Scrutinising cosmic ray accelerators with spectral features

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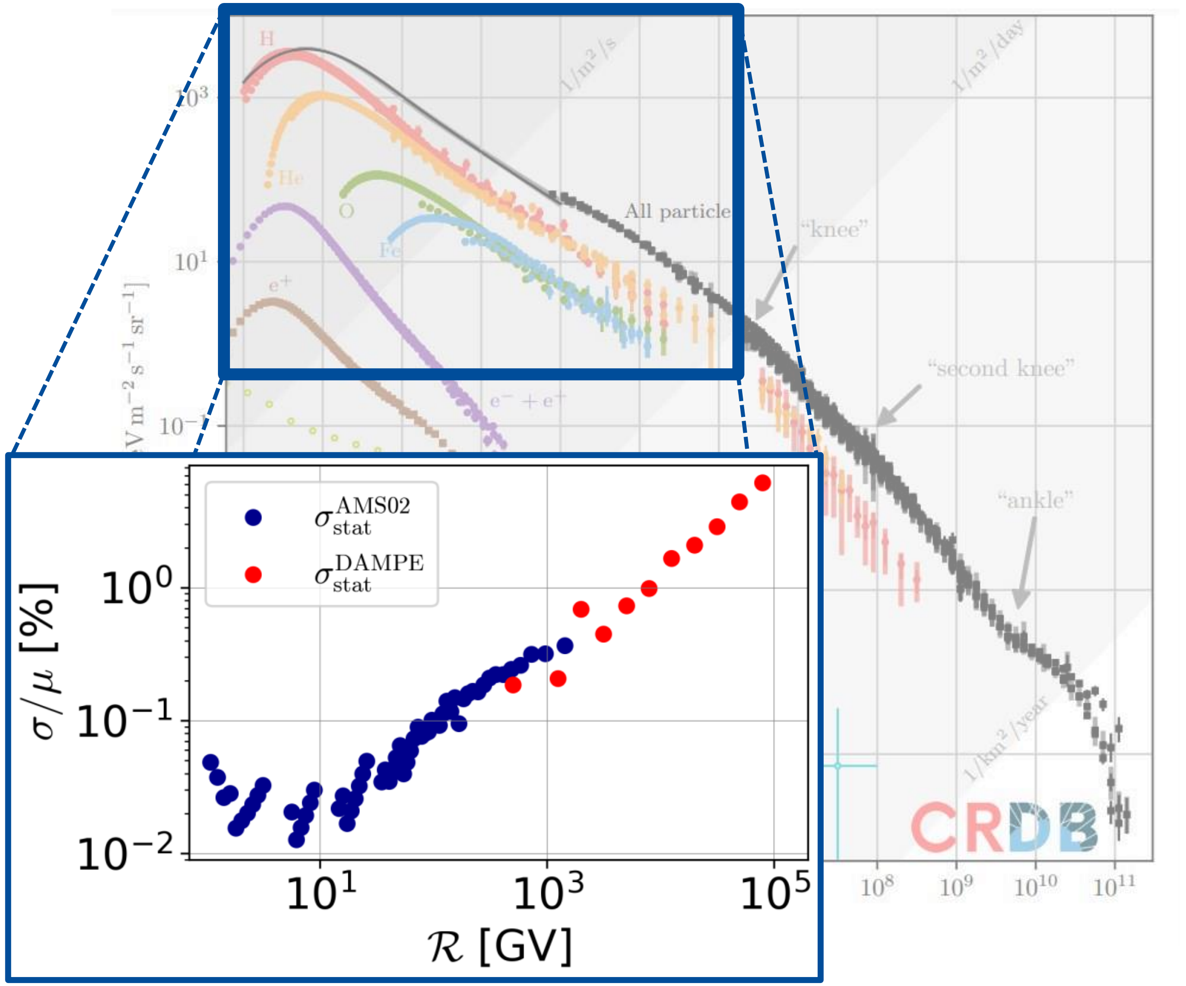
Cosmic ray sources

Long-standing questions

What are the sources of cosmic rays?

How can galactic cosmic rays reach **PeV** energies?

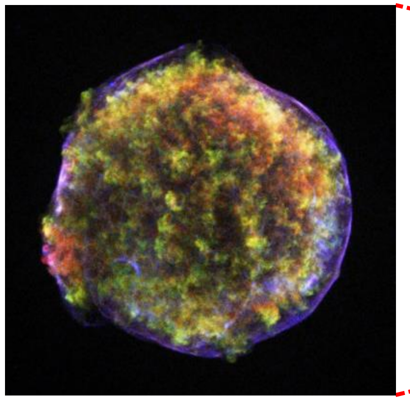
How do cosmic rays **escape** their sources?



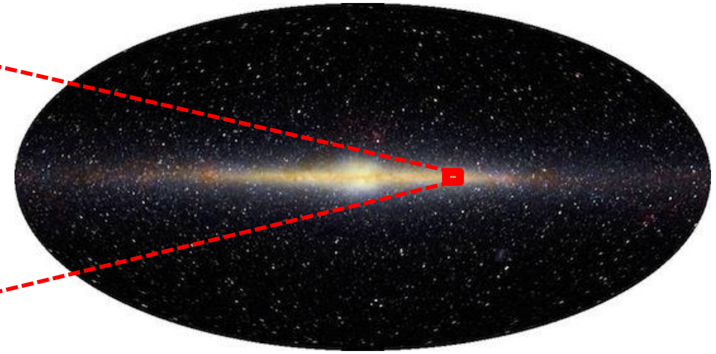
Aguilar et al., PhR 894, 1 (2021)
An et al., SciA 5, eaax3793 (2019)

[CRDB – 2023]

Source scales



$\mathcal{O}(10\ pc)$



$\mathcal{O}(10\ kpc)$

CR sources are point-like on Galactic scales.

