Mapping the structure and kinematics of the Milky Way using the entire Gaia catalogue

Eugene Vasiliev

University of Surrey

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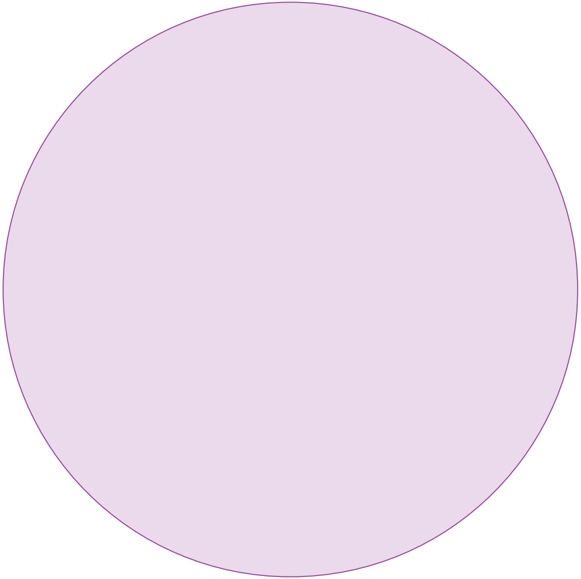
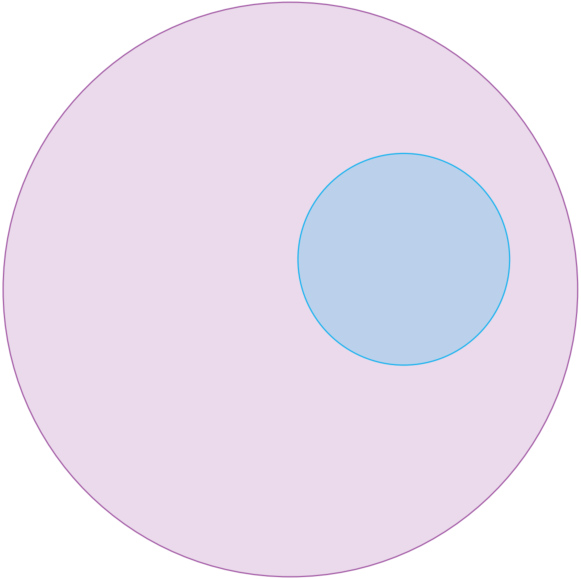
Murnau am Staffelsee
[Gabriele Münter]

