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Determining Star Formation Histories and Metallicity Evolution with Convolutional Neural Networks

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Abstract

We present the first results of a project to derive spatially resolved Star Formation Histories and Chemical Enrichment for a sample of nearby, star forming galaxies from the PHANGS survey, using Convolutional Neural Networks. 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.

1 Introduction

Age-dating stellar clusters and stellar associations is crucial to studying the timescales of star formation and cloud disruption and investigating the sources of stellar feedback, among others.

2 Methodology

We have implemented our CNN with two different architectures. The first version processed the spectra and photometry independently, combined both results into the latent space and processed the latent space independently to generate the Star Formation History (SFH) and the metallicity evolution (Fig. 1). However, the SFH and metallicity evolution are highly dependent of each other, therefore we decided to combine the decoding half of the model. Additionally, the use of attention layers [15] in conjunction with convolutional layers is extremely effective in identifying the relevant aspects of the features. Thus, the current version of the model adds both tools and creates a far more compact model that has better results (Fig. 2).

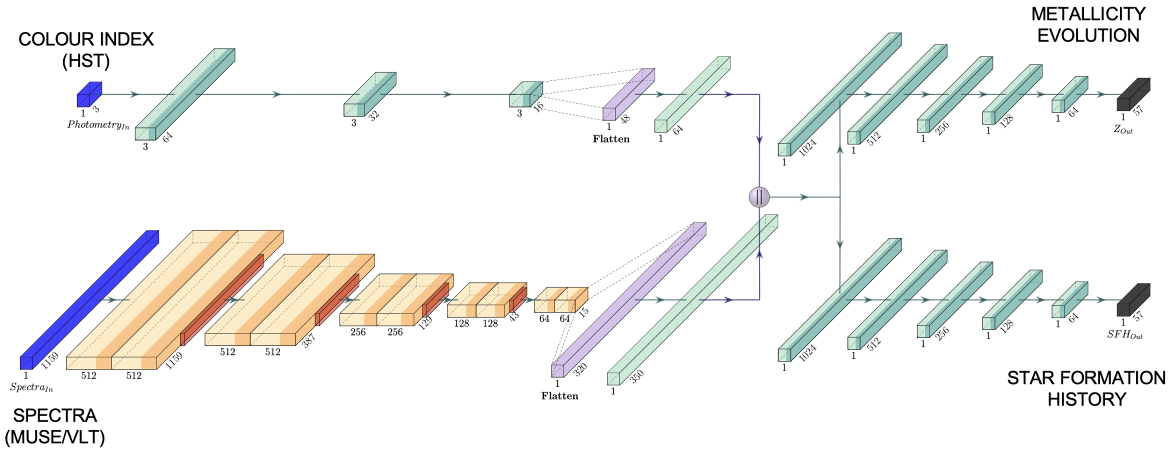

Figure 1: First version of the CNN. Four branches, each specialized in a single task.

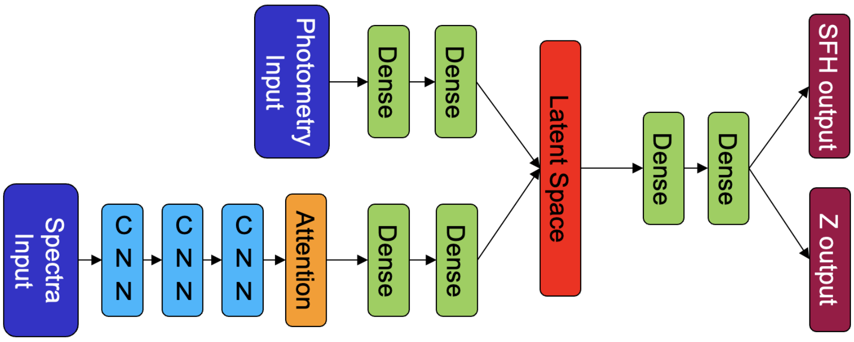

Figure 2: Latest version of the CNN. The spectral encoding branch now uses Attention layers. Additionally, the decoding section has been combined into a single branch.

We generate synthetic data for the SFHs described with a combination of skewed-normal distribution (characterized with the parameters skewness, peak of star formation, and period) to which a short short starburst is added (characterized by the age, intensity, and duration of the starburst), and with the "dense-basis" method [6] with $\alpha = 1$. The use of both methods of describing SFHs allows for varied and complete sets of SFH which follow comprehensive and realistic chemical evolutions. Figure 3 shows an example of these two types of SFHs.

