

Emulating the interstellar medium chemistry with neural operators

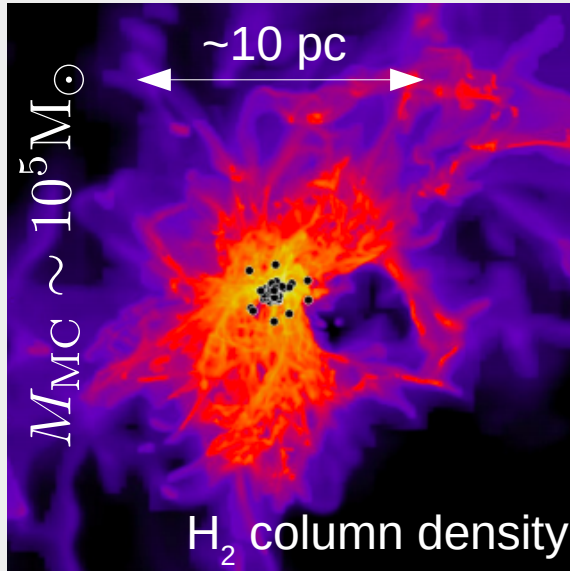
a recap & update on the project:

- why should we focus on the chemistry of the ISM?
- what are the problems for numerical solvers?
- which are the ways to speed-up our computations?

Andrea Pallottini

Example: breakdown of a Molecular Cloud

Decataldo+2020



physical processes

CPU cost per step

(self)-gravity

Guillet & Teyssier 2011

$$\Delta\Phi = 4\pi G\rho$$

~10%

hydro

Teyssier 2002

$$\dot{\mathcal{U}} + \nabla\mathcal{F} = \mathcal{S}$$

~15%

radiation

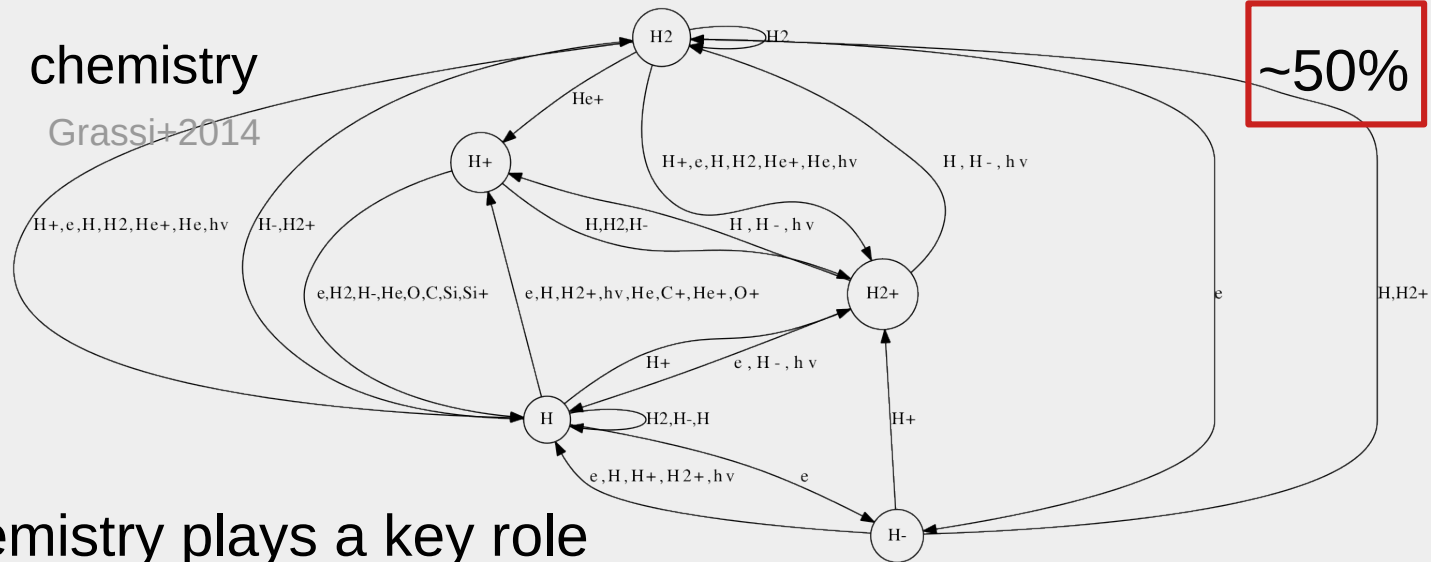
Roshadal+2015

$$\dot{I}_\nu/c + \hat{n}\vec{\nabla}I_\nu = j_\nu - k_\nu I_\nu$$

~20%

chemistry

Grassi+2014



- about 900-60 mpc spatial resolution
- about 10^9 finite (AMR) elements
- about 0.4 MCPUhr for 3 Myr evolution

