Differentiable Vertex Fitting for Jet Flavour Tagging

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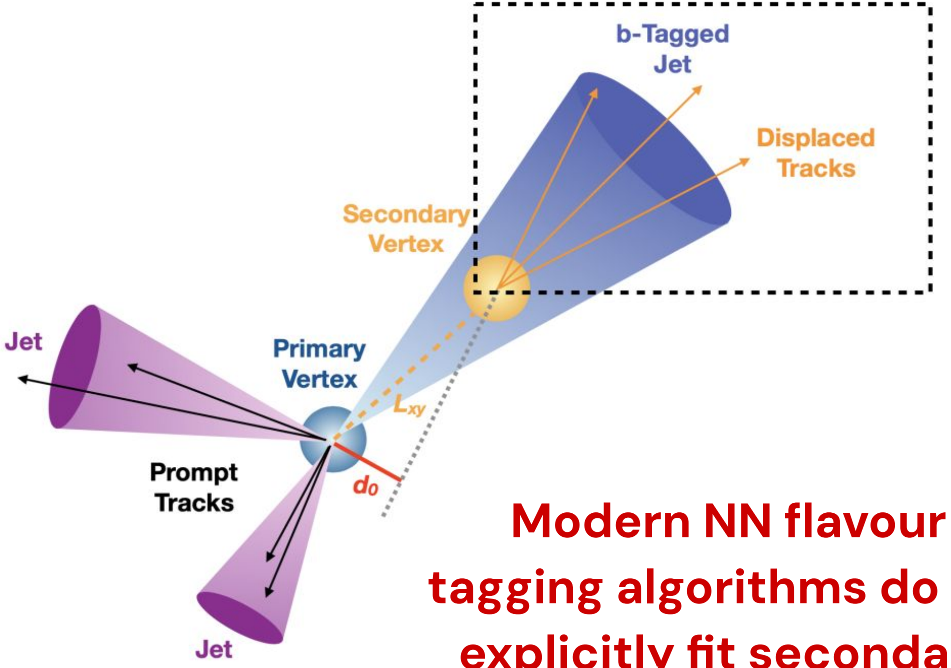
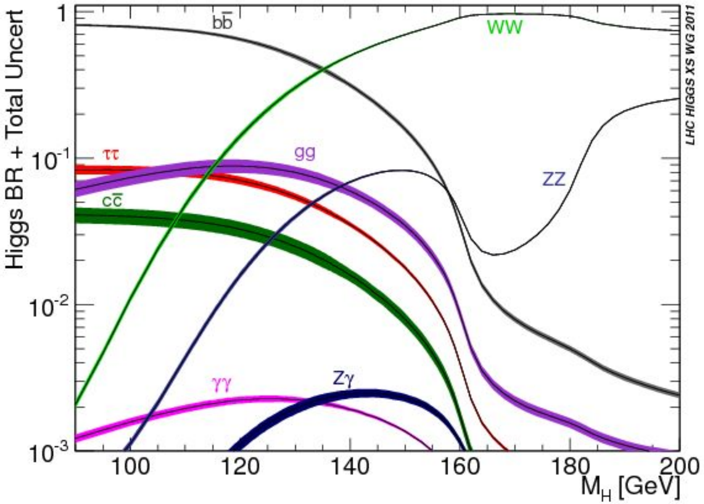
Jet flavour tagging in high energy physics

