Determining Star Formation Histories and Metallicity Evolution with Convolutional Neural Networks

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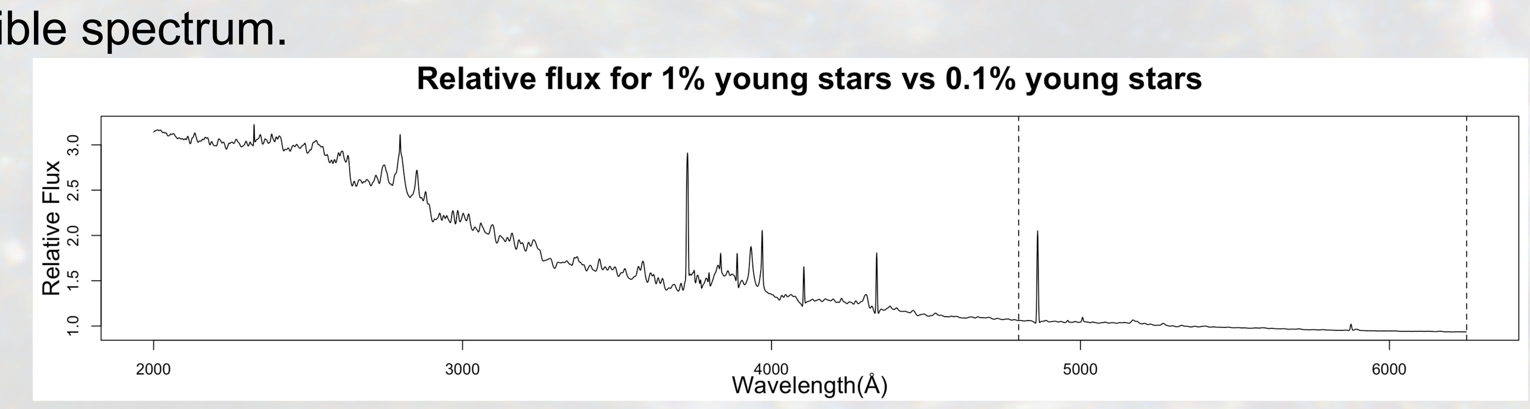
Abstract

We present spatially resolved Star Formation Histories and Chemical Enrichment on nearby galaxies using **Convolutional Neural Networks**. We infer Star Formation Histories and Chemical Enrichment from a combination of **MUSE optical spectroscopy and HST photometry in the UV range**. Combined with the high-resolution CO emission information, this analysis will allow inferring the timescales for star formation and cloud destruction in different galaxy environments, providing clues about the dominant mechanisms of stellar feedback. **The Convolutional Neural Network has been trained with simulated spectra, generated based on observational data from the PHANGS catalogue**. One of the main challenges of this work resides in the degeneracy in the resulting spectra as a result of combinations of Star Formation History and Metallicity. To break this degeneracy, Ultraviolet photometric observations from HST are added to the Neural Network's input. This additional information allows the Convolutional Neural Network to improve the prediction and distinguish between different Star Formation Histories and Metallicities. The outputs are weighted favouring younger star formation, as these are the star formation histories, we are interested in using further on.

Introduction

Age dating stellar clusters and stellar associations is crucial to study the timescales of star and cloud disruption, and to investigate the impact of different sources of stellar feedback. The largest advantage presented in our work resides on combining spectral and photometric information, specifically UV flux. Young stars have most of their emission in the UV range, which is not detected in the visible spectrum.

