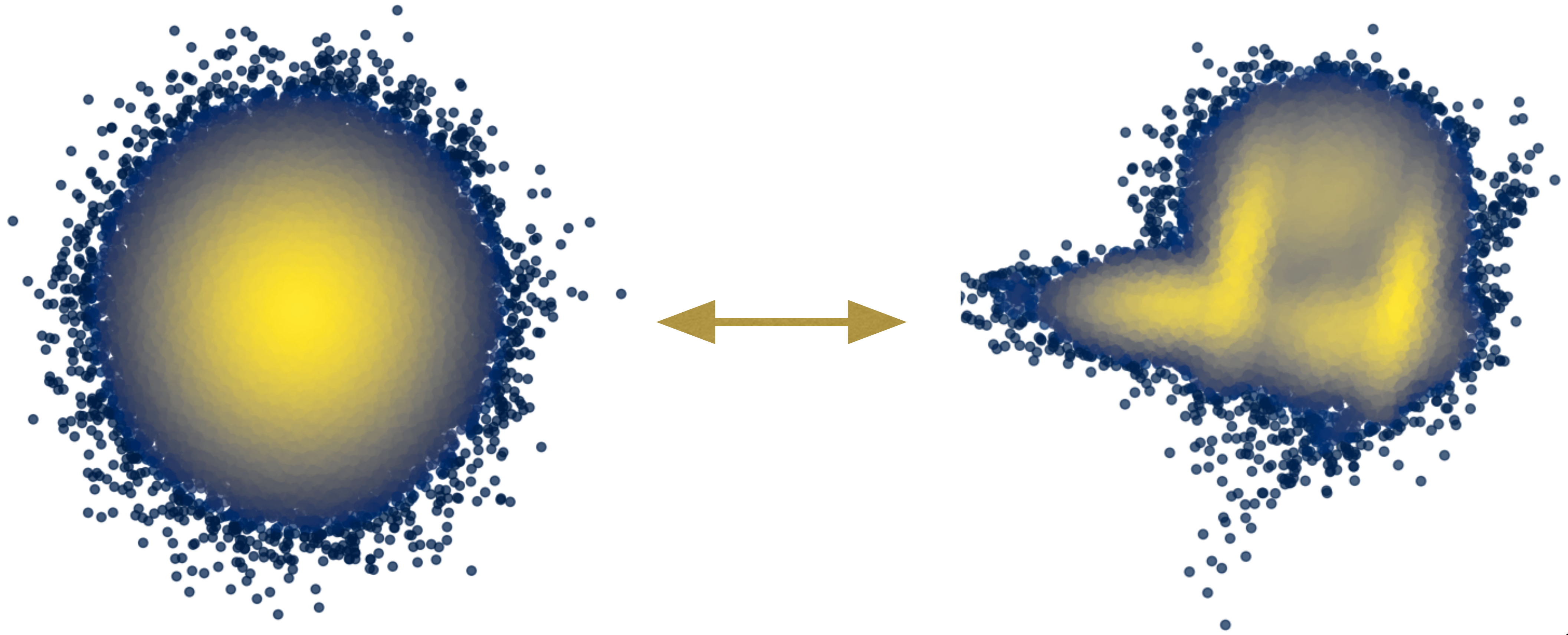
EUROPEAN AI FOR FUNDAMENTAL PHYSICS CONFERENCE EuCAIFCon 2024

FloZ

SISSA DATASCIENCE Machine Learning for the Natural Sciences

Poster # 120

NORMALIZING FLOWS AND THE BAYESIAN EVIDENCE



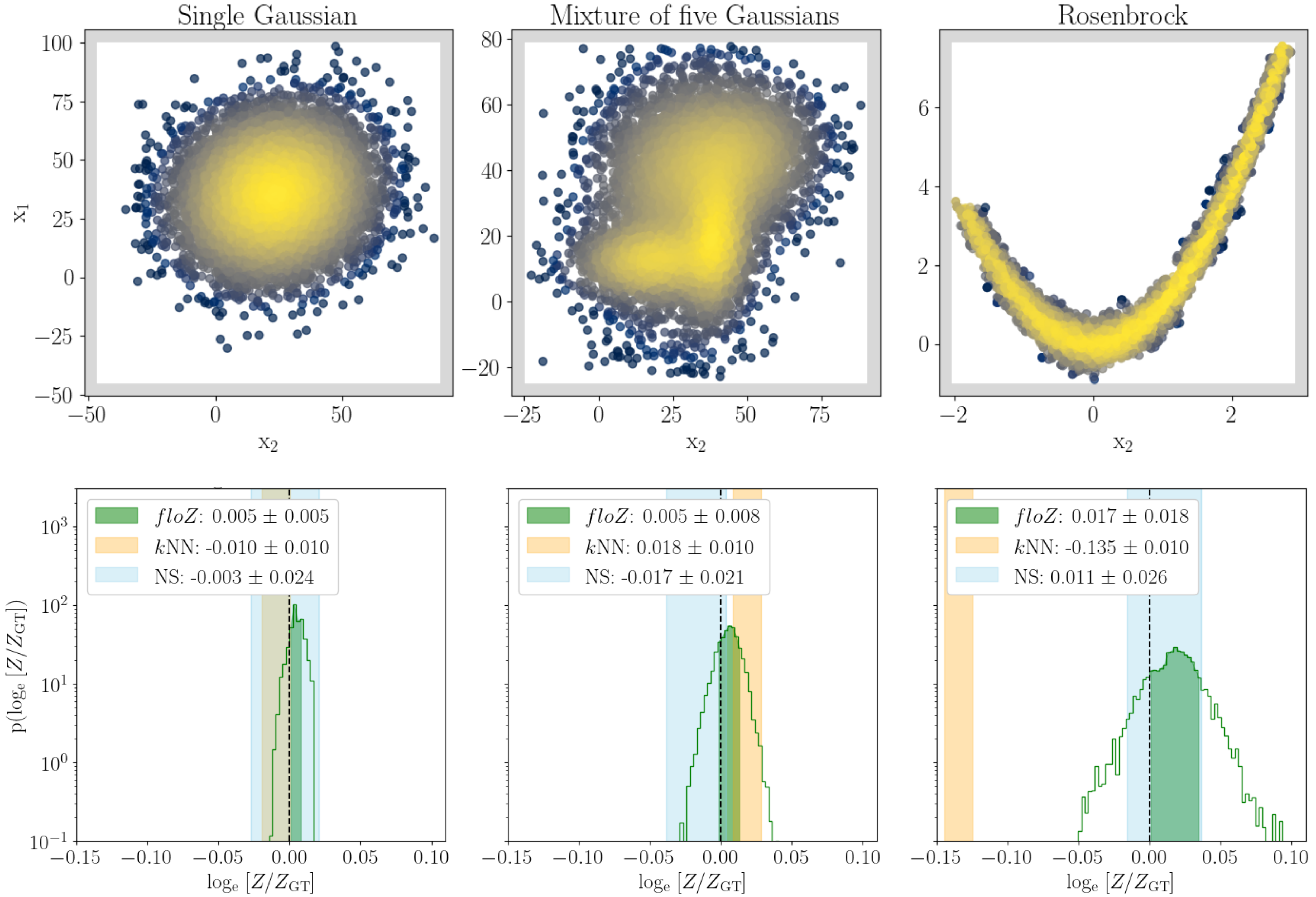
Bayesian Evidence : $$Z = \frac{\overbrace{L(\theta)}^{\text{Likelihood}}\overbrace{\Pi(\theta)}^{\text{Prior}}}{\underbrace{p(\theta)}_{\textbf{Posterior}}}$$

