



**Sowmiya
Balan**



**Kathrin
Nippel**



**Michael
Korsmeier**



**Silvia
Manconi**



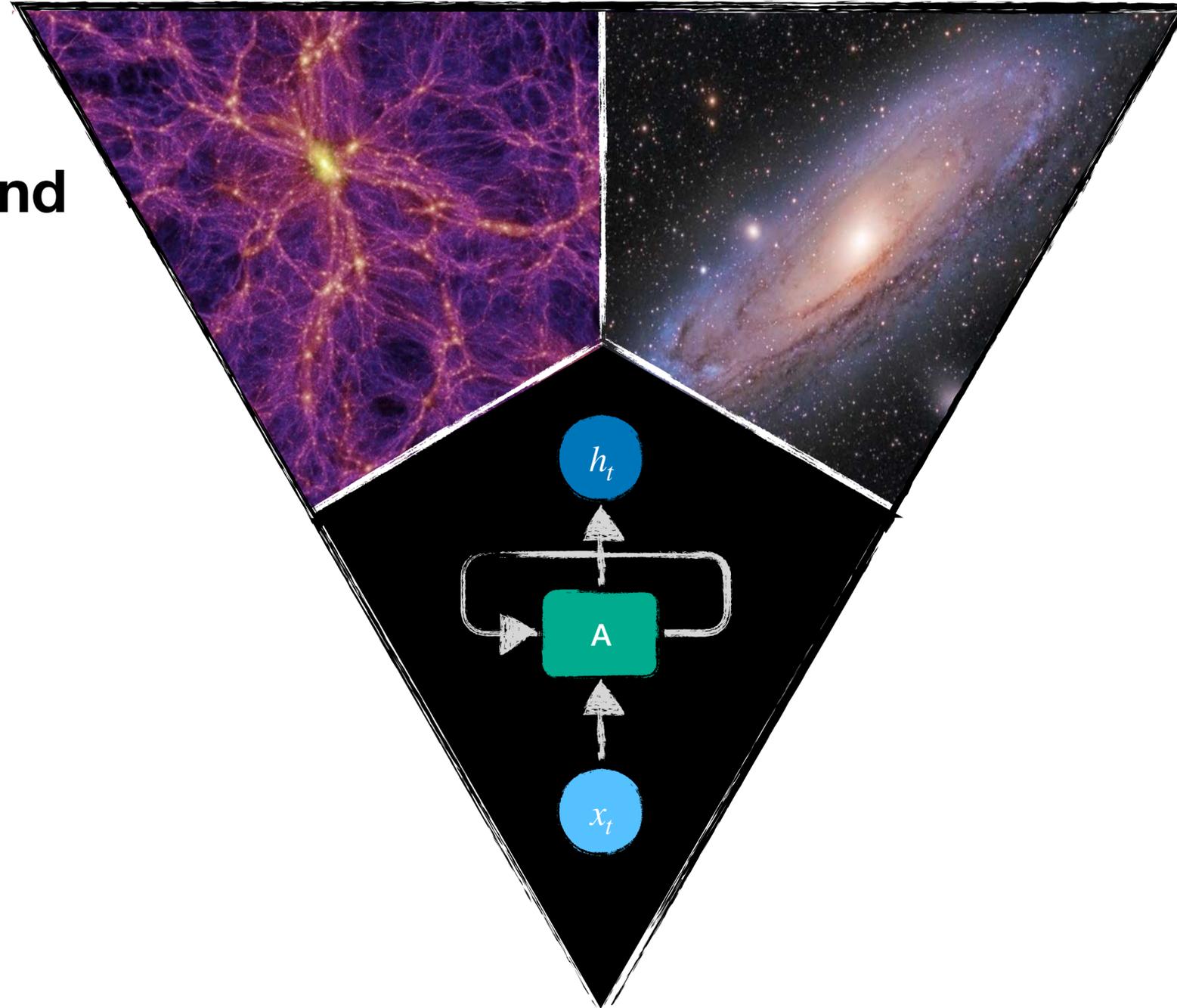
**Felix
Kahlhoefer**

Fast and Accurate AMS-02 Antiproton Likelihoods for Global Dark Matter Fits

**Balan, Sowmiya et al., JCAP 08 (2023) 052
Kahlhoefer, Felix et al., JCAP 12 (2021) 037**



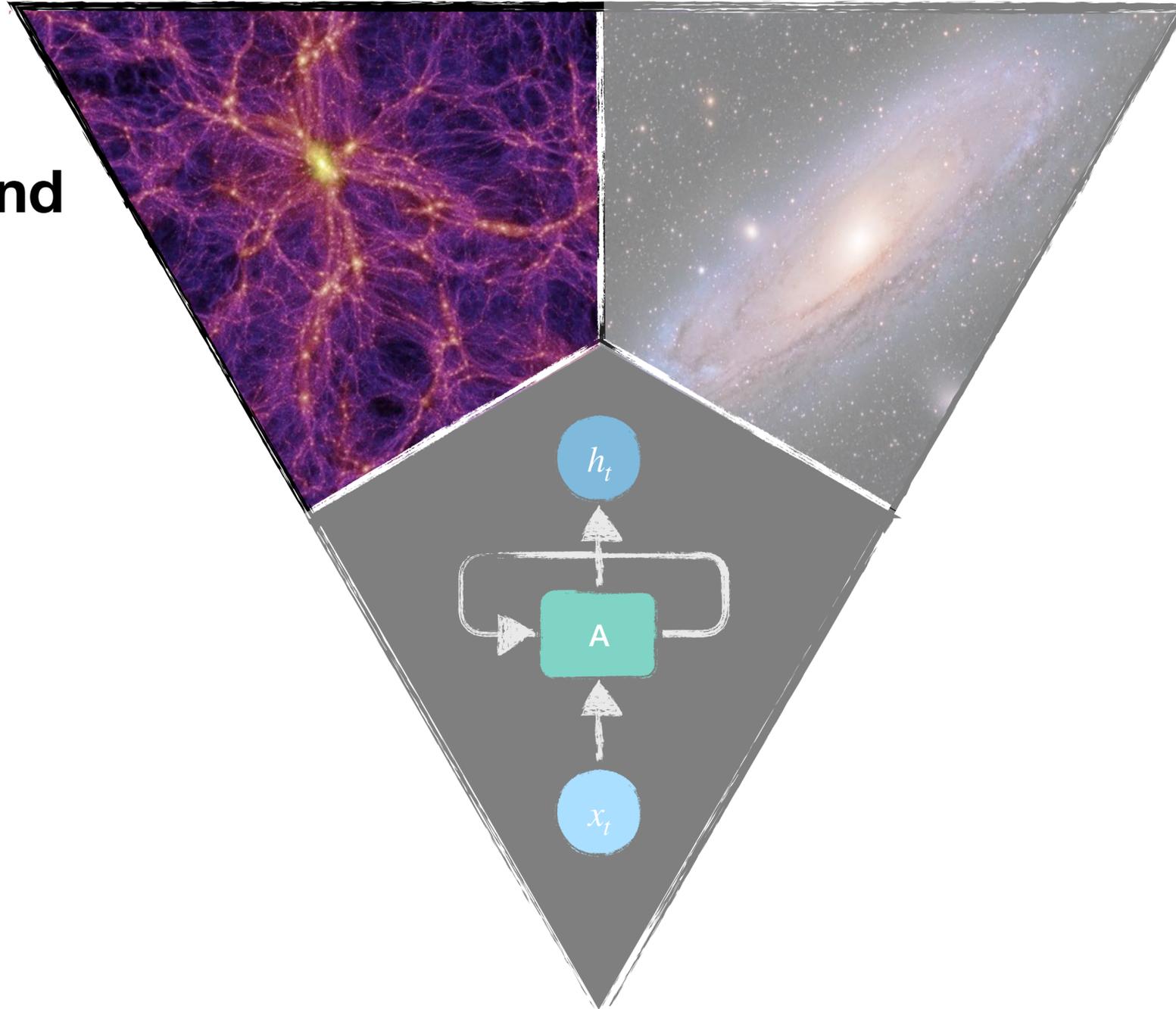
**Motivation:
Dark Matter Limits and
Indirect Detection**



**Cosmic Rays:
Propagation and the
Role of Antiprotons**

**Speed-up: Neural Networks
and Importance Sampling**

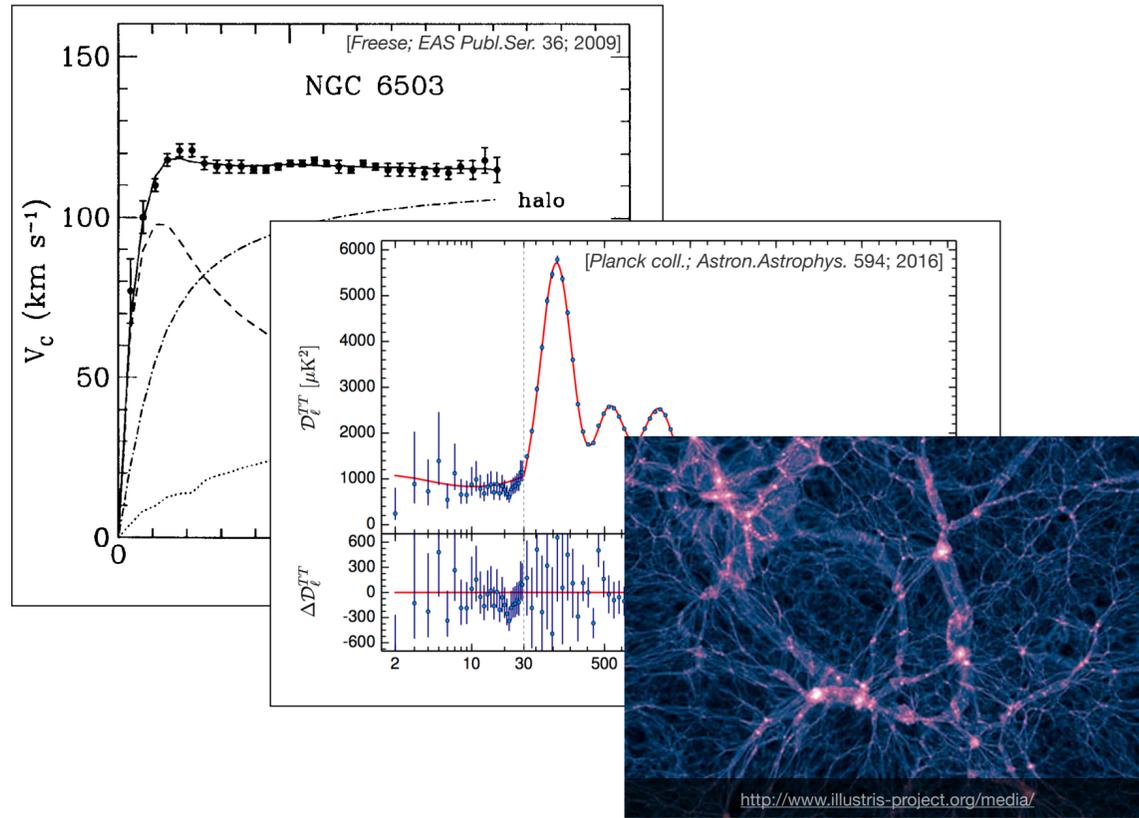
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Motivation

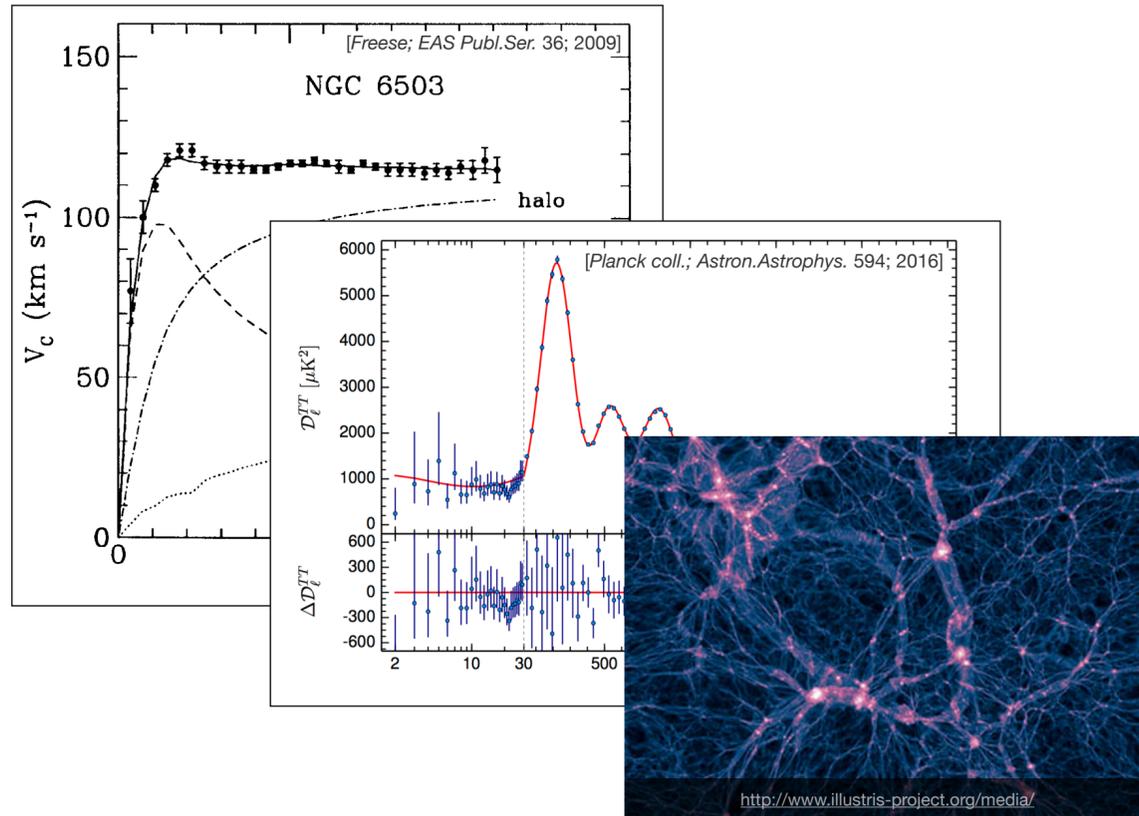


Gravitational evidence at various scales is overwhelming.

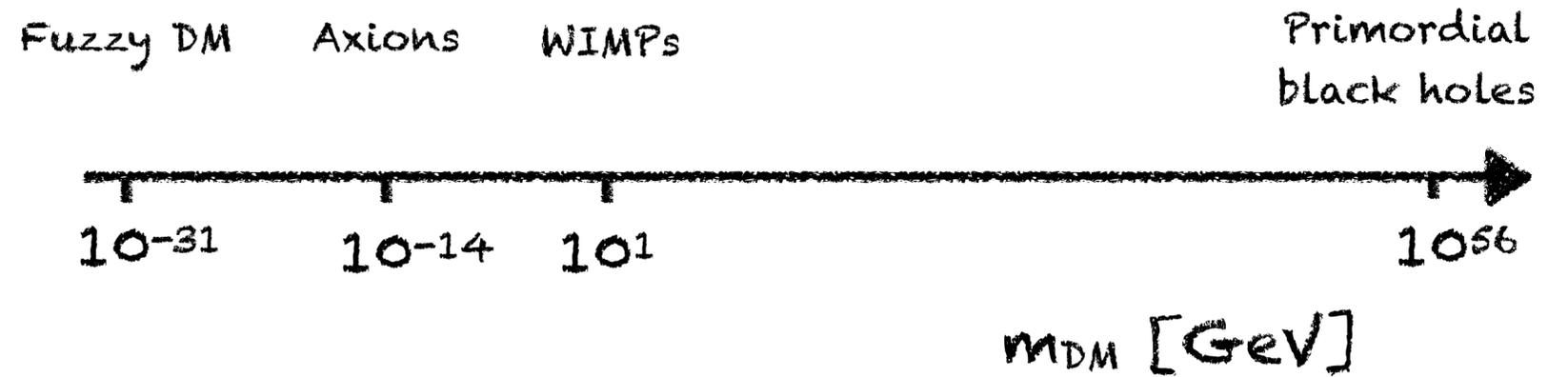


More details:
Kenny CY Ng
Tuesday, 9:00 am

Motivation



Gravitational evidence at various scales is overwhelming.

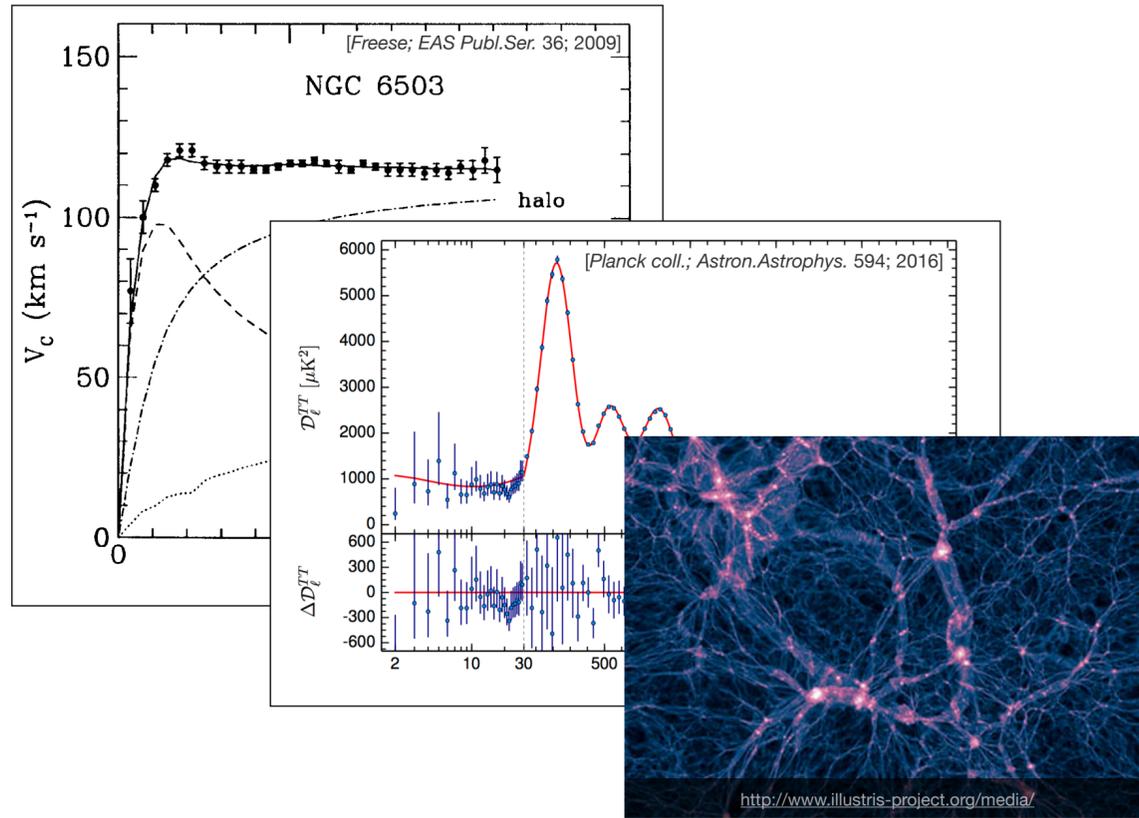


Nature of dark matter remains unknown!

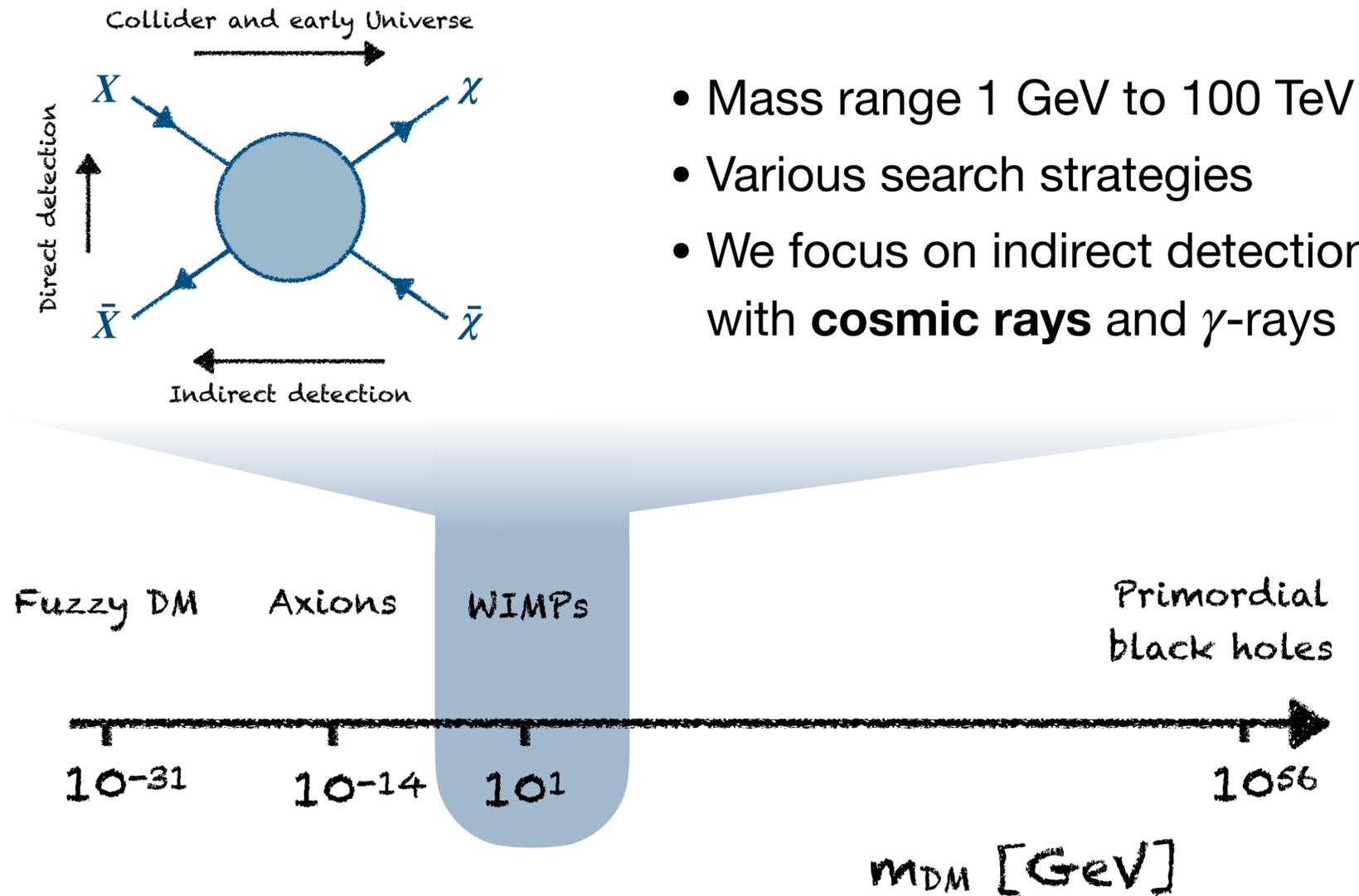


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Motivation



Gravitational evidence at various scales is overwhelming.



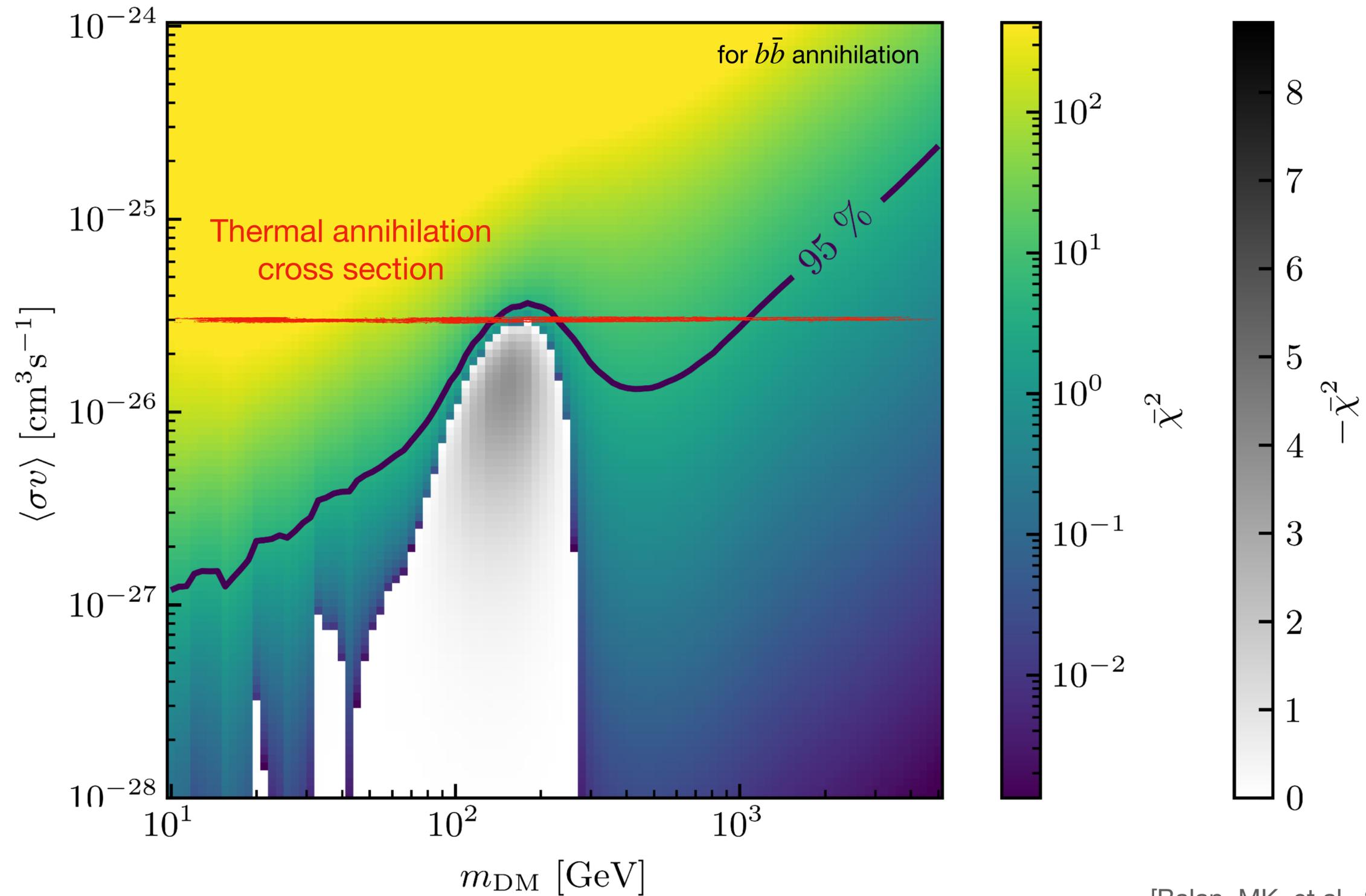
- Mass range 1 GeV to 100 TeV
- Various search strategies
- We focus on indirect detection with **cosmic rays** and **γ -rays**



