

JAXtronomy: A JAX port of lenstronomy

Alan Huang¹, Simon Birrer¹, Natalie B. Hogg², Aymeric Galan^{3,4},
Daniel Gilman⁵, Anowar J. Shajib^{5,6,7}, and Nan Zhang⁸

¹ Department of Physics and Astronomy, Stony Brook University, Stony Brook, NY 1794, USA ² Laboratoire Univers et Particules de Montpellier, CNRS and Université de Montpellier (UMR-5299), 34095 Montpellier, France ³ Max-Planck-Institut für Astrophysik, Karl-Schwarzschild Straße 1, 85748 Garching, Germany ⁴ Technical University of Munich, TUM School of Natural Sciences, Physics Department, James-Frank-Straße 1, 85748 Garching, Germany ⁵ Department of Astronomy and Astrophysics, University of Chicago, Chicago, Illinois 60637, USA ⁶ Kavli Institute for Cosmological Physics, University of Chicago, Chicago, IL 60637, USA ⁷ Center for Astronomy, Space Science and Astrophysics, Independent University, Bangladesh, Dhaka 1229, Bangladesh ⁸ Department of Physics, University of Illinois, 1110 West Green St., Urbana, IL 61801, USA

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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 lenstronomy¹ (Birrer, 2021; Birrer & Amara, 2018) using JAX². 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>

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), hercules
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 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 a singular isothermal ellipsoid (SIE) mass profile, Sersic-ellipse
 109 source and lens light profile, and a quadruply-imaged point source. The image is simulated
 110 using a 100x100 grid and FFT convolved using a PSF kernel with a size of 13 pixels. These
 111 benchmarks were performed using the same hardware as in the previous section.

Device	64 Particles	128 Particles	256 Particles	512 Particles
<code>lenstronomy</code> (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

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

119 References

- 120 Birrer, S. (2021). Gravitational lensing formalism in a curved arc basis: A continuous
 121 description of observables and degeneracies from the weak to the strong lensing regime.
 122 *The Astrophysical Journal*, 919(1), 38. <https://doi.org/10.3847/1538-4357/ac1108>
- 123 Birrer, S., & Amara, A. (2018). `Lenstronomy`: Multi-purpose gravitational lens modelling
 124 software package. *Physics of the Dark Universe*, 22, 189–201. [https://doi.org/10.1016/j.](https://doi.org/10.1016/j.dark.2018.11.002)
 125 [dark.2018.11.002](https://doi.org/10.1016/j.dark.2018.11.002)
- 126 Birrer, Simon, & Treu, Tommaso. (2021). TDCOSMO - v. Strategies for precise and accurate
 127 measurements of the hubble constant with strong lensing. *Astronomy & Astrophysics*, 649,
 128 A61. <https://doi.org/10.1051/0004-6361/202039179>

