \alpha_P (P - P_0) + \alpha_\rho (\rho_{\text{d}} - \rho_0) + \beta_\rho (\widetilde{\rho} - \rho_{\text{d}})\right]$$

Equation 1: Correction from Pierre Auger to adjust for weather conditions. S(r_opt) is the detected signal, S_o is the expected signal, alpha and beta are coefficients, P_0 and p_o are the yearly averages for pressure and density, P and p_d are the measured pressure and density, and p_~ is the density two hours ago (to account for changes in density higher up in the atmosphere where the air shower began [4]

SHAP (SHapley Additive exPlanations)

- Method for interpreting machine-learning models by explaining how each feature contributes to a single prediction and to the model overall
- Based on Shapley Game Theory, treats each feature as a player in a game and assigns each feature a share of responsibility in making a decision
- Model Agnostic
- Allows us to directly see which features have the greatest impact on the final predicted cosmic ray flux
- Greater model transparency and illustrates direct relationships between the prediction and feature values [5]

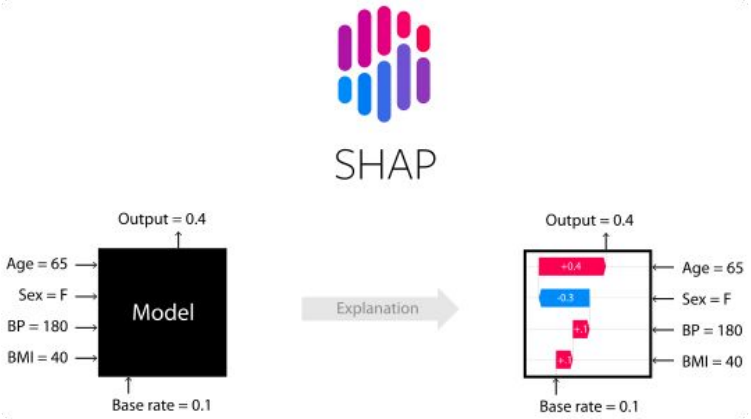


Figure 4: Water Detector at Pierre Auger [7]

Data

- Data is from the Pierre Auger Open-Release Scalar Data set [7]
- Has 10% of all cosmic ray data, and 100% of all weather data collected from March 2005 to December 2020
- Weather data used is a culmination of data collected at every station
- Scalar mode counts the total number of hits across all 1660 detectors within a 1 second coincidence window and is uncorrected for weather effects and operable detectors
- Scalar Data has been used to measure solar activity, and Forbush decreases [8]

Pre-Processing

- Scalar data has average particle count rates over 15 minute intervals
- Atmospheric data has average data collected over 5 or 10 minute periods
- Inspection of Data revealed high dependency on the year the data was taken
- Dependency on year comes from changes in data-taking strategy [9]
- Trained on Data taken post 2012
- Trained models with year as a one hot encoded feature and without it

