NEURAL INFORMATION PROCESSING SYSTEMS

kaggle

7th Place Solution: A Hybrid Physics-Based Method with Neural and Tree-Based Model Corrections

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Ariel DATA CHALLENGE

Background

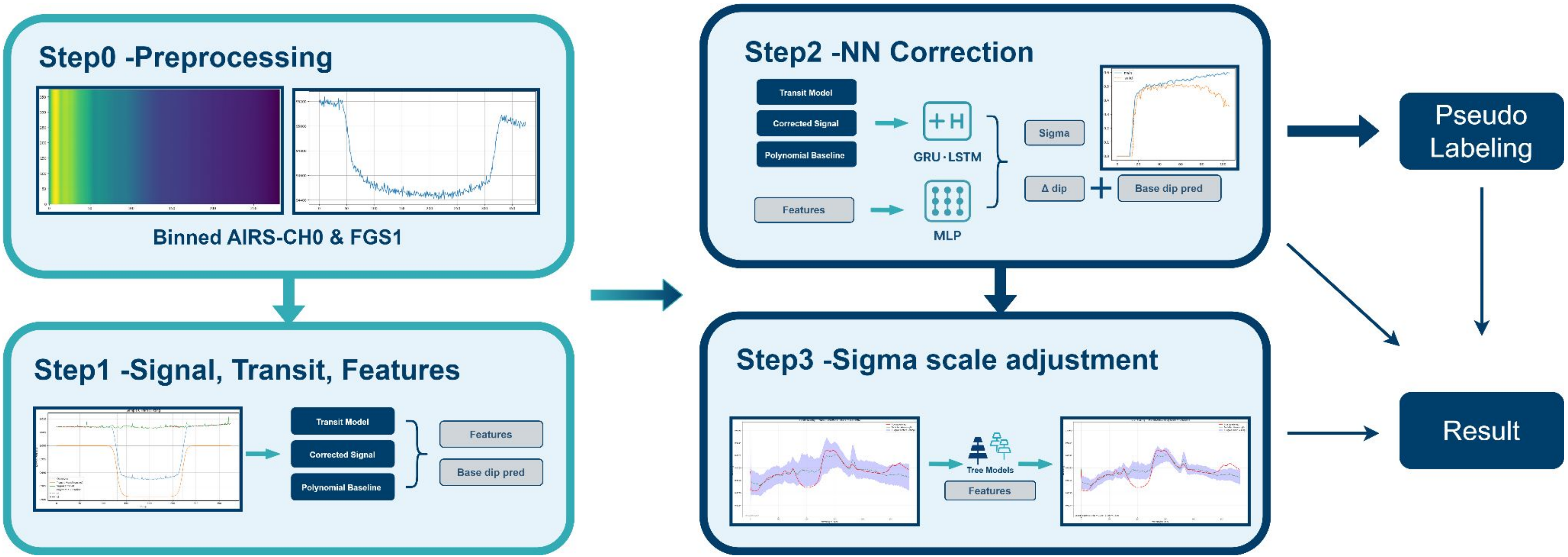
- YuXuan Wu (Kaggle ID: Horikita Saku）
  - Research Assistant at *China National Center for Bioinformation*
  - Machine Learning / Genetics / Single-cell omics
  - Interested in Astronomy
  - Applying for PhD. horikitasaku@outlook.com

- Kaito Takano (Kaggle ID: takaito）
  - Quantitative Analyst at *Nomura Asset Management Co., Ltd.*
  - Visiting Researcher at *Osaka Metropolitan University*
  - Finance / Natural Language Processing / Machine Learning
  - Ph.D. (Science and Technology)
  - I like competitions!

