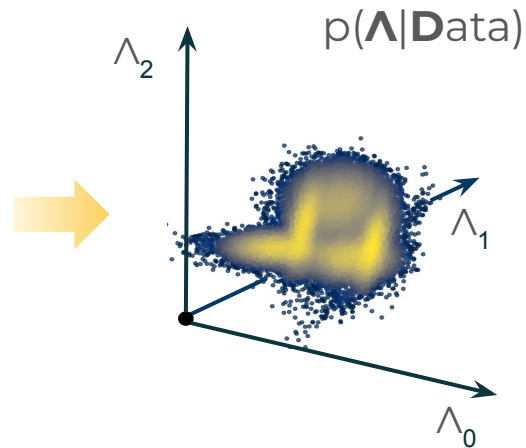
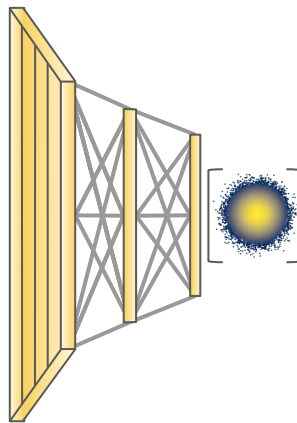
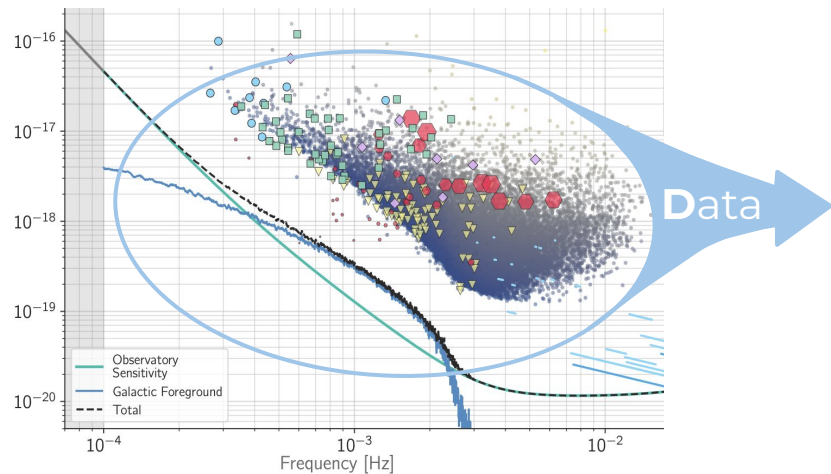


Simulation Based Population Inference

Galactic Binaries in LISA



Rahul Srinivasan
 Postdoc, SISSA, Italy

The Galactic Double White Dwarf Population

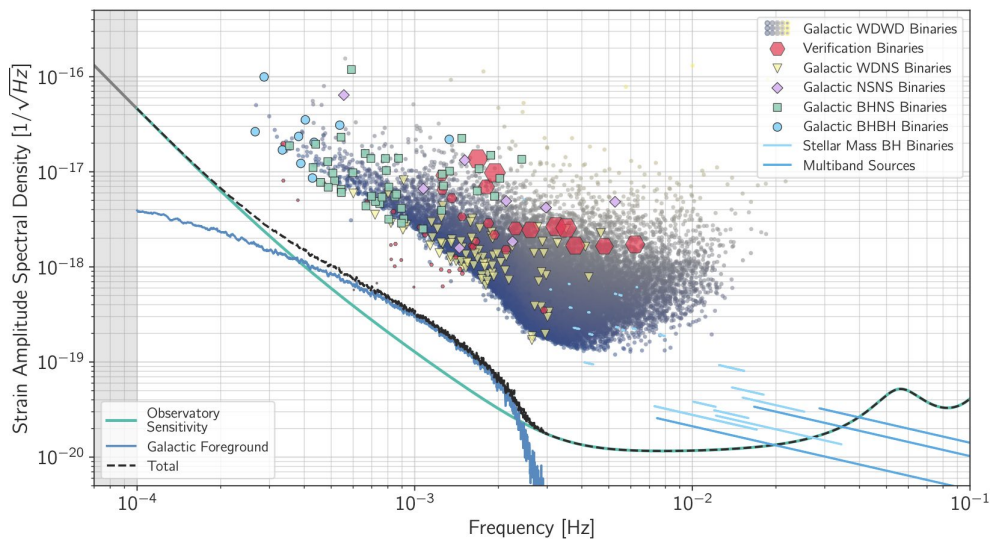
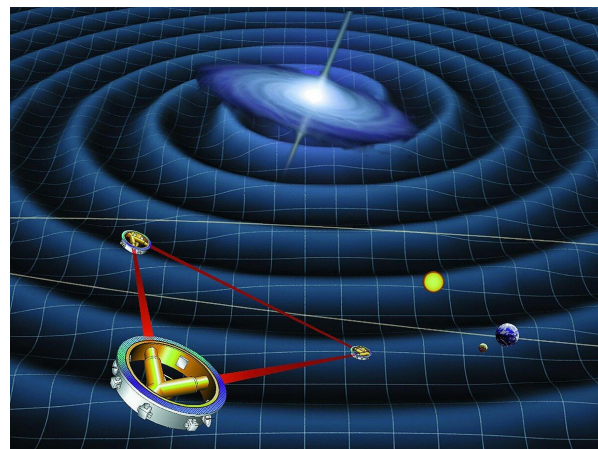