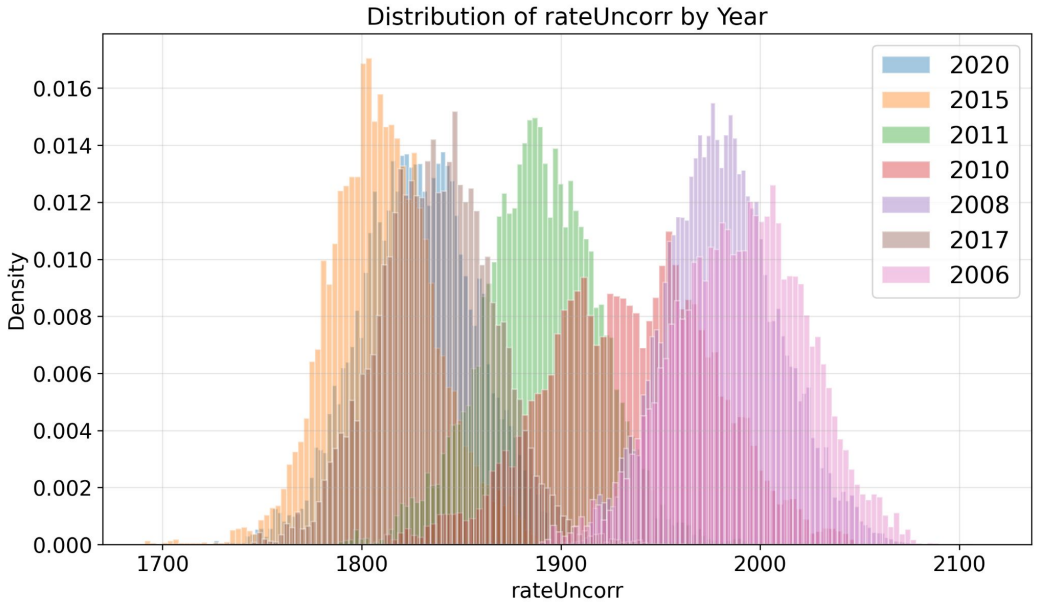


Figure 4: Histogram of counts/s by year. Shows high variance between years when data was taken. Each year appears to have its own gaussian distribution

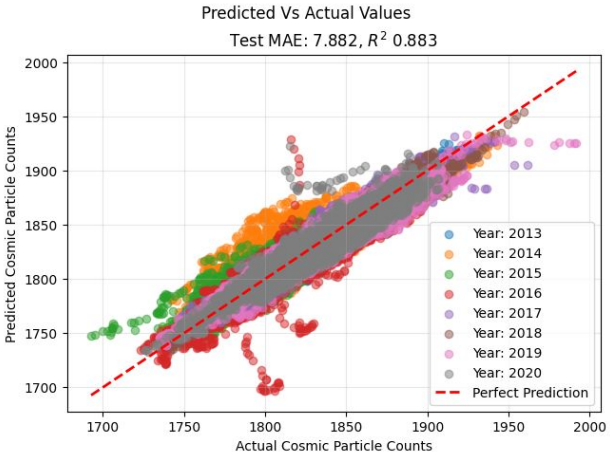
Models

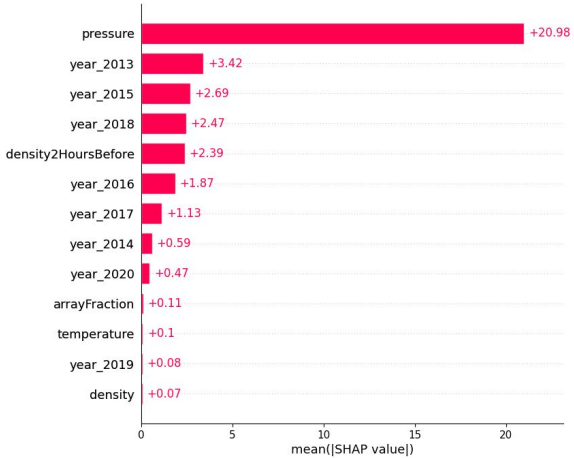
SGDRegressor and HistGradientBoosting

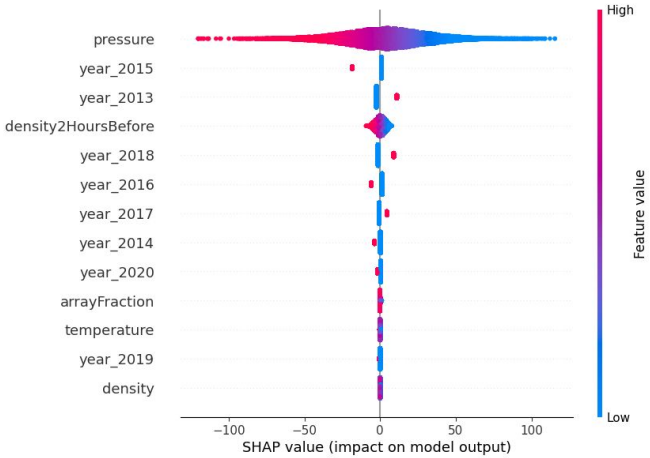
- Performed Nested Cross Validation:
  - 5 Fold Outer CV
  - 3 Fold Inner CV
- Grid Search for Hyper-parameter optimization
- Goal: Minimize Mean Absolute Error
- Trained two models, one with OneHotEncoder Year features, one without

