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How to Map Dark Matter Distribution with Using Strong Gravitational Lensing

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Abstract. Dark mater substructures, modeled by the ΛCDM framework, are pivotal in the formation of cosmic structures, yet they are constrained by their weak observational characteristics.This study introduces a new pipeline that enables the maping of dark mater distributions at an unprecedented level, leveraging strong gravitational lensing.We create a forward simulation framework that includes realistic dark mater subhalos (modeled as truncated NFW profiles), line-of-sight halos, and Huble Space Telescope (HST) observational effects, thereby generating 50,0 synthetic lensing images. A neural posterior estimator (NPE) based on a modified xResNet-34 architecture is trained to infer the subhalo mass function (SHMF) normalization parameter (Σ_{sub}) directly from images, bypassing traditional baryon-dependent methods. Our approach achieves 82% detection efficiency for low-mass subhalos (10<sup>6</ sup>M<sub>⊙</ sub>), a 100× speedup over Markov Chain Monte Carlo (MCMC) techniques, and recovers ground-truth parameters within 10% error in hierarchical validation on 20 simulated systems. The results show strong alignment with ΛCDM predictions, alowing for systematic testing of alternative dark mater theories.This work makes machine learning-powered lensing a transformative tol to probe dark mater substructure, which has direct aplicability to next-generation surveys like LSST and Euclid.

Keywords: dark matter, strong gravitational lensing, neural networks, simulation-based inference, ΛCDM, substructure

1. Research background and scientific significance

Dark mater comprises roughly 85% of the universe's mater, yet its absence presents substantial hurdles for direct detection.The standard cosmological model (ΛCDM) sugests that dark mater forms a hierarchical structure, from galaxy-scale host halos to low-mas subhalos, which shape large-scale cosmic structures via gravitational interactions.Given this framework, strong gravitational lensing provides a unique method to probe dark mater—when light from background galaxies interacts with dark mater halos, gravitational deflection results in distorted images, and the presence of low-mas subhalos introduces subtle distortions.So, knowing the relationship betwen these signals and dark mater distributions is key to validate the ΛCDM model and explore alternative dark mater theories.

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A significant aspect is that the Huble Space Telescope (HST) and other instruments have colected data on numerous strong lensing systems, yet the observed images are chalenging due to the complex mas distributions in main deflector galaxies, line-of-sight contaminants, and instrumental noise.So, building a forward model of "dark mater distribution-lens image" [1].

The unique gravitational imprint captured by strong lensing provides an observationally unbiased avenue to test ΛCDM predictions, where traditional baryon-dependent methods face inherent limitations.

2. Research status and technical challenges

2.1. Limitations of existing detection methods

Traditional dark matter detection methods (such as counting Milky Way satellite galaxies and Lyman-α Forest measurements) rely on baryonic matter as tracers, requiring precise modeling of baryonic physical processes, which introduces significant uncertainties. For example, the mass-luminosity relation of Milky Way satellite galaxies has strong model dependence at the low-mass end. While strong gravitational lensing directly detects gravitational signals, it faces two major challenges: first, the gravitational deflection amplitude of a single subhalo is extremely small (equivalent to the scale of a grain of sand on the lunar surface observed from Earth), and thus it is necessary to constrain by statistically analyzing the signal characteristics of a large number of lensing systems; second, line-of-sight halo populations, non-uniform mass distributions of main deflectors, and Hubble Telescope imaging effects (such as point spread function blurring) will confuse dark matter signals. These challenges motivate the development of a lensing-specific approach that bypasses baryonic tracers and directly targets the gravitational signatures of dark matter substructures.

2.2. Development of simulation and inference technologies

For example, methods like using the Bayesian Information Criterion for screning can only handle the most masive subhalos, but they fail to acount for the masive population of subhalos.In recent years, simulation-based inference methods like Aproximate Bayesian Computation (ABC) have steadily emerged, yet they face chalenges information los, primarily through the reduction of dimensionality via sumary statistics, and also sufer from lower computational eficiency.But the development of neural network density estimators has enabled the direct extraction of dark matter parameters from images [2]. Recent neural network advances [2] present a paradigm shift—transforming lensing images into probabilistic constraints for dark matter parameters, while preserving physical interpretability

3. Research objectives and methodological framework

3.1. Core scientific objectives

This study seks to create a comprehensive inference pipeline that conects strong gravitational lensing images with dark mater distributions.

Constructing simulation datasets that include realistic dark mater subhalos, line-of-sight halos, and HST observational efects.

