Teaching Dust Models to a Machine

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Motivations: Computing Fast Dust Models

Computing grain spectra – Computing the emitted IR spectrum of an interstellar dust mixture exposed to an arbitrary radiation field requires (*e.g.* Galliano, 2022):

1. Computing the temperature distribution of the smallest grains, which are out of equilibrium with the radiation field (***intensive***);
2. Computing the emission of large grains, which are at thermal equilibrium (***fast***);
3. Integrating the spectra of every individual grain size bin over the size distribution (***fast***).

Problematic applications – Some wide-spread practical applications require computing a large number of dust spectra:

SED fitting (especially Bayesian inference; *e.g.* Galliano, 2018) requires computing:

$$\underbrace{N_{\text{sources}}}_{\text{arbitrary}} \times \underbrace{N_{\text{parameters}}}_{3\text{ to }15} \times \underbrace{N_{\text{MCMC}}}_{10^4\text{ to }10^6} \times \underbrace{N_{\text{PDF}}}_{100} \simeq 3 \times 10^6 \text{ to } 10^{12}.$$

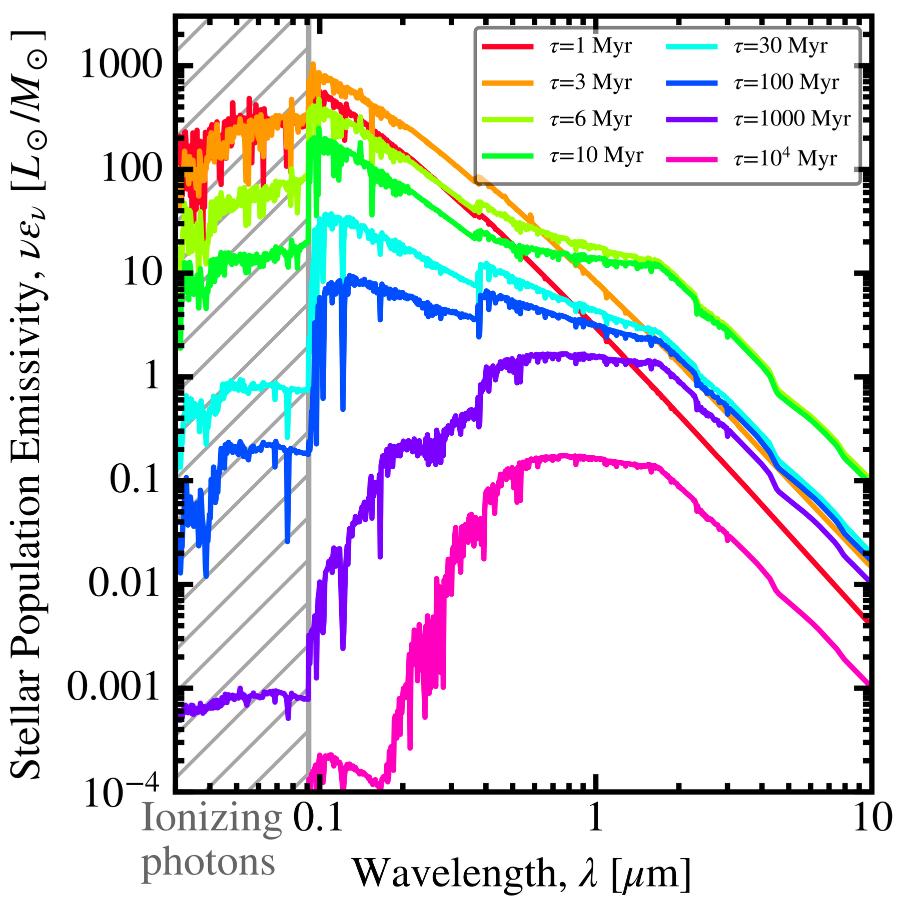
Radiative transfer models also require to compute one dust spectrum per cell for each iteration until equilibrium is reached (*e.g.* Nersesian et al., 2020):

