FERMILAB-SLIDES-22-051-SCD

DeepQuasar: Simulation-based inference for lensed quasar modeling

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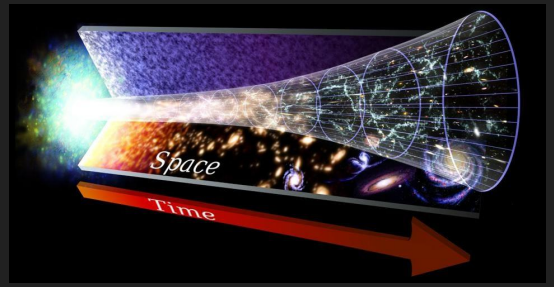
Hubble constant H_0 in LCDM

Expansion of the Universe

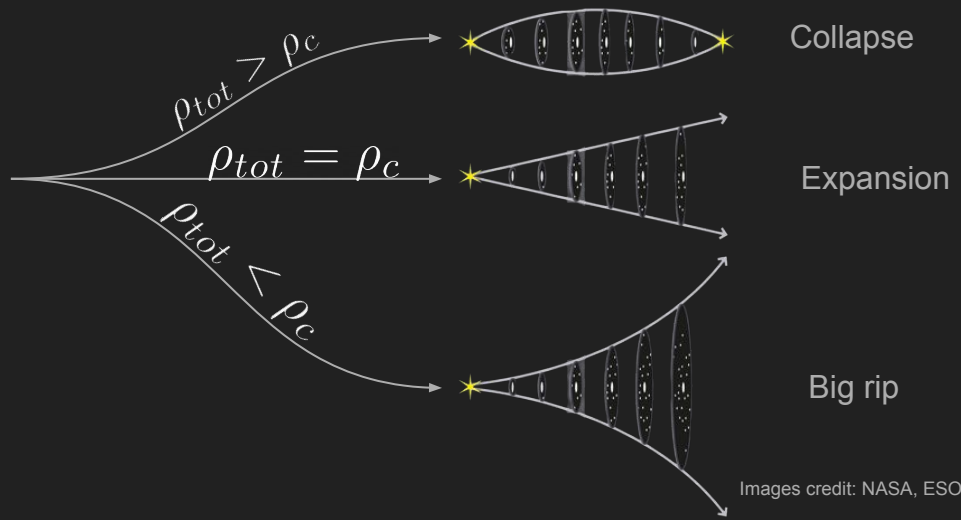


Expansion of the Universe $a(t) = a_0 e^{Ht} + \ldots$

Insight into dark energy $\Lambda = 3H_0^2 + \ldots$

Fate of the Universe

Critical density of the Universe $\rho_c = \dfrac{3H_0^2}{8\pi G}$



Images credit: NASA, ESO Supernova

Measurement discrepancies

Hubble rate H_0

Direct methods → $H_0 = 74.03 \pm 1.42\ km\ s^{-1} Mpc^{-1}$

Indirect methods → $H_0 = 67.4 \pm 0.5\ km\ s^{-1} Mpc^{-1}$

>3σ discrepancy

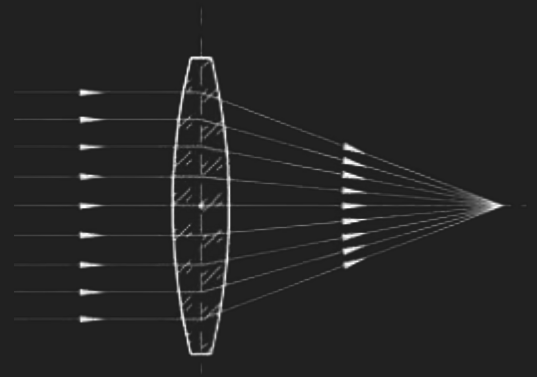
→ Mistakes in detectors

→ New physics

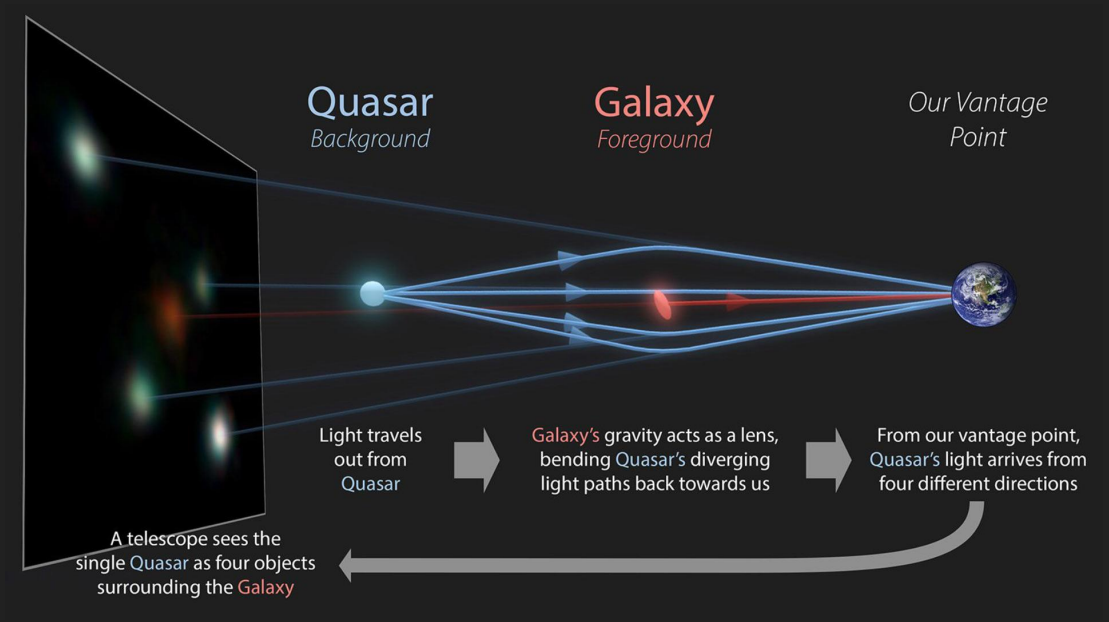
Solution: Time delay cosmology

Gravitational lensing

Ordinary lensing



Gravitational lensing

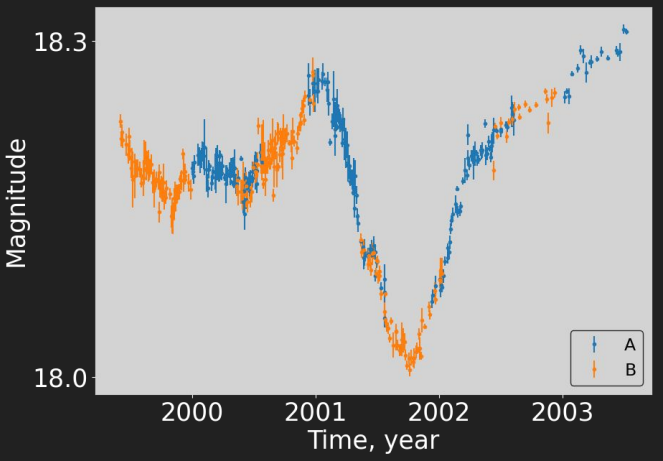


Time delay: $t(\vec{\theta}) = \frac{D_{\Delta t}}{c}\phi(\vec{\theta}) \propto \frac{1}{H_0}\phi(\vec{\theta})$

Image credit: R. Hurt, IPAC & Caltech / Gaia Gravitational Lenses group

Gravitationally Lensed Quasars (LQSO)

