

# Parameter Estimation and Model Selection of Gravitational-Wave Signals Contaminated by Transient Detector Noise Glitches

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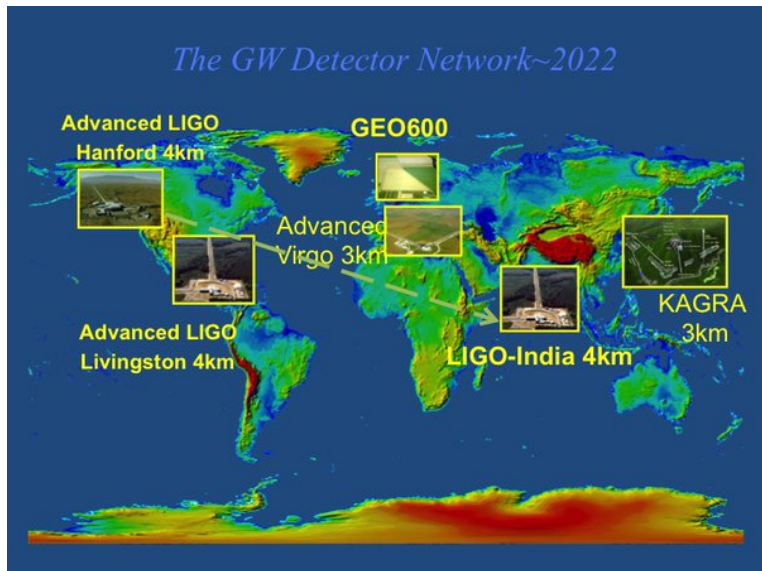
OzGrav, Swinburne University of Technology



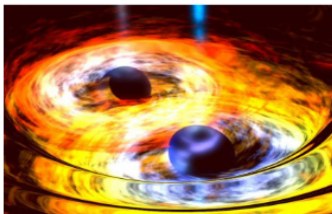
## 2. Gravitational Wave Detectors



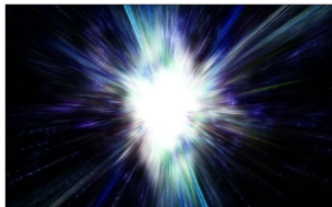
### 3. Detector Locations



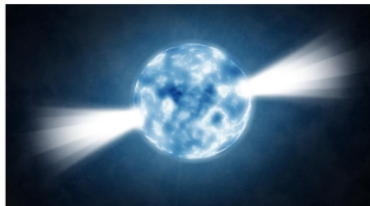
## 4. Gravitational Wave Sources



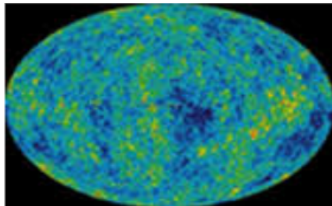
Compact Binary Systems



Bursts



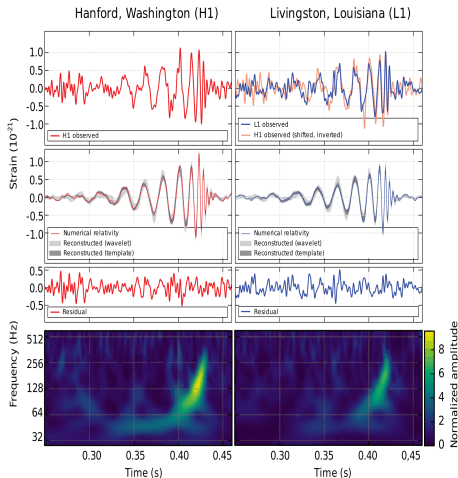
Isolated Compact Objects



Stochastic Background

## 5. Current Black Hole Detections

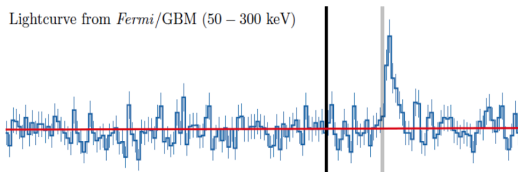
- 6 Binary black hole signals detected so far.
- Estimated distances between 340 and 1000 Mpc.
- One signal detected by three detectors.
- Image from first detection paper GW150914 (Phys-RevLett.116.061102)



