HENRIQUE CÂMARA
PhD in Physics Student @ CFTP
FCT PhD Grant: 2021.06340.BD
henrique.b.camara@tecnico.ulisboa.pt
Supervisors: Filipe Joaquim (CFTP/IST)
Ricardo Felipe (CFTP, ISEL)

Unraveling particle dark matter with Physics-Informed Neural Networks

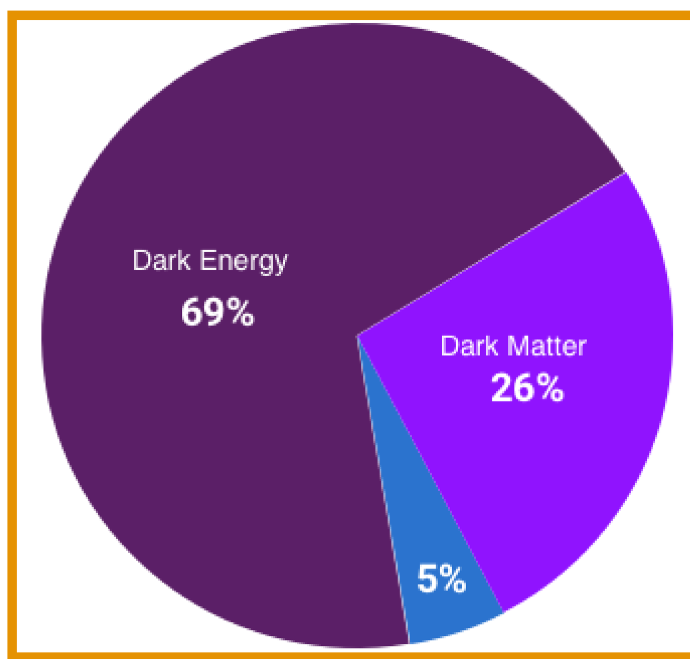
Authors: M.P. Bento (CFTP), H.B. Câmara, J.F. Seabra (CFTP)

CFTP Centro de Física Teórica de Partículas

Publication:
Phys. Lett. B 868 (2025) 139690

fct Fundação para a Ciência e a Tecnologia — REPÚBLICA PORTUGUESA — COMPETE 2020 — PORTUGAL 2020
Projects: UIDB/00777/2020, UIDP/00777/2020, CERN/FIS-PAR/0019/2021, 2024.02004.CERN

Particle Dark Matter in Alternative Cosmologies



Dark Matter

Requires a **stable**, **non-baryonic**, electrically **neutral** and **cold particle** to account for **observed dark matter relic abundance**

$$\Omega_{\rm CDM} h^2 = 0.120 \pm 0.001$$

How to find particle dark matter models ?
How to determine the model parameters that explain the data ?

Freeze-in dark matter Boltzmann equations

Cross-section particle interactions

$$\frac{dY(x)}{dx} = \frac{1}{x^2}\frac{S(m)}{H(m)}\langle\sigma v\rangle Y_{\rm eq}(x)^2 \,, \quad Y(x_0 \ll 1) = Y_0 \ll 1$$

Hubble parameter
expansion of Universe
in alternative cosmology

$$\Omega h^2 = \frac{S_0}{\rho^0_{\rm crit}/h^2} m Y(x \to \infty)$$

$$H(x) \to H(x) \times F(x, x_t, \gamma)\,, \quad F(x, x_t, \gamma) = \begin{cases} \left(\frac{x_t}{x}\right)^\gamma & \text{for } x < x_t \\ 1 & \text{for } x > x_t \end{cases}$$

