Gravitational-Wave Detection with Recurrent Autoencoders

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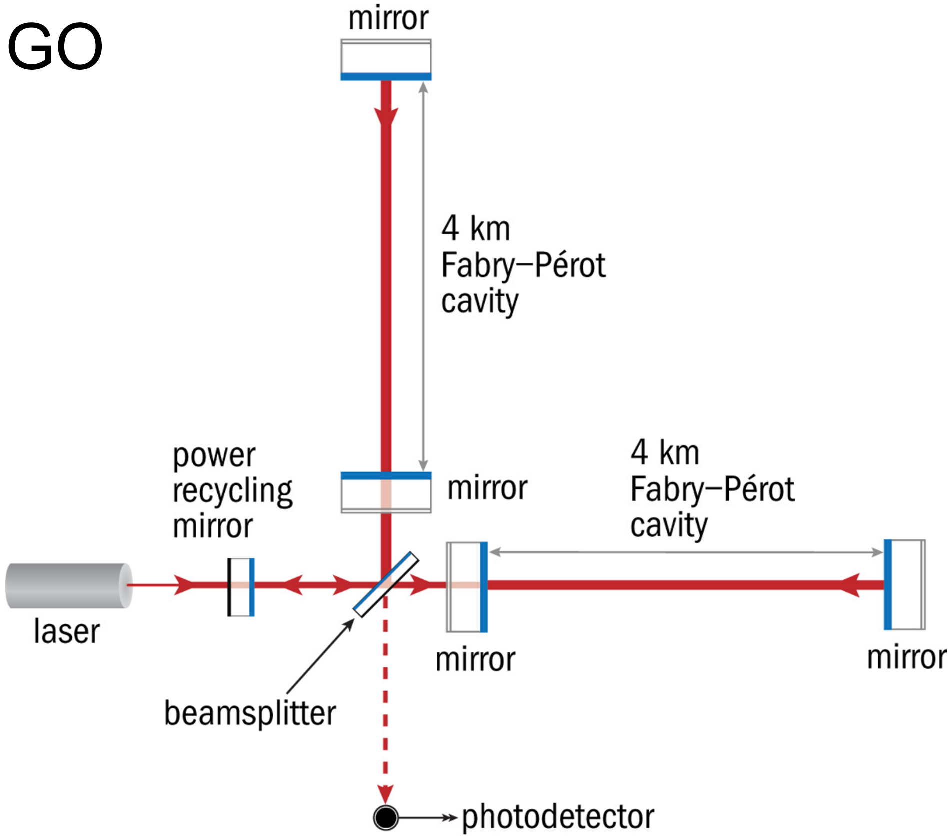
Introduction to the project

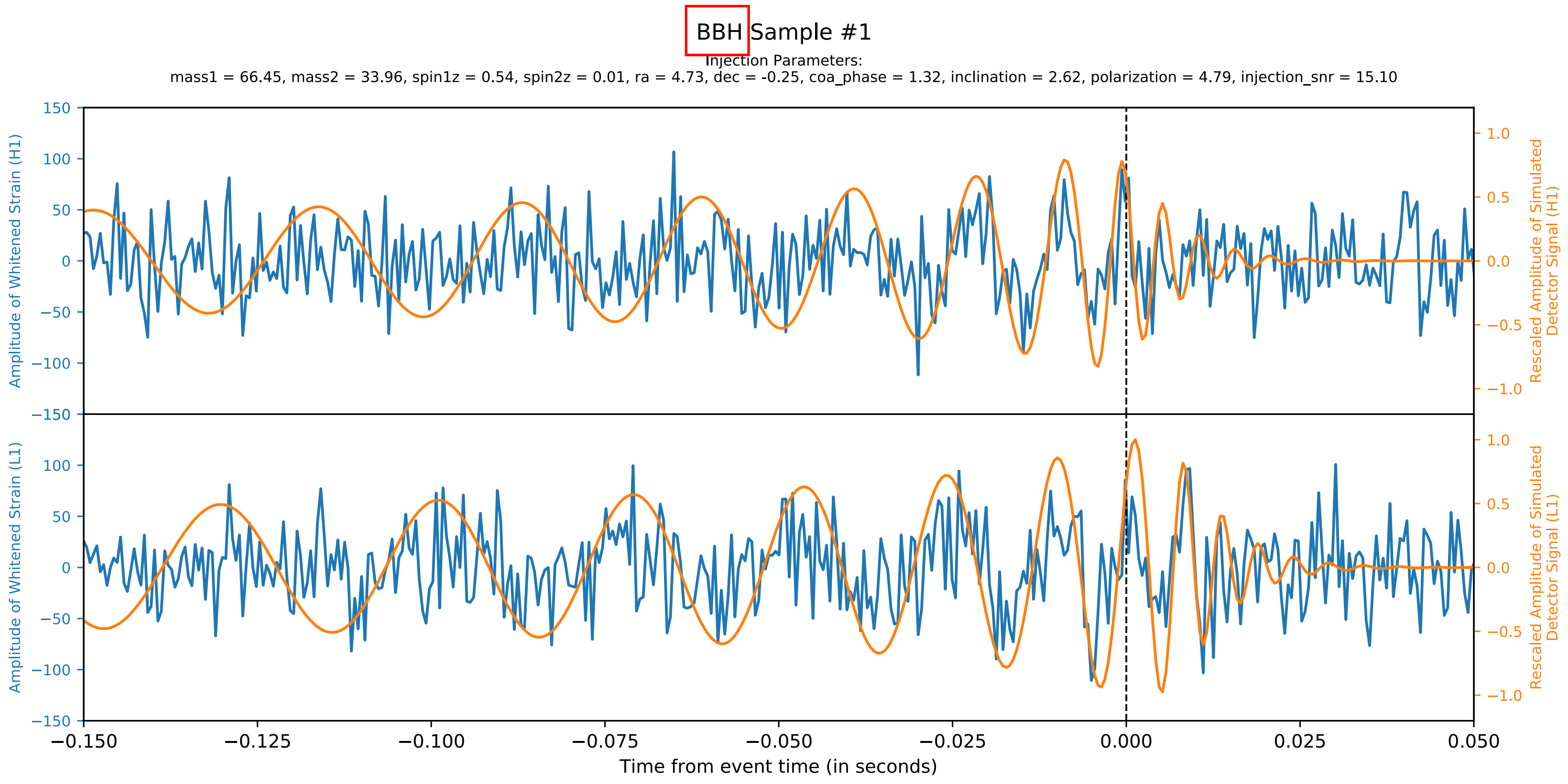
- Detection of gravitational waves (GWs) at LIGO