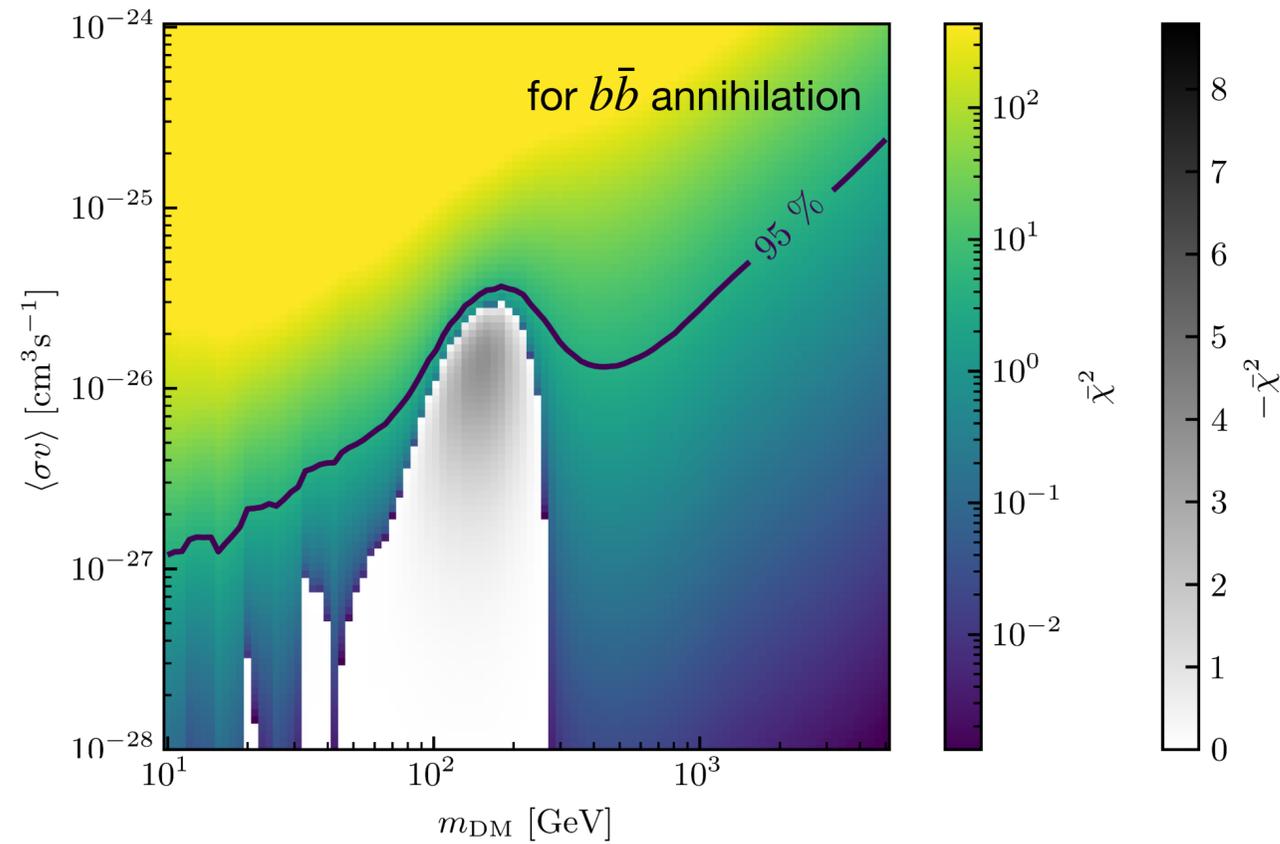
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Tuesday, 9:00 am

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Limits for DM Annihilation



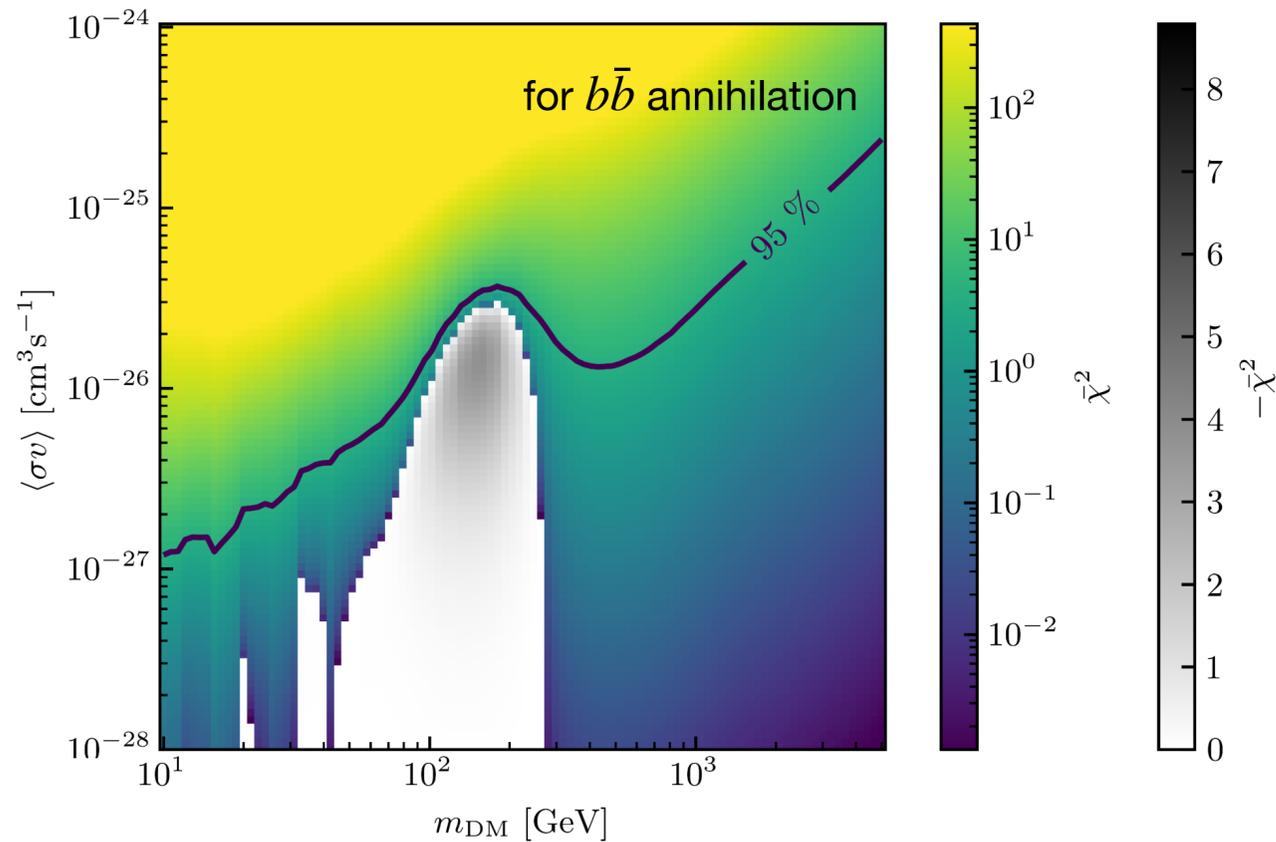
Limits for DM Annihilation



pbarLike



Limits for DM Annihilation

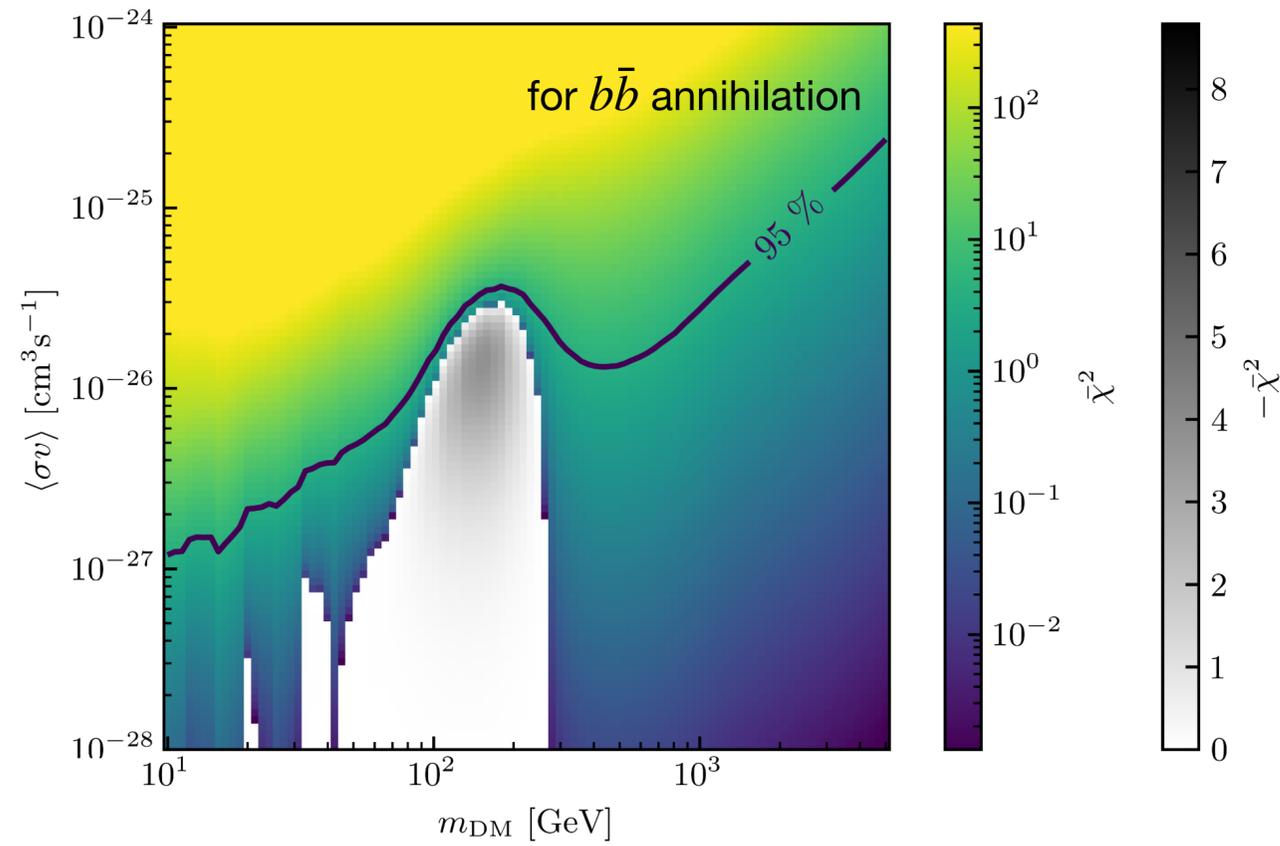


pbarlike



- Neural Network predicting CR signals
- Wide range of propagation parameters/models
- Likelihood of AMS-02 data
- Correlation, \bar{p} cross section uncertainties, marginalization over propagation
- Global fits of DM models including pbarlike

Limits for DM Annihilation



pbarLike

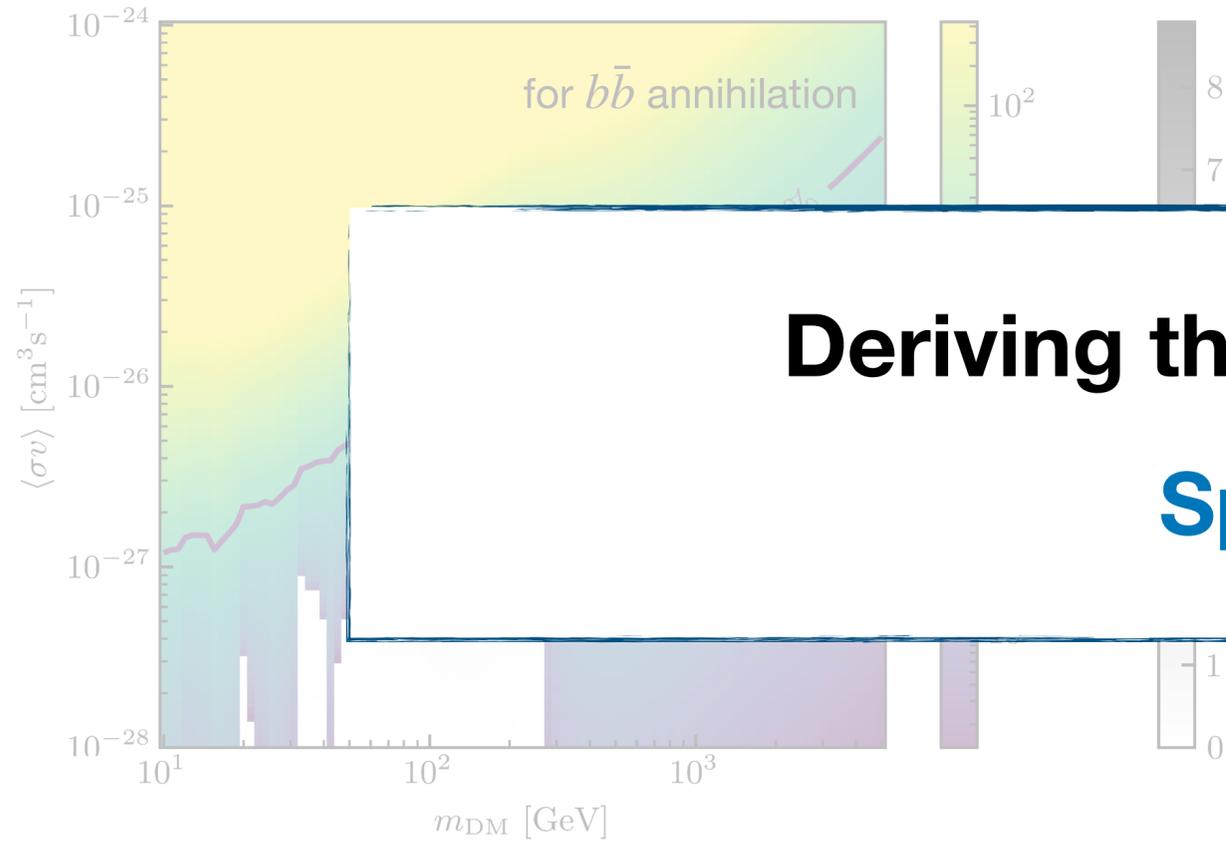


Expert: Kathrin Nippel



Expert: Sowmiya Balan

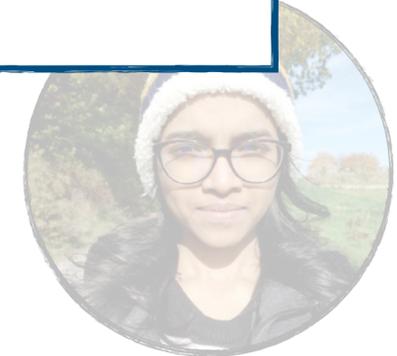
Limits for DM Annihilation



Nippel

Deriving the limit takes ~ 60 cpu-hours.

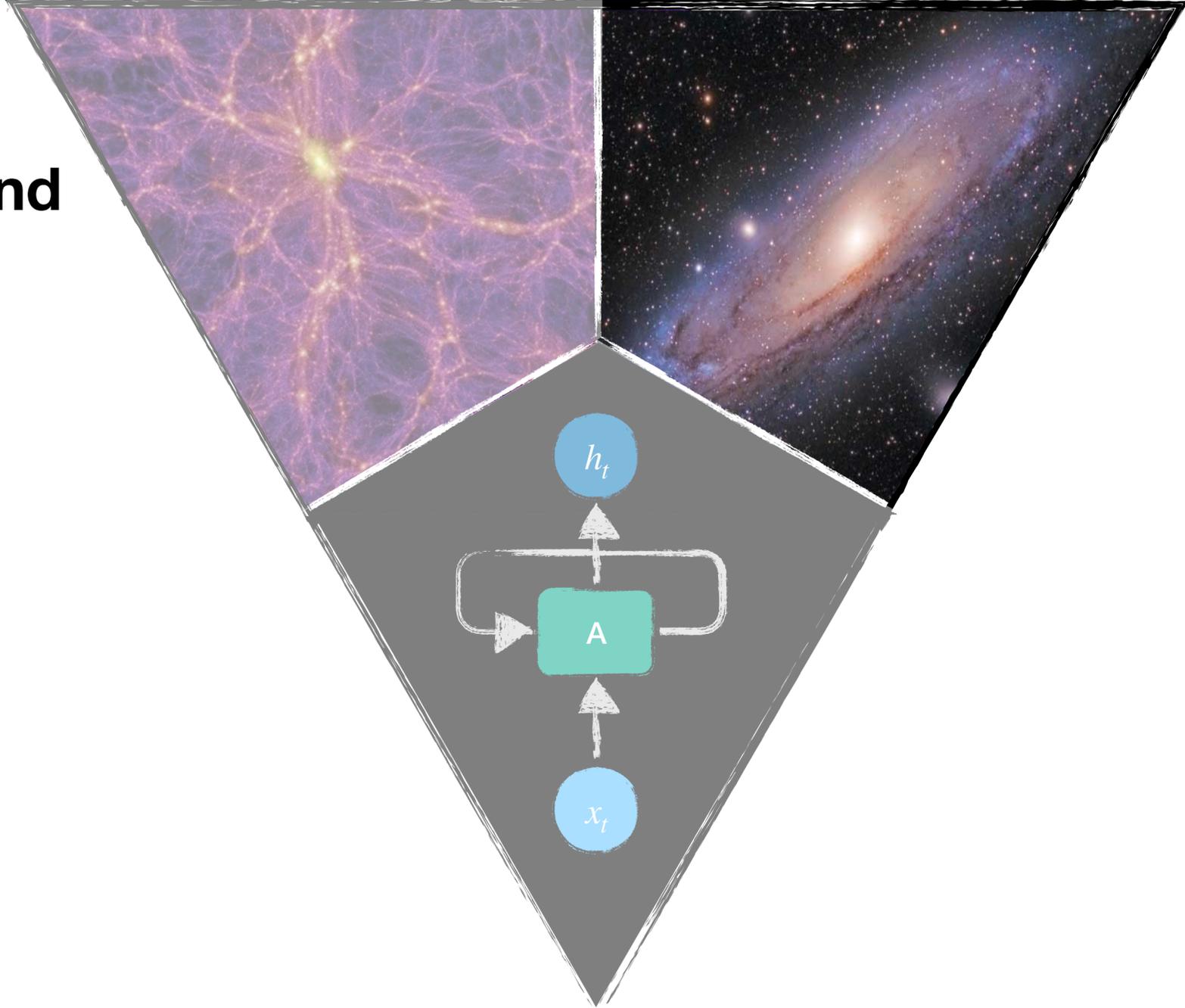
Speed-up of $\mathcal{O}(100)$!



Expert: Sowmiya Balan



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**Cosmic Rays:
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**Speed-up: Neural Networks
and Importance Sampling**

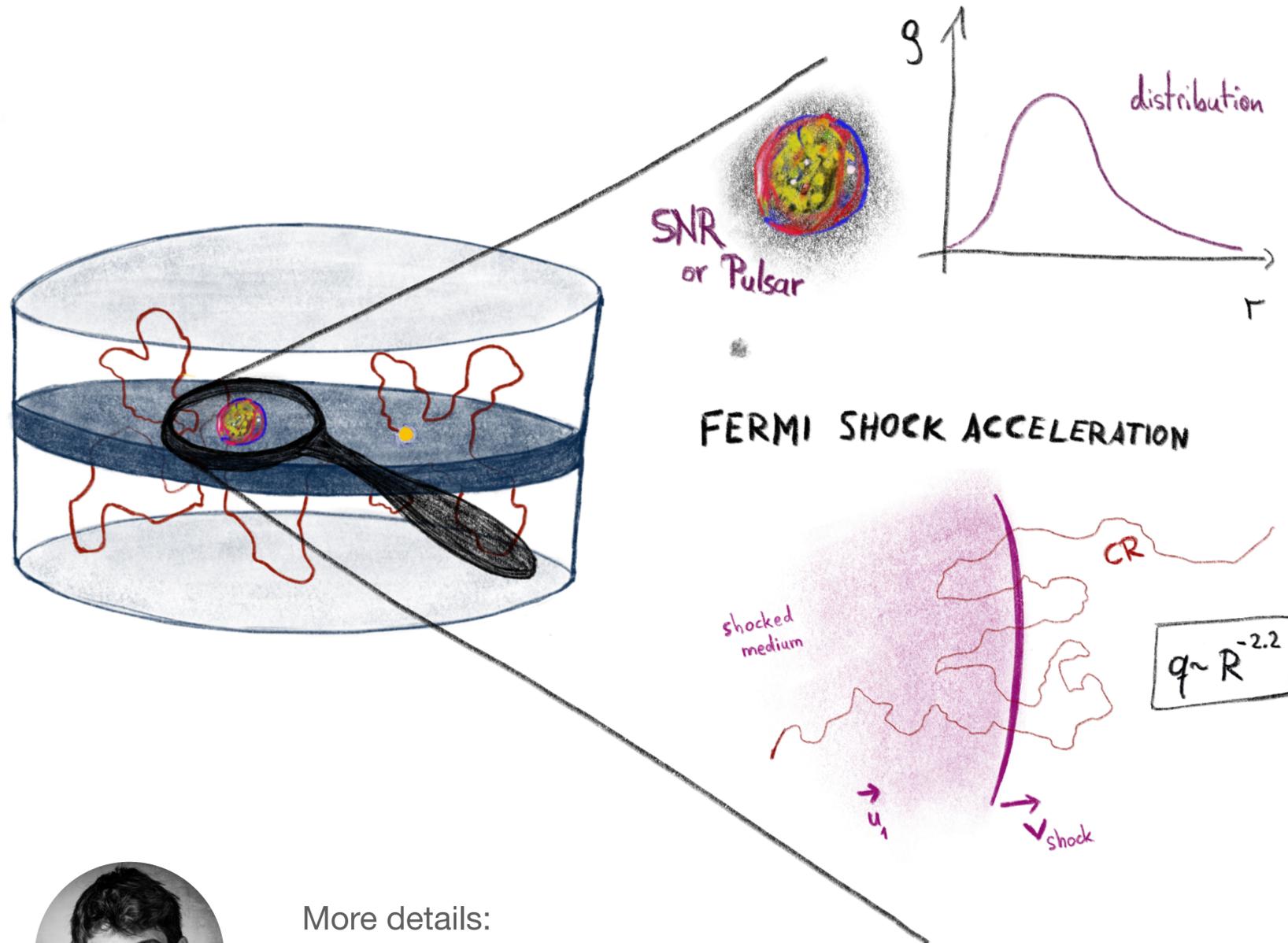
State of the Art CR Modeling

$$\begin{aligned} \frac{d\psi_i}{dt} &= q_i(\mathbf{x}, p) && \text{Source term} \\ &+ \nabla D_{xx} \nabla \psi_i && \text{Diffusion} \\ &- \nabla V \psi_i + \frac{\partial}{\partial p} \left(\frac{p}{3} \nabla \cdot \mathbf{V} \psi_i \right) && \text{Convection} \\ &- \frac{\partial}{\partial p} \left(\frac{dp}{dt} \psi_i \right) && \text{Energy losses} \\ &- \frac{\psi_i}{\tau_f} - \frac{\psi_i}{\tau_r} && \text{Fragmentation and decay} \\ &+ \frac{\partial}{\partial p} p^2 D_{pp} \frac{\partial}{\partial p} \frac{1}{p^2} \psi_i && \text{Reacceleration} \end{aligned}$$



More details:
Yoann Genolini
Monday, 10:20 am

State of the Art CR Modeling

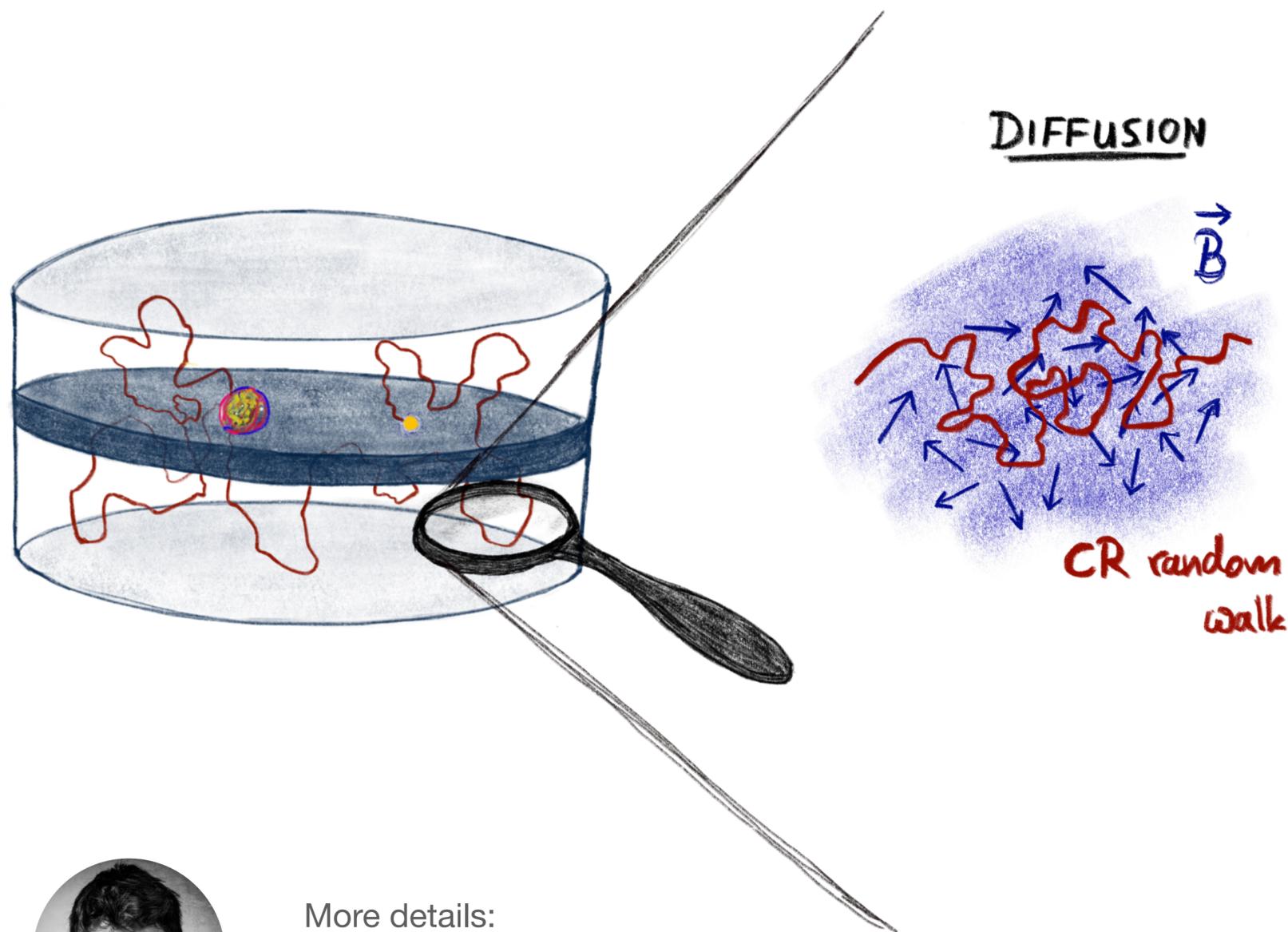


$$\frac{d\psi_i}{dt} = \begin{aligned} & \boxed{q_i(\mathbf{x}, p)} && \text{Source term} \\ & + \nabla D_{xx} \nabla \psi_i && \text{Diffusion} \\ & - \nabla \mathbf{V} \psi_i + \frac{\partial}{\partial p} \left(\frac{p}{3} \nabla \cdot \mathbf{V} \psi_i \right) && \text{Convection} \\ & - \frac{\partial}{\partial p} \left(\frac{dp}{dt} \psi_i \right) && \text{Energy losses} \\ & - \frac{\psi_i}{\tau_f} + \frac{\psi_i}{\tau_r} && \text{Fragmentation and decay} \\ & + \frac{\partial}{\partial p} p^2 D_{pp} \frac{\partial}{\partial p} \frac{1}{p^2} \psi_i && \text{Reacceleration} \end{aligned}$$



