Intro to Bayesian Hierarchical Modeling

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UTSSRP

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Basics of a Hierarchical Model

- One way to think about it: adding layers to the Bayesian model
- In the m&m's example, we had the posterior

$$p(\theta|y) \propto p(y|\theta)p(\theta)$$

Where our **prior** was $p(\theta) \propto Beta(\alpha, \beta)$ and α and β were chosen as fixed values.

• But we could have also set a *hyperprior distribution* on α and β , and then we'd have

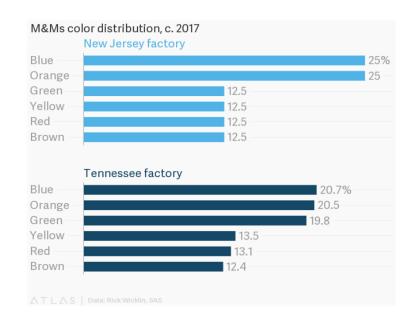
$$p(\theta, \alpha, \beta|y) \propto p(y|\theta)p(\theta|\alpha, \beta)p(\alpha, \beta)$$

This is now a hierarchical model.

Basics of a Hierarchical Model

• Another reason to do hierarchical modeling: want to infer parameters at different levels in the hierarchy, and account for structure in the variation

 In N. America, two factories make m&m's



Imagine we had m bags from New Jersey and q bags from Tennessee, but we only know that m+q=45.

What should we do if we want to know

1. what the colour distribution of the m&m's made in each factory is?

AND

2. The value of m?

Again, a hierarchical model will work here.

Hierarchical Model Example

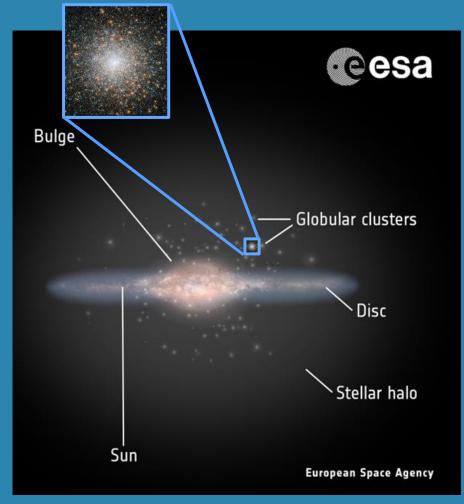
- The proportion of blues made at the factory may vary from one day to the next (random fluctuation)
 - The **true** θ (% of blue) changes subtly over time
- Imagine:
 - Each time I do the m&m's exercise with the class, I buy a box of m&m's.
 - I always buy boxes from the same country and factory (only one factory)
- Now I want to infer the variation in θ from class to class.
- \rightarrow To do this, we need to *estimate* α and β
- Set a *hyperprior distribution* on α and β , and then we'd have

$$p(\theta, \alpha, \beta | y) \propto p(y|\theta)p(\theta | \alpha, \beta)p(\alpha, \beta)$$

This is now a hierarchical model.

Detailed Example from Astronomy Research

Globular Cluster (GC)



Sketch of Milky Way

Estimating the mass of the Milky Way

Using hierarchical Bayes and "kinematic tracers"

Hierarchical Bayesian Model for MW Mass Estimate in Pictures

Likelihood



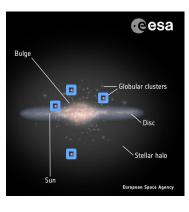




Each GC has Individual parameters:

- True position
- True velocity

Prior



Shared population parameters for galaxy:

- Spatial density of GCs
- Gravitational potential
- Velocity anisotropy

Hyperprior



Hyperparameters:

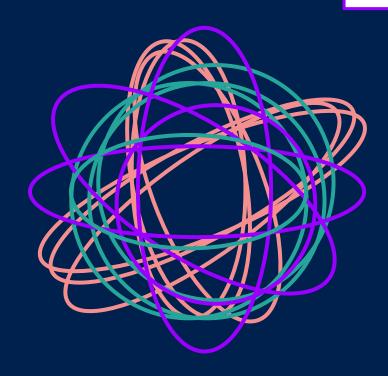
- Bounds for model parameters
- Mean and variance for parameters