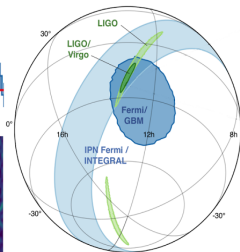
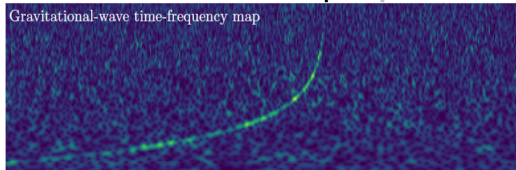
## 6. The Neutron Star Detection GW170817

- Source masses  $1.36 - 2.26 M_{\odot}$  and  $0.86 - 1.36 M_{\odot}$
- Distance 40 Mpc

Lightcurve from *Fermi*/GBM (50 – 300 keV)

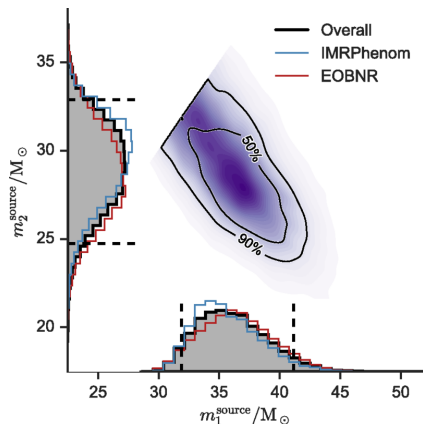


Gravitational-wave time-frequency map



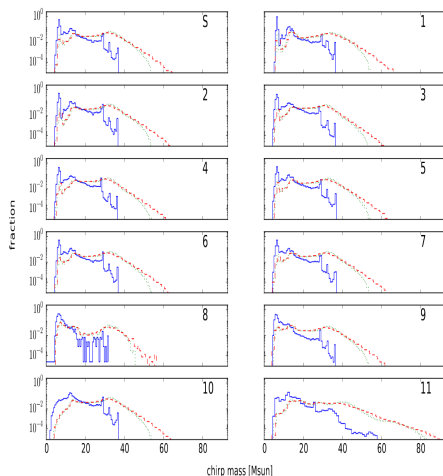
# 7. Parameter Estimation

- Measuring parameters of a source is essential for astrophysics with gravitational wave detections.
- With GW detectors we can measure the chirp mass, spin, eccentricity, distance, and sky position.
- Chirp mass is given by  $\mathcal{M} = (m_1 m_2)^{3/5} / (m_1 + m_2)^{1/5}$



## 8. Astrophysics with Source Parameters

- Constrain the mass distribution of black hole binaries.
- Distinguish between different black hole formation channels.
- Attempt to constrain parameters in binary evolution using population synthesis models.
- Measure the evolution of merger rate / mass distribution with redshift.





## 9. Bayesian Model Selection

- Bayes Theorem:

$$p(M|D, I) = \frac{p(D|M, I) \times p(M|I)}{p(D|I)}$$

- Compute Bayes Factors for two competing models,  $M_S$  and  $M_N$ , to find the correct model

