GWOSC
(data/Poster)

| O1 | O2 | O3a | O3b |
|---|---|---|---|
| 3 GW events | 8 GW events | 44 GW events | 35 GW events |

$\underbrace{\hspace{6cm}}_{90\ \text{events}}$

DATA

Strain data

Bulk data released in
4 Khz & 16KHz sampling rate

Download software (data extraction tools)

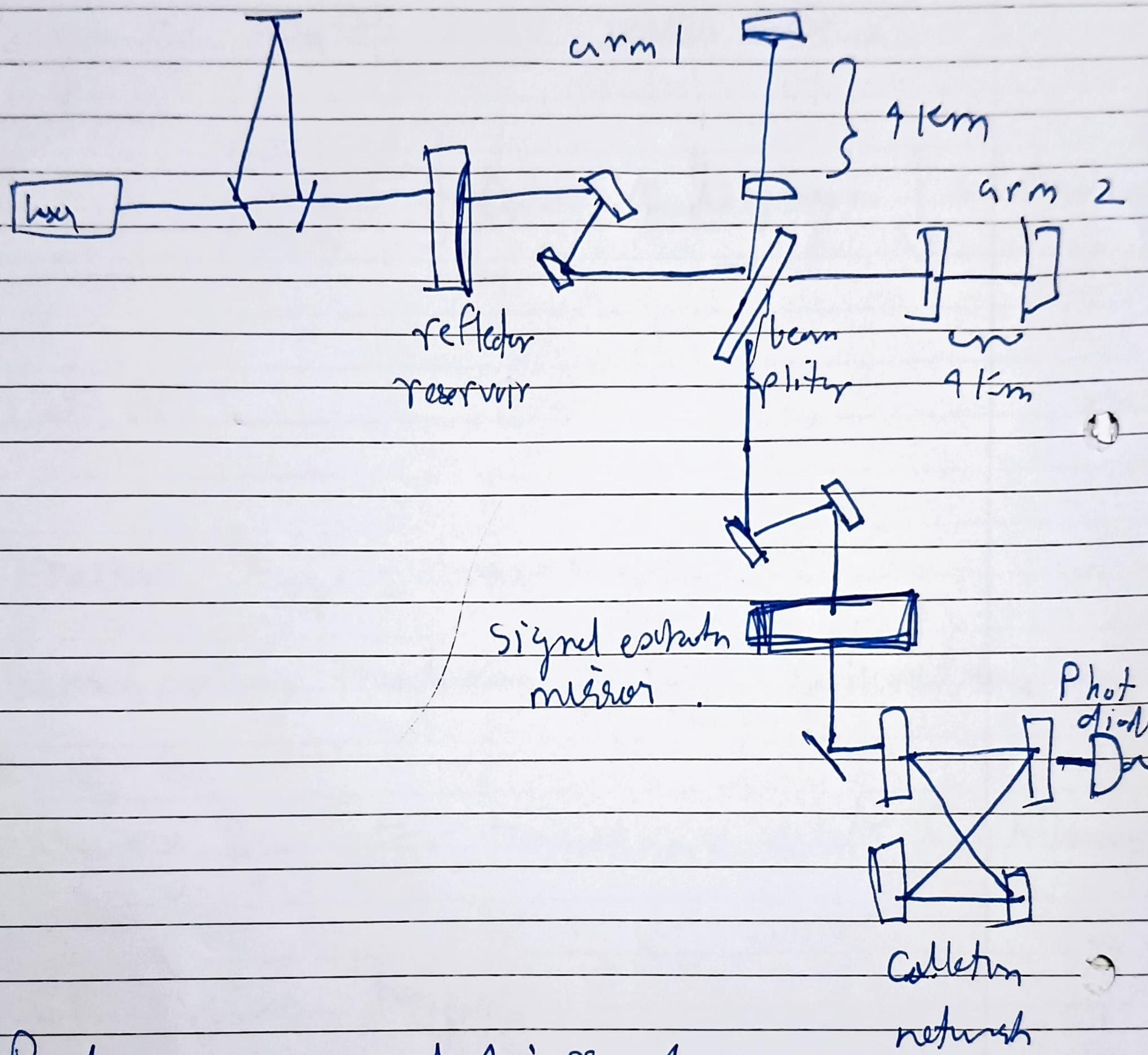
Cer VM-FS
NDS2
GWpy

Versions in events: Diff analysis of data.
Diff calibration / noise removal.

Timeline App: Segments of strain data based on GPS interval

GRACE DB: Showing immediate alerts for other observations.

