

A Strong Lens Is Worth a Thousand Dark Matter Halos: Inference on Small-Scale Structure Using Sequential Methods

EuCAIFCon 2024

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Simon Birrer, Risa H. Wechsler

arXiv: [2404.14487](https://arxiv.org/abs/2404.14487)

github: [paltax](https://github.com/paltax)

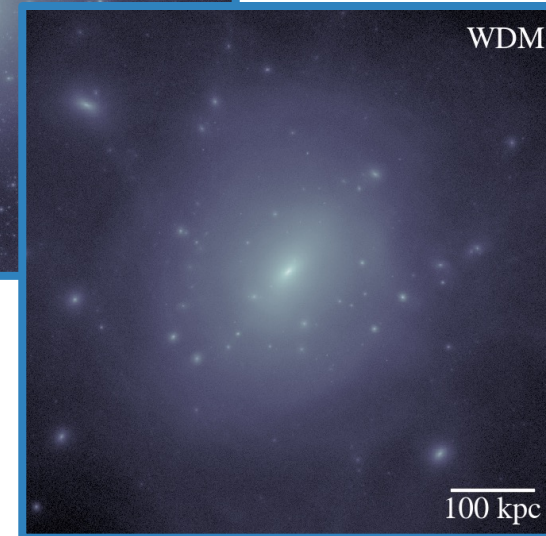
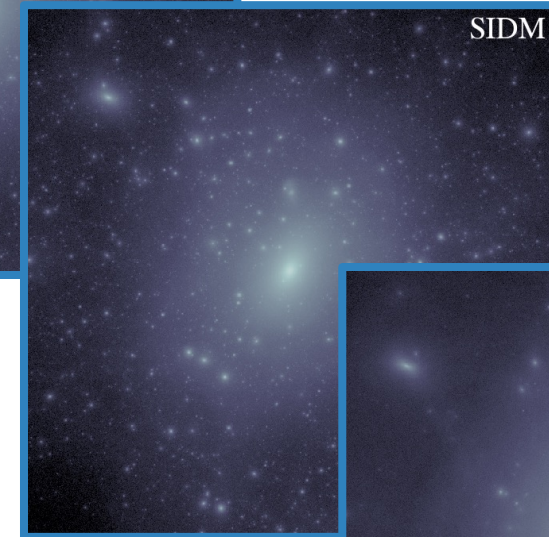
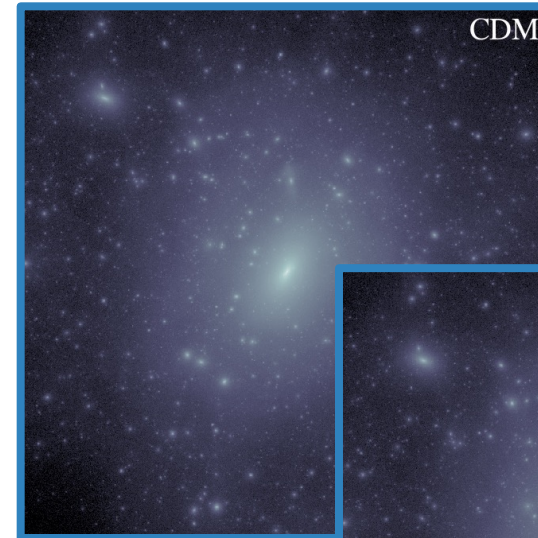


CDM Open Question

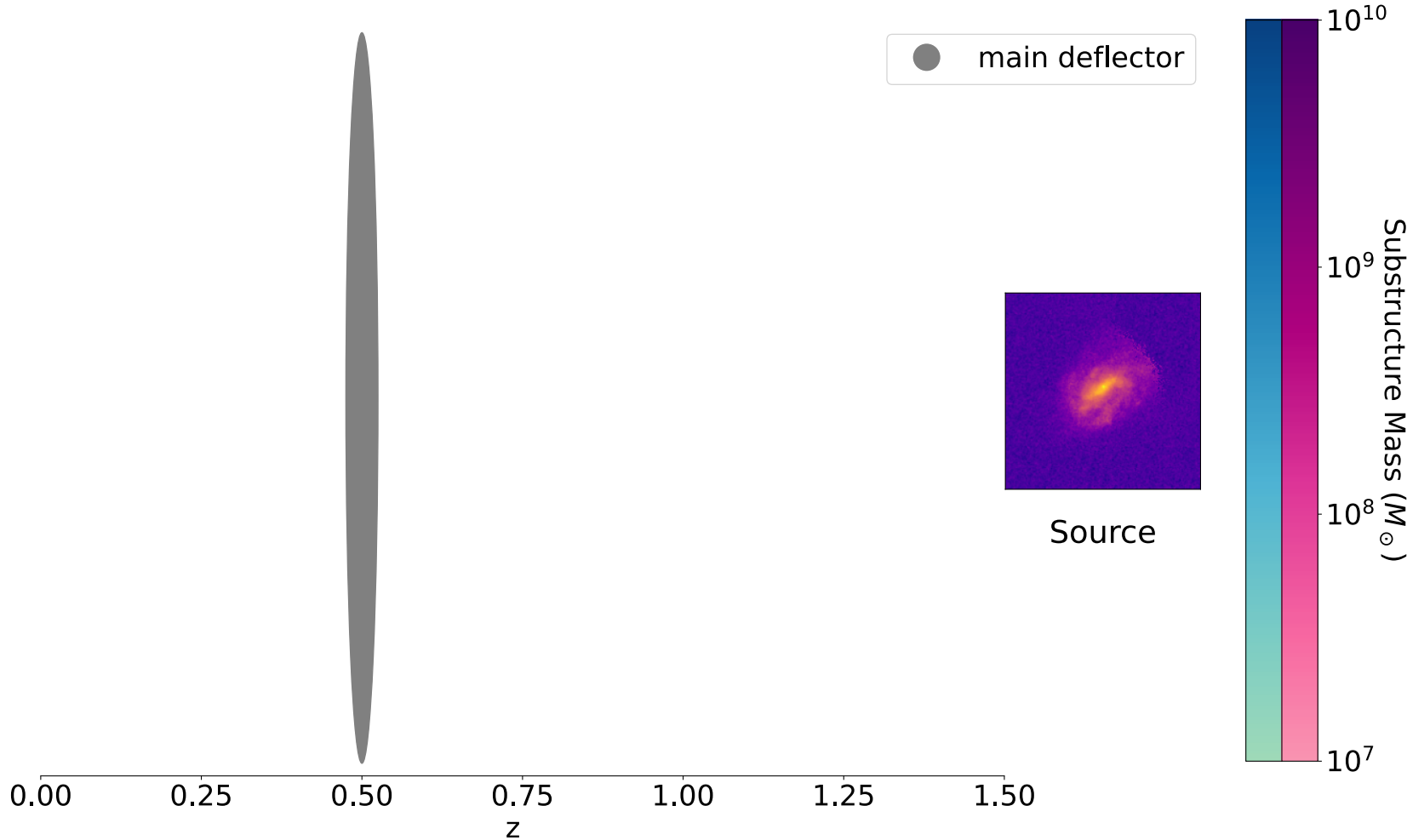
- CDM is a description of the **behavior** of dark matter, not a fundamental model

What is the fundamental nature of dark matter?

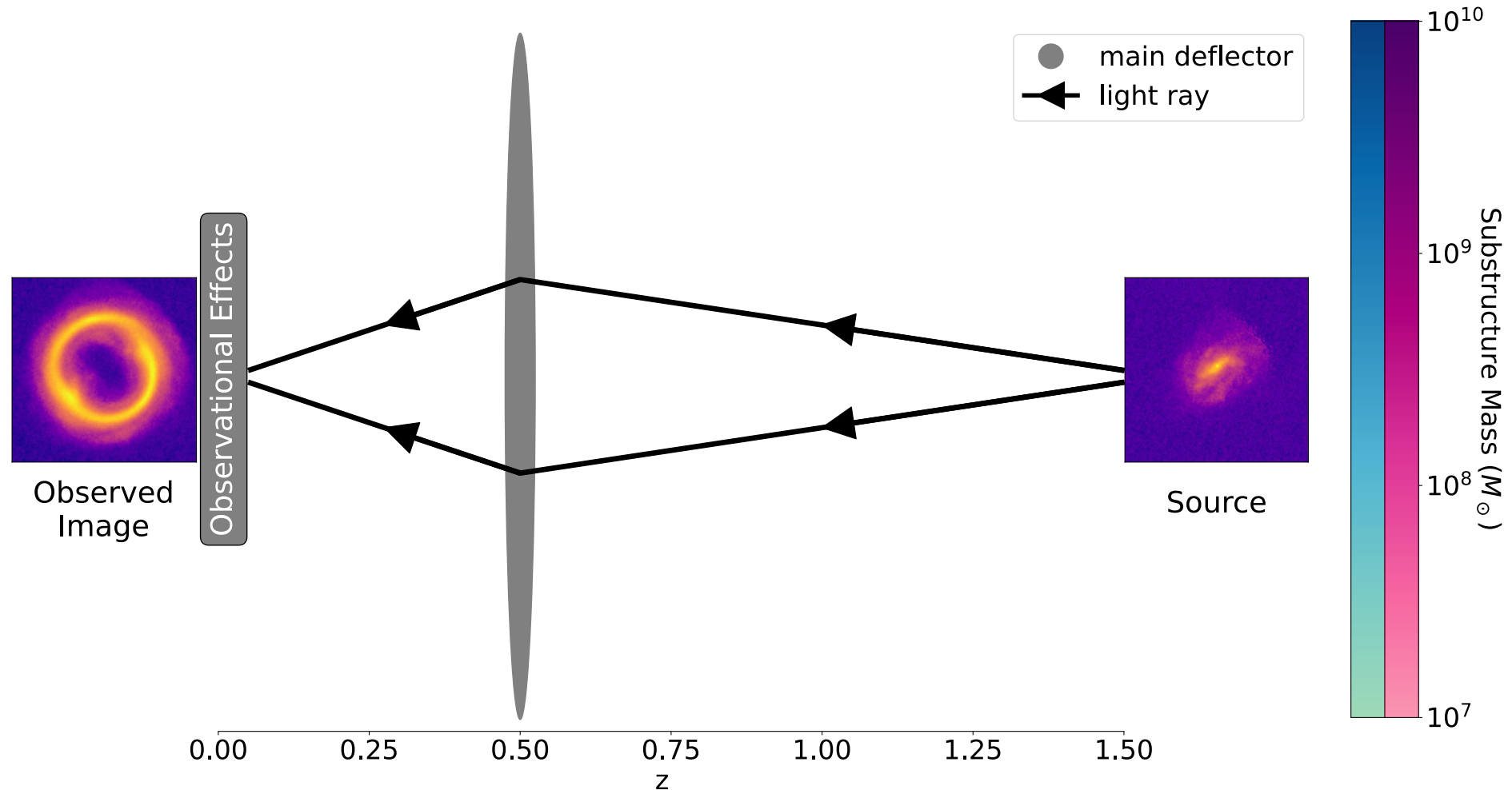
- Many compelling theories for dark matter **violate** the CDM paradigm
- **Low-mass** halos → **dark matter physics**



