The Milky Way's dark matter halo:

A Bayesian Estimation of the Milky Way's Circular Velocity Curve using Gaia DR3

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Published in A&A
[arXiv:2309.02895]

Speaker: **Sven Põder**

CERN Baltic Conference 2023

Broader context

- In the absence of direct/indirect DM signal, astrophysical and cosmological probes seem to be the only ways to constrain the particle nature of DM
- The circular velocity curve is a reflection of the **smooth distribution** of DM
- Hierarchical structure formation predicts substructure to the Galactic DM halo and thus a myriad of subhaloes are expected to orbit the Galaxy
    - **The abundance of which is a powerful discriminator between proposed DM models!**
    - In our previous work **[2203.08161]**, we looked at the possible detection of these subhalos in the stellar phase-space and we are currently expanding this analysis

Motivation

DM density measurements are crucial to DM detection experiments

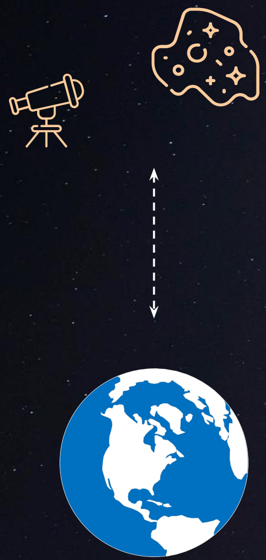
↓

Encourages us to transcend disciplinary boundaries and foster interdisciplinary collaboration - we need to work together!

↓

Our work provides the astro part in the DM detection machinery

Observations



DM experiments

From observables to constraints

Astrophysical observables

We provide this

DM density

Measurements not perfect:
Systematic biases stemming from assumptions in tracer star modelling

Direct searches

Indirect searches

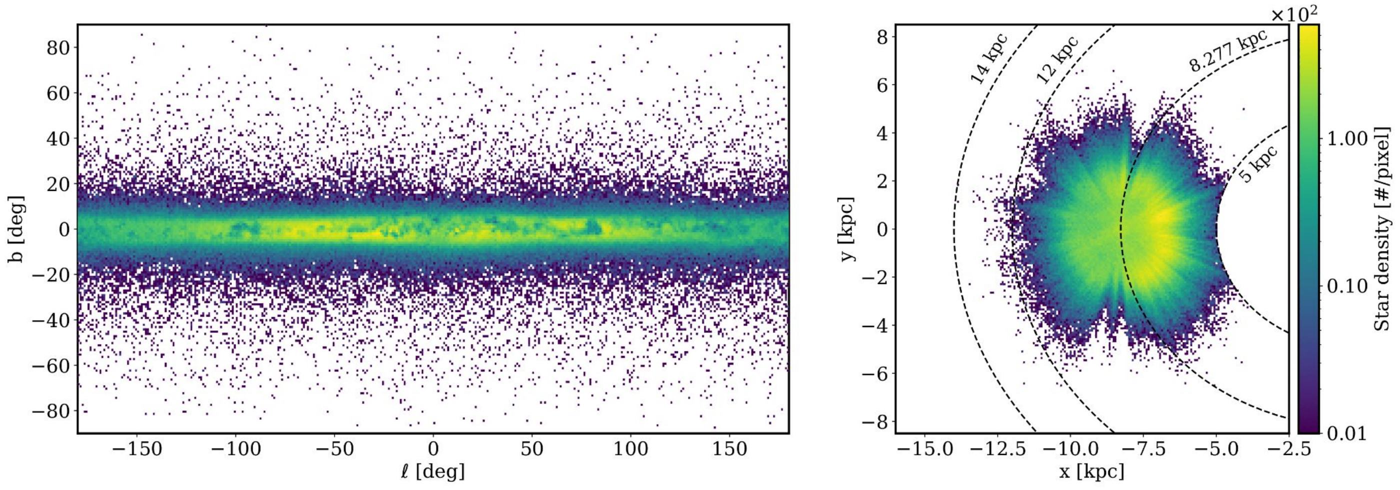
Particle physics constraints

Gaia DR3 & RGB sample

- Gaia DR3 released in 2022: spectroscopic data for 33 M stars
- We started with a sample of almost 6M red giant branch (RGB) stars from Gaia DR3 **[arXiv:2206.06207]**
- Applied various spatial, kinematic and quality cuts, resulting in a sample of 665,660 stars
- RGB stars are old, bright and are less susceptible to perturbations

