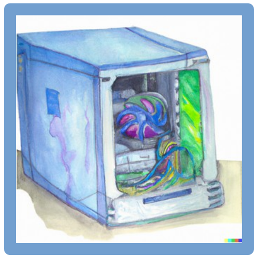
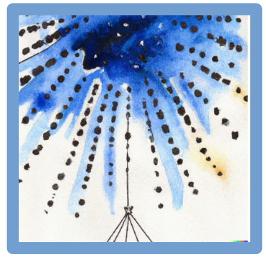
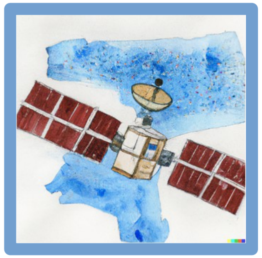
High Performance Computing in astroparticle theory



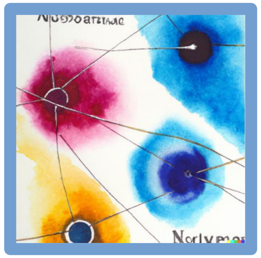
GPUs



Cosmic rays



Gamma rays



Multimessenger

Yoann Génolini

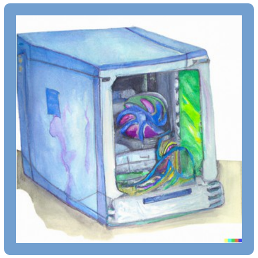
LAPTh

UNIVERSITÉ SAVOIE MONT BLANC

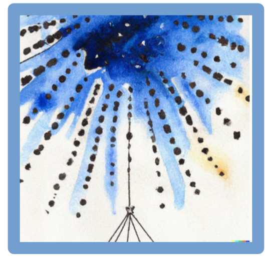
cnrs

AG Enigmass 2023

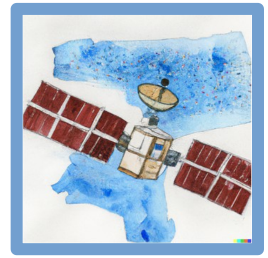
High Performance Computing in astroparticle theory



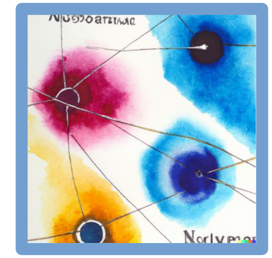
GPUs



Cosmic rays



Gamma rays



Multimessenger

Acknowledgments:

Enigmass & MUST &

Pierre Aubert

Yoann Génolini

LAPTh

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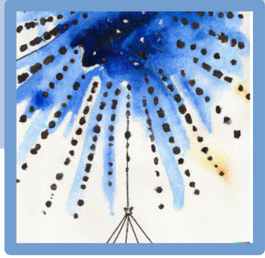


What is the origin of cosmic rays?
(multiples underlying questions)

Direct observable: Local differential flux

$$\Psi_i = \frac{dN_i}{dE\, dT\, d\Omega\, dS}$$

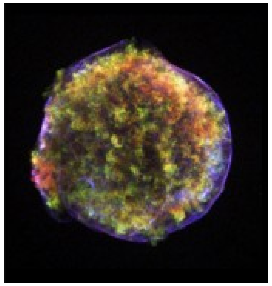
→ Charged particles : Lorentz's force

$$R_L(1\,\mathrm{PeV}) = 1\,\mathrm{pc} \ll 100\,\mathrm{pc}$$

→ What are the generic properties of the CR sources/transport?

→ What is the interstellar B field?

Indirect observables in multi-wavelengths



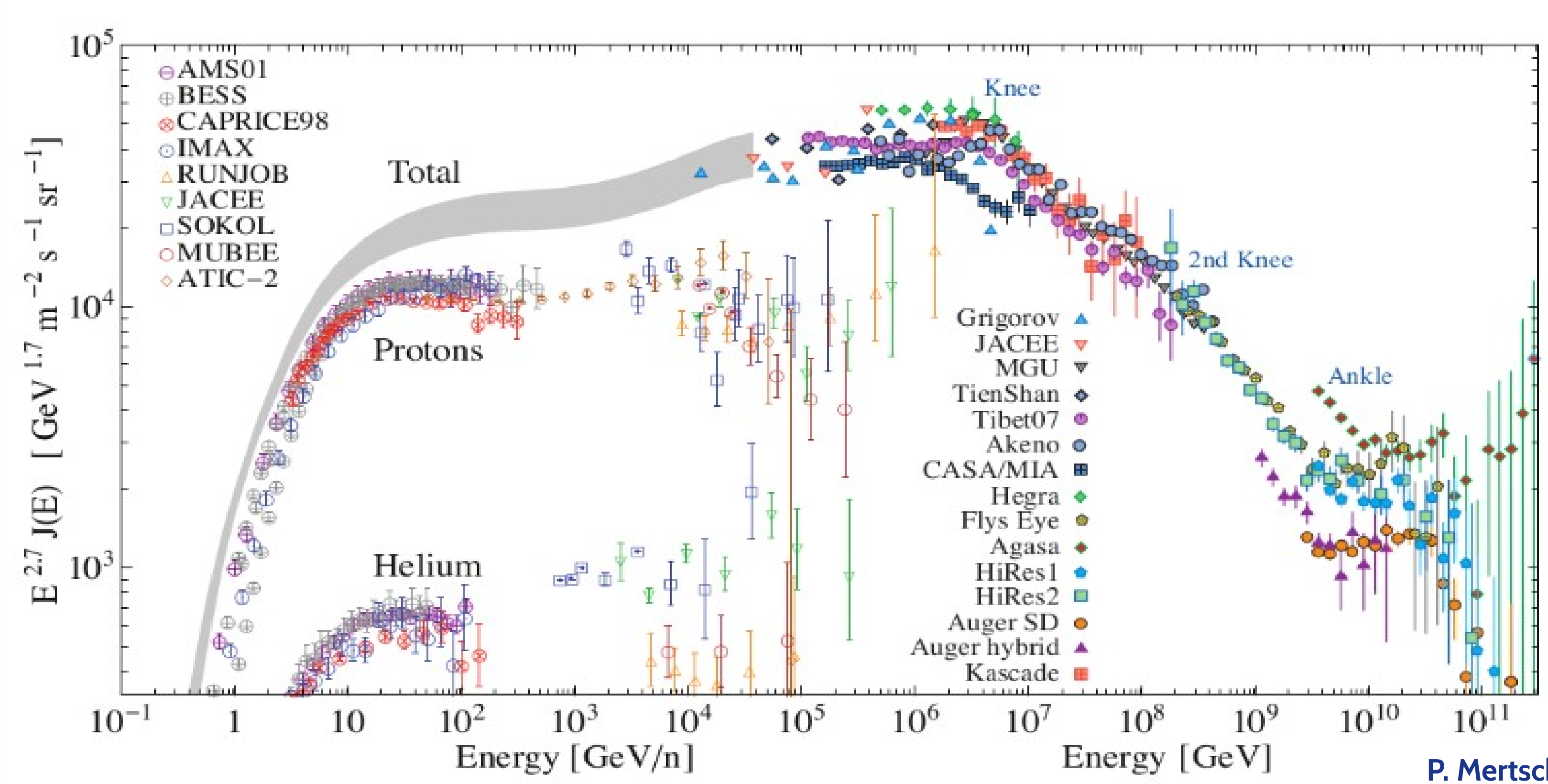
→ Non-thermal processes: pinpoint potential CR sources
→ What are the environments of acceleration and injection?

