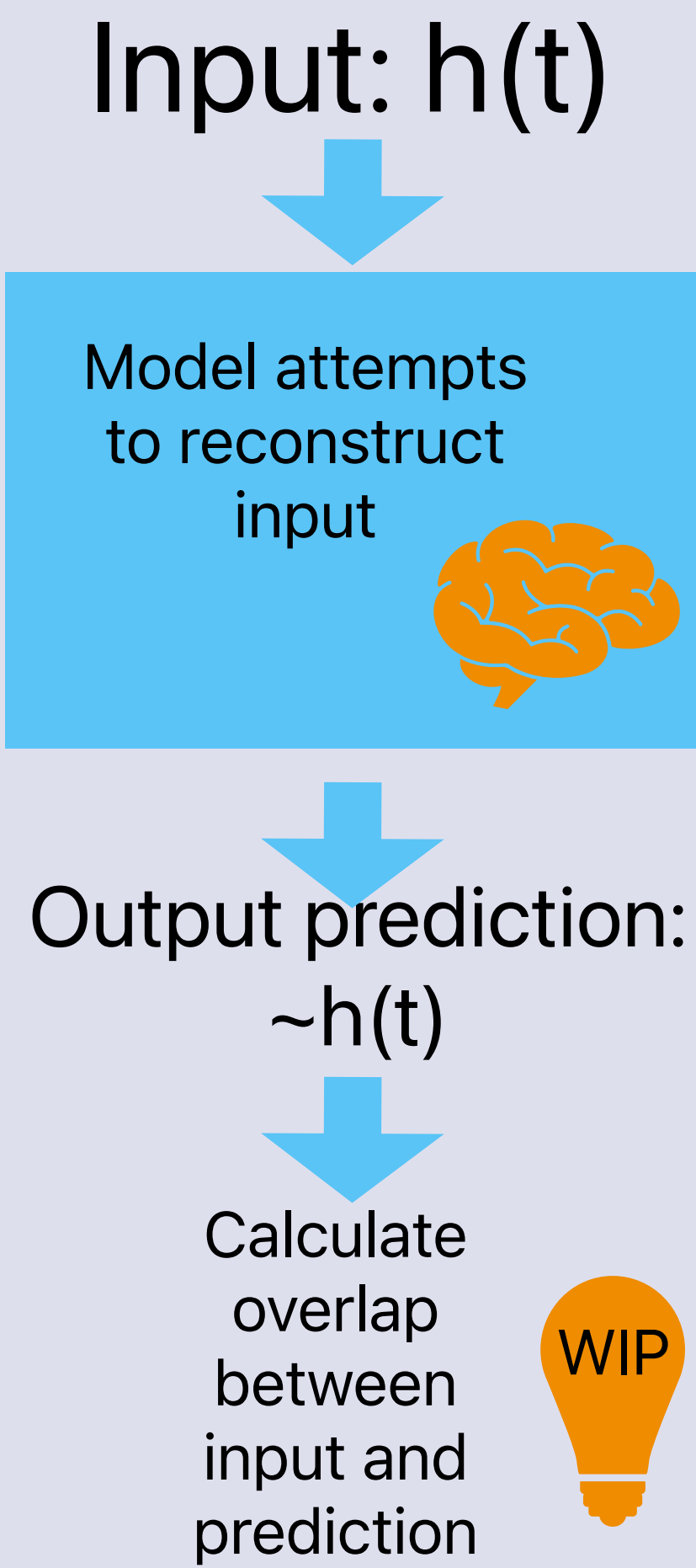