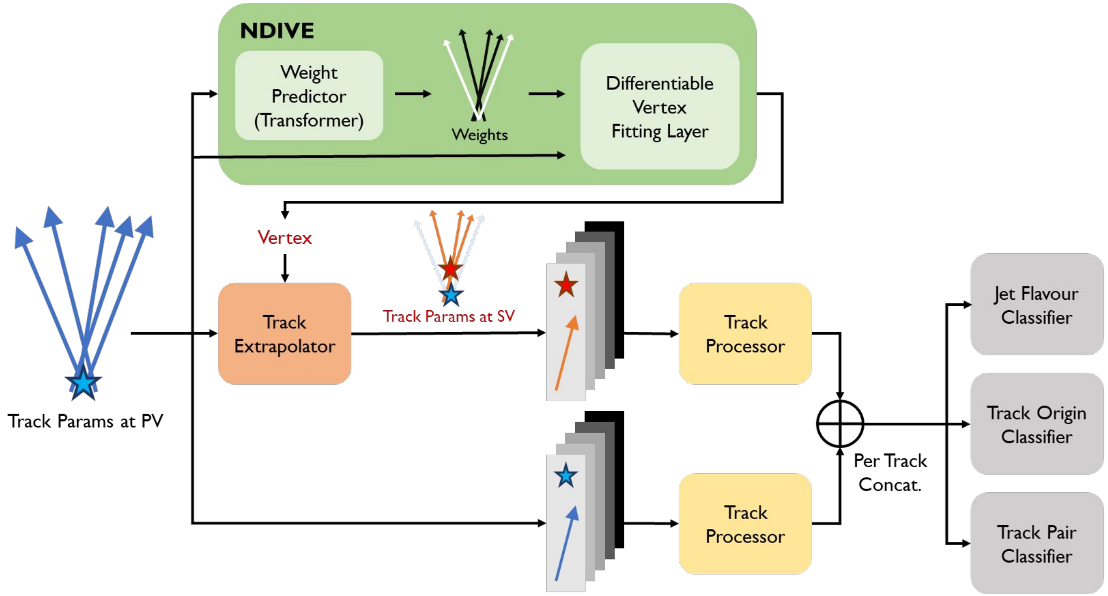


Modern NN flavour tagging algorithms do not explicitly fit secondary vertices...

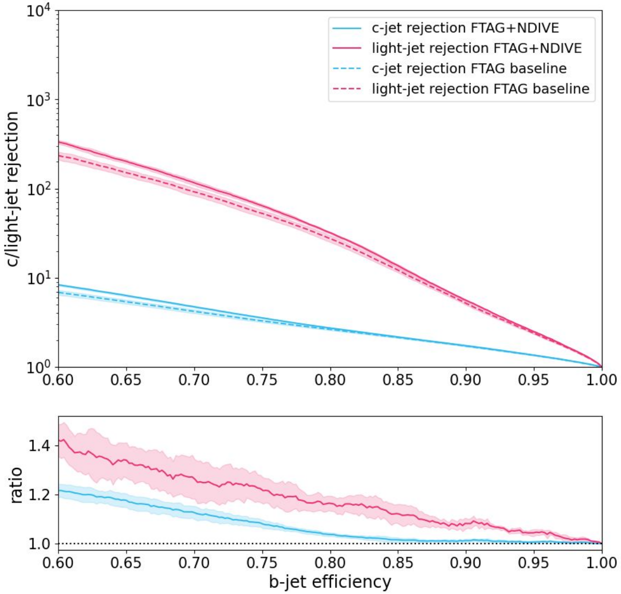
Standard Model Higgs boson decays preferentially to a pair of b-quarks



NDIVE (Neural DIfferentiable VErtexer)



NDIVE integration into NN flavour tagging model improves performance:

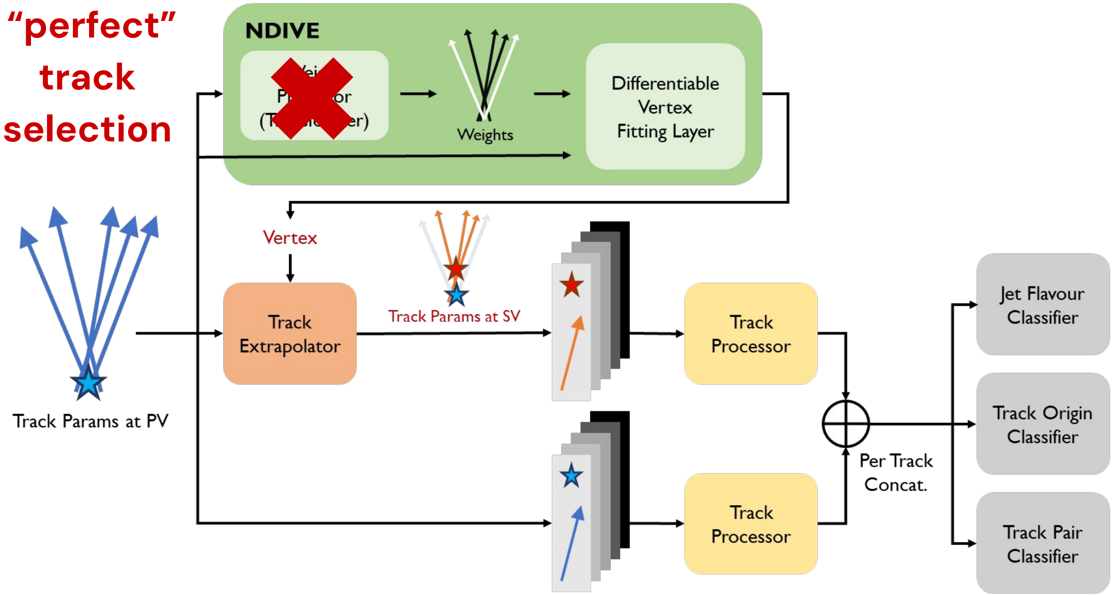


fully integrated and jointly optimizable;

explicitly introduce physics knowledge into NNs!

NDIVE (Neural DIfferentiable VErtexer)

“perfect” track selection



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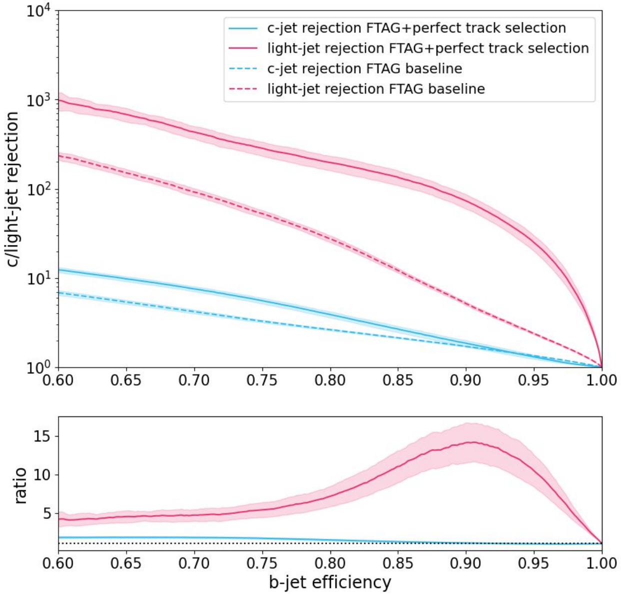


Significant improvements possible with better track selection!

Introduction

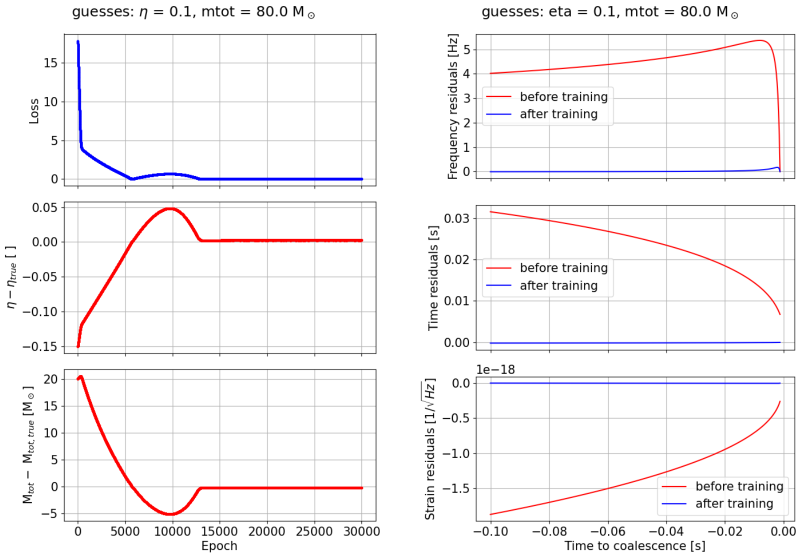
- **PINNGraPE** is a PyTorch algorithm which **does PE for a Gravitational-Wave (GW) signal's source thanks to a Physics-Informed Neural Network (PINN) [?].**

