# GW Burst searches in ground based detectors

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The Future of Gravitational Wave Astronomy
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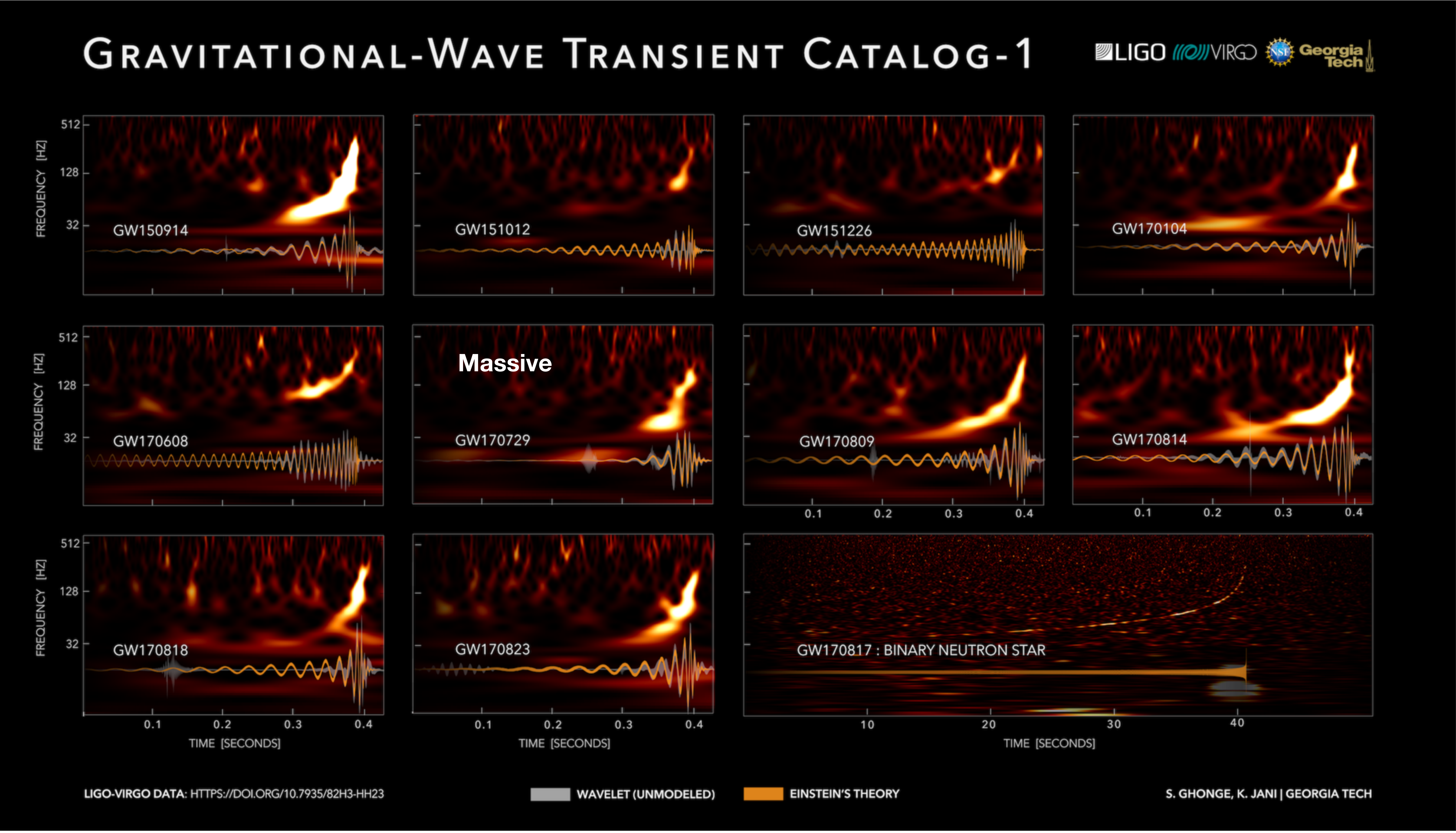



O1-O2 LIGO-Virgo compact binaries

Total mass 18.5-85.1 Msun

LVC, GWTC-1 Catalog arXiv:1811.12907

# Main features of burst search

- Search does not assume any signal model.
- Minimal assumptions about the signal morphology
- Maps the multi-detector data in the time-frequency representation
- Obtain energetic pixels
- Scheme to cluster pixels either seed-based or seedless
- Veto methods to remove the noisy transients

Coherent WaveBurst [Klimenko etal PRD 2016]

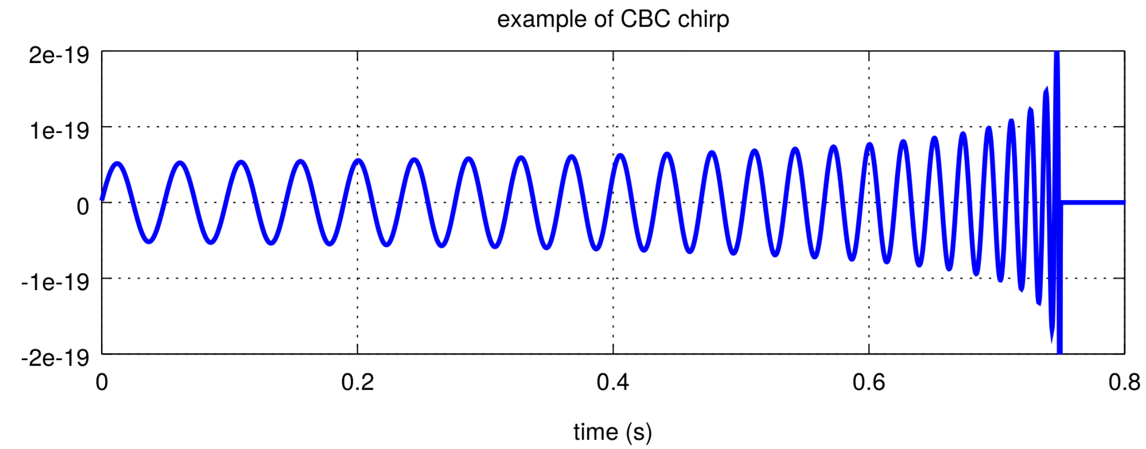
Omicron-LALInferenceBurst (OLIB) Littenberg et.al. PRD 2017

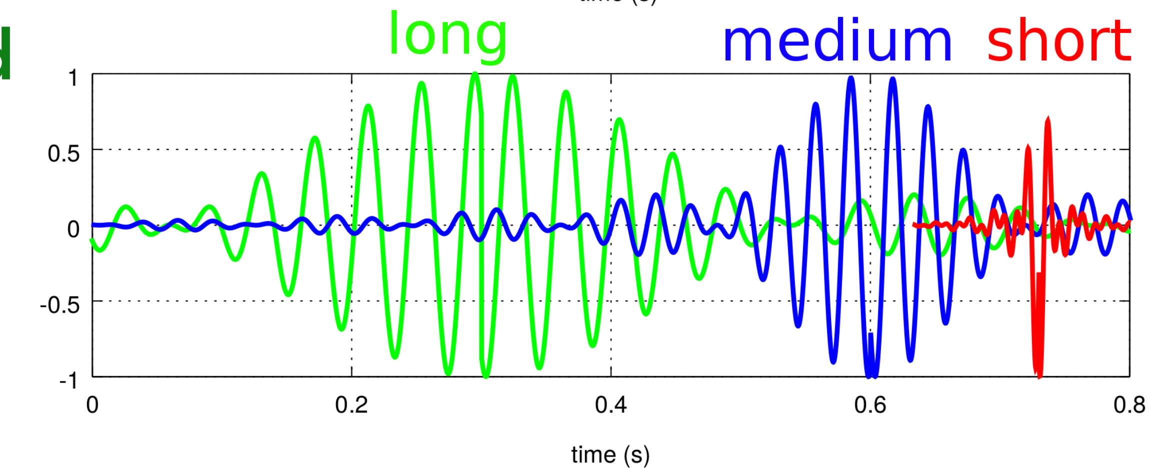
BayesWave: Cornish and Littenberg, CQG 2015