Agenda

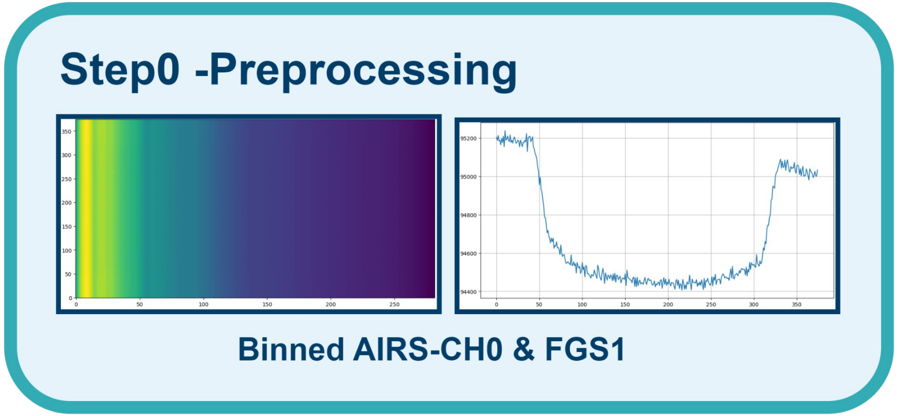
1. Background
2. **Main Solution**
   - Step0: Preprocessing
   - Step1: Signal, transit, and feature extraction
   - Step2: Neural Network Correction
   - Step3: Sigma scale adjustment
   - Step4: Pseudo Labeling
3. What didn’t work
4. Summary

Main Solution : Overview

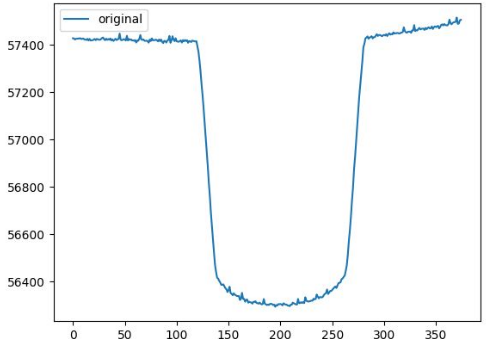


Step0: Preprocessing

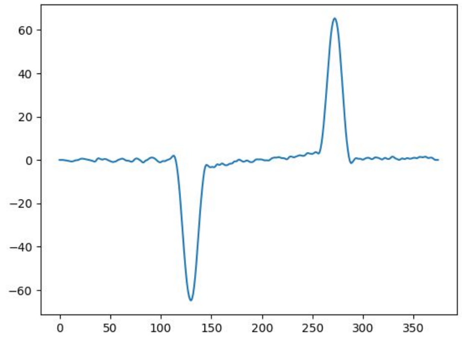
By *Ariel 2025*, we failed to discover any more magic or unique perspectives. Therefore, allow me to skip this part.