⁵<https://github.com/google-deepmind/optax>

- 129 Birrer, S., Shajib, A. J., Galan, A., Millon, M., Treu, T., Agnello, A., Auger, M., Chen, G.
 130 C.-F., Christensen, L., Collett, T., Courbin, F., Fassnacht, C. D., Koopmans, L. V. E.,
 131 Marshall, P. J., Park, J.-W., Rusu, C. E., Sluse, D., Spiniello, C., Suyu, S. H., ... Van de
 132 Vyvere, L. (2020). TDCOSMO - IV. Hierarchical time-delay cosmography – joint inference
 133 of the hubble constant and galaxy density profiles*. *Astronomy & Astrophysics*, 643, A165.
 134 <https://doi.org/10.1051/0004-6361/202038861>
- 135 Collaboration, T., Birrer, S., Buckley-Geer, E. J., Cappellari, M., Courbin, F., Dux, F.,
 136 Fassnacht, C. D., Frieman, J. A., Galan, A., Gilman, D., Huang, X.-Y., Knabel, S.,
 137 Langeroodi, D., Lin, H., Millon, M., Morishita, T., Motta, V., Mozumdar, P., Paic, E., ...
 138 Wong, K. C. (2025). *TDCOSMO 2025: Cosmological constraints from strong lensing time*
 139 *delays*. <https://arxiv.org/abs/2506.03023>
- 140 DeepMind, Babuschkin, I., Baumli, K., Bell, A., Bhupatiraju, S., Bruce, J., Buchlovsky, P.,
 141 Budden, D., Cai, T., Clark, A., Danihelka, I., Dedieu, A., Fantacci, C., Godwin, J., Jones,
 142 C., Hemsley, R., Hennigan, T., Hessel, M., Hou, S., ... Viola, F. (2020). *The DeepMind*
 143 *JAX Ecosystem*. <http://github.com/google-deeppmind>
- 144 Ding, X., Silverman, J., Treu, T., Schulze, A., Schramm, M., Birrer, S., Park, D., Jahnke, K.,
 145 Bennert, V. N., Kartaltepe, J. S., Koekemoer, A. M., Malkan, M. A., & Sanders, D. (2020).
 146 The Mass Relations between Supermassive Black Holes and Their Host Galaxies at $1 < z$
 147 < 2 HST-WFC3. *The Astrophysical Journal*, 888(1), 37. [https://doi.org/10.3847/1538-](https://doi.org/10.3847/1538-4357/ab5b90)
 148 [4357/ab5b90](https://doi.org/10.3847/1538-4357/ab5b90)
- 149 Galan, A., Vernardos, G., Peel, A., Courbin, F., & Starck, J.-L. (2022). Using wavelets
 150 to capture deviations from smoothness in galaxy-scale strong lenses. *Astronomy &*
 151 *Astrophysics*, 668, A155. <https://doi.org/10.1051/0004-6361/202244464>
- 152 Gilman, D., Birrer, S., Nierenberg, A., Treu, T., Du, X., & Benson, A. (2019). Warm dark
 153 matter chills out: Constraints on the halo mass function and the free-streaming length of
 154 dark matter with eight quadruple-image strong gravitational lenses. *Monthly Notices of the*
 155 *Royal Astronomical Society*, 491(4), 6077–6101. <https://doi.org/10.1093/mnras/stz3480>
- 156 Gilman, D., Birrer, S., & Treu, T. (2020). TDCOSMO - III. Dark matter substructure meets
 157 dark energy. The effects of (sub)halos on strong-lensing measurements of H0. *Astronomy*
 158 *& Astrophysics*, 642, A194. <https://doi.org/10.1051/0004-6361/202038829>
- 159 Gu, A., Huang, X., Sheu, W., Aldering, G., Bolton, A. S., Boone, K., Dey, A., Filipp, A.,
 160 Jullo, E., Perlmutter, S., Rubin, D., Schlafly, E. F., Schlegel, D. J., Shu, Y., & Suyu, S. H.
 161 (2022). GIGA-lens: Fast bayesian inference for strong gravitational lens modeling. *The*
 162 *Astrophysical Journal*, 935(1), 49. <https://doi.org/10.3847/1538-4357/ac6de4>
- 163 Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95*
 164 *- International Conference on Neural Networks*, 4, 1942–1948 vol.4. [https://doi.org/10.](https://doi.org/10.1109/ICNN.1995.488968)
 165 [1109/ICNN.1995.488968](https://doi.org/10.1109/ICNN.1995.488968)
- 166 Millon, M., Galan, A., Courbin, F., Treu, T., Suyu, S. H., Ding, X., Birrer, S., Chen, G. C.-F.,
 167 Shajib, A. J., Sluse, D., Wong, K. C., Agnello, A., Auger, M. W., Buckley-Geer, E. J.,
 168 Chan, J. H. H., Collett, T., Fassnacht, C. D., Hilbert, S., Koopmans, L. V. E., ... Van
 169 de Vyvere, L. (2020). TDCOSMO - i. An exploration of systematic uncertainties in the
 170 inference of H0 from time-delay cosmography. *Astronomy & Astrophysics*, 639, A101.
 171 <https://doi.org/10.1051/0004-6361/201937351>
- 172 Schmidt, T., Treu, T., Birrer, S., Millon, M., Sluse, D., Galan, A., Shajib, A., Lemon, C.,
 173 Dux, F., & Courbin, F. (2025). TDCOSMO. XVIII. Strong lens model and time-delay
 174 predictions for J1721+8842, the first einstein zigzag lens. *Astronomy & Astrophysics*.
 175 <https://doi.org/10.1051/0004-6361/202449984>
- 176 Shajib, Anowar J., Nihal, N. S., Tan, C. Y., Sahu, V., Birrer, S., Treu, T., & Frieman, J. (2025).
 177 *dolphin: A fully automated forward modeling pipeline powered by artificial intelligence for*

