





# popclass: A Python Package for Classifying Microlensing Events

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## Summary

popclass is a Python package that provides a flexible, probabilistic framework for classifying the lens of a gravitational microlensing event. Gravitational microlensing occurs when a massive foreground object (e.g., a star, white dwarf or a black hole) passes in front of and lenses the light from a distant background source. This causes an apparent brightening, and shift in position, of the background source. In most cases, characteristics of the microlensing signal do not contain enough information to definitively identify the lens type. Different lens types lie in different but overlapping regions of the characteristics of the microlensing signal. For example, black holes tend to be more massive than stars and therefore cause microlensing signals that are longer. Current Galactic simulations enable us to predict where different lens types lie in the observational space and can therefore be used to classify events (e.g., [Lam et al., 2020](#)).

popclass allows the user to match the characteristics of a microlensing signal with a simulation of the Galaxy to calculate lens type probabilities for the event (see Figure 1). Constraints on any microlensing signal properties and any Galactic model can be used. popclass comes with an interface to ArviZ ([Kumar et al., 2019](#)) and pymultinest ([Buchner et al., 2014](#)) for microlensing signal constraints, as well as pre-loaded Galactic models, plotting functionality, and methods to quantify the classification uncertainty. The probabilistic framework for popclass was developed in Perkins et al. (2024), used in Fardeen et al. (2024) and has been applied to classifying events in Kaczmarek et al. (2025).

## Statement of need

The advent of the Vera C. Rubin Observatory ([Ivezić et al., 2019](#)) and the *Nancy Grace Roman Space Telescope* ([Spergel et al., 2015](#)) will provide tens of thousands of microlensing events per year (e.g., [Abrams et al., 2025](#); [Penny et al., 2019](#)). To maximize the scientific output from this event stream, it is critical to identify events that have a high probability of being caused by a certain lens type such as a black hole ([Lam et al., 2022](#); [Sahu et al., 2022](#)), before we allocate expensive follow-up observations such as space-based astrometry (e.g., [Sahu et al., 2022](#)) or ground-based adaptive optics imaging (e.g., [Terry et al., 2022](#)) to confirm their nature.

Current microlensing software packages such as DarkLensCode ([Howil et al., 2025](#)) or PyLiMASS ([Bachelet et al., 2024](#)) estimate lens mass and distance constraints using the light curves of microlensing events and auxiliary information (e.g., source proper motions, distances, color, or finite source effects). Using auxiliary information makes these current methods powerful

but limits their application to only be effective for events with the available auxiliary data. Moreover, no current software tools explicitly predict the lens type, and they always assume a fixed Galactic model. `popclass` fills the need for a flexible microlensing classification software package that can be broadly applied to classify all events from the Vera C. Rubin Observatory and *Nancy Grace Roman Space Telescope* and can be used with any Galactic model in the form of a simulation.

## Method

`popclass` is based on the Bayesian classification framework in (Perkins et al., 2024). Consider the data from a single microlensing event  $\mathbf{d}$ , and a model of the Galaxy  $\mathcal{G}$ . `popclass` calculates the probability that the lens of the event belongs to each lens class,  $\text{class}_L$ , where  $\text{class}_L \in \text{classes}$  and, for example,  $\text{classes} = \{\text{star, neutron dtar, white dwarf, black hole}\}$ . Namely, `popclass` calculates

$$p(\text{class}_L|\mathbf{d}, \mathcal{G}) \text{ for } \text{class}_L \in \text{classes}.$$

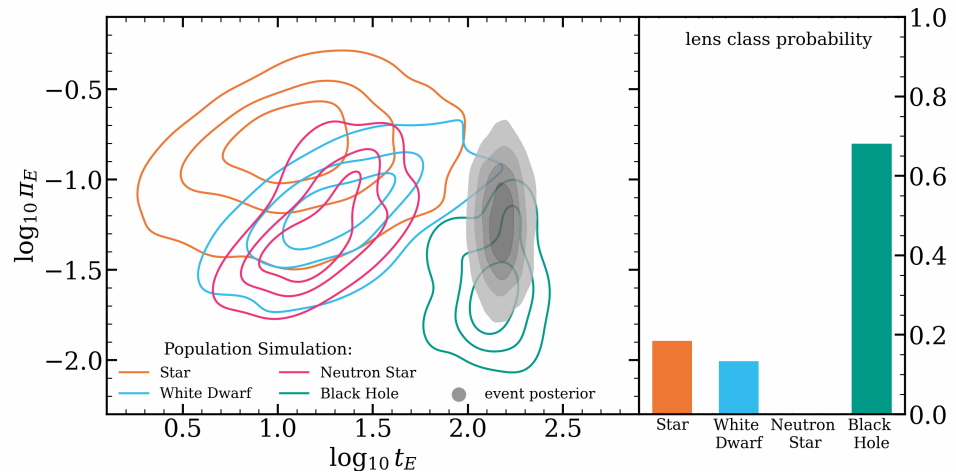
Using Bayes' theorem,

$$p(\text{class}_L|\mathbf{d}, \mathcal{G}) = \frac{p(\text{class}_L|\mathcal{G})p(\mathbf{d}|\text{class}_L, \mathcal{G})}{p(\mathbf{d}|\mathcal{G})}.$$

