

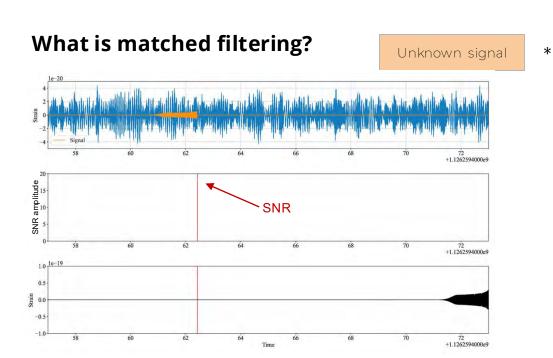


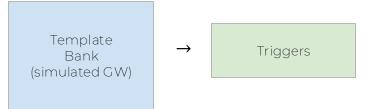
Neural network classifiers for distinguishing signals from instrumental noise

Melissa Lopez ICERM 2025



Modelled searches: matched filtering (MF) for CBC





Idea: unknown signals generate *multiple* triggers. Can we find *patterns* with Machine Learning?

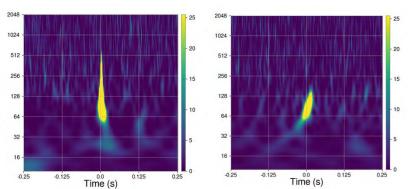


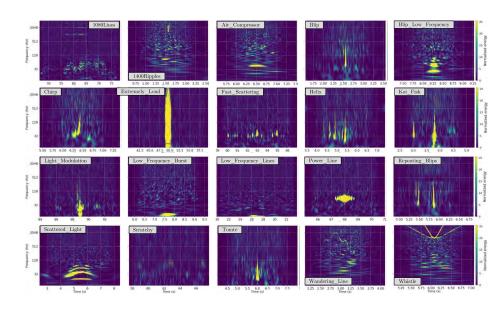
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Transient noise burst (glitches)

- Caused by instruments or environment (known or unknown)
- Diminish scientific data available
- Hinder GW detection (mask and/or mimic)





Example of a blip glitch (left) and a intermediate-mass black hole (right)

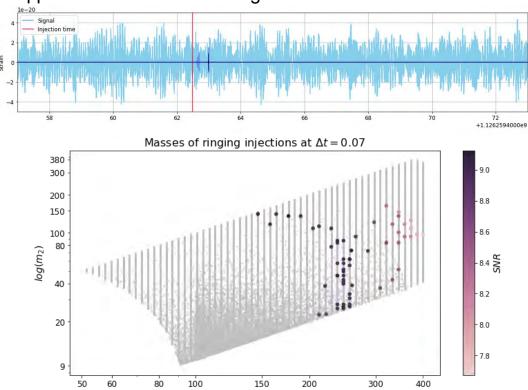


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A simulated GW through a detection pipeline

 Δt : time when trigger happened – time when GW signal was added to the noise



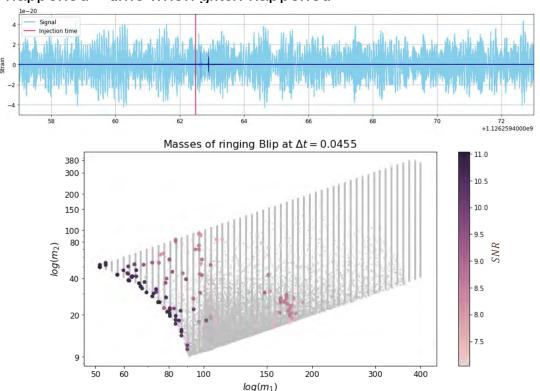


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A glitch through a detection pipeline