- 178 galaxy-scale strong lenses. <https://arxiv.org/abs/2503.22657>
- 179 Shajib, Anowar J., Treu, T., Birrer, S., & Sonnenfeld, A. (2021). Dark matter haloes of
180 massive elliptical galaxies at $z \sim 0.2$ are well described by the Navarro-Frenk-White
181 profile. *Monthly Notices of the Royal Astronomical Society*, 503(2), 2380–2405. <https://doi.org/10.1093/mnras/stab536>
- 182
- 183 Shajib, A. J., Wong, K. C., Birrer, S., Suyu, S. H., Treu, T., Buckley-Geer, E. J., Lin, H., Rusu, C.
184 E., Poh, J., Palmese, A., Agnello, A., Auger-Williams, M. W., Galan, A., Schuldt, S., Sluse,
185 D., Courbin, F., Frieman, J., & Millon, M. (2022). TDCOSMO. IX. Systematic comparison
186 between lens modelling software programs: Time-delay prediction for WGD 2038–4008.
187 *Astronomy & Astrophysics*, 667, A123. <https://doi.org/10.1051/0004-6361/202243401>
- 188 Sheu, W., Shajib, A. J., Treu, T., Sonnenfeld, A., Birrer, S., Cappellari, M., Oldham, L. J., &
189 Tan, C. Y. (2025). Project Dinos II: redshift evolution of dark and luminous matter density
190 profiles in strong-lensing elliptical galaxies across $0.1 < z < 0.9$. *Monthly Notices of the*
191 *Royal Astronomical Society*, 541(1), 1–27. <https://doi.org/10.1093/mnras/staf976>
- 192 Stone, C., Adam, A., Coogan, A., Yantovski-Barth, M. J., Filipp, A., Setiawan, L., Core,
193 C., Legin, R., Wilson, C., Barco, G. M., Hezaveh, Y., & Perreault-Levasseur, L. (2024).
194 Caustics: A python package for accelerated strong gravitational lensing simulations. *Journal*
195 *of Open Source Software*, 9(103), 7081. <https://doi.org/10.21105/joss.07081>
- 196 Tan, C. Y., Shajib, A. J., Birrer, S., Sonnenfeld, A., Treu, T., Wells, P., Williams, D.,
197 Buckley-Geer, E. J., Drlica-Wagner, A., & Frieman, J. (2024). Project Dinos I: A joint
198 lensing-dynamics constraint on the deviation from the power law in the mass profile of
199 massive ellipticals. *Monthly Notices of the Royal Astronomical Society*, 530(2), 1474–1505.
200 <https://doi.org/10.1093/mnras/stae884>
- 201 Wagner-Carena, S., Aalbers, J., Birrer, S., Nadler, E. O., Darragh-Ford, E., Marshall, P. J., &
202 Wechsler, R. H. (2023). From images to dark matter: End-to-end inference of substructure
203 from hundreds of strong gravitational lenses. *The Astrophysical Journal*, 942(2), 75.
204 <https://doi.org/10.3847/1538-4357/aca525>
- 205 Wagner-Carena, S., Lee, J., Pennington, J., Aalbers, J., Birrer, S., & Wechsler, R. H.
206 (2024). A strong gravitational lens is worth a thousand dark matter halos: Inference on
207 small-scale structure using sequential methods. *The Astrophysical Journal*, 975(2), 297.
208 <https://doi.org/10.3847/1538-4357/ad6e70>
- 209 Wang, H., Suyu, S. H., Galan, A., Halkola, A., Cappellari, M., Shajib, A. J., & Cernetic, M.
210 (2025). GPU-accelerated gravitational lensing & dynamical (GLaD) modeling for cosmology
211 and galaxies. <https://arxiv.org/abs/2504.01302>
- 212 Wedig, B., Daylan, T., Birrer, S., Cyr-Racine, F.-Y., Dvorkin, C., Finkbeiner, D. P., Huang, A.,
213 Huang, X., Karthik, R., Khadka, N., Natarajan, P., Nierenberg, A. M., Peter, A. H. G., Pierel,
214 J. D. R., Tang, X. T., & Wechsler, R. H. (2025). The roman view of strong gravitational
215 lenses. *The Astrophysical Journal*, 986(1), 42. <https://doi.org/10.3847/1538-4357/adc24f>