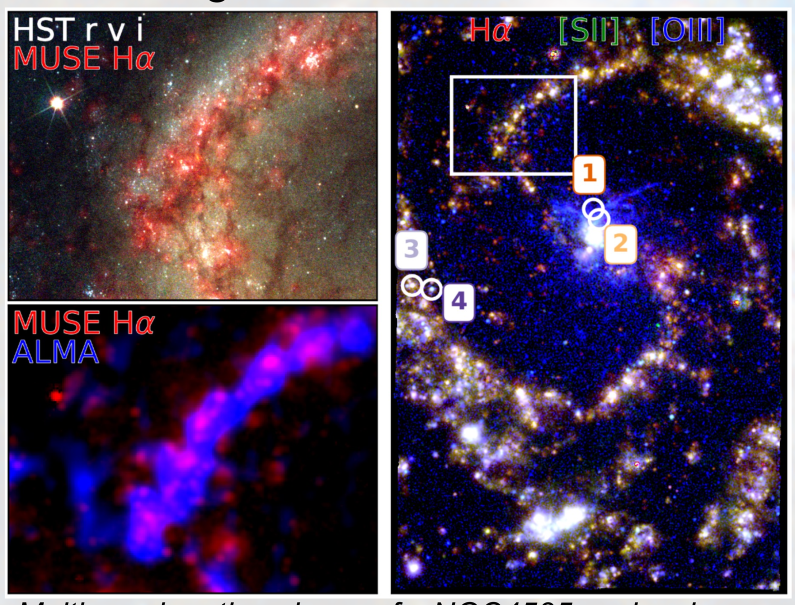


Relative flux between having 1% or 0.1% of the mass being young stars. The dotted line represent the limit of the MUSE the spectral range

Data

Training Data: The CNN has been trained with 300.000 synthetic star formations, generated from combinations of delayed log normal functions and young starbursts with different mass fractions, delay times, ages for the peak star formation, etc. To calculate them, we used *ProSpector* (Robotham, et al. 2020) and include chemical enrichment, ionized gas emission and a two-component extinction law.

Observational Data: The spectra and magnitudes were generated following the structure of the PHANGS-MUSE (Emsellem et al. 2022) and PHANGS-HST (Lee et al. 2022) catalogues. These catalogues contain high angular resolution data through HST which allow to identify young clusters, which can be further constrained with the MUSE spectra.

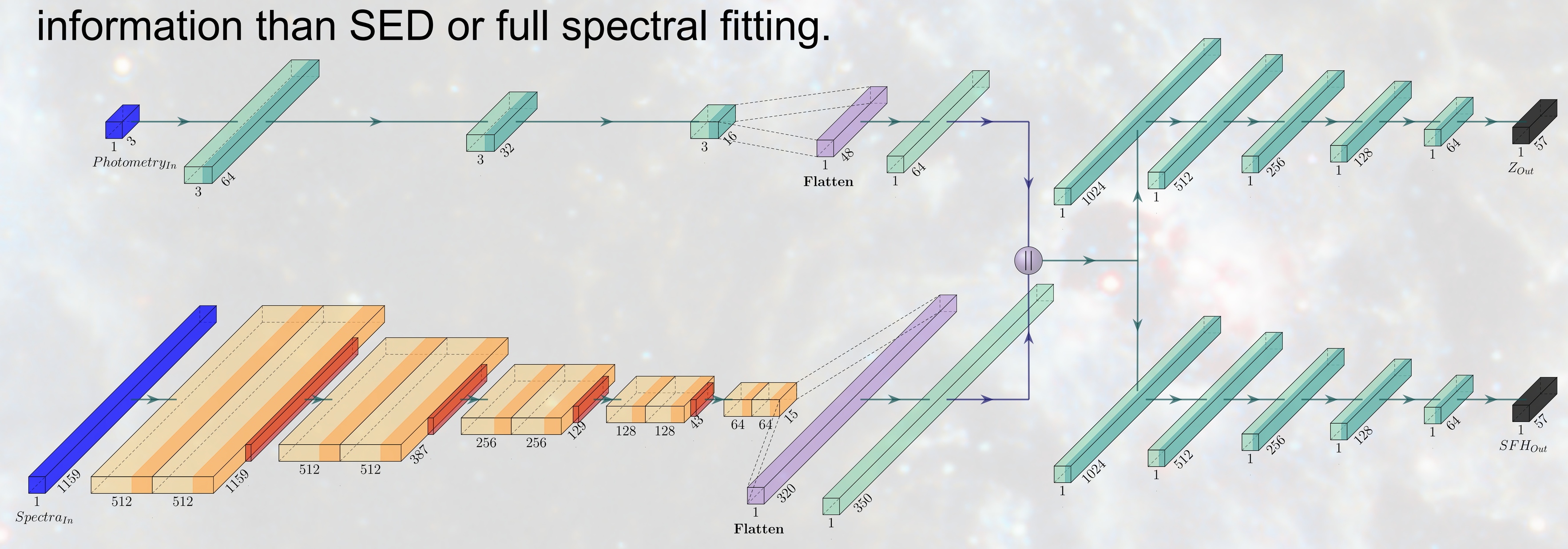


Multiwavelength view of NGC4535, showing a combination of HST, MUSE, and ALMA observations (Emsellem, et al. 2022)