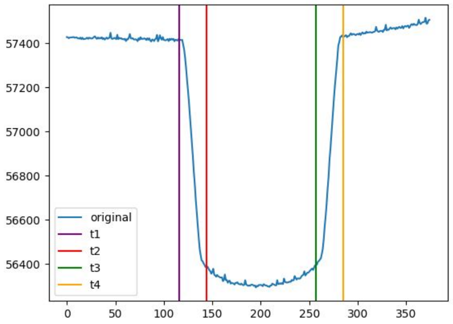
Step1.1: Phase Detector



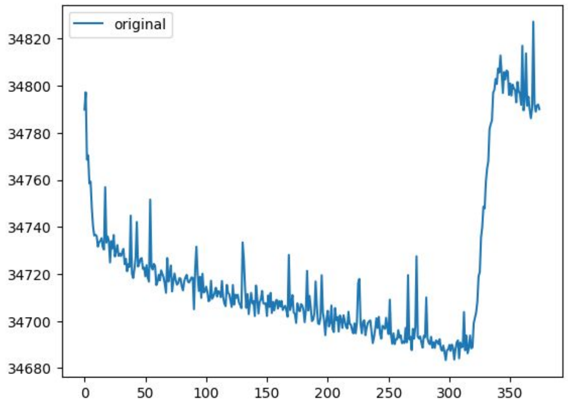
Smoothed Averaged Raw signal



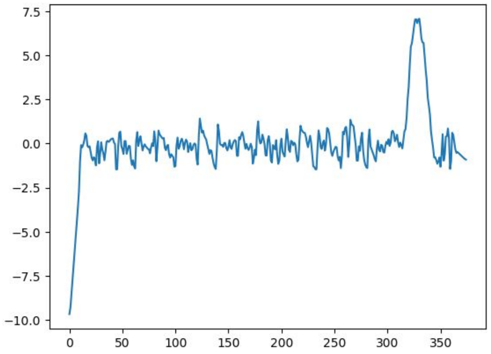
Smoothed Gradient

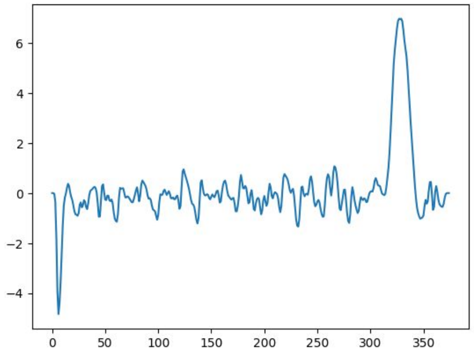


Step1.1: Phase Detector - Robustness



Planet 561423413





Step1.1: Phase Detector - Robustness

50 Samples From pre-ingress

50 Samples From ingress-transit

Difference

depth_samples_ingress

$$\mu_{\text{in}} = \mathbb{E}\big[\text{depth\_samples\_in}\big],$$

$$\sigma_{\text{in}} = \text{Std}\big[\text{depth\_samples\_in}\big],$$

depth_samples_egress

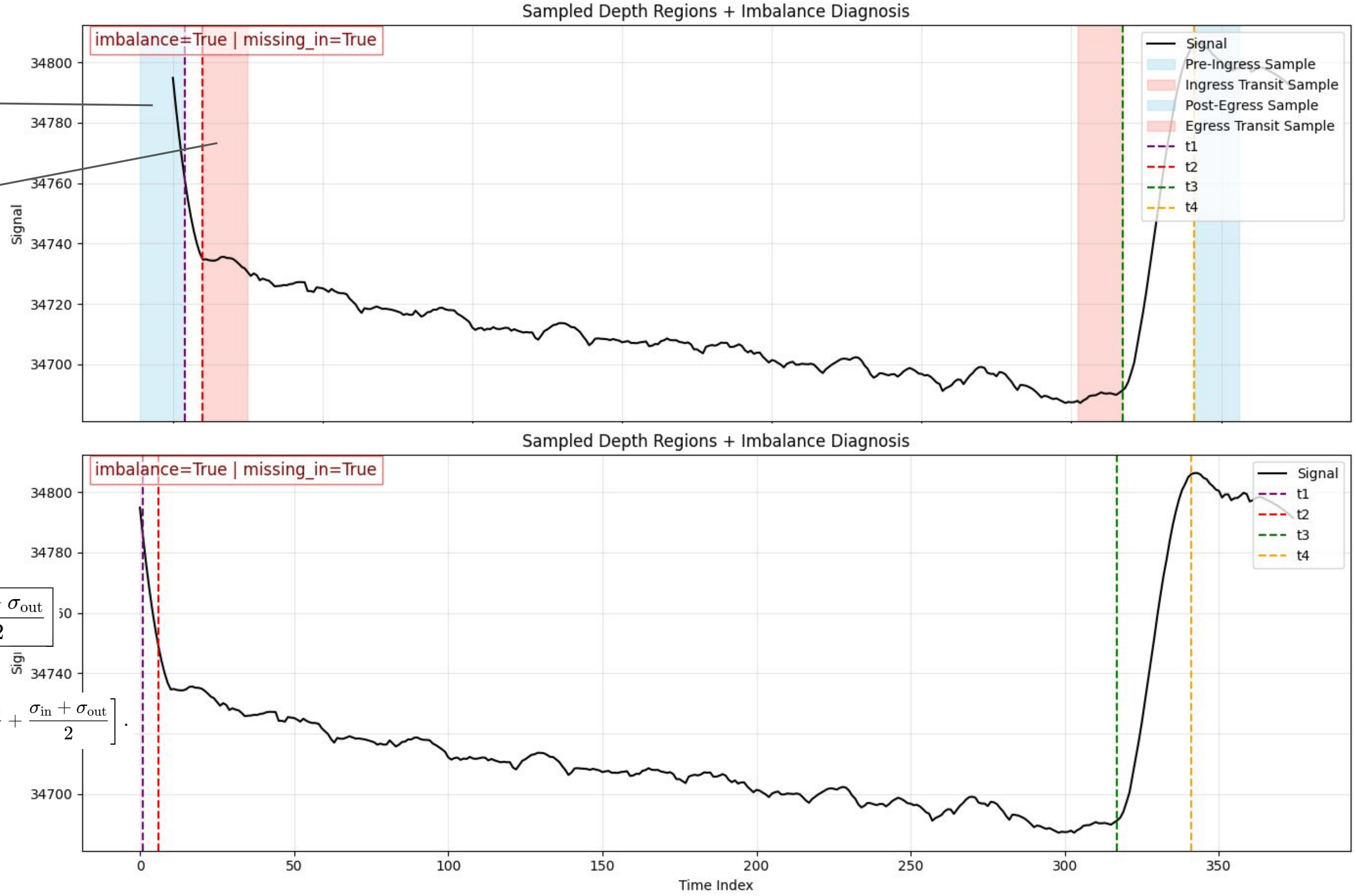
$$\mu_{\text{out}} = \mathbb{E}\big[\text{depth\_samples\_e}\big],$$

