Machine learning in spectroscopy. NLTE analysis of the Gaia-ESO survey.

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Motivation

- Use library of NLTE spectral models to analyse Gaia-ESO spectra to explore NLTE effects on stellar parameters and elemental abundances.
- Use this parameters for better understanding of the Galactic chemical evolution

Traditional spectroscopic analysis methods are slow and therefore not applicable for large-scale ($>10^4$-10^6 stars) surveys.

Machine learning in stellar spectroscopy

Allows us to predict stellar parameters for many spectra using a model trained on some spectral library.

Forward and inverse models:

Canon (Ness 2015), Payne (Ting 2018) - forward
MATISSE (Recio-Blanco 2006), Starnet (Fabro 2017), AstroNN (Leung&Bovy 2018) - inverse

Data-driven and model-driven (what is a training set?):
Canon, AstroNN, Starnet, Payne -DD
MATISSE, Starnet, Payne - MD

Machine learning in stellar spectroscopy

-very fast analysis of individual spectra

-transfer stellar parameters between surveys (i.e Xiang 2019 APOGEE, GALAH -> LAMOST)

-require big training set (large -> better)

-require training set to be complete (no missing values)

-uncertainties are usually underestimated

-limited extrapolation ability

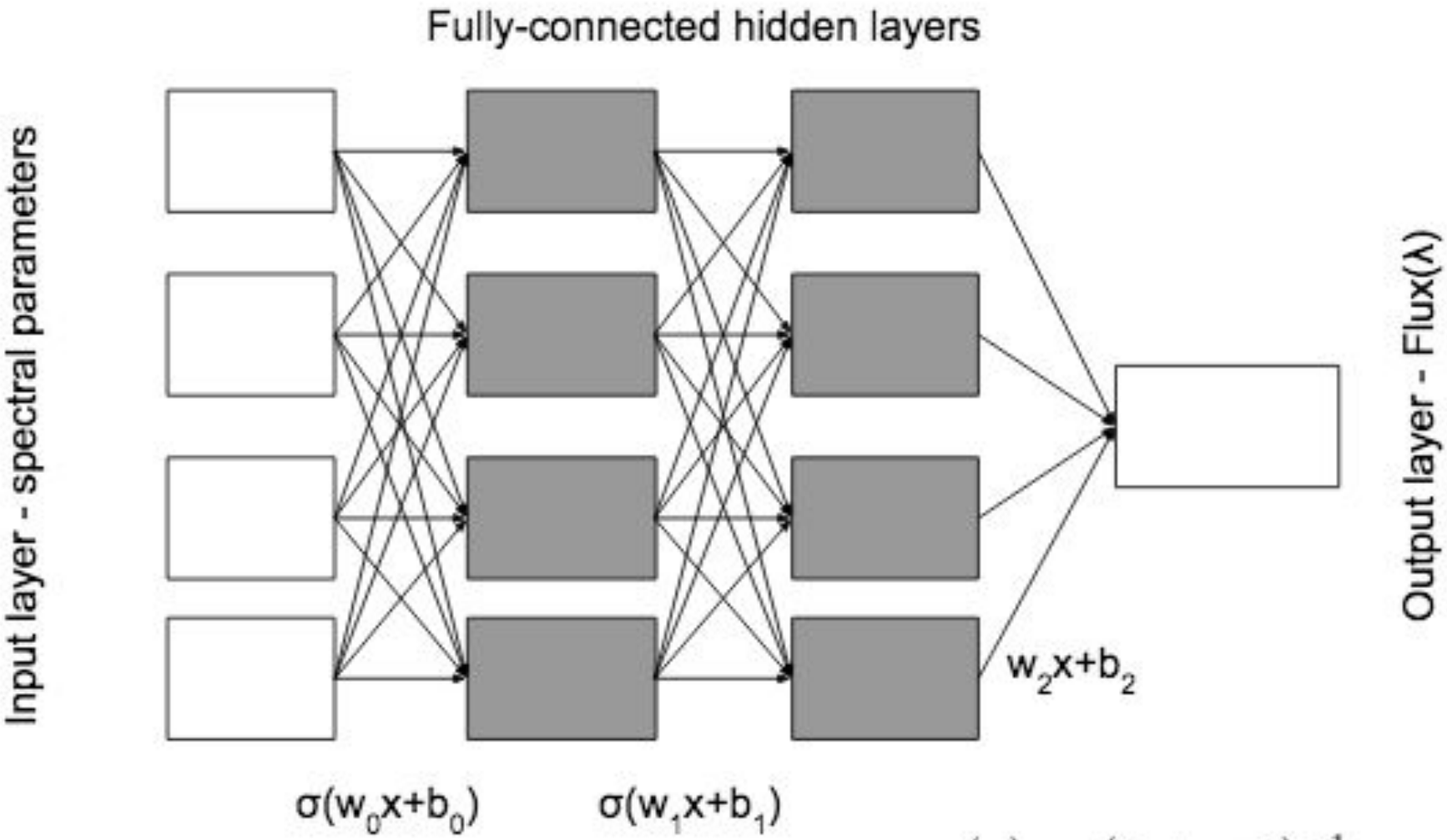
The Payne

A forward model for *ab-initio* spectrum fitting based on artificial neural-networks (ANNs) (Ting et al. 2018).

