# Analysing the SEDs of protoplanetary disks with machine learning Till Kaeufer<sup>1,2,3,4</sup>, P. Woitke<sup>1</sup>, M. Min<sup>2</sup>, I. Kamp<sup>3</sup>, and C.Pinte<sup>5,6</sup>

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## Introduction

Spectral energy distributions (SEDs) are one of the most common observations of protoplanetary disks. However, deriving disk properties with models from these observations is known to be degenerate. While Bayesian analysis can tackle this problem, radiative transfer codes are usually to slow to make this technique feasible.

## Approach

### **Bayesian Analysis**

We use the Bayesian inference tool MultiNest to fit the SED observations of 30 protoplanetary disks:

49Cet, AATau, ABAur, BPTau, CITau, CQTau, CYTau, DFTau, DMTau, DNTau, DOTau, FTTau, GMAur, HD100546, HD135344B, HD142666, HD163296, HD169142, HD95881, HD97048, LkCa15, MWC480, PDS66, RECX15, RULup, RYLup, TWCha, TWHya, UScoJ1604-2130,V1149Sco

As seen in the example of Fig. 3 the resulting model SEDs overlap well with the observations.









We created Neural Networks (NNs) that predict SEDs of protoplanetary disks within milliseconds.

#### The model

These NNs are trained and tested on about 2 million SEDs of models created by the radiative transfer code MCFOST.

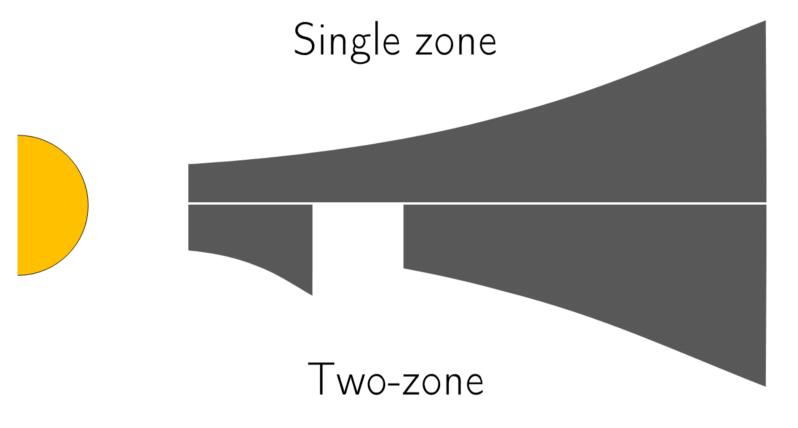
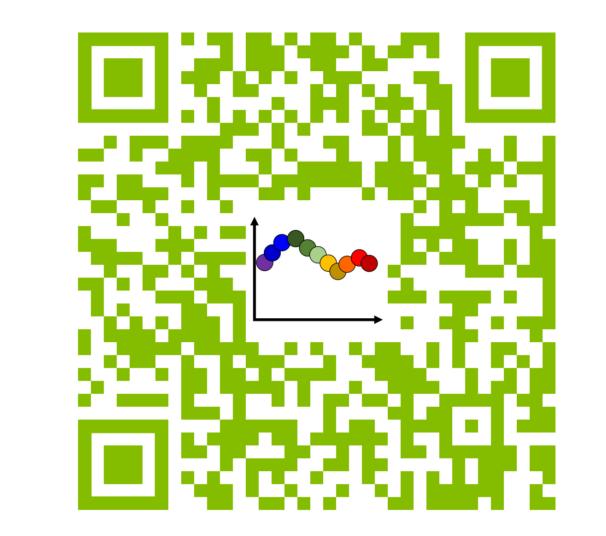


Fig.1: Sketch of a single and two-zone model.

We created these models in two different complexities: continuous single zone and discontinuous twozone models (Fig. 1). Additionally, all stellar parameters, all disk shape parameters, the dust composition (amorphous carbon to silicate ratio), and the amount and charge of PAHs are varied between models. We created Neural Networks that predict SEDs of protoplanetary disks within milliseconds.



Explore the interactive online tool yourself!

