NAZARBAYEV UNIVERSITY

ENERGETIC COSMOS LABORATORY

Distinguishing Time Delays from Multi-Messenger Transients with Deep Learning

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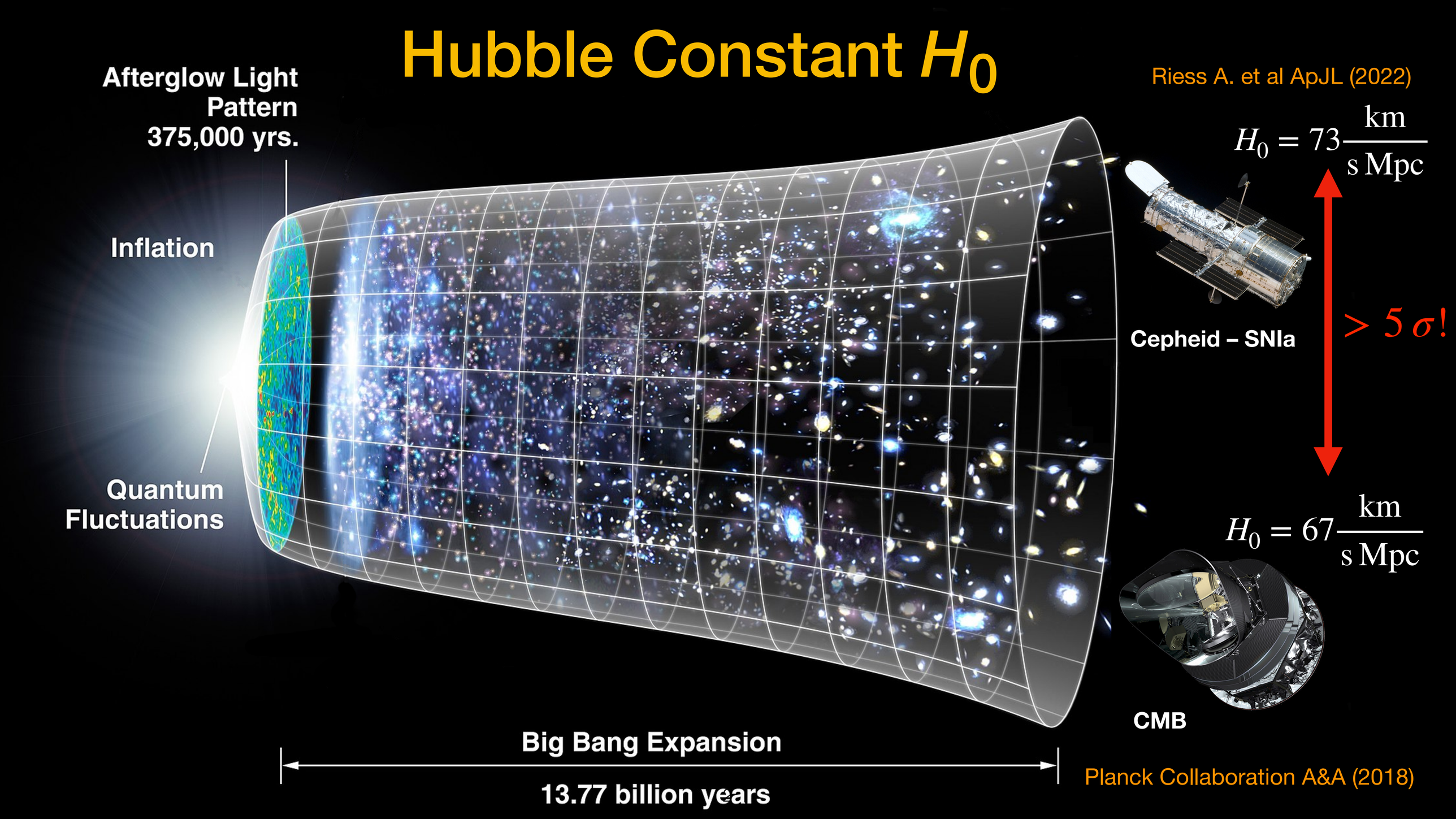
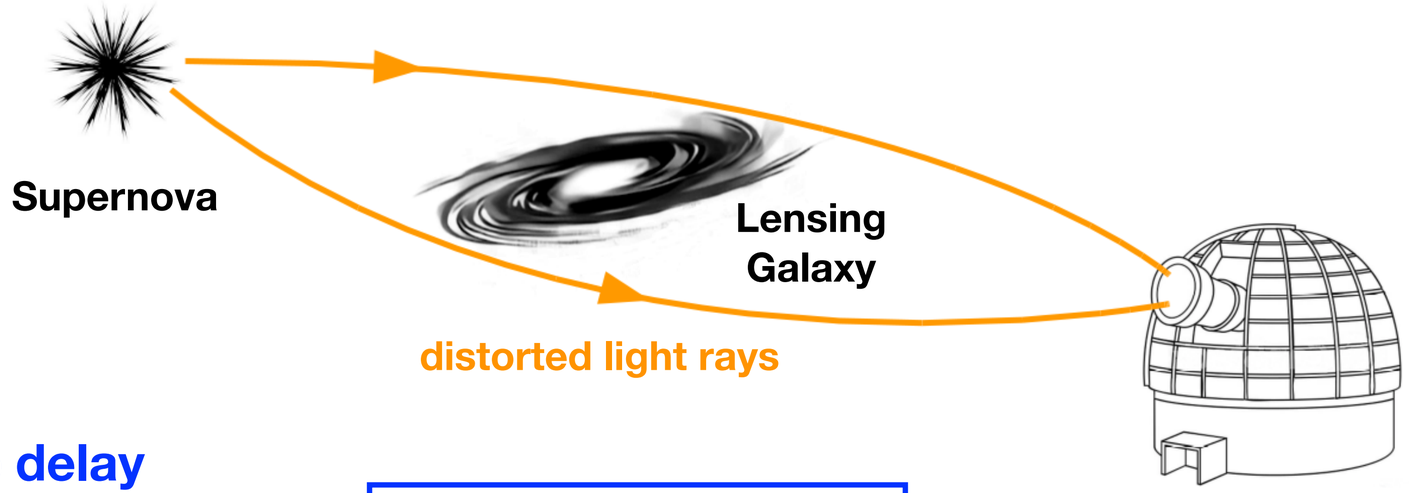
Probing the Universe with Multimessenger Astrophysics
September 27, 2022

