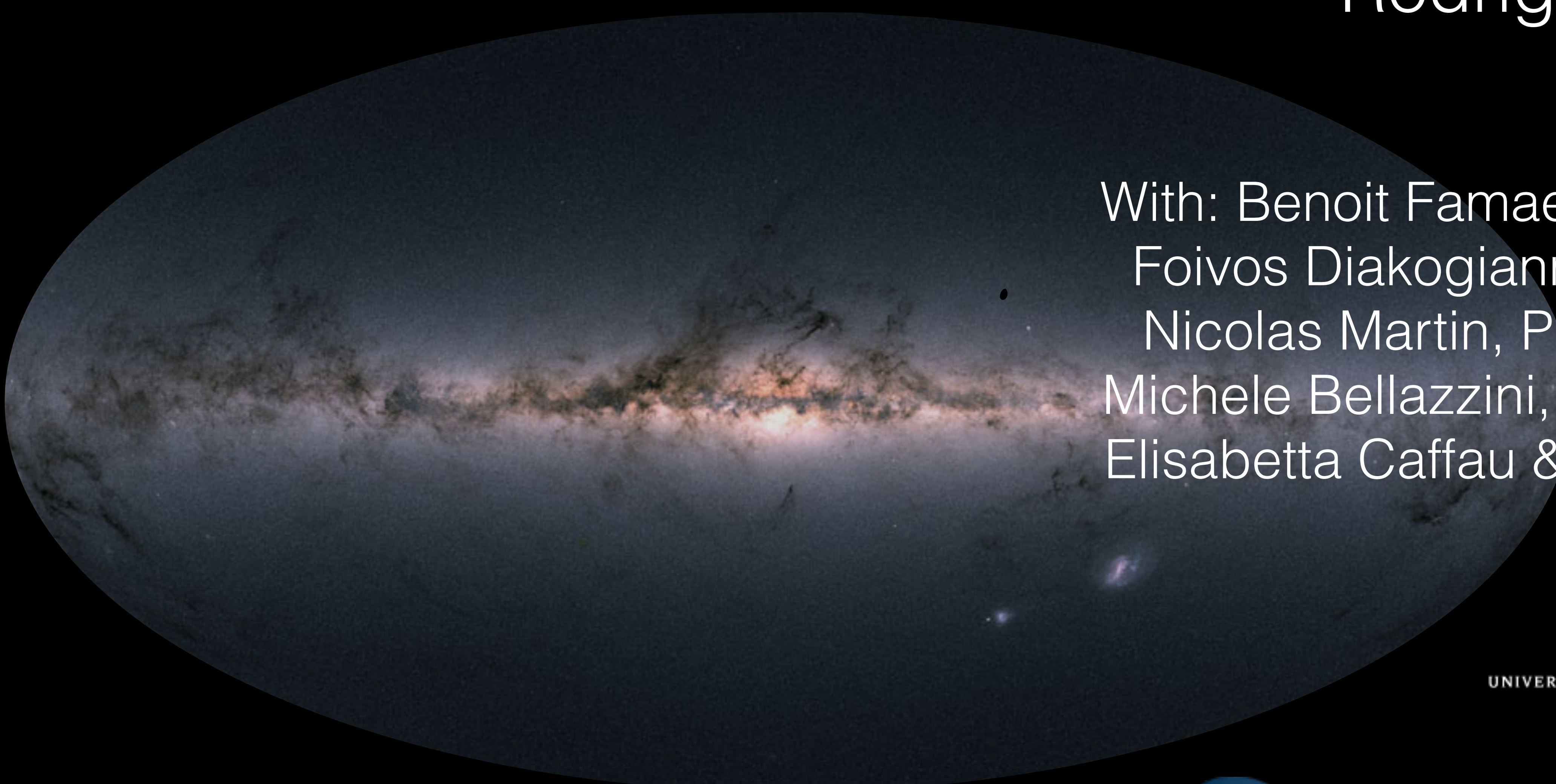
Learning the properties of our Galaxy's Dark Matter with Stellar Streams

Rodrigo Ibata

With: Benoit Famaey, Giacomo Monari, Foivos Diakogiannis, Khyati Malhan, Nicolas Martin, Pierre-Antoine Oria, Michele Bellazzini, Piercarlo Bonifacio, Elisabetta Caffau & Guillaume Thomas



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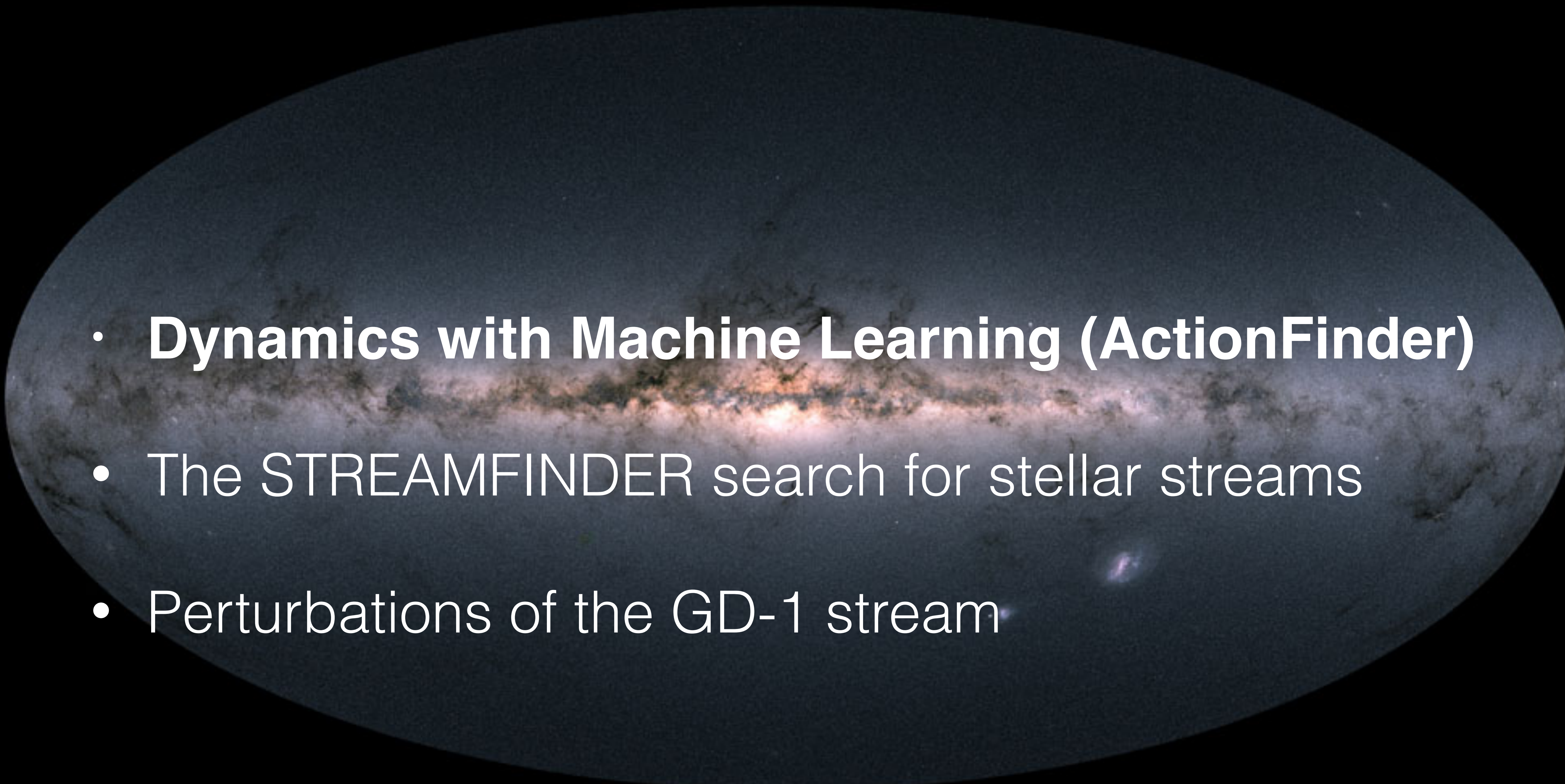
Outline



- **Dynamics with Machine Learning (ActionFinder)**
- The STREAMFINDER search for stellar streams
- Perturbations of the GD-1 stream

Canonical Transformations

$$\dot{q} = \frac{\partial H}{\partial p} \qquad \dot{p} = -\frac{\partial H}{\partial q}$$

H is the scalar field whose derivatives (rotated by $\pi/2$) show how to advance the point through (q, p) phase space

consider a change of coordinates (q, p) to (Q, P), that preserves this "canonical" form, i.e.

$$\dot{Q} = \frac{\partial K}{\partial P} \qquad \dot{P} = -\frac{\partial K}{\partial Q}$$

so again:
K is the scalar field whose derivatives (rotated by $\pi/2$) show how to advance the point through (Q, P) phase space

Action-angle variables

consider further a canonical transformation (q, p) to (θ, J), in which the new Hamiltonian K is independent of θ

Then:

$$\dot{\theta} = \frac{\partial K(J,t)}{\partial J} \qquad \dot{J} = -\frac{\partial K(J,t)}{\partial \theta} = 0$$

Hence: $J = J_0$ (the constant "action" along the path)

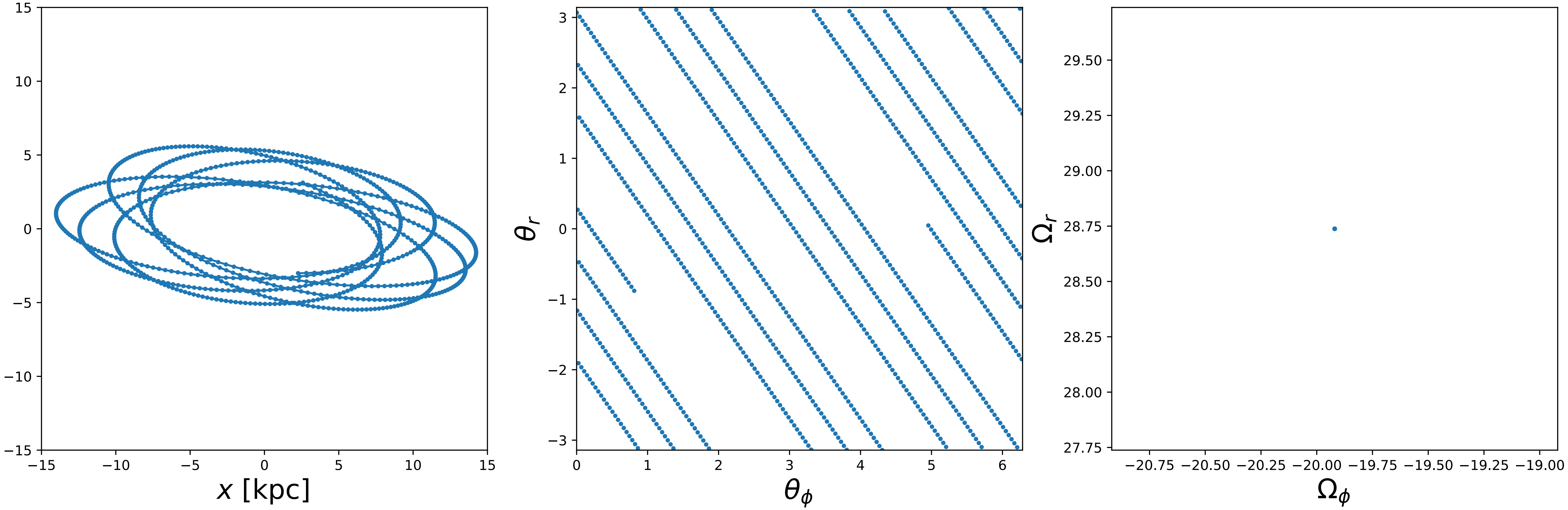
θ is called the "angle" variable

Dynamics in action-angle variables is very simple if K is independent of t:

$$\theta = \theta_0 + t\left.\frac{\partial K}{\partial J}\right|_{J_0}$$

(i.e. θ advances linearly in time)

orbit (like that of Palomar 5)



positions **angles** **frequencies**

2 Gyr integration in isochrone model with $v_c(R = 8\,\mathrm{kpc}) = 220\,\mathrm{km\,s^{-1}}$

Action-angle variables

Avantages:

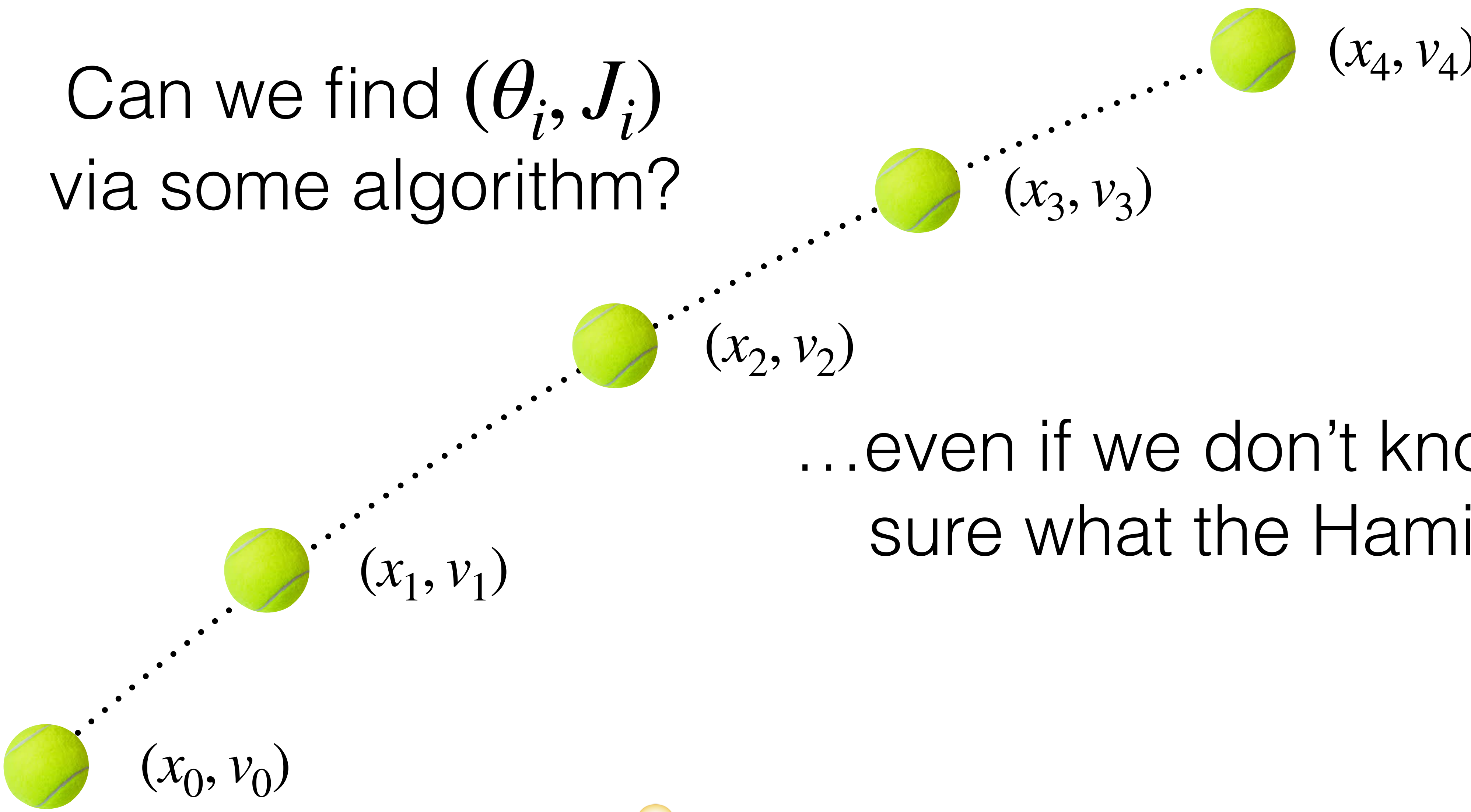
- J are integrals of motion, giving a means to identify objects on the same phase-space trajectory
- J are adiabatic invariants, hence are the best "archeological" coordinates
- (θ, J) are natural coordinates for perturbation theory
- If system is static: $H(J)$
- Acceleration field can be derived from

$$\dot{J}_i = \frac{\partial J_i}{\partial x_j}\dot{x}_j + \frac{\partial J_i}{\partial \dot{x}_j}\ddot{x}_j = 0$$

But the coordinate transformation is challenging to compute.

Suppose we have measurements of phase space trajectories of a deterministic and reversible system

Can we find (θ_i, J_i) via some algorithm?



…even if we don't know or are not sure what the Hamiltonian is?

💡 **Lockdown idea 1:**

Can we implement this with a neural net

$$(\theta, J) = N_{\text{net}}(x, v) \text{ ?}$$

💡**Lockdown idea 1:**

Can we implement the transformation in 6D phase space with a neural net

$$\eta = N_{\rm net}(\xi) \text{ ?}$$

Objective function: minimize spread of J on same trajectory, & minimize symplectic constraint $M^T \mathbb{J} M - \mathbb{J}$

where

$$M_{ij} = \partial\eta_i / \partial\xi_j \qquad \mathbb{J} = \begin{pmatrix} 0 & \mathbb{I}_3 \\ -\mathbb{I}_3 & 0 \end{pmatrix}$$

Result: a huge waste of time!

reason: $M_{ij}(\xi)$ has $(2n)^2 = 36$ entries, whereas only $2n^2 + n = 21$ should be independent if symplectic

💡 Lockdown idea 2:

Actually ~200 year old idea of Jacobi of using a generating function involving the old and new canonical coordinates

Consider the transformation generated by $S(q, P, t)$

$$p = \frac{\partial S}{\partial q} \qquad Q = \frac{\partial S}{\partial P}$$

This transformation is canonical as $\{Q_i, P_j\}_{q,p} = \delta_{ij}$

In general S is very challenging to find!

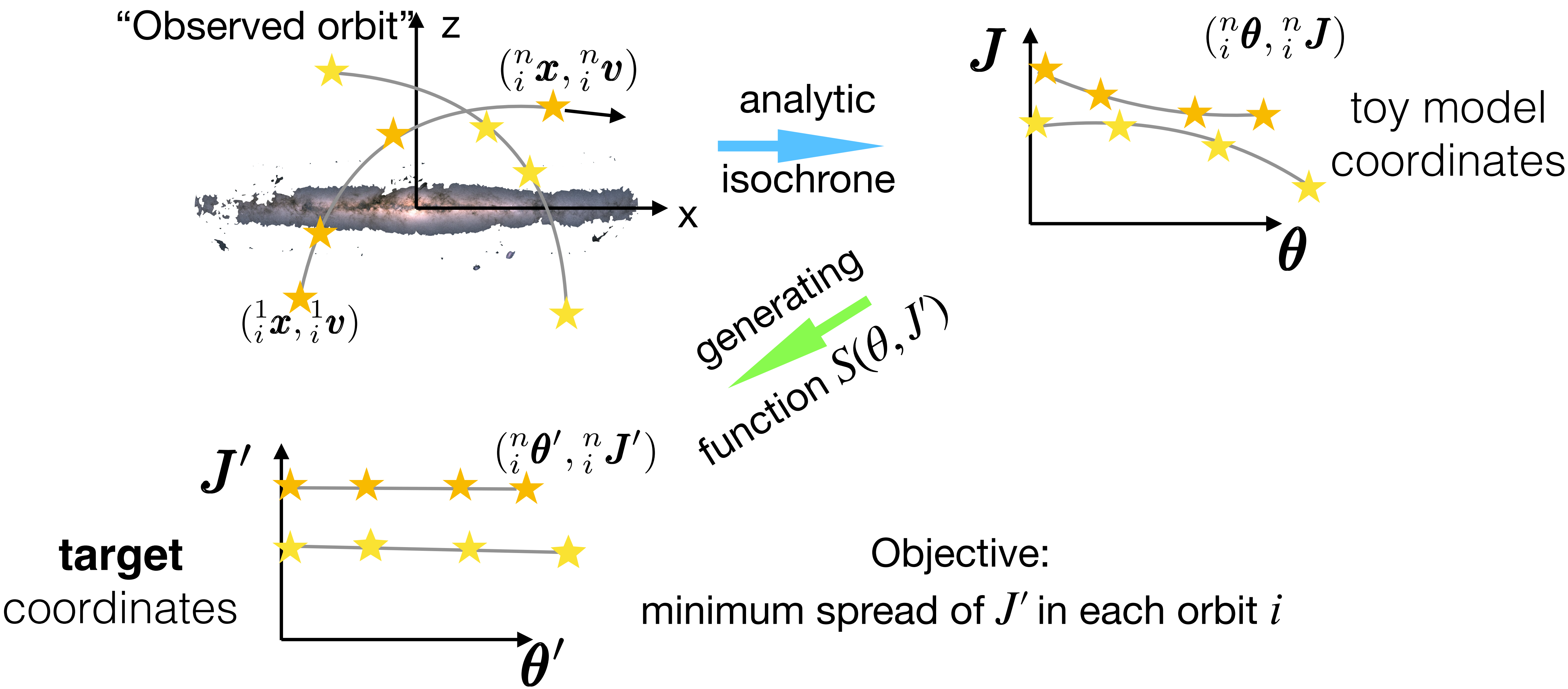
If H is known and system is axisymmetric S can be approximated with a Fourier series (McGill & Binney 1990)

Can we make this more powerful with a **neural network**, and avoid needing to know H in advance?

