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JAXtronomy: A JAX port of lenstronomy

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Summary

Gravitational lensing is a phenomenon where light bends around massive objects, resulting in distorted images seen by an observer. Studying graviationally lensed objects can give us key insights into cosmology and astrophysics, such as constraints on the expansion rate of the universe and dark matter models.

Thus, we introduce `JAXtronomy`, a re-implementation of the gravitational lensing software package `lenstronomy`[1] (Birrer, 2021; Birrer & Amara, 2018) using`JAX`[2]. `JAX` is a Python library that uses an accelerated linear algebra (XLA) compiler to improve the performance of computing software. Our core design principle of `JAXtronomy` is to maintain an identical API to that of `lenstronomy`.

The main `JAX` features utilized in `JAXtronomy` are just-in-time-compilation, which can lead to significant reductions in execution time, and automatic differentiation, which allows for the implementation of gradient-based algorithms that were previously impossible. Additionally, `JAX` allows code to be run on GPUs or parallelized across CPU cores, further boosting the performance of `JAXtronomy`.

Statement of need

`lenstronomy` has been widely applied to numerous science cases, with more than 200 publications making use of the software, and has an increasing number of dependent packages relying on features of `lenstronomy`. For instance, science cases directly involving `lenstronomy` include galaxy evolution studies using strong lensing (Anowar J. Shajib et al., 2021; Sheu et al., 2025; Tan et al., 2024) and detailed lens modeling for measuring the Hubble constant using time-delay cosmography by the TDCOSMO collaboration (Birrer, S. et al., 2020; Birrer, Simon & Treu, Tommaso, 2021; Collaboration et al., 2025; Gilman, D. et al., 2020; Millon, M. et al., 2020; Schmidt et al., 2025; A. J. Shajib et al., 2022; **?**).

Examples of packages dependent on `lenstronomy` for general-purpose lensing computations and image modelling include the `dolphin` package (Anowar J. Shajib et al., 2025) for automated lens modeling, the `galight` package (Ding et al., 2020) for galaxy morphology measurements,

[1] https://github.com/lenstronomy/lenstronomy
[2] https://github.com/jax-ml/jax

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SLSim (Khadka et al, 2025, in prep) for simulating large populations of strong lenses, pyHalo (Gilman et al., 2019) and mejiro (Wedig et al., 2025) for simulating strong lenses with dark matter substructure, and PALTAS (Wagner-Carena et al., 2023) for neural network inference tasks.

In many of these applications, computational constraints are the key limiting factor for strong gravitational lensing science. For example, increased data quality and number of lenses to analyze makes lens modeling a computational bottleneck, and expensive ray-tracing through tens of thousands of dark matter substructures limit the amount of images that can be simulated, especially for the training of neural networks and simulation-based inferences. These ever-increasing computational costs have lead to the development of several JAX-accelerated and GPU-accelerated strong-lensing packages, such as gigalens (Gu et al., 2022), herculens (Galan et al., 2022), paltax (Wagner-Carena et al., 2024), GLaD (Wang et al., 2025), caustics[3] (Stone et al., 2024) and Google Research's jaxstronomy[4].

Why JAXtronomy?

JAXtronomy inherits a wide range of features from lenstronomy that are not offered by any of the aforementioned JAX-accelerated or GPU-accelerated software. Such features include lenstronomy's linear amplitude solver, which reduces the number of sampled parameters during lens modeling, as well as a variety of log likelihood functions and optional punishment terms to improve robustness during fitting. Furthermore, JAXtronomy aims to maintain an identical API to lenstronomy so that packages dependent on lenstronomy can transition seamlessly to JAXtronomy.

Improvements over lenstronomy in image simulation

The simulation of a lensed image comes in three main steps. The first step begins with a coordinate grid in the angles seen by the observer. These coordinates are ray-traced through the deflectors back to the source plane. This process requires the calculation of light ray deflection angles at each deflector. Second, the surface brightness of the source is calculated on the ray-traced coordinate grid. This produces a lensed image. Third, the lensed image gets convolved by the point spread function (PSF) originating from diffraction of the telescope optics and atmospheric turbulence. Due to the various choices in deflector mass profiles, light model profiles, grid size, and PSF kernel size, the overall runtime of the pipeline can vary significantly.

In the following sections, we outline the improvements in performance that JAXtronomy has over lenstronomy for each step in the pipeline. These performance benchmarks were run using an Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz, an NVIDIA A100 GPU, and JAX version 0.7.0.

Deflection angle calculations

Each entry in the table indicates how much faster JAXtronomy is compared to lenstronomy at computing deflection angles for the corresponding deflector profile and grid size. Some comparisons vary significantly with values of function arguments, so a range is given rather than a number.