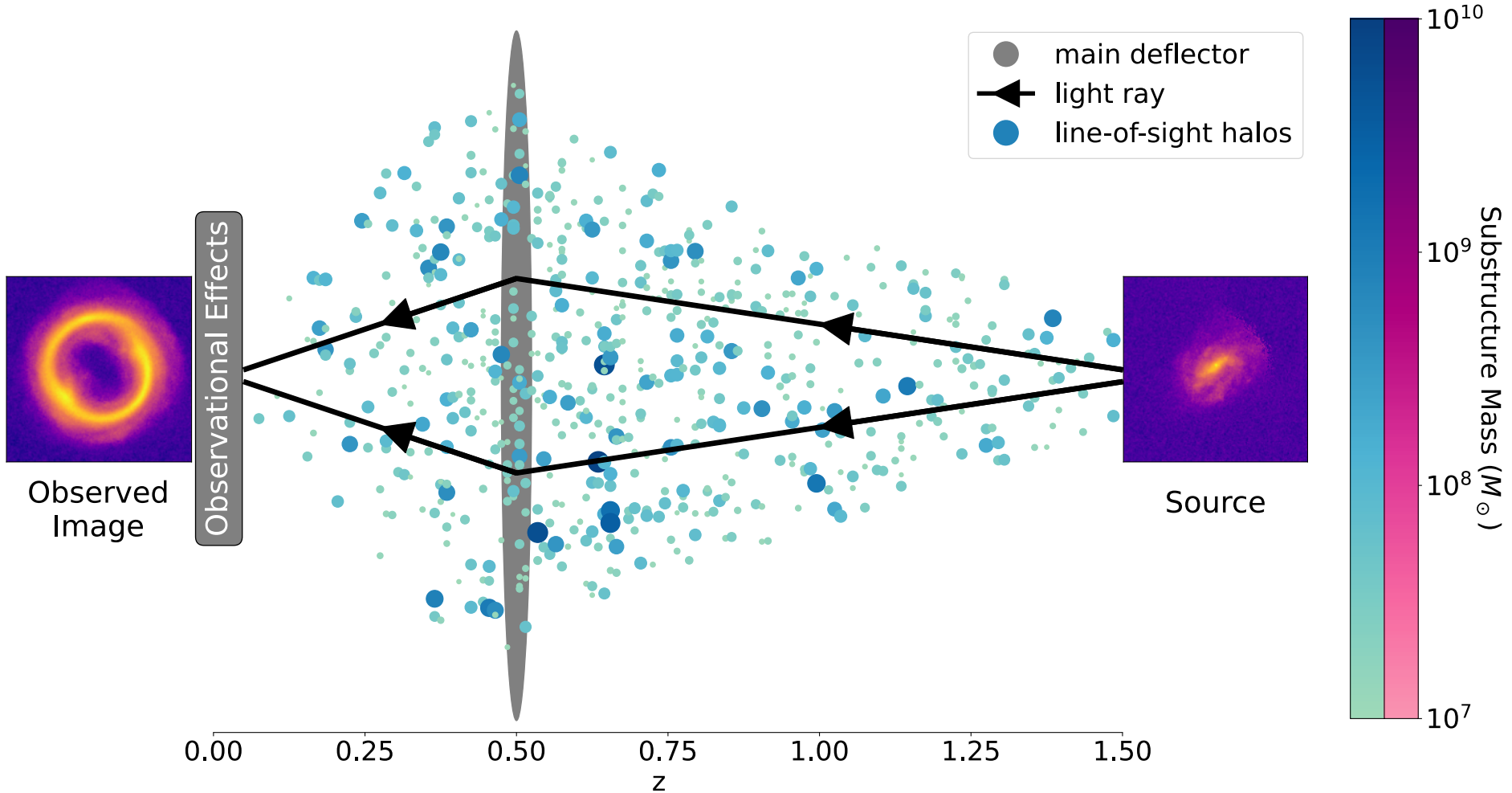
Measuring Halos: Strong Lensing



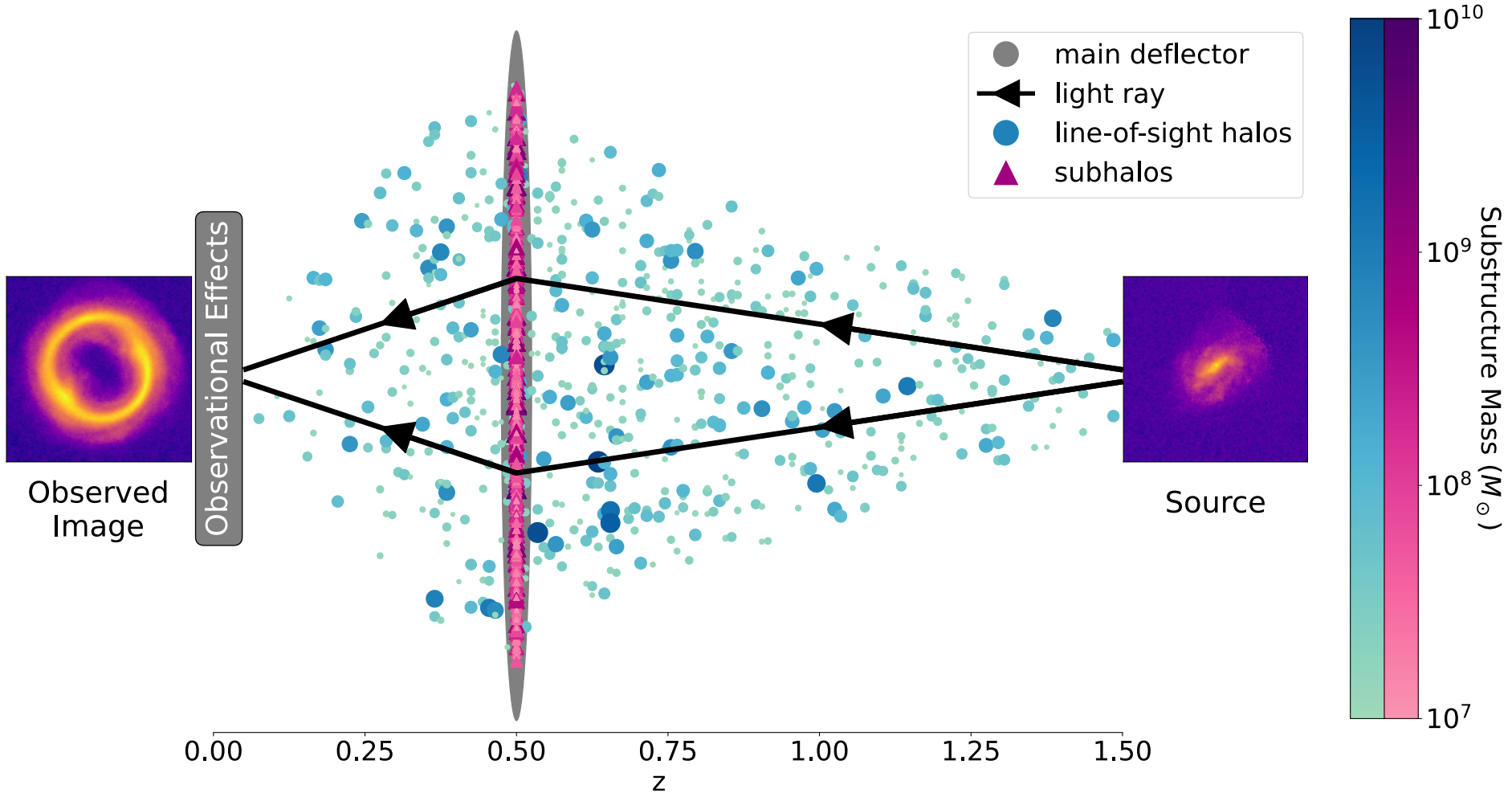
Measuring Halos: Strong Lensing



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Measuring Halos: Strong Lensing

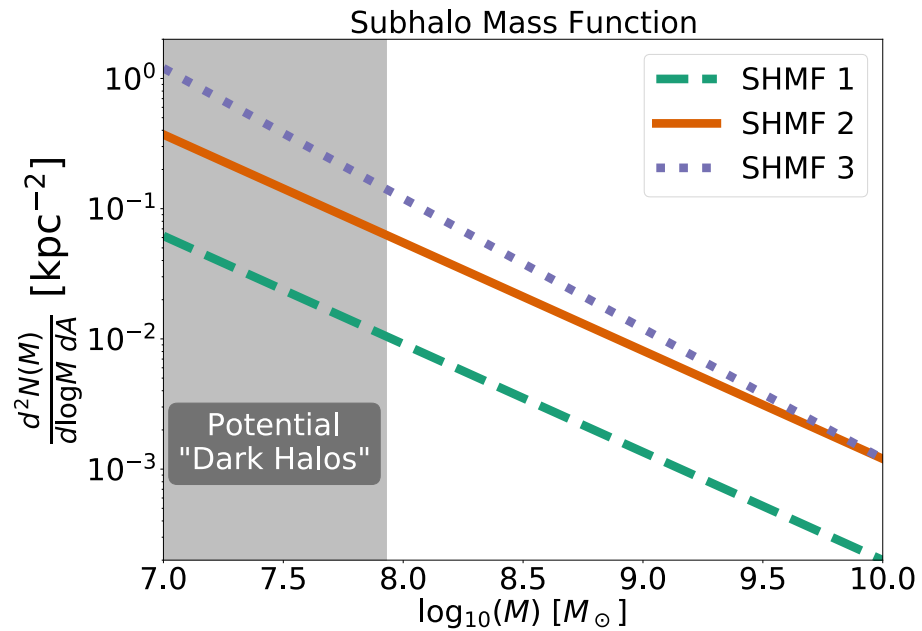


“Statistical” Detection

$$\frac{d^2 N_{\text{sub}}}{dA dm_{\text{sub}}} = \boxed{\Sigma_{\text{sub}}} \frac{m_{\text{sub}}^{\gamma_{\text{sub}}}}{m_{\text{pivot,sub}}^{\gamma_{\text{sub}}+1}}$$

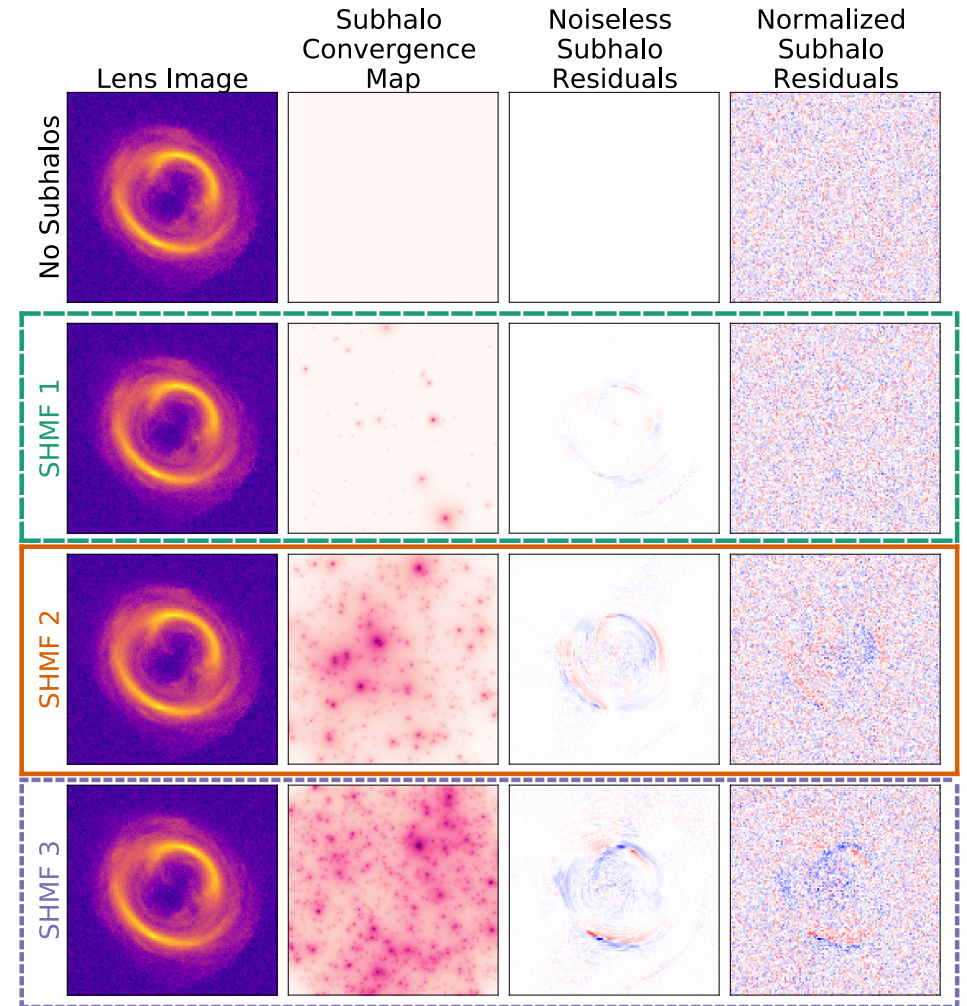
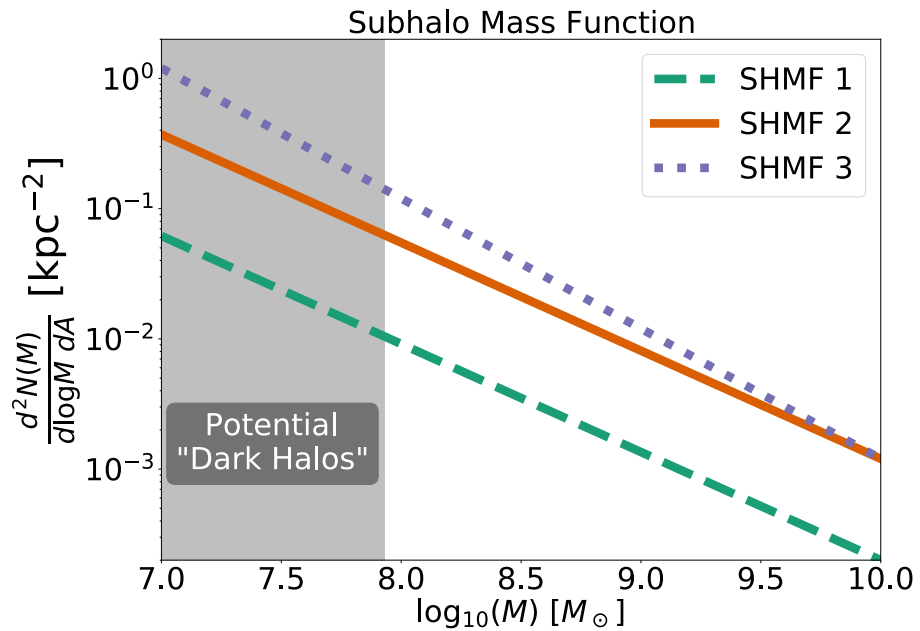
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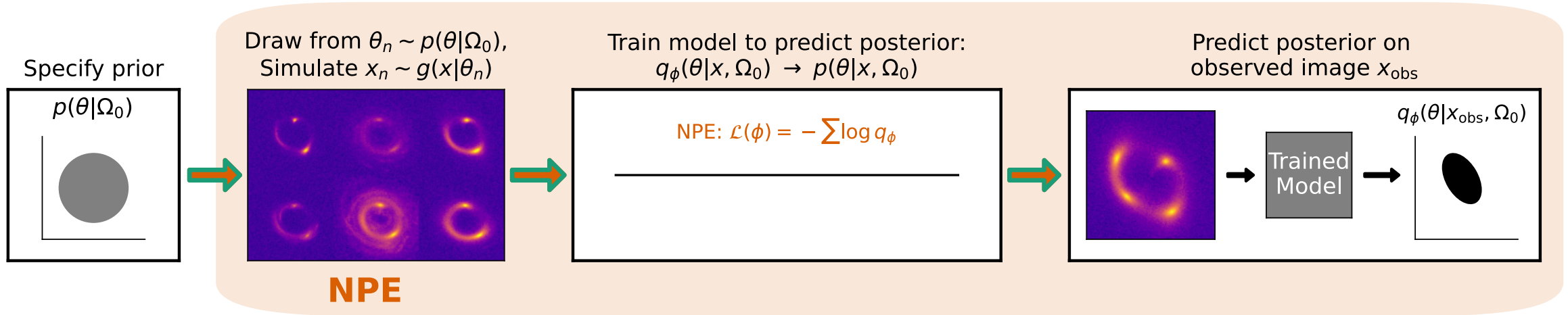