The flux variation in every wavelength approximated by ANN, depending on stellar parameters and chemical abundances (Teff, logg, [Fe/H], [X/H]...).

Optimal parameters of observed spectrum are found through the χ^2 minimisation

$$F(\lambda|\mathbf{l}) = \mathbf{w_2}(\lambda)\sigma(\mathbf{w_1}(\lambda)\sigma(\mathbf{w_0}(\lambda)\mathbf{l} + \mathbf{b_0}(\lambda)) + \mathbf{b_1}(\lambda)) + \mathbf{b_2}(\lambda)$$



$$\sigma(z) = (1 + e^{-z})^{-1}$$

Non-Local Thermodynamic Equilibrium

<u>NLTE</u>

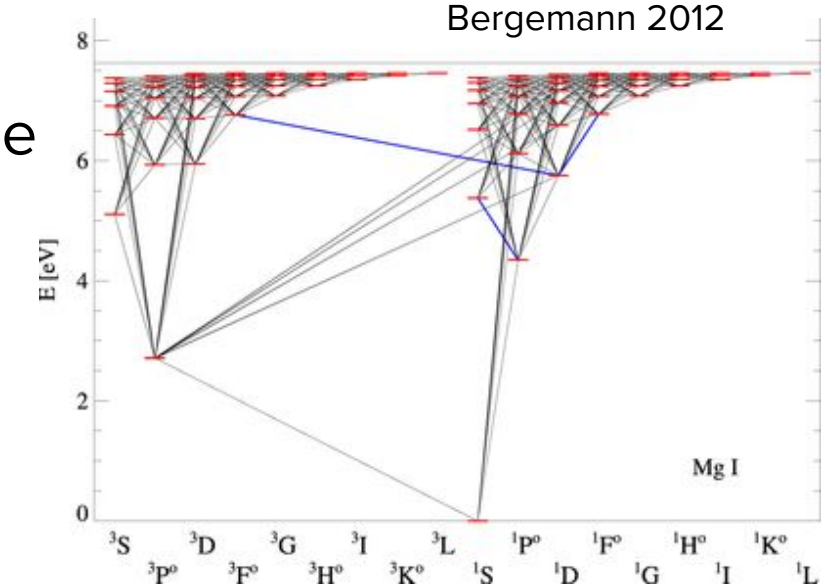
energy level populations need to be calculated using the statistical equilibrium

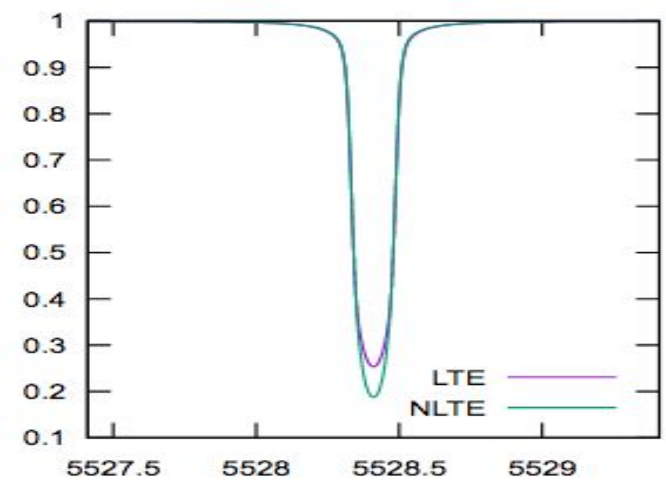
$$n_i \sum_{j \neq i} P_{ij} - \sum_{j \neq i} n_j P_{ji} = 0$$

$$P_{ij} = R_{ij} + C_{ij}$$

non-LTE effects are important, when densities are low enough and the non-local radiation field affects the populations

