

# Reconstructing Gravitational Wave Signals with Information Field Theory

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IMPRS Recruitment Workshop  
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# Outline

- Preamble

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- Laser Interferometers

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Data

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Theory

# Outline

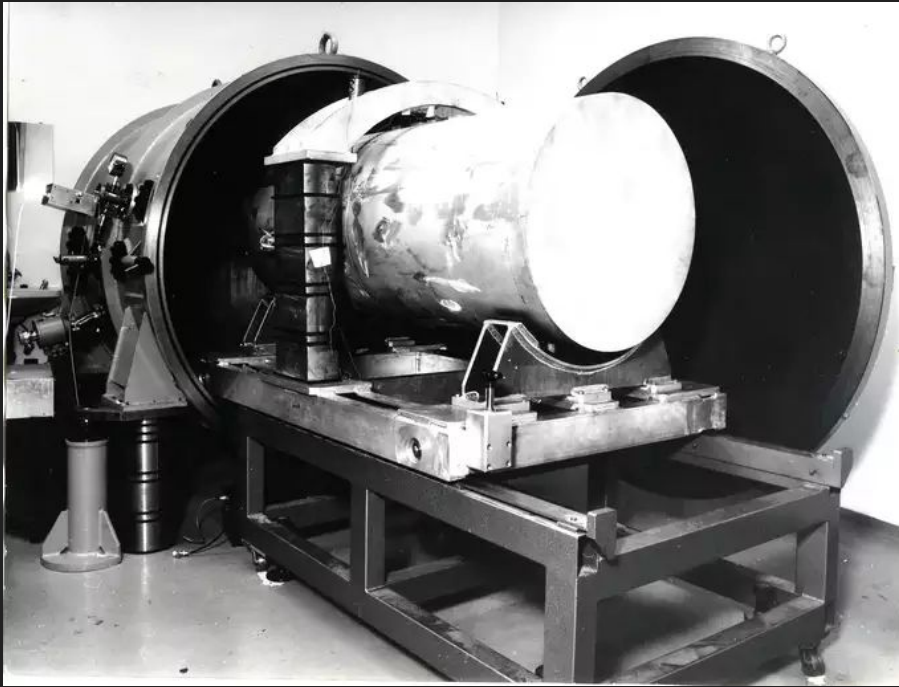
- Preamble
- Laser Interferometers
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Theory
- Implementation Details

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- Preamble
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- Gravitational Wave  
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Theory
- Implementation Details
- Results

# Preamble





Left: the Munich resonant-mass gravitational detector (1972-1975)  
 Right: MPQ's 1987 proposal for a laser interferometer prototype

**Proposal for the Construction of a Large Laser Interferometer  
 for the Measurement of Gravitational Waves**

Translation of Summaries of the Report MP Q 129

**Vorschlag zum Bau eines großen Laser-Interferometers  
 zur Messung von Gravitationswellen  
 – Erweiterte Fassung –**

Gerd Leuchs, Karl Maischberger, Albrecht Rüdiger  
 Roland Schilling, Lise Schnupp, Walter Winkler



# The Nobel Prize in Physics 2017



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Elmehed

**Rainer Weiss**

Prize share: 1/2



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**Barry C. Barish**

Prize share: 1/4



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**Kip S. Thorne**

Prize share: 1/4

$$\begin{aligned}
 &= (P_{ac}P_{bd} - \frac{1}{2}P_{ab}P_{cd} - \frac{1}{2}P_{ab}P_{cd} + \frac{1}{2}P_{ab}P_{cd}) B_{ab}B_{cd} \quad \odot \\
 &= (P_{ac}P_{bd} - \frac{1}{2}P_{ab}P_{cd}) B_{ab}B_{cd} \\
 &= P_{ac}P_{bd} B_{ab}B_{cd} - \frac{1}{2}(P_{ab}B_{ab})(P_{cd}B_{cd}) \\
 &= \underbrace{P_{ac}P_{bd} B_{ab}B_{cd}}_{(\delta_{ac} - n_a n_c)(\delta_{bd} - n_b n_d) B_{ab}B_{cd}} - \frac{1}{2}(-B_{ab}n_a n_b)(-B_{cd}n_c n_d) \\
 &= (\delta_{ac}\delta_{bd} + n_a n_b n_c n_d) B_{ab}B_{cd}
 \end{aligned}$$

$$\Rightarrow B_{ab}B_{ab} - 2B_{ac}B_{bc}n_a n_b + \frac{1}{2}B_{ab}B_{cd}n_a n_b n_c n_d$$

Since this holds for any symmetric trace free tensor,

and using the given relations, we have that

$$\begin{aligned}
 \cdot \frac{1}{4\pi} \int d^2\Omega \ddot{Q}_{ac} \ddot{Q}_{bc} n_a n_b &= \frac{1}{3} \ddot{Q}_{ac} \ddot{Q}_{bc} S_{ab} = \frac{1}{3} \ddot{Q}_{ab} \ddot{Q}_{ab} \\
 \cdot \frac{1}{4\pi} \int d^2\Omega \ddot{Q}_{ab} \ddot{Q}_{cd} n_a n_b n_c n_d \\
 &= \frac{1}{15} \ddot{Q}_{ab} \ddot{Q}_{cd} (S_{ab}S_{cd} + S_{ac}S_{bd} + S_{ad}S_{bc}) = \frac{2}{15} \ddot{Q}_{ab} \ddot{Q}_{ab}
 \end{aligned}$$

$$\Rightarrow \frac{G}{2} \frac{1}{4\pi} \int d^2\Omega \langle {}^{(T)}\ddot{Q}_{lm} {}^{(T)}\ddot{Q}_{lm} \rangle = \frac{G}{2} (\ddot{Q}_{ab} \ddot{Q}_{ab}) \left(1 - \frac{2}{3} + \frac{1}{2} \cdot \frac{2}{15}\right)$$

$$\Rightarrow \boxed{\frac{dE}{dt} = -\frac{G}{5} \langle \ddot{Q}_{ij} \ddot{Q}_{ij} \rangle}$$

${}^{(T)}\ddot{Q}_{ij} {}^{(T)}\ddot{Q}_{ij}$   
 $= \ddot{Q}_{ij} \ddot{Q}_{ij} - 2\ddot{Q}_{ik} \ddot{Q}_{jk} n_i n_j$   
 $+ \frac{1}{2} \ddot{Q}_{ij} \ddot{Q}_{kl} n_i n_j n_k n_l$



$$= (P_{ac} P_{bd} - \frac{1}{2} \delta_{ab} \delta_{cd}) B_{ab} B_{cd}$$

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$$B_{ab} B_{cd} - \frac{1}{2} (-B_{ab} n_a n_b + B_{cd} n_c n_d)$$

$$(P_{ac} - n_a n_c)(\delta_{bd} - n_b n_d) B_{ab} B_{cd}$$

$$(\delta_{ac} \delta_{bd} + n_a n_b n_c n_d) B_{ab} B_{cd}$$

$$\Rightarrow B_{bc} n_a n_b + \frac{1}{2} B_{ab} B_{cd} n_a n_b n_c n_d$$

Since  $B_{ab}$  is a symmetric trace free tensor,

we have that

$$S_{ab} = \frac{1}{3} \ddot{Q}_{ab} \ddot{Q}_{ab}$$

$$= \frac{1}{4\pi} \int d^2 \Omega \ddot{Q}_{ab} \ddot{Q}_{ab}$$

$$= \frac{1}{4\pi} \int d^2 \Omega \ddot{Q}_{ab} \ddot{Q}_{cd} n_a n_b n_c n_d$$

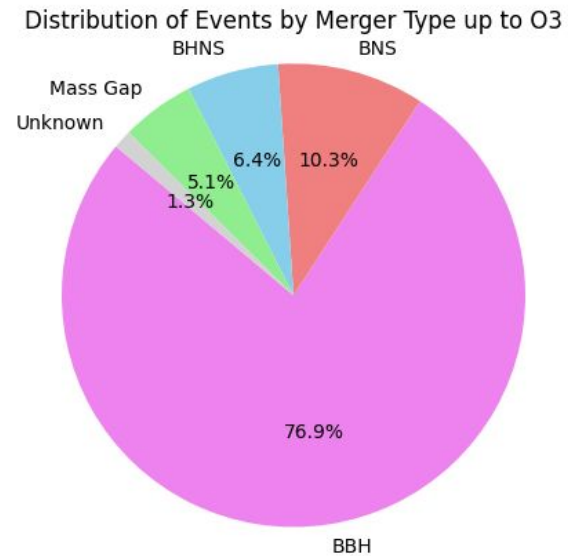
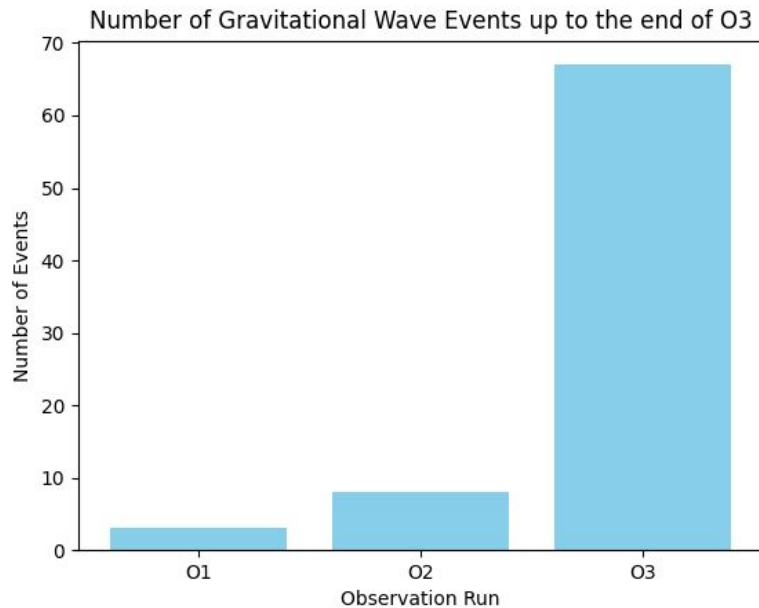
$$= \frac{1}{15} \ddot{Q}_{ab} \ddot{Q}_{cd} (\delta_{ab} \delta_{cd} + \delta_{ac} \delta_{bd} + \delta_{ad} \delta_{bc})$$

$$\Rightarrow \frac{G}{4\pi} \int d^2 \Omega \langle {}^{(TT)}\ddot{Q}_{lm} {}^{(TT)}\ddot{Q}_{lm} \rangle = \frac{G}{2}$$

$(TT)\ddot{Q}_{lm}$

$\ddot{Q}_{lm}$

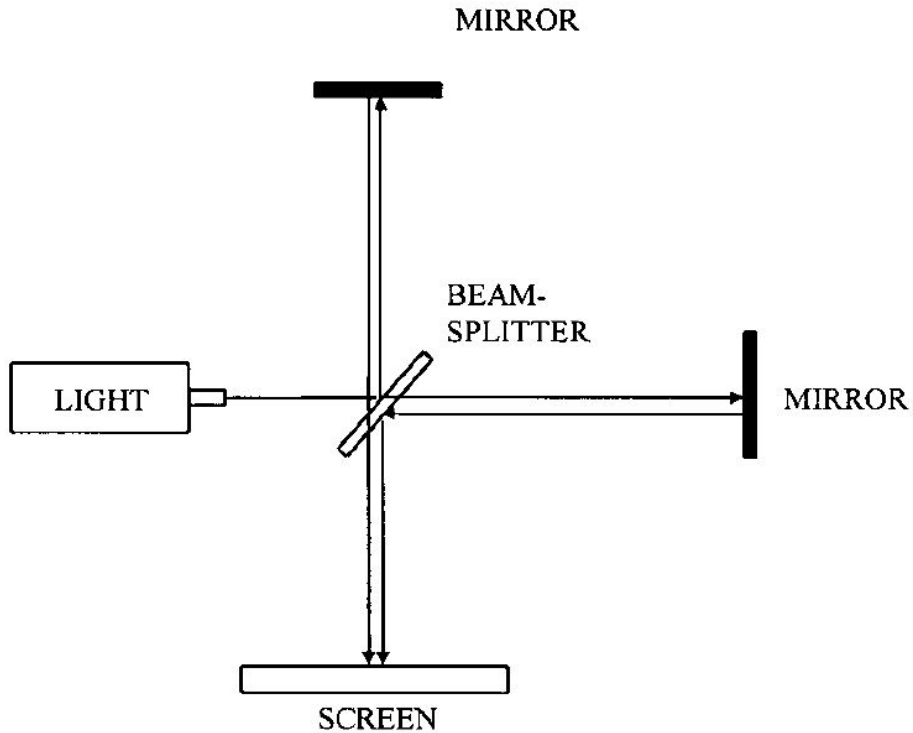
$\ddot{Q}_{lm} n_a n_b$   
 $\ddot{Q}_{lm} n_a n_b$



BBH = black hole - black hole merger  
BHNS = black hole - neutron star merger  
Mass Gap = underdetermined by evidence

# Laser Interferometers

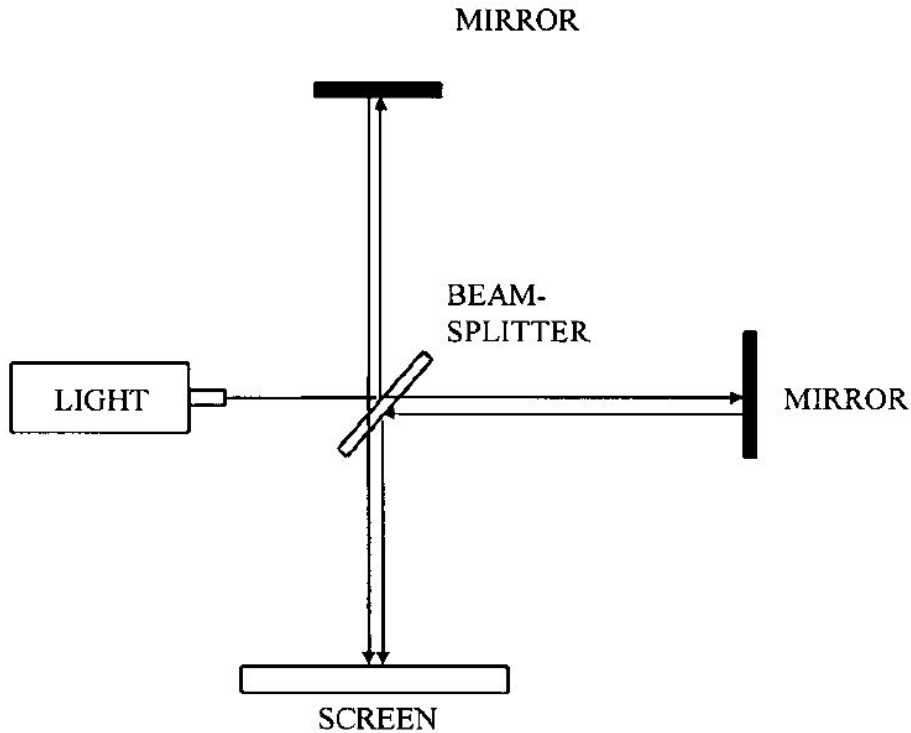
# The Big Picture



- Differences in the path length travelled by light along the interferometer arms produce an interference pattern

