Differentiable Stellar Atmospheres
with Physics-Informed Neural Networks

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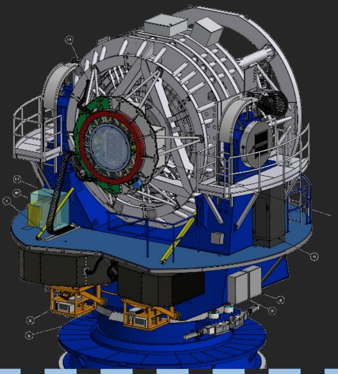
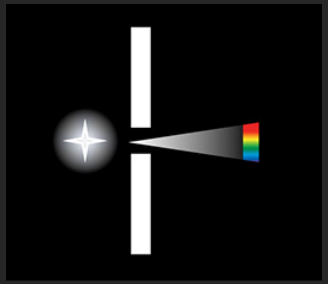
Galactic archaeology

- Know the formation and evolution of our Milky Way
- Know thy Star, know thy Galaxy
- An 'ID card' for every star
  - 2D position, distance, proper motion
  - Temperature, density -> evolution phase
  - Chemical composition (Li, Al, Ca, …)

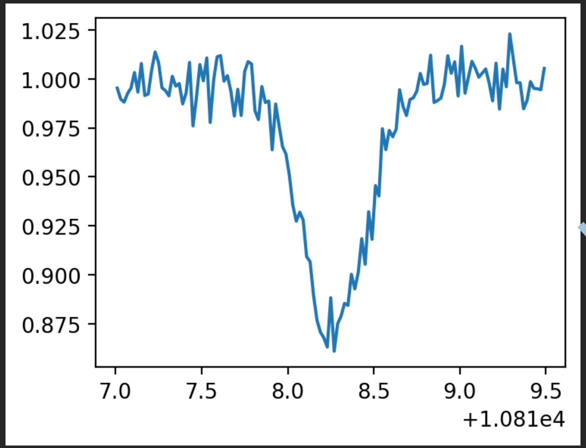
Stellar parameters

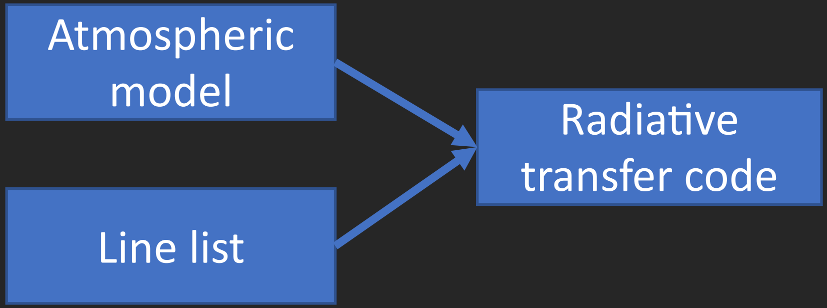
From spectra to parameters



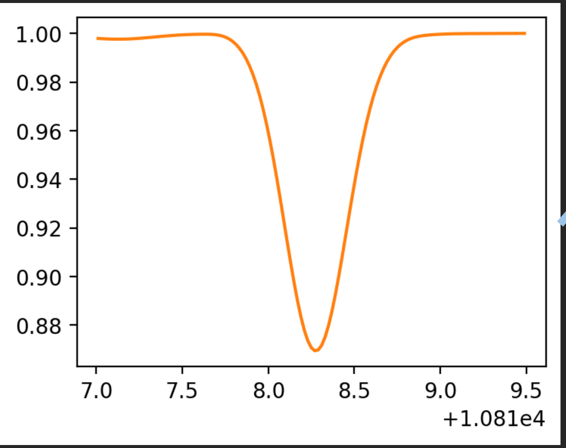