SGDRegressor Performance and Interpretability

- Performance with time features: Nested CV MAE = 7.88 +/- 0.01

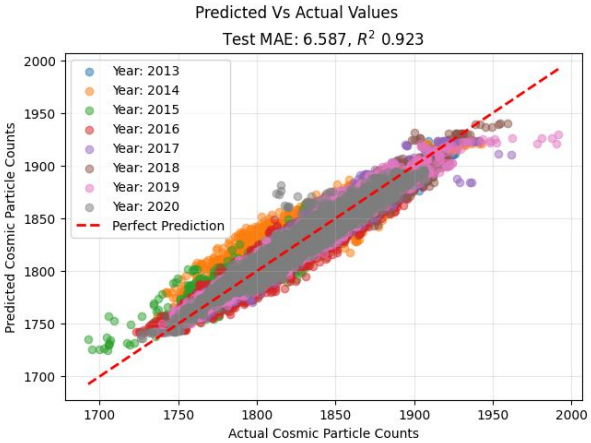


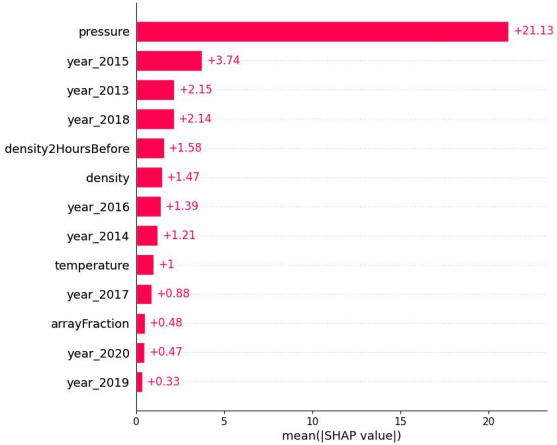


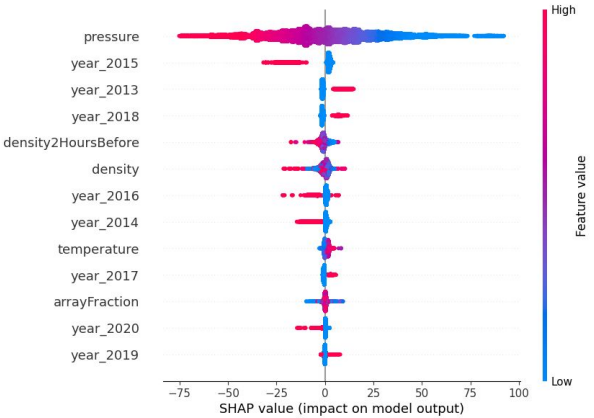


HistGradientBoostingRegressor Performance and Interpretability

- Performance without time features: Nested CV MAE = 6.59 +/- 0.02







Conclusions

Results:

- HistGradient Boost outperformed SGDRegressor, much faster run time and lower MAE
- Both models met out goal of MAE < 15 counts per second with and without year data
- Feature Importance confirmed pressure was the major player in decision making
- Revealed year as an unexpected important player, revealed inconsistencies in data-taking that the model would have been unable to account for otherwise

Future:

- Investigate Weather dependence on particle phenomenology (types of particles, energies, spatial distribution)
- Generalize model to work for different locations

References

[1]astronomers-highest-energy-particles(Picture on Presentation Outline Slide)

[2] what-are-cosmic-rays (Picture on Cosmic Ray Slide)

[3]hybrid-detector (Picture of Water Tank on Pierre Auger Slide)

[4]1ef8bb507e47d8bc4ac3b456b7ff55ef(Weather Correction Pierre Auger)

[5]8a20a8621978632d76c43dfd28b67767-Paper.pdf[SHAP Citation]