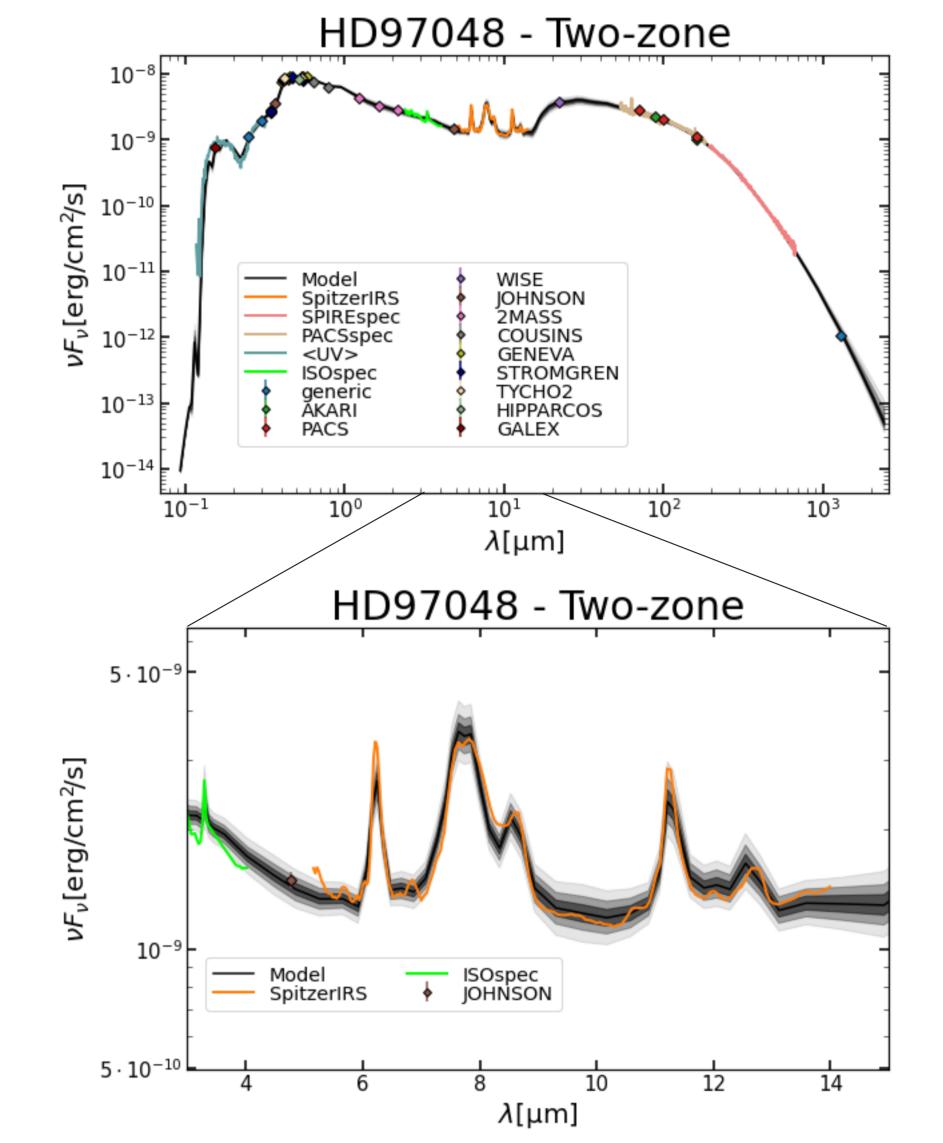
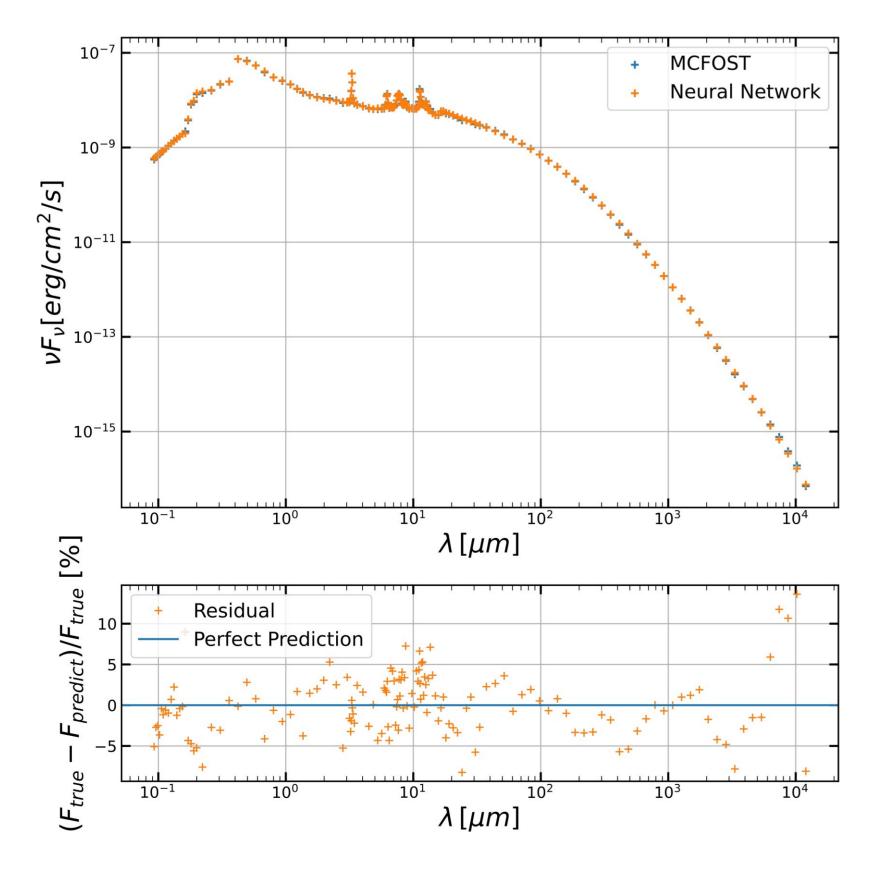


Fig.3: Fitted SED of HD97048 with a two-zone model. The black contours show the sigma levels of the derived model SEDs.

