Compact Binary Coalescence Searches

Gravitational Wave Open Data Workshop

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Overview

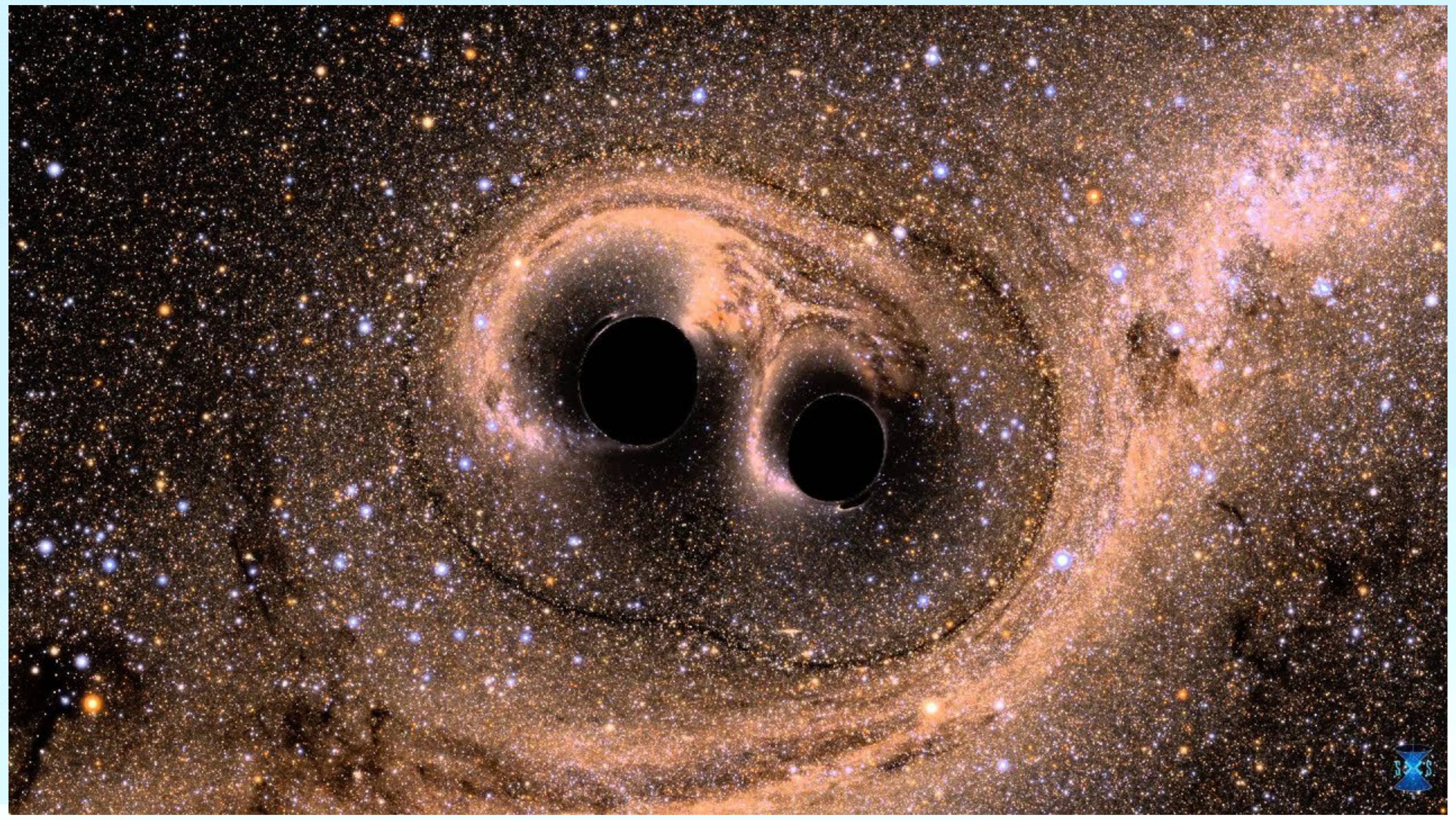
- CBC sources
- CBC Signal in Ground Based detectors
- Match filtering
- Signal consistency tests—-> Chi-squared test
- Towards optimisation of signal consistency
- Ranking Statistics
- Machine learning and CBC searches

