The data-driven approach to measuring stellar parameters

Tuesday, June 4, 2019 — 2.15-3.30

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Outline

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- Motivate data-driven approach to spectroscopy
- The Cannon - how it works
- Applications
  - Precision abundances
  - Low-res spectra
  - Stellar ages

Data Analysis principles

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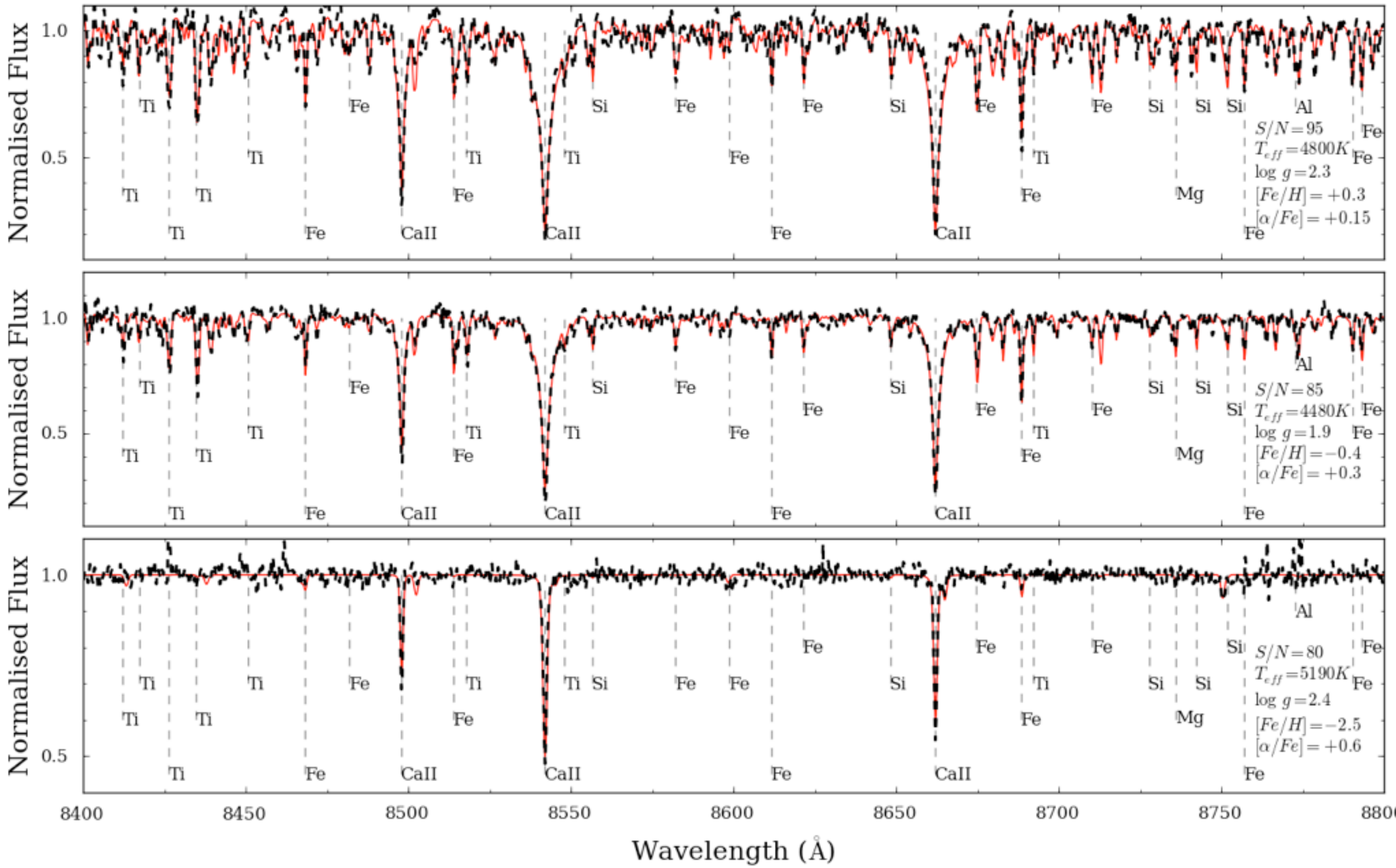
- start with simple, interpretable approaches and build in complexity as needed

Measuring stellar parameters with physics

1. Take model atmospheres from Castelli/Kurucz model atmospheres
2. Add a linelist from atomic and molecular library
3. MOOG (Sneden 1983) to create library of synthetic spectra.
4. Program to determine best fitting spectra in Teff, logg, [Fe/H], [α/Fe]
5. Calibrate: modify log gf values the Sun/Arcturus, compare results to literature and “benchmarks”, fit out trends

Stellar parameters measured

template
model



Bigger picture

- Multitude of surveys at different R, λ
- Independent pipelines for parameters

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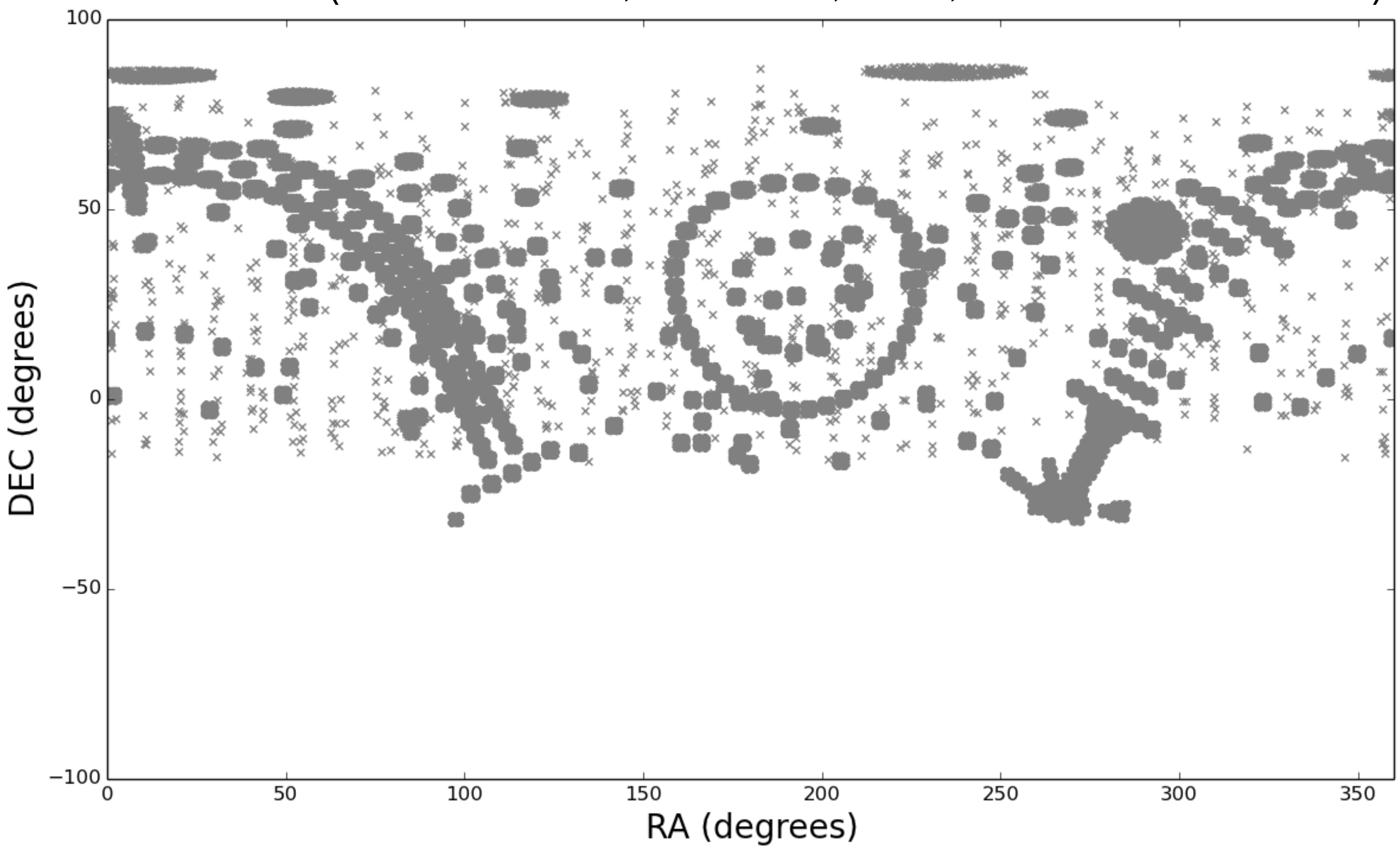
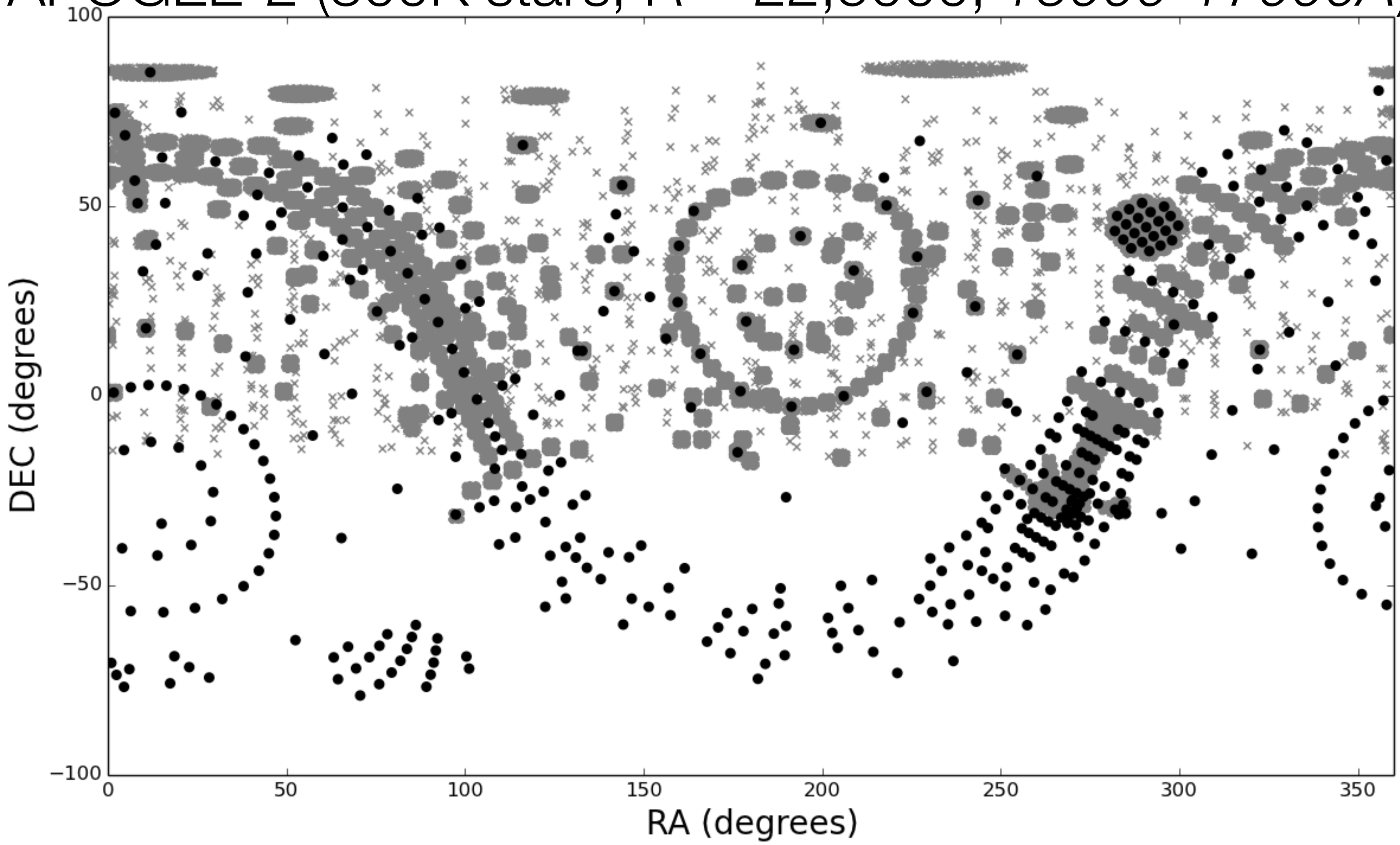
APOGEE (150K stars, R = 22,500, *15000-17000A*)



Bigger picture

APOGEE-2 (300K stars, R = 22,5000, *15000-17000A*)



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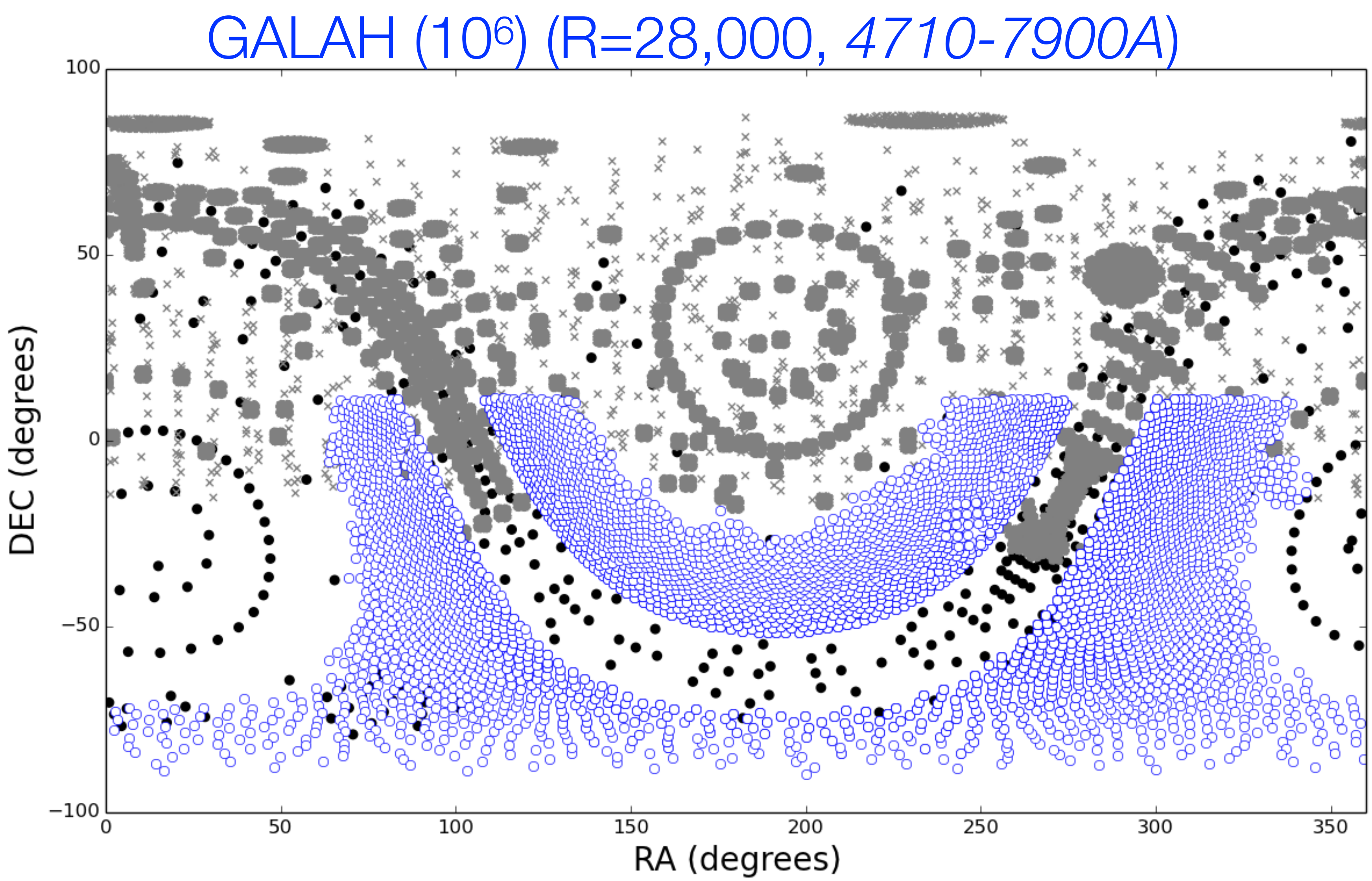
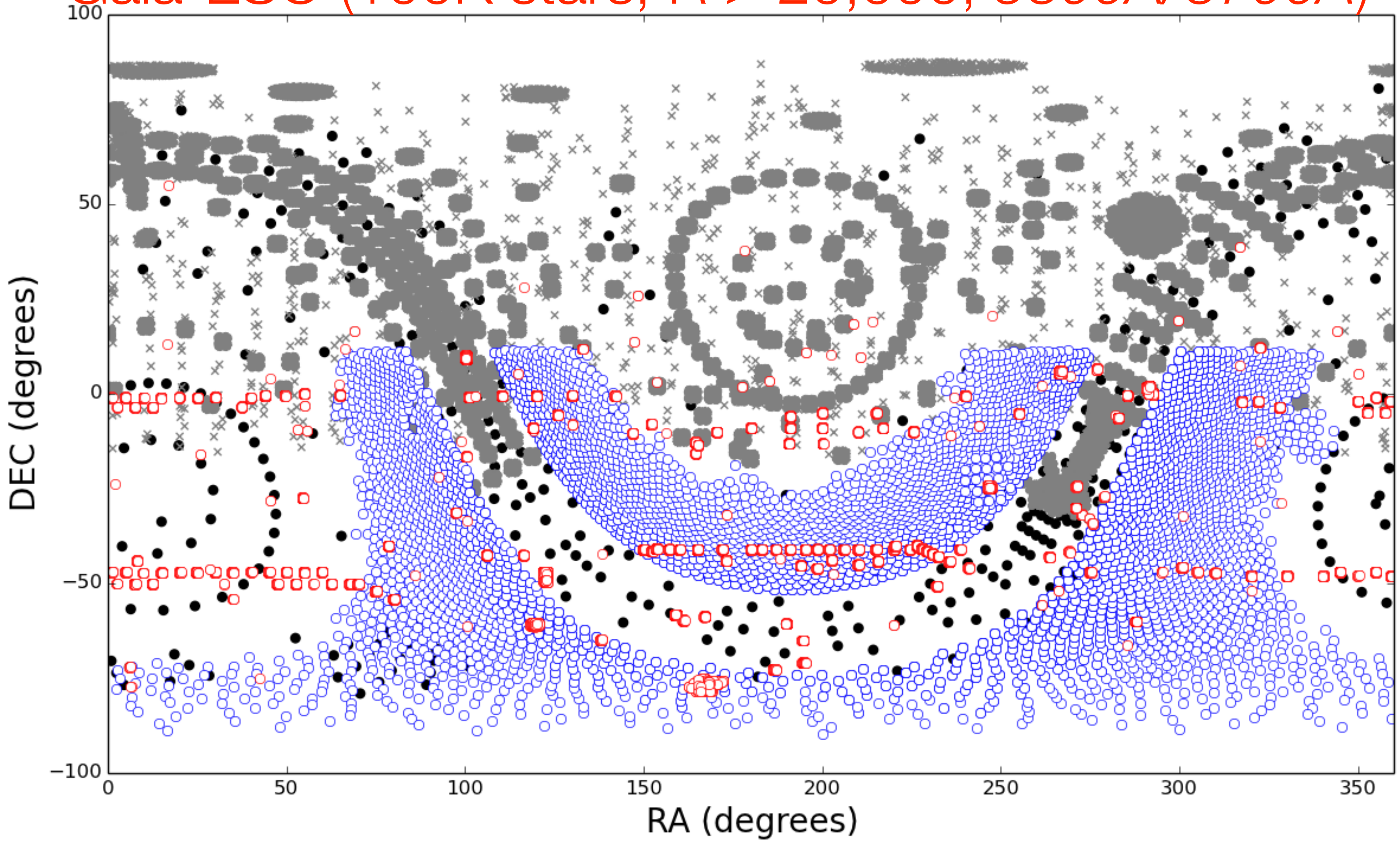


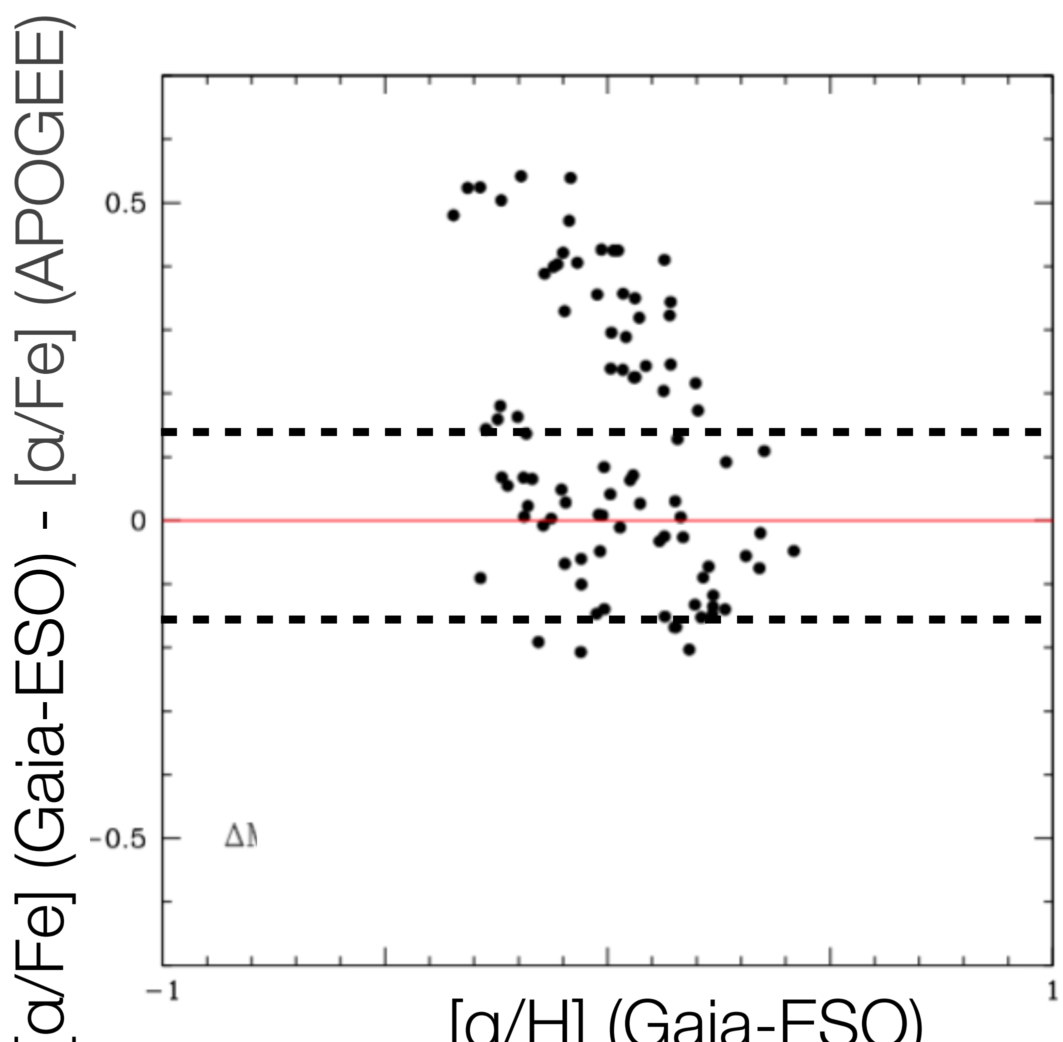
Bigger picture

Gaia-ESO (100K stars, R > 20,000, *5800A/8700A*)



The problem:

Different surveys have different scales for Teff, logg, [Fe/H], [X/Fe]



The solution

Sub-set of reference objects: stellar parameters, abundances (labels) known with high(er) fidelity.

- astroseismology
- clusters
- high SNR, well studied benchmarks, (e.g Jofre+ 2014)

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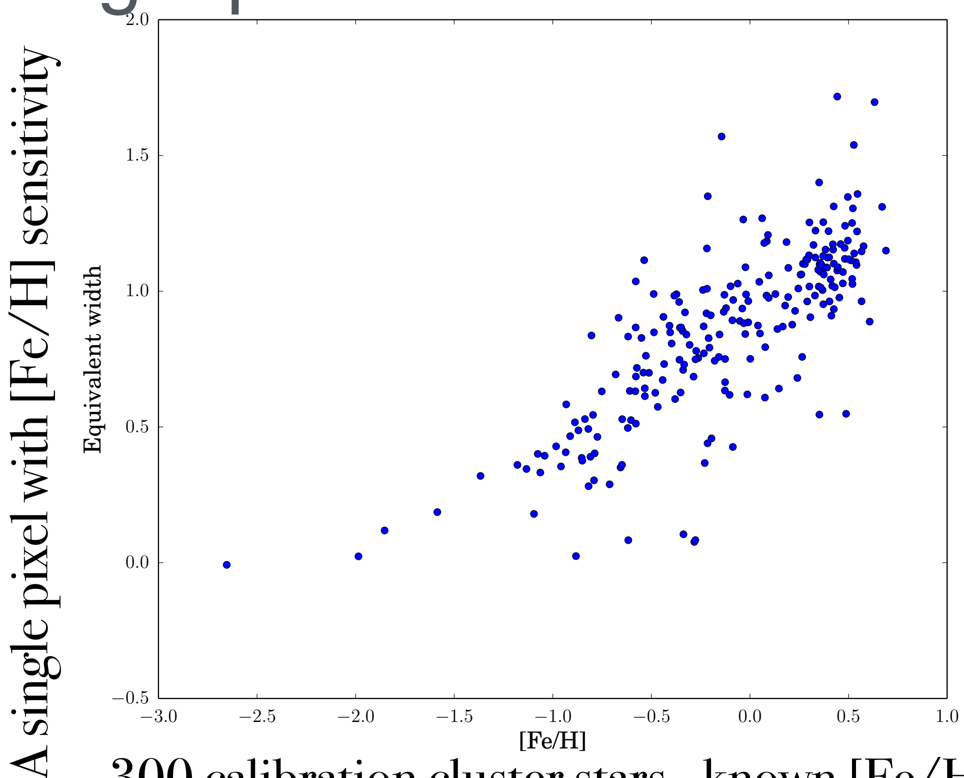
use these labels *directly*: data-driven model

A very simple empirical model

A single pixel is information-rich



300 calibration cluster stars - known [Fe/H]

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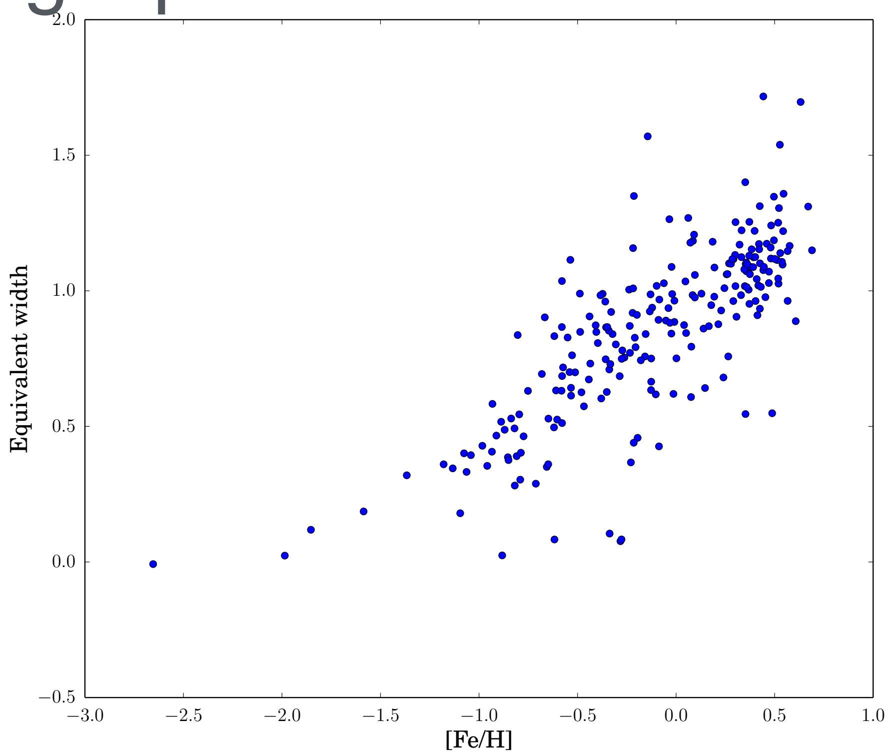
A single pixel with [Fe/H] sensitivity



