

## Machine Learning in Characterization and Commissioning @ GW Detectors

NIKHIL MUKUND MENON

**IUCAA PUNE** 

## GOLDEN AGE OF MACHINE LEARNING



Monitoring Lock-losses at Sites

### LOCKLOSS MONITOR GOAL: MAXIMIZE IFO UPTIME

N. Mukund, A. Pele, J. Betzwieser, A. Mullavey, M. Kasprzack, S. Kandhasamy, S. Aston, J. Romie, B.O. Reilly, S. Mitra



### DENSITY BASED SPATIAL CLUSTERING APPLICATIONS WITH NOISE



# **Best Guess: Results**

#### Identify the channel that lead to LOCKLOSS

#### L1:ASC-ADS\_PIT4\_DOF\_OUTPUT L1:ASC-ADS\_YAW4\_DOF\_OUTPUT 2000 1000 -1000 -2000 -80 -60 -40 -60 -40 -20 0 -100 L1:ASC-AS A RF36 Q PIT OUT DQ 1dtASC-ADS\_PIT3\_DOF\_OUTPUT 1 0.5 -0.5 -1 -60 -40 -20 0 -100 -80 -60 -40 L1:PSL-ISS AOM DRIVER MON OUT DQ L1:SUS-ETMY L3 LVESDAMON UL OUT DQ 3000 2000 1000 -60 -40 -20 0 -100 -80 -60 -40 L1:SUS-ETMY\_L3\_LVESDAMON\_LR\_OUT\_DQ L1:ASC-AS A DC PIT OUT DQ -60 -40 -20 -100 0 -80 -60 -40 L1:ASC-AS A DC YAW OUT DQ L1:ASC-REFL A DC YAW OUT DQ

0.1

0.05

-0.05

-0.1

-100

-80

-60

-40

-20

-20

-20

-20

-20

0

0

0

0

0

![](_page_5_Figure_3.jpeg)

![](_page_5_Figure_4.jpeg)

![](_page_5_Figure_5.jpeg)

![](_page_5_Figure_6.jpeg)

![](_page_5_Figure_7.jpeg)

![](_page_5_Figure_8.jpeg)

![](_page_5_Figure_9.jpeg)

-60

-40

-80

![](_page_5_Figure_10.jpeg)

-100

-80

-60

-40

-20

0

#### LOCKLOSS MONITOR RESULTS LOW NOISE to LOCKLOSS at GPS 1167654616

5000

-5000

5000

-5000

0.48

0.47

0.4

0 45

3000

2000

1000

-100

-100

-100

-100

-80

-80

-80

-80

0

6

# Best Guess: Results

#### Identify the channel that lead to LOCKLOSS

LOCKLOSS MONITOR RESULTS

0

![](_page_6_Figure_2.jpeg)

![](_page_6_Figure_3.jpeg)

![](_page_6_Figure_4.jpeg)

![](_page_6_Figure_5.jpeg)

![](_page_6_Figure_6.jpeg)

![](_page_6_Figure_7.jpeg)

![](_page_6_Figure_8.jpeg)

![](_page_6_Figure_9.jpeg)

![](_page_6_Figure_10.jpeg)

![](_page_6_Figure_11.jpeg)

![](_page_6_Figure_12.jpeg)

![](_page_6_Figure_13.jpeg)

![](_page_6_Figure_14.jpeg)

![](_page_6_Figure_15.jpeg)

![](_page_6_Figure_16.jpeg)

L1:LSC-POP\_A\_LF\_OUT\_DQ

-40

-40

-60

-60

L1:ISI-ITMY\_ST1\_ISO\_Y\_OUTPUT

L1:ISI-ETMY ST1 ISO Y OUTPUT

-20

-20

0

0

E attackate !!!!

890

1000

-1000

1000

0

-100

-100

-80

-80

![](_page_6_Figure_17.jpeg)

![](_page_6_Figure_18.jpeg)

![](_page_6_Figure_19.jpeg)

![](_page_6_Figure_20.jpeg)

![](_page_6_Figure_21.jpeg)

![](_page_6_Figure_22.jpeg)

![](_page_6_Figure_23.jpeg)

![](_page_6_Figure_24.jpeg)

![](_page_6_Figure_25.jpeg)

## **Best Guess: Results**

#### Identify the channel that lead to LOCKLOSS

![](_page_7_Figure_2.jpeg)

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ML Based Recommendation System

## ΜοτινατιοΝ

#### Commissioning Perspective

- Issues within a detector are often seen to reappear
- LLO-LHO-Virgo-GEO : Can benefit from each others wisdom
- Current GW search engines are not smart enough
- Fast & accurate knowledge discovery saves time & resource

#### **Detector Characterization Perspective**

- Better understand the status of the instrument
- Identify the right person to contact
- Understand trends within or among the detectors
- Bridge the gap btw on-site work & off-site data analysis

![](_page_10_Picture_0.jpeg)

![](_page_10_Picture_1.jpeg)

heyligo.gw.iucaa.in

#### "ML based Contextual Learning"

#### Answers queries about

- \* DAC glitches
- \* Bounce and roll mode damping
- \* Operator reports on earthquakes
- \* PSL ISS second loop instability
- \* Jitter Coupling
- \* Scattering noise
- \* GRB Alerts

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![](_page_10_Figure_12.jpeg)

N Mukund et al, 2017

Key Idea : Uses a shallow neural network to perform semantic learning by converting LIGO logbook data to word vectors

## **HEY LIGO ! WEB INTERFACE**

## <u>heyligo.gw.iucaa.in</u>

Most discussed issues for the day

![](_page_11_Picture_3.jpeg)

https://alog.ligo-wa.caltech.edu/aLOG/iframeSrc.php?authExpired=&content=1&step=&callRep=18219&startPage=&preview=&printCall=&callUser=&addCommentTo=&callHelp=&callFileType=#

#### TRANSIENTS SEEN AT THE SITE

#### <u>heyligo.gw.iucaa.in</u>

H1:LSC-DARM\_IN1\_DQ at 1152078617.000 with Q of 45.3

![](_page_12_Figure_2.jpeg)

![](_page_12_Figure_3.jpeg)

Related to DAC, timing systems, electronic pickup, control loops, optical levers, RF coupling, thunderstorms, overflows.....