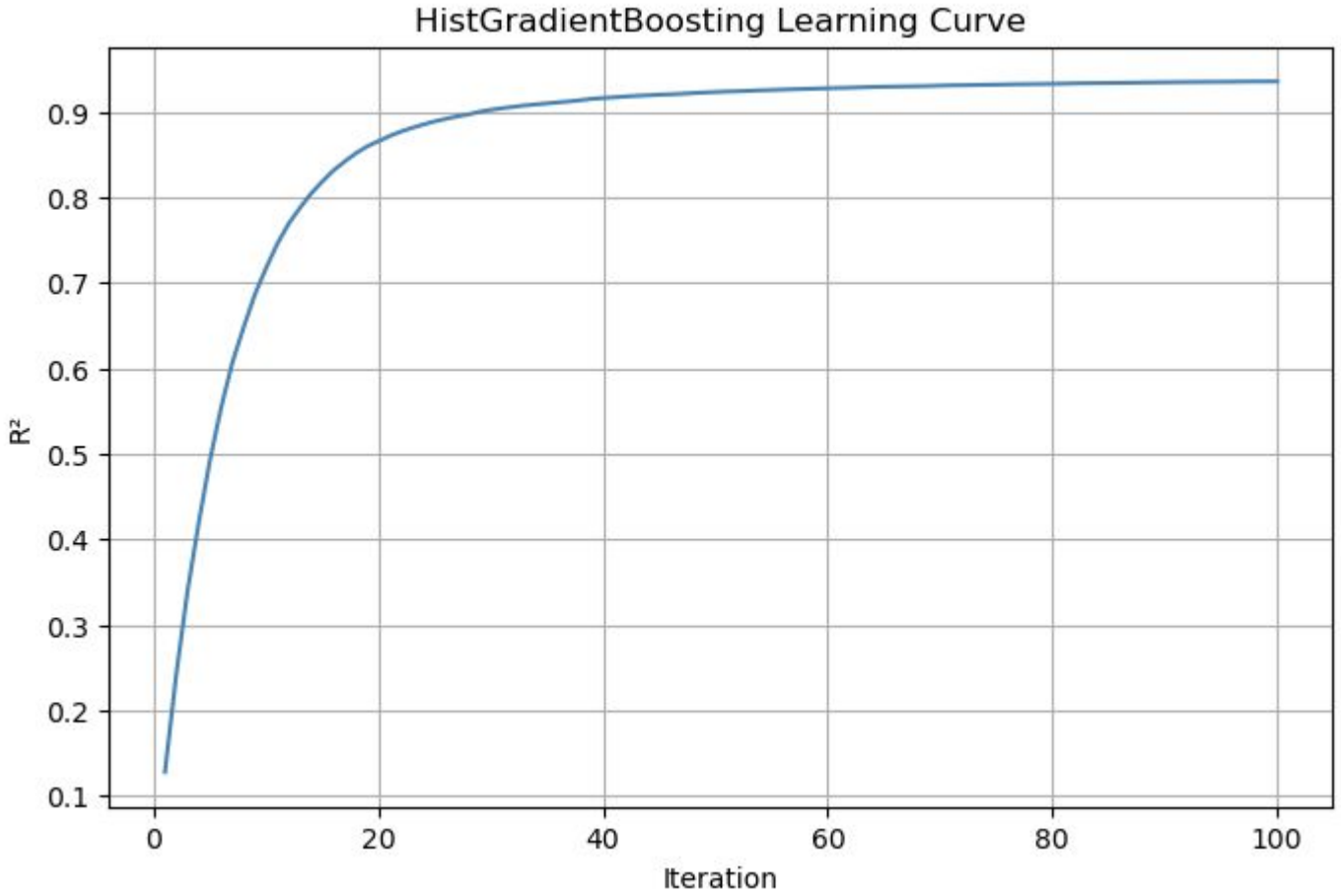
[6]shap (Shap Image and Github)