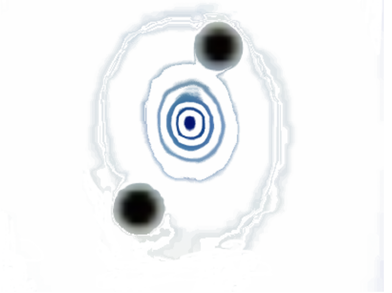
Hubble Constant H_0

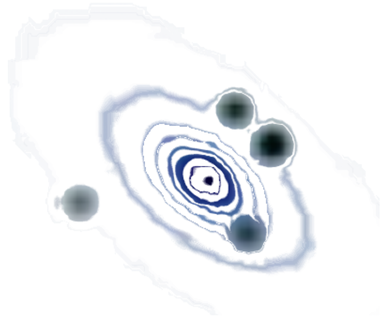


Gravitationally Lensed Type Ia Supernovae



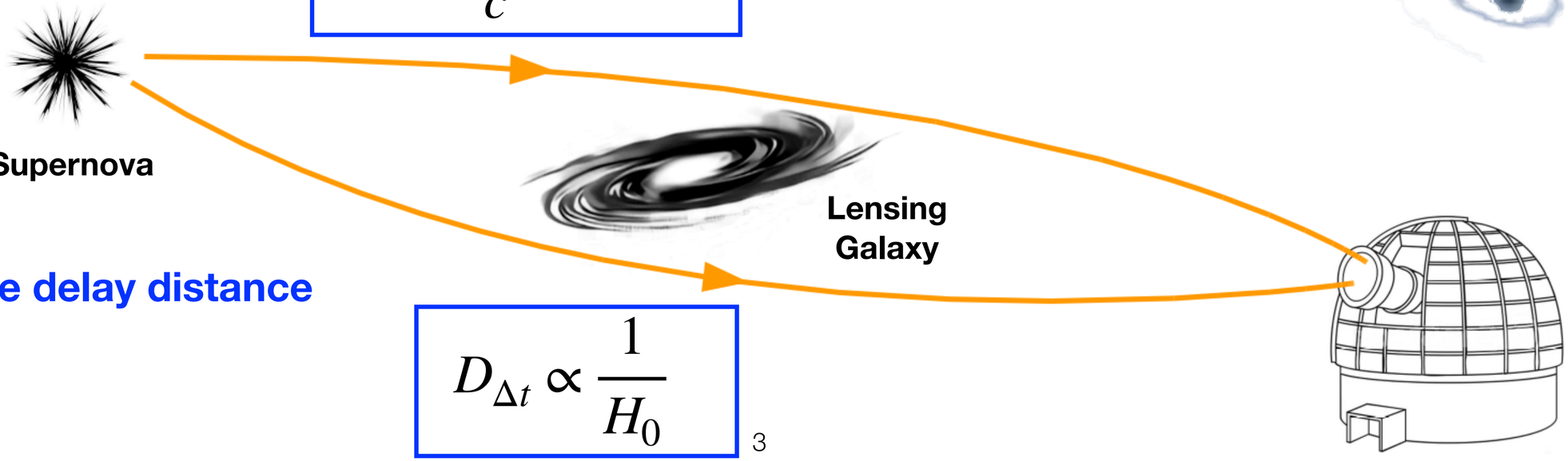
RESOLVED





Time delay

$$\Delta t = \frac{1}{c} D_{\Delta t}\, \phi_{\text{lens}}$$



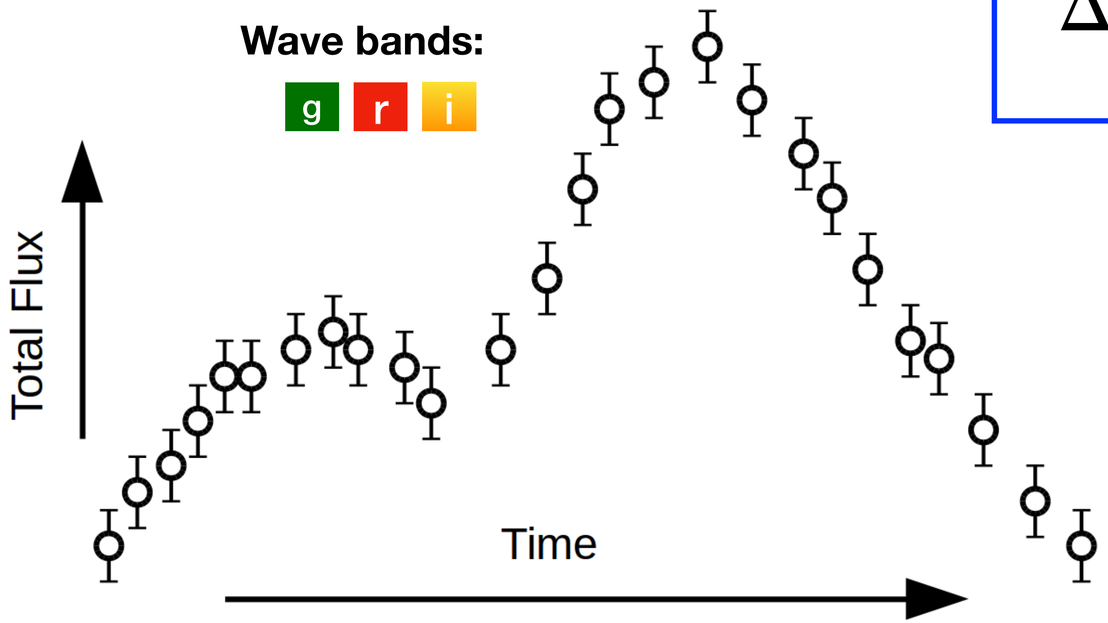
Time delay distance

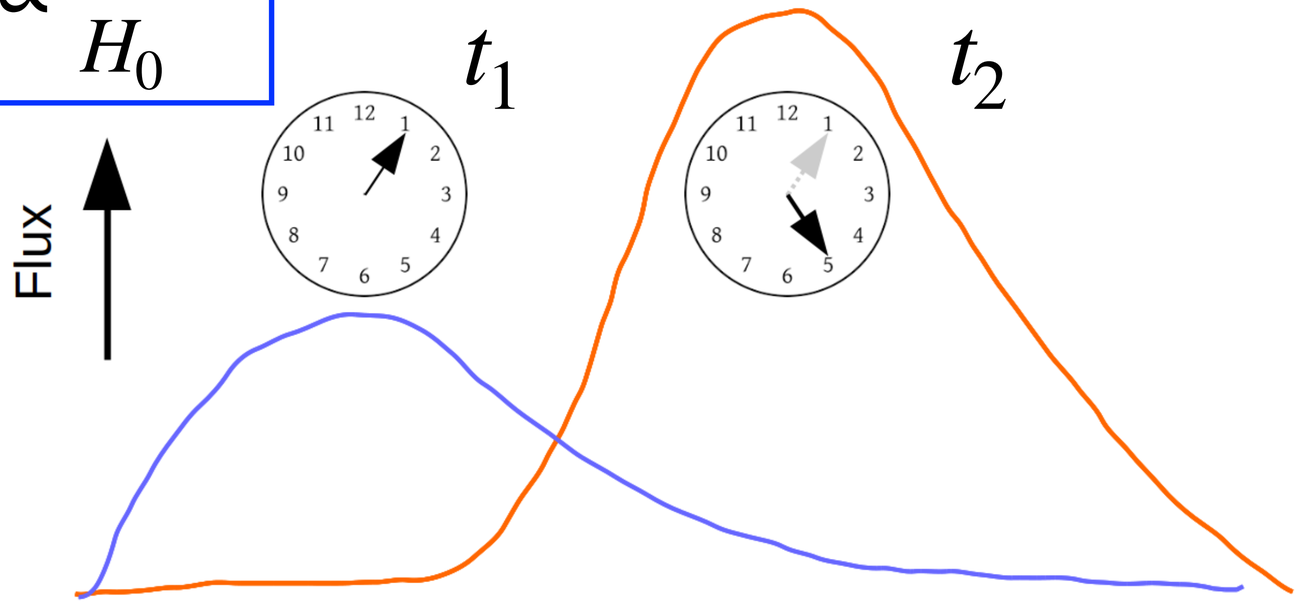
$$D_{\Delta t} \propto \frac{1}{H_0}$$

Probing Cosmic Expansion with Lensing Time Delays

Lensing time delays encode information on Hubble expansion rate

$$\Delta t \propto \frac{1}{H_0}$$





Only few lensed type Ia supernovae are resolved

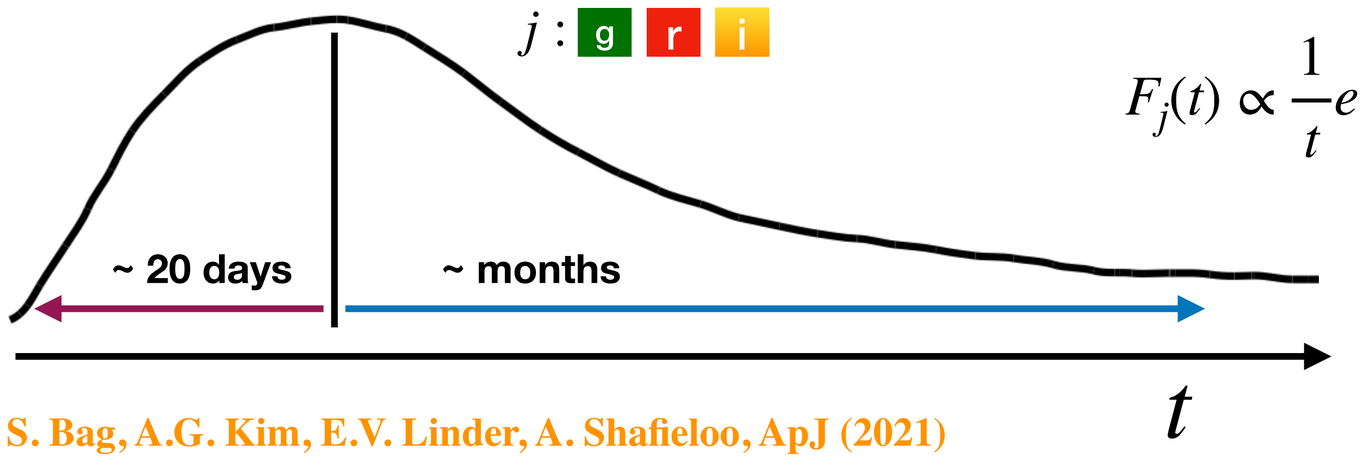
We focus on unresolved lensed lightcurves from type Ia supernovae