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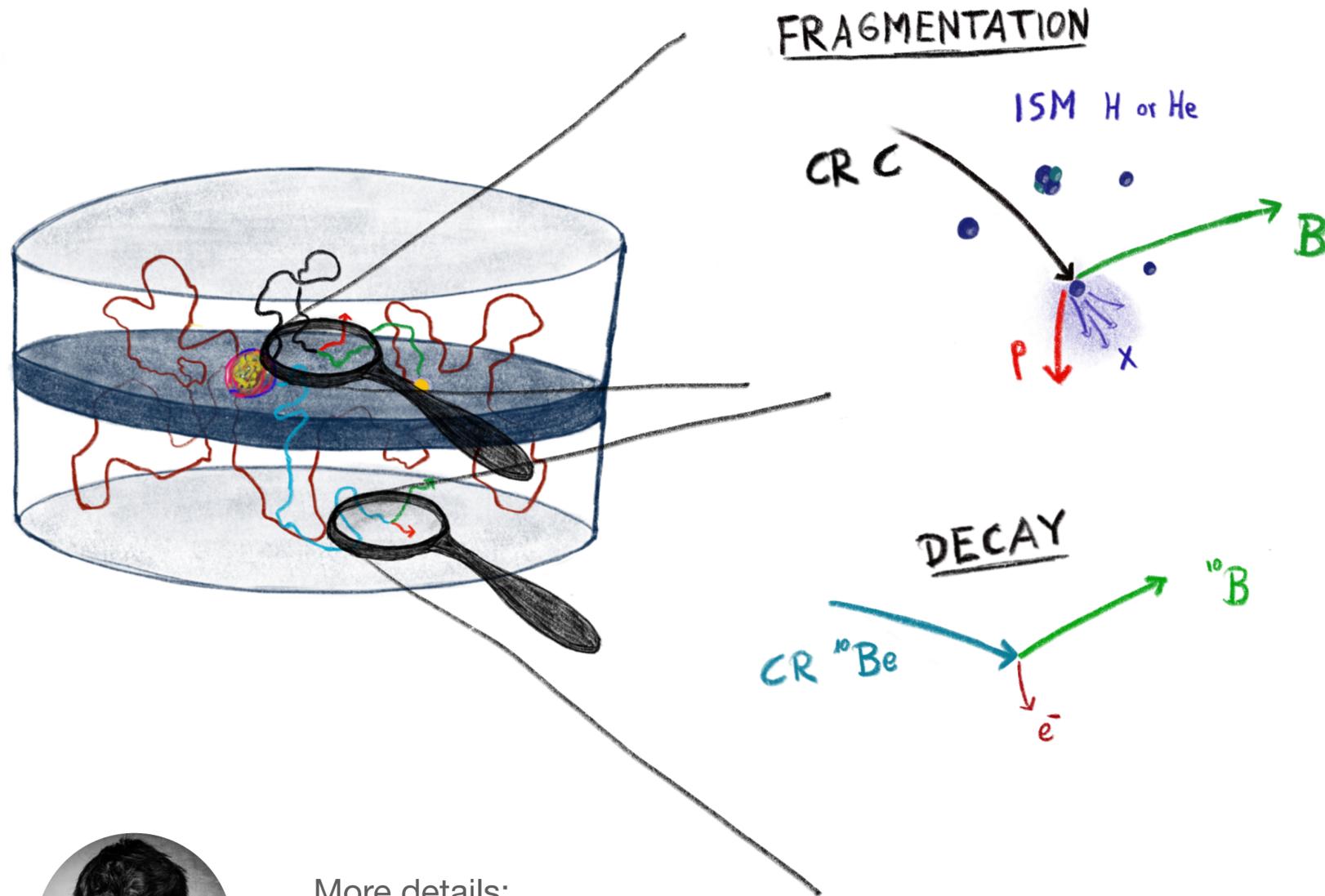


$$\begin{aligned}
 \frac{d\psi_i}{dt} = & q_i(\mathbf{x}, p) && \text{Source term} \\
 & + \nabla D_{xx} \nabla \psi_i && \text{Diffusion} \\
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 \end{aligned}$$



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State of the Art CR Modeling



$$\frac{d\psi_i}{dt} = q_i(\mathbf{x}, p) \quad \text{Source term}$$

$$+ \nabla D_{xx} \nabla \psi_i \quad \text{Diffusion}$$

$$- \nabla \mathbf{V} \psi_i + \frac{\partial}{\partial p} \left(\frac{p}{3} \nabla \cdot \mathbf{V} \psi_i \right) \quad \text{Convection}$$

$$- \frac{\partial}{\partial p} \left(\frac{dp}{dt} \psi_i \right) \quad \text{Energy losses}$$

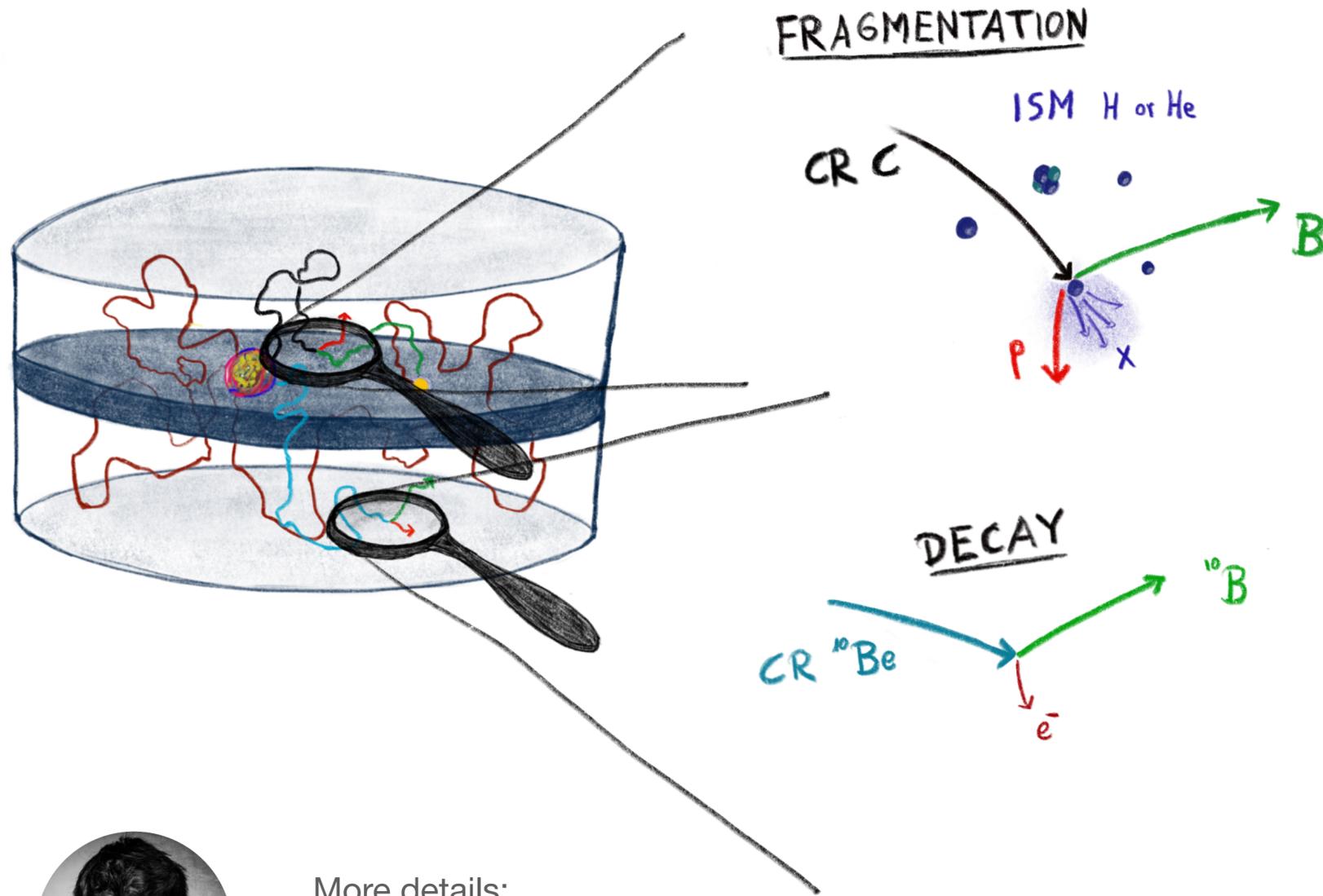
$$\frac{\psi_i}{\tau_f} - \frac{\psi_i}{\tau_r} \quad \text{Fragmentation and decay}$$

$$+ \frac{\partial}{\partial p} p^2 D_{pp} \frac{\partial}{\partial p} \frac{1}{p^2} \psi_i \quad \text{Reacceleration}$$



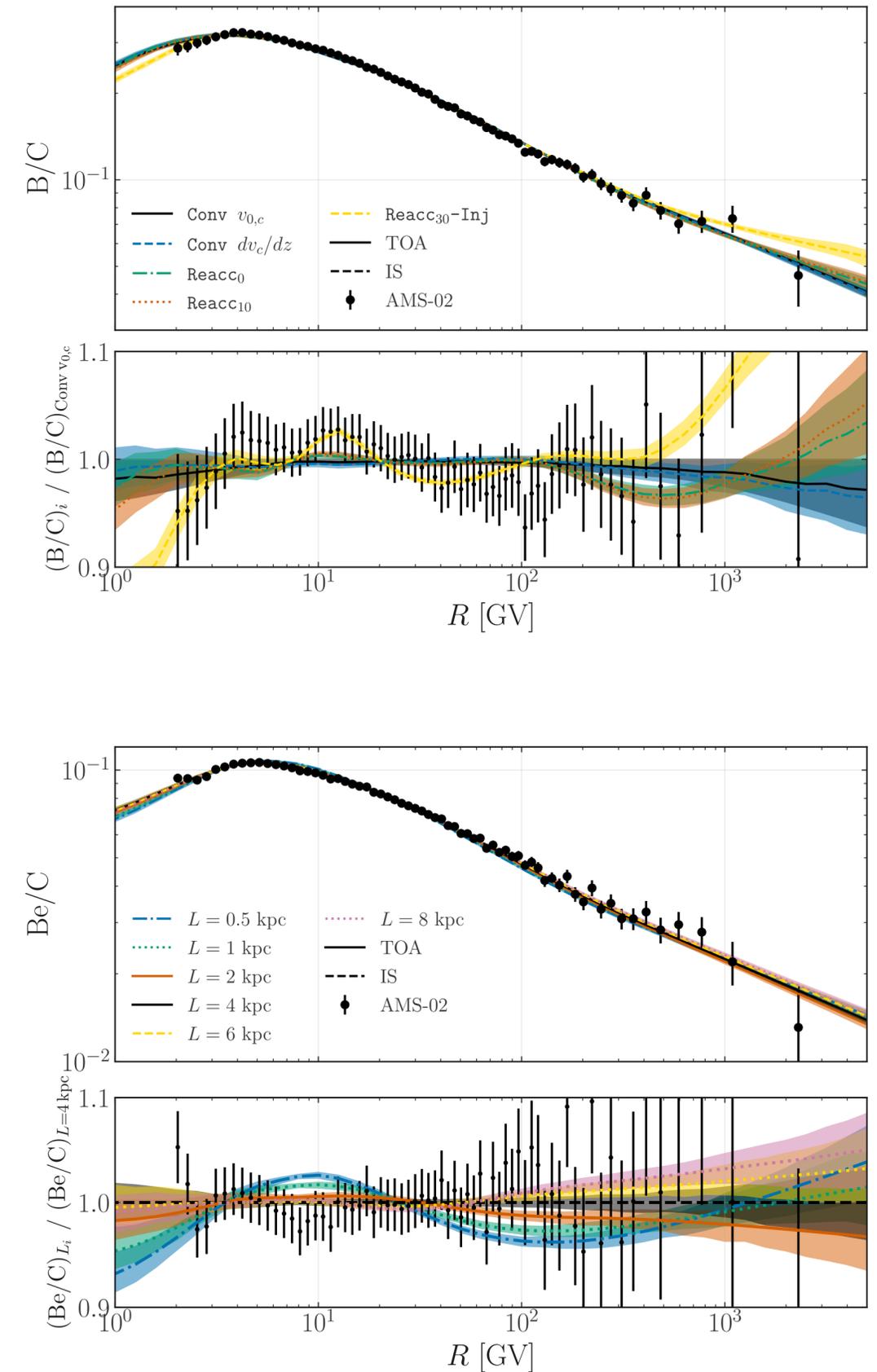
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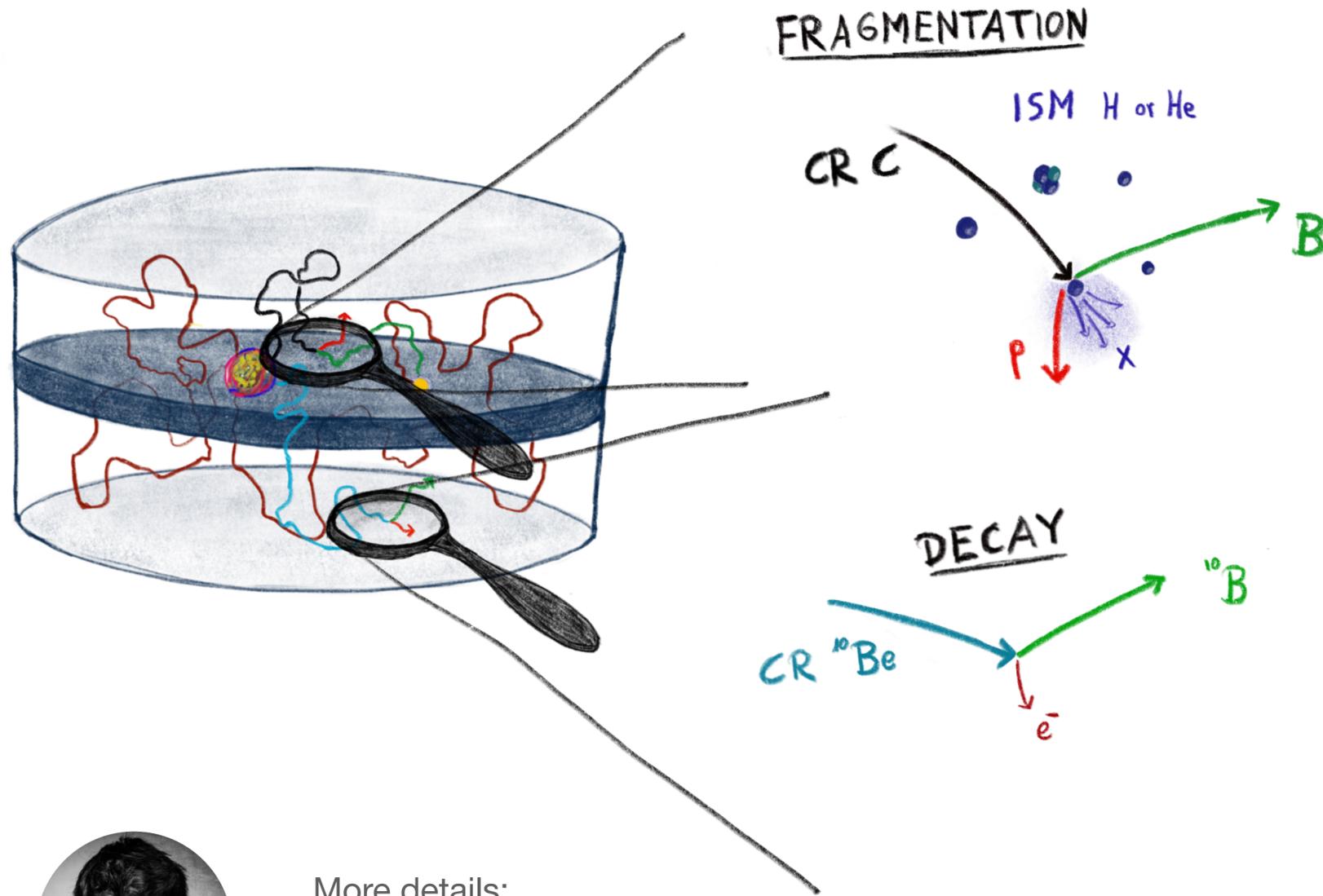
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Michael Korsmeier - 2023/09/12



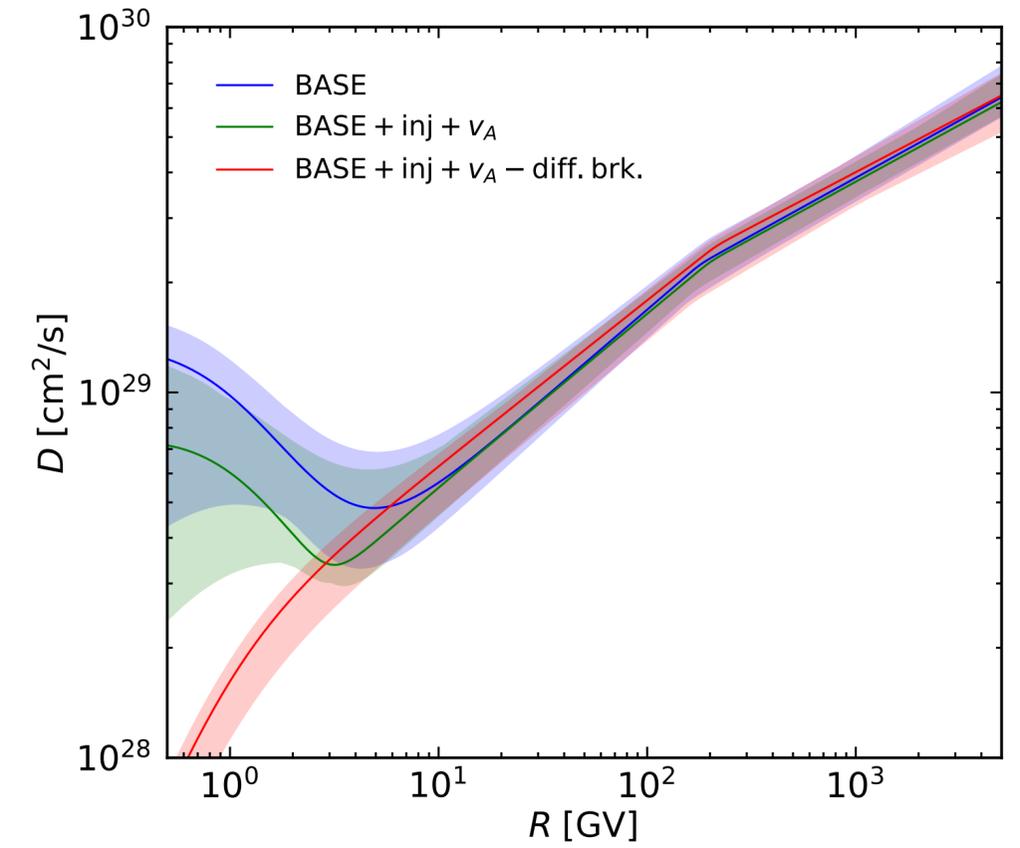
[Di Mauro, MK, et al. 2023]

State of the Art CR Modeling

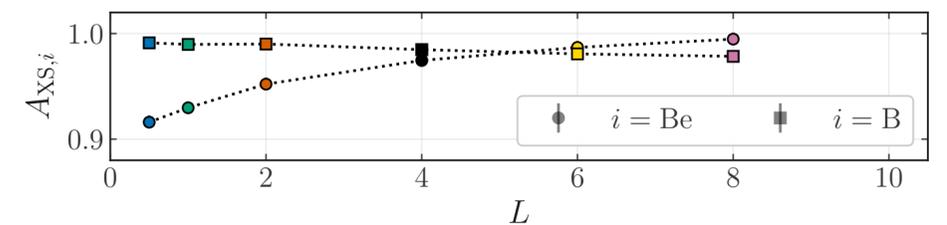
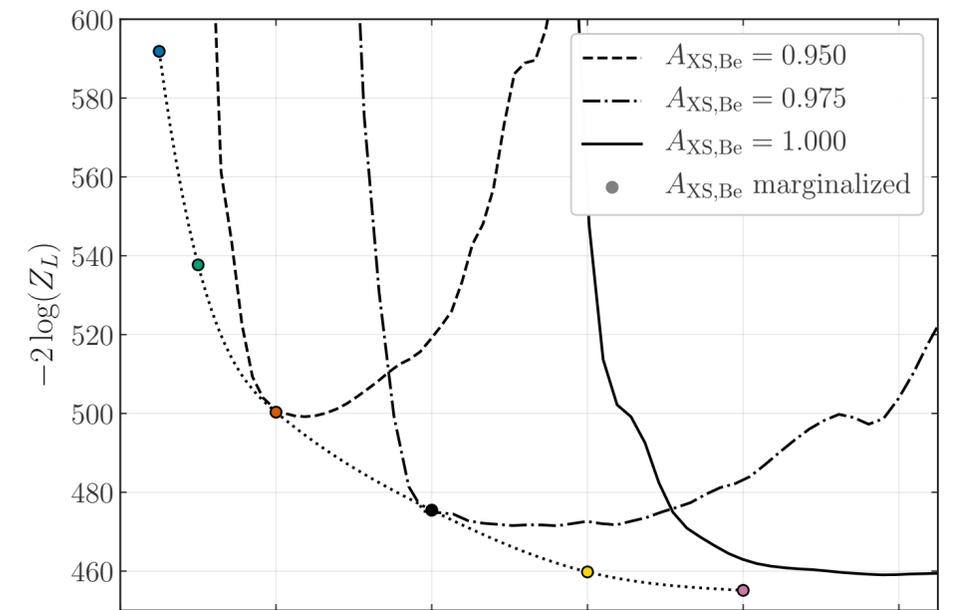


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Michael Korsmeier - 2023/09/12



[MK, Cuoco, 2021]

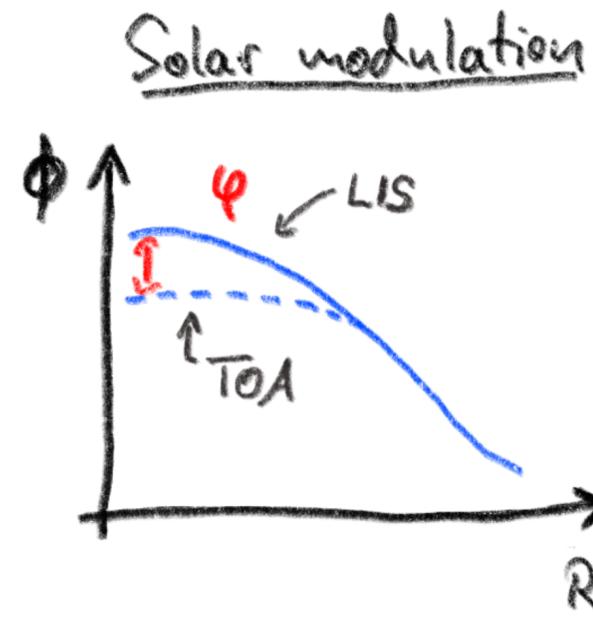
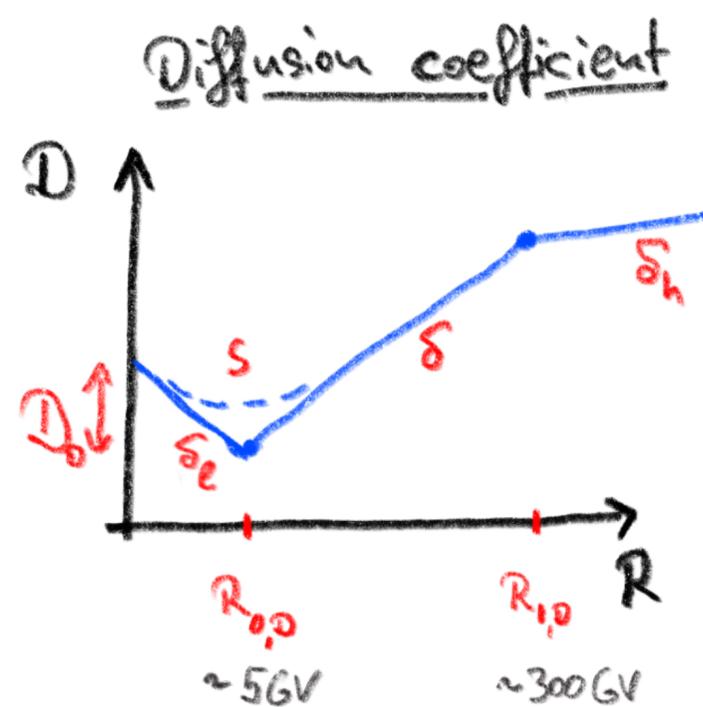
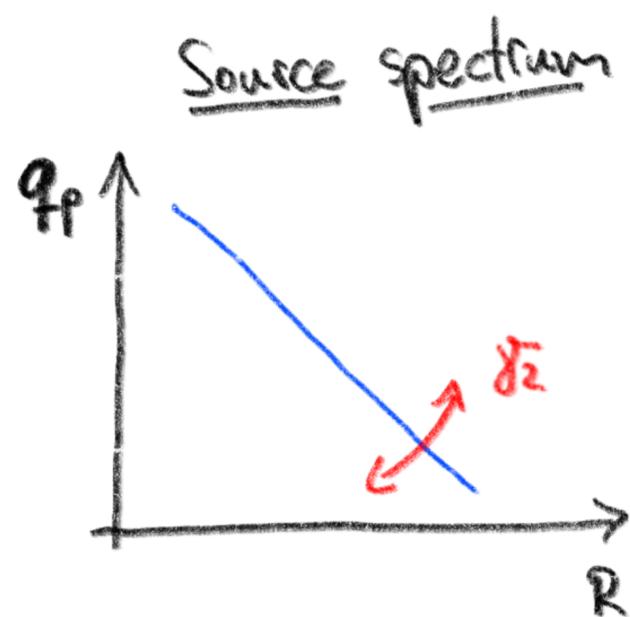


[Di Mauro, MK, et al. 2023]