Differential flux: $$\Psi_i = \frac{dN_i}{dE\, dT\, d\Omega\, dS}$$

Energy

Composition

Direction



P. Mertsch PhD (2010)

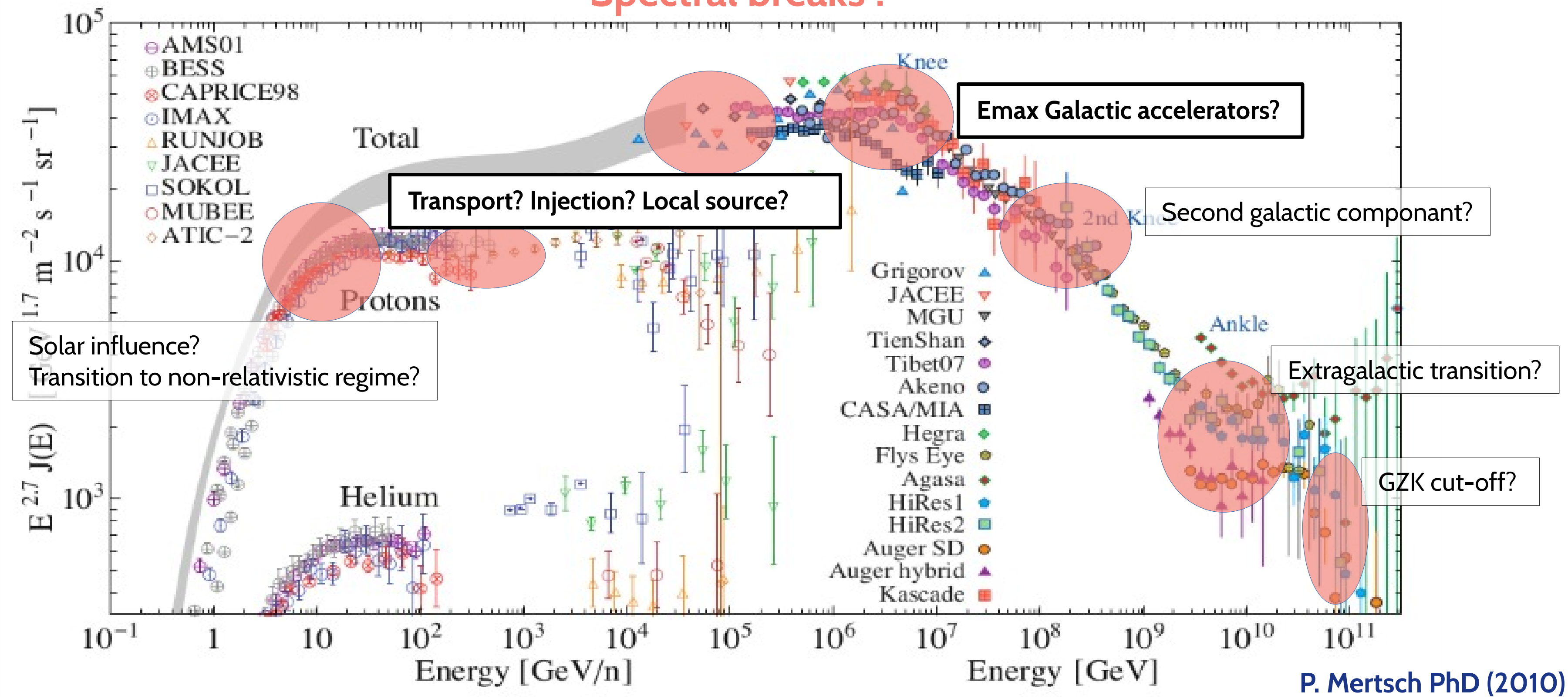
Differential flux: $$\Psi_i = \frac{dN_i}{dE\,dT\,d\Omega\,dS}$$

Energy

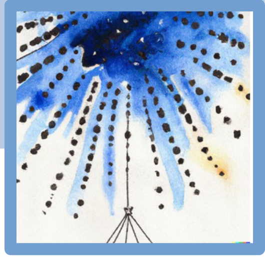
Composition

Direction

Spectral breaks !



P. Mertsch PhD (2010)



Differential flux: $$\Psi_i = \frac{dN_i}{dE\, dT\, d\Omega\, dS}$$

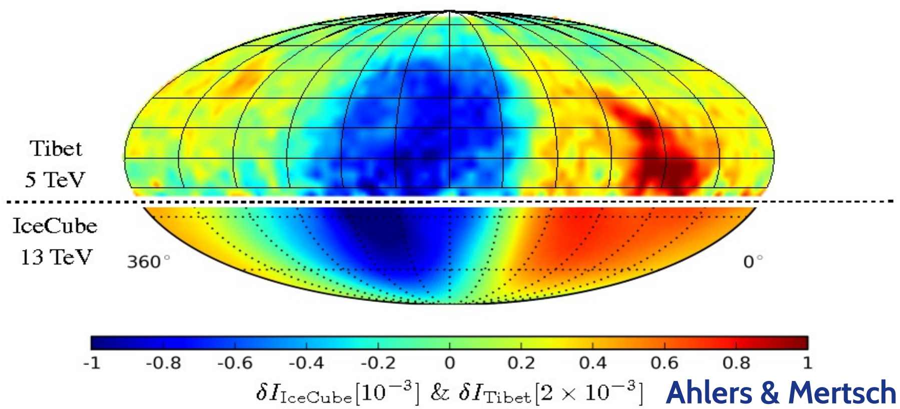
Energy

Composition

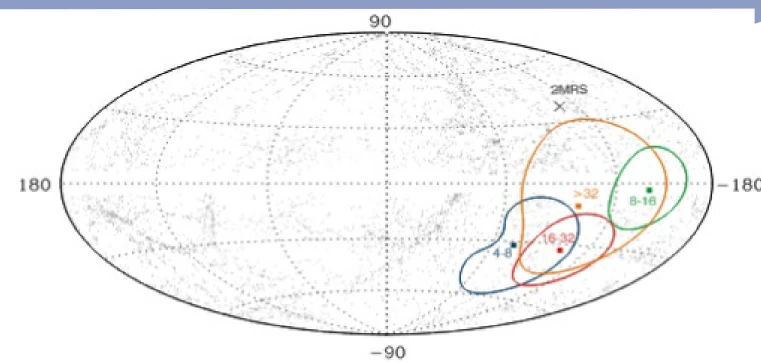
Direction

TeV

EeV



Ahlers & Mertsch PPNP (2016)

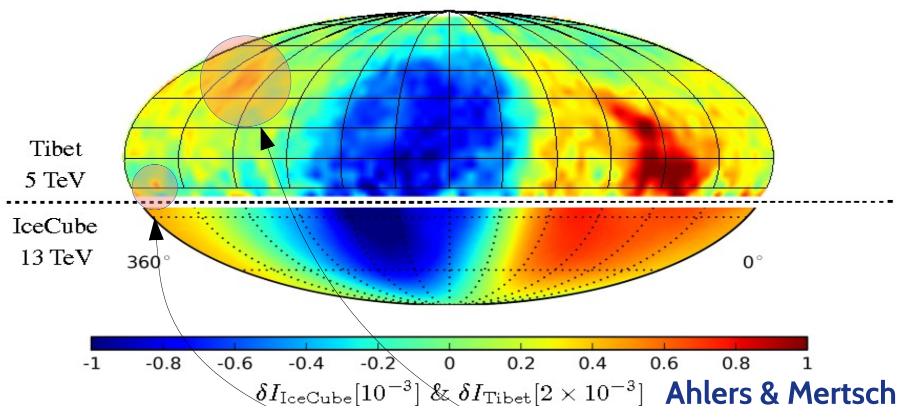


Auger collab. ApJ 868 (2018)

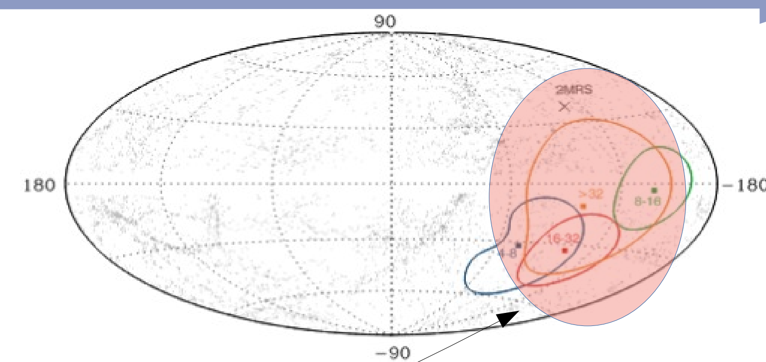
Differential flux: $$\Psi_i = \frac{dN_i}{dE\,dT\,d\Omega\,dS}$$

Energy **Composition** **Direction**

TeV **EeV**



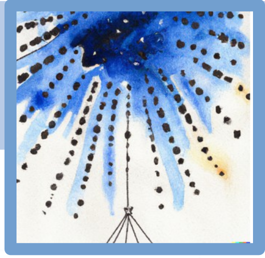
Ahlers & Mertsch PPNP (2016)



Auger collab. ApJ 868 (2018)

Multi-scale anisotropies

→ In the following we focus on the dipole anisotropy



Data

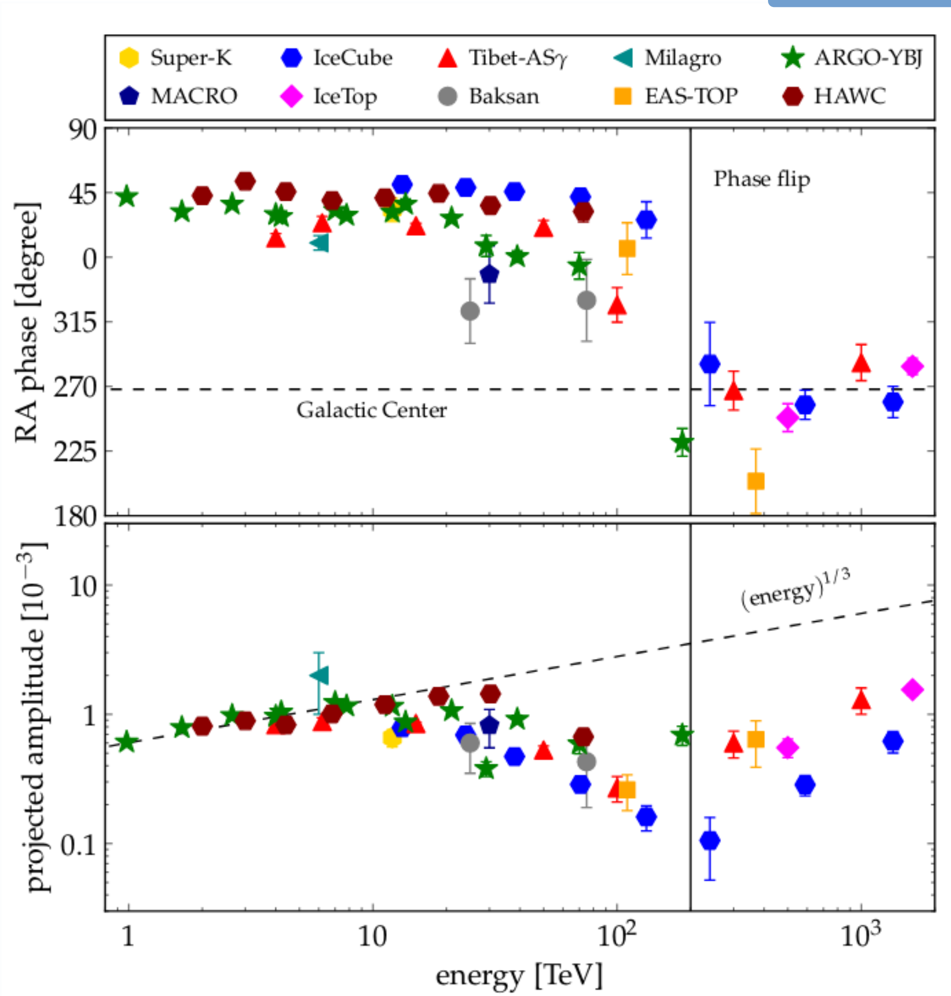
→ Relative intensity can be decomposed as:

