Ideas for discussions

- **Does everyone understand the question?**
- **What other areas of GWs/science does this question relate to?**
- **What are the challenges to implementing a related data analysis pipeline?**
- **What types of expertise are needed to answer this question?**
- **How does the answer to this question change in 10 years?**

Detchar Topics

1. **What types of new information can ML provide us about glitch populations?**
    - What kinds of ML models could we use, and how would we know a glitch is "new" and/or problematic for analyses?
2. **How can machine learning help us understand where glitches come from?**
    - Can we design explainability tools linking glitches to their physical sources?
3. **How can we better account for "realistic data" in other ML pipelines?**
    - Are there tests we can run to see how noise patterns influence ML predictions?
4. **What additional information from GW observatories can ML use to improve searches?**
    - What if we included auxiliary data?

Search Topics

1. **How do we extend the ML successes with high mass CBCs to other types of signals? (e.g., early warning, GRB follow up, non-GR)**
    - How can we guarantee the robustness and reliability needed for multi-messenger?
2. **How can we build confidence in a detection that is claimed by a ML pipeline but not traditional pipelines?**
    - How do we make sure we can trust and explain their decisions?
3. **How can traditional detection methods benefit from ML?**
    - For example, can ML inform us about the background of glitches?

Additional Topics

-

Short link: https://shorturl.at/BIil6

Group chairs:

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

Extending ML-based searches

How do we extend the ML successes with high mass CBCs to other types of signals? (e.g., early warning, GRB follow up, non-GR)

1. **Why does ML work better at high mass?**
    a. AFRAME effectively being coherent search works better for CBCs with compact objects above 35 msun
    b. This search could ideally be extended to lower masses however training on long-duration signals could be expensive
2. **Why is it hard to make a ML-based search that is fully coherent?**
    a. Data transfer issues?
    b. High-dimensional space is required for the training → difficult to train
3. **What kind of source could one search using ML?**
    a. Precessing
    b. Eccentric
    c. Non-GR waveforms
4. **Where ML could be used?**
    a. **Augmentation**- Modifying the template bank for Eccentric precessing sources such that we train the search space where template banks go large and signal loss is more

Focused mostly on ML as a detection algorithm:

1. What kinds of tests could we do to prove ML is working / substantiate a detection?
    a. Comparisons with Bayesian inference – do
2. How could we show that ML can deal with time-dependent noise?
    a. If we don't know how the noise is changing, what do we do?
        i. Is the detection significance just getting worse or is the noise changing?
        ii. Retrain model?
    b. Injections most promising way, but only for modelled source
3. How do we find new things but "trust" it for old cases?
    a. Does the model extend to new datasets?
    b. But not too far..
    c. Will be more important in LISA b/c harder to distinguish models

We devised a list of tests that can be performed to prove that ML is not working

1. Give it crap, prediction says it's really different
    a. Give it a CW when trained on CBC
    b. How to set the criteria for "different"
        Injections, Give purely synthetic, and real one, to cover all bases
        Domains of validity
2. If noise is changing , what tests?
    a. Visualization of latent space structure (linear replacements, autoencoders, and check the principle components and check if noise and signal are in different parts of the latent space)
    b. Response: But could just have whitened data
        i. but might learn simple strategies, woul fail if non gaussian noise
4. Criteria for training
    a. Train on different types of noise
5. Diversify the training data
    a. But at what point does the network become too big, unrealistic, etc.
6. Replace complicated models with simple ones (e.g. symbolic regression)
    a. Do you trust analytic one more?
        Doesn't give you more physical meaning
7. Limiting cases
    a. Overfitting for strong signals, see nothing for weak ones

8. Robustness in high dimensions
    a. Magic noise patterns, shift it ever so slightly so that the image ends up in a different noise class
    b. What changes could one make to data to decrease detection probability?
9. Global fit? Signal/noise interpretation simultaneously
10. Look at other fields' / industry criteria
    a. Validity checks,
11. Quantify false alarm rate
    a. Adding magic noise
    b. Do dropout tests: train different realizations of NNs on data, see what you get

PINNs:

Case study: ML to reproduce Hamiltonian

If PINs can arrive at physics it wasn't constrained to follow
Can check consistency of output with PINs

ML component of analysis

Placement of ML in analyses:
What is more trustworthy? Enhanced or independent?

