

# JAXtronomy: A JAX port of lenstronomy

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## Summary

JAXtronomy is a re-implementation of the gravitational lensing software package lenstronomy<sup>1</sup> (Birrer, 2021; Birrer & Amara, 2018) using JAX<sup>2</sup>, 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, 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; Williams et al., 2025).

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, 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

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

<sup>2</sup><https://github.com/jax-ml/jax>

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 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), and Google Research’s jaxstronomy<sup>3</sup>. Such packages have been directly inspired by lenstronomy and/or support specific use cases. With JAXtronomy, we aim to support a wide range of features offered by lenstronomy while maintaining an identical API 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. Those profiles which are already computationally inexpensive for lenstronomy are excluded from this table. 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)
CSE	1.6x	2.6x	2.6x
EPL	5.1x - 15x	9.2x - 17x	37x - 120x
EPL (jax) vs EPL_NUMBA	1.4x	3.0x	13x
EPL_MULTI- POLE_M1M3M4	2.1x - 7x	6.4x - 13x	42x - 108x
HERNQUIST	2.0x	3.4x	5.8x
HERNQUIST_EL- LIPSE_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
NFW	1.6x	3.3x	4.5x
NFW_ELLIPSE_CSE	4.1x	6.7x	31x
TNFW	2.4x	5.8x	7.5x

<sup>3</sup><https://github.com/google-research/google-research/tree/master/jaxstronomy>

## Flux calculations

An analogous table for the different light profiles is shown below.

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
SERSIC	1.0x	1.7x	3.9x
SERSIC_ELLIPSE	1.9x	5.7x	3.2x
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 all of the lens modelling algorithms from lenstronomy while benefitting from the increased performance outlined above. Additionally, using JAX's autodifferentiation, we have implemented the L-BFGS gradient descent algorithm from the Optax<sup>4</sup> library (DeepMind et al., 2020) for optimization. This is a significant improvement over lenstronomy's PSO, which does not have access to gradient information.

## References

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

<sup>4</sup><https://github.com/google-deepmind/optax>

- 104 Birrer, S., Shajib, A. J., Galan, A., Millon, M., Treu, T., Agnello, A., Auger, M., Chen,  
105 G. C.-F., Christensen, L., Collett, T., Courbin, F., Fassnacht, C. D., Koopmans, L. V.  
106 E., Marshall, P. J., Park, J.-W., Rusu, C. E., Sluse, D., Spiniello, C., Suyu, S. H., ...  
107 Van de Vyvere, L. (2020). TDCOSMO - IV. Hierarchical time-delay cosmography –  
108 joint inference of the hubble constant and galaxy density profiles★. *A&A*, 643, A165.  
109 <https://doi.org/10.1051/0004-6361/202038861>
- 110 Collaboration, T., Birrer, S., Buckley-Geer, E. J., Cappellari, M., Courbin, F., Dux, F.,  
111 Fassnacht, C. D., Frieman, J. A., Galan, A., Gilman, D., Huang, X.-Y., Knabel, S.,  
112 Langeroodi, D., Lin, H., Millon, M., Morishita, T., Motta, V., Mozumdar, P., Paic, E., ...  
113 Wong, K. C. (2025). *TDCOSMO 2025: Cosmological constraints from strong lensing time*  
114 *delays*. <https://arxiv.org/abs/2506.03023>
- 115 DeepMind, Babuschkin, I., Baumli, K., Bell, A., Bhupatiraju, S., Bruce, J., Buchlovsky, P.,  
116 Budden, D., Cai, T., Clark, A., Danihelka, I., Dedieu, A., Fantacci, C., Godwin, J., Jones,  
117 C., Hemsley, R., Hennigan, T., Hessel, M., Hou, S., ... Viola, F. (2020). *The DeepMind*  
118 *JAX Ecosystem*. <http://github.com/google-deeppmind>
- 119 Ding, X., Silverman, J., Treu, T., Schulze, A., Schramm, M., Birrer, S., Park, D., Jahnke,  
120 K., Bennert, V. N., Kartaltepe, J. S., Koekemoer, A. M., Malkan, M. A., & Sanders, D.  
121 (2020). The Mass Relations between Supermassive Black Holes and Their Host Galaxies  
122 at  $1 < z < 2$  HST-WFC3. 888(1), 37. <https://doi.org/10.3847/1538-4357/ab5b90>
- 123 Galan, A., Vernardos, G., Peel, A., Courbin, F., & Starck, J.-L. (2022). Using wavelets  
124 to capture deviations from smoothness in galaxy-scale strong lenses. 668, A155. <https://doi.org/10.1051/0004-6361/202244464>
- 125 <https://doi.org/10.1051/0004-6361/202244464>
- 126 Gilman, D., Birrer, S., Nierenberg, A., Treu, T., Du, X., & Benson, A. (2019). Warm dark  
127 matter chills out: Constraints on the halo mass function and the free-streaming length of  
128 dark matter with eight quadruple-image strong gravitational lenses. *Monthly Notices of the*  
129 *Royal Astronomical Society*, 491(4), 6077–6101. <https://doi.org/10.1093/mnras/stz3480>
- 130 Gilman, D., Birrer, S., & Treu, T. (2020). TDCOSMO - III. Dark matter substructure meets  
131 dark energy. The effects of (sub)halos on strong-lensing measurements of H0. *A&A*, 642,  
132 A194. <https://doi.org/10.1051/0004-6361/202038829>
- 133 Gu, A., Huang, X., Sheu, W., Aldering, G., Bolton, A. S., Boone, K., Dey, A., Filipp, A.,  
134 Jullo, E., Perlmutter, S., Rubin, D., Schlafly, E. F., Schlegel, D. J., Shu, Y., & Suyu, S. H.  
135 (2022). GIGA-lens: Fast bayesian inference for strong gravitational lens modeling. *The*  
136 *Astrophysical Journal*, 935(1), 49. <https://doi.org/10.3847/1538-4357/ac6de4>
- 137 Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. *Proceedings of ICNN'95*  
138 *- International Conference on Neural Networks*, 4, 1942–1948 vol.4. <https://doi.org/10.1109/ICNN.1995.488968>
- 139 <https://doi.org/10.1109/ICNN.1995.488968>
- 140 Millon, M., Galan, A., Courbin, F., Treu, T., Suyu, S. H., Ding, X., Birrer, S., Chen,  
141 G. C.-F., Shajib, A. J., Sluse, D., Wong, K. C., Agnello, A., Auger, M. W., Buckley-  
142 Geer, E. J., Chan, J. H. H., Collett, T., Fassnacht, C. D., Hilbert, S., Koopmans, L.  
143 V. E., ... Van de Vyvere, L. (2020). TDCOSMO - i. An exploration of systematic  
144 uncertainties in the inference of H0 from time-delay cosmography. *A&A*, 639, A101.  
145 <https://doi.org/10.1051/0004-6361/201937351>
- 146 Schmidt, T., Treu, T., Birrer, S., Millon, M., Sluse, D., Galan, A., Shajib, A., Lemon, C.,  
147 Dux, F., & Courbin, F. (2025). TDCOSMO. XVIII. Strong lens model and time-delay  
148 predictions for J1721+8842, the first einstein zigzag lens. *Astronomy & Astrophysics*.  
149 <https://doi.org/10.1051/0004-6361/202449984>
- 150 Shajib, Anowar J., Nihal, N. S., Tan, C. Y., Sahu, V., Birrer, S., Treu, T., & Frieman, J. (2025).  
151 *dolphin: A fully automated forward modeling pipeline powered by artificial intelligence for*  
152 *galaxy-scale strong lenses*. <https://arxiv.org/abs/2503.22657>

