Physics-Informed Neural Networks, Particle Physics, Dark Matter and the Milky Way

KSHEP 2026 Spring Meeting

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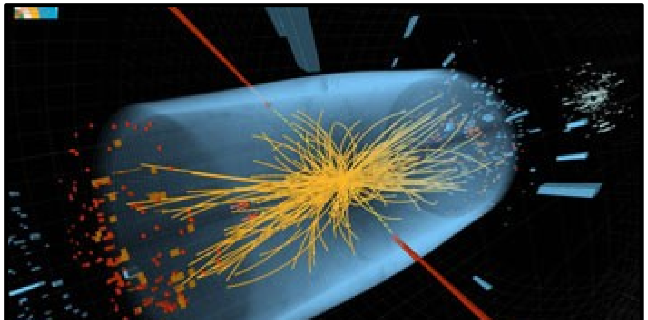
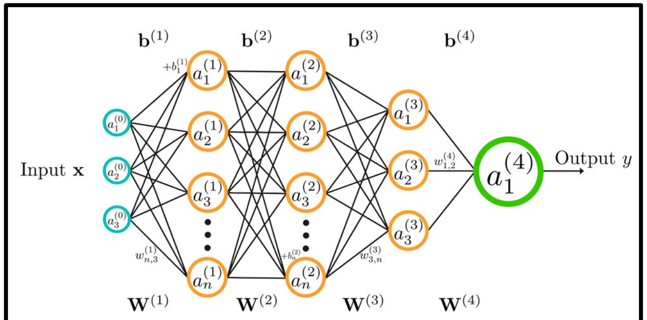
Institute for Basic Science

Research Interests

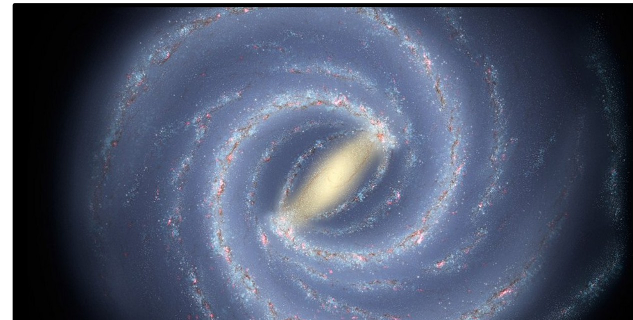
ML × Physics — **Data-Driven Studies on New Physics & Dark Matter**



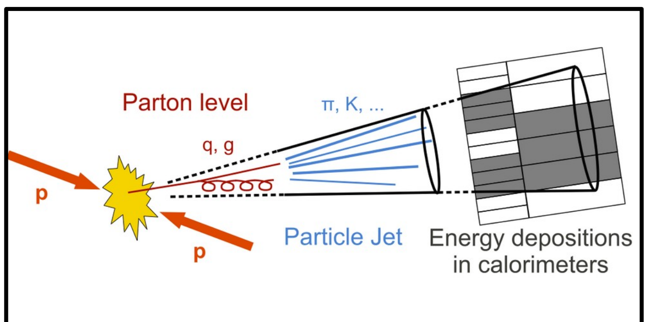
Collider Physics for BSM



Machine Learning



Astrophysics of Galaxies



Jet Physics and QCD

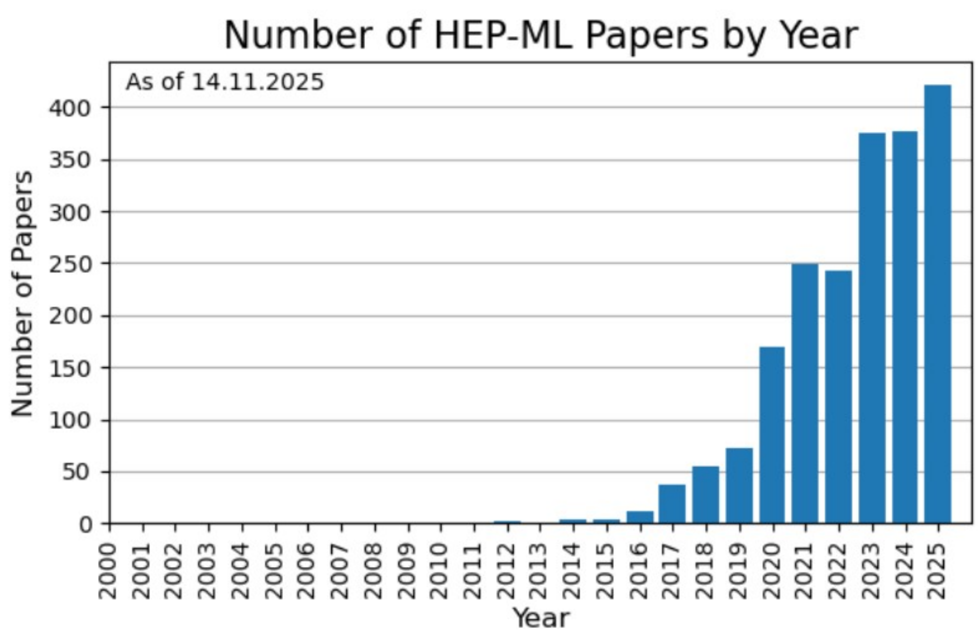
Dark Matter Physics

Data Physicist — **Connecting Data Science and Physics to Supercharge *Discovery***

A Living Review of Machine Learning for Particle Physics

Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

download review GitHub



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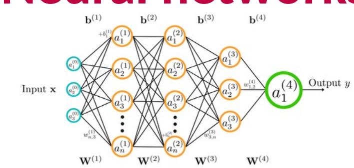
https://iml-wg.github.io/HEPML-LivingReview/

Physics-Informed Neural Network

Physics-Informed Neural Network **is**
a class of machine learning model incorporating with
physics knowledge.

Data Inputs
what we measuring ---
event records, images,
astronomical surveys,

Neural networks



Physics
Domain-specific knowledge ---
theory, symmetry, differential
equations, conservation laws,
constraints

Physics-Informed Models

Why make physics built-in?

Data-driven

Fully using information in dataset

Consistent

Making predictions consistent with physics

Transparent

Interpretable in terms of injected physics

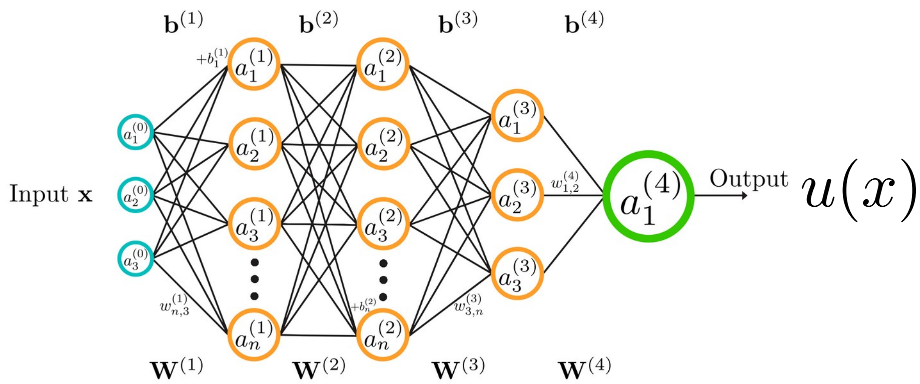
Physics-Informed Neural Network

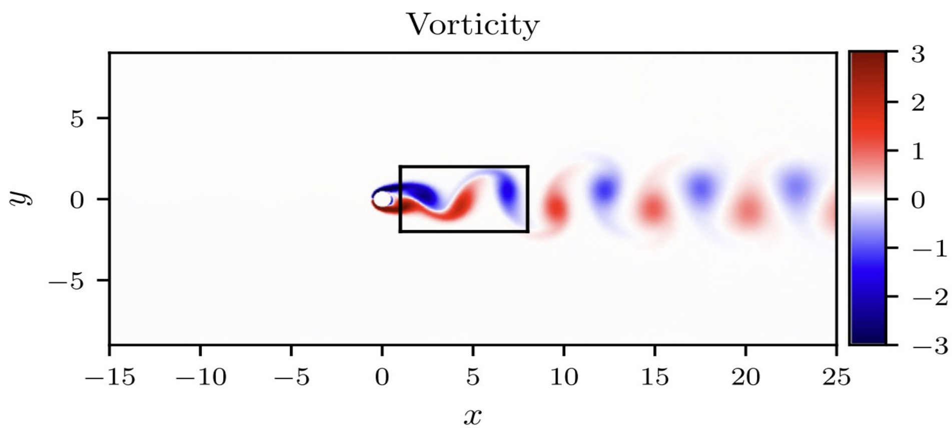
Neural Network Learning PDE Solutions

Raissi et. al. (arXiv:1711.10561, 1711.10566)

PINN **is a neural network modeling solution of differential equations, simply minimizing the residuals.**

Neural network as solution model





Data loss

$$\mathcal{L}_{\mathrm{Data}}(u) = \mathbf{E}\,|u - u_{\mathrm{true}}|^2$$

PDE residual loss

$$\mathcal{L}_{\mathrm{PDE}}(u) = \mathbf{E}\,|\mathrm{PDE}(u)|^2$$

Boundary condition loss

$$\mathcal{L}_{\mathrm{BC}}(u) = \mathbf{E}\,|\mathrm{BC}(u)|^2$$

Minimize

PDE solution

Is Physics-Informed Neural Network new idea or trivial?

Is Physics-Informed Neural Network new idea or trivial?

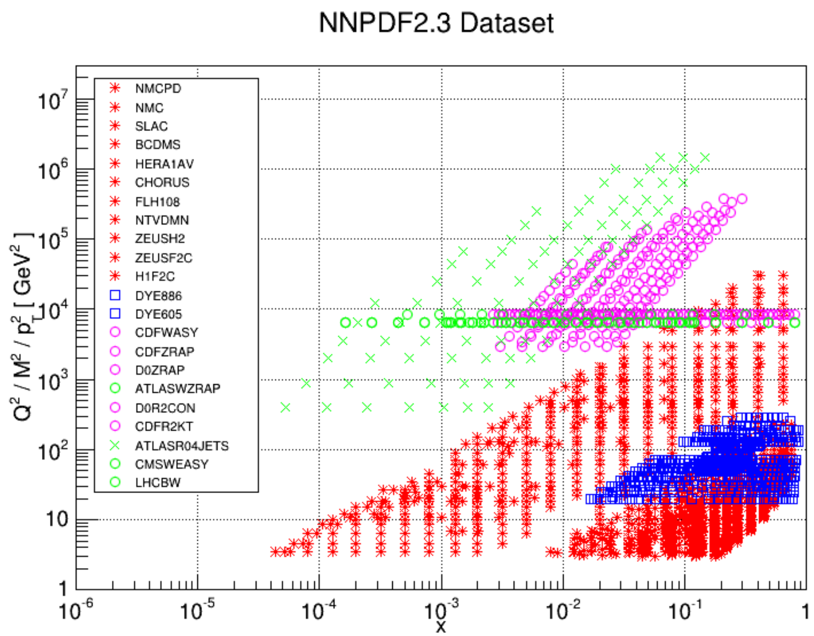
Yes, it has been studied heavily for last 10 years in ML domain.

But, HEP people already have been using this concept more than decades.

NNPDF – modeling parton distribution function with neural networks

Data

Deep inelastic scattering, drell-yan, LHC...



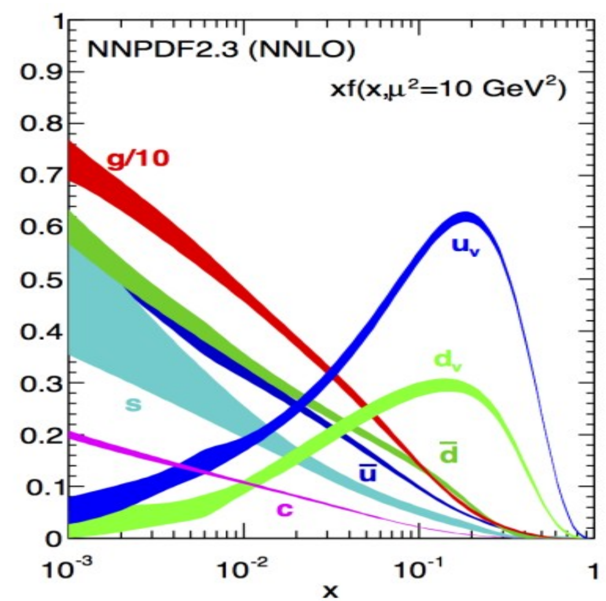
Inputs

- x: momentum fraction
- Q: scale

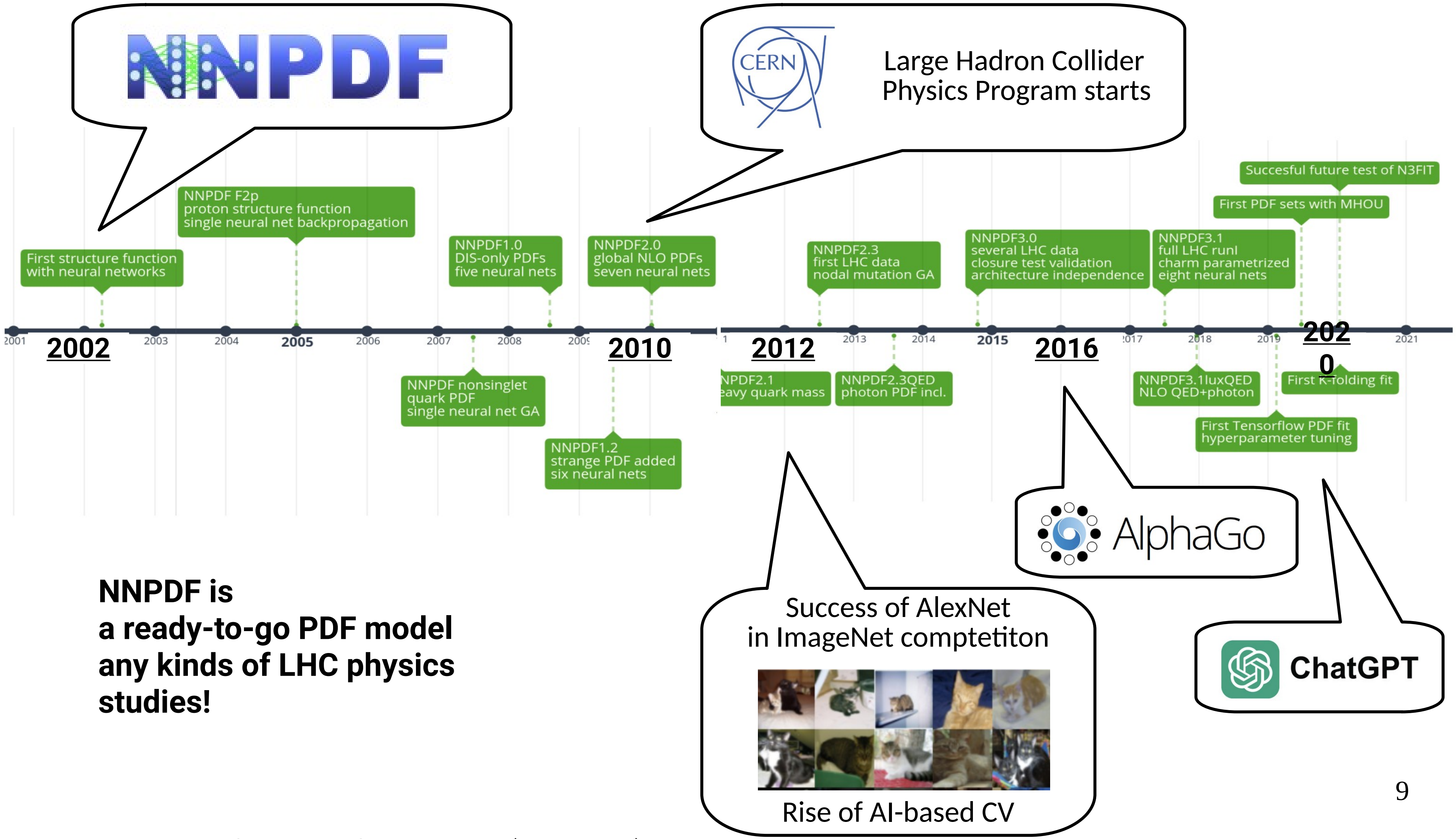
Physics

DGLAP evolution,
PDF physics

Neural network modeling PDF f(x; Q)