“Statistical” Detection

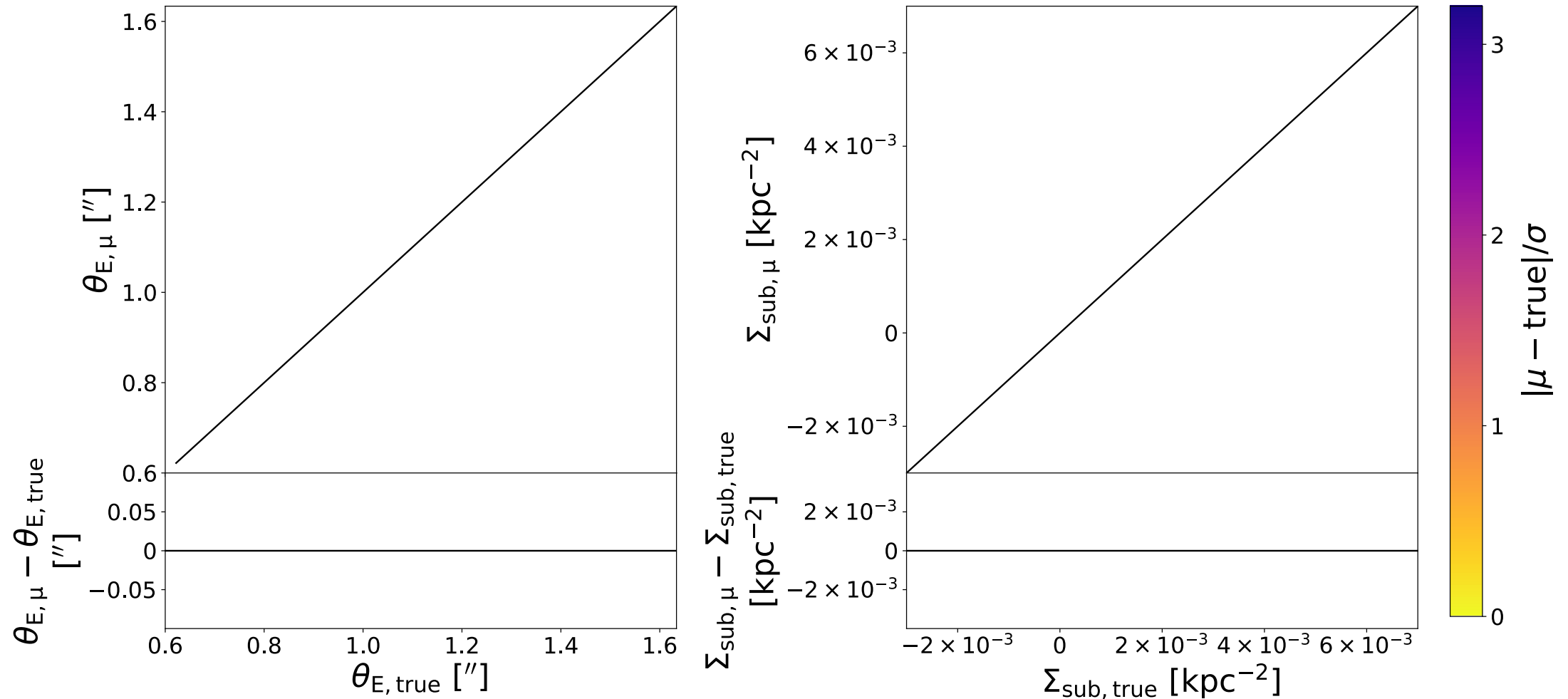
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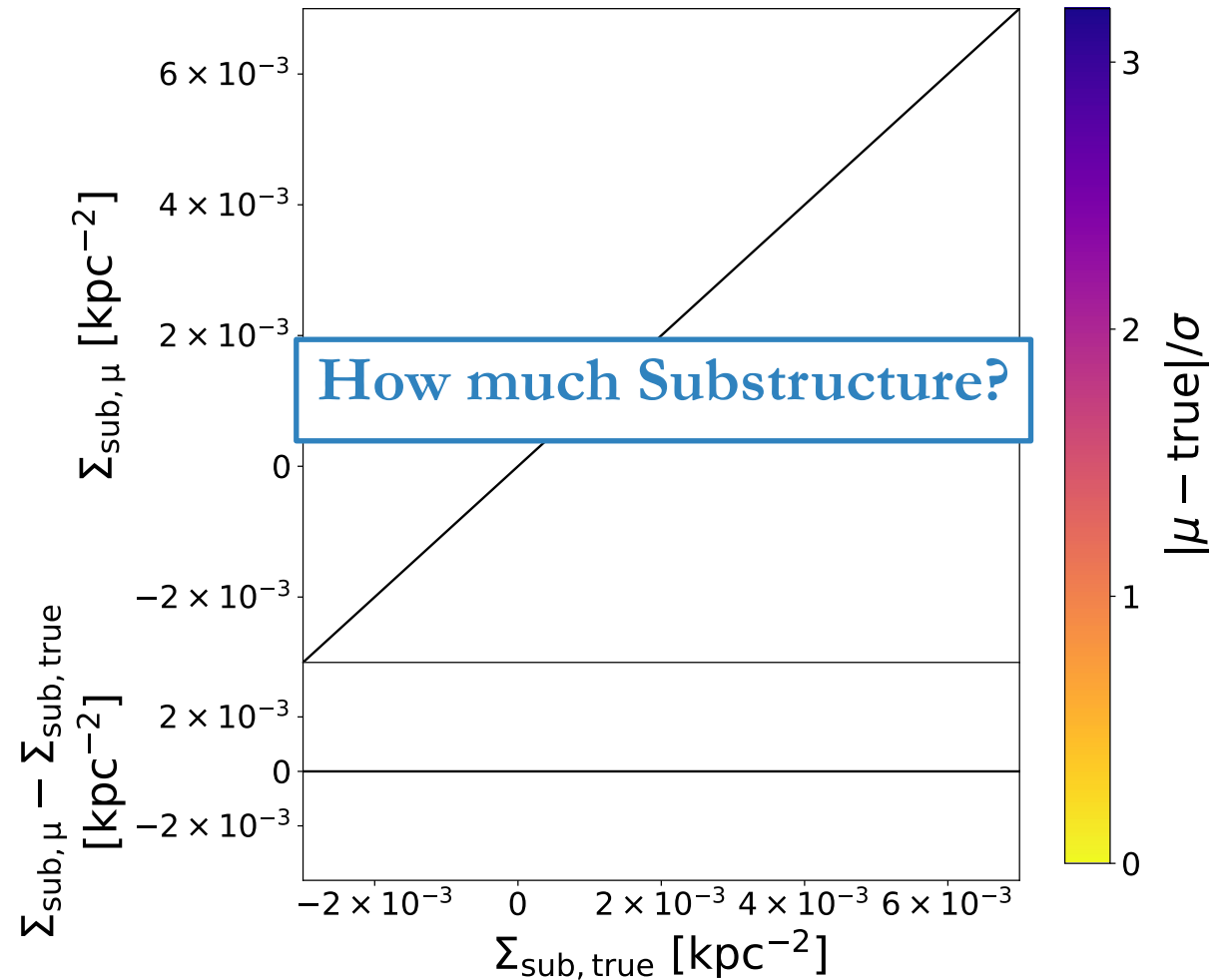
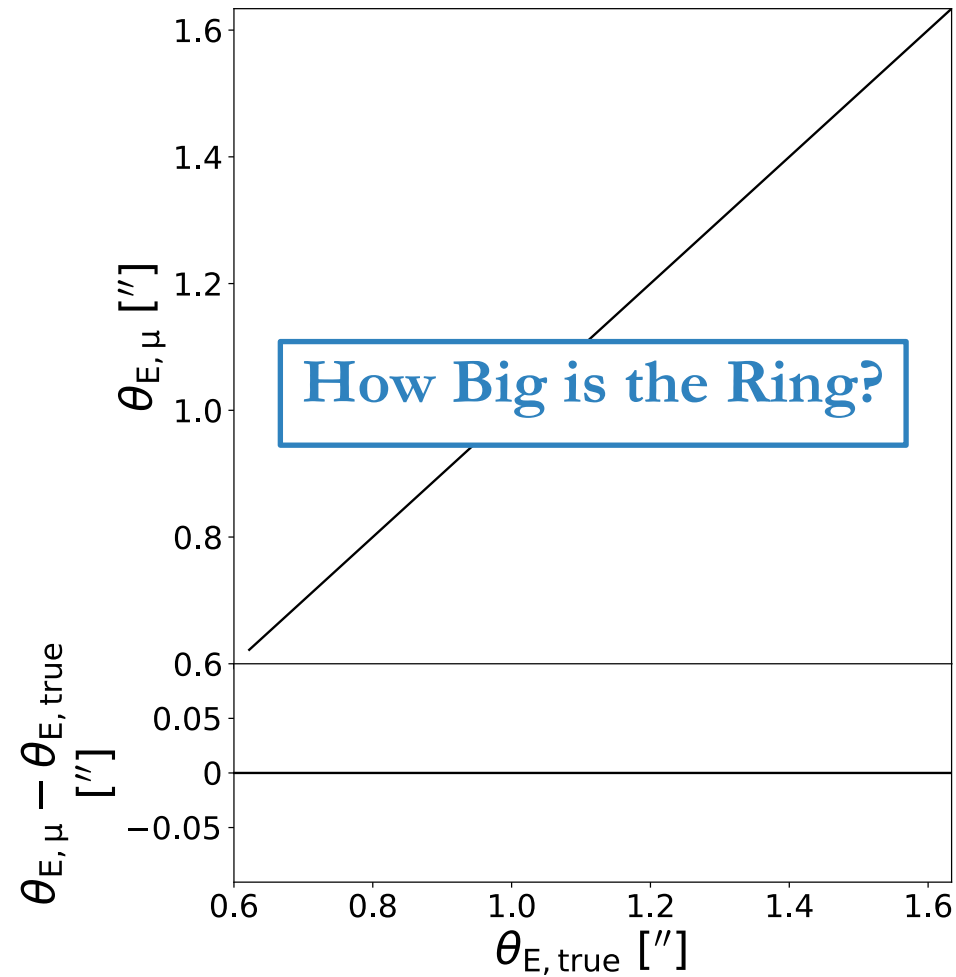
The Framework: Neural Posterior Estimation



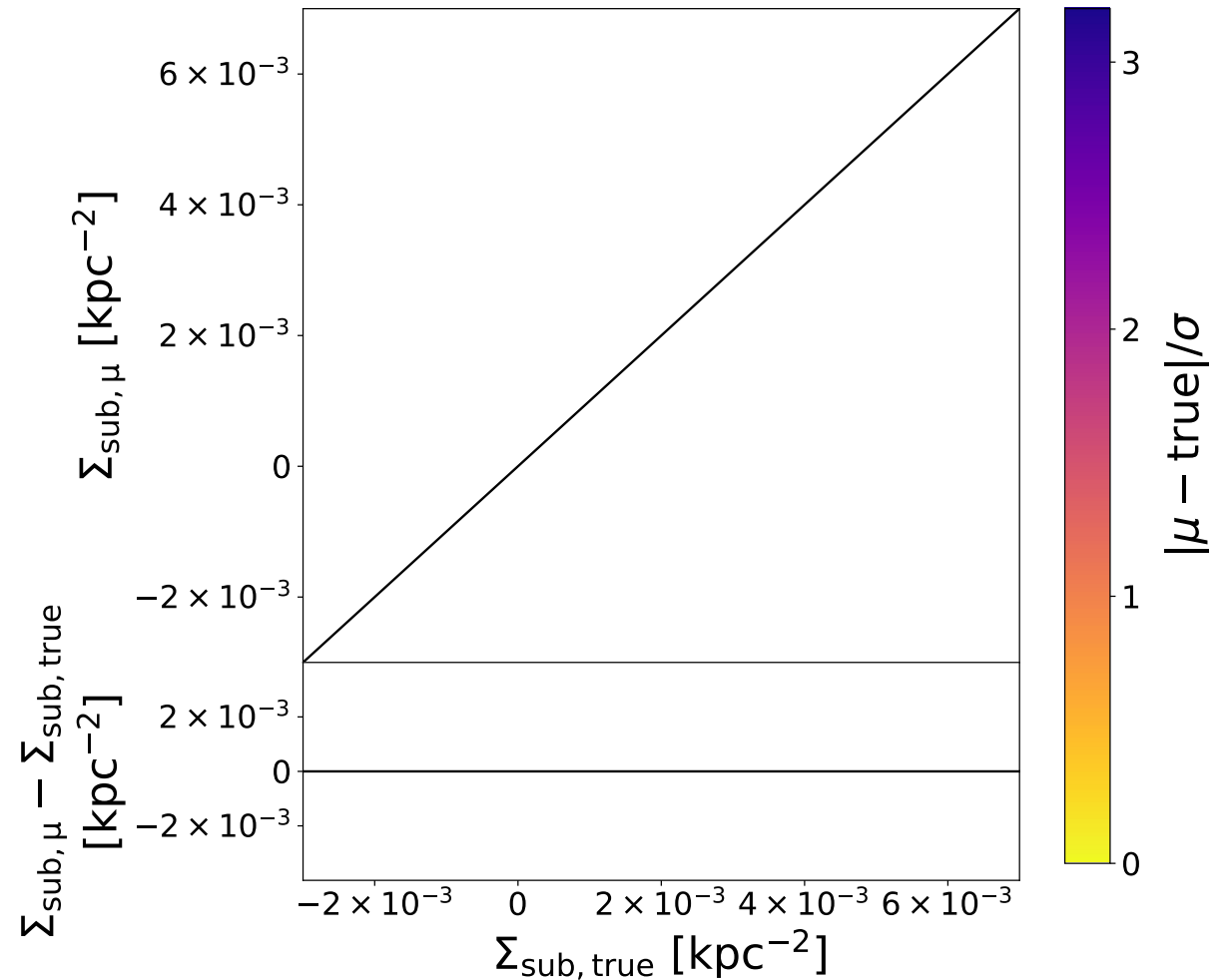
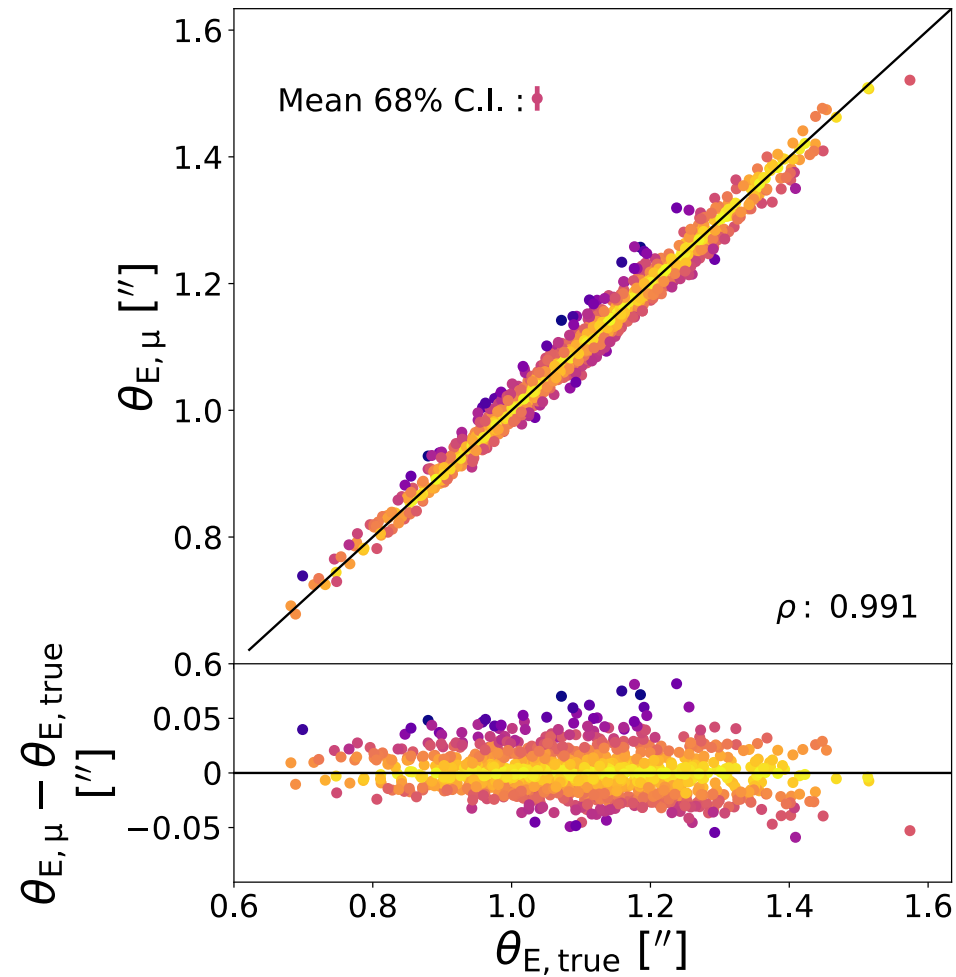
Individual Constraints



