Training and Deploying a Neural Network for Noise Regression in Gravitational Wave Astronomy

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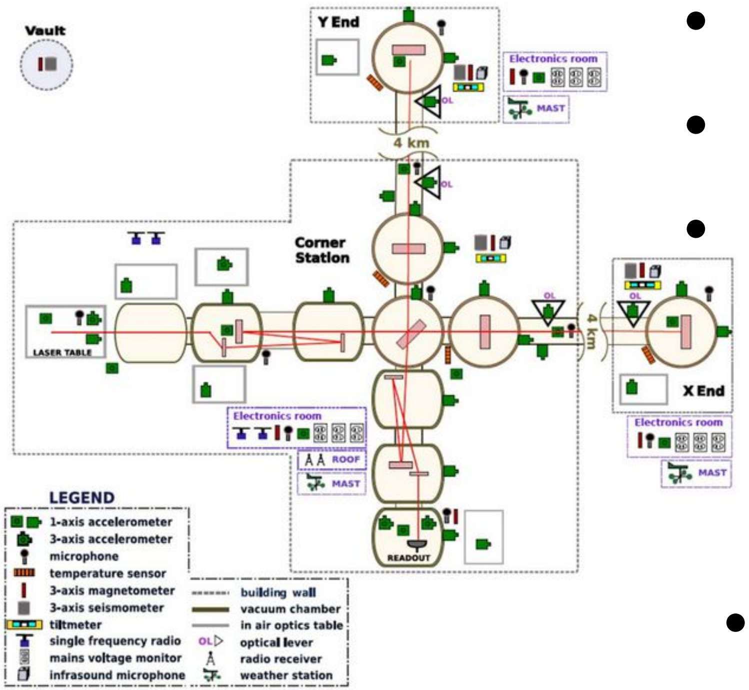
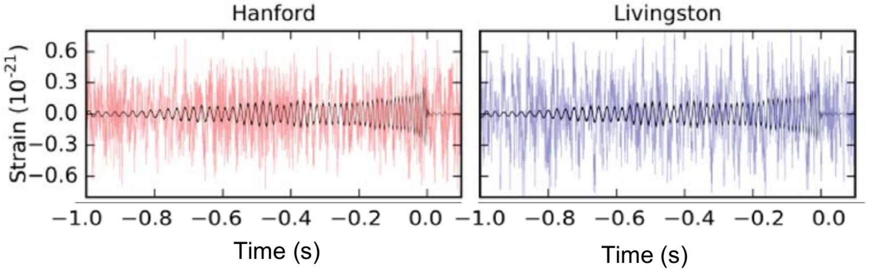
Gravitational Waves and LIGO



LIGO and Virgo Collaborations, *CQG* **33**, 134001 (2016)

- Large scale astrophysical events cause distortions in spacetime known as gravitational waves
- Tiny amplitude of these distortions makes them difficult to detect
- LIGO - pair of enormous interferometers that use destructively interfering lasers to measure perturbations in spacetime



- Measurement of distortion typically given by unitless quantity “strain”, related to relative change in displacement of objects caught in the wave
- Inferred from intensity of photons detected as GWs distort laser paths and bring them in-phase

Noise, MMA, and FastML

- Environmental noise can degrade the perfect destructive interference of the lasers
- Leads to spurious photon detection, leads to noisy strain measurements
- Makes it difficult to pick out signals with amplitude less than noise, limits detection range
- Auxiliary sensors measure noise for removal

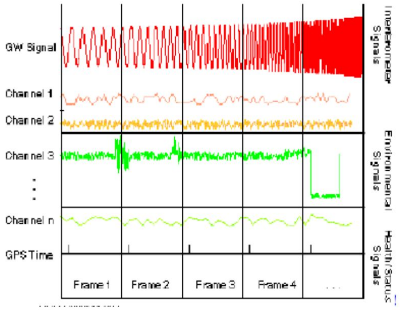
Gravitational-wave Detector Data

Continuous time series (1Hz, 128Hz … 16kHz)

Gravitational Wave channel: ~20GB/day (per instrument)

Physical Environment Monitors (seismometers, accelerometers, magnetometers, microphones etc)

