Machine Learning *techniques* *for* Stellar Spectroscopy

Part 2

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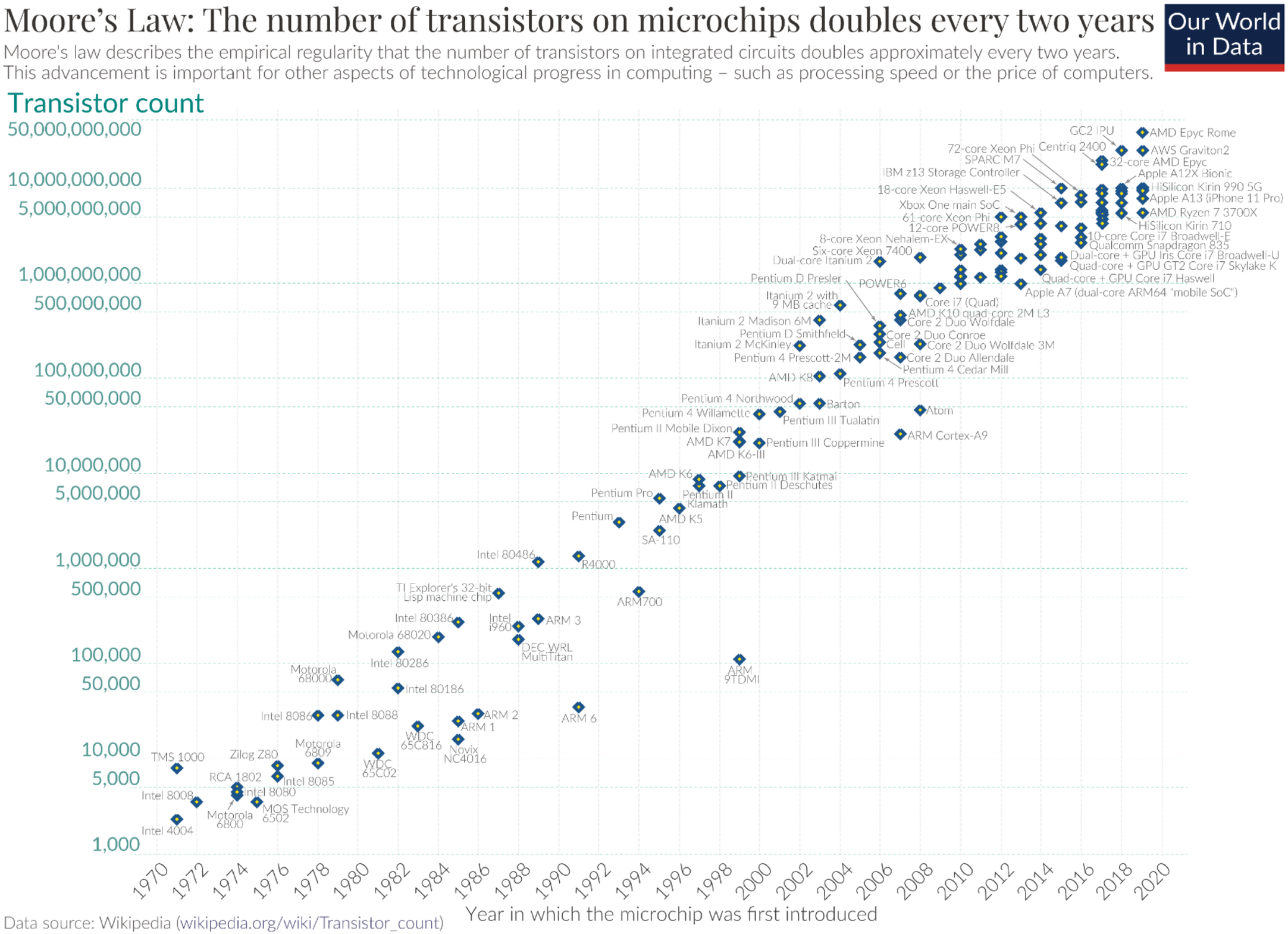
Part 1

- What is Machine Learning?
- How does it work?
- Brief introduction to Artificial Neuronal Networks.

Part 2

- The Cannon
- The Payne
- Issues of using ML for stellar spectroscopy and possible solutions

Machine Learning: why should we care?



Machine Learning: why should we care?

Tsunami of data (especially with the advent of new telescopes and missions).

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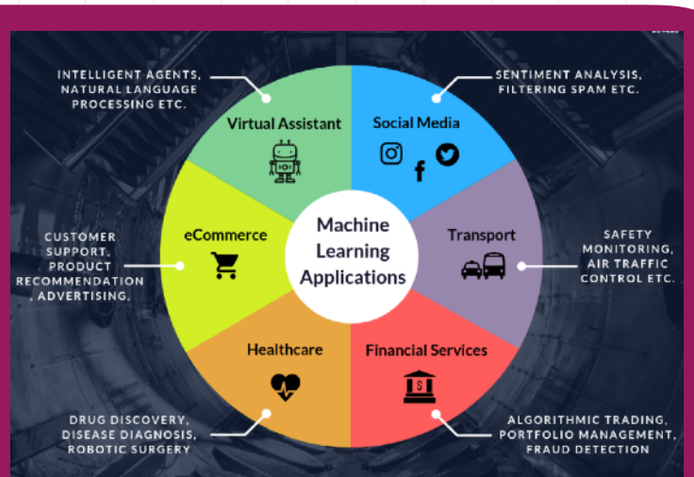
Machine learning is fully transferable to a broad range of fields.



In our dreams...

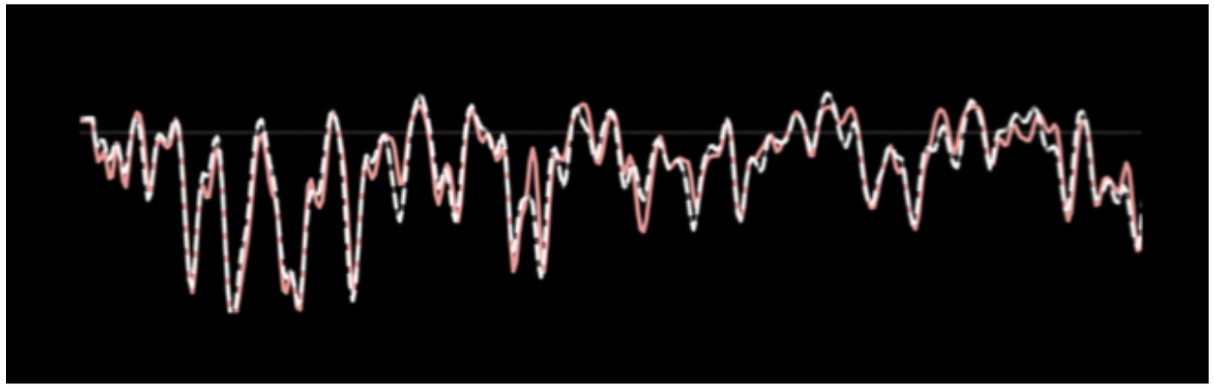
Stellar labels
(T_{eff}, log g, [Fe/H], [X/Fe])

↓

ML algorithm

(magics happen)

↓



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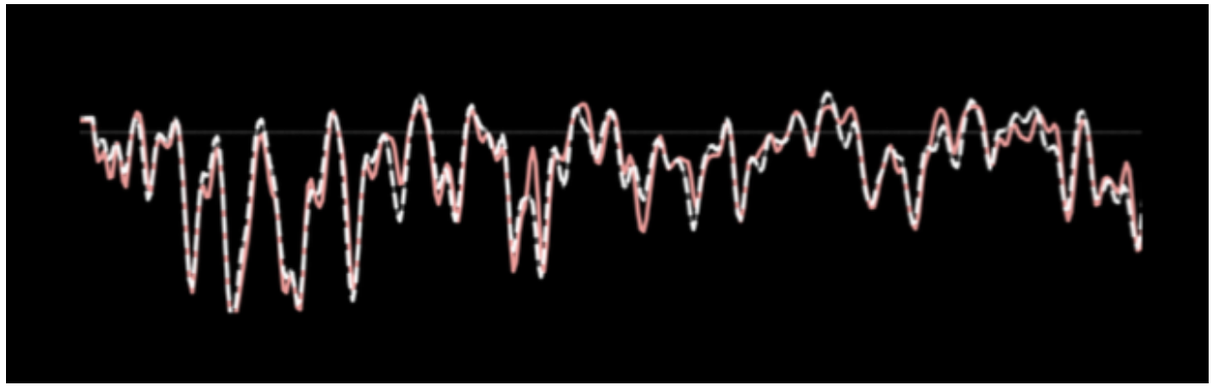

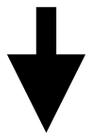

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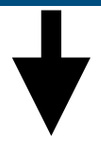

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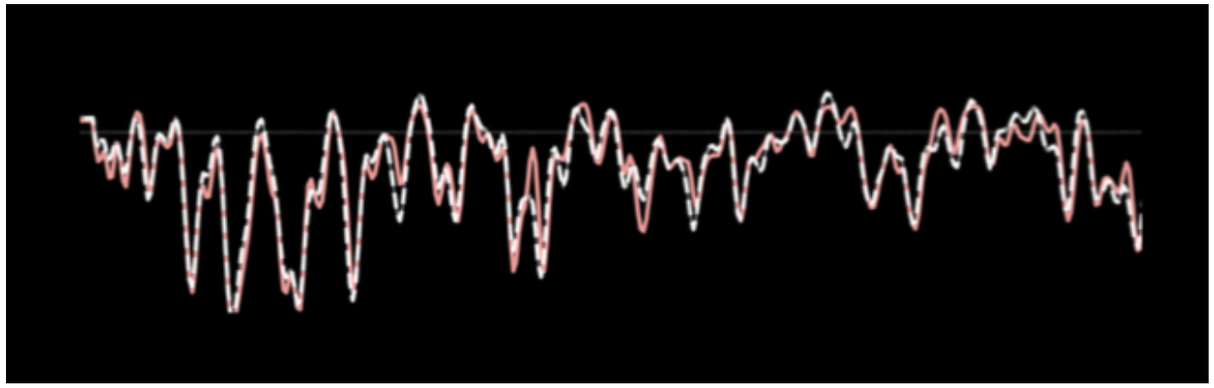

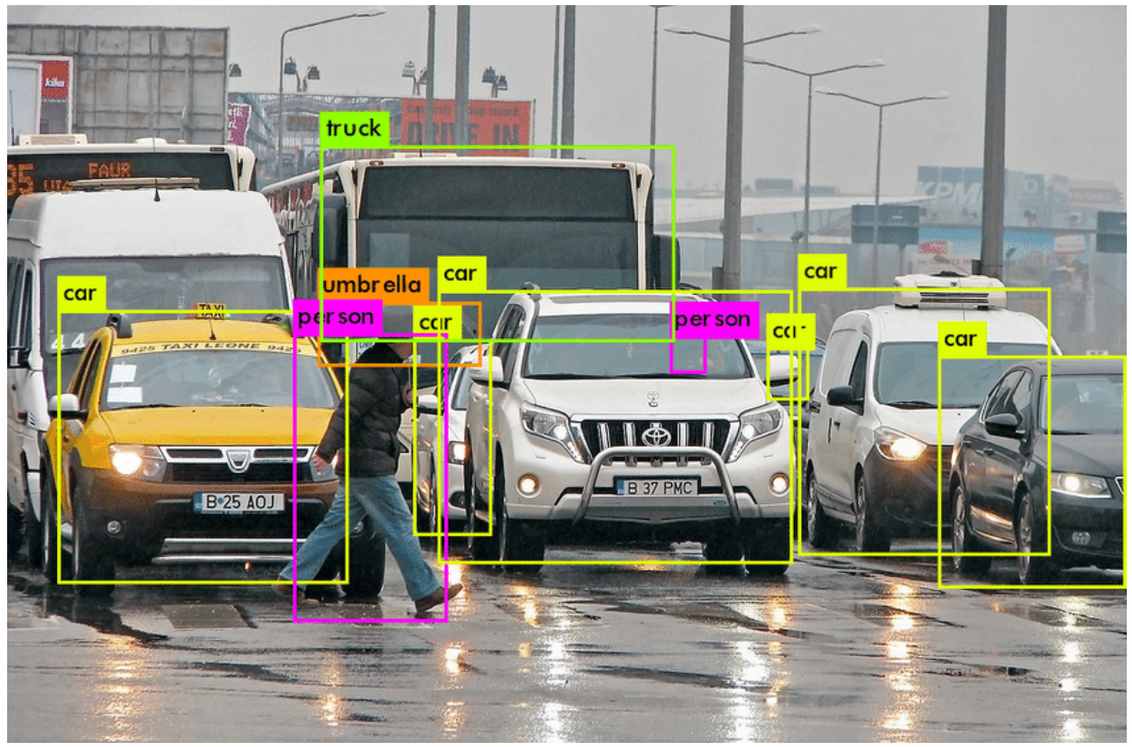

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Computer vision VS stellar spectroscopy

a cat

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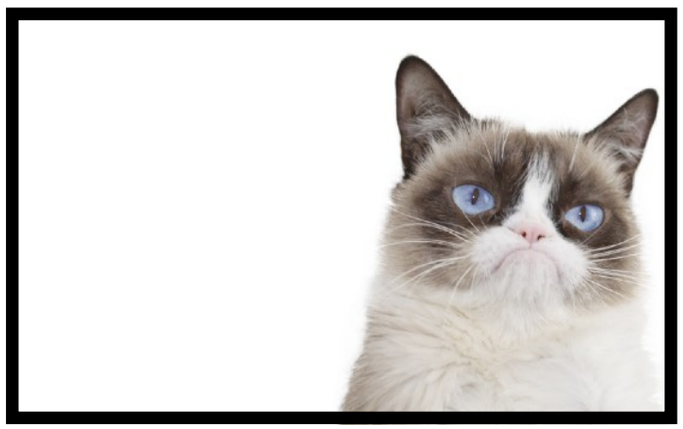

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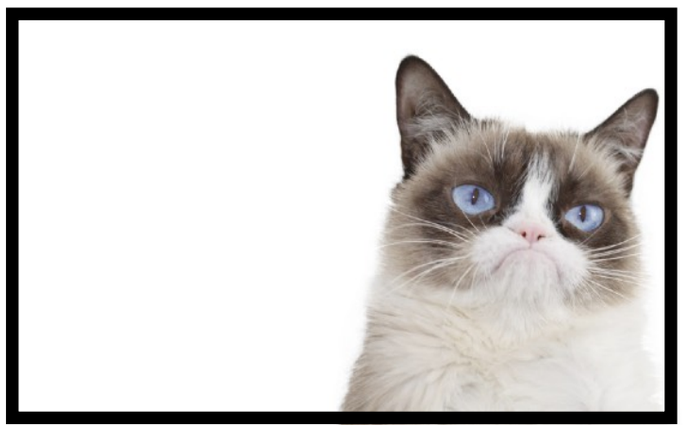