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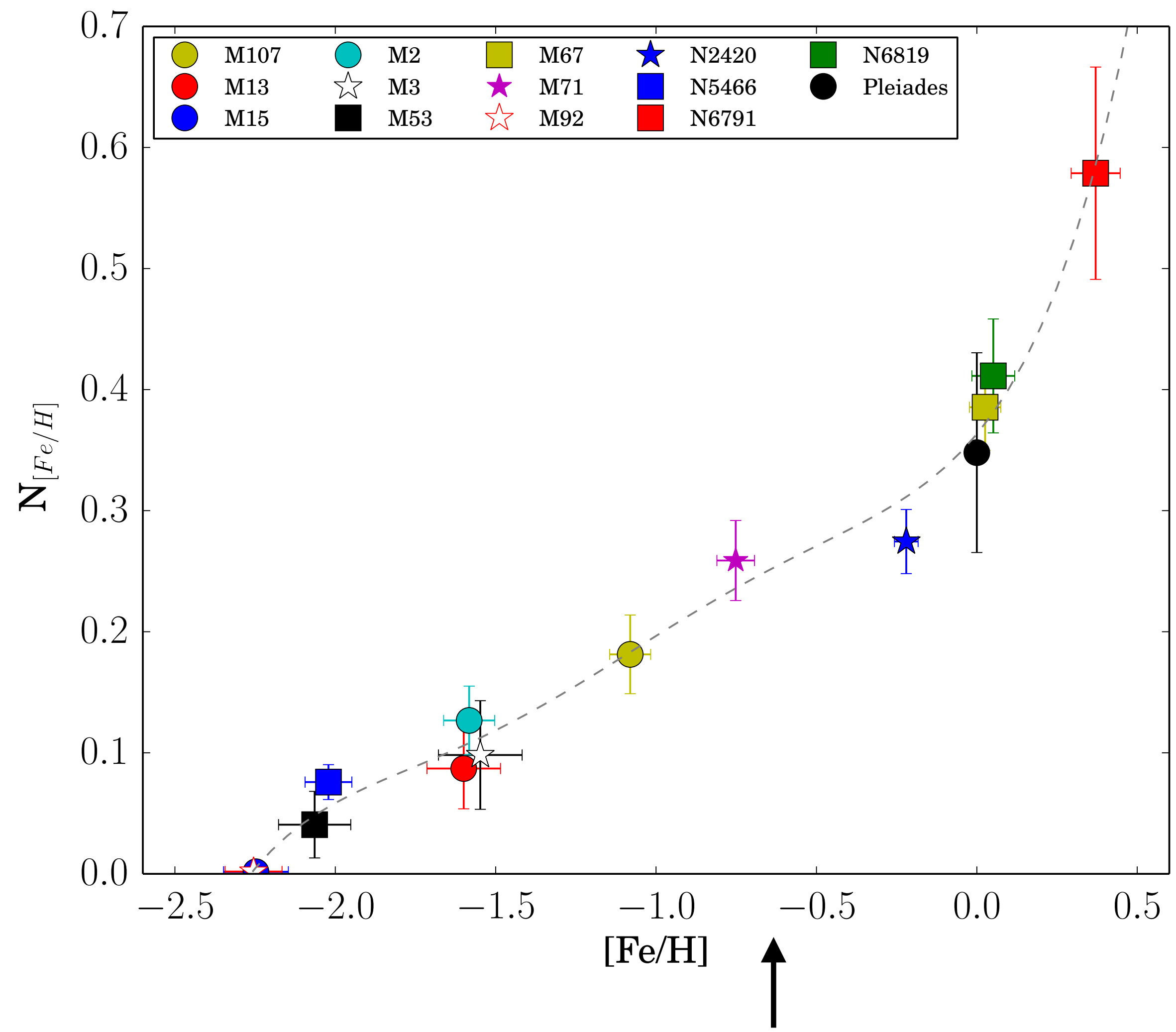
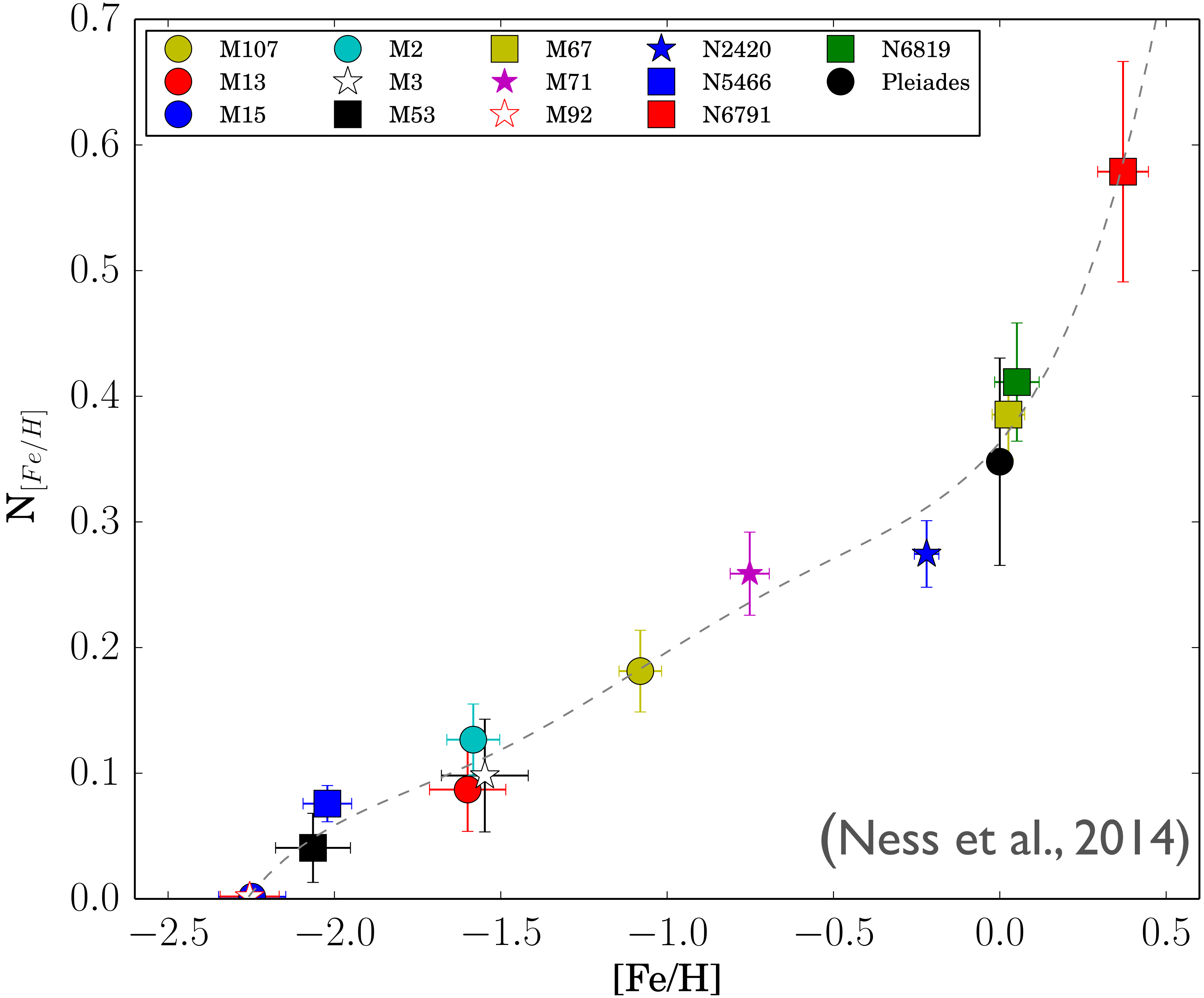
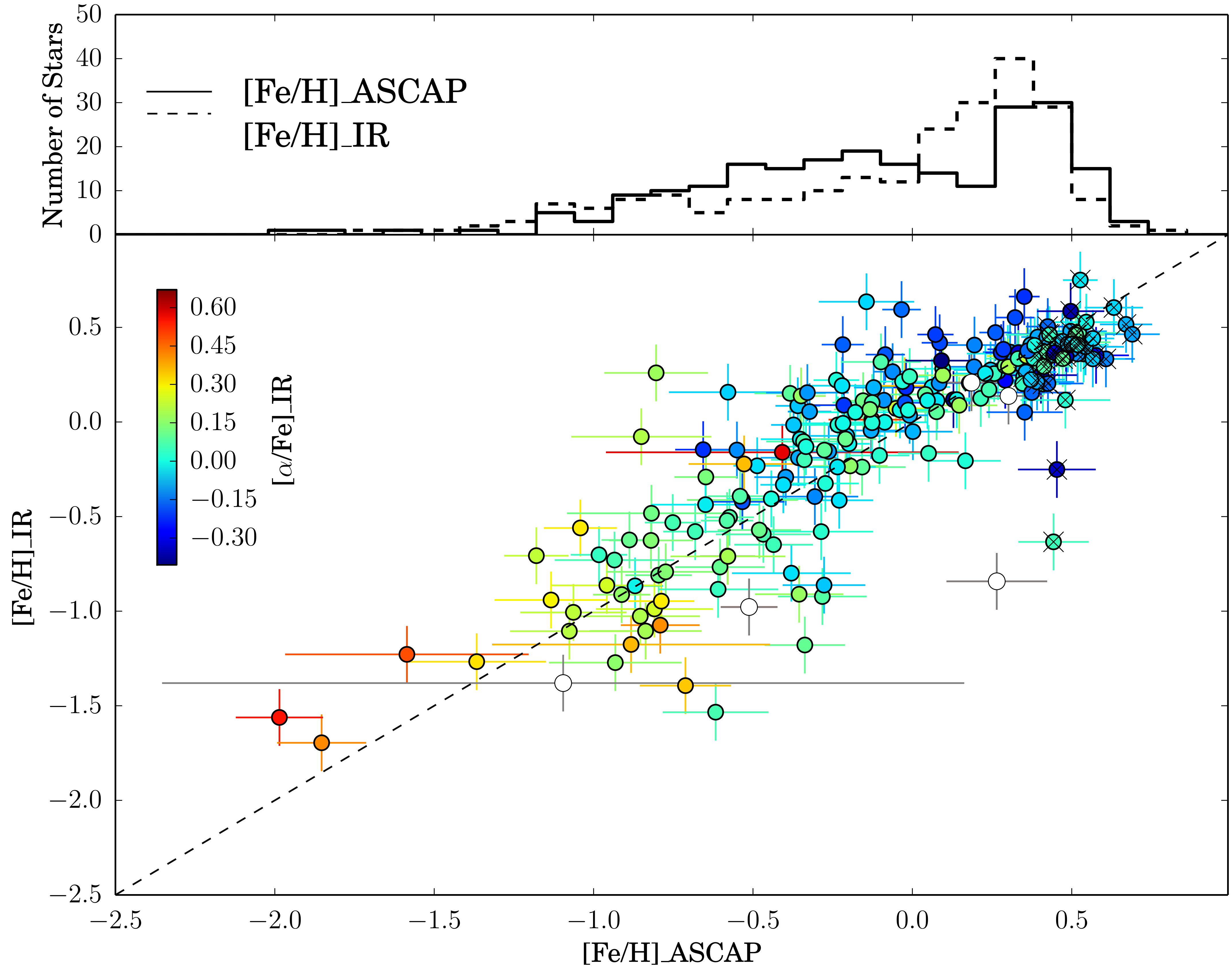


proof of concept: an index made (measuring EW of 5 features) using **1%** of the spectrum can use open and globular clusters to calibrate this index to be a precise [Fe/H] measure

5 x Features (30 Angstroms of spectra) metallicity sensitive features (log g, Teff insensitive)





Number of Stars
[Fe/H]_ASCAP
[Fe/H]_IR
[α/Fe]_IR
0.60
0.45
0.30
0.15
0.00
−0.15
−0.30

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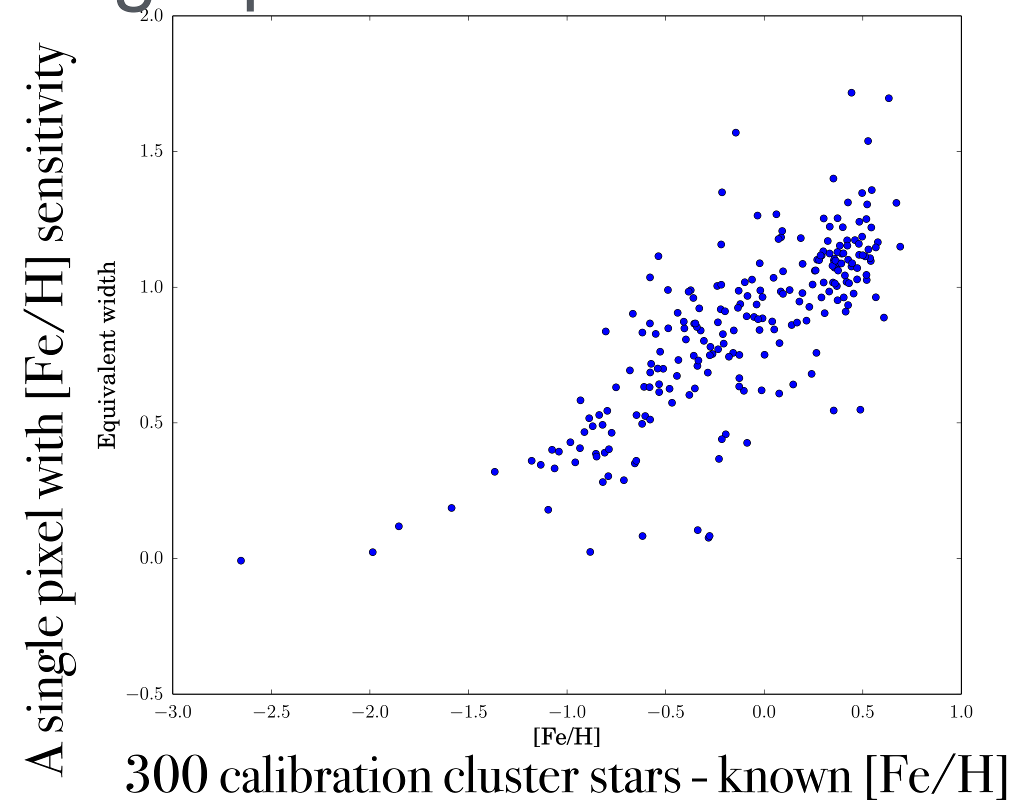

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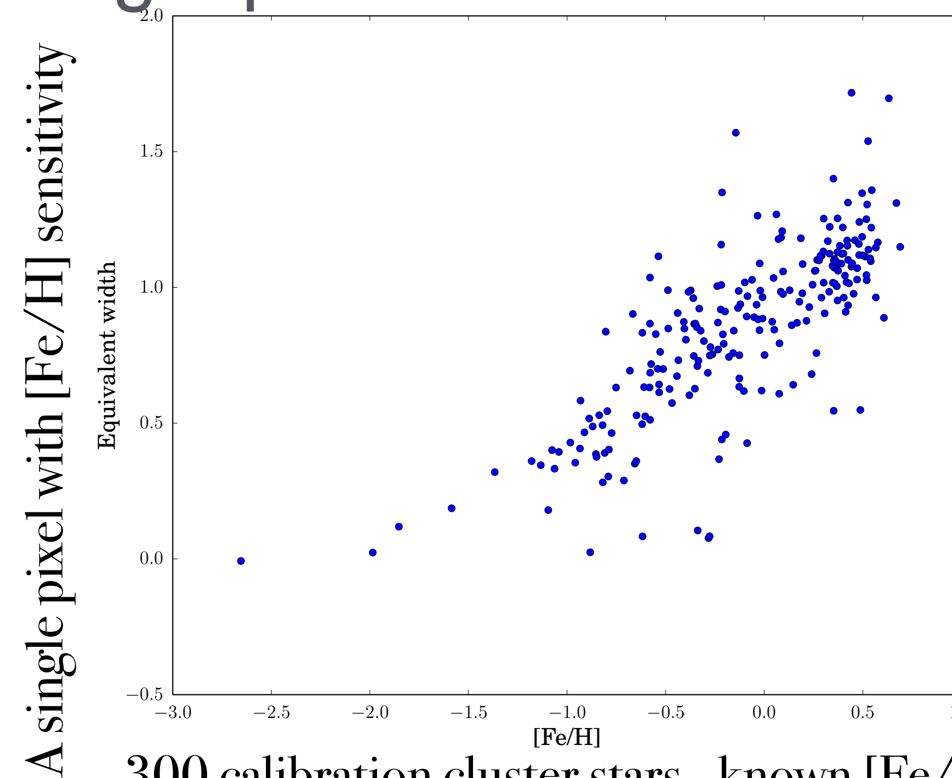

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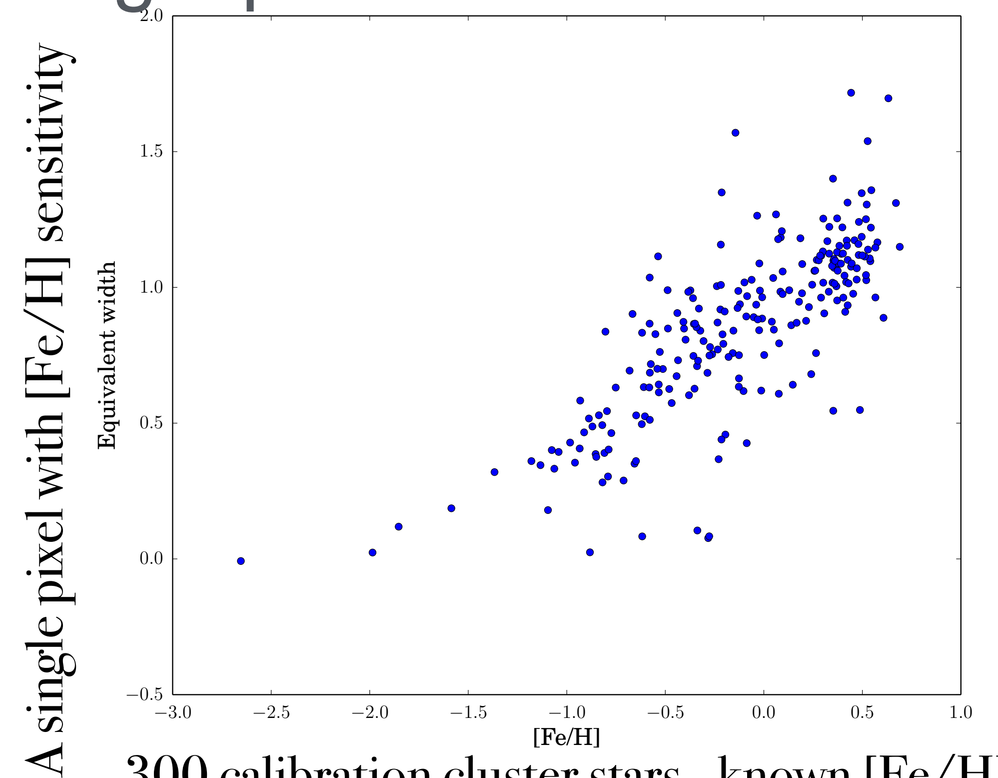

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http://arxiv.org/pdf/1501.07604v2.pdf

M. Ness, David W. Hogg, H.W. Rix, Anna Ho, & G. Zasowski

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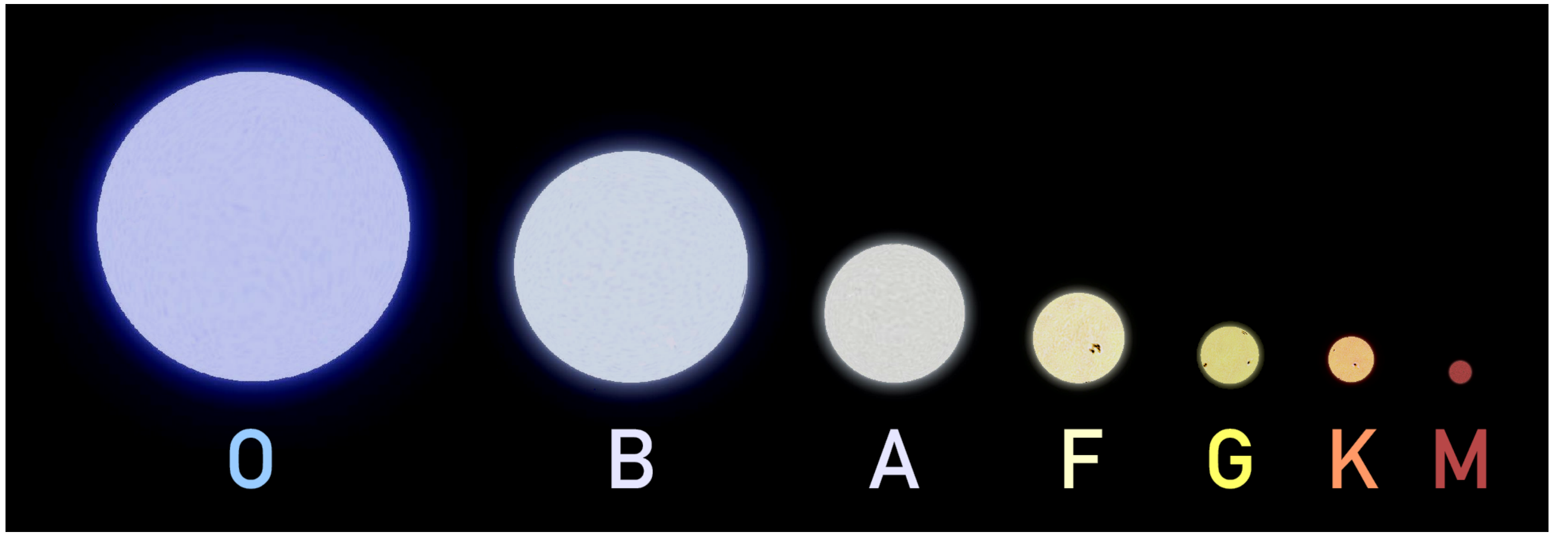

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That model is then used to infer the stellar labels for the remaining stars in the survey: *Test*

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

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

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Unfortunately, this is too simple

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$$\eta\left(\begin{bmatrix} T_{\mathrm{eff}} \\ \log g \\ [X/\mathrm{Fe}] \end{bmatrix}\right) = \begin{bmatrix} 1 \\ T_{\mathrm{eff}} \\ \log g \\ [X/\mathrm{Fe}] \\ (T_{\mathrm{eff}})^2 \\ (\log g)^2 \\ ([X/\mathrm{Fe}])^2 \\ (T_{\mathrm{eff}})(\log g) \\ (T_{\mathrm{eff}})([X/\mathrm{Fe}]) \\ (\log g)([X/\mathrm{Fe}]) \end{bmatrix}$$

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Pivot the labels:

$$T'_{\text{eff}} = \frac{T_{\text{eff}} - \overline{T_{\text{eff}}}}{\text{std}(T_{\text{eff}})}$$

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The Cannon 2: A data-driven model of stellar spectra for detailed chemical abundance analyses

Andrew R. Casey[1], David W. Hogg[2,3,4,5], Melissa Ness[5], Hans-Walter Rix[5], Anna Y. Q. Ho[6], and Gerry Gilmore[1]

The Cannon in Action

Training set: 540 open and globular cluster stars, labels from ASPCAP (Teff, log g, [Fe/H])

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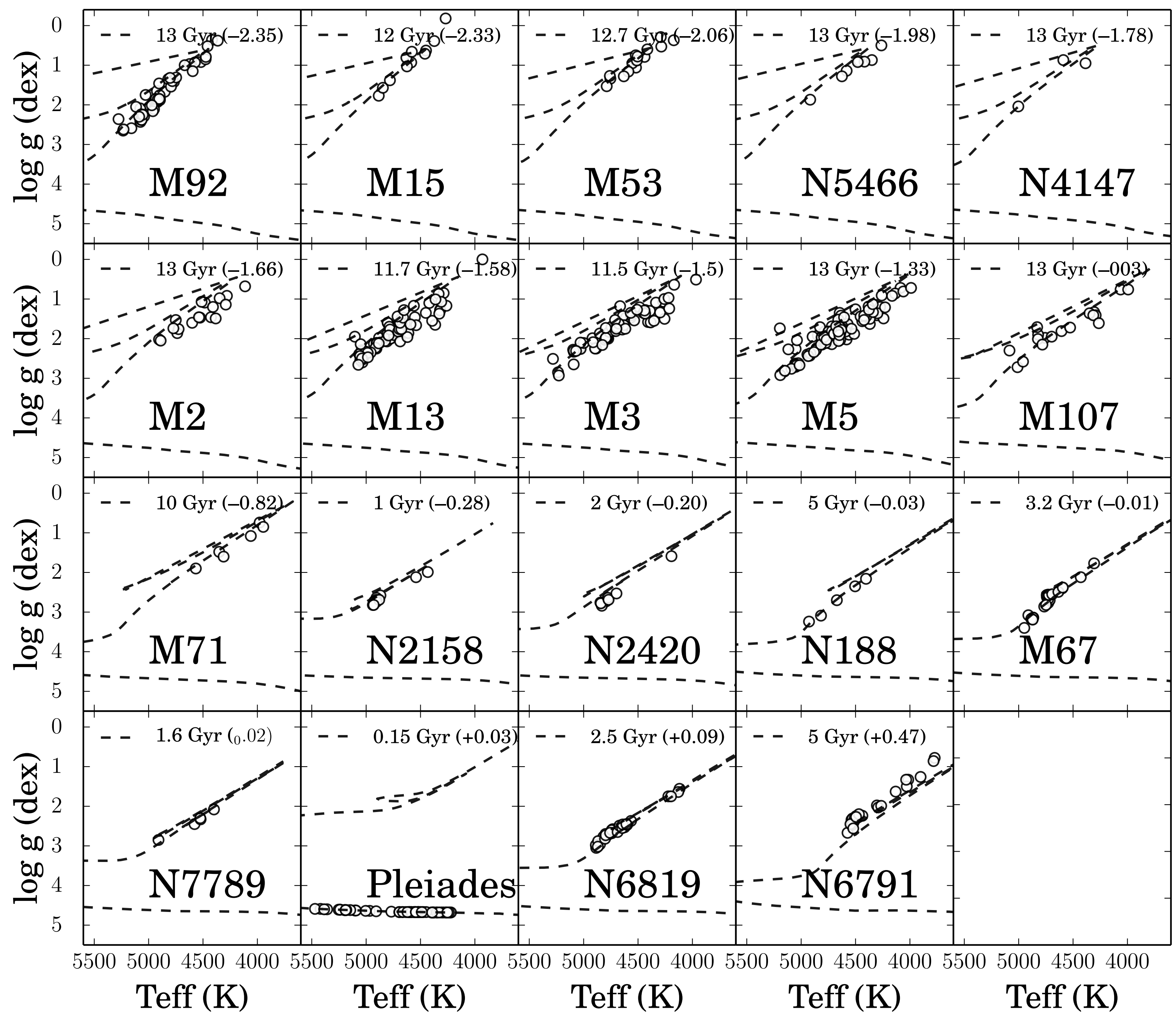
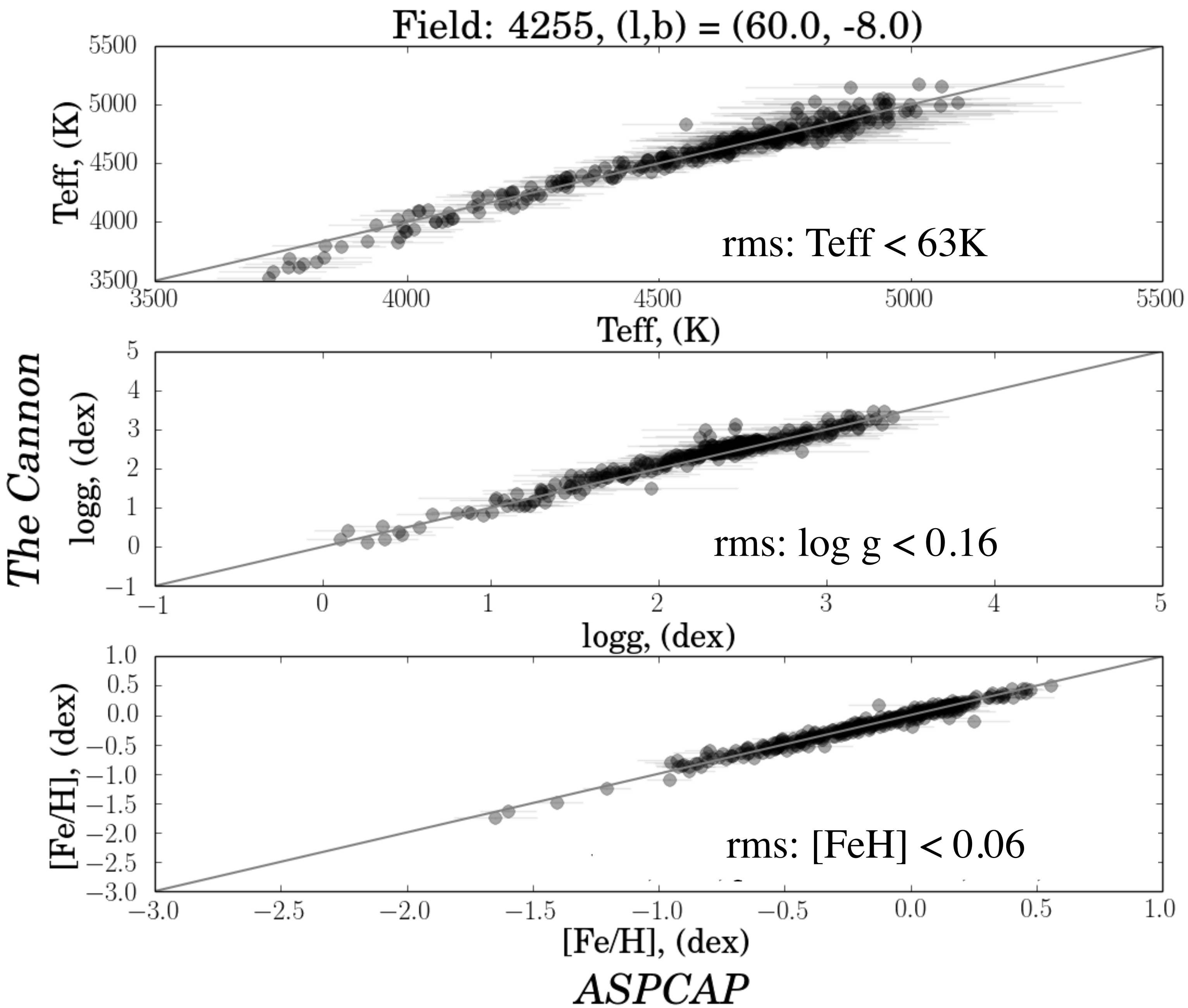


Cross-Validation

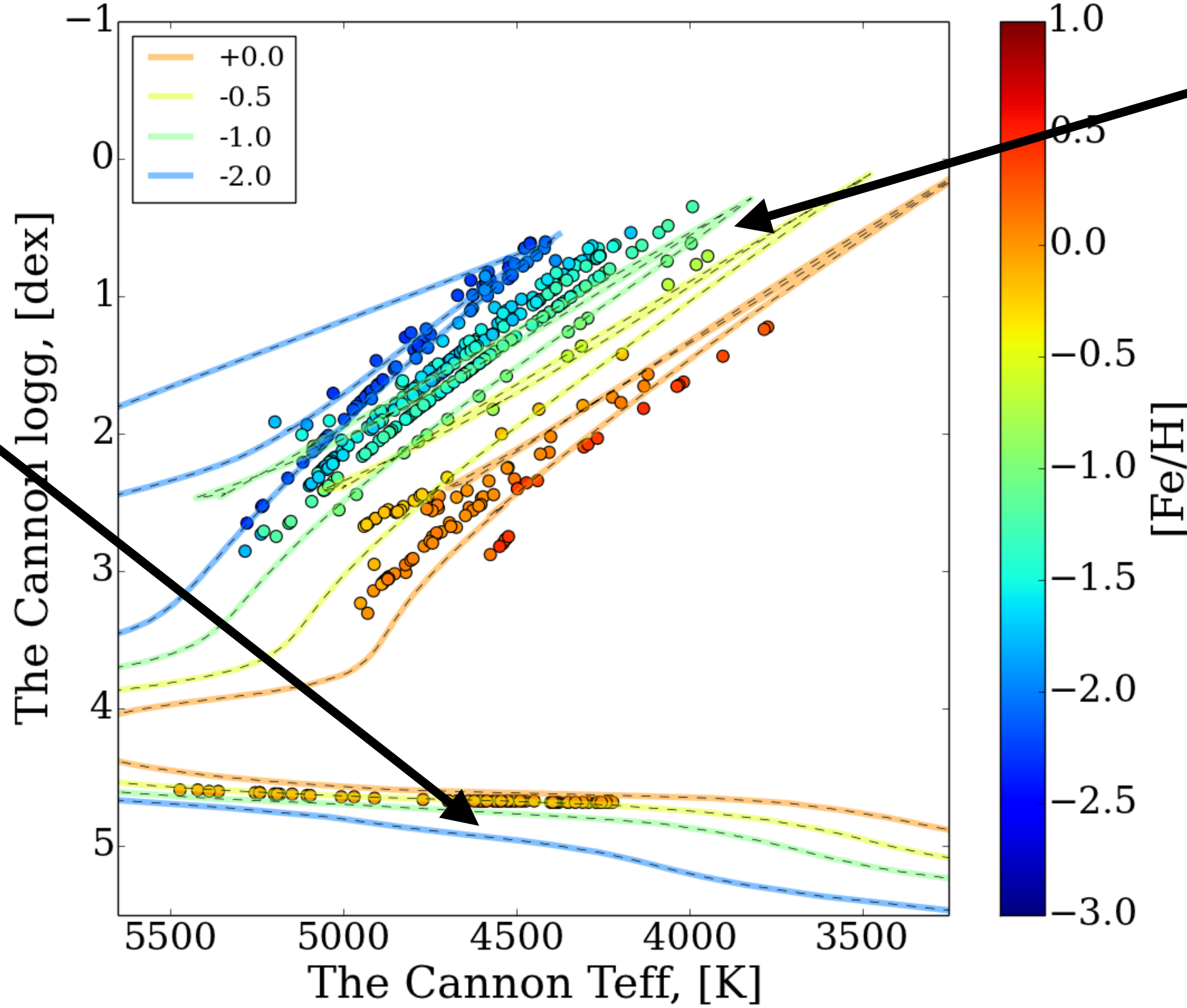


rms is the order of the ASPCAP errors — first indicator of high precision using this approach

APOGEE Results

Labels for 120,000 stars - 540 reference stars with high fidelity labels

only 1 cluster with main sequence stars amongst the reference objects



no isochrone priors

very fast!

