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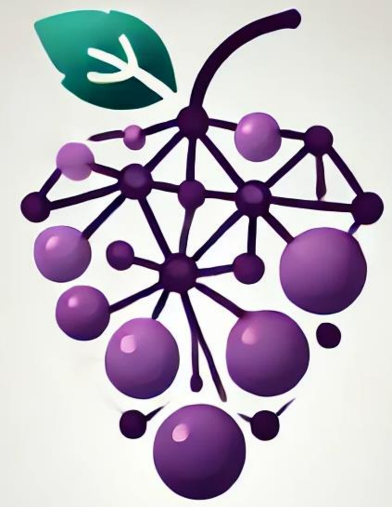
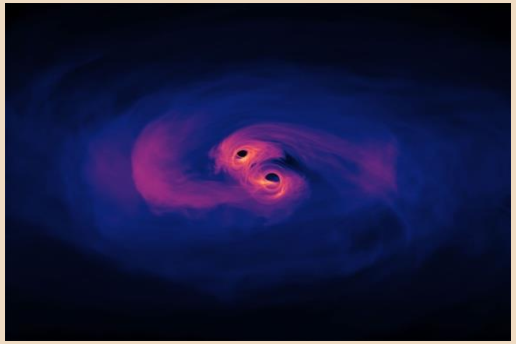
PINNGraPE

Physics-Informed Neural Network for Gravitational-wave Parameter Estimation





ET Symposium 2025

May 28th, 2025

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Ferrara and Trieste University, Italy – INFN

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FERRARIAE UNIVERSITAS 13 91 EX LABORE FRUCTUS

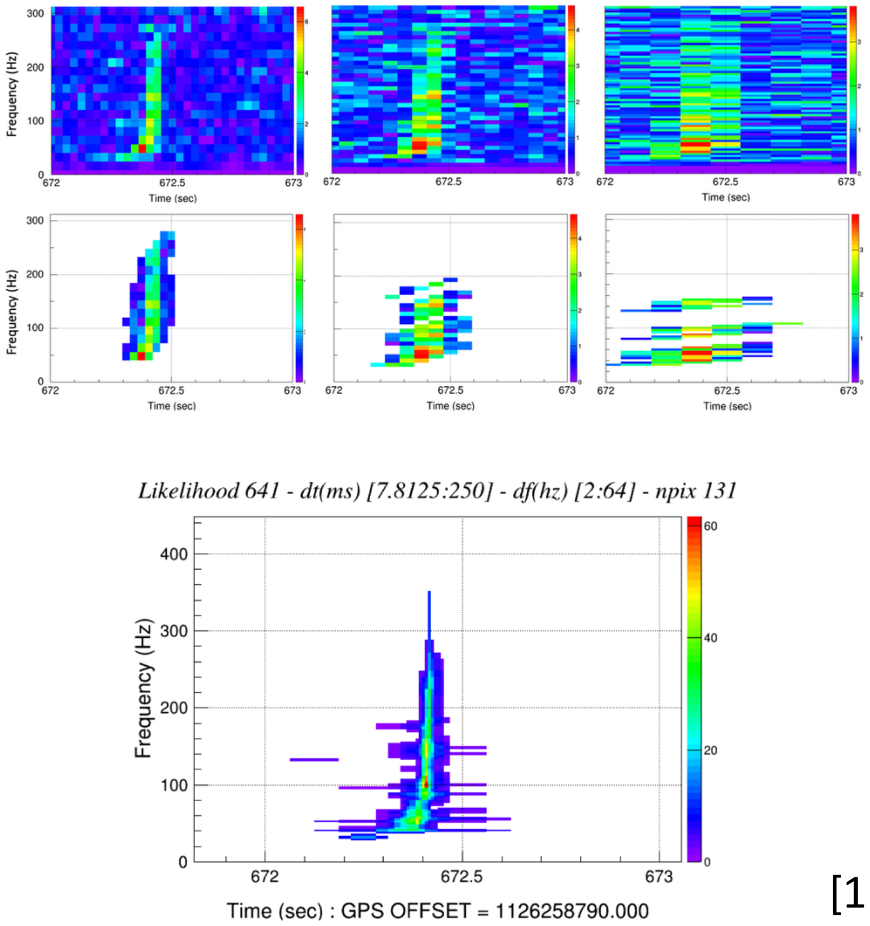
Introduction

- PINNGraPE is a ML algorithm which performs PE on CBC burst unmodeled signals.
- Based on Physics Informed Neural Networks.
- It is developed for LVK, but the technique could be exploited in ET.

Introduction: cWB

- cWB is an unmodeled pipeline used by LVK collaboration [1].
- **Unmodeled**: based on pure coherence between energy pixels in the frequency domain.
- **No theoretical background** needed to detect sources:
    - **Pro**: search for **new signals**.
    - **Con**: when detecting CBCs, the **PE** on the source, i.e. the chirp mass estimation, is **only given by a fit** on the likelihood plot.

Let's fix it!



[1]

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Introduction: PINNs

- Physics-Informed Neural Networks are a ML technique developed to **exploit, discover or solve differential equations** as physical laws behind the data [2, 3].

- The base of the physical information is the **loss function:** the physics is implented inside the loss itself in form of PDE and auxiliary physics relations.

Main goal for PINNGraPE

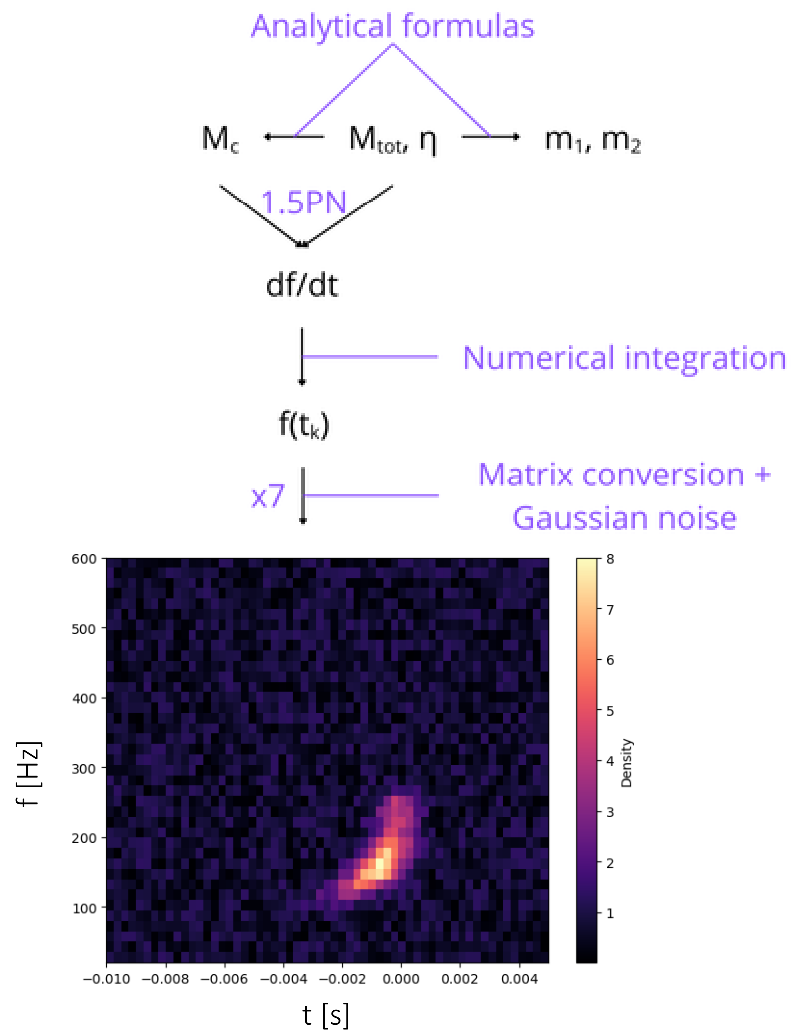
To infer the two BH masses m_1 and m_2 from a dataset of simulated burst CBCs signals.