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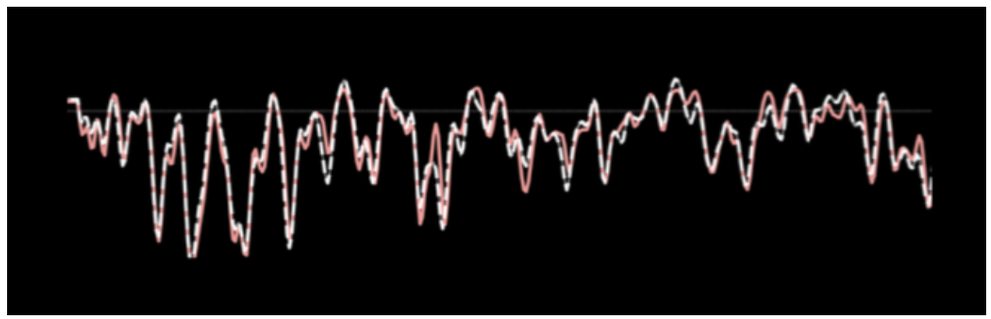
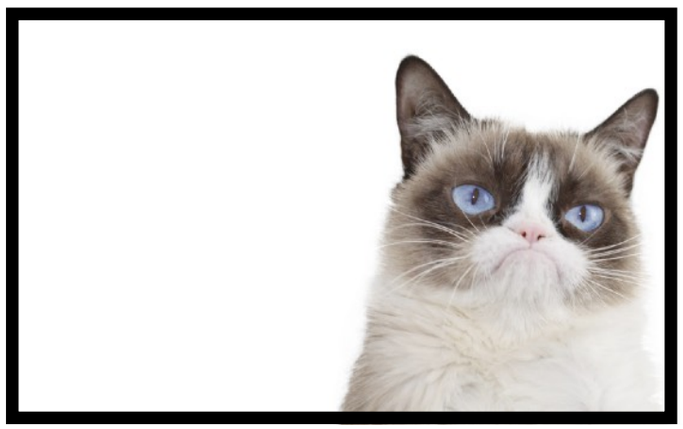


a spectrum



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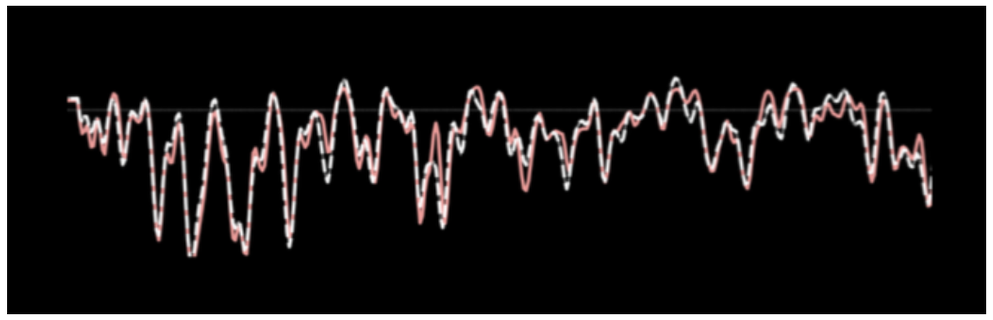

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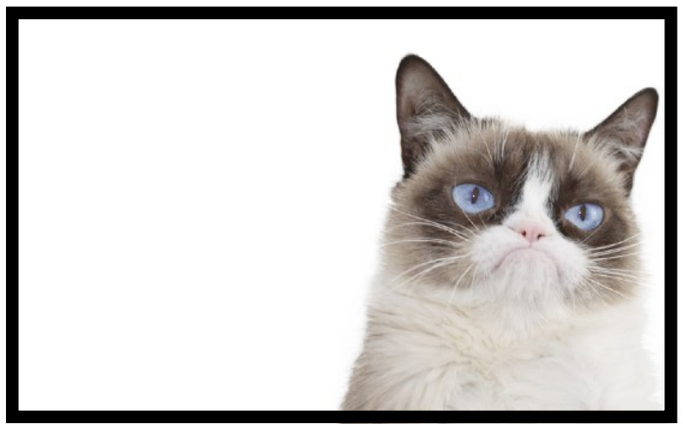

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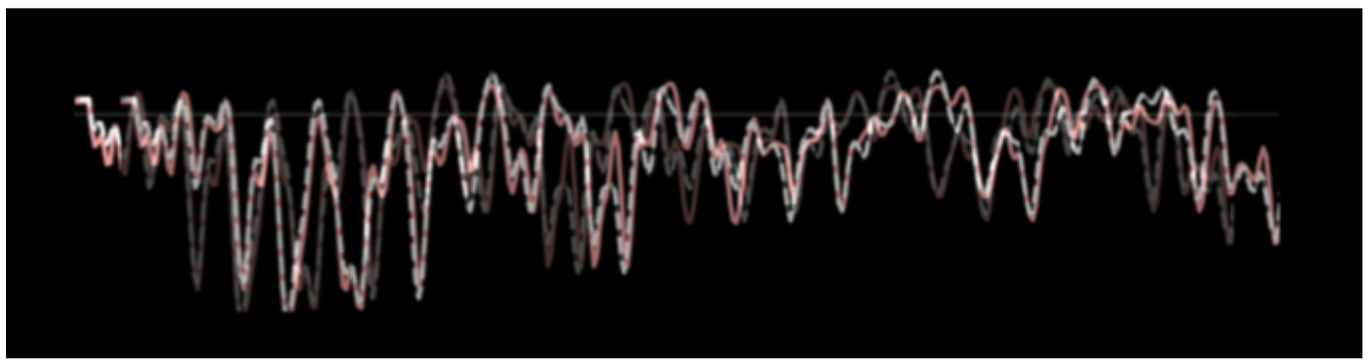

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not the same spectrum!

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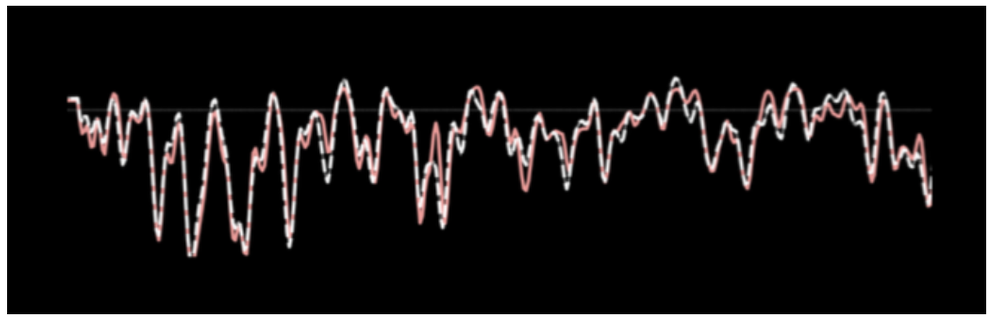

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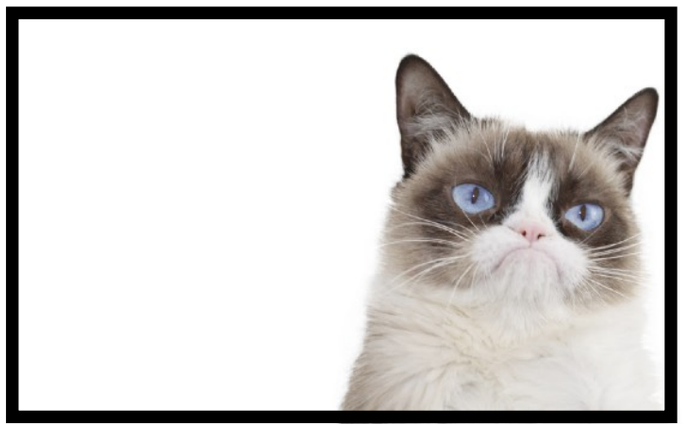

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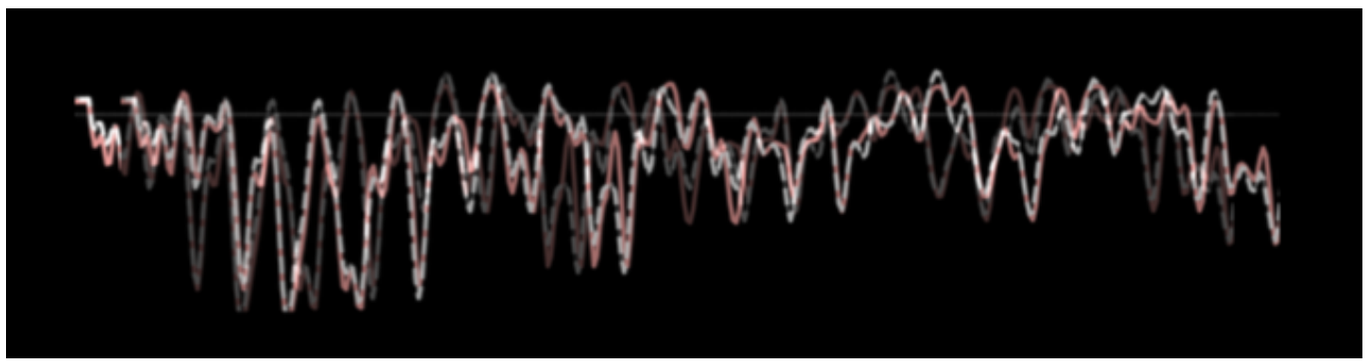

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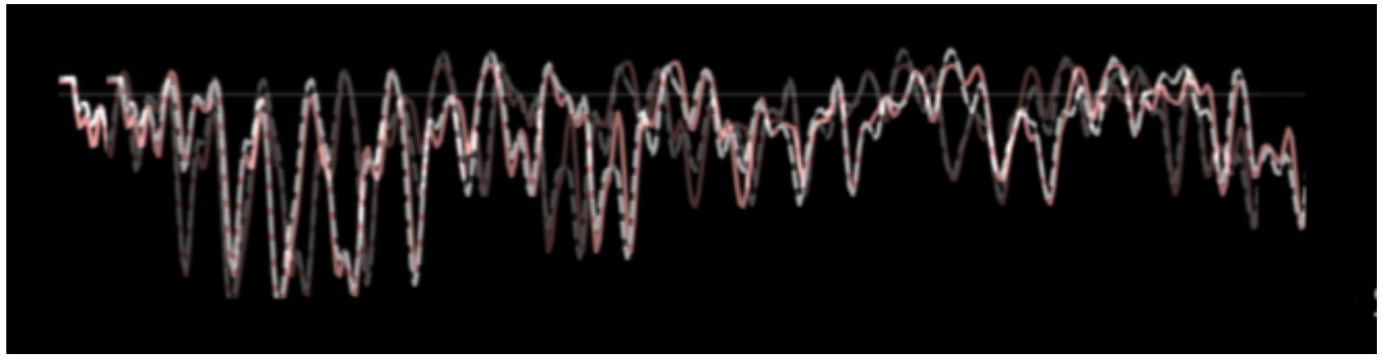

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https://annayqho.github.io/TheCannon/

The Cannon Ness et al. (2015)

A pure data-driven approach to Spectroscopic Analysis.

Flux at every pixel for the nth-star

$$f_{n\lambda} = g(\mathbf{l_n} | \theta_\lambda) + \mathbf{noise}$$

Stellar parameters and abundances of the nth-star. (known labels)

Coefficients. One per pixel. (unknown, trainable)

The **coefficients** and the **noise** can be "learnt" from a training set of spectra whose stellar parameters are already know.

Once the model is ready, you can apply it to other stars with unknown labels.

The Cannon relies on the following to be true:

- stellar flux varies smoothly with stellar labels
- stars with the same labels have the same spectra

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The g function is a polynomium, whose order is set by the user.

First-order polynomium. The most simple model.

$$f_{n\lambda} = a_\lambda + b_\lambda(\mathrm{Teff})_n + c_\lambda(\mathrm{logg})_n + d_\lambda([\mathrm{Fe/H}])_n + \text{noise}$$

$$\theta_\lambda = (a_\lambda, b_\lambda, c_\lambda, d_\lambda)$$

Authors suggest to use a second-order polynomium (quadratic-in-label case).

$$\begin{aligned}
F_{n\lambda} = {} & \theta_0 && \text{(constant term)} \\
& + \theta_{T_{\rm eff}} T_{\rm eff} + \cdots + \theta_{X_N}[X_N/\mathrm{Fe}] && \text{(linear terms)} \\
& + \theta_{T^2_{\rm eff}} T^2_{\rm eff} + \cdots + \theta_{X^2_N}([X_N/\mathrm{Fe}])^2 && \text{(squared terms)} \\
& + \theta_{T_{\rm eff}\,\log(g)} T_{\rm eff}\log(g) + \ldots \\
& \quad + \theta_{X_N X_{N-1}}[X_N/\mathrm{Fe}][X_{N-1}/\mathrm{Fe}] && \text{(cross-terms)} \\
& + \text{error}
\end{aligned}$$

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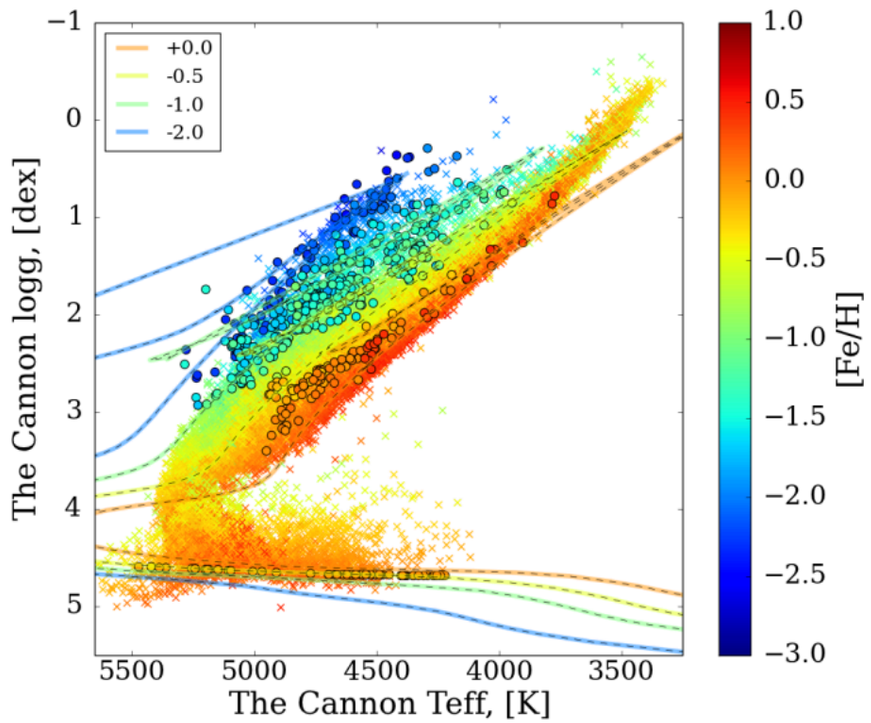

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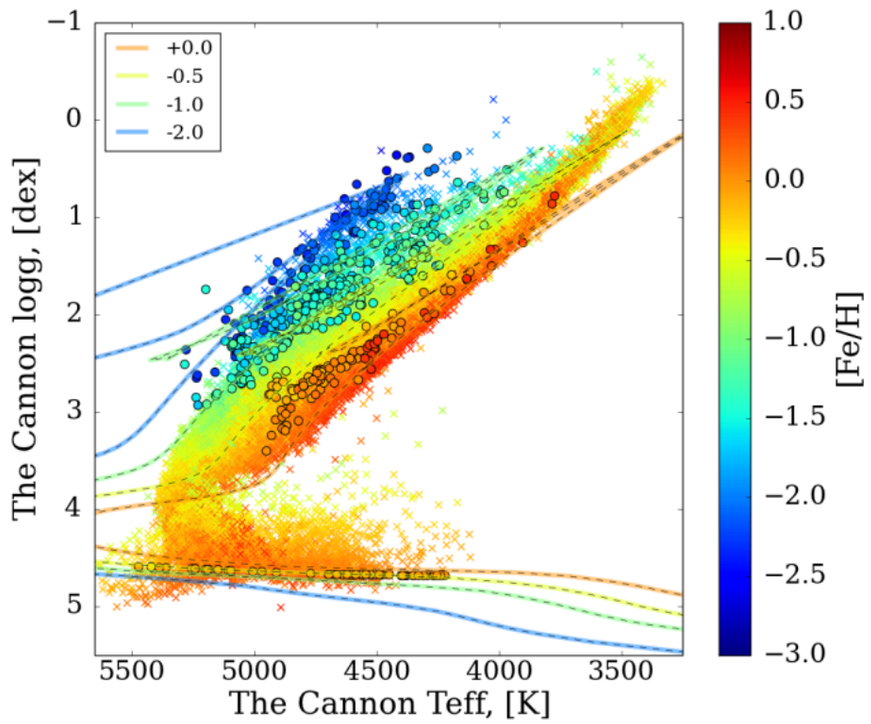