Credit: NASA/JPL-Caltech

Our sample distribution



Galactic coordinates
(edge-on view)

Cartesian coordinates
(top-down view)

Radial Jeans equation + kinematic model

Assuming that the MW is in a steady-state and has an axisymmetric gravitational potential, we collapse the data along the azimuthal coordinate and bin the data into 8 radial bins as

$$v_c = f(R)$$

In each bin, the rotational velocity is modelled as

$$v_{\phi \mathrm{model}} = v_c - v_a$$

circular velocity — asymmetric drift

Accounts for the diffusion of stars in phase-space

The asymmetric drift component we obtain from the axisymmetric radial Jeans equation

$$v_a = \frac{\sigma_R^{*2}}{v_c + \overline{v_\phi}} \left[\frac{\sigma_\phi^{*2}}{\sigma_R^{*2}} - 1 + R\left(\frac{1}{h_r} + \frac{2}{h_\sigma} \right) \right]$$

Circular velocity fitting

- Usually, circular velocities are computed directly from the Jeans equation
- In our approach, we used an MCMC algorithm to sample the posterior probability of our parameters, e.g.

$$p(\theta|D) \approx p(D|\theta)p(\theta)$$

Such that our model parameters are

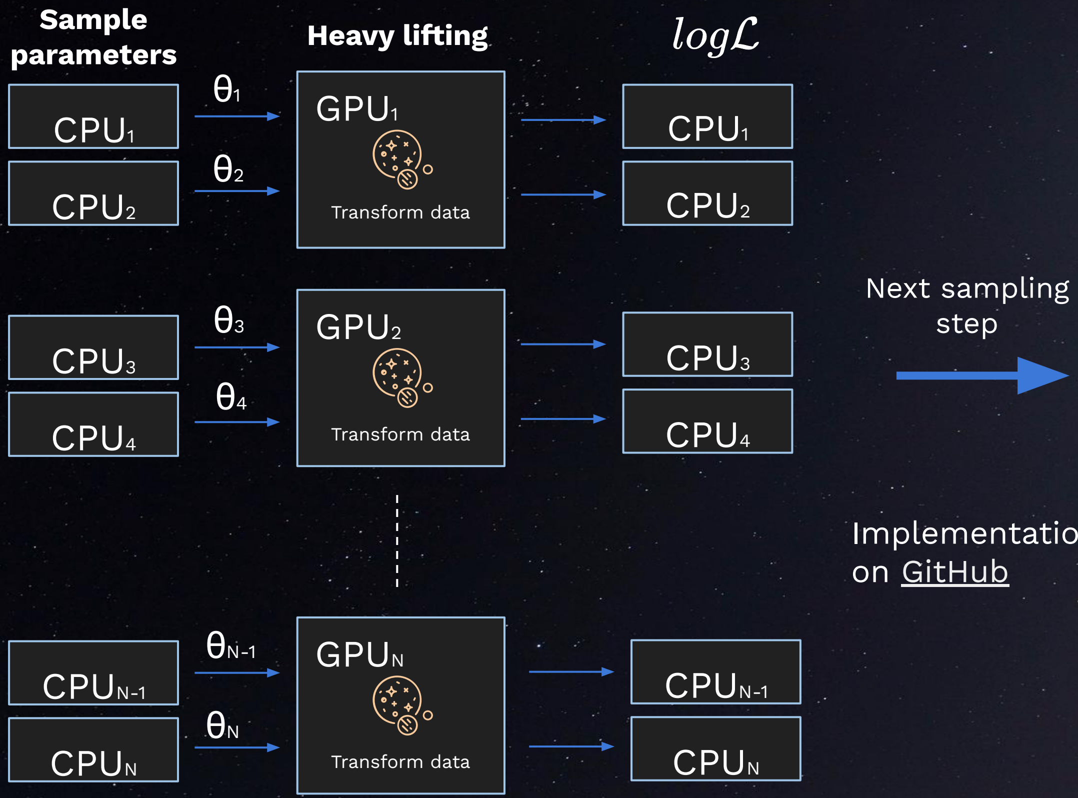
$$\theta = [v_{c,0}\,..\,v_{c,j}, \underbrace{h_R, h_\theta, R_0}_{\text{Nuisance parameters}}]$$