Figure from the LISA red book

LISA



The Galactic Double White Dwarf Population

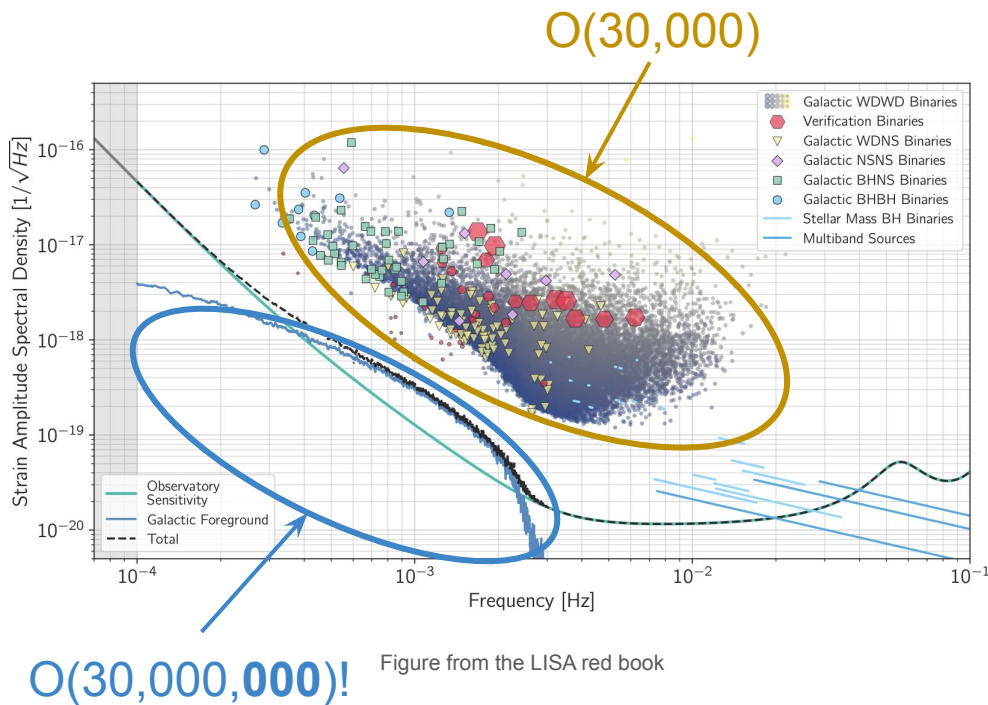
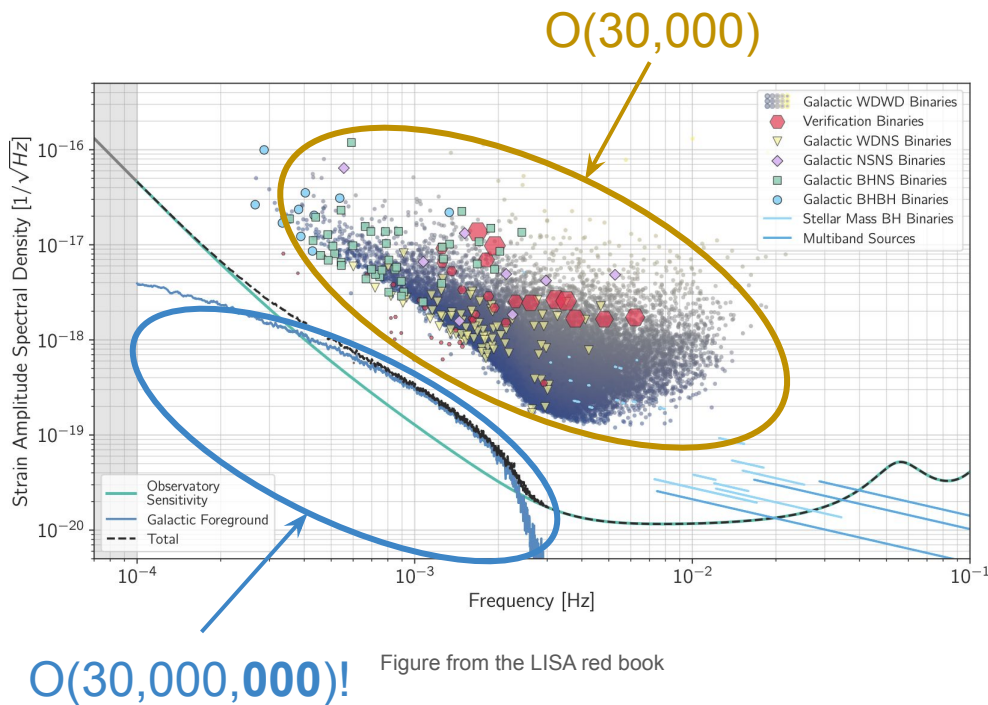


Figure from the LISA red book

A cocktail party of a few, loud, resolvable sources, and an overlapping, cacophonous, incoherent foreground.

The Galactic Double White Dwarf Population



Where lies the population signature:
the few resolvable sources¹ or
the many unresolvable sources²?

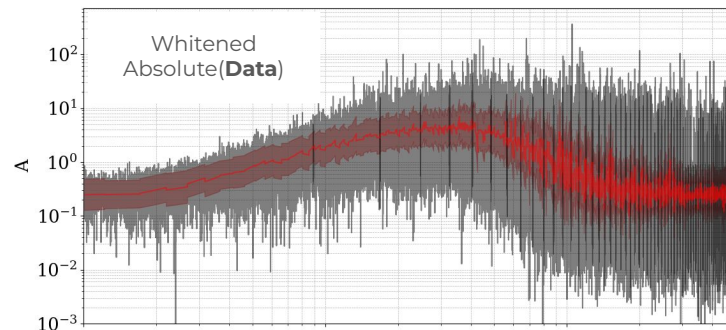
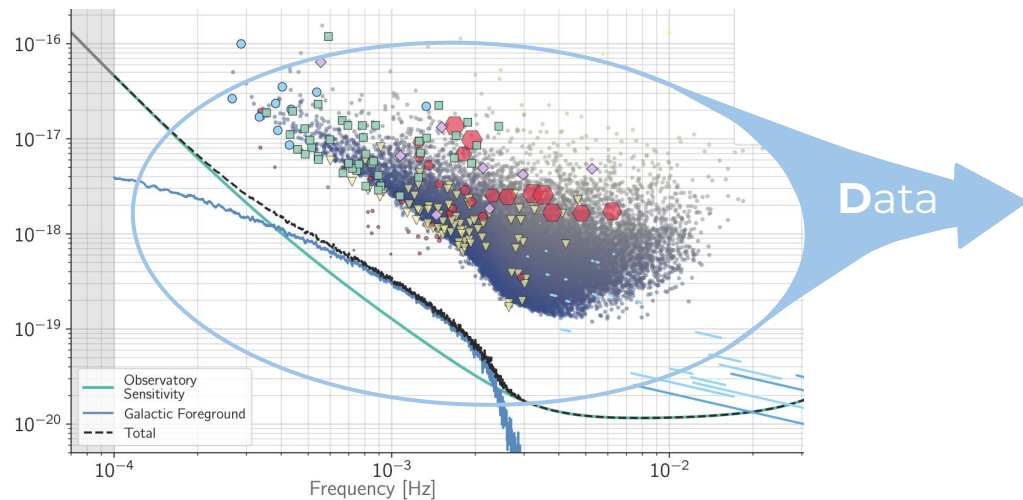
Figure from the LISA red book

¹ Korol, Rossi, Barausse, MNRAS 483 no. 4 5518–5533

² Smith et al 2020; 2004.09700

The Data

GPU-leveraged forward simulator

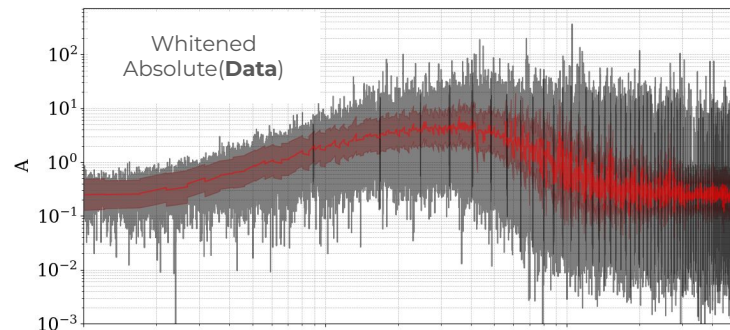
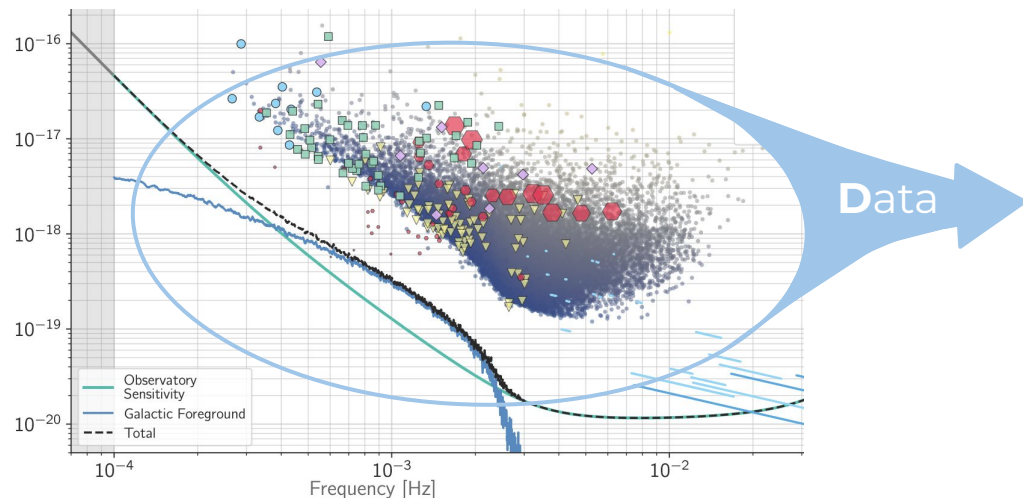


The Data

$O(10^6)$ frequency bins!

