

# 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 gravitationally 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<sup>1</sup> (Birrer, 2021; Birrer & Amara, 2018) using JAX<sup>2</sup>. 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,

<sup>1</sup><https://github.com/lenstronomy/lenstronomy>

<sup>2</sup><https://github.com/google/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), caustics<sup>3</sup>  
52 (Stone et al., 2024) and Google Research's jaxstronomy<sup>4</sup>.

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

<sup>3</sup><https://github.com/Ciela-Institute/caustics>

<sup>4</sup><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
PJAFPE	1.0x	1.2x	2.8x
PJAFPE_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	6.2x	3.4x	15x
(n_max=6)			
SHAPELETS	6.0x	4.5x	17x
(n_max=10)			

## 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.

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  
104 & Eberhart, 1995) for optimization and Monte Carlo Markov Chains for posterior sampling.  
105 JAXtronomy retains these lens modelling algorithms from `lenstronomy` while benefitting from  
106 the increased performance outlined above.

107 In the following table, we compare JAXtronomy's PSO performance to that of `lenstronomy`  
108 when modeling a lens with an elliptical power-law mass profile, Sersic light profile, and a  
109 quadruply-imaged point source. We use a 100x100 grid and a size 13 PSF kernel. These  
110 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 `Optax`<sup>5</sup> 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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