

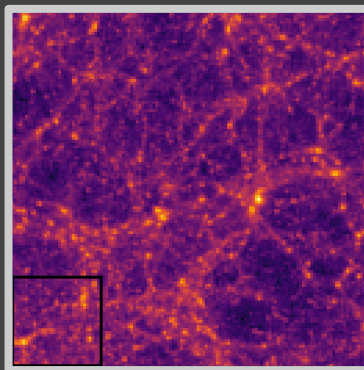
Super-Resolution in Dark-Matter Simulations

John Brennan, John Regan

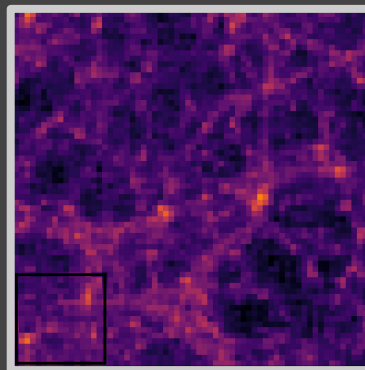


- Neural Networks can be used to enhance data resolution.
- We are exploring neural networks to enhance the resolution of dark-matter simulations.

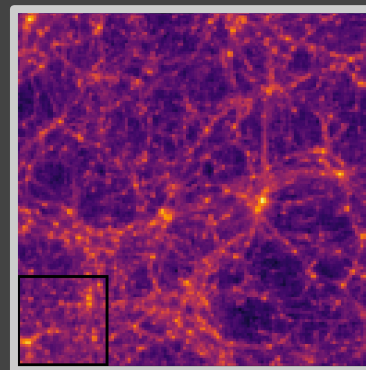
High Resolution



Low Resolution

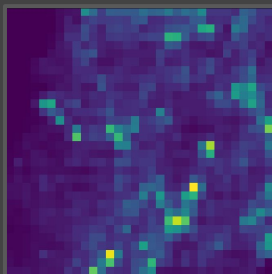


Reconstruction

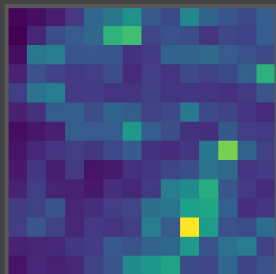


SR can generate data with summary statistics that align with HR simulations.