Velocity Anisotropy Parameter

$$\beta = 1 - \frac{\sigma_{\theta}^2 + \sigma_{\phi}^2}{2\sigma_r^2}$$



Tangentially anisotropic $(\beta < 0)$

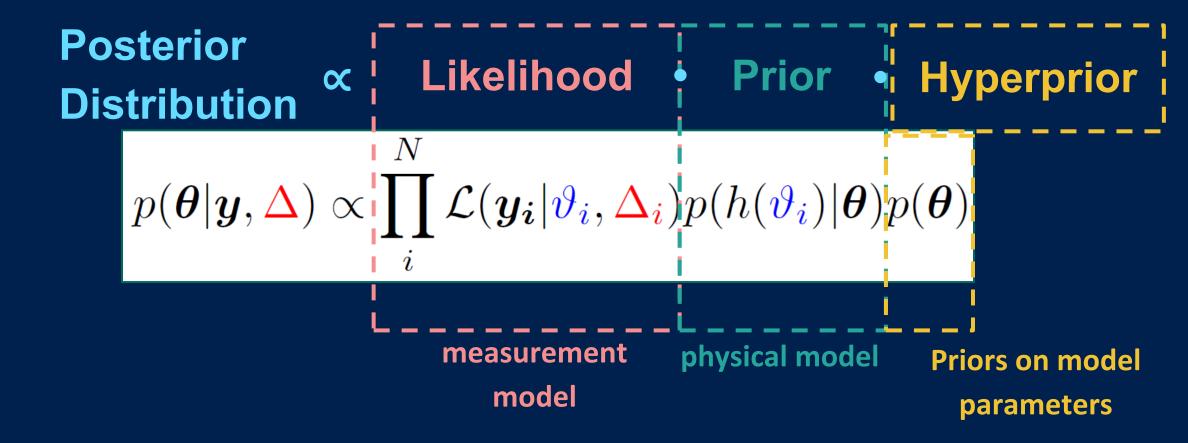


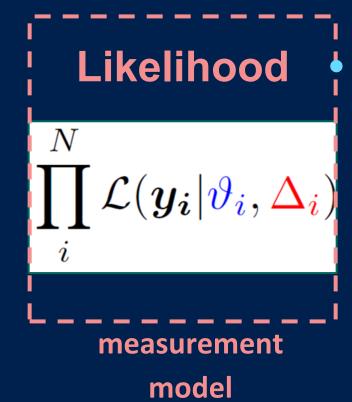
Isotropic $(\beta = 0)$



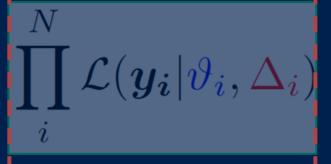
Radially anisotropic $(\beta > 0)$

Hierarchical Bayesian Model for Milky Way



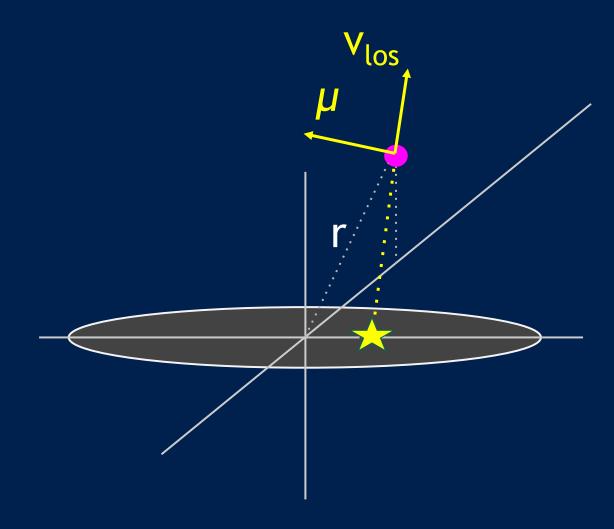


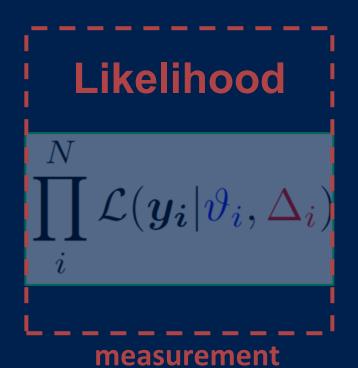
Likelihood



measurement model Velocity components observed (data):







