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Utilizing gamma-rays to study AGN jets

Sarah Wagner

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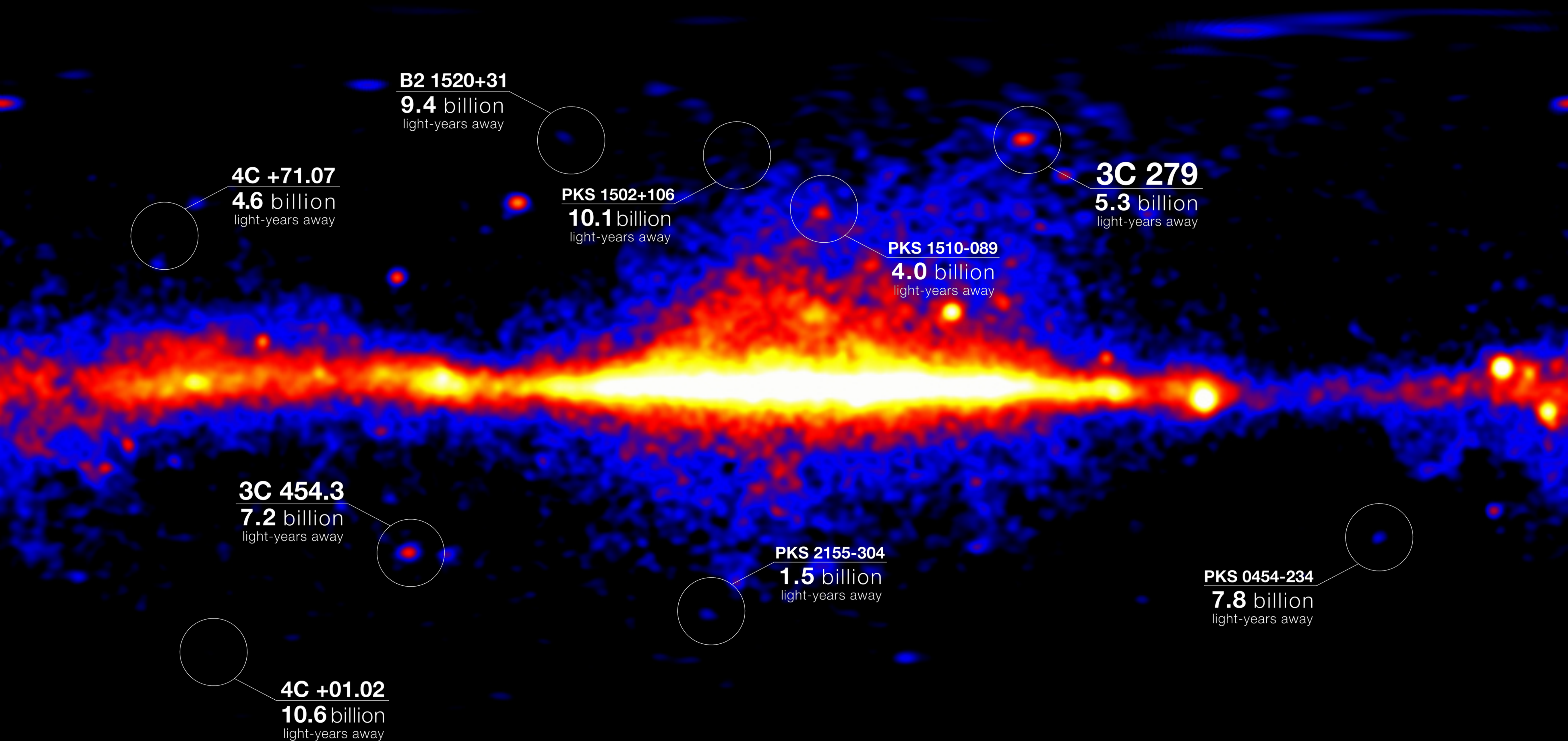
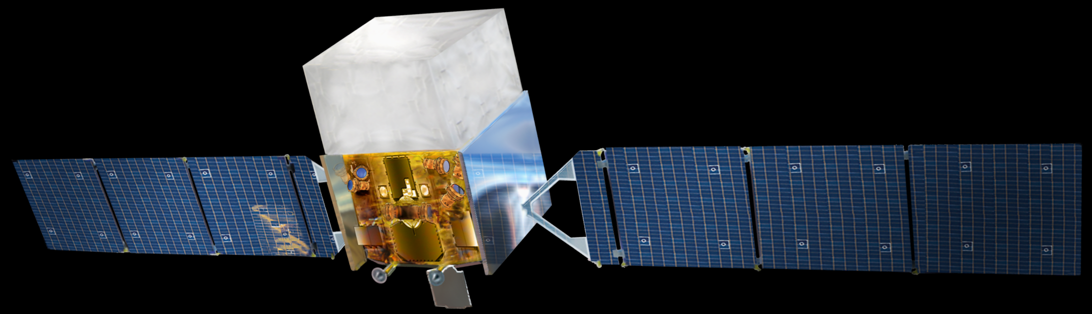
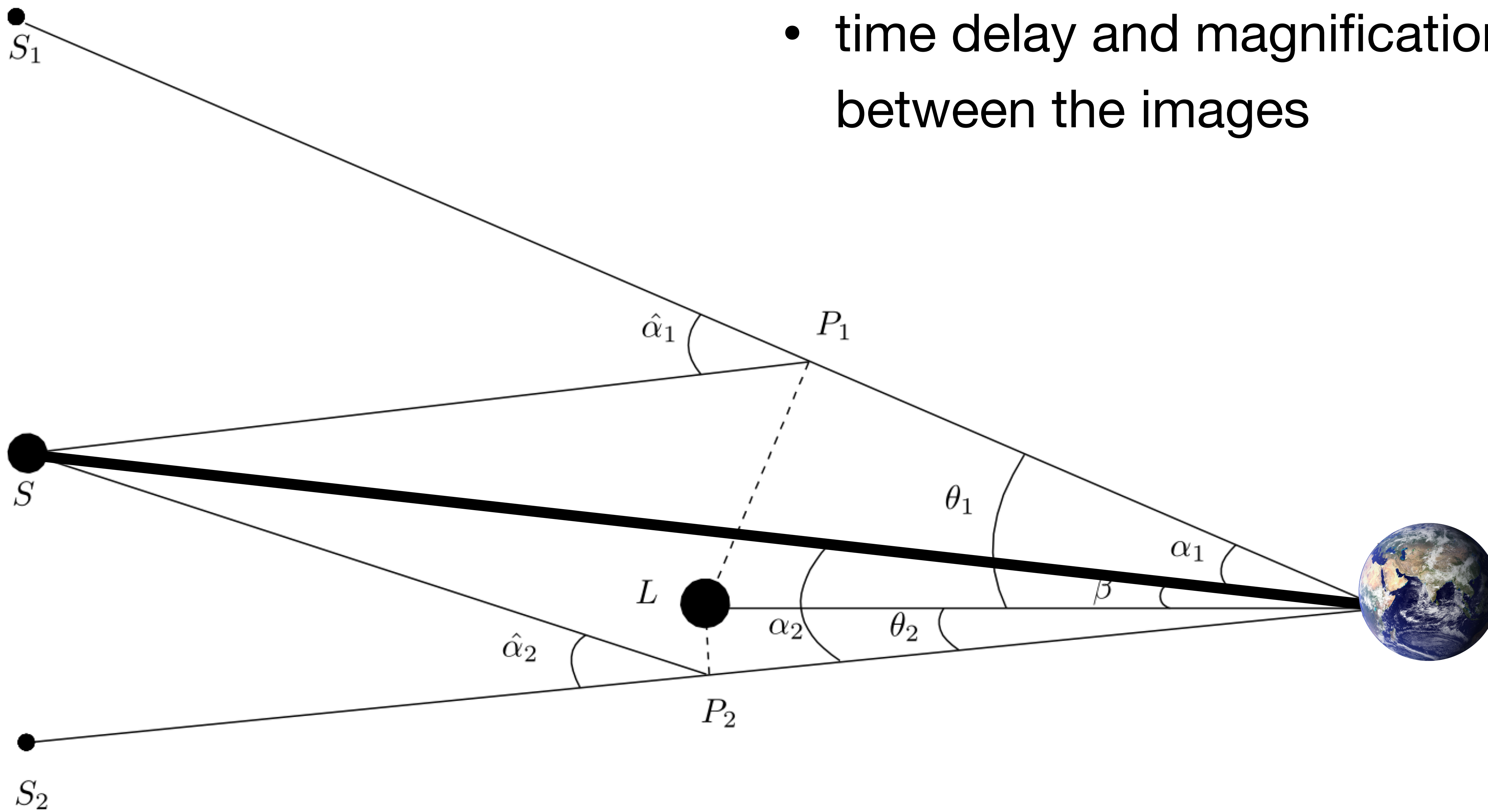
Würzburg



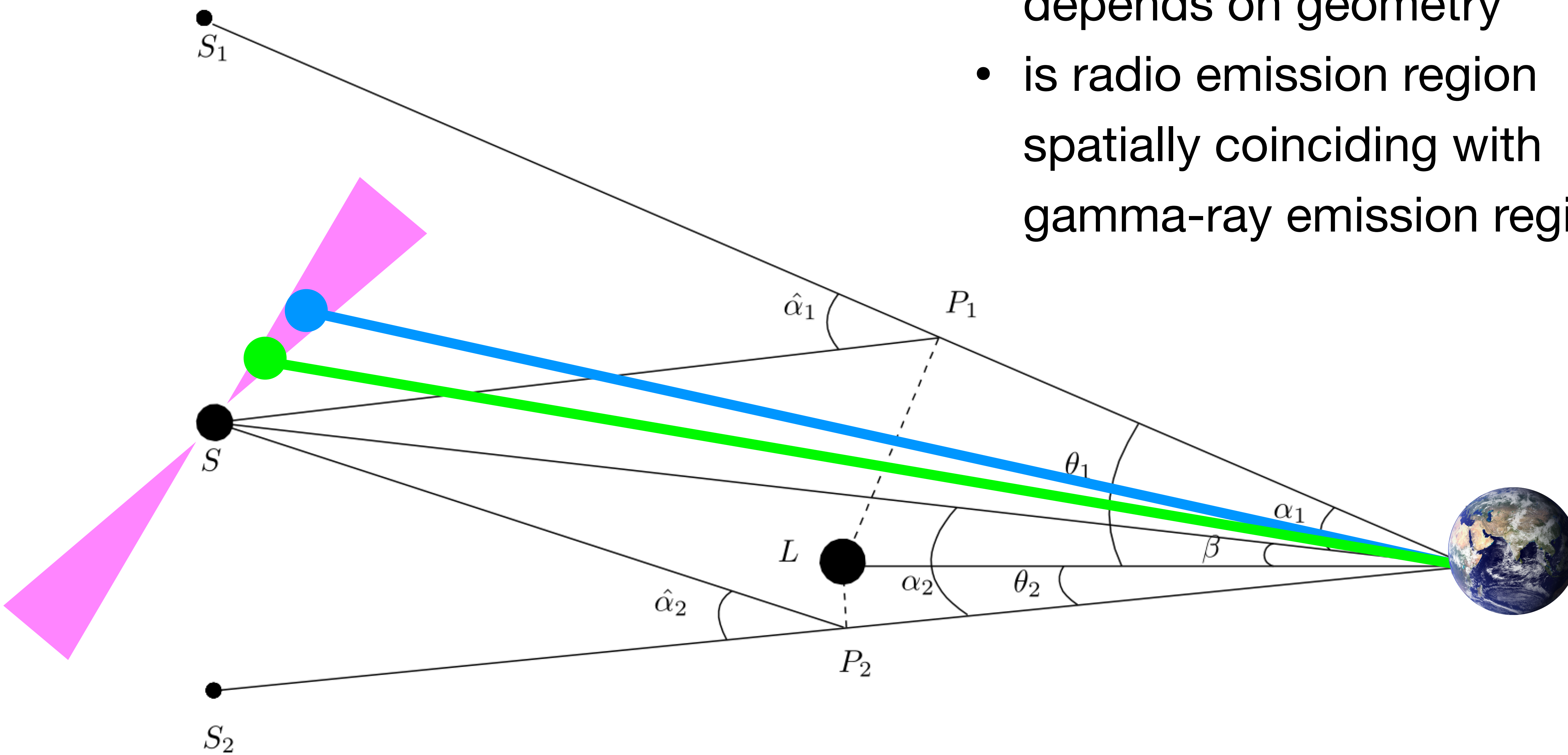


Gravitational Lensing

- multiple images of one source
- time delay and magnification between the images



Gravitational Lensing



- delay is achromatic, only depends on geometry
- is radio emission region spatially coinciding with gamma-ray emission region?

PKS 1830-211 in γ-rays

Lensed images are not resolved —> light curve is a superposition of the source intrinsic light curve x(t) and delayed, magnified copies of itself.

in case of two images: $y(t) = x(t) + a\,x(t - t_0)$

magnification ratio and delay = lens observables

Determine Delay

Lensed images are not resolved —> light curve is a superposition of the source intrinsic light curve x(t) and delayed, magnified copies of itself.