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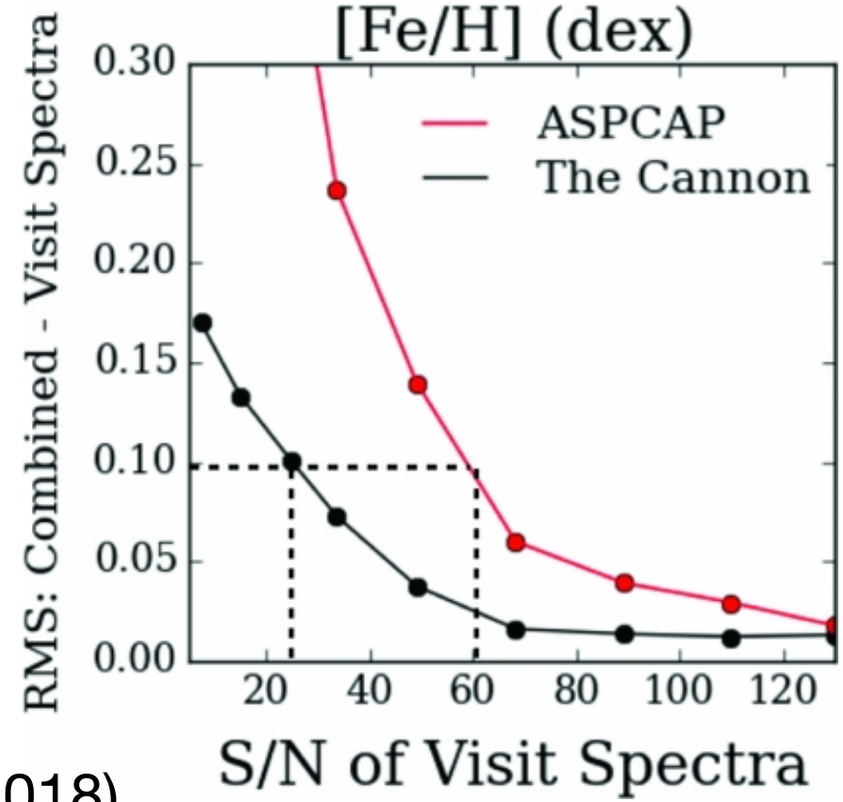

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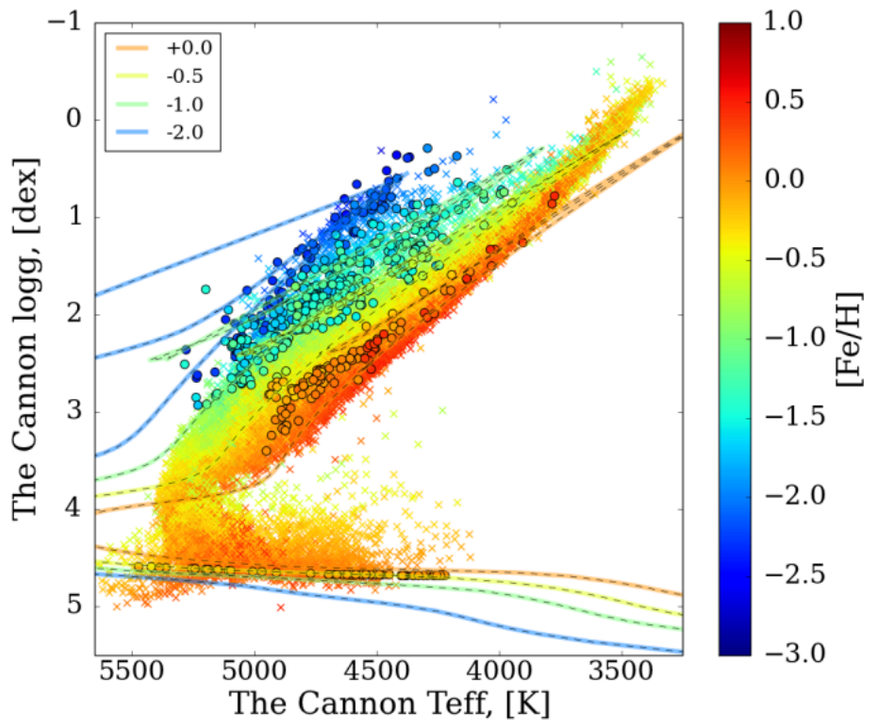

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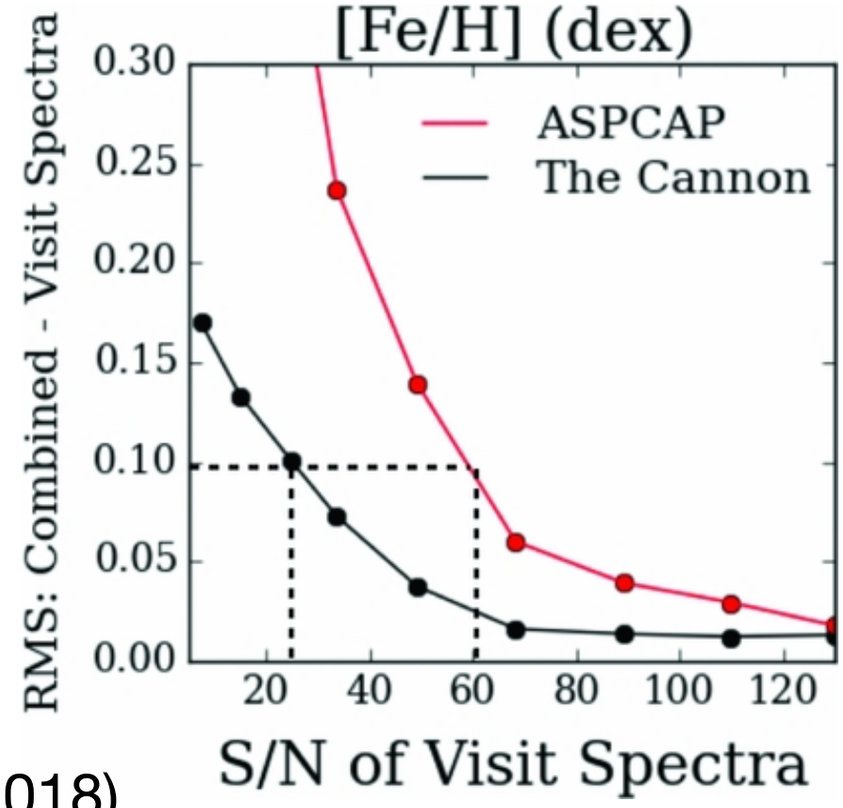

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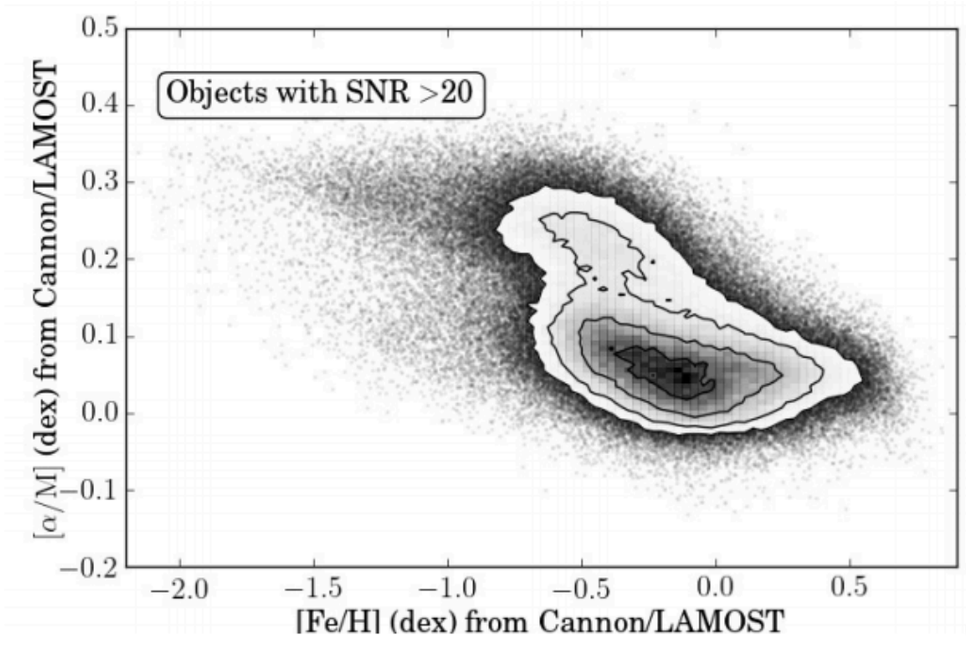

Oh et al. (2017)

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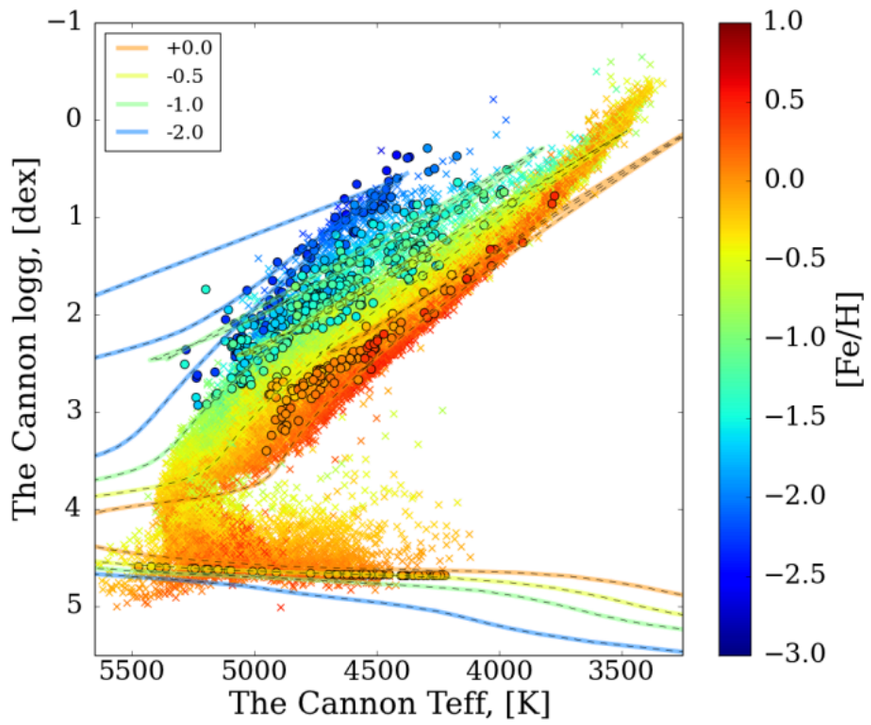

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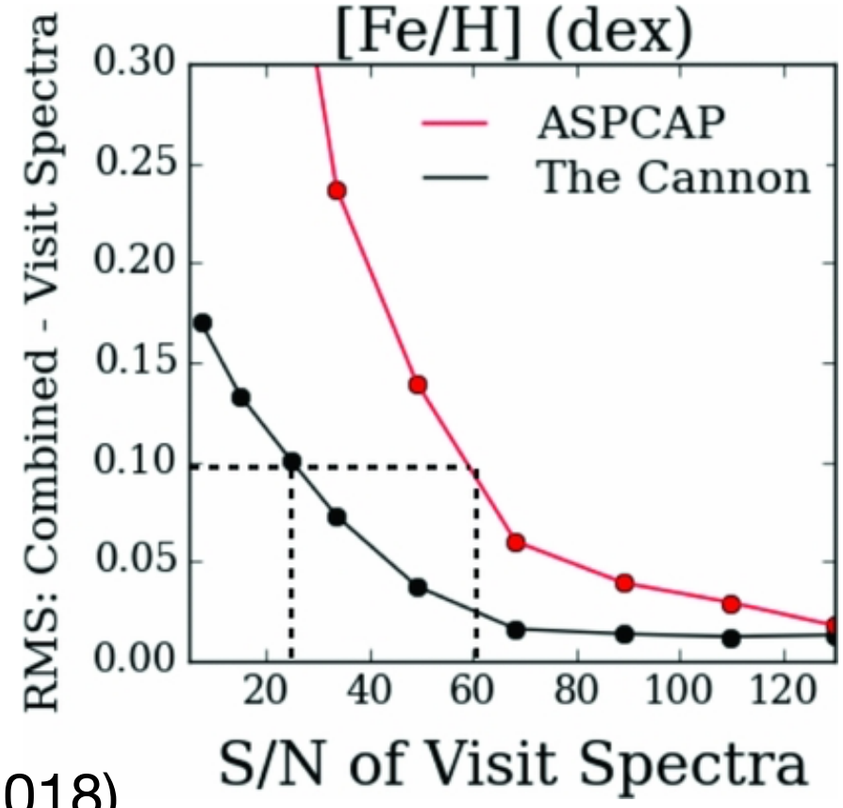

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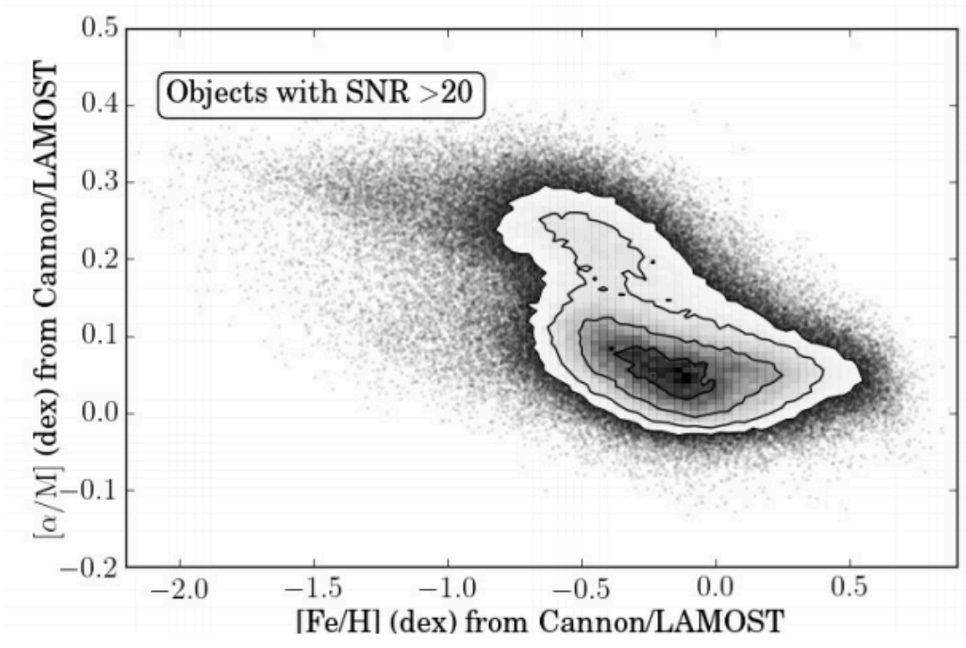

Oh et al. (2017)

Advantage

The method is extremely symple and fast.

