

¹ JAXtronomy: A JAX port of lenstronomy

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¹³ Summary

¹⁴ Gravitational lensing is a phenomenon where light bends around massive objects, resulting in ¹⁵ distorted images seen by an observer. Studying gravitationally lensed objects can give us key ¹⁶ insights into cosmology and astrophysics, such as constraints on the expansion rate of the ¹⁷ universe and dark matter models.

¹⁸ Thus, we introduce JAXtronomy, a re-implementation of the gravitational lensing software ¹⁹ package lenstronomy¹ ([Birrer, 2021; Birrer & Amara, 2018](#)) using JAX². JAX is a Python ²⁰ library that uses an accelerated linear algebra (XLA) compiler to improve the performance of ²¹ computing software. Our core design principle of JAXtronomy is to maintain an identical API ²² to that of lenstronomy.

²³ The main JAX features utilized in JAXtronomy are just-in-time-compilation, which can lead to ²⁴ significant reductions in execution time, and automatic differentiation, which allows for the ²⁵ implementation of gradient-based algorithms that were previously impossible. Additionally, ²⁶ JAX allows code to be run on GPUs or parallelized across CPU cores, further boosting the ²⁷ performance of JAXtronomy.

²⁸ Statement of need

²⁹ lenstronomy has been widely applied to numerous science cases, with more than 200 ³⁰ publications making use of the software, and has an increasing number of dependent packages ³¹ relying on features of lenstronomy. For instance, science cases directly involving lenstronomy ³² 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 ³³ 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; ?](#)).

³⁷ Examples of packages dependent on lenstronomy for general-purpose lensing computations and ³⁸ image modelling include the dolphin package ([Anowar J. Shajib et al., 2025](#)) for automated ³⁹ 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>

40 SLSim (Khadka et al, 2026, in prep) for simulating large populations of strong lenses, pyHalo
 41 (Gilman et al., 2019) and mejiro (Wedig et al., 2025) for simulating strong lenses with dark
 42 matter substructure, and PALTAS (Wagner-Carena et al., 2023) for neural network inference
 43 tasks.

44 In many of these applications, computational constraints are the key limiting factor for strong
 45 gravitational lensing science. For example, increased data quality and number of lenses to
 46 analyze makes lens modeling a computational bottleneck, and expensive ray-tracing through
 47 tens of thousands of dark matter substructures limit the amount of images that can be
 48 simulated, especially for the training of neural networks and simulation-based inferences. These
 49 ever-increasing computational costs have lead to the development of several JAX-accelerated
 50 and GPU-accelerated strong-lensing packages, such as gigalens (Gu et al., 2022), herculens
 51 (Galan et al., 2022), paltax (Wagner-Carena et al., 2024), GLaD (Wang et al., 2025), caustics³
 52 (Stone et al., 2024) and Google Research's jaxstronomy⁴.

53 Why JAXtronomy?

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

61 Improvements over lenstronomy in image simulation

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

71 In the following sections, we outline the improvements in performance that JAXtronomy has
 72 over lenstronomy for each step in the pipeline. These performance benchmarks were run using
 73 an Intel(R) Xeon(R) Gold 6338 CPU @ 2.00GHz, an NVIDIA A100 GPU, and JAX version
 74 0.7.0.

75 Deflection angle calculations

76 Each entry in the table indicates how much faster JAXtronomy is compared to lenstronomy
 77 at computing deflection angles for the corresponding deflector profile and grid size. Some
 78 comparisons vary significantly with values of function arguments, so a range is given rather
 79 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	1.4x	3.0x	13x
EPL_NUMBA			
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

⁸⁰ JAXtronomy computes deflection angles slower than lenstronomy when using computationally
⁸¹ simple deflector profiles on small enough grids. This is because function call overheads are
⁸² significantly higher in JAX than in standard Python, so computations that are already fast in
⁸³ Python can end up slower in JAX. However, these deflector profiles have higher gains from
⁸⁴ parallelization.

Flux calculations

⁸⁵ An analogous table for the different light profiles is shown below. The MULTI_GAUSSIAN
⁸⁶ and MULTI_GAUSSIAN_ELLIPSE profiles include five GAUSSIAN and GAUSSIAN_ELLIPSE
⁸⁷ 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

⁸⁸ We find that FFT convolution using JAX on CPU results in variable performance boosts or
⁸⁹ slowdowns compared to lenstronomy (which uses scipy's FFT convolution). On a 60x60
⁹⁰ grid, and kernel sizes ranging from 3 to 45, JAX on CPU ranges from being 1.1x to 2.9x faster
⁹¹ than lenstronomy, with no obvious correlation to kernel size. On a 180x180 grid, and kernel
⁹² sizes ranging from 9 to 135, JAXtronomy on CPU ranges from being 0.7x to 2.5x as fast as
⁹³ lenstronomy, with no obvious correlation to kernel size.

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

101 Improvements over `lenstronomy` in lens modelling

102 The process of lens modelling involves finding best-fit parameters describing a lensed system from
 103 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.
 104 `JAXtronomy` retains these lens modelling algorithms from `lenstronomy` while benefitting from
 105 the increased performance outlined above.

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

Device	64 Particles	128 Particles	256 Particles	512 Particles
lenstronomy (baseline)	59s	138s	245s	555s
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

111 Additionally, using JAX's autodifferentiation, we have implemented the L-BFGS gradient
 112 descent algorithm from the `Optax`⁵ library ([DeepMind et al., 2020](#)) for optimization. This is
 113 a significant improvement over `lenstronomy`'s PSO, which does not have access to gradient
 114 information. Due to the stochastic nature of the PSO, we do not present a concrete comparison
 115 between `lenstronomy`'s PSO and `JAXtronomy`'s minimizer for the time it takes to find best-fit
 116 parameters.

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