Dataset: 10^4 simulated signals. For every signal:

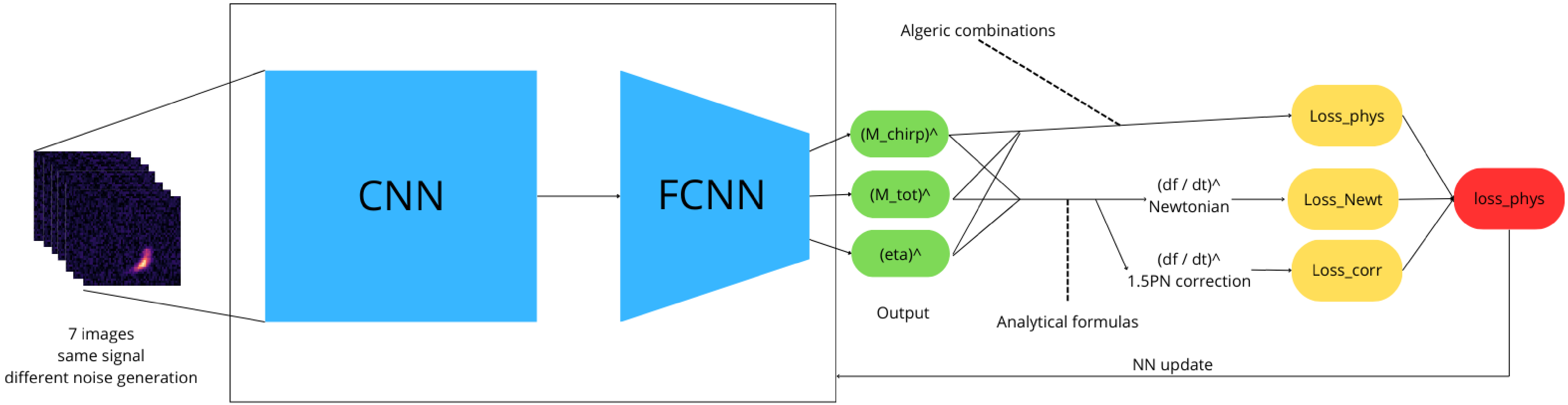
- 7 spectrogram-like images
- Stored values for target:
  - $\{m_1, m_2, M_c, M_{tot}, \eta, \{df/dt\}_{k,\ Newt}, \{df/dt\}_{k,\ 1.5PN\_corr}, f_k\}$,
- 1.5PN formalism [4]:

$$\varepsilon = \frac{GM_\odot}{c^3}\left(\frac{M_{\rm tot}}{M_\odot}\right)\pi f$$

$$\frac{df}{dt} = \frac{96}{5}\pi^{8/3}\left(\frac{GM_\odot}{c^3}\frac{M_{\rm tot}}{M_\odot}\eta^{3/5}\right)^{5/3} f^{11/3}\left[1-\left(\frac{743}{336}+\frac{11}{4}\eta\right)\varepsilon^{2/3}+4\pi\varepsilon\right]$$



Architecture



Loss function

$$\mathcal{L} = \mathcal{L}_{Newt} + \mathcal{L}_{1.5PN} + \mathcal{L}_{phys} = \frac{\beta_1}{B}\sum_{i=1}^{B}\left(\frac{d\hat{f}_i}{dt} - \frac{df_i}{dt}\right)^2_{Newt} + \frac{\beta_2}{B}\sum_{i=1}^{B}\left(\frac{d\hat{f}_i}{dt} - \frac{df_i}{dt}\right)^2_{1.5PN-Newt} + \mathcal{L}_{phys}$$

$$\mathcal{L}_{phys} = \frac{\beta_3}{B}\sum_{i=1}^{B}\left(\hat{M}_{tot,\,i}\,\hat{\eta}_i^{3/5} - \hat{\mathcal{M}}_i\right)^2 + \frac{\beta_4}{B}\sum_{i=1}^{B}\left(\hat{\mathcal{M}}_i\,\hat{\eta}_i^{-3/5} - \hat{M}_{tot,\,i}\right)^2 + \frac{\beta_5}{B}\sum_{i=1}^{B}\left(\left(\frac{\hat{\mathcal{M}}_i}{\hat{M}_{tot,\,i}}\right)^{3/5} - \hat{\eta}_i\right)^2$$

- Main terms: df/dt ones.

  Newtonian one depends only on M_c, while the correction one depends on M_{tot} and η.
- Physical loss terms exploit physical redundancy between M_c, M_{tot} and η.

  Physical redundancy explained in detail in Di Clemente et al. [5] and in a new paper in the writing stage.
- Notice: no direct output vs target term.