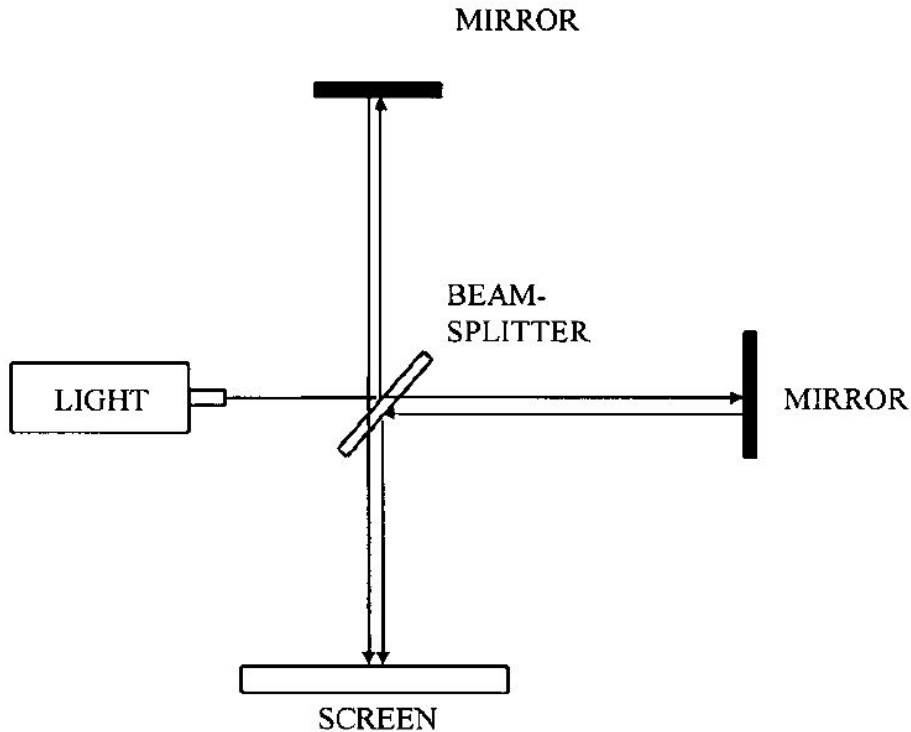


# The Big Picture



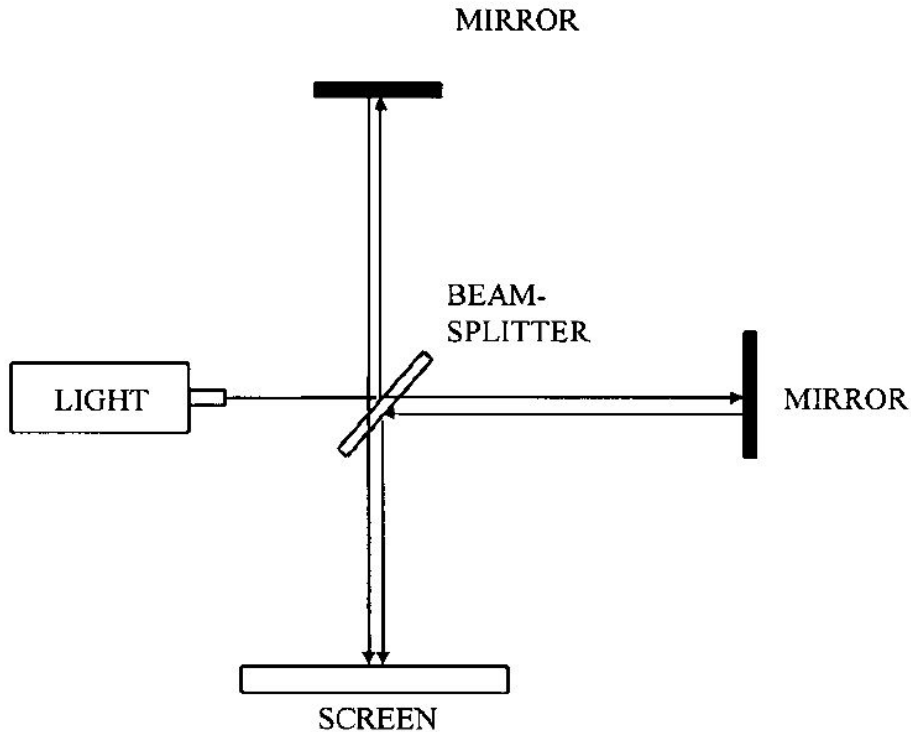
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# The Big Picture



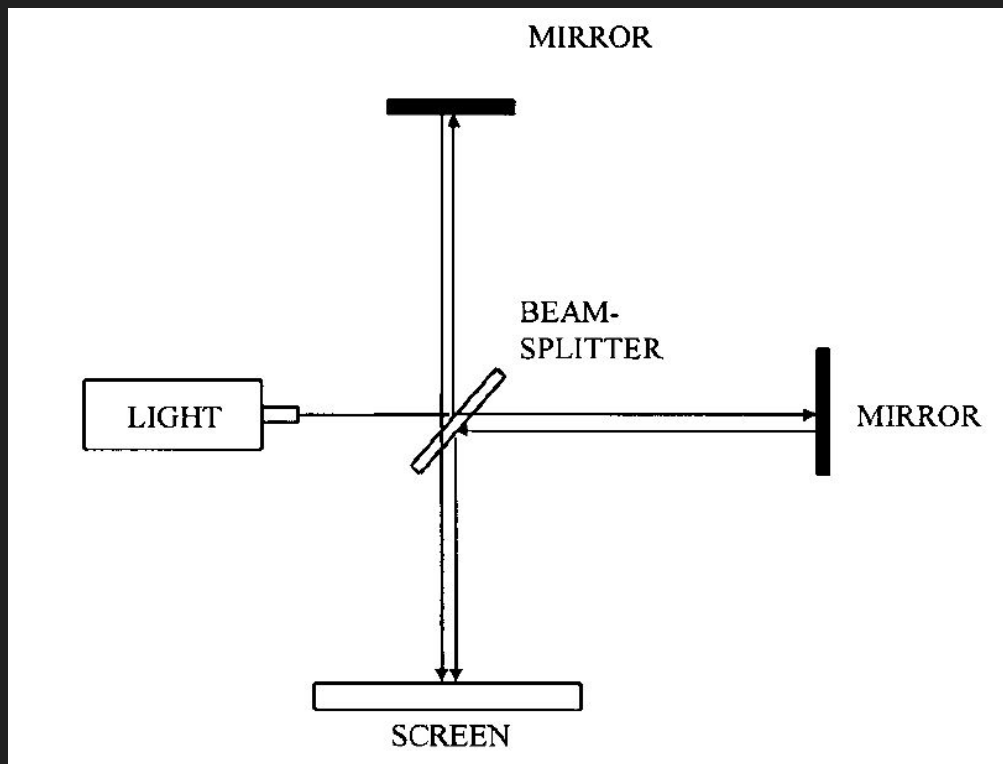
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- By the equivalence principle, a passing gravitational wave will perturb the test masses away from their inertial frames of reference

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- Differences in the path length travelled by light along the interferometer arms produce an interference pattern
- Fix the end mirrors to approximate test masses in free fall
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- This produces a measurable strain

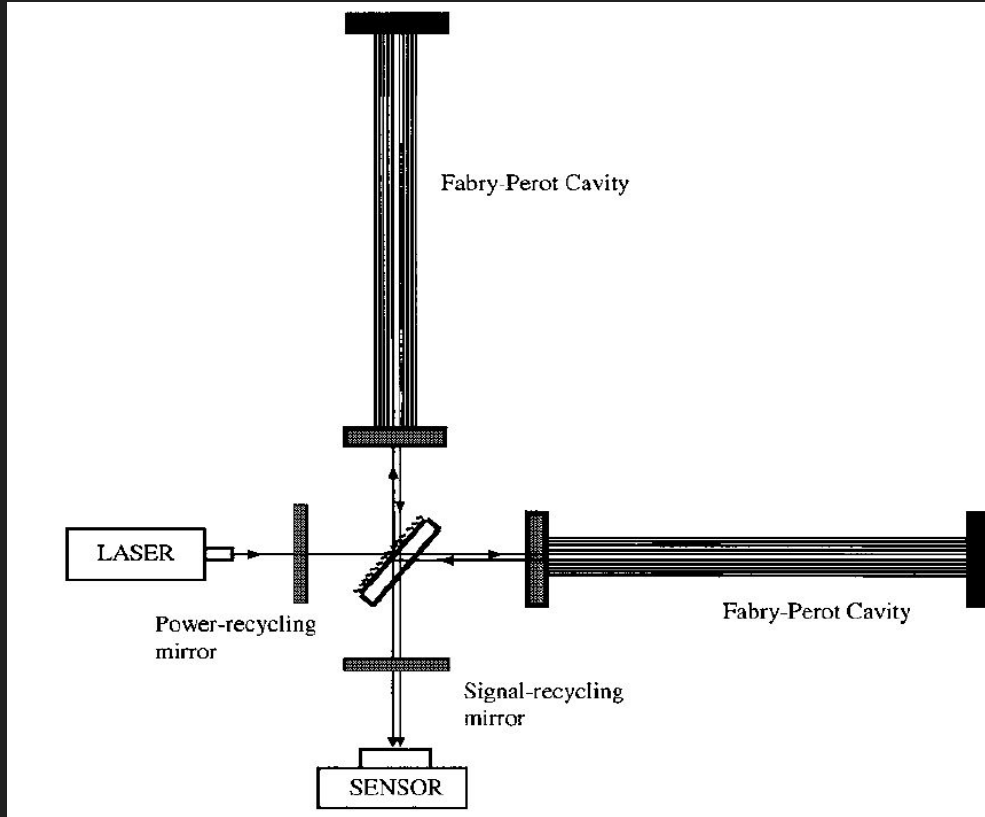
# The Big Picture? Easy enough...



- Differences in the path length travelled by light along the interferometer arms produce an interference pattern
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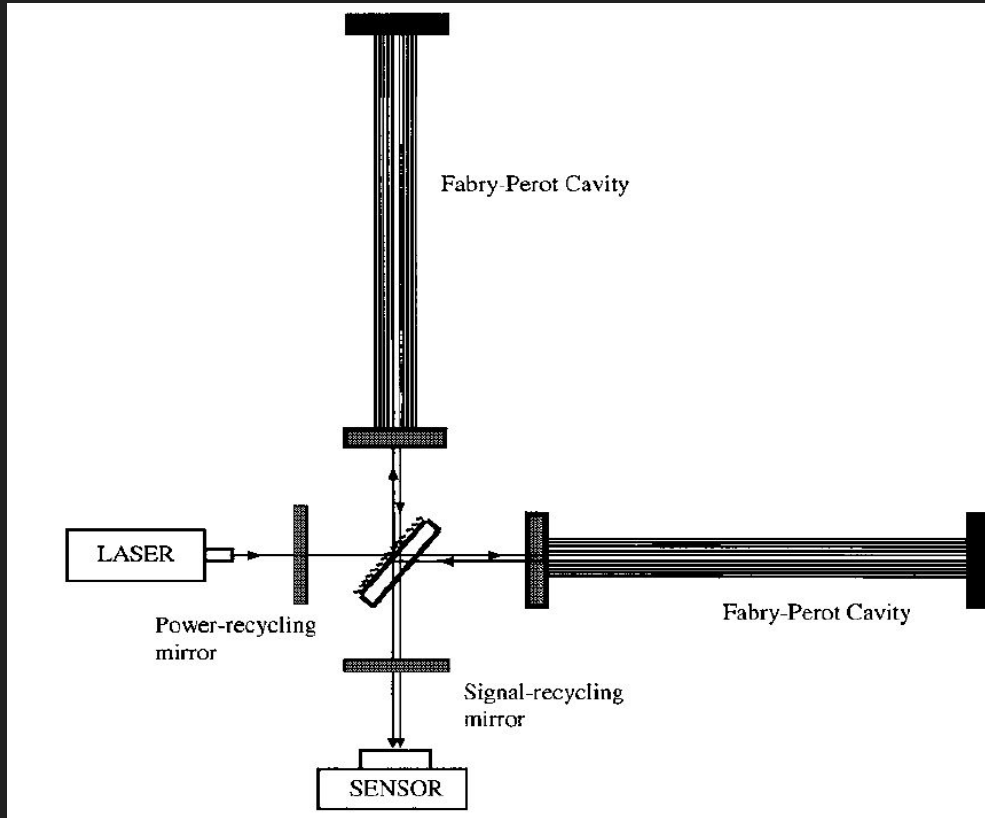
$$h(t) = \frac{\Delta L_x - \Delta L_y}{L}$$

...but the devil is in the details



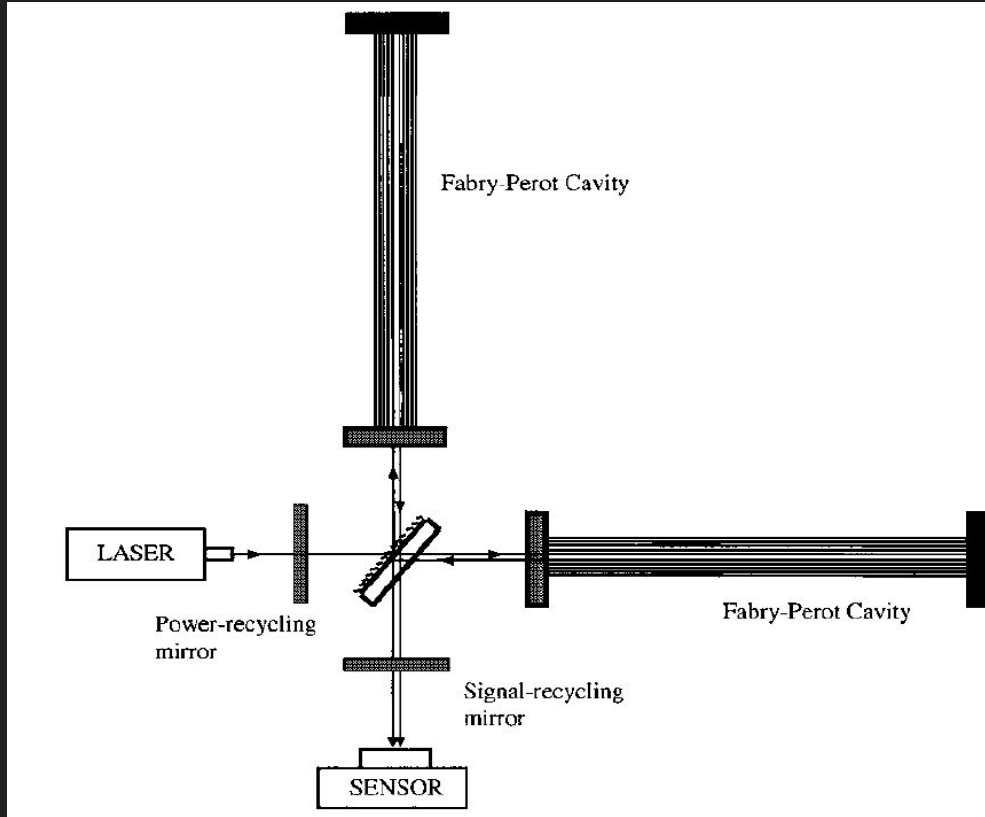
- The arms contain Fabry-Pérot cavities to increase the interaction time with potential signals

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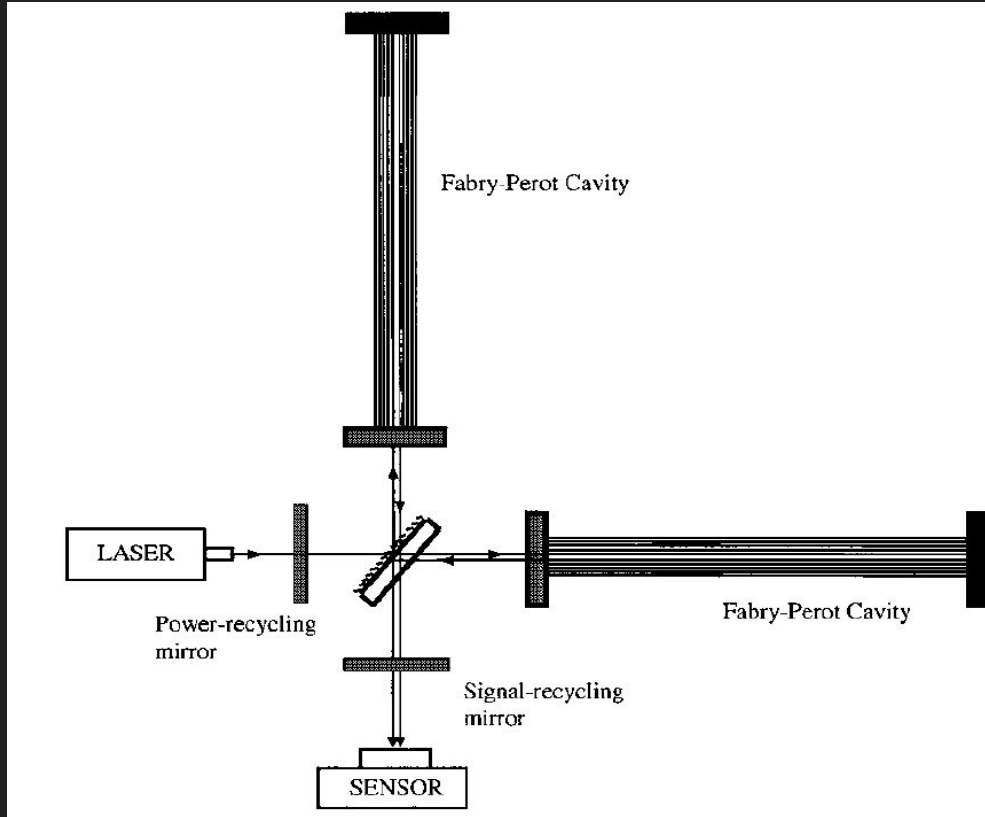
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# ...but the devil is in the details



- The arms contain Fabry-Pérot cavities to increase the interaction time with potential signals
- Power-recycling mirrors reflect laser light back into the interferometer to increase the power stored
- Signal-recycling mirrors enhance the interferometer's sensitivity in the band of interest

