Spatially Coherent 3D Distributions of HI and CO in the Milky Way

Talk by **Laurin Söding**, Philipp Mertsch and Vo Hong Minh Phan

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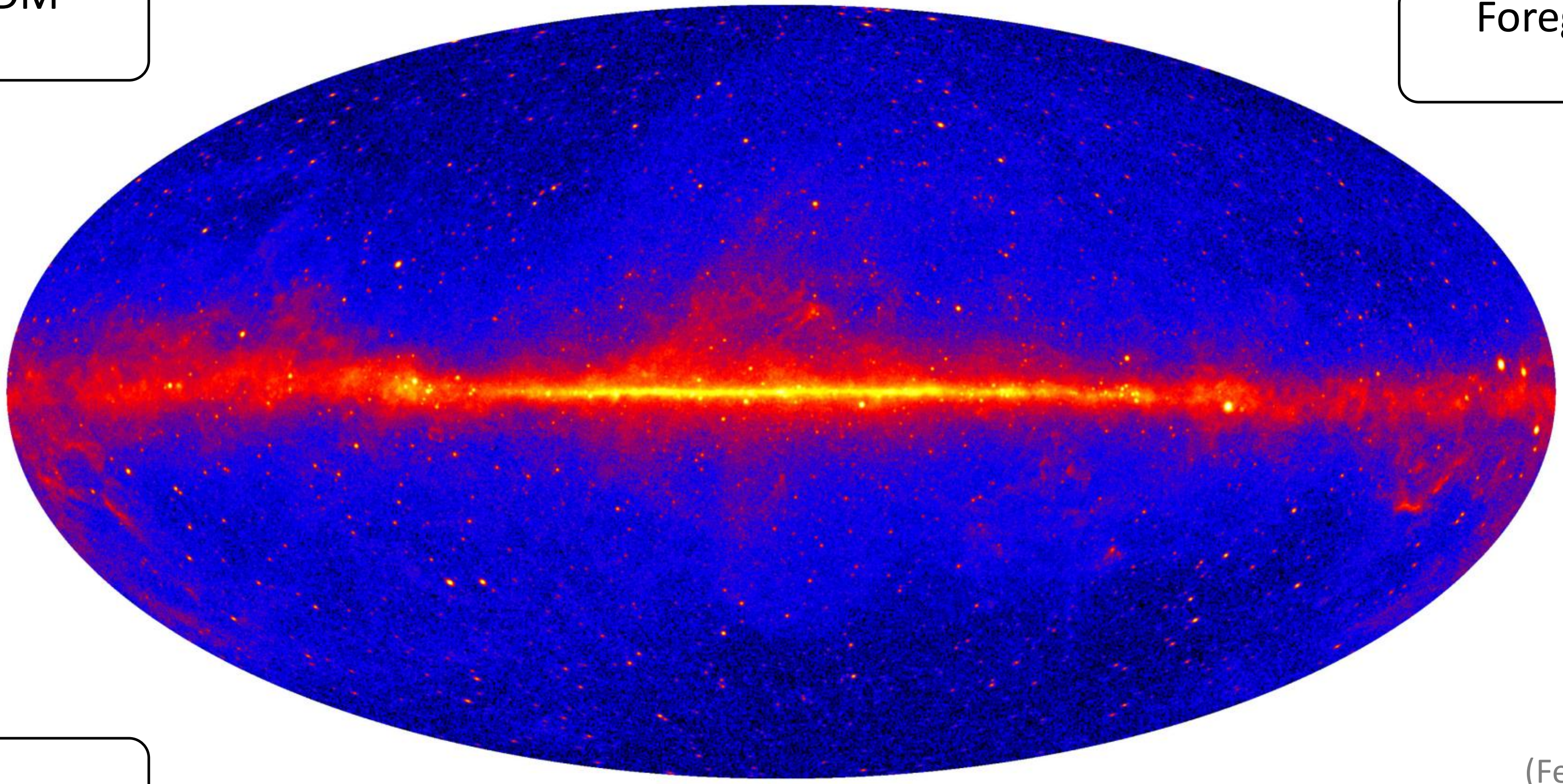
Karlsruhe, 04.03.2024

The Diffuse (Galactic) Gamma-Ray Sky

Foreground for DM searches

Foreground for γ-ray astronomy



(Fermi LAT Collaboration)

Probe for cosmic rays

The Diffuse (Galactic) Gamma-Ray Sky

Cosmic rays + { Gases Magnetic fields Interstellar radiation fields }

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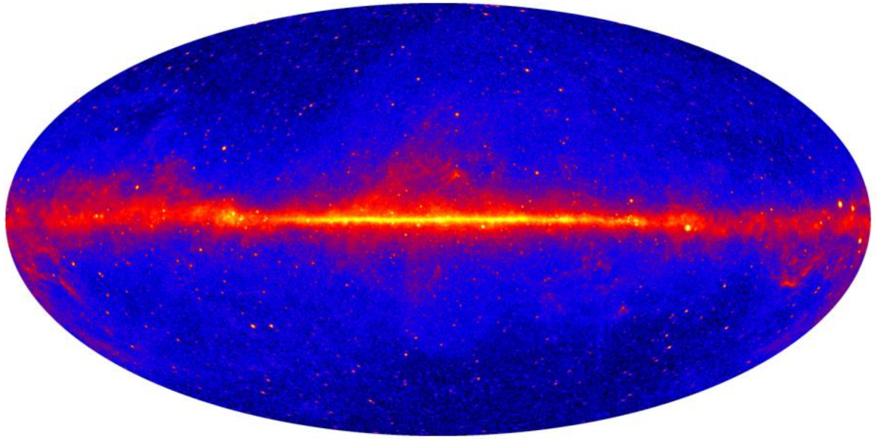
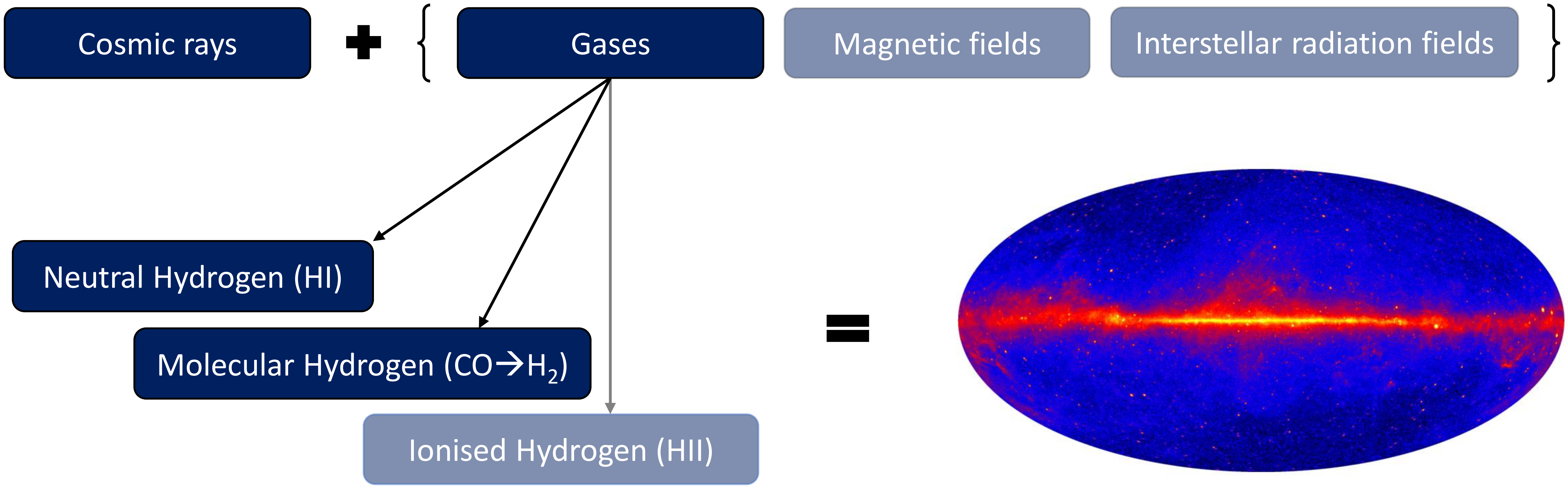


(Fermi LAT Collaboration)

The Diffuse (Galactic) Gamma-Ray Sky



Cosmic rays ✚ { Gases | Magnetic fields | Interstellar radiation fields }

Gases → Neutral Hydrogen (HI)

Gases → Molecular Hydrogen (CO→H_2)

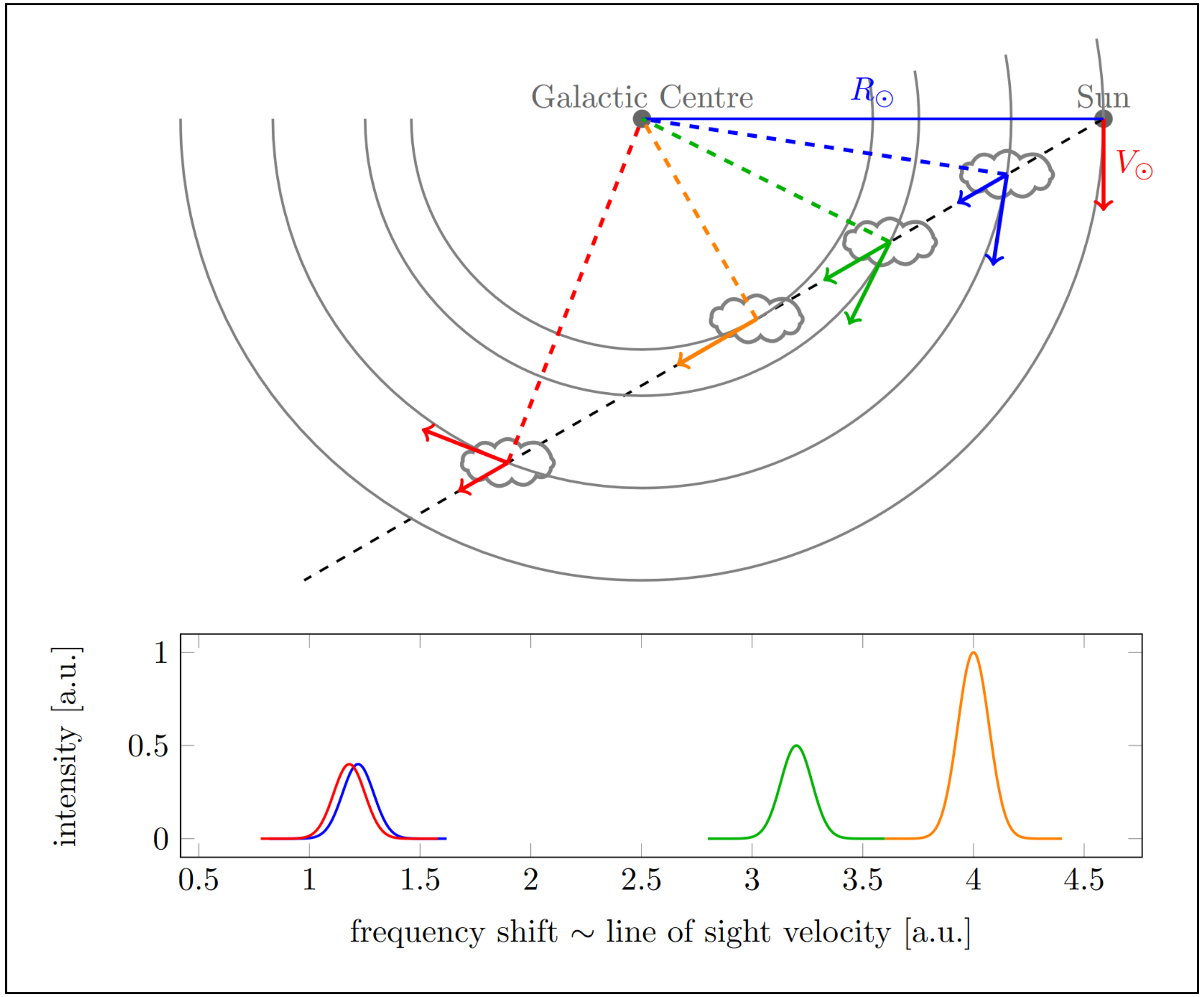
Gases → Ionised Hydrogen (HII)

=

(Fermi LAT Collaboration)

The Idea: Reconstructing the 3D Gas Distributions

- ❖ Gas on (circular) paths around the Galactic Centre
- ❖ Narrow emission lines become Doppler-shifted



