

GSpyNetTree-O: An Extension to *GSpyNetTree*'s Signal vs. Glitch Classification Algorithm for Overlapping Compact Binary Coalescence Signals

Steven Hsueh

Supervisor: Dr. Jess McIver

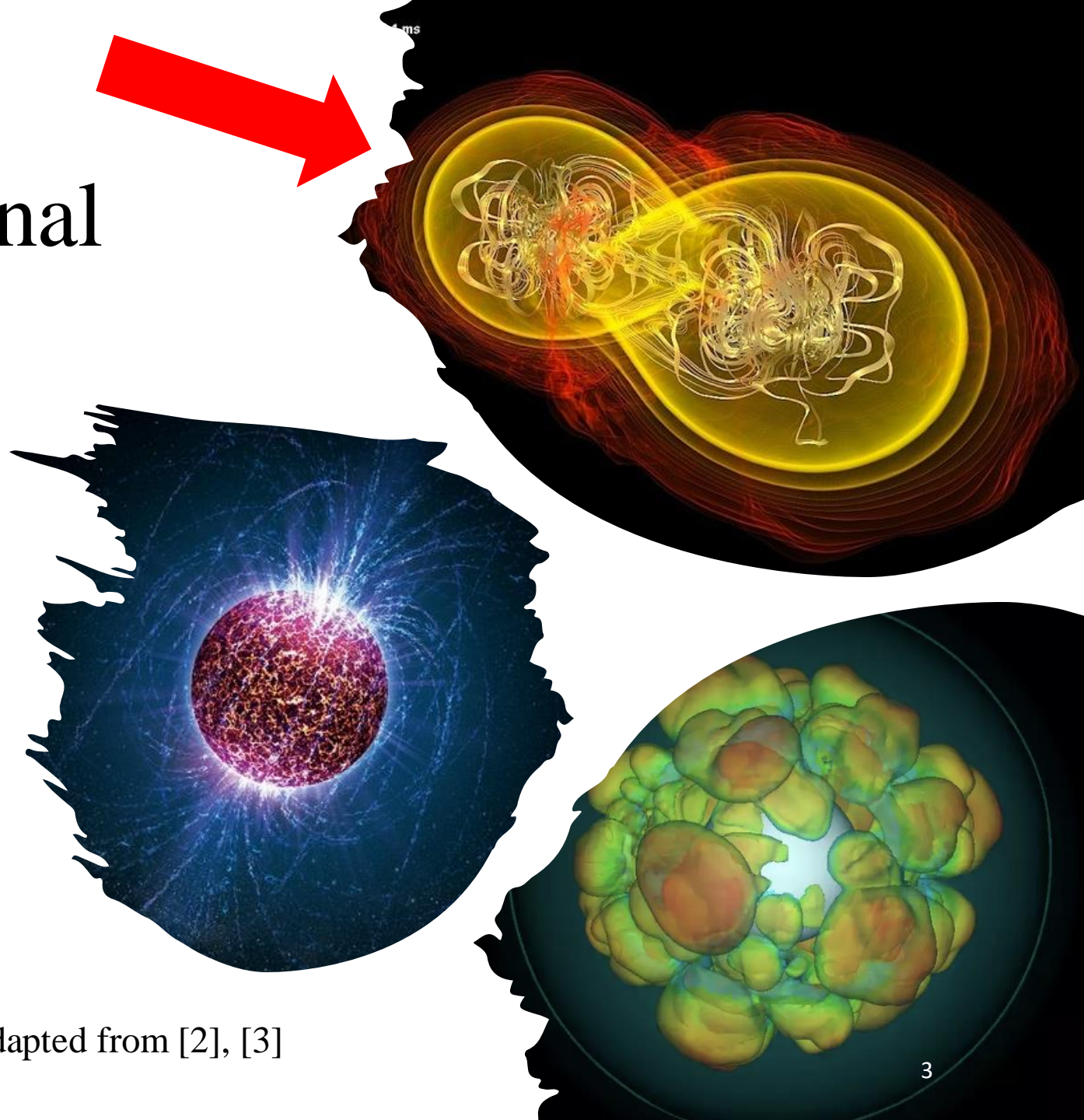
Guided by: Dr. Mervyn Chan and Yannick Lecoecuche

Table of Contents

- Scientific Motivation
- Theory – Machine Learning
- Methods
- Results
- Future Work

What are Gravitational Waves (GW)?

- “Ripples” in spacetime
- Can originate from various sources
- Very hard to detect
 - Thousands time smaller than diameter of proton