Rahul Srinivasan, SISSA, Italy
(with Marco Crisostomi, Roberto Trotta, Enrico Barausse)

Poster # 120

FloZ

Posterior distributions in increasing complexity



floZ perform <u>comparable</u> and often <u>*better*</u> than ***nested sampling***.

Rahul Srinivasan
Post-doctoral researcher, SISSA, Italy

EuCAIFCon 24

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SISSA DATASCIENCE Machine Learning for the Natural Sciences

Why does it work well?

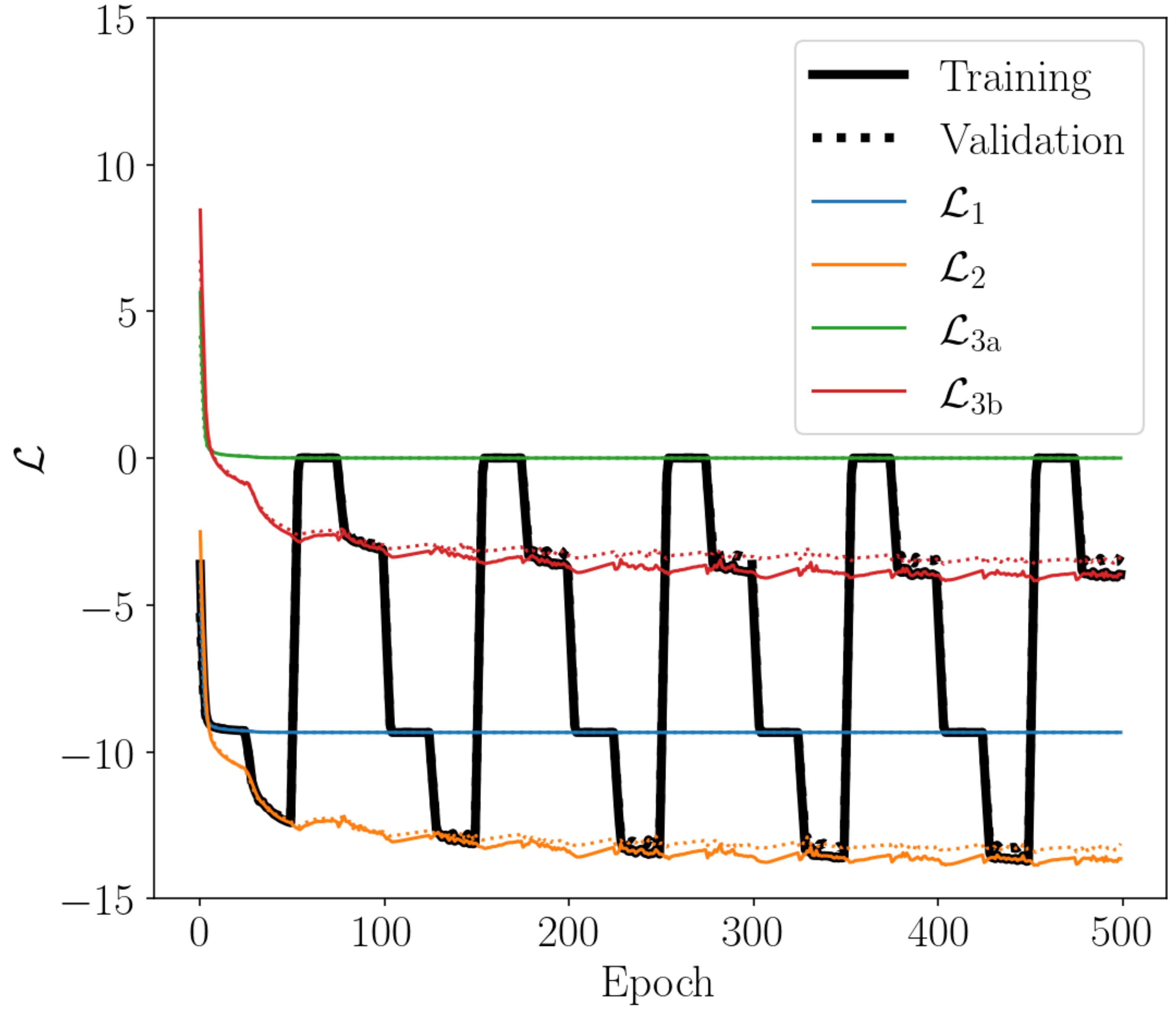
Transfer learning over different losses that:

1) Includes the standard cross-entropy loss of flow training $\mathscr{L}_1$.

2) Minimizes the <u>error</u> in the evidence estimation $\mathscr{L}_2$.

3) <u>Robust</u> to low sample statistics $\mathscr{L}_{3a}$, $\mathscr{L}_{3b}$:
   - Trained over $\mathcal{O}(\mathrm{N}^2_{\mathrm{samples}})$ data points.

Loss scheduling



Applications?

Evidence of higher modes in gravitational waves? (Ongoing analysis)

Evidence of stochastic gravitational wave background from Pulsar Timing Arrays observations?