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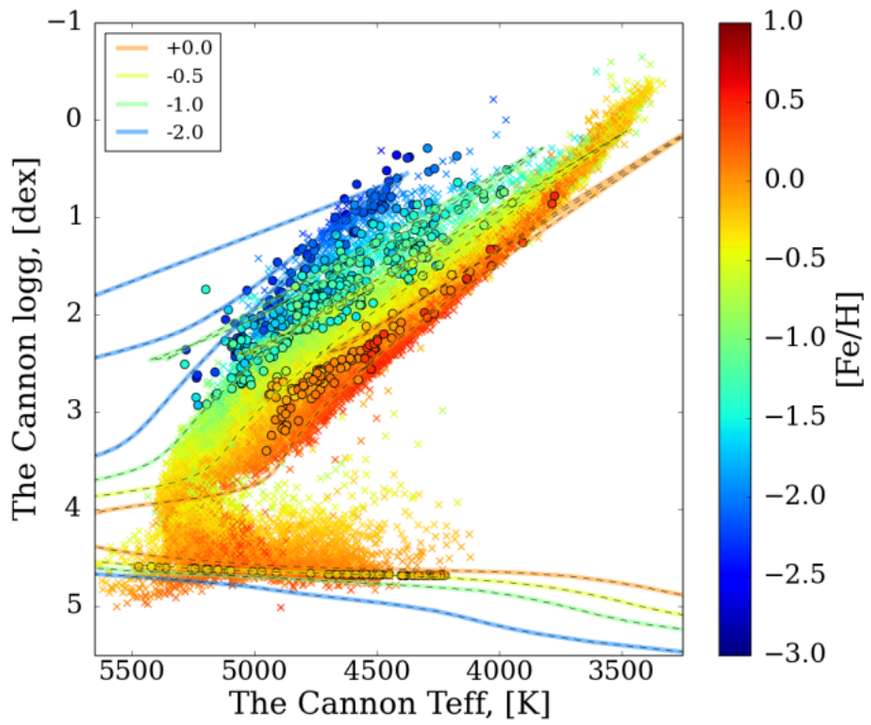

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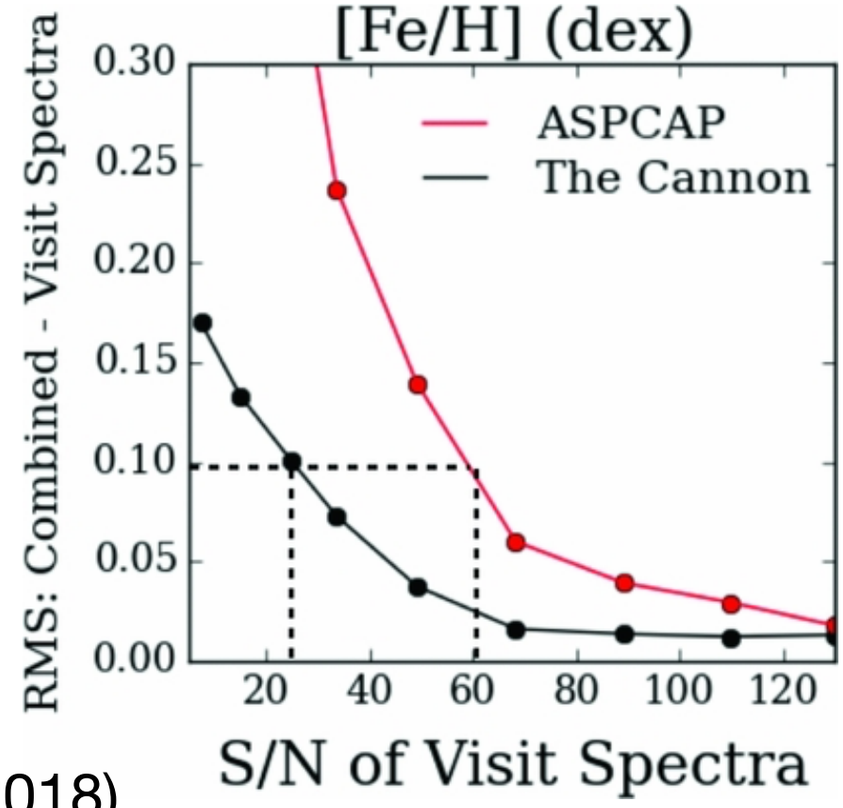

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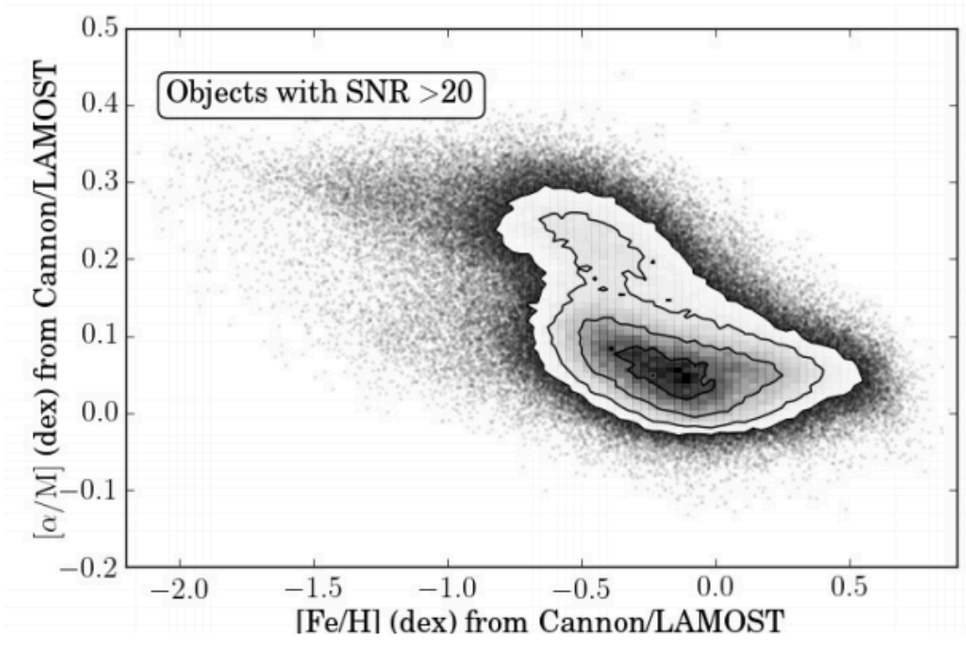


Oh et al. (2017)

Advantage

The method is extremely symple and fast.

Danger

The method uses no physical stellar models.

The pitfalls of a data-driven approach

Beware of hidden **bias** and **correlations**!

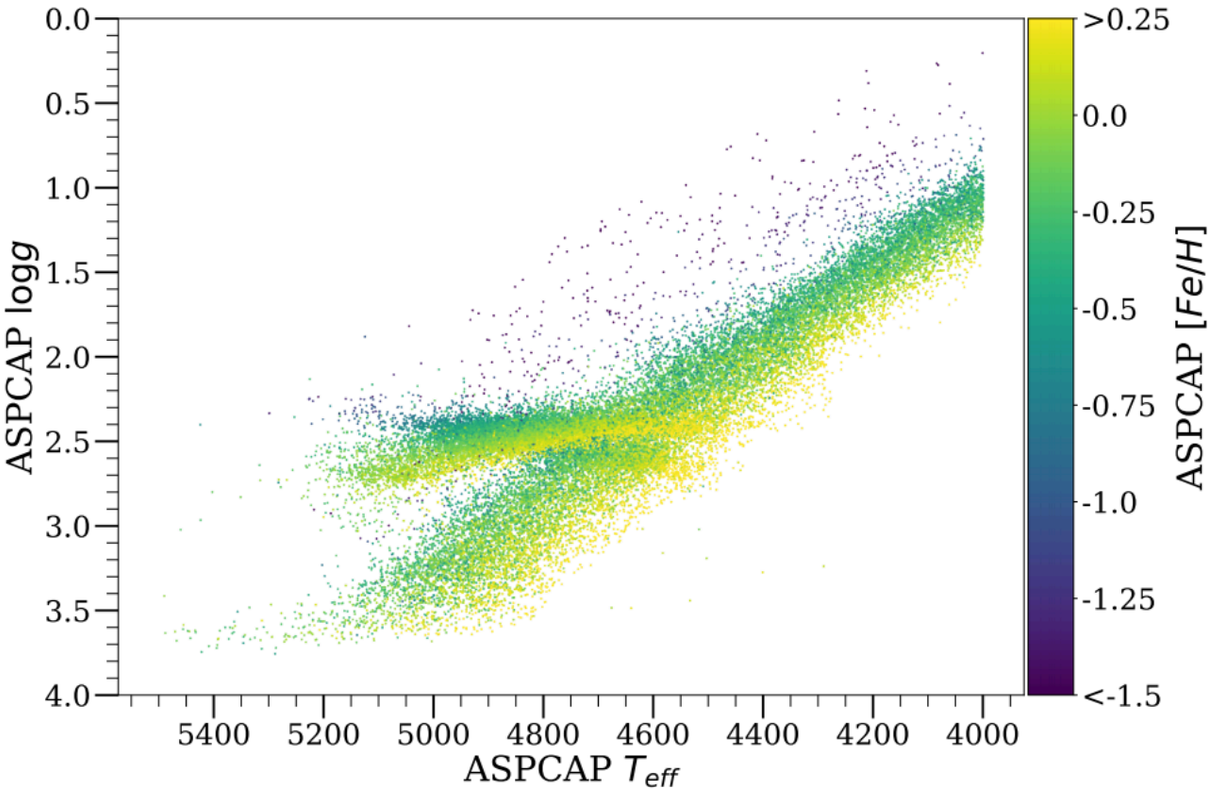
The danger of using data-driven models.

We need to be extra cautious of what the ML algorithms are "learning" and what training sets we build.

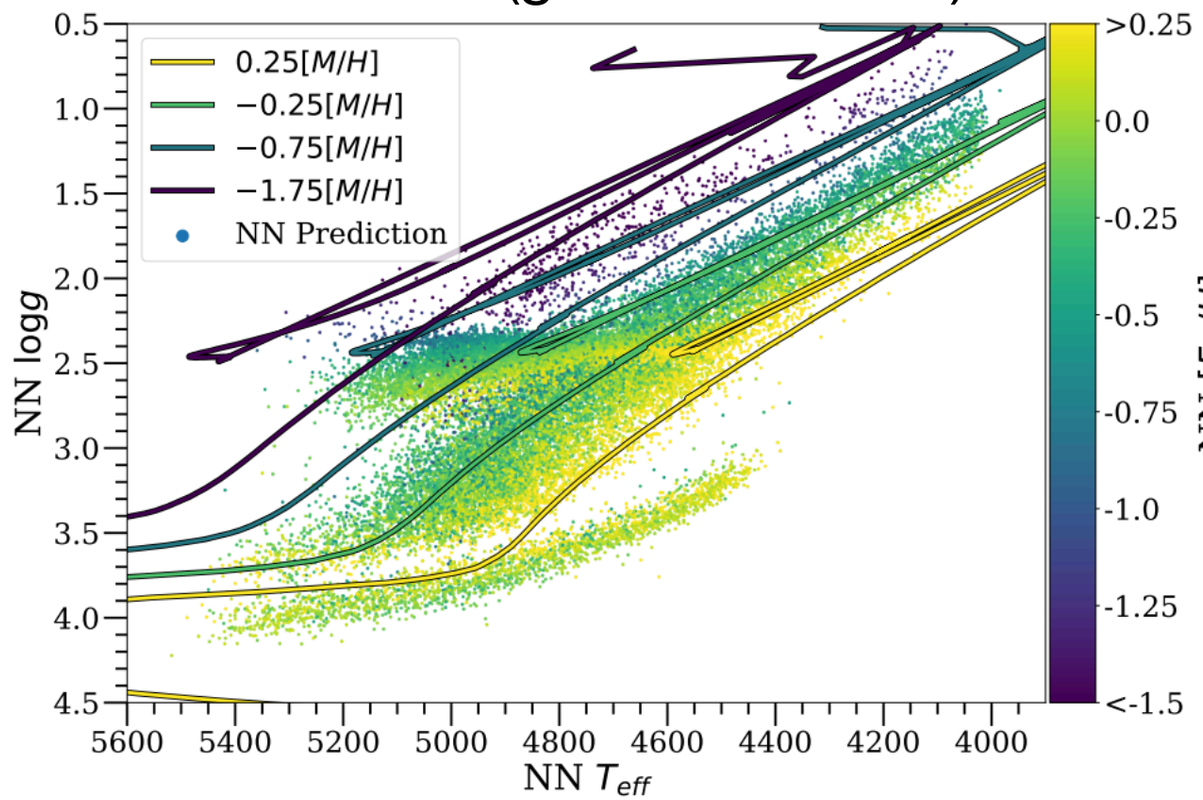
The pitfalls of a data-driven approach

The effect of **biases** in the training set...

Training set (only giants)



Test set (giants + dwarfs)



Leug & Bovy (2018)

Take-home messages:

The training set must be representative of the specific problem we want to address.

Any bias that exists in the training set will be folded into the test set.

The pitfalls of a data-driven approach

The effect of **correlations** in the training set.

Is the model
"learning"
measurements?