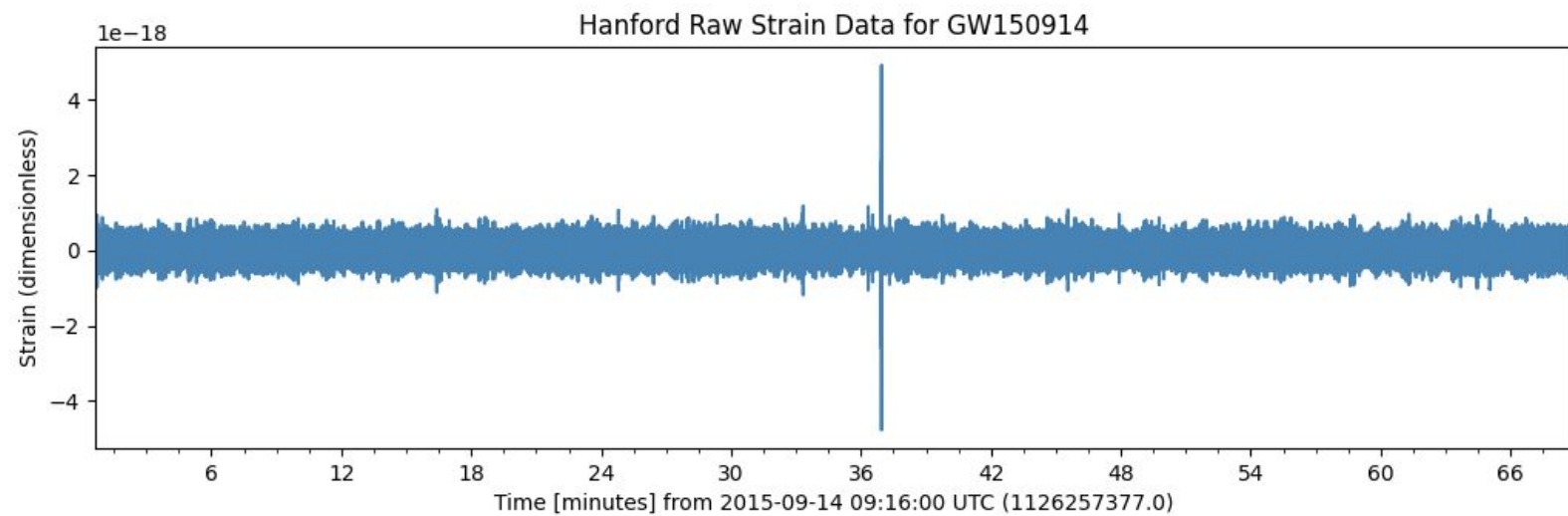
# ...but the devil is in the details

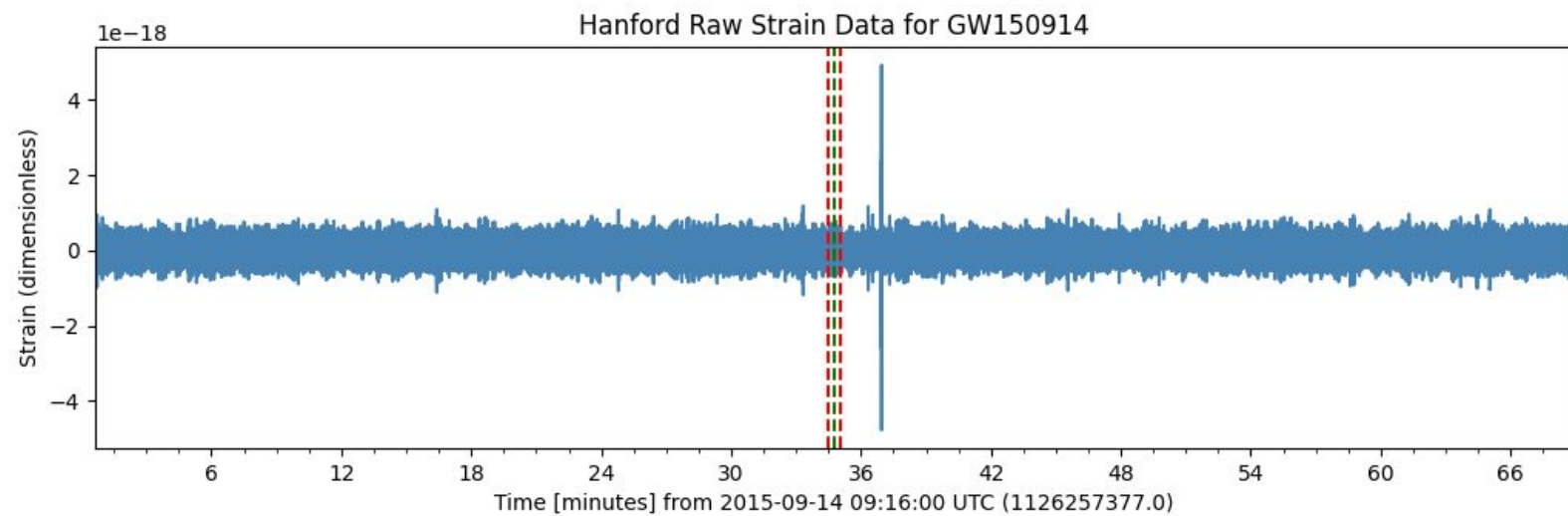


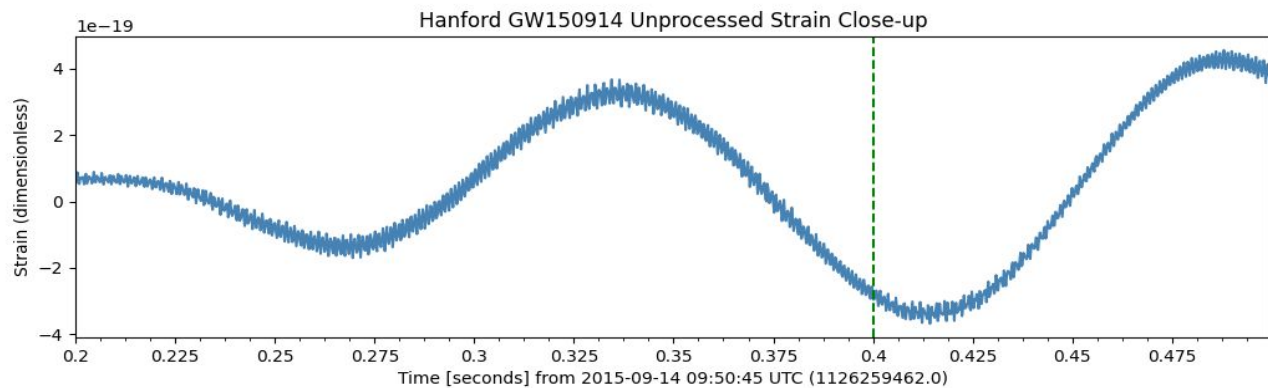
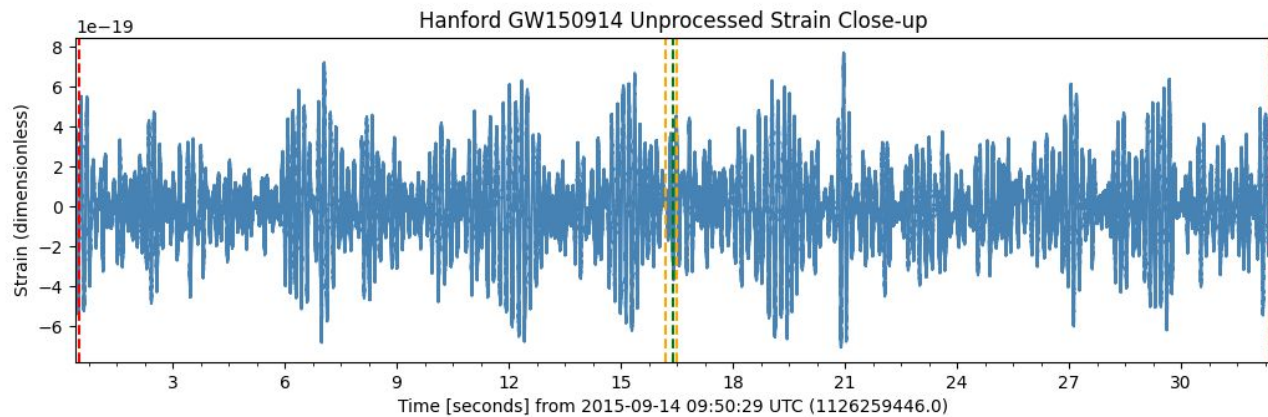
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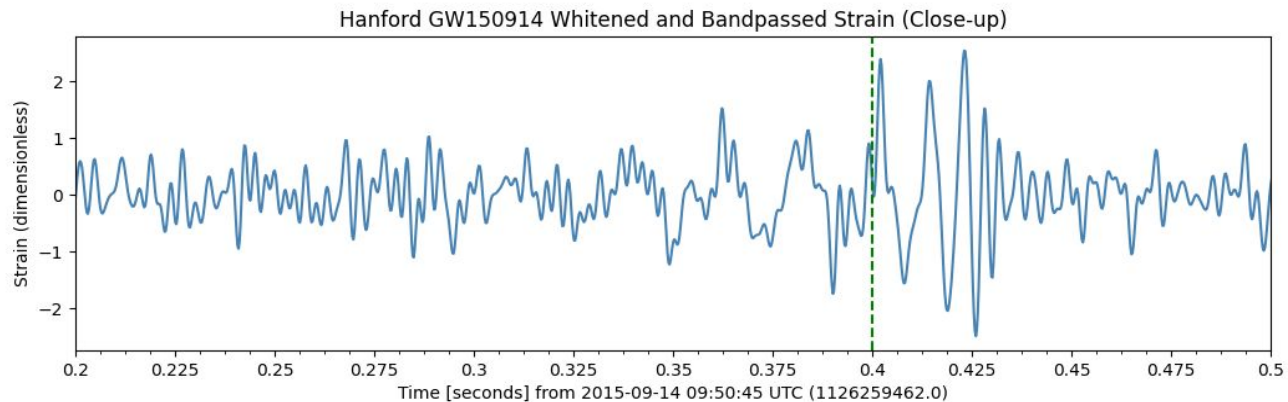
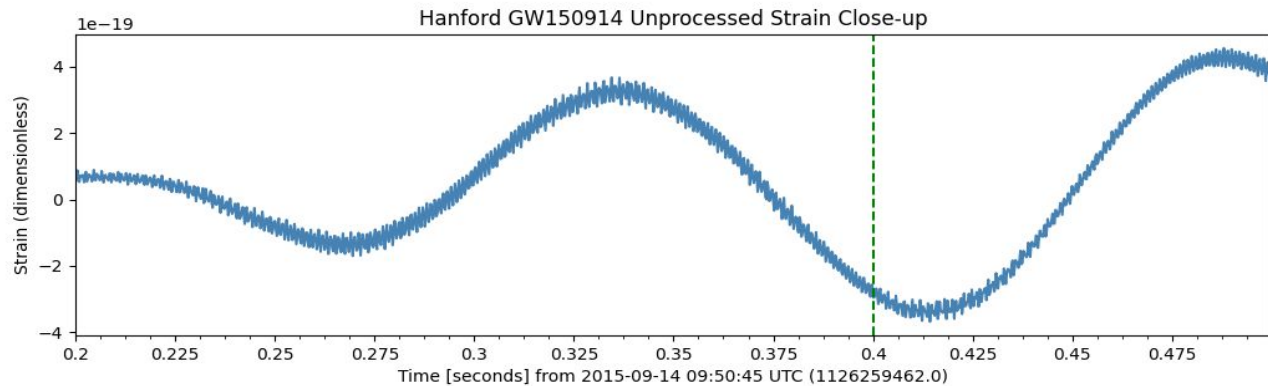


# A Look at the Data

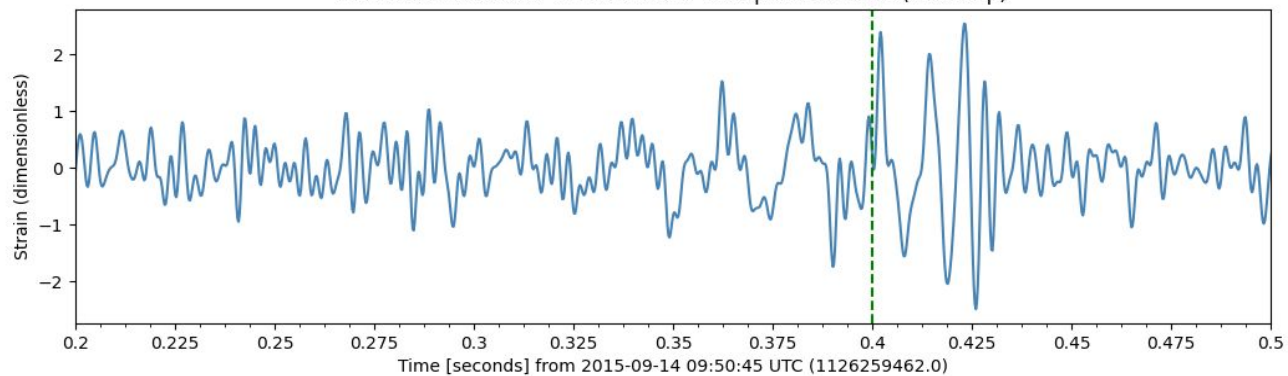




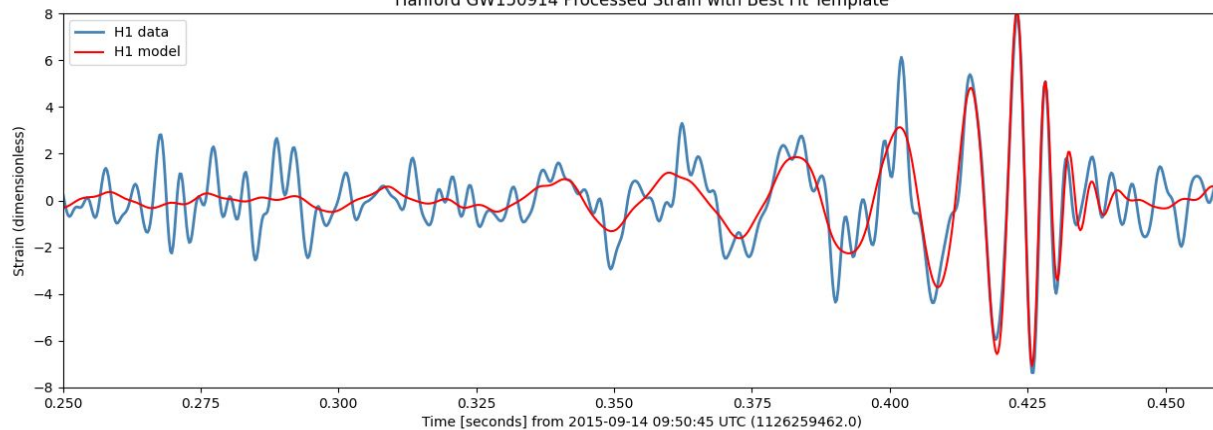




Hanford GW150914 Whitened and Bandpassed Strain (Close-up)



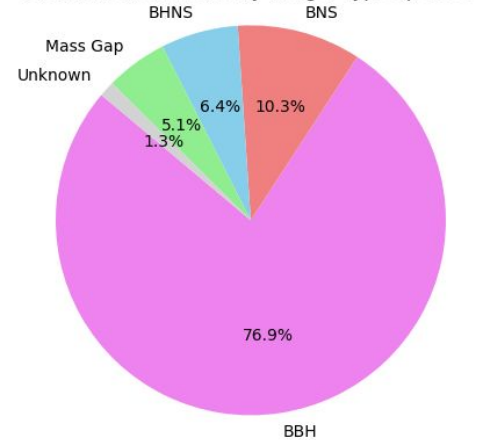
Hanford GW150914 Processed Strain with Best Fit Template



# So what's the problem?

Stellar Binaries	$10^{-12}$ Hz to $10\text{ }\mu\text{Hz}$
Super Massive Black Hole Binaries	10 nHz to 10 mHz
Star-Exoplanet Binaries (ultra-short orbital period)	$1\text{ }\mu\text{Hz}$ to 1 mHz
Stellar Mass Black Hole Binaries	$10\text{ }\mu\text{Hz}$ to $\sim 1\text{ kHz}$
White Dwarf Binaries	1 mHz to 1 Hz
Black Hole–Neutron Star Binaries	10 mHz to 10 kHz
Neutron Star Binaries	100 mHz to $\sim 1\text{ kHz}$

Distribution of Events by Merger Type up to O3

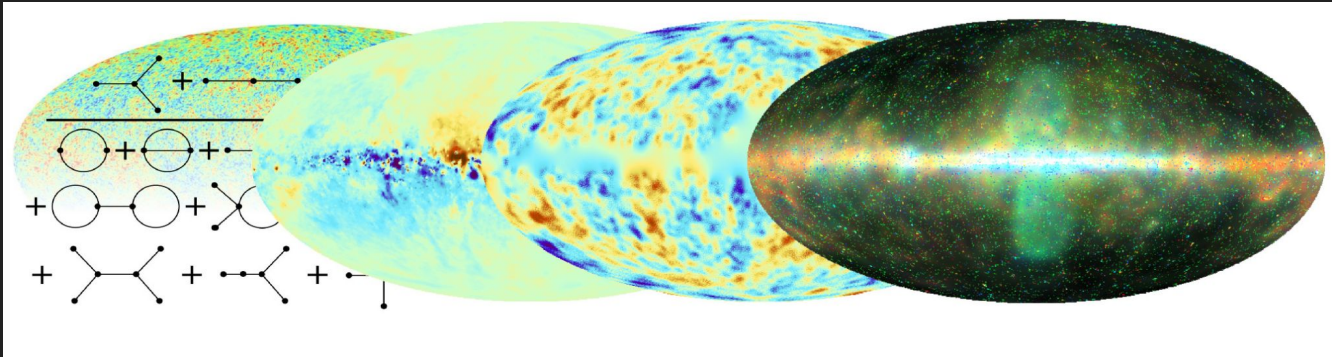


So what's the problem?

