Multi-transient segmentation in LIGO using computer vision

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Overview

- LIGO and Detector Characterization
- Computer Vision
- Computer Vision in LIGO
- Summary

Ground based Gravitational Wave detectors

Purpose: To detect GWs in the band 20 - 2000 Hz

Where: 2 LIGO detectors in USA, Virgo in Italy, KAGRA in Japan

Operations: Have completed 3 Observing runs (O1, O2, O3), O4 is currently ongoing

Detections: More than 200 detections have been made since the start of O1

LIGO Livingston, Louisiana, USA

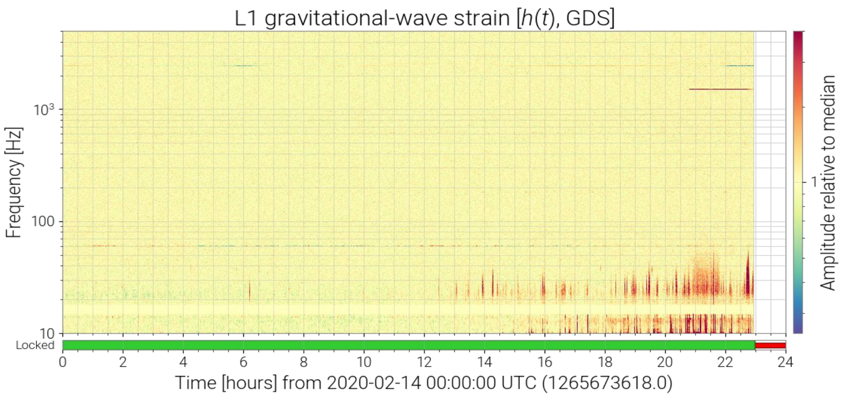
LIGO Hanford, Washington, USA

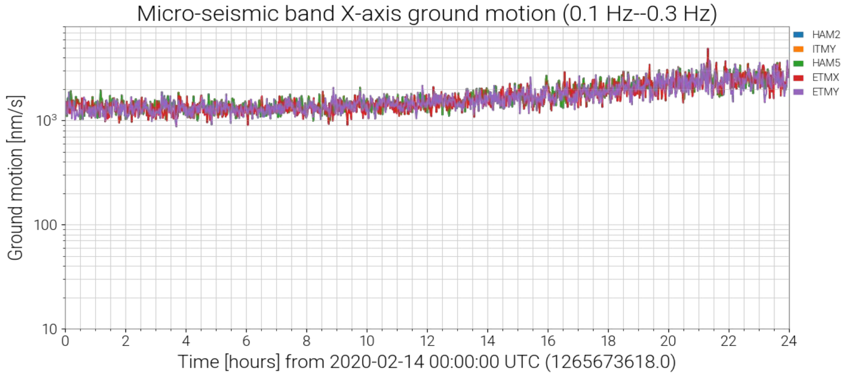
Virgo Cascina, Italy

https://www.ligo.caltech.edu/

Detector Characterization

- Monitor the status of detector : Instrumental and data quality investigations
- Physical Environment Monitoring: injection tests and noise coupling calculations
- Event Validation: Check data quality around the events
- Summary pages and Detchar tools: maintenance and development

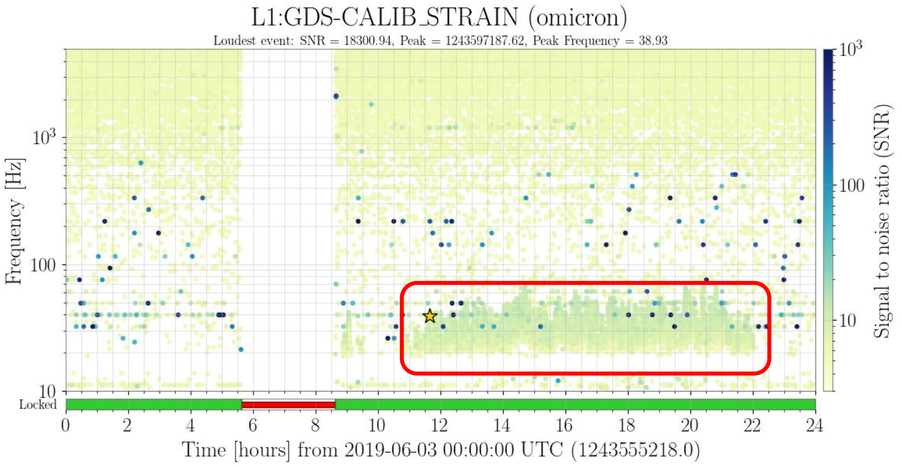


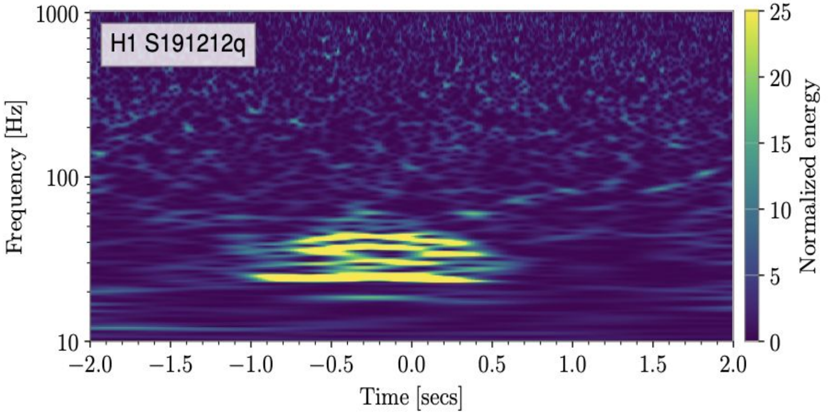


LIGO detector characterization in the first half of fourth Observing run. S Soni *et al* 2025 *Class. Quantum Grav.* **42** 085016

Transient noise aka glitches

- Short duration excess power
- Environmental or instrumental coupling
- Reduce sensitivity/range of the detector
- Mess up with the real events, parameter estimation, create false alerts, reduce sensitivity for stochastic searches
- Originate in detector hardware. Investigate using detchar tools, injections, on/off tests etc





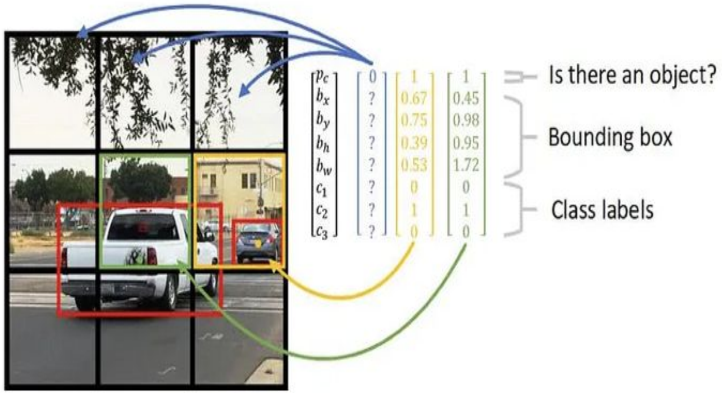
Computer Vision

Computer Vision

- Field within AI, enabling computers to interpret visual information
- Object recognition, image classification, feature detection, image (pixel) segmentation, tracking motion
- Dominated by Convolutional Neural Networks from 1980-2015
- You Only Look Once (YOLO) since 2016 being used for object detection in real time

You Only Look Once aka YOLO

- YOLO is a family of real-time object detection algorithms.
- Input → YOLO → (bounding box/masks, class label) single shot detection
- Divides the image into an NxN grid and for each grid cell it predicts:
  - Object detection: Object exists or not
  - Localization: Bounding box parameters (x,y)
  - Confidence: Class probability
- Really fast: 150 fps, great for real time prediction.
- Applications:
  - Self-driving cars
  - Medical imaging
  - Industrial defect detection and so much more

