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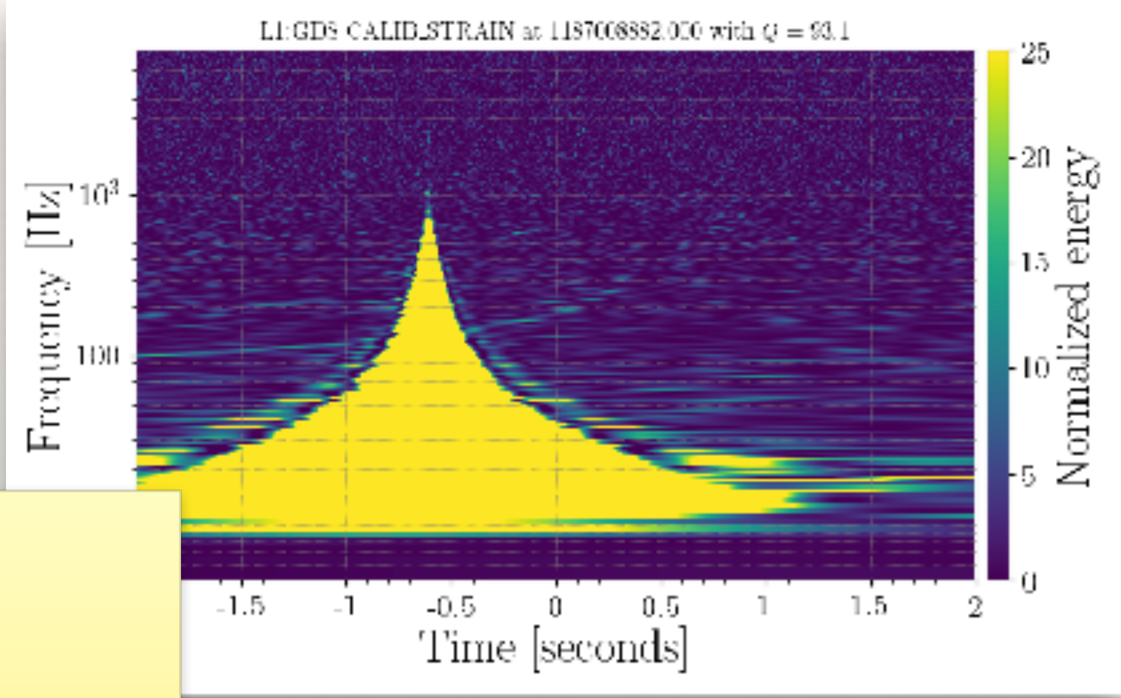
Sub-Classification of Blip Glitches

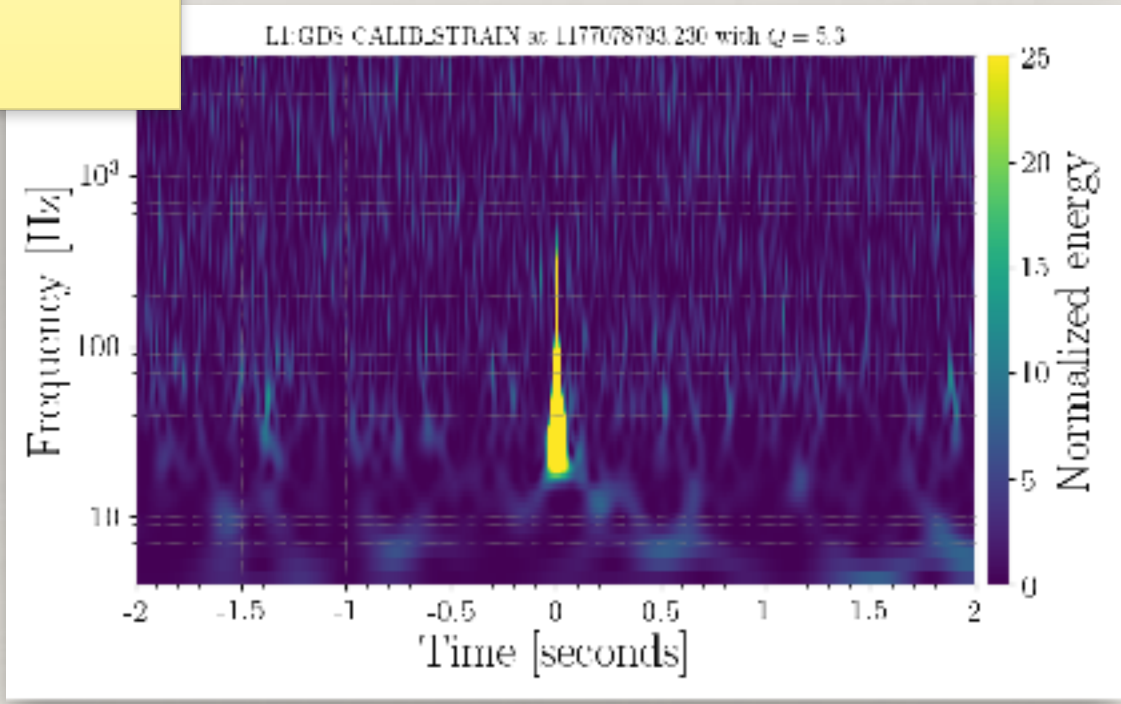
Using Q-Transforms and Convolutional Neural Networks with GravitySpy

LIGO and Blip Glitches

- Glitches: transient noise in the calibrated strain data, often picked up by auxiliary channels
- All glitches can obscu signals, but blip glitch binary black hole mer match template signals
- The source of blip glitches is unknown
- Solution: sub-classification!

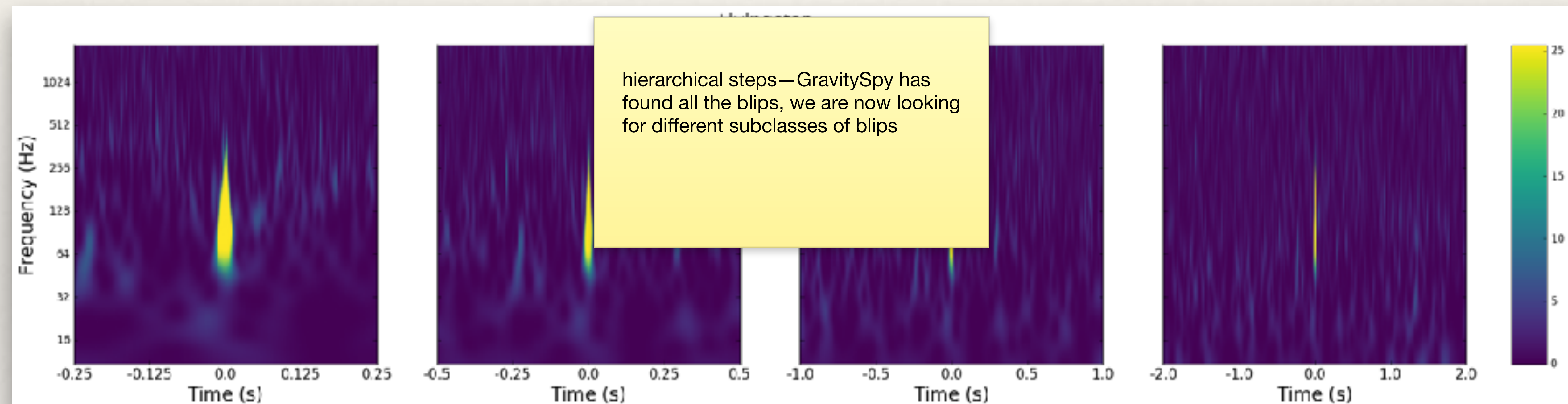
quickly explain images!!!





GravitySpy

- LIGO collaborators use multi-layer image classification techniques and GravitySpy, a machine learning software package, to classify glitches and find their sources



- GravitySpy is good at classification of blips but not at finding a source

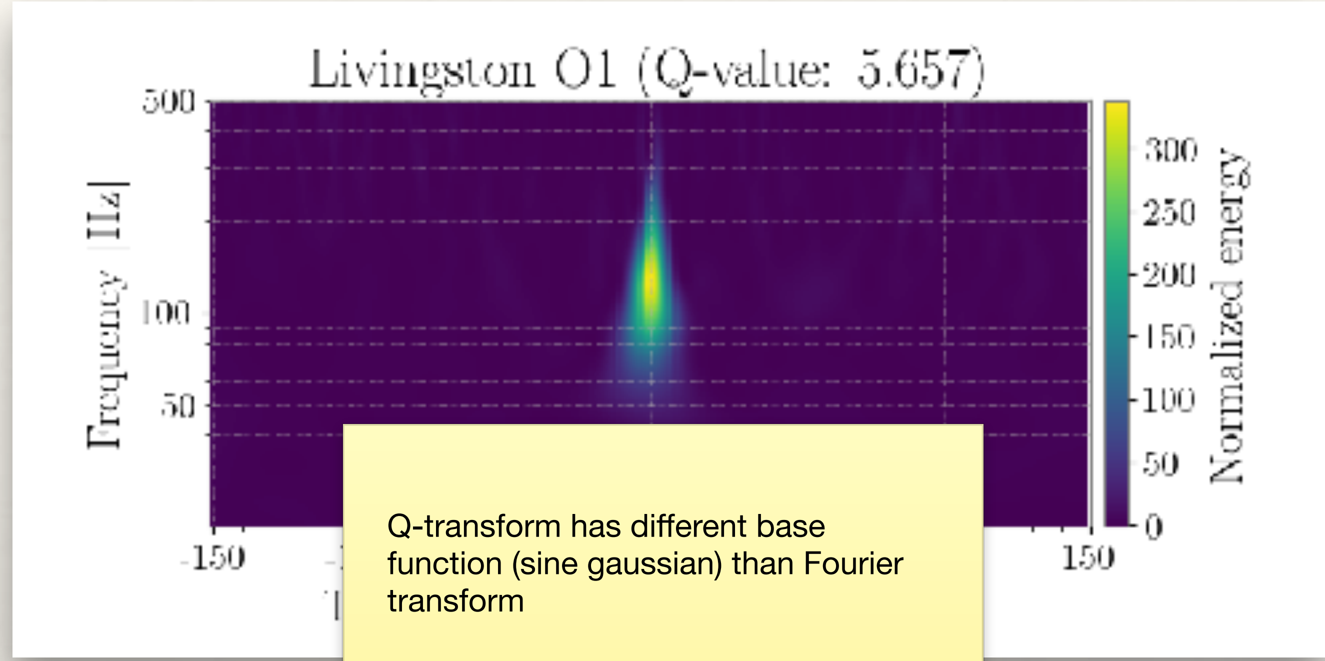
Summer Project Goals

- Create spectrogram images different than those produced by Omega Scans and GravitySpy to find possible subclasses