non-equilibrium ISM chemistry plays a key role in astrophysical and cosmological studies for galactic environments see Pallottini+2017

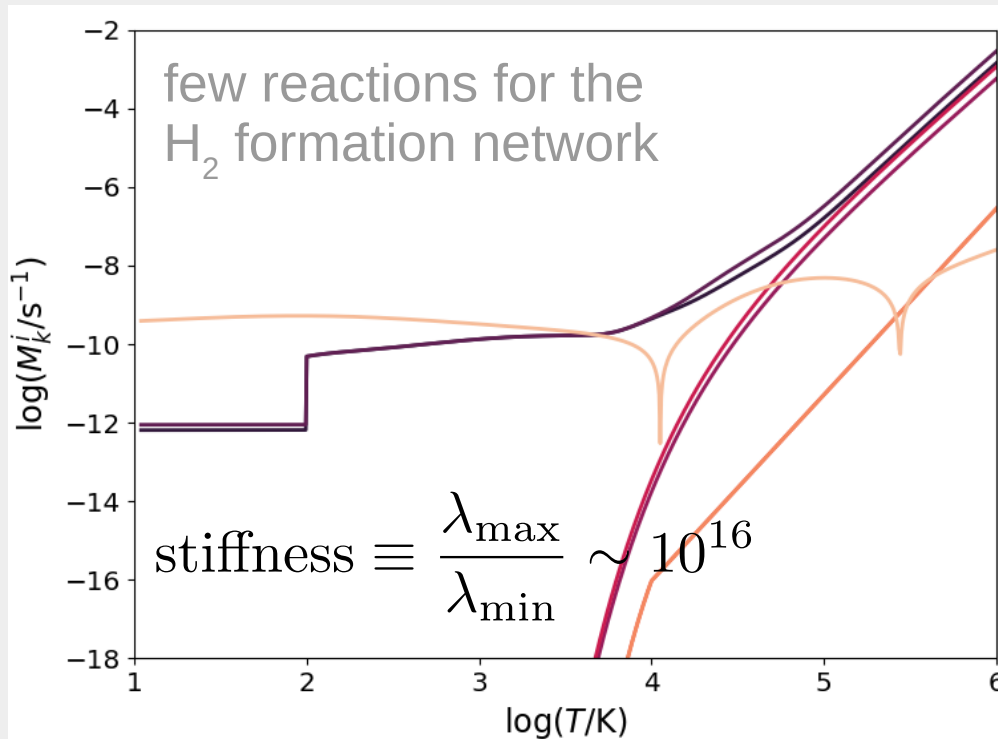
Solving the chemistry in the InterStellar Medium

$$\begin{cases} \dot{n}_k = \boxed{A_k^{ij}(T)n_jn_i} + \boxed{B_k^i(I_\nu)n_i} & \equiv M_k^i n_i \\ \dot{T} = \boxed{\Gamma(I_\nu) - \Lambda(n_k, T)} & \text{heating/cooling} \end{cases} \quad \begin{array}{l} \text{2-body reactions} \\ \text{photo-chemistry/CR} \\ \text{Bovino+2015,} \\ \text{Pallottini+2017,} \\ \text{Decataldo+2020} \\ \\ \text{9 species (+T) and 52 reactions} \\ \text{to follow up to H}_2 \text{ formation} \end{array}$$

robust implicit solvers are needed

- CPU cost is high
- load balancing can be spoiled

can we use fast emulators instead?