Produces: 1-D time-series strain

Source: Elena Cuoco - Real Time Classifier for transient signals in Gravitational Waves, From raw data to classified triggers

LIGO Dataset



1. Simulates typical detector noise conditions from a PSD
2. Simulates GW waveforms for the following conditions:
   - Binary masses of black hole mergers (BBH) or neutron star mergers (BNS)
   - SNR of 5-20
   - Variable angles in the sky
3. Adds GW strain into noise for signal events
4. Data is whitened, bandpass, and normalized

Source: github.com/timothygebhard/ggwd, https://www.gw-openscience.org/data/

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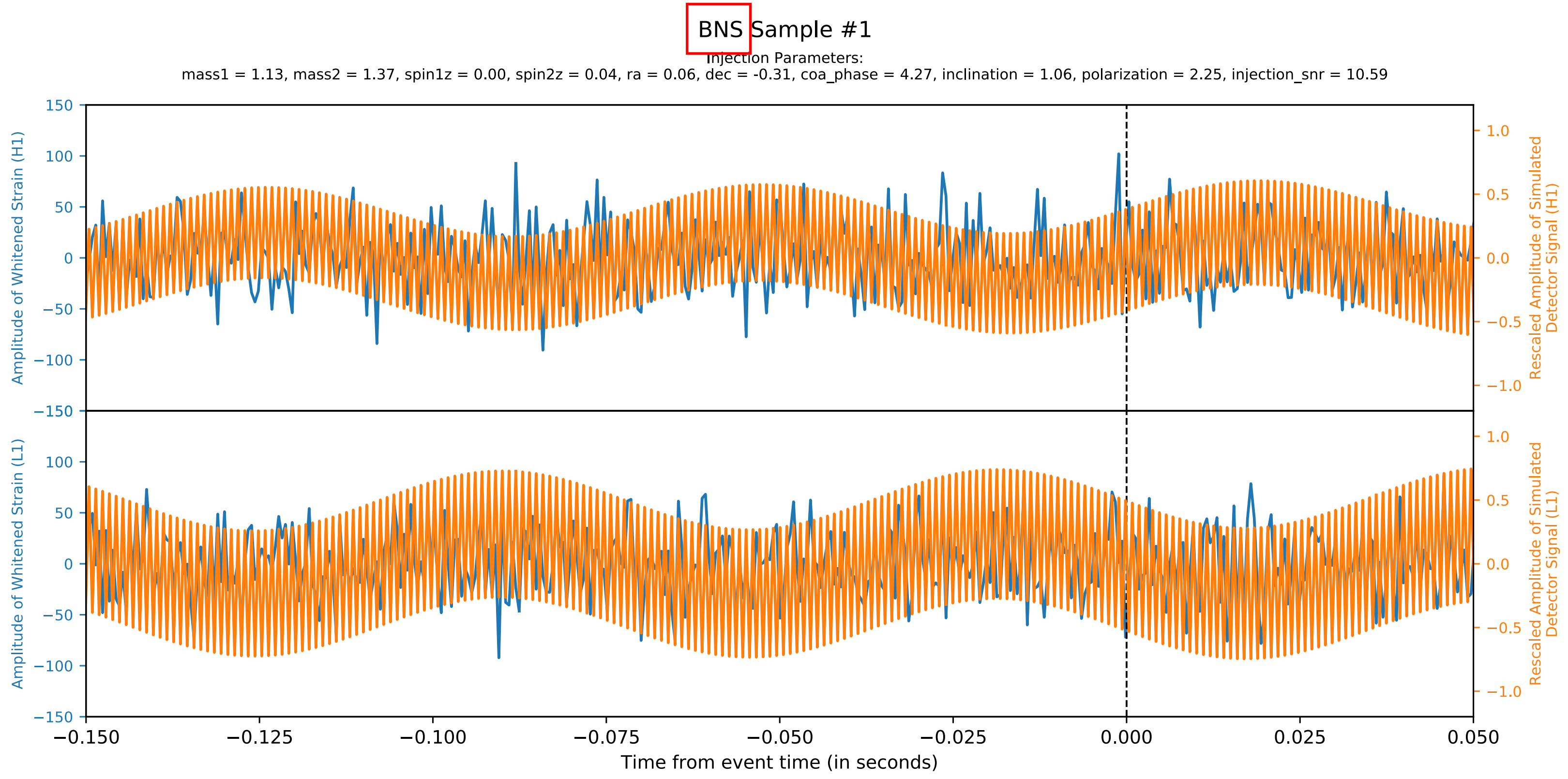

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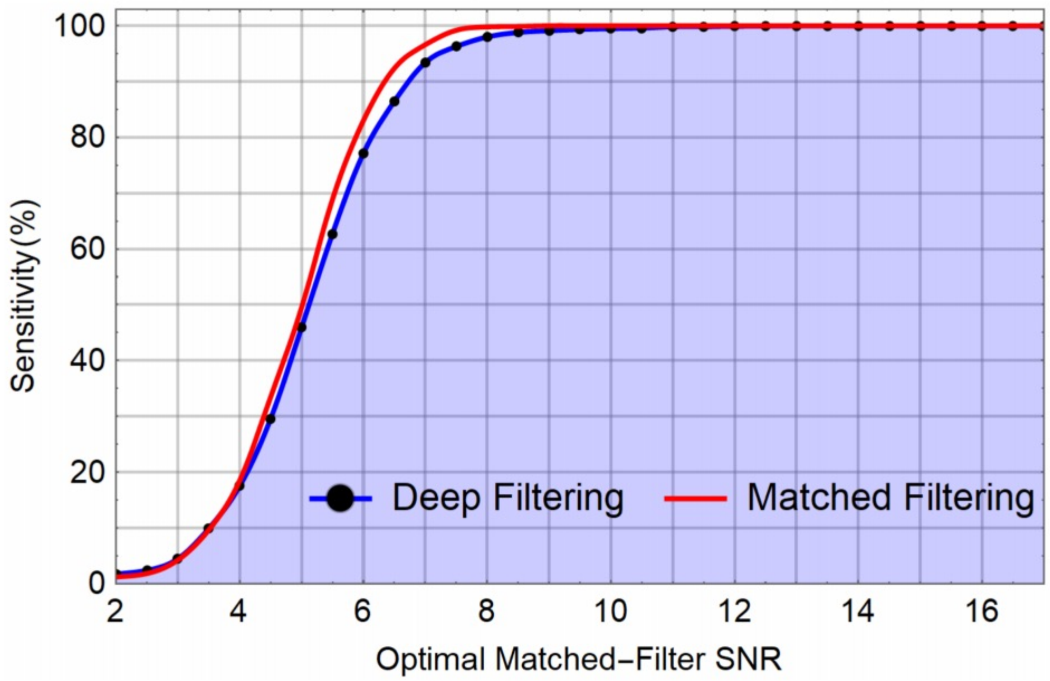
Currently used methods