- Build Convolutional Neural Networks that can distinguish between subclasses

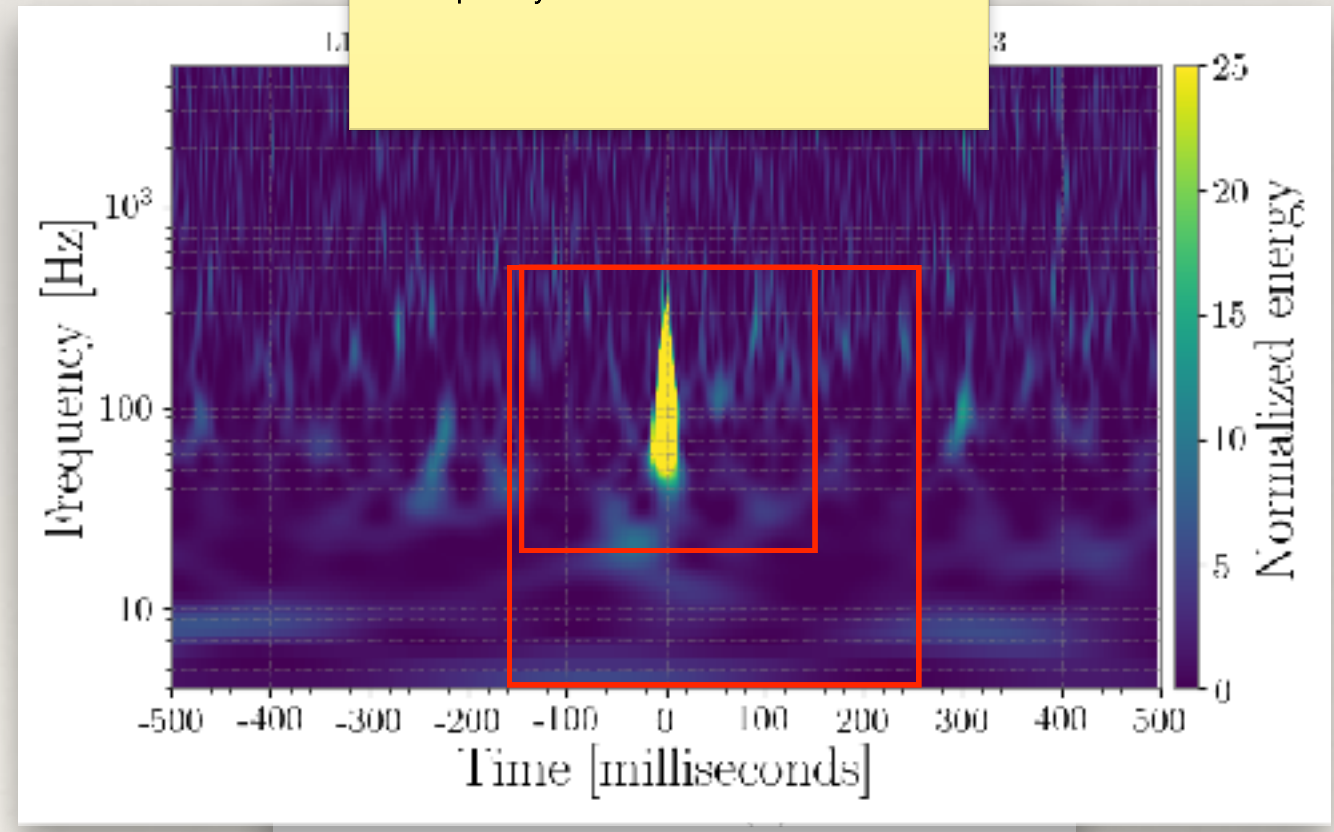
Creating Q-Transform Images

- Q-Transform: time-to-frequency transform more suited to short duration signals than the Fourier Transform
- I started by creating simple Q-Transform spectrograms, cropped to smaller time and frequency domains than GravitySpy and Omega Scans
- All parameters set to default other than the amount of raw strain data (20 surrounding seconds)



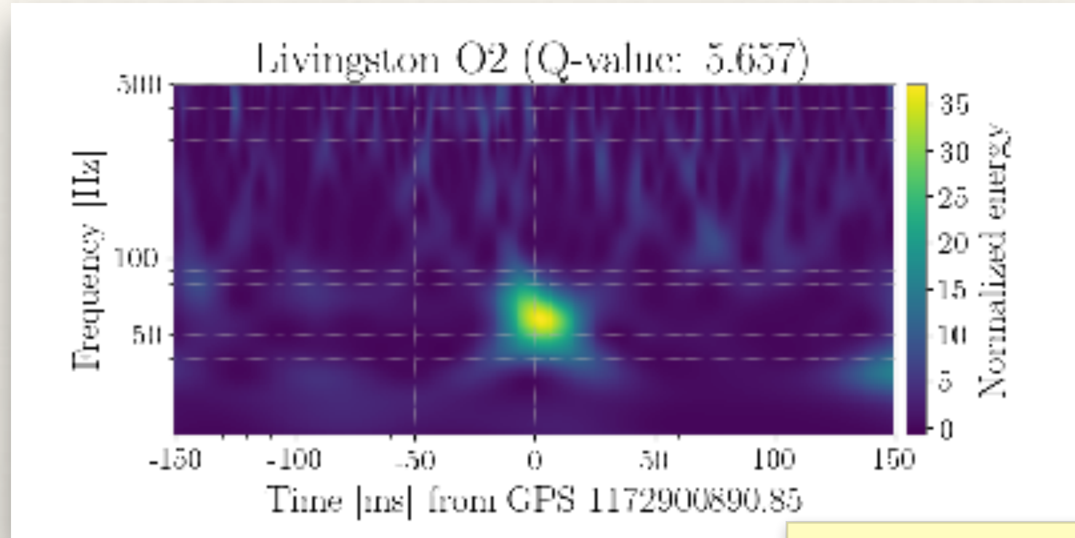
Q-transform has different base function (sine gaussian) than Fourier transform