PROTON STRUCTURE AS AN AI PROBLEM: NNPDF

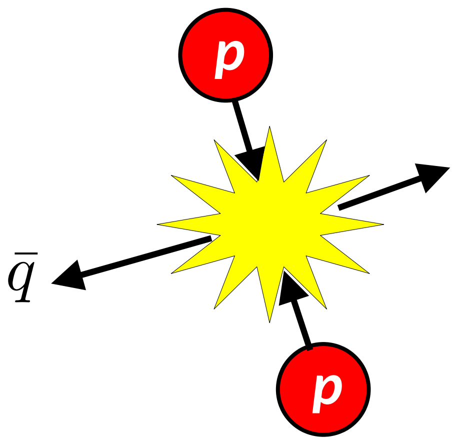


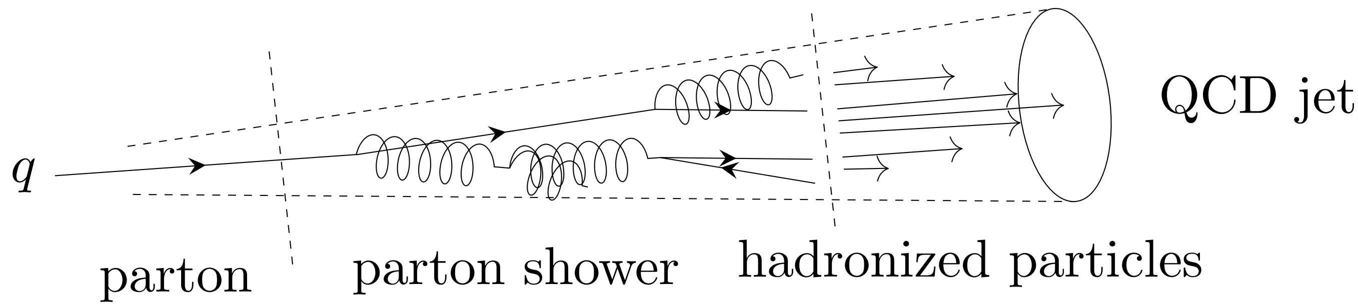
**NNPDF is
a ready-to-go PDF model
any kinds of LHC physics
studies!**

Background: Slide from Stefano Forte (U. Milan)

Jet Classification

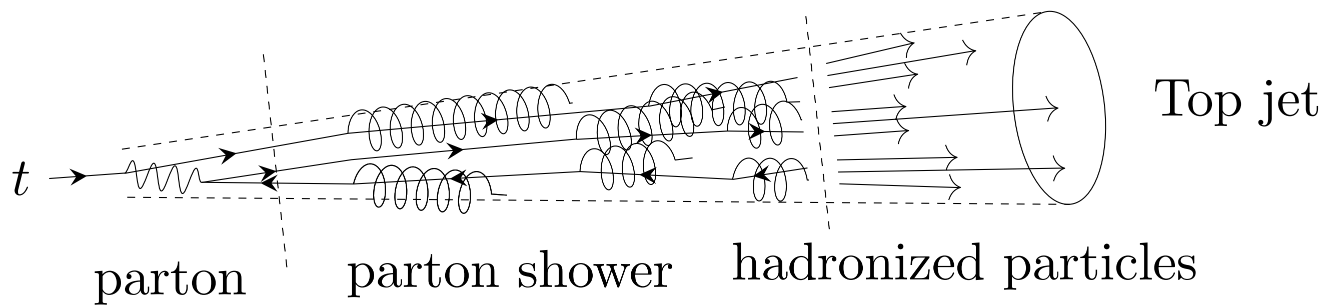
At the LHC, when proton-proton collision happens, the process often creates particle clusters originating from colored partons.





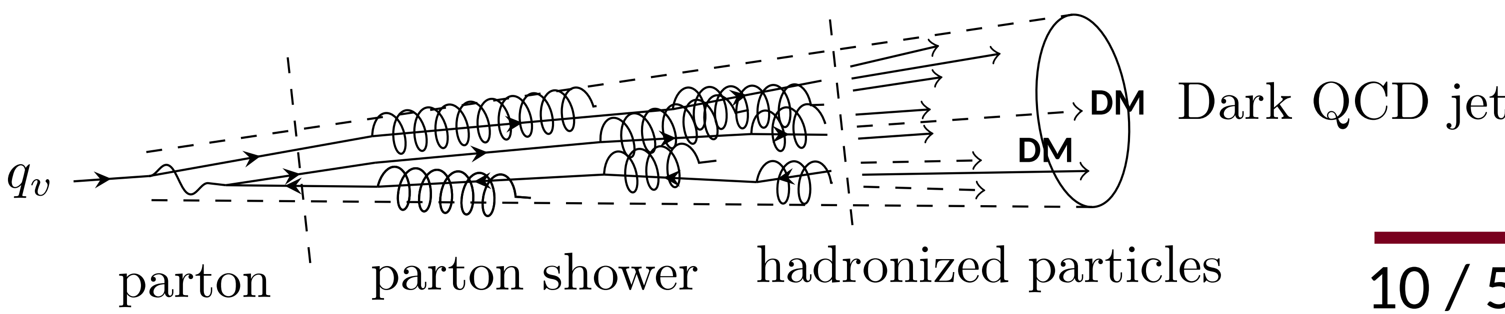
But quarks and gluons are not only objects creating jets!

$t \rightarrow bq\bar{q}$



Even there are BSM signatures may be hidden in jets.

Dark QCD interactions (Hidden Valley Models)



Equivariant Jet Taggers
--- Physics-Informed Architectures

Neural networks have been used for identifying the origin of jets.

- Convolutional NN (1511.05190)
- Graph NN
- Transformer (2202.03772)

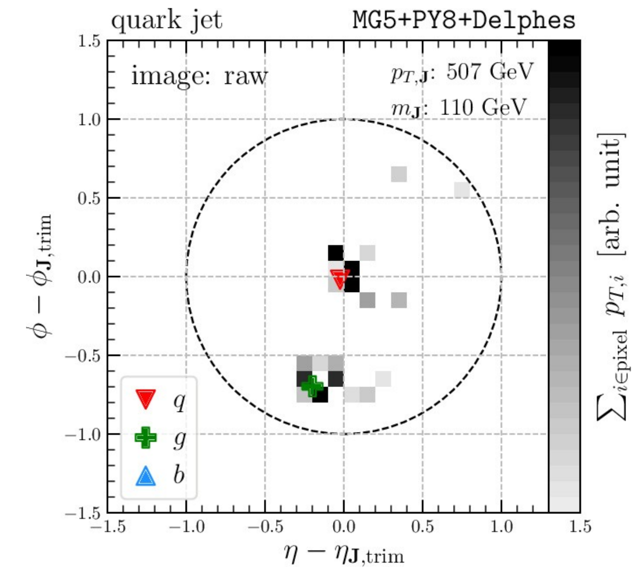
Current state-of-the-art jet taggers are **equivariant models**:

Lorentz Symmetry

- **LorentzNet (Gong et. al., arXiv:2201.08187)**
- **L-Gatr (Spinner et. al., arxiv:2405.14806)**
- **...**

Permutation Symmetry

- **PELICAN (Bogatskiy et. al., arXiv:2307.16506)**
- **...**



Best jet tagging models!

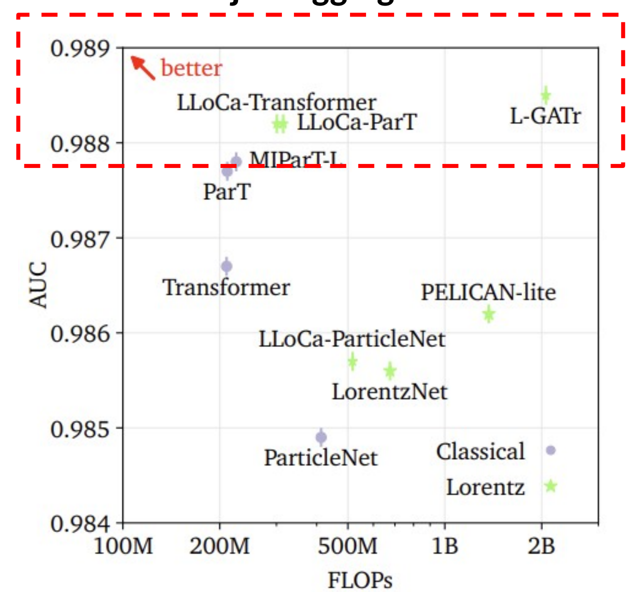
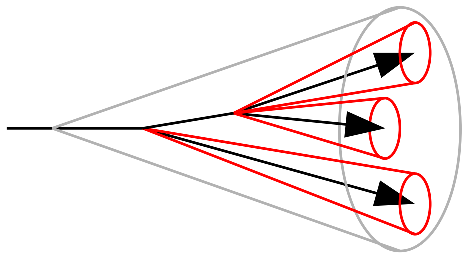


Fig from Luigi et. al., 2508.14898

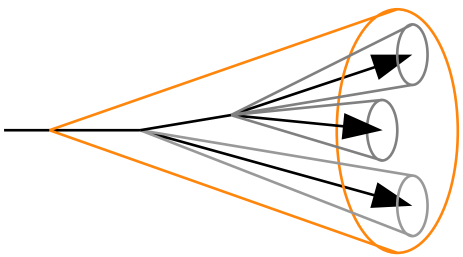
Anatomy of Top Jets
--- Physics-Informed Inputs

In order to build an **<u>high performing HLF based top jet tagger</u>**, we have to build up HLFs capturing the all <u>features of **top jets** completely</u>.
What are the features of top jets?

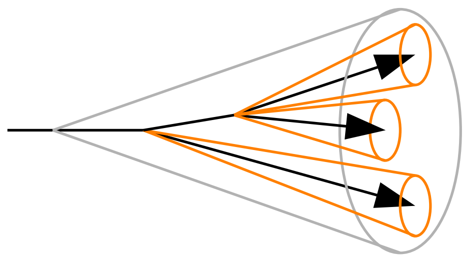
Three-prong



Color triplet

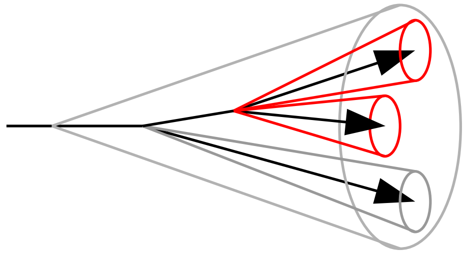


Color triplet subjets

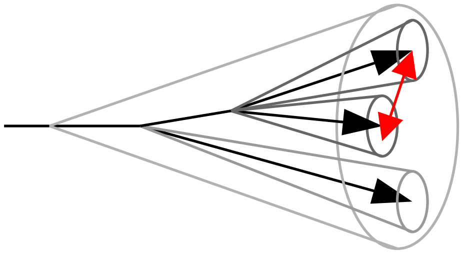


Top jet also have **<u>W boson jet</u>** inside.

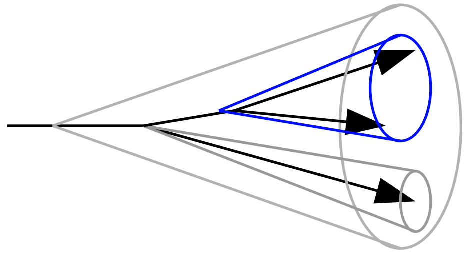
Two-prong subjet inside



Color connection



Color singlet



We will introduce an **<u>analysis model</u>** combining HLF analyzing architectures specialized for analyzing the above features.

Physics-Informed High-Level Features

Jet **Kinematics**
(PT, mass, ...)

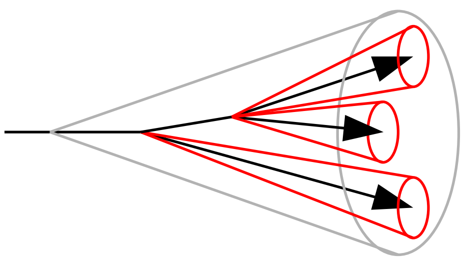
Generalization of
Constituent Multiplicity:
Minkowski Functionals
(Euler Char., Length, Area)

We consider
a neural network
analyzing
all these features.

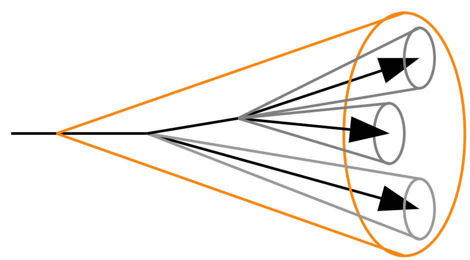
Two-Point
Energy Correlations S2
(Relation Network)

Subjet
Constituent Multiplicity
+ constituent PT histogram

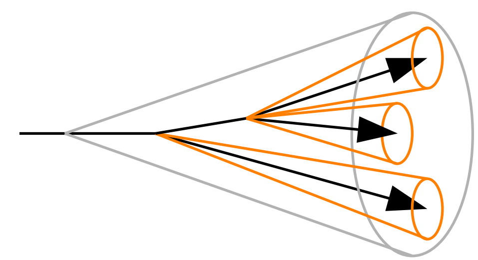
Three-prong



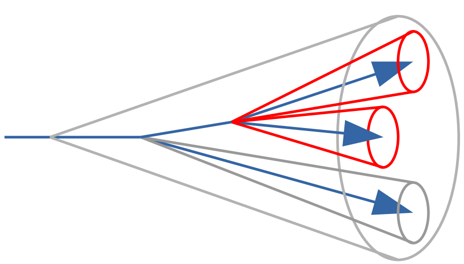
Color triplet



Color triplet subjets



Two-prong subjet inside



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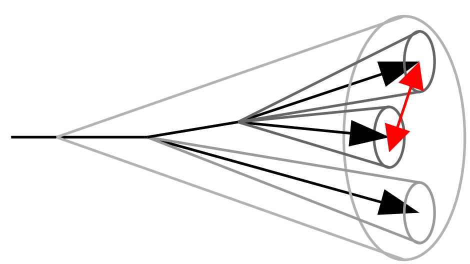

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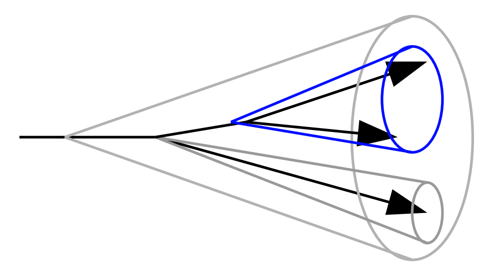