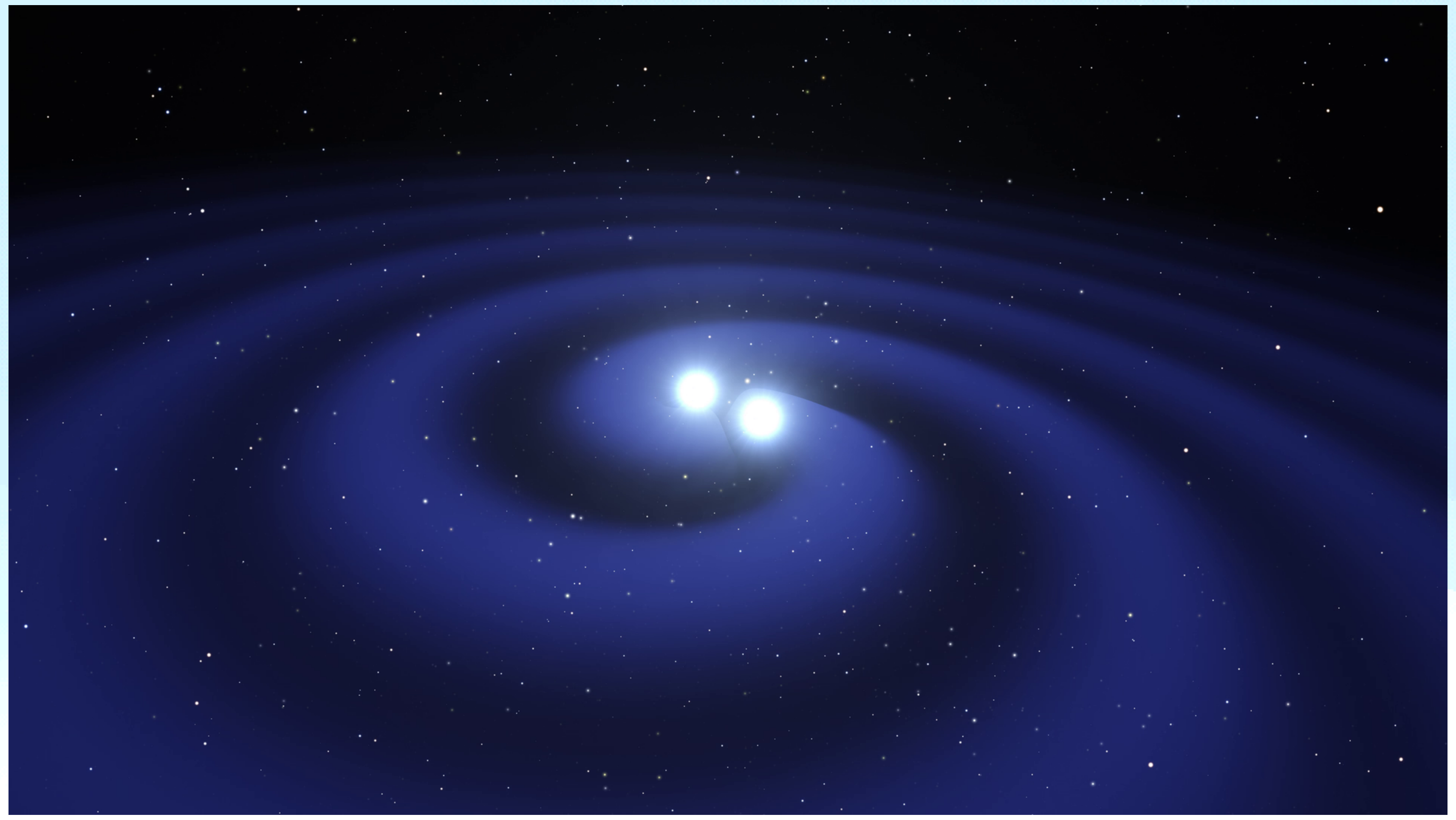
GW sources

Credit: Ben Gilliland

CBC Sources

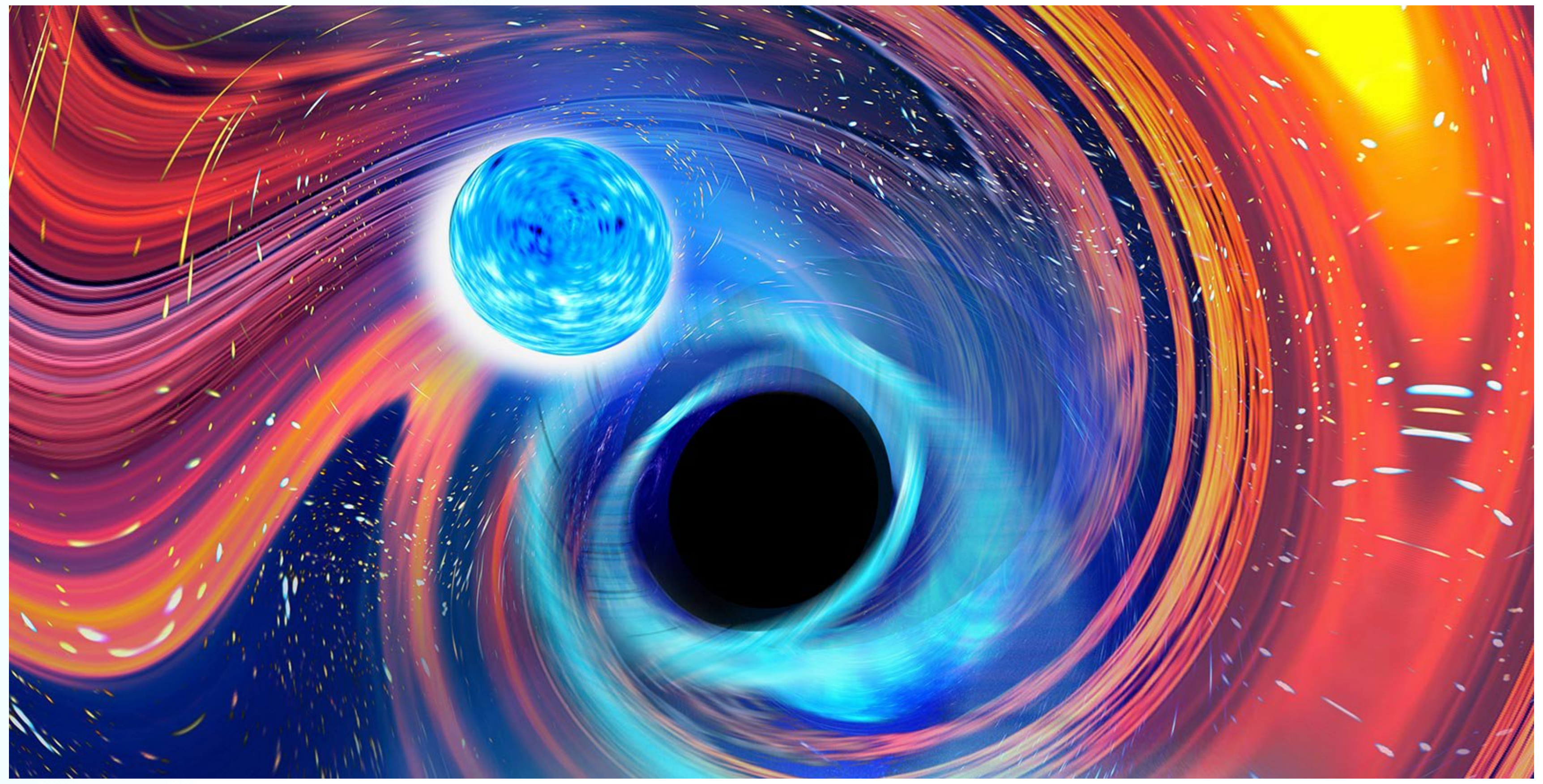
BBH





BNS

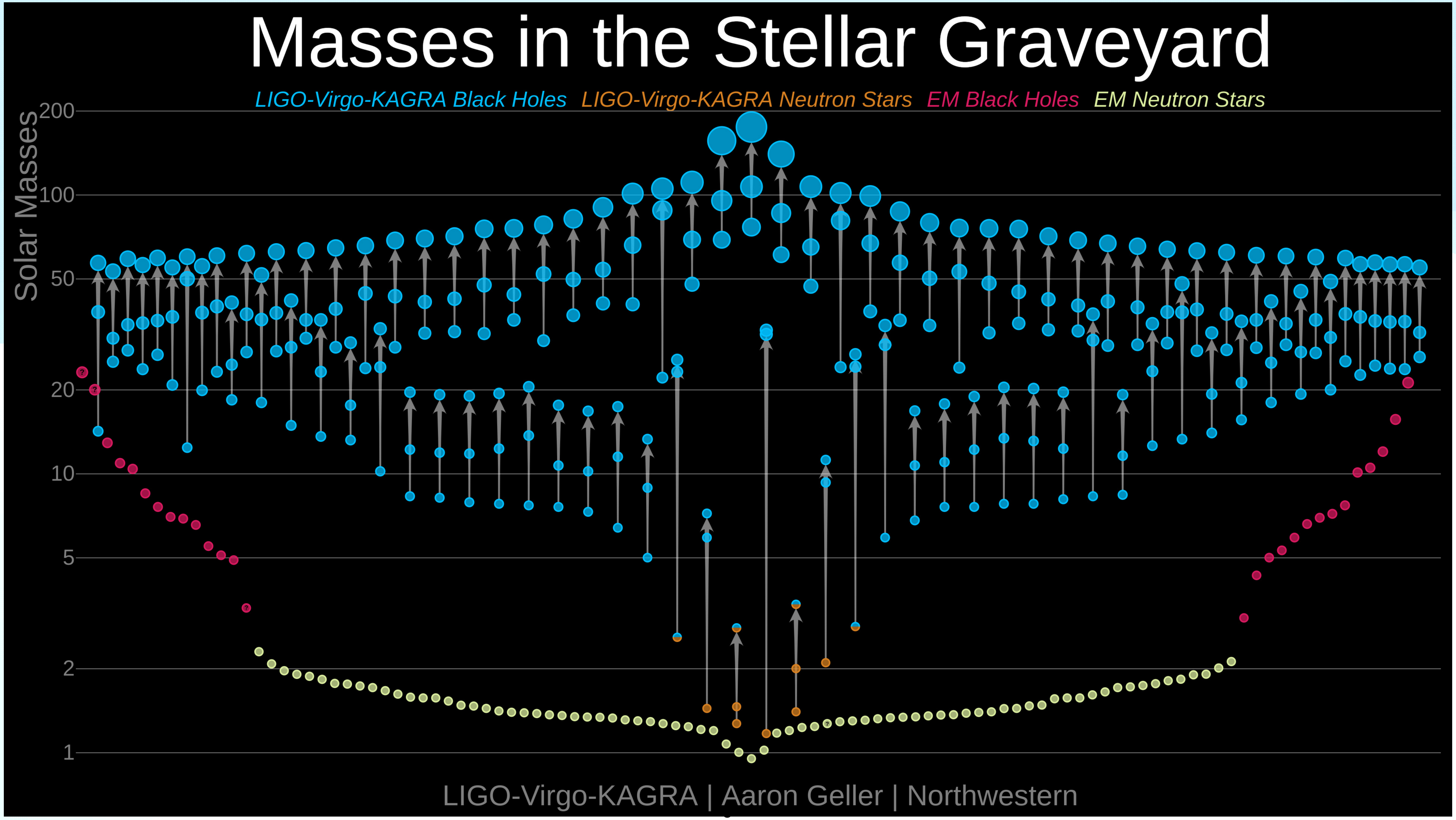
NSBH



Sub-solar masses

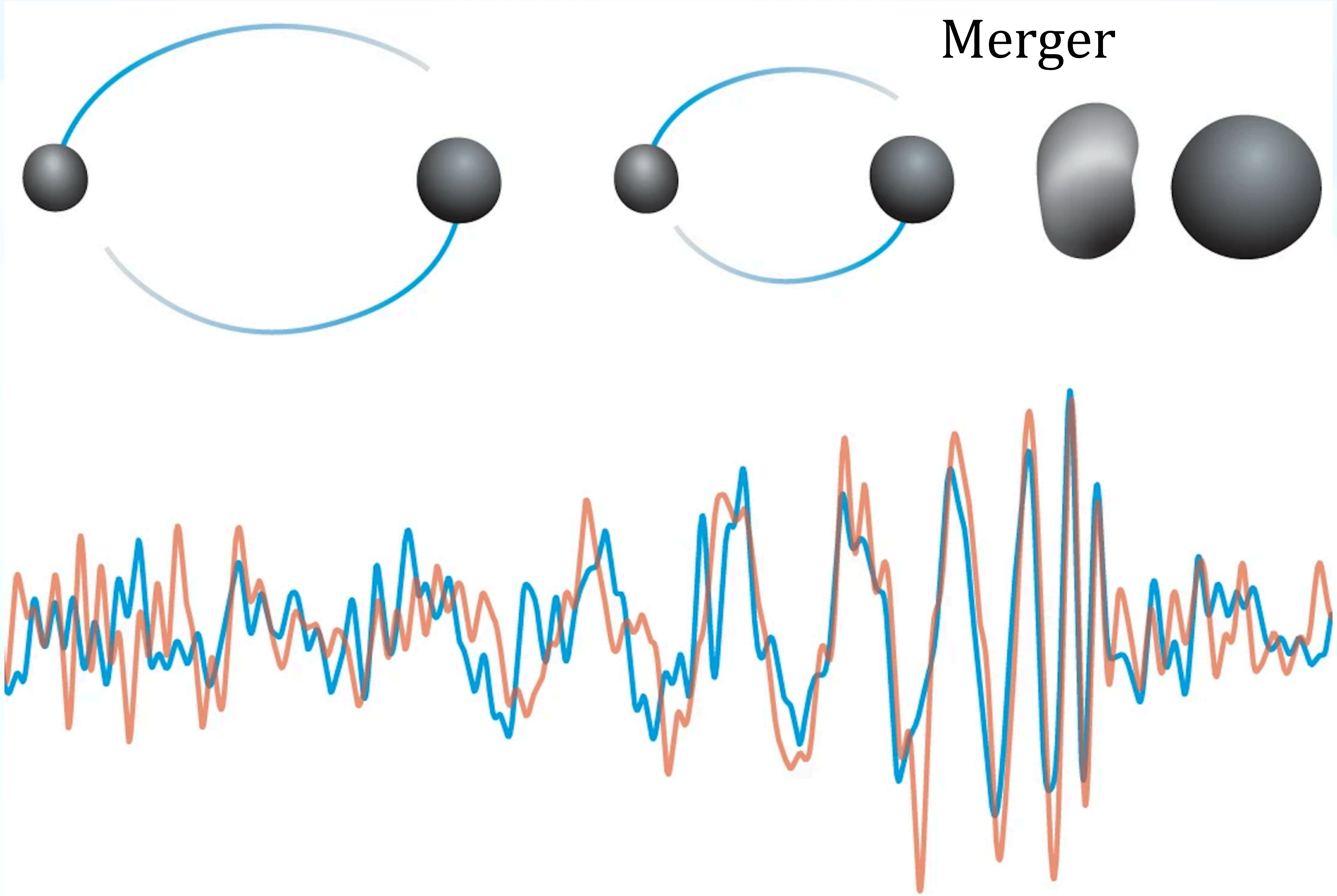
(White Dwarf, Neutron star, Primordial Black hole)