Rahul Srinivasan
Post-doctoral researcher, SISSA, Italy

SYMBOLIC REGRESSION FOR PRECISION LHC PHYSICS (# 117)

Josh Bendavid, Daniel Conde, Manuel Morales-Alvarado, Maria Ubiali, Veronica Sanz

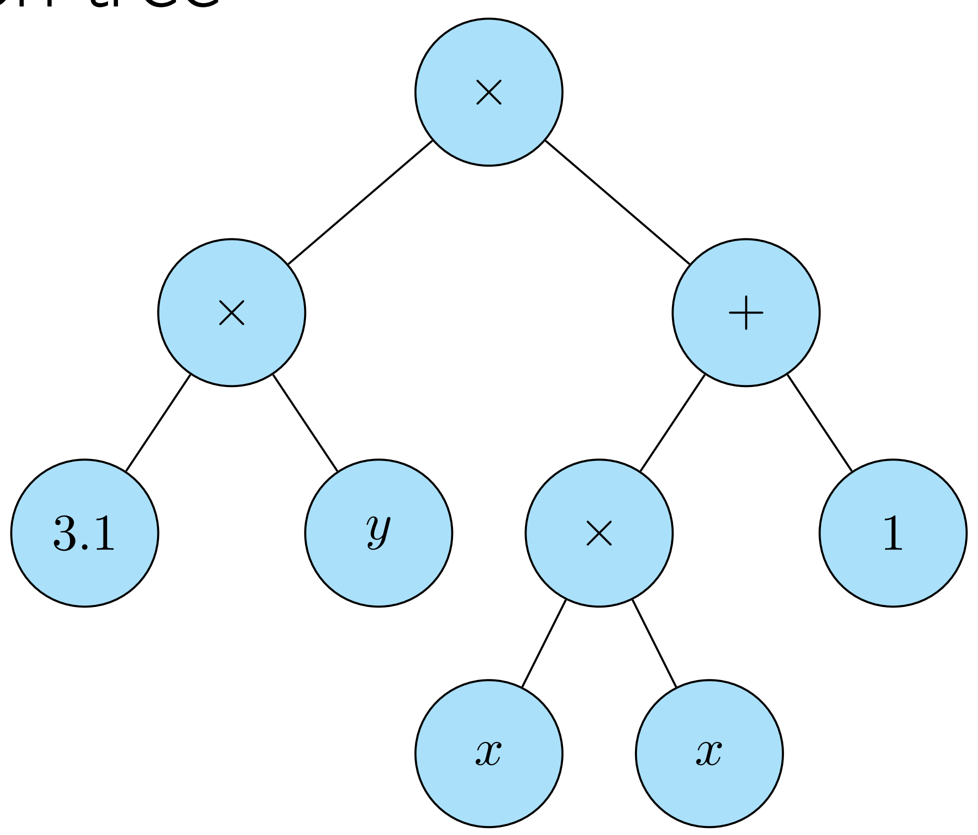
Our goal: find robust, simple, analytical expressions to describe collider observables

- We simulate particle collisions and use event-level kinematics as input data
- We use symbolic regression (SR) to find accurate, simple equations that describe the data

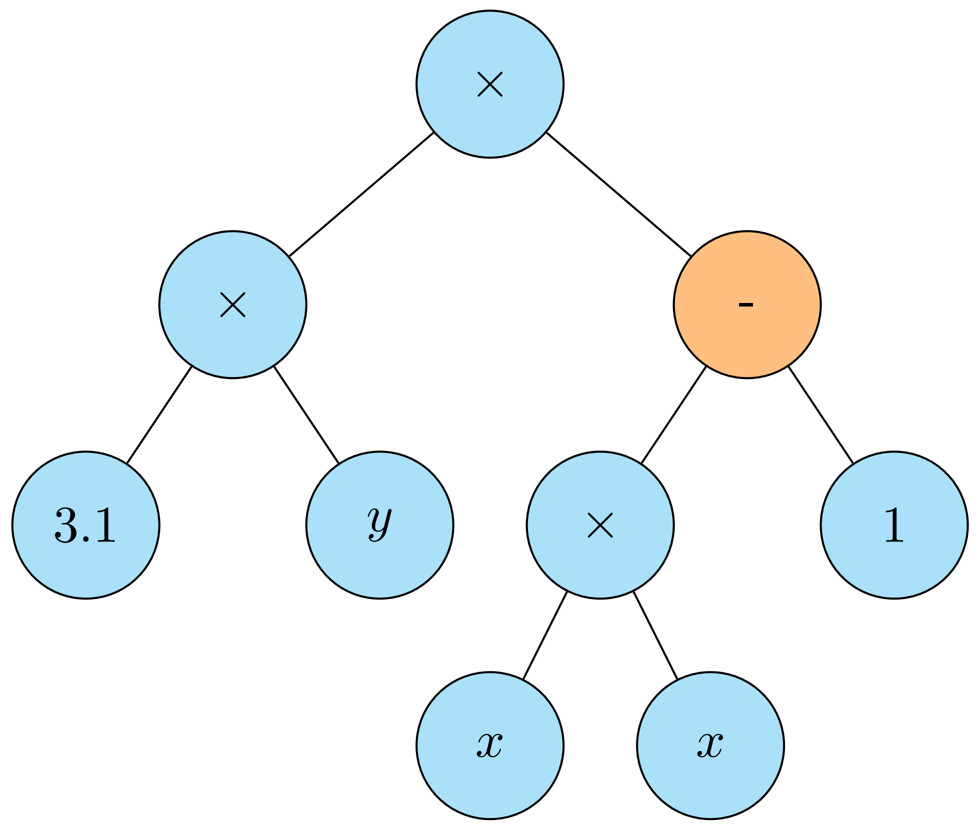
In SR, equations are represented by expression trees. During optimisation, they mutate and mix to provide better candidates

Expression tree

$$3.1y\,(x^2+1) \quad \leftrightarrow$$



Mutation

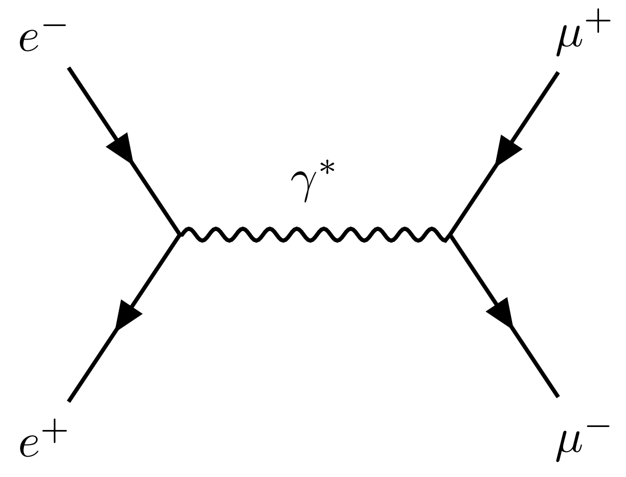


SYMBOLIC REGRESSION FOR PRECISION LHC PHYSICS (# 117)