Computational *prohibitive* likelihood evaluation.

Major bottleneck for Bayesian samplers.



SBI might be a necessity.

Simulation-based Inference

Population $\Lambda := \rho_{\text{Distribution}}(\text{Mass, Separation}), N_{\text{Sources}}, \text{Milky Way}_{\text{Scale}}$

Simulation-based Inference

Population $\Lambda := \rho_{\text{Distribution}}(\text{Mass, Separation}), N_{\text{Sources}}, \text{Milky Way}_{\text{Scale}}$



Simulator

Source $\Theta := \text{Mass, Separation, Sky-position, Distance}$

Simulation-based Inference

Population $\Lambda := \rho_{\text{Distribution}}(\text{Mass, Separation}), N_{\text{Sources}}, \text{Milky Way}_{\text{Scale}}$

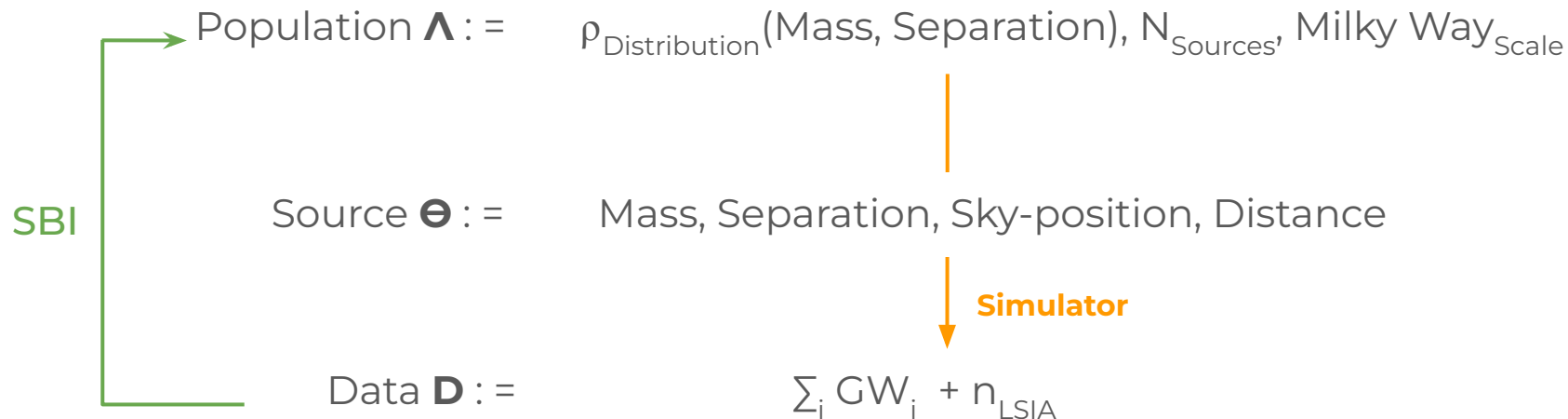
Source $\Theta := \text{Mass, Separation, Sky-position, Distance}$

Data $\mathbf{D} :=$

$\sum_i \text{GW}_i + n_{\text{LSIA}}$

Simulator

Simulation-based Inference



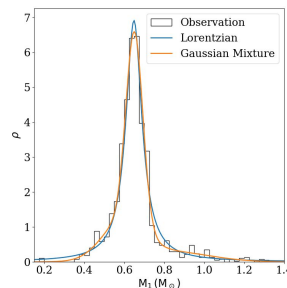
Given examples of $\Lambda \rightarrow \mathbf{D}$,
 SBI solves the *inverse problem* $\mathbf{D} \rightarrow \Lambda$, i.e., $p(\Lambda | \mathbf{D}, \mathbf{M}_{\text{Simulator}})$

Λ : Parameterizing the Population

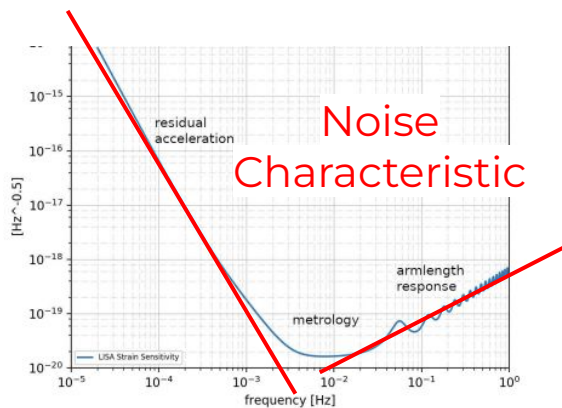
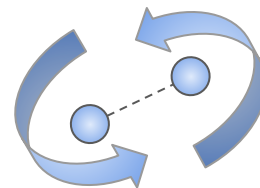
Total DWD Number	:1
Primary DWD Mass Dist.	:2
Separation Dist.	:1
MW Disc	:2
MW Bulge	:2
LISA Noise Parameters	:2

