

EMRI Search and Inference within the LISA Global Fit II



Machine learning for Quasi periodic eruptions(QPEs) from Extreme mass-ratio inspirals (EMRIs)

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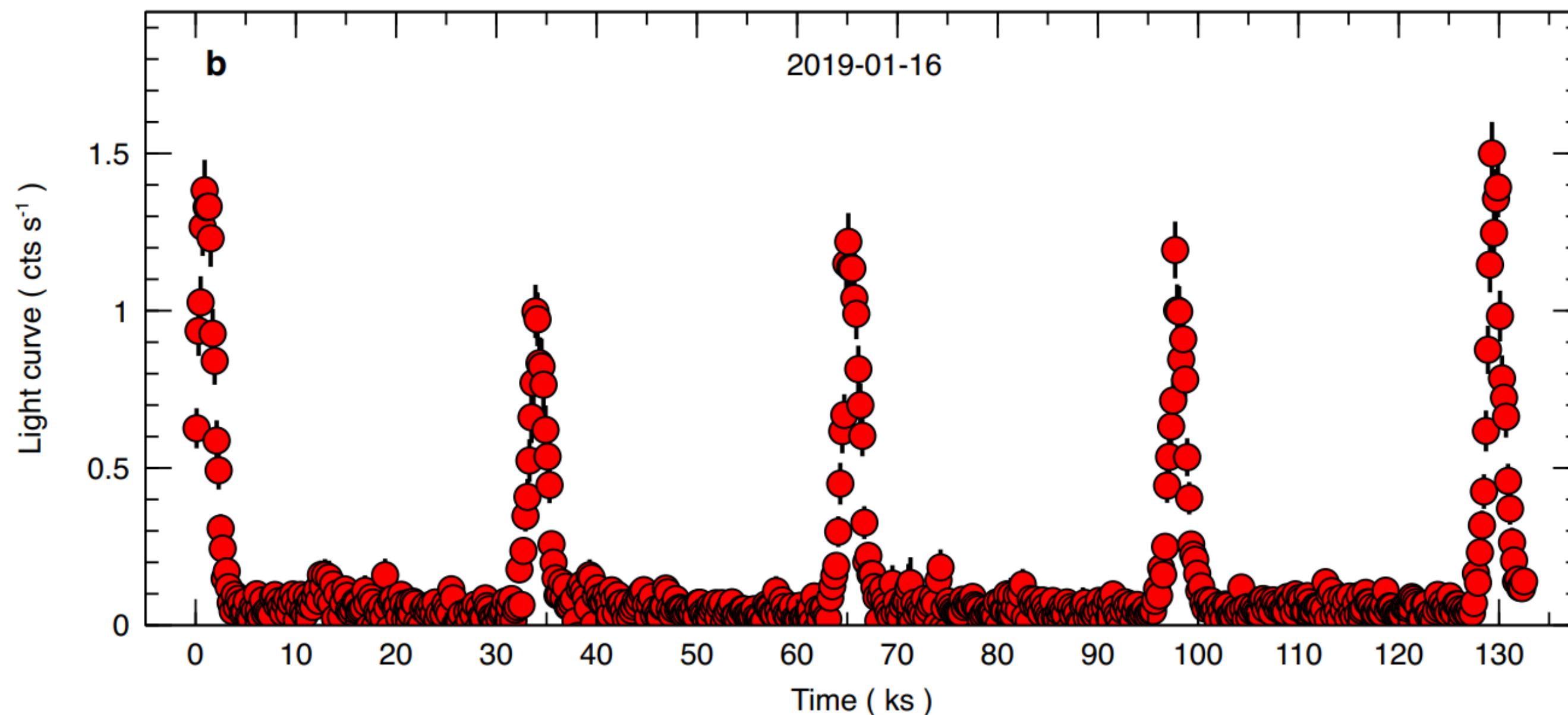
In collaboration with: Shubham Kejriwal, Alvin J. K. Chua,
Josh Mathews, Soichiro Isoyama

Outline

- What is QPEs?
- EMRI
- Model
- Motivation
- Machine Learning Model
- Initial results artificial neural networks.
- Summary and future directions

What is QPEs?

Quasi-periodic eruptions (QPEs) are intense repeating soft X-ray bursts with recurrence times about a few to ten hours from nearby galactic nuclei. The origin of QPEs is still unclear.



The 0.2-2 keV light curve from XMM Newton Director Discretionary Time (DDT) observation performed on 2019 January 16/17 (XMM4)

What is QPEs?

Characteristics:

- Eruptions typically occur every **few hours to every ~ 20 hours**.
- Each flare usually lasts between **30 minutes and an hour**.
- The emission is "soft," meaning it is dominated by lower-energy X-rays, typically consistent with thermal emission from an accretion disk.

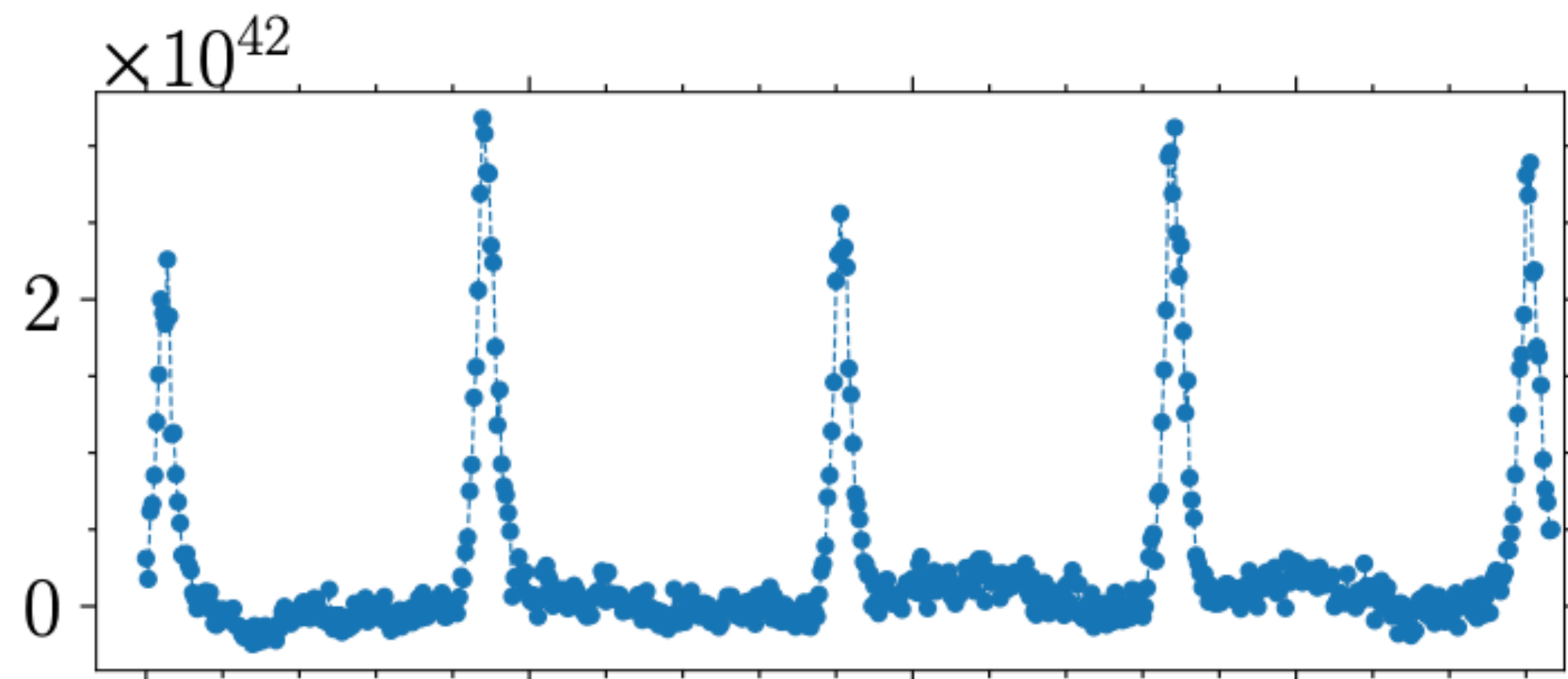


Fig 1: 0.2-2 keV X-ray luminosity light curve from the XMM-Newton observation XMM5 of GSN 069A
36.6 hrs long

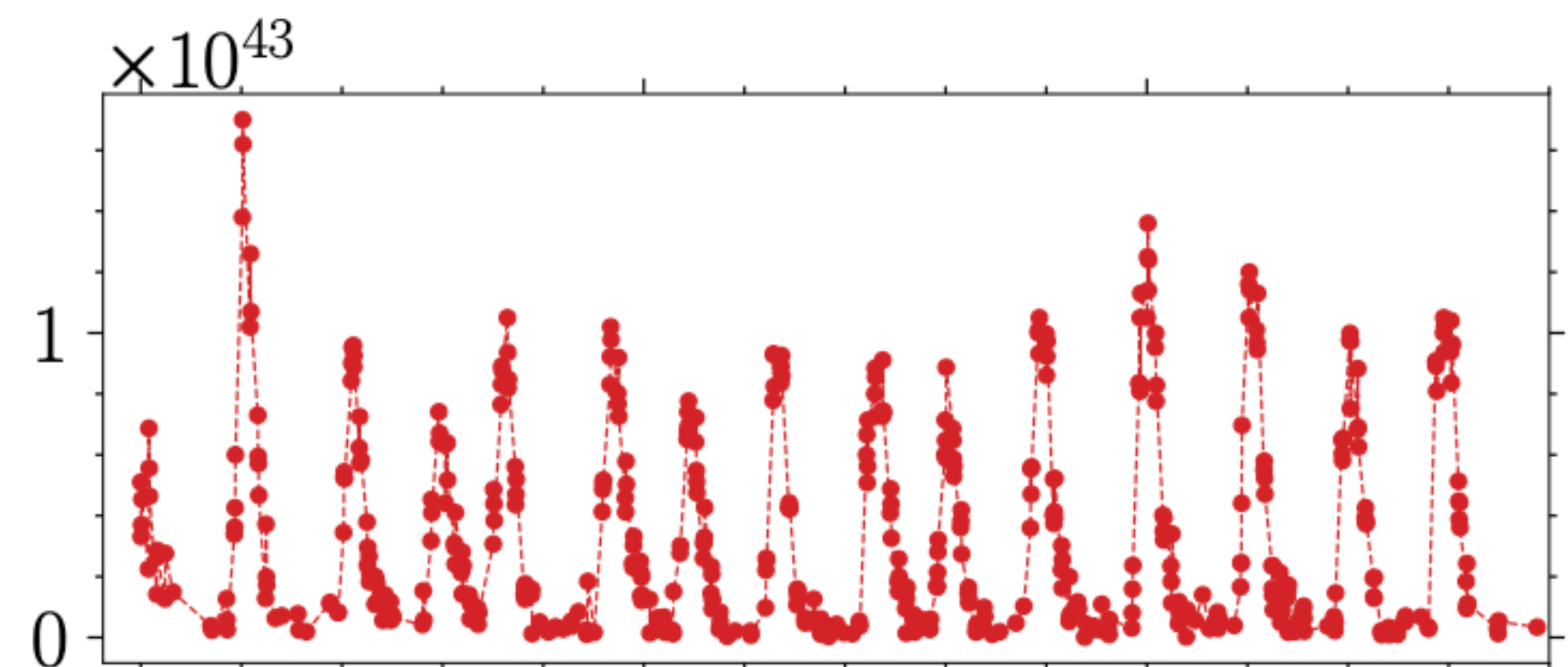
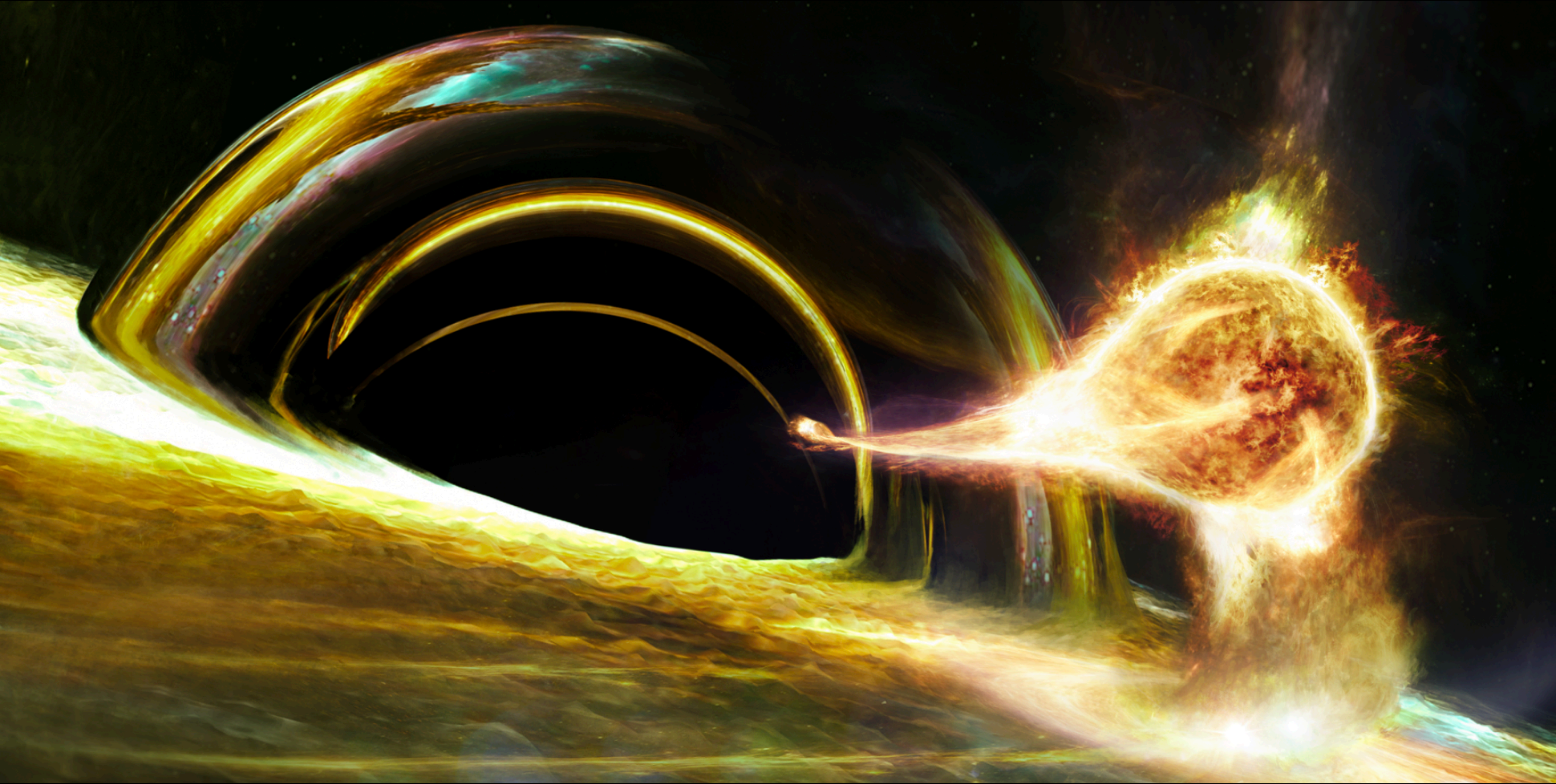