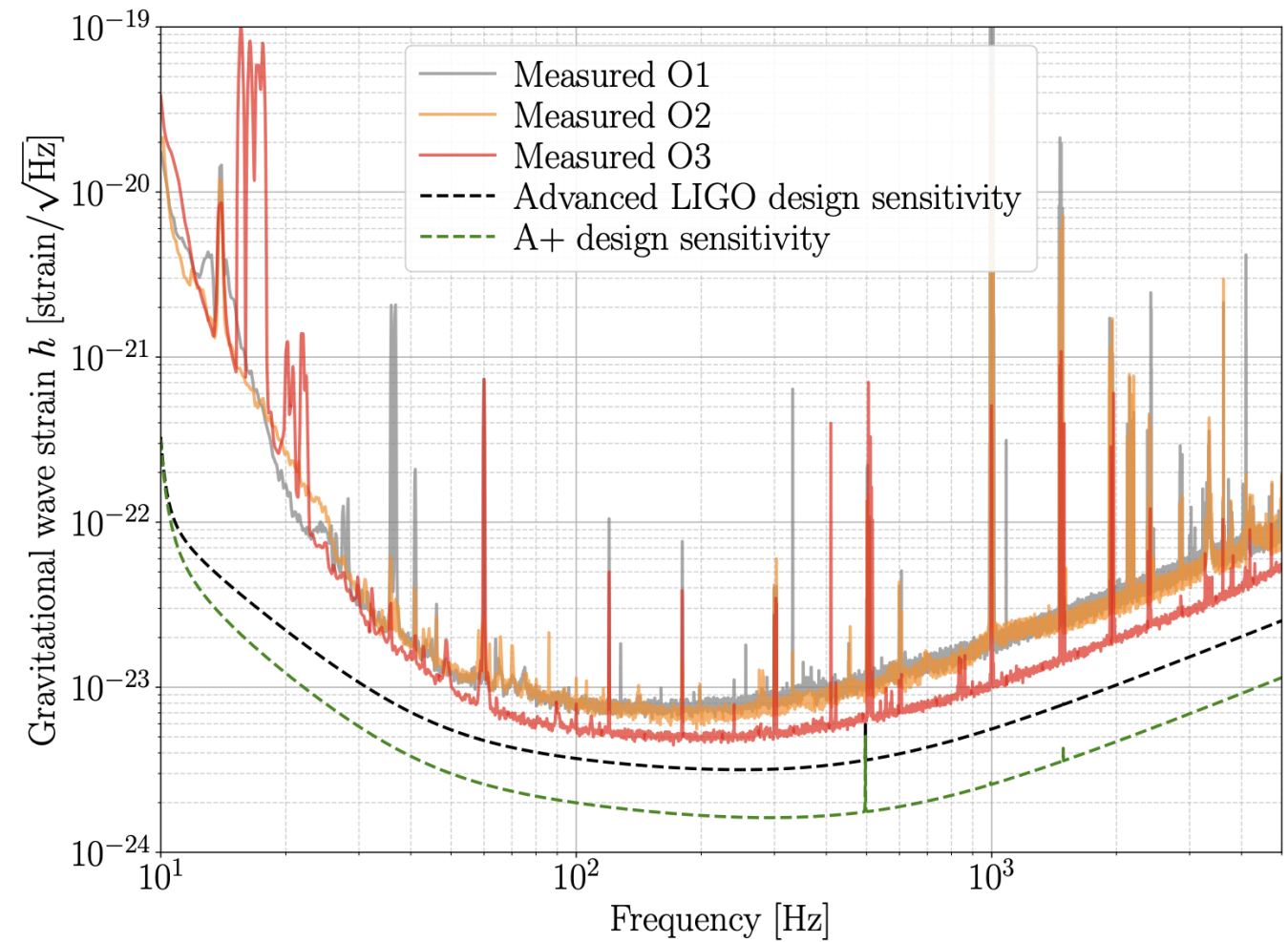


Figures adapted from [2], [3]

Motivation – O4 and Sensitivity Range

- Fourth Observation Run (O4) scheduled to start in May 2023
- Detector Sensitivity Upgrades
 - Lower noise floor
 - Frequency range approximately 10-2000 Hz

Motivation – O4 and Sensitivity Range



C. Cahillane and G. Mansell., 2022 [4]

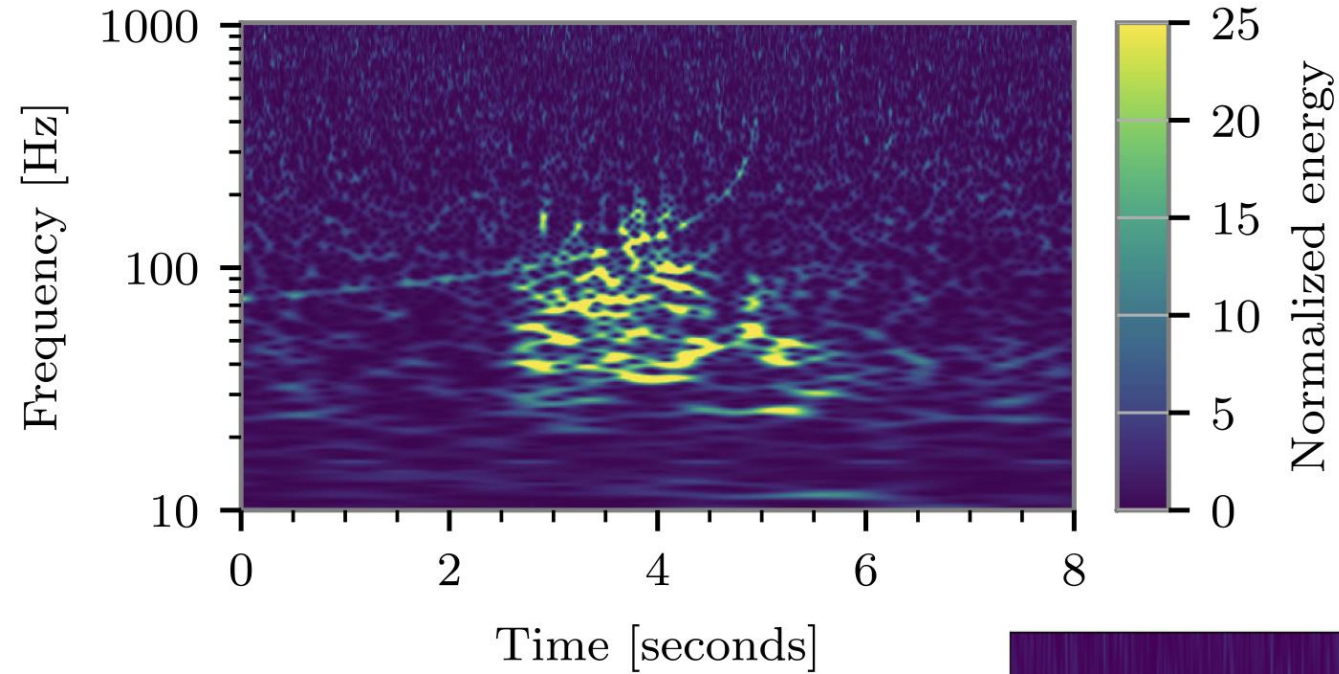
Motivation – Probability of Overlapping in O4

- Projected O4 detection rate = ~ 1 event per day
- Example for a very conservative estimate:
 - 1s in duration, 1.5s for offset for second event
 - 0.0012% and 0.0035% separately
 - Not accounting for other possible observation (Low SNR, long event time)

Motivation – *GravitySpy* and *GSpyNetTree*

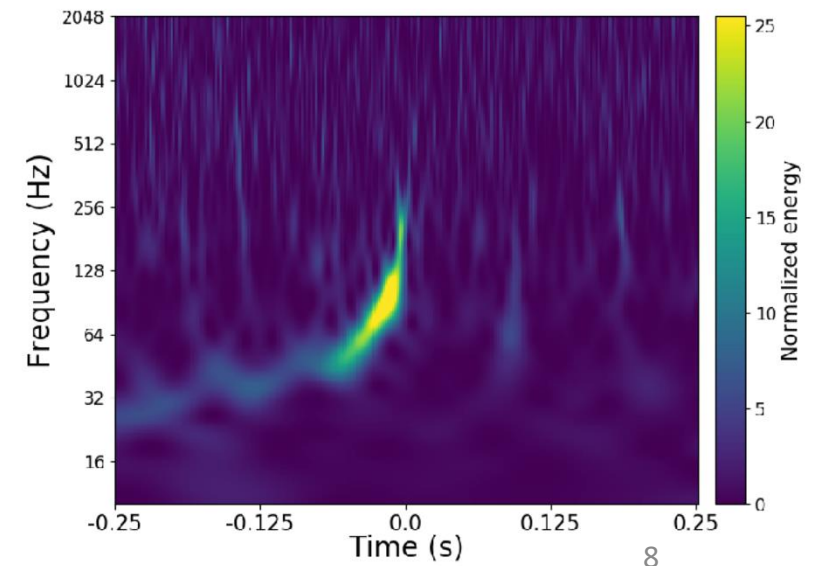
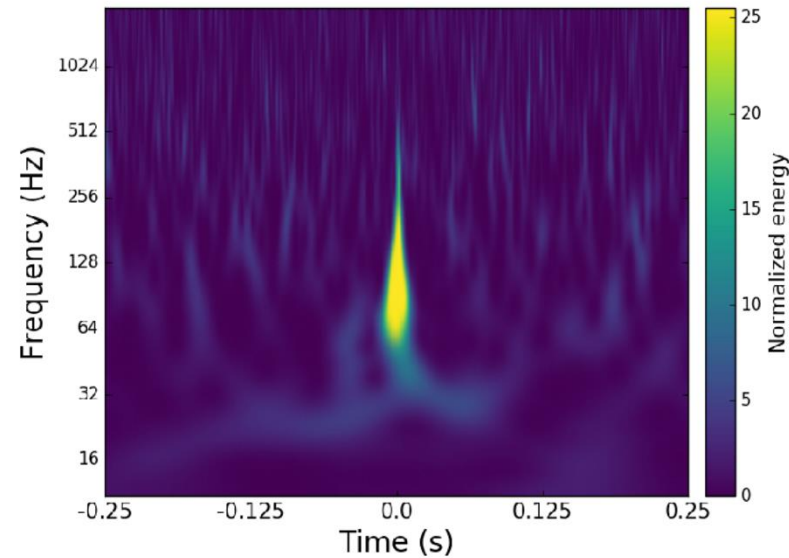
- Data collection → impossible to validate all candidates by human
- *GravitySpy*
 - Combined **Machine Learning** (ML) techniques and citizen science to develop algorithm
 - Categorize glitches - transient, non-Gaussian noise artifacts