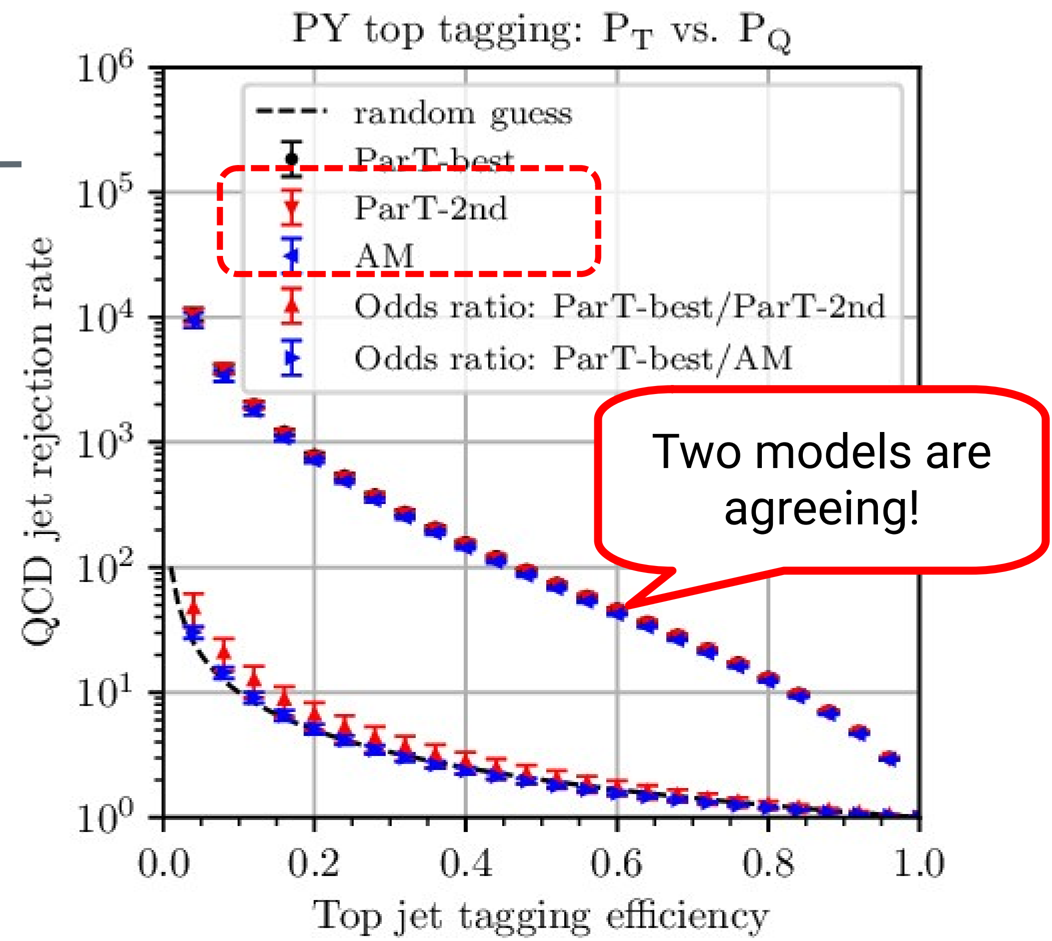
ROC curves

We compare the tagging performance of our analysis model to Particle Transformer working on pixellated jet constituents in **<u>HCAL resolution scale (0.1)</u>**

ROC curves and AUCs agrees within 3sigma of statistical and training uncertainty!

metric	P_T vs. P_Q	H_T vs. H_Q
AUC	2.76	2.58
$R_{50\%}$	2.19	1.56
$R_{30\%}$	1.64	0.51

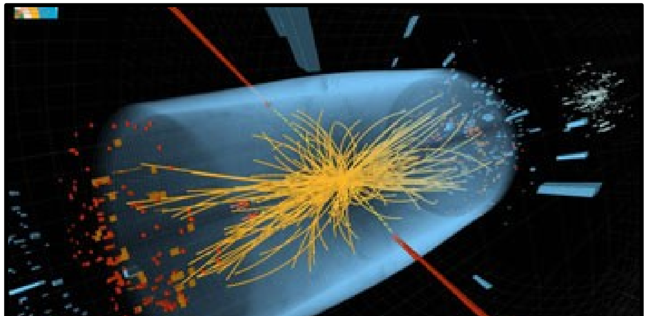
Table: Significance of difference in sigma



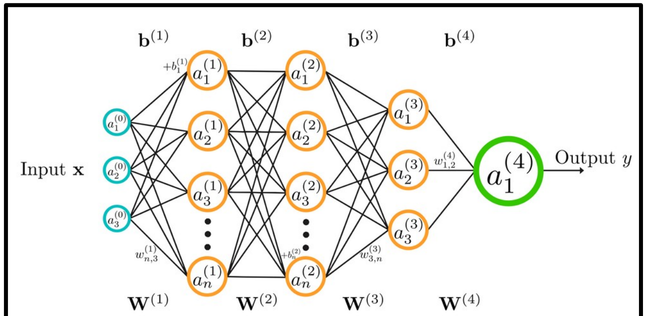
Model	P_T vs. P_Q	H_T vs. H_Q
	AUC	AUC
CNN [28]	0.940	0.924
Full AM	0.943	0.928
ParT [33]	**0.944**	**0.929**

Research Interests

ML × Physics — **Data-Driven Studies on New Physics & Dark Matter**

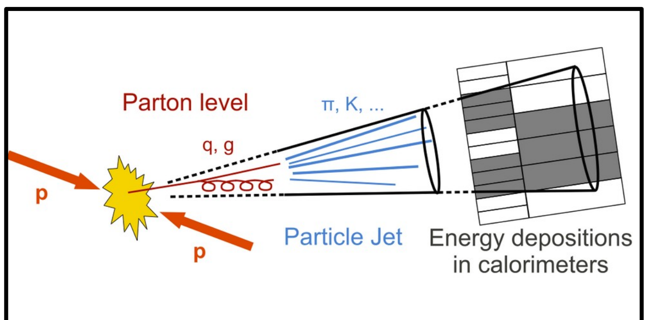


Collider Physics for BSM



Machine Learning

Astrophysics of Galaxies



Jet Physics and QCD

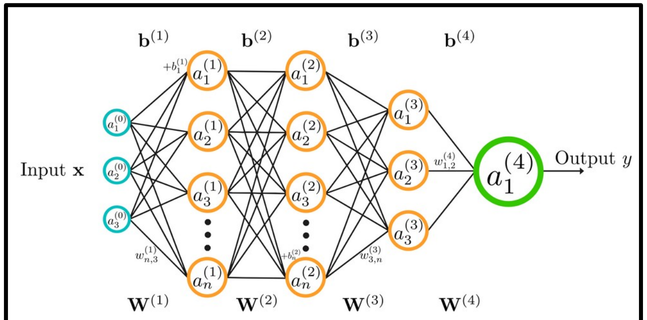
Dark Matter Physics

Data Physicist — **Connecting Data Science and Physics to Supercharge** ***Discovery***

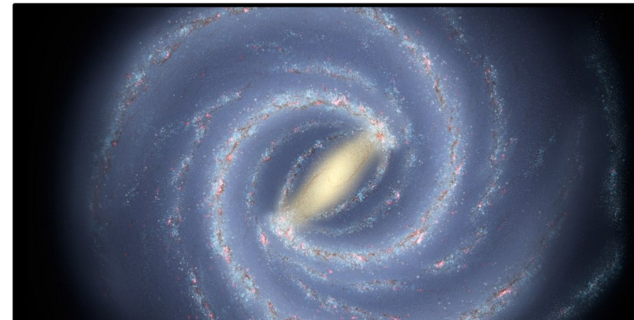
Research Interests

ML × Physics — Data-Driven Studies on New Physics & Dark Matter

Collider Physics for BSM



Machine Learning



Astrophysics of Galaxies

Jet Physics and QCD

Astrophysics topic —
Machine Learning + Galaxies + Dark Matter

Dark Matter Physics

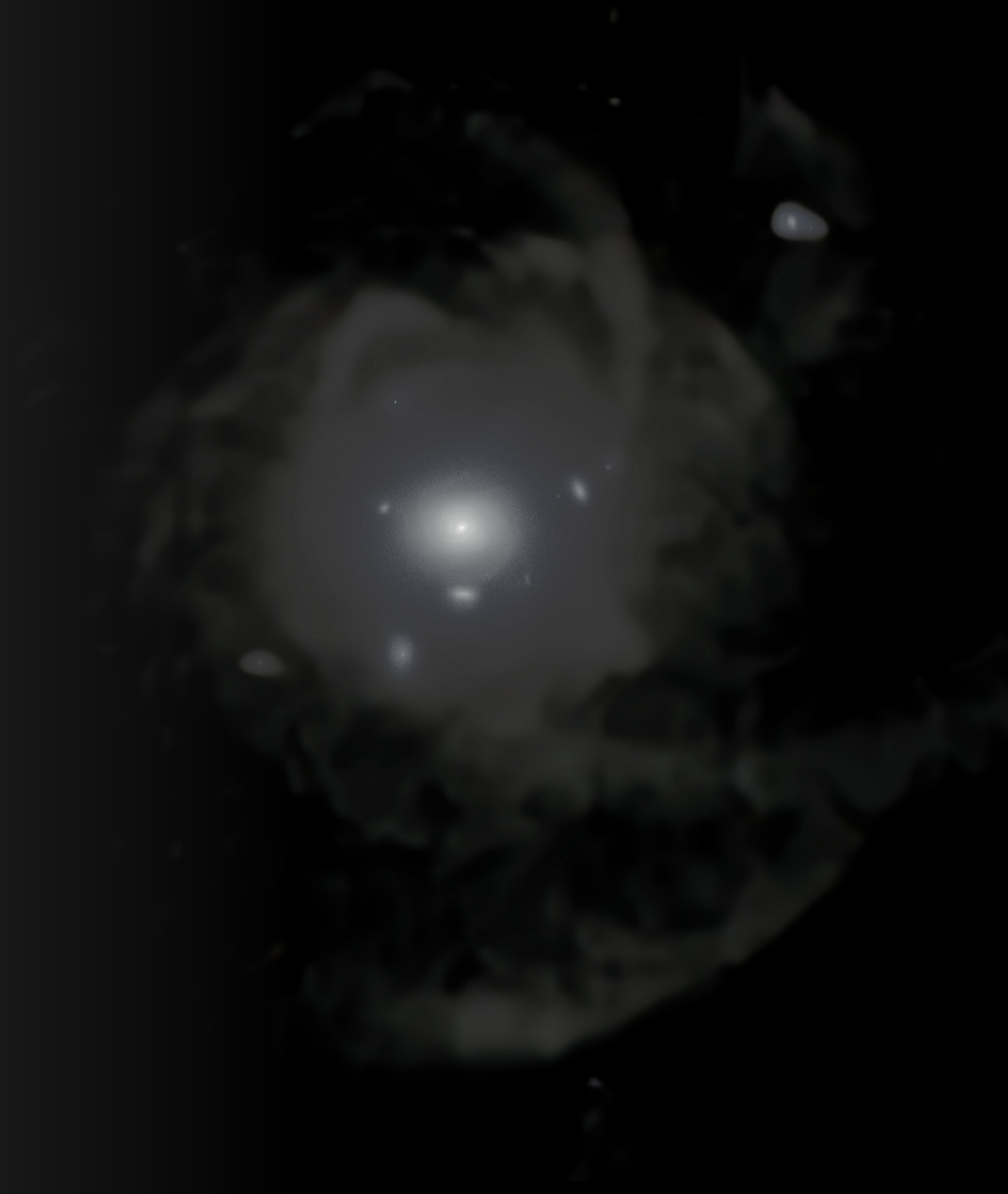
Data Physicist — Connecting Data Science and Physics to Supercharge *Discovery*

Formation of simulated Milky Way-like galaxy h277: https://nbody.shop/data.html

Galaxies have various substructures.

Each substructure is
a **dynamical probe** —

for gravitational potential and dark matter.



Background: Simulated galaxy h277:
https://nbody.shop/data.html

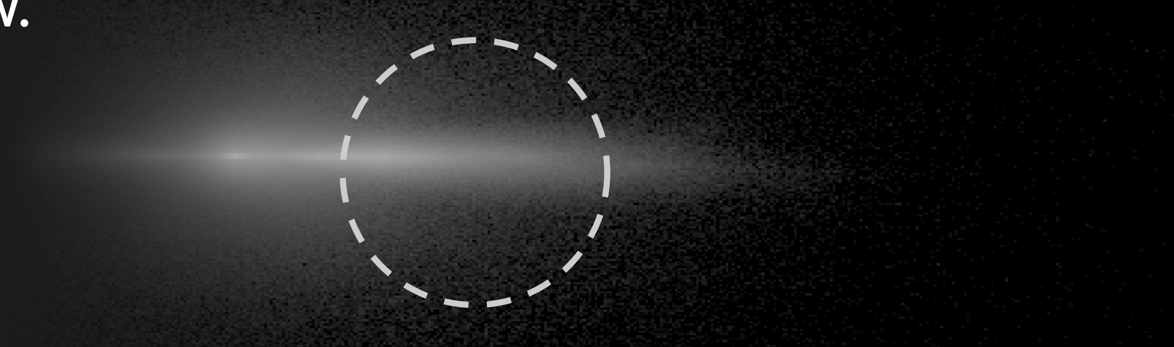
Stellar Halo

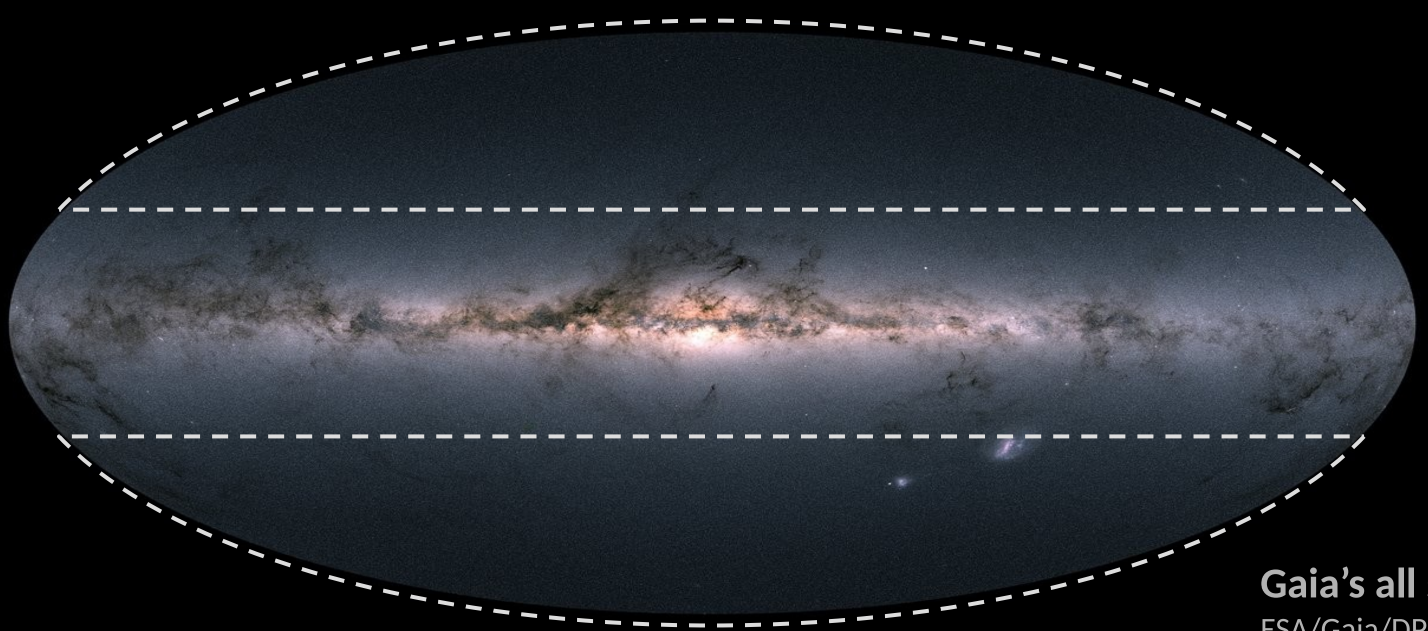
Around the solar system

Old stellar population in the MW.

