Applications of Machine Learning in Low-latency LIGO Searches for Gravitational Waves

Kyle Rose '19, Donald Moffa '18, Madeline Wade, and Leslie Wade

Department of Physics, Kenyon College, 2017

Abstract

LIGO's search for gravitational wave signals is negatively affected by the presence of transient excitations from non-astrophysical sources, called glitches, in the data. Efficient glitch identification and removal will greatly improve LIGO's ability to detect astrophysical signals. LIGO is exploring the application of various classifiers, including Machine Learning Algorithms (MLAs), to this problem because they have the potential to make accurate predictions about the data (glitch or no glitch) with low-latency. Machine Learning Algorithms take in a large set of inputs, called a feature vector. The contents of the feature vector can impact the accuracy of MLAs. LIGO uses a handful of characteristics about glitches in its auxiliary channels (seismic activity, thermal, etc.) to build the feature vector. From this information, the MLA is able to make predictions about when there is a corresponding glitch in the gravitational-wave channel. This work demonstrates the effect of adding a new feature to the feature vector on the performance of MLAs. This new feature is the elapsed time between the interferometer attaining lock and the auxiliary channel glitch. In this work we show that the time since lock feature positively affected the performance of the classifiers.

Background

When a strong enough gravitational wave reaches Earth, it will produce a signal in the gravitational-wave channel of the LIGO detectors.

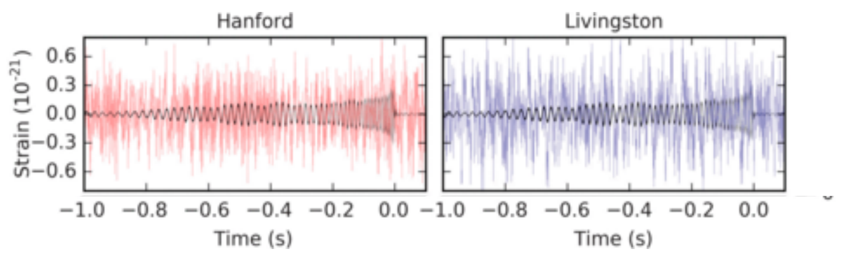

Figure 1. Gravitational-wave signal hidden in noise

LIGO generates statistics about the data which can reveal the hidden signal. Unfortunately, the efficacy of their method is hindered by the presence of a large population of glitches in the data.

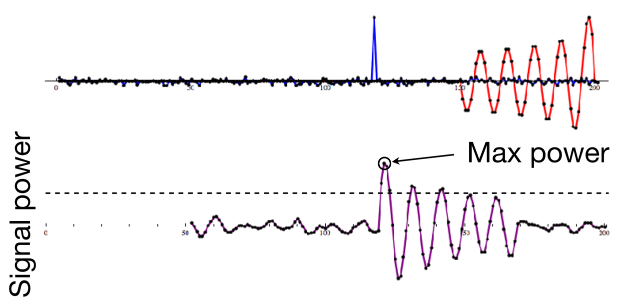

Figure 2. Glitch "fooling" the statistics

MLAs

Machine Learning Algorithms are a popular way to analyze large datasets. They are designed to recognize patterns and groups within the data and "learn" as more data is fed in. One type of MLA is the Artificial Neural Network (ANN).

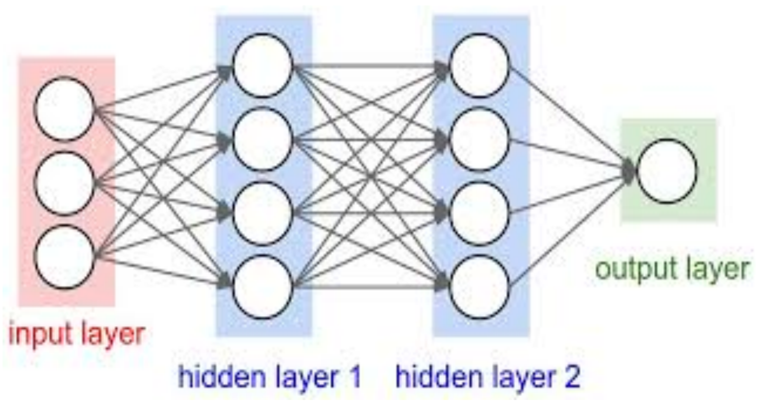

Figure 3. Artificial Neural Network

The input layer as labeled in Figure 3, is also known as the feature vector. The information it contains is multiplied by the weights of the various hidden layers until it reaches the output layer. This process mimics the firing neurons of the human brain. The output is a single number between 0 and 1, classifying the data as likely to be class 1 (in this context: glitch) or class 0 (no glitch).