Motivation – Glitches & Event Detection



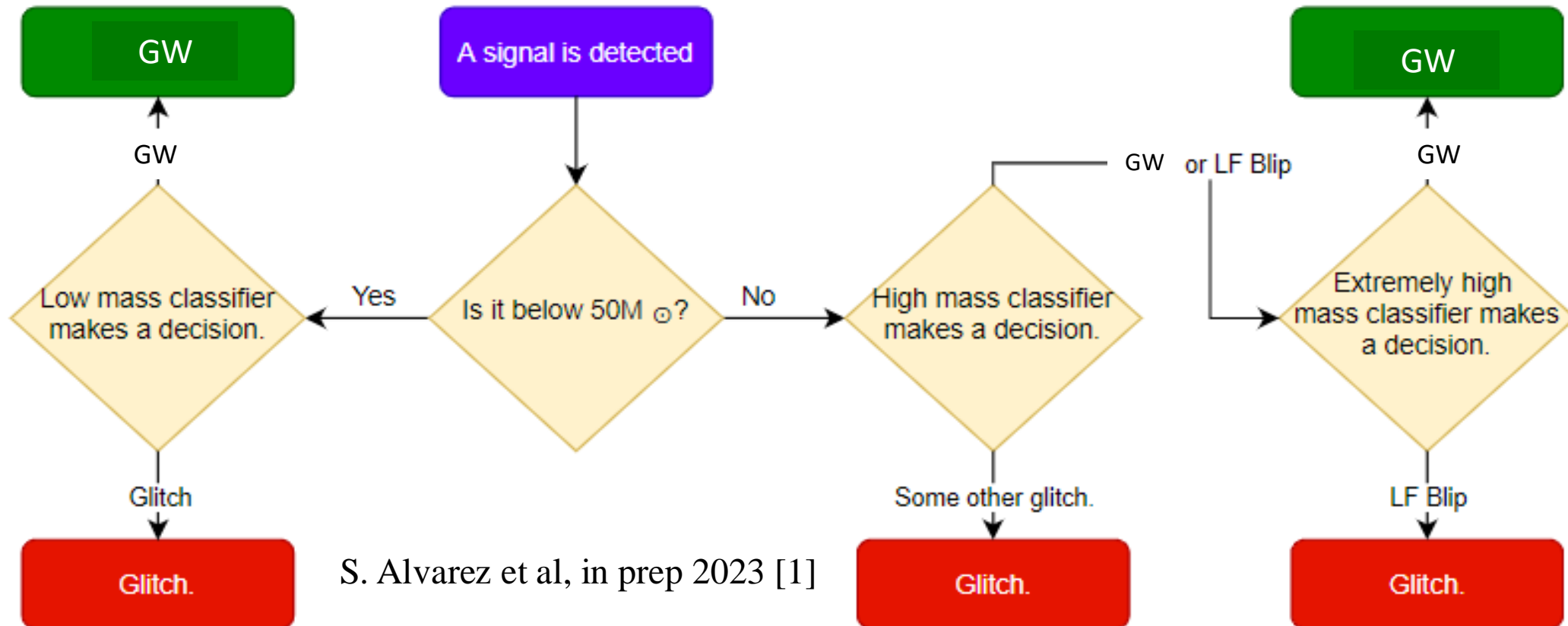
R. Macas, J. Pooley, et al., 2022 [6]