CBC Sources

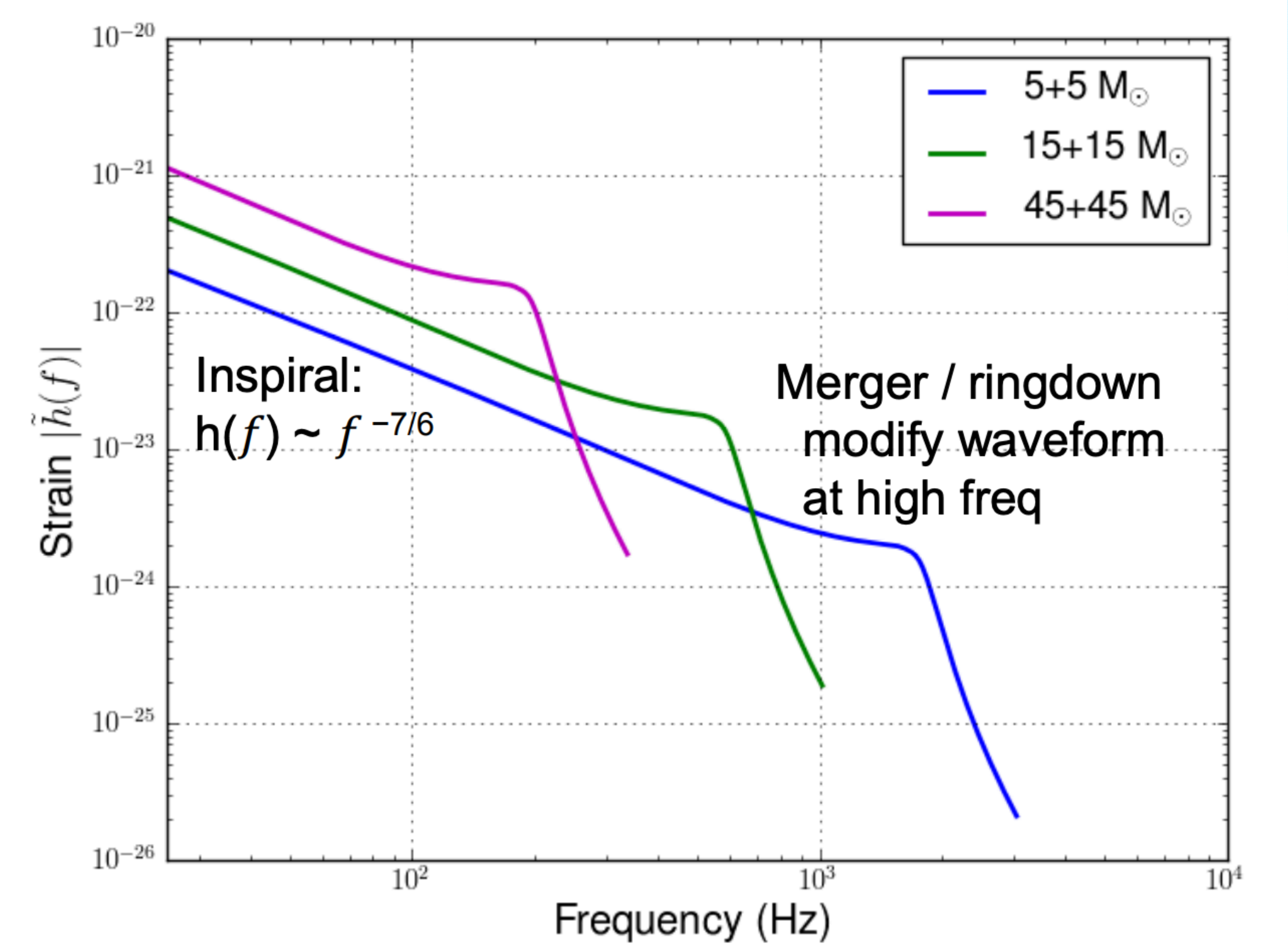


Masses in the Stellar Graveyard
LIGO-Virgo-KAGRA Black Holes
LIGO-Virgo-KAGRA Neutron Stars
EM Black Holes
EM Neutron Stars
Solar Masses
200
100
50
20
10
5
2
1
LIGO-Virgo-KAGRA | Aaron Geller | Northwestern