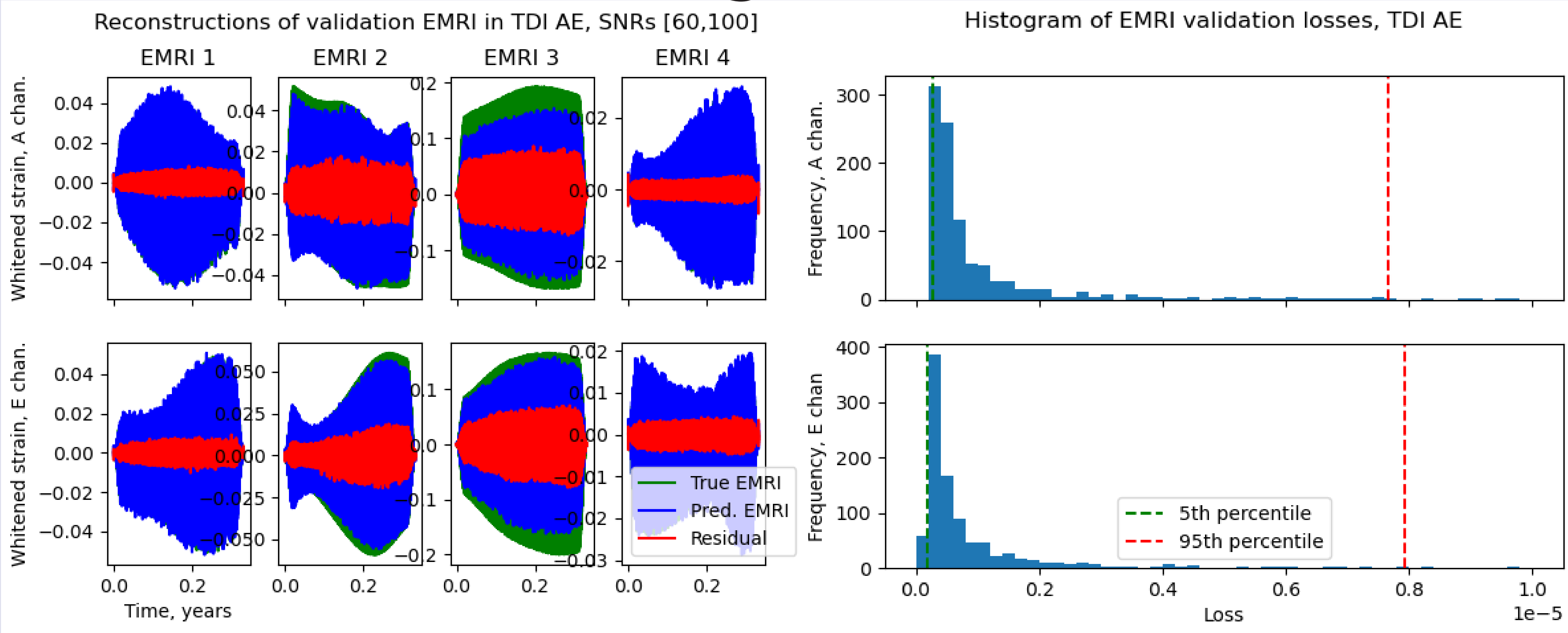