$$\sigma_{\text{out}} = \text{Std}\big[\text{depth\_samples\_e}\big].$$

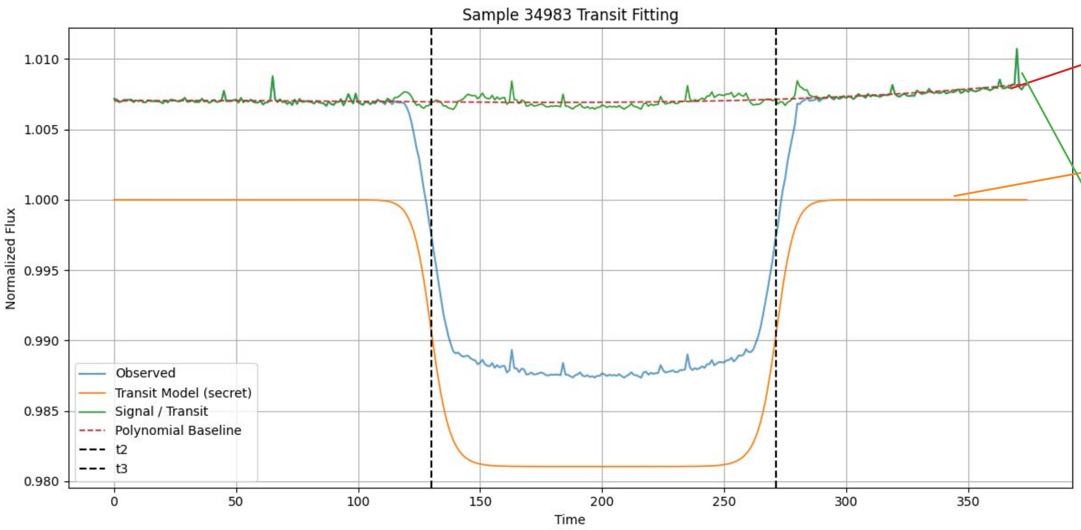
$$\boxed{\text{depth\_gap} = |\mu_{\text{in}} - \mu_{\text{out}}| + \frac{\sigma_{\text{in}} + \sigma_{\text{out}}}{2}}$$

$$\text{imbalance} = \left[\text{depth\_gap} > \frac{\mu_{\text{in}} + \mu_{\text{out}}}{2} + \frac{\sigma_{\text{in}} + \sigma_{\text{out}}}{2}\right].$$

Check whether the "depth_gap" is greater than the "upper bound of the normal difference"



Step1.2: Physics-based modeling and feature extraction



Polynomial Baseline

Obtained from the OOT

Following the approach of 2024 10th, define a bell-shaped function as the ideal model.

Fitting

Reconstructed signal:
If there is no transit

SOLUTION WRITEUP

10th Place Solution

Thanks to the participants and organizers for this competition. It was very interesting and educational. I hope to see Ariel on kaggle in a year. Approach We used a polynomial approximation approach. Thanks a lot to...

Nov 4, 2024 · NeurIPS - Ariel Data Challenge 2024 · 10th Place

XoMoX

...

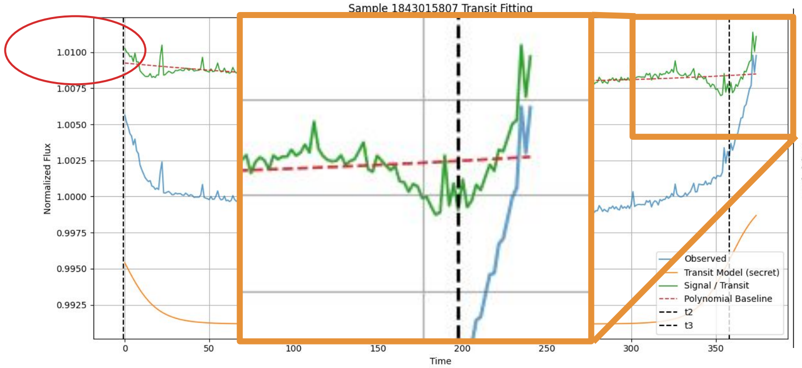
TALK
IN
COMPETITION: ARIEL DATA CHALLENGE 2024: EXTRACTING EXOPLANETARY SIGNALS FROM THE ARIEL SPACE TELESCOPE