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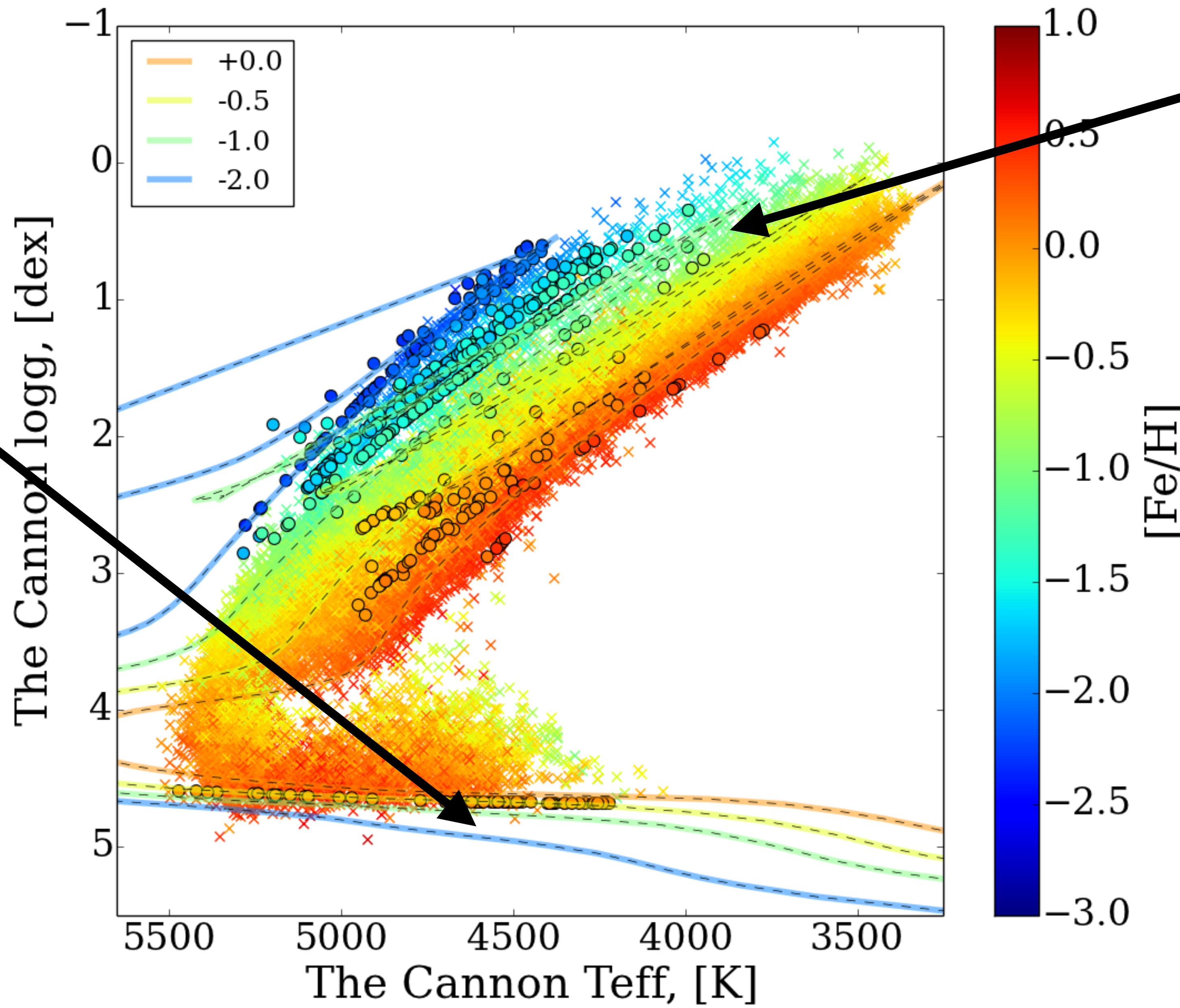
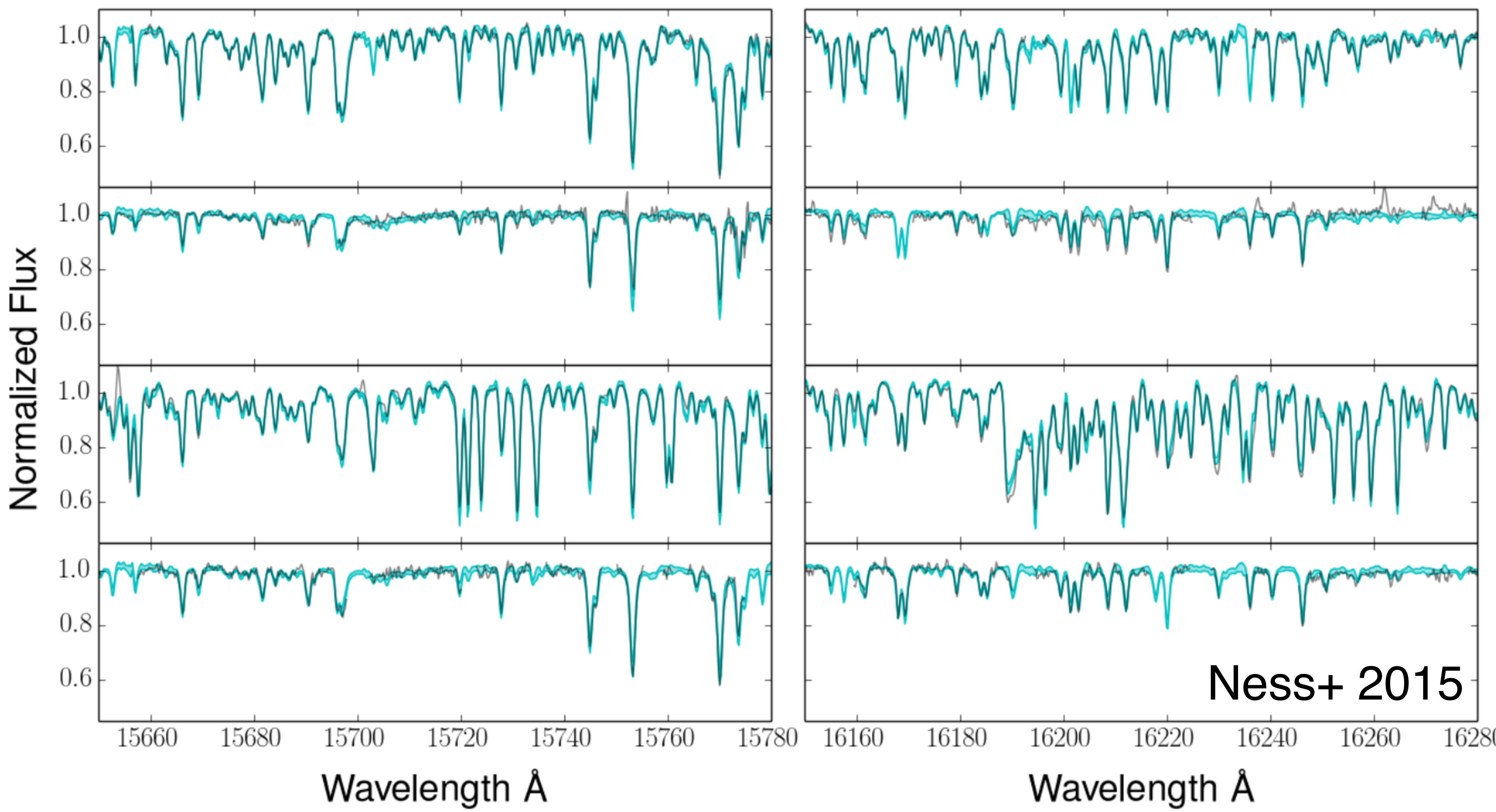


very fast!

The model matches the data (3 labels!)



uses full spectrum & error-weighted information in each pixel

match becomes even better with abundance labels (see next example)

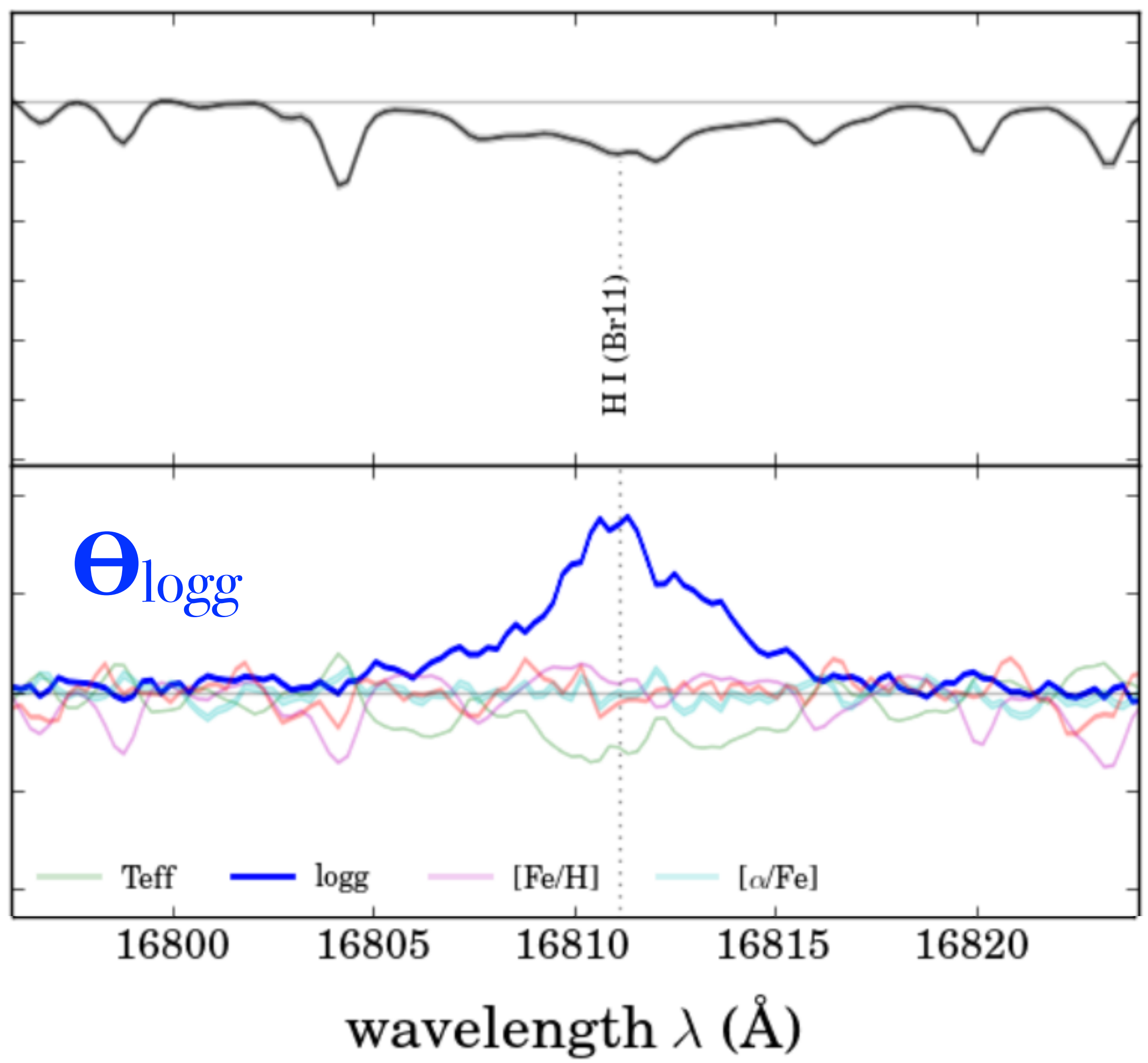
Where the information resides

$$F_{n\lambda} = \theta_\lambda \cdot \eta(\ell_n) + \text{error}$$

this line is where spectroscopists expect logg sensitivity from stellar physics - The Cannon learns this from the data ensemble (data-driven)

zeroth coefficient →

label coefficients →

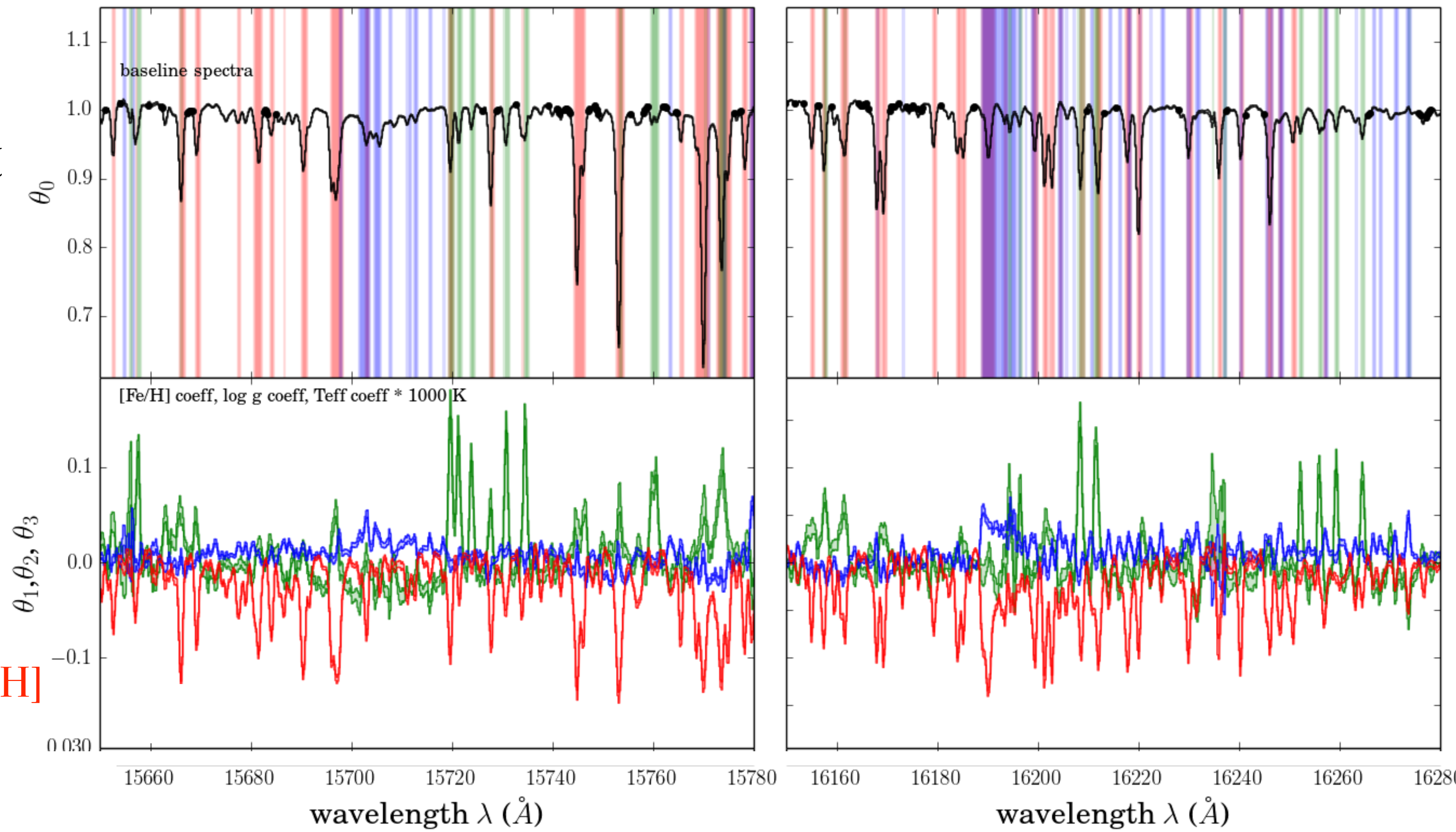


Where the information resides

zeroth coefficient →

label coefficients →

θ_{Teff}, θ_{logg}, $\theta_{[Fe/H]}$



Implementations

github.com/ajwheeler/TheCannon.jl (minimalmist)

github.com/andycasey/AnniesLasso (maximalist)

Applications…

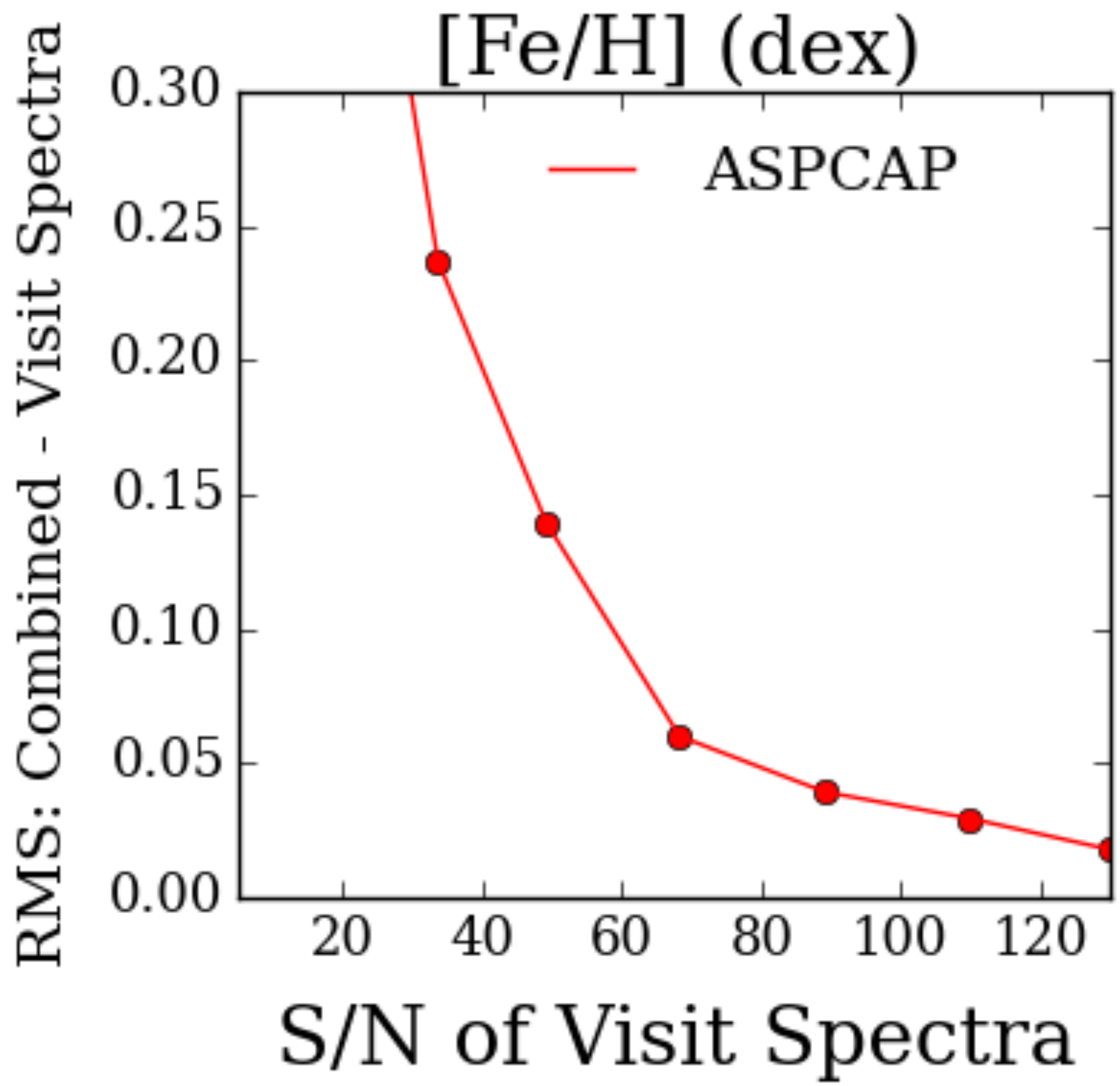
Precision abundances

Applications…

Precision abundances

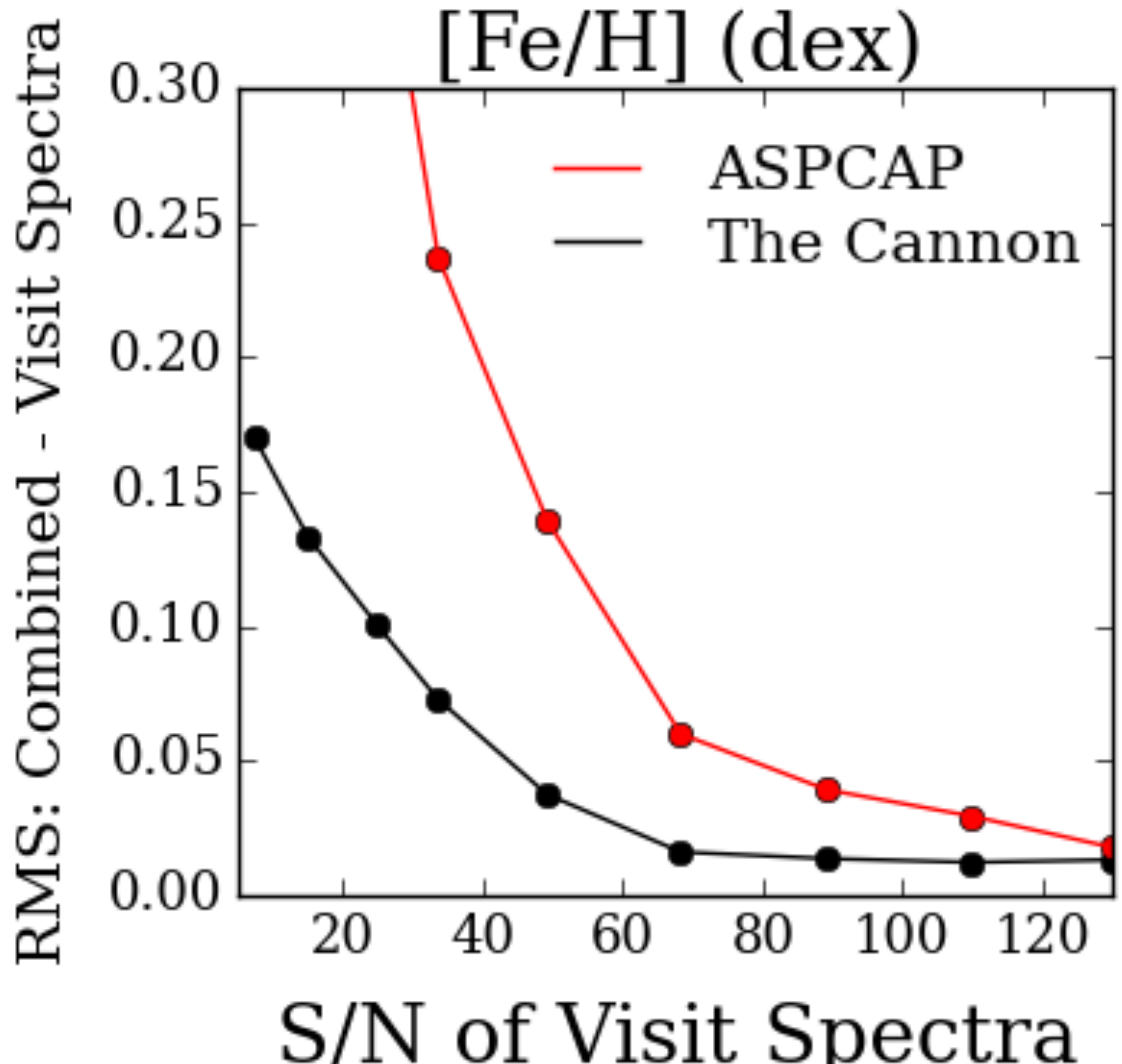
Advantages: The Cannon delivers 2-3 times smaller

The Cannon delivers 2-3 times smaller errors



using multiple observations to assess precision

The Cannon delivers 2-3 times smaller errors



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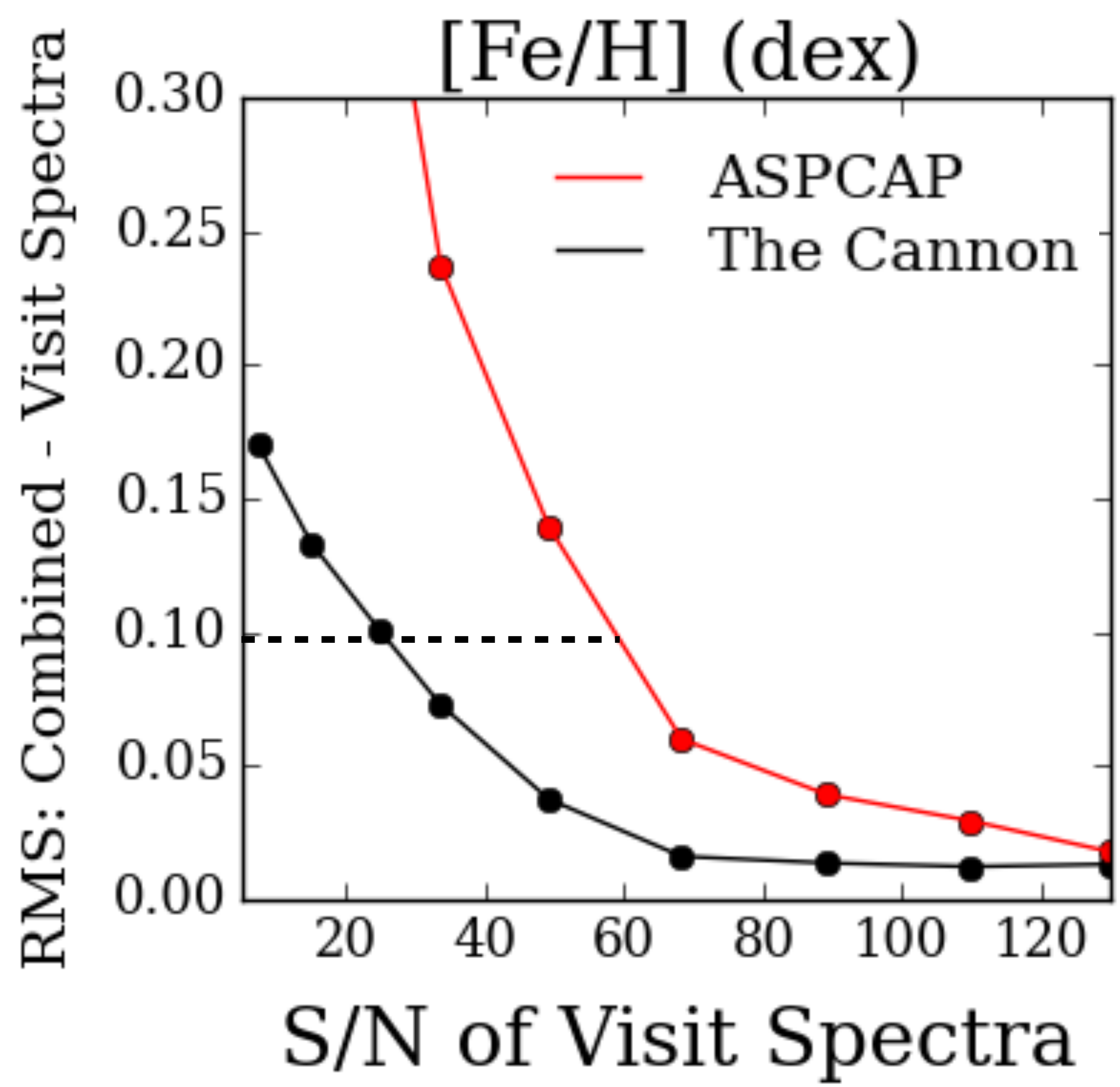