CBC signal



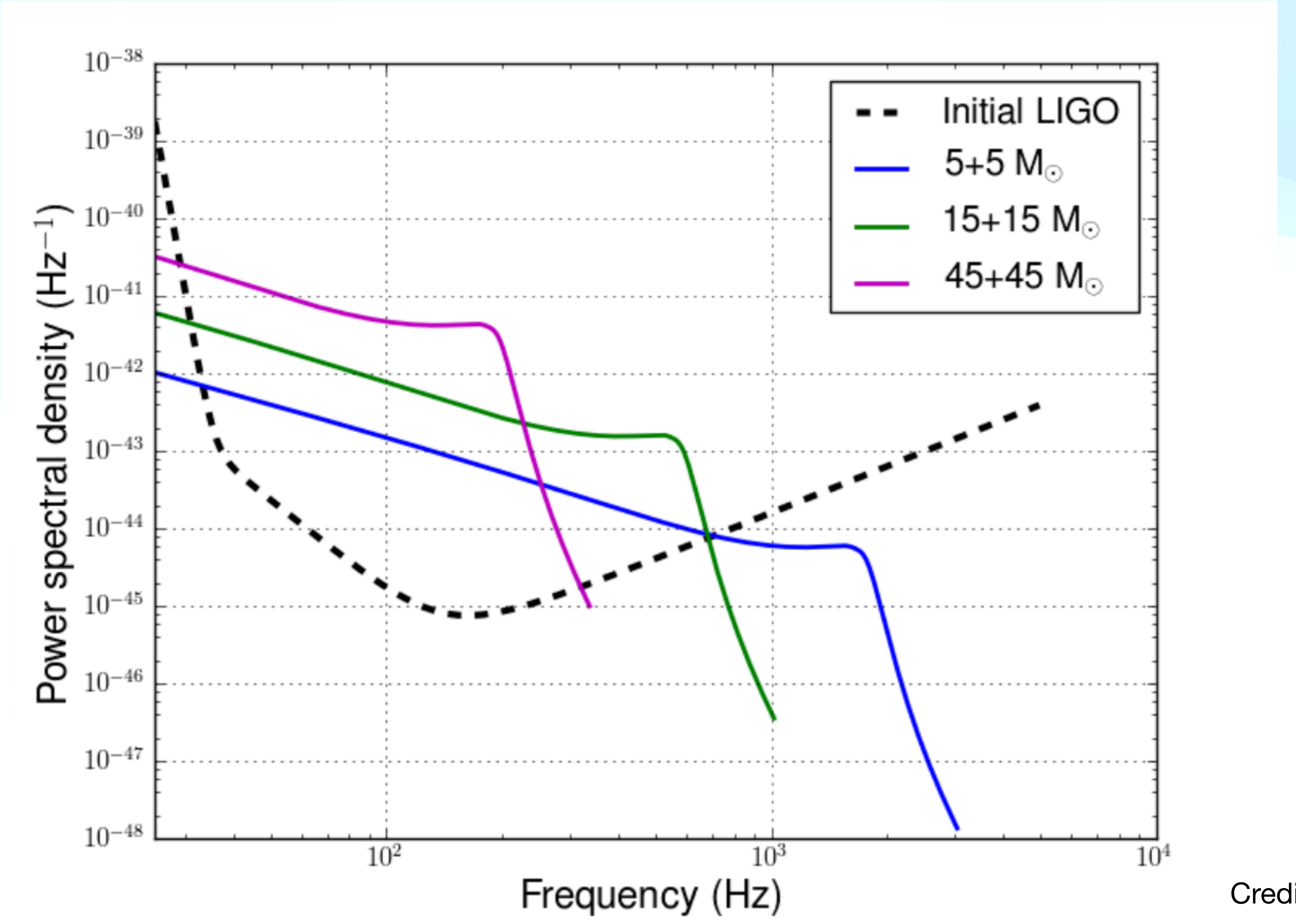
CBC signals
(Frequency domain)



Credit: Thomas Dent, USC

Power spectral density

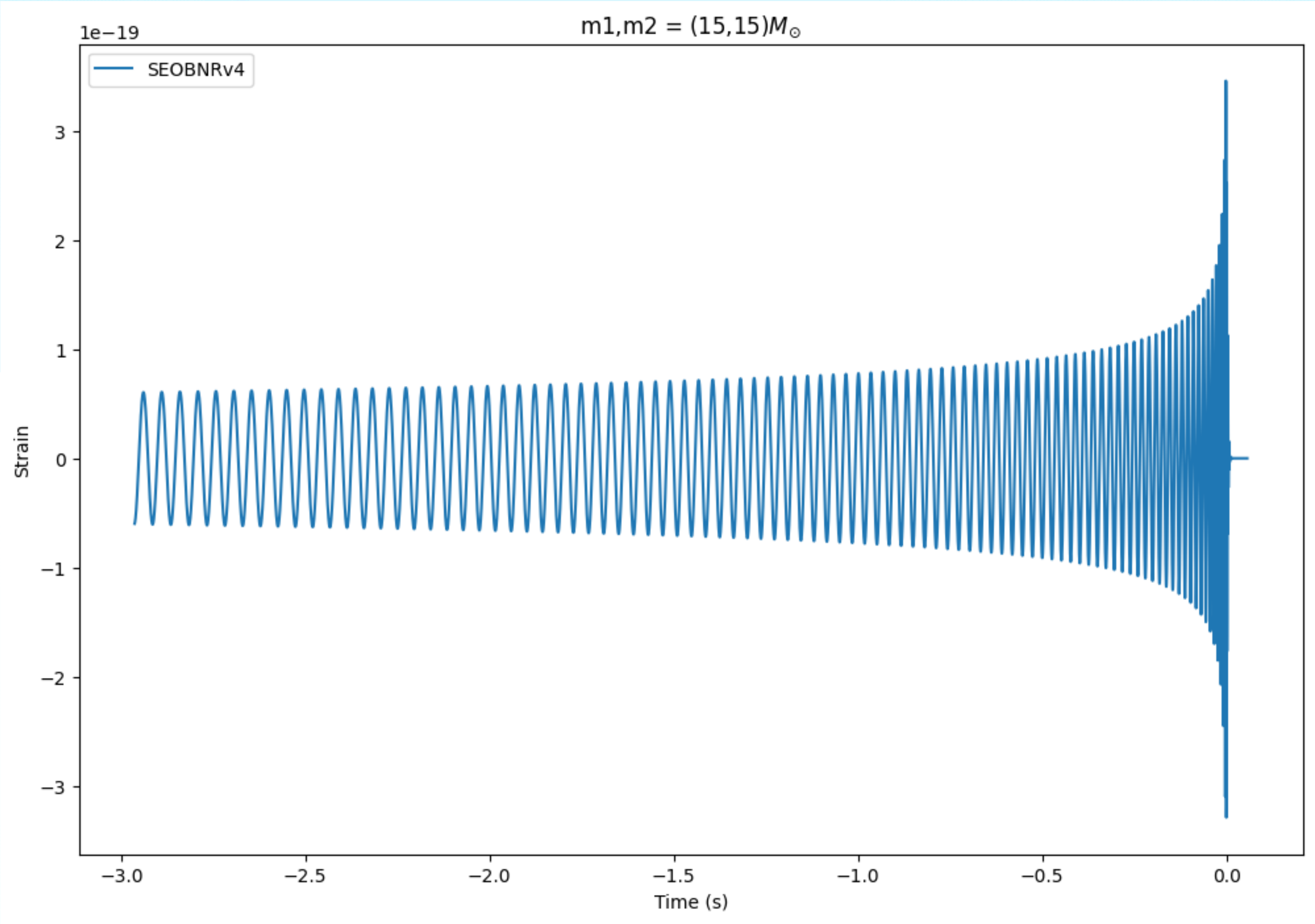
(Noise vs Signals)