Learn the transformation from orbits

We convert **(x,v)** → (θ**',J'**) in an **unsupervised** way,

learning a generating function S(θ**,J'**) for the canonical transformation…



Objective:

minimum spread of J' in each orbit i

ADVANTAGE: We have not had to assume H(x,v) or $\Phi(\mathbf{x})$ or any symmetry

Network **derives** the acceleration field.

RI, Diakogiannis, Famaey, Monari (2021)

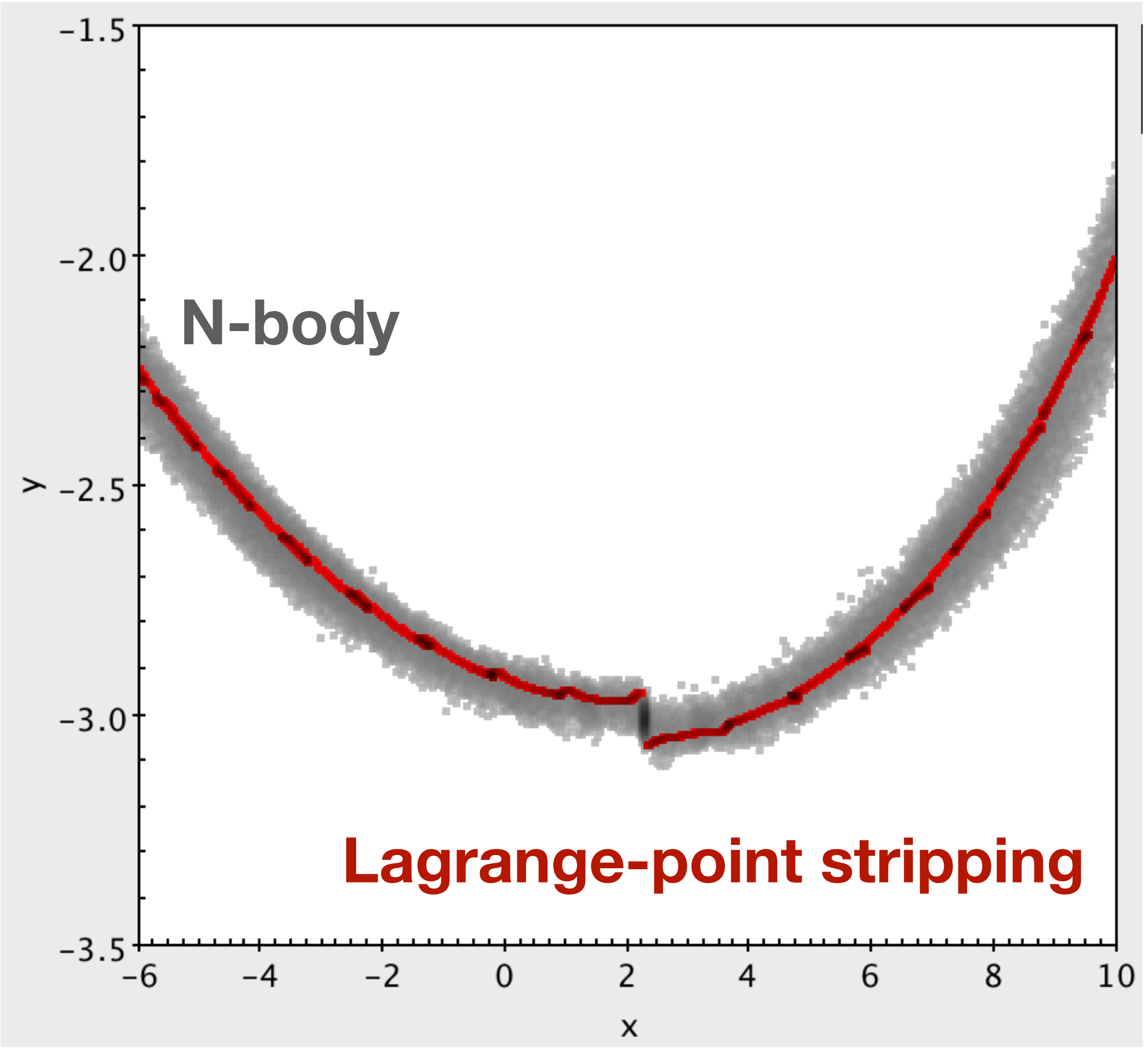
https://github.com/RodrigoIbata/ActionFinder

But we don't observe orbits, as $T_{\rm human} \ll T_{\rm orbit}{}^{\dagger}$

$\dagger$ **except in the Galactic center**

Could we apply the ActionFinder to real data from stellar streams?

Stream model by Lagrange-point stripping
(Varghese, RI & Lewis 2011)

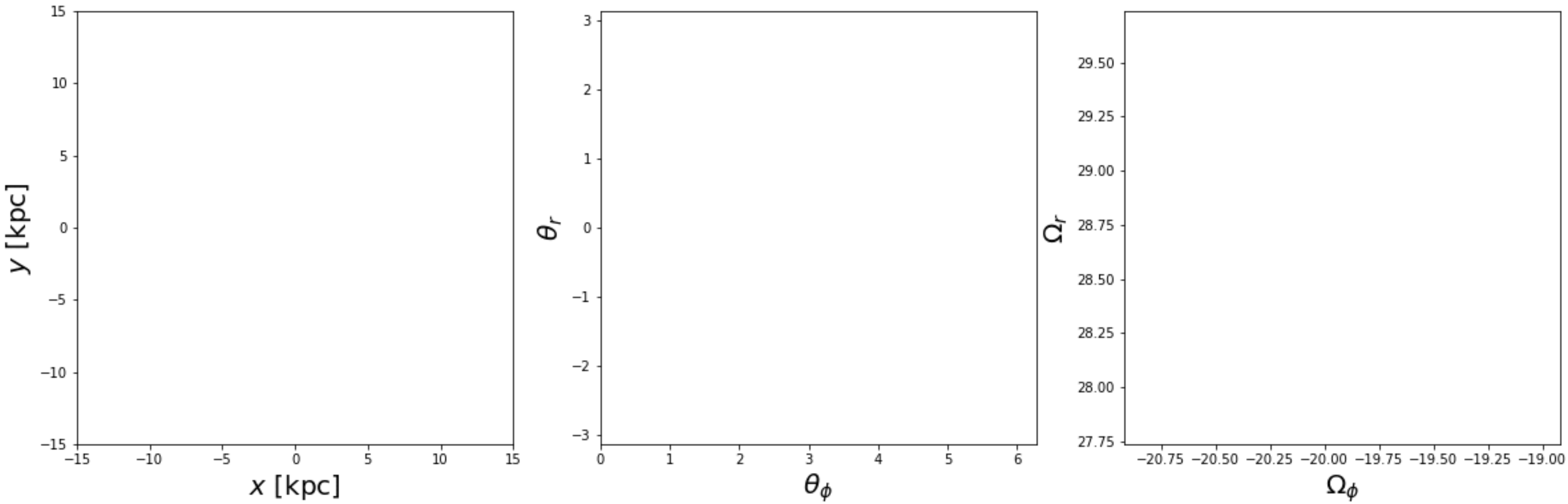


Palomar 5 -like model

Simple stream by Lagrange-point stripping

Blue: orbit

Red: evolving stream **Red: evolving stream** **Red: evolving stream**



positions **angles** **frequencies**

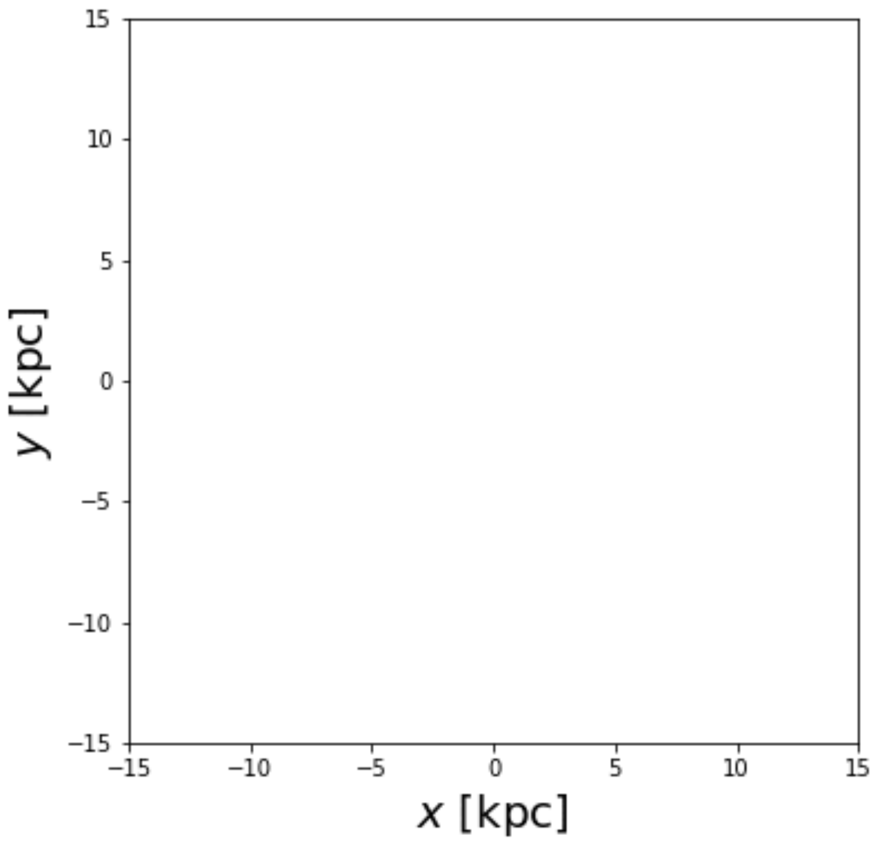
Palomar 5 -like model

2 Gyr integration in isochrone model with $v_c(R = 8\,\mathrm{kpc}) = 220\,\mathrm{km\,s^{-1}}$

Simple stream by Lagrange-point stripping

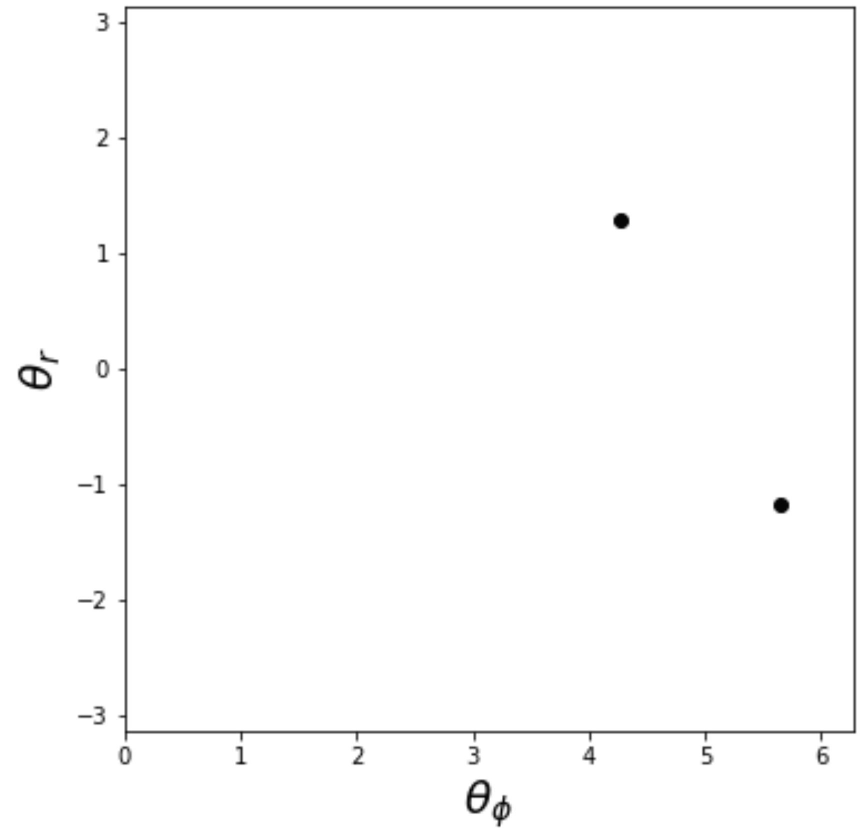
Blue: orbit

Red: final stream



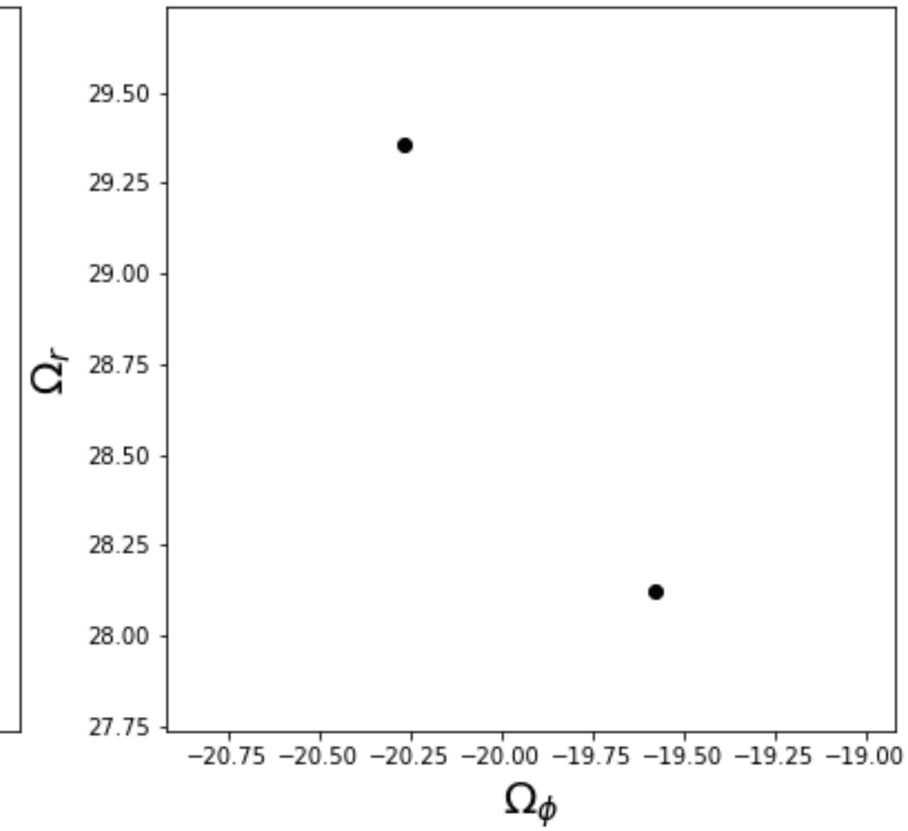
positions

Red: final stream



angles

Red: final stream



frequencies

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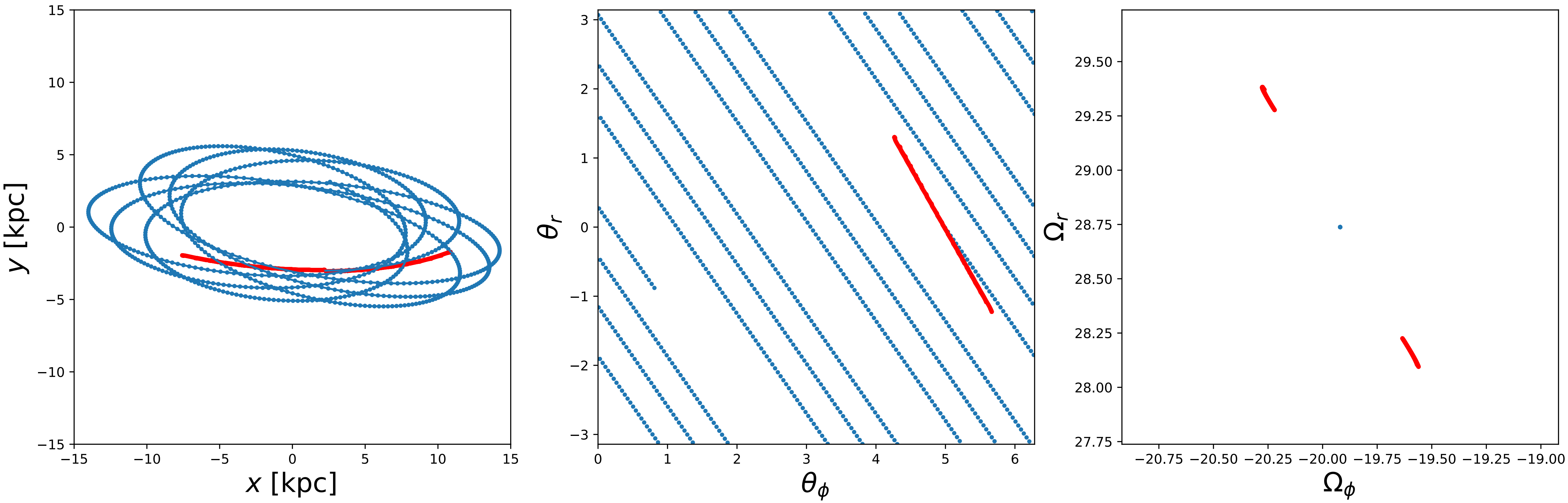


positions **angles** **frequencies**

Palomar 5 -like model

2 Gyr integration in isochrone model with $v_c(R = 8\,\mathrm{kpc}) = 220\,\mathrm{km\,s^{-1}}$

ActionFinder for streams

Start by treating stream as if it were an orbit. The objective (i.e. loss function) is to minimize:

$$\mathscr{L} = \left\langle \left\langle |\mathbf{J} - \langle \mathbf{J}_{\text{stream}} \rangle| \right\rangle_{\text{stream}} \right\rangle_{\text{set of streams}}$$

Then refine solution of neural net representation of $S(\theta, J')$ using insight from Sanders & Binney (2013). As $\Delta \overrightarrow{\theta} = t\overrightarrow{\Omega}$, revised objective:

$$\mathscr{L} = 1 - \left\langle \langle \hat{\mathbf{e}}_\theta \rangle_{\text{stream}} \cdot \langle \hat{\mathbf{e}}_\Omega \rangle_{\text{stream}} \right\rangle_{\text{set of streams}}$$