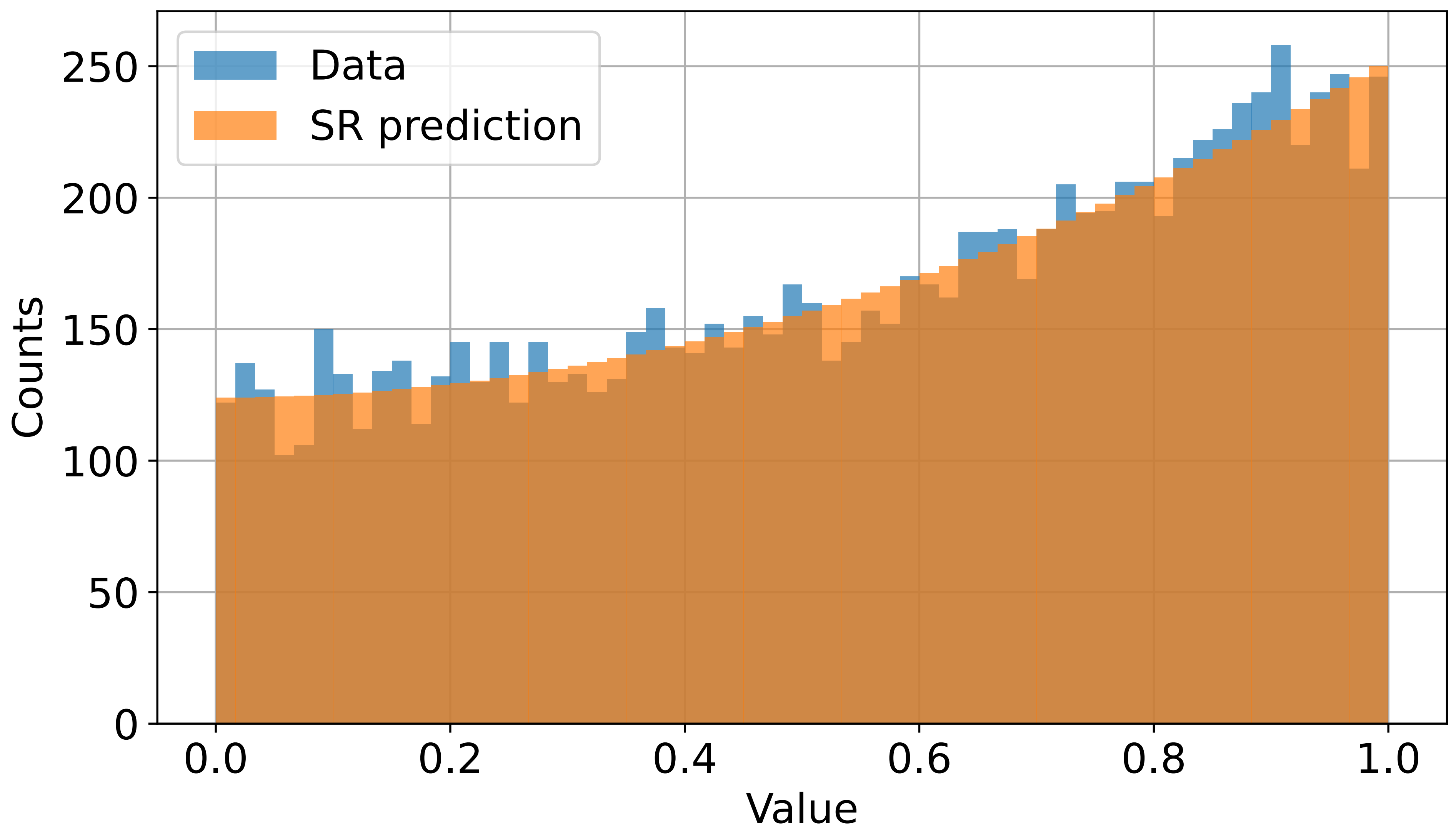
Josh Bendavid, Daniel Conde, Manuel Morales-Alvarado, Maria Ubiali, Veronica Sanz

We assess the quality and the robustness of the SR results by equation recovery. Consider an angular distribution:

$$e^- e^+ \to \mu^- \mu^+$$



Distribution of $|\cos\theta|$



SR formulas $(x_0 = \cos\theta)$

Bins	Accuracy	Score	**Best**
10	$x_0^2 \cdot (296.52358194355 \cdot x_0^4 + 7046.0674) + 7613.42$	$7250.1396 \cdot x_0^2 + 7589.319$	$7250.1396 \cdot x_0^2 + 7589.319$
30	$x_0^2(123.43398x_0^4 + 2326.98053420264) + 2538.3494$	$2415.3643x_0 + 2125.6453$	$2417.7627x_0^2 + 2527.635$
100	$x_0(207.340216x_0 + 428.81232) + 109.830989048 + 750.30175$	$725.2477x_0 + 637.3749$	$726.08685x_0^2 + 757.9762$

$$\frac{d\sigma}{d\Omega} = \frac{\alpha^2}{4s}\left(1 + \cos^2\theta\right)$$

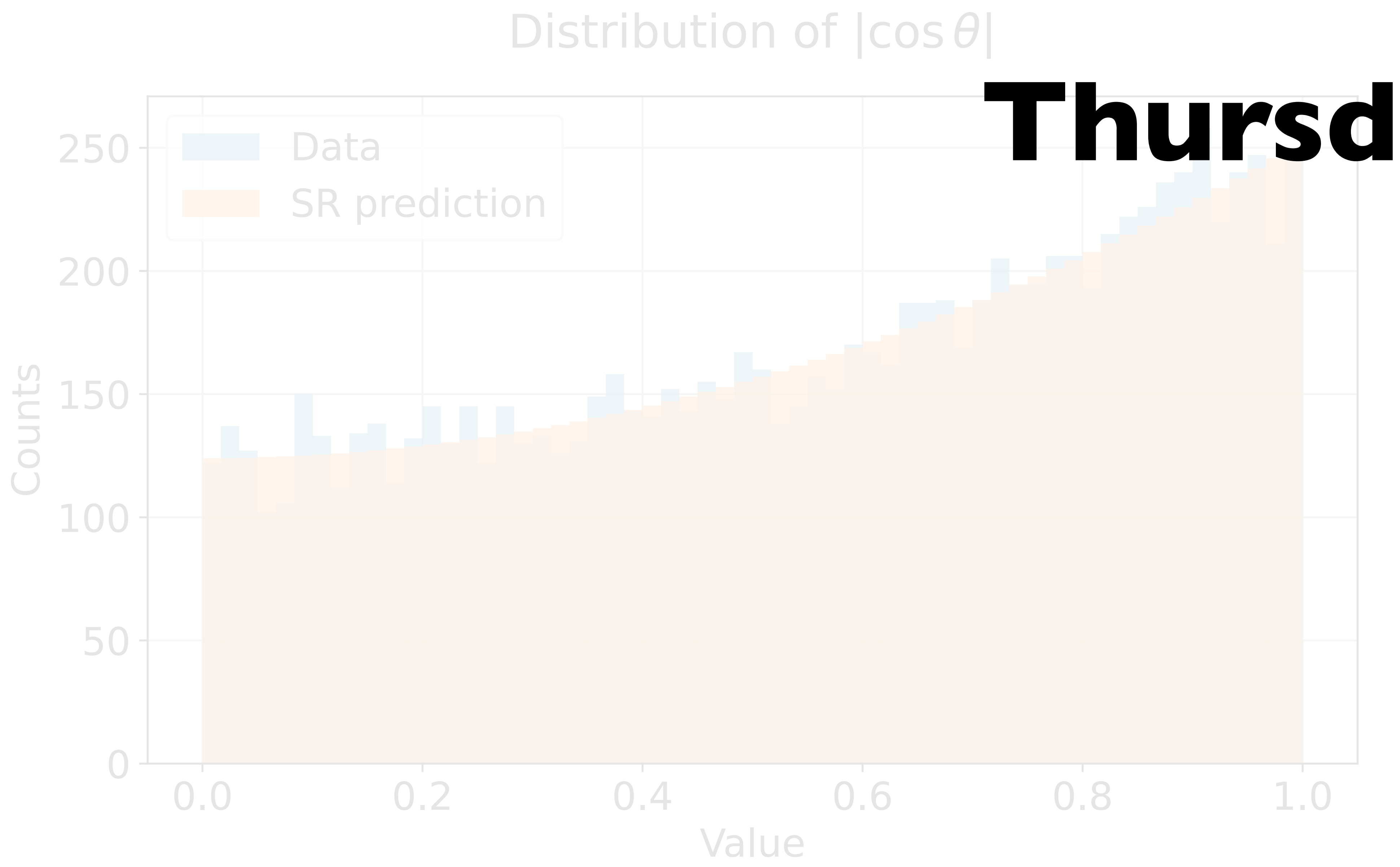
SYMBOLIC REGRESSION FOR PRECISION LHC PHYSICS (# 117)