Bergemann 2012





Synthetic library

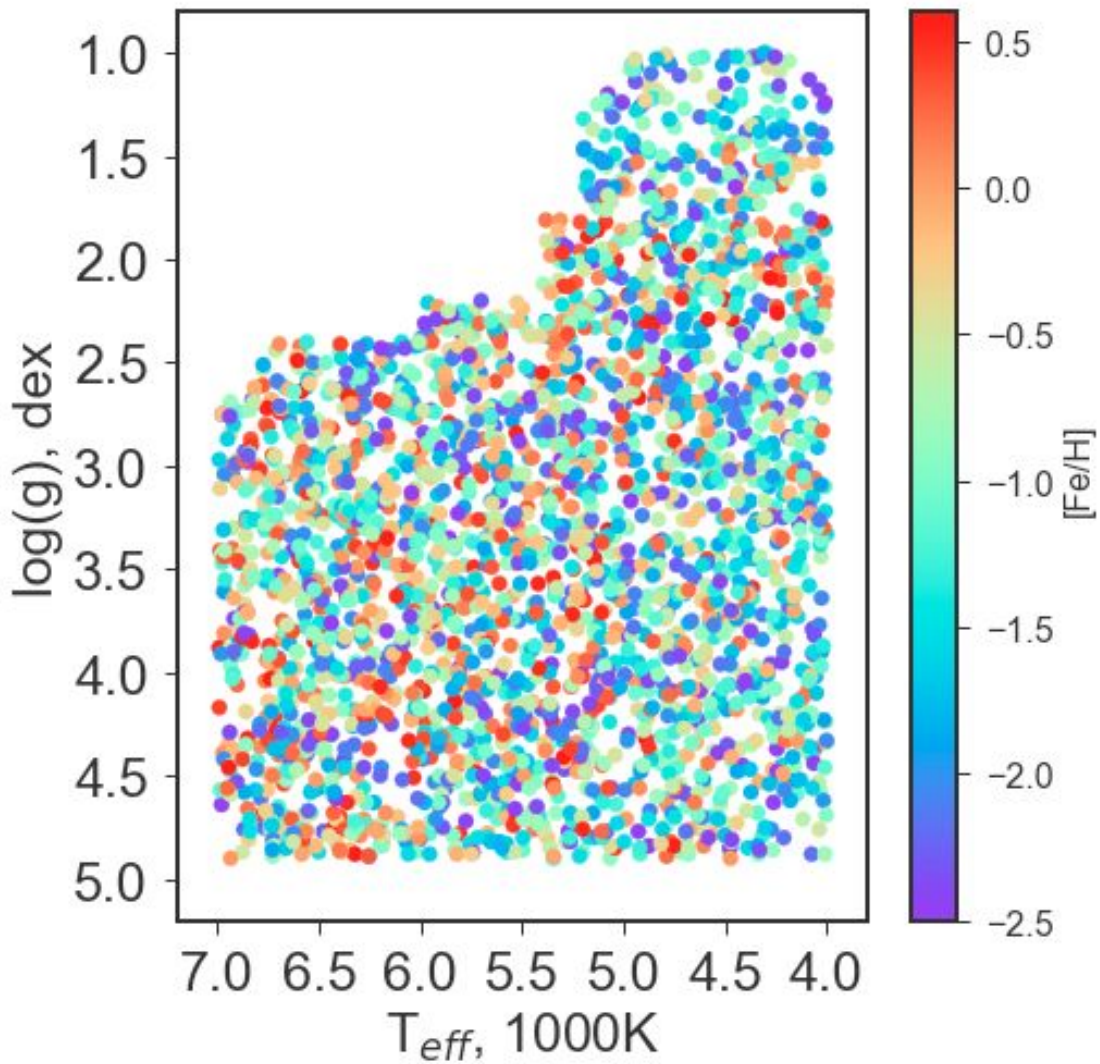
NLTE and LTE grids were computed with online tool http://nlte.mpia.de

2000 models in each grid

Models are:

- computationally expensive
- based on 1D hydrostatic atmospheric models MAFAGS-OS

Spectral lines of Fe, Mg, Ti and Mn are computed in NLTE, while other lines computed in LTE.