The Gaia world



Gaia 5d astrometric catalogue: 1.5×10^9

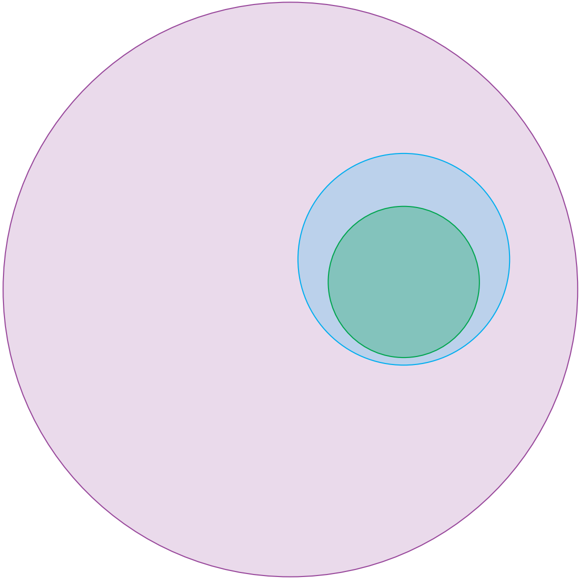
The Gaia world



Gaia 5d astrometric catalogue: 1.5×10^9

$\varpi/\epsilon_\varpi > 5$: 2×10^8

The Gaia world

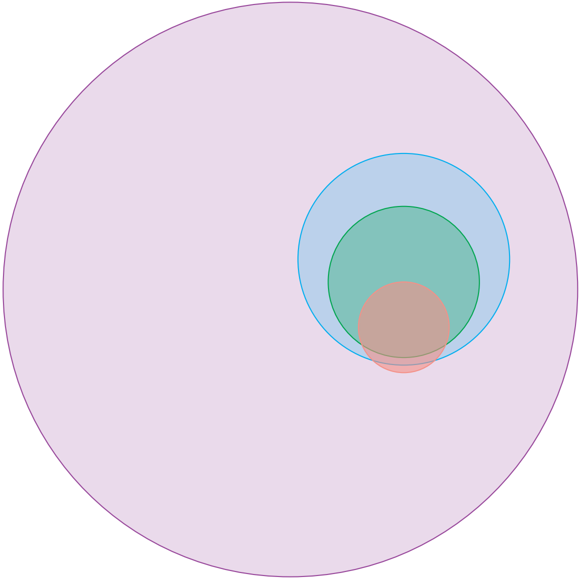


Gaia 5d astrometric catalogue: 1.5×10^9

$\varpi/\epsilon_\varpi > 5$: 2×10^8

$\varpi/\epsilon_\varpi > 10$: 1×10^8

The Gaia world



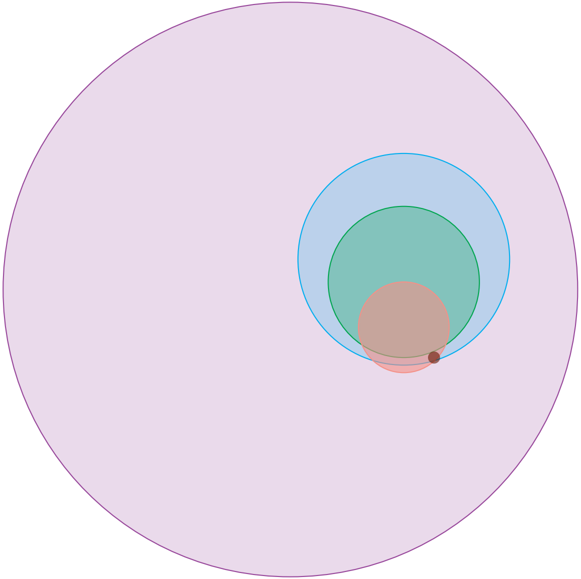
Gaia 5d astrometric catalogue: 1.5×10^9

$\varpi/\epsilon_\varpi > 5$: 2×10^8

$\varpi/\epsilon_\varpi > 10$: 1×10^8

Gaia RVS sample: 3×10^7

The Gaia world



Gaia 5d astrometric catalogue: 1.5×10^9

$\varpi/\epsilon_\varpi > 5$: 2×10^8

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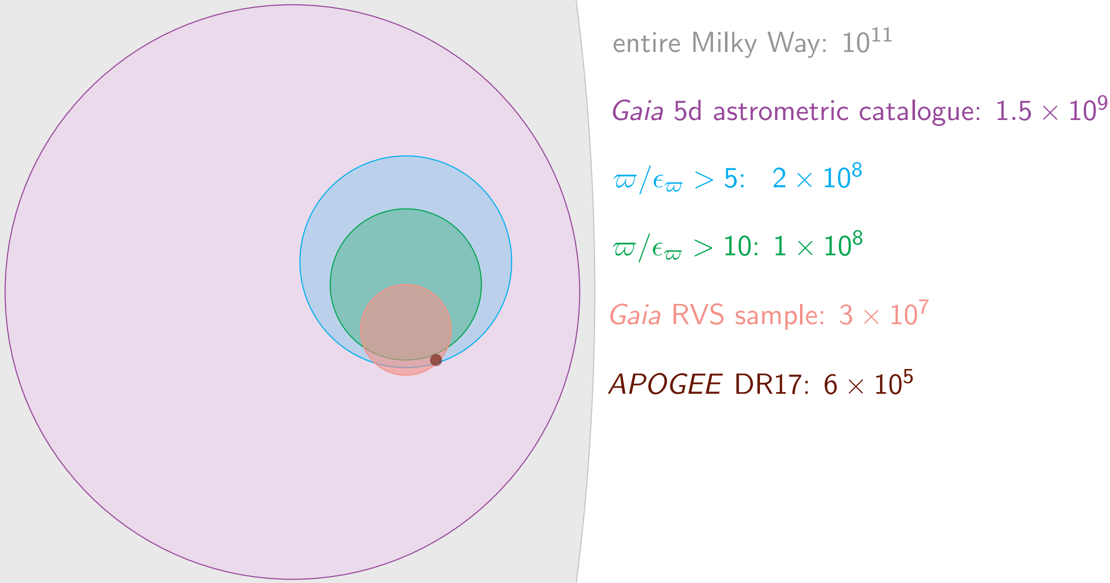