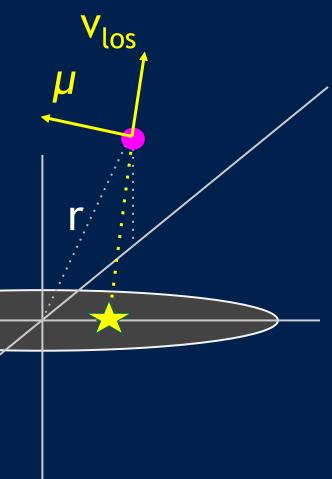
model

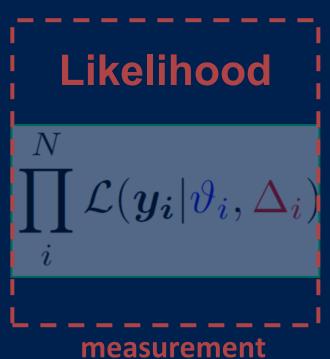
Velocity components observed (data):

Line-of-sight velocity: V_{los}

Proper motion (R.A.): $\mu_a cos \delta$

Proper motion (Decl.): μ_{δ}





Velocity components observed (data):

Line-of-sight velocity: V_{los}

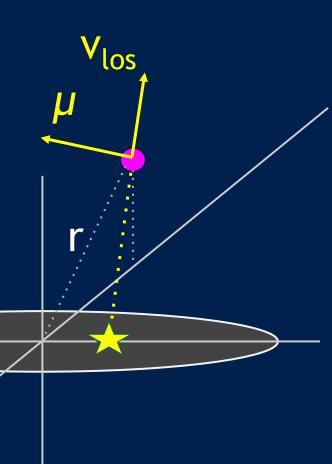
Proper motion (R.A.): $\mu_a cos \delta$

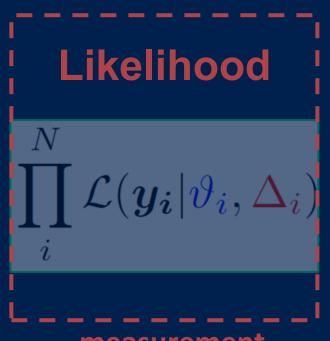
Proper motion (Decl.): µ_δ

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model

"Known" measurement uncertainties: $\Delta \mu_{\delta}$





Velocity components observed (data):

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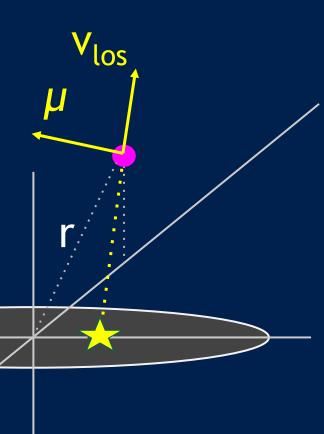
Proper motion (Decl.): µ₈

measurement

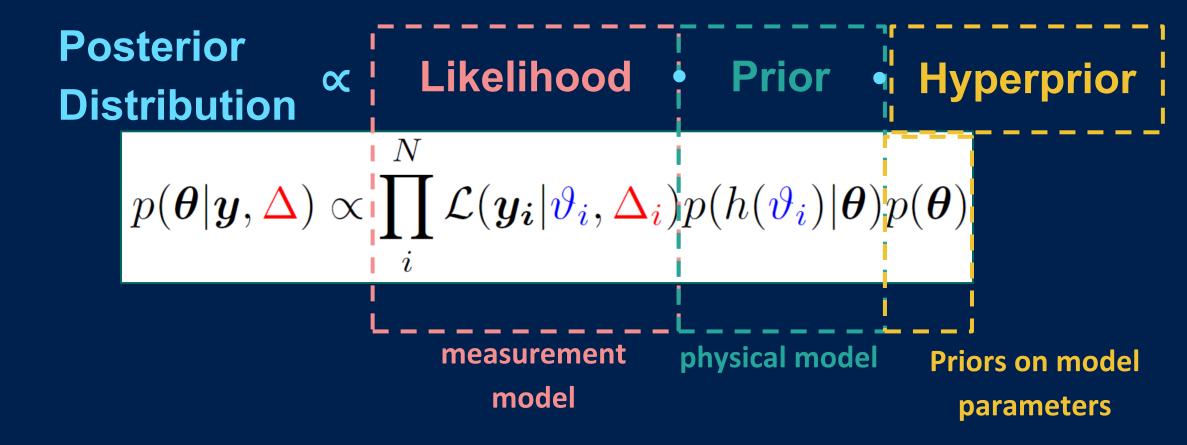
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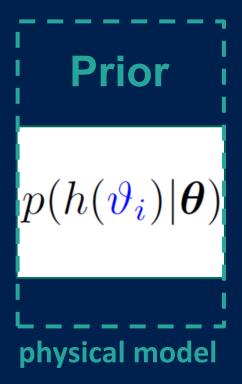
"Known" measurement uncertainties: $\Delta \mu_{s}$