The Idea: Reconstructing the 3D Gas Distributions

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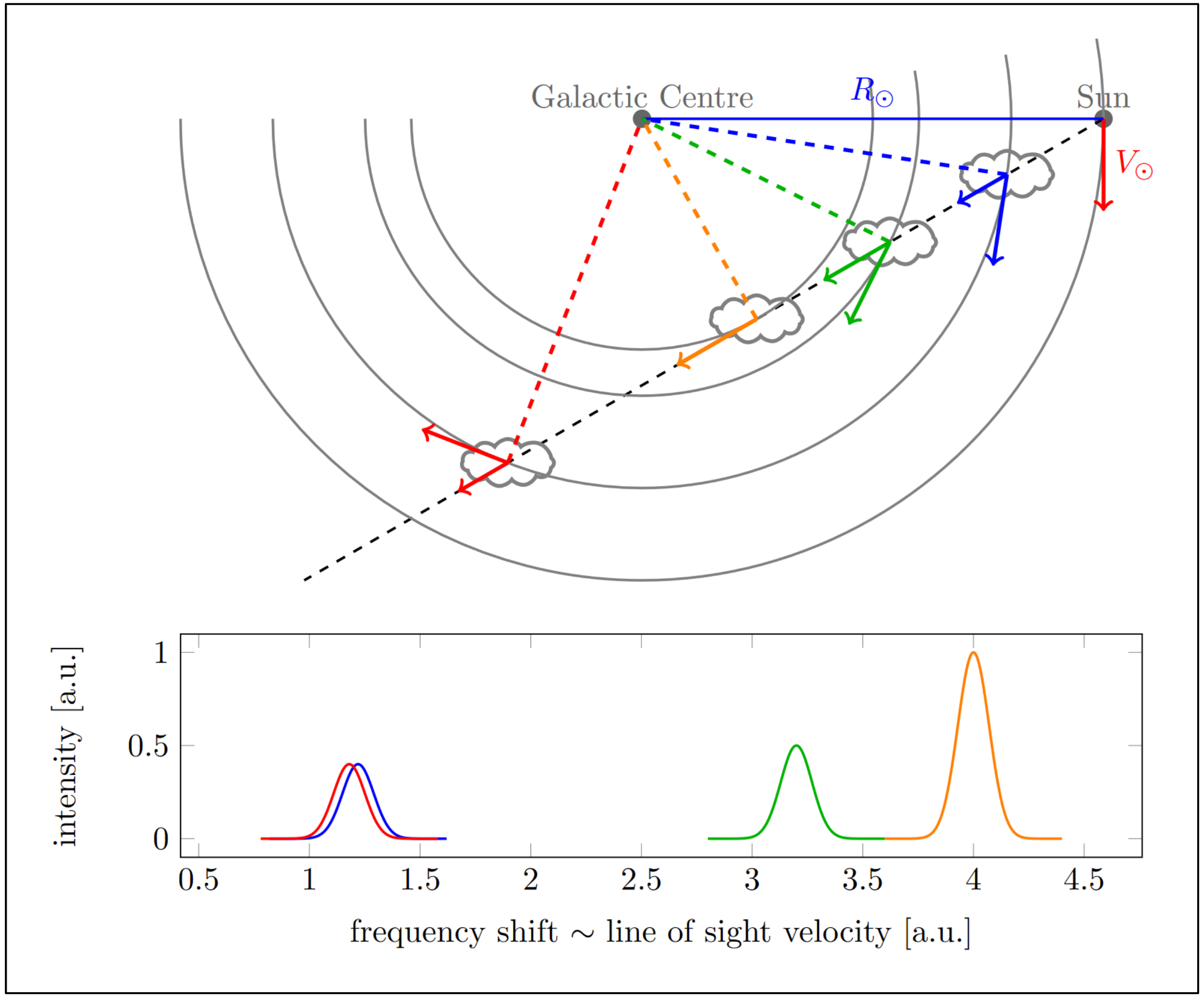
1) Match Doppler-shift → velocity
2) Match velocity → distance



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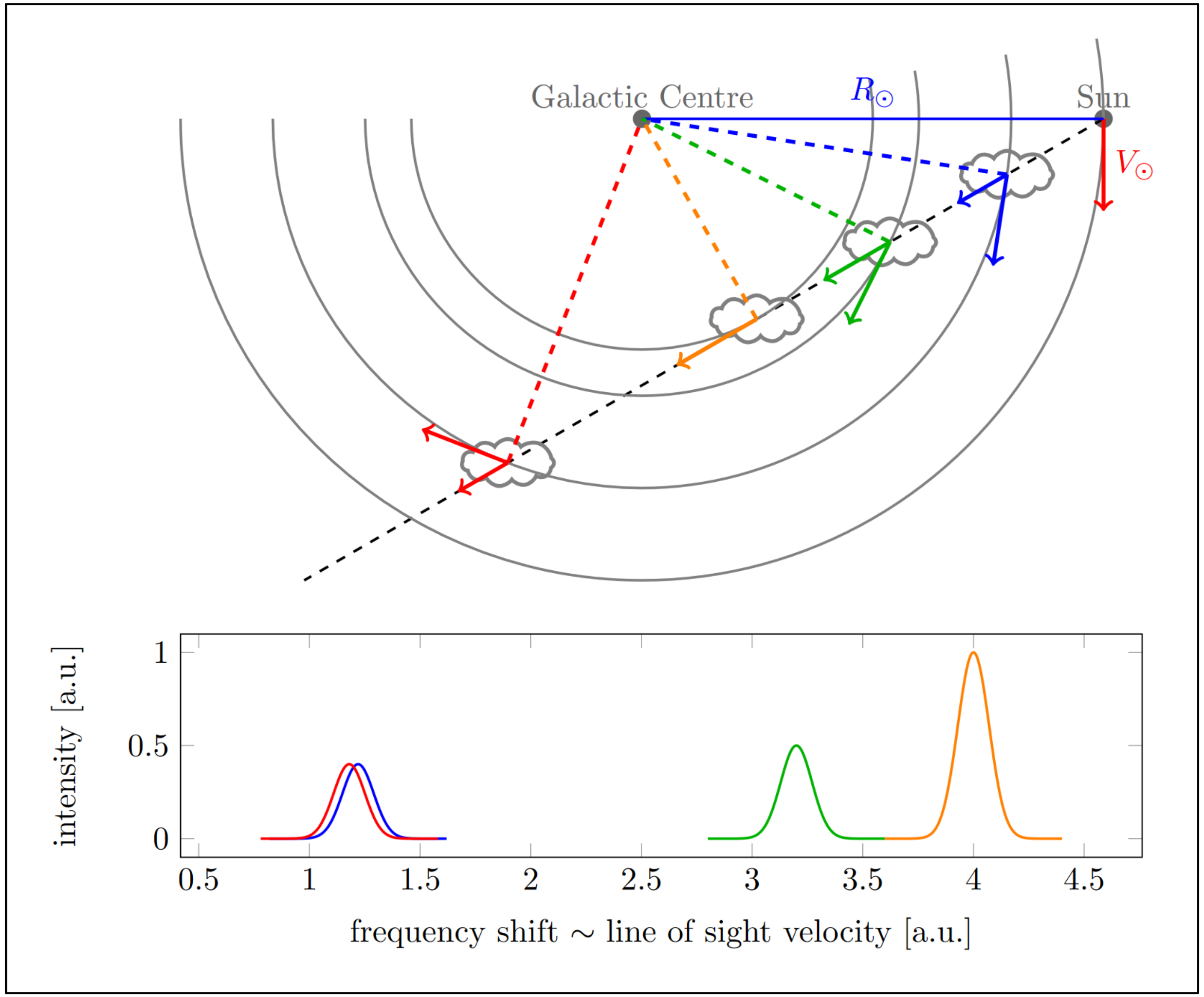
Problems:

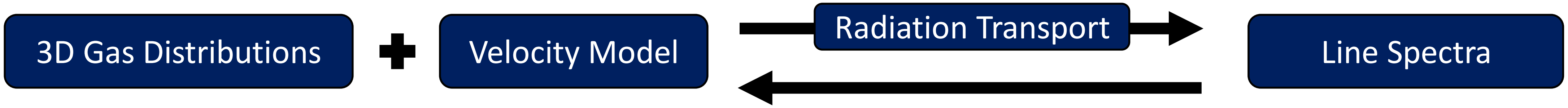
I. Velocity → distance is ambiguous!
II. True orbits are unknown! ~5-10% deviations!



Basic Idea: Bayesian Inference

3D Gas Distributions + Velocity Model → Radiation Transport → Line Spectra

Basic Idea: Bayesian Inference

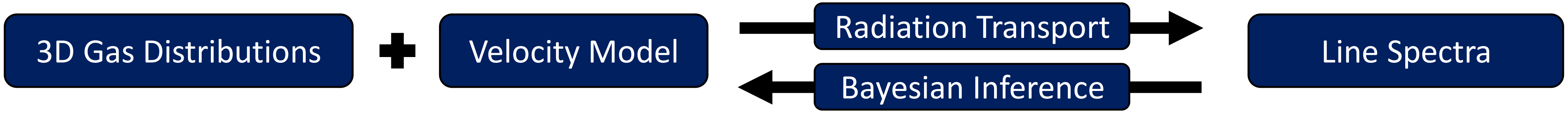


3D Gas Distributions + Velocity Model

Radiation Transport

Line Spectra

Basic Idea: Bayesian Inference



3D Gas Distributions + Velocity Model

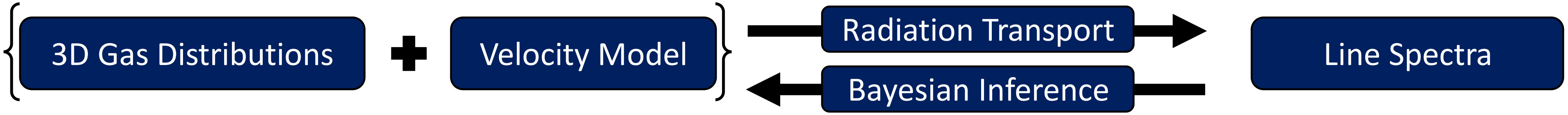
Radiation Transport

Bayesian Inference

Line Spectra

Bayes‘ law: $P\left(\rho_{\mathrm{HI}}, \rho_{\mathrm{CO}}, \boldsymbol{v}, \ldots \,|\, d\right) = \dfrac{P\left(d \,|\, \rho_{\mathrm{HI}}, \rho_{\mathrm{CO}}, \boldsymbol{v}, \ldots\right) \cdot P\left(\rho_{\mathrm{HI}}, \rho_{\mathrm{CO}}, \boldsymbol{v}, \ldots\right)}{P\left(d\right)}$

Basic Idea: Bayesian Inference



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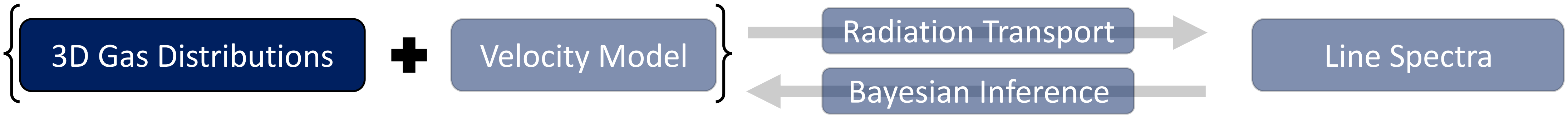
We reconstruct a set of samples $\{\rho_{\mathrm{HI},i},\ \rho_{\mathrm{CO},i},\ \boldsymbol{v}_i\}_{i=1\ldots N}$ that approximate the posterior distribution

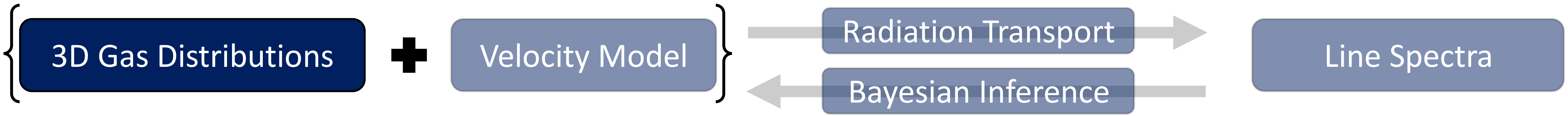
For more detail: arXiv:1901.11033

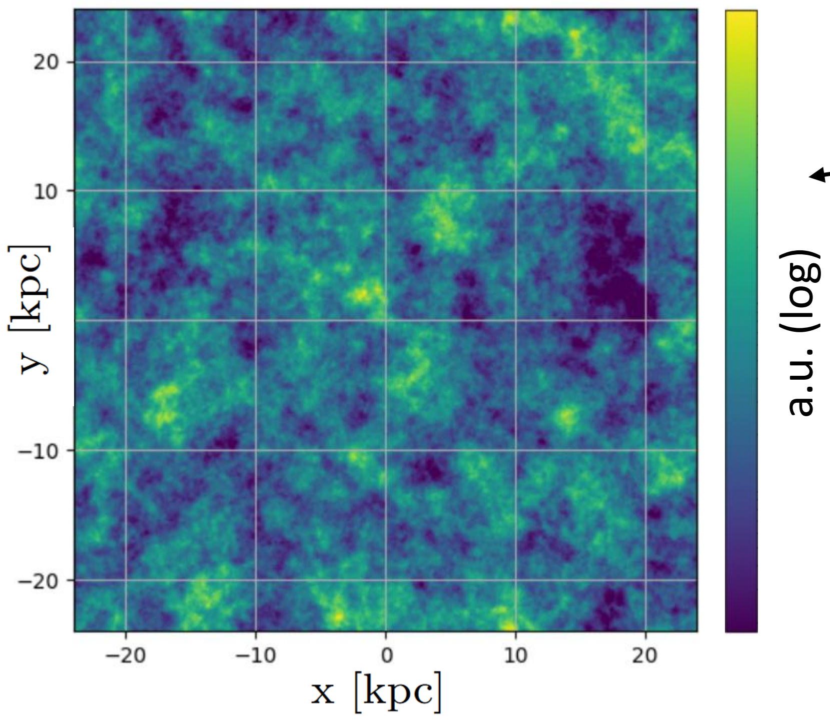
A Model for the Gas Distributions



- Key requirement: **Spatial coherence**
- Homogeneous (log)normal Gaussian random fields $g(\vec{x})$:
  - Generated e.g. by correlating random numbers
- Superimposed:
  1) Radial profile: Milky Way is (roughly) axisymmetric
  2) Z-profile: Milky Way is disk-shaped