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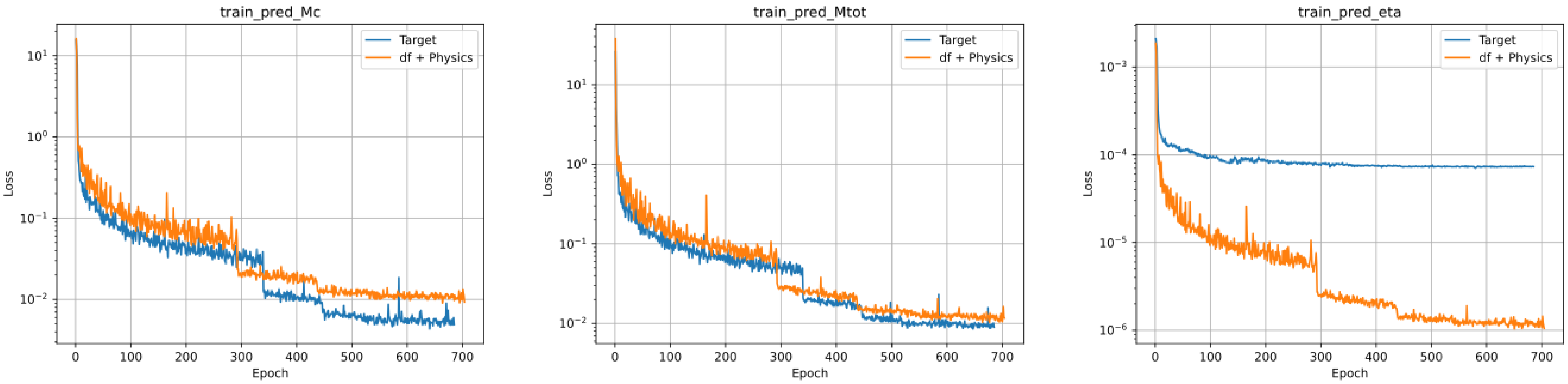
Loss function



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