



Prayush Kumar ICTS-TIFR

TATA INSTITUTE OF FUNDAMENTAL RESEARCH

# Machine Learning in Gravitational-wave Astronomy

#### 25 May 2022 LABORATORY FOR INTERDISCIPLINARY BREAKTHROUGH SCIENCE, ICTS-TIFR

# Gravitational-wave Astronomy

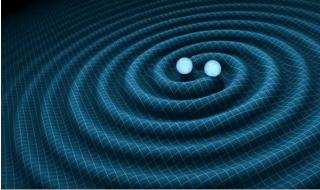






# Gravitational-wave Astronomy





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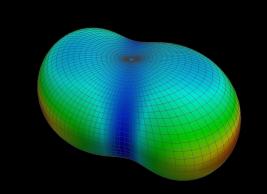
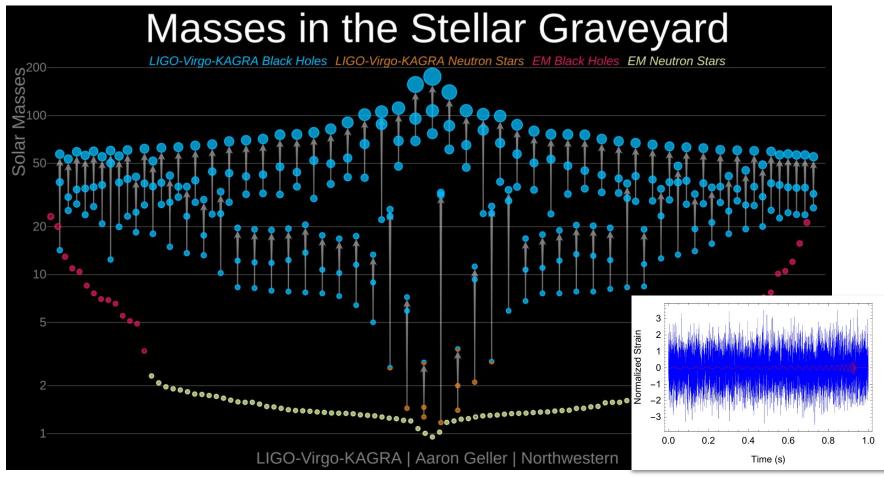
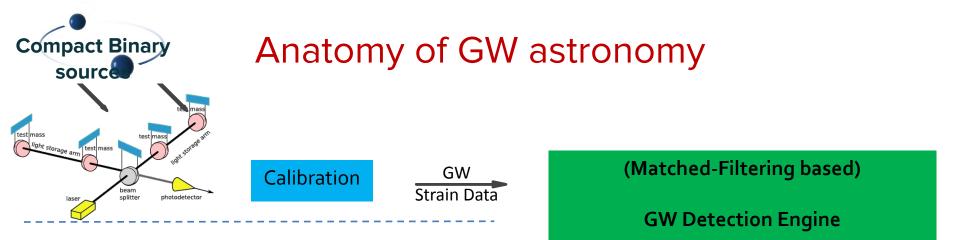
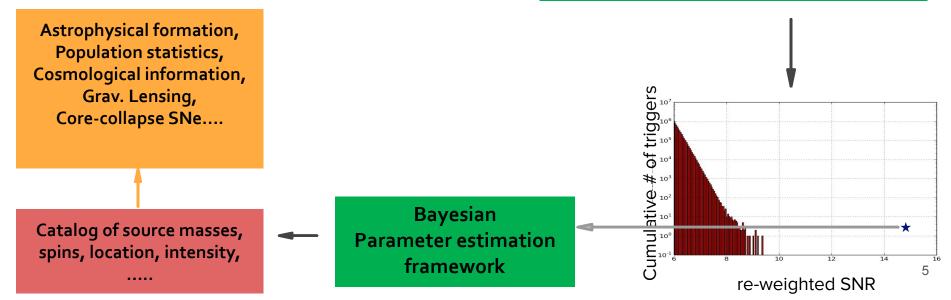


Image credit: Kavli Foundation, LSC; <a href="https://cggplus.files.wordpress.com">https://cggplus.files.wordpress.com</a>;

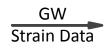
# GW observations: nearly 100 and counting!