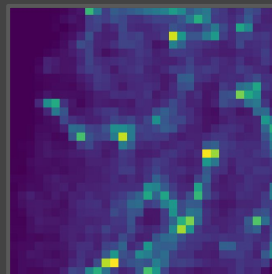
HR



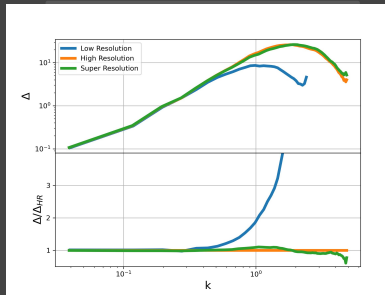
LR



SR



Power Spectrum



HR
LR
SR

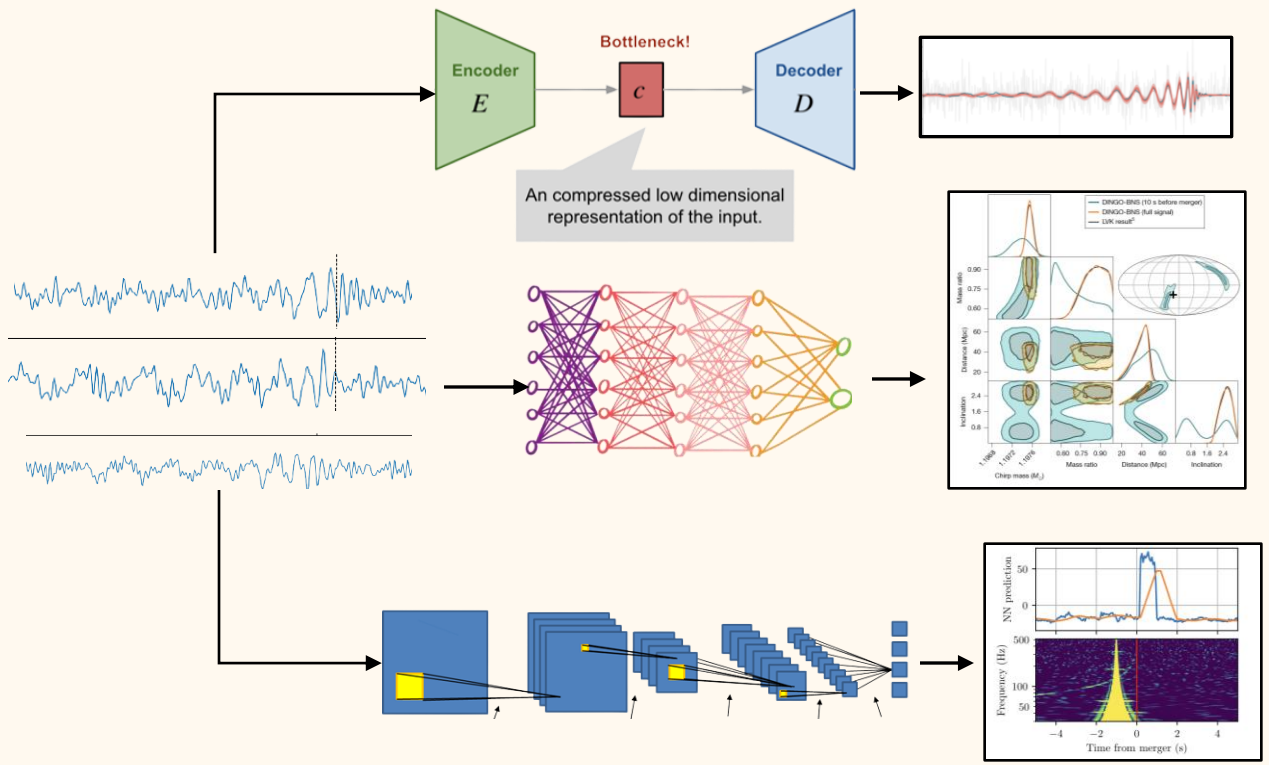
Towards a Foundation AI Model for Gravitational Waves



Chayan Chatterjee, Abigail Petulante, Karan Jani, Jesse Spencer-Smith, Roy Lau, Suyash Deshmukh