Matched Filtering

- **Current method** used by LIGO
- Compares incoming GW data to bank of simulated waveforms
- Can only identify GWs that are available in GW banks (no exotic events)

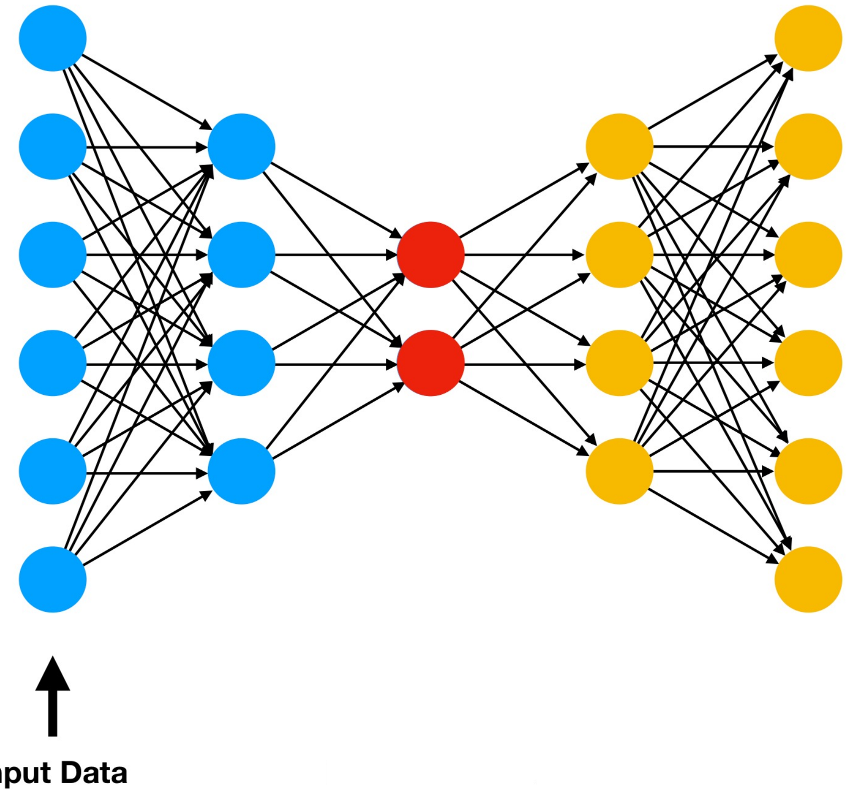
Deep Filtering

- Convolutional Neural Networks (CNNs)
- Take time-series inputs, can determine detections and estimate parameters of events
- Still can miss events that aren't included in training set



Source: https://arxiv.org/pdf/1711.03121.pdf, https://arxiv.org/pdf/2005.06534.pdf