$$B_{S,N} = \frac{p(D|M_S)}{p(D|M_N)}$$

- log Bayes factor for comparing a signal model and noise only model is then

$$\log(B_{S,N}) = \log[p(D|M_S)] - \log[p(D|M_N)]$$

- Compare two signal models  $S_i$  and  $S_j$  by computing

$$\log(B_{S_i,S_j}) = \log(B_{S_i,N}) - \log(B_{S_j,N})$$

## 10. Parameter Estimation

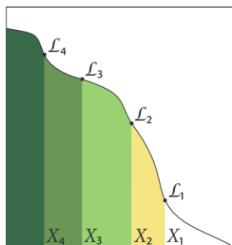
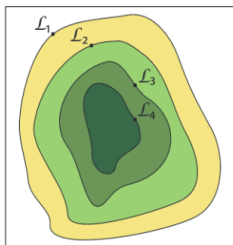
- To calculate the evidence for each model we integrate the likelihood multiplied by the prior over all possible parameter values  $\theta$

$$p(D|M) = \int_{\theta} p(\theta|M)p(D|\theta, M)d\theta. \quad (1)$$

- The evidence integral is difficult for a large number of parameters.
- This problem is solved using nested sampling.

# 11. Nested Sampling

- First the likelihood is calculated for selected points distributed over the entire prior.
- The point with the smallest likelihood and largest prior mass is selected and becomes the limiting values.
- A new point is generated inside the new limits.
- This is repeated so that it iterates inwards in prior mass and upwards in likelihood until the highest value is found.
- Produces Bayes factors and posterior distributions on the signal parameters.



## 12. Burst Sources

- For a burst source we don't know exactly what a signal should look like.
- We use sine Gaussian's as a signal model.
- They are defined as,

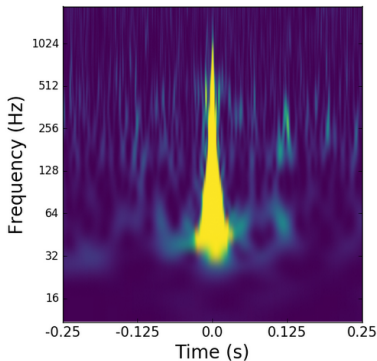
$$h_x(t) = h_0 \sin(2\pi ft) \exp(-t^2/\tau^2) \quad (2)$$

$$h_+(t) = h_0 \cos(2\pi ft) \exp(-t^2/\tau^2) \quad (3)$$

- where  $\tau = Q/\sqrt{2\pi}f$ ,  $f$  is the frequency,  $Q$  is the quality factor,  $t$  is time of the signal and  $h_0 = hrss/\sqrt{\tau}$ , where  $hrss$  is the root sum squared amplitude of the signal.
- Produces posterior distributions on  $hrss$ ,  $Q$ ,  $f$ , and sky position.

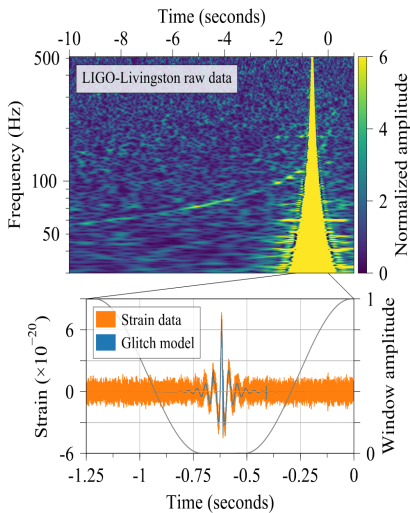
# 13. Glitches

- Glitches are short duration excess power noise created by the detector or the environment.
- The detectors have 1000's of auxiliary channels of data from monitors around the detector.
- Some glitches don't show up in any monitors making it difficult to determine their origin.
- They limit the sensitivity of gravitational wave searches.



