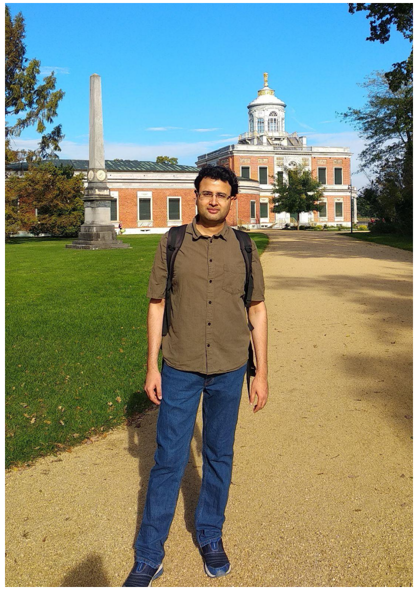
A Convolutional Neural Network Approach for Stellar Atmospheric Parameters and Lithium Abundance Determination

Annual Meeting AG-2021 Date: 2021/09/17

Presented by: Samir Nepal
Supervisor: Dr. Guillaume Guiglion

My Introduction:



Machine Learning

Astrophysics

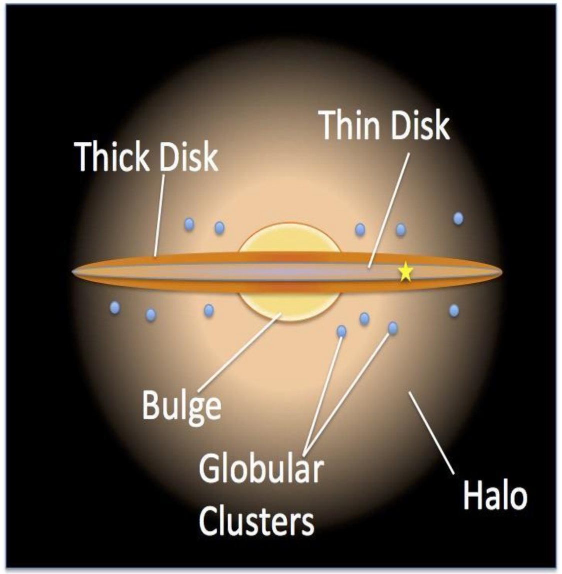
Galactic Archaeologist

Galactic Archaeology:

- Study of formation and evolution of the Milky way by analyzing stars and stellar populations as relics.
- The ΛCDM model provides a framework to understand how galaxies form and evolve. (hierarchical mergers)
- Milky way is an ideal test bed for Galaxy formation and evolution theories as it is the only galaxy which can be studied in detail with resolved stars.

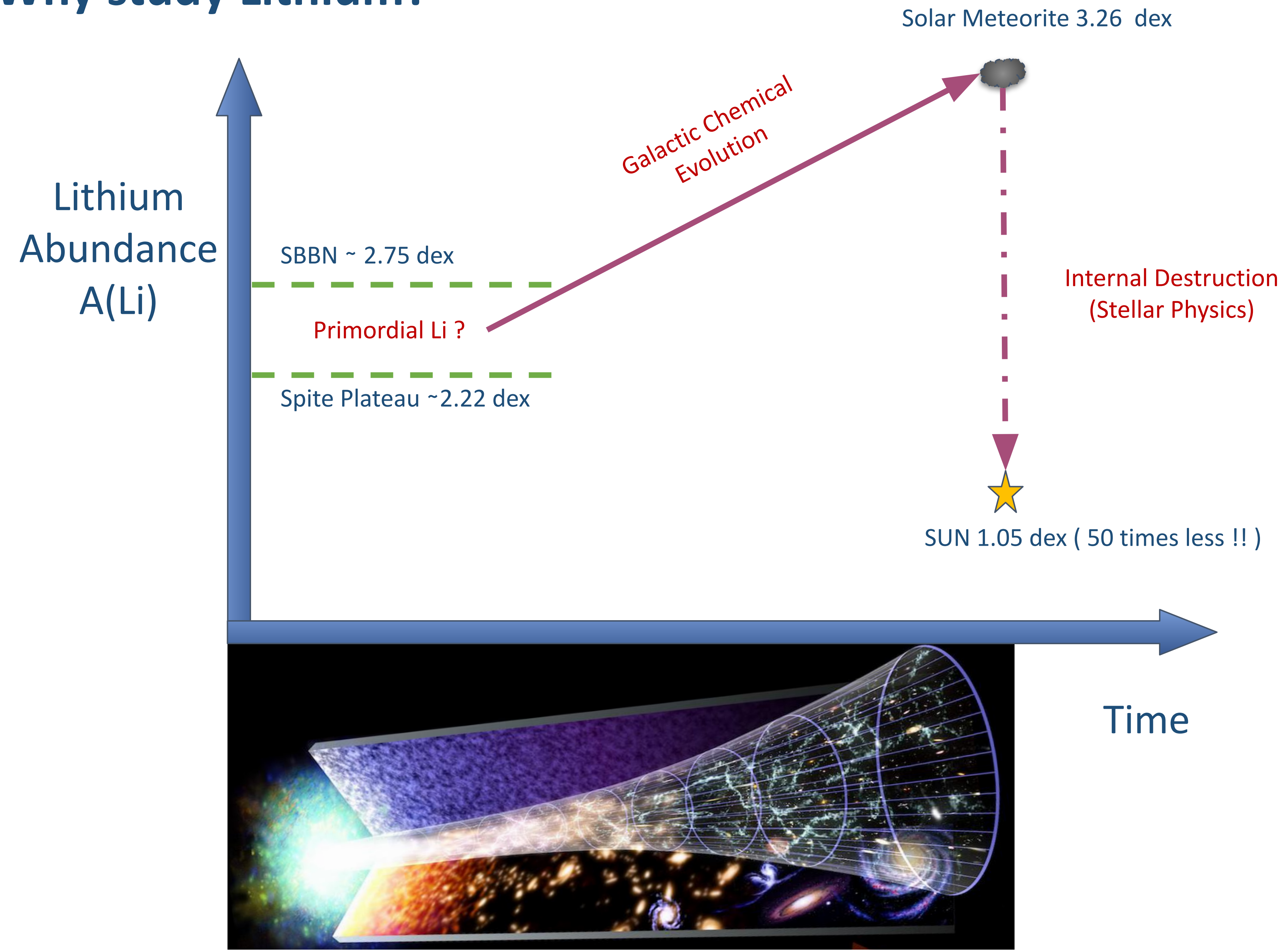
“Man meets Milky Way”
Credit: ESO/P. Horálek

1. Deconstruct the Galaxy into its components.
2. Photospheric chemistry = ISM composition at T_{birth}.
3. ***Chemical Composition, Ages, Positions and Kinematics*** of a large number of stars is necessary for the complete picture.



Source:
http://www.astro.lu.se/~greg/milkyway.html

Why study Lithium?



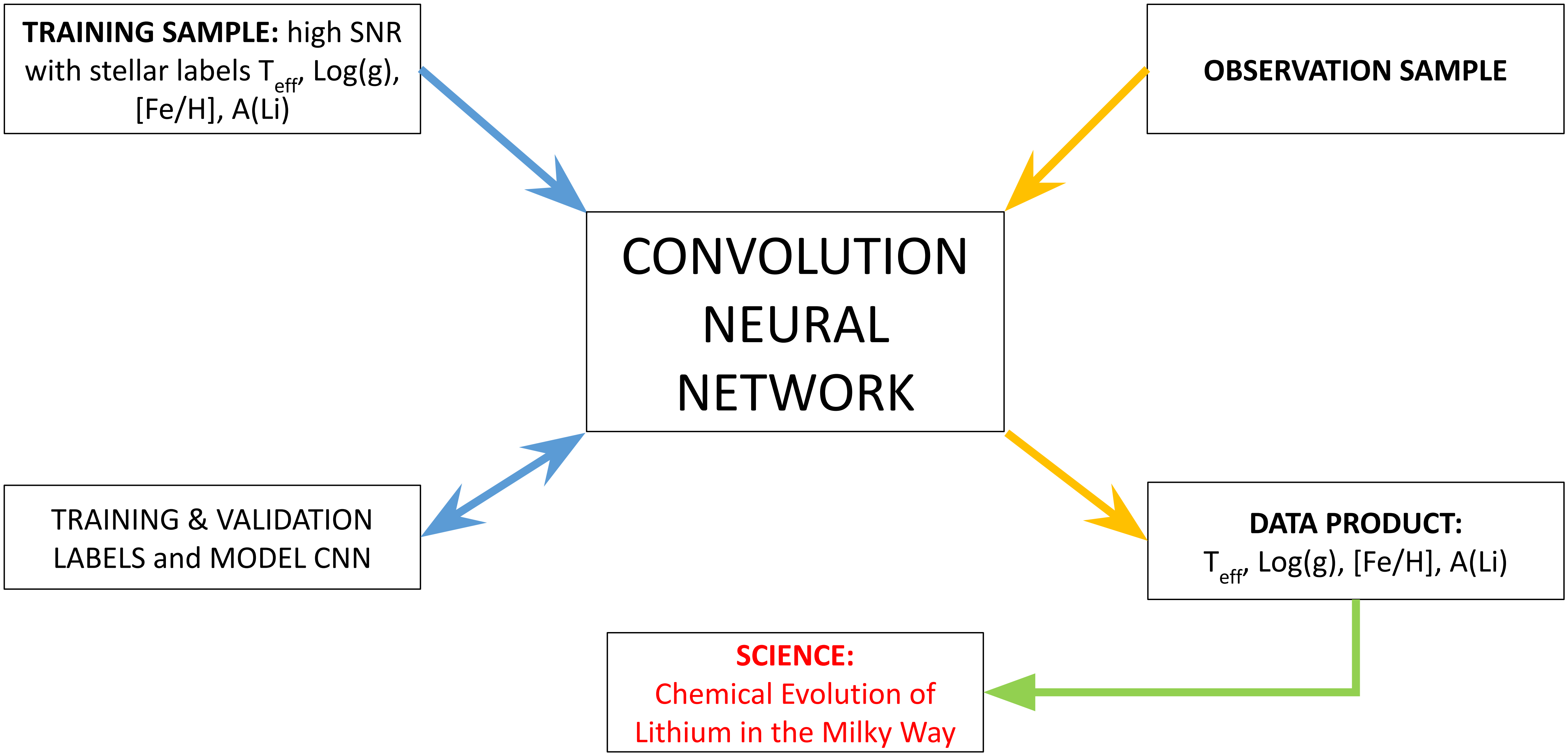
Chemical Evolution of Lithium: --> CNN

To help tighten the constraints on cosmological, stellar and galactic chemical evolution models, analysis of larger number of Li abundances A(Li) is necessary. **To derive chemical abundances we need stellar spectroscopy!!**