Josh Bendavid, Daniel Conde, Manuel Morales-Alvarado, Maria Ubiali, Veronica Sanz

UNIVERSITY OF CAMBRIDGE · PBSP · European Research Council, Established by the European Commission

We assess the quality and the robustness of the SR results by equation recovery. Try, for example, an angular distribution:

$$e^-e^+ \to \mu^-\mu^+$$



SR formulas $(x_0 = \cos\theta)$

Bins	Accuracy	Score	Best
10	$x_0^2 \cdot$ (206.52358194355 [illegible] x_0 + 7046.0074) + 7613.42	$7250.1396 \cdot x_0^2 + 7589.319$	$7250.1396 \cdot x_0^2 + 7589.319$
[illegible]	[illegible] 3.423898 [illegible] 2326.98053420264) + 2538.3494	$2415.3643x_0 + 2125.6453$	$2417.7627x_0^2 + 2527.635$
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$$\frac{d\sigma}{d\Omega} = \frac{\alpha^2}{4s}\left(1 + \cos^2\theta\right)$$

Can’t wait to know more?

Thursday, poster 117!

Reconstructing the Neutron Star Equation of State with Bayesian Deep Learning

Giulia Ventagli

CEICO, Institute of Physics of the Czech Academy of Sciences

FZU Institute of Physics of the Czech Academy of Sciences

From observations to nuclear matter properties

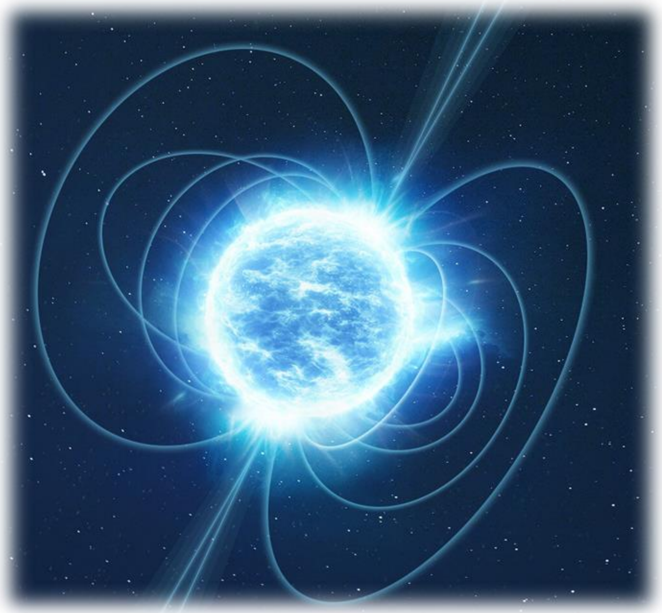
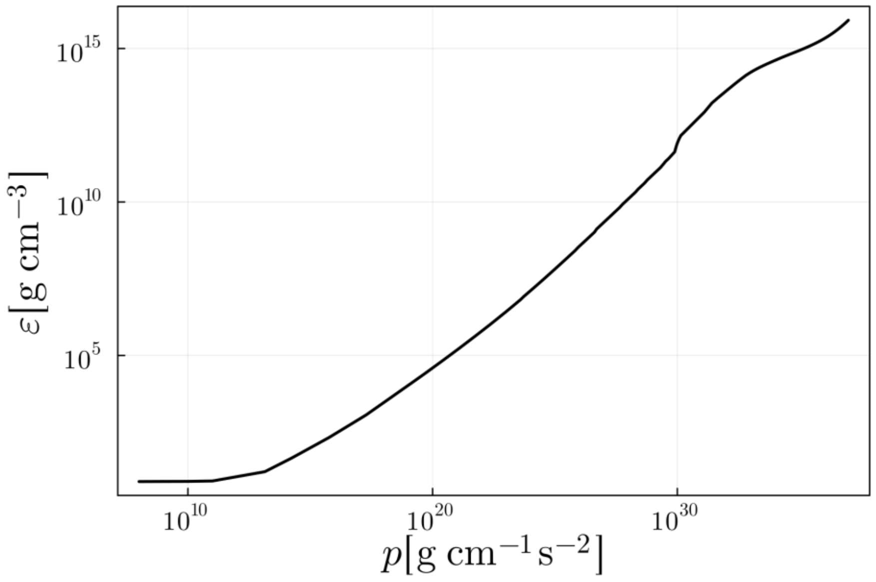