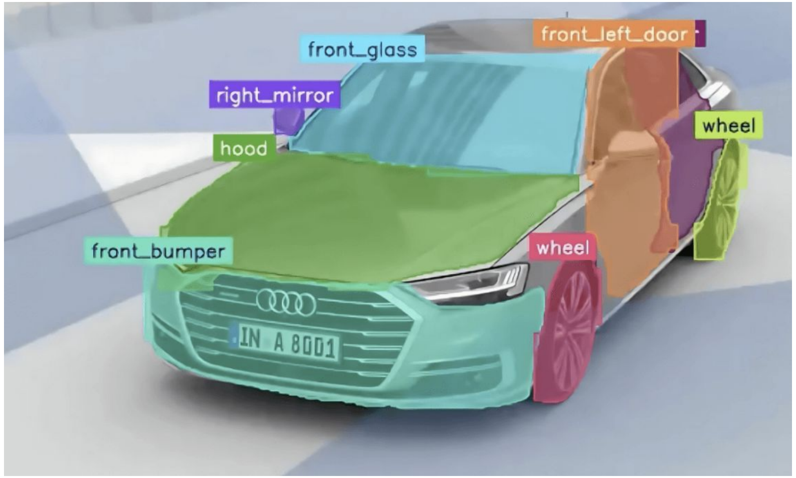


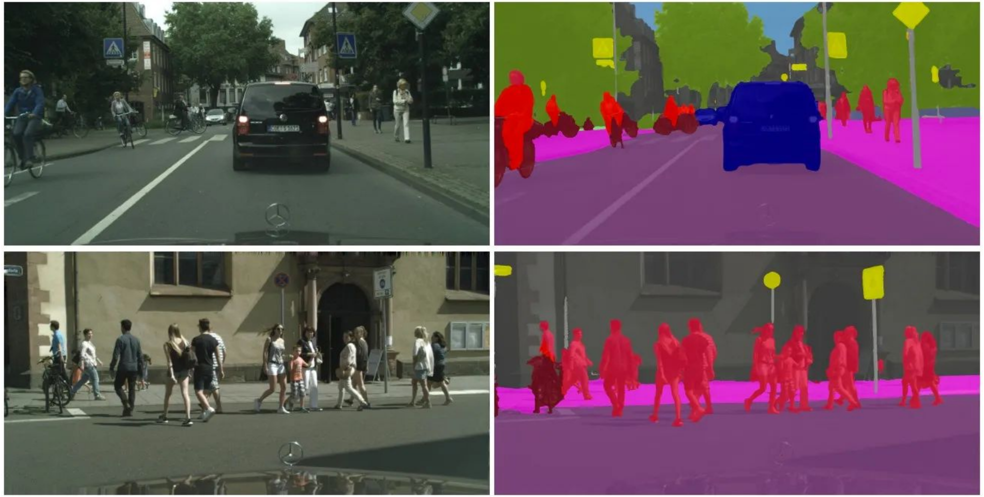
YOLO algorithm
https://arxiv.org/abs/1506.02640

Image source

Image Segmentation

- Beyond object detection or classification
- **Pixel level masks** that outline the shape of the object
- Instance segmentation: ***what*** the object is and ***where*** it is
- Multiclass image segmentation
- Used in autonomous driving





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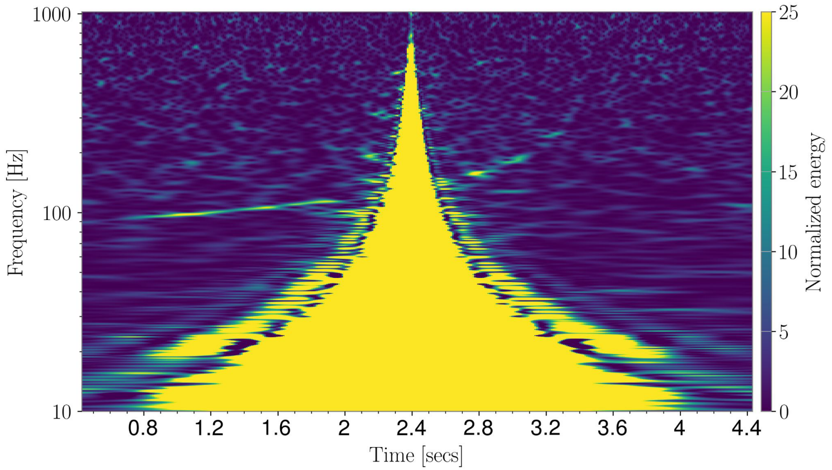
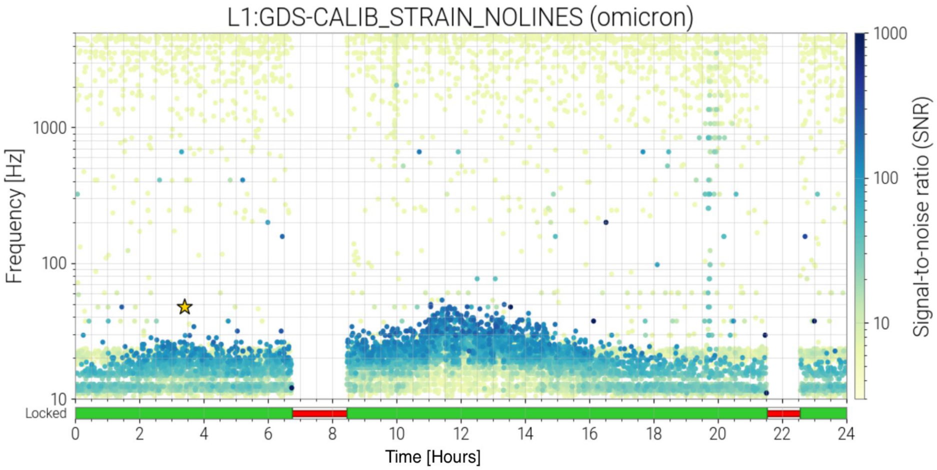
Computer Vision in LIGO

Motivation

GW170817





As detectors become more sensitive, the rate of transient noise may go up

Main Idea

Spectrogram as Input → YOLO based Segmentation Model → Output Image: Class label (Noise or Chirp) & Segmentation masks

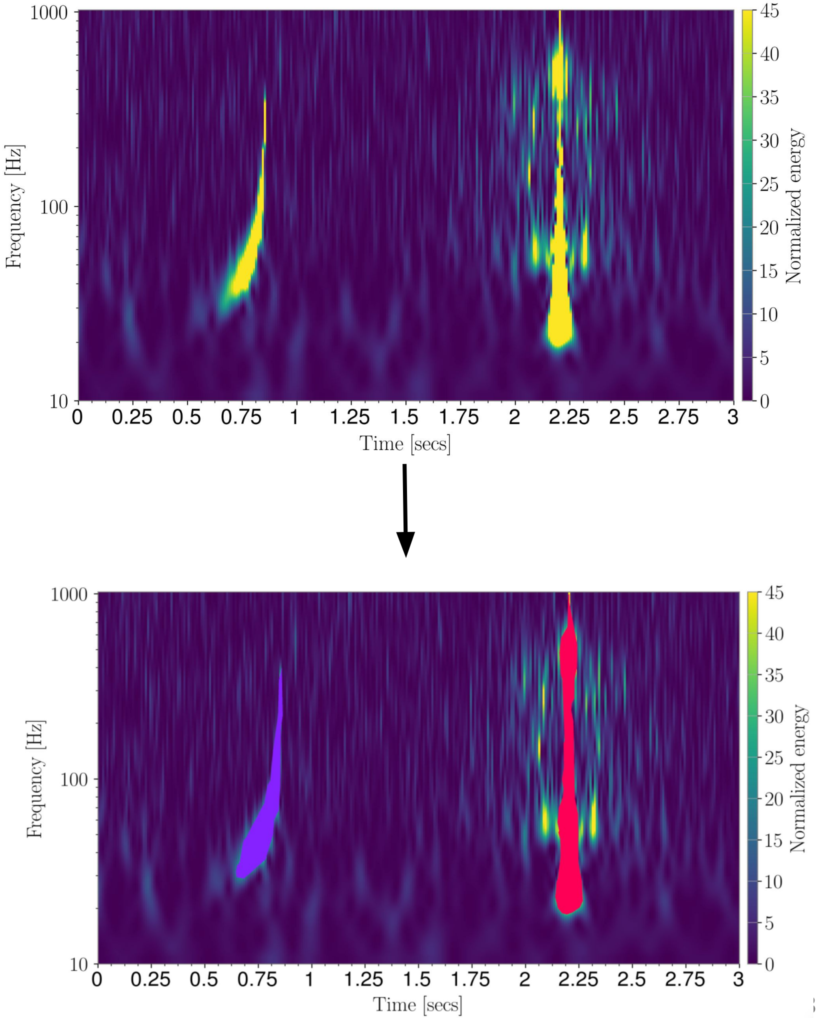
We feed Q transforms (or event times) to the script and it outputs a Q scan showing different class labels and segmented pixel-masks for each class

For this, we first need to train our model on lots of annotated spectrograms of transient noise and chirps.