Quasar light curves

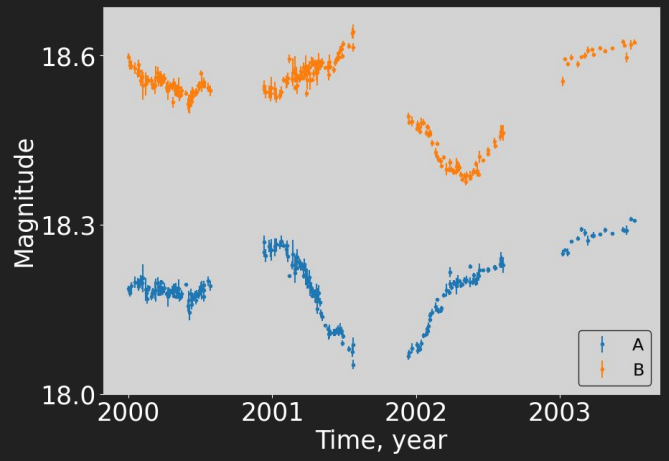


Lensing

Shifts: time and magnitude

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

Lensed quasar light curves



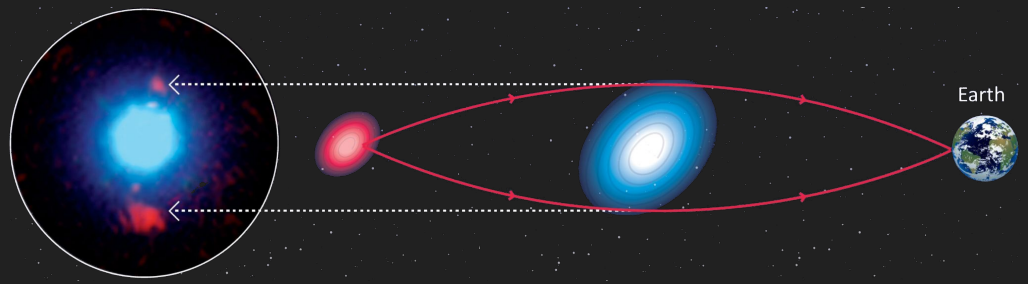


Image credit: fftech.net

Outline of the presentation

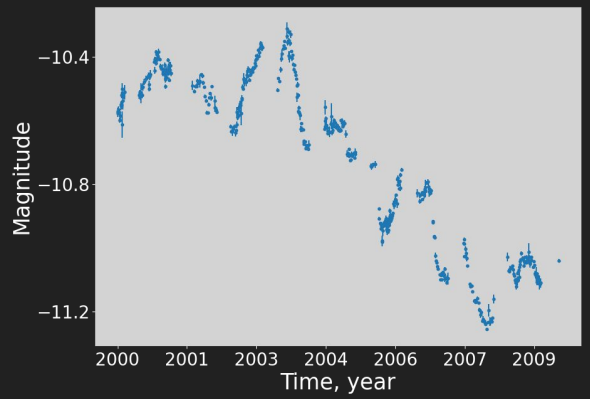
1. Challenges of inference
2. Neural networks-based method
3. Performance of neural networks

Challenges of inference

Quasar model - accretion + reverberation

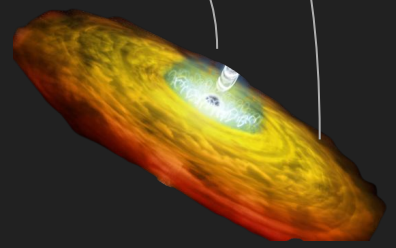
$$\underbrace{I(t)} \propto \int_0^\infty \underbrace{f_{acc}(t - t_\lambda \rho)}\underbrace{P_{disk}(\rho)} d\rho \sim \underbrace{\mathcal{N}(\mu, \Sigma[\hat{\sigma}^2, \tau, t_\lambda])}$$

Quasar light curve

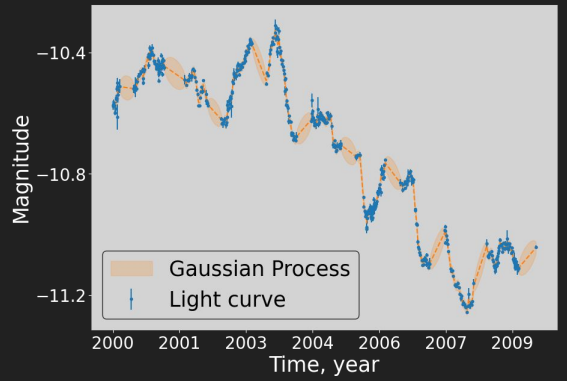


Accretion onto black hole

Reverberation of the disk



Gaussian stochastic process



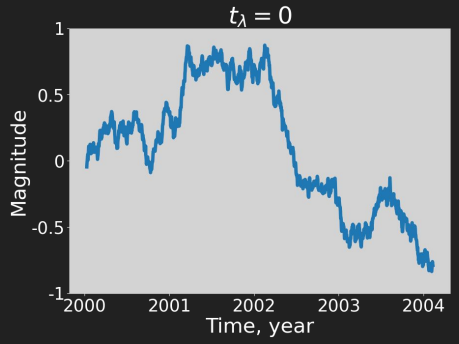
Images credit: NASA

Quasar model - Reverberating Damped Random Walk

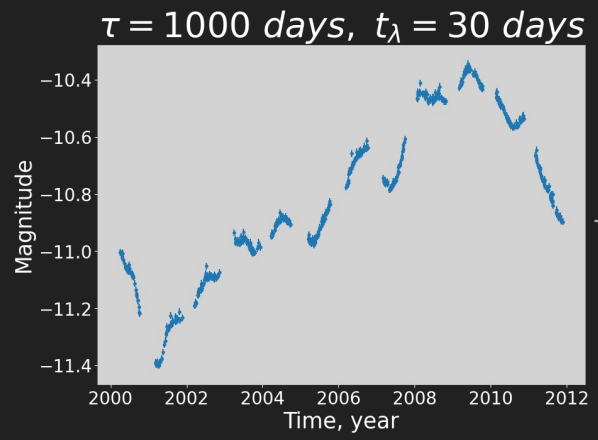
Autocorrelation: $$\int_{-\infty}^{\infty} f(t'+\Delta t) f(t') dt' \propto \tau \cdot exp\left(-\frac{|\Delta t|}{\tau}\right) - 4t_\lambda \cdot exp\left(-\frac{|\Delta t|}{4t_\lambda}\right)$$

Correlation time τ
global evolution (years)

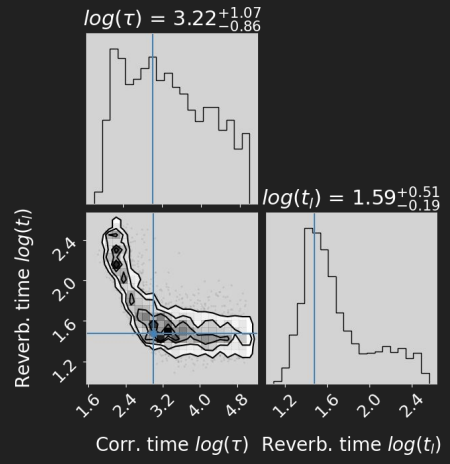
Reverberation time t_λ
local evolution (days)



Challenge of inference



Gaussian likelihood MCMC

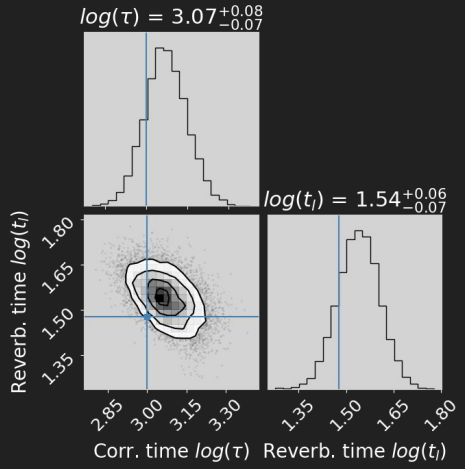


1σ constraints:

$$200 < \tau < 20000\ days$$

$$25 < t_\lambda < 125\ days$$

Neural Network

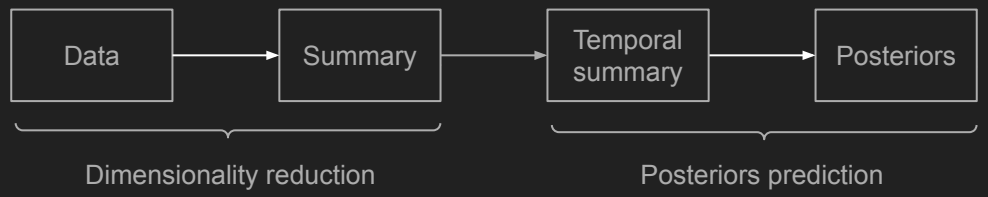


1σ constraints:

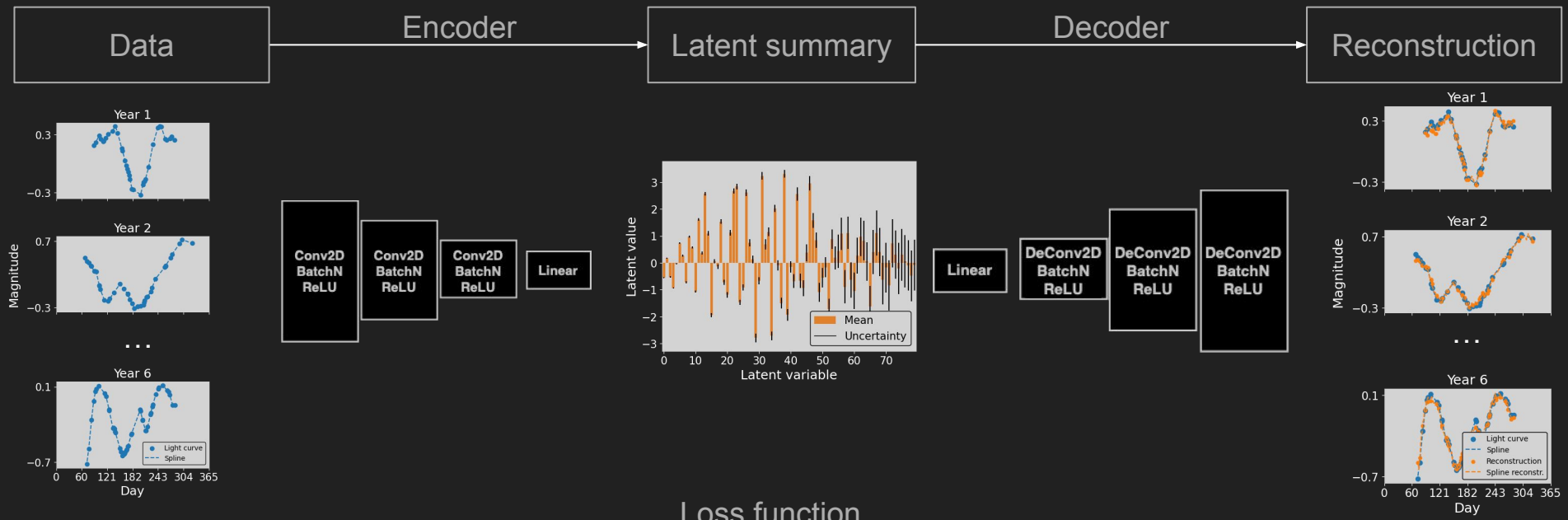
$$990 < \tau < 1410\ days$$

$$29 < t_\lambda < 40\ days$$

Neural networks-based method



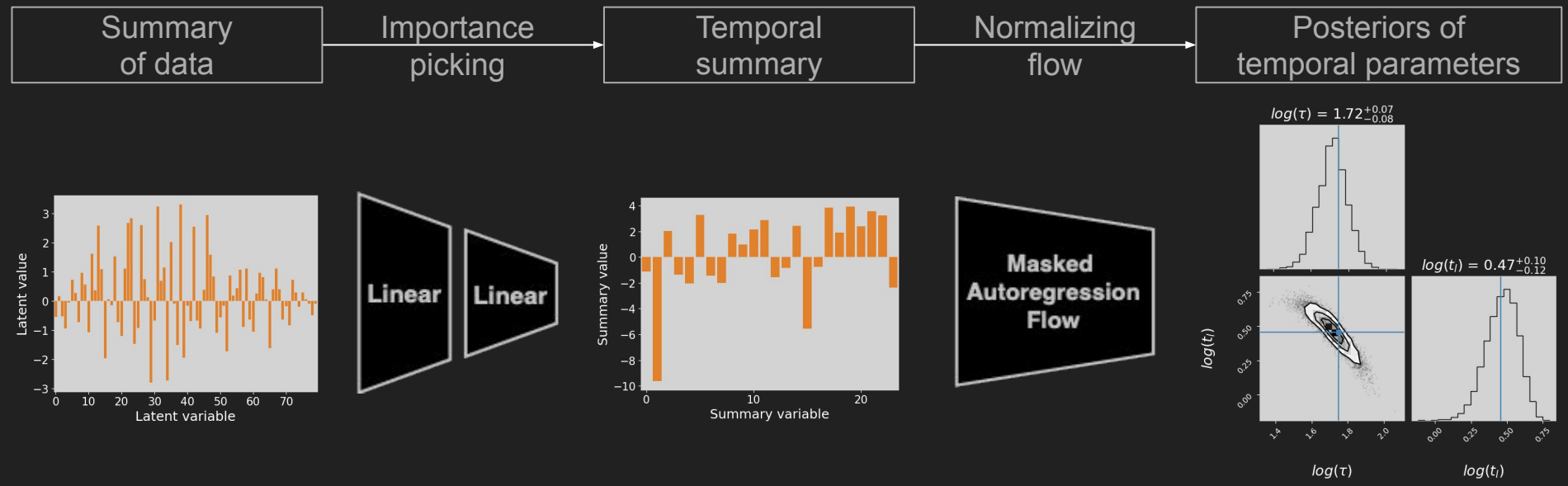
Dimensionality reduction with VAE



Loss function

$$\mathcal{L} = \underbrace{MSE(x, x')}_{\text{Quality of reconstruction}} + \beta \cdot \underbrace{D_{KL}(p(z|x)||p(z))}_{\text{Amount of information}}$$

