Understanding Galactic Dark Matter with Neural Networks

The Frontier of Particle Physics: Exploring Muons, Quantum Science and the Cosmos

YITP, Kyoto, Japan

June 2025

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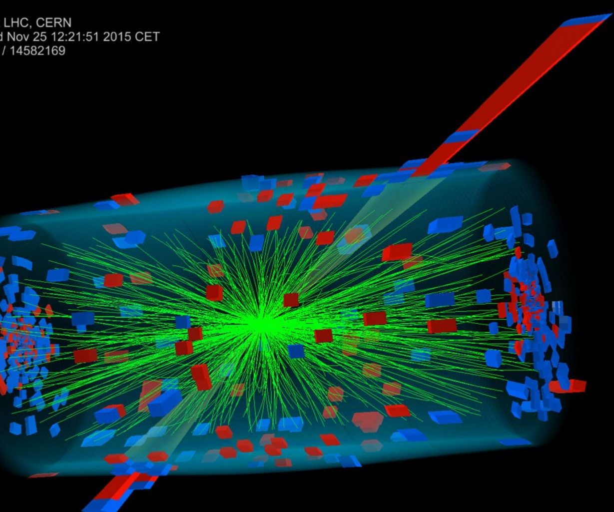
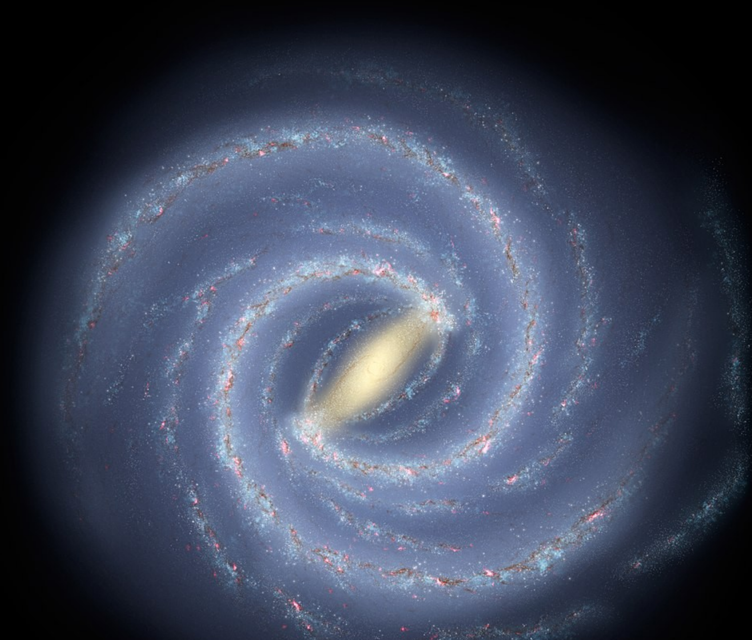
ibs Institute for Basic Science

Phenomenology of Dark Matter appears in Various Length Scales!



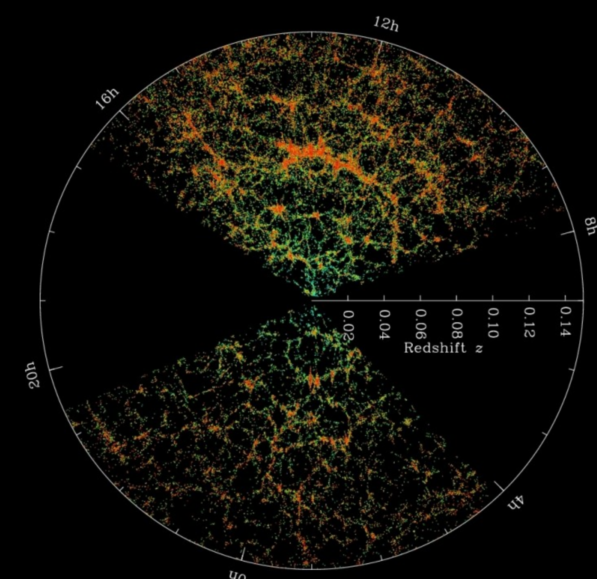
Particle Physics

(small length scale)



Galactic Astrophysics

(medium length scale?)



Cosmology

(large length scale)

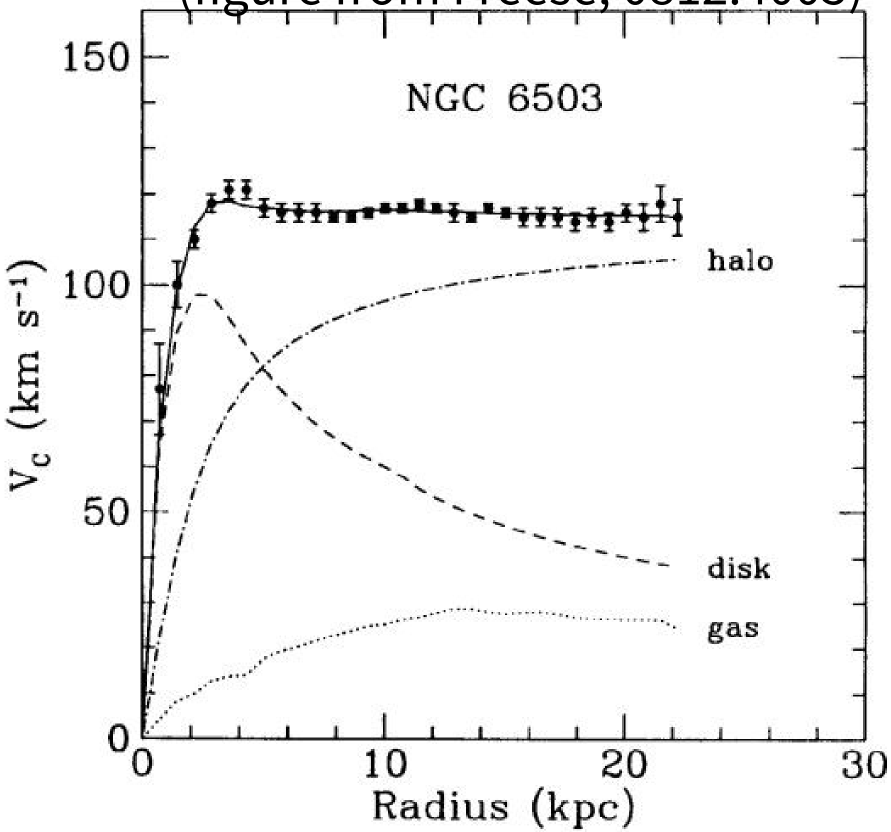
There are many interesting things but…
perhaps, most interested topic in galactic astrophysics to high energy particle physicists is…

There are many interesting things but...
perhaps, most interested topic in galactic astrophysics to high energy particle physicists is…

about dark matter.

Galaxy rotation curve and dark matter

(figure from Freese, 0812.4005)



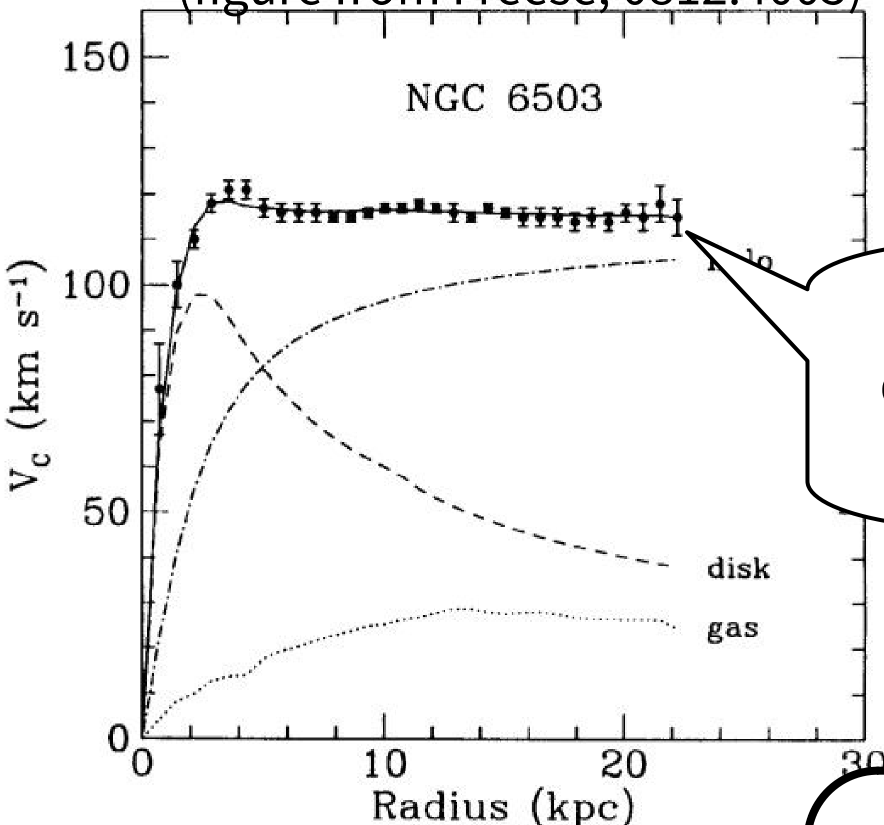
NGC 6503 from NASA Hubble telescope

$$v_{\rm circ}(R) = \sqrt{\frac{GM(R)}{R}}$$

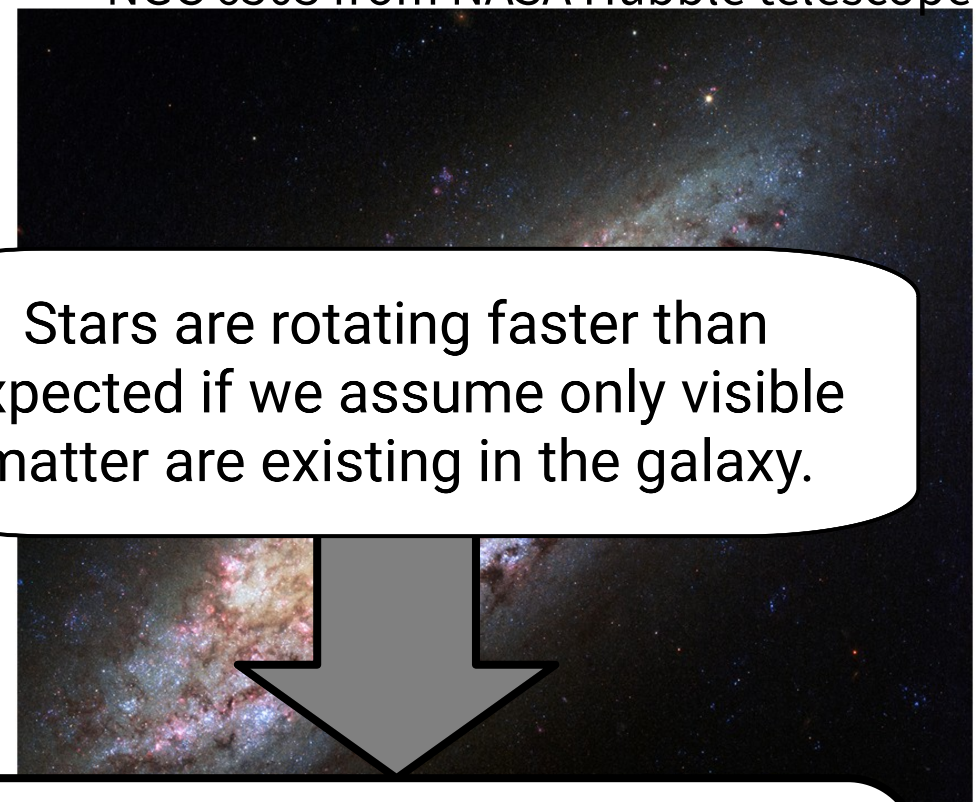
Obtain mass density from enclosed mass M(R)

Galaxy rotation curve and dark matter

(figure from Freese, 0812.4005)



NGC 6503 from NASA Hubble telescope



Stars are rotating faster than expected if we assume only visible matter are existing in the galaxy.

$$v_{\mathrm{circ}}(R) = \sqrt{\frac{GM(R)}{R}}$$

<u>DARK MATTER!</u>

Probably, you heard about the dark matter density on Earth...

How much is the dark matter density at the Solar location?

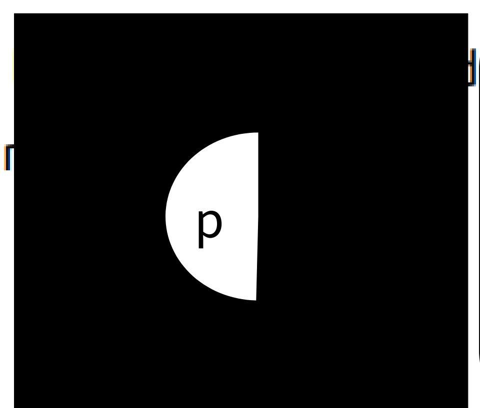
The local dark matter density at the Solar location (i.e., in the vicinity of the Sun within the Milky Way) is typically estimated to be around:

$$\rho_{\mathrm{DM},\odot} \approx 0.3\,\mathrm{GeV}/\mathrm{cm}^3$$

This value is based on dynamical studies of the Milky Way's rotation curve and stellar kinematics. However, there is some uncertainty, and estimates range from about **0.2 to 0.6 GeV/cm³** depending on the specific model and data used.

Would you

observatio



About half-proton
in a cubic centimeter box!

Galaxy rotation curve of Milky Way

Ou, et. al., 2303.12838

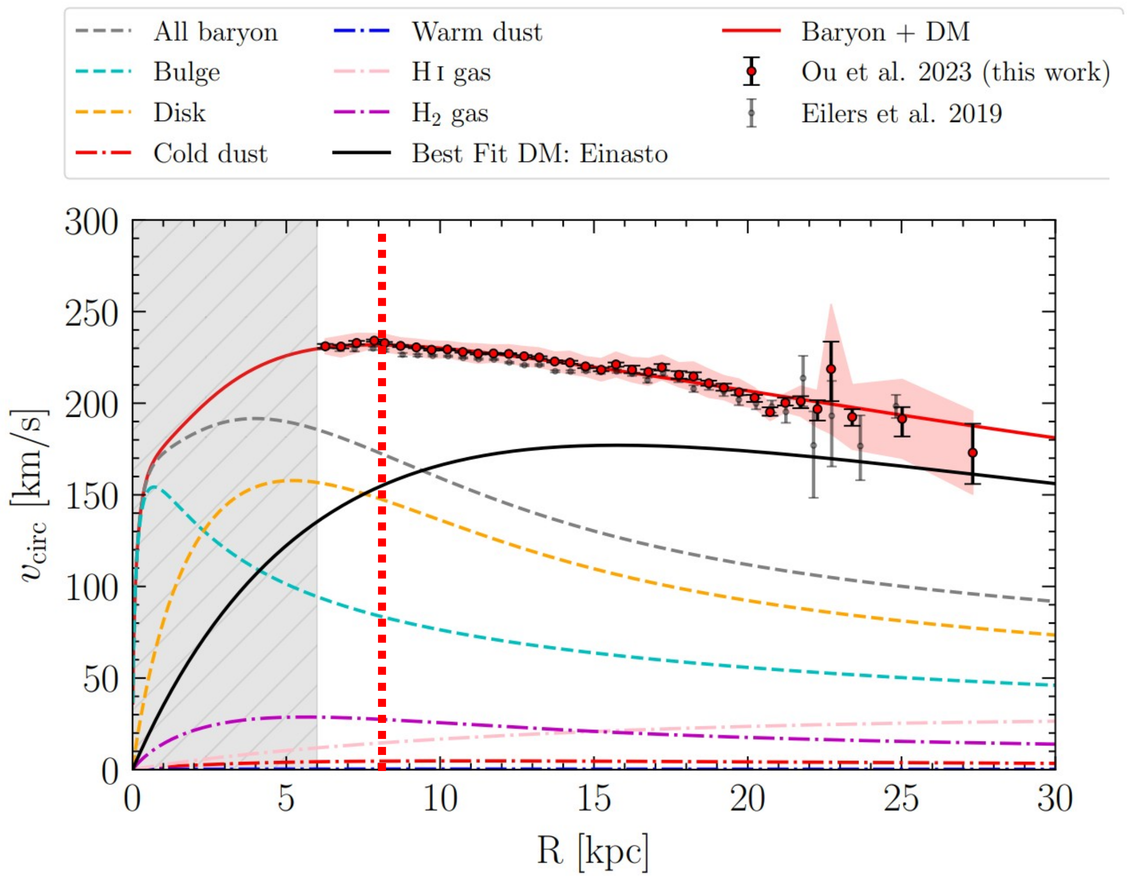


Figure 4. Comparison between the circular velocity curve measured from Eilers et al. (2019) (black) and this work (red). The best-fit Einasto DM profile, with the baryonic model from de Salas et al. (2019), is also shown here. The grey shaded region represents the bulge region, which we do not model due to the non-axisymmetric potential near the galactic bar. The red shaded region represents the total uncertainty estimate from the dominating systematic sources, as shown in Figure 5.

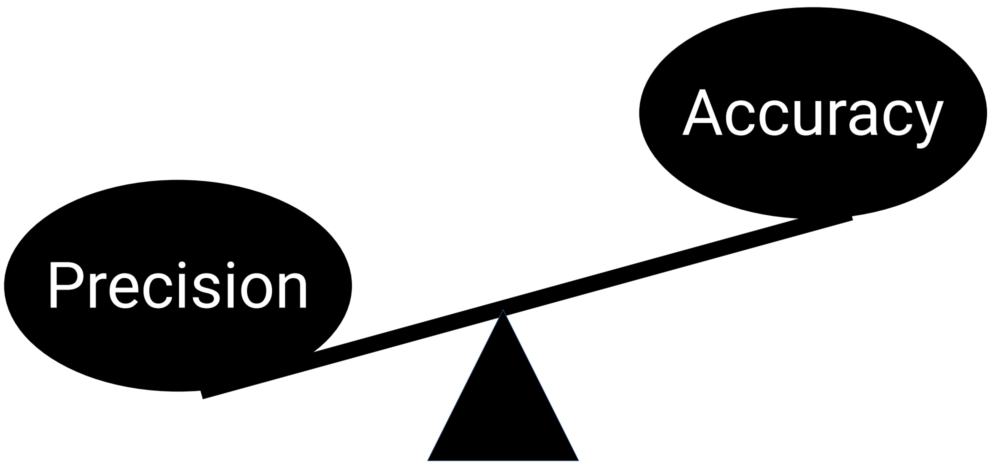
	Einasto
Normalization Mass (M_0)	$0.62^{+0.12}_{-0.11} \times 10^{11}\ M_\odot$
Scale Radius (r_s)	$3.86^{+0.35}_{-0.38}$ kpc
Slope Parameter (α, β)	$0.91^{+0.04}_{-0.05}$
Virial Mass (M_{200})	$1.81^{+0.06}_{-0.05} \times 10^{11}\ M_\odot$
Virial Radius (r_{200})	$119.35^{+1.37}_{-1.21}$ kpc
Concentration (c_{200})	$13.02^{+0.11}_{-0.10}$
Local Dark Matter Density ($\rho_{\rm DM,\odot}$)	$0.447^{+0.004}_{-0.004}$ GeV cm^{-3}
***J*-factor** ($J(\theta < 15°)$)	$15.8^{+1.08}_{-0.93} \times 10^{22}$ GeV^2 cm^{-5}
χ^2 **per d.o.f.** (χ^2_ν)	2.97

[a] Fitted in logarithmic scale.

Very precise
DM density
measurement!

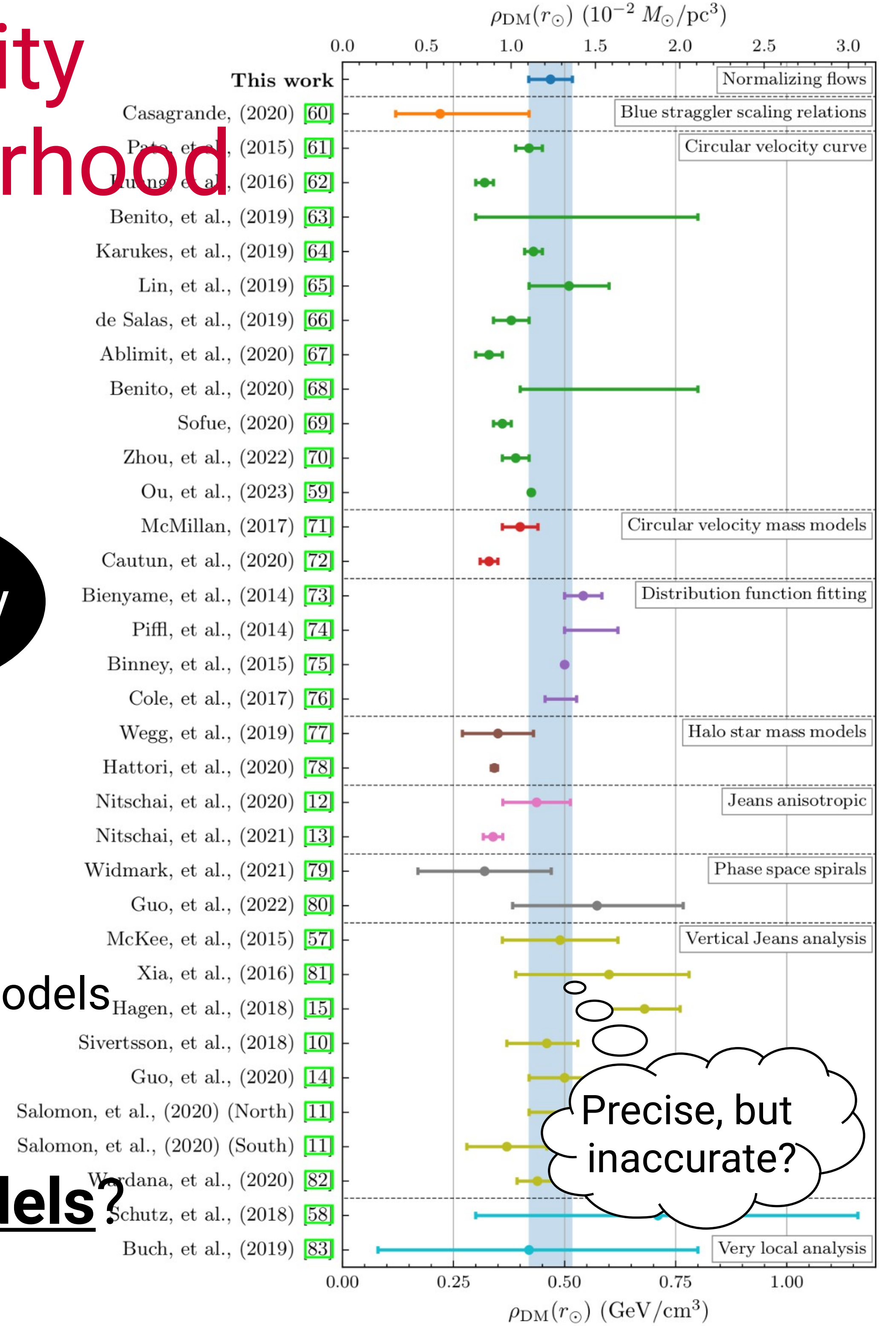
Measuring DM density in the Solar Neighborhood

Thanks to recent progress in observing stars in the Milky Way, we can measure **<u>the dark matter density in the Solar neighborhood</u>** in very high precision using model-based analyses.



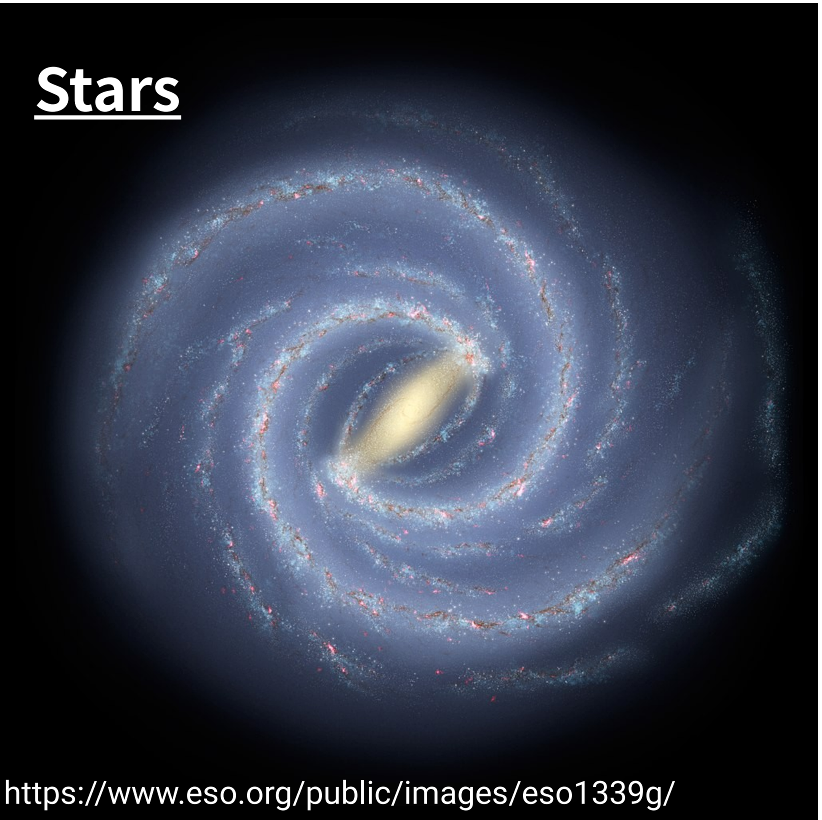
When **<u>sufficient number of data are available</u>**, using over-constrained models may results in inaccurate results.

Need of analysis without assumed **<u>symmetries</u>** and **<u>models</u>**?



In **galactic dynamics** for studying **dark matter**,
one important and interesting task is…

Q: How to use **stellar distribution** of a galaxy to understand **its galactic dark matter density with less assumptions**?

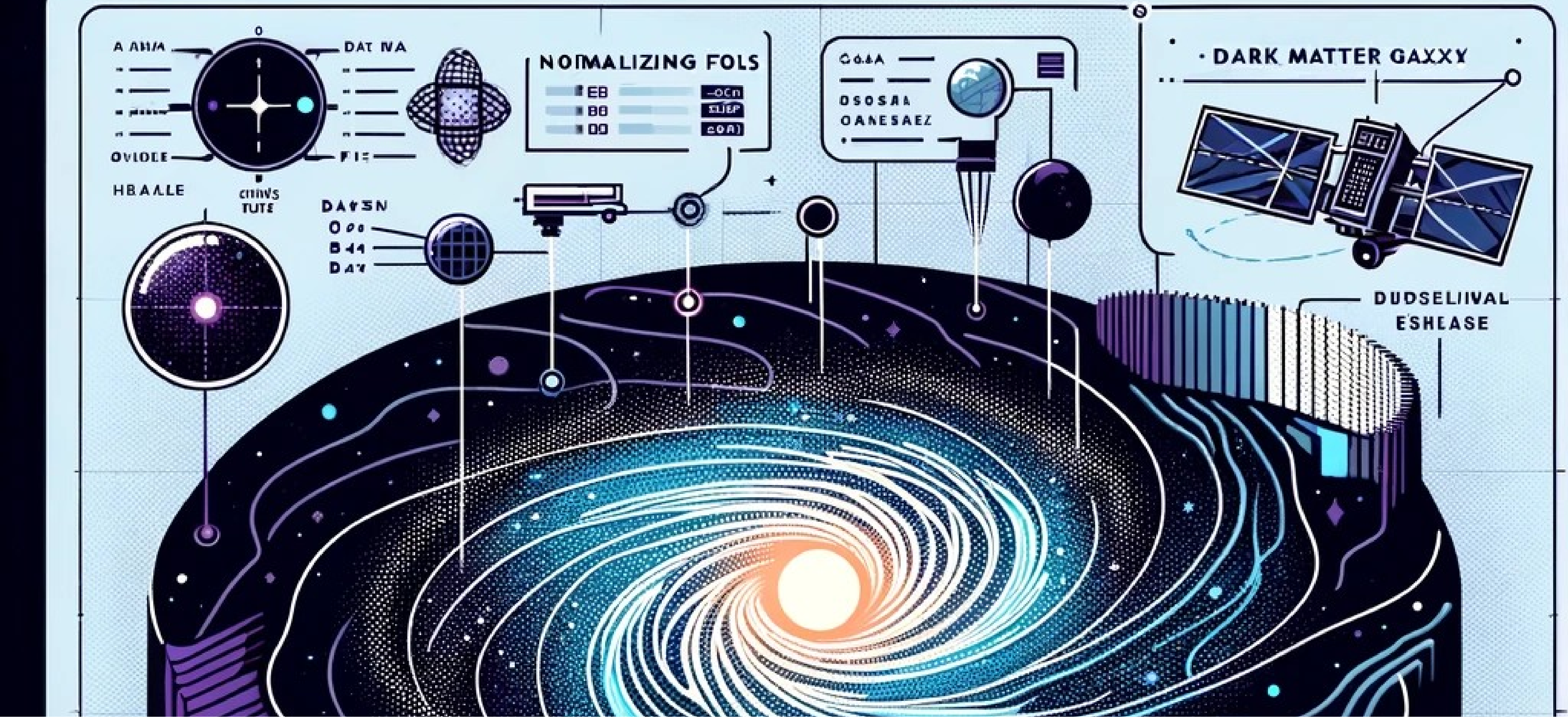


https://www.eso.org/public/images/eso1339g/

Dark Matter Halo

?