 Δt : time when trigger happened – time when glitch happened



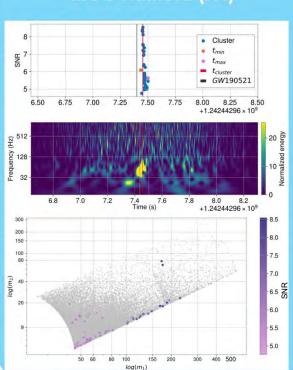


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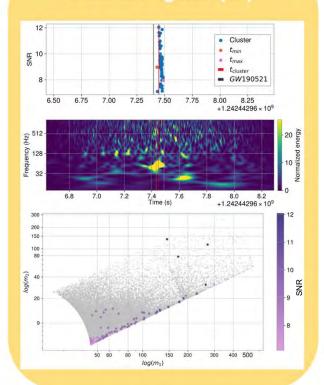


GW190521

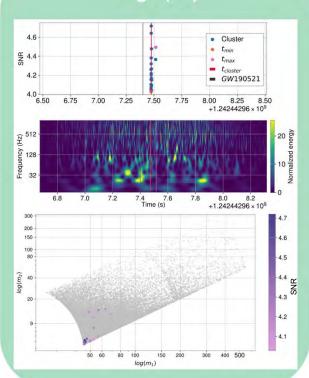
LIGO Hanford (H1)



LIGO Livingston (L1)



Virgo (V1)





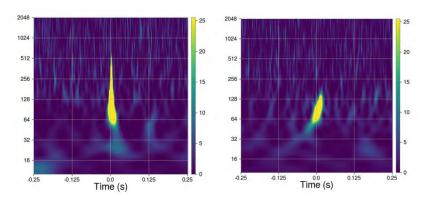
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Motivation

Context: intermediate-mass black holes (IMBH) are the missing link between stellar black holes and supermassive black holes, but they are hard to detect!

Idea: use triggers from matched filtering (free information) from detection algorithms to learn the background (glitches) and foreground (GW signals) with ML



Example of a blip glitch (left) and a IMBH (right)

- MF searches use *strict* conditions for detection.
- Can we relax the search with the interpolation ability of ML?



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Multi-class classification demo

Demo data from PhysRevD.111.103020 - arXiv 2412.17169

Task: Distinguish IMBH from different glitch classes in single detector → we have 3 detectors!

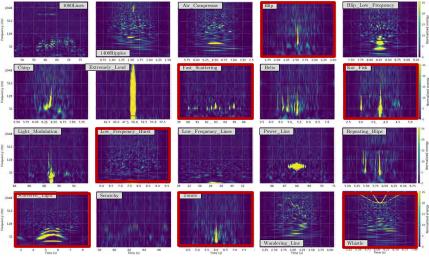
Algorithm: Multi-layer perceptron (MLP)

Input: Adding time is hard, so let's simplify the problem. Each template is defined by $m_1, m_2, s_{1z}, s_{2z}, \chi^2, SNR$. We weight average by SNR to get the feature vector

 $\mu(m_1, m_2, s_{1z}, s_{2z}, \chi^2, SNR)$

Output: class probability





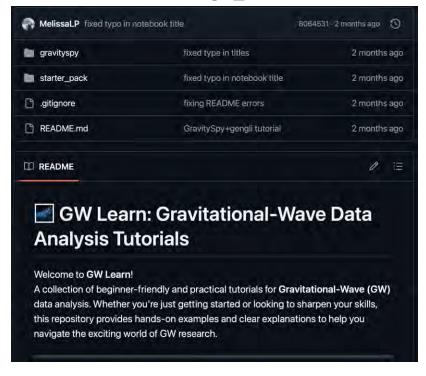
Idea: MLP differentiates **6 classes**: 5 different types of background (glitches) and single foreground (GW signals). It uses only **6 parameters** in **single detector**