### Anatomy of GW astronomy



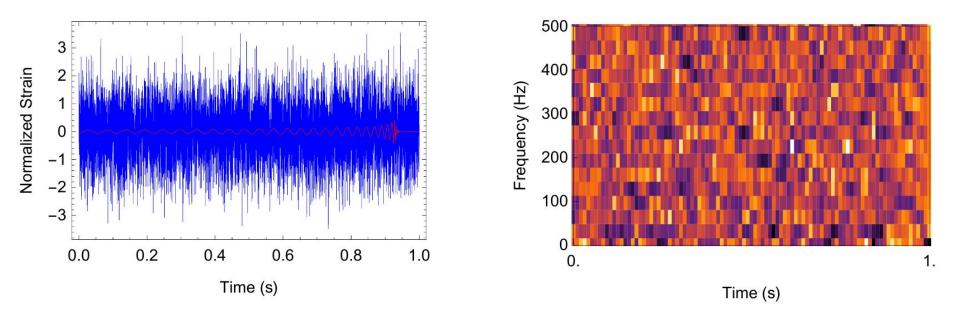
(Matched-Filtering based)

**GW Detection Engine** 

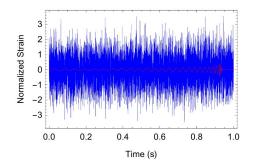


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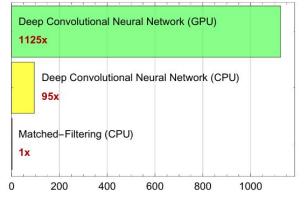
# 1. Detection of GW signals



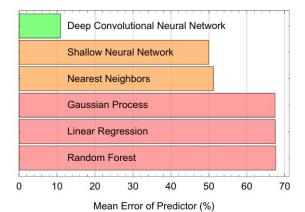
### Detection of GW signals: George & Huerta (2016)

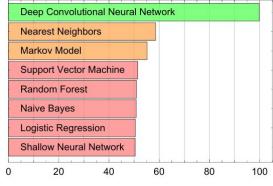


	Input	vector (size: 8192)
	Reshape Layer	tensor (size: 1 × 1 × 8192)
	Convolution Layer	tensor (size: 16 × 1 × 8177)
	Pooling Layer	tensor (size: 16 × 1 × 2045)
	Ramp	tensor (size: 16 × 1 × 2045)
	Convolution Layer	tensor (size: 32 × 1 × 2017)
	Pooling Layer	tensor (size: 32 × 1 × 505)
	Ramp	tensor (size: 32 × 1 × 505)
	Convolution Layer	tensor (size: 64 × 1 × 477)
	Pooling Layer	tensor (size: 64 × 1 × 120)
)	Ramp	tensor (size: 64 × 1 × 120)
	Flatten Layer	vector (size: 7680)
	Linear Layer	vector (size: 64)
3	Ramp	vector (size: 64)
Ļ.	Linear Layer	vector (size: 2)
5	Softmax Layer	vector (size: 2)
	Output	vector (size: 2)