Nearby stars from us
→ **<u>precisely and completely measured</u>**.

A good probe for
the local dark matter density in
the solar neighborhood.





Gaia's all sky view
ESA/Gaia/DPAC

Dwarf Galaxies

Faint, DM-dominated
satellite galaxies
with little baryonic activity.

→ cleanest probe of **DM halo shape** (cored vs. cuspy)

→ clean targets for indirect detection

Fornax Dwarf
Digitized Sky Survey 2

Ursa Minor Dwarf
Palomar Sky Survey

Draco Dwarf
Digitized Sky Survey

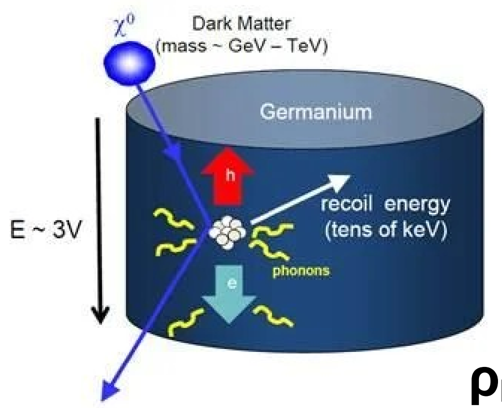
All these substructures encode

the gravitational potential
and the nature of dark matter.

For this talk, let us focus on

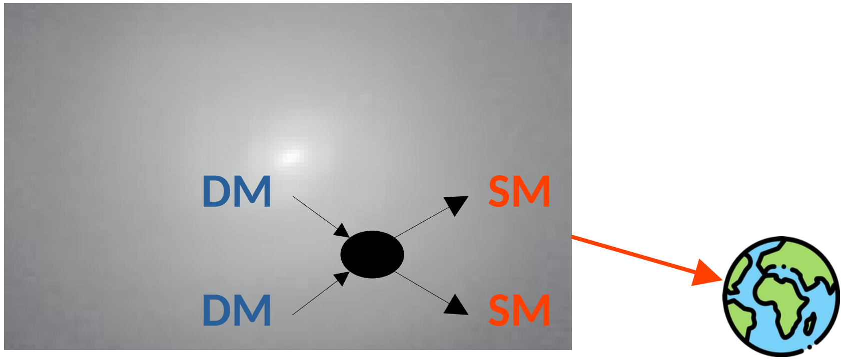
studies about **galactic dark matter**
by measuring **local dark matter density**.

Why measure local DM density?



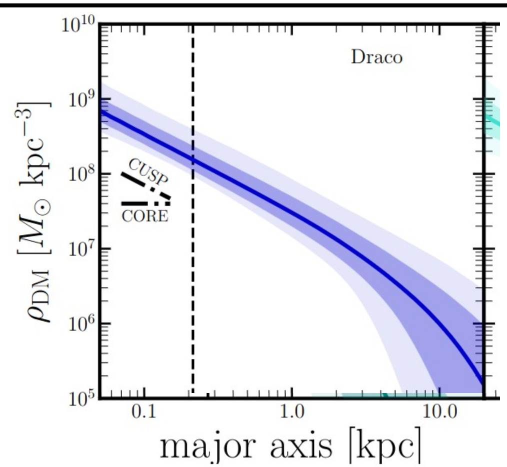
ρ_{DM} on earth?

Direct Detection of DM



ρ_{DM} at the source?

Indirect Detection of DM



Cored or Cuspy ρ_{DM}?

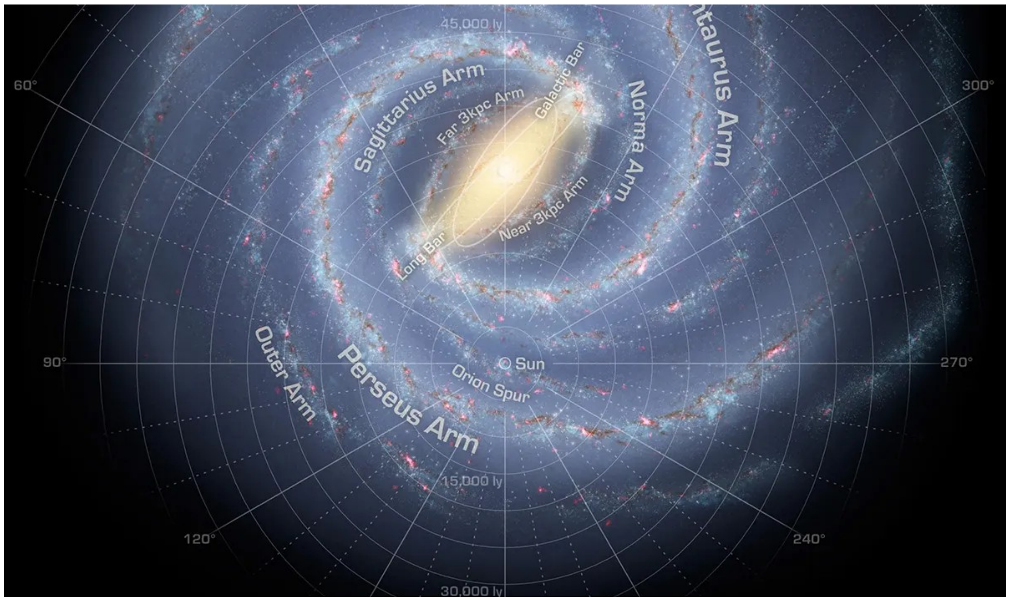
Understanding the Nature of Dark Matter

Local Dark Matter Density of the Milky Way

—

the key input for understanding dark matter physics!

How to measure local DM density?



Stars are moving under the gravitational potential of DM.

$\rightarrow$

***Galactic dynamics* provides insight on local DM density!**

Observable:
Stellar kinematics catalog

$$\{(x_i, v_i)\}$$

position and velocity of stars

?

Inference target:
Dark matter distribution

$$\rho_{DM}$$

Local dark matter density

***Key Question* — How to estimate ρ_{DM} from stellar kinematics catalog?**

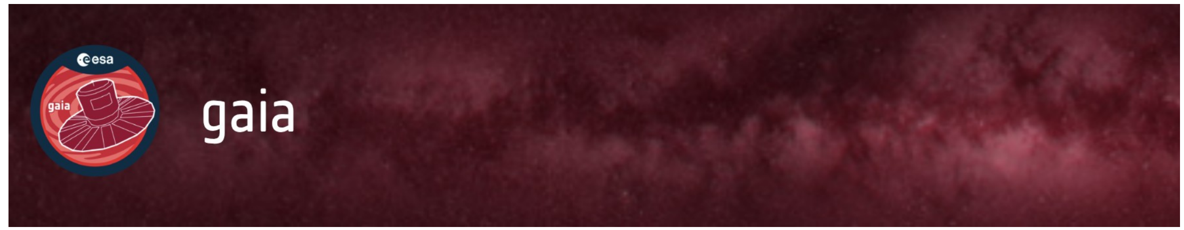
Supercharging Inference Pipeline with ML

Stellar catalog
$\{(x_i, v_i)\}$

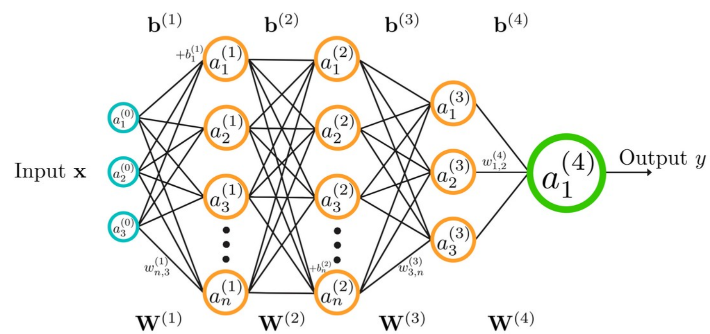
Phase-space density
$f(x,v)$

Grav. Accel.
$a(x)$

Mass density
$\rho(x)$, $\rho_{DM}(x)$



Neural Networks for Galaxy and Gravitational Field Modeling

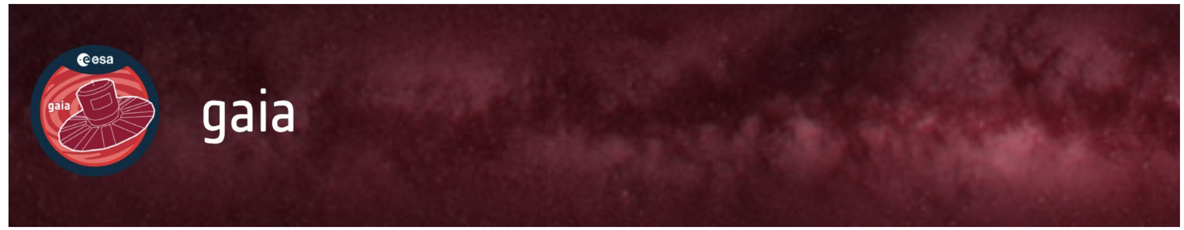


Solve Poisson's equation

$$\rho(\vec{x}) = -\frac{1}{4\pi G}\nabla\cdot\vec{a}(\vec{x})$$

A Neural Estimator for Local Dark Matter Density

Stellar catalog
$\{(x_i, v_i)\}$



Phase-space density
$f(x,v)$

Normalizing Flows

Fit $f(x,v)$ by NN learning change of variables

Grav. Accel.
$a(x)$

Solve CBE (Physics-Informed Neural Network)

Model $a(x)$ by NN minimizing CBE residual

Mass density
$\rho(x)$, $\rho_{DM}(x)$

Solve Poisson's equation

$$\rho(\vec{x}) = -\frac{1}{4\pi G}\nabla \cdot \vec{a}(\vec{x})$$

Acceleration Estimation with Physics-Informed Neural Network

PINN **is a neural network modeling solution of differential equations, simply minimizing the residuals.**

$$\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}}+\vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]f(\vec{x},\vec{v})=0$$

- Equilibrium CBE residual

How to solve?

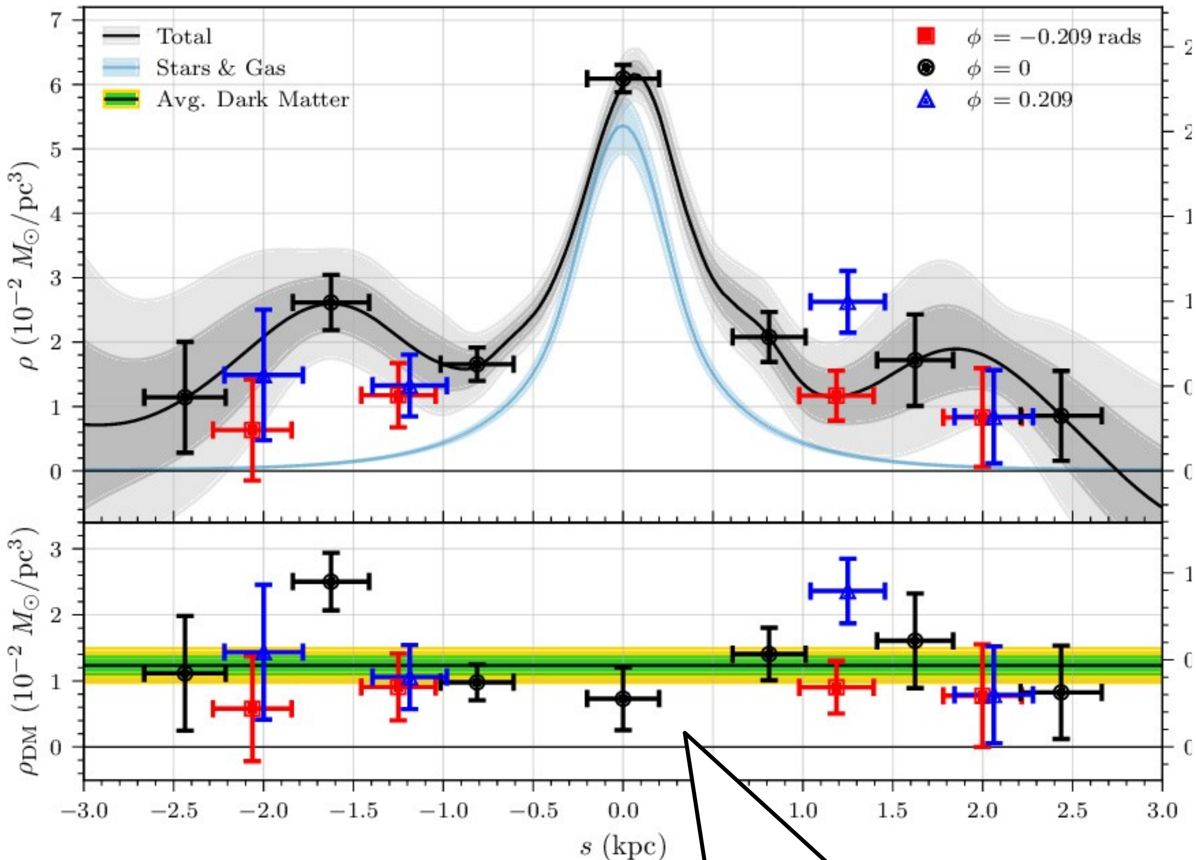
NF **allows us to resample** ***v*** **at fixed** ***x*****, so stacking CBE across multiple velocities gives an** ***overdetermined system*** **for** ***a*****(*****x*****).**

$$\mathcal{L}(a(x))=\mathbf{E}_x\ \mathbf{E}_{v|x}\left[\vec{v}\cdot\frac{\partial f}{\partial\vec{x}}+\vec{a}\cdot\frac{\partial f}{\partial\vec{v}}\right]^2$$

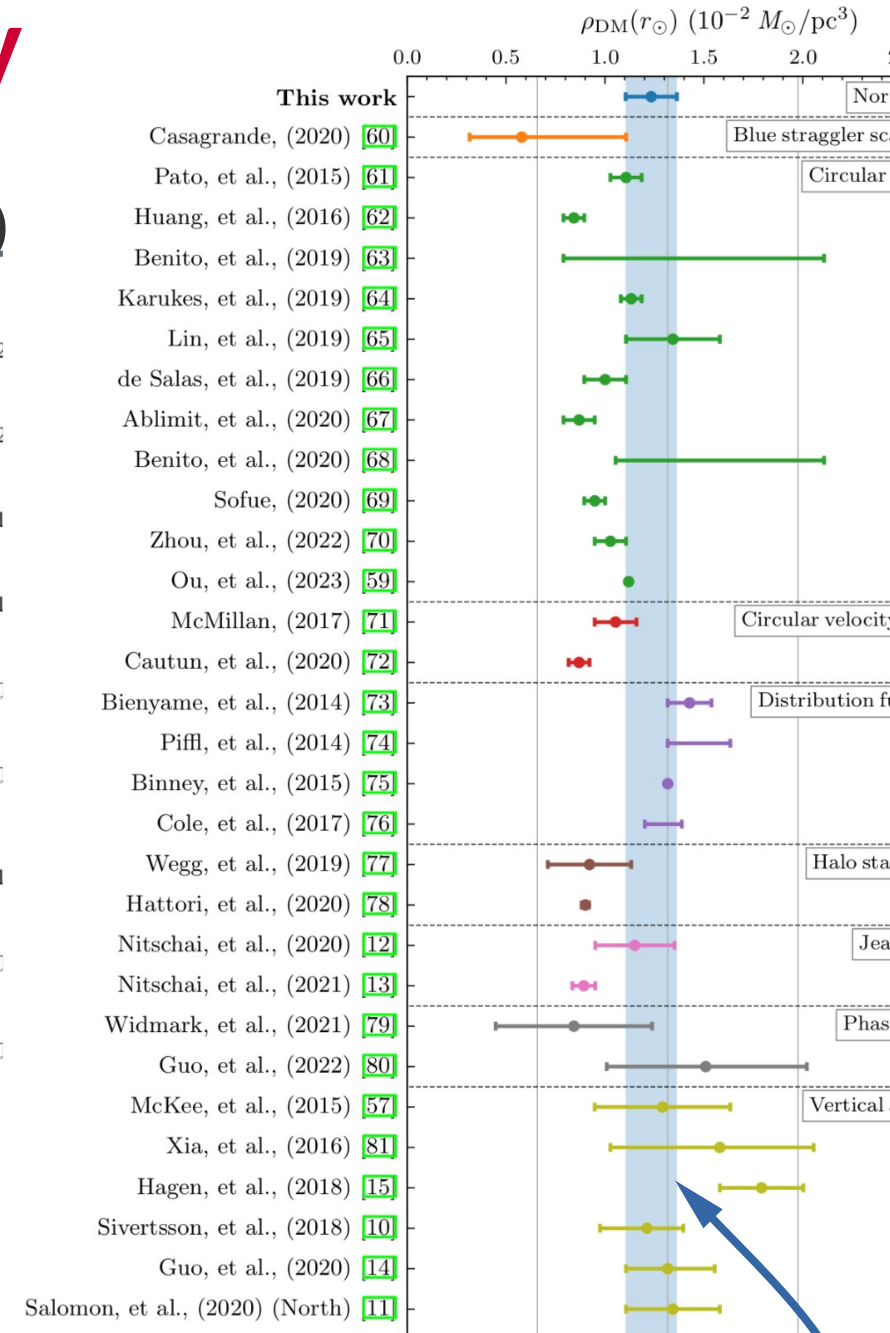
Train a(x) by minimizing the CBE residual squared across data points.