A Model for the Gas Distributions





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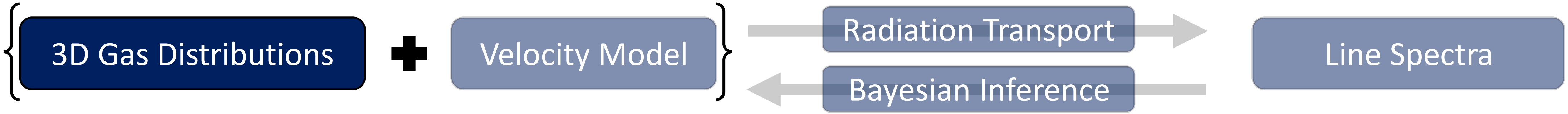
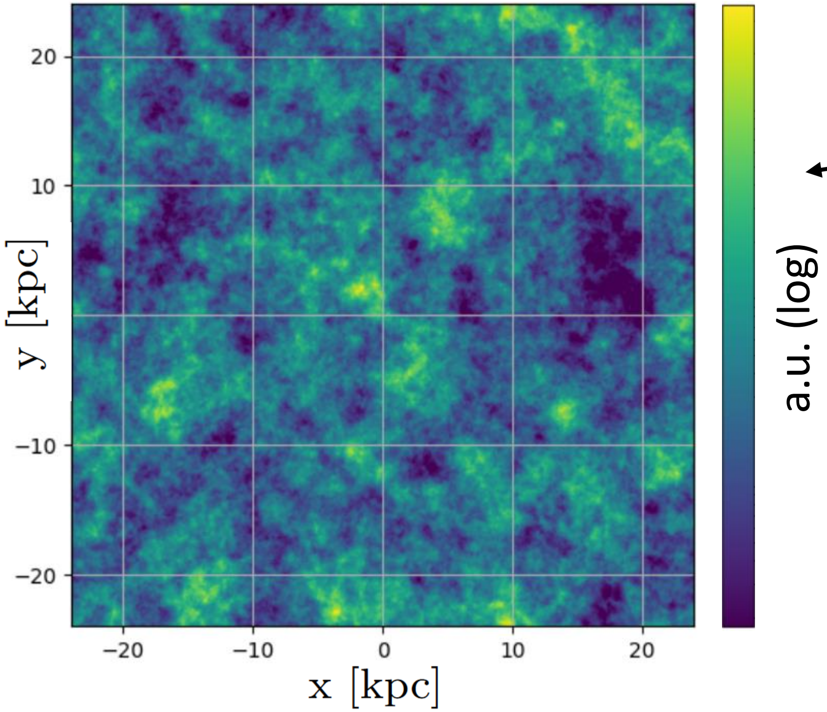


3D Gas Distributions + Velocity Model

Radiation Transport

Bayesian Inference

Line Spectra



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- ❖ Homogeneous (log)normal Gaussian random fields $g(\vec{x})$:
  - ❖ Generated e.g. by correlating random numbers
- ❖ Superimposed:
  1) Radial profile: Milky Way is (roughly) axisymmetric
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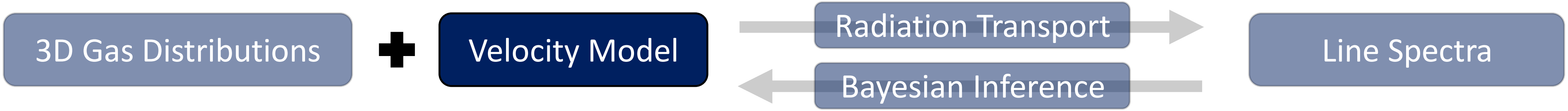
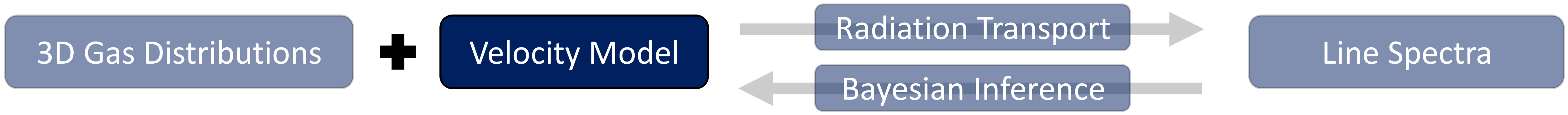
Model for gas densities: $\rho(\vec{x}) = f_1(r) \cdot f_2(z) \cdot e^{g(\vec{x})}$

A Model for the Line-Of-Sight Velocity



- ❖ Need only line-of-sight component
- ❖ Rotation curve from Gaia DR3 analyses
- ❖ Additional information by 2 populations of tracers:
  1) Masers
  2) Young-Stellar-Objects clusters

A Model for the Line-Of-Sight Velocity



3D Gas Distributions ✚ **Velocity Model**

Radiation Transport

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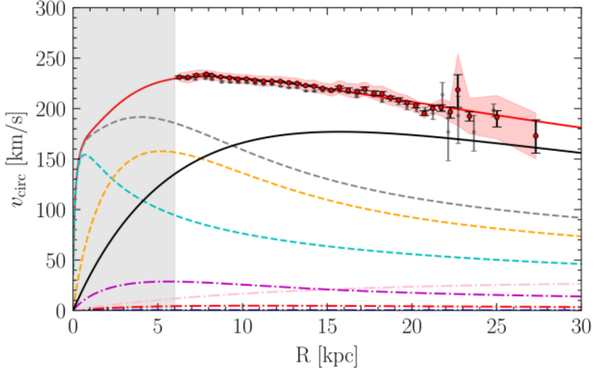
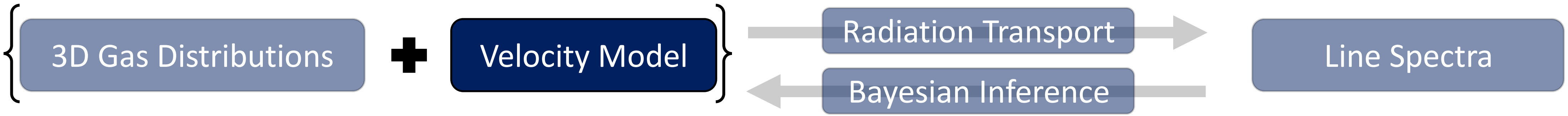


Rotation curve

(Ou et al (2023))

A Model for the Line-Of-Sight Velocity



3D Gas Distributions ✚ Velocity Model

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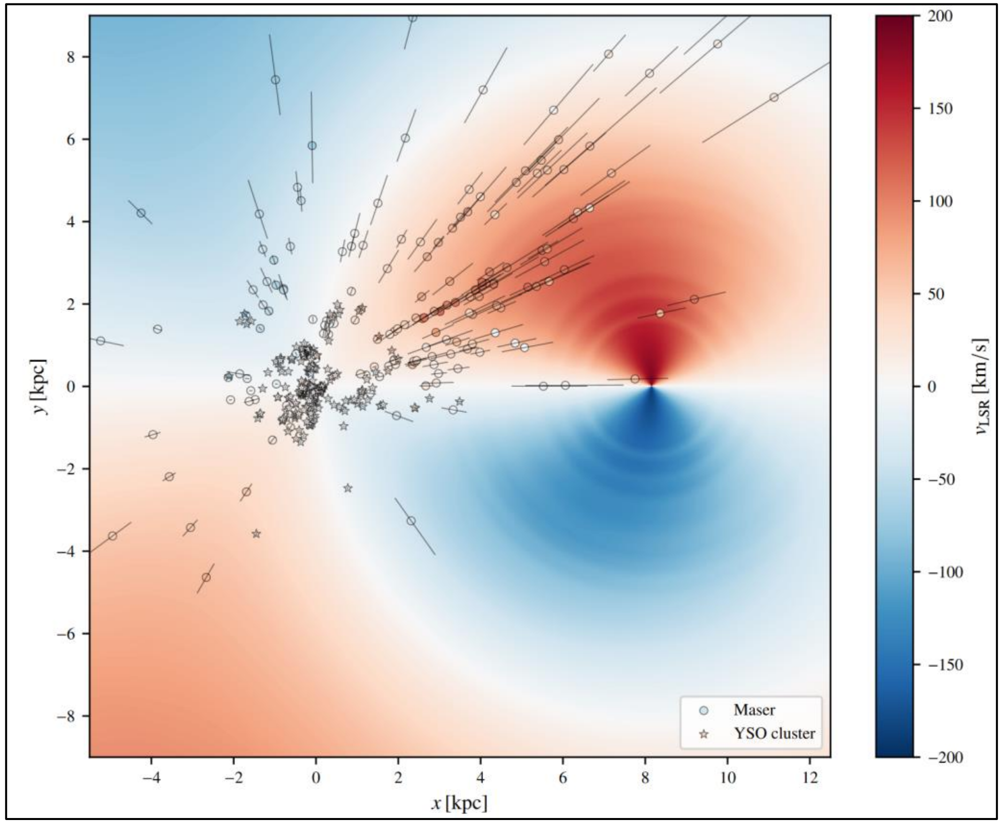

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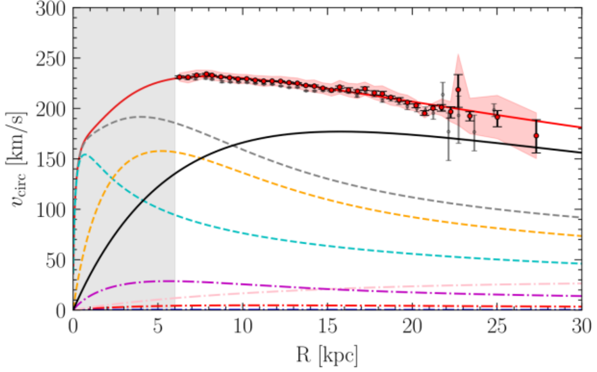
Model for gas velocities:

$$v_{\mathrm{LSR}}(\vec{x}) = v_{\mathrm{circ}}(\vec{x}) - v_{\odot} + g(\vec{x})$$

Rotation curve



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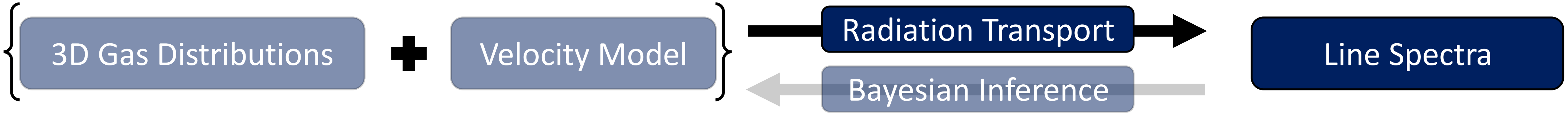
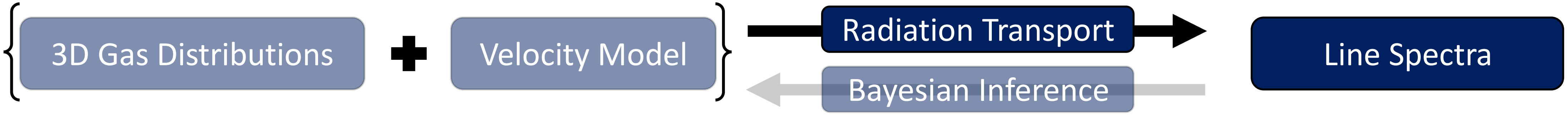
The Emission Line Spectra: HI and CO



Calculate synthetic data as line-of-sight integral: $\mathrm{d}I_\nu = -I_\nu \kappa_\nu \,\mathrm{d}s + j_\nu \,\mathrm{d}s$

The Emission Line Spectra: HI and CO



3D Gas Distributions + Velocity Model

Radiation Transport

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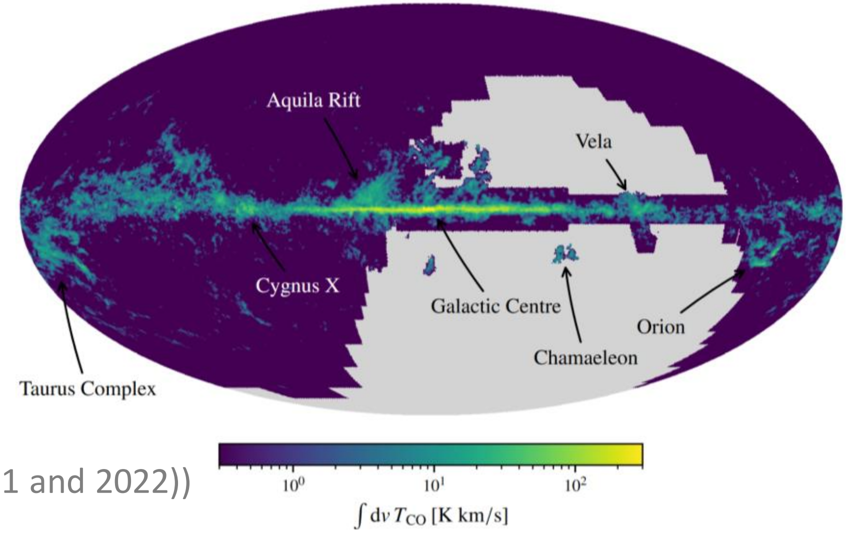
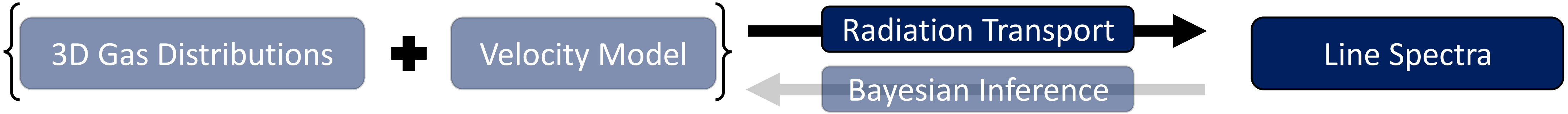


