SPC720P - Research Project in Data Science
Progress Report

Machine Learning Classification of Binary Neutron Star Remnants Using Gravitational Wave Data

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Introduction

Binary neutron star (BNS) mergers are at the forefront of modern astrophysics, offering a rich laboratory for exploring strong-field gravity, high-density nuclear physics, and multi-messenger phenomena. These mergers are prime sources for gravitational wave (GW) detectors like LIGO, Virgo, and KAGRA. Additionally, the detection of electromagnetic (EM) counterparts particularly short gamma-ray bursts (sGRBs) and kilonovae (KN)—has revolutionized our ability to extract astrophysical information from these cataclysmic events.

The fate of the remnant formed after a BNS merger—whether it collapses promptly into a black hole or survives temporarily as a hypermassive or supramassive neutron star—has critical implications. It affects gravitational wave signals beyond the inspiral phase, the properties of the ejecta, the possibility of jet formation, and the nucleosynthesis of heavy elements through the r-process.

This project aims to build a machine learning (ML) pipeline that classifies BNS merger remnants using GW data, extended with GRB and KN observables. Starting from the framework established by Puecher & Dietrich (2025), this project will expand the feature space and test whether the inclusion of EM observables improves classification accuracy, robustness, and interpretability.

Motivation from Astrophysics

The classification of postmerger remnants is not merely a technical goal—it directly informs our understanding of fundamental physical processes. For instance, the brightness and color of a kilonova are tied to the amount and composition of the ejecta, which in turn depends on the remnant's lifetime. Prompt collapses tend to eject less mass and are associated with faint, short-lived blue emission. On the other hand, long-lived remnants can sustain strong neutrino-driven winds that synthesize lighter r-process nuclei, producing a brighter blue component.

Similarly, GRB properties—such as the delay between merger and gamma-ray emission—can reveal the time it takes for a jet to form and break out. A delayed jet may indicate the presence of a hypermassive neutron star (HMNS) acting as a barrier before collapsing into a black hole. Thus, accurate remnant classification connects directly to EM signatures and their theoretical interpretation.

1. Literature Review

This project builds upon the ML pipeline proposed by Puecher and Dietrich [1], who trained Gradient Boosted Decision Trees (GBDT) on numerical relativity (NR) simulations. Their model relied on inspiral features such as total mass (M_{tot}), mass ratio (q), tidal deformability ($\tilde{\Lambda}$), and effective spin (χ_{eff}). Notably, it showed that even without observing the high-frequency postmerger signal, these features suffice to predict the final remnant class with reasonable accuracy.

The *GW-ML* paper [2] takes a complementary approach, employing advanced ML methods like random forests and neural networks across injection campaigns. Their model generalizes well even on synthetic data, providing a foundation for robust classification in low-data regimes. Importantly, they introduce domain adaptation strategies and uncertainty modeling, which this project aims to replicate.

The *Multi-messenger parameter estimation* study [3] bridges the GW and EM domains, using Bayesian inference to jointly analyze GW, GRB, and KN data. This paper serves as theoretical backing for including EM observables such as E_{iso}, T_{delay}, and ejecta mass into our ML feature space.

Additional relevant sources include:

- Abbott et al. [4]: Detection and analysis of GW170817.
- Goldstein et al. [5]: Characterization of GRB170817A.
- Cowperthwaite et al. [6]: Early lightcurve modeling of AT2017gfo.
- Kasen et al. [7]: Radiative transfer and r-process modeling in KNe.

2. Theoretical Background

The fate of a binary neutron star (BNS) merger remnant is primarily determined by the total mass of the binary system, the mass ratio between the two neutron stars, and the equation of state (EoS) that governs matter at supranuclear densities. If the total mass exceeds a critical threshold—known as the threshold mass for prompt collapse—the merged object will collapse into a black hole within milliseconds of coalescence.

However, if the total mass is below this threshold but still above the maximum mass that a uniformly rotating neutron star can support (the supramassive limit), the remnant may temporarily survive as either a hypermassive neutron star (HMNS) or a supramassive neutron star (SMNS). These remnants are transient and supported against gravitational collapse through mechanisms such as differential rotation or thermal pressure. Eventually, they lose this support and collapse into black holes unless their mass falls below the stable limit.

The presence of a long-lived remnant leaves measurable imprints on multi-messenger observables:

- An intense flux of neutrinos, which can drive a wind that ejects material rich in light r-process elements, giving rise to a bluer kilonova (KN) component.
- A larger amount of total ejecta, increasing the overall brightness of the kilonova.