Dedicated spectroscopic surveys like RAVE, Gaia-ESO, LAMOST, APOGEE, GALAH, 4MOST, WEAVE, etc. have and will provide with high-quality spectra for several million stars. → ***This demands automated and supervised/unsupervised data reduction and parameters estimation.***

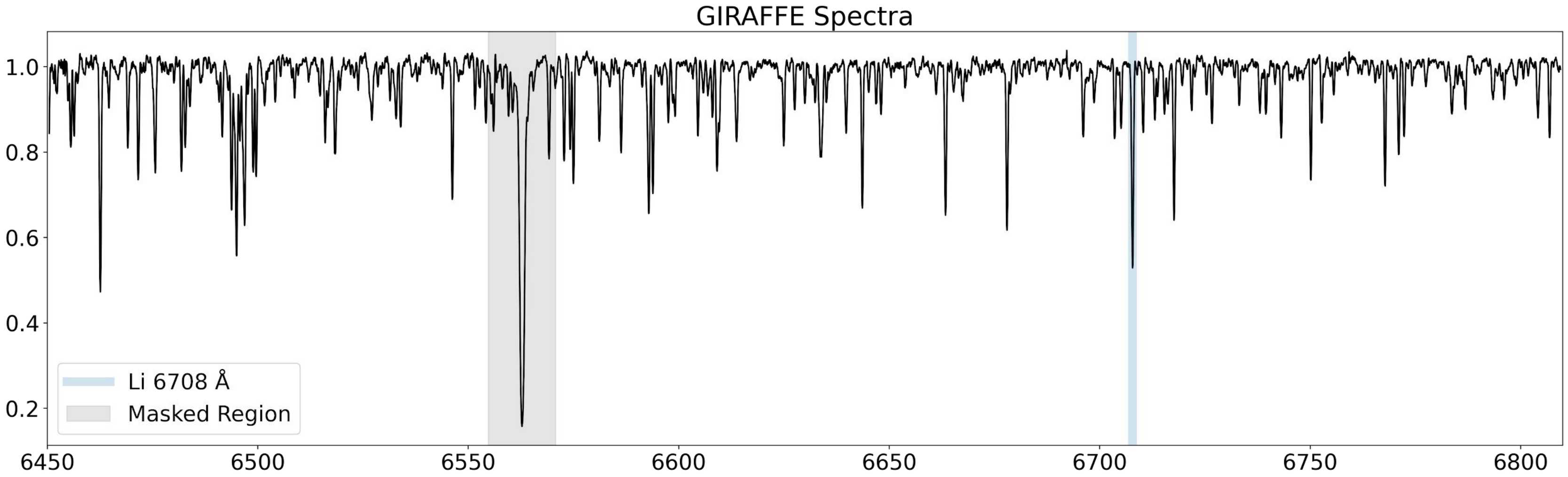
Prepare ML groundwork

The Project Idea:



Data: Gaia-ESO Survey

- We use GES-iDR6 labels and Spectras from ~41,000 GIRAFFE HR15 setup. (the ^{7}Li Line)
- iDR6 data coming from COG and spectral fitting classical pipelines. **LABELS = STELLAR LABELS (physics)**



T_{eff}	4897 K
Log(g)	2.55 dex
[Fe/H]	-0.11 dex
A(Li)	2.63 dex

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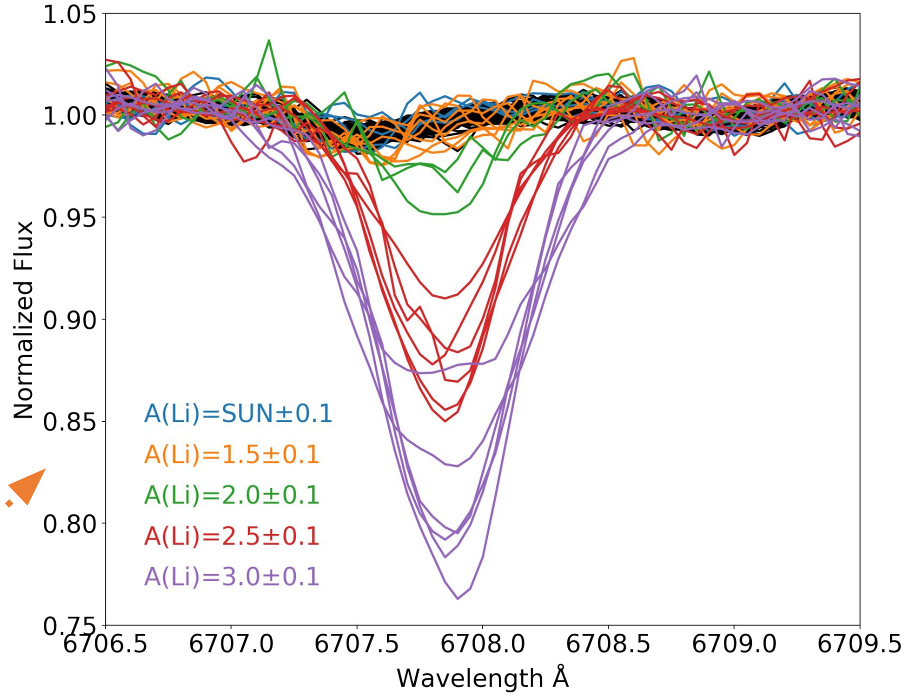