Methods

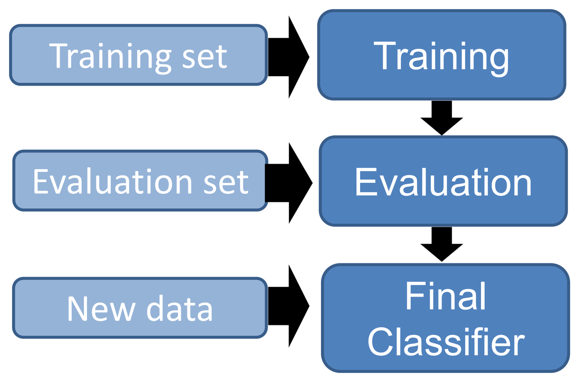

Figure 4. Classifier usage

- LIGO's classifier: an MLA called MVSC
- Donald's classifier: an ANN built using TensorFlow
- Trained the classifiers over a month of data and evaluated over another two weeks

The Feature Vector

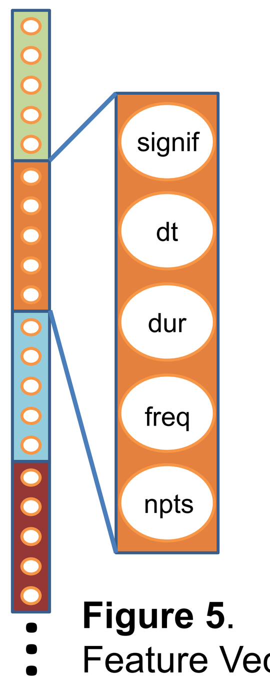

Figure 5. Feature Vector

- Consists of information about auxiliary channel glitches at a given time
- Auxiliary channels record a time series of a degree of freedom not affected by gravitational waves, such as temperature and seismic activity
- Explored the effect of adding a feature: the time elapsed since the detector acquired lock
- Lock defines a state when the detector is aligned and able to take data
- Tested the effect of the 6th feature on MVSC and TensorFlow ANN

Results

The performance of a classifier is represented by receiver operating characteristic (ROC) curves. Plotted on the y axis is the probability that a glitch will be correctly classified as such. The x axis displays the probability that a clean time will be incorrectly identified as a glitch. The ROC curve produced from a perfect classifier is a horizontal line at y=1, with an area under the curve of 1. The red dashed line in these plots is the curve produced by a random classifier.