Q: data quality factor—related to time complexity of transform

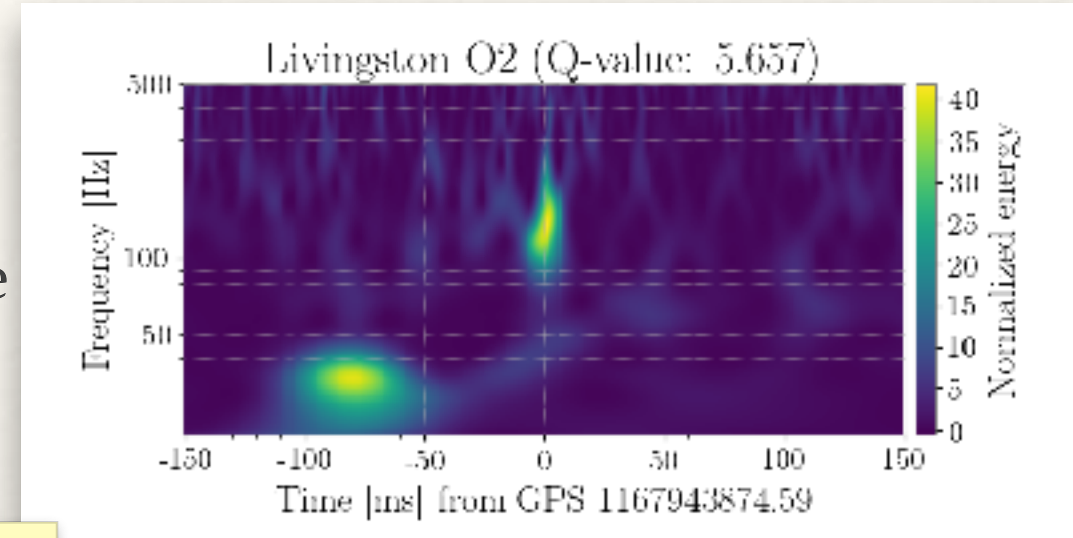


Discovery of Six Distinct Blip Shapes

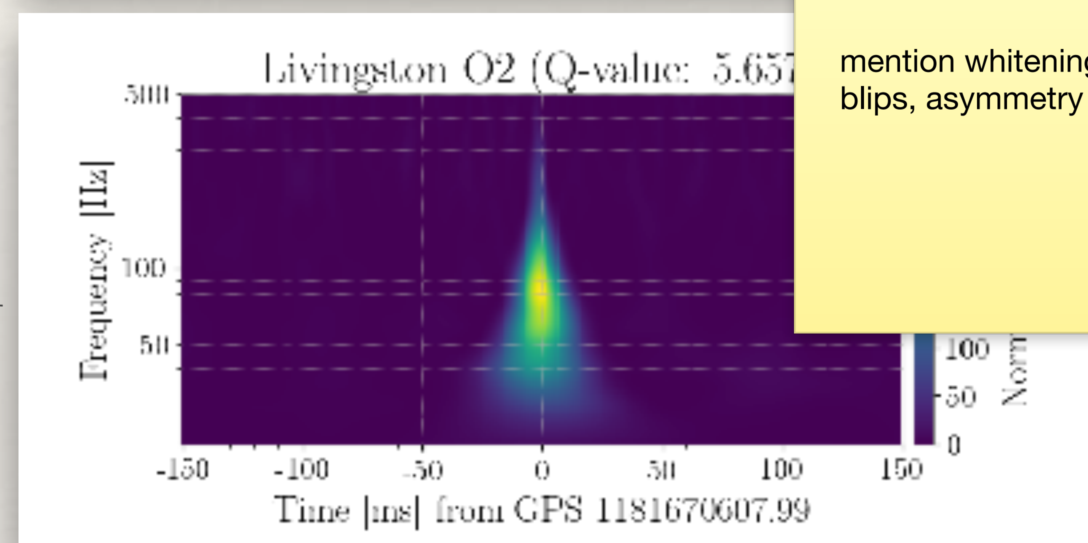
Dot



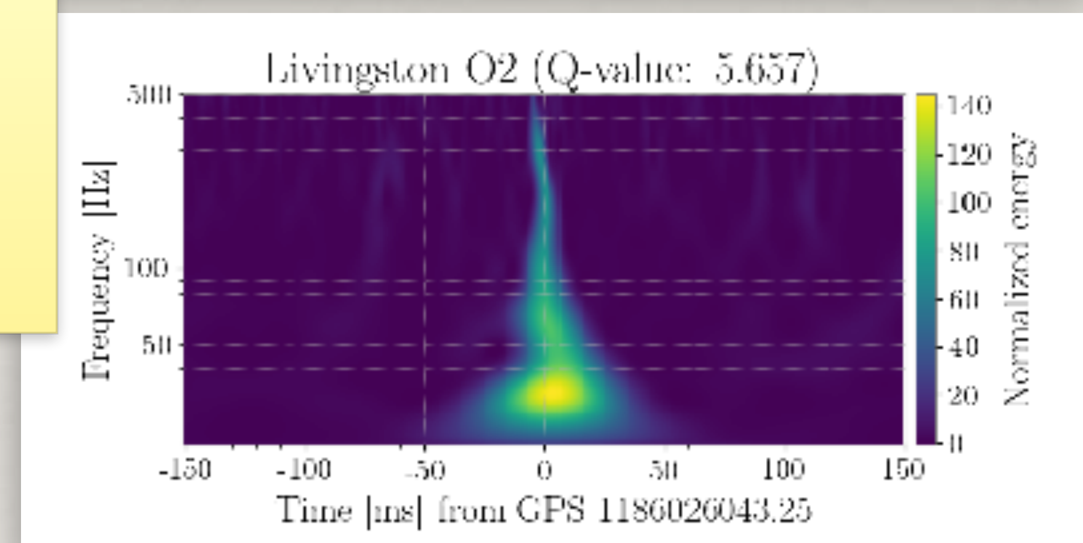
Double



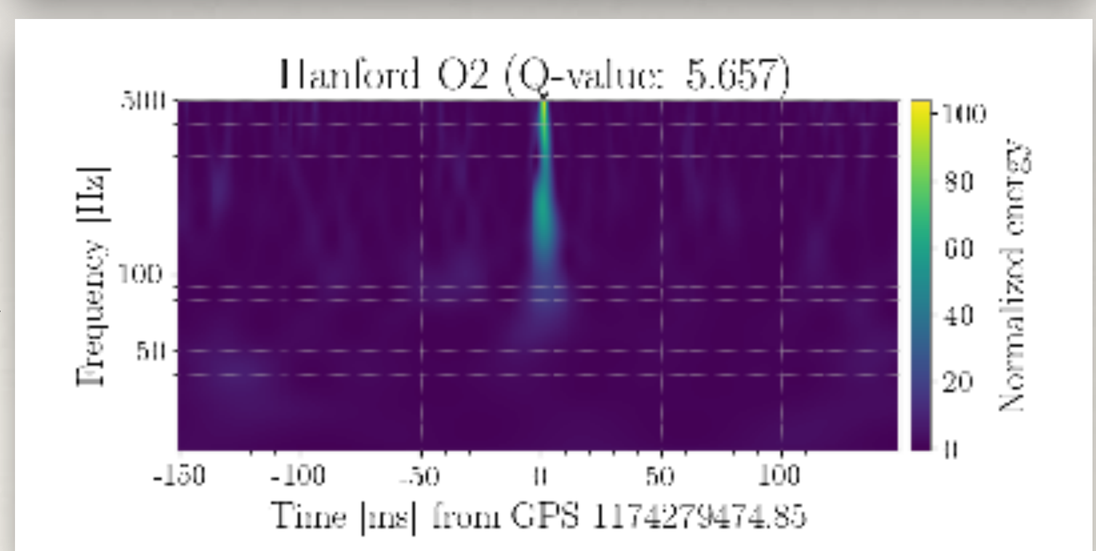
Normal



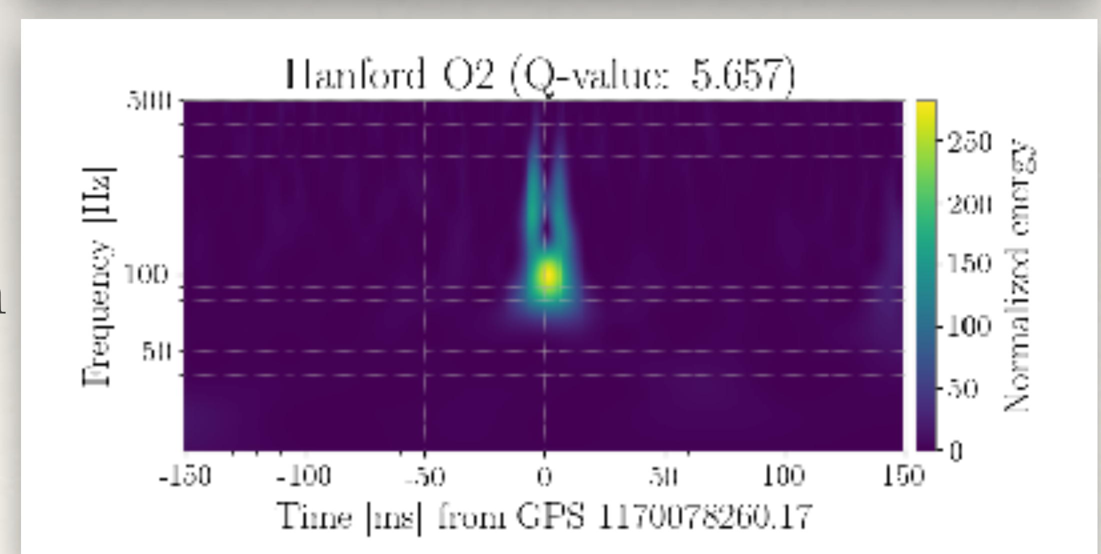
mention whitening artifacts in double blips, asymmetry in hat blip, and