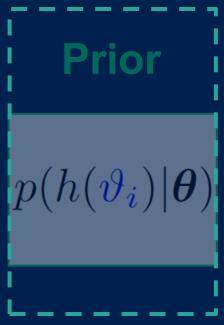




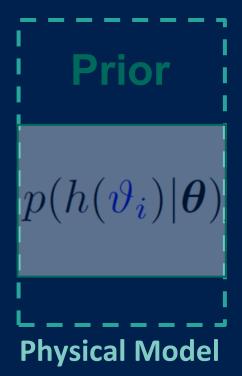
Hierarchical Bayesian Model

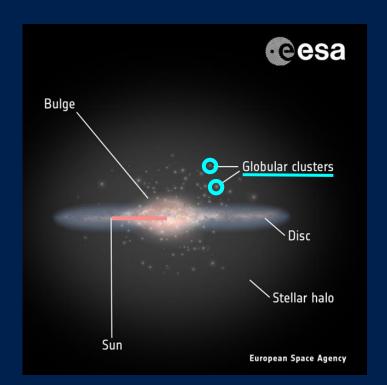






Physical Model

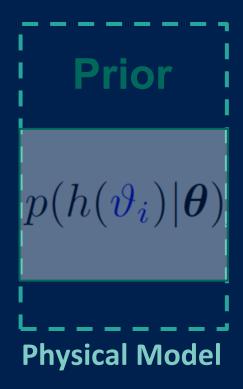


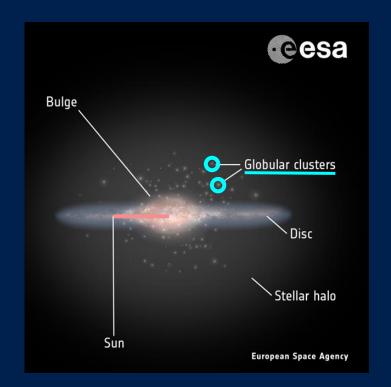












$$\mathcal{E} = -\frac{1}{2}(v_r^2 + v_t^2) + \Phi(r)$$

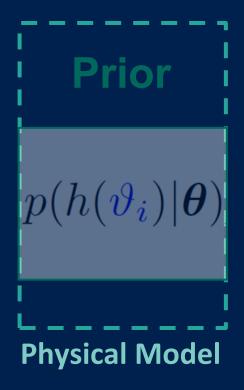
Angular momentum:

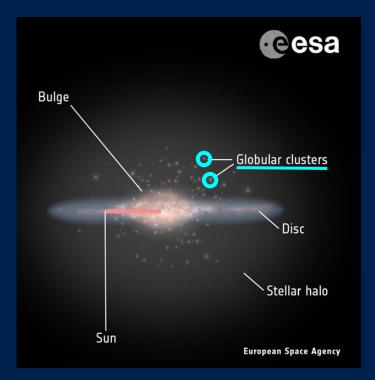
$$L = rv_t$$









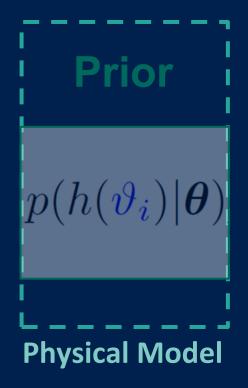


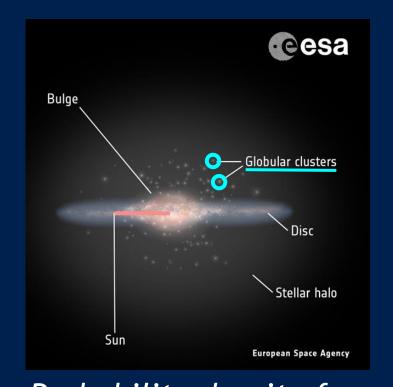
$$\mathcal{E} = -\frac{1}{2}(v_r^2 + v_t^2) + \Phi(r)$$

Angular momentum:

Probability density for specific energy and angular momentum

$$f(\mathcal{E}, L)$$





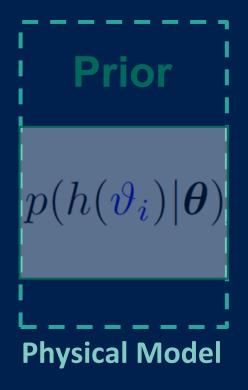
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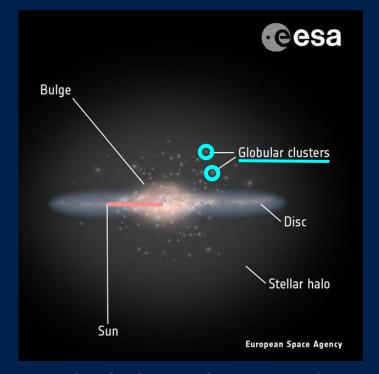
Angular momentum:

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Cuddeford (1991)

Probability density for specific energy and angular momentum
$$f(\mathcal{E},L) \propto L^{-2\beta}f(\mathcal{E})$$





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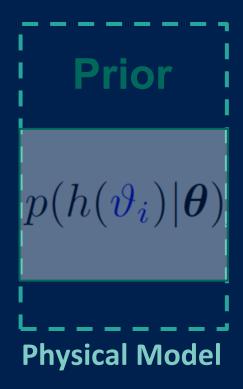
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$$f(\mathcal{E}) = \frac{1}{\sqrt{8}\pi^2} \int_0^{\mathcal{E}} \frac{1}{\sqrt{\mathcal{E} - \Phi}} \left(\frac{d^2 \rho_t}{d\Phi^2} \right) d\Phi + \frac{1}{\sqrt{\mathcal{E}}} \left(\frac{d\rho_t}{d\Phi} \right)_{\Phi=0}$$

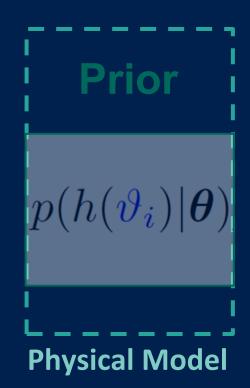


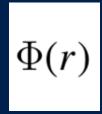
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Number density profile of globular clusters:

$$\rho(r)$$

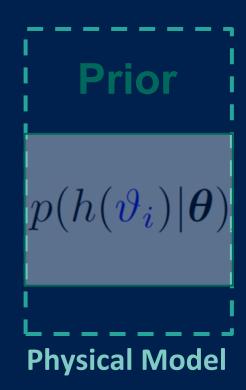
Assuming: spherical symmetry and equilibrium state

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$$\Phi(r) = \frac{\Phi_o}{r^{\gamma}}$$

Number density profile of globular clusters:

$$\rho(r) \propto \frac{1}{4\pi r^2} \times \frac{1}{r^{\alpha-2}}$$

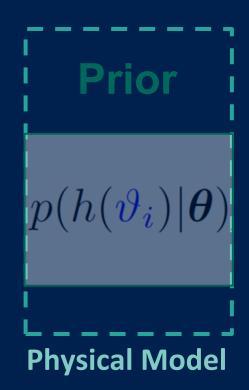
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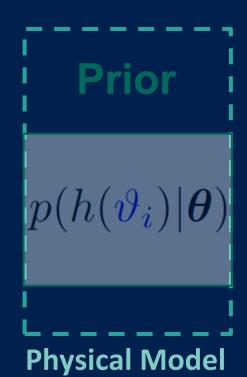
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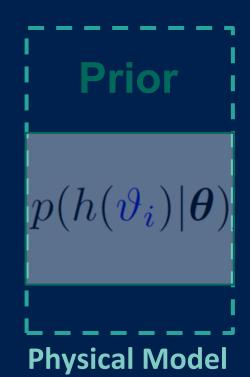
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Assuming: spherical symmetry and equilibrium state