(Dame et al (2001 and 2022))

CO: $\mathrm{J} = 1 - 0$ rotational transition: 2.6mm wavelength

The Emission Line Spectra: HI and CO



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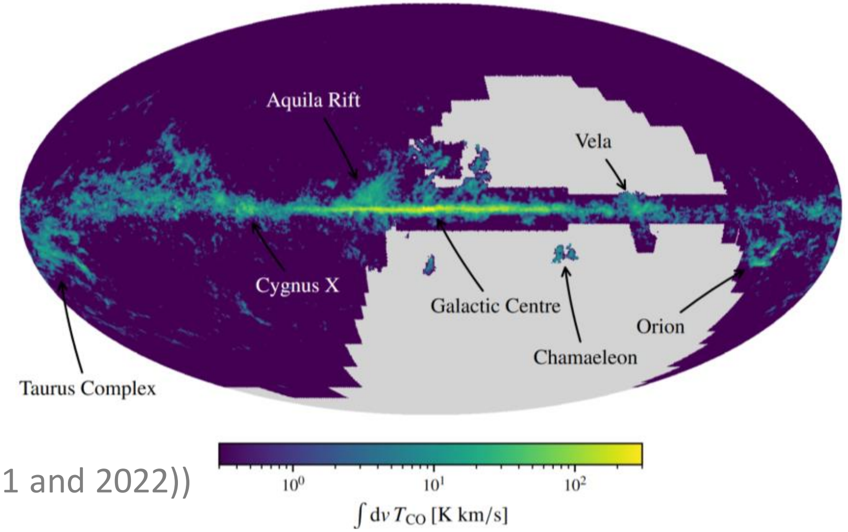

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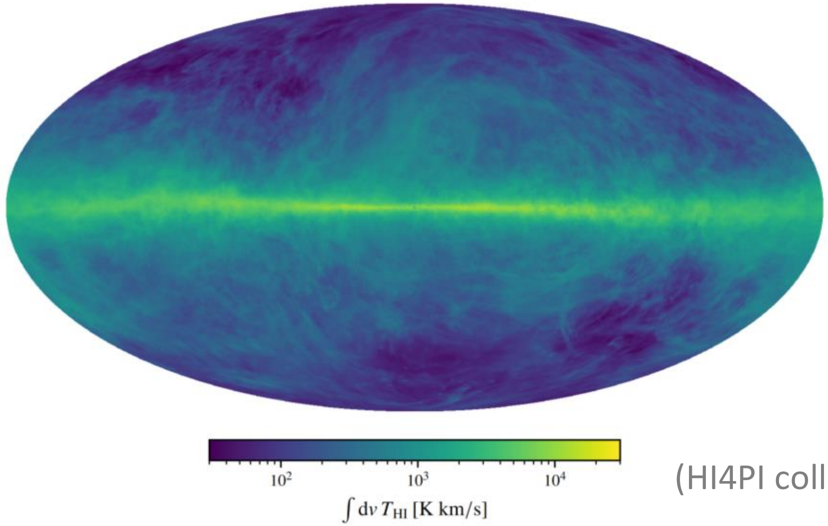


(HI4PI collaboration (2016))

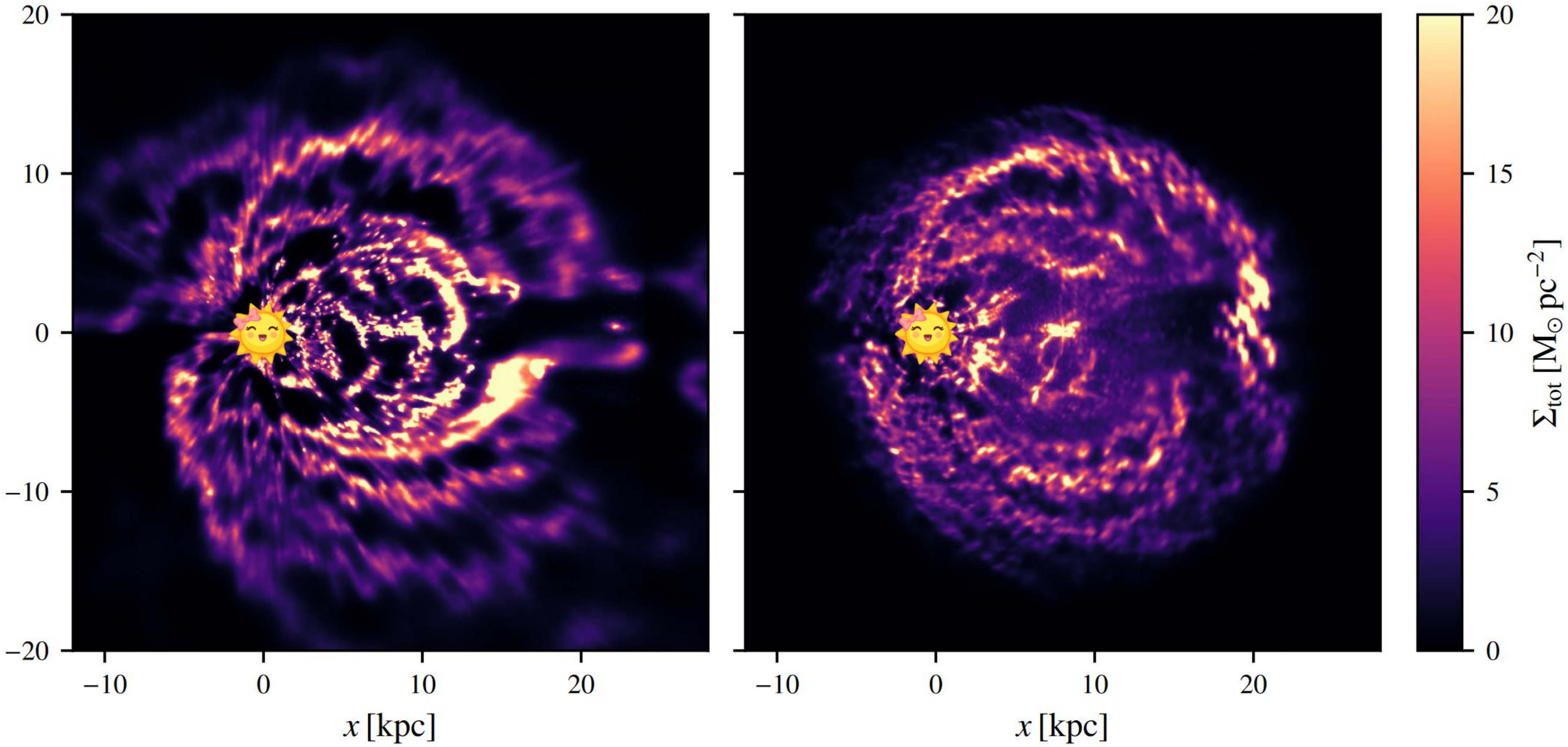
CO: $\mathrm{J} = 1 - 0$ rotational transition: 2.6mm wavelength

HI: Fine structure transition: 21cm radiation

Results: Top-down view (global)

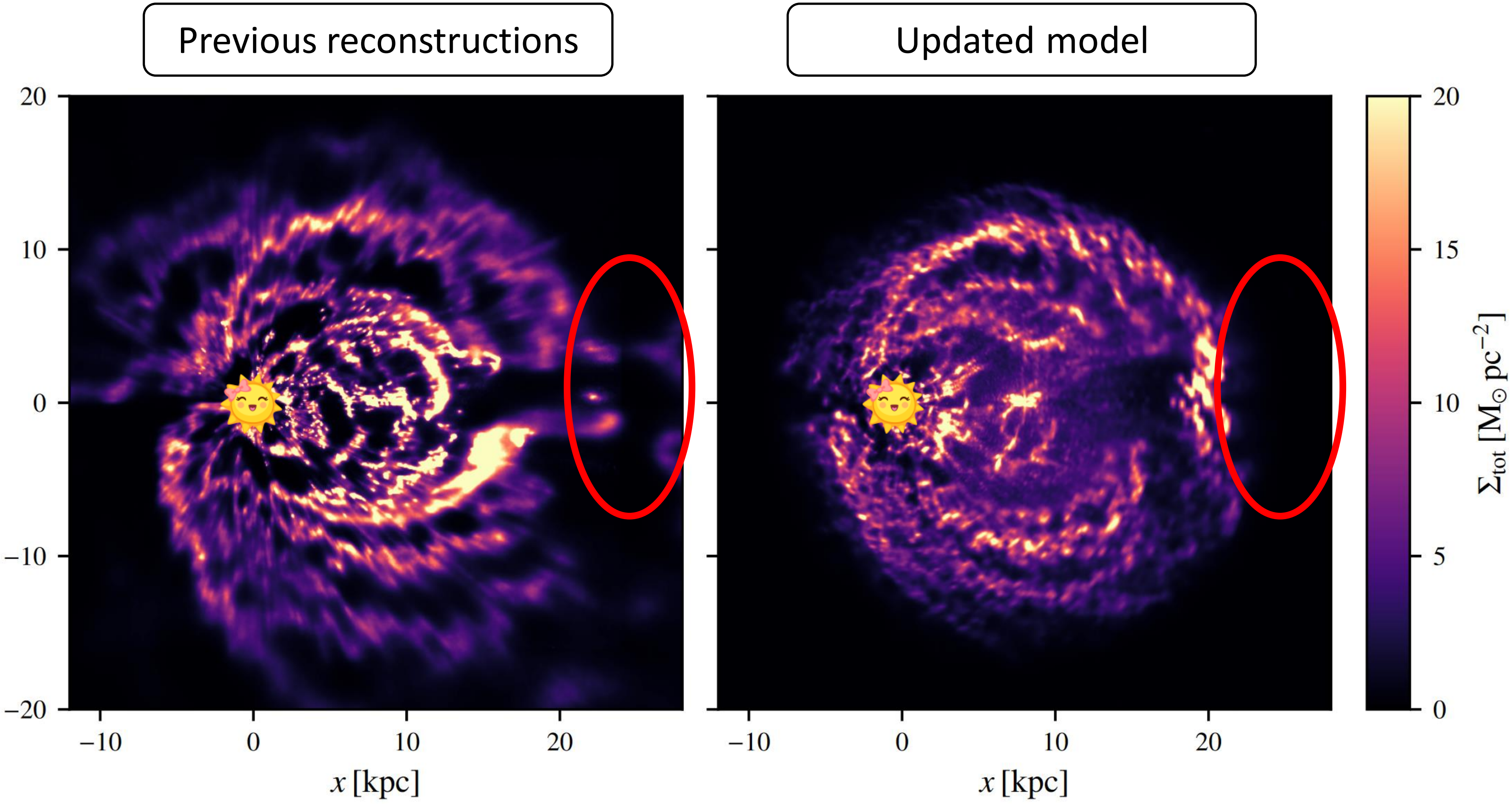
Previous reconstructions

Updated model



Results: Top-down view (global)