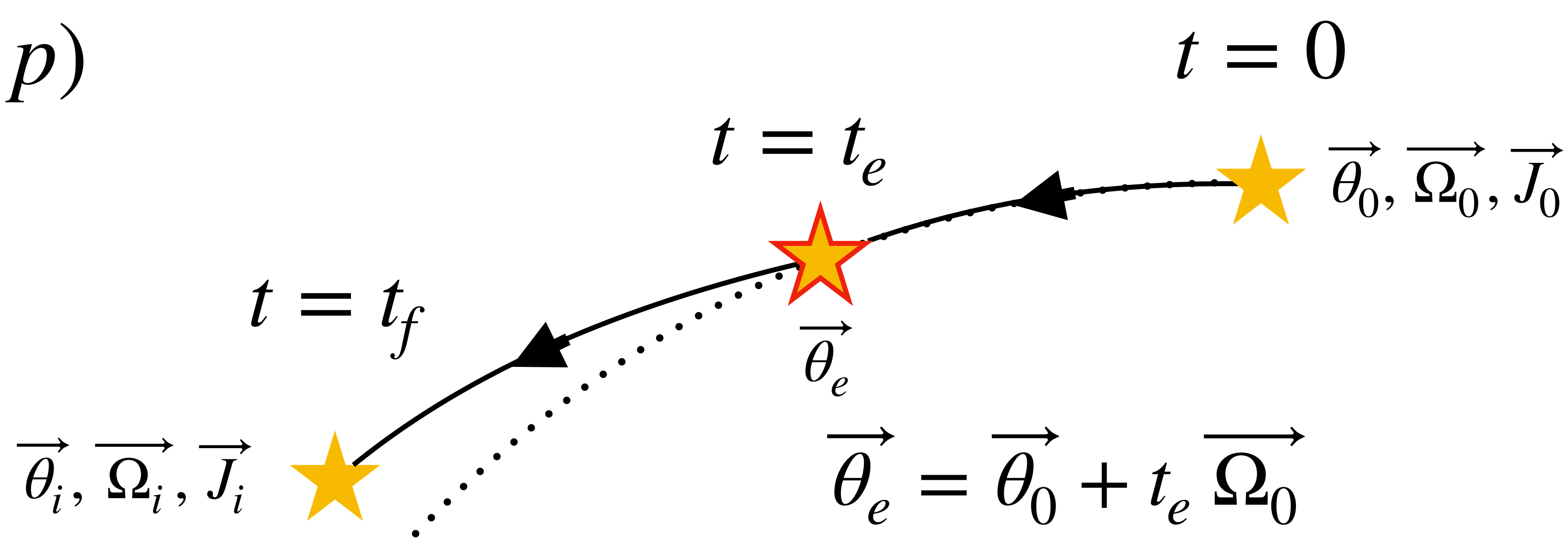
This gives <0.1% bias with simple potentials with 8,000 particles.

We also only need full 6-D phase space information for small subsample of each stream (with further loss function tweak)

A Time Machine for Streams

Easy if $H = H(q, p)$

(as $\Delta \vec{\theta} = t\vec{\Omega}$)



$$\vec{\theta}_i = \vec{\theta}_e + (t_f - t_e)\vec{\Omega}_i$$

$$\vec{\theta}_i = \vec{\theta}_0 + t_e(\vec{\Omega}_0 - \vec{\Omega}_i) + t_f \vec{\Omega}_i$$

global parameter of stream

parameter of star

$$\vec{\theta}(\text{remnant}) = \vec{\theta}_0 + t_f \vec{\Omega}_0$$

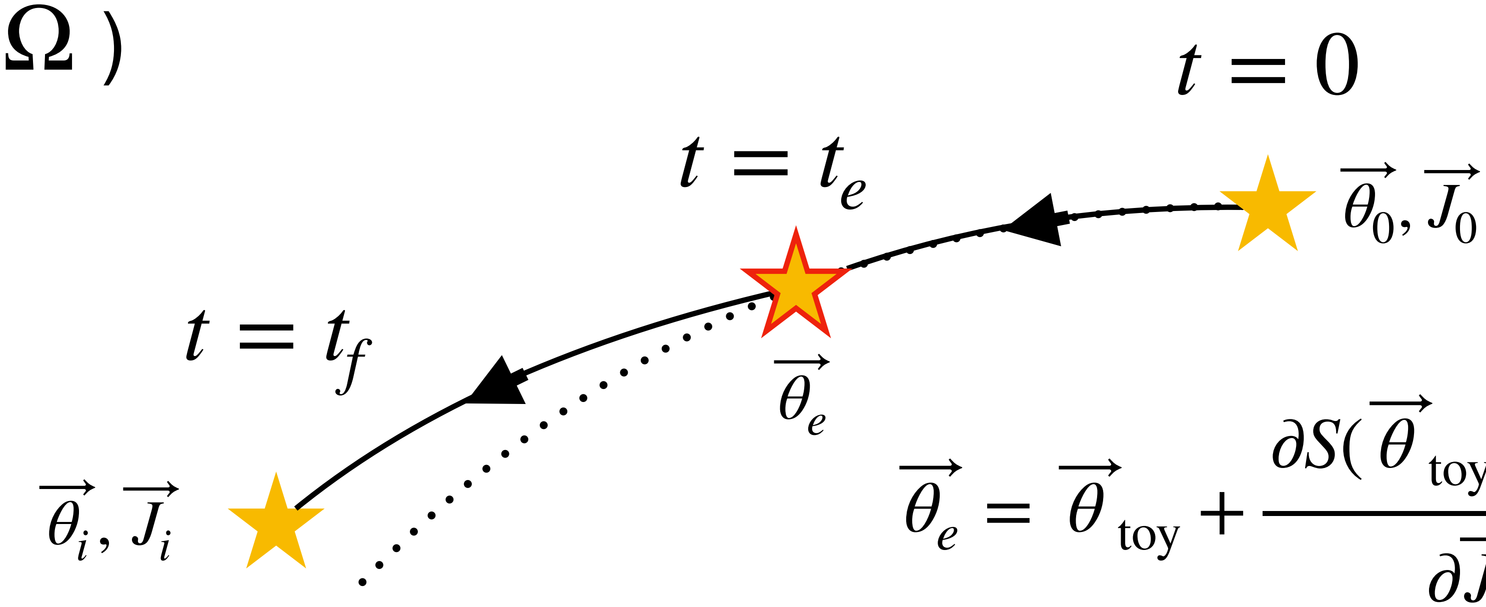
This gives progenitor orbit and past path $(\vec{x}, \vec{v}, t)$ of stars, and hence also when (and perhaps “why?”) stars were lost

A Time Machine for Streams

If $H = H(q, p, t)$, i.e., $S = S(\vec{\theta}_{\rm toy}, \vec{J}, t)$

(note $\Delta \vec{\theta} \neq t\vec{\Omega}$)

$$\vec{\theta}_0 = \vec{\theta}_{\rm toy} + \frac{\partial S(\vec{\theta}_{\rm toy}, \vec{J}_0, 0)}{\partial \vec{J}_0}$$



$$\vec{\theta}_e = \vec{\theta}_{\rm toy} + \frac{\partial S(\vec{\theta}_{\rm toy}, \vec{J}_0, t_e)}{\partial \vec{J}_0} \quad \textbf{(1)}$$

$$\vec{\theta}_i = \vec{\theta}_{\rm toy} + \frac{\partial S(\vec{\theta}_{\rm toy}, \vec{J}_i, t_f)}{\partial \vec{J}_i}$$

$$\vec{\theta}_e = \vec{\theta}_{\rm toy} + \frac{\partial S(\vec{\theta}_{\rm toy}, \vec{J}_i, t_e)}{\partial \vec{J}_i} \quad \textbf{(2)}$$

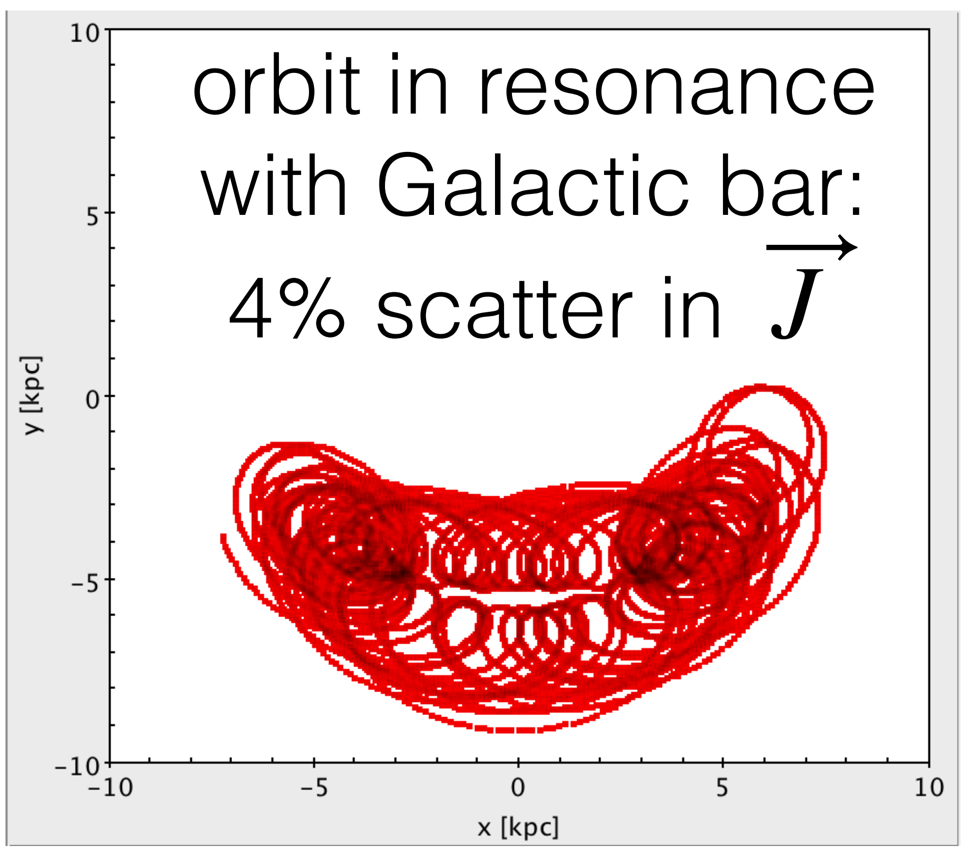
We haven't coded this up yet, but it *should* be straightforward.

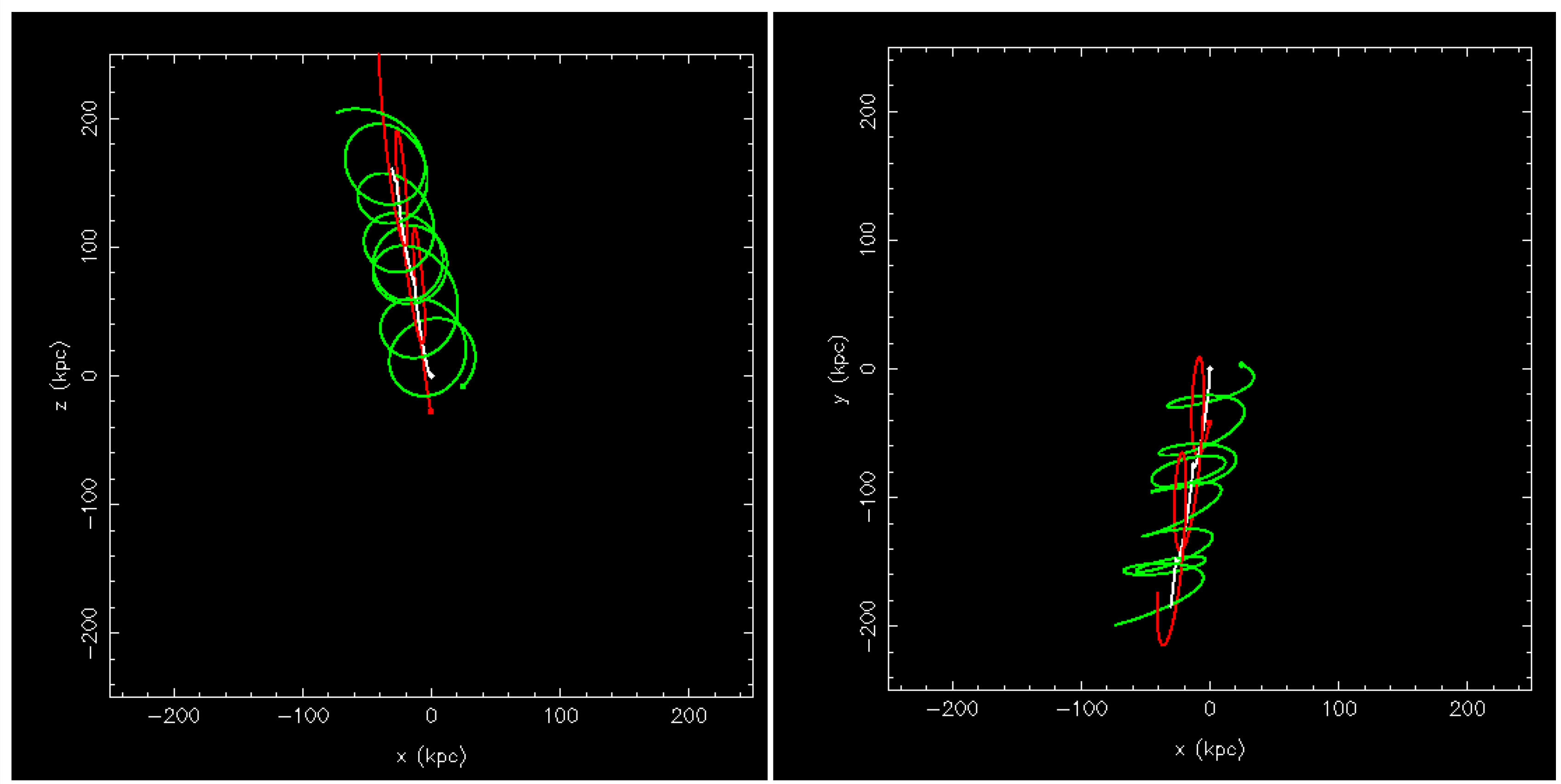
Search for t_e values that obey **(1)** & **(2)**

This could reveal how the acceleration field changes in time.

Time-dependence in orbits

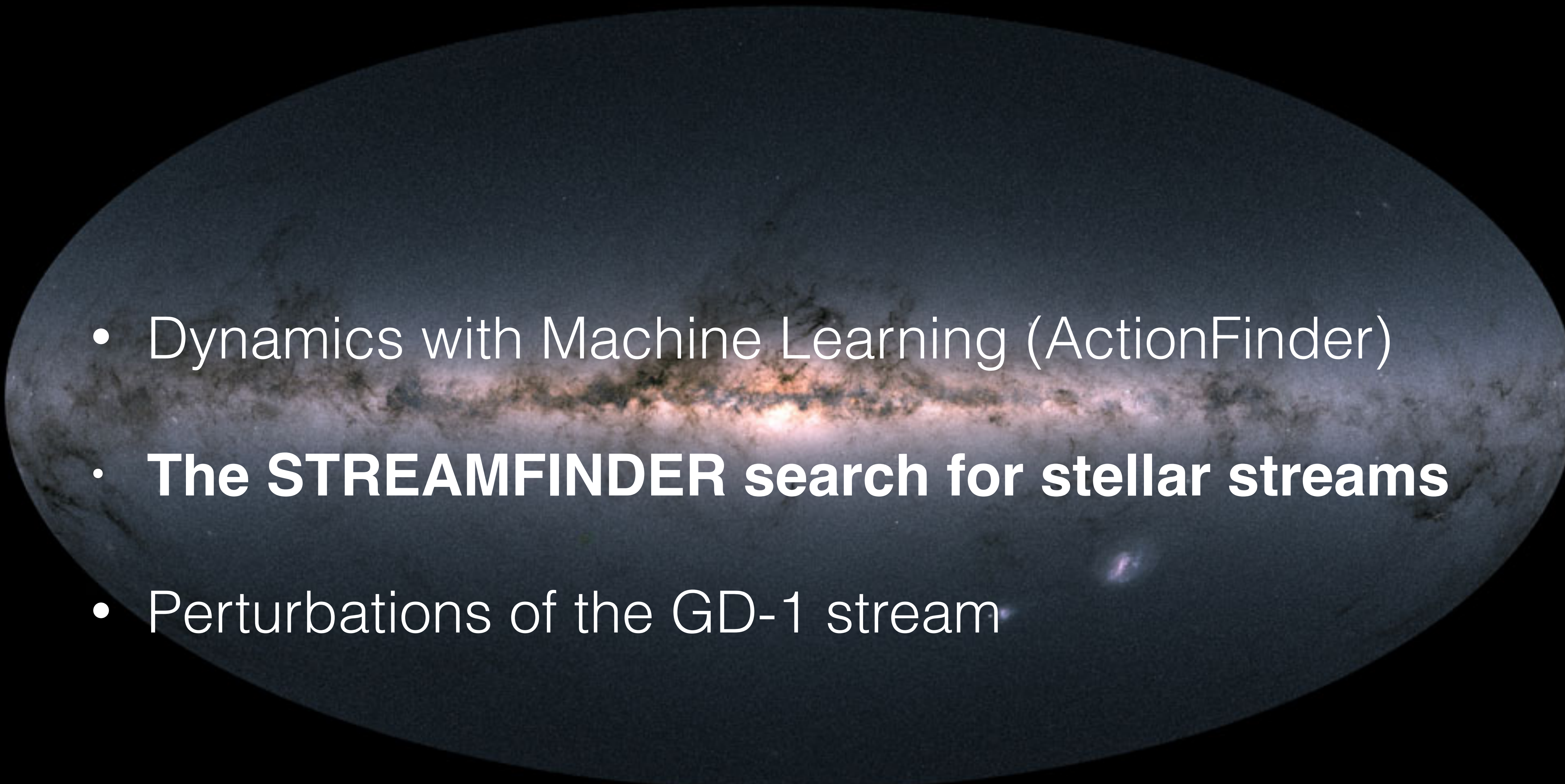
We have already upgraded the ActionFinder to find time-dependent generating functions $S(\vec{\theta}_{\rm toy}, \vec{J}, t)$ when t is provided explicitly





Toy MW+LMC+Sgr system, 1% scatter in $\vec{J}$

Outline



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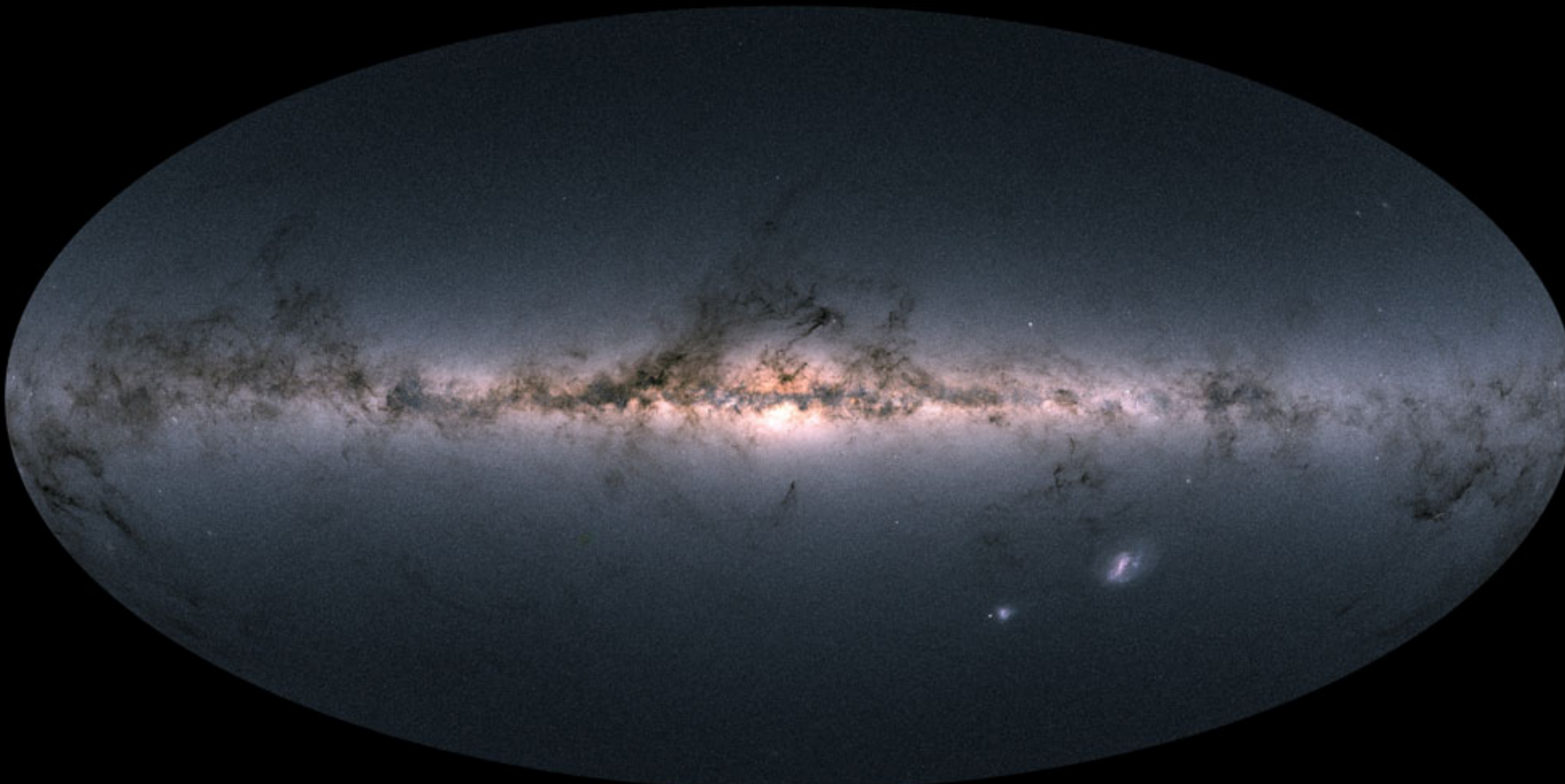
How do we best find streams with Gaia?



