# Transient noise in the LIGO detectors

Jess McIver for the LIGO Scientific Collaboration

TASSGW ICTS-SAMSI Workshop
Bangaluru, March 2017
LIGO DCC G1700512

Caltech

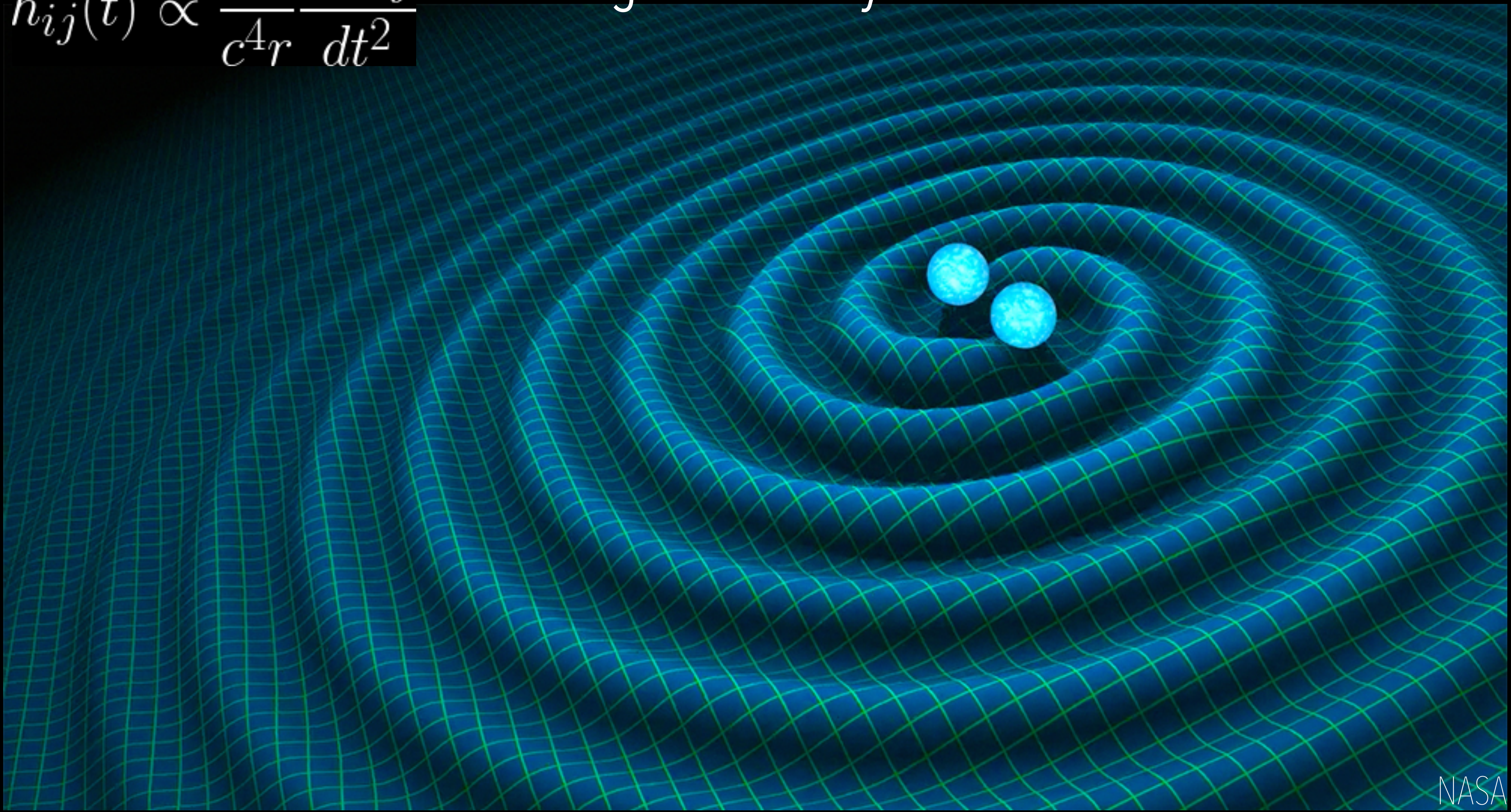
LSC

# Gravitational waves

Ripples in the fabric of spacetime

generated by the acceleration of matter

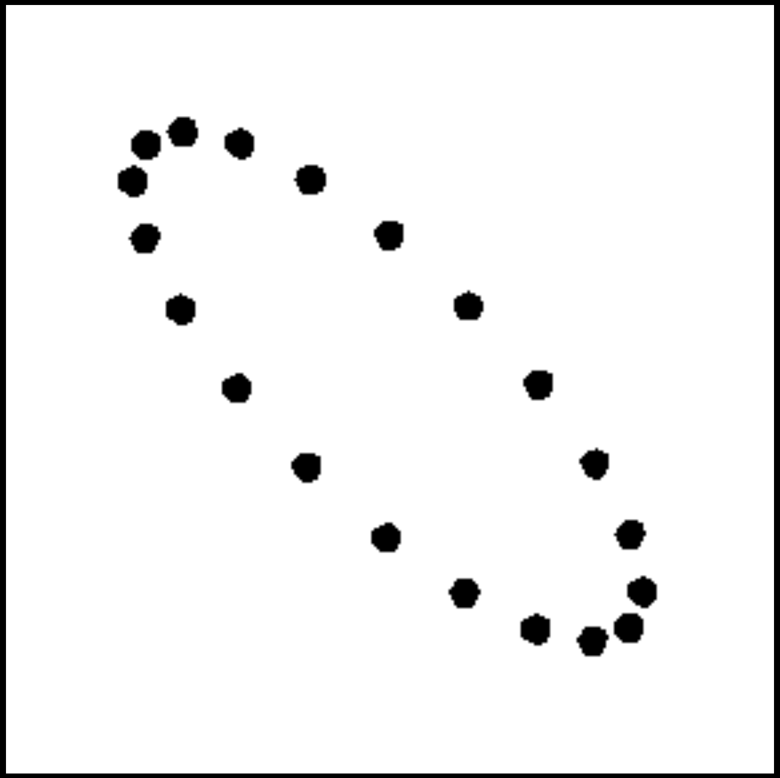
$$h_{ij}(t) \propto \frac{G}{c^4 r}\frac{d^2 I_{ij}}{dt^2}$$

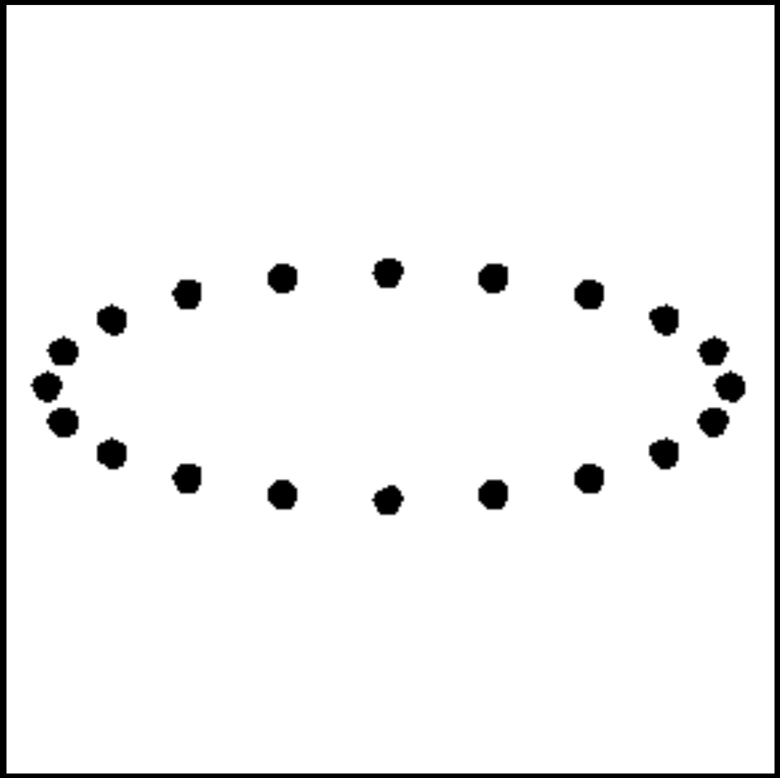


# Gravitational wave propagation

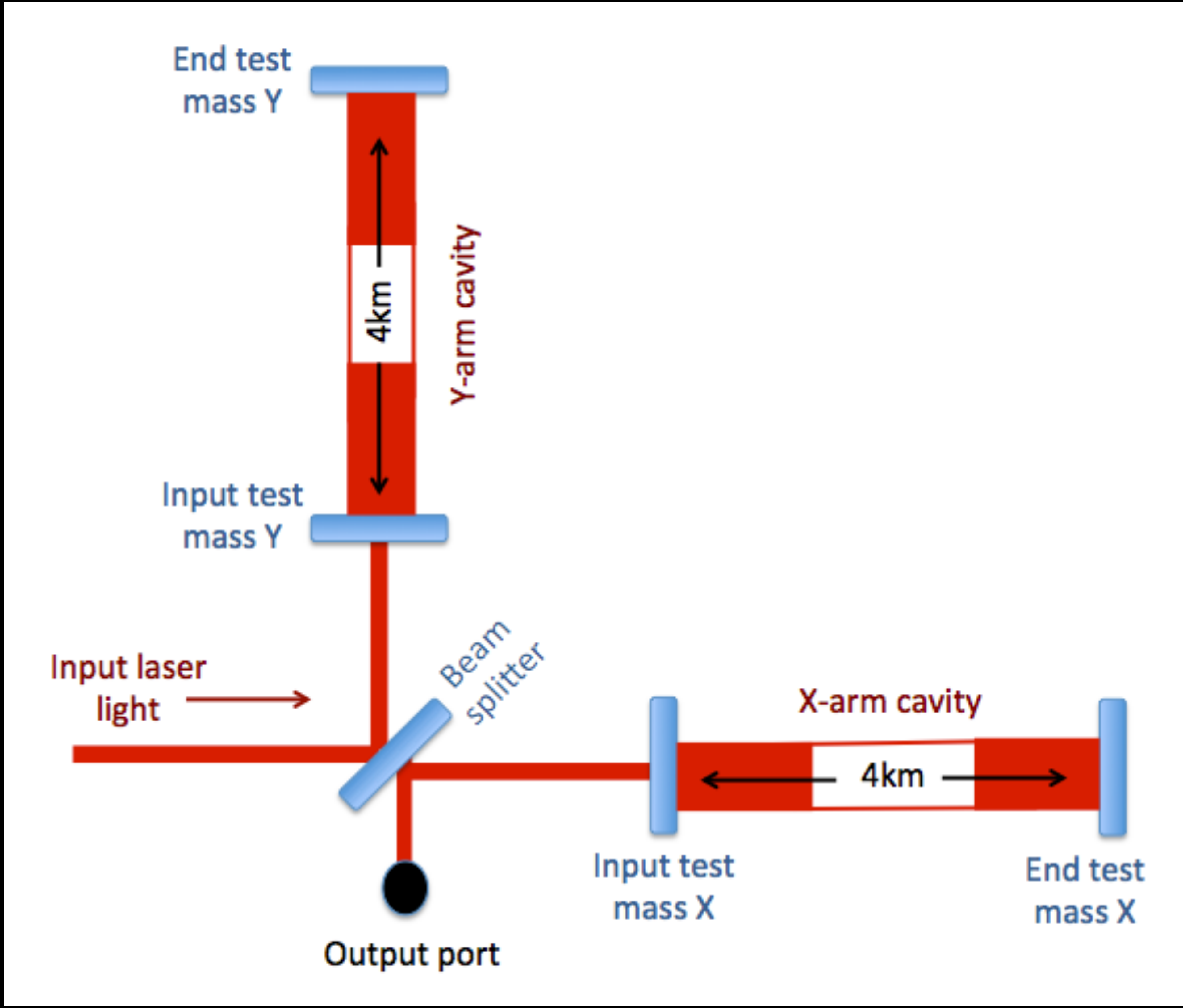
$$h(t) = Ae^{i(2\pi ft - \mathbf{k}\cdot\mathbf{r})}$$

