LASER INTERFEROMETER GRAVITATIONAL WAVE OBSERVATORY
- LIGO -
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Interim Report 1: Identifying Witnesses to LIGO Glitches Using Auxiliary Channels

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1 Introduction

The Laser Interferometer Gravitational Wave Observatory (LIGO) is a ground-based gravitational wave (GW) detector that operates using the principles of a modified Michelson interferometer. Highly energetic astrophysical events such as the mergers of compact objects (e.g., black holes, neutron stars) produce ripples in spacetime that travel at the speed of light. The ripples induce changes in the spacetime metric which become manifest when LIGO detects changes in the length of the interferometer arms. Hence, the resulting time-dependent data, $h(t)$, encodes the physical properties of the origin of the GW phenomena [1].

The GW signals detected are extremely faint; the change in the length of the interferometer arm is smaller than a proton's diameter. The small amplitude of the signal requires the LIGO detectors to have exquisite sensitivity. As a result, however, the detectors become vulnerable to terrestrial noise, which may include environmental and instrumental noise. Despite efforts at noise shielding, short-lived, noise transient artifacts often called "glitches" plague the main channel. Glitches may mimic or mask real GW signals which may result in false alarms [2].

Alongside the main channel, LIGO maintains a set of auxiliary channels that may bear witness to these glitches. As a result, previous work has been dedicated to associating glitches within the main channel to loud triggers found within auxiliary channels. By doing so, the aim is to find witness auxiliary channels that may serve as veto generators in order remove time segments within the main channel data contaminated with glitches.

Given the large number of degrees of freedom, algorithmic and machine learning methods have been employed to tackle this problem. Algorithms such as hveto and UPV utilized iterative processes to determine the most efficient witness channels [3, 4]. On the other hand, pipelines such as iDQ, employed supervised machine learning techniques to determine in near real-time the probability of glitches within a time segment given the data recorded within auxiliary channels. They combined the results with algorithms such as the Ordered Veto List (OVL) to determine suitable veto generators within a time segment [5].

Recent work, on the other hand, by [2] employed unsupervised machine learning techniques such as Non-Negative Matrix Factorization (NMF) and CP/PARAFAC Tensor Decomposition to cluster triggers within auxiliary channels as a method of finding valid veto generators. This method is unique in that it searches for witness channels in an "all-at-once" fashion, in contrast to previous methods which relied on iteration. In addition to determining veto generators, this method is able to discover groups of auxiliary channels associated with glitch morphologies which may help domain experts discover glitch generation mechanisms to potentially fix the glitches at their source.

2 Background and Objectives

In this work, we aim to utilize the proposed method by [2] to explore various models (e.g., factorization techniques, clustering methods) to compare with existing results using established metrics. More specifically, the primary goal is to find sets of auxiliary channels which may serve as veto generators. As a secondary goal, we also aim to use the techniques to cluster glitch morphology classes to channels based on data obtained from the Gravity Spy catalog.

To approach this problem, we will use the time-dependent data recorded through the main channel and the auxiliary channels. Loud triggers defined to be recorded signals that have SNR ≥ 7.5, which may include glitches, are converted into a data matrix $Z \in \mathbb{R}^{|G|\times|A|}$ and a 3-mode tensor $\chi \in \mathbb{R}^{|G|\times|A|\times|F|}$ through an established pipeline, where $|G|$ is the number of glitches, $|A|$ is the number of auxiliary channels, and $|F|$ is the number of features in the tertiary tensor mode.

Given this information, we can use the pipeline established by [2] to test different clustering and factorization models. For this work, we will approach the problem in different ways. First, we will test Boolean Matrix Factorization (BMF) as a factorization model. Second, we will also use Coupled Matrix-Tensor Factorization (CMTF) to discover morphologically coherent glitches. This will allow us to investigate whether the introduction of glitch morphology information (e.g., labels) can lead to the discovery of patterns within glitch classes that are linked to similarities in morphology and behaviors within the auxiliary channel space.

2.1 Boolean Matrix Factorization (BMF)

Boolean Matrix Factorization (BMF) is a method developed to factorize a data matrix Z to two separate matrices, such that $Z \approx XY$. Although this method works using the same principle as traditional factorization methods, the matrix decomposition is performed over the Boolean semi-ring. More explicitly, if we apply this factorization method to our data matrix, we can decompose $Z \in \{1,0\}^{|G|\times|A|}$ such that in index notation:

$$Z_{ij} \approx (X \circ Y)_{ij} = \bigvee_{l=1}^{k} B_{il}C_{lj}, \tag{1}$$

where we define $X \in \{0,1\}^{|G|\times k}$ and $Y \in \{0,1\}^{k\times|A|}$, and $k << \min\{|G|,|A|\}$ the rank of the data matrix [6].