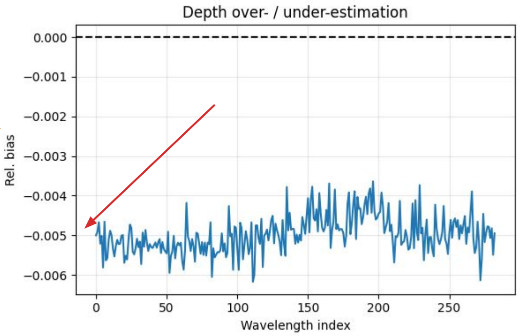
10th place: polynomial approximation, does it solve the problem?

Georgii Aparin

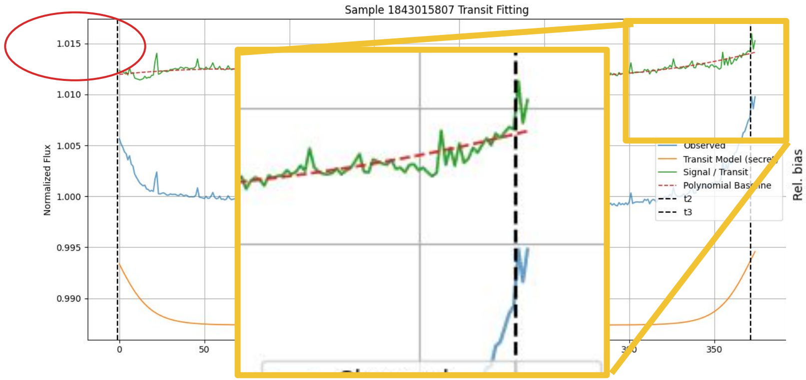
2024 Talk
in
Competition: Ariel Data Challenge 2024: Extracting exoplanetary signals from the Ariel Space Telescope