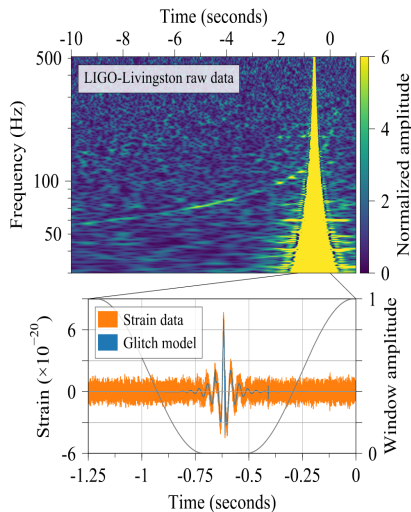
# 14. Signals with glitches

- $10^6$  glitches above SNR 6 were observed in 51.5 days of O1.
- GW170817 had a large glitch in L1.
- High probability that as detections increase, more will occur at the same time as a glitch.



# 15. Glitch Removal

- For GW170817 we already know what we expected the signal to look like.
- The glitch was very loud and easy to identify as being a glitch.
- It was removed by gating and subtracting the reconstructed waveform.
- The glitch is short duration compared to the signal, which means some signal is still left over after gating.
- It might not be so easy next time!



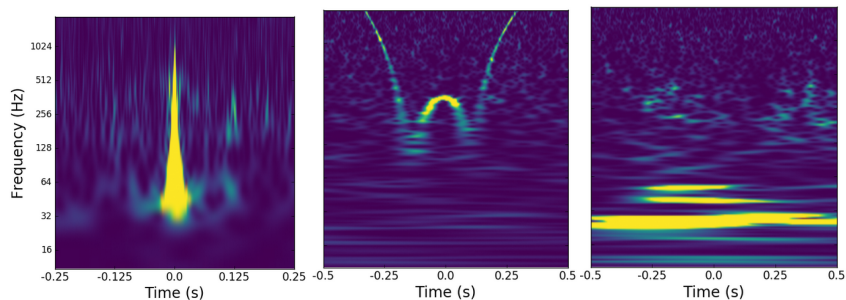
## 16. This Analysis

- We inject three different types of gravitational wave signals on top of three different types of glitches.
- We measure the parameters of the signals at different signal to noise ratios and offsets in time between the signal and glitches.
- What happens if the glitch is not obvious because it does not occur in auxiliary channels and the exact shape of the signal waveform is unknown?
- We determine the effects of glitches that can't be gated.
- We investigate if the effects of glitches is worse when there is a mis-match between signal and template.



## 17. The Glitches

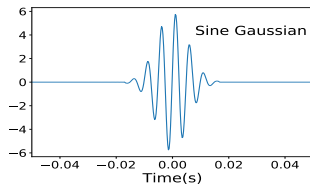
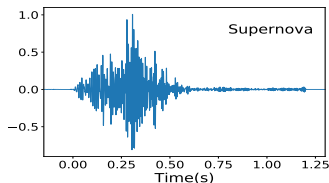
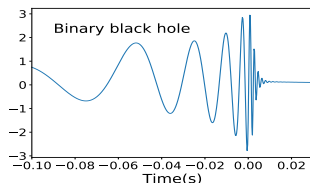
Three types of O1 glitches are used that occur in L1 at the same time as good quality H1 data.



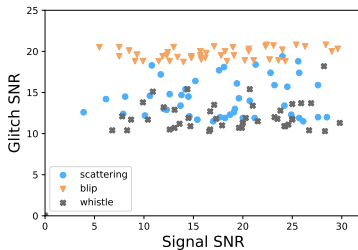
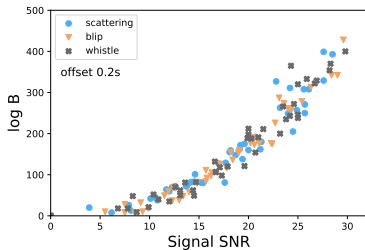
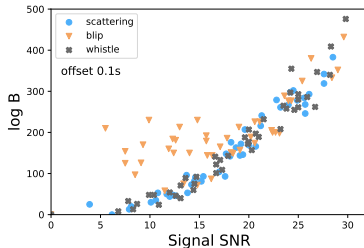
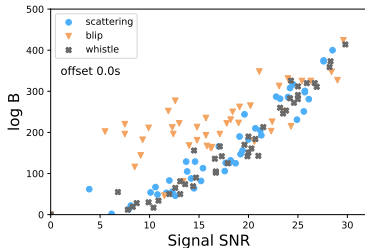
**Figure:** Images taken from Gravity Spy.