Can we find a gravitational wave signal in the calibrated strain data *without* relying on any numerical relativity templates?



# Information Field Theory



# IFT in Brief

- IFT is a Bayesian inference framework that recovers signal fields from noisy, incomplete, or otherwise corrupted measurements

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

$$H(d, s) = -\ln[P(d, s)]$$

# IFT in Brief

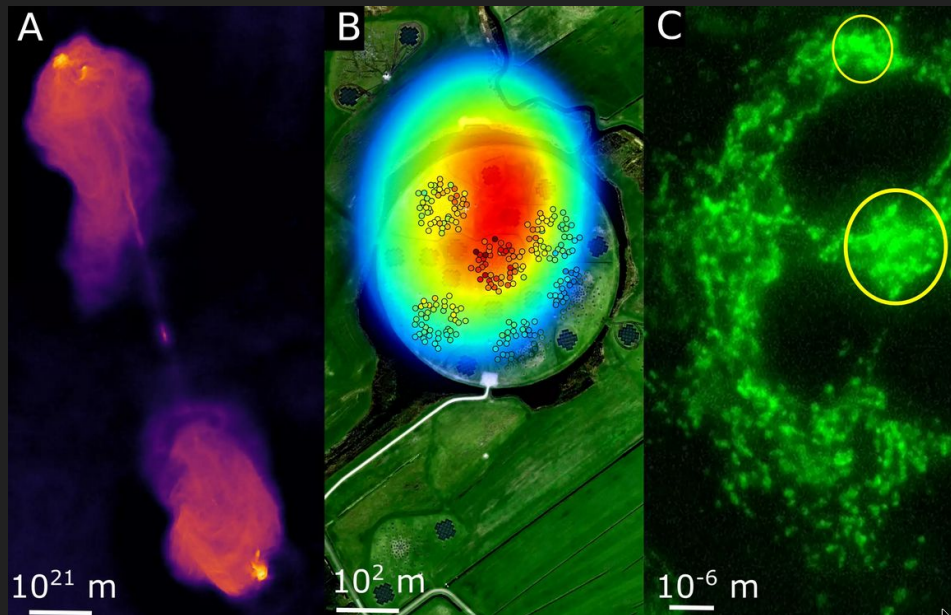
- IFT is a Bayesian inference framework that recovers signal fields from noise, incomplete, or otherwise corrupted measurements
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$$P(s|d) = \frac{e^{-H(d,s)}}{Z(d)}$$

$$H(d, s) = -\ln[P(d, s)]$$

# IFT in Brief

- IFT is a Bayesian inference framework that recovers signal fields from noise, incomplete, or otherwise corrupted measurements
- By analogy to statistical field theory, IFT recasts the Bayesian inference posterior as the **information Hamiltonian** to set up optimization problems
- Proven successes:
  - analysis of the CMB
  - X-ray and radio tomography
  - medical imaging



# The Measurement Equation

$$d = R s + n$$



# The Measurement Equation

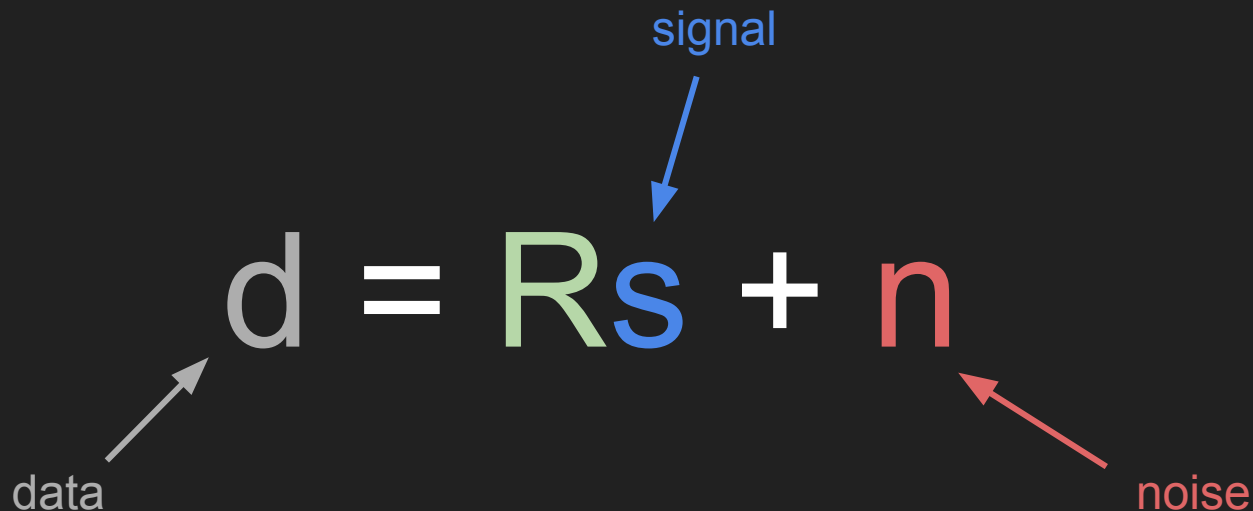
$$\text{data} \nearrow d = R s + n$$

# The Measurement Equation

$$\text{data} \nearrow d = R \overset{\text{signal}}{\downarrow} s + n$$

The diagram illustrates the Measurement Equation,  $d = R s + n$ . The variable  $d$  is labeled "data" with a grey arrow pointing to it. The variable  $s$  is labeled "signal" with a blue arrow pointing to it. The variable  $n$  is colored red. The variable  $R$  is colored green.

# The Measurement Equation



The diagram illustrates the Measurement Equation,  $d = Rs + n$ , with the following components and annotations:

- d**: Data, represented by a grey letter. An arrow labeled "data" points to it.
- =**: Equals sign, represented by a white symbol.
- R**: Regression matrix, represented by a green letter.
- s**: Signal, represented by a blue letter. An arrow labeled "signal" points to it.
- +**: Plus sign, represented by a white symbol.
- n**: Noise, represented by a red letter. An arrow labeled "noise" points to it.

# The Measurement Equation

The diagram illustrates the Measurement Equation:  $d = R s + n$ . The variables are color-coded and labeled with arrows:  $d$  (grey) is labeled 'data' with a grey arrow;  $R$  (green) is labeled 'Response' with a green arrow;  $s$  (blue) is labeled 'signal' with a blue arrow; and  $n$  (red) is labeled 'noise' with a red arrow. The equals sign and plus sign are white.

$$d = R s + n$$

data

Response

signal

noise

# The Likelihood

$$P(d|s) = G(d - Rs, N)$$

# The Likelihood

$$P(d|s) = G(d - Rs, N)$$

Noise  
Covariance



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Noise  
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Operator derived from  
hyperparameters



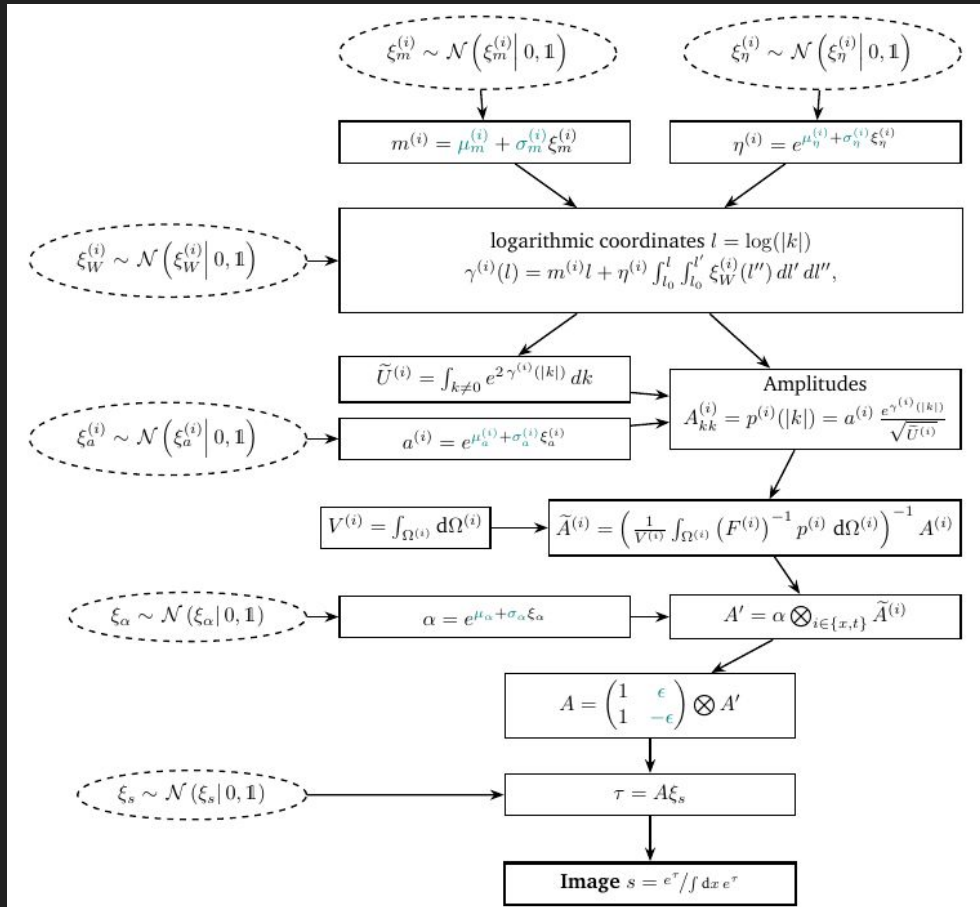
# What about the Prior?

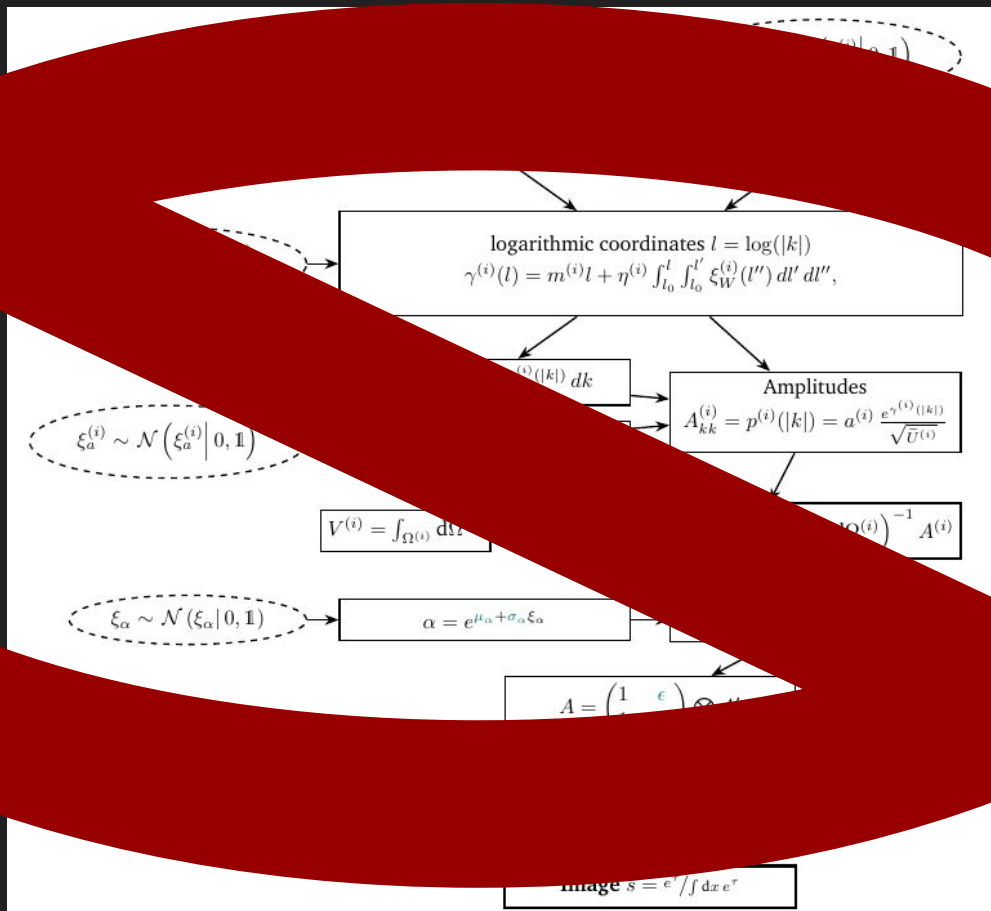
- Bayesian inference requires an initial guess of the prior,  $P(s)$
- To arrive at a Wiener filter reconstruction, we'll use NIFTy's correlated field model

$$s_0 = A\xi$$

Operator derived from  
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# NIFTy Implementation

# Roadmap to Reconstruction

1. Acquire strain data for a confirmed event

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3. Set up a correlated field for the generative model
4. Specify the instrument response and noise covariance operators
5. Define the likelihood energy
6. Minimize the Kullback-Leibler divergence thereof
7. Draw samples from the optimization results for comparison with the LVC's published signal