Two Distinct CR Propagation Models

DIFF.BRK

INJ.BRK



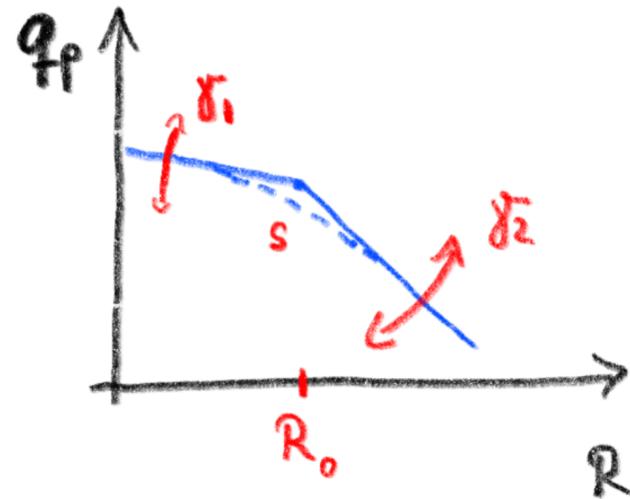
+ convection $v_{0,c}$

Two Distinct CR Propagation Models

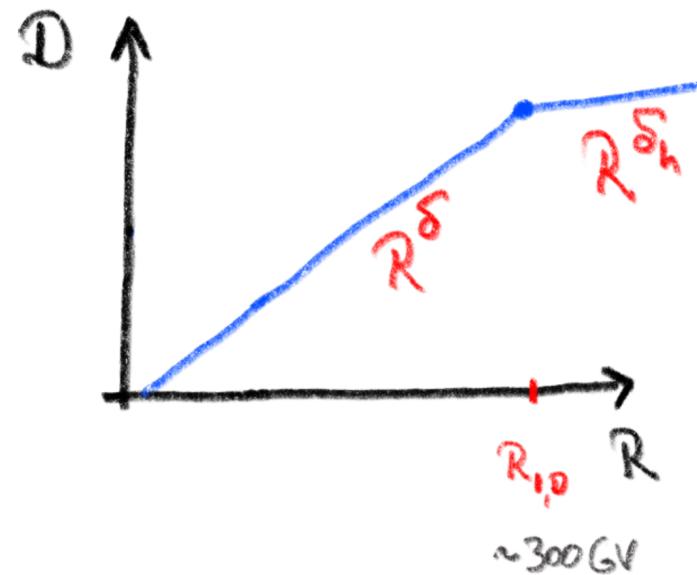
DIFF.BRK

INJ.BRK

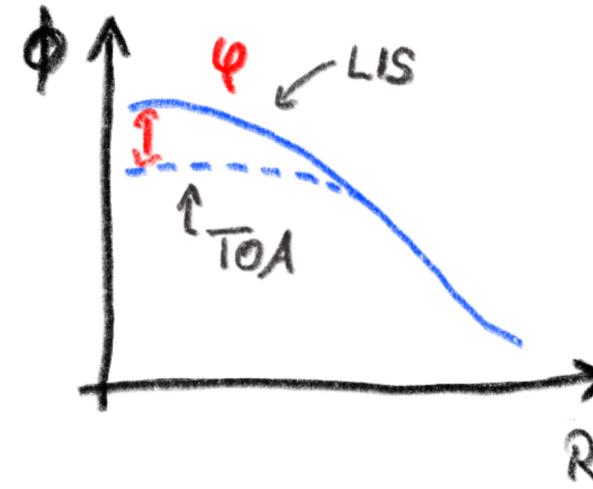
Source spectrum



Diffusion coefficient



Solar modulation



- + convection $v_{0,c}$
- + reacceleration v_A

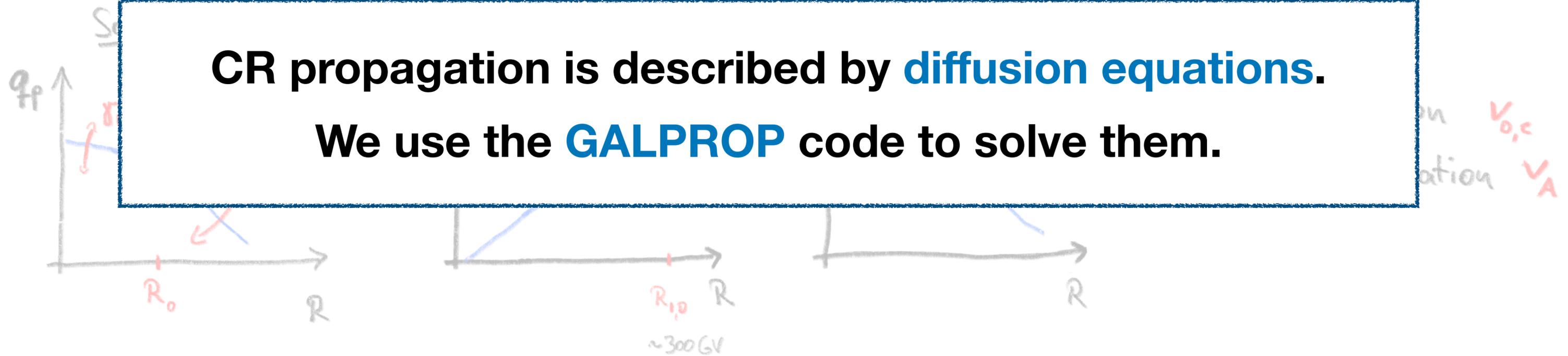
Two Distinct CR Propagation Models

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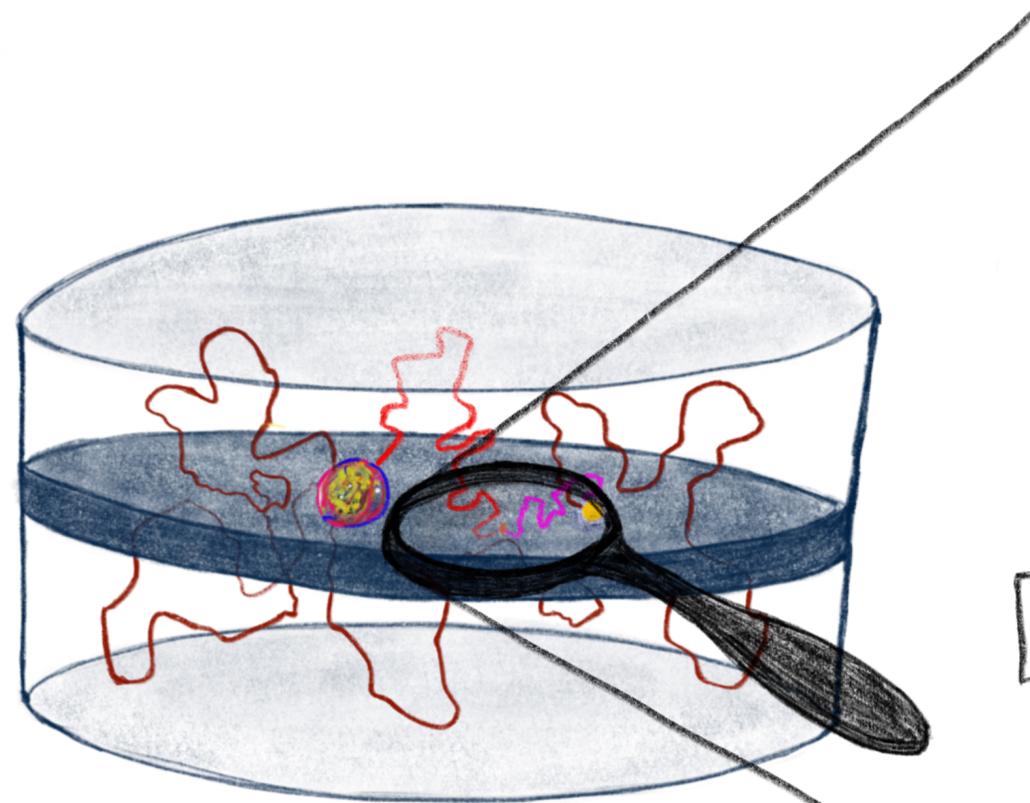
INJ.BRK

CR propagation is described by **diffusion equations**.

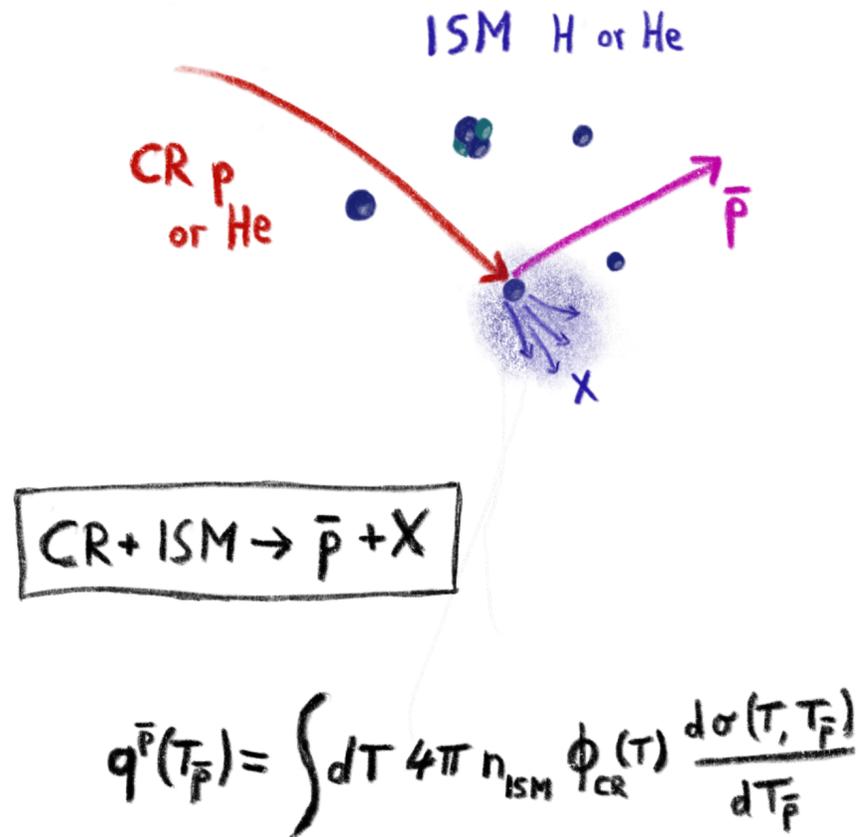
We use the **GALPROP** code to solve them.



Secondary CR Antiprotons

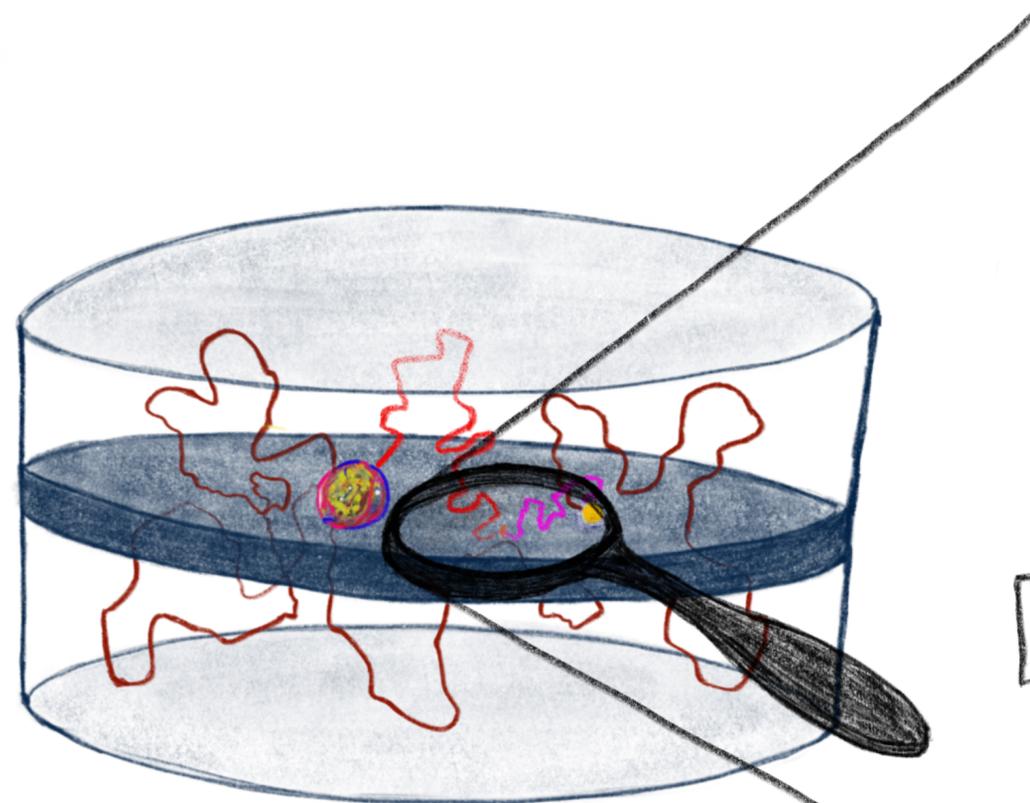


ANTIPROTONS

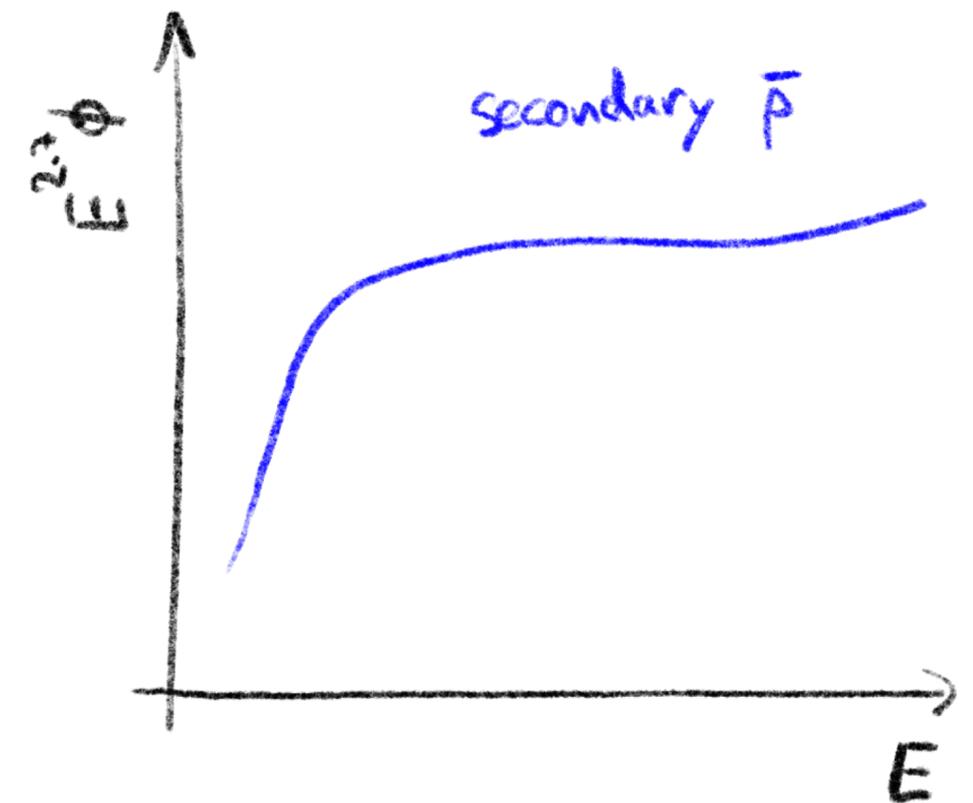
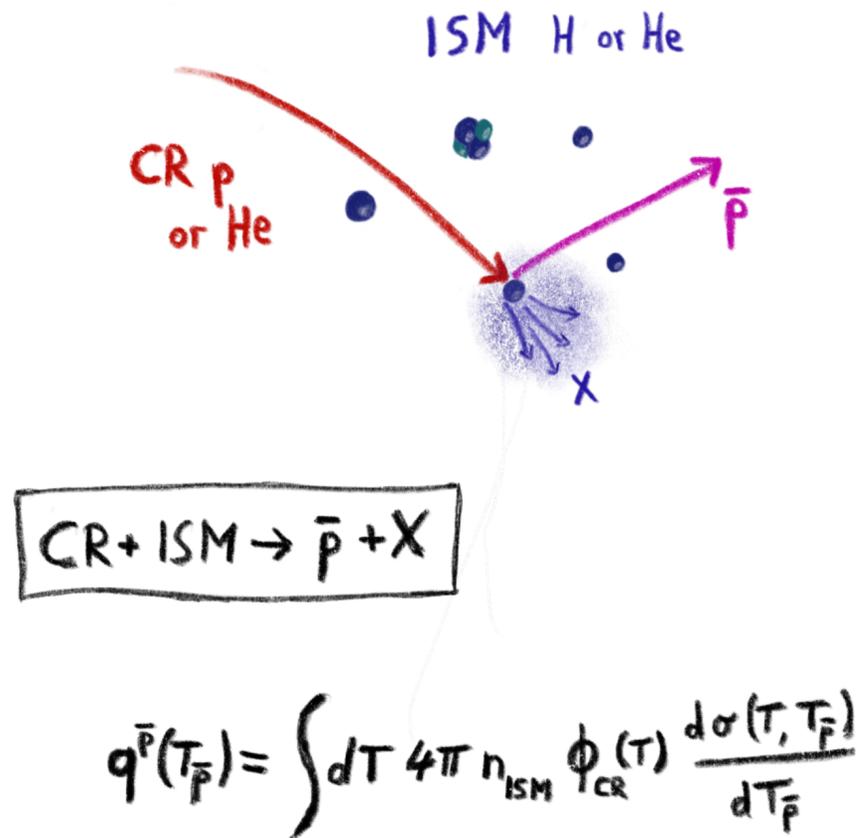


More details:
Zhicheng Tang
Monday, 15:10 am

Secondary CR Antiprotons



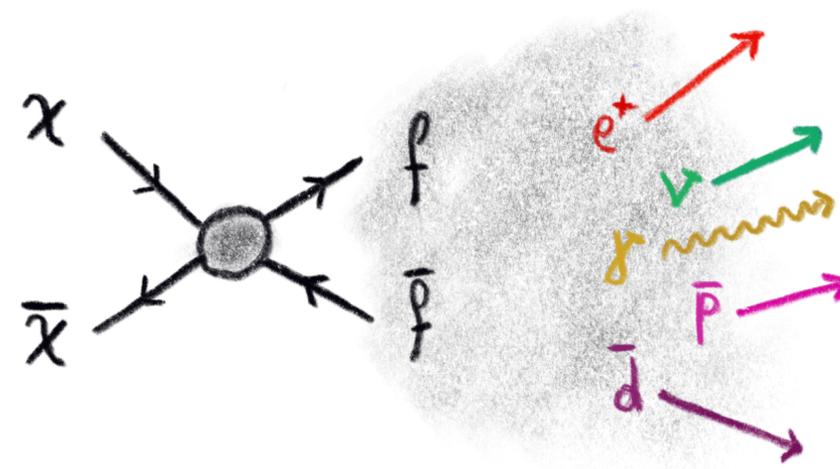
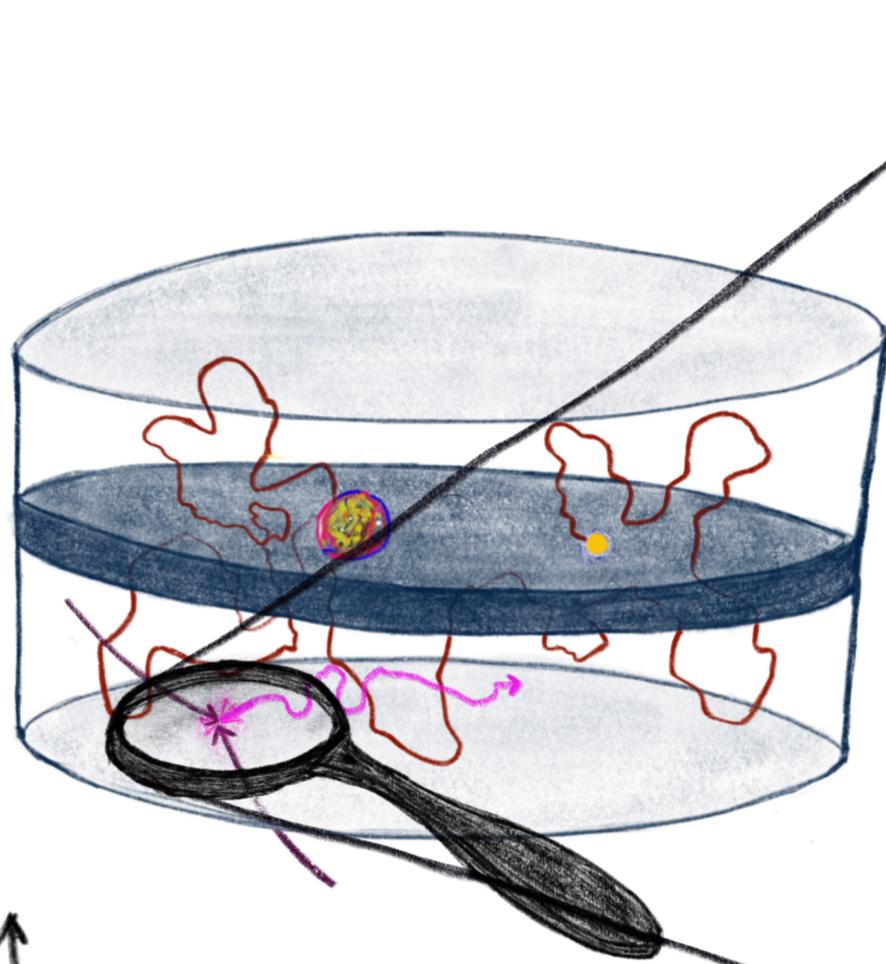
ANTIPROTONS



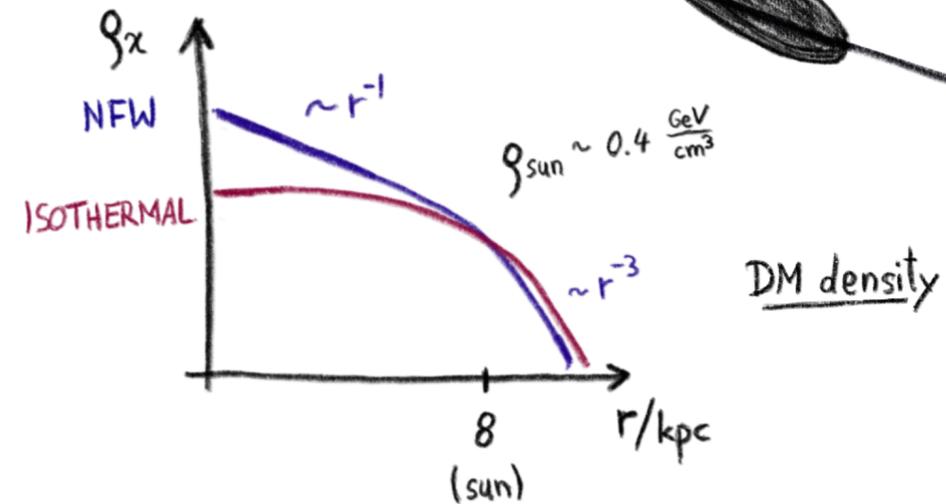
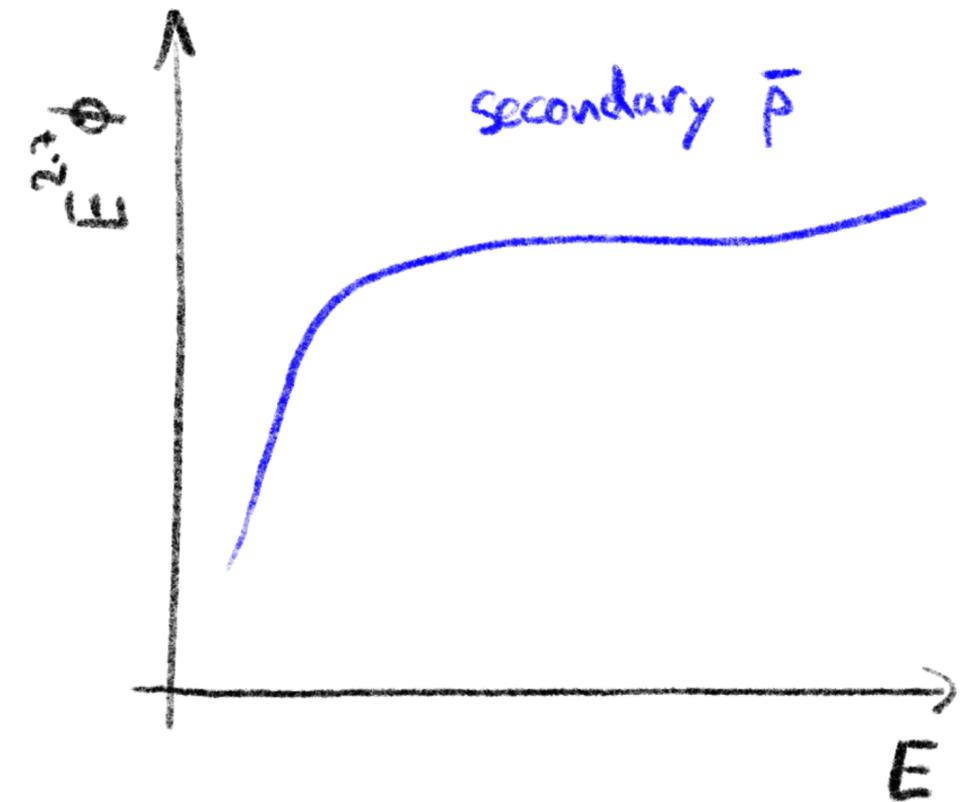
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Antiprotons from Dark Matter

DM ANNIHILATION



Final states depend on DM mass and velocity averaged annihilation cross section $\langle \sigma v \rangle$!