Observed spectra

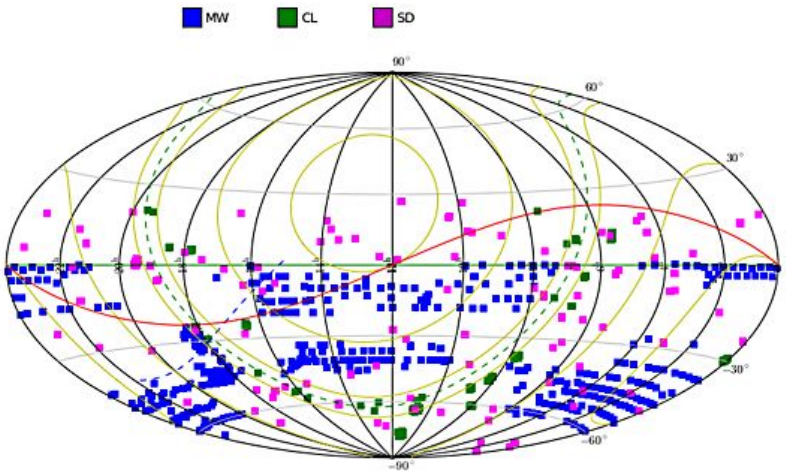
Gaia-ESO Public data release 3

Spectra were taken by GIRAFFE spectrograph in MEDUSA mode

HR10 λ:5334 - 5616 A, R=19800

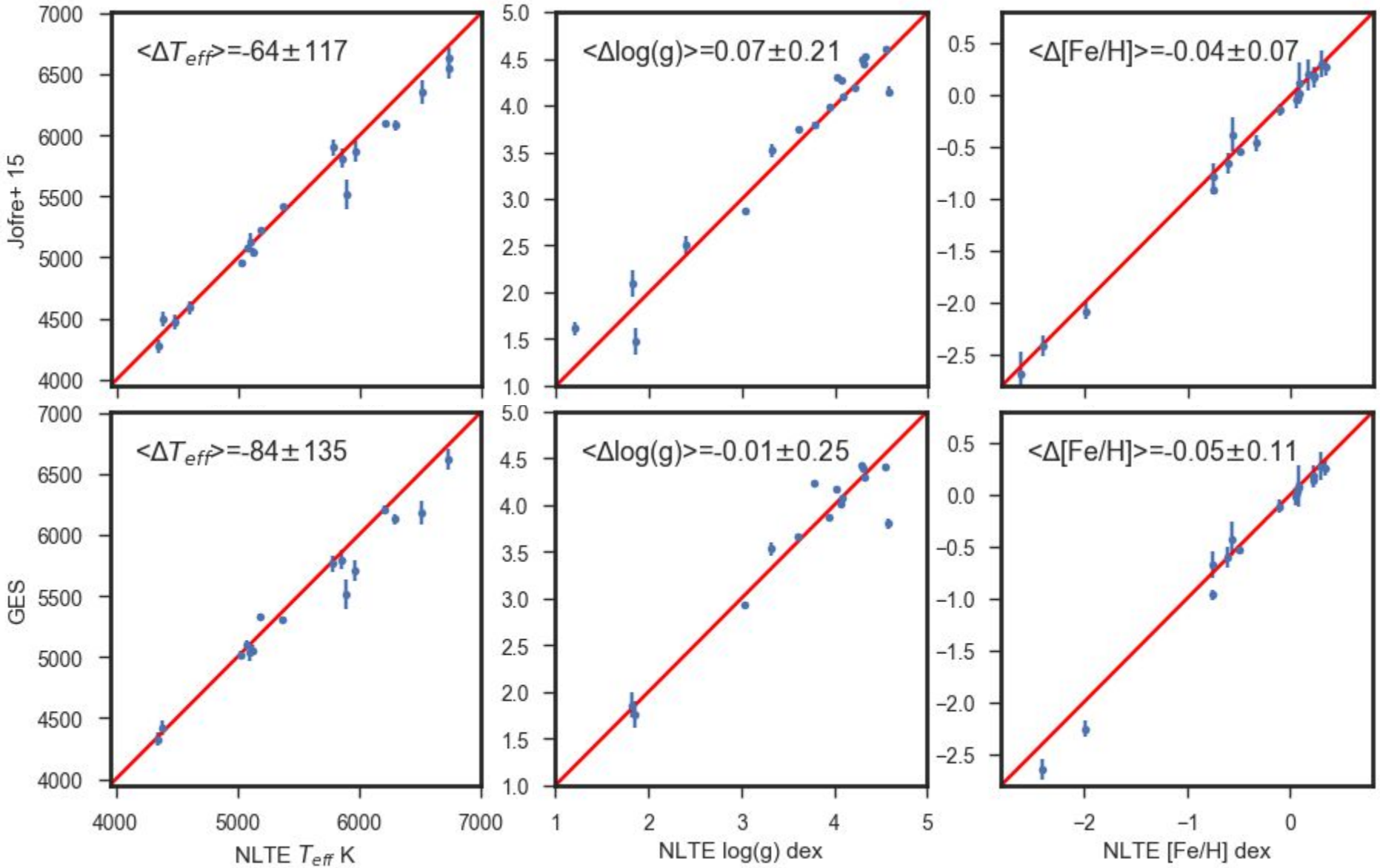
We analyzed 7000+855+19 stars