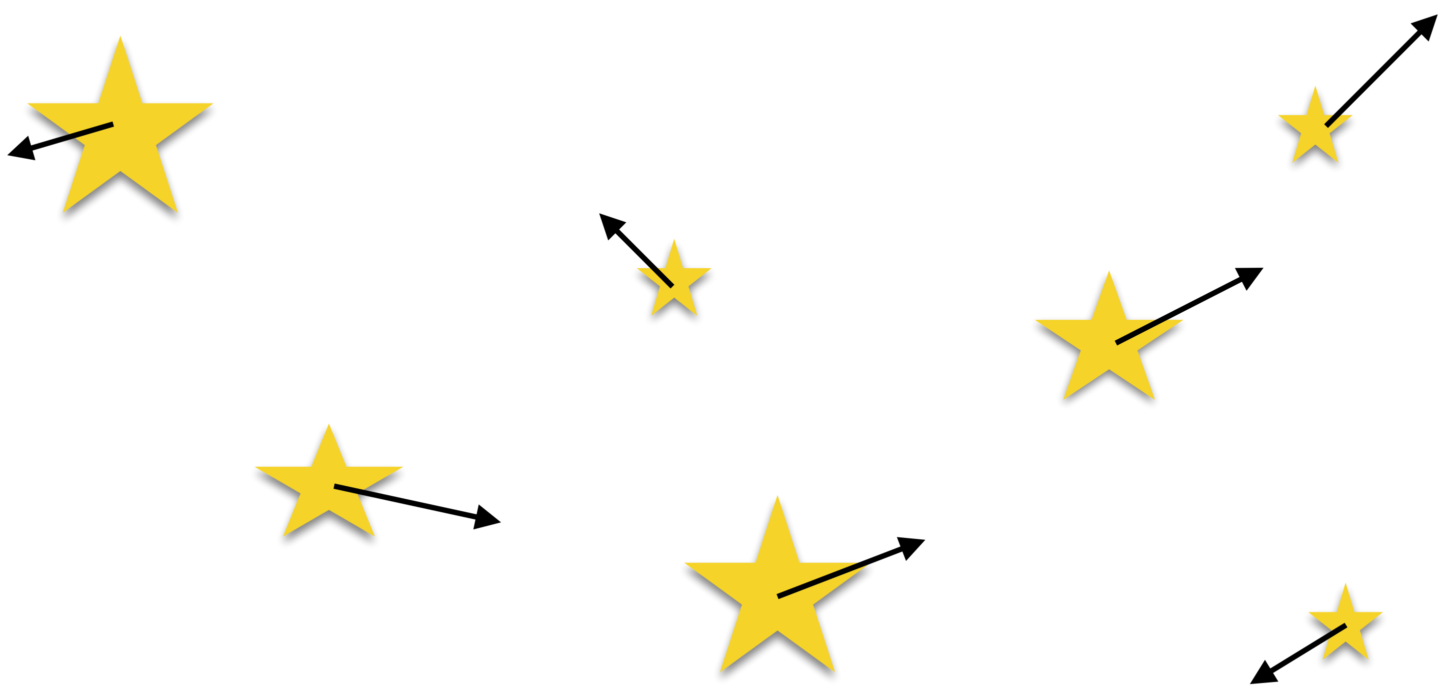
Finding streams in heterogenous datasets

position 1/dist. motion brightness temperature

Gaia: $\alpha, \delta, \varpi, \mu_\alpha, \mu_\delta, G, G_{BP}, G_{RP}$ for > 10^9 stars

heliocentric velocity for 7.2×10^6 stars

Distance, chemistry & line of sight velocity information much poorer than proper motions and photometry



Malhan, RI (MNRAS 2018)
Malhan, RI, Martin (MNRAS 2018);
Malhan et al. (MNRAS 2019)
RI, Malhan, Martin (ApJ 2019)
RI, Bellazzini, Malhan, Martin, Bianchini (Nature Ast. 2019)

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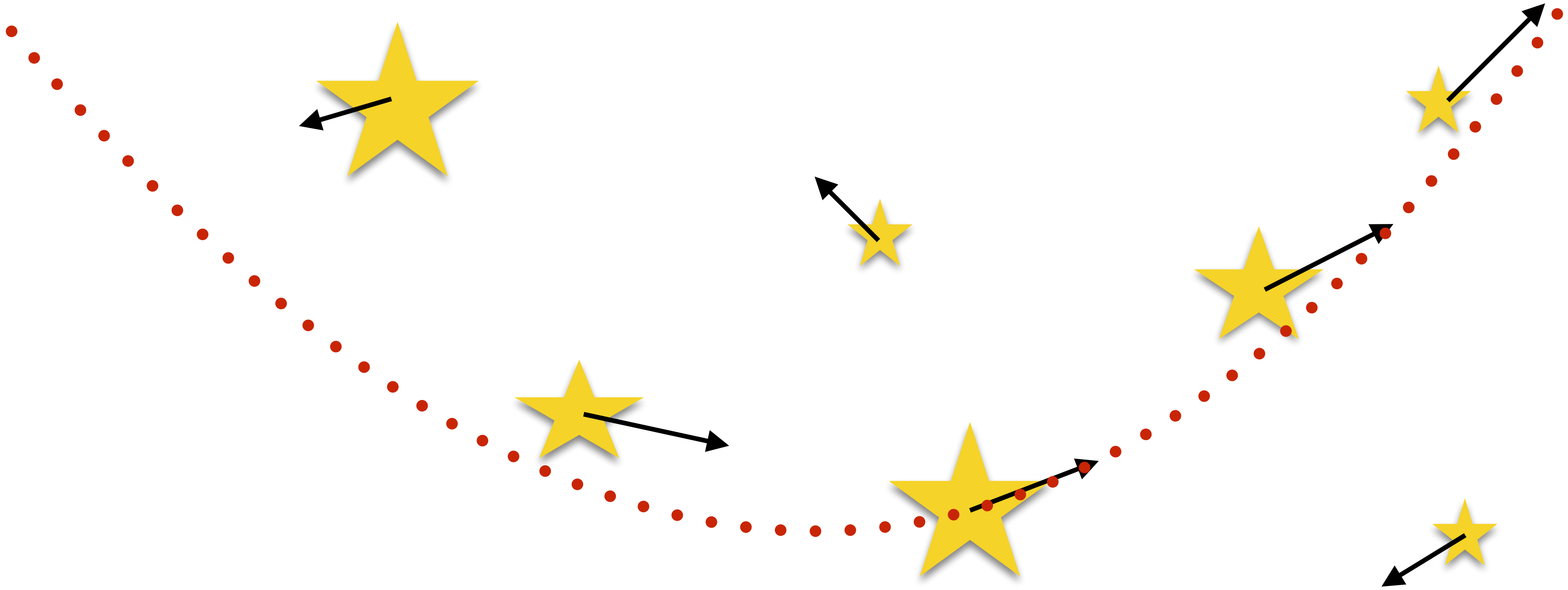

model in:

$\alpha, \delta, \varpi,$

$\mu_\alpha, \mu_\delta,$

$G, G_{BP} - G_{RP}$

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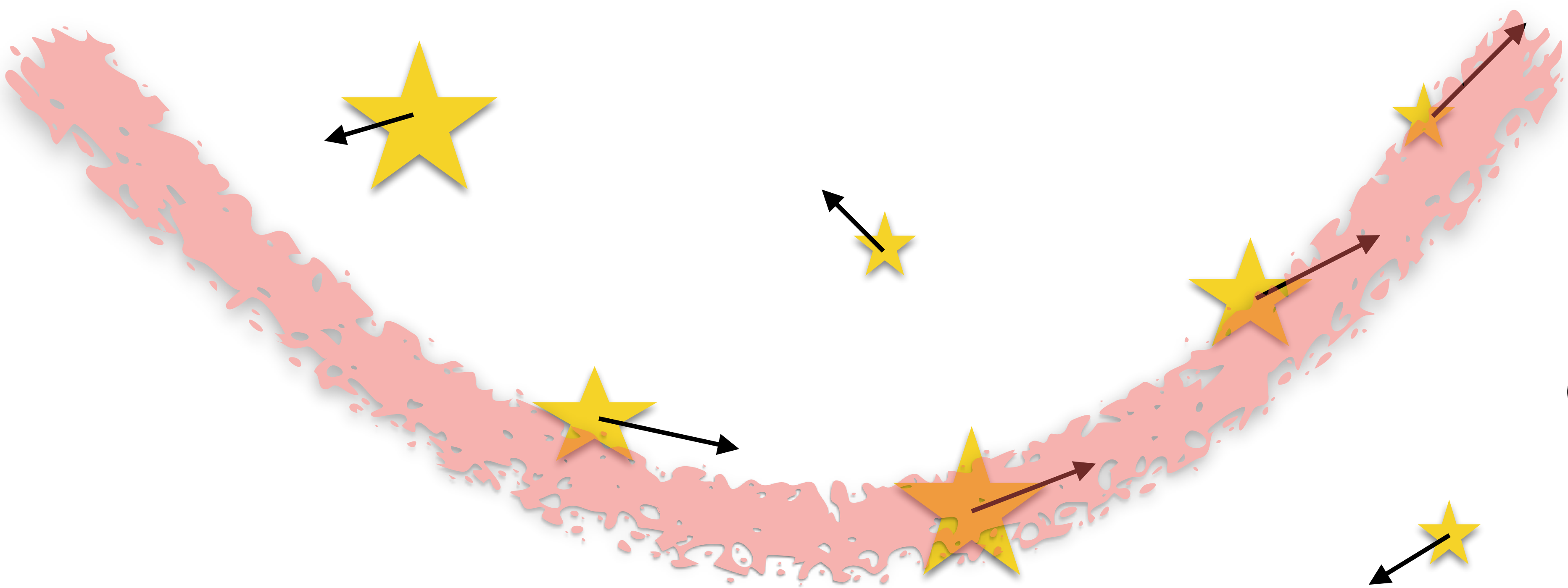

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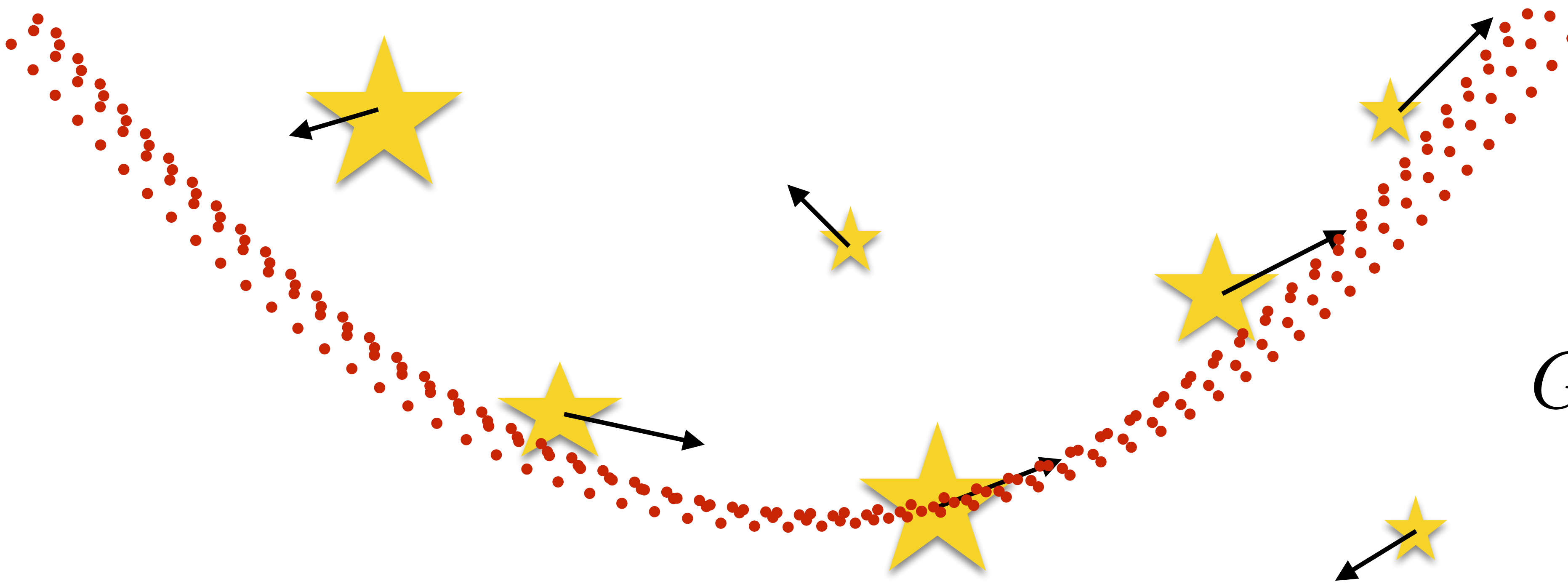

model in:

$\alpha, \delta, \varpi,$

$\mu_\alpha, \mu_\delta,$

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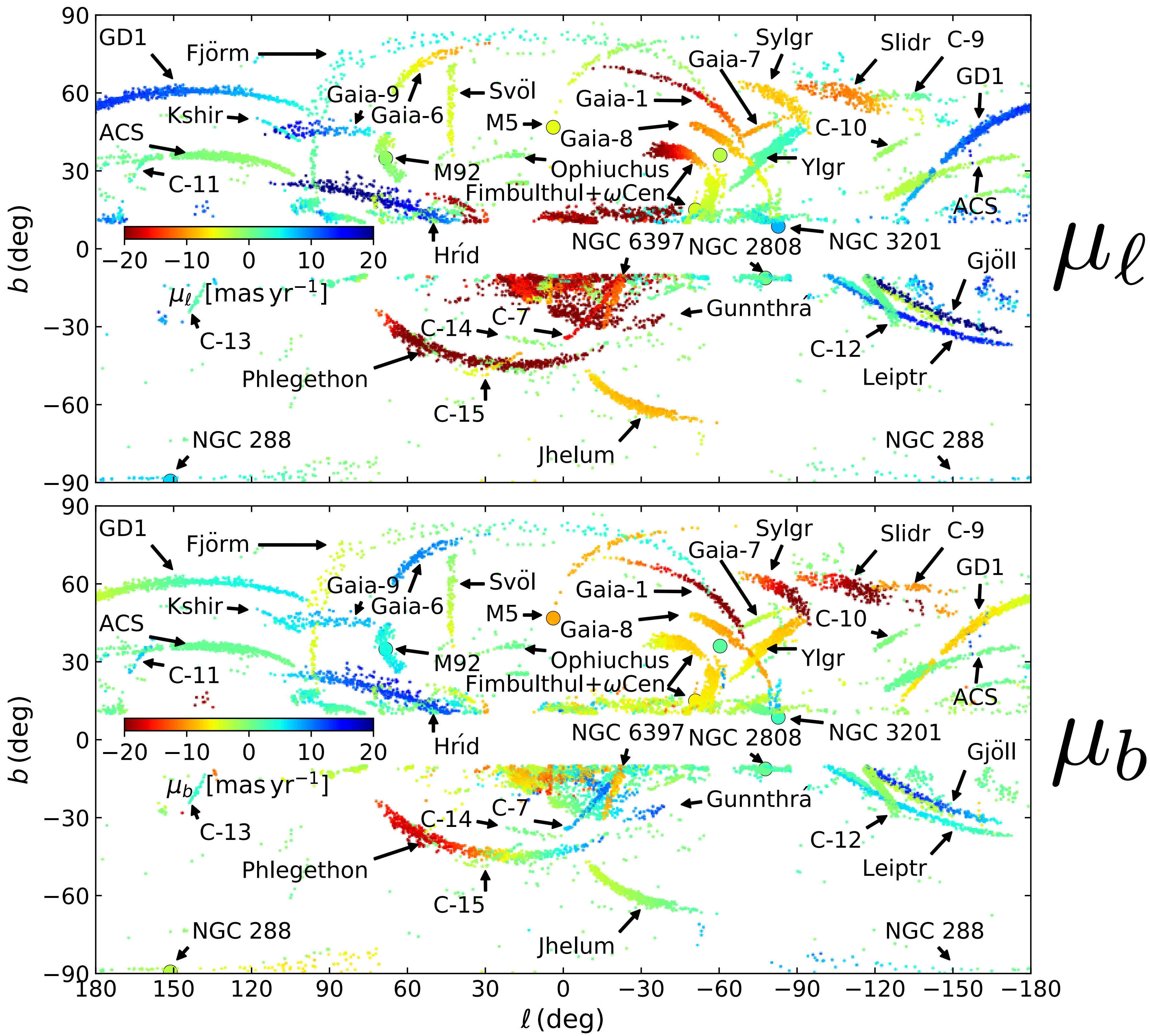
$$\ln \mathcal{L} = \sum_{\text{data}} \ln \left[\eta \mathcal{P}_{\text{stream}}(\theta) + (1 - \eta) \mathcal{P}_{\text{cont}} \right]$$

For each star: What is $\ln \mathscr{L}$ of the most likely value of eta?

