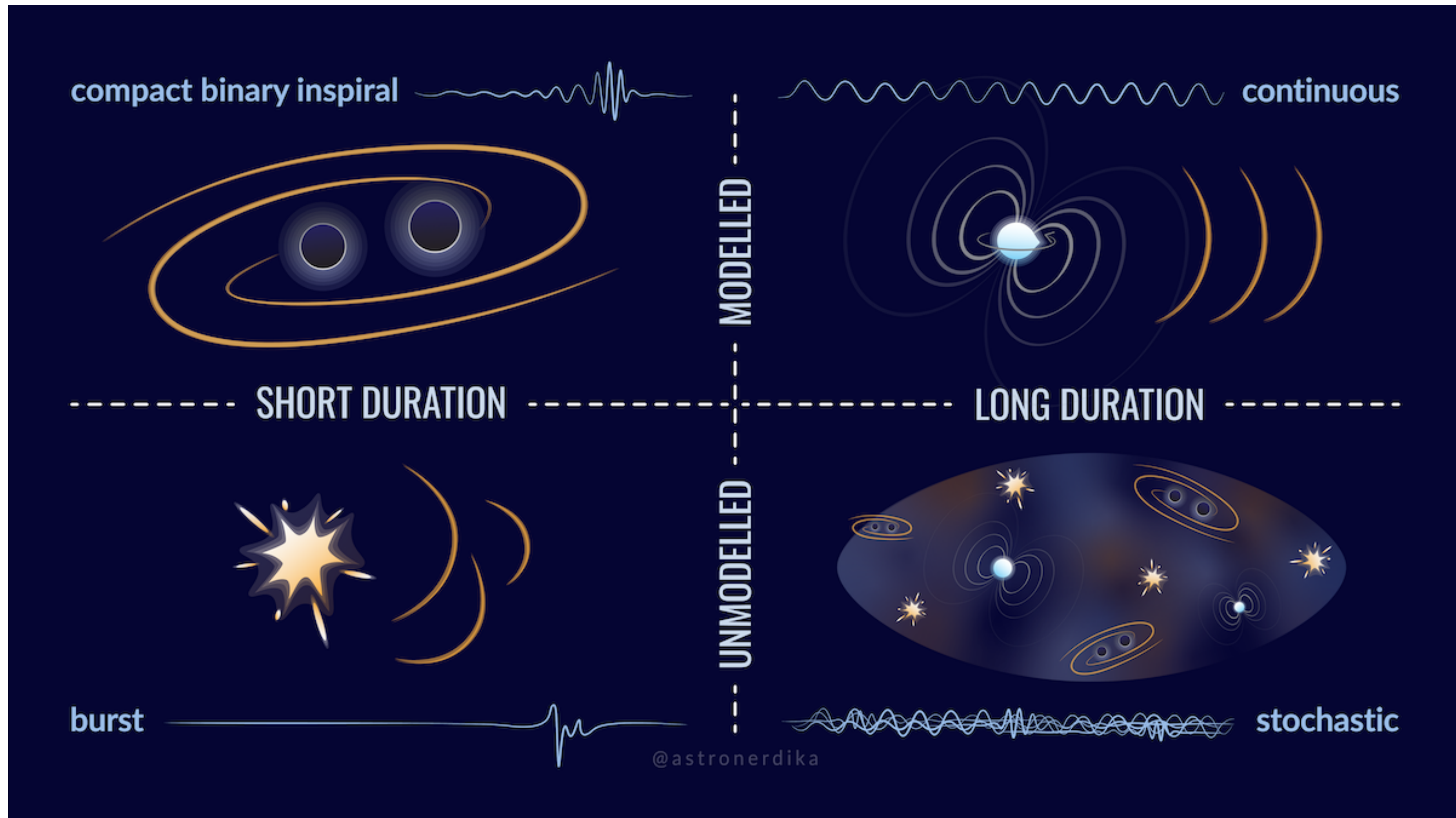


# Stochastic GW background

# Content

- What is stochastic GW background
- How to detect?

# What is stochastic GW background?



# What is stochastic GW background ?

Superposition of many GW signals which are  
**uncorrected**

Fractional GW energy density  $\Omega_{GW}(f) = \frac{1}{\rho_c} \frac{d\rho_{GW}}{d \ln f} = \frac{32\pi^3}{3H_0^2} f^3 I(f)$

GW intensity  $I(f) = \frac{1}{2} \sum_A |h_A(f)|^2$

Critical energy density  $\rho_c$

Hubble constant  $H_0$

# What is stochastic GW background ?

From the Friedman equation we have:

$$H(z) = H_0(\Omega_R(1+z)^4 + \Omega_M(1+z)^3 + \Omega_K(1+z)^2 + \Omega_\Lambda)^{\frac{1}{2}}$$

$$\Omega_R = \Omega_\gamma + \Omega_N + \Omega_{GW} + \dots\dots$$

Important constraints on  $\Omega_{GW}$

$$\Omega_{GW} < \boxed{1.2 \times 10^{-6}} \left( \frac{H_0}{100 \text{ km s}^{-1} \text{ Mpc}^{-1}} \right)^{-2}$$

# What is stochastic GW background?

$$\Omega_{GW}(f) = \frac{1}{\rho_c} \frac{d\rho_{GW}}{d \ln f} = \frac{32\pi^3}{3H_0^2} f^3 I(f)$$

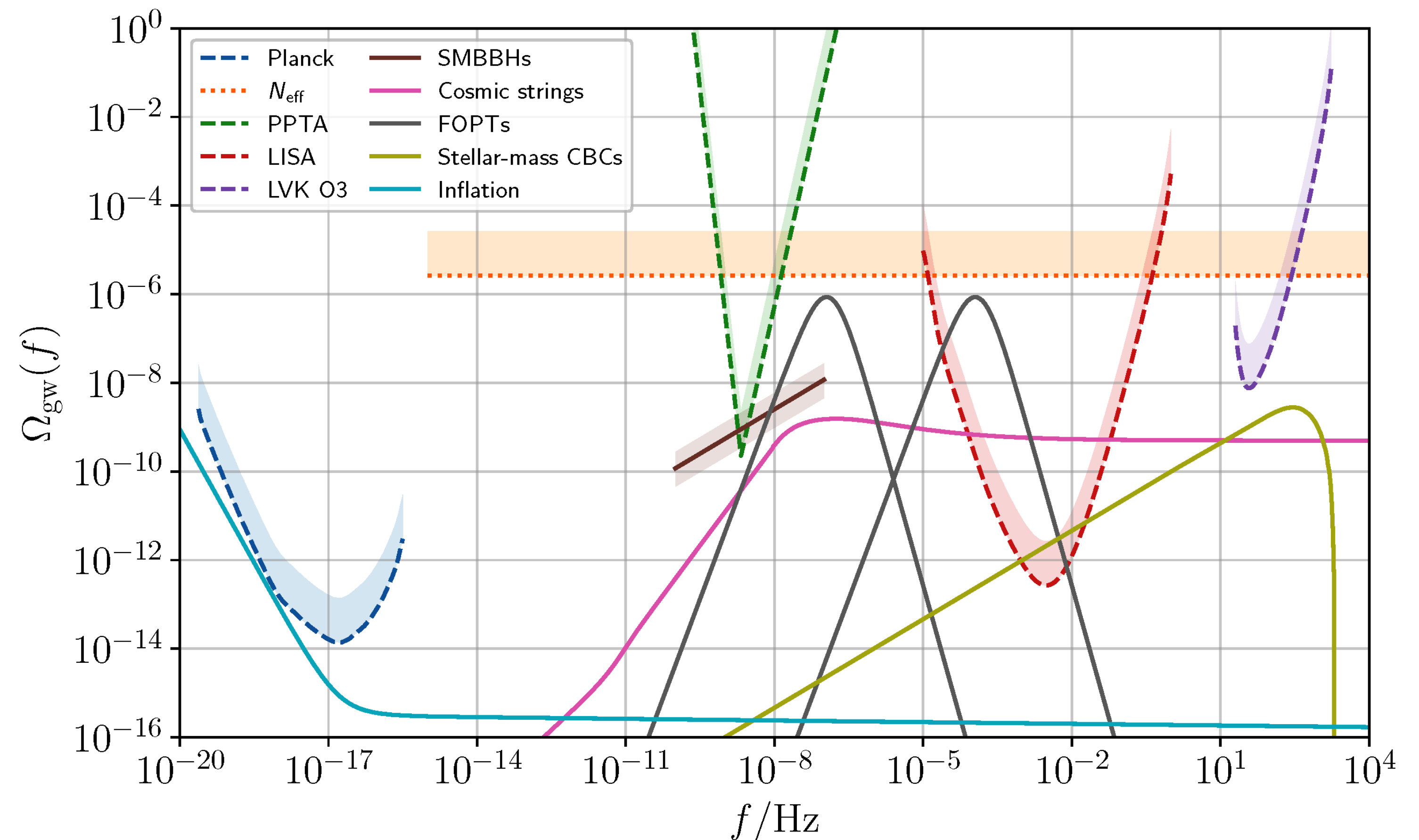
Superposition of many GW signals which are uncorrected

