LIGO

# Understanding Interferometer Lock Losses with Machine Learning

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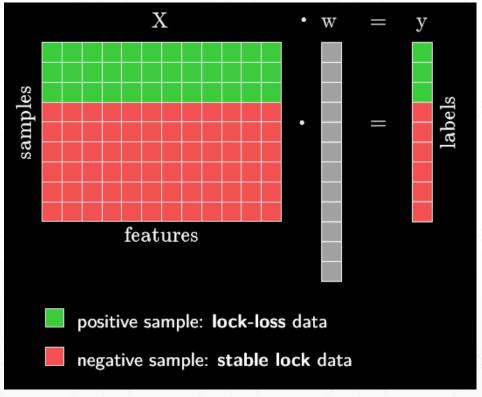
# Our approach

- Identify features in the auxiliary channel data that might be characteristic of impending lock loss
  - Ex. Large spikes, unstable oscillations
- Use a regression algorithm to identify the most interesting features and channels out of thousands that we test



# Our approach

- Compile extracted features into matrix X
- Use positive/negative labels to generate output vector y
- Solve for w, which maps X onto y



Courtesy of Jamie Rollins



#### **Generating the dataset**

- Use O2 data from Hanford
- Channels: start with DQ channels, remove calibration channels, flat channels, and channels created during O2
- Positive samples: just prior to lock losses that occurred during observing mode
- Negative samples: stable, locked times spaced by 10,000 seconds and 1,000 seconds removed from the start and end of lock
- Sample length is a tunable parameter (we use 4 seconds)
- Left with 4,338 channels, 276 positive samples, and 1,086 negative samples



## **Step 1: Feature Extraction**

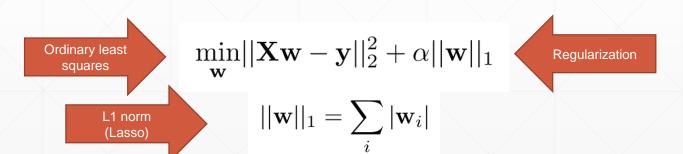
- Cannot use raw time series data
  - Too much data would hide interesting features in the regression
- We select a set of calculations that return single-value outputs for each sample
  - Difference between maximum and minimum
  - Complexity
  - Absolute energy
  - Mean value
  - Standard deviation

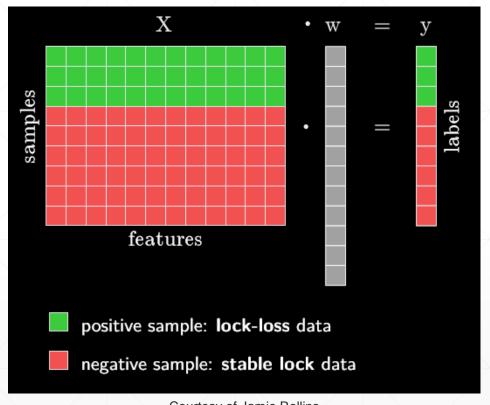
- Variance
- Kurtosis
- Skewness
- Absolute sum of changes
- Mean absolute change
- Permutation entropy



# **Step 2: Regression**

- Matrix is underdetermined, so we use Lasso regression
  - Alpha parameter controls degree of regularization
  - Use of L1-norm drives some coefficients to be zero so final model relies on less features



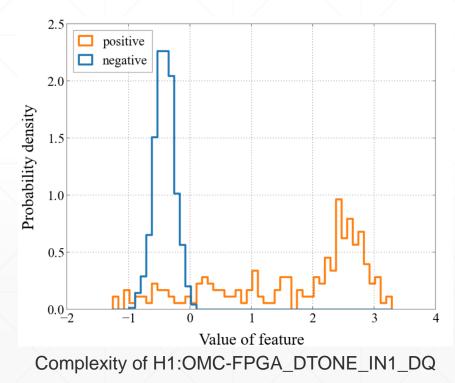


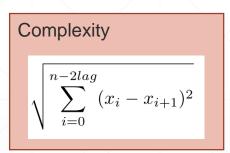
Courtesy of Jamie Rollins



# Follow-Up: H1:OMC-FPGA\_DTONE\_IN1\_DQ

The complexity of the data in this channel tends to be higher before a lock loss

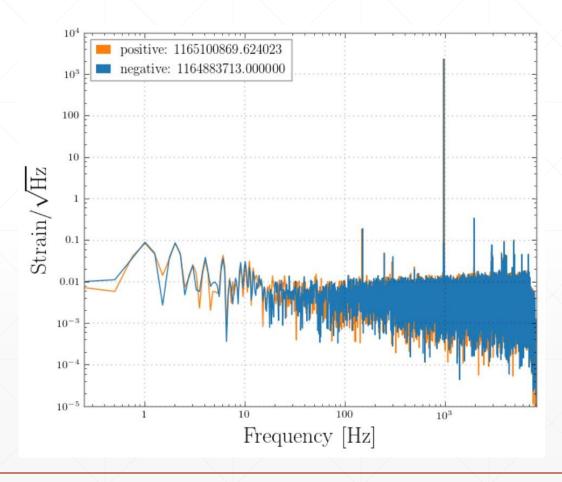






# Follow-Up: H1:OMC-FPGA\_DTONE\_IN1\_DQ

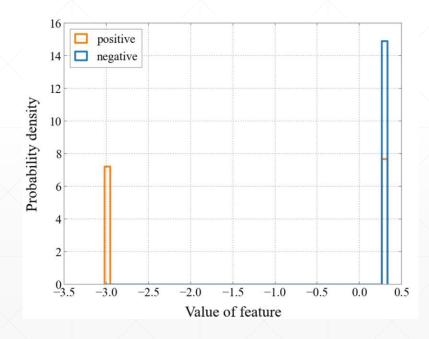
 When we plot the ASDs, it reveals little about the difference in behavior of this channel





# Follow-Up: H1:OMC-LSC\_DITHER\_OUT\_DQ

 The permutation entropy always hovers around one value for the negative samples, but it is split between two values for the positive samples



Permutation entropy

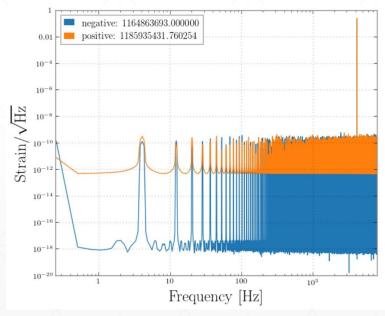
Compute n!

permutations based on specified order  $H = -\sum_{i=1}^{n!} p(\pi)log_2(p(\pi))$ 

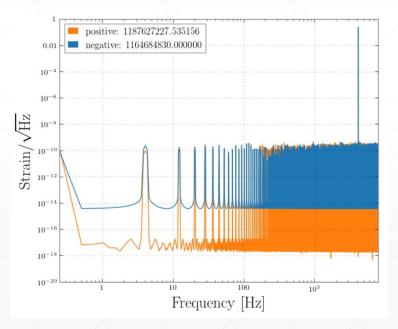


# Follow-Up: H1:OMC-LSC\_DITHER\_OUT\_DQ

 Plotting the ASDs shows no pattern among the noise levels for the positive or negative samples, regardless of the values of the permutation entropy



Both samples have high permutation entropy



The positive sample has low permutation entropy



#### **Conclusions**

- It seems like there is something interesting happening in each of these channels, but we haven't been able to pin down what
- Could the DUOTONE channel be picking up on something happening in another channel?
- Is something switching on/off in the DITHER channel?



#### References

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