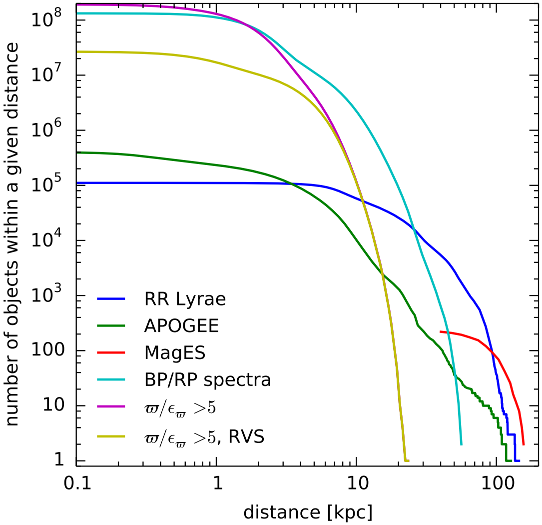
Gaia RVS sample: 3×10^7

APOGEE DR17: 6×10^5

The Gaia world



Distance distribution of various catalogues



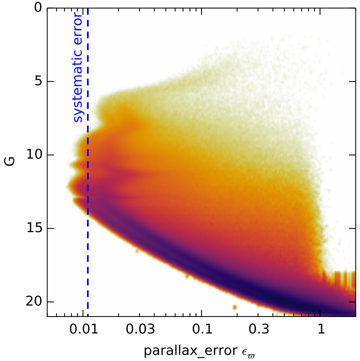
[Clementini+ 2023; Li+ 2023]
[Abdurro'uf+ 2022; Queiroz+ 2023]
[Chandra+ 2024]
[Zhang+ 2023]

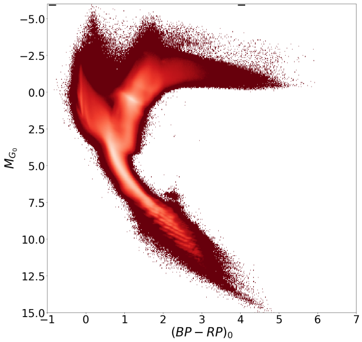
Astro-photometric distance measurements

- untitled [Bailer-Jones+ 2018, 2021]
- StarHorse [Queiroz+ 2018, 2020, Anders+ 2019, 2022]
- GSP-Phot [Andrae+ 2023]
- etc...

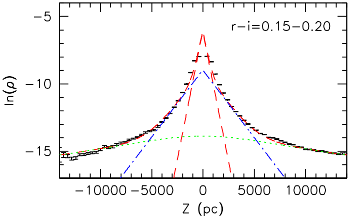
$$\mathcal{P}(D) \propto \mathcal{P}\big(D \mid \varpi, \epsilon_\varpi\big) \times \mathcal{P}\big(D \mid G, G_{\text{BP-RP}}\big) \times \mathcal{P}\big(D \mid \rho(\mathbf{x})\big)$$

usually kept fixed!