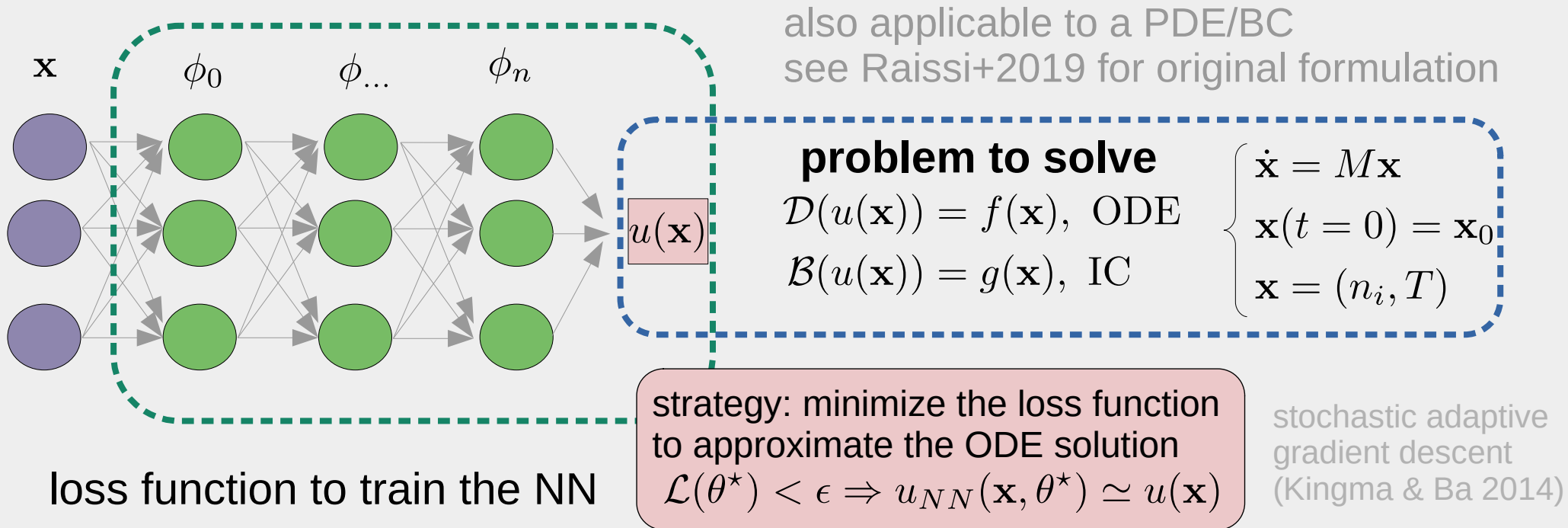
features of the numerical system:

- wide range of initial conditions: cold/warm neutral medium, molecular gas, hot ionized gas ...
- problem size increases superlinearly with number of chemical species
- non trivial dependencies with T
- incredibly stiff ODE system
- timescale are short wrt hydro, gravity, ...
- ...

Physics-Informed Neural Networks: a sketch

Branca & Pallottini 2023

image for a simple feed-forward network,
actually we adopt Deep Galerkin layers (Sirignano & Spiliopoulos 2018)



$$\mathcal{L}(\theta) = |\mathcal{D}(u_{NN}(\mathbf{x}, \theta)) - f(\mathbf{x})| + |\mathcal{B}(u_{NN}(\mathbf{x}, \theta)) - g(\mathbf{x})|$$