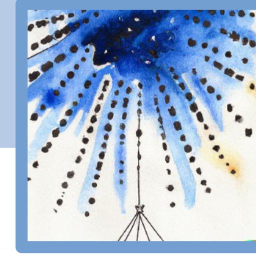
$$I(\boldsymbol{n}) = 1 + \boldsymbol{\delta}\cdot\boldsymbol{n} + \mathcal{O}(Y_{l>1})$$

→ CR observatories sensitive to 2 param.

→ Small dipole anisotropy of GCRs

→ Rapid change of the phase & amplitude with E





Data

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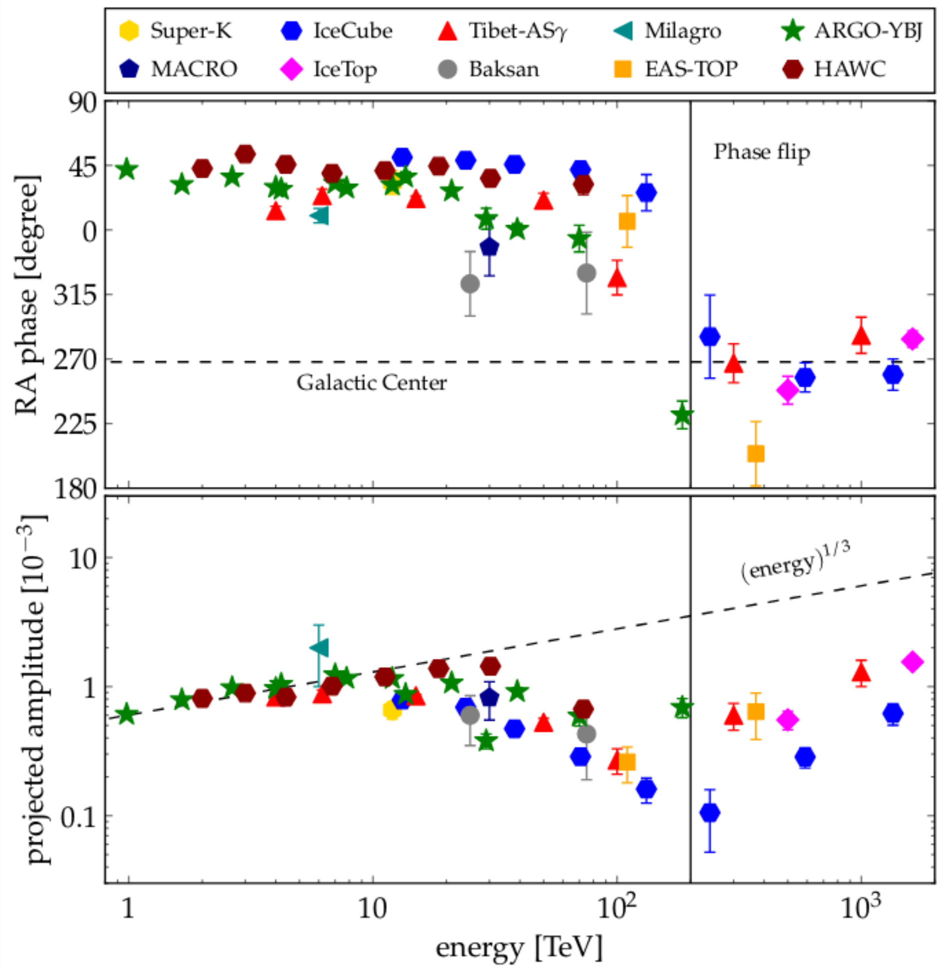


Interpretation

$$\boldsymbol{\delta} \propto \boldsymbol{j}_{\rm CR}$$

→ Compton Getting effect?
Small in the local standard of rest

→ Diffusion approximation

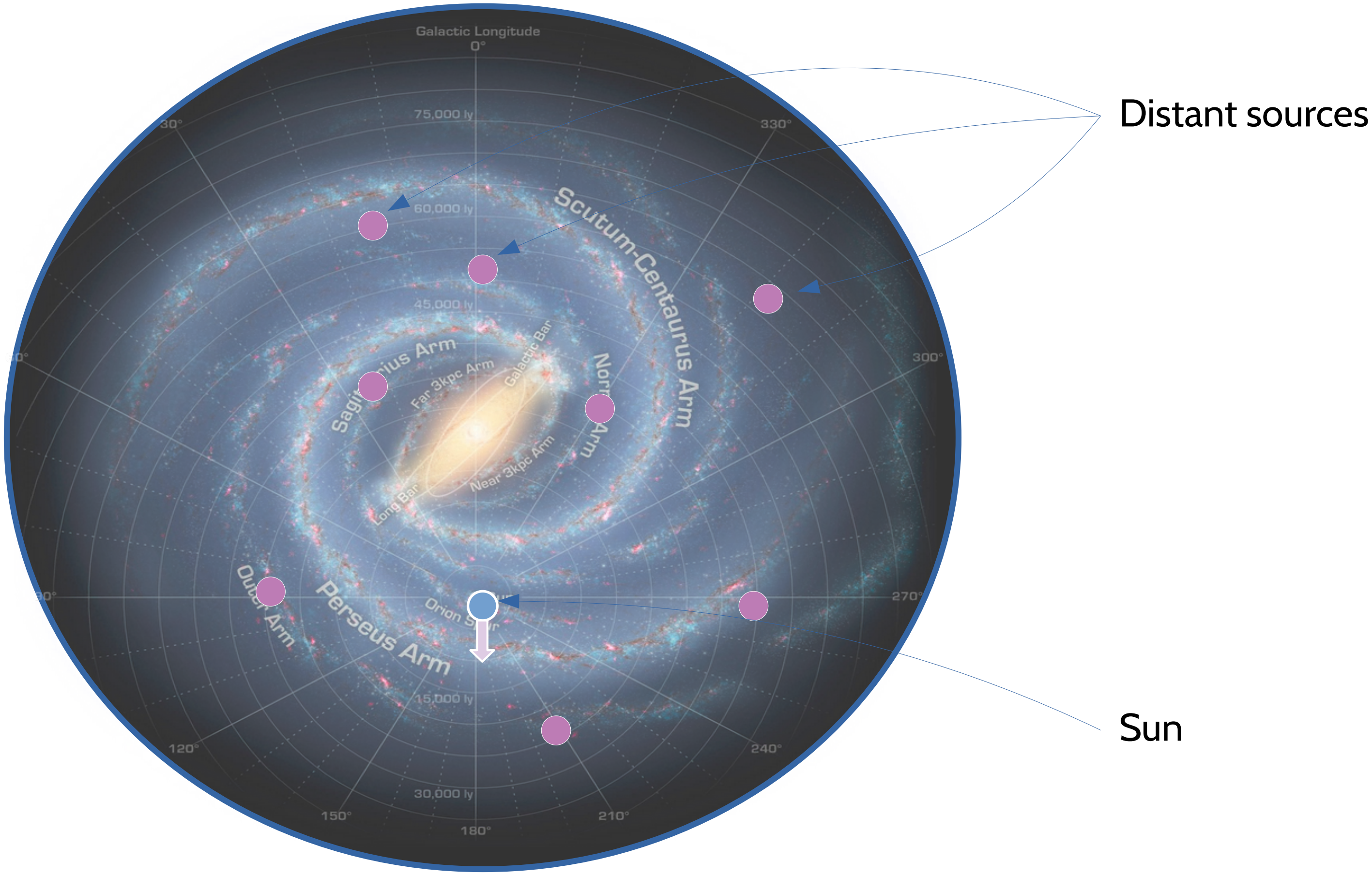
Fick's law: $\boldsymbol{j}_{\rm CR} = -\boldsymbol{K} \cdot \nabla\Psi$

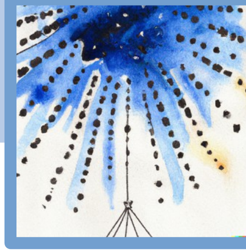
Energy dependence at odd with diffusion

Depends on:
- Distribution of sources and halo geometry halo?
- Structure of local magnetic field?