Observation





Synthetic spectra

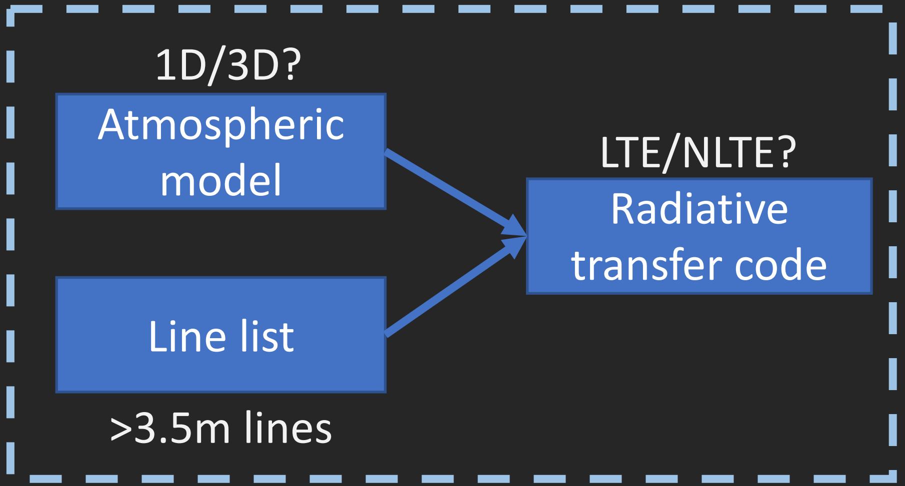


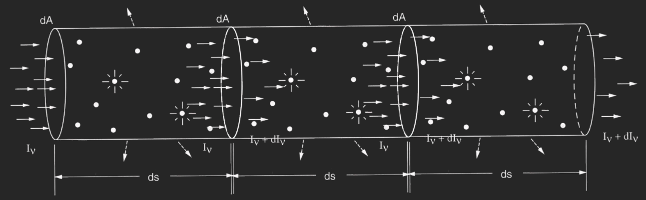
$$T_{\mathrm{eff}} = 5777\mathrm{K}$$
$$\log g = 4.0$$
$$[\mathrm{M/H}] = 0$$
$$V_{\mathrm{micro}} = 2$$
$$v \sin i = 10$$
……

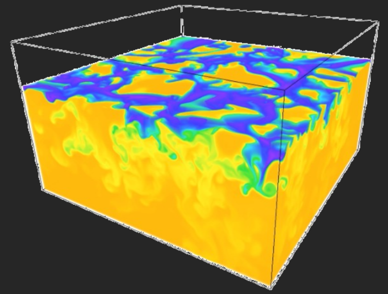
Challenge

Perform radiative transfer for every spectrum is impractical for analyzing the current and future survey data.

- Realistic stellar spectral synthesis requires more and more computational resources and time.
- The scale of all-sky survey is increasing, making traditional data analysis impractical for present day data amount.