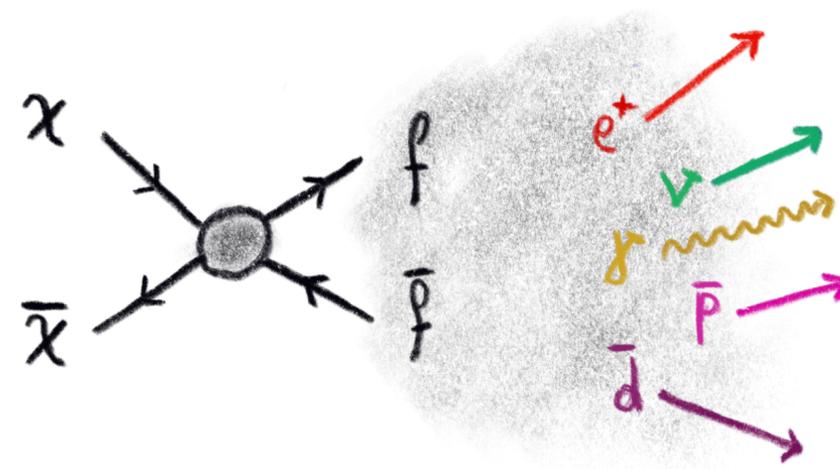
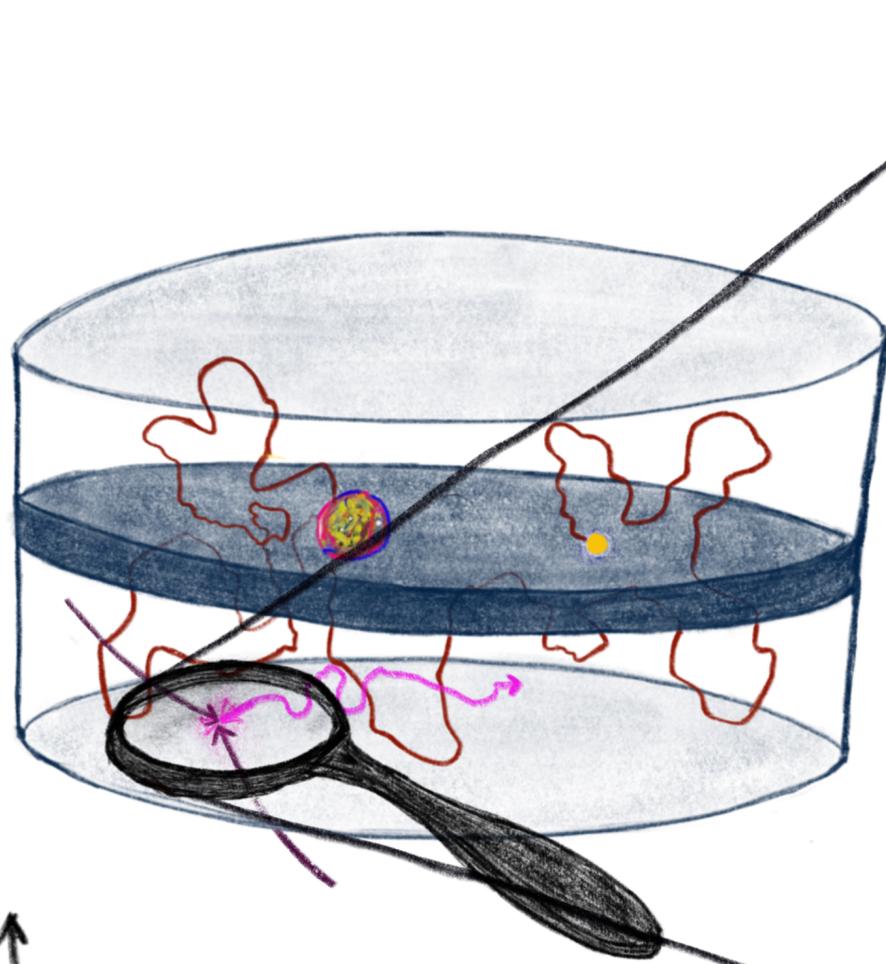


Source term

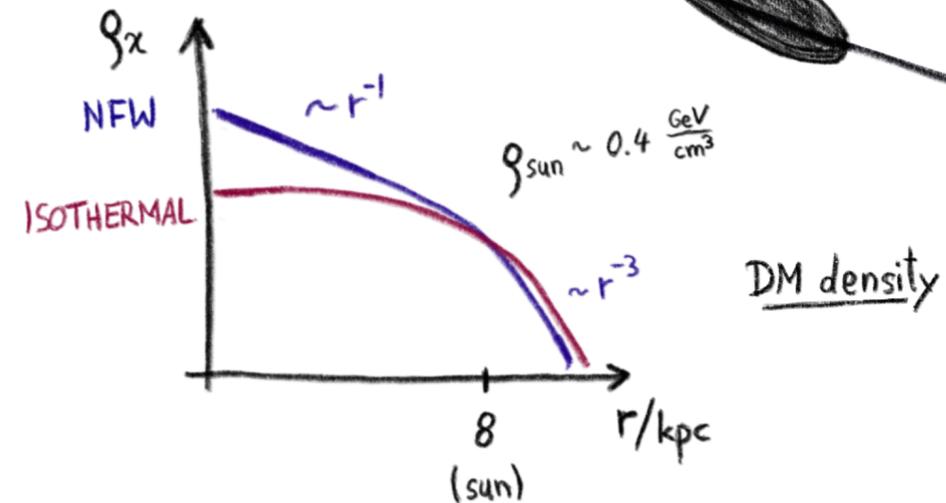
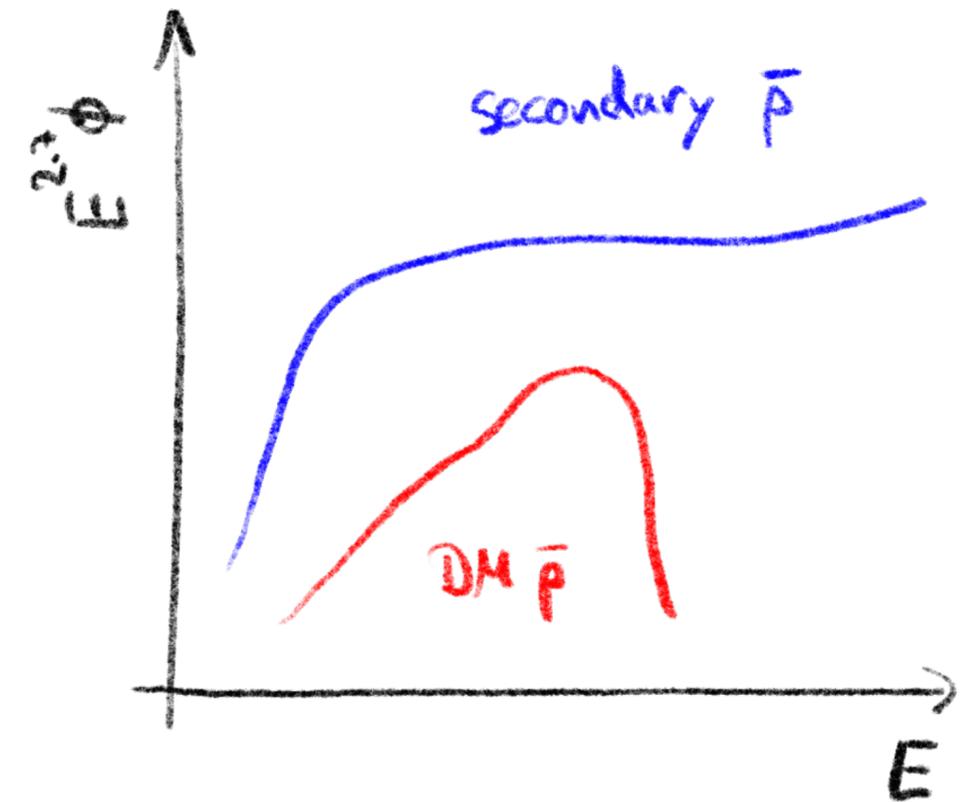
$$q^{DM} = \frac{1}{2} \langle \sigma v \rangle \left(\frac{\rho}{m_{DM}} \right)^2 \frac{dN}{dE}$$

Antiprotons from Dark Matter

DM ANNIHILATION



Final states depend on DM mass and velocity averaged annihilation cross section $\langle\sigma v\rangle$!

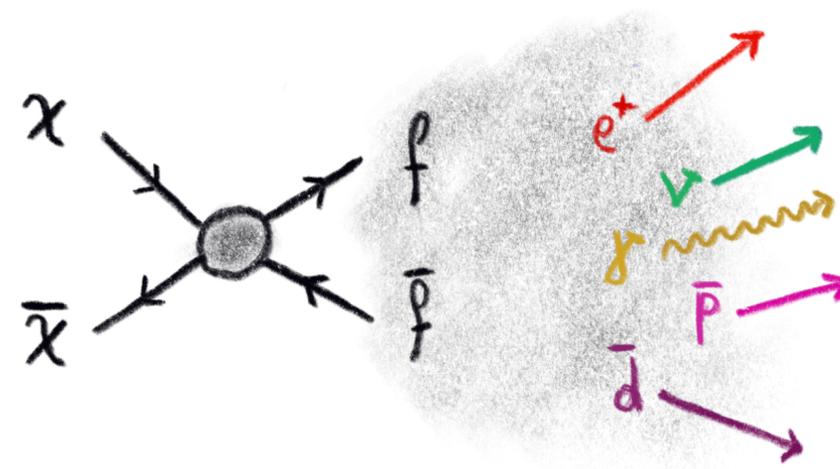
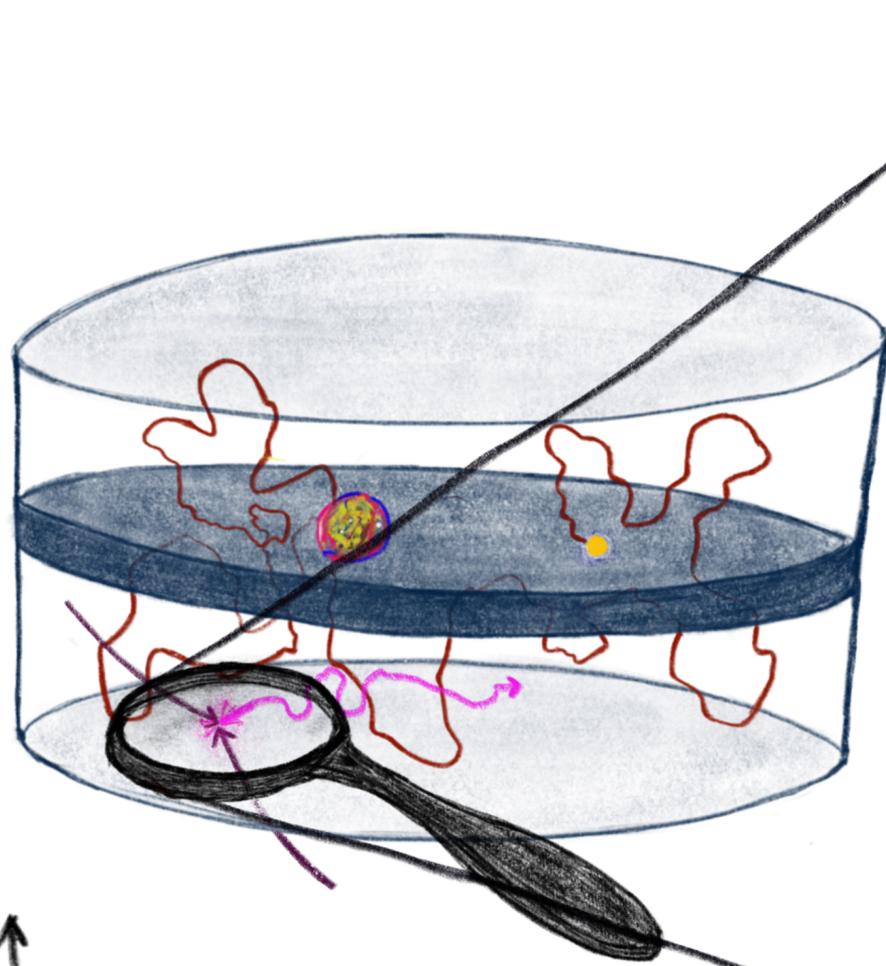


Source term

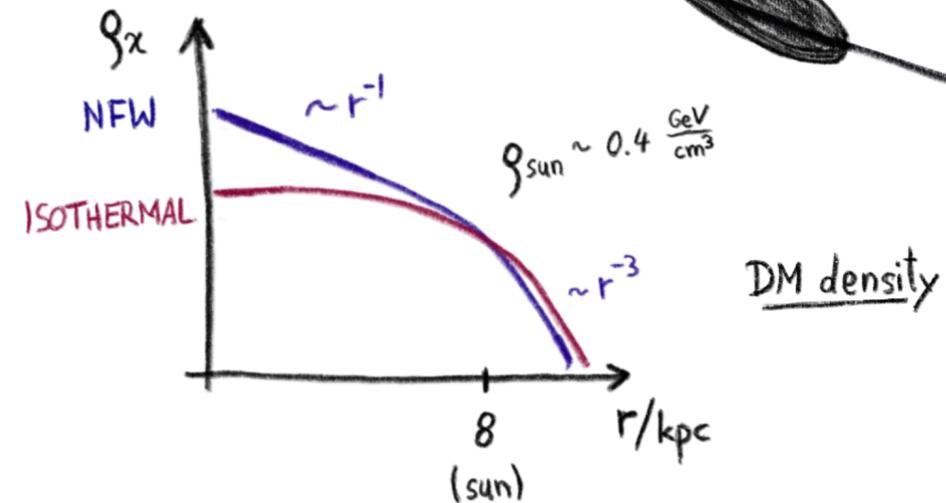
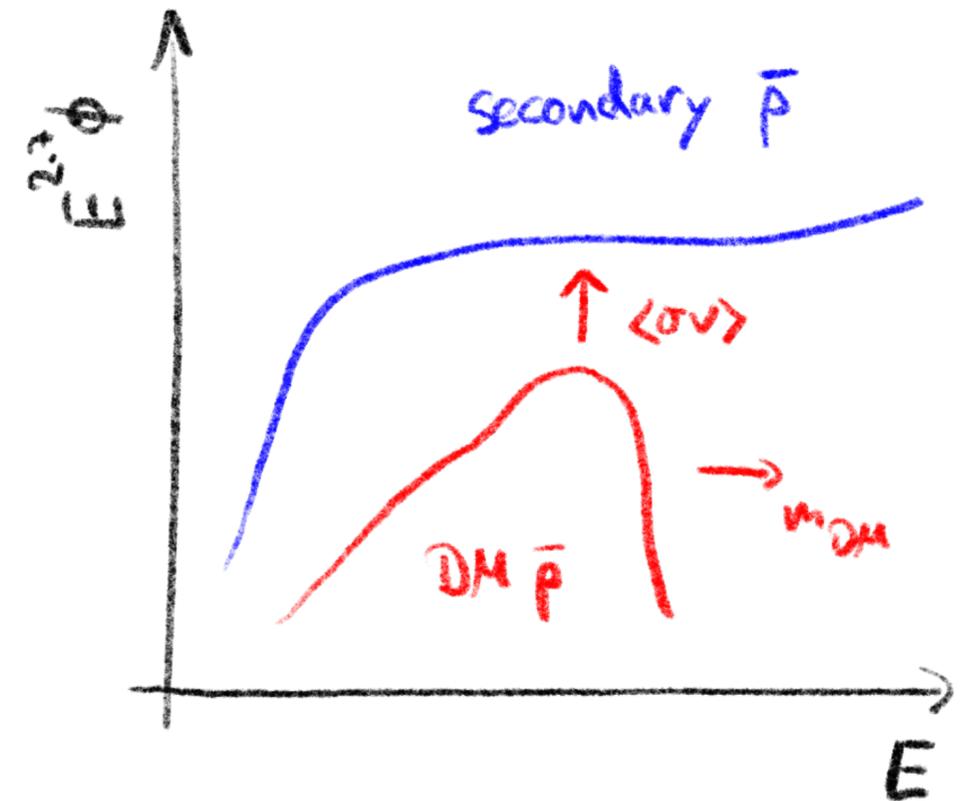
$$q^{DM} = \frac{1}{2} \langle\sigma v\rangle \left(\frac{\rho}{m_{DM}}\right)^2 \frac{dN}{dE}$$

Antiprotons from Dark Matter

DM ANNIHILATION



Final states depend on DM mass and velocity averaged annihilation cross section $\langle\sigma v\rangle$!



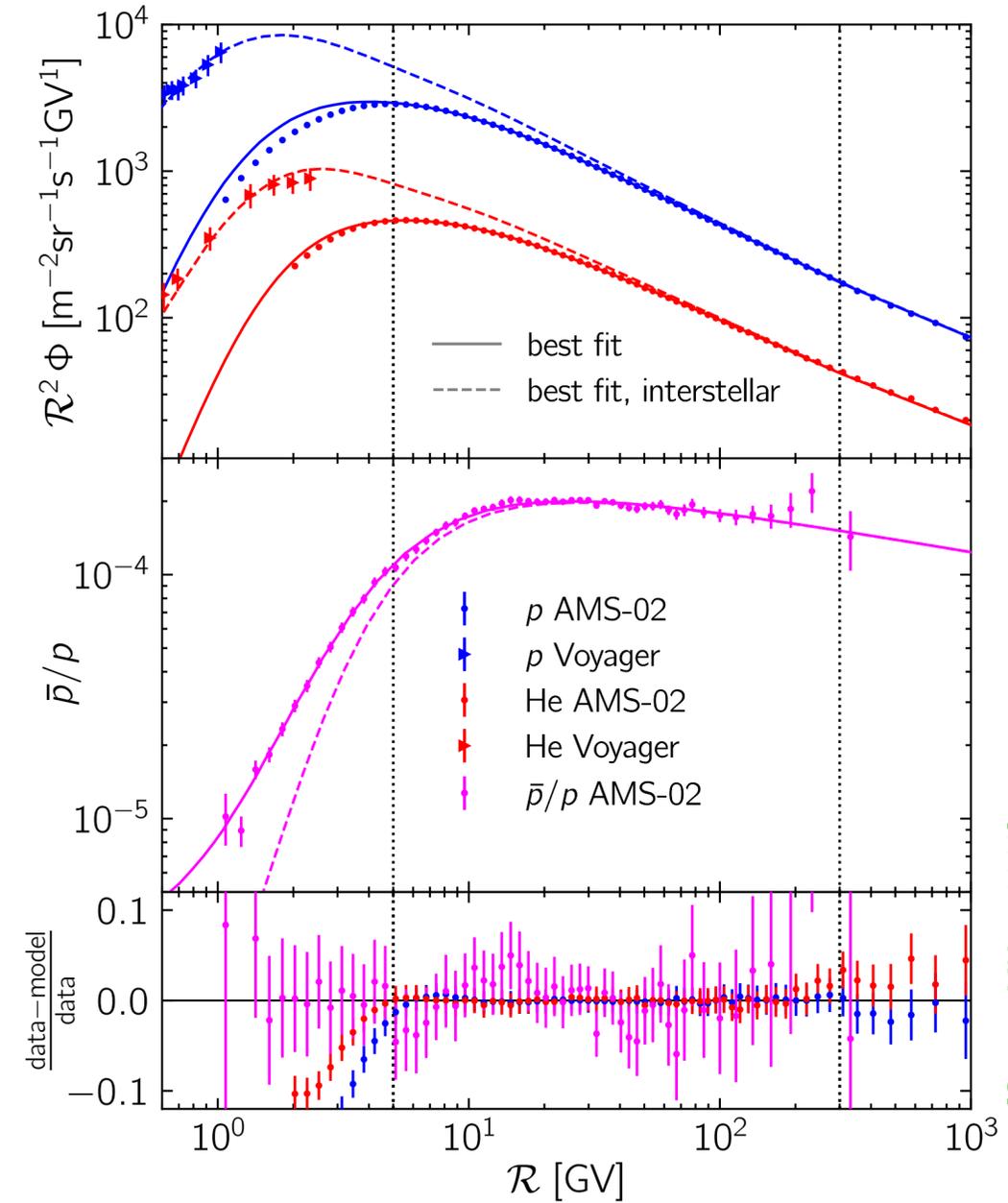
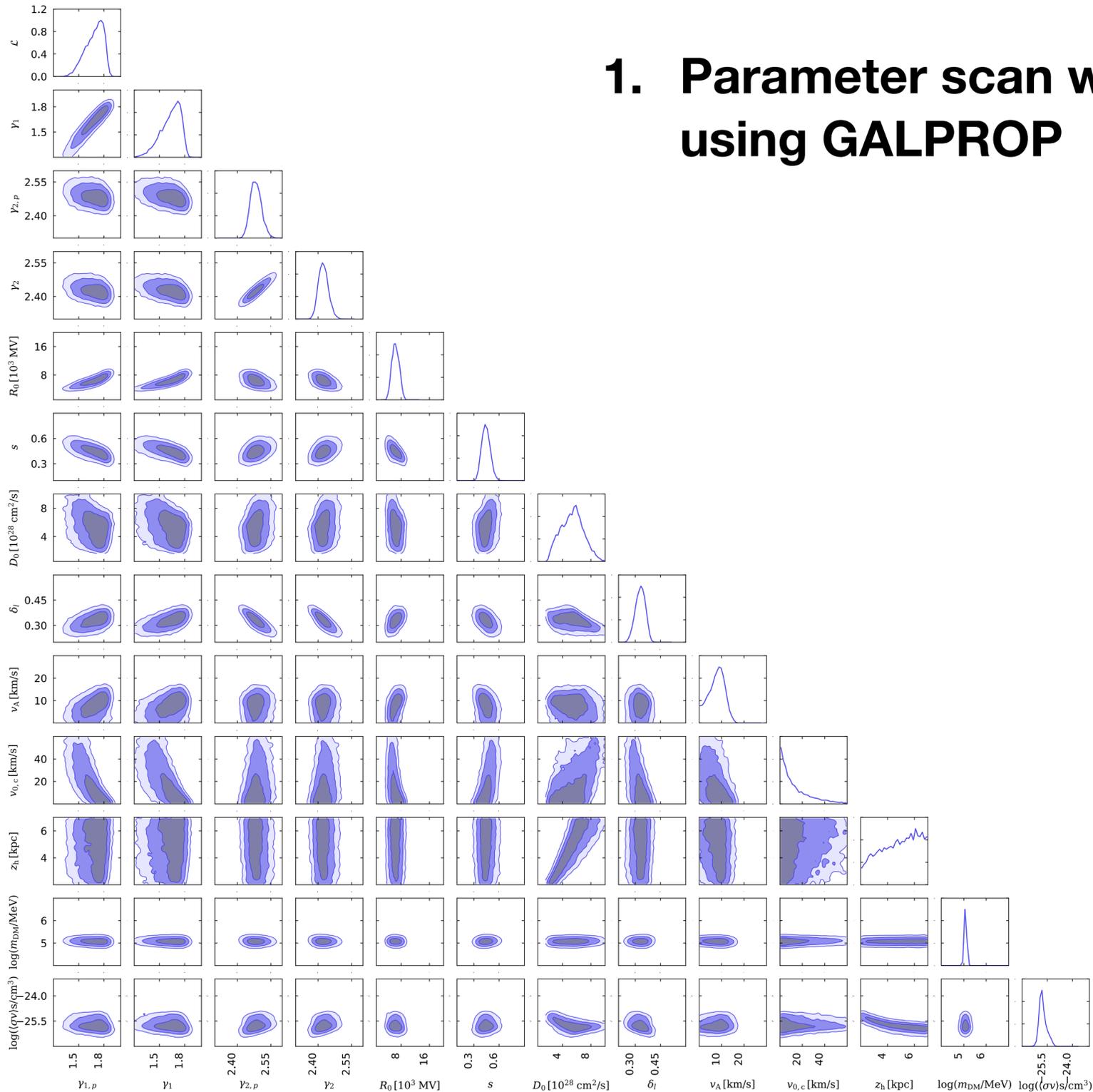
Source term

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DM Limit — the Traditional Way

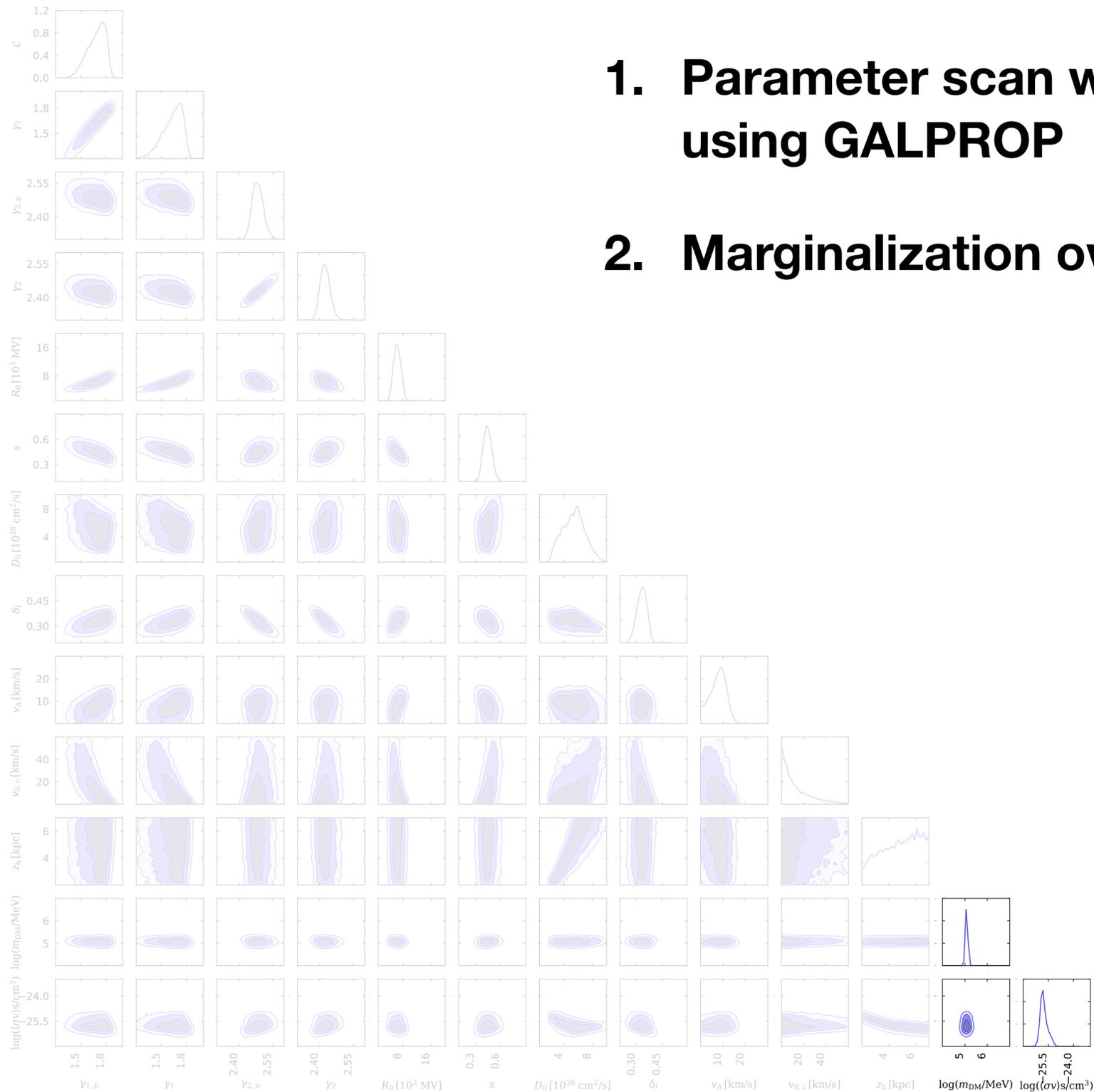
DM Limit – the Traditional Way

1. Parameter scan with $\mathcal{O}(10^6)$ likelihood evaluations using GALPROP



[Cuoco, MK, +; 2019]
(replotted results of the default setup w/o DM)