- losses for protons above some 10 GV dominated by escape from Galaxy
- escape if $L_{diff} = \sqrt{2\kappa t} \approx z_{max}$

➢ **At 10 GV, 100 times more sources contribute than at 100 TV.**

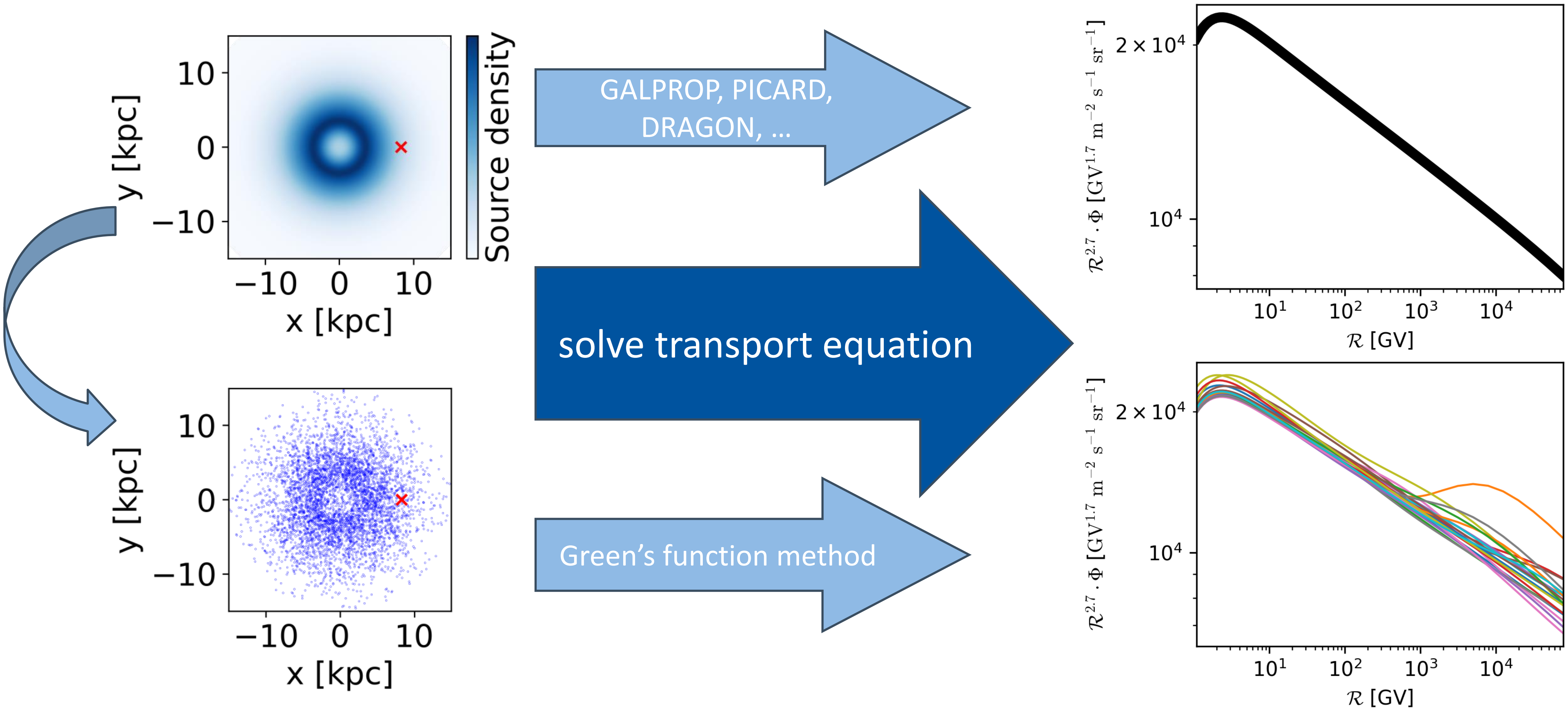
- lifetime of SNR ~100 kyr

$$t_{\mathrm{inj}}(\mathcal{R}) \ll t_{\mathrm{transp}}(\mathcal{R})$$

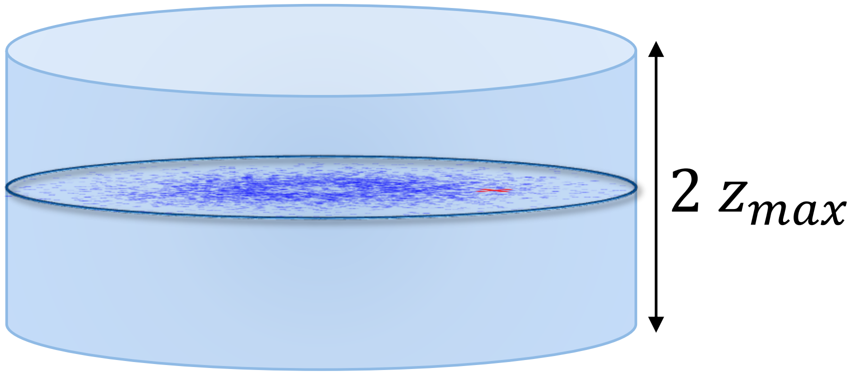
➢ **Most sources are modeled well by a burst-like injection.**

NASA/CXC/Rutgers/J.Warren & J.Hughes et al. - http://chandra.harvard.edu/photo/2005/tycho/ (25.03.2024)
E. L. Wright/UCLA, The COBE Project, DIRBE, NASA

Smooth distribution vs. discrete sources



Stochastic source modelling – Protons



$$\kappa(\mathcal{R}) \propto \mathcal{R}^{0.6}$$

$$Q(\mathcal{R}) \propto \mathcal{R}^{-2.2}$$

Cosmic ray transport (diffusion) equation

Isotropic diffusion coefficient

Burst-like injection (δ-function)

$$\frac{\partial \psi(\mathbf{x}, t, \mathcal{R})}{\partial t} - \kappa(\mathcal{R}) \cdot \nabla^2 \psi(\mathbf{x}, t, \mathcal{R}) = S(\mathbf{x}, t)\, Q(\mathcal{R})$$