in case of two images: $$y(t) = x(t) + a\,x(t - t_0)$$

magnification ratio and delay = lens observables

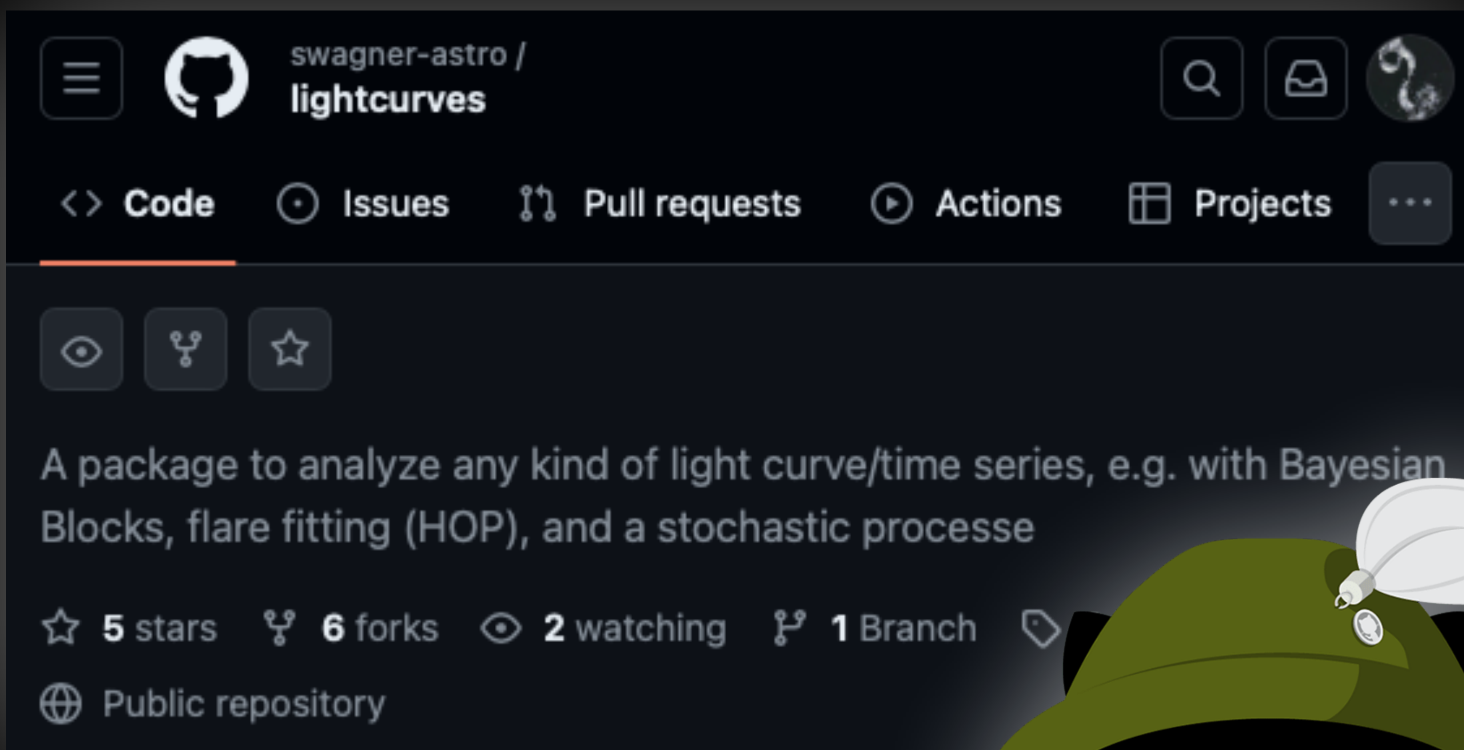
(A)
Peak distances

(B)
Auto correlation

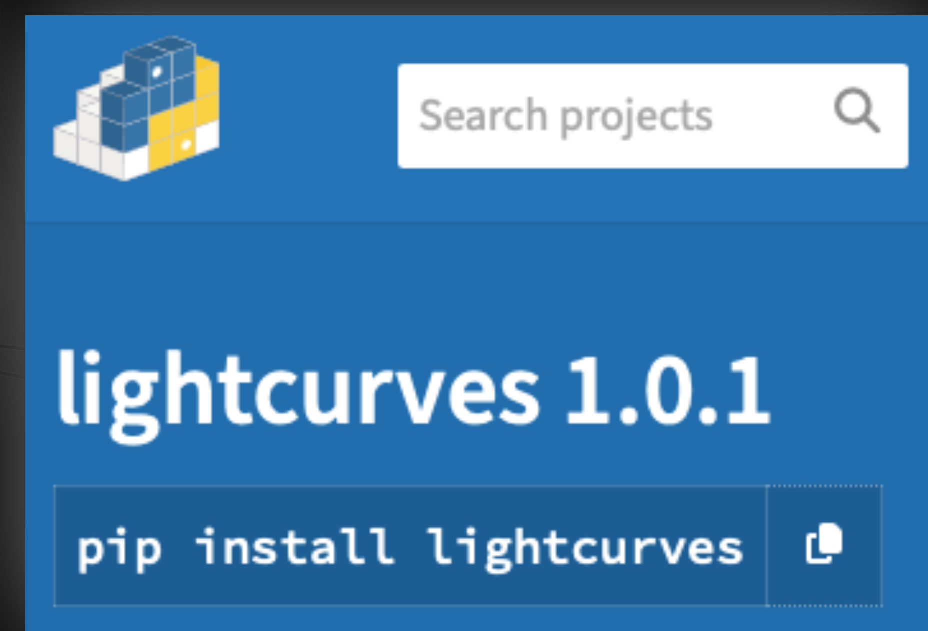
(C)
Metric optimization

Wagner+ in prep

lightcurves



let's connect!



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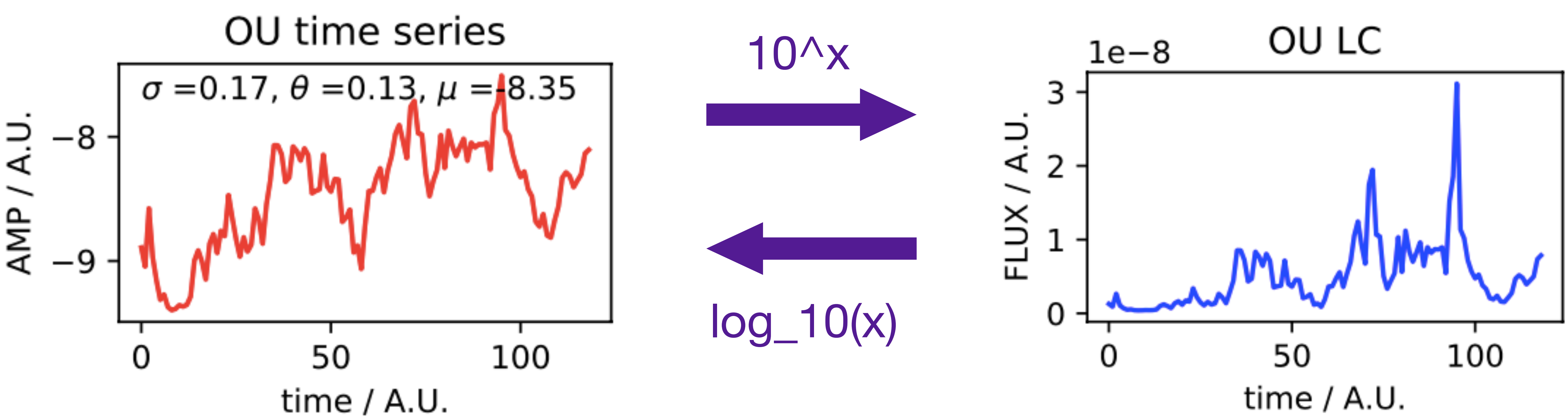
LCs and SDEs

A&A 645, A62 (2021)
https://doi.org/10.1051/0004-6361/202039097

Astronomy & Astrophysics

Ornstein-Uhlenbeck parameter extraction from light curves of *Fermi*-LAT observed blazars

Paul R. Burd[1], Luca Kohlhepp[1], Sarah M. Wagner[1], Karl Mannheim[1], Sara Buson[1], and Jeffrey D. Scargle[2]



Monthly binned Fermi-LAT LCs show characteristic OU parameters.. physical interpretation?

OU Process

$$u_{T+1} = u_T + \theta \Delta t(\mu - u_T) + \sigma \sqrt{\Delta t} \mathcal{N}_T$$

Drift

„draw back“ to mean revision level μ at mean revision rate θ.

Diffusion

white noise described with Gaussian around 0 and variance σ^2.

Particle Acceleration

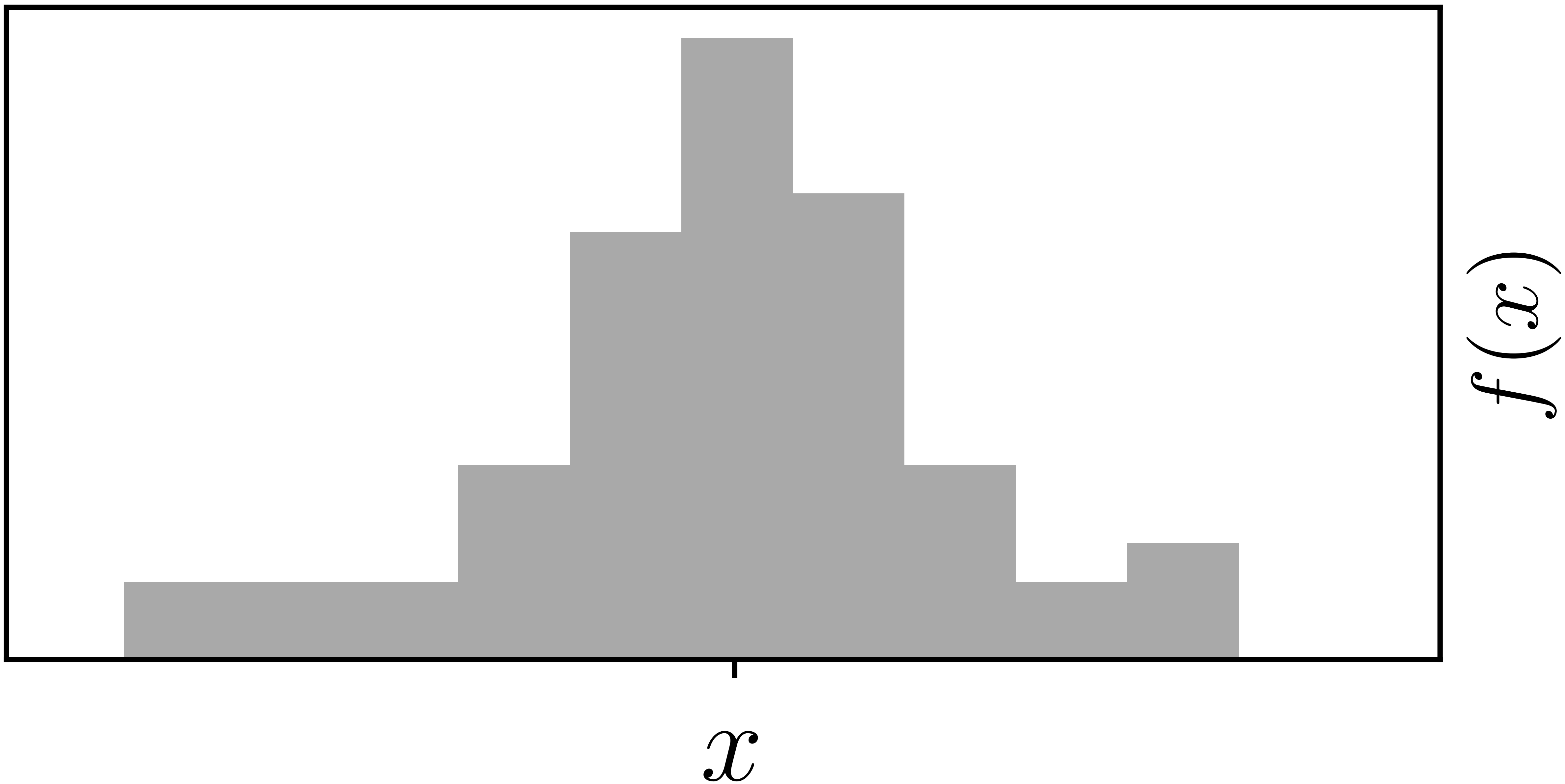
Charged particles interacting with turbulent waves propagating parallel to a background magnetic field satisfy a transport equation in the diffusion approximation which includes first- and second-order Fermi acceleration as well as synchrotron losses and particle injection through a source term $\mathcal{Q}$. This equation is given by (Kirk et al. 1988; Schlickeiser 1989a)

$$\frac{\partial f}{\partial t} = - c\beta(z)\frac{\partial f}{\partial z} + \frac{\partial}{\partial z}\left(\kappa(z,p)\frac{\partial f}{\partial z}\right) + \left(\frac{c}{3}\frac{d\beta}{dz}p + \frac{\partial a_1}{\partial z}\right)\frac{\partial f}{\partial p} + \frac{1}{p^2}\frac{\partial}{\partial p}\left(a_2(z,p)p^2\frac{\partial f}{\partial p}\right) - \frac{1}{p^2}\frac{\partial}{\partial p}\left(a_1(z,p)p^2\right)\frac{\partial f}{\partial z} + \frac{1}{p^2}\frac{\partial}{\partial p}\left(\frac{2}{3}k_{\rm syn}(z)p^4 f\right) + \mathcal{Q}\,, \qquad (10)$$

Krülls & Achterberg 1994

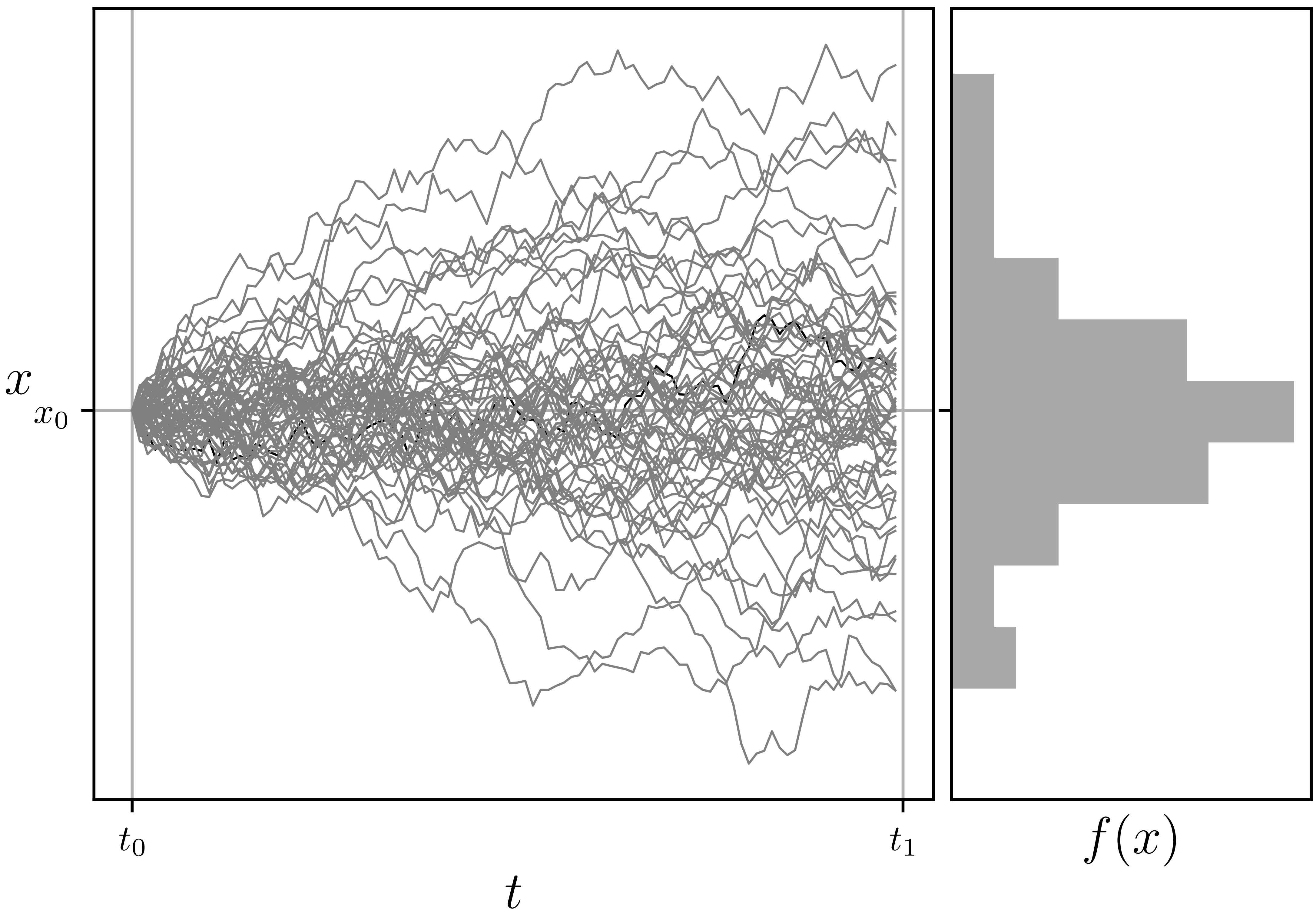
Fokker Planck Equation

Evolution of probability density function over time



Fokker Planck Equation

Evolution of probability density function over time



Solving Fokker-Planck Eq

Fokker-Planck equation

$$\frac{\partial f(t,\mathbf{x})}{\partial t} = -\sum_{i=1}^{N} \frac{\partial}{\partial x_i}\Big(A_i(t,\mathbf{x}) f(t,\mathbf{x})\Big) + $$

$$+ \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{\partial^2}{\partial x_i\, \partial x_j}\left(\frac{1}{2}\sum_{k=1}^{N} B_{i,k}(t,\mathbf{x}) B_{i,k}(t,\mathbf{x})\right)$$