Most specific

Most general



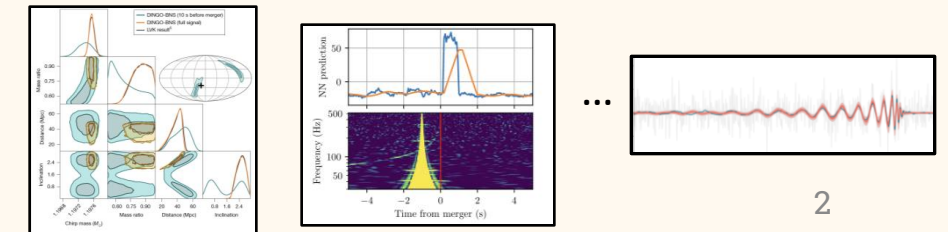
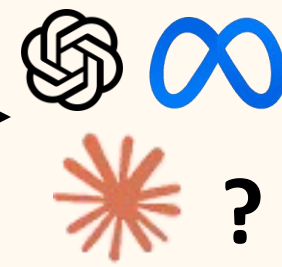
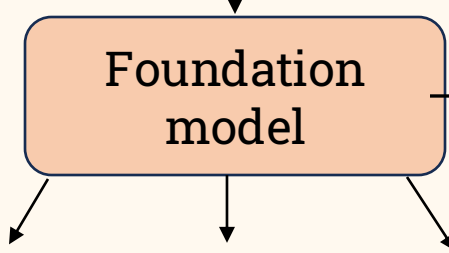
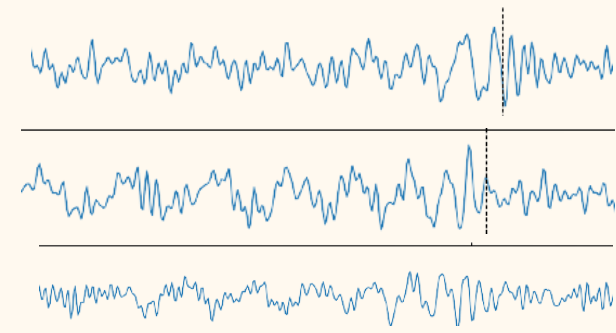
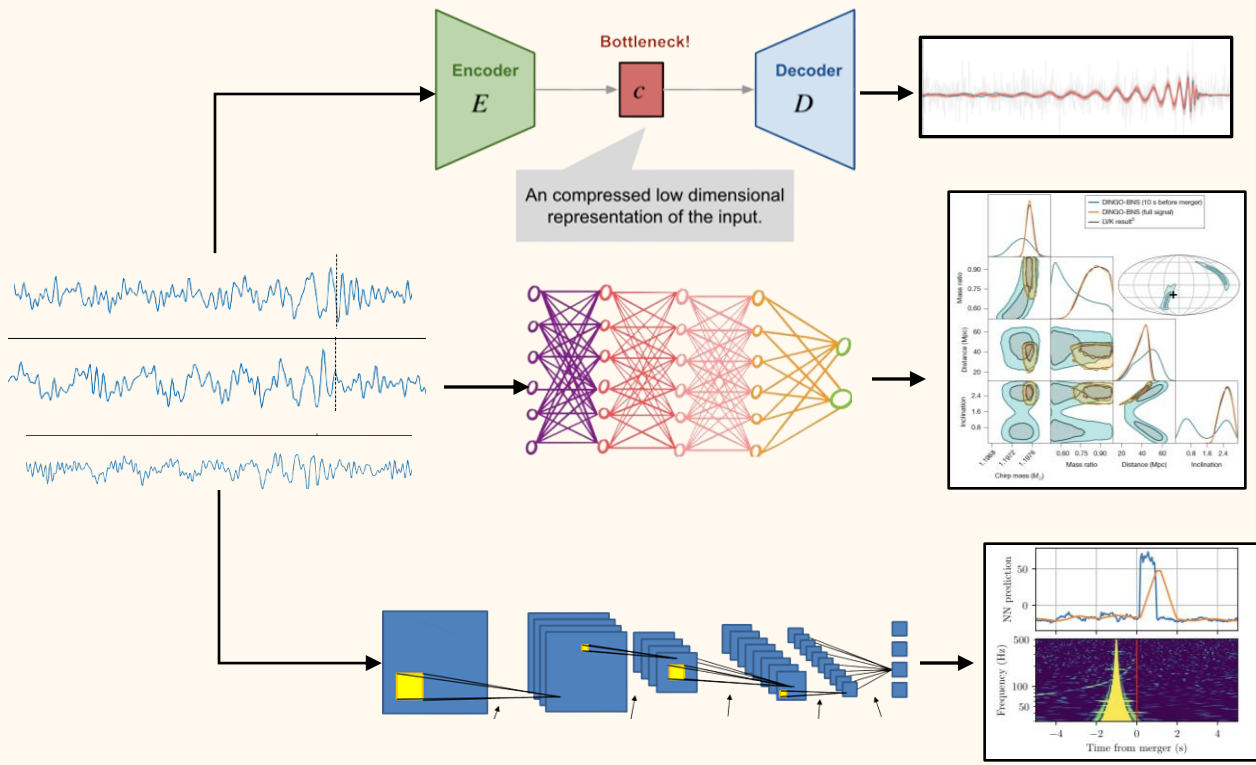
Towards a Foundation AI Model for Gravitational Waves



Chayan Chatterjee, Abigail Petulante, Karan Jani, Jesse Spencer-Smith, Roy Lau, Suyash Deshmukh