- Shajib, Anowar J., Treu, T., Birrer, S., & Sonnenfeld, A. (2021). Dark matter haloes of massive elliptical galaxies at  $z \sim 0.2$  are well described by the Navarro-Frenk-White profile. *503*(2), 2380–2405. <https://doi.org/10.1093/mnras/stab536>
- Shajib, A. J., Wong, K. C., Birrer, S., Suyu, S. H., Treu, T., Buckley-Geer, E. J., Lin, H., Rusu, C. E., Poh, J., Palmese, A., Agnello, A., Auger-Williams, M. W., Galan, A., Schuldt, S., Sluse, D., Courbin, F., Frieman, J., & Millon, M. (2022). TDCOSMO. IX. Systematic comparison between lens modelling software programs: Time-delay prediction for WGD 2038–4008. *667*, A123. <https://doi.org/10.1051/0004-6361/202243401>
- Sheu, W., Shajib, A. J., Treu, T., Sonnenfeld, A., Birrer, S., Cappellari, M., Oldham, L. J., & Tan, C. Y. (2025). Project Dinos II: redshift evolution of dark and luminous matter density profiles in strong-lensing elliptical galaxies across  $0.1 < z < 0.9$ . *541*(1), 1–27. <https://doi.org/10.1093/mnras/staf976>
- Tan, C. Y., Shajib, A. J., Birrer, S., Sonnenfeld, A., Treu, T., Wells, P., Williams, D., Buckley-Geer, E. J., Drlica-Wagner, A., & Frieman, J. (2024). Project Dinos I: A joint lensing-dynamics constraint on the deviation from the power law in the mass profile of massive ellipticals. *530*(2), 1474–1505. <https://doi.org/10.1093/mnras/stae884>
- Wagner-Carena, S., Aalbers, J., Birrer, S., Nadler, E. O., Darragh-Ford, E., Marshall, P. J., & Wechsler, R. H. (2023). From images to dark matter: End-to-end inference of substructure from hundreds of strong gravitational lenses. *The Astrophysical Journal*, *942*(2), 75. <https://doi.org/10.3847/1538-4357/aca525>
- Wagner-Carena, S., Lee, J., Pennington, J., Aalbers, J., Birrer, S., & Wechsler, R. H. (2024). A strong gravitational lens is worth a thousand dark matter halos: Inference on small-scale structure using sequential methods. *The Astrophysical Journal*, *975*(2), 297. <https://doi.org/10.3847/1538-4357/ad6e70>
- Wang, H., Suyu, S. H., Galan, A., Halkola, A., Cappellari, M., Shajib, A. J., & Cernetic, M. (2025). GPU-accelerated gravitational lensing & dynamical (GLaD) modeling for cosmology and galaxies. <https://arxiv.org/abs/2504.01302>
- Wedig, B., Daylan, T., Birrer, S., Cyr-Racine, F.-Y., Dvorkin, C., Finkbeiner, D. P., Huang, A., Huang, X., Karthik, R., Khadka, N., Natarajan, P., Nierenberg, A. M., Peter, A. H. G., Pierel, J. D. R., Tang, X. T., & Wechsler, R. H. (2025). The roman view of strong gravitational lenses. *The Astrophysical Journal*, *986*(1), 42. <https://doi.org/10.3847/1538-4357/adc24f>
- Williams, D. M., Treu, T., Birrer, S., Shajib, A. J., Wong, K. C., Morishita, T., Schmidt, T., & Stiavelli, M. (2025). TDCOSMO: XX. WFI2033–4723, the First Quadruply-Imaged Quasar Modeled with JWST Imaging. *arXiv e-Prints*, arXiv:2503.00099. <https://doi.org/10.48550/arXiv.2503.00099>