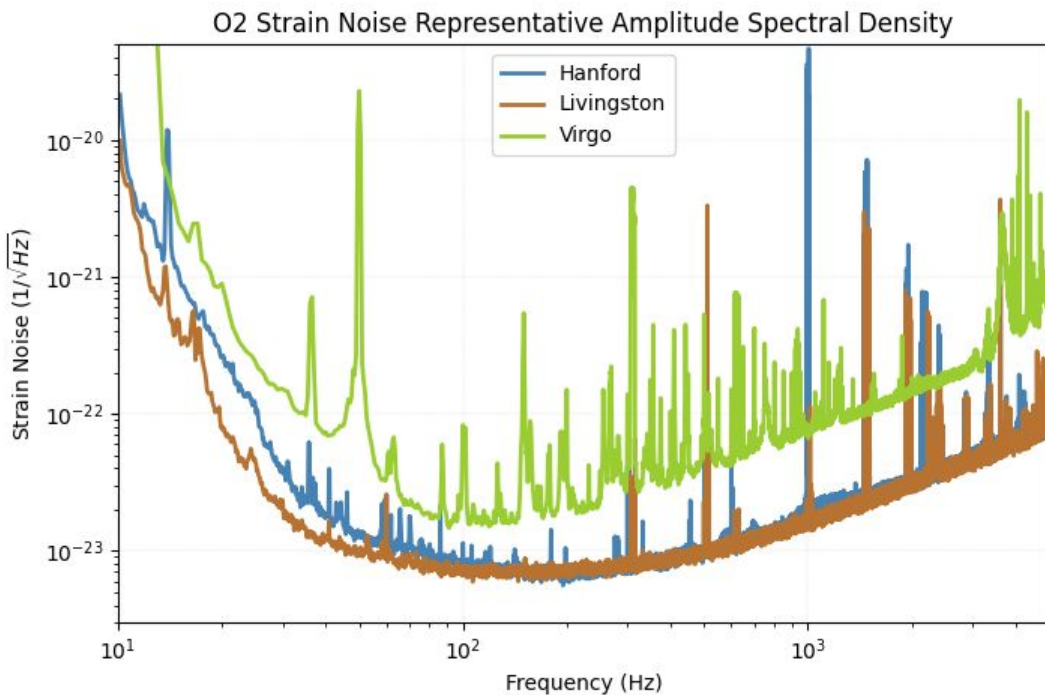


# Determining the Operators

# Instrument Noise

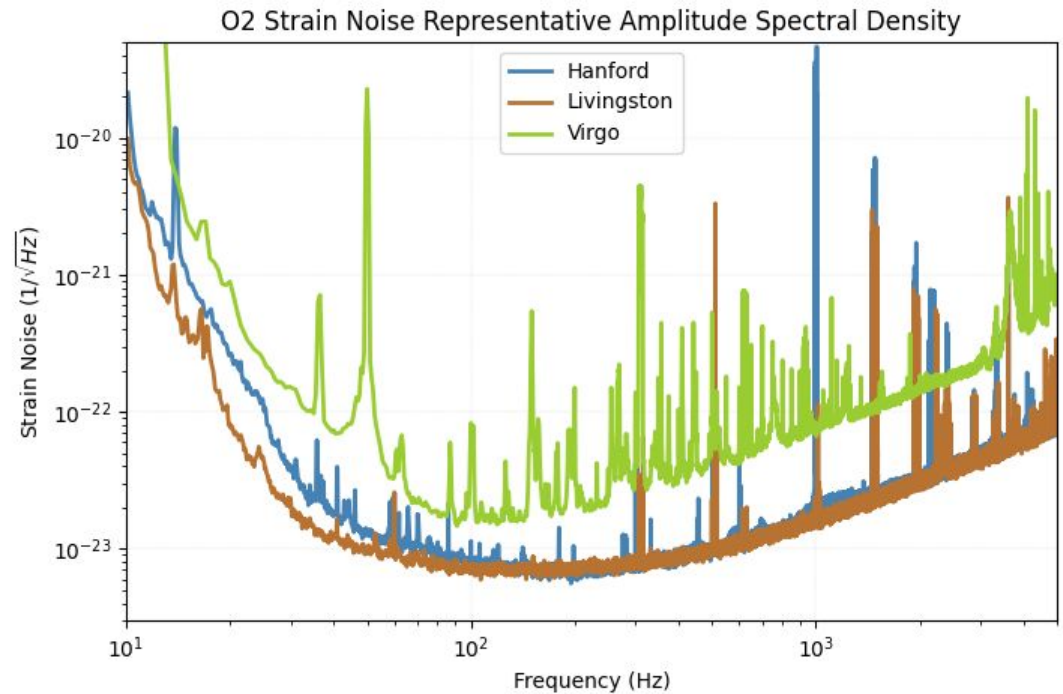
# Noise Sources

- Shot noise



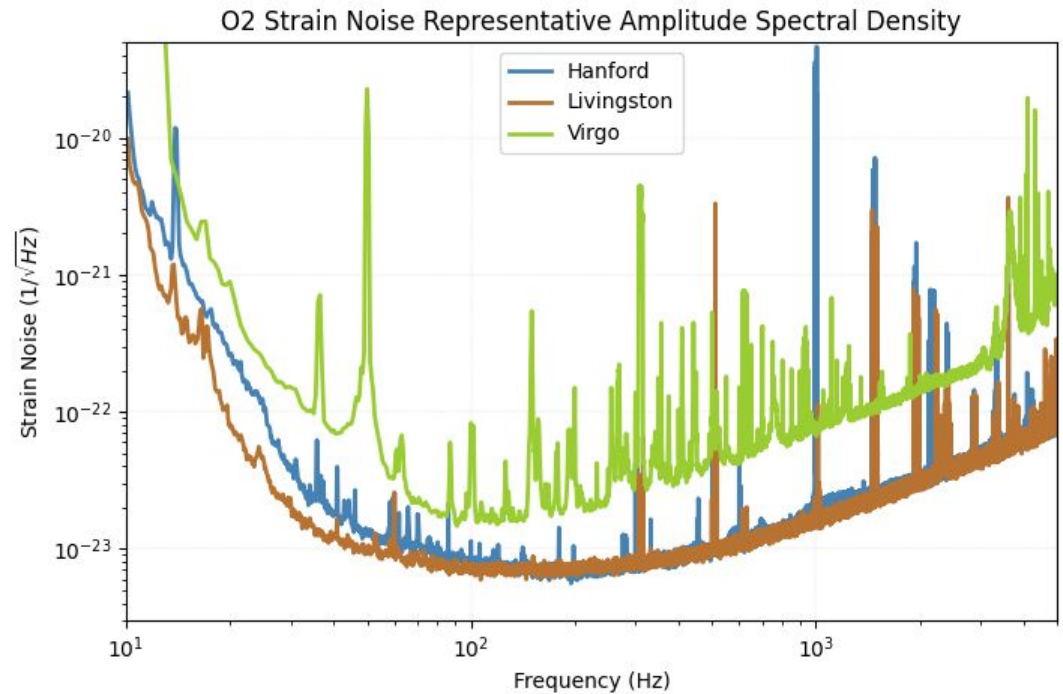
# Noise Sources

- Shot noise
- Radiation pressure noise



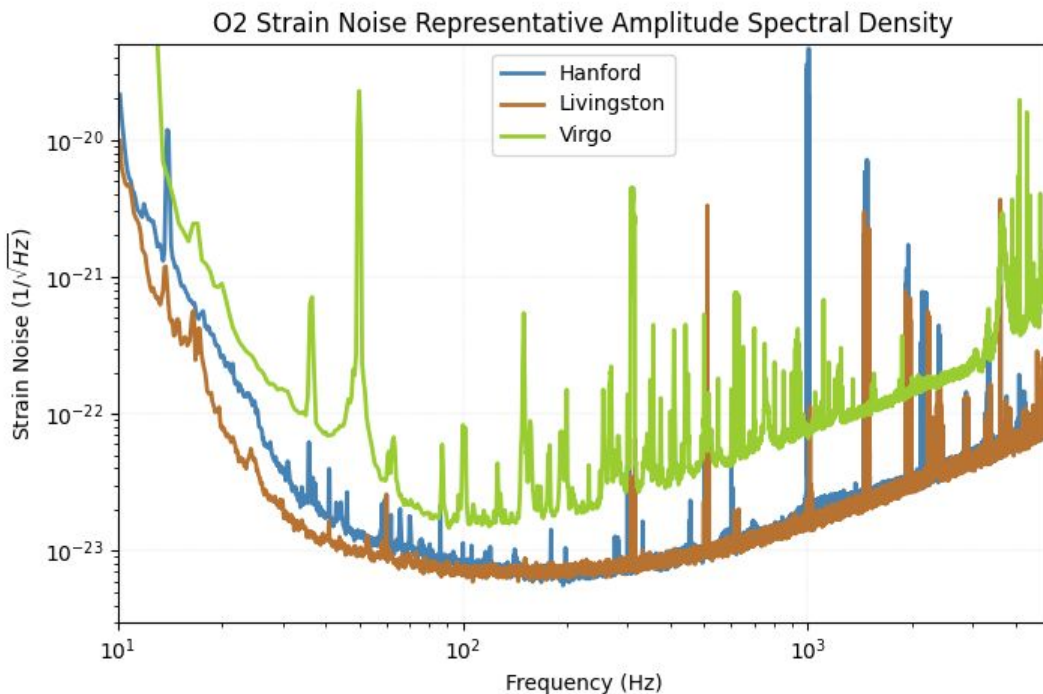
# Noise Sources

- Shot noise
- Radiation pressure noise
- Test mass thermal noise



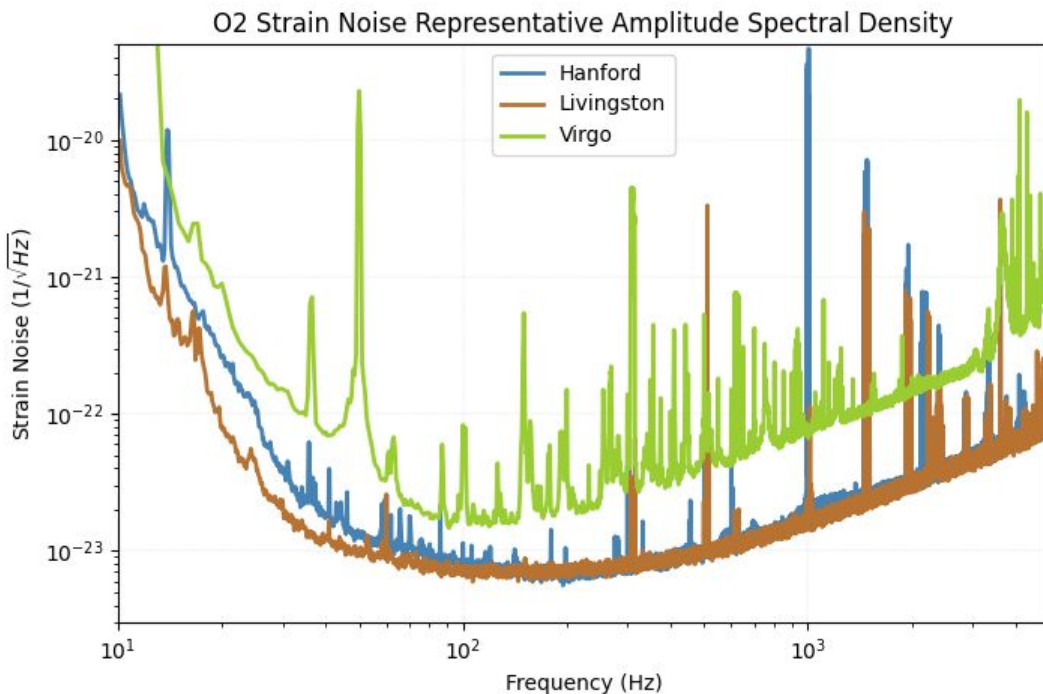
# Noise Sources

- Shot noise
- Radiation pressure noise
- Test mass thermal noise
- Coating Brownian noise



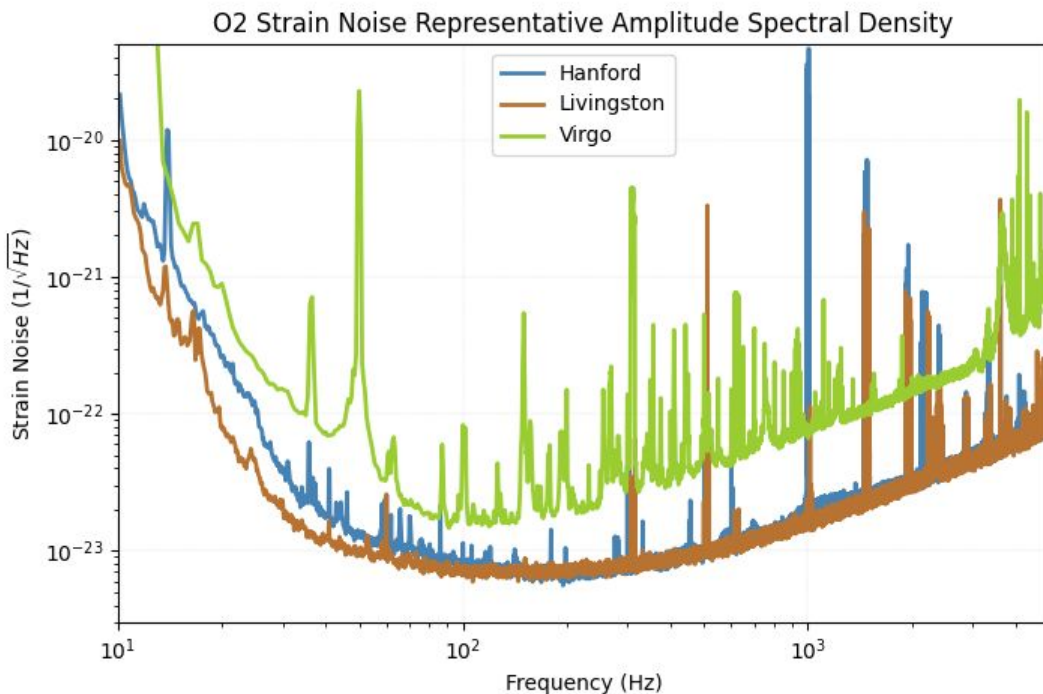
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- Shot noise
- Radiation pressure noise
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- Thermo-optic noise



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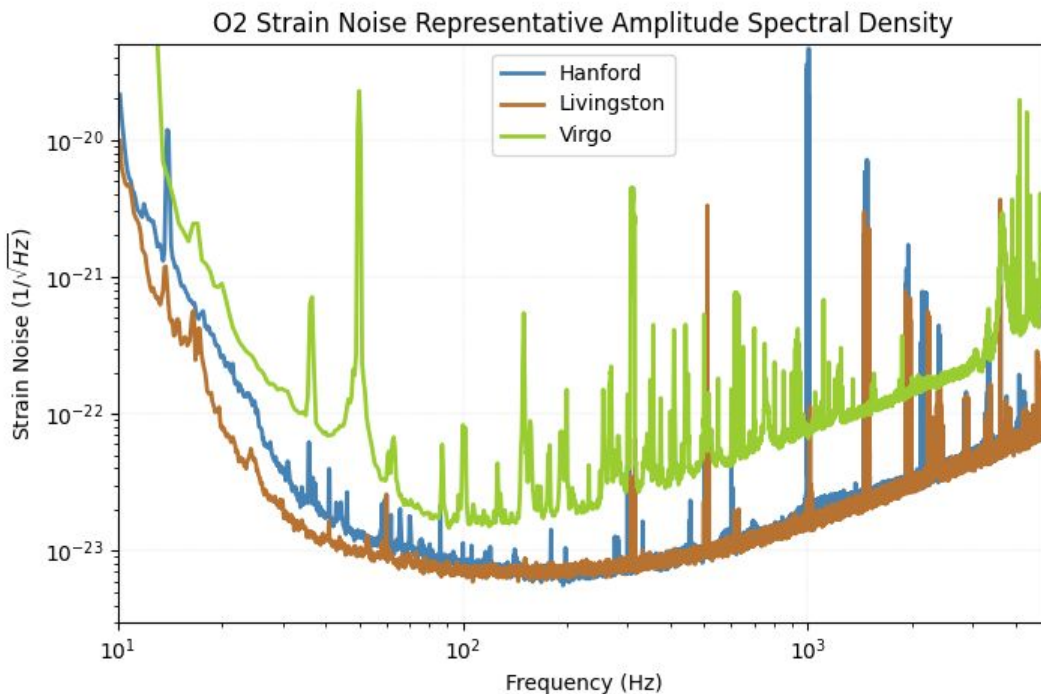
- Shot noise
- Radiation pressure noise
- Test mass thermal noise
- Coating Brownian noise
- Thermo-optic noise
- Suspension thermal noise





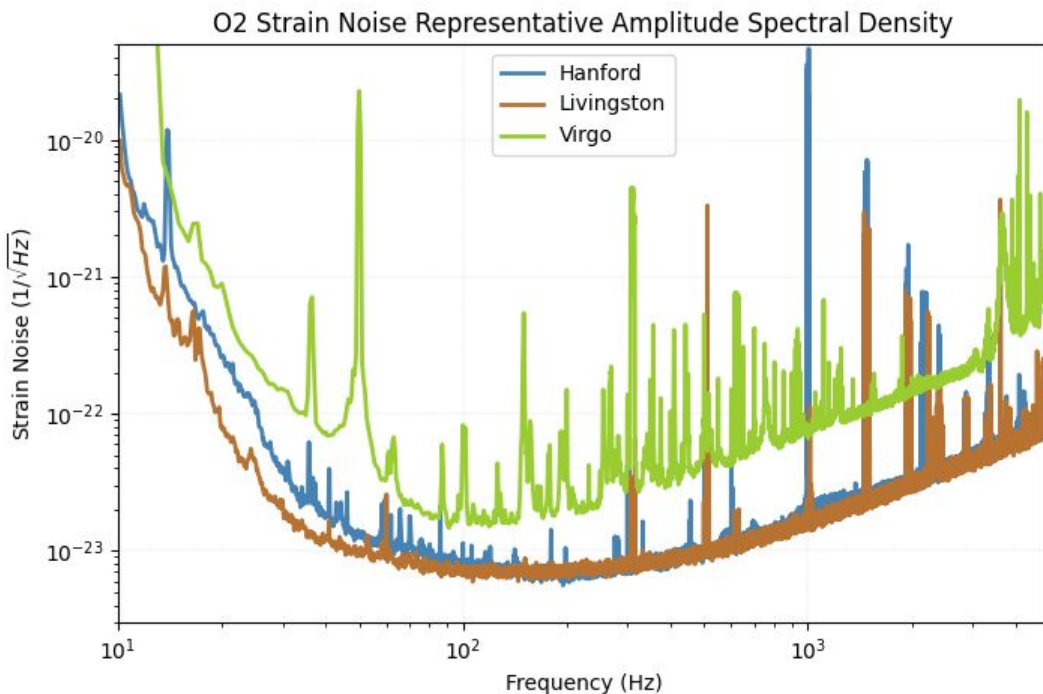
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- Shot noise
- Radiation pressure noise
- Test mass thermal noise
- Coating Brownian noise
- Thermo-optic noise
- Suspension thermal noise
- Gravity gradient noise