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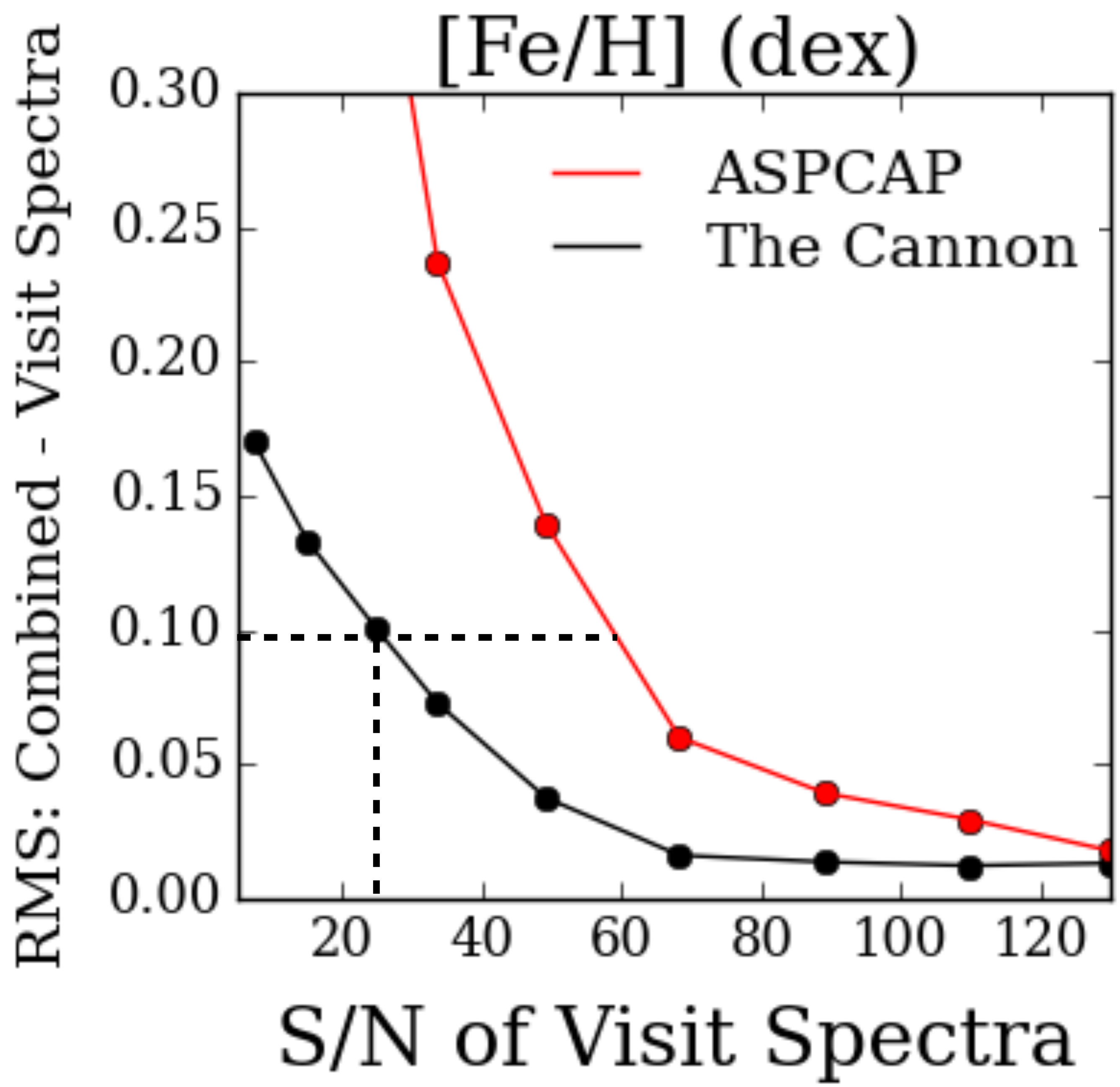

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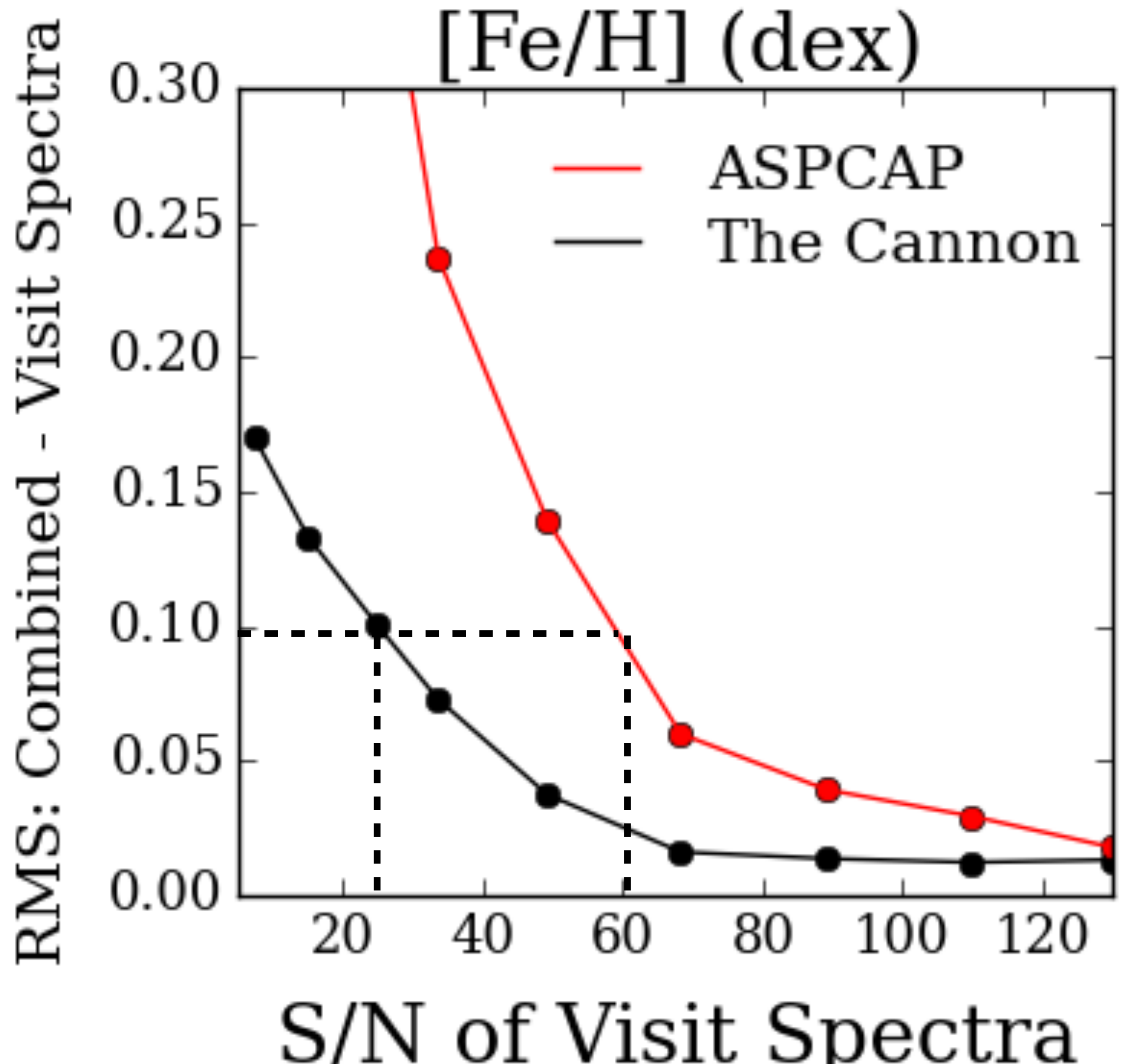

using multiple observations to assess precision

Individual abundances

Add more labels to The Cannon - [X/Fe]

Individual abundances

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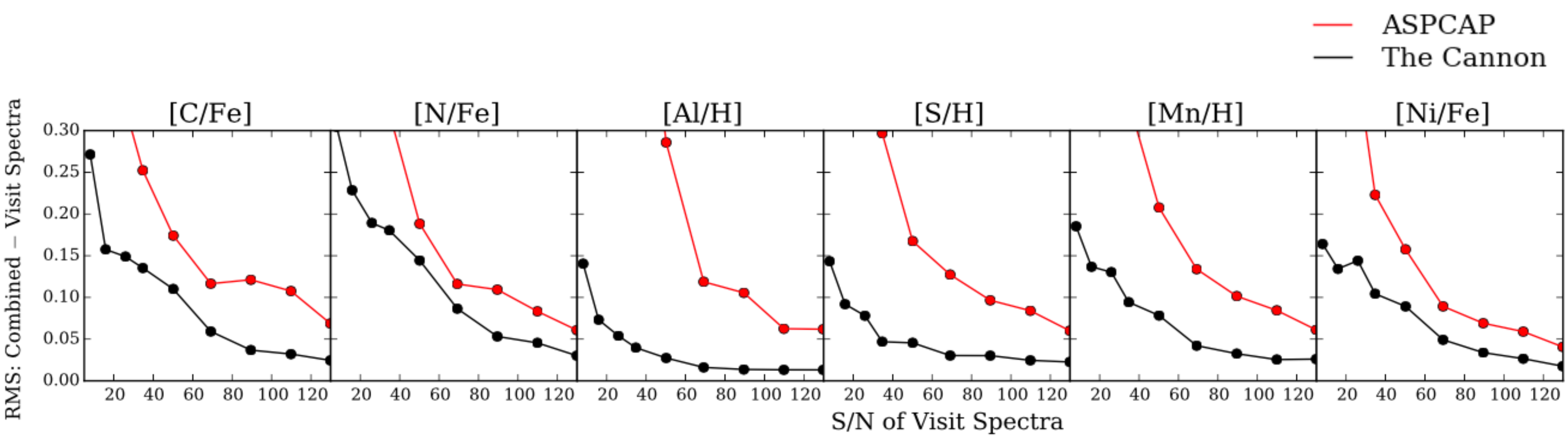

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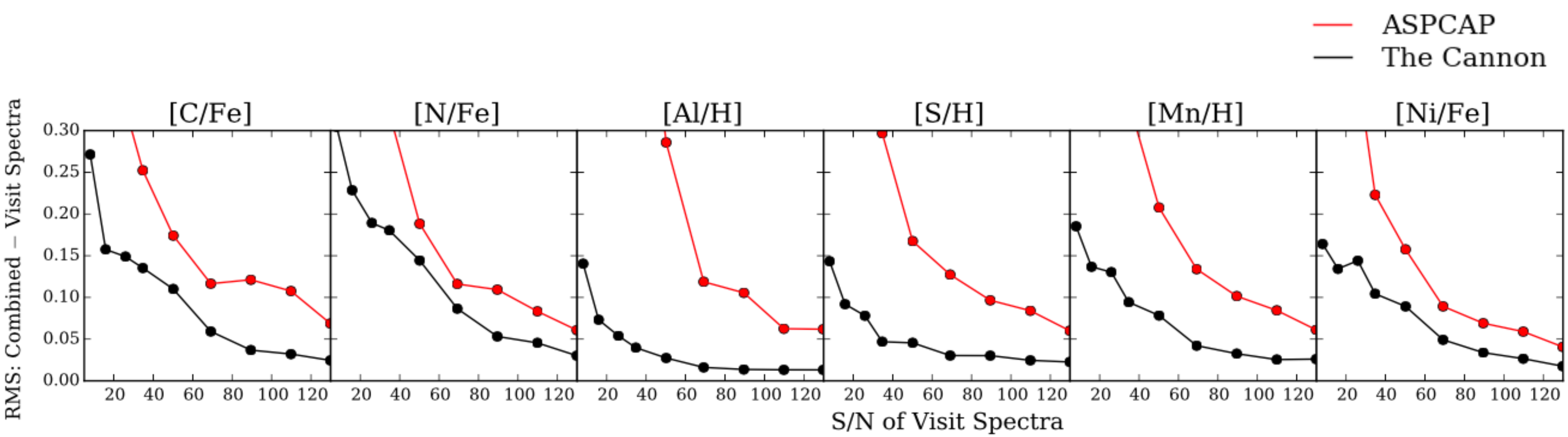
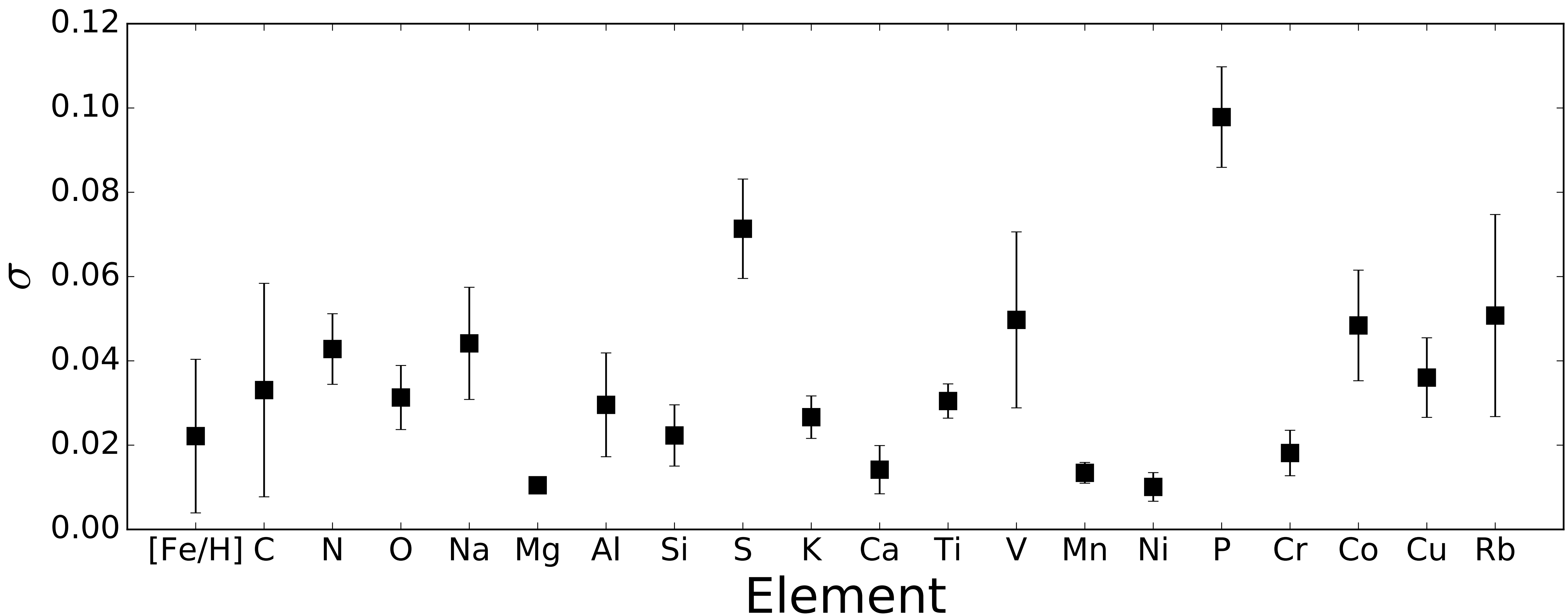


APOGEE DR14 data release has catalogue using The Cannon

Median precision of 0.03 dex for 20 elements

Carefully assessed precision (Ness et al., 2018)



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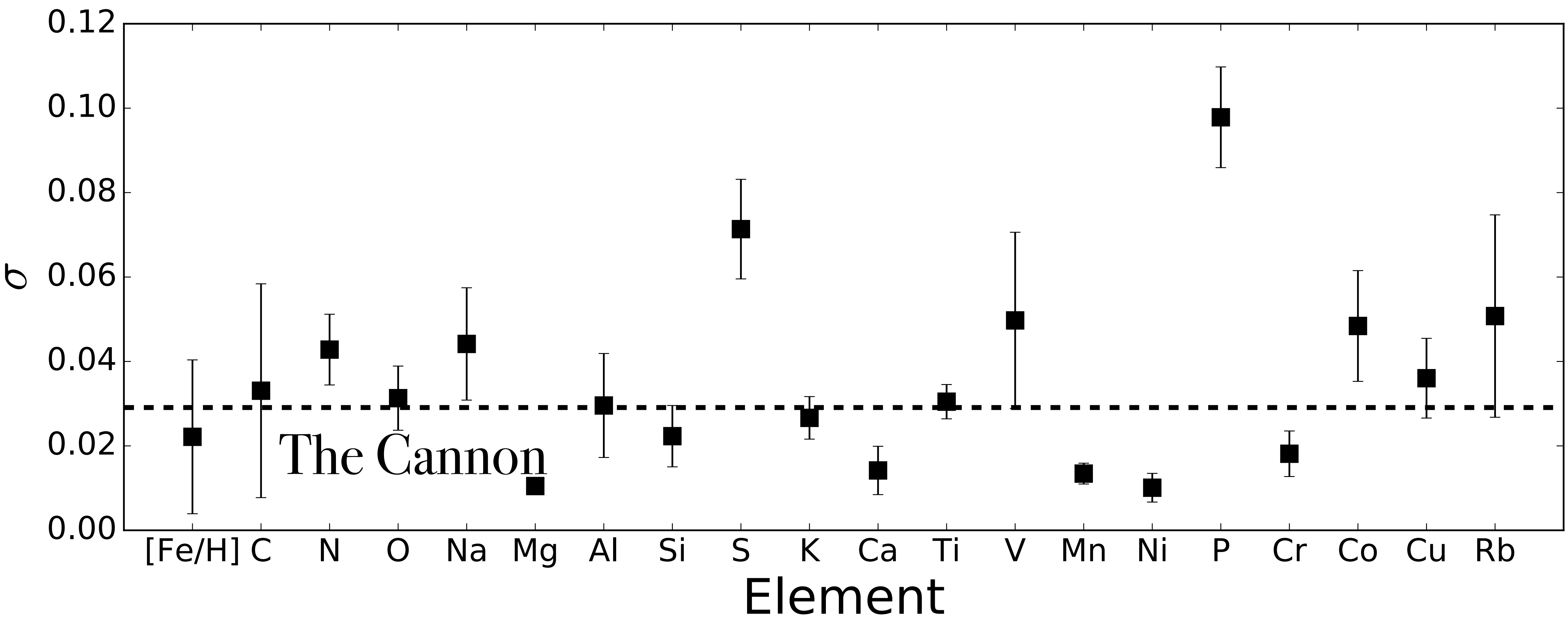

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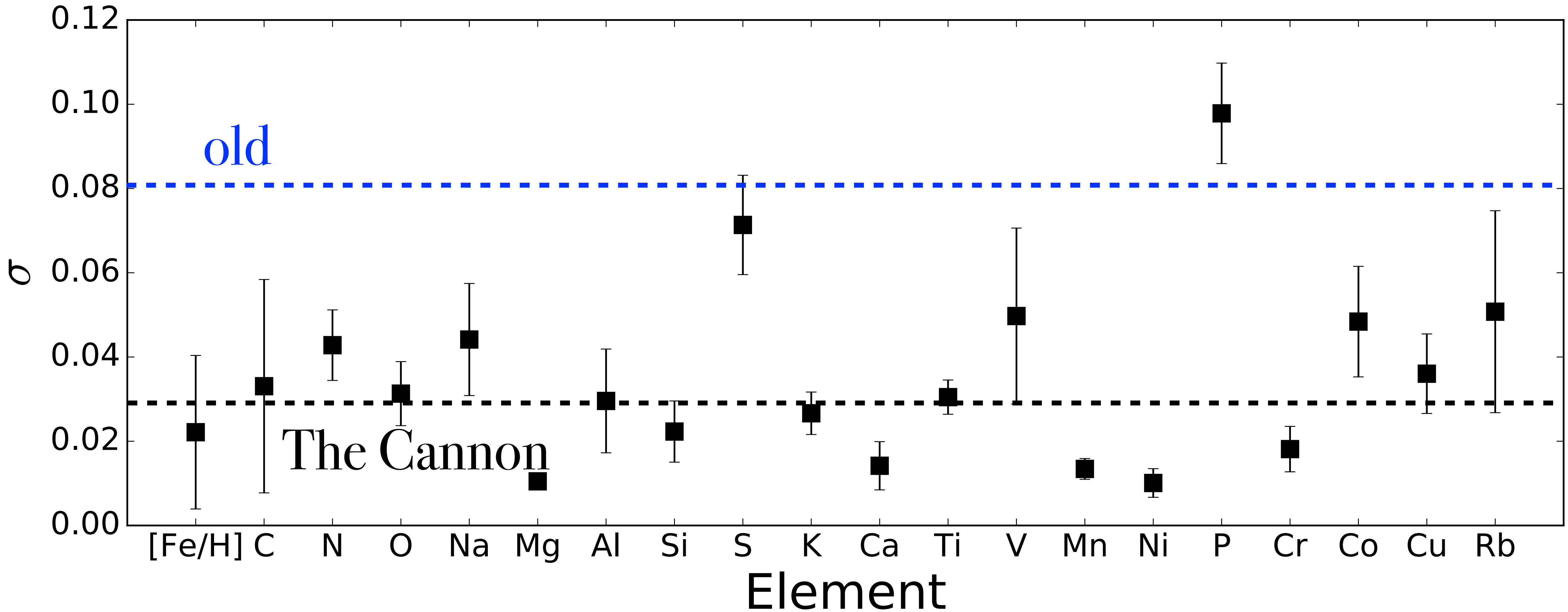
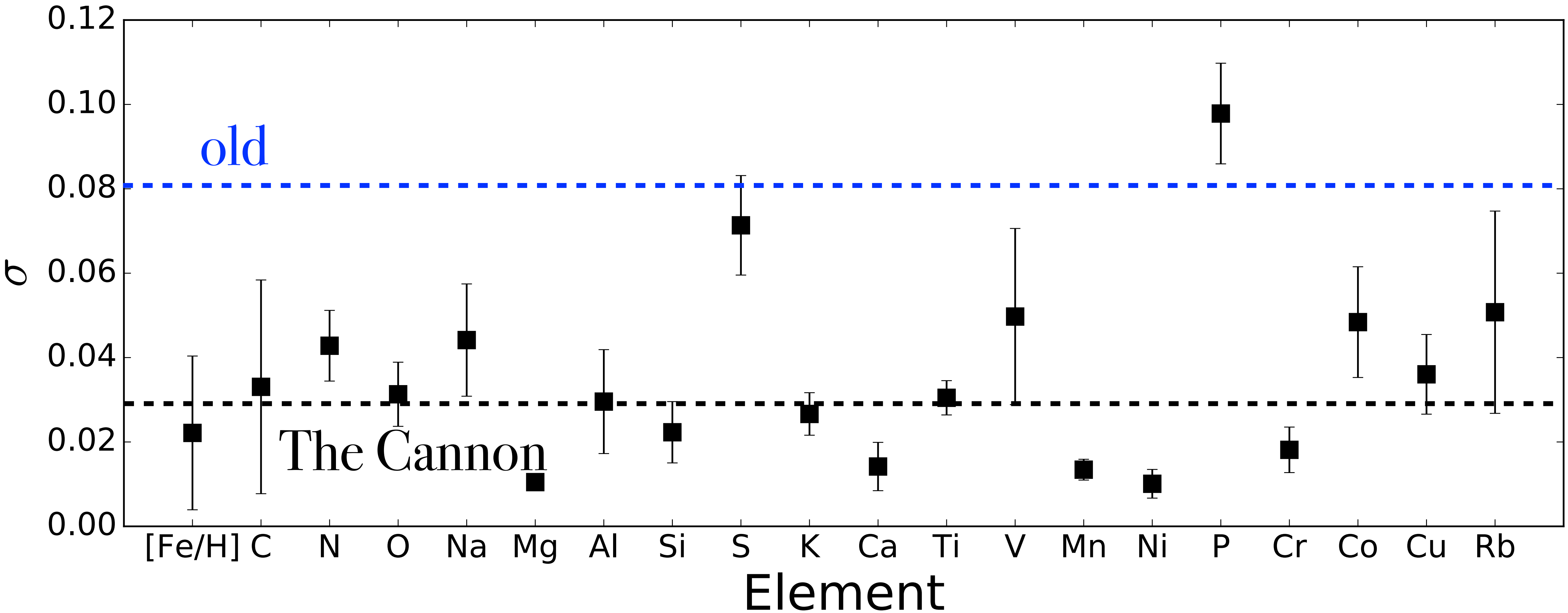


Median precision of 0.03 dex for 20 elements

Carefully assessed precision (Ness et al., 2018)

with higher precision, more discriminating power in measurements



Galah


Sven Buder

Galah

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350,000 stars (R=30,000) 23 element abundances inc. Ti, Si, Mg, O, Li, Ba, Y

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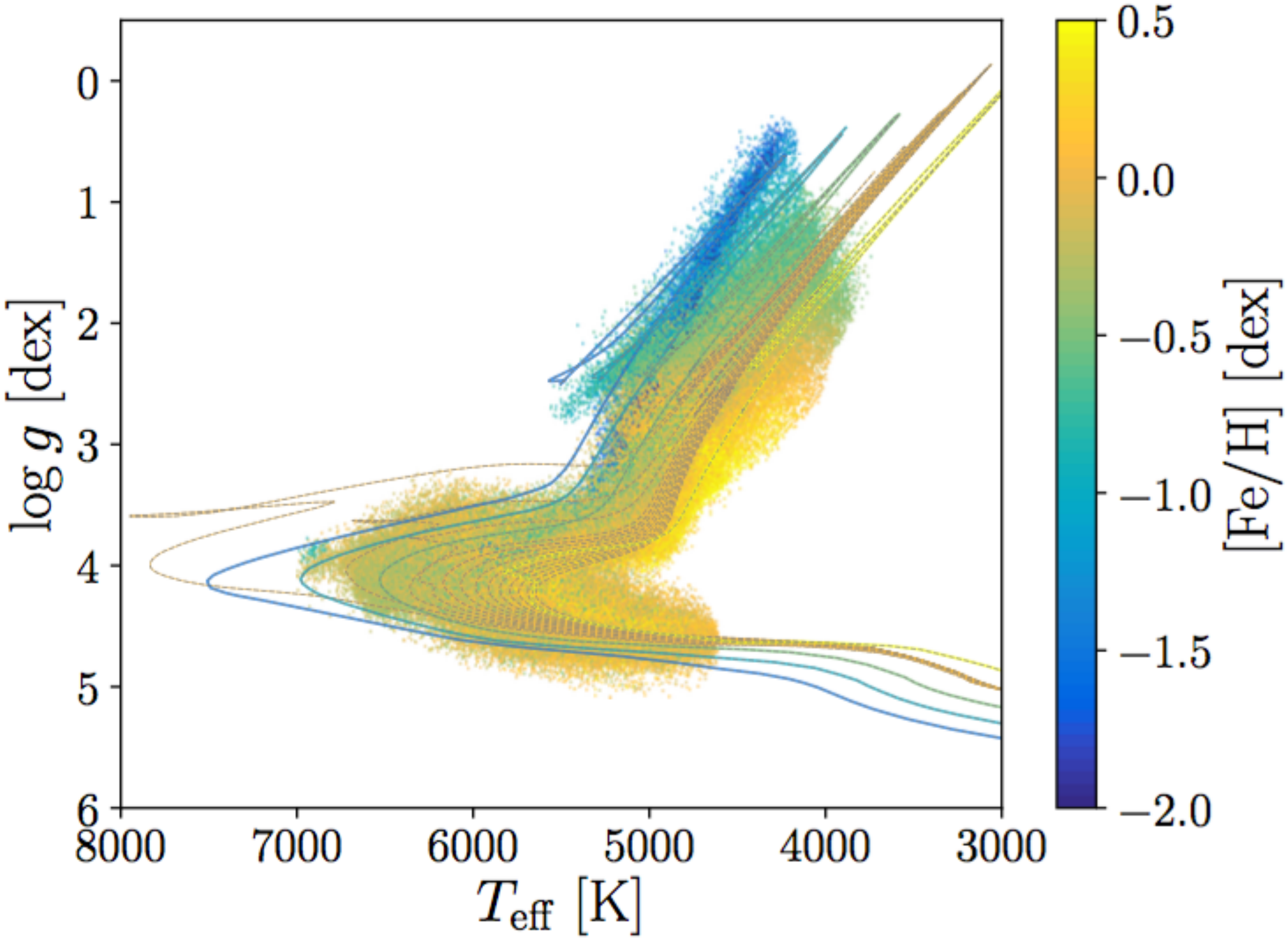

Gaia DR2 spectroscopic complement

(Buder et al., 2018a,b)

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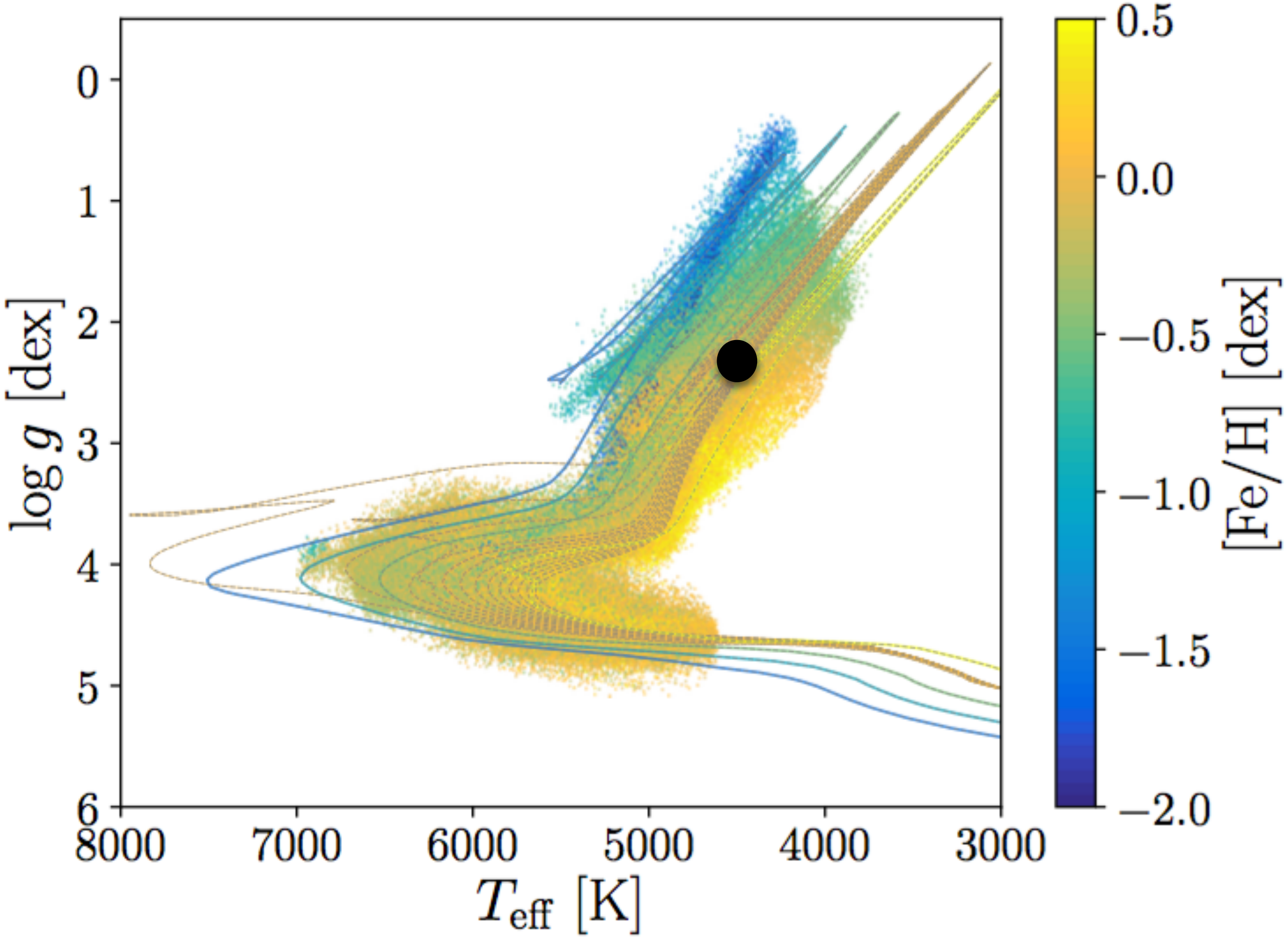