Hence maps of “streaminess”

New stream maps [3,12] kpc

10σ detections,
50 pc half-width



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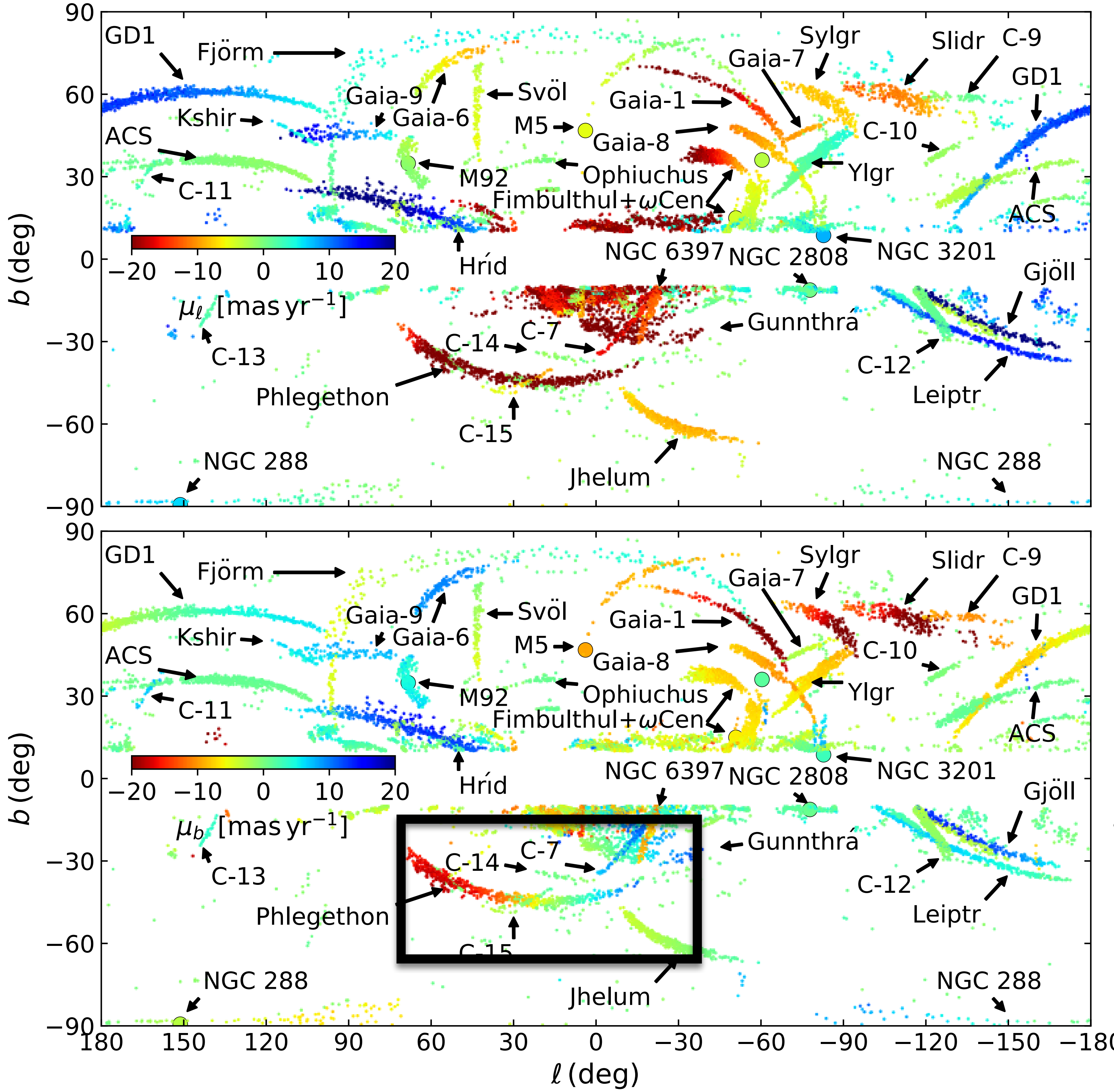

μ_ℓ

μ_b

New stream maps [3,12] kpc

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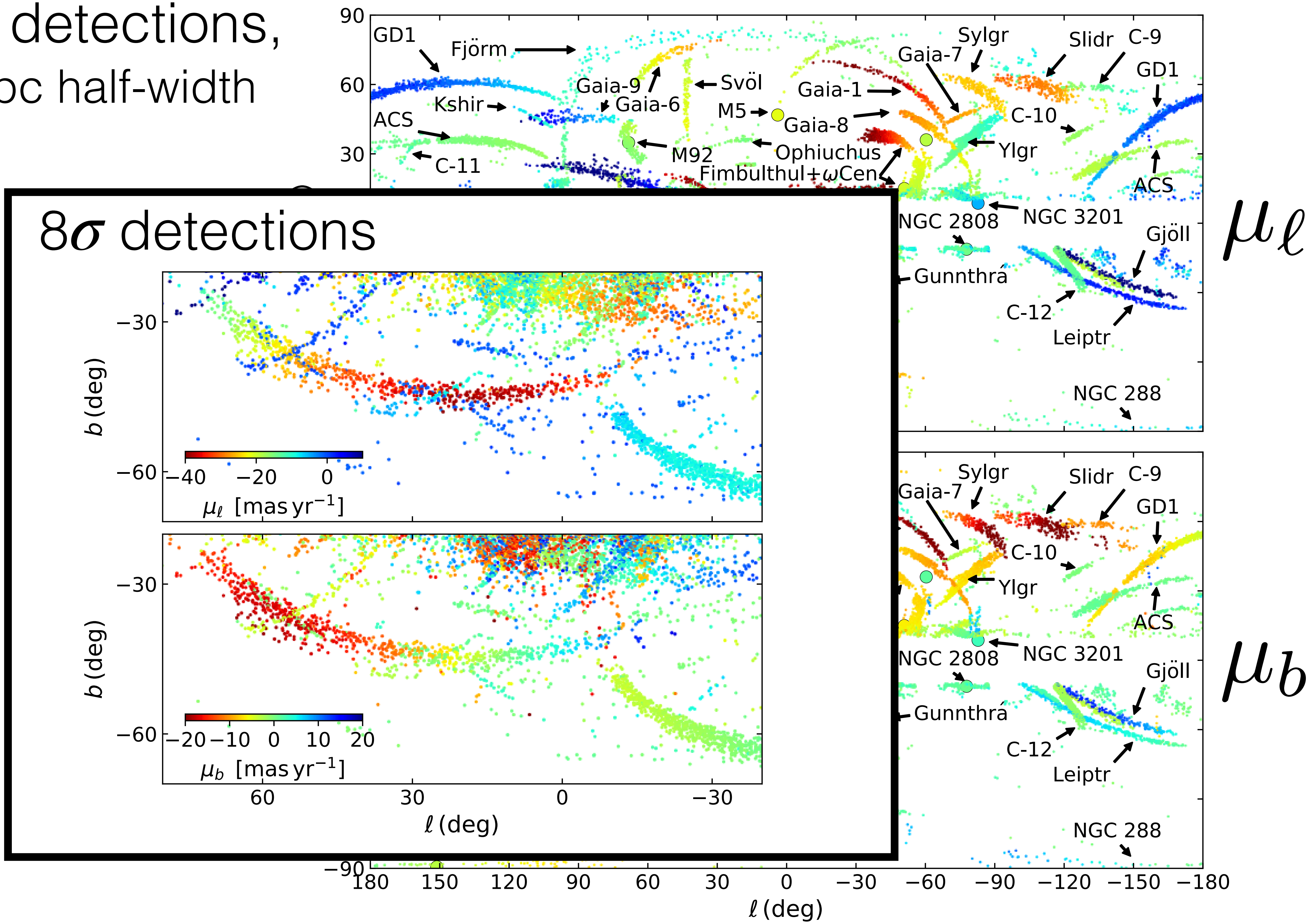
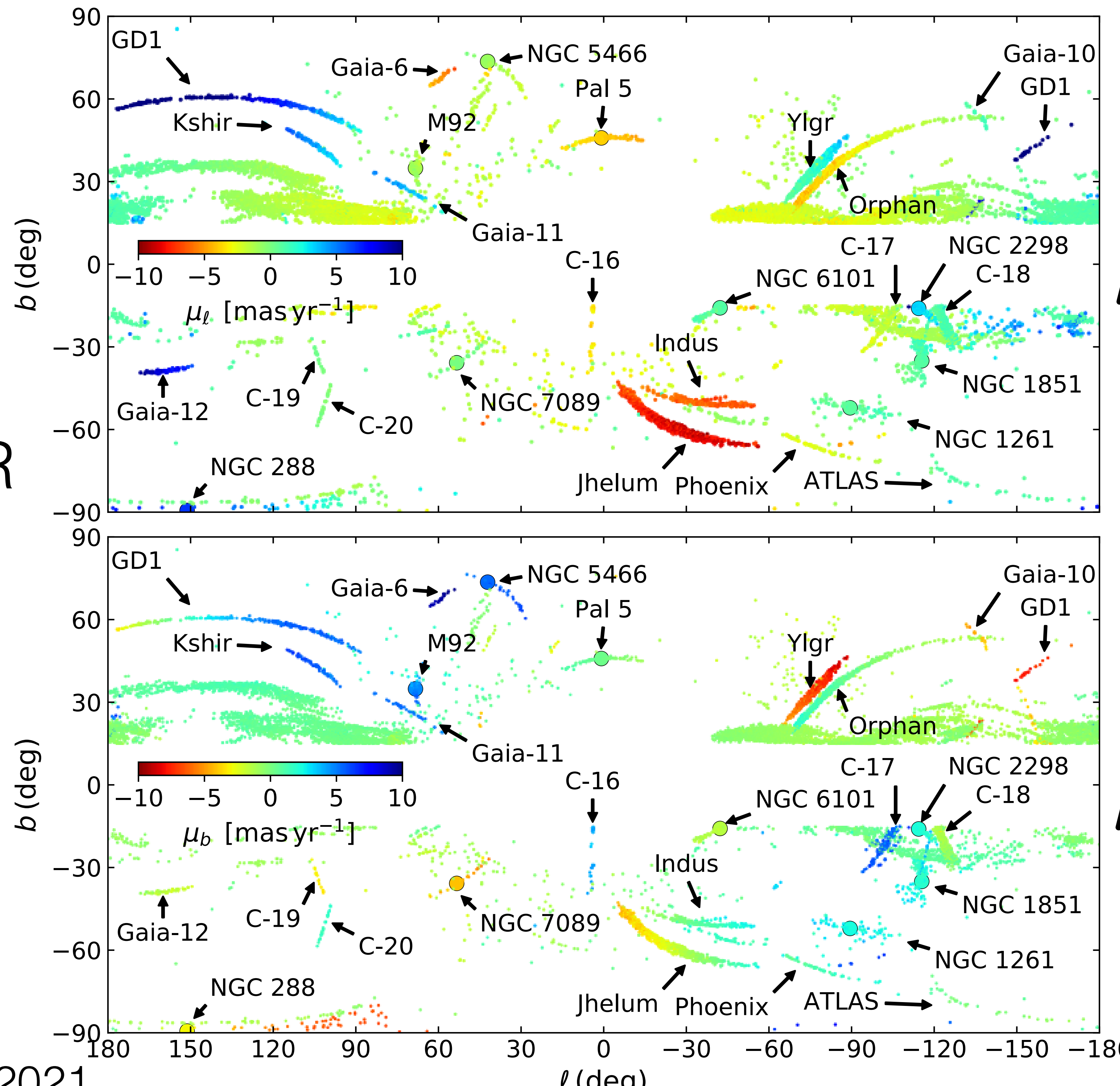


New stream maps [10,30] kpc

10σ detections,
50 pc half-width



μ_ℓ

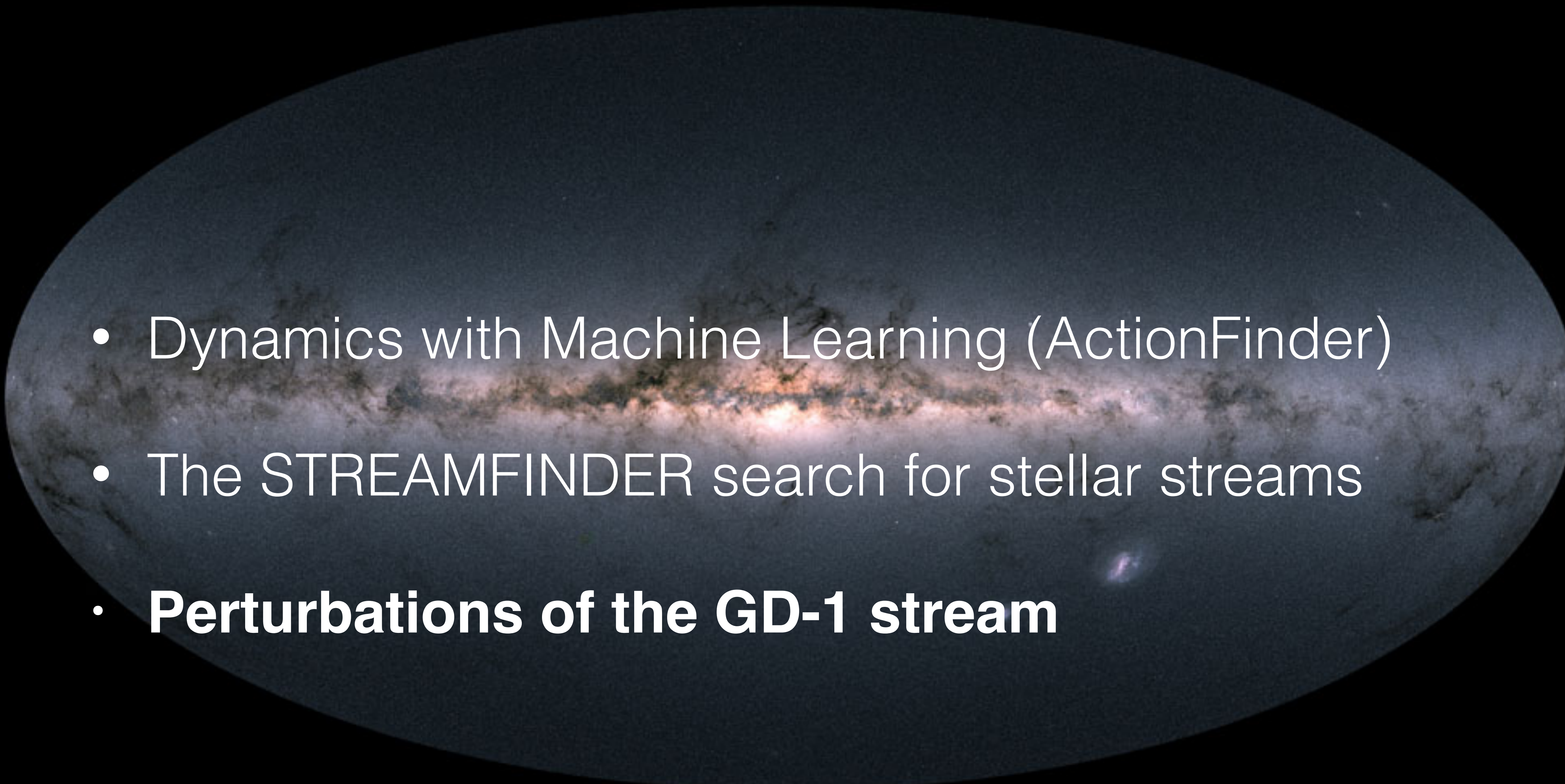
μ_b

STREAMFINDER
high-resolution
spectroscopic
survey

ESPaDOnS(CFHT)
+ UVES(VLT)

RI, Malhan, Martin et al. 2021

Outline



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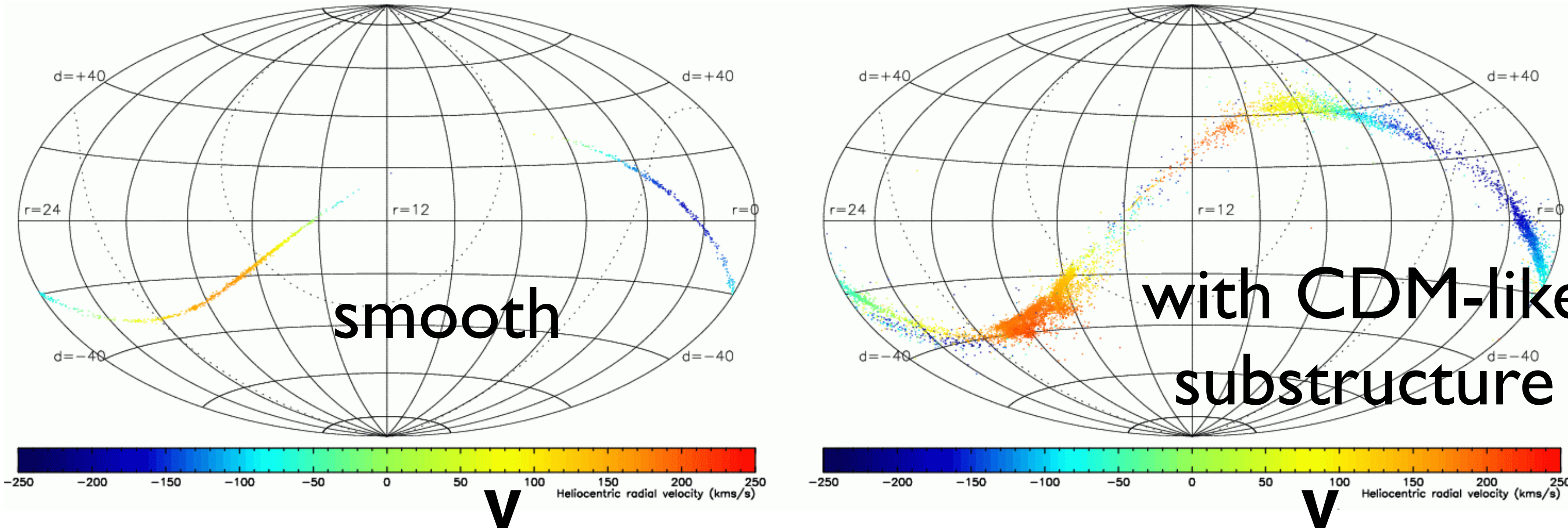
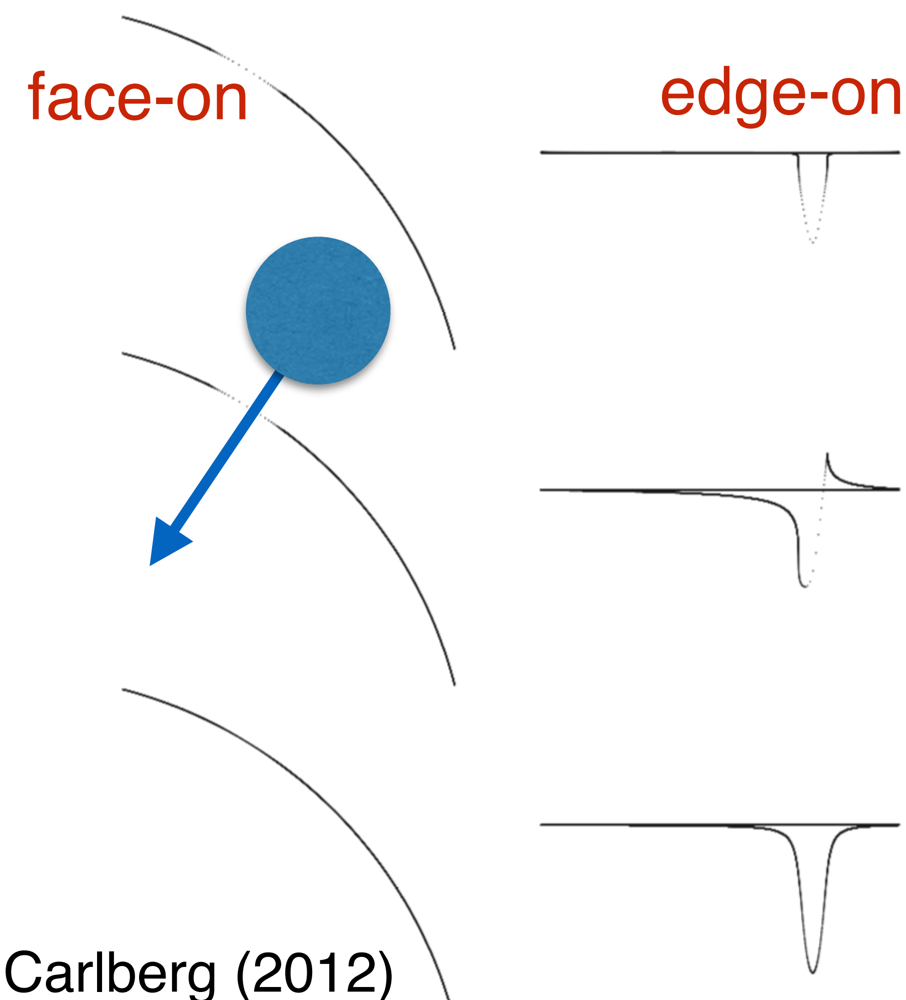
Stellar Streams as seismometers