Convolutional Neural Network

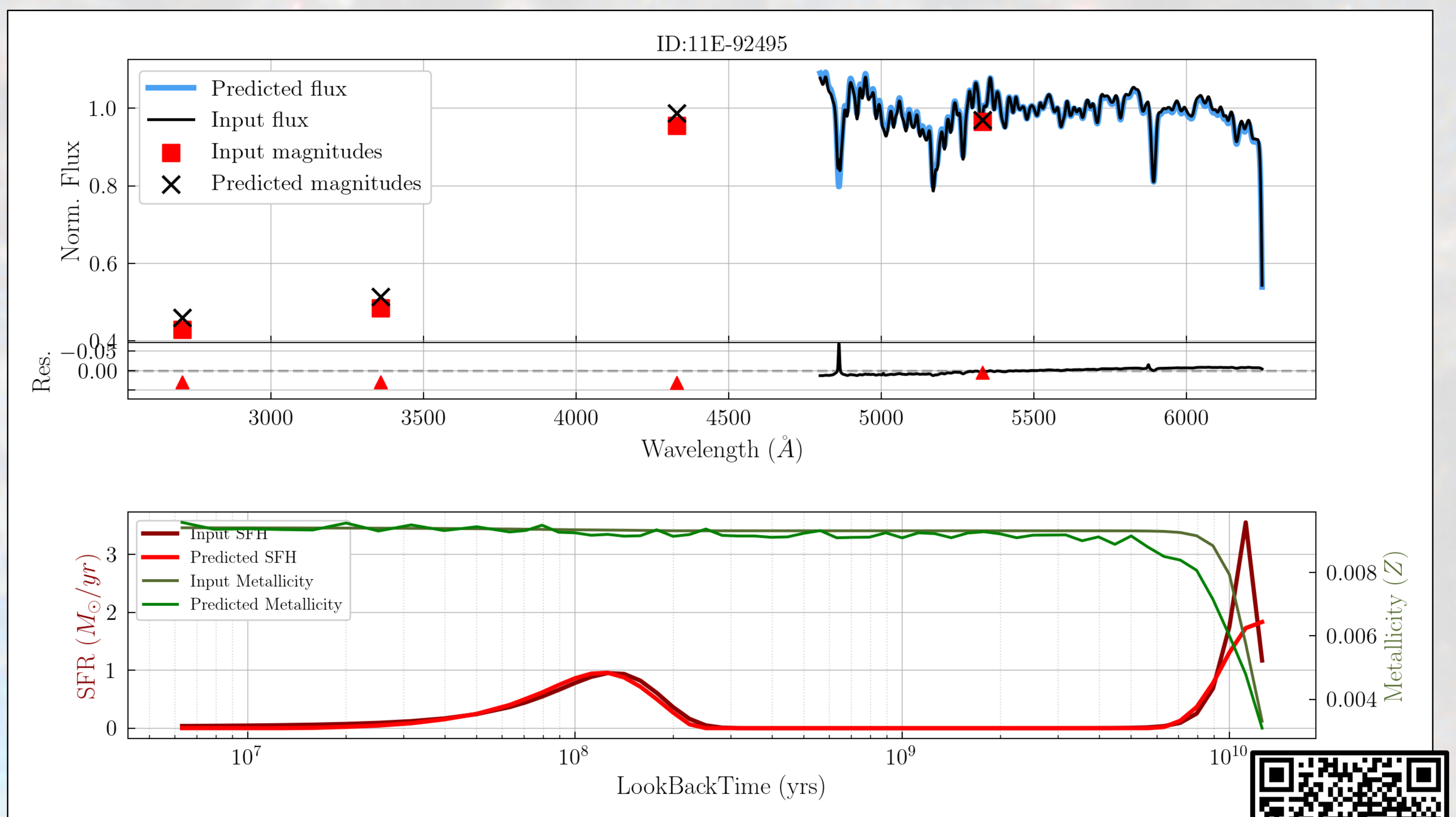
Our Neural Network reads the spectra in the 4800Å-6250Å range and HST's F275W, F336W, F438W, and F555W filters in the UV and visible range, processes it into a reduced latent space, and infers their corresponding SFH and Z.