Switch transition

Physics-Informed Neural Networks (PINNs) Approach

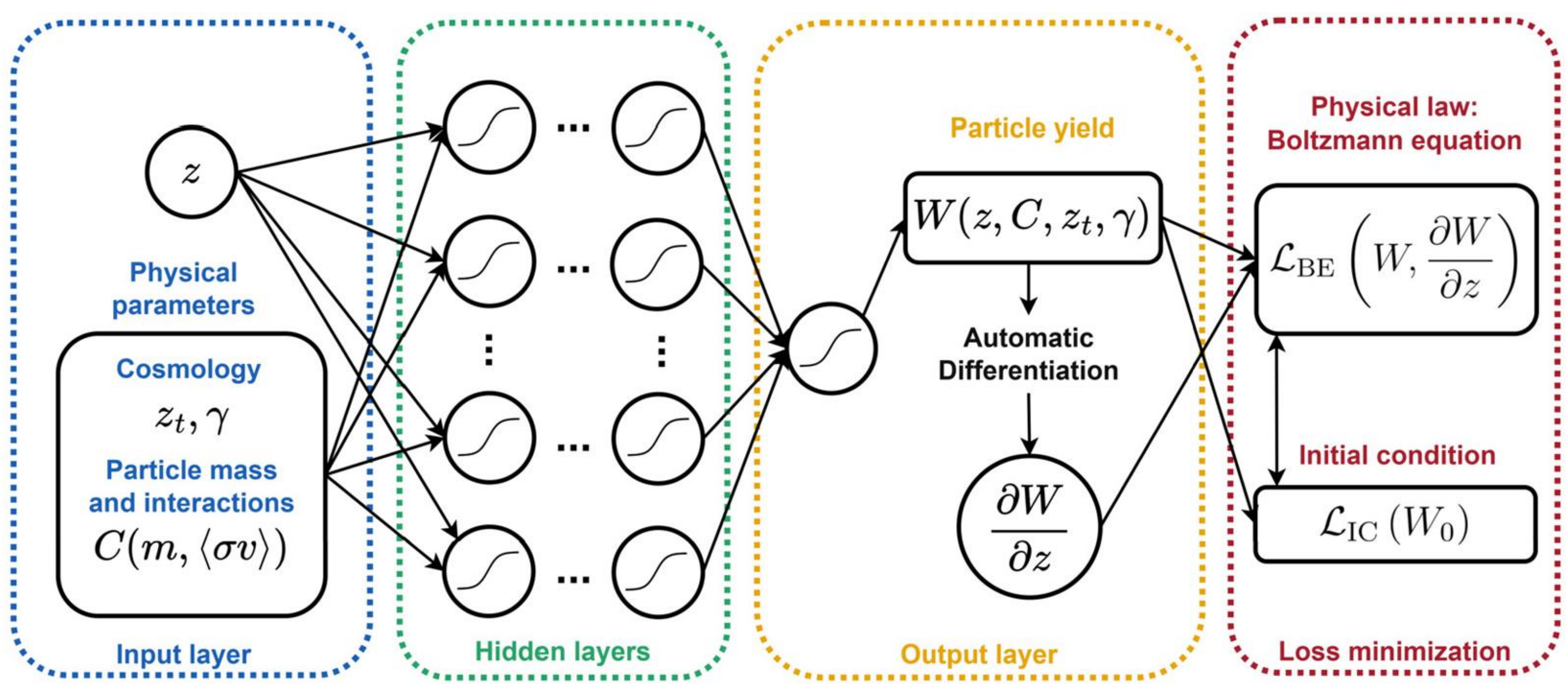
$$z \equiv \ln x$$
$$W(z) \equiv \ln Y(z)$$

$$\mathcal{E}\left[z, W, \frac{dW}{dz}; C, z_t, \gamma\right] \equiv \frac{dW}{dz} - \exp(C - \gamma\, \text{ReLU}(z_t - z) - z + 2W_{\rm eq} - W) = 0$$

$$\exp[C(m, \langle\sigma v\rangle)] \equiv \frac{\langle\sigma v\rangle S(m)}{H(m)}$$

$$F(z, z_t, \gamma) = \exp\left[\gamma\, \text{ReLU}(z_t - z)\right]$$

Forward PINNs



$$\mathcal{L}_{\rm Fwd} = \lambda_{\rm BE}\, \mathcal{L}_{\rm BE} + \lambda_{\rm IC}\, \mathcal{L}_{\rm IC}$$