RI, Lewis, Irwin, Quinn (2002)
Johnston et al. (2002)
Dalal & Kochanek (2002)



Carlberg (2012)

Gaps in streams from sub-halo encounters

matched filter map around Palomar 5:

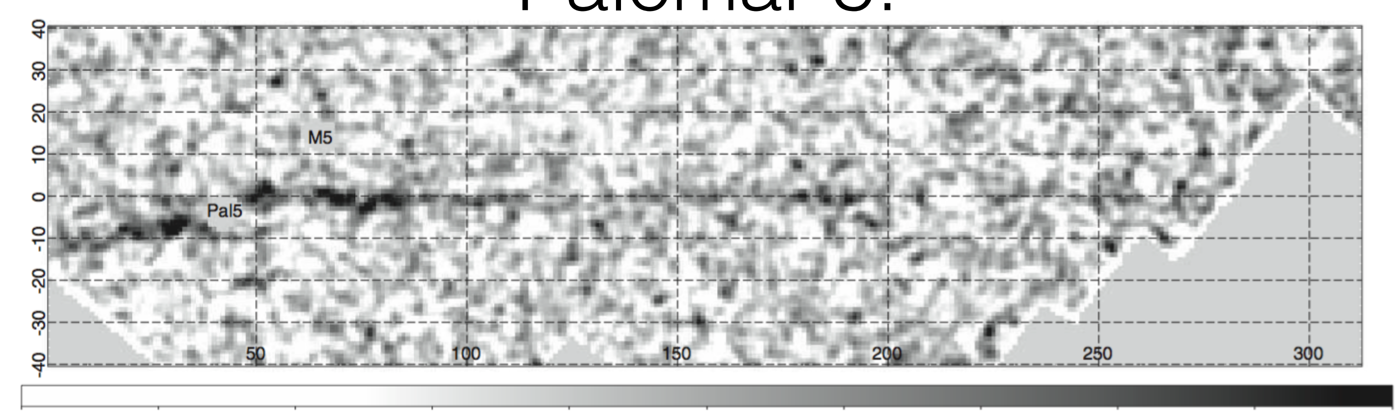
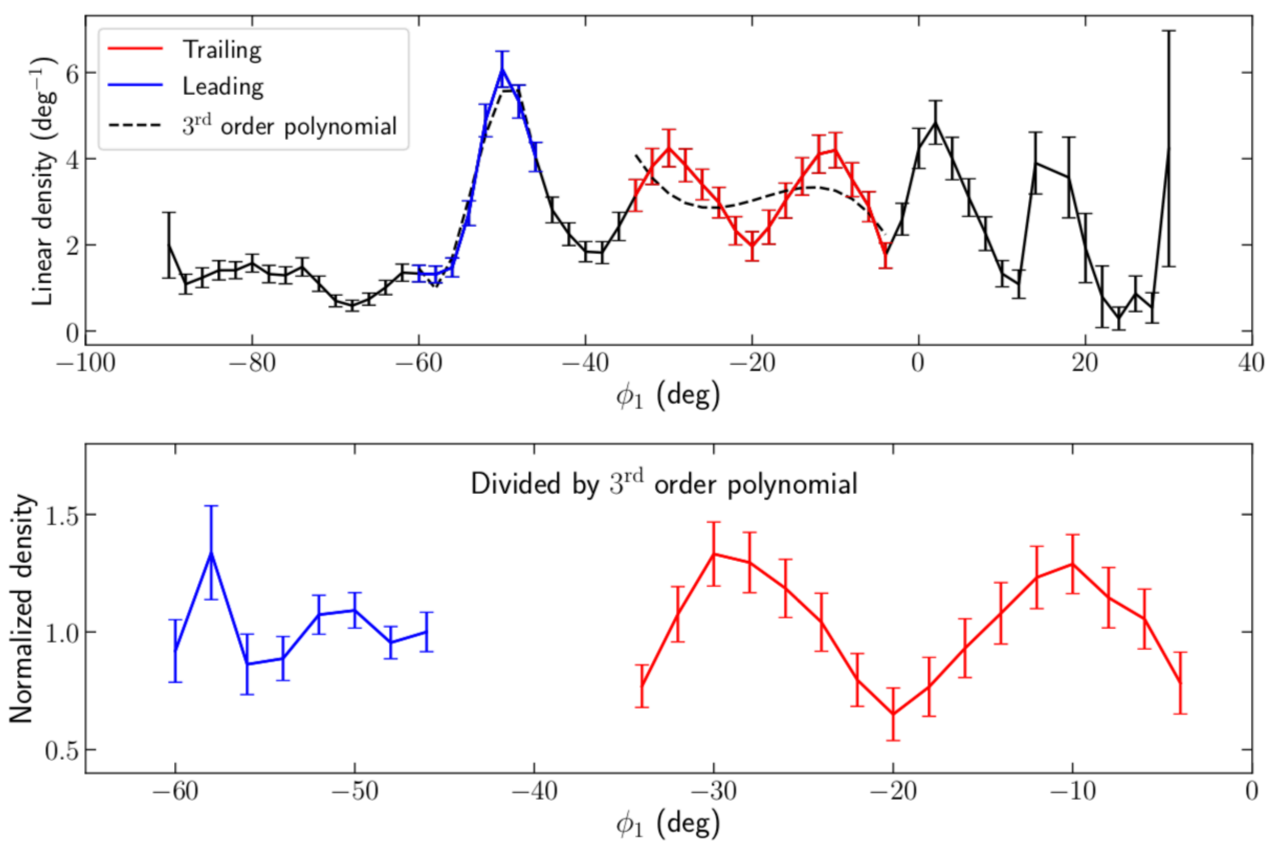


Figure 2. Matched filtered star map of the Pal 5 field, with Pal 5 and the foreground M5 cluster masked out. To remove the varying background, the masked image has been smoothed over 4° subtracted from the original image, and then smoothed with a 2 pixel, or, 0.°2 Gaussian. The analysis is conducted on the original uncorrelated pixels. We have made no attempt to straighten the southern part of the stream, left of the cluster in this image.

Gaps in the GD1 stream

Data

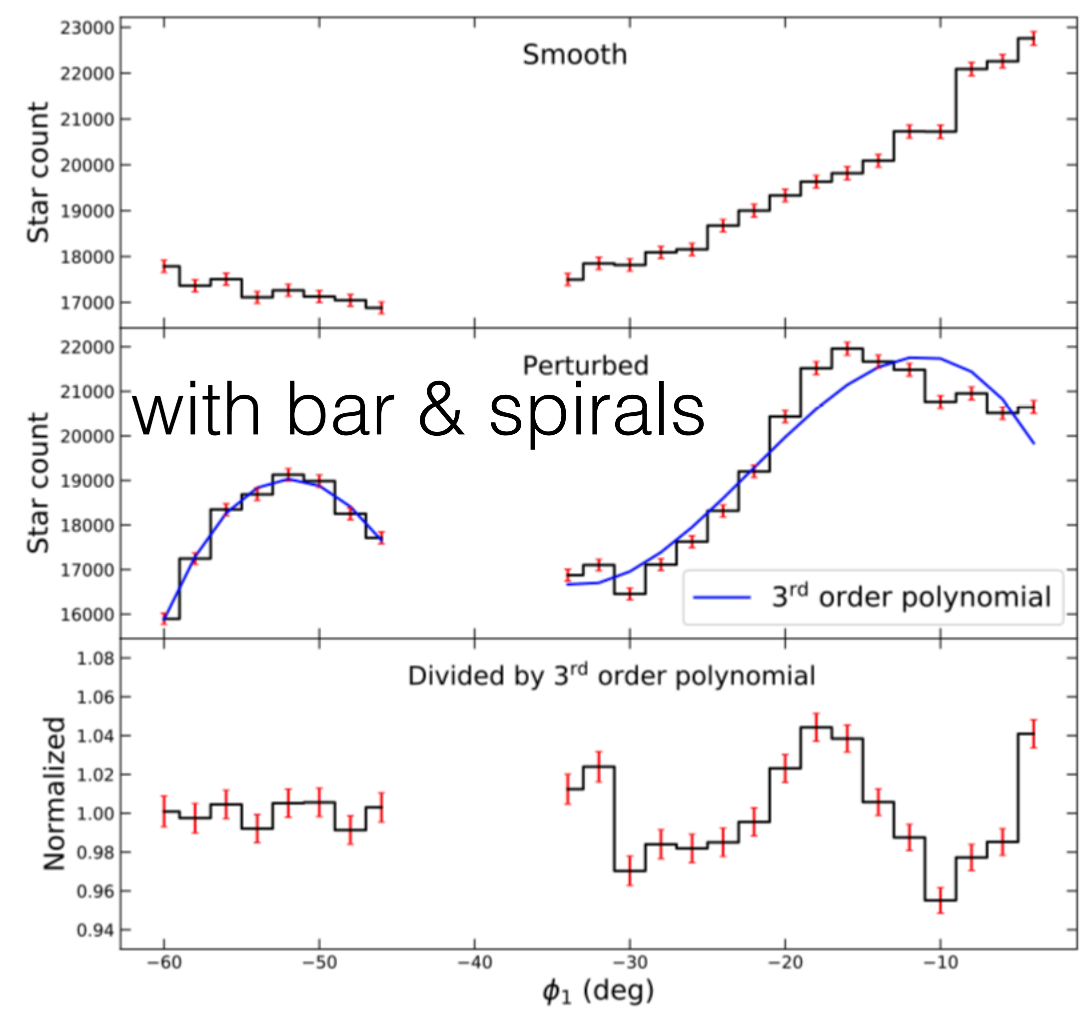
Counts



angle along stream

Simulations

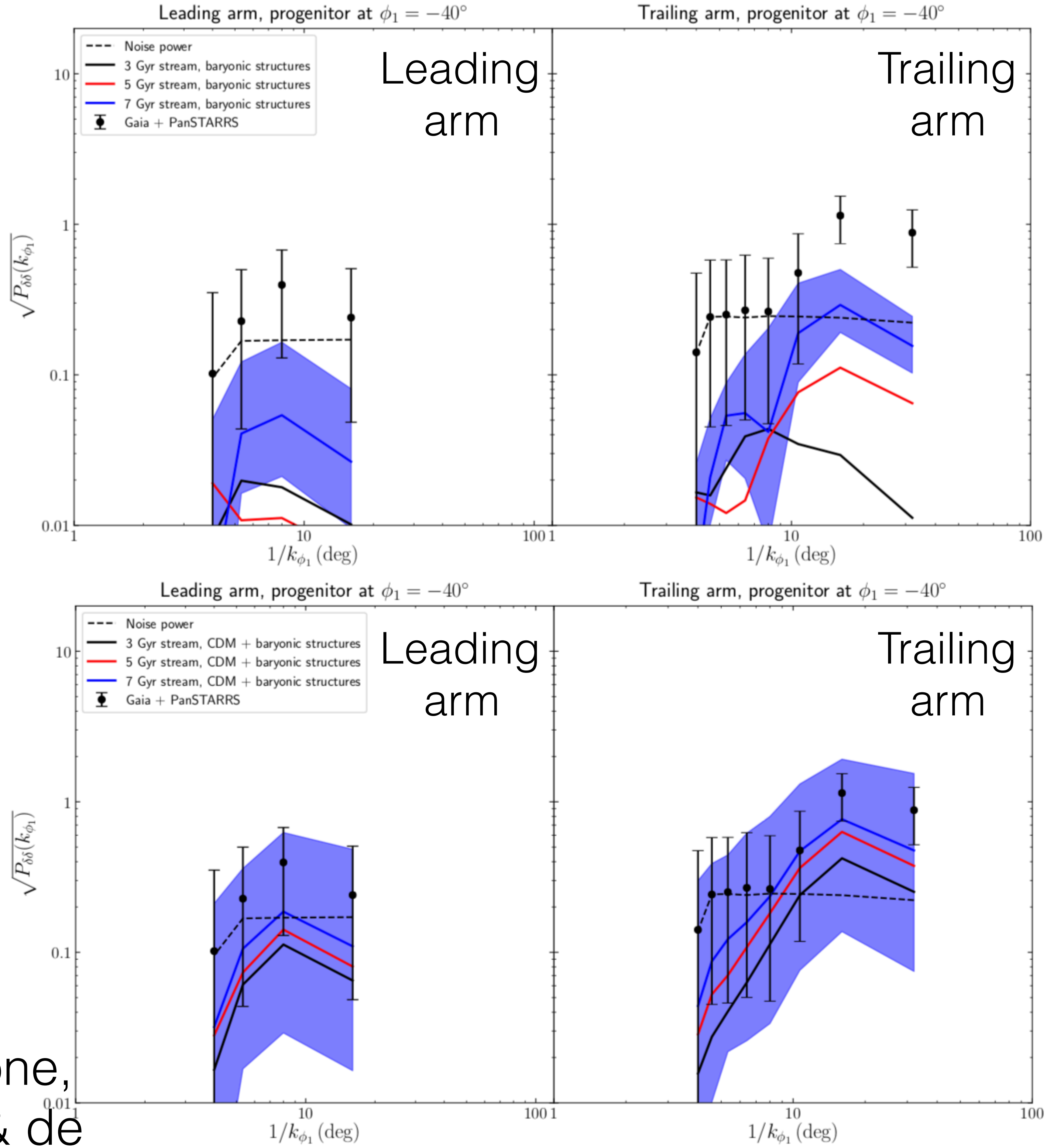
Counts



angle along stream

Banik, Bertone, Bovy, Erkal & de Boer (2021)

Power



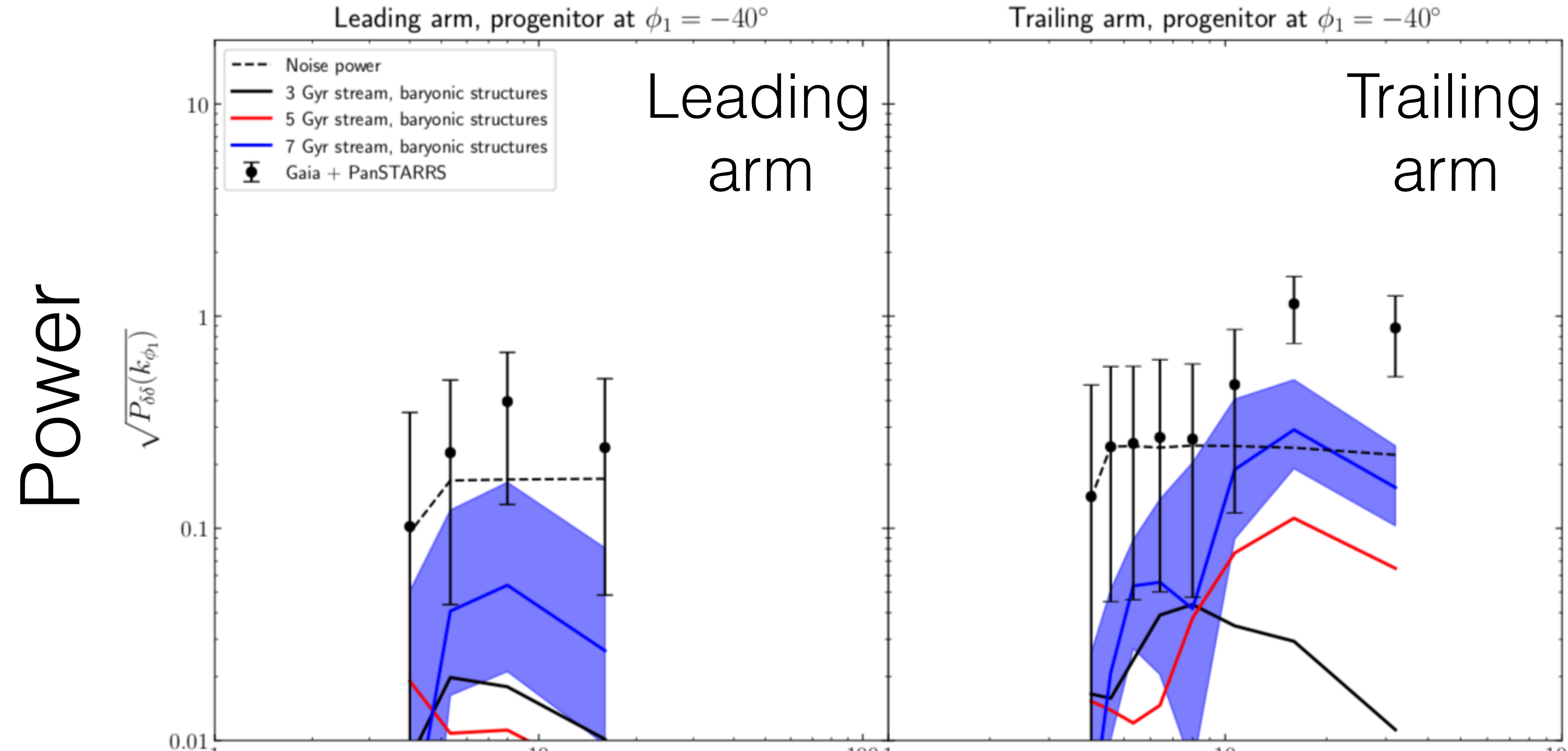
no LCDM lumps

Power

with LCDM lumps

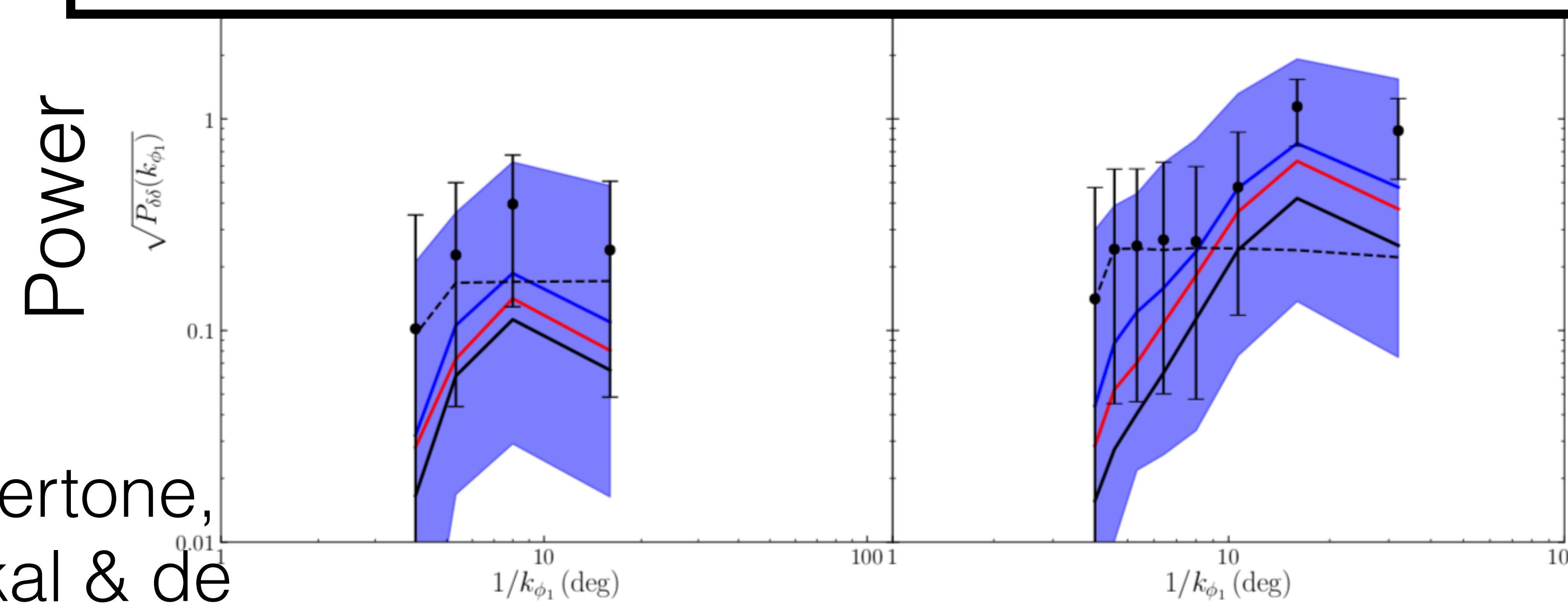
Banik, Bertone, Bovy, Erkal & de Boer (2021)