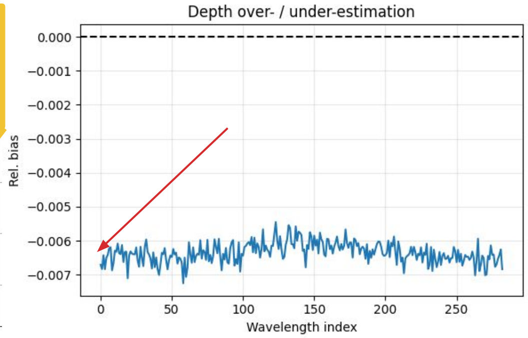
Step1.2: Low-degree polynomials and GP





Degree 2

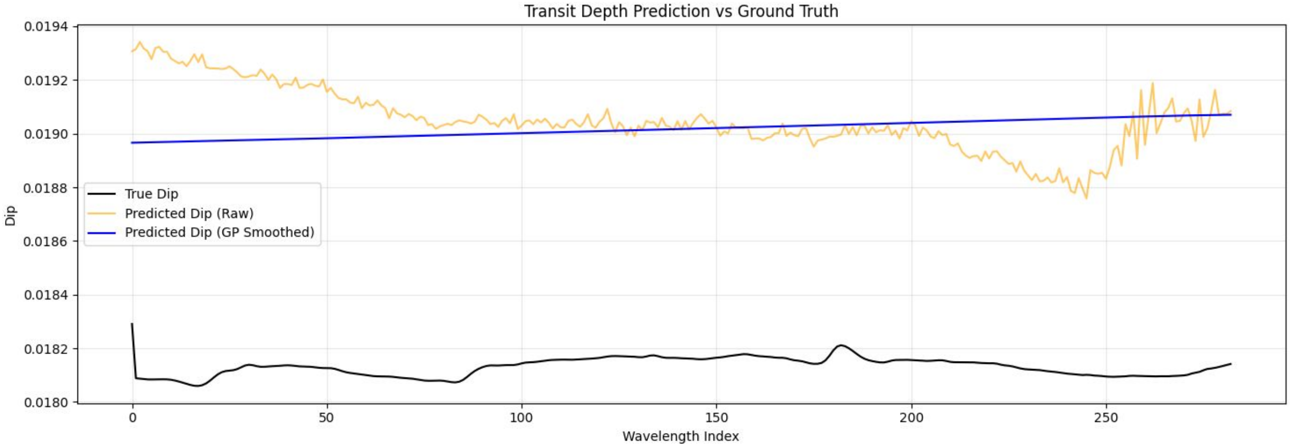




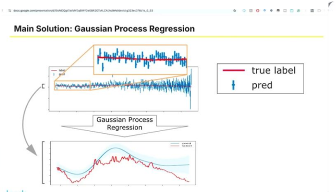
Degree 3

⭐The complexity of the baseline, and the OOT used for fitting the baseline

Step1.2: Low-degree polynomials and GP



Utilize GP to smooth the signal.
It works for all downstream corrections!



TALK
IN
COMPETITION: ARIEL DATA CHALLENGE 2024: EXTRACTING EXOPLANETARY SIGNALS FROM THE ARIEL SPACE TELESCOPE

1st Place Solution: Leveraging Knowledge of the Physical Model

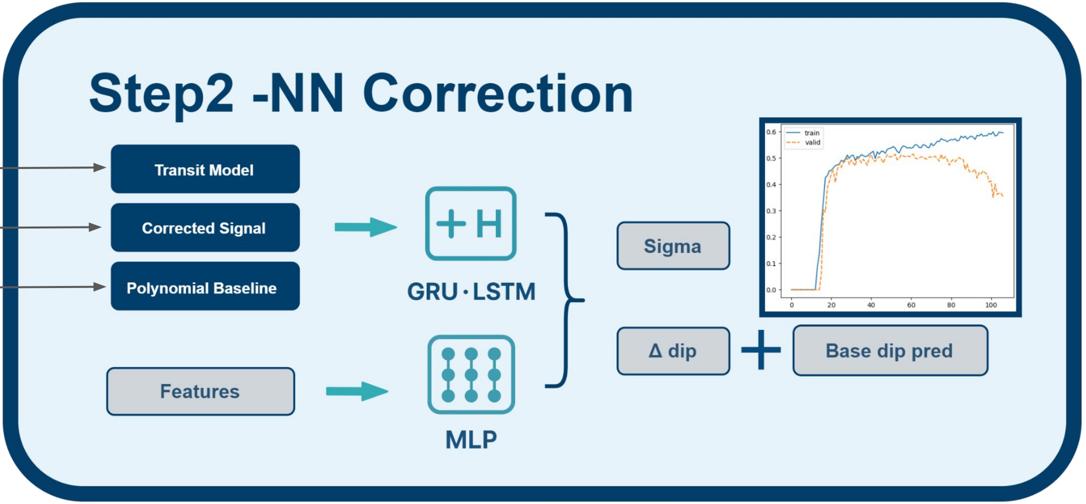
Kohki Horie · Yamato Arai

2024 Talk
in
Competition: Ariel Data Challenge 2024: Extracting exoplanetary signals from the Ariel Space Telescope

Step2: Difference correction with NN and base sigma prediction

Different combinations

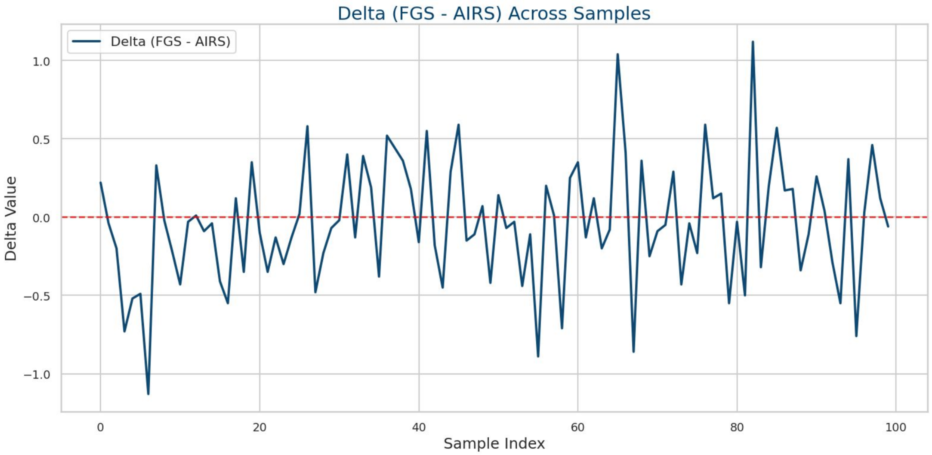
- Multilayer Perceptron (MLP)
- BiGRU + CNN + MLP
- BiLSTM + CNN + MLP
- BiLSTM + CNN + BiLSTM