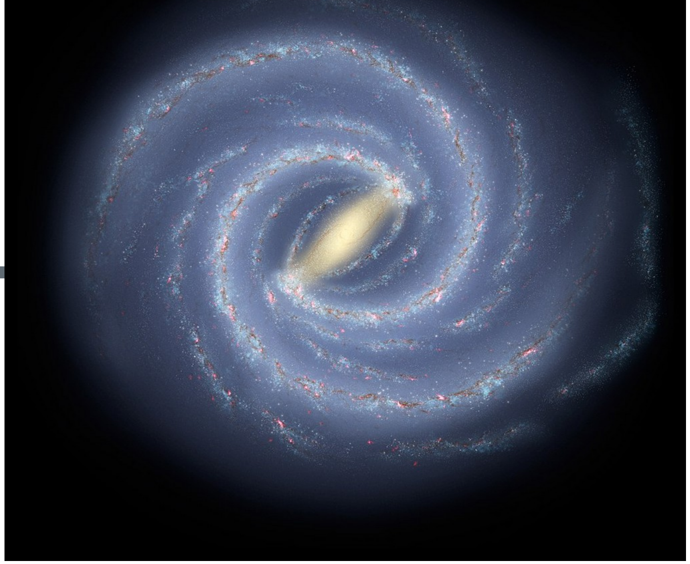
So we initiated a project ...



Mapping Dark Matter in the Milky Way using Normalizing Flows and Gaia DR3

M. R. Buckley, **SHL**, E. Putney, and D. Shih, arXiv:2205.01129, published in MNRAS
SHL, E. Putney, M. R. Buckley, and D. Shih, arXiv:2305.13358, published in JCAP
E. Putney, D. Shih, **SHL**, and M. R. Buckley, arXiv:2412.14236,

Hydrodynamics and Galactic Dynamics



If we consider a galaxy as a hydrodynamic system $N \to \infty$ consisting of stars, phase-space density of a star (probability of finding a star with given position and velocity) describes the system.

$$f(\vec{x}, \vec{v})$$

Equation of motion: Boltzmann Equation

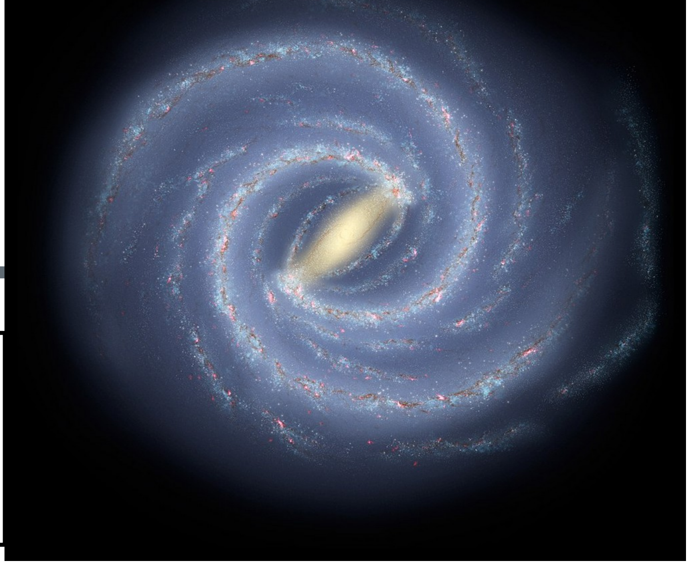
$$\left[\frac{\partial}{\partial t} + \vec{v} \cdot \frac{\partial}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial}{\partial \vec{v}}\right] f(\vec{x}, \vec{v}) = 0$$

If **phase-space density** is determined **without assumptions**...

We can estimate the **gravitational acceleration field**!

+no unnecessary assumptions are involved

Outline of Strategy



Star catalog
$\{(\vec{x}, \vec{v})\}$

Galaxy:
hydrodynamic
system

Phase space density
$f(\vec{x}, \vec{v})$

Neural Networks for Density Estimation:
Normalizing Flows

$$\vec{u}_0 \to \vec{u}_1 \to \cdots \to \vec{u}_n = (\vec{x}, \vec{v})$$

Gravitational accel.
$\vec{a}(\vec{x})$

Solving EOM (Boltzmann Equation)

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

Mass density
$\rho(\vec{x})$

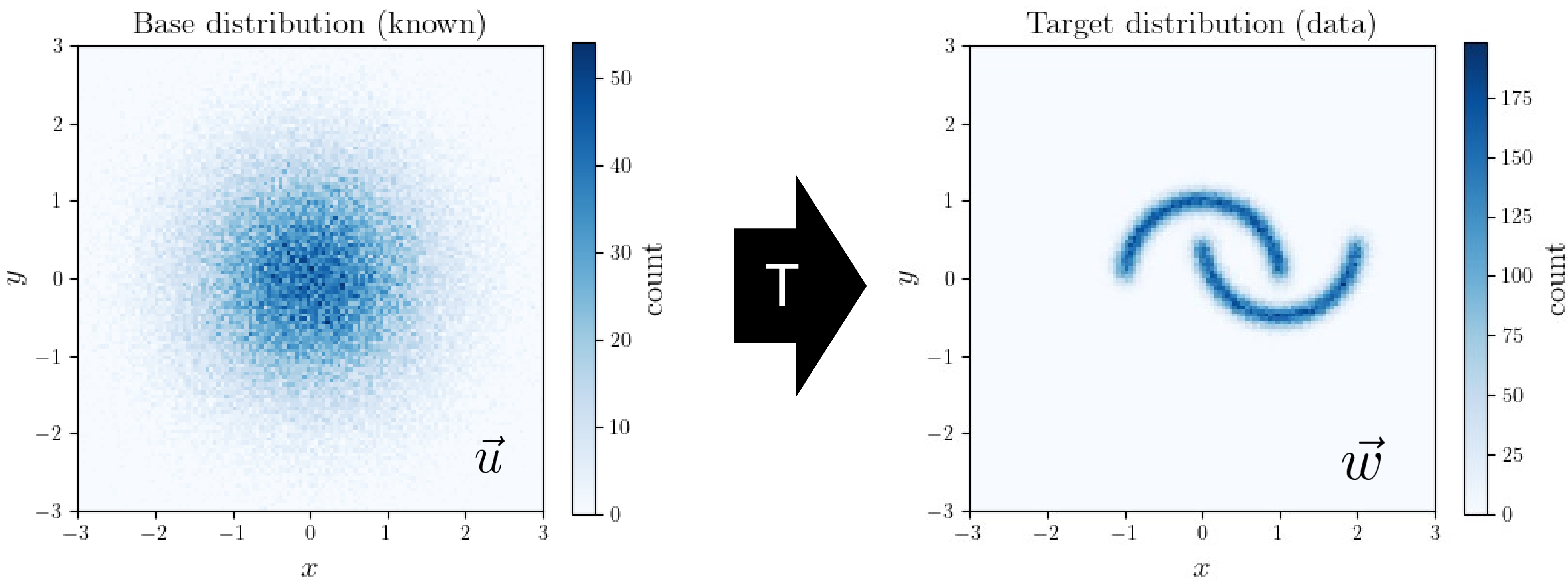
Solving Gauss's Equation

$$-4\pi G\rho = \nabla \cdot \vec{a}$$

arXiv: 2205.01129, 2305.13358
See also Green et. al. arXiv:2011.04673, arXiv:2205.02244

Normalizing Flows: Neural Network learning a Transformation

Normalizing Flows (NFs) is an artificial neural network that learns a transformation of random variables.



Main idea: if we could find out such transformation, we can use the transformation formula for the density estimation:

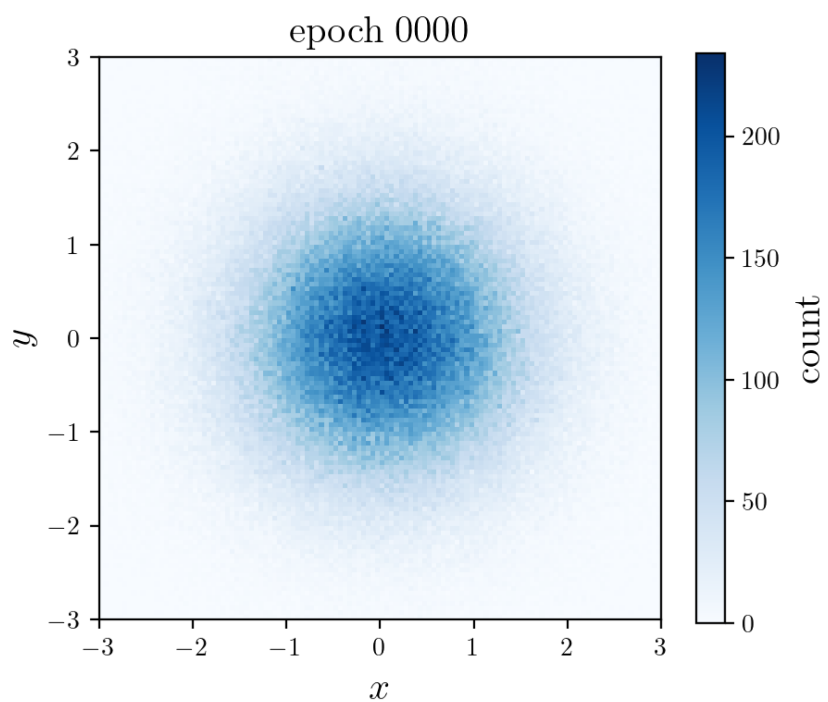
$$p_W(\vec{w}) = p_U(\vec{u}) \cdot \left| \frac{d\vec{u}}{d\vec{w}} \right| \qquad \vec{w} = \underset{\text{Neural Network}}{T}(\vec{u})$$

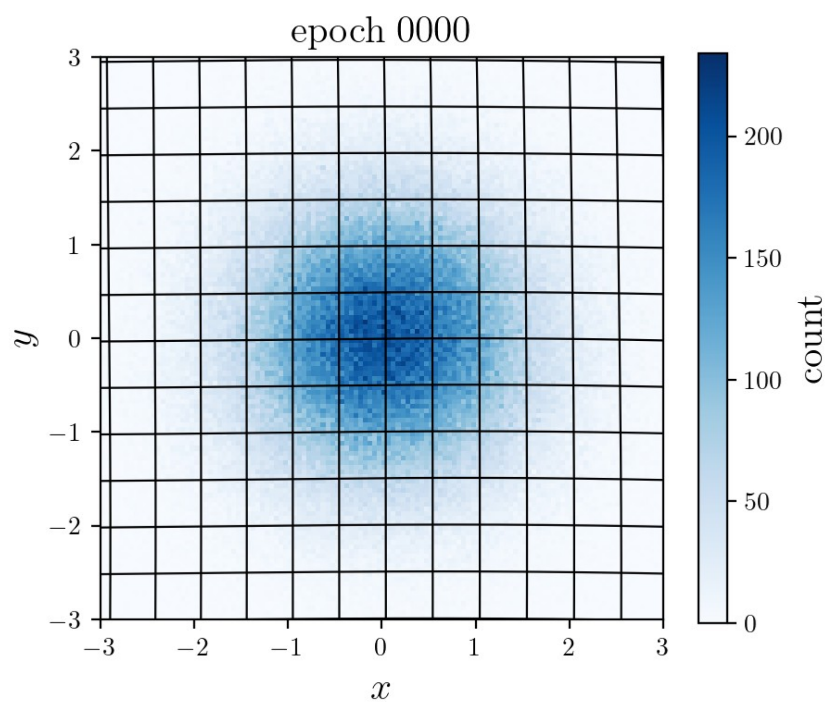
This formula can be used for training normalizing flows, too:

Maximum likelihood estimation

Training Normalizing Flows

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N} \log p_W(\vec{w}^{(i)};\theta) \qquad p_W(\vec{w}) = p_U(\vec{u}) \cdot \left|\frac{d\vec{u}}{d\vec{w}}\right|$$





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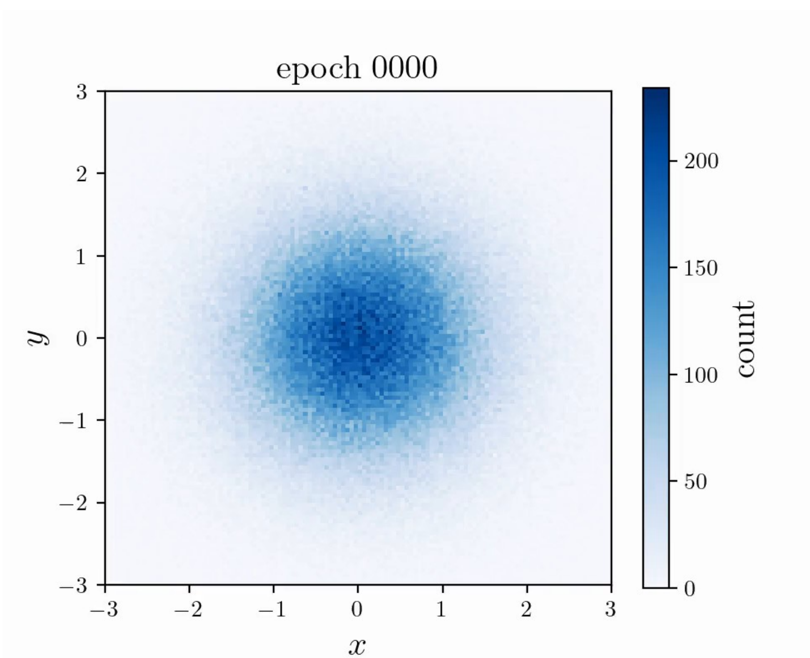
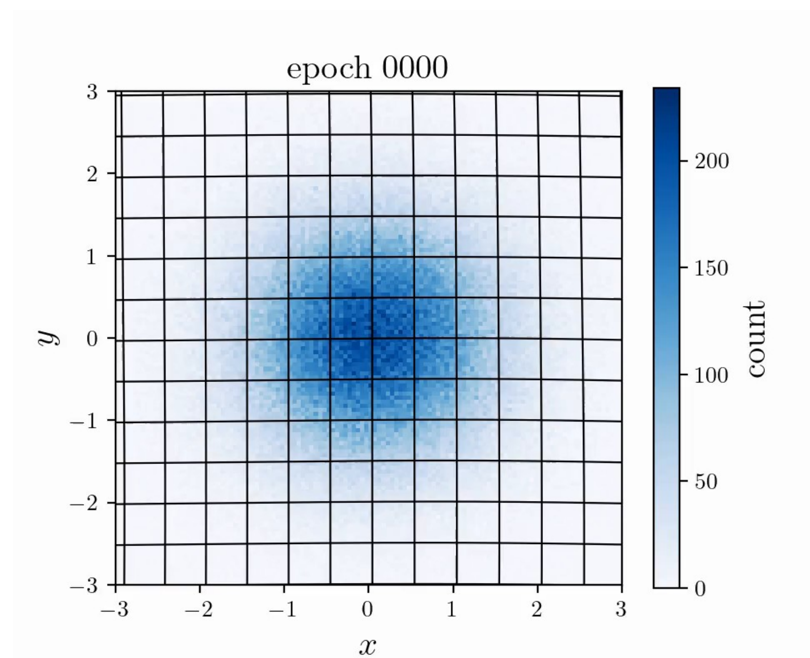
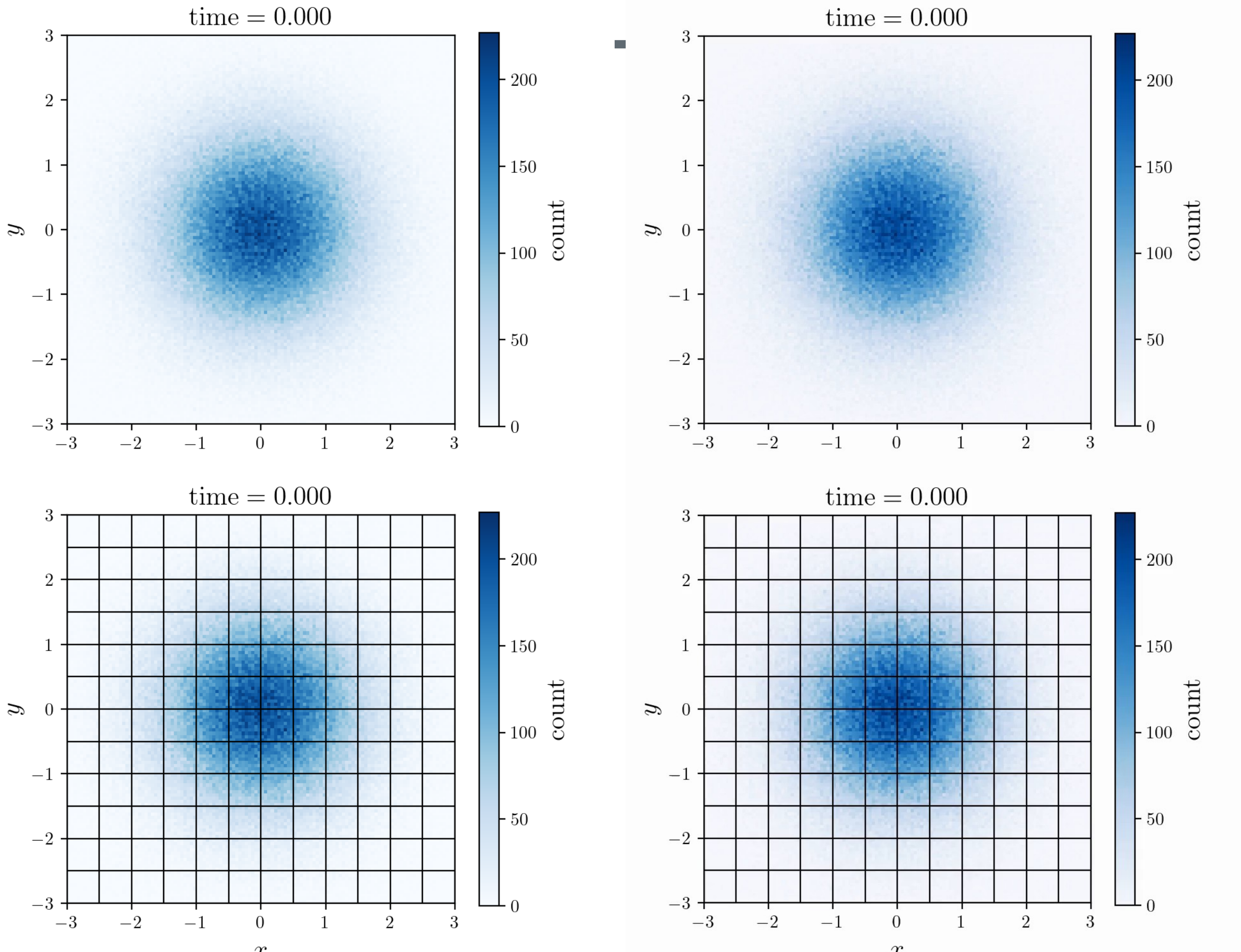




Learned transformation



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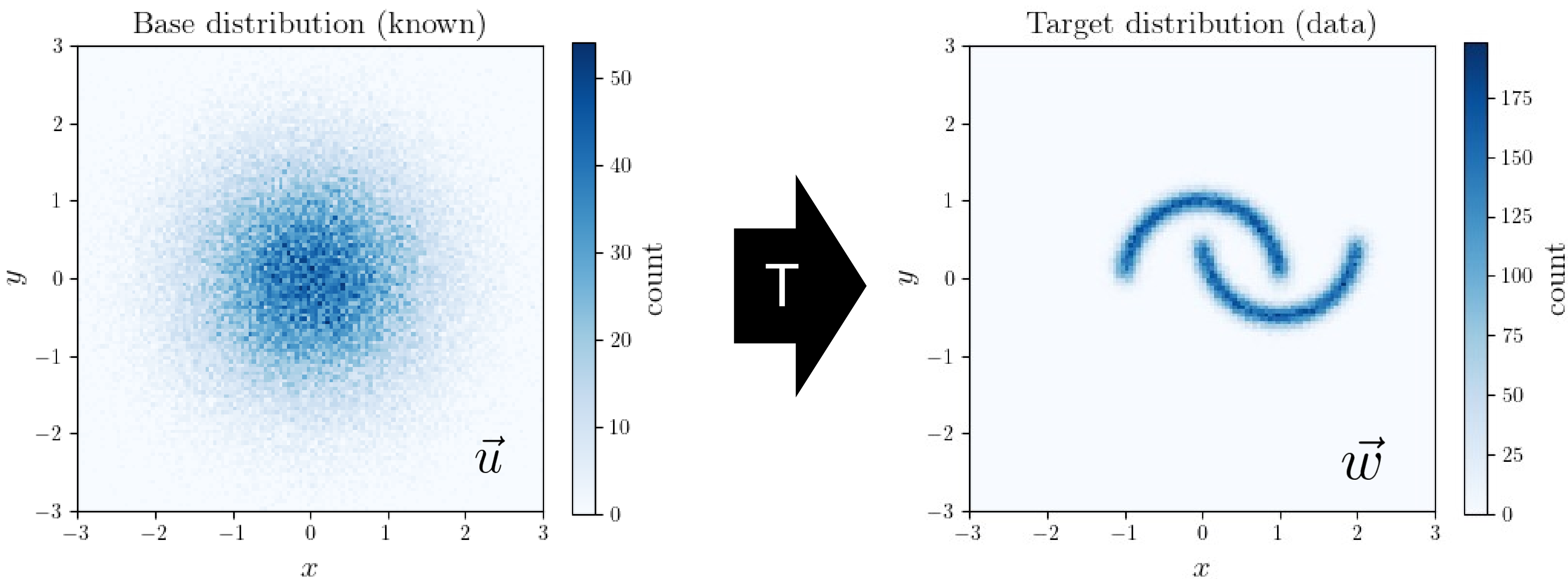

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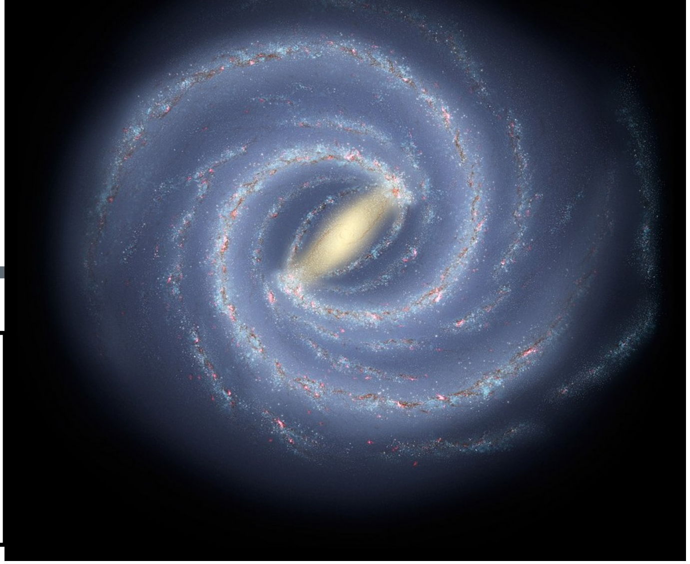
We will use this model for estimating the phase space density f(x,v) from the data.

Outline of Strategy



Star catalog
$\{(\vec{x}, \vec{v})\}$

Gaia DR3: star catalog of the Milky Way

Phase space density
$f(\vec{x}, \vec{v})$

Neural Networks for Density Estimation:
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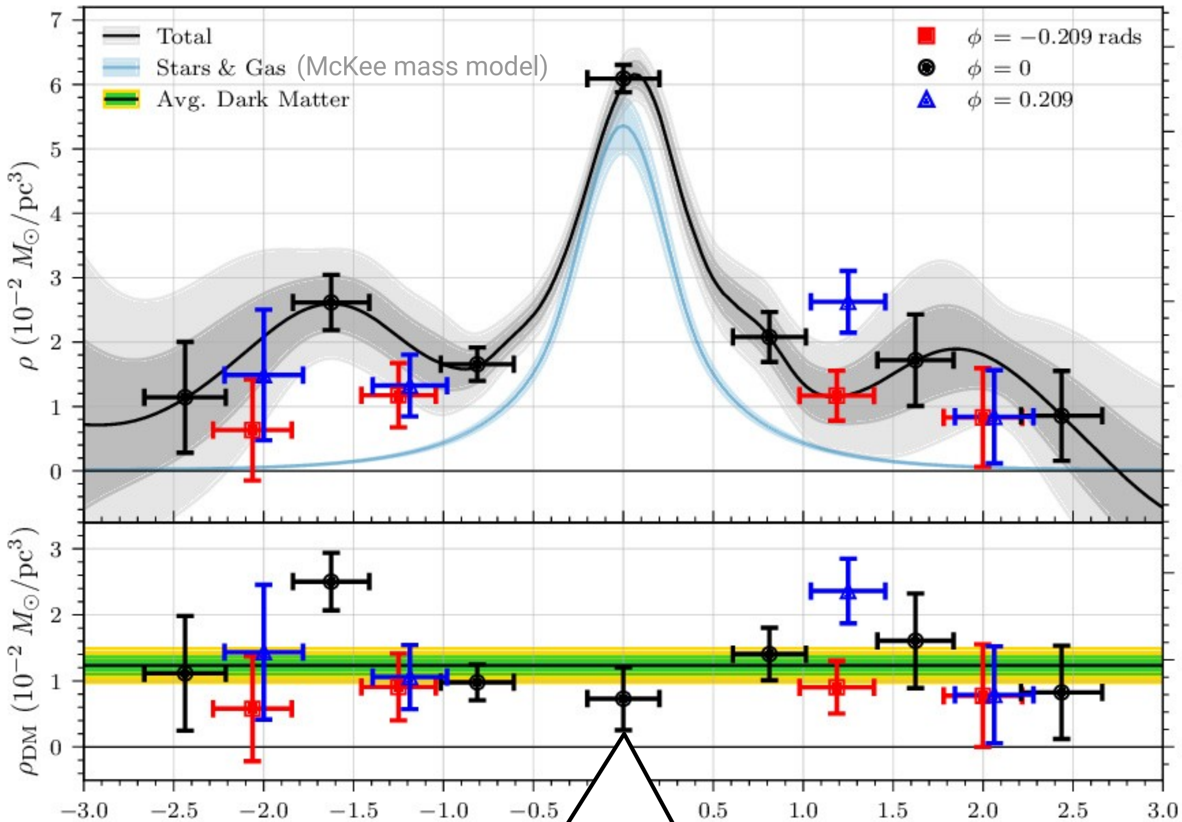
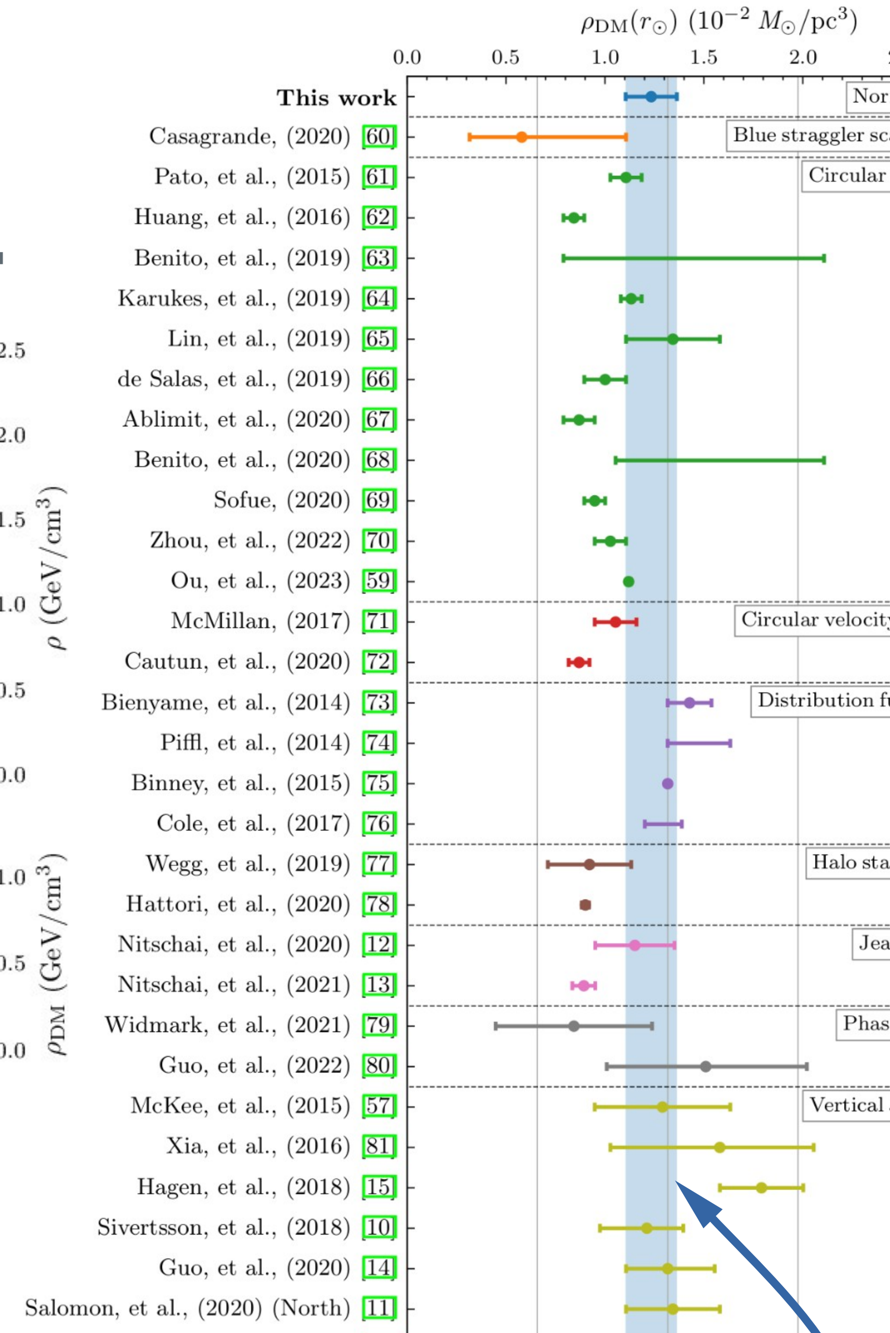
arXiv: 2205.01129, 2305.13358
See also Green et. al. arXiv:2011.04673, arXiv:2205.02244