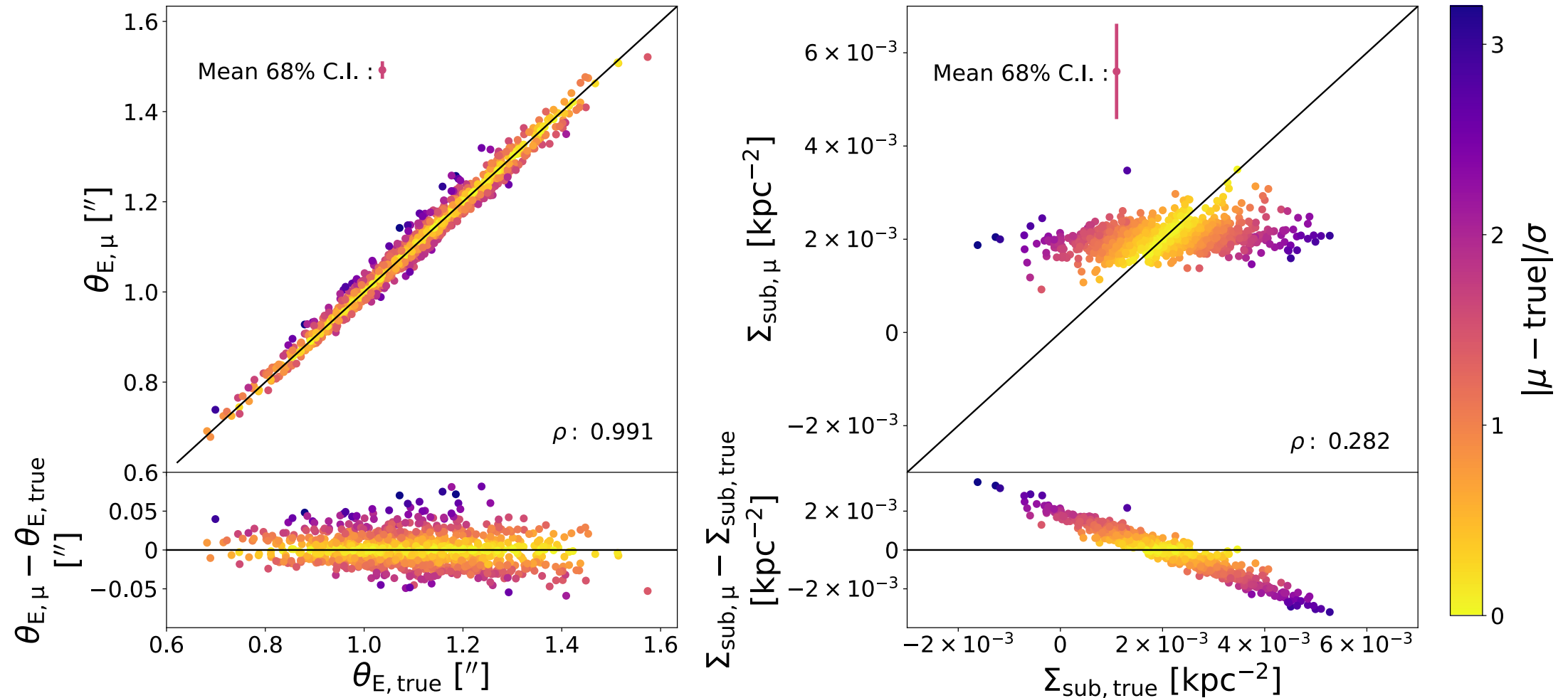
Individual Constraints



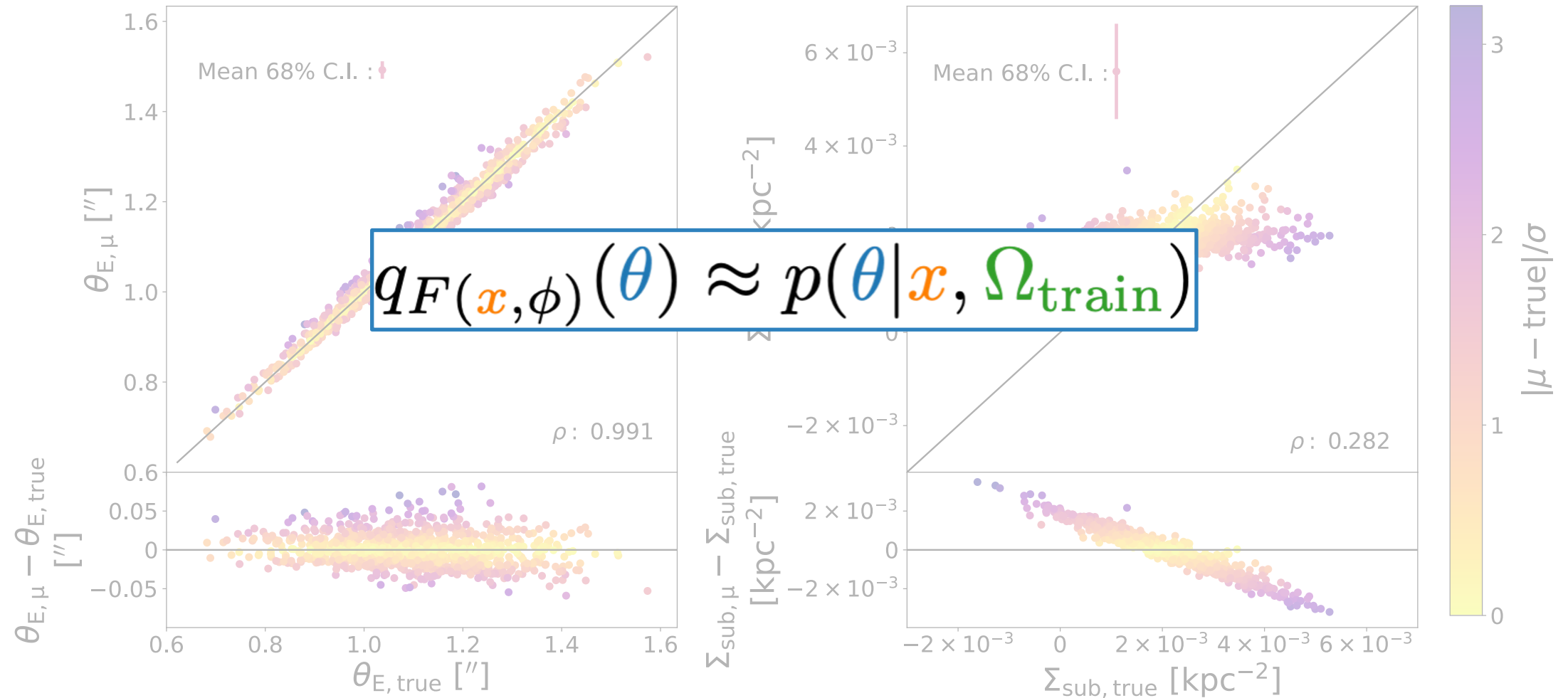
Individual Constraints



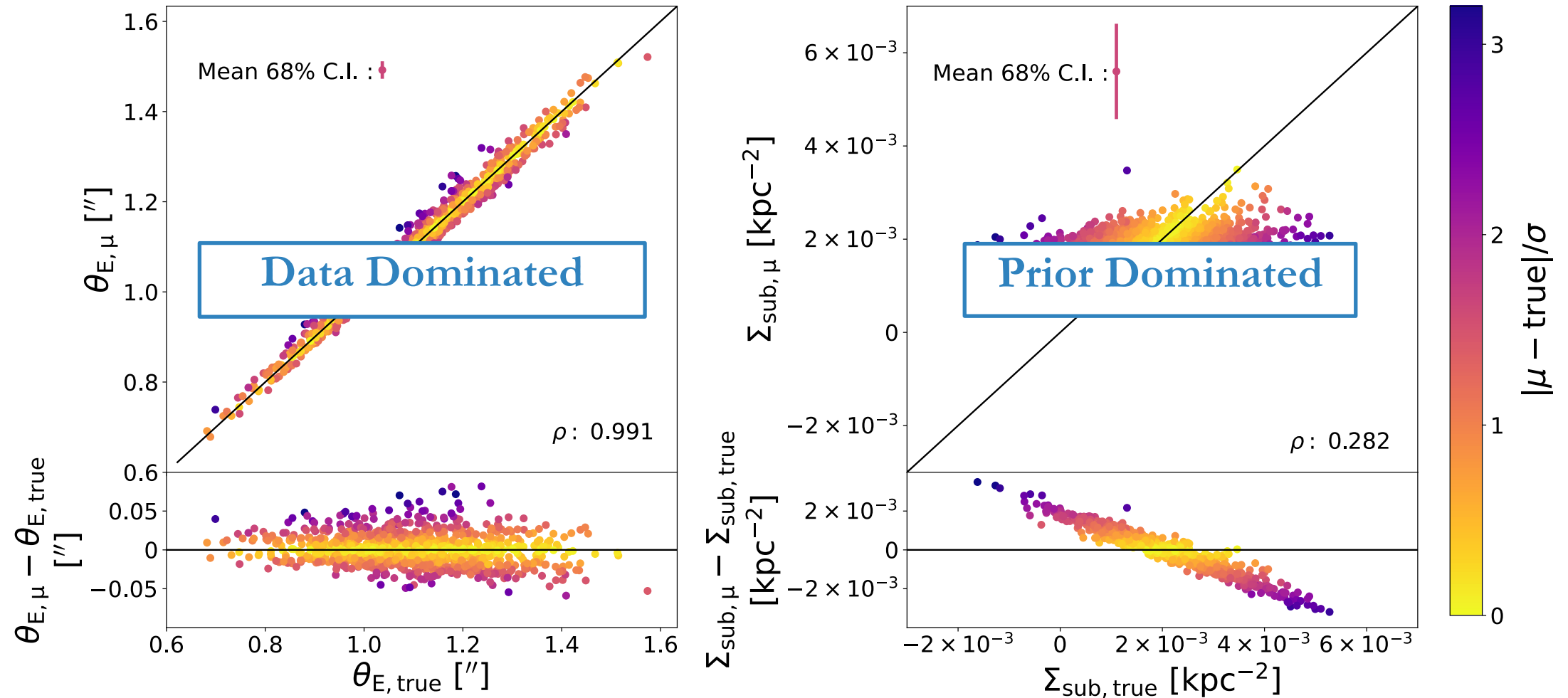
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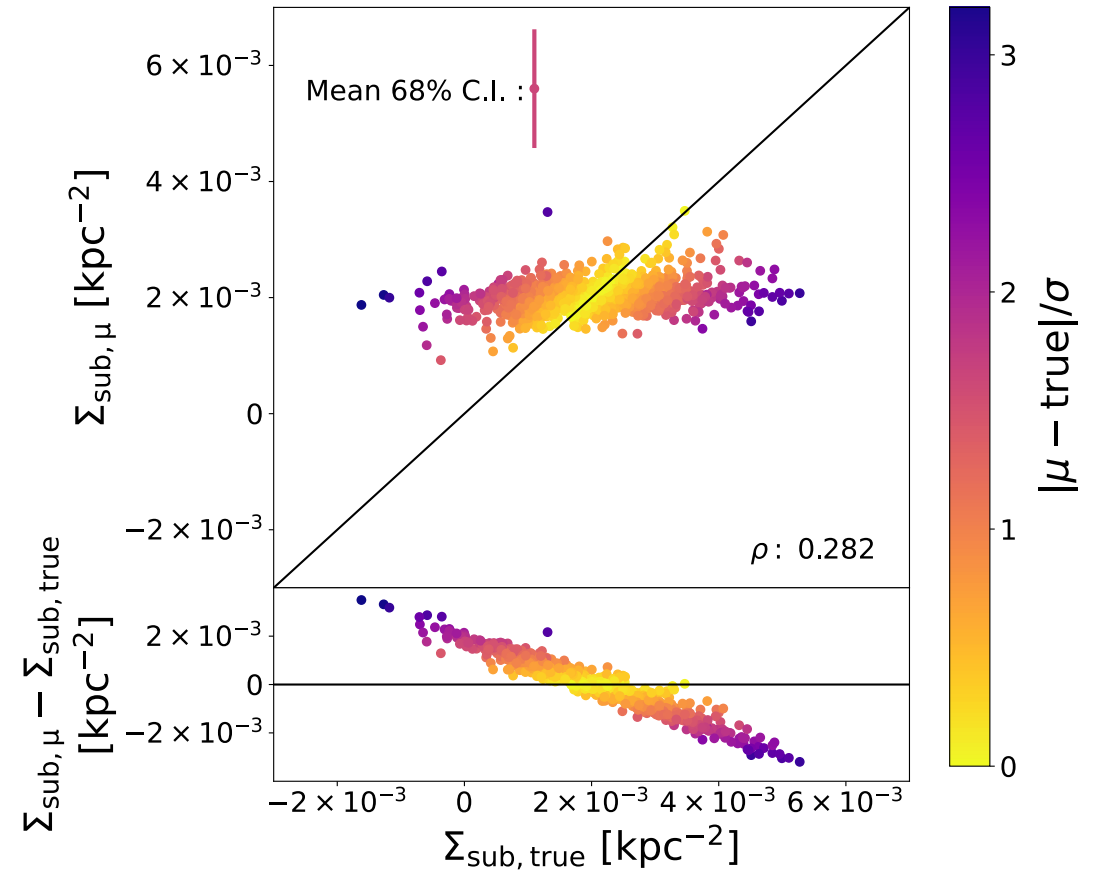
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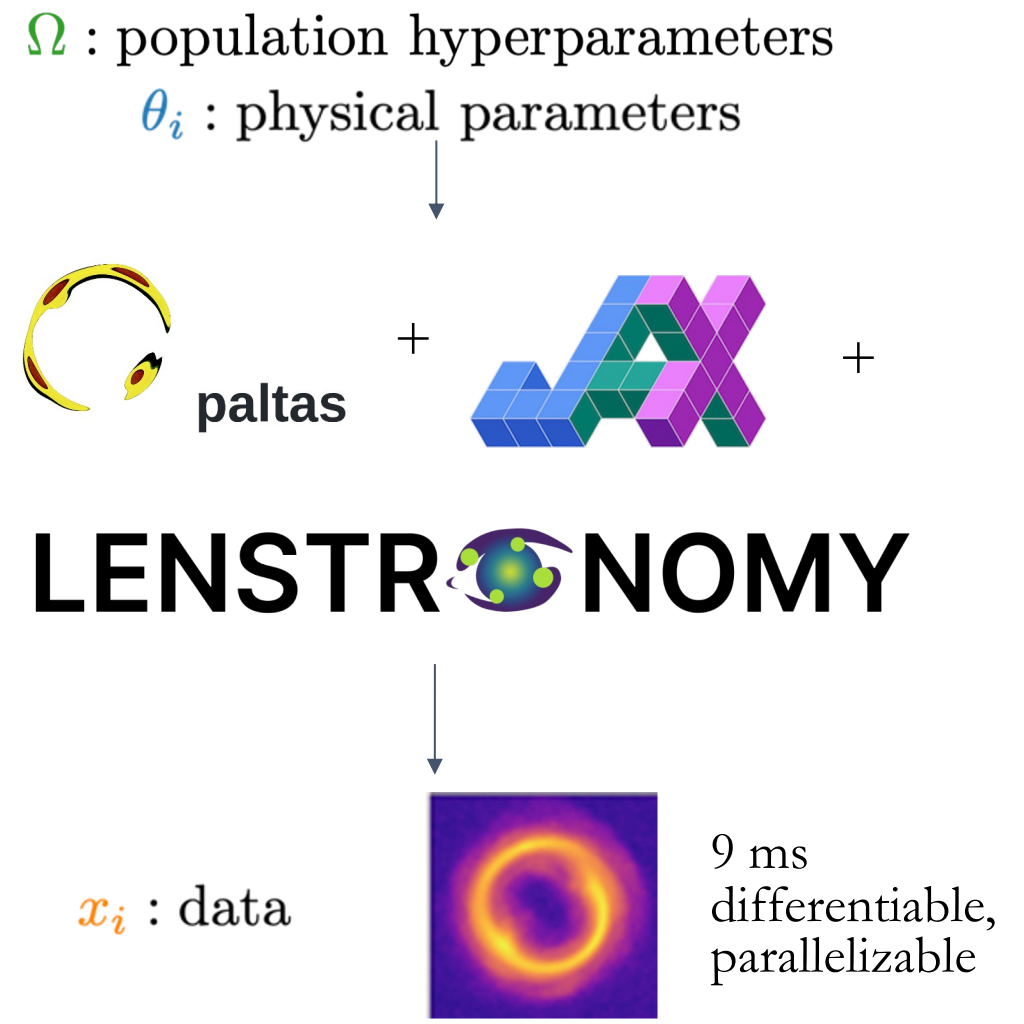
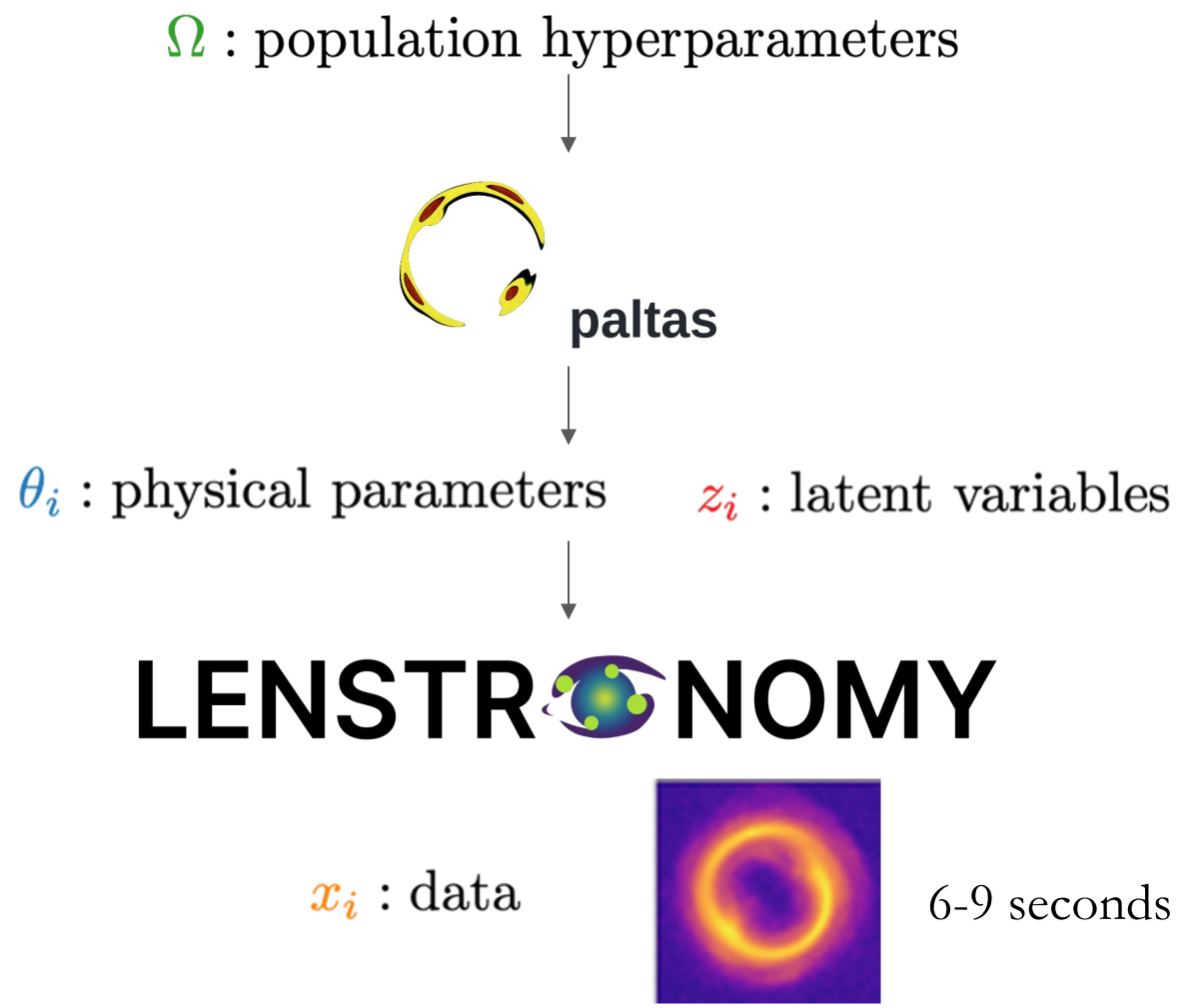
Our Current Limitation?