Spacetime strain h(t) measured as $\frac{\Delta L}{L}$

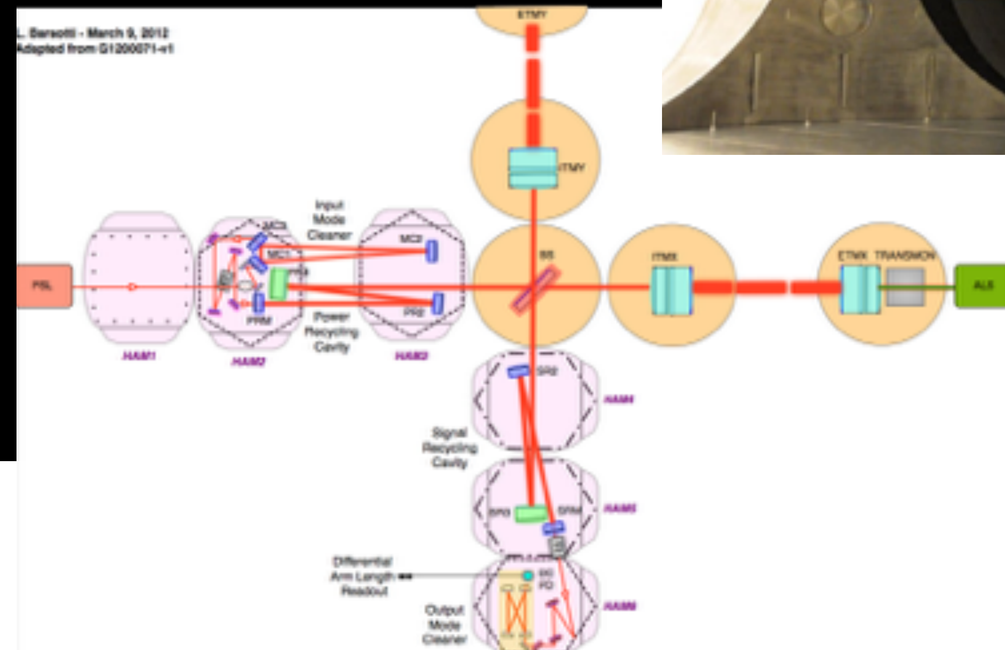


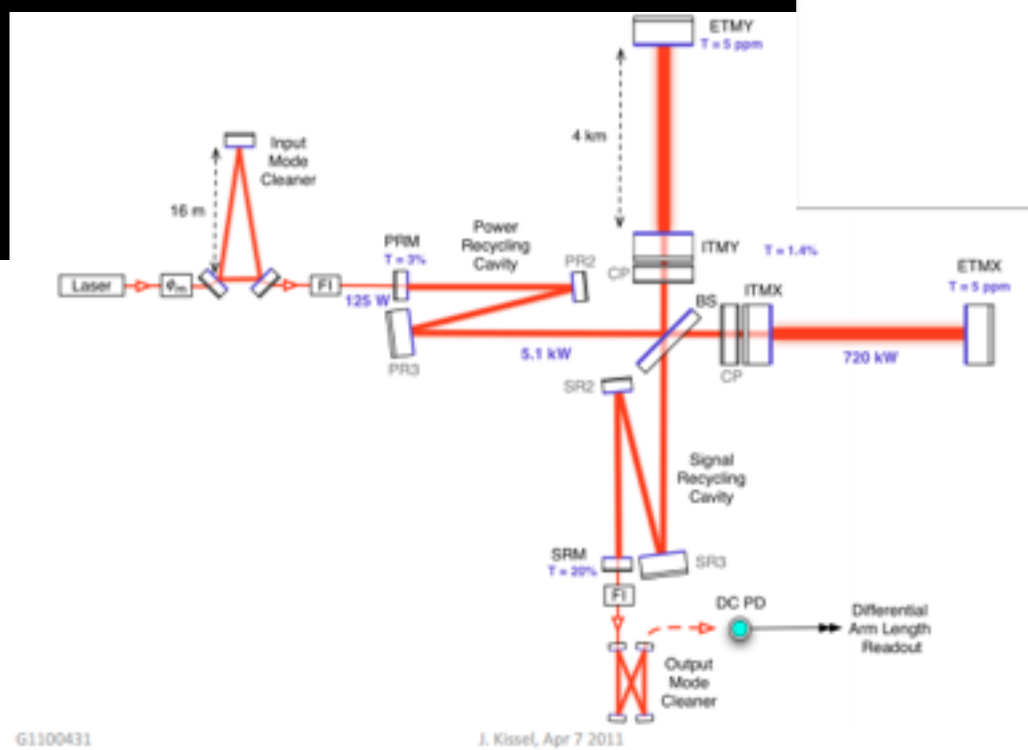


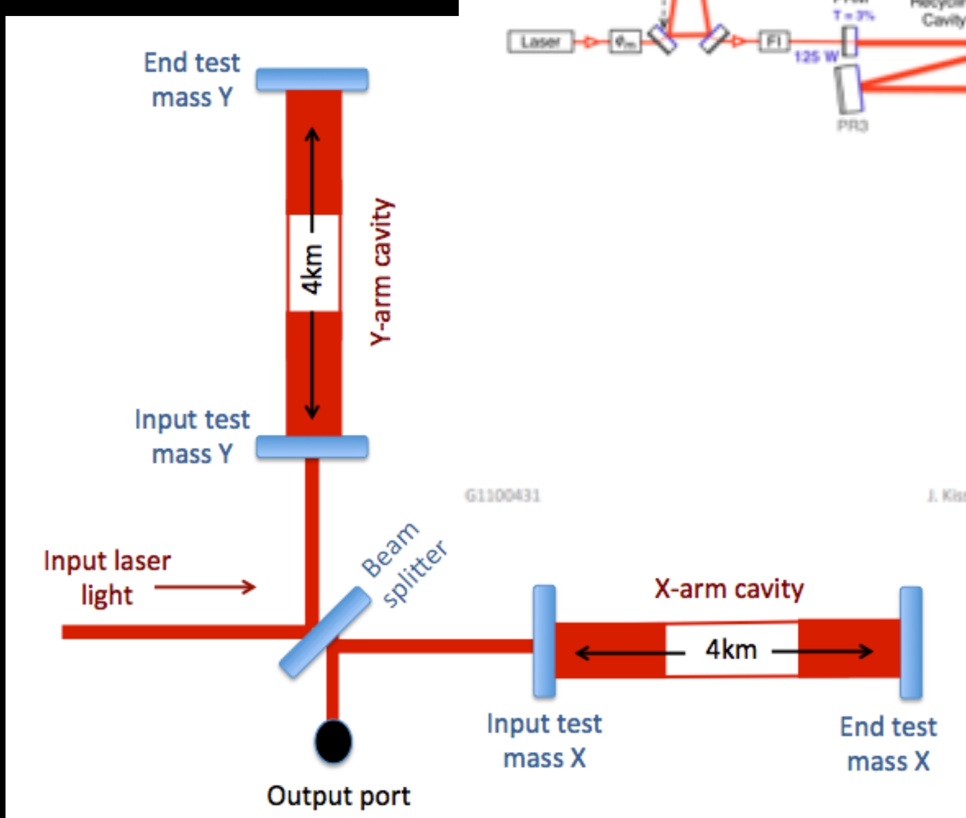
# Observing GWs with interferometry



# Advanced LIGO is extremely complex.



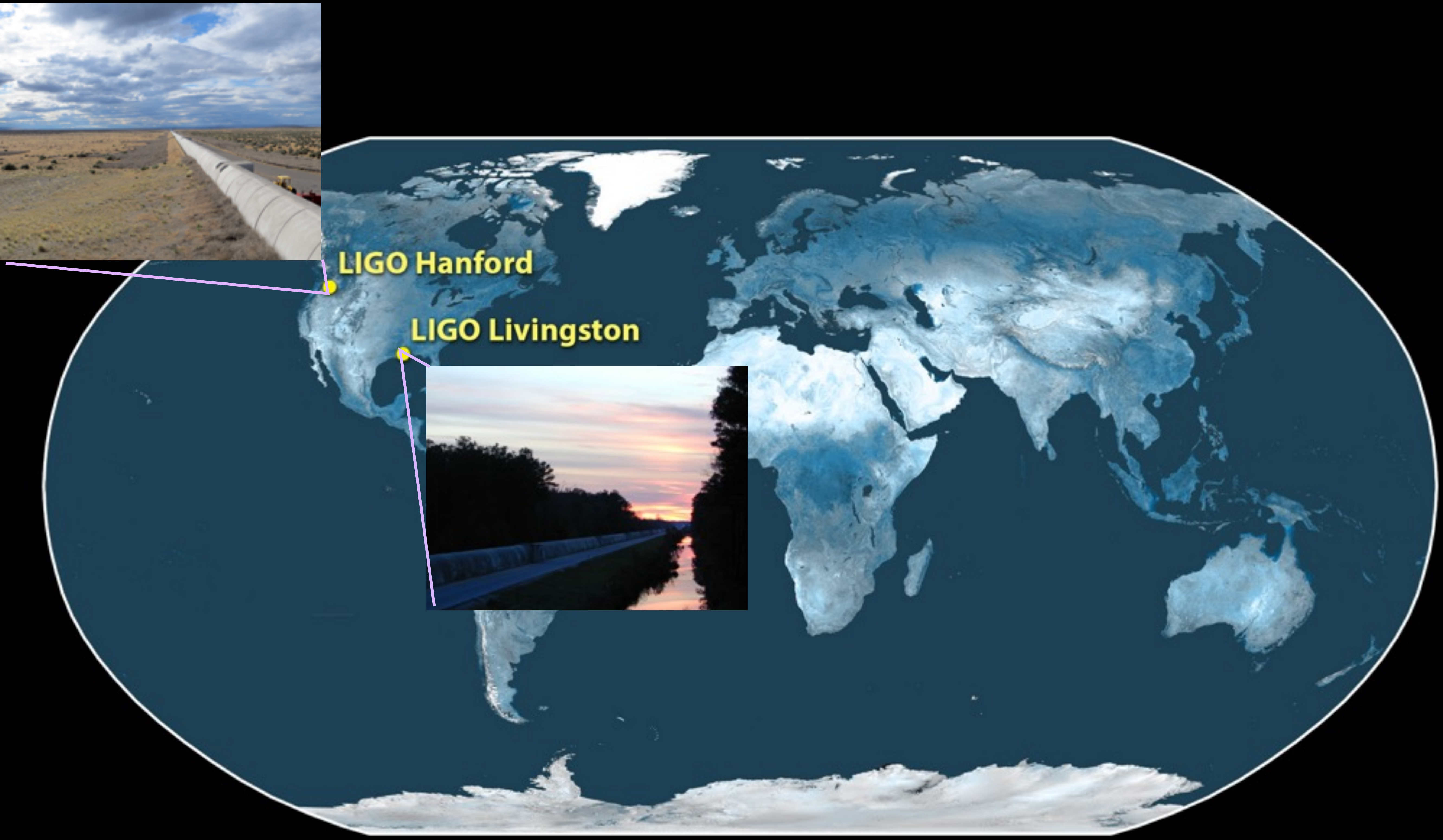




Reality

Adapted from D. Shoemaker

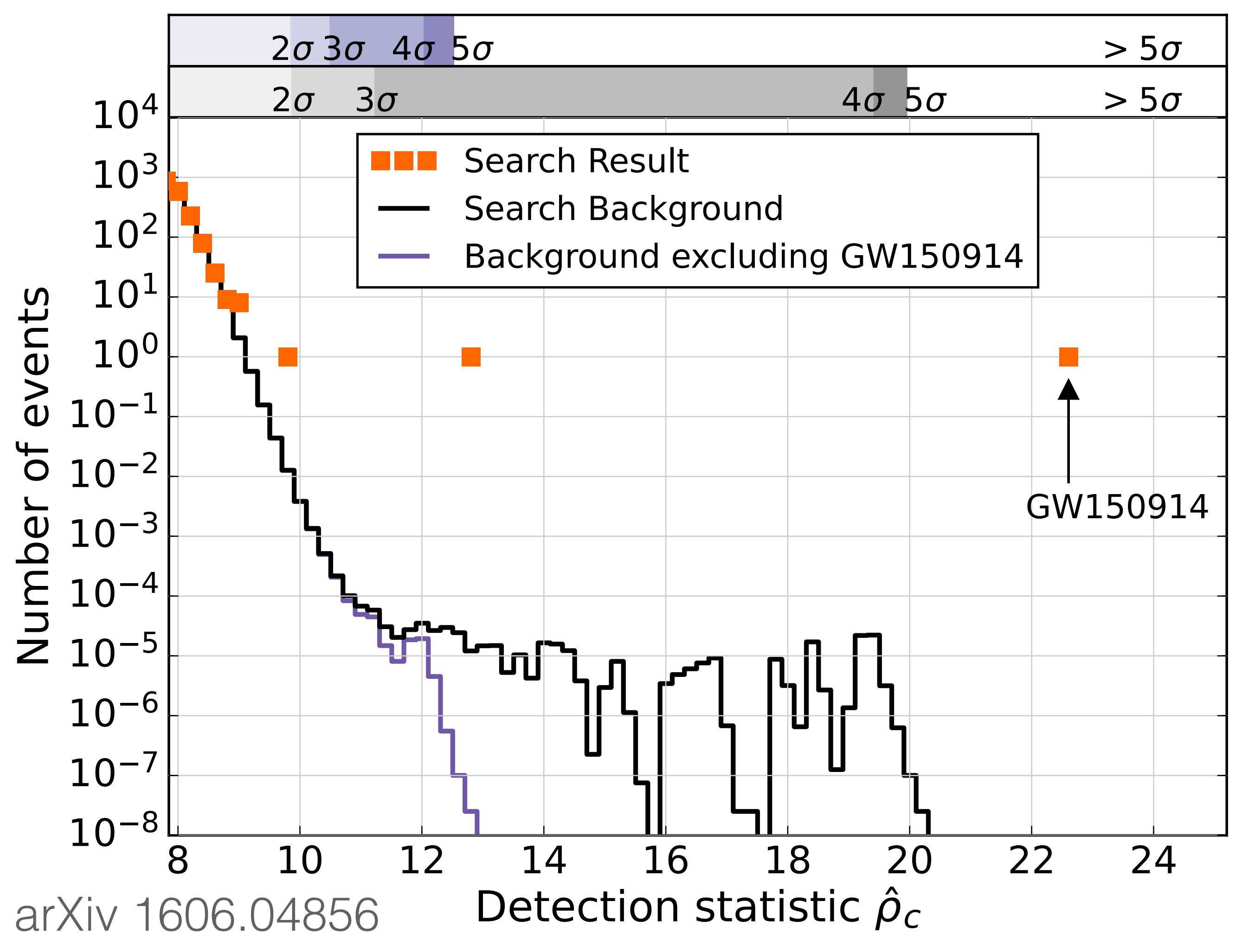
# Where are the LIGO detectors?