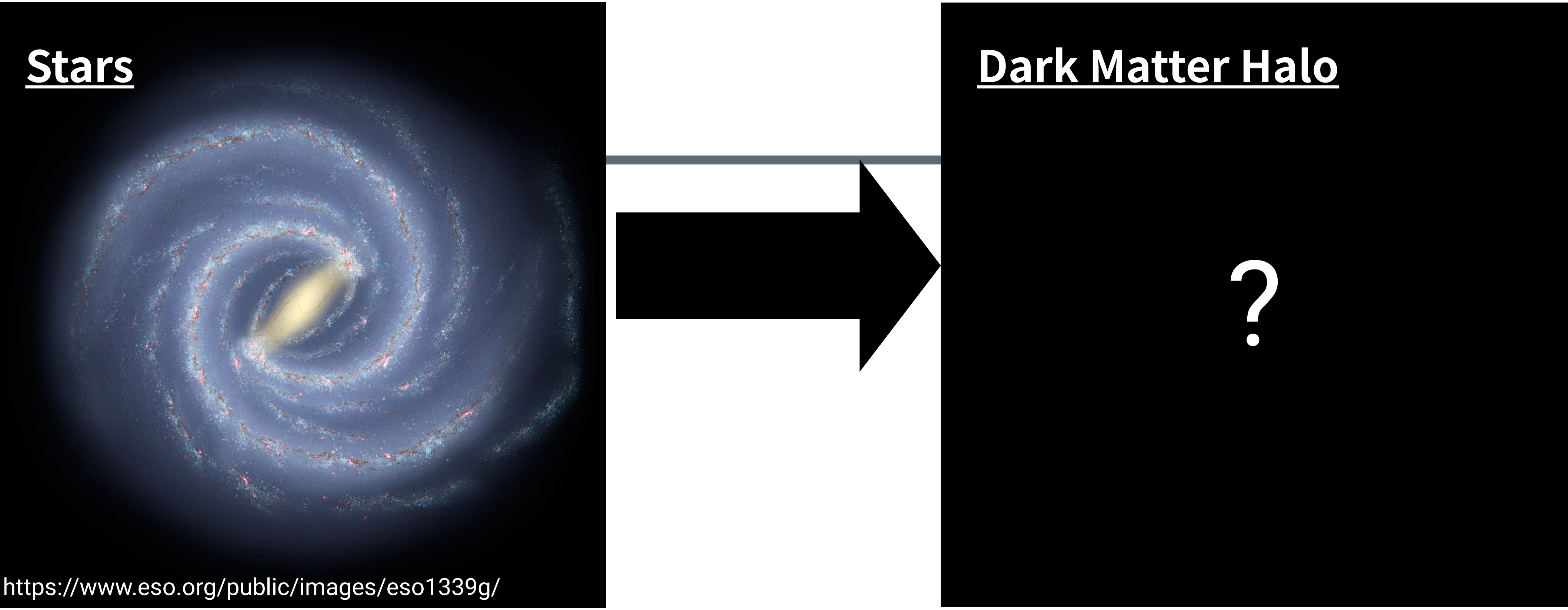
Local DM Mass Density of the Milky Way



0.32±0.18 GeV/cm^3

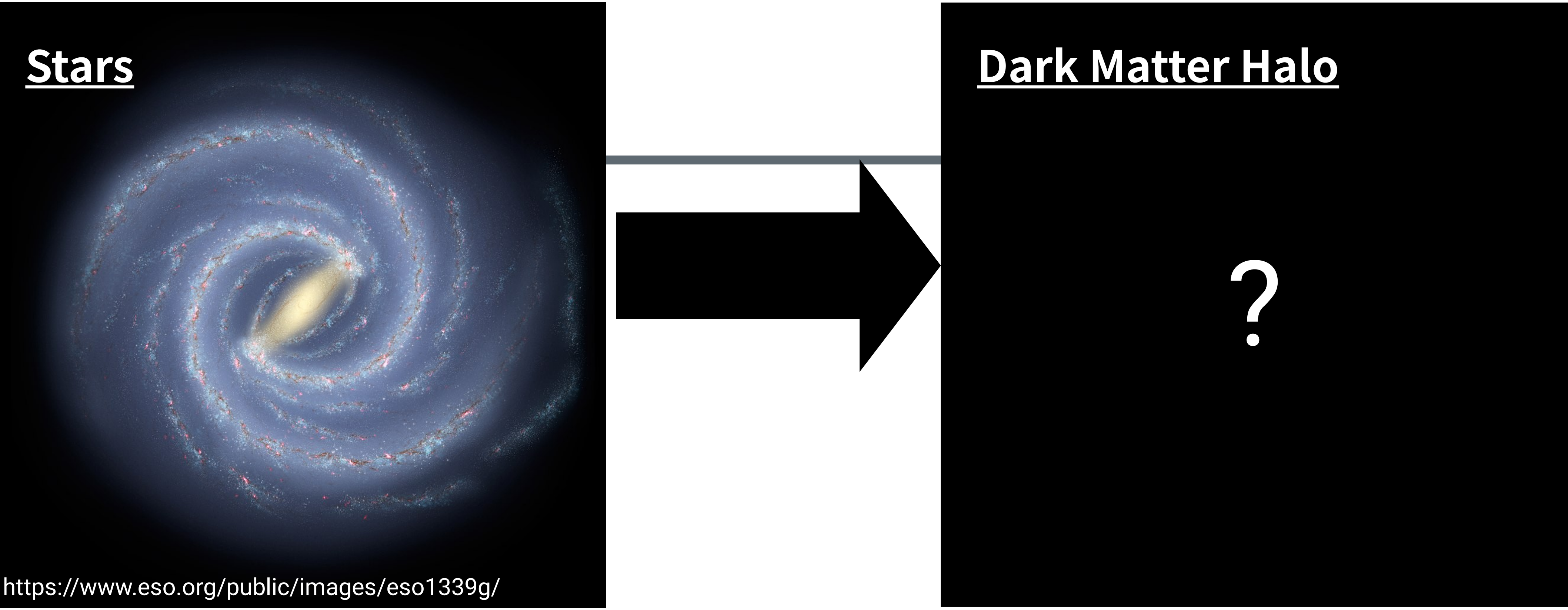


Taking the average of the DM mass density at the Solar radius, we find a local dark matter density: **0.47±0.05 GeV/cm^3**



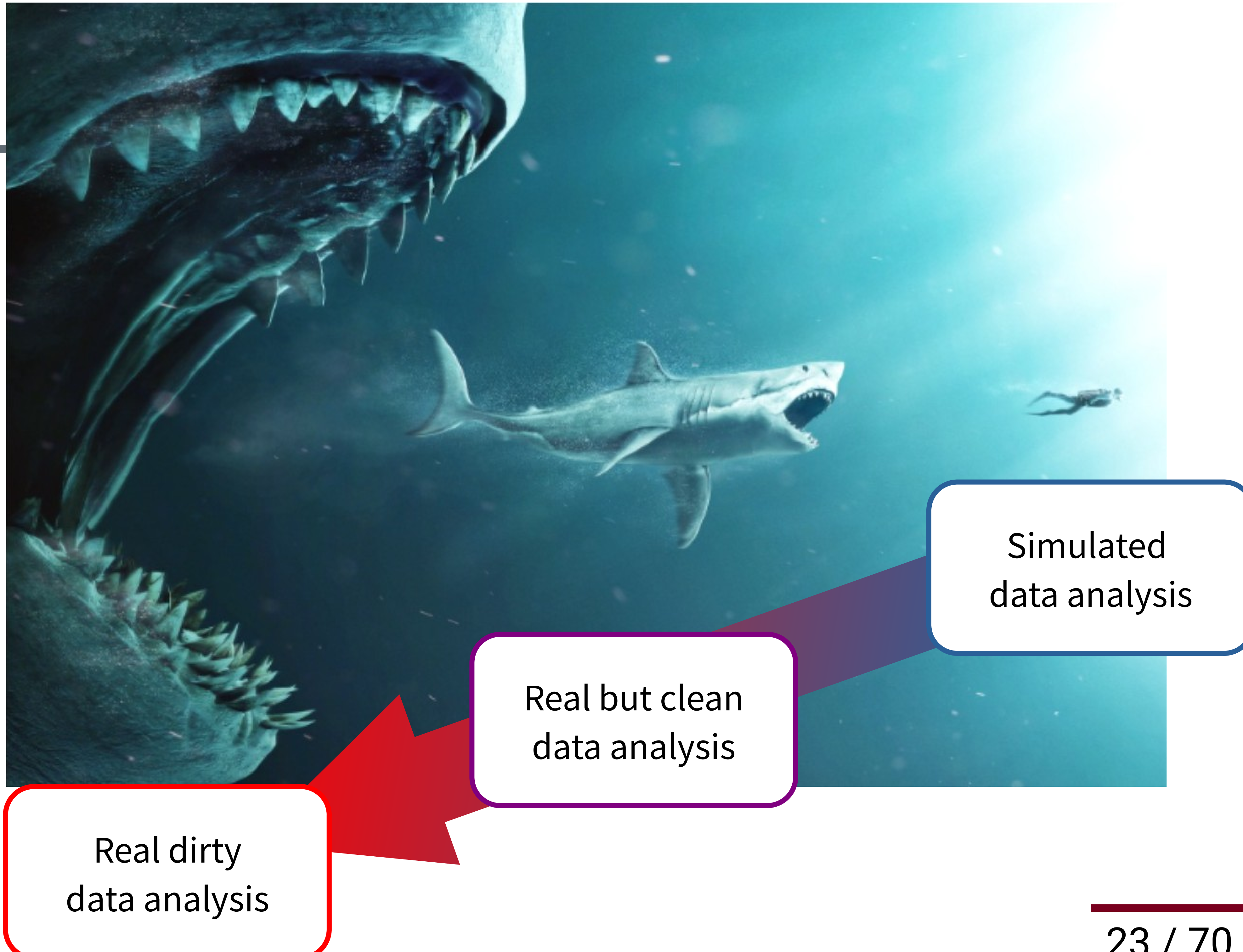
We have an unsupervised ML method to estimate **dark matter density** given **stellar distribution of a galaxy**.

END of story?

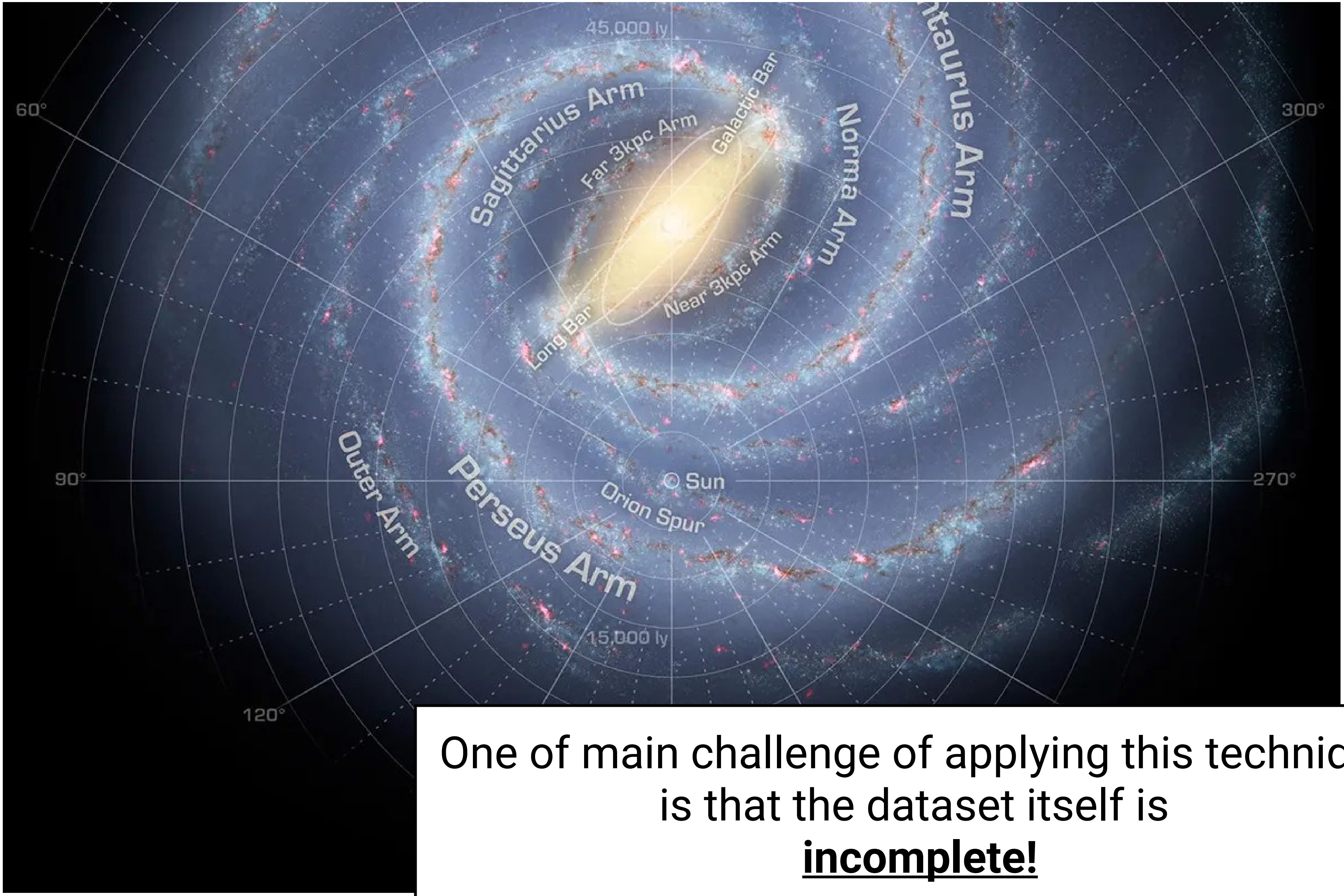


We have an unsupervised ML method to estimate **dark matter density** given **stellar distribution of a galaxy**.

END? → Of course not!

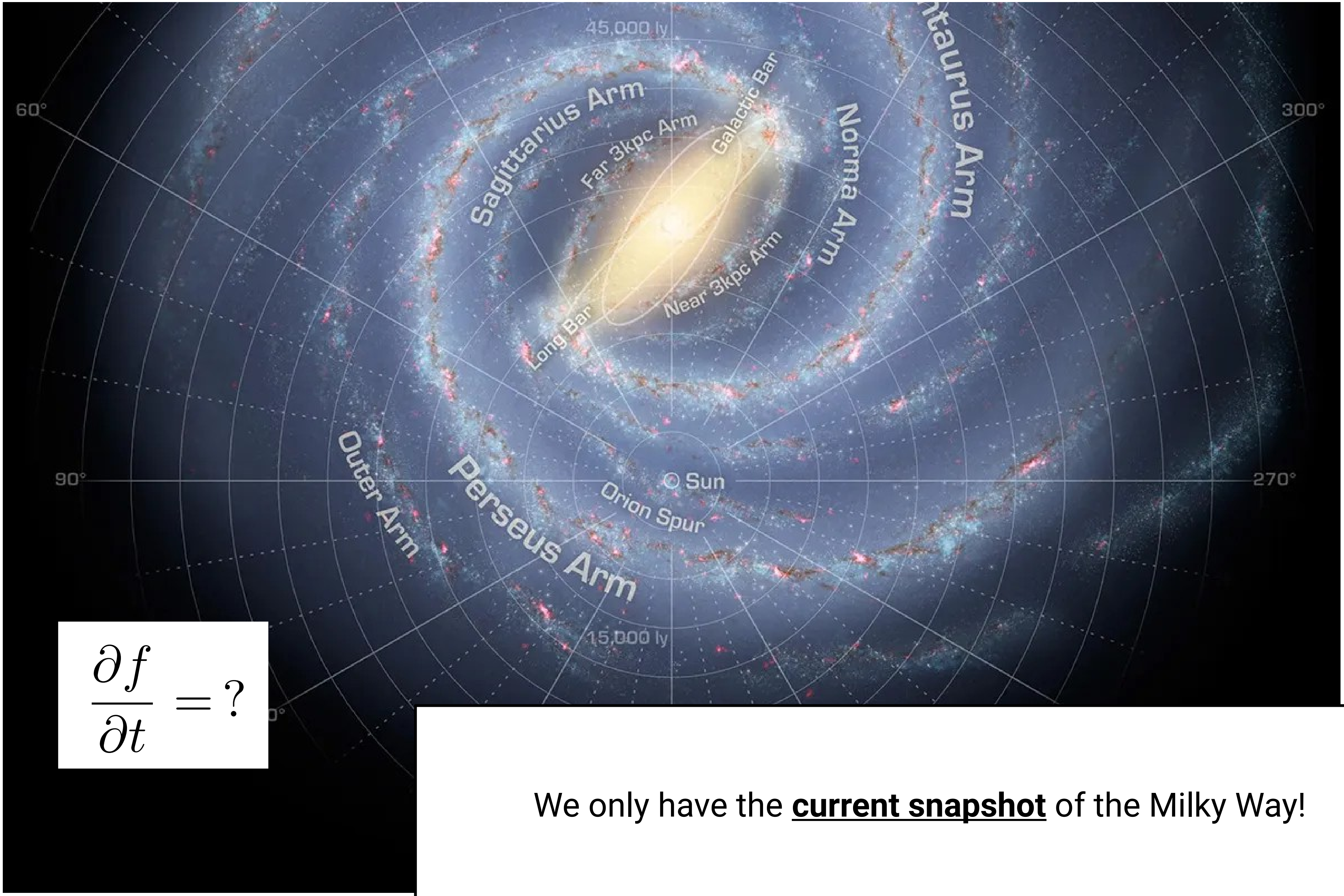

Simulated
data analysis
Real but clean
data analysis
Real dirty
data analysis

Galactic Dynamics and Incomplete Datasets



One of main challenge of applying this technique is that the dataset itself is **incomplete!**

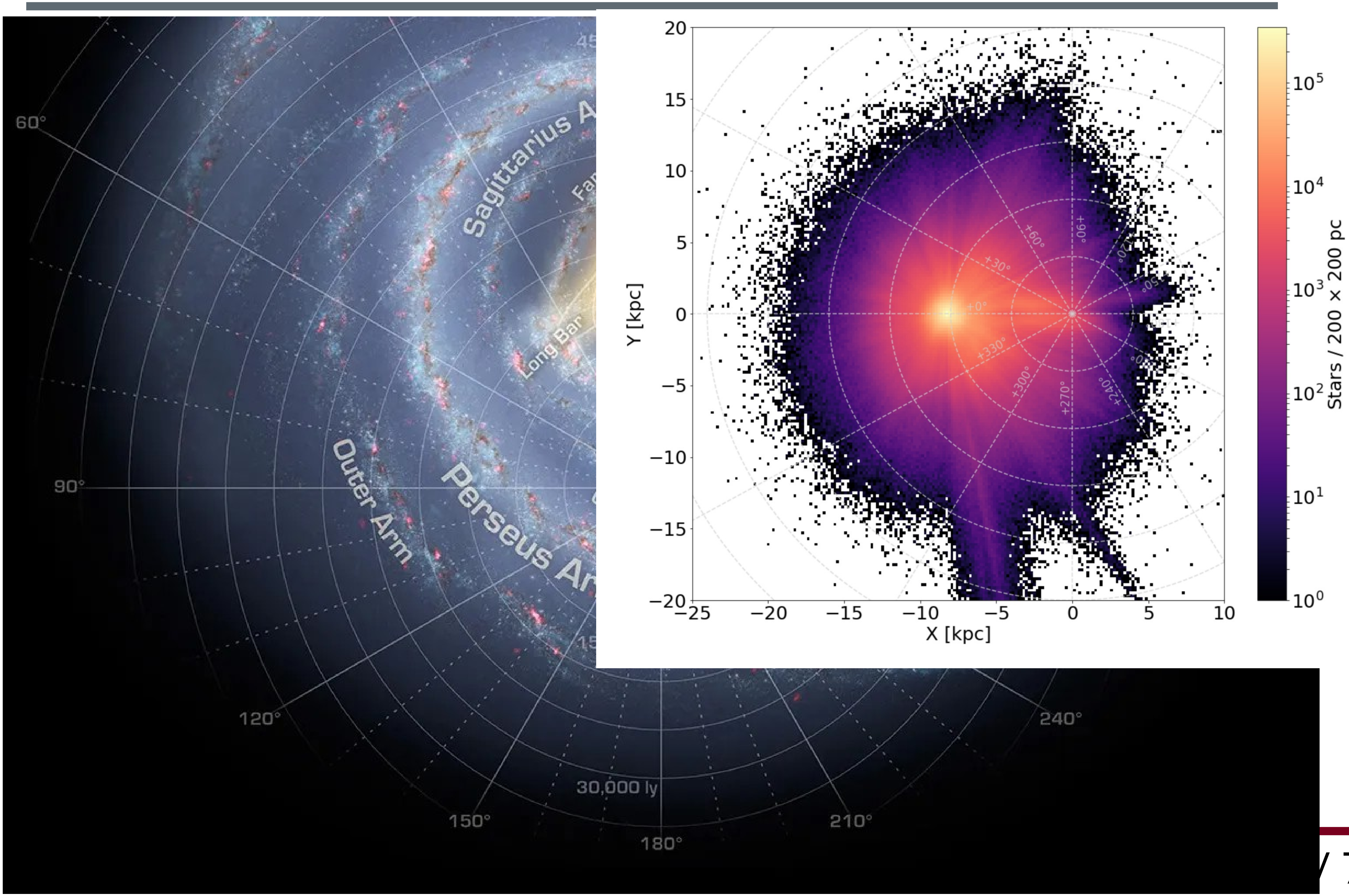
No time derivative information



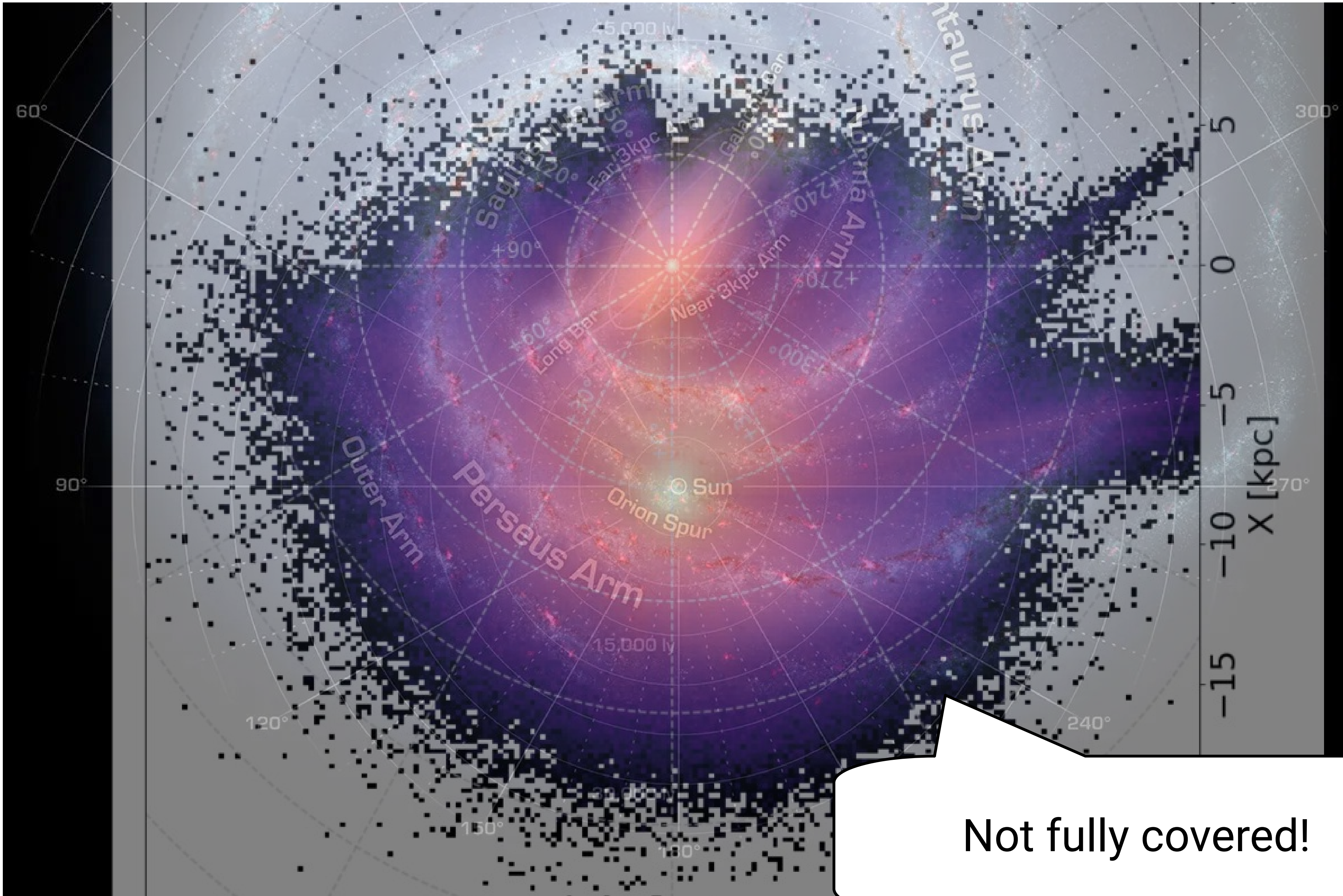
$$\frac{\partial f}{\partial t} = ?$$

We only have the **current snapshot** of the Milky Way!

Radial Velocity Distribution of Gaia DR3

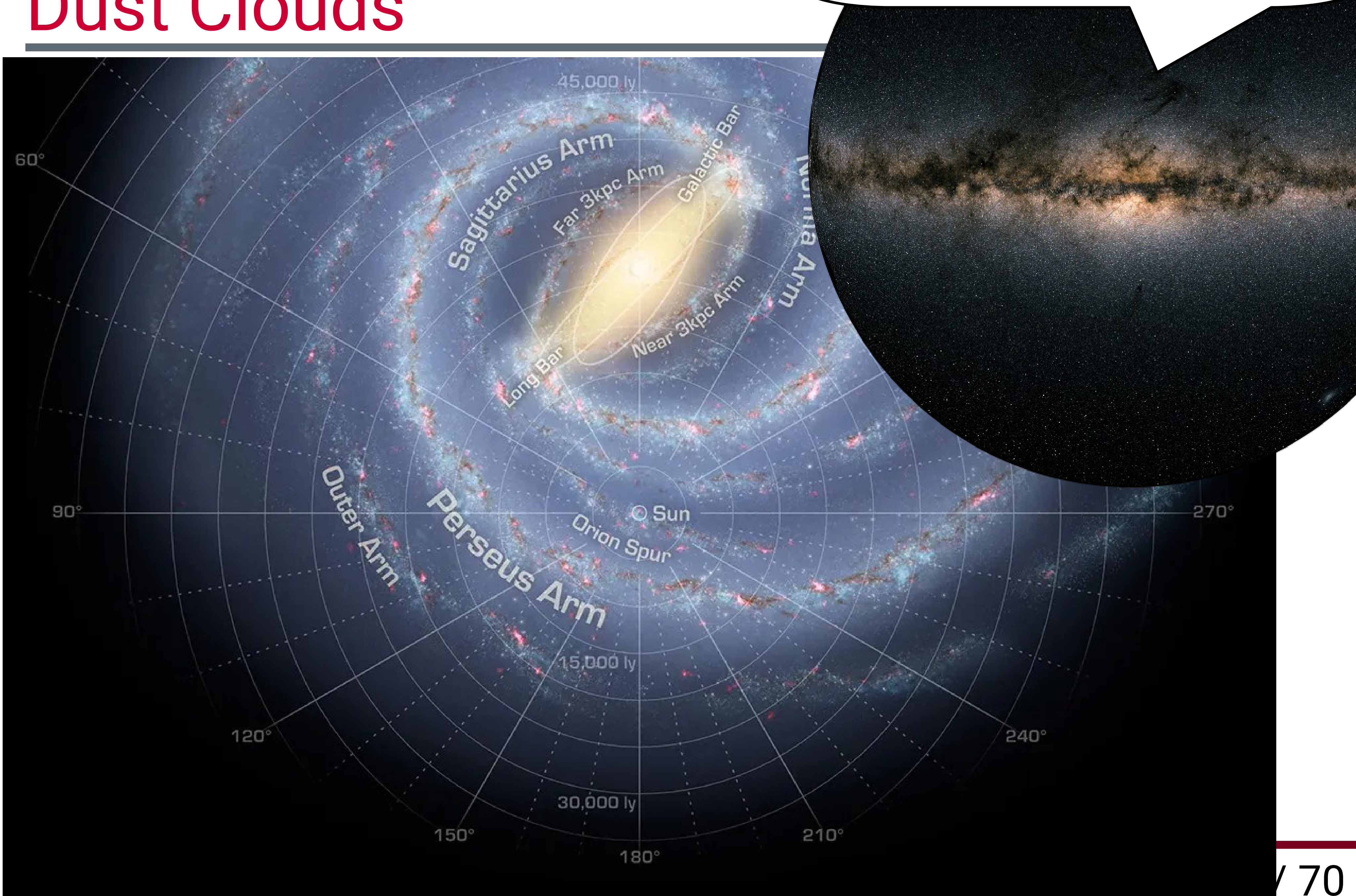


Incompleteness in Spacial Coverage



Not fully covered!