Training data

- Noise: Glitches from O3
- Signals: BBH , BNS signal waveforms, generated using PyCBC and O3 injection dataset
- Combine the glitches and chirps, make the Q-transform, annotate the chirps and noise
- Variation in chirp strength, types of glitches, temporal separation (including overlap) between glitch and chirp in the training set

1. https://zenodo.org/records/5649212
2. https://zenodo.org/records/7890437



Training Metrics

- Metrics to quantify training performance
- **MAP@50:** Mean Avg precision @50 means prediction is correct if Intersection Over Union area between predicted and ground truth is > 50. So better localization.
- **Precision**: TP/(TP + FP). High precision leads to fewer wrong guess.
- **Recall**: TP/(TP + FN). High recall means smaller number of missed detections.
- Next: Inference on new examples and then a larger statistical study

DataSet	mAP50	Precision	Recall
Validation	94.7 %	89.0 %	90.0 %
Test	95.3 %	91.5 %	92.0 %

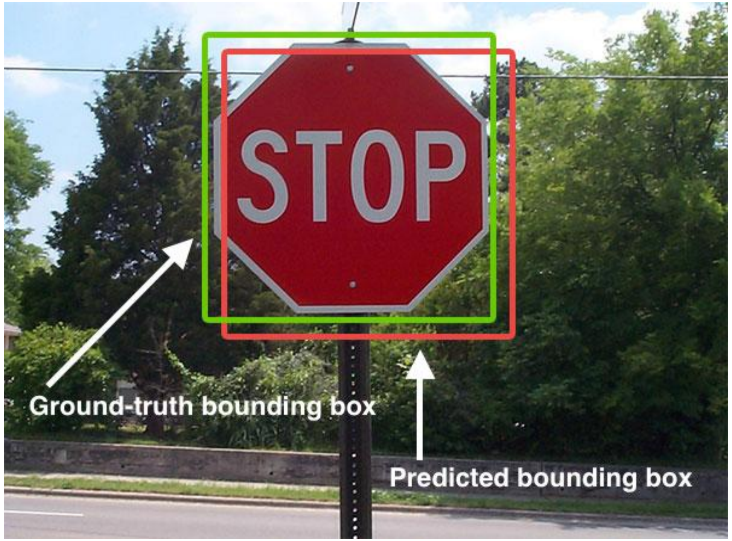
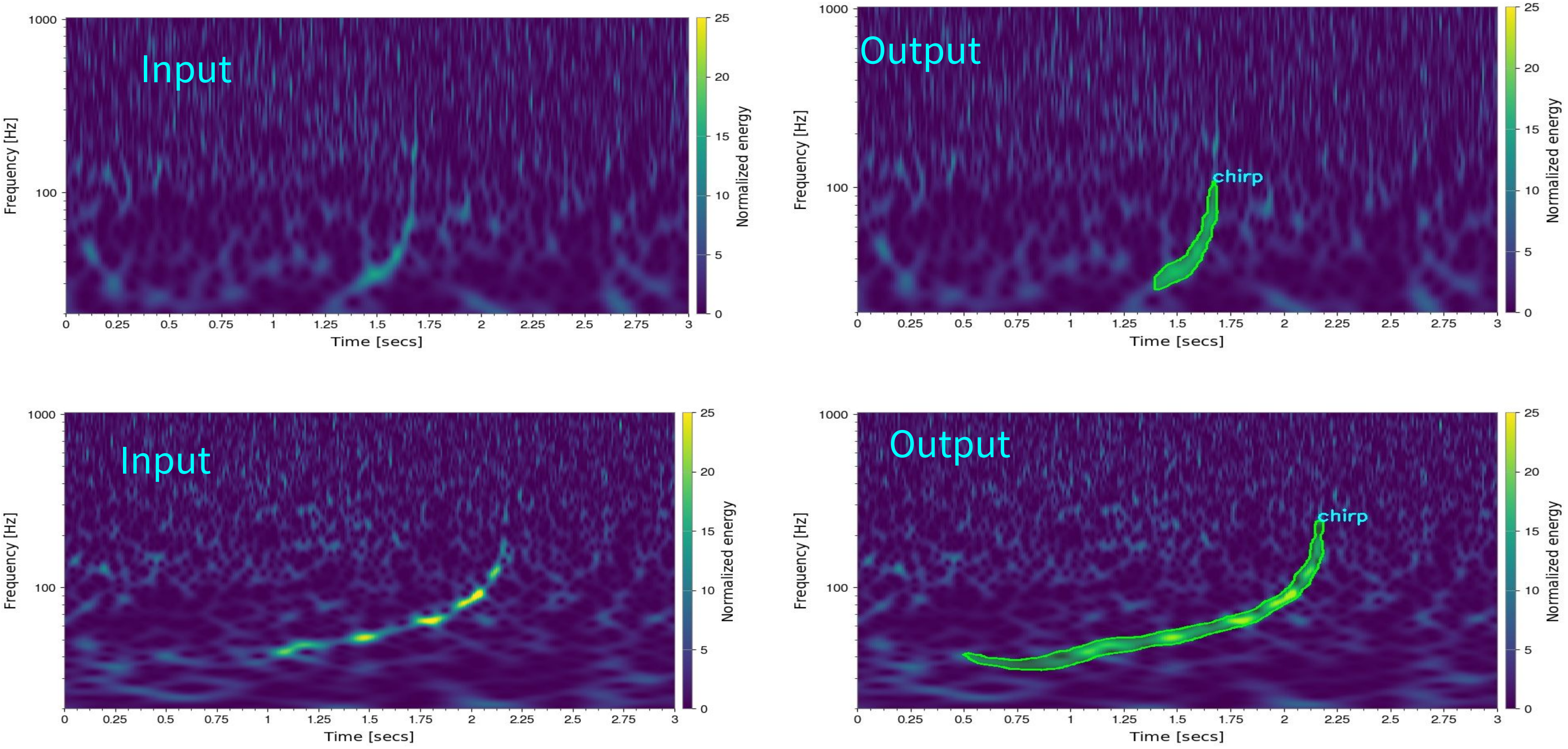


