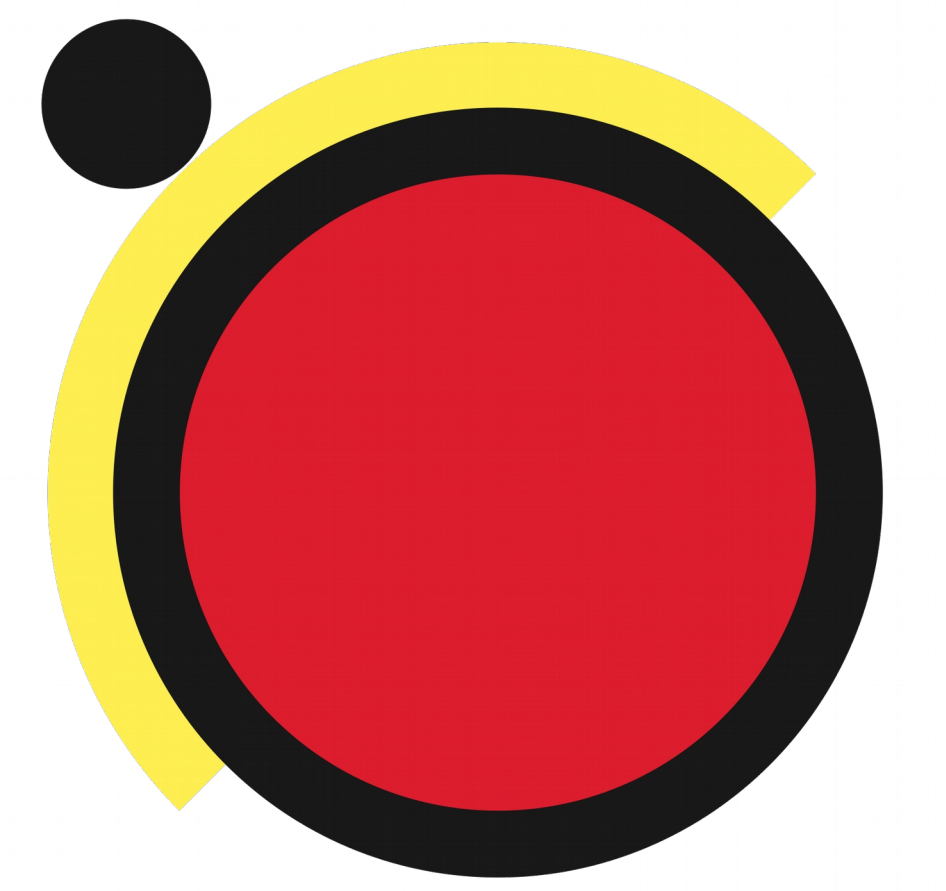


# A Deep Learning Approach to photospheric Parameters of CARMENES Target Stars



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**carmenes**

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**Abstract.** We construct an individual convolutional neural network architecture for each of the four stellar parameters effective temperature ( $T_{eff}$ ), surface gravity ( $\log g$ ), metallicity  $[M/H]$ , and rotational velocity ( $v \sin i$ ). The networks are trained on synthetic PHOENIX-ACES spectra, showing small training and validation errors. We apply the trained networks to the observed spectra of 283 M dwarfs observed with CARMENES. Although the network models do very well on synthetic spectra, we find large deviations from literature values especially for metallicity, due to the synthetic gap.

**Method.** A detailed description is provided in [1]. Incorporating synthetic PHOENIX-ACES spectra [2] allows us to construct a sufficiently large training set. We build  $\sim 400$  different convolutional neural network models from  $\sim 70$  different architectures (i.e. number and arrangement of layers) to answer the following questions:

- Influence of different  $\lambda$ -ranges and their combinations
- Influence of deriving stellar parameters individually or combined
- Influence of training networks on synthetic spectra and applying them to observed spectra