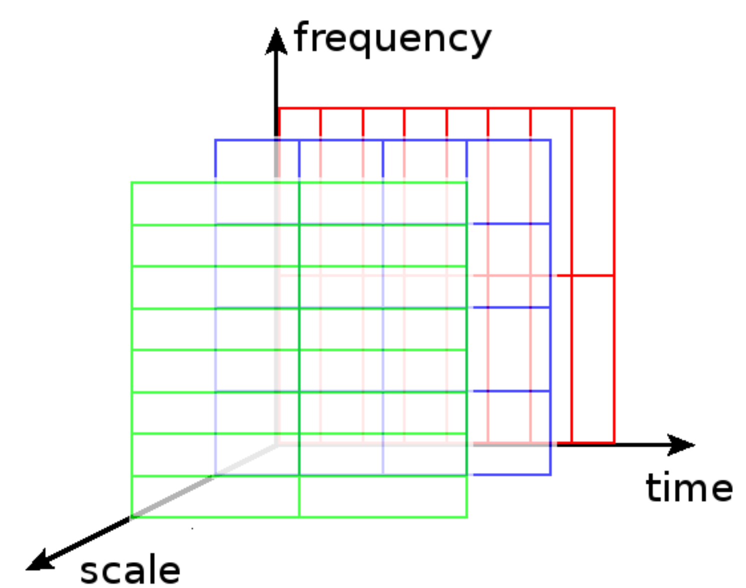
# Coherent Wave-Burst

[Klimenko etal PRD 2016]

- Project the data on the wavelet domain characterised by (time,freq,scale).
- Combine the time-frequency energy from detectors (incorporating possible delays) and obtain pixel energy for each scale.
- Obtain energetic pixels.
- Clustering scheme combines the TF pixels from different scales which constructs clusters.
- Maximum likelihood ratio statistic is used for each cluster to obtain multi-detector statistic.
- Detection Statistic incorporates the correlation between the detectors.



## cWB Math

**Network pixel-wise data**

$$w[p] = \left[ \frac{x_1[p, \tau_1(\theta,\phi)]}{\sqrt{S_1[p]}}, \ldots, \frac{x_k[p, \tau_k(\theta,\phi)]}{\sqrt{S_k[p]}}, \ldots, \frac{x_K[p, \tau_K(\theta,\phi)]}{\sqrt{S_K[p]}} \right].$$

**Maximum likelihood statistic**

$$L_{max} = \frac{\langle w[p] \mid f_+[p] \rangle^2}{\langle f_+[p] \mid f_+[p] \rangle^2} + \frac{\langle w[p] \mid f_\times[p] \rangle^2}{\langle f_\times[p] \mid f_\times[p] \rangle^2},$$

$$= \sum_{nm} \left[ (w_m[p] e_{+m}[p] w_n[p] e_{+n}[p]) + (w_m[p] e_{\times m}[p] w_n[p] e_{\times n}[p]) \right],$$

$$L_{max} = \sum_{p \in C} w^T[p]\, P[p]\, w[p].$$

$$\text{with } P_{nm}[p] = e_{n+}[p] e_{m+}[p] + e_{m\times}[p] e_{m\times}[p].$$

**Incoherent energy**

$$E_{in} = \sum_{p \in C} \sum_{n} w_n[p]\, P_{nn}[p]\, w_n[p],$$

**Coherent Energy**

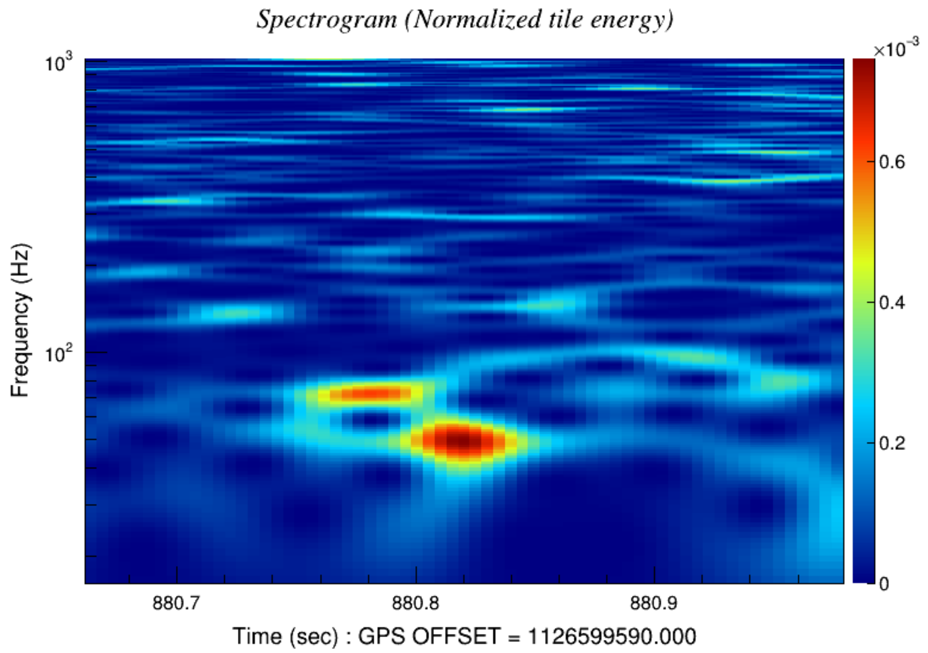
$$E_{coh} = \sum_{p \in C} \sum_{n \neq m} w_n[p]\, P_{nm}[p]\, w_m[p].$$