*Have neural-density based SBI methods already reached the **information limit of the data**, or are there **methodology choices** that are imposing artificial bottlenecks?*

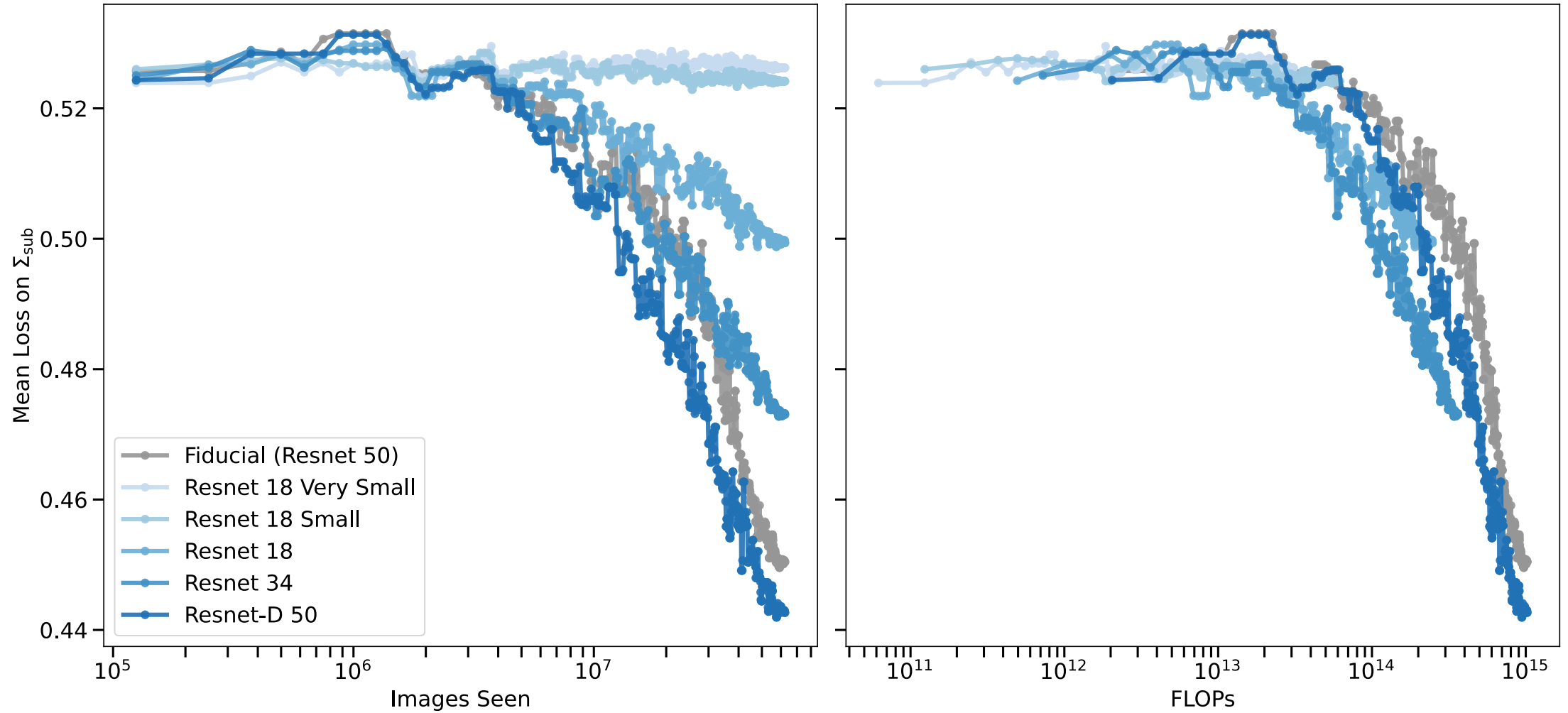
- NPE has theoretical guarantees, but only in the limits of **infinite data**, a sufficiently **expressive model**, and **perfect optimization**



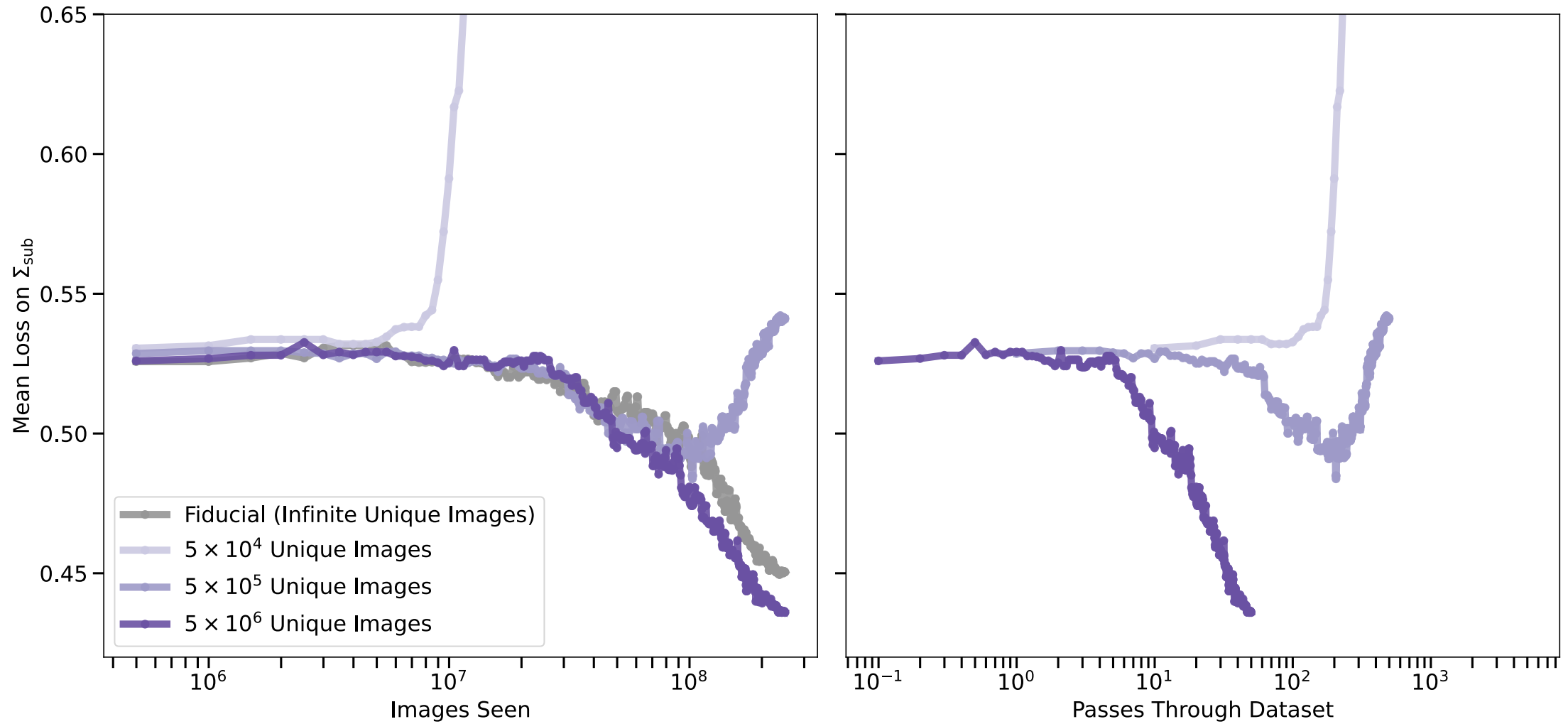
Infinite Training Data



Limits: Model



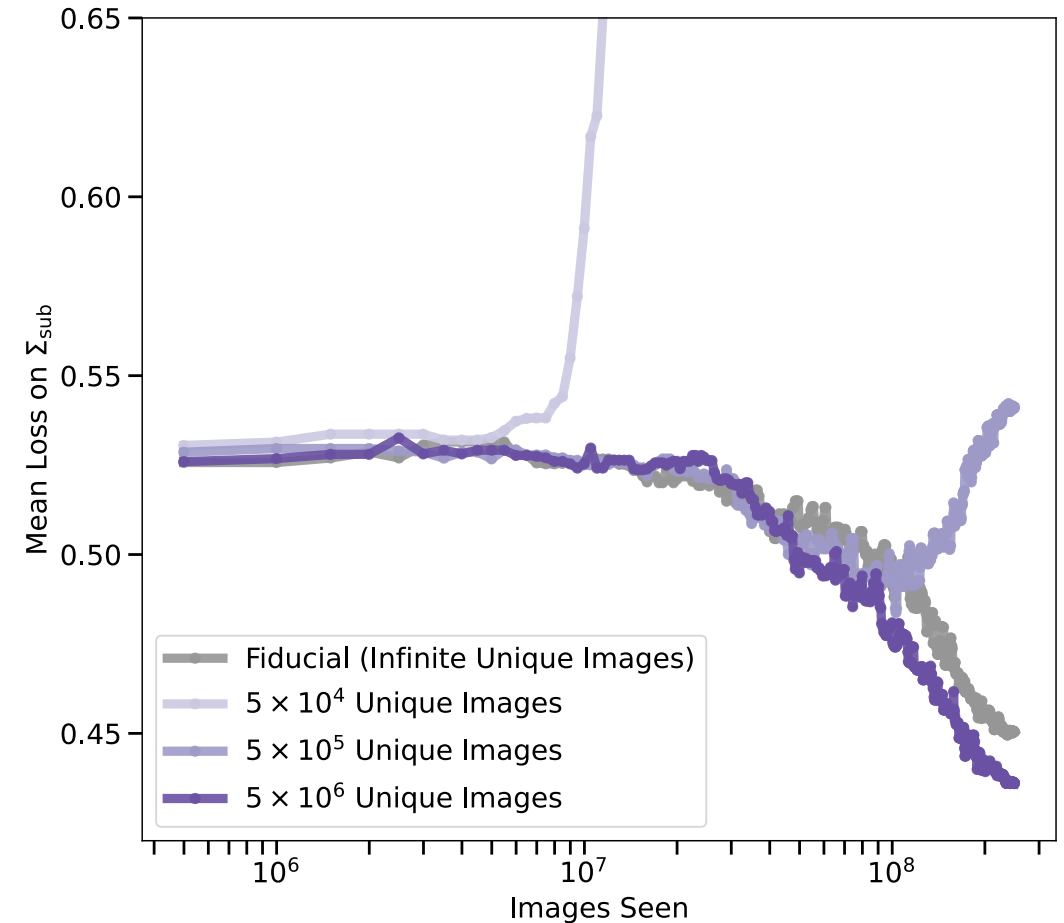
Limits: Training Set Size



Our Current Limitation?