field stars, 11 globular clusters, 2 open clusters and 19 Gaia benchmark stars

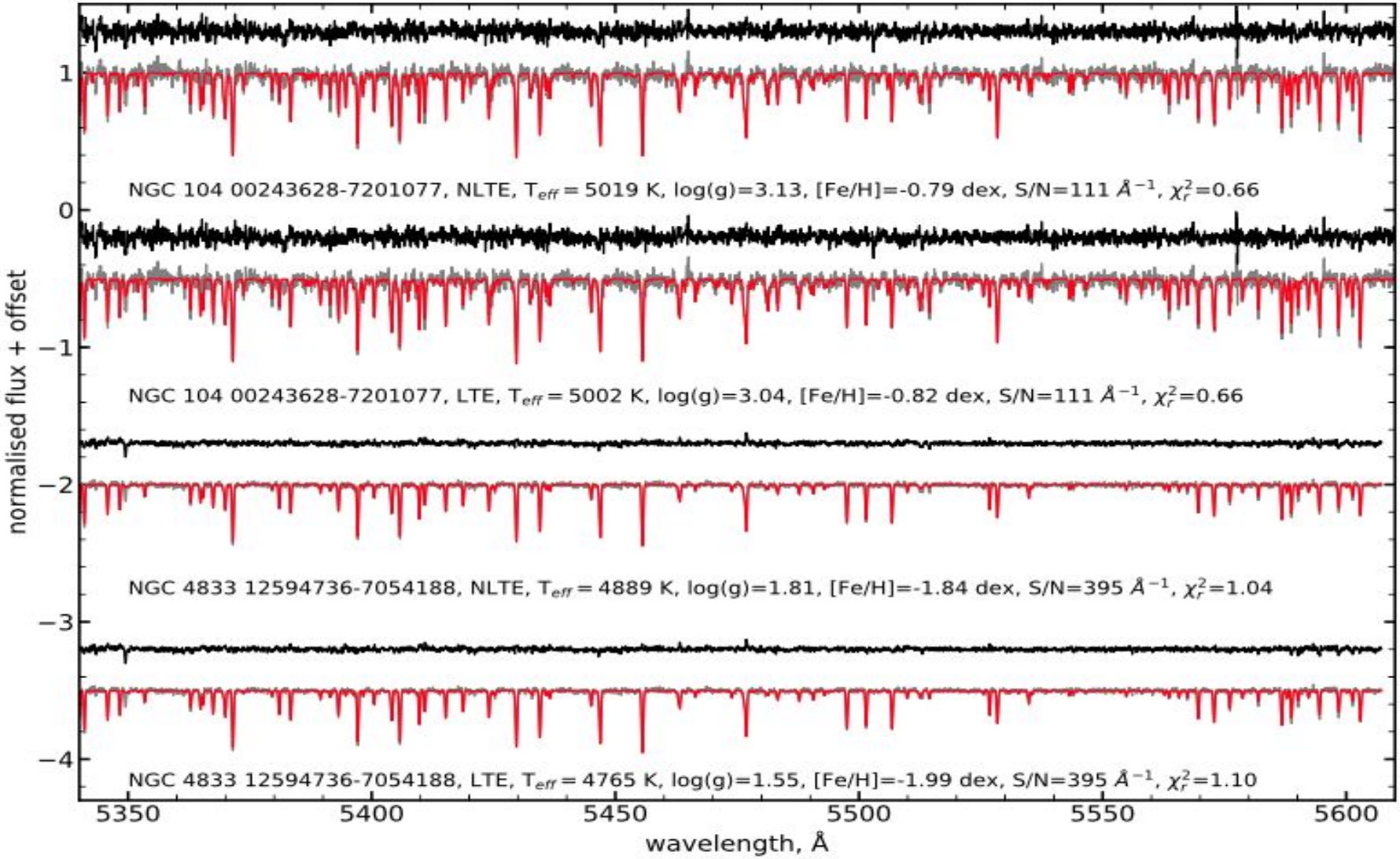


Validation on the Gaia benchmark stars

Spectroscopic estimates: no calibration on isochrones or any other independent parameter