Diffusion term

Source term

Spectrum of CRs escaping the source region

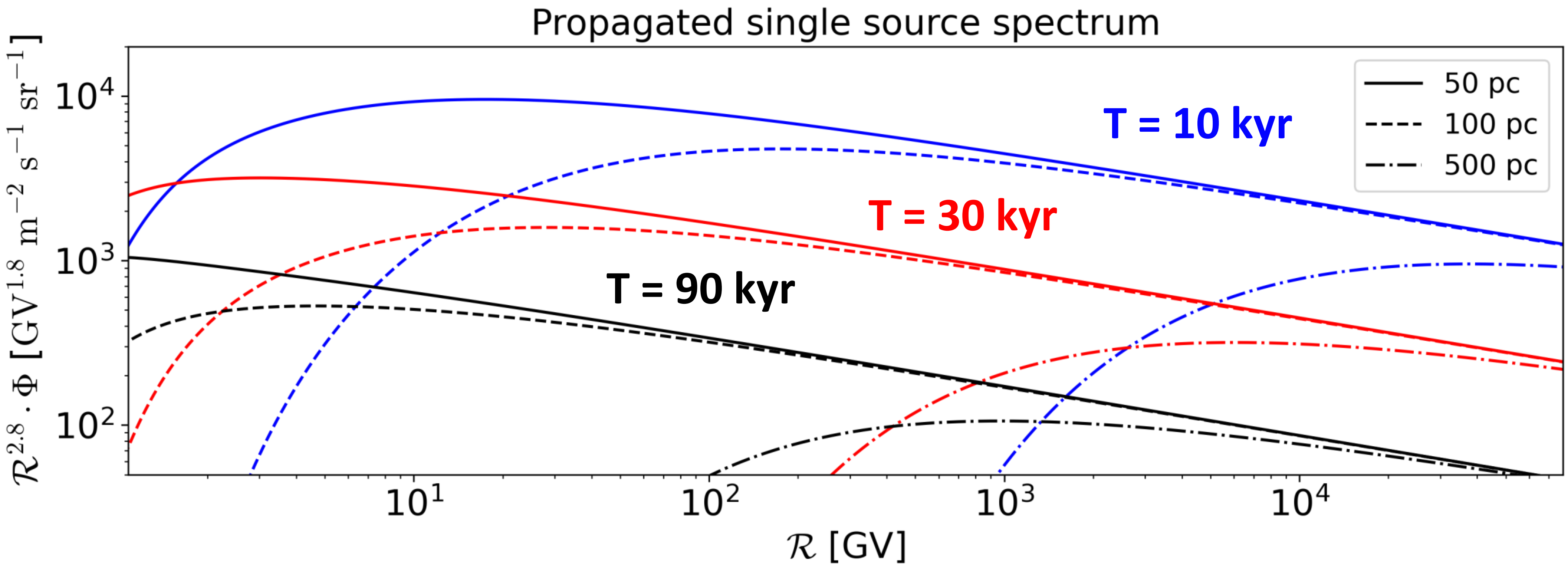
- Free escape boundary at $\pm z_{max}$
- Analytic solution for isotropic cosmic ray density ψ

$$\mathcal{R} = \frac{pc}{Ze}$$

Source modelling – BURST model

Solve cosmic ray transport equation for point source (Green's function)

$$\mathcal{L}\left[G\right](t, \mathbf{x}, \mathcal{R}; t_i, \mathbf{x}_i) = \delta\left(t - t_i\right)\delta\left(\mathbf{x} - \mathbf{x}_i\right)Q\left(\mathcal{R}\right)$$ + boundary condition



Source modelling – BURST model

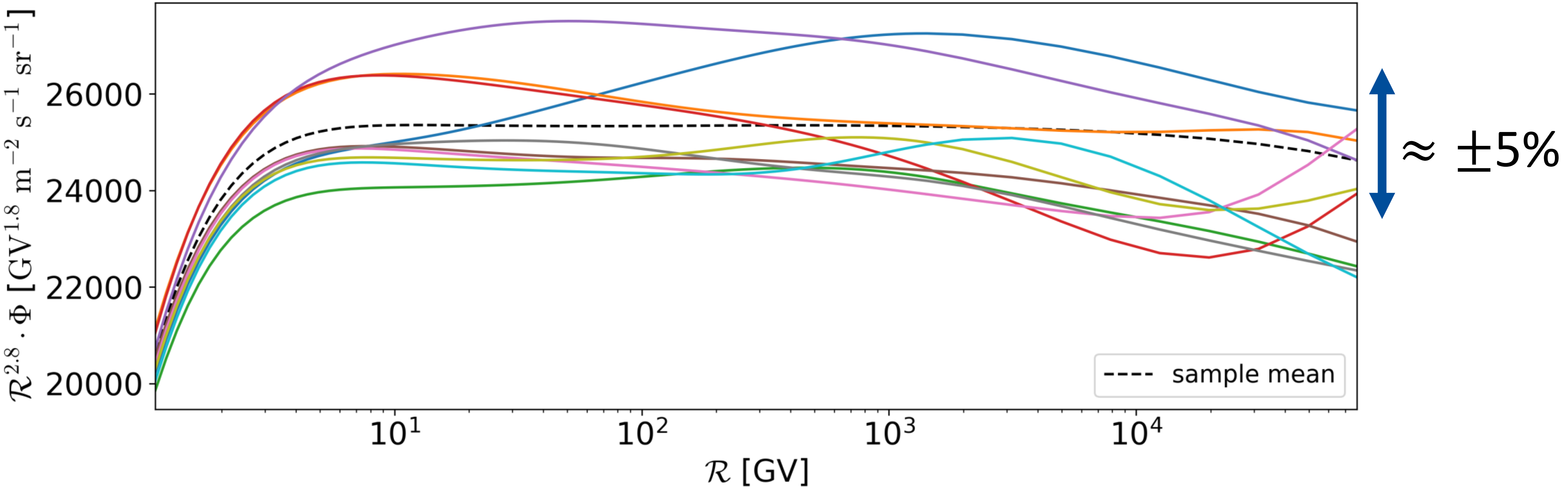
Add contributions from sources with randomly drawn positions $\mathbf{x}_i$ and ages t_i

- flux at position $\mathbf{x}_0$ and time t_0 is calculated as sum over all source contributions:

$$\Phi = \sum_{i=1}^{N} G\left(t_0, \mathbf{x}_0, \mathcal{R}; t_i, \mathbf{x}_i\right)$$

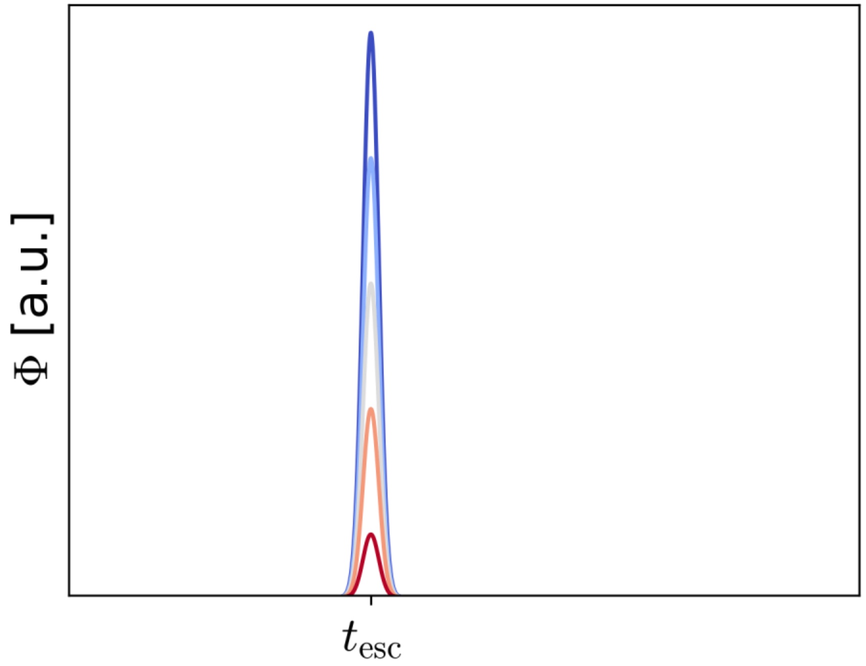
each contribution calculated **the same way**