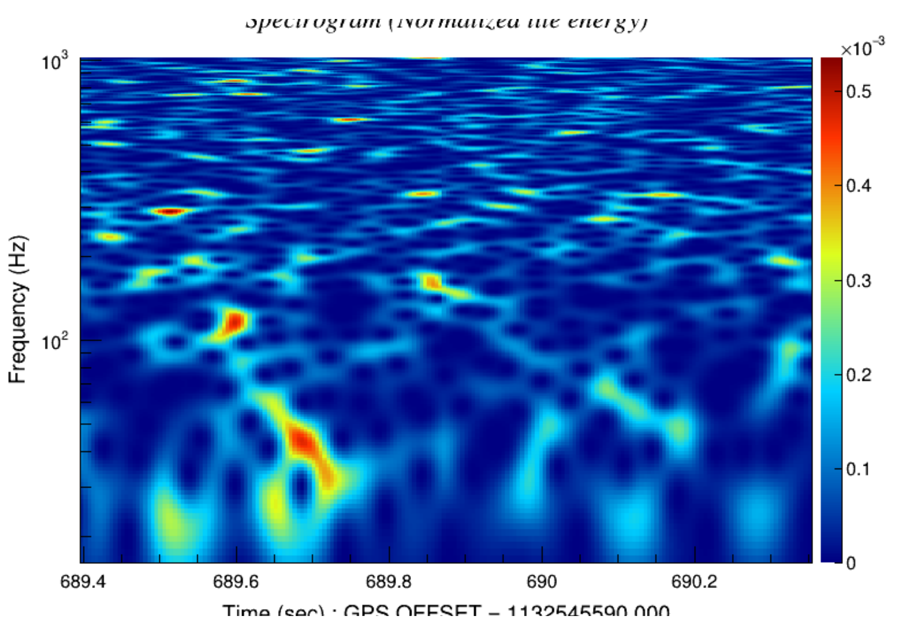
**Network correlation**

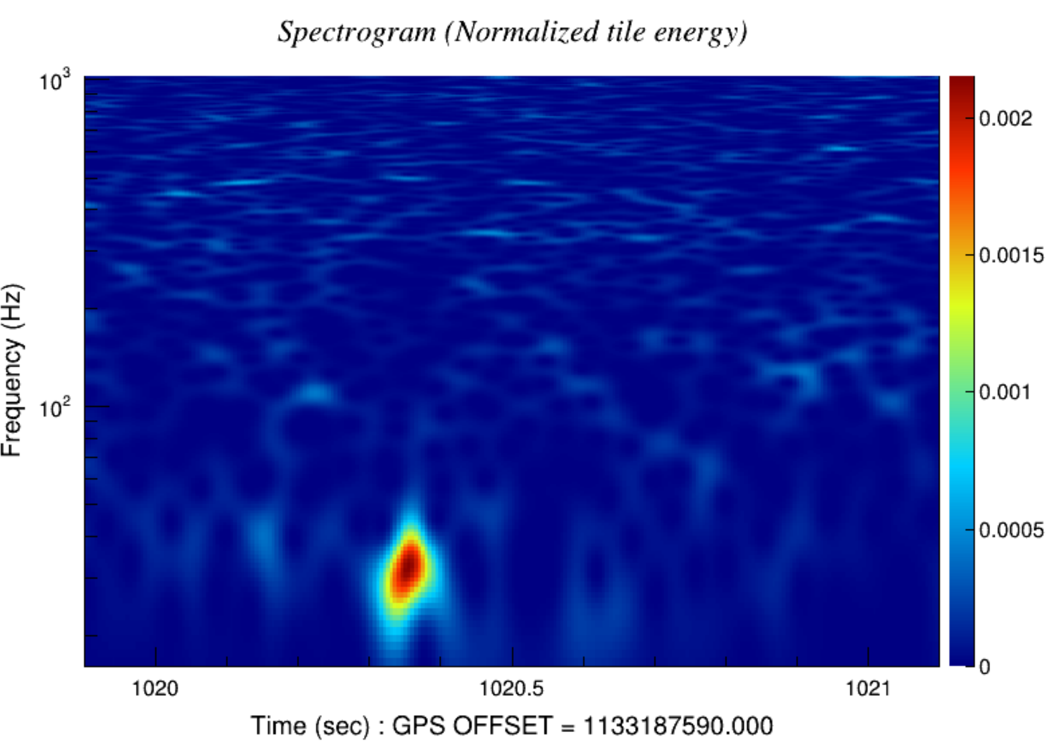
$$c_c = E_{coh} / (|E_{coh}| + E_{null}).$$

**Statistic:**

$$\eta_c = (c_c E_{coh} K / (K-1))^{1/2}.$$



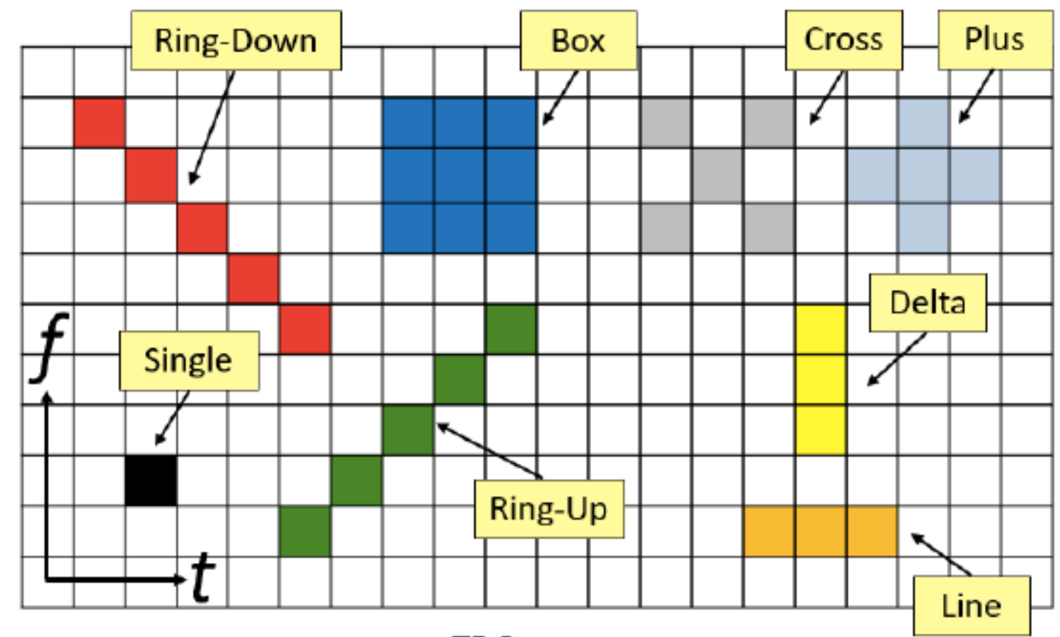

# Variety of noisy transients

**Different class of Noisy transients have distinct representation in the TF map.**

**Noise vetos use this information**

1. **Fraction of the event energy in the secondary TF pixels — Qveto**
2. **Distribution of energy in TF plane as opposed to the time domain: Norm**
3. **Chi-square — based on average residual energy**
4. **…**
5. **….**

# Tune the search based on the signal one is looking for……




*TF-Patterns*

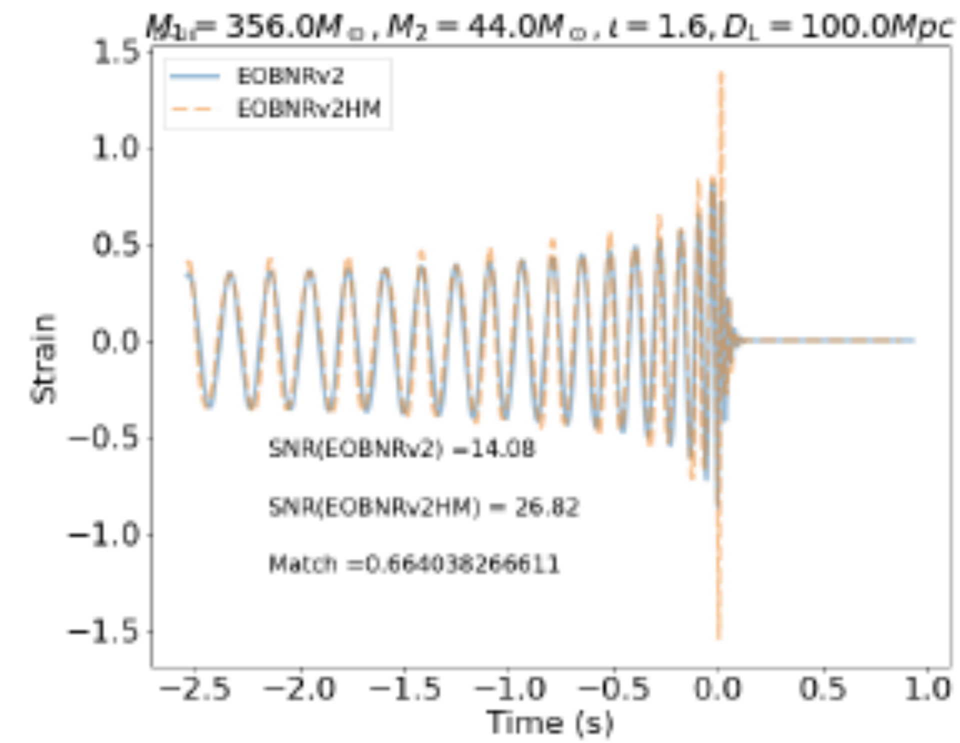
| Event | UTC Time | FAR [$y^{-1}$] PyCBC | FAR [$y^{-1}$] GstLAL | FAR [$y^{-1}$] cWB | Network SNR PyCBC | Network SNR GstLAL | Network SNR cWB |
|---|---|---|---|---|---|---|---|
| GW150914 | 09:50:45.4 | $< 1.53\times10^{-5}$ | $< 1.00\times10^{-7}$ | $< 1.63\times10^{-4}$ | 23.6 | 24.4 | 25.2 |
| GW151012 | 09:54:43.4 | 0.17 | $7.92\times10^{-3}$ | – | 9.5 | 10.0 | – |
| GW151226 | 03:38:53.6 | $< 1.69\times10^{-5}$ | $< 1.00\times10^{-7}$ | 0.02 | 13.1 | 13.1 | 11.9 |
| GW170104 | 10:11:58.6 | $< 1.37\times10^{-5}$ | $< 1.00\times10^{-7}$ | $2.91\times10^{-4}$ | 13.0 | 13.0 | 13.0 |
| GW170608 | 02:01:16.5 | $< 3.09\times10^{-4}$ | $< 1.00\times10^{-7}$ | $1.44\times10^{-4}$ | 15.4 | 14.9 | 14.1 |
| GW170729 | 18:56:29.3 | 1.36 | 0.18 | 0.02 | 9.8 | 10.8 | 10.2 |
| GW170809 | 08:28:21.8 | $1.45\times10^{-4}$ | $< 1.00\times10^{-7}$ | – | 12.2 | 12.4 | – |
| GW170814 | 10:30:43.5 | $< 1.25\times10^{-5}$ | $< 1.00\times10^{-7}$ | $< 2.08\times10^{-4}$ | 16.3 | 15.9 | 17.2 |
| GW170817 | 12:41:04.4 | $< 1.25\times10^{-5}$ | $< 1.00\times10^{-7}$ | – | 30.9 | 33.0 | – |
| GW170818 | 02:25:09.1 | – | $4.20\times10^{-5}$ | – | – | 11.3 | – |
| GW170823 | 13:13:58.5 | $< 3.29\times10^{-5}$ | $< 1.00\times10^{-7}$ | $2.14\times10^{-3}$ | 11.1 | 11.5 | 10.8 |