Fig 2: 0.2-2 keV X-ray luminosity light curve from a NICER ~ 250 hr long monitoring of eRO-QPE1

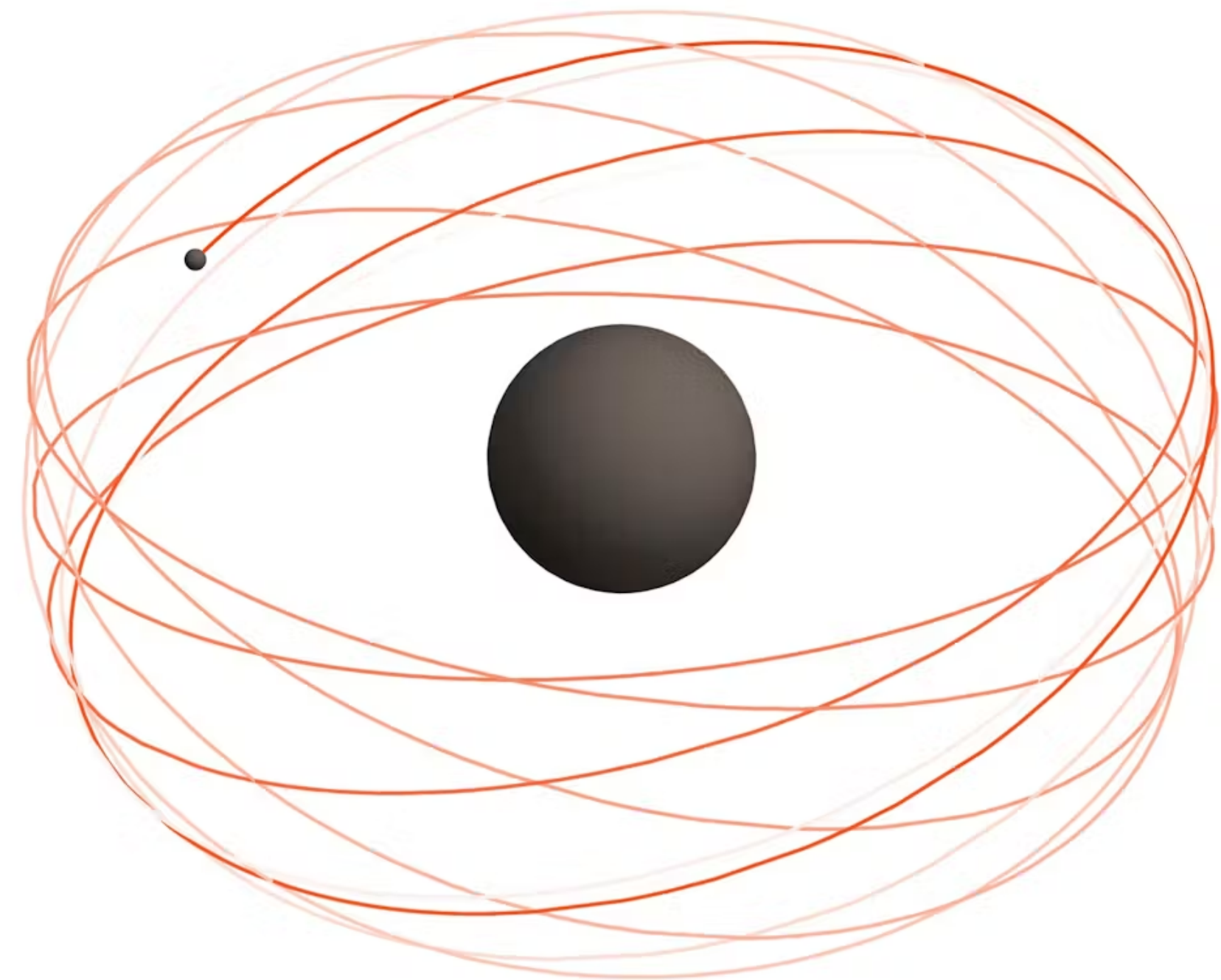
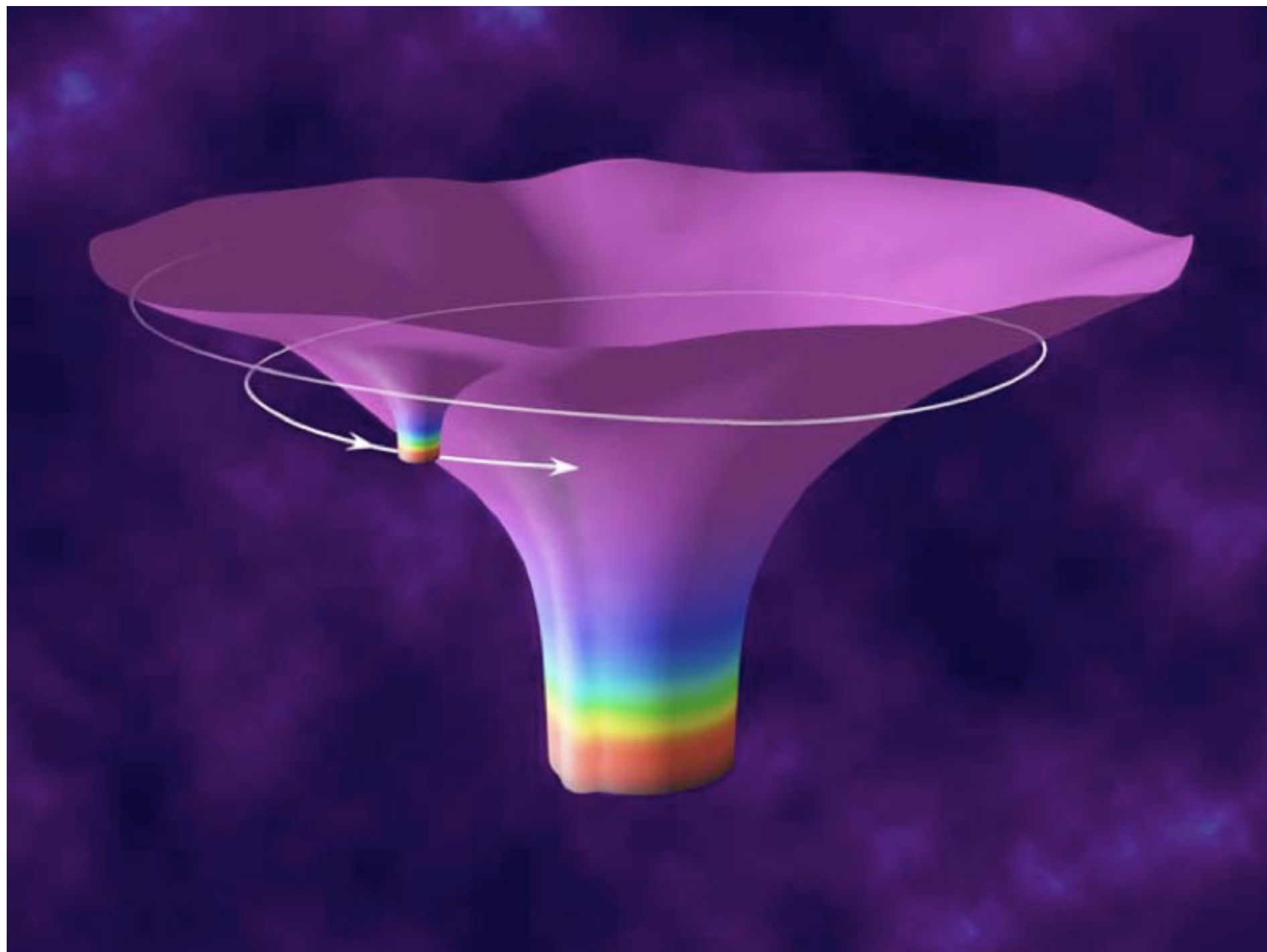
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EMRI

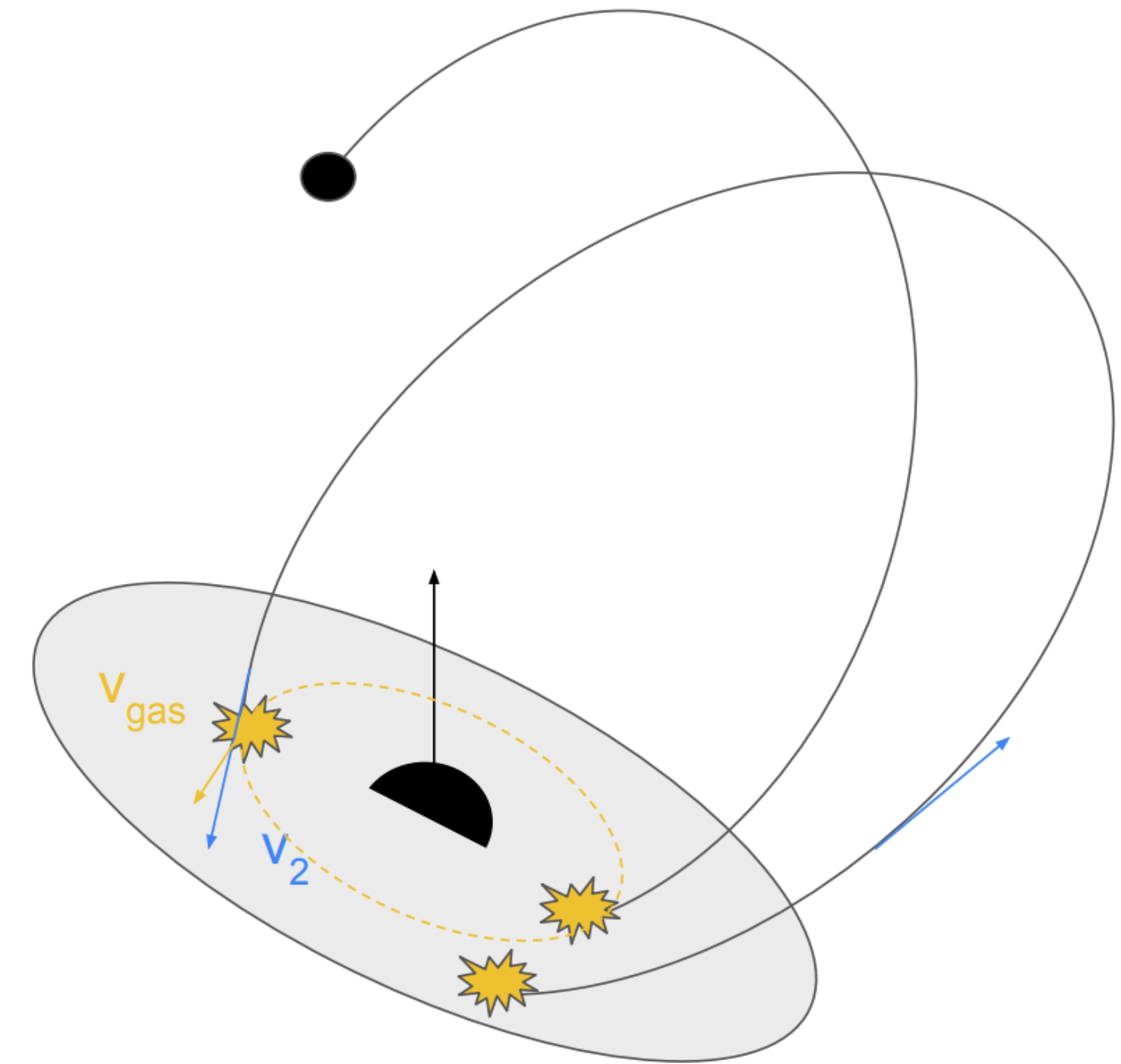
Extreme Mass Ratio Inspirals (EMRIs)- black hole binary system that are characterized by a small compact object of mass typically $\mu \in [1, 100]M_{\odot}$ inspiralling around a Massive Black Hole (MBH) of mass $M \in [10^5, 10^7]M_{\odot}$