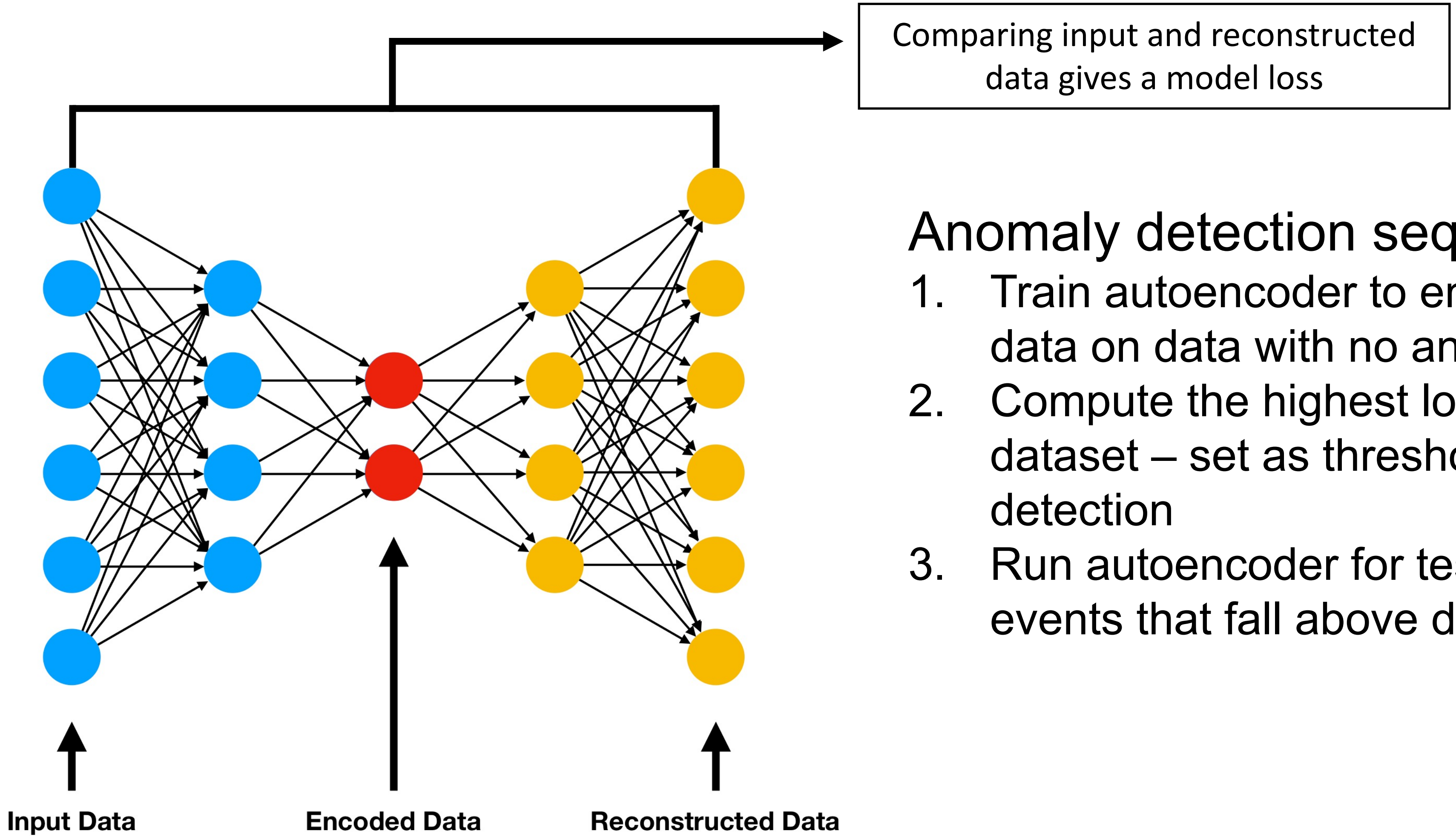
Unsupervised Learning: Autoencoder



- Encoders and decoders made of:
  - Dense Neural Networks
  - Recurrent Neural Networks (RNNs) such as LSTMs or GRUs which are good with dealing with time-dependent data
  - Convolutional layers
  - Spiking Neural Networks (interesting proposition!)

Unsupervised Learning: Detection

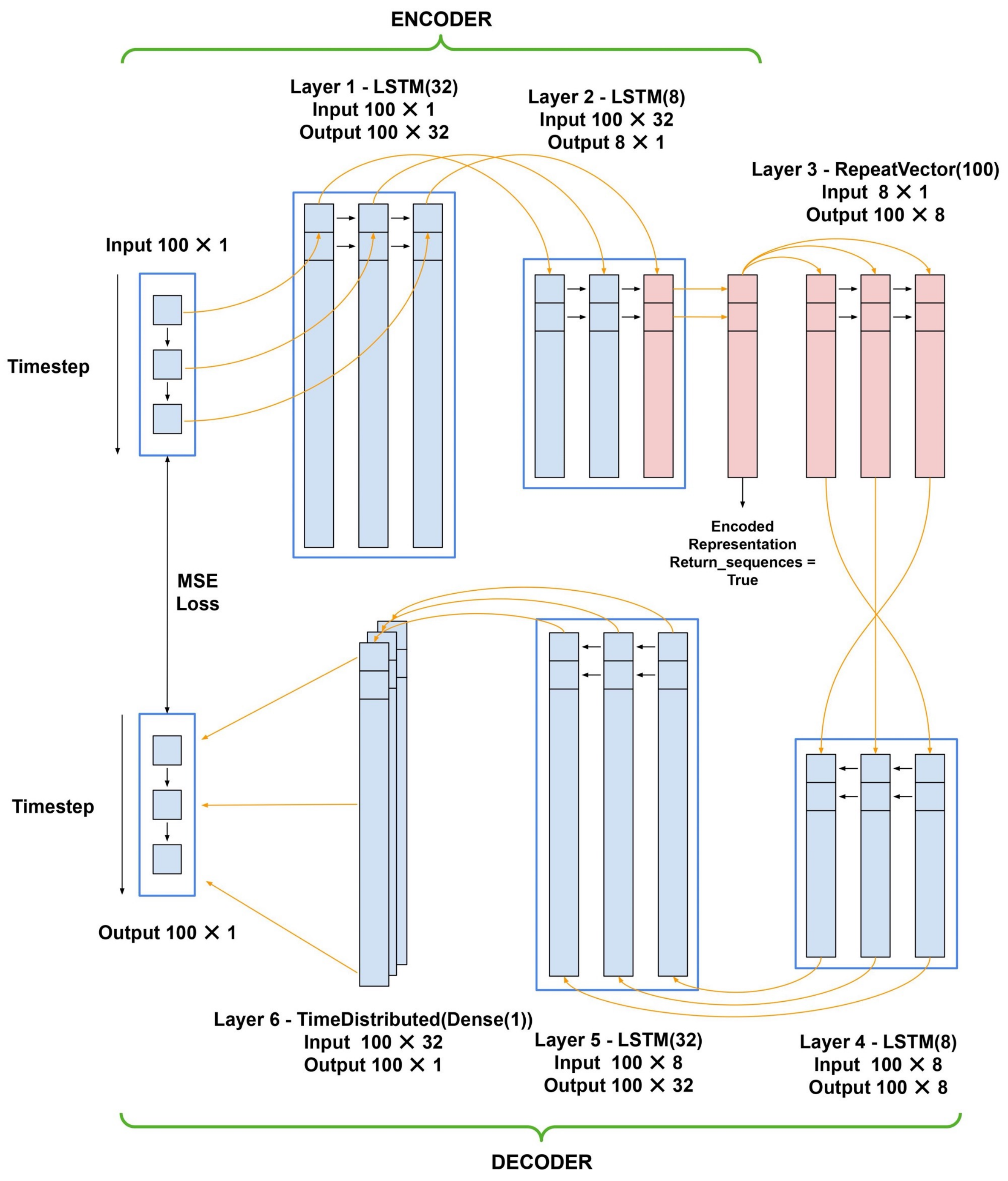
https://github.com/eric-moreno/LSTM-Autoencoder



Anomaly detection sequence:

1. Train autoencoder to encoder and decode data on data with no anomalies.
2. Compute the highest loss on the training dataset – set as threshold for anomalous detection
3. Run autoencoder for test data, identify events that fall above detection threshold