Example of the best fit to observations



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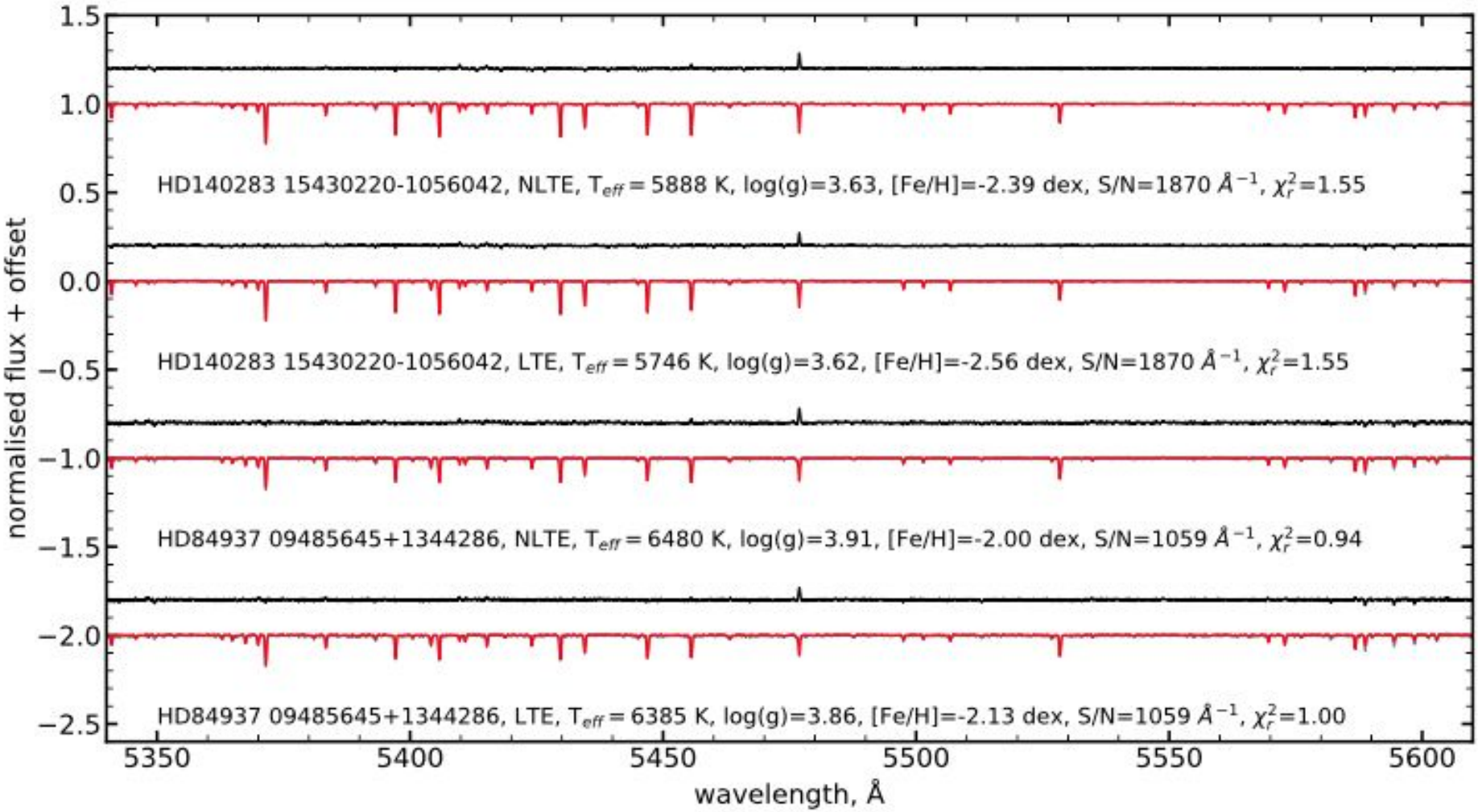
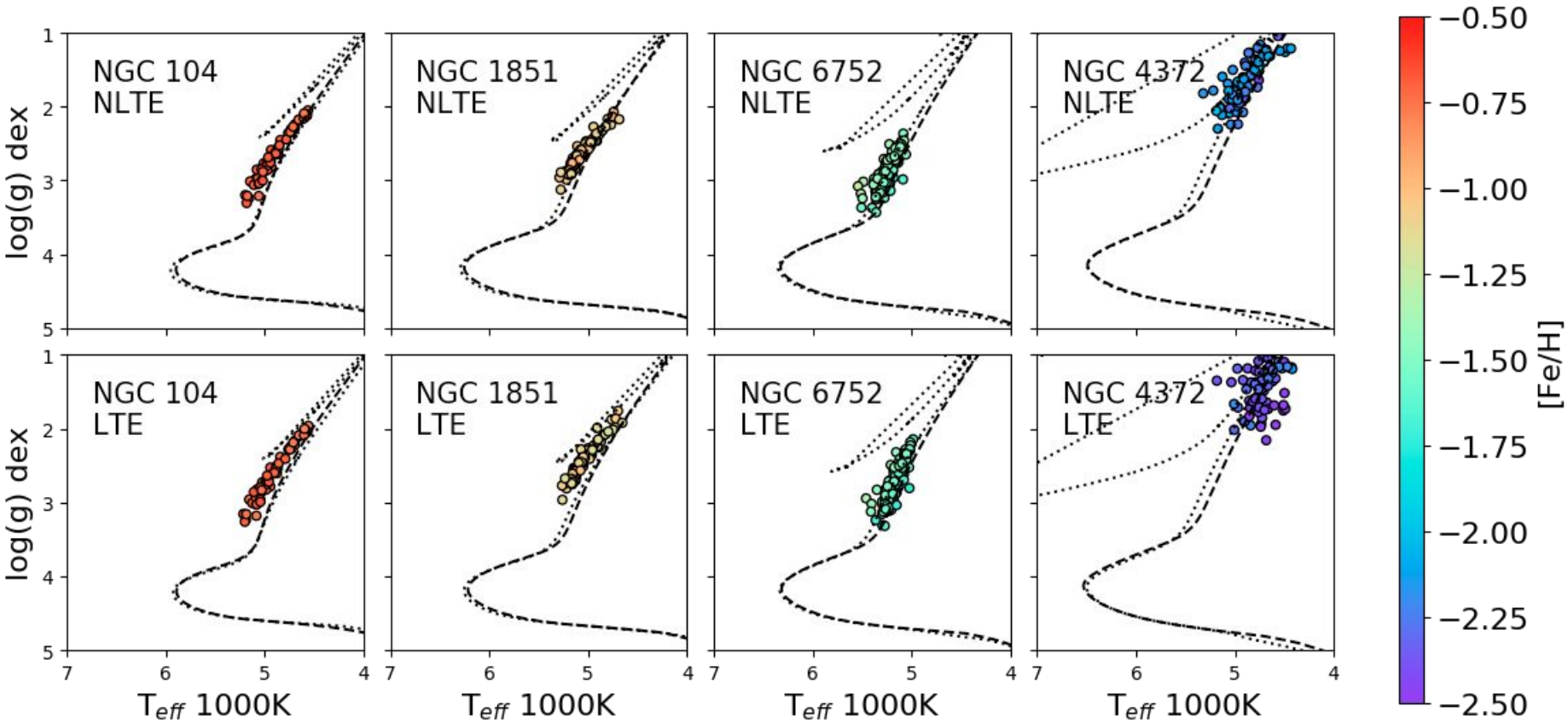
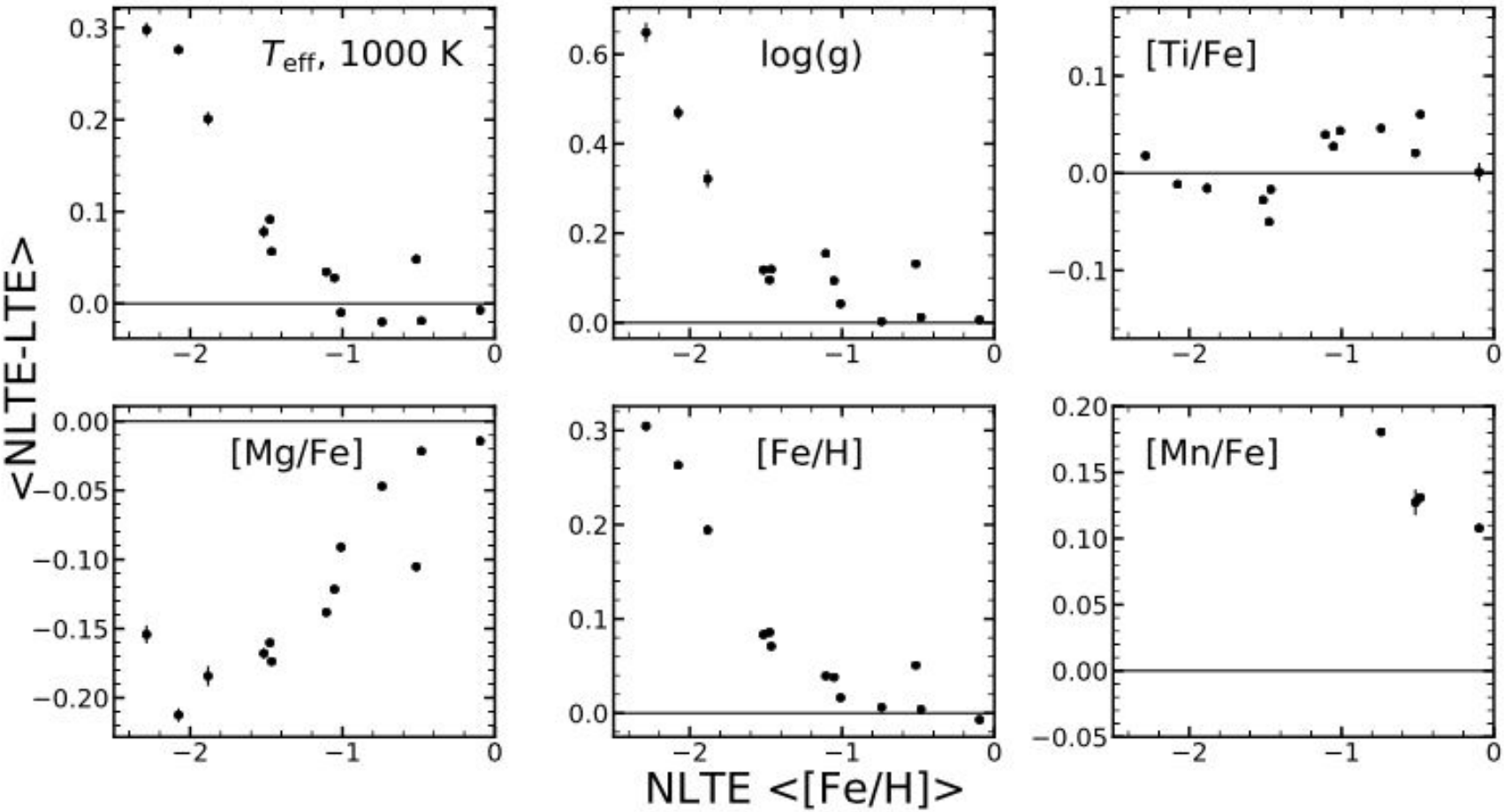