contributions can be calculated in **parallel**

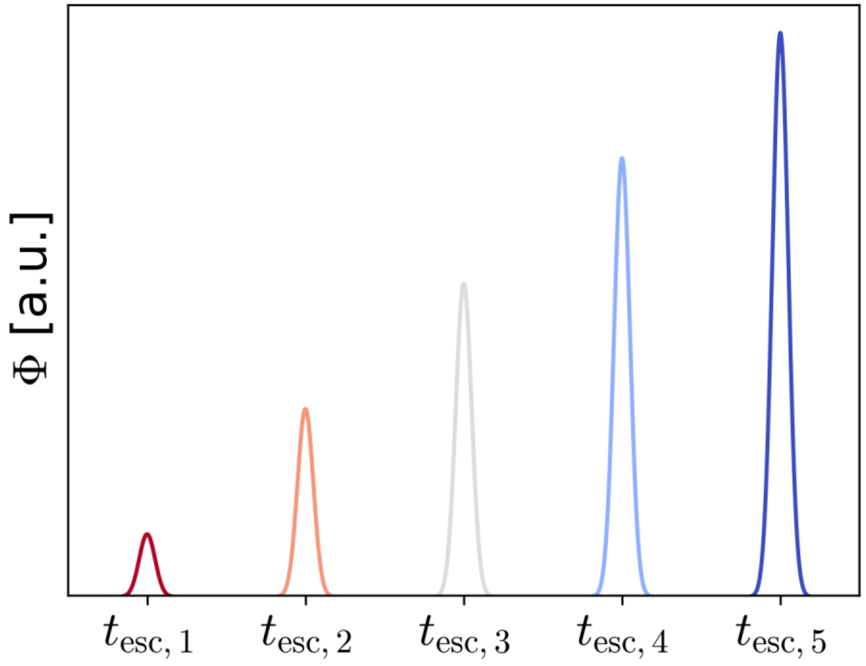


CREDIT – Cosmic Ray Energy Dependent Injection Times

BURST model



CREDIT model



- all rigidities are injected at once
- **does not account for mechanisms that confine cosmic rays around sources**

- high rigidity particles injected first
- **Why?**

Motivation for escape history

- **Maximum rigidity** achievable in diffusive shock acceleration **around 10 TV** (much lower than CR knee at some PeV) [Lagage, Cesarsky 1983]

➢ **Magnetic field amplification** ([Bell 2004] and many more) due to coupling of cosmic rays with MHD waves

Ejecta dominated phase → Sedov-Taylor phase (after ~1 kyr)

- Particles are accelerated up to multiple PV ($\mathcal{R}_{max}$ increases)
- Negligible escape to upstream infinity (towards observer ☺)

CREDIT – Cosmic Ray Energy Dependent Injection Times

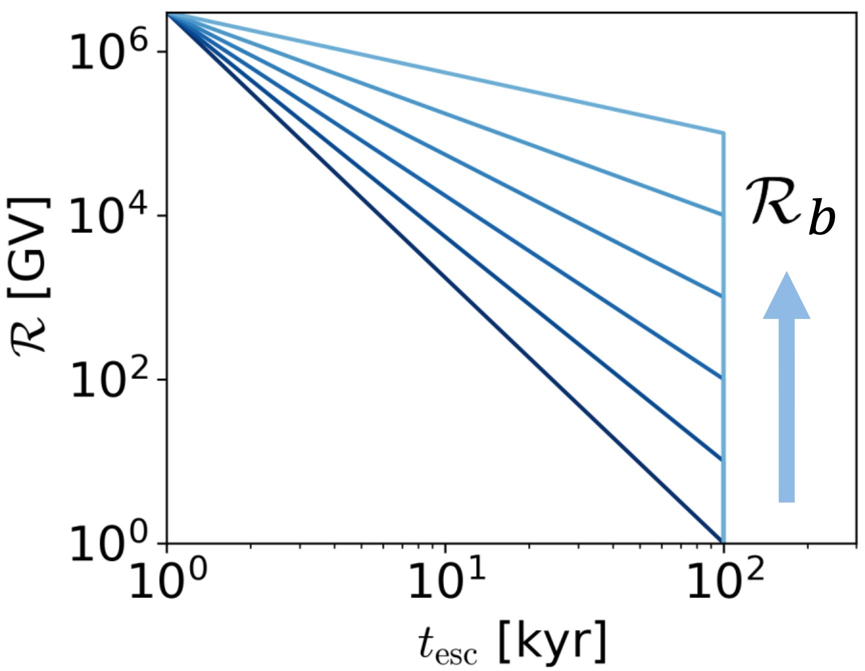
Ejecta dominated phase → Sedov-Taylor phase (after ~1 kyr)