→ **Both!**

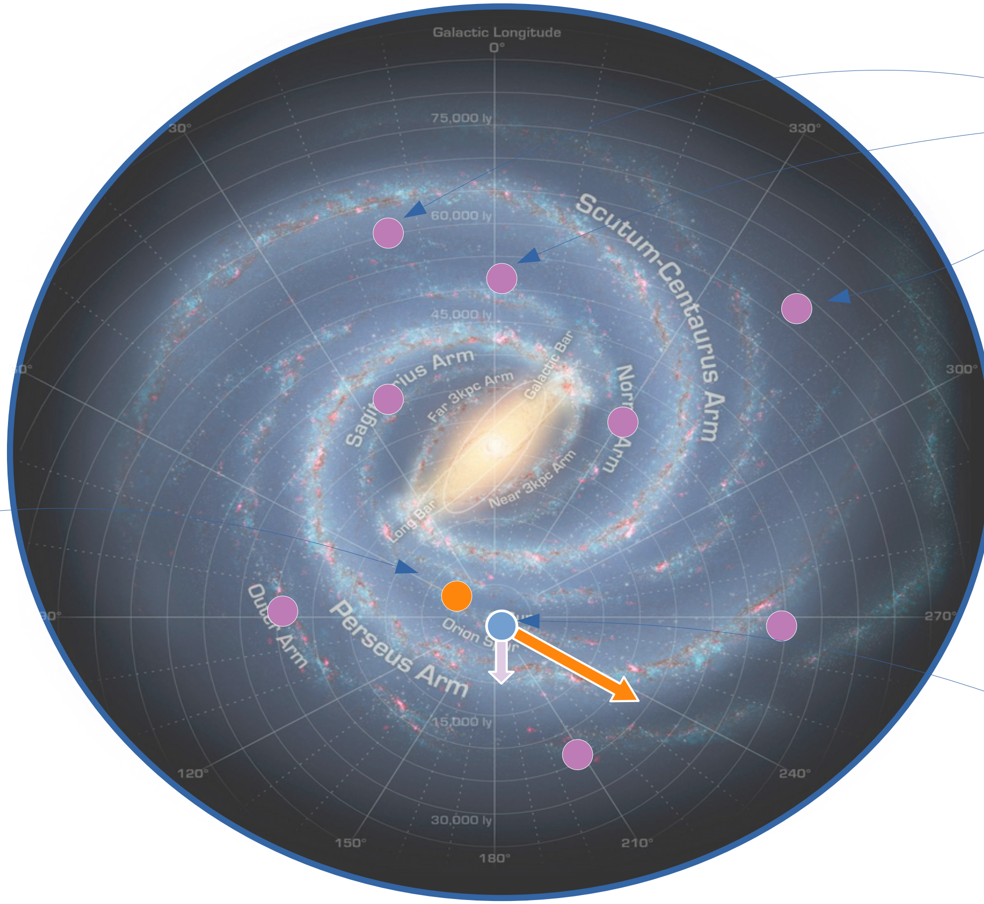
Effect of a local source on the anisotropy





Effect of a local source on the anisotropy

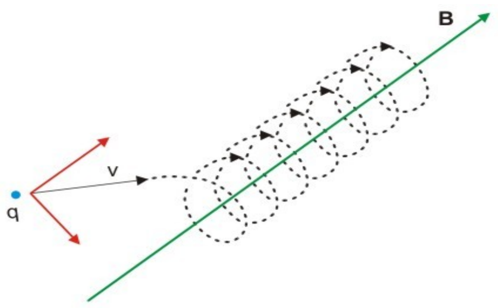
$$j_{\mathrm{CR}} = -\boldsymbol{K} \cdot \nabla\Psi$$



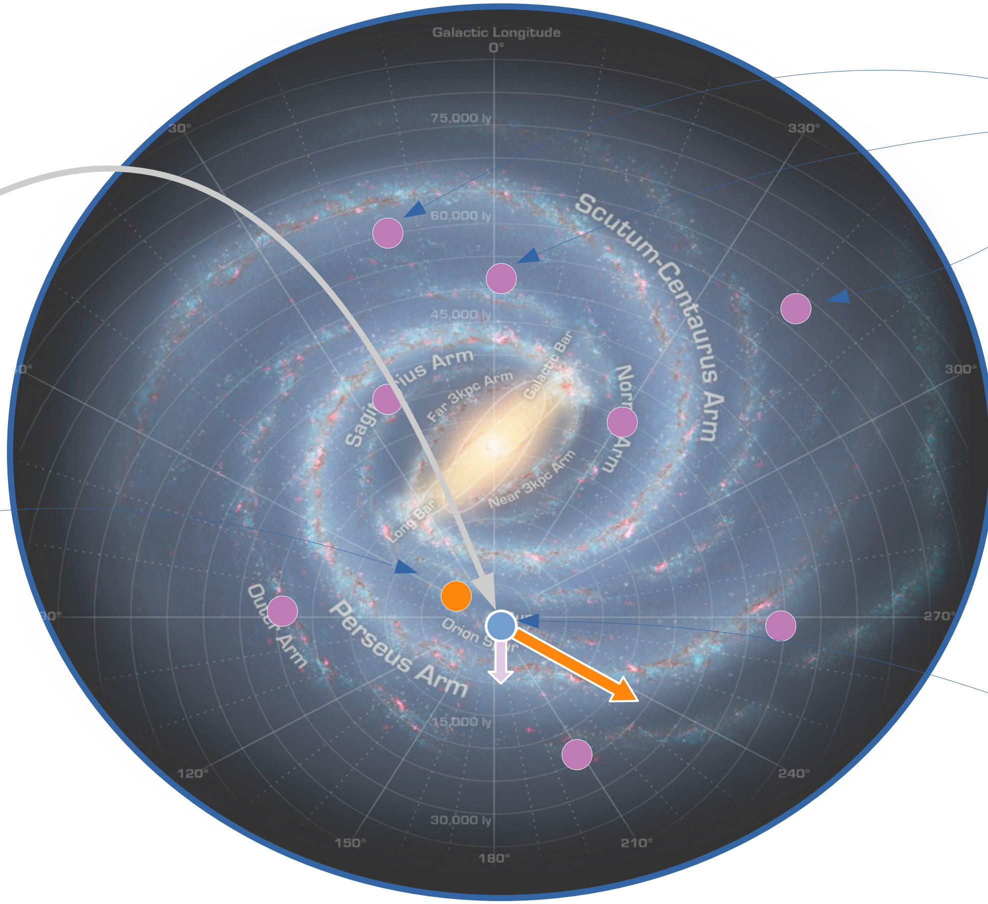
→ Local sources may dominate the dipole but not the flux

Effect of a local source on the anisotropy

$$j_{\mathrm{CR}} = -\boldsymbol{K} \cdot \nabla\Psi$$



→ Projection effect



→ Local sources may dominate the dipole but not the flux

Formalism

Angular power spectrum of CR arrival directions:

$$\frac{C_\ell}{4\pi} \simeq \int \frac{\mathrm{d}\widehat{\mathbf{p}}_1}{4\pi} \int \frac{\mathrm{d}\widehat{\mathbf{p}}_2}{4\pi} P_\ell(\widehat{\mathbf{p}}_1 \widehat{\mathbf{p}}_2) \lim_{\tau\to\infty} \left(\Delta r_{1i}(-\tau)\Delta r_{2j}(-\tau)\right) \frac{\partial_i n \partial_j n}{n^2}$$

Ahlers & Mertsch AJL (2015)

CR dipole power: $\frac{C_1}{4\pi} \simeq \mathrm{S}_{ij} \frac{\partial_i n \partial_j n}{n^2}$ with $\mathbf{S} \equiv \mathcal{K}^T \mathcal{K}$ and $\mathcal{K}_{ij} \equiv \lim_{\tau\to\infty} \langle \widehat{p}_i(0) \Delta r_j(-\tau) \rangle_\Omega$