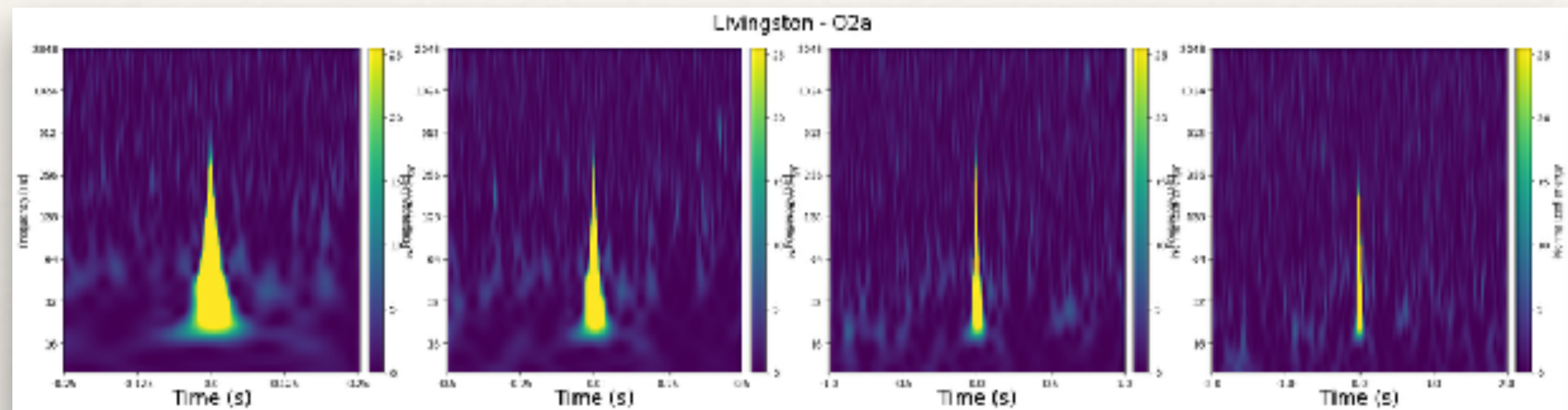
Stick

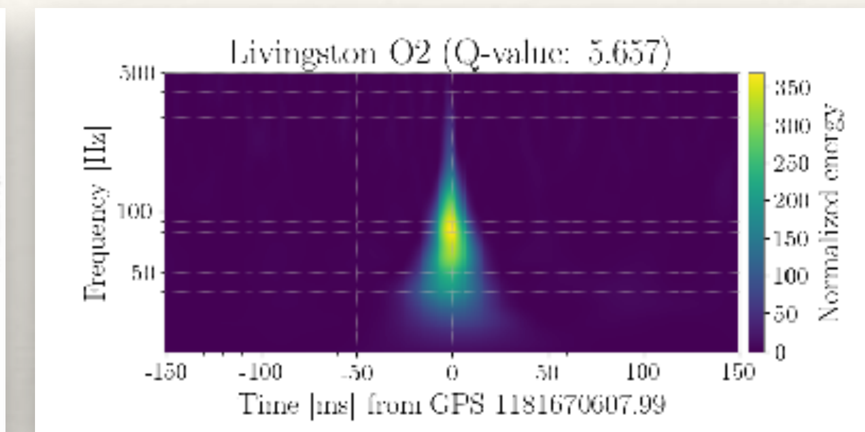


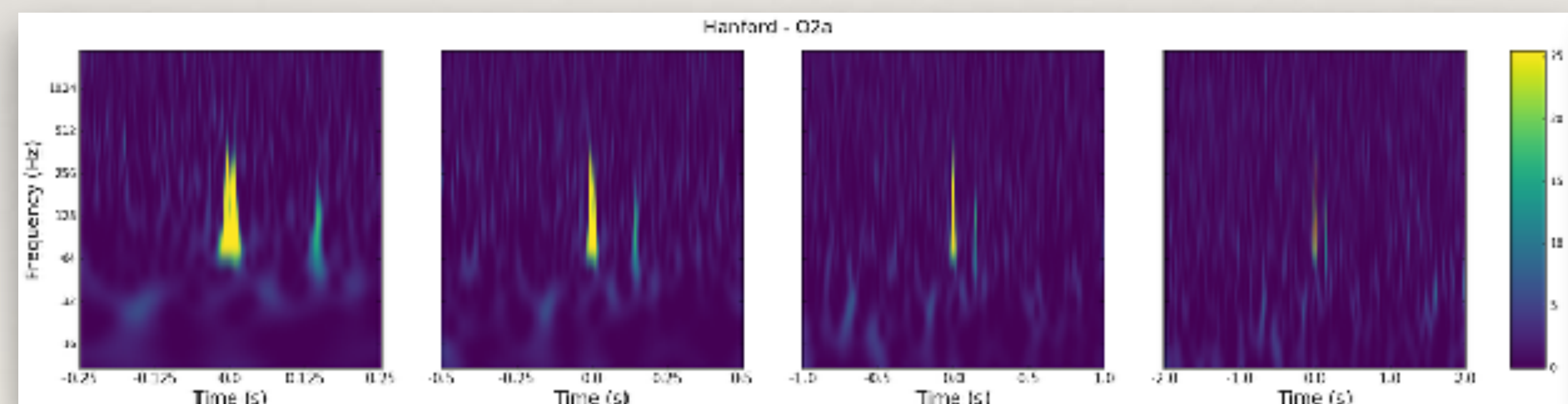
Snitch

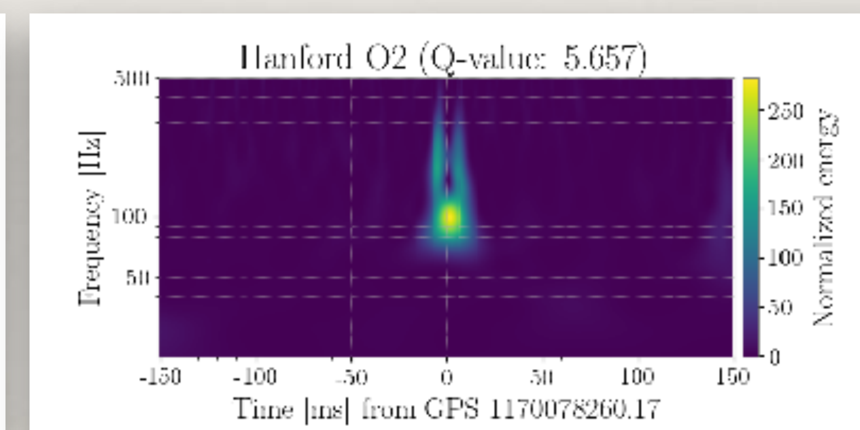


Comparison with GravitySpy Spectrograms



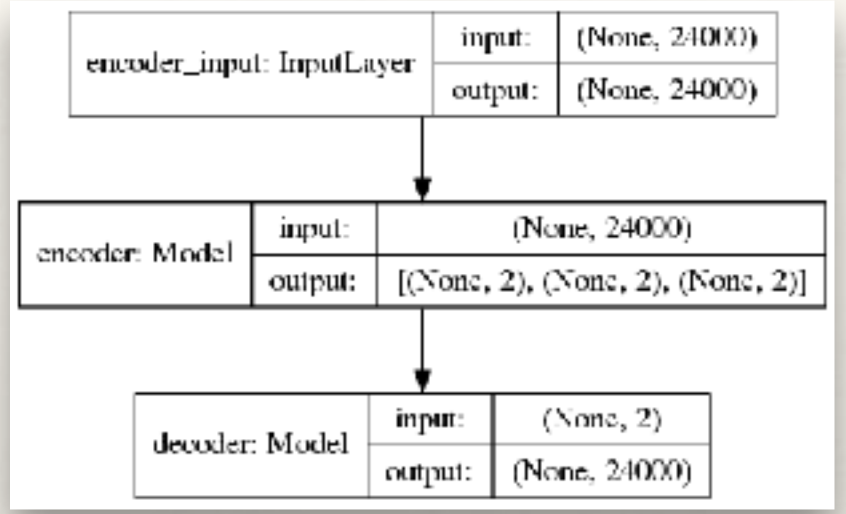


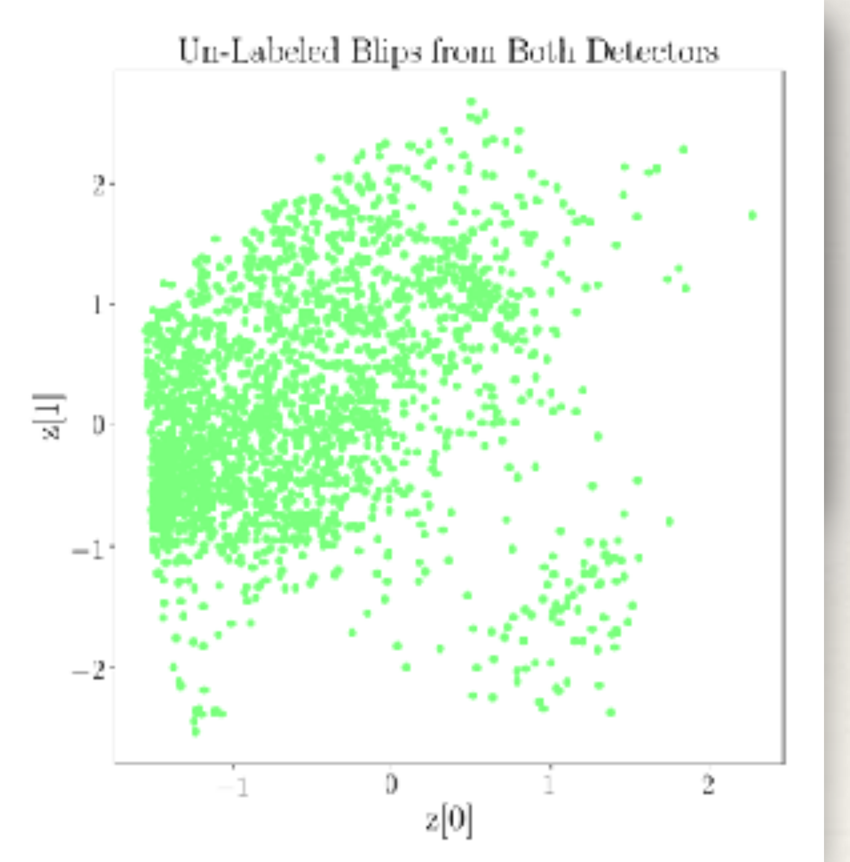




Unsupervised Learning: Variational Auto-Encoder (VAE)

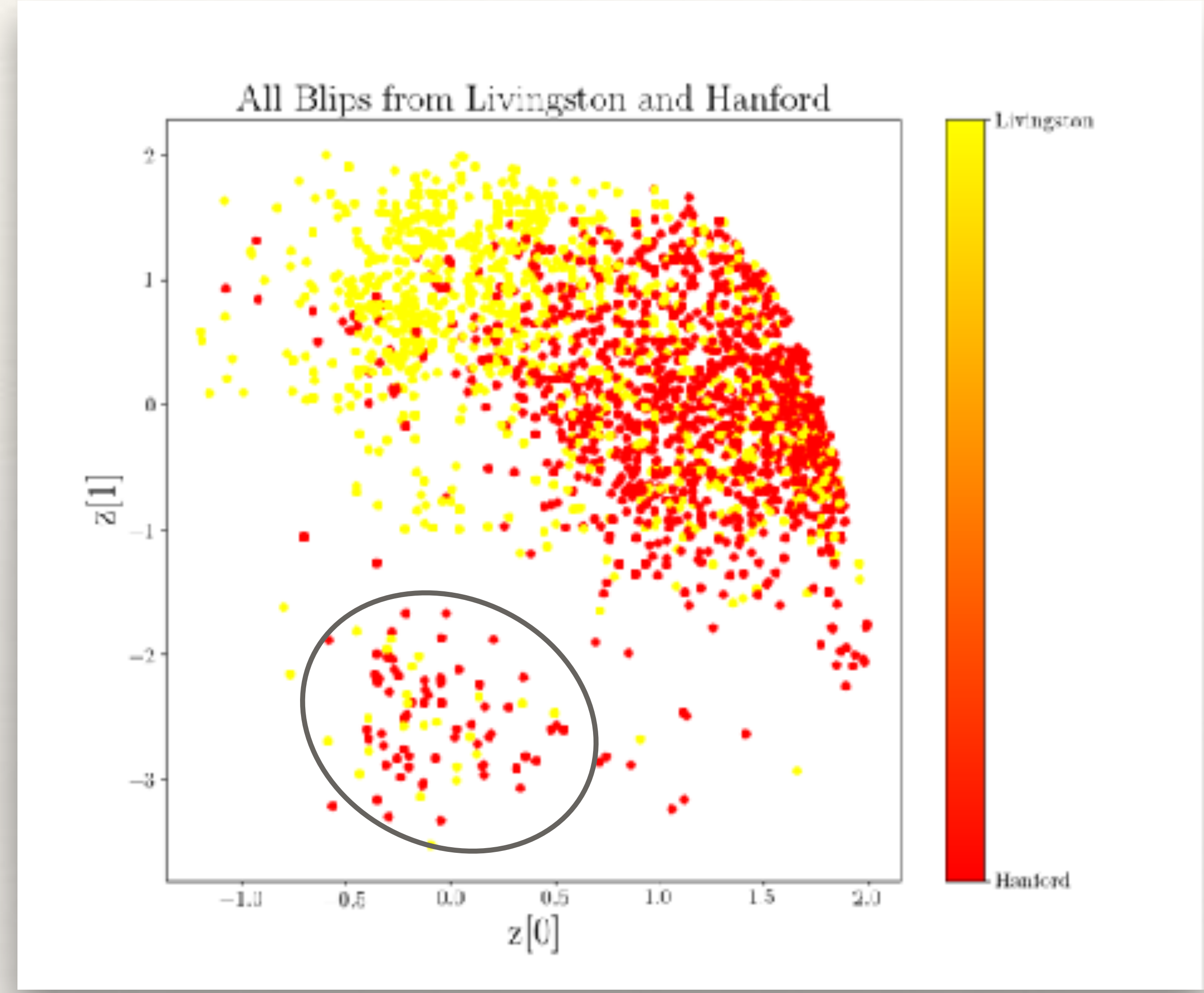
- How does a Variational Auto-Encoder work?
  - Put images through a convolutional encoder that outputs meaningful statistical values
  - Create a decoded image based on the statistical values
  - Train based on the similarity of the decoded image to the original
  - Put test images through the trained encoder
  - Create a scatter plot using the statistical values from the output of the encoder
- Images that are very similar to each other should cluster together