Assuming that the set of considered lens classes is complete,  $p(\mathbf{d}|\mathcal{G})$  is a normalization factor such that all lens class probabilities sum to unity. Using importance sampling (e.g., Hogg et al., 2010) with  $S$  independent posterior samples  $\theta_c \sim p(\theta|\mathbf{d})$  drawn under some prior,  $\pi(\theta)$ , obtained from fitting some set of microlensing signal parameters,  $\theta$ ,

$$p(\text{class}_L|\mathbf{d}, \mathcal{G}) = \frac{p(\text{class}_L|\mathcal{G})}{p(\mathbf{d}|\mathcal{G})} \times \frac{1}{S} \sum_{c=0}^S \frac{p(\theta_c|\text{class}_L, \mathcal{G})}{\pi(\theta_c)}$$

This allows the use of previously calculated posterior samples to perform lens classification for a single event in the context of a Galactic model. The term  $p(\theta_c|\text{class}_L, \mathcal{G})$  is calculated using kernel density estimation in `popclass` over  $\theta$  with a simulated catalog of microlensing events from  $\mathcal{G}$ .  $p(\text{class}_L|\mathcal{G})$  is the prior probability that an event belongs to each class before any data is seen, which is simply set by the relative number of expected events predicted by the Galactic model  $\mathcal{G}$ .



**Figure 1:** Left: posterior distribution of an event in  $\log_{10}(\text{timescale})$ - $\log_{10}(\text{parallax})$  space, overlaid on 'star', 'white dwarf', 'neutron star' and 'black hole' contours. Right: bars showing probabilities of that event belonging to each of the lens populations.

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## References

- Abrams, N. S., Hundertmark, M. P. G., Khakpash, S., Street, R. A., Jones, R. L., Lu, J. R., Bachelet, E., Tsapras, Y., Moniez, M., Blaineau, T., Di Stefano, R., Makler, M., Varela, A., & Rabus, M. (2025). Microlensing Discovery and Characterization Efficiency in the Vera C. Rubin Legacy Survey of Space and Time. *The Astrophysical Journal Supplement*, 276(1), 10. <https://doi.org/10.3847/1538-4365/ad91b0>
- Bachelet, E., Hundertmark, M., & Calchi Novati, S. (2024). Estimating Microlensing Parameters from Observables and Stellar Isochrones with pyLIMASS. *The Astronomical Journal*, 168(1), 24. <https://doi.org/10.3847/1538-3881/ad4862>
- Buchner, J., Georgakakis, A., Nandra, K., Hsu, L., Rangel, C., Brightman, M., Merloni, A., Salvato, M., Donley, J., & Kocevski, D. (2014). X-ray spectral modelling of the AGN obscuring region in the CDFS: Bayesian model selection and catalogue. *Astronomy and Astrophysics*, 564, A125. <https://doi.org/10.1051/0004-6361/201322971>
- Fardeen, J., McGill, P., Perkins, S. E., Dawson, W. A., Abrams, N. S., Lu, J. R., Ho, M.-F., & Bird, S. (2024). Astrometric Microlensing by Primordial Black Holes with the Roman Space