...or is it "learning"
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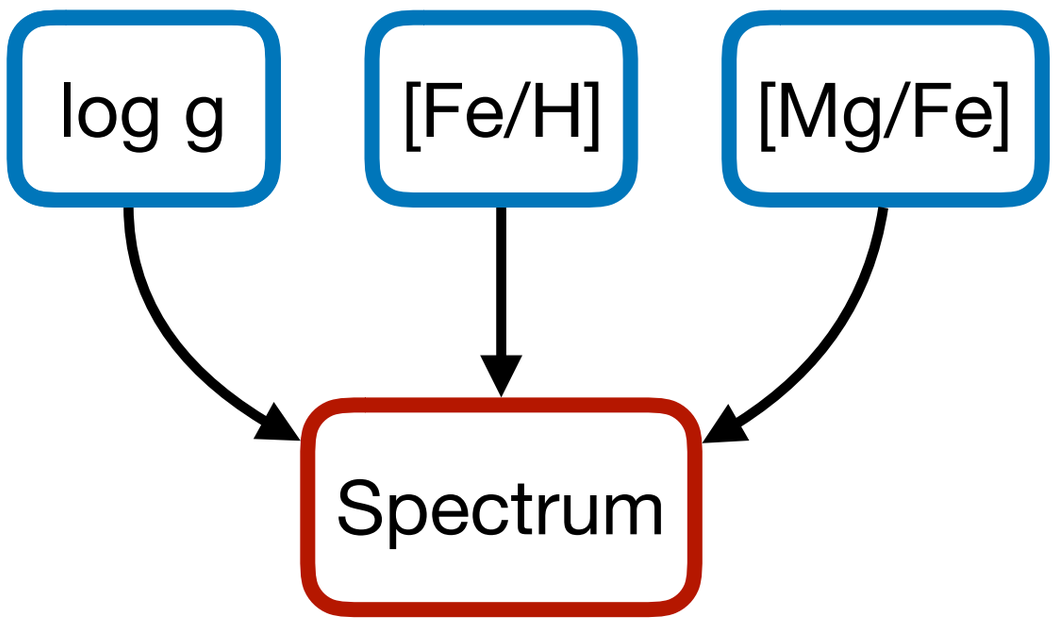

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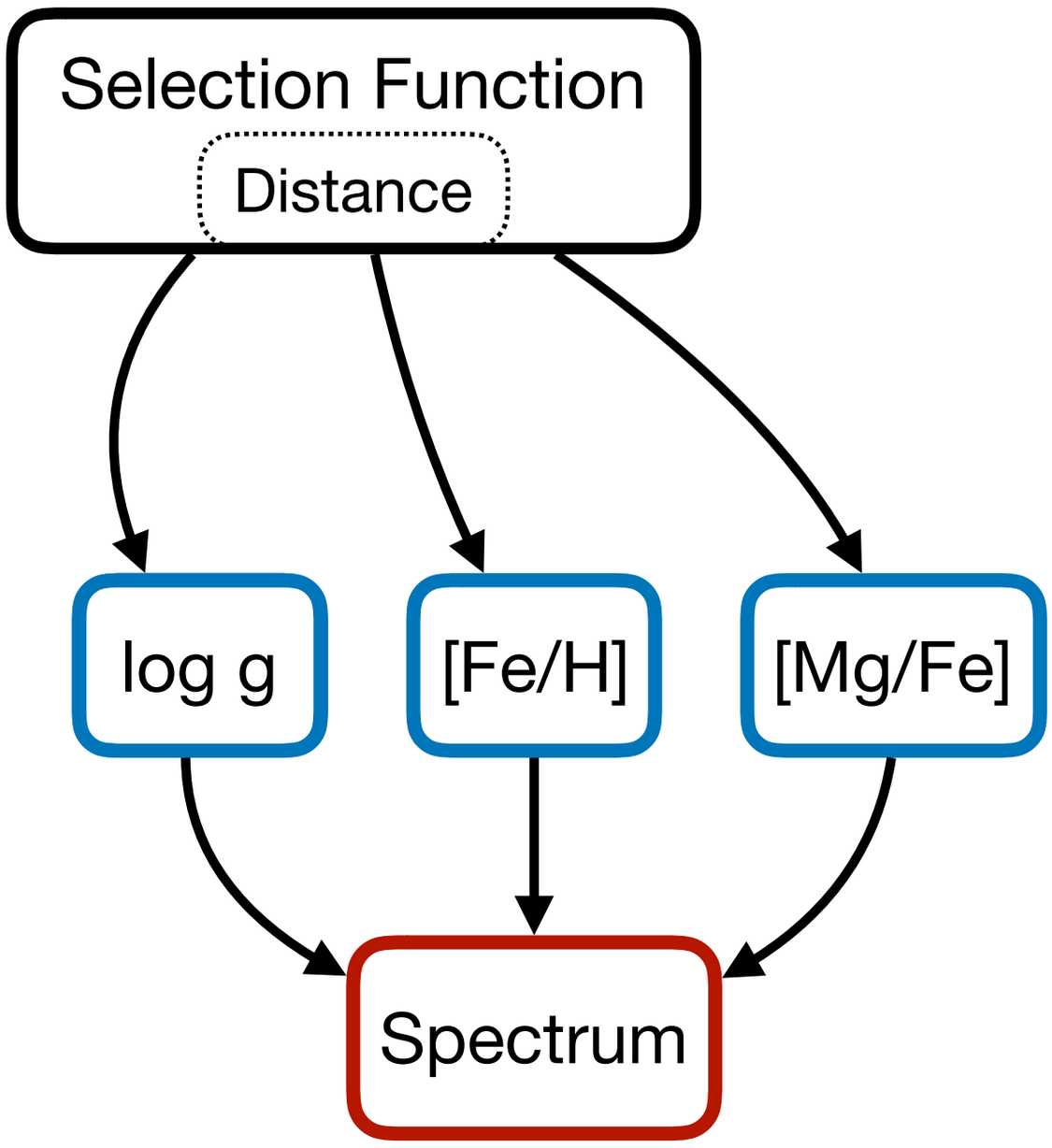

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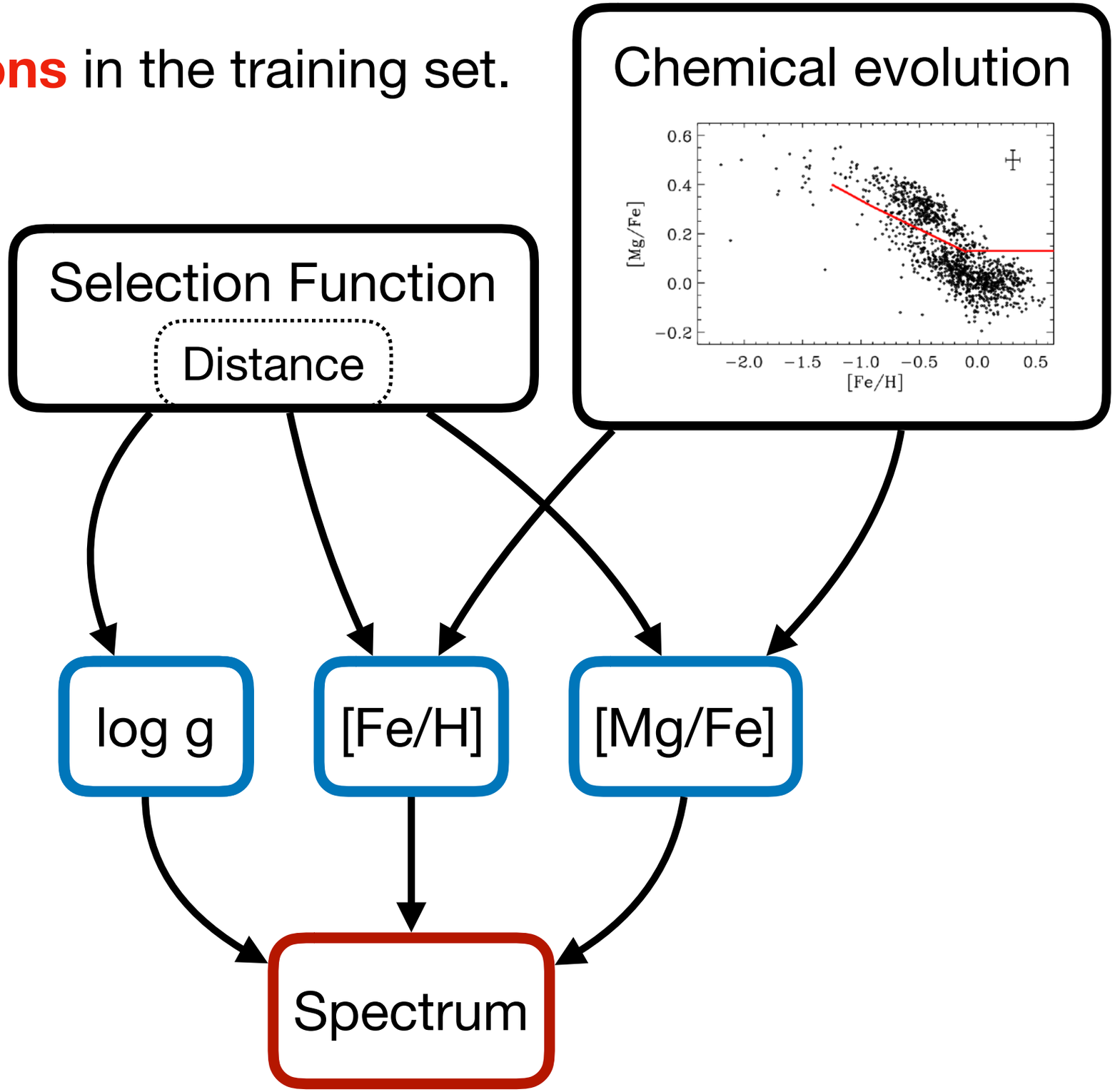

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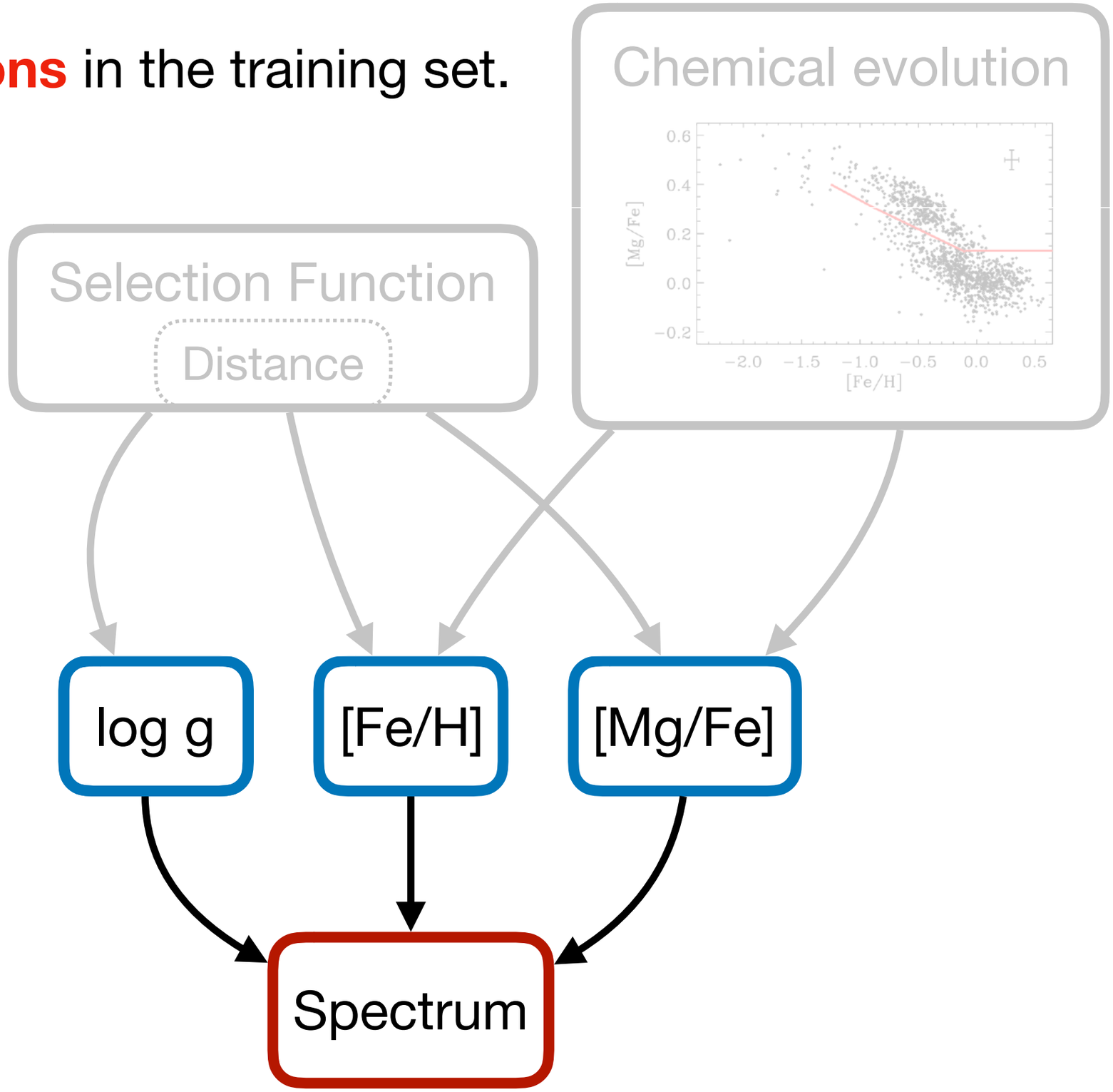

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The pitfalls of a data-driven approach

Beware of hidden **bias** and **correlations**!

The danger of using data-driven models.

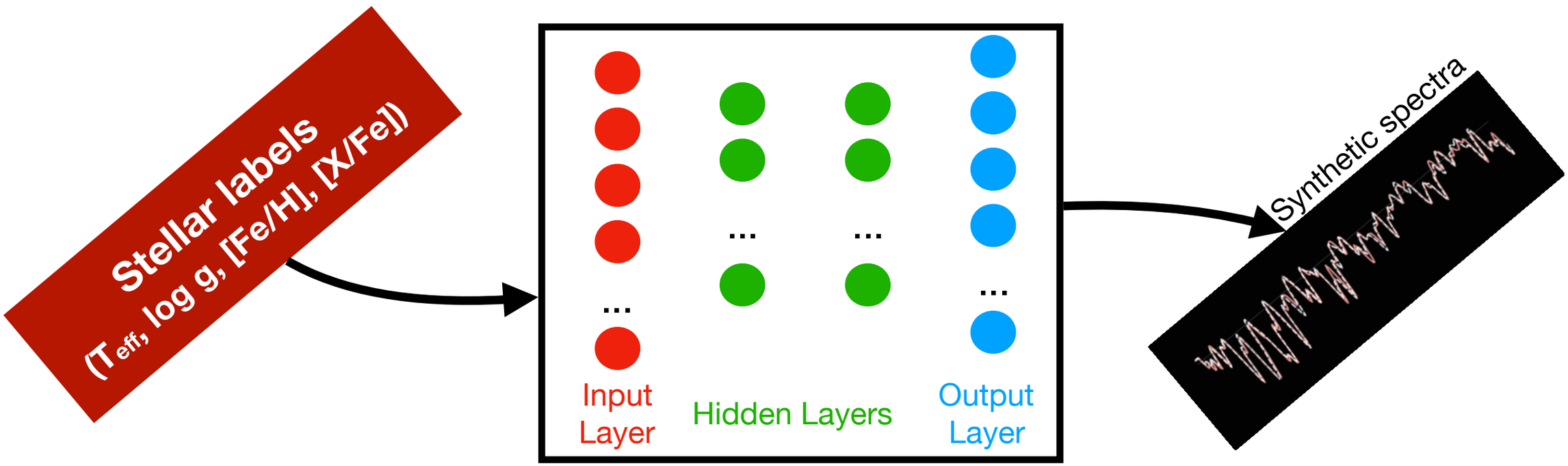
We need to be extra cautious of what the ML algorithms are "learning" and what training sets we build.

Unfortunately bias and correlations are unavoidable in stellar spectroscopy...

https://github.com/tingyuansen/The_Payne

The Payne Ting et al. (2019)

Physical generalization: the training sample is composed by synthetic spectra.