Loss function is minimized during training

Residuals

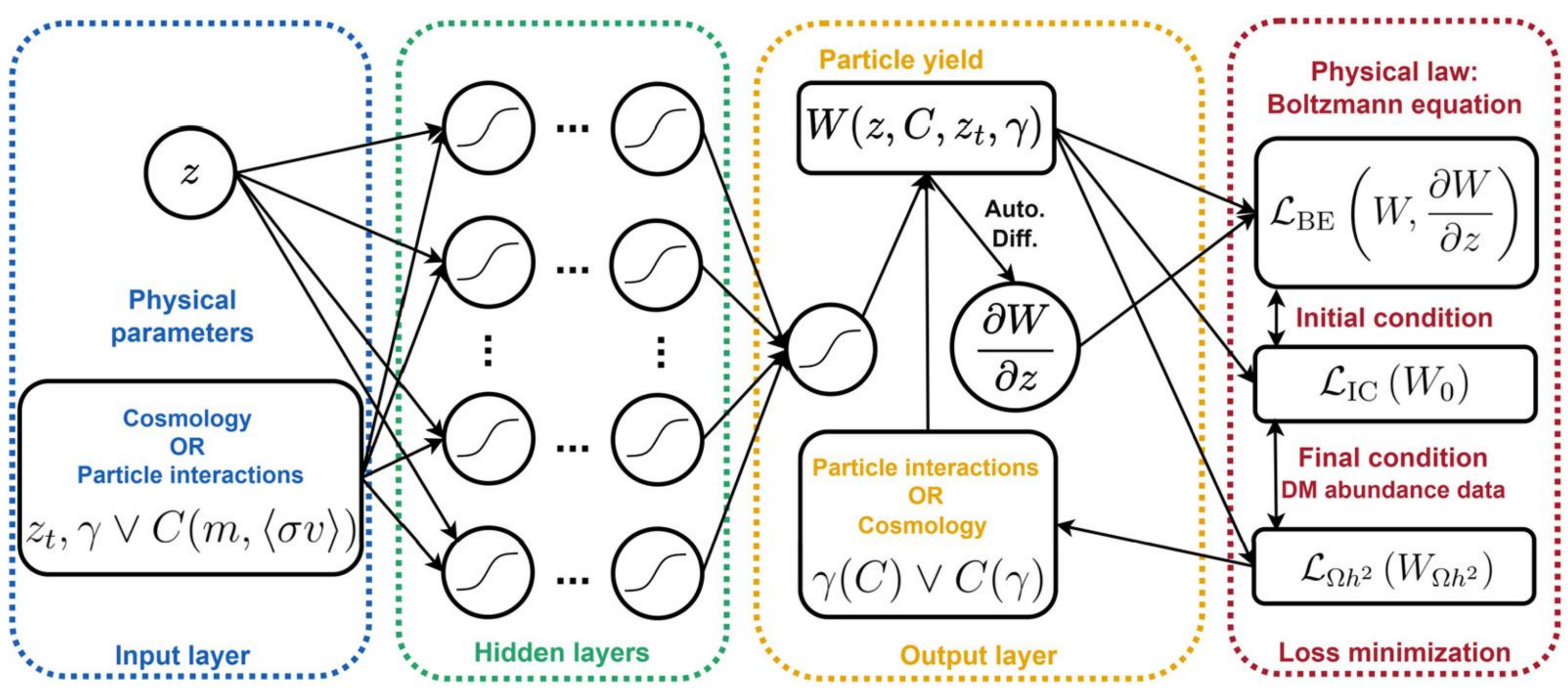
$$\mathcal{L}_{\rm BE} = \frac{1}{N_z}\sum_{j=1}^{N_z}\left|\mathcal{E}\left[z_j, W(z_j), \frac{dW}{dz}(z_j); C, z_t, \gamma\right]\right|$$

Initial condition

$$\mathcal{L}_{\rm IC} = |W(z_0) - W_0||$$

Given a physical theory, what testable predictions does it lead to ?

Inverse PINNs



$$\mathcal{L}_{\rm Inv} = \mathcal{L}_{\rm Fwd} + \lambda_{\Omega h^2}\, \mathcal{L}_{\Omega h^2}$$

Final condition: data DM relic density

$$\mathcal{L}_{\Omega h^2} = |W(z_f) - W_{\Omega h^2}|$$

Given the experimentally observed data, what are the physical theories that can explain this data ?