[Anders+ 2019]



[Jurić+ 2008]

Measuring the density profile

Optimizing a model for $\rho(\mathbf{x})$ can be part of the inference procedure:

$$\ln \mathcal{L} = \sum_{i=1}^{N_{\text{stars}}} \ln \int \mathrm{d}D \, \rho\big(\mathbf{x}(D);\ \mathbf{p}\big) \ \times\ \mathcal{P}\big(D \mid \varpi_i, \epsilon_{\varpi,i}\big) \ \times\ \mathcal{P}\big(D \mid G_i, G_i^{\text{BP-RP}}\big),$$

where $\mathbf{p}$ are parameters of the density model.

Even if the distances to individual stars are not precisely measured, the distance distribution of the entire catalogue can be recovered.

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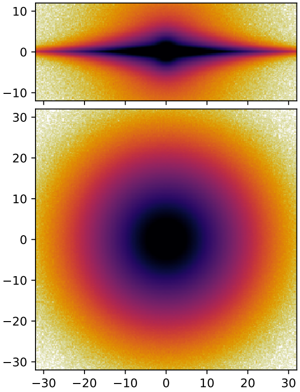
$\rho(\mathbf{x}) = \rho^\mathrm{true}(\mathbf{x}) \times \mathcal{S}(\mathbf{x}, G, G^\mathrm{BP\text{-}RP}, \dots)$ is the observed density of tracers;
$\mathcal{S}(\dots)$ is the selection function of the catalogue – assumed to be known (!)

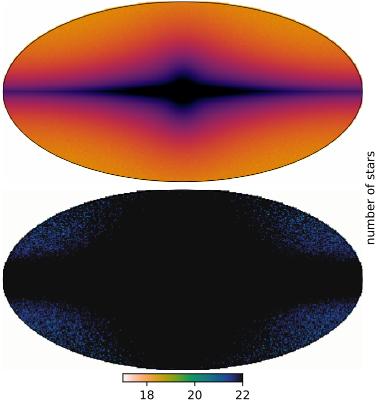
see e.g. `https://gaia-unlimited.org` for the SF of various subsets of Gaia.