Model

Schematic view of the model where the central big black dot represents the primary MBH, the small black dot represents the EMRI companion, the grey area represents the disc and the EMRI-disc crossings are shown with yellow stars.

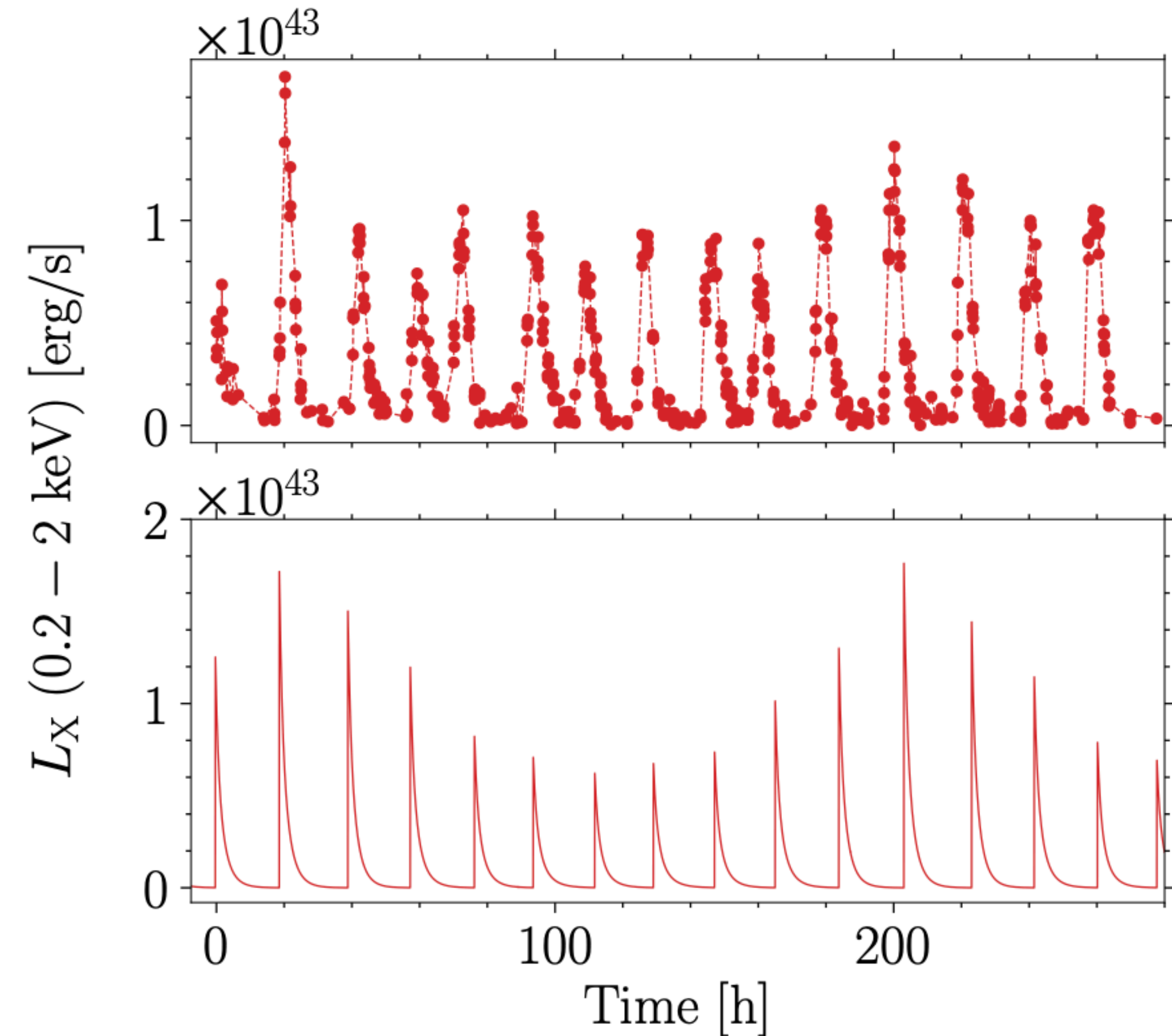
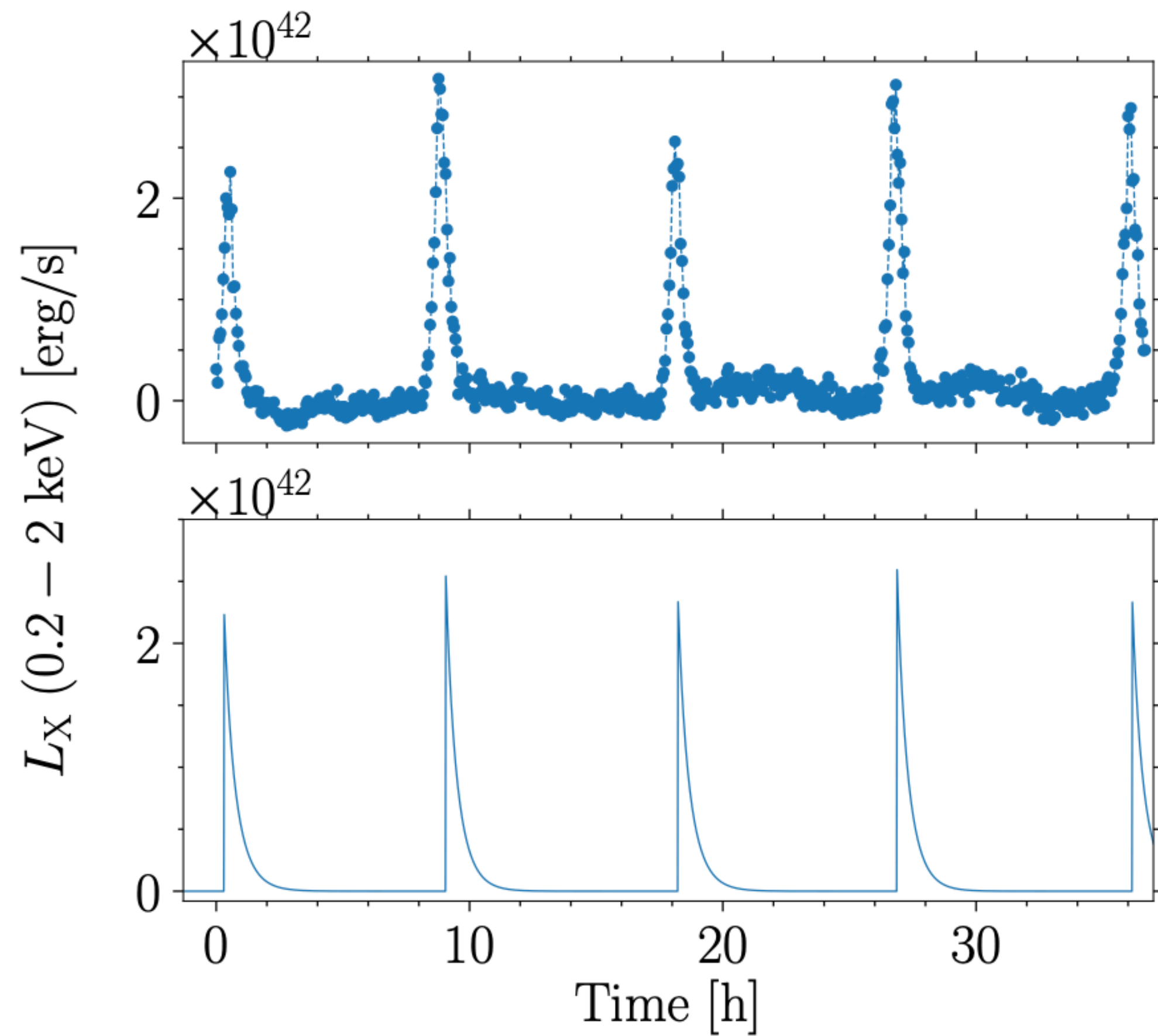
For our case we use $M_2 = 100M_\odot$ and $M = 10^5 - 10^6 M_\odot$ and mass ratio $q = M_2/M \ll 1$



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Model

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Comparison between observed and predicted light curve. Upper panel: 0.2-2 keV quiescence-subtracted X-ray luminosity light curve from the XMM-Newton observation XMM5 of GSN 069

Comparison between observed and predicted light curve. Upper panel: 0.2-2 keV X-ray luminosity light curve from a NICER~250 hr-long monitoring of eRO-QPE1.

Model

Equation of motion:

$$\frac{d^2\mathbf{r}}{dt^2} = -\frac{GM}{r^2} \left((1 + A)\mathbf{n} + B\mathbf{v} \right) + C_{1.5} + O\left(\frac{1}{c^8}\right)$$

A, B — coefficient which encodes the interaction due to the non-spin terms

$C_{1.5}$ — coefficient which introduces the spin-orbit interaction

$\mathbf{r}, \mathbf{v}$ — relative separation and velocity vector

$$\mathbf{n} = \mathbf{r}/|\mathbf{r}|$$

Radius of cloud:

$$R_{\text{in}} = \frac{GM_2}{c_s^2 + v_{\text{rel}}^2} \quad R(t) = R_{\text{in}} + \frac{2R_{\text{in}}}{\Delta t_{\text{QPE}}} t$$

v_{rel}, c_s — relative velocity between the gas and secondary object, and gas sound speed

$R_{\text{in}}, R(t)$ — initial radius and radius over time t

Δt_{QPE} — Duration of QPE

Model

Luminosity:

$$L_X = 4\pi R(t)^2 \int_{0.2 \text{ keV}}^{2 \text{ keV}} \frac{2h\nu^3}{c^2} \frac{d\nu}{\exp\left(\frac{h\nu}{k_B T_{\text{exp}}}\right) - 1}$$

Expansion temperature:

$$T_{\text{exp}} = T_2 \left(\frac{R_{\text{in}}}{R(t)} \right) \qquad T_2 = \left[1 + \frac{8}{7} \left(\mathcal{M}_{e,1}^2 - 1 \right) \right]^{1/4} T_1$$