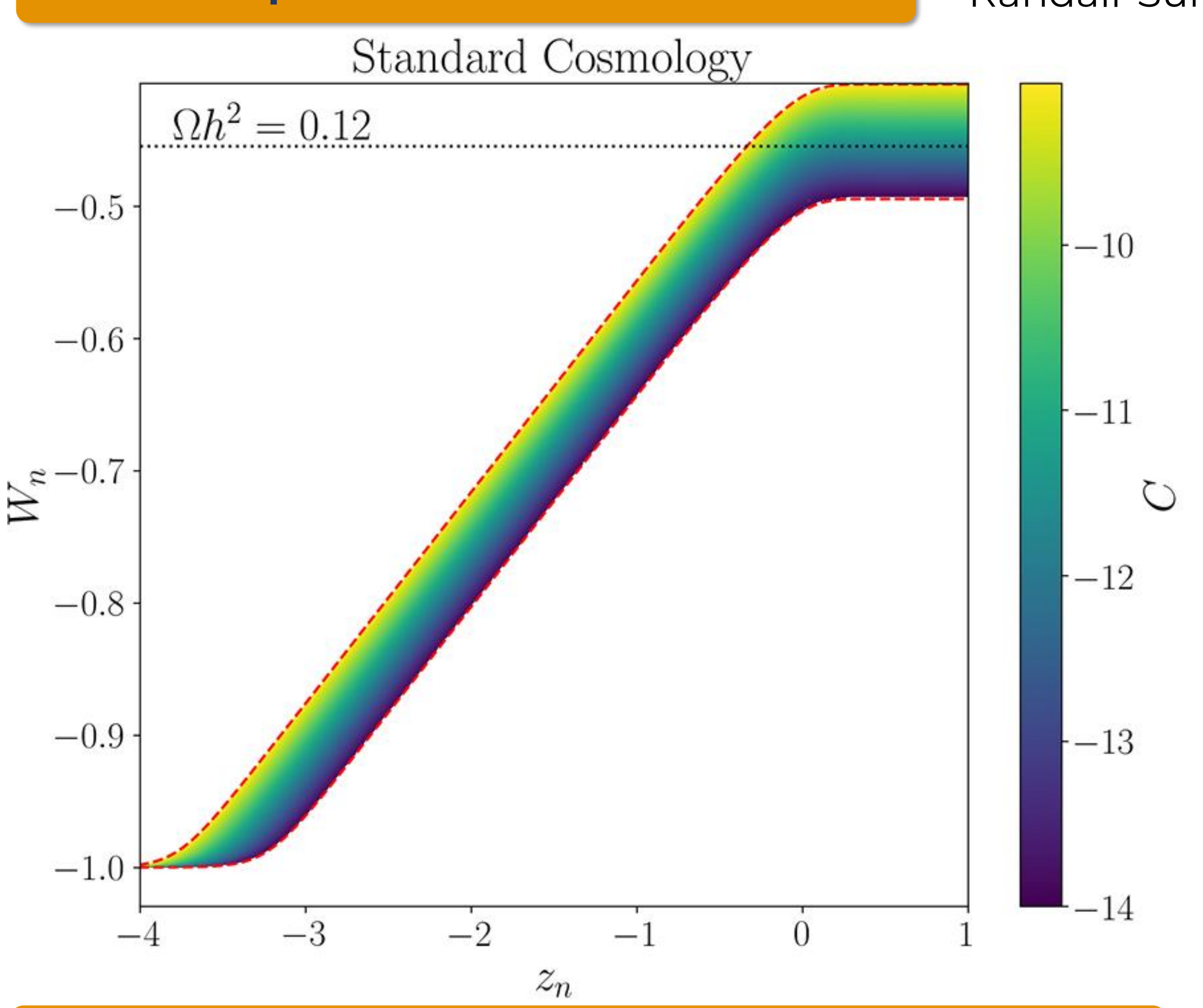
Results

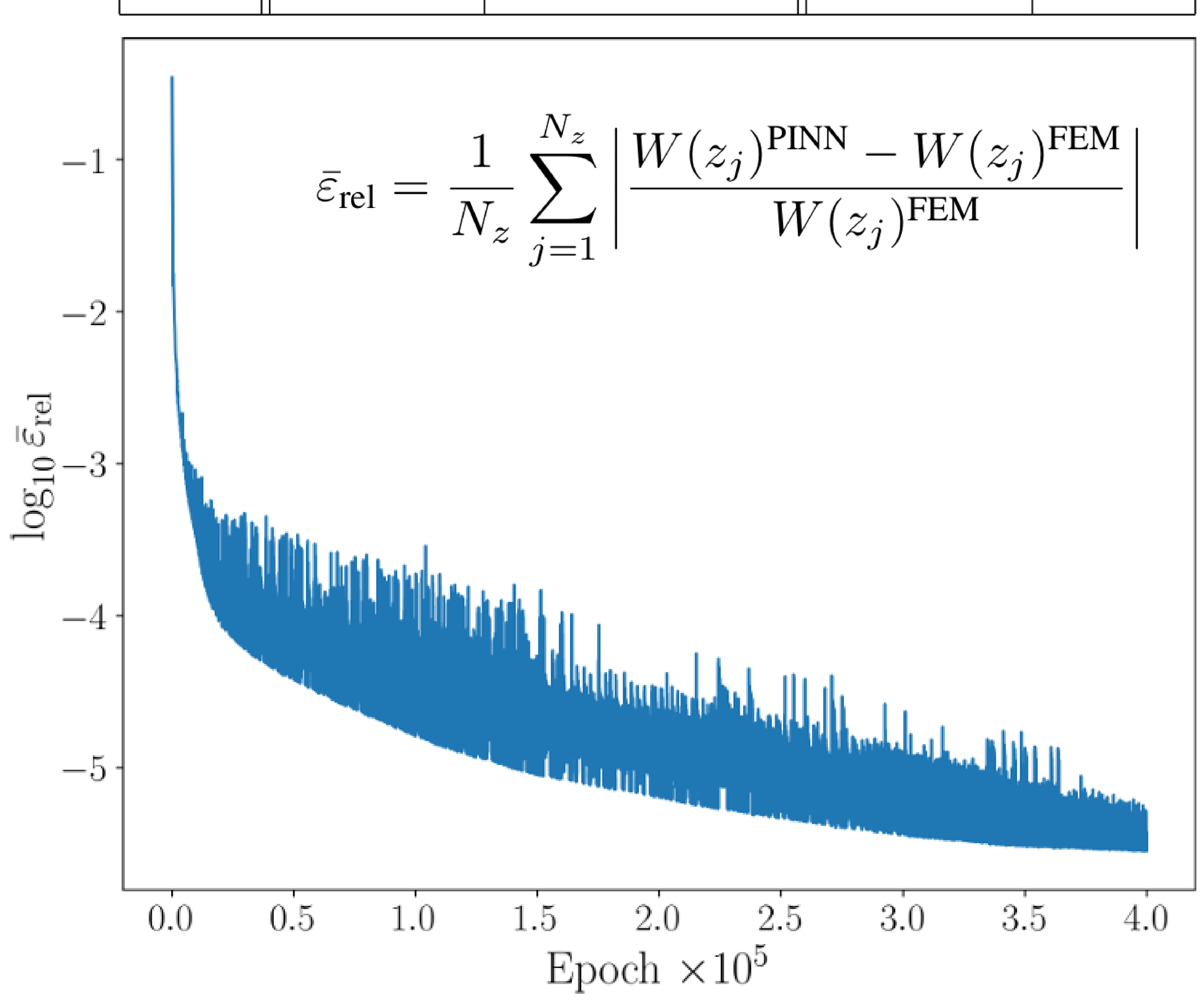
PINNs provide a valuable model-building theory tool useful in unraveling theories that can explain data.