- Nuisance parameters given flat priors where there range encompasses values from the literature

MCMC scheme example

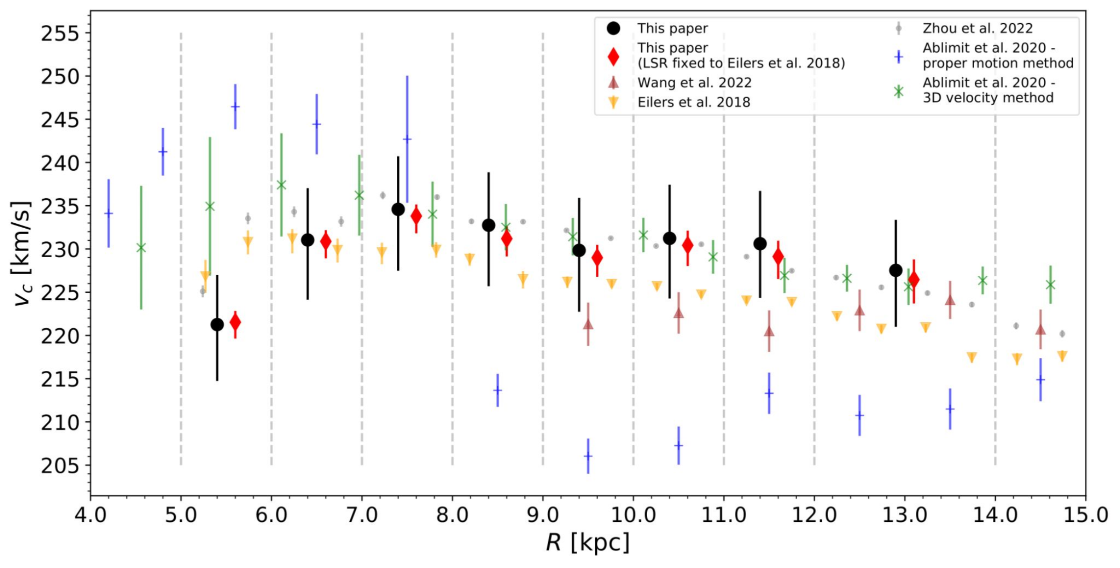
Courtesy of the Nvidia Academic hardware grant