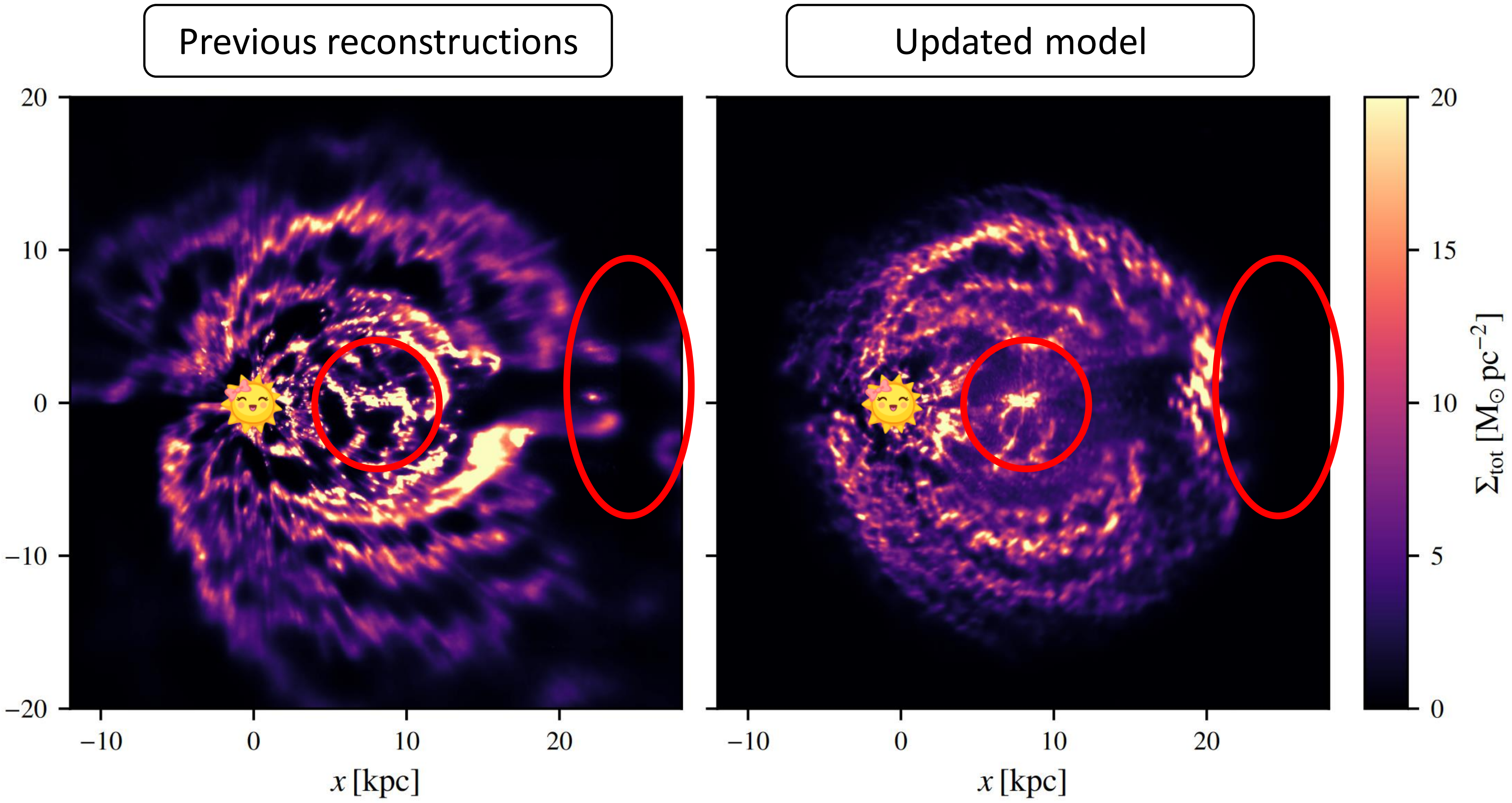
Fewer artifacts



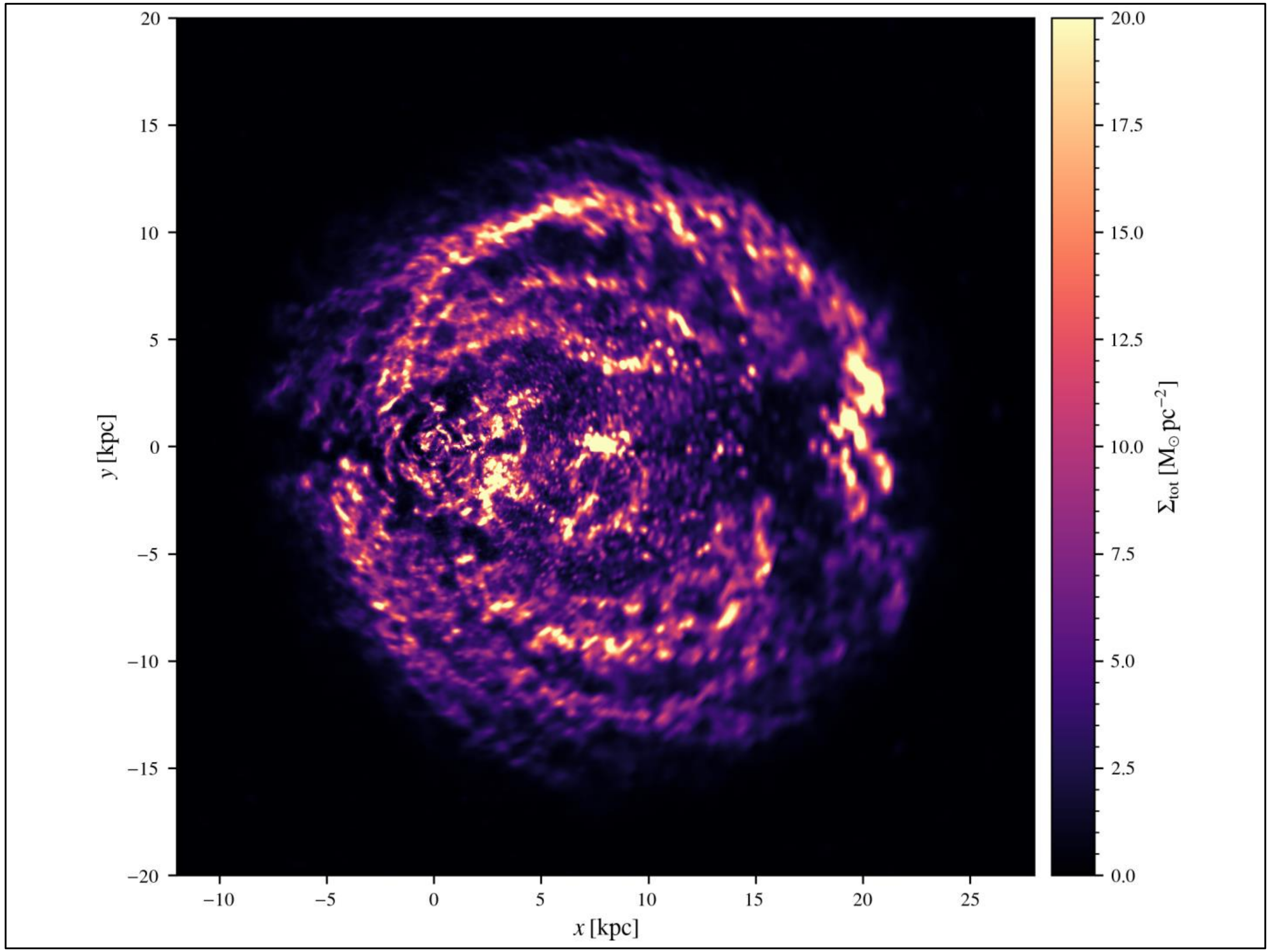
Results: Top-down view (global)

Fewer artifacts

Strongly cored galactic centre



Results: Top-down view (global) – Sample Flipbook



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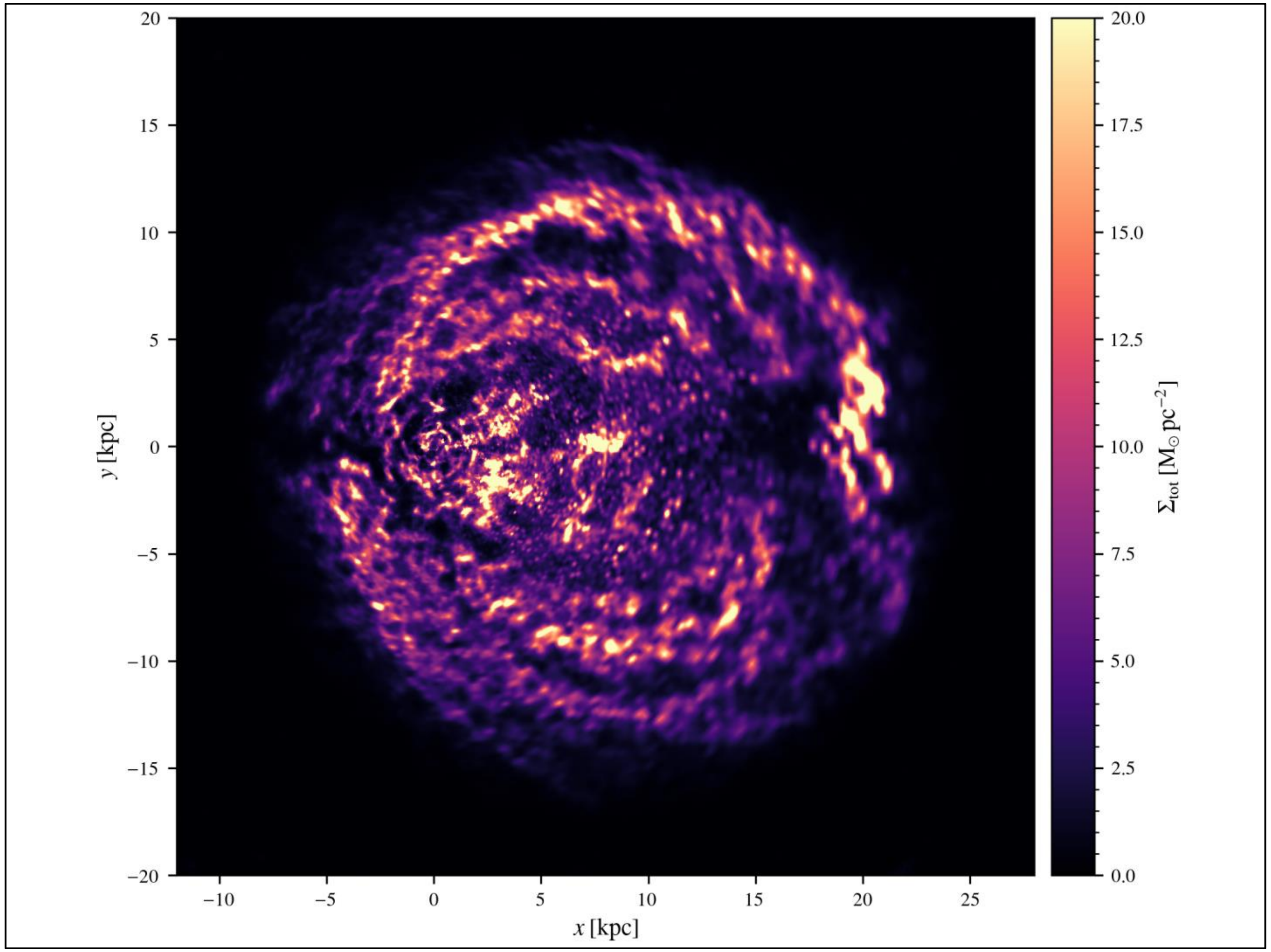

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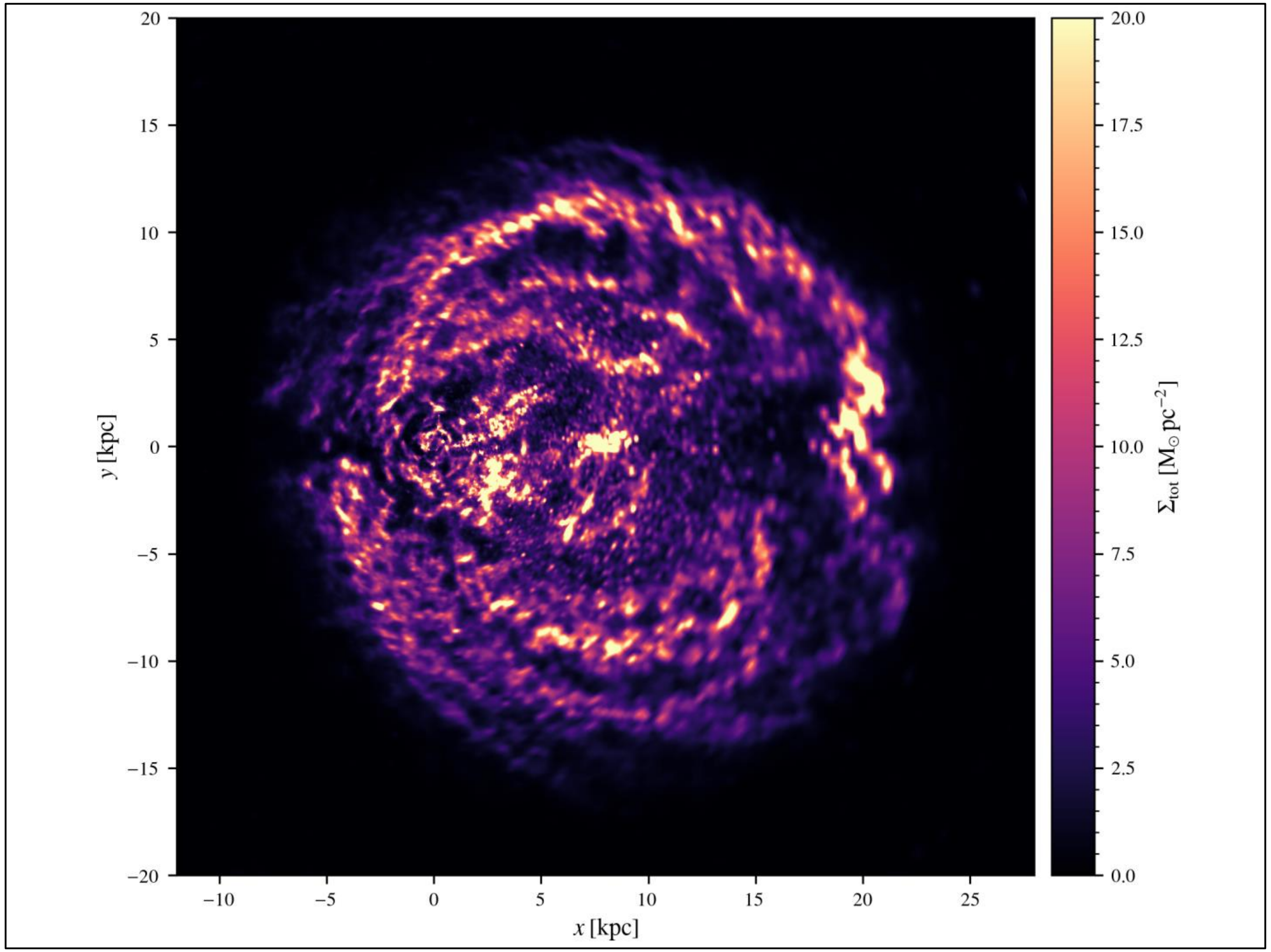