1.Constructing simulation datasets that incorporate realistic dark matter subhalos, line-of-sight halos, and HST observational effects;

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2.Developing a neural posterior estimator to enable efficient inference of subhalo mass function (SHMF) parameters from lensing images;

3.Mapping the statistical distribution of dark matter substructures by integrating data from multiple lensing systems via a hierarchical inference framework.

By bridging high-fidelity simulations with observational data, this pipeline ensures that ΛCDM predictions are tested against empirical lensing signals at an unprecedented resolution.

3.2. Technical route and document support

The simulation framework uses the paltas package to generate strong lensing images, incorporating the main deflector (PEMD model), subhalos (truncated NFW profile), line-of-sight halos (Sheth–Tormen model), and HST observational effects (PSF, noise, Drizzle processing) [3]. Correspondingly, the inference methodology involves training an xResNet-34 neural network on 500,000 simulated images to invert the subhalo mass function (SHMF) normalization parameter $\sum_{sub}$, with validation via hierarchical inference on 20 test sets.

4. Methods

4.1. Strong gravitational lensing simulation framework

To construct a realistic mapping from dark matter distributions to lensing images, we employ a forward simulation pipeline based on the paltas package, integrating astrophysical models and observational effects [3, 4].

1) Main Deflector Galaxy Model

The primary lensing galaxy is described by a Power Elliptical Mass Distribution (PEMD) (Barkana 1998), with parameters (Einstein radius θ_E , ellipticity e, rexternal shear γ) sampled from observed distributions of early-type galaxies (Auger et al. 2010). The mass profile combines baryonic and dark matter components, constrained by dynamical measurements (Cappellari et al. 2013) to mimic real-world galaxy properties.

2) Dark Matter Subhalo Population

Subhalos are modeled using truncated Navarro-Frenk-White (NFW) profiles (Navarro et al. 1997), with masses ranging from $10^6 M_\odot$ to $10^{10} M_\odot$ .The subhalo mass function (SHMF) follows a power-law form $\frac{dN}{dM} = \sum_{sub} \left(\frac{M}{10^8 M_\odot} \right)^{-1.9}$, where $\sum_{sub}$ is the normalization parameter to be constrained (Vegetti et al. 2014). Subhalo positions are distributed Poissonially within the host halo's virial radius to reflect hierarchical structure formation.

3) Line-of-Sight (LOS) Halo ContributionsForeground and background halos are incorporated using the Sheth-Tormen formalism, with mass-concentration relations from N-body simulations [3]. Their gravitational impact is weighted by the lensing kernel [5], accounting for cumulative deflection along the LOS

4) Observational Effects SimulationSynthetic images are generated to replicate Hubble Space Telescope (HST) observations, including:

-PSF Convolution: HST ACS/WFC3 point-spread functions (Krist 2003) to model optical blurring.

-Noise Sources: Poisson noise from the sky and source, read noise (3 e^- /pixel RMS), and drizzle artifacts (Fruchter & Hook 2002).

-Resolution: 0.05 arcsec/pixel sampling to match HST imaging specifications.

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A total of 500,000 synthetic lensing images is generated; each paired with its corresponding $\sum_{sub}$ value to form a supervised training dataset for neural inference.

4.2. Neural posterior estimation for dark matter parameters

To overcome the computational inefficiency of traditional MCMC methods (e.g., Oguri 2010), we develop a neural posterior estimator (NPE) using simulation-based inference (SBI; Cranmer et al. 2020):

1) Network Architecture:The model employs a modified xResNet-34 (He et al. 2016) with:

Residual Blocks: 34 layers to capture hierarchical features in 256×256 pixel images.

Attention Gates (Wang et al. 2018): To prioritize substructure-related distortions in the lensing arcs.

Normalizing Flow Output (MAF; Papamakarios et al. 2017): Generates posterior distributions for $\sum_{sub}$ and SHMF slope α ,rather than point estimates.

2) Training Protocol

Dataset Split: 80% (400,000 images) for training, 10% (50,000) for validation, and 10% (50,000) for testing

Loss Function: Negative log-likelihood of true parameters under the predicted posterior.

Regularization: Dropout (p=0.2)and early stopping to prevent overfitting.

3) Performance Metrics

The network's accuracy is evaluated using:

KL Divergence: Between predicted and true posterior distributions.

Coverage Probability: Of 90% credible intervals to assess uncertainty quantification.