inverse angular wavenumber **[deg]**



no LCDM lumps

Implies abundance of sub halos of $0.4^{+0.3}_{-0.2}$ compared to CDM



with LCDM lumps

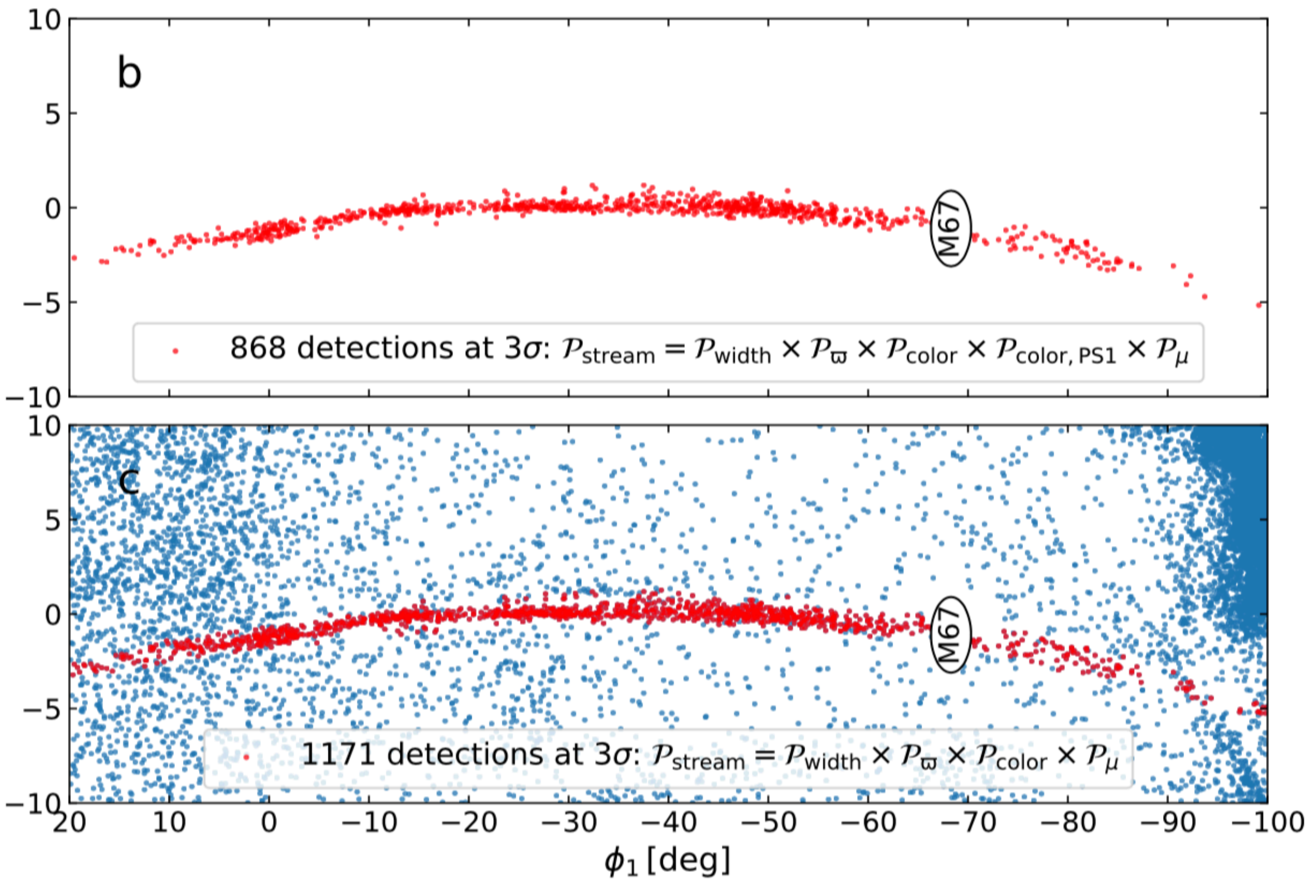
Banik, Bertone, Bovy, Erkal & de Boer (2021)

inverse angular wavenumber **[deg]**

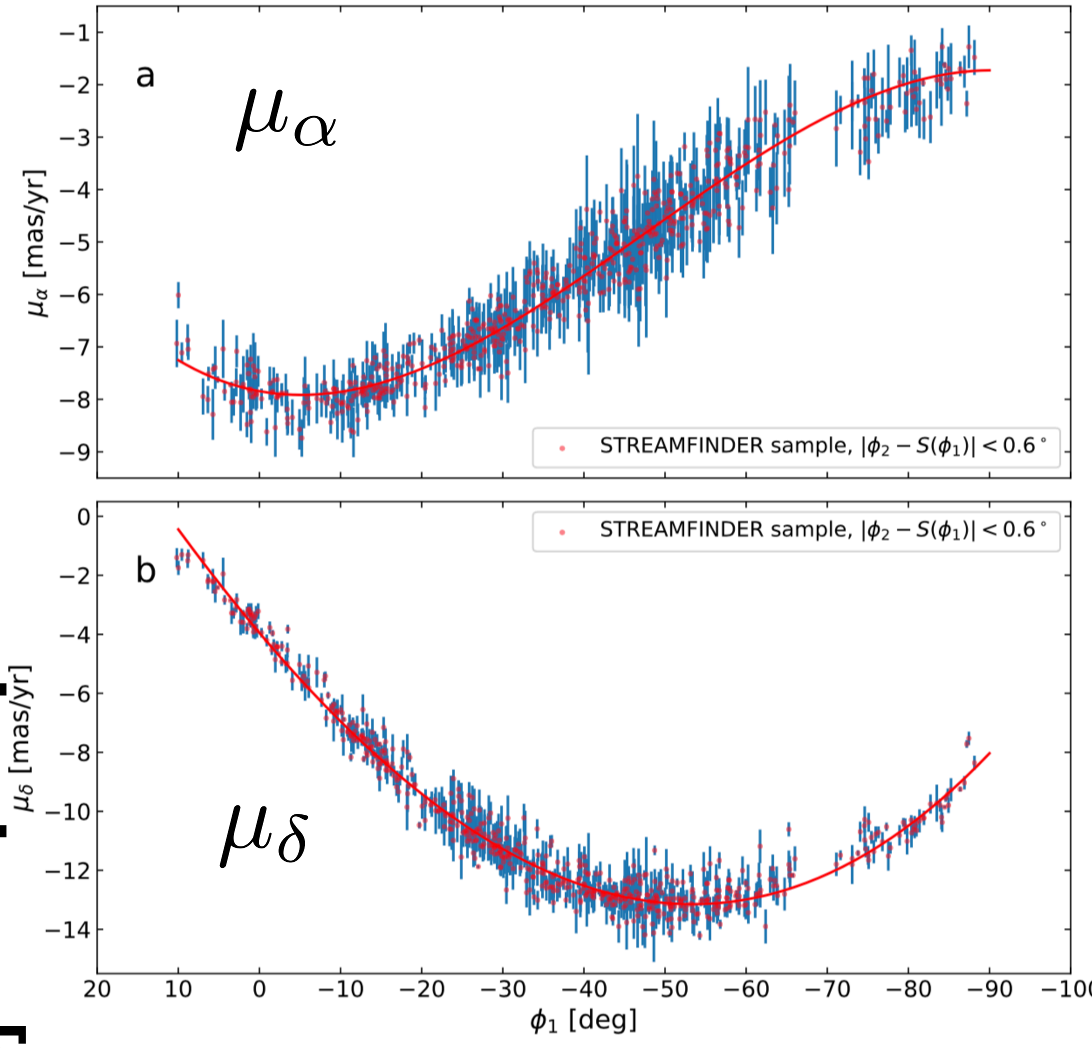
GD1 stream

RI, Thomas, Famaey, Malhan, Monari (2020)

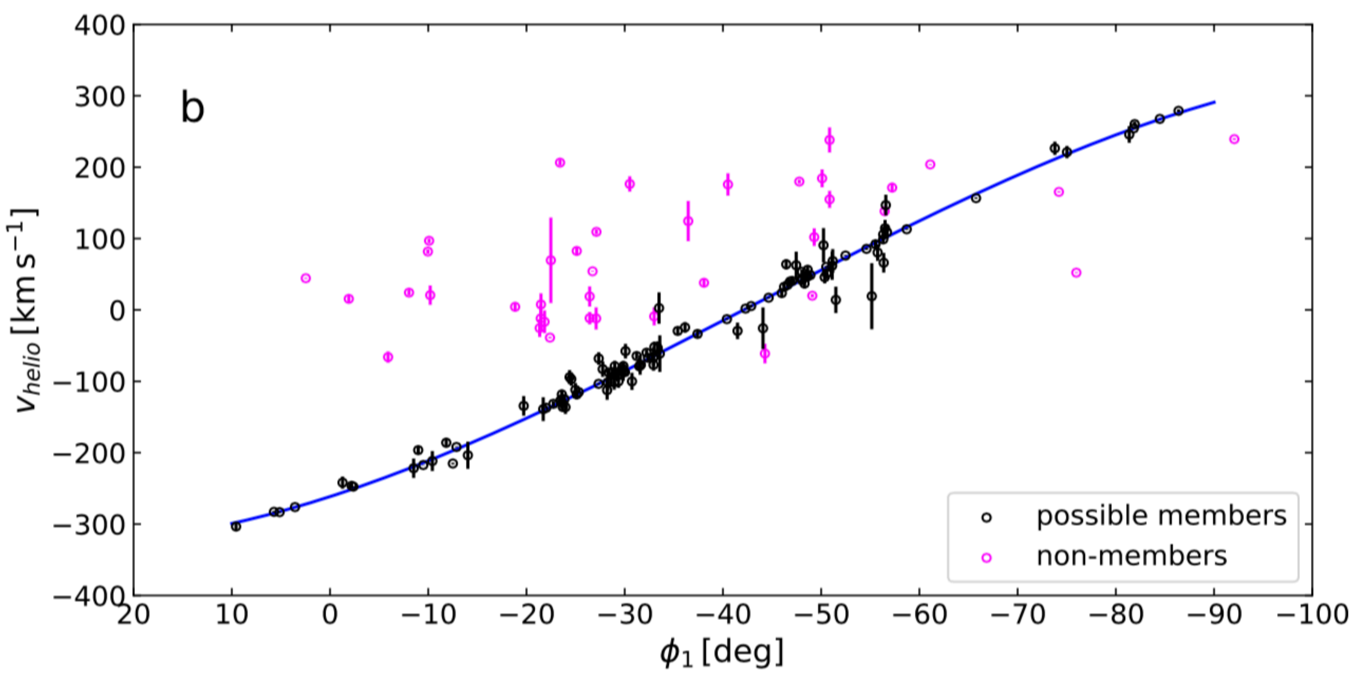
perpendicular angle



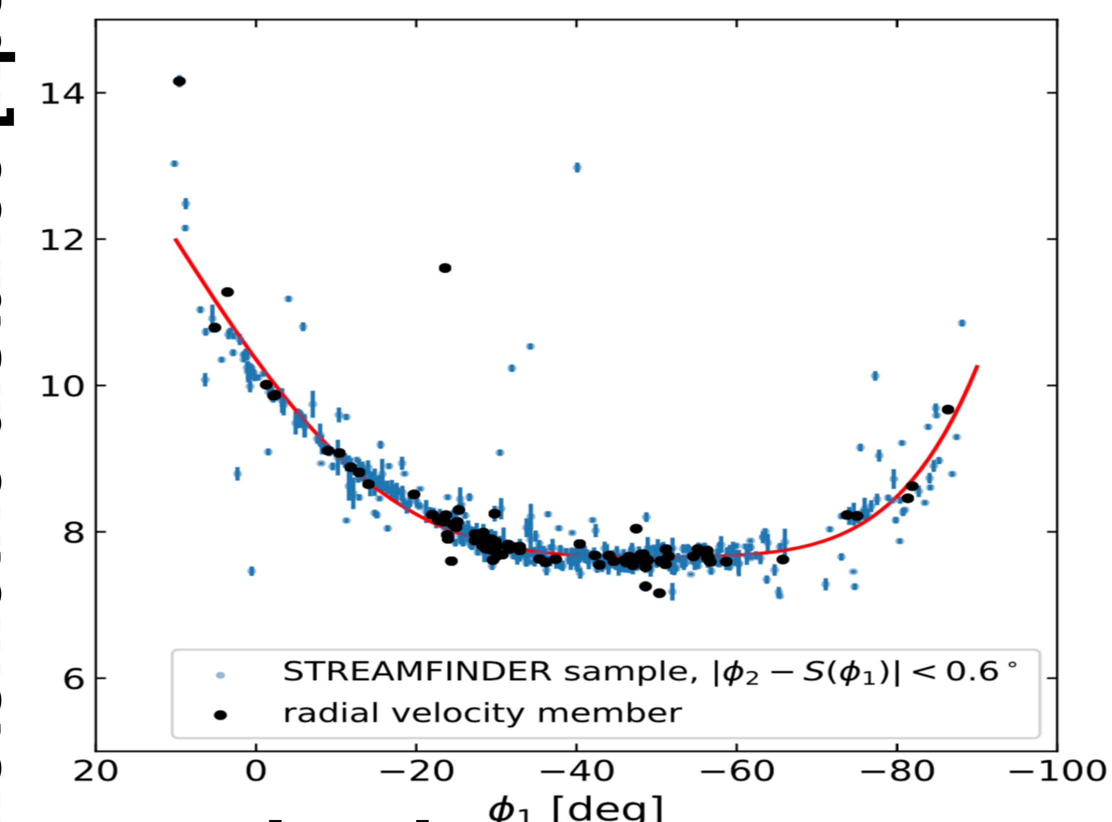
proper motions



v



photometric distance [kpc]

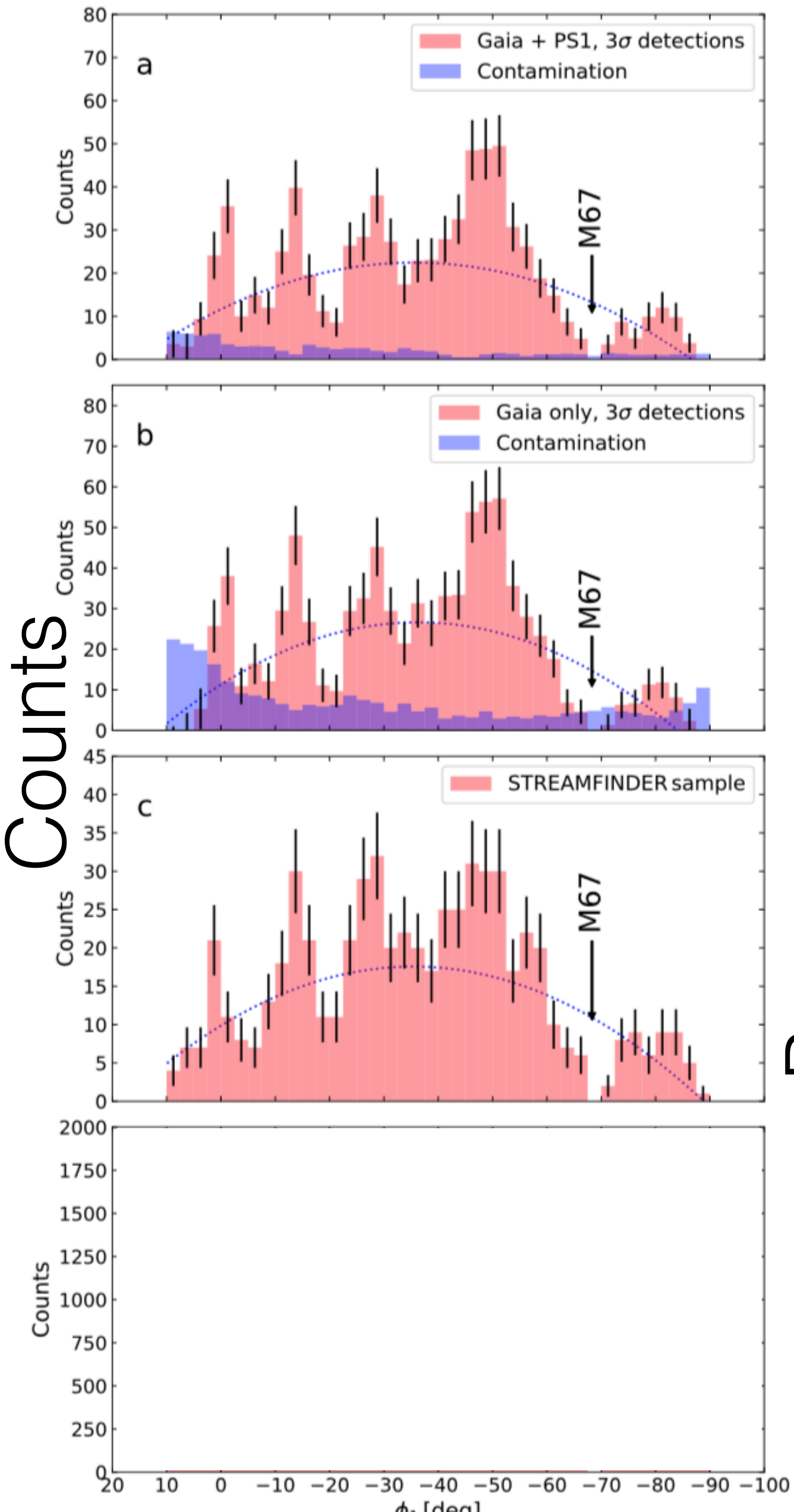


angle along stream

angle along stream

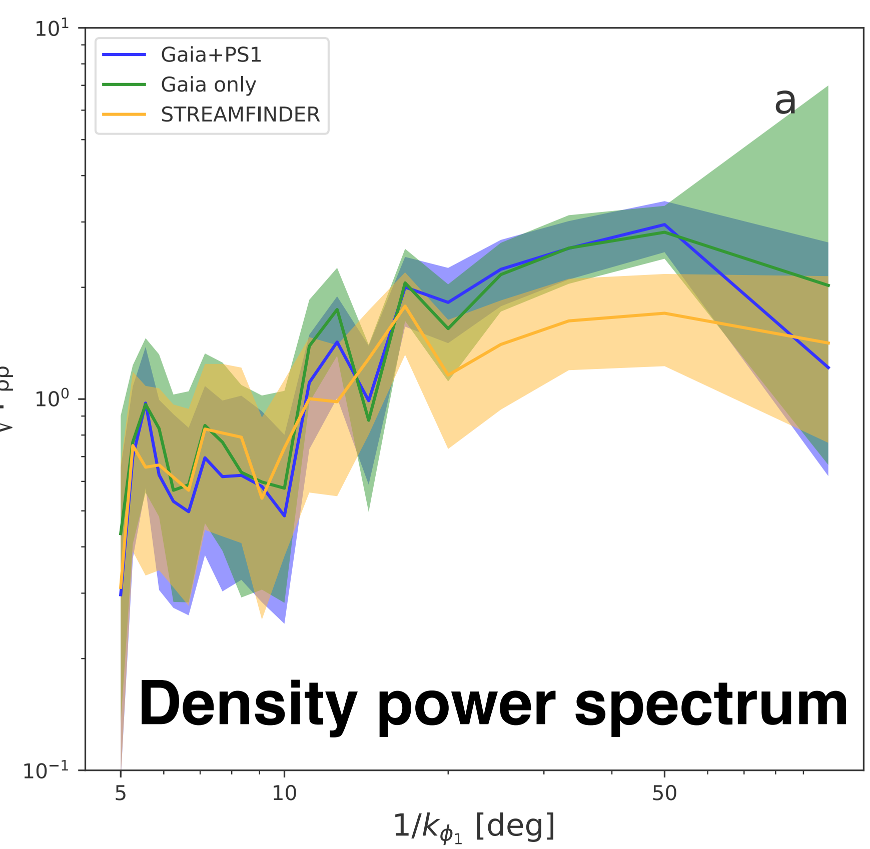
RI, Thomas, Famaey, Malhan, Monari (2020)