**O1-O2 Compact binaries** **GWTC-1, LVC 2019**

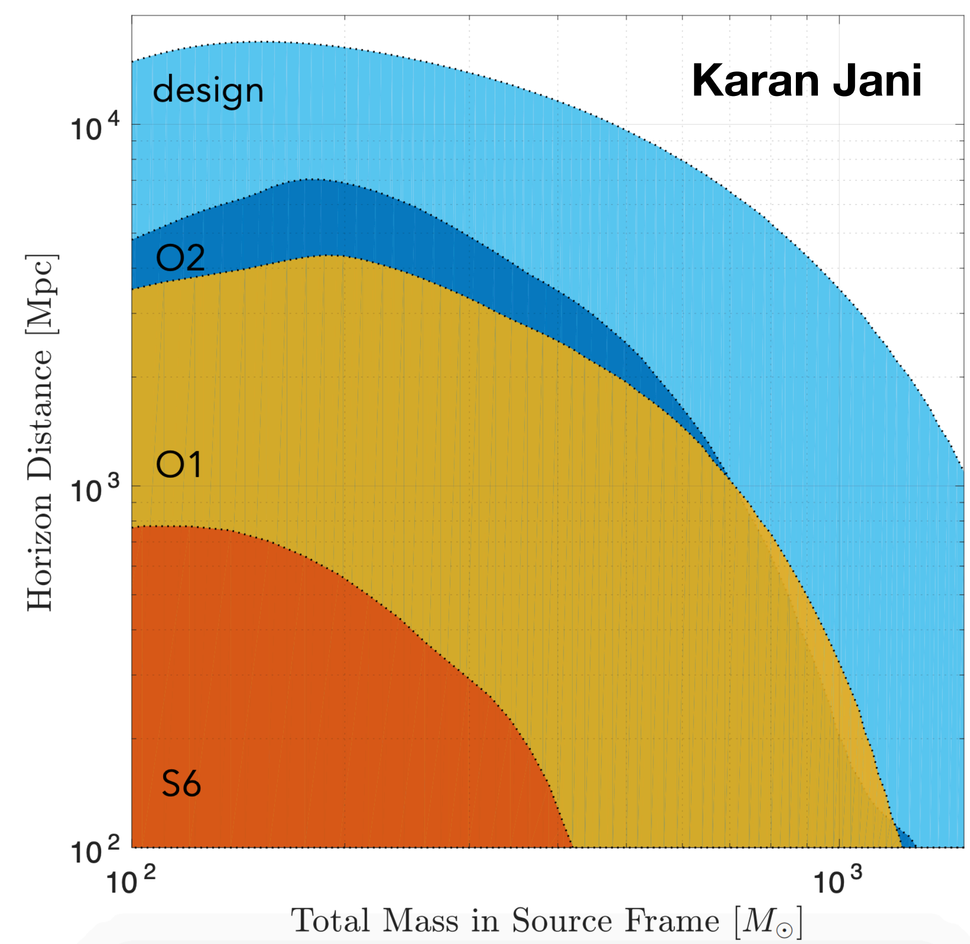
- cWB shows sensitivity to loud and massive binary BH events.
- It does not assume any signal morphology. Can capture complexities of the signal.

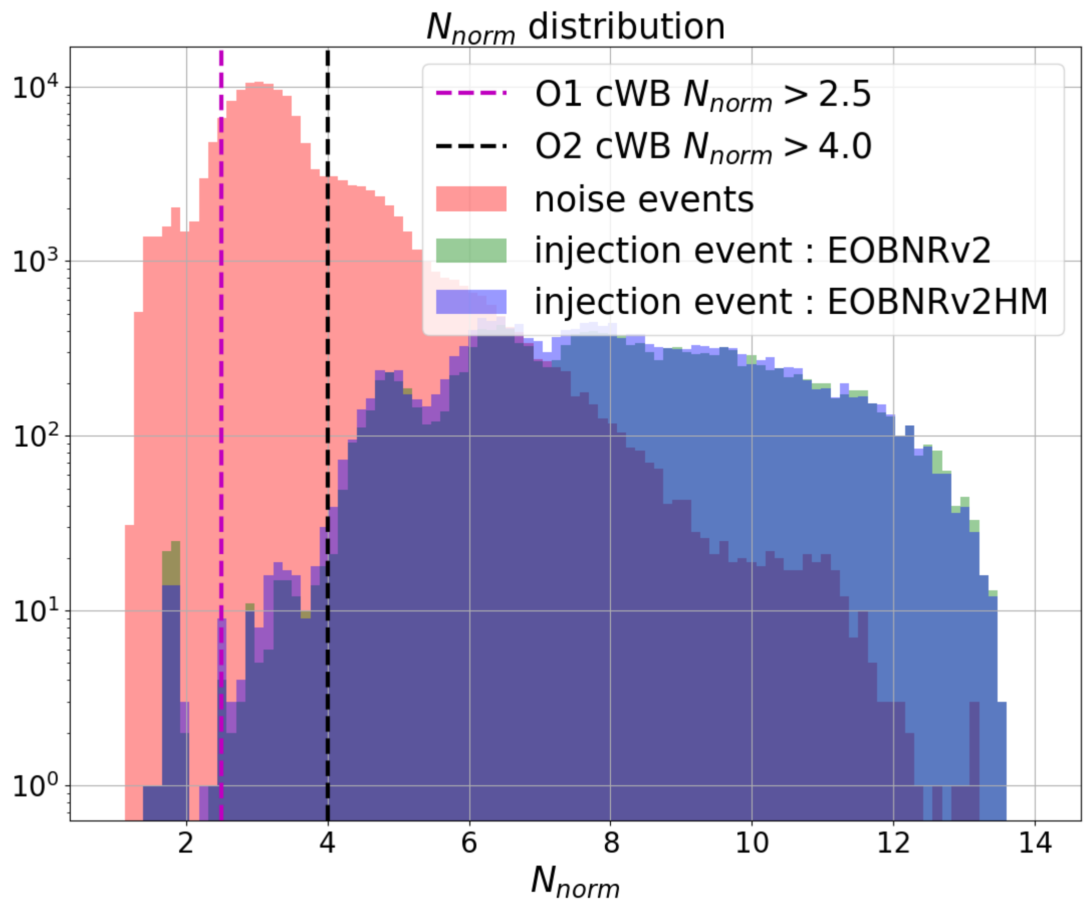
# Tune the search based on the signal one is looking for……

