Deep Learning Parameter Estimation of Black Hole Mergers from LIGO Signals

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Introduction

Gravitational wave astronomy provides direct observations of colliding black holes through detectors like LIGO (Laser Interferometer Gravitational-Wave Observatory). By measuring masses, distances, and spins from gravitational wave signals, scientists can reconstruct how binary systems form and evolve. Traditional computational methods demand substantial resources per event, creating detection bottlenecks. Deep learning can accelerate this process by mapping detector signals directly to physical parameters. Multiple neural network architectures exist for gravitational wave analysis, but direct comparisons of their performance is lacking. Another important question is: what do these models actually learn?

Research Question

This study compares ResNet and Vision Transformer architectures and asks: a) Which architecture achieves better parameter estimation performance? b) What signal features does each architecture learn? c) Do both models identify physically meaningful patterns?

Hypothesis

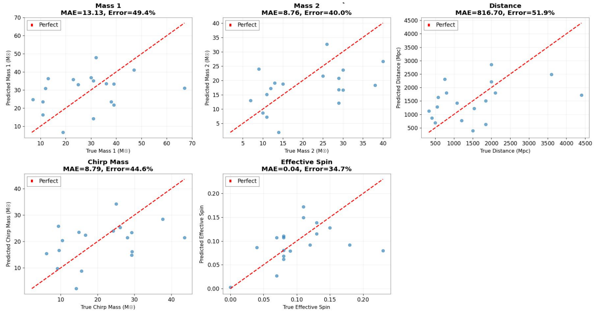
Both models will achieve comparable parameter estimation performance. Interpretability analysis will reveal that both architectures focus on the characteristic chirp pattern, while feature extraction mechanisms may differ.

Methodology

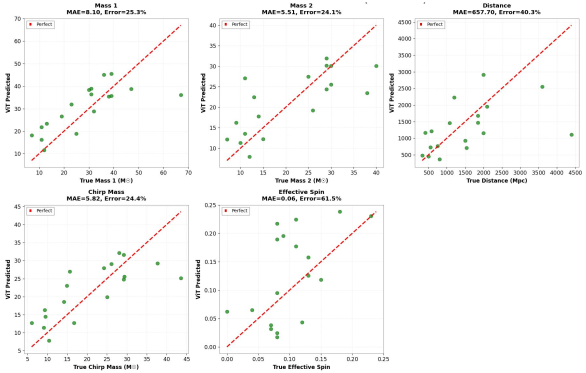
- ➢ Gravitational wave data from 54 confirmed black hole merger events was obtained from the Gravitational Wave Open Science Center (GWOSC). Spectrograms were extracted from both LIGO detectors separately.
- ➢ Additional training samples were generated through data augmentation, including temporal shifts, frequency shifts, noise addition, and intensity scaling
- ➢ A vision transformer and a convolutional architecture based on ResNet-18 were trained on the spectrograms
- ➢ After training interpretability techniques examined what each architecture actually learned
- ➢ The vision transformer and ResNet-18 model's performance was compared

Results: Parameter Estimation

ResNet



Vision Transformer



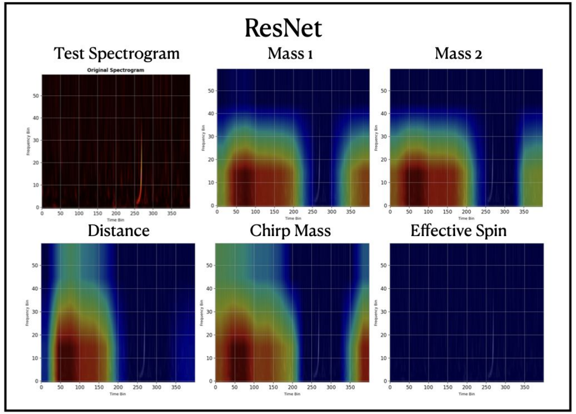
<u>Performance Comparison</u>

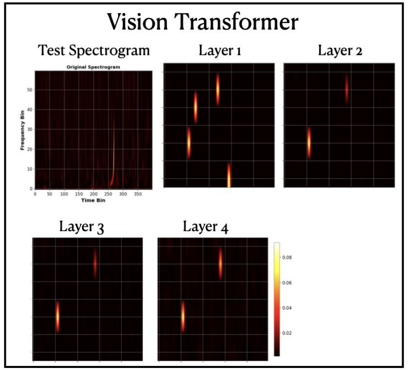
- ➢ Primary mass (m1):
  - Vision Transformer: 25.3% median error, 8.10 M⊙ mean absolute error
  - ResNet: 49.4% median error, 13.13 M⊙ mean absolute error
- ➢ Secondary mass (m2):
  - Vision Transformer: 24.1% median error, 5.51 M⊙ mean absolute error
  - ResNet: 40.0% median error, 8.76 M⊙ mean absolute error
- ➢ Luminosity distance:
  - Vision Transformer: 40.3% median error, 657.70 Mpc mean absolute error
  - ResNet: 51.9% median error, 816.70 Mpc mean absolute error
- ➢ Chirp mass:
  - Vision Transformer: 24.4% median error, 5.82 M⊙ mean absolute error
  - ResNet: 44.6% median error, 8.79 M⊙ mean absolute error
- ➢ Effective spin (chi_eff):
  - Vision Transformer: 61.5% median error, 0.06 mean absolute error
  - ResNet: 34.7% median error, 0.04 mean absolute error

<u>Synopsis</u>

- ➢ Overall, in terms of median error, the Vision Transformer achieved 35.12 ± 7.26% compared to ResNet's 44.12 ± 3.13%.
- ➢ While ResNet exhibits a higher mean error, the substantial overlap in error bounds (ViT: 27.9–42.4%, ResNet: 41.0–47.3%) indicates no statistically significant performance difference.

Results: Interpretability Analyses





- <u>ResNet Grad-CAM Spatial Patterns:</u>
  - Primary mass: Horizontal band organization; high importance (red) in 0–25 Hz extending across time bins, with moderate importance (yellow/orange) to 35 Hz.
  - Secondary mass: Similar horizontal structure, 0-20 Hz high importance extending to ~40 Hz mid-frequencies.
  - Distance: Asymmetric pattern with high importance concentrated in early time bins (0–50 ms) at low frequencies (0–30 Hz).
  - Chirp mass: Broad frequency coverage (0–40 Hz) with horizontal band structure across time.
  - Effective spin: Minimal activation throughout spectrogram.
- All parameters emphasize lower frequencies (0–30 Hz) with horizontal organization.

- <u>Vision transformers attention maps across the transformer layers show progressive spatial refinement:</u>
  - Layer 1 exhibits distributed attention across multiple time bins with vertical structure.
  - Layers 2 and 3 show increasing concentration while maintaining vertical organization.
  - Layer 4 displays sharp vertical features at specific temporal locations, representing the final features used for parameter prediction.
- The model focuses on discrete time bins extending across frequency ranges. The temporal localization strategy identifies when signal characteristics are most informative.

Conclusion & Discussions

- The hypothesis that both architectures would achieve comparable performance was supported. Both architectures had very similar overall performances only differing by a few percentage points in average.
- Neither architecture consistently outperformed the other across all parameters.
- Scatter plots of predicted vs true values show that both vision transformer and ResNet learned relationships between spectrograms and physical parameters with predictions generally clustering around the diagonal line representing perfect prediction
- Convolutional networks and vision transformers can be used to accurately process LIGO gravitational wave data while minimizing computational energy.

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