<u>**Conclusions**</u>

Criteria to confirm detection will be case- and algorithm- dependent, hard to establish universal criteria

Lack of "trust" also appeared in ATLAS and probably others 20 years ago – politics?

Group - 5 (Leads - Chayan, Sofia)

Members - Jeff Riley, Bhaskar Verma, Filippo Santoliquido, Melissa Lopez, Derek Davis

Initial discussion:

- Discussion on glitch sources - how can we characterize them? We have analytical waveforms for few types of glitches.
- Why do we care about glitches at all? Why don't we subtract them? - Effects PE.
- How to subtract glitches in 3G detectors?
- Current tools to remove glitches - BayesWave, DetChar event validation, environmental sensors.

What other areas of GWs/science does this question relate to?

- All of them! Understanding glitch populations, where they come from, and subtracting them from signals impacts PE searches, which can also impact, e.g., astro population analyses.
- We don't know all glitches out there, similar to we don't know how many GW formation channels are there?

What types of new information can ML provide us about glitch populations?

- Melissa - low dimensional space using AE +TSNE to identify structure in glitches.
- Need knowledge of detectors
- Q-transforms work generically because you have a fixed number of cycles per frequency.
- Use time series data for glitch classification rather than Q-transforms? Can ML models pick something in the timeseries data that isn't visible in images?
- Automate event validation using AI.
- Landscape of ML has changed a lot recently; is it time to migrate from image-based approaches?
    - Fine-tune open source models?
    - Glitch template banks?
    - Self-supervised learning?
- Anomaly detection to single-day data. Can use to know if there's something new → Anomaly within the anomaly.

- **Backbone:** Learn strain data, and have small modules for glitches, etc.
    - Imbalanced data sets.
    - Derek - how would the foundational model be able to detect anomalies (within anomalies)?

- Synergy between detcharians and instrumentalists.

What additional information from the detectors do we need to make our ML approaches better?

- Most of the data from auxiliary channels unexplored. Mine data from these channels?
- Most of our approaches assume linearity between the witness channel and the accelerometers. We can do pretty well in coincidences with glitches, but is that witness good enough to actually have fully linear correlations?
- Data issues – we don't have all the information.
- We need to understand these to be able to tackle them in 3G. Cost of sensors to address issues is huge.

Conclusions:

- Current landscape of Detchar work: what problems are out there? E.g., why do we care about glitches at all, Where do glitches come from, how can we characterize them, how do we subtract them, which current tools are out there to detect them/subtract them, what's their impact on GW science?
- **What types of new information can ML provide us about glitch populations?**
    - To identify populations of glitches: embedding, low-dimensional representation of glitch representation (use t-SNE, UMAP).
    - What data representation do we use to analyze glitches? Mostly Q-transforms to visualize glitches. But are they *still* ideal ? (E.g., effect of Q-value and evolving glitches with time).
    - Maybe use time series instead? Open source – trained on a lot of data (e.g., Whisper can convert to log-mel spectrograms).
        - Newer representations can be useful.
        - Have already proven to be really good in the audio domain.
        - Self-supervised and unsupervised learning: we cannot rely on labeled data since it evolves with time.
        - Anomaly detection (but actually, anomaly *of* anomaly).
    - Knowledge of the instruments themselves: non-linear coupling between accelerometers and witness
- **What additional information from the detectors do we need to make our ML approaches better?**
-
- **How does the answer to this question change in ten years?**
    - Automation of event validation.
    -

Q. Can ML filters be better than the optimal-linear MF filter? Can ML searches be better than MF-based searches?

Beating MF

1. Time saving / latency
2. Costly and large template banks
3. Sensitivity
    a. Linearity?
    b. Known Template?
    c. ML Training data
4. Noise Model
    a. Glitches
    b. Non-Gaussianity
    c. Overlapping signals → problem for the future
    d. PDF
    e. Non-stationarity
5. New physics
6. Auxiliary info for glitches
7. Precessing searches
    a. Will a template bank be much larger? 100x or more?
    b.