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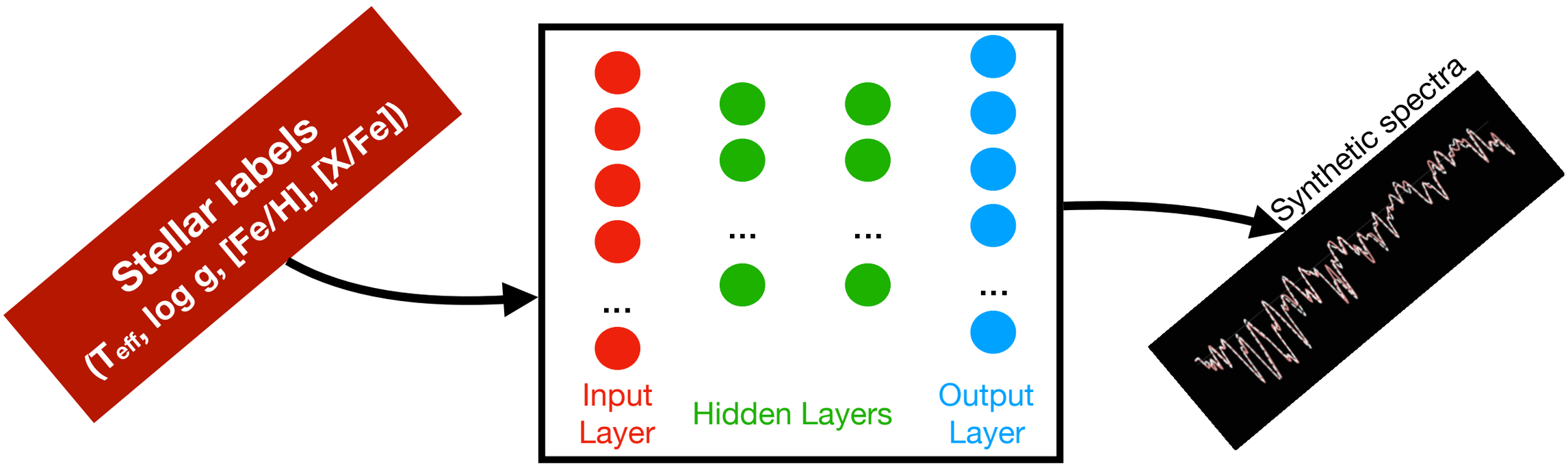

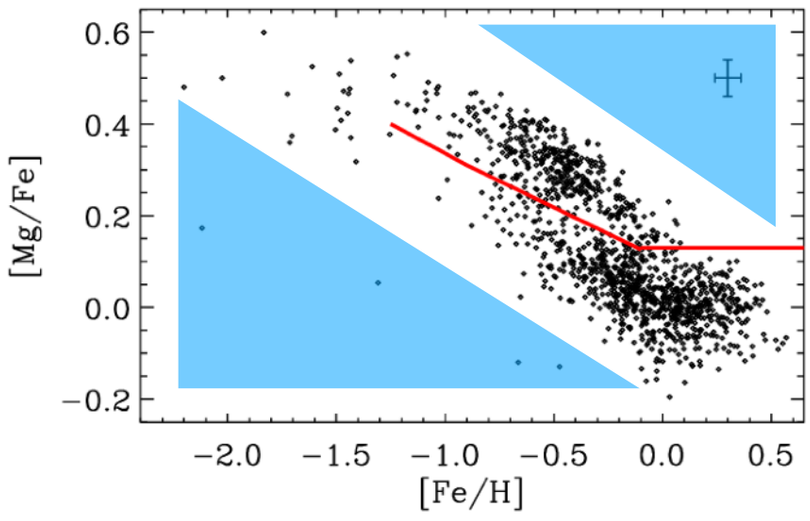

Full control on the training sample
You can sample the entire space of parameters.

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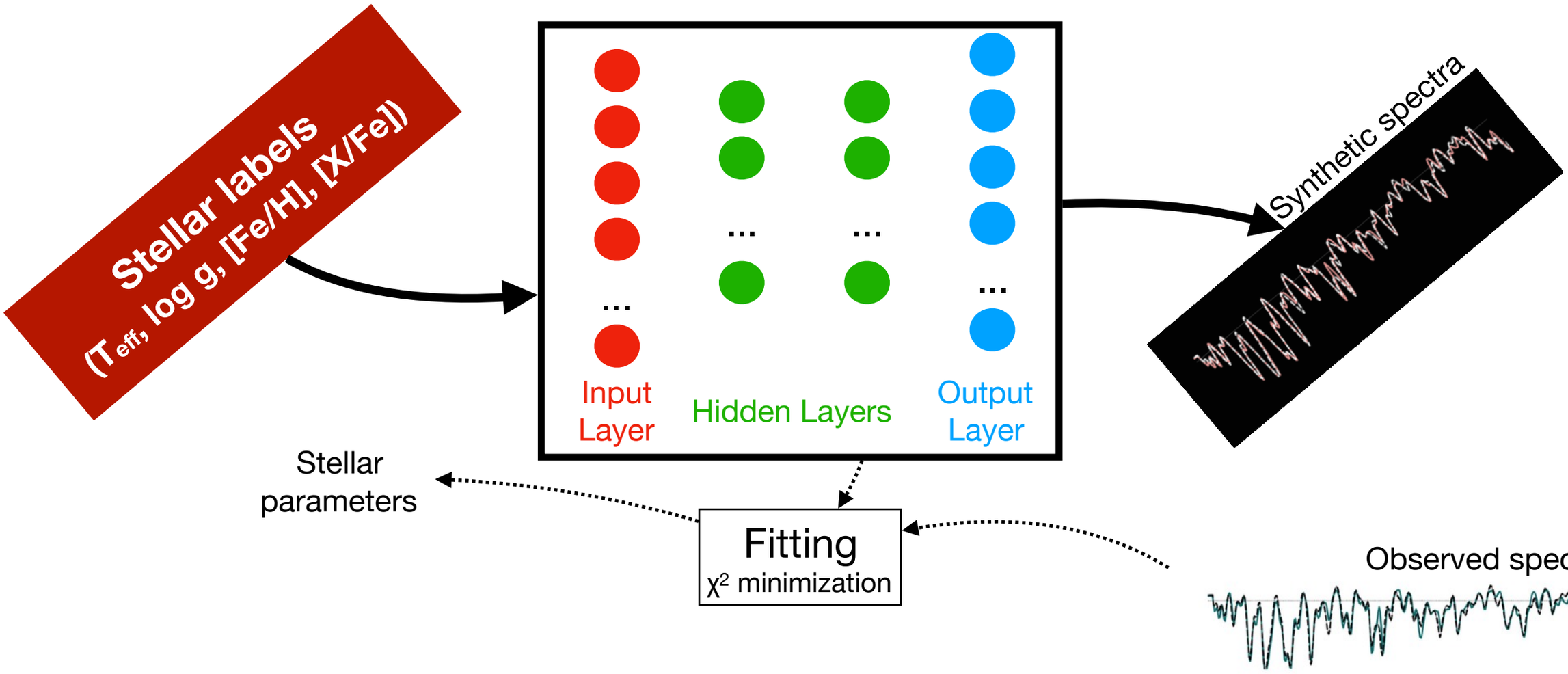
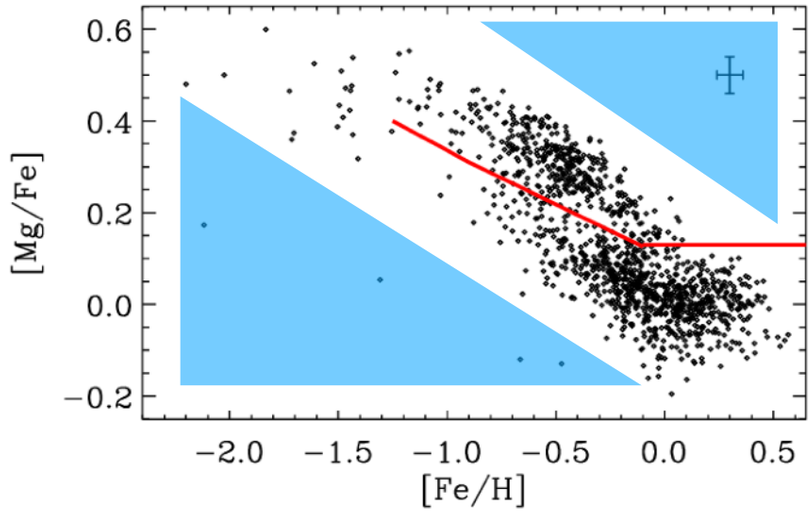
Physical generalization: the training sample is composed by synthetic spectra.





Full control on the training sample
You can sample the entire space of parameters.

Thanks to this fast interpolator of atmospheric models you can simply fit your spectra in order to calculate the atmospheric parameters.

https://github.com/tingyuansen/The_Payne

The Payne Ting et al. (2019)

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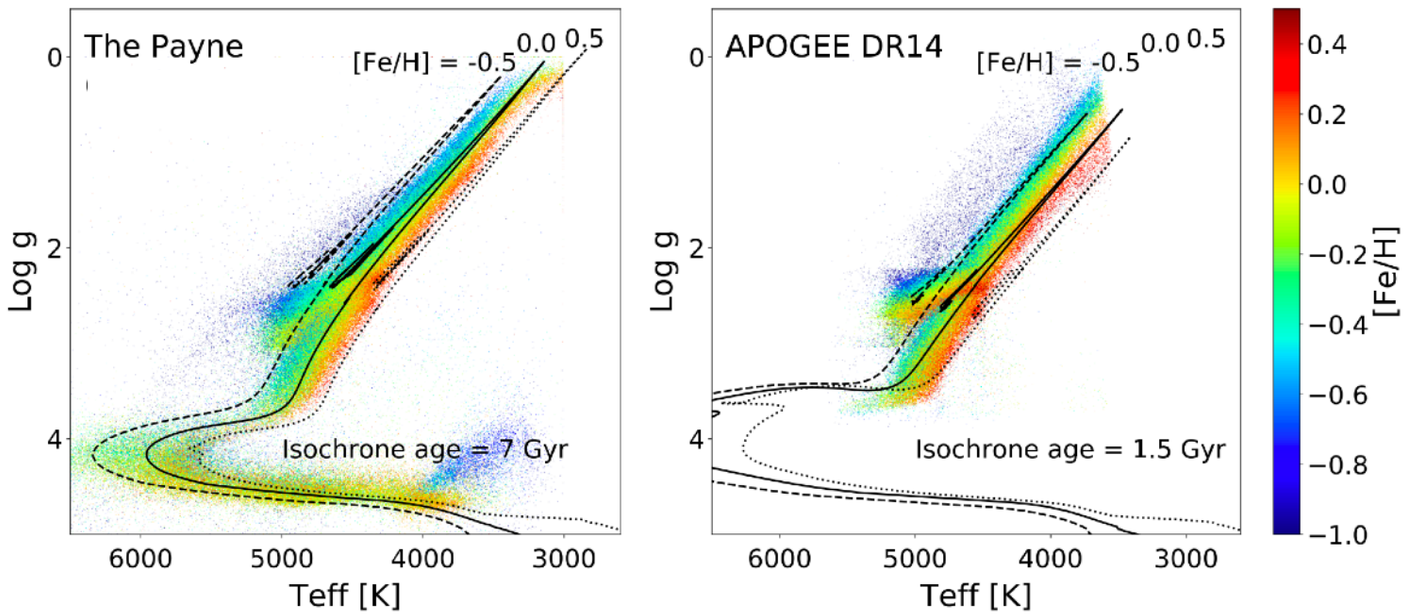
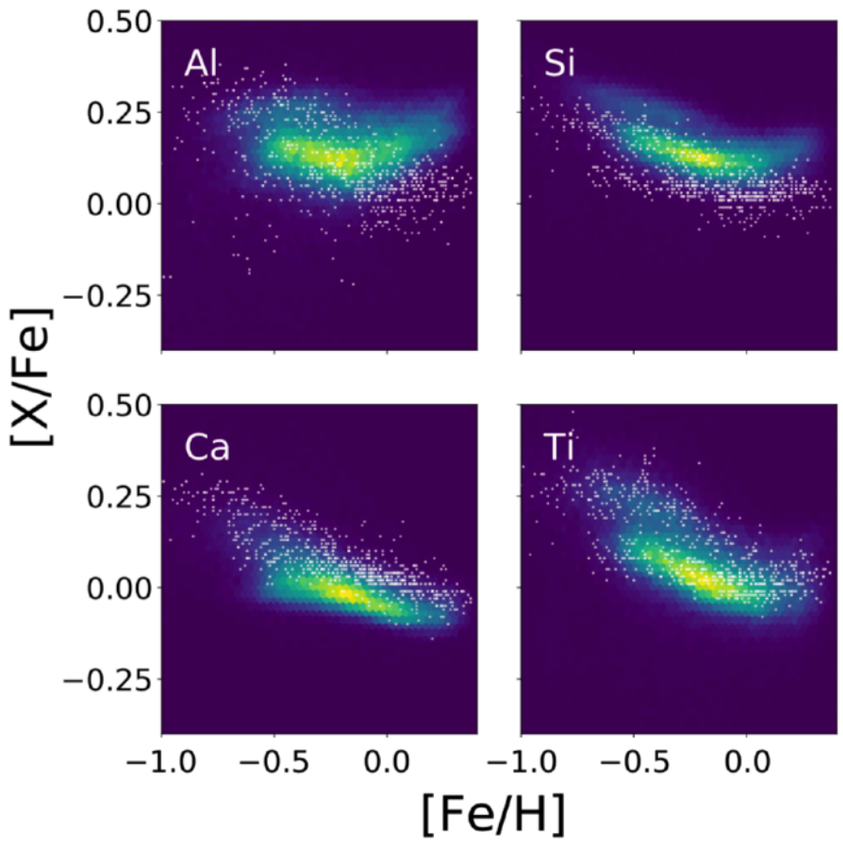
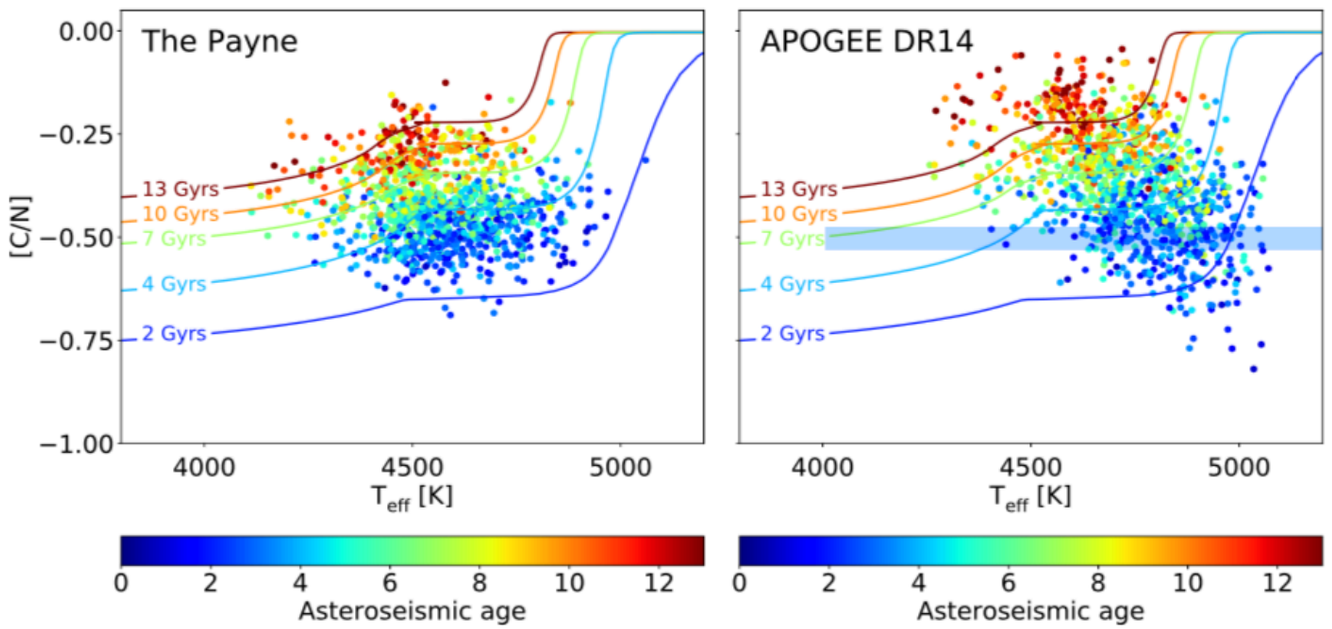


Analysis of the APOGEE DR14 dataset with The Payne (Ting et al 2019).