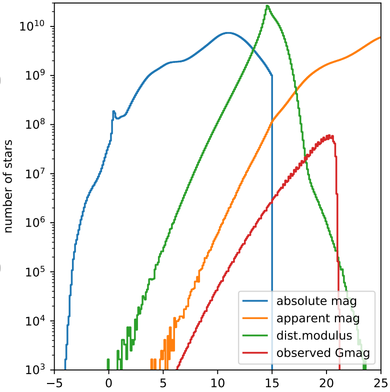
Effect of spatial selection function

Entire Milky Way

density of stars





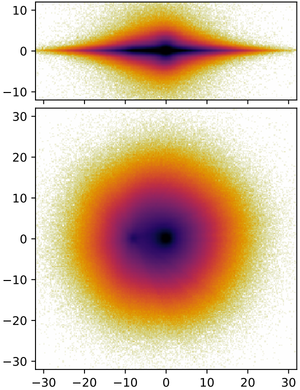


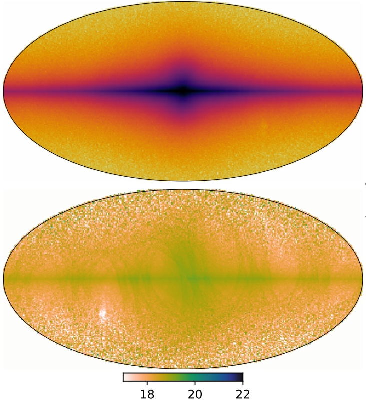
mean apparent magnitude

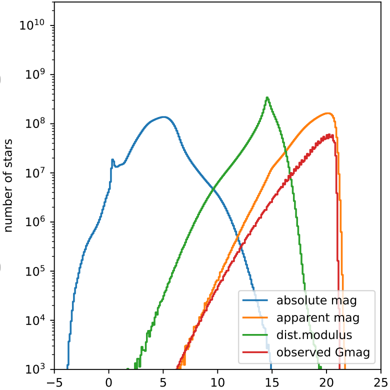
Effect of spatial selection function

Accounting for Gaia magnitude limit and scanning law

density of stars





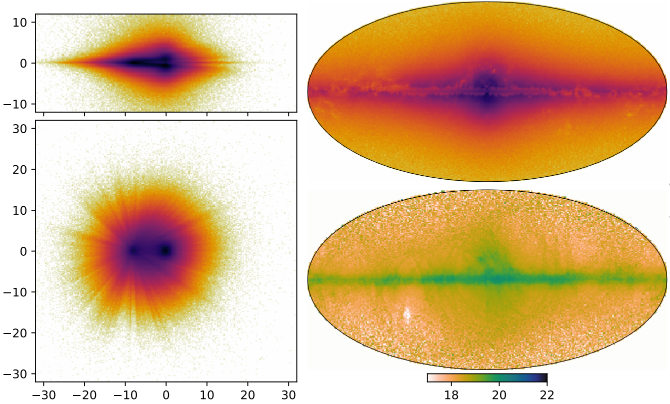


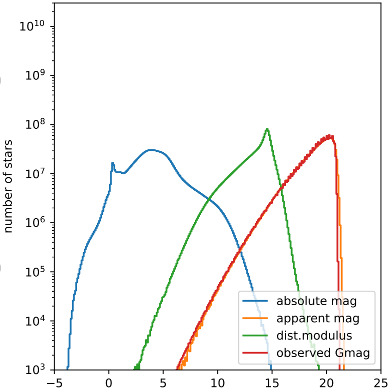
mean apparent magnitude

Effect of spatial selection function

Accounting for Gaia magnitude limit, scanning law and dust extinction

density of stars

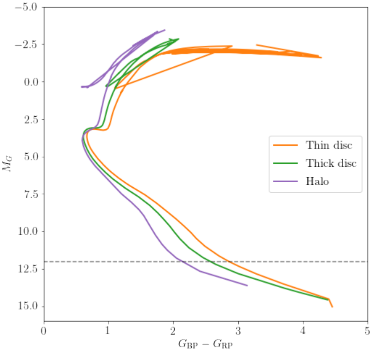


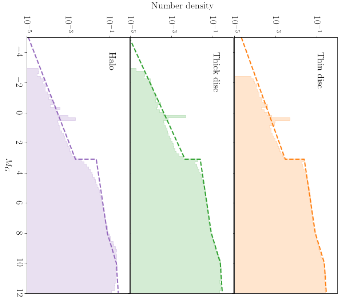


mean apparent magnitude

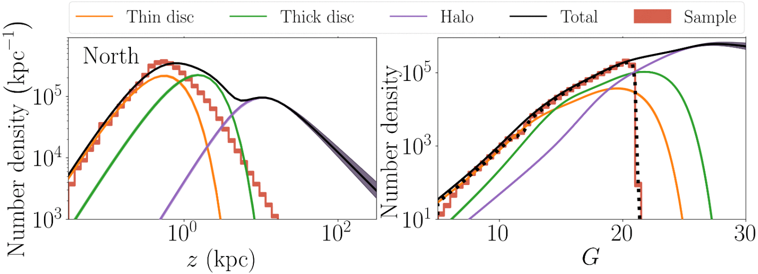
Measuring the density profile using Gaia

In a recent study Everall+ 2022a,b considered just the two narrow cone around Galactic poles, which is nearly dust-free, and made a number of further simplifications regarding the distribution of stars in absolute magnitudes. Then the observed distribution of parallaxes and apparent magnitudes was used to measure the vertical density profile $\rho(R_\odot, z)$.