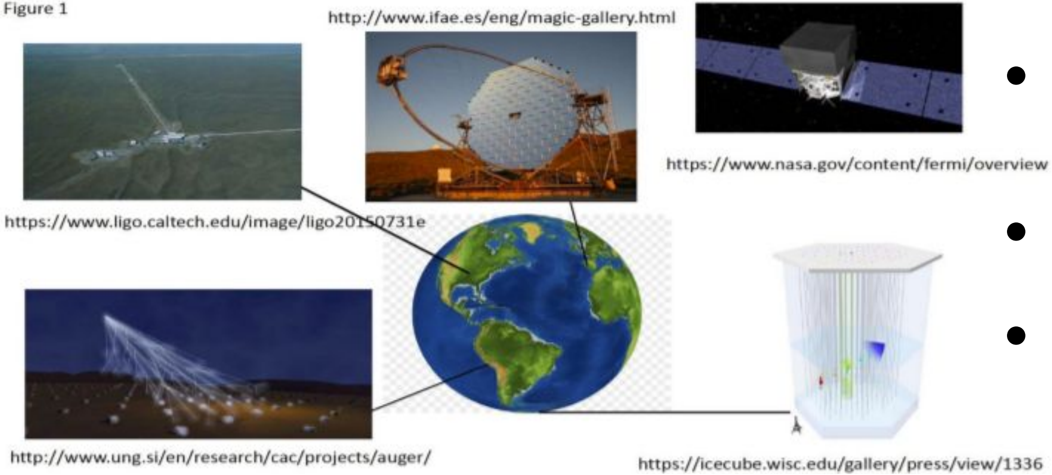
Internal Engineering Monitors (sensing, housekeeping, status etc)



Together with various intermediate data products >2TB/day (per instrument)