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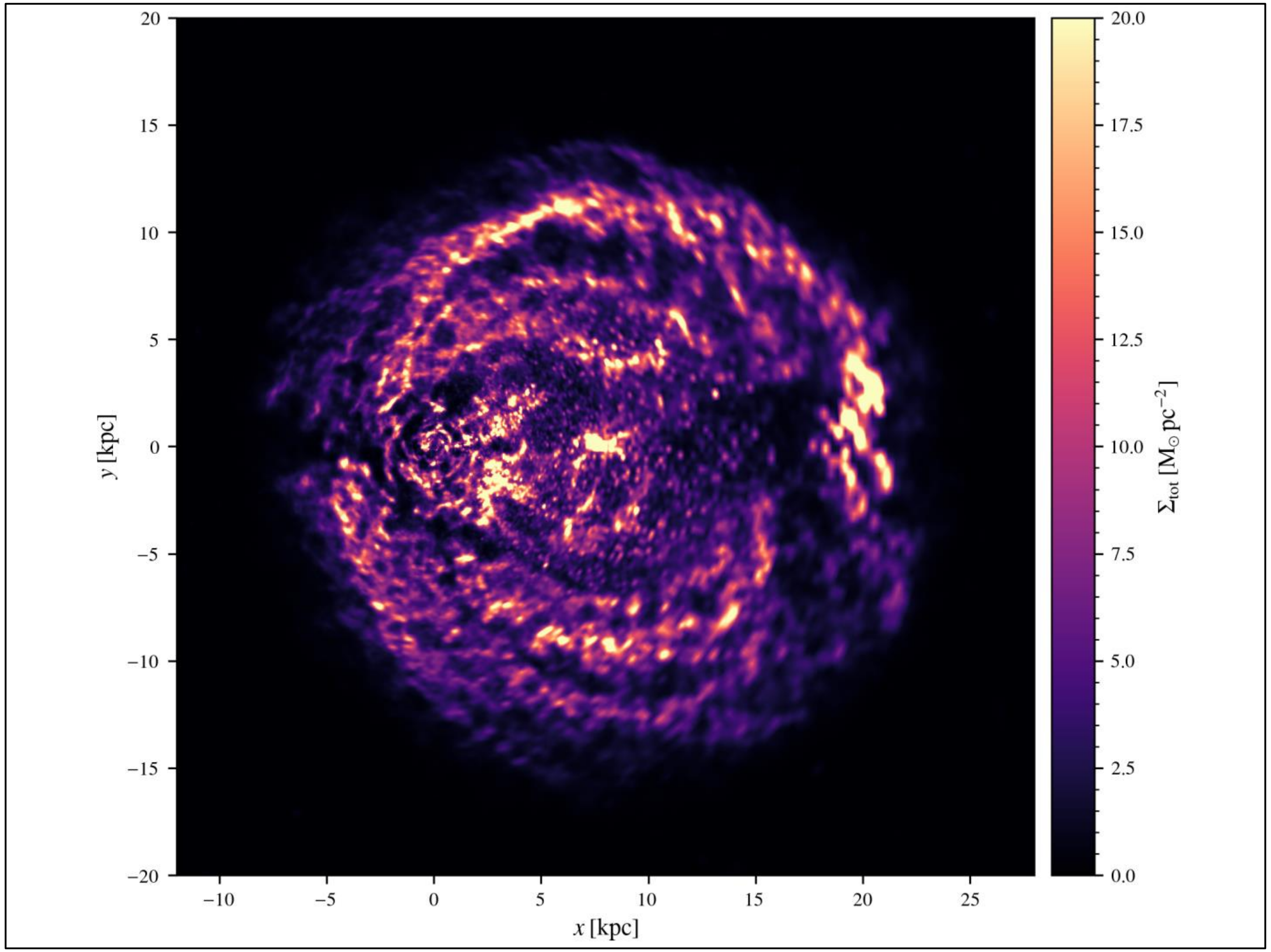
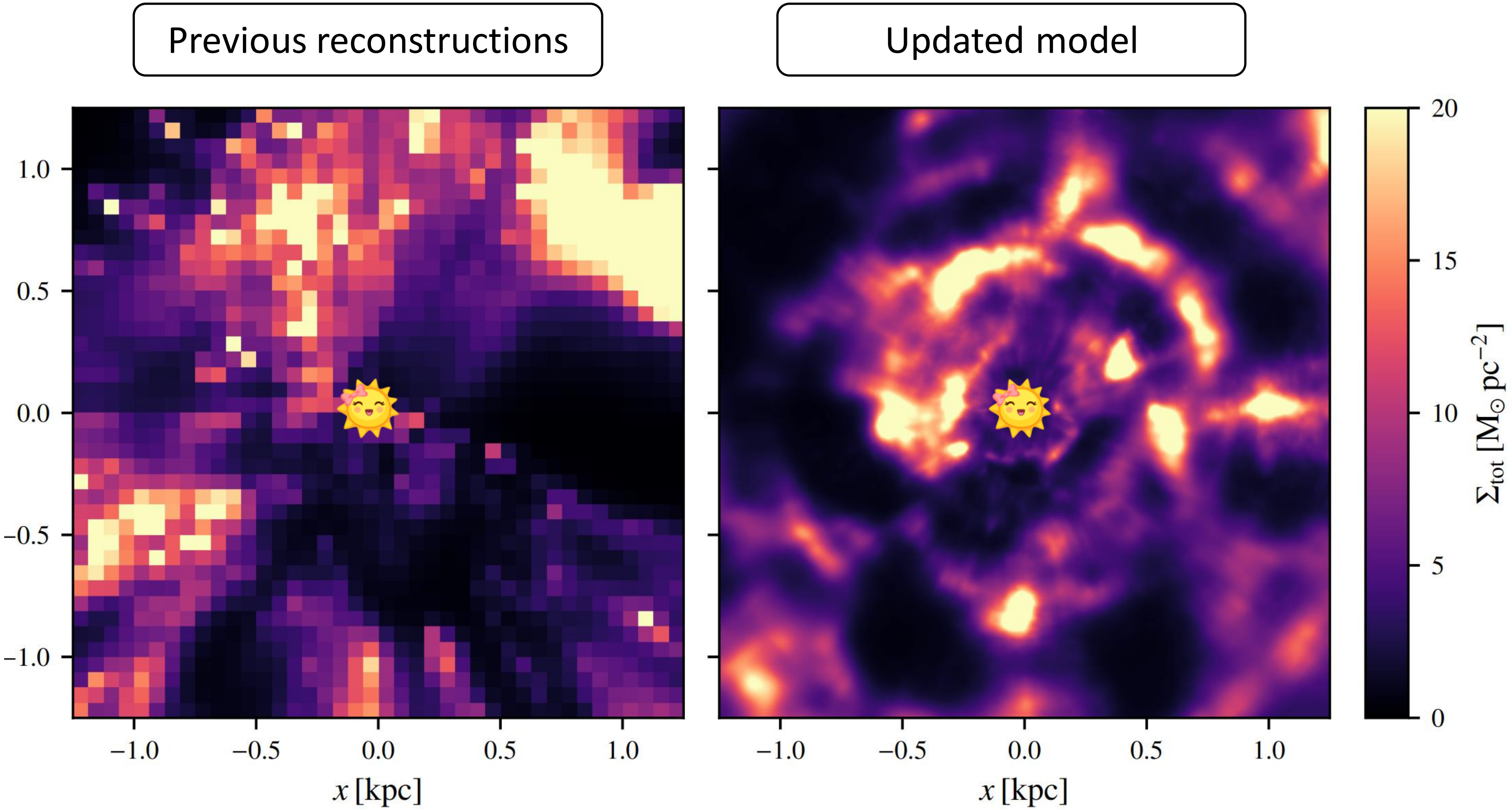


Results: Top-down view (local)

Much higher resolution

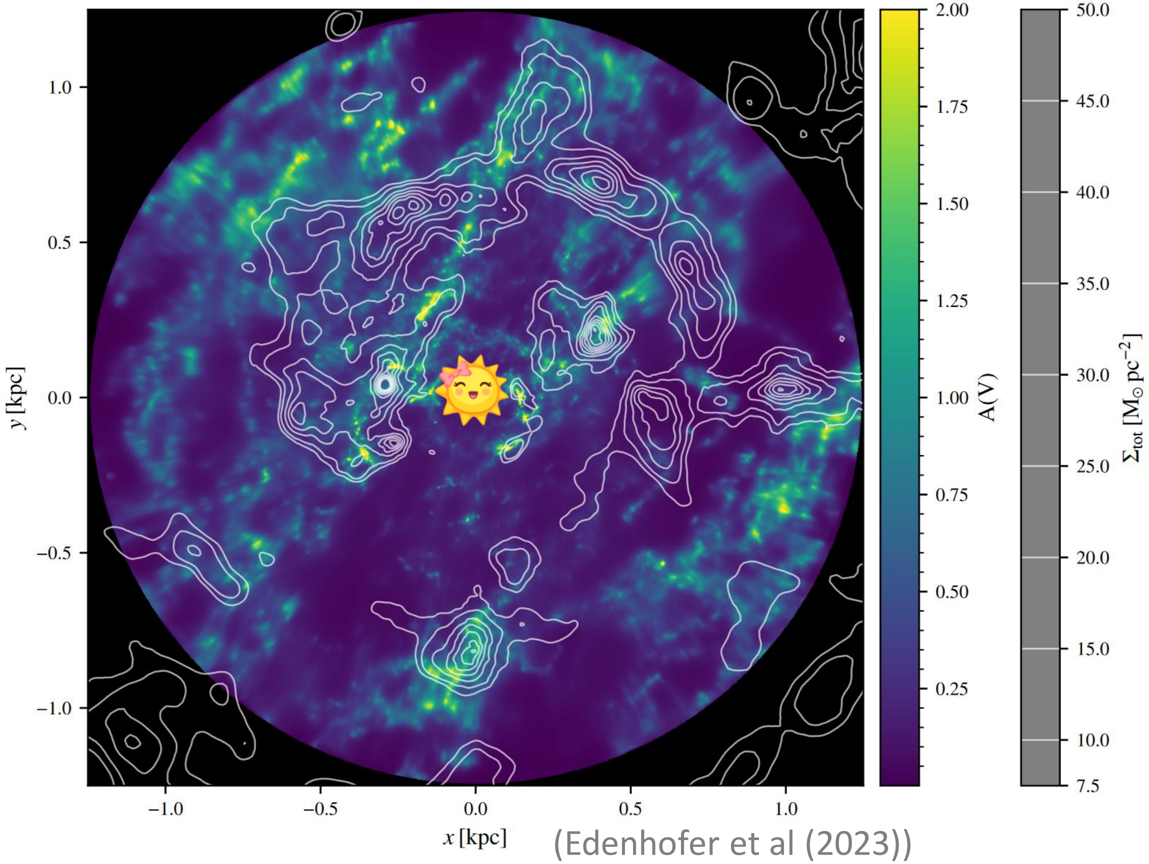
Detailed local substructures

Some obvious artifacts remain



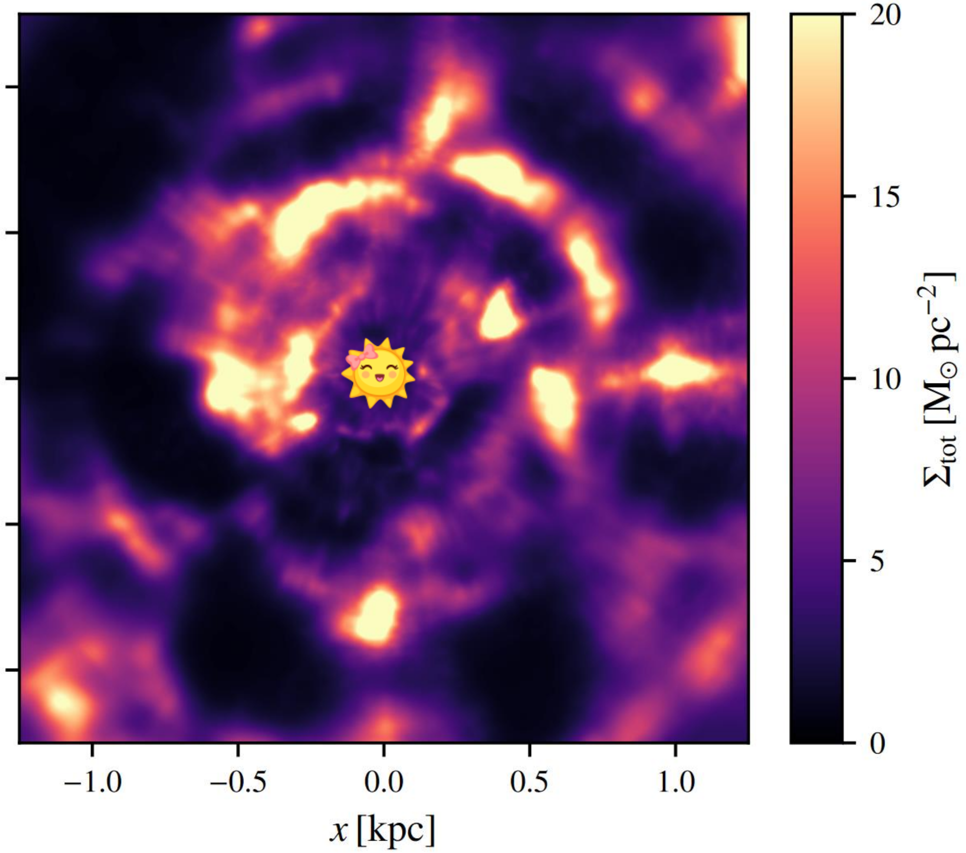
Results: A comparison to dust (local)

Updated gas vs. dust



(Edenhofer et al (2023))

Updated model

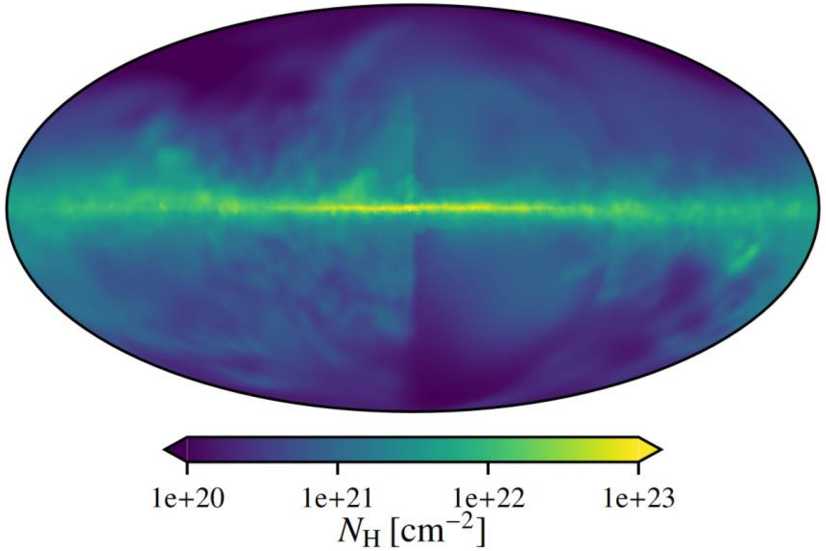


Surprisingly good match!