- when mass swept up by supernova shock equals mass of ejecta

- shock slows down, magnetic field amplification less effective

$$B \downarrow \quad \Longrightarrow \quad \mathcal{R}_{\max} \downarrow$$

➢ **highest rigidity particles can escape first, lower rigidity ones later**



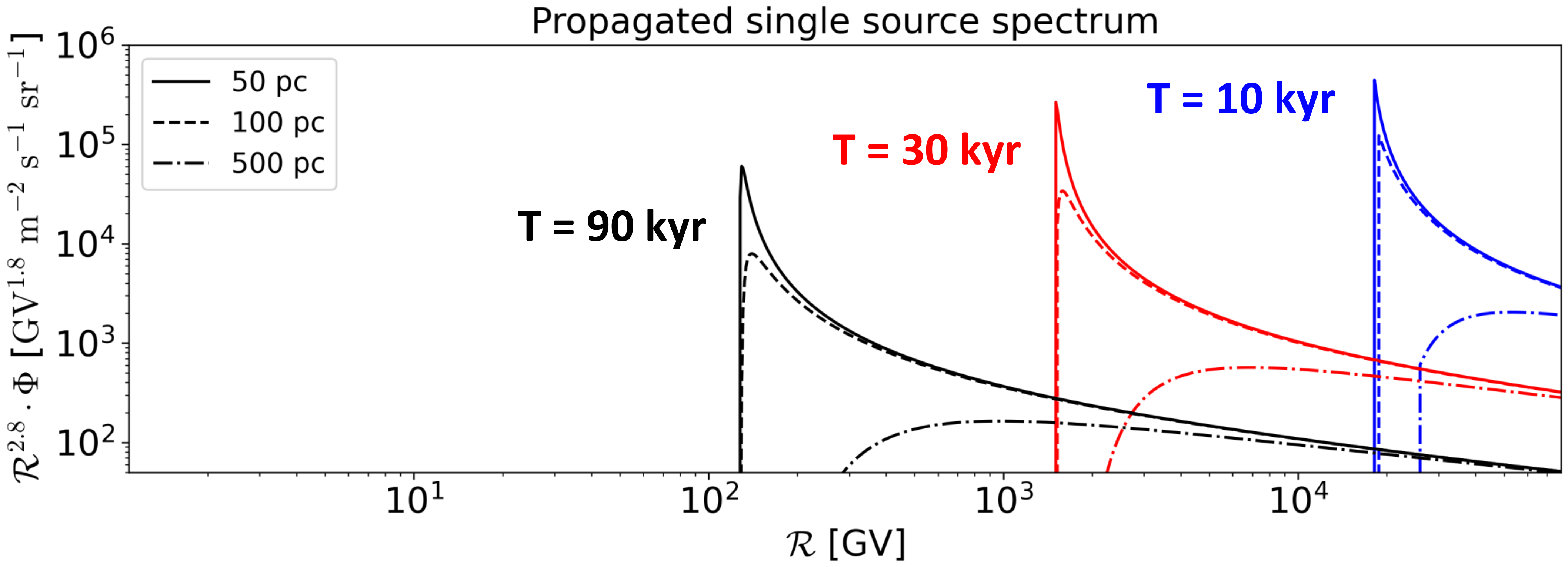
CREDIT – Cosmic Ray Energy Dependent Injection Times

Green's function

$$\mathcal{L}\left[G\right]\left(t, \mathbf{x}, \mathcal{R}; t_i, \mathbf{x}_i\right) = \delta(t_i - t_{\rm esc}(\mathcal{R}) - t)\delta(\mathbf{x_i} - \mathbf{x})Q(\mathcal{R})$$

Add contributions from N sources

$$\Phi = \sum_{i=1}^{N} G\left(t_0, \mathbf{x}_0, \mathcal{R}; t_i, \mathbf{x}_i\right)$$



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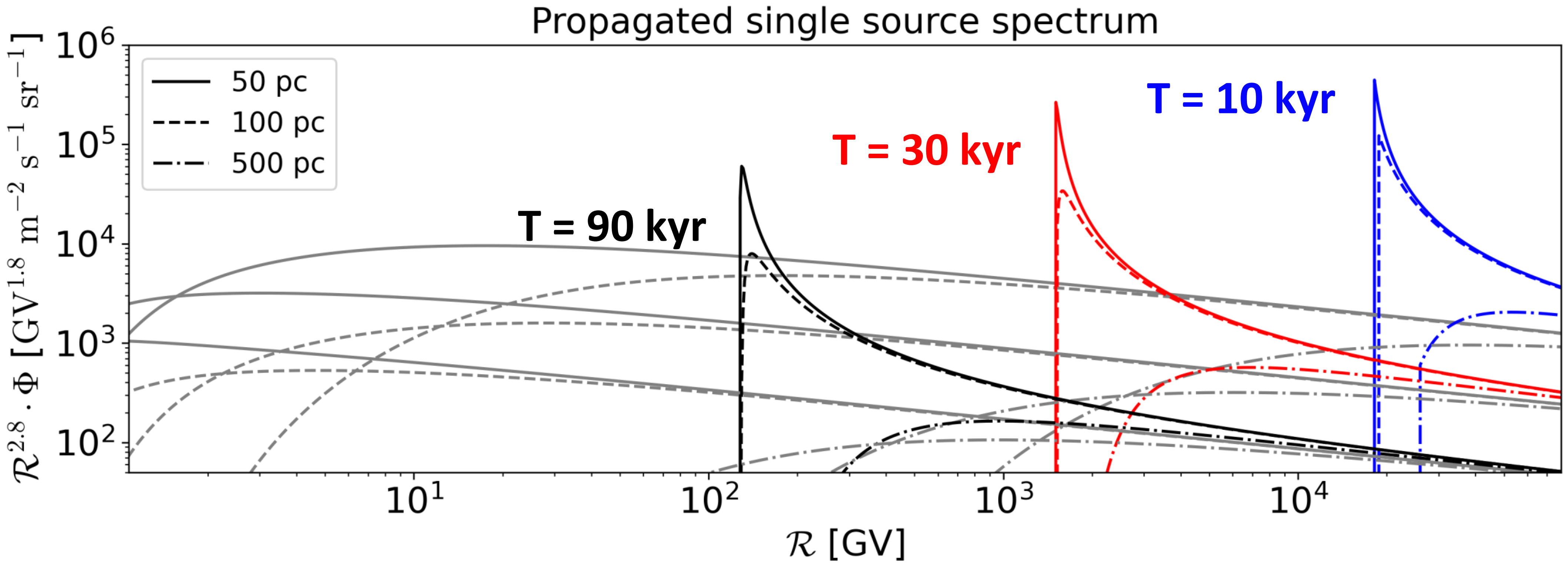