*Have neural-density based SBI methods already reached the **information limit of the data**, or are there **methodology choices** that are imposing artificial bottlenecks? - No*

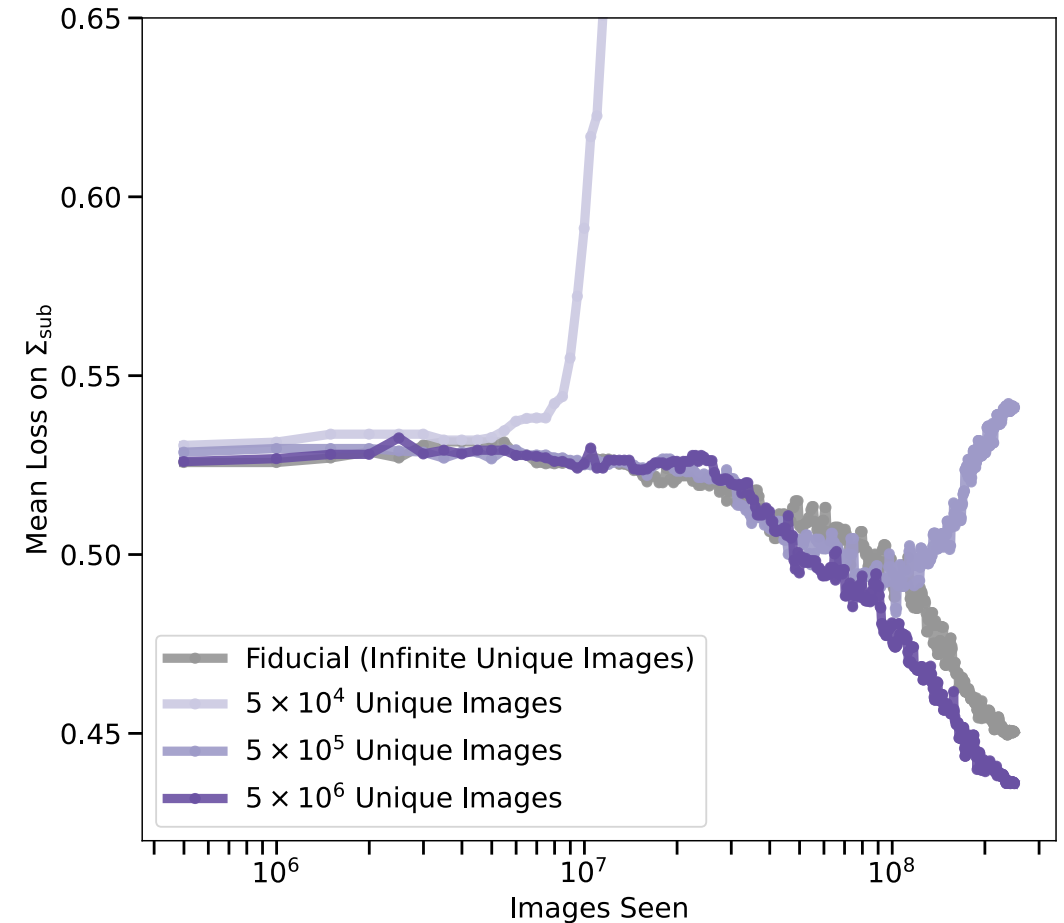
- Pushing farther limited by **power-law scaling** in images seen



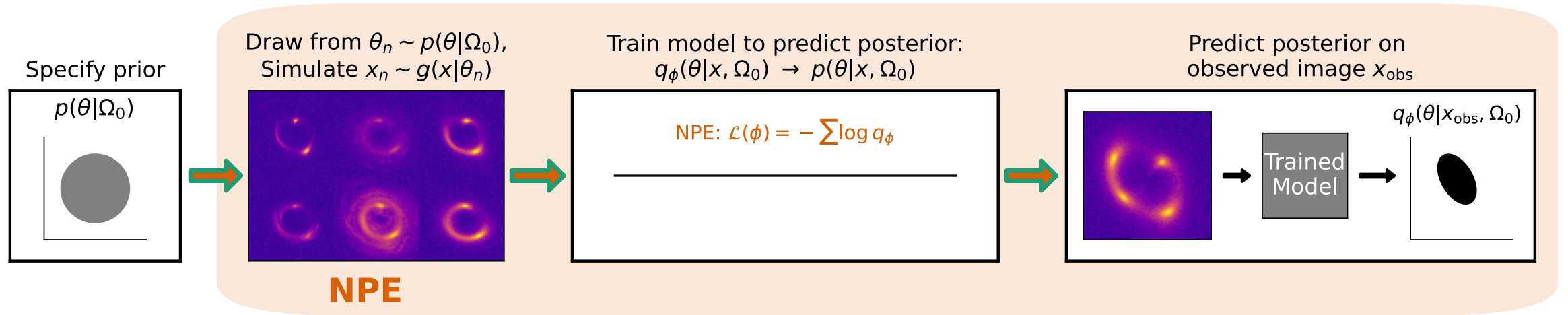
Our Current Limitation?

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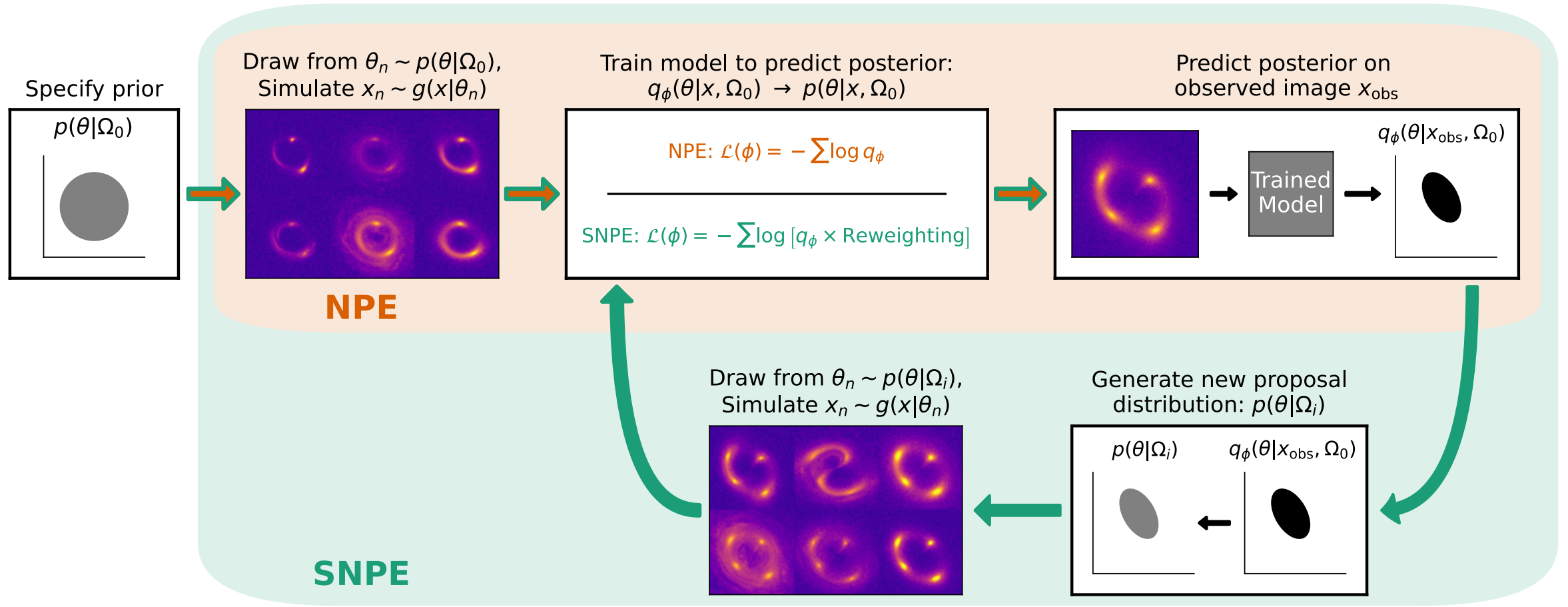
- Pushing farther limited by **power-law scaling** in images seen
- If only we had a **more efficient** training set...
 - ... but **I made the training set**



Sequential Neural Posterior Estimator



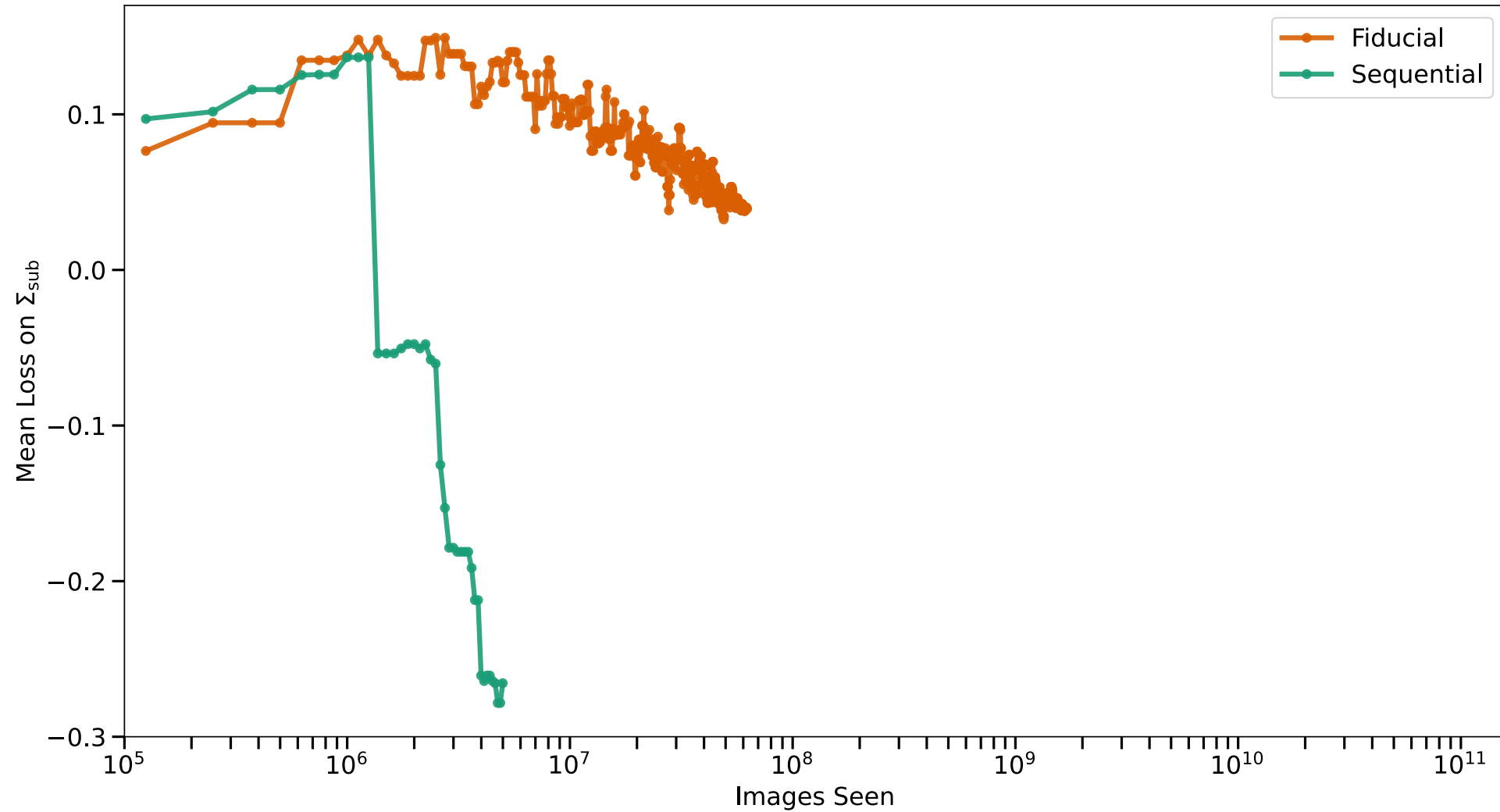
Sequential Neural Posterior Estimator



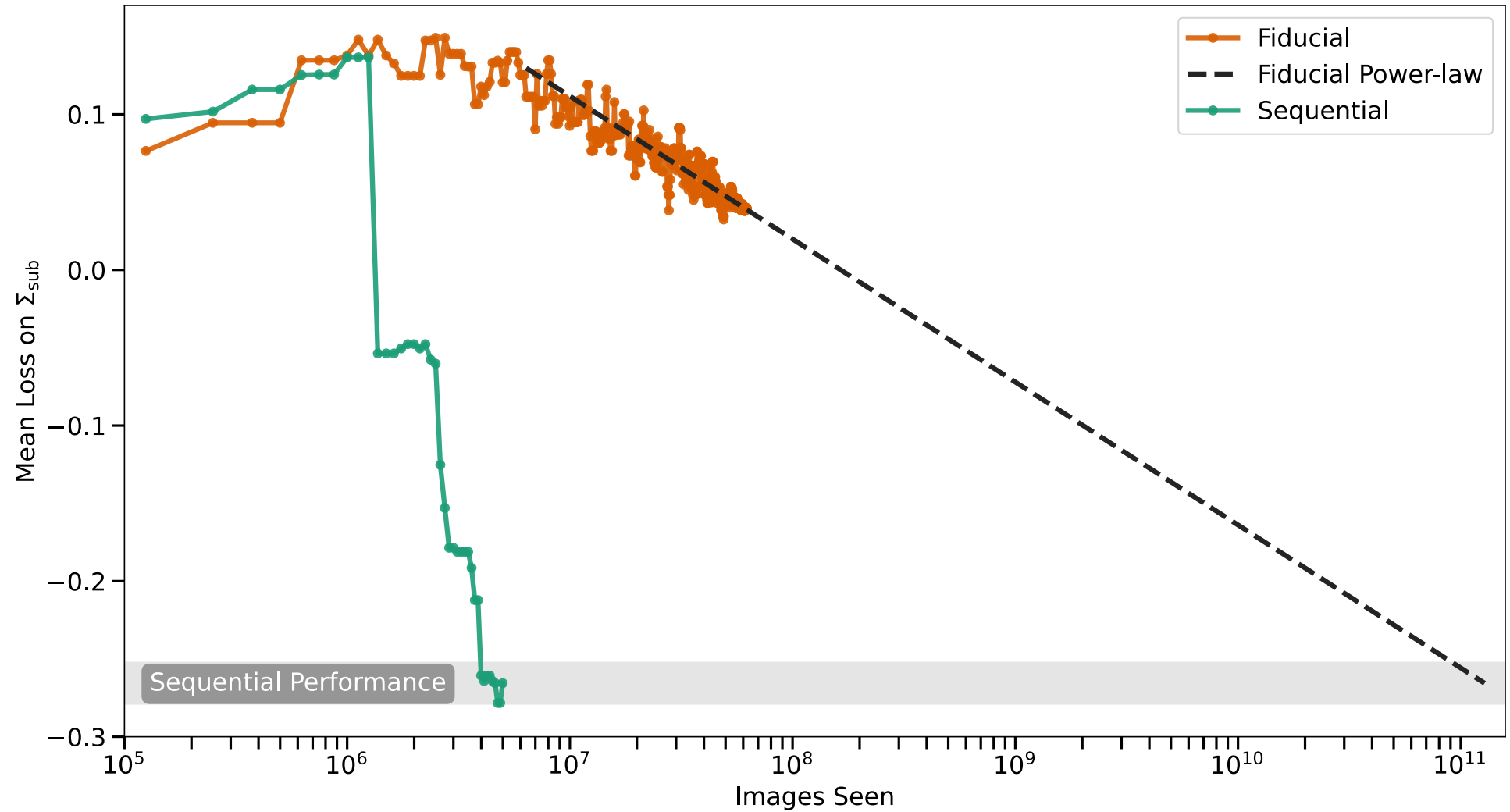
SNPE Comparison

- Generate a set of **30 ‘true’ observations** with the mean and scatter in the SHMF normalization **from N-body simulations**.
- Run sequential inference to answer:
 - *Are we still limited by the same power-law scaling, or do we accelerate learning?*
 - *Are we more data-efficient at the population level?*