About today's tutorial

⚠ Promotion time! gw_learn tutorials



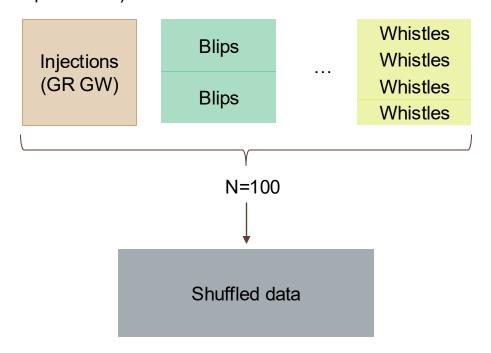
Acess tutorial of today:

https://shorturl.at/vxMH4



Dealing with imbalanced data

1. Accounting for imbalanced data (boostrapping with replacement)





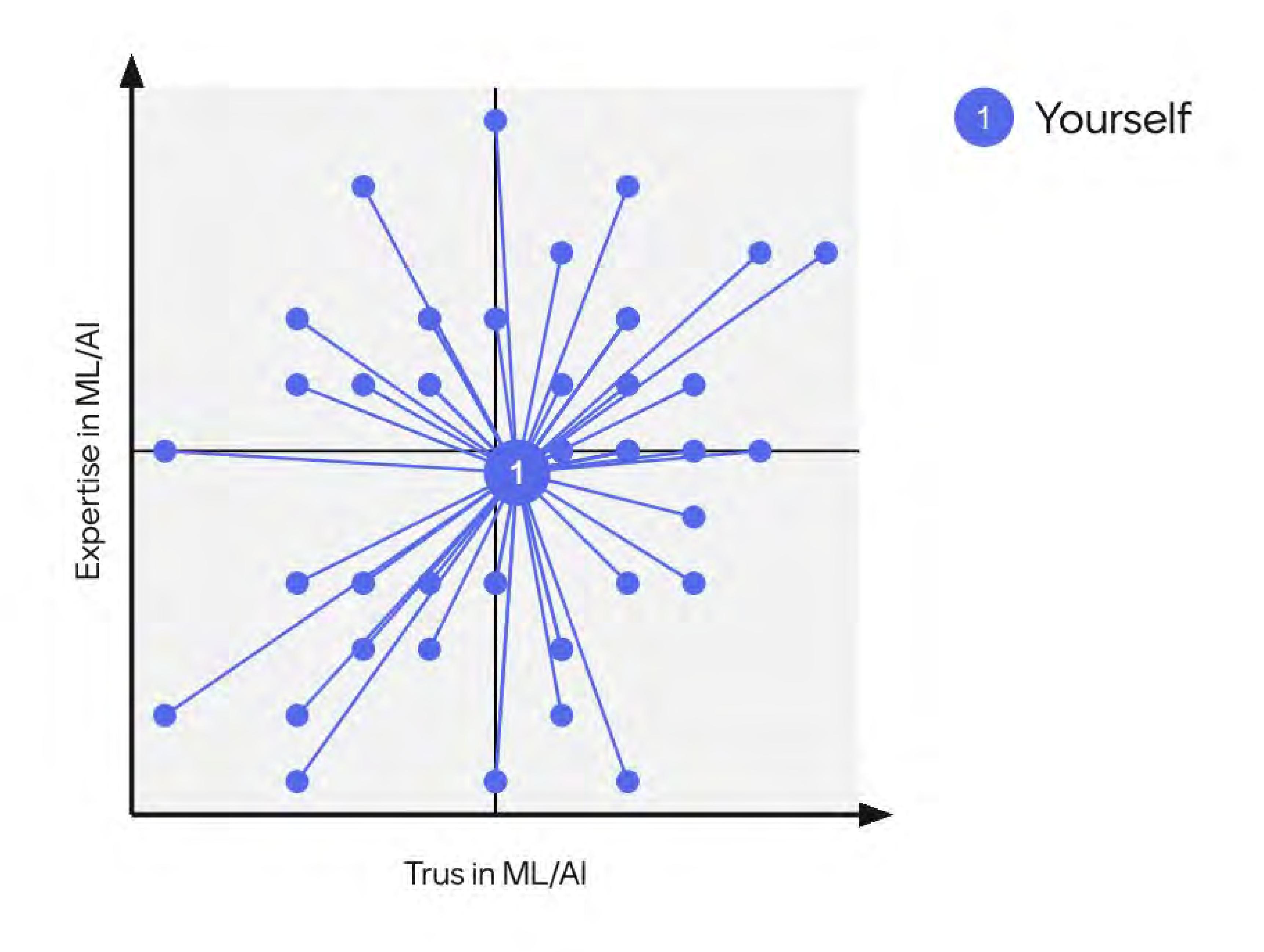
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Access the tutorial: https://shorturl.at/vxMH4



Where do you stand with ML/AI?