Deflector Profile	60x60 grid (cpu)	180x180 grid (cpu)	180x180 grid (gpu)
CONVERGENCE	0.4x	1.1x	0.5x
CSE	1.6x	2.6x	2.6x

[3]https://github.com/Ciela-Institute/caustics

[4]https://github.com/google-research/google-research/tree/master/jaxstronomy

Deflector Profile	60x60 grid (cpu)	180x180 grid (cpu)	180x180 grid (gpu)
EPL	5.1x - 15x	9.2x - 17x	37x - 120x
EPL (jax) vs EPL_NUMBA	1.4x	3.0x	13x
EPL_MULTIPOLE_M1M3M4	2.1x - 7x	6.4x - 13x	42x - 108x
HERNQUIST	2.0x	3.4x	5.8x
HERNQUIST_ELLIPSE_CSE	3.8x	5.4x	40x
MULTIPOLE	0.9x	1.0x	8.3x - 14x
MULTIPOLE_ELL	1.5x - 2.1x	2.0x - 2.8x	70x
NIE/SIE	0.5x	0.5x	2.0x
NFW	1.6x	3.3x	4.5x
NFW_ELLIPSE_CSE	4.1x	6.7x	31x
PJAFFE	1.0x	1.2x	2.8x
PJAFFE_ELLIPSE_POTENTIAL	1.4x	1.6x	3.1x
SHEAR	0.7x	2.0x	0.9x
SIS	1.4x	3.3x	2.0x
TNFW	2.4x	5.8x	7.5x

For small enough grid sizes, `JAXtronomy` computes deflection angles slower than `lenstronomy` when using certain deflector profiles. This is because function call overheads are significantly higher in JAX than in standard Python, so computations that are already fast in Python can end up slower in JAX. In these cases, the benefit of using JAX is to have automatic differentiation for lens modeling.

Flux calculations

An analogous table for the different light profiles is shown below. The MULTI_GAUSSIAN and MULTI_GAUSSIAN_ELLIPSE profiles include five GAUSSIAN and GAUSSIAN_ELLIPSE components, respectively, highlighting JAX's improved performance in sequential computations.

Light Profile	60x60 grid (cpu)	180x180 grid (cpu)	180x180 grid (gpu)
CORE_SERSIC	2.0x	6.7x	4.2x
GAUSSIAN	1.0x	2.5x	1.3x
GAUSSIAN_ELLIPSE	1.5x	3.6x	2.0x
MULTI_GAUSSIAN	3.7x	11x	7.8x
MULTI_GAUSSIAN_ELLIPSE	4.0x	13x	6.9x
SERSIC	1.0x	1.7x	3.9x
SERSIC_ELLIPSE	1.9x	5.7x	3.2x
SERSIC_ELLIPSE_Q_PHI	1.7x	5.5x	3.3x
SHAPELETS (n_max=6)	6.2x	3.4x	15x
SHAPELETS (n_max=10)	6.0x	4.5x	17x

FFT Convolution

We find that FFT convolution using `JAX` on CPU results in variable performance boosts or slowdowns compared to `lenstronomy` (which uses `scipy`'s FFT convolution). On a 60x60 grid, and kernel sizes ranging from 3 to 45, `JAX` on CPU ranges from being 1.1x to 2.9x faster than `lenstronomy`, with no obvious correlation to kernel size. On a 180x180 grid, and kernel sizes ranging from 9 to 135, `JAXtronomy` on CPU ranges from being 0.7x to 2.5x as fast as `lenstronomy`, with no obvious correlation to kernel size.

However, FFT convolution using `JAX` on GPU is significantly faster than `scipy`. On a 60x60 grid, and kernel sizes ranging from 3 to 45, JAX on GPU ranges from being 1.5x to 3.5x faster than `lenstronomy`, with `JAX` performing better at higher kernel sizes. On a 180x180 grid, and kernel sizes ranging from 9 to 135, `JAXtronomy` on GPU is about 10x to 20x as fast as `lenstronomy`, again with `JAX` performing better at higher kernel sizes.

Improvements over lenstronomy in lens modelling

The process of lens modelling involves finding best-fit parameters describing a lensed system from real data. In `lenstronomy`, this typically involves a Particle Swarm Optimizer (PSO) (Kennedy & Eberhart, 1995) for optimization and Monte Carlo Markov Chains for posterior sampling. `JAXtronomy` retains these lens modelling algorithms from `lenstronomy` while benefitting from the increased performance outlined above.

In the following table, we compare `JAXtronomy`'s PSO performance to that of `lenstronomy` when modeling a lens with an elliptical power-law (EPL) mass profile, Sersic light profile, and a quadruply-imaged point source. The image is simulated using a 100x100 grid and FFT convolved using a PSF kernel with a size of 13 pixels. These benchmarks were performed using the same hardware as in the previous section.

Device	64 Particles	128 Particles	256 Particles	512 Particles
1 CPU core	4x	4x	5x	5x
2 CPU cores	6x	7x	9x	8x
4 CPU cores	11x	11x	17x	15x
8 CPU cores	14x	17x	24x	30x
16 CPU cores	16x	21x	33x	38x
32 CPU cores	16x	18x	30x	34x
GPU	5x	6x	9x	11x

The following table shows the same comparison but with the EPL mass profile replaced by a singular isothermal ellipsoid (SIE).

Device	64 Particles	128 Particles	256 Particles	512 Particles
1 CPU core	3x	3x	3x	4x
2 CPU cores	5x	6x	6x	7x
4 CPU cores	8x	12x	11x	12x
8 CPU cores	11x	17x	17x	24x
16 CPU cores	13x	20x	22x	29x
32 CPU cores	13x	20x	20x	29x
GPU	8x	7x	27x	46x

Additionally, using `JAX`'s autodifferentiation, we have implemented the L-BFGS gradient descent algorithm from the `Optax`[5] library (DeepMind et al., 2020) for optimization. This is a significant improvement over `lenstronomy`'s PSO, which does not have access to gradient information. Due to the random nature of the PSO, we do not present a concrete comparison between `lenstronomy` and `JAXtronomy` for how long it takes to find best-fit parameters. However, we note that `JAXtronomy` can find a good fit within one minute, while `lenstronomy` can take hours.

[5] https://github.com/google-deepmind/optax

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