Physics-Inspired Neural Network for Kilonova Modeling

Surojit Saha* & Albert Kong
Institute of Astronomy, National Tsing Hua University, Taiwan, R.O.C.

Introduction: Physics-inspired neural networks (PINNs) have gained considerable importance in recent years in the domain of Astronomy & Astrophysics, particularly, being a potential tool to solve differential equations within the given boundary conditions, not limiting to accurate predictions but also providing efficient approach for large computations. In this work, we have focused on solving the kilonova equations adopted from a specific kilonova model, through direct implementation of the PINN on the differential equations and respected boundary conditions provided in the model.

Solving Ordinary Differential Equations With Neural Networks

Strategy & Methodology

- Choose the KNe model
- Define the differential equations.
- Build the neural network
- Optimize the loss function
- Predict and compare results

Kilonova Model (Bulla 2023)

- Dynamical Ejecta
- Mass: 0.005 M_0
- Velocity: 0.1c-0.6c
- Y_e= 0.16-0.38
- Lanthanide rich and lanthanide poor.

ODEs Solution & Light Curve Generation Accelerated By 10^5 Times

Workflow

Input Physical Parameters
(ejecta mass, velocity, Y_e, opacities, etc.)

PDE Constraints
(energy deposition equations)

Initial Boundary Conditions
(u(0) = 0, known luminosity at t = 0)

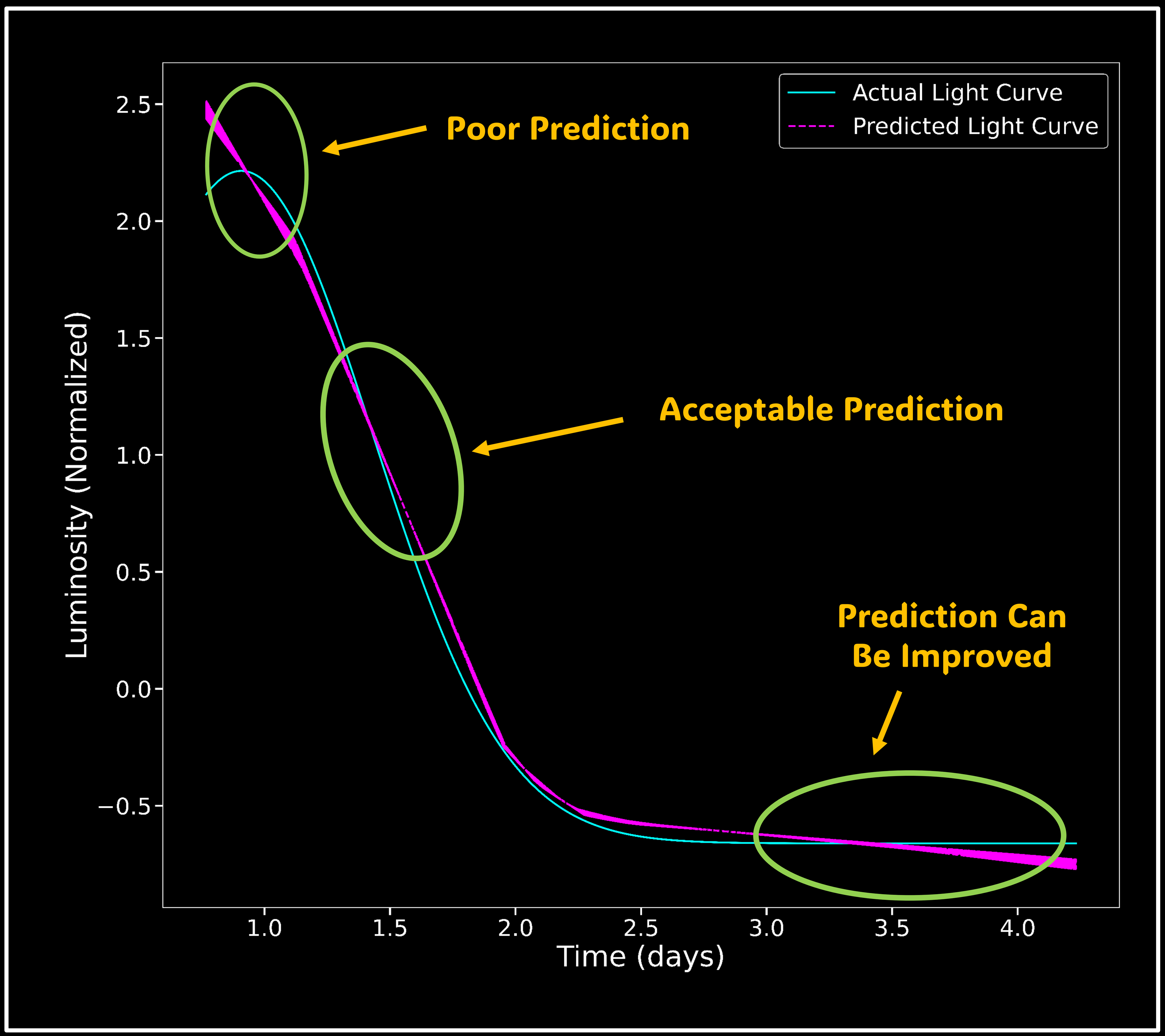
Neural Network Approximation
PINN u(t, λ) predicts solution to PDE

Autograd & Derivative Engine
(Compute $\partial u/\partial t$, $\partial^2 u/\partial \lambda^2$. via automatic differentiation)

Physics-Informed Loss Function
MSE from PDE residual + boundary condition loss

Predicted Light Curves
L(t, λ): Output of trained PINN

Preliminary Results



- Predicted light curves from the PINN is plotted against the true light curve and extent of overlap is promising.
- Certain evolution are predicted correctly whereas others require improvements.
- **Future Work:** More KNe models can be included to cover other parameter space.

References: 1. TensorDiffEq: Scalable Multi-GPU Forward and Inverse Solvers for Physics Informed Neural Networks, Levi D. McClenny, Mulugeta A. Haile, Ulisses M. Brago-Neto, arXiv:2103.16034
2. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear and partial differential equations, Raissi, M. and Perdikaris, P. and Karniadakis, G.E., Journal of Computational Physics, 2019