The pitfall of physical generalisation: the synthetic gap

Models are good approximations of reality, but they are not perfect.
Synthetic gap: differences in feature distributions between synthetic and observed spectra.

Tips to reduce the synthetic gap:

- pre-processing the spectra: matching the resolution and sampling of the spectra to a common wavelength scale and removing the continuum.
- argumenting the spectra data set: adding Gaussian noise, rotational and radial velocities, masking telluric regions, and zeroing flux values to mimic bad pixels

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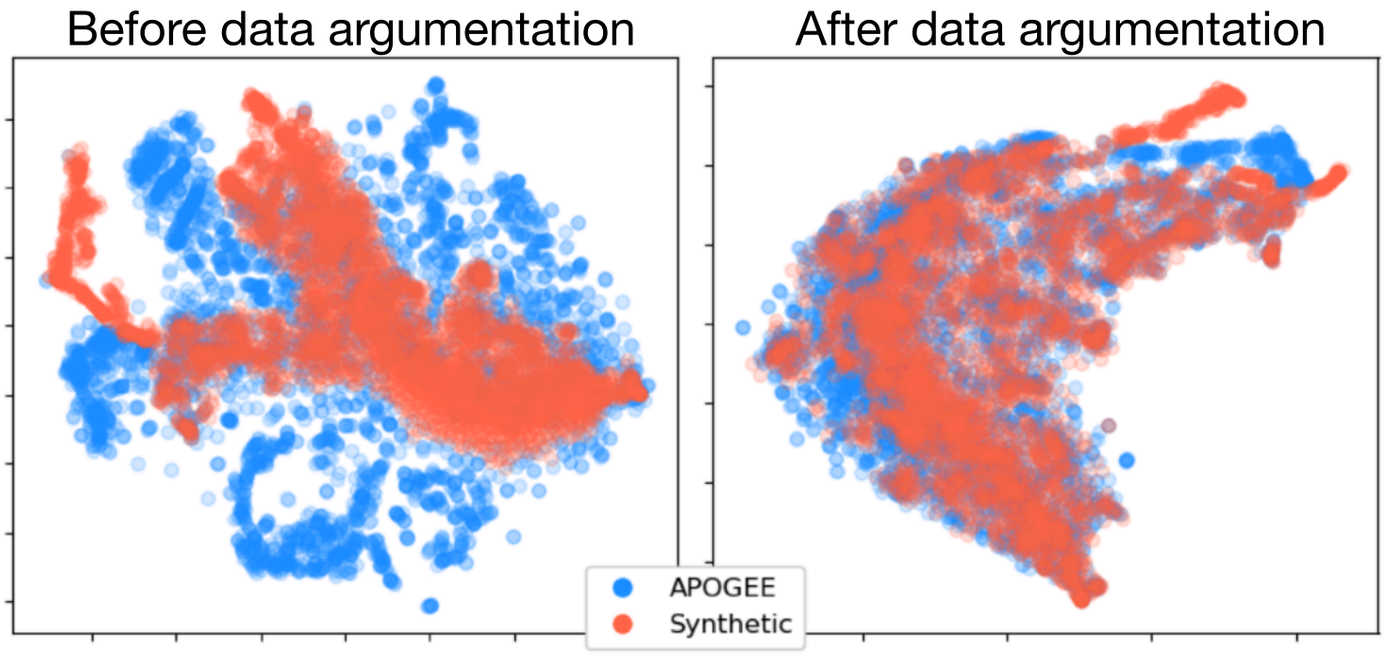
t-SNE visualization of the synthetic and APOGEE spectra



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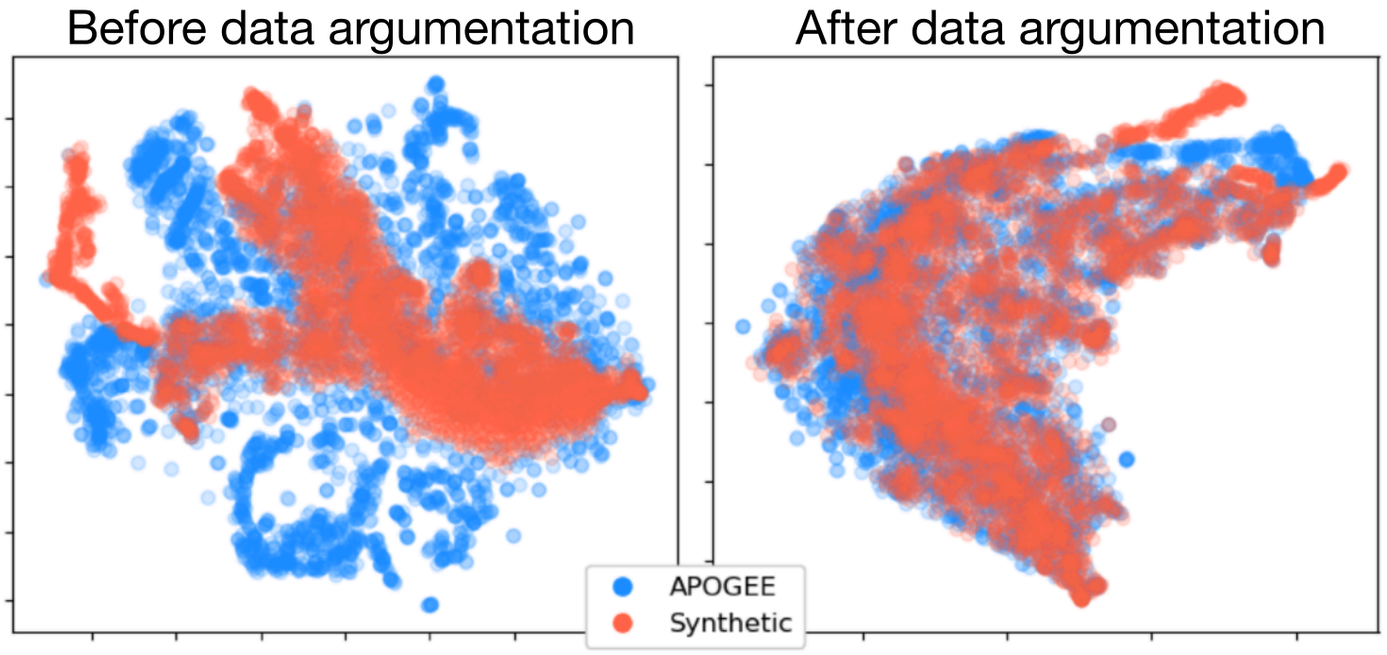
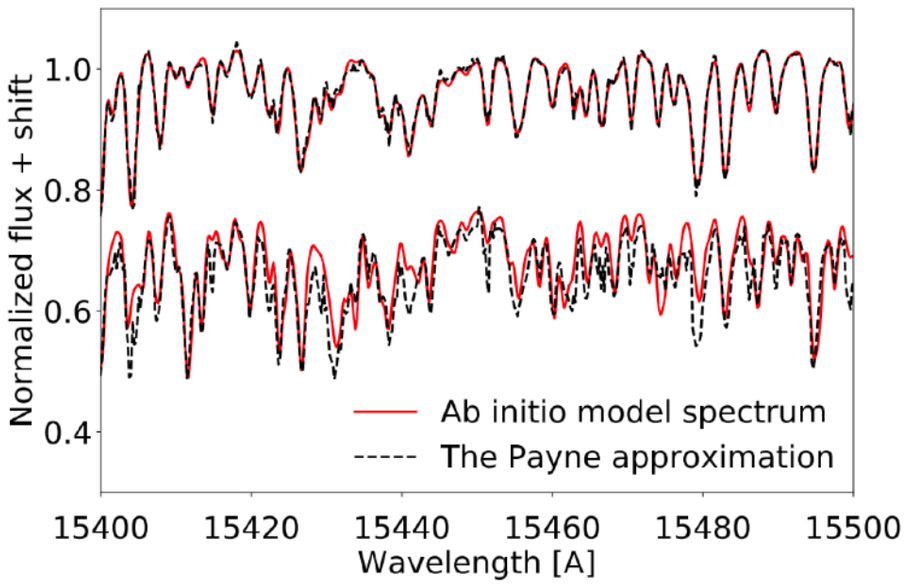


Fabbro et al. (2017)

Spectra generalisation



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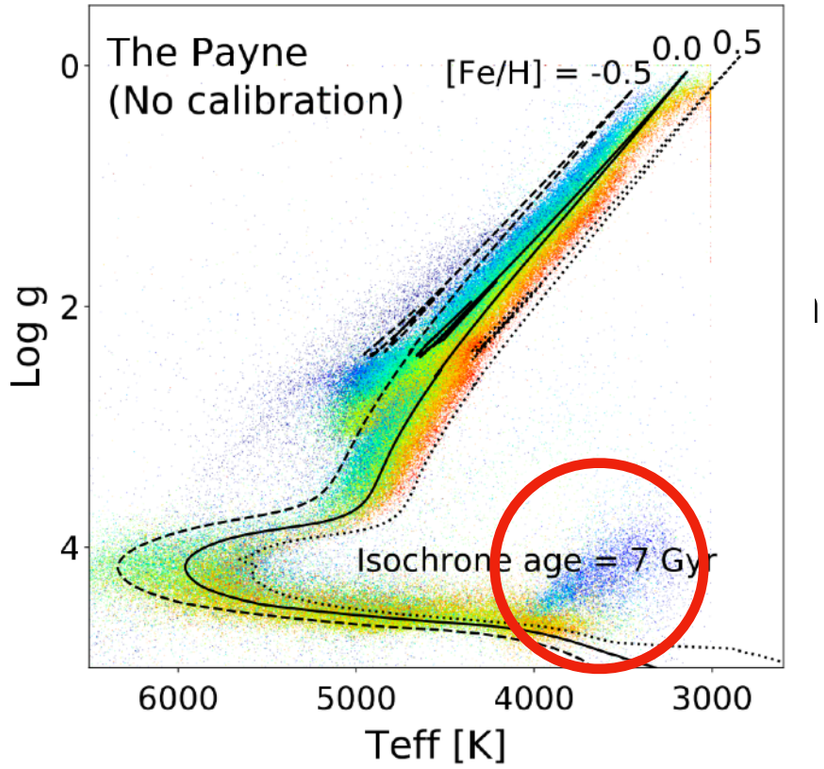

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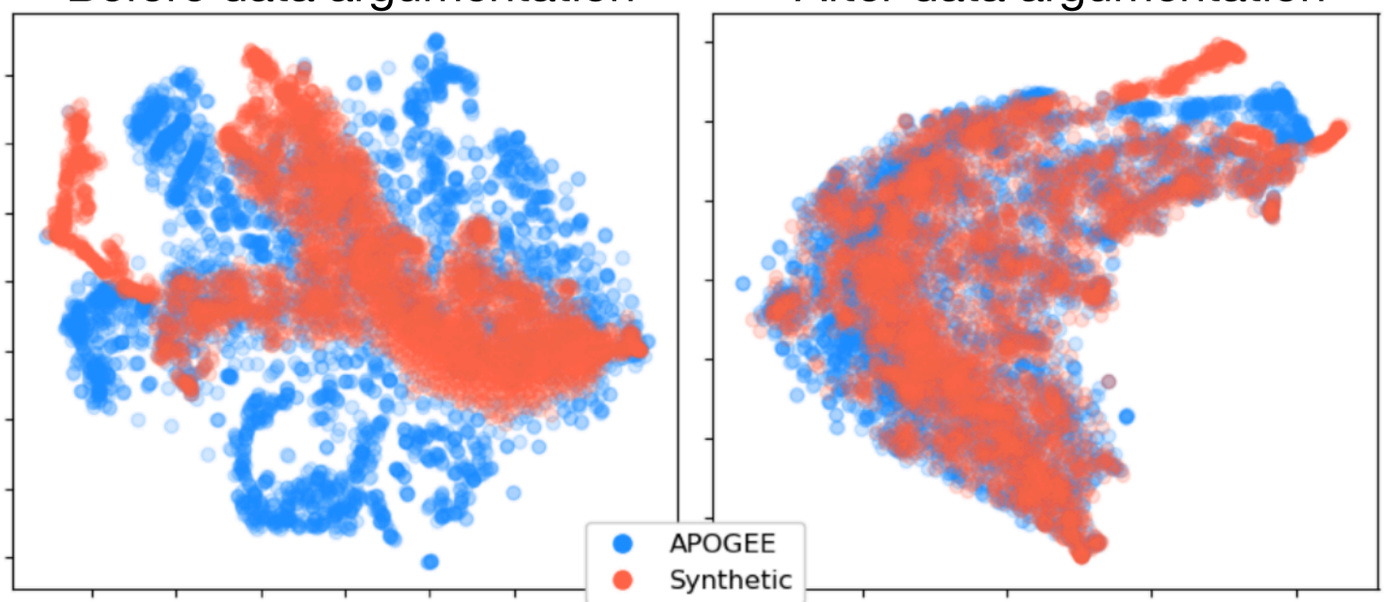

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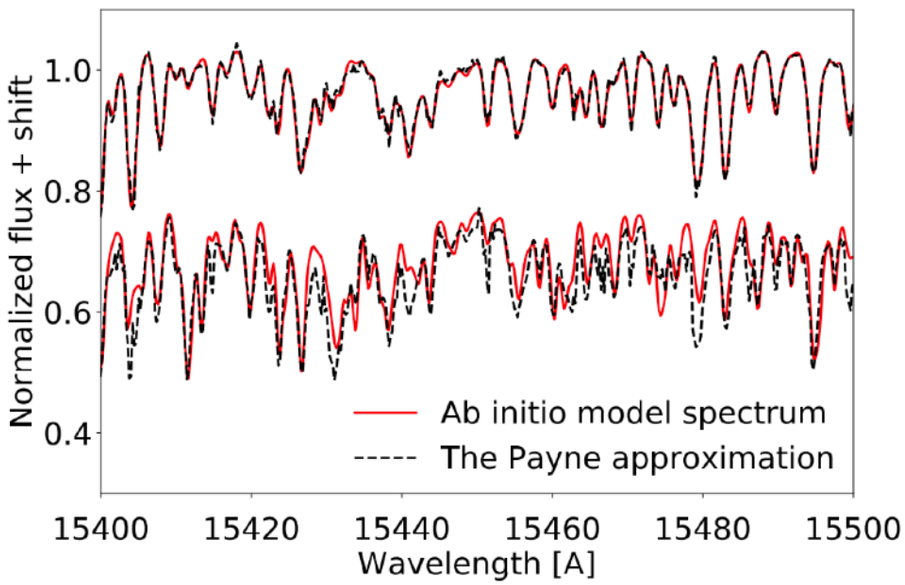

Ting et al. (2019)

The two approaches with machine learning

Pro. Better causual inference.
Cons. Models suffer from systematics and neglect part of physics.

Pro. Real data are a better representation of the real world.
Cons. Surveys always suffer of selection functions and hiddden biases

The two approaches with machine learning

Physical generalization

Data-driven

The Payne

Sweet spot?