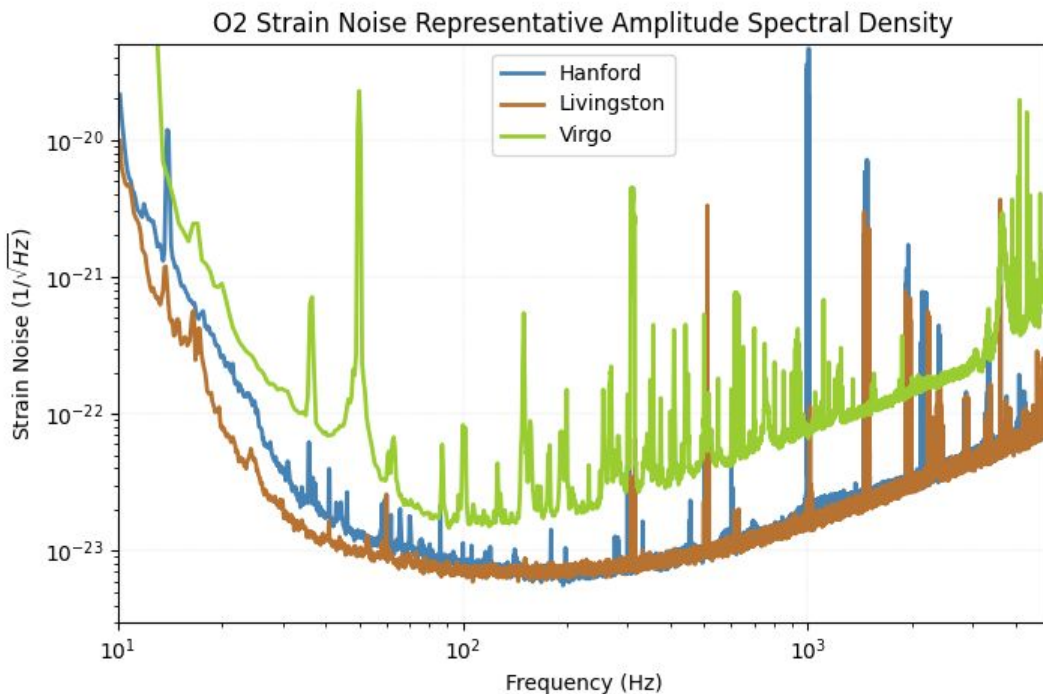
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- Shot noise
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- Test mass thermal noise
- Coating Brownian noise
- Thermo-optic noise
- Suspension thermal noise
- Gravity gradient noise
- Residual gas noise



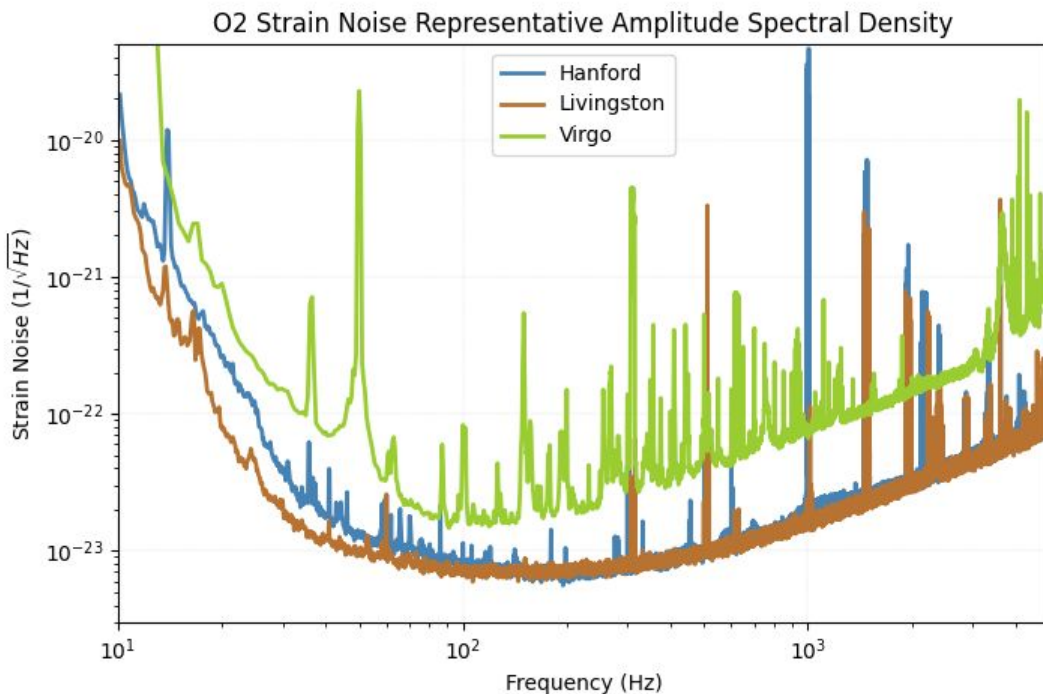
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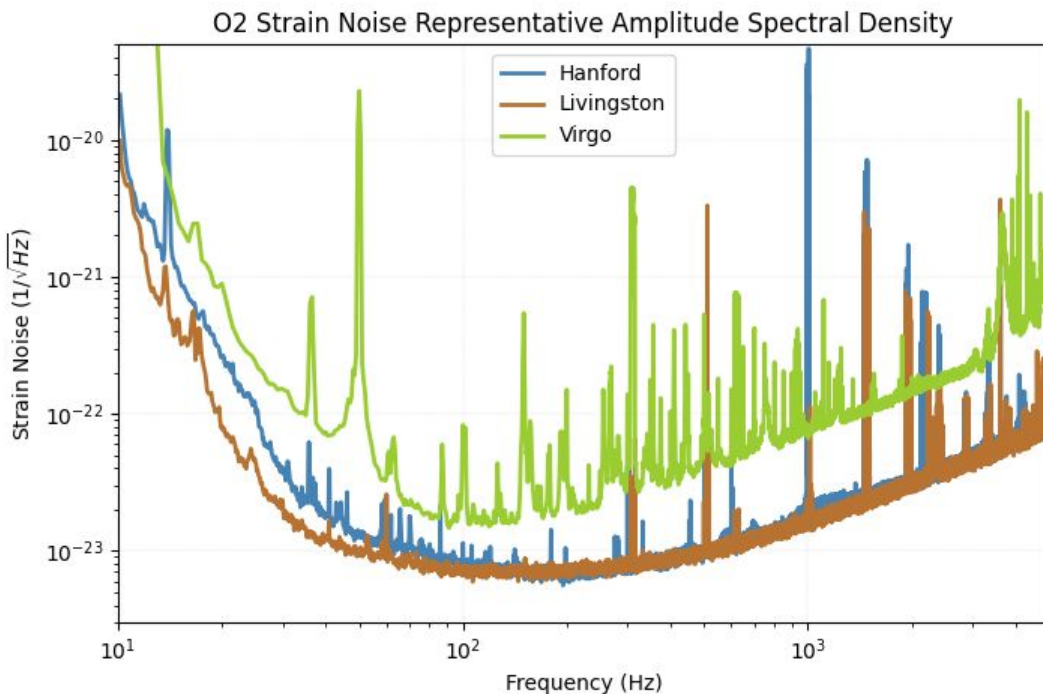
# Modelling the Noise

- For a given run, the LVC chooses a quiet time series interval during the interferometer's operation



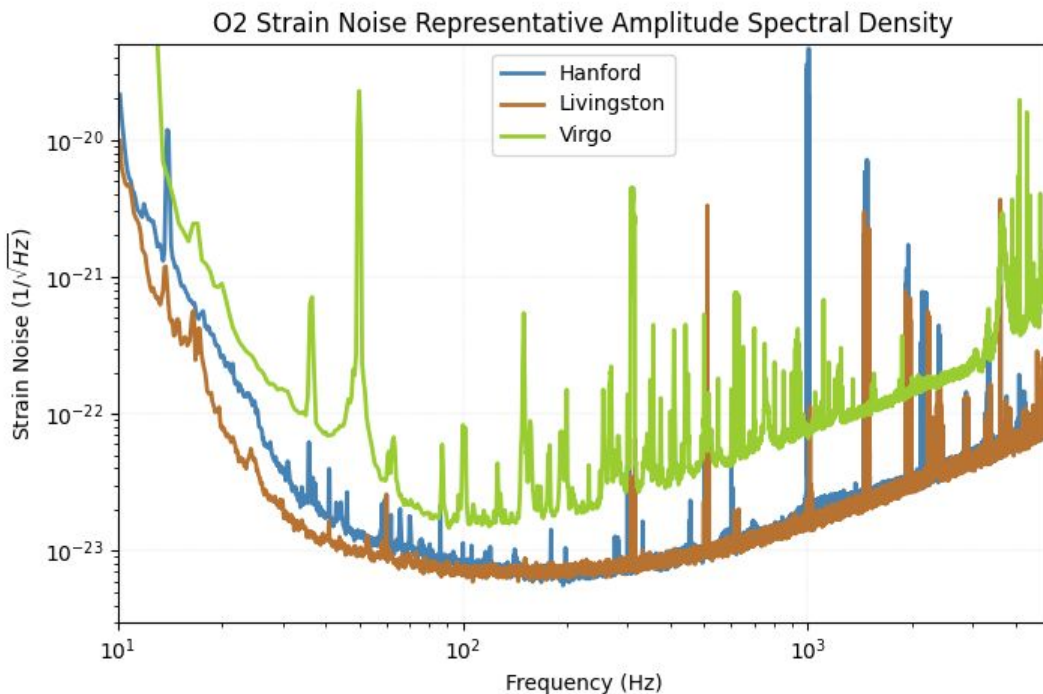
# Modelling the Noise

- For a given run, the LVC chooses a quiet time series interval during the interferometer's operation
- If no signals have been found at sufficiently high confidence, the interval's amplitude spectral density works as a good enough model of the overall noise



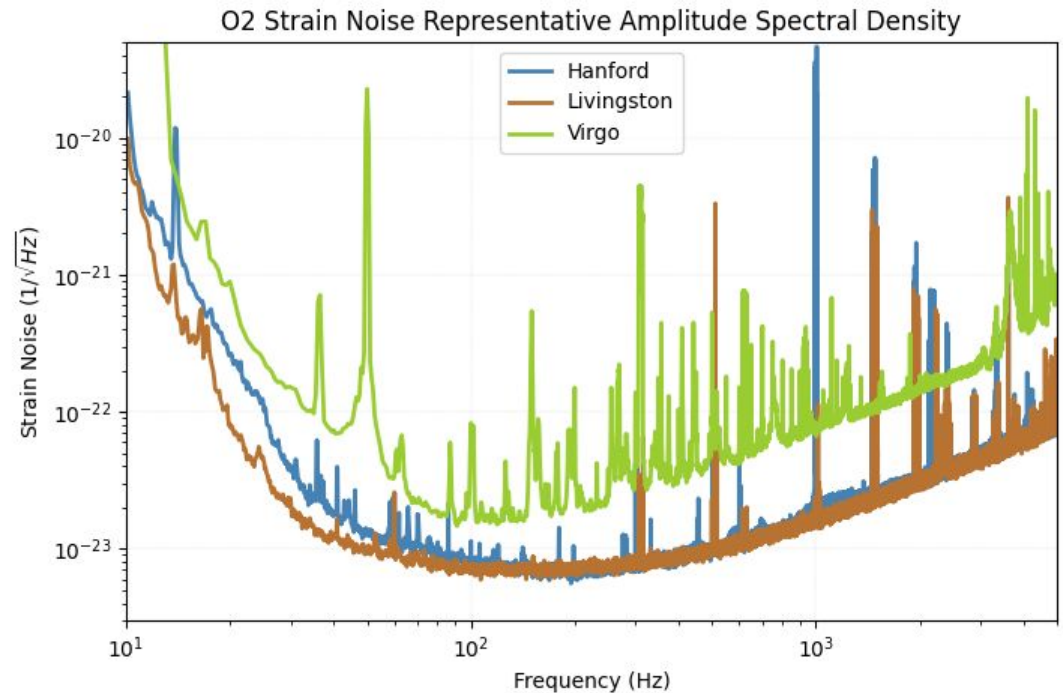
# Modelling the Noise

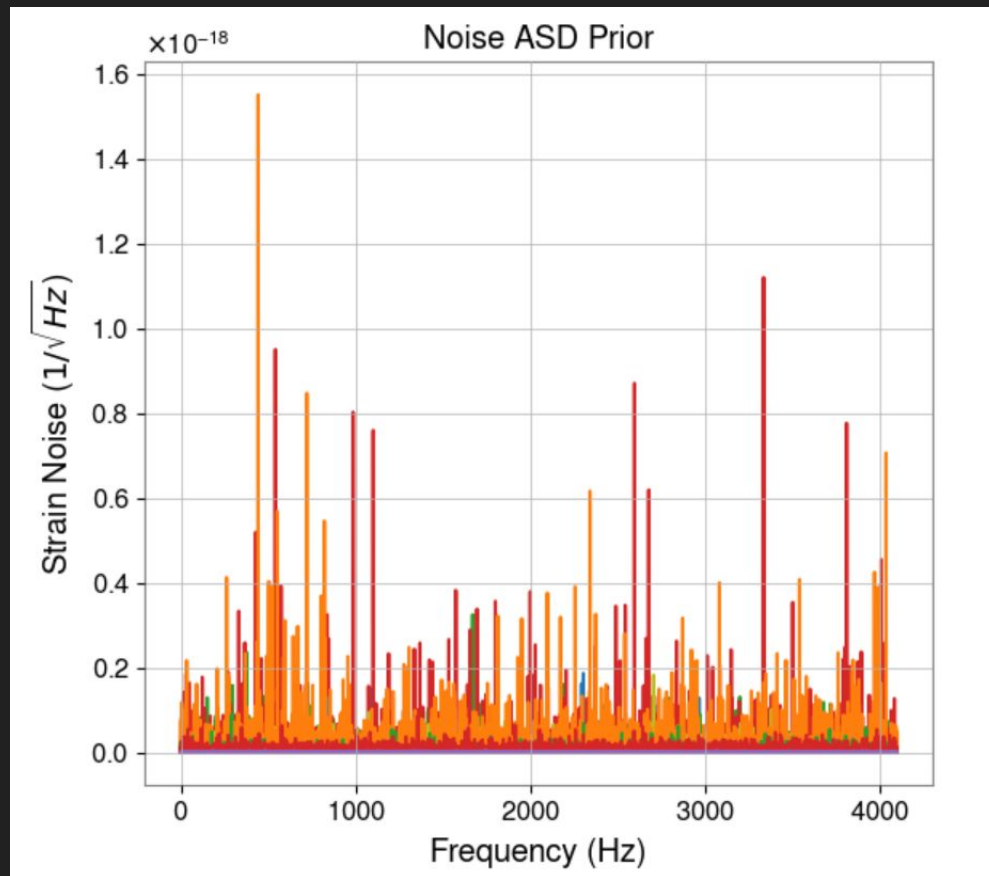
- For a given run, the LVC chooses a quiet time series interval during the interferometer's operation
- If no signals have been found at sufficiently high confidence, the interval's amplitude spectral density works as a good enough model of the overall noise
- This works because the strain data has a very low signal-to-noise ratio



# Modelling the Noise

**Upshot:** We can use another correlated field in our measurement equation to *learn* the noise model!



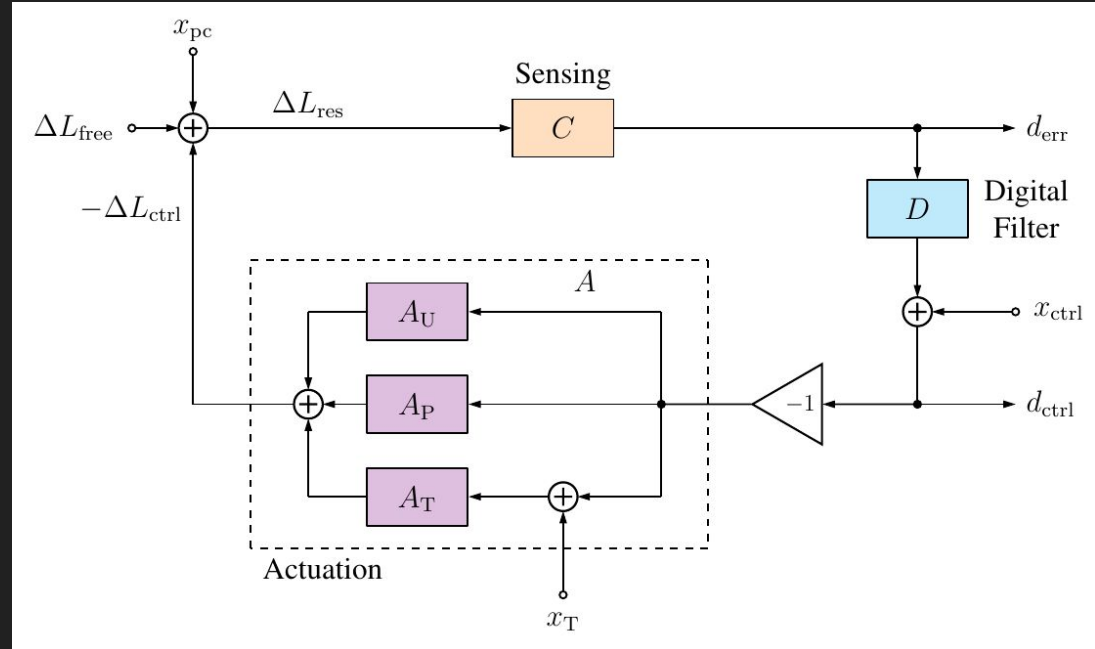




# Instrument Response

# The Open-loop Control Diagram

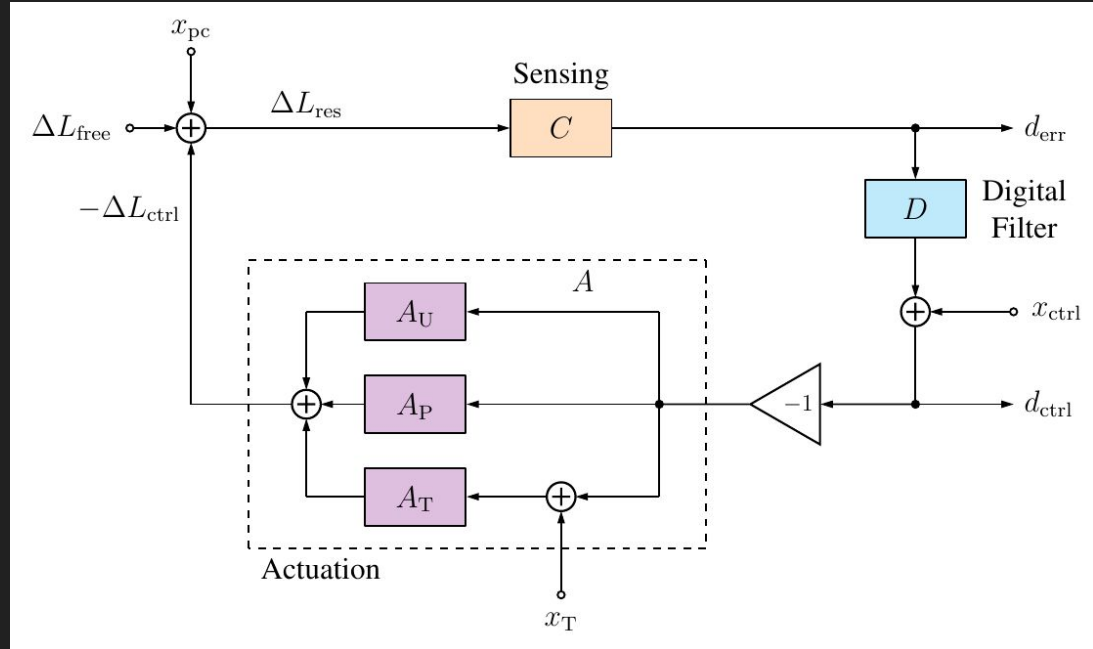
To keep the interferometer in resonance, **actuation** on the multi-stage pendula suspending the test masses is necessary:



# The Open-loop Control Diagram

To keep the interferometer in resonance, **actuation** on the multi-stage pendula suspending the test masses is necessary:

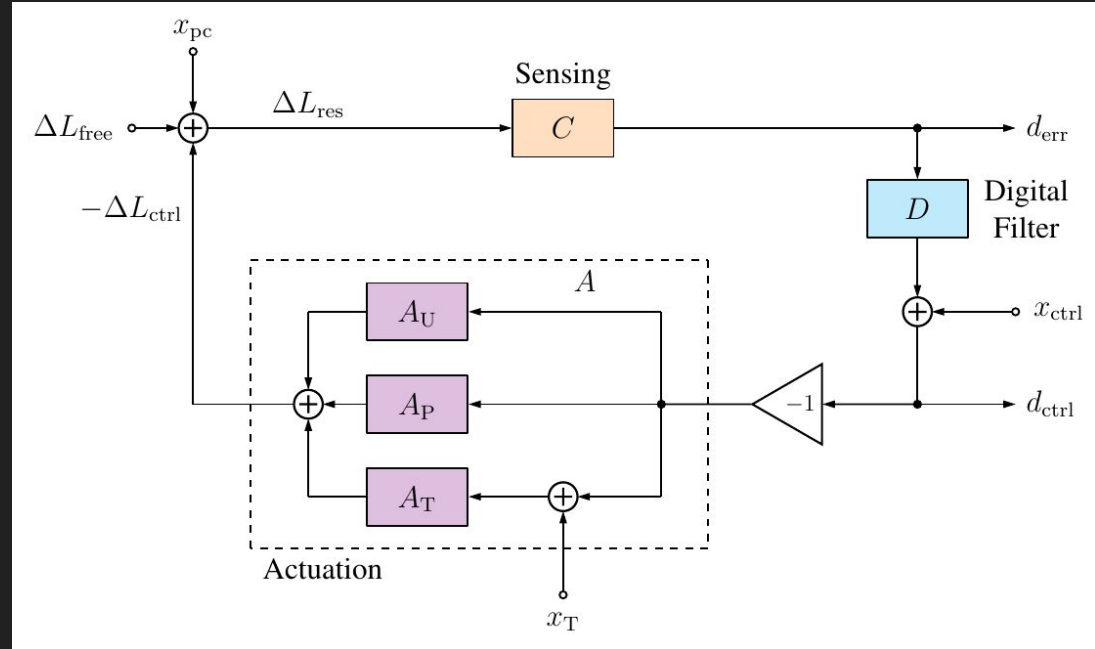
1. Subtracting a controlled differential arm length  $\Delta L_{ctrl}$  from the free-running changes in the differential arm length,  $\Delta L_{free}$ , produces a suppressed signal  $\Delta L_{res}$



# The Open-loop Control Diagram

To keep the interferometer in resonance, **actuation** on the multi-stage pendula suspending the test masses is necessary:

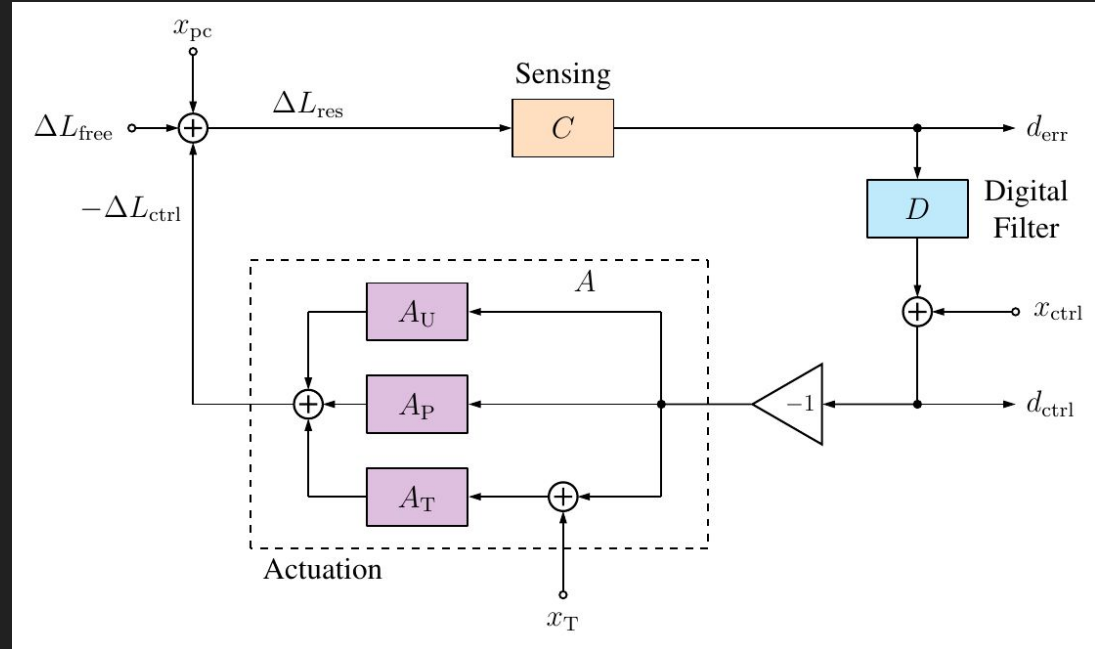
1. Subtracting a controlled differential arm length  $\Delta L_{ctrl}$  from the free-running changes in the differential arm length,  $\Delta L_{free}$ , produces a suppressed signal  $\Delta L_{res}$
2. Applying a **sensing function** to the residual displacement,  $\Delta L_{res}$ , produces the digital error signal,  $d_{err}$ , containing both astrophysical signals and displacement noise



# The Open-loop Control Diagram

To keep the interferometer in resonance, **actuation** on the multi-stage pendula suspending the test masses is necessary:

1. Subtracting a controlled differential arm length  $\Delta L_{ctrl}$  from the free-running changes in the differential arm length,  $\Delta L_{free}$ , produces a suppressed signal  $\Delta L_{res}$
2. Applying a **sensing function** to the residual displacement,  $\Delta L_{res}$ , produces the digital error signal,  $d_{err}$ , containing both astrophysical signals and displacement noise
3. Applying **digital filters** to the  $d_{err}$  signal produces the control signal  $d_{ctrl}$  which governs the **actuators'** behavior