T_{exp} — temperature during the expansion

T_1 — pre-shock disc gas temperature

T_2 — post-shock disc gas temperature

$\mathcal{M}_{e,1}$ — effective pre-shock Mach number

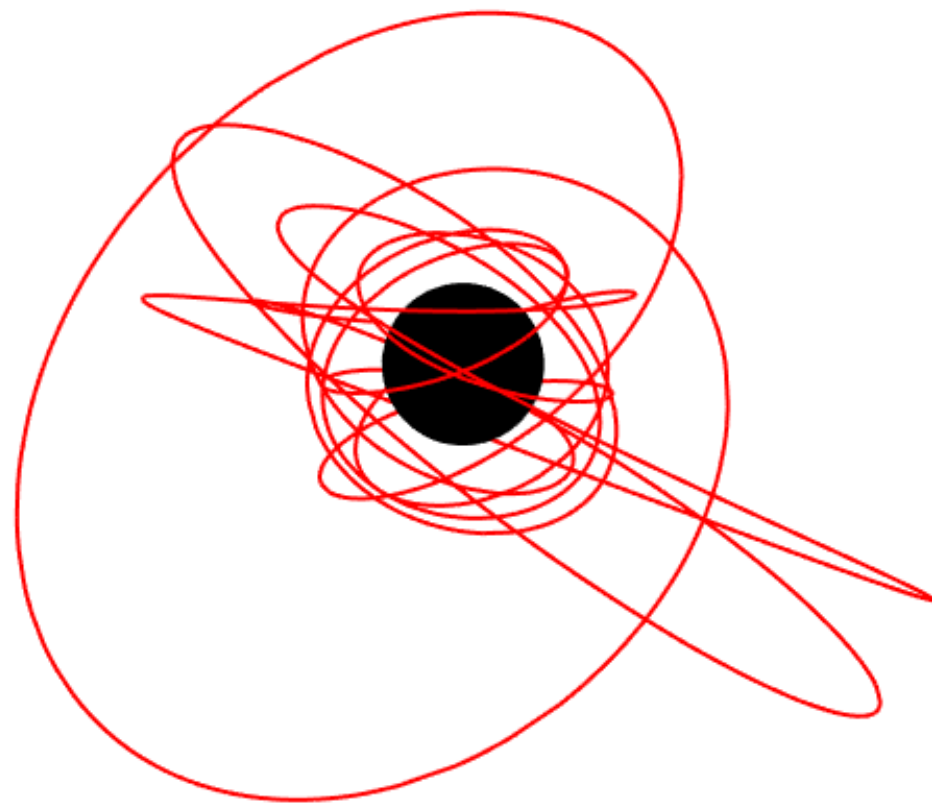
Model

Due to mass ratio is so small we use Kerr geodesics:

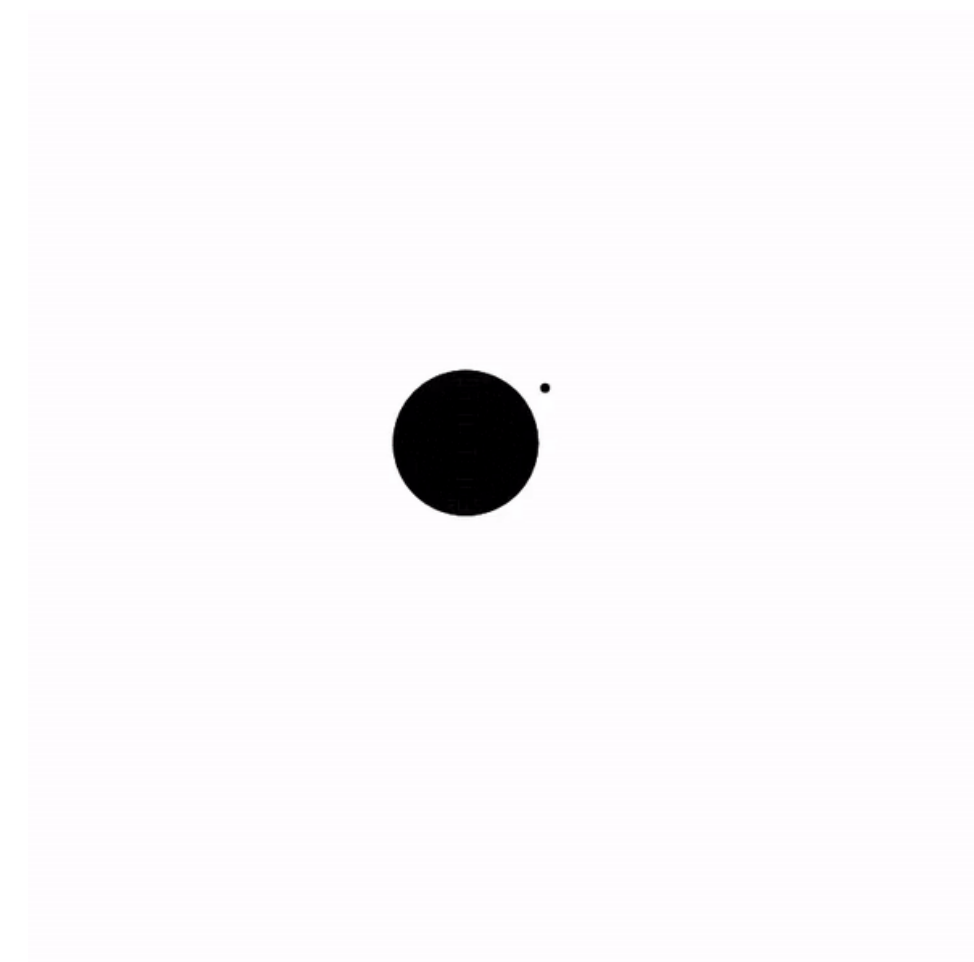
For this we have Wolfram Mathematica and Python packages which are part of the Black Hole Perturbation Toolkit:

1) Python package KerrGeoPy: <https://kerrgeopy.readthedocs.io/en/latest/>

2) Wolfram package KerrGeodesics: <https://bhptoolkit.org/KerrGeodesics/>



KerrGeodesics



KerrGeoPy

Motivation

QPE parameter inference

Bayesian inference:

- ✓ statistically rigorous
- ✓ uncertainty estimates

BUT

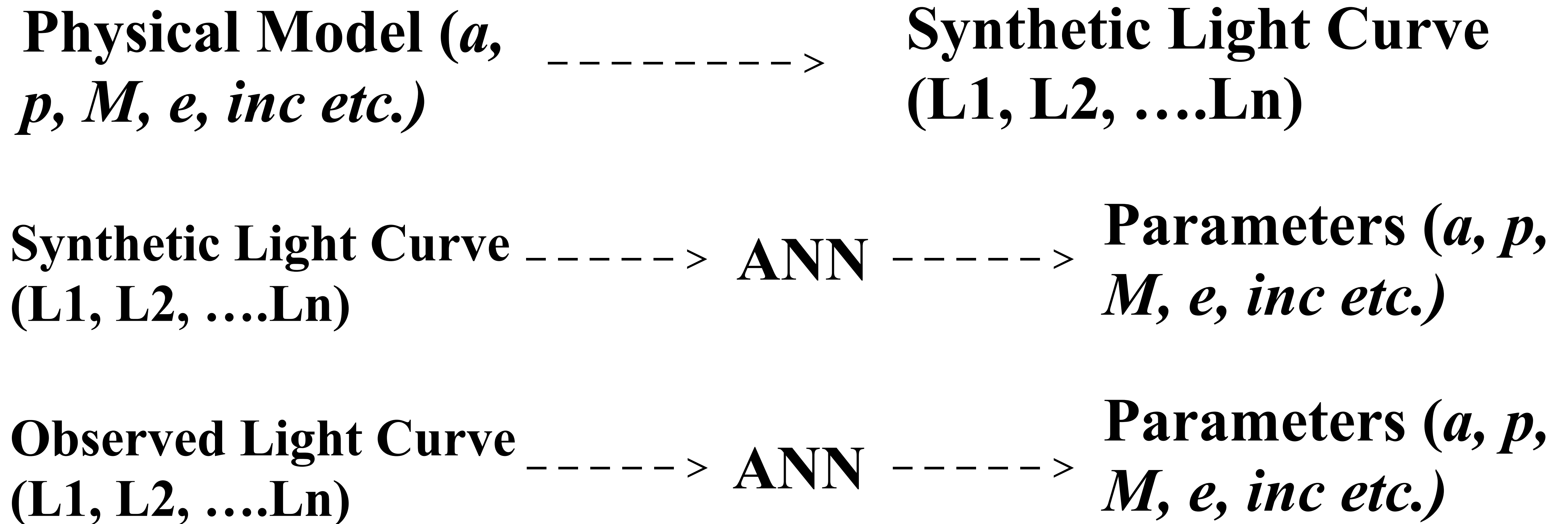
- computationally expensive
- multimodal posterior due to parameter degeneracies (J. Chakraborty et al. 2025)

Our approach:

Learn the inverse mapping EMRI parameters using neural networks

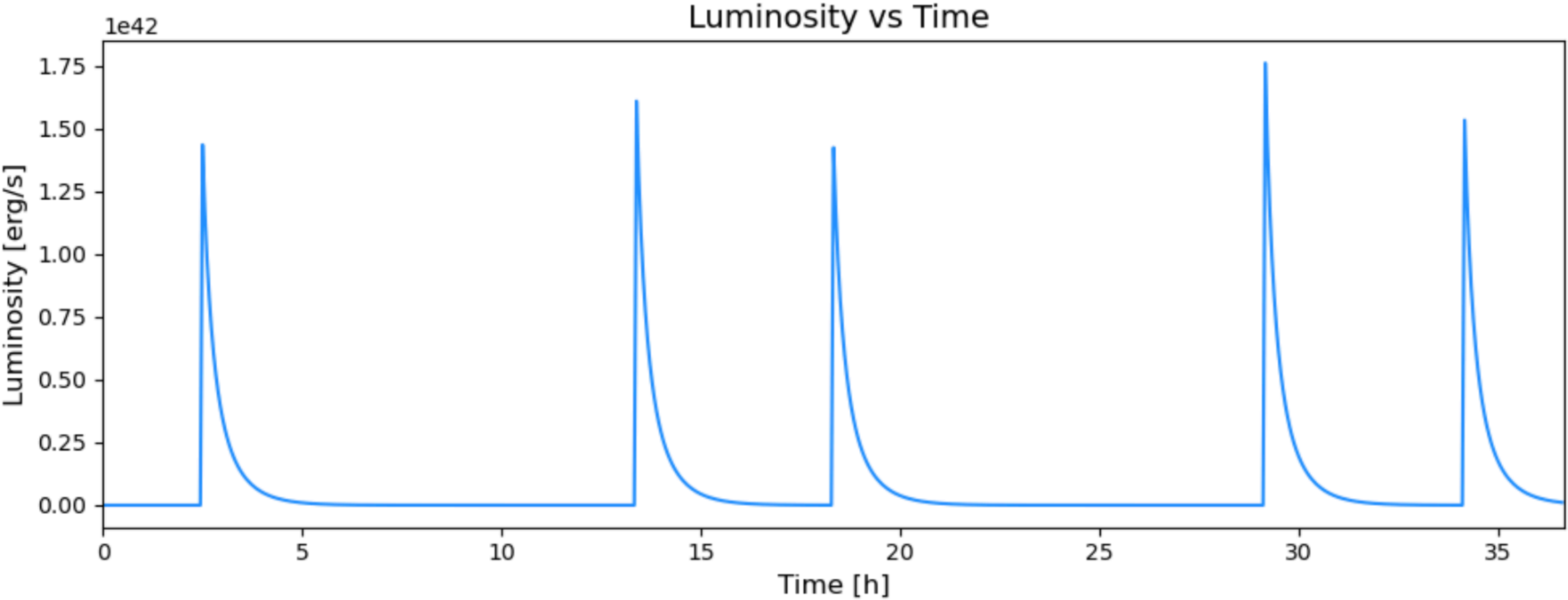
- ✓ inference in milliseconds after training
- ✓ Point parameter estimation

Machine Learning Model



Machine Learning Model

	a	p	e	inc	M	L0	L1	L2	L3	L4	...	L651	L652	L653	L654	L655	L656	L657	L658	L659	N_Cross
0	0.5	61.261051	0.487310	34.300602	954381.757632	0.0	0.0	0.0	0.0	0.0	...	2.680626e+38	2.438670e+38	2.220831e+38	2.024549e+38	1.847547e+38	1.687798e+38	1.543496e+38	1.413034e+38	1.294977e+38	12
1	0.5	114.909728	0.361487	7.949184	541519.851978	0.0	0.0	0.0	0.0	0.0	...	3.924660e+40	3.561463e+40	3.232646e+40	2.934810e+40	2.664921e+40	2.420262e+40	2.198394e+40	1.997132e+40	2.192147e+42	11
2	0.5	226.667158	0.332280	23.411017	152944.055067	0.0	0.0	0.0	0.0	0.0	...	4.757518e+42	4.598319e+42	4.445543e+42	4.298859e+42	4.157962e+42	4.022564e+42	3.892396e+42	3.767203e+42	3.646750e+42	14
3	0.5	71.614024	0.412322	17.318240	948351.441185	0.0	0.0	0.0	0.0	0.0	...	1.107205e+40	1.027933e+40	9.545946e+39	8.867092e+39	8.238411e+39	7.655930e+39	7.116028e+39	6.615398e+39	6.151015e+39	11
4	0.5	238.390571	0.346069	36.716751	209561.013919	0.0	0.0	0.0	0.0	0.0	...	7.969936e+41	7.665069e+41	7.374274e+41	7.096731e+41	6.831679e+41	6.578411e+41	6.336273e+41	6.104653e+41	5.882984e+41	9
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
59719	0.5	50.921362	0.762311	42.961347	871624.156423	0.0	0.0	0.0	0.0	0.0	...	4.429705e+38	4.269535e+38	4.115408e+38	3.967078e+38	3.824310e+38	3.686880e+38	3.554573e+38	3.427186e+38	3.304523e+38	7
59720	0.5	114.282379	0.079790	16.184305	842851.552952	0.0	0.0	0.0	0.0	0.0	...	3.945001e+38	3.379135e+38	2.894170e+38	2.478576e+38	2.122459e+38	1.817336e+38	1.555928e+38	1.331993e+38	1.140179e+38	8