Formalism

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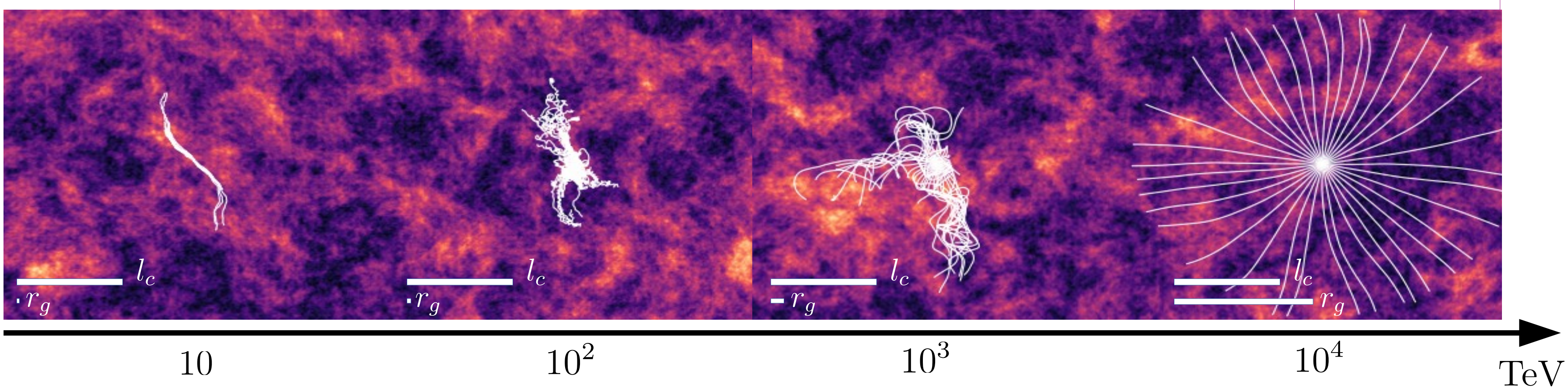
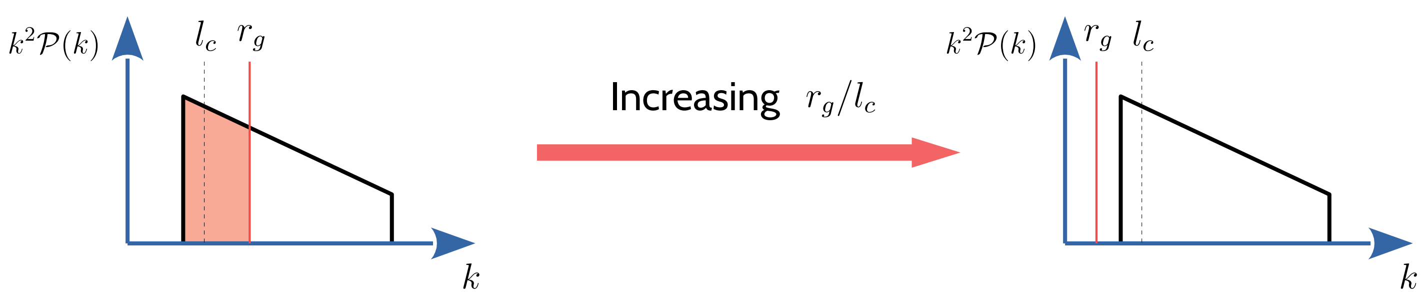
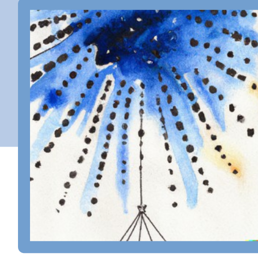
→ **Study the diffusion tensor with test-particle simulations**: backtracking in **isotropic turbulence**

$$l_c = 2\,\mathrm{pc}$$
$$B_{\mathrm{rms}} = 4\mu\mathrm{G}$$



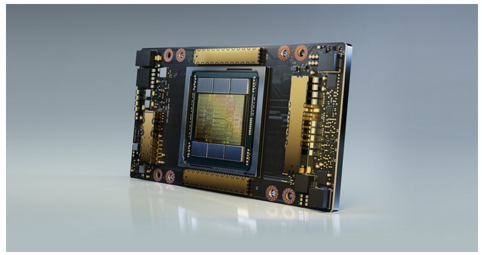


Tests de performance



GPU *vs* **CPU**

(Graphics Processing Units) (Central Processing Unit)



GPU A100
40 x 3145728 particules/38 min → 55188 part/seconde → **gain = 155**

GPU V100
3145728 particules/14 min → 5242 part/seconde → **gain = 15**

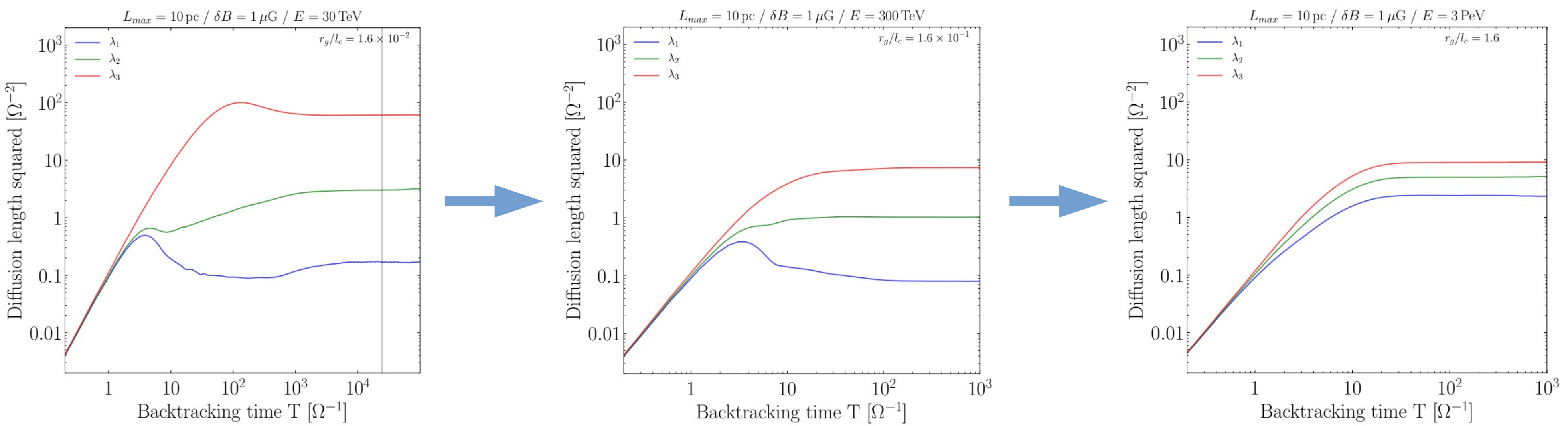
GPU P6000
3145728 particules/44 min → 1191 part/seconde → **gain = 3.4**

My computer (with tbb, 8 threads 2.4 GHz)
49152 particules/140 secondes → 354 part/seconde → **gain = 1**

How does behave the CR dipole in **isotropic turbulence**?

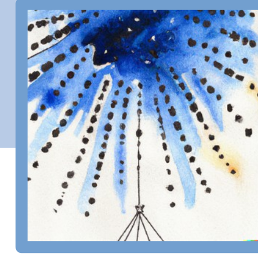
$$\boldsymbol{\delta} \propto \boldsymbol{j}_{\mathrm{CR}} = -\boldsymbol{K} \cdot \nabla\Psi$$

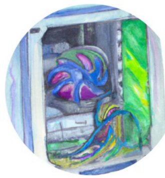
$$K_{local} = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}$$



$10 \quad 10^2 \quad 10^3 \quad 10^4$ TeV

HPC and Cosmic-Ray Physics





High Performance Computing
Particle-test simulations

Local cosmic-ray current

→ Methodology to study the dipole anisotropy
→ Related phenomenology

Collaboration with:

- M. Ahlers (NBI)

UNIVERSITY OF COPENHAGEN

Beyond Quasi-Linear-Theory

→ Numerical study of diffusion
→ Theoretical developments
→ Related phenomenology

Collaboration with:

- A. Marcowith (LUPM)

- P. Mertsch (RWTH)

LUPM LABORATOIRE UNIVERS & PARTICULES MONTPELLIER

RWTH AACHEN UNIVERSITY

Bridging with microphysics

→ Diffusion in MHD turbulence
→ Non-linearities and instabilities

Collaboration with:

- A. Marcowith (LUPM)

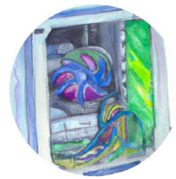
- S. Cerri (OCA)

OBSERVATOIRE DE LA CÔTE D'AZUR
UNIVERSITÉ CÔTE D'AZUR

Supports: **AAP USMB 2022&2023**

PNHE 2023
Possible PhD 2024

ANR project 2024 (PI: S. Cerri)



High Performance Computing at LAPTh

Project run on Must GPUs

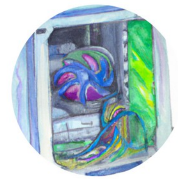
→ Machine Learning

Eckner, C., & Calore, F. PRD (2022)
Caron, S., Eckner, C., et al. JCAP (2023)

→ Solving cascade equation

Hooper, D., **Juan, J. I.**, & Serpico, P. D. PRD. (2023)

CoopIntEER CNRS-UChicago



@ LAPTh

High Performance Computing at LAPTh

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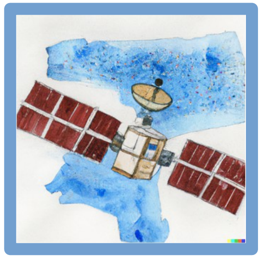
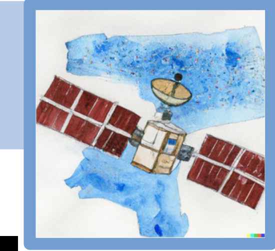