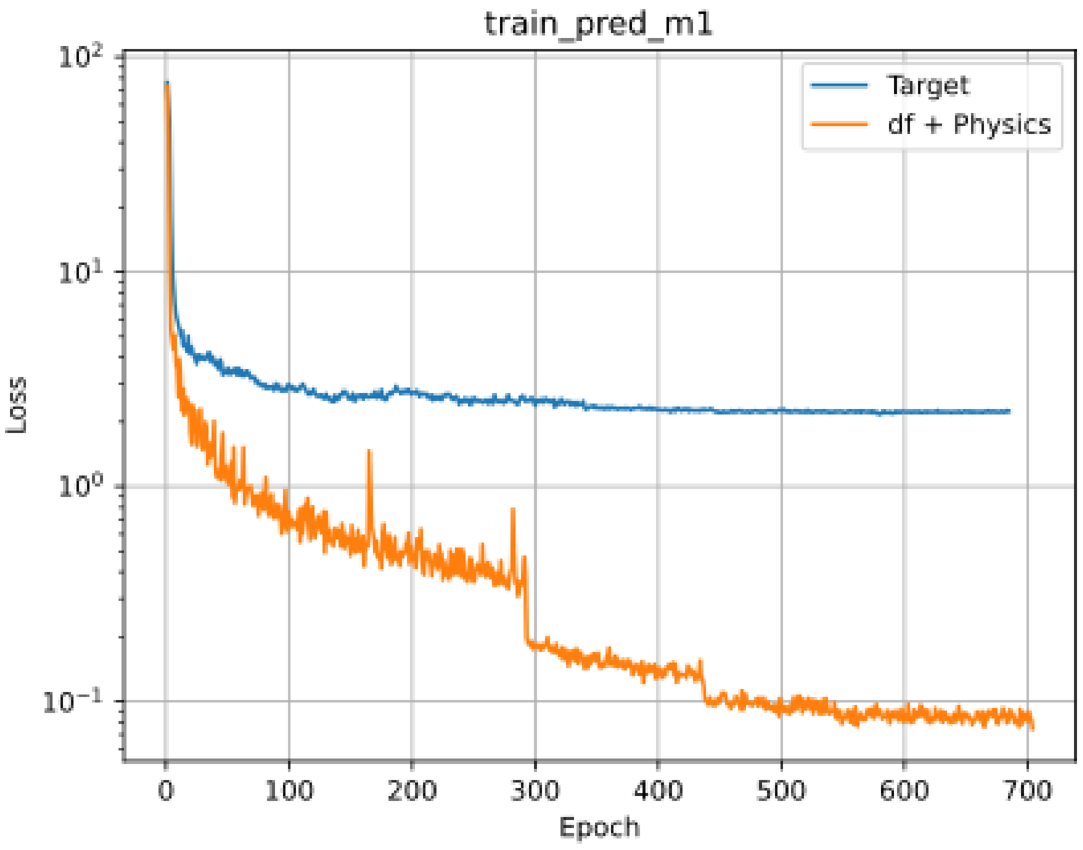
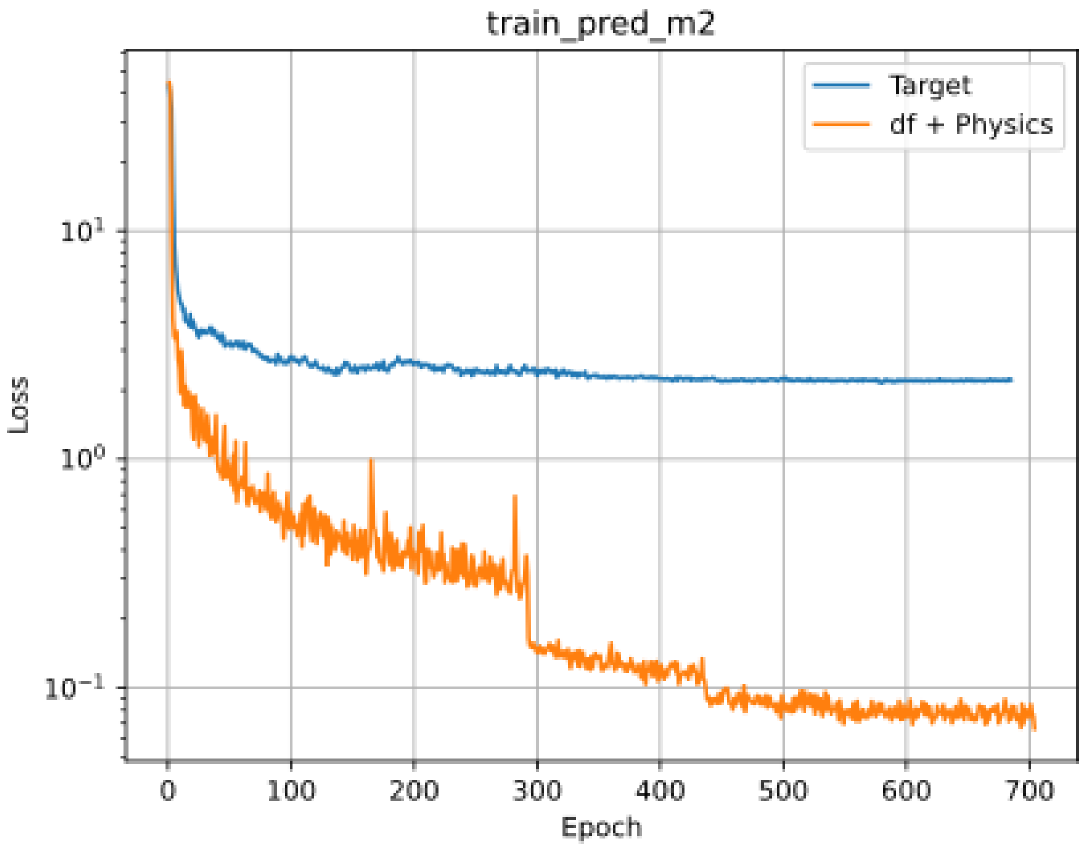
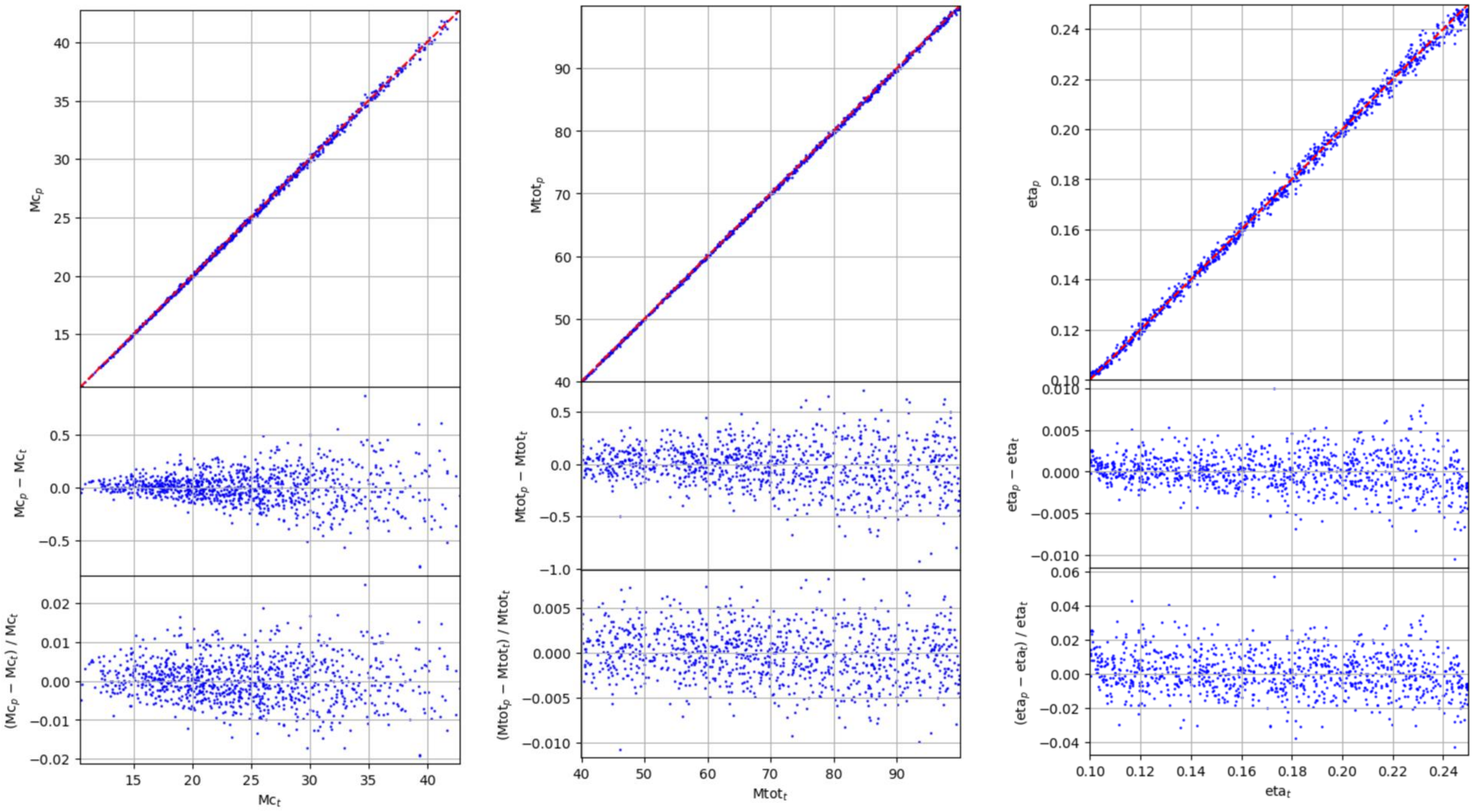
Loss function