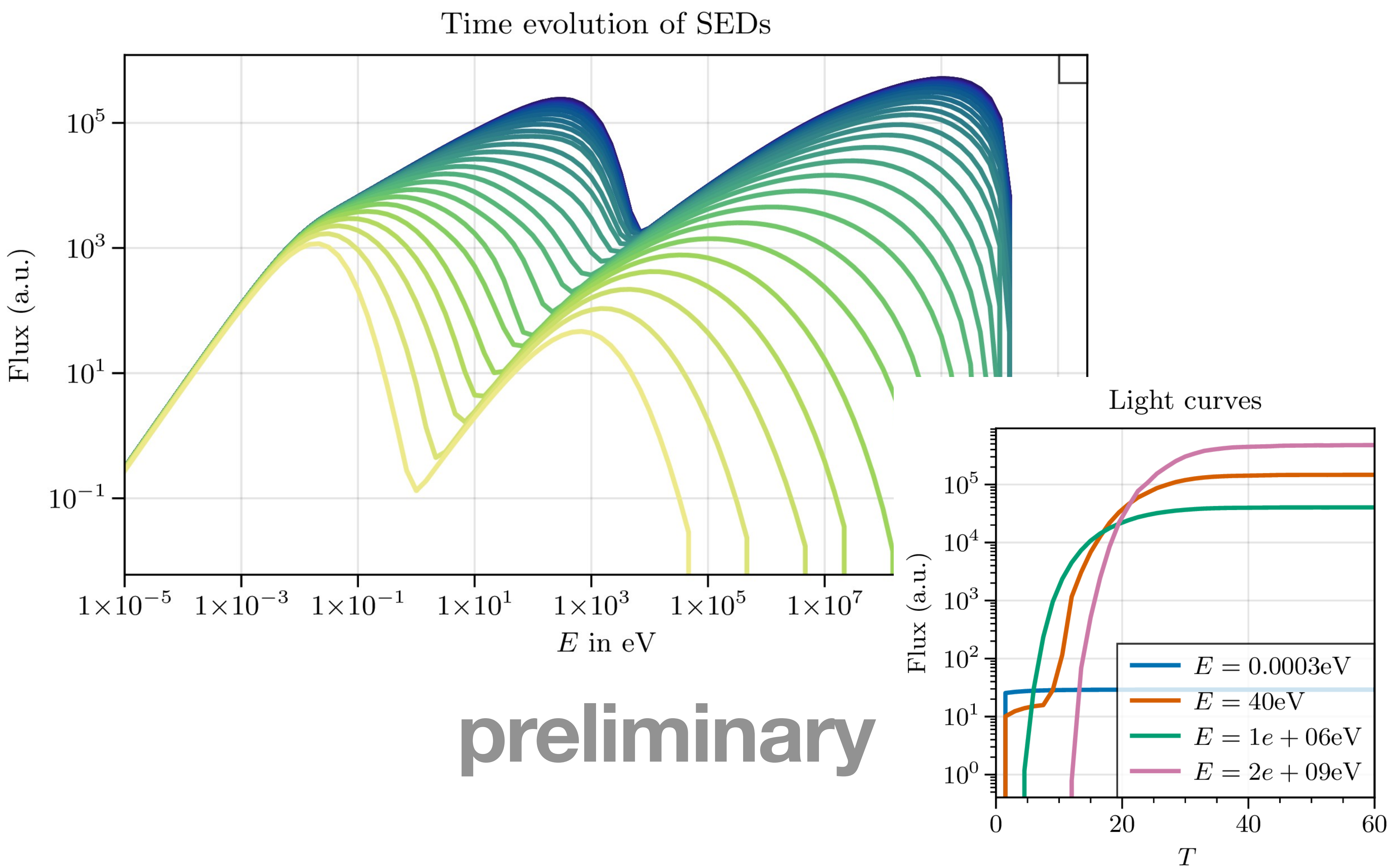
is equivalent to (Arnold 1973)

$$\frac{d\mathbf{X}_{t,i}}{dt} = A_i(t,\mathbf{X}_t) + \sum_{j=1}^{N} B_{i,j}(t,\mathbf{X}_t)\,\frac{dW_\tau}{d\tau}$$

a system of Stochastic Differential Equations (SDEs)

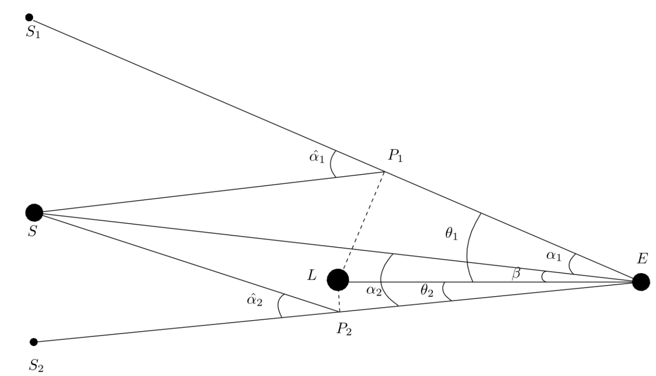
Solving Fokker-Planck Eq

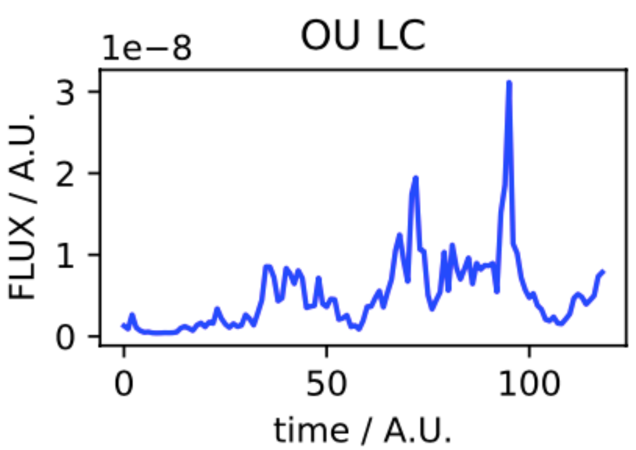
Gives probability density of charged particles in every time step also accounting for losses —> compute time resolved emission



Utilizing gamma-rays to study AGN jets

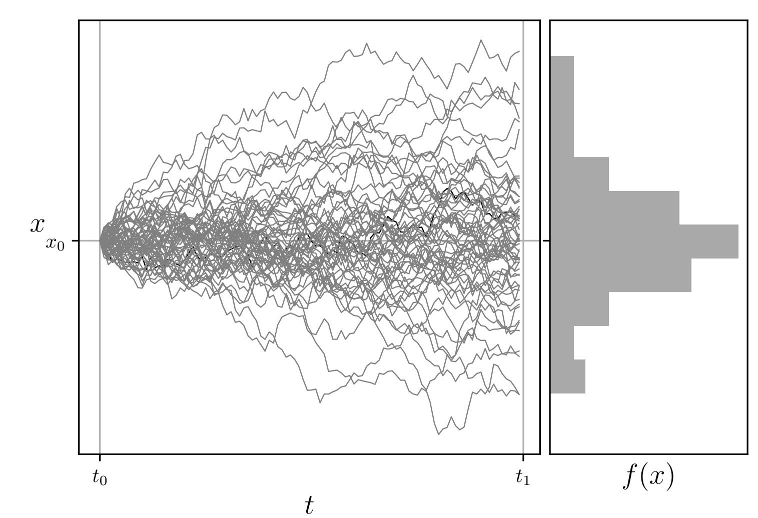
- delay induced by gravitational lensing can be utilized to study emission region, e.g. PKS 1830-211





- monthly Fermi-LAT light curves can be described by OU process with constrained parameters

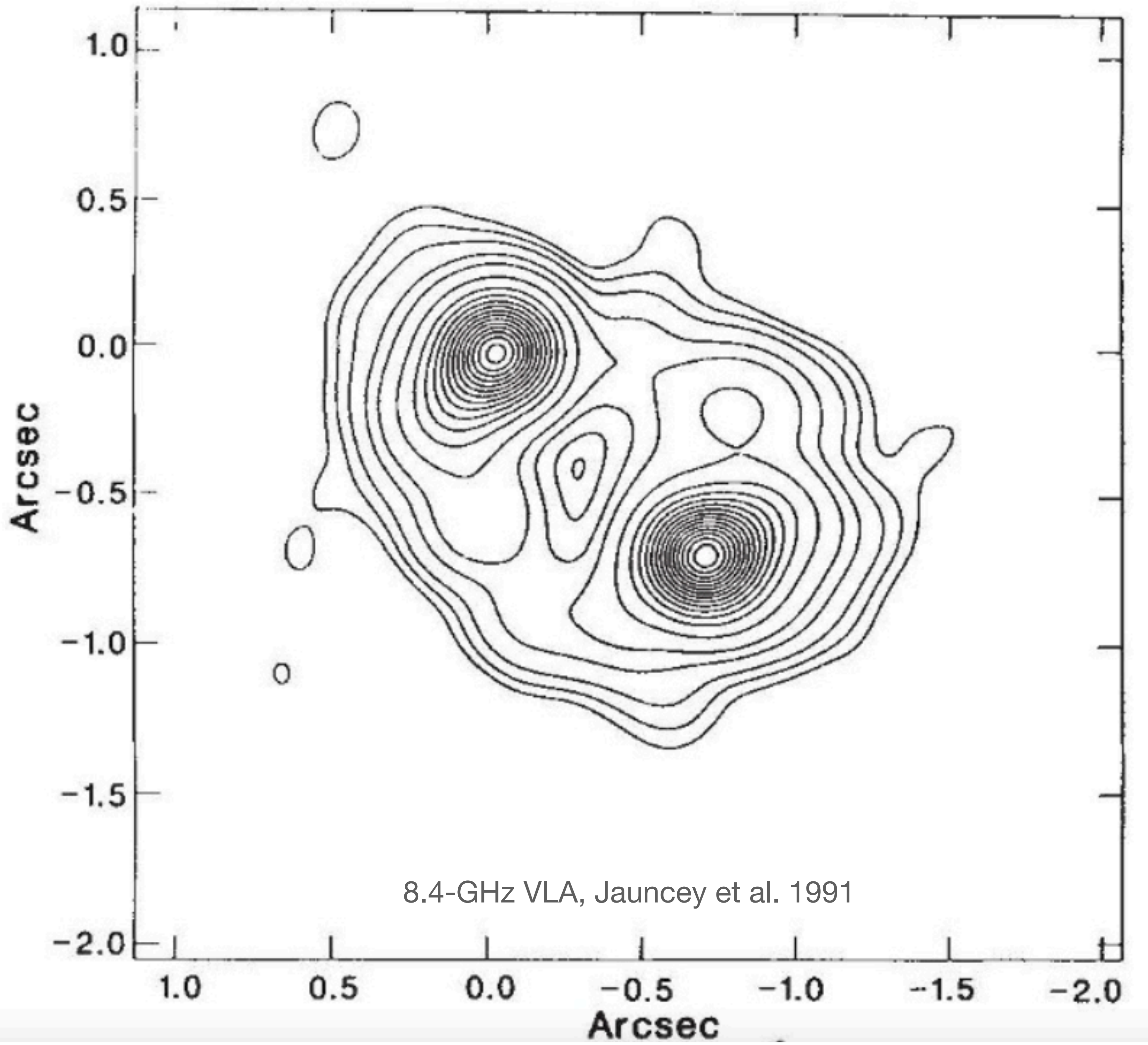
- self consistent model for acceleration mechanisms resulting in time resolved SEDs and light curves



Thank you! Any questions?