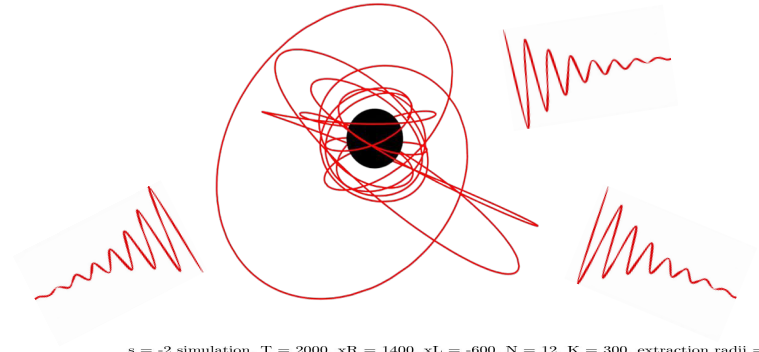
Most specific

Most general



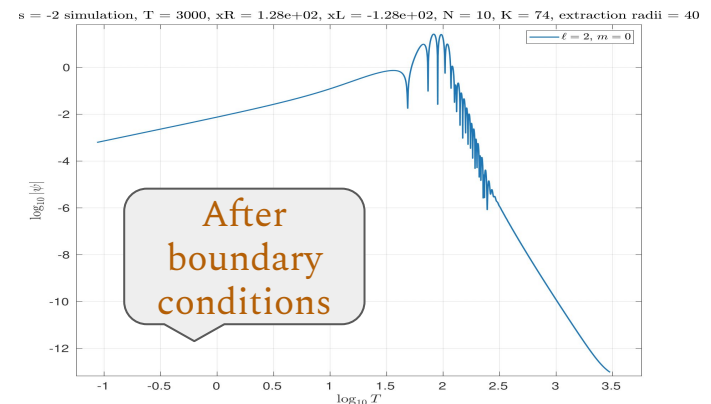
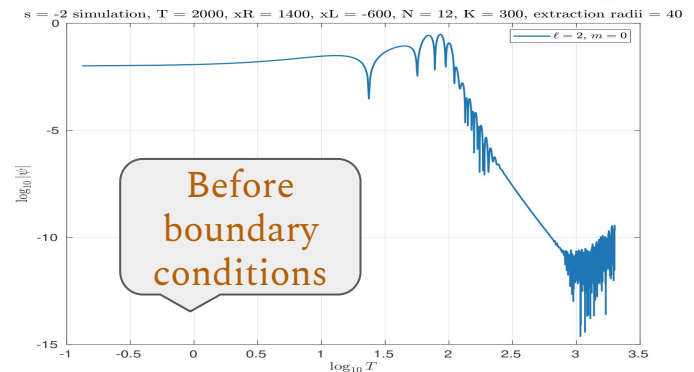
Exact Boundary Conditions for the Teukolsky Equation

Motivation: Fast and accurate waveform modelling of EMRIs.



Problem: Solving the *Teukolsky equation* in time-domain is challenging.

Solution: *Boundary Kernels* provide exact outer boundary conditions.

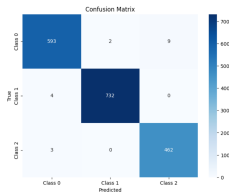


Hyperspectral Time-Series Classification via GADF and Deep CNNs

Presenter: Sanaz Hami Hassan Kiyadeh
Ph.D. Candidate, The University of Alabama

GADF Encoding: Normalize $x_i \in [-1, 1]$, set $\theta_i = \arccos(x_i)$, then
$$G_{ij} = \sin(\theta_i - \theta_j).$$

Samson Result: ResNet101 on GADF \rightarrow **99.0%** test accuracy.



Confusion Matrix (Samson)

Cross-Dataset Performance & Future Directions

Dataset	Acc. (%)	Observation
Salinas	98.00	Strong generalization
SalinasA	96.78	Minor boundary confusion
PaviaU	95.65	Slight misclassifications
Indian Pines	96.74	Robust to noise and imbalance

- Dual-branch 3D CNN + GADF (best of three trials).
- **Next:** Standardize splits; compare deep vs. classical.
- Fuse GADF with recurrence plots or graph encodings.
- GAN-based augmentation for minority classes.
- Lightweight CNN–transformer hybrids via compression.

Advisor: Dr. Brendan Ames



Matteo Boschini

Ph.D. student @ Unimib

m.boschini1@campus.unimib.it



NR surrogate models

Training

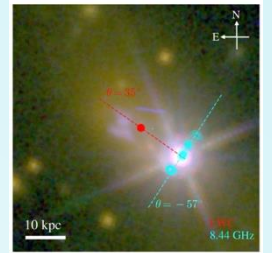
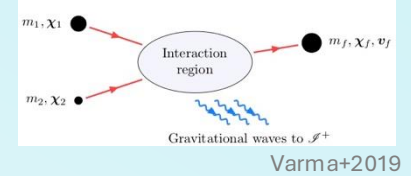
MB+2023 “*Extending black-hole remnant surrogate models to extreme mass ratios*”

MB+2025 (ongoing) “*New extension for black-hole remnant surrogate models at extreme mass ratios*”