Counts



angle along stream

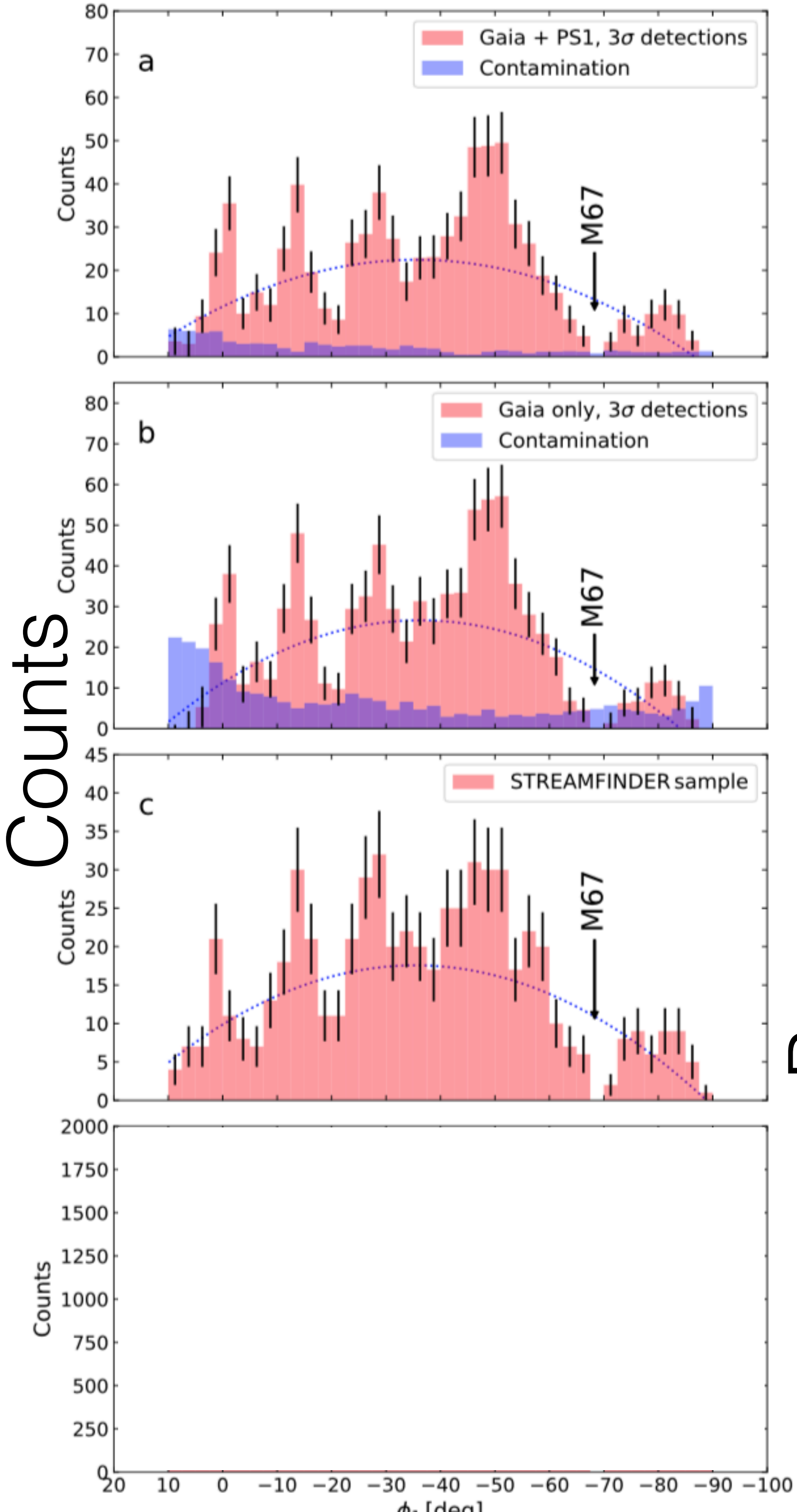
Power



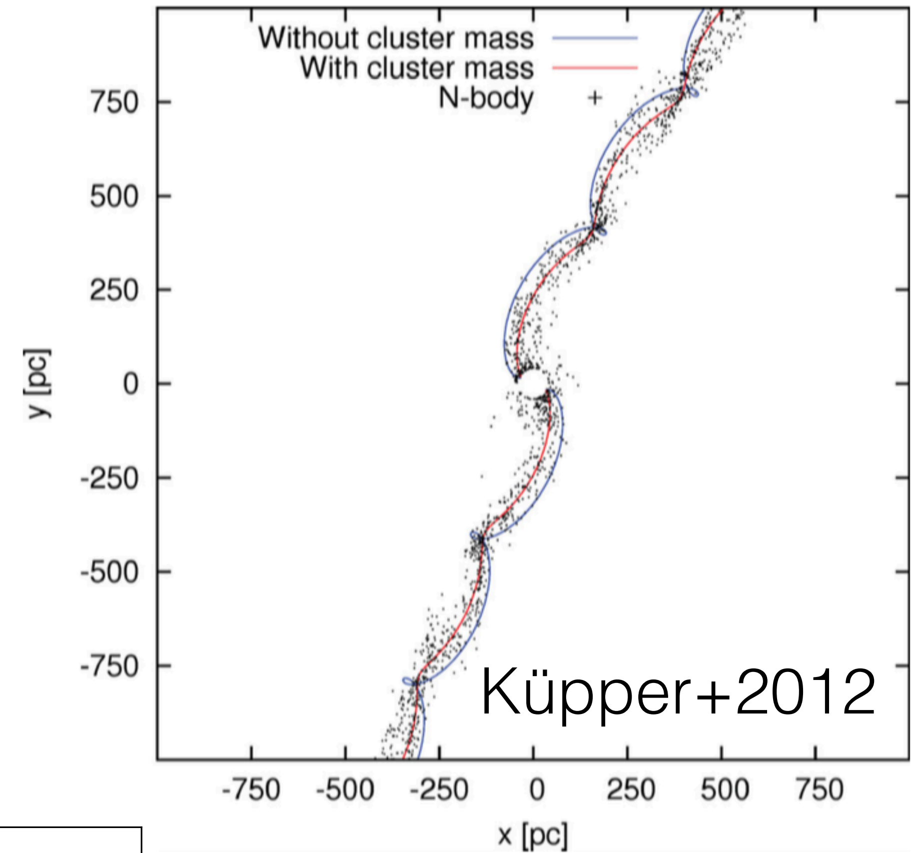
inverse wavenumber **[deg]**

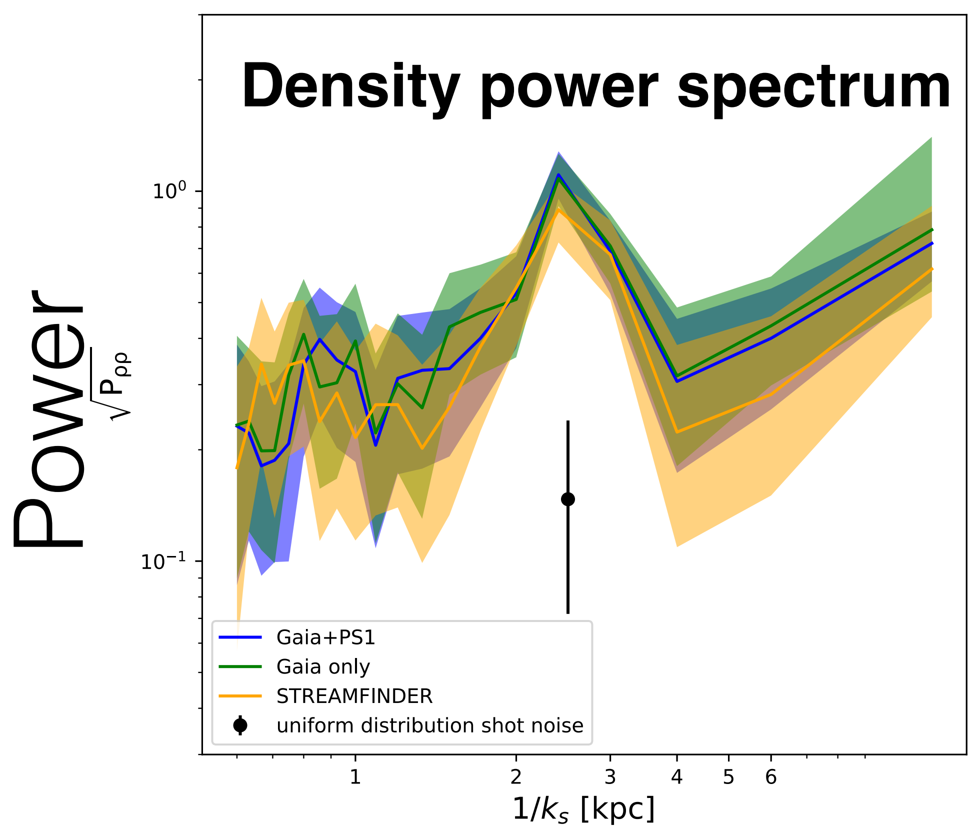
Epicycles!

RI, Thomas, Famaey, Malhan, Monari (2020)



angle along stream



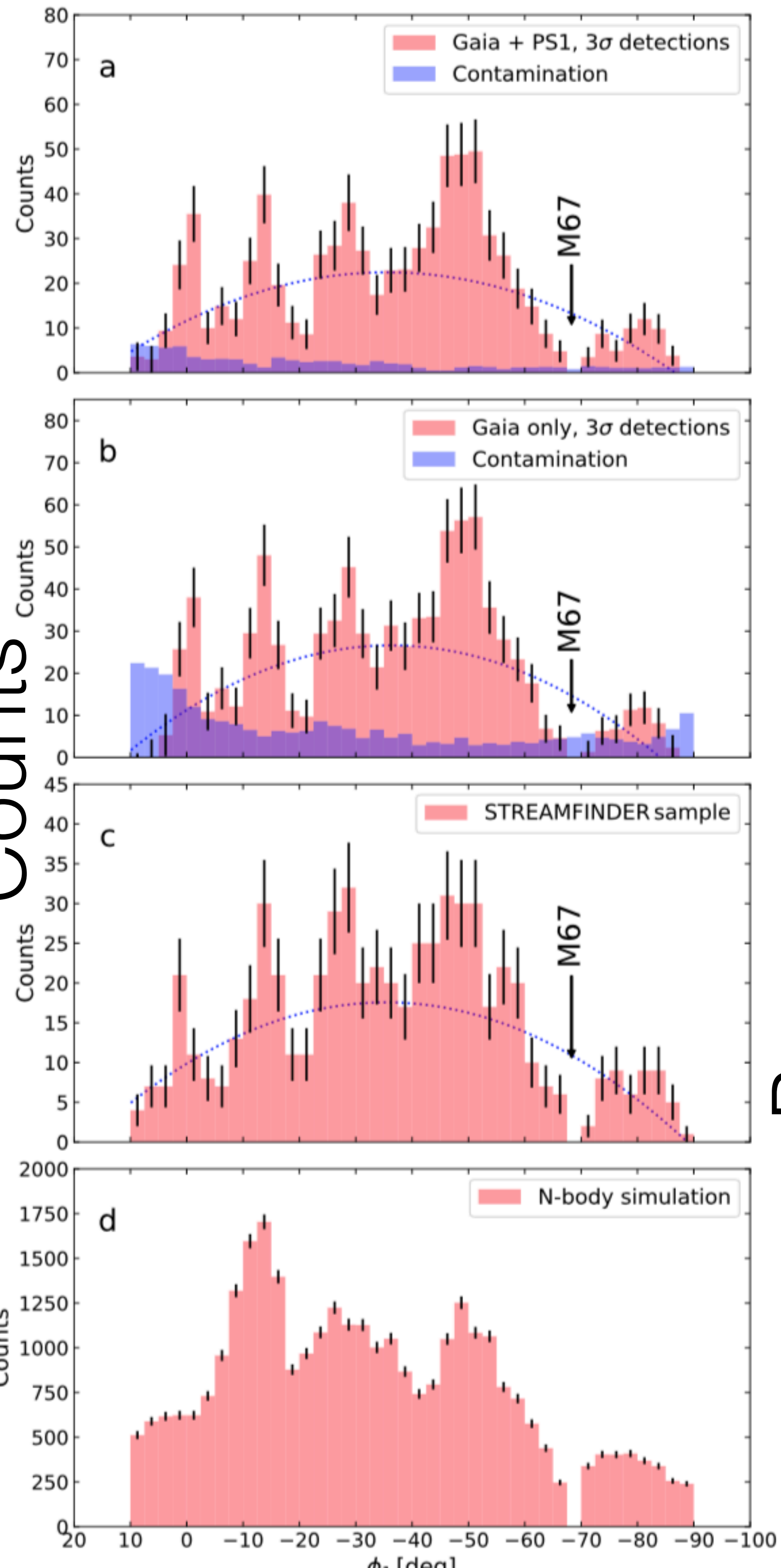


inverse wavenumber **[kpc]**

Epicycles!

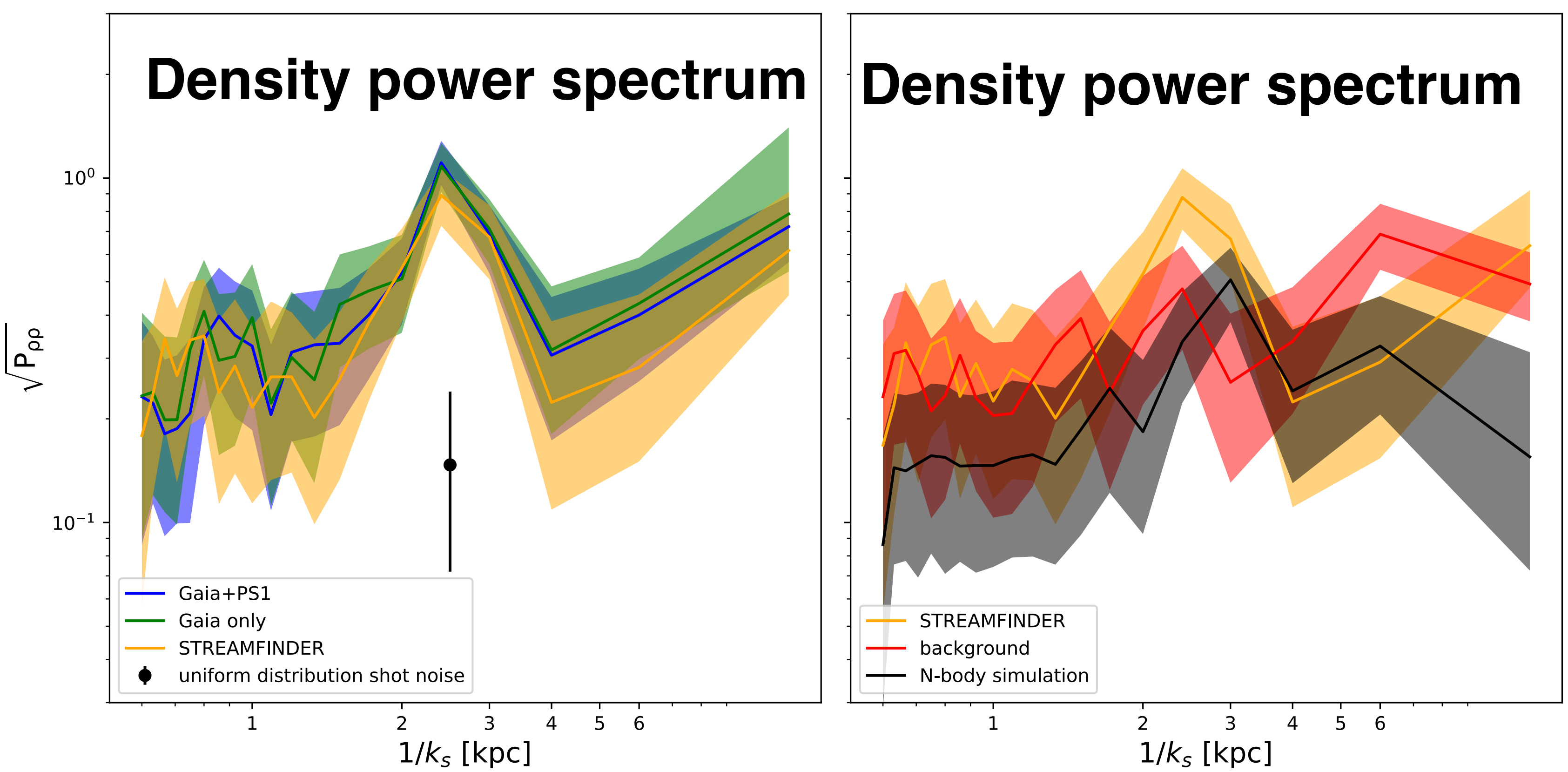
RI, Thomas, Famaey, Malhan, Monari (2020)

Counts



angle along stream

Power



inverse wavenumber **[kpc]**

Epicycles, not LCDM subhalo flybys…!

Wrapping up…

- Stellar streams hold much promise as probes of the dark matter
- Have developed a Deep Learning algorithm to find canonical transformations $(x, v) \rightarrow (\theta, J)$, and recover Φ and $H(J)$. Now works with realistic stream (6D+5D) astrometric observables.
- This is a fairly generic method that may work throughout much of physics!
- Very soon: Galactic acceleration field from streams
- TBD: Confront acceleration field with predictions of different theories of dark matter & gravity
- TBD: Confront stream properties with predictions of DM & gravity theories