Backups

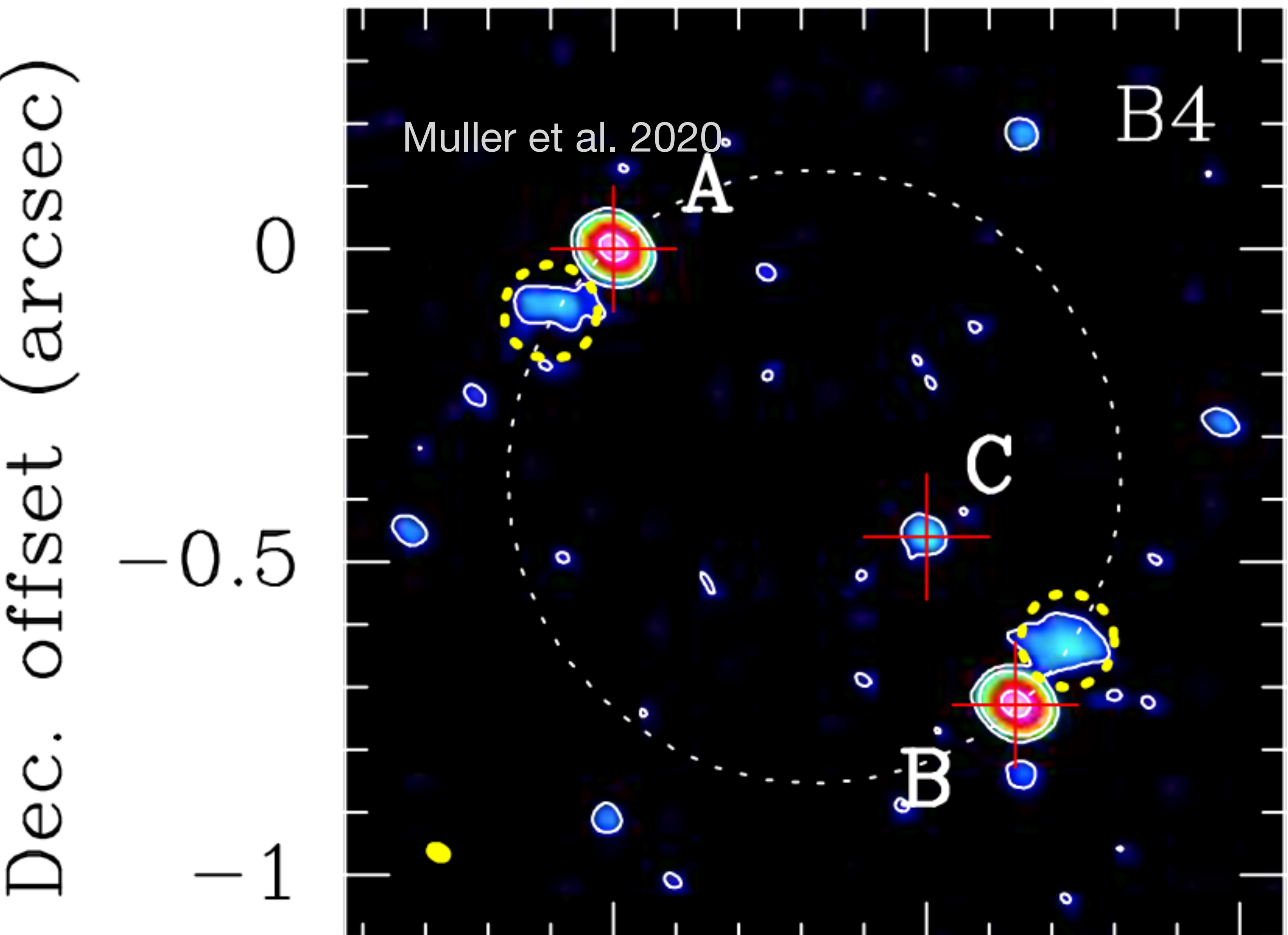
PKS 1830-211 in radio



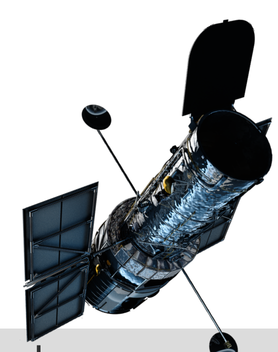
8.4-GHz VLA, Jauncey et al. 1991

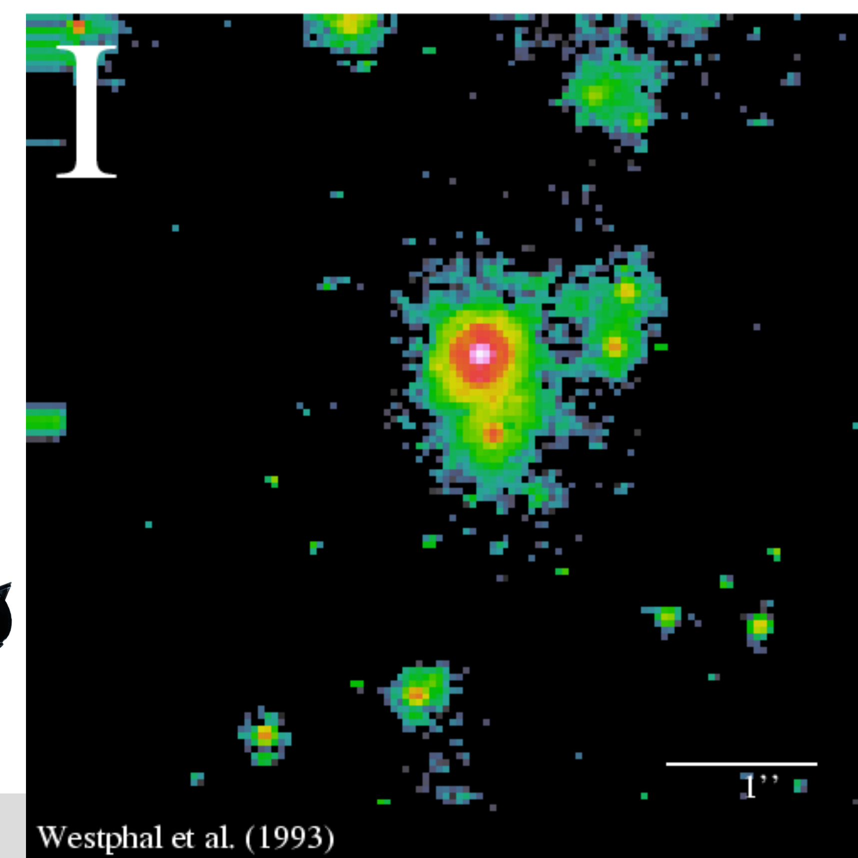
- FSRQ
- two images
- separated by ~1 arcsec
- Lovell et al. (1998) for radio core:
  - time delay: 26 $^{+4}_{-5}$

PKS 1830-211

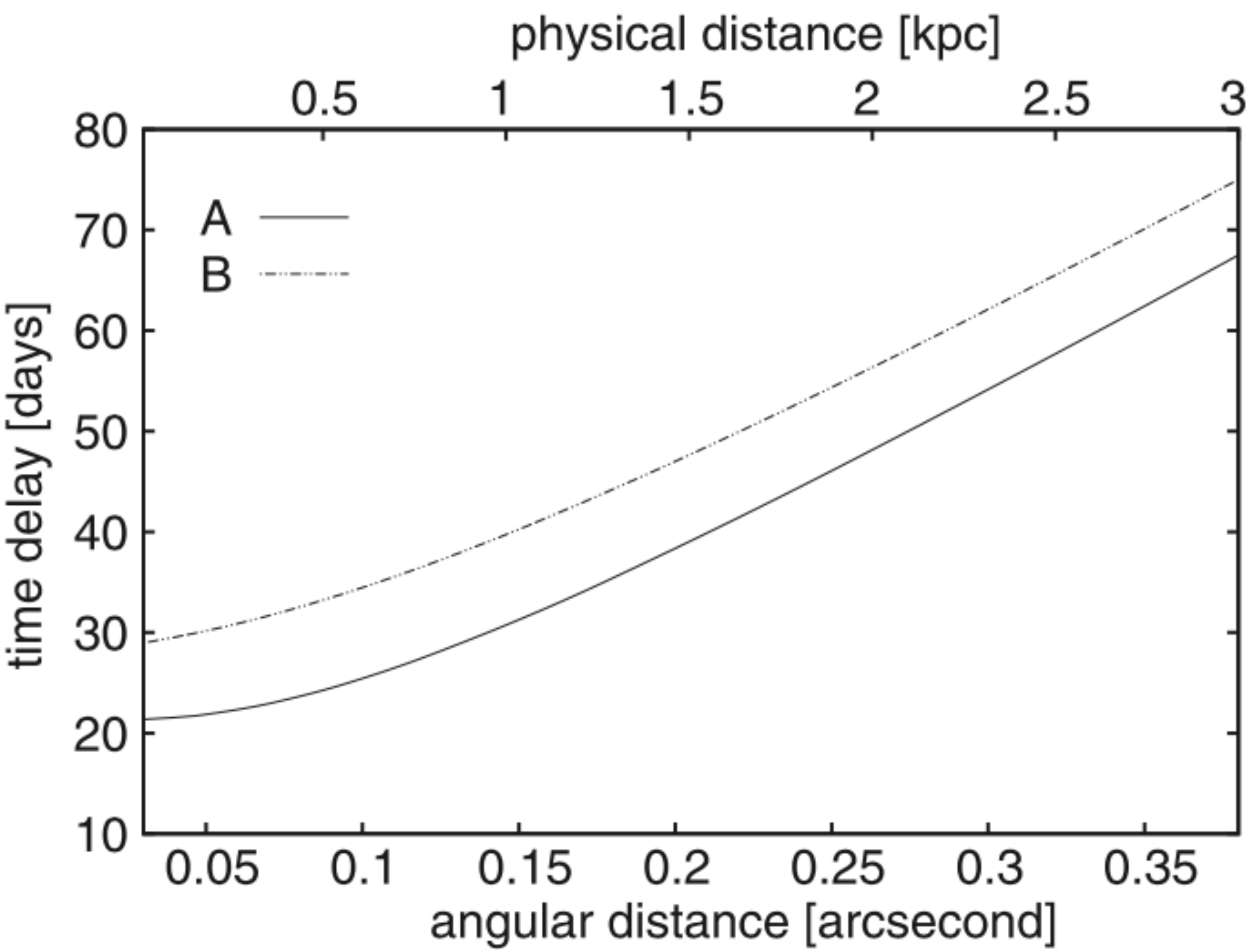


- FSRQ, relatively close to galactic plane
- gravitationally lensed
  - two images (A & B) with core (red cross) and faint extension (yellow circle)
  - separated by ~1 arcsec
  - much fainter third image (C) neglected here





Barnacka 2015



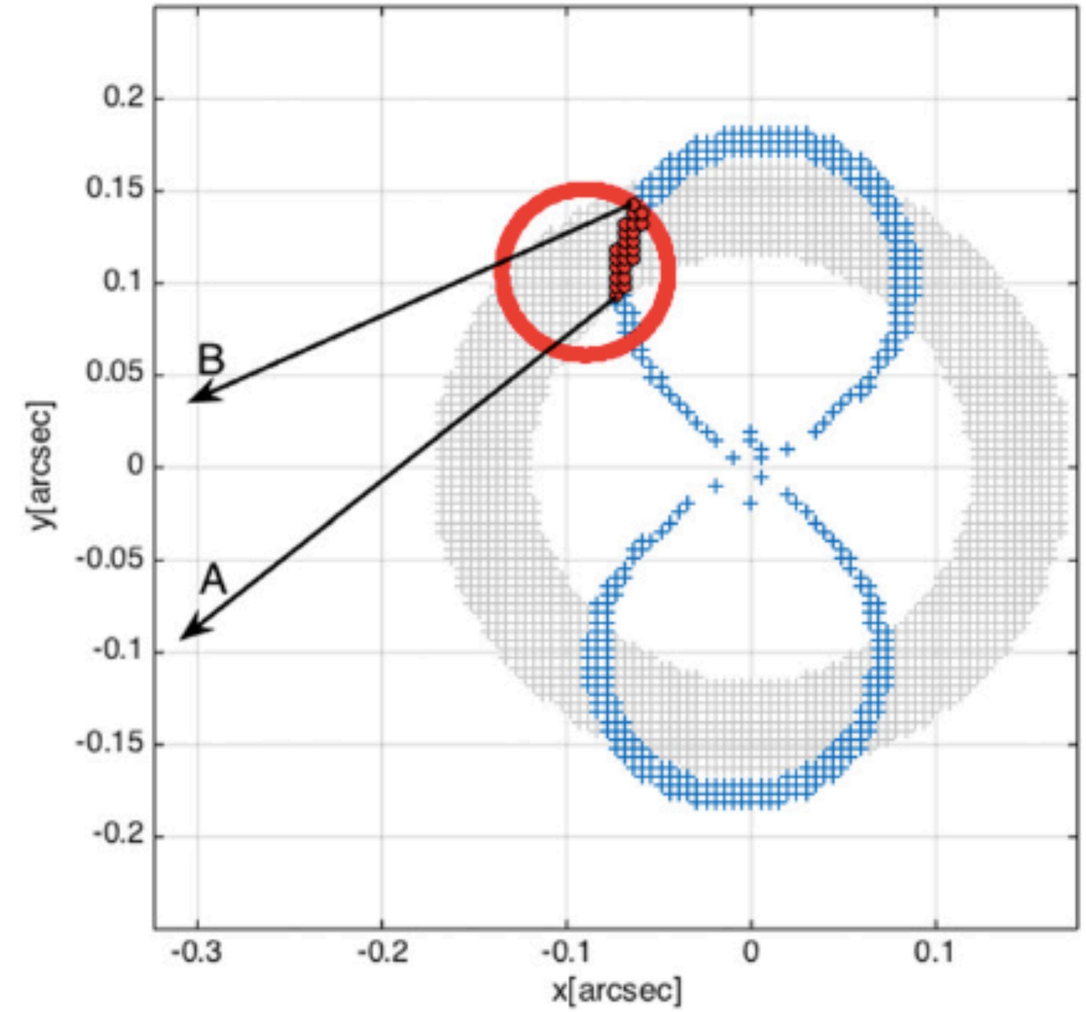


Figure 2. Range of possible core locations and the jet projections in the source plane. The gray area shows the allowed range (1σ boundary) of the core positions with time delays from 21 to 30 days (Lovell et al. 1998). The corresponding magnification ratio between the resolved images is 1.52 ± 0.05. The blue area represents the positions of the core constrained by the magnification ratio measurement. The red circle delimits the allowed core positions derived by Sridhar (2013). Arrows A and B indicate the limiting jet projections constrained by resolved radio images.

PKS 1830-211 in γ-rays

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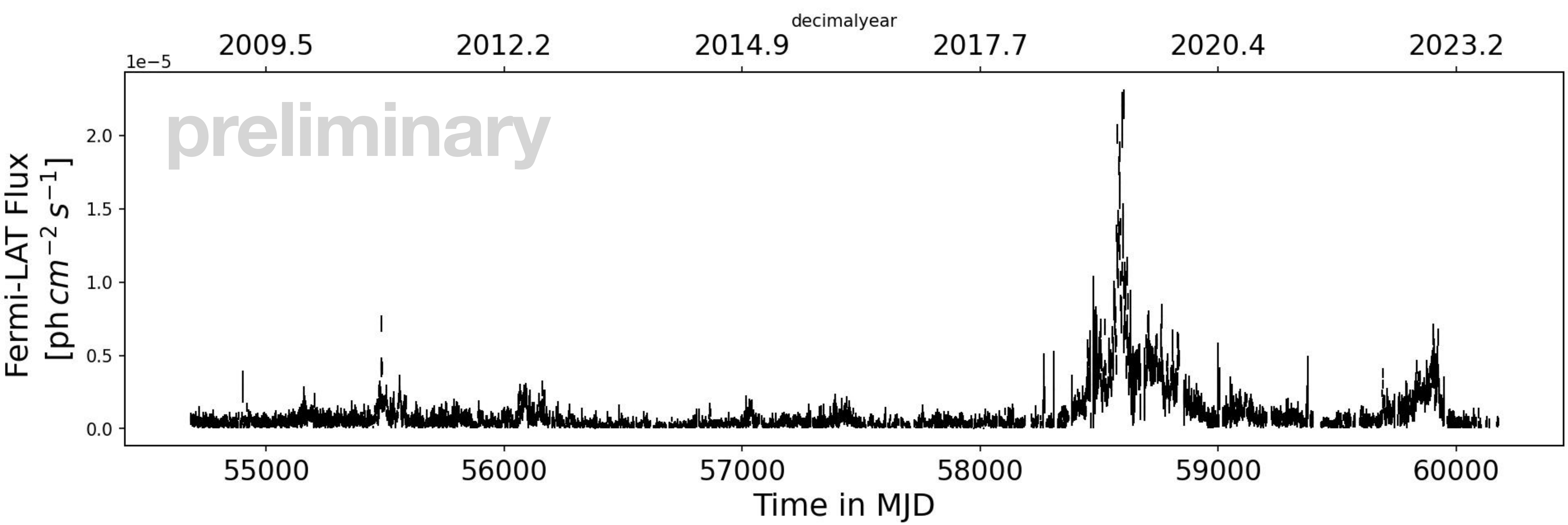
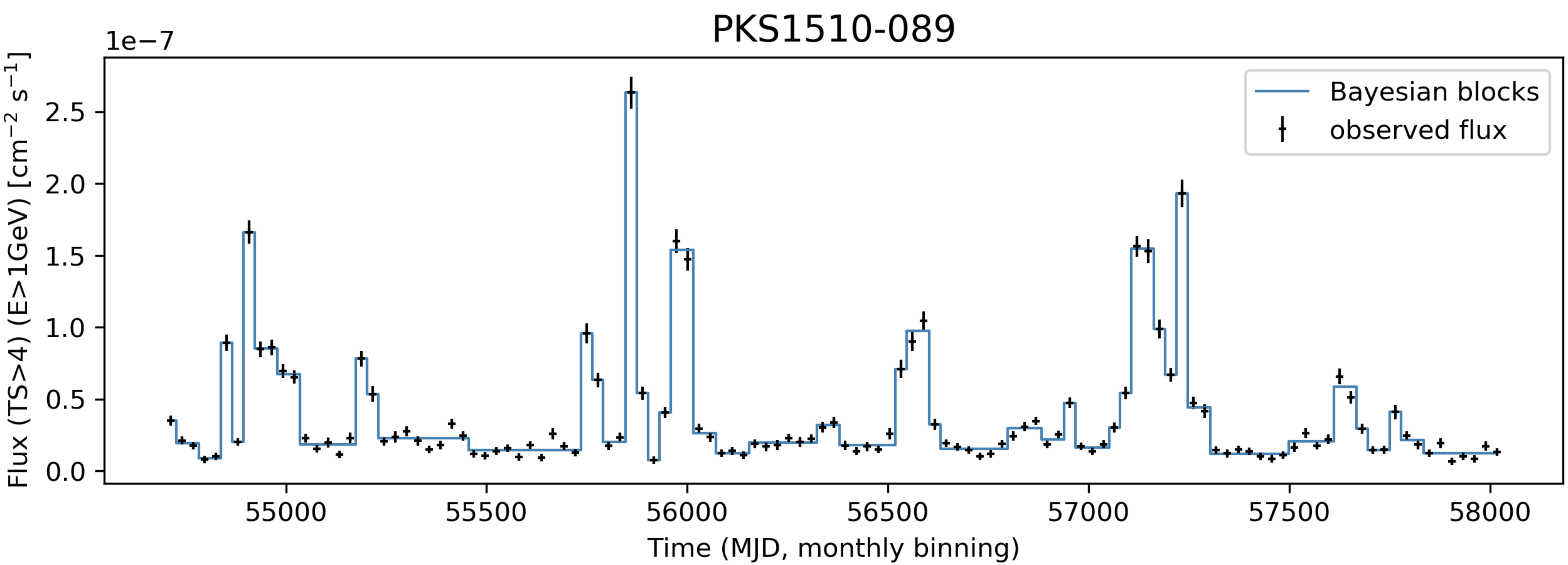
in case of two images: $$y(t) = x(t) + a\,x(t - t_0)$$