UNRESOLVED

Lightcurve Fitting Approaches

Log-normal Fitting

Unlensed lightcurve



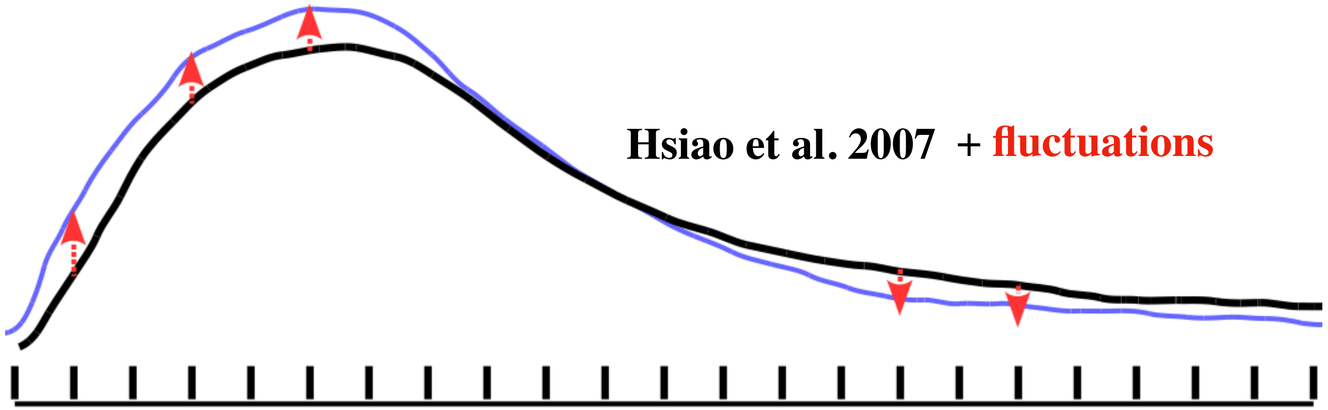
S. Bag, A.G. Kim, E.V. Linder, A. Shafieloo, ApJ (2021)

$$F_j(t) \propto \frac{1}{t} e^{-\frac{(\ln t - b_j)^2}{2\sigma_j^2}} \left(\sum_{k=1}^{4} \text{Chebyshef polynomials} \right)$$

Number of images: 2

Number of parameters: a few dozens

Freeform Fitting



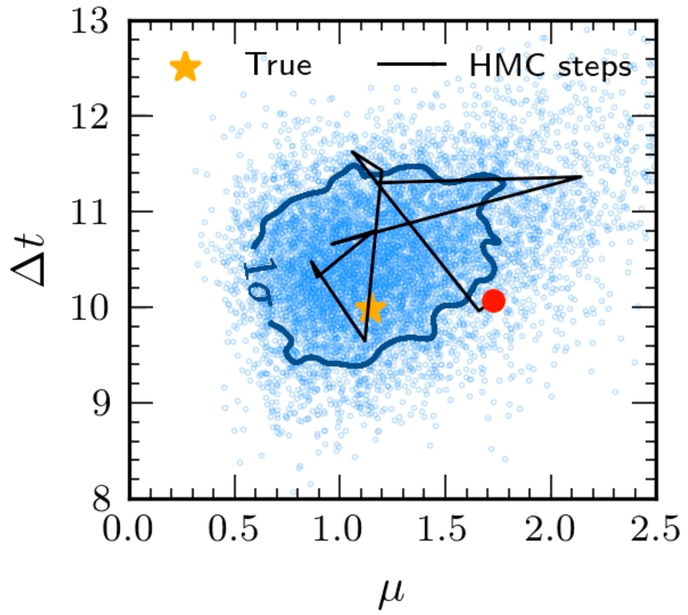
M. Denissenya, S. Bag, A.G. Kim, E.V. Linder, A. Shafieloo, MNRAS (2022)

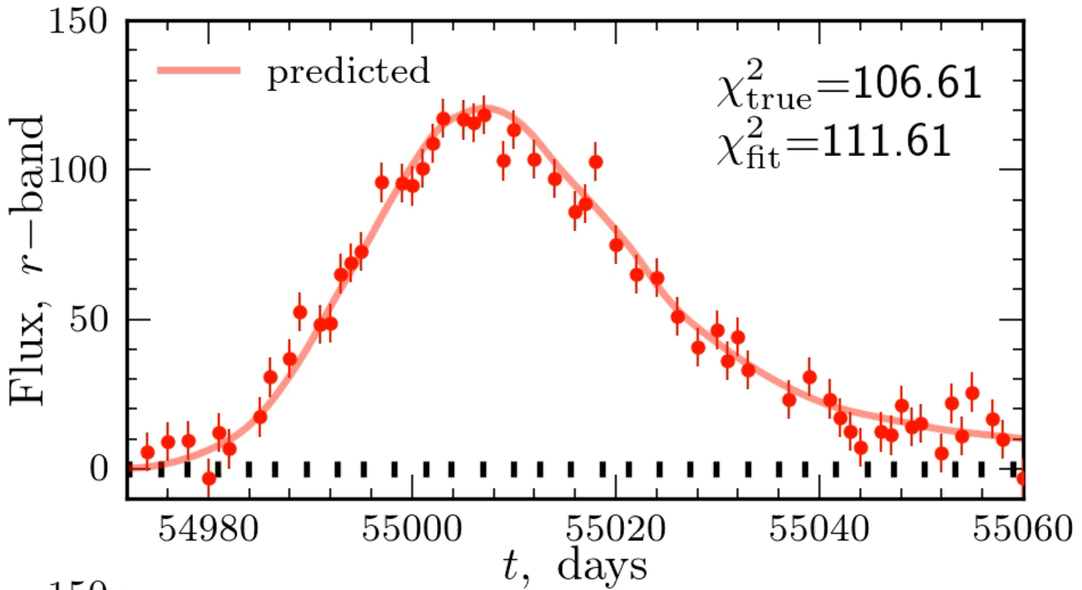
$$F_j(t) = \sum_{i \in \text{images}} \mu_i \, U_j(t - \Delta t_i)$$