Probability density function:

$$f(\mathcal{E}, L) = \frac{L^{-2\beta} \mathcal{E}^{\frac{\beta(\gamma-2)}{\gamma} + \frac{\alpha}{\gamma} - \frac{3}{2}} \Gamma(\frac{\alpha}{\gamma} - \frac{2\beta}{\gamma} + 1)}{\sqrt{8\pi^3 2^{-2\beta}} \Phi_0^{\frac{-2\beta}{\gamma} + \frac{\alpha}{\gamma}} \Gamma(\frac{\beta(\gamma-2)}{\gamma} + \frac{\alpha}{\gamma} - \frac{1}{2}) \Gamma(1 - \beta)}$$



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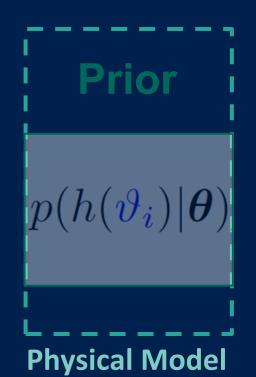
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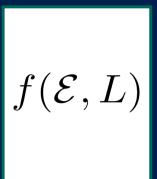
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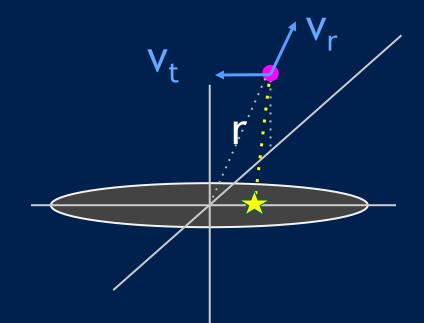
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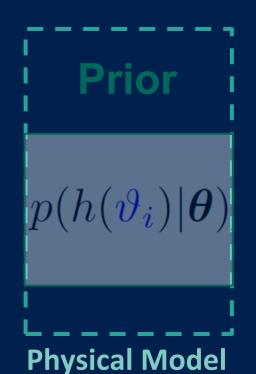
Assuming: spherical symmetry and equilibrium state

Probability density function:



Galactocentric





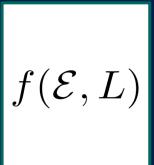
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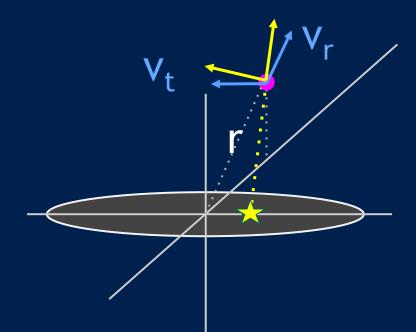
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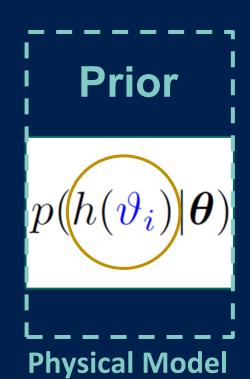
Probability density function:



Galactocentric

Heliocentric





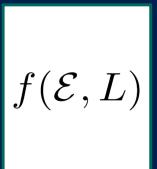
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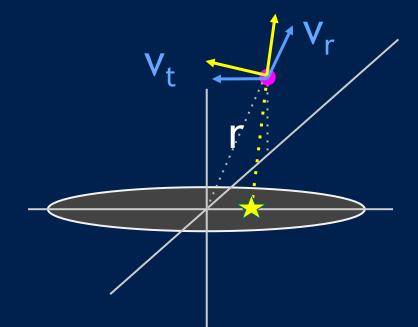
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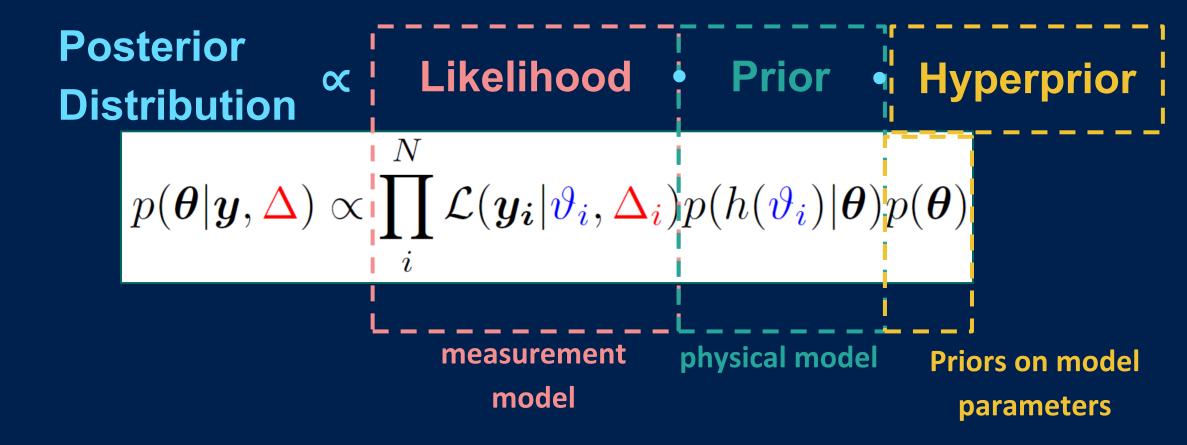


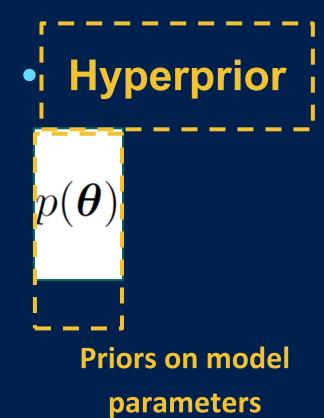
Galactocentric

Heliocentric



Hierarchical Bayesian Model





Hyperprior

 $p(oldsymbol{ heta})$

Priors on model parameters

 Φ_o the scale factor for the gravitational potential

 γ the power-law slope of the gravitational potential

 α the power-law slope of the satellite population

 β the velocity anisotropy parameter

Hyperprior

Priors on model
parameters

Hyperprior Probability Distributions

Parameter	Distribution	Hyperparameters
Φ_o	Uniform	$\Phi_{o,\mathrm{min}} = 1, \Phi_{o,\mathrm{max}} = 200$
γ	Uniform	$\gamma_{\min} = 0.3, \gamma_{\max} = 0.7$
α	Gamma	b = 0.4 kpc, c = 0.001, p = 0.001
β	Uniform	$\beta_{\min} = -0.5$, $\beta_{\max} = 1$