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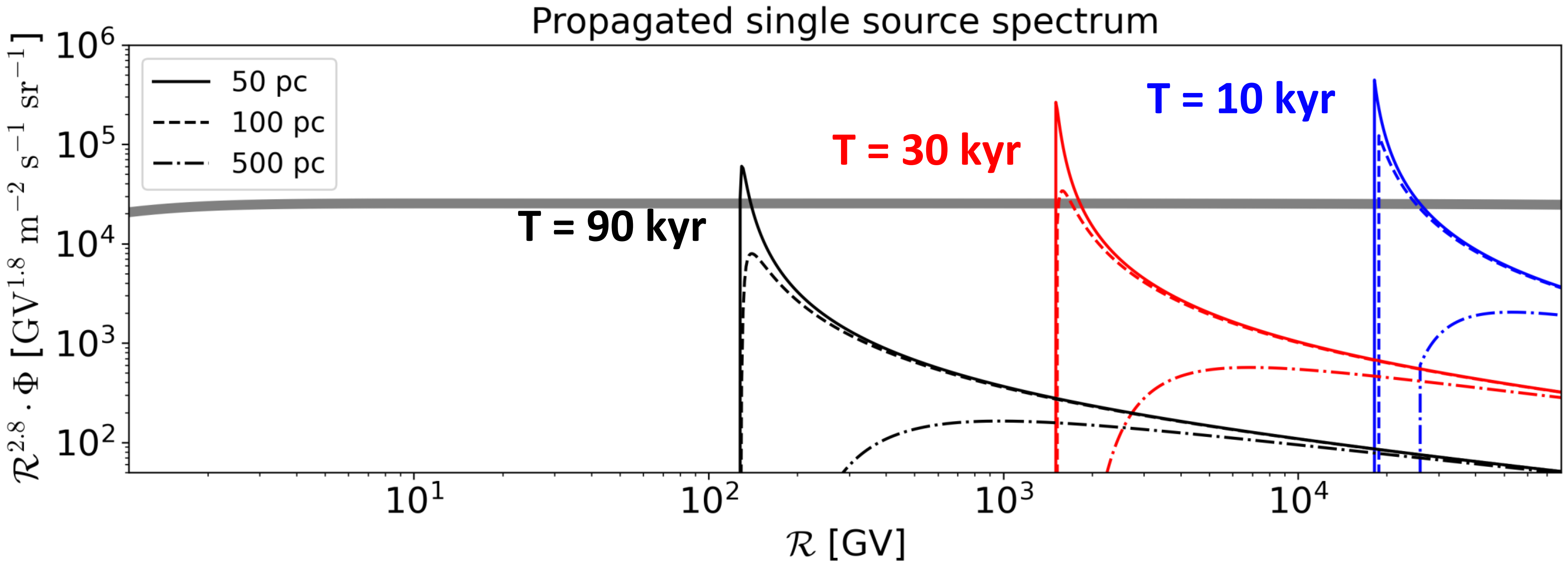

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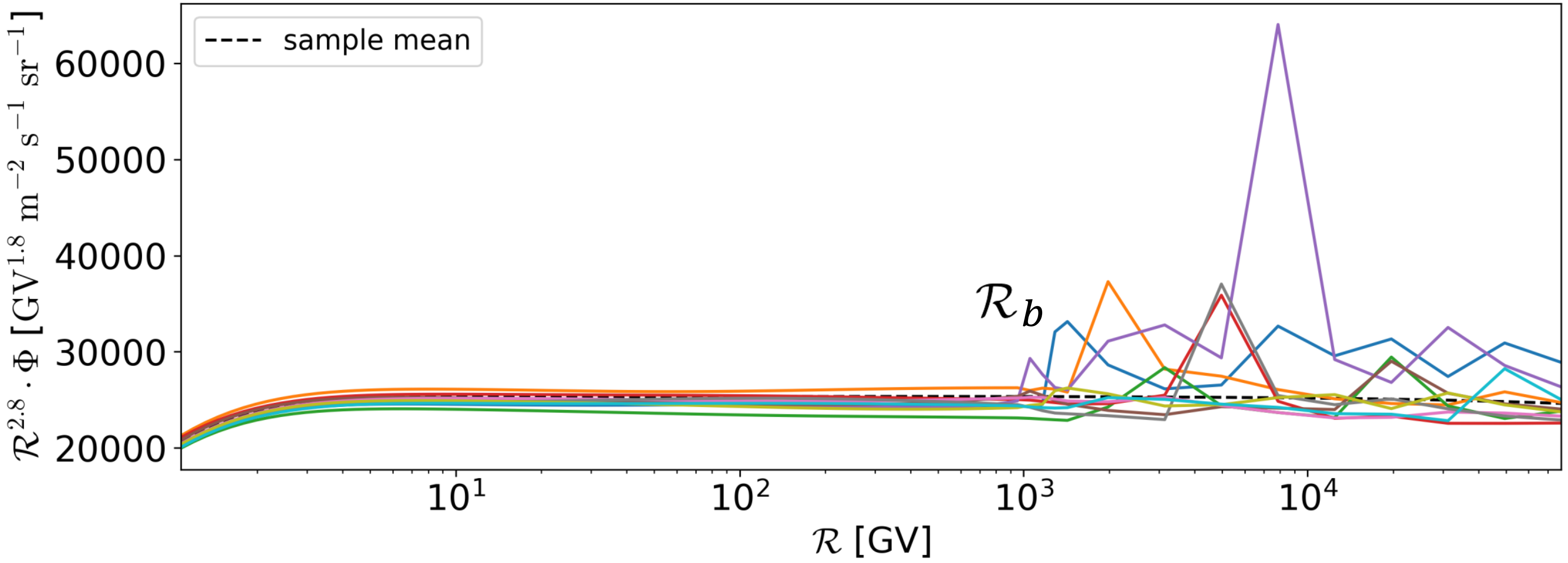
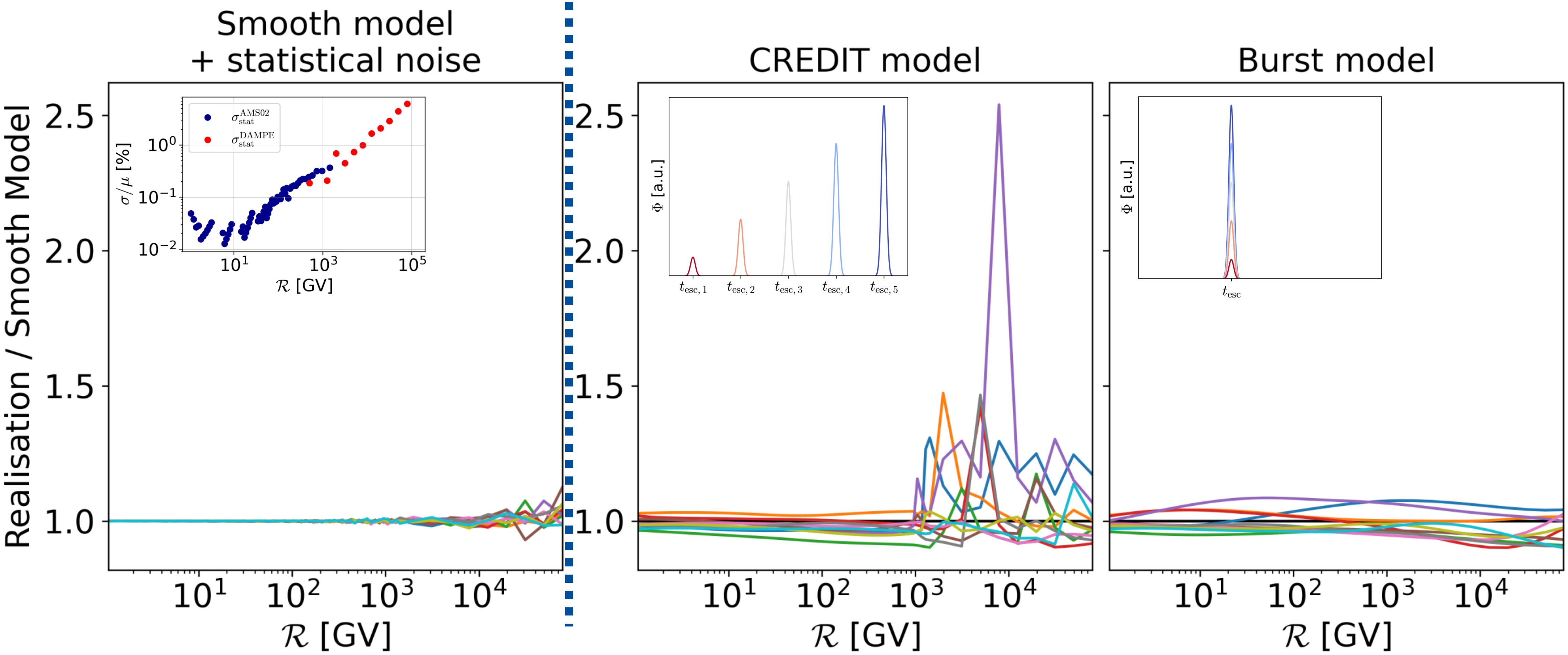