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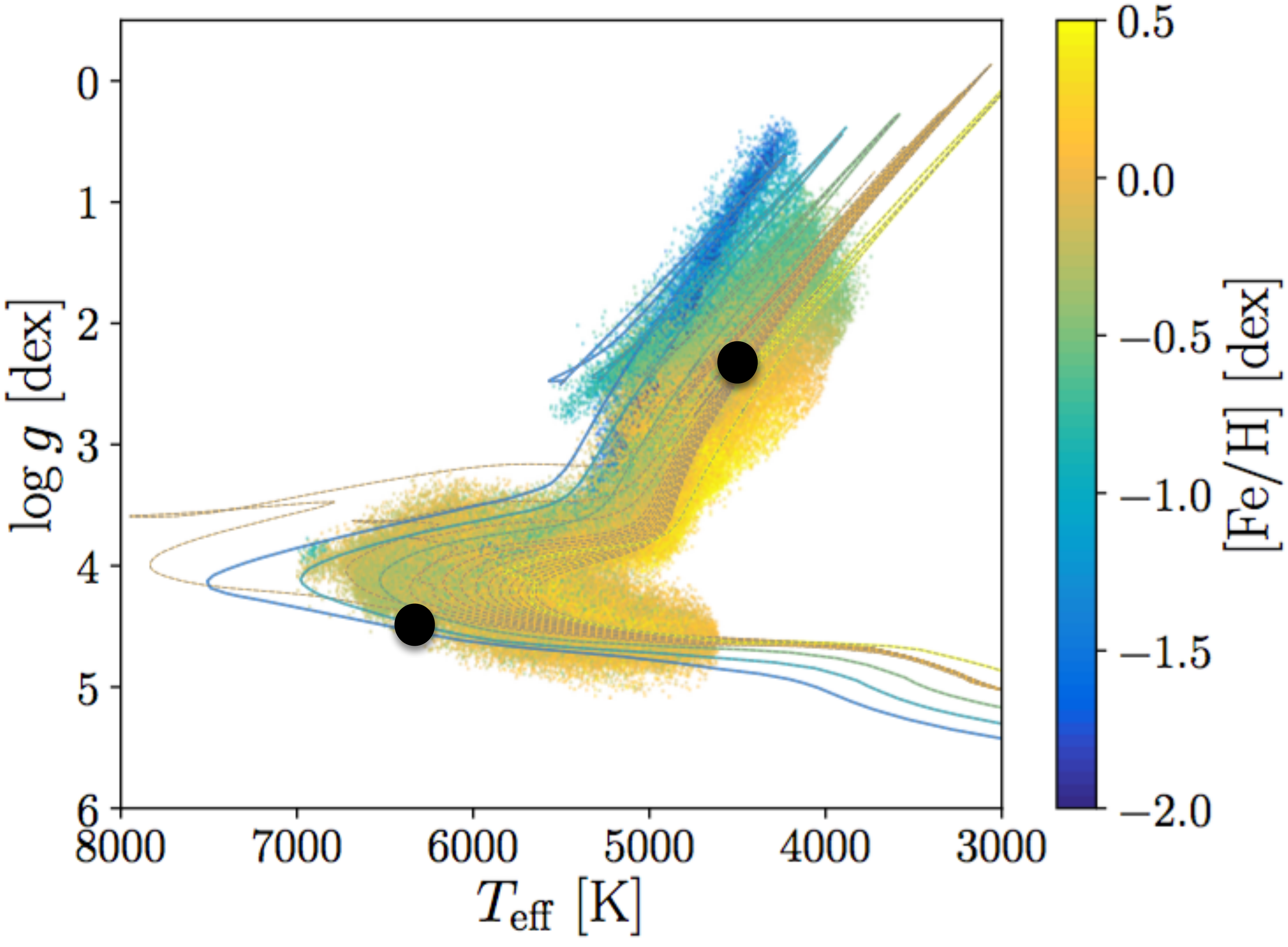
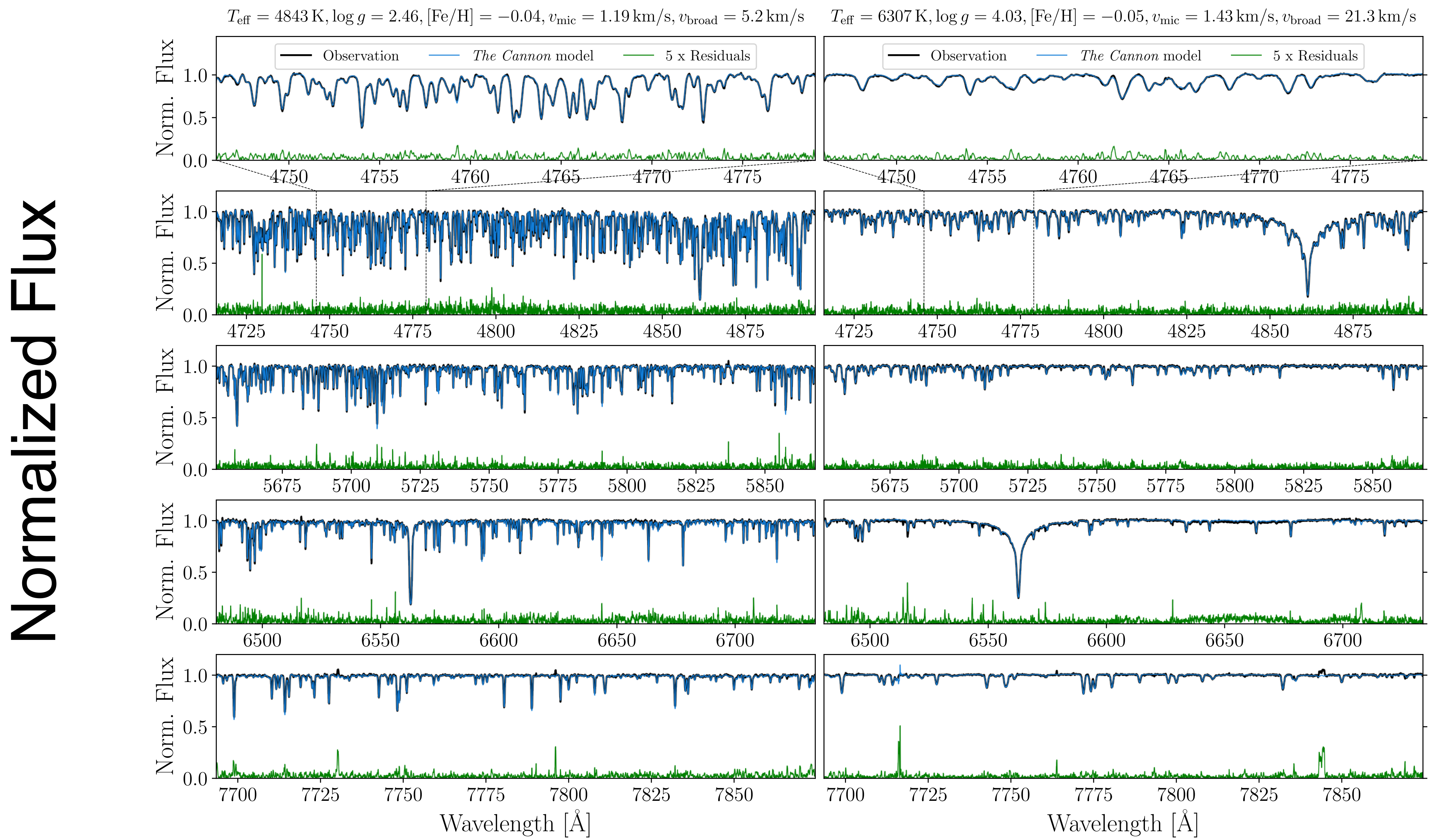


Gaia DR2 spectroscopic complement

(Buder et al., 2018a,b)

Galah model versus data - 23 elements

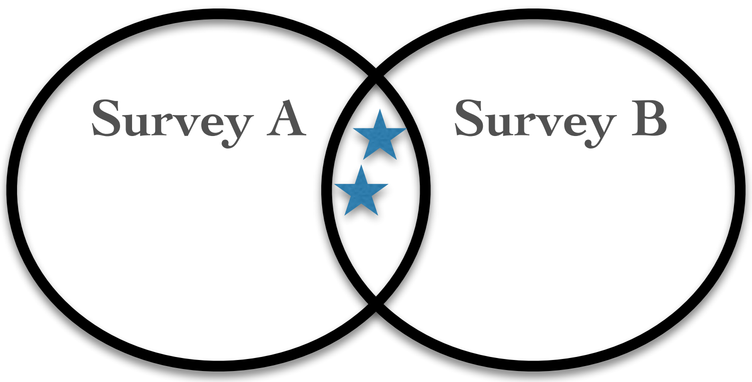


Applications…

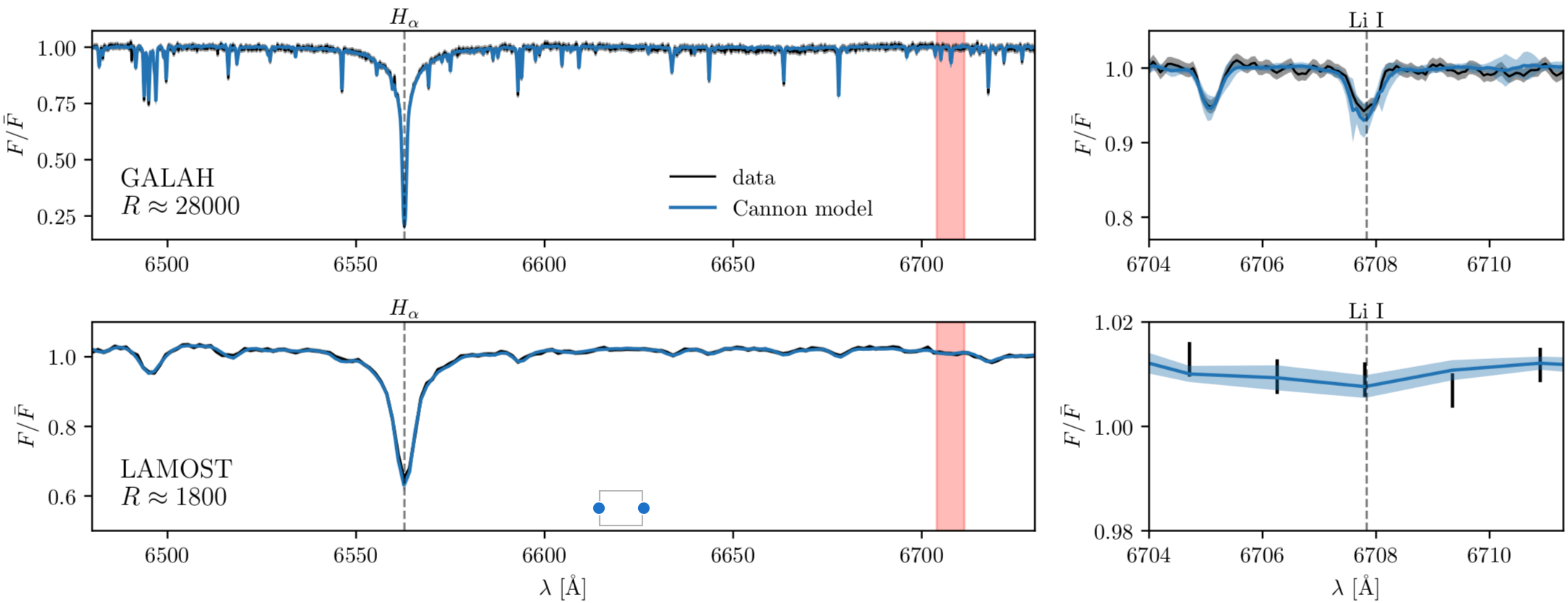
Low-resolution spectra

Individual abundances from LAMOST

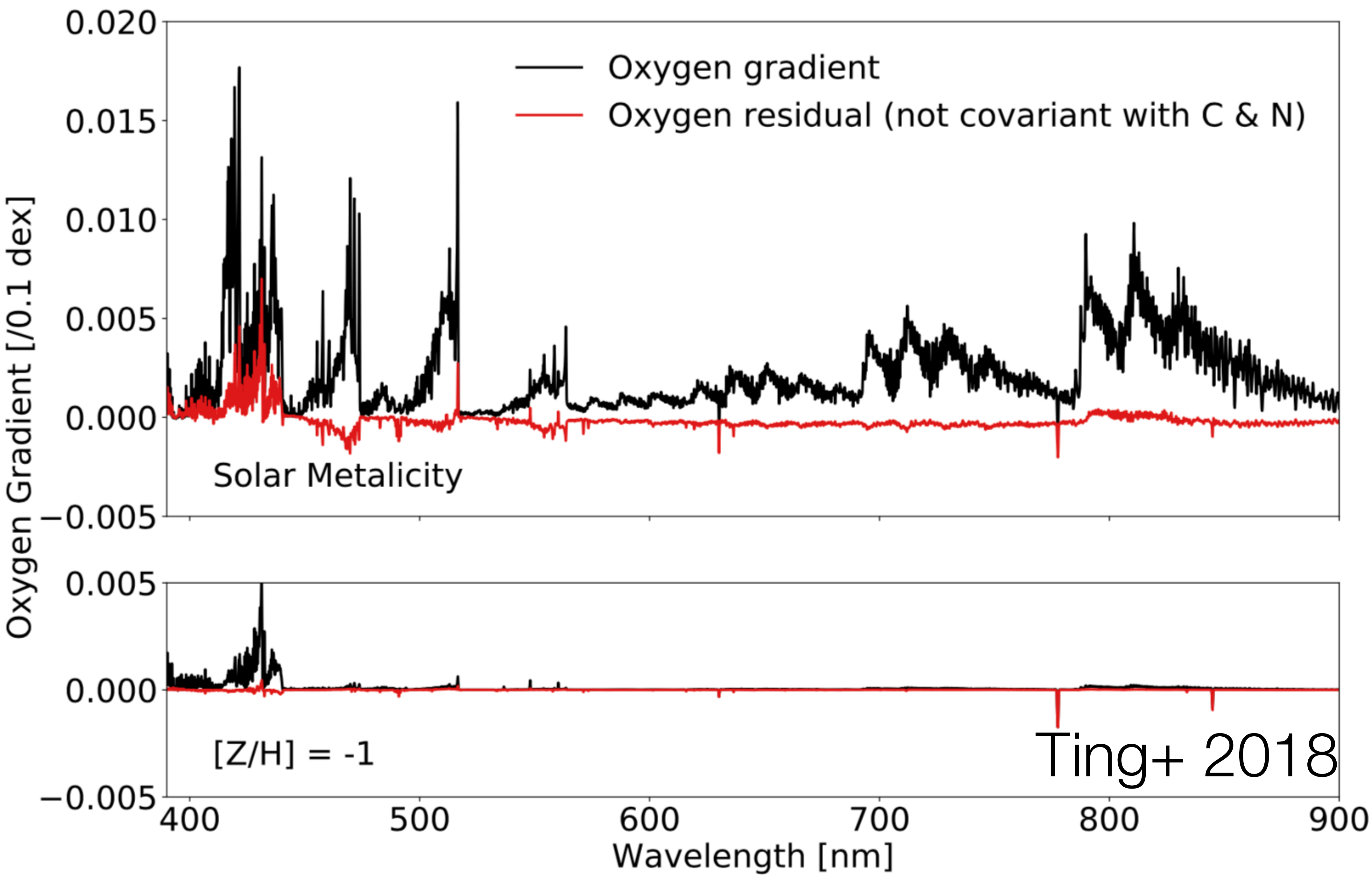
Wheeler & Ness (in prep) - catalogue of 4 million stars with 7 abundances



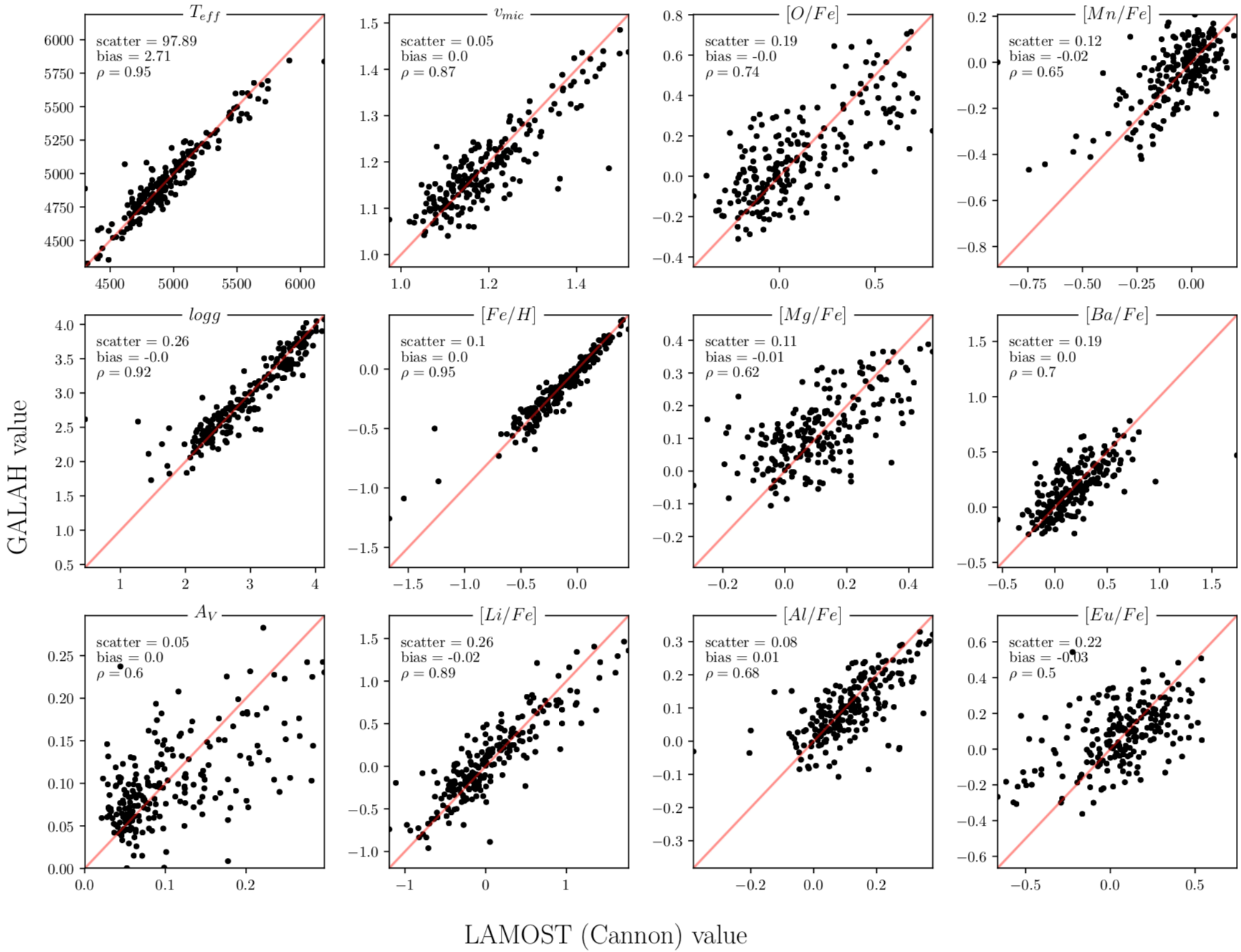
labels from A (GALAH)
spectra from B (LAMOST)



You don’t always need nice lines



Cross-validation



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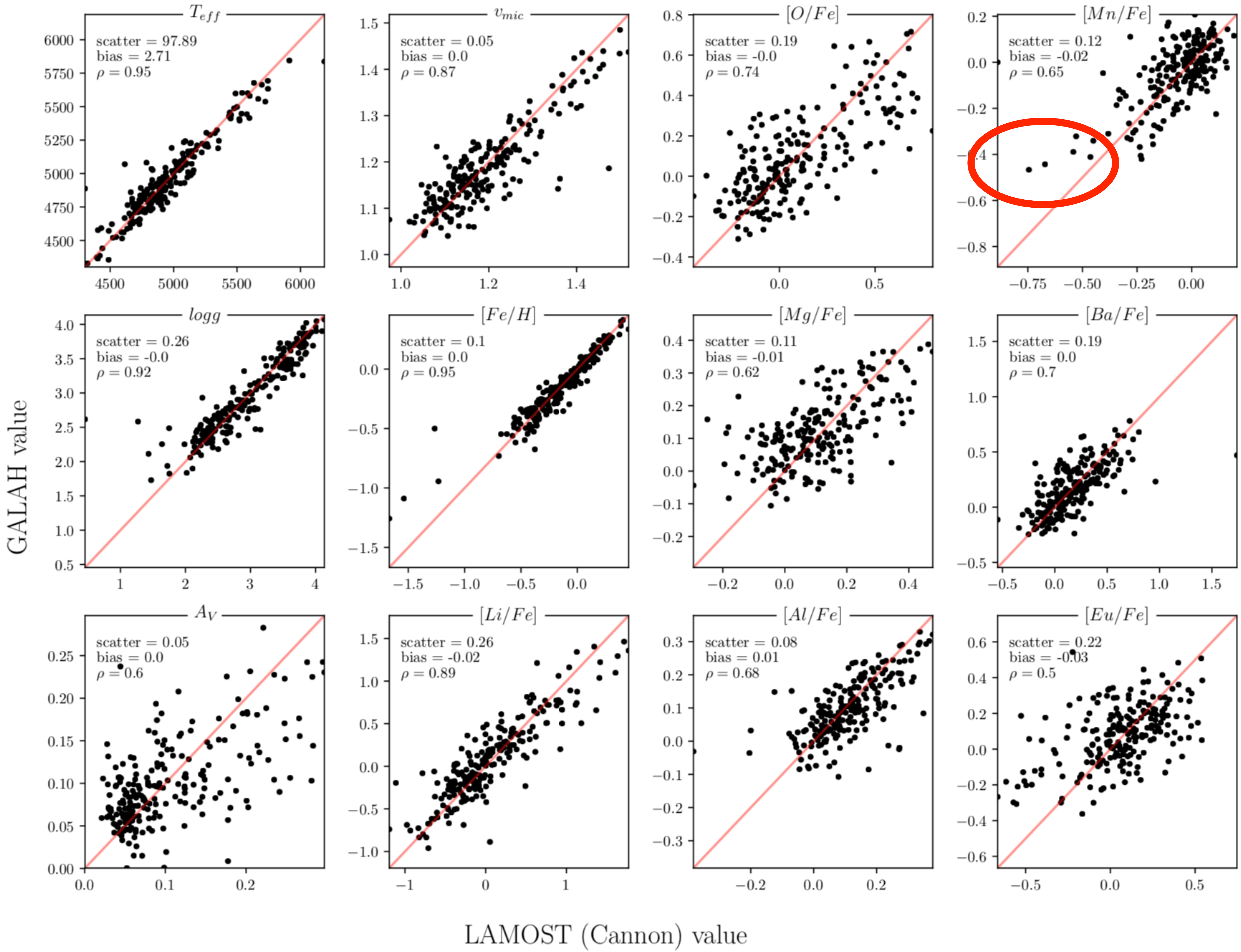

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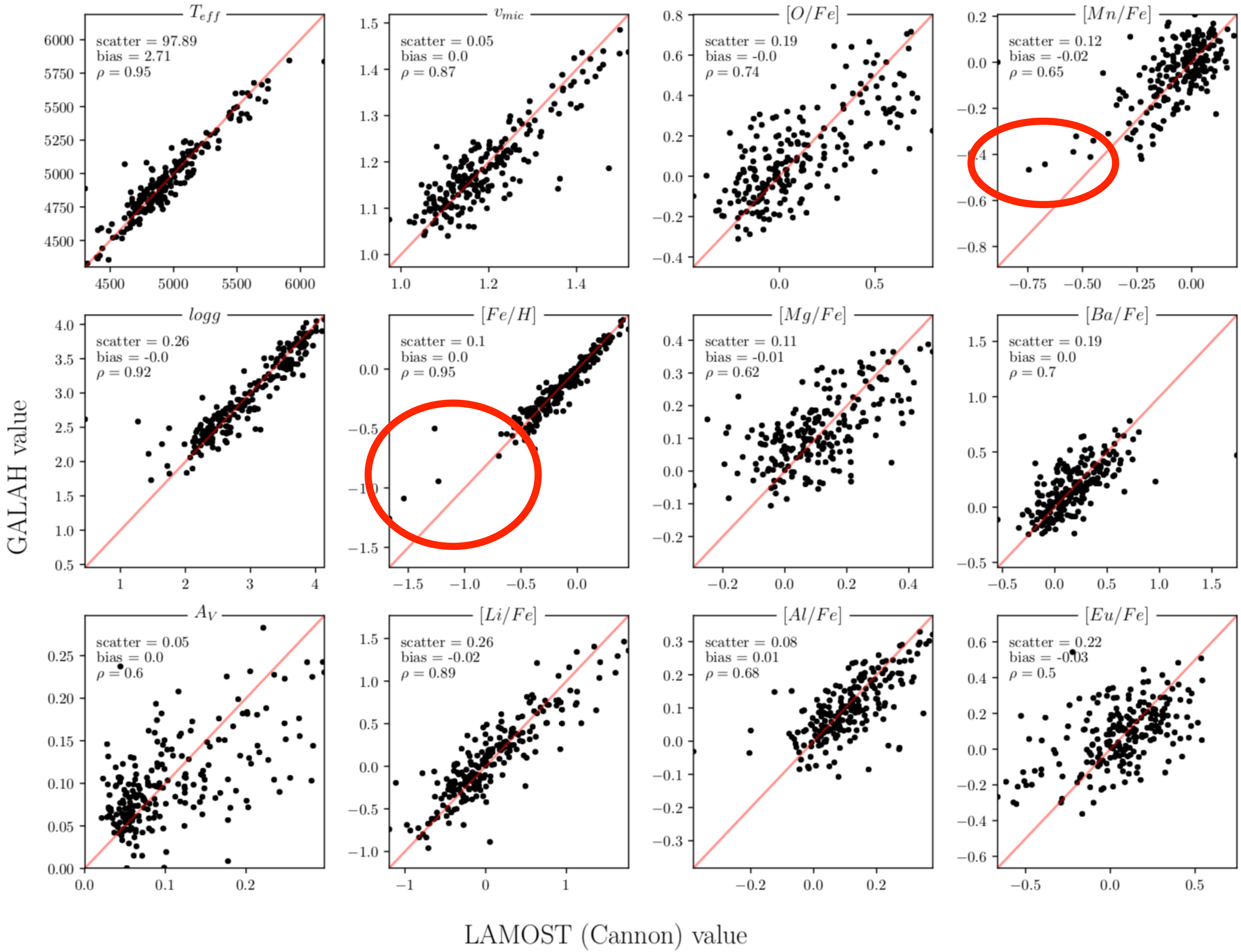

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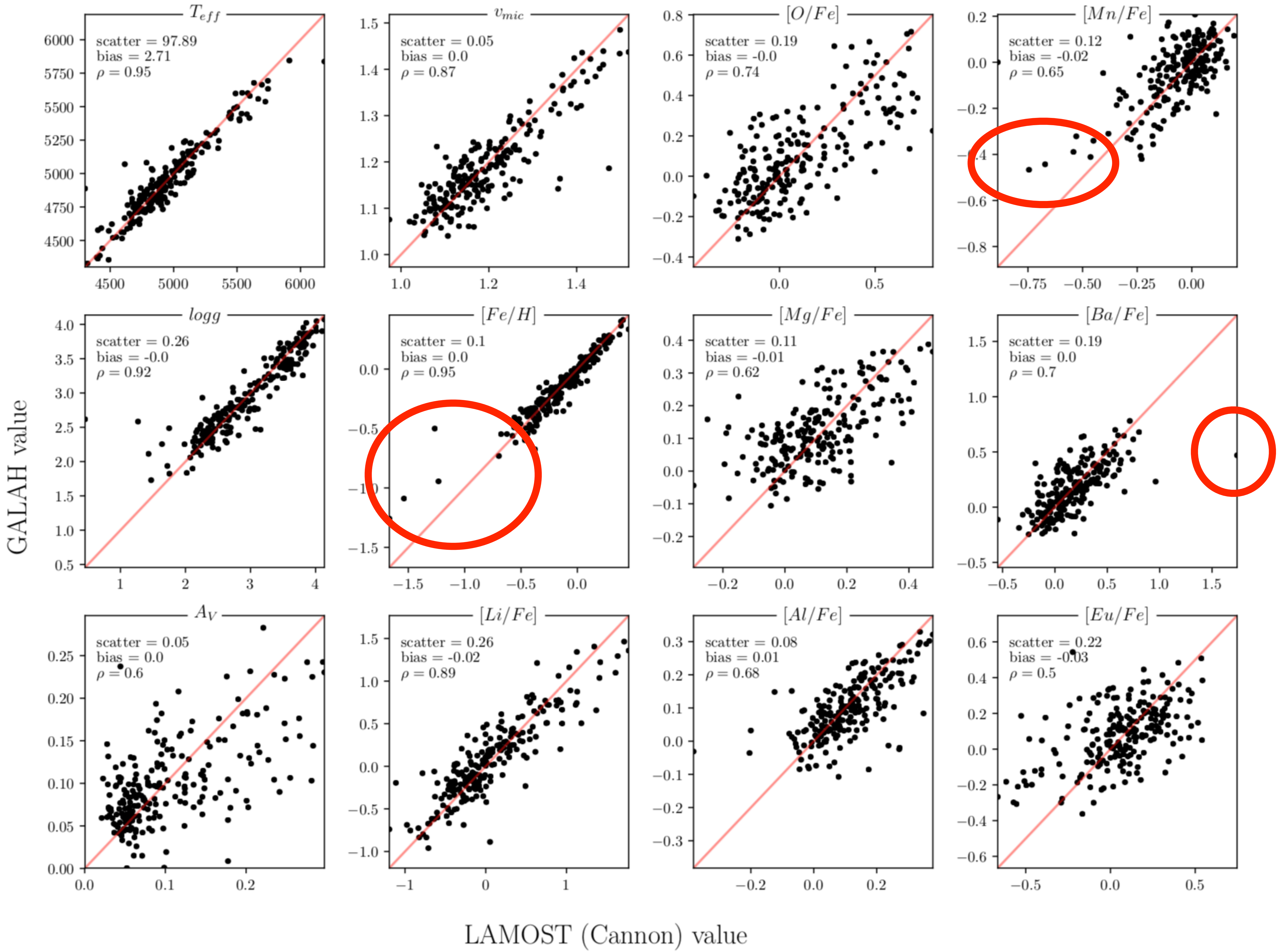