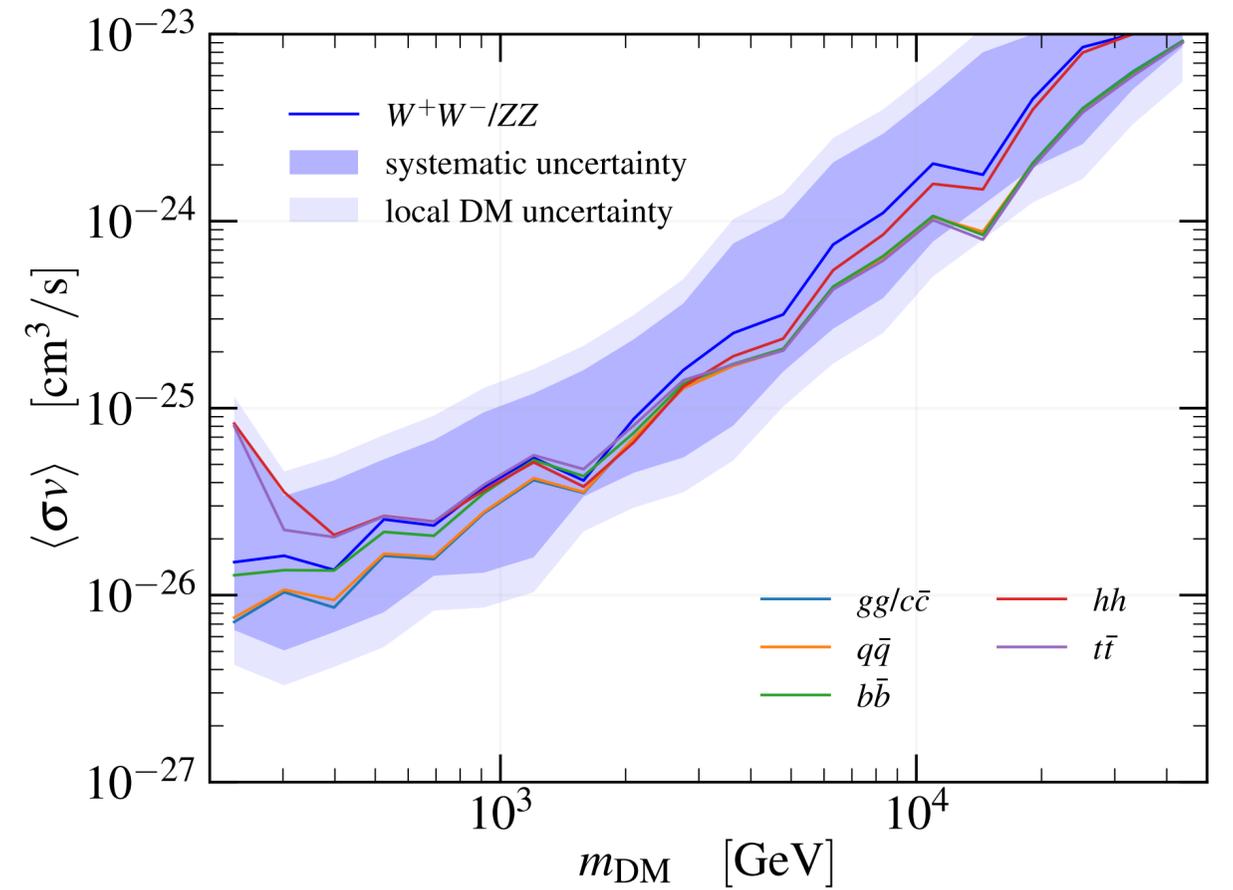
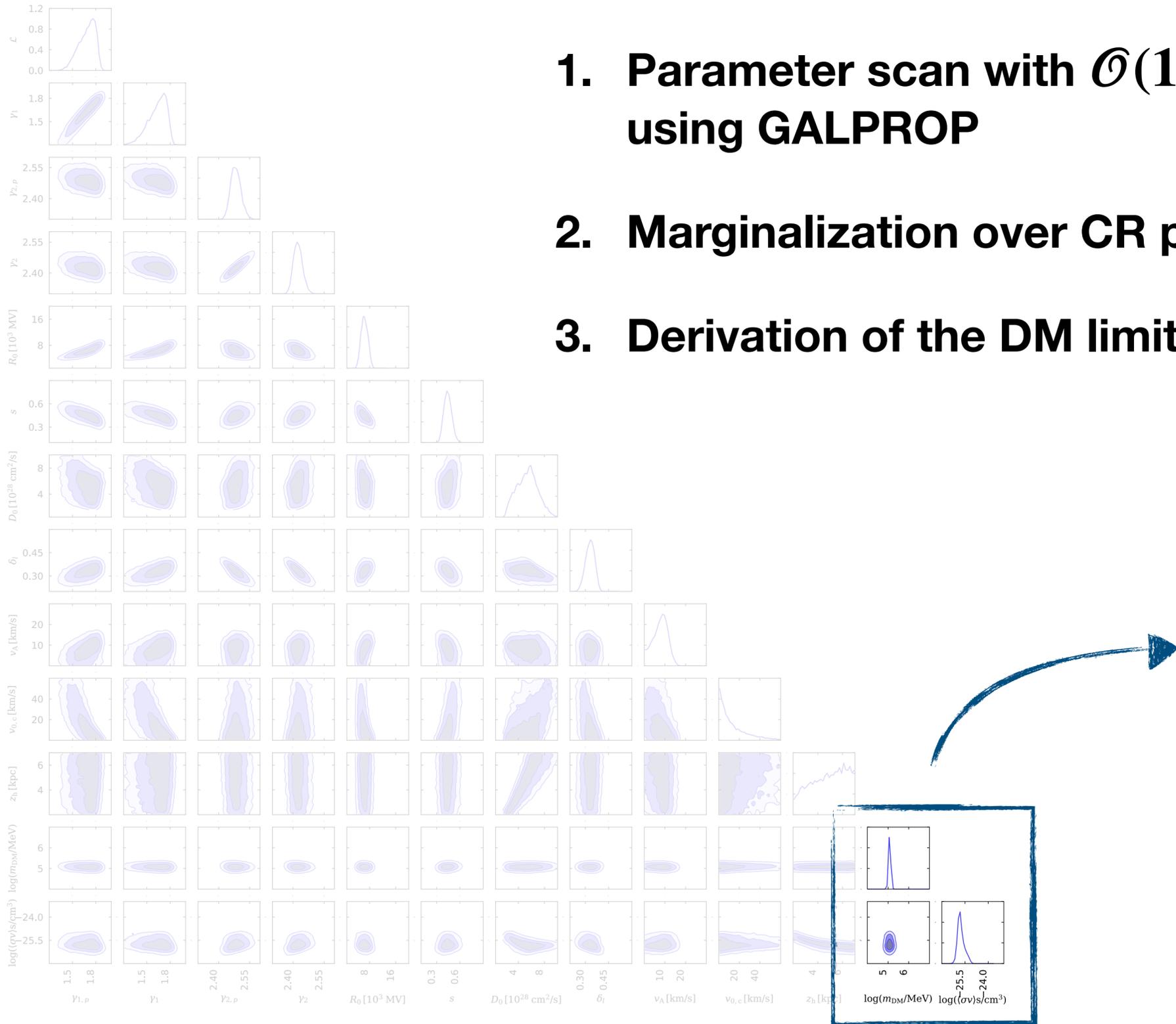
DM Limit – the Traditional Way



1. Parameter scan with $\mathcal{O}(10^6)$ likelihood evaluations using GALPROP
2. Marginalization over CR parameters

DM Limit – the Traditional Way

1. Parameter scan with $\mathcal{O}(10^6)$ likelihood evaluations using GALPROP
2. Marginalization over CR parameters
3. Derivation of the DM limit

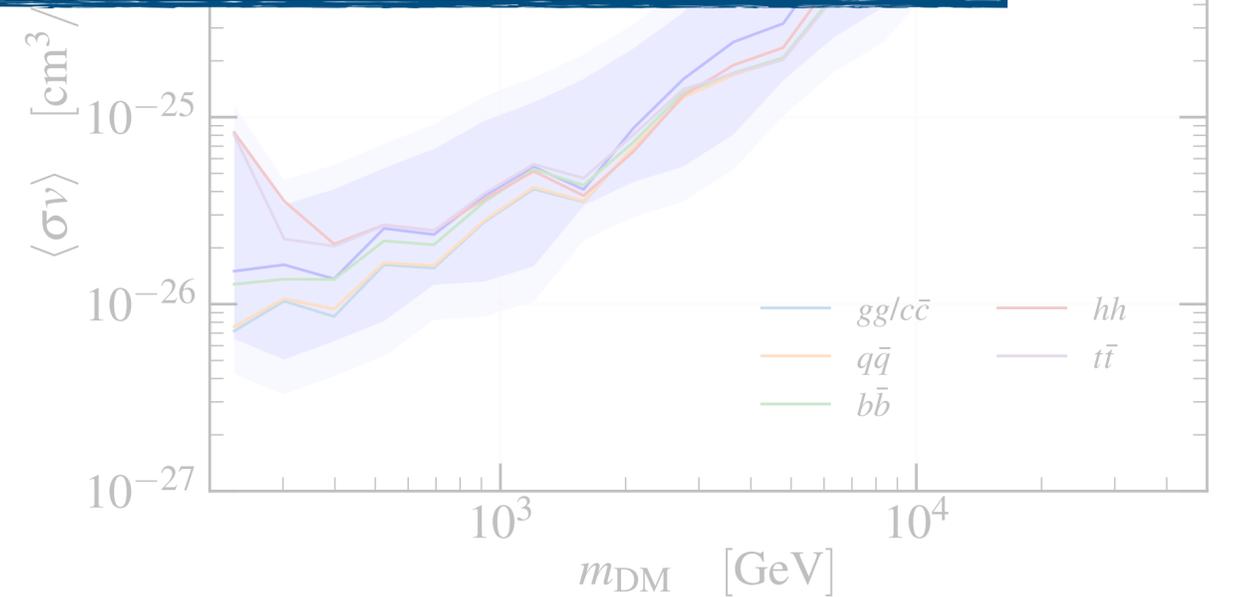
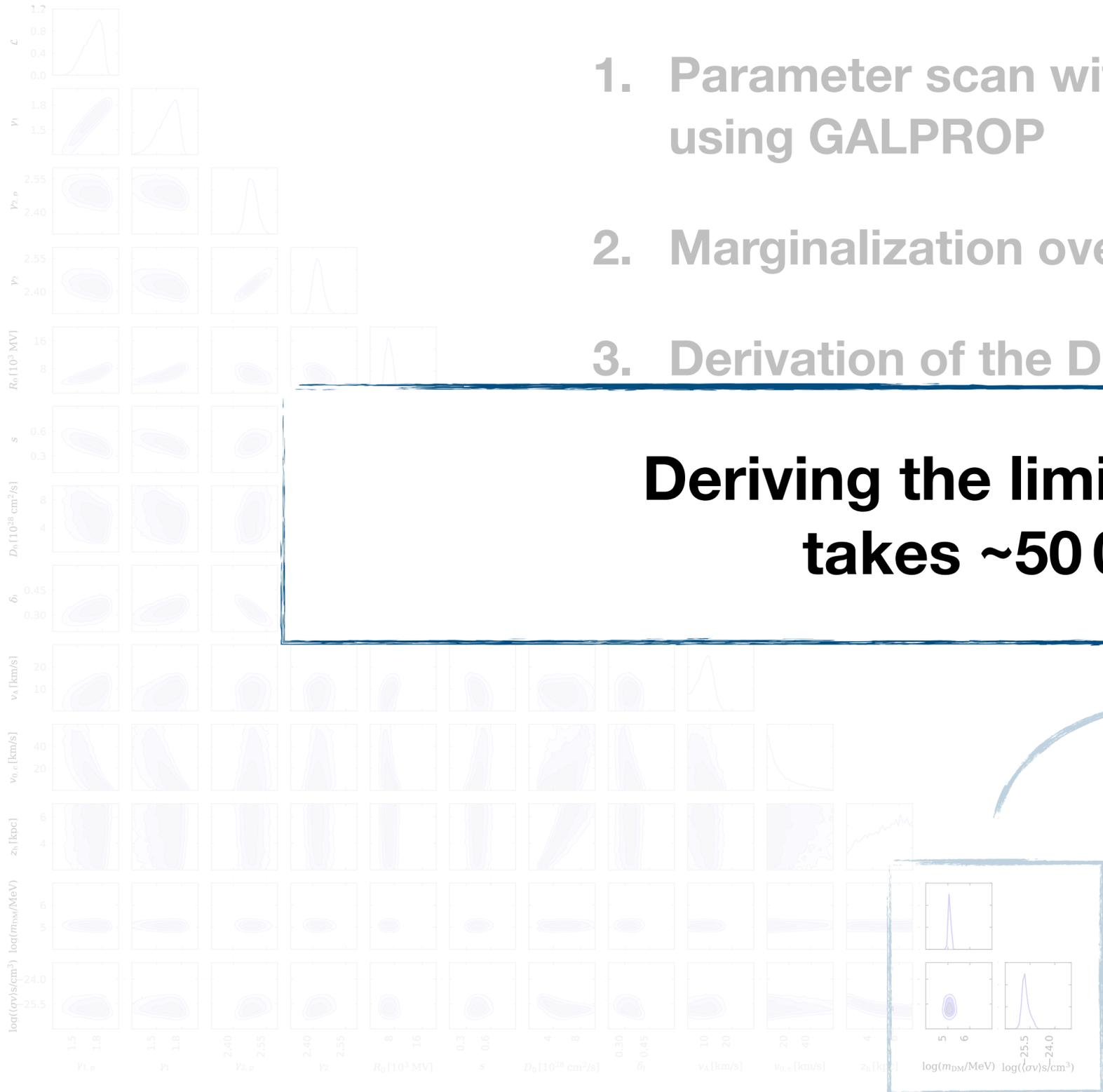


[Cuoco, Heisig, MK, Krämer; 2018]

DM Limit – the Traditional Way

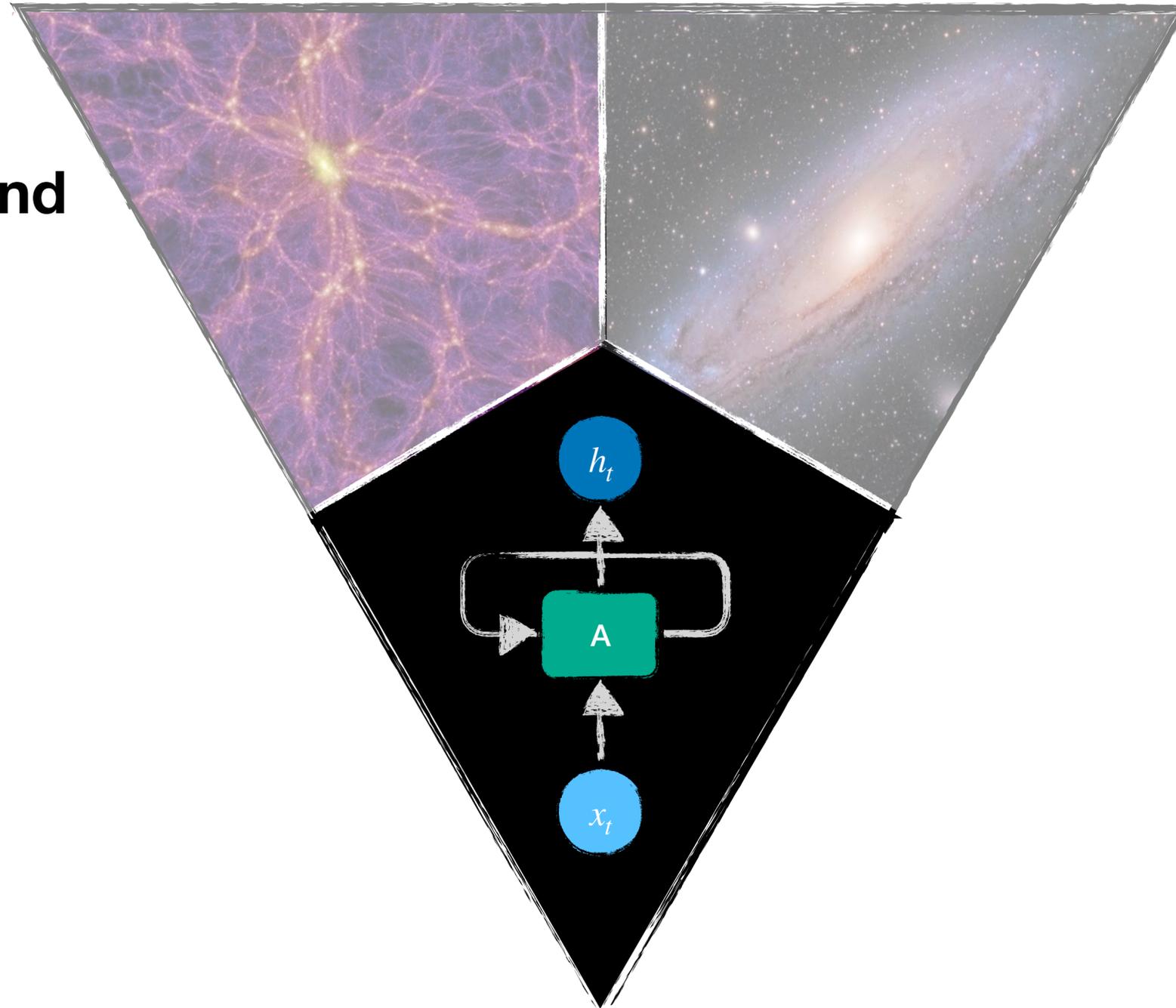
1. Parameter scan with $\mathcal{O}(10^6)$ likelihood evaluations using GALPROP
2. Marginalization over CR parameters
3. Derivation of the DM limit

Deriving the limit for one DM model takes $\sim 50\,000$ cpu-hours.



[Cuoco, Heisig, MK, Krämer; 2018]

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**Cosmic Rays:
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Role of Antiprotons**

**Speed-up: Neural Networks
and Importance Sampling**

Importance Sampling

$\mathcal{L}(\boldsymbol{\theta})$ Likelihood **without DM** signal

$\mathcal{L}(\boldsymbol{\theta}, \boldsymbol{x})$ Likelihood **with DM** signal

$\pi(\boldsymbol{\theta}) = \pi(\boldsymbol{\theta})$ Prior CR propagation

$$\boldsymbol{\theta} = \{\gamma_{1,p}, \gamma_{1,\text{He}}, \gamma_{2,p}, \gamma_{2,\text{He}}, R_0, s, D_0, \delta, v_A, v_{0,c}, z_h, \varphi, \varphi_{\bar{p}}\}$$

$$\boldsymbol{x} = \{m_{\text{DM}}, \langle \sigma v \rangle_{gg}, \langle \sigma v \rangle_{q\bar{q}}, \langle \sigma v \rangle_{c\bar{c}}, \langle \sigma v \rangle_{b\bar{b}}, \langle \sigma v \rangle_{t\bar{t}}, \langle \sigma v \rangle_{hh}, \langle \sigma v \rangle_{WW}, \langle \sigma v \rangle_{ZZ}\}$$

$$\{\boldsymbol{\theta}_i\} \sim \mathcal{L}(\boldsymbol{\theta})\pi(\boldsymbol{\theta})$$

$$\overline{\mathcal{L}}(\boldsymbol{x}) = \int d\boldsymbol{\theta} \mathcal{L}(\boldsymbol{\theta}, \boldsymbol{x})\pi(\boldsymbol{\theta})$$

Importance Sampling

$\mathcal{L}(\theta)$ Likelihood **without DM** signal

$\mathcal{L}(\theta, \mathbf{x})$ Likelihood **with DM** signal

$\pi(\theta) = \pi(\theta)$ Prior CR propagation

$$\theta = \{\gamma_{1,p}, \gamma_{1,\text{He}}, \gamma_{2,p}, \gamma_{2,\text{He}}, R_0, s, D_0, \delta, v_A, v_{0,c}, z_h, \varphi, \varphi_{\bar{p}}\}$$

$$\mathbf{x} = \{m_{\text{DM}}, \langle \sigma v \rangle_{gg}, \langle \sigma v \rangle_{q\bar{q}}, \langle \sigma v \rangle_{c\bar{c}}, \langle \sigma v \rangle_{b\bar{b}}, \langle \sigma v \rangle_{t\bar{t}}, \langle \sigma v \rangle_{hh}, \langle \sigma v \rangle_{WW}, \langle \sigma v \rangle_{ZZ}\}$$

$\{\theta_i\} \sim \mathcal{L}(\theta)\pi(\theta)$ ← **We have this!**

$$\overline{\mathcal{L}}(\mathbf{x}) = \int d\theta \mathcal{L}(\theta, \mathbf{x})\pi(\theta)$$

Importance Sampling

$\mathcal{L}(\boldsymbol{\theta})$ Likelihood **without DM** signal

$\mathcal{L}(\boldsymbol{\theta}, \mathbf{x})$ Likelihood **with DM** signal

$\pi(\boldsymbol{\theta}) = \pi(\boldsymbol{\theta})$ Prior CR propagation

$$\boldsymbol{\theta} = \{\gamma_{1,p}, \gamma_{1,\text{He}}, \gamma_{2,p}, \gamma_{2,\text{He}}, R_0, s, D_0, \delta, v_A, v_{0,c}, z_h, \varphi, \varphi_{\bar{p}}\}$$

$$\mathbf{x} = \{m_{\text{DM}}, \langle \sigma v \rangle_{gg}, \langle \sigma v \rangle_{q\bar{q}}, \langle \sigma v \rangle_{c\bar{c}}, \langle \sigma v \rangle_{b\bar{b}}, \langle \sigma v \rangle_{t\bar{t}}, \langle \sigma v \rangle_{hh}, \langle \sigma v \rangle_{WW}, \langle \sigma v \rangle_{ZZ}\}$$

$\{\boldsymbol{\theta}_i\} \sim \mathcal{L}(\boldsymbol{\theta})\pi(\boldsymbol{\theta})$ ← We have this!

$$\overline{\mathcal{L}}(\mathbf{x}) = \int d\boldsymbol{\theta} \mathcal{L}(\boldsymbol{\theta})\pi(\boldsymbol{\theta}) \frac{\mathcal{L}(\boldsymbol{\theta}, \mathbf{x})}{\mathcal{L}(\boldsymbol{\theta})} \approx \frac{1}{\tilde{N}} \sum_{i=1}^N \frac{\mathcal{L}(\boldsymbol{\theta}_i, \mathbf{x})}{\mathcal{L}(\boldsymbol{\theta}_i)}$$

Importance Sampling

$\mathcal{L}(\theta)$ Likelihood **without DM** signal

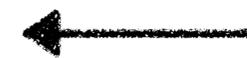
$\mathcal{L}(\theta, \mathbf{x})$ Likelihood **with DM** signal

$\pi(\theta) = \pi(\theta)$ Prior CR propagation

$$\theta = \{\gamma_{1,p}, \gamma_{1,\text{He}}, \gamma_{2,p}, \gamma_{2,\text{He}}, R_0, s, D_0, \delta, v_A, v_{0,c}, z_h, \varphi, \varphi_{\bar{p}}\}$$

$$\mathbf{x} = \{m_{\text{DM}}, \langle \sigma v \rangle_{gg}, \langle \sigma v \rangle_{q\bar{q}}, \langle \sigma v \rangle_{c\bar{c}}, \langle \sigma v \rangle_{b\bar{b}}, \langle \sigma v \rangle_{t\bar{t}}, \langle \sigma v \rangle_{hh}, \langle \sigma v \rangle_{WW}, \langle \sigma v \rangle_{ZZ}\}$$

$$\{\theta_i\} \sim \mathcal{L}(\theta)\pi(\theta)$$

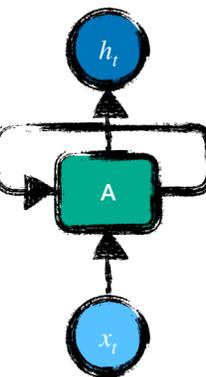


We have this!

$$\overline{\mathcal{L}}(\mathbf{x}) = \int d\theta \mathcal{L}(\theta)\pi(\theta) \frac{\mathcal{L}(\theta, \mathbf{x})}{\mathcal{L}(\theta)} \approx \frac{1}{\tilde{N}} \sum_{i=1}^N \frac{\mathcal{L}(\theta_i, \mathbf{x})}{\mathcal{L}(\theta_i)}$$

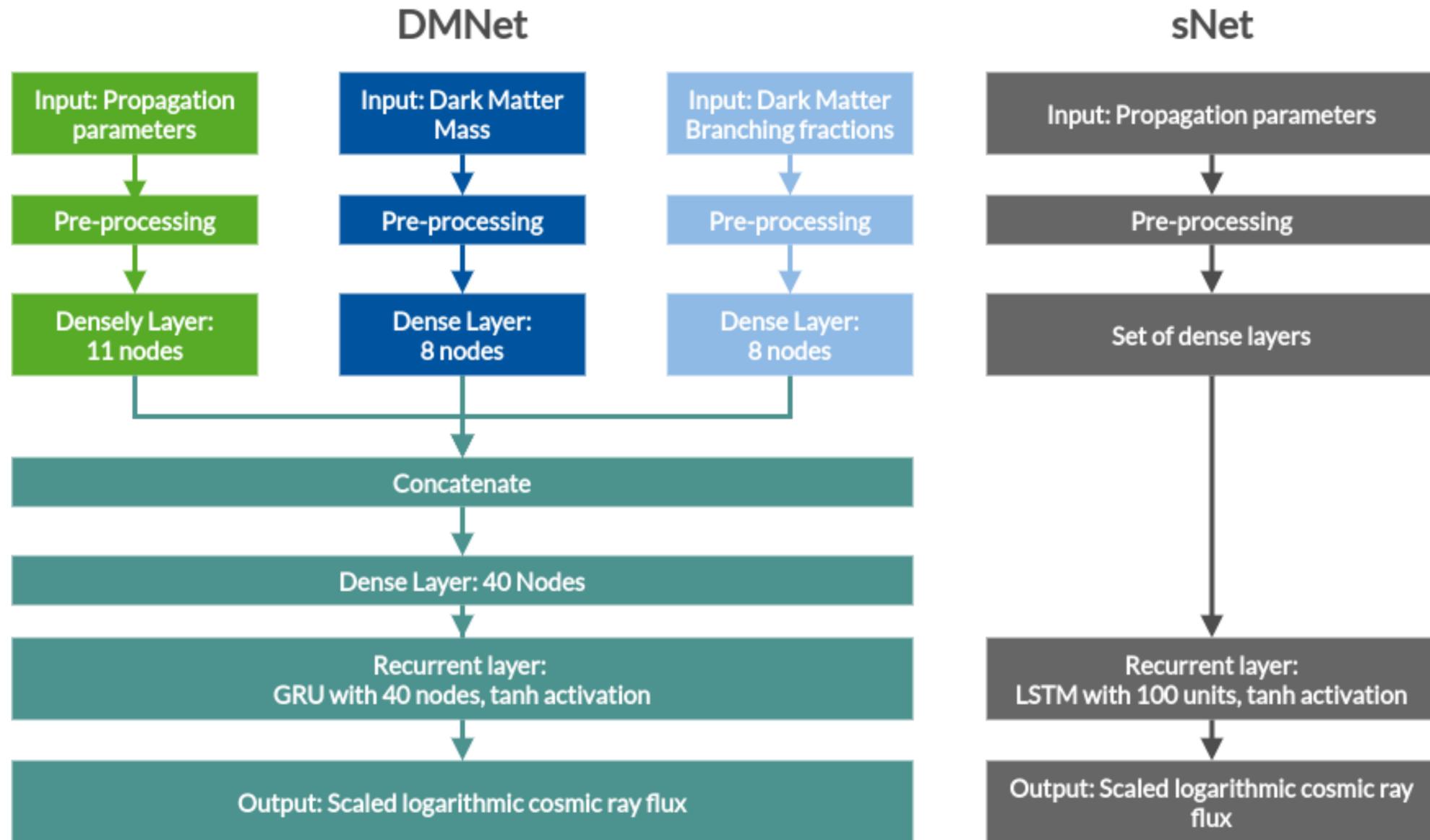


We make it fast!