Results with PARSEC (dotted lines) and Victoria-Regina (dashed lines) isochrones.
No calibration

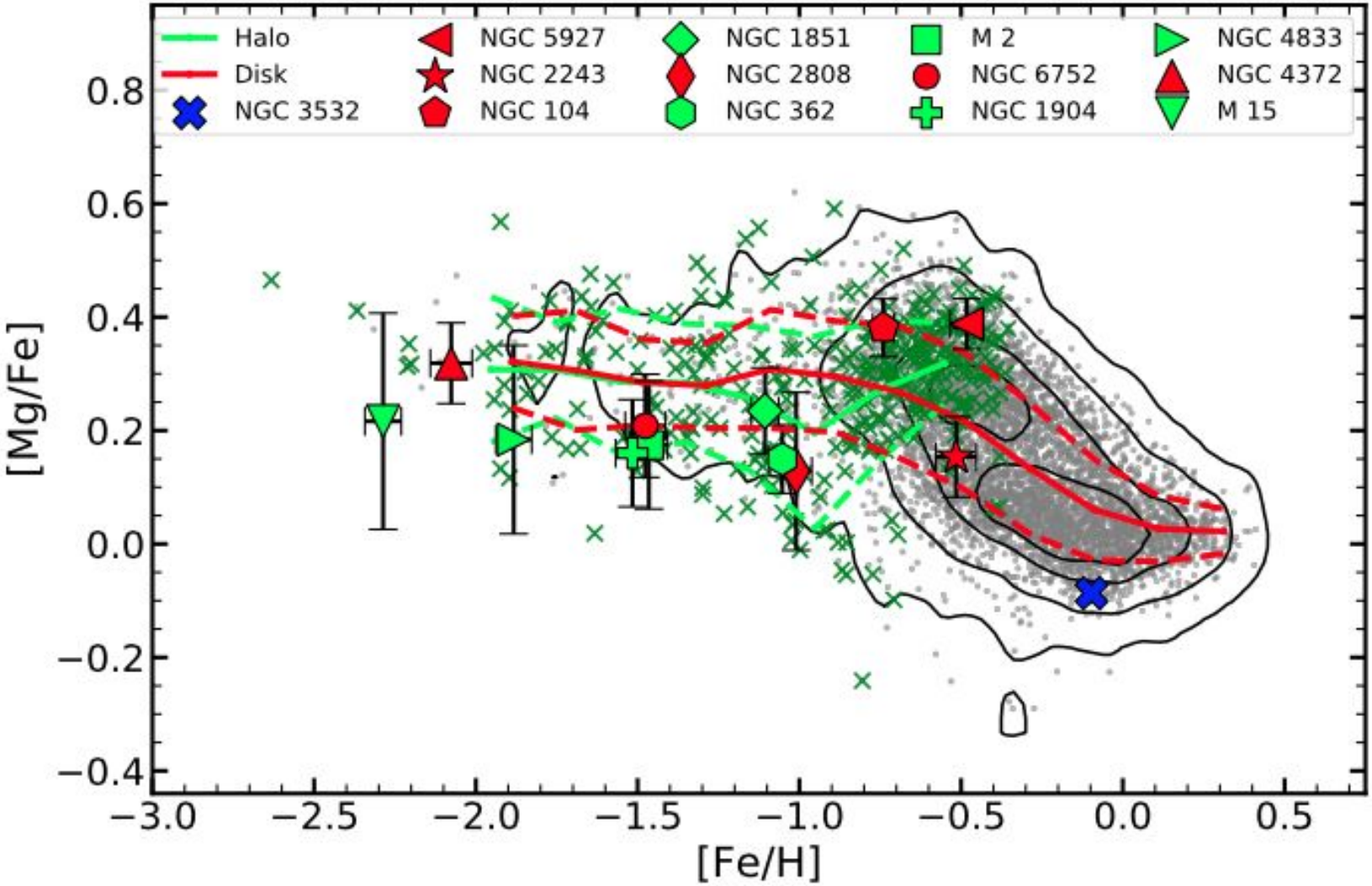


mean Δ(NLTE - LTE) for clusters



ΔT_{eff} up to 300 K, Δ log(g) up to 0.6 dex, Δ[Fe/H] up to 0.30 dex

field stars and clusters



Summary

- machine learning is very useful for analysis of large-scale spectroscopic surveys.

- analysed Gaia-ESO spectra of the field stars, 13 clusters and Gaia benchmark stars with *The Payne* in NLTE

- good agreement with isochrones for clusters with no calibration

- NLTE effects are very important i.e. estimates of T_{eff}, log(g), and [Fe/H] are higher for more metal-poor stars compared to LTE.