Local Dark Matter Density of the Milky Way

SHL et. al. (arXiv:2305.13358)



0.32±0.18 GeV/cm^3



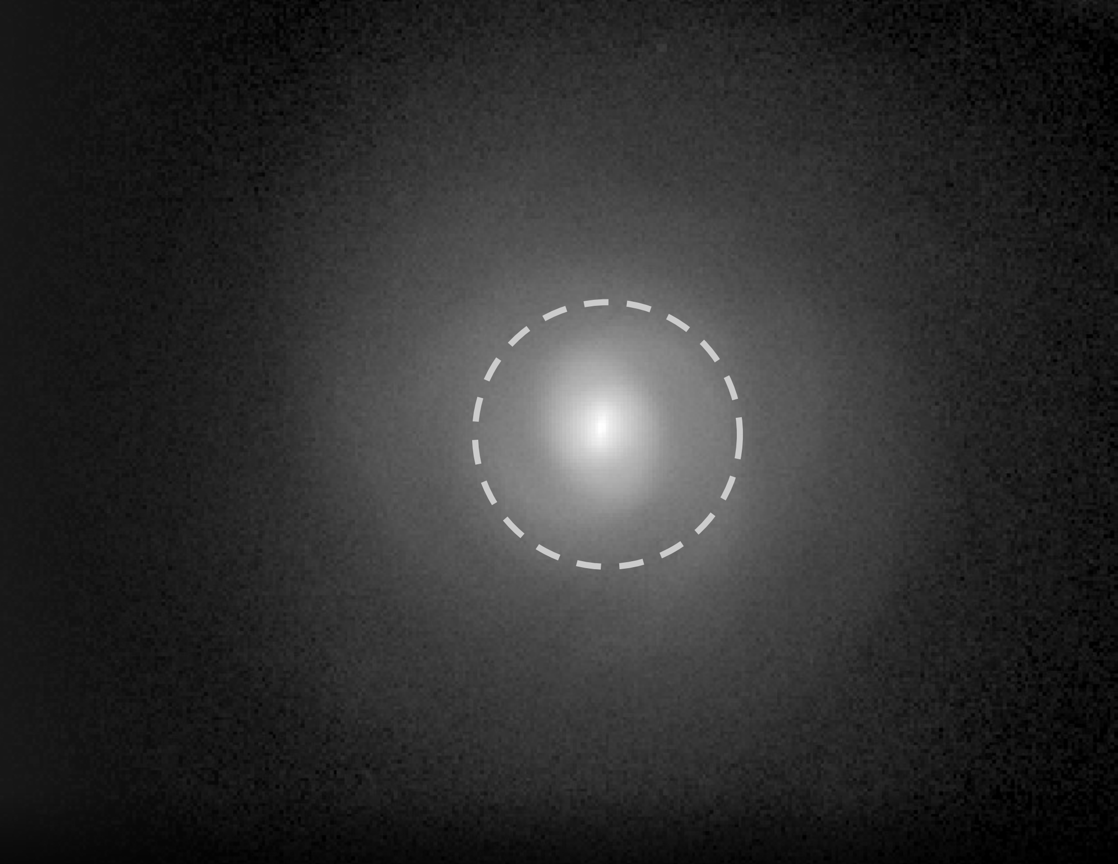
Taking the average of the DM mass density at the Solar radius, we find a local dark matter density: **0.47±0.05 GeV/cm^3**

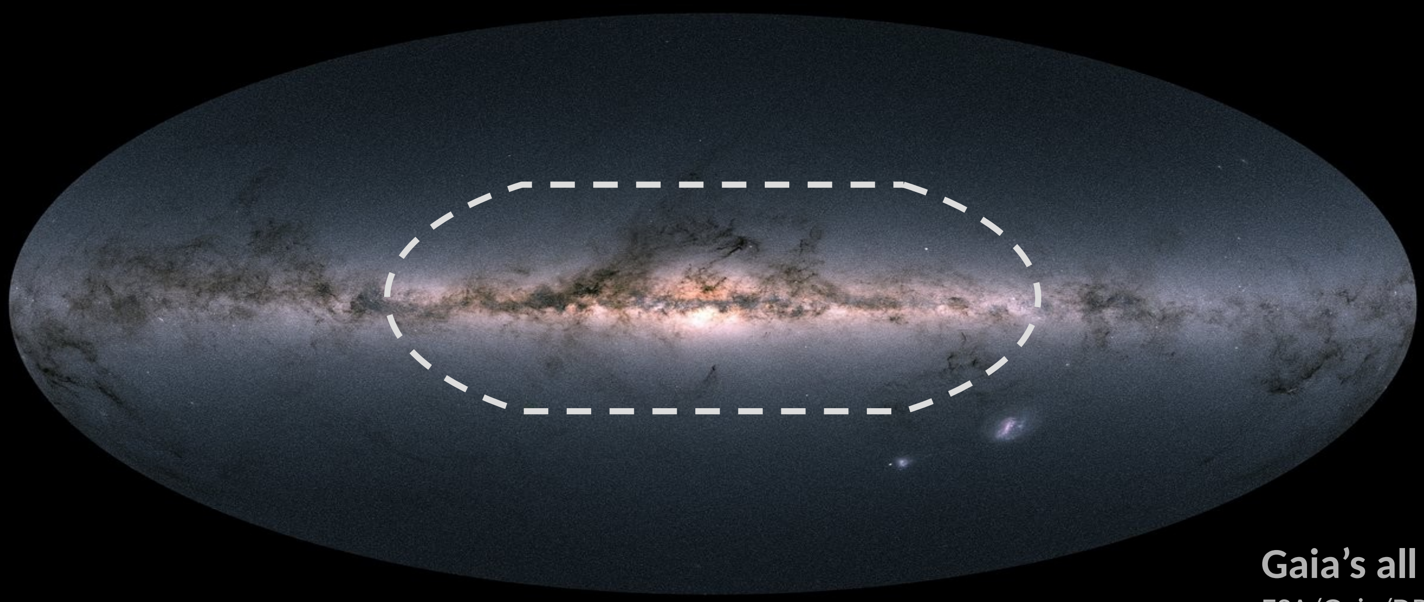
Galactic Center

Dense core of the Milky Way.

→ probe of central **<u>DM halo shape</u>** of a massive galaxy (cored vs. cuspy).

→ brightest source of indirect DM detection.

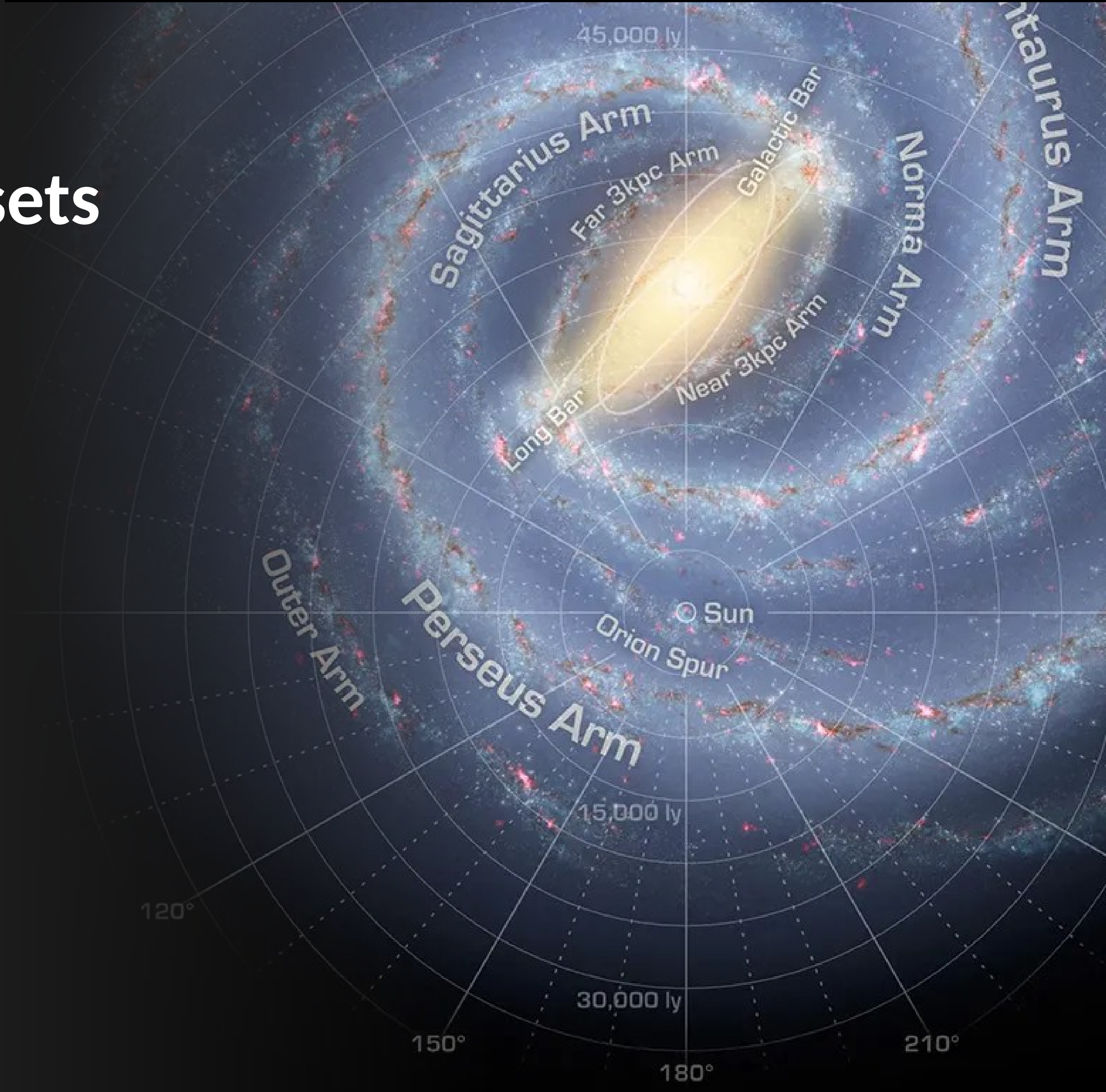




Gaia's all sky view
ESA/Gaia/DPAC

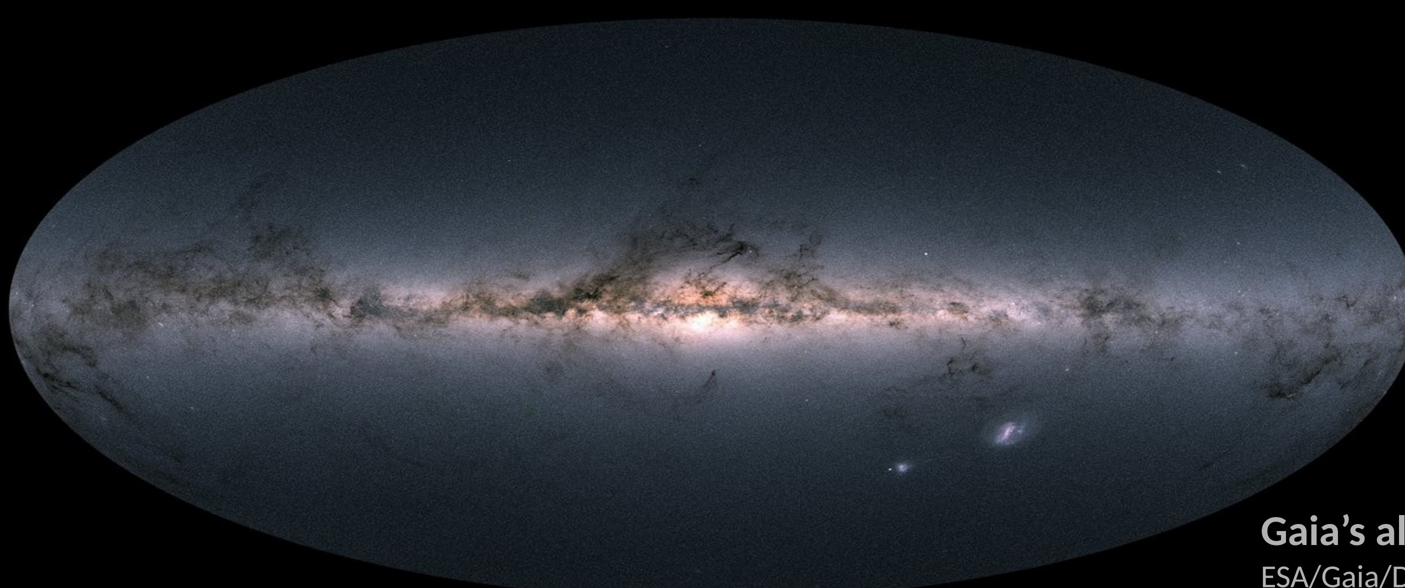
Galactic Dynamics and Incomplete Datasets

One of main challenges of applying this technique is that the dataset itself is **incomplete.**



Dust Clouds

Interstellar dust clouds **obscure** light
from stars behind them.
→ Obscured stars are
missing in Gaia catalog.