## Cosmological:

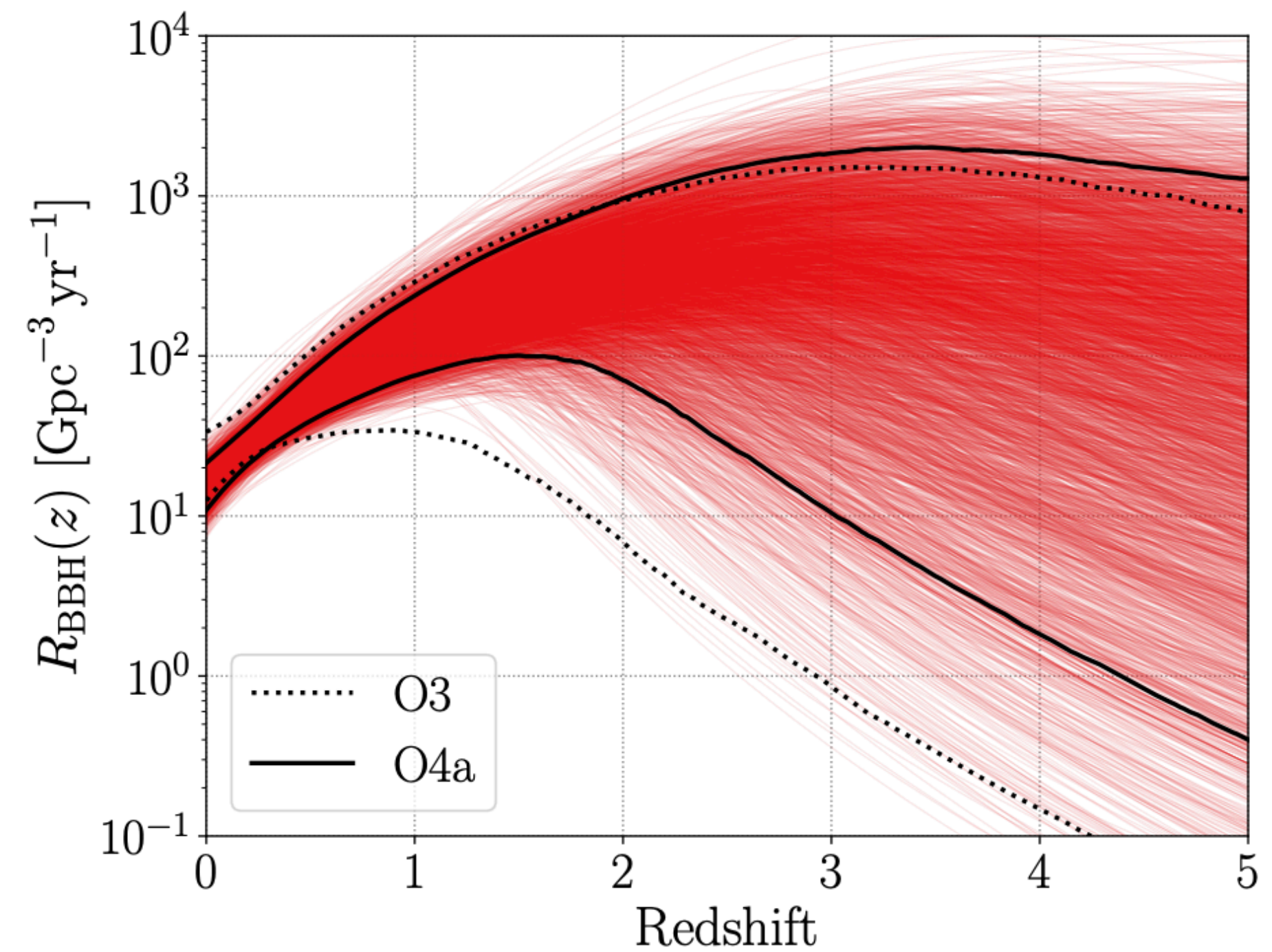
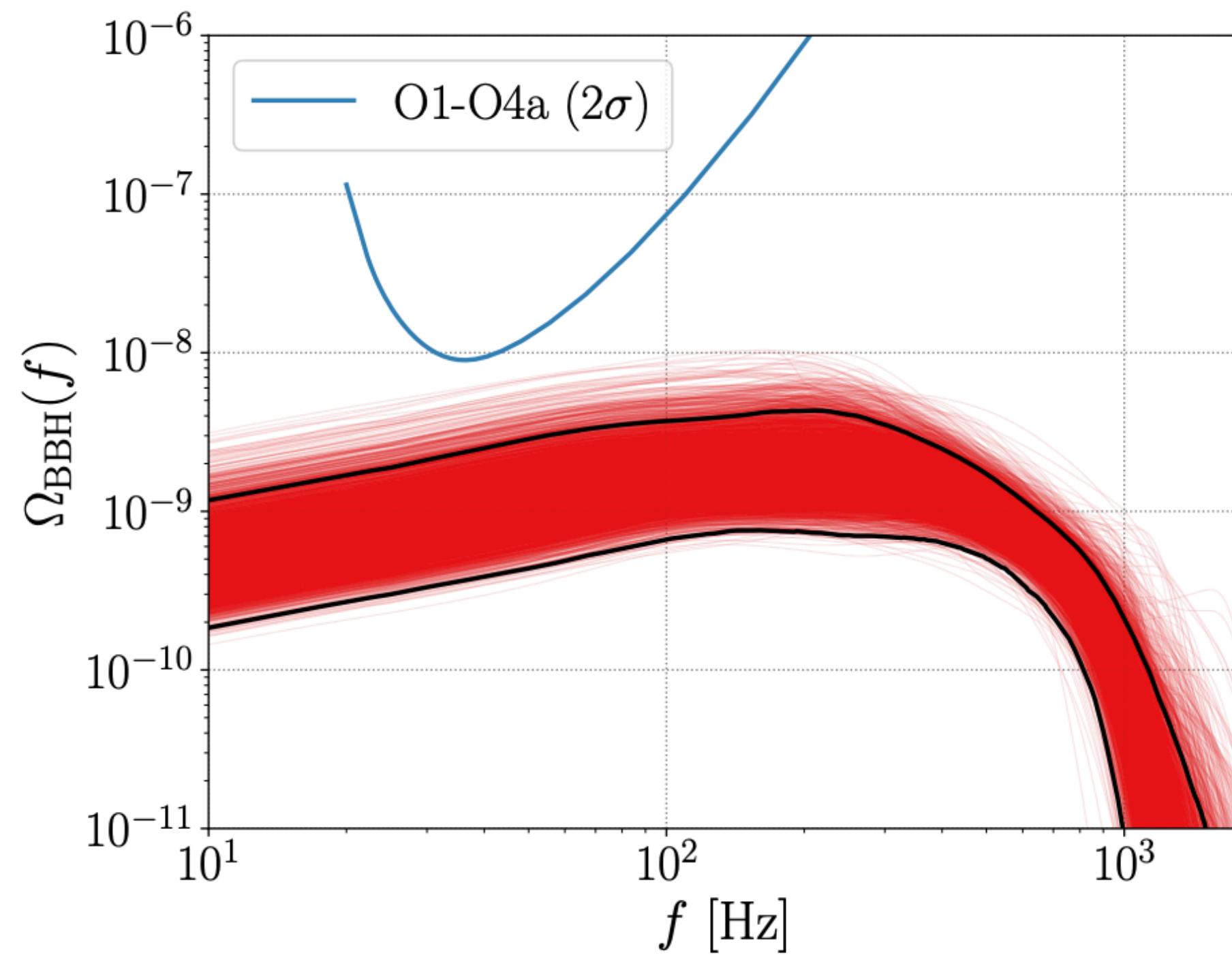
- Cosmic strings
- Inflation
- Phase transitions and others

## Astrophysical:

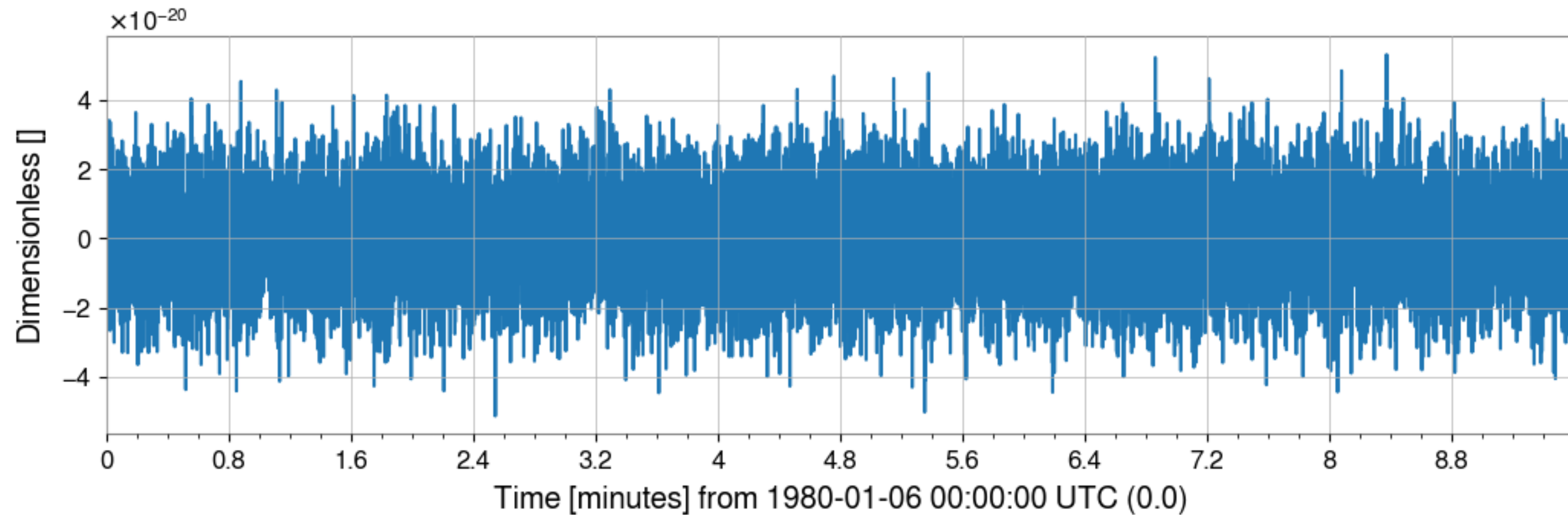
- BBH, NSBH, SMBBHs...
- Supernove
- Rotating NS and others



# What is stochastic GW background?



# How to detect?



Main detection strategy in pygwb : Cross correlation

# Cross-correlation of GW

Uncorrelated, Gaussian, unpolarized

$$s_I(t) = h_I(t) + n_I(t)$$

- It's hard to claim that the signal detected with one detector. However, we can confirm the gravitational wave once we have another detector because signal will have a time shift in two detectors.

$$\begin{aligned} \langle \tilde{s}_{I_1}(f) \tilde{s}_{I_2}^*(f) \rangle &= \langle \tilde{h}_{I_1}(f) \tilde{h}_{I_2}^*(f) \rangle + \langle \tilde{h}_{I_1}(f) \tilde{n}_{I_2}^*(f) \rangle \\ &\quad + \langle \tilde{n}_{I_1}(f) \tilde{h}_{I_2}^*(f) \rangle + \langle \tilde{n}_{I_1}(f) \tilde{n}_{I_2}^*(f) \rangle \end{aligned}$$

- Because the signal and noise are uncorrelated, and the expectation value of the noise is zero in principle, which simply the equation into

$$\langle \tilde{s}_{I_1}(f) \tilde{s}_{I_2}^*(f) \rangle \approx \langle \tilde{h}_{I_1}(f) \tilde{h}_{I_2}^*(f) \rangle$$

which can help us draw out the GW sneaking inside the noise.

How to detect?

What about the detector site?

# From antenna pattern to overlap reduction function

- In gravitational wave radiometry, we first set up the notation we need. In terms of spherical polar coordinates  $(\theta, \phi)$ , the source direction is given by

$$\hat{\Omega} = \cos\phi \sin\theta \hat{x} + \sin\phi \sin\theta \hat{y} + \cos\theta \hat{z}$$

and the polarization tensor  $e^A(\hat{\Omega})$  are defined by the following expression:

$$e^\times(\hat{\Omega}) = \hat{e}_\theta \otimes \hat{e}_\theta - \hat{e}_\phi \otimes \hat{e}_\phi \quad , \quad e^+(\hat{\Omega}) = \hat{e}_\phi \otimes \hat{e}_\theta + \hat{e}_\theta \otimes \hat{e}_\phi$$

$$\hat{e}_\theta = \cos\phi \cos\theta \hat{x} + \sin\phi \cos\theta \hat{y} - \sin\theta \hat{z}$$

$$\hat{e}_\phi = -\sin\phi \hat{x} + \cos\phi \hat{y}$$

and  $(\hat{e}_\theta, \hat{e}_\phi)$  are two orthonormal basis vectors on a two-sphere.<sup>(10)</sup>

# From antenna pattern to overlap reduction function

- Now we consider two GW detectors located at  $x_I(t)$ ,  $I = 1, 2$ . The detector frames are denoted by the coordinates  $(X_I, Y_I, Z_I)$  where the arms of the respective detectors lie along the  $(X_I, Y_I)$  axis. Then the detector tensors  $d_I$  are given by

$$d_I = \frac{1}{2}[\hat{X}_I \otimes \hat{X}_I - \hat{Y}_I \otimes \hat{Y}_I]$$

- Owing to the Earth's rotation, the detector coordinates and  $d_I$  are functions of  $t$ . Thus in matrix form:

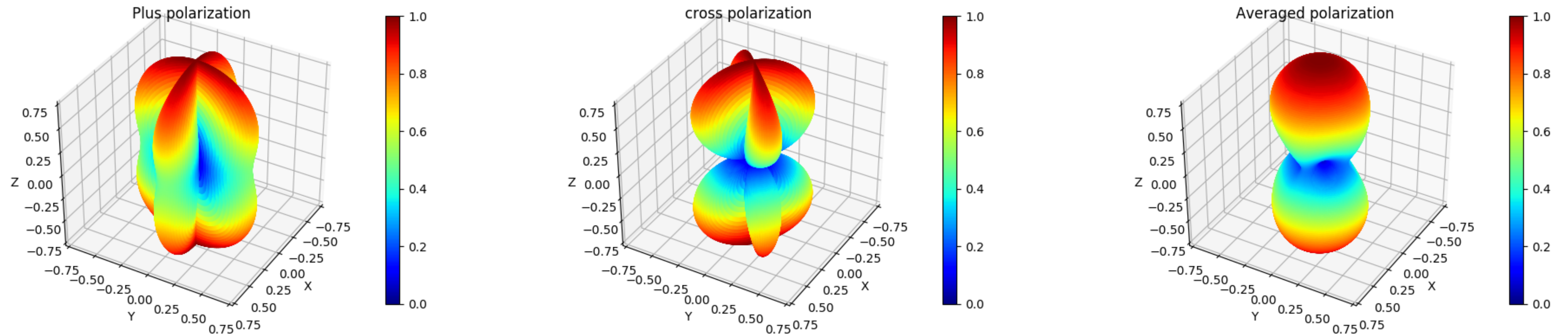
$$d_I(t) = R^T(t) \cdot d_I(t=0) \cdot R(t)$$

where  $R(t)$  is the rotation matrix describing a rotation of angle  $\omega_E t$  around the Earth's rotation axis, namely, the z-axis. Now we can define the antenna pattern functions

$$F_I^A(t, \hat{\Omega}) = \varrho_{ij}^A(\hat{\Omega}) d_I^{ij}(t)$$

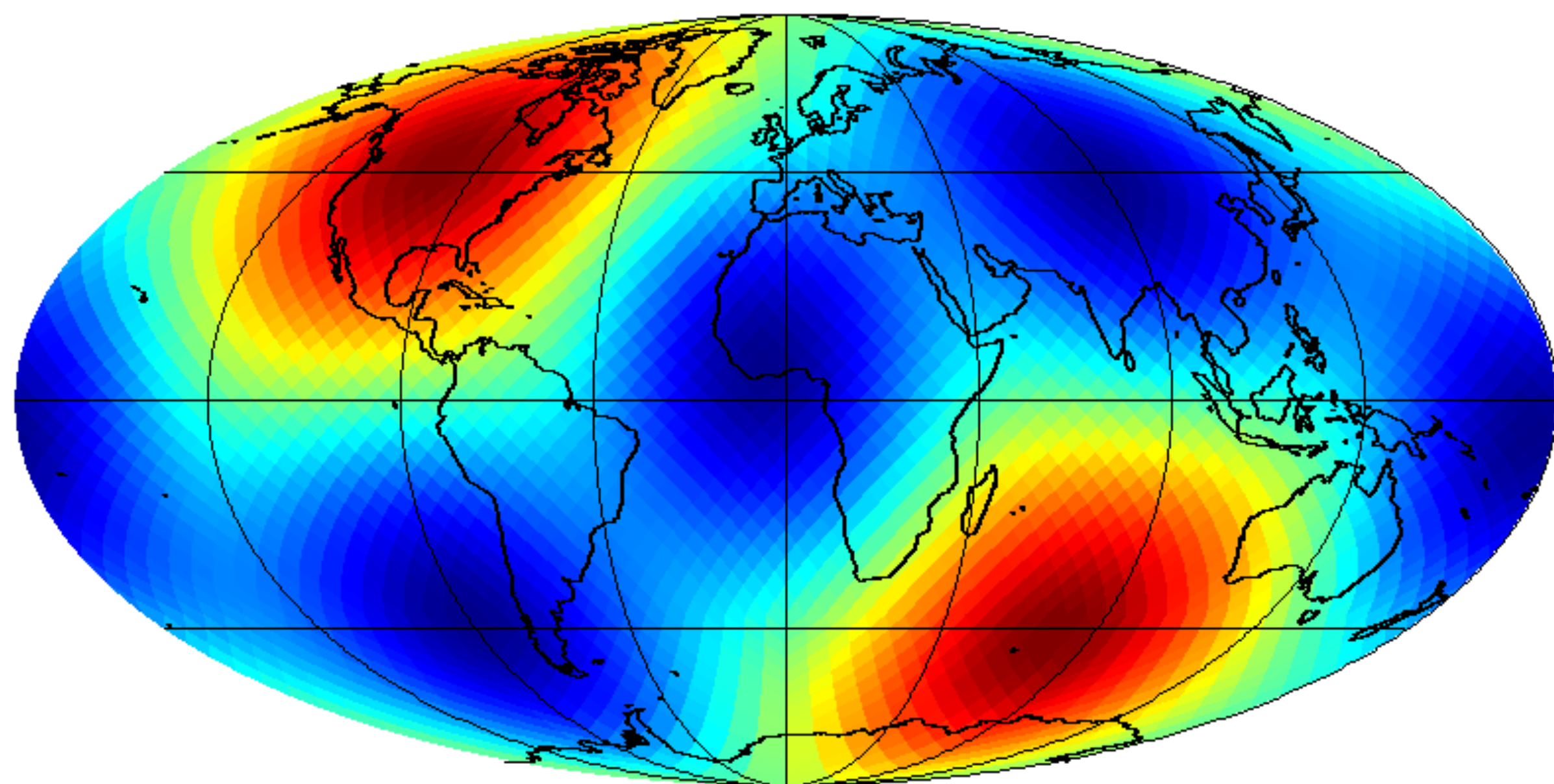
for a wave that incident from the direction  $\hat{\Omega}$ .

# From antenna pattern to overlap reduction function



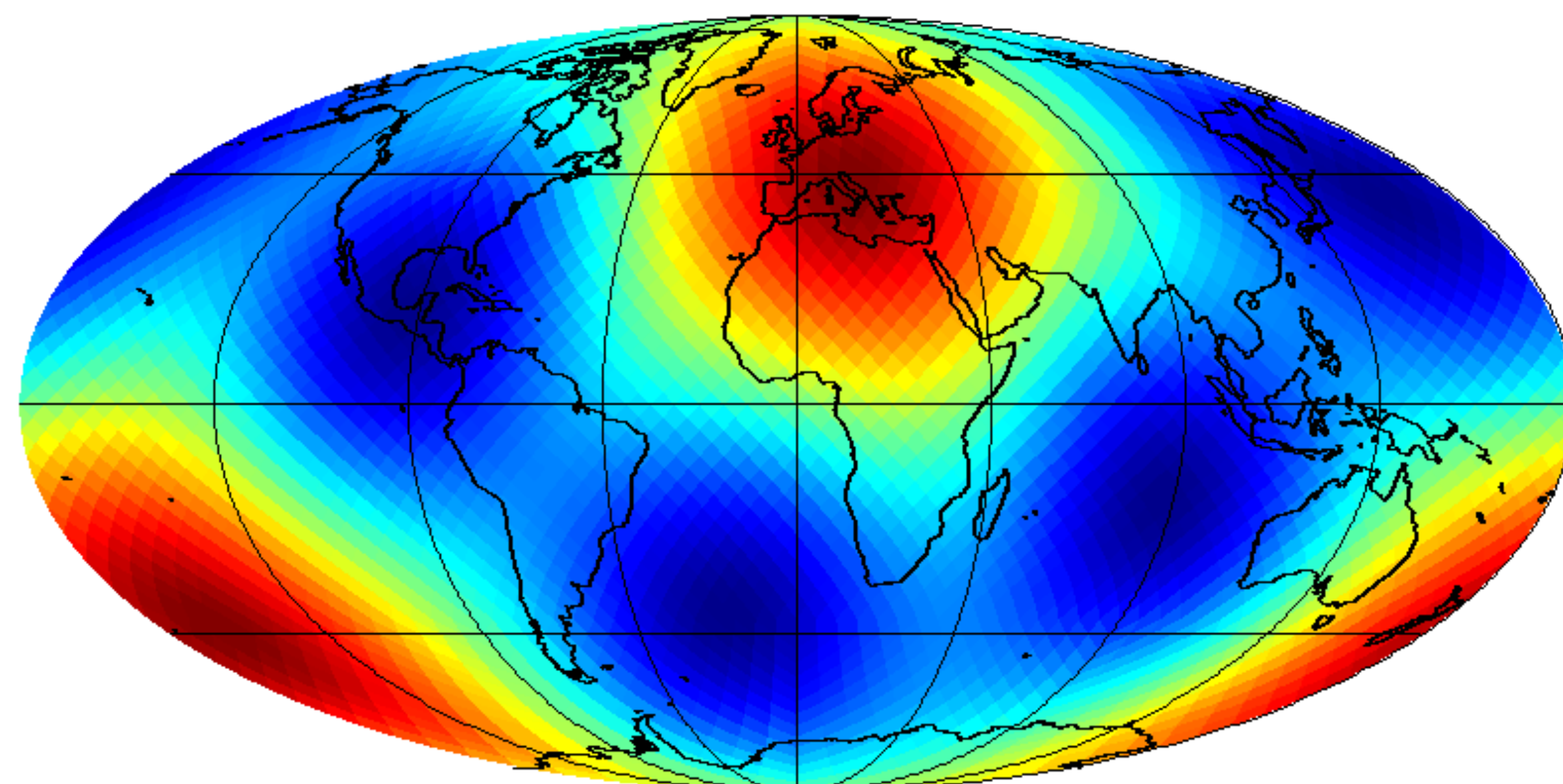
$$F_I^A(t, \hat{\Omega}) = \rho_{ij}^A(\hat{\Omega}) d_I^{ij}(t)$$

Hanford sensitivity



0.00051  1.0

Virgo sensitivity



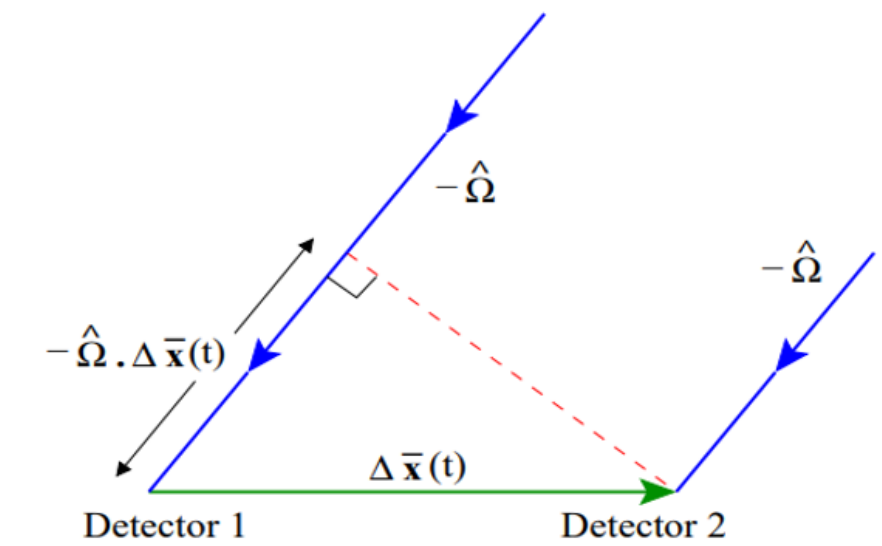
0.00046  1.0

# From antenna pattern to overlap reduction function

- Finally, consider the rotation of the Earth and time delay from one to the other detector, we can generate a geometric factor  $\gamma^I$  known as the overlap reduction function (ORF),