Initial and Enhanced LIGO archive (2002-2010) exceeds 1PB of data

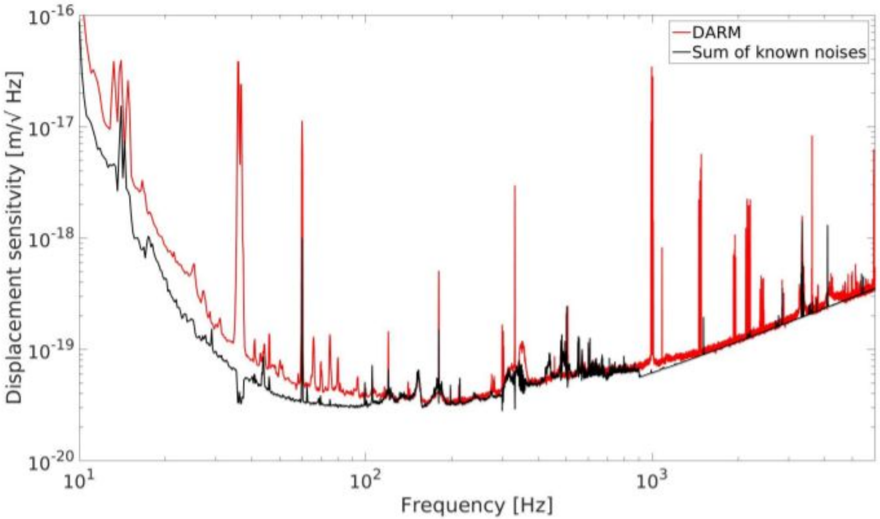
Figure 1



Meszaros et. al. https://arxiv.org/pdf/1906.10212.pdf

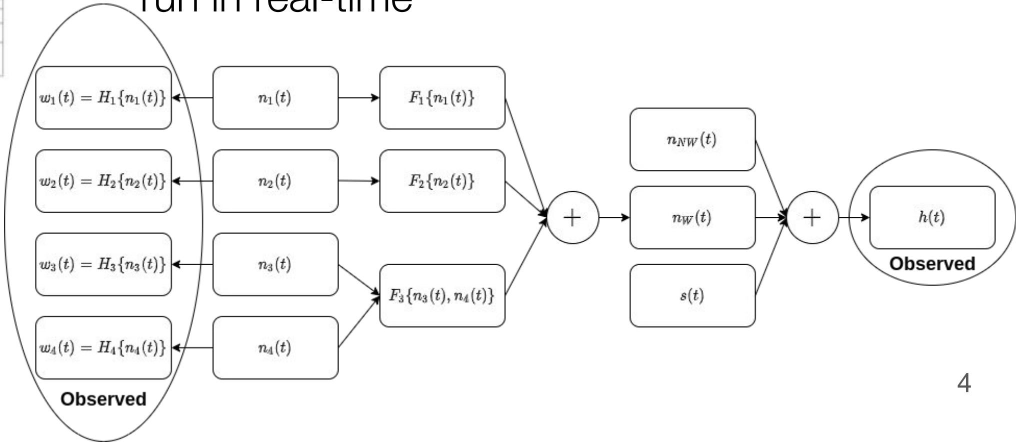
- Multi-messenger astrophysics offers promising insights by comparing different cosmic messengers from same phenomena
- LIGO + VIRGO critical for detecting and locating events to alert other observers
- Noise subtraction and downstream algorithms need to work in real-time to capture as much data as possible

Low Frequency Noise

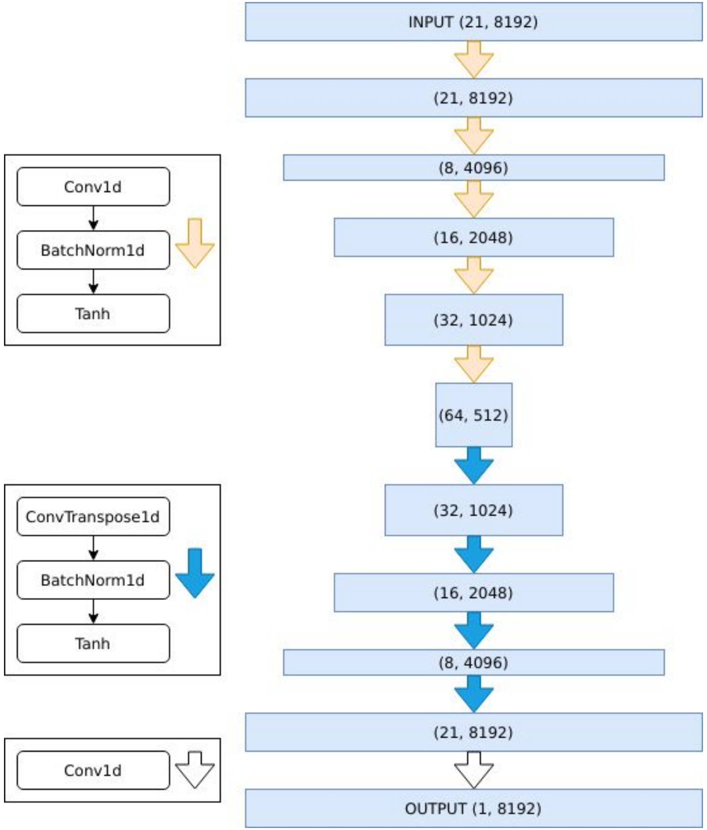


- Unmodelled noise sources below 100 Hz

- Noise is coupled with auxiliary channel measurements, astrophysical signal isn't
- Use auxiliary channels to regress to observed strain noise
- Previously proposed techniques e.g. Wiener filter have limited expressivity and/or can't be run in real-time