Total :10d

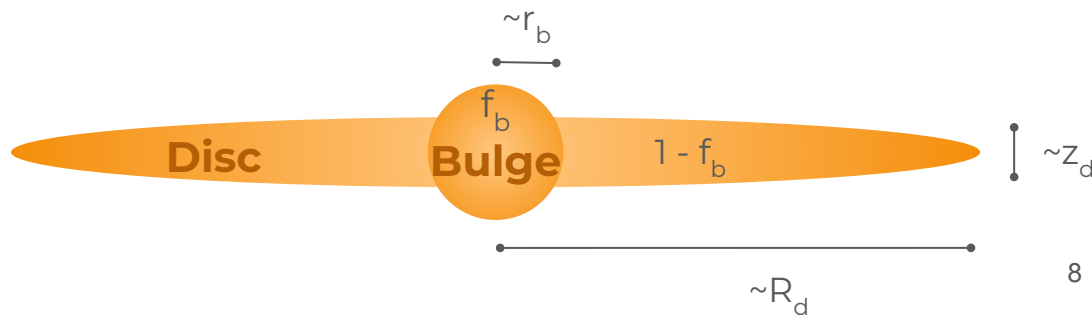
M_1 distribution



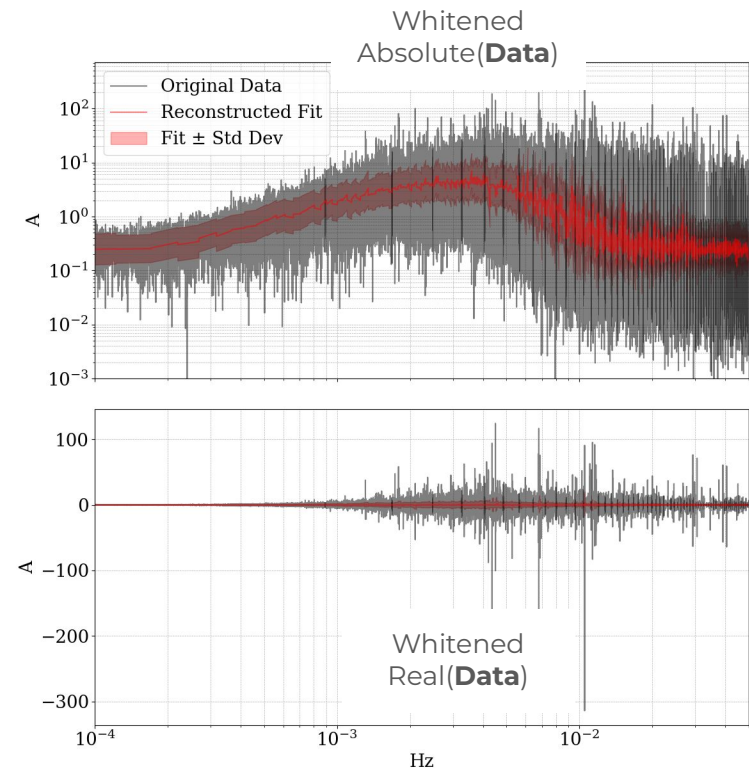
Separation Index



Milky Way Scale



Data summary



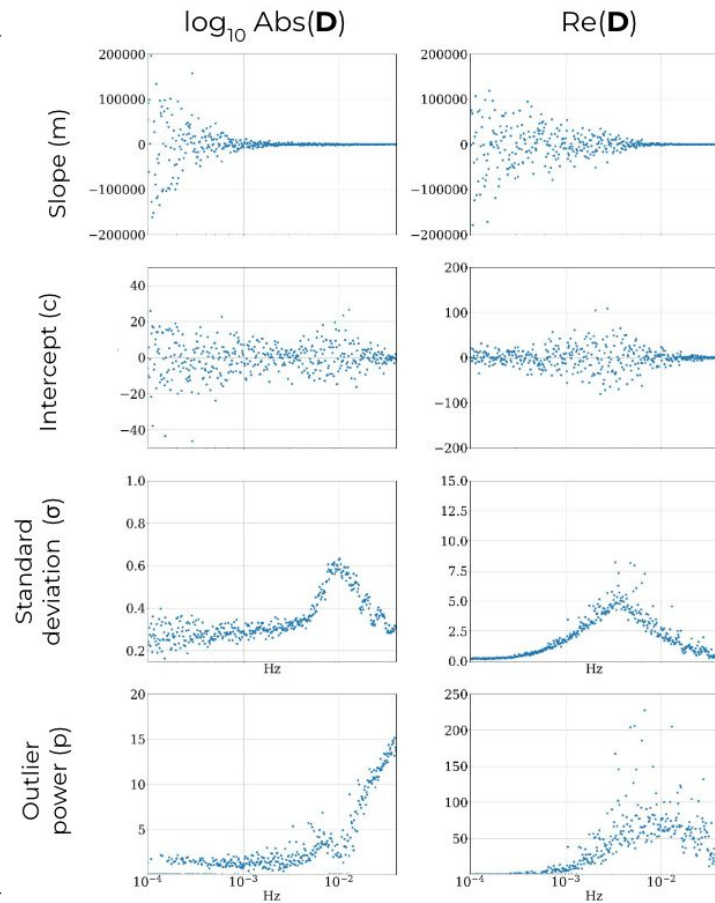
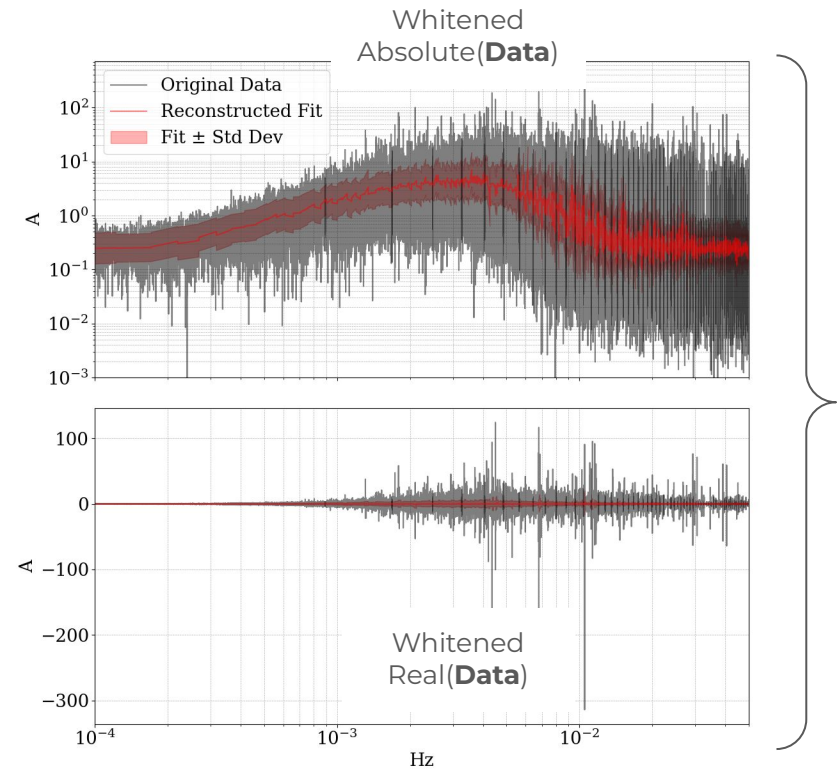
A network with $O(10^6)$ input neurons is very memory intensive and data hungry.
Need to summarize the data.

Our *current* prescription:

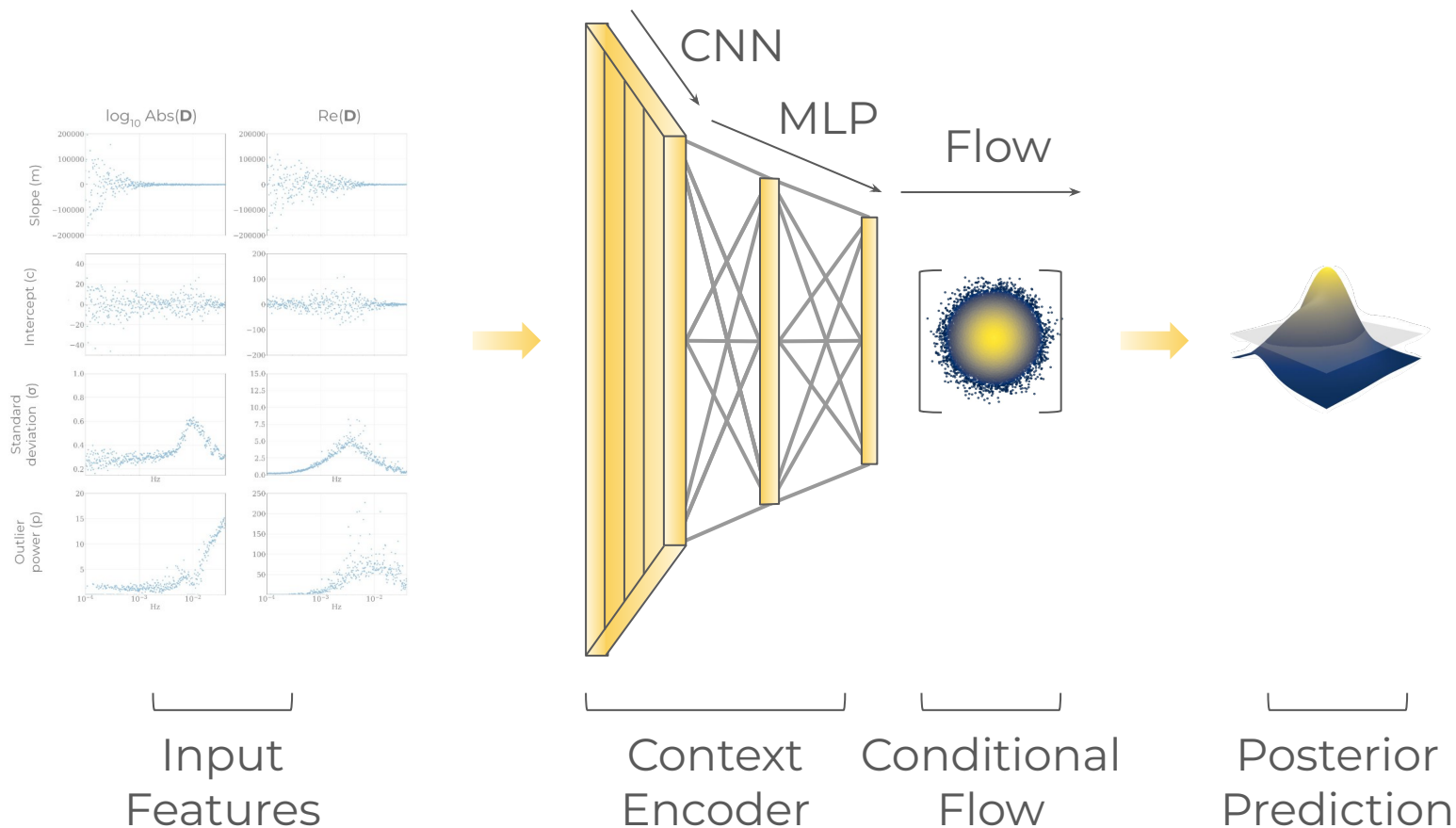
Linear fit of data within frequency batches
Summary: fit and residual parameters.