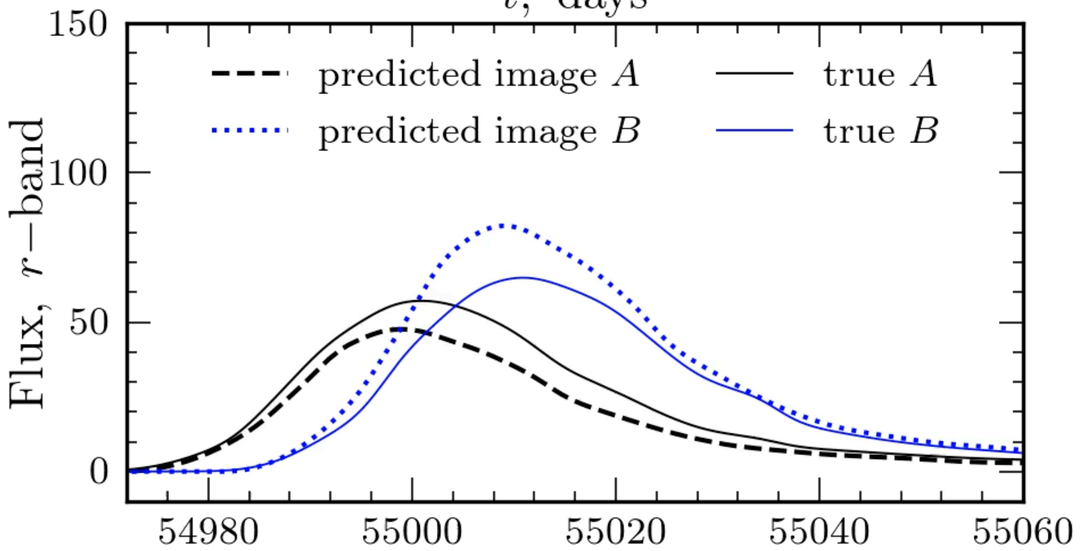
Number of images: 2 or 4

Number of parameters: a few hundreds

Freeform Fit Example with MCMC



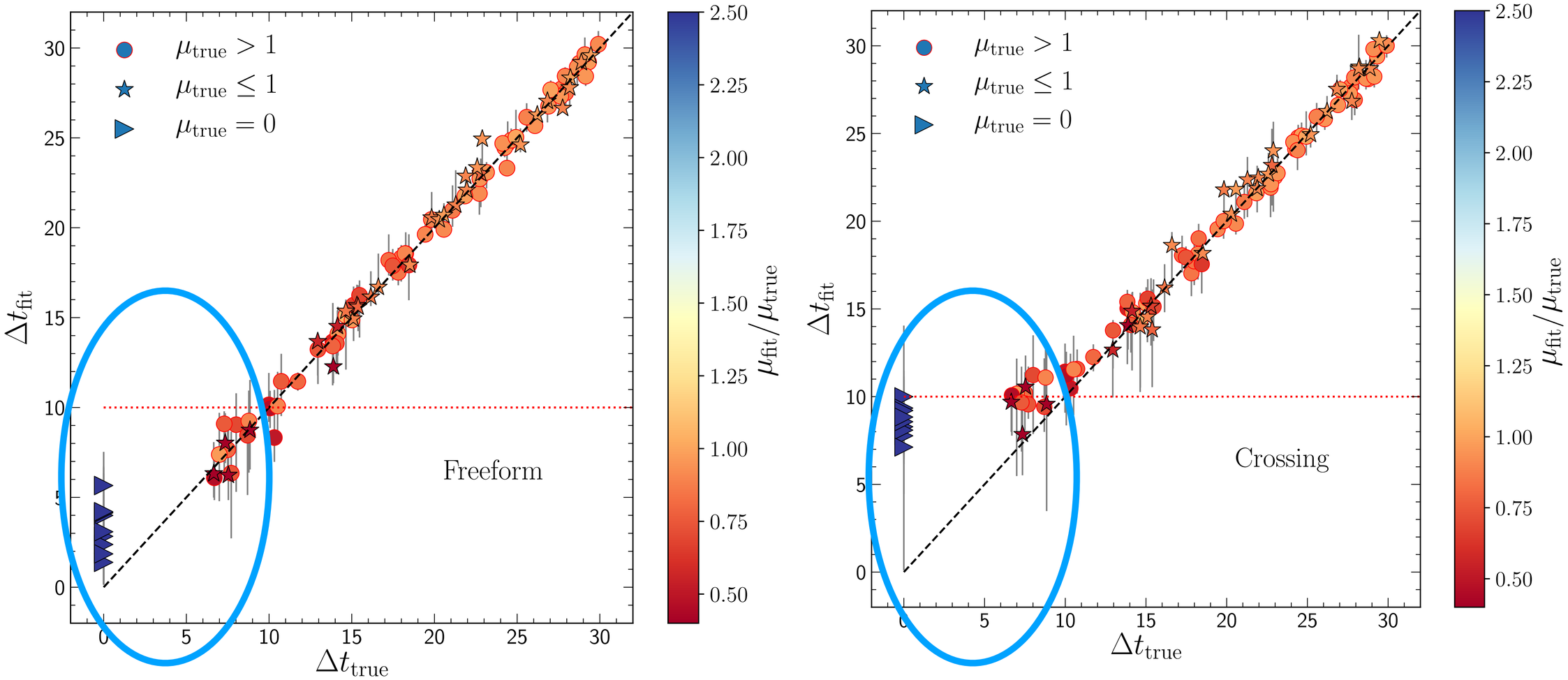




Drawbacks:

- Markov Chain Monte Carlo optimization is time consuming (~ hours/system)
- Fits are robust for time delays $\gtrsim 10$ days
- One, two or four image classification is based on Goodness-of-Fit criterion

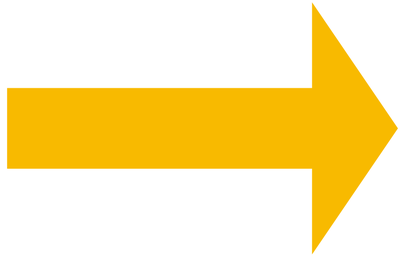
Freeform vs Log-normal



Idea: Let Neural Network estimate time delays from an **ensemble** of lensed lightcurves

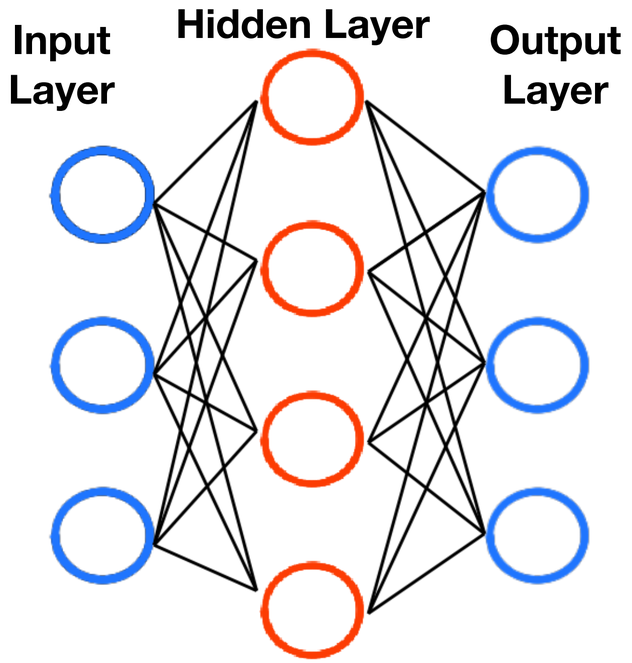
Deep Learning Lensed Lightcurves

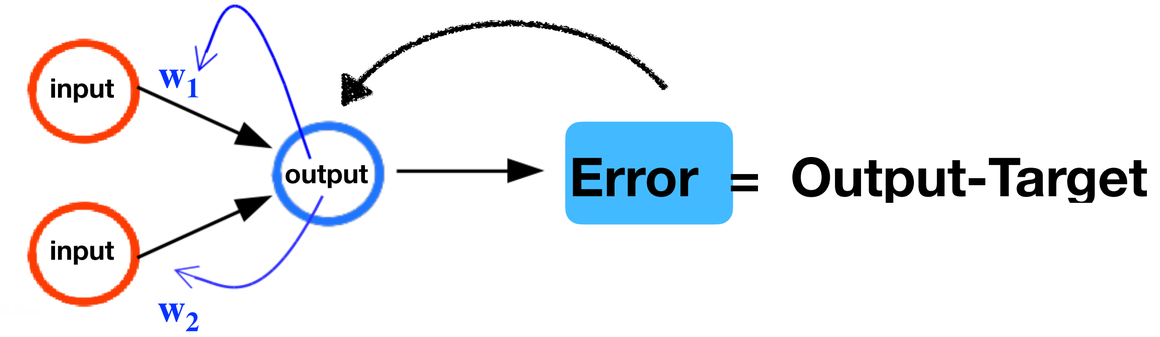
Hand Designed Model



Mapping Learned by Machine

Artificial Neural Network





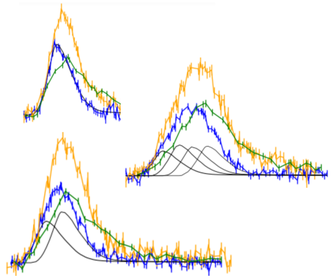
Weights update rule

$$w :\to w - \eta \Delta_w C$$

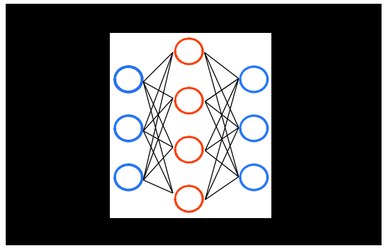
where η is the learning rate

CNNc:

Input:



Neural Network

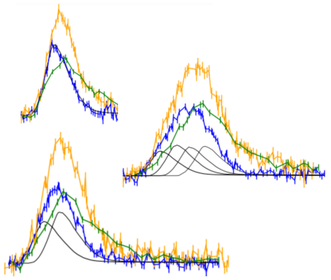


Output:

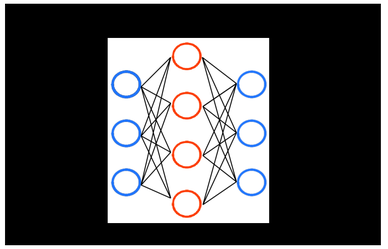
Number of images

CNN2/4:

Input:



Neural Network

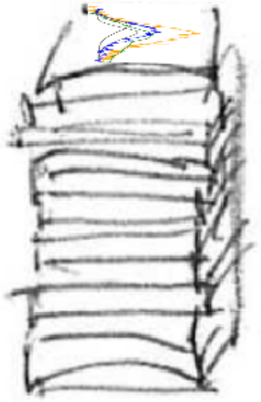


Output:

Time Delays

Neural Net for Classification (CNNc)