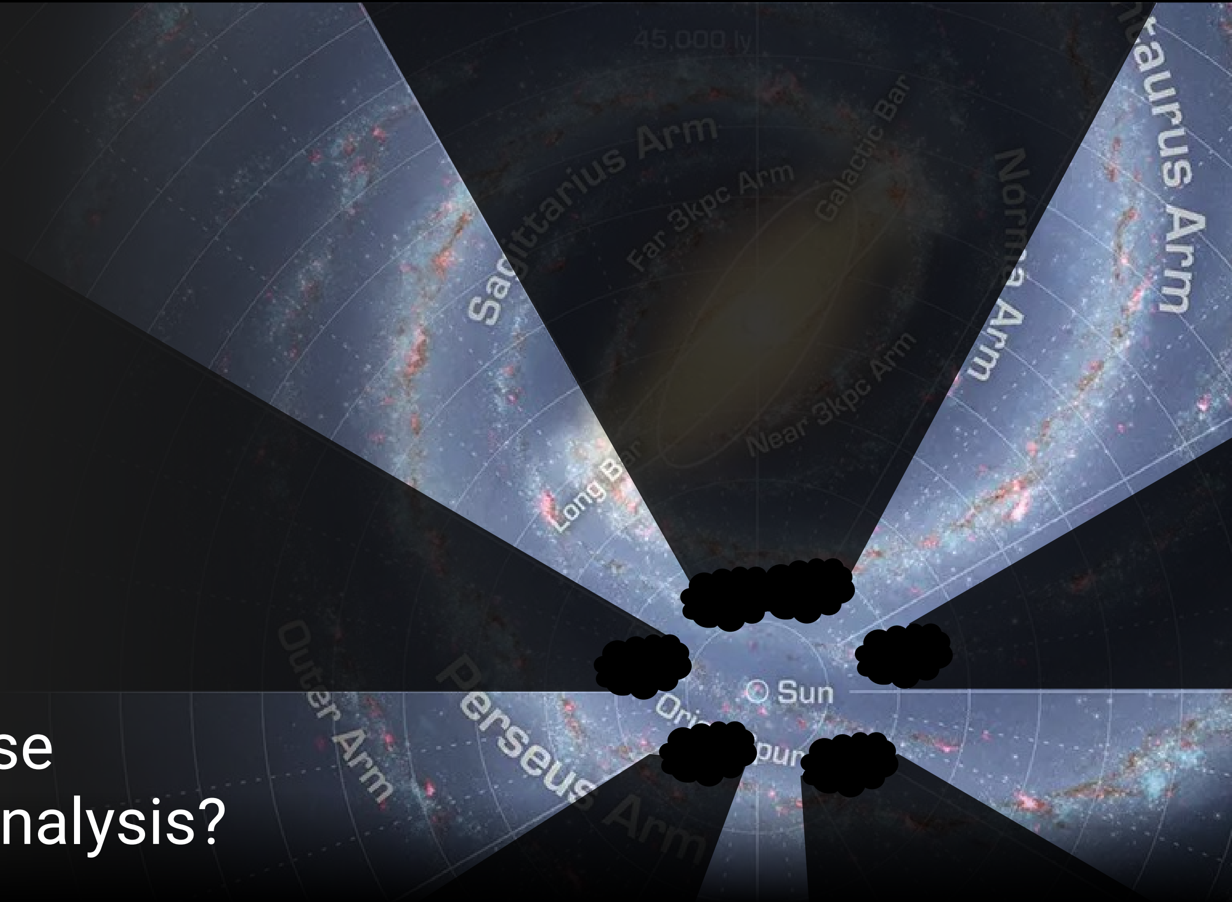
Gaia's all sky view
ESA/Gaia/DPAC

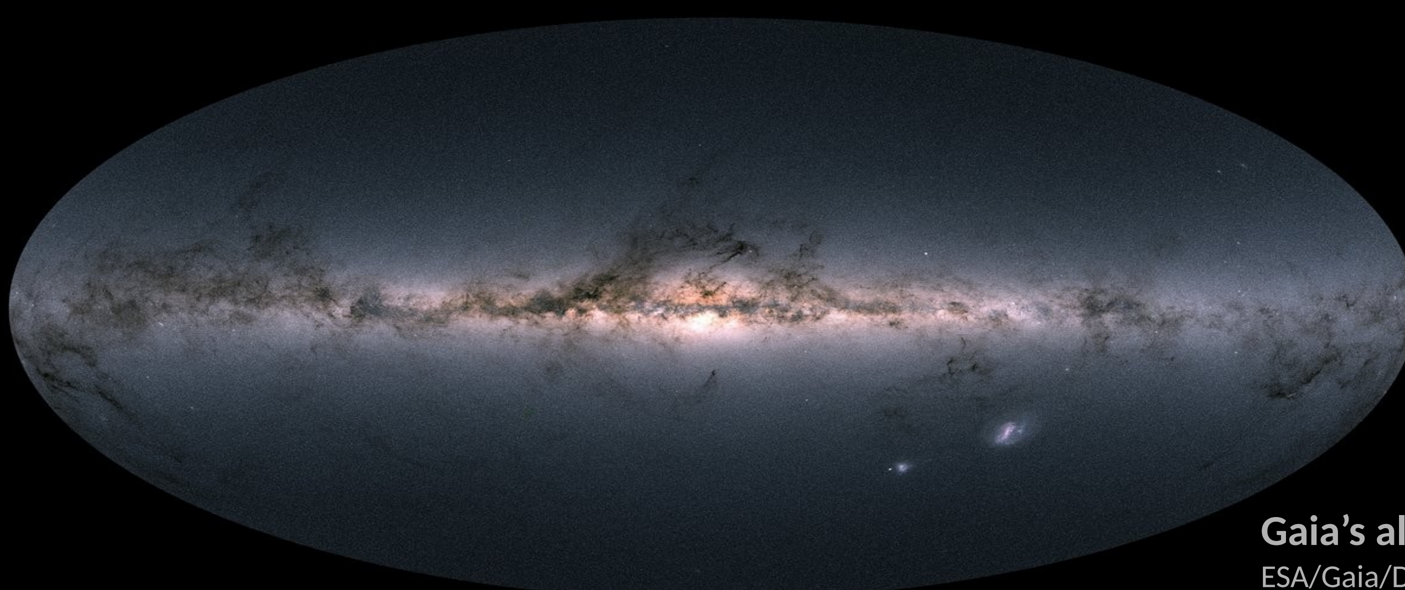
Dust Clouds

Interstellar dust clouds **obscure** light from stars behind them.

→ Obscured stars are missing in Gaia catalog.

→ How can we **recover** those for full 6D phase-space analysis?



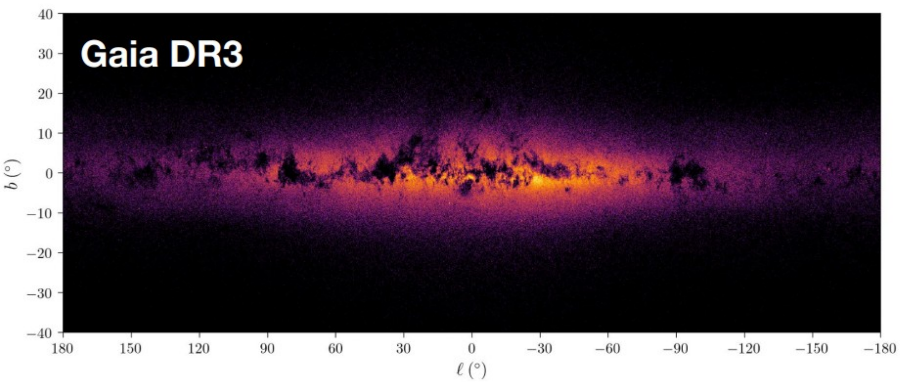


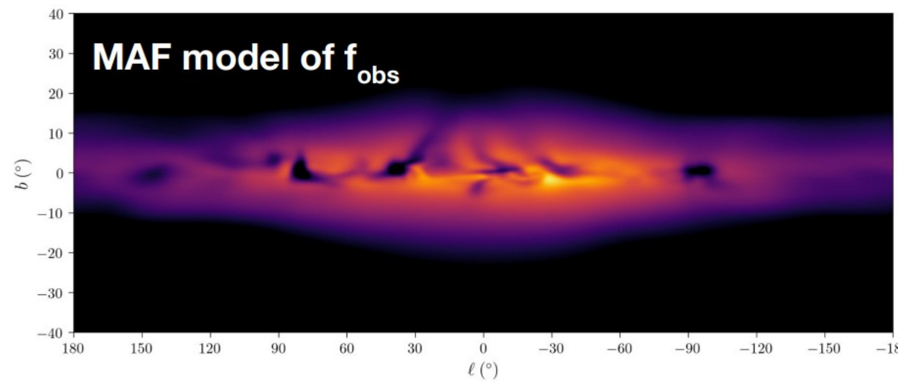
Gaia's all sky view
ESA/Gaia/DPAC

Sweeping the Dust Away -- Correcting the Phase Space Density of the Milky Way with Unsupervised Machine Learning

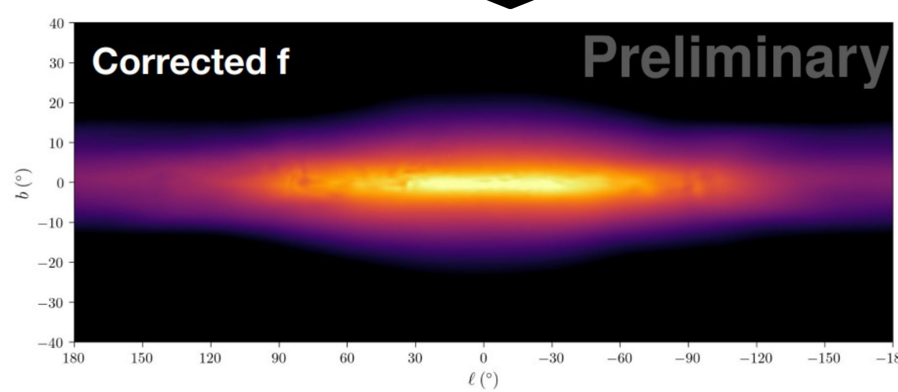
Eric Putney, David Shih, **SHL**, Matthew R. Buckley (arXiv:2412.14236)

PINN for Removing Dust Clouds





$$\frac{\partial f}{\partial t} = 0$$



Key Idea **—**

Equilibrium assumption can be utilized for inferring selection efficiency <u>without referring dust map.</u>

PINN-based Selection Efficiency Modeling

$$f_{\mathrm{obs}}(\vec{x},\vec{v}) = f_{\mathrm{true}}(\vec{x},\vec{v}) \times \epsilon(\vec{x})$$

NF model (observed PS, learned) **Selection efficiency** (dust, ...)

↓ Apply CBE to log f_{true}

$$\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}} + \vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]\log f_{\mathrm{obs}}(\vec{x},\vec{v}) - \vec{v}\cdot\frac{\partial}{\partial\vec{x}}\log\epsilon(\vec{x}) = 0$$

Acceleration model **<u>Two unknowns</u>: a(x), ∇ log ϵ(x)**

↓ Linear in unknowns — solvable by MSE minimization

$$\mathcal{L}(\phi,\log\epsilon) = \mathrm{E}_{\vec{x},\vec{v}}\left|\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}} + \vec{a}\cdot\frac{\partial}{\partial\vec{v}}\right]\log f_{\mathrm{obs}}(\vec{x},\vec{v}) - \vec{v}\cdot\frac{\partial}{\partial\vec{x}}\log\epsilon(\vec{x})\right|^2$$

PINN loss for *<u>selection efficiency</u>* — no dust map required.

Dust-Corrected Local Dark Matter Density

Normalizing Flows (NFs):

fits *f(x,v)* by learning change of variables

$$\vec{w}_{\mathrm{data}} = \mathrm{NN}(\vec{u}), \quad \vec{u} \sim \mathcal{N}(0, I)$$

$$f(\vec{w}) = p_U(\vec{u}) \cdot \left| \frac{d\vec{u}}{d\vec{w}} \right|$$

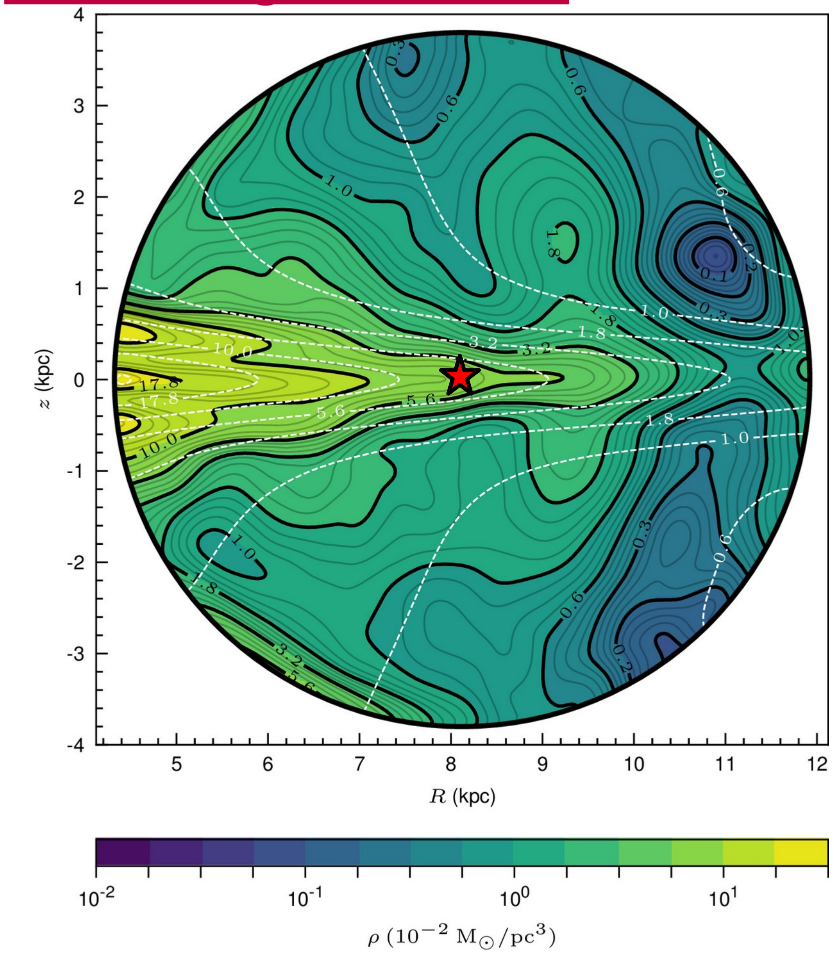
Physics-Informed NN (PINN):

solves *CBE* by minimizing residuals

$$\mathcal{L} = \mathbf{E}\left[\left| \vec{v} \cdot \frac{\partial f}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial f}{\partial \vec{v}} \right|^2 \right]$$

Results of ρ_{DM} in solar neighborhood

Gaia DR3 based res.

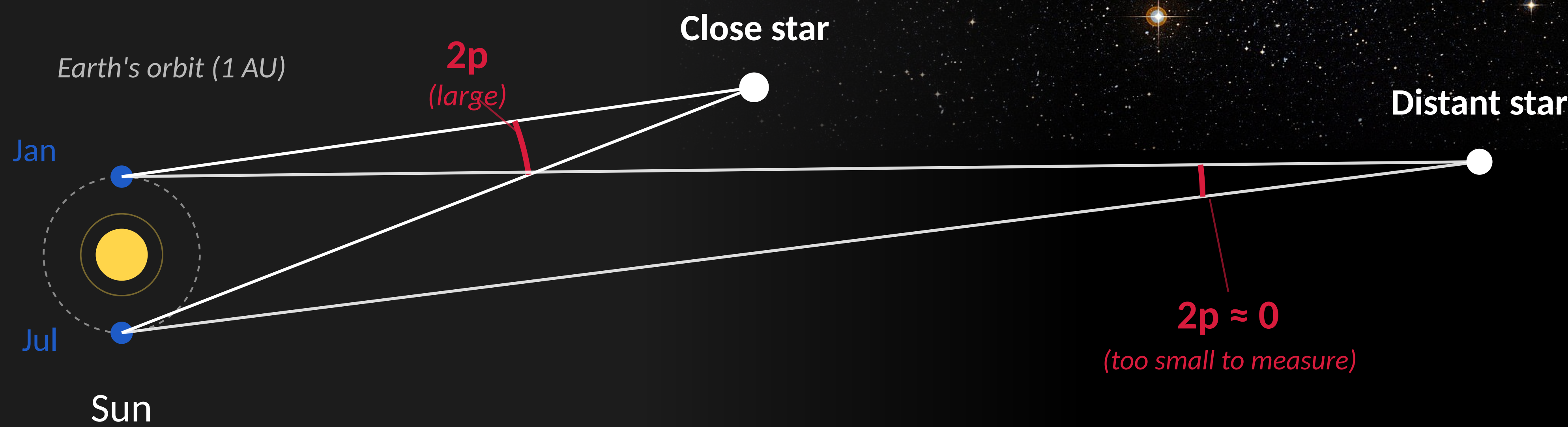


E. Putney, D. Shih, **SHL**, and M. R. Buckley, arXiv:2512.09989.
also in workshop paper at NeurIPS 2025 ML4PS workshop

Is the same technique applicable to other galaxies?