Posteriors from Normalizing flow

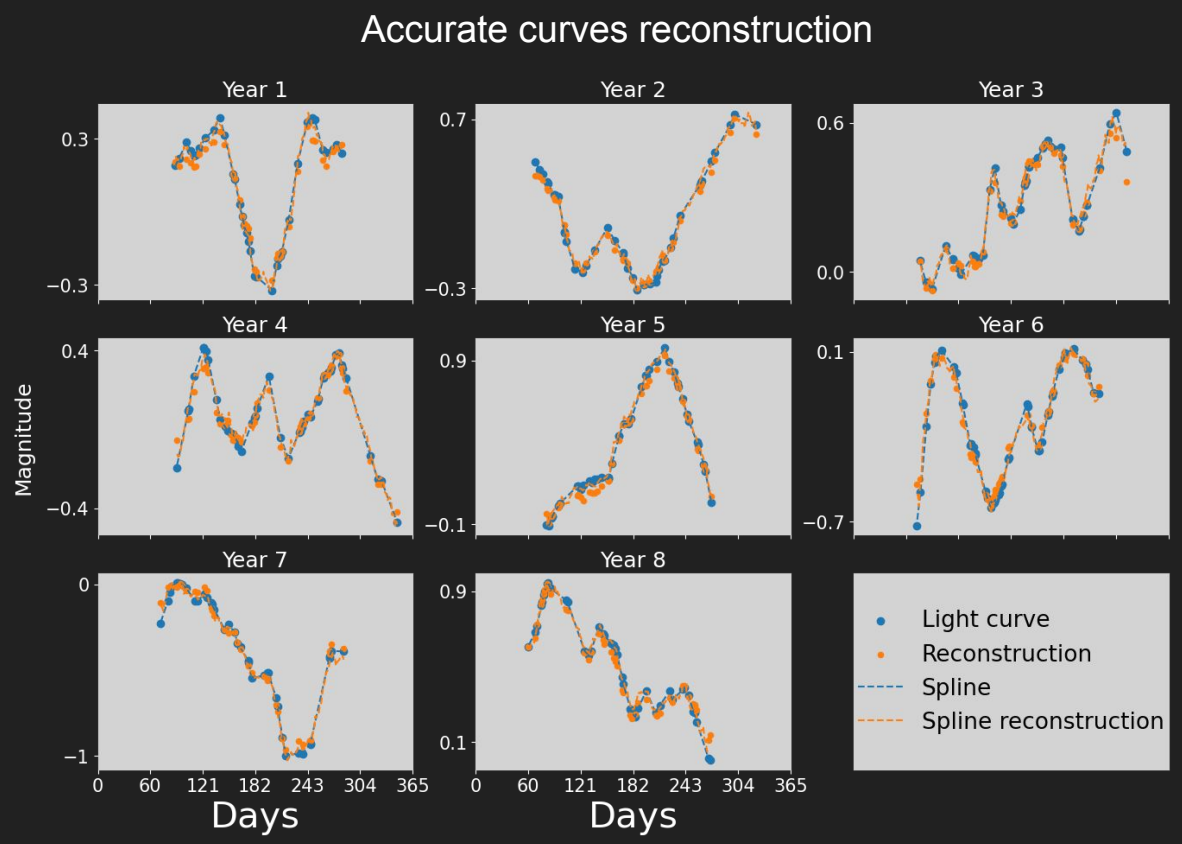


Result performance

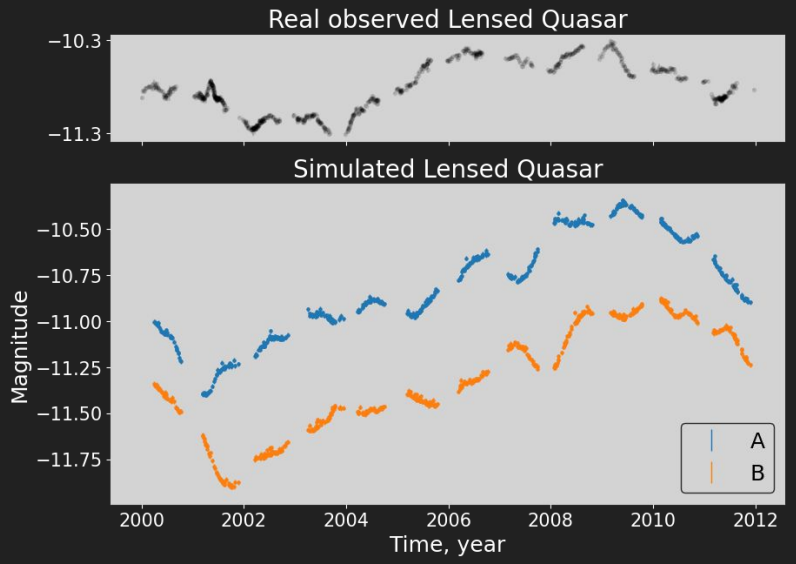
Variational autoencoder's reconstruction

Relative error: 4%

Error: RMSE=0.08



Quasar parameters inference



Truth:

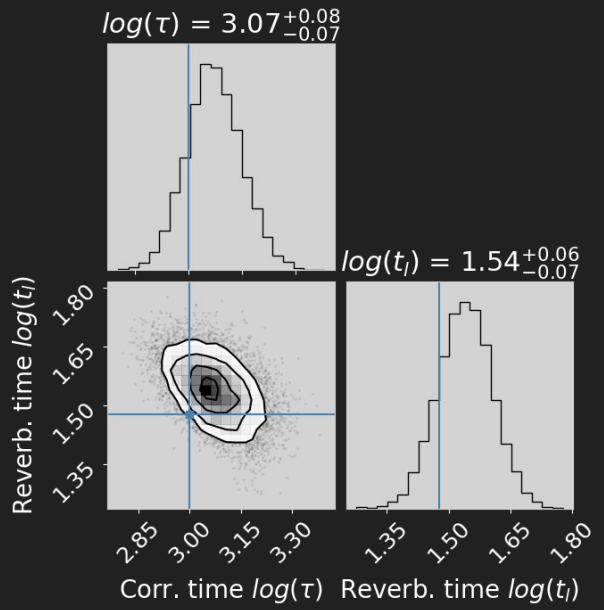
$\tau = 1000\ days$

$t_\lambda = 30\ days$

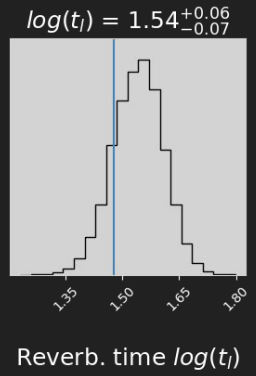
1σ constraints:

$990 < \tau < 1410$

$29 < t_\lambda < 40$



Errors of prediction



Prediction:

$$x = x_{pred} \pm \sigma_x$$

Absolute error:

$$x_{pred} - x_{g.t.}$$

Should be:

$$\Delta x \to 0$$

Normalized error (Chi):

$$\chi(x) = \frac{x_{pred} - x_{g.t.}}{\sigma_x}$$

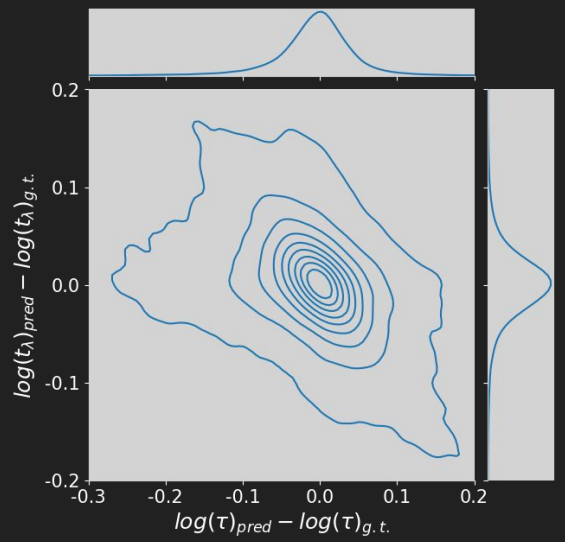
Should be:

$$\chi(x) \to \mathcal{N}(0,1)$$

Statistical distribution of errors

Distribution of absolute errors

$$x_{pred} - x_{g.t.}$$

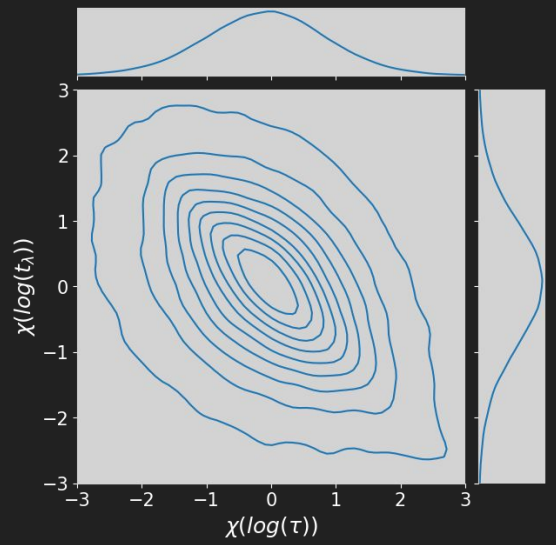


Conclusion: accurate prediction

$$0.5 < \frac{x_{pred}}{x_{g.t.}} < 2$$

Distribution of normalized errors

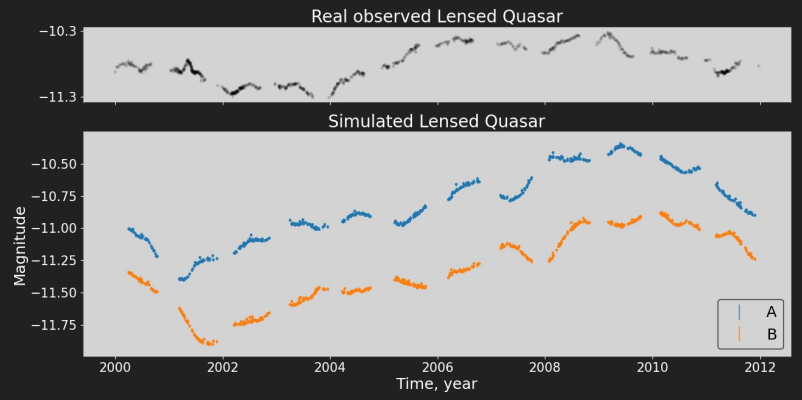
$$\chi(x) = \frac{x_{pred} - x_{g.t.}}{\sigma_x}$$