Gamma rays

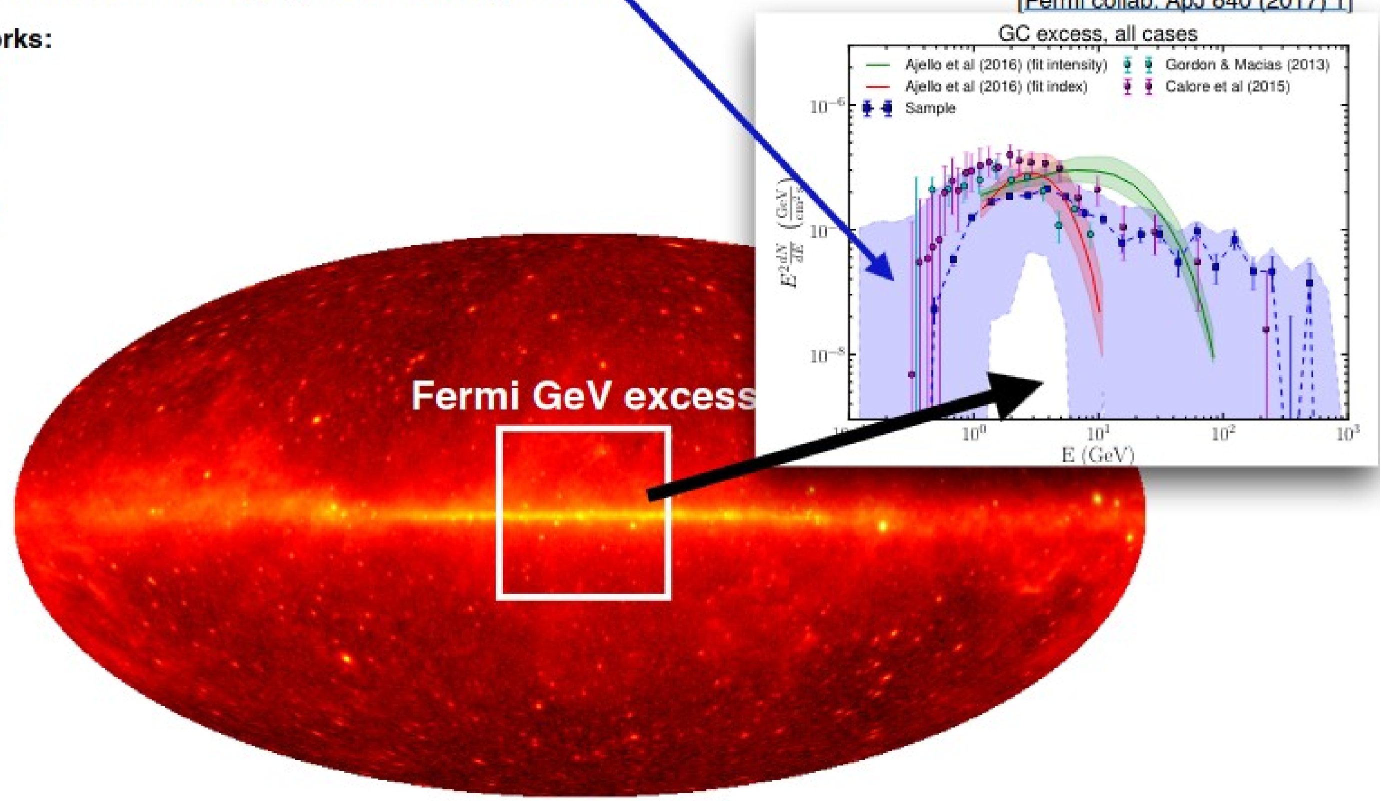


Caron, S., Eckner, C., et al. JCAP (2023) → https://indico.cern.ch/event/1199289/contributions/5449346/

What is the Fermi GeV excess ?

We all agree: There is an excess of GeV gamma rays (GCE) toward the Galactic centre measured by Fermi-LAT **above known astrophysical backgrounds**.

[Fermi collab. ApJ 840 (2017) 1]



An incomplete list of works:

Goodenough & Hooper (2009)
Vitale & Morselli (2009)
Hooper & Goodenough (2011)
Hooper & Linden (2011)
Boyarsky et al (2011)
Abazajian & Kaplinghat (2012)
Gordon & Macias (2013)
Macias & Gordon (2014)
Abazajian et al (2014, 2015)
Calore et al (2014)
Daylan et al (2014)
Selig et al (2015)
Huang et al (2015)
Gaggero et al (2015)
Carlson et al (2015, 2016)
de Boer et al (2016)
Yang & Aharonian (2016)
Fermi Coll. (2016)
Horiuchi et al (2016)
Linden et al (2016)
Ackermann et al (2017)
Macias et al (2018)
Bartels et al (2018)
Balaji et al (2018)
Zhong et al (2019)
Macias et al (2019)
Chang et al (2020)
Buschmann et al (2020)
Leane & Slatyer (2020)
Abazajian et al (2020)
List et L (2020)
Di Mauro (2020)
Burns et al (2020)
Cholis et al (2022)
Pohl, Macias+ (2022)
...

Where we do not agree:

1. What is the preferred spatial morphology of the excess?
2. **What is causing the Fermi GeV excess?**

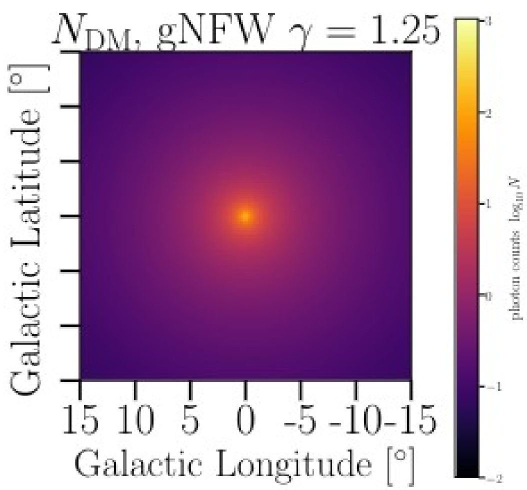
Credits: Christipher Eckner

Caron, S., Eckner, C., et al. JCAP (2023) → https://indico.cern.ch/event/1199289/contributions/5449346/

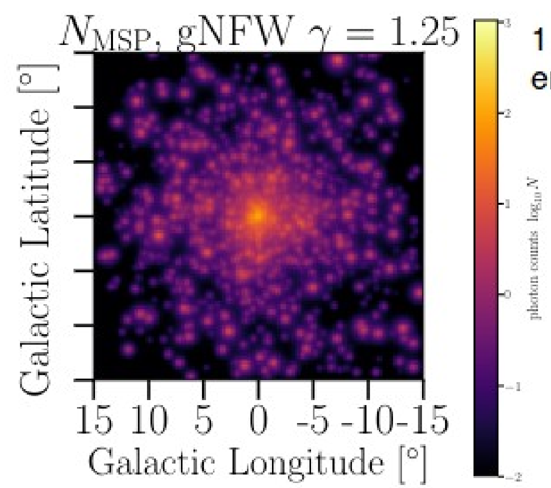
How machine learning can help

A decisive feature of the GeV excess is its **photon clustering behaviour**, spectrally they can be almost identical.

DM annihilation
(smooth morphology,
Poisson-distributed photon events)



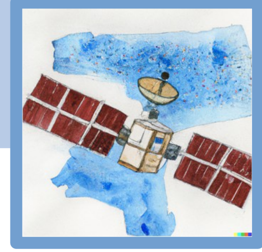
Faint millisecond pulsar population
(photon clustering on small scales,
non-Poissonian noise component)



- Traditional likelihood methods cannot explore this difference in any practical way (probabilistic nature of point source locations and fluxes!)
- Effective methods have been proposed: **non-Poissonian template fitting, 1pPDF, wavelet analysis**. These approaches seem to prefer an excess due to MSPs (e.g. [F. Calore et al., PRL 127 (2021) 16]; [M. Buschmann et al. PRD 102 (2020) 2]; [R. Bartels et al., PRL 116 (2016) 5]).
- **Machine learning with convolutional networks could generalise over point source distribution as a generic feature and include uncertainties in astrophysical background modelling!**