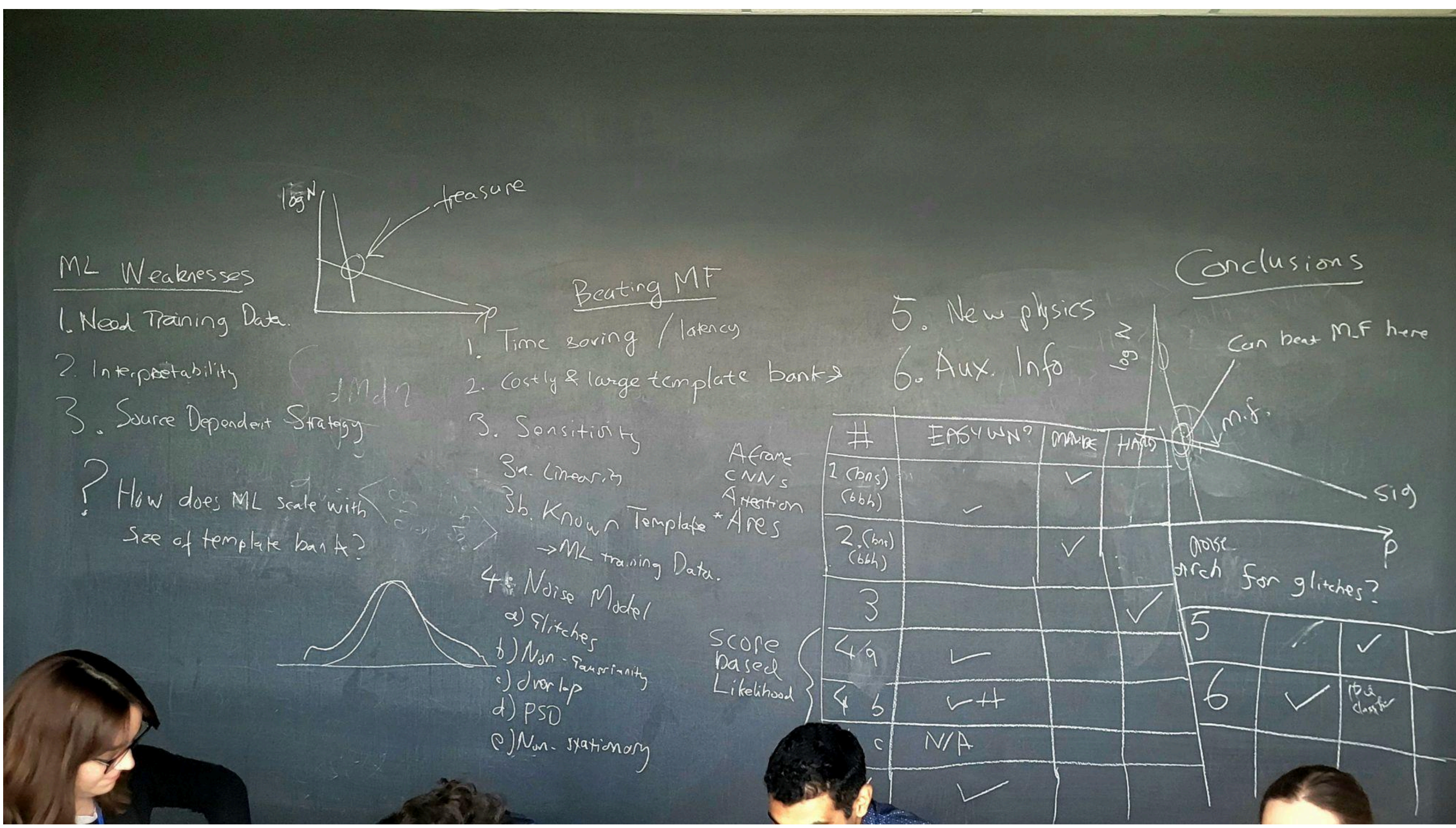
ML Weaknesses

1. Need training data
2. Interpretability
3. Source dependent strategy
4. How does ML scale with the size of template bank?

Conclusions

1. Classify discussion points under “Beating MF” on how easy each is to achieve in practice:

#	Easy Win?	Maybe?	HARD
1. (bns, bbh)	Yes (bbh)	Yes (bns)	
2. (bns, bbh)		yes	
3.			yes
4a.	yes		
4b.	yes		
4c.	N/A		
4d, 4e	yes		
5.		yes	
6.	yes	?	



