

Analysing Gravitational Waveform using Machine Learning

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Abstract

recent detections of compact binary systems, there has been growing interest in gravitational wave astronomy. Gravitational waves emitted by carry ample information about the source and hence are useful to study. However, a major challenge in this area is to extract these triggers burried deep inside the noise and then analyze them to obtain information about the source.

In this work, we use methods of machine learning as the initial steps towards this goal. We implement supervised machine learning algorithms to extract out the mass ratio and spin signature of the binary using binary black hole waveforms.

Gravitational Waves

Gravitational Waves are perturbations in the fabric of spacetime which result from gravitational interactions of accelerating objects or asymmetric collapses. Far away from the source, under weak gravity field, these waves can be described in terms of two polarization components – h_{+} and h_{x} .

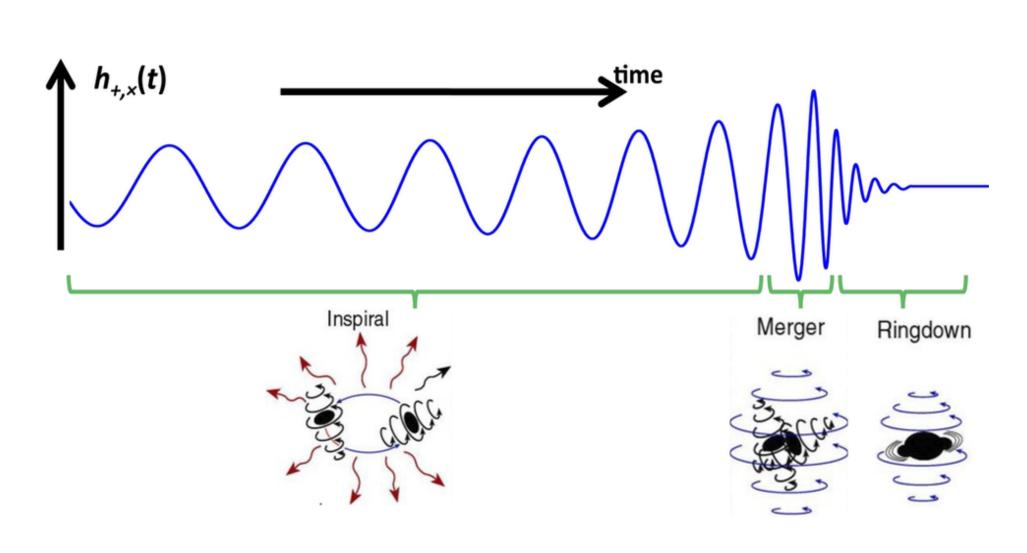


Figure 1. Gravitational Wave.

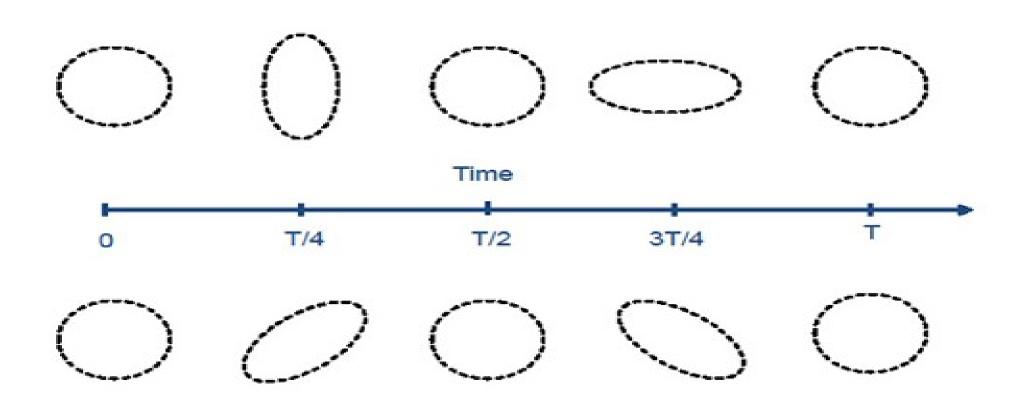


Figure 2. Gravitational Wave Polarizations.

♣ == **o** or **♣** == **∤**? My Cat's Decision-Making Tree. Is that for me? No. That's I don't want it. for me.