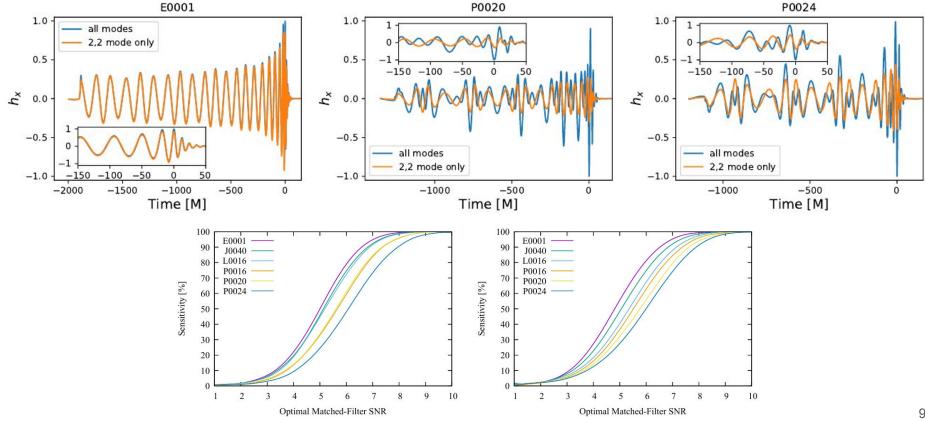
Speed-up Factor for Inference



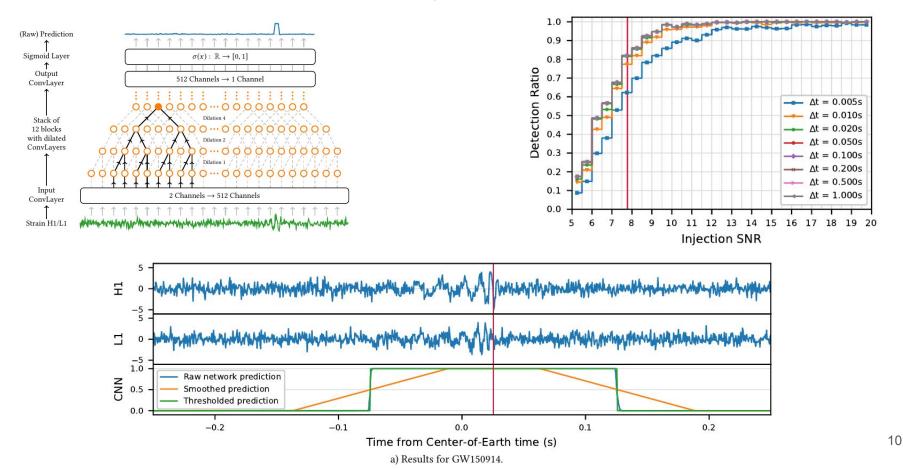


Accuracy of Classifier (%)

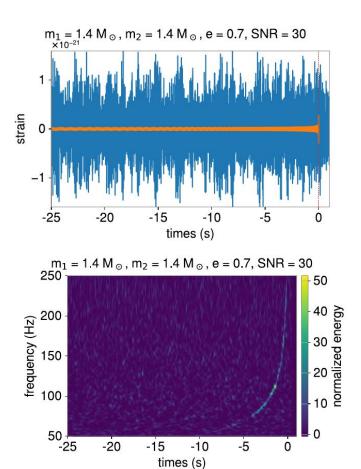
#### Detection of GW signals: Rebei et al (2019)

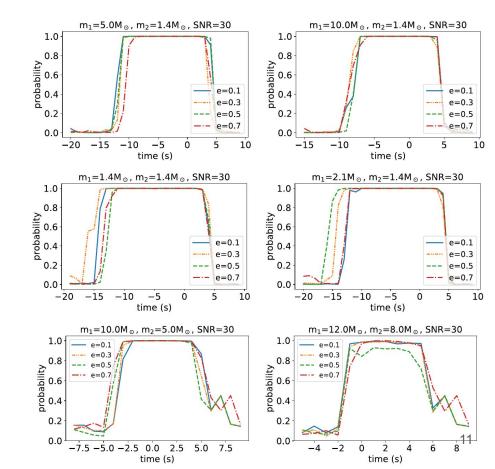


#### Detection of GW signals: Gebhard et al (2019)

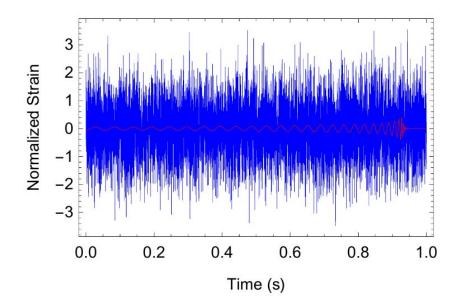


### Forecasting (detection) of GW signals: Wei et al (2021)



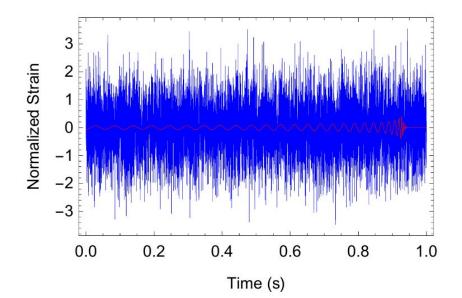


# 2. Measuring source parameters



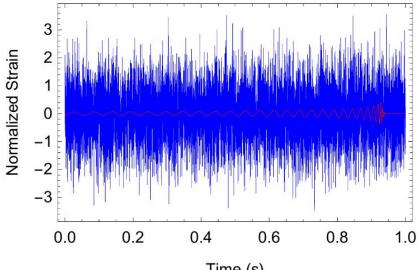
Difficulties are the same as for the detection problem: **Signal is weaker than instrument noise**, we therefore need clever techniques for precisely characterizing the source of GW signals

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Difficulties are the same as for the detection problem: **Signal is weaker than instrument noise**, we therefore need clever techniques for precisely characterizing the source of GW signals Here also we **need low-latency** results since follow-up of GW events for EM counterparts needs prompt alerts to be sent to telescope partners!