# 18. The Signals

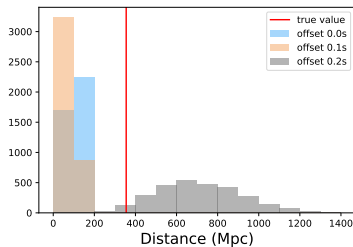
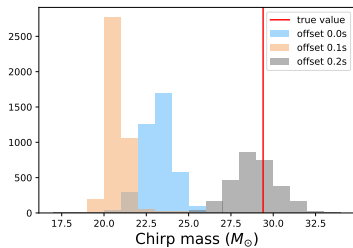
- We measure parameters of all signals injected near glitches with time offsets of 0.0s, 0.1s and 0.2s.
- IMRPhenomPv2 signal model is used for the CBC signals.
- A sine Gaussian signal model is used for the sine Gaussian signals.
- A sine Gaussian model is used for the supernova signals to determine if effects are worse when there is a mis-match between signal and model.



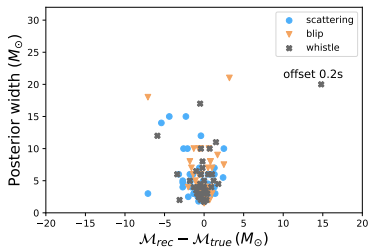
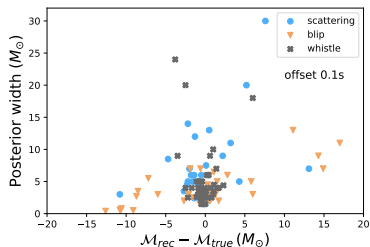
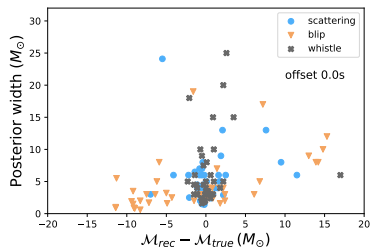
# 19. BBH Bayes Factors



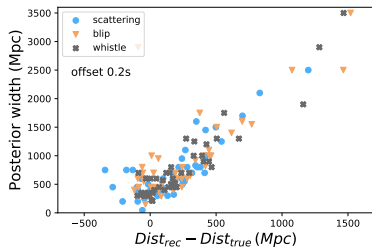
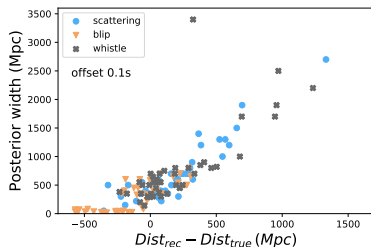
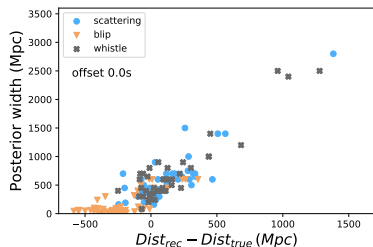
## 20. BBH Example Posteriors