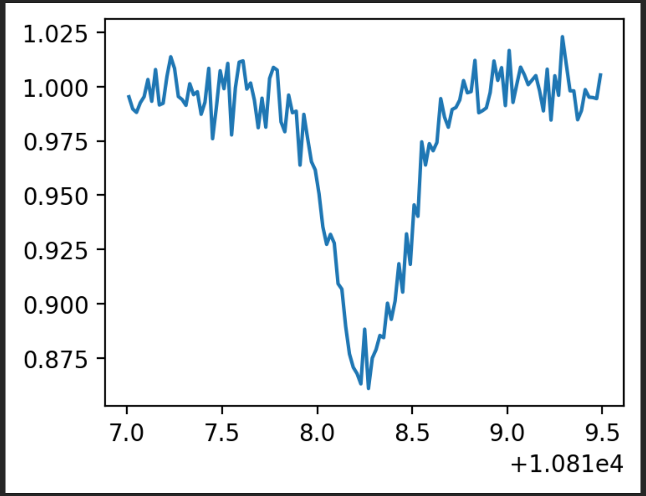


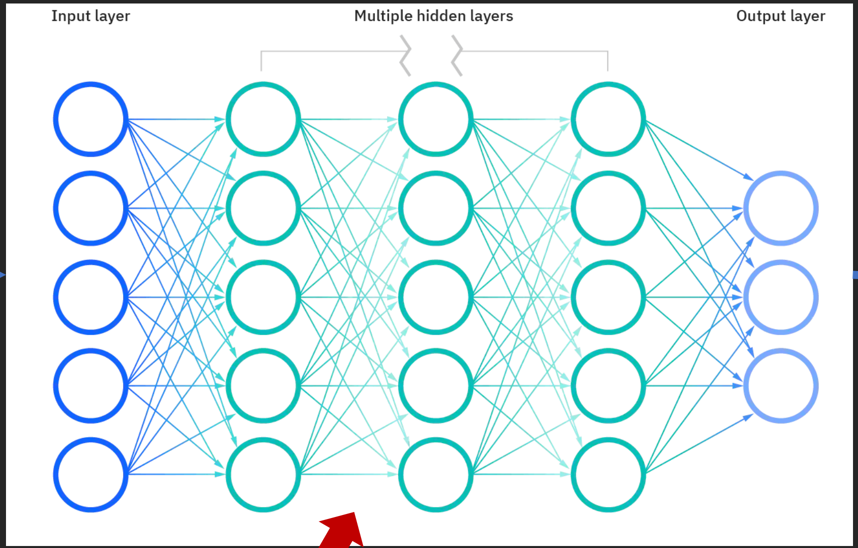




- LAMOST DR12: 13M spectra
- 4MOST (in 5 years): > 25M spectra

Solution: data-driven approach





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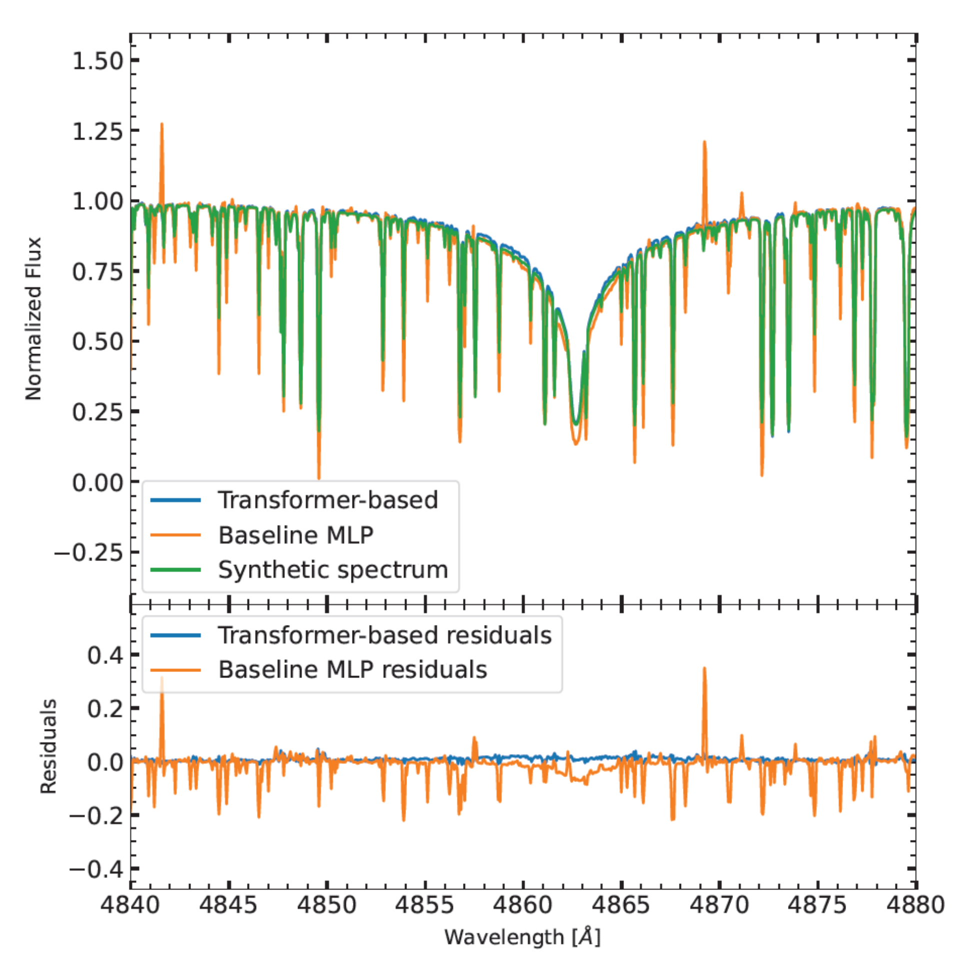
Template with stellar parameters

- Canon
  - Template: observed spectra
  - Ness+2013
- Payne
  - Template: synthetic spectra
  - Ting+2018

“Machine Learning Is a Tool, Not Theology” --- ChatGPT

- Data-driven (e.g., The Payne):
  - fast and scalable,
  - Sometimes un-physical.