Exercise 1: What is bootstrapping and why is it important?

This is a trick question ---E. T. Jaynes dixit I'm not sure — I'm a physicist and I've ever heard of bootstrapping. Is it like dimensionality reduction or some kind of data compression technique?

Resampling

Computing uncertainties when you don't know what else to do

resampling

A way to estimate the unknown sampling/data distribution using the current data to derive estimators for target (usually Frequentist) statistics.

When you want to report uncertainties but don't have the ability/compute/will to draw additional samples from the distribution of interest.

I think it's important for uncertainty quantification





Exercise 1: What is bootstrapping and why is it important?

Getting data is hard how can we maximize what we have? to generate more data and reduce potential risk of biases Adding: Bootstrapping cannot fix out-of-distribution problems, since it assumes the unknown target distribution and the current distribution are drawn from the same underlying sampling process.

Generate new data points conforming to certain fiducial statistical properties

to increase ML accuracy at lower FARs

Low cost generation of samples whose statistical properties remain faithful to the underlying process one is trying to sample from.

When more data is created by using previous data. It is useful if the data you have is not enough for proper analysis, and it's not feasible to get more data using standard methods.

Bootstrapping is a statistical resampling method where samples are drawn with replacement from the original dataset. It's important because it allows us to estimate the uncertainty of a model.

ChatGPT



- Who

Exercise 2: What are the main problems with this network?

Too shallow

Not wide enough

too small.

Data are not normalized

It's very small — it only has two layers. Maybe include more layers and also include a variable learning rate, as well as dropout. Maybe it's overfitting? I noticed the accuracy goes up only to .75.

Input data not scaled appropriately

Neural network architecture is a "prior" over the structure you expect in your data. MLP assumes just a general curve, and with few parameters/layers the functions are probably too simple.

Change the activation to RELU may better performance.



Exercise 2: What are the main problems with this network?

6x more glitch examples than signal examples

relu better for training than tanh Significant confusion between injections and low frequency burst. Probably needs to lower frequency high pass while simulating injection samples?