Dust Clouds

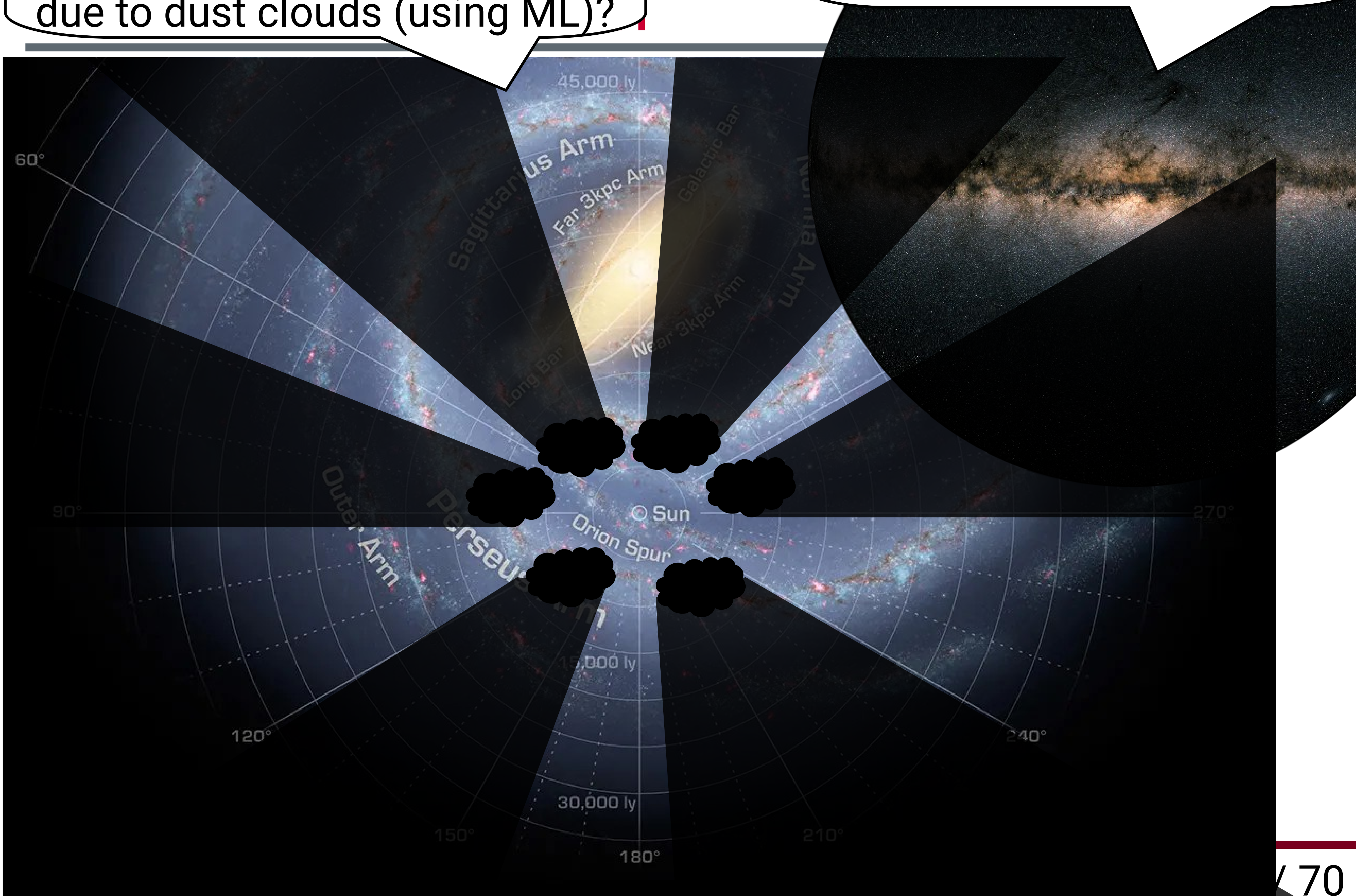

45,000 ly
Sagittarius Arm
Far 3kpc Arm
Galactic Bar
Norma Arm
Long Bar
Near 3kpc Arm
60°
90°
Outer Arm
Perseus Arm
Sun
Orion Spur
270°
15,000 ly
120°
240°
30,000 ly
150°
210°
180°
Intergalactic dust cloud
obscuring light from stars!

Dust Obscuring Stars

Intergalactic dust cloud obscuring light from stars!

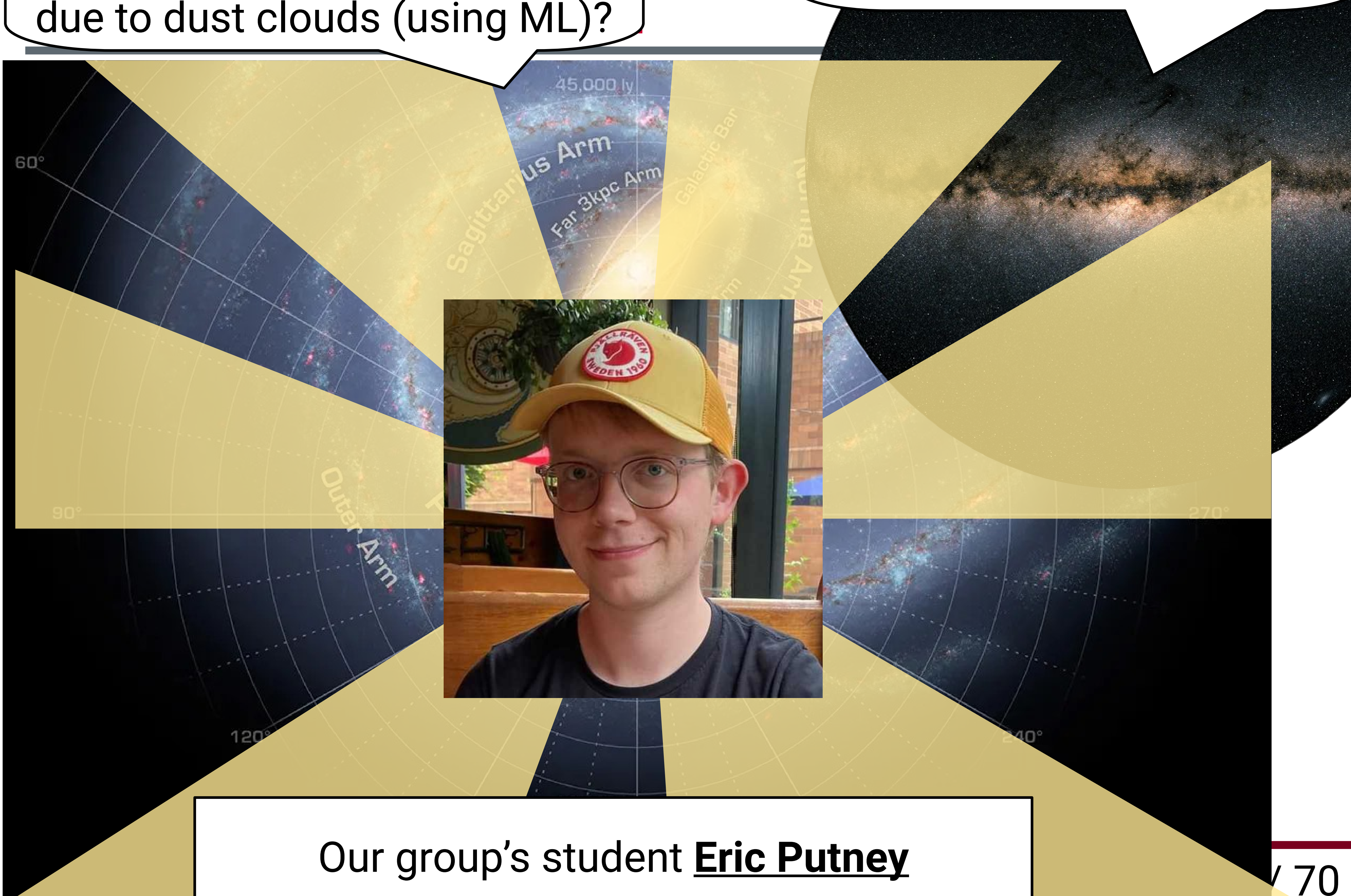
How could we overcome this data **incompleteness** due to dust clouds (using ML)?

Intergalactic dust cloud obscuring light from stars!



How could we overcome this data **incompleteness** due to dust clouds (using ML)?

Intergalactic dust cloud obscuring light from stars!



Our group's student **Eric Putney**

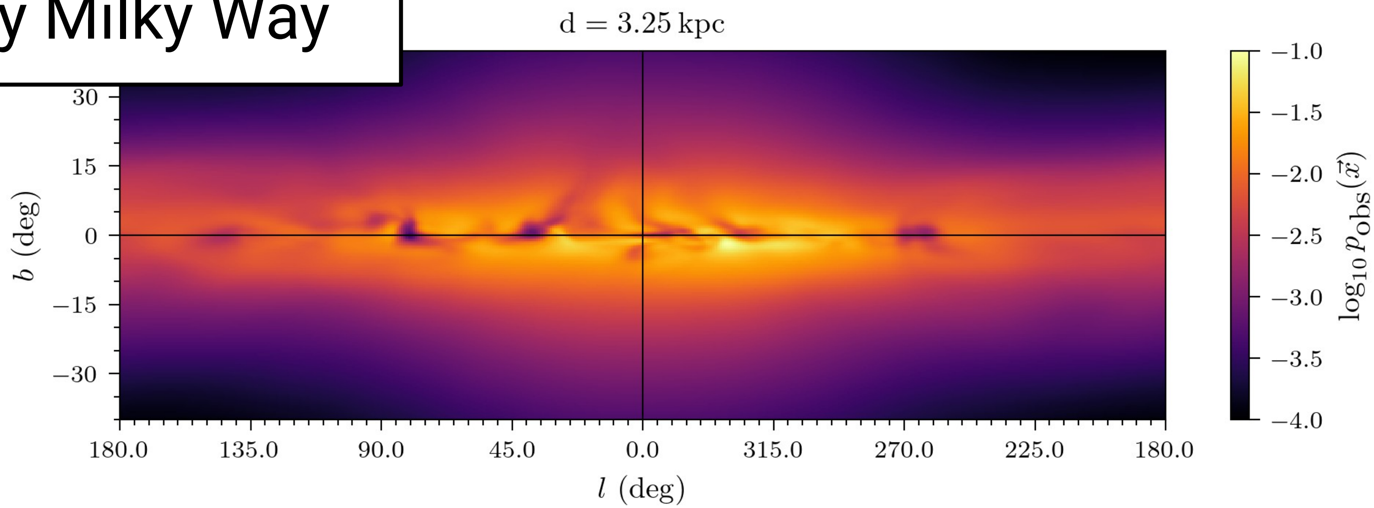
arXiv:2412.14236

Mapping Dark Matter Through the Dust of the Milky Way Part I: Dust Correction and Phase Space Density

E. Putney, D. Shih, **SHL**, and M. R. Buckley, arXiv:2412.14236,

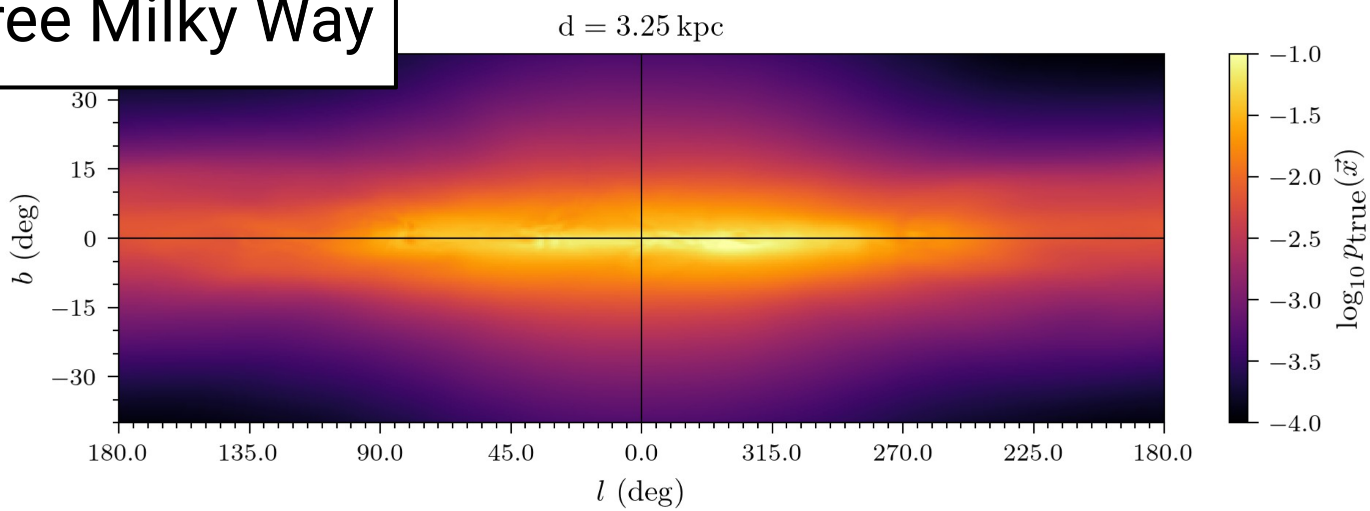
Erasing Dust using Neural Network and Equilibrium Assmptions

Dusty Milky Way



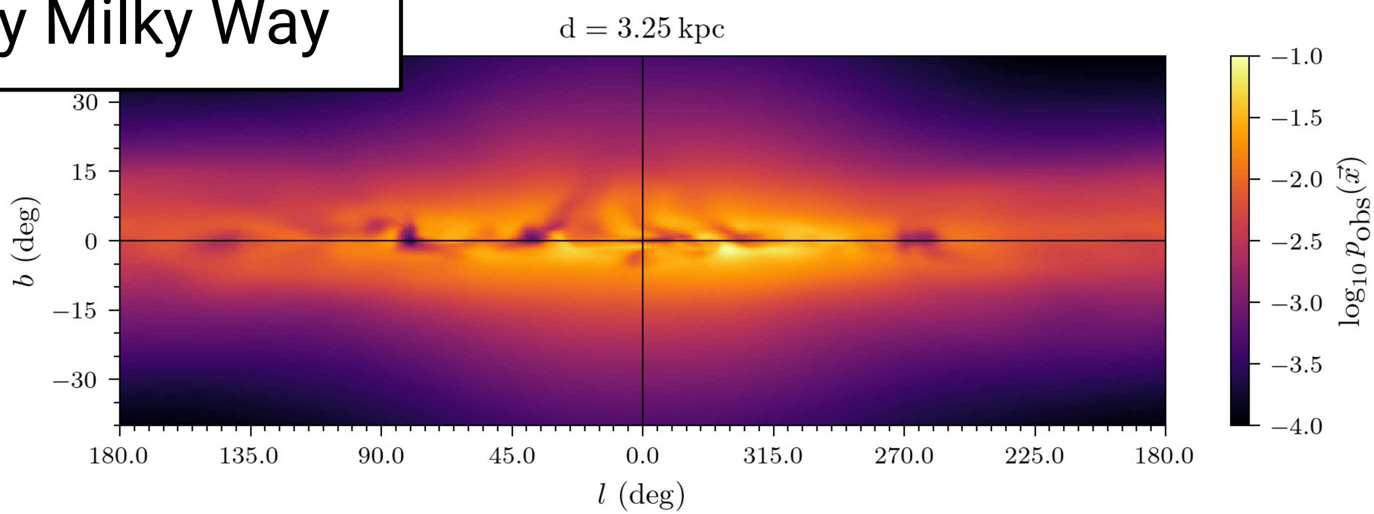
$$\frac{\partial f}{\partial t} = 0$$

Dust-free Milky Way



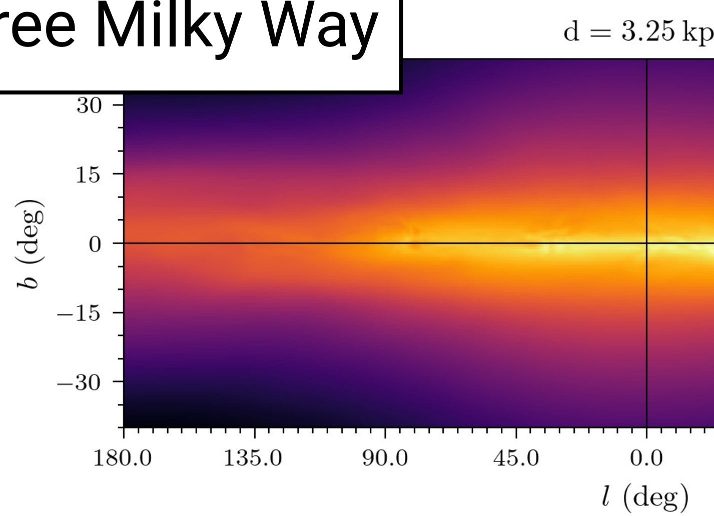
Erasing Dust using Neural Network and Equilibrium Assmptions

Dusty Milky Way



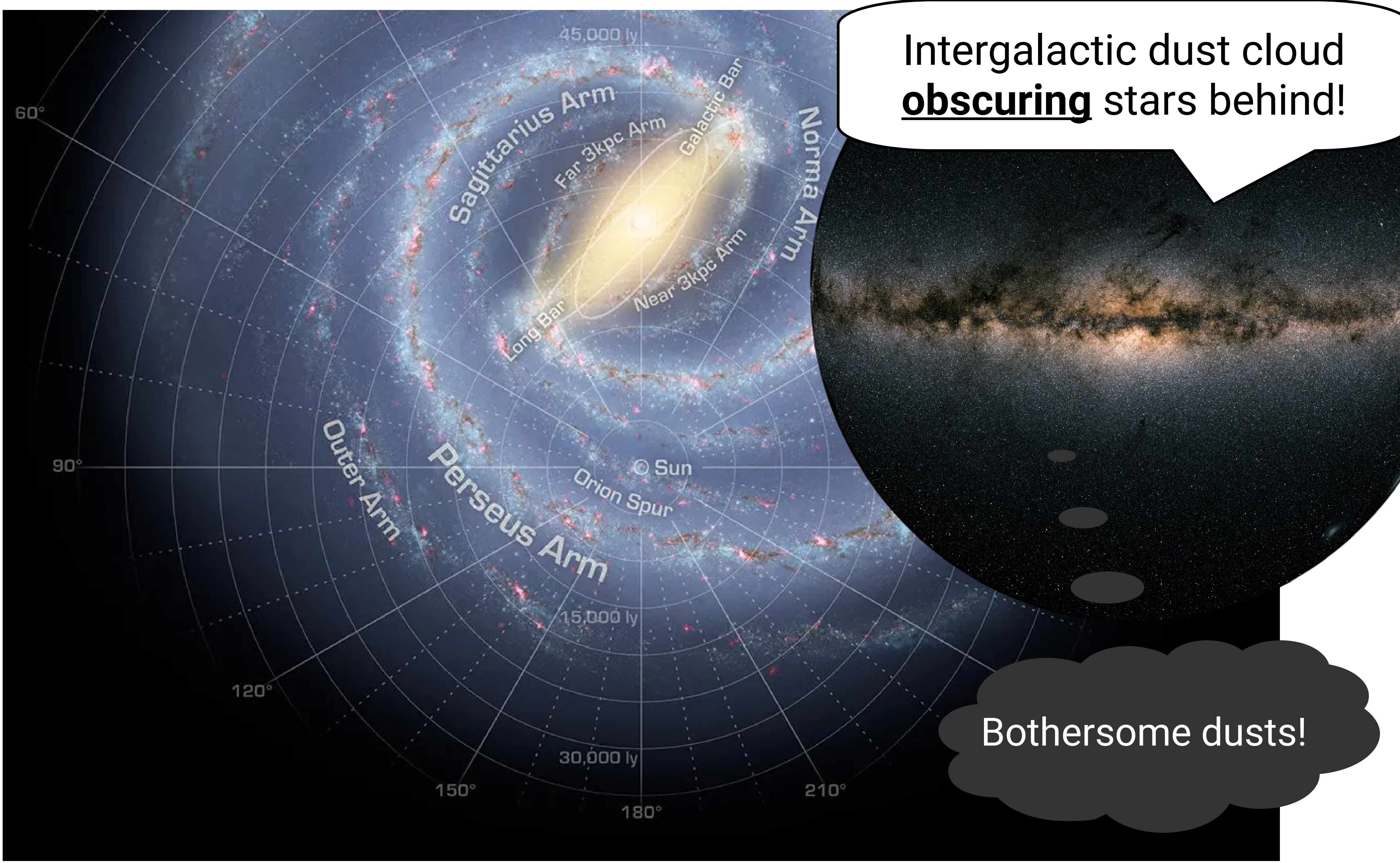
$$\frac{\partial f}{\partial t} = 0$$

Dust-free Milky Way



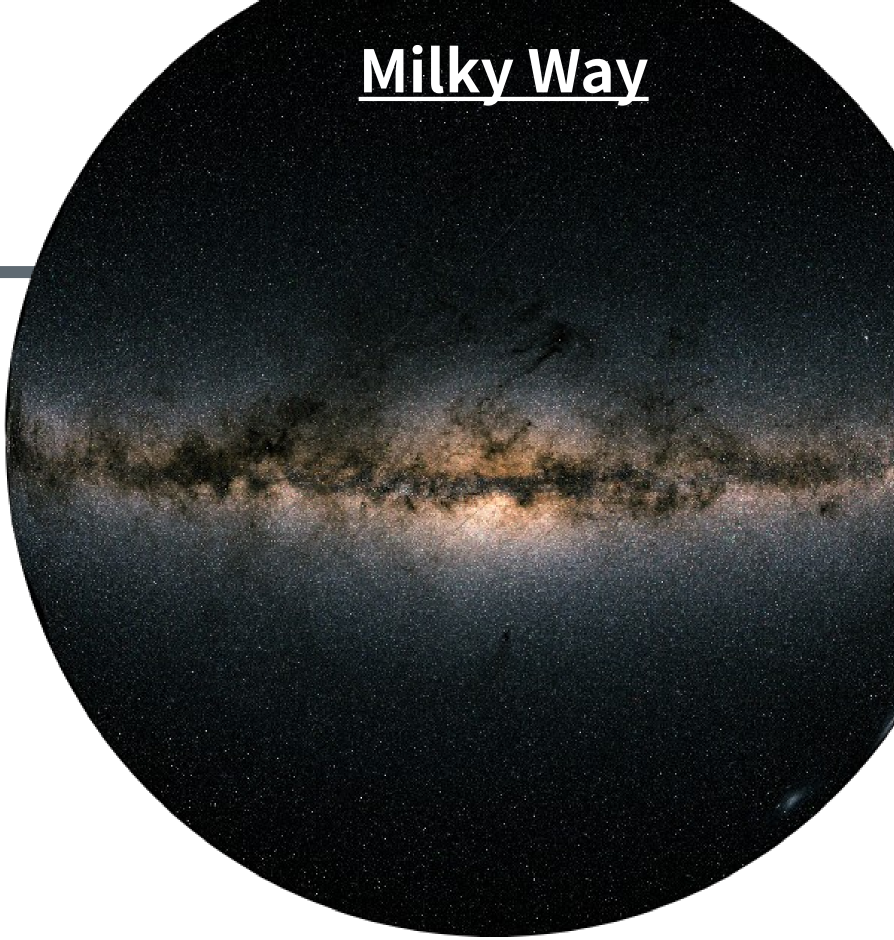
Key points

- <u>Unsupervised</u> regression
- <u>Dustmap</u> is *not* used
  → alternative measurement of dust!



So far, we have discussed how to deal with **dusty** environment of **the Milky Way**.

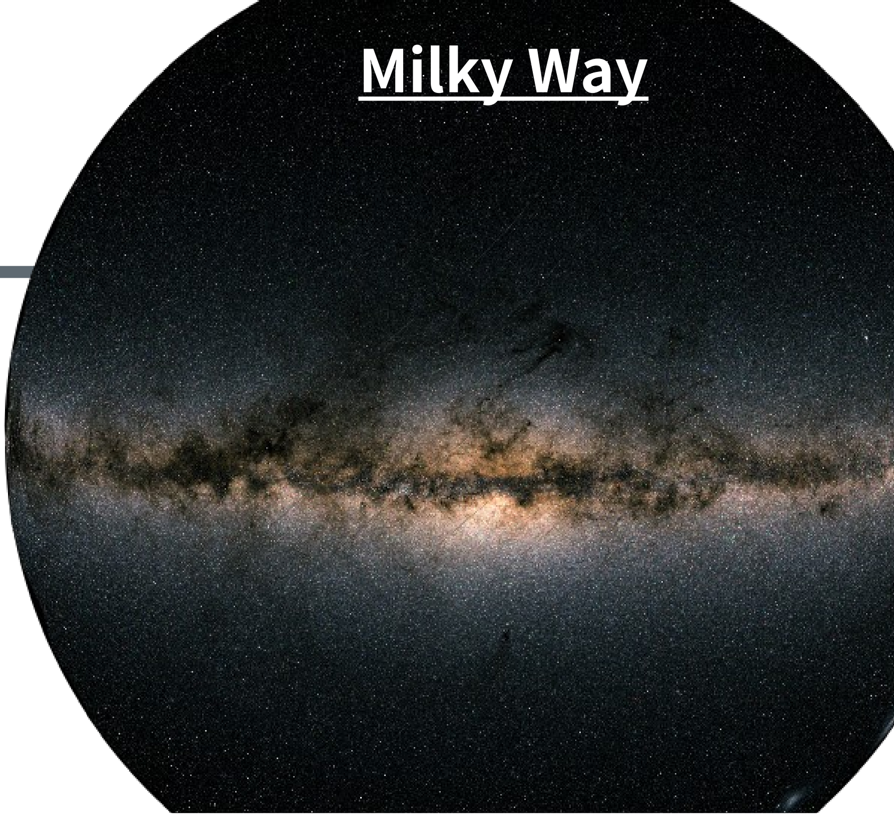
Q: Are there any **dust-free** galaxies to make this analysis simple?

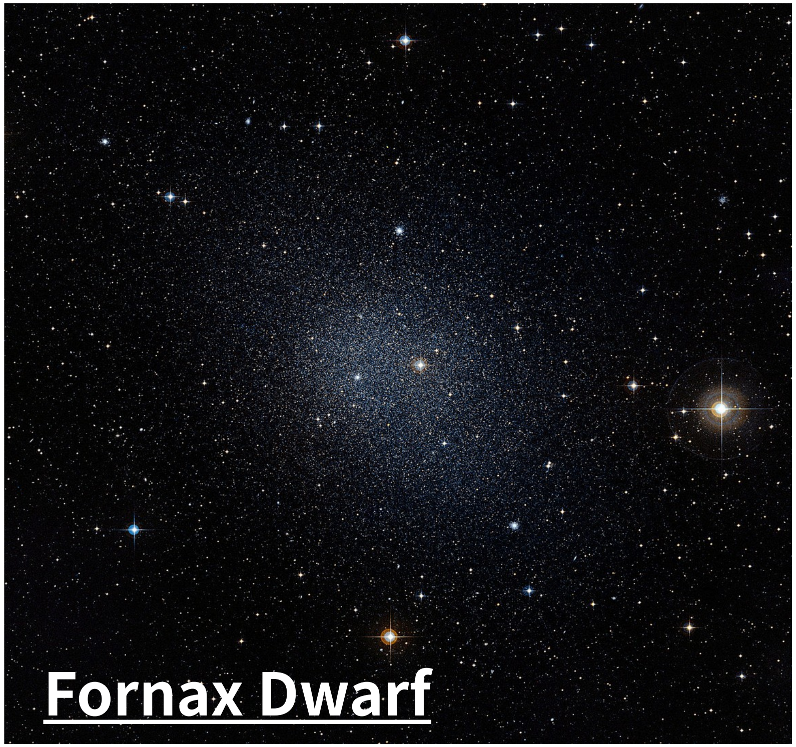


Q: Are there any **dust-free** galaxies to make this analysis simple?

Yes, there are some **dust-free satellite galaixes** of the Milky Way!

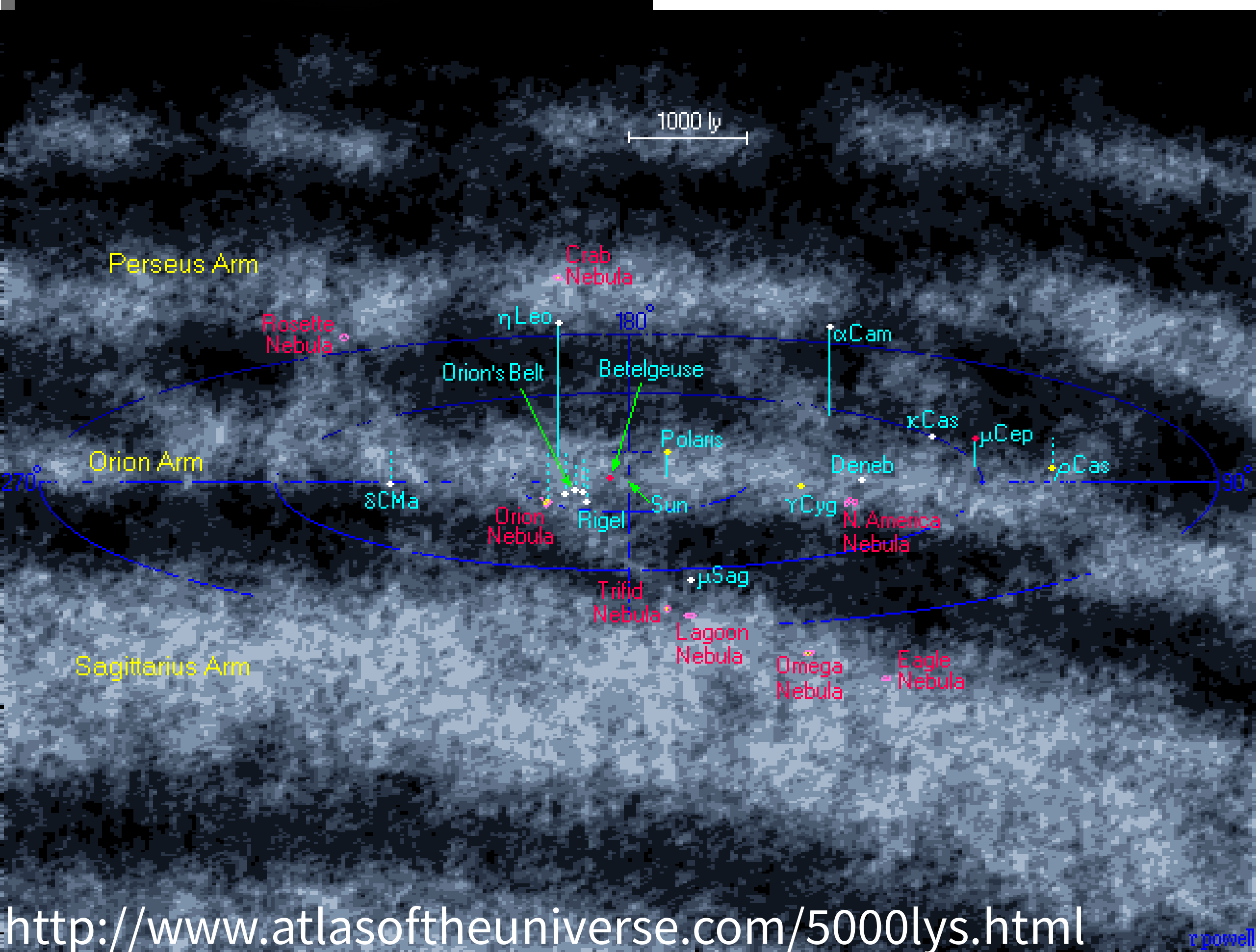
Where are they?