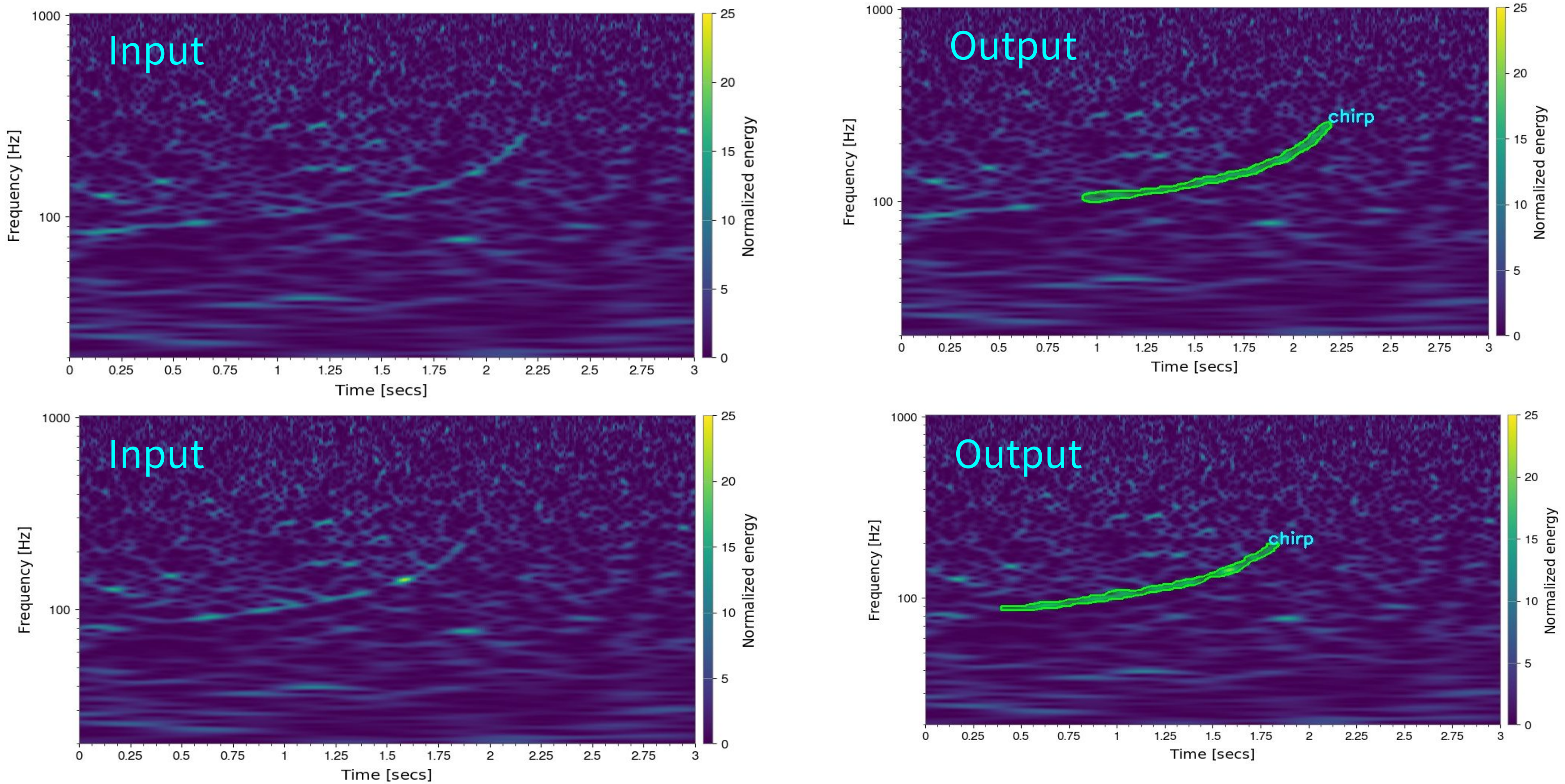
Image source

Example results (inference) : BBH chirps



Source: https://zenodo.org/records/5649212, https://zenodo.org/records/7890437

Example results (inference): BNS chirps



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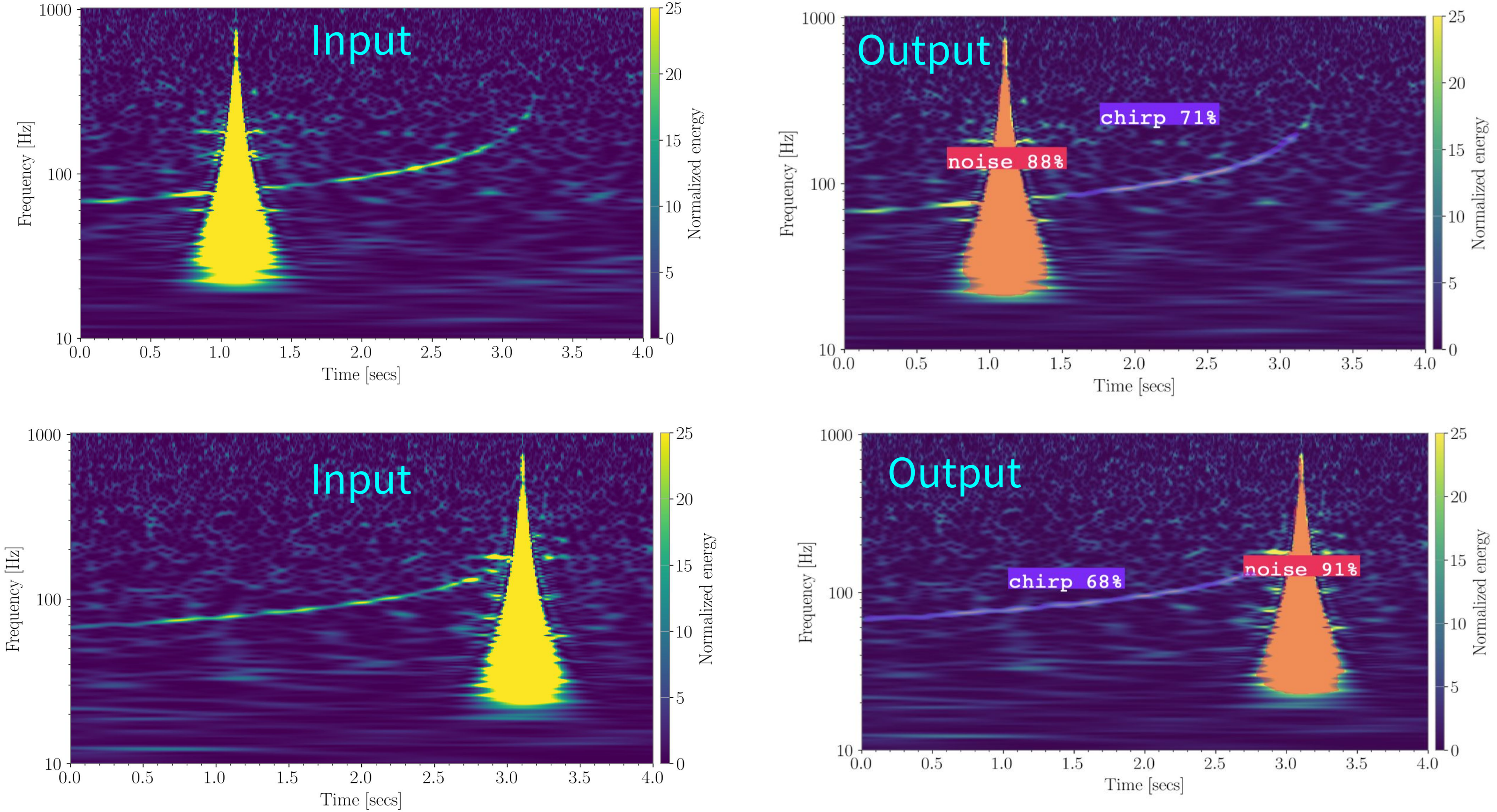
Example results (inference): Chirps + Glitch