LIGO - Laser Interferometer Gravity Observatory.




Baseline noise is point of improvement

$$\text{Gravitational Wave strain} = \frac{\text{Mirror precision}}{\text{Length between arms}}$$

$$\text{for ligo} = \frac{10^{-19}\,m}{4\,Km}$$

Noise: Quantum shot limits laser power

Total control noise – biggest noise factor.

Segments: On off time series data.

CAT 1
CAT 2
CAT 3 } Data Quality flags ↓ severity decrease

Web API:

Omicron triggers = transient noise

Ground motion, thunderstorm, change in humidity

Gravity Spy => transient noise detection CNN based

CAT 3 vetoes target

# Compact Binary Coalescense.

Stellar evolution
Endphase (Graveyard)

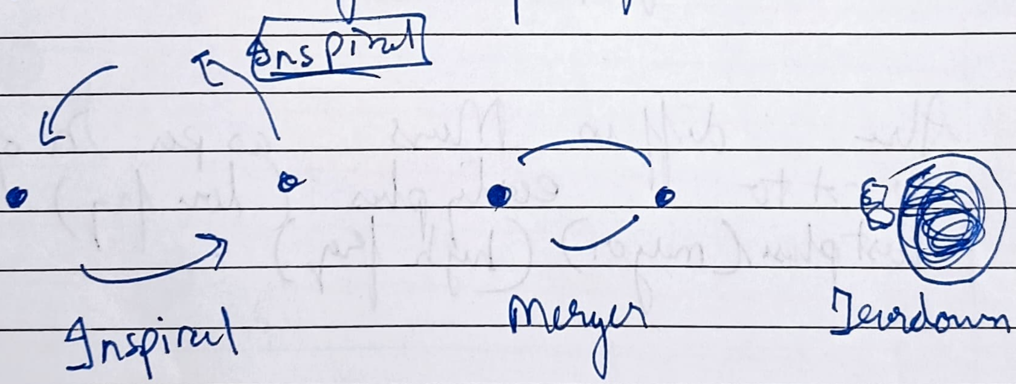
Massive Star (10 x Sun)

Explosion / Implosion → Supernova

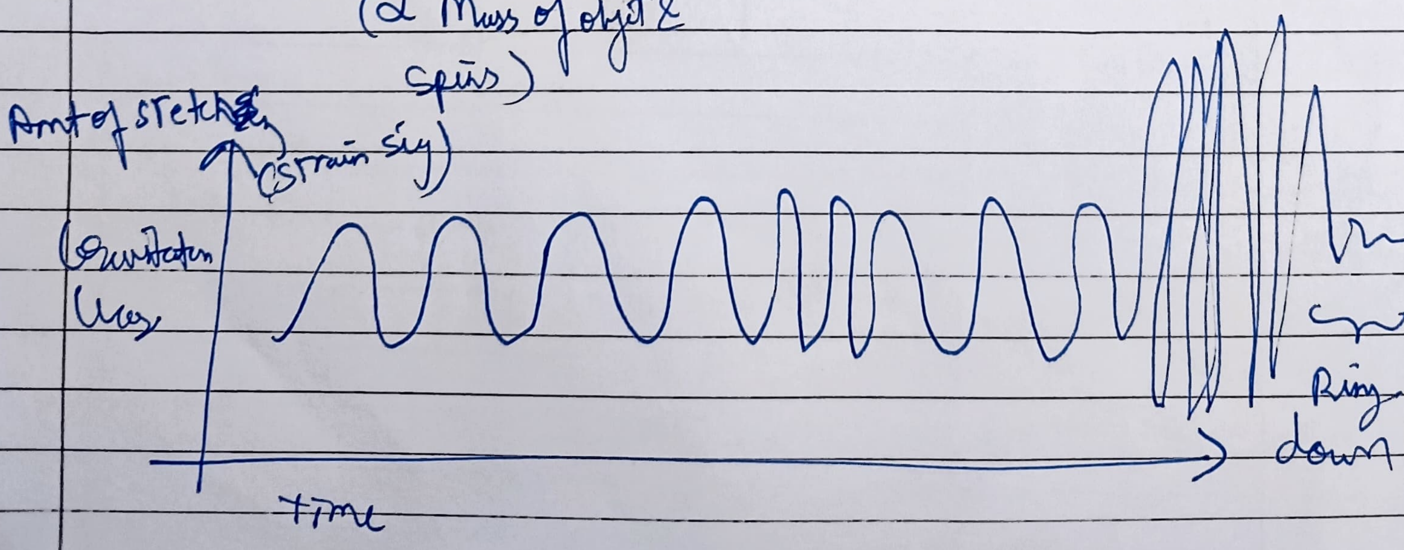
→ Black Holes / Neutron Stars.