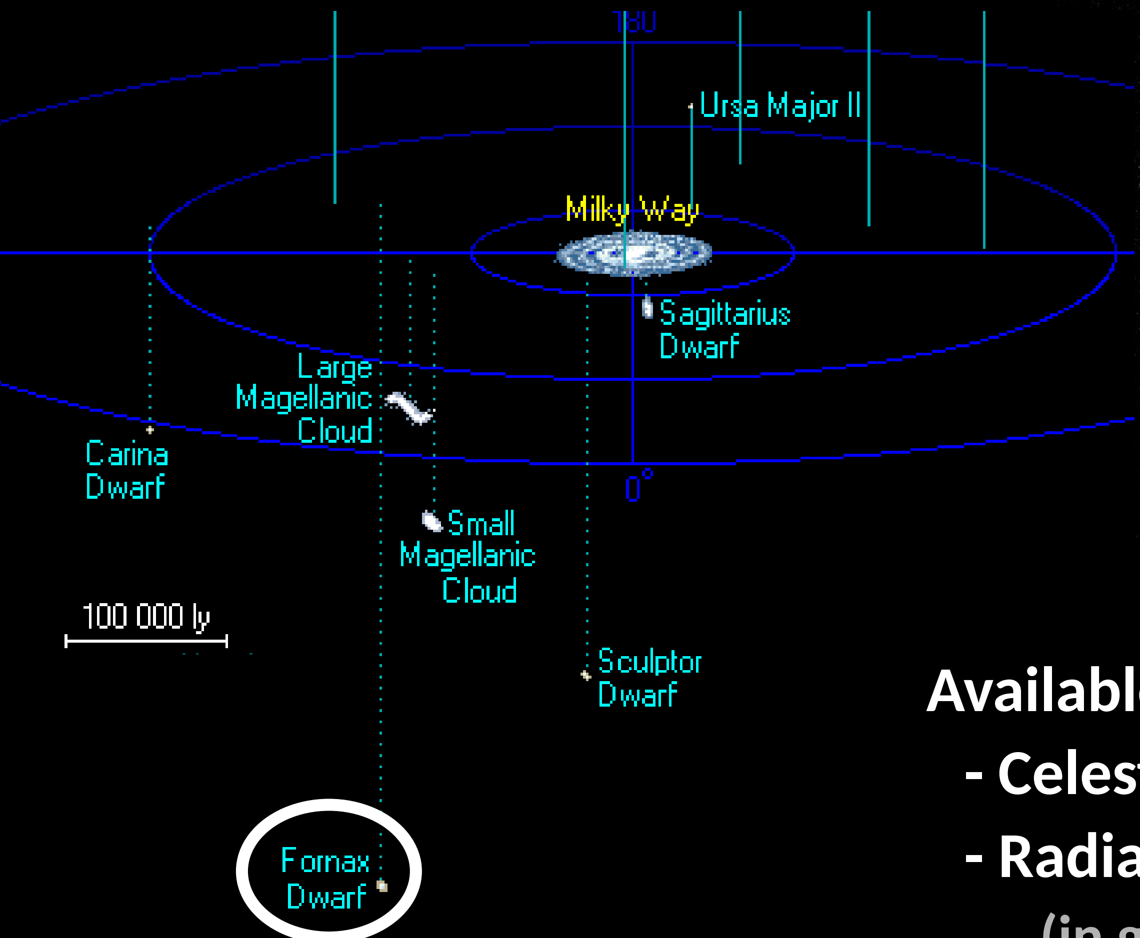
✓ Yes, if full 6D information is available.

✗ No, many surveys for distant galaxies provides only limited information.

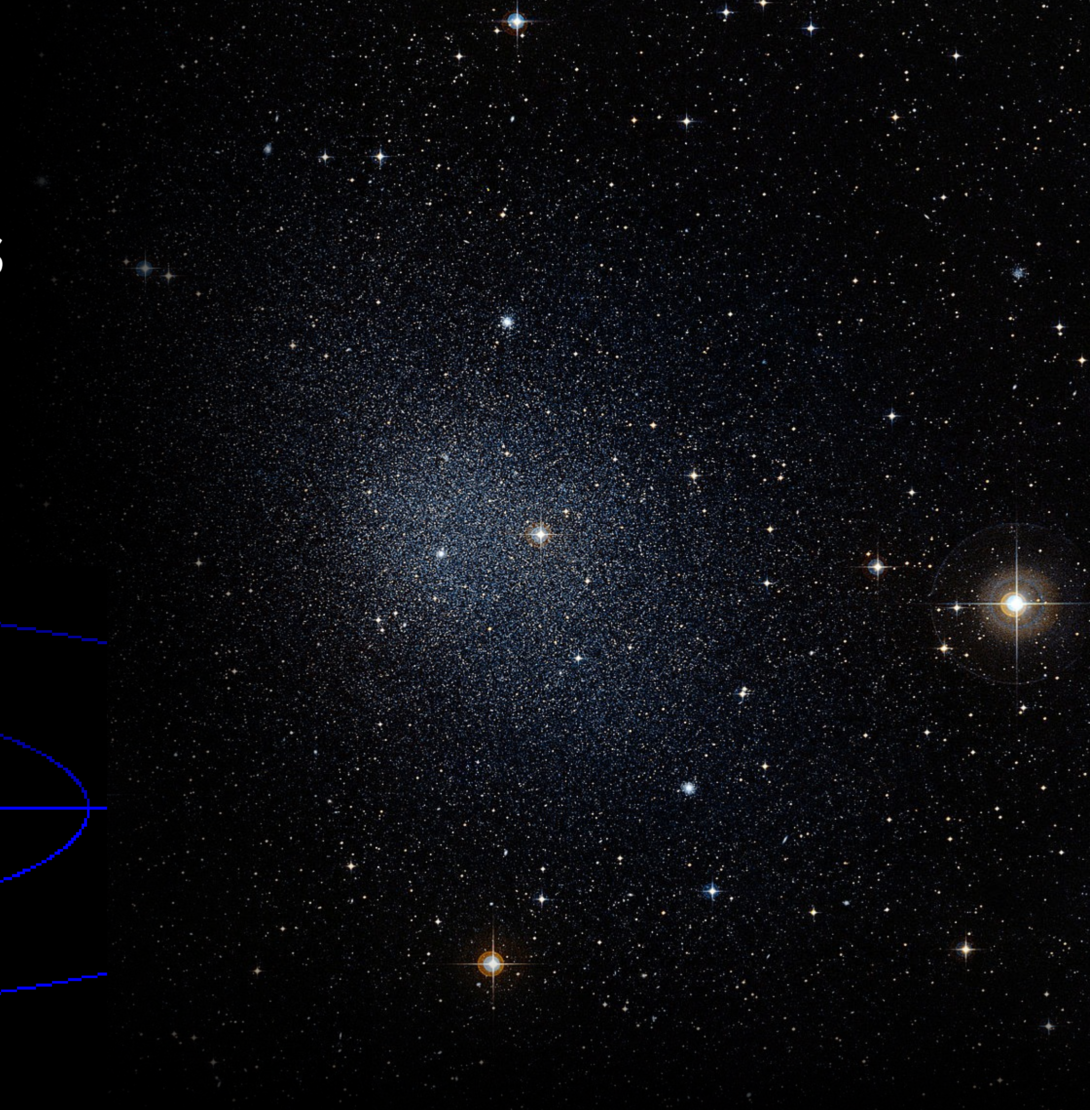


Example:
Dwarf Spheroidal Galaxies

Round faint satellite galaxies orbiting the Milky Way.



http://www.atlasoftheuniverse.com/sattelit.html



Fornax Dwarf
Digitized Sky Survey 2

Available info. for member stars

- **Celestial position on the sky (*x*, *y*)**
- **Radial velocity (v_z)**

(in galactocentric coordinate of dSph.)

But,
we need a full 6D phase space density.

Can we recover those from 3D info?

But,
we need a full 6D phase space density.

Can we recover those from 3D info?

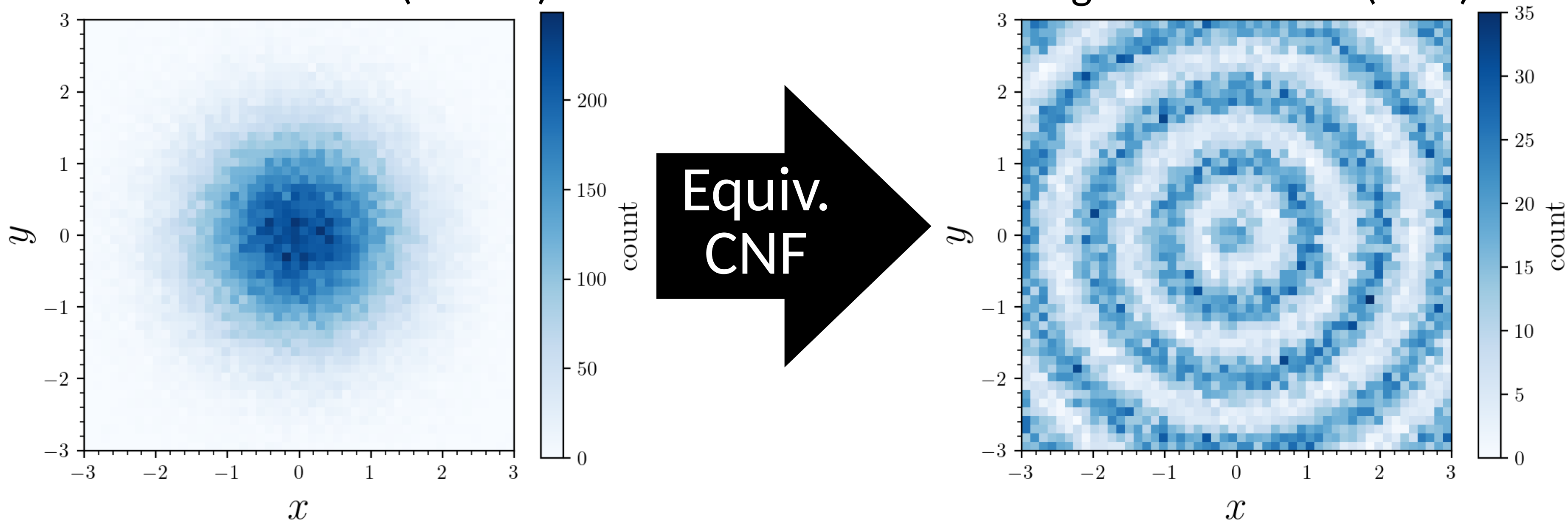
Yes, we can impose
symmetry and physics constraints.

Equivariant Continuous Normalizing Flows

Continuous Normalizing Flows (CNFs) are NFs learning infinitesimal coordinate transformation.

$$\frac{d\vec{x}}{dt} = \vec{G}(\vec{x}, t) \longrightarrow \frac{d\vec{x}}{dt} = \hat{r} g(\vec{x}, t)$$

Base distribution (known) Target distribution (data)



Conditions:

- **Base distribution** is **invariant**: spherically symmetric Gaussian
- **Transformation** is **equivariant**: transformation is confined to radial direction

Equivariant CNFs: cored profile

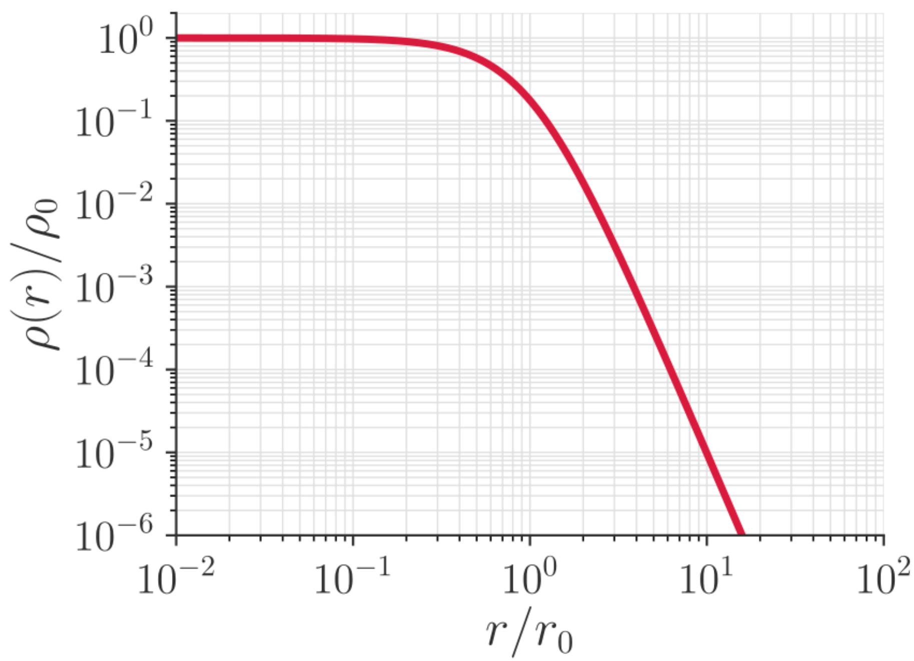
CNFs can be further constrained to model only **cored** density profile.

$$\frac{d\vec{x}}{dt} = \hat{r} g(\vec{x}, t) \longrightarrow \frac{d\vec{x}}{dt} = \hat{r} \tanh\left[\frac{|\vec{x}|}{r_0}\right] g(\vec{x}, t)$$

Mechanism:
- Base Gaussian distribution is already cored at origin.
- Suppressed flow at the origin → Flat core remains flat.

Example: Plummer profile

$$\rho(r) = \rho_0 \left[1 + \frac{r^2}{r_0^2}\right]^{-\frac{5}{2}}$$



JFlow Loss Function Construction

Obstacle:

- Our likelihood model is **6D** phase space density model.
- Data has only **3D** info.

Solution:

- Use **generative approach** to perform MLE at a space with **matched** dimension.

$$
\begin{tikzcd}
 & \textbf{likelihood} & \textbf{sample} \\
\textit{6D} & f(\vec{w};\theta) \arrow[r, "\text{sampling}"] \arrow[d, dashed, "\text{Abel transform}"'] & \vec{w} = T(\vec{\epsilon}_B;\theta) \arrow[d, "\text{projection}"] \\
\textit{3D} & f_\perp(\vec{w}_\perp;\theta) \arrow[d, dashed, "\text{KDE convolution}"'] & \vec{w}_\perp = \mathrm{Proj}_\perp T(\vec{\epsilon}_B;\theta) \arrow[d, "\text{smear} + \vec{\epsilon}_K"] \arrow[dl, "\text{KDE estimator}"'] \\
\textit{smoothed 3D} & (f_\perp * K_h)(\vec{w}_\perp;\theta) \arrow[r, dashed, leftrightarrow, "\textbf{match}"] & \vec{w}_\perp + \vec{\epsilon}_K
\end{tikzcd}
$$

dashed grey: analytic but intractable.
solid: computable from CNF samples.
dashed red: the equality we optimize.