25

20

15

10

1.5

13

- ISC : Interferometric Sensing & Control
- AOS : Auxiliary Optics Support
- CDS : Control & Data System
- SEI : Seismic External Isolation
- SUS : Suspension
- TCS : Thermal Compensating System
- PSL : Pre-Stabilized Laser
- PEM : Physical Environment Monitoring
- CAL : Calibration

#### Glitch distribution across different subsystems

![](_page_12_Figure_16.jpeg)

#### SAME ISSUE: MULTIPLE DETECTORS

heyligo.gw.iucaa.in

Rate of occurrence of Scatter

![](_page_13_Figure_3.jpeg)

#### **Rate of occurrence of Glitch**

![](_page_13_Figure_5.jpeg)

Rate of occurrence of bounce and roll

![](_page_13_Figure_7.jpeg)

Classifying the non-astrophysical background

## **GLITCH STUDIES : MOTIVATION**

- Many of them have distinct time-frequency morphology
- Some of them share similarity with GW signals
- Leads to false triggers in various search pipelines
- Matched filtering and Burst pipelines mostly affected
- Often such triggers leave no signature in auxiliary channels
- Morphology based veto needs to be implemented
- Commissioning activities often hampered

### HIERARCHICAL CLUSTERING OF TRANSIENTS

N. Mukund, S. Abraham, S. Kandhasamy, S. Mitra, and N. S. Philip Phys. Rev. D 95, 104059

#### Morphology progressively changes

![](_page_16_Figure_3.jpeg)

#### **BOOSTING THE DIFFERENCES USING NEURAL NETWORKS**

N. Mukund, S. Abraham, S. Kandhasamy, S. Mitra, and N. S. Philip Phys. Rev. D 95, 104059

![](_page_17_Figure_2.jpeg)

System Identification via Transfer Function Fitting

### MODELLING SYSTEM DYNAMICS

- Often system dynamics are inaccessible to direct modelling
- Possible to built empirical models by fitting the measured frequency response data
- Use these surrogate models to predict behaviour
- Measurements are often noisy
- Fitting by hand takes few hours, not scalable
- Multi-parameter optimization/regression subject to stability constraints
- Some Applications : Seismic feedforward Length to angle decoupling Time domain Newtonian noise filters

## MODELLING SYSTEM DYNAMICS

https://github.com/Nikhil-Mukund/TFestimate

![](_page_20_Figure_2.jpeg)

ML will be used to determine the optimal algorithm and optimal input parameters. This will require collection of user feedback and more input data.

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## **TFESTIMATE : FITS OBTAINED**

https://github.com/Nikhil-Mukund/TFestimate

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![](_page_21_Figure_2.jpeg)

Frequency (Hz)

![](_page_21_Figure_3.jpeg)

![](_page_21_Figure_4.jpeg)

# Regression / Multiparameter Optimization

## PREDICTING EARTHQUAKE IMPACT AT SITES

M. Coughlin, P. Earle, J. Harms, S. Biscans, C. Buchanan, E. Coughlin, F. Donovan, J. Fee, H. Gabbard, M. Guy, N. Mukund, and M. Perry

Classical and Quantum Gravity, Volume 34, Number 4

![](_page_23_Figure_3.jpeg)

Model that predicts ground motion from earthquakes. It is currently used to issue early warning at GW Observatories.

	Time: Tue Apr 04 22:08:38 UTC 2017 Location: 69km SSE of Adak, Alaska; LAT: 51.0, LON: -176.4 Magnitude: 5.7							
<u>USGS event link</u>								
	ifo P-phase Arrival Time	S-phase Arrival Time	R-wave Arrival Time	R-Wave Velocity (micro m/s)	EQ Distance (km)	GPS P-phase Arrival Time	GPS S-phase Arrival Time	GPS R-wave Arrival Time
	H1 15:15:47 PST	15:15:48 PST	15:28:07 PST	4.81367	4091.405	1175379365.1	1175379366.0	1175380105.0
	L1 17:19:14 CST	17:19:15 CST	17:42:40 CST	3.6175	7148.653	1175379572.8	1175379573.8	1175380978.5
	G1 00:20:31 CET	00:20:32 CET	00:49:19 CET	1.74679	8543.346	1175379649.4	1175379650.4	1175381377.0
	V1 00:21:16 CET	00:21:17 CET	00:53:50 CET	2.39336	9495.016	1175379694.9	1175379695.9	1175381648.9

## PREDICTING EQ LOCKLOSS AT SITES

Will this earthquake cause a lockloss ?

Earthquake Parameters

![](_page_24_Figure_3.jpeg)

https://dcc.ligo.org/LIGO-G1602420

## PREDICTING EARTHQUAKE IMPACT AT SITES

### Model Improvements:

![](_page_25_Figure_2.jpeg)

## CONCLUSION

- ML : Growing field, lot of opportunities
- Not a single technique but an agglomeration

Clustering, Classification, Regression, Dimensionality Reduction, Contextual Learning, Reinforcement learning, Deep Learning...

- Extensive code development happening worldwide
- Well-suited for big data problems
- •Will aid automated and adaptive control

![](_page_26_Picture_7.jpeg)