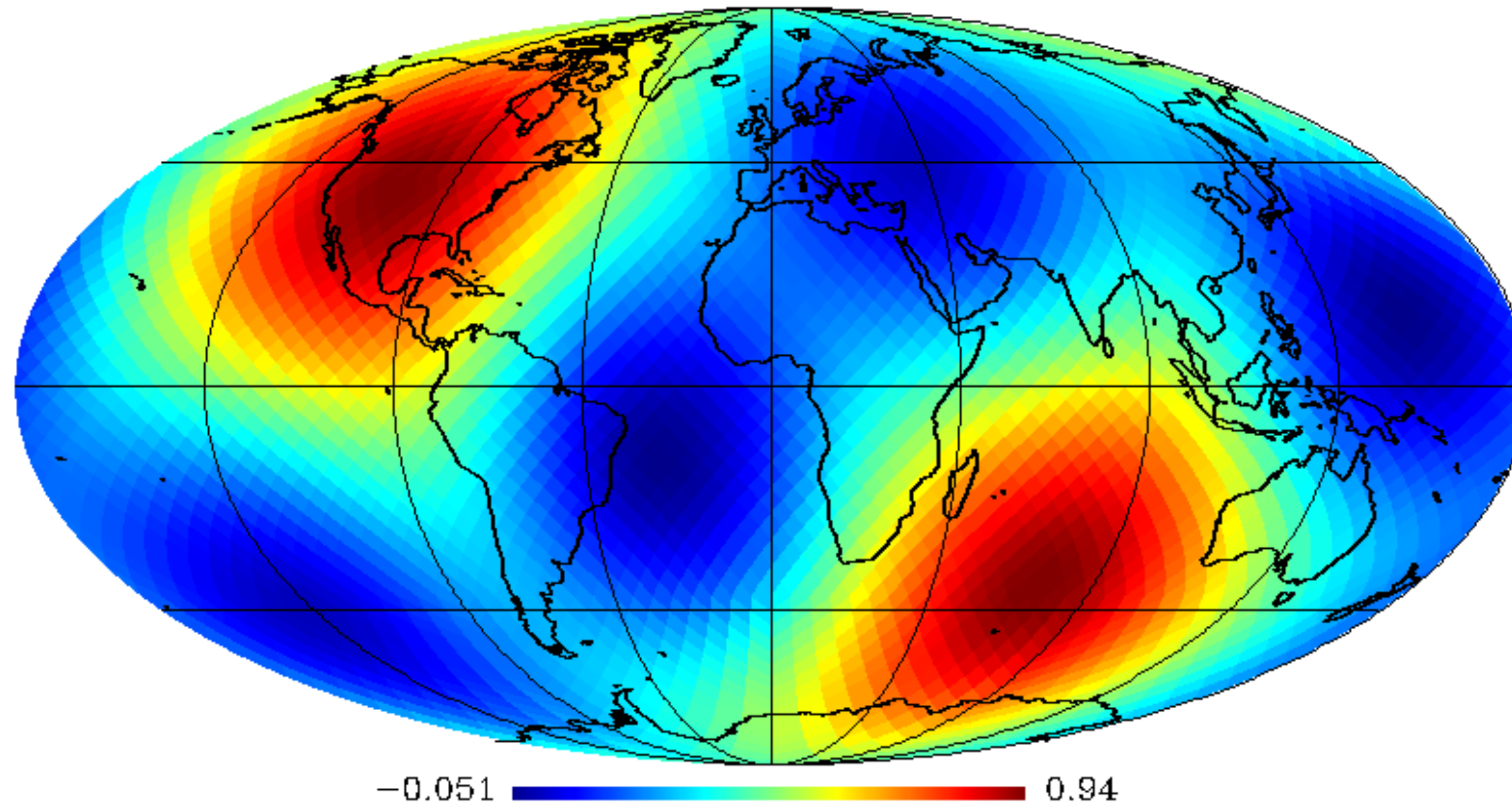
$$\gamma^I = \frac{1}{\pi} \int_0^\pi \int_0^{2\pi} \hat{n}^T \hat{A}_1(\hat{n}) \hat{A}_2(\hat{n}) e^{i2\pi f \hat{n} \cdot \Delta \mathbf{x}_I(t)} d\Omega$$

ORF at 0Hz



,  $I$  denotes the baseline

where  $\Delta \mathbf{x}_I(t)$  is the  
constituted by two

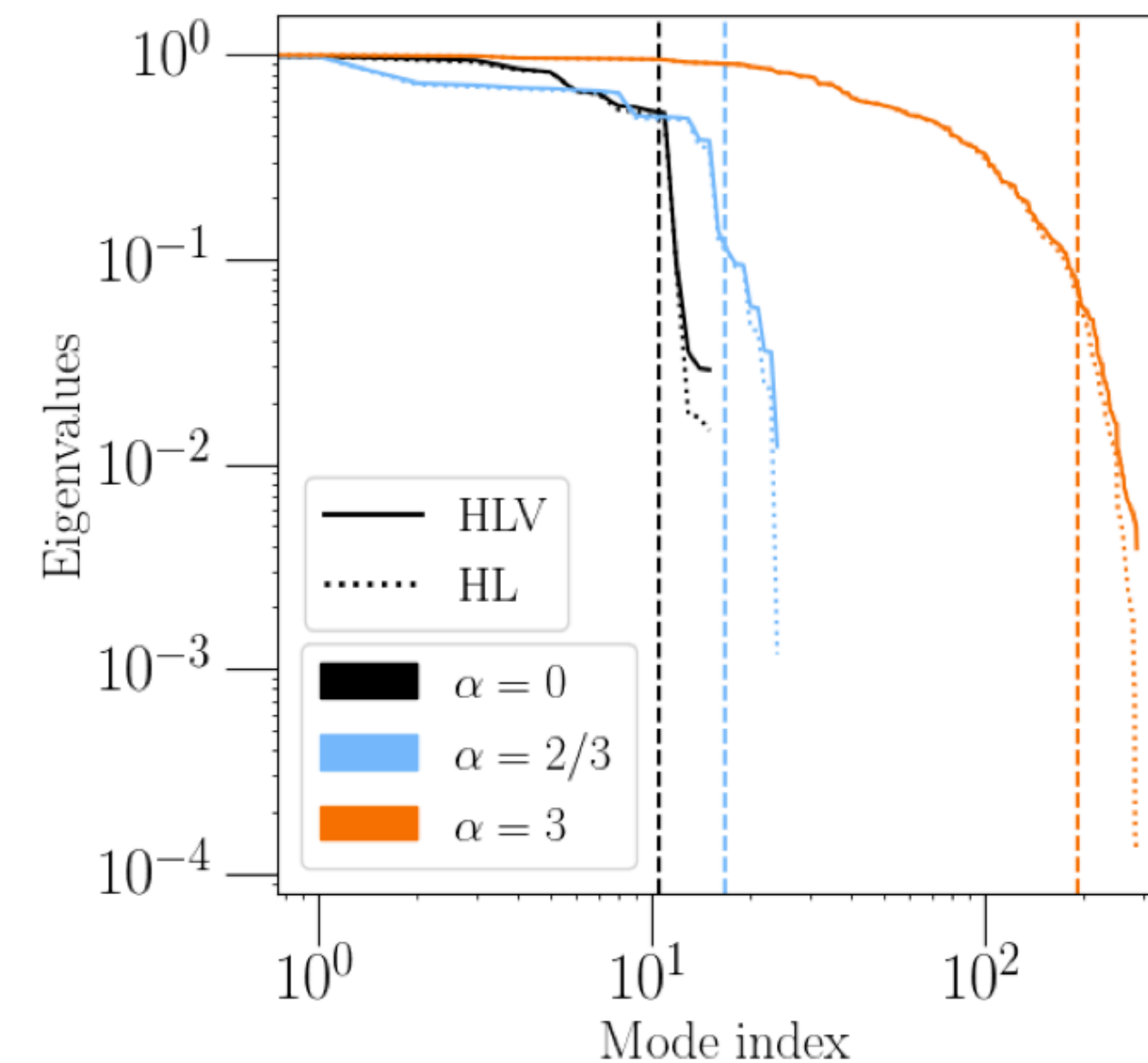


# The limit of overlap reduction function

$$\mathbf{X} = \frac{4}{\tau} \sum_{Ift} \frac{H(f) \gamma_{ft,p}^{I*}}{P_{\mathcal{I}_1}(t;f) P_{\mathcal{I}_2}(t;f)} \tilde{s}_{\mathcal{I}_1}^*(t;f) \tilde{s}_{\mathcal{I}_2}(t;f) \quad \mathbf{\Gamma} = 4 \sum_{Ift} \frac{H^2(f)}{P_{\mathcal{I}_1}(t;f) P_{\mathcal{I}_2}(t;f)} \gamma_{ft,p}^{I*} \gamma_{ft,p'}^I$$

$$\hat{\mathcal{P}}_p \equiv \hat{\mathcal{P}} = \mathbf{\Gamma}^{-1} \cdot \mathbf{X},$$

Singular Value Decomposition helps with the  
inverting matrix problem



# How to detect?

Recall the equations before, and also considering the simplest case :