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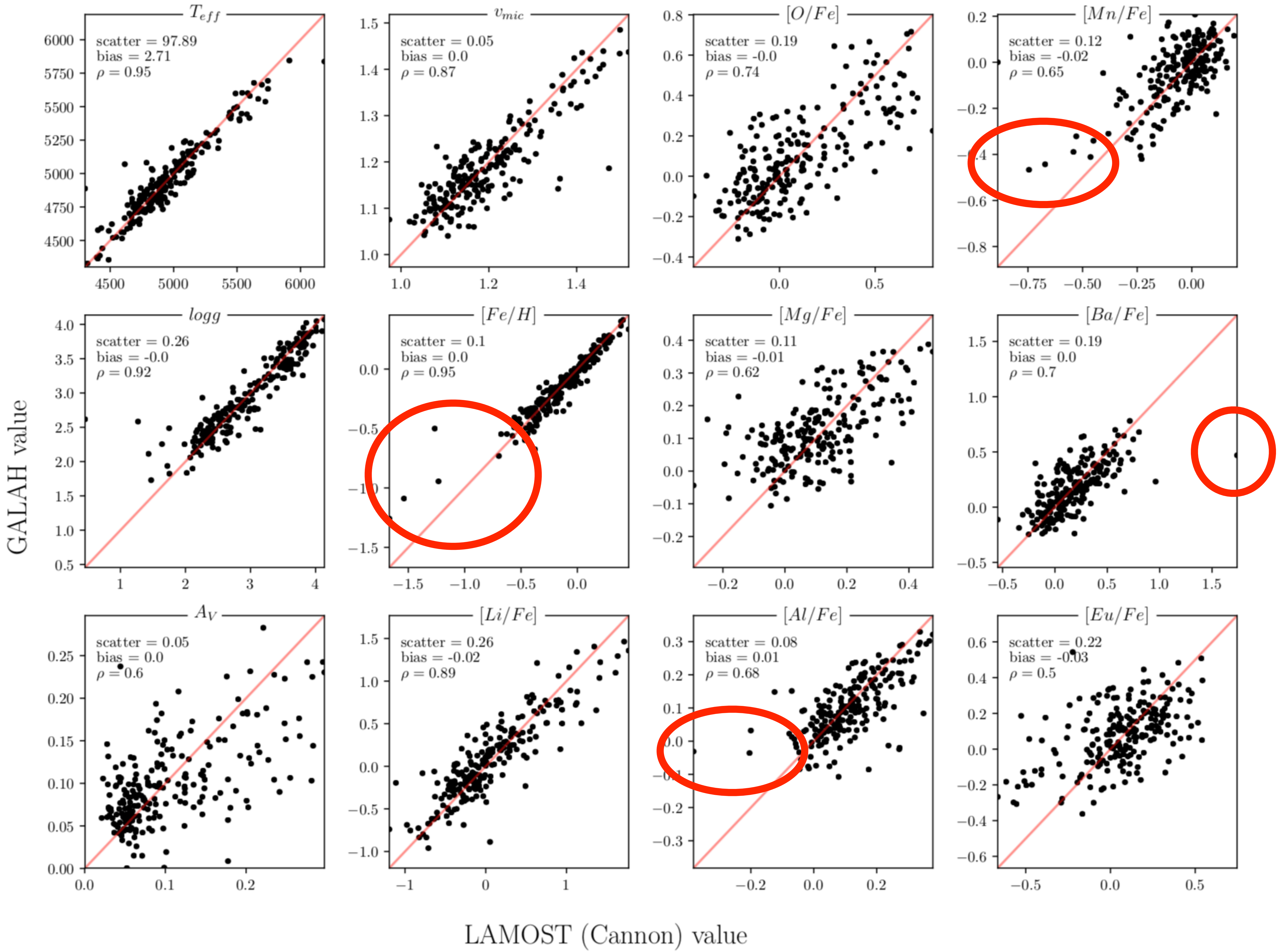
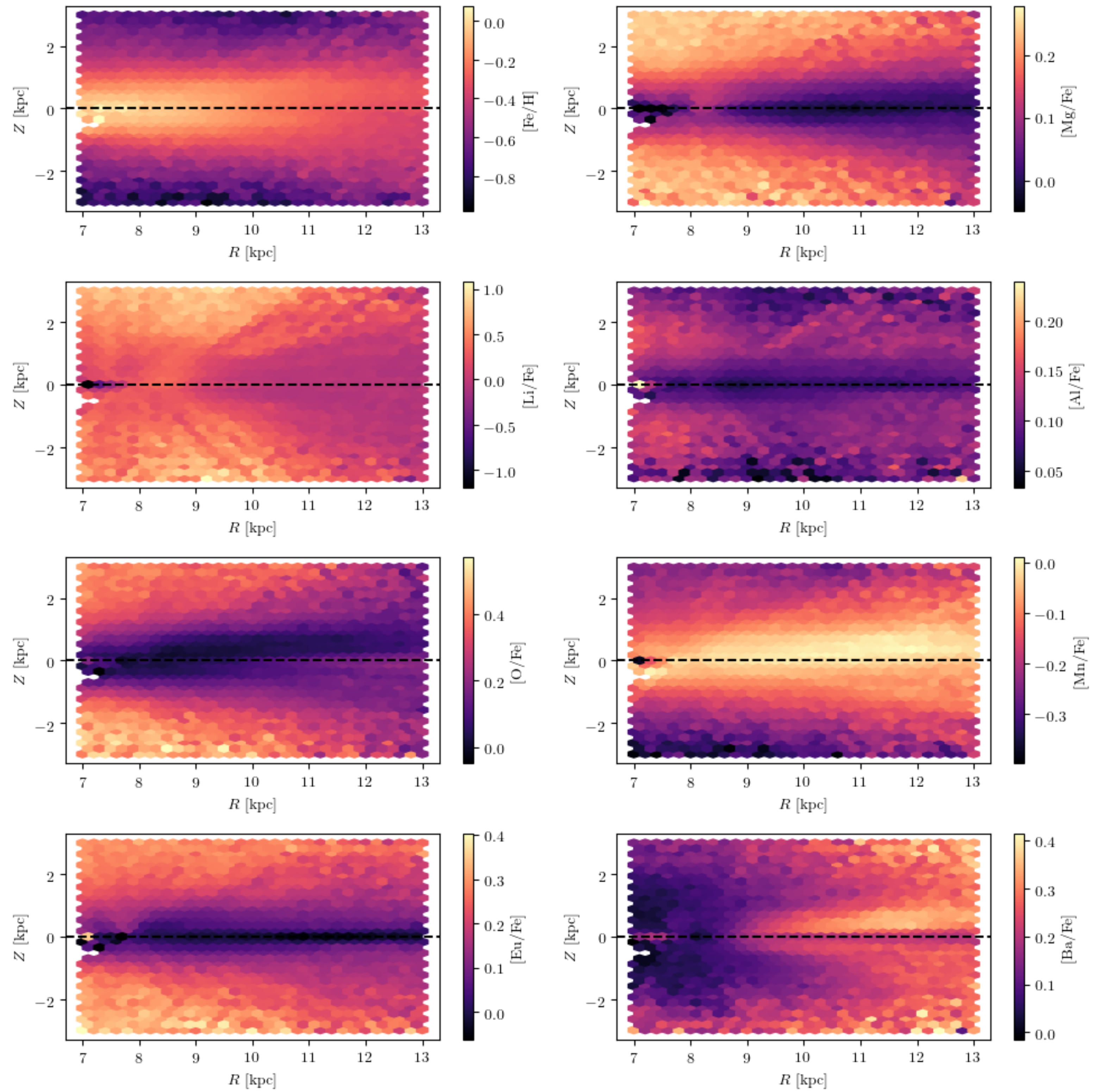
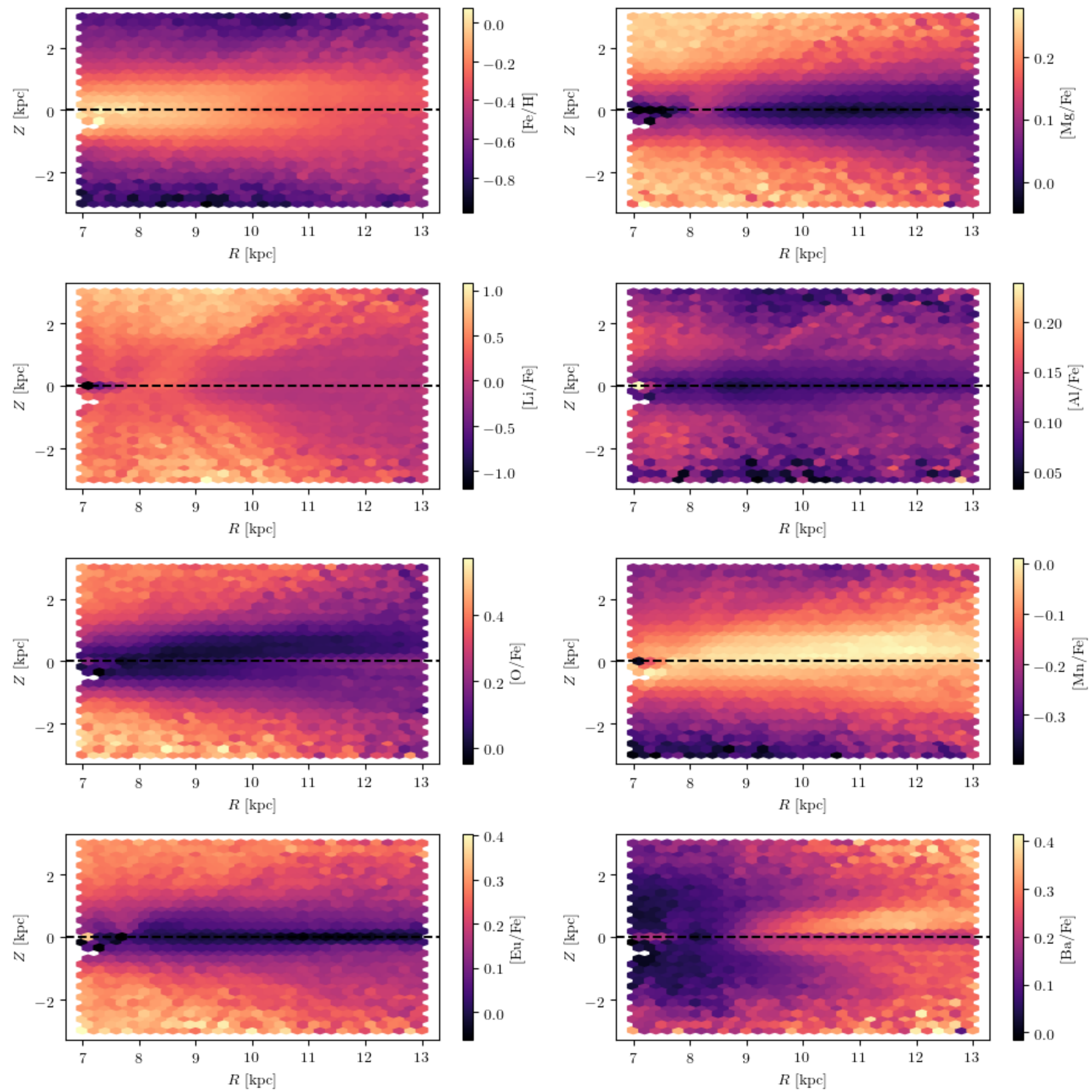


Opportunity - do this for any low resolution spectra (i.e. SLOAN)



Opportunity - do this for any low resolution spectra (i.e. SLOAN)

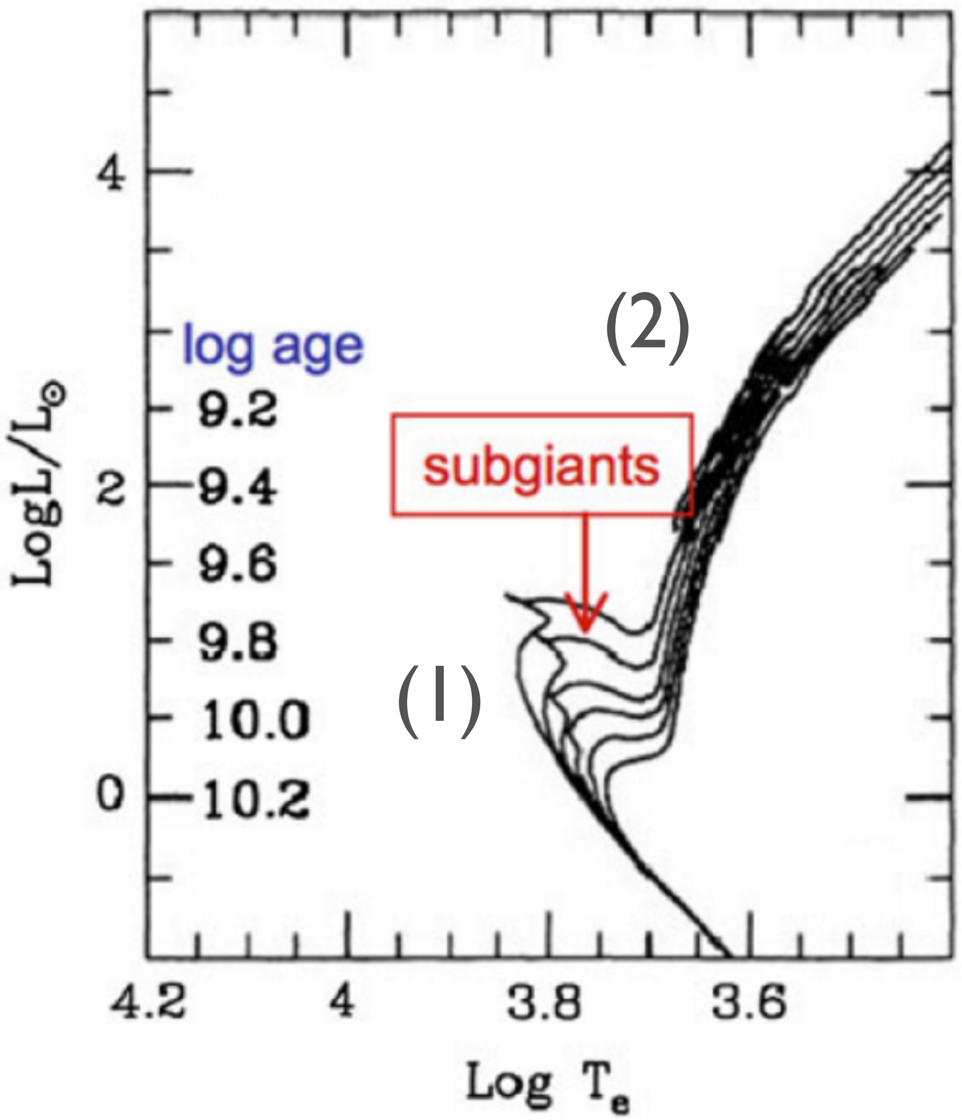
Can learn a lot from many low-precision measurements



Applications to Galactic archeology…

Empirical Spectroscopic ages

How are ages typically measured?



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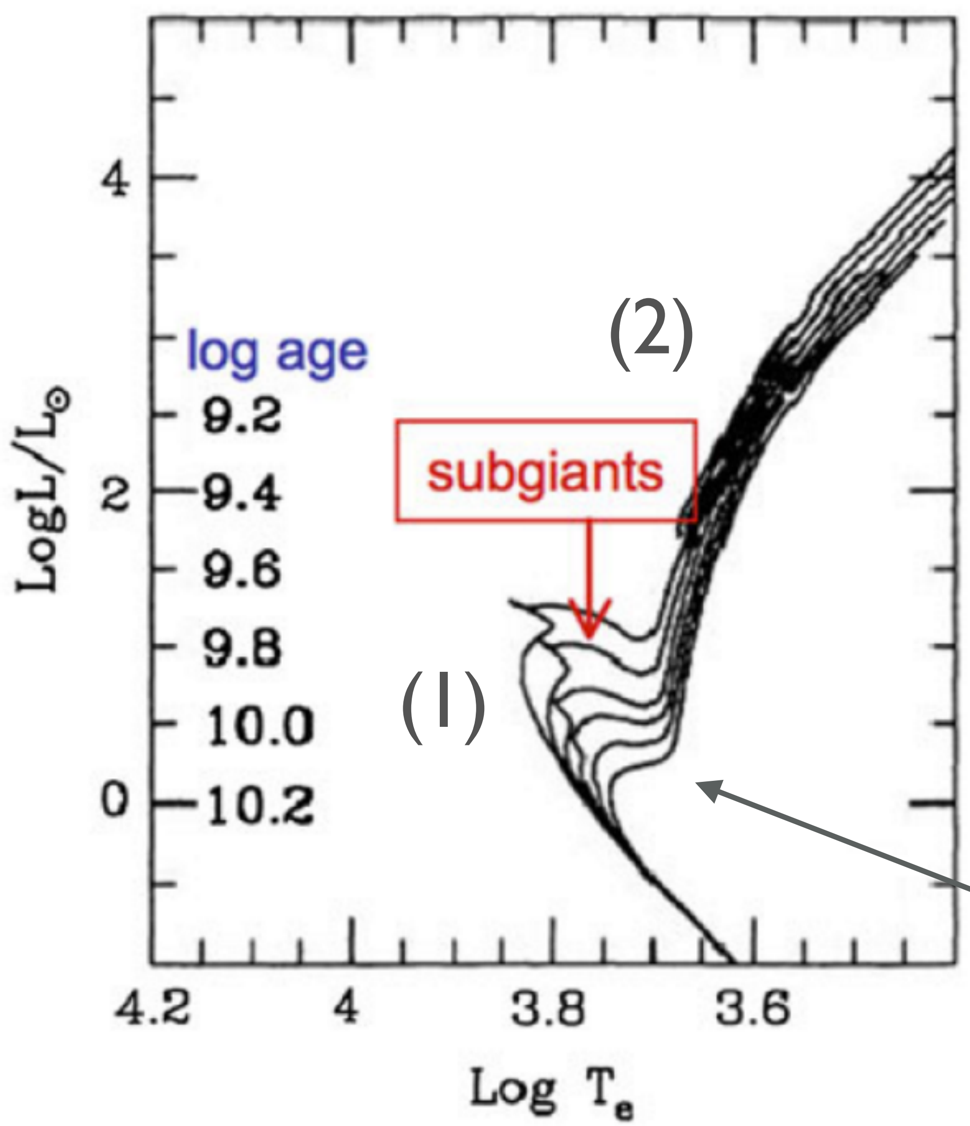

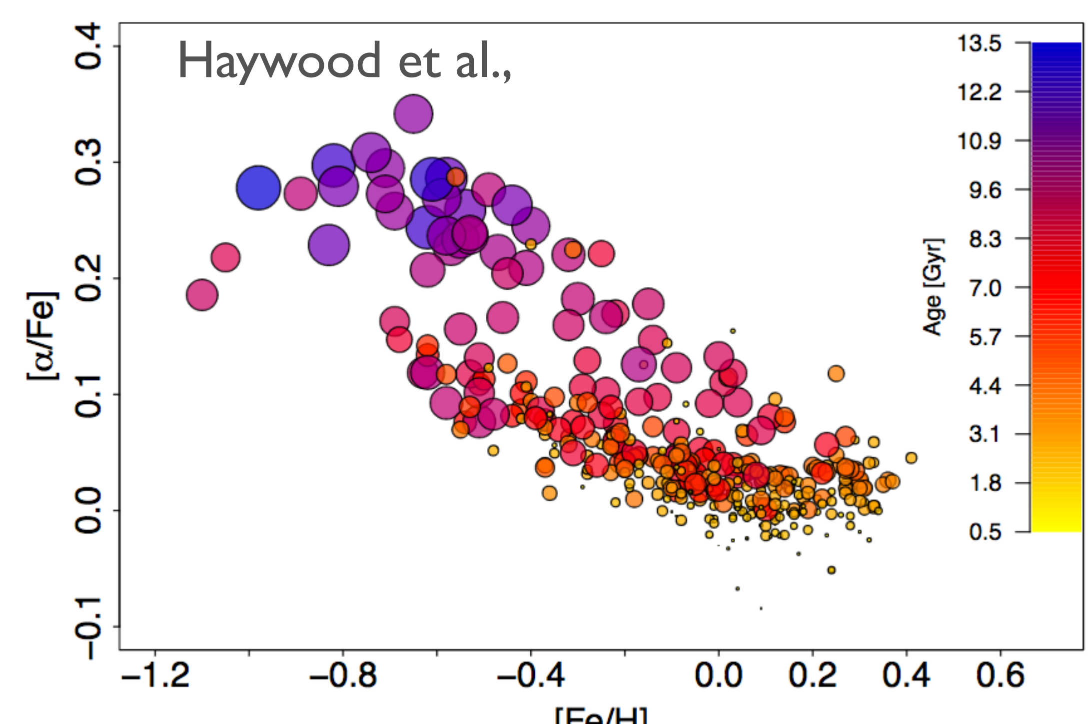

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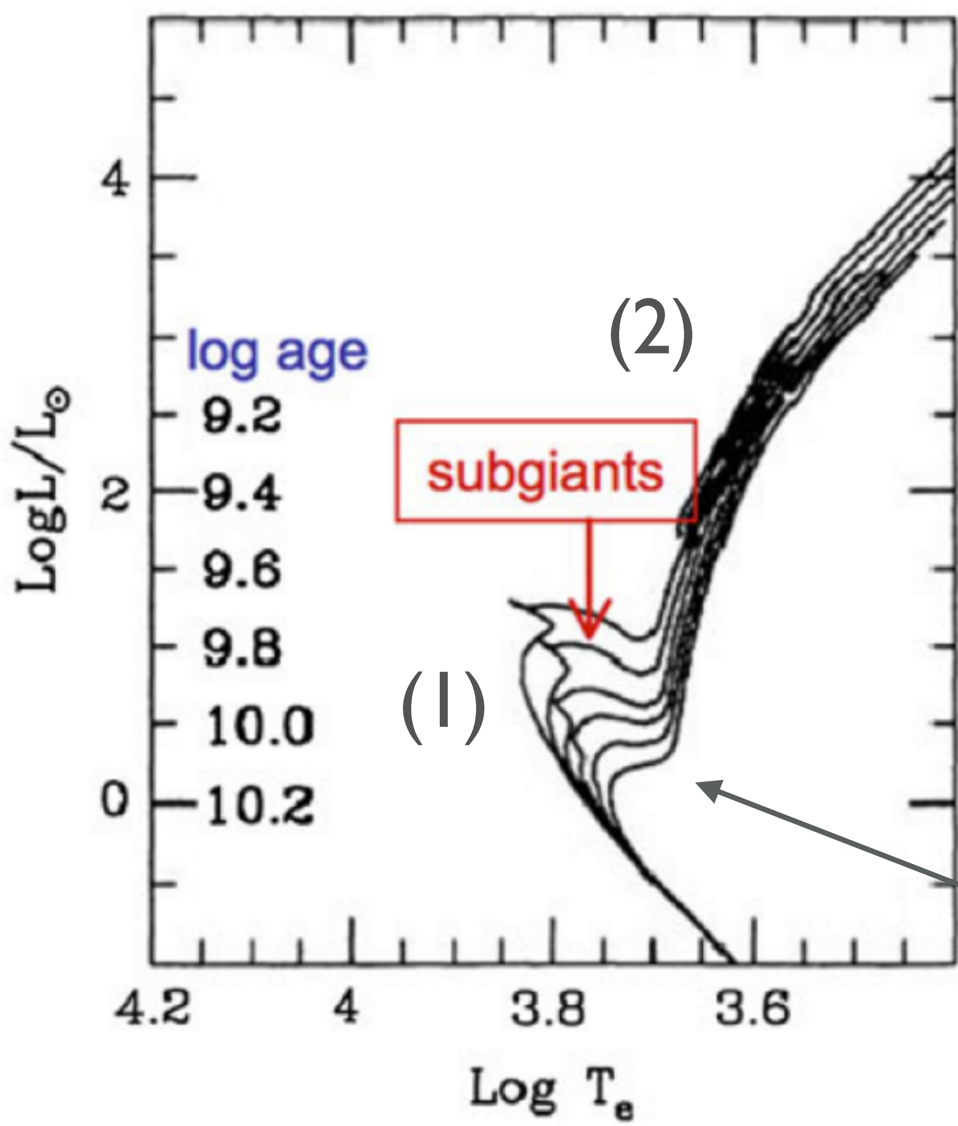
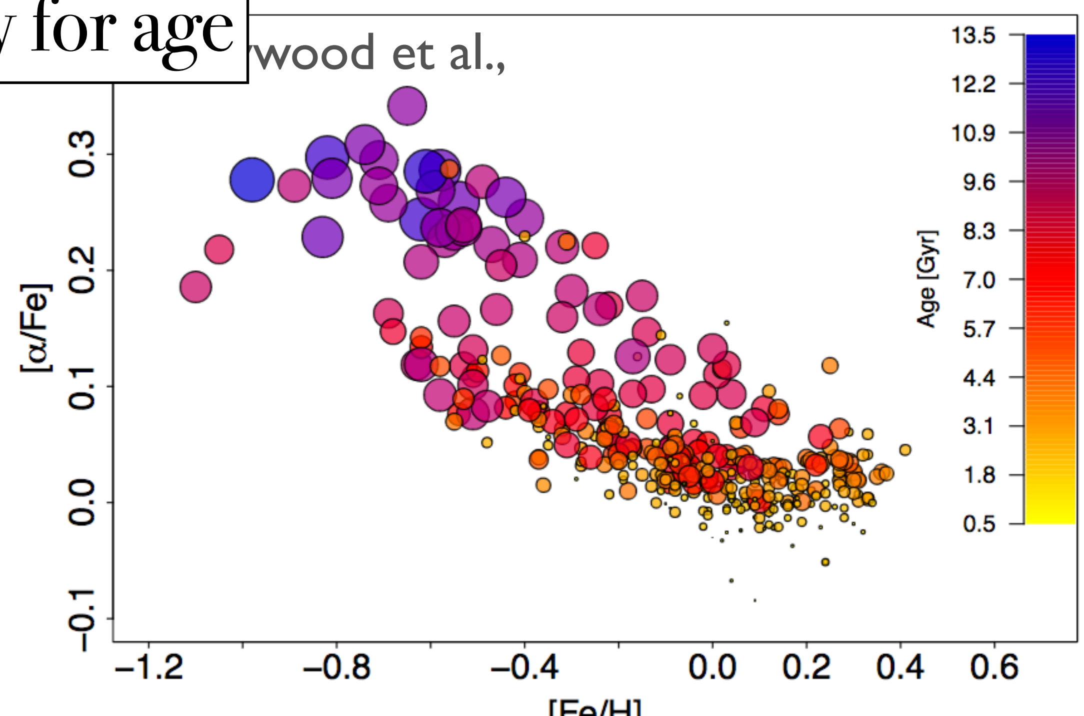
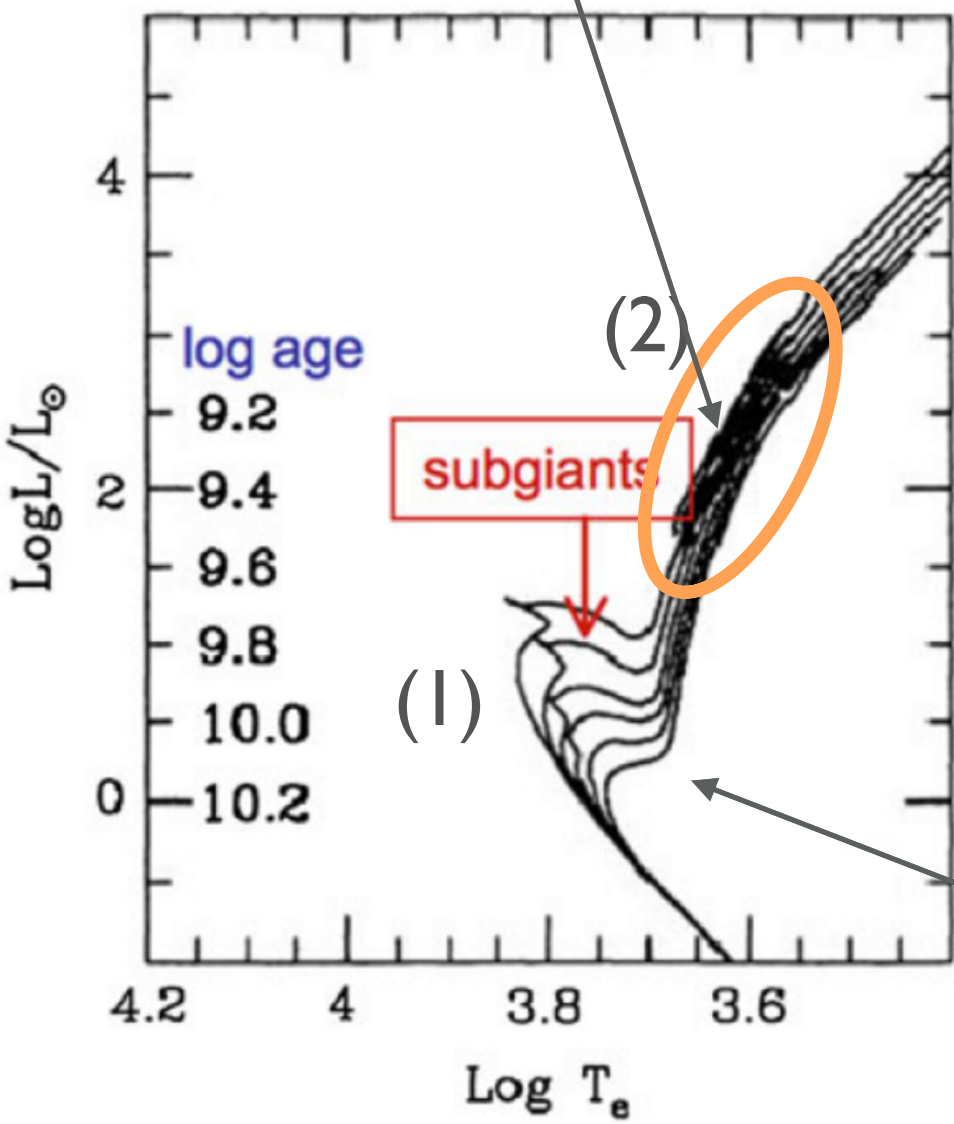


proxy for age



How are ages typically measured?