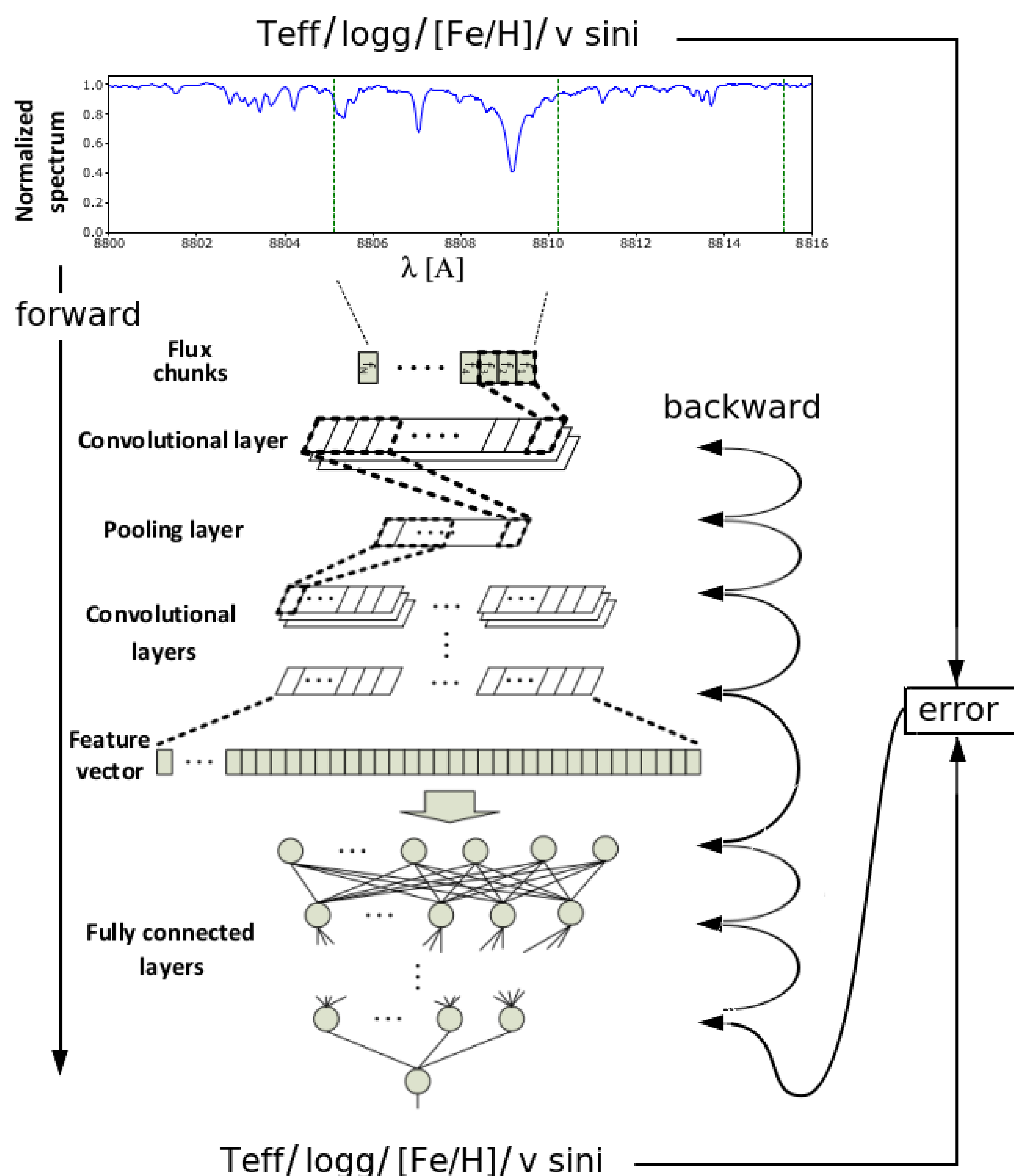


Fig. 1: Illustration of neural network and training process. A  $\lambda$ -range is fed into the network, the stellar parameter is derived (forward propagation). The result is compared to the known input parameter and the error is calculated. The weights of the layers are adjusted through backward propagation. This is done until error converges.