PyTorch

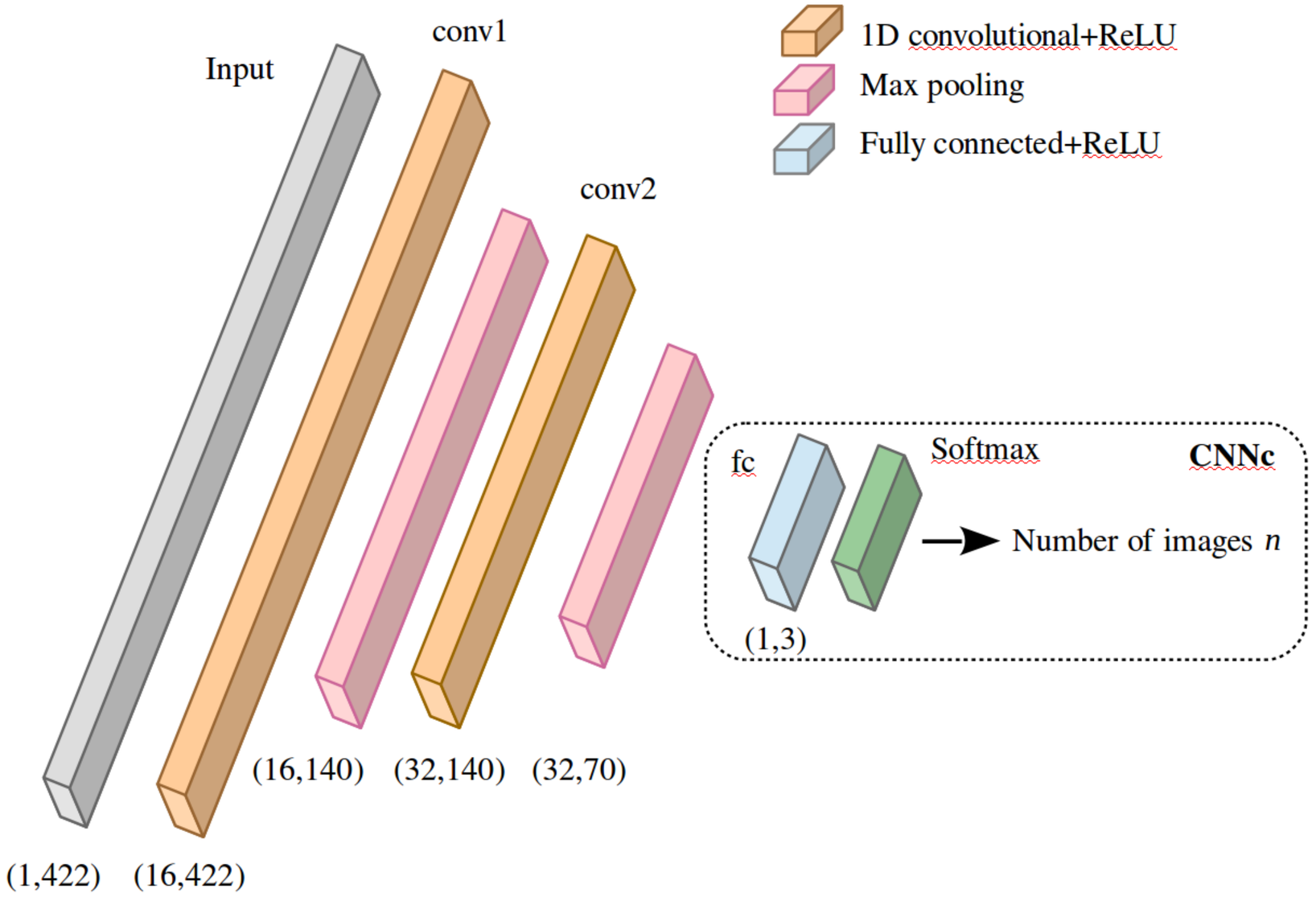


8000 training samples

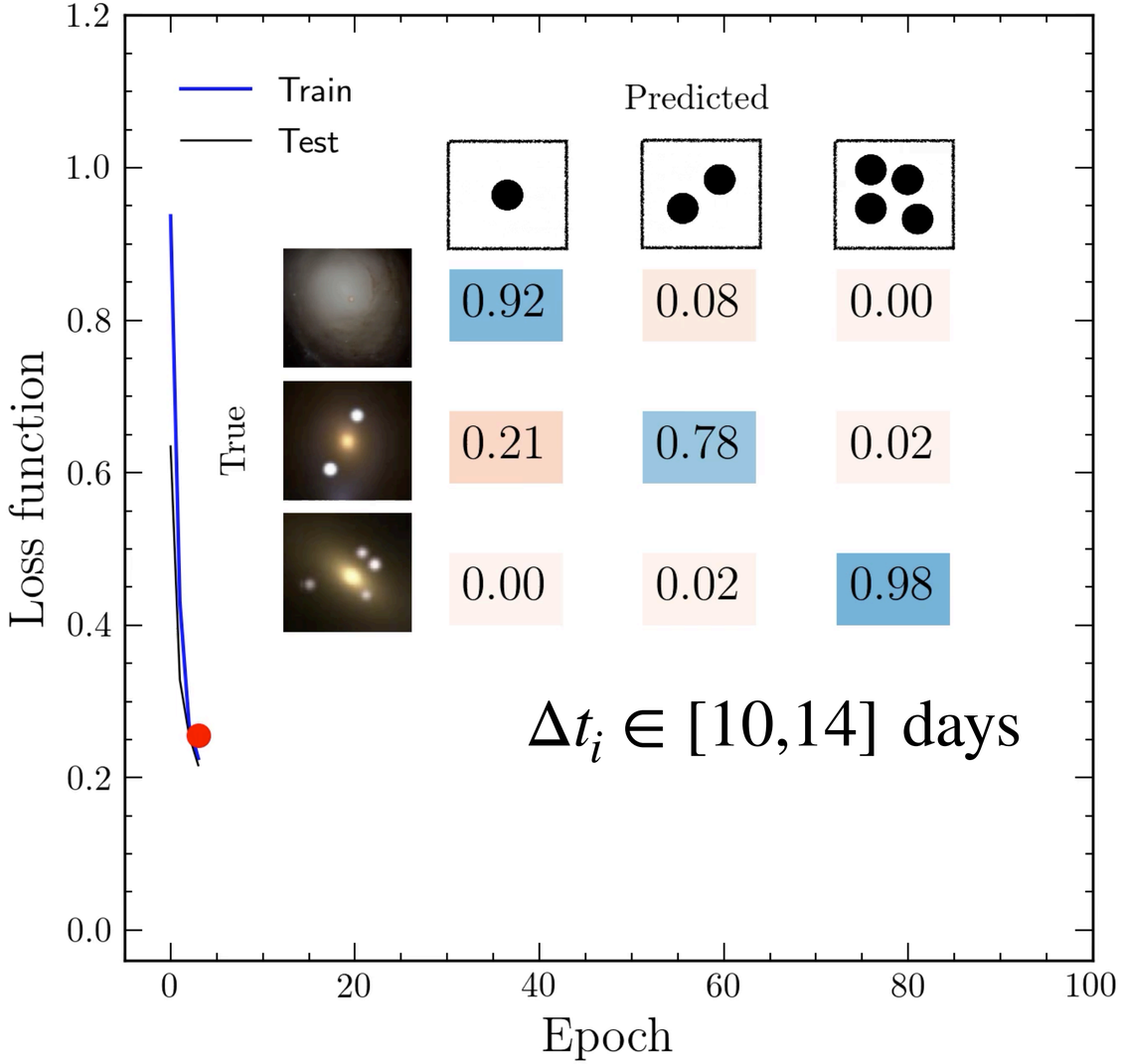
2000 test samples

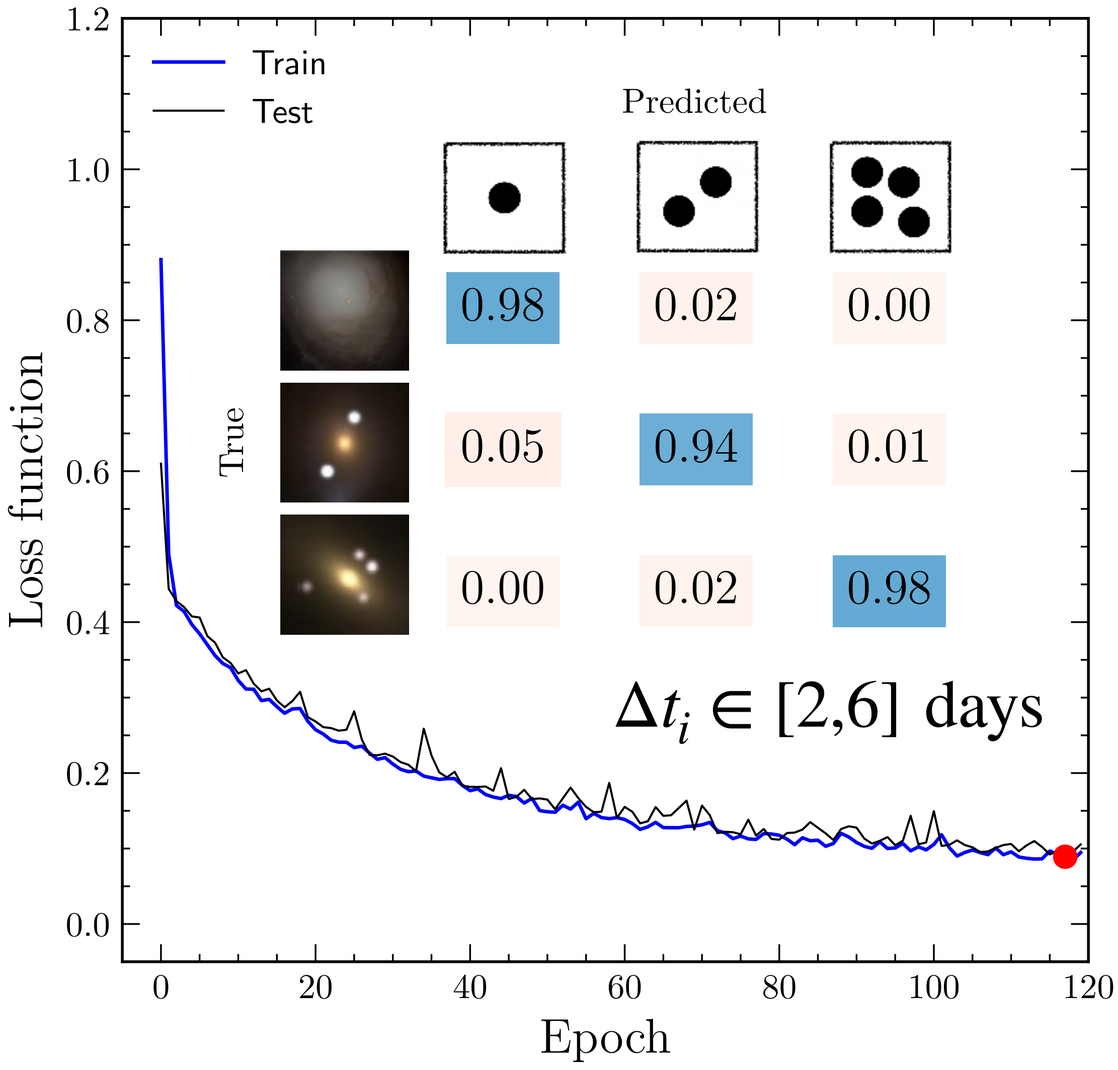
$\Delta t_i \in [10,14]$ days