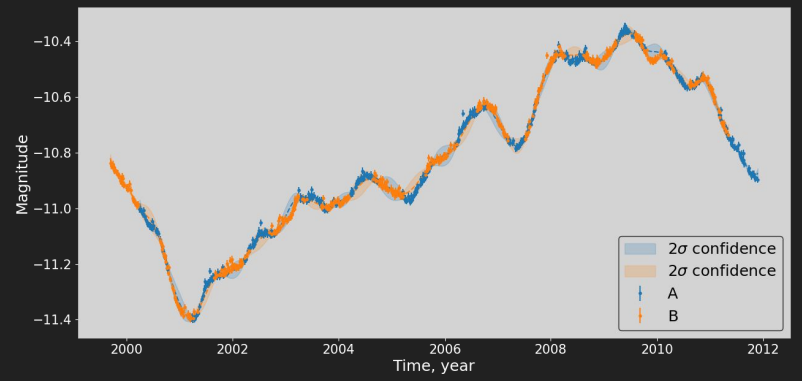
Conclusion: reliable uncertainties

$$\sigma_{pred} \approx 0.93 \cdot \sigma_{truth}$$

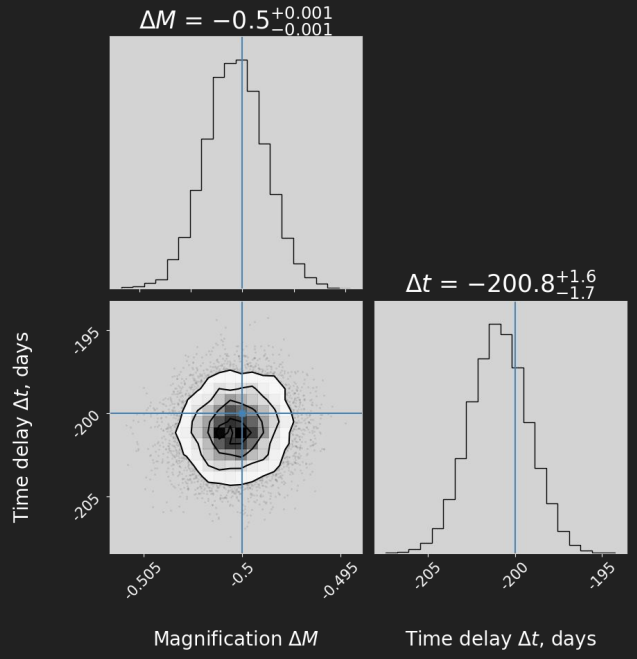
Lensing inference



Removed lensing effect



Posteriors of lensing parameters



- Negligible magnification error
- Accurate time delay prediction

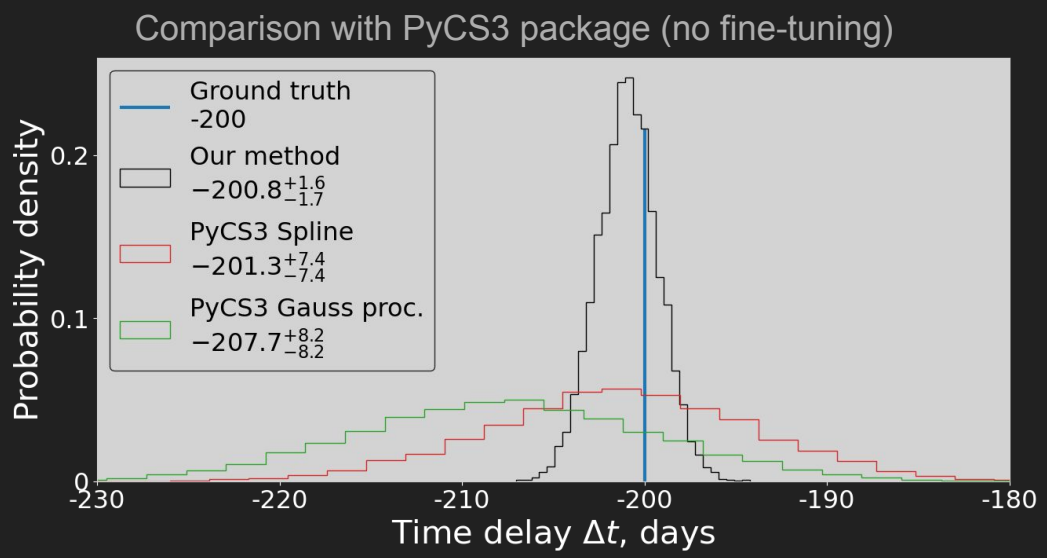
Comparison with standard software

PyCS3 setup:

- Adjusted necessary hyperparameters
- The rest left to default

PyCS3 warnings:

- does not guarantee realistic time-delay uncertainty estimates
- Please try to avoid publishing time delays with overly optimistic uncertainty estimates



Method	Inference time	Uncertainty
Our method	**20 sec**	**±1.6 days**
PyCS3 Splines	13 min	±7.4 days
PyCS3 Gauss proc.	9 min	±8.2 days

Package credit: Millon et al. 2020, Tewes et al. 2013

Improvement of Hubble rate H_0

Uncertainty from time delay:

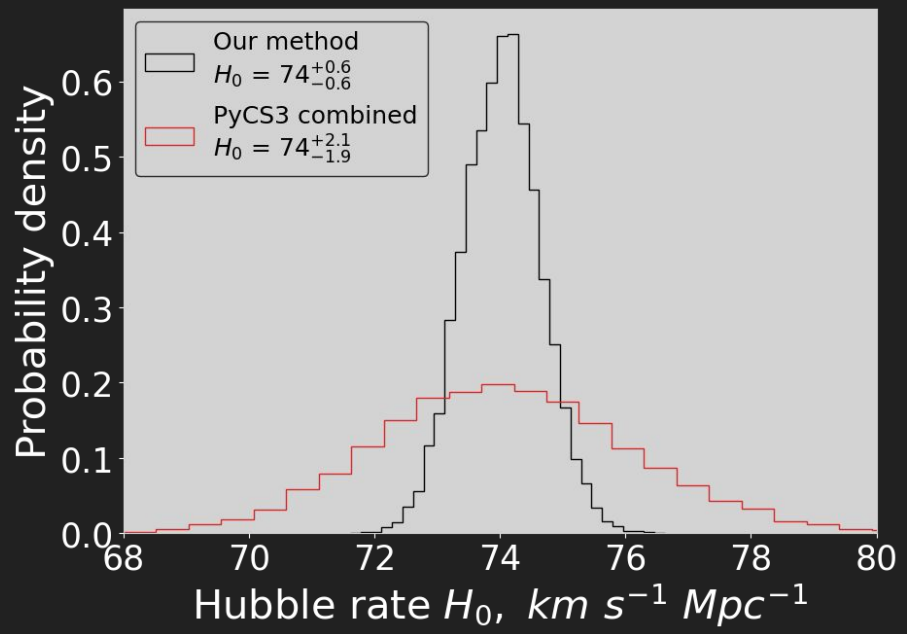
$$H_0 \pm \sigma_H \propto \frac{\Delta\phi_{g.t.}}{\Delta t \pm \sigma_t}$$

