

Made with GWpy: <u>gwpy.github.io</u>

Dr. Jess Mclver AstroInformatics 2019 June 26, 2019 LIGO DCC G1901218











Outline

LIGO detector noise

Noise mitigation

Improving GW search sensitivity

Maximizing duty cycle

Conclusions

LIGO: the basics



LIGO: a more detailed view





The global network of current gen interferometers



What does LIGO data look like?



Properties of averaged LIGO noise



LIGO data is non-stationary!



https://ldas-jobs.ligo-la.caltech.edu/~detchar/summary/

New noise feature in O3!



Searching for signals with matched filtering

Slide adapted from S. Caudill



Challenge: non-Gaussianity



B.P Abbott et al. CQG (2018)

The Chi-squared test



Adapted from slide by Alex Nitz

Chi-squared re-weighting

$$\hat{\rho} = \begin{cases} \rho / [(1 + (\chi_r^2)^3)/2]^{\frac{1}{6}}, & \text{if } \chi_r^2 > 1, \\ \rho, & \text{if } \chi_r^2 \le 1. \end{cases}$$

Redefine SNR to downweight the SNR of triggers with high Chi-squared



GW150914: an example

Adapted from slides by Alex Nitz

"Un-modeled" burst searches

cWB - an all-sky coherent burst search

- Projects the data onto a Meyer wavelet basis.
- Extracts significant events using a coherent likelihood statistic maximized over all potential sky positions.



Klimenko et al. CQG 2011

Low latency glitch correlations: iDQ

- iDQ is an engine for statistical inference
- Will produce a time series of the probability of a glitch in h(t) in the LIGO detectors based on auxiliary channel information in O3 — a key data quality product that will inform Open Public Alerts
- iDQ supports a variety of supervised learning techniques
- Broadly useful architecture for streaming classification



Time [sec] relative to 1010.000

R. Essick et al. CQG (2013)

Low latency DQ mitigation



Low latency DQ mitigation



Citizen science and machine learning

gravityspy.org



Zevin et al, 2017, CQG

Identifying glitches by type



J. Areeda et al. Astronomy and Computing (2017), S. Coughlin et al *in prep*

GWTC-1: confident detections

Eleven total events 10 BBHs 1 BNS

			FAR $[y^{-1}]$			Network SNR	
Event	UTC Time	PyCBC	GstLAL	cWB	PyCBC	GstLAL	cWB
GW150914	09:50:45.4	$< 1.53 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	$< 1.63 \times 10^{-4}$	23.6	24.4	25.2
GW151012	09:54:43.4	0.17	7.92×10^{-3}	-	9.5	10.0	_
GW151226	03:38:53.6	$< 1.69 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	0.02	13.1	13.1	11.9
GW170104	10:11:58.6	$< 1.37 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	2.91×10^{-4}	13.0	13.0	13.0
GW170608	02:01:16.5	$< 3.09 \times 10^{-4}$	$< 1.00 \times 10^{-7}$	1.44×10^{-4}	15.4	14.9	14.1
GW170729 V	18:56:29.3	1.36	0.18	0.02	9.8	10.8	10.2
GW170809 V	08:28:21.8	1.45×10^{-4}	$< 1.00 \times 10^{-7}$	-	12.2	12.4	_
GW170814 V	10:30:43.5	$< 1.25 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	$< 2.08 imes 10^{-4}$	16.3	15.9	17.2
GW170817 V(G) 12:41:04.4	$< 1.25 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	_	30.9	33.0	_
GW170818 V	02:25:09.1	-	4.20×10^{-5}	-	—	11.3	-
GW170823	13:13:58.5	$< 3.29 \times 10^{-5}$	$< 1.00 \times 10^{-7}$	2.14×10^{-3}	11.1	11.5	10.8

B.P. Abbott et al. arXiv 1811.12907 (2018)

GW candidates in O3 thus far

16 alerts issued since April 1st.14 un-retracted events in 8.5 weeks!