- Telescope. *The Astrophysical Journal*, 965(2), 138. <https://doi.org/10.3847/1538-4357/ad3243>
- Greenfield, P., Droettboom, M., & Bray, E. (2015). ASDF: A new data format for astronomy. *Astronomy and Computing*, 12, 240–251. <https://doi.org/10.1016/j.ascom.2015.06.004>
- Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., ... Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, 585(7825), 357–362. <https://doi.org/10.1038/s41586-020-2649-2>
- Hogg, D. W., Myers, A. D., & Bovy, J. (2010). Inferring the Eccentricity Distribution. *The Astrophysical Journal*, 725(2), 2166–2175. <https://doi.org/10.1088/0004-637X/725/2/2166>
- Howil, K., Wyrzykowski, Ł., Kruszyńska, K., Zieliński, P., Bachelet, E., Gromadzki, M., Mikołajczyk, P. J., Kotysz, K., Jabłońska, M., Kaczmarek, Z., Mróz, P., Ihanec, N., Ratajczak, M., Pylypenko, U., Rybicki, K., Sweeney, D., Hodgkin, S. T., Larma, M., Carrasco, J. M., ... Wicker, M. (2025). Uncovering the invisible: A study of Gaia18ajz, a candidate black hole revealed by microlensing. *The Astronomy and Astrophysics*, 694, A94. <https://doi.org/10.1051/0004-6361/202451046>
- Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, 9(3), 90–95. <https://doi.org/10.1109/MCSE.2007.55>
- Ivezić, Ž., Kahn, S. M., Tyson, J. A., Abel, B., Acosta, E., Allsman, R., Alonso, D., AlSayyad, Y., Anderson, S. F., Andrew, J., Angel, J. R. P., Angeli, G. Z., Ansari, R., Antilogus, P., Araujo, C., Armstrong, R., Arndt, K. T., Astier, P., Aubourg, É., ... Zhan, H. (2019). LSST: From Science Drivers to Reference Design and Anticipated Data Products. *The Astrophysical Journal*, 873(2), 111. <https://doi.org/10.3847/1538-4357/ab042c>
- Kaczmarek, Z., McGill, P., Perkins, S. E., Dawson, W. A., Huston, M., Ho, M.-F., Abrams, N. S., & Lu, J. R. (2025). On Finding Black Holes in Photometric Microlensing Surveys. *The Astrophysical Journal*, 981(2), 183. <https://doi.org/10.3847/1538-4357/adb1d7>
- Kumar, R., Carroll, C., Hartikainen, A., & Martin, O. (2019). ArviZ a unified library for exploratory analysis of bayesian models in python. *Journal of Open Source Software*, 4(33), 1143. <https://doi.org/10.21105/joss.01143>
- Lam, C. Y., Lu, J. R., Hosek, Jr., Matthew W., Dawson, W. A., & Golovich, N. R. (2020). PopSyCLE: A New Population Synthesis Code for Compact Object Microlensing Events. *The Astrophysical Journal*, 889(1), 31. <https://doi.org/10.3847/1538-4357/ab5fd3>
- Lam, C. Y., Lu, J. R., Udalski, A., Bond, I., Bennett, D. P., Skowron, J., Mróz, P., Poleski, R., Sumi, T., Szymański, M. K., Kozłowski, S., Pietrukowicz, P., Soszyński, I., Ulaczyk, K., Wyrzykowski, Ł., Miyazaki, S., Suzuki, D., Koshimoto, N., Rattenbury, N. J., ... Terry, S. K. (2022). An Isolated Mass-gap Black Hole or Neutron Star Detected with Astrometric Microlensing. *The Astrophysical Journal Letters*, 933(1), L23. <https://doi.org/10.3847/2041-8213/ac7442>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.
- Penny, M. T., Gaudi, B. S., Kerins, E., Rattenbury, N. J., Mao, S., Robin, A. C., & Calchi Novati, S. (2019). Predictions of the WFIRST Microlensing Survey. I. Bound Planet Detection Rates. *The Astrophysical Journal Supplement*, 241(1), 3. <https://doi.org/10.3847/1538-4365/aafb69>

- Perkins, S. E., McGill, P., Dawson, W., Abrams, N. S., Lam, C. Y., Ho, M.-F., Lu, J. R., Bird, S., Pruett, K., Golovich, N., & Chapline, G. (2024). Disentangling the Black Hole Mass Spectrum with Photometric Microlensing Surveys. *The Astrophysical Journal*, 961(2), 179. <https://doi.org/10.3847/1538-4357/ad09bf>
- Sahu, K. C., Anderson, J., Casertano, S., Bond, H. E., Udalski, A., Dominik, M., Calamida, A., Bellini, A., Brown, T. M., Rejkuba, M., Bajaj, V., Kains, N., Ferguson, H. C., Fryer, C. L., Yock, P., Mróz, P., Kozłowski, S., Pietrukowicz, P., Poleski, R., ... RoboNet Collaboration. (2022). An Isolated Stellar-mass Black Hole Detected through Astrometric Microlensing. *The Astrophysical Journal*, 933(1), 83. <https://doi.org/10.3847/1538-4357/ac739e>
- Spiegel, D., Gehrels, N., Baltay, C., Bennett, D., Breckinridge, J., Donahue, M., Dressler, A., Gaudi, B. S., Greene, T., Guyon, O., Hirata, C., Kalirai, J., Kasdin, N. J., Macintosh, B., Moos, W., Perlmutter, S., Postman, M., Rauscher, B., Rhodes, J., ... Zhao, F. (2015). Wide-Field Infrared Survey Telescope-Astrophysics Focused Telescope Assets WFIRST-AFTA 2015 Report. *arXiv e-Prints*, arXiv:1503.03757. <https://doi.org/10.48550/arXiv.1503.03757>
- Terry, S. K., Bennett, D. P., Bhattacharya, A., Koshimoto, N., Beaulieu, J.-P., Blackman, J. W., Bond, I. A., Cole, A. A., Lu, J. R., Marquette, J. B., Ranc, C., Reksini, N., & Vanderou, A. (2022). Adaptive Optics Imaging Can Break the Central Caustic Cusp Approach Degeneracy in High-magnification Microlensing Events. *The Astronomical Journal*, 164(5), 217. <https://doi.org/10.3847/1538-3881/ac9518>
- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., ... SciPy 1.0 Contributors. (2020). SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nature Methods*, 17, 261–272. <https://doi.org/10.1038/s41592-019-0686-2>