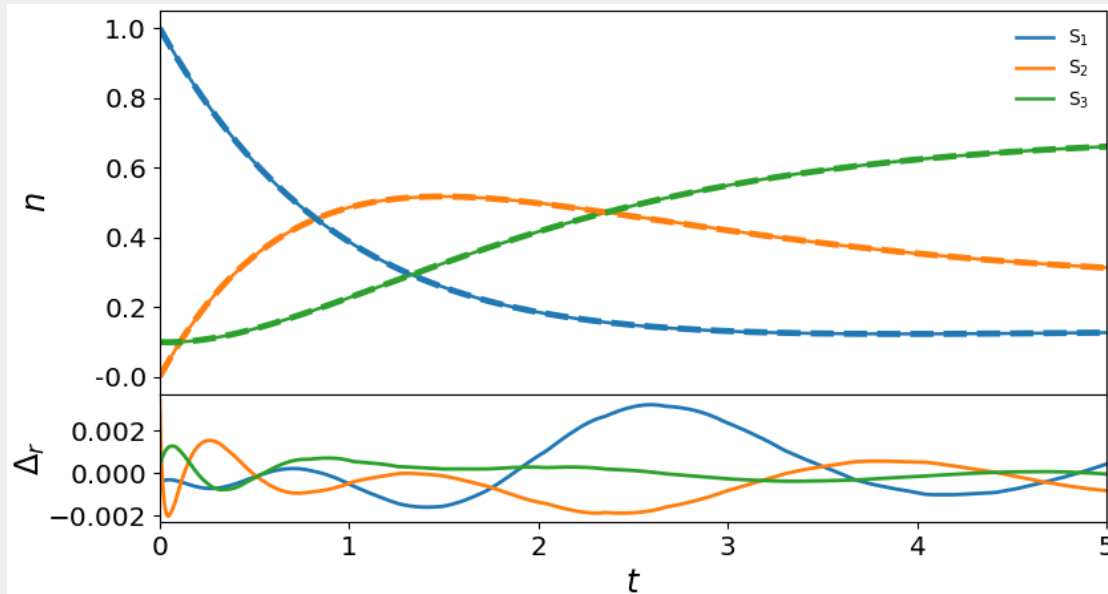
Physics-Informed
part of the NN

- NN built to be differentiable at machine precision
- evolution equations directly embedded in the loss

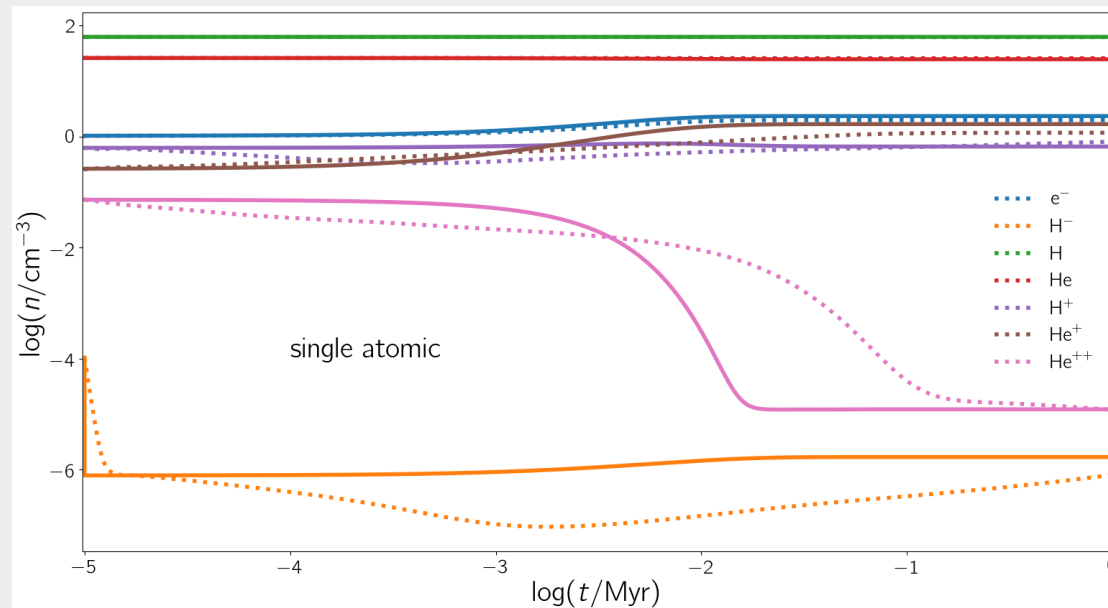
Performance of a PINN emulator

Branca & Pallottini 2023

stiff ODE



ISM chemistry



performances similar to with Grassi+2022 and Holdship+2021, (for slightly different problems)