Signal Detection of EMRIs with Convolutional Autoencoders

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Extreme mass ratio inspirals (EMRIs) are the mergers of massive and compact objects with mass ratio $<10^{-4}$, and are characterised by a **highly dynamic years-long GW signal**. Because EMRIs are modelled with **wide and high-dimensional parameter spaces**, conventional signal detection techniques e.g. matched filtering are unfeasible, requiring 10^{40} template waveforms (Gair et. al., 2004). This project explores **EMRI signal detection with the use of convolutional autoencoders**, a type of ML model which learns how to represent input data in a low dimensionality. A well-trained autoencoder will accurately reconstruct EMRIs while poorly reconstructing other signal types. Hence, this technique could form the basis of a novel signal detection procedure for EMRIs.

Training & validation results



What are autoencoders?

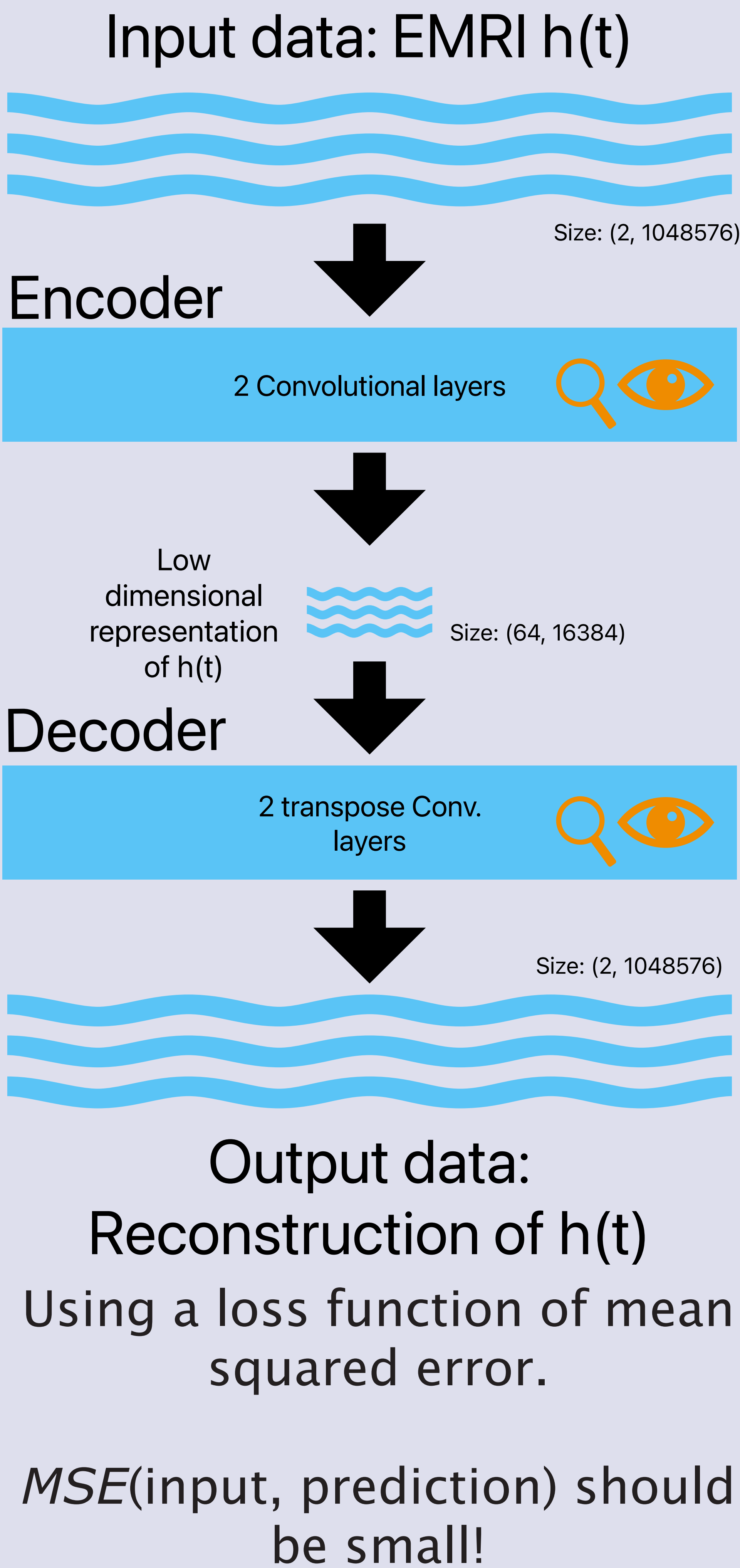
Autoencoders are:

- A type of neural network that learns how to encode data in a low dimensionality
- It consists of an encoder and decoder
- The model is trained to minimise the difference between input and output

Common applications:

- Dimensionality reduction
- Anomaly detection
- Denoising of data
- Generating new data

How do autoencoders work?



Main findings

- Convolutional autoencoders can learn short windows of EMRIs
- It currently struggles to reconstruct high amplitude EMRIs e.g. EMRI 3 from the reconstruction plot

Next steps

- Test out dilated convolutions for enhanced detection of long-term time dependencies
- Test out longer windows of EMRIs
- Test out lower SNR signals

References & acknowledgements

- FastEMRIWaveforms: New tools for millihertz gravitational-wave data analysis, Katz et. al. 2021
- Assessing the data-analysis impact of LISA orbit approximations using a GPU-accelerated response model, Katz et. al. 2022
- Event rate estimates for LISA extreme mass ratio capture sources Gair et. al. 2004

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Dataset parameters

- Whitened $h(t)$ generated with FastEMRIWaveforms
- Loss function: mean squared error
- EMRIs modelled with the Fast Schwarzschild eccentric flux model
- TDI applied with FastLISAresponse
- ML training done with PyTorch

Dataset parameters	
Dataset size	11011
SNR range	[60, 100]
Window of signal	$\sim 1/3$ y
Sampling interval	10s
Channels	(A,E)

EMRI model parameters	
Massive object mass	$U[10^{-6}, 10^{-4}]$
Mass ratio	$U[10^{-6}, 10^{-4}]$
Spin	0
Initial eccentricity	$U[0, 0.7]$
Initial semilatus rectum	$U[10, 16 + \text{initial eccentricity}]$
Redshift	0.1
Sky coordinates (θ, ϕ)	$U[-\pi/2, \pi/2]$
	$U[0, 2\pi]$