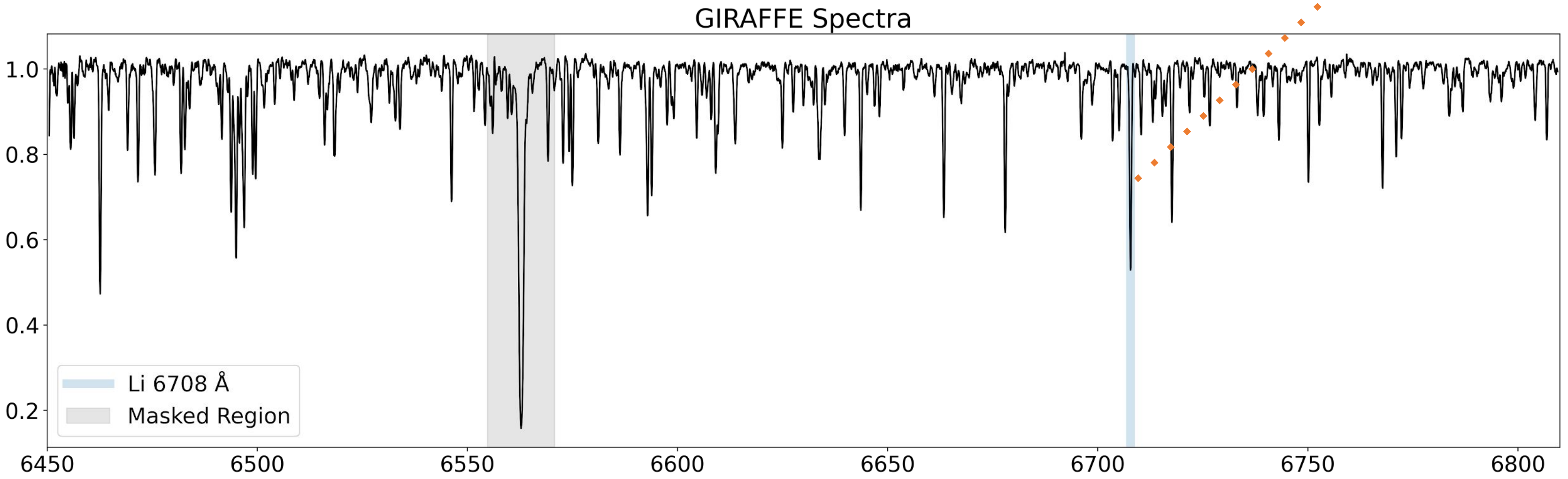

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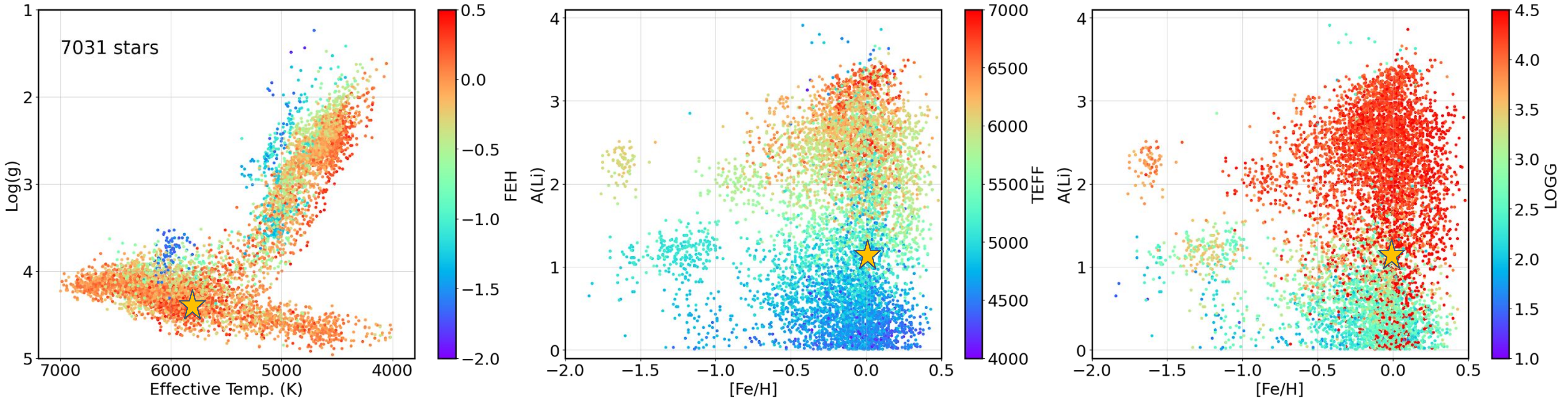
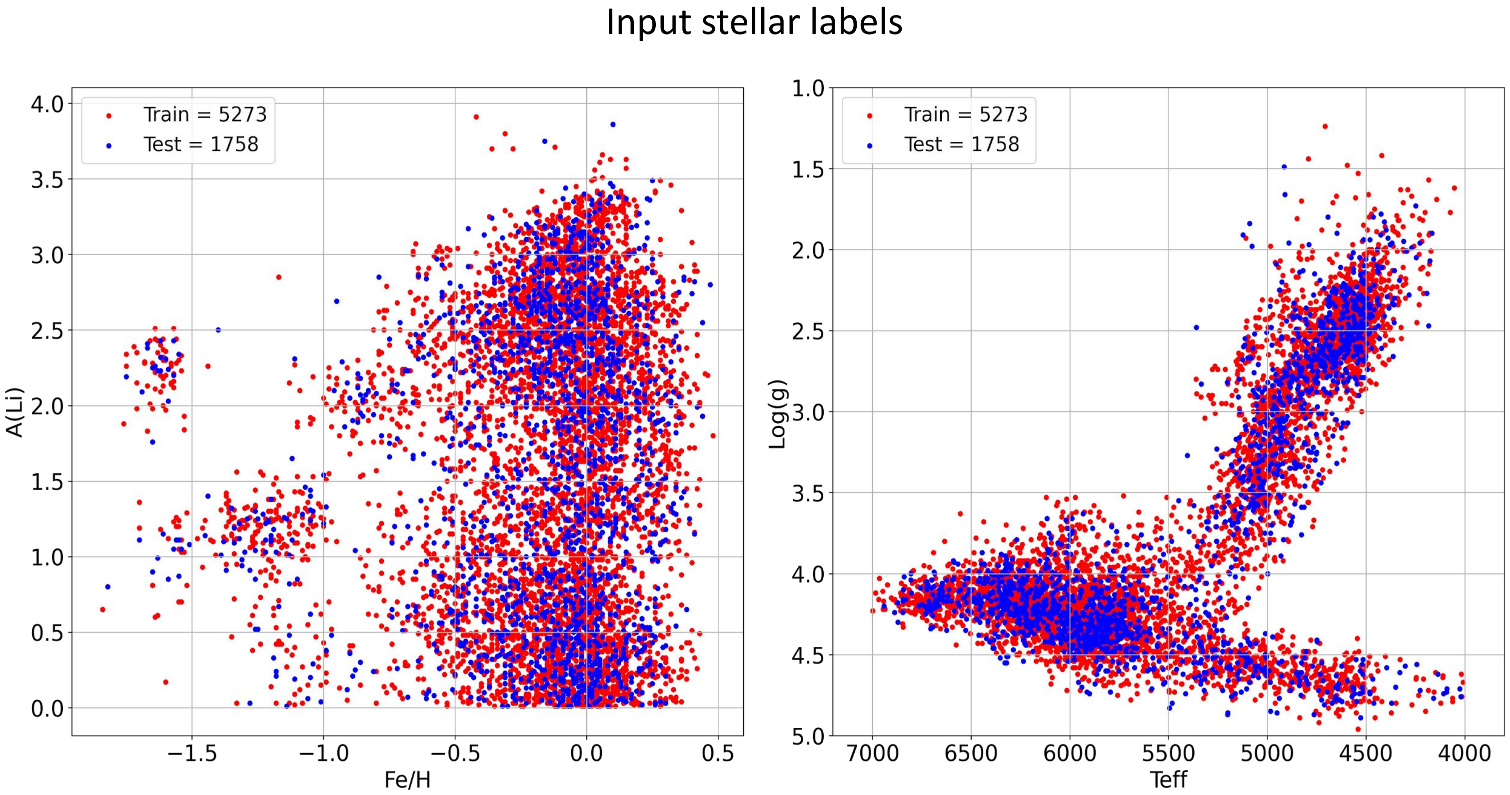
Training Sample:



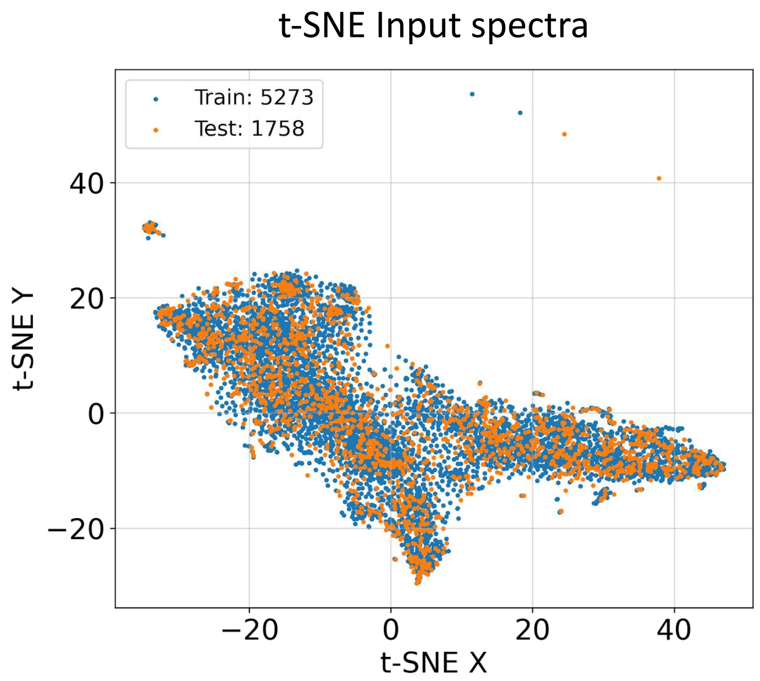
Good performances are achieved by meticulously building a high quality and homogeneous training sample as well problem specific optimization of the CNN.

In our chosen label range, we have good physical models.

Training Sample: Train(75%) + Test(25%)



Using t-SNE: an unsupervised ML method



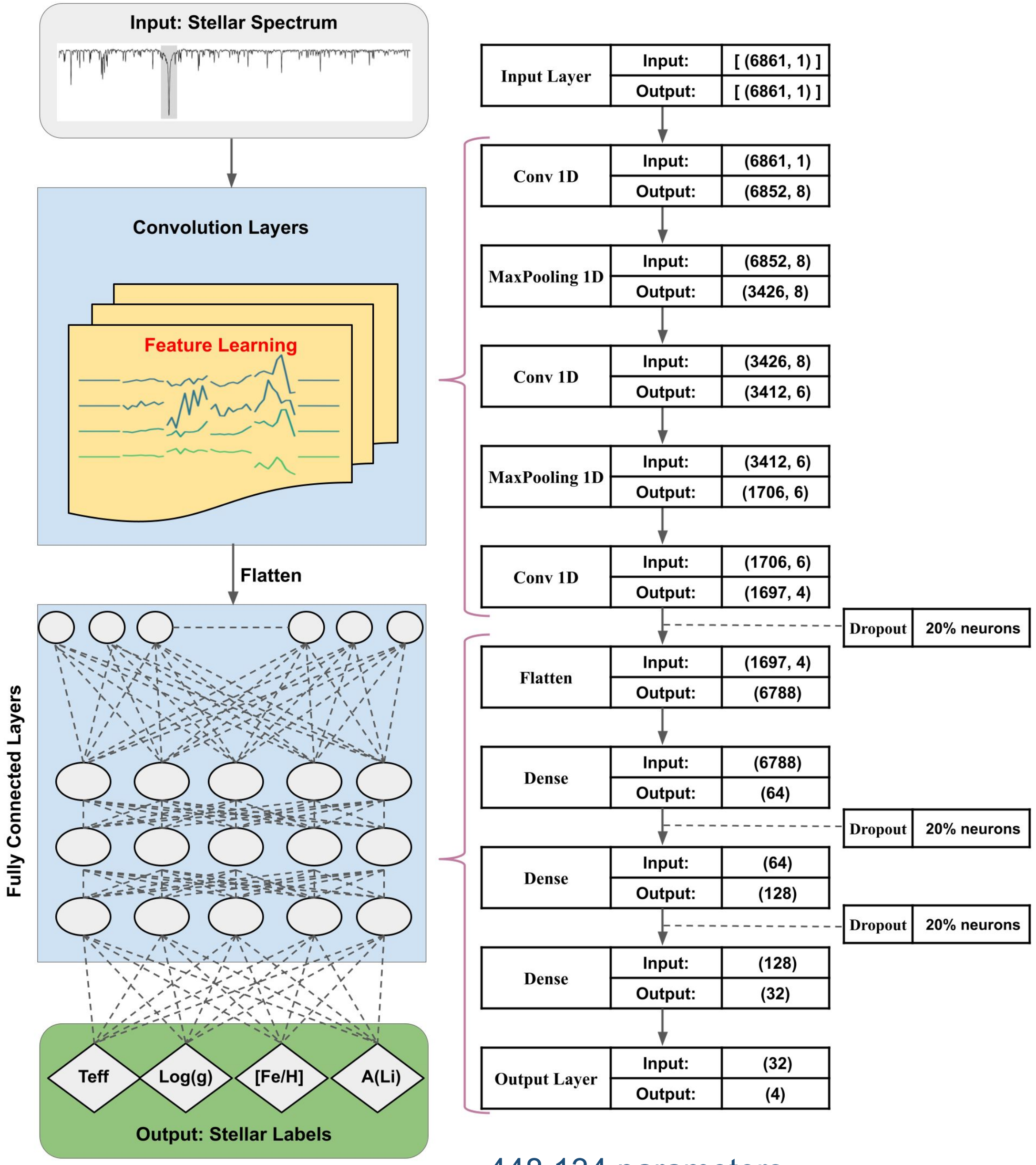
- Using t-SNE for outlier detection.
- Train-Test Homogeneity Check.
- To highlight the complex relation between spectra and the labels.