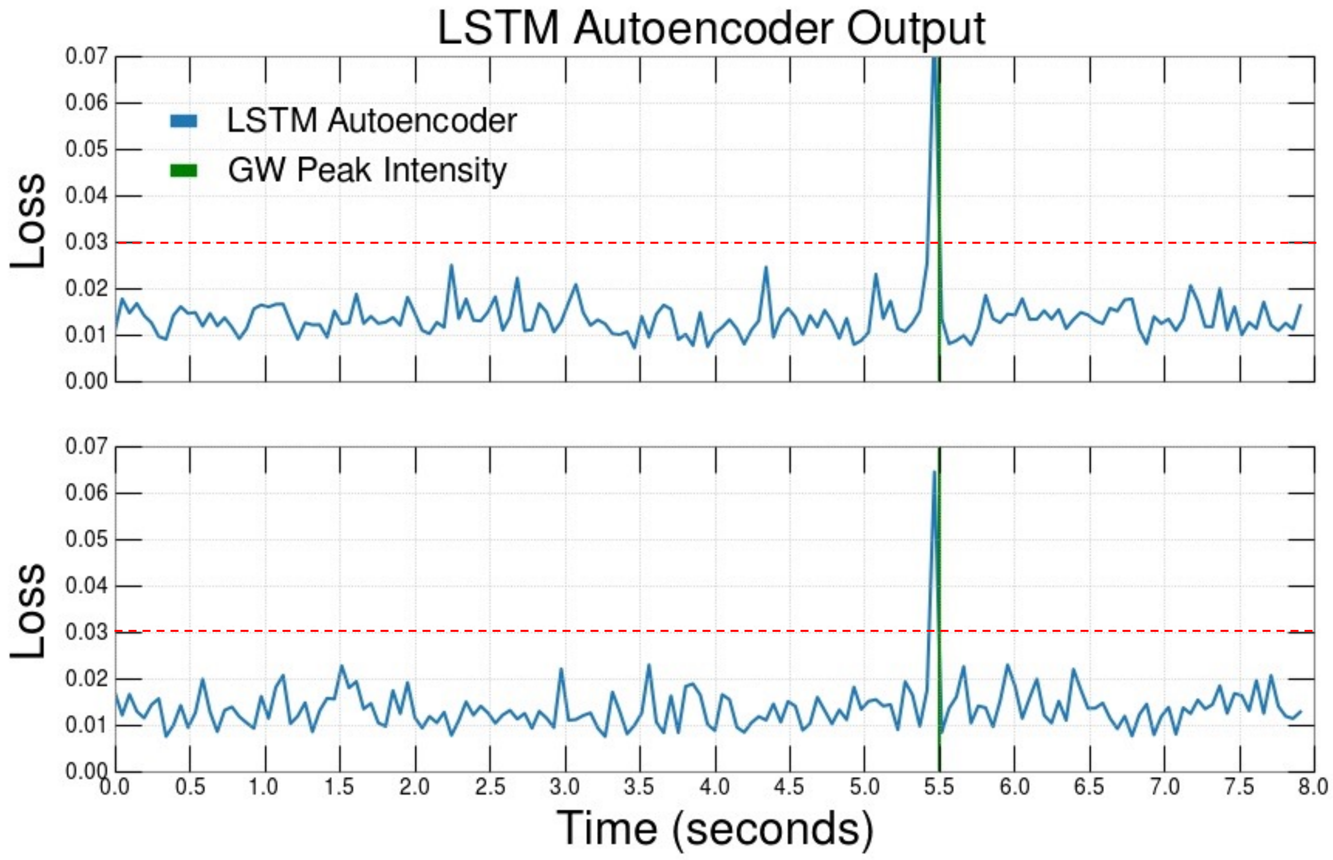
LSTM AE Architecture



https://github.com/eric-moreno/LSTM-Autoencoder

Event Loss with Autoencoders

- LSTM AE evaluated BBH and BNS events yields promising results
- **Red dotted line represents detection threshold** which can be determined according to FPR
- During training, **AE never receives information about any GW (signal) -> Source Agnostic**

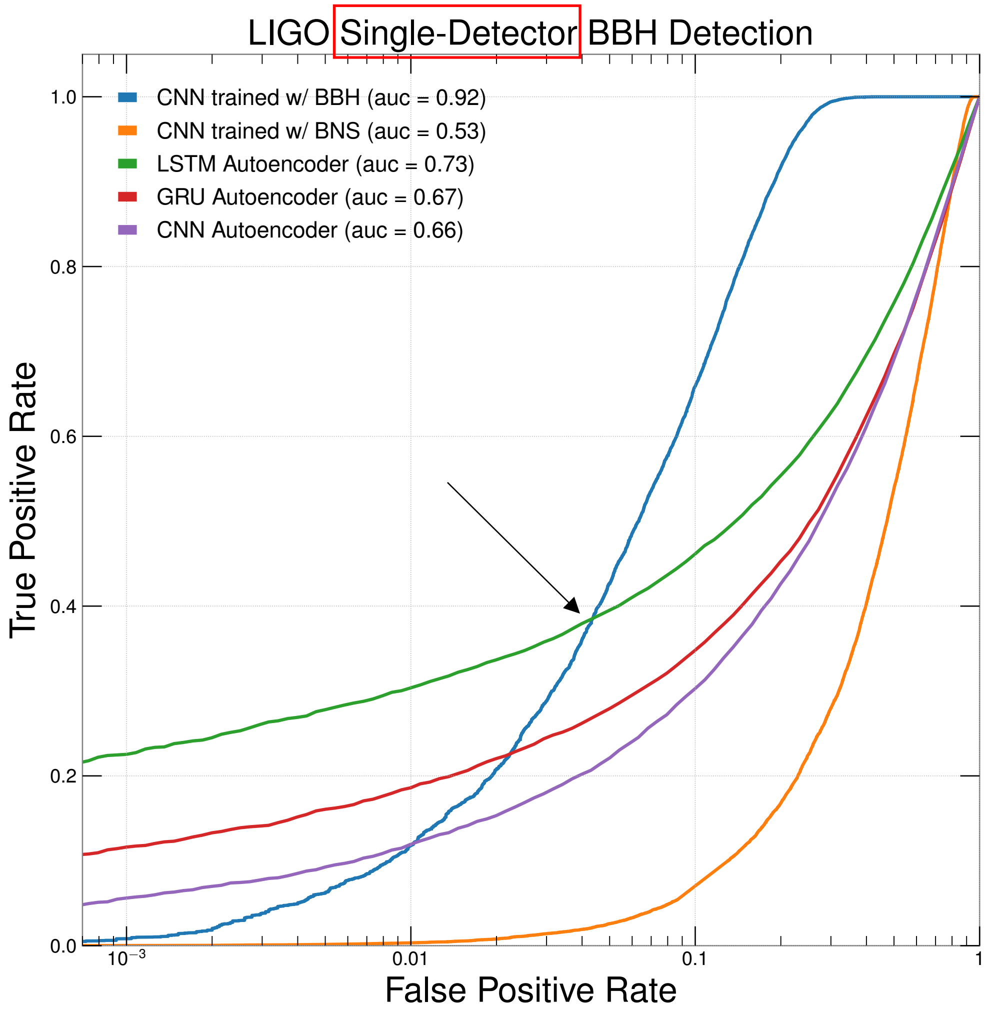


Supervised vs Unsupervised BBH

https://arxiv.org/abs/2107.12698

- BBH generated from SEOBNRv4 Approximant
- High mass BH (10–80+ solar masses) produce large amplitude events
- Both autoencoders perform better than supervised models generalized from BNS data
- **Outperforms supervised methods (trained on equivalent length data) at below FPR = 0.04**