- **We solve (1) thanks to a Recurrent Neural Network** (RNN) with a Runge-Kutta integrator at 4^{th} order implemented inside.

$$\frac{df}{dt} = \mathcal{F}[f, \eta, M_{tot}] \tag{1}$$

$$\begin{aligned} \mathcal{L} =& \frac{\beta_f}{N}\sum_{k=1}^{N}|f_k - f(t_k)| + \\ &+ \frac{\beta_t}{N}\sum_{k=1}^{N}|t_k - t(f(t_k))| + \\ &+ \frac{\beta_h}{N}\sum_{k=1}^{N}|h_k - h(f(t_k))| \end{aligned} \tag{2}$$

Results


guesses: η = 0.1, mtot = 80.0 M⊙
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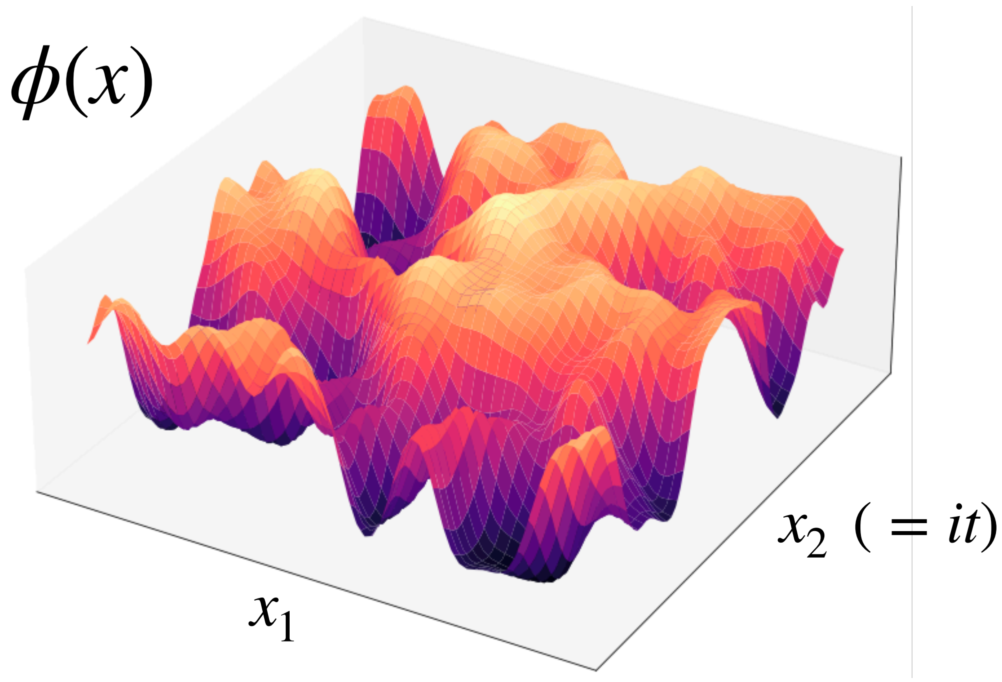
Loss
η − η_true [ ]
M_tot − M_tot, true [M⊙]
Epoch
Frequency residuals [Hz]
Time residuals [s]
Strain residuals [1/√Hz]
1e−18
Time to coalescence [s]
before training
after training