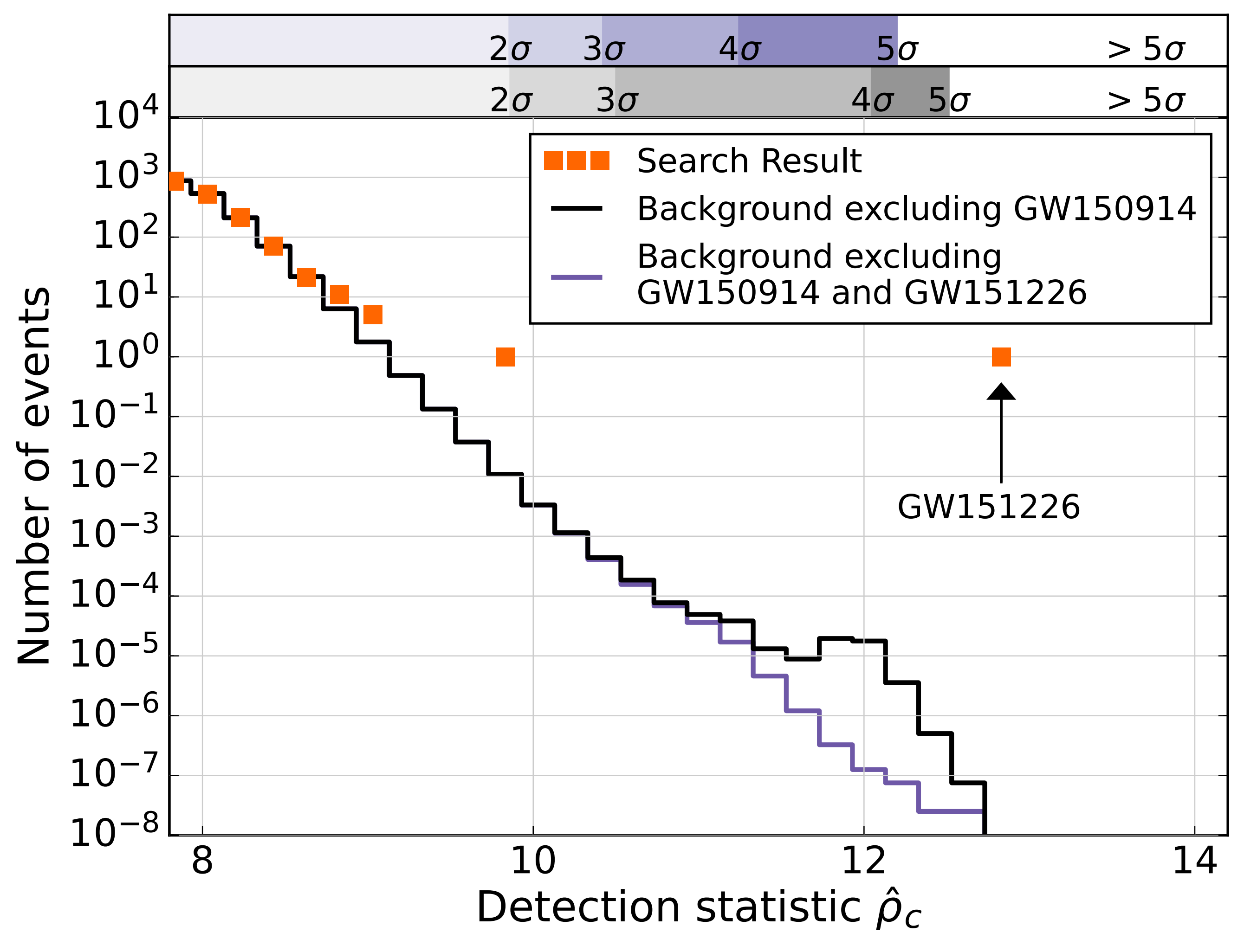


# The analysis

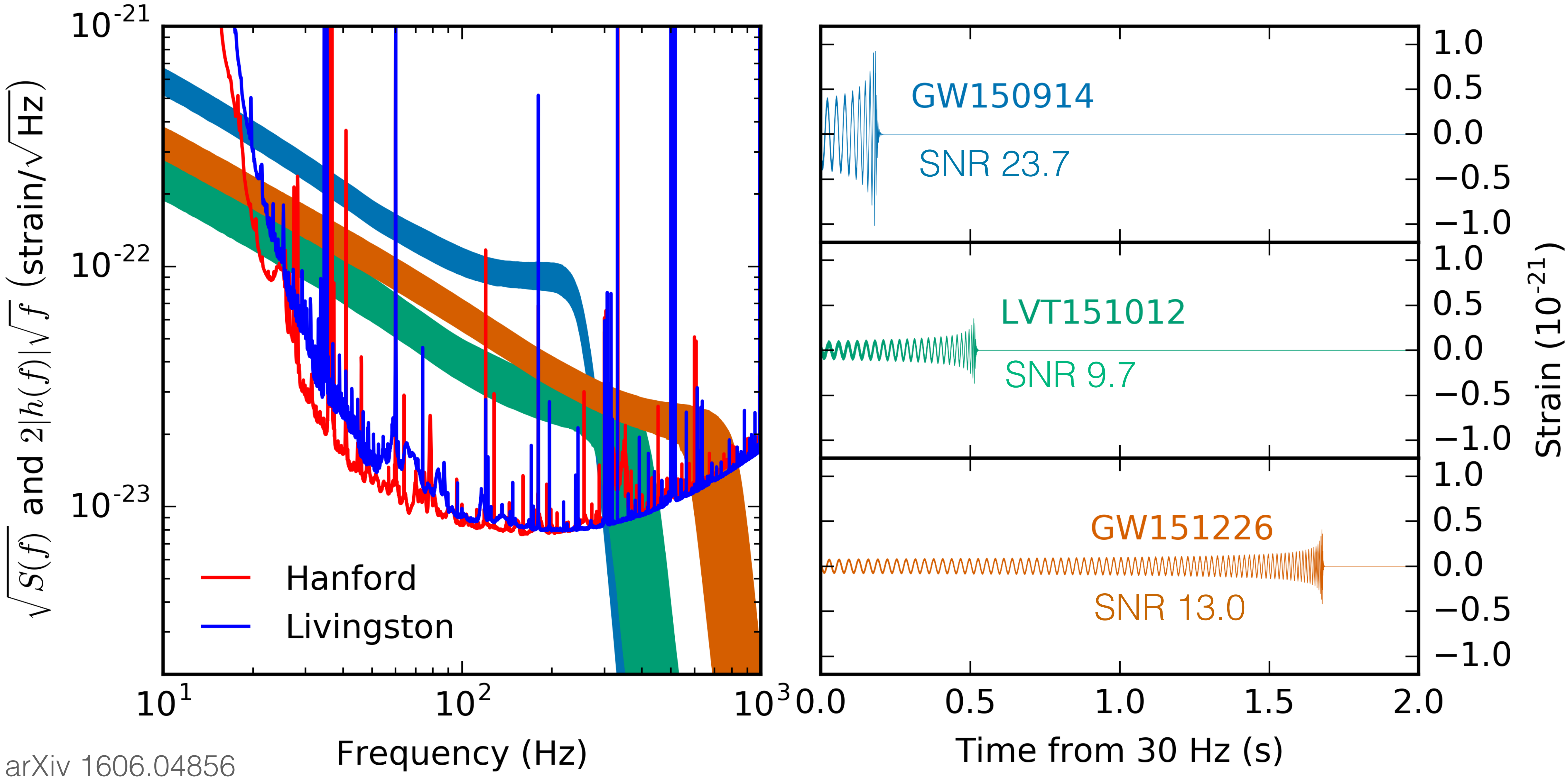
$$\rho^2(t) = \left[\langle s|h_c\rangle^2(t) + \langle s|h_s\rangle^2(t)\right]$$

$$\langle s|h\rangle = 4\mathrm{Re}\int_0^\infty \frac{\tilde{s}(f)\tilde{h}^*(f)}{S_n(f)}e^{2\pi i f t}df$$