Swish is evenbetter than ReLU

maybe its small

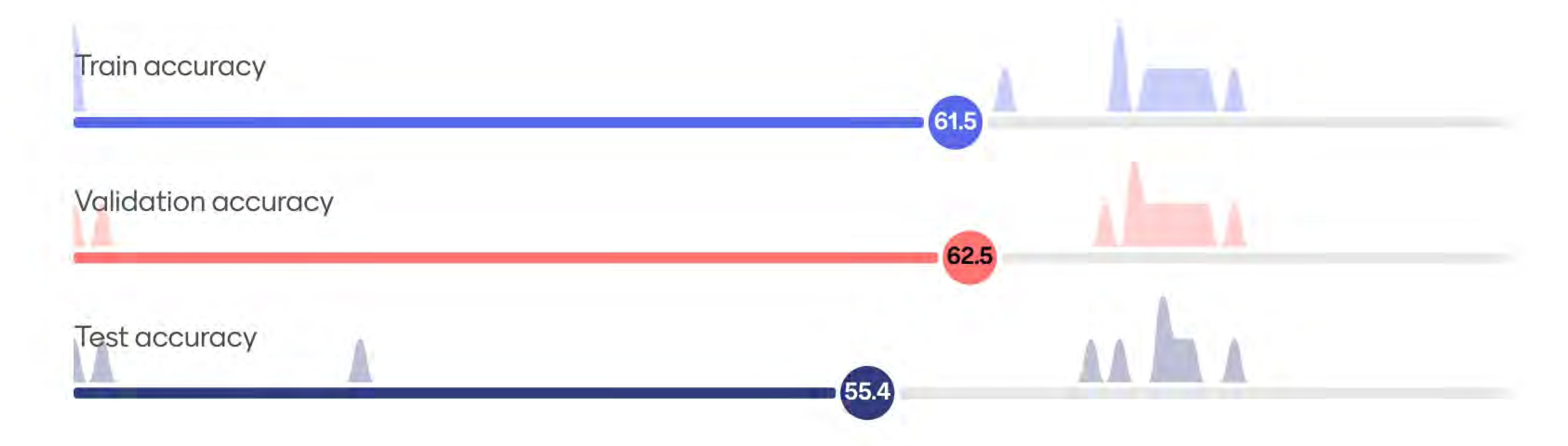
Just keep running can improve

ML is trial and error





Exercise 3: How much did your network improve?



0 10



This is the end of the tutorial! What did you learn?

great tutorial the architecture for mlps

ml is trial and error mlp swish Selu marchitecture is imp

tuning ml is painful useful tricks

hourglass architecture

work with many classes applied ml in gw

activation functions





D1: Sofia Alvarez-Lopez

S1:Rodrigo Tenorio

D2: Mervyn Chan

S2: Andrew Miller

D3: Sidd Soni

S3: Collin Capano

D4: Chayan Chatterjee

S4: John Veitch

Access to the solutions: https://shorturl.at/OVfMw

Senior group chairs

Why do we need ML in GW physics

Hamiltonian dynamics of binary black hole systems!

What is the best data representation for doing ML detchar

How to make GW searches interpretable? (aka how do you make it define a consistent FAR)

Is uncertainty quantification necessary or relevant for ML models used in GW physics?

potential solutions for glitch removal in 3G detectors' era Critically evaluating where ML can uniquely improve GW detection vs. improved implementations/understan ding of 'classical' techniques

Are there ways to get around the Black Box issue?





ML in the context of waveform modelling

Neural ODEs and PINNs in GWs?

What does detection mean for overlapping signals?

Relationship between glitch identifications and PE.

Downsteam implication (astrophysics / test GR / etc) of erroneous glitch identification / data cleaning

How do we trust ML outputs for detchar applications?

ML workflow for overlapping signals

Ways to understand what exactly is happening in the layers of a neural net to learn about novel hidden structures in the data

How can we do background estimation in a foreground of tons of long-lived GW signals?





Matched filter is the "optimal statistic". Can we quantify how much more we can (theoretically) learn by employing ML methods?

using ML for unmodeled searches or parts of parameter space where we don't have templates in traditional searches Do we need global fit for next 3G GW detection

Improved CBC classification methods

a complete ml pipeline vs a traditional pipeline with ml replacing one step in the middle. Is there a balance to be achieved? Detecting and doing PE of events which are contaminated with glitches using ML

ML in the context of waveform modelling

Do we actually need to remove glitches in 3G (signal very long, who cares if there's a small glitch on top)





how much extra volume improvement can ML bring to the table? Is there a particular region in the search parameter space where ML has a unique advantage?

How do we trust ML outputs for detchar applications?

PINNs in GW

Ways to improve ml training for detchar purposes.

Application of Transformer in GW search

Ways to improve ml training for detchar purposes.

can ML do unmodeled GW searches? How do we know whether ML is giving us the correct waveform or not for very complicated systems like BBHs in eccentric precessing orbits?





Incorporating diagnostic data channels from GW detectors in searches directly by assimiliating them using ML stages, and using that to discriminate signals from noise transients invariantly

How to design a search pipeline around ML in practice?

Calibration uncertainty reduction using ML

At which SNR levels will template-banks-based methods become too computationally expensive? Will they at all?

How would we actually verify a detection of an unmodeled signal by a ML algorithm?

What can traditional searches learn from ML?

Is an end to end joint model for noise transients and astrophysical sources feasible with ML?

how often does the distribution of noise change during the run roughly? Or how often do ML models need to be trained/recalibrated during the obs run?





ML for unmodelled/unknown signals