PyCS3: $\sigma_H = 2.1\ km\ s^{-1}\ Mpc^{-1}$

Our method: $\sigma_H = 0.6\ km\ s^{-1}\ Mpc^{-1}$

3.5 times less

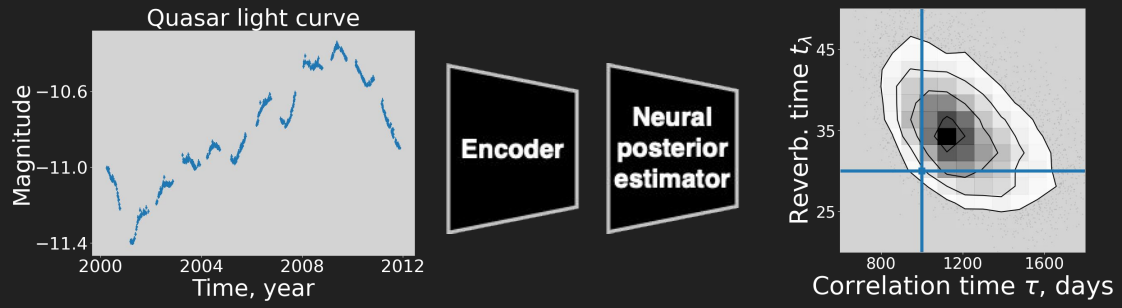
Comparison with PyCS3 package (no fine-tuning)



Summary

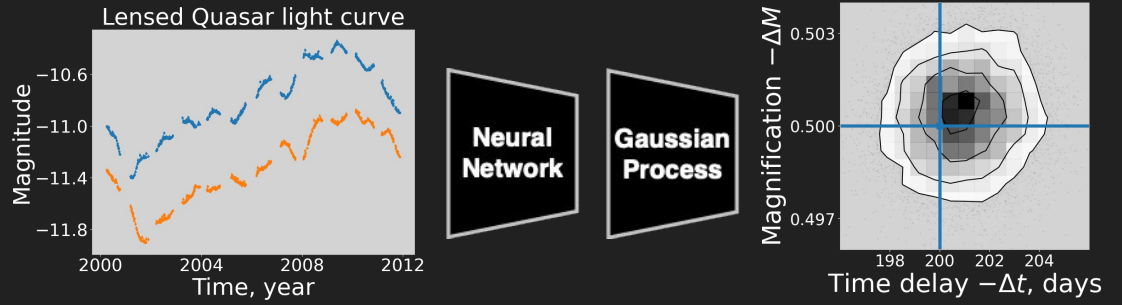
Quasar light curves

- Relative error: $0.5 < \frac{x_{pred}}{x_{g.t.}} < 2$
- Uncertainty $\sigma_{pred} \approx 0.93 \cdot \sigma_{truth}$



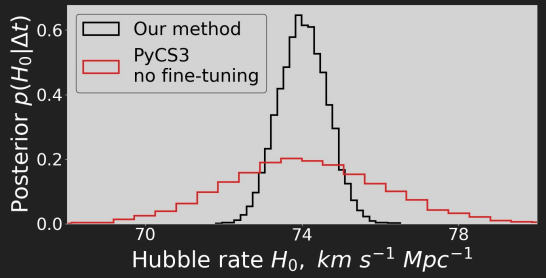
Lensing inference

- Magnification uncertainty 0.001
- Time delay uncertainty ±1.6 days



Hubble rate improvement

- Uncertainty from time delay 0.6
- Uncertainty improved in 3.5 times



Contact email:
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Thank you for your attention

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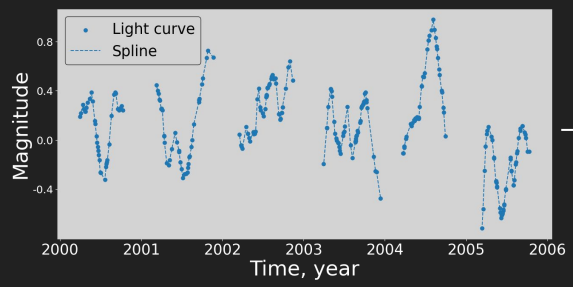
Additional materials

Data preprocessing

Target parameter	Time scale	Image axis
Correlation time $\mathcal{T}$	Years	Y axis
Reverberation time t_λ	Days	X axis



Annual split
Spline interpolation

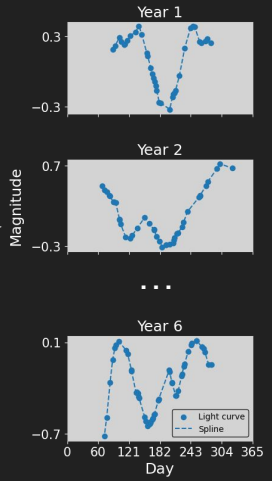
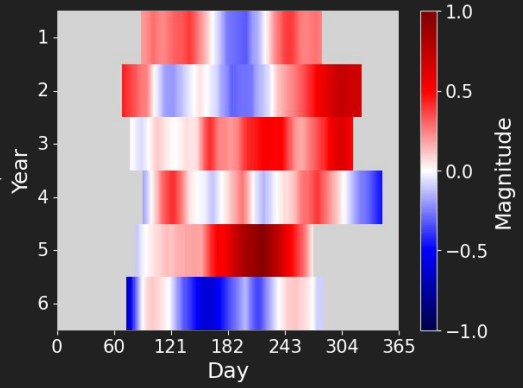
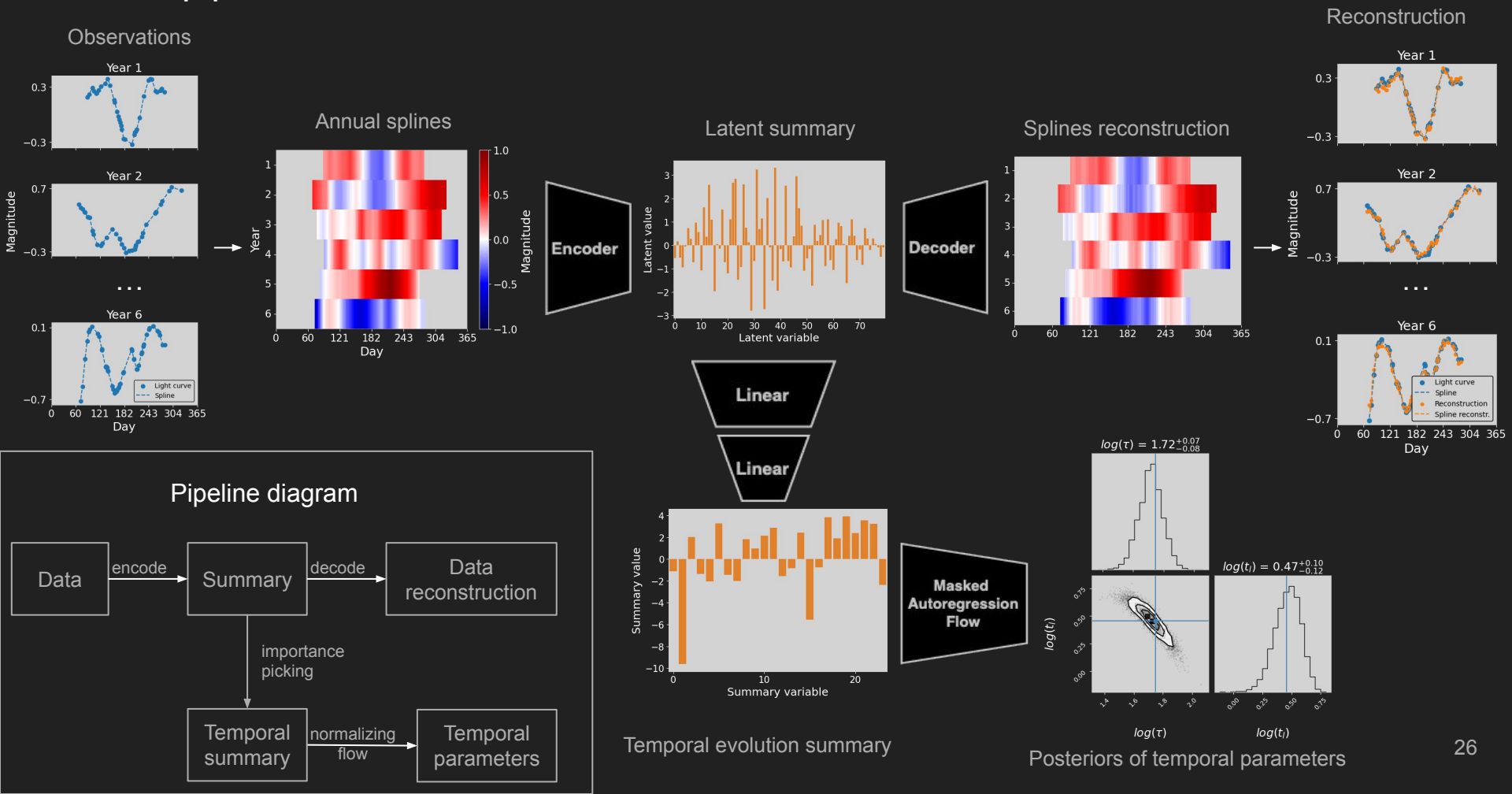