So far, we have been focused on the analysis
on **our corner** of the Milky Way.

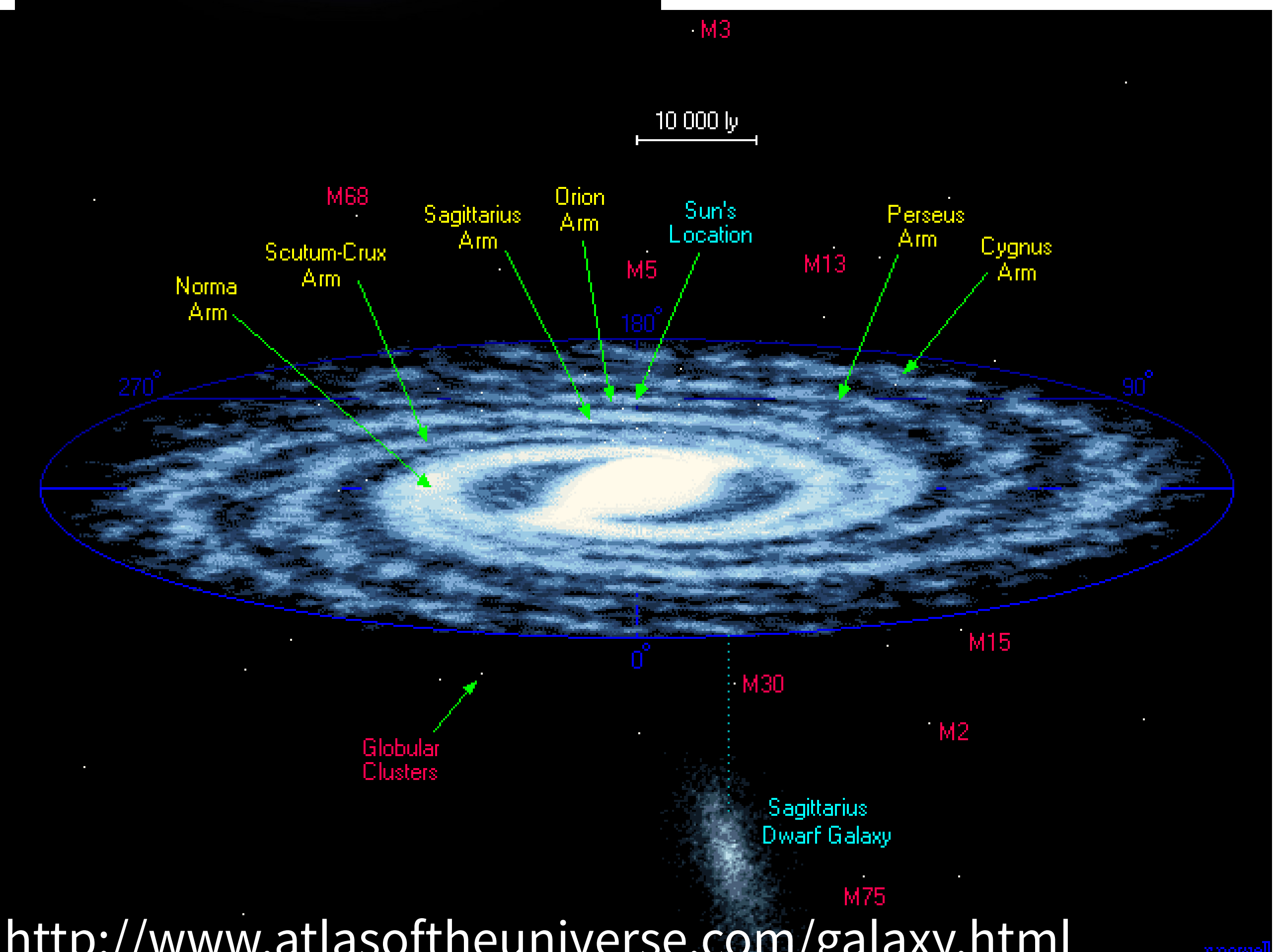
If you go further away…



http://www.atlasoftheuniverse.com/5000lys.html

So far, we have been focused on the analysis on **our corner** of the Milky Way.

If you go further away, you see whole Milky Way, but it is difficult to get **all the kinematic information** of stars visible here.



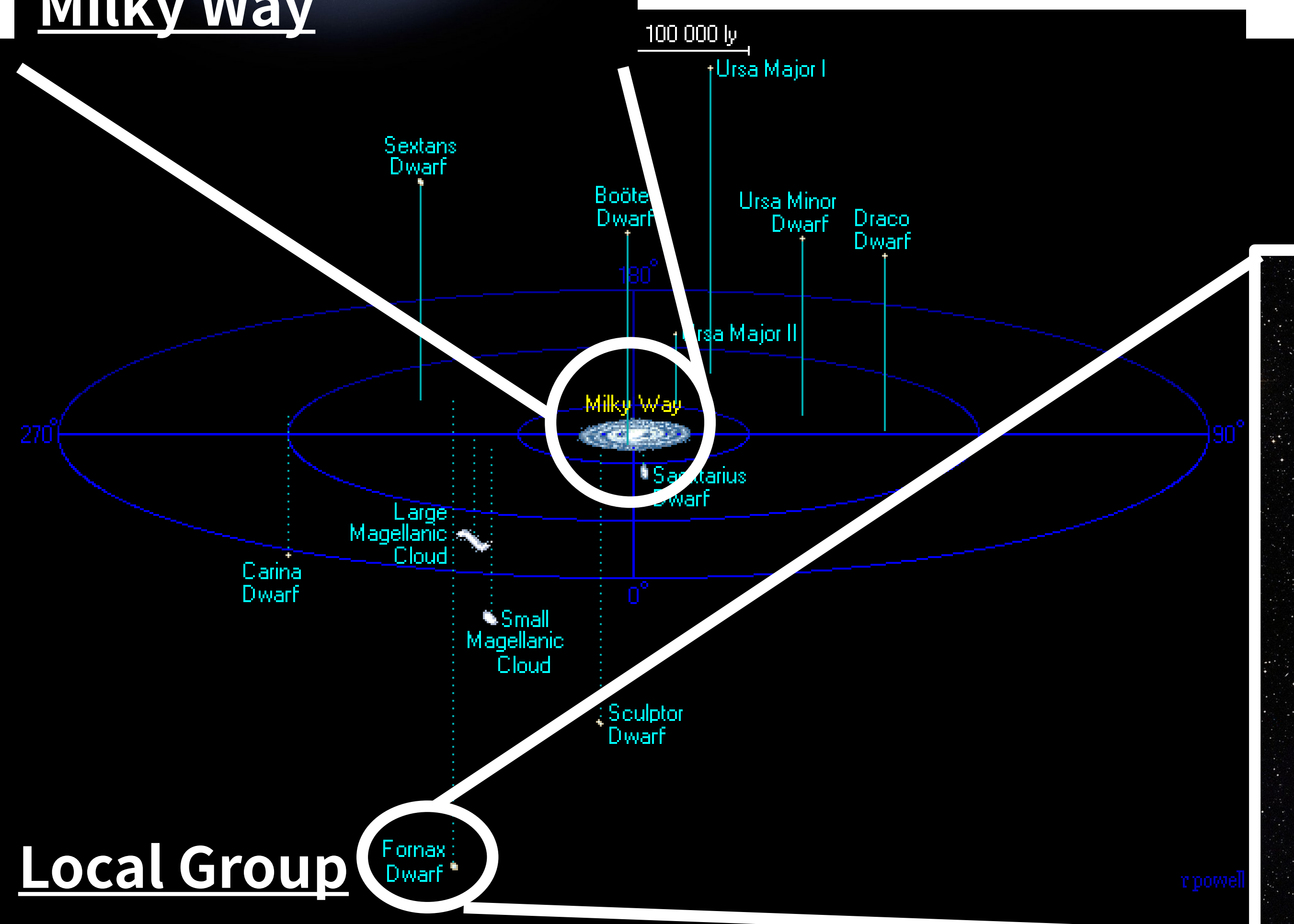
http://www.atlasoftheuniverse.com/galaxy.html

No local dark matter density estimate on the **opposite corner**!

So far, we have been focused on the analysis on **our corner** of the Milky Way.

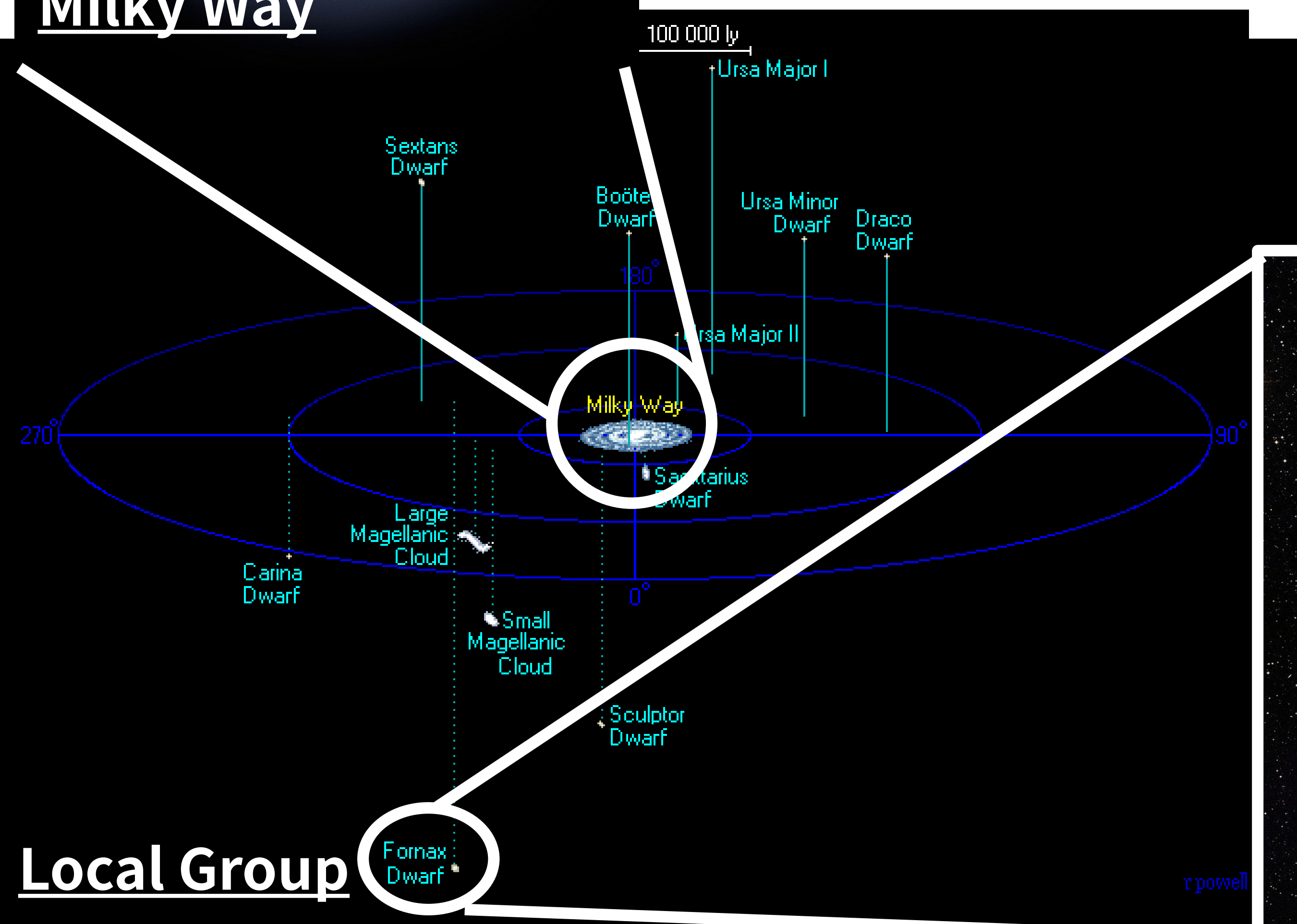
If you go further further away,

You see other satellite galaxies!



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

we will focus on a type of satellite galaxy called **<u>dwarf speheroidal galaxy</u>**.

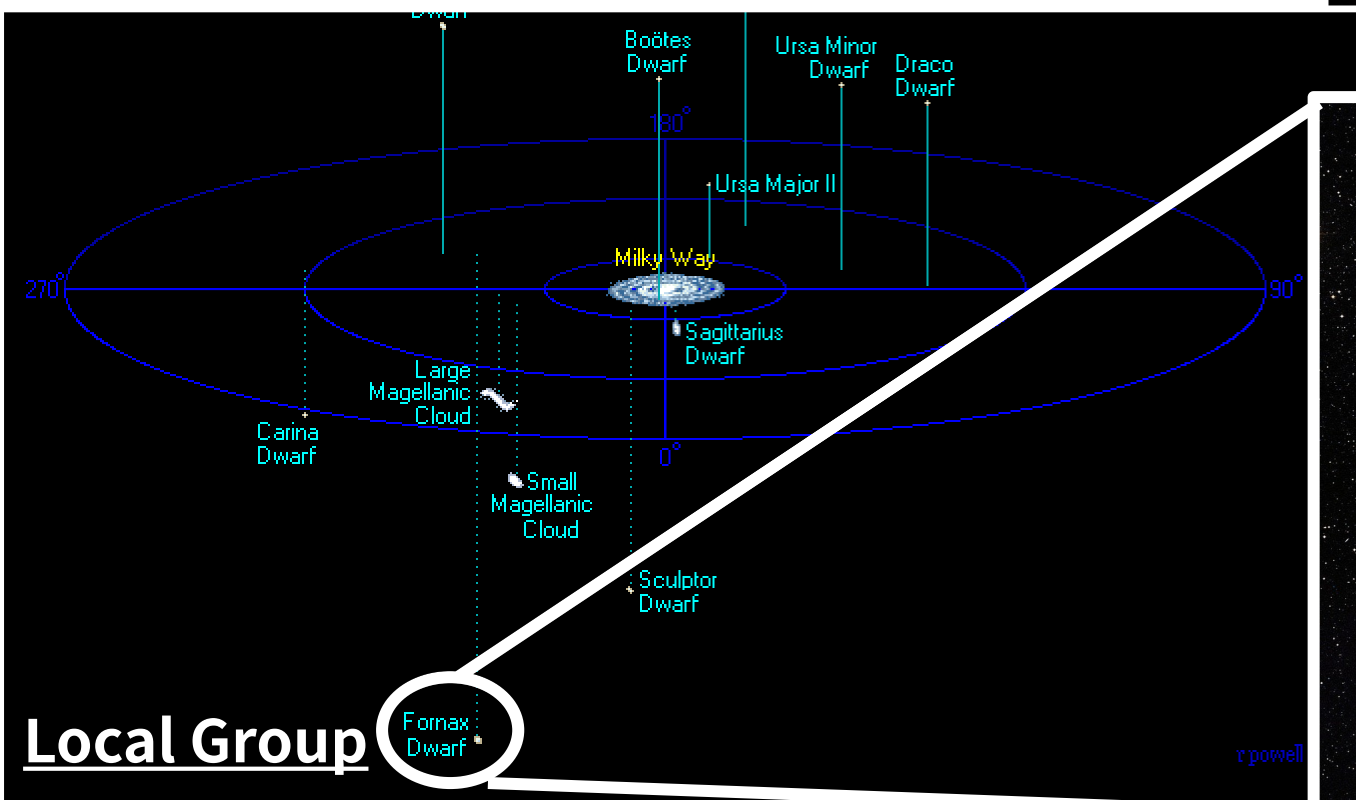


http://www.atlasoftheuniverse.com/sattelit.html

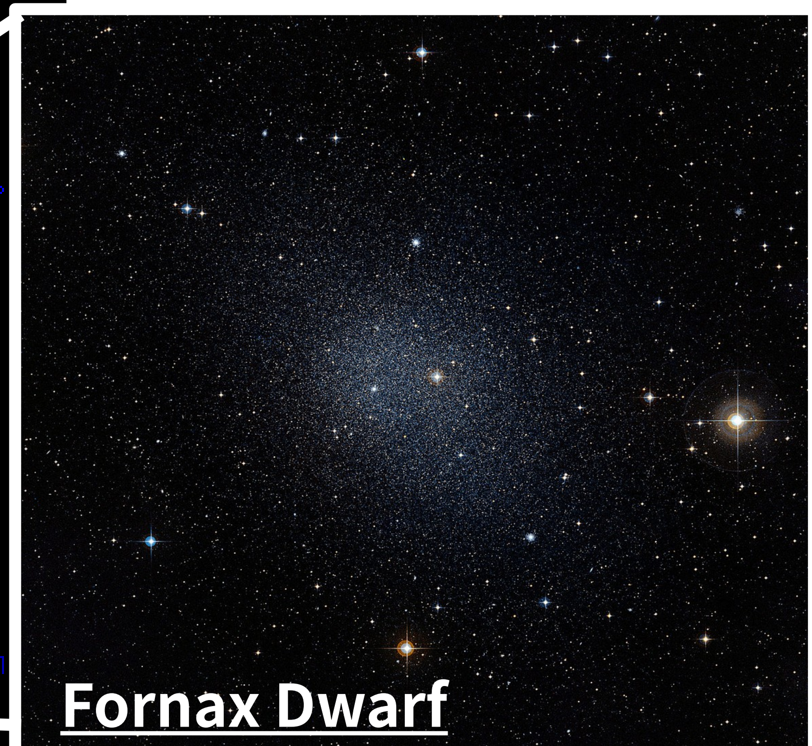
Dwarf Spheroidal Galaxy?

- A round and faint satellite galaxy, orbiting the Milky Way.
- Almost no gas and dust obscuring stars. Whole galaxy is clearly visible.


Milky Way from Ground



Local Group

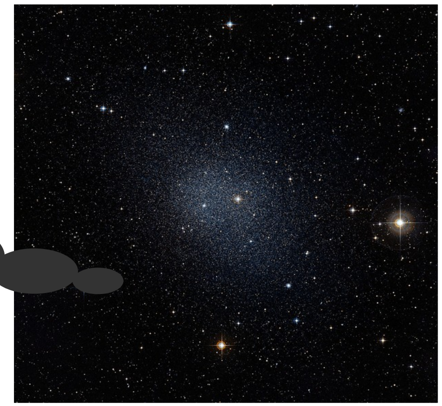

Fornax Dwarf

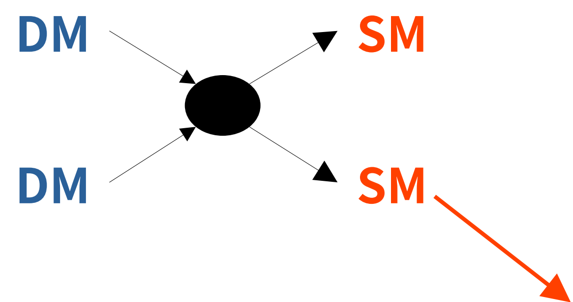
http://www.atlasoftheuniverse.com/sattelit.html

Dwarf spheroidal galaxy is a dark matter laboratory!

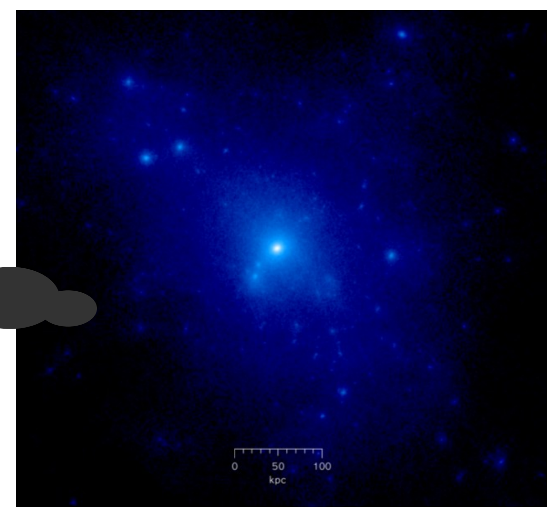
Clean signal source as
dsph exhibits
less baryon activity.

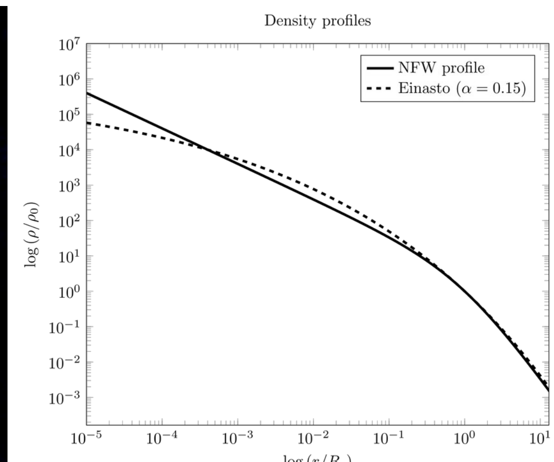
Indirect Detection
experiments





Understanding
the dark matter halo shape
→ insights on
DM interactions?



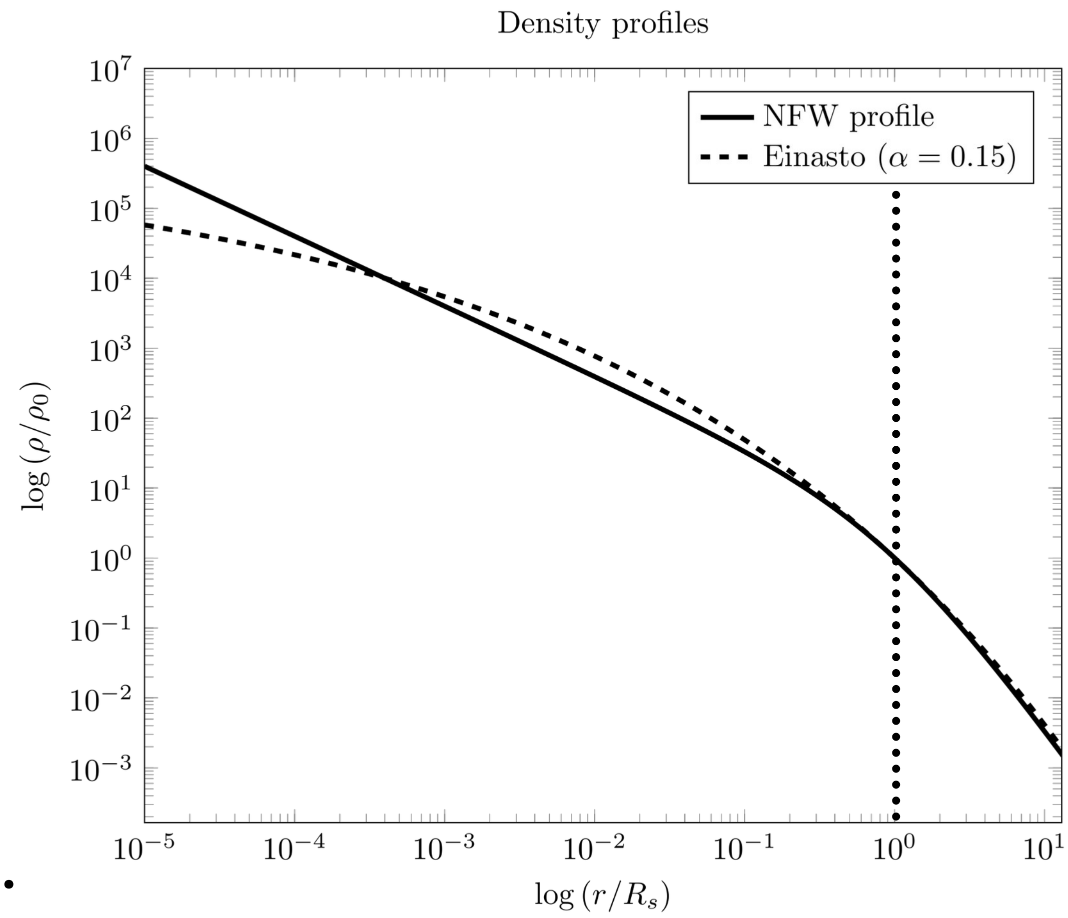


Navarro–Frenk–White (NFW) profile

A commonly used
dark matter halo model
empirically identified
in N-body simulations

$$\rho(r) = \frac{\rho_0}{\frac{r}{R_s}\left(1+\frac{r}{R_s}\right)^2}$$

If dark matter exhibits
non-trivial interactions,
the **<u>halo shape may vary</u>**.



Self-interacting dark matter, <u>wave dark matter</u> ....

https://en.wikipedia.org/wiki/Navarro%E2%80%93Frenk%E2%80%93White_profile

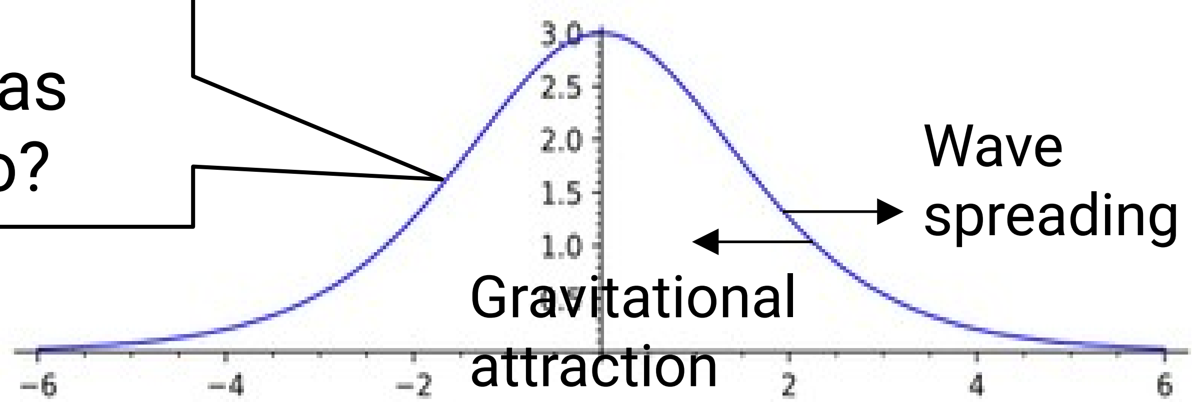
Example: Wave Dark Matter

If DM mass is so light (e.g. very light axions) so that

inter-particle spacing << de Broglie wavelength

DM exhibits **wave-like** behavior.

Nontrivial stable solution:
Soliton
→ Soliton solution as
a dark matter halo?