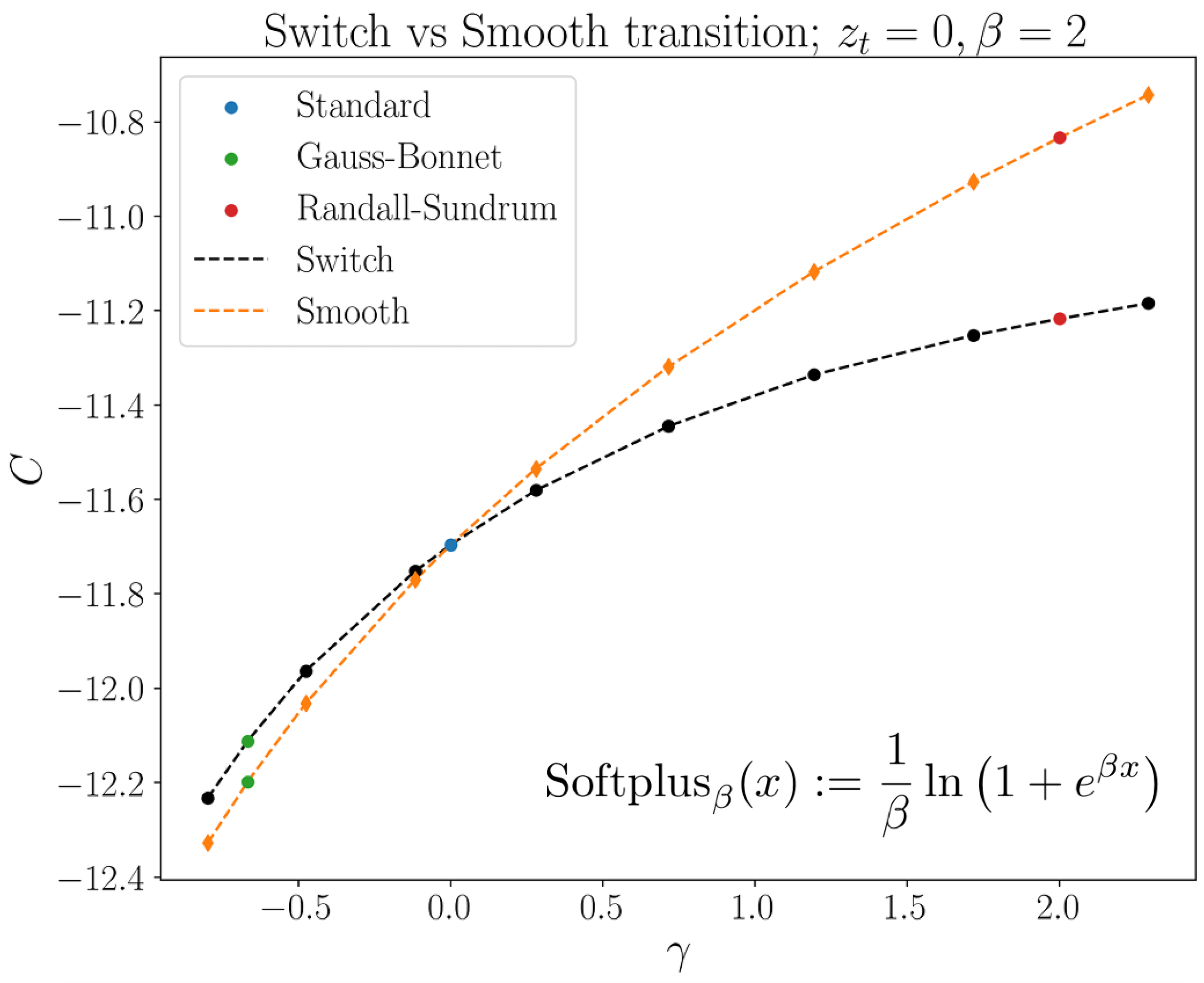
	γ	$C_{\rm PINN}$	$\langle\sigma v\rangle$ (GeV^{-2})	$W(z_f)_{\rm FEM}$	$\Omega h^2_{\rm FEM}$
Gauss-Bonnet	$-2/3$	-13.5806	3.9245×10^{-28}	-26.1588	0.1200
Standard	0	-11.6963	2.5825×10^{-27}	-26.1585	0.1200
Randall-Sundrum	2	-7.4961	1.7225×10^{-25}	-26.1580	0.1201

Smooth transition

$$\frac{dW}{dz} - \exp(C - \gamma\, \text{Softplus}_\beta(z_t - z) - z + 2W_{\rm eq} - W) = 0$$







Parametric Forward PINN solution predicts relic abundance value for a range of particle interaction values: mesh-free method

Comparison with finite element method shows that PINN accuracy is below 0.001 % at the end of training

Inverse PINNs find relation between particle interaction values and alternative cosmology exponents. FEM are not inherently designed for such inverse inference.