Unpolarized, Gaussian, isotropic

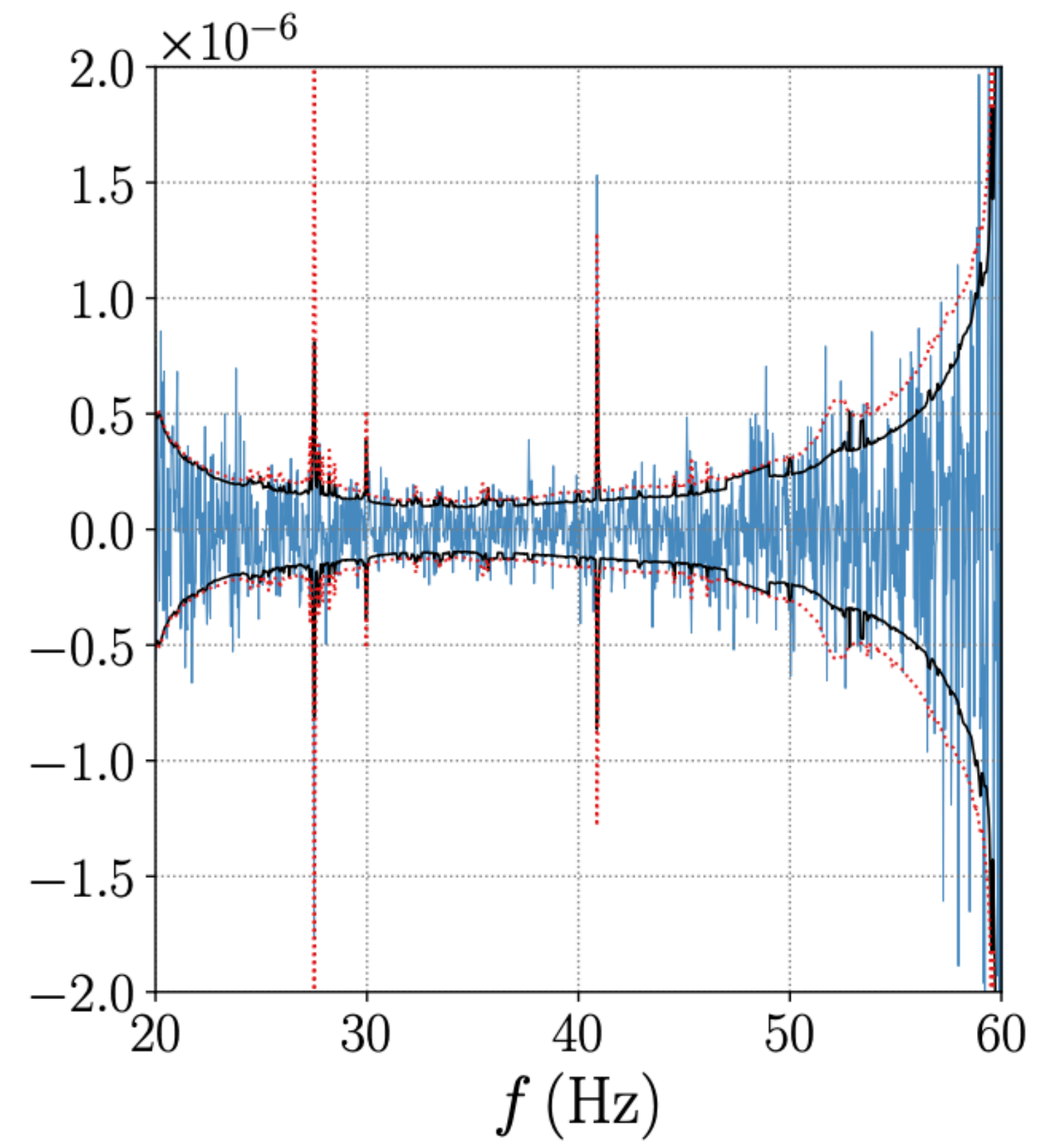
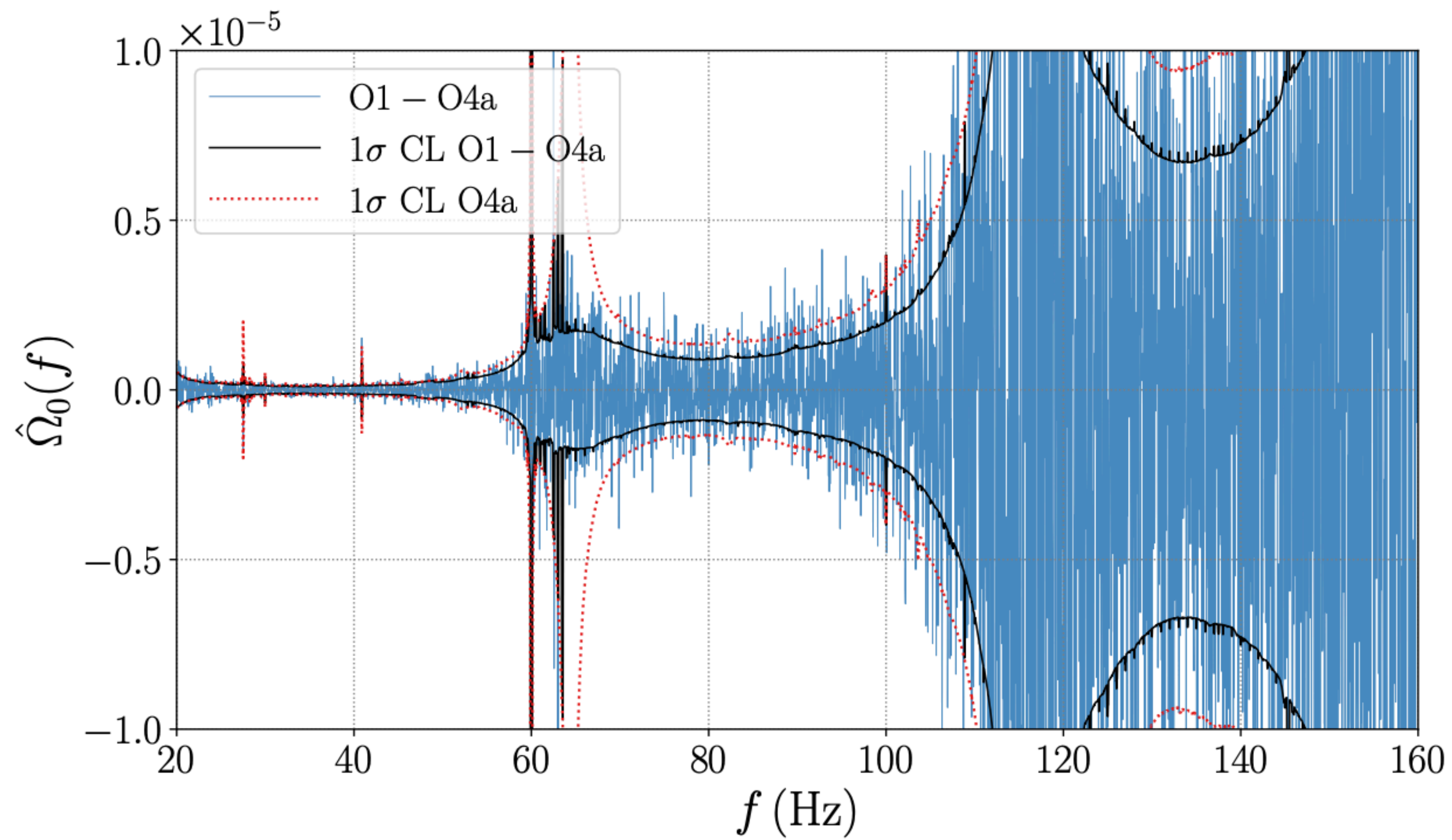
then we can generate the cross-correlation statistic for GWB search

$$\langle C_{12}(f) \rangle = R_1(f)R_2^*(f)\langle \tilde{h}_{I_1}(f)\tilde{h}_{I_2}^*(f) \rangle = T_{OBS}\Gamma^I(f)I(f)$$

where

$$\langle C_{12}(f) \rangle \approx T_{OBS}\Gamma^I(f)f^{-3}\Omega_{GW}(f)$$

# How to detect?

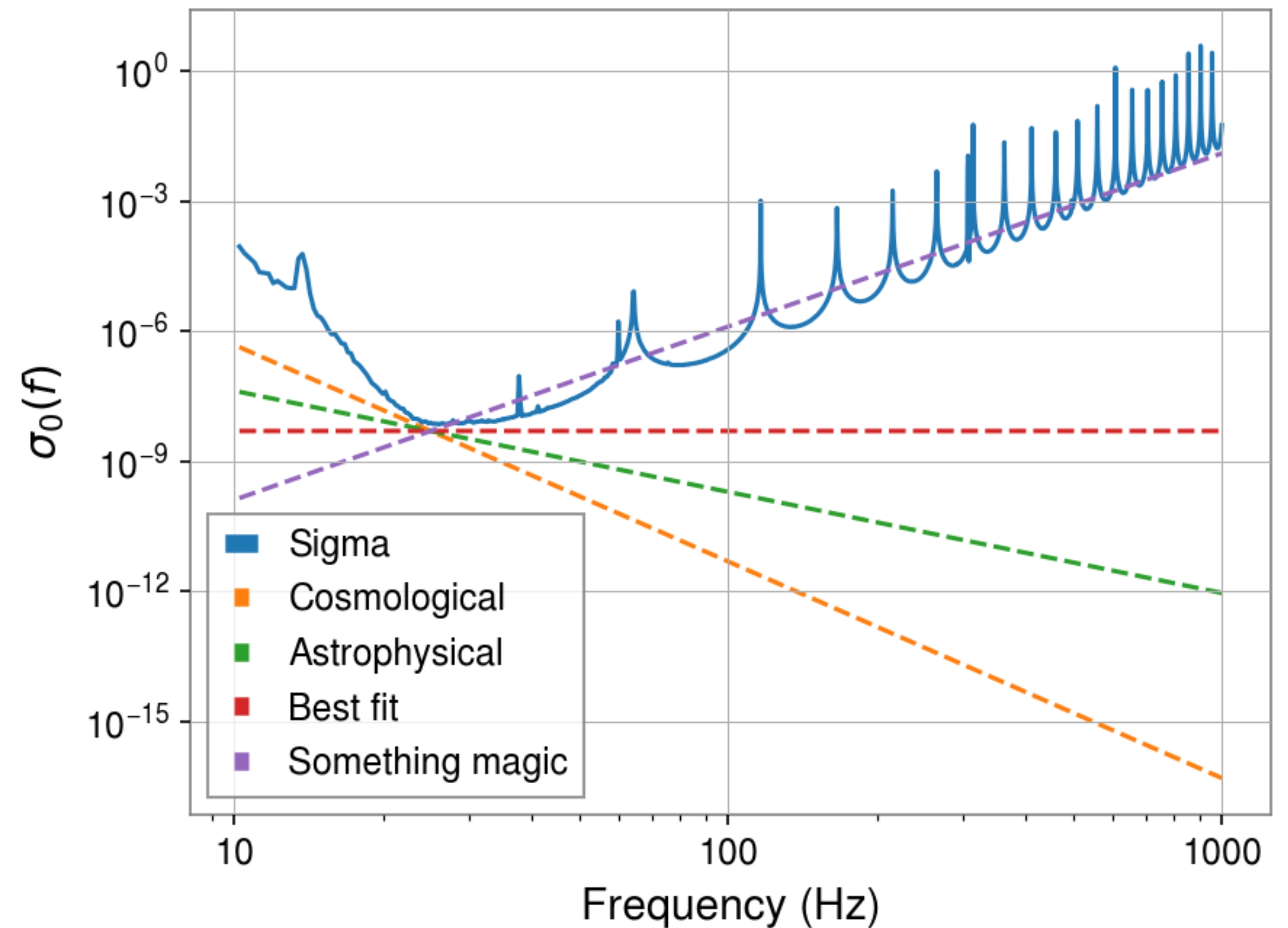
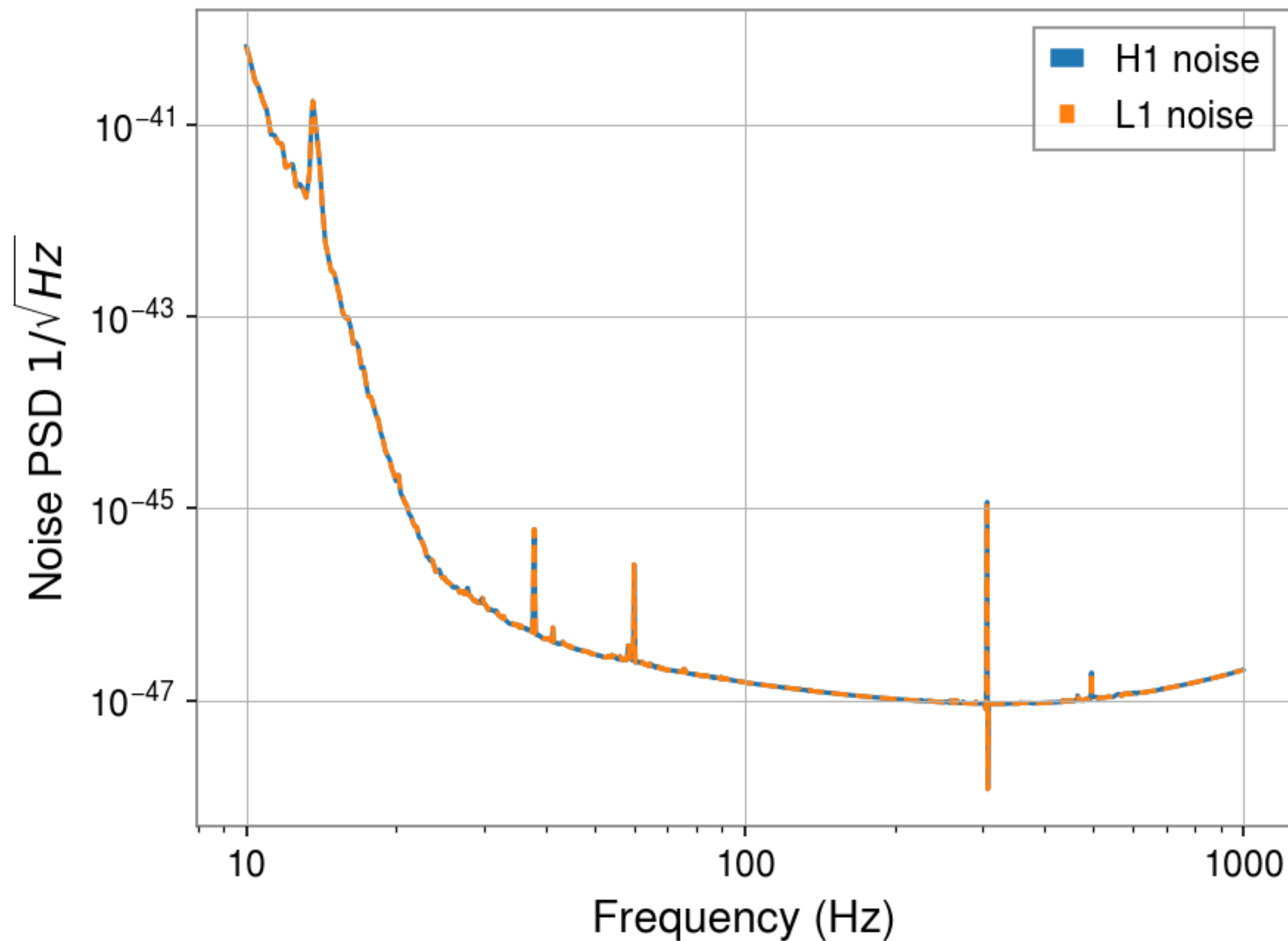