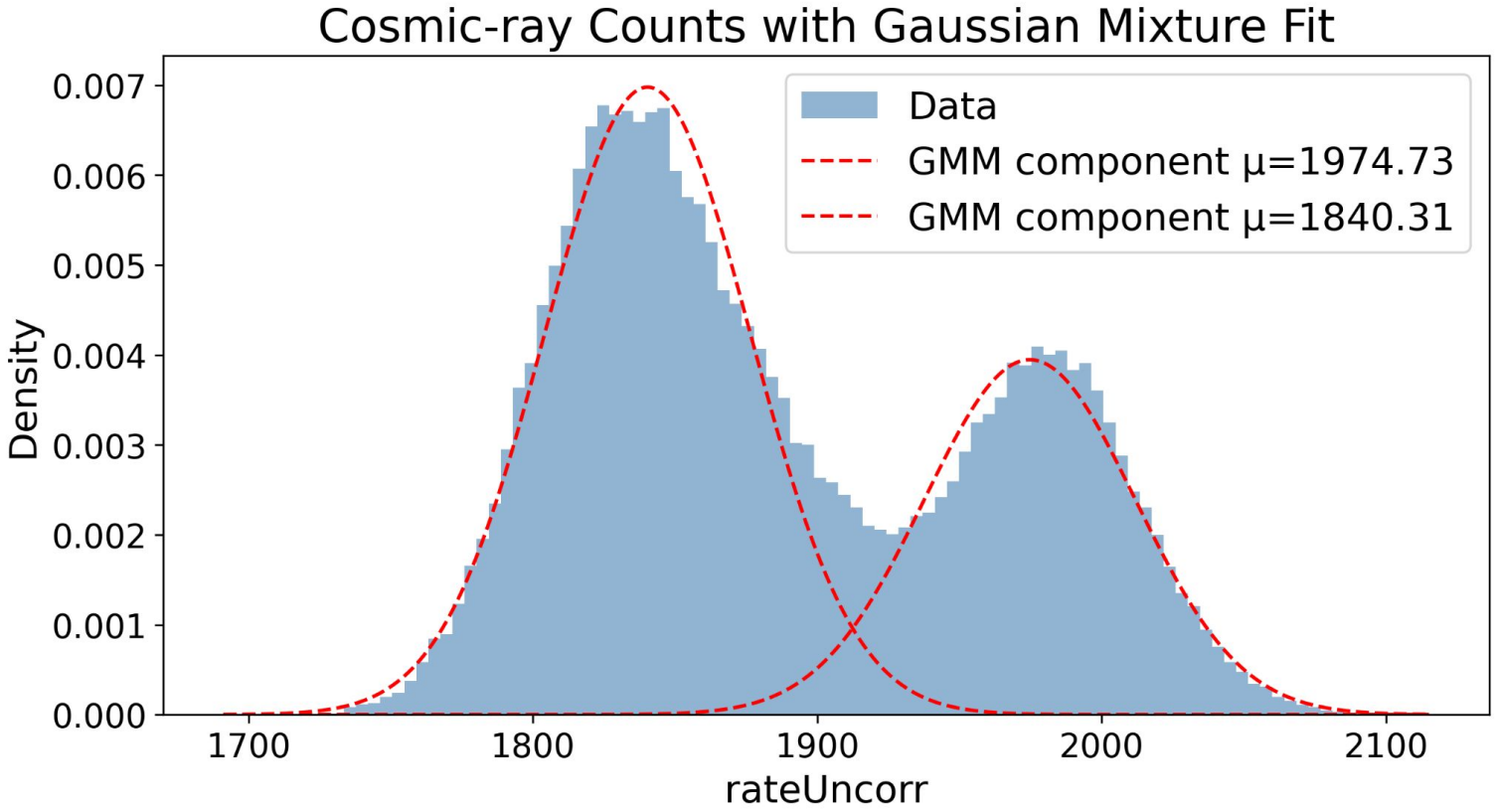
[7]10488964[Open-Data]