#### Neural networks

The SEDs predicted for single/two-zone models by the NNs (Example in Fig. 2) have differences compared to the SEDs calculated by MCFOST of 3.4%/ 3.6%. This allows use to use the NNs instead of the modelling software for the Bayesian Analysis.



## Analysing the results

We analysed the results with respect to typical uncertainties, degeneracies, trends between parameters, the evidence for two-zone over single zone models, and the validity of analytic dust mass determinations. Two highlights are shown below.

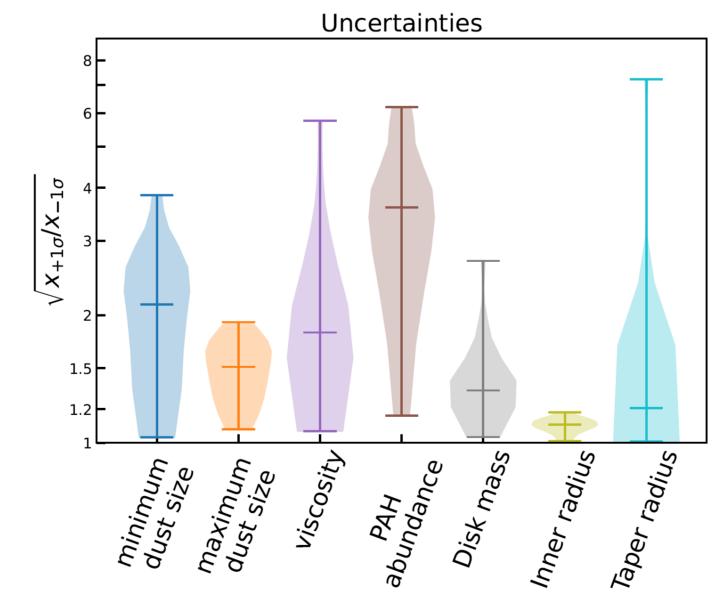


Fig.4: Uncertainty derived from Bayesian analysis for a selection of parameters.

#### **Typical uncertainties**

We calculate the uncertainty of parameters as the ratio of the plus/minus  $1-\sigma$  level. Figure 4 shows the distributions of uncertainties for some parameters over all 30 objects. The disk mass and inner radius are the best constrained parameters with typical uncertainty factors of less than 1.5.

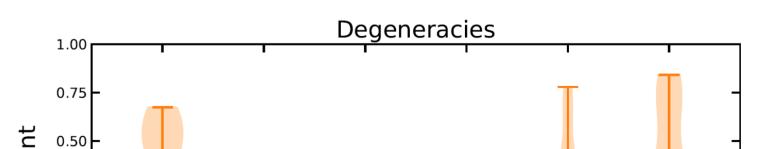


Fig.2: Predicted SED by the NN compared to the MCFOST SED. The lower panel shows the residual in percent.

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#### **Typical degeneracies**

We detect and quantify the strongest degeneracies between two parameters using the Pearson correlation coefficient of all joint posterior distributions (Fig. 5). Especially the scale height is degenerate with many parameters.

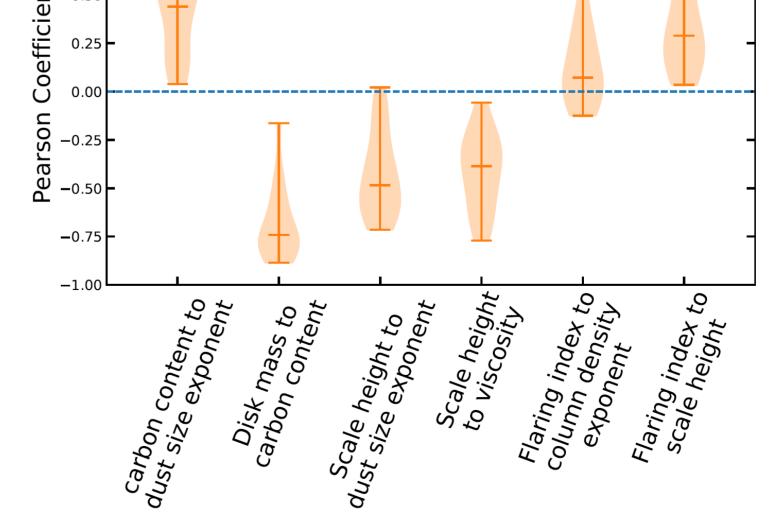


Fig.5: Selection of the strongest degeneracies found between parameters. The absolute values indicate the strength of a degeneracy.