To do this, BMF finds X and Y such that the "distance", defined to be the Frobenius norm $||.||_F$ of $Z - X \circ Y$ is minimized. Explicitly, BMF performs the minimization as:

$$||Z - X \circ Y||_F^2 = \sum_{i,j} Z_{ij} \oplus (X \circ Y)_{ij}. \tag{2}$$

Once the matrices are factored, X and Y become highly interpretable due to the binary nature of the data. In particular, we can use X and Y to learn more information about the associated glitches and auxiliary channels [6].

2.2 Glitch Morphology Analysis

We aim to use Coupled Matrix-Tensor Factorization (CMTF) to approach a glitch morphology-based analysis. To do this, we utilize the 1-1 correspondence between the data matrix or tensor and the matrix that contains information about the trigger, in this case, the gravity spy label matrix. As a result, we can express the "coupled" data as a factorization, where the coupled mode shares the same latent factor variable. This would enable joint clustering of the two-datasets and the structure of the labeled dataset will (ideally) influence the extracted factors in such a way that triggers that cluster within the same latent factor will be morphologically similar, on the basis of the information that the second matrix is providing.

Using CMTF, our aim is to discover morphologically coherent glitches and identify potential Gravity spy glitches which consistently exhibit the same behavior in the auxiliary channel space. By doing so, we can potentially point to a consistent mechanism which generates glitches which can help domain experts localize and possibly fix the problem at the source.

3 Progress

3.1 Data Collection

Using the pipeline established by [2], we are currently collecting data using the Omicron trigger catalog from the end of O3a and the beginning of O3b runs of the Livingston detector. More specifically, we will use data collected between September 25-28, 2019 for the O3a *training* interval and September 29-30, 2019 for the *validation* interval. For the O3b runs, we will collect data between November 1-4, 2019 for the *training* interval and November 5-6, 2019 for the *validation* interval. The goal of collecting data from the two different periods is to compare glitches before and after LIGO was able to mitigate noise derived from scattering [7].

3.2 Synthetic Data Generation

To approach our problem, we first established a synthetic data generator. The generator aims to mimic the data matrix obtained from LIGO through the pipeline established by [2]. There are two reasons for creating a generator. One is the time-intensive nature of data collection. Hence, creating a generator will allow us to "crash-test" the methods and algorithms we propose to explore. More importantly, a synthetic data generator can be used as a controllable testbed that helps us determine how our proposed methods behave in the presence of different kinds of patterns, before we attempt to identify them "in the wild" given the open-ended nature of the problem.

The first step of the synthetic data generation is generating a glitch catalog that emulates the Gravity Spy Catalog. To do this, we generate a dictionary which associates a glitch class to a set of channels. In this case, we simply label as "gs_i", where i denotes the i-th glitch class in the catalog. Each glitch class is associated randomly with a set of channels ranging between $n^c_{min} = 3$ to $n^c_{max} = 6$, determined randomly. Note that for cases which require a tertiary tensor mode, the generator also appends a feature value to each class that allow for the generation of the third tensor mode.

Using the generated channels, we can cluster glitch classes in multiple ways. One is to have a proportion of the glitch classes share a set of channels, which represents multiple glitches being triggered by the same source. Alternatively, we can cluster glitch classes such that a given morphology can be triggered by different sets of channels. We explore both methods within this work.

Once the catalog is generated, it can be used to generate data matrices and tensors, where entries represent the SNR value associated to a glitch, channel, and possibly tensor features. We will discuss, in explicit detail, the construction of the synthetic data matrix. First, an empty matrix is constructed. At each entry, a Poisson-distributed "background" noise is randomly generated. Following this, we randomly select which row to inject the glitch. Then, a glitch class is randomly selected along with the associated channels. At each of those channels, which in this case is associated with the columns of the data matrix, a Poisson-distributed signal is generated. We then apply the "loud" trigger threshold and zero out any entry less than the threshold of SNR ≥ 7.5. Note that the selection of this threshold is arbitrary for the synthetic data, the relative differences between the SNR values are the most relevant for our analysis. For the application to BMF, we simply replace all non-zero matrix elements with "1". Note that the tensor generation works similarly, with the exception of the third mode, where instead the signal is generated with reference to the i-th glitch and j-th auxiliary channel, and k-th feature bin. Overall, the resulting matrices and tensors are sparse, which to a first approximation matches the behavior of data collected. Note that the feature bin may represent other features of the data (e.g., frequency with peak SNR as in [2]).