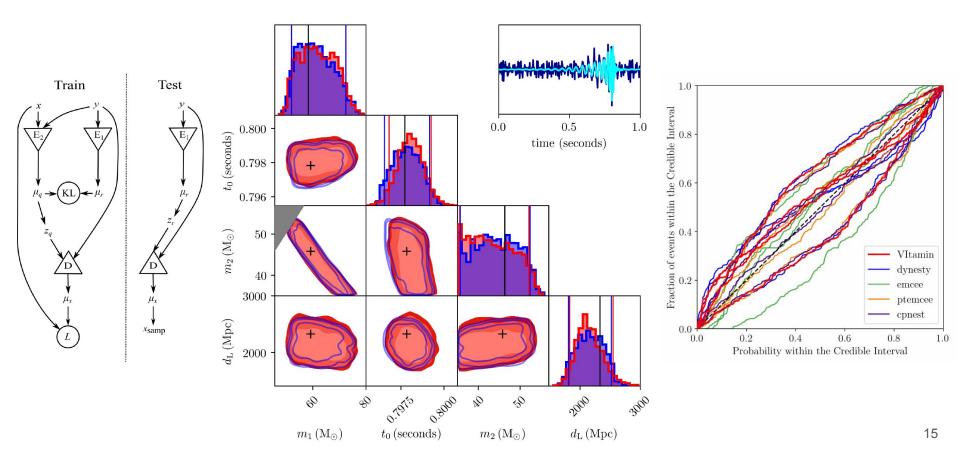
# 2. Measuring source parameters



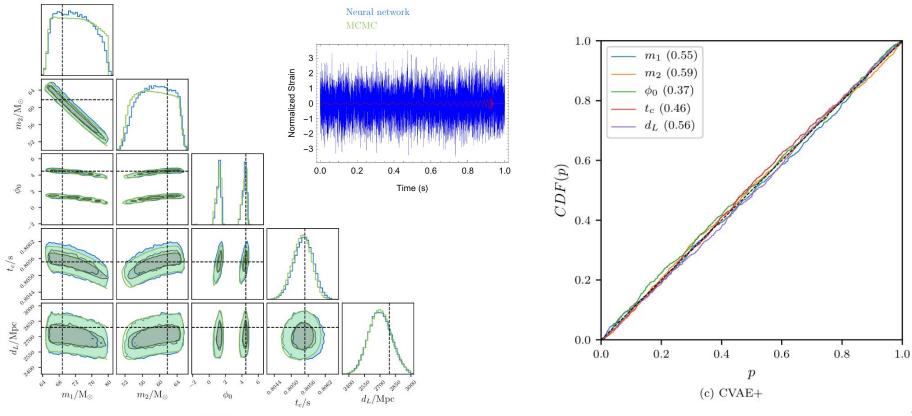
Time (s)

Difficulties are the same as for the detection problem: **Signal is weaker than instrument noise**, we therefore need clever techniques for precisely characterizing the source of GW signals Here also we **need low-latency** results since follow-up of GW events for EM counterparts needs prompt alerts to be sent to telescope partners! Matched-filtering based Bayesian parameter estimation takes between **5 hours to 5 days per event**!

#### Measuring source parameters: Gabbard et al (2020)

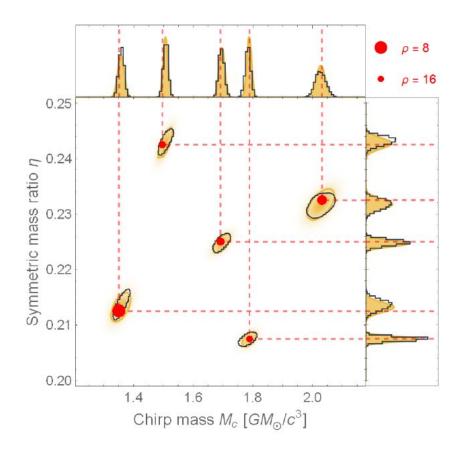


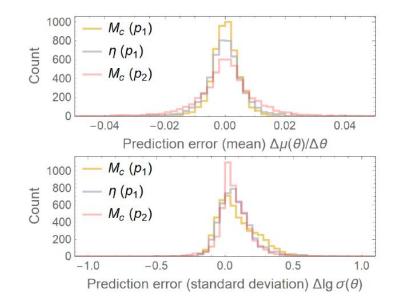
#### Measuring source parameters: Green et al (2020)