Deep Learning for Noise Regression

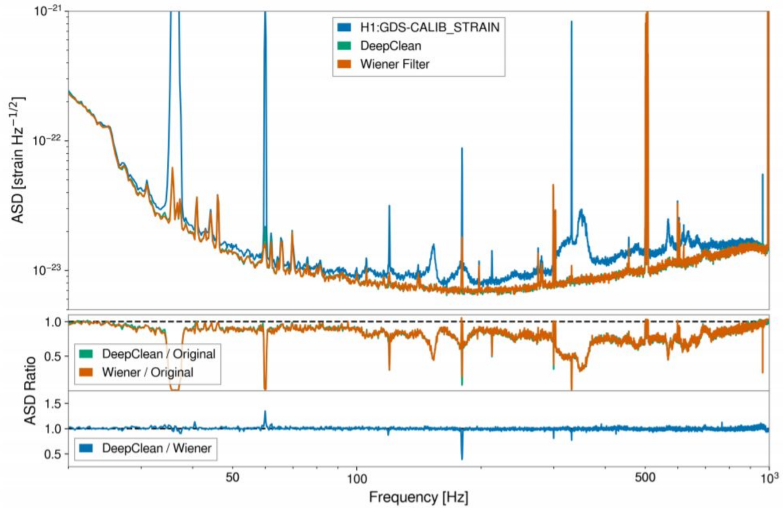


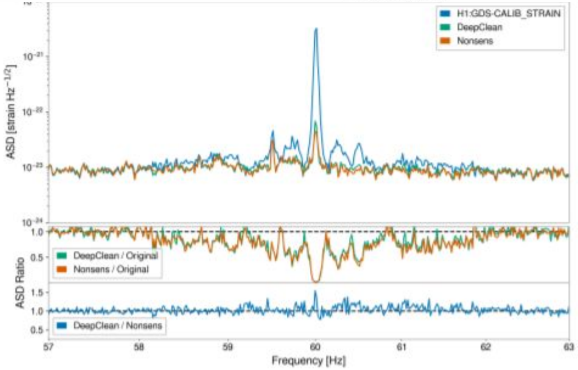
- Neural network can learn complicated nonlinear interactions between auxiliary or “witness” channels
- Fully convolutional network maps from witness measurements to noise estimate
- Regress noise estimates to strain measurements h(t) since signal is independent
- In practice, wide disparities in contributions of various noise sources. Normalize MSE in frequency space by ASD of h(t) to compensate

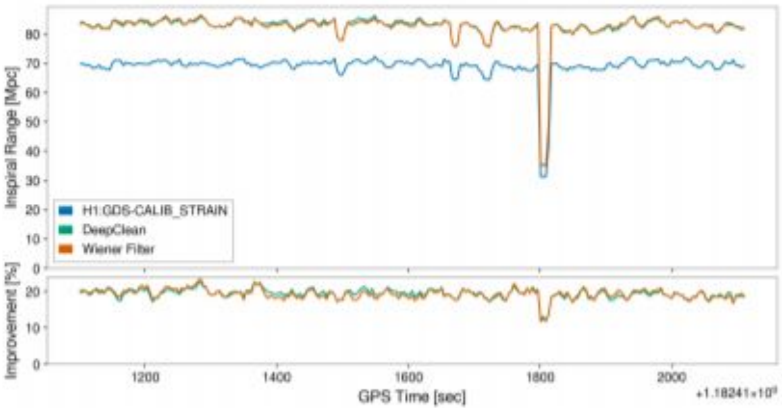
$$J(r) = w\frac{1}{M}\sum_{i=1}^{M}\sqrt{\frac{S_{[r,r]}[i]}{S_{[h,h]}[i]}} + (1-w)\sum_{i=1}^{N} r[i]^2 \ ; \ r = h - \mathcal{F}(\vec{w};\theta)$$

Ormiston et al. (https://arxiv.org/abs/2005.06534)