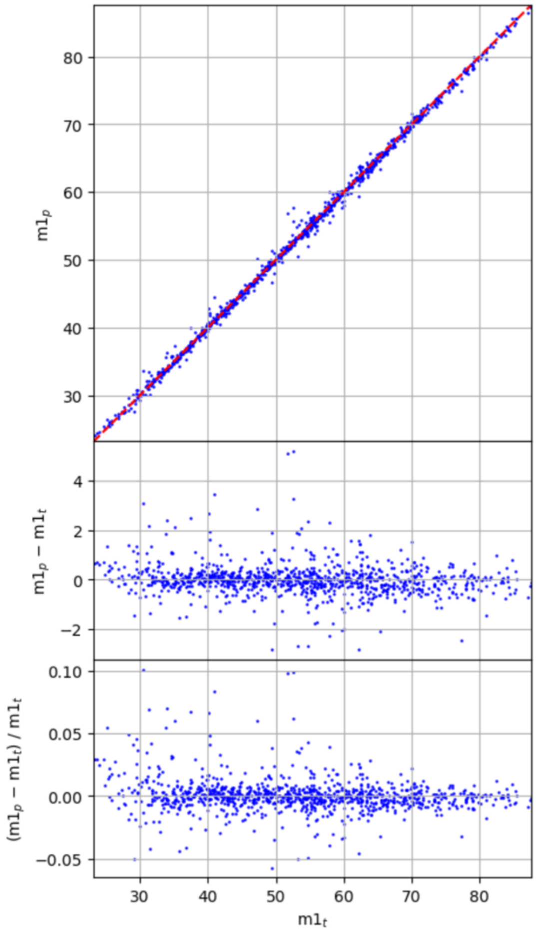
Results

M_c $[M_\odot]$ | M_{tot} $[M_\odot]$ | η

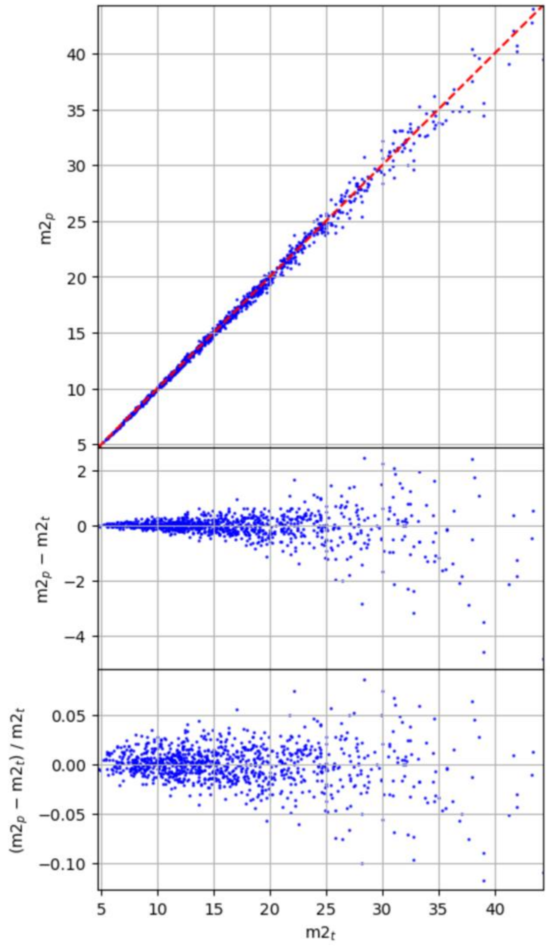


Results

m_1 [$M_\odot$]



m_2 [$M_\odot$]



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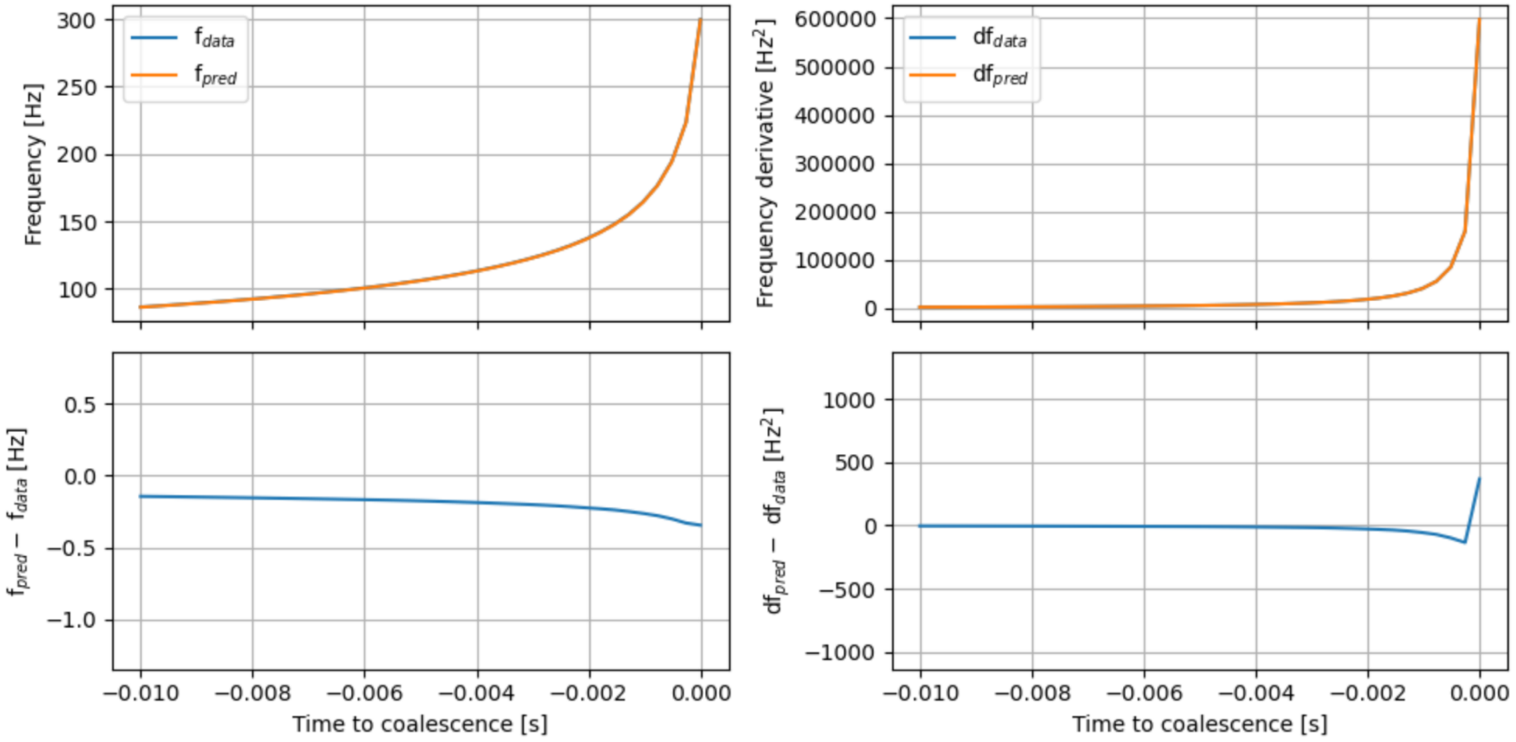
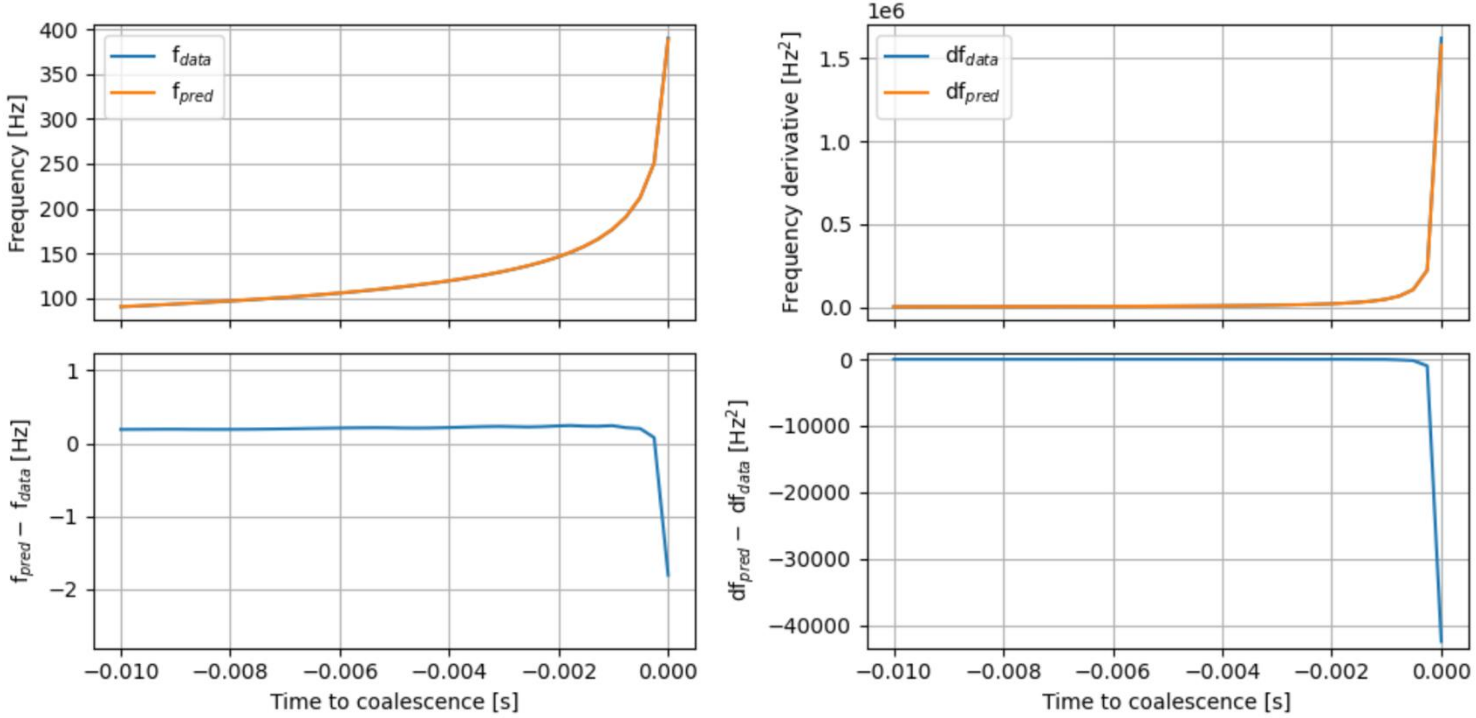
Results