Smoking gun signatures

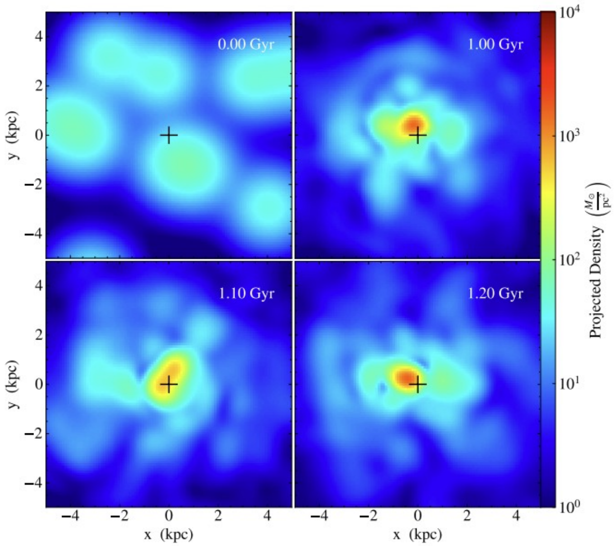
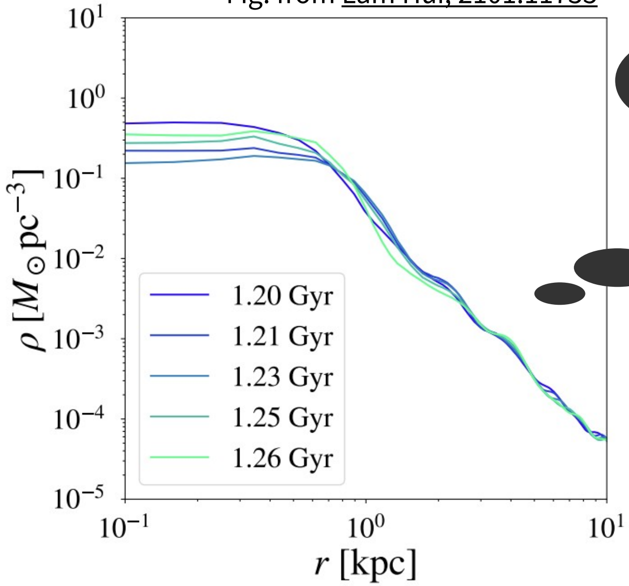


Fig. from Lam Hui, 2101.11735



Soliton Oscillations

Soliton Core

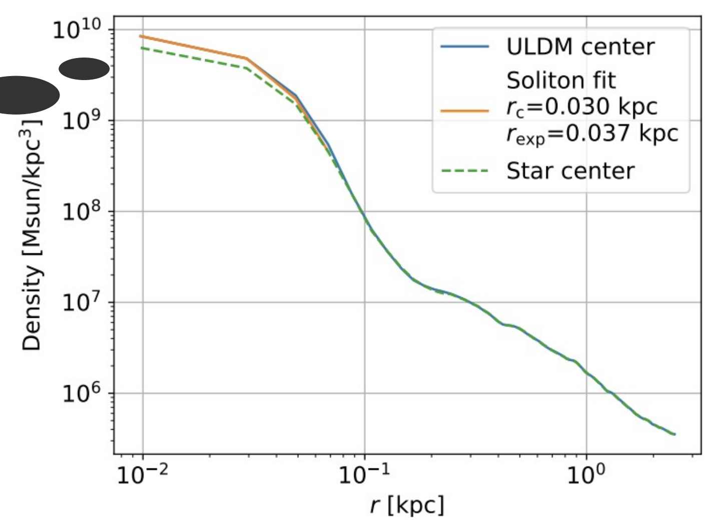
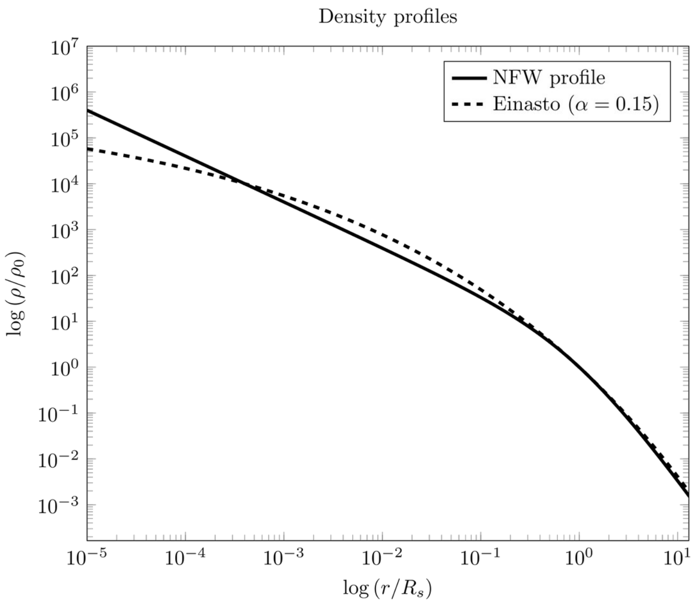
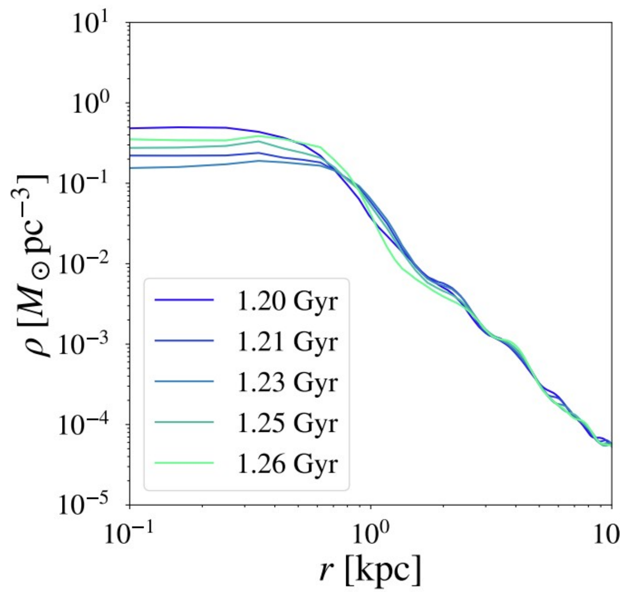
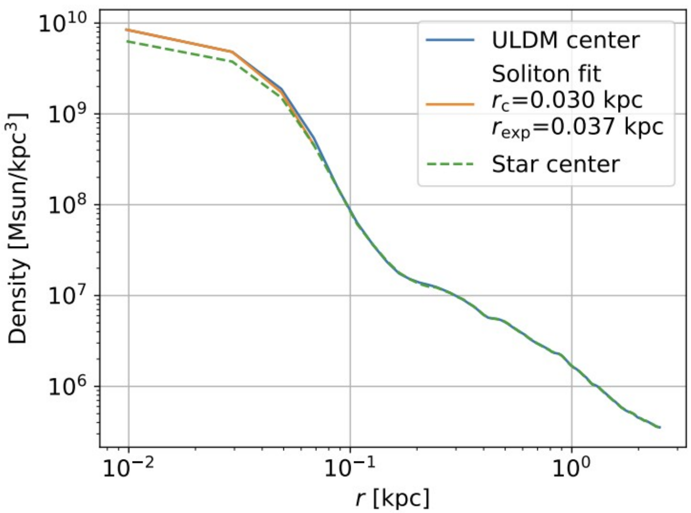


Fig. from talk by Teodori Luca, IBS Let there be light (particles) Workshop

Need for model-independent analysis





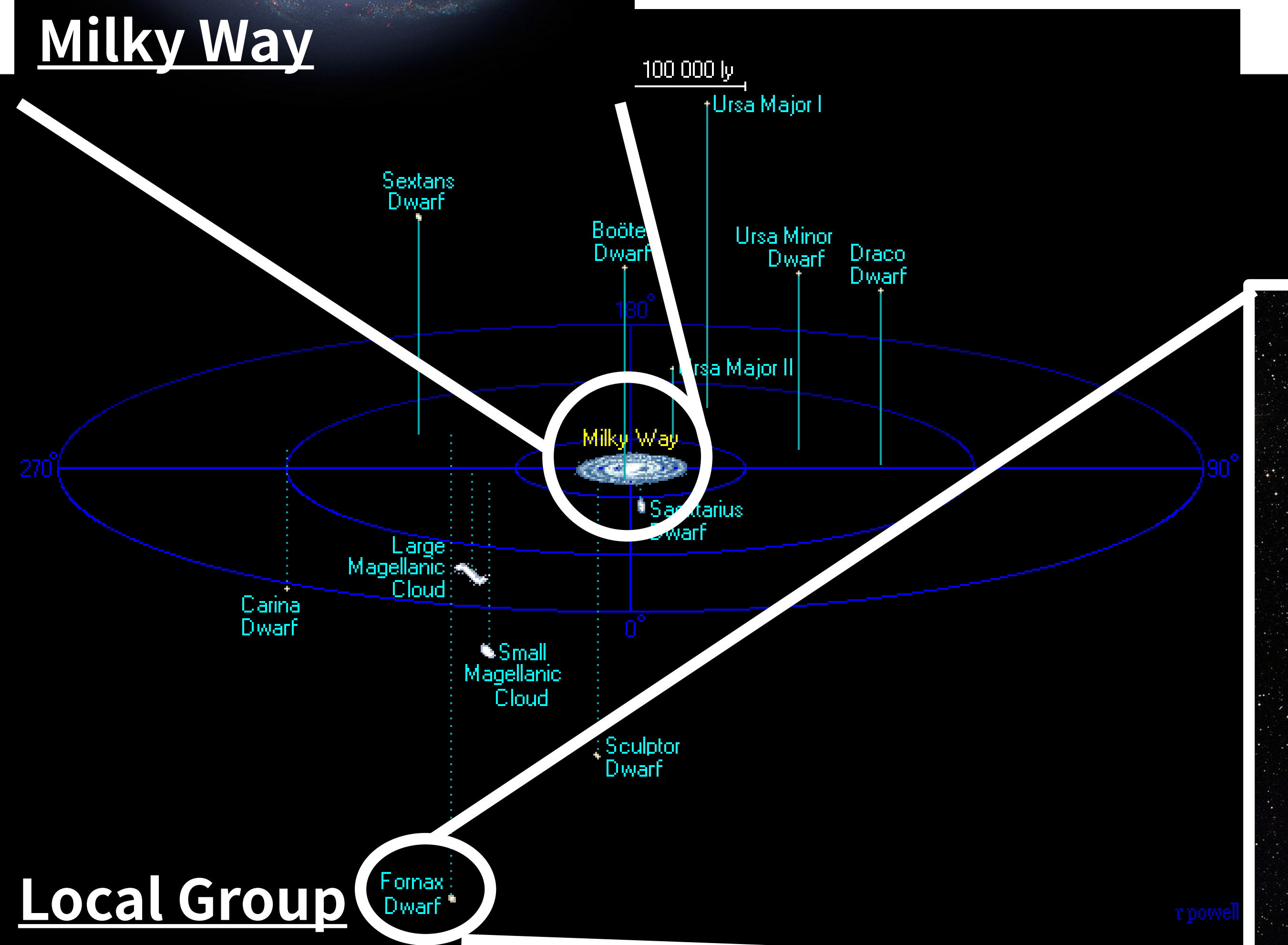


As many non-trivial DM halos are considered nowadays, we need a **free-form DM density estimation** in order to do a **model-indepdent** DM halo analysis.

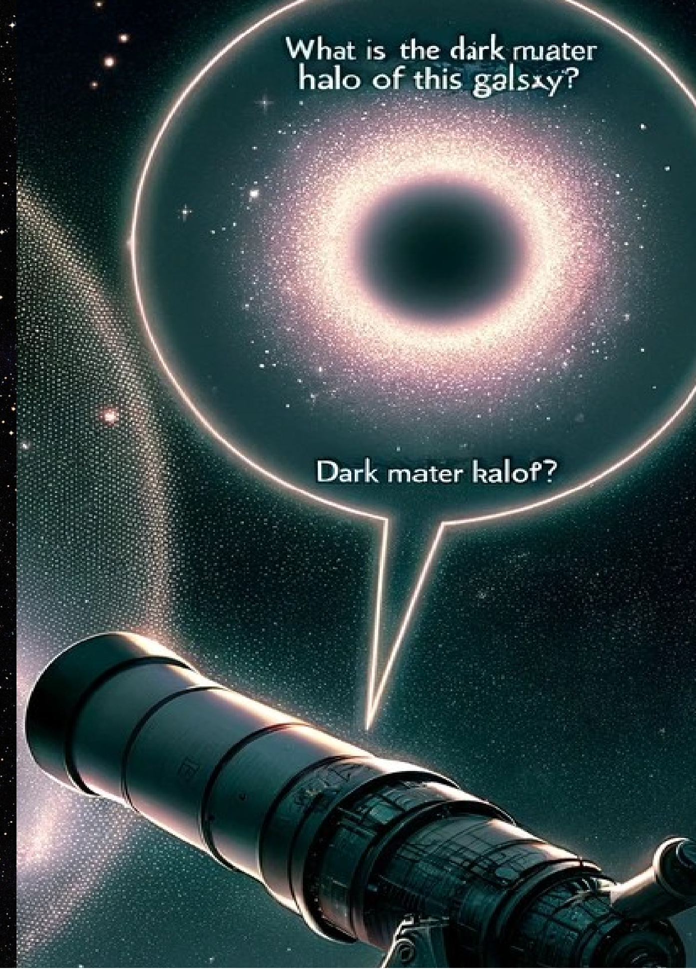
Again, unsupervised **machine learning** can help solving this type of problem!

Is the ML technique easily applicable to any of **distant dust-free galaxies, like dwarf spheroidal galaxy?**

Answer: both yes and no



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



JFlow: Model-Independent Spherical Jeans Analysis using Equivariant Continuous Normalizing Flows

Collaboration with
K. Hayashi (NIT, Sendai College), S. Horigome (Tohoku),
S. Matsumoto (IPMU), M. M. Nojiri (KEK),

New Paper!

JFlow: Model-Independent Spherical Jeans Analysis using Equivariant Continuous Normalizing Flows

Sung Hak Lim, Kohei Hayashi, Shun'ichi Horigome, Shigeki Matsumoto, Mihoko M. Nojiri

The kinematics of stars in dwarf spheroidal galaxies have been studied to understand the structure of dark matter halos. However, the kinematic information of these stars is often limited to celestial positions and line-of-sight velocities, making full phase space analysis challenging. Conventional methods rely on projected analytic phase space density models with several parameters and infer dark matter halo structures by solving the spherical Jeans equation. In this paper, we introduce an unsupervised machine learning method for solving the spherical Jeans equation in a model-independent way as a first step toward model-independent analysis of dwarf spheroidal galaxies. Using equivariant continuous normalizing flows, we demonstrate that spherically symmetric stellar phase space densities and velocity dispersions can be estimated without model assumptions. As a proof of concept, we apply our method to Gaia challenge datasets for spherical models and measure dark matter mass densities given velocity anisotropy profiles. Our method can identify halo structures accurately, even with a small number of tracer stars.

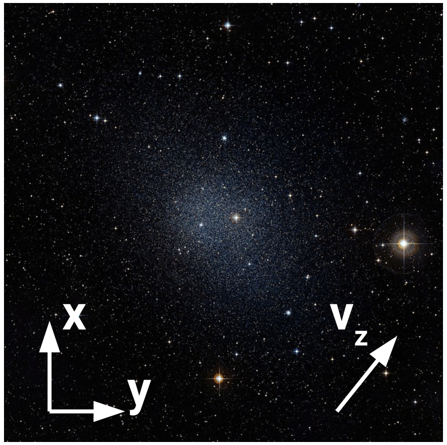
Comments:	9 pages, 3 figures, 1 table
Subjects:	**Astrophysics of Galaxies (astro-ph.GA)**; Cosmology and Nongalactic Astrophysics (astro-ph.CO Physics - Experiment (hep-ex); High Energy Physics - Phenomenology (hep-ph)
Report number:	CTPU-PTC-25-15
Cite as:	arXiv:2505.00763 **[astro-ph.GA]**
	(or arXiv:2505.00763v1 **[astro-ph.GA]** for this version)
	https://doi.org/10.48550/arXiv.2505.00763

Check it out!
arXiv:2505.00763

Challenges in Analyzing dSphs

- Faint galaxy
  → less number of observed stars O[100] ~ O[1000]

- Available kinematic information is **limited**!
  - Position of stars on the sky (x, y) (phot.)
  - ~~Distance to the stars (z)~~
  - ~~Proper motion of stars on the sky (v_x, v_y)~~
  - Radial velocity (v_z) (spec.)



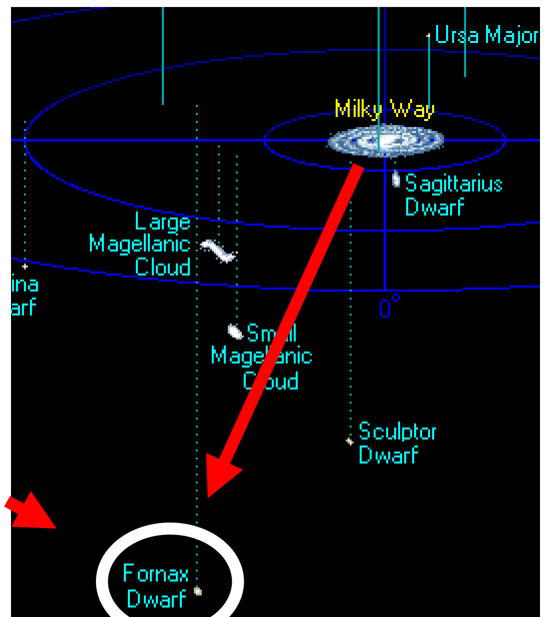
- Phase space density of stars are not accessible, and hence we cannot solve the equation of motion yet.. (Jeans equation)

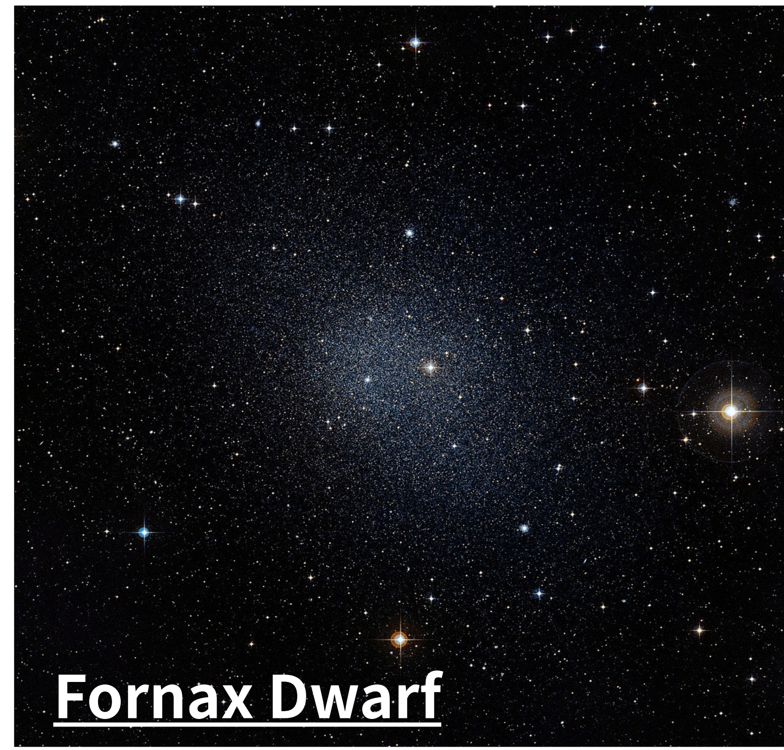
$$\frac{\partial n \langle v_j \rangle}{\partial t} + n \frac{\partial \Phi}{\partial x_j} + n \frac{\partial n \langle v_i v_j \rangle}{\partial x_i} = 0$$

Can we recover the full 6D information somehow?

Radon Transformation

- Can we recover the full 6D information somehow?
  → Yes, if we have a 3D projected snapshot of the dSph from all the direction





- This tomographic reconstruction is possible **(e.g. MRI imaging)**,
- but we only have a snapshot from only one direction…
  → Classic solution: assume **spherical symmetry**.

Spherical Jeans Equation

Introducing spherical symmetry simplifies the Jeans equation, too.

$$\frac{d}{dr} n \overline{v_r^2} + \frac{2\beta}{r} n \overline{v_r^2} = -n \frac{d\Phi}{dr}$$

List of functions needed for inferring gravitational field (Φ)

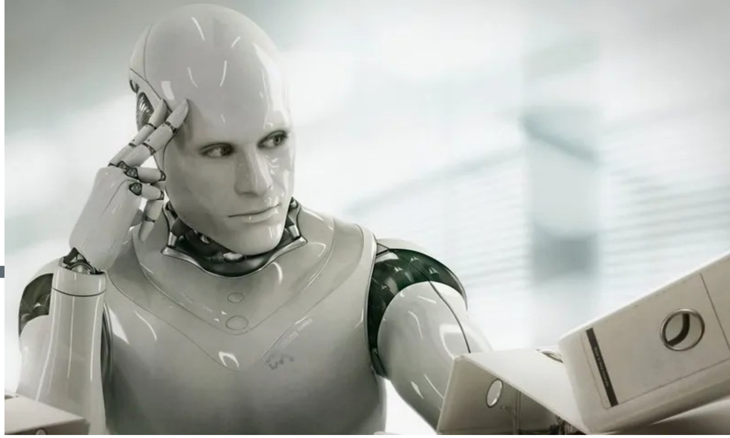
- Number density $n(r)$
- Radial velocity dispersion (variance) $\overline{v_r^2}(r)$
- Velocity anisotropy

$$\beta(r) = 1 - \frac{\overline{v_\theta^2}(r) + \overline{v_\phi^2}(r)}{2\overline{v_r^2}(r)}$$

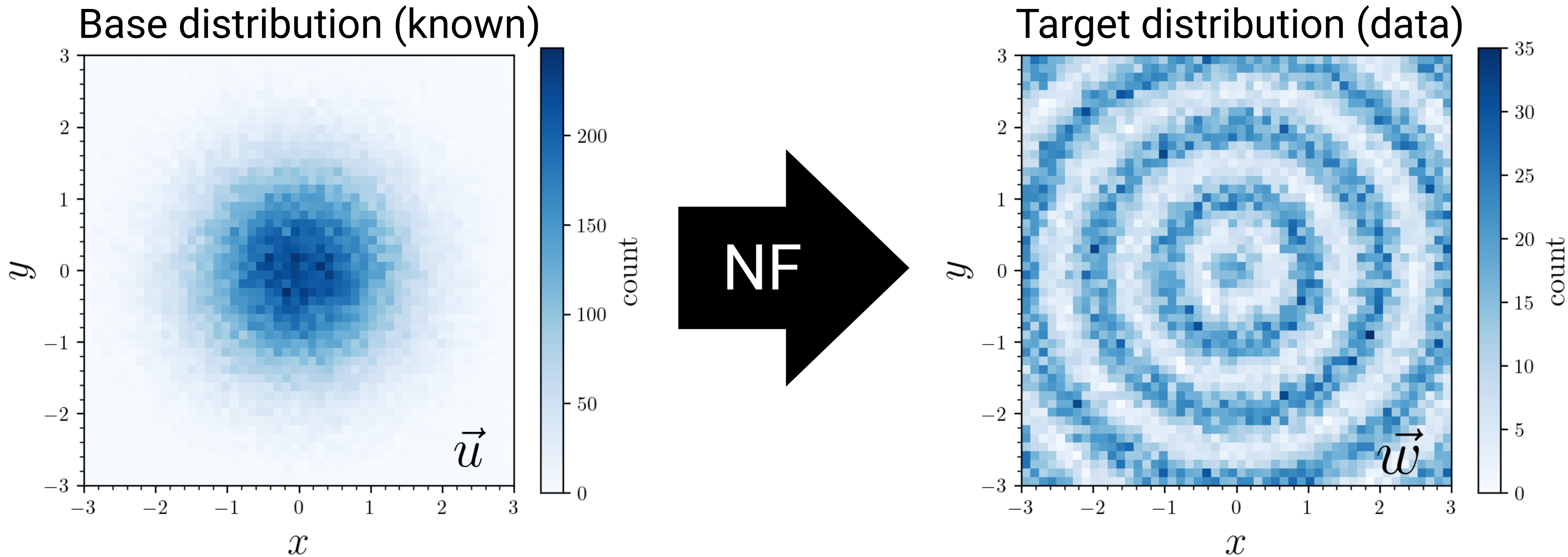
Note: velocity anisotropy cannot be determined only using line-of-sight velocity distribution, we will provide the function (can be true or not) by hand.

Need to estimate 2 functions from data: $\boxed{n(r)}$ $\boxed{\overline{v_r^2}(r)}$

Normalizing Flows: Neural Density Estimator



Normalizing Flows (NFs) is an artificial neural network that learns a transformation of random variables.



Main idea: if we could find out such transformation, we can use the transformation formula for the density estimation:

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

We will use this model for estimating the phase space density f(x,v) from the data.

$n(r)$

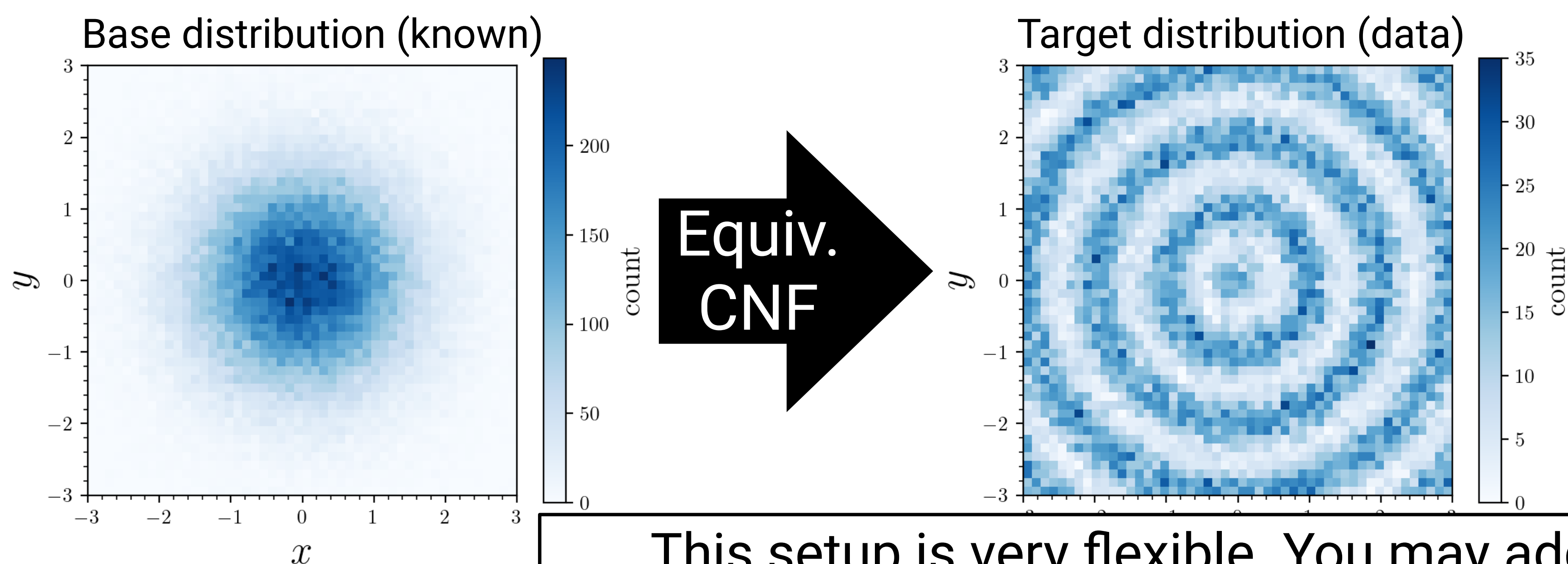
Equivariant Continous Normalizing Flows

How to model spherically symmetric density using normalizing flows?

→ Use Equivariant Continuous Normalizing Flows!

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

- Invariant (Gaussian) base distribution
- Equivariant vector field

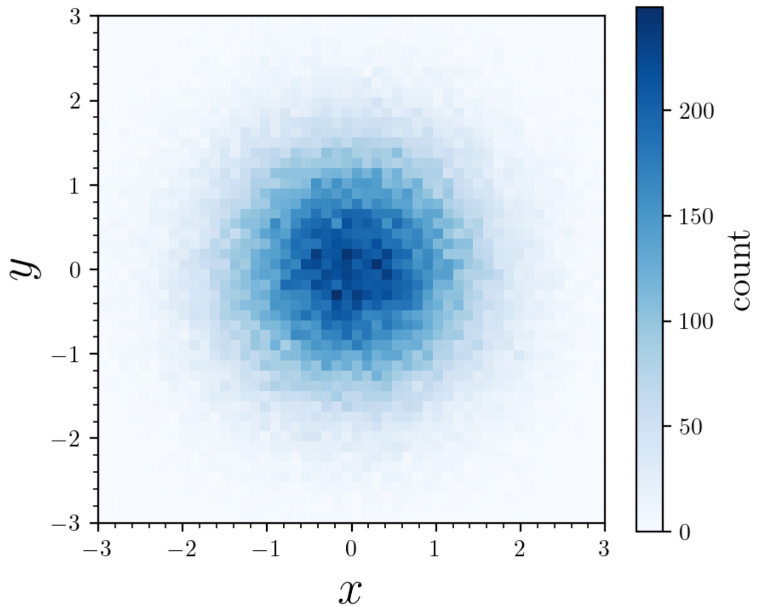


This setup is very flexible. You may add **physics constraints** to **neural networks**, too!

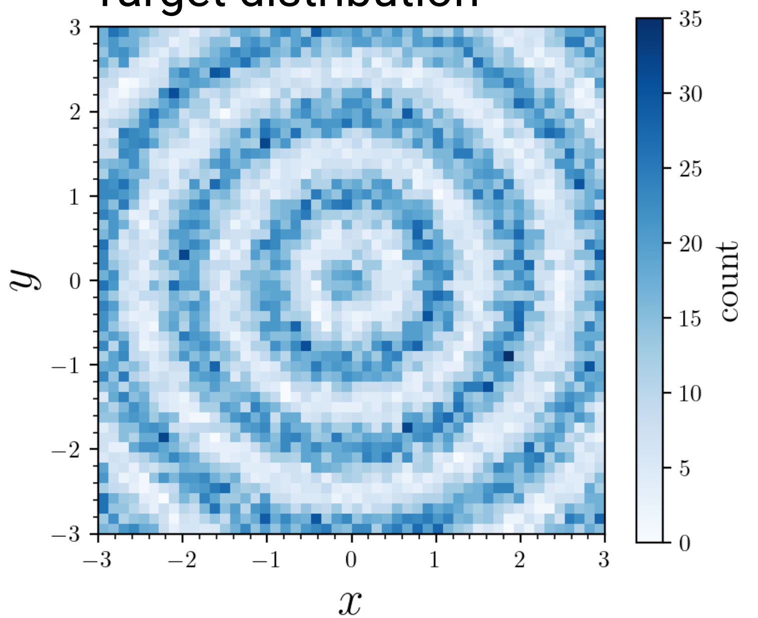
Normalizing Flows: How it works?