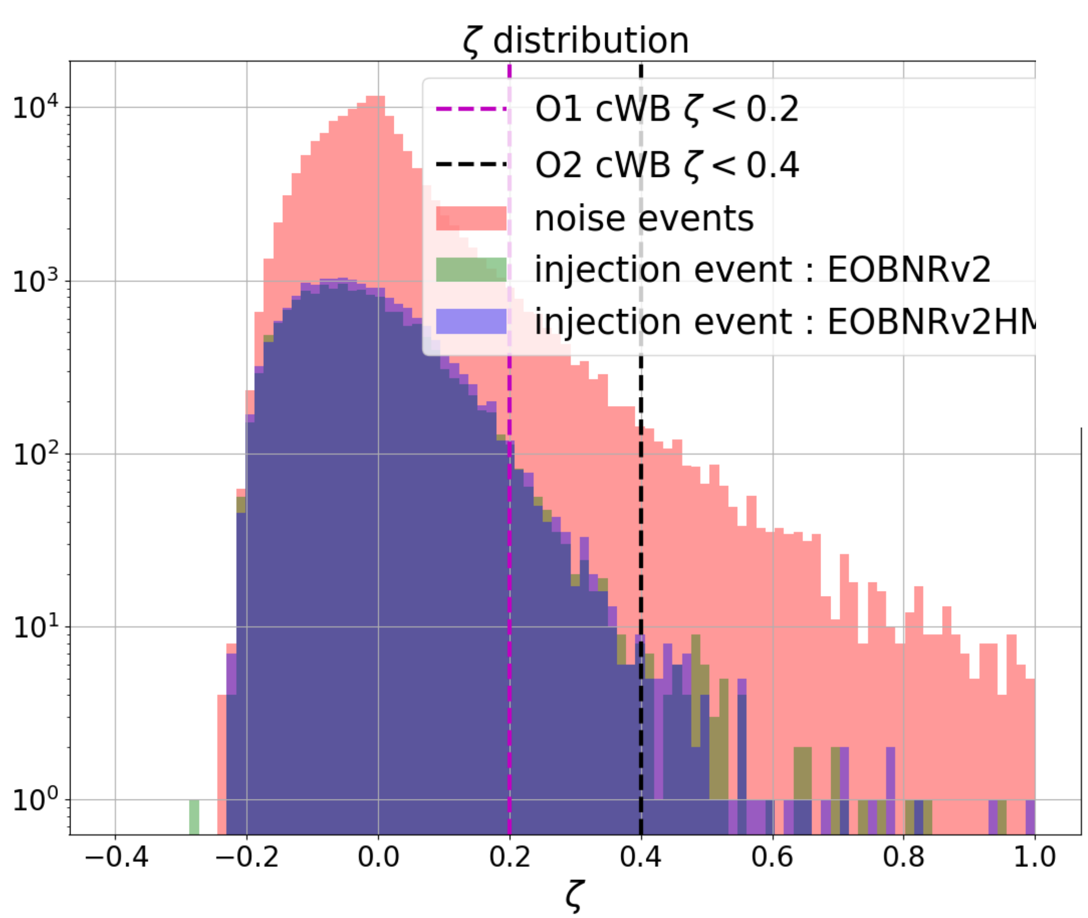
- Current detectors are sensitive to IMBHB (BH> 100 Msun in a binary)
- IMBHB Detection challenges
  - signal is dominated by merger and ringdown
  - existing templates are not accurate — they do not contain either precession or higher order modes
  - Noisy transients appear like a signal



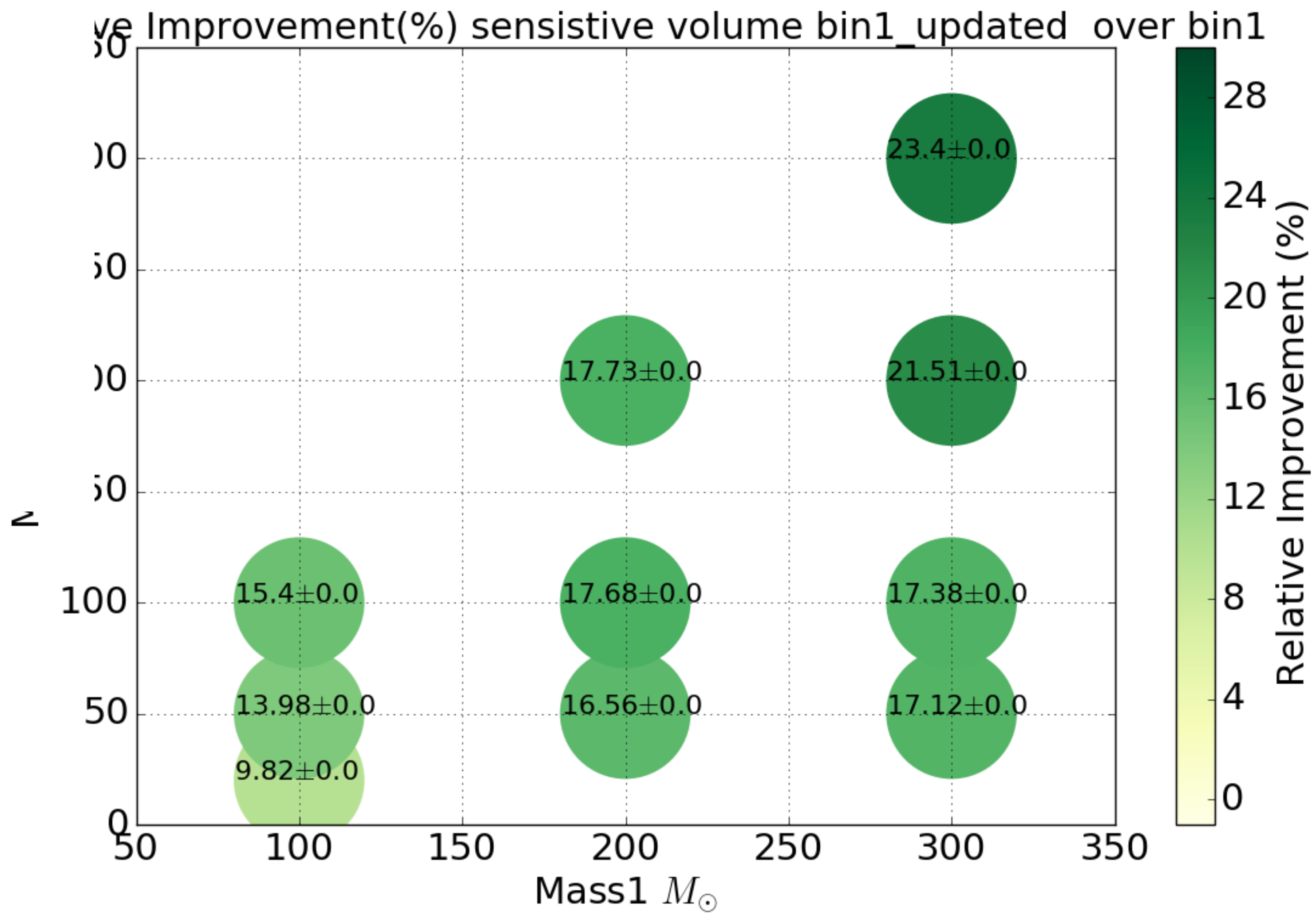

O1-O2 IMBHB search —
With special tuning of cWB, the burst search outperformed the template based search
[1906.08000, O1O2 IMBHB LVC, 2019]






