Time Delay Lens Modeling Challenge

Tak (Hyungsuk) Tak

SAMSI / UNC / CHASC

17 Apr 2018

Special thanks to Simon Birrer (UCLA) and Kaisey Mandel (Cambridge University & CfA).

Strong gravitational lensing

Video source: https://www.youtube.com/watch?v=iE8x9kDHCFo

Strong gravitational lensing effect: The strong gravitational field of the lensing galaxy splits light into multiple images, and we see these multiple images of the same quasar in the sky.

Strong lens time delay

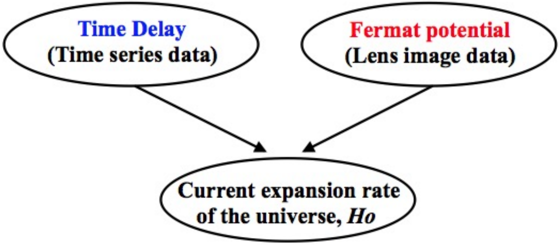
Credit: NASA's Goddard Space Flight Center

Time delay: Light rays take different routes and travel through different gravitational potential, and thus their arrival times can differ.

Strong lens cosmography

One way to infer the current expansion rate of the universe (H_o) is to model time delay and lensing galaxy (Schneider+, 2006).

$$\text{Time delay } (\Delta t_{ij}) = \frac{\text{Time delay distance } (\ D_{\Delta t}(H_o, z, \Omega)\ )}{\text{Speed of light } (c)} \times \text{Fermat potential difference } (\Delta \phi_{ij})$$



Time delay challenge

Time delay challenge (Dobler+, 2015; Liao+, 2016; Tak+, 2017; Hu+,?):
A blind competition to improve existing time delay estimation methods.

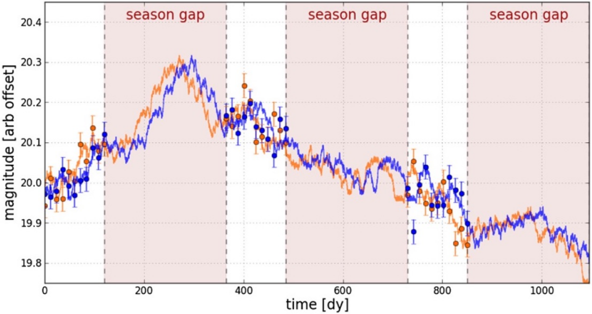
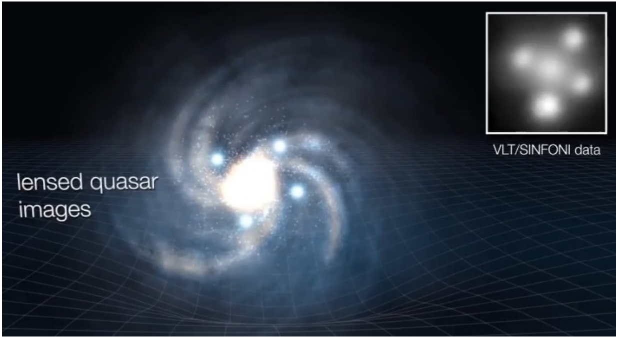


Image Credit: Dobler et al. (2015)

Modeling time delay: The blue time series of brightness is lagging behind by unknown amount of time due to time delay.

Time delay lens modeling challenge

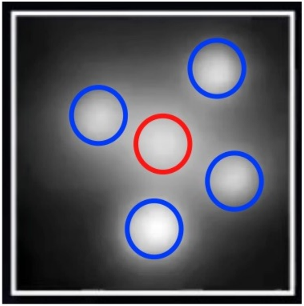
Time delay lens modeling challenge (Ding+, 2018):
Another blind competition to improve existing lens-modeling techniques.



https://www.youtube.com/watch?v=iE8x9kDHCFo

Modeling lens: Lens mass → lens potential → Fermat potential!

Time Delay Lens Modeling Challenge (cont.)



Challenges in lens modeling:

(1) Distributions for lens mass & brightness?

(2) Distribution for source brightness?

(3) How to estimates the unknown parameters in these distributions and unknown positions of lensed images?

Time Delay Lens Modeling Challenge (cont.)

Elliptical power-law mass density for an angular position $\theta_i = (\theta_{i1}, \theta_{i2})$:

$$\kappa_{\rm lens}(\theta_{i1}, \theta_{i2}) = \frac{3-\gamma'}{2} \left(\frac{\sqrt{q\theta_{i1}^2 + \theta_{i2}^2/q}}{\theta_E} \right)^{1-\gamma'},$$

where θ_E is the Einstein radius, q is the ellipticity, and γ' is the radial power-law slope.

Surface brightness density (elliptical Sérsic model):

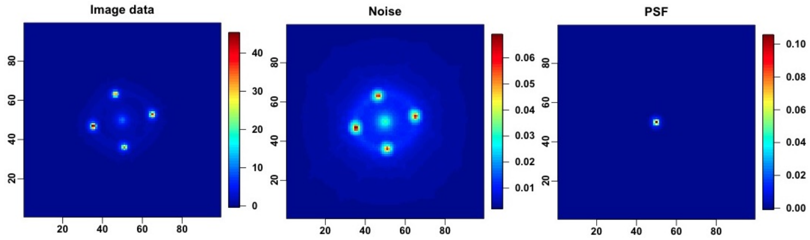
$$I(\theta_{i1}, \theta_{i2}) = A \, \exp \left[-k \left(\frac{\sqrt{\theta_{i1}^2 + \theta_{i2}^2/q_{\rm L}^2}}{\theta_{\rm eff}} \right)^{1/n_{\rm sersic}} - k \right],$$

where A is an amplitude, k is a constant (s.t. $\theta_{\rm eff}$ is the effective half-light radius), $q_{\rm L}$ is the axis ratio, and $n_{\rm sersic}$ is the Sérsic index.