Gravitational Wave signal of Merger

Phases of contact




2 × orbital f
(∝ Mass of object & spins)



Information :

How big & neutron stars / black holes
How fast is their spin
Where & when did they merge
How squishy are neutron stars.

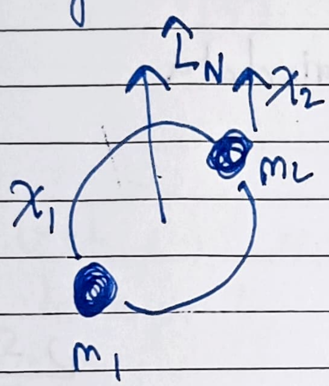
Posterior Probability range values available.

Also, GW can be cross referred to RS for measure age of univ.

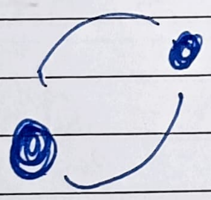
Also diff in Mass as per fn of strain w.r.t to early phase (low freq) signal vs last phase (merger) (high freq).

PyCBC

## Merger Phases




inspiral



inspiral

Merger

ringdown

intrinsic paramets : $m_1, m_2$ etc masses, spins.

★ Matched Filtering

Ligo data [Notation]

Discrete time series strain data
with stationary noise.
&
with Gaussian noise

Assumption

$$d[t_i] = n[t_i] + s[t_i]$$

Strain data. noise signal

$$\rho(t) = 2\int_{-\infty}^{\infty} df\, \tilde{h}(f)\,\tilde{d}(f)\exp 2\pi i f t$$

$$= 2\int_{-\infty}^{\infty} d\tau\, h(\tau)\, d(t+\tau)$$

P.O.I 4D template banks

$$\{m_1, m_2, s_{1z}, s_{2z}\}$$

Noise is not stat, Gaussian or white (Power across freq is not same

$$p(t) = \int_{-\infty}^{+\infty} d\tau \, \underbrace{\hat{h}(\tau)\,\hat{d}(t+\tau)}_{\text{whitened \& Temp data}}$$

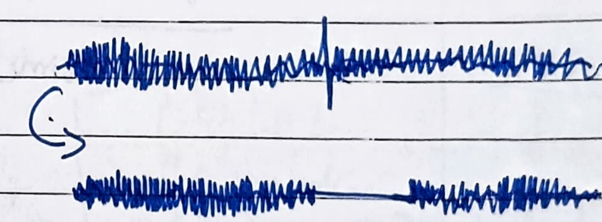
$$d(\tau) = \int_{-\infty}^{\infty} df \, \frac{\tilde{d}(f)}{\sqrt{S_n(|f|)}} \exp 2\pi i f \tau$$

GstLAL, MBTA, PyCBC Matched filtering techniques.

GstLAL -

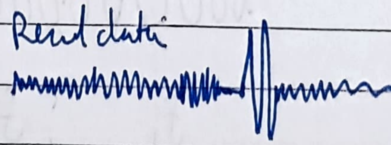
1. Gating

Gating

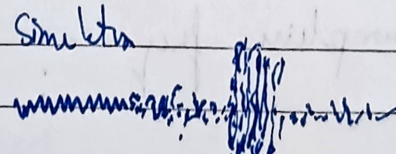


2. Signal Consistency test

Real data



Simulation



Hence mismatch.

~~8~~ 3. IDQ

Intelligent data Quality.

based on sensor data channels to verify glitches

Matched filtering LLOID method

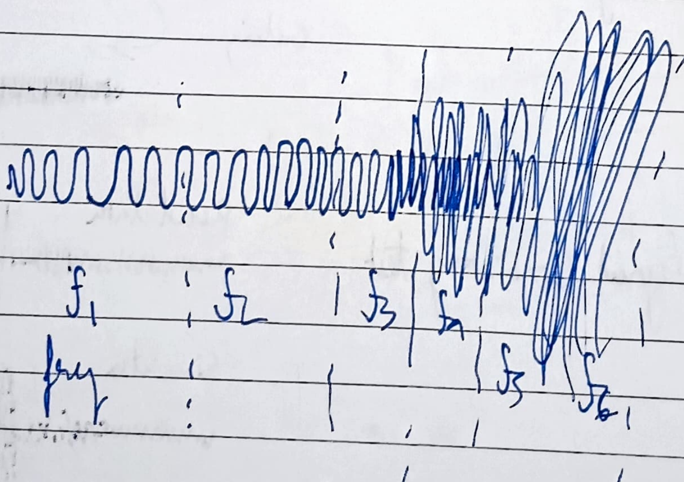
Low Latency Online Inspiral Detection

LLOID = TimeSlice & Down Sample + Singular Value Decomposition (SVD)