Reusing memory: data loaded to GPUs before running sampler

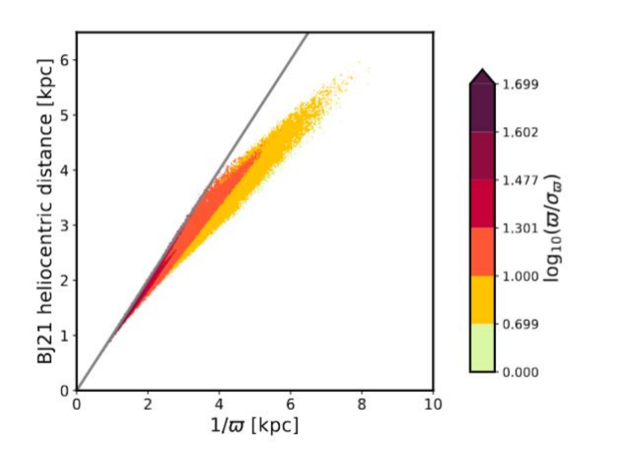


Implementation on GitHub

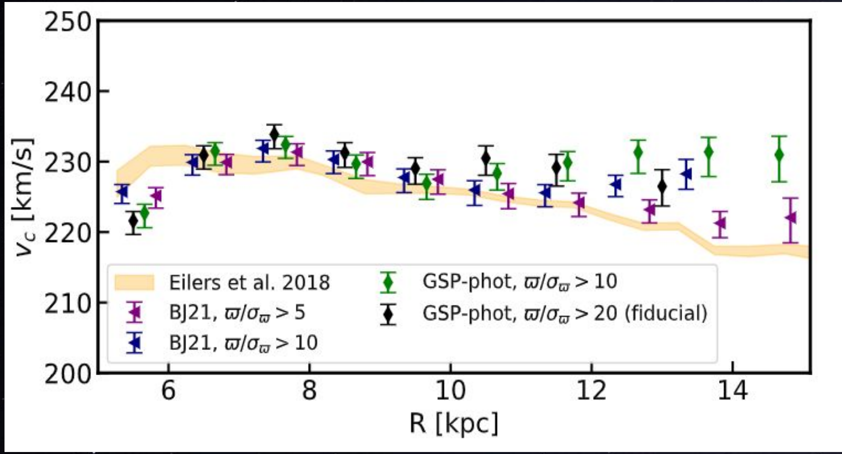
The circular velocity curve



The devil is in the distances



Bias in distance estimates, where the colour bar indicates the mean parallax quality



The circular velocity curve for different distances estimates at a fixed Sun's galactocentric distance

DM density profile estimation

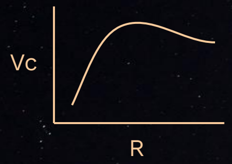
Sample of 600k stars on the Red Giant Branch within 5-14 kpc

Rotational velocity curve

Gaia DR3 data

Jeans equations + kinematic model

Circular velocity curve



(total) dynamical mass + baryons

DM density profile

- Circular velocities used as a tracer for the dynamical mass within 5-14 kpc
- The velocity curve is decomposed in terms of its contributions from visible (known) baryonic components and the DM halo -> observed velocities fitted to predictions
- DM halo assumed to follow generalised Navarro-Frenk-White (NFW) density profile

DM density

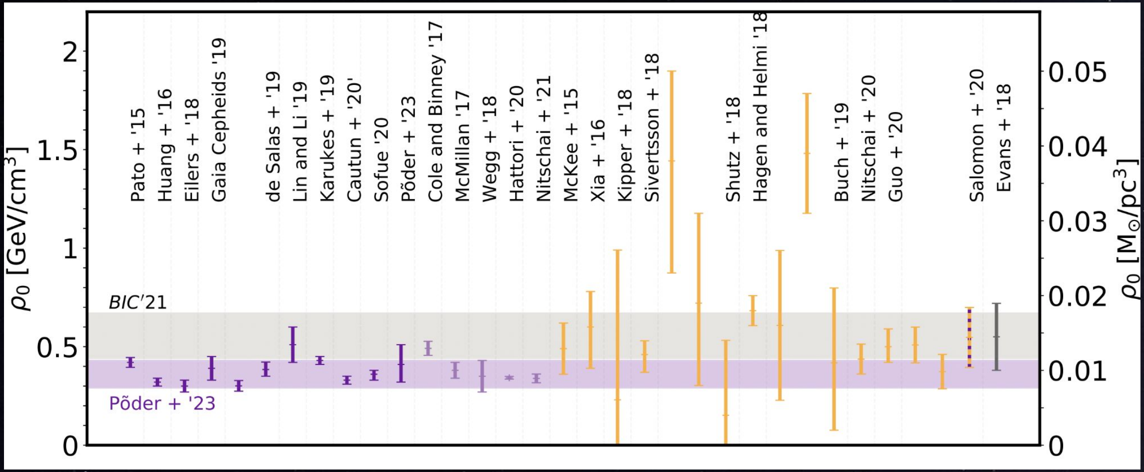
Local (spherically-average) DM density

$$\rho_{\rm DM}(R_0) = (0.41^{+0.10}_{-0.09})\ {\rm GeV/cm^3}$$

DM mass within 15 kpc

$$M_{\rm DM}(R < 14\,{\rm kpc}) = 10^{11.2^{+2.0}_{-2.3}}\,M_\odot$$

New result lower than Benito et al. '21



Source:
Adapted from Benito et al. (2021) [arXiv:2009.13523]

DM subhalos and stellar wakes

We now turn our focus to wakes caused by passing subhalos - stellar wakes

Orbiting subhalo imprints a gravitational signature in the position and velocity of stars

Can we detect these disturbances from the data?