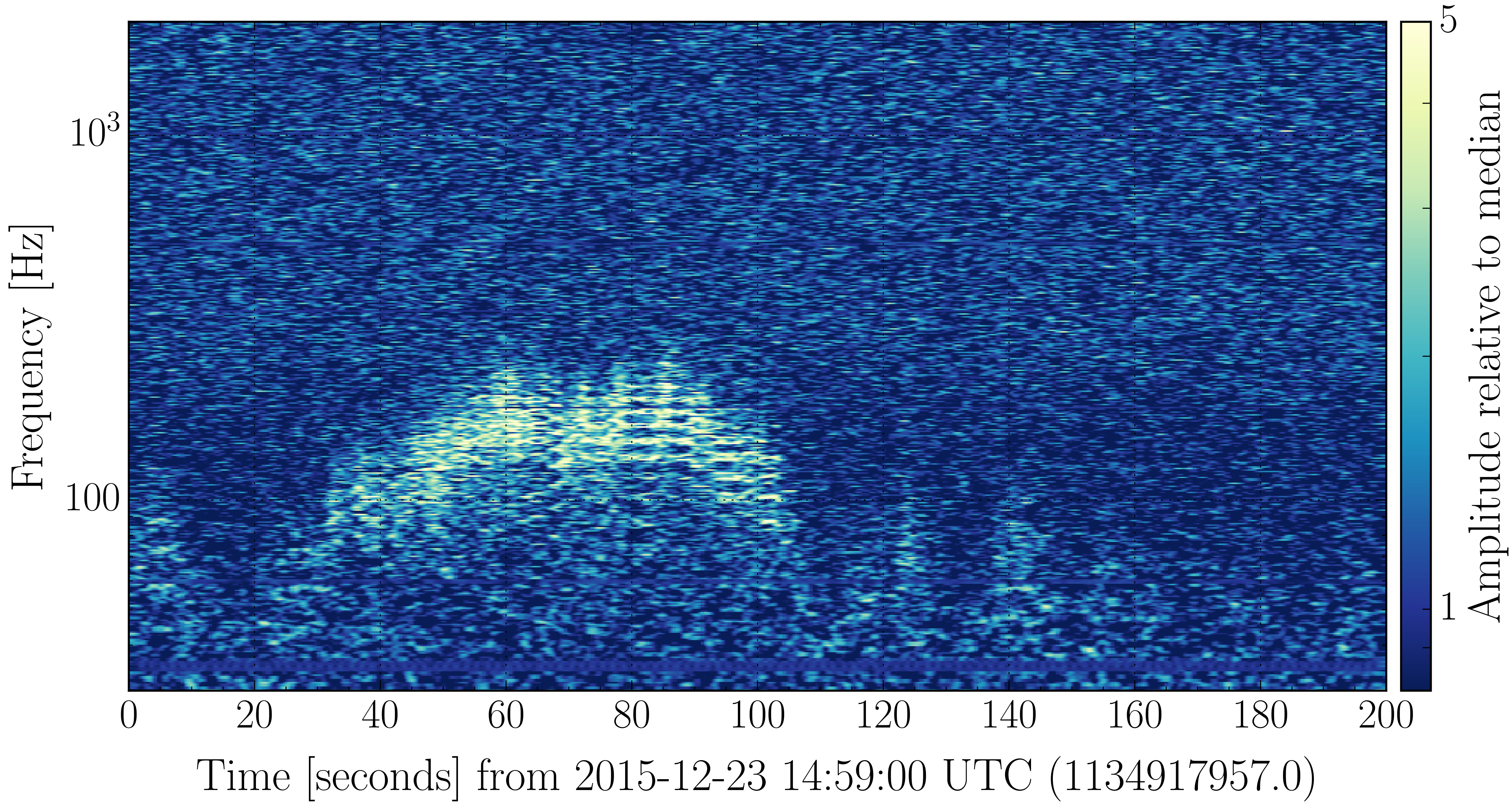



# Comparing LIGO events

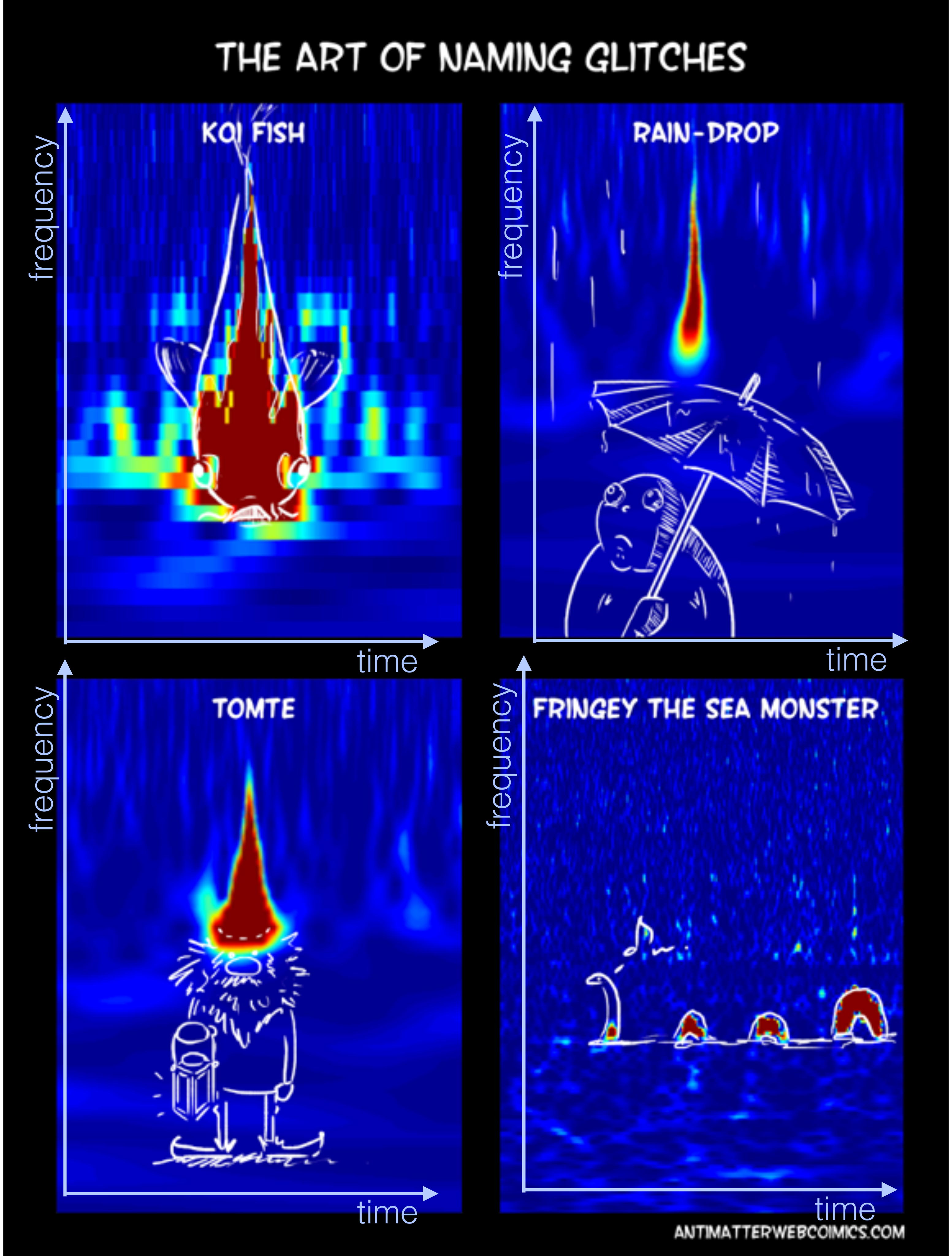



arXiv 1606.04856

# LIGO data is non-stationary!



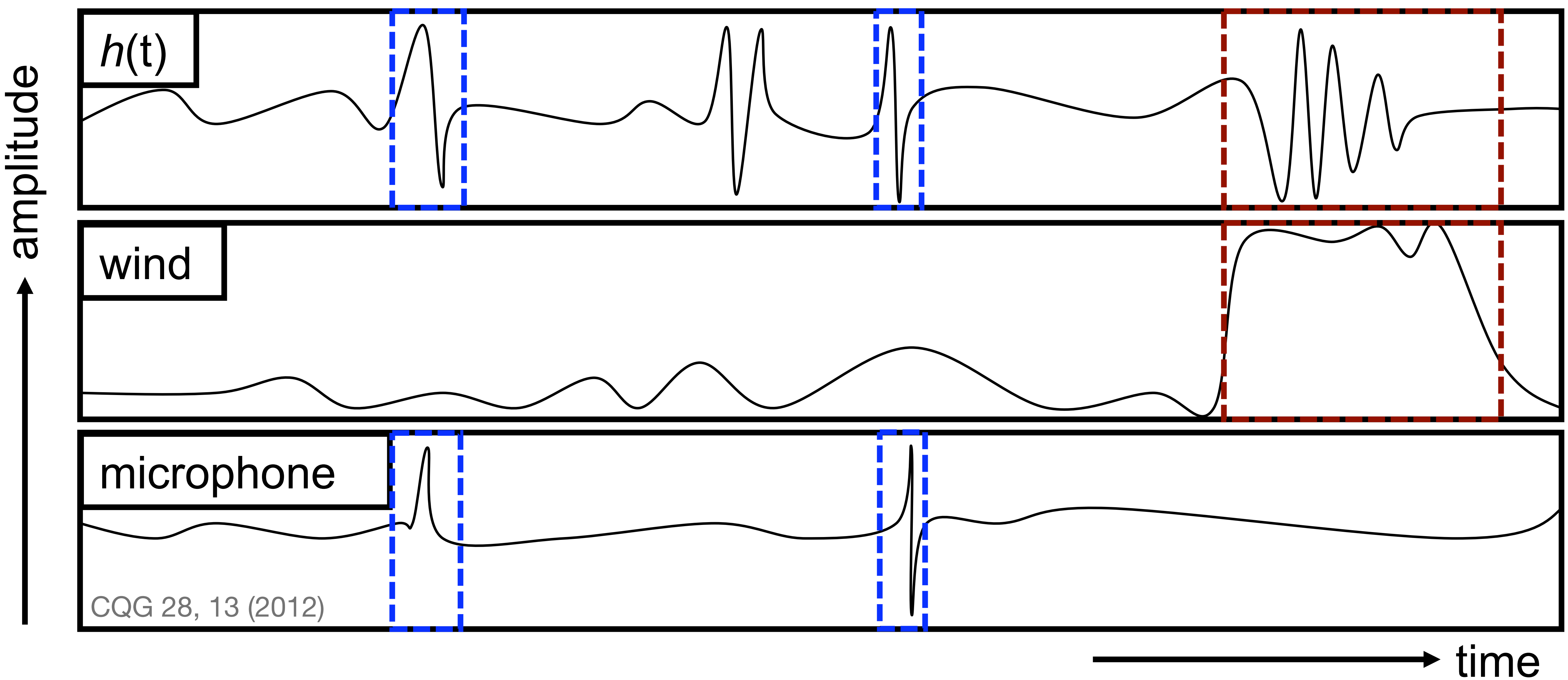

B. P. Abbott et al., in preparation


THE ART OF NAMING GLITCHES
KOI FISH
frequency
time
RAIN-DROP
frequency
time
TOMTE
frequency
time
FRINGEY THE SEA MONSTER
frequency
time
ANTIMATTERWEBCOMICS.COM

# Diagnosing noise: auxiliary channels

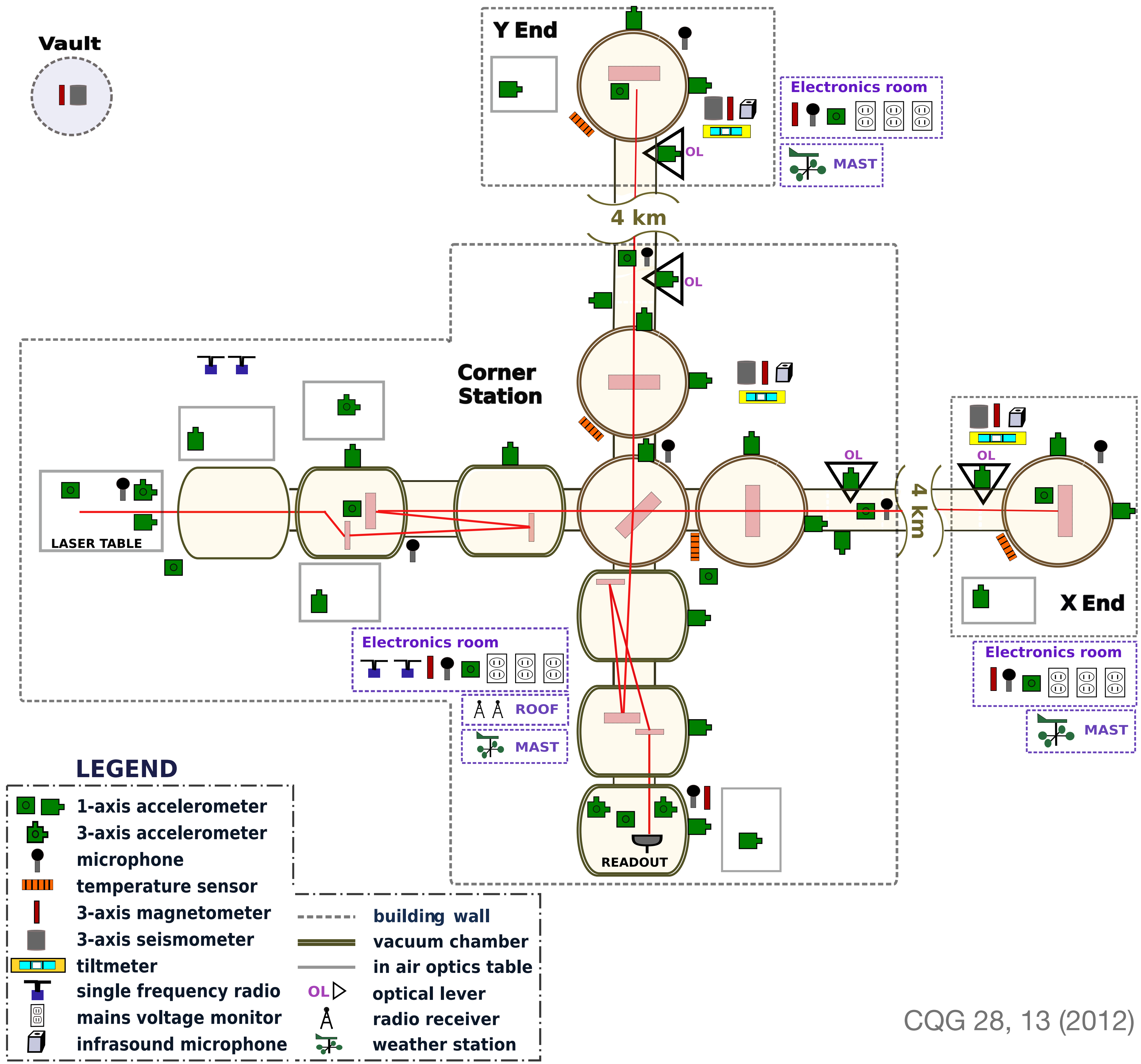