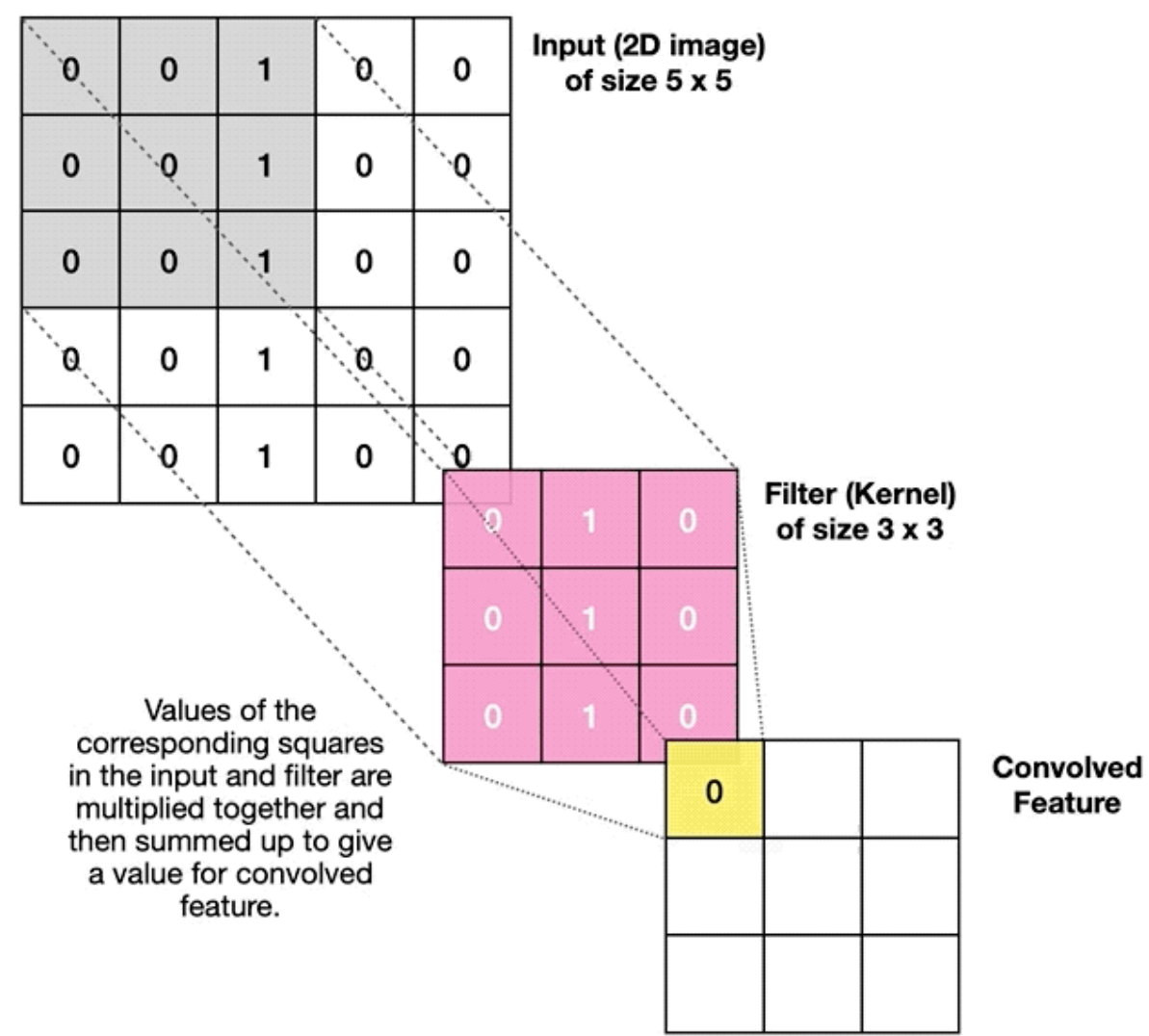
Number of datapoints: 59724

Machine Learning model

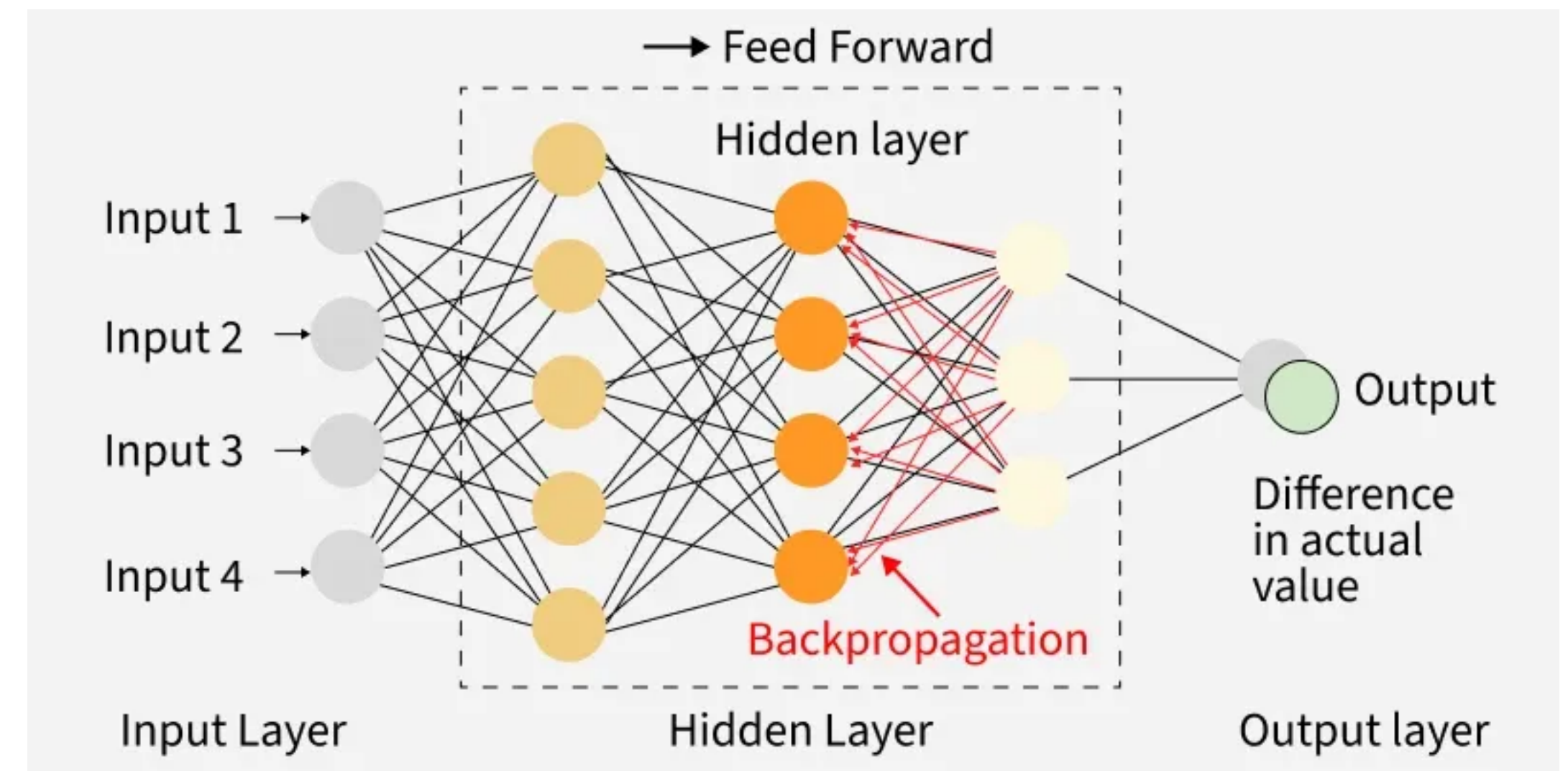
We use supervised machine learning model: Deep learning

Deep learning: Multilayer Perceptrons (+Convolutional NN)

$$f(x_n; \theta) - > y_{pred}$$



----->



Machine Learning model

For our case input vector x_n is luminosities in each time bucket

$$x_0 \text{ --- } > L_{01}, L_{02}, L_{03}, L_{04} \dots L_{0k}$$

$$x_1 \text{ --- } > L_{11}, L_{12}, L_{13}, L_{14} \dots L_{1k}$$

And output vector y_n is predicted parameters of EMRI

$$y_0 \text{ --- } > p_0, M_0, e_0, inc_0$$

ANN model results

The parameter space:

$$M \sim \mathcal{U}[10^5 - 10^6]$$

$$e \sim \mathcal{U}[0.05, 0.8]$$

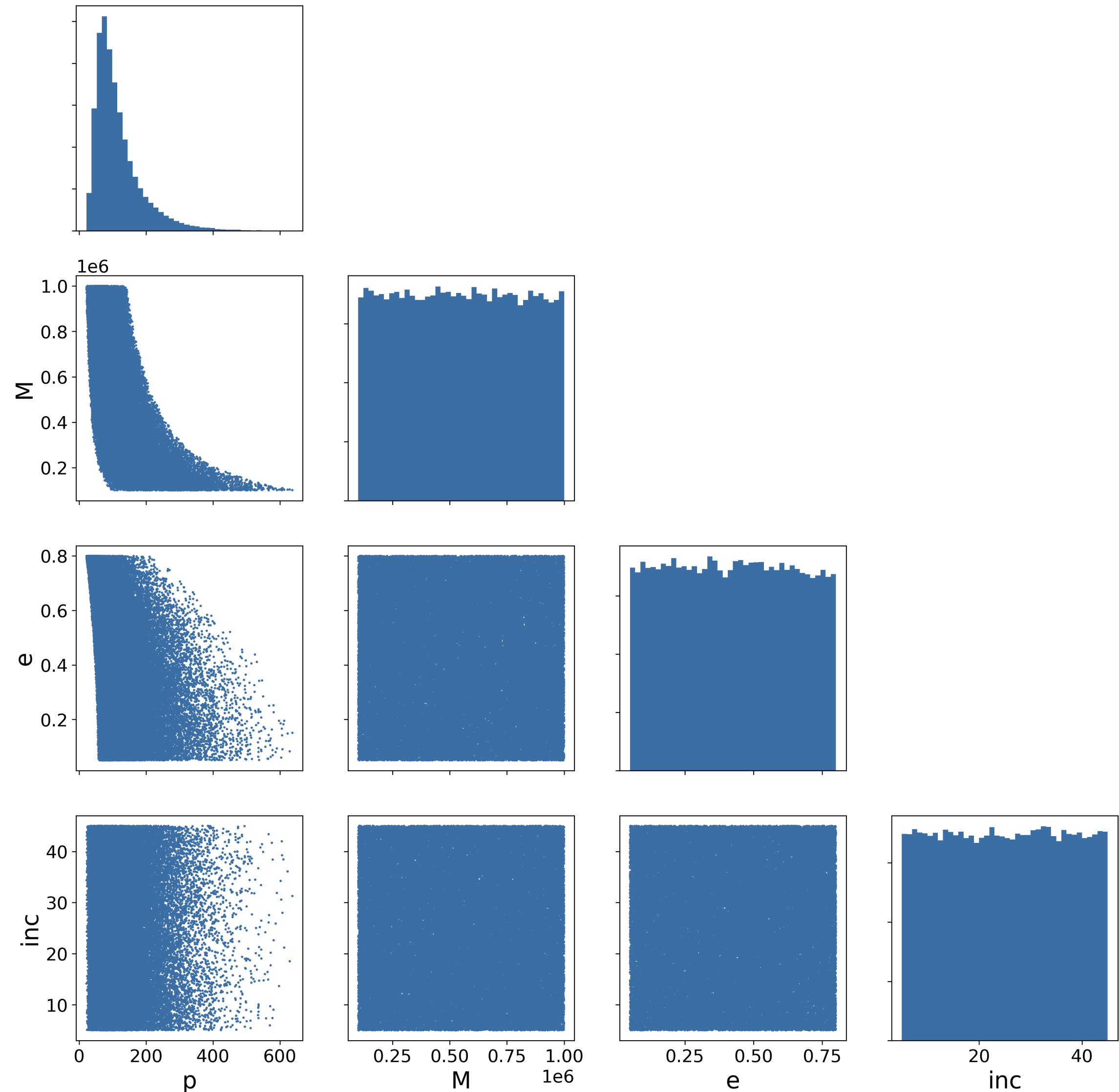
$$\text{inc} \sim \mathcal{U}[5^\circ, 45^\circ]$$

$$p_{\min} = 21.97, p_{\max} = 637.33$$

$$N_{\min} = 5 \text{ and } N_{\max} = 20$$

We introduce a new parameter:

$$A = p^{-3/2} M^{-1} (1 - e^2)^{3/2} \sim \Omega_{\text{orb}}$$



Initial results ANNs

And now we have:

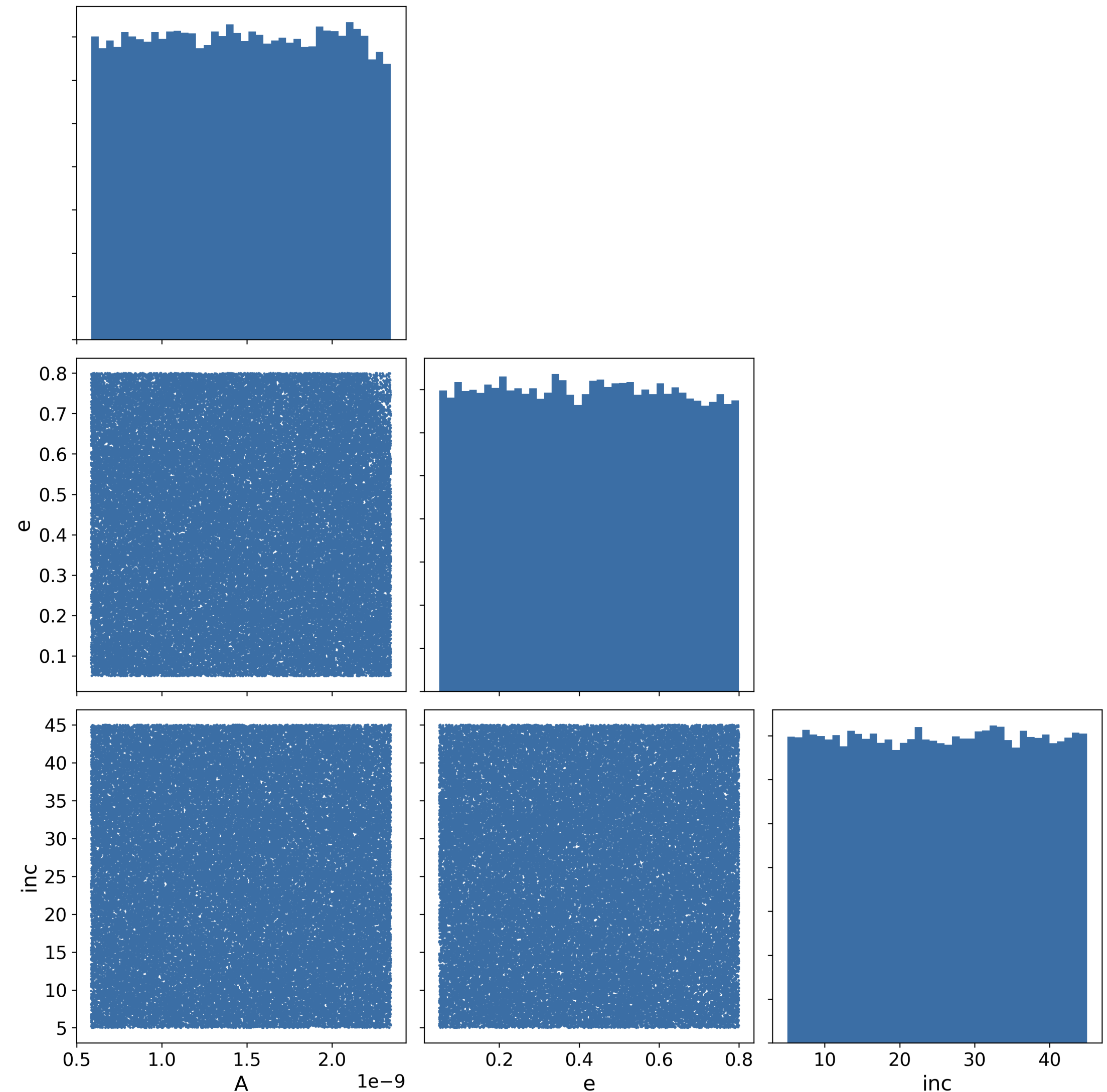
$$A \sim \mathcal{U}[5.86 * 10^{-10} - 2.34 * 10^{-9}]$$

$$e \sim \mathcal{U}[0.1, 0.8]$$

$$\text{inc} \sim \mathcal{U}[5^\circ, 45^\circ]$$

Number of crossings:

$$N_{\min} = 5 \text{ and } N_{\max} = 20$$



Initial results ANN (Train)

Error statistics for parameters:

For A:

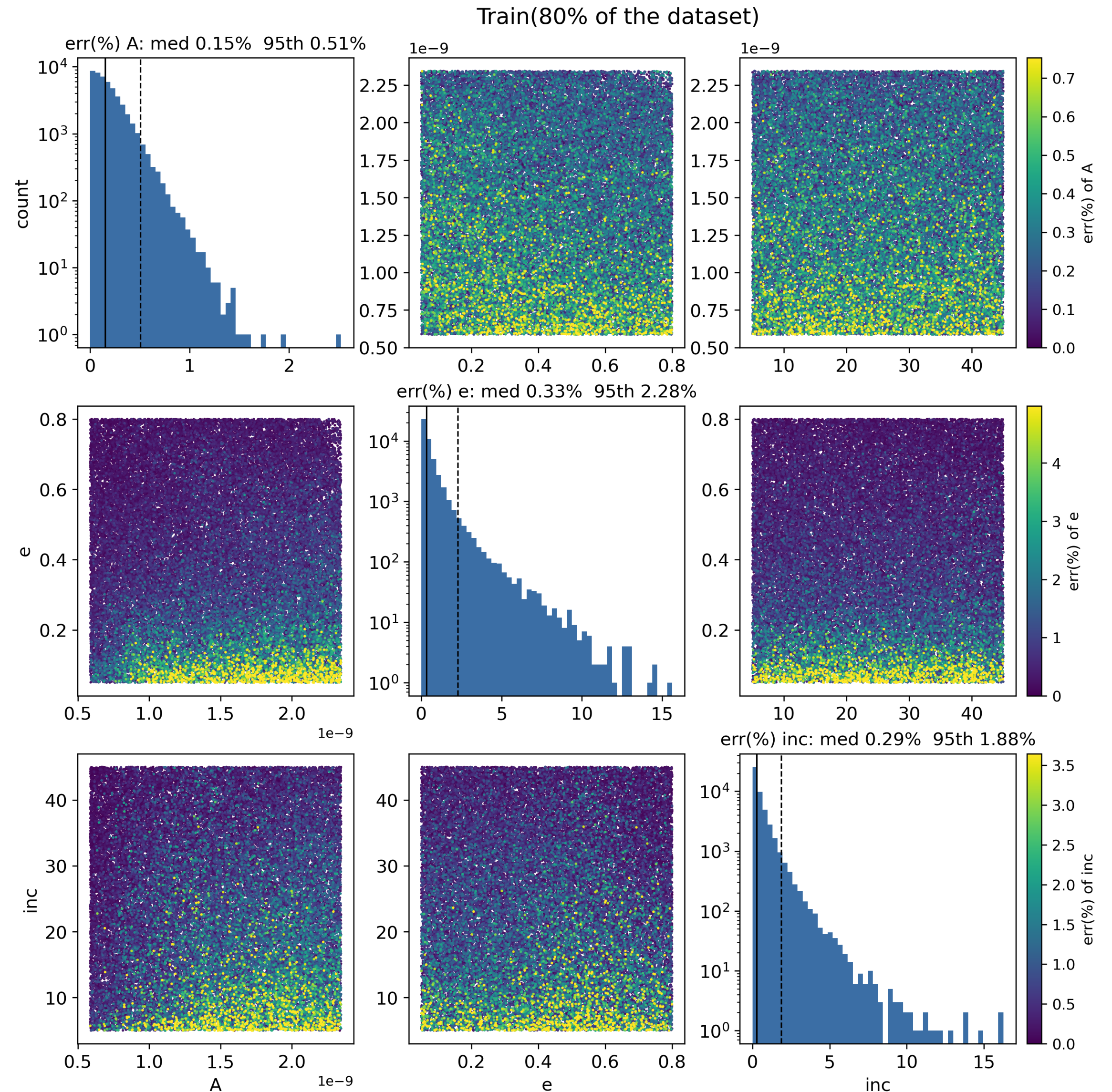
Mean- 0.1899 %
 Median- 0.1509 %
 Max- 2.522 %
 Min- 0.0 %

For e:

Mean- 0.6399 %
 Median- 0.3263 %
 Max- 15.6236 %
 Min- 1.38402 e-05 %

For inc:

Mean- 0.5400 %
 Median- 0.2886%
 Max- 16.2468 %
 Min- 0.0%



Initial results ANN (Test)

Error statistics for parameters:

For A:

Mean- 0.3199 %

Median- 0.2508 %

Max- 3.1610 %

Min- 3.9222 e-05 %

For e:

Mean- 1.5299 %

Median- 0.8300 %

Max- 31.2035 %

Min- 9.5860 e-05 %

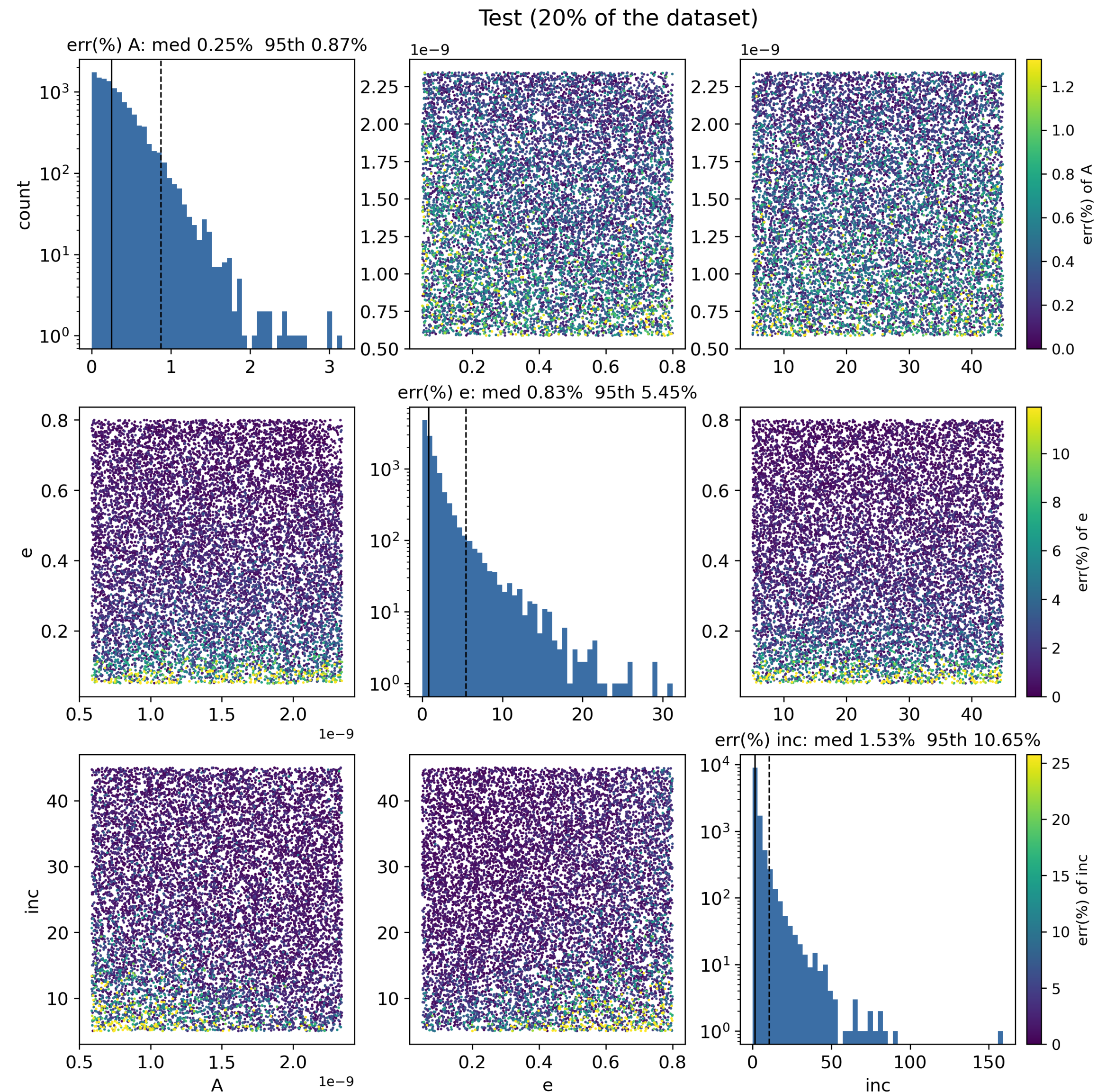
For inc:

Mean- 3.0199 %

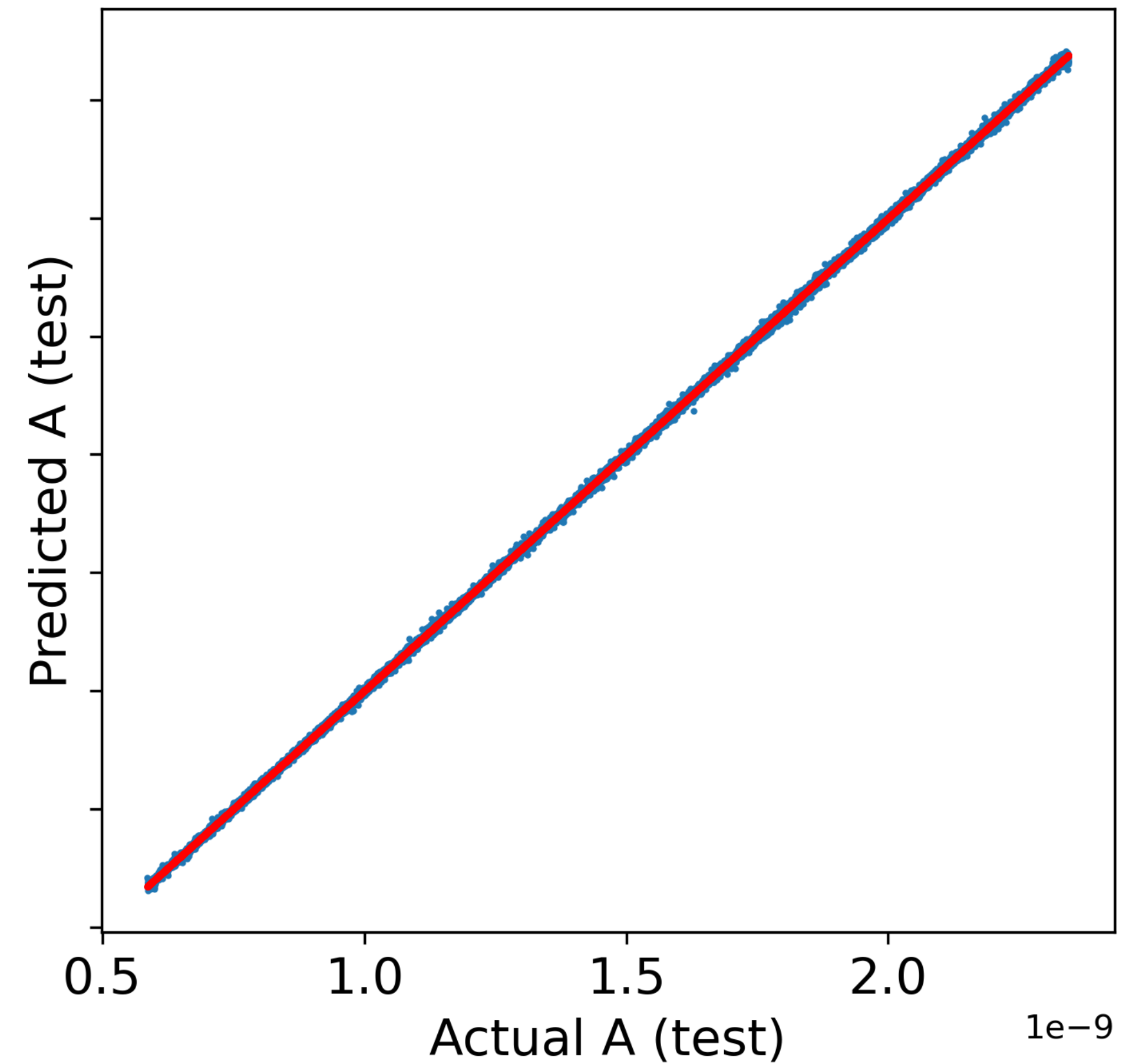
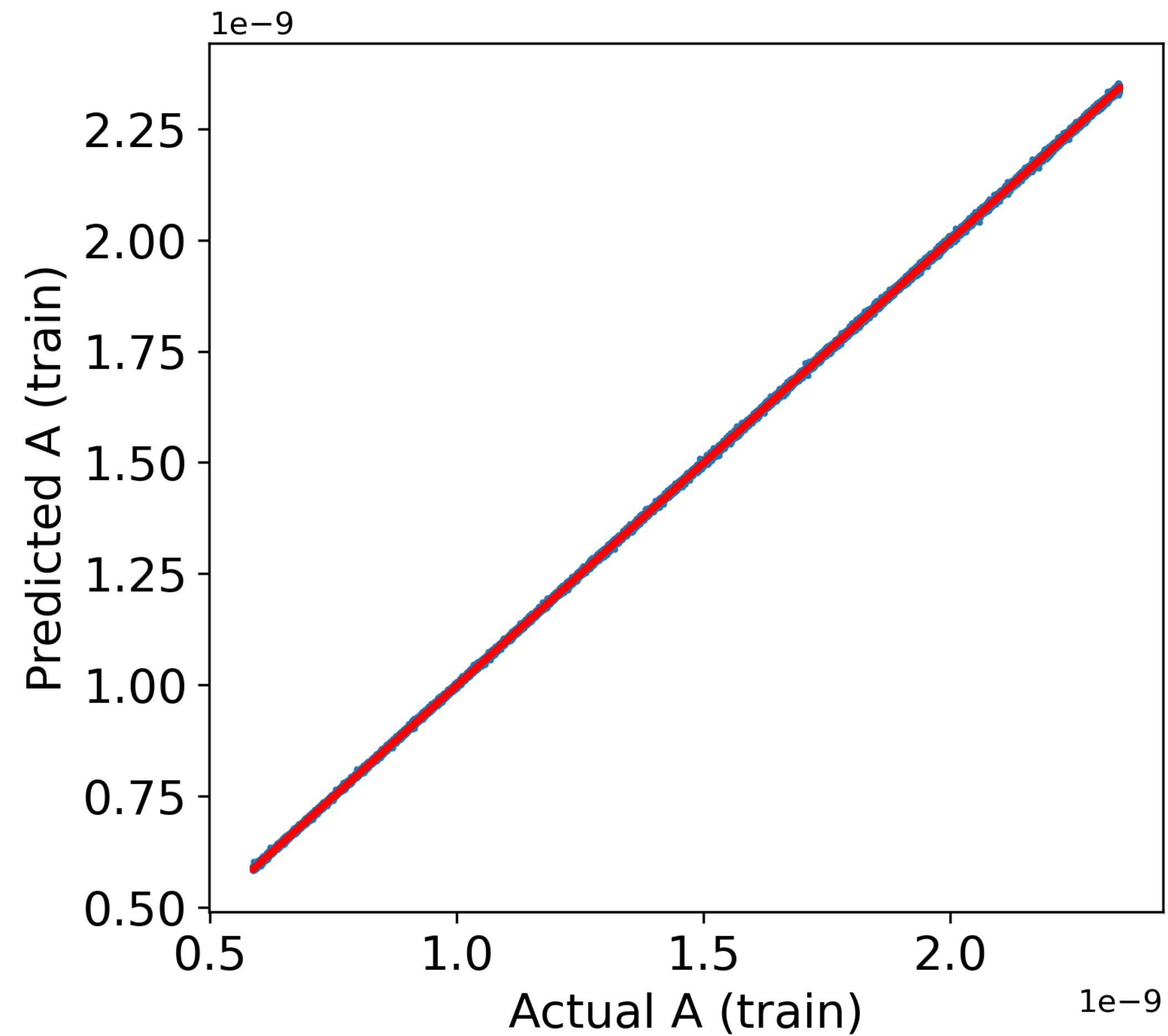
Median- 1.5300 %

Max- 158.9307 %

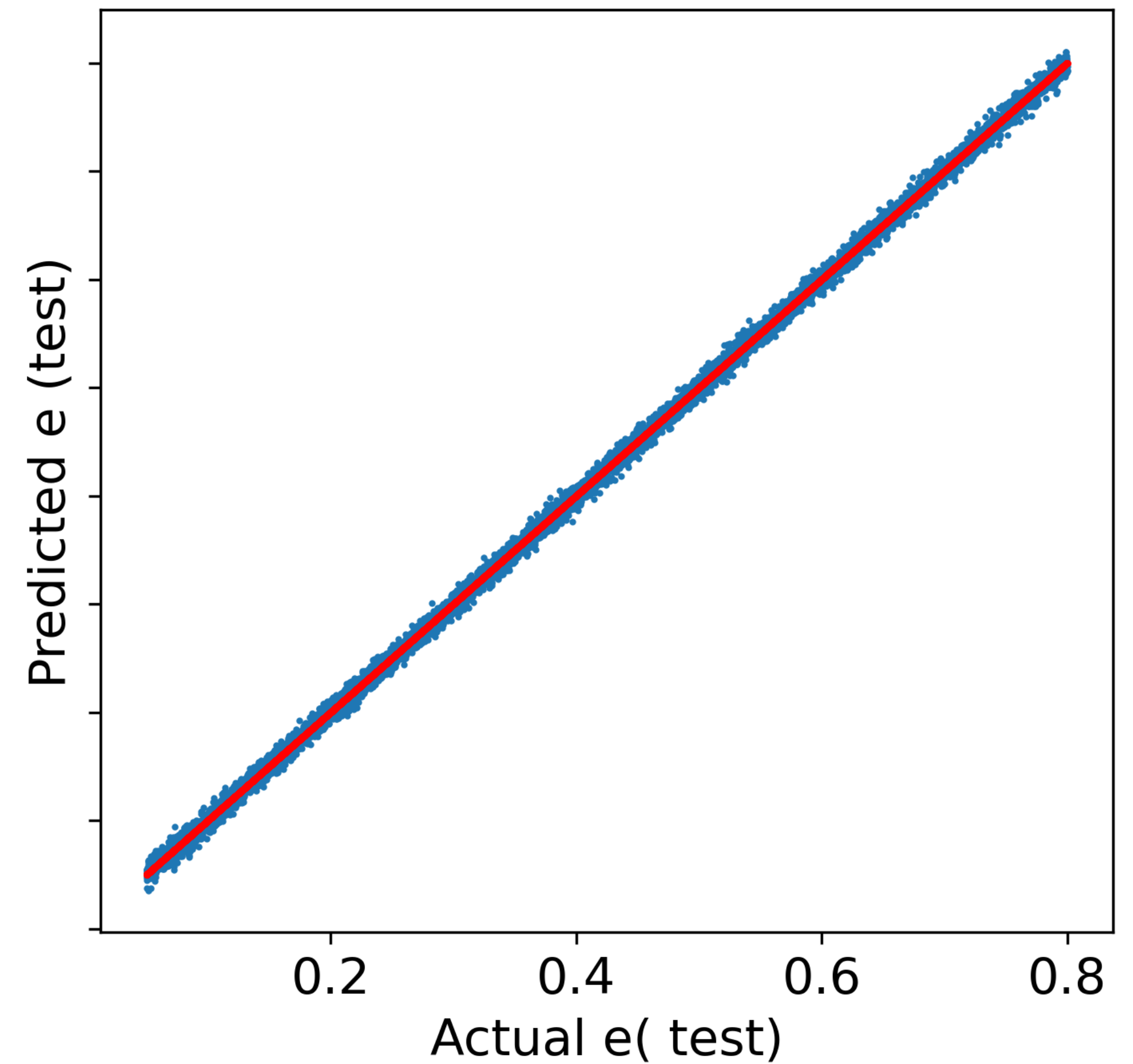
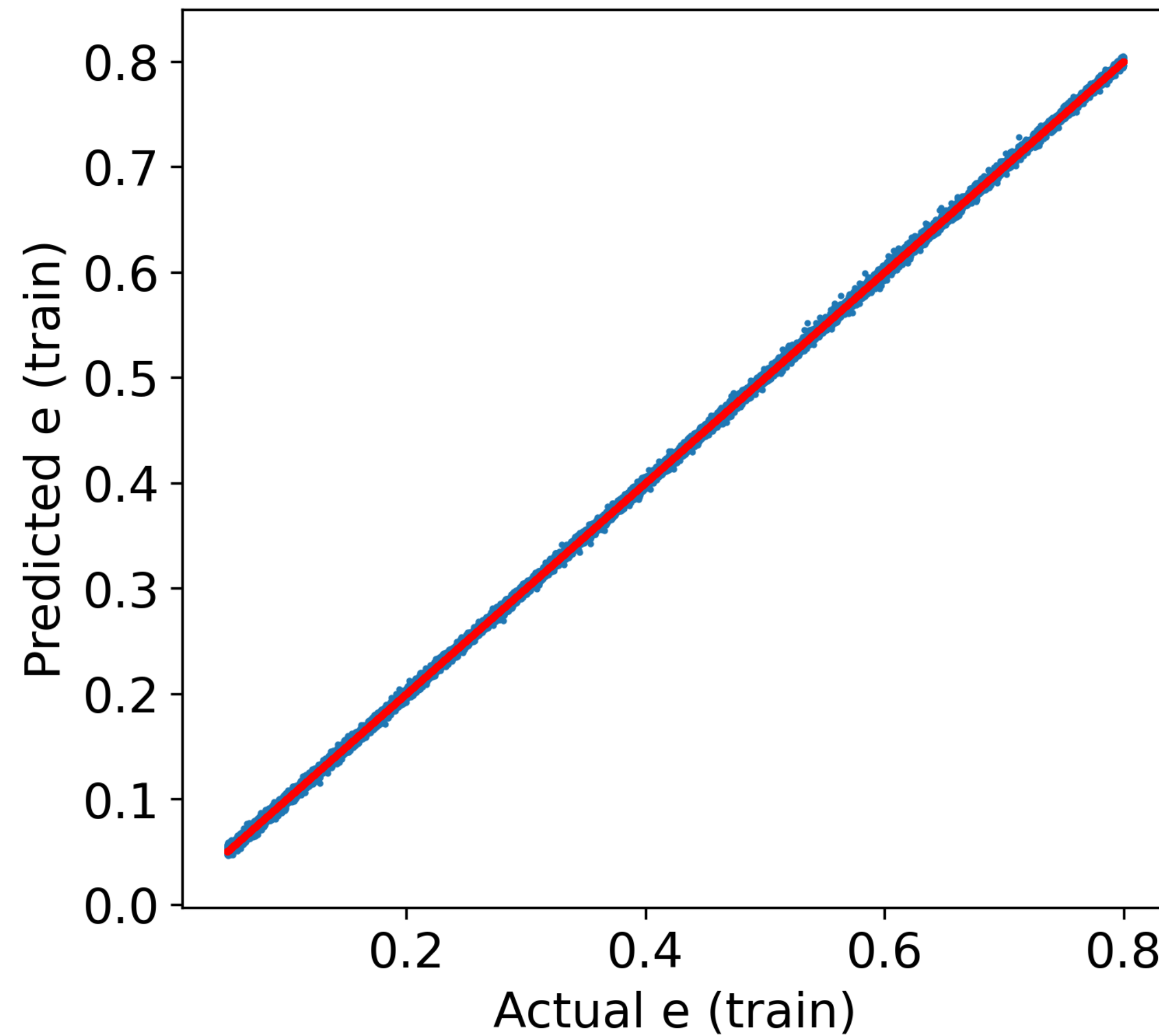
Min- 0.0001 %