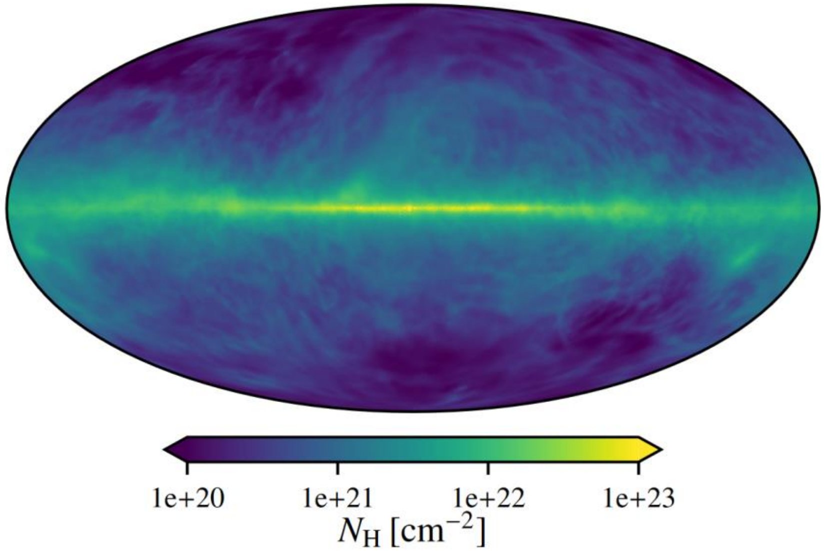
Using only implicit local distance information

Results: Sky-view Proton Column Density

Previous reconstructions



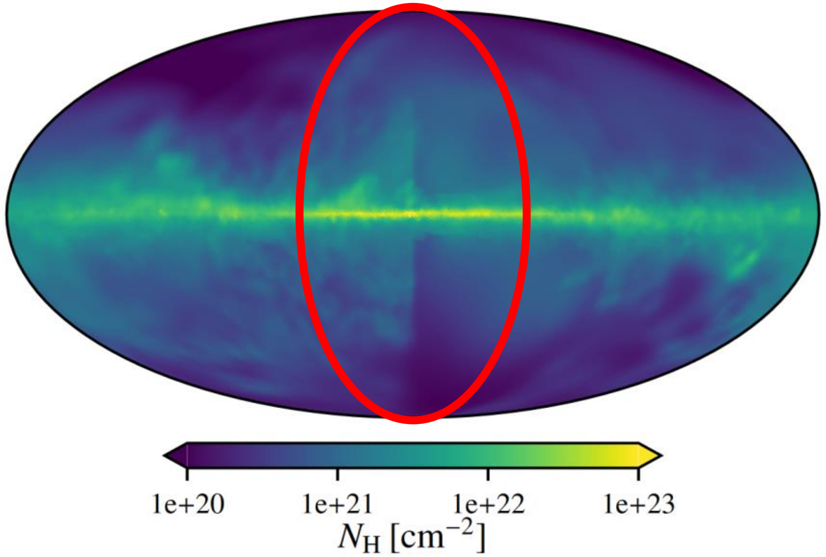
Updated model



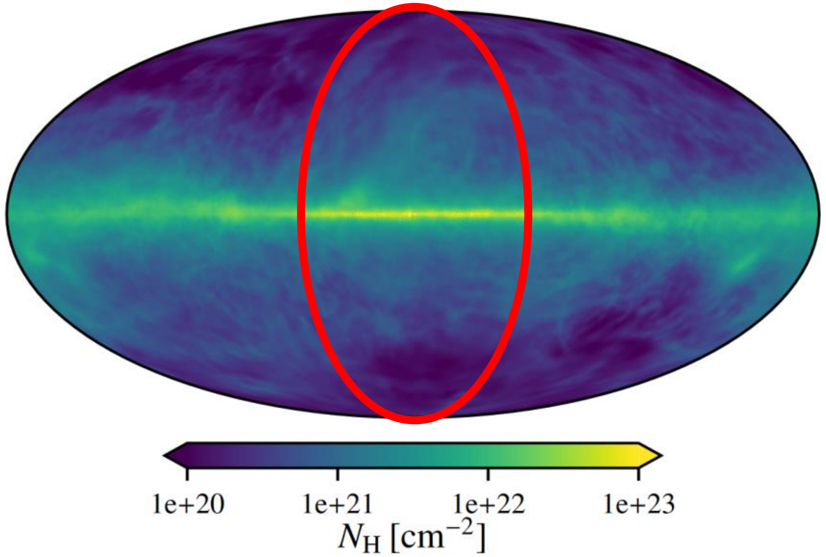
Results: Sky-view Proton Column Density

No sharp discontinuities

Previous reconstructions



Updated model



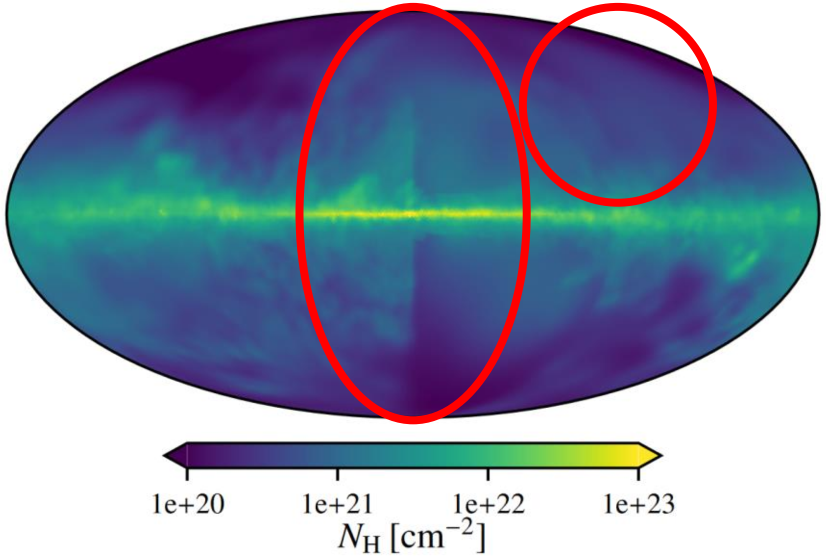
Results: Sky-view Proton Column Density

No sharp discontinuities

Detailed substructure

Tightly matches observed data

Previous reconstructions



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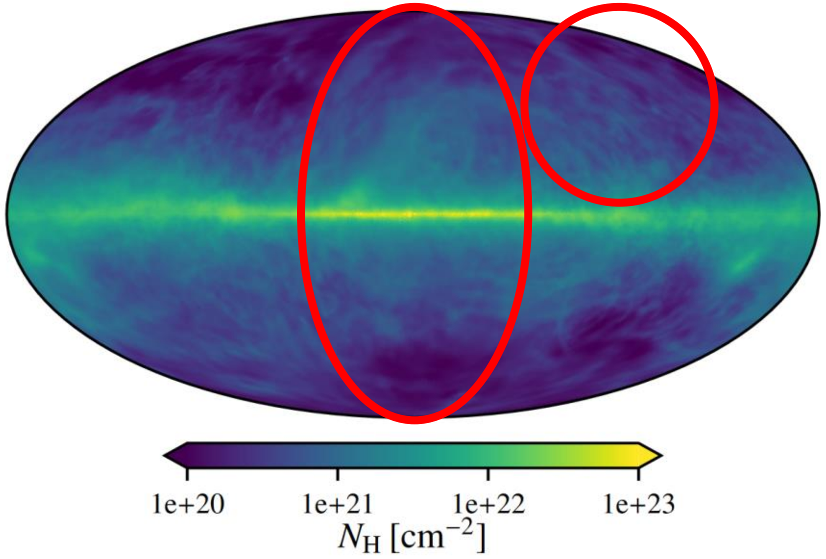


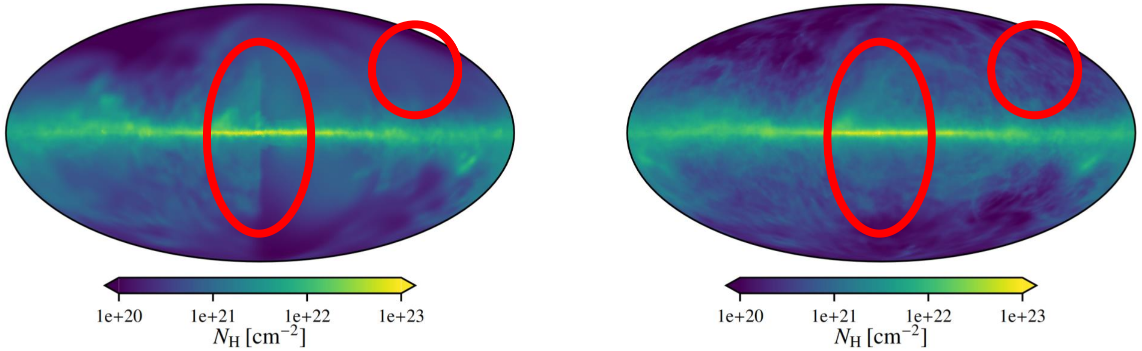
Conclusions

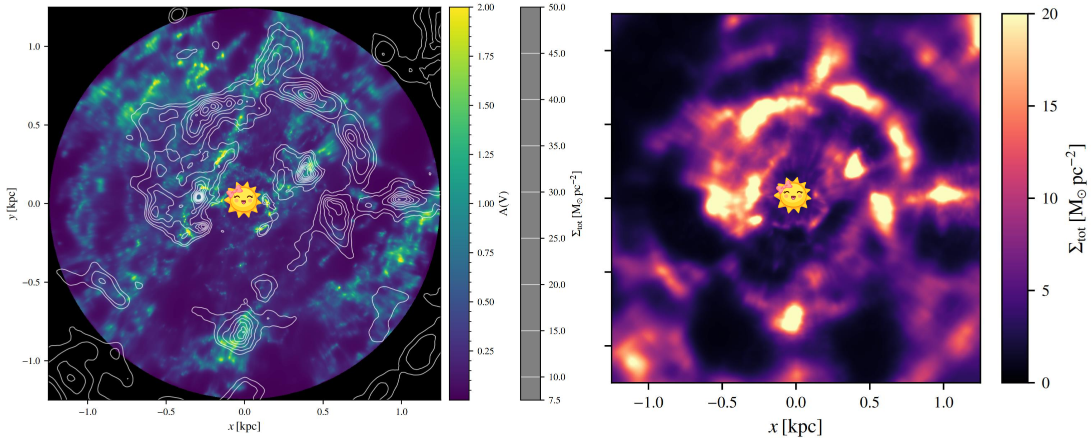
Coherent picture of Milky Way gas distribution

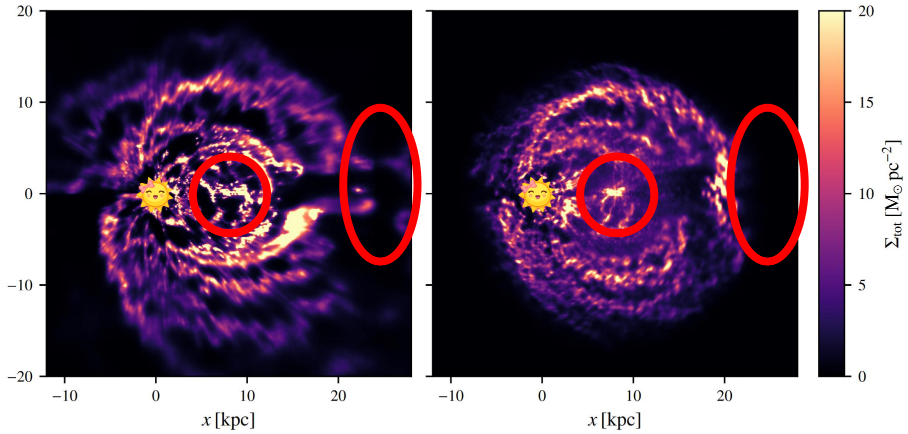
Uncertainty estimation possible with multiple samples

High resolution near-by

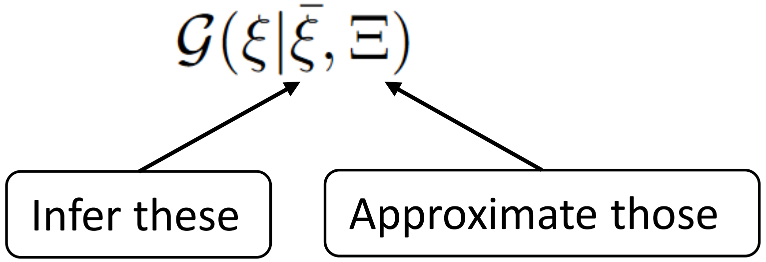
Publication in preparation → results available soon!