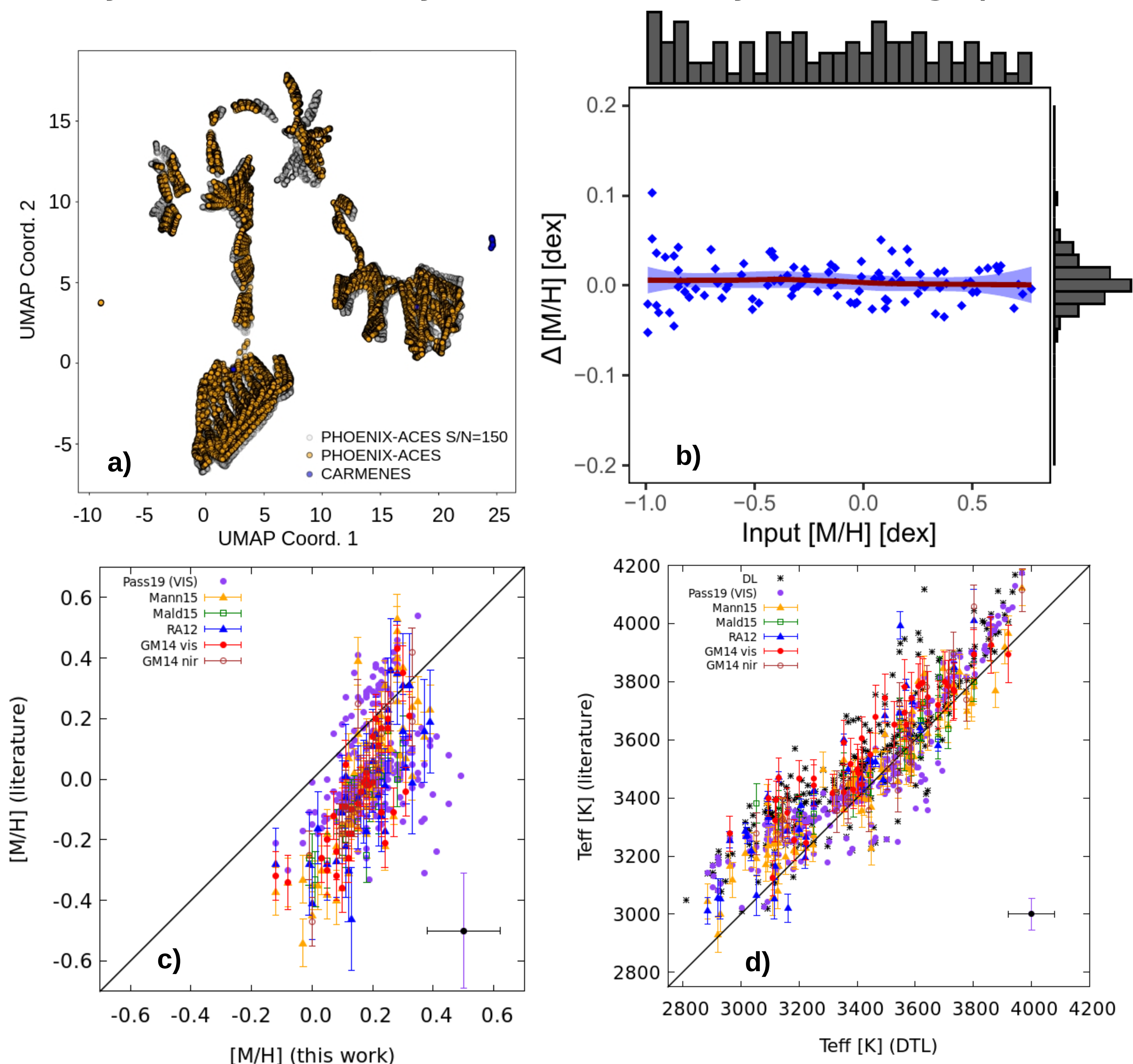


Fig. 2: a) UMAP projection of PHOENIX spectra (orange/grey), CARMENES spectra (blue). b) Test error for  $[M/H]$  from synthetic training. c) Literature comparison for  $[M/H]$ . d) DTL literature comparison for effective temperature (preliminary).

**Results.** All network models show very small training/validation errors  $< 10^{-4}$ . However, applying the neural network to observed CARMENES spectra reveals the significant influence of the synthetic gap (difference in feature distribution between synthetic and observed spectra, see Fig.2a). Summarizing, we found:

- **Great accuracy and precision** of the network during training (see Fig. 2b).
- No influence on results regarding different  $\lambda$ -ranges.
- Deriving parameters individually gives slightly smaller errors.
- Due to the **synthetic gap**,  $[M/H]$  deviates significantly from literature values [3-7] (Fig. 2c).
- With **Deep Transfer Learning** we 'transfer' additional information (e.g. interferometric  $T_{eff}$ ) into the neural network, in order to reduce the synthetic gap (Fig. 2d).

**References.** [1] Passegger et al. 2020, A&A, 642, A22. [2] Husser et al. 2013, A&A, 553, A6. [3] Passegger et al. 2019, A&A, 627, A161. [4] Maldonado et al. 2015, A&A, 577, A132. [5] Rojas-Ayala et al. 2012, ApJ, 748, 93. [6] Gaidos & Mann 2014, ApJ, 791, 54. [7] Mann et al. 2015, ApJ, 804, 64.