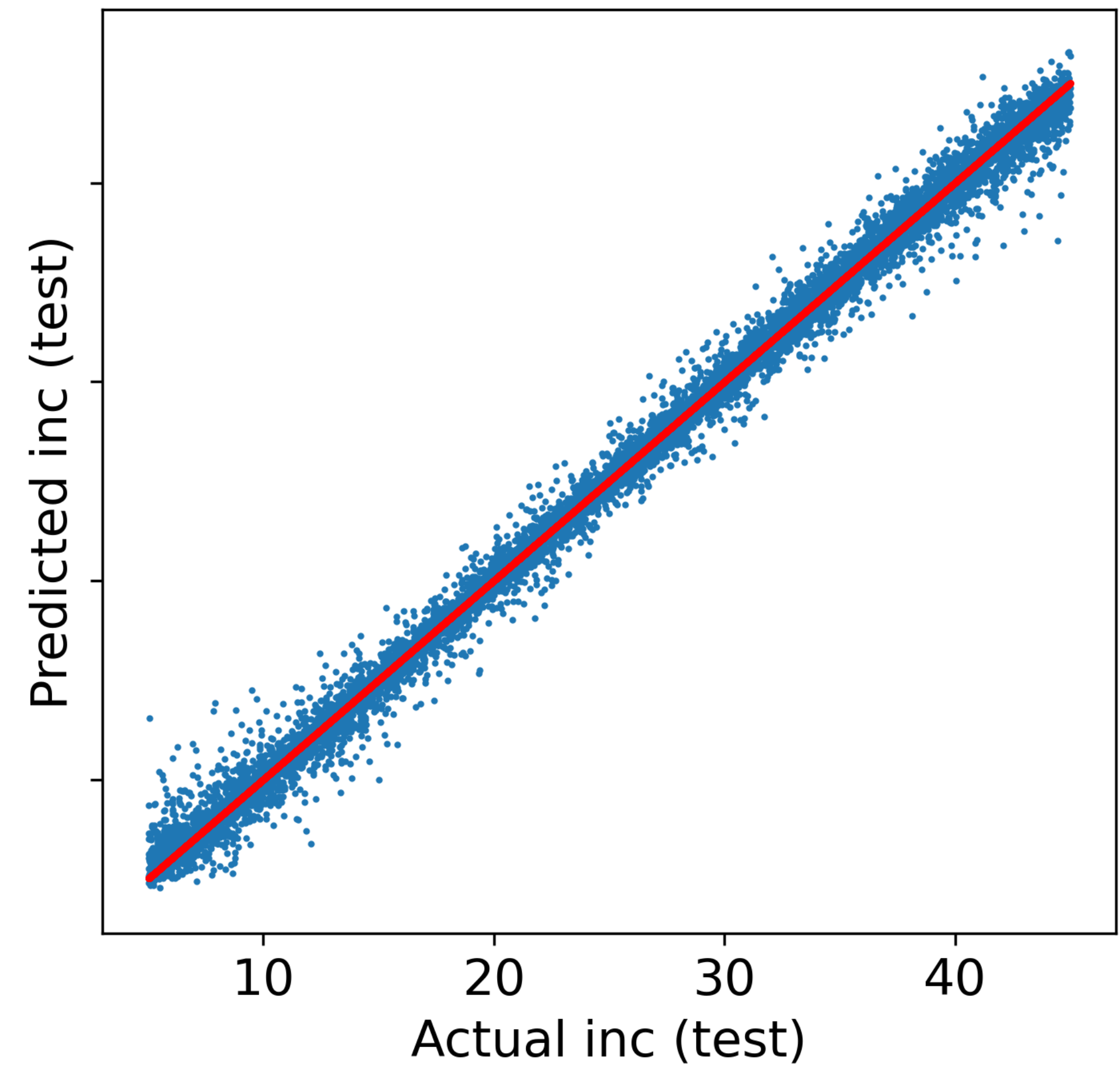
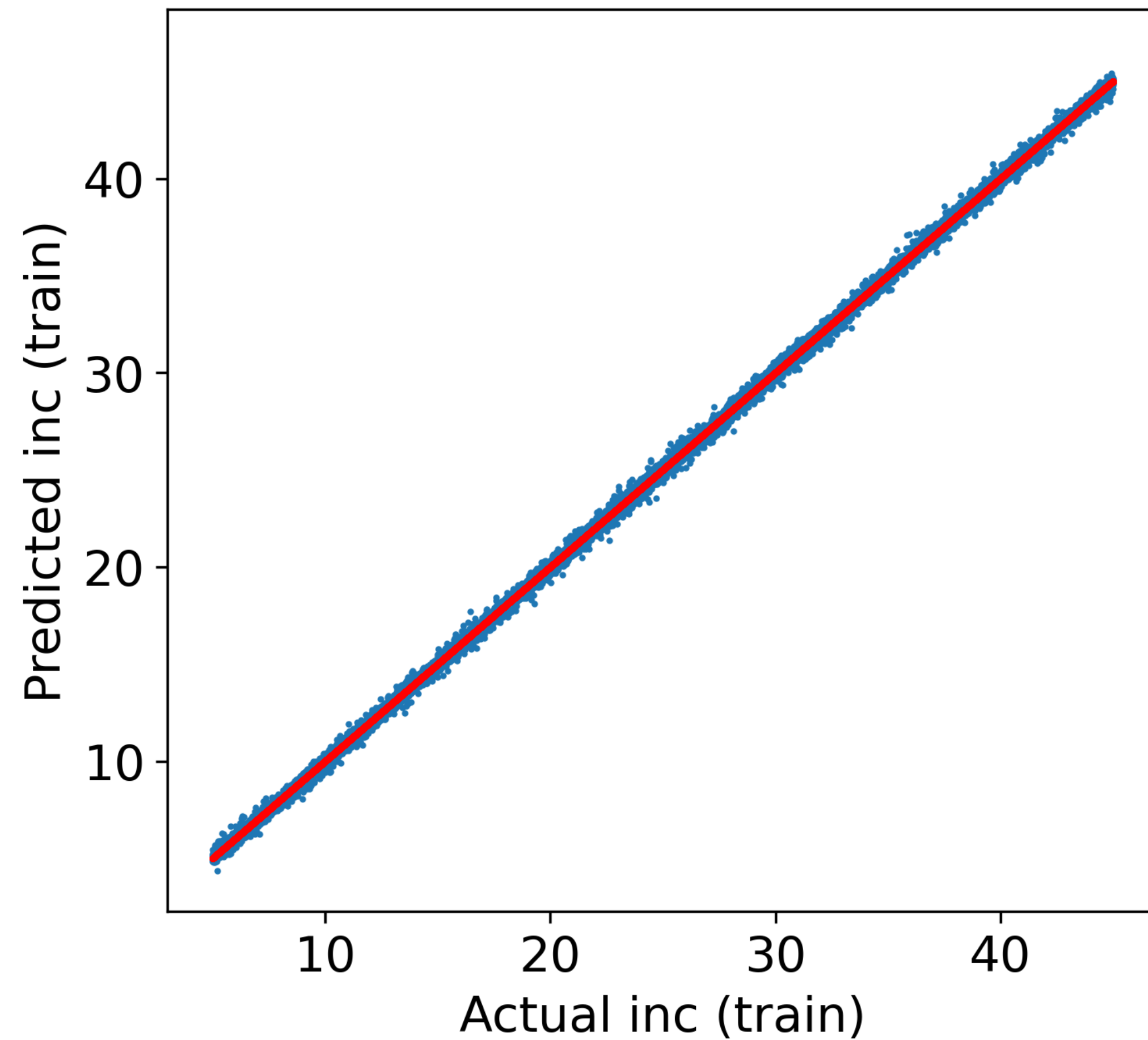
Initial results ANN



Initial results ANN



Initial results ANN



Summary and future direction

Completed:

- Developed a neural-network framework for EMRI parameter inference from simulated QPE light curves.
- Achieved accurate recovery of the orbital parameters

Future work:

- Improve inclination (inc) inference by investigating parameter degeneracies and alternative network architecture
- Assess robustness to observational noise using realistic detector and astrophysical noise models
- Apply the framework to real QPE observational data (in collaboration with J. Chakraborty).

References

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- 2. G. Miniutti¹, R. D. Saxton, M. Giustini, K. D. Alexander, R.P Fender, I. Heywood, I. Monageng, M. Coriat, A. K. Tzioumis, A. M. Read, C. Knigge, P. Gandhi, M. L. Pretorius and B. Agís-González. Nine-hour X-ray quasi-periodic eruptions from a low-mass black hole galactic nucleus. (2019)**
- 3. J. Chakraborty, L. V. Drummond, M. Bonetti, A. Franchini, Sh. Kejriwal, G. Miniutti, R. Arcodia, S. A. Hughes, F. Duque, E. Kara, A. Sesana, M. Giustini, A. Motta, and K. Burdge. Prospects for EMRI/MBH parameter estimation using Quasi-Periodic Eruption timings: short-timescale analysis. (2025)**

Thank you