Image source: ESA

Masses, radii, tidal deformabilities

Deterministic deep network

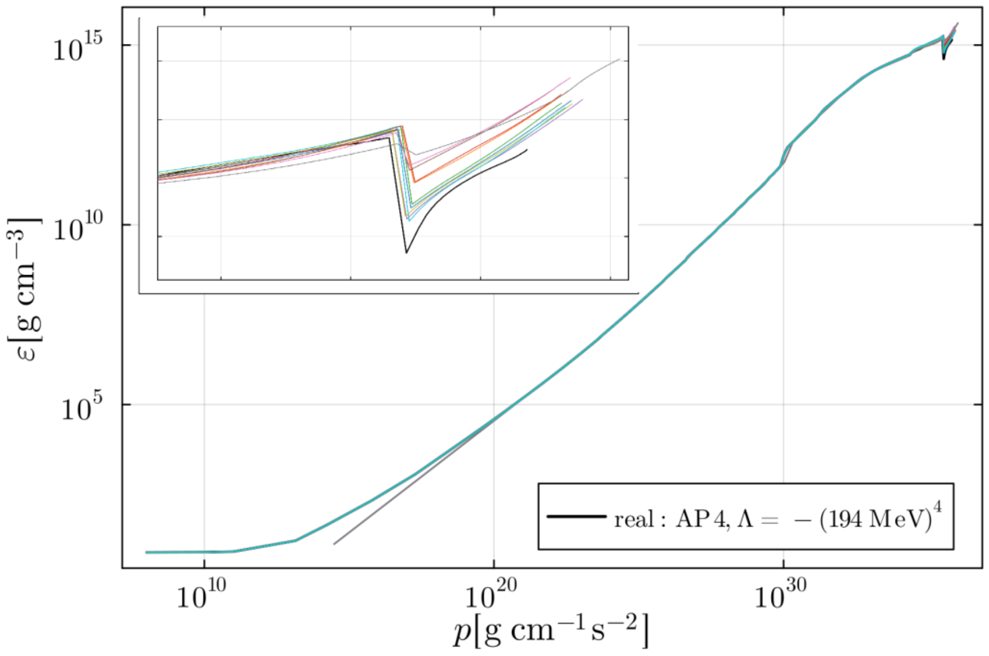
Bayesian deep network

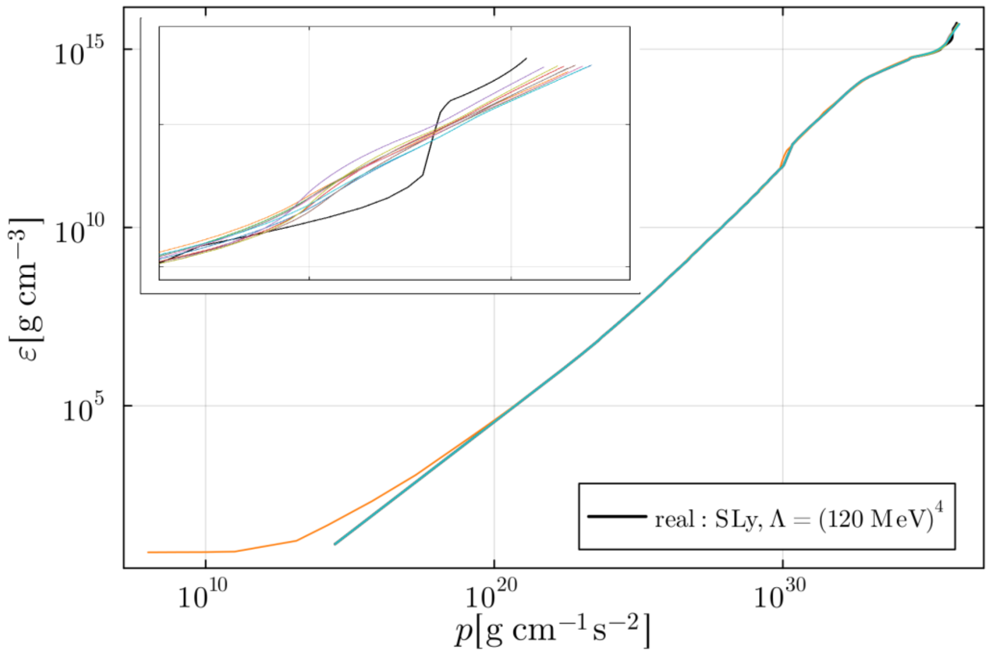


Reconstruct

$\varepsilon = \varepsilon(p)$

Our predictions





We also include and predict a *vacuum energy phase transition*!

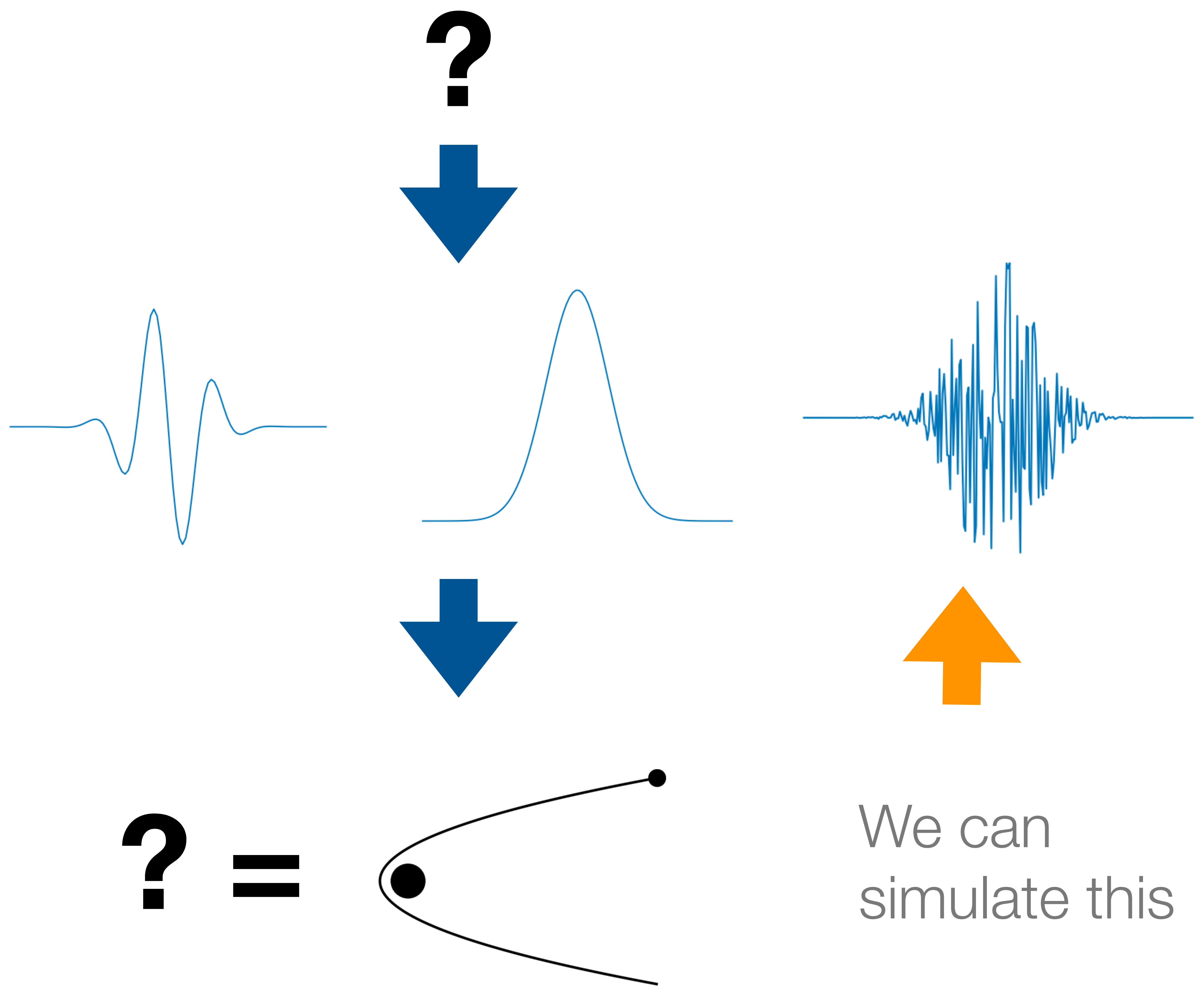
Reconstructing dynamic from gravitational wave signals