Step1: TimeSlice & Down Sample

Inspiral freq (monotonic increase)

time

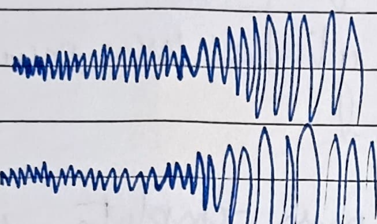



Sampling freq

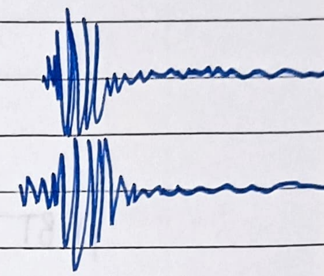
$f_6 > f_5 > f_4 > f_3 > f_2 > f_1$

## Step 2: Singular Value Decomposition.

Slicing to base waveforms.



$H_{\nu j} = \sum_\nu u_{\nu\nu}\sigma_\nu u_{\nu j}$ $\longrightarrow$



PyCBC & MBTA → Matched filtering

→ in freq domain

→ multiplication.

$\tilde{\rho}[k] = \tilde{d}[k]\cdot\tilde{h}^*[k]$

GstLAL

→ Convolution

$\rho[j] = d[j] * h[j]$

→ Perform FFT on blocks of data, then correlate with template.

$$\tilde{d}[k] = \sum_{j=0}^{N-1} d[j]\exp(-2\pi i jk/N)$$

DFFT

Noise handling:

Gating & signal consistency tool

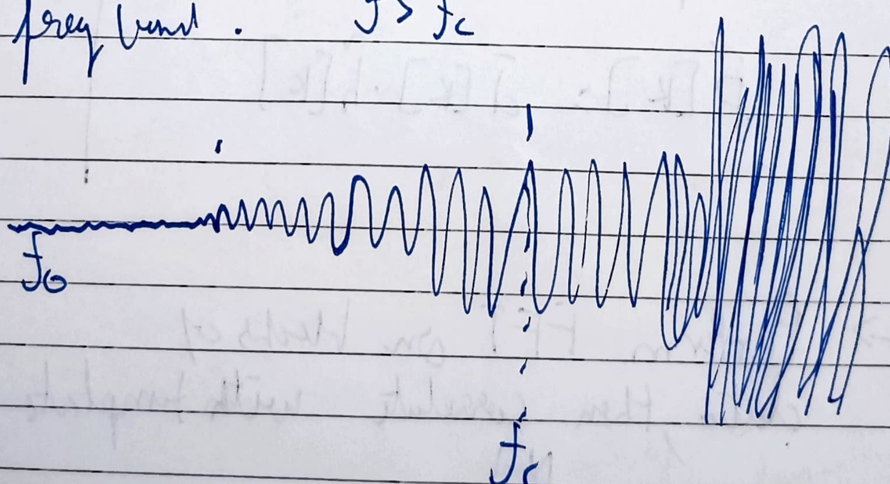
~~DQ~~ ce values :- flags to stretch of data telling if glitches were made.

MBTA : refilter high mass templates w/o gating

Step 2: Multi Banding

Low freq band $f_0 < f < f_c$

High freq band. $f > f_c$



# Parameter Estimation

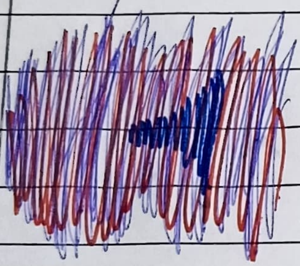
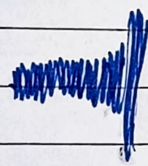
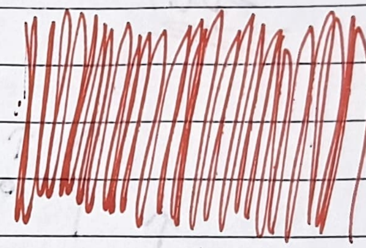
Tools:

Baye's theorem $P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$

Stochastic Samplers: emcee, dynesty

BILBY

Data | Signal | Noise

 $\Rightarrow$  $+$ 

$d(t)$ | $h(t;\theta)$ | $n(t)$

Signal : Two polarizations.
$+$ & $\times$

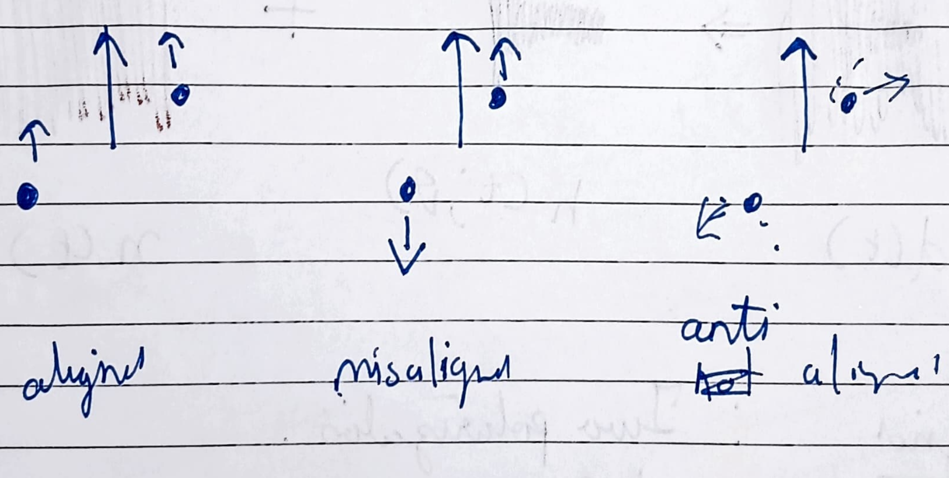
Each polarization depends on 15 parameters
- Intrinsic: 3D spin vectors, masses (of CBC)
- Extrinsic: distance, (RA, Dec), polarization angle $\psi$.

$$h(\theta;t) = \sum_{p=+,\times} F_p(RA, Dec, \psi)\, h_p(\theta;t)$$

## Mass

Mass ↑ ; signal length ↓ ; Amplitude ↑

## Spin




Individual spin vectors if aligned with orbital momentum, longer stretch of signal ;
Anti aligned .
~~Misaligned~~ spin vectors if not aligned / opposite, shortest signal length .

Same Amplitude All over

When best fit data is subtracted from all data, all left is noise. hence following a gaussian distribution.

Likelihood distribution for each freq.

$$\mathcal{L}(d_i|\theta) = \frac{2\Delta f}{\pi S_n(f_i)} \exp\left(-2\Delta f \frac{|d(f_i) - h(f_i;\theta)|^2}{S_n(f_i)}\right)$$

Total Likelihood $\mathcal{L}(d|\theta) = \prod_{i=1}^{N} \mathcal{L}(d_i|\theta)$

Prior: human limits about Physically possible or not & etc.

Evidence for S vs N.

$$N \Rightarrow Z_n = \frac{2\Delta f}{\pi S_n(f_i)} \exp\left(-2\Delta f \frac{|d(f_i)|^2}{S_n(f_i)}\right)$$

Bayes factor

$$BF^S_N = \frac{Z_s}{Z_n}$$

PSD parameter estimation:

$\mu = 0$

$$P(n_i) \sim \exp\left(-2\Delta f \frac{n_i^2}{S_n(f_i)}\right)$$

Welch Method:

Divide time series into small segments

Fourier transform $|d(f)|^2$

Bayes theorem

$$P(\theta|d) = \frac{P(d|\theta)P(\theta)}{P(d)}$$

d = data,

$$\underbrace{P(\theta|d) = p(\theta|d)}_{\text{Posterior distribution}}$$

$$\underbrace{\mathcal{L}(d|\theta)}_{\text{Likelihood}}, \underbrace{\pi(\theta)}_{\text{Prior}} = P(d|\theta)\, P(\theta)$$

$$Z_s = \underbrace{p(d)}_{\text{Evidence}} = \int d\theta\, \mathcal{L}(d|\theta)\, \pi(\theta)$$

$\theta \geq 15$ so computation is costly for

$p(\theta|d)$ posterior

## Stochastic Sampler

Populate space with random points
Converge based on posterior function.

## BILBY : Package.

LVK data.

Samplers : emcee, dynesty, bilby-mcmc, multinest.

## Output of a PE

ra, dec, luminosity_distance, mass_1, mass_2

PESummary Data viz package.