We record **over 200,000 channels per detector** that monitor the environment and detector behavior.

We can use these to **help trace the instrumental causes of glitches** that pollute the search backgrounds.



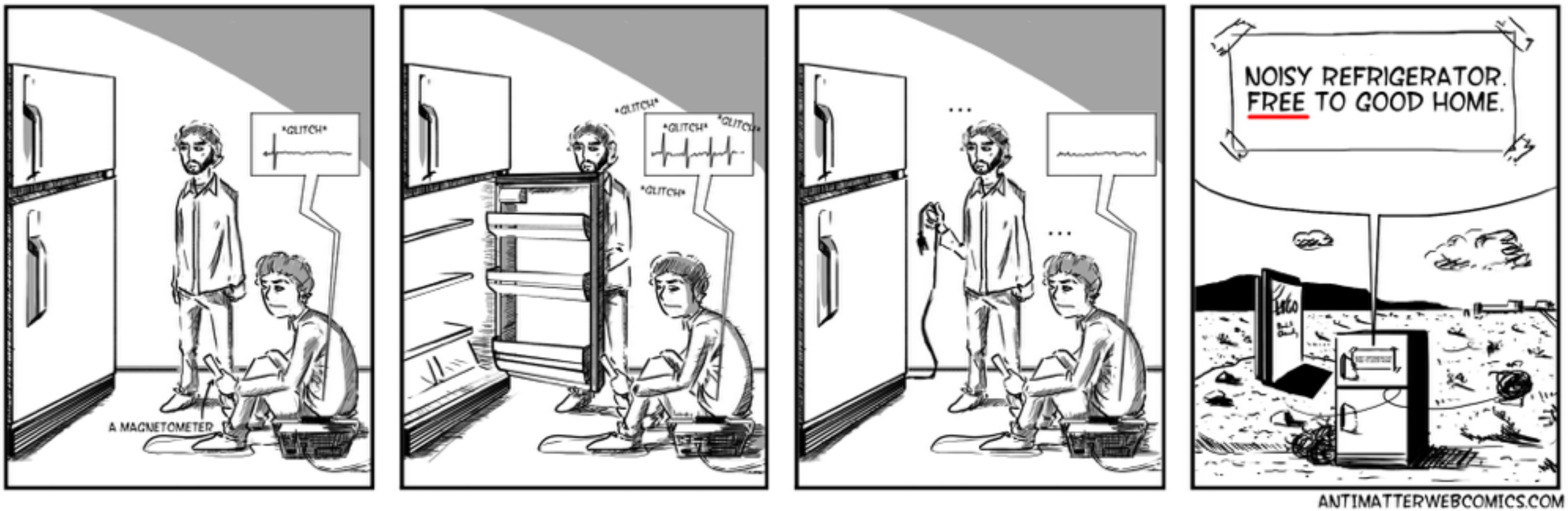
# Physical environment channels

SAMSI astro working group III (Multivariate and Irregularly Sampled Time Series) should expect to have access to two weeks of LIGO h(t) and PEM channels for a prior science run (S6) soon from an MOU with the LIGO Scientific Collaboration.