# Reduce background without loosing events



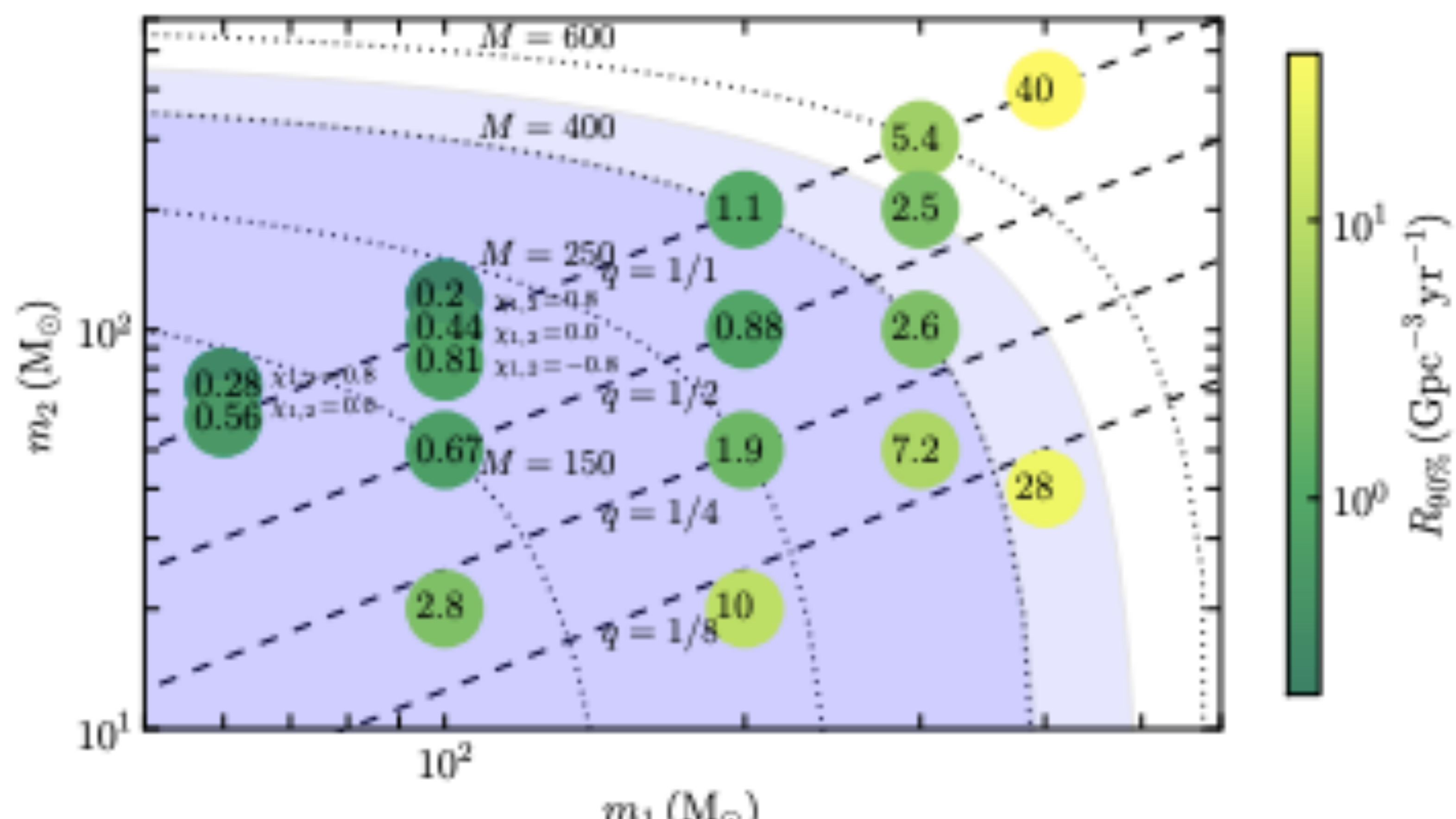

# Increase events without increasing background

| $m_1$ $M_\odot$ | $m_2$ $M_\odot$ | spin $\chi_{1,2}$ | $M$ $M_\odot$ | NR-simulation | $D_{\langle VT \rangle_{sen}}$ (Gpc) cWB | GstLAL | PyCBC | combined |
|---|---|---|---|---|---|---|---|---|
| 60 | 60 | 0 | 120 | SXS:BBH:0180, RIT:BBH:0198:n140, GT:0905 | 1.2 | 1.2 | 1.2 | 1.3 |
| 60 | 60 | 0.8 | 120 | SXS:BBH:0230, RIT:BBH:0063:n100, GT:0424 | 1.6 | 1.0 | 1.5 | 1.6 |
| 100 | 20 | 0 | 120 | SXS:BBH:0056, RIT:BBH0120:n140, GT:0906 | 0.72 | 0.69 | 0.70 | 0.76 |
| 100 | 50 | 0 | 150 | SXS:BBH:0169, RIT:BBH:0117:n140, GT:0446 | 1.2 | 0.79 | 1.1 | 1.2 |
| 100 | 100 | -0.8 | 200 | SXS:BBH:0154, RIT:BBH:0068:n100 | 1.1 | 1.0 | 0.99 | 1.2 |
| 100 | 100 | 0 | 200 | SXS:BBH:0180, RIT:BBH:0198:n140,GT:0905 | 1.4 | 0.90 | 1.3 | 1.4 |
| 100 | 100 | 0.8 | 200 | SXS:BBH:0230, RIT:BBH:0063:n100, GT:0424 | 1.8 | 1.2 | 1.7 | 1.8 |
| 200 | 20 | 0 | 220 | RIT:BBH:Q10:n173, GT:0568 | 0.48 | 0.30 | 0.36 | 0.49 |
| 200 | 50 | 0 | 250 | SXS:BBH:0182, RIT:BBH:0119:n140, GT:0454 | 0.85 | 0.48 | 0.67 | 0.87 |
| 200 | 100 | 0 | 300 | SXS:BBH:0169, RIT:BBH:0117:n140, GT:0446 | 1.1 | 0.59 | 0.86 | 1.1 |
| 300 | 50 | 0 | 350 | SXS:BBH:0181, RIT:BBH:0121:n140, GT:0604 | 0.55 | 0.18 | 0.27 | 0.56 |
| 200 | 200 | 0 | 400 | SXS:BBH:0180, RIT:BBH:0198:n140, GT:0905 | 1.0 | 0.47 | 0.72 | 1.0 |
| 300 | 100 | 0 | 400 | SXS:BBH:0030, RIT:BBH:0102:n140, GT:0453 | 0.78 | 0.23 | 0.34 | 0.78 |
| 400 | 40 | 0 | 440 | RIT:BBH:Q10:n173, GT:0568 | 0.35 | 0.10 | 0.16 | 0.35 |
| 300 | 200 | 0 | 500 | RIT:BBH:0115:n140, GT:0477 | 0.79 | 0.16 | 0.14 | 0.79 |
| 300 | 300 | 0 | 600 | SXS:BBH:0180, RIT:BBH:0198:n140, GT:0905 | 0.61 | 0.09 | 0.18 | 0.61 |
| 400 | 400 | 0 | 800 | SXS:BBH:0180, RIT:BBH:0198:n140, GT:0905 | 0.31 | 0.10 | 0.23 | 0.31 |