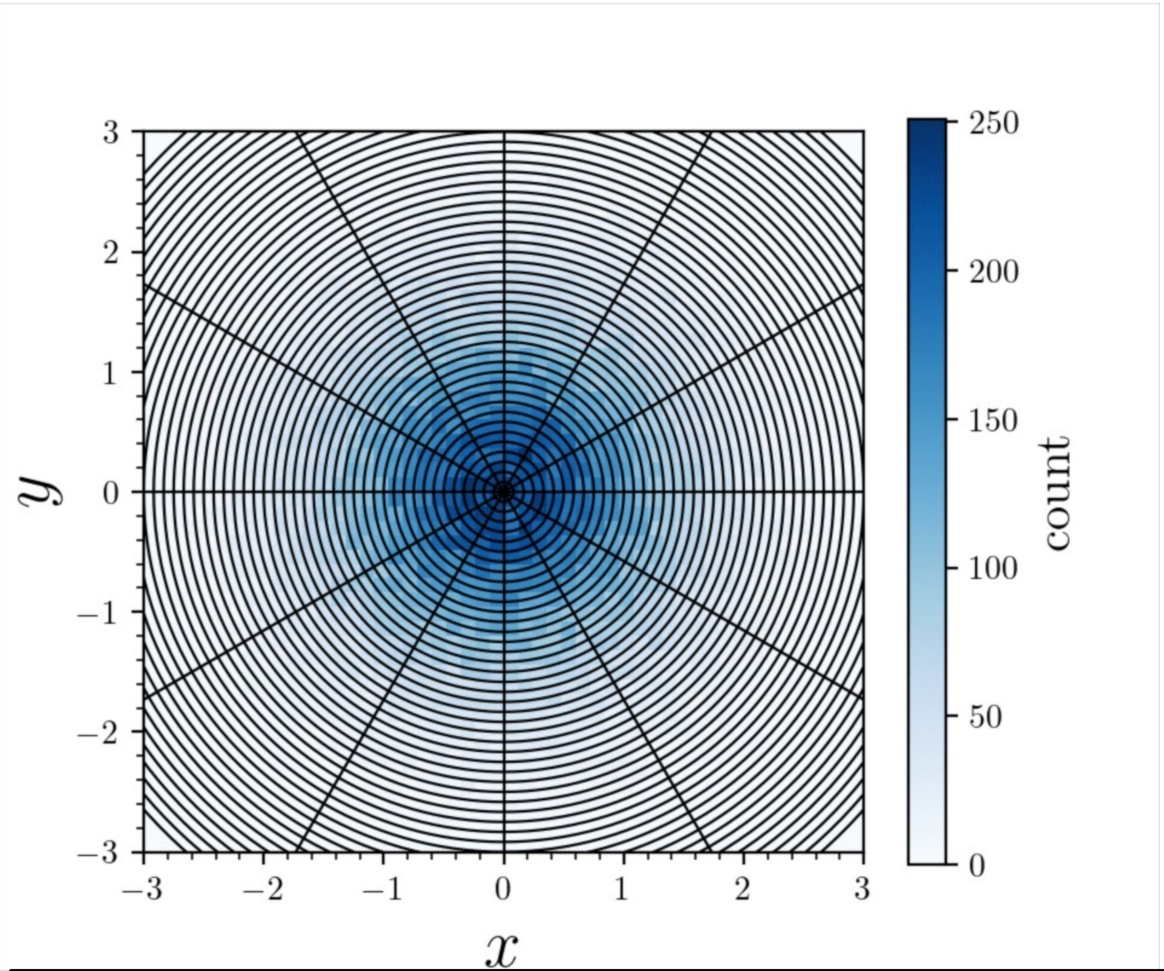
$n(r)$

Base distribution



Target distribution





Normalizing flows can fit **arbitrary** probability density, suitable for **model-independent** analysis!

* result of a continuous normalizing flow learning infinitesimal transformations

Cored Spherical Density Model

In dSph analysis, we may further constrain the density model as conventional analysis often only consider the following type of densities.

- **Cored** density (constant density at r << 0)
- **Cuspy** density

ex) plummer sphere:

$$p(r) = \left(1 + \frac{r^2}{r_0^2}\right)^{-5/2}$$

Equivariant CNF for modeling **cored** density profile

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

Transformation at the origin is suppressed, remaining as Gaussian-shape. → cored density

Cuspy Spherical Density Model

In dSph analysis, we may further constrain the density model as conventional analysis often only consider the following type of densities.

- **Cored** density (constant density at r << 1)
- **Cuspy** density

Equivariant CNF for modeling cuspy density profile

ex) NFW profile:

$$p(r) = \left(\frac{r}{r_0}\right)^{-1} \left(1 + \frac{r}{r_0}\right)^{-2} \to \frac{1}{r}$$

Apply power-law transform to radial component

$$|r| \to |r|^{c+1} \qquad \text{Jacobian} \propto r^{-\frac{3c}{1+c}}$$

to **cored** spherical symmetric density model

Velocity Dispersion Estimation

The velocity dispersion can be simply estimaed using Gaussian model conditioned on position, as the MLE on variance parameter of Gaussian is a variance estimator.

$$\Sigma(r;\theta) = \begin{pmatrix} \overline{v_r^2}(r;\theta) & 0 & 0 \\ 0 & \overline{v_\theta^2}(r;\theta) & 0 \\ 0 & 0 & \overline{v_\phi^2}(r;\theta) \end{pmatrix}$$

Note that only radial velocity dispersion is modeled by a neural network, others are given by velocity anisotropy function provided.

$$\overline{v_\theta^2}(r;\theta) = \overline{v_\phi^2}(r;\theta) = \overline{v_r^2}(r;\theta) \cdot (1 - \beta(r))$$

Here is a 6D density model, but...

Now we have a full 6D phase-space density model ready for solving spherical Jeans equation.

$$p(\vec{r}) = n(r;\theta)$$ modeled by equivariant CNF for cuspy halos

$$p(\vec{v}|\vec{r}) = \mathrm{GaussPDF}(\vec{v};\mu=0,\Sigma(r;\theta))$$

$$f(\vec{r},\vec{v}) = p(\vec{r}) \times p(\vec{v}|\vec{r})$$

Wait, we only have x, y, vz.
How can we train this network by MLE?
We cannot use a conventional loss function.

How to train this model?

Model parameters are defined at here

Likelihood

samples

$$
\begin{array}{lccc}
\text{6D space} & f(\vec{r}, \vec{v}; \theta) & \xrightarrow{\text{Sampling}} & (\vec{r}, \vec{v}) = T(\vec{\epsilon}; \theta) \\
& \Big\downarrow \text{Abel} & & \Big\downarrow \text{Projection} \\
\text{3D space} & f(x, y, v_z; \theta) & & (x, y, v_z) = \mathrm{Proj}_{3\mathrm{D}}\, T(\vec{\epsilon}; \theta) \\
& \Big\downarrow \text{Convolution} & \swarrow \text{KDE} & \Big\downarrow \text{Smearing} \\
\text{3D smeared space} & f * K(x, y, v_z; \theta) & \Longleftrightarrow & (x, y, v_z) + \vec{n}, \quad \vec{n} \sim K
\end{array}
$$

Training samples are at this level

Do MLE using 3D smeared density
and
measured data!

Loss Function for Modeling Dwarf Spheroidal Galaxy

- In order to train the normalizing flow with spherical symmetry using limited kinematic information, we minimize the following entropy:

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

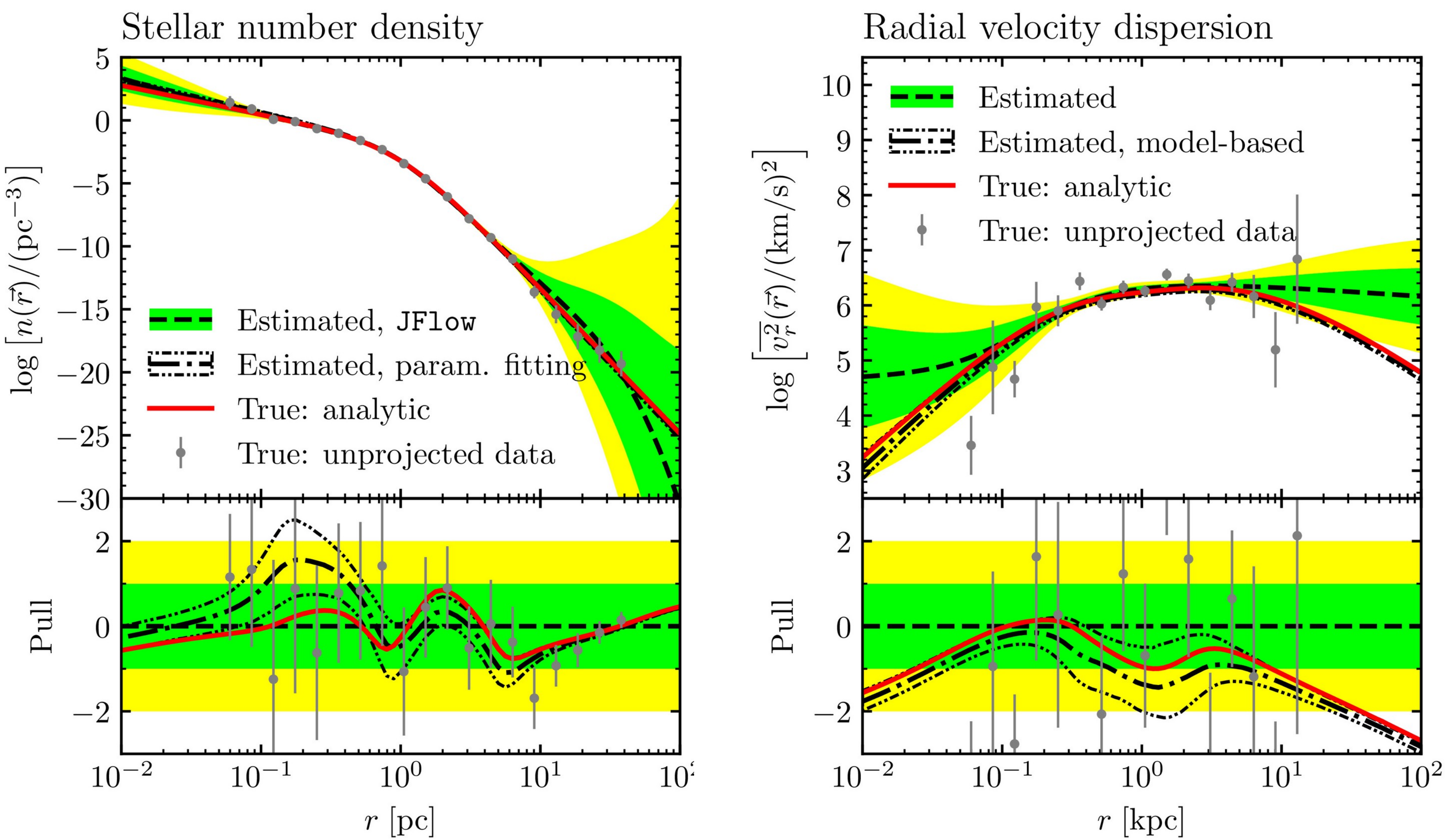
- Importance sampling: N_T training sample (stars) ~ p, N_K noise samples ~ K_h

$$\mathcal{L}(\theta) = \frac{1}{N N_K} \sum_{a=1}^{N} \sum_{b=1}^{N_K} \log \hat{p} * K_h(\vec{w}_\perp^{(a)} + \vec{\epsilon}^{(b)}; \theta)$$

- KDE for the smeared likelihood model:
  N_G generated stars from the normalizing flows~ \hat{p}

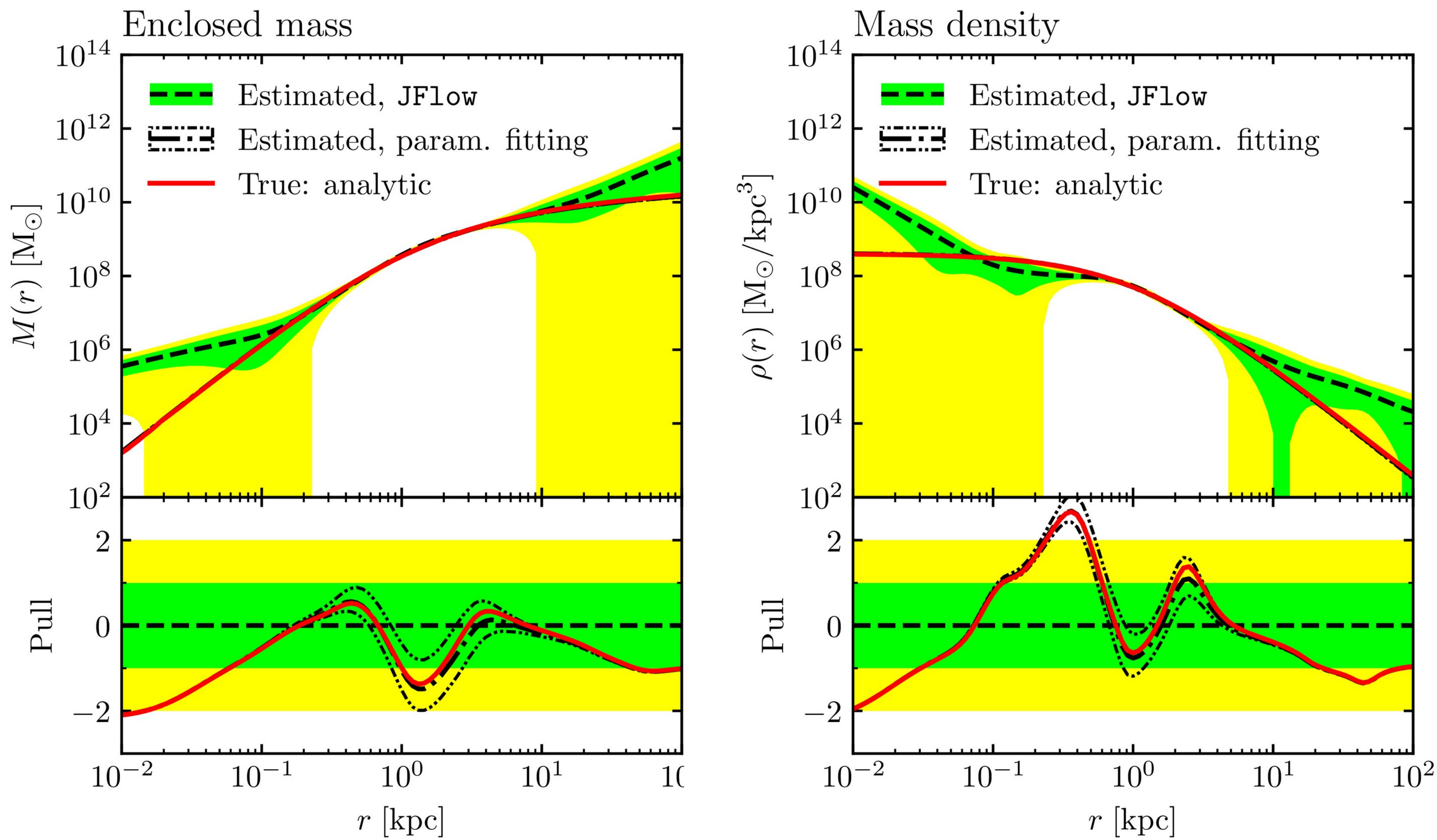
$$\mathcal{L}(\theta) = \frac{1}{N N_K} \sum_{a=1}^{N} \sum_{b=1}^{N_K} \log \frac{1}{N_G} \sum_{c=1}^{N_G} K_h \left[\vec{w}_\perp^{(a)} + \vec{\epsilon}^{(b)} - \vec{T}(\vec{z}^{(c)}; \theta) \right]$$

Results: stellar number density & radial velocity dispersion



Dataset: simulated dwarf spherodal galaxy from Gaia Challenge Dataset
https://astrowiki.surrey.ac.uk/doku.php?id=tests:sphtri

Results: dark matter mass density



Dataset: simulated dwarf spherodal galaxy from Gaia Challenge Dataset
https://astrowiki.surrey.ac.uk/doku.php?id=tests:sphtri

Conclusions

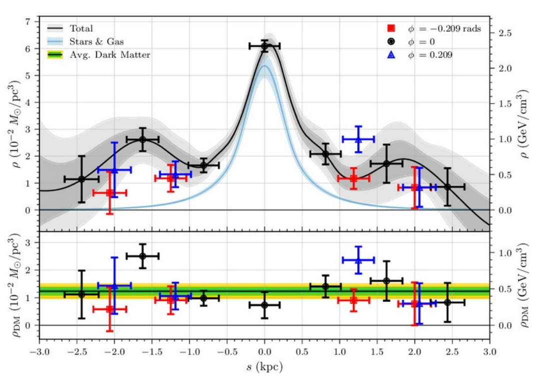
- We introduce a model-independent and unbinned spherical Jeans analysis using **normalizing flows**, a neural density estimator utilizing transformation of random variables.
- We **invented a loss function** for training normalizing flows modeling dSphs only using projected information, without performing Abel transformation.
- Using a mock spherical galaxy from Gaia Challenge dataset, we demonstrated that normalizing flows are capable of estimating **phase-space density** information for required solving Jeans equation.
- To do?:
  - Generalizing the framework to axisymmetric system.
  - Applying our analysis to real dwarf spheroidal galaxies, and estimate the effect to J-factors when the assumptions are relaxed.

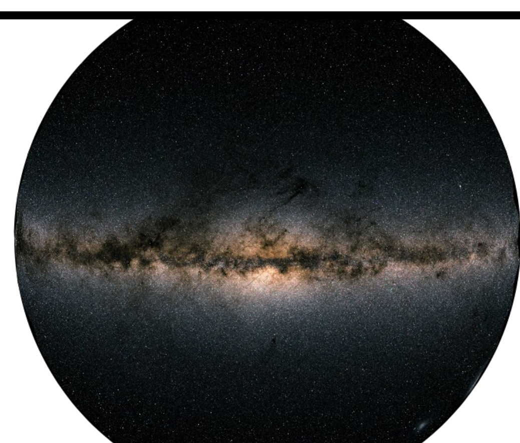
Future Timeline

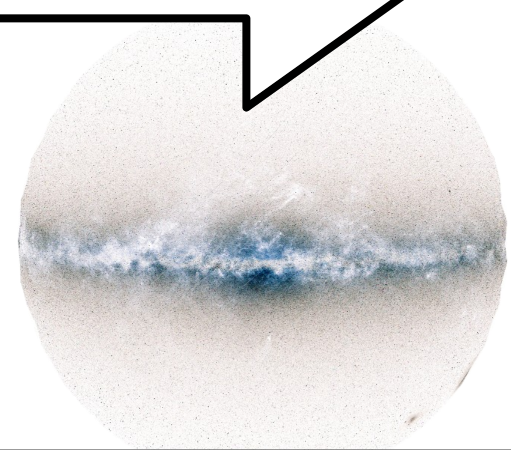
2023 | 2024 | 2025 | 2026

Gaia DR3

Gaia DR4, SuperPFS, and so on!







Understanding DM in dust-free region (halo, solar neighborhood)

Understanding DM in dusty region (disk)

More precision and new opportunities!

Awesome collaborators of my projects:

Prof. David Shih
(Rutgers)

Prof. Matthew Buckley
(Rutgers)

Prof. Mihoko Nojiri
(KEK)

Prof. Kohei Hayashi
(NIT, Sendai College)

Eric Putney
(Ph.D. student at Rutgers)

Prof. Shigeki
Matsumoto
(IPMU)

Dr. Shunichi
Horigome
(Tohoku)

Buliding a regional community:

AI+HEP in East Asia

About Organizers Workshops Seminars Journal Clubs Curriculum Project Board

Organizers

- Tianji Cai
- Sung Hak Lim
- Vinicius Mikuni
- Huilin Qu

AI+HEP in East Asia

AI+HEP in East Asia

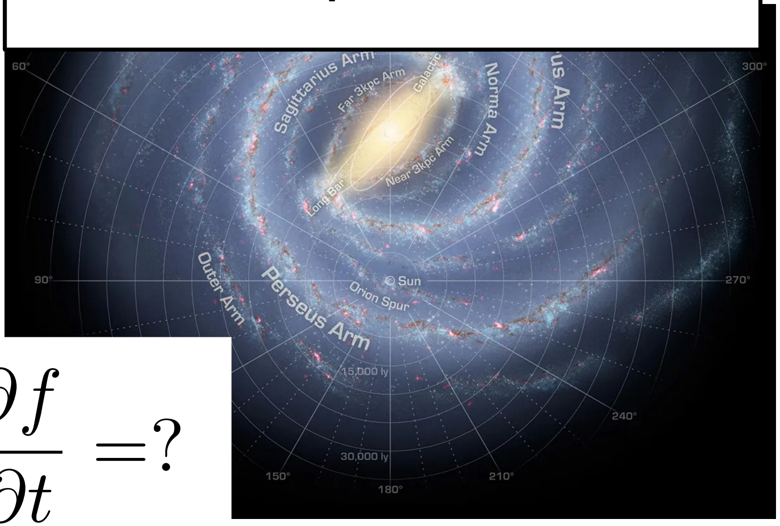
Page under construction :)

Thank you for listening!

Backups

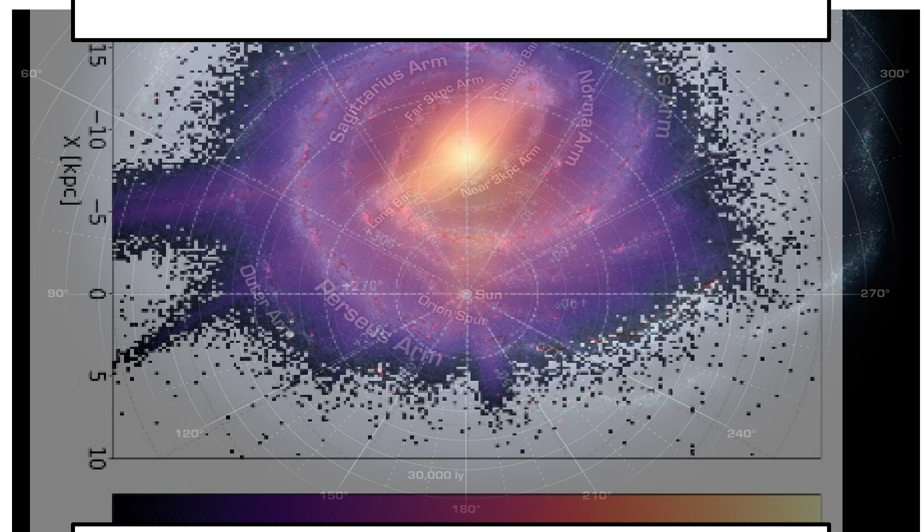
Various challenging incompleteness!

Disequilibrium

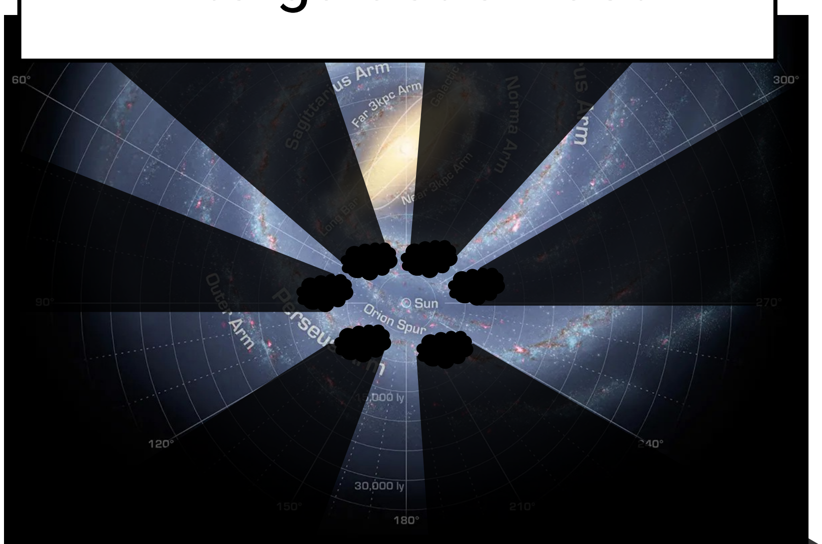


$$\frac{\partial f}{\partial t} = ?$$

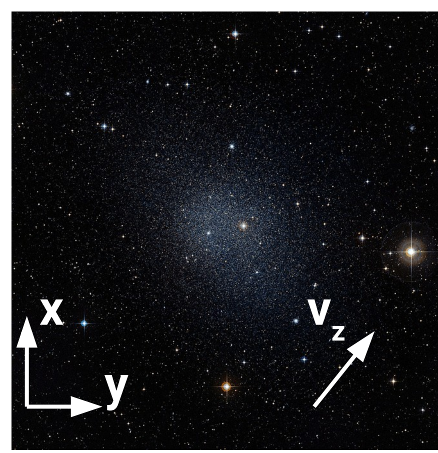
Spatial Incompleteness



Intergalactic Dust



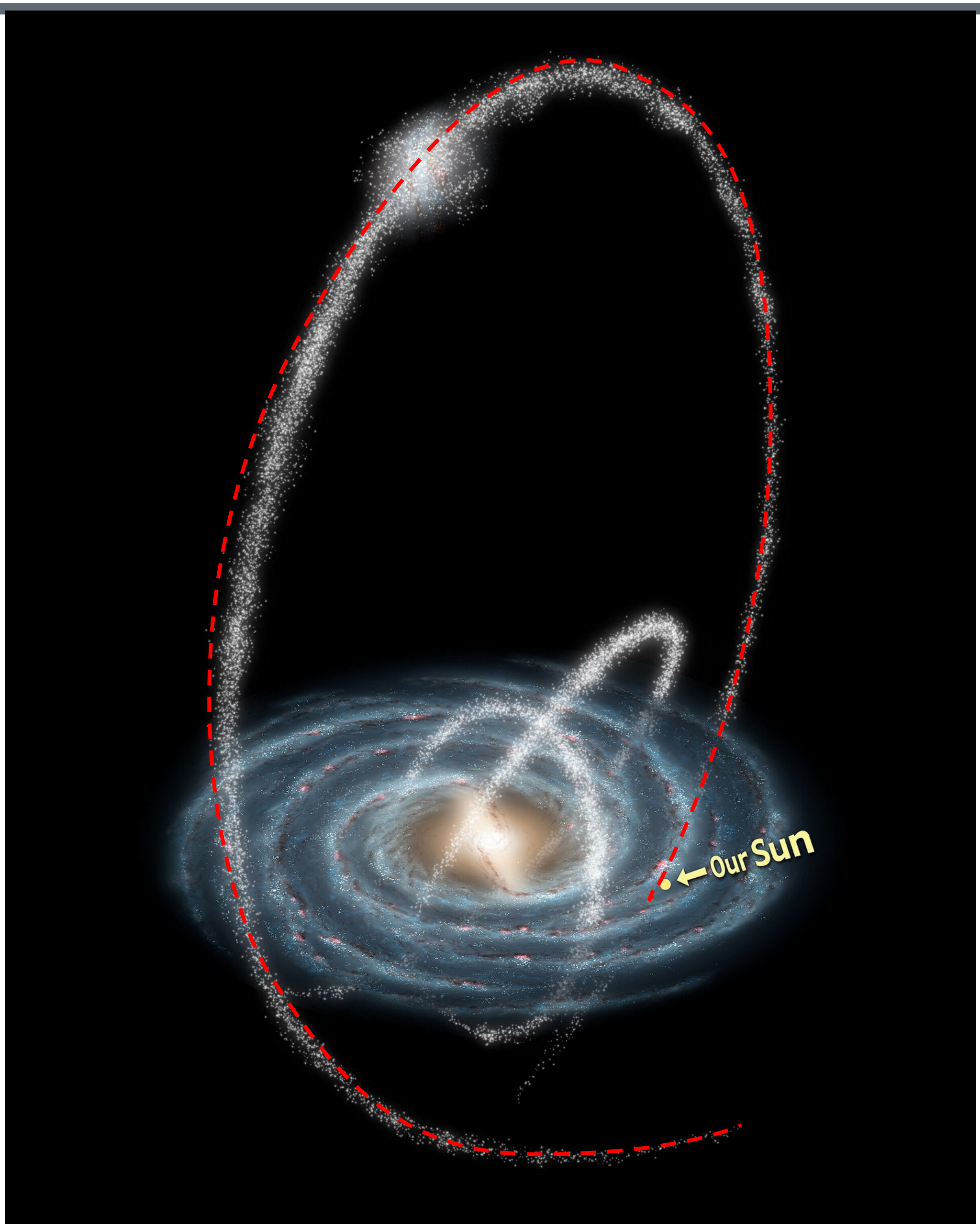
Lack of information



Only 3D info. available, not the full 6D PS info.

More challenges are waiting!

How we infer mass density? → Gravity!