UID 🜲	Labels	FAR
<u>S190602aq</u>	PE_READY ADVOK SKYMAP_READY	1.90052750535e-09
<u>S190521r</u>	PE_READY ADVOK SKYMAP_READY	3.16754584224e-10
<u>S190521g</u>	PE_READY ADVOK SKYMAP_READY	3.80105501069e-09
<u>S190519bj</u>	PE_READY ADVOK SKYMAP_READY	5.70158251604e-09
<u>S190517h</u>	PE_READY ADVOK SKYMAP_READY	2.37290998502e-09
<u>S190513bm</u>	ADVOK SKYMAP_READY EMBRIGHT_F	3.73400311637e-13
<u>S190512at</u>	PE_READY ADVOK SKYMAP_READY	1.90052750535e-09
<u>S190510g</u>	ADVOK SKYMAP_READY EMBRIGHT_F	8.8335691573e-09
<u>S190503bf</u>	ADVOK SKYMAP_READY EMBRIGHT_F	1.63611159504e-09
<u>S190426c</u>	PE_READY ADVOK SKYMAP_READY	1.94694181763e-08
<u>S190425z</u>	ADVOK SKYMAP_READY EMBRIGHT_F	4.53764787126e-13
<u>S190421ar</u>	PE_READY ADVOK SKYMAP_READY	1.48874654585e-08
<u>S190412m</u>	PE_READY ADVOK SKYMAP_READY	1.68289586112e-27
<u>S190408an</u>	PE_READY ADVOK SKYMAP_READY	2.81096164616e-18

- 11 likely BBHs
- 2 BNSs (one likely, one 58% terrestrial)
- 1 potential NSBH candidate
- (BNS (49%), MassGap (24%), NSBH (13%), Terrestrial (14%))

Outline

Gravitational waves

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LIGO-Virgo duty cycle



Network duty factor

 $[1238166018\hbox{-}1248652818]$

- Triple interferometer [45.5%]
- Double interferometer [35.6%]
- Single interferometer [16.1%]
- No interferometer [2.7%]



Ground motion and "lock loss"



Improving LIGO duty cycle with machine learning Ayon Biswas, Jess McIver, Ashish Mahabal

Study of ~1000 LIGO lock loss times during O2.

Goals of our work:

Can we diagnose the detector mechanisms for lock losses to increase uptime?

What is the minimum number of auxiliary witnesses needed to correctly predict a lock loss?

Can we predict a lock loss *before it happens*?

Could we automatically change the interferometer state to compensate, as we do for earthquake mitigation?

Approach 1/3: clustering algorithm (t-SNE) with dmdt

Biswas et al. In prep.



Optic cavity channels are better predictors than ground motion!

Signal recycling cavity length



0.03-0.1 Hz ground motion



Approach 2/3: random forest with *dmdt* features

Biswas et al. In prep.



Combination of cavity sensing and control channels (majority vote) yields 0.95 accuracy.

Channel	Test accuracy
IMC_MC2+LSC_REFL+LSC_POP	0.92
MICH + SRCL + PRCL	0.94
All the above	0.95





Stacked dmdt features of channel combinations yields > 0.98 accuracy!

channels	Test accuracy	Test loss
$IMC_MC2+LSC_REFL+LSC_POP$	0.910	0.280
MICH + SRCL + PRCL	0.968	0.111
All the above	0.986	0.080



Study findings (preliminary)

Biswas et al. In prep

A subset of just three channels, MICH, LSC POP, and SRCL, predict > 97% of all LIGO-Livingston lock losses during O2!

Using those three channels, lock losses can be accurately predicted 10-15 prior to losing lock.

Ground motion channels alone are not good predictors of lock loss!

Overall conclusions

- Transient noise in gravitational wave detector data presents a major challenge for the astrophysical analyses
- Computational solutions have allowed us to successfully extract astrophysical signals with higher confidence and more accuracy.
- Investment in understanding causes of lock loss will allow us to improve detector duty cycle— crucial for sky localization!
- As the detectors progress toward design sensitivity, new and different noise sources will be unearthed!
- Novel approaches will be needed!

Searching for known GW signals Step 1: Building a template bank



Challenge: S190518bb case study

Automatic Preliminary Notice sent ~6 minutes after the event: FAR: 1.004e-08 [Hz] (one per ~3 years) PROB_NS: 1.00 [range is 0.0-1.0] PROB_REMNANT: 1.00 [range is 0.0-1.0] PROB_BNS: 0.75 [range is 0.0-1.0] PROB_TERRES: 0.24 [range is 0.0-1.0]



Challenge: S190518bb case study

H1:GDS-CALIB_STRAIN, reduced at 1242242379.923 with Q of 45.3



Challenge: S190518bb case study



LIGO DCC G1900994