R. Mesuga and B. J. Bayanay., 2022 [5]



Motivation – *GravitySpy* and *GSpyNetTree*

- *GSpyNetTree* is an extension to *GravitySpy*

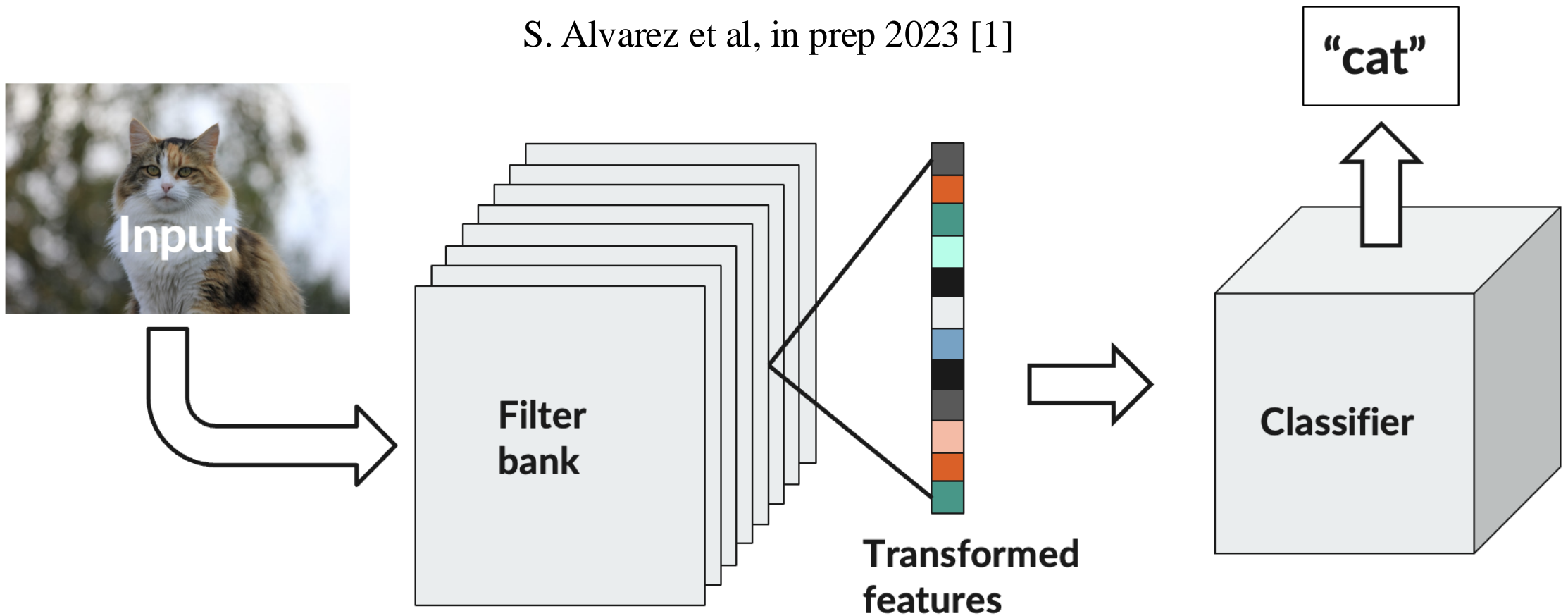


Motivation – *GravitySpy* and *GSpyNetTree*

- Not trained with an implicit assumption of overlapping signals
- May lead to rejection of real astrophysical candidate
- Goal: develop a ML model that is robust to the presence of overlapping signals – *GSpyNetTree-O*

Theory – Convolutional Neural Network (CNN)

S. Alvarez et al, in prep 2023 [1]



Theory – CNN

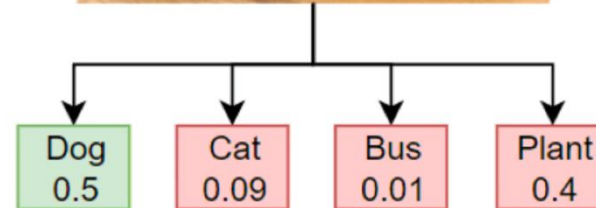
- *GravitySpy* & *GSpyNetTree* employs CNN
- Advantages:
 - Computationally cheap
 - Sensitive to feature in input data (such as shapes)

Theory – *Multi-Class* vs *Multi-Label*

Binary Classification

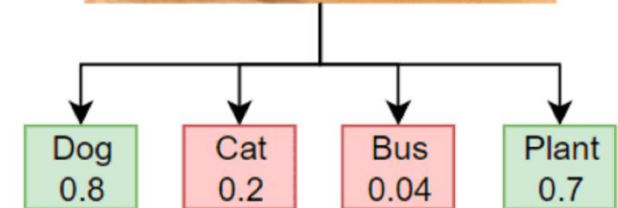


Multiclass Classification



CNN can only output one class (plant class is ignored)

Multilabel Classification

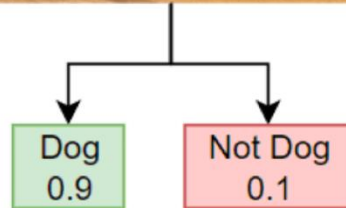


CNN may predict 0+ classes.

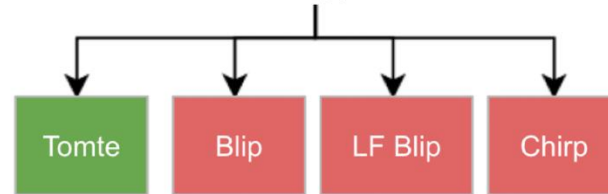
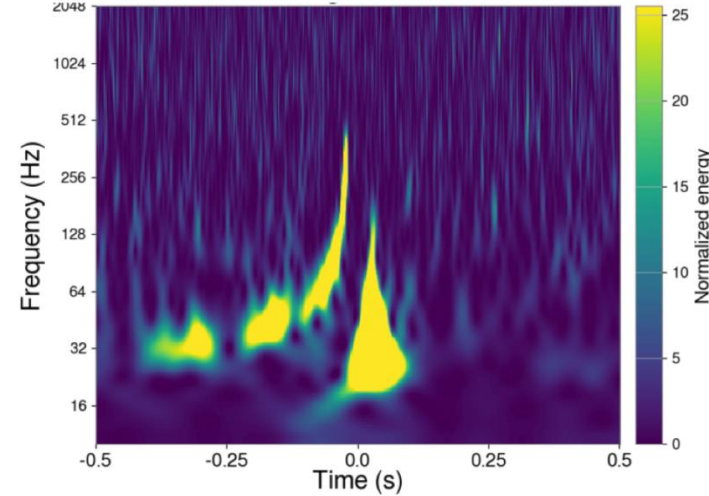
37

Theory – *Multi-Class* vs *Multi-Label*

Binary Classification

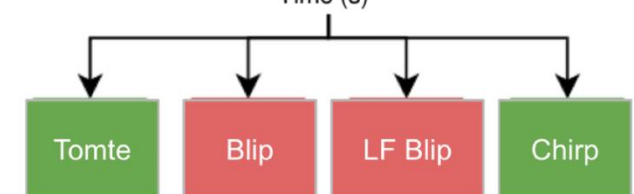
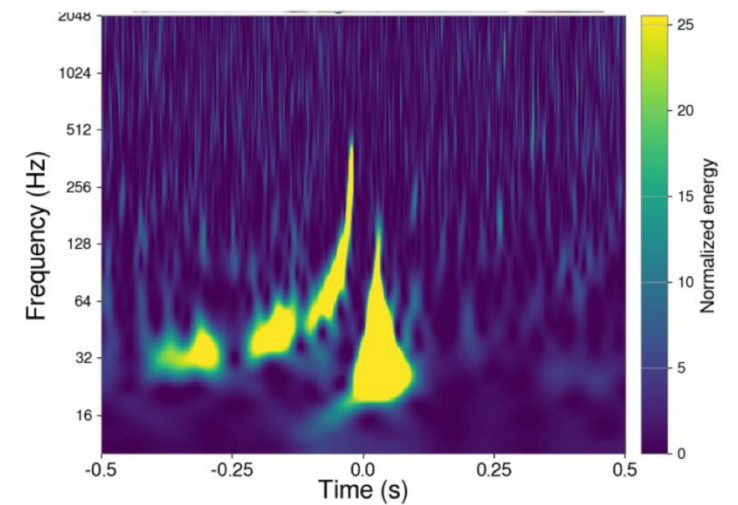


Multiclass Classification



CNN can only output one class (Chirp class is ignored)