Dark Ray Net

[Kahlhoefer, MK, et al. 2021]



**Training Data:
Chain of a
MultiNest fit**

**RNNs efficiently learn
smooth spectra**

$$\tilde{\phi}_s(E) = \log_{10}(E^{2.7} \phi(E))$$

$$\tilde{\phi}_{DM}(x) = \log_{10}(m_{DM}^3 x \phi(E))$$

Dark Ray Net



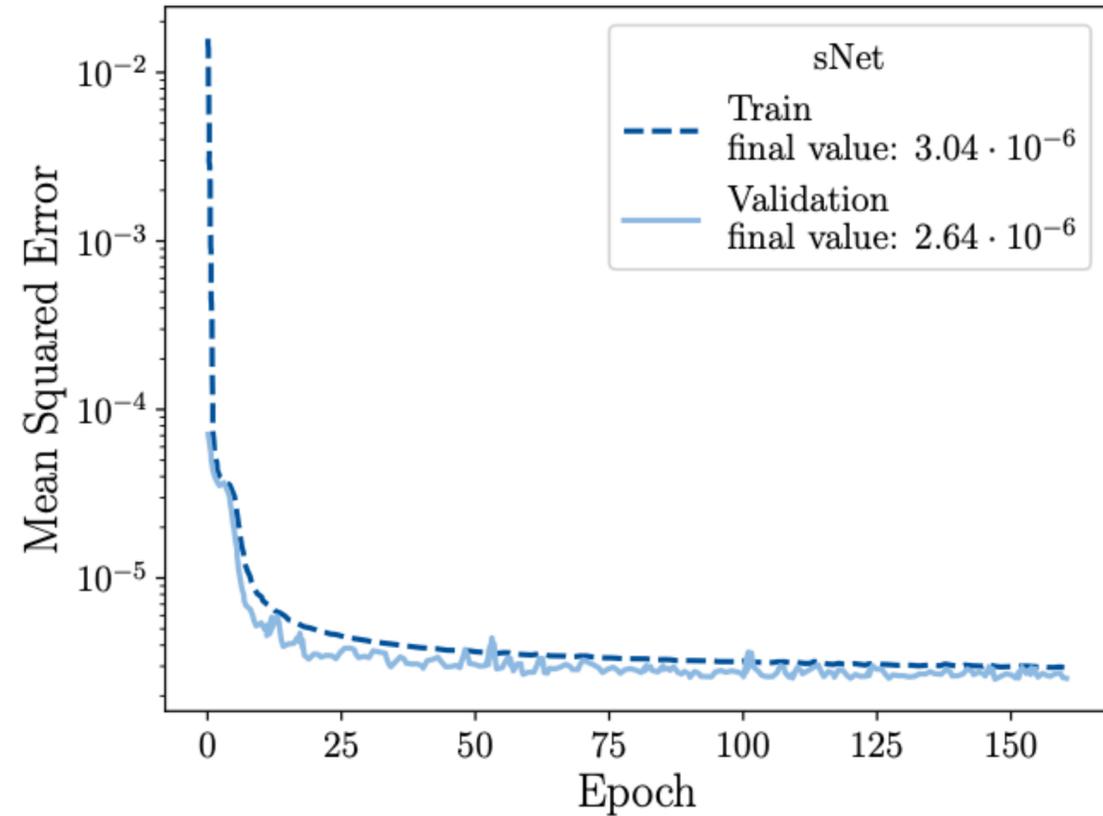
DMNet

sNet

Input: Propagation

Input: Dark Matter

Input: Dark Matter



Hyperparameters

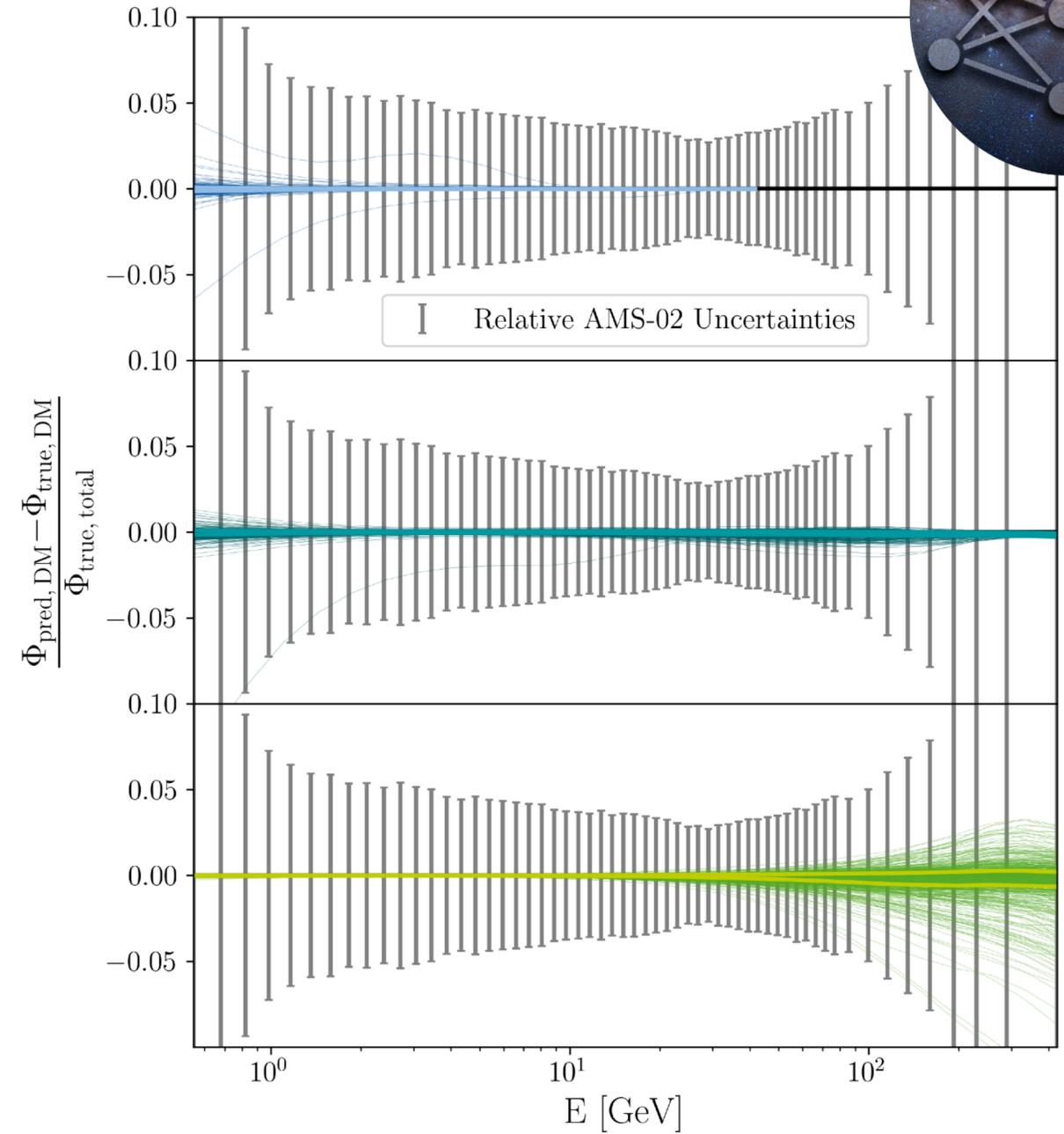
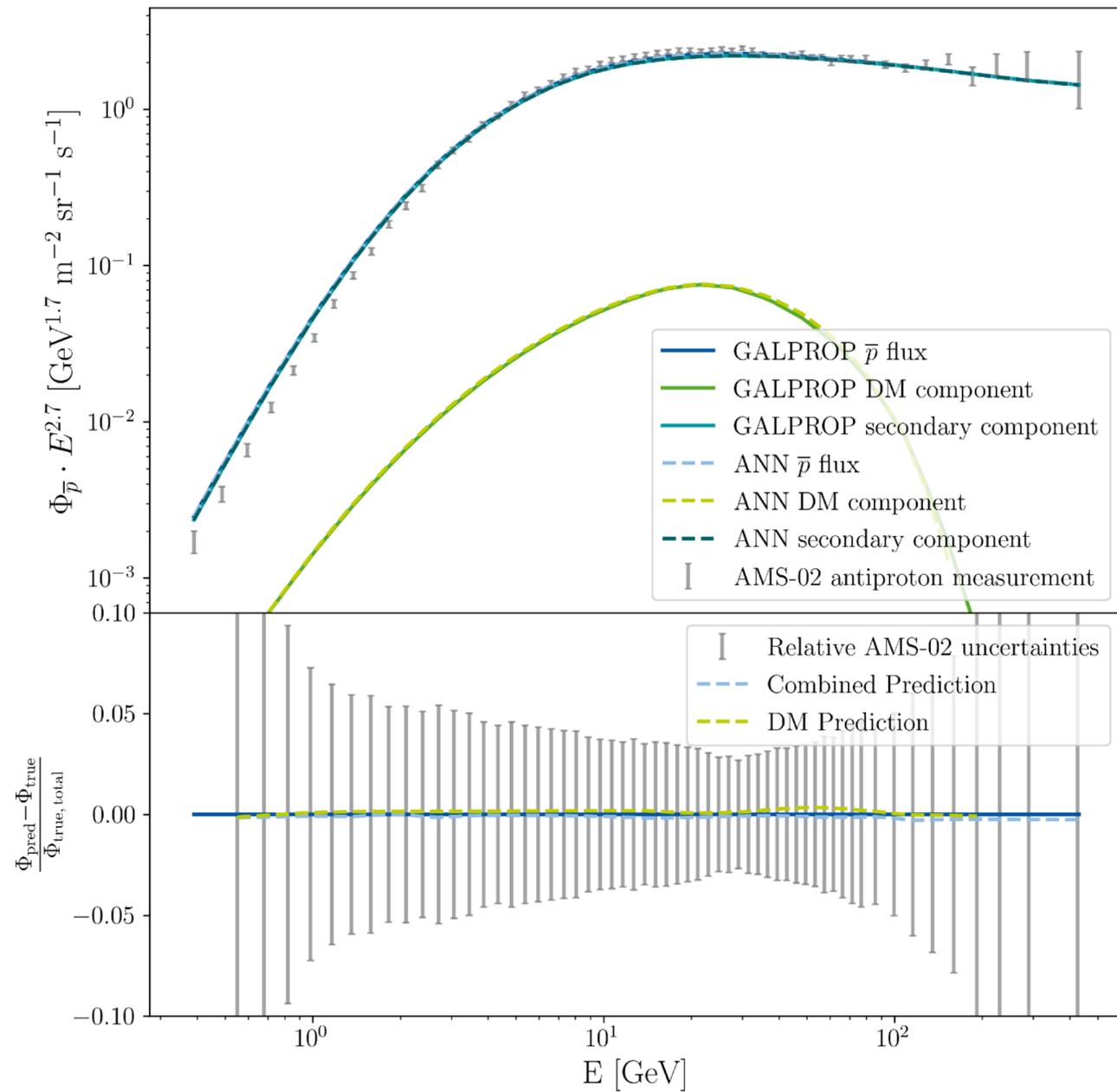
Activation	ReLU
Dropout fraction	0.1 %
Optimizer	Adam, learning rate scheduling $l \in [10^{-2}, 10^{-5}]$, patience 10 epochs
Loss	Mean squared error (MSE)
Batch size	500
Validation split	20 %
Early stopping	Monitor val. loss, patience = 40

$$\tilde{\phi}_s(E) = \log_{10}(E^{2.7} \phi(E))$$

$$\tilde{\phi}_{\text{DM}}(x) = \log_{10}(m_{\text{DM}}^3 x \phi(E))$$

[Kahlhoefer, MK, et al. 2021]

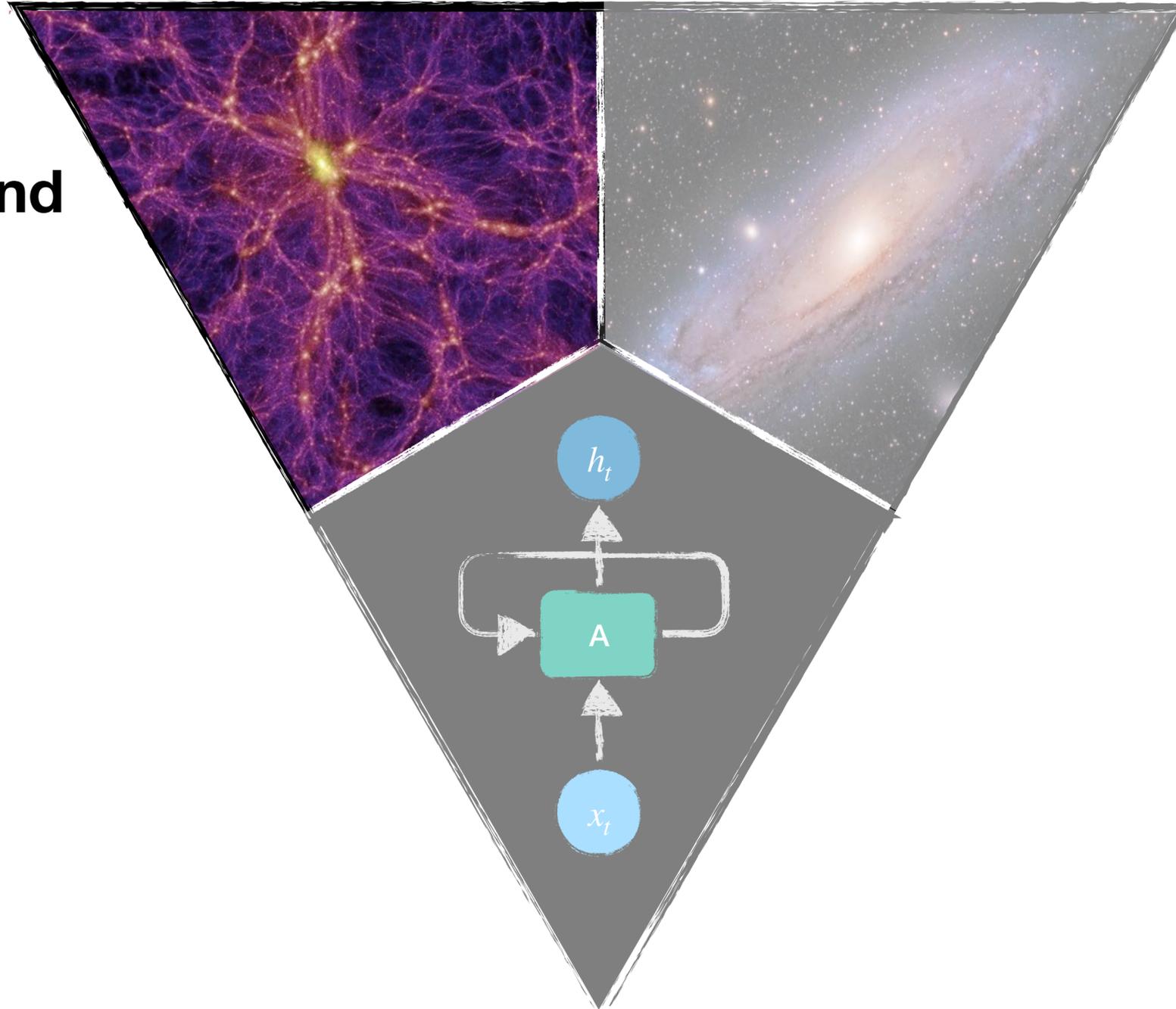
Performance of Dark Ray Net



[Kahlhoefer, MK, et al. 2021]

Uncertainties from the NN prediction are almost negligible compared to AMS-02 measurement uncertainties.

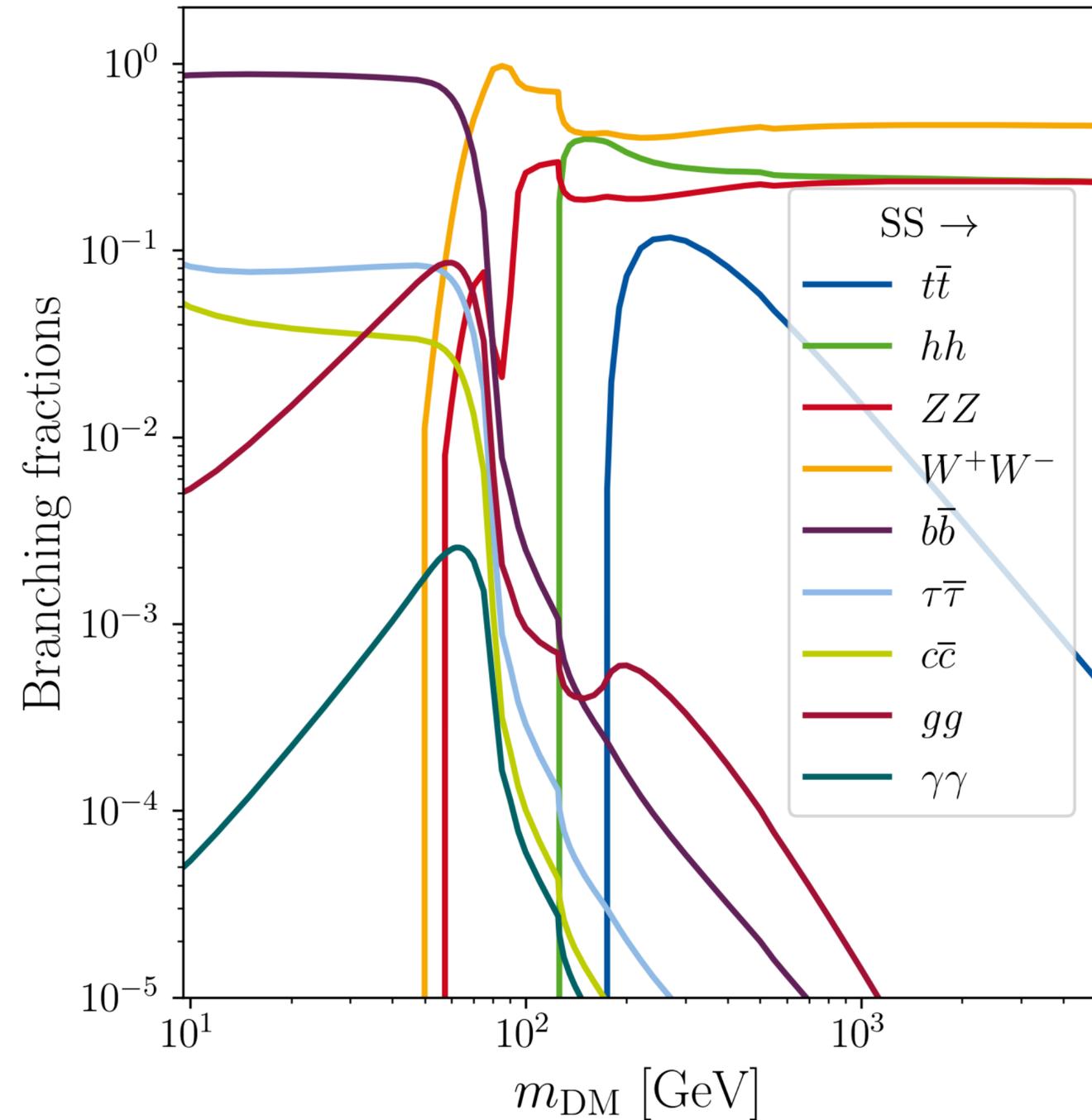
**Motivation:
Dark Matter Limits and
Indirect Detection**



**Cosmic Rays:
Propagation and the
Role of Antiprotons**

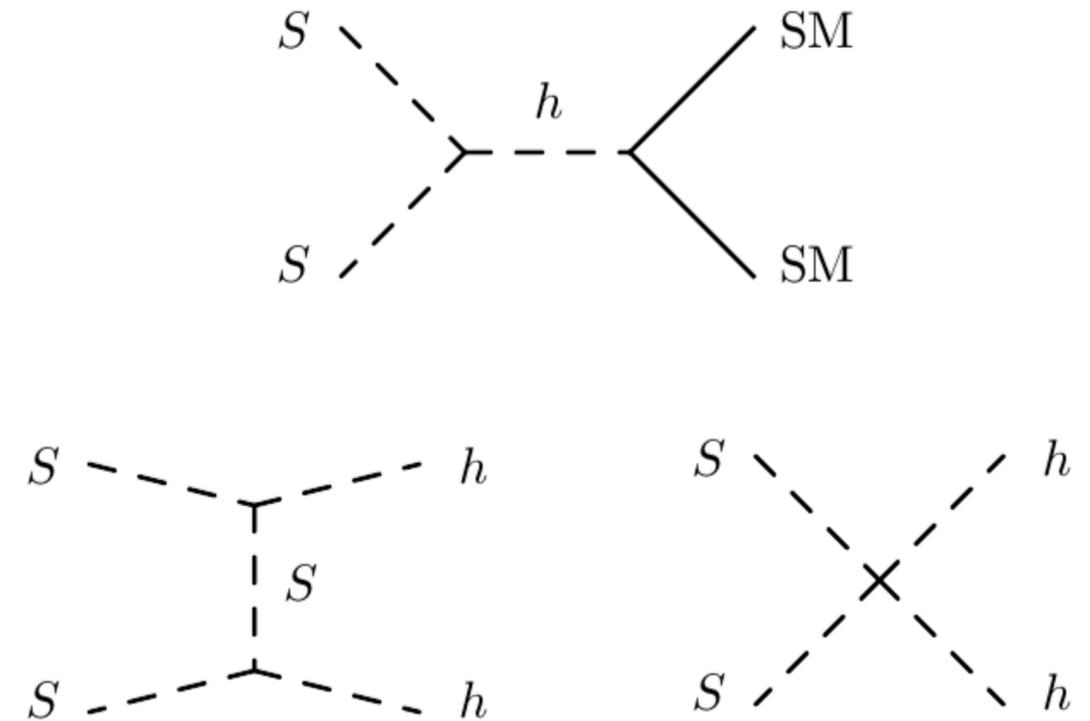
**Speed-up: Neural Networks
and Importance Sampling**

Application: Scalar Singlet DM

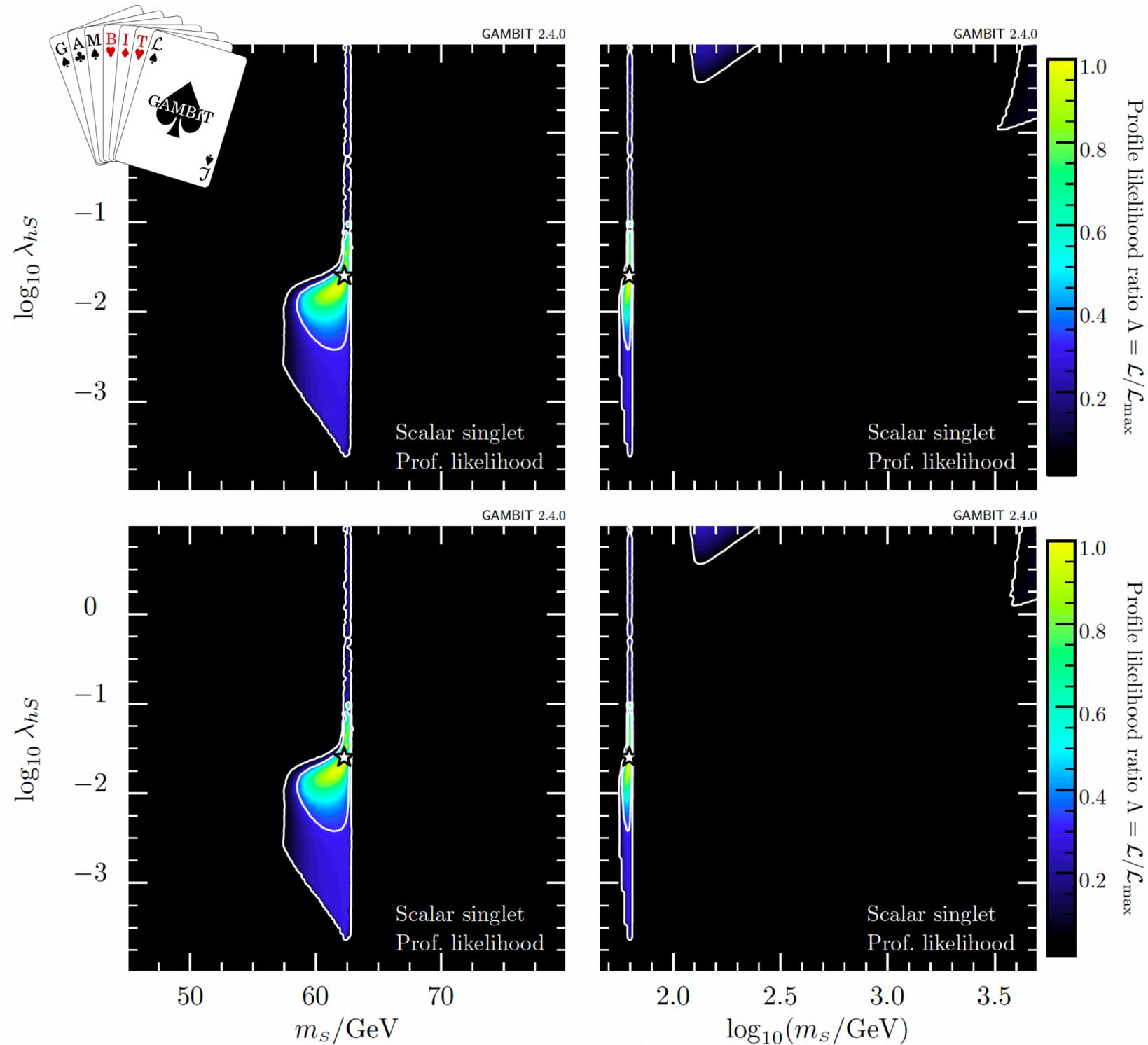


After EW symmetry breaking:

$$\mathcal{L} \supset -\frac{1}{2}m_S^2 S^2 - \frac{1}{4}\lambda_S S^4 - \frac{1}{4}\lambda_{HS} h^2 S^2 - \frac{1}{2}\lambda_{HS} v h S^2$$

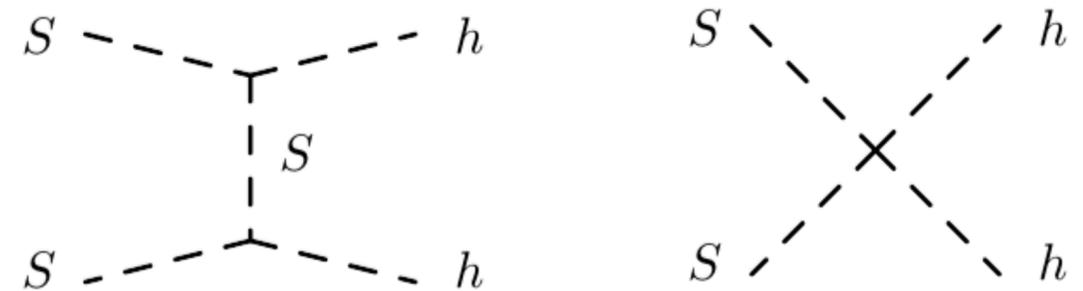
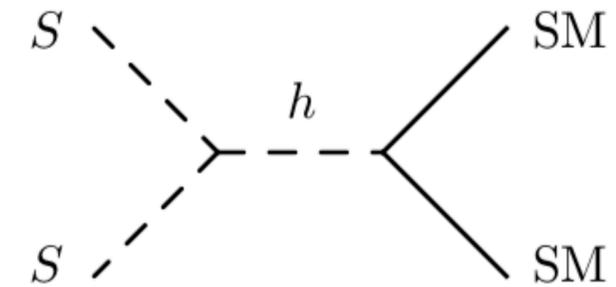


Application: Scalar Singlet DM



After EW symmetry breaking:

$$\mathcal{L} \supset -\frac{1}{2}m_S^2 S^2 - \frac{1}{4}\lambda_S S^4 - \frac{1}{4}\lambda_{HS} h^2 S^2 - \frac{1}{2}\lambda_{HS} v h S^2$$