Key techniques

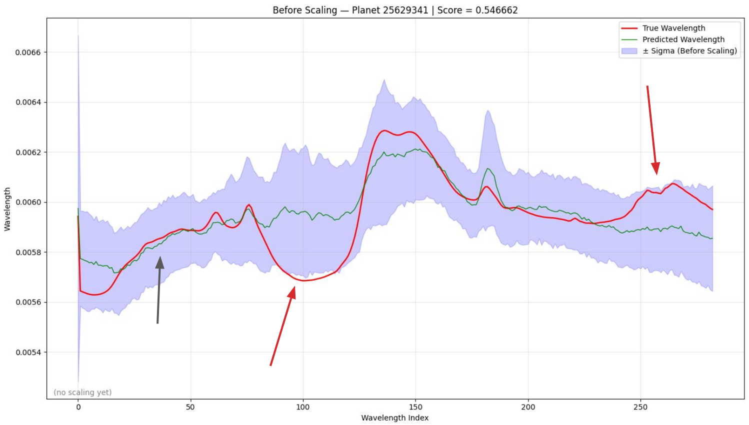
- Used **quantile regression** so the model can also predict sigma.
- Applied **Adversarial Weight Perturbation (AWP)**.
- Performed data augmentation by flipping signal and transit sequences along the time axis.
- Added noise to the data for further augmentation.

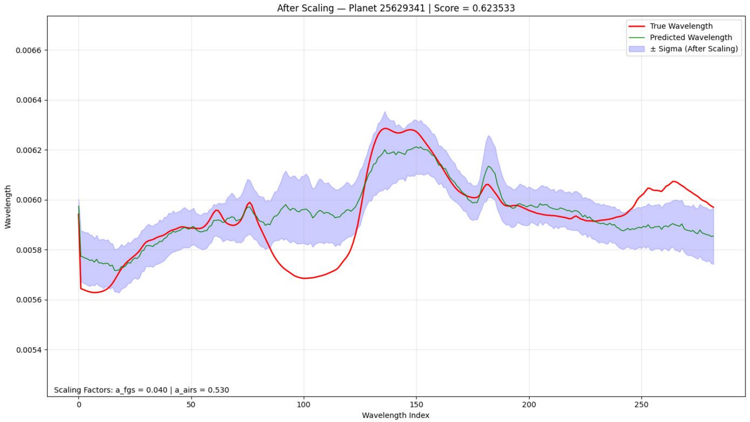
Step3: Sigma scale adjustment with Gradient Boosting



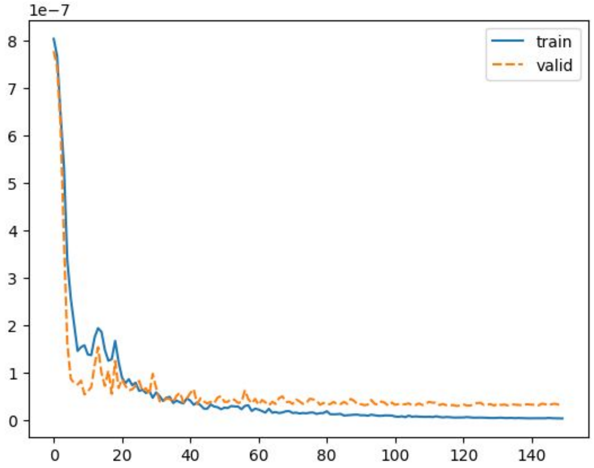
Separate the scaling factors for FGS and AIRS.
a_fgs * σ FGS : Scaling factor for FGS
a_airs * σ AIRS : Scaling factor for AIRS-CH0