Multilabel Classification



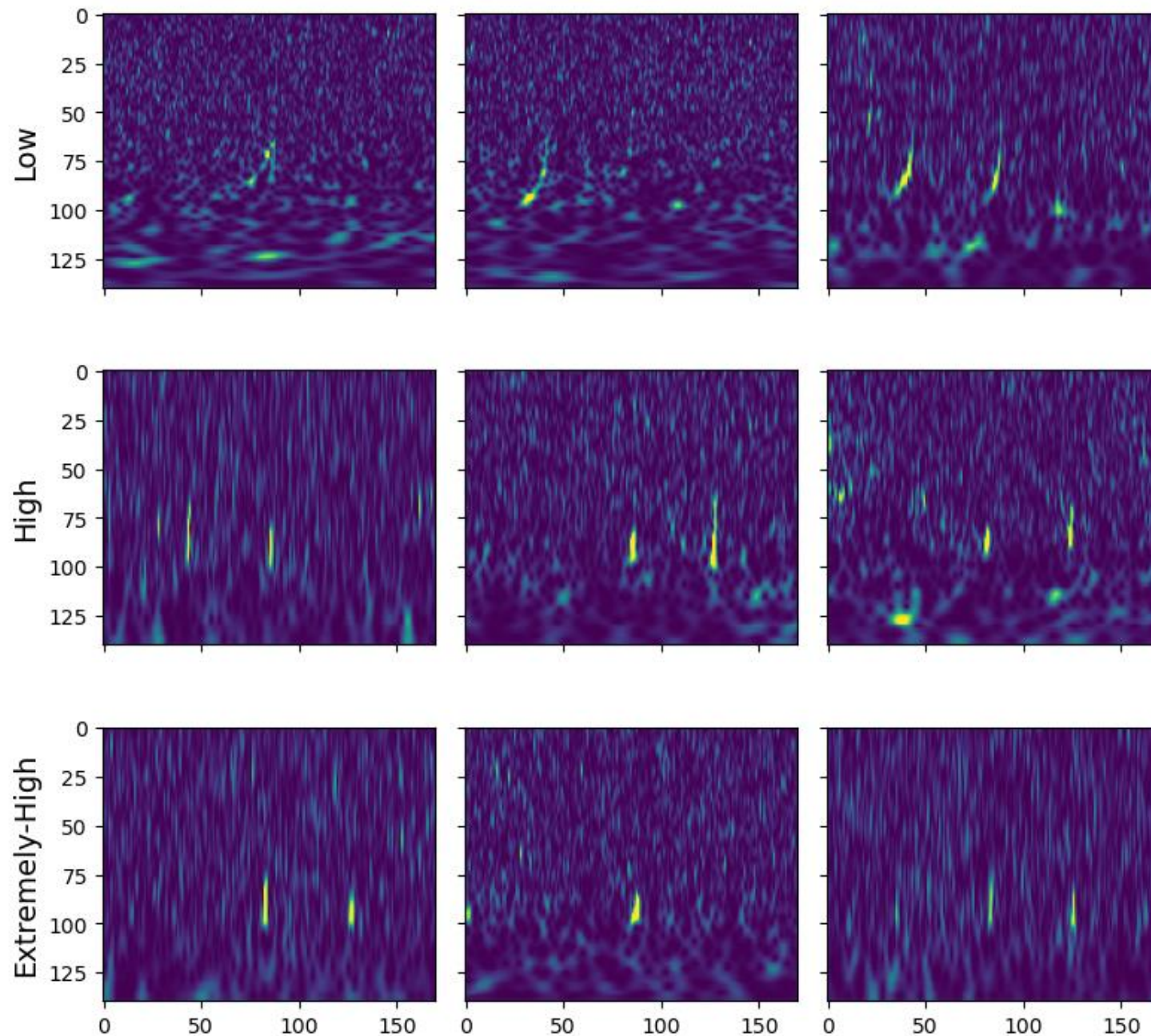
CNN may predict 0+ classes.

Methods - Simulation

- Modifying the existing scripts to generate overlapping signals
- Two overall training sets: O2 and O3
- Each overall set has three individual sets for each classifier
 - Low-mass (LM), High-mass (HM), Extremely-high-mass (EH)

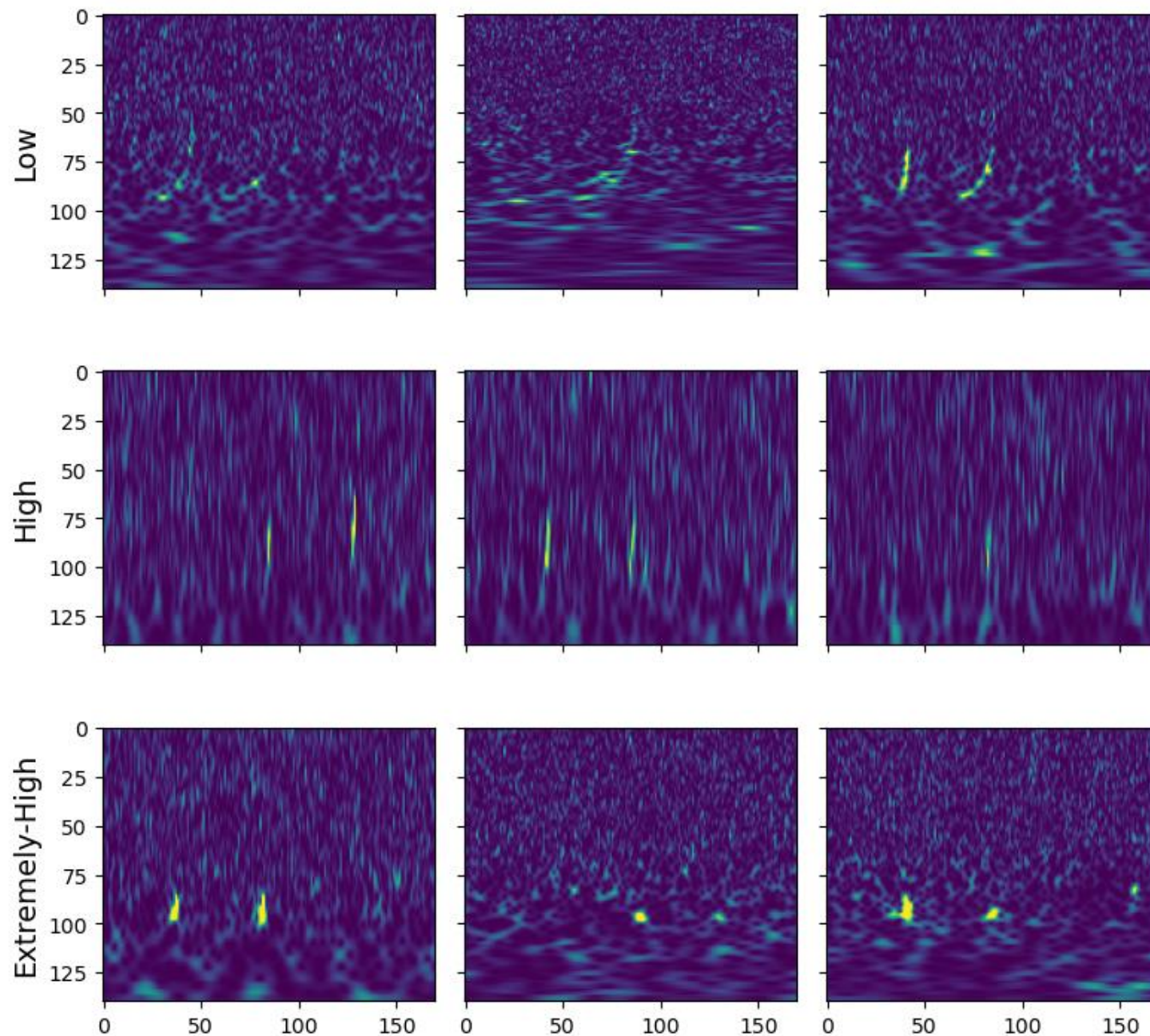
Methods - O2 Simulated Samples

O2 Overlapping Samples



Methods - O3 Simulated Samples

O3 Overlapping Samples



Methods – Training

- Training with Mutli-Class Model (MCM)
- Training with trained Multi-Label Model (MLM)
 - This model is developed by S. Alvarez, J. Ding, A. Liyanage, F. Herbst, et al.
- The following results are the **initial performance** against the test set