CNN: The Architecture

The Neural Network learns a mapping function between the input spectra and the set of stellar labels.

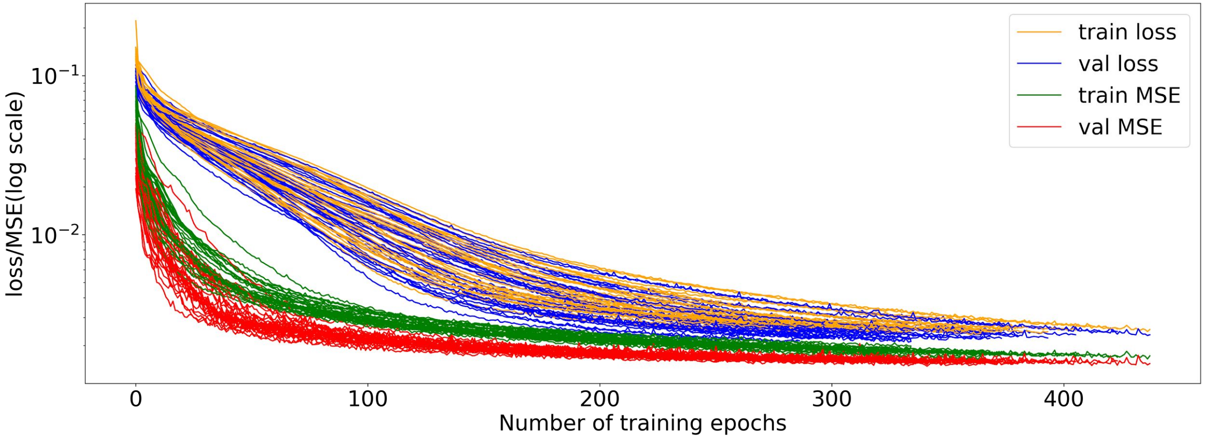
Avoids difficult task of feature engineering.

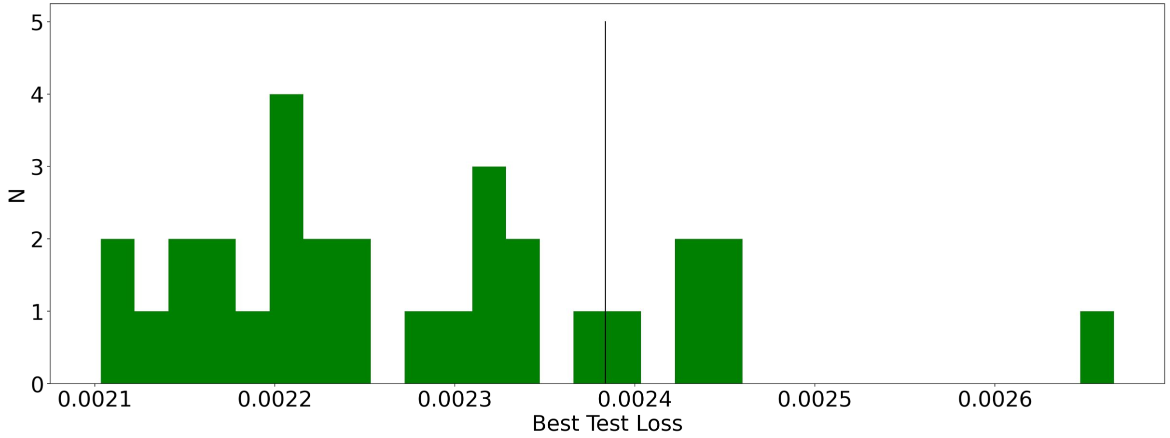
Training process optimizes the values of these parameters.