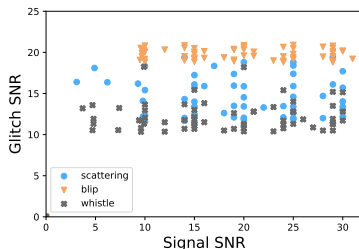
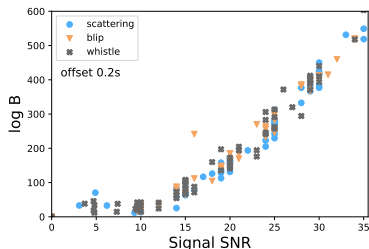
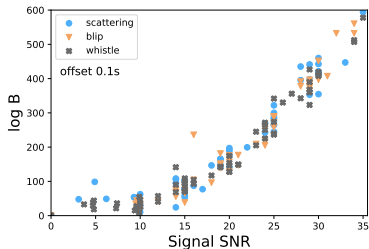
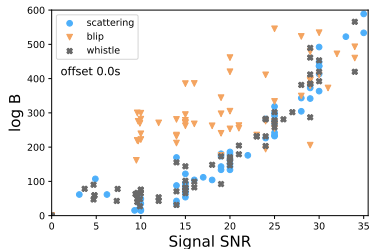
# 21. BBH Chirp Mass Summary



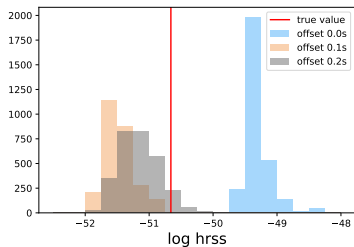
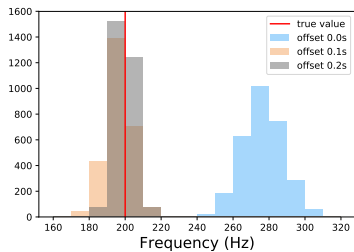
## 22. BBH Distance Summary



## 23. Sine Gaussian Bayes Factors

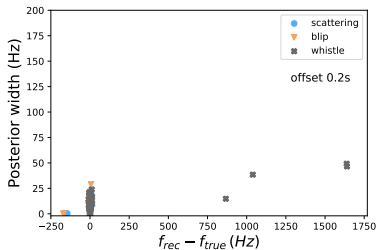
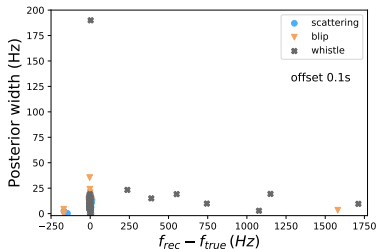
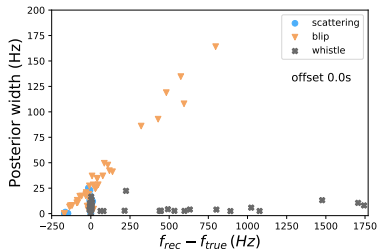


## 24. Sine Gaussian Example Posteriors

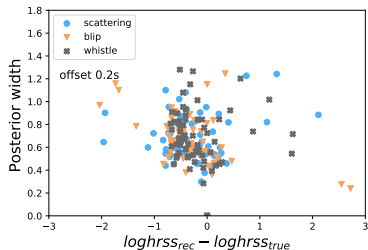
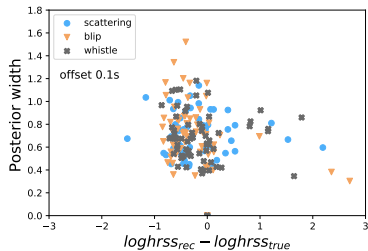
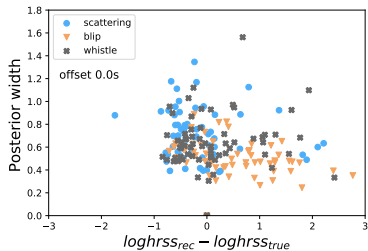