Loss on Σ_{sub} Comparison



Loss on Σ_{sub} Comparison

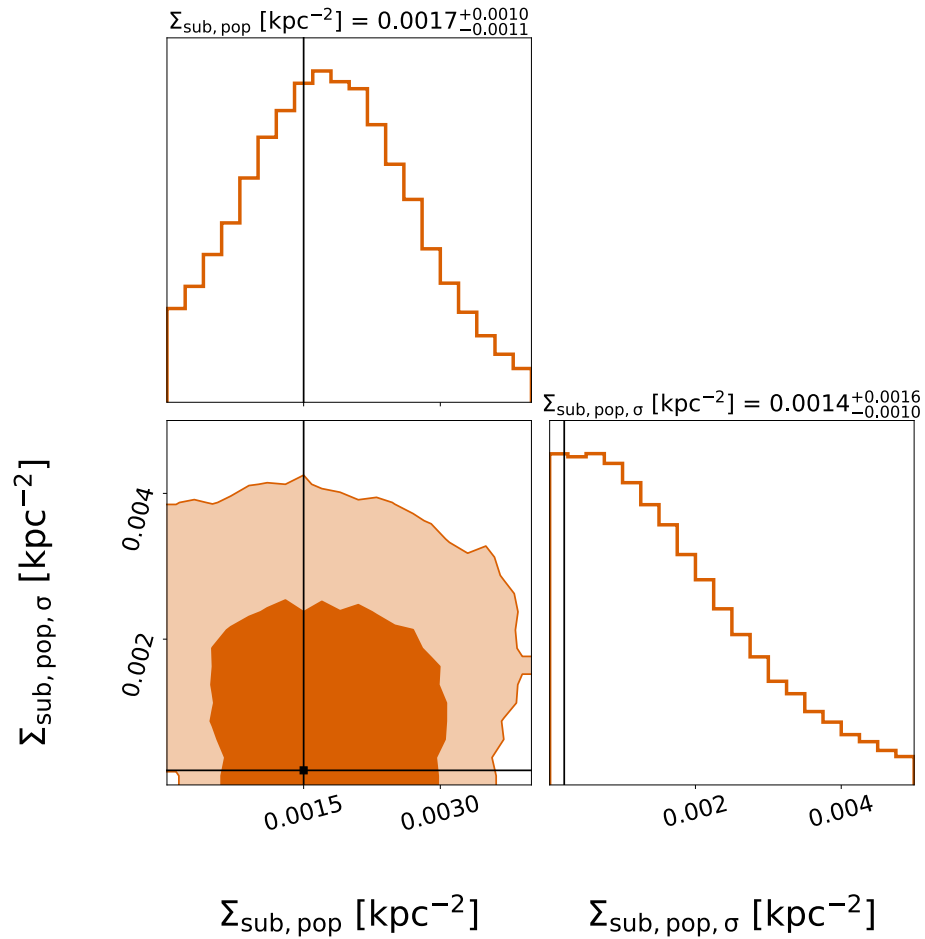


SNPE Comparison

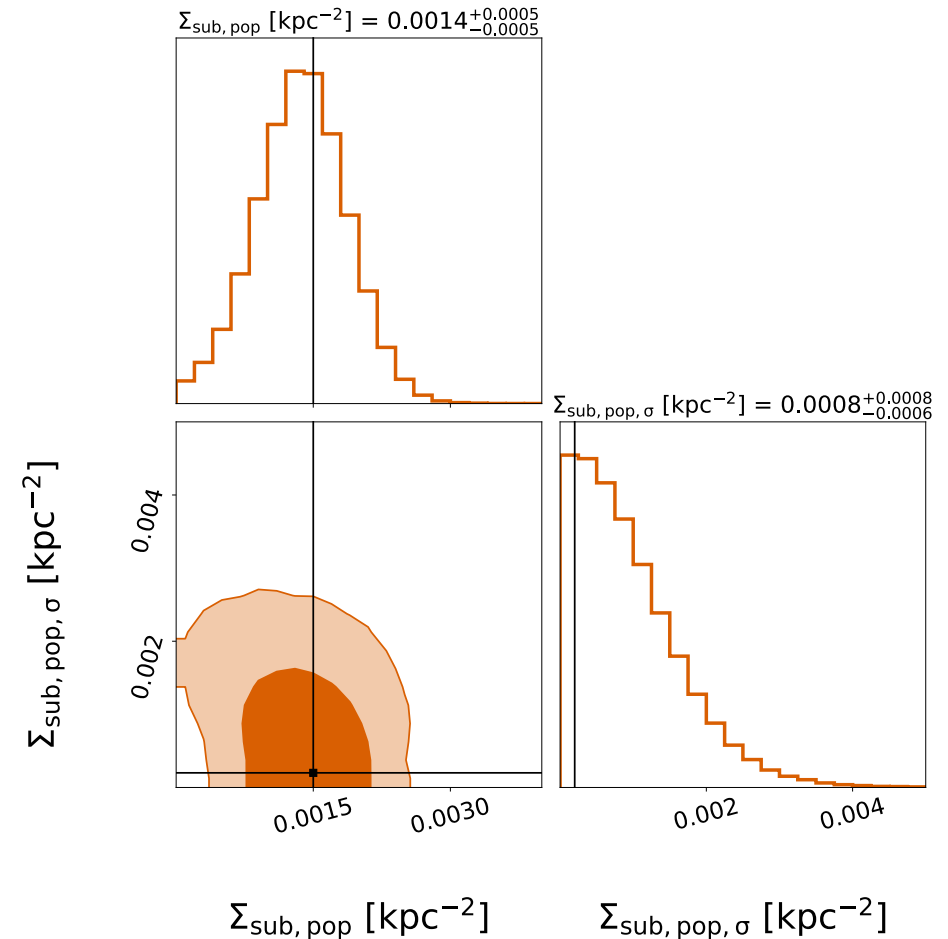
- *Are we still limited by the same power-law scaling, or do we accelerate learning?*
 - On our ‘difficult’ parameter-of-interest, sequential achieves performance gains equivalent to over **three orders-of-magnitude more images**
- *Are we more data-efficient at the population level?*

Hierarchical Inference - NPE

NPE: 10 Lenses

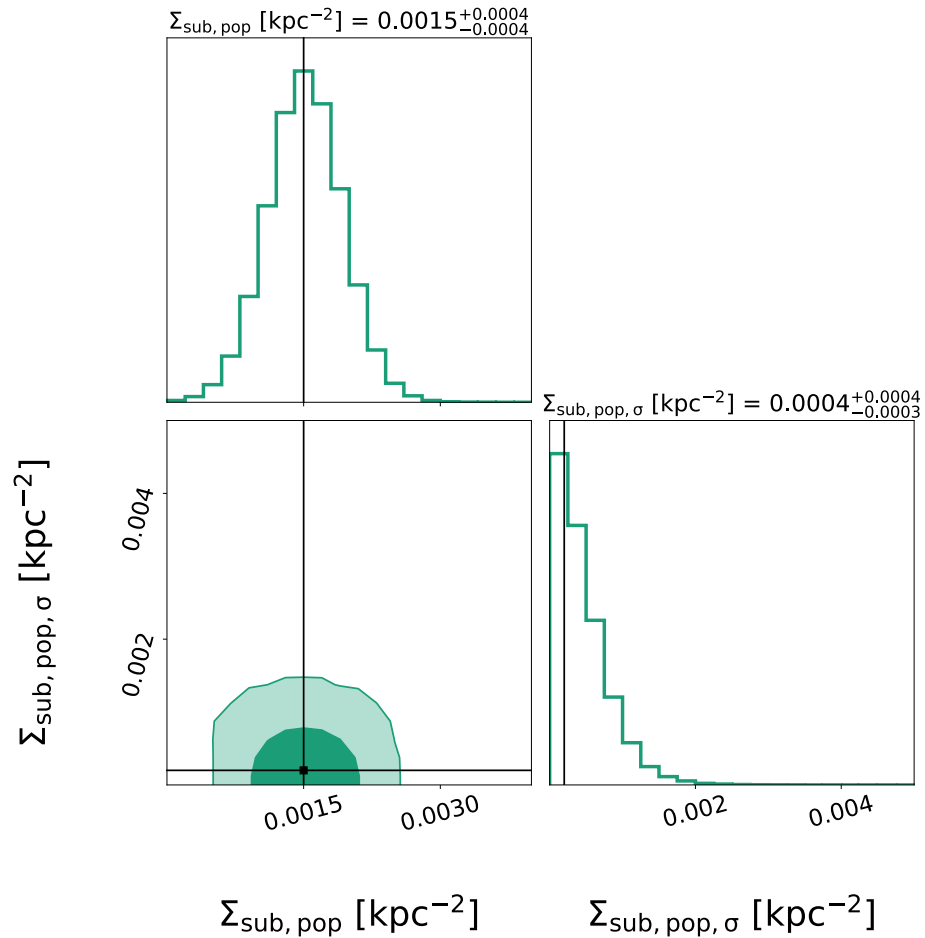


NPE: 30 Lenses

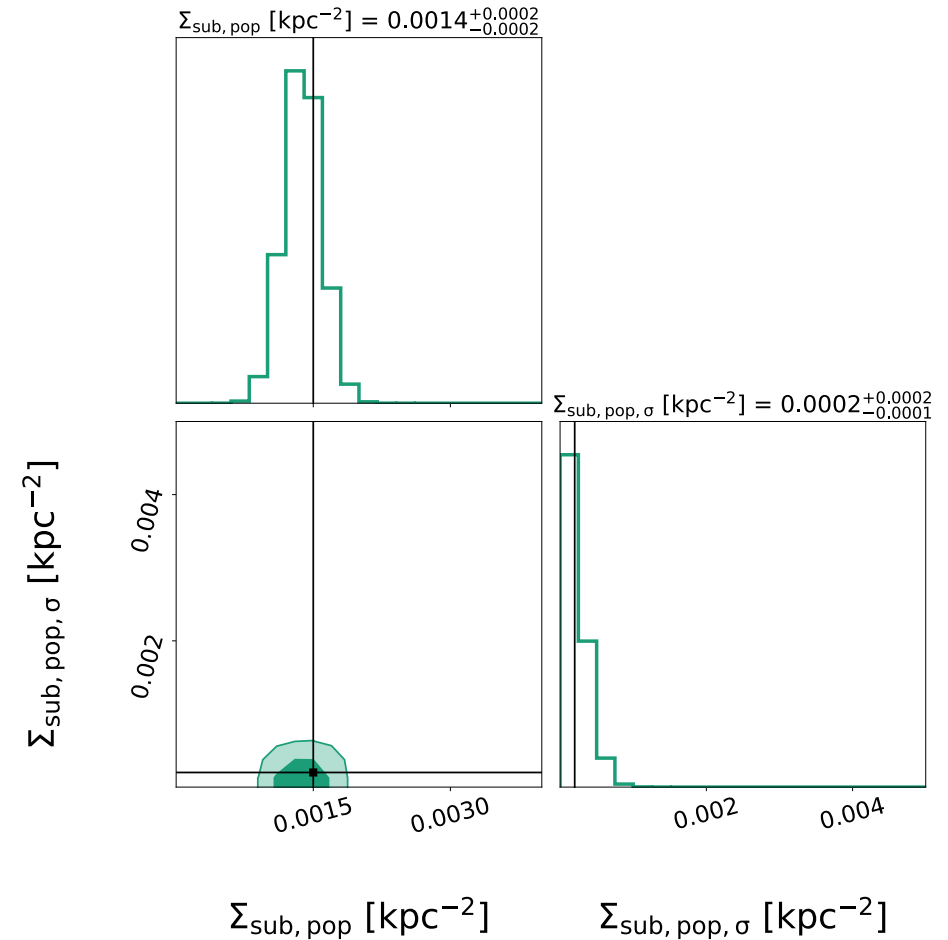


Hierarchical Inference - SNPE

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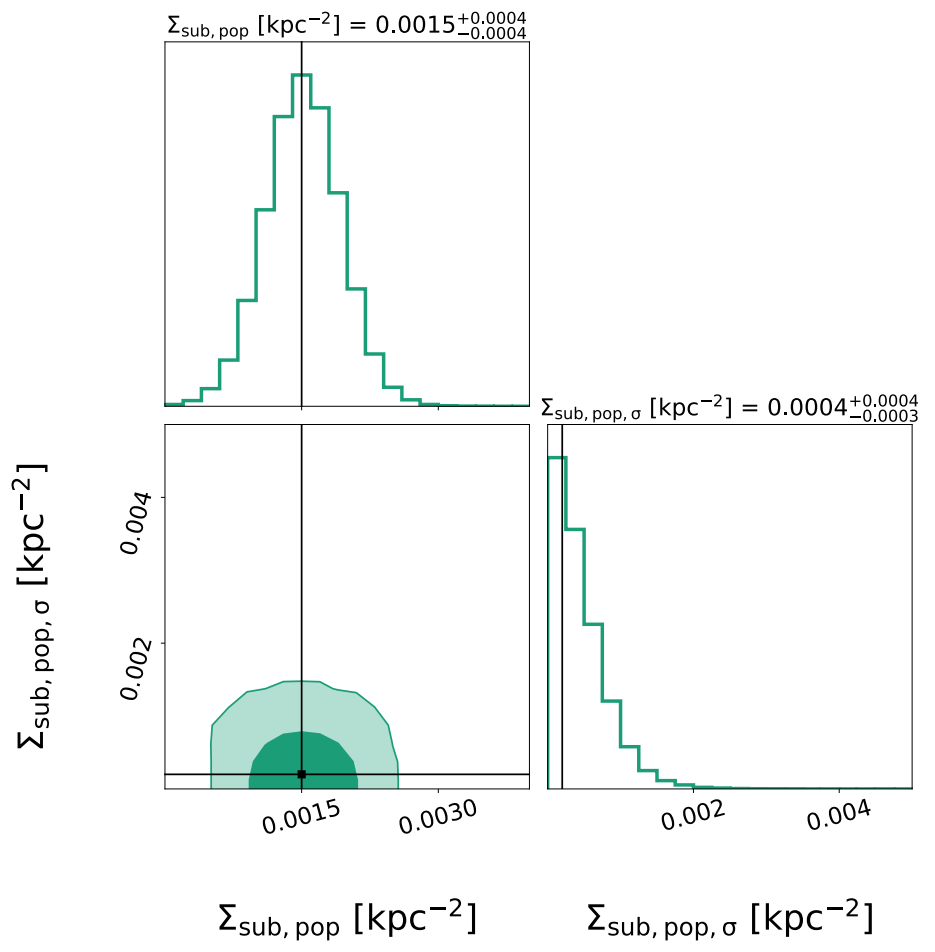