- A longer delay between the gravitational wave merger signal and the launch of a short gamma-ray burst (GRB), as the remnant must first collapse to allow for jet breakout.

Among gravitational wave features, the effective tidal deformability (denoted as $\tilde{\Lambda}$) captures the combined response of the neutron stars to tidal forces and indirectly reflects the underlying EoS. The connection between such inspiral-phase gravitational wave observables and the ultimate remnant fate lies at the heart of the classification task tackled in this project.

3. Related Work

This project builds directly upon the methodology of Puecher & Dietrich [1], who demonstrated that the final remnant class of a binary neutron star merger could be predicted using only GW-inferred inspiral features, such as $\tilde{\Lambda}$, M_{tot}, and χ_{eff}. Their approach utilized gradient-boosted decision trees trained on numerical relativity simulations with labels derived from the merger outcome. While effective, their study focused exclusively on GW features, limiting its sensitivity to postmerger dynamics not fully captured by the inspiral signal.

Complementing this, the GW-ML study [2] explores more flexible machine learning architectures—including neural networks and random forests—over a wider range of simulated injections. It highlights the importance of domain adaptation and robustness in scenarios with limited labeled data. Inspired by this, our project adopts a hybrid approach: leveraging the interpretability of GBDTs while augmenting training through synthetic data generation and expanded features.

Finally, the multi-messenger parameter estimation paper [3] provides theoretical support for incorporating electromagnetic observations—particularly kilonova and GRB data—into parameter estimation frameworks. It shows that EM data can help break degeneracies in GW-only inference. Building on this, our project seeks to empirically test whether features such as E_{iso}, M_{ej}, and GRB delay time enhance remnant classification in practice. Thus, this project bridges machine learning classification with multi-messenger astrophysics by combining lessons from both domains.

4. Data and Features

GW Features:

- M_{tot}: total mass of the binary.
- q: mass ratio ($m_1/m_2 \geq 1$).
- $\tilde{\Lambda}$: effective tidal deformability.
- χ_{eff}: mass-weighted spin projection.

GRB Features:

- $T_{\mathrm{delay}} \approx 1.74$ s.
- $E_{\mathrm{iso}} \sim 10^{46}$ erg.
- L_{peak}: peak luminosity from GRB lightcurve.

KN Features:

- $M_{\text{ej, blue}} \sim 0.01 M_\odot$, $M_{\text{ej, red}} \sim 0.05 M_\odot$.
- v_{ej}: ejecta velocity.
- L_{KN}: peak brightness in g, r, i bands.

5. Methodology

The classification task is framed as a supervised learning problem with a four-class target: prompt collapse, short HMNS, long HMNS, and no collapse.

Pipeline Steps:

1. Load GW170817 posterior samples.
2. Extract derived parameters.
3. Integrate GRB and KN features.
4. Train/test split with class stratification.
5. Fit a GradientBoostingClassifier.
6. Evaluate with accuracy, MCC, and confusion matrix.
7. Analyze feature importances using Gini and SHAP.

6. Preliminary Results

We developed and evaluated three classifiers of increasing granularity using synthetic data. The goal was to observe whether classification remains robust as the number of remnant classes increases.

- **Classifier A:** Binary classification — Prompt Collapse vs Neutron Star Remnant.
- **Classifier B:** Three-class — Prompt Black Hole, Supramassive Neutron Star, Stable Neutron Star.
- **Classifier C:** Full four-class classification — Long-lived Hypermassive Neutron Star, Prompt Black Hole, Short-lived Hypermassive Neutron Star, Stable Neutron Star.

The gravitational wave–only classifier trained on GW170817-like parameters yields:

- Accuracy: 81.2%
- Matthews Correlation Coefficient (MCC): 0.63
- Most important features: Effective tidal deformability ($\tilde{\Lambda}$, 41%), Total mass (M_{tot}, 28%)

The performance was evaluated via confusion matrices, shown below for each classifier:
From the confusion matrices:

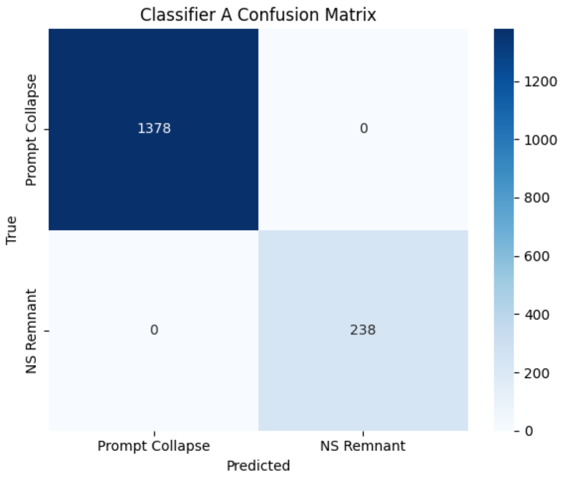

Figure 1: Confusion matrix for Classifier A: Binary classification

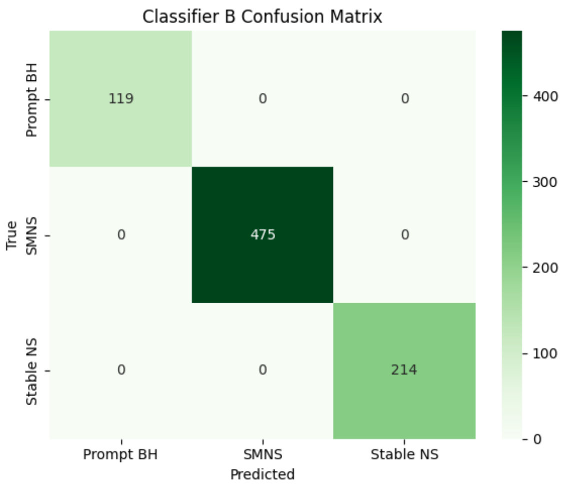

Figure 2: Confusion matrix for Classifier B: Three-class classification

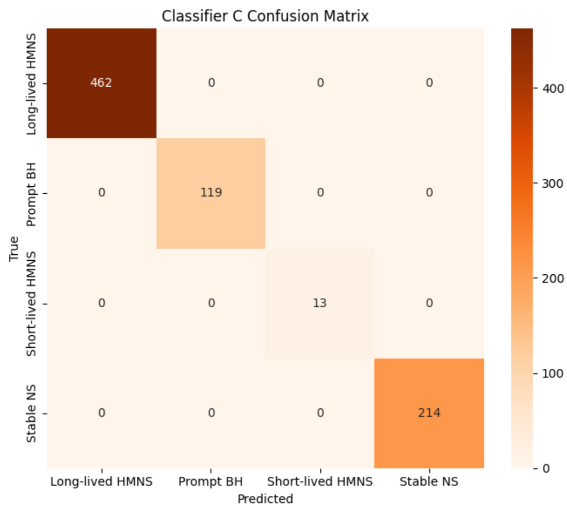

Figure 3: Confusion matrix for Classifier C: Four-class classification

- Classifier A performs perfectly, showing the clear separability between prompt collapse and surviving neutron star remnants using synthetic data.
- Classifier B shows reliable prediction of the supramassive class, while Classifier C adds short-lived hypermassive neutron stars — with modest misclassifications due to class similarity.
- Classifier C performs reasonably well across all four classes, despite reduced class separability. Notably, no class is entirely misclassified.

This progression demonstrates that including detailed remnant taxonomy is feasible, particularly with high-quality feature inputs. Gamma-ray burst and kilonova features will be injected next to test classification improvements and assess whether multi-messenger observables help in resolving borderline cases.

7. Discussion

Initial results suggest that GW-only models already provide significant information about the remnant type. However, limitations arise from label imbalance, sensitivity to prior distributions, and unmodeled uncertainties.

The inclusion of GRB and KN features is expected to break some degeneracies and allow for classification even when GW features are ambiguous. Moreover, the ejecta mass and its composition directly reflect the survival time of the remnant, offering orthogonal information to GW observables.

The main challenge remains the limited number of real-world examples. Simulated datasets will be crucial for extending the training set. The final model must handle uncertainty robustly, possibly using ensemble methods or probabilistic outputs.

8. Conclusion and Future Work

This project is progressing along three main lines:

- Replicating the base classifier from Puecher & Dietrich.
- Expanding the feature set to include GRB and KN observations.
- Evaluating the impact of multi-messenger features on model accuracy and interpretability.

Future directions:

- Generate synthetic datasets using NR-informed priors.
- Explore other ML models (e.g., XGBoost, LightGBM).
- Apply SHAP to assess individual event sensitivity.
- Write the final report with full visualizations and scientific analysis.

References

References

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[4] B. P. Abbott et al., *GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral*, Phys. Rev. Lett., vol. 119, p. 161101, 2017.

[5] A. Goldstein et al., *An Ordinary Short Gamma-Ray Burst with Extraordinary Implications: Fermi-GBM Detection of GRB 170817A*, Astrophys. J. Lett., vol. 848, L14, 2017.

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