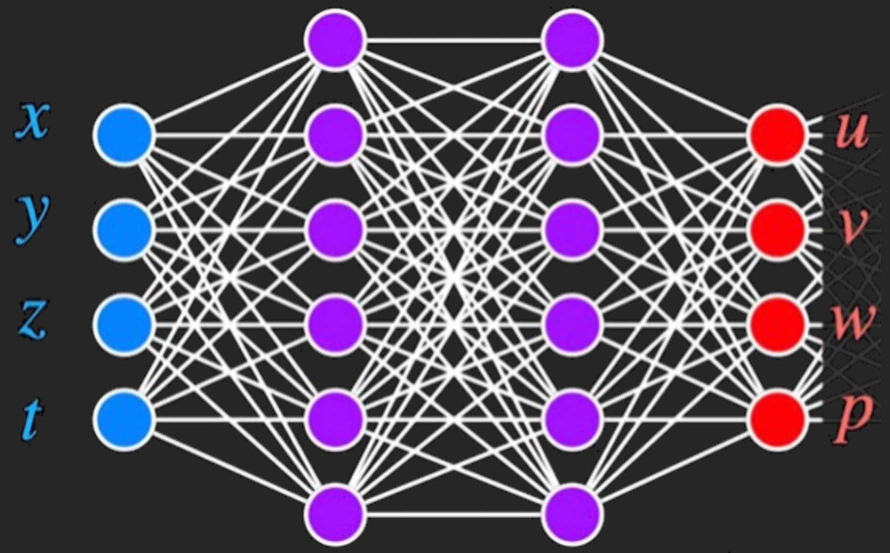
- We often rely on 'interpolation'—which is not physics.



Rozanski+2023

Physics X Neural Network?

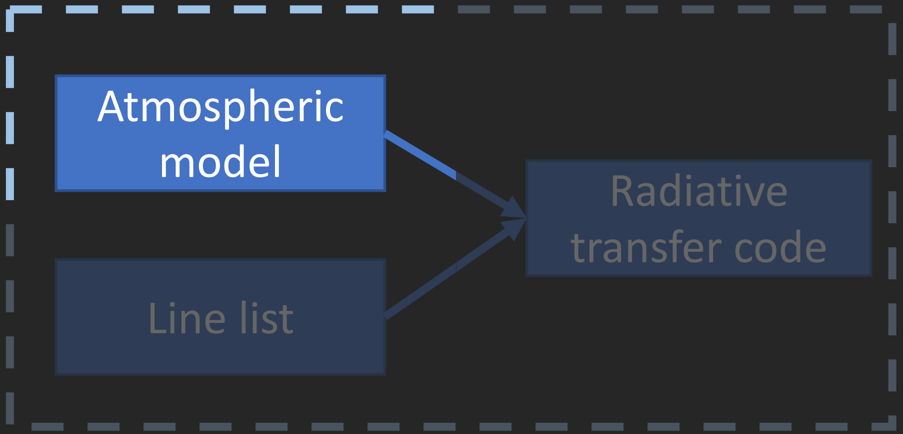
- Physics-Informed Neural Networks (PINNs)
  - Raissi+2019
- Encode physics as differentiable constraints/losses/boundary conditions.
- Reduce nonphysical solutions.

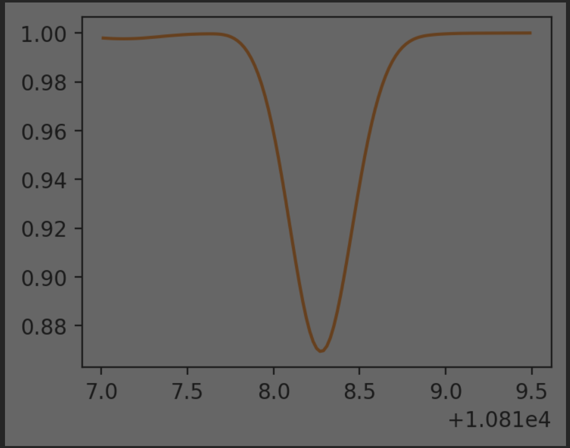


Loss:

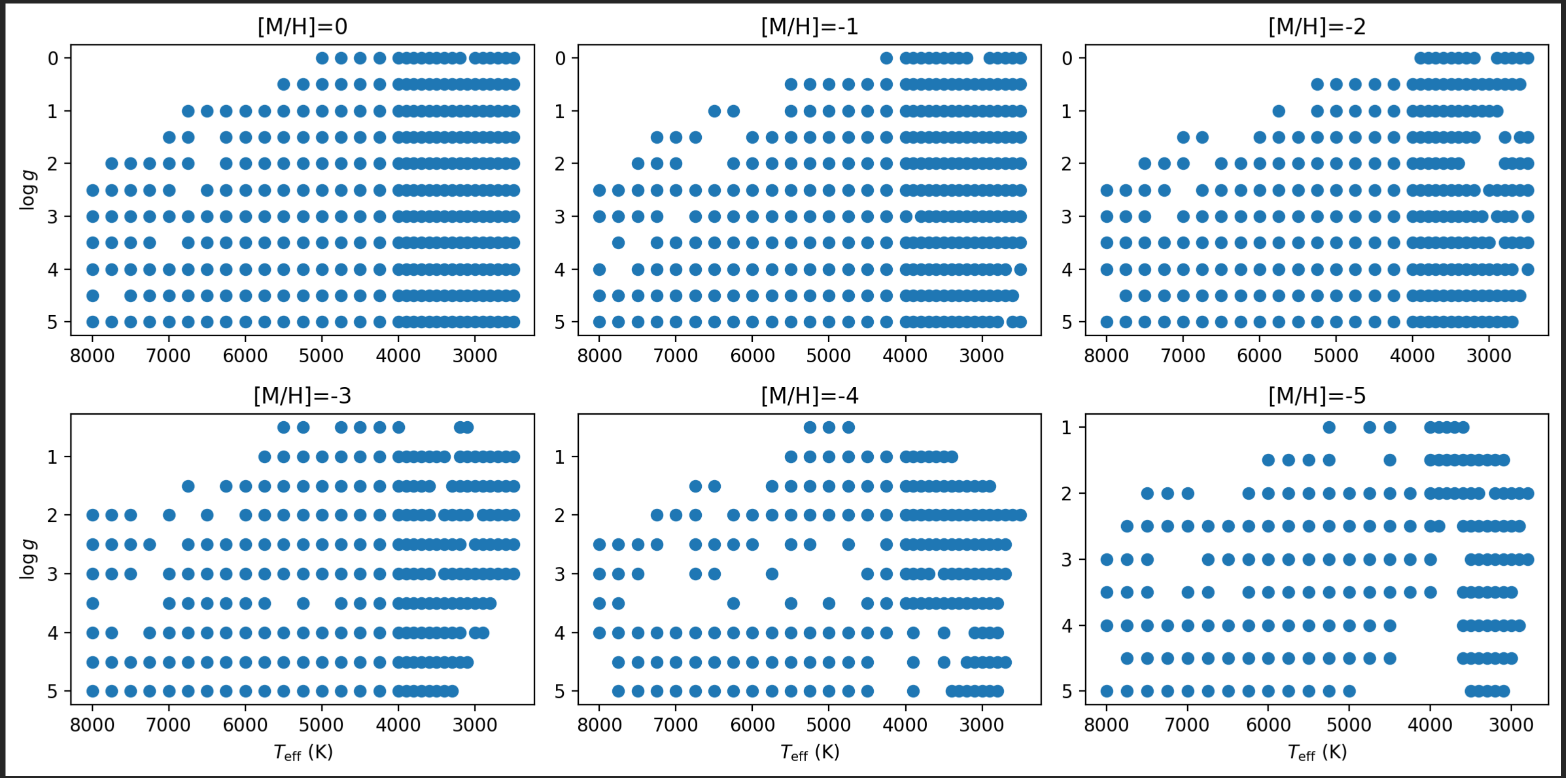
- loss from the data
- loss from the physical constraints

The first step:





- 1D stellar atmosphere models
  - Kurucz-ATLAS
  - MARCS
  - Phoenix
- Linear interpolation
  - No physical constrain is applied, pure data-driven.