Learned by LGBM/CatBoost/XGB

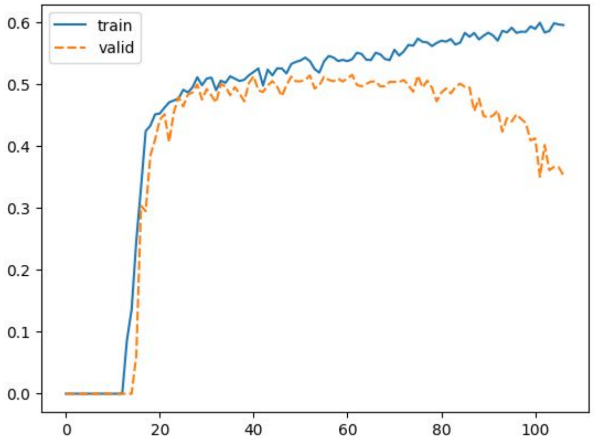




Step4: Pseudo Labeling



MSE transition
Almost no folds showed clear overfitting.



Competition metric
Tended to overfit more easily.

we only used the predictions for **dip**

What didn’t work

1. More Complex Physic Models
2. Using 1st Place Solution from ADC 2024’s Physic Model
3. More Complex NN model architectures
4. Some Magics during preprocessing

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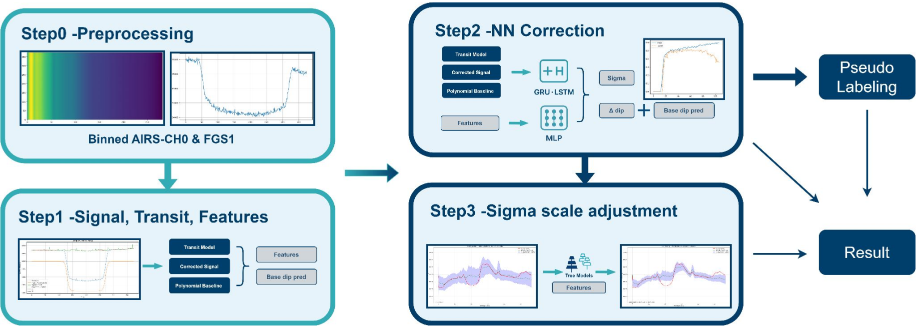
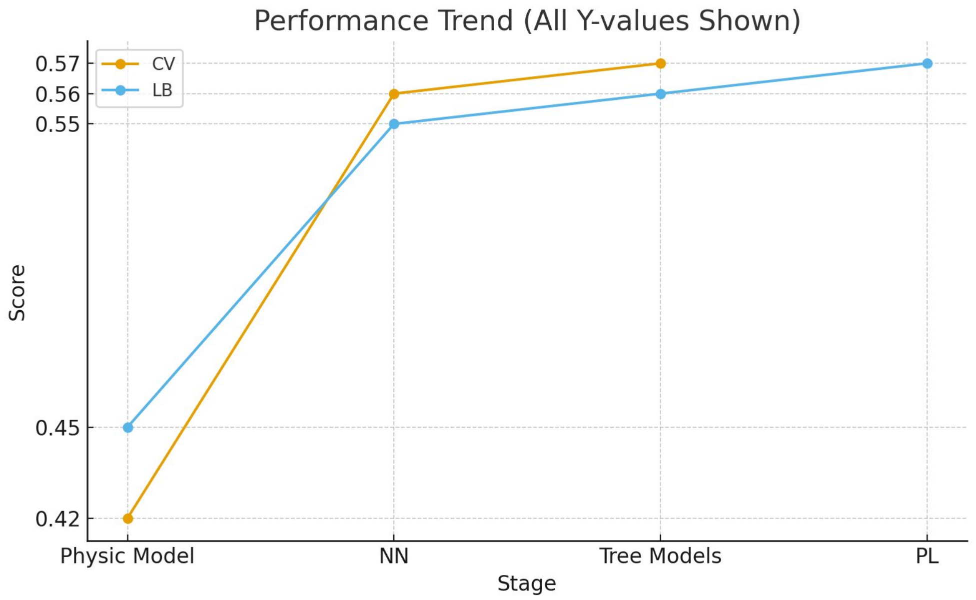
Summary





The scores at each stage are highly correlated with each other.
By using physical models to assist neural networks, we can enhance the **generalization** ability and **robustness** in different situations.

Thanks!

I'm currently seeking a PhD opportunity. Please contact me!

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