

¹ JAXtronomy: A JAX port of lenstronomy

² Alan Huang  ¹, Simon Birrer  ¹, Natalie B. Hogg  ², Aymeric Galan  ^{3,4},
³ Daniel Gilman  ⁵, Anowar J. Shajib  ^{5,6,7}, and Nan Zhang  ⁸

⁴ 1 Department of Physics and Astronomy, Stony Brook University, Stony Brook, NY 11794, USA
⁵ Laboratoire Univers et Particules de Montpellier, CNRS and Université de Montpellier (UMR-5299),
⁶ 34095 Montpellier, France ³ Max-Planck-Institut für Astrophysik, Karl-Schwarzschild Straße 1, 85748
⁷ Garching, Germany ⁴ Technical University of Munich, TUM School of Natural Sciences, Physics
⁸ Department, James-Franck-Straße 1, 85748 Garching, Germany ⁵ Department of Astronomy and
⁹ Astrophysics, University of Chicago, Chicago, Illinois 60637, USA ⁶ Kavli Institute for Cosmological
¹⁰ Physics, University of Chicago, Chicago, IL 60637, USA ⁷ Center for Astronomy, Space Science and
¹¹ Astrophysics, Independent University, Bangladesh, Dhaka 1229, Bangladesh ⁸ Department of Physics,
¹² University of Illinois, 1110 West Green St., Urbana, IL 61801, USA

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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 `lenstronomy`¹ ([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, 2025, 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 during
⁵⁷ lens modeling, as well as a variety of log likelihood functions and optional punishment terms
⁵⁸ to improve robustness during fitting. Furthermore, JAXtronomy aims to maintain an identical
⁵⁹ API 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 For small enough grid sizes, JAXtronomy computes deflection angles slower than lenstronomy
 81 when using certain deflector profiles. This is because function call overheads are significantly
 82 higher in JAX than in standard Python, so computations that are already fast in Python
 83 can end up slower in JAX. In these cases, the benefit of using JAX is to have automatic
 84 differentiation for lens modeling.

85 Flux calculations

86 An analogous table for the different light profiles is shown below. The MULTI_GAUSSIAN
 87 and MULTI_GAUSSIAN_ELLIPSE profiles include five GAUSSIAN and GAUSSIAN_ELLIPSE
 88 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

89 FFT Convolution

90 We find that FFT convolution using JAX on CPU results in variable performance boosts or
 91 slowdowns compared to lenstronomy (which uses scipy's FFT convolution). On a 60x60
 92 grid, and kernel sizes ranging from 3 to 45, JAX on CPU ranges from being 1.1x to 2.9x faster
 93 than lenstronomy, with no obvious correlation to kernel size. On a 180x180 grid, and kernel
 94 sizes ranging from 9 to 135, JAXtronomy on CPU ranges from being 0.7x to 2.5x as fast as
 95 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 an elliptical power-law mass profile, Sersic light profile, and a
 108 quadruply-imaged point source. We use a 100x100 grid and a size 13 PSF kernel. These
 109 benchmarks were performed using the same hardware as in the previous section.

Number of Particles	1 CPU core	64 CPU cores (parallelized)	GPU
64	4x	16x	5x
128	4x	18x	5.5x
256	4.7x	30x	9x
512	4.7x	34x	11x

111 Additionally, using JAX's autodifferentiation, we have implemented the L-BFGS gradient descent
 112 algorithm from the Optax⁵ library ([DeepMind et al., 2020](#)) for optimization. This is a significant
 113 improvement over `lenstronomy`'s PSO, which does not have access to gradient information.
 114 Due to the random nature of the PSO, we do not present a concrete comparison between
 115 `lenstronomy` and `JAXtronomy` for how long it takes to find best-fit parameters. However, we
 116 note that `JAXtronomy` can find a good fit within one minute, while `lenstronomy` can take
 117 hours.

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