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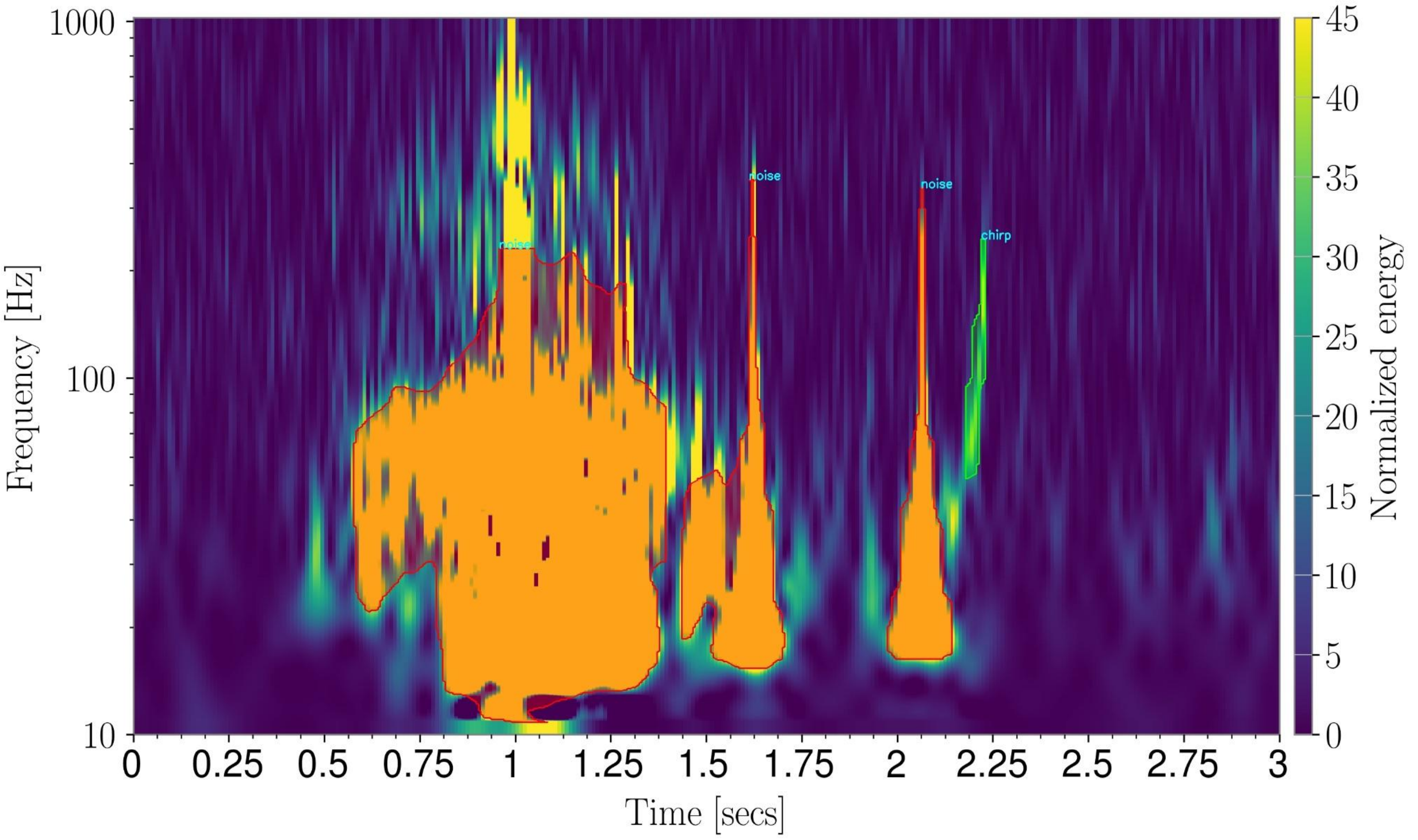
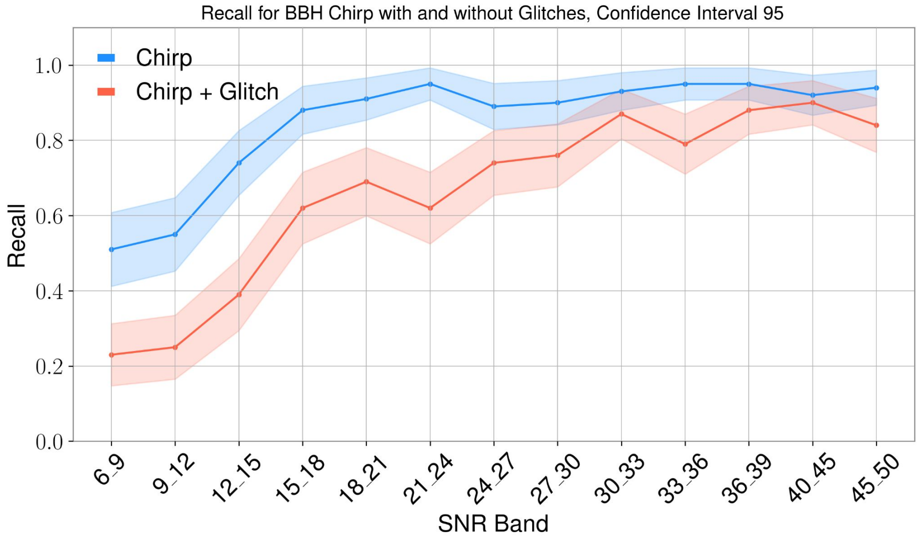


Source: https://zenodo.org/records/5649212, https://zenodo.org/records/7890437

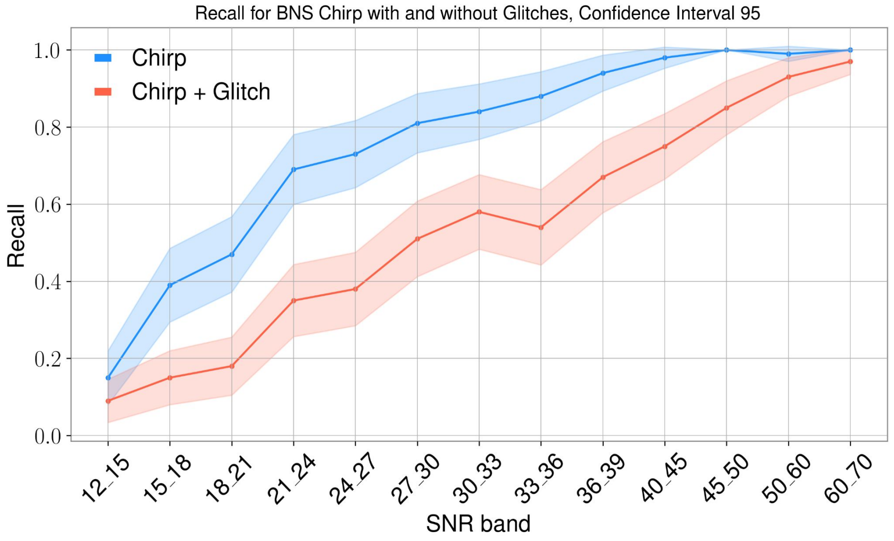
Large Sample Inference study

- Single-detector analysis (used LIGO-Livingston data only)
- BBH chirps from SNR 6 to 50 divided into multiple SNR bands
- BNS Chirps from SNR 12 to 70 divided into multiple SNR bands
- Glitch population is randomly sampled with SNR above 7.5 from O3 data
- Four datasets: BBH Chirps, BBH Chirps + Glitch, BNS Chirps, BNS Chirps + Glitch
- Measuring recall- what fraction of data is correctly classified as Chirp
- Around 1300 examples for better statistical results