To generate synthetic spectra and photometry we use ProSpect [14]. ProSpect is a package to generate spectra from star formation histories that include the stellar, ionized gas and dust components. We use the EMILES [16] stellar population models, with the extension for young populations presented in [1], covering a total range of ages from 6.3 Myrs to 14.1 Gyrs at 5 metallicities. We use the Charlot and Fall (2000) [3] model for birth cloud and screen dust

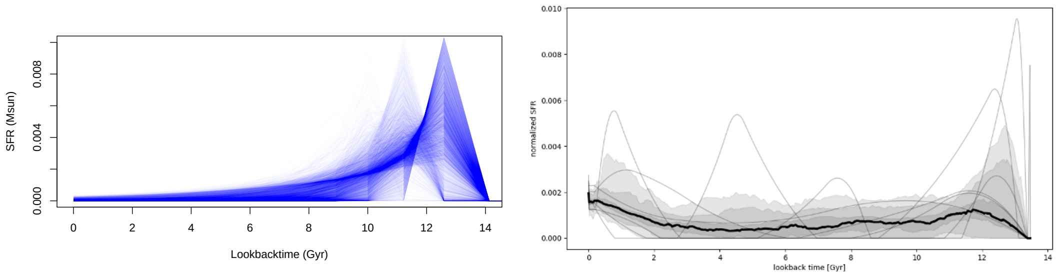

Figure 3: Left: Example of family of SFHs generated using skew normals. Right: Example of family of SFHs generated using dense-basis.

attenuation. Nebular emission (both, continuum and emission lines) is included using the Levesque, Kewley & Larson code (2010) [11]. The ionizing continuum is obtained from the star formation rate following Kennicutt (1998) [7].

We measure the flux convolved resulting spectra according to the 5 HST-PHANGS filters (F275W, F336W, F438W, F555W, F814W) and using the PHANGS-MUSE observations to cut the spectra to the MUSE wavelength range. Finally, we broadened the synthetic spectra to match the wavelength dependent resolution of the MUSE spectrograph [2][1], and to a velocity dispersion of 150 km/s.

3 Results

Figure 4 shows the input and recovered star formation history and age-metallicity relation for three galaxies in the validation sample. As can be seen, the network is able to obtain good results for galaxies with different characteristics, especially for intermediate- and young-populations. The predictions at old ages are worse, due to the low contribution of old stars to the observed spectra at redshift z = 0.

4 Conclusions

The use of Machine Learning for determining the Star Formation History and the metallicity evolution is a possibility that returns accurate and precise results. Old ages present difficulties and have a higher level of error, as they present a high degree of degeneration. The use of both spectra and photometry allows to break the degeneracy for young stellar populations, which is the main objective of our project.

The addition of the attention layer allows the model to identify the relevant information within the CNN's features. However, the model depends on the training data that is used, implying that a balanced, varied, and realistic dataset is required for the model to work. The model is agnostic to the aperture of the input used, resulting in multi-scale capabilities.

[1] https://www.eso.org/sci/facilities/develop/instruments/muse.html

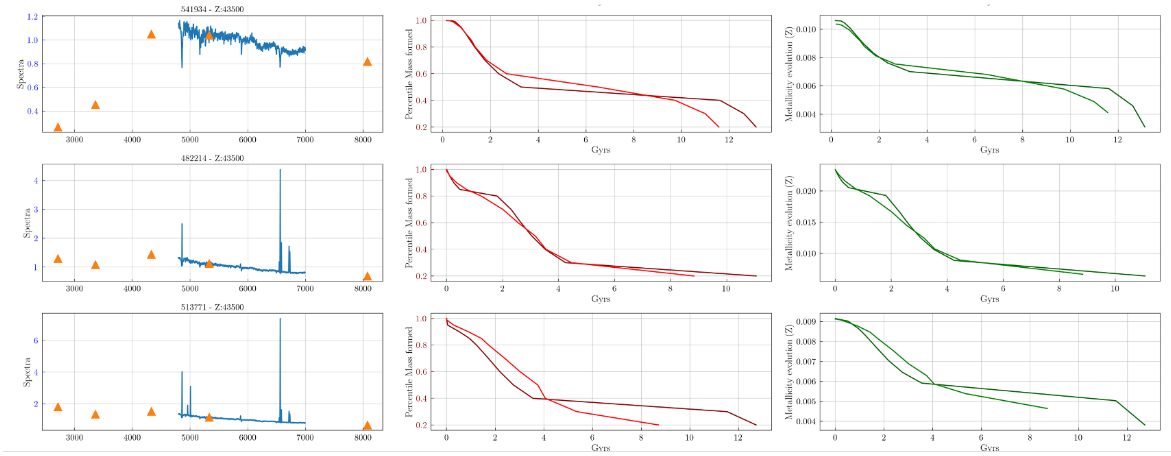

Figure 4: The first column presents the synthetic spectra and fluxes used as inputs in the CNN. The Central column show the input (dark red) and recovered (light red) cumulative SFH. The third column shows the same for the metallicity evolution with the ground truth and recovered answers plotted in dark and light green respectively.

4.1 Future work

- **Better coverage of the parameter space:** Improving the representation of different types of SFH in our training dataset will improve how the network identifies outliers and special cases.
- **Domain-related performance:** The "synthetic valley" is one of the hardest hurdles to surpass in Machine Learning. Domain-related methods should help in improving observational results.
- **Transfer Learning:** Together with Domain-related performances, transfer learning allows to learn and distinguish subtleties of observational data. This method has already had success in [13].
- **Addition of JWST-PHANGS data:** The addition of NUV-UV data for identifying young stars can be extended into the NIR-FIR with the use JWST's NIRCAM and MIRI for older star formation.

Acknowledgments

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