good effort, but likely too costly to reach the required precision

training set

$$T/K \in [20, 10^{5.5}]$$

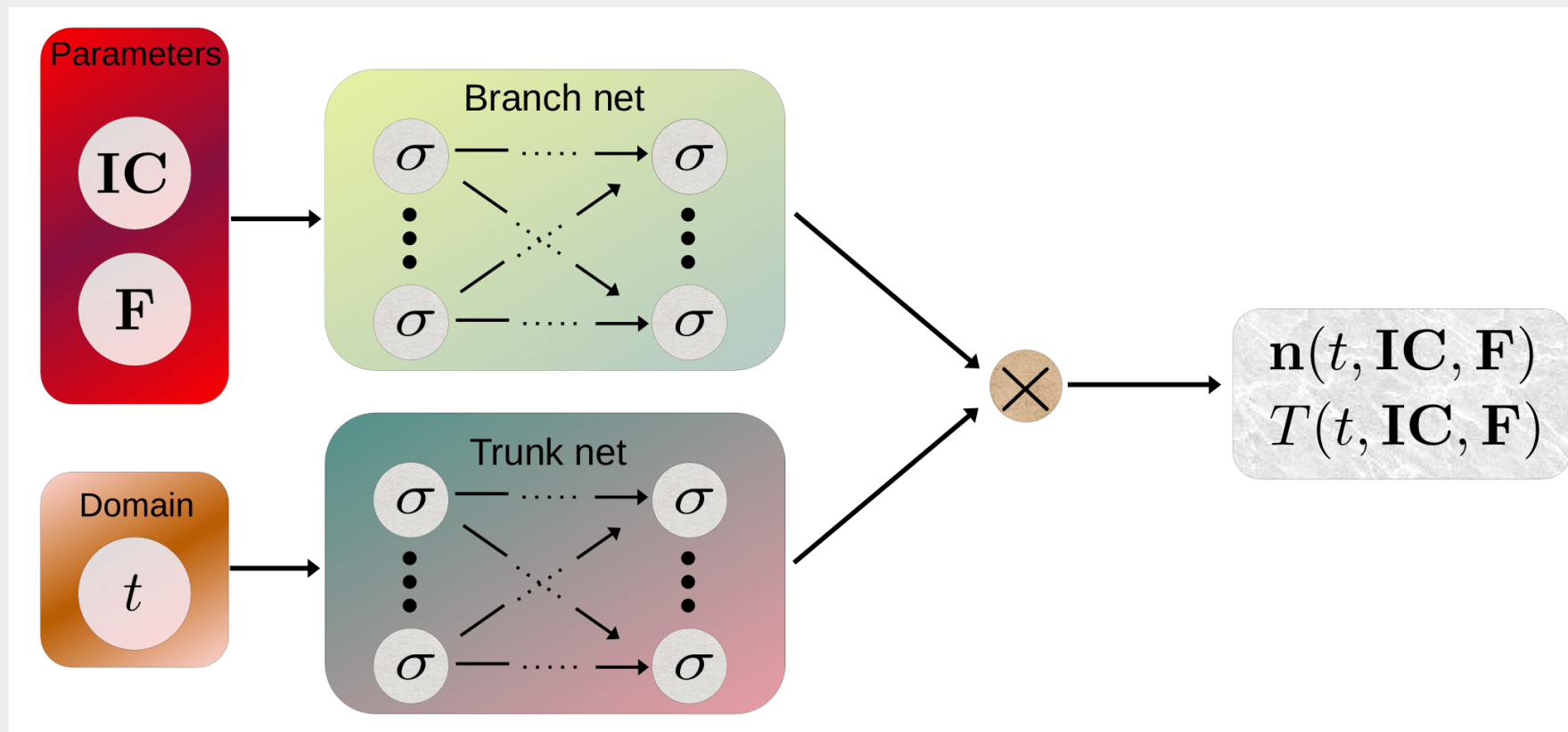
$$n/\text{cm}^{-3} \in [10^{-2}, 10^3]$$

$$n_k/n \in [10^{-6}, 0.8]$$

relative error $\simeq 0.1$
 speed up $\times 100$
 training time $\simeq 2k$ GPUhr

Changing gears: Deep Neural Operator

Branca & Pallottini submitted



main differences wrt the PINN model

- DeepONet is a implementation UAT for operators
- the emulator is data driven
- shape and intensity of the radiation Field can change