magnification ratio and delay = lens observables



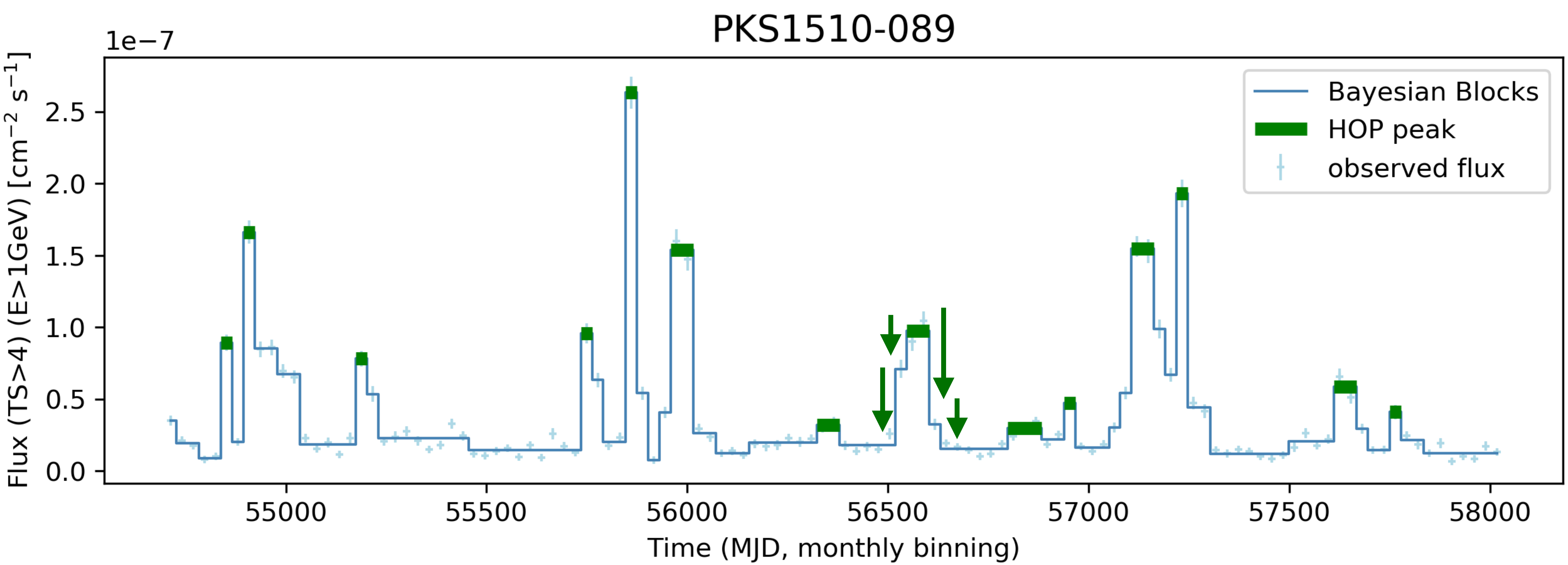
Bayesian Blocks

„Identify and characterize statistically significant variations while suppressing the inevitable corrupting observational errors“
(Scargle et al. 2013)



HOP algorithm

„Hop to highest neighbor of each data point“= identify peaks
Proceed downwards analogous to watershed method
(Wagner 2021, Meyer 2019)



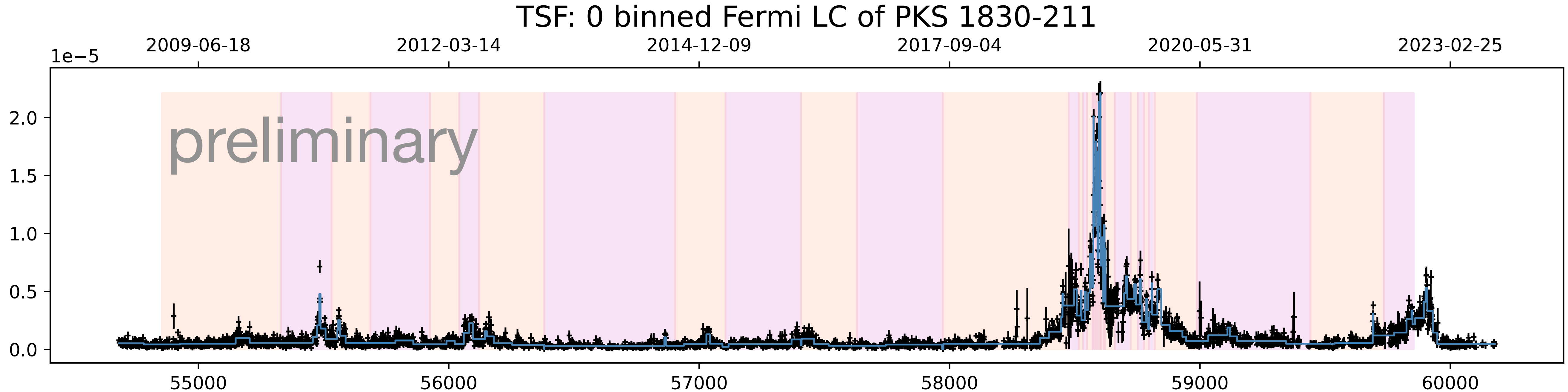
Peak distances

Delay imprinted in structure of light curve?

➡ apply Bayesian block and HOP analysis

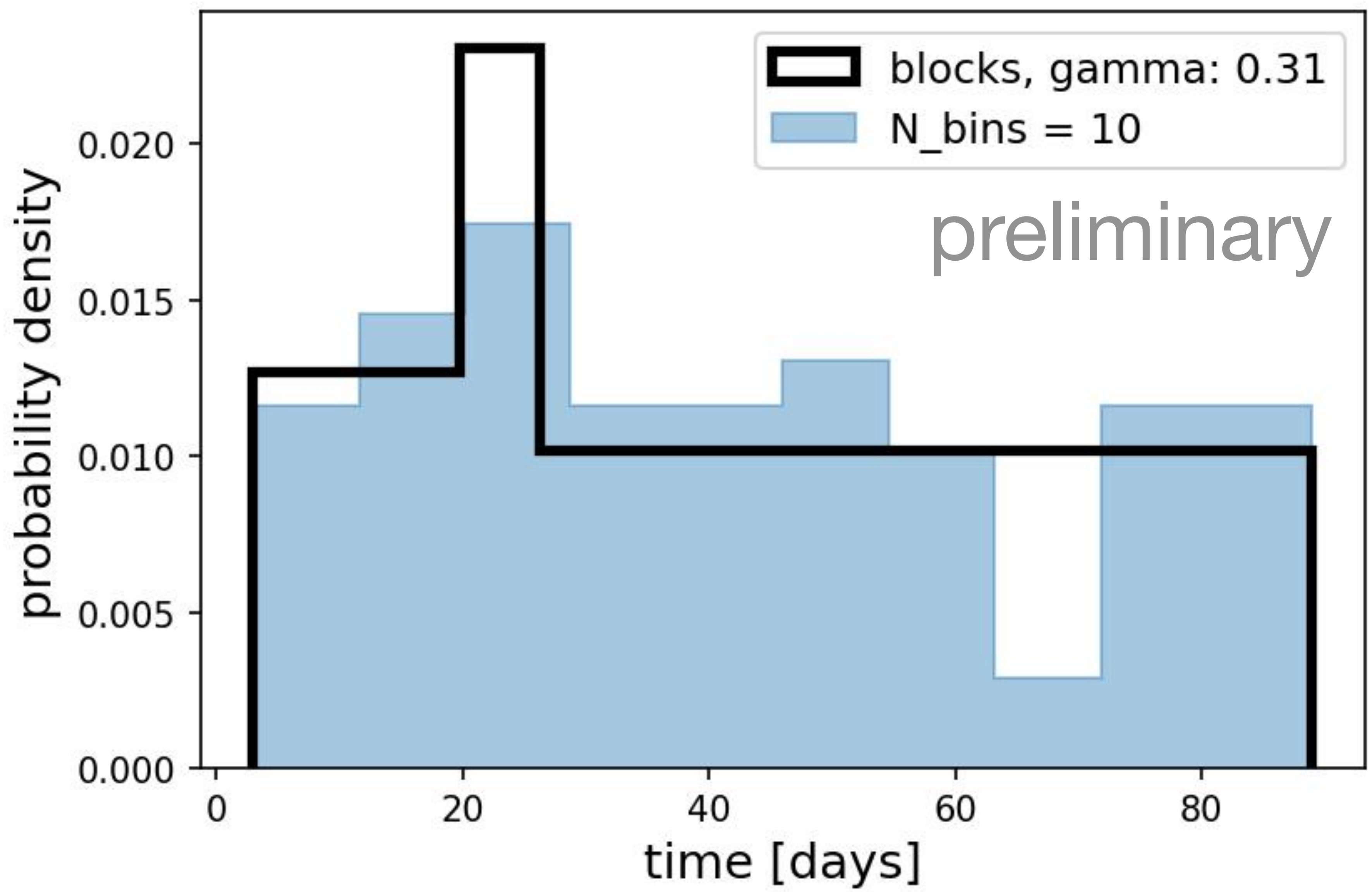
➡ detection of 33 flares (“hopjects”)

➡ distribution of distances between all peaks



Peak distances

Peak distances < 90d in regular (blue) and Bayesian binning (black), total: 80



significantly higher probability for distance to lay between 19.75 and 26.25 days

Auto-correlation

Self correlated signal would show peak in ACF

Definition:

$$R_y(\tau) = \mathbf{E}[y(t)\ y(t+\tau)] = \int_{-\infty}^{+\infty} y(t)\ y(t+\tau)\, dt = \int_{-\infty}^{+\infty} |Y(s)|^2 e^{i2\pi st}\, ds$$

Auto-corr Theorem:

BUT: unevenly sampled measurements over a finite observation period

Discrete Correlation Function (DCF)

Edelson & Krolik (1988)

similar: zDCF, structure function

Lomb-Scargle Periodogram (LSP)

Scargle et al (1982)

Discrete Correlation Function

Edelson & Krolik 1988

Consider all measurement pairs a_i and b_i from the two time series and compute

$$UDCF_{i,j} = \frac{(a_i - \bar{a})(b_j - \bar{b})}{\sqrt{(\sigma_a^2 - e_a^2)(\sigma_b^2 - e_b^2)}}$$

detrend

normalize

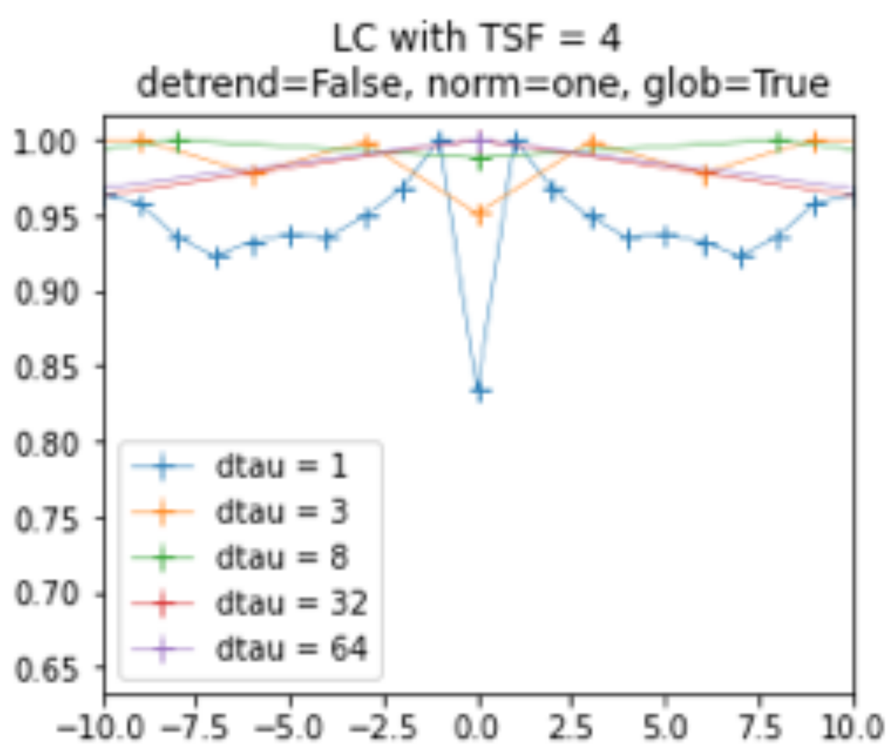
as well as the time shift between the corresponding times: $\Delta t_{i,j} = t_j - t_i$

To compute DCF, average over all UDCF values within a chosen bin $\Delta\tau$

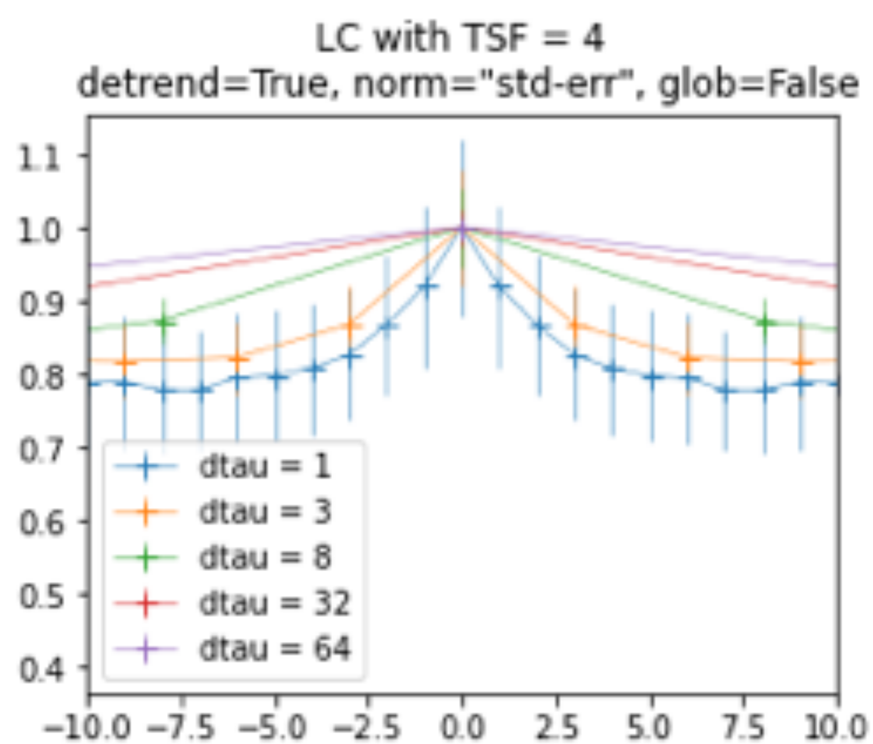
This can be done over the whole light curve or a certain lag range.