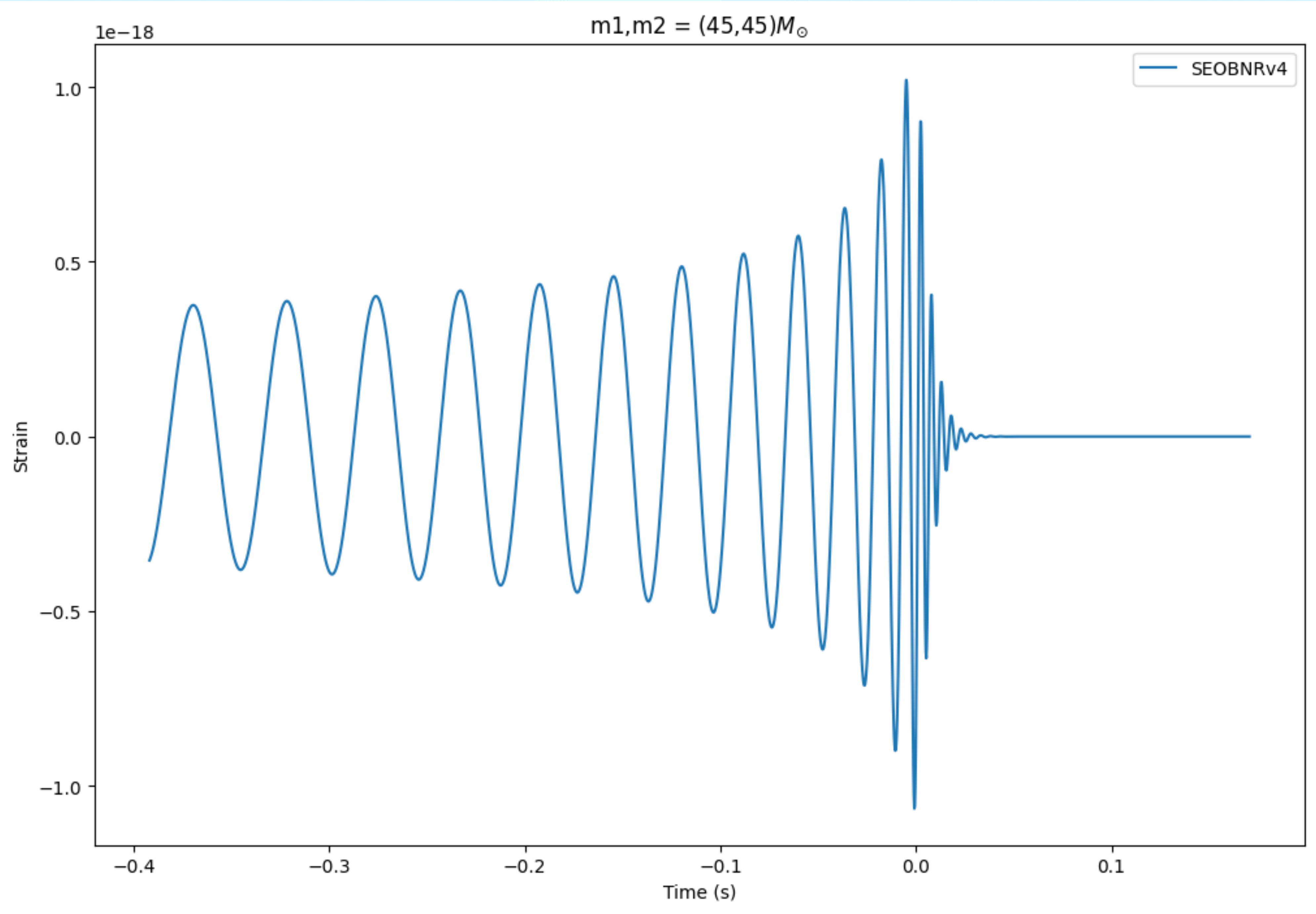


Credit: Thomas Dent, USC

Time spent in the sensitive bend

(Low mass)





To know more about signal morphology: see here

Noise Power Spectral Density (PSD) calculation

$$S_n(f) \equiv \lim_{T\to\infty} \frac{1}{T} \left| \int_{-T/2}^{T/2} dt\, n(t) e^{-2\pi i f t} \right|^2$$

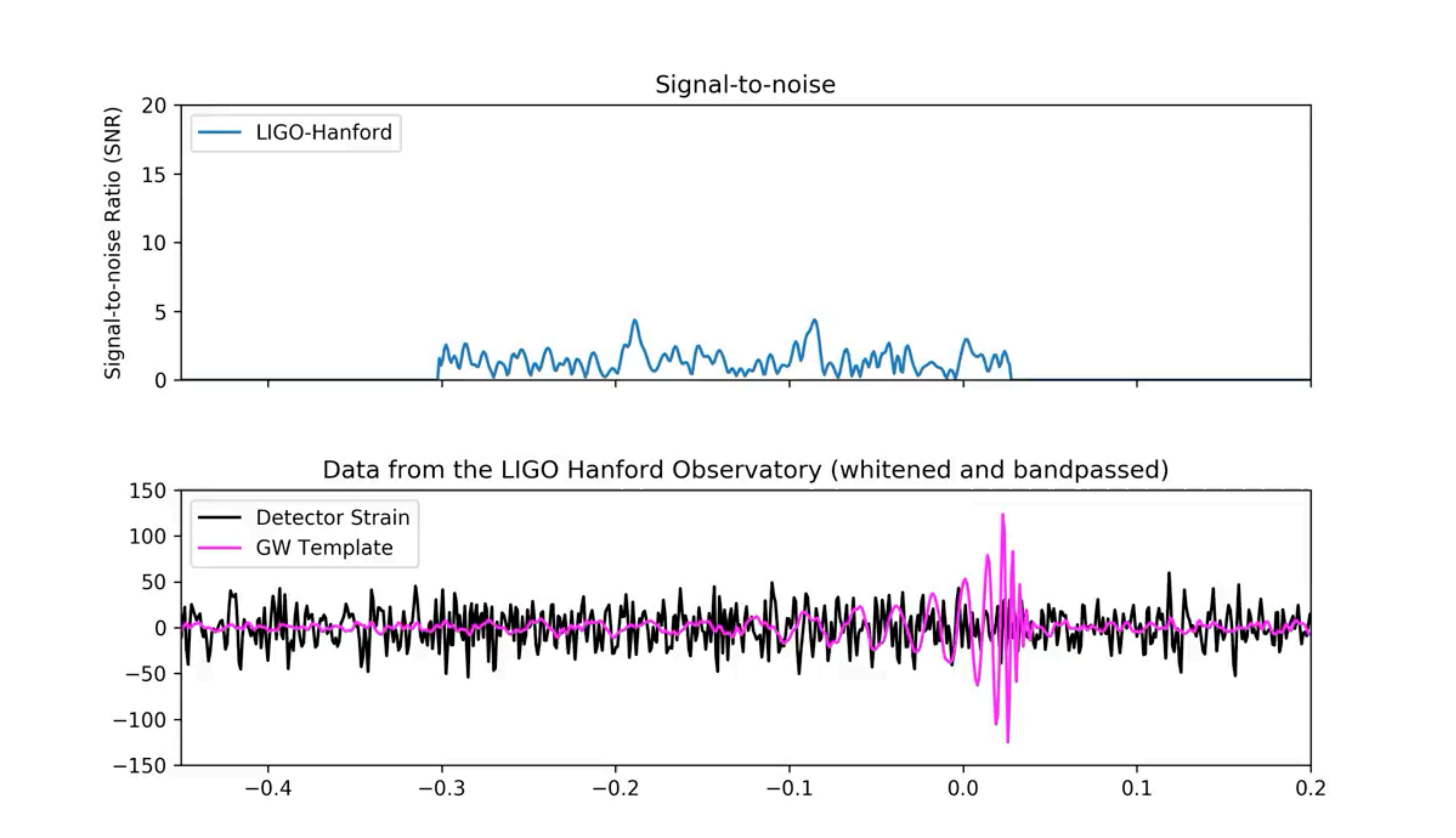
- PSD can be calculated using [Welch method]
- Take a long enough strain data segment—-> Divide the segment into overlapping sub-segments of equal length—-> Calculate the Discrete Fourier Transform—-> Take magnitude squared average over sub-segments —-> Power Spectral Density
- Used to whiten strain Data (Weigh-down the contribution from frequency bands where noise is dominant)

LIGO search pipelines
(Low-Latency)

- SPIIR - Summed Parallel Infinite Impulse Response, uses IIR filter representation and coherent search
- GstLAL - SVD reduced filtering, Time domain match filtering
- PyCBC Live - Uses rigorous signal-consistency and optimised FFT
- MBTA - Multi-Band Template Analysis
- cWB - Coherent Wave Burst (Unmodeled search)

Matched-Filtering

$$\rho = \frac{|(s,h)|}{\sqrt{(h,h)}}$$ Where, $$(s,h) = 4\int_0^\infty \frac{\tilde{s}(f)\,\tilde{h}(f)^*\,df}{S_n(f)}$$