4.3. Hierarchical inference for ensemble analysis

To aggregate constraints from multiple lensing systems, we implement a hierarchical Bayesian framework [5]:

1) Individual System InferenceFor each observed lensing system, the trained NPE provides a posterior distribution P $\left(\sum_{sub} \left| D_i \right.\right)$, where D_i is the image data

2) Population-Level Aggregation

Posteriors from N systems are combined under a hyperprior, accounting for cosmic variance and observational biases:

P($\sum_{sub}$ |{ D_i })∝P($\sum_{sub}$) $\prod_i^N$ =1N∫P(D_i | $\sum_{sub}$, ψ_i) P(ψ_i)d ψ_i , where ψ_i are lens-specific nuisance parameters (Marshall et al. 2006).

3) Validation

The framework is tested on 20 simulated lensing systems with known $\sum_{sub}$ values, verifying parameter recovery within 10% accuracy and consistency with ground-truth distributions.

4.4. Comparison with traditional methods

We benchmark our approach against conventional techniques:

(1) BIC-Based Subhalo Screening

Traditional methods using the Bayesian Information Criterion (BIC) suffer from low sensitivity to subhalos below $10^8 M_\odot$ In contrast, our neural network recovers $10^6 M_\odot$ subhalos with 82%

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efficiency (ROC curve AUC = 0.91 vs. 0.65 for BIC).

(2) Computational Efficiency

While MCMC methods require >100 CPU hours per lens[4], our NPE achieves inference in <1 minute per image on a single GPU, enabling analysis of large survey datasets (e.g., LSST's expected 200,000 strong lenses).

The orders-of-magnitude improvement in sensitivity and speed demonstrate how data-driven methods can unlock previously inaccessible regimes of dark matter science.

5. Result

5.1. Construction of strong gravitational lensing simulation dataset

Using the paltas framework, we generated 500,000 synthetic lensing images integrating astrophysical models and Hubble Space Telescope (HST) observational effects. The main deflector follows a Power-Law Elliptical Mass Distribution (PEMD) with parameters—Einstein radius θ_E (mean: 1.1 arcsec, σ: 0.15 arcsec), ellipticity (e_1, e_2), and external shear γ—sampled from early-type galaxy observations. Dark matter subhalos adopt truncated NFW profiles with masses spanning $\frac{\mathrm{dN}}{\mathrm{dM}} = \sum_{\mathrm{sub}} \left(\frac{\mathrm{M}}{10^8 \mathrm{M}_\odot} \right)^{-1.9}$, where $\sum_{sub}$ (normalization) is the key parameter to constrain, following a normal distribution (mean: $2\times 10^{-3} kpc^{-2}, \sigma : 1.1\times 10^{-3} kpc^{-2}$;) [4].

Line-of-sight (LOS) halos are modeled via the Sheth-Tormen formalism with mass-concentration relations from N-body simulations (Diemer & Kravtsov 2015), and their gravitational effects are weighted by the lensing kernel. Observational effects include HST ACS/WFC3 point-spread function (PSF) convolution, 3 e^-/pixel read noise, Poisson noise, and drizzle processing, yielding 0.05 arcsec/pixel resolution images (Krist 2003). Each image is paired with its $\sum_{sub}$ label for supervised training.

5.2. Performance of neural posterior estimator (NPE)

- The modified xResNet-34 network demonstrates robust parameter inference:

Single-Lens Inference: On 50,000 validation images, the network predicts main deflector parameters (e.g., θ_E , ellipticity) with Pearson correlation coefficients ρ > 0.98 against true values. For $\sum_{sub}$, the 90% credible intervals exhibit >90% coverage probability, and the posterior standard deviation ($1.0\times 10^{-3} kpc^{-2}$)matches the training distribution, validating uncertainty quantification.

- Subhalo Detection Efficiency: The NPE achieves 82% efficiency in recovering $10^6 M_\odot$ subhalos (ROC AUC = 0.91), outperforming Bayesian Information Criterion (BIC)-based methods (AUC = 0.65). This stems from end-to-end feature extraction of subtle perturbations in lensing arcs, avoiding information loss from summary statistics.

-Computational Efficiency: Inference time per image is <1 minute on a single GPU, a >100× speedup over traditional MCMC methods (Vegetti et al. 2014), enabling analysis of large surveys (e.g., LSST's 200,000 strong lenses; (2).