Figure 8. Principal Components

Figure 3. Decision Tree

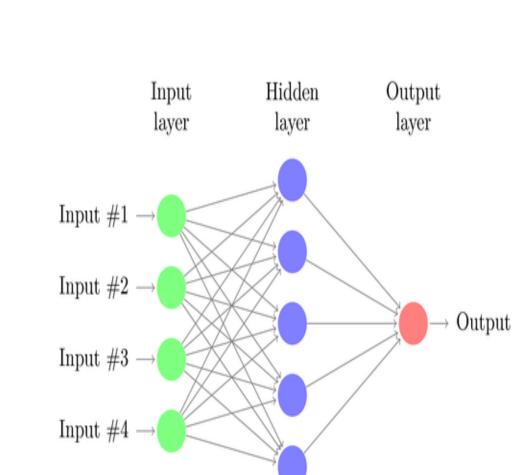


Figure 4. KNN

Figure 5. Boosting

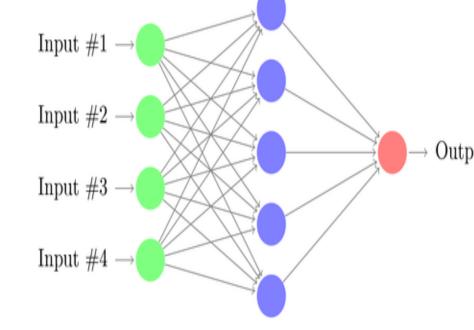


Figure 6. Neural Network

Dataset

We use waveforms produced from numerical simulations of binary black holes. These waveforms are described by time series data of h₊ and h_x and contains information about the curvature of the spacetime and thus, information about the binary. For this work, we used waveforms developed by Georgia Tech and SXS collaboration.

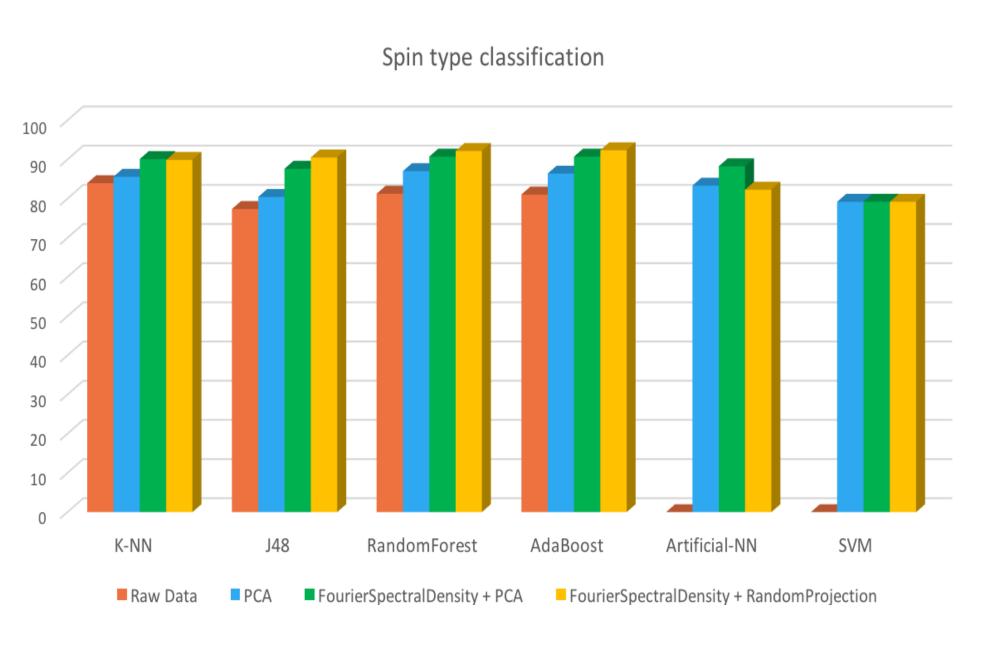
- 1. Principal Component Analysis
- 2. Independent Component Analysis
- 3. Random Projections