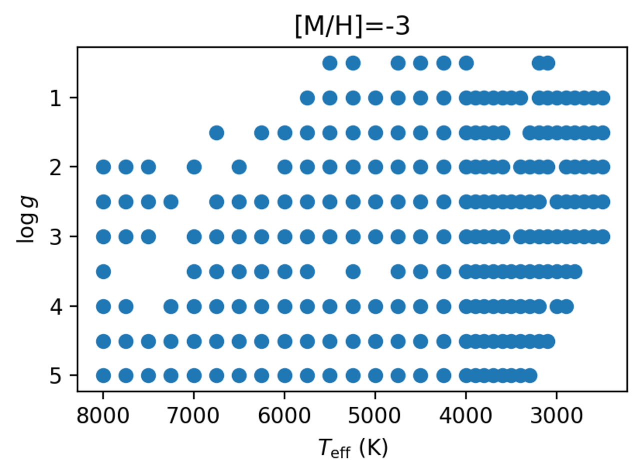


Kurucz-a1:
Differentiable Stellar Atmospheres with PINN

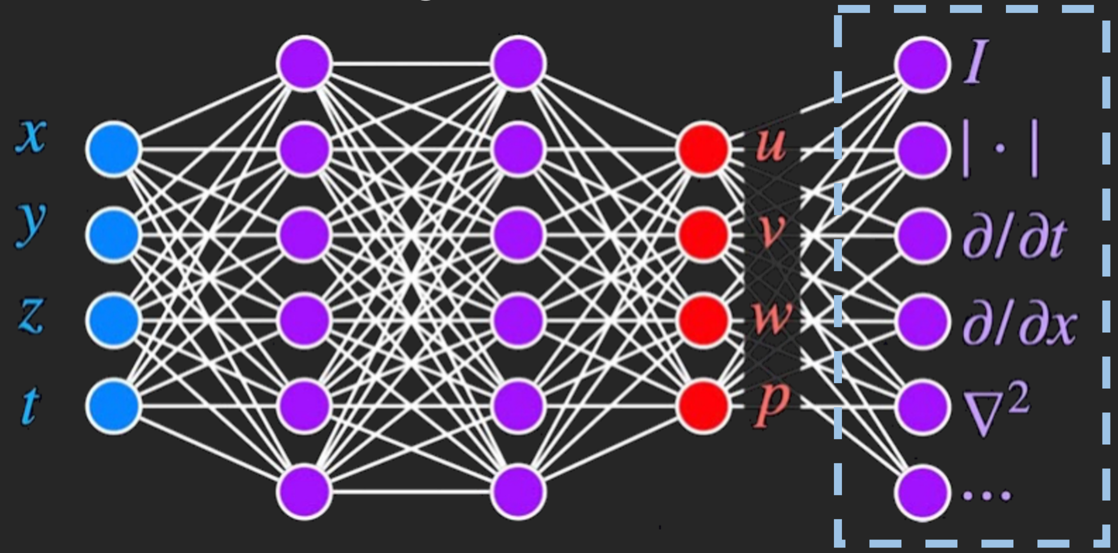
Hydrostatic equilibrium:

$$\frac{\mathrm{d}P}{\mathrm{d}\tau} = \frac{g}{\kappa}$$

A collection of >4000 files



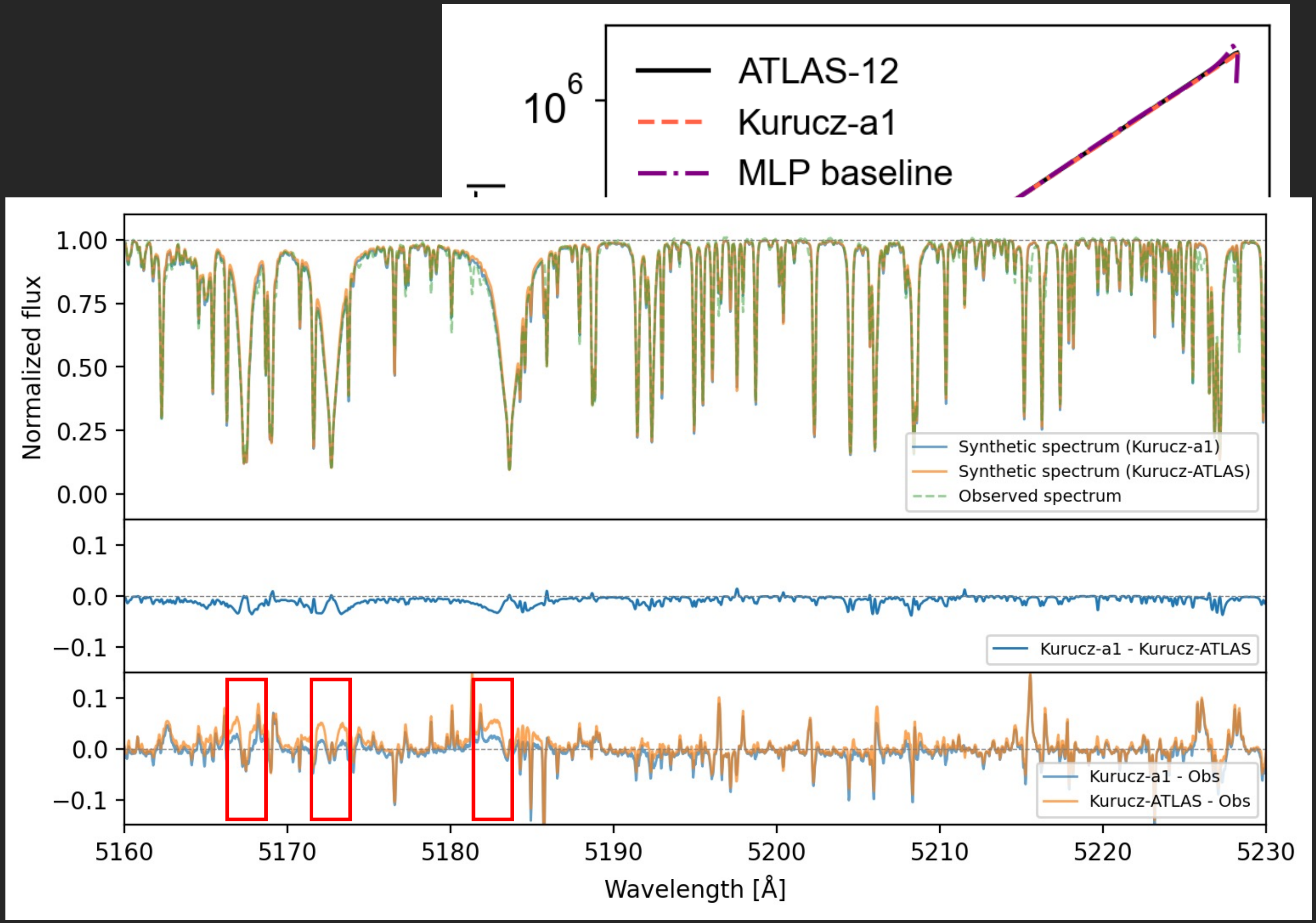
A single NN



$$\mathcal{L}_{\mathrm{total}} = (1-\alpha)\times\mathcal{L}_{\mathrm{data}} + \alpha\times\mathcal{L}_{\mathrm{phisics}}$$

Better performance

- Kurucz-a1 follows hydrostatic equilibrium better;
- Fit the (solar) observation better;
- Able to cover more dimensions;
- End-to-end differentiable stellar spectroscopy.



Summary: 旧瓶装新酒 / new wine in old bottles

- We developed Kurucz-a1, the first PINN for stellar atmosphere models.
- Kurucz-a1 put physics into the model so the atmosphere models is both physically consistent and scalable.
- The whole radiative transfer process could be replaced by PINN
  - Ready for the analysis of survey-scale data and can be modified to include other dimensions (e.g., abundances).

- Kurucz-a1: arxiv 2507.06357 (ICML2025 AI4Astro) https://github.com/jiadonglee/kurucz-a1
- PySME: https://github.com/MingjieJian/SME