Lu+2021
Grassi+2014
10 energy bins

DeepONet: performance & validation

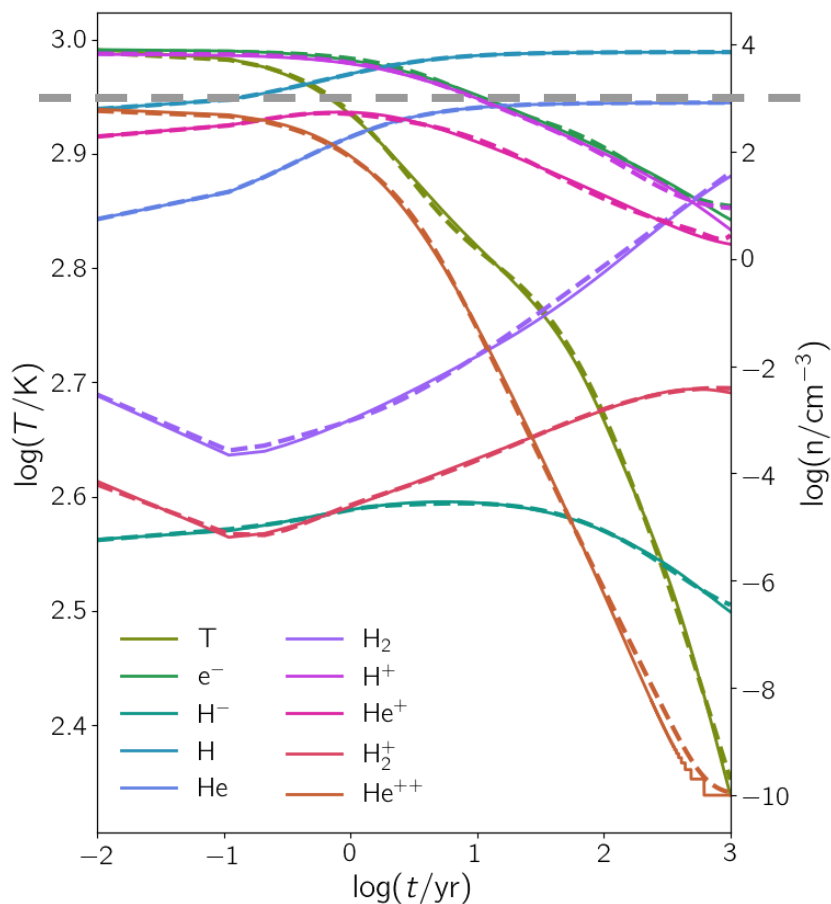
relative error $\simeq 0.01$

speed up $\times 128$

training time $\simeq 40$ GPUhr

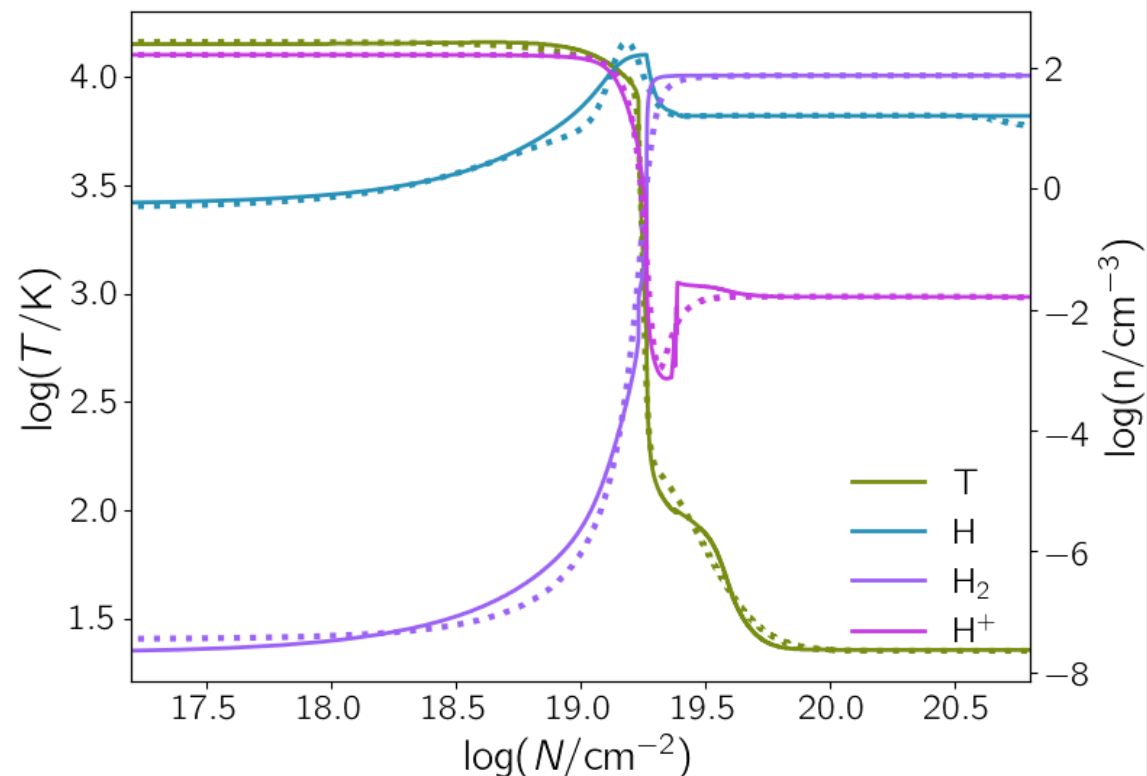
Branca & Pallottini submitted