Data reduction: $O(10^6) \rightarrow O(10^3)$

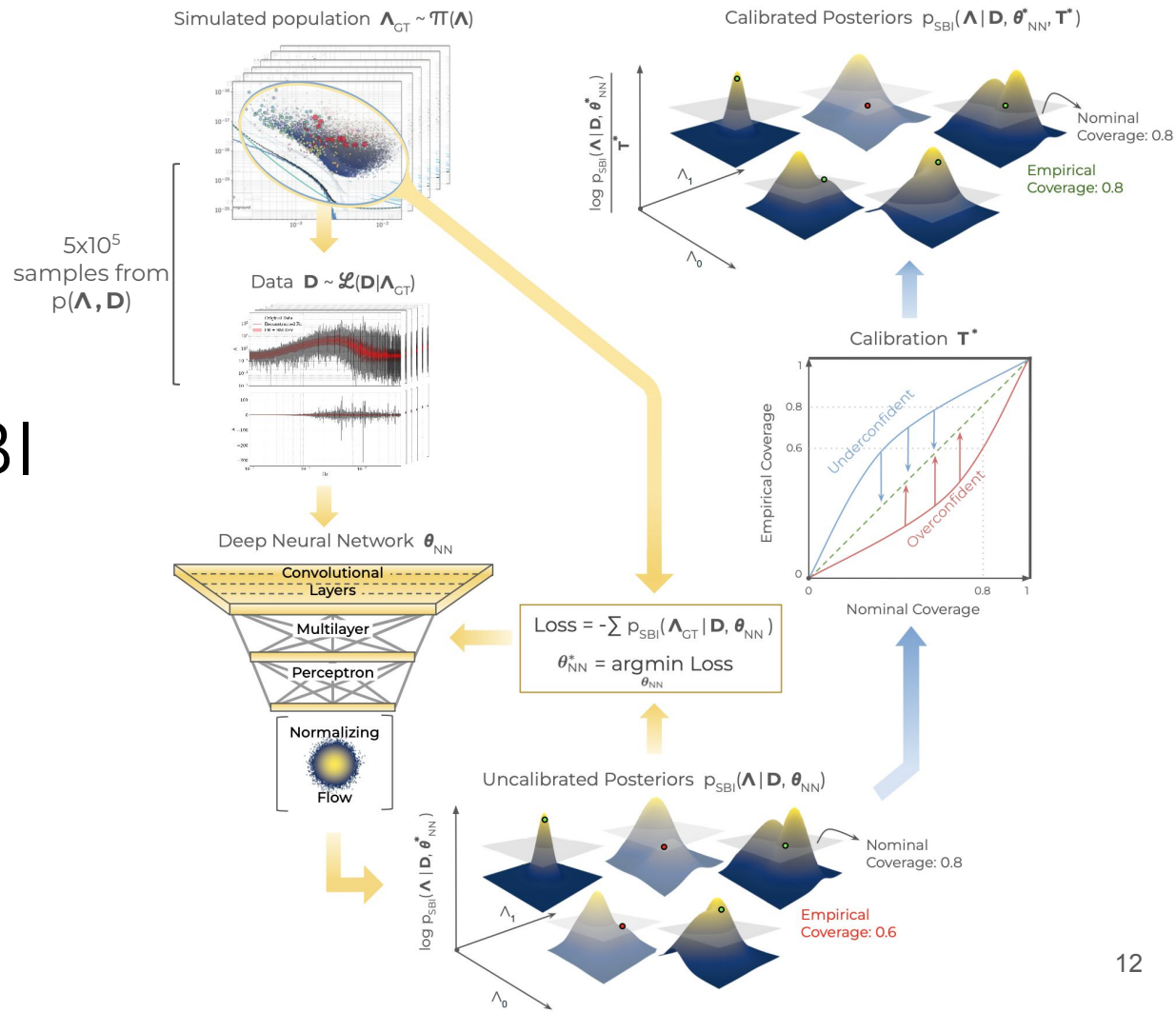
Data summary

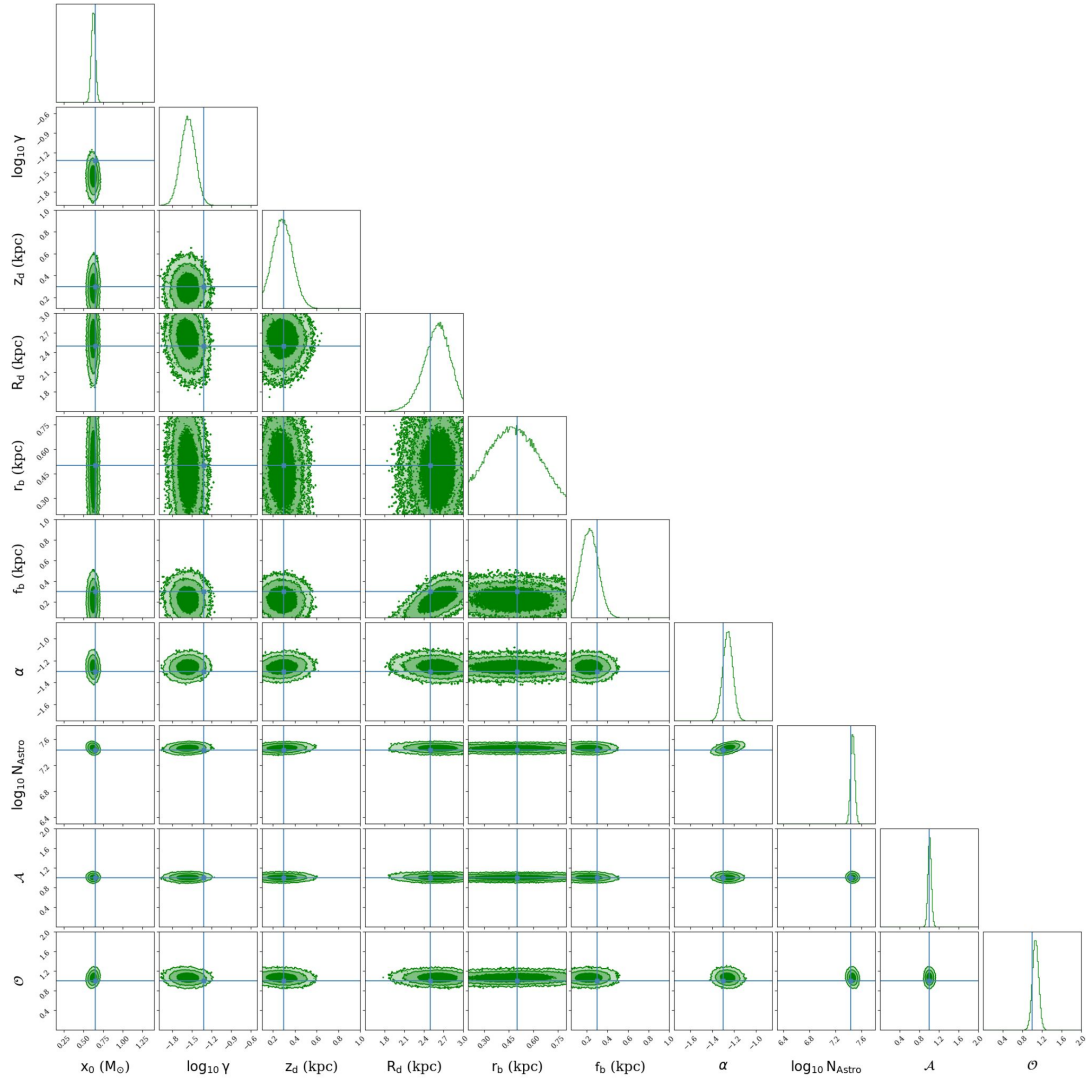


Network Architecture