$\mu \in [0.25,4]$



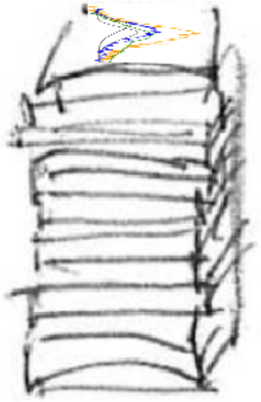
CNNc Neural Network Performance





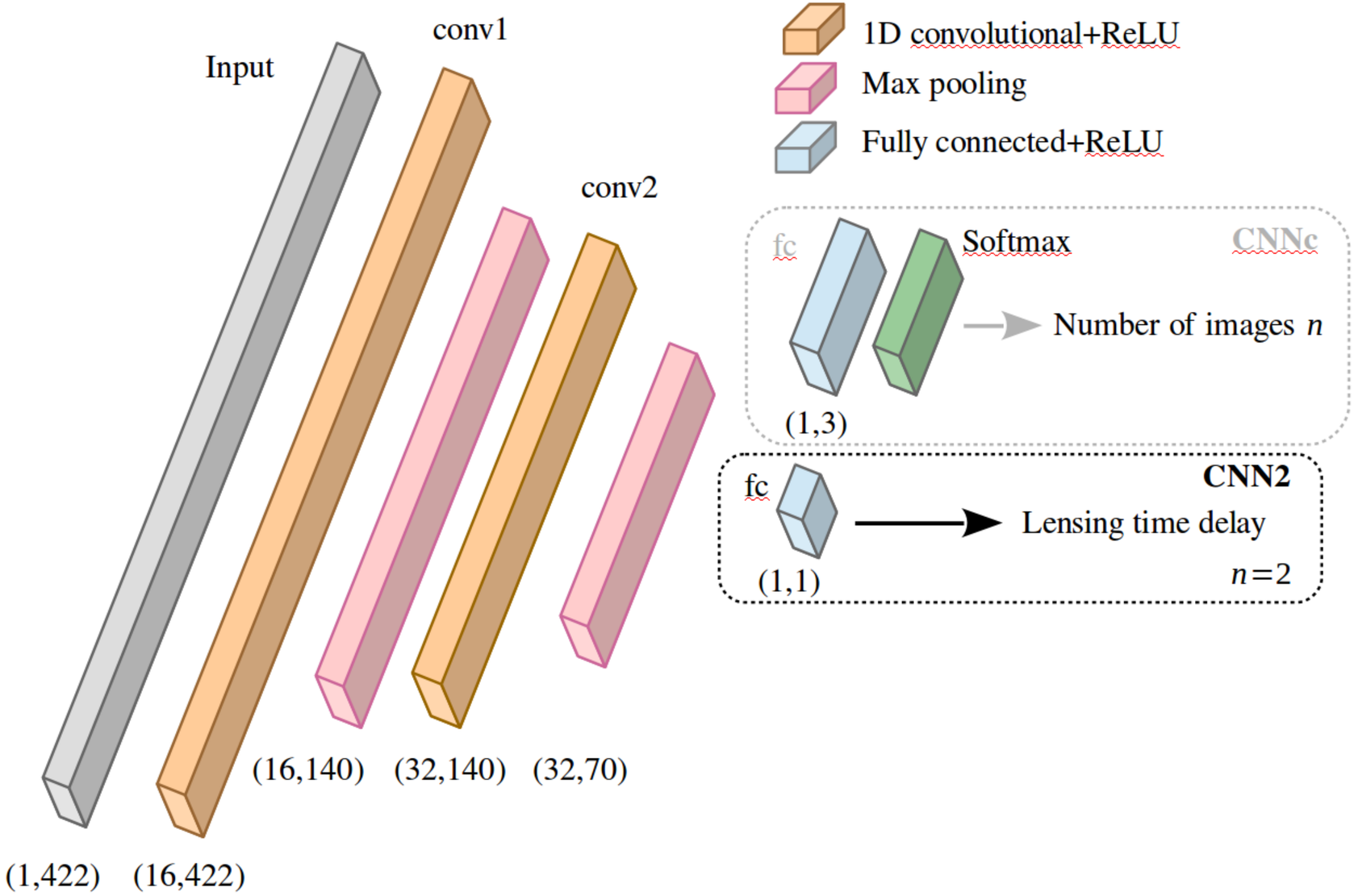
Neural Net for Time Delay Estimation (CNN2)