Variables	Target [M_sun]	Predicted [M_sun]	Difference [M_sun]	Relative Difference [ ]
m1	62.2199211	62.2788620	0.0589409	0.0009473
m2	14.1337042	14.1629267	0.0292225	0.0020676
Mc	24.5439987	24.6159897	0.0719910	0.0029331
Mtot	76.3536224	76.4417877	0.0881653	0.0011547
eta	0.1508433	0.1509496	0.0001063	0.0007045



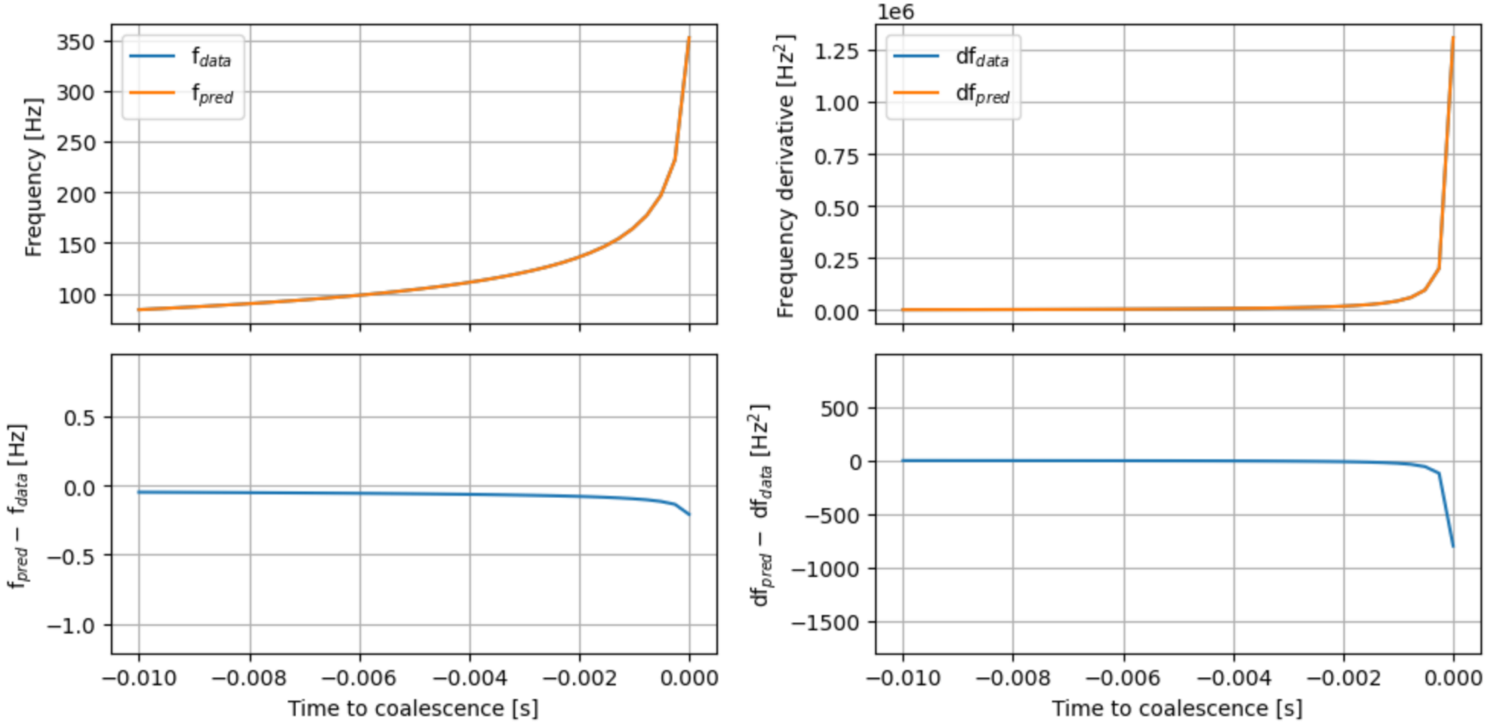
Results

Variables	Target [M_sun]	Predicted [M_sun]	Difference [M_sun]	Relative Difference [ ]
m1	30.4501419	33.5333672	3.0832253	0.1012549
m2	28.1909962	25.3806343	-2.8103619	-0.0996900
Mc	25.5023003	25.3342171	-0.1680832	-0.0065909
Mtot	58.6411400	58.9140015	0.2728615	0.0046531
eta	0.2496290	0.2452125	-0.0044165	-0.0176921



Results – test with GW150914 like masses

	Target [M_sun]	Predicted [M_sun]	Difference [M_sun]	Relative difference [ ]
m1	36.0000000	35.9720192	-0.0279808	-0.0007772
m2	29.0000000	29.0668106	0.0668106	0.0023038
Mc	28.0955563	28.1226387	0.0270824	0.0009639
Mtot	65.0000000	65.0388336	0.0388336	0.0005974
eta	0.2471006	0.2471820	0.0000814	0.0003293



What about ET?