The Cannon

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Feature transfer

Feature transfer

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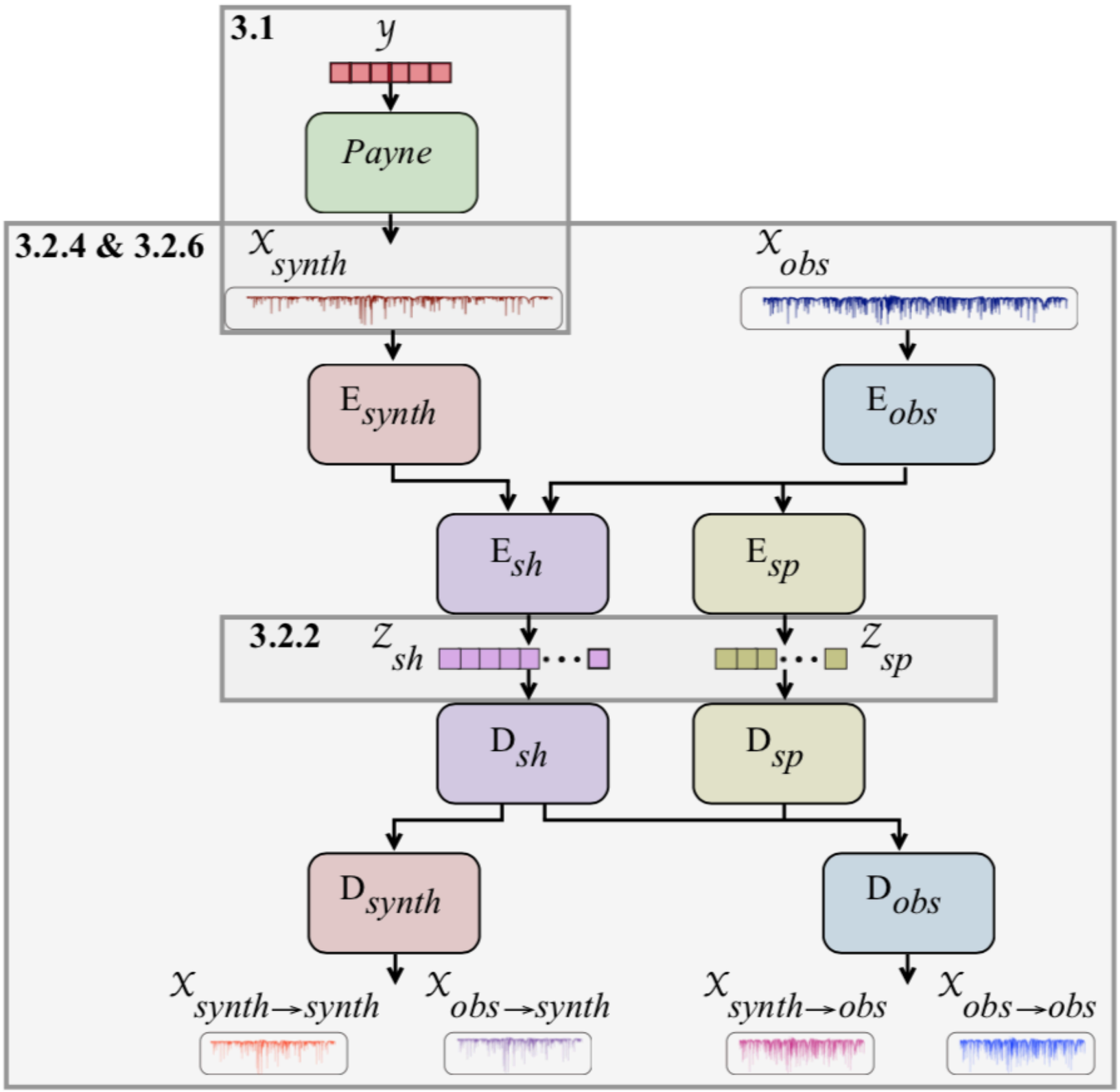
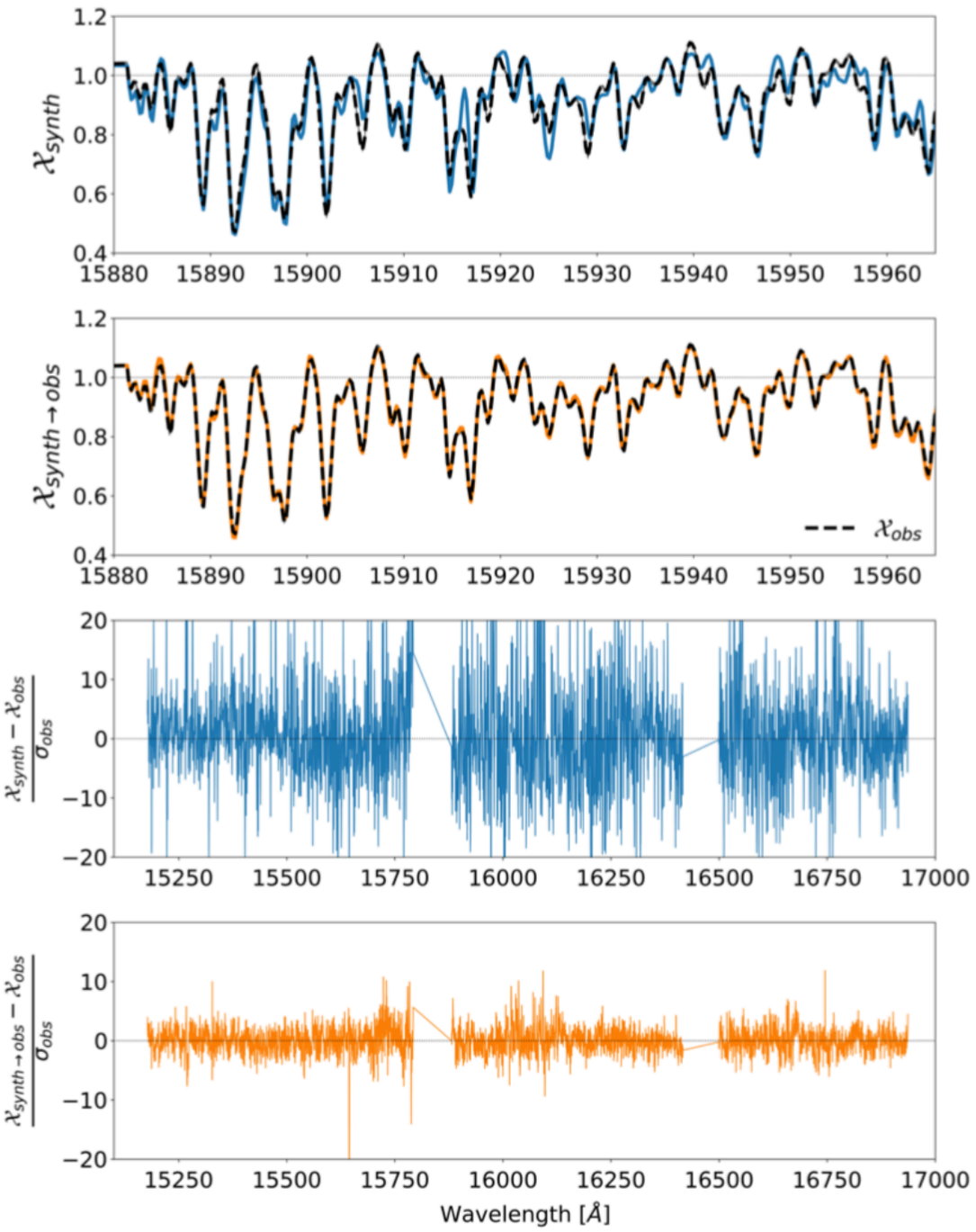
Feature transfer

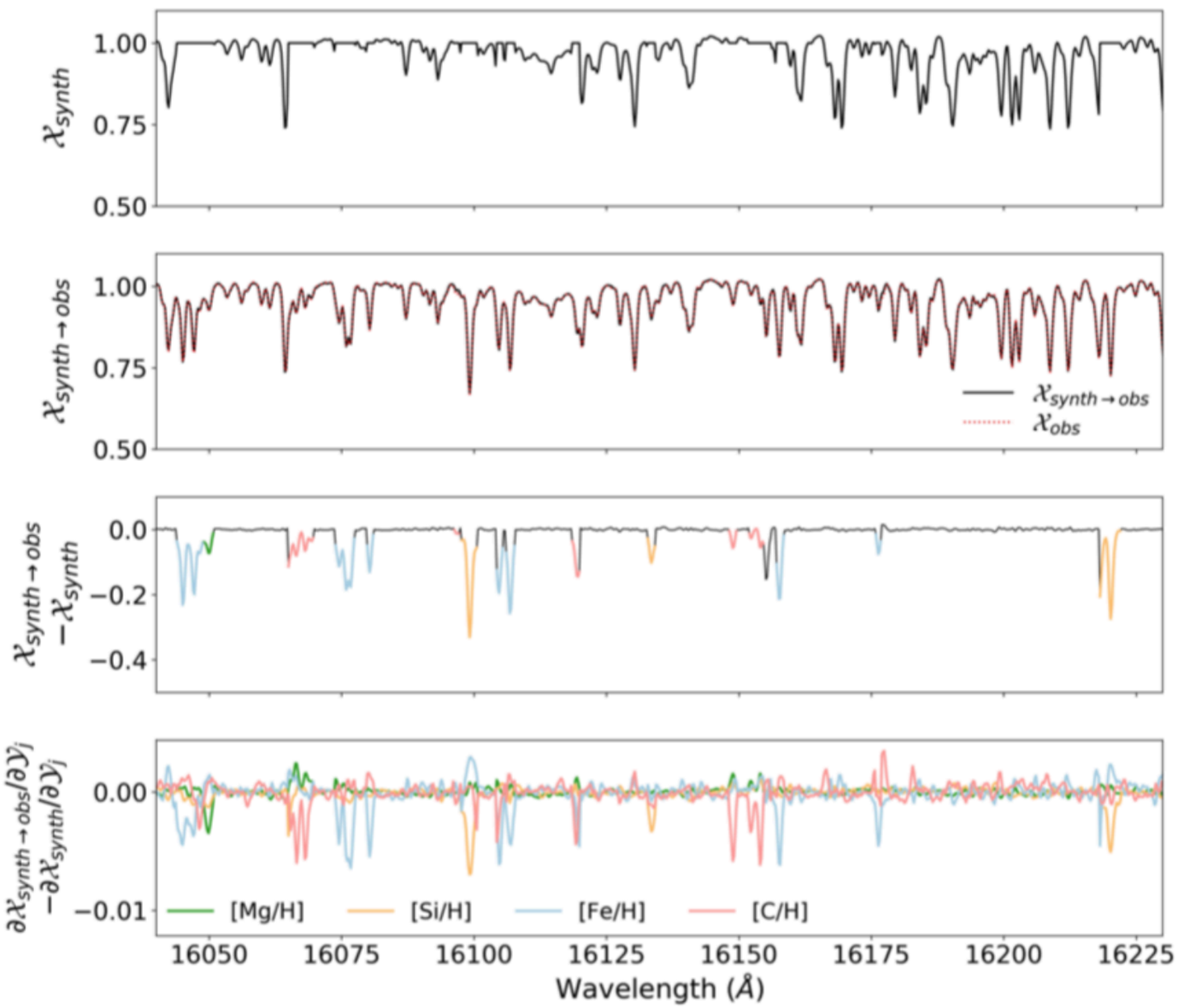
Cycle-Starnet

O'Briain et al. (2021)



Cycle-Starnet O'Briain et al. (2021)





Cycle-Starnet

Limitations:

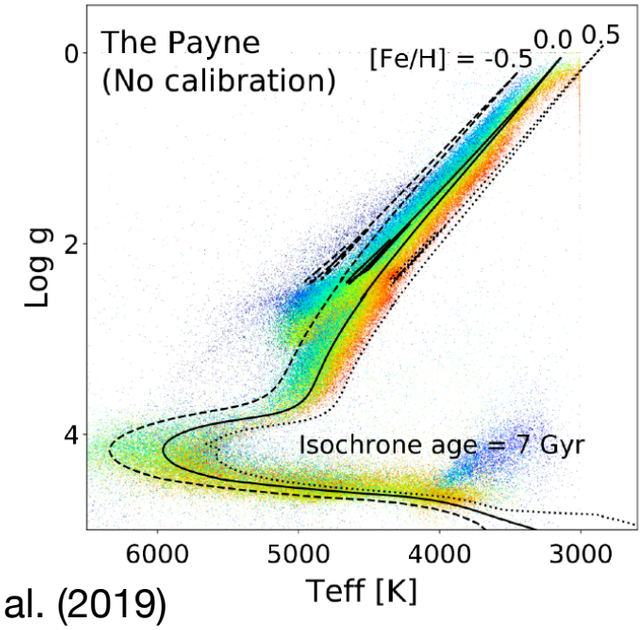
- It is not always straightforward to make the algorithm converge during training.
- It relies on the assumption that the uncertainties in the observed spectra are perfectly known. How a mis-characterisation of the noise affect the final results is yet to be studied.
- Labels from the synthetic and observad domains must span the same range. However, for a new survey we may not know the range of stellar labels.
- Cycle-Starnet may not extrapolate well for outliers and exotic stellar objects.
- Cycle-Starnet can correct for inaccurate atomic parameters in the linelist. However, this adds much more complexity in the analysis.
- It is impossible to correct for all the possible unknowns. The synthetic gap is reduced but not completely eliminated.

However, the study of Tranfer Features algorithms is currently proceeding at high speed. It is very likely that in the next few years we will have better algorithms that could alleviate all these limitations.

Conclusions

- Machine learning algorithms are a powerful tool.
  Significant computational power, huge amount of data, new algorithms: we can embrace new methods in our research, passing from a model-drive approach to a data-driven approach.

- Machine learning algorithms applied to stellar spectroscopy have some pitfalls and limitations.
  Data-driven models: bias and correlations.
  Physical generalisation models: synthetic gap.
  These are unavoidable pitfalls. However there are codes that achieve reasonably good results.



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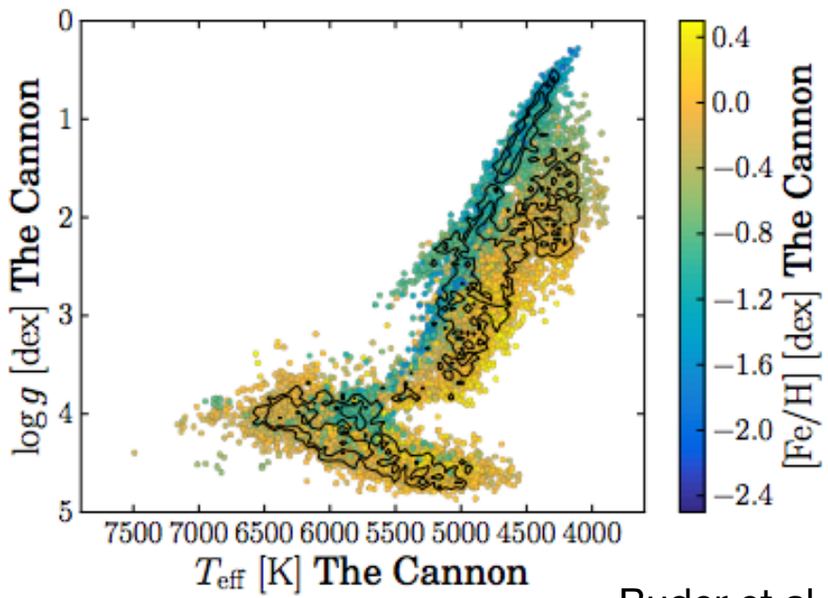

Buder et al. (2018)

...also see Nandakumar et al. (2020) for a nice example of data homogeneisation (GALAH-APOGEE) with the Cannon.

- There is a huge effort in researching new machine learning algorithms. The "state-of-the-art" is fluid and can evolve very rapidly. Stay tuned!