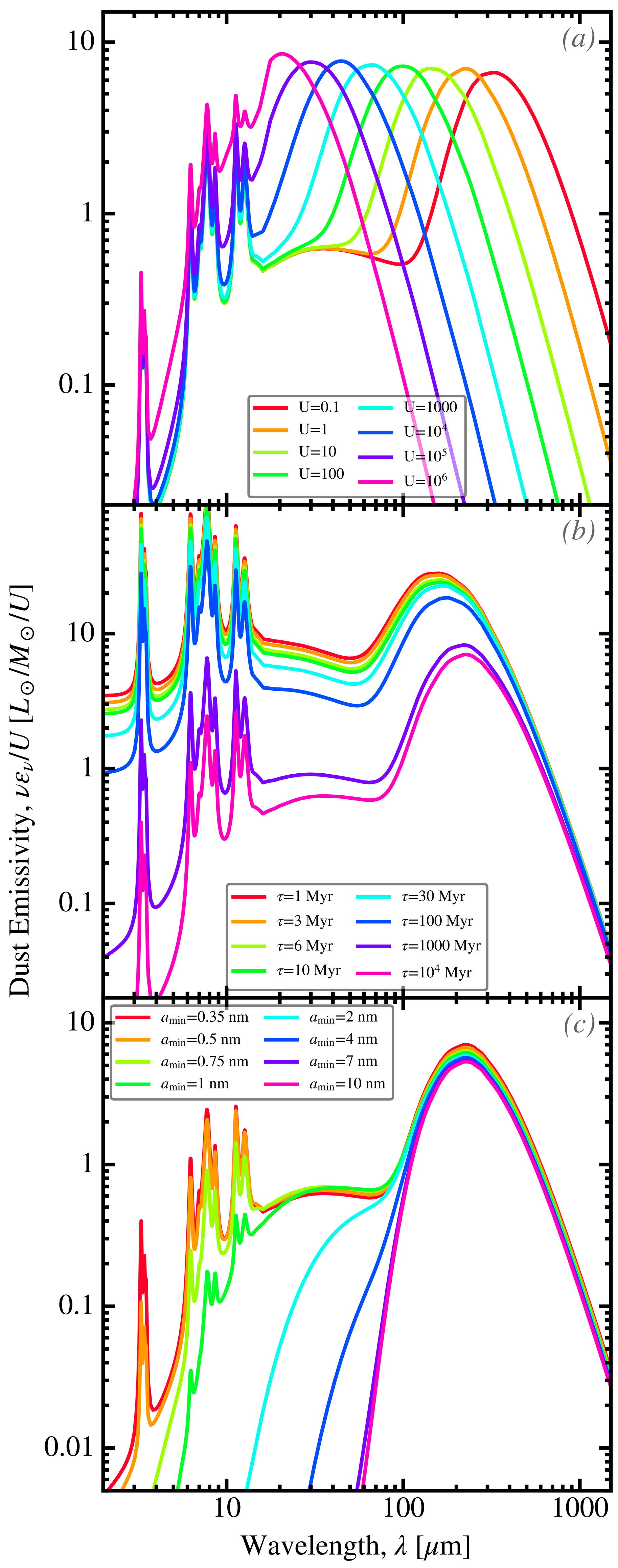
$$\underbrace{N_{\text{cells}}}_{1\,000\,000} \times \underbrace{N_{\text{iterations}}}_{10} \simeq 10^7.$$

The Dust Model Grid Used for Training

We have generated a large grid of dust emission spectra, using:

- the `THEMIS` model (Jones et al., 2017);
- heated by a radiation field modeled using the stellar population synthesis code `BPASS` (Eldridge et al., 2017, right panel).





Radiation field:

- Initial metallicity, $Z = 0.04$.
- Salpeter IMF.
- Scales with U, the starlight intensity between $\lambda = 0.0912\ \mu$m and $8\ \mu$m ($U = 1 \Leftrightarrow 2.2 \times 10^{-5}$ W/m^2; panel a).
- Varies as a function of, τ, the time since the start of the star formation burst (panel b).

Dust model:

- Vary the minimum size, $a_{\min}$ (panel c).
- Represent the emission per dust mass, per U.
- Take log quantities for the machine-learning training.

Grid size:

- 481 wavelengths.
- 91 U.
- 51 τ.
- 51 $a_{\min}$.

$\Rightarrow$ 236 691 dust spectra.

This is our training data set

Our Neural Network Architecture & Training

Training data set:

- We use our whole model grid as a training data set (236 691 spectra).
- Testing is performed by recomputing 8 000 new models at random parameter values.

Neural Network (NN) – The machine-learning training was performed using the `Keras` library (Chollet, 2015). Here is our NN architecture:

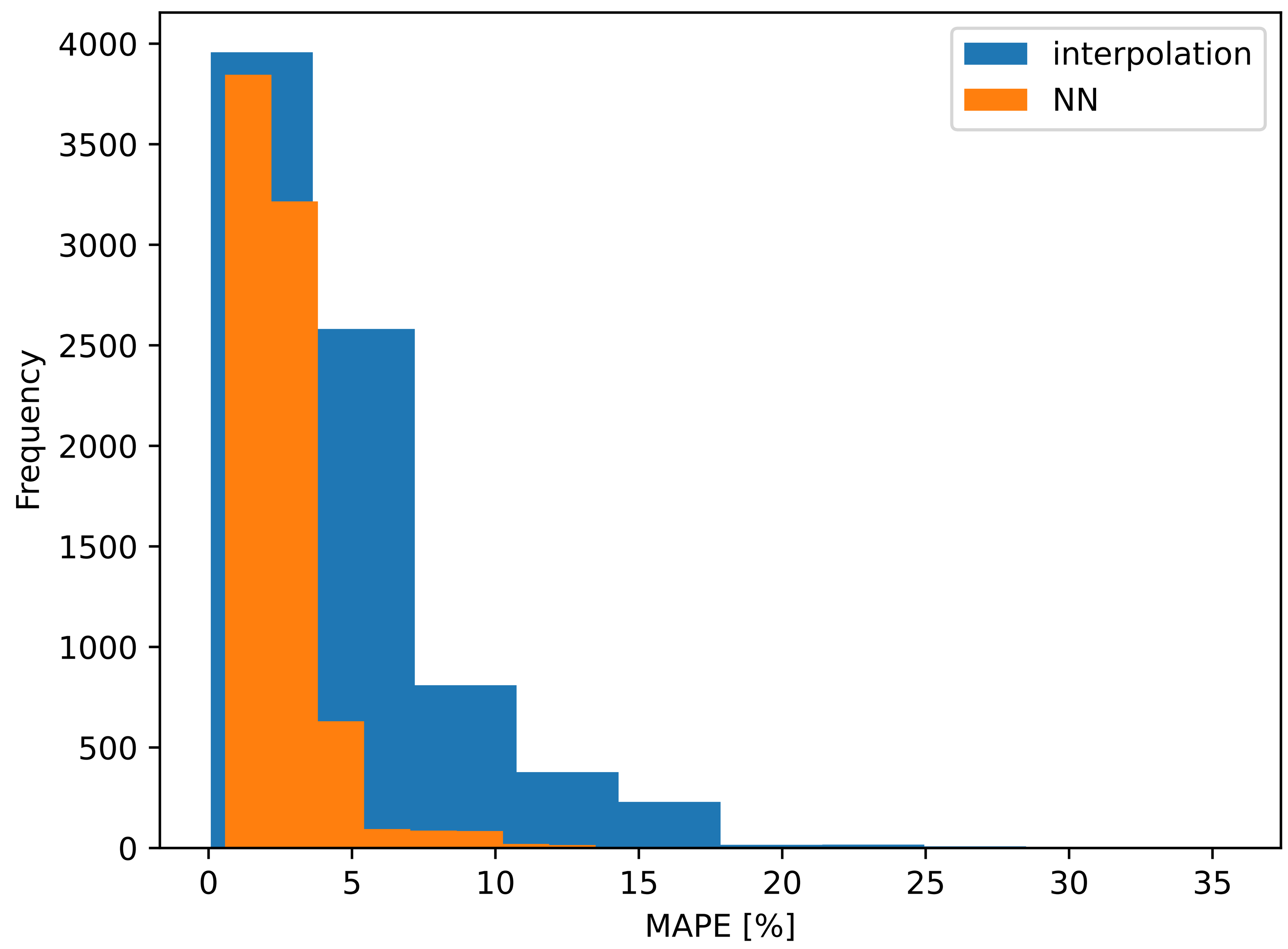
1 input layer of 3 neurons (number of parameters, U, τ and $a_{\min}$);
8 hidden layers of 256 neurons, chosen by minimizing the loss;
1 output layer of 481 neurons (size of the wavelength grid).

Accuracy & Efficiency of the NN Model

Goodness metric – To estimate the quality of the model produced by the NN, we use the *Median Absolute Percentage Error* (MAPE):

$$\text{MAPE}(y, \hat{y}) = 100 \times \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right|,$$

where the y_i are the log of the emissivity at each one of the $N = 481$ wavelengths. Below, we compare the MAPE when using our NN and when performing linear interpolation within our model grid. Our NN performs better than linear interpolation. It is most of the time more accurate than a few percents.



Computing speed – The following table compares the accuracy and running time for the 8 000 spectra of our testing grid.

Method	Mean MAPE	CPU time
Full computation	0 %	200 hours
Linear interpolation	4.7 %	8 minutes
NN	2.6 %	1 second

Open-Source Python & Fortran Modules

The following tools, implementing this model are freely available at: https://github.com/jctdrs/SwING_external/. This repository mainly contains the following.

- A Python program that computes the emission spectrum, quasi-instantaneously, on the command line.
- This Python program can also be called as a Python module.
- A Fortran module is also provided.
- Several options can be used: *(i)* running the NN to estimate the dust emission; *(ii)* running the NN to estimate the photometry in 70 broadband filters (*Spitzer*, *AKARI*, *WISE*, *Herschel*, *Planck*, *etc.*); *(iii)* running the NN backward to estimate the parameters from the spectrum.

References

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