BBH Study



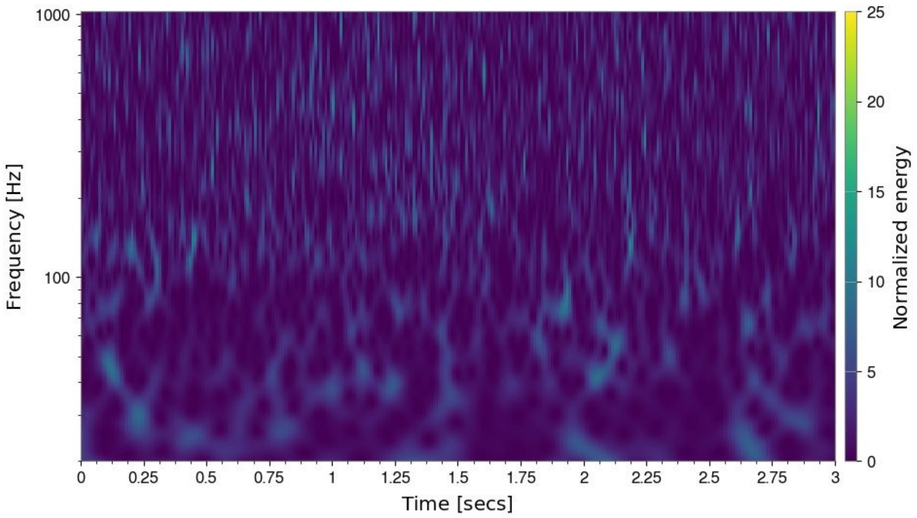
BNS Study

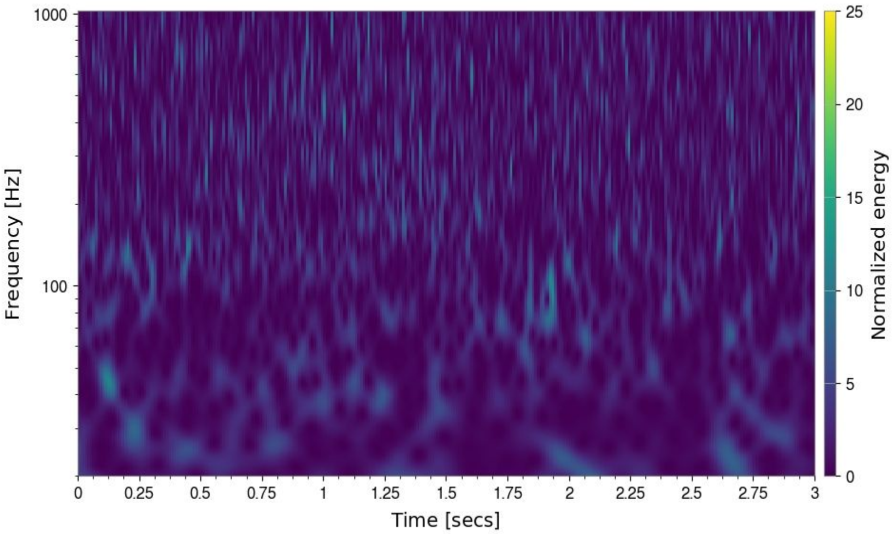


- Recall = TP/(TP + FN) : what fraction of data is correctly classified as Chirp

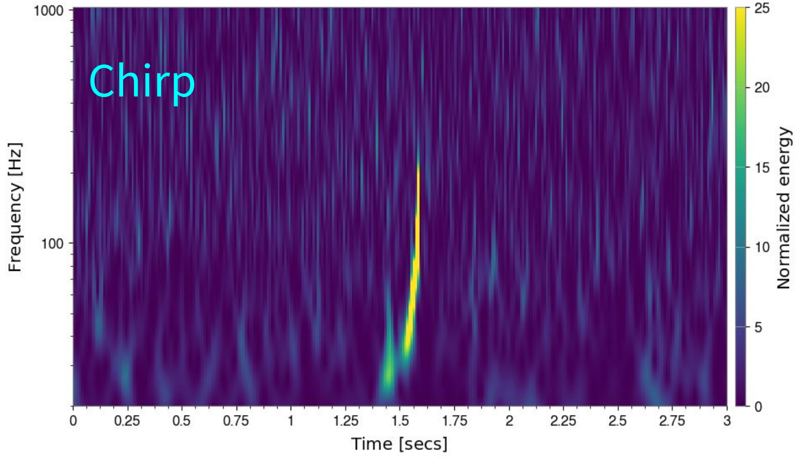
- Addition of glitches reduces recall
- Despite that, the model maintains a high level of performance