CQG 28, 13 (2012)

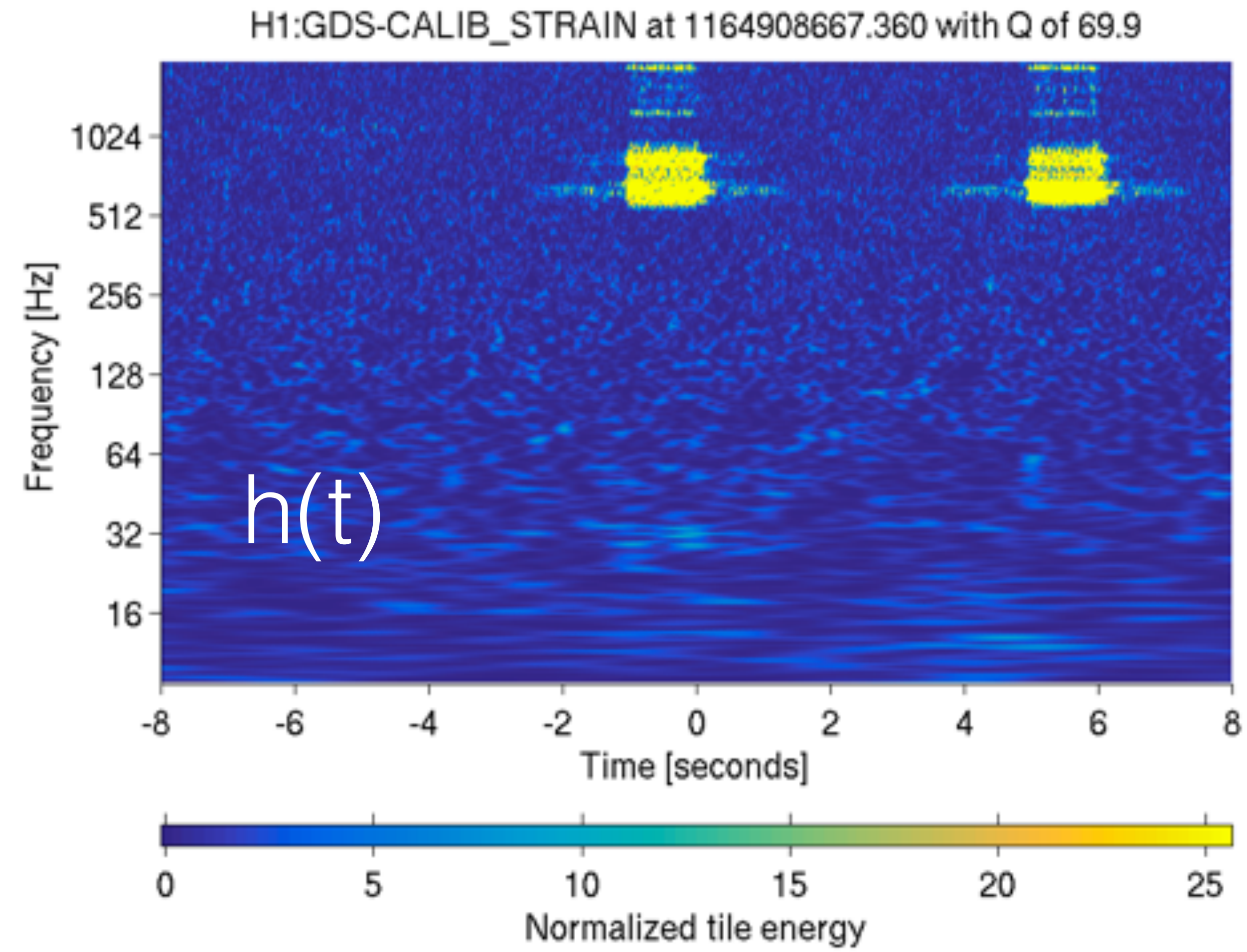
# The tale of the noisy refrigerator

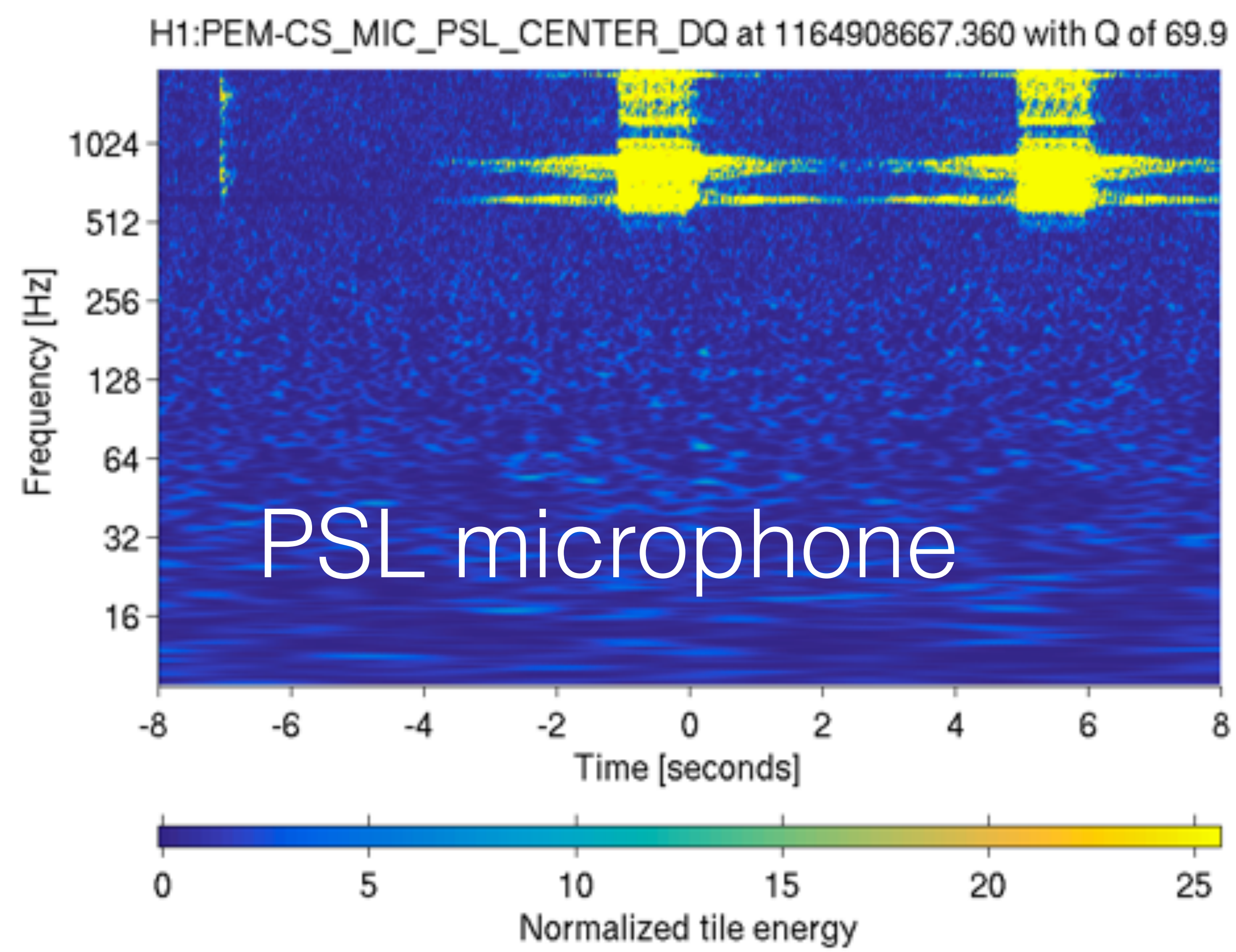



Once a noise source that contributes to the background is identified, ideally it is fixed in hardware or software.