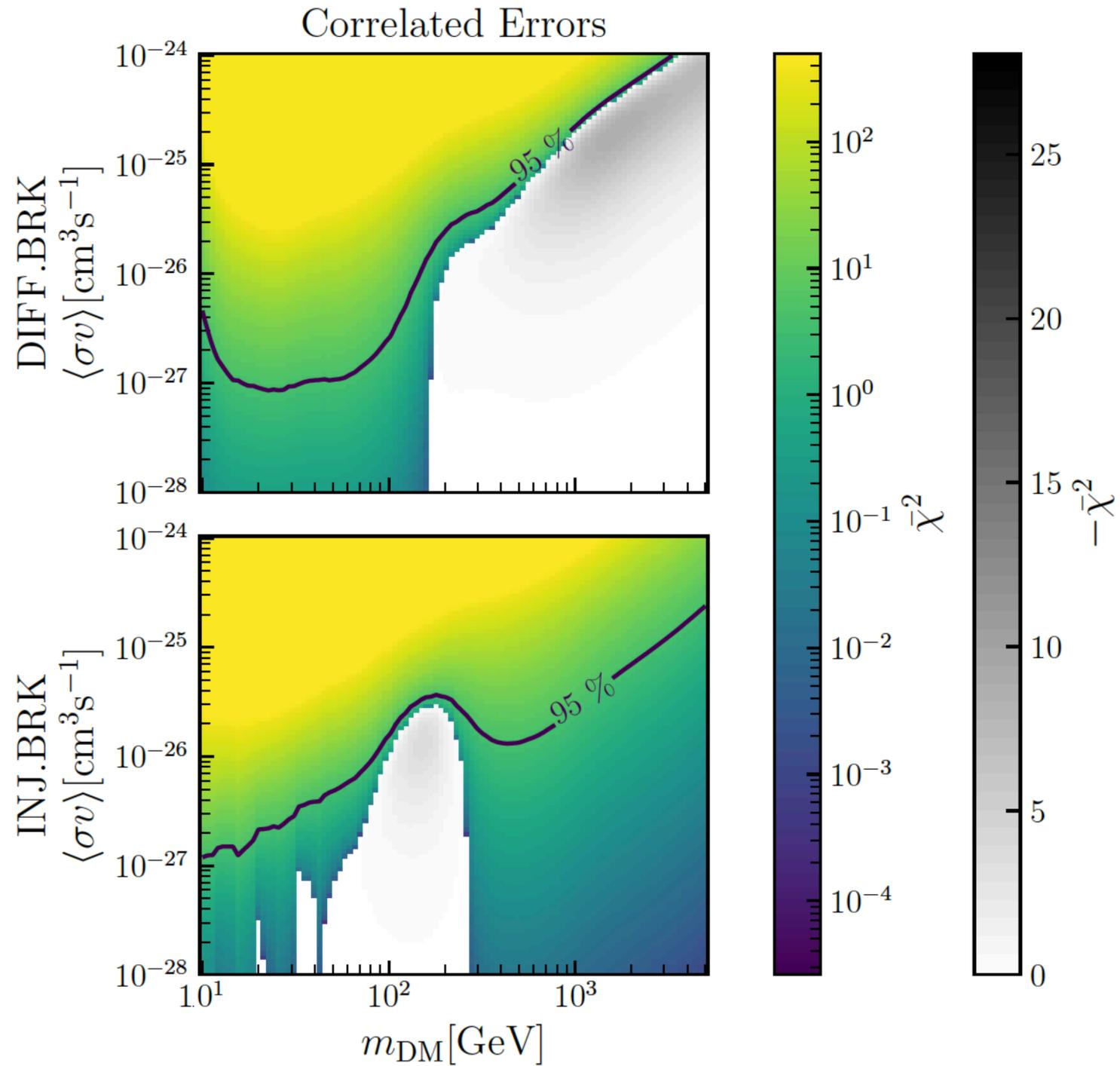


[Balan, MK, et al. 2023]

Summary



pbarlike



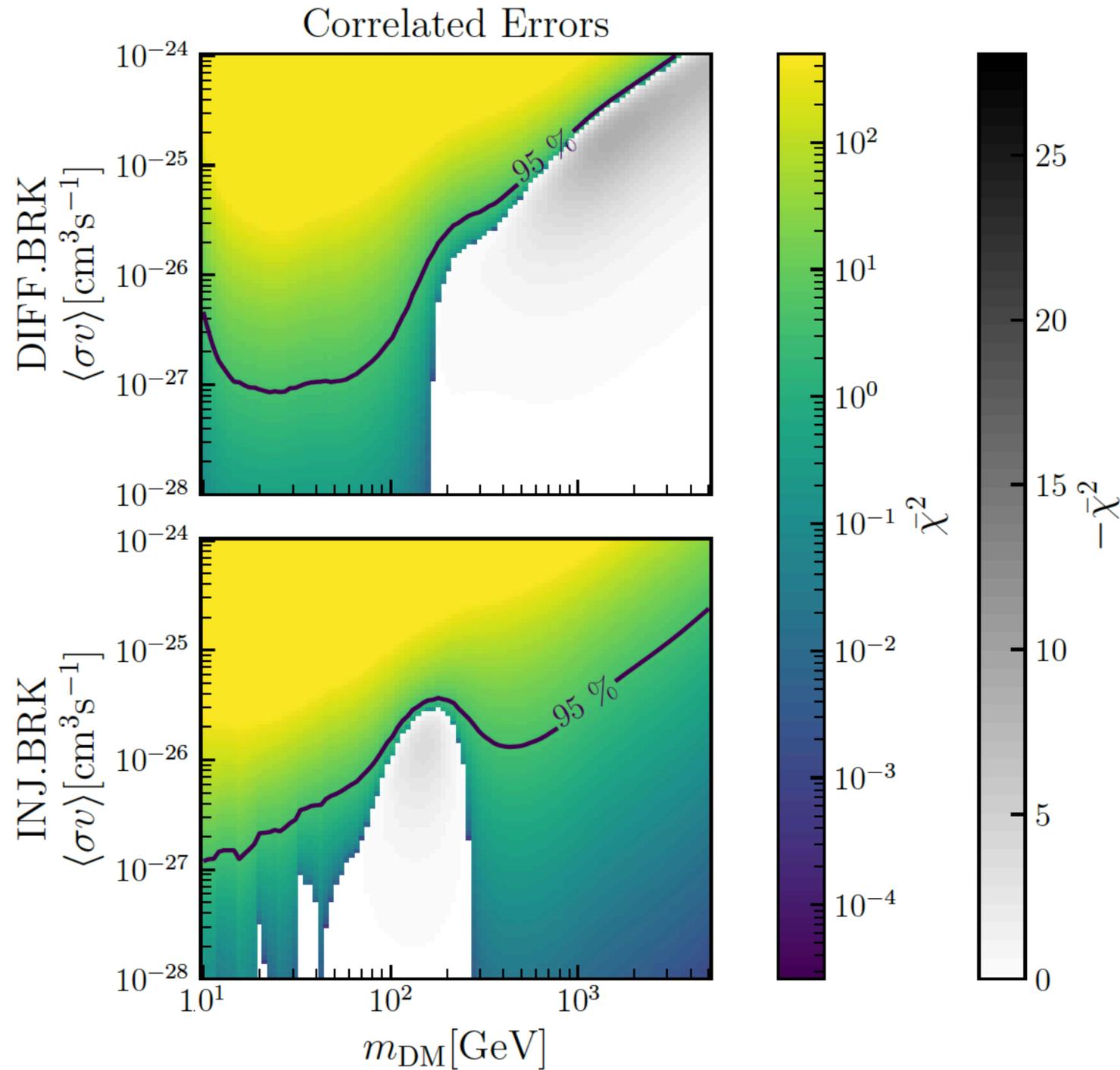
[Balan, MK, et al. 2023]



Summary



pbarlike



Fast DM Limits from CR antiprotons

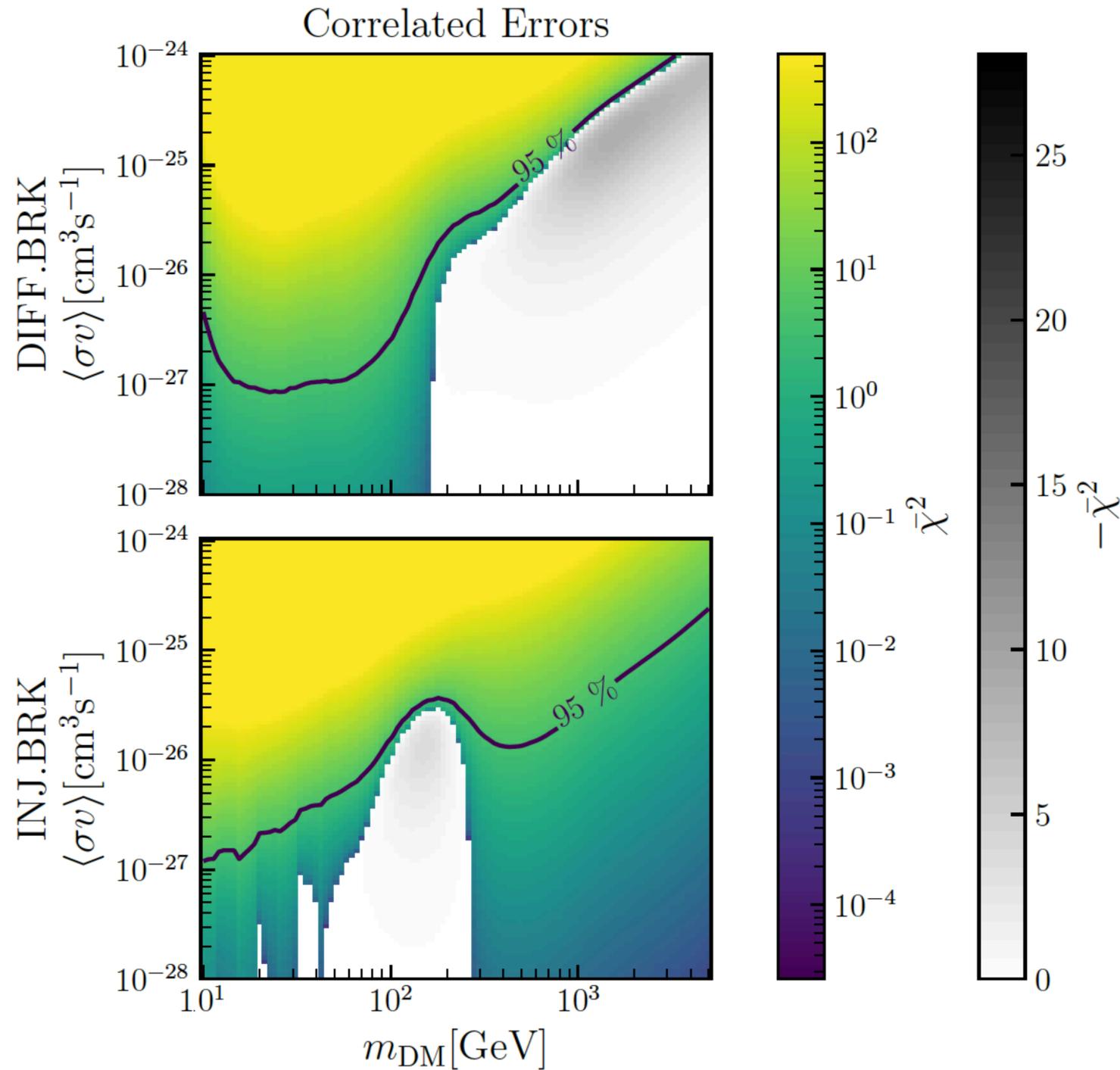
[Balan, MK, et al. 2023]



Summary



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Fast DM Limits from CR antiprotons

State of the art propagation and uncertainty treatment

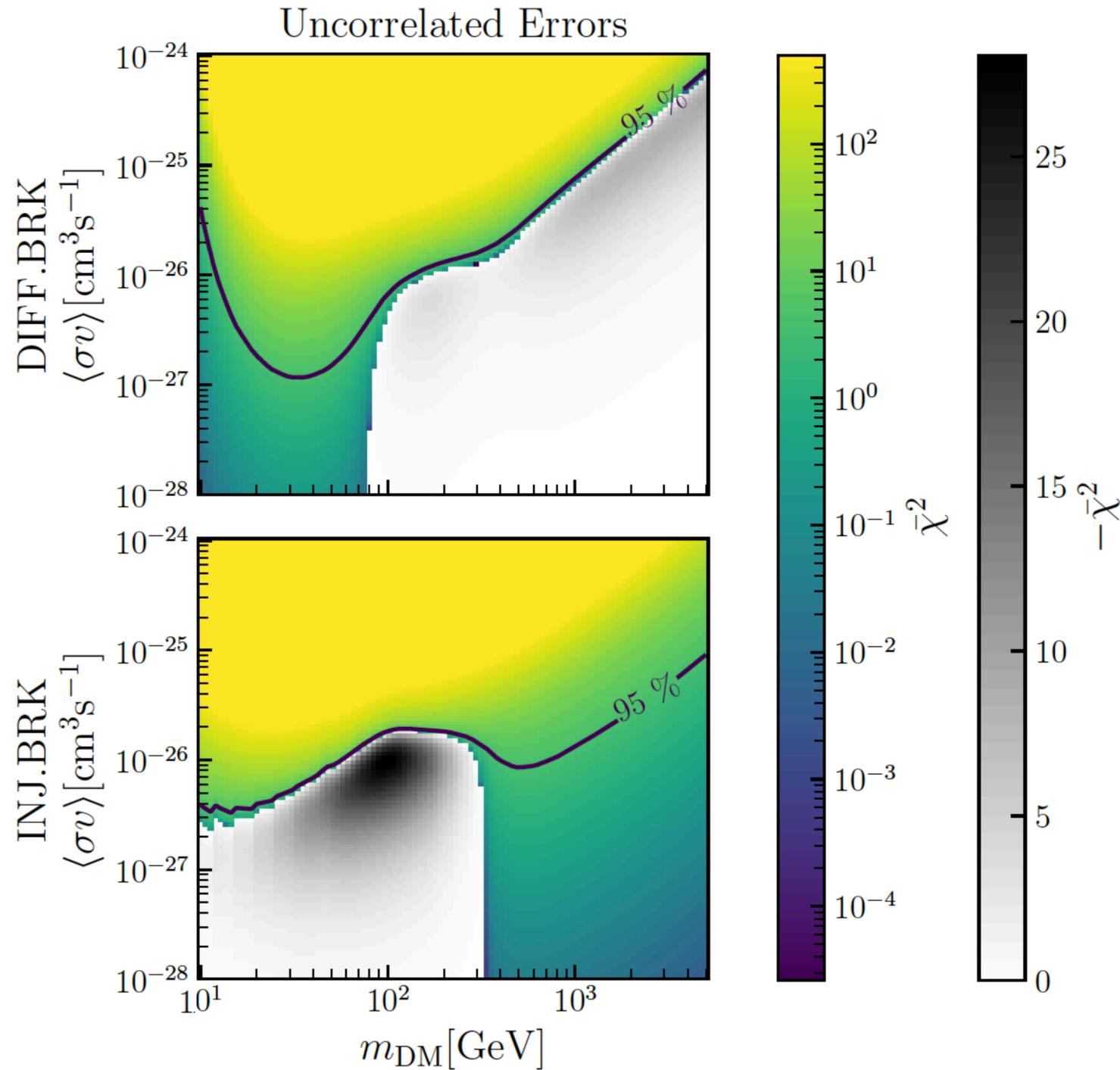
[Balan, MK, et al. 2023]



Summary



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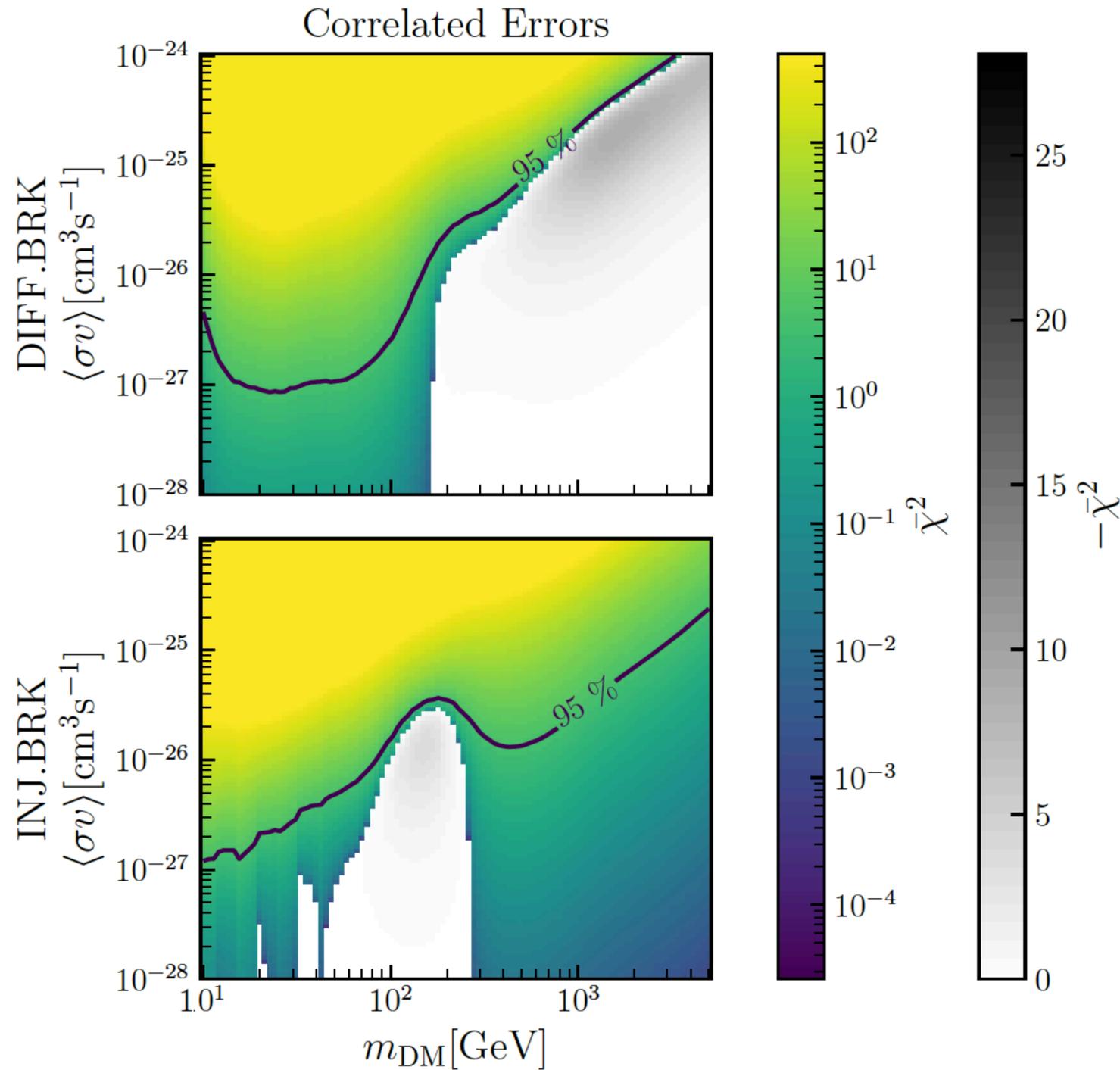
[Balan, MK, et al. 2023]



Summary



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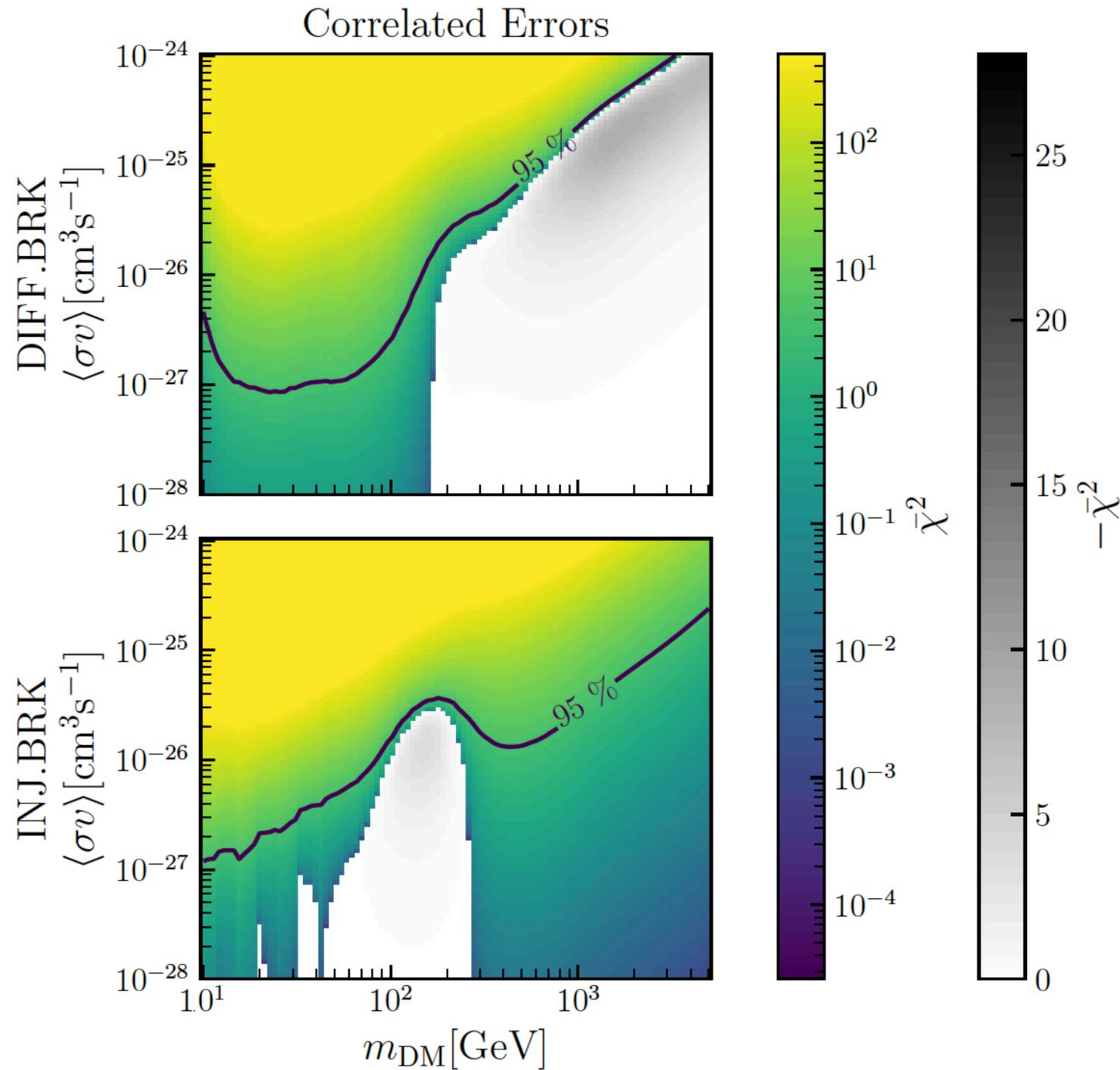
[Balan, MK, et al. 2023]



Summary



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[Balan, MK, et al. 2023]

Fast DM Limits from CR antiprotons

State of the art propagation and uncertainty treatment

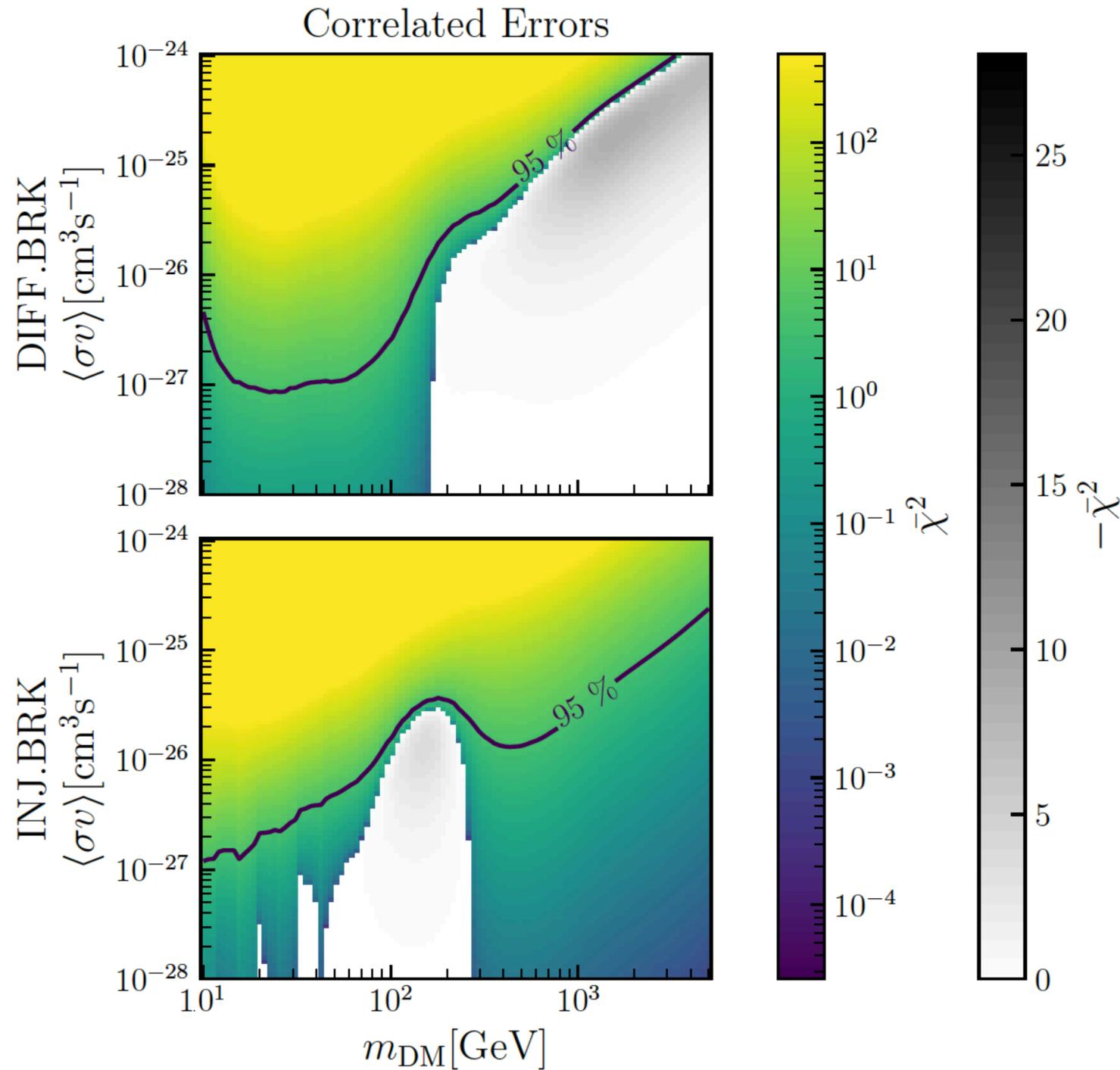
Public code for CR spectra and likelihood marginalization



Summary



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[Balan, MK, et al. 2023]

Fast DM Limits from CR antiprotons

State of the art propagation and uncertainty treatment

Public code for CR spectra and likelihood marginalization

Global fits with GAMBIT