JFlow Loss Function

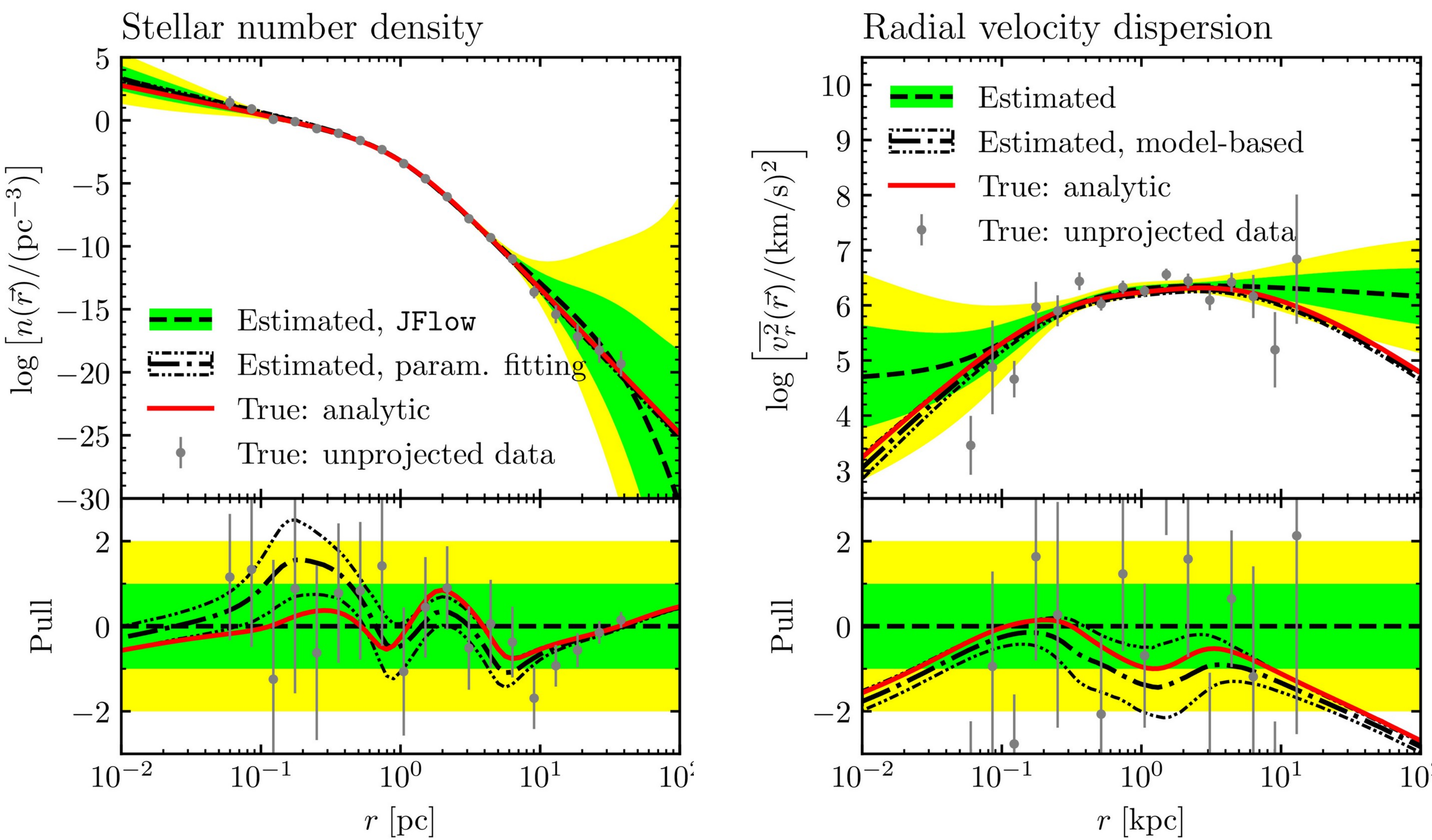
The JFlow algorithm trains 6D likelihood model by minimizing
KL divergence at smoothed 3D space.

$$\mathcal{L}(\theta) = \int d\vec{w}_\perp \; p * K_h(\vec{w}_\perp) \; \log \hat{p} * K_h(\vec{w}_\perp; \theta)$$

Resulting JFlow training objective:

$$\mathcal{L}(\theta) = \frac{1}{N N_K} \sum_{a=1}^{N} \sum_{b=1}^{N_K} \log \frac{1}{N_G} \sum_{c=1}^{N_G} K_h \left[\vec{w}_\perp^{(a)} + \vec{\epsilon}^{(b)} - \vec{T}(\vec{z}^{(c)}; \theta) \right]$$

Results: stellar number density & radial velocity dispersion

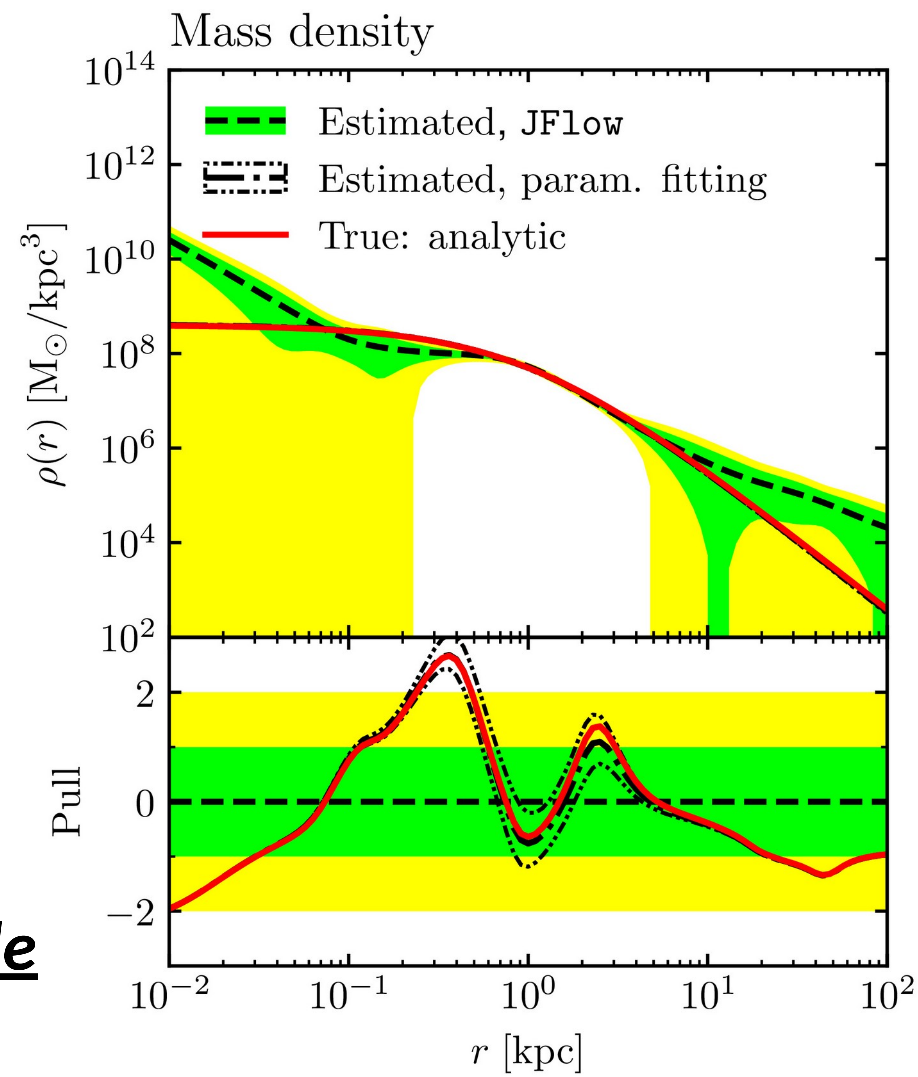


Results: dark matter mass density

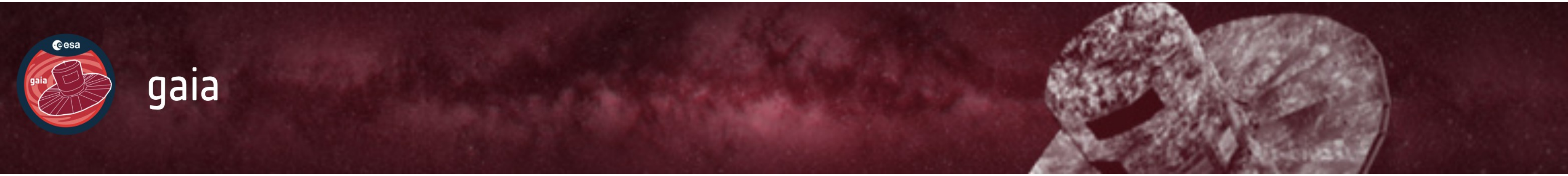
Dataset

- Simulated spherical galaxy
- Cored dark matter density profile (known)
- 10K samples
- See Gaia Challenge repository

  astrowiki.surrey.ac.uk



JFlow successfully recovers the *true dark matter density profile* from *limited information*.



GAIA DATA RELEASE 4 (GAIA DR4)

The original Gaia DR4 data will become available from the Gaia ESA Archive. The expected content of Gaia DR4, pending certain processing and validation activities, is described here and summarised in this table.

Current: Gaia DR3
1.5 billion sources

Future: Gaia DR4
2.8 billion sources

×2 in stat.

* Gaia DR3: Full 6D phase space for 33M sources.

With new survey data delivered from 2026~, it will be exciting time for galactic dynamics researches!

and AI / ML will be a game changer in this research direction!

Physics-Informed Machine Learning

Input-level

- Physics-Informed inputs for jet tagging
- ...

Architecture-level

- Equivariant jet taggers
- JFlow – neural model of dwarf spheroidal galaxies
- ...

Loss function-level

- NNPDF
- CBE solver for dark matter density estimations
- ...

Physics-Informed Machine Learning is useful framework for data-driven studies on various physics!

Awesome collaborators of my projects:

Prof. David Shih
(Rutgers)

Prof. Matthew Buckley
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Prof. Mihoko Nojiri
(KEK)

Prof. Kohei Hayashi
(NIT, Sendai College)

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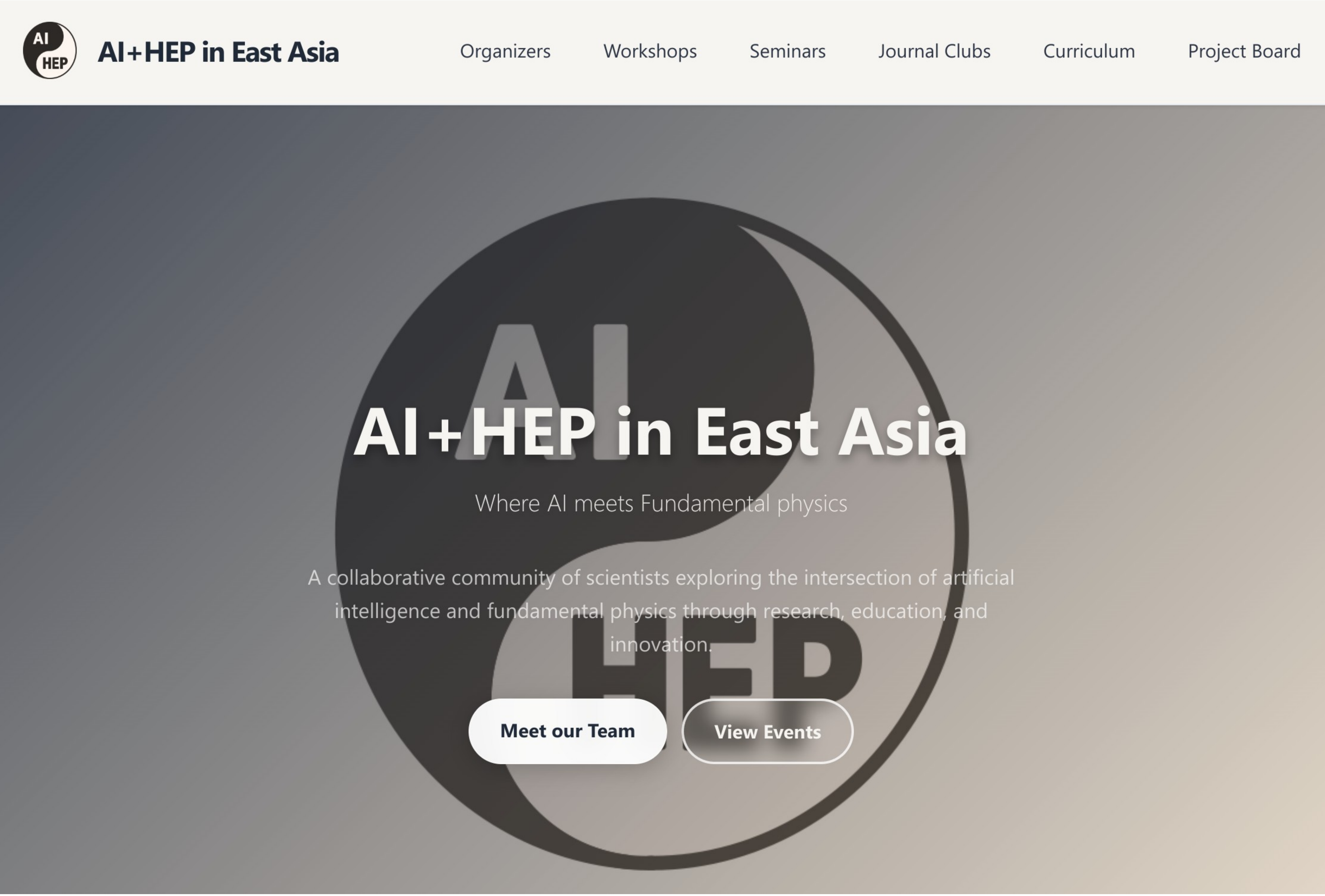
Dr. Shunichi
Horigome
(Tohoku)



URL: http://ai-hep.github.io

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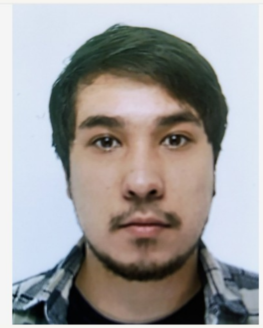

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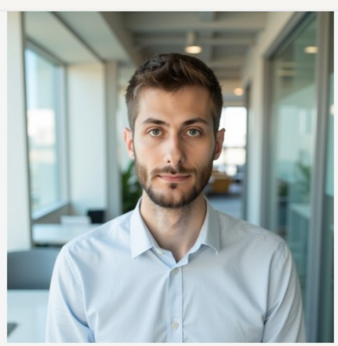
STAFF RESEARCH PHYSICIST

CERN

JET TAGGING · DEEP LEARNING · COLLIDER PHYSICS · AI INTEGRATION

Dr. Huilin Qu (曲慧麟) is a staff research



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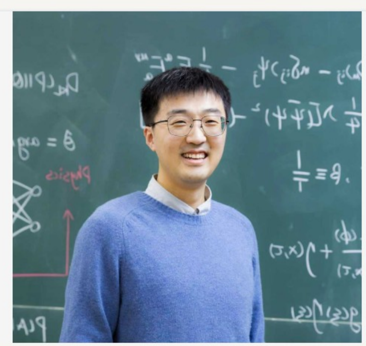
AI FOR SCIENCE · GRAVITATIONAL WAVES · FUTURE COLLIDERS · QUANTUM CHROMODYNAMICS · PION PHENOMENOLOGY



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Dates: Jan 19–23, 2026

Location: KEK, Tsukuba, Japan

Event Page

AI+HEP Workshop 2025

Dates: Feb 23–28, 2025

Location: IBS (Institute for Basic Science), Daejeon, Korea

Event Page

Thank you
for listening.