Discrete Correlation Function

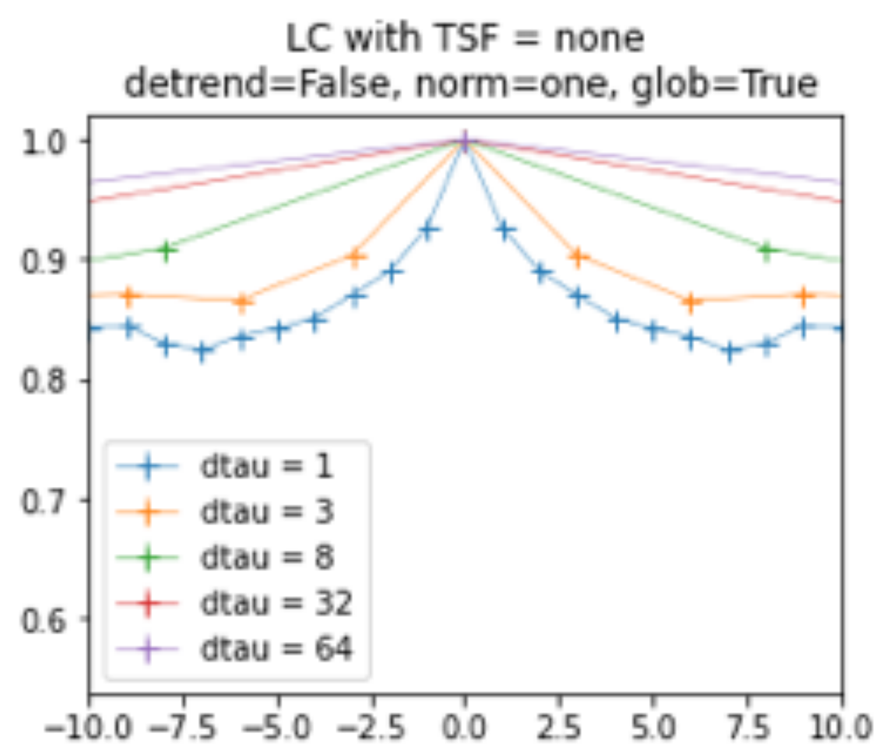
Bias of DCF can be minimized either by
—> not applying a TS filter or
—> detrending and normalizing the DCF



biased
eg dip at center due
to TS filter



not biased
(to be discussed)



not biased
(to be discussed)

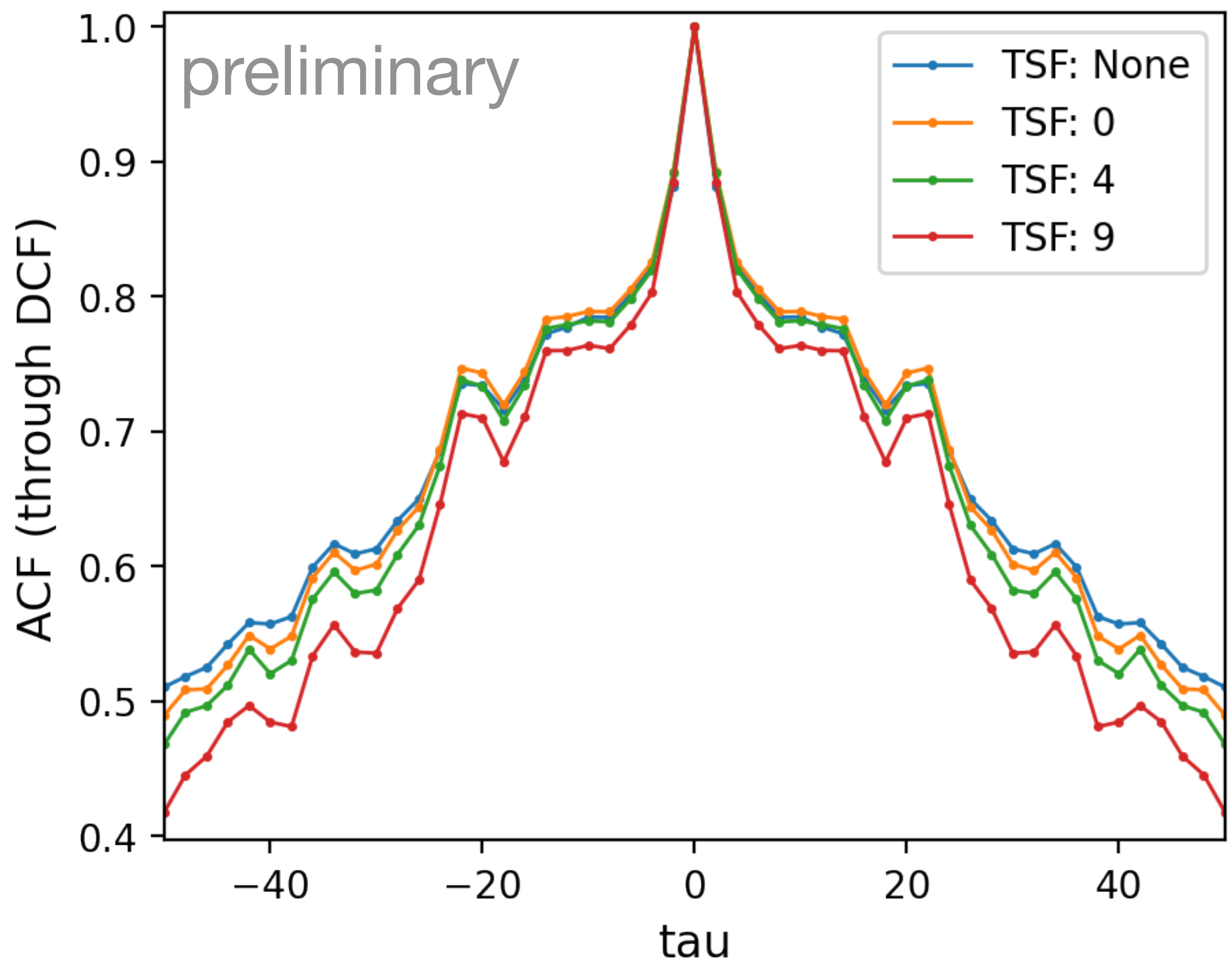
A) Auto-correlation: DCF

Discrete Correlation Function (Edelson & Krolik 1988)

$$UDCF_{i,j} = \frac{(a_i - \bar{a})\,(b_j - \bar{b})}{\sqrt{(\sigma_a^2 - e_a^2)\,(\sigma_b^2 - e_b^2)}}$$

detrend per bin

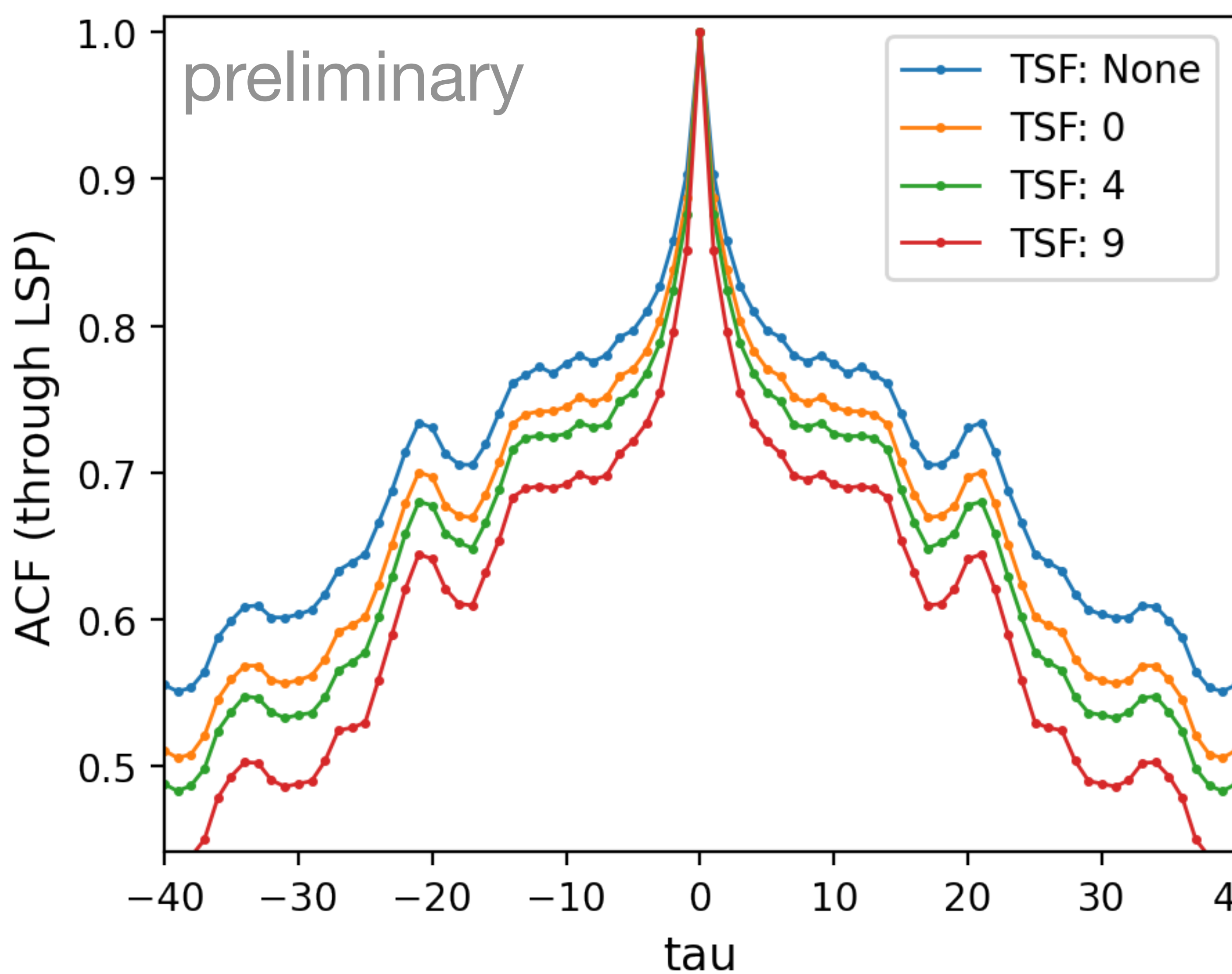
normalize



A) Auto-correlation: LSP

The auto-correlation approximated with the FT of the (Lomb-Scargle) Periodogram:

$$R(x) = \int_{-\infty}^{+\infty} f(u) f^*(u-x) du = \int_{-\infty}^{+\infty} |F_{LS}(s)|^2 e^{i2\pi sx} ds$$



Metric Optimization

We know behavior of light curve based on lensing

$$y(t) = x(t) + a\,x(t - t_0) \xleftrightarrow{\text{FT}} Y(s) = X(s)(1 + ae^{-i2\pi t_0 s})$$

➡ solve for intrinsic light curve

$$x(t) = IFT\left[\frac{FT[y(t)]}{1 + a\,e^{-i\omega t_0}}\right]$$

➡ fit for lens observables

- define a metric M to judge whether x(t) is a "good" intrinsic light curve
- find values for lens observables a, t_0 that optimize metric

$$\text{Estimated}(a, t_0) = \text{argmin } M[x(t|a, t_0)]$$

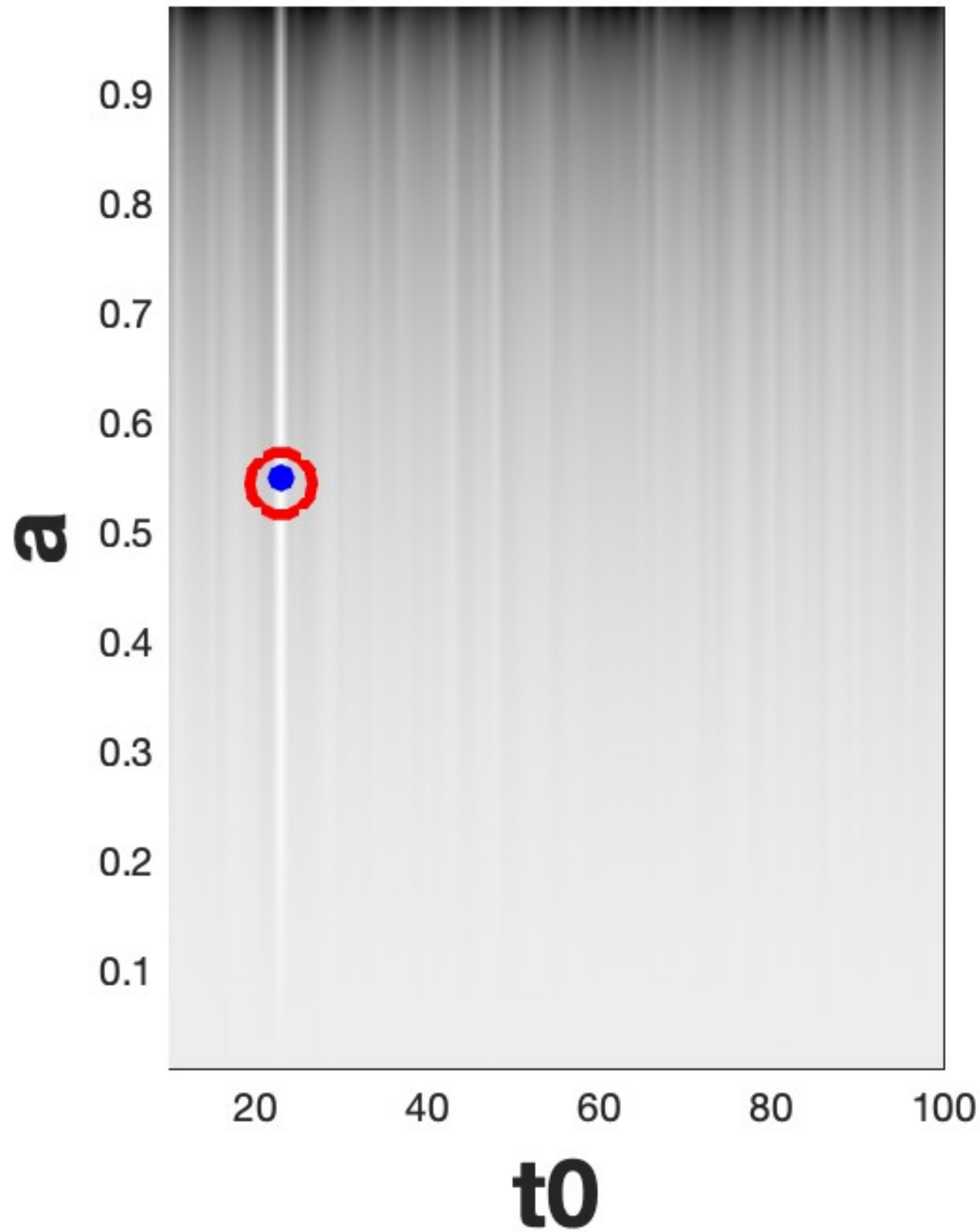
MO example

Many properties could be utilized as metric. One example:

➡ Variance of intrinsic light curve

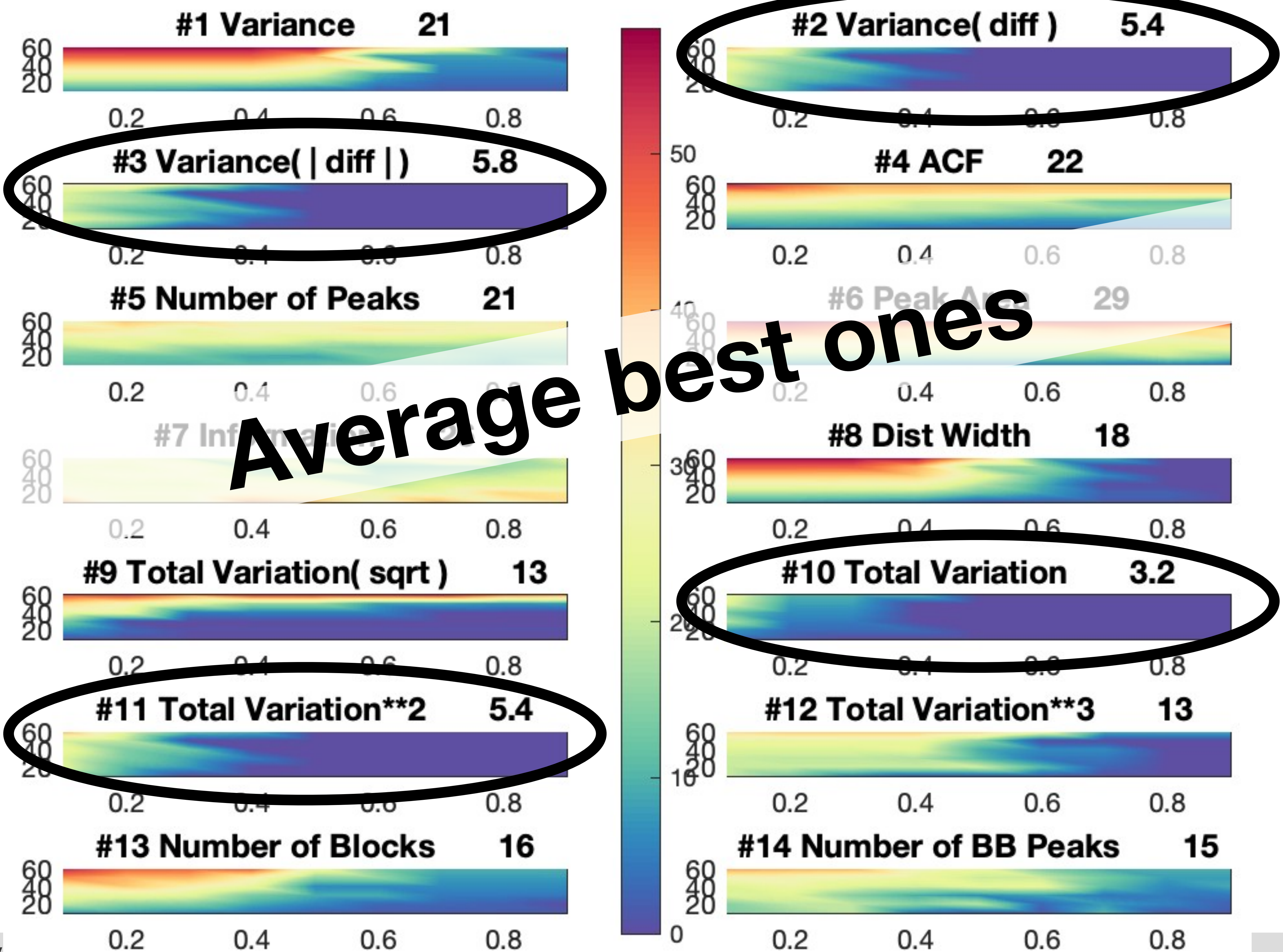
$$M[x(t)] = \mathrm{var}(x(t))$$

Figure to the right:
test case for noise-free simulated data.
Known parameter values: blue dot,
estimated values (minimum of variance
of x(t)): red circle



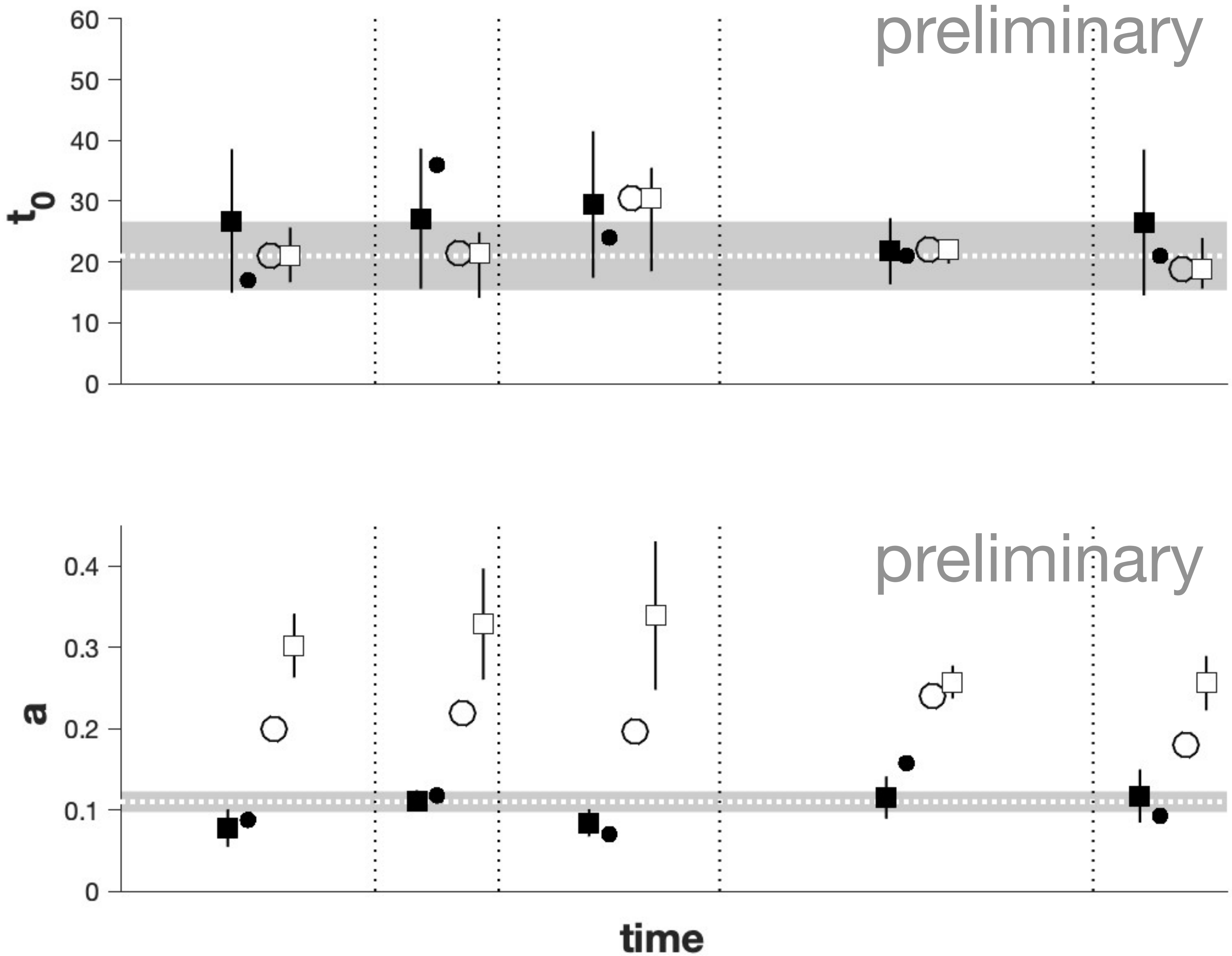
Metrics for Optimization

Error of predicted time delay in dependence of true values in simulations

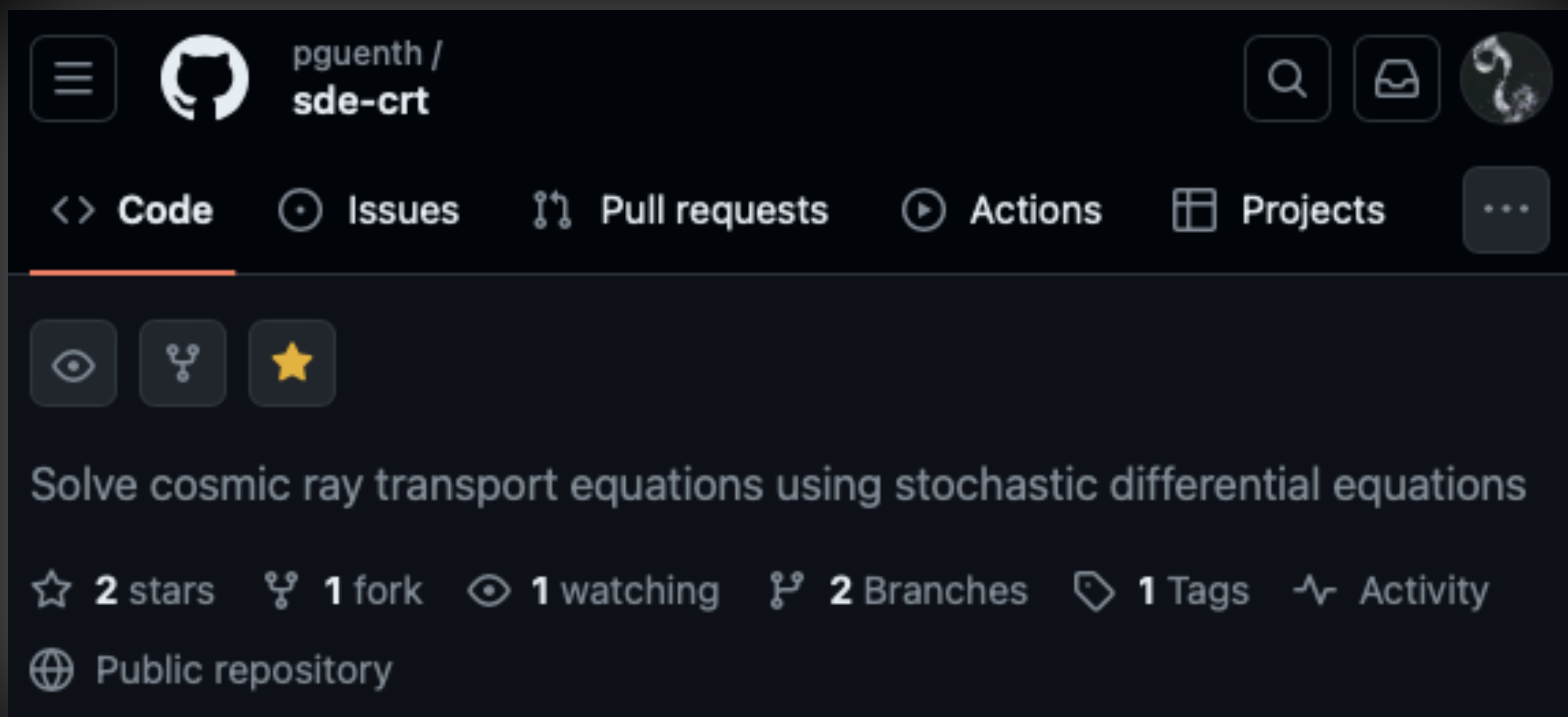


Overall results

solid circles are the metric optimized estimates; solid squares and lines are the bootstrap means and variances. Open symbols at similarly for the autocorrelation-based estimates using Equation



sde-crt



Patrick Günther

Stochastic Differential Eqs

SDE: next step of a process X_t is defined by:

$$\frac{d\mathbf{X}_{t,i}}{dt} = A_i(t, \mathbf{X}_t) + \sum_{j=1}^{N} B_{i,j}(t, \mathbf{X}_t)\,\frac{dW_\tau}{d\tau}$$