Image-like
representation



Inference pipeline architecture



Variational autoencoder's reconstruction

Dataset:

- 12 years-long mock light curves
- 800k / 100k / 100k split

Architecture:

- Latent space size 128
- Temporal summary size 24

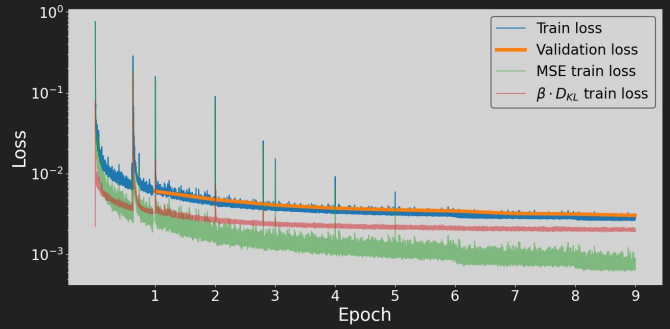
Training:

- 9 epochs, batch size = 128
- Regularization β = 0.05
- Loss:

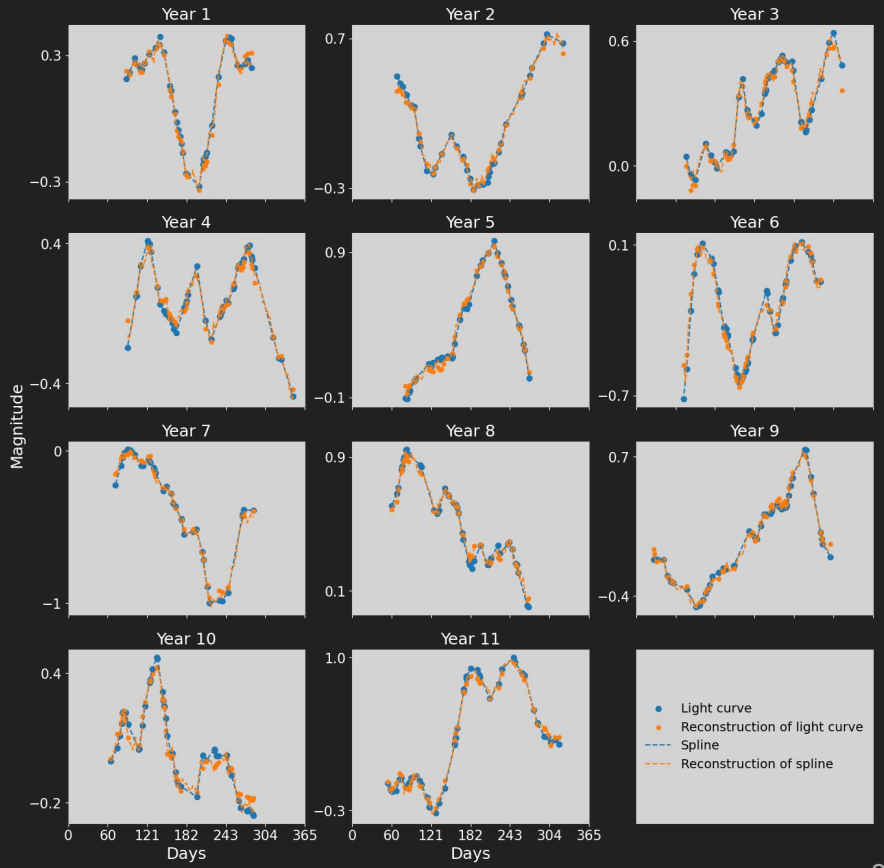
$$\mathcal{L} = MSE(x, x') + \beta \cdot D_{KL}(p(z|x)||p(z))$$

Result:

- RMSE = 0.04 for data in [0,1]
- Learning curve

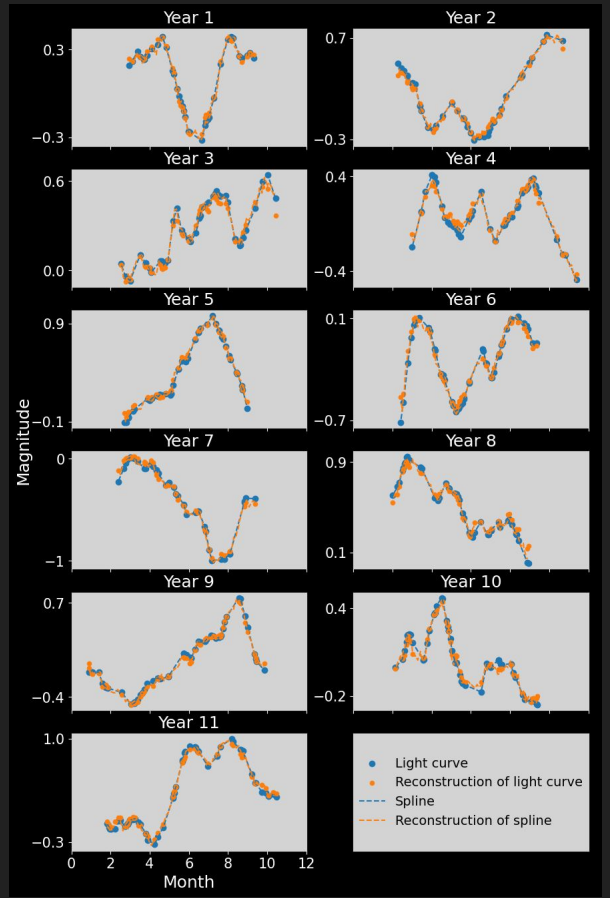


Accurate curves reconstruction

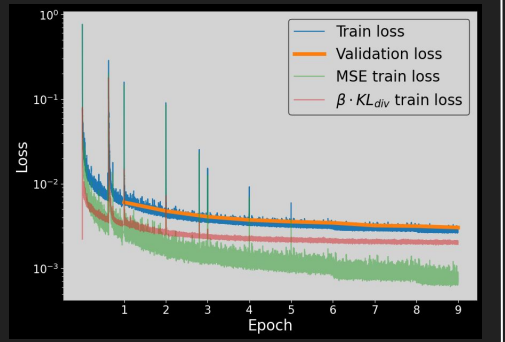


Variational autoencoder

Reconstruction performance



Learning curve



Dataset:

- 12 years long light curves
- 800k / 100k / 100k split

$log(\tau)$	$\sim$	$\mathcal{N}_{tr}(\mu = 2.8, \sigma = 0.52)$
$log(t_\lambda)$	$\sim$	$\mathcal{N}_{tr}(\mu = 0.64, \sigma = 0.43)$
$Cadence$	$\sim$	$\exp(\frac{1}{\lambda} = 4.9)$

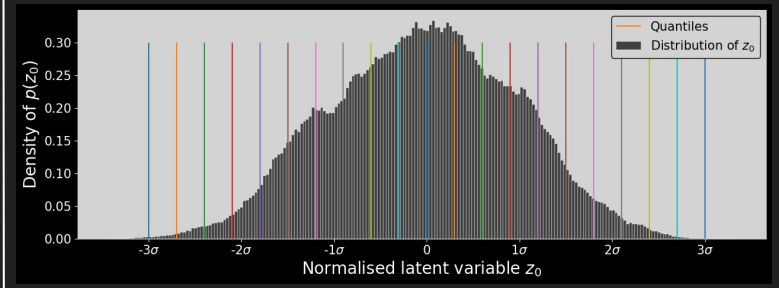
Training:

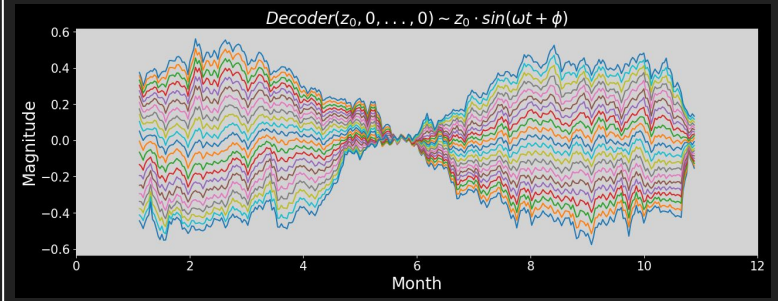
- 9 epochs, batch size = 128
- Loss - MSE and KL divergence
- Regularization β = 0.05

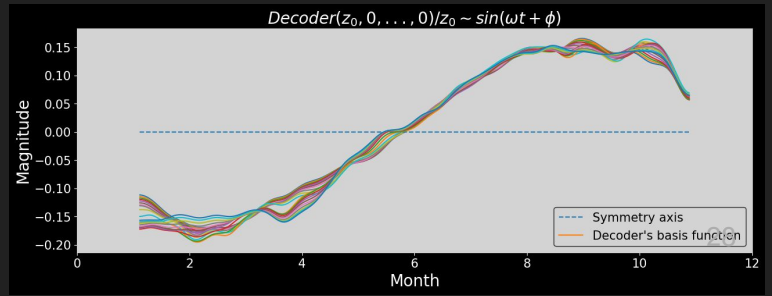
Result:

- RMSE = 0.04 for data in [0,1]

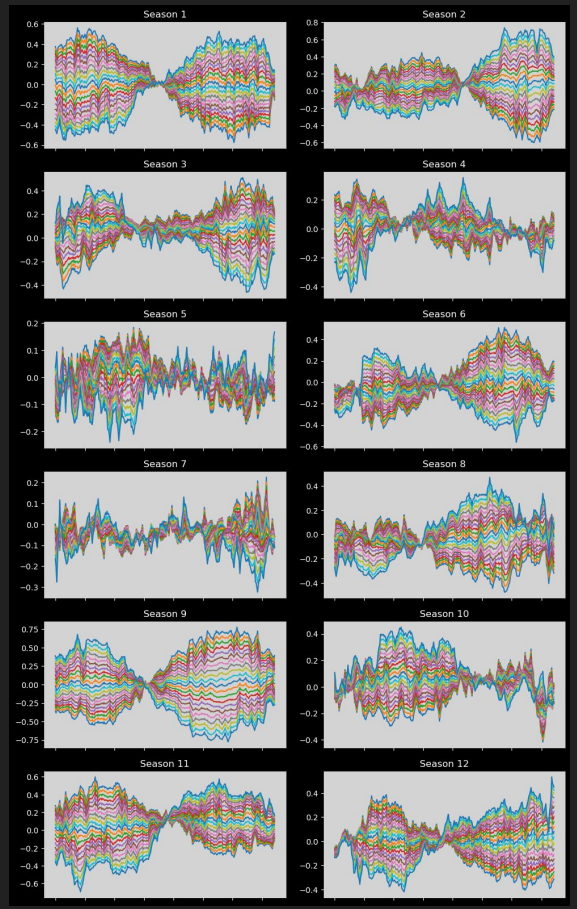
Vary one latent variable

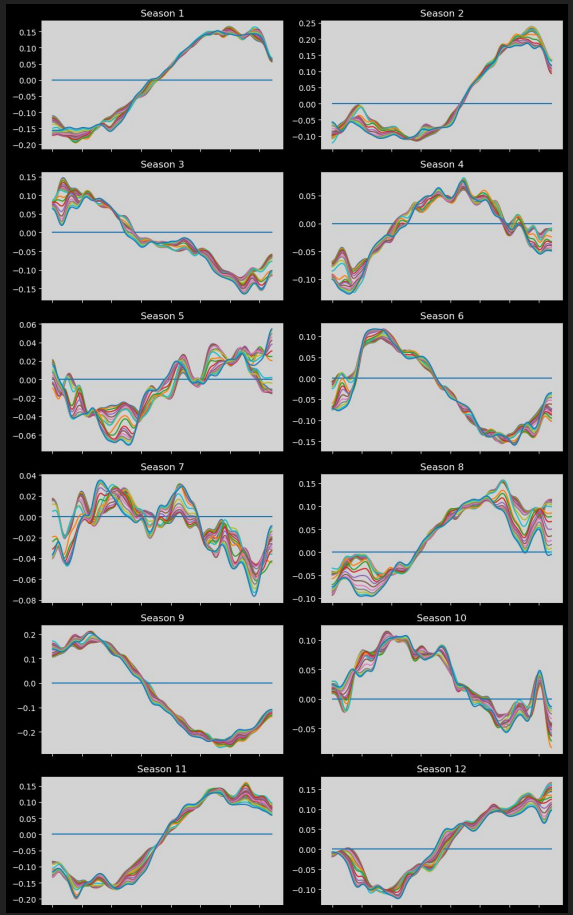






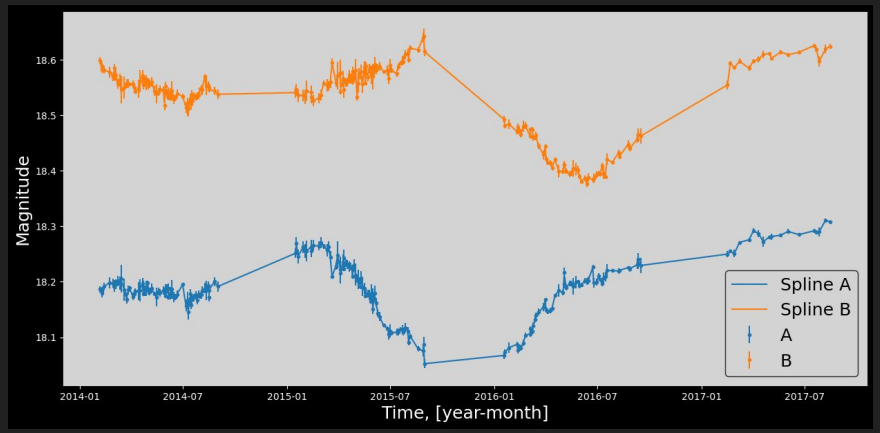
Variational autoencoder latent effects





Models of a quasar light curve

Spline



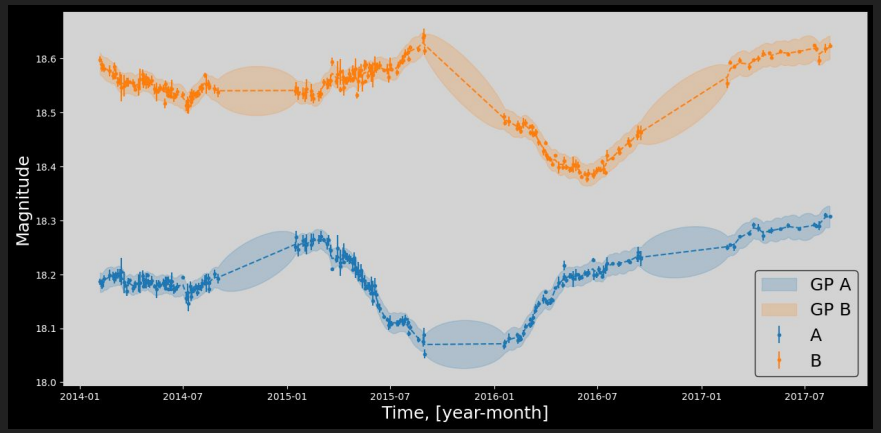
Advantages:

- No hyperparameters except for degree

Disadvantages:

- Not interpretable
- No uncertainties

Gaussian process (GP)



Advantages:

- Physically interpretable parameters
- Get uncertainties for free

Disadvantages:

- Degeneracies between parameters
- Difficult optimization for disbalanced gradients