AI summary by zoom on next page

(Vaishak: whatever my mic could pick up)

Quick recap

The meeting focused on challenges and potential solutions in signal processing and data analysis, with a particular emphasis on using machine learning techniques to improve efficiency and accuracy. Discussions covered topics such as modeling noise and signal distributions, handling glitches, improving search algorithms, and addressing latency issues in various applications. The team explored the trade-offs between different approaches and considered potential areas for improvement, while also acknowledging the limitations and computational requirements of implementing machine learning solutions across different systems.

Next steps

- Search team to investigate machine learning approaches for improving latency and overall cost in BNS searches.
- Search team to explore machine learning techniques for template bank compression and interpolation.
- Noise modeling team to develop and test machine learning methods for glitch classification and removal.
- Search team to investigate incorporating auxiliary channel information into machine learning search algorithms.
- Team to evaluate the potential of score-based likelihood methods for non-Gaussian noise modeling.
- Team to explore machine learning approaches for handling non-stationary noise and PSD variations.
- Team to investigate machine learning techniques for detecting eccentric and precessing systems.

Summary

Modeling Noise and Signal Distributions

We discussed the challenges of modeling noise and signal distributions, emphasizing the need to distinguish between glitches (outliers) and the underlying statistical distribution caused by instrument fundamentals. He suggested building a statistical model specifically for glitches and using machine learning to handle the complexity, noting that while traditional methods might require assumptions about signal characteristics, machine learning could learn from data without such preconceptions. We also touched on the potential issue of non-stationary signals over long durations and the need to consider day-night variations, while highlighting the accuracy of variance measurements over short data segments.

Machine Learning System Weaknesses

The team discussed how machine learning could address various identified weaknesses in their system. They considered whether these issues were solvable with ML, already attempted elsewhere, or just theoretical. We suggested they should evaluate if certain costs could be amortized offline, and noted a general challenge in ML of data exhaustion for specific tasks. The conversation ended with a plan to have a separate discussion about weaknesses in ML.

Glitch Detection in Data Analysis

We discussed the challenges and opportunities in dealing with glitches in data analysis, focusing on the need to identify and handle glitches effectively to improve signal detection. He emphasized that machine learning could be valuable in dealing with glitches, particularly in areas where traditional methods are less effective. We also highlighted the importance of auxiliary information in identifying glitches and suggested building a search for glitches to reduce background noise. He concluded that the most significant gains in improving sensitivity could be made in specific regions of parameter space where glitches are most problematic.

Search Algorithm Optimization Strategies

The team discussed search algorithms and signal detection, focusing on the trade-offs between including high-mode signals and increased noise triggers. They explored the possibility of using machine learning to marginalize parameters and improve efficiency, though concerns were raised about the computational requirements and template construction. The group identified potential "easy wins" for latency improvements and cost reductions, particularly in low-latency pipelines, while acknowledging that certain applications like PNS searches would be more challenging.

GPU Latency and Efficiency Challenges

We discussed the challenges and potential solutions for improving latency and efficiency in GPU-based systems, particularly for BNS and search applications. He noted that while there are innovations in encoding and data production, the difficulty lies mainly with the encoder. We also mentioned that ML search for BNS is already well-known, but the specific application in this context is still uncertain. He expressed doubt about the feasibility of implementing this across all PBA systems, highlighting that it might be brand-specific and require significant processing cycles.

ML Model Scaling Challenges Discussed

We discussed the challenges and potential solutions for scaling machine learning models in template generation and application, particularly in the context of signal processing and data analysis. He highlighted the trade-offs between sensitivity and coverage in training models and suggested exploring techniques like transfer learning to improve performance. We also noted the need to balance the complexity of templates and the computational resources required for training and using them effectively.

Signal Analysis: ML vs Traditional Methods

The team discussed various aspects of machine learning and signal processing, focusing on comparing different approaches to signal analysis. We emphasized the need for fairness in comparisons and highlighted the potential of machine learning methods, expressing optimism about their capabilities. The group also considered the challenges and limitations of different techniques, including match filtering and machine learning models. They concluded by discussing the possibility of using auxiliary information in signal processing and agreed to leave some topics for further exploration by other team members.

Project Review and Algorithm Discussion

We discussed various aspects of a project, including algorithms, examples, and pricing. He mentions reviewing some easy examples and suggests that the group has covered the main points. We indicate that they will likely be brought together in the main room afterwards, and he expresses a need for coffee.