Astro modeling

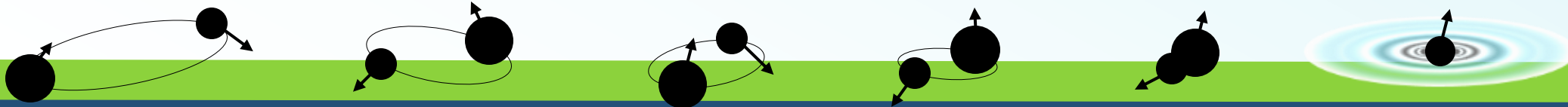
MB+2024 “*Astrophysical and relativistic modeling of the recoiling black-hole candidate in quasar 3C 186*”

M.Chiaberge+2025 “*A recoiling supermassive black hole in a powerful quasar*”

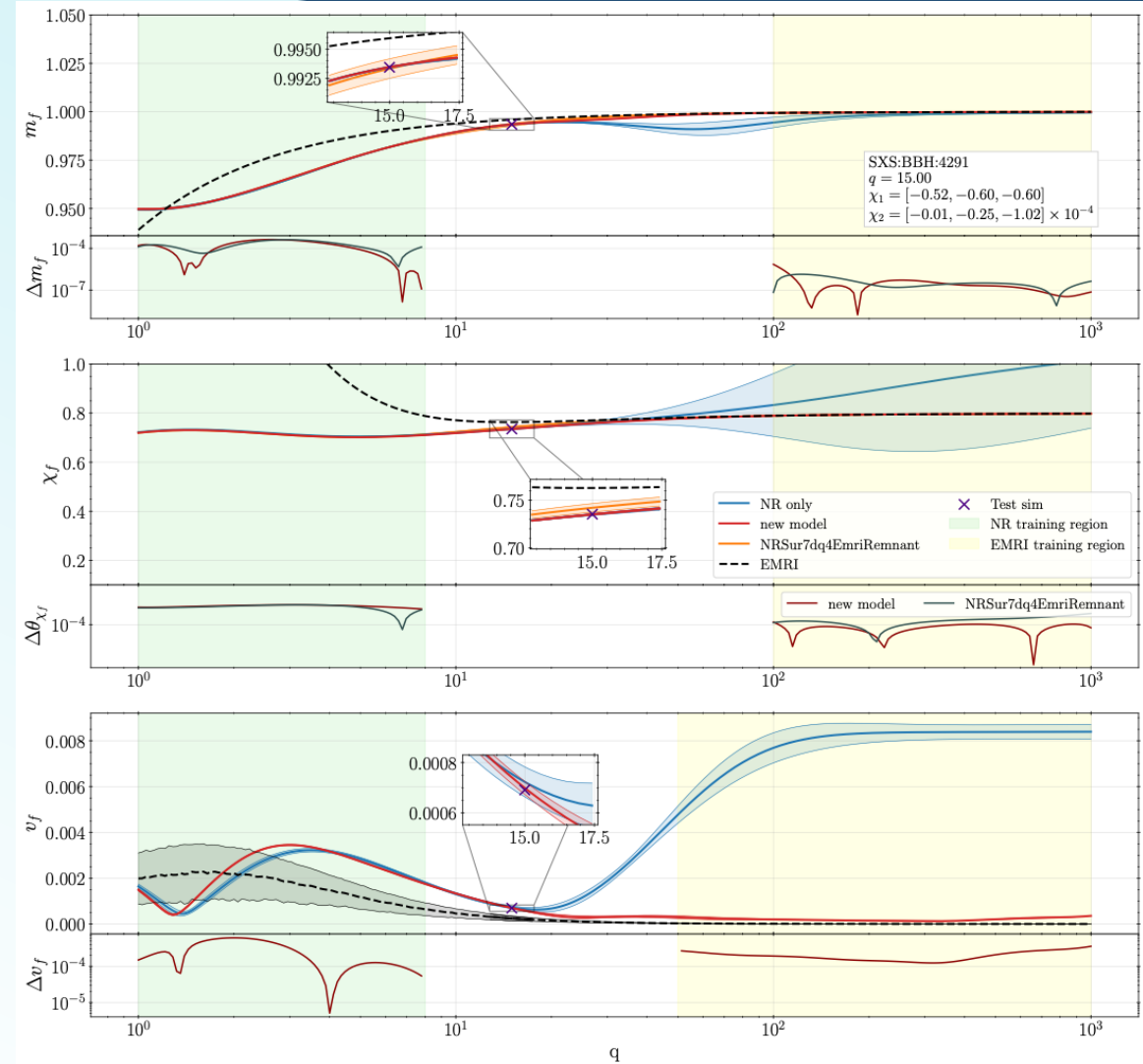
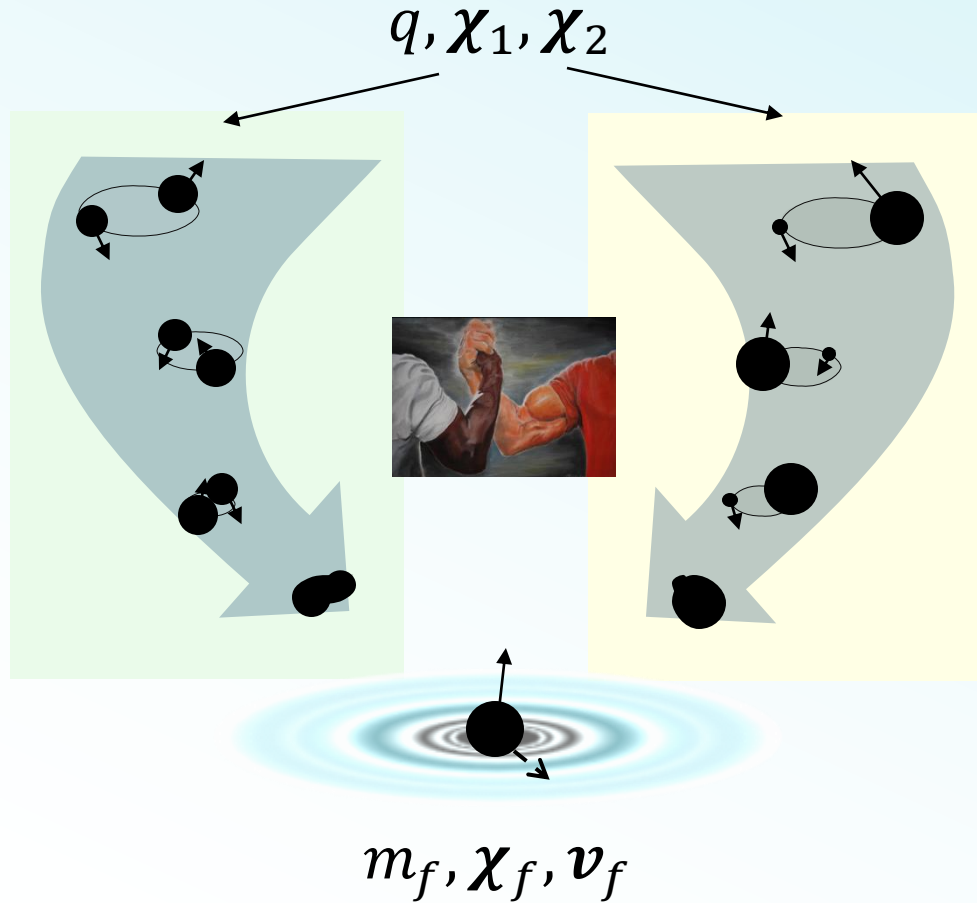