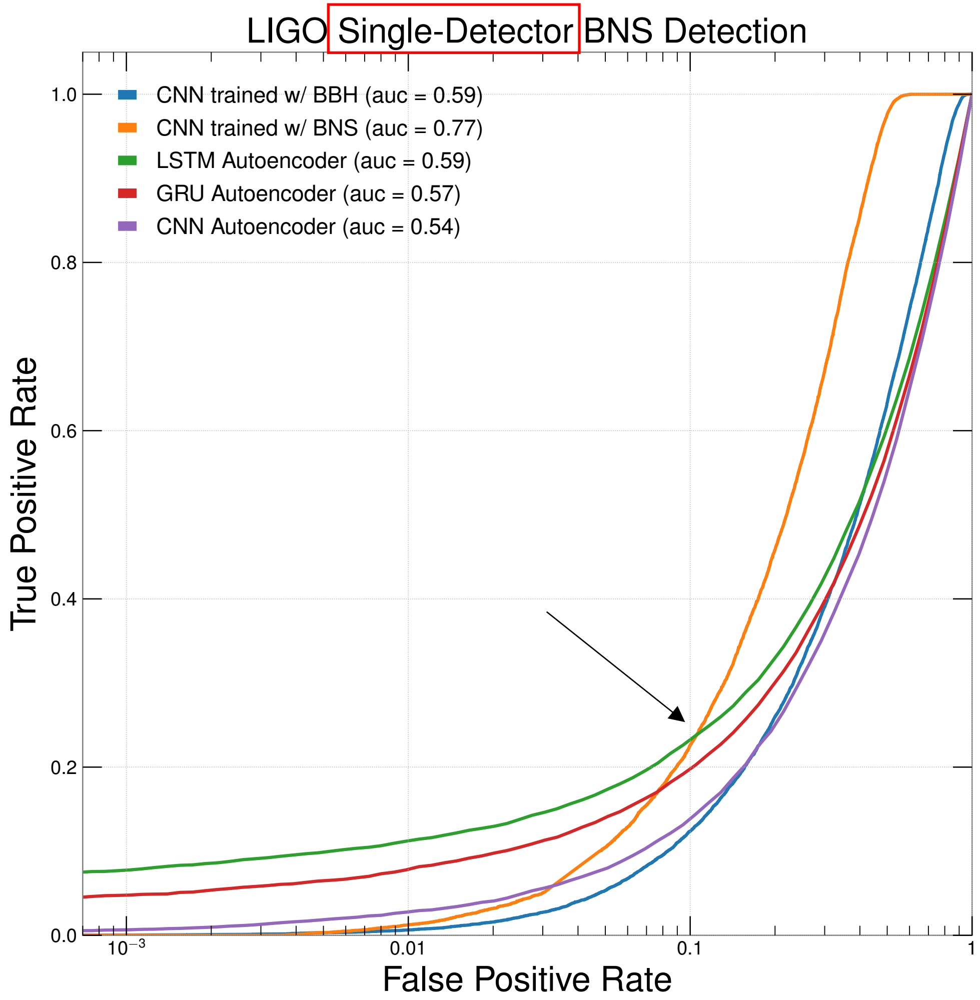
AE can be used for:
- Triggering on high SNR rare events
- Glitch detection within LIGO apparatus
    - Glitches are hard to simulate and more easily identifiable with AE