Result – O2 MCM Performance (LM)

| Ground truth | Blip | Blip_Low_Frequency | Chirp | No_Glitch | Scratchy |
|--------------------|--------------|--------------------|---------------|---------------|--------------|
| | Blip | Blip_Low_Frequency | Chirp | No_Glitch | Scratchy |
| | Blip | Blip_Low_Frequency | Chirp | No_Glitch | Scratchy |
| | Blip | Blip_Low_Frequency | Chirp | No_Glitch | Scratchy |
| | Blip | Blip_Low_Frequency | Chirp | No_Glitch | Scratchy |
| Blip | 50 47.17% | 7 6.60% | 28 26.42% | 21 19.81% | 0 0.00% |
| Blip_Low_Frequency | 0 0.00% | 76 76.77% | 15 15.15% | 8 8.08% | 0 0.00% |
| Chirp | 10 1.63% | 0 0.00% | 570 92.99% | 33 5.38% | 0 0.00% |
| No_Glitch | 7 6.19% | 0 0.00% | 0 0.00% | 106 93.81% | 0 0.00% |
| Scratchy | 21 30.43% | 0 0.00% | 16 23.19% | 6 8.70% | 26 37.68% |
| Prediction | | | | | |

Result – O2 MCM Performance (HM)

| | | | | | | |
|--------------|--------------------|---------------|--------------------|---------------|--------------|--------------|
| Ground truth | Blip | 100 80.00% | 0 0.00% | 25 20.00% | 0 0.00% | 0 0.00% |
| | Blip_Low_Frequency | 17 19.77% | 51 59.30% | 9 10.47% | 0 0.00% | 9 10.47% |
| | Chirp | 46 7.41% | 5 0.81% | 565 90.98% | 0 0.00% | 5 0.81% |
| | Koi_Fish | 8 14.04% | 0 0.00% | 8 14.04% | 41 71.93% | 0 0.00% |
| | Tomte | 0 0.00% | 10 9.01% | 10 9.01% | 16 14.41% | 75 67.57% |
| | | Blip | Blip_Low_Frequency | Chirp | Koi_Fish | Tomte |
| | | Prediction | | | | |

Result – O2
MCM
Performance
(EH)

| Ground truth | Prediction | | |
|--------------------|---------------|--------------------|---------------|
| | Blip | Blip_Low_Frequency | Chirp |
| | Blip | Blip_Low_Frequency | Chirp |
| Blip | 116 65.17% | 16 8.99% | 46 25.84% |
| Blip_Low_Frequency | 0 0.00% | 86 61.87% | 53 38.13% |
| Chirp | 42 6.15% | 26 3.81% | 615 90.04% |

Result – O2
MLM
Performance
(LM)

Label:Blip

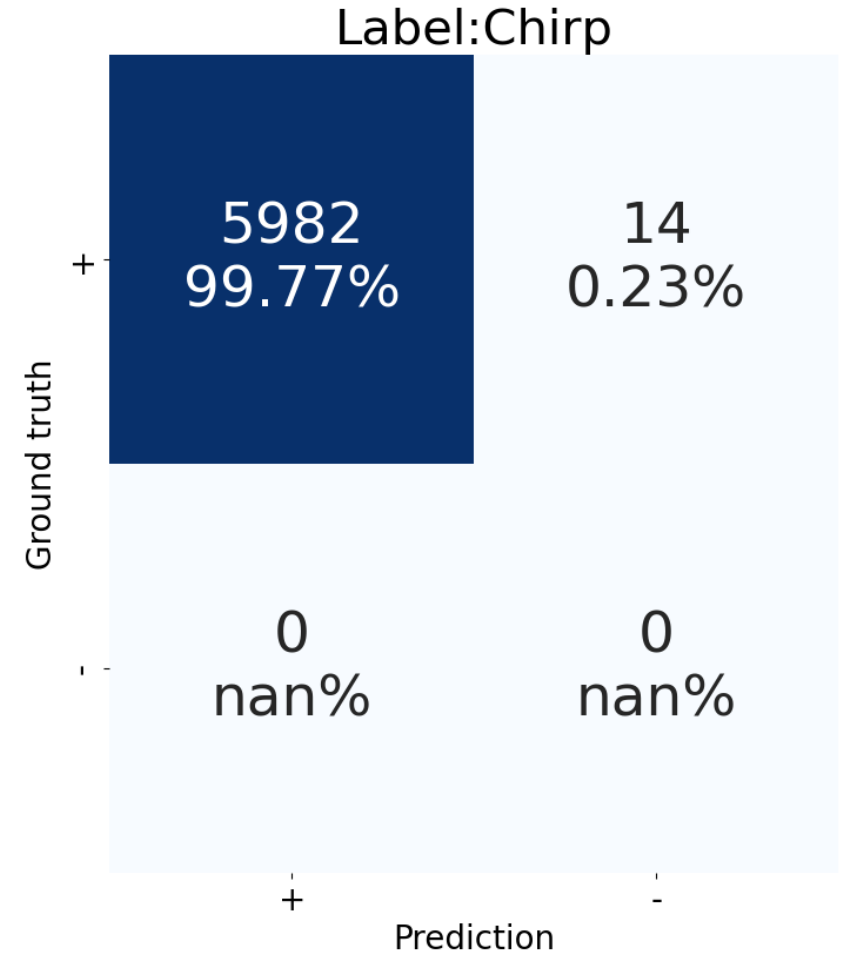
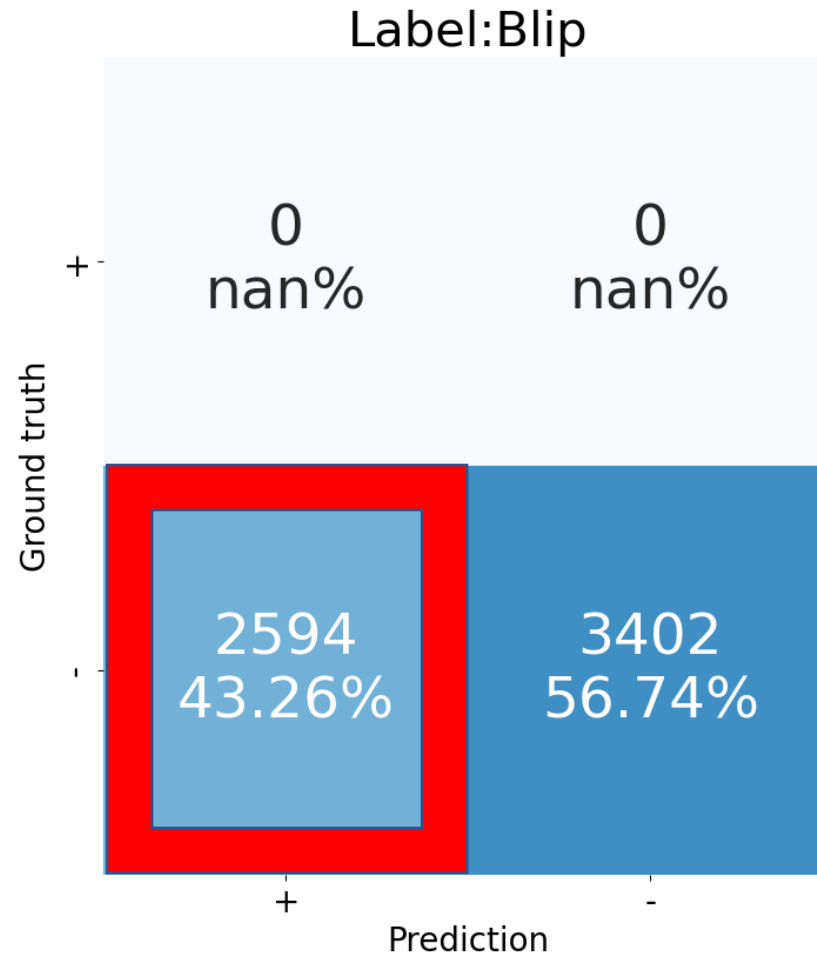
| | | | |
|--------------|------------|---------------|----------------|
| | + | 0 nan% | 0 nan% |
| Ground truth | | | |
| | - | 647 10.78% | 5353 89.22% |
| | | | |
| | Prediction | + | - |