giants: asteroseismology: Kepler, CoRoT = mass



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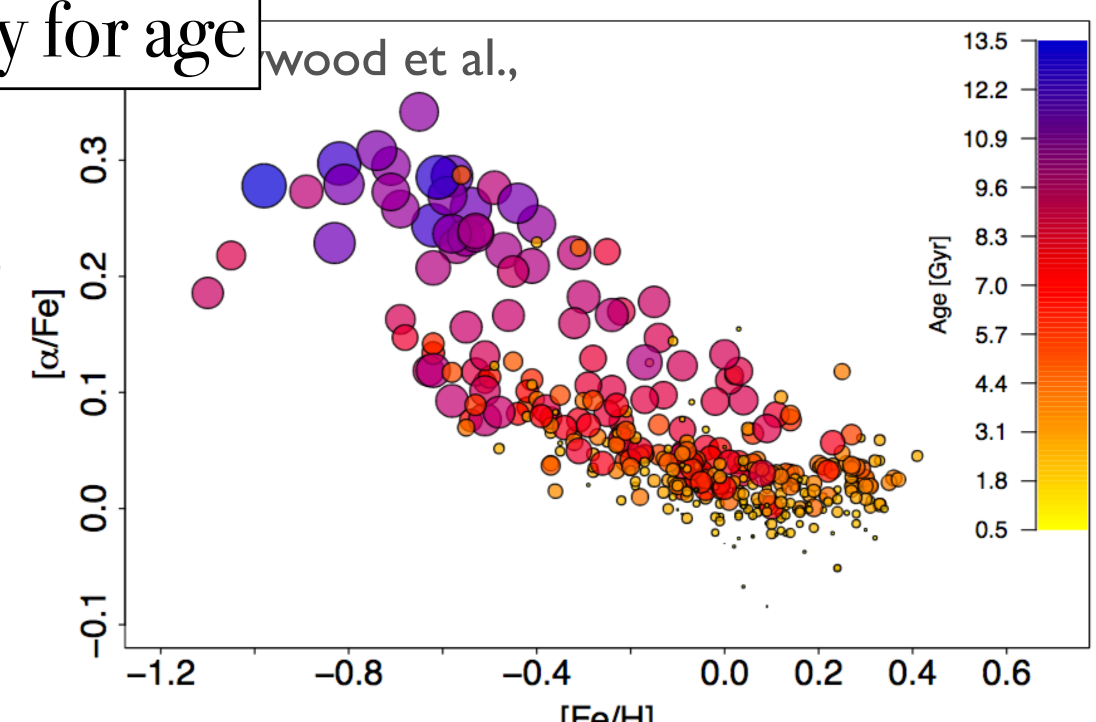

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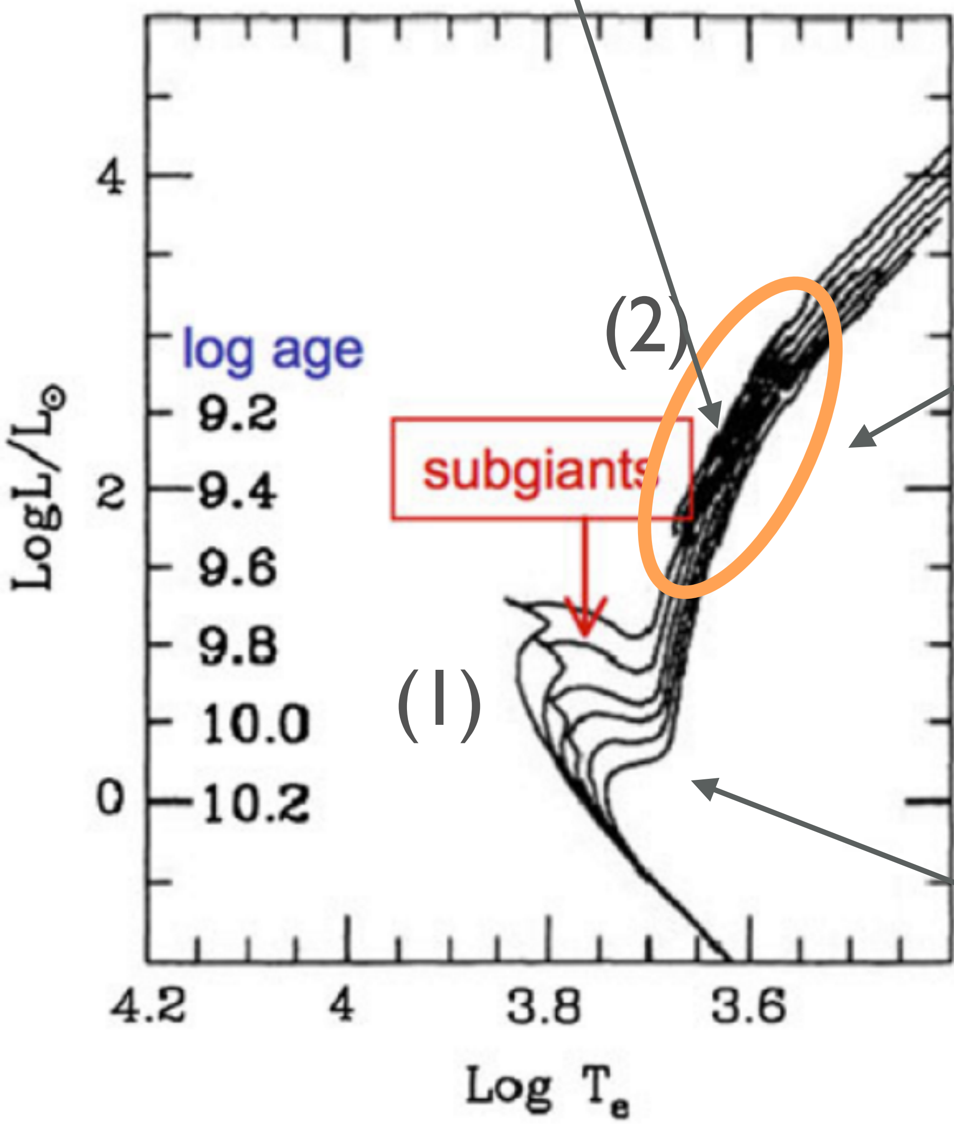
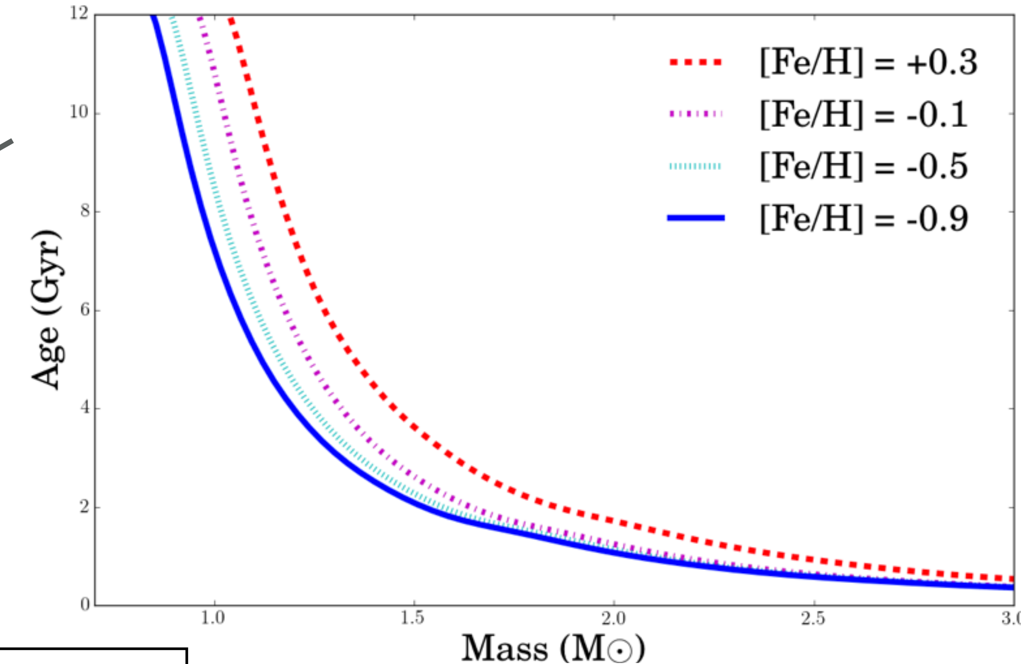
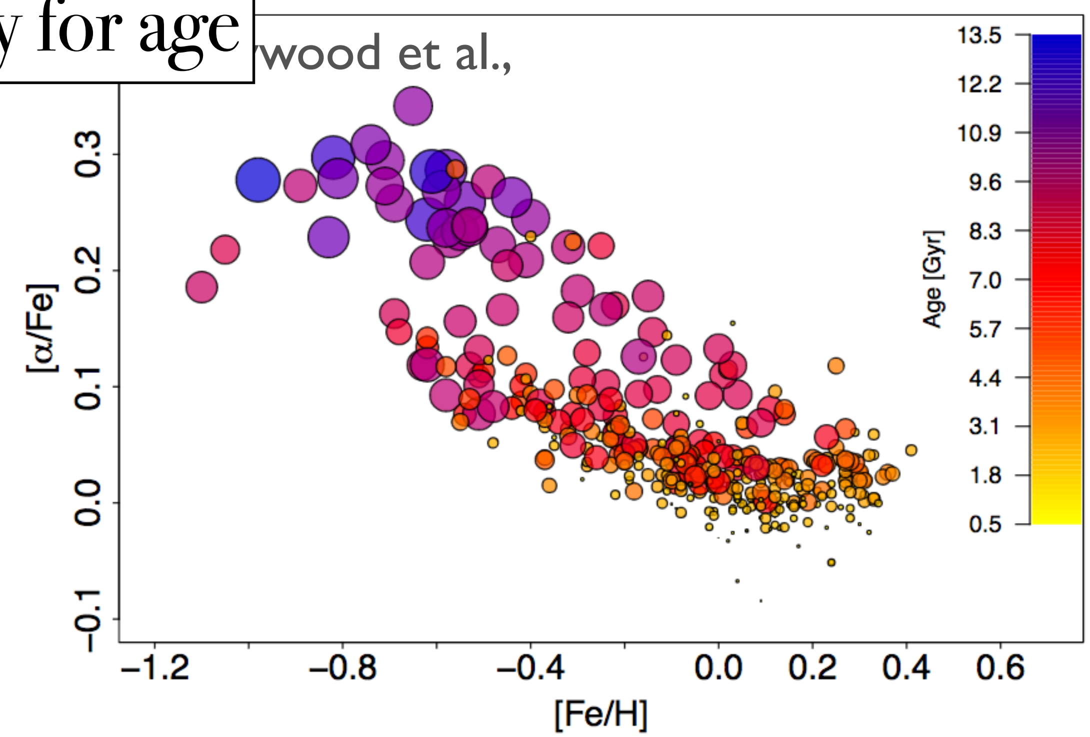


giant masses → giant ages

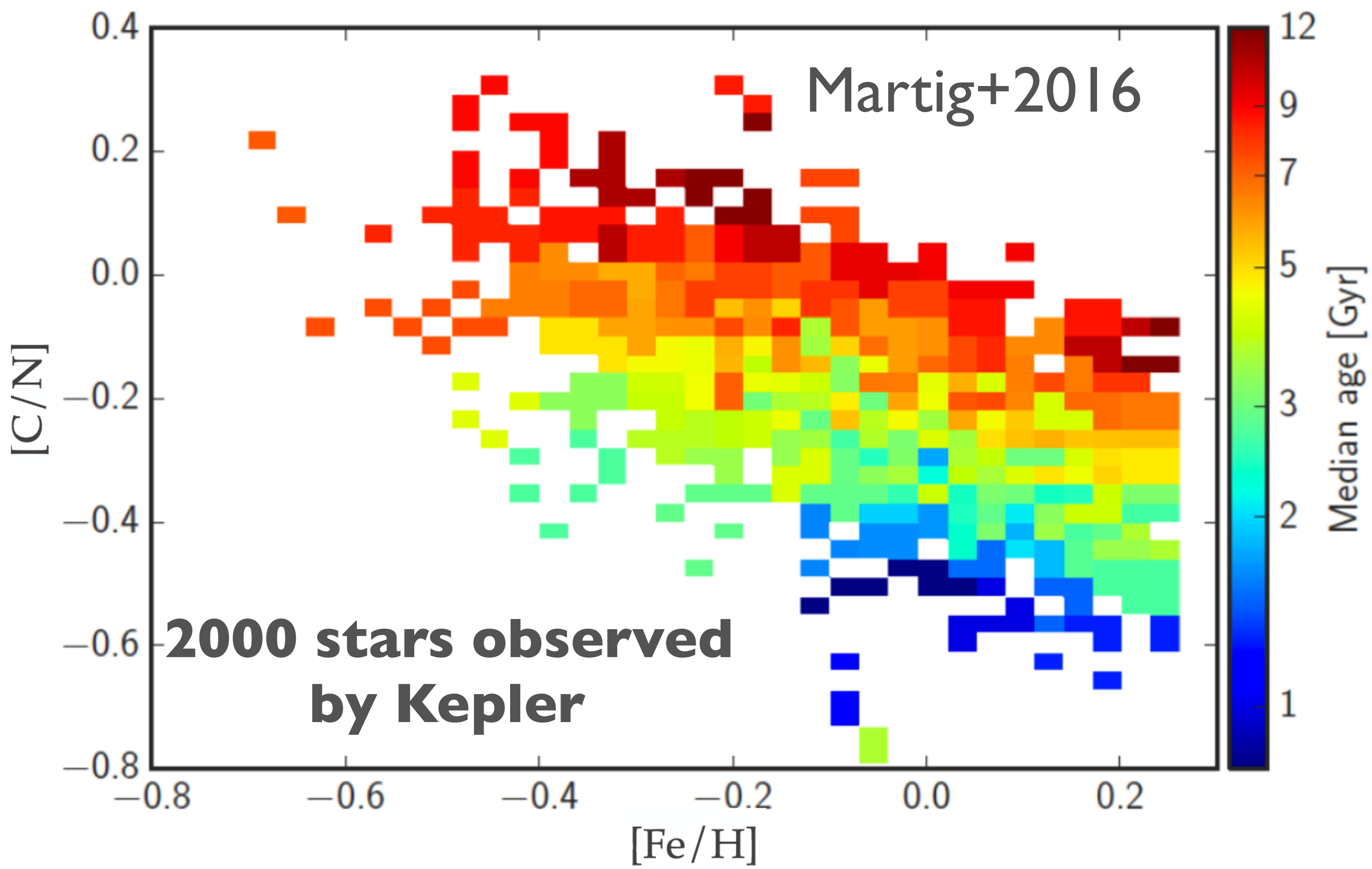


proxy for age



Origin of mass information in the red giants

mass-dependent dredge up changes surface C&N abundance



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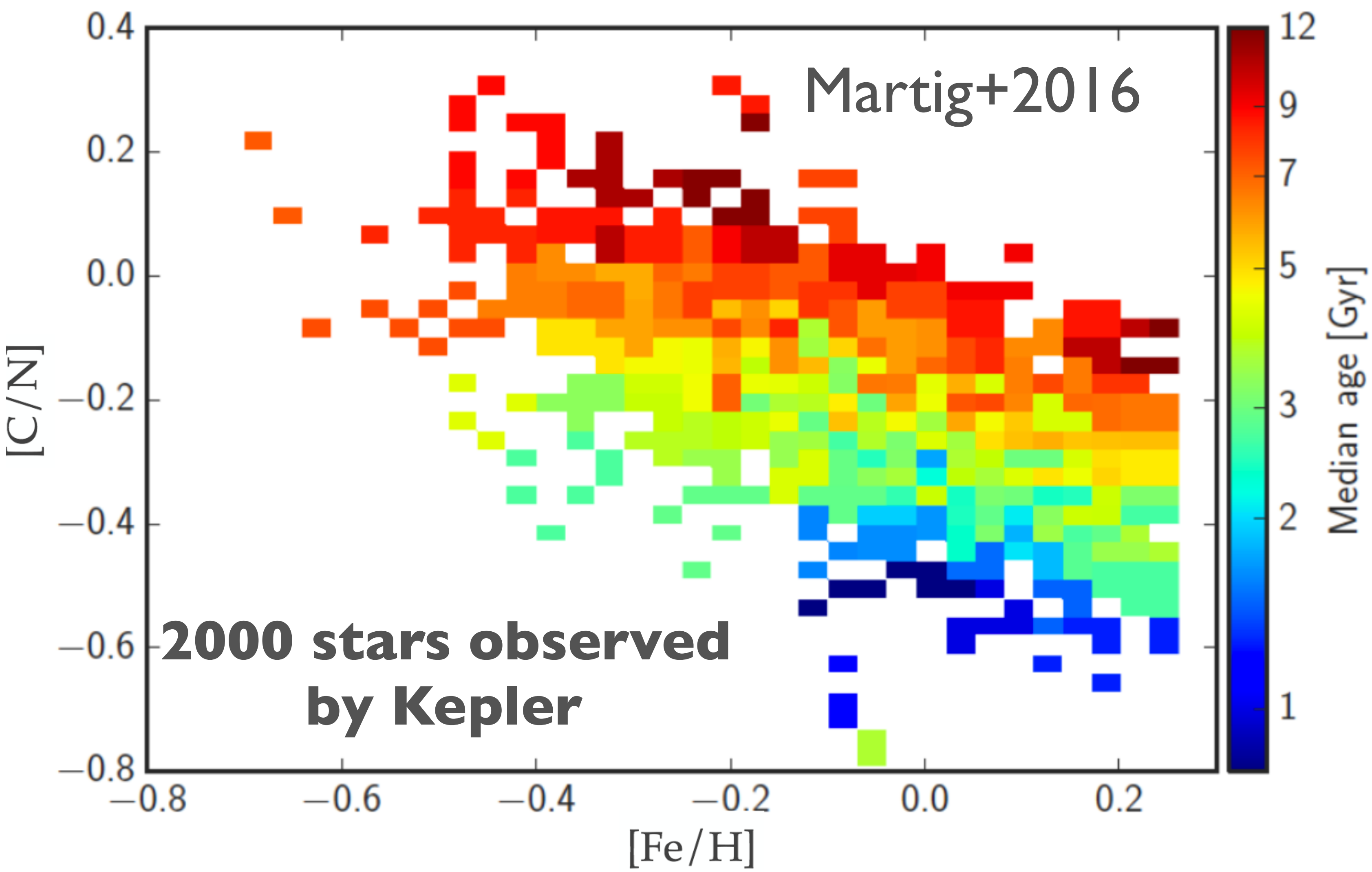
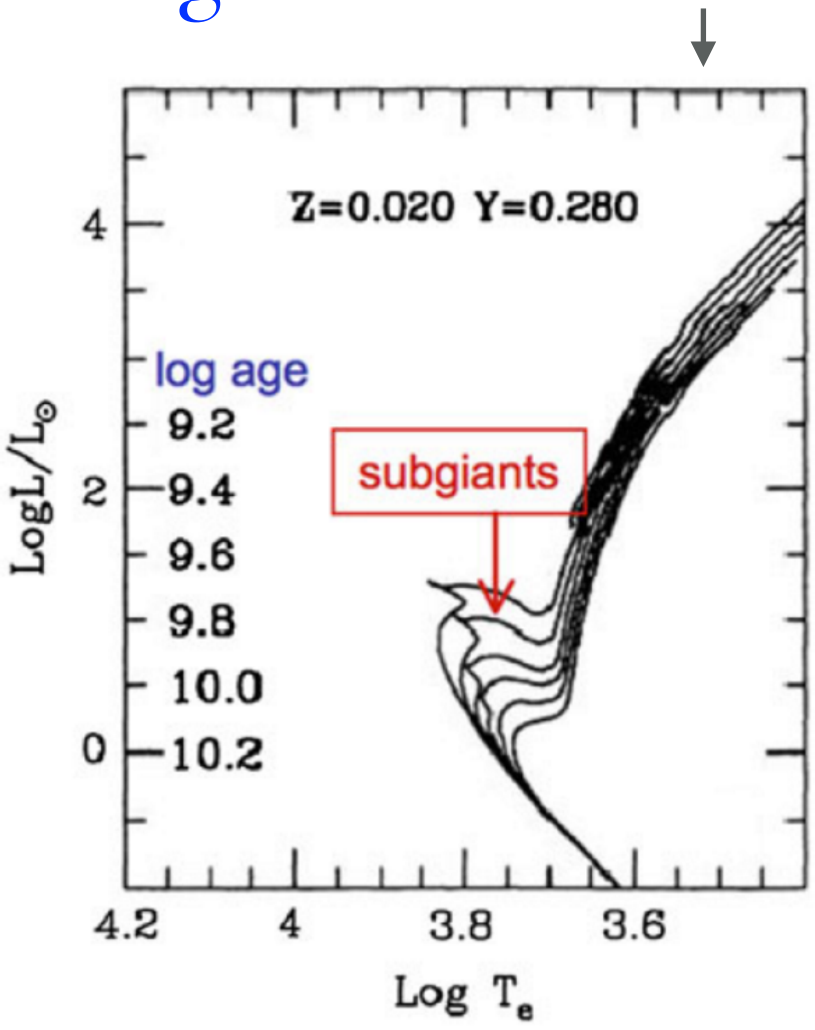


Regime change
small local samples to spectroscopic stellar ages **throughout the disk**

We can now measure ages for giants spectroscopically

regime change:
from stars in the solar neighbourhood....



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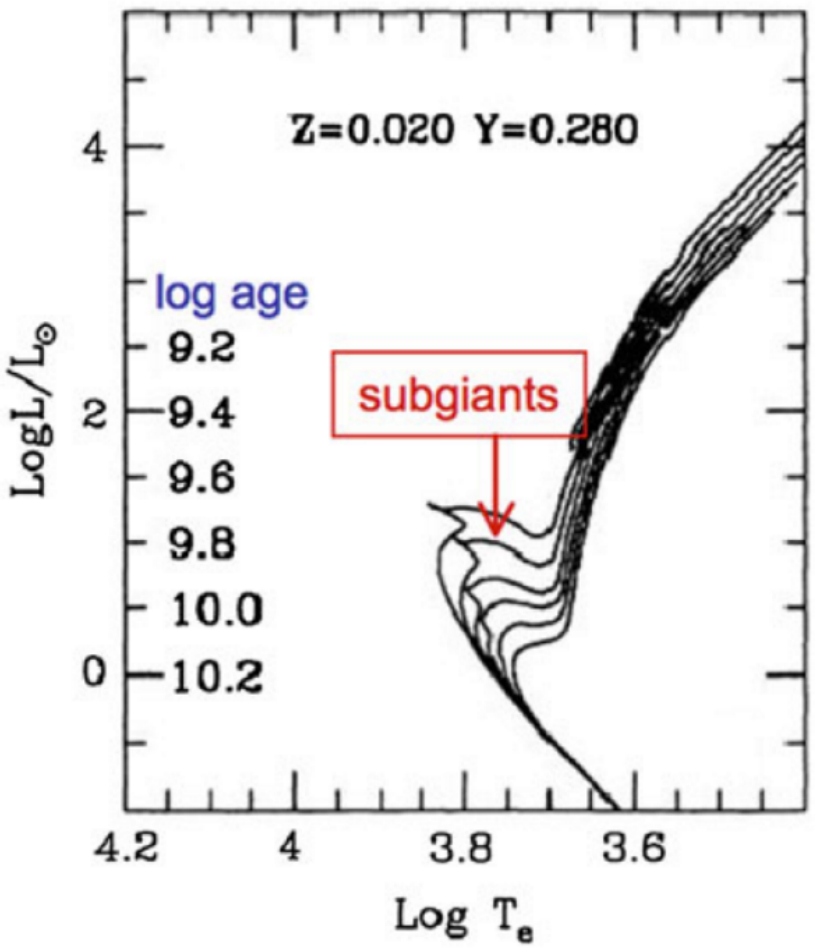

large, vast maps

20kpc

6kpc

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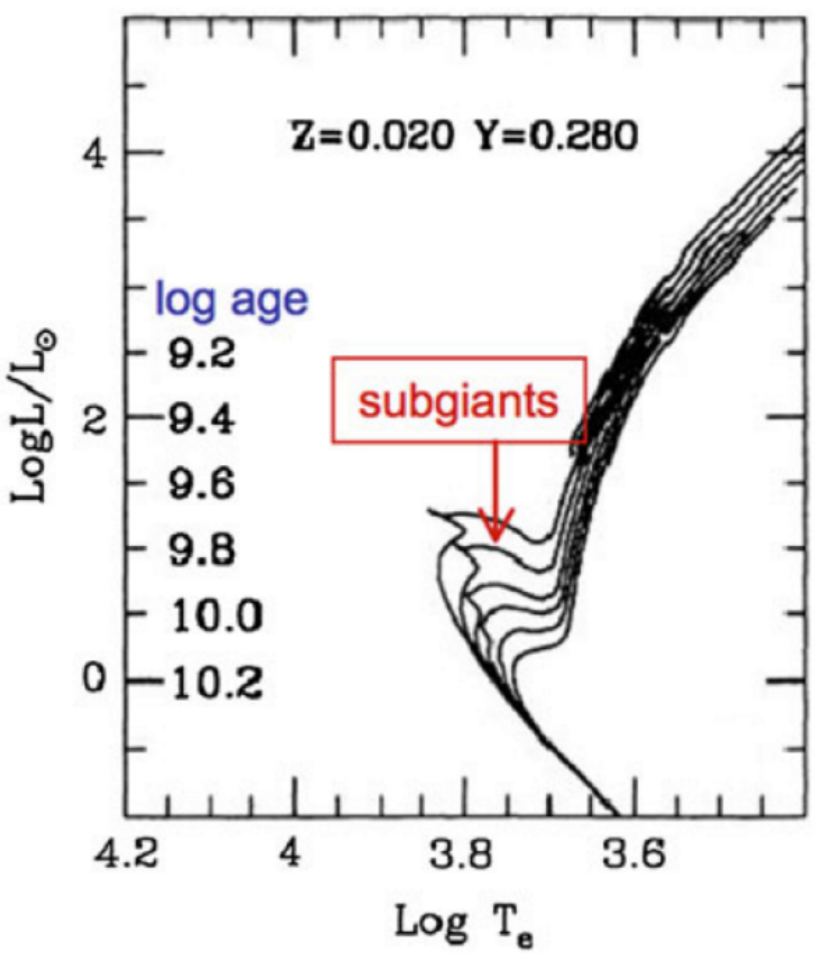

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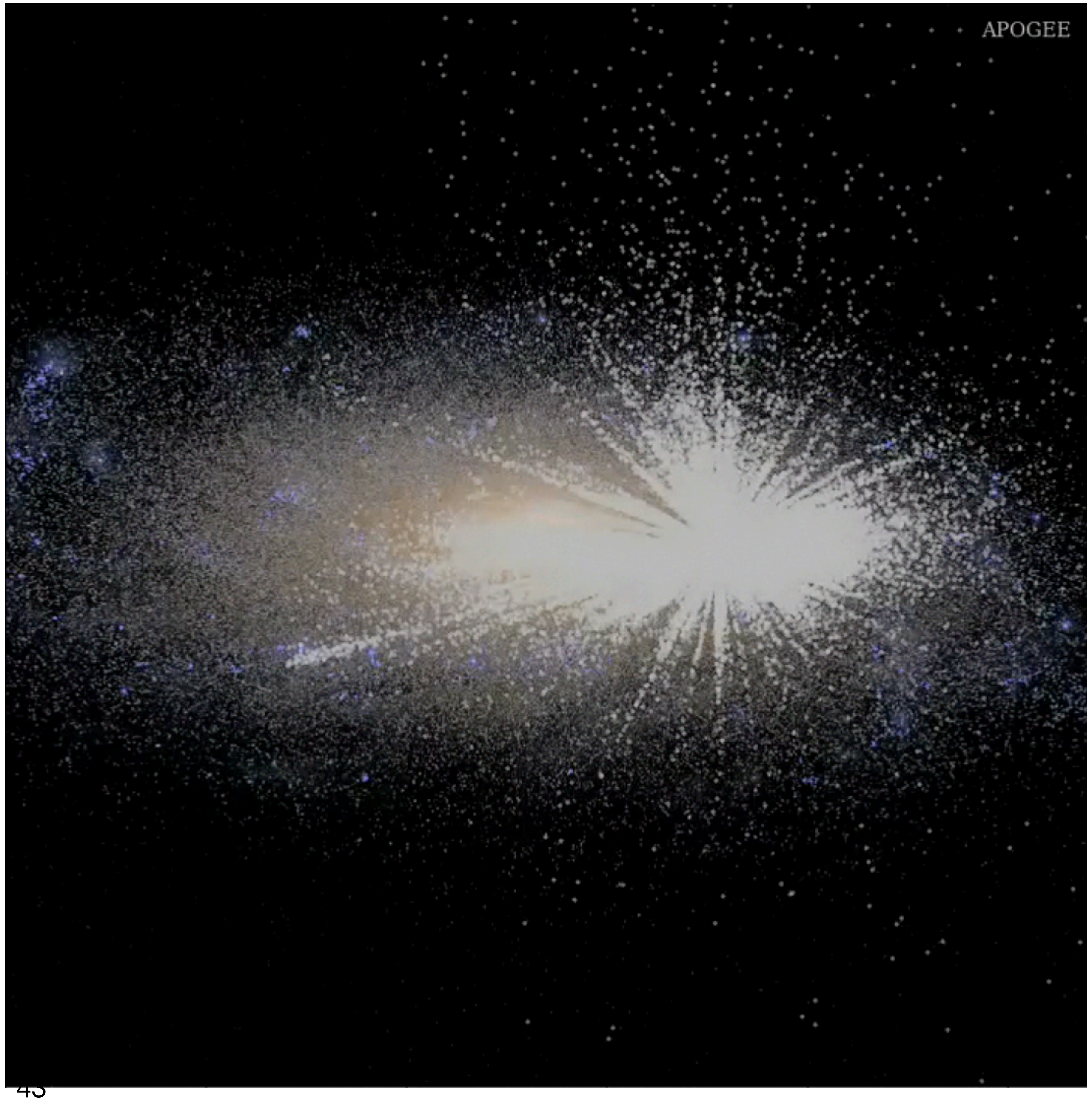