Time Delay Lens Modeling Challenge (cont.)

Given information:

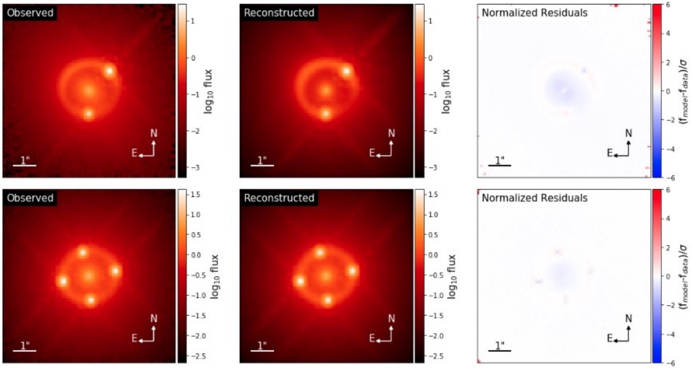
- HST-like image data (99×99 pixels), noise, and PSF.



- Time delay estimates and uncertainties, e.g., $24.2^{+0.1}_{-0.2}$ days.
- Line-of-sight lens velocity dispersion (stellar kinematic information), and external convergence, $\kappa_{\rm ext} \sim [0, 0.025^2]$.

Example: TDLMC Stage 1

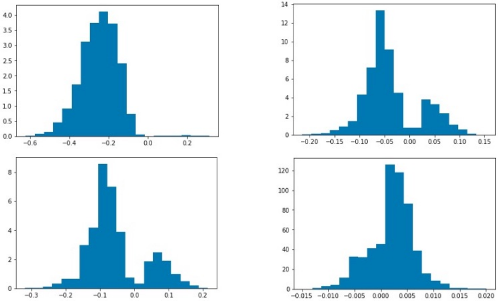
- The first stage (out of four) has two lenses with the true H_o known.
- A Python package `lenstronomy` (Birrer+, 2015, 2016, 2018) fits a lens model on each image (1st column), reconstructs images using the fitted model (2nd), and shows residual plots (3rd = 2nd − 1st).



Example: TDLMC Stage 1

`lenstronomy` (Birrer+, 2015, 2016, 2018) also returns posterior distributions of Fermat potential differences.

Double lens ($\Delta\phi_{\mathrm{BA}}$) Quad lens ($\Delta\phi_{\mathrm{BA}}$)



Quad lens ($\Delta\phi_{\mathrm{CA}}$) Quad lens ($\Delta\phi_{\mathrm{DA}}$)

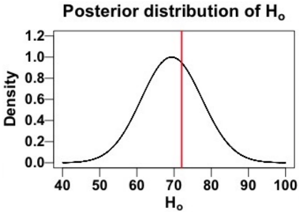
Now we have all necessary information to infer H_o!

EXAMPLE: TDLMC STAGE 1 (CONT.)

Considering that $\Delta t_{ij} = \frac{D_{\Delta t}(H_o, z, \Omega)}{c} \Delta\phi_{ij}$, Marshall+ (2016) suggest a simple likelihood function of H_o based on

$$\Delta\phi_{ij} \mid \Delta t_{ij}, H_o \sim \mathrm{N}\left[\frac{c}{D_{\Delta t}(H_o)} \Delta t_{ij},\ \sigma^2_{\Delta\phi_{ij}}\right],$$
$$\Delta t_{ij} \sim \mathrm{N}(\Delta t^*_{ij},\ \sigma^{2*}_{\Delta t_{ij}}).$$

The resulting posterior of H_o with known Δt^*_{ij}, $\sigma^{2*}_{\Delta t_{ij}}$, z, and Ω is



Note: I fitted a lens model, fixing some parameters at their true values.

Concluding remarks

Challenges (at least to me!)

- Python!
- No clear likelihood specification in articles → black-box packages?
- In using `lenstronomy`, how to reflect all the given information including "Noise" data and "lens velocity dispersion"?
- A better model for H_o?
- 48 lenses (16 lenses for each of 3 stages) to be analyzed by Aug 4.

Please join this project, if you are interested in analyzing image data!

Image Credit: James Montgomery Flagg

Reference

1. Birrer et al. (2015) "Gravitational Lens Modeling with Basis Sets." *ApJ* **813**, 102.
2. Birrer et al. (2016) "The Mass-Sheet Degeneracy and Time-Delay Cosmography: Analysis of the Strong Lens RXJ1131-1231." *JCAP* **2016** (8), 20.
3. Birrer and Amara (2018) "lenstronomy: Multi-Purpose Gravitational Lens Modelling Software Package." arXiv preprint 1803.09746.
4. Ding et al. (2018) "Time Delay Lens Modeling Challenge: I. Experimental Design." arXiv preprint 1801.01506.
5. Dobler et al. (2015) "Strong lens time delay challenge: I. Experimental design." *ApJ*, **799**, 168.
6. Liao et al. (2015) "Strong lens time delay challenge: II. Results of TDC1." *ApJ*, **800**, 23.
7. Mashall et al. (2016) "The Second Strong Lens Time Delay Challenge: I. Experimental Design." Unpublished work.
8. Schneider et al. (2006) "Gravitational Lensing: Strong, Weak and Micro", Springer.
9. Tak et al. (2017) "Bayesian and Profile Likelihood Strategies for Time Delay Estimation from Stochastic Time Series of Gravitationally Lensed Quasars", *AoAS*, **11** (3), 1309–1348.