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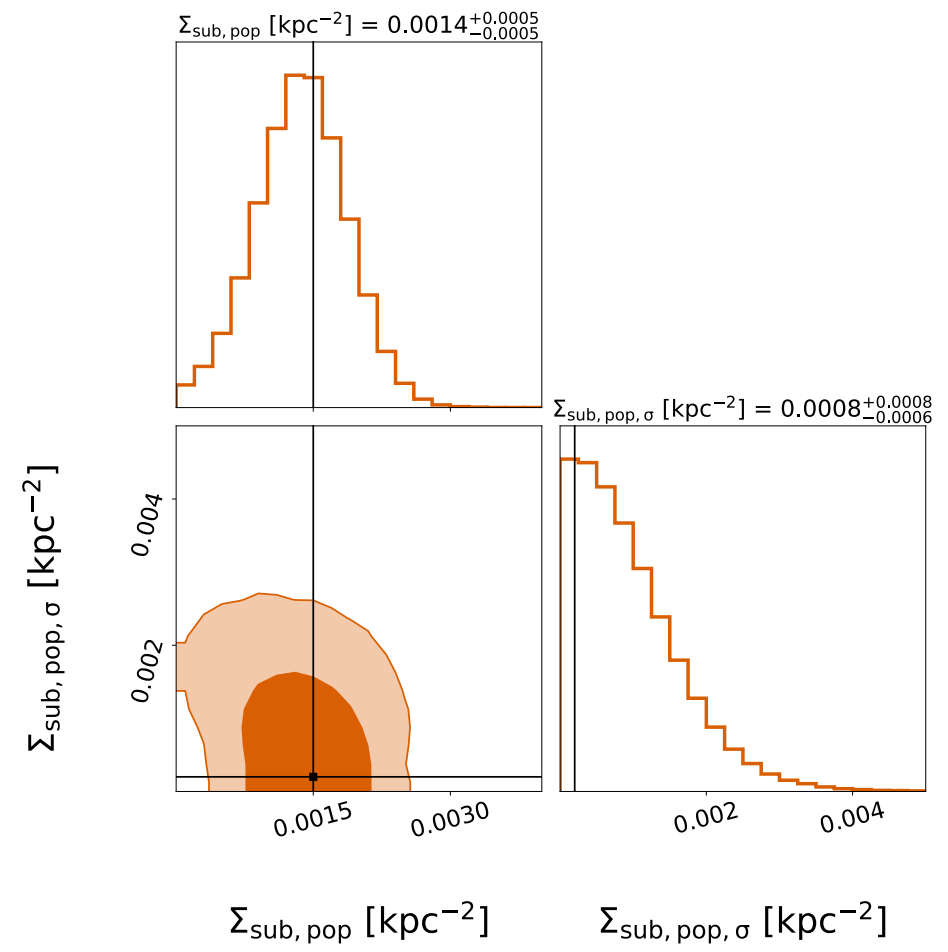


Hierarchical Inference - Comparison

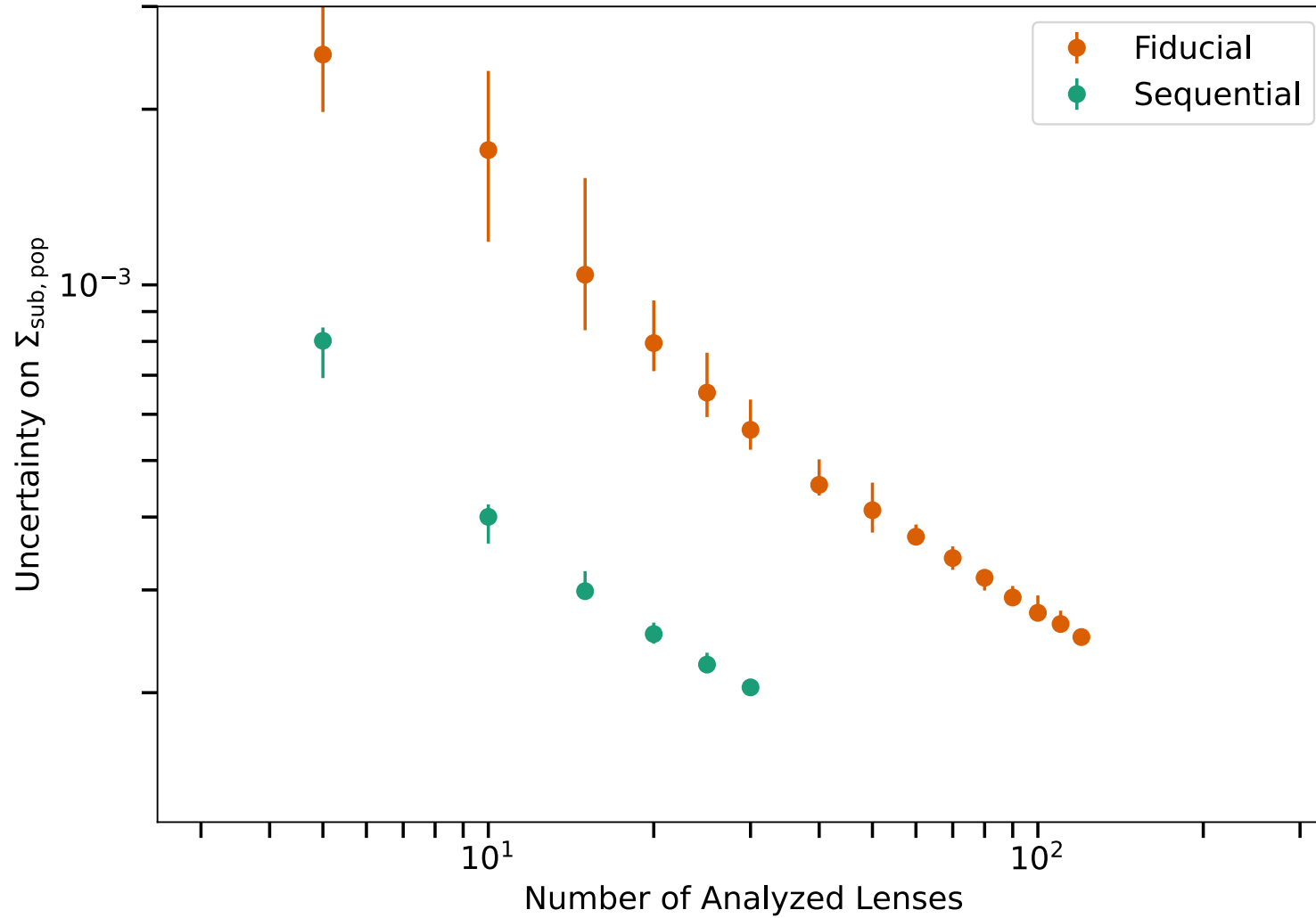
SNPE: 10 Lenses



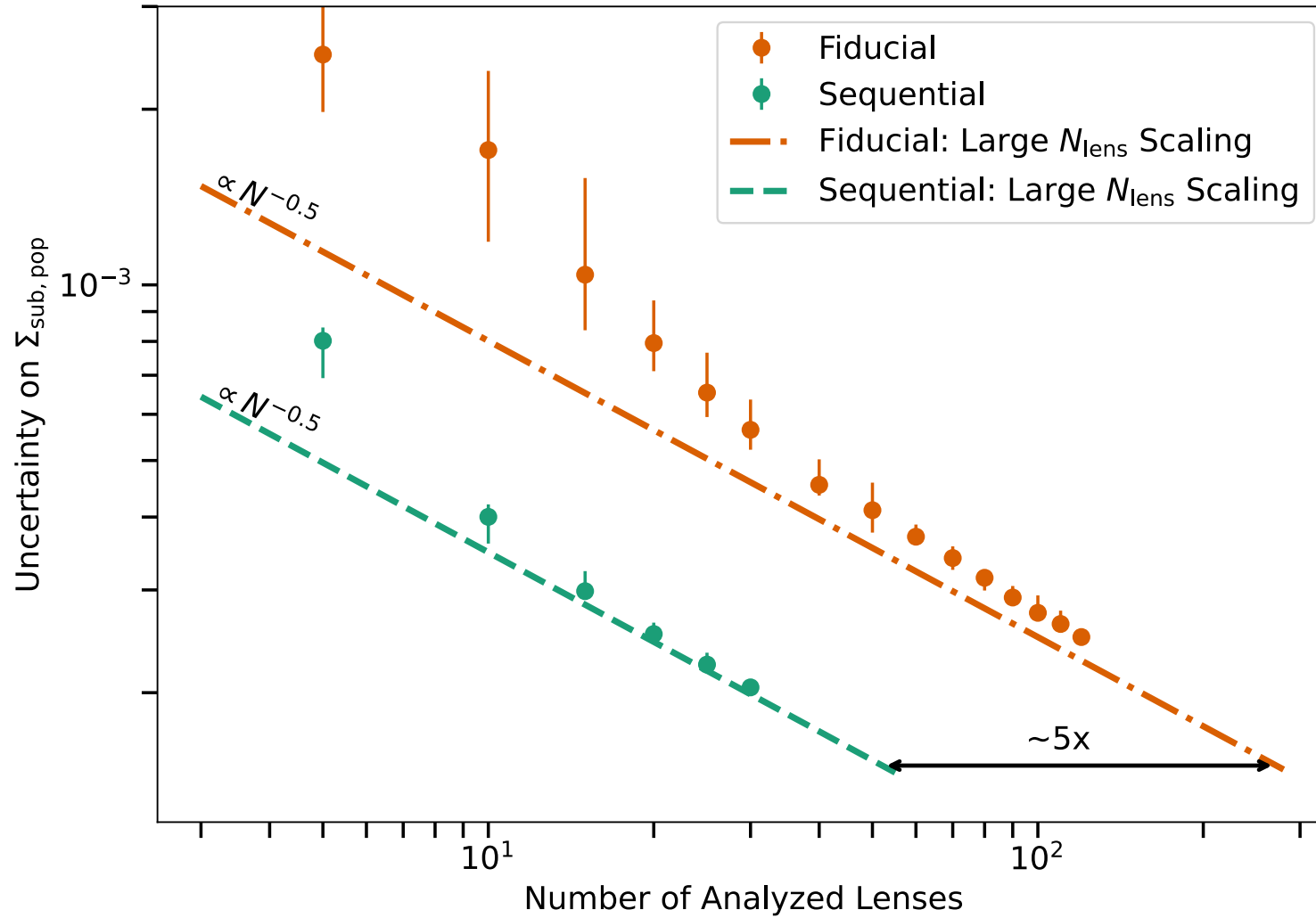
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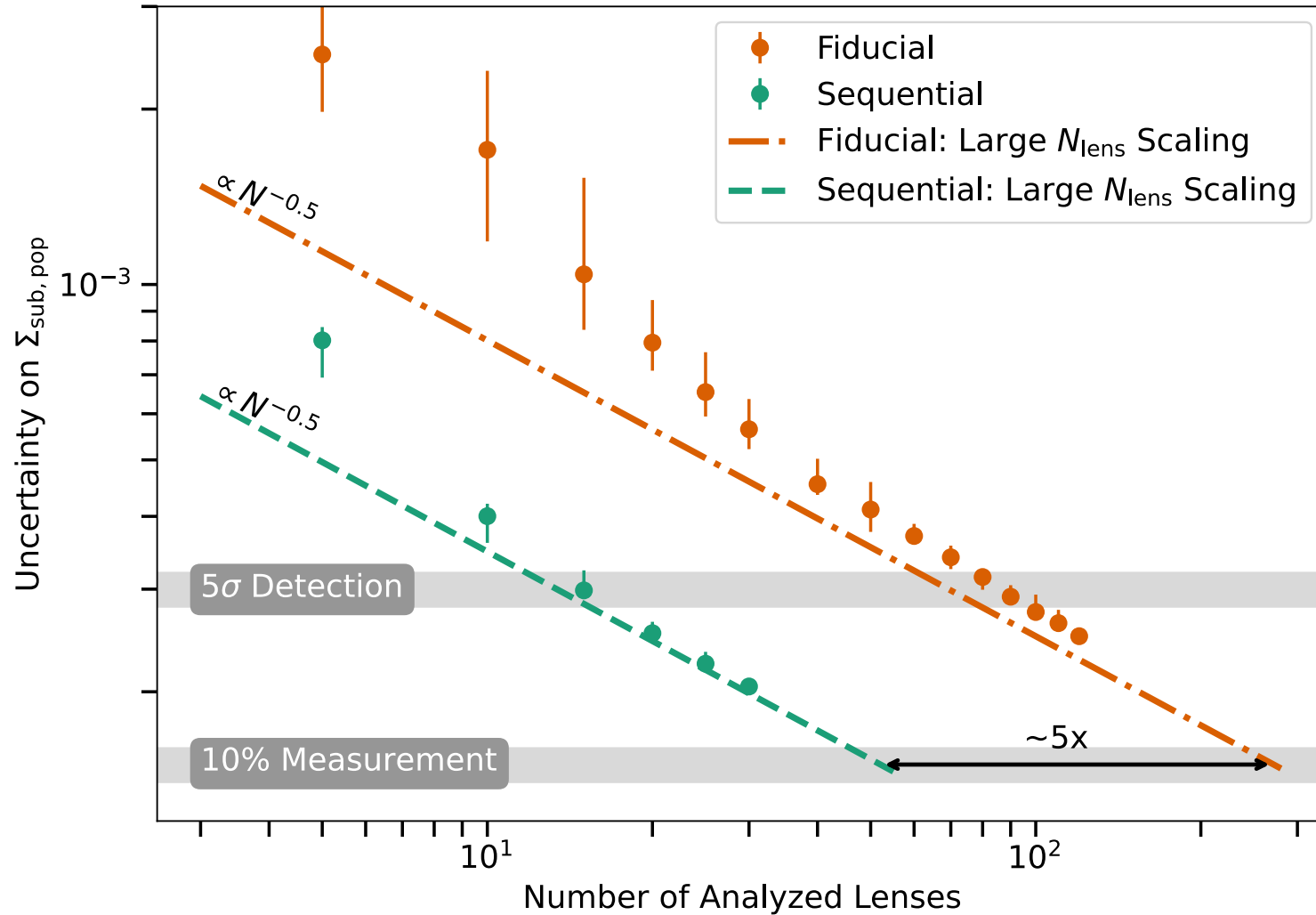
Hierarchical Inference - Comparison



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Hierarchical Inference - Comparison



SNPE Comparison

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 - On our ‘difficult’ parameter-of-interest, sequential achieves performance gains equivalent to over **three orders-of-magnitude more images**
- *Are we more data-efficient at the population level?*
 - Unbiased population constraints that are **~5x more efficient per lens**
 - ~50 lenses to produce a 10% measurement compared to ~300 lenses

Conclusions

Strong Lensing

- We are not **data limited**, we are limited by our training sets
 - Sequential methods drastically improve constraining power – similar improvements from the naïve approach would be **computationally untenable**
-

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-

Broader Implications

- The **quality** of our training sets is not just determined by **size**
- As we employ SBI, we need to treat training set generation and model optimization as **interconnected stages** of our analysis