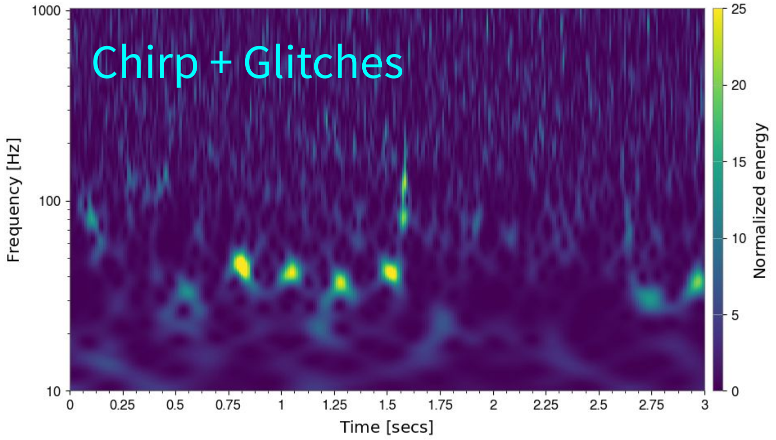
No chirp detected

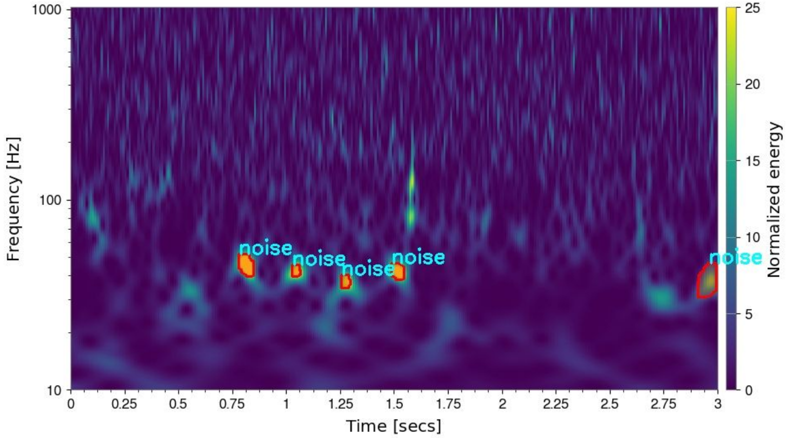




No chirp detected

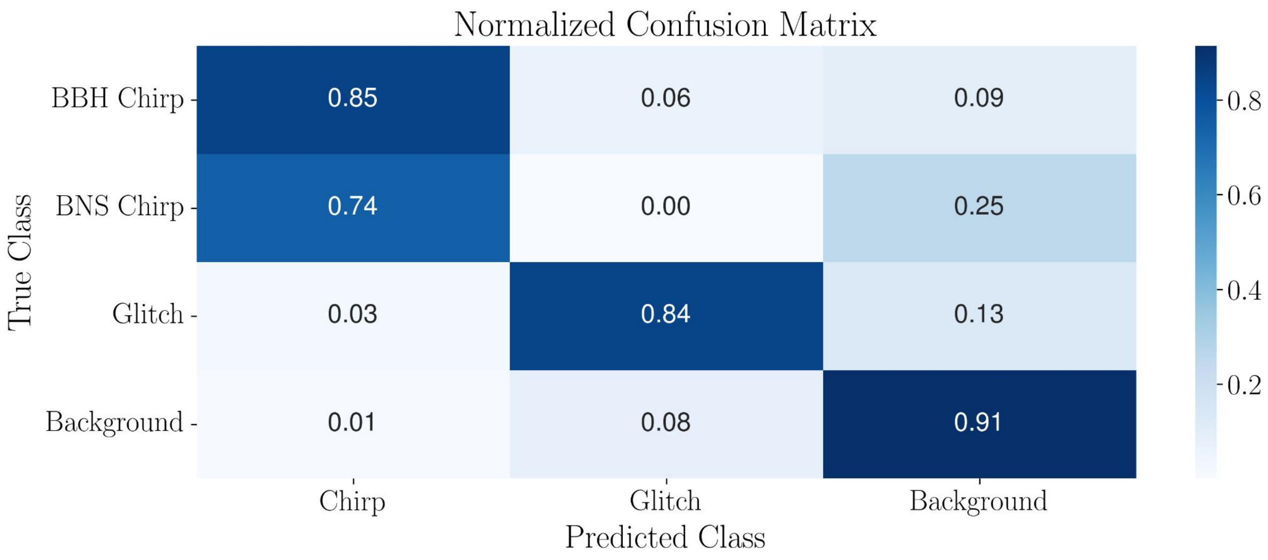




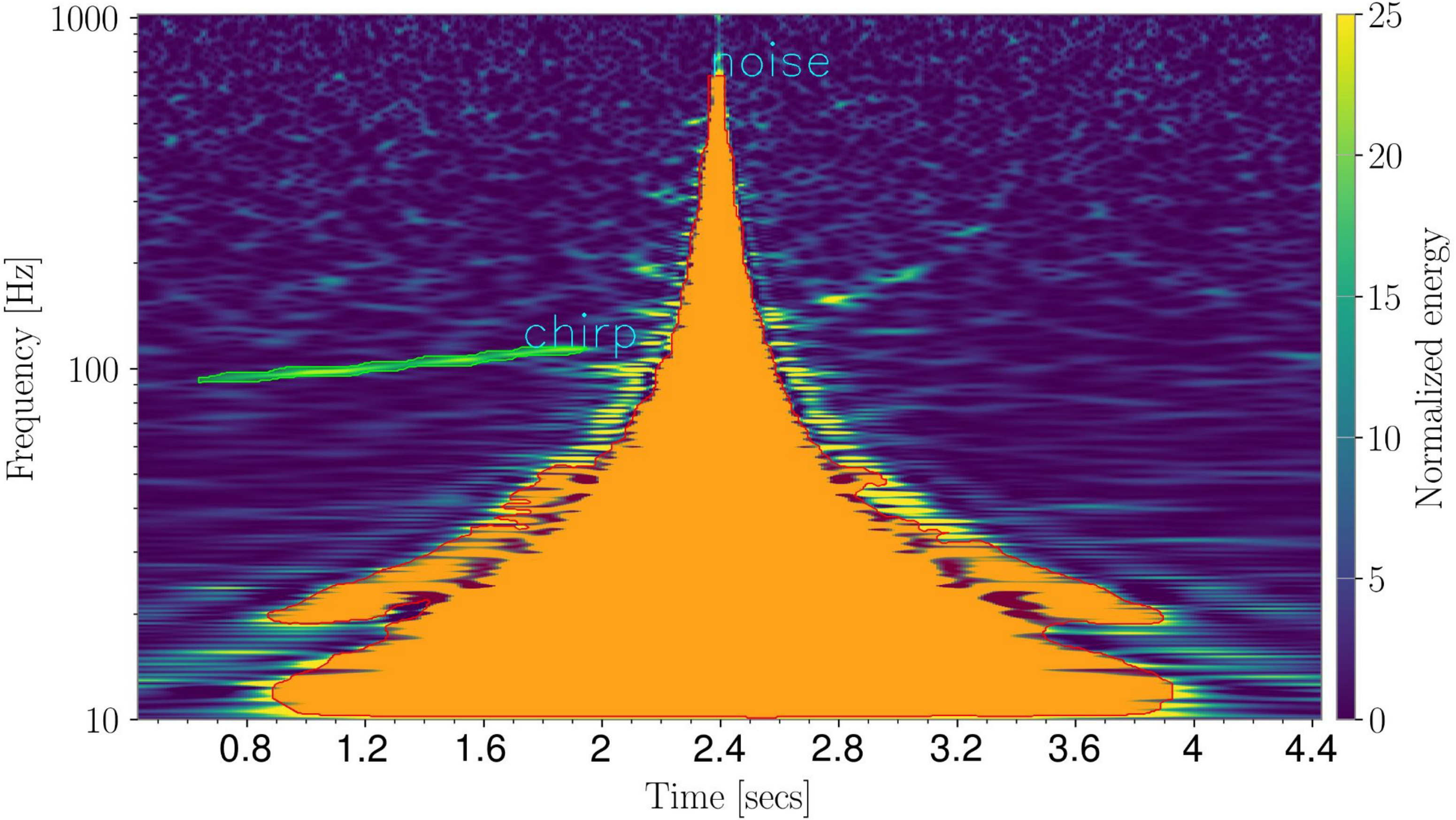


Confusion Matrix

- Previous plots show the ability of the model to identify chirps, given there are chirps in the data
- We also want to understand the general performance
- Background is defined as instrument data devoid of transient events (no signals or glitches)



Example inference: GW170817



Summary and Outlook

1. Image segmentation model can successfully **identify** and **localize** transient events in gravitational-wave Q-scan spectrograms
2. Method can **delineate transient events down to the pixel level**, providing analytic information for each one of them, including time-frequency localization/specification
3. **Multi-object identification** particularly powerful in gravitational-wave transient event analysis in the case of:
    a. signal + noise, e.g., binary coalescences in proximity/overlap with glitches
    b. multiple signals occurring in close proximity, e.g., high rate of binary events resulting to almost overlapping events, lensing events
4. Algorithm can **run at near zero-latency**, once Q-transform and YOLO pass data completely in memory (currently intermediate file I/O is used)
5. Method effectively **replaces human(eye)-in-the-loop for at-scale applications**; offers quantitative statements, accompanied by efficiency and false alarm rates associated with them that can assist in:
    a. noise mitigation by offering improved localization of transient noise near the signal thus leading to automated noise subtraction
    b. overall efforts for automating Gravitational-Wave event validation

References

1. YOLO: https://arxiv.org/abs/1506.02640
2. Ultralytics: https://www.ultralytics.com/
3. GW170817: https://arxiv.org/abs/1710.05832
4. Q-transform: https://dspace.mit.edu/handle/1721.1/34388
5. LIGO Detector Characterization in the first half of fourth Observing run: https://arxiv.org/abs/2409.02831
6. O3 Injections Dataset: https://zenodo.org/records/7890437
7. PyCBC: https://pycbc.org
8. Noise dataset: https://zenodo.org/records/5649212

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Thank You!
Questions?

Extra Slides

YOLO Model Architecture

BackBone

Extract features from input: edges textures, shapes

Summarizes “what” is “where”

Neck

Acts as a bridge between Backbone and Head

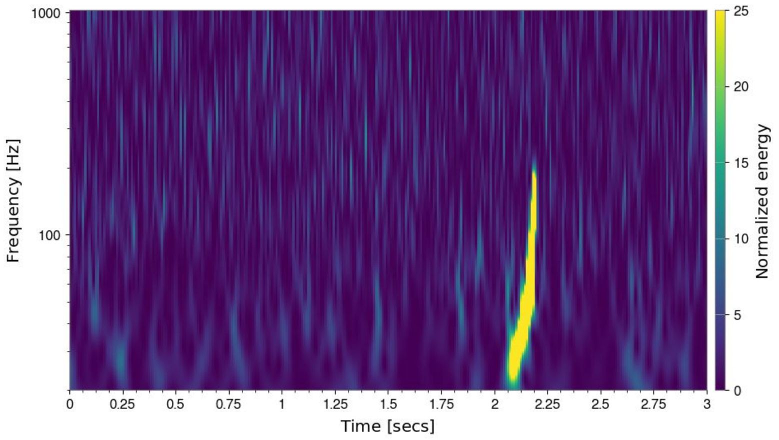
Provides contextual information

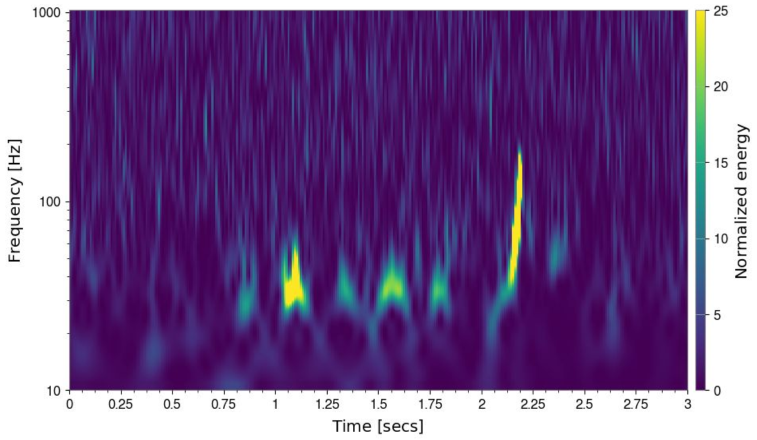
Merges information of different size features