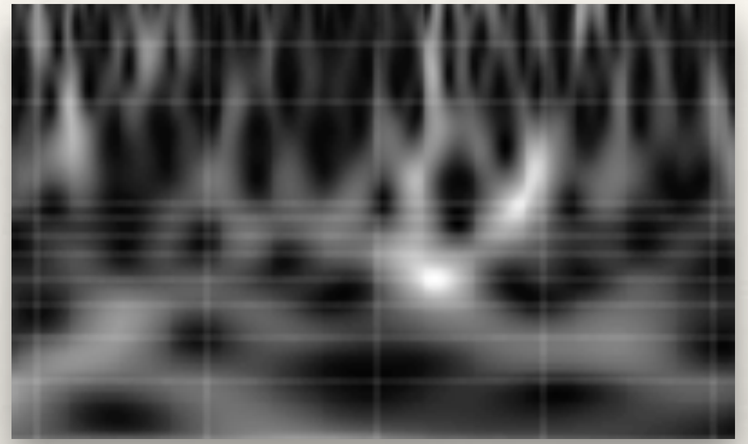


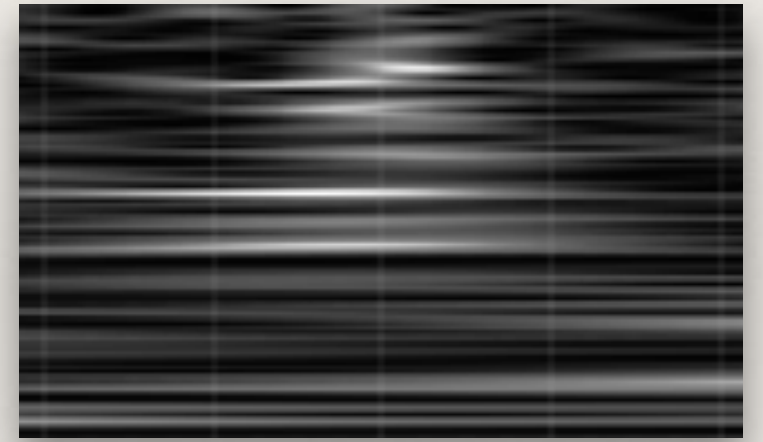


Variational Auto-Encoder Results

- Although training doesn't include labels, we can still label the test data however we want

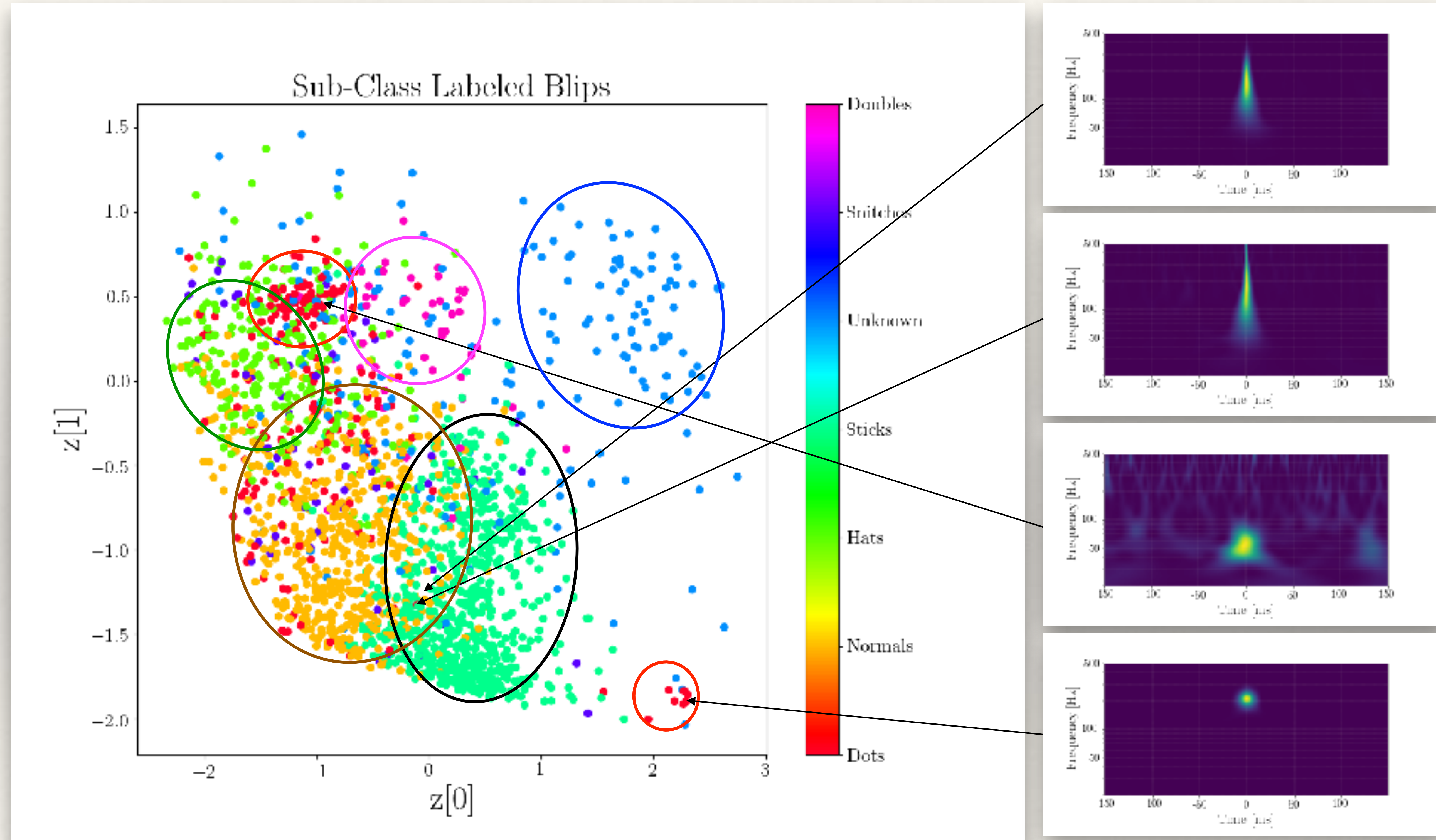






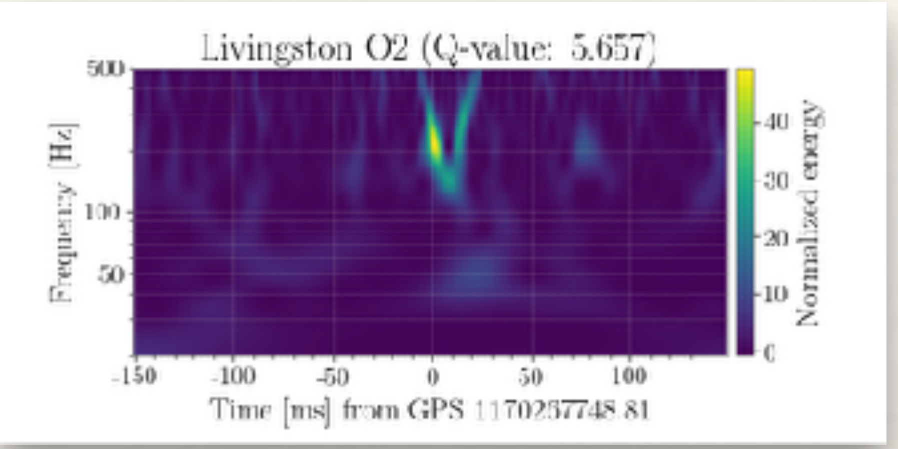
- Hanford and Livingston appear to have some overlap, but this scatter further shows that the blips are different at each detector.
- Side cluster turns out to be images without clear signals

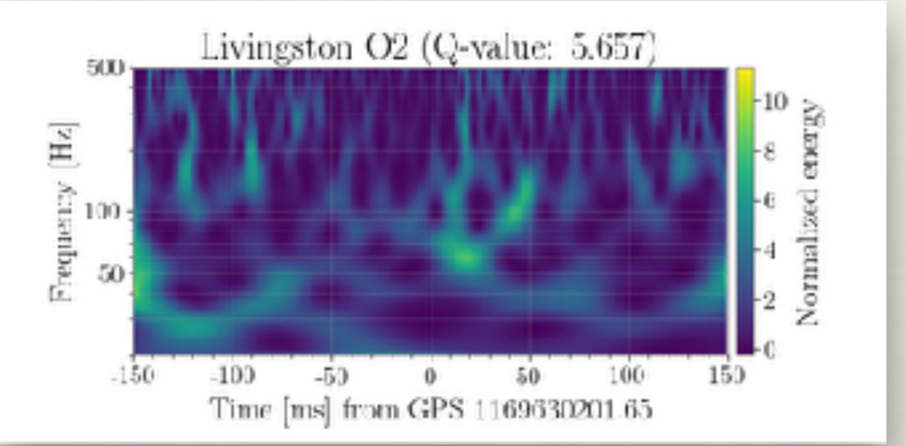
Sub-Class Labeled Blips

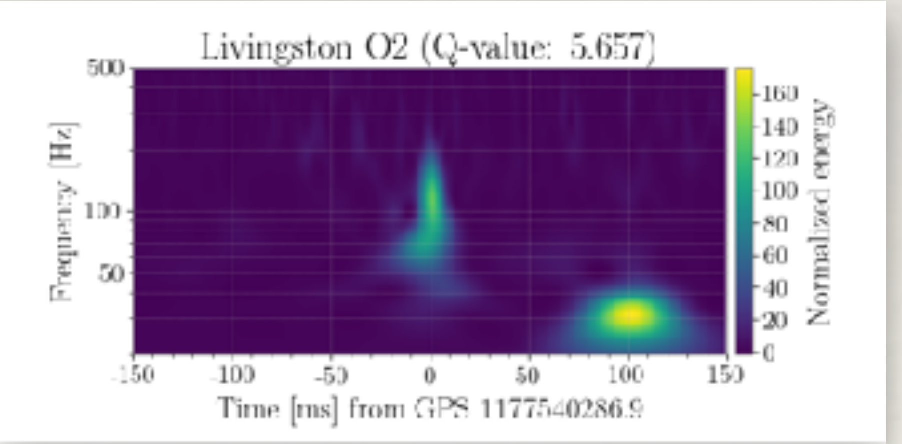


Future Work

- Re-examine sub-classes based on VAE scatter plots and saved neural network info
- Remake images
  - Larger frequency range
  - Resolve images with no signal
  - Change parameters on double-blips
- Implement multi-layer input and RGB images with the Variational Auto-Encoder