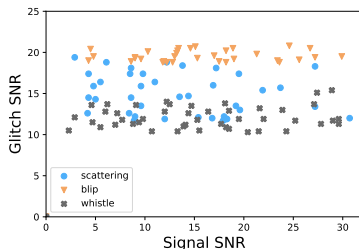
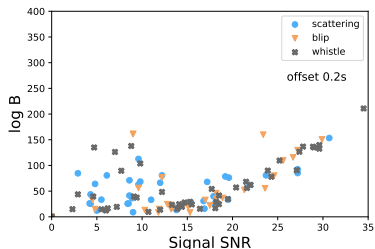
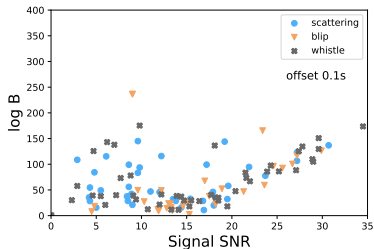
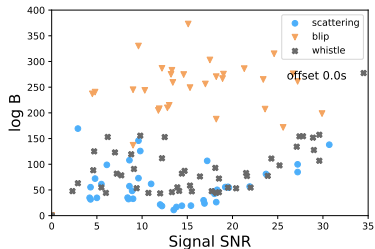
# 25. Sine Gaussian Frequency Summary



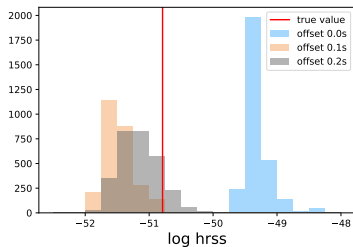
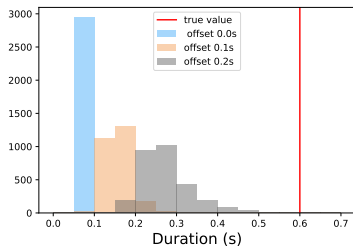
## 26. Sine Gaussian Log Hrss Summary



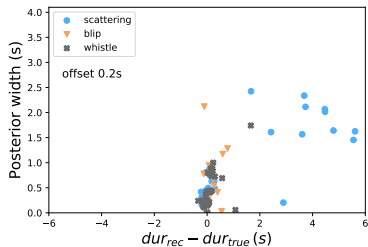
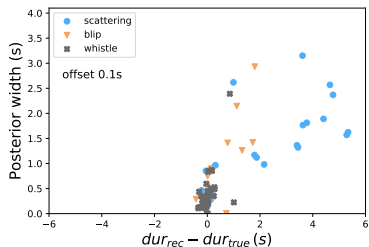
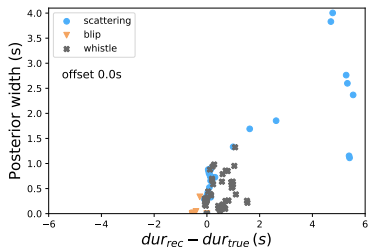
# 27. Supernova Bayes Factors



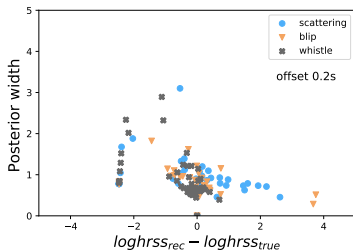
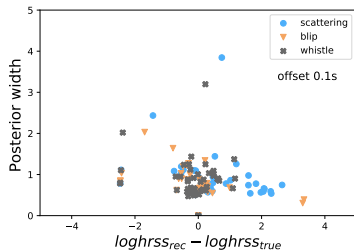
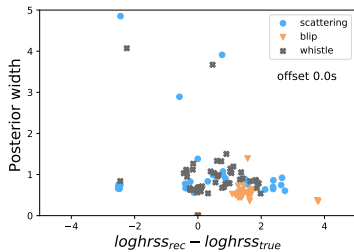
## 28. Supernova Example Posteriors



# 29. Supernova Duration Summary



# 30. Supernova Log Hrss Summary



## 31. What's next?

- Next step is to apply techniques designed to reduce the effect of glitches to the data set.
- We are attempting to reconstruct the glitch and the signal at the same time to reduce the error on signal parameters.
- Currently Bayes factors can be produced to tell you if there is a signal or a glitch in the data.
- Next we hope to produce a Bayes factor that tells you there is both a signal and a glitch.