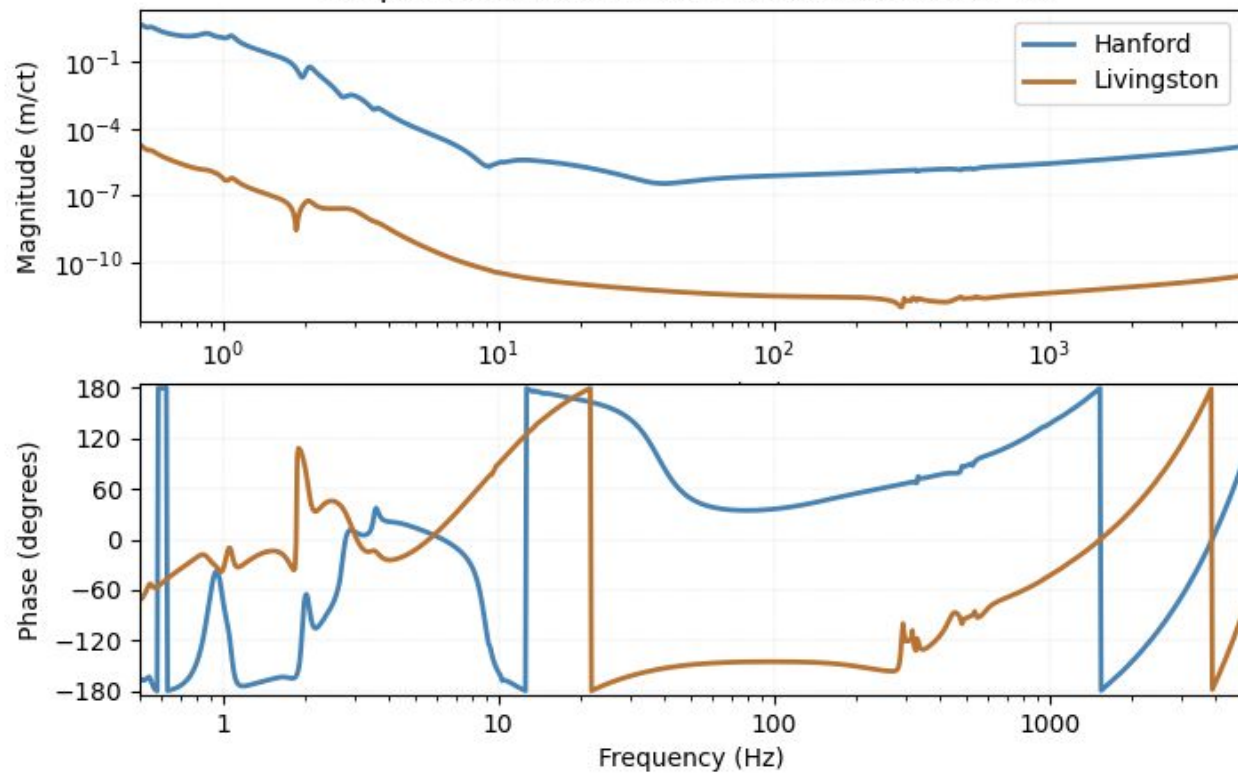
# The Response Function

$$\Delta L_{\text{free}} = R d_{\text{err}}$$

# The Response Function

$$\Delta L_{\text{free}} = \frac{1 + ADC}{C} d_{\text{err}}$$

Response Function of Both LIGO Detectors for O2





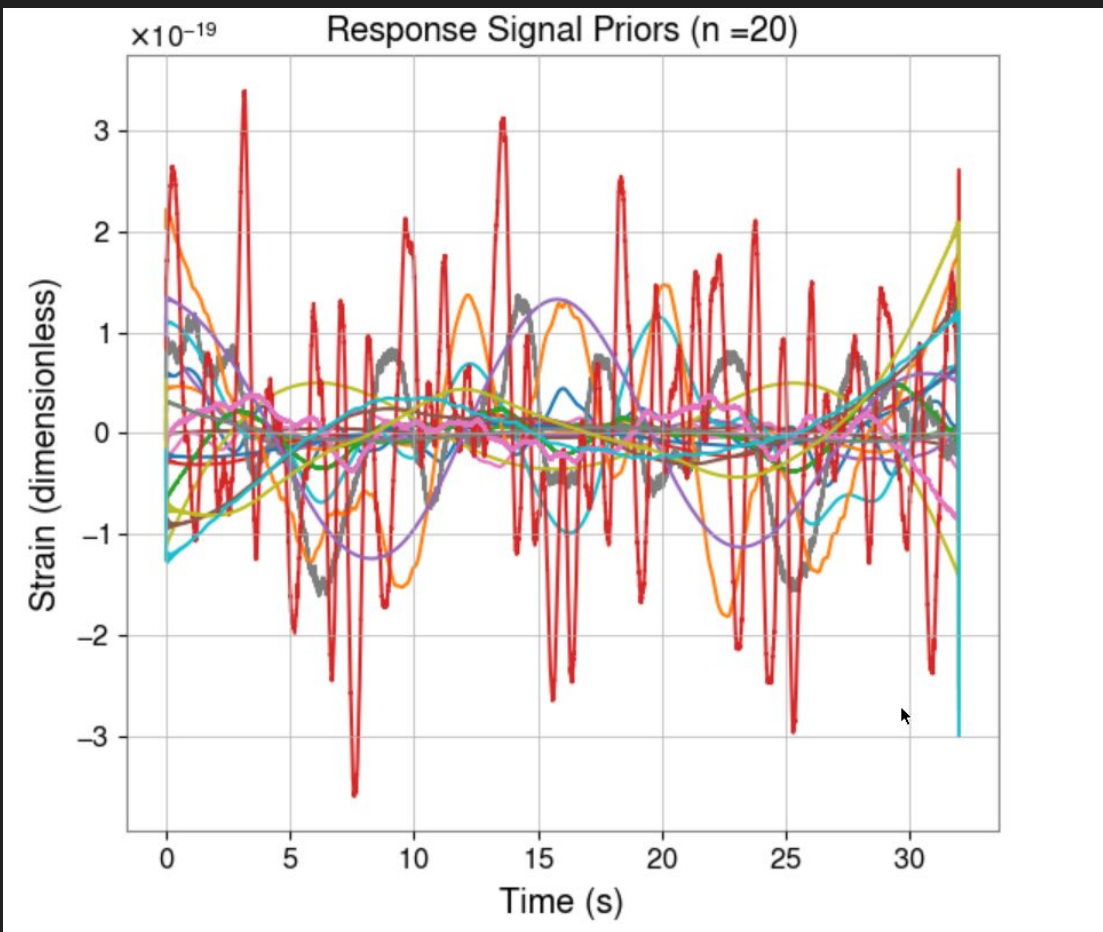
# Our Measurement Equation

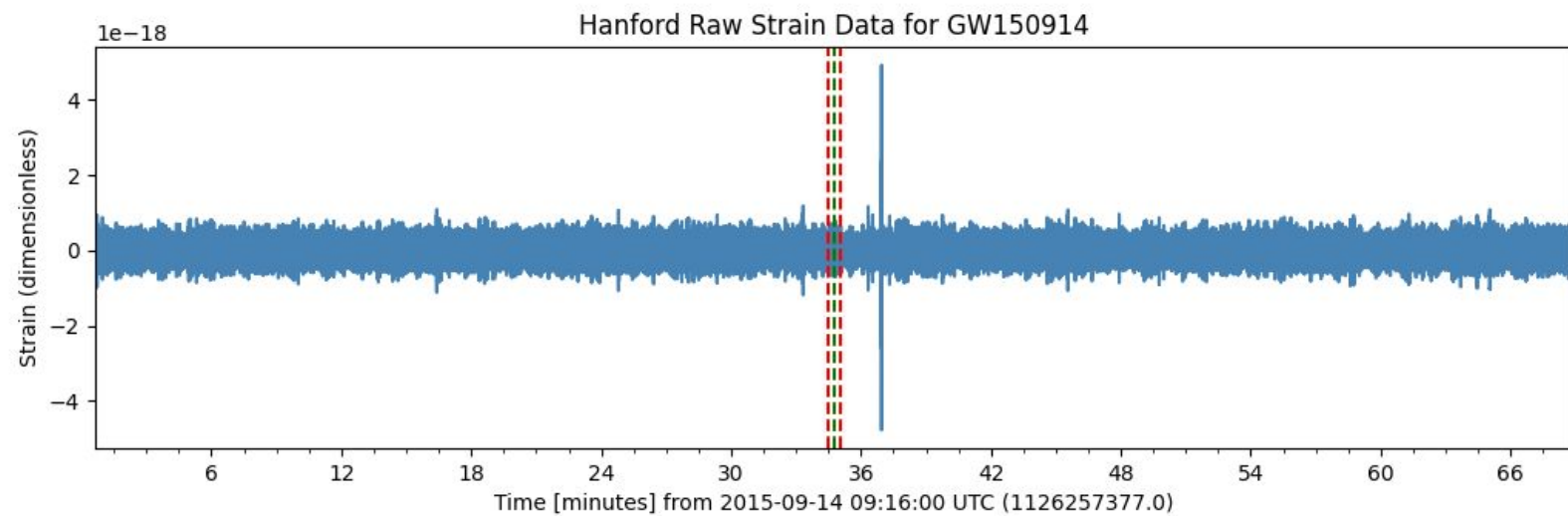
$$d(f) = (1 + \text{ADC})s_0 + n'$$

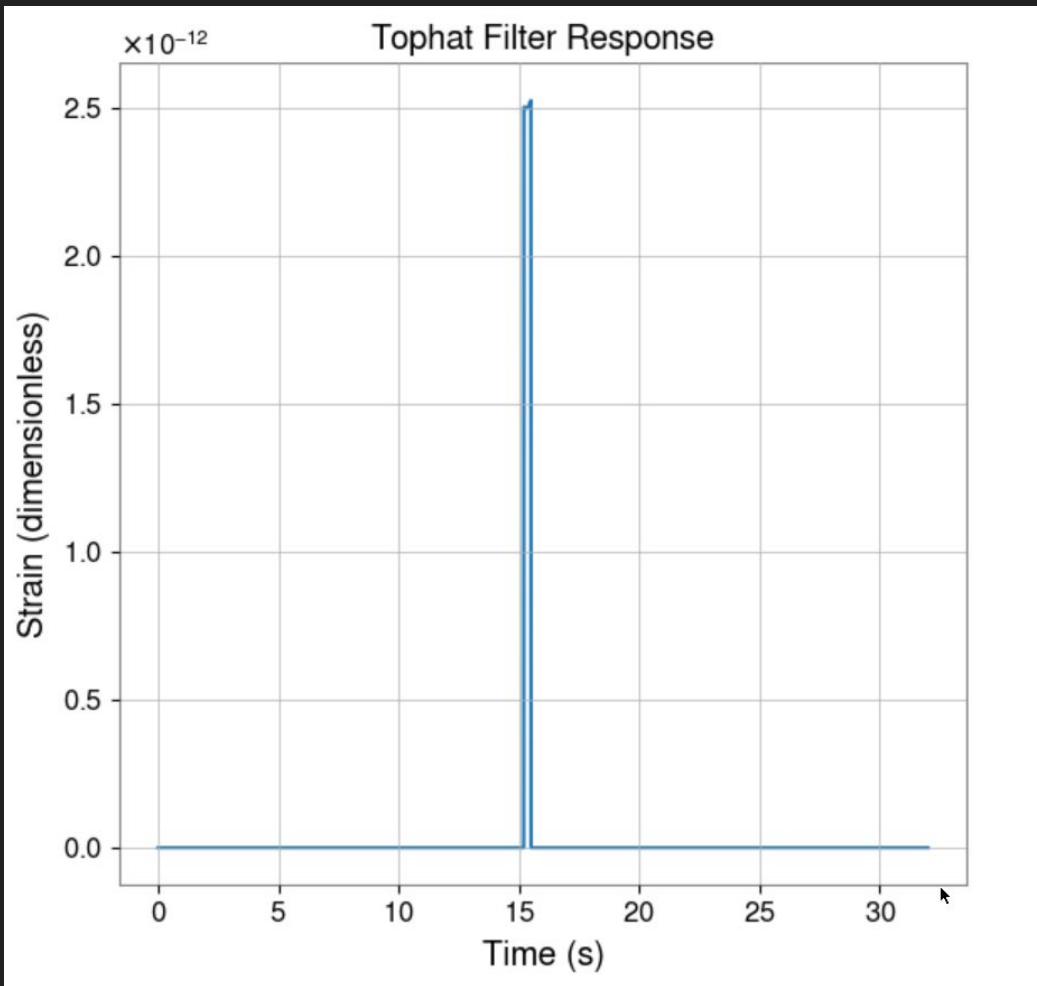
# Results

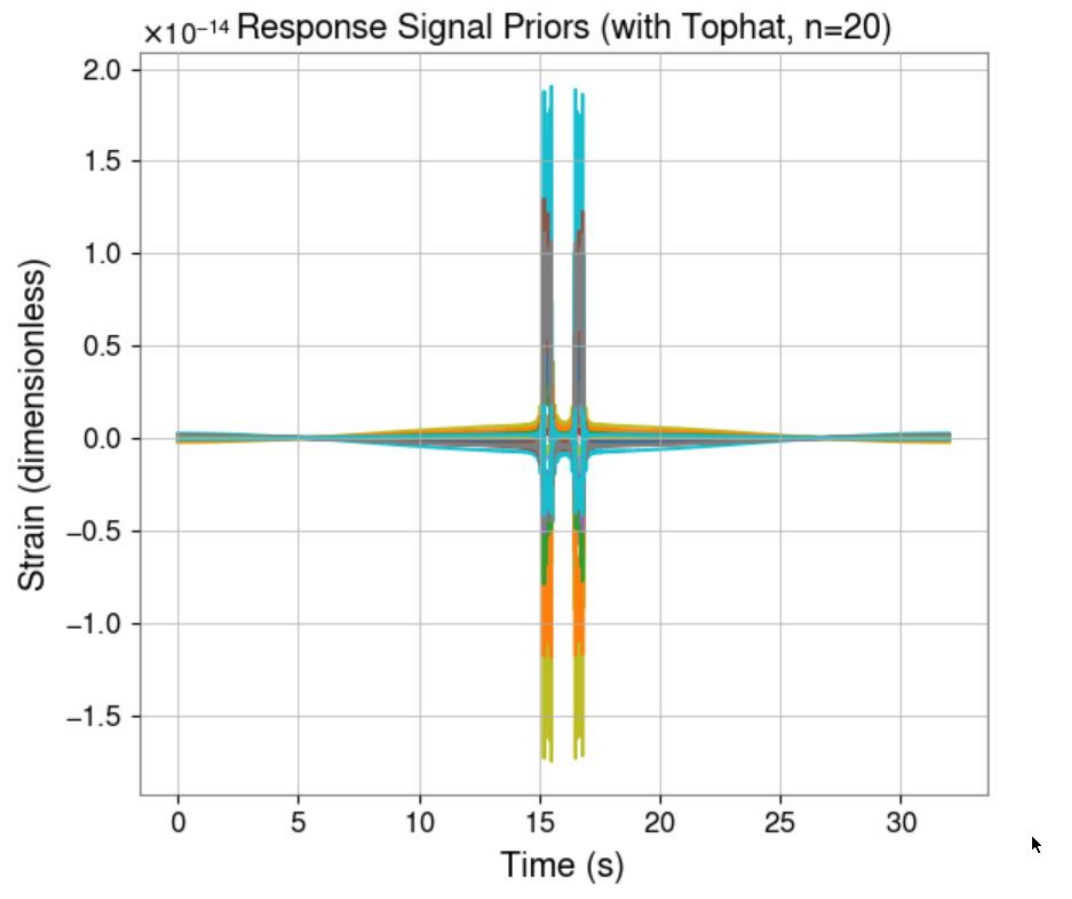
(Preliminary) Results



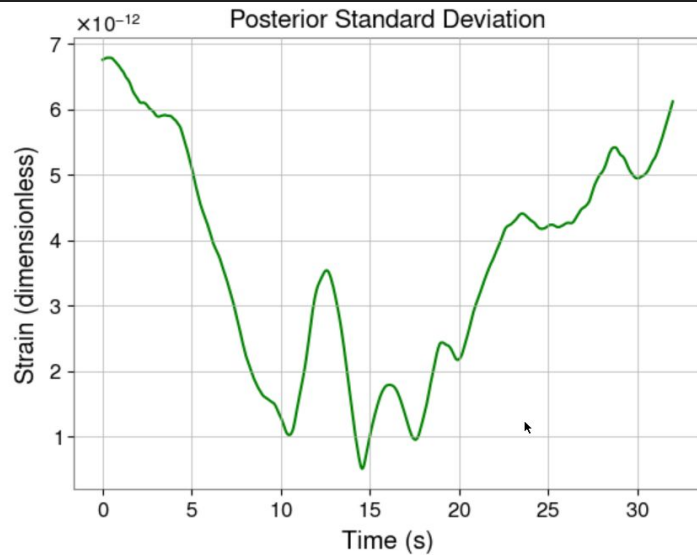
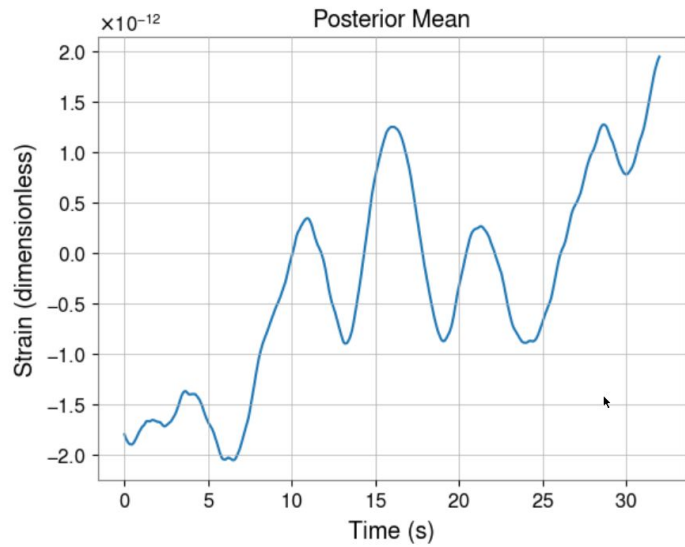












## The problem

Can we find a gravitational wave signal in the calibrated strain data *without* relying on any numerical relativity templates?

# The problem

Most likely, but we have to improve our noise covariance and instrument response models first!

## EXPLORER

## GRAVITATIONAL WAVES

- > \_\_pycache\_\_
- > .ipynb\_checkpoints
- > cache
- > data\_sets
- > exploratory\_notebooks
- > ms\_thesis
- > plots
- > reference\_scripts
- > tests
- ◆ .gitignore
- 🔗 forward\_model.py
- 📄 get\_imprs\_plots.ipynb
- 🔗 gwosc\_gestalt.py
- 🔗 instrument\_noise.py
- 🔗 instrument\_responses.py
- 🔗 inverse\_problem.py
- 📄 tophat\_run\_testing.ipynb

forward\_model.py ×

instrument\_responses.py

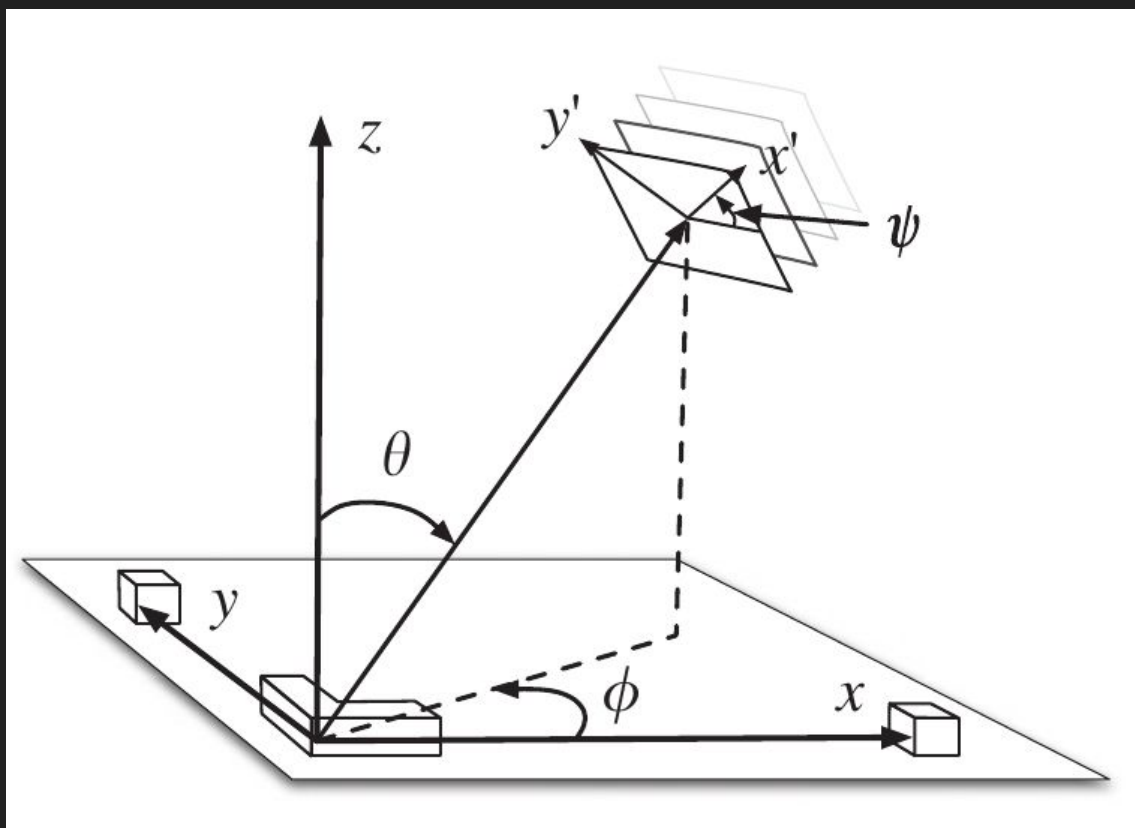
instrument\_noise.py

forward\_model.py

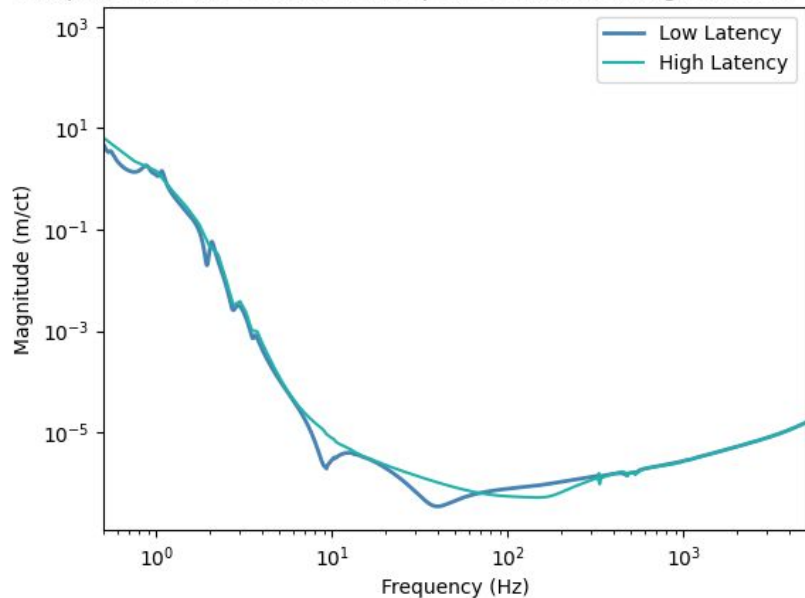
```
132         deltaE=0.5, iteration_limit=100,
133         ic_newton = ift.AbsDeltaEnergyController(name='Newton', deltaE=0.5,
134         convergence_level=2, iteration_limit=100),
135         ic_sampling_nl = ift.AbsDeltaEnergyController(name='Sampling (nonlin)',
136         deltaE=0.5, iteration_limit=15,
137         convergence_level=2)
138     minimizer = ift.NewtonCG(ic_newton)
139     minimizer_sampling = ift.NewtonCG(ic_sampling_nl)
140
141     # We use variable covariance Gaussian energy because we want to learn the noise
142
143     # We first need to define the keys
144     noise_operator = field_u_operator.power(-1).ducktape_left('inverse_covariance')
145
146
147     # we are getting r = Rs - d and ducktape
148     residuals = (ift.Adder(FFT_operator(strain_field), neg=True) @ instrument_responses)
149     residual_noise = noise_operator + residuals
150
151     # define the likelihood energy and apply it to r
152     likelihood_energy = ift.VariableCovarianceGaussianEnergy(domain=frequency_domain,
153     inverse_covariance_key='inverse_covariance',
154     sampling_dtype=np.float64, use_full_fisher=True) @ residuals
155
156     # Minimize the Kullback-Leibler divergence
157     n_iterations = 1
158     n_samples = lambda iiter: 10 if iiter < 5 else 20
159     samples = ift.optimize_kl(likelihood_energy, n_iterations, n_samples,
160     minimizer, ic_sampling, minimizer_sampling,
161     output_directory="plots/tophat_filter", # TO DO: add output directory
162     comm=None)
```

Thanks!

Backup Slides



Comparison of the O2 Hanford Response Function at High and Low Latency



Comparison of the O2 Livingston Response Function at High and Low Latency