Orbital mechanics

↓

Gravitational Acceleration

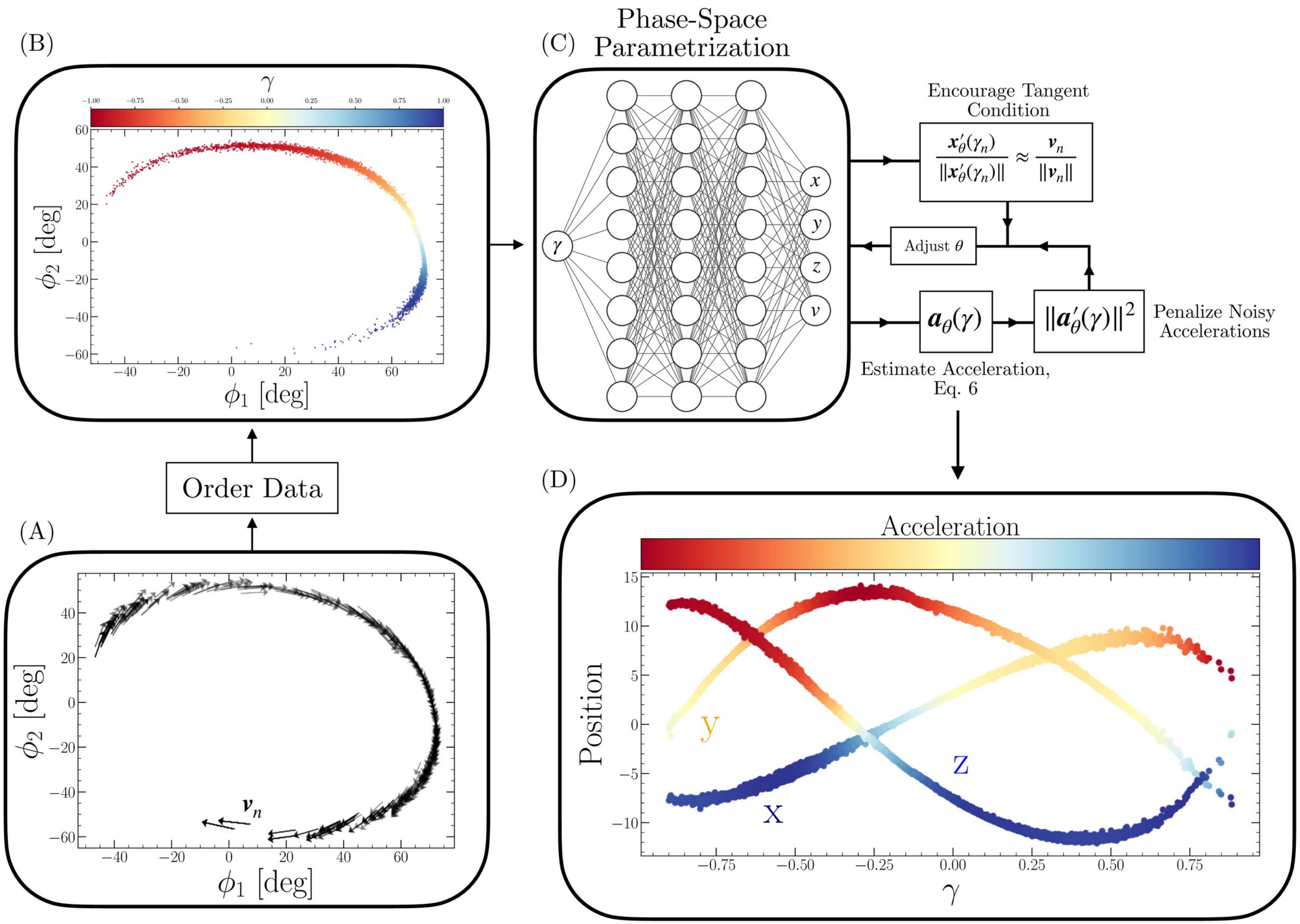
↓

Mass Density

↓

Stellar Streams and Machine Learning

Nibauer, Belokurov, Cranmer, Goodman, Ho, arXiv:2205.11767



Preliminary: Dust Correction

Boltzmann equation also provides us an alternative way of measuring intergalactic dust clouds.

Observed density modeled by Normalizing flows

Selection Efficiency of measuring obscured stars due to **dust clouds**

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

True phase-space density of stars

$$\left[\vec{v} \cdot \frac{\partial}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial}{\partial \vec{v}}\right] f_{\mathrm{true}}(\vec{x}, \vec{v}) = 0, \quad \vec{a} = -\frac{d\Phi(\vec{x})}{d\vec{x}}$$

Preliminary: Dust Correction

Boltzmann equation also provides us an alternative way of measuring intergalactic dust clouds.

Observed density
modeled by
Normalizing flows

Efficiency of measuring
obscured stars
due to **dust clouds**

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

True phase-space
density of stars

Linear equation in
acceleration and **efficiency**
↓
Solvable by MSE minimization!

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

Credit: **Eric Putney** (Rutgers)

Preliminary: Dust Correction

Boltzmann equation also provides us an alternative way of measuring intergalactic dus

$f_{\rm obs}(\vec{x},\vec{v})$

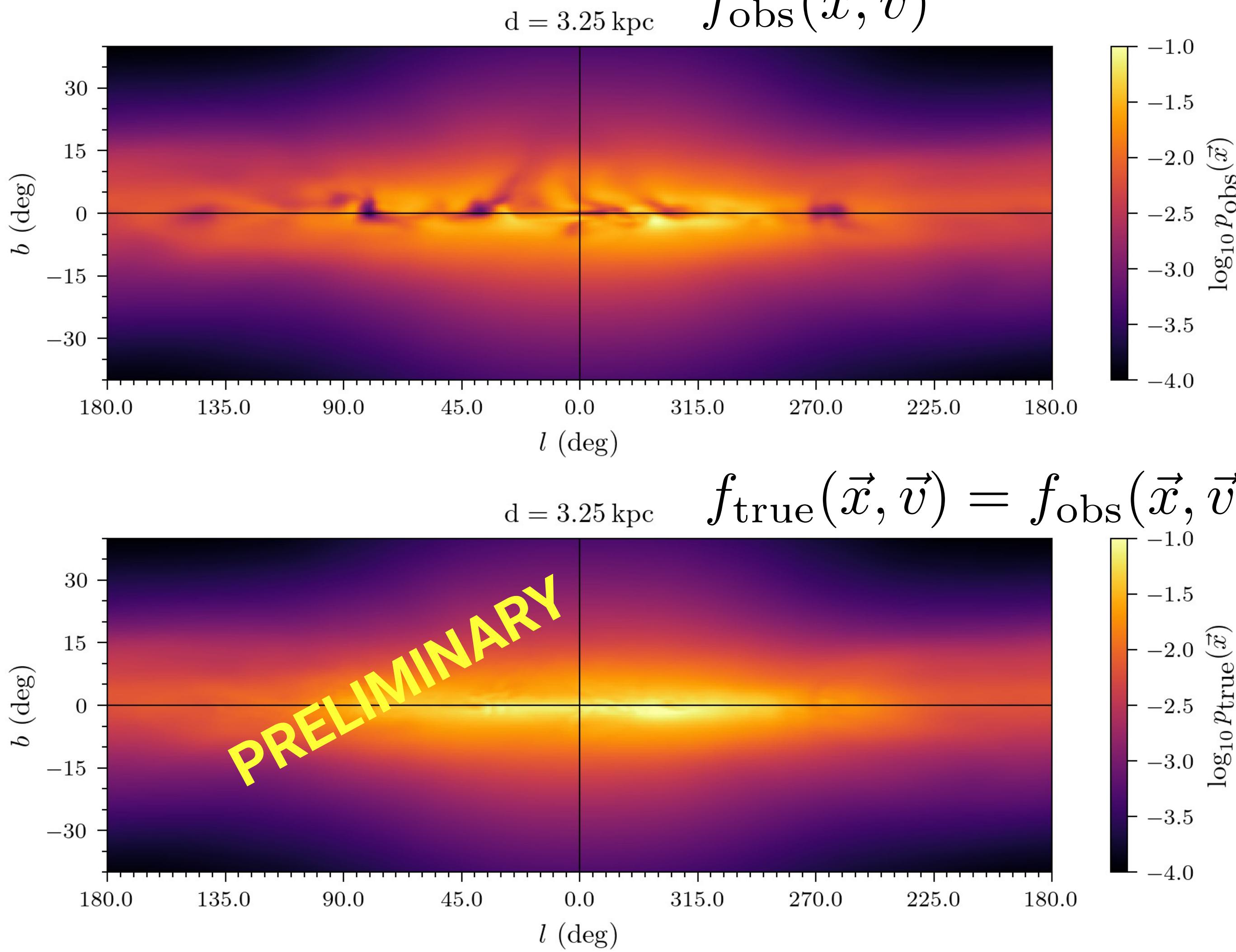
Observed densi
modeled by
Normalizing flov

$f_{\rm obs}(\vec{x},\vec{v}) =$

$f_{\rm true}(\vec{x},\vec{v}) = f_{\rm obs}(\vec{x},\vec{v})/\epsilon(\vec{x})$

True phase-
density of

$\left[\vec{v}\cdot\frac{\partial}{\partial\vec{x}} + \vec{a}\cdot\frac{\partial}{\partial\vec{\imath}}\right.$



Credit: **Eric Putney** (Rutgers)

Magic Dust Eraser

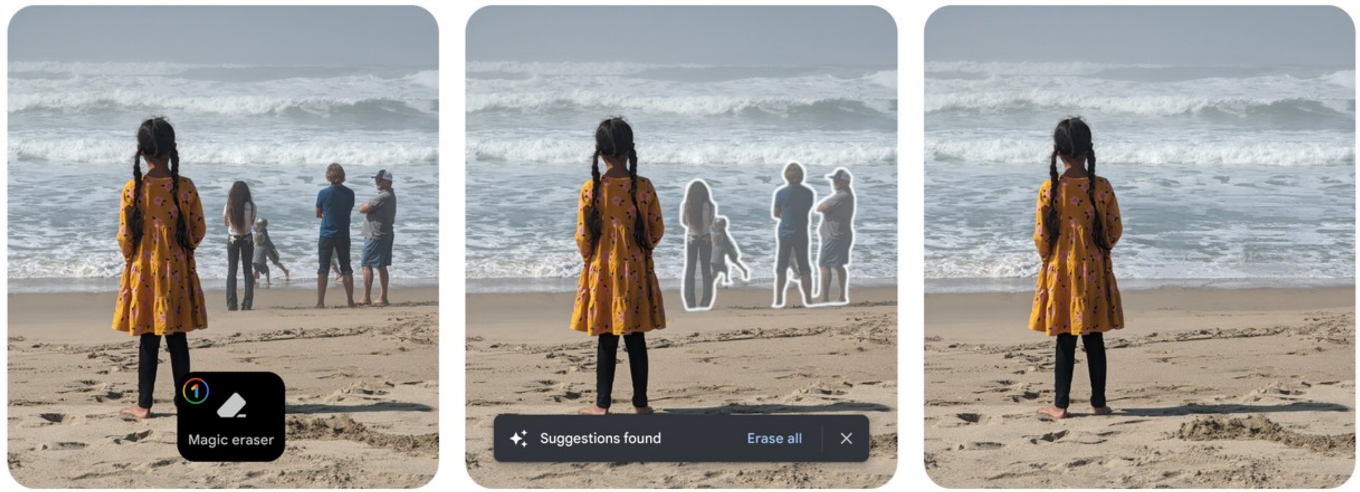
Boltzmann equati
intergalactic dus

Observed densit
modeled by
Normalizing flov

$$f_{\text{obs}}(\vec{x}, \vec{v}) =$$

True phase-
density of

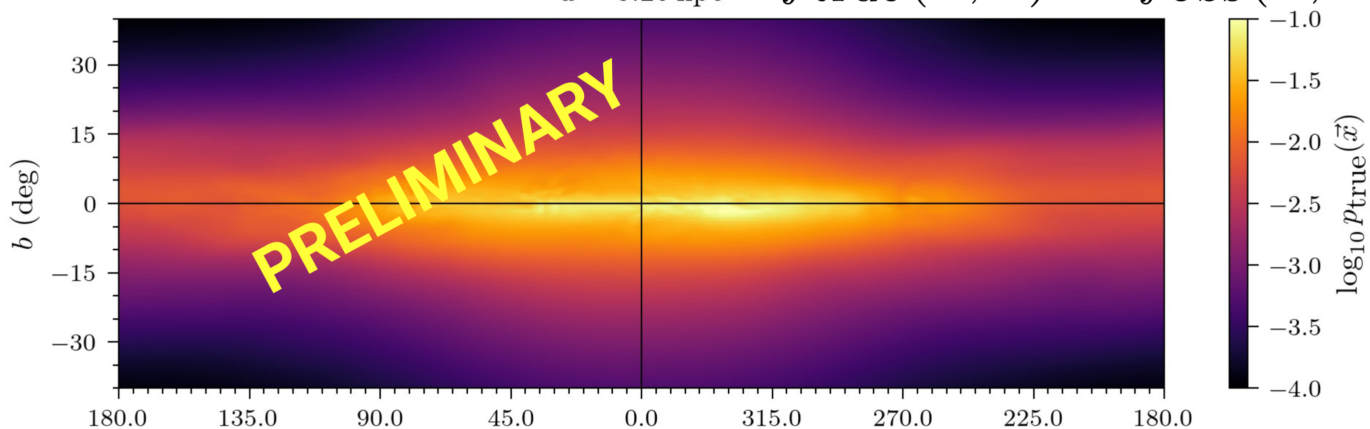
$$\left[\vec{v} \cdot \frac{\partial}{\partial \vec{x}} + \vec{a} \cdot \frac{\partial}{\partial \vec{\imath}}\right.$$



l (deg)

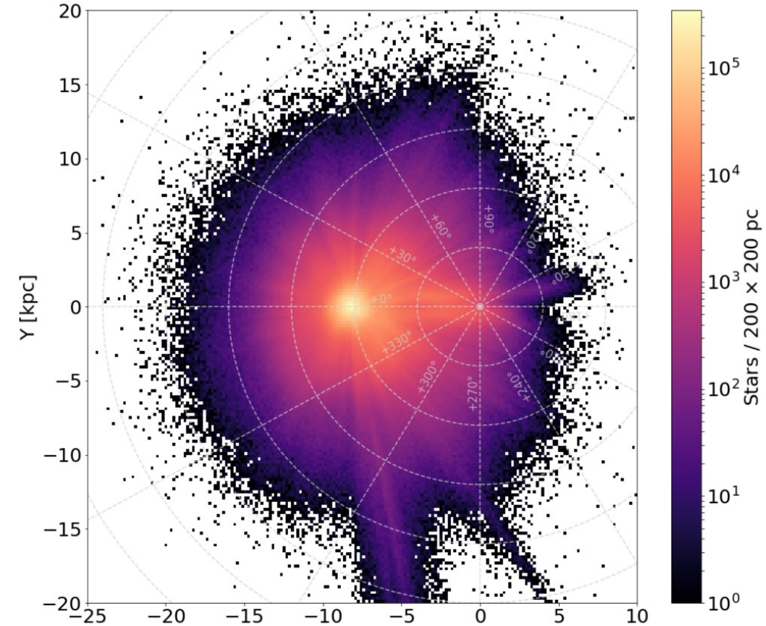
d = 3.25 kpc

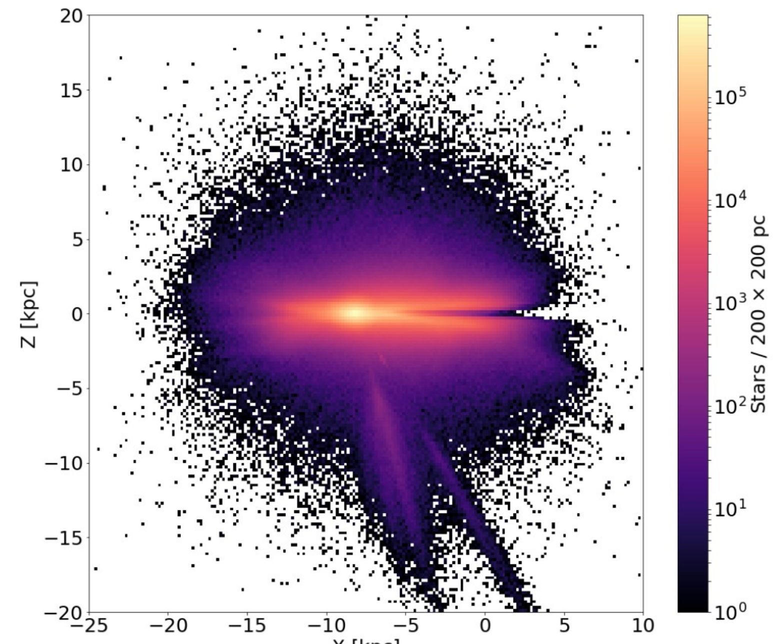
$$f_{\text{true}}(\vec{x}, \vec{v}) = f_{\text{obs}}(\vec{x}, \vec{v})/\epsilon(\vec{x})$$



Work in progress!

Milky Way vs. Distant Galaxy





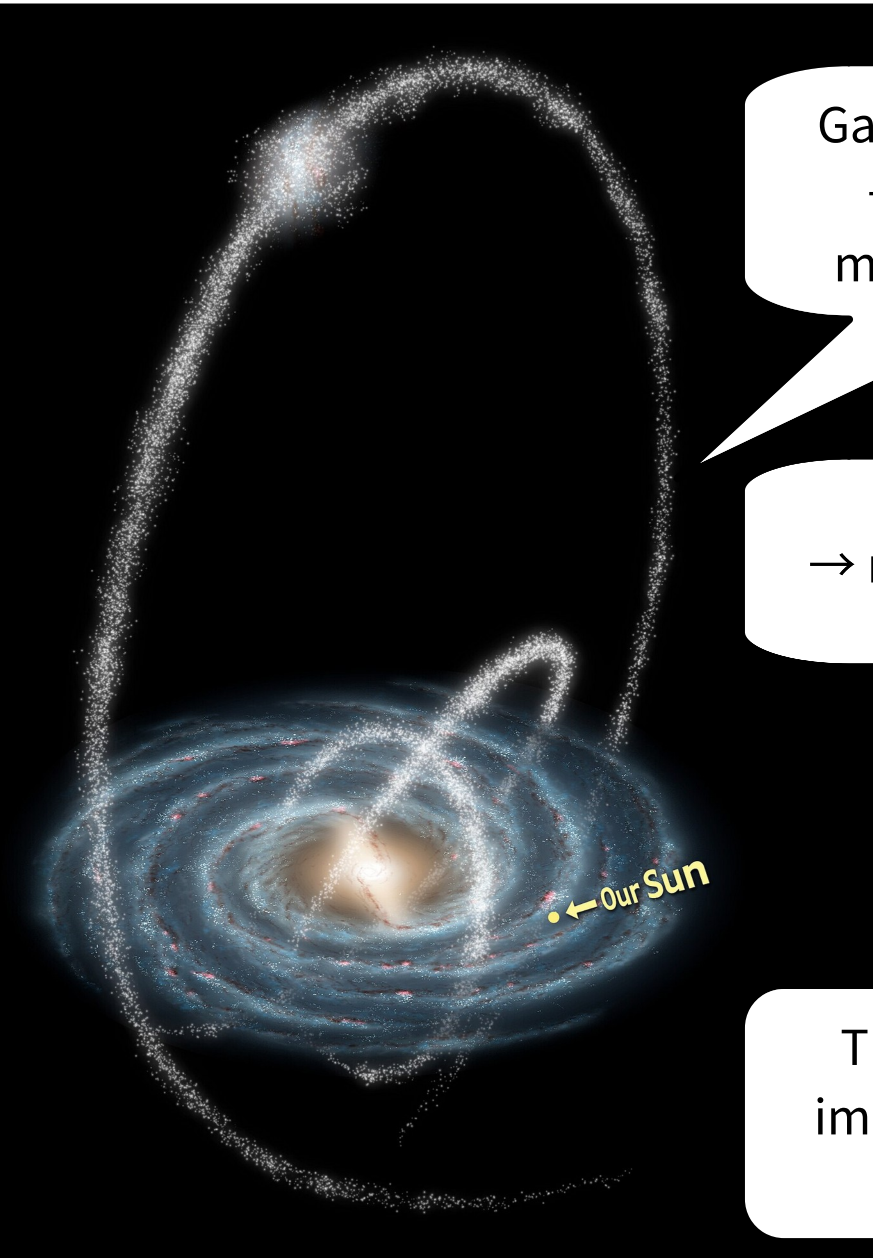
(+) Stars are closer, we can observe full kinematics in high precision.
(-) Stars with full kinematics info. are limited to nearby stars.

Milky Way vs. Distant Galaxy

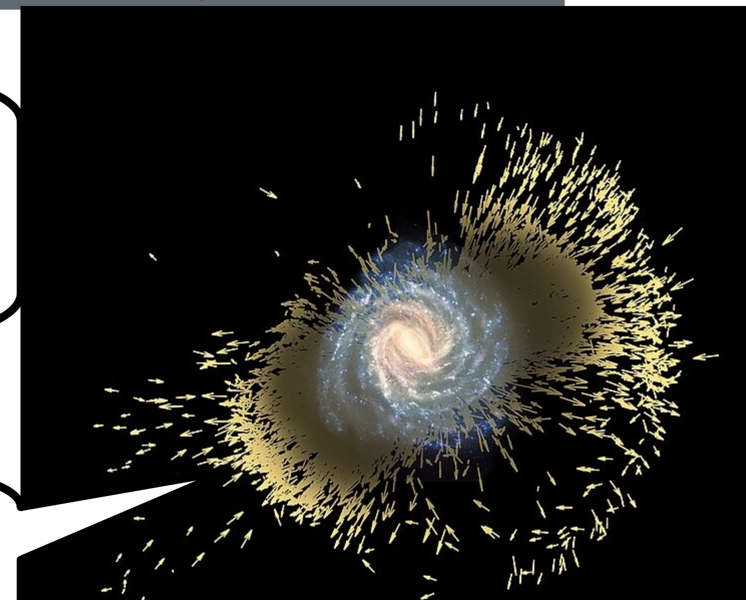
(+) Stars are closer, we can observe full kinematics in high precision.
(-) Stars with full kinematics info. are limited to nearby stars.

(+) Whole galaxy is visible
(-) Only limited kinematic information is available:
- position on the sky
- radial velocity

Example: Stellar Distribution and Merger History of the Milky Way

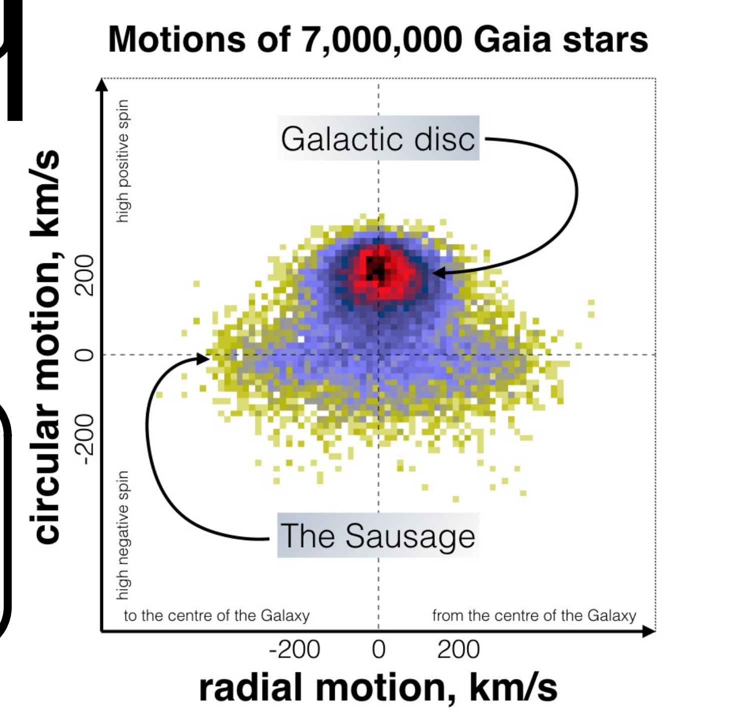


Galactic Tidal Streams
→ tidally stripped
merged dwarf galaxy



Gaia Sausage
→ recent major merger
event?

These substructures
imprint merger history
of the Milky Way!



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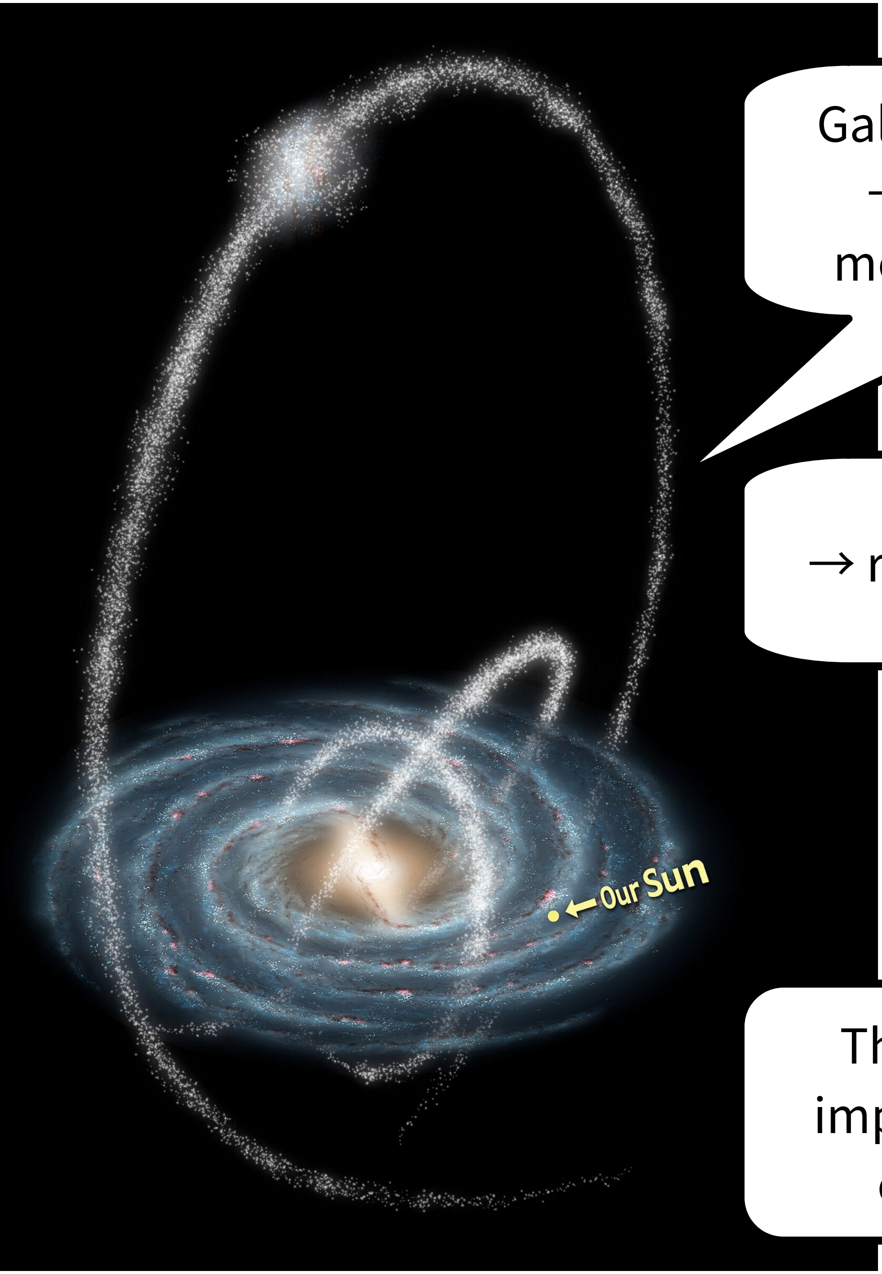

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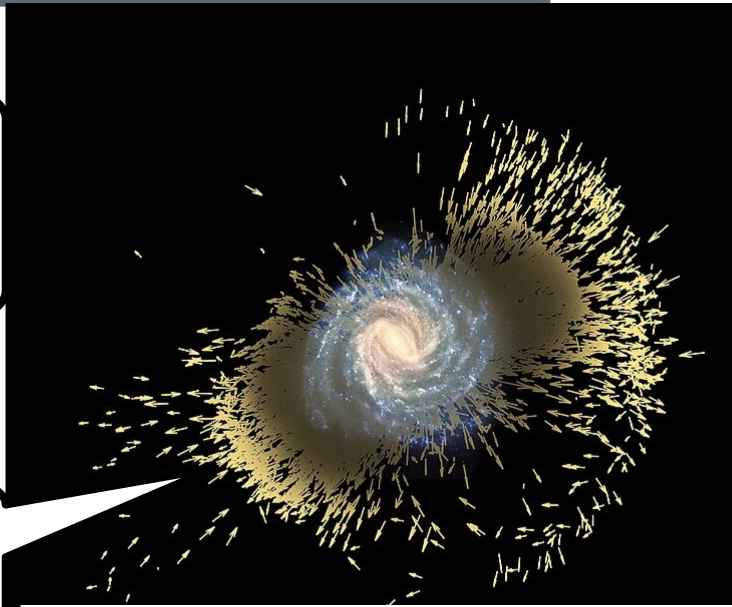

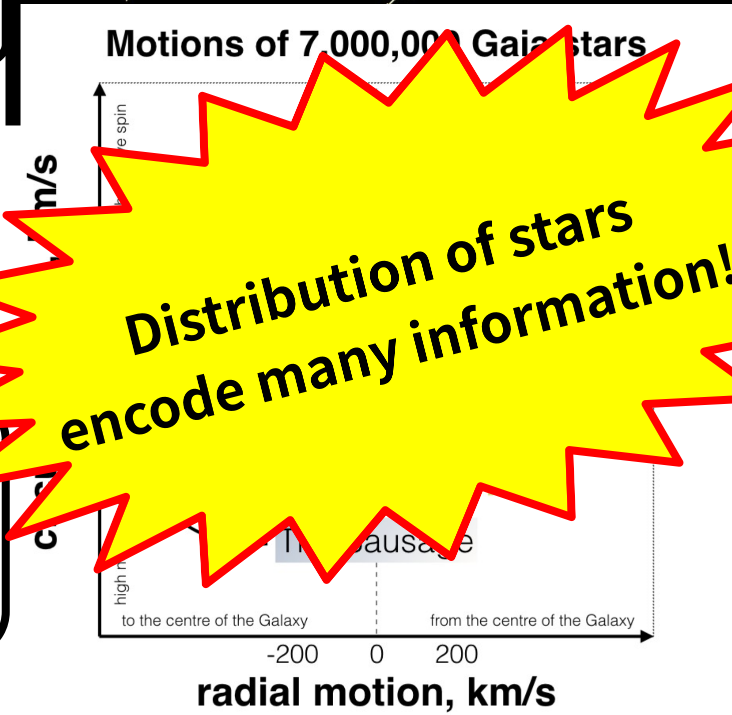

Distribution of stars encode many information!