 Φ_o the scale factor for the gravitational potential

 γ the power-law slope of the gravitational potential

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Hierarchical Bayesian Model

Posterior Distribution

Likelihood • Prior • Hyperprior

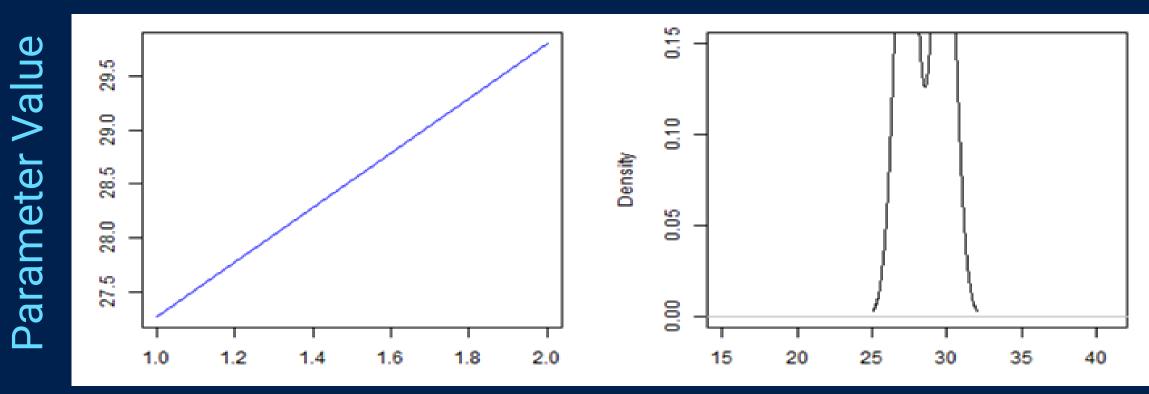
measurement model

physical model

parameter assumptions

$$p(\boldsymbol{\theta}|\boldsymbol{y}, \boldsymbol{\Delta}) \propto \prod_{i}^{N} \mathcal{L}(\boldsymbol{y_i}|\boldsymbol{\vartheta_i}, \boldsymbol{\Delta_i}) p(h(\boldsymbol{\vartheta_i})|\boldsymbol{\theta}) p(\boldsymbol{\theta})$$

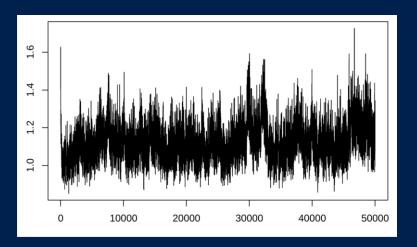
Sampling the posterior distribution → MCMC



Iteration (Step)

Parameter Value

Parameter Value



Iteration (Step)

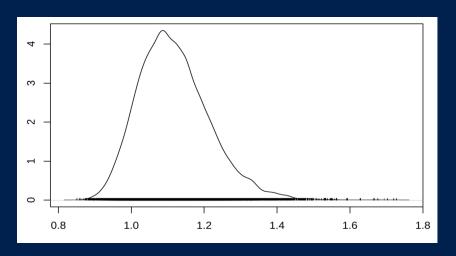
Density Plot

 Smoothed histogram of parameter values in Markov chain

Trace Plot of Markov Chain

Value of parameter as Markov chain walks through parameter space

Density



Parameter Value

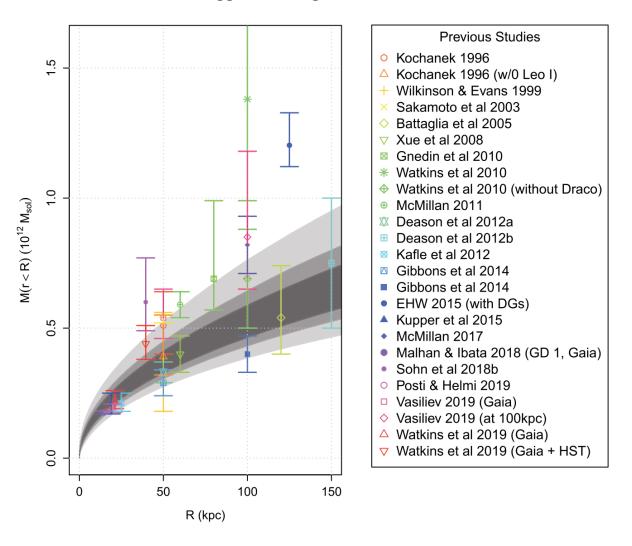
Sampling the posterior distribution

- Adaptive-tuning algorithm for efficient mixing
 - Roberts, G. O., & Rosenthal, J. S. 2009, J. Comput. Graphical Stat., 18, 349
- R-hat statistic to monitor convergence
 - Gelman, A., Carlin, J., Stern, H., & Rubin, D. (2003) Bayesian Data Analysis
 Chapman & Hall/CRC Press)
- Hybrid-Gibbs sampler that incorporates incomplete data
 - Gelman, A., Carlin, J., Stern, H., & Rubin, D. (2003) Bayesian Data Analysis
 Chapman & Hall/CRC Press)

Posterior Distribution is then used to calculate a

cumulative mass profile

with credible regions



Eadie & Juric (2019), ApJ 875:159