Model classification

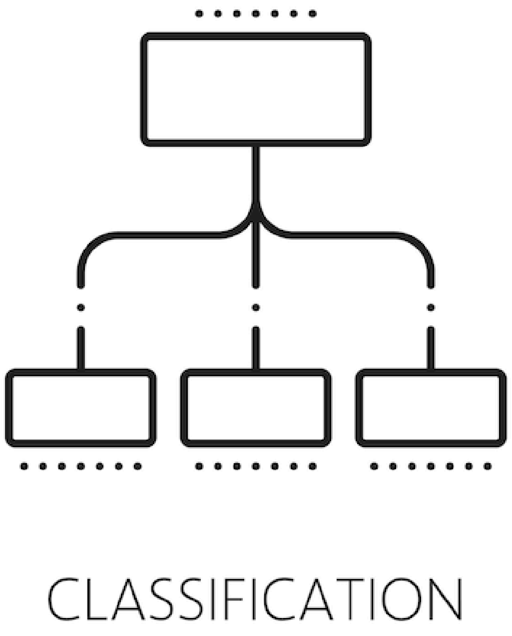


Can realisations of different models be classified reliably?

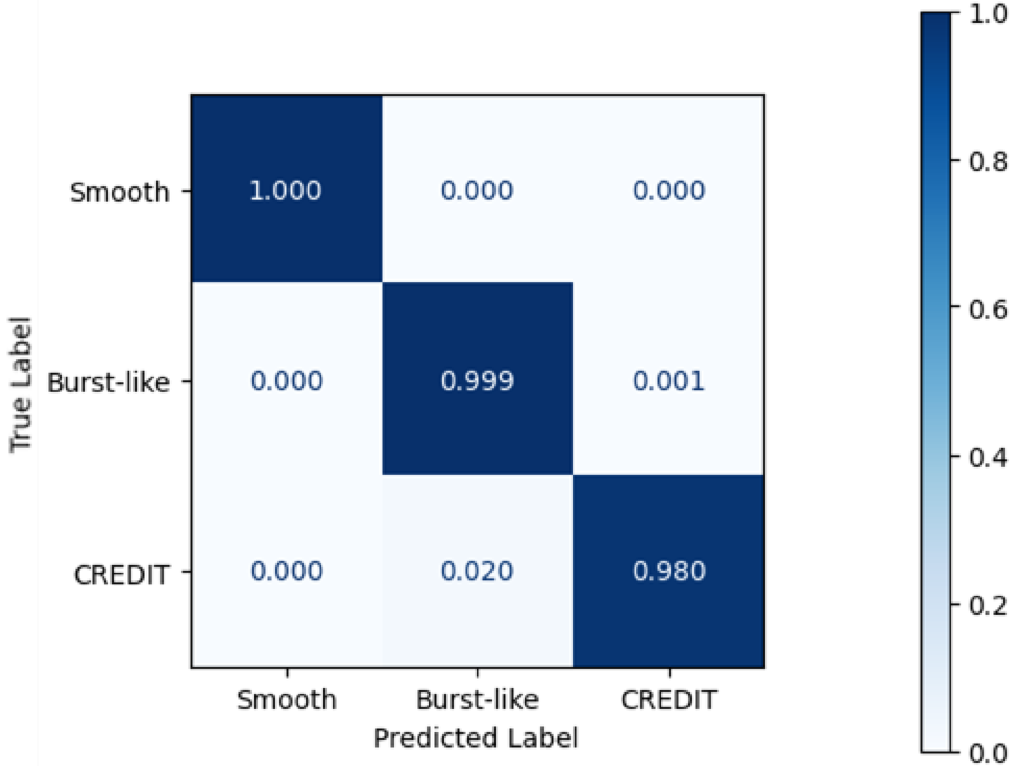
Model classification

Decision tree

Classifies input giving it a label of a certain model

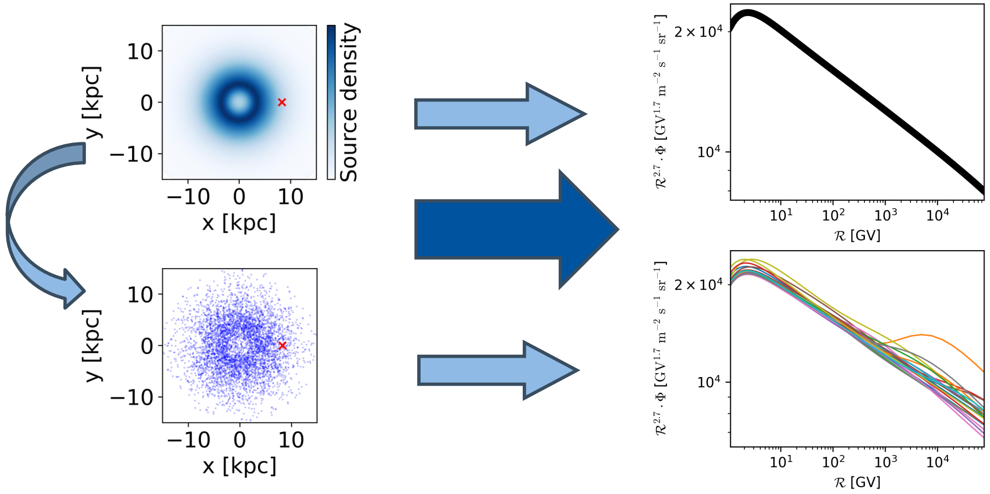


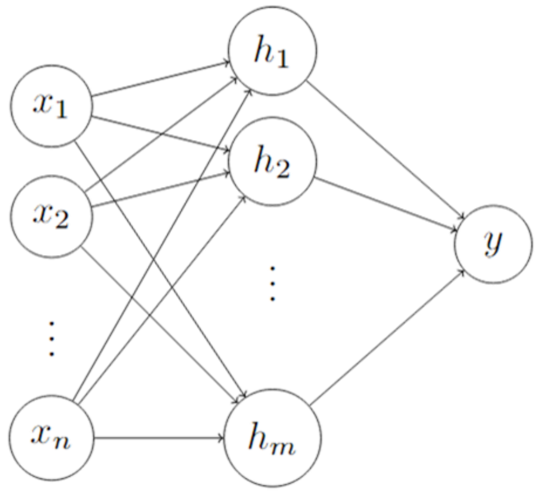
Accuracy of classification (Smooth+stat. errors) vs. (BURST/CREDIT) is on the level of 99.99%