In order to gain insight to the structure of the data, we performed Singular Value Decomposition (SVD) and plot the singular values of the constructed data matrices. Figure 1 plots the singular values for different data matrices sampled from different glitch class catalogs generated using the synthetic data generator. For comparison, we plot the singular values of a data matrix obtained from the Livingston detector between September 29-30, 2019. The resulting singular values across the simulated and real datasets indicate a fairly low cutoff for the rapid decline in the magnitude of singular values which suggests a low-rank structure across the data.

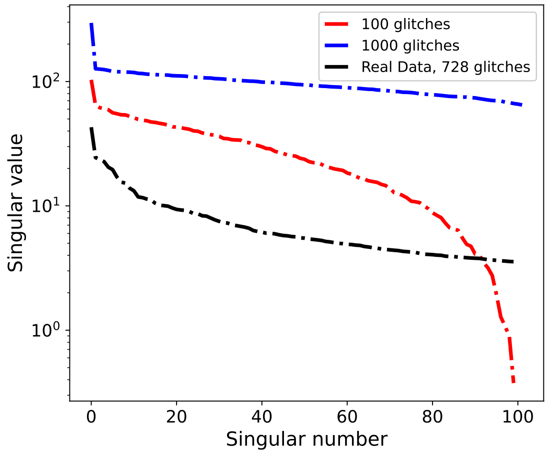
3.3 Testing BMF

The next step is to use a BMF implementation to test the synthetic data. Currently, we are exploring the pipelines established from https://cs.uef.fi/~pauli/bmf/sofa/ and https://github.com/mravanba/BooleanFactorization.

4 Future Work and Challenges

The immediate next steps within this work lies within data collection and testing BMF. Our goal is to determine and implement BMF as a way to cluster glitches using the synthetic data within the next two weeks. Then, we will then use the data collected from the pipeline to inject the pipeline we develop. We will then compare the results of our work to recent results by [2] that utilized NMF as the model.

Aside from BMF, we are also planning to explore utilizing different features (e.g., amplitude,



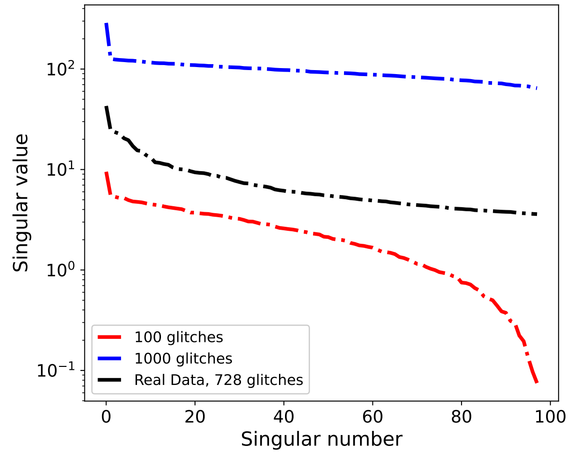


Figure 1: Singular values plot across four different Boolean data matrices. (*Upper*): Singular values plot of the data matrix generated with 100 and 1000 glitches sourced from a glitch catalog that had 50% of glitch classes share one channel. The *upper* plot represents a scenario where different glitch classes that may occur from similar sources. (*Lower*: Singular values plot of the data matrix generated with 100 and 1000 glitches sourced from a glitch catalog where a given glitch class can have multiple sets of auxiliary channels associated. The *lower* plot simulates a scenario glitch classes that could be sourced from different sets of auxiliary channels. For comparison to a real dataset, we plot the singular values of a data matrix obtained from the Livingston detector between September 29-30, 2019. Overall, the plots indicate a fairly steep cutoff within the low singular index regime, despite different sample sizes, which suggests that a low-rank approximation should work well within BMF and other low-rank factorization models.

bandwidth) in tensor modes to determine suitable veto generators. Furthermore, if time permits, we plan to investigate whether introducing glitch morphology information (e.g., in the form of Gravity Spy catalog labels) steers the discovery of patterns in a way that can identify glitches which are morphologically similar and have a consistent behavior in the auxiliary channel space.

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