In **[2203.08161]** we studied the detection of phase space disturbances in MW-like galaxy simulations

Subhalos: simulating the environment

We are using PKDGRAV3 to simulate a massive perturber moving through a field of stars

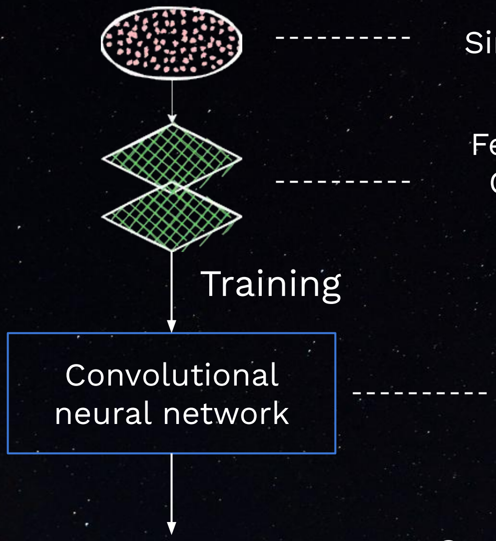
Phase space distribution parameters are chosen to mimic the conditions in the Galactic halo at different Galactocentric distances

What is the minimum subhalo mass that leave a detectable imprint? And how this mass changes with the Galactocentric distance of the subhalo?

Two types of background simulation particles: **stars + DM**

See also Buschman et al 2017, Foote et al 2023

Subhalos: deep learning



Simulation data: 2 x 512^3 particles

Feature histograms (N x N x features): Overdensity, mean velocity, velocity dispersion, divergence

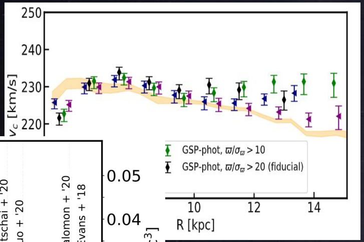
Learns the relevant spatial features in the images

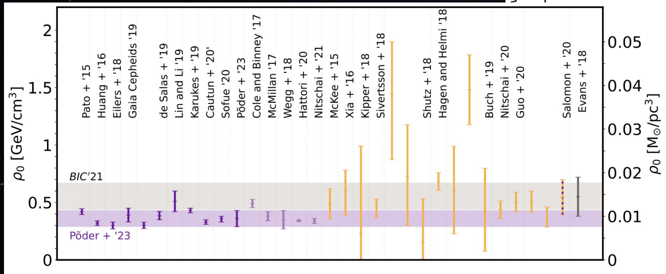
Predict model on unseen data

Our ML approach is two-pronged by seeking to answer:

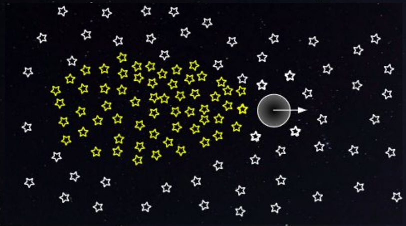
- Is there a subhalo in the image? **(Binary classification)**
- If so, what is the mass of the subhalo? **(Regression)**

Takeaways





1) Smooth dark matter distribution in MW essential for interpreting results from particle DM searches

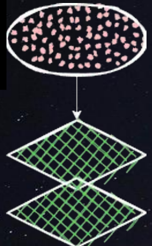


2) Stellar wakes are dynamical effects produced by dark subhalos - Their detection can be key to understanding particle properties of dark matter

3) The exploration of humongous datasets is made easier/possible by modern advances in computer hardware and software: e.g. GPU computing and machine/deep learning analyses

NVIDIA

PKDGRAV3



Convolutional neural network

Thank you!