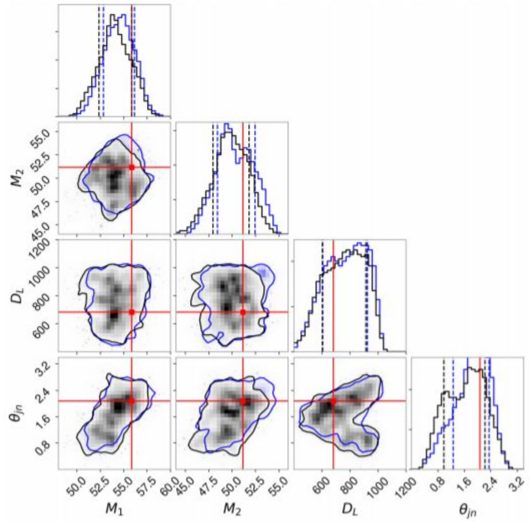
Validation





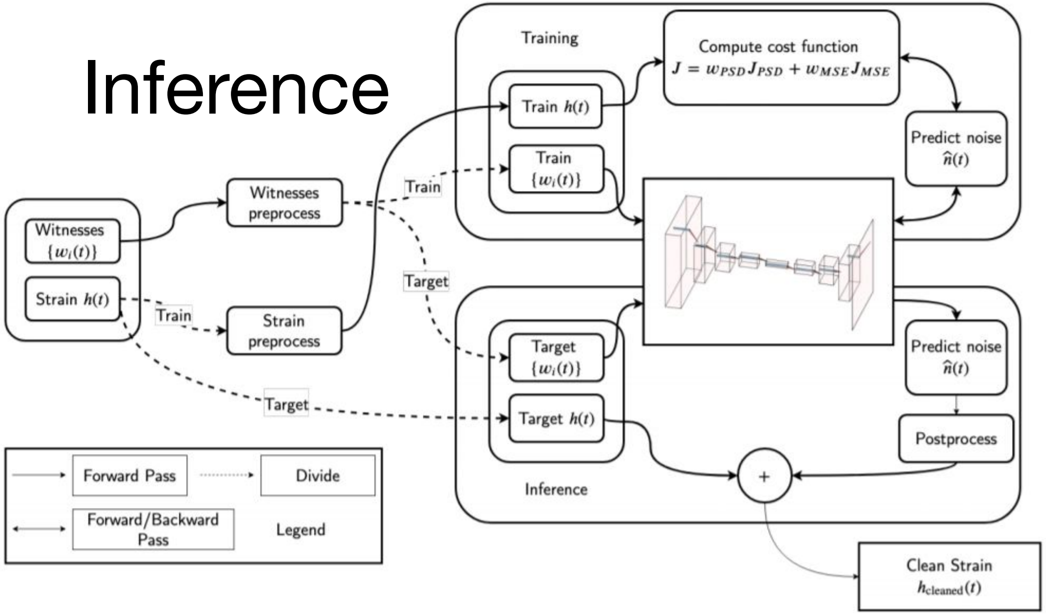


- No corruption of astrophysical signal



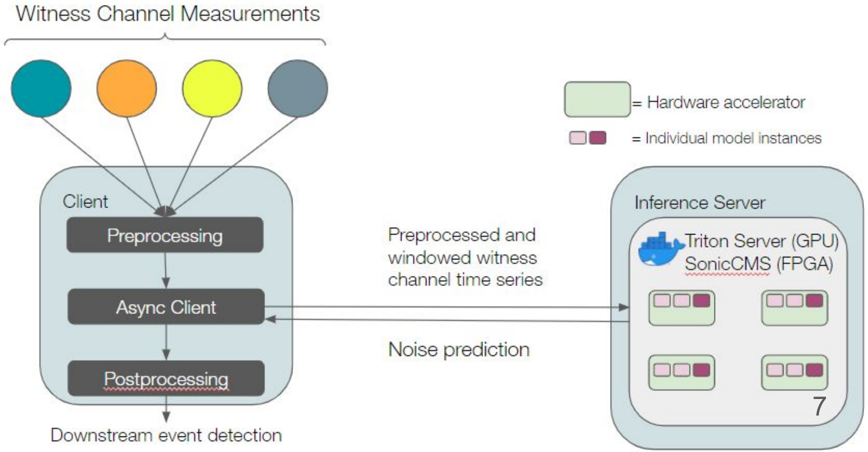
- Consistency with existing explicitly modelled noise removal mechanisms

Inference



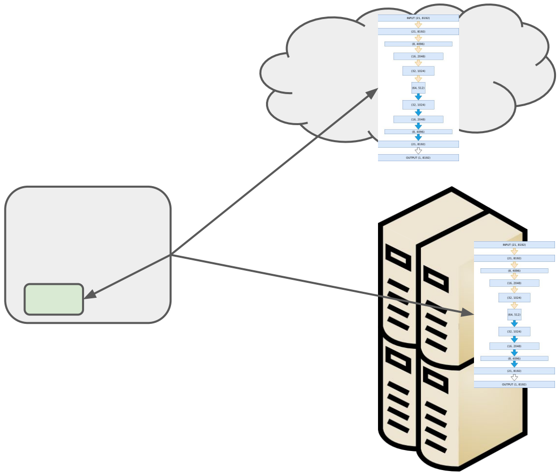
- Implement steps as asynchronous processes to maximize throughput
- Implement model inference on dedicated inference server using accelerated hardware/software