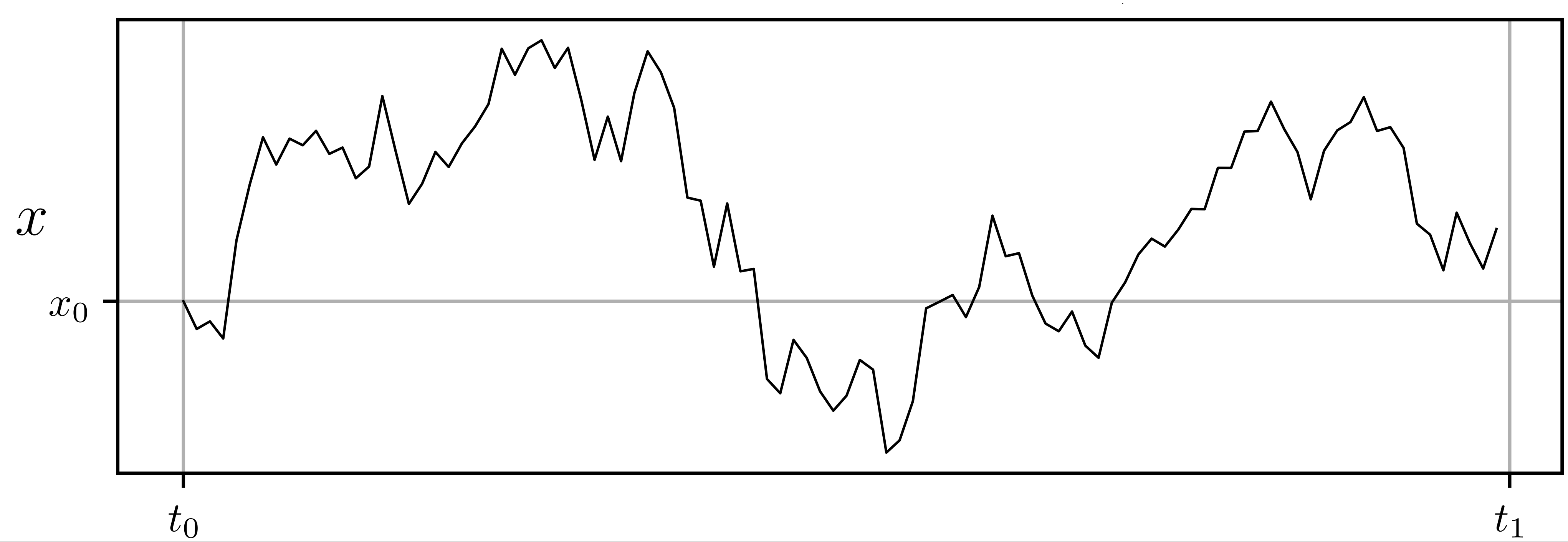
Drift

e.g. „draw back“ to mean

+

Diffusion

white noise (random contribution) expressed through Wiener process

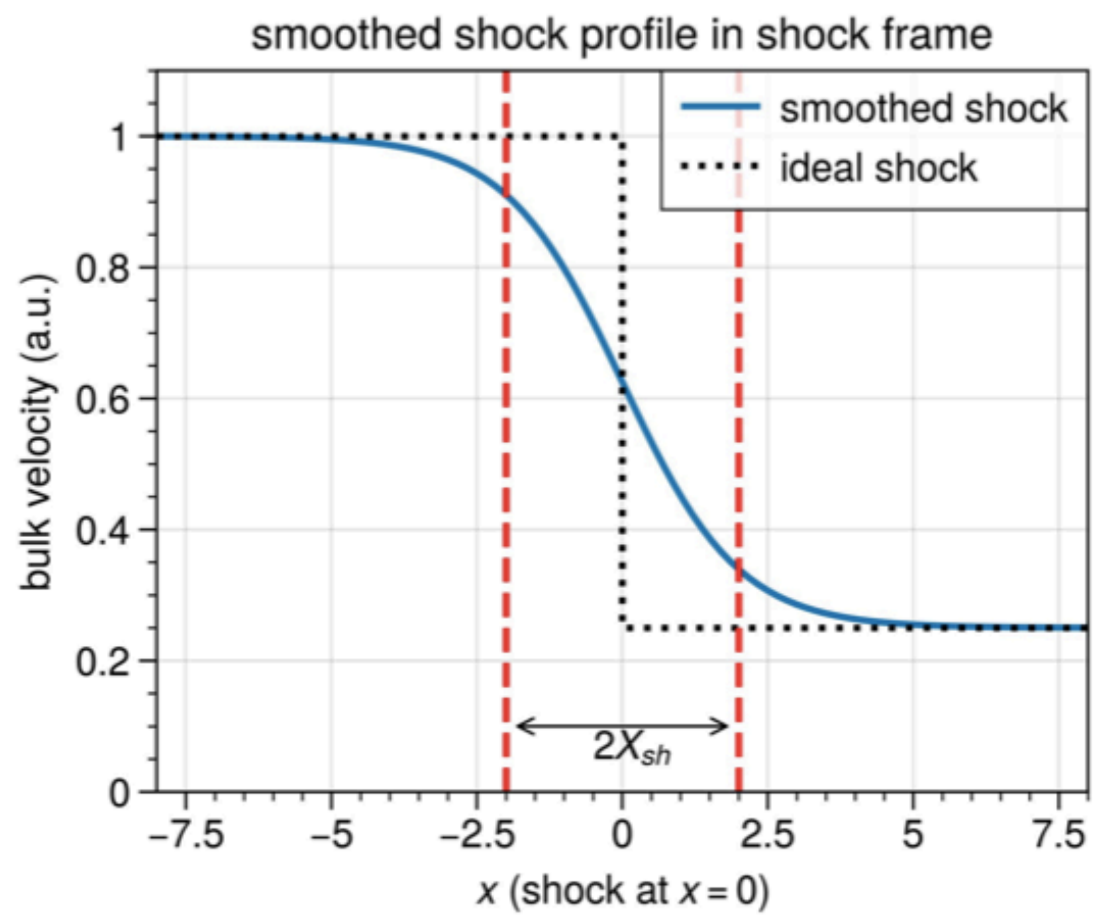


Particle Acceleration

Goal: create self-consistent model with multiple time dependent acceleration mechanisms (diffusive shock acceleration, stochastic acceleration, shock-drift) described by diffusion-convection simulations

Toy Model

- 1D, single shock/acceleration region with high compression ratio
- High-energy particles (electrons) are injected at the shock front



→ Diffusive shock acceleration

Constant energy gain $\frac{4}{3}\frac{\Delta u}{c}$ and loss rate $\frac{4u_d}{c}$ per cycle

Electron energy density index $s = -\frac{r+2}{r-1}$

Ornstein Uhlenbeck Process

see Burd et al. 2021 A&A 645, A62

$$u_{T+1} = u_T + \theta \Delta t(\mu - u_T) + \sigma\sqrt{\Delta t}\mathcal{N}_T$$

Drift

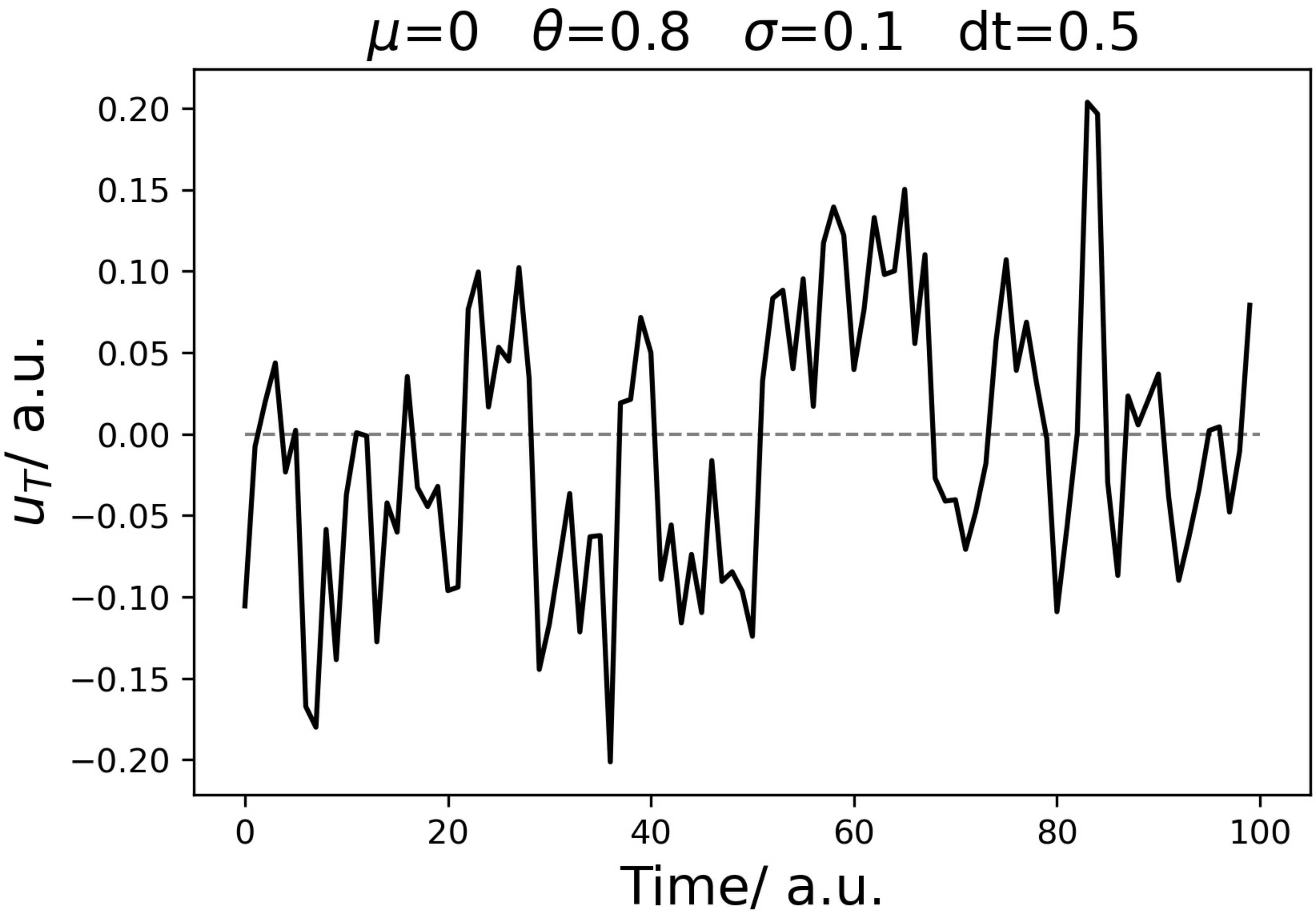
„draw back" to mean revision level μ at mean revision rate θ.

Diffusion

white noise described with Gaussian around 0 and variance σ^2.

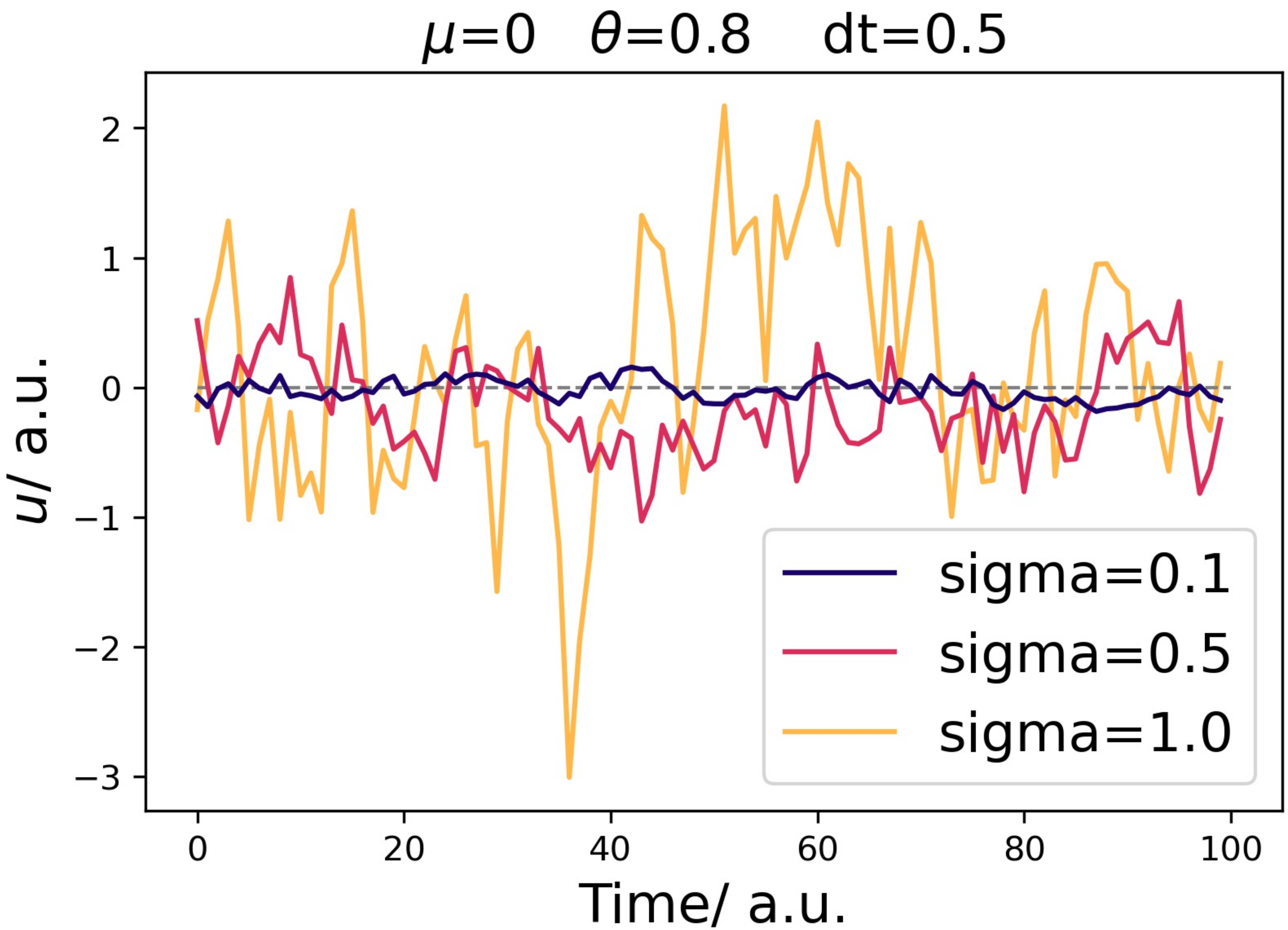
Ornstein Uhlenbeck Process

$$u_{T+1} = u_T + \theta \Delta t (\mu - u_T) + \sigma \sqrt{\Delta t} \mathcal{N}_T$$



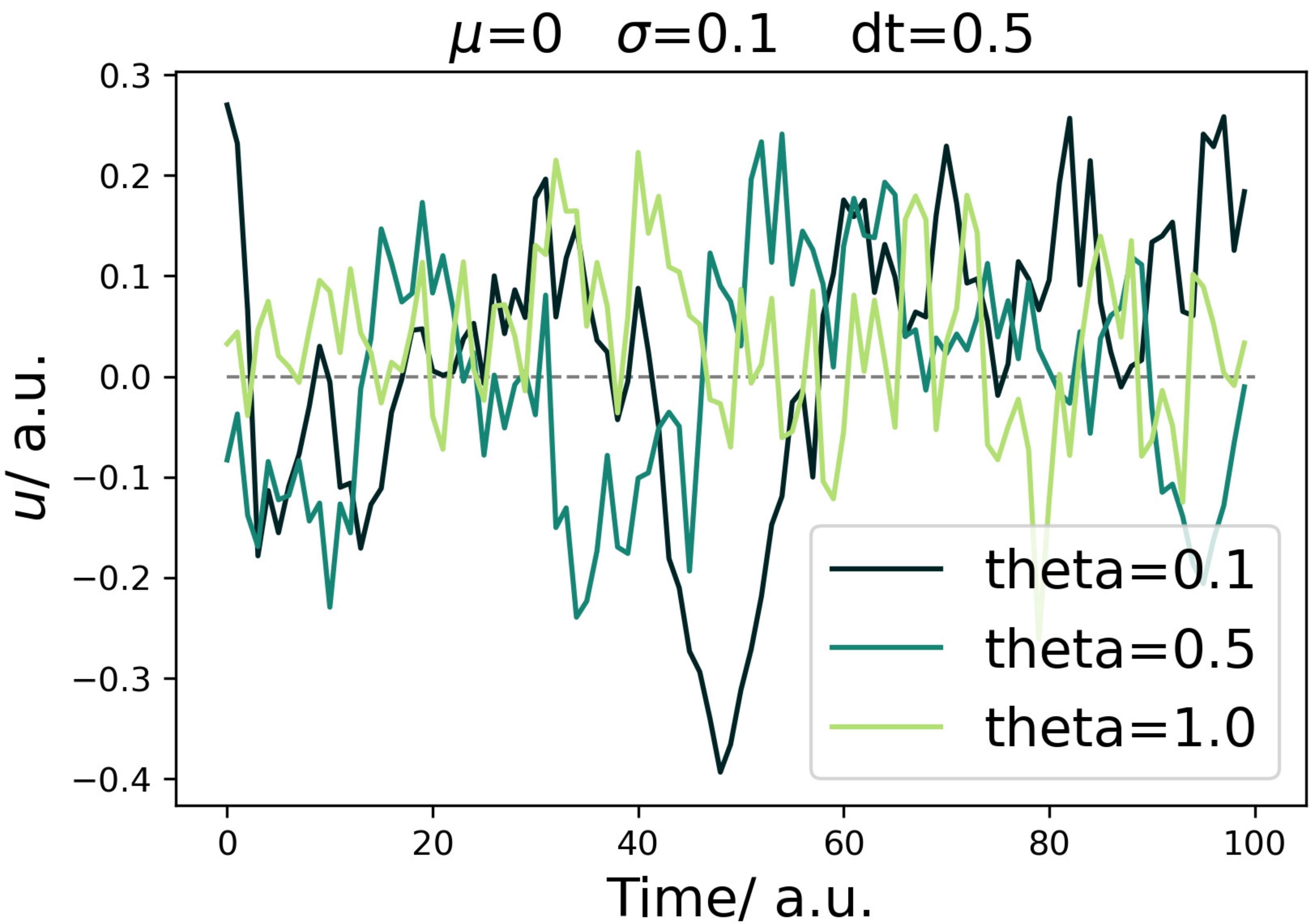
Ornstein Uhlenbeck Process

$$u_{T+1} = u_T + \theta \Delta t (\mu - u_T) + \sigma \sqrt{\Delta t} \mathcal{N}_T$$



Ornstein Uhlenbeck Process

$$u_{T+1} = u_T + \theta \Delta t(\mu - u_T) + \sigma\sqrt{\Delta t}\mathcal{N}_T$$



High-energy variability of the gravitationally lensed blazar PKS 1830-211