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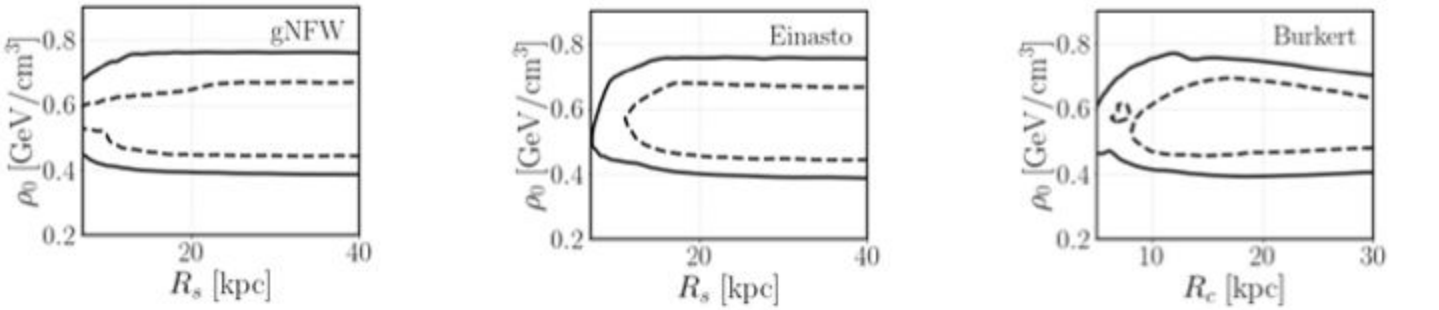
- Not enough precision to distinguish between DM density profiles

[1901.02460] / [2009.13523]



$$\rho_0 = 0.44 - 0.67\,\mathrm{GeVcm^{-3}}(1\sigma) \quad = 0.39 - 0.76\,\mathrm{GeVcm^{-3}}(2\sigma)$$

$$\rho_0 = 0.44 - 0.68\,\mathrm{GeVcm^{-3}}(1\sigma) \quad = 0.39 - 0.76\,\mathrm{GeVcm^{-3}}(2\sigma)$$

$$\rho_0 = 0.46 - 0.69\,\mathrm{GeVcm^{-3}}(1\sigma) \quad = 0.39 - 0.77\,\mathrm{GeVcm^{-3}}(2\sigma)$$

The analysis in a nutshell

Sample of 600k stars on the Red Giant Branch within 5-14 kpc

Gaia DR3 data

Jeans equations + kinematic model

Circular velocity curve

(total) dynamical mass + baryons

DM density profile

Uncertainties included in our error bars:

Statistical ← Negligible due to large sample

\+

Spatial-kinematic morphology of tracer sample

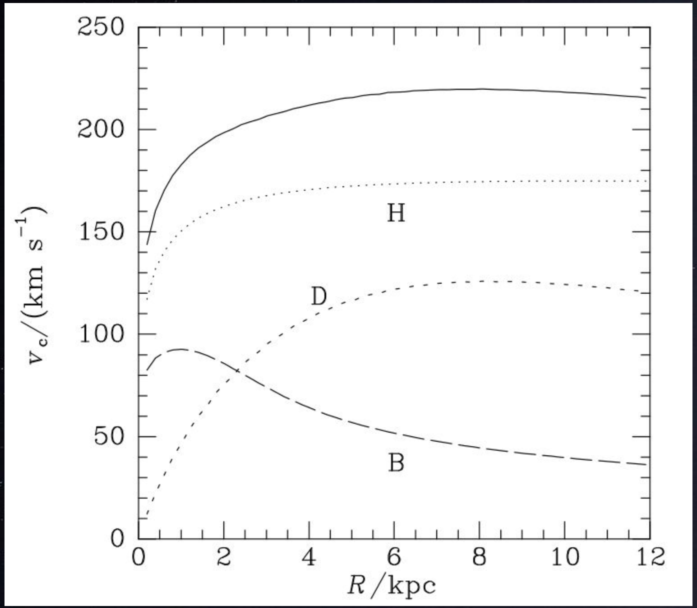
\+

Sun's galactocentric distance

} Systematics - 3%

About circular velocities

- The circular velocity is the velocity a star exhibits in a perfectly axisymmetric gravitational potential
- Measured at various Galactocentric distances (R), the resulting circular velocity curve encodes valuable information about the Galactic gravitational potential and thus the mass distribution within the Galaxy
- By accounting for the contribution of visible baryonic matter, the circular velocity curve is useful tool for estimating the DM density profile of the Galaxy



Credit: Binney & Tremaine (2007)