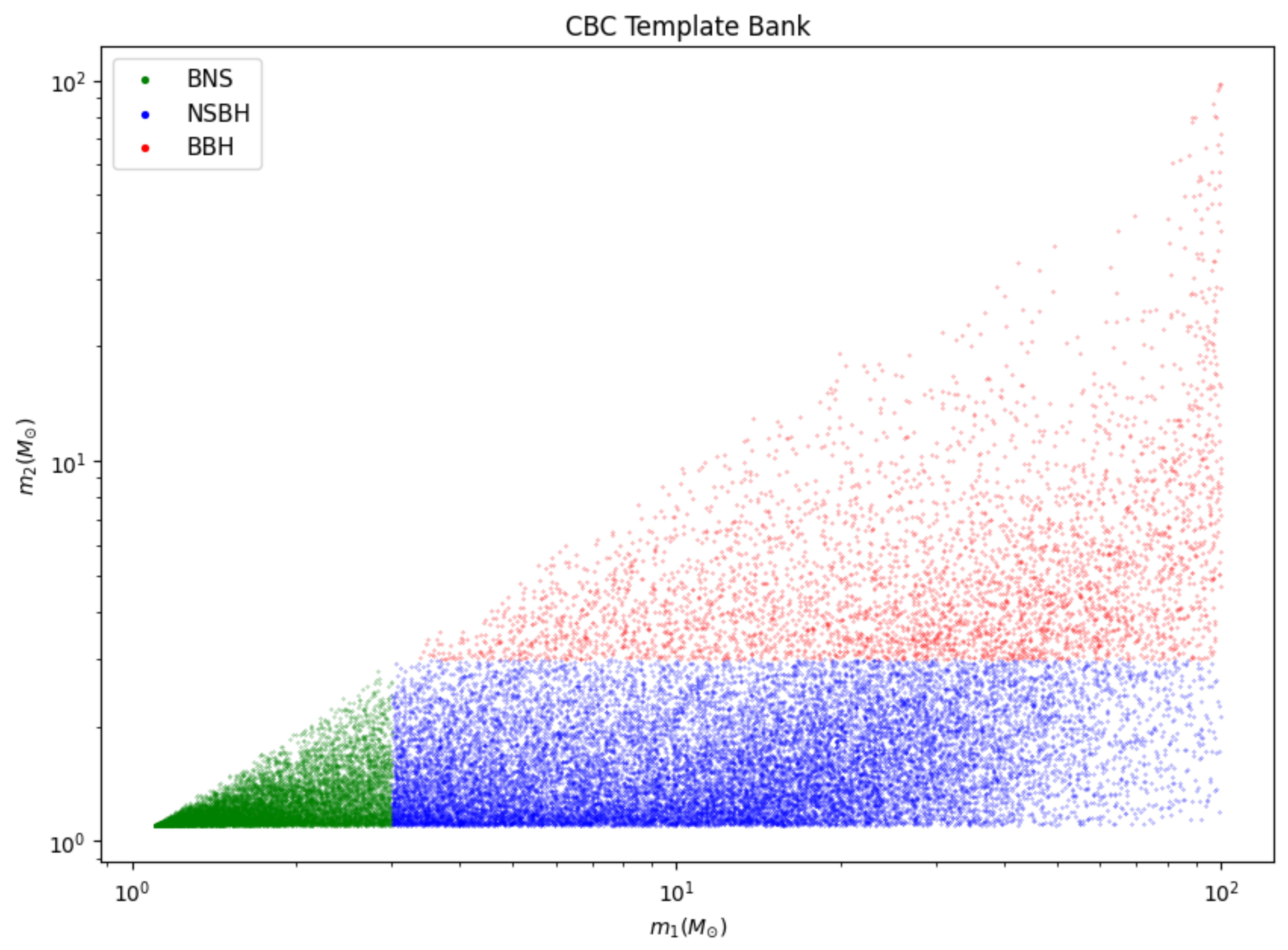


Credit: Alex Nitz, Syracuse University

Computational issue with Matched-Filtering

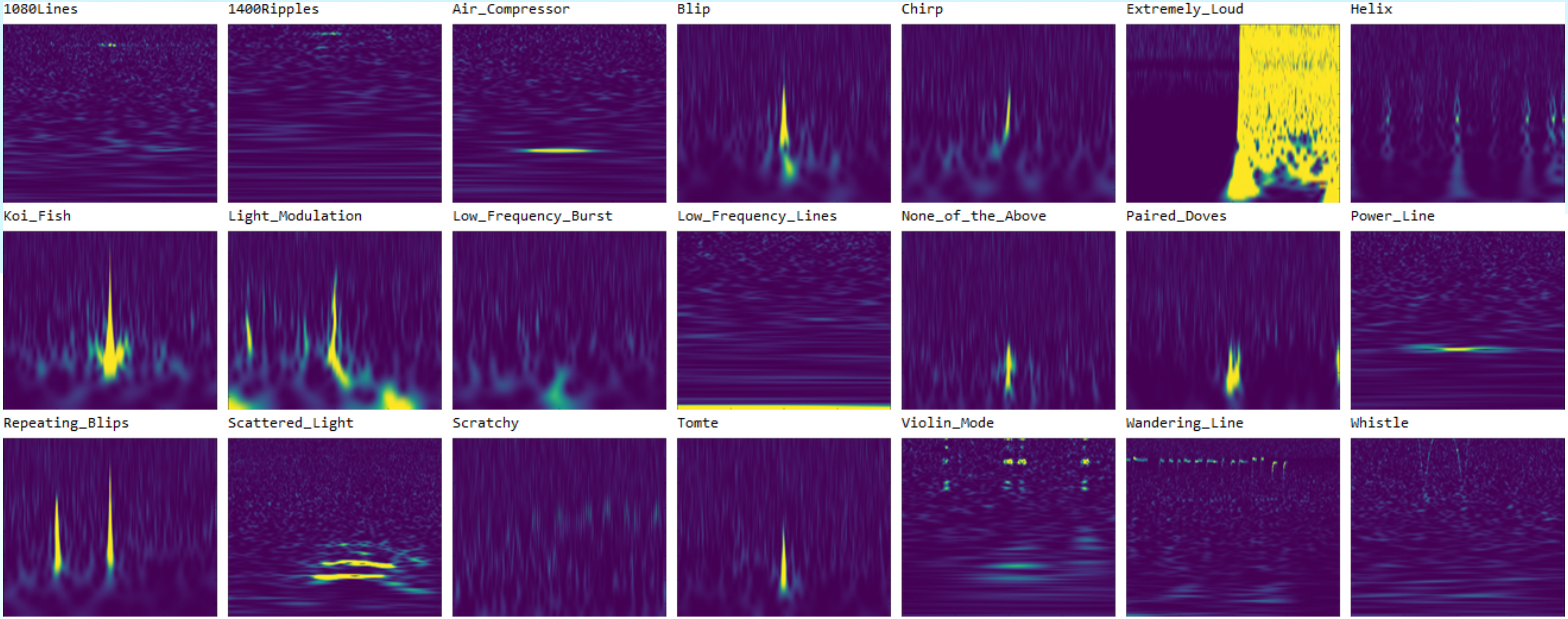
*Large number of templates

Millions of template in O4



Each template has 97% match with neighbour

No-Gaussian artefacts (Noise transients or Glitches)