5.3. Hierarchical bayesian inference for population-level constraints

Integrating 20 test sets (1,000 images each) via a hierarchical framework:

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1) Parameter Recovery Precision: For test sets with $\sum_{sub}$ means ranging from 2×10^{-4} to $4\times 10^{-3}kpc^{-2}$, 10 lens systems distinguish $\sum_{sub} > 0$, 50 systems reduce errors to 32%, and 100 systems achieve 22% precision. In 20 simulated systems with known $\sum_{sub}$,recovery errors are within 10%, consistent with ground-truth distributions (Marshall et al. 2006).

2) Consistency with ΛCDM Simulations: Comparing to dark matter-only (DMO) simulations, 50 lens systems detect deviations from DMO-predicted $\sum_{sub}$ ranges (2×10^{-3} to $4\times 10^{-3}kpc^{-2}$), and 100 systems enable 22% precise normalization measurements, providing critical tests of the ΛCDM model.

5.4. Comparison with traditional methods

Subhalo Sensitivity: BIC methods fail to detect subhalos below $10^8 M_\odot$,while the NPE extends the detection limit to $10^6 M_\odot$, capturing the low-mass subhalo population missed by traditional approaches.

Scalability: Unlike MCMC's exponential computational cost, the NPE's linear scaling with dataset size allows efficient joint analysis of hundreds of lenses, foundational for next-generation wide-field surveys.

5.5. Scientific implications and limitations

This end-to-end pipeline establishes strong lensing as a robust probe of $10^6 M_\odot - 10^8 M_\odot$ dark matter substructures, consistent with ΛCDM predictions. Deviations in $\sum_{sub}$ from DMO simulations would signal alternative dark matter physics (e.g., warm dark matter). Limitations include systematic biases in large datasets ($\sum_{sub} > 3.6\times 10^{-3}kpc^{-2}$ underestimated, $<2\times 10^{-3}kpc^{-2}$ overestimated) due to training prior mismatches, and ~1σ uncertainties from LOS halo-subhalo signal degeneracies. Future work will refine these via iterative retraining and high-redshift source simulations. These limitations do not diminish the method's transformative potential but rather outline pathways for future refinements in dark matter mapping.

6. Conclusion

This study has developed a robust and effective pipeline for extracting dark mater substructure properties from strong gravitational lensing images by employing advanced machine learning algorithms. By integrating high-fidelity simulations with neural network-based inference, we have demonstrated the feasibility of mapping dark matter distributions at unprecedented resolution and scale, addressing key challenges in modern cosmology. Our methodology leverages a forward simulation framework that incorporates realistic models of host galaxies, dark matter subhalos, line-of-sight halos, and observational effects. The neural posterior estimator (NPE), built upon a modified xResNet-34 architecture, enables rapid and accurate inference of subhalo mass function (SHMF) parameters directly from lensing images. This approach significantly outperforms traditional methods, such as Bayesian Information Criterion (BIC)-based screening and Markov Chain Monte Carlo (MCMC) techniques, in both sensitivity and computational efficiency. Specifically, the NPE achieves an 82% detection efficiency for subhalos as light as $10^6 M_\odot$, a regime previously inaccessible, while reducing inference time from hundreds of CPU hours to under a minute per image.

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Hierarchical Bayesian inference further allows us to aggregate constraints from multiple lensing systems, providing robust population-level measurements of dark matter substructure abundance. Validation on simulated datasets confirms the method's accuracy, with parameter recovery errors within 10% and consistent coverage probabilities. These results align with predictions from the ΛCDM model, while also offering a powerful tool to test alternative dark matter scenarios, such as warm dark matter or self-interacting dark matter, through deviations in the inferred SHMF.

Despite these advancements, our pipeline is not without limitations. Systematic biases may arise from mismatches between training priors and observational data, particularly at the extremes of the parameter space. Additionally, degeneracies between subhalo and line-of-sight halo signals introduce uncertainties that warrant further refinement. Future work will focus on iterative retraining with expanded simulation datasets and the incorporation of high-redshift source models to mitigate these effects.

In summary, this research bridges the gap between theoretical predictions and observational data, transforming strong gravitational lensing into a precise probe of dark matter substructure. The closed-loop framework of "simulation construction – parameter inference – population statistics" not only validates the ΛCDM paradigm but also opens new avenues for exploring the fundamental nature of dark matter. As upcoming surveys like LSST and Euclid deliver thousands of new lensing systems, our method promises to unlock the full potential of these datasets, paving the way for groundbreaking discoveries in dark matter physics and cosmology.

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