within the waveform can be contained within a few

Supervised Machine Learning

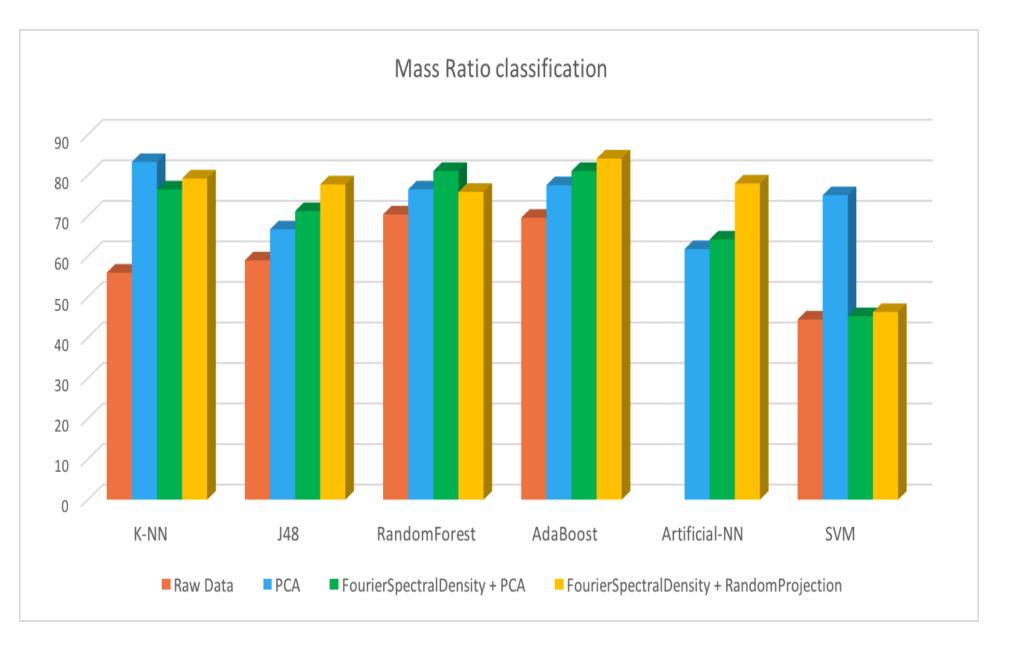
- Decision Tree Learning Classifies the data based on its attributes using decision trees. The order of attributes depends on their information content.
- Bagging This method relies on unstable weak learners which are trained over small sets of data randomly drawn from dataset with replacement.
- Boosting This is another ensemble learning method which also uses multiple weak learners. However, the training sample is drawn from dataset without replacement with increased weight for misclassified instances.
- Support Vector Machine Classifies the data by constructing hyperplanes in high/infinite dimensions.
- Neural Networks These are collection of units called neurons organized in layers each of which transforms the data and transfer to another.
- K Nearest Neighbours Classifies the data by assigning the label based on majority vote from nearest neighbours.

RESULTS



Spin Type Classification:

- Correctly distinguish between waveforms with zero spins, aligned spins and precessing cases with max 93% accuracy.
- Dimensionality reduction best achieved using Fourier modes with PCA or Randomized Projections.
- Random forest (decision tree+ bagging) shows best performance followed closely by KNN. This is because both of them are weighted neighbourhood algorithms.



Mass Ratio Classification:

- Classification of binaries with mass ratio varying between 1 to 10.
- Lower accuracy of prediction shows that mass ratio is not as distinguishable feature as spin type.
- Boosting dominates bagging methods followed closely by KNN.

Conclusion

With our simple analysis, we depict the applications of Machine Learning for GW data analysis. Our results show that ensemble learning methods and weighted neighbourhood algorithms perform quite well in distinguishing between waveforms and predicting the properties of binary system. We plan to extend this work from classification to regression problems and explore this with noise weighted signals.

- 'Catalog of 174 Binary Black Hole Simulations for Gravitational Wave Astronomy', Phys. Rev. Lett. 111 (2013).
- 'Georgia Tech Catalog of Gravitational Waveforms', Class. Quant. Grav. 33 (2016)

Dimensionality Reduction

Dimensionality Reduction: We choose h₊ and h_x at each point of time as our attributes and all the waveforms as our samples. Since feature space is much larger than sample space, to avoid the curse of dimensionality, we first reduce the dimensionality of feature space. For this we explore four different methods:

- 4. Fourier Transforms

Using these methods, we find that most information components and thus feature space can be reduced.

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