i.e. 10x more precise at x40 less cost wrt the PINN, which did not allowed for a varying radiation field



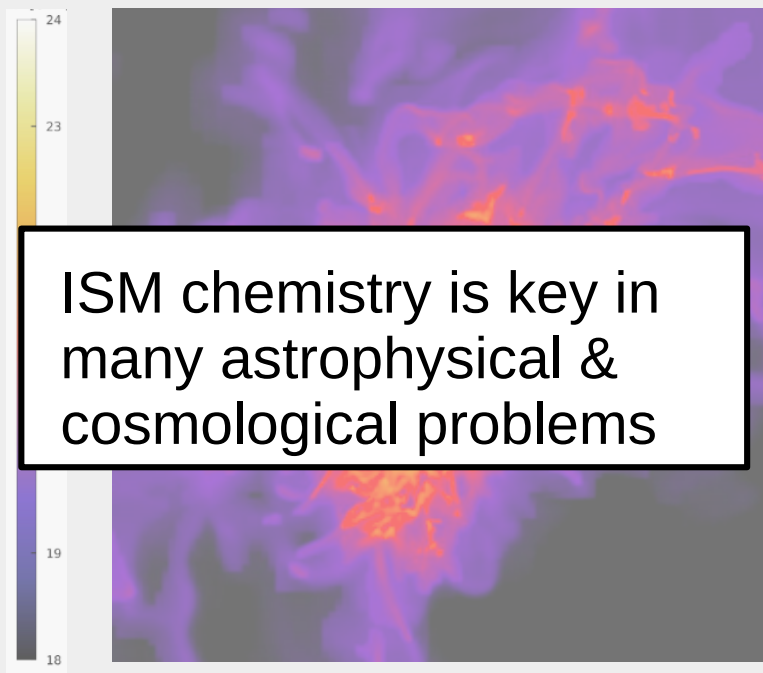
--- boundary of the training set

very adaptable: validation with PDR

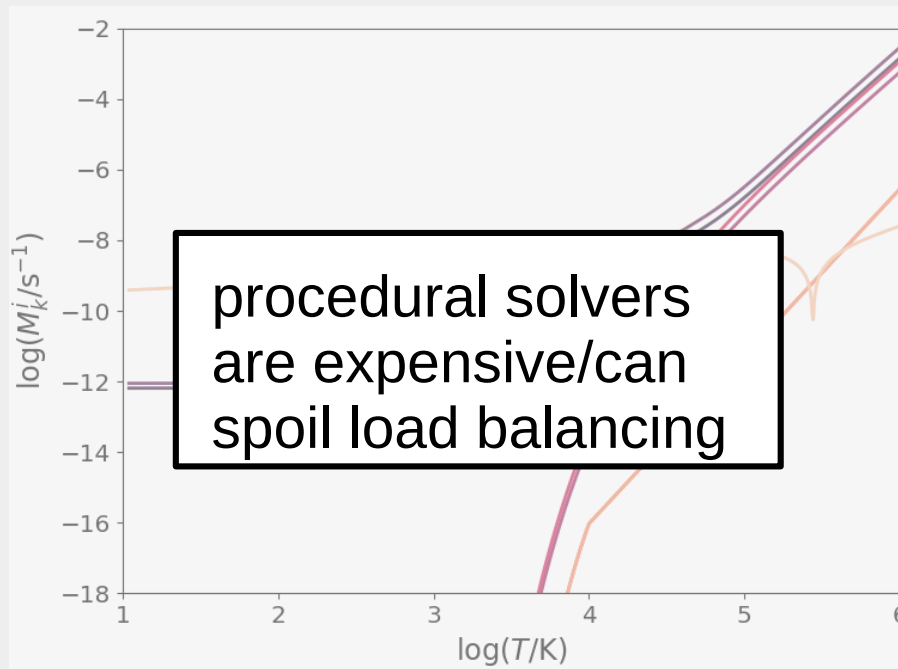


Conclusions:

Decataldo+2020



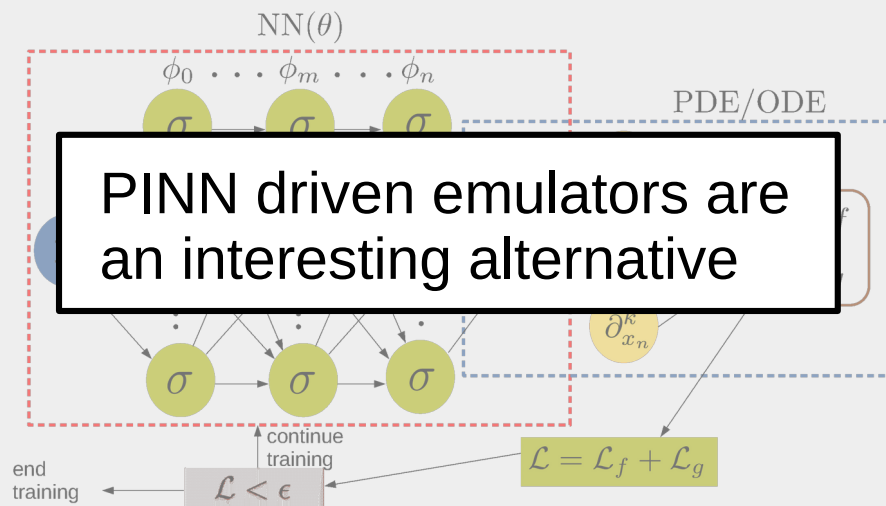
ISM chemistry is key in many astrophysical & cosmological problems



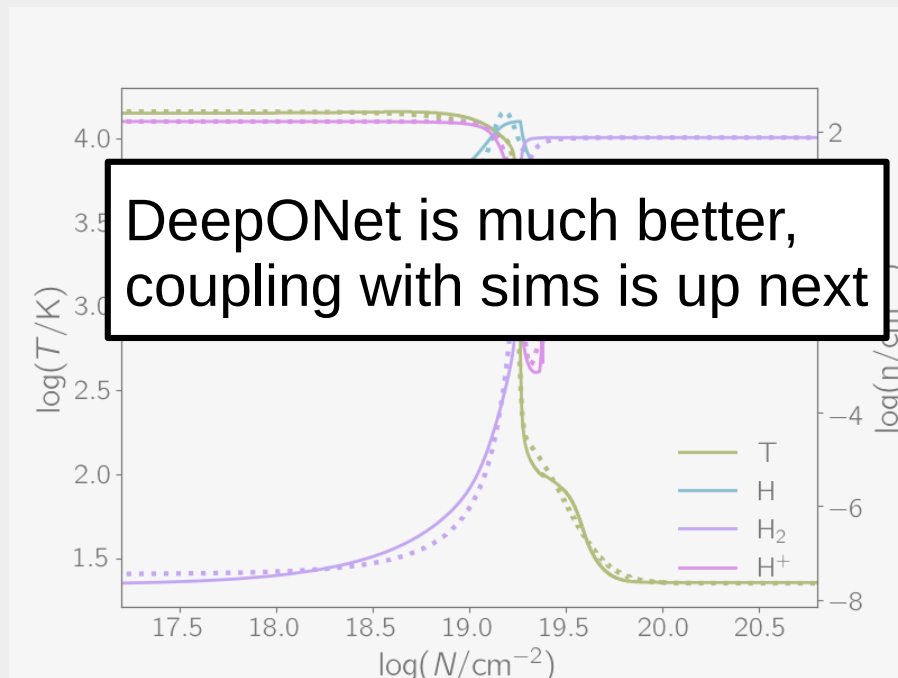
procedural solvers are expensive/can spoil load balancing

Branca & Pallottini 2023

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PINN driven emulators are an interesting alternative



DeepONet is much better, coupling with sims is up next

Branca & Pallottini submitted

✓ KPI: paper submitted