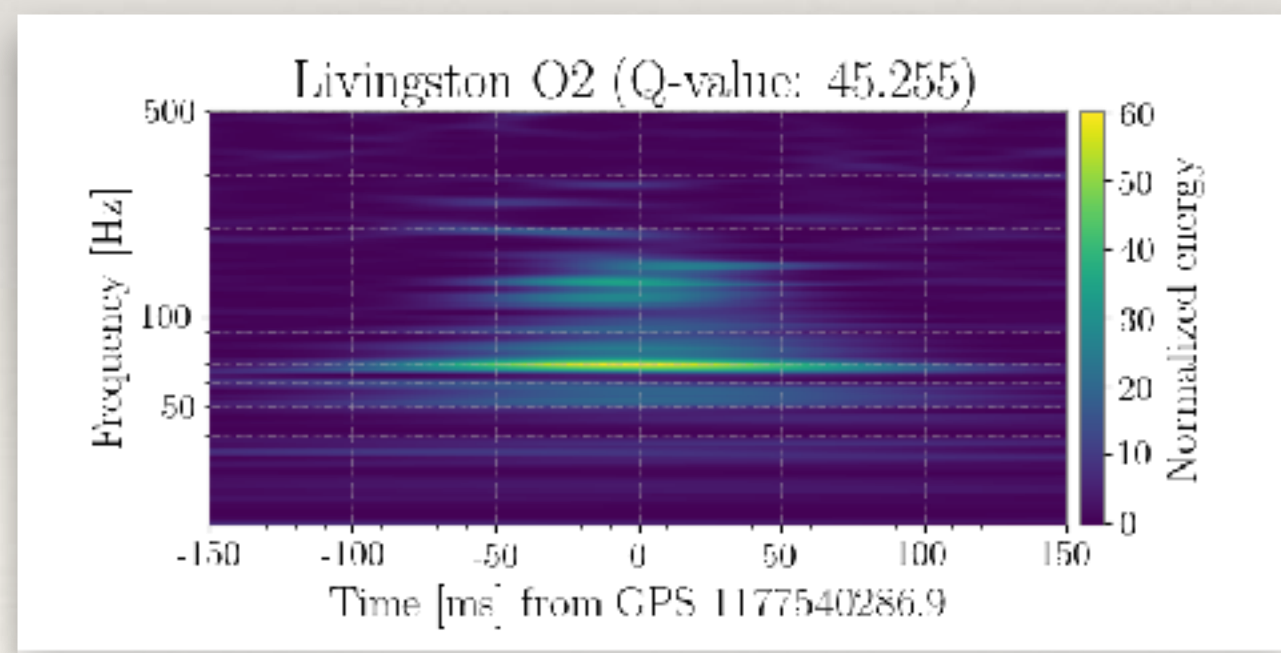


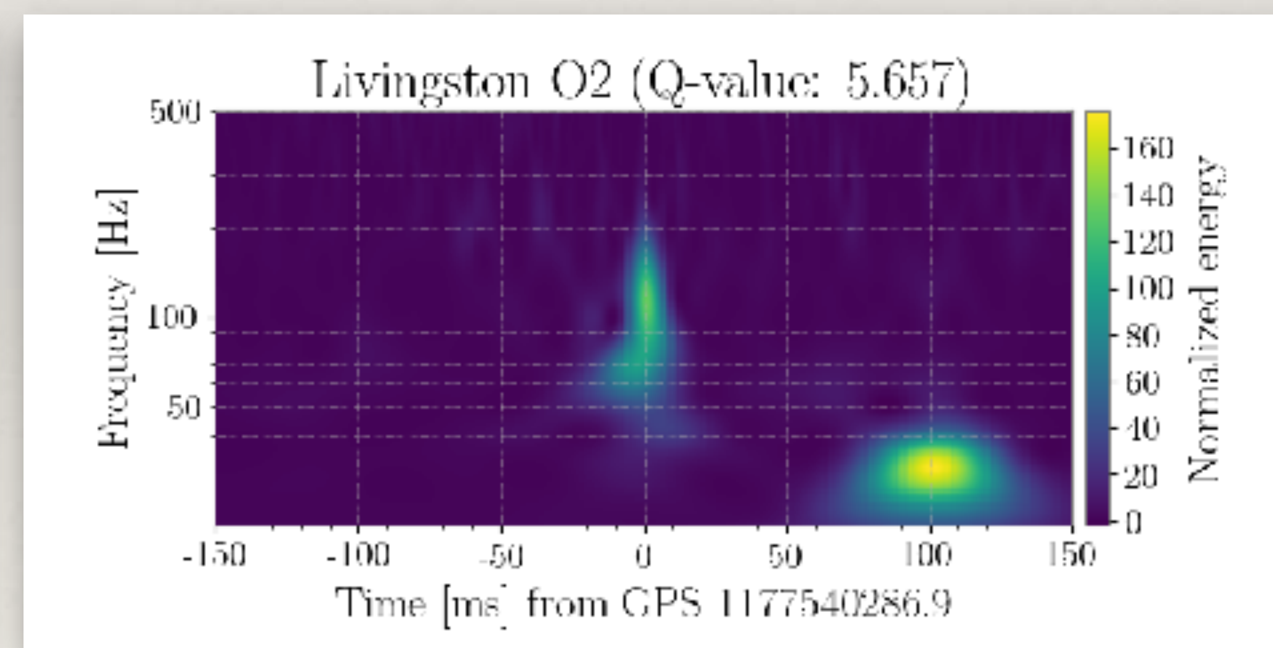
Acknowledgements

- Special thanks to Alex Urban, my mentor, and Scott Coughlin
- Caltech LIGO
- LIGO SURF

Spreading Effect

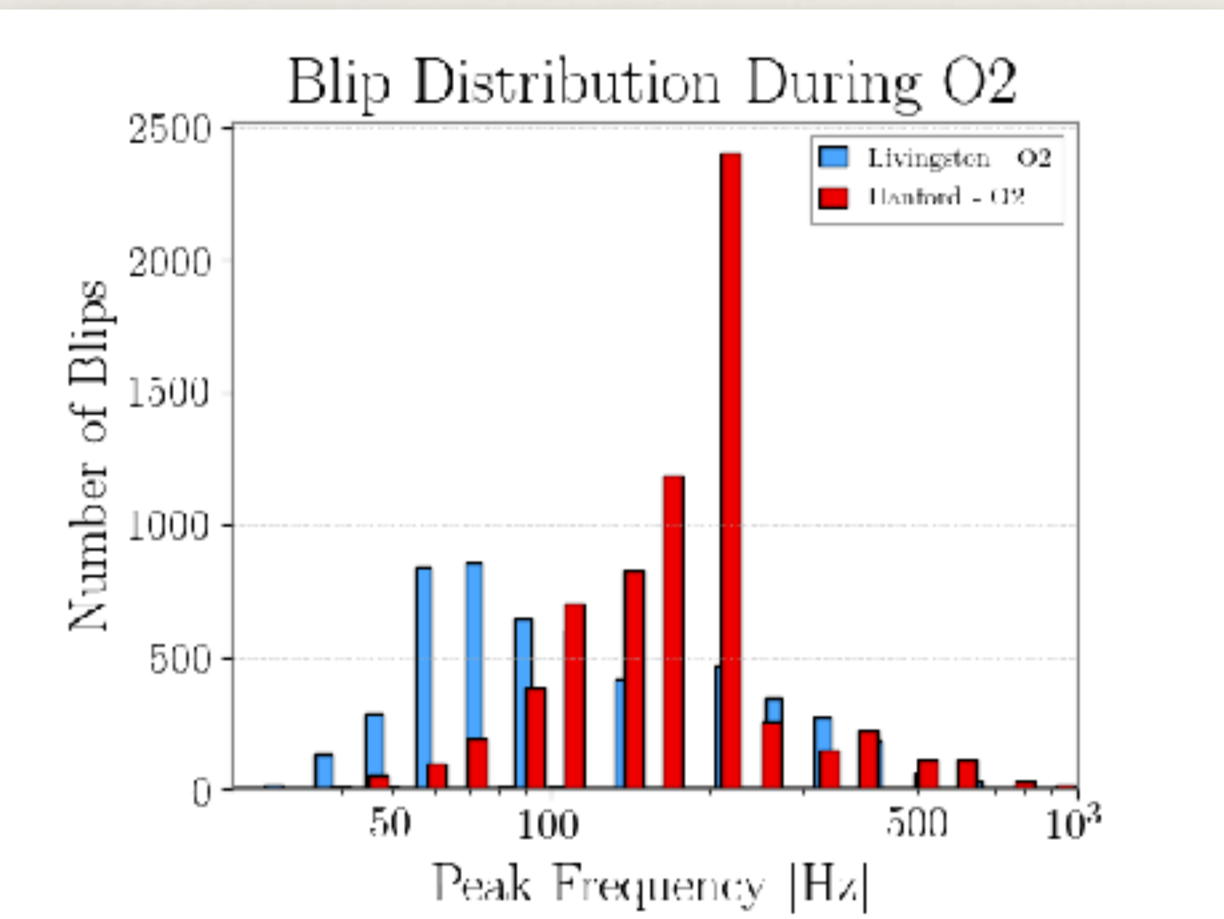
- The spreading in some non-signal images appears to be an effect of the Q-Transform, possibly indicating a problem with whitening or the specified Q-range
- Quick solution is to use 20 seconds of surrounding data instead of 30 seconds—resolves most spreads
- See my final paper for specifics on spreading