Joe Bayley, Chris Messenger, Graham Woan

Often burst gravitational signals do not have clear waveform models.

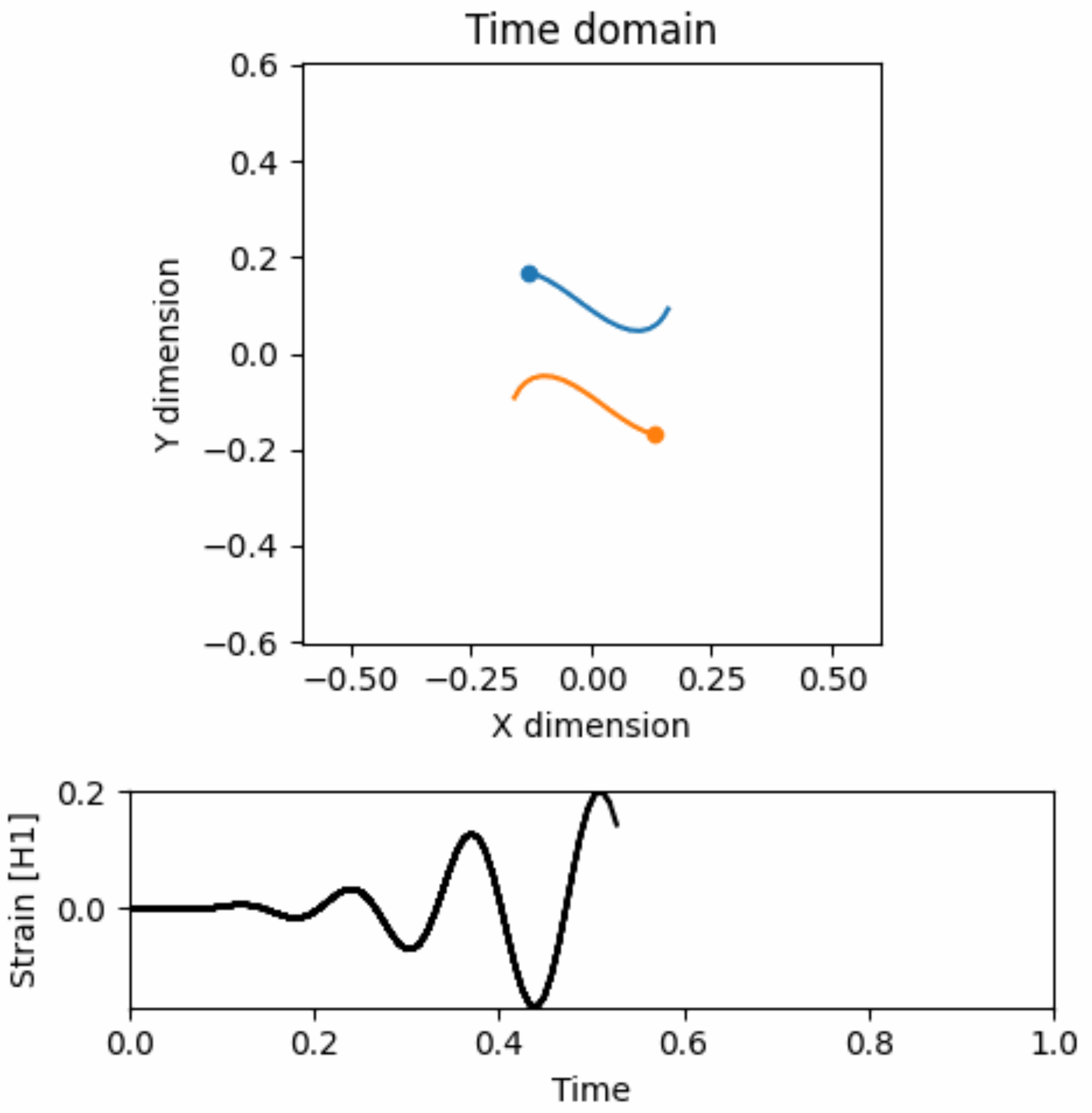
What information about the source can we recover from the gravitational wave signal alone?