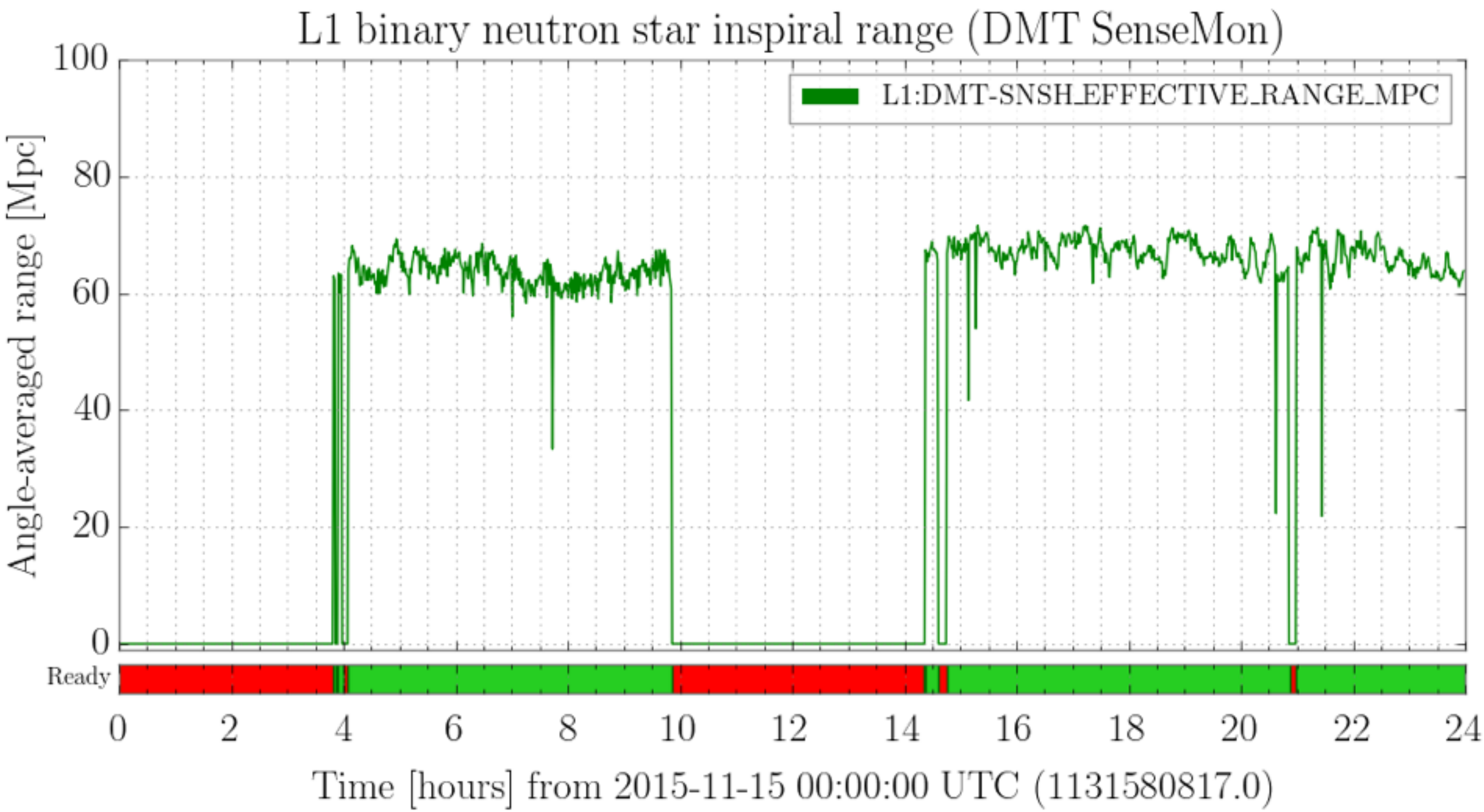
If this is not possible, the noisy data is **vetoed** using auxiliary channel data.

# Laser glitches
# h(t) vs. microphones

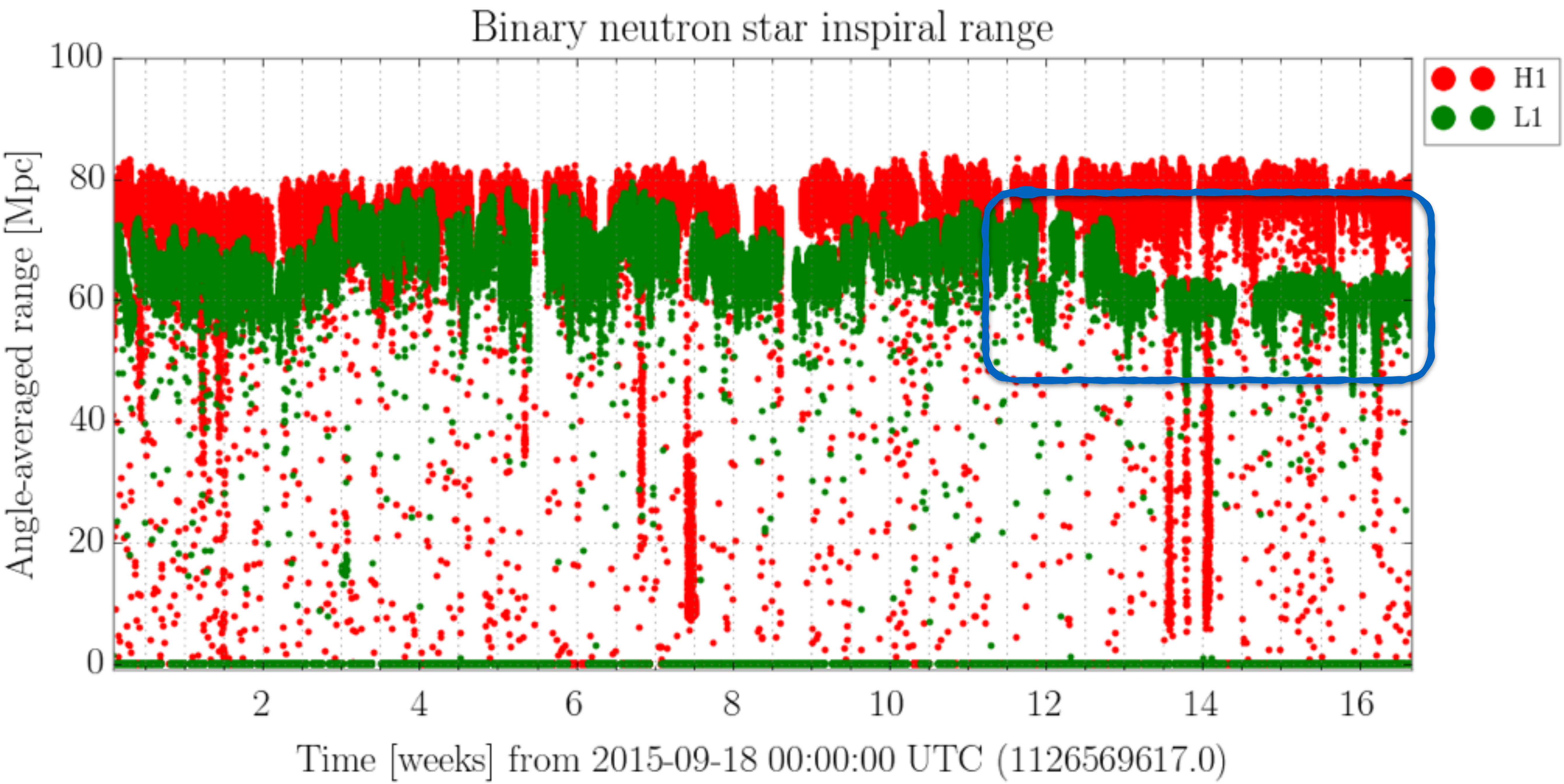


# Problem 1: diagnosing LIGO sensitivity with slow correlations



# LIGO-Livingston sensitivity drop during O1



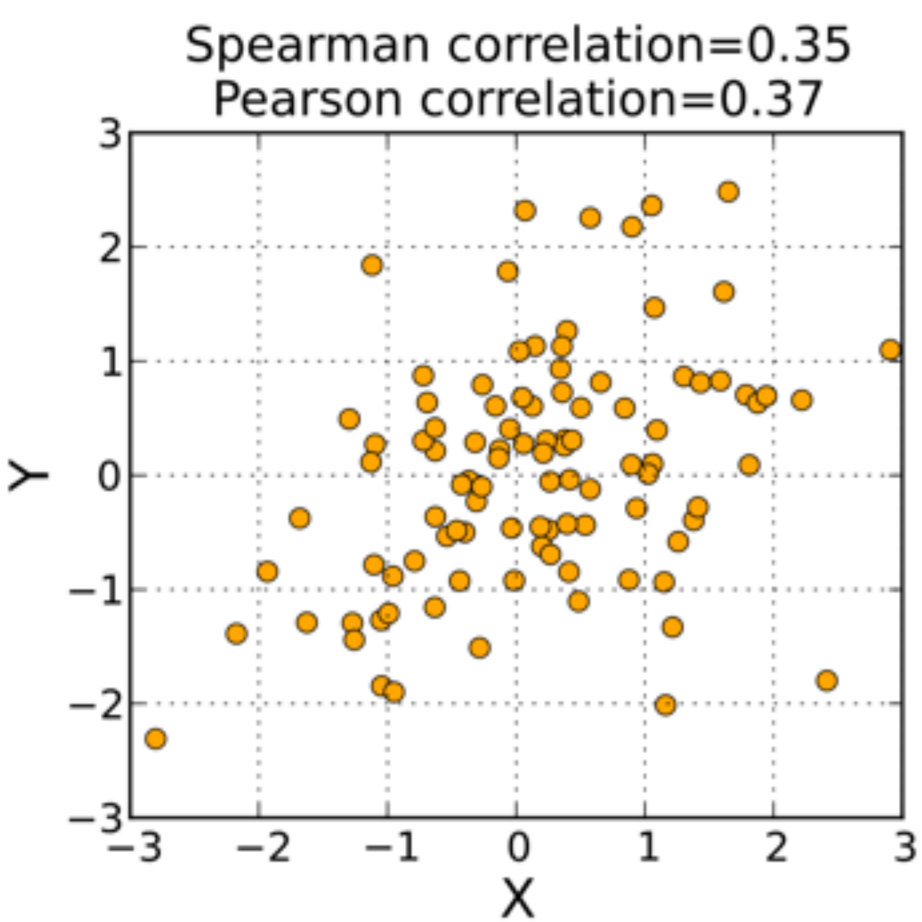
# What we're trying now

Patane et al, CSU Fullerton

## Pearson's Correlation Coefficient (r)

A measure of **linear correlation** between two variables X and Y.

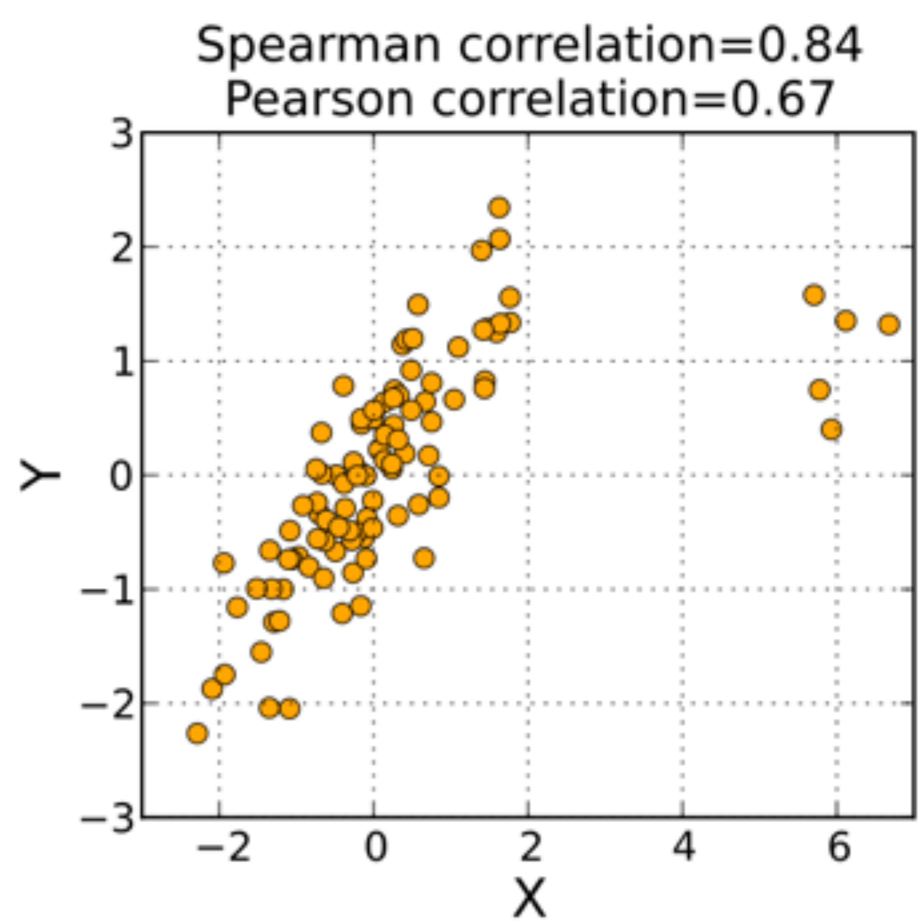
$$\rho_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y}$$




## Spearman's Correlation Coefficient (ρ)

A measure of the **rank correlation** that assesses how well the relationship between two variables can be described using a **monotonic function**.