# How to detect?

$$\Omega_{GW} \propto f^\alpha$$

Fix the alpha

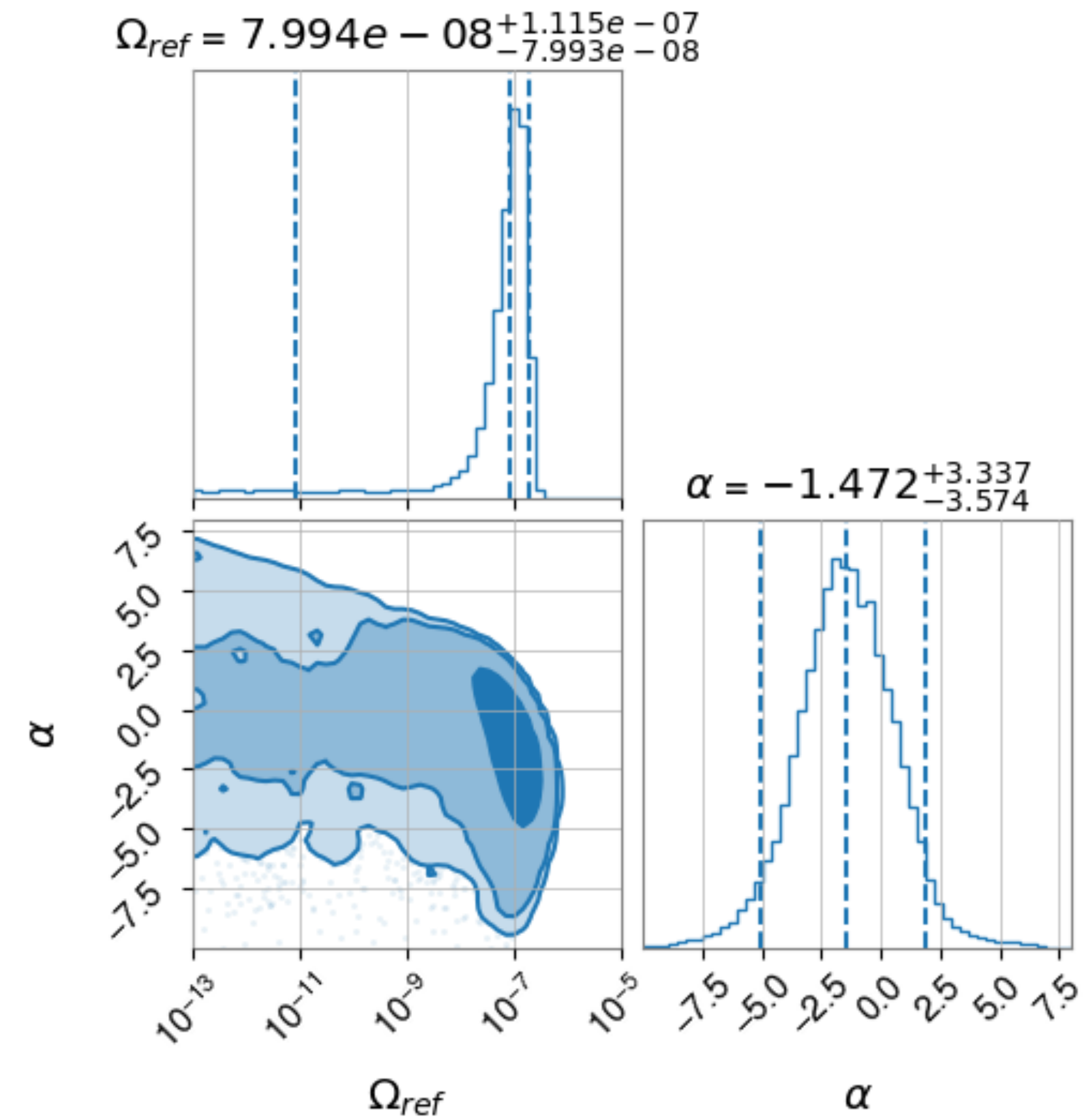
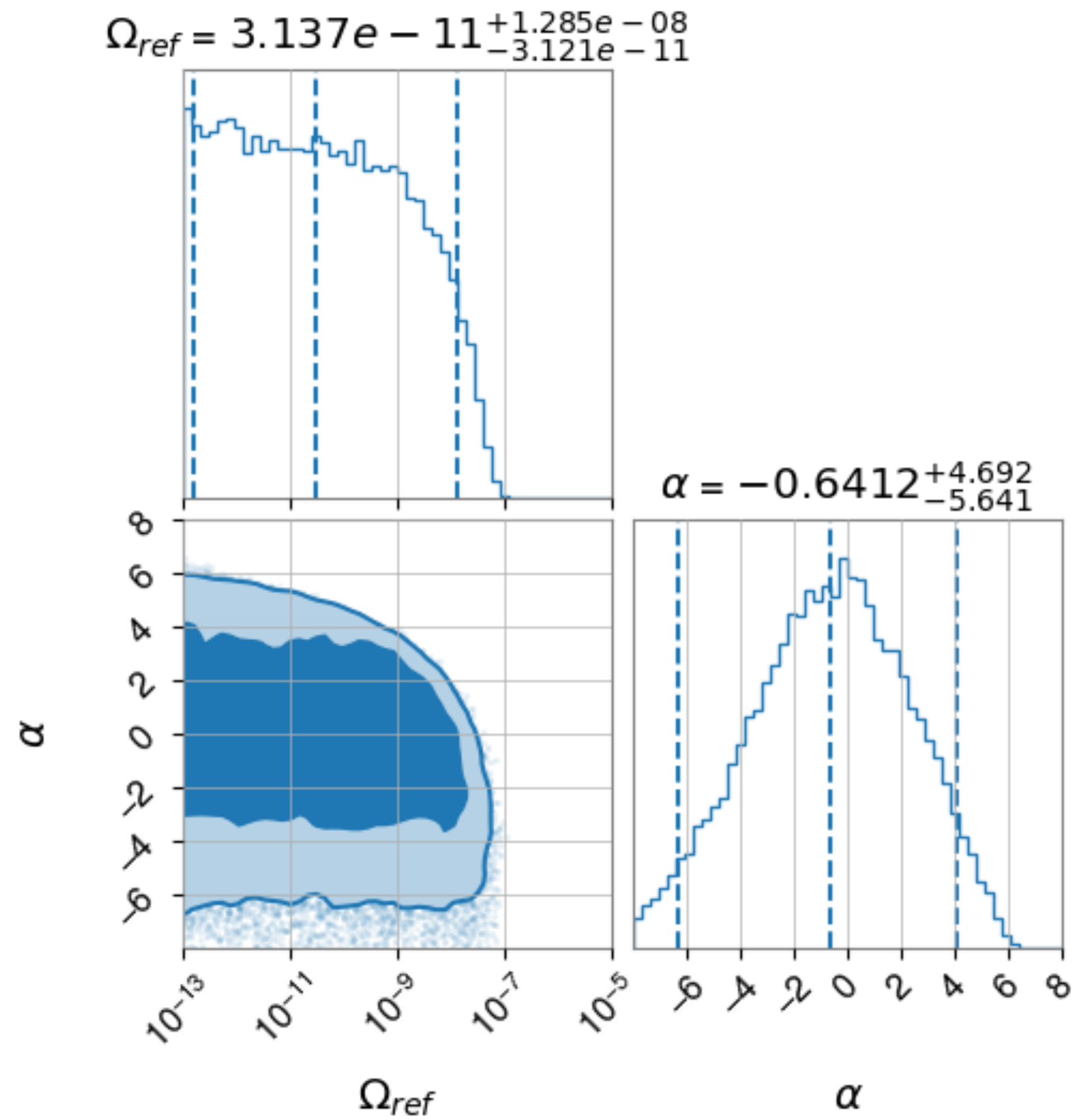
$$\sigma_0^2(f) = \frac{1}{2T\Delta f} \frac{P_I(f)P_J(f)}{\gamma_{IJ}^2(f)S_0^2(f)}$$



# How to detect?

$$\Omega_{GW} \propto f^\alpha$$

Parameter estimation



# How to detect?

Bayesian fit estimate

$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{GW}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