**cWB outperforms in all the masses**

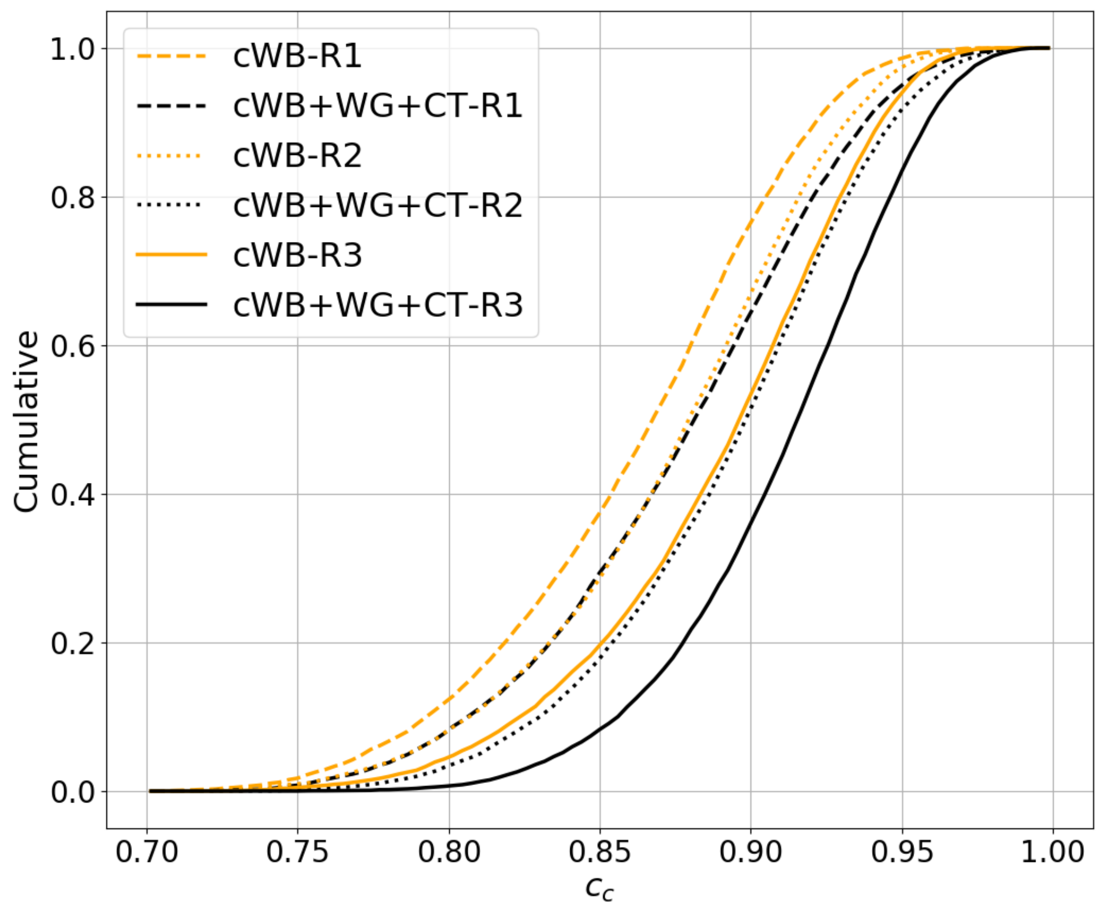
**O1-O2 Rate upper limit on 100-100 aligned spin of 0.8 IMBHB is 0.2 per Gpc^3 per yr**

**[1906.08000, O1O2 IMBHB LVC, 2019]**



# Astrophysical model at the clustering stage

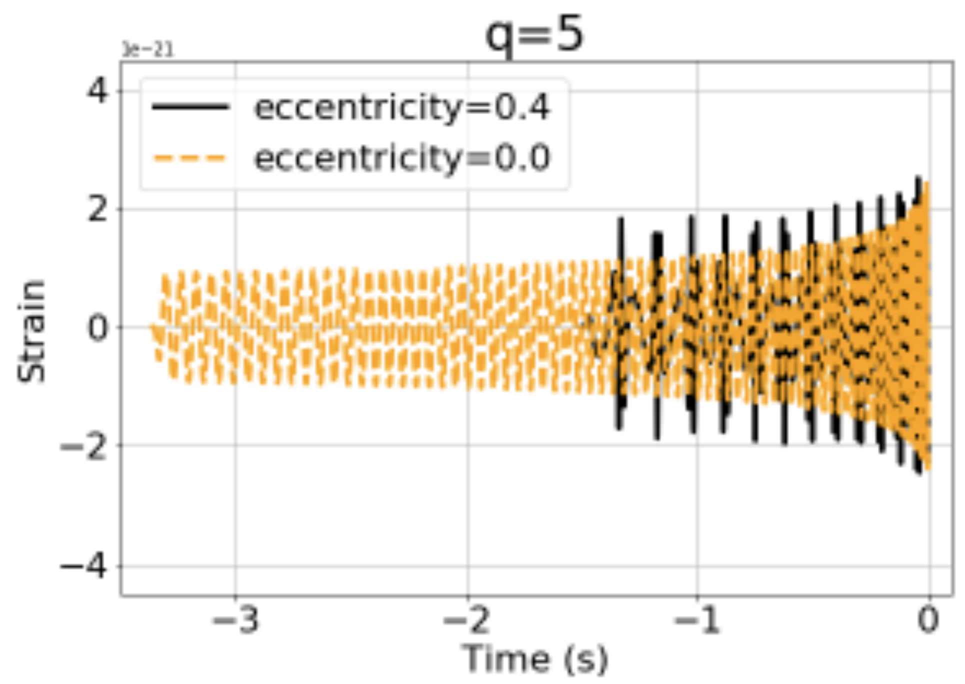
- cWB works well for short duration bursts.
- Improve the cWB sensitivity by incorporating signal model
- Fold in the phase modulation in terms of the signal path
- Path=connections and ancestors — ingredients of the mathematical graph
- Use graph to construct events.
- Nominally applied for simulated BBH systems in O1 noise —
    - Recovered events with high network correlation.
    - Additional 20% events can be recovered




Gayathri, Bacon, AP, Chassande-Mottin, Salemi, Vedovato, arXiv:1907.10851

# Future extension

**[50-10]Msun**




- Eccentric binary black hole systems

- Possibility of eccentric systems exists in the dense environment.

- No templates are available for the eBBH search.

- eBBH search with O1-O2 data shows that cWB based search is not sensitive to the eccentricity [LVC, 1907.09384]

- Need clustering scheme which captures the long duration more efficiently.