Credits: Christipher Eckner

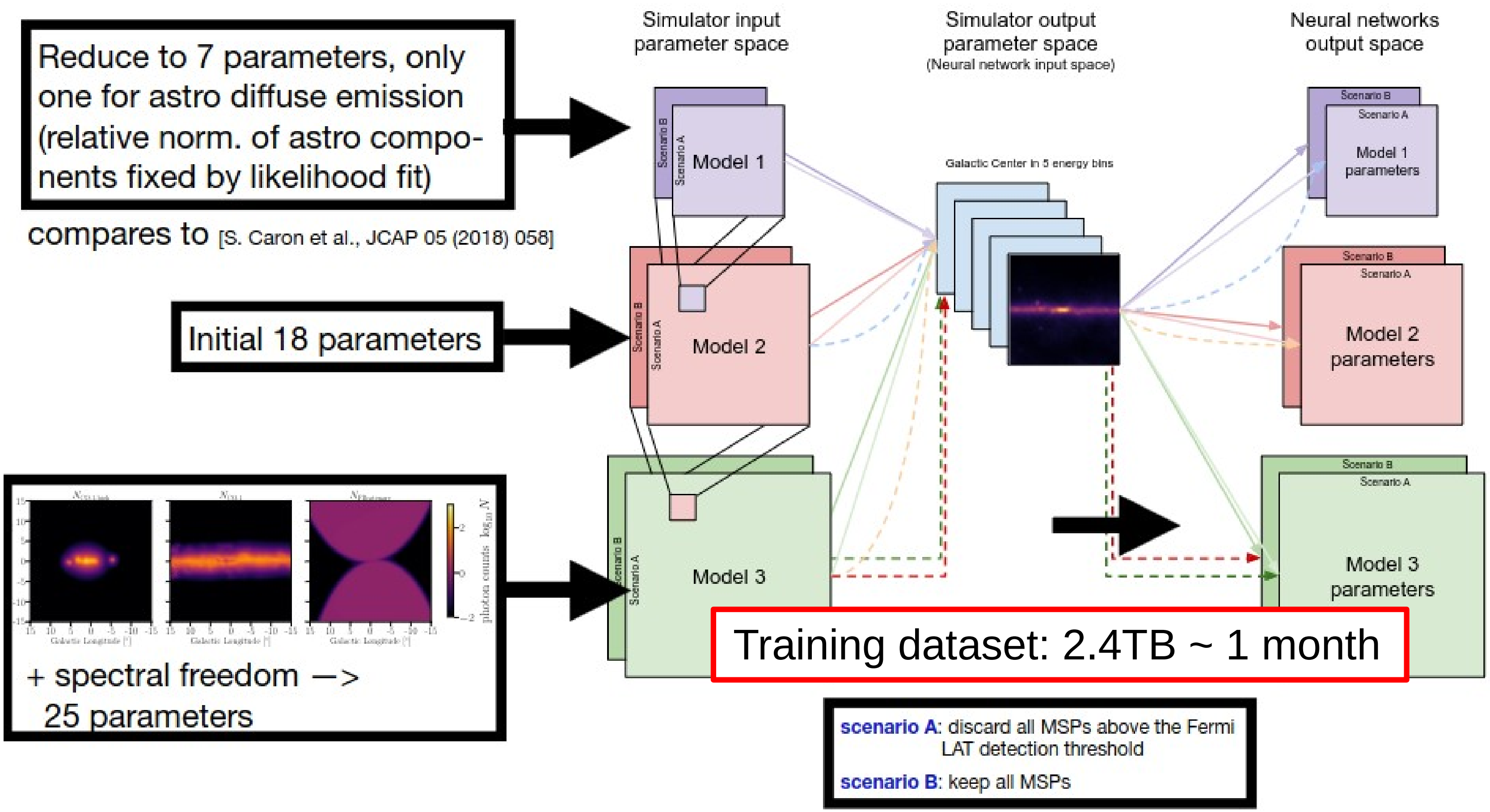
HPC at LAPTh → Solving a cascade equation



Caron, S., Eckner, C., et al. JCAP (2023) → https://indico.cern.ch/event/1199289/contributions/5449346/

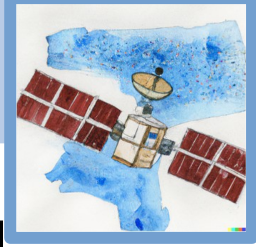
Neural network architecture and scope

Model setup to explore the impact of the **background model complexity** on the interpretation of the GCE with **Bayesian convolutional neural networks** used in a **DeepEnsembles** setup. We probe the '**reality gap**' — the discrepancy between modelled and real data.



Credits: Christipher Eckner

HPC at LAPTh → Solving a cascade equation



Caron, S., Eckner, C., et al. JCAP (2023) → https://indico.cern.ch/event/1199289/contributions/5449346/

Conclusions

DeepEnsemble Networks are capable of recovering the background and the presence of the GCE. We found that:

- Bright components are detected robustly and consistently between our models. They are also detected consistently with the prediction from the traditional likelihood method.

- The networks robustly detect the presence of the GCE in all our models, with the properties (flux and spatial distribution) consistent with other works.

However, the picture is not as clear as we (and everyone else!) wished:

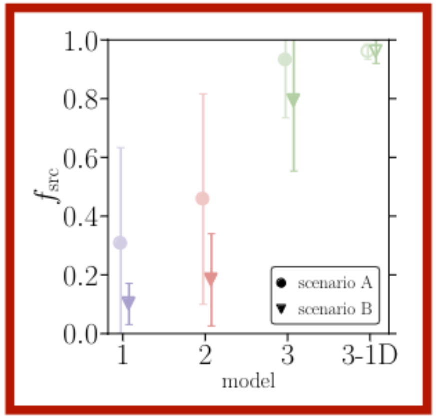
- The nature of the GCE however, while well predicted within each model, **does not appear to be robust when networks are applied outside of their domain. We can predict anything from no DM to no MSPs by selecting a fitting background model.**

- ***Mind the gap: - the fact that reality is not part of the (background) model has been a limiting factor of many (all?) current works. What results can we trust at the moment?***

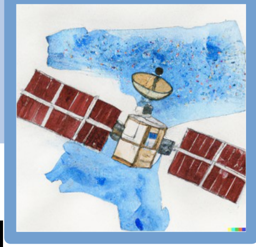
- **Deep SVDDs** offer a possibility to test severity of the reality gap. We are currently probing state-of-the-art models of the GC in this way. **Stay tuned!**

$$f_{\mathrm{src}} = \frac{F_{\mathrm{MSP}}}{F_{\mathrm{MSP}} + F_{\mathrm{DM}}}$$

fraction of MSPs contribution to GCE



Credits: Christipher Eckner



HPC at LAPTh → Solving a cascade equation

Caron, S., Eckner, C., et al. JCAP (2023) → https://indico.cern.ch/event/1199289/contributions/5449346/

Conclusions

DeepEnsemble Networks are capable of recovering the background and the presence of the GCE. We found that:

- Bright components are detected robustly and consistently between our models. They are also detected consistently with the prediction from the traditional likelihood method.

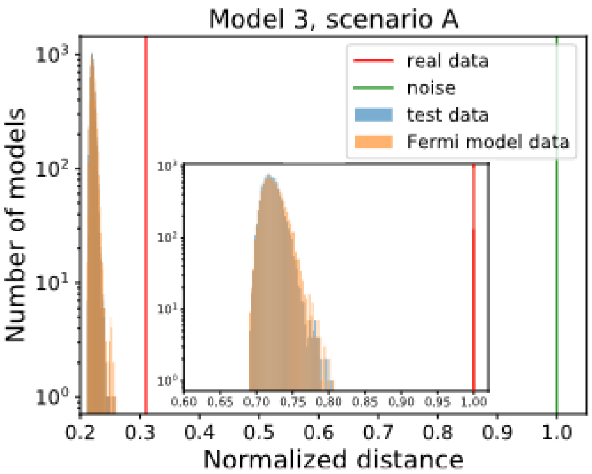
- The networks robustly detect the presence of the GCE in all our models, with the properties (flux and spatial distribution) consistent with other works.

However, the picture is not as clear as we (and everyone else!) wished:

- The nature of the GCE however, while well predicted within each model, **does not appear to be robust when networks are applied outside of their domain. We can predict anything from no DM to no MSPs by selecting a fitting background model.**

- ***Mind the gap: - the fact that reality is not part of the (background) model has been a limiting factor of many (all?) current works. What results can we trust at the moment?***

- **Deep SVDDs** offer a possibility to test severity of the reality gap. We are currently probing state-of-the-art models of the GC in this way. **Stay tuned!**



Credits: Christipher Eckner

HPC at LAPTh

High Performance Computing at LAPTh

Project run on Must GPUs

→ Machine Learning

Eckner, C., & Calore, F. PRD (2022)
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→ Solving cascade equation

Hooper, D., **Juan, J. I.**, & Serpico, P. D. PRD. (2023)

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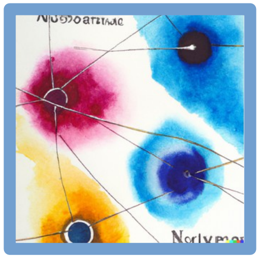

Multimessenger

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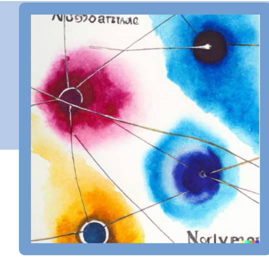


Hooper, D., **Juan, J. I.**, & Serpico, P. D., PRD (2023)

Motivation

$$\Delta a_\mu \equiv a_\mu^{\text{EXP}} - a_\mu^{\text{SM}} = 251(59) \times 10^{-11}$$

T. Aoyama et al., Phys. Rept. 887, 1 (2020)

4.2σ discrepancy!

↓

SOLUTION: NEW PHYSICS?