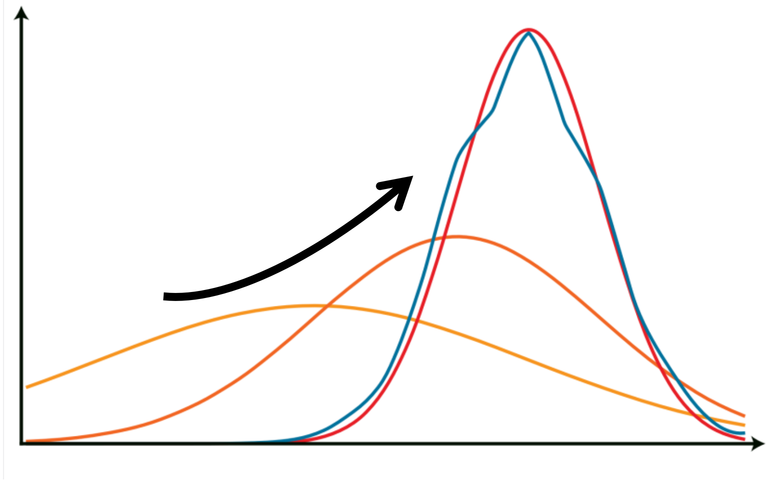
Backup 1.1: Metric Gaussian Variational Inference



$$\mathcal{G}(\xi|\bar{\xi},\Xi)$$

Infer these

Approximate those



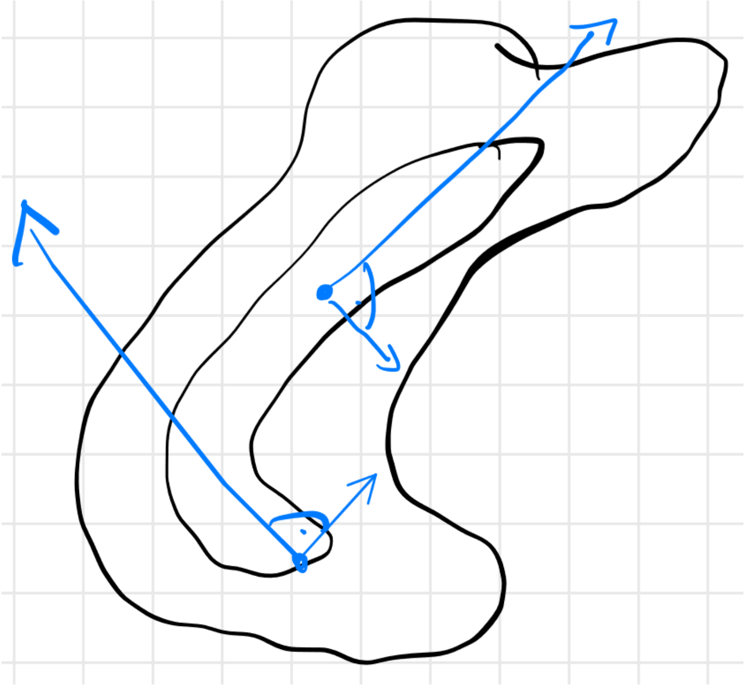
Bayes’ theorem:

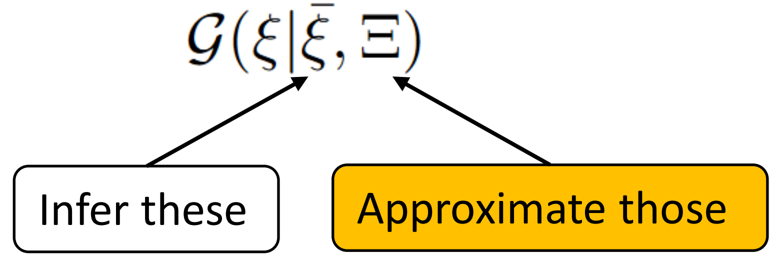
$$\underbrace{p(\xi|\text{data})}_{\text{Posterior}} \propto \underbrace{p(\text{data}\;|\xi)}_{\text{Likelihood}}\;\underbrace{p(\xi)}_{\text{Prior}}$$

1. Guess a starting point for the mean
2. **Draw samples** from the approximated posterior distribution at the mean
3. **Estimate “distance”** to true posterior via Kullback-Leibler-Divergence
4. **Update mean** estimation
5. Repeat

Backup 1.2: MGVI-Sampling: Inverse Fisher Metric as Covariance

How to sample from the (approximated) Posterior?
→ Approximate Covariance by inverse **Fisher metric**





$$\mathcal{G}(\xi|\bar{\xi}, \Xi)$$

Infer these

Approximate those

$$\Xi = \Xi(\widehat{\xi}) = \left(J(\widehat{\xi})^{\dagger} I_d(f(\widehat{\xi}))J(\widehat{\xi}) + \mathbb{1}\right)^{-1}$$

With Fisher metric of likelihood $I_d(\xi) = \left\langle \frac{\partial \mathcal{H}(d|\xi)}{\partial \xi} \frac{\partial \mathcal{H}(d|\xi)}{\partial \xi^{\dagger}} \right\rangle_{\mathcal{P}(d|\xi)}$

Application of (inverse of) this **scales linearly with model parameters** due to implicit operators.
There is no need to store the full covariance matrix at any point!

Backup 1.3: MGVI: Optimising the Mean

How to optimise the estimate of the mean?

$$\mathcal{G}(\xi|\bar{\xi}, \Xi)$$

Infer these

Approximate those

Evaluate Kullback-Leibler-Divergence stochastically:

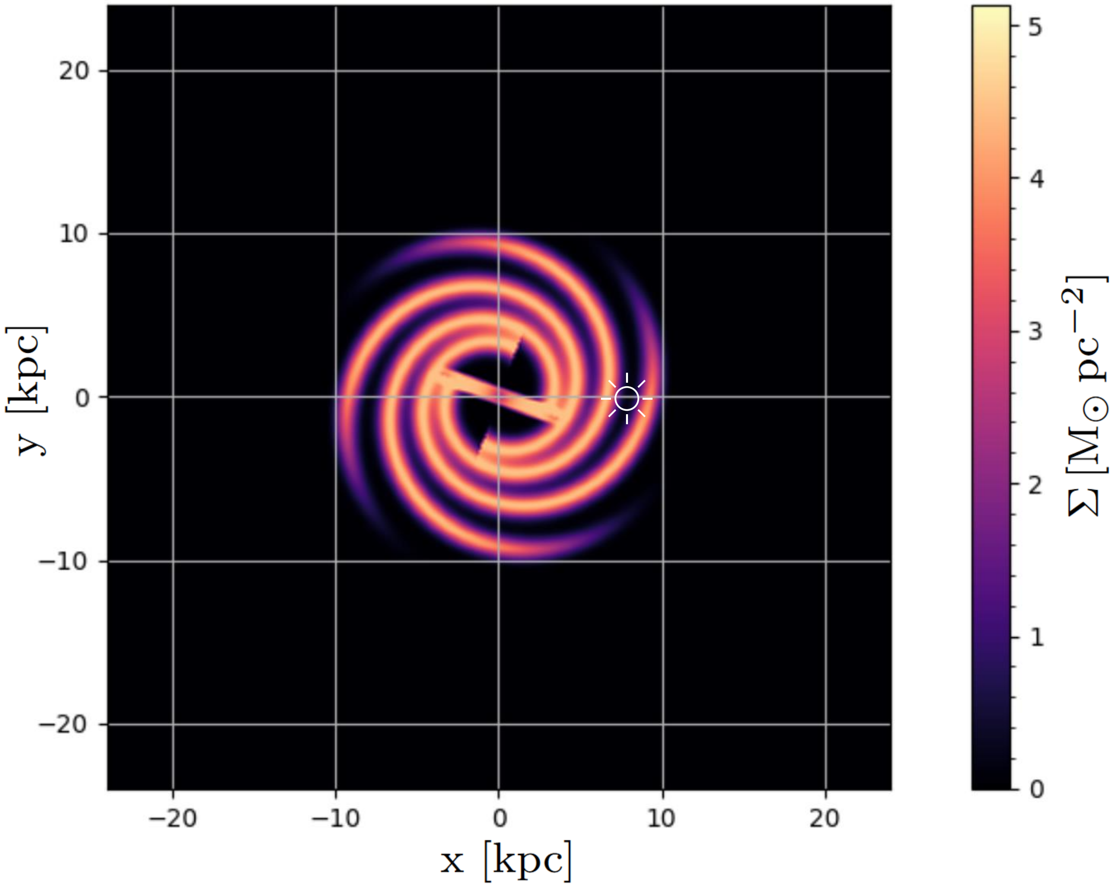
$$\mathcal{D}_{\mathrm{KL}}\left(\mathcal{G}(\xi|\bar{\xi}, \Xi(\widehat{\xi}))||\mathcal{P}(\xi|d)\right) \widehat{=} \langle \mathcal{H}(d, \xi)\rangle_{\mathcal{G}(\xi|\bar{\xi}, \Xi(\widehat{\xi}))}$$

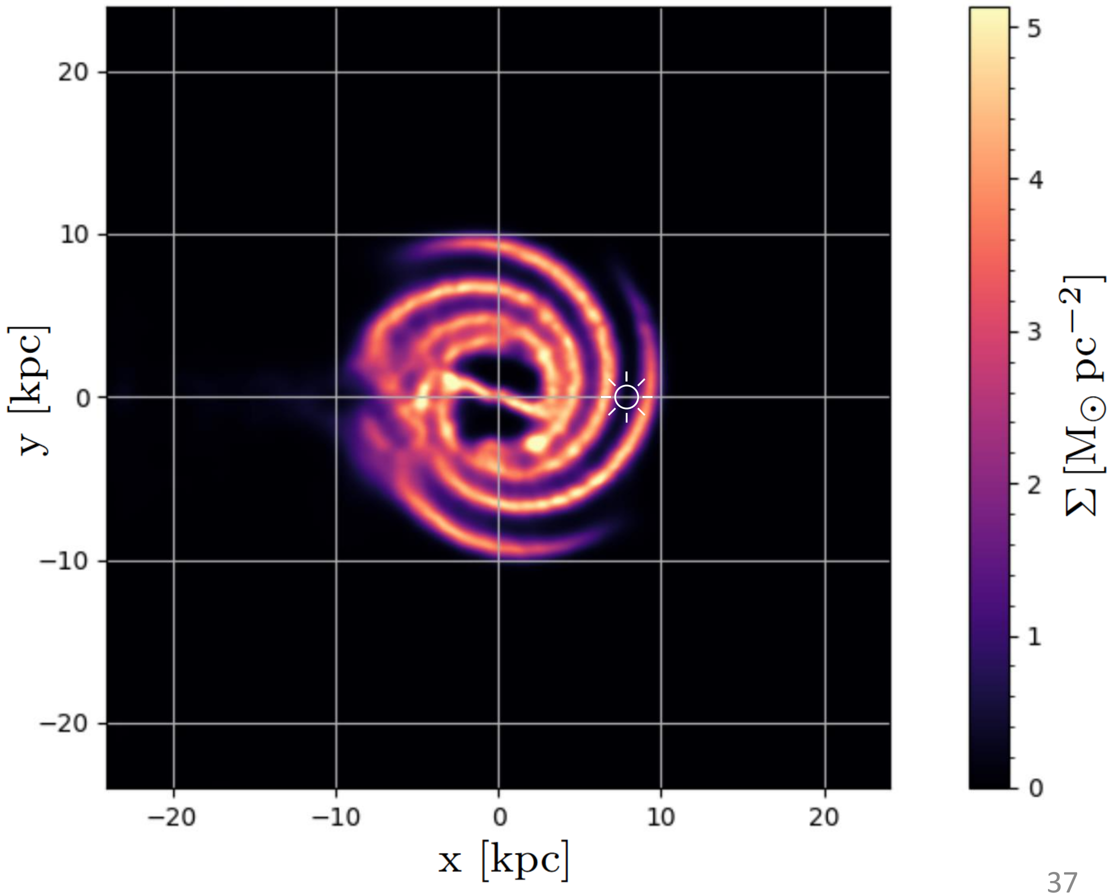
$$\approx \frac{1}{N}\sum_{i=1}^{N} \mathcal{H}(d, \bar{\xi} + \Delta\xi_*^i)$$

gradients via autodifferentiation

And minimise w.r.t the mean parameters

Backup 2: Verification of the Method


Ground truth


Reconstruction