448,134 parameters

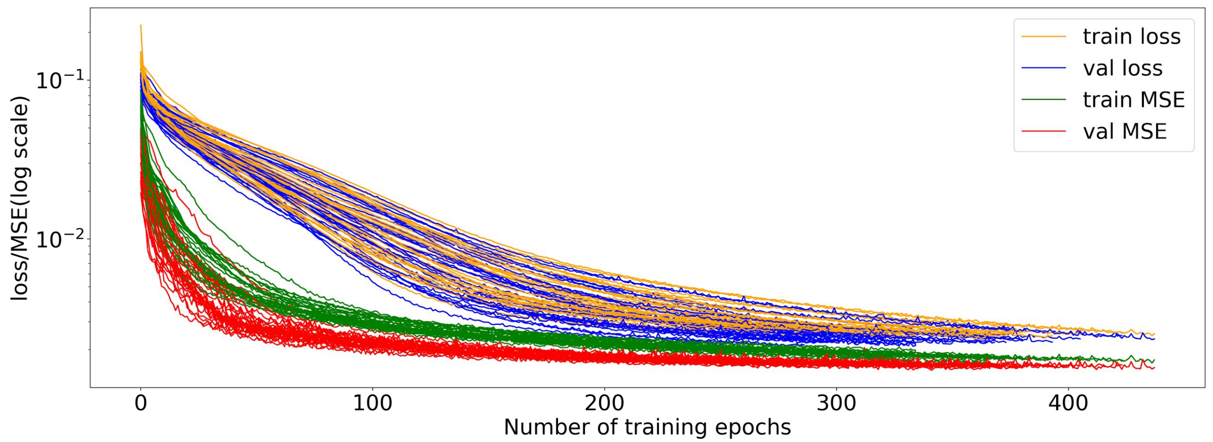
CNN: Training

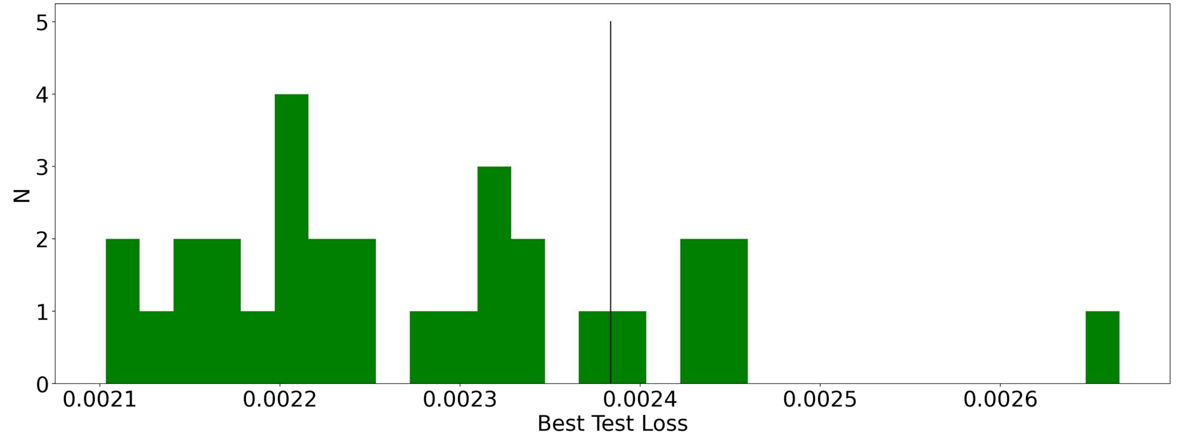


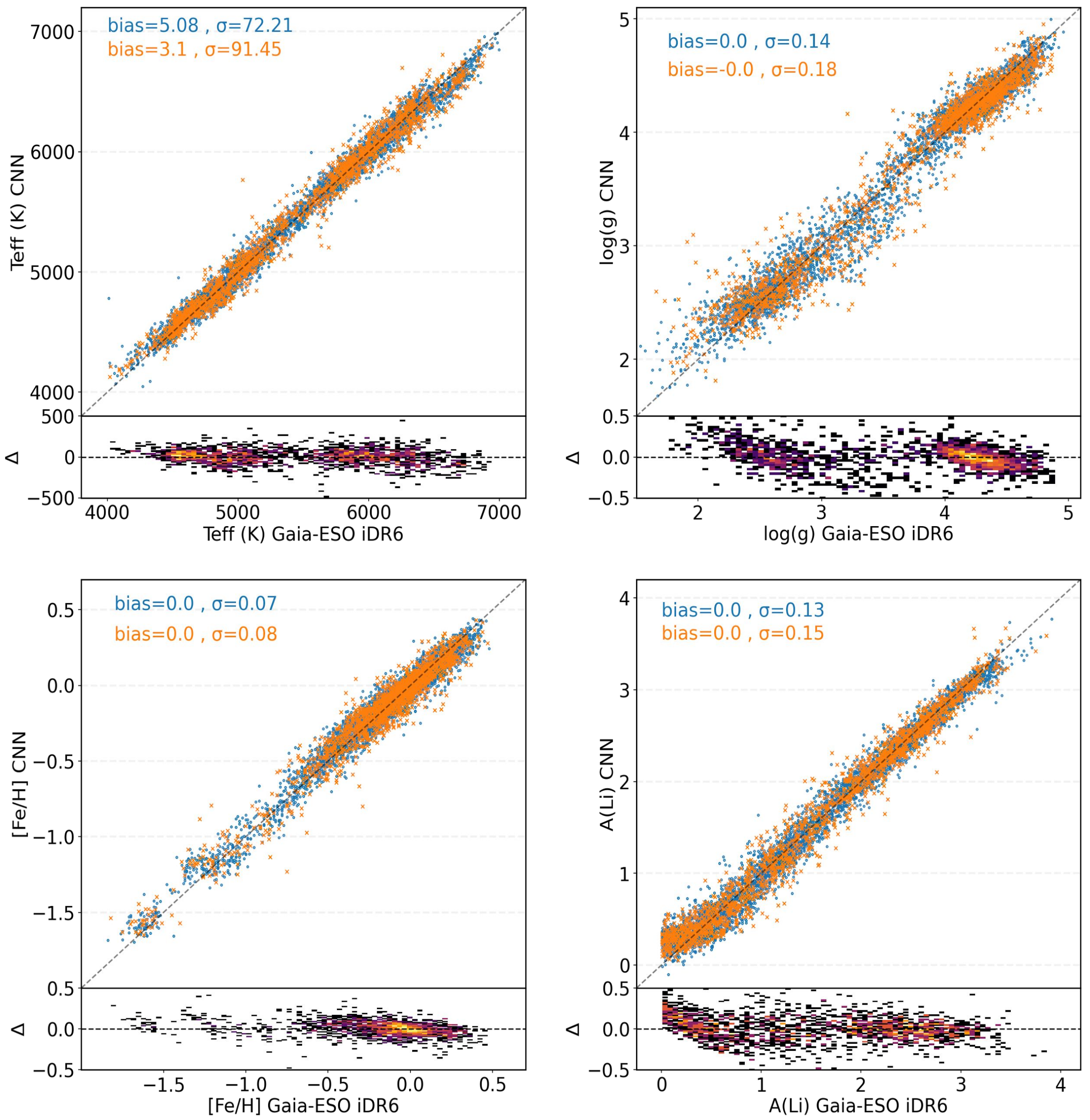


- 30 models trained.
- Training using CPU. (16-26 minutes)
- 80% selected based on best test loss.