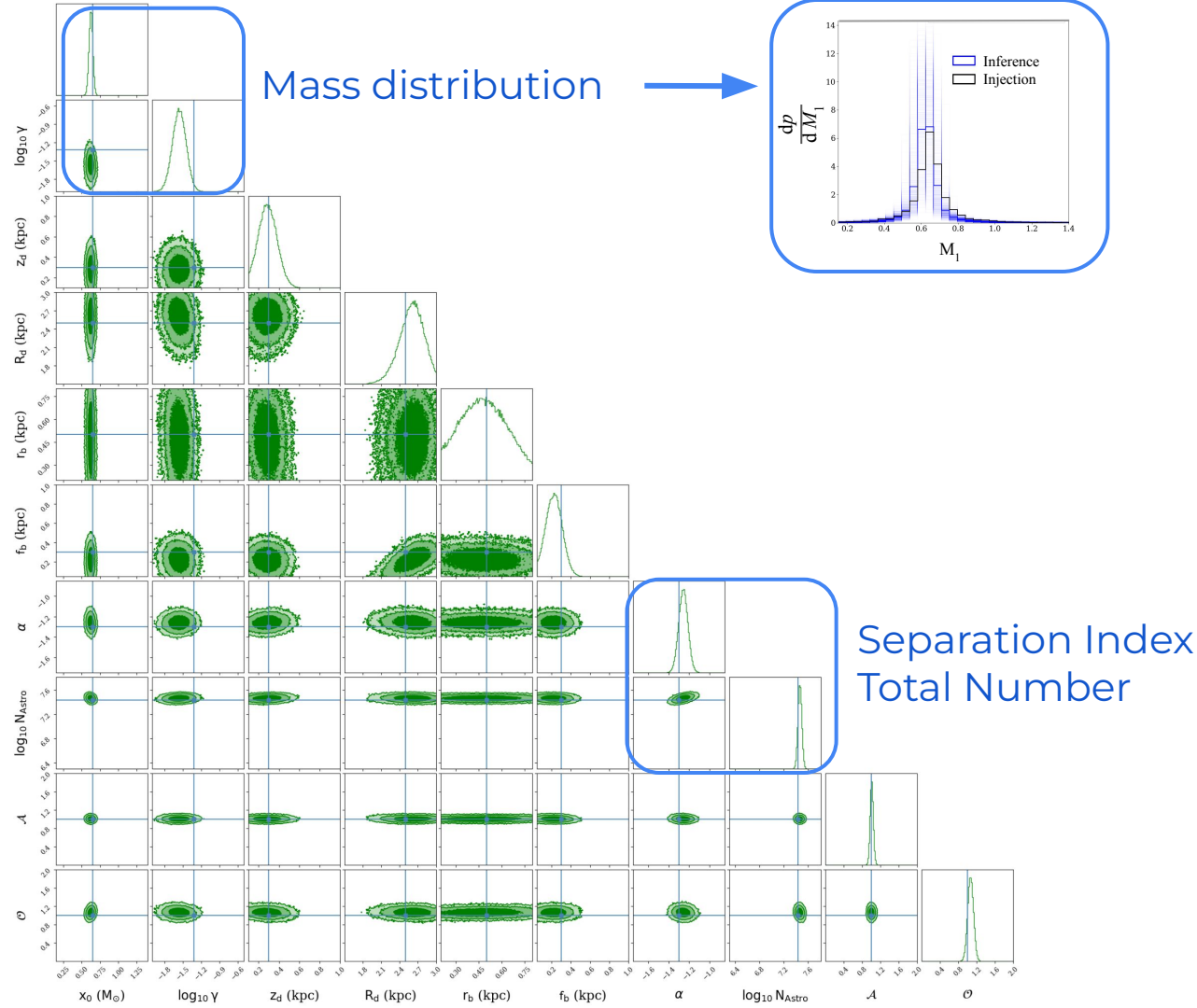


Training the SBI

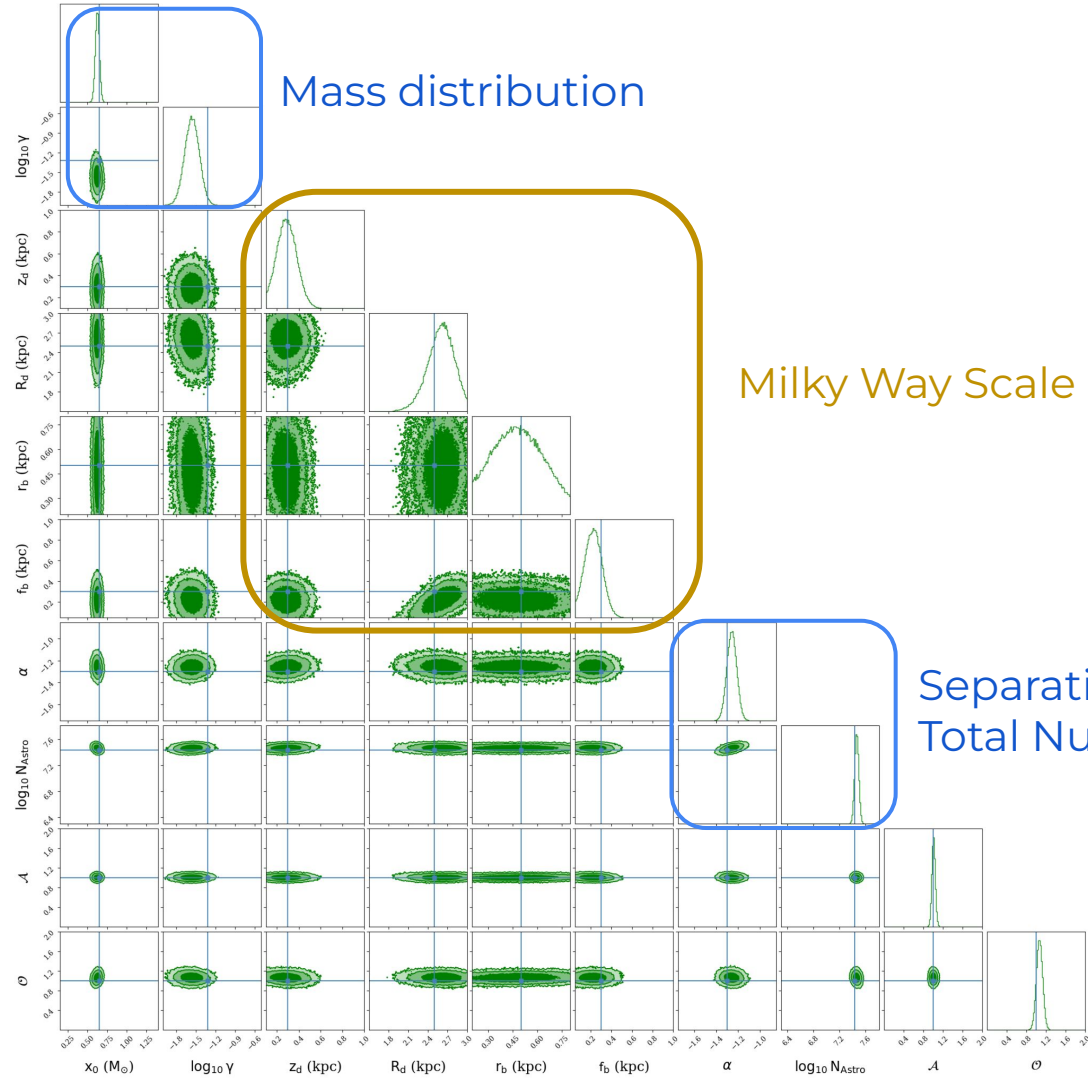




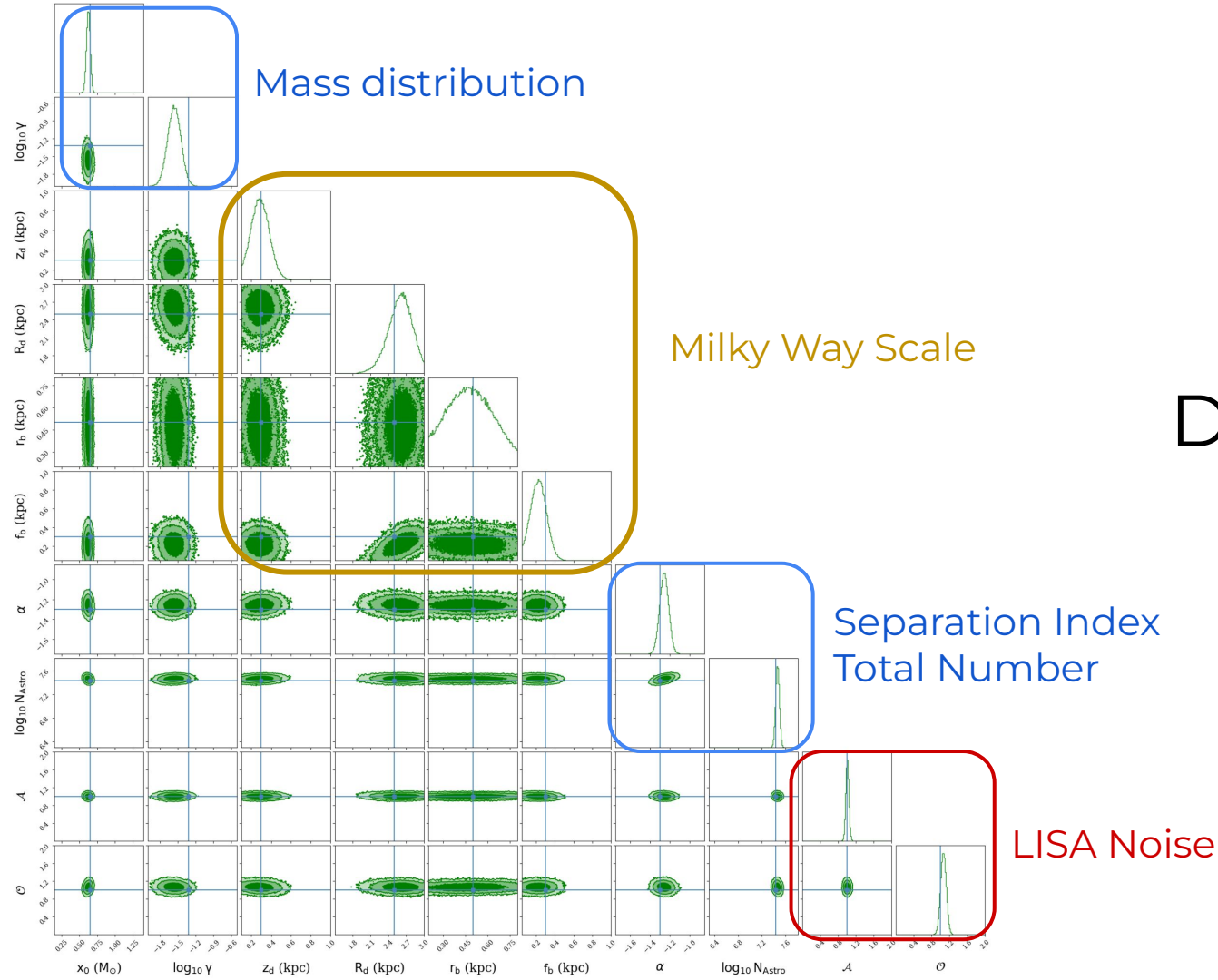
Galactic D_{ouble} W_{hite} D_{warf} Population Inference