(c) CVAE+

#### Measuring source parameters: Chua et al (2020)





# Summary & Future Outlook

#### ML / AI can now be applied to:

- Low-latency detection of GW signals
- Measurement of source parameters from GW signals
- Characterization of GW detector noise transients

#### Future:

- Most of these applications are in **proof-of-concept** stage
- No sufficiently clear understanding yet of the

   (a) statistical confidences in AI detections, and
   (b) source parameter measures in Bayesian framework
   ⇒ More nuanced applications of AI needed
- AI-based methods **need to be scalable** to future networks of 5 detectors: HLVKI
- Development of AI based algos needs substantial computing expertise & hardware
- Discover yet-undetected signal types
- Develop GW signal models by solving PDEs with neural-network based operators

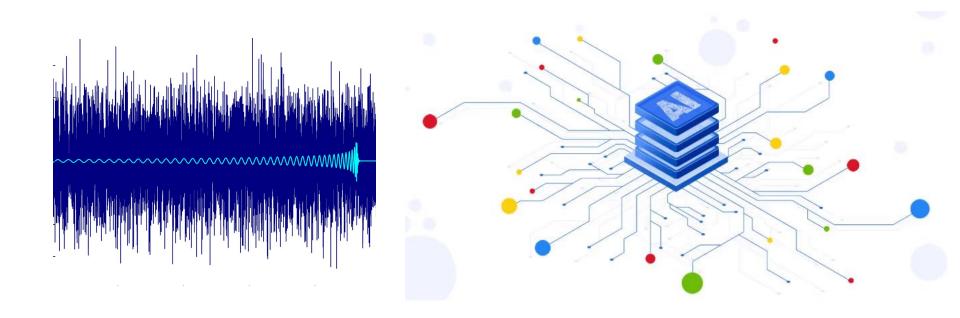


#### LIGO-India Scientific Collaboration

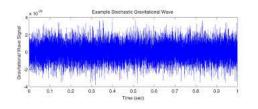


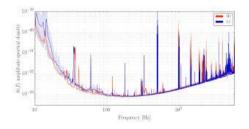
भारतीय प्रोटोनिकी संस्थान डेटराबाट

### **Questions?**



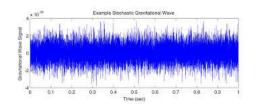
# Detector Noise Characterization: George et al (2017)

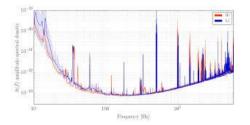


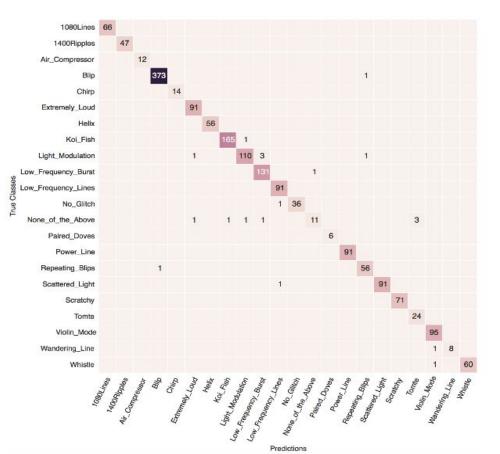


1080Lines	1400Ripples	Air_Compressor	Blip	Chirp	Extremely_Loud	Helix
Koi_Fish	Light_Modulation	Low_Frequency_Burst	Low_Frequency_Lines	None_of_the_Above	Paired_Doves	Power_Line
S. S	M.			Sec. Marks		
Repeating_Blips	Scattered_Light	Scratchy	Tonte	Violin_Mode	Wandering_Line	Whistle
		1 Acres				

# Detector Noise Characterization: George et al (2017)







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