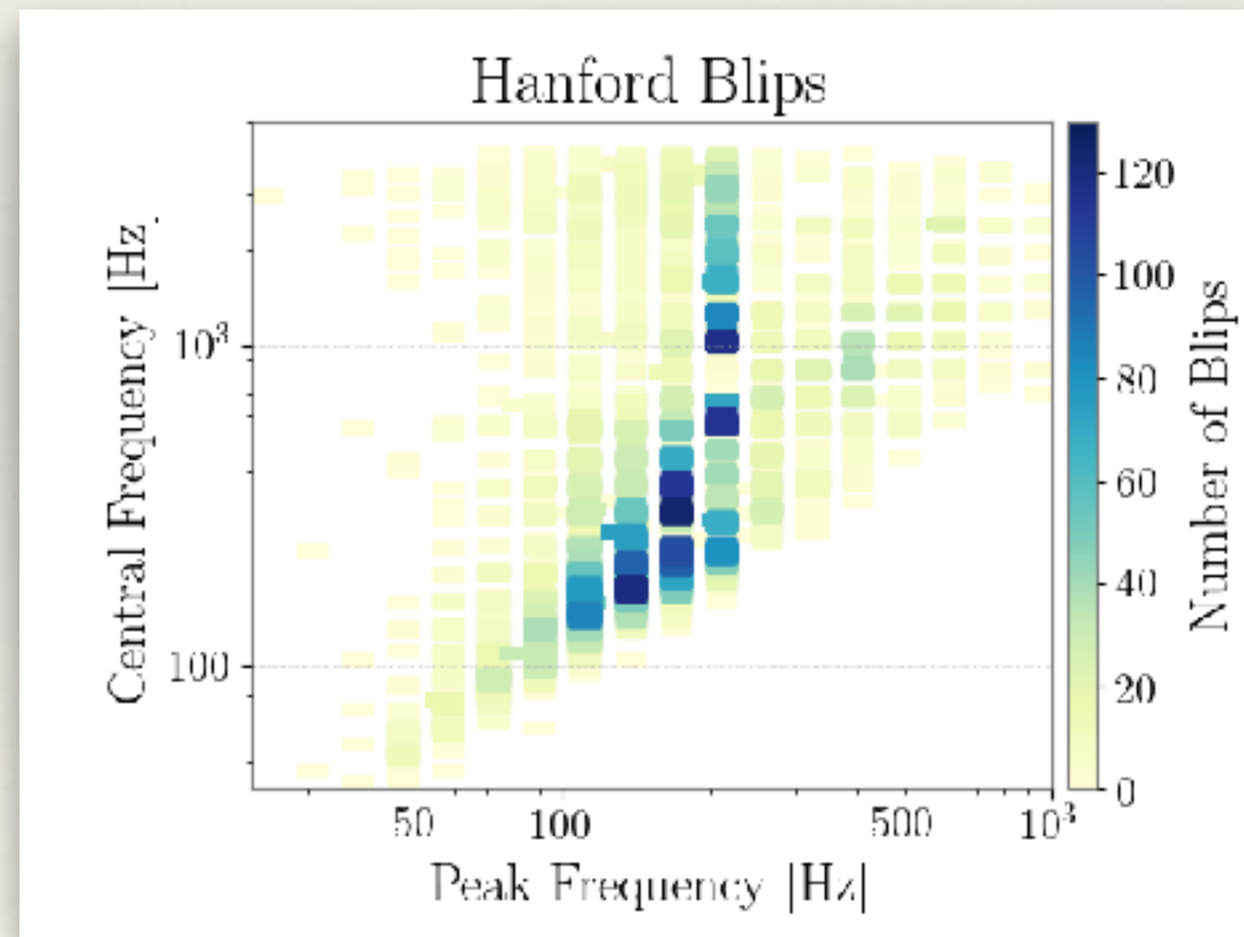




Trends in Blip Attributes

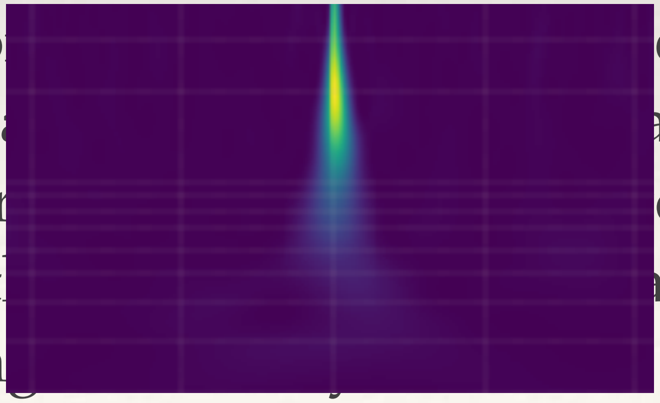
- Each glitch has saved data, including peak frequency, Signal to Noise Ratio (SNR), duration, central frequency, and bandwidth
- Do high-density bins in the histograms correspond to different shapes in the Q-Transform images?

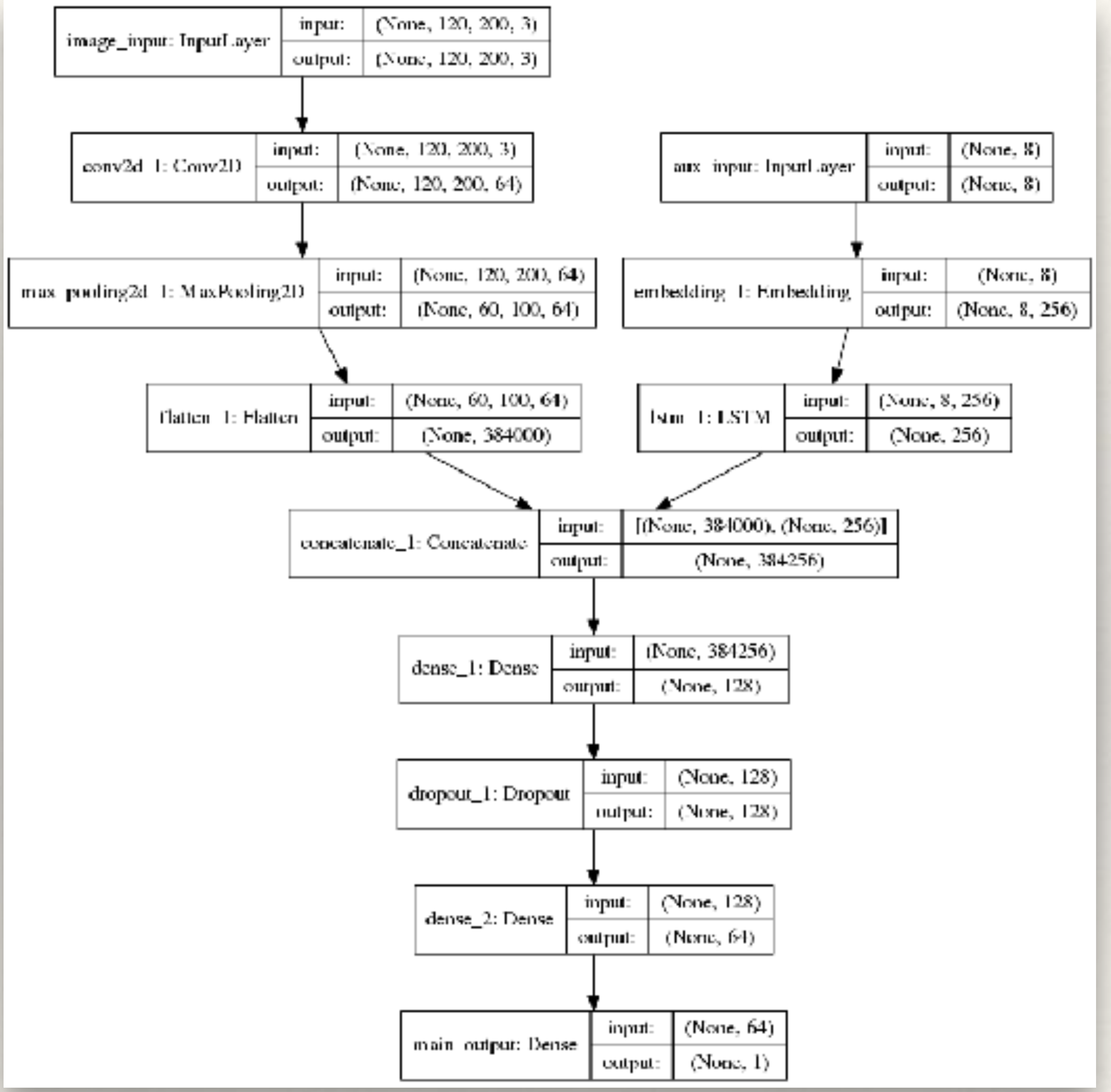




Supervised Learning: Convolutional NNs

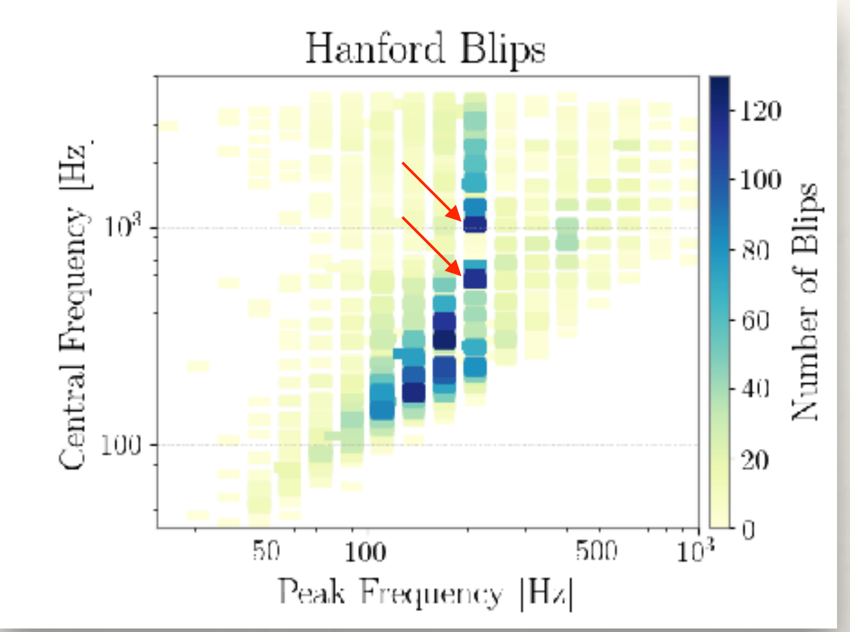
- Main idea for supervised learning:
    - Label images based on auxiliary information and look for test accuracy close to 50% or 100%
- Input:
    - 120 x 200 x 3 (RGB images)
    - Auxiliary input array for two-input networks
- Output:
    - Either binary or multi-class
- Co etter for im all su o account, rat ge as a sin