New particle with an **MeV-scale mass** coupling to muons with $g \sim 10^{-4}$

C.-Y. Chen et al., Phys. Rev. D 95, 115005 (2017)
P. Fayet, Phys. Rev. D 75, 115017 (2007)

Model

New broken abelian $U(1)$ symmetry

Grand Unified Theory: D. London et al., Phys. Rev. D 34, 1530 (1986)
Little Higgs: N. Arkani-Hamed et al., JHEP 08, 021 (2002)
Extra dimensions: M. Carena et al., Phys. Rev. D 68, 035010 (2003)

New Z' massive boson

$(L_\mu - L_\tau)$

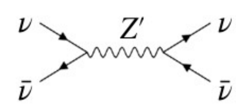
X. G. He et al., Phys. Rev. D 43, 22 (1991) and Phys. Rev. D 44, 2118 (1991)

$$\mathcal{L} = \mathcal{L}_{\text{SM}} - \frac{1}{4} Z'^{\alpha\beta} Z'_{\alpha\beta} + \frac{m_{Z'}^2}{2} Z'_\alpha Z'^\alpha + Z'_\alpha J^\alpha_{\mu-\tau}$$

$$J^\alpha_{\mu-\tau} = g_{Z'} \left(\bar{\mu}\gamma^\alpha \mu + \bar{\nu}_\mu \gamma^\alpha P_L \nu_\mu - \bar{\tau}\gamma^\alpha \tau - \bar{\nu}_\tau \gamma^\alpha P_L \nu_\tau \right)$$

Signatures

$\nu - \nu$ **SCATTERING**

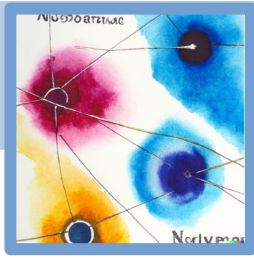


Resonant scattering!

$$\sigma(\nu_i \bar{\nu}_j \to \nu\bar{\nu}) = \frac{2 g_{Z'}^4 s \left(U_{\mu i}^\dagger U_{\mu j} - U_{\tau i}^\dagger U_{\tau j} \right)^2}{3\pi [(s - m_{Z'}^2)^2 + m_{Z'}^2 \Gamma_{Z'}^2]}$$

$U_{\alpha i}$ is the PMNS matrix

Credits: Joaquim Iguaz



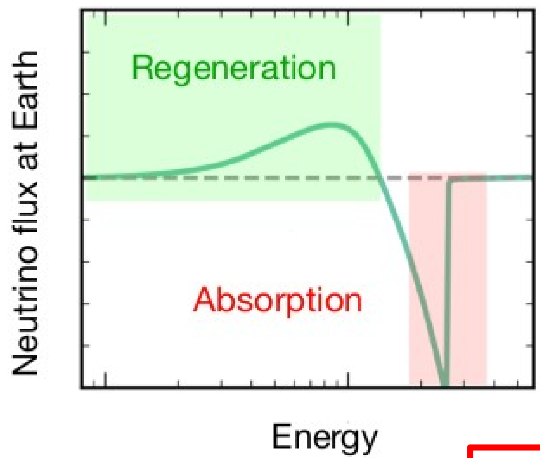
Hooper, D., **Juan, J. I.**, & Serpico, P. D., PRD (2023)

$\nu - \nu$ scattering: Absorption & Regeneration

The neutrino spectrum that reached Earth follows:

$$-(1+z)\frac{H(z)}{c}\frac{\mathrm{d}\tilde{n}_i}{\mathrm{d}z} = \underbrace{J_i(E_0,z)}_{\text{SOURCE}} - \underbrace{\tilde{n}_i \sum_j \langle n_{\nu j}(z)\sigma_{ij}(E_0,z)\rangle}_{\text{ABSORPTION}} + \underbrace{P_i \int_{E_0}^{\infty} \mathrm{d}E' \sum_{j,k} \tilde{n}_k \left\langle \overbrace{n_{\nu j}(z)}^{\text{C}\nu\text{B}} \frac{\mathrm{d}\sigma_{kj}}{\mathrm{d}E_0}(E',z) \right\rangle}_{\text{REGENERATION}}$$

High-energy neutrinos scattering off neutrinos from CνB

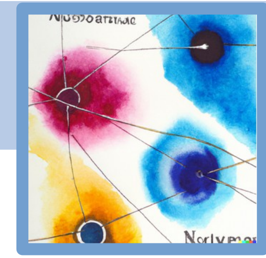


$$\tilde{n}_i \equiv \frac{\mathrm{d}N_i}{\mathrm{d}E}(E_0,z),$$

$$P_i \equiv \sum_l \mathrm{Br}(Z' \to \nu_l \nu_i)$$

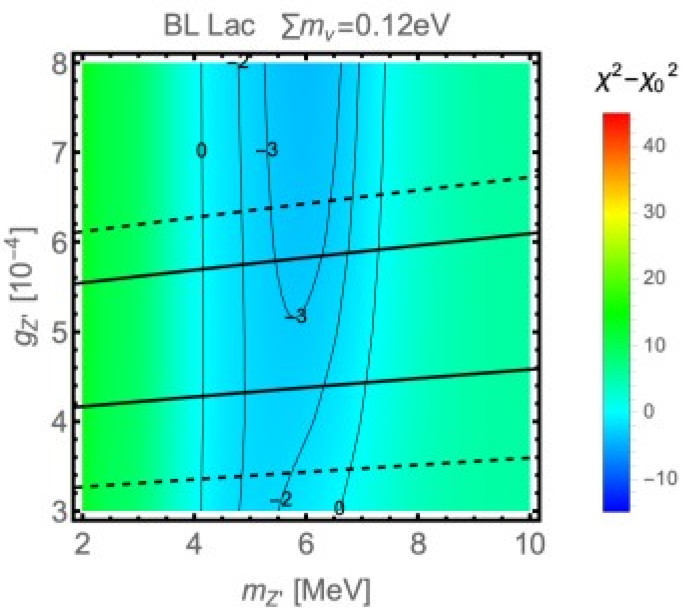
Credits: Joaquim Iguaz

$\boxed{\text{CPU: ~ 1 day } \textbf{vs} \text{ GPU: ~ few min}}$

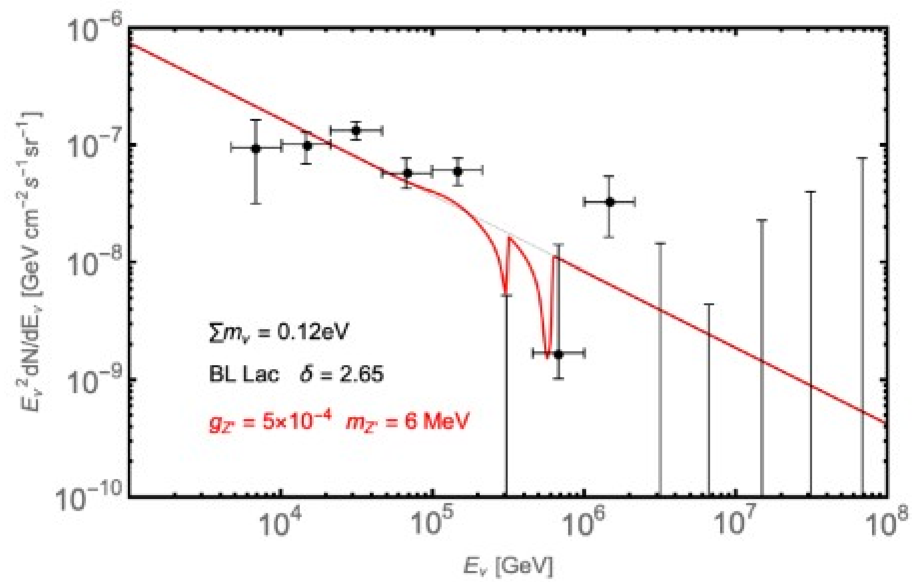


Hooper, D., **Juan, J. I.**, & Serpico, P. D., PRD (2023)

BL Lac distribution

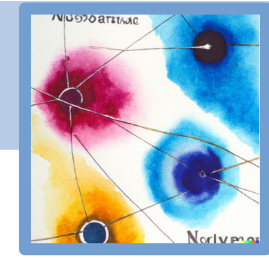


(Normal hierarchy)



Credits: Joaquim Iguaz

HPC at LAPTh → Solving a cascade equation



Conclusions

Motivated by the measured value of $g_\mu - 2$ we have considered models with a broken $U(1)_{L_\mu - L_\tau}$, giving rise to a new gauge boson.

Muon's magnetic moment +
Laboratory constraints +
Cosmological constraints
→
$m_{Z'} \sim 10 - 200\mathrm{MeV}$
$g_{Z'} \sim 10^{-4}$

Z' mediates resonant scattering between high-energy neutrinos and CνB, leading to spectral features measurable by IceCube.

We have studied a range of scenarios that can nominally improve the fit to IceCube data at the level of $\sim 2\sigma$.

BL Lac and SFR	Higher redshifts
$m_{Z'} \sim 5 - 8\mathrm{MeV}$	$m_{Z'} \sim 10 - 15\mathrm{MeV}$
In tension with N_{eff}	

Besides modest statistics, main limitations are the g-2 value, neutrino masses, IceCube spectrum and N_{eff} value, to be substantially reduced in the near future!

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Enigmass R&D booster LAPTh AstroComo team

→ New A100 Nvidia GPU
→ 80Gb
+ dedicated server

→ Organised trainings:
e.g. https://indico.in2p3.fr/event/29755/

→ Also open for other groups
Now operating

Future activities !

→ GCE with Swift!

→ Open up new projects
e.g. Extensive MCMC, Machine learning

→ Benefit to new CNRS CPJ
Azadeh Moradinezhad
cosmological simulations