Label:Chirp

| | | | |
|--------------|------------|----------------|-------------|
| | + | 5910 98.50% | 90 1.50% |
| Ground truth | | | |
| | - | 0 nan% | 0 nan% |
| | | | |
| | Prediction | + | - |

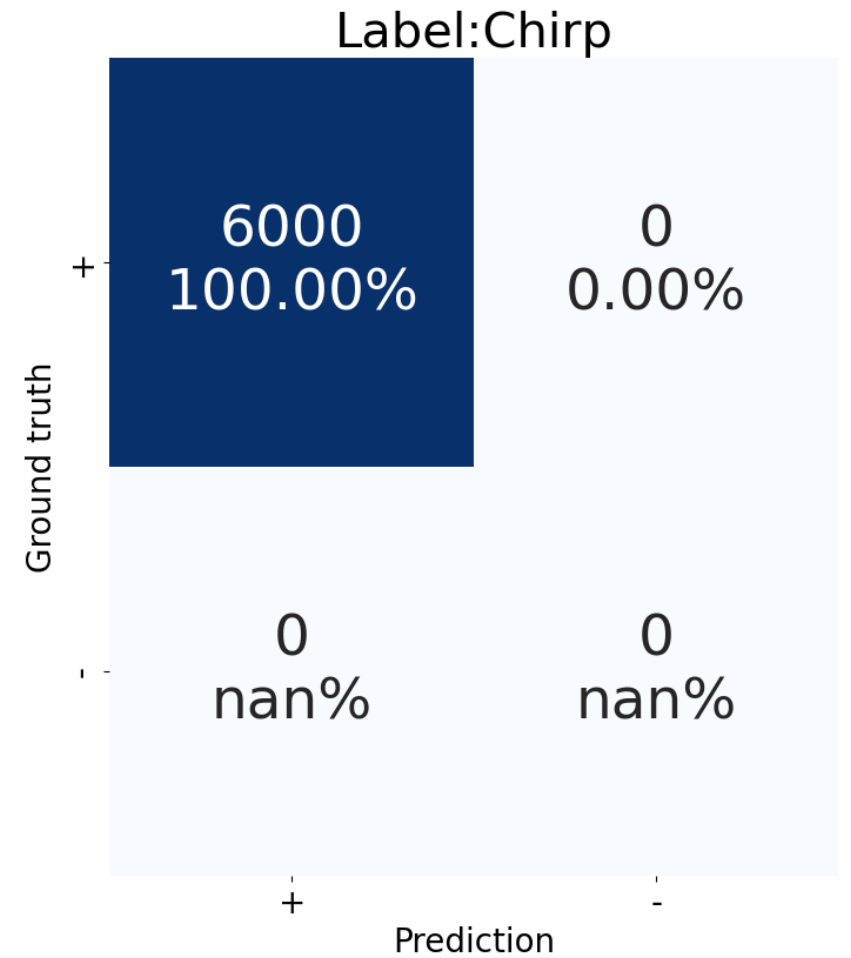
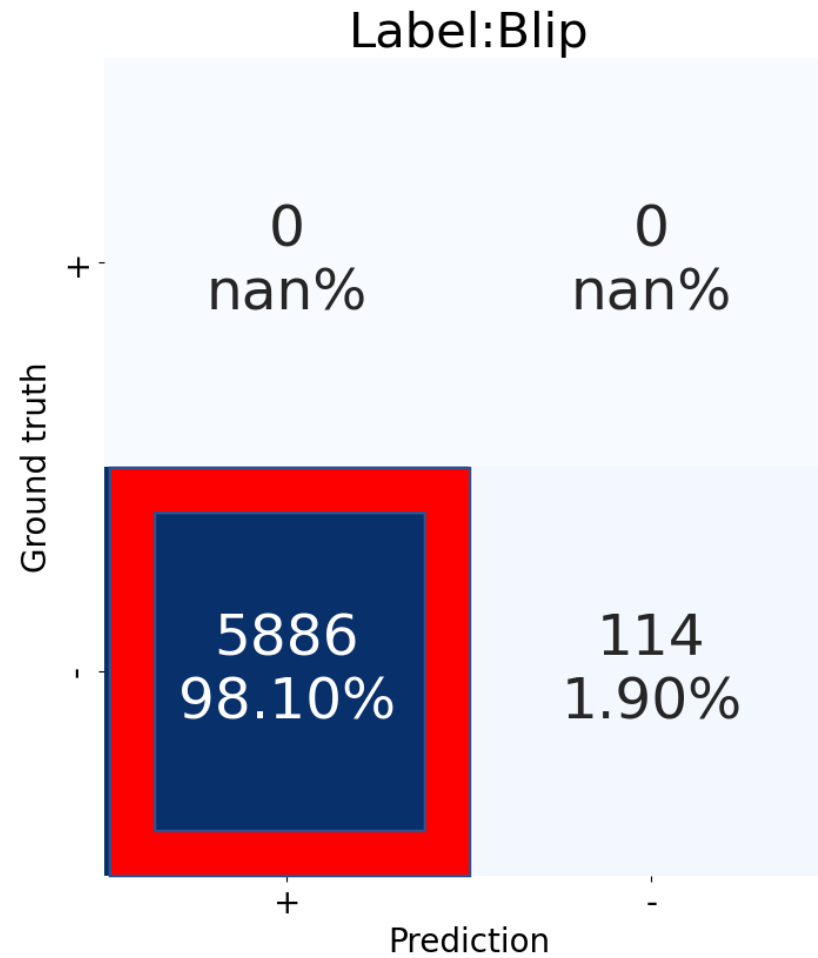
Permission and modified from S. Alvarez