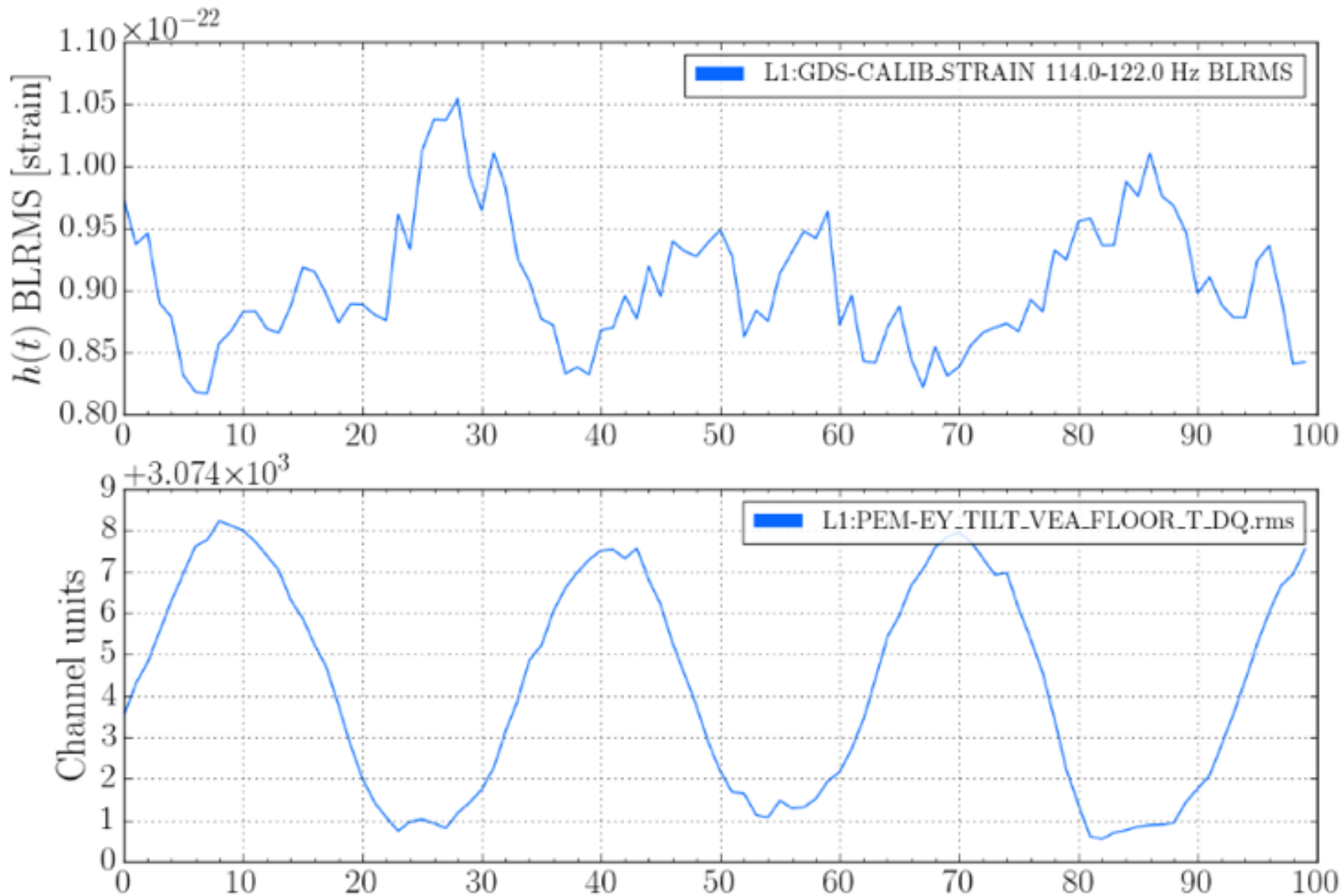
$$r_s = \rho_{\text{rg}_X,\text{rg}_Y} = \frac{\text{cov}(\text{rg}_X,\text{rg}_Y)}{\sigma_{\text{rg}_X}\sigma_{\text{rg}_Y}}$$



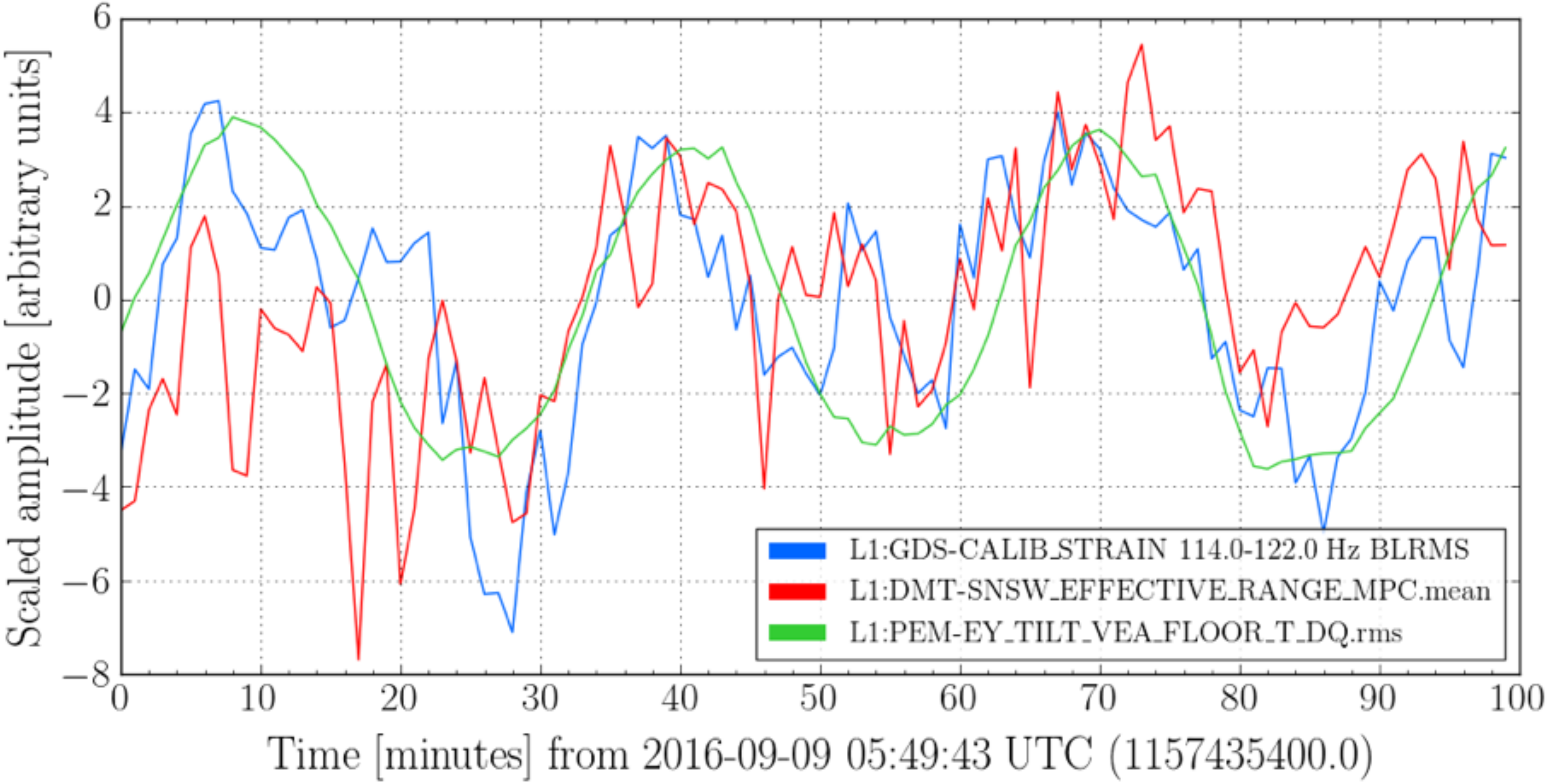

Example grabbed from wikipedia

# Looking for slow correlations in Advanced LIGO's second observing run

L1:PEM-EY_TILT_VEA_FLOOR_T_DQ.rms [$r_{blrms}{}^2 = 0.49$, $r_{range}{}^2 = 0.16$] [$\rho_{blrms}{}^2 = 0.54$, $\rho_{range}{}^2 = 0.18$]



# Looking for slow correlations in Advanced LIGO's second observing run



# Question 1

LIGO sensitivity range fluctuations are sometimes composed of the superposition of many independent noise sources correlated with different auxiliary channels.

Are there better or more appropriate time-series correlation techniques we could try?

# Question 2

**Is there some feature in h(t) that only appears in some consistent subset of auxiliary channels?**

- Can we predict h(t) response when a certain subset of auxiliary channels has an elevated RMS amplitude in some frequency range? (Perhaps not linear.)
    - h(t) response of interest may be very short duration (glitches)
    - Irrelevant trends need to be ignored
    - Some auxiliary channels are not clean
    - Time and duration of excess noise are irregular and unpredictable
    - Change point detection

# Problem 2: machine learning glitch classification

Gravity Spy

gravityspy.org    Zevin et al, 2017, CQG