Calibration errors  $\Lambda$

GW model  $\Omega_{GW}(f; \theta)$

Model selection : Bayes factor

$$\mathcal{K} = \frac{\hat{p}(M_1; data)}{\hat{p}(M_2; data)}$$

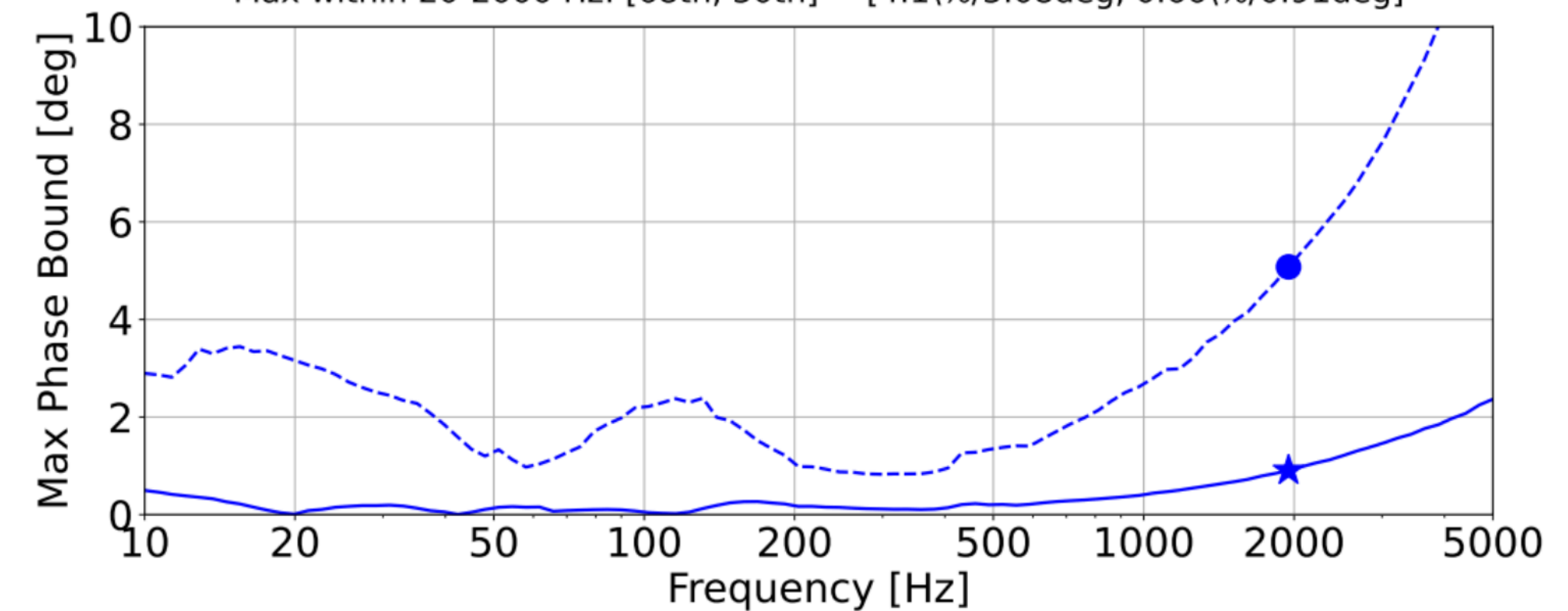
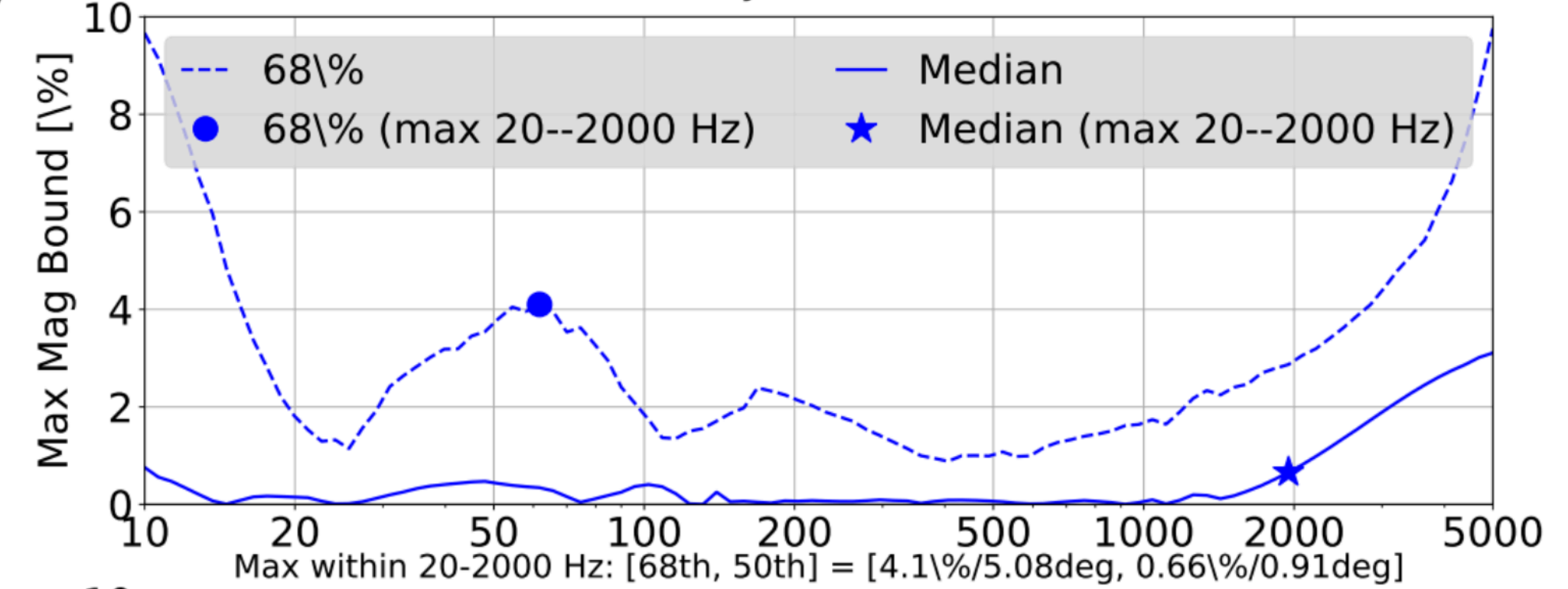
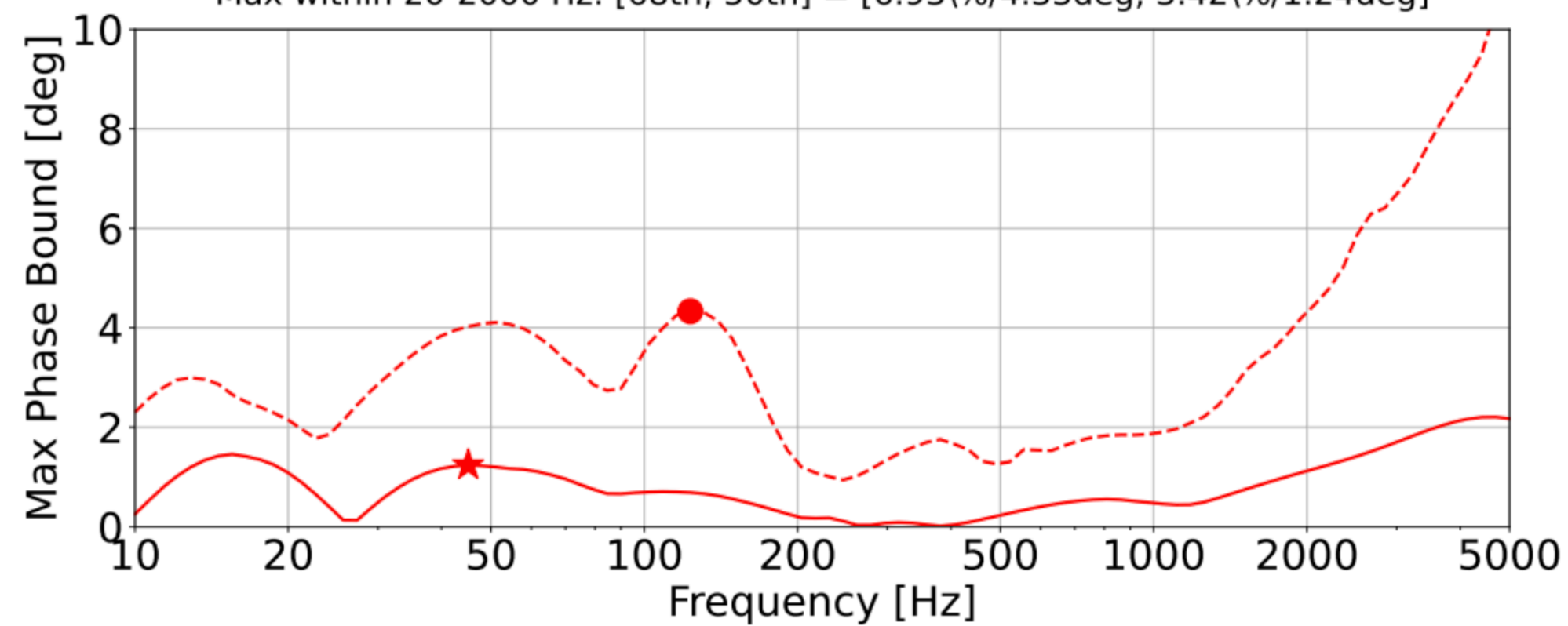
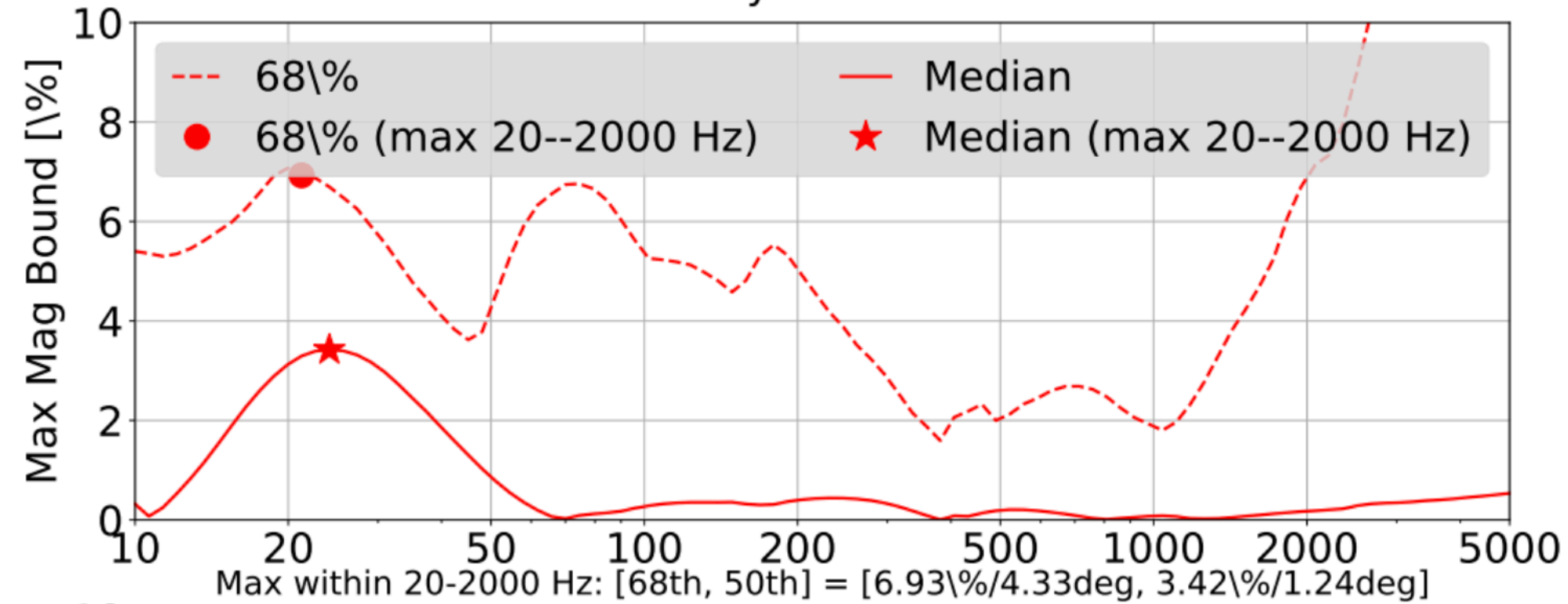
Noise by default

# How to detect?

$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{\text{GW}}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

## Calibration errors $\Lambda$

LHO O4 C00 Max bounds - Median systematic error and 1- $\sigma$  overall uncertainty LLO O4 C00 Max bounds - Median systematic error and 1- $\sigma$  overall uncertainty



# How to detect?

$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{\text{GW}}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

Calibration errors  $\Lambda$

	LHO (%)	LLO (%)
Max 68% (magnitude)	6.93	4.10
Max 68% (phase)	4.33	5.08
Max 50% (magnitude)	3.42	0.66
Max 50% (phase)	1.24	0.91

- We only keep the maximum value of the magnitude at 68%
- Maximum values of phase is  $\sim$  or  $<$  5 deg  $\rightarrow$  imaginary part is negligible
- As expected, uncertainties at LLO are smaller

# How to detect?

$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{GW}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

GW model

Noise

$$\Omega_{GW}(f; \theta) = 0$$

Simple power law

$$\Omega_{GW}(f; \theta) = \Omega_{ref} \left( \frac{f}{25\text{Hz}} \right)^\alpha$$

Magnetics

$$\Omega_{GW}(f; \theta) = \Omega_{ref} \left( \frac{f}{25\text{Hz}} \right)^\alpha + \Omega_{MAG}(f; MAG)$$

Scalar-vector-tensor (SVT)  
power law

$$\Omega_{GW}(f; \theta) = \sum_p \frac{\gamma_{IJ}^p(f)}{\gamma_{IJ}(f)} \Omega_{ref}^{(p)} \left( \frac{f}{25\text{Hz}} \right)^\alpha$$

