# Machine Learning Applications in Particle Accelerators

Presenter: Yuan Gao

Collider-Accelerator Department (C-AD), BNL

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U.S. DEPARTMENT OF ENERGY

# Outlines

- Bayesian Optimization Applications:
  - LEReC cooling rate optimization;
  - Calibration of IPM monitor;
  - Booster injection optimization;
  - Xopt overview;
- Reinforcement Learning Applications
  - AGS bunch merging;
  - CERN Proton Synchrotron (PS) bunch splitting;
  - Advantage & Limitations;
- Natural Language Processing:
  - Enhancing Electronic Logbooks;