The same technique could be exploited in ET:

- it offers a **PE technique for CBC detected with unmodeled pipelines**;
- it is suitable for **new kind of signals**:
  - if we know the physics behind the system, we can optimize for different parameters and add different loss terms;
  - if we know the physics behind the system only partialy, PINNs are also able to approximate the unknown physics.

Conclusions and future steps

- Main goal reached:

  m_1 and m_2 are infered within an error < 5%.
- PINNs really represents a promising approach for acheaving fast PE for unmodeled singals.
- Next steps:
  - Almost ready to implement on cWB.
  - Study on the error estimate on a new incoming signal.
  - Increase the parameters to estimate: add further PN terms.

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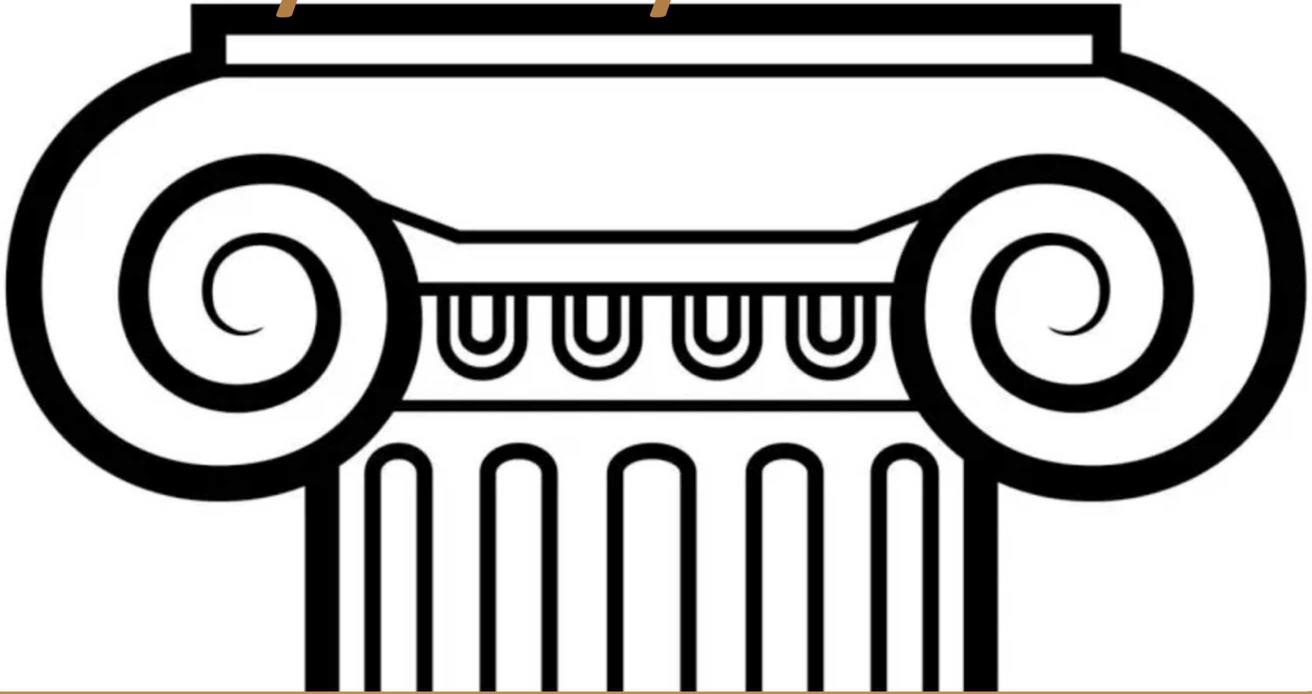
Thank you for your attention!



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References

[1] Drago, M., Klimenko, S., Lazzaro, C., Milotti, E., Mitselmakher, G., Necula, V., O'Brian, B., Prodi, G. A., Salemi, F., Szczepanczyk, M., Tiwari, S., Tiwari, V., V, G., Vedovato, G., and Yakushin, I. 2021). coherent waveburst, a pipeline for unmodeled gravitational-wave data analysis. SoftwareX, 14:100678.

[2] Raissi, M., Perdikaris, P., and Karniadakis, G. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378:686–707.

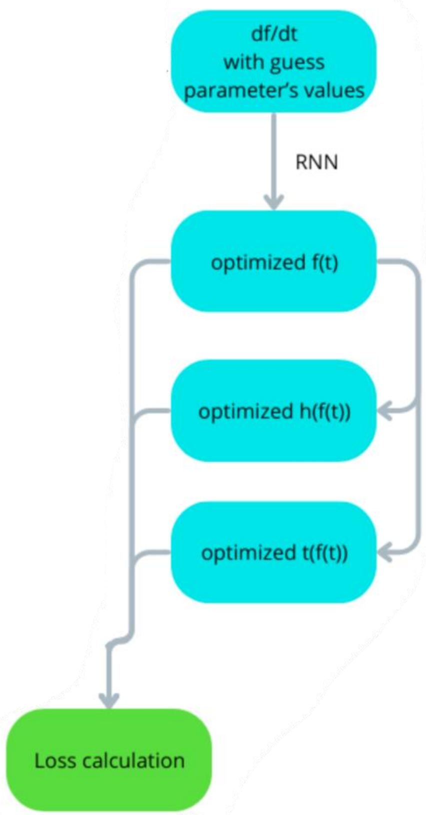
[3] Nascimento, R. G., Fricke, K., and Viana, F. A. (2020). A tutorial on solving ordinary differential equations using python and hybrid physics-informed neural network. Engineering Applications of Artificial Intelligence, 96:103996.

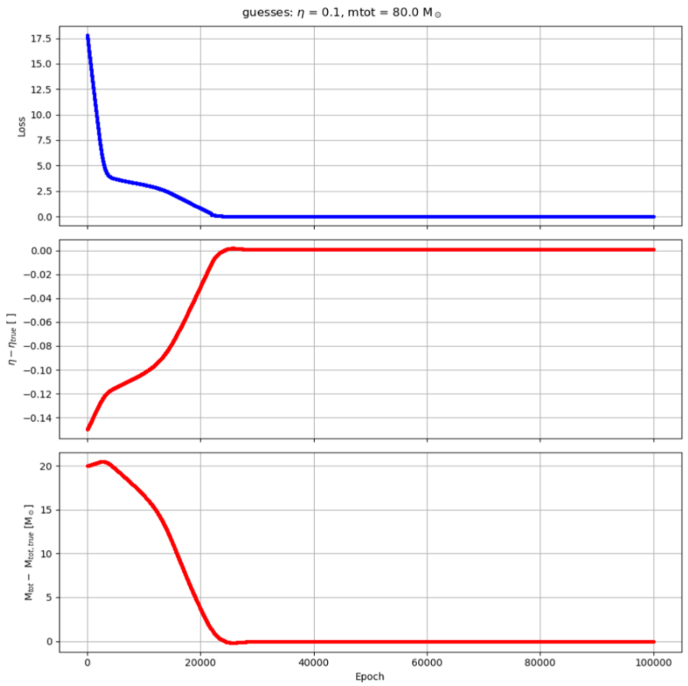
[4] Cutler, C. and Flanagan, E. E. (1994). Gravitational waves from merging compact binaries: How accurately can one extract the binary's parameters from the inspiral waveform? Physical Review D, 49(6):2658–2697.