Galactic D_{ouble} W_{hite} D_{warf} Population Inference

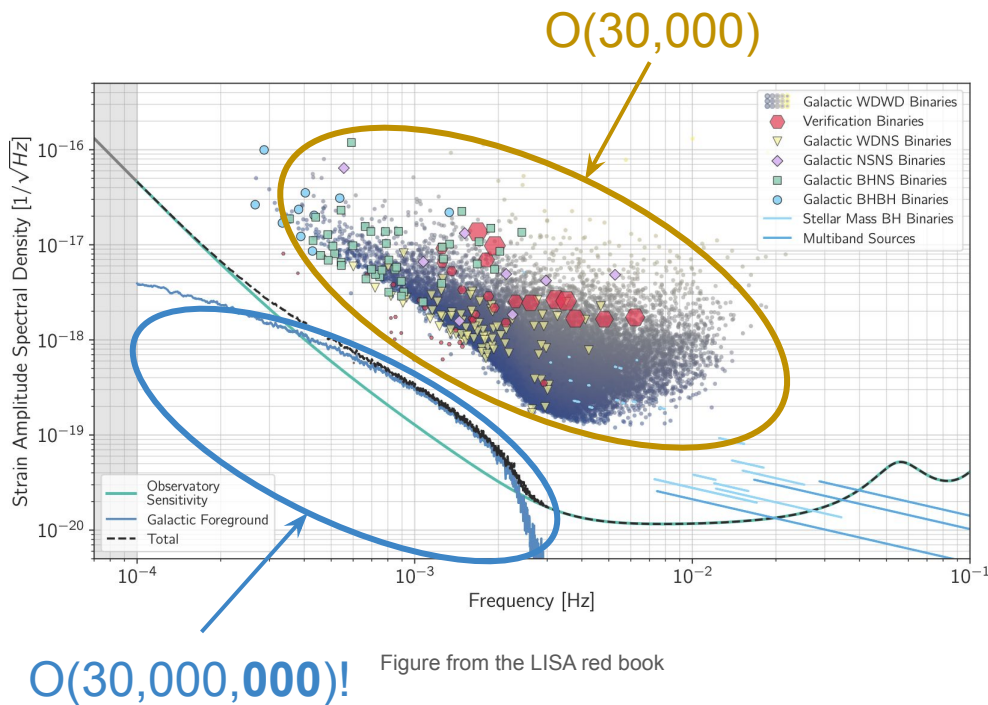


Galactic D_{Double} W_{White} D_{dwarf} Population Inference



Galactic Double White Dwarf Population Inference

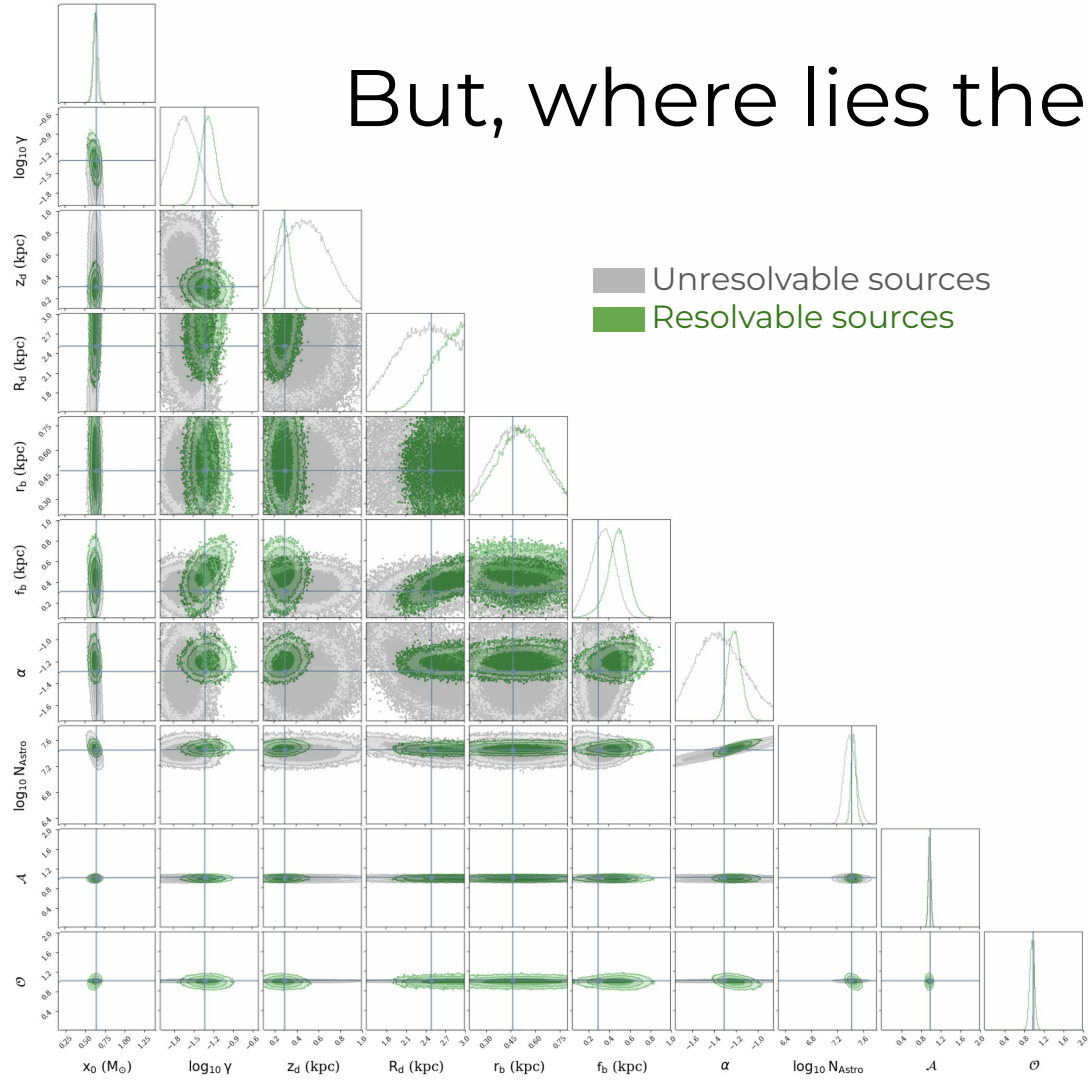
But, where lies the information?



Where's the population signature?
the few resolvable sources or
the many unresolvable sources ?

Figure from the LISA red book

But, where lies the information?



Probably the resolvable !
(at least for this particular data summary)

Caveats, caveats, caveats

- * The inference can only be as good as the simulator/model $p(\mathbf{\Lambda}|\mathbf{D}, \mathbf{M}_{\text{Simulator}})$.
- * The inference can only be as good as the data summary.
- * The intractable (or at least hard-to-pose) likelihood prevents testing SBI for convergence to an “optimal” posterior.
- * The SBI can often be underconfident: Calibration required.