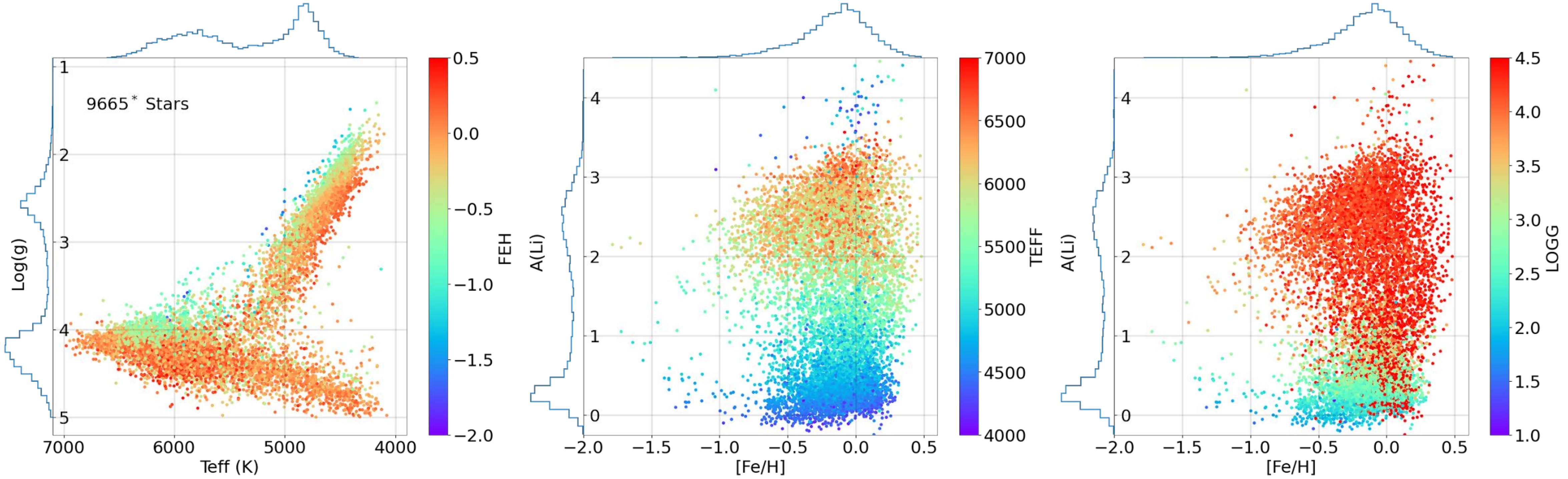
CNN: Training



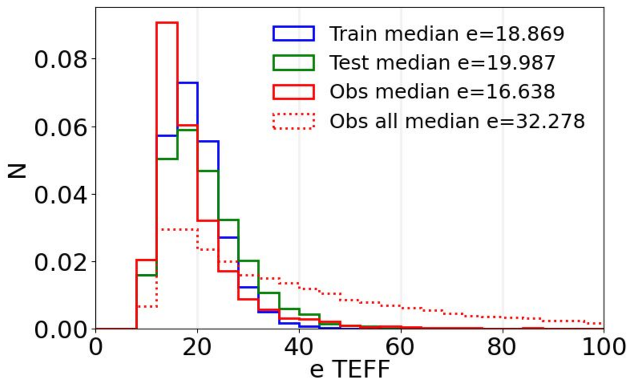


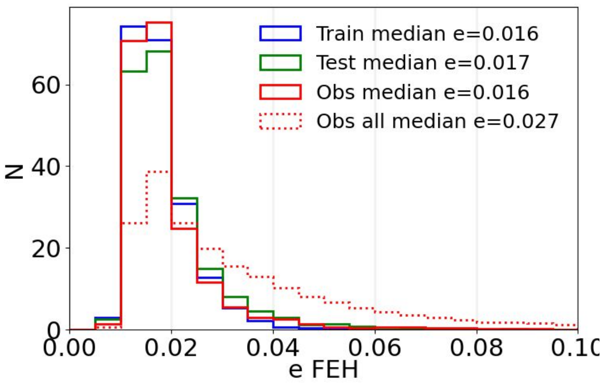


CNN Results: Observed Sample

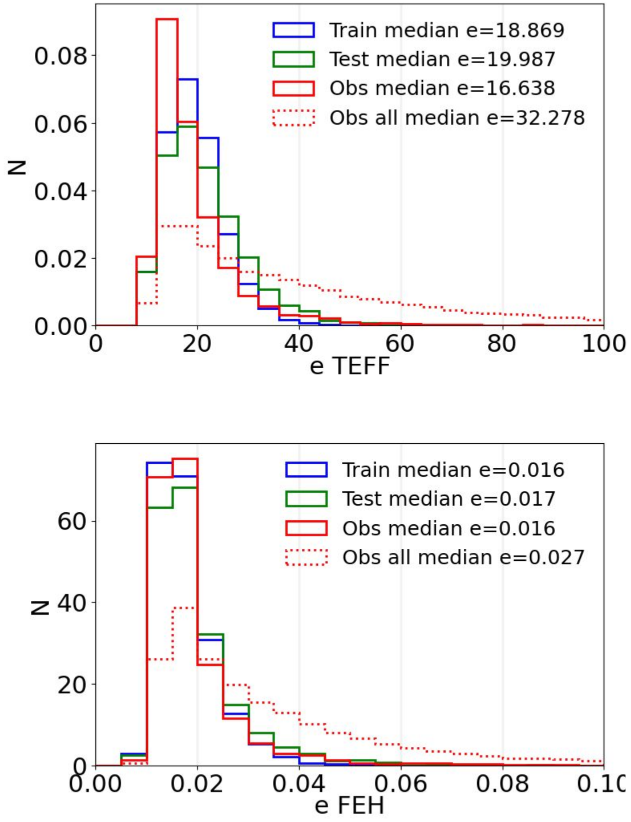


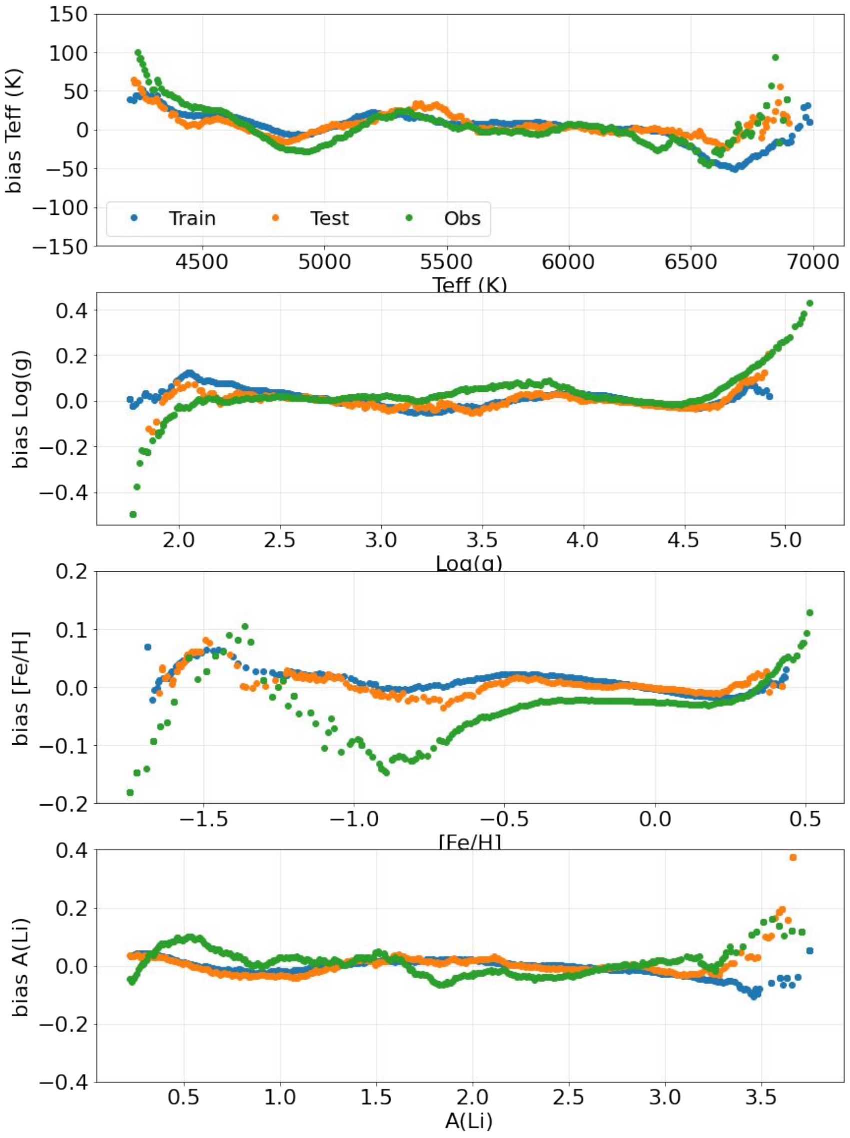
CNN: Accuracy and Precision

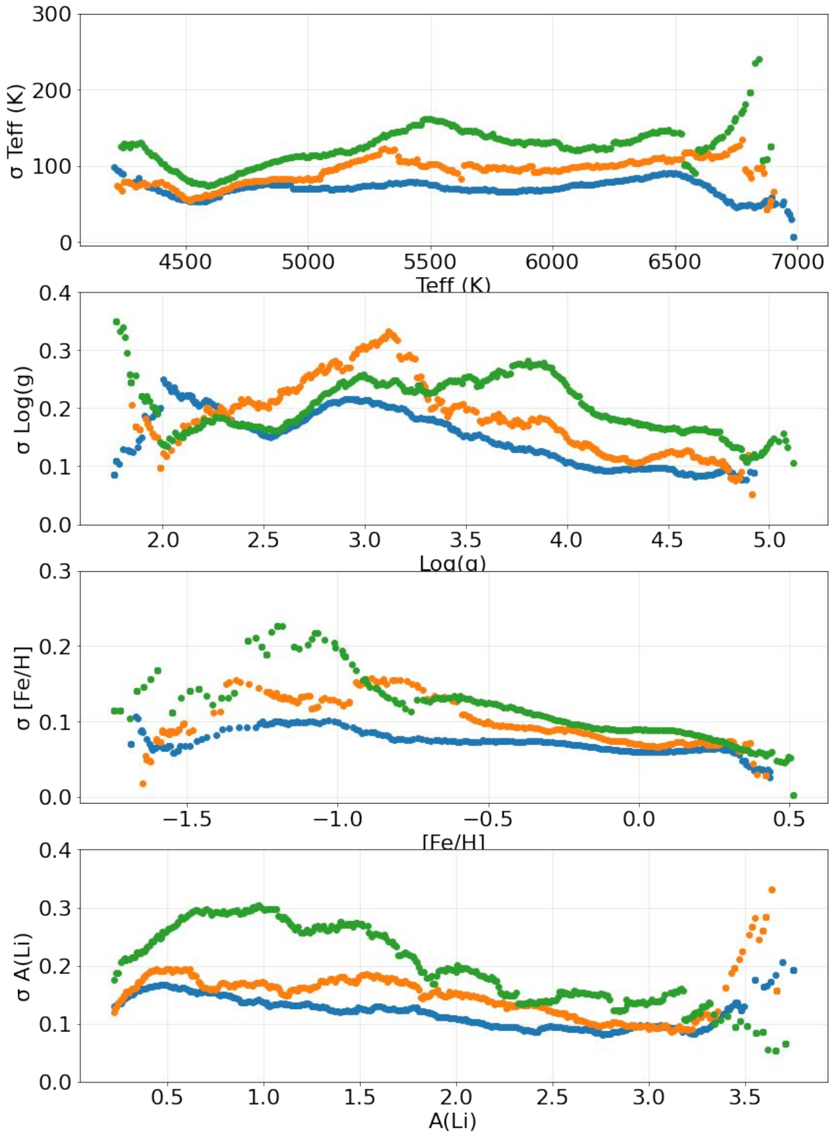




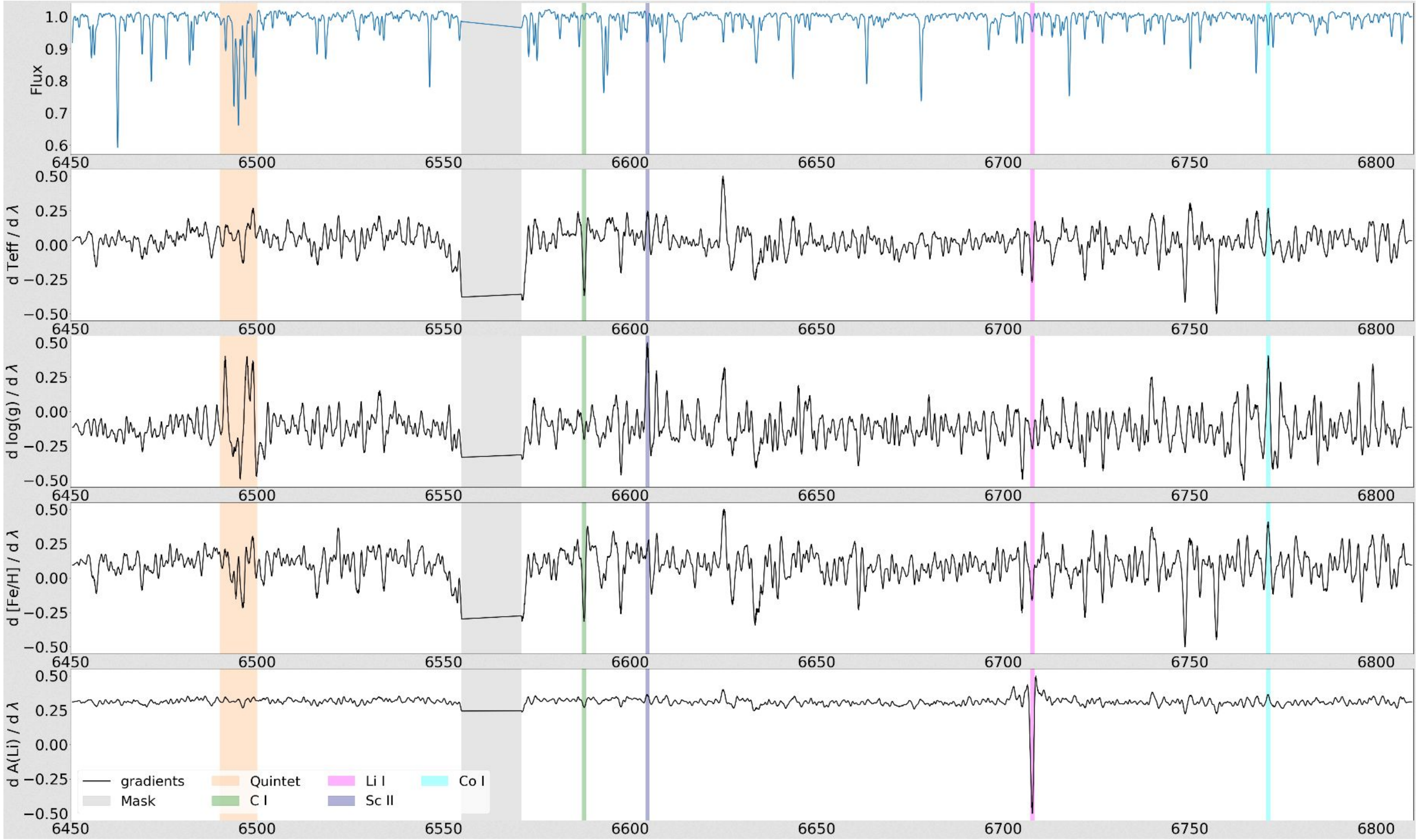
CNN: Bias and Sigma curves for accuracy and precision