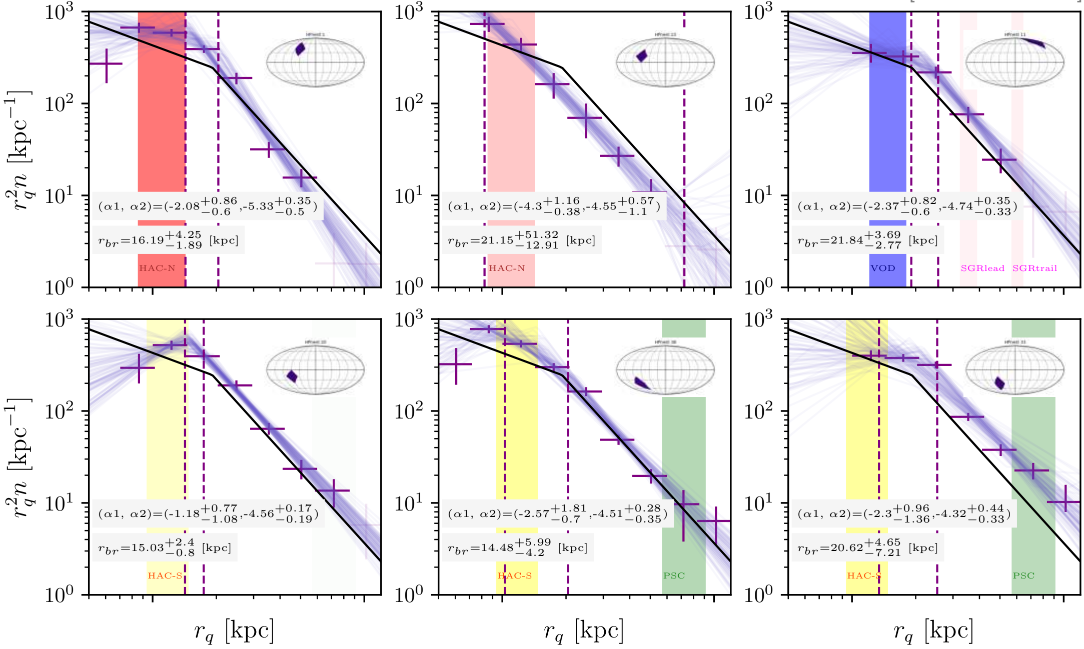


Ideally one needs to perform this fit in a larger volume, using colours and proper motion information to distinguish nearby dwarfs from distant giants.



Measuring the density profile using DECam legacy surveys

[Amarante+ 2024]



Adding kinematic information

If a star has small PM, it is more likely to be at large distance...

$$\begin{aligned}\ln \mathcal{L} &= \sum_{i=1}^{N_{\text{stars}}} \ln \int \mathrm{d}D \\ &\quad \times \rho^{\text{true}}\big(\mathbf{x}(D);\ \mathbf{p}\big) \\ &\quad \times \mathcal{S}\big(\mathbf{x}, G_i, G_i^{\text{BP-RP}}\big) \\ &\quad \times \mathcal{P}\big(D \mid \varpi_i, \epsilon_{\varpi,i}\big) \\ &\quad \times \mathcal{P}\big(D \mid G_i, G_i^{\text{BP-RP}}\big) \\ &\quad \times \mathcal{P}\big(\boldsymbol{\mu} \mid \boldsymbol{\mu}_i, \epsilon_{\mu,i}\big)\end{aligned}$$

e.g., $\mathcal{N}\left(\boldsymbol{\mu}_i \,\middle|\, \left[\frac{\sigma\big(\mathbf{x}(D);\ \mathbf{p}\big)}{D}\right]^2 + \epsilon_{\mu,i}^2\right)$