Eccentricity in BBH

MB+2025 “*Orbital eccentricity in general relativity from catastrophe theory*”



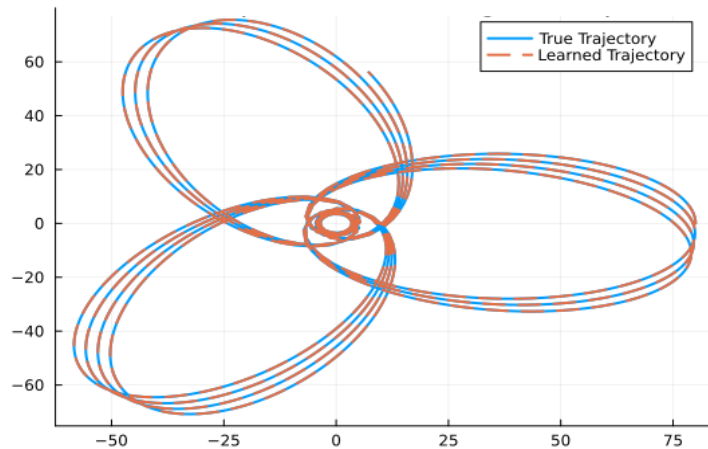
New extension for black-hole remnant surrogate models at extreme mass ratios