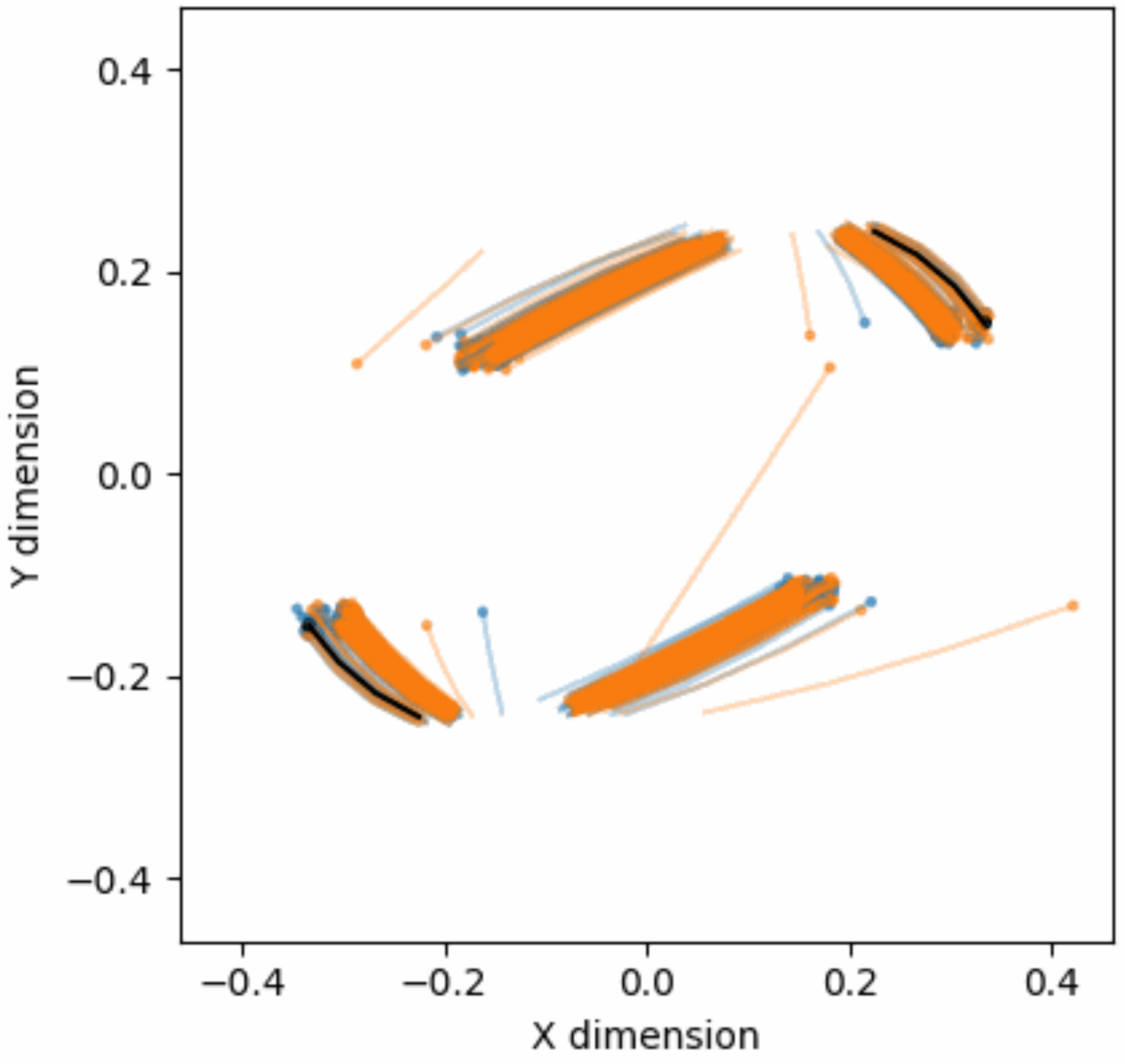
We aim to reconstruct the mass dynamics of the system:
- masses
- spatial position of masses

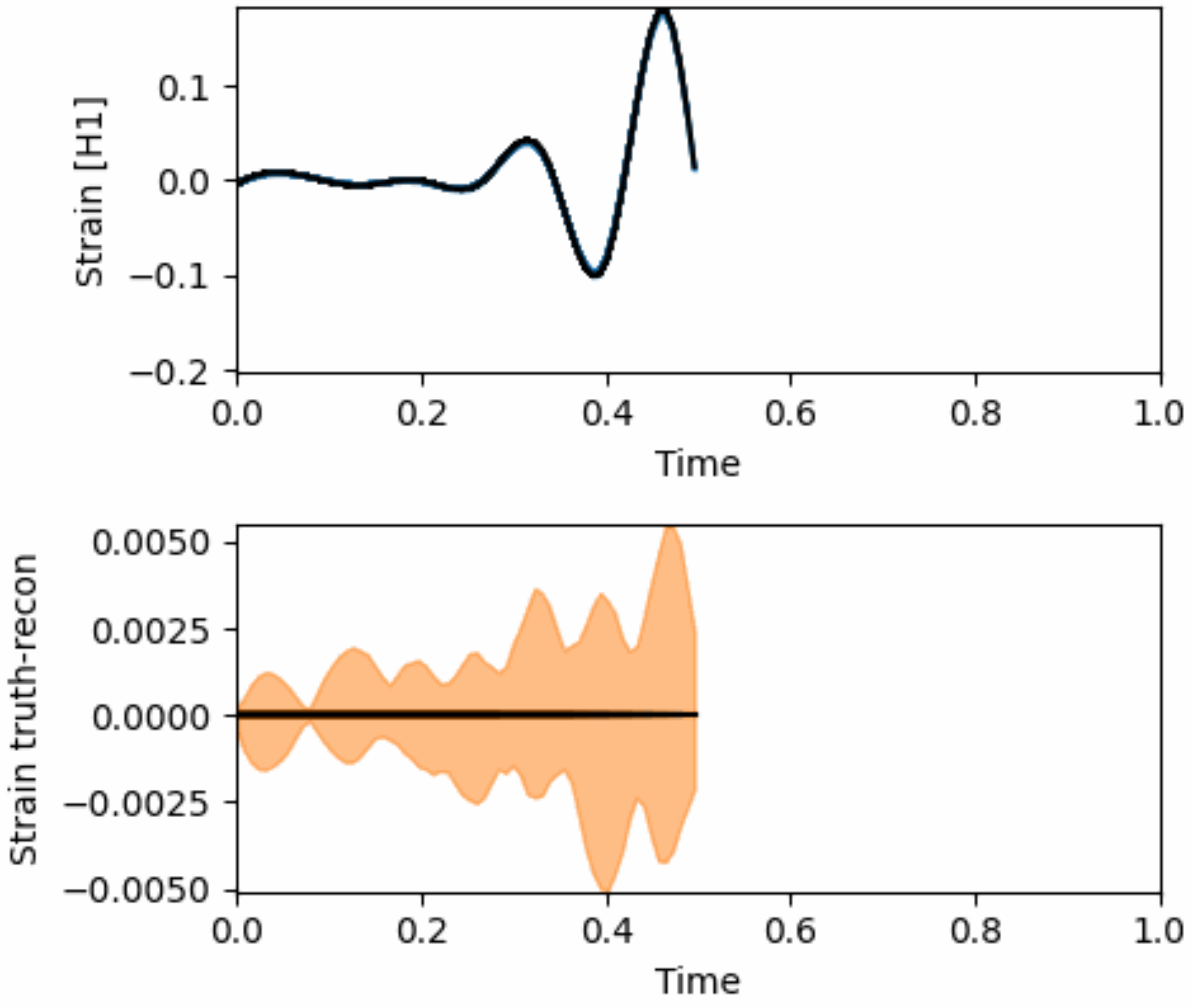


Models

We simulate lots of random non physical motion and can reconstruct physical motions.







If you're interested come and see my poster.
Poster number 115.

See here for animations.
https://github.com/jcbayley/massdynamics