Conclusions

- **PINNGraPE is able to infer η and M_{tot} values with 10^{-2} relative error from frequency and strain data, implementing 1.5PN formalism.**
- **Near future steps**:
  - to build a real dataset spanning a physical parameter space;
  - to test robustness against noise and glitches;
  - to extend the number of parameters to infer.
- (Not so) **remote future step**:
  - use of cWB real outputs,
  - apply PINNs approach to TOV equations, in order to constrain NS's equation of state.

Lattice Quantum Field Theory

as a sampling problem



(Euclidean) action

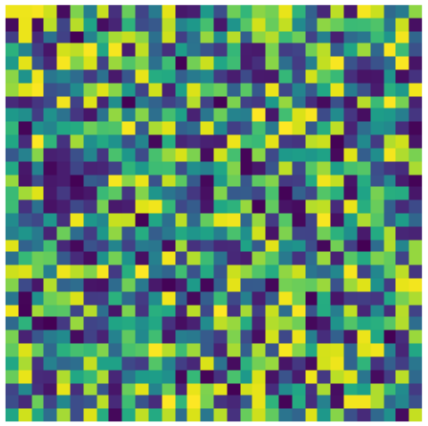
$$S[\phi] = \int d^D x \, \frac{1}{2} \left((\partial_\mu \phi)^2 + m^2 \phi^2 \right) + \lambda \phi^4$$

$$p(\phi) \propto e^{-S[\phi]}$$

Samples: $\phi \sim e^{-S[\phi]}$ —**estimate observables**→ $\langle \mathcal{O}[\phi] \rangle$

Generative models

trivial theory



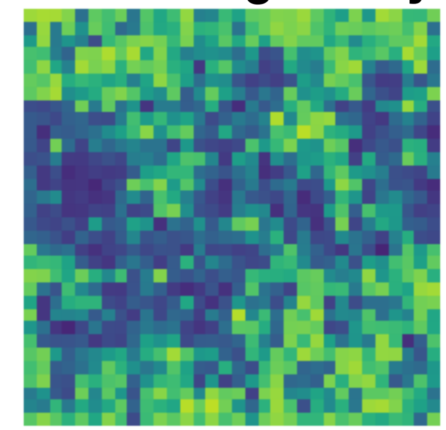
$\mathcal{N}$

bijection f

"Normalizing flow"

Computable likelihood

interacting theory



$e^{-S[\phi]}$

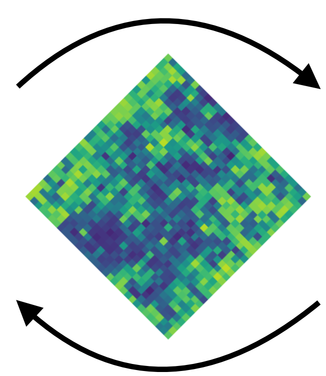
---

continuous flow

$$\dot{f} = g_\theta[\phi]$$

$$\phi_0 \longrightarrow \phi_1$$

built-in symmetry



transfer learning

$\lambda = 0.7$ ⬇ $\lambda = 0.8$

L=6 ⬇ L=12

Importance nested sampling with normalizing flows

(for gravitational-wave inference)

Michael J. Williams, John Veitch, Chris Messenger

arXiv:2302.08526

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University of Glasgow

Can we accelerate nested sampling with machine learning?

nessai

Nested sampling + normalizing flows

➕ Improved sampling efficiency
➖ Limited by nested sampling design

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Importance nested sampling with normalizing flows

(for gravitational-wave inference)

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What if we design a nested sampling algorithm around normalizing flows?

i-nessai

Importance nested sampling + normalizing flows

➕ Addresses the main bottlenecks

➕ Further improvements to sampling efficiency

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