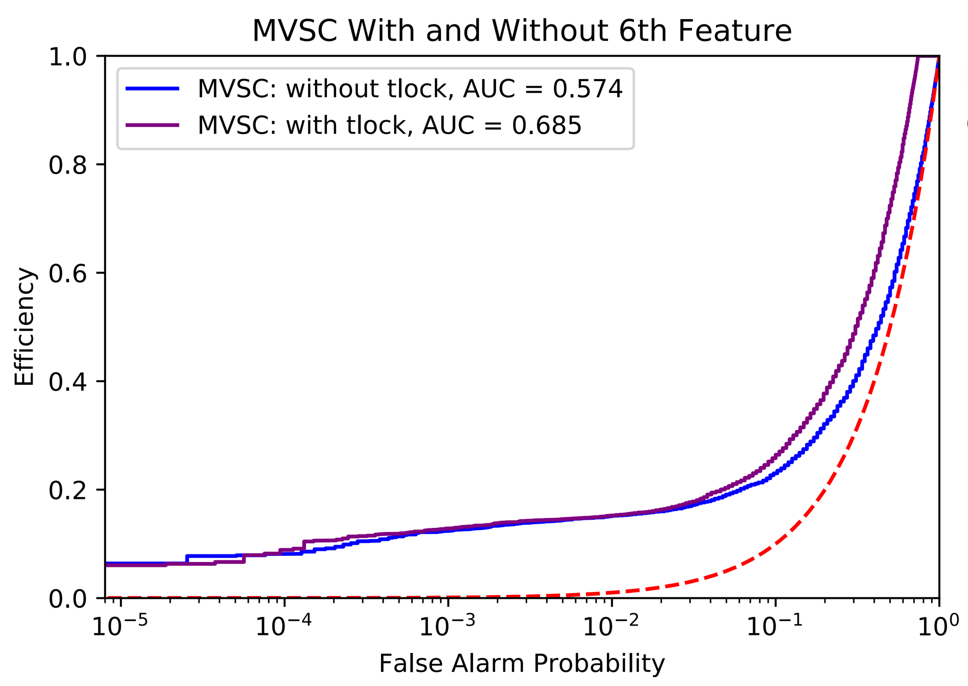

Figure 6. MVSC ROC curves.

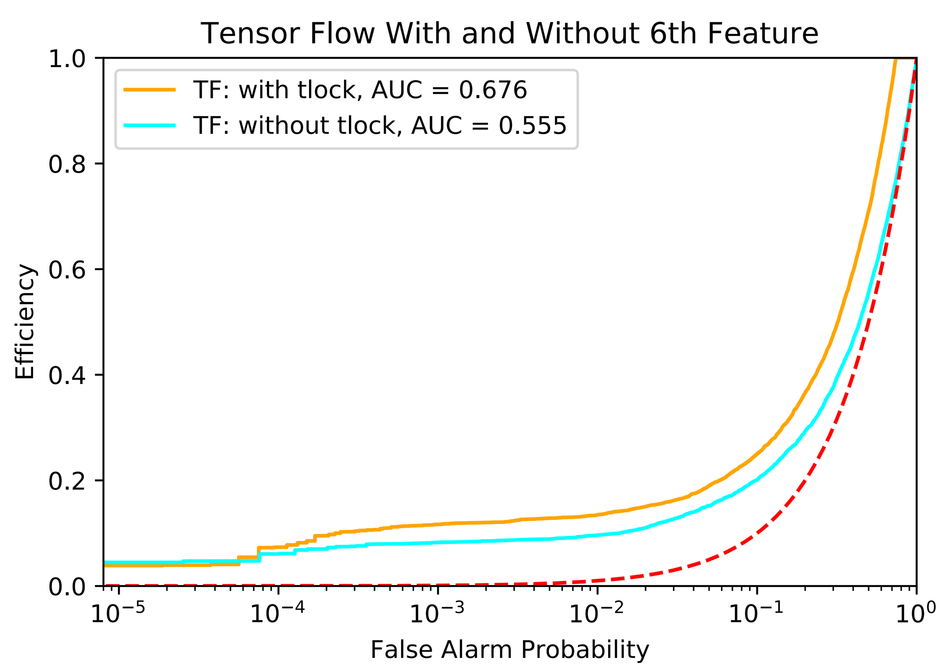

Figure 7. TensorFlow ANN ROC curves

Conclusions

The time since lock feature had a positive effect on both classifiers' performance. The area under the curve of both MVSC and TensorFlow improved with the addition of the 6th feature.

The TensorFlow ANN saw a more significant improvement, suggesting that an artificial neural network is more responsive to feature set expansion.

Unfortunately, the ROC curves of both classifiers display poor performance overall. While these plots are consistent with production runs, they are still cause for some concern and certainly incentive to continue to search for ways of improving the classifiers' ability to accurately predict when there is a glitch in the gravitational-wave channel.

Future Work

Future efforts will go toward:

- Understanding why the time since lock feature improved the classifiers' performance
- Implementing the feature into the full production pipeline
- Additional feature set expansion.
- Inclusion of long term auxiliary channel glitch information in the feature vector

References

1. Image credit Figures 1 and 2: Wade, E. Leslie.
2. Wade, E. Leslie. *Gravitational Waves from Rotating Neutron Stars and Compact Binary Systems*. Diss. University of Wisconsin-Milwaukee, 2015.
3. Mitchell, M. Tom. *The Discipline of Machine Learning*. School of Computer Science Carnegie Mellon University, 2006.
4. R. Biswas *et. al*. "Application of machine learning algorithms to the study of noise artifacts in gravitational-wave data" (2013).

Acknowledgments

I would like to thank my research advisor Madeline Wade, my collaborators Donald Moffa and Leslie Wade, Reed Essick, and the Penn State LIGO group for their guidance throughout this project. Additionally I would like to thank the Kenyon Summer Science program for funding this research.