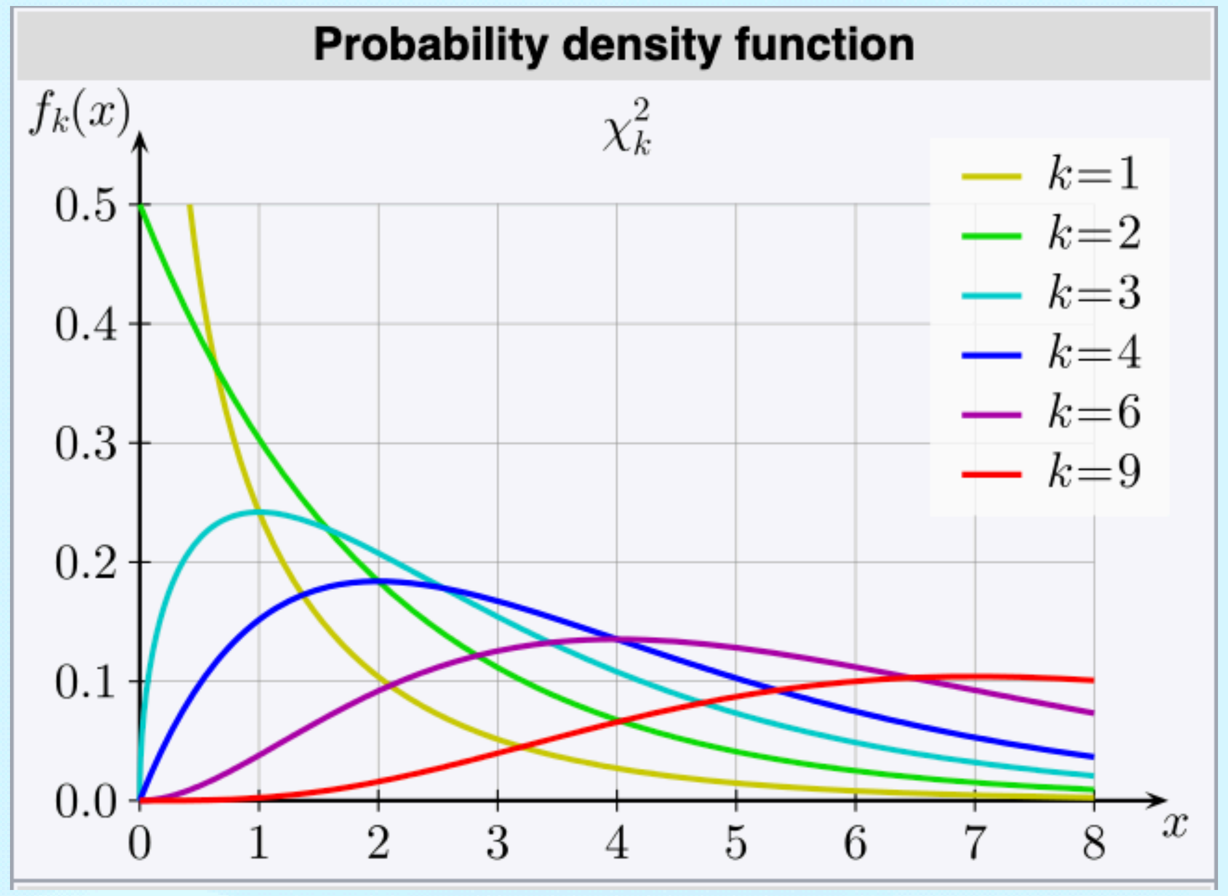


Credit: GravitySpy

How to generate Q-transform: see here

Signal consistency tests

Chi-squares



$$\chi^2 = \sum \alpha_i^2$$

α_i - Independent, Gaussian random variable

DOF = number of α_i

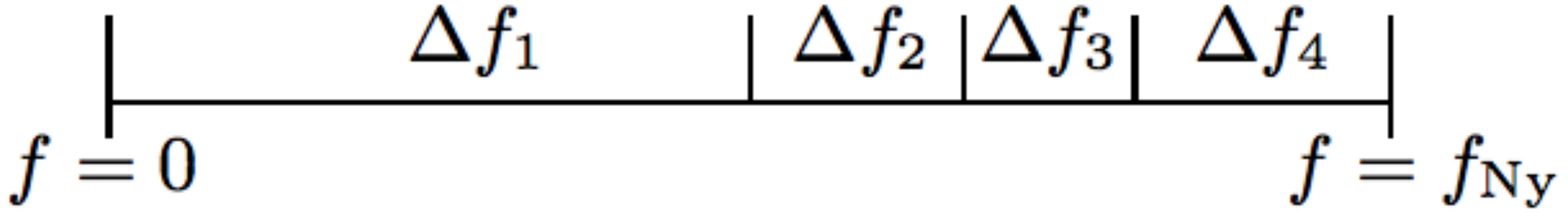
$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

O_i - Observed Value

E_i - Expected Value

Bruce Allen's χ^2
(AKA power χ^2 or traditional χ^2)

- Consistency of matched-filtering SNR contribution from for triggered template vs Observed signal
- Used by PyCBC pipeline



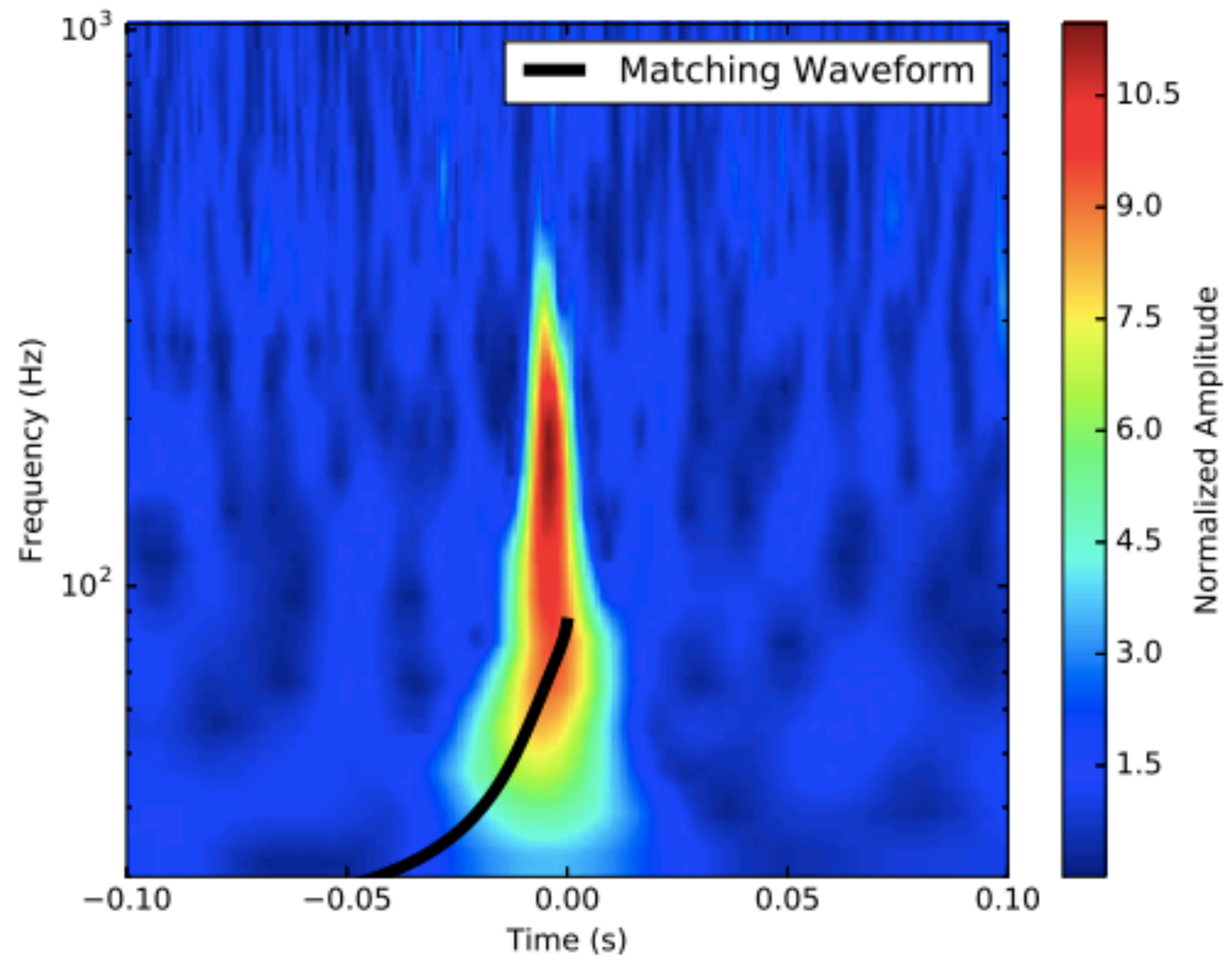
Sine-Gaussian χ^2

Sine-Gaussian waveform

$$g(t; t_0, f_0, Q) = A \cdot \sin(2\pi f_0 t + \phi_0)) \cdot e^{\frac{-4\pi f_0^2 (t - t_0)^2}{Q^2}}$$