Summary and Outlook

1. **Individual sources** must be considered for the realistic modelling.
2. **Local measurements** can be used to **constrain source properties.**
3. **Machine learning techniques** can do the **classification reliably at a level beyond 99% for this toy model.**





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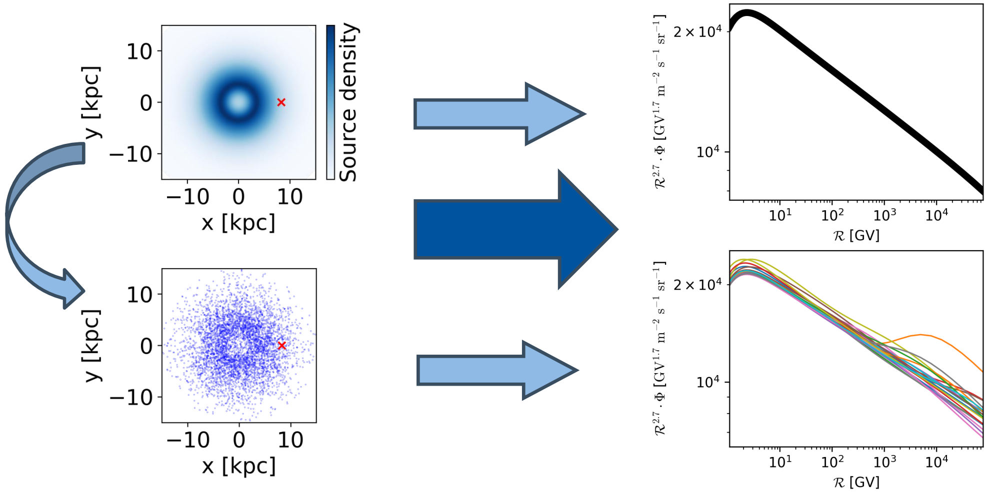
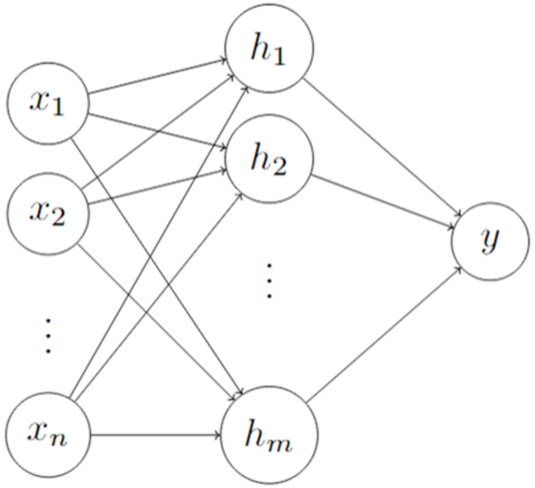




Thank you!
Questions?

Backup

Motivation for escape history

- **Maximum rigidity** achievable in diffusive shock acceleration **around 10 TV** (much lower than CR knee at some PeV) [Lagage, Cesarsky 1983]

$$\underbrace{t_{acc} \sim \frac{D}{u_{sh}^2} \qquad R_{SNR} = u_{sh}\, t_{acc}} \qquad \underbrace{\lambda_{mfp} \geq r_{Larmor} = \frac{\mathcal{R}}{B\, c}}$$

$$R_{SNR} \sim \frac{D}{u_{sh}} \sim \frac{\lambda_{mfp} c}{u_{sh}} \geq \frac{\mathcal{R}_{max}}{B\, u_{sh}}$$

$$\mathcal{R}_{max} \lesssim R_{SNR}\, B\, u_{sh} \approx 10\ \mathrm{TV} \left(\frac{R_{SNR}}{10\ pc}\right)\left(\frac{B}{1\ \mu G}\right)\left(\frac{u_{sh}}{c/30}\right)$$

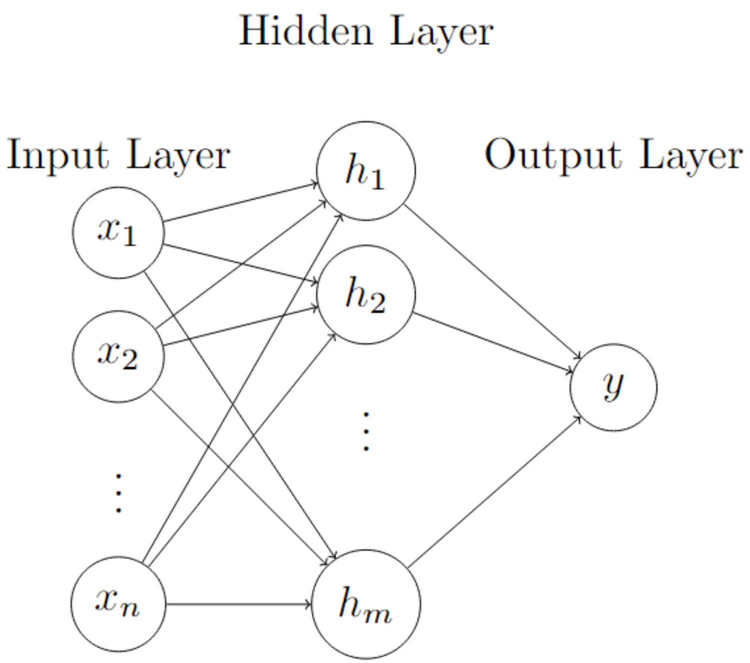
[Bell]

↑ further suppression of factor 10 with a more detailed analysis [Lagage, Cesarsky 1983]

Model classification

Neural network

classifier score between 0 (statistical fluctuations) and 1 (CREDIT model)



Classifier scores