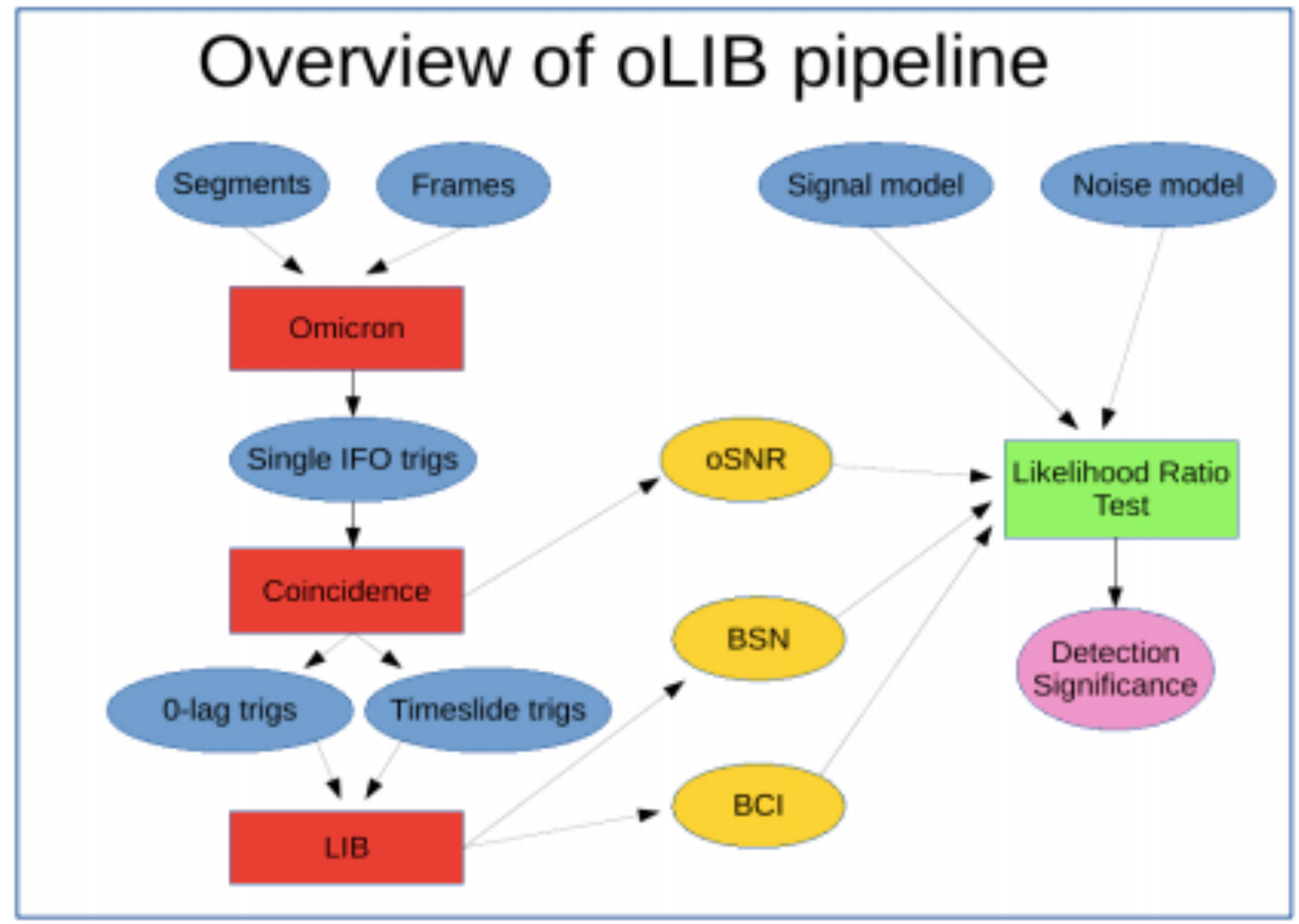
# GW transient burst sources

- Short duration burst (millisecond to one sec.) —
  - BBH systems with total mass > 90 Msun (Massive BBH and IMBHBs)
  - Core-collapse supernovae [Fryer and New, Liv. Rev. in Rel, (2011)]
  - Pulsar glitches [Anderson and Comer, PRL (2001)]
- Long duration burst (one sec to hundreds of seconds) —
  - Accretion driven instability and inspiraling of the stellar material [van Putten, ApJ 2001, ApJ 2008]
  - Fallback accretion of ejected material on newborn NS [Piro and Ott, ApJ 2011, Piro and Thrane, ApJ 2012]
  - Highly eccentric BBH coalescence [Huerta et.al, PRD 2018]

# Burst algorithms for Short duration

**Minimal assumption about the signal morphology**

- Hierarchical scheme — coincident triggers followed up by fully coherent MCMC Bayesian analysis
- Data is projected by the Omicron (Q-transform), triggers are clustered to form an event. Coincident events between the detectors are obtained.
- Bayes factor by LIB: Model selection algorithm
  Coherent signal vs Gaussian noise
  Coherent signal vs incoherent glitch
- Statistic ~ Product of the bayes factor





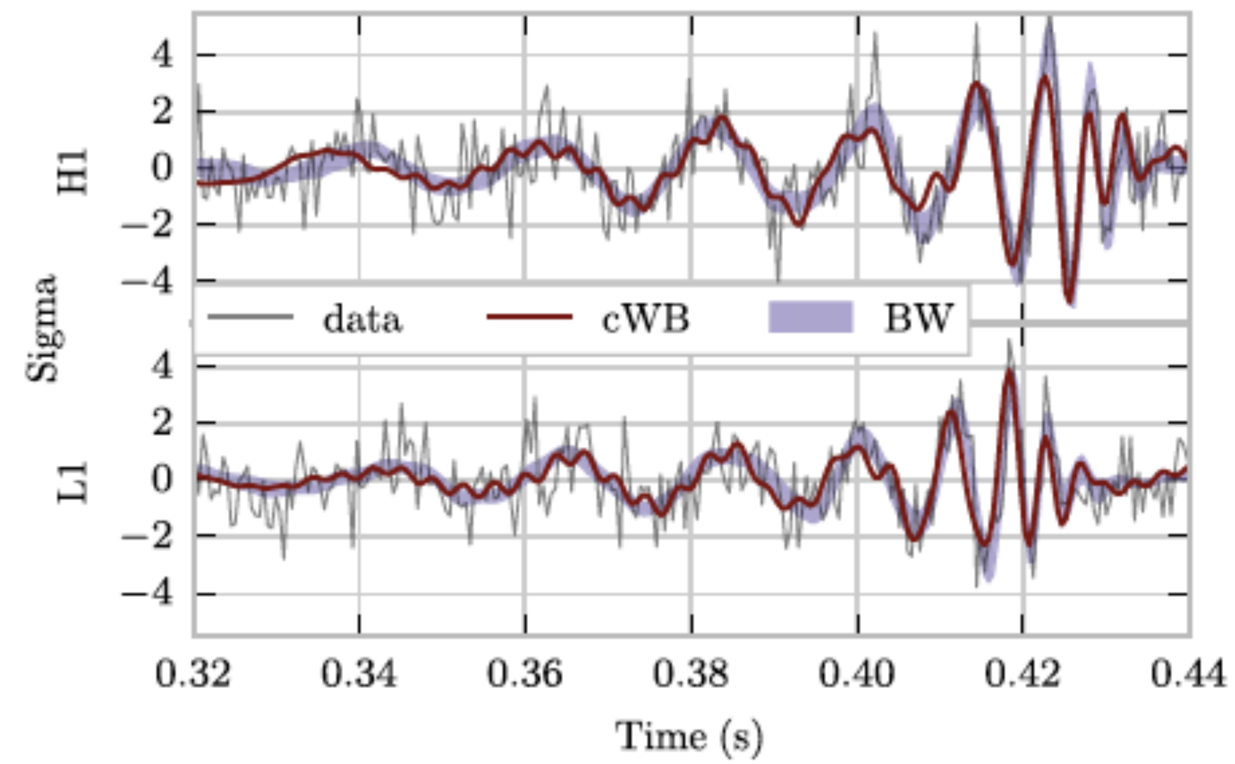
**Omicron-LALInferenceBurst (OLIB)**
**Littenberg et.al. PRD 2017**

# Burst algorithms for Short duration

**Minimal assumption about the signal morphology**

- BayesWave is a Bayesian algorithm used to distinguish between the GW signal and the noisy glitch.
- Models signals and glitches as a linear combination of sine-Gaussian wavelets.
- Folds in the detector location, location dependent detector response to compute the Bayes factor.
- cWB events are followed up by BayesWave. Signal reconstruction between the two are compared.

**GW150914 Reconstruction**




BayesWave
Cornish and Littenberg, CQG 2015

**Thank you**

# Burst algorithms for Long duration

**Minimal assumption about the signal morphology**

- Stochastic Transient Analysis Multi-detector Pipeline (STAMP)
- Cross-power SNR between the two detectors.
- Clustering algorithm — seed based as well as seedless
-