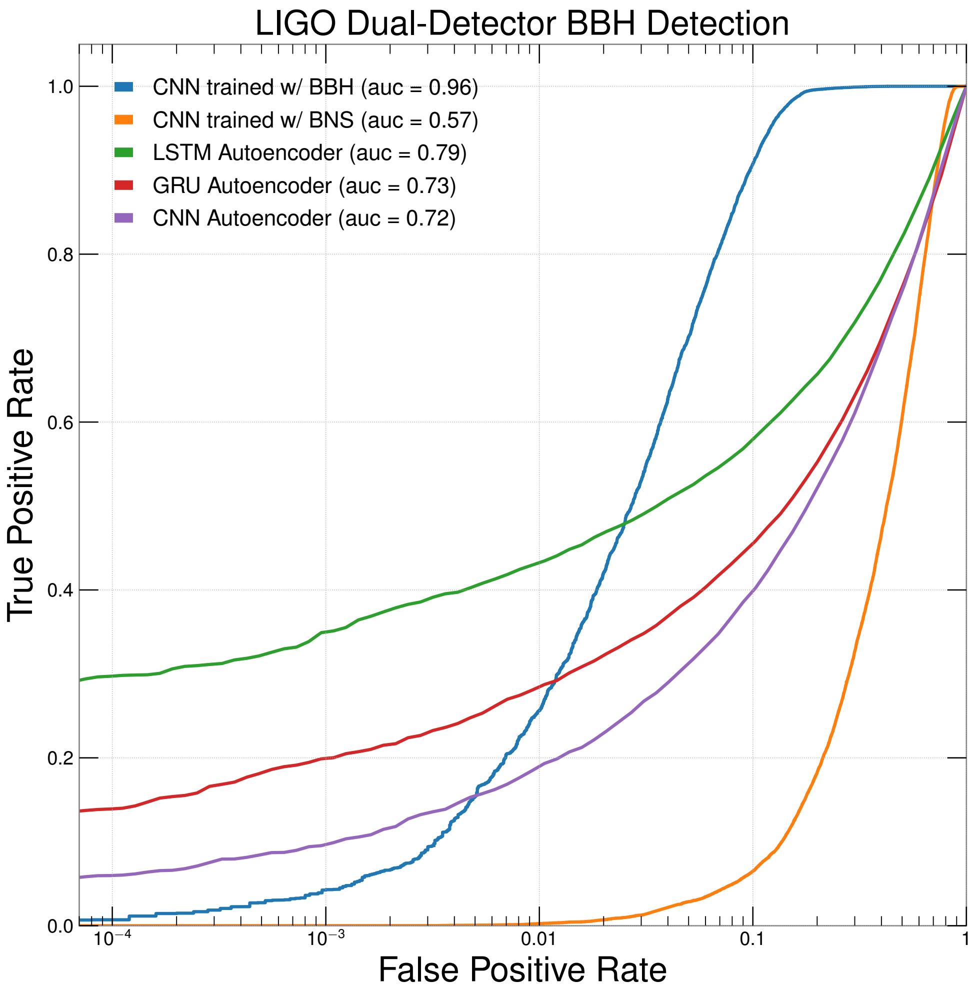
Supervised vs Unsupervised BNS

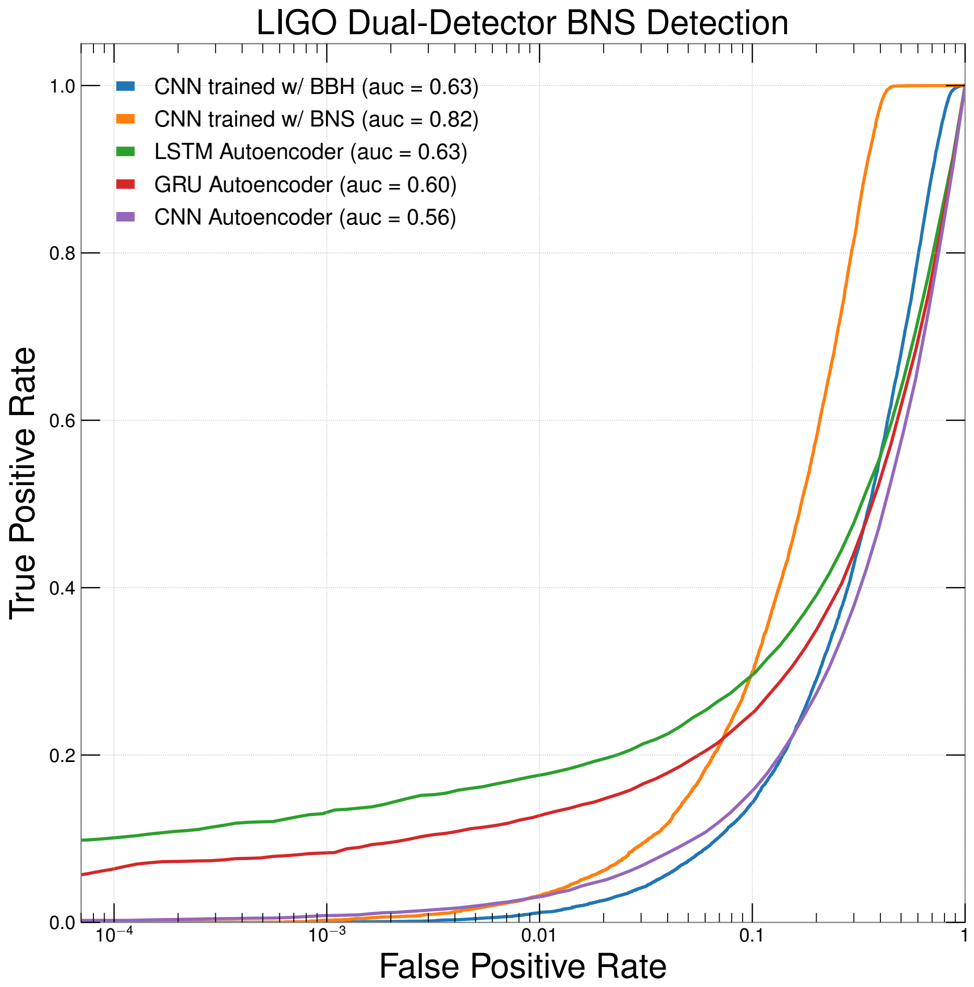
https://arxiv.org/abs/2107.12698

- BNS generated from IMRPhenomDNRTidal_v2 Approximant
- BNS are lower mass (1.1–2.1 solar masses) than black holes and produce lower amplitude (and higher frequency) signatures
- Generalization performance stagnates for both models meaning that they are extracting the same amount of signal from events
- **Outperforms supervised methods (trained on equivalent length data) at below FPR = 0.1**