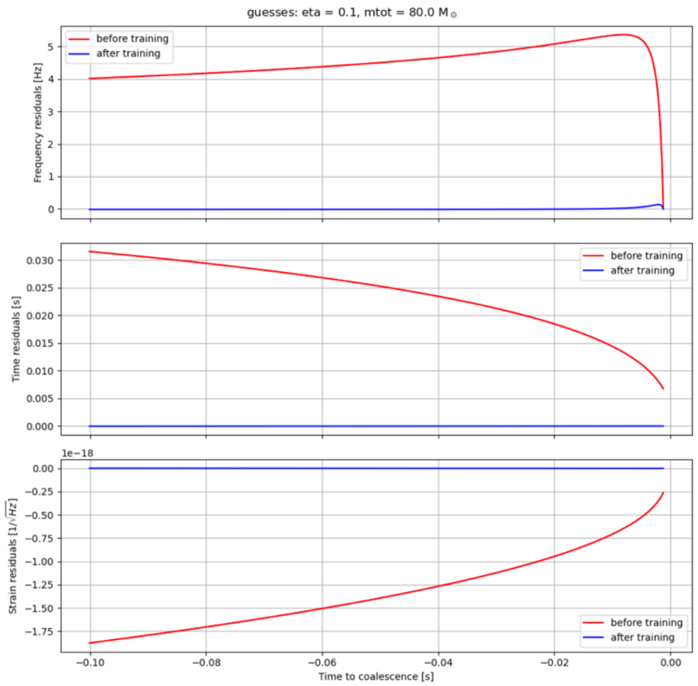
[5] F. Di Clemente, M. Scialpi, and M. Bejger, "Explainable autoencoder for neutron star dense matter parameter estimation", 2025.

Backup slides

RNN version







- Final loss value: 2.385 * 10^(-2).
- AdamW optimizer
- Total time: -1h on CPU (4000 epochs).

	η	M_{tot} $[M_\odot]$
Guess	0.1000	80.00
Target	0.2500	60.00
Inferred	0.2507	59.95

1.5PN formalism [4]

$$M_{\text{tot}} = m_1 + m_2$$

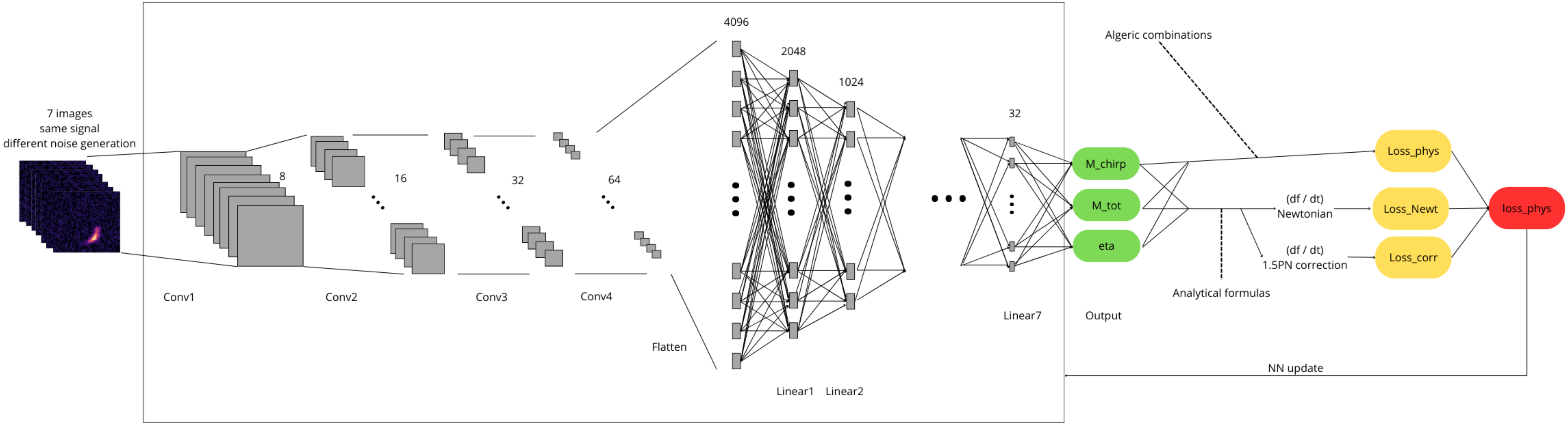
$$\eta = \frac{m_1 m_2}{(m_1 + m_2)^2} = \frac{m_1 m_2}{M_{\text{tot}}^2}$$

$$\mathscr{M} = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}} = M_{\text{tot}} \eta^{3/5}$$

$$\varepsilon = \frac{G M_\odot}{c^3} \left(\frac{M_{\text{tot}}}{M_\odot} \right) \pi f$$

$$\frac{df}{dt} = \frac{96}{5} \pi^{8/3} \left(\frac{G M_\odot}{c^3} \frac{M_{\text{tot}}}{M_\odot} \eta^{3/5} \right)^{5/3} f^{11/3} \left[1 - \left(\frac{743}{336} + \frac{11}{4} \eta \right) \varepsilon^{2/3} + 4\pi\varepsilon \right]$$

Architecture



PINNs theory

$$u_t + \mathcal{N}[u;\lambda] = 0, \; x \in \Omega, \; t \in [0, T],$$

$$f := u_t + \mathcal{N}[u],$$

$$MSE = MSE_u + MSE_f,$$

where

$$MSE_u = \frac{1}{N_u}\sum_{i=1}^{N_u} |u(t_u^i, x_u^i) - u^i|^2,$$

and

$$MSE_f = \frac{1}{N_f}\sum_{i=1}^{N_f} |f(t_f^i, x_f^i)|^2.$$

Task: find an approximation for u (= solve the differential equation) and optimize λ.

Data: (u^i, t^i, x^i).

How: approximate u with a NN and minimize the loss.

Why this should work? Since u is a NN, f is a PINN: they share the same parameters.

PINNs theory