[Rehemtulla+ 2022] – proof of concept for RR Lyrae ; [Bailer-Jones 2023] – kinegeometric distances

Adding kinematic information

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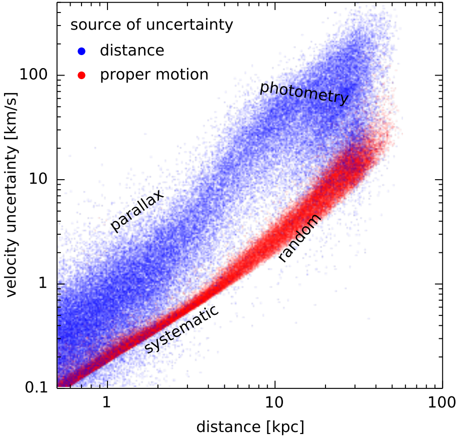
$$\ln \mathcal{L} = \sum_{i=1}^{N_\text{stars}} \ln \int \mathrm{d}D$$
$$\times\ \rho^\text{true}\big(\mathbf{x}(D);\ \mathbf{p}\big)$$
$$\times\ \mathcal{S}\big(\mathbf{x},\, G_i,\, G_i^\text{BP-RP}\big)$$
$$\times\ \mathcal{P}\big(D \mid \varpi_i, \epsilon_{\varpi,i}\big)$$
$$\times\ \mathcal{P}\big(D \mid G_i,\, G_i^\text{BP-RP}\big)$$
$$\times\ \mathcal{P}\big(\boldsymbol{\mu} \mid \boldsymbol{\mu}_i, \epsilon_{\mu,i}\big)$$

$$\text{e.g., } \mathcal{N}\left(\boldsymbol{\mu}_i \,\middle|\, \left[\frac{\sigma\big(\mathbf{x}(D);\ \mathbf{p}\big)}{D}\right]^2 + \epsilon^2_{\mu,i}\right)$$

[Rehemtulla+ 2022] – proof of concept for RR Lyrae

side note: velocity uncertainty is dominated by distance rather than PM error



catalogue of distances from BP/RP spectra [Zhang+ 2023]

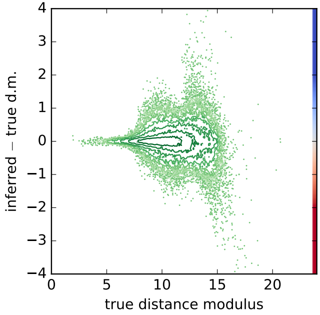
Putting it all together: the ultimate data-mining exercise

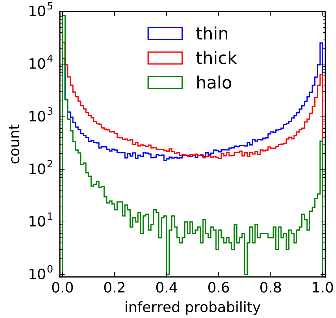
- use as large dataset as possible (entire GAIA 5d astrometric catalogue + all complementary photometric and spectroscopic surveys).
- assume some functional form (e.g., splines) for the spatial and kinematic profiles of several Galactic components (discs, stellar halo): $\rho(\mathbf{x})$, $\overline{\mathbf{v}}(\mathbf{x})$, $\sigma_{ij}(\mathbf{x})$.
- fit the parameters of these profiles, marginalising over the distances to individual stars, *separately for many sightlines* (e.g., HEALpix).
- to enforce continuity between adjacent sightlines while preserving spatial resolution, rely on some sort of interpolation (e.g., spherical harmonics).
- at this stage, no dynamical prior is imposed – this is a purely empirical model of the Galactic structure and kinematics.