- Glitches with excess power in the high frequency range
- This excess power is captured using sine-Gaussian waveforms and turned into a chi-squared test
- Triggers with high chi-squared value are rejected

$$\chi^2_{sg,r} = \frac{1}{2N} \sum_i^N \rho_i^2$$

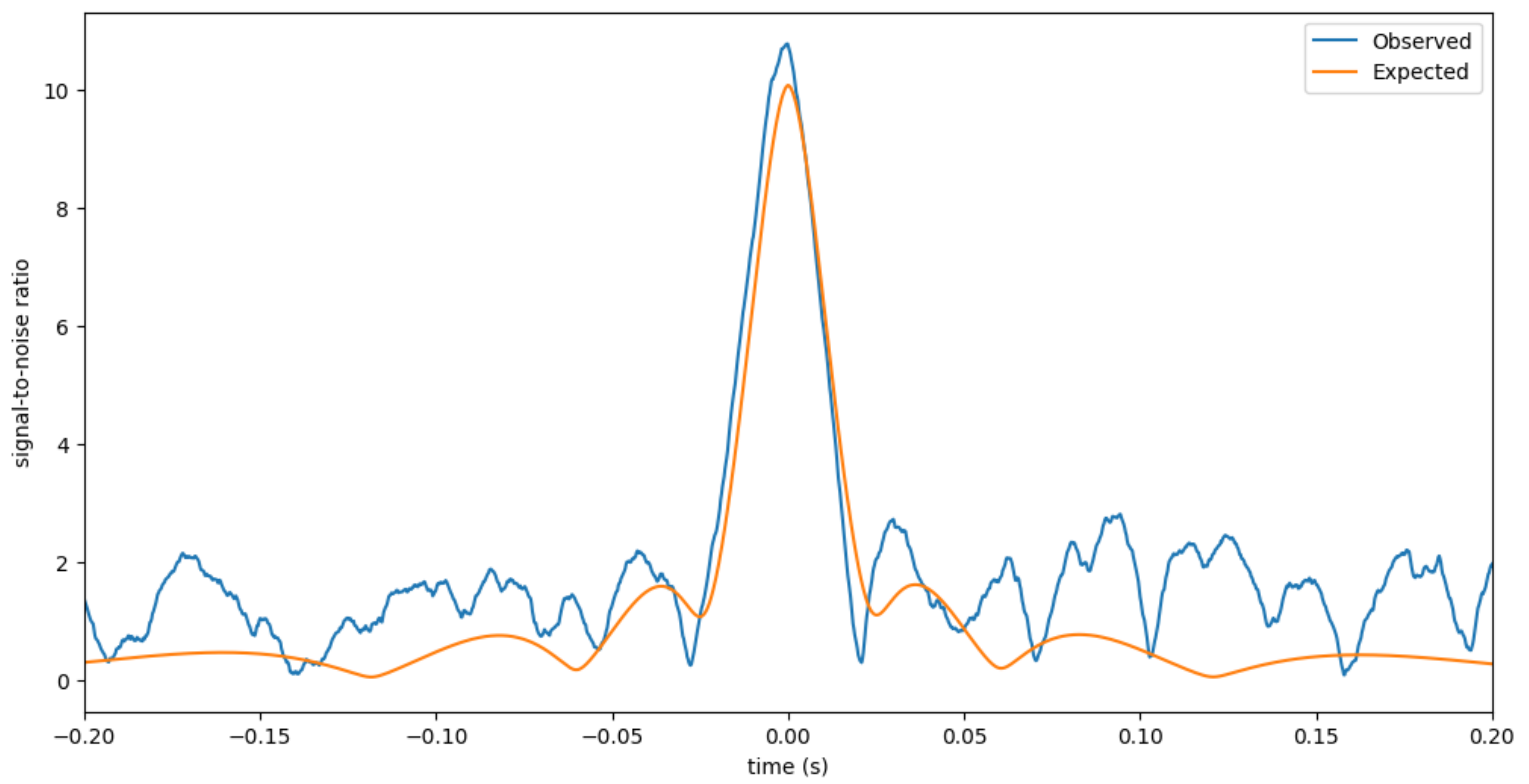


Alex Nitz, 2017

Autocorrelation χ^2 tests

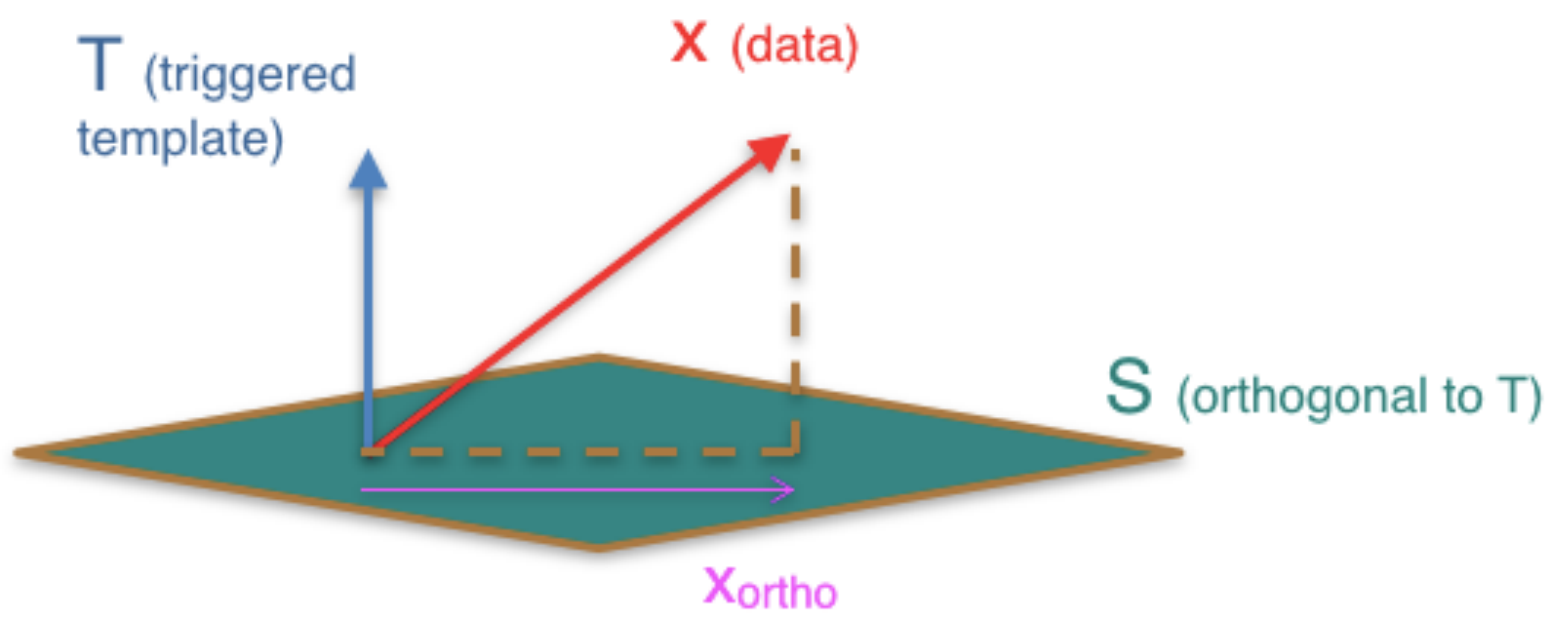
- Used by SPIIR and GstLAL pipeline
- Based on difference in expected versus observed SNR series

Cody Messick et al, 2017



Many χ^2s —-> Unified framework

(Key to formulation of optimised χ^2)



$$\chi^2 = |x_{ortho}|^2$$

Ian Harry et al, 2011

Sanjeev Dhurandhar et al, 2017

Ranking Statistics (How detection is made)

- Ranking statistics

—-> Combine the calculated quantities like SNR and chi-square values to determine significance

Examples

$$L = \frac{P(\overrightarrow{O}, \vec{\rho}, \vec{\xi}^2, \vec{t}, \overrightarrow{\phi}, \theta | H_s)}{P(\overrightarrow{O}, \vec{\rho}, \vec{\xi}^2, \vec{t}, \overrightarrow{\phi}, \theta | H_n)}$$

GstLAL

$$\tilde{\rho} = \rho \left(\frac{1}{2} \left(1 + \left(\chi_r^2 \right)^{\left(\frac{q}{n} \right)} \right) \right)^{-\frac{1}{q}}$$

PyCBC

SPIIR uses K-Nearest Neighbour method

CBC searches with Machine Learning

- Match-filtering —-> computationally expensive
- Many works in last few years
- Machine learning networks have shown promising results in case of higher-mass BBH searches
- ML Noise cleaning —-> Another way to improve search sensitivity
- Lower-mass searches still a challenge
- ML network are being used to calculate source properties

Deep Chatterjee et al, 2019

Summary

- CBC sources - BBH, NSBH and BNS. Also, SSM.
- Matched-filter—-> Primary filter
- Non-gaussian artefacts —-> main cause of concern in CBC searches
- Signal consistency tests like Chi-squared test provide solution
- Signal-Consistency test still improving
- CBC searches with Machine learning—-> Future?