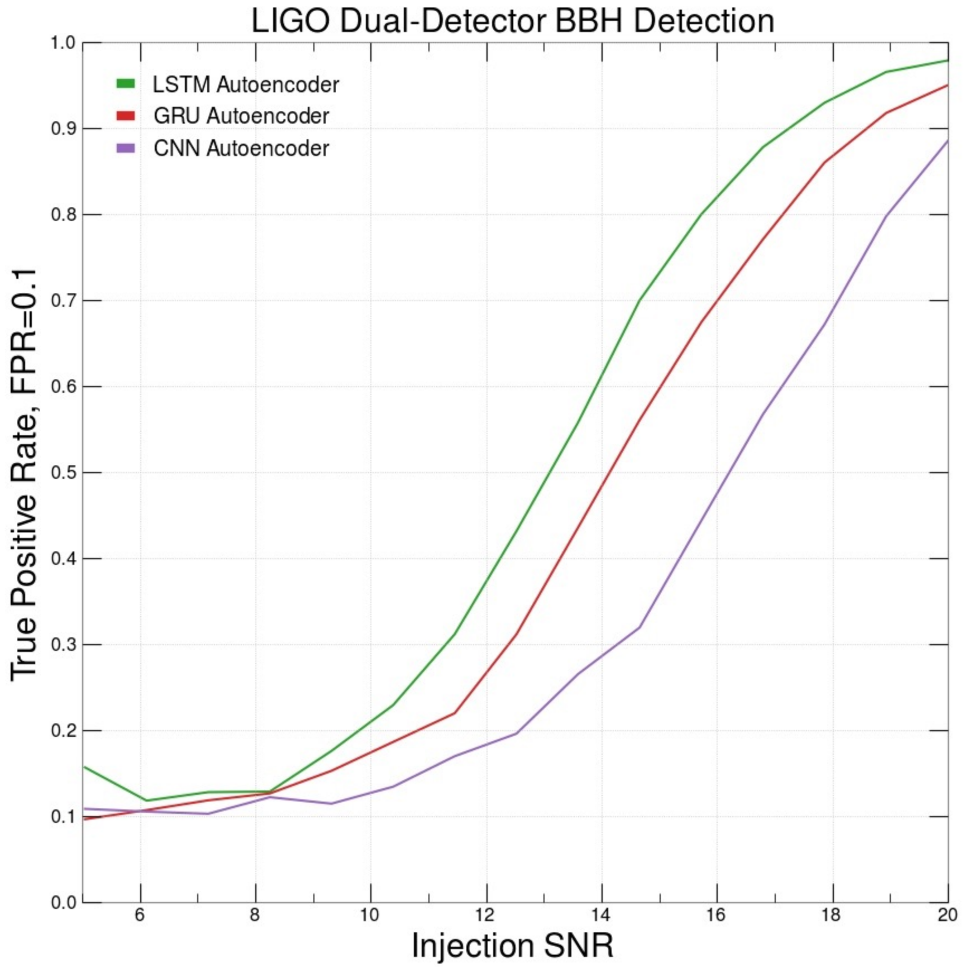


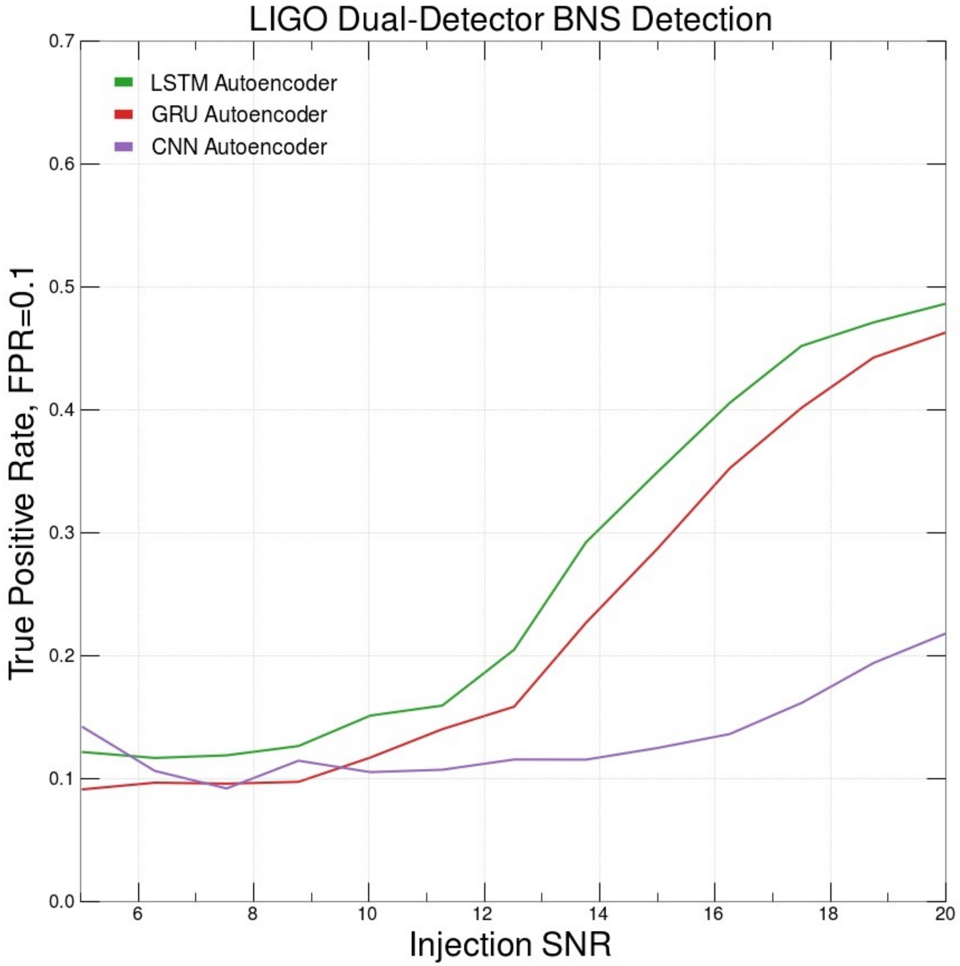
Exploiting Dual-Detector Coincidence





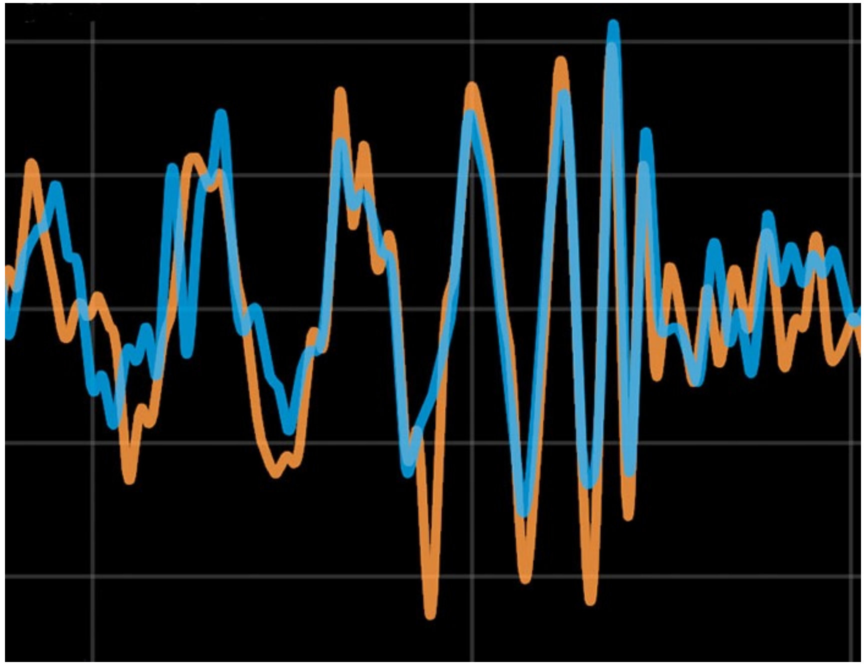
Dependence on SNR





Summary - Recurrent-AE

- We have **developed a recurrent unsupervised anomaly detection learning method to detect GWs** (or other anomalies) in LIGO detector [2107.12698]
  - Builds on CNN-AE methods [2103.07688], providing an upgraded performance
- This source-agnostic method **generalizes better to exotic events than supervised learners**
- Source-agnostic method trained on same length of data **outperforms supervised methods at low FPRs**
- Squares FPR at TPR working-point for each additional LIGO detector built
- Optimization for real-detector conditions is ongoing (but demonstrates similar performance to simulated LIGO data)
- Beyond scope of this talk: the **algorithm has been accelerated for real-time use at LIGO** by a team at ICL, CERN [2106.14089]
- Could yield promising discoveries of new GW sources that haven't been sufficiently simulated or are computationally prohibitive (Supernova, Gravitational Bremsstrahlung, etc.)
- Could be used for any number of time-series anomaly detection applications – possibly HEP?
- Next step: **Transformers**!



Thank you for your attention!

Questions?