Result – O2
MLM
Performance
(HM)



Permission and modified from S. Alvarez

Result – O2
MLM
Performance
(EH)



Discussion and Analysis

- Both MCM and MLM shows confidence in categorizing GW
 - Potentially due to high volume of GW samples
- Both MCM and MLM shows trouble in HM and EH
 - In particular with “Blip” glitch class
 - For MCM, other glitches also get misinterpret as GW

Future Work

- Obtain the initial performance against O3 test set
- Retrain both MCM and MLM for improvements
- Obtain the post-trained performance against test sets
- Compare the result between MCM and MLM

Thank you
for listening



Reference

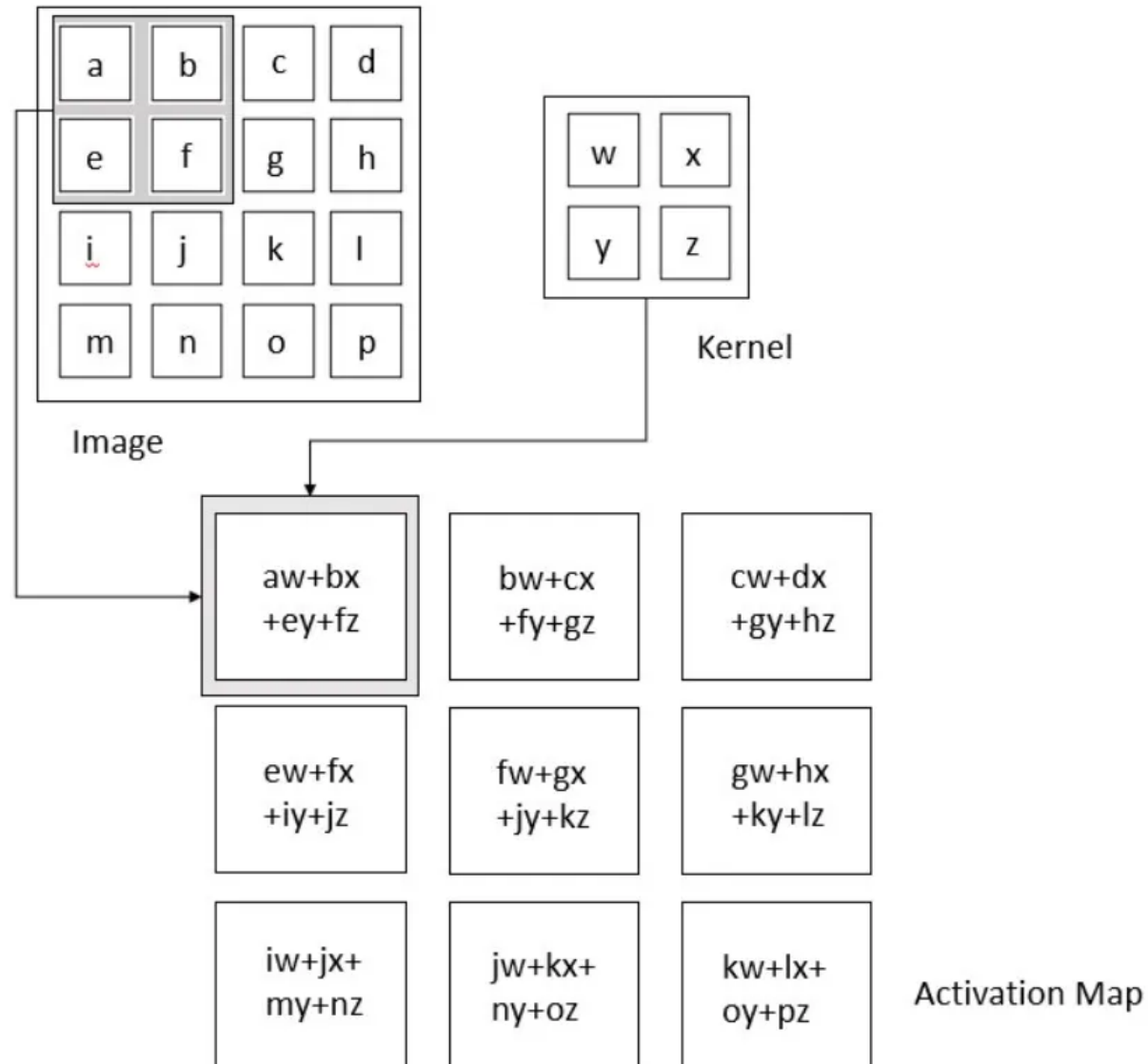
- [1] Ding, J., Alvarez, S., Liyanage, A. GSpyNetTree Presentation to DetChar. August 2022, <https://wiki.ligo.org/DetChar/Telecon20220808>. Power-Point Presentation.
- [2] Sources and types of gravitational waves. Caltech. (n.d.). Retrieved November 27, 2022, from <https://www.ligo.caltech.edu/page/gw-sources>
- [3] Core-collapse supernovae. Max Planck Institute for Astrophysics. (n.d.). Retrieved November 28, 2022, from <https://www.mpa-garching.mpg.de/84411/Core-collapse-supernovae>
- [4] C. Cahillane and G. Mansell. Review of the advanced ligo gravitational wave observatories leading to observing run four. *Galaxies*, 10(1):36, 2022. doi:10.3390/galaxies10010036
- [5] Mesuga and B. J. Bayanay. A deep transfer learning approach on identifying glitch wave-form in gravitational wave data. 2022. doi:10.36227/techrxiv.19687590.v1
- [6] R. Macas, J. Pooley, L. K. Nuttall, D. Davis, M. J. Dyer, Y. Lecoecuche, J. D. Lyman, J. McIver, and K. Rink. Impact of noise transients on low latency gravitational-wave event localization. *Physical Review D*, 105(10), 2022. doi:10.1103/physrevd.105.103021



Extra Slides - *GSpyNetTree*

- We can still detect signals that cannot see
 - There are other components within the network
- CNN can pick up pattern that human can't, but not always reliable and still requires some human analysis
- A multi-label architecture, different from *GravitySpy*
 - One input can have more than one label

Extra Slides – CNN in-depth



Extra Slides – CNN in-depth