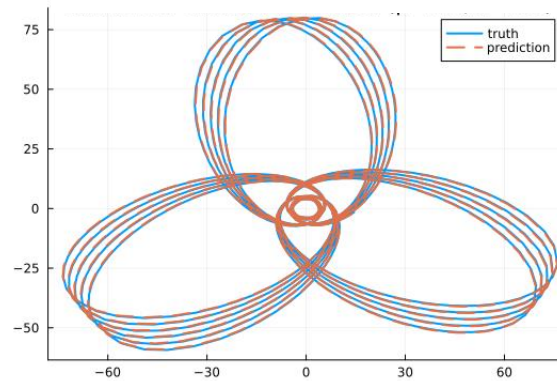
Training techniques for learning orbital dynamics of binary black hole systems

Pranav Vinod

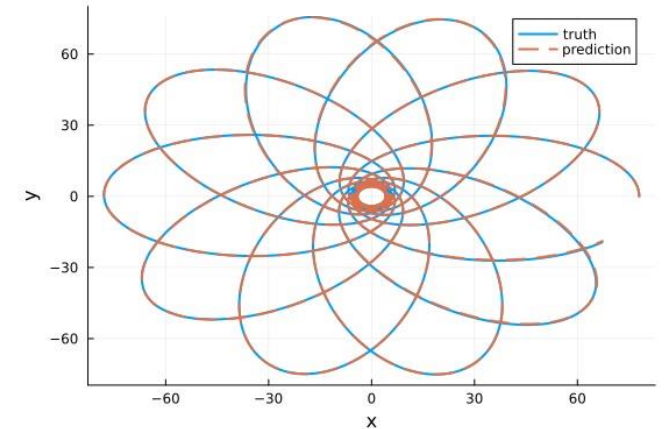
WE PRESENT A NEURAL ODE MODEL THAT CAN



Learn dynamics of simple
BBH systems



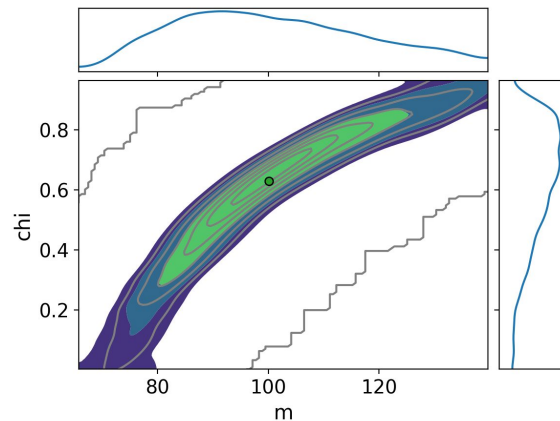
Accurately predict long term
behavior from short training
data



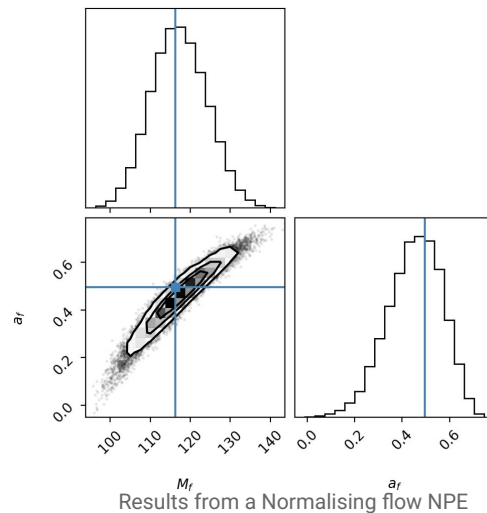
Learn systems that are close
to stable parameter boundary

Time Domain Neural Posterior Estimation for Black-Hole Ringdowns

- Frequency domain Inference not applicable to ringdowns, a time domain method needs to be applied.
- Time domain inference is computationally expensive
- Our approach: Use Amortised Simulation Based Inference on time domain ringdown signals
- Two Approaches: Gaussian NPE, Normalising Flow NPE
- Injected parameters recovered in both methods, and compare well with traditional methods



MCMC results from *ringdown*



Results from a Normalising flow NPE