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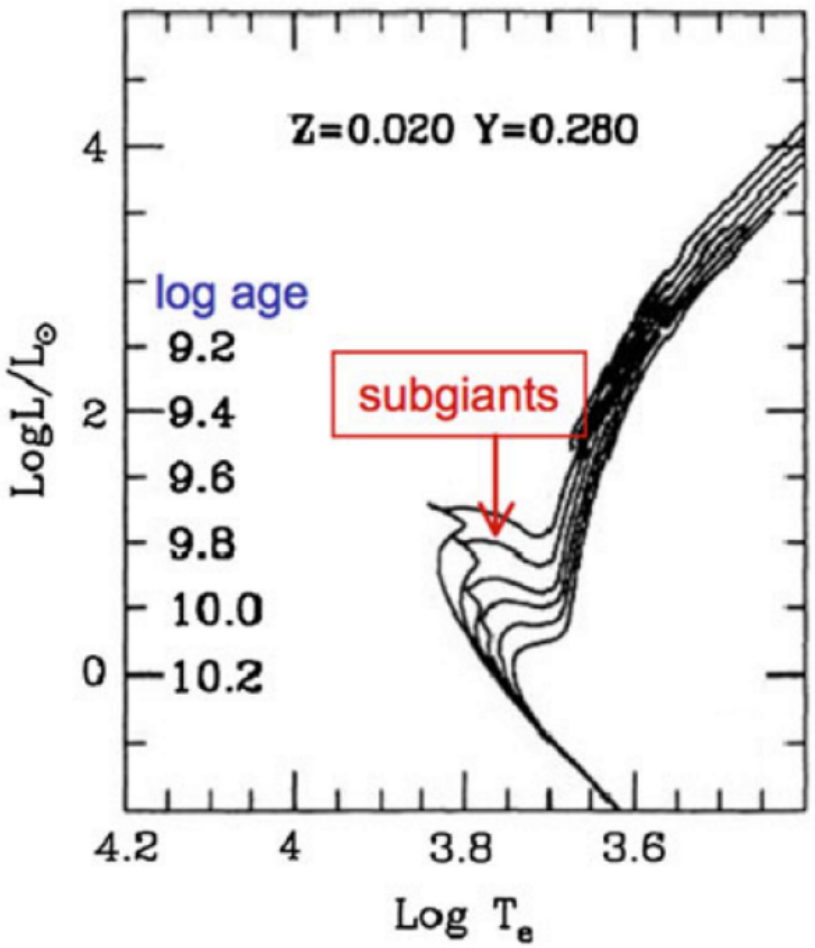

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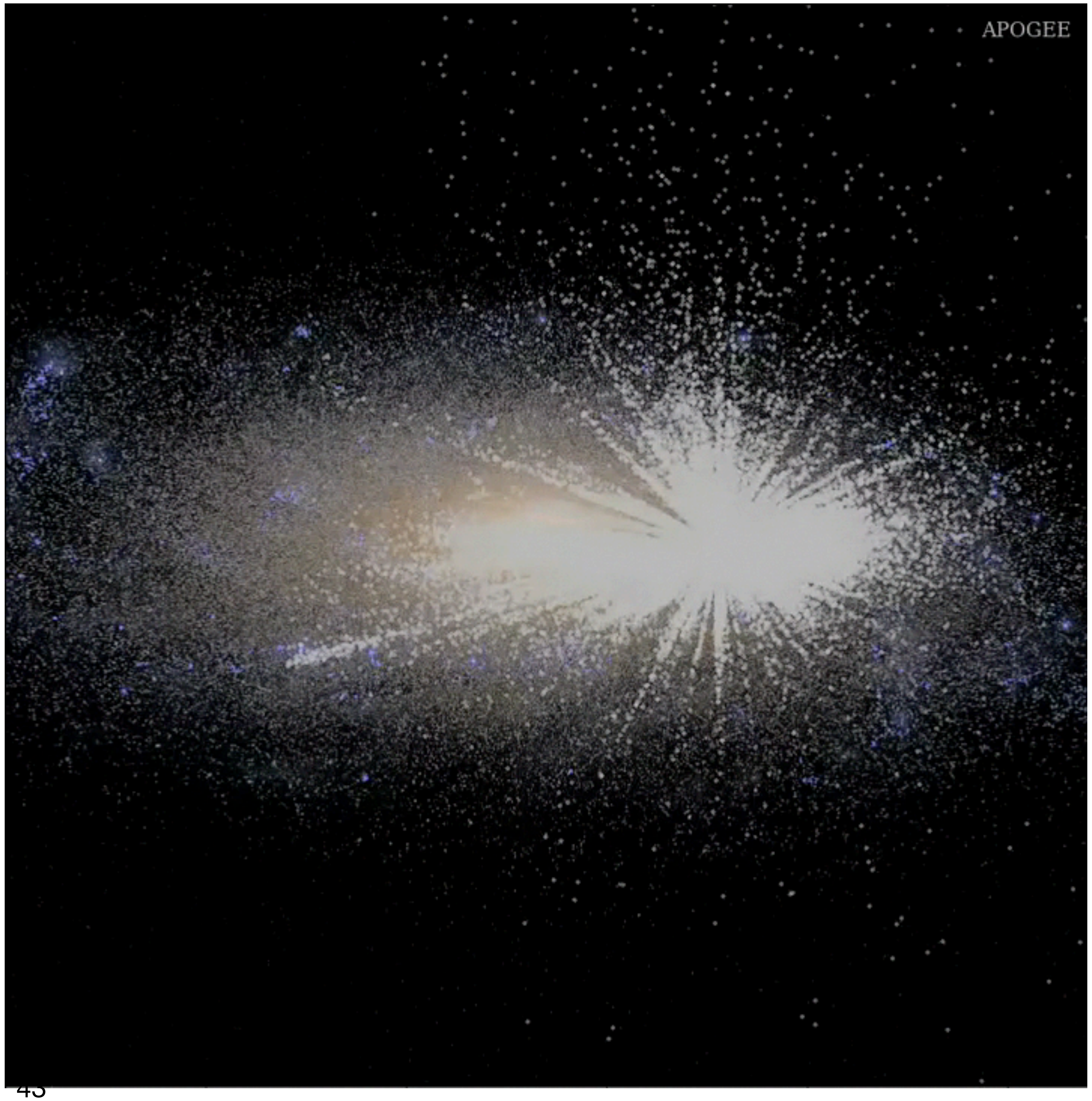
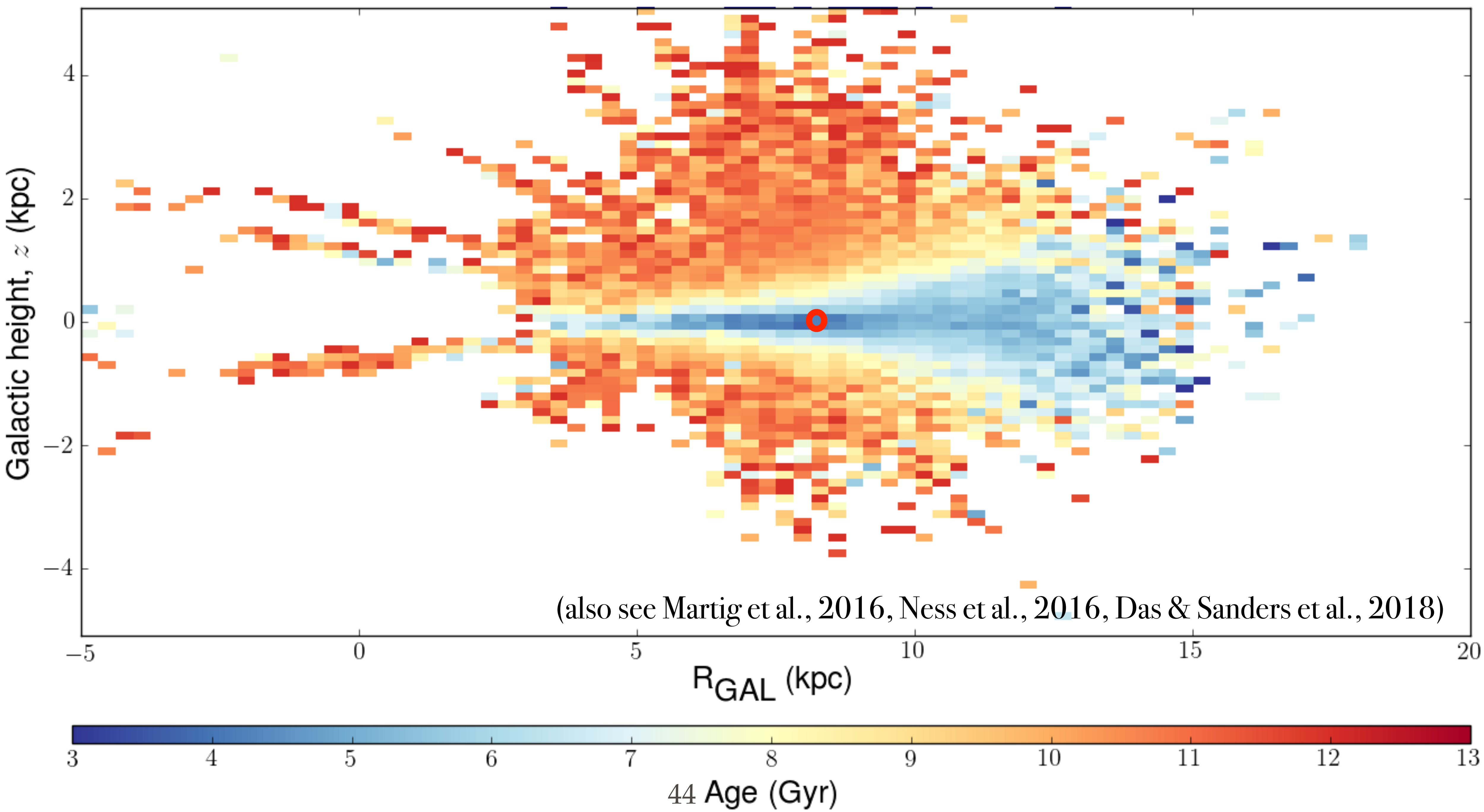


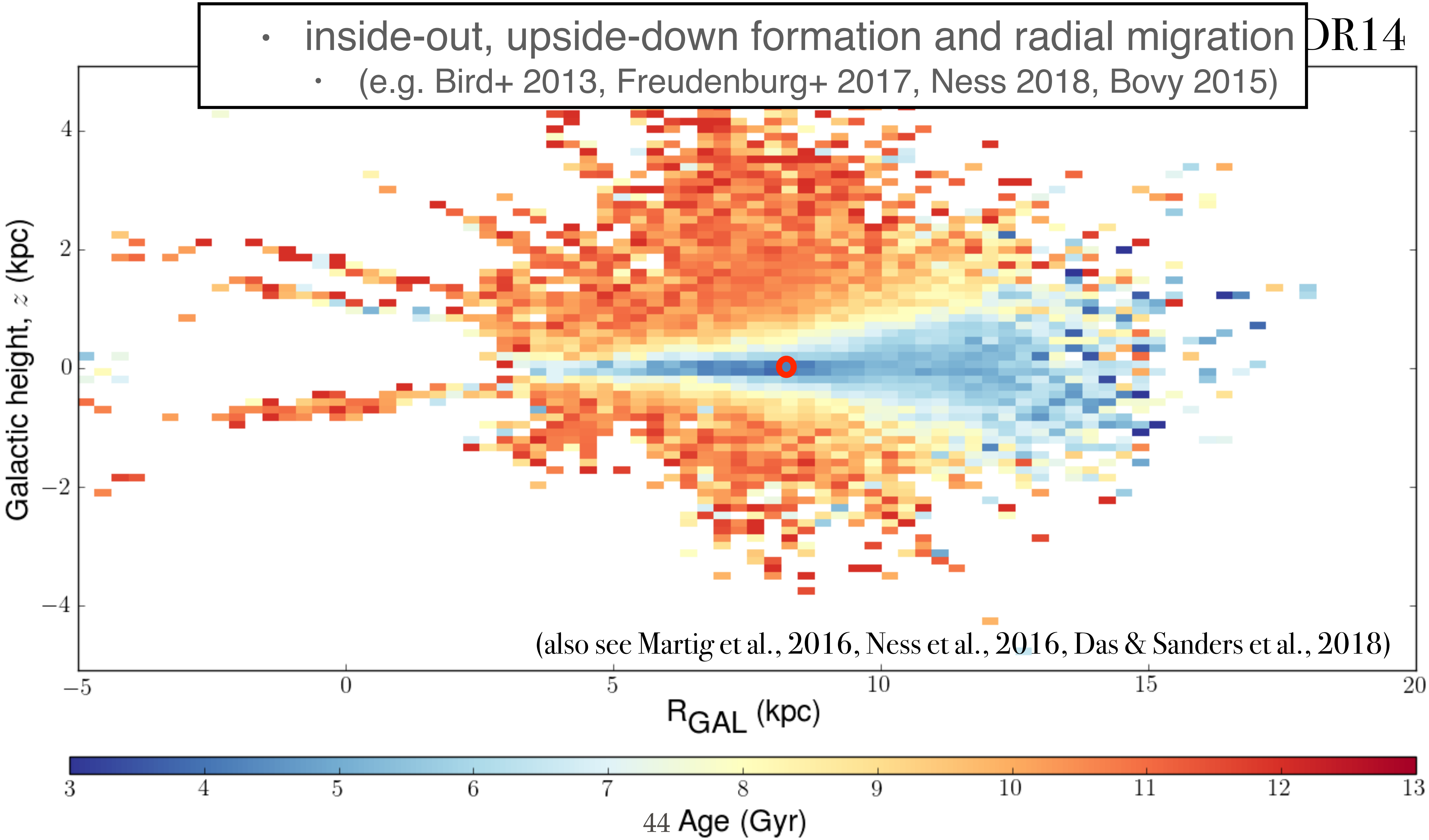
Ages: formation history of disk

150,000 stars from APOGEE DR14

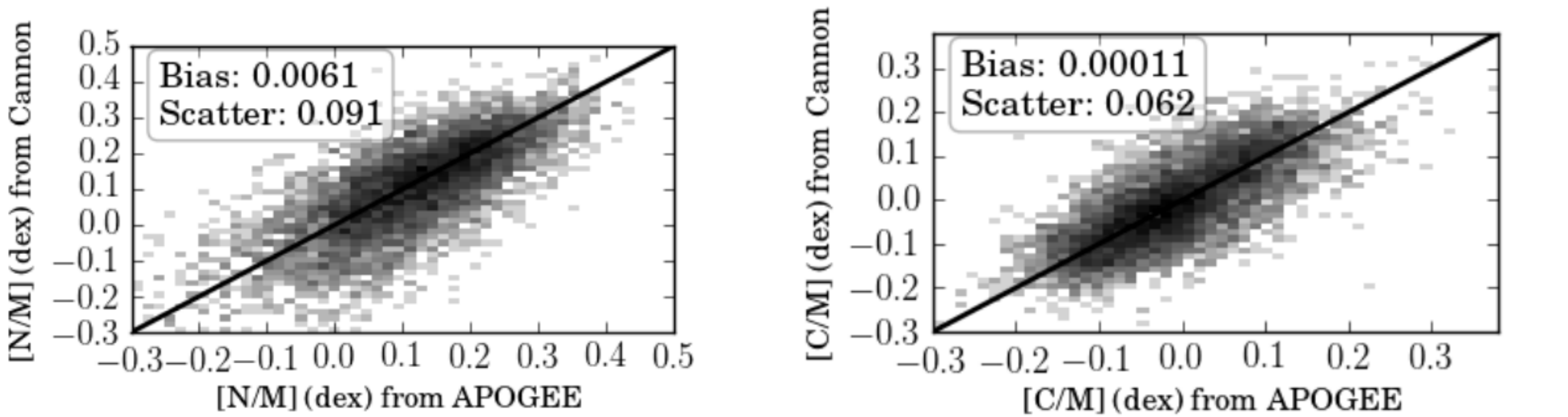


Ages: formation history of disk

- inside-out, upside-down formation and radial migration
  - (e.g. Bird+ 2013, Freudenburg+ 2017, Ness 2018, Bovy 2015)



Learning Carbon & Nitrogen from LAMOST spectra

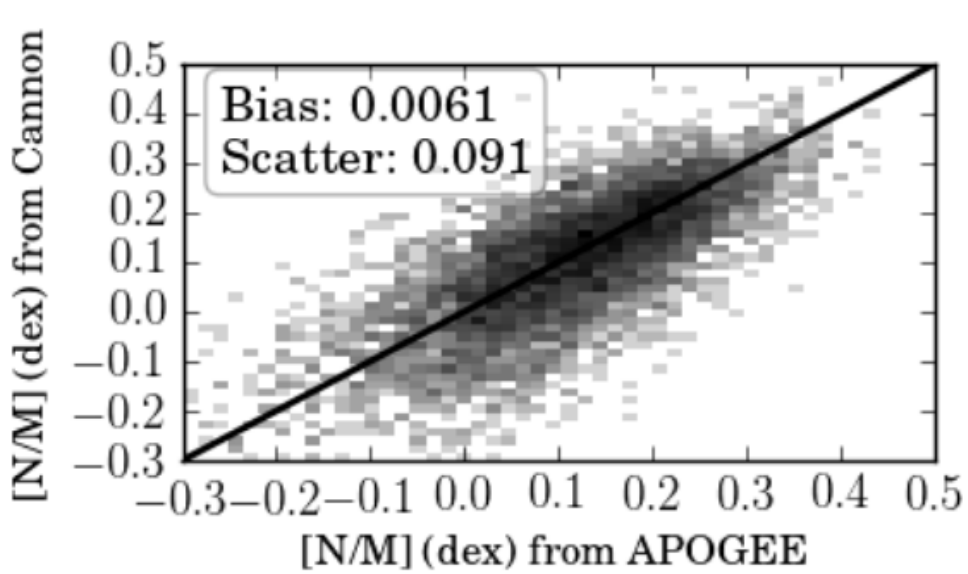


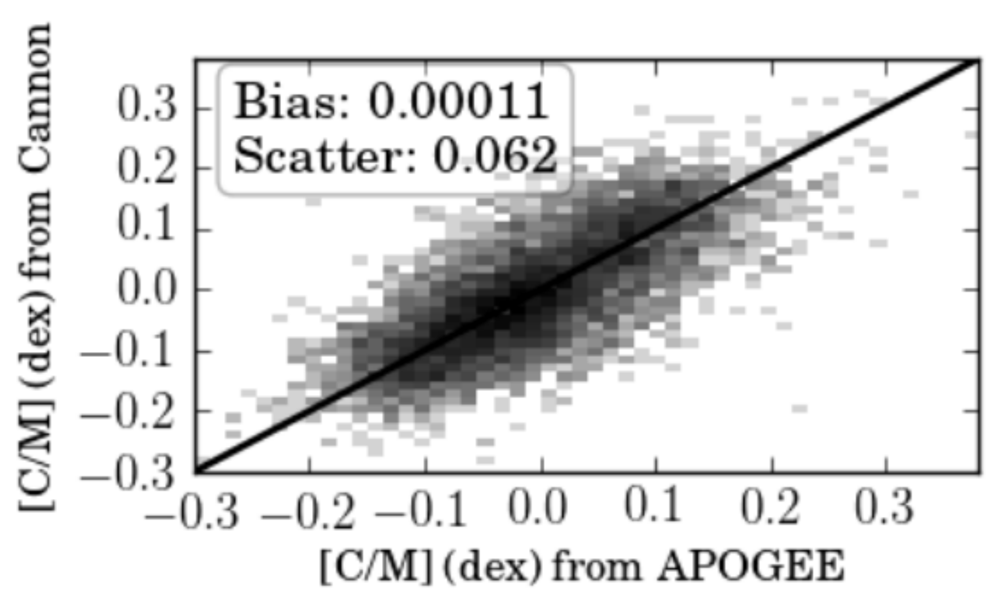
Ho et al., 2016b

C & N ⟶ ages (Martig et al., 2016)

Learning Carbon & Nitrogen from LAMOST spectra

Low resolution spectra is [X/Fe] information rich



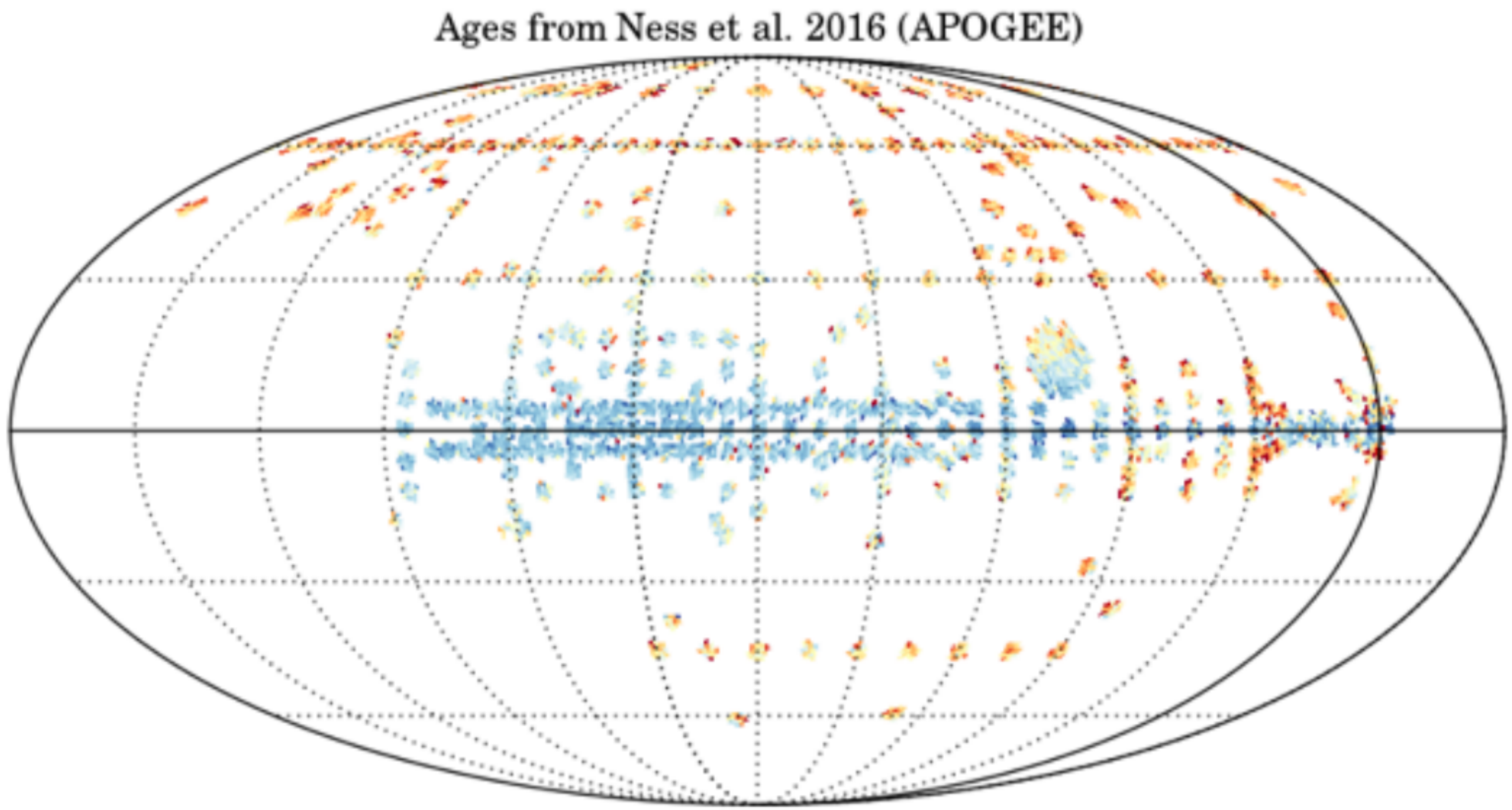


Ho et al., 2016b

C & N $\longrightarrow$ ages (Martig et al., 2016)

APOGEE AGES ON SKY

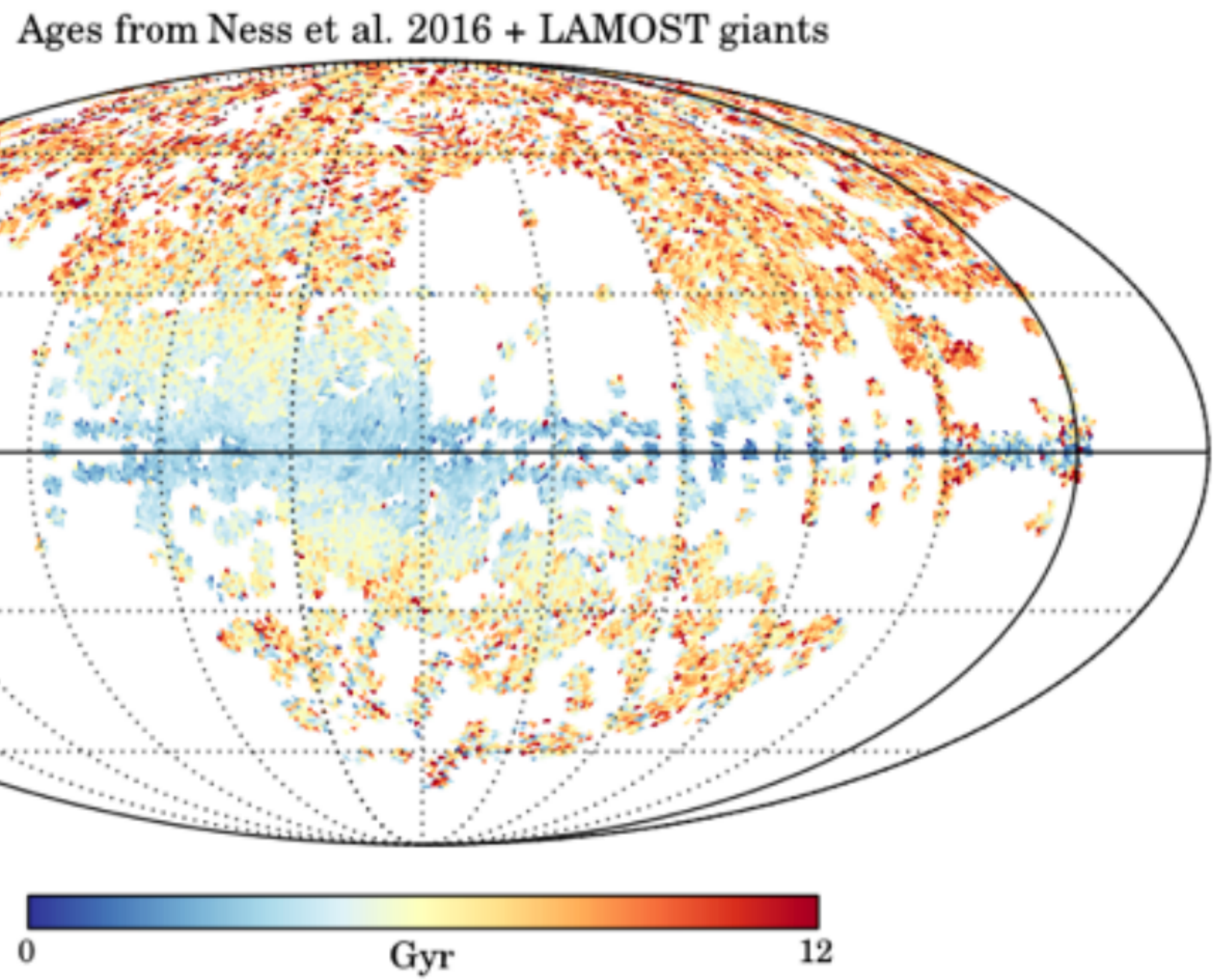
75,000 APOGEE stars



Ho et al., 2016b

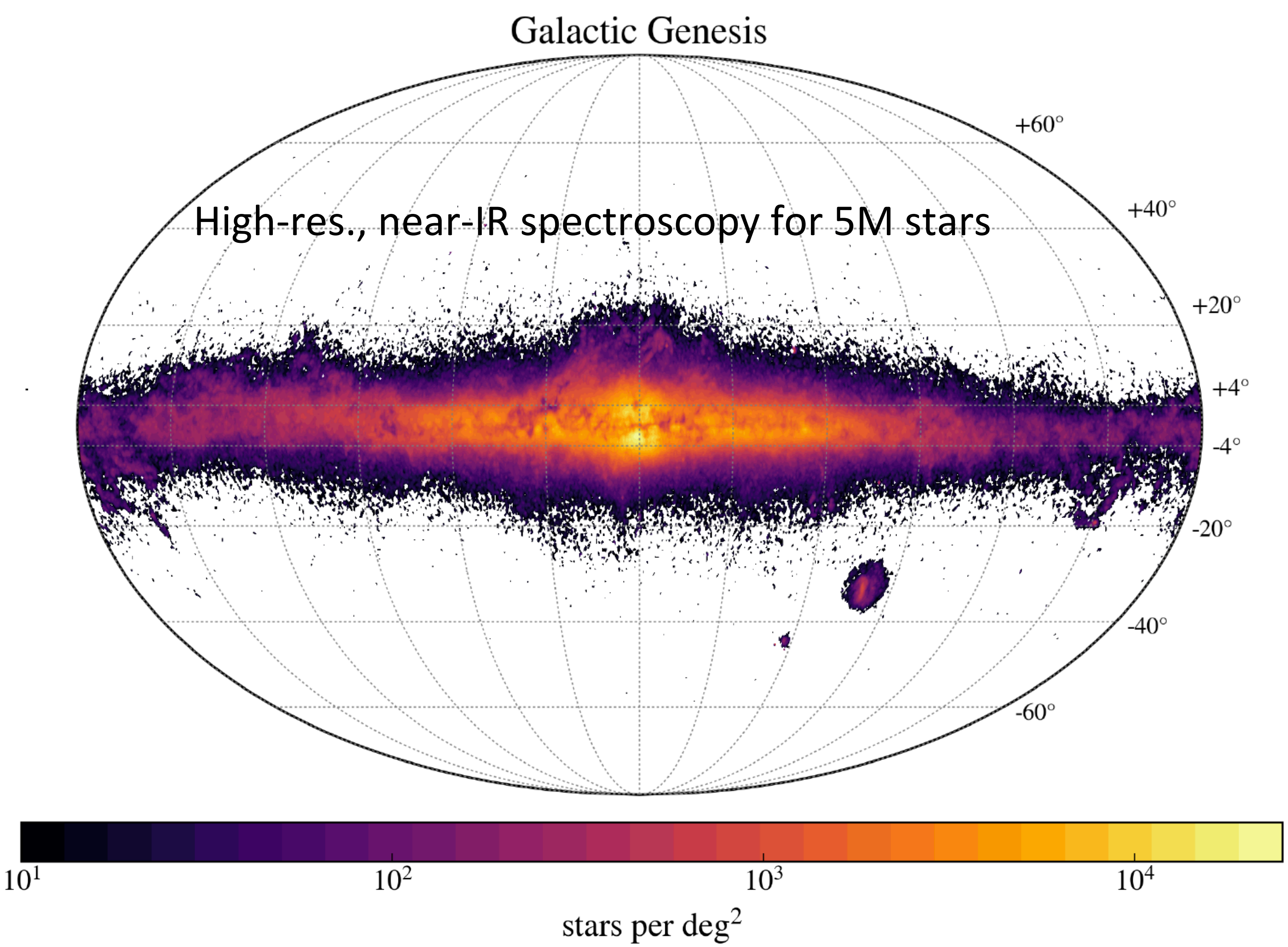
APOGEE + LAMOST AGES

75,000 APOGEE stars
+
230,000 LAMOST stars



Ho et al., 2016b

All the data now is just a warm up for the 2020's



+

Gaia RVS spectra,
higher precision motions