Once trained, this process is orders of magnitudes faster in processing information than SED or full spectral fitting.



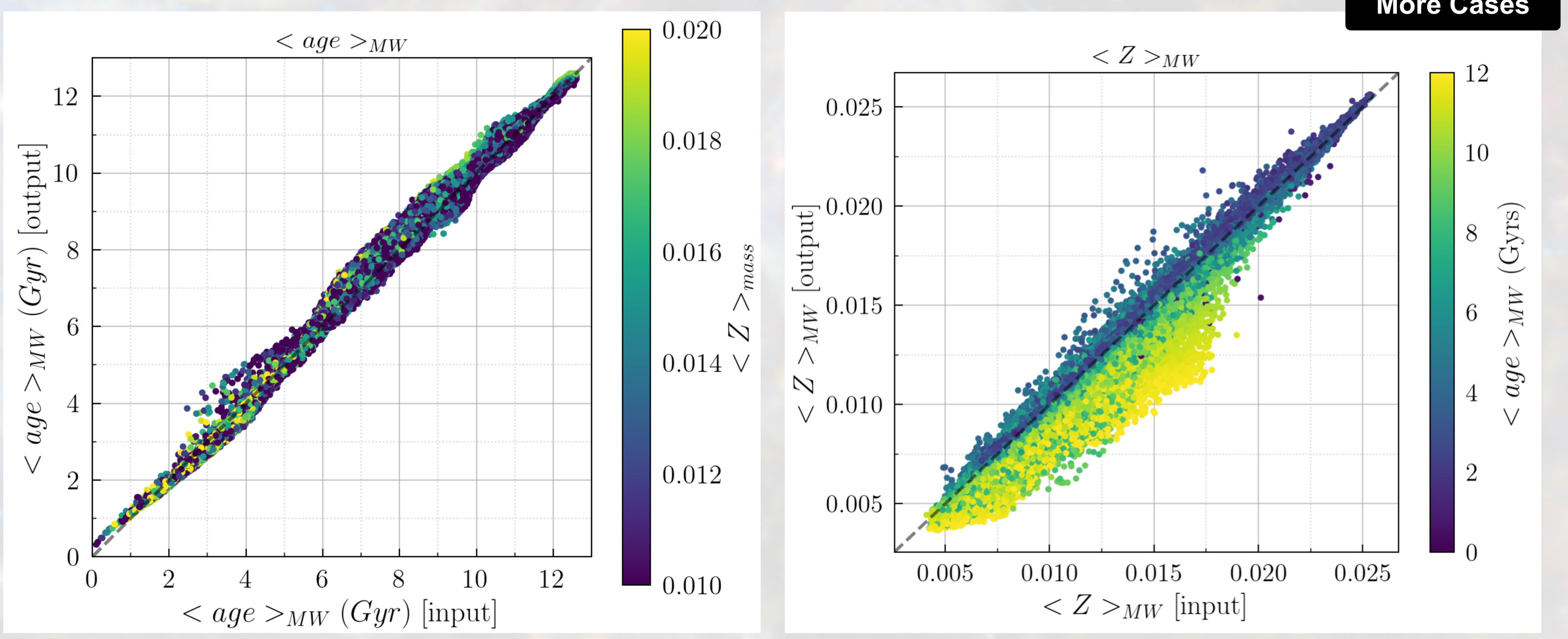
Results

Testing with our validation data (specific datapoints which the Neural Network has not trained with), we can see how the final prediction compares to the original input. For this test we generate the spectra that we would observe from the prediction and compare it with the input spectra.



Validation results. Top: Comparison between Input and Predicted spectra and magnitudes; Bottom: True and Predicted Histories for SFH Metallicity.

More Cases



Comparison between the predicted and true values for the mass-weighted age of the stellar populations (left) and the mass-weighted metallicity of the stellar populations (right). Both refer to the validation dataset.

Conclusions

- **CNNs have been successfully applied to recover SFH and Chemical Enrichment.**
- **We can apply this method to highly resolved data and obtain better histories.**
- **This improvement is going to help advance the knowledge on stellar feedback mechanisms.**

Future work: Expand wavelength range to **NIR** and **MIR** with **PHANGS-JWST**.

Acknowledgements

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Background image: NGC628/M74 by PHANGS-JWST