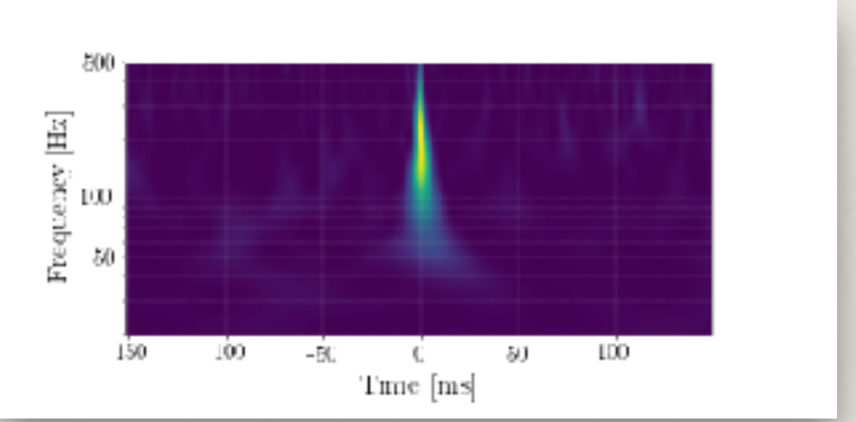


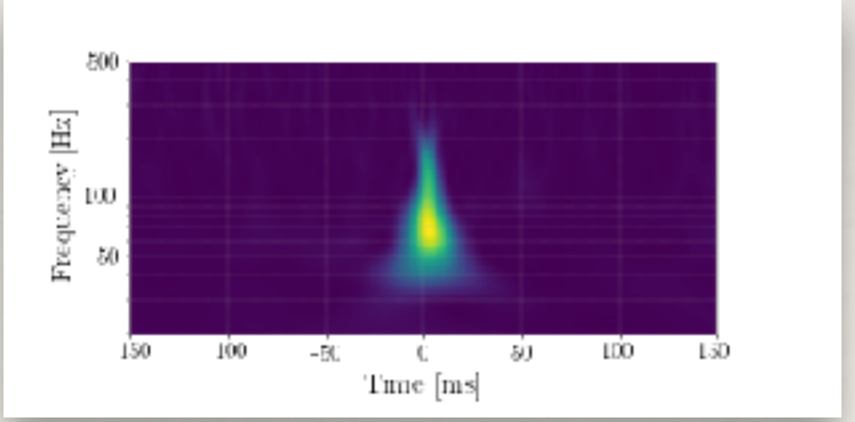


Supervised Learning Results

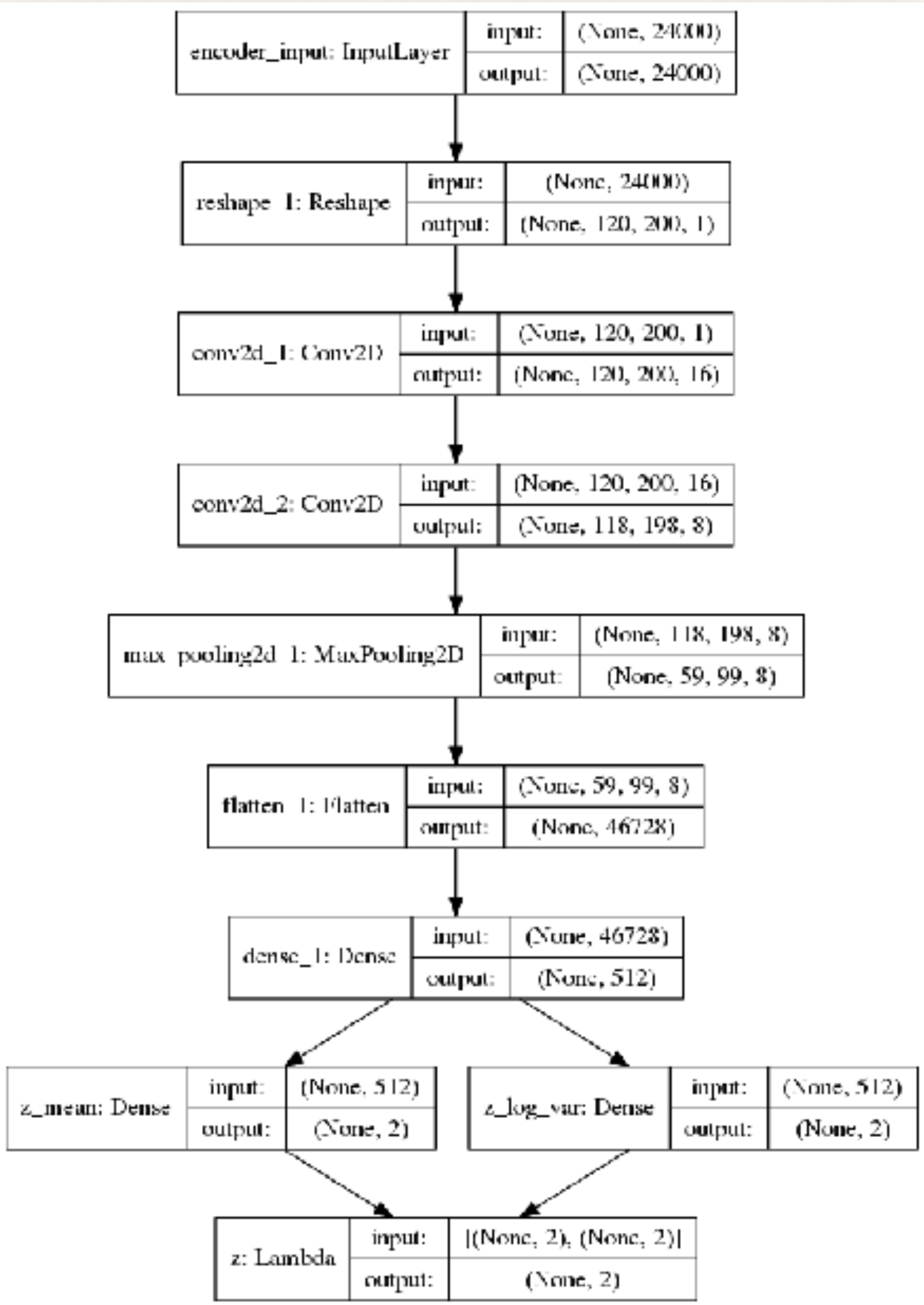
- Are the 200 Hz peak frequency blips different at Hanford versus Livingston?
  - Test Accuracy: 0.1585
  - Problems: Amount disparity (2405 to 270) between classes leads to skewed and inaccurate training.
- Do the central frequency high-density bins within Hanford's 200 Hz peak frequency spike have different shapes?
  - Test Accuracy: 0.7317
  - Problems: Size of training data is only 369, so results are speculative at best.
- Can a network be trained based on a set of self-labeled images?
  - Test Accuracy: 0.3923 (at best)
  - Problems: Images don't magically fit into boxes, and if two labels have very similar images, multi-classification is inconsistent

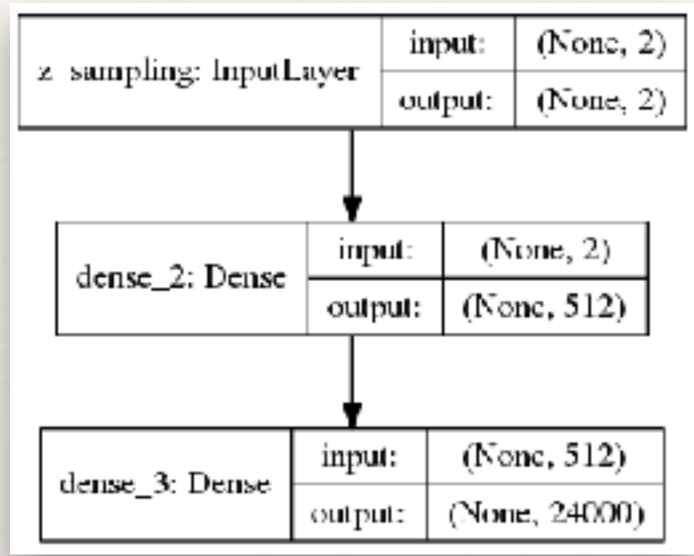


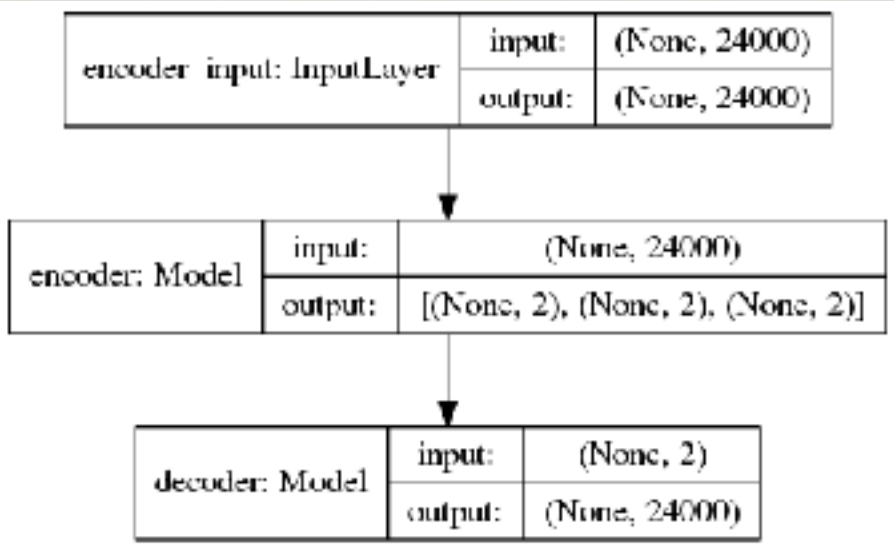




Detailed VAE Layers







2D Histograms