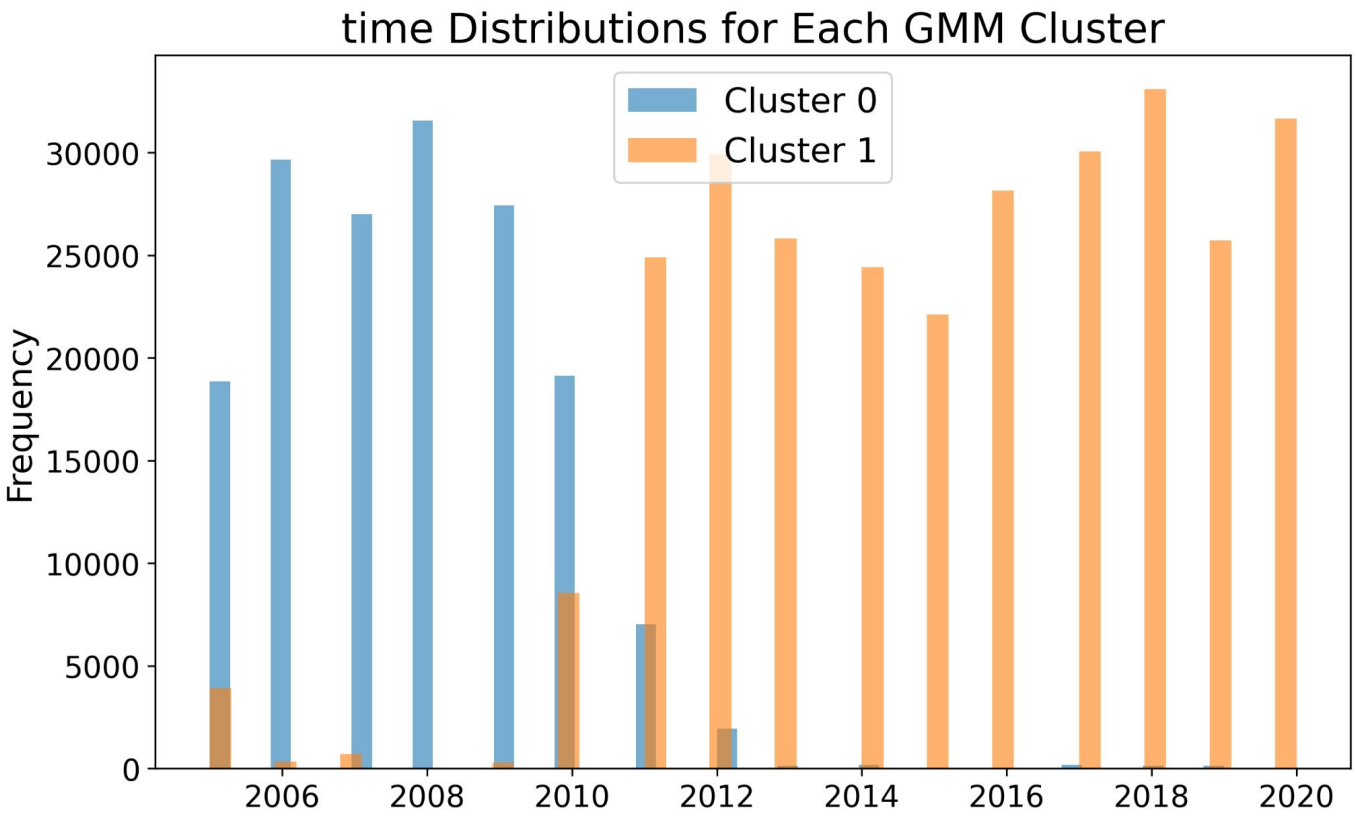
[8] pdf (Pierre Solar Activity Paper)

[9]pdf(Pierre Scalar Data Paper)

Questions?


HistGradientBoosting Learning Curve
R²
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
0
20
40
60
80
100
Iteration


Cosmic-ray Counts with Gaussian Mixture Fit
Data
GMM component μ=1974.73
GMM component μ=1840.31
Density
0.000
0.001
0.002
0.003
0.004
0.005
0.006
0.007
1700
1800
1900
2000
2100
rateUncorr


time Distributions for Each GMM Cluster
Cluster 0
Cluster 1
Frequency
0
5000
10000
15000
20000
25000
30000
2006
2008
2010
2012
2014
2016
2018
2020