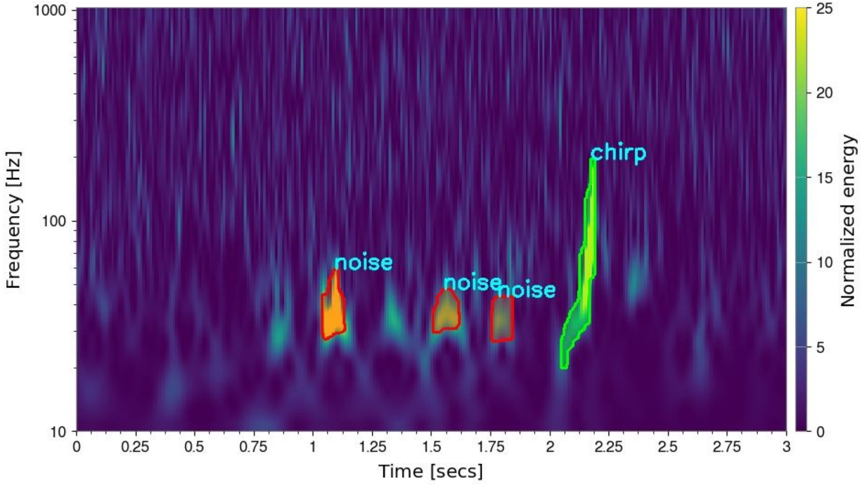
Head

Generates network outputs: bounding boxes, pixel masks, class labels

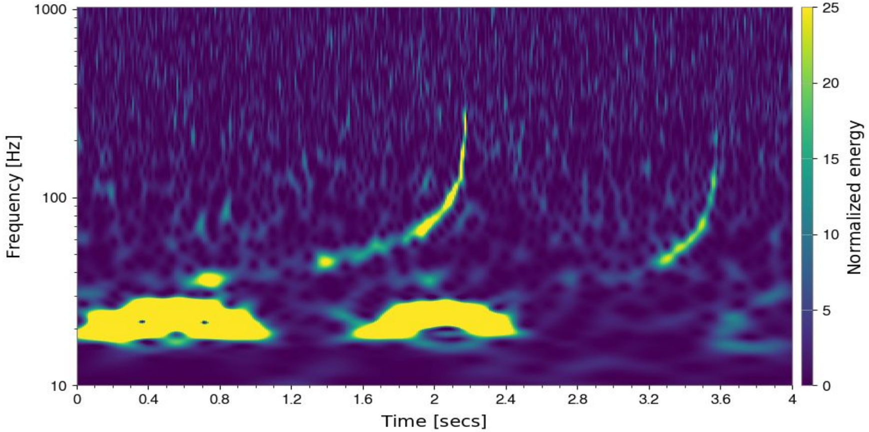
Transforms the feature maps prepared by Neck and Backbone into detections

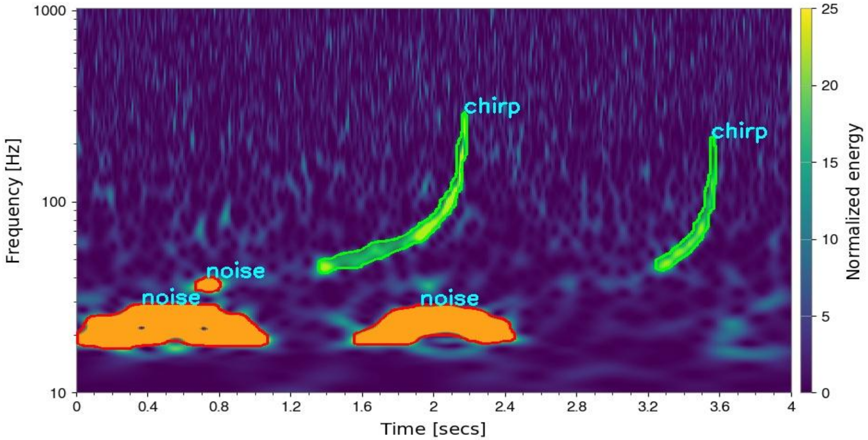

Frequency [Hz]
Time [secs]
Normalized energy

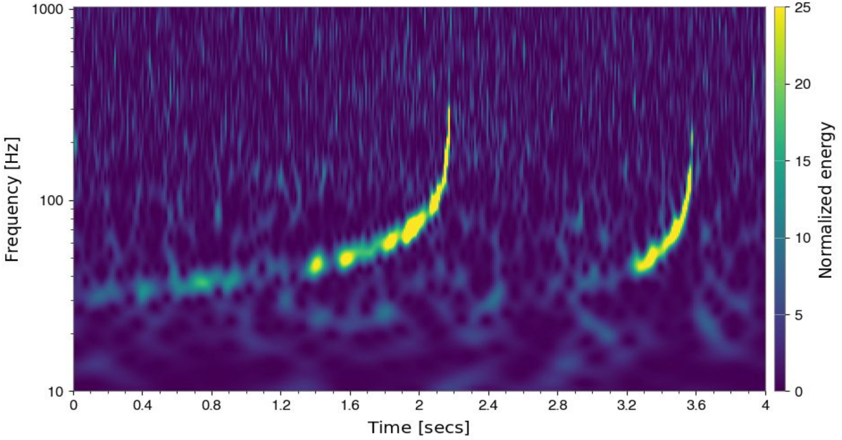

Frequency [Hz]
Time [secs]
Normalized energy

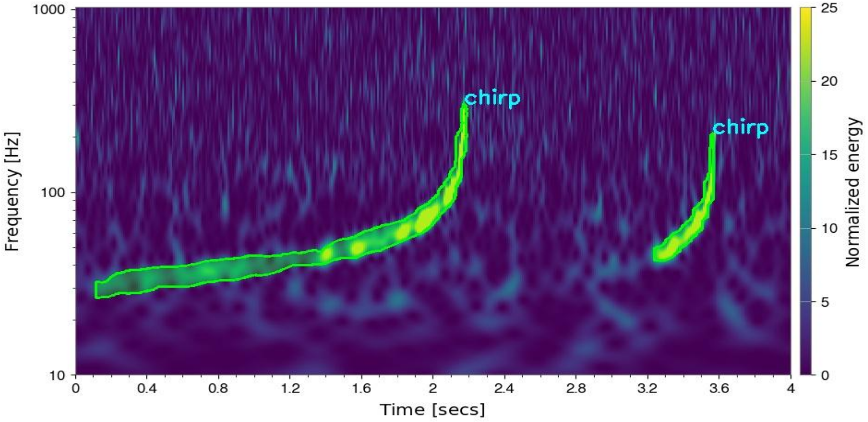

noise
noise
noise
chirp
Frequency [Hz]
Time [secs]
Normalized energy

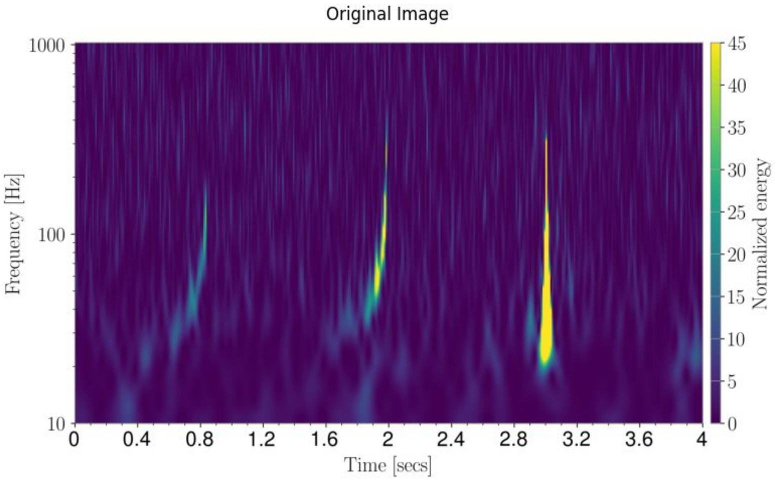
Multiple Chirps + Noise

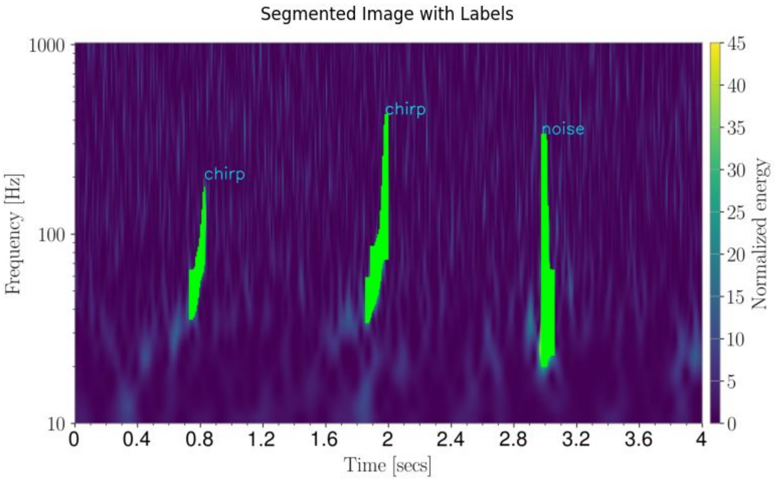









Original Image
1000
100
10
Frequency [Hz]
0
0.4
0.8
1.2
1.6
2
2.4
2.8
3.2
3.6
4
Time [secs]
45
40
35
30
25
20
15
10
5
0
Normalized energy


Segmented Image with Labels
chirp
chirp
noise
1000
100
10
Frequency [Hz]
0
0.4
0.8
1.2
1.6
2
2.4
2.8
3.2
3.6
4
Time [secs]
45
40
35
30
25
20
15
10
5
0
Normalized energy