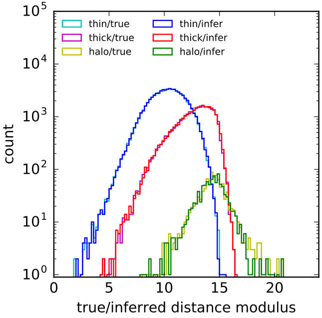
Pilot run on mock data

- 10^5 stars drawn from a mixture of three components (thin & thick discs and halo).
- use photometry (CMD), parallax and PM as input data.
- fit scale radii & heights for both discs, density slope for the halo, and $\overline{v}_\phi$, σ for all components.
- membership and distances to individual stars are not strongly constrained, but the parameters of the populations are well recovered.
- need to test on more realistic mocks!

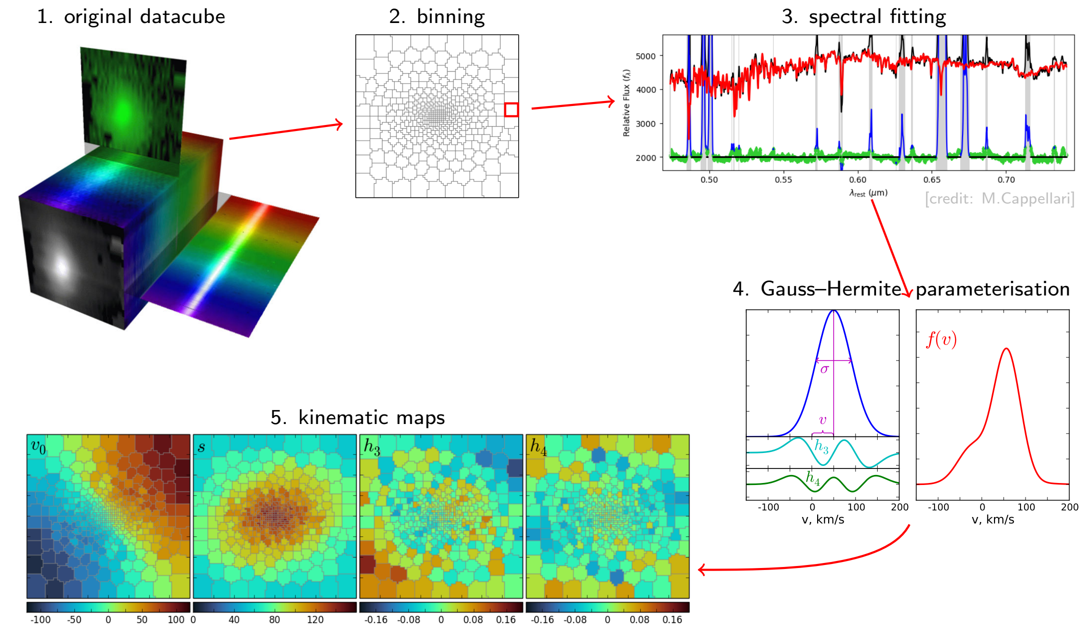
inferred class \ true class	thin	thick	halo	total
thin	63431	5630	5	69066
thick	5561	24054	349	29964
halo	8	316	646	970
total	69000	30000	1000	100000







Extragalactic analogy: analysis of IFU datacubes



Overall context and next steps

- fitting full-scale dynamical models directly to the GAIA data (e.g., [Nitschai+ 2020, 2021; Robin+ 2022; Binney & Vasiliev 2023, 2024]) is expensive and usually relies on high-quality 6d subsamples (although see [McMillan & Binney 2013; Bovy & Rix 2013; Trick+ 2016] for the formalism of fitting incomplete datasets and [Hattori+ 2022; Li & Binney 2022] for the application to the 5d catalogue of RR Lyrae).
- by reducing the entire catalogue to an empirical data-driven model with $\mathcal{O}(10^4)$ *physically interpretable* parameters, one can take care of selection function and error deconvolution *relatively cheaply*.
- this "intermediate representation" could serve as input for proper dynamical models (e.g., Schwarzschild-type), even allowing for disequilibrium effects.

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