PyTorch

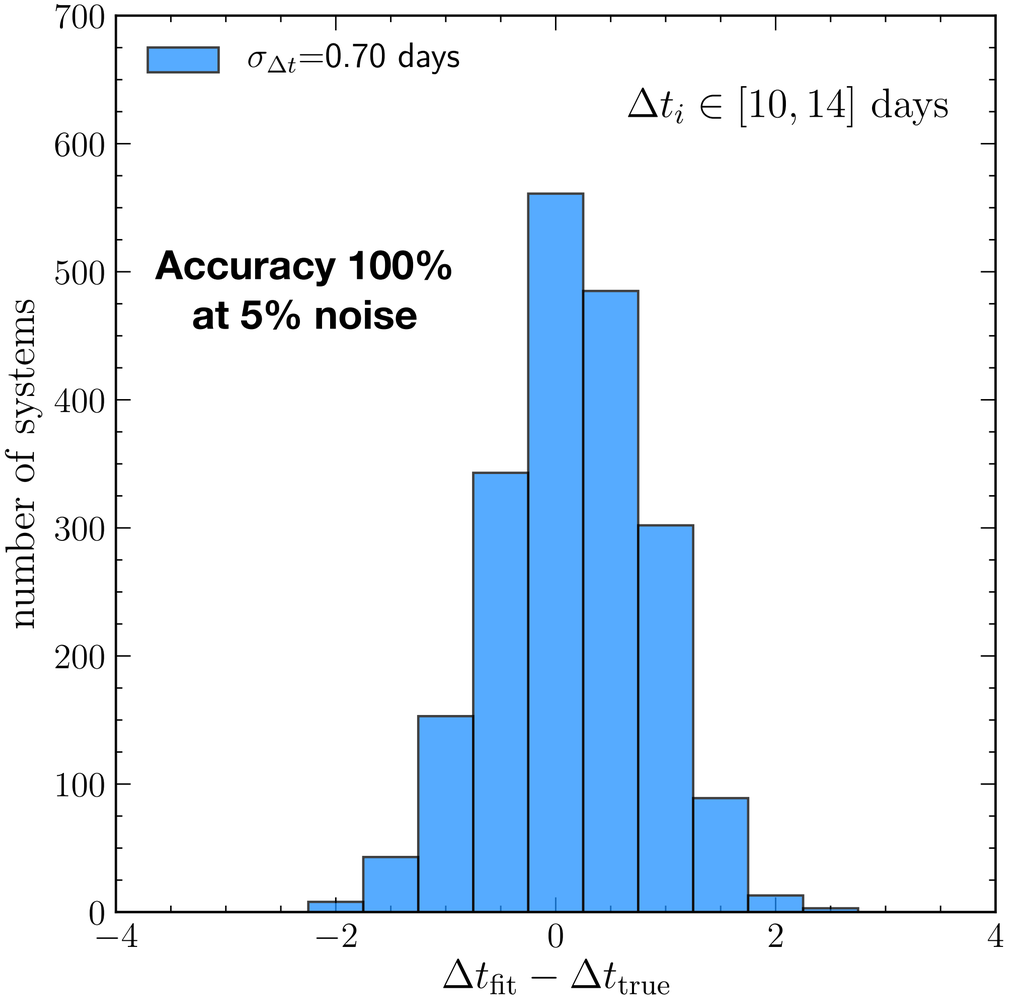


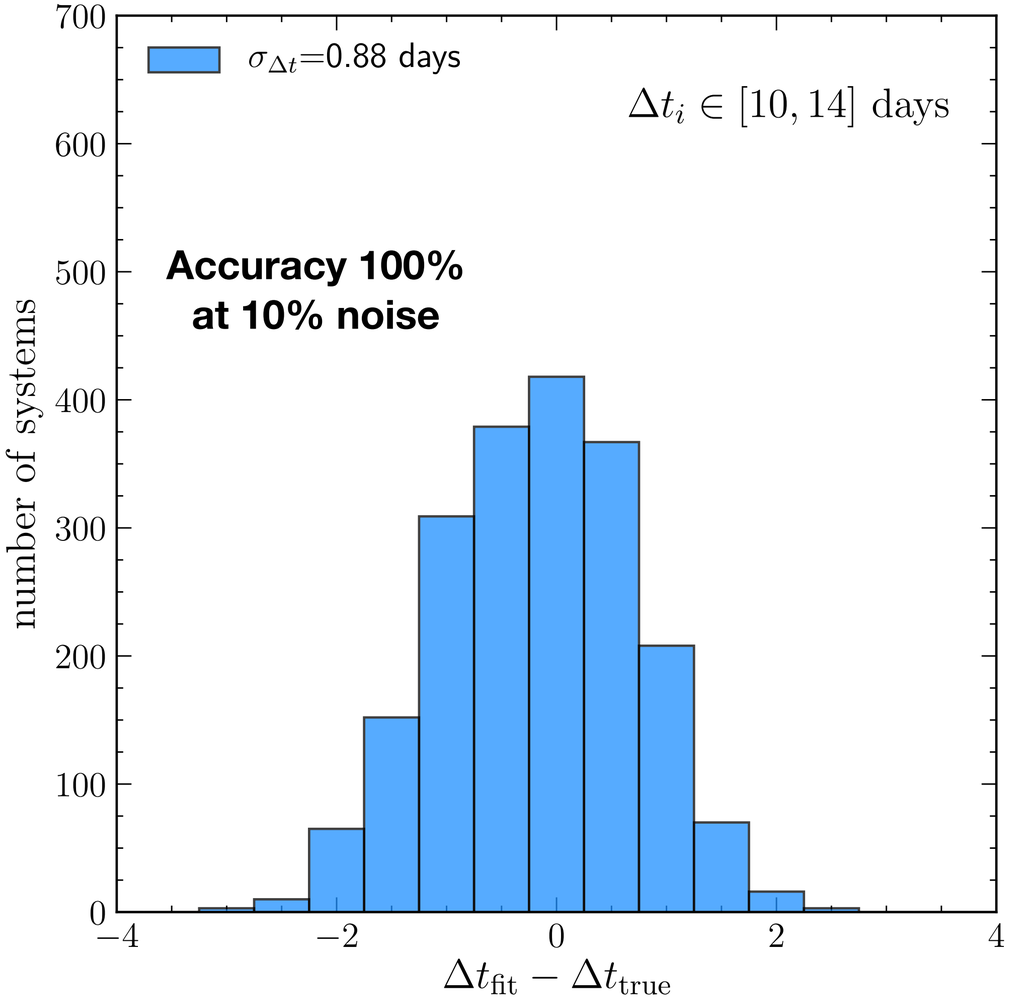
8000 training samples

2000 test samples

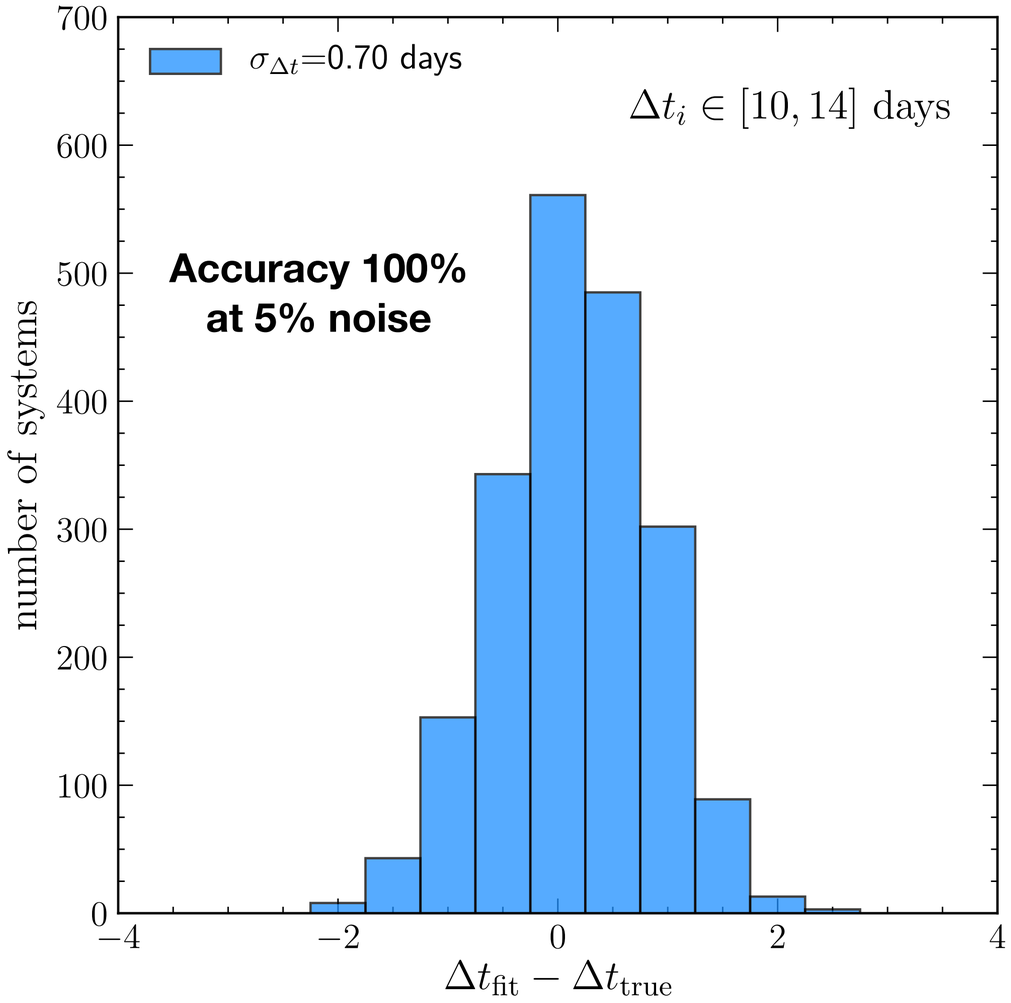


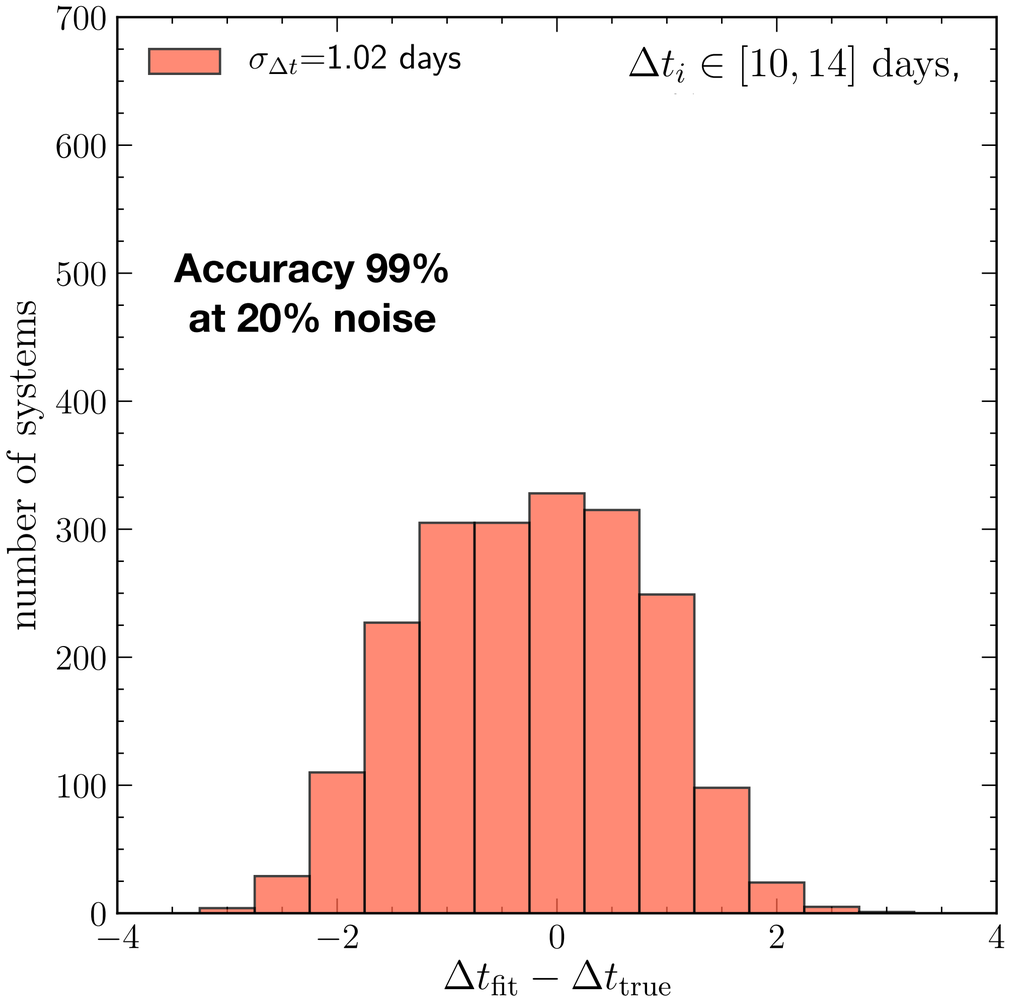
Lensing Time Delays: 2-image



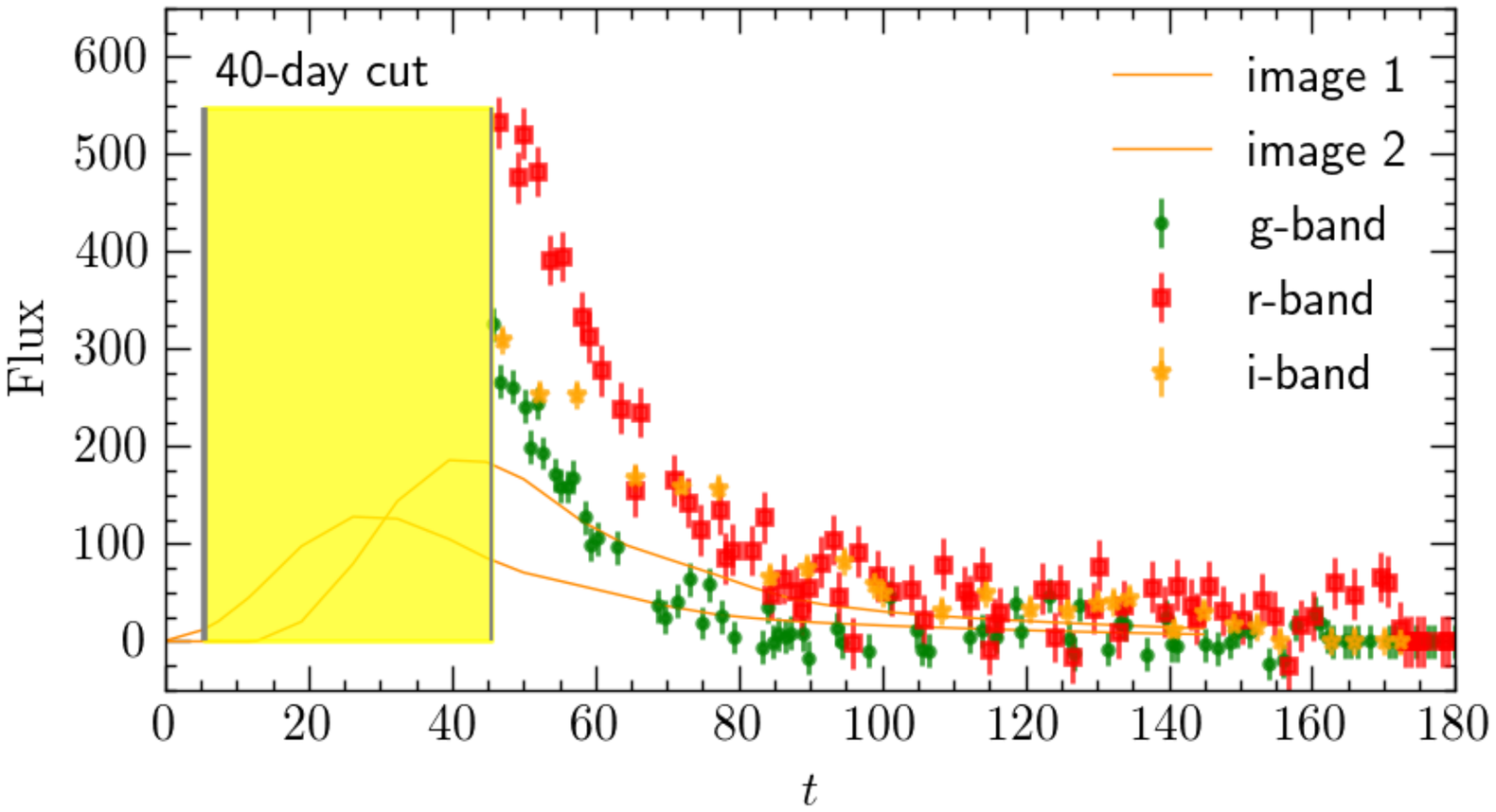


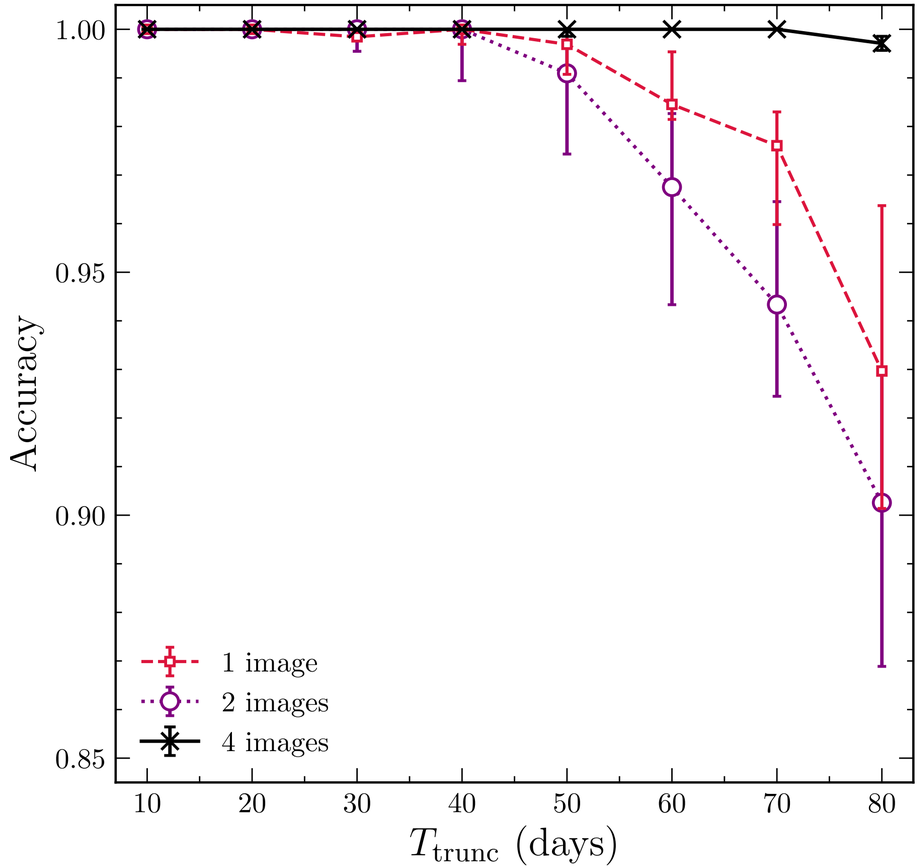
Lensing Time Delays: 2-image





CNNc Net Test on Partial Lightcurves





Summary

- Deep learning allows to successfully distinguish lensed and unlensed systems, determine number of images and extract time delays with ~1 day precision down to $\gtrsim 6$ days.
- We obtain $\times 1000$ speed up compared to both the freeform and log-normal fitting approaches with MCMC technique. The neural network performance is robust up to $\times 4$ increase in the noise level.
- Our deep learning implementation reliably identifies the systems and estimates the time delays for lensed supernova lightcurves with missing early time observations up to 40 days.

M. Denissenya, E. V. Linder MNRAS(2022), Vol515

Thank you for your attention!