CBC

$$\Omega_{GW}(f; \theta_k) = \frac{f}{\rho_c H_0} \int_0^{z_{\max}} dz \frac{R_m(z; \theta_k) \langle \frac{dE_{GW}}{df_s}(f_s; \theta_k) \rangle}{(1+z)E(\Omega_{m,0}, \Omega_{\Lambda,0}, z)}$$

# How to detect?

$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{\text{GW}}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

$\alpha$	Uniform prior			Log-uniform prior		
	O1-O4a	O1-O3	Improvement	O1-O4a	O1-O3	Improvement
0	$8.6 \times 10^{-9}$	$1.7 \times 10^{-8}$	2.0	$2.8 \times 10^{-9}$	$5.8 \times 10^{-9}$	2.1
2/3	$6.3 \times 10^{-9}$	$1.2 \times 10^{-8}$	1.9	$2.0 \times 10^{-9}$	$3.4 \times 10^{-9}$	1.7
3	$1.0 \times 10^{-9}$	$1.3 \times 10^{-9}$	1.3	$3.2 \times 10^{-10}$	$3.9 \times 10^{-10}$	1.2
Marginalized	$1.5 \times 10^{-8}$	$2.7 \times 10^{-8}$	1.8	$2.9 \times 10^{-9}$	$6.6 \times 10^{-9}$	2.3

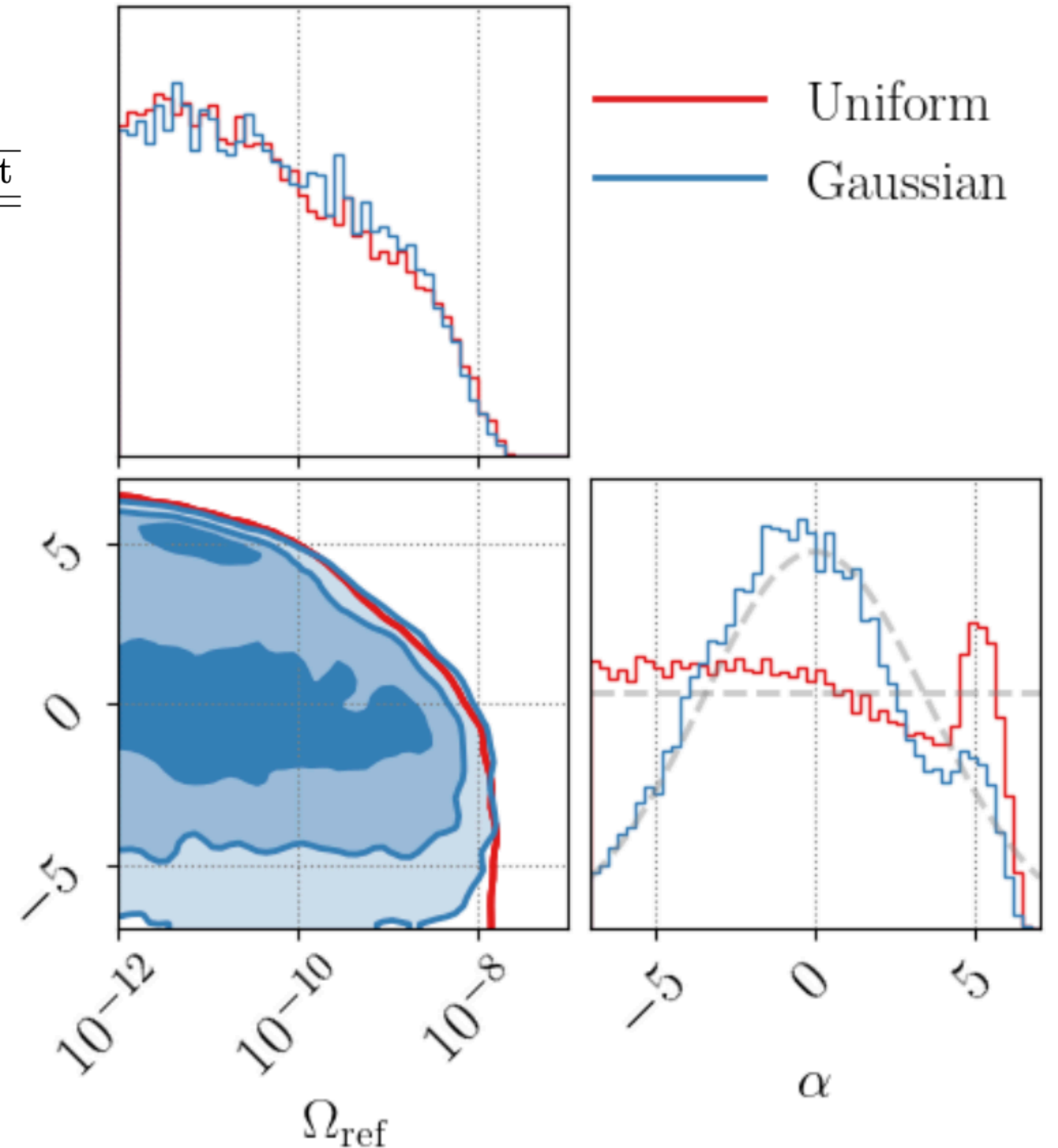
```

kwargs_PL = {"baselines": [HL_04c1], "model_name": "PL", "fref": fref}

model_PL = pe.PowerLawModel(**kwargs_PL)

priors = {'omega_ref': bilby.core.prior.LogUniform(1e-13, 1e-6, '$\omega_{\text{ref}}$'),
         "alpha": bilby.core.prior.Uniform(-3.5, 3.5, '$\alpha$')}

hlv_pl = bilby.run_sampler(likelihood=model_PL, priors=priors, sampler="dynesty",
                          nlive=5000, walks=30, npool=5, printdt=500, maxmcmc=10000,
                          outdir=path_to_save, check_point=False,
                          resume=False, dlogz=0.1, clean=True, label=label_name)
    
```



# How to detect?

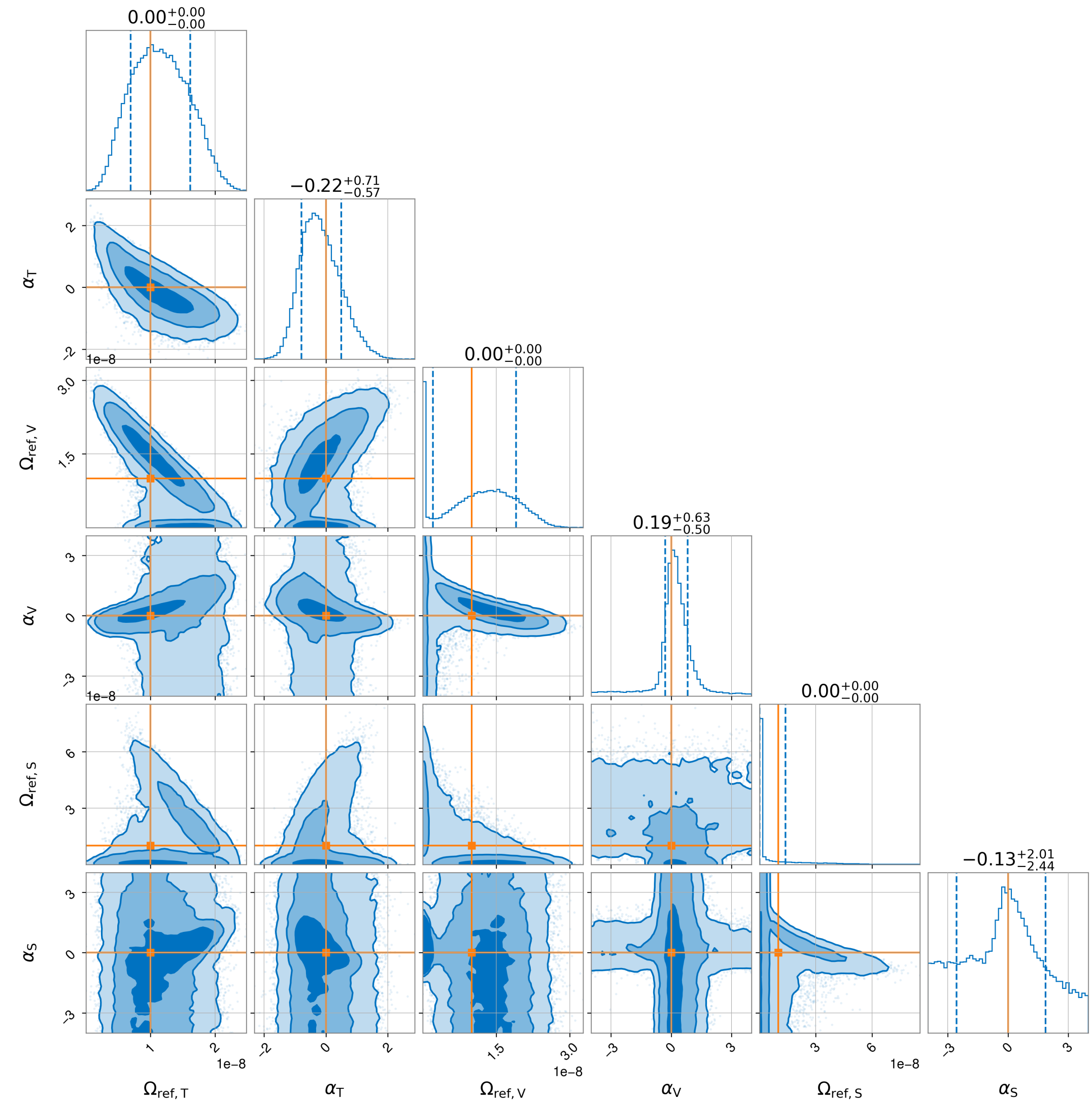
$$p(\hat{\Omega}_0 | \Theta, \Lambda) \propto \exp \left[ -\frac{1}{2} \sum_f \frac{(\hat{\Omega}_0(f) - \Lambda \Omega_{\text{GW}}(f; \Theta))^2}{\sigma_0^2(f)} \right]$$

## Non - GR polarization

```
kwargs = {"baselines": [HL], "model_name": 'TVSPowerLawModel', "polarizations": ['tensor', 'vector', 'scalar'], "fref": 25}
model = pe.TVSPowerLawModel(**kwargs)
priors = {'omega_ref_tensor': bilby.core.prior.LogUniform(10**(-6), 10**(-2), '$\Omega_{\text{ref, T}}$'),
          'alpha_tensor': bilby.core.prior.Uniform(-4, 4, '$\alpha_{\text{T}}$'),
          'omega_ref_vector': bilby.core.prior.LogUniform(10**(-6), 10**(-2), '$\Omega_{\text{ref, V}}$'),
          'alpha_vector': bilby.core.prior.Uniform(-4, 4, '$\alpha_{\text{V}}$'),
          'omega_ref_scalar': bilby.core.prior.LogUniform(10**(-6), 10**(-2), '$\Omega_{\text{ref, S}}$'),
          'alpha_scalar': bilby.core.prior.Uniform(-4, 4, '$\alpha_{\text{S}}$')}

result = bilby.run_sampler(likelihood=model, priors=priors, sampler='dynesty', npoints=10000, walks=10, npool=5,
                          outdir=outdir, label='hlv_result_non_GR_pols_chh', resume=False, clean=True, dlogz=0.1)
```

```
08:27 bilby INFO      : Summary of results:
nsamples: 27617
ln_noise_evidence: 0.000
ln_evidence: 11834.865 +/- 0.031
ln_bayes_factor: 11834.865 +/- 0.031
```



Take a break now, and be ready for  
Hand on section of PyGWB