- Resample and center witness data
- Use trained model to estimate noise
- Uncenter and bandpass filter
- Subtract from strain data

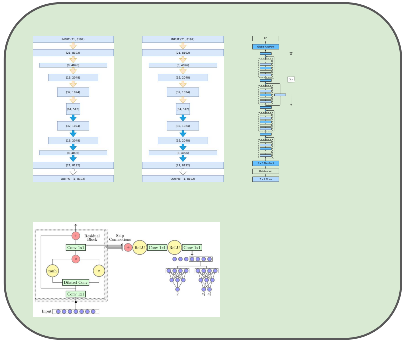


Inference-as-a-Service

- Portable

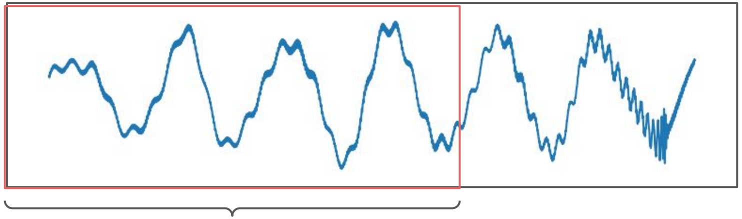


- Framework and architecture agnostic
- Critical for applications like DeepClean that need frequent retraining



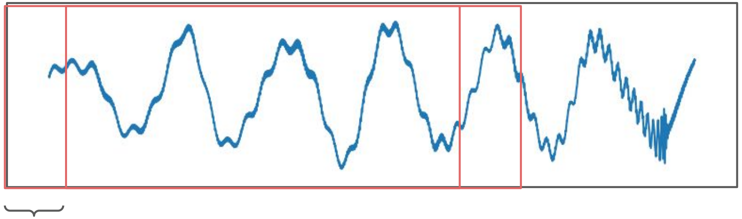
- Co-locate downstream models for better resource allocation/autoscaling
- Manage and accelerate end-to-end latency of DeepClean + downstream algorithms to meet requirements

Inference-as-a-Service - DeepClean challenges



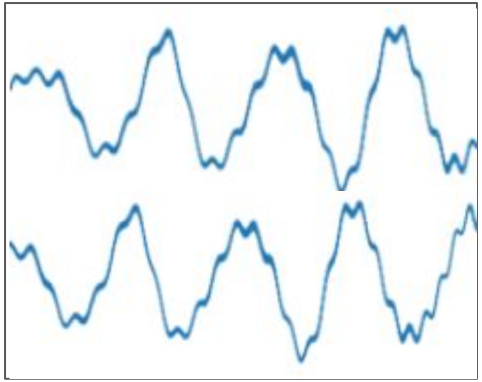
- Frame width dictated at train time

Inference-as-a-Service - DeepClean challenges



- Stride between subsequent frames is an inference time parameter that affects estimation quality and arrival rate to inference pipeline
- If pipeline throughput can't meet arrival rate, frames pile up and queue latency explodes

  - Current pipeline running with 2 copies of model, frame stride of 2 ms, batch size of 8, achieving throughput of ~450 frames / s
  - Working on custom backend for streaming as well as tools to explore cost landscape



- Batching subsequent frames linearly reduces arrival rate
- Introduces unavoidable latency
- Makes streaming picture nontrivial: send duplicate data or build custom backend to batch on server side
- High throughput ML inference critical to mitigating these issues

Summary

- DeepClean low-frequency noise estimation can increase our capacity to detect and analyze astrophysical events
- Inference-as-a-service deployment represents a powerful model for accelerating the pace at which new architectures and applications can be adopted
- Further optimization and tools for exploring the relevant parameters will allow each use case to fit their own latency/throughput/cost constraints

Thank You