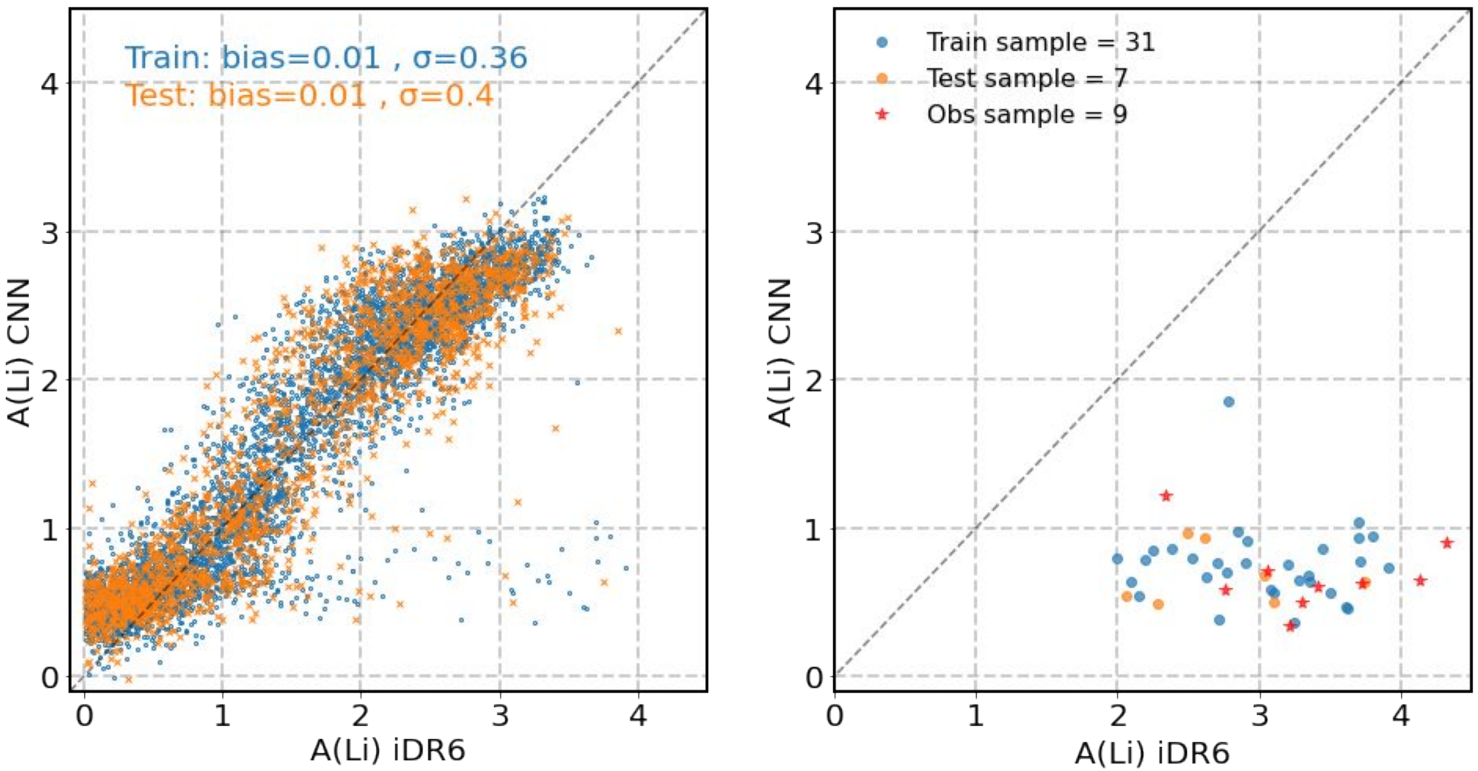
Does the CNN learn from spectral features?



Gradients of the output labels with respect to input GIRAFFE pixels (wavelength)

Measuring A(Li) without the Li line?

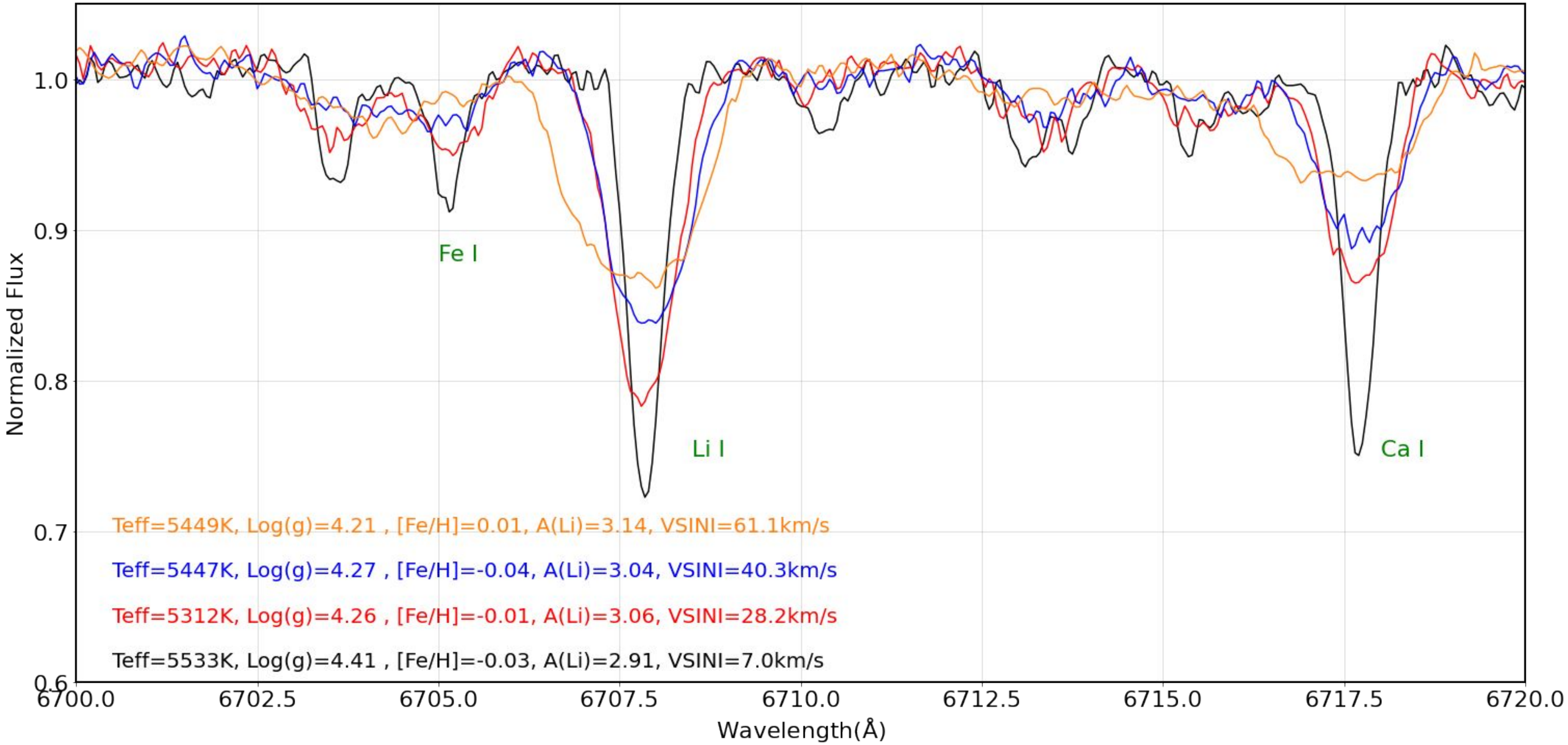
ML algorithms are efficient at learning astrophysical correlations, for example inferring Oxygen abundances from spectra with no Oxygen feature (Ting & Weinberg 2021).



Comparison of CNN Li abundances with GES-iDR6 Li abundance after training the CNN on GIRAFFE spectra, masking the 6707.8 Å line.

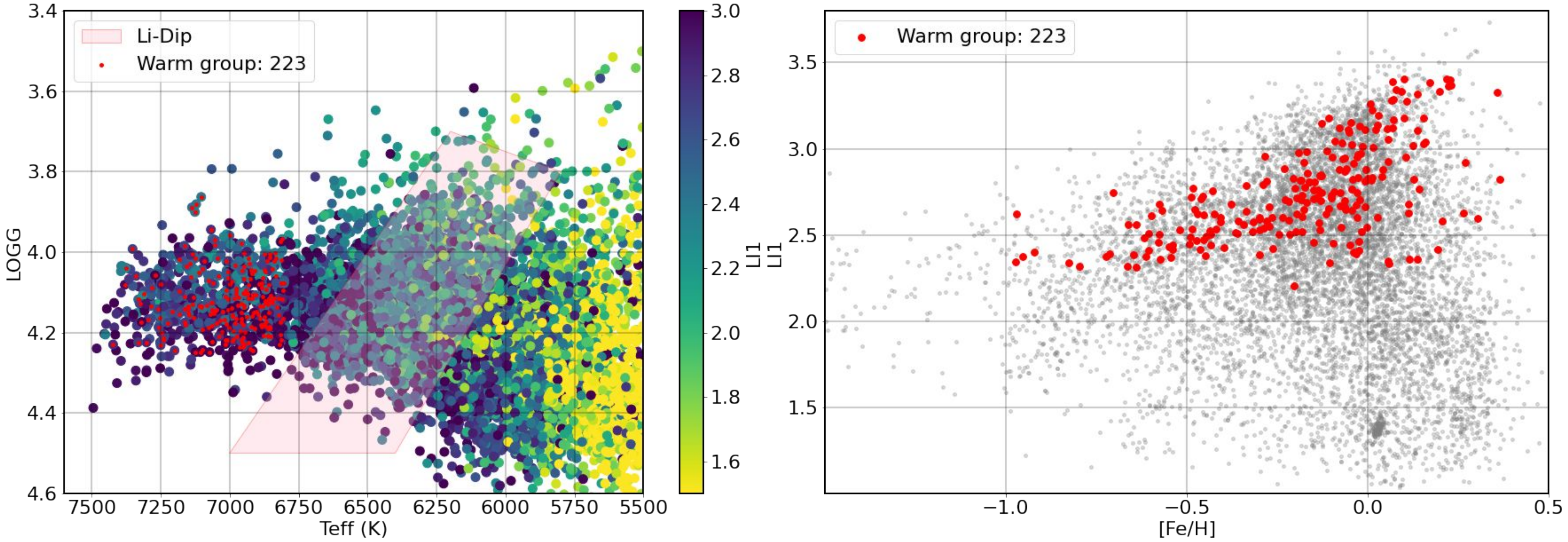
What about the Fast rotators?

As the projected rotational velocity (VSin*i*) increases, the spectral lines get wider and shallower and there is increased blending.



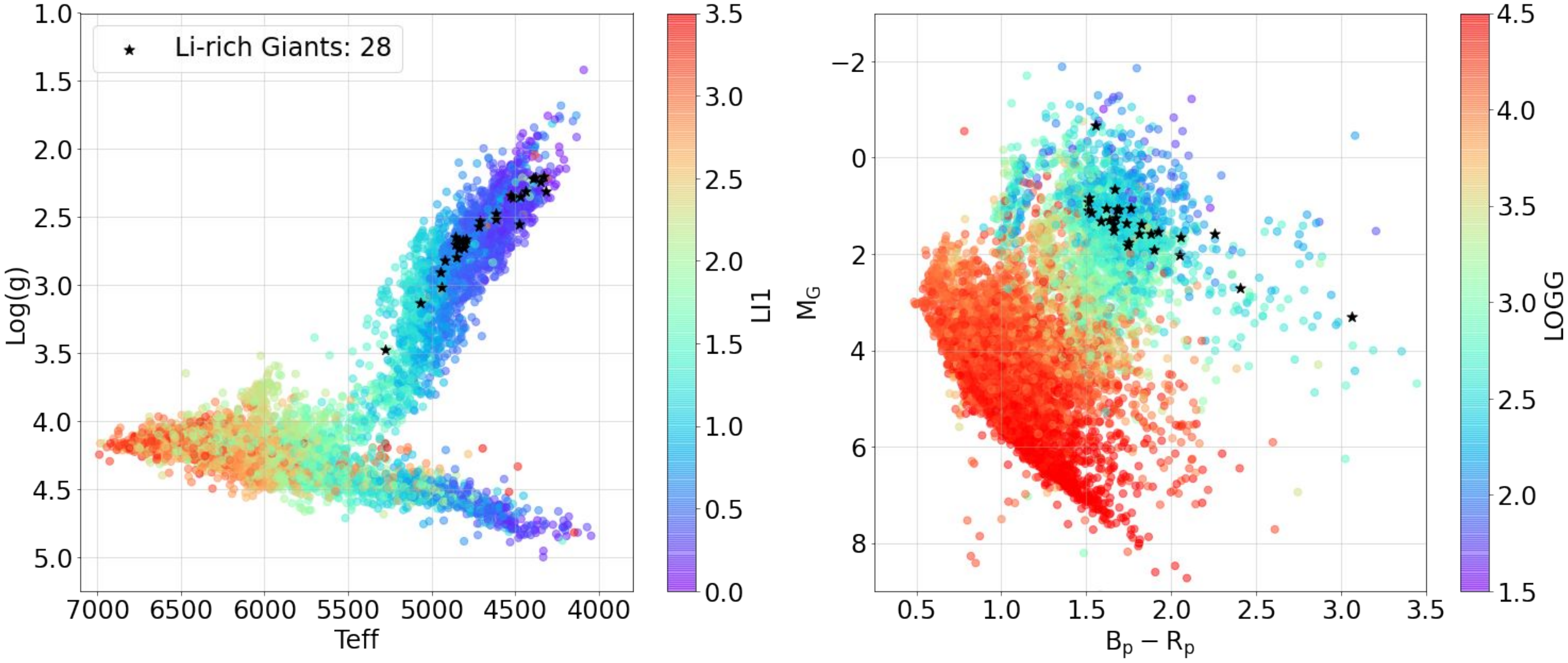
Science application of the CNN results

Investigation of galactic chemical evolution using hot stars doesn't show the usual steep rise. This finding could have implications on later contribution of Li by long lived sources.



Science application of the CNN results

Discovery of 28 new Li-rich giants in the Gaia-ESO iDR6 observations!!



Future Prospects: On CNN Method

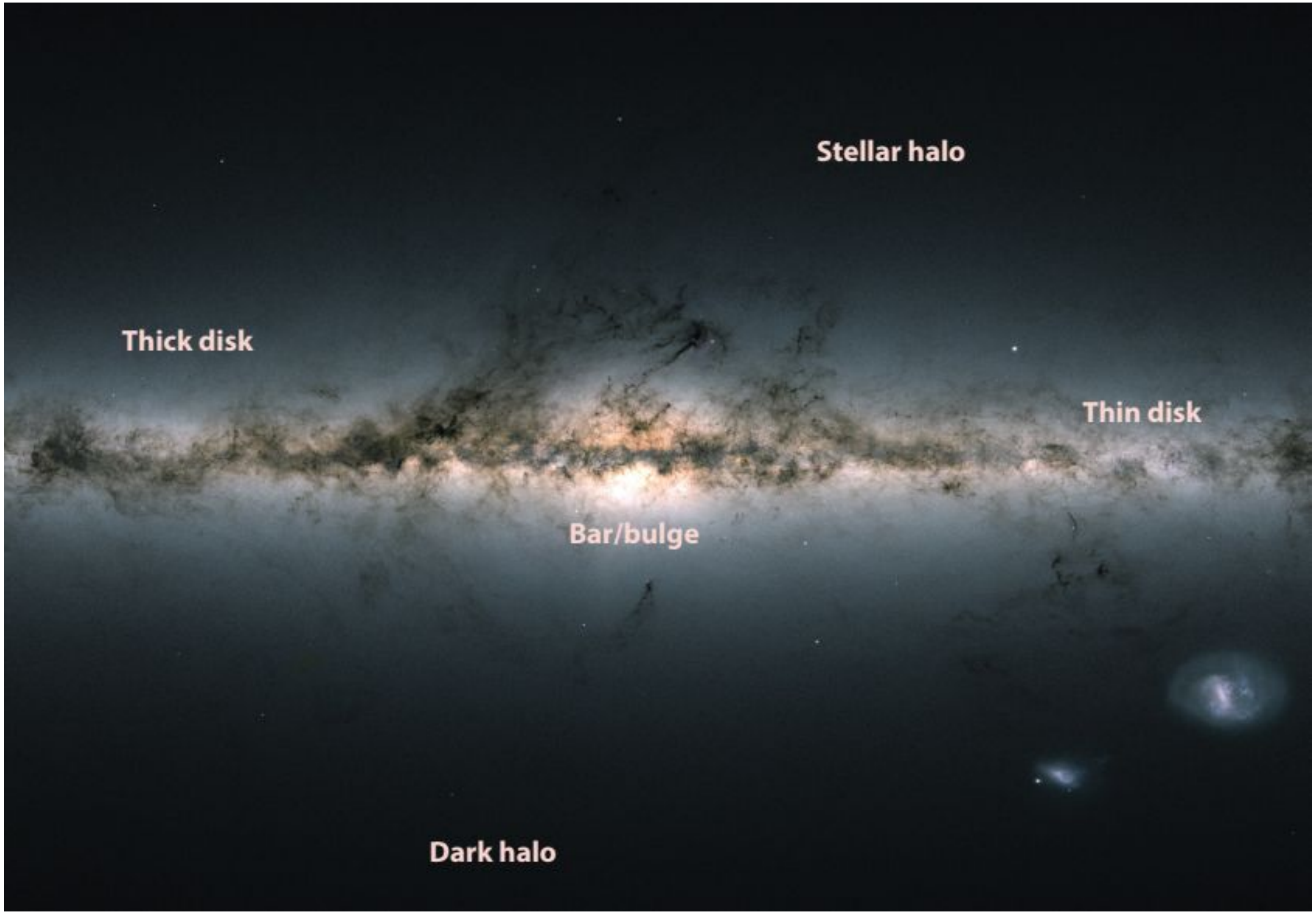
- Smoothly fit ***bias and sigma curves*** with high-order polynomial functions and then estimate the precision and accuracy on the labels determined, taking the training set as a reference.

- Explore ***Bayesian NNs and log likelihood loss functions*** can account for both uncertainties in input data as well as model uncertainties yielding well-defined estimates of uncertainties.

- For surveys using a training set based on ***standard spectroscopy, coupled with a CNN method***, the CNN gradients could be used to detect sensitive features unused by the standard pipeline.

- For the future use of CNN or in general machine-learning for stellar abundances measurements, one will have to ***develop an objective criterion*** to decide whether an abundance is a real detection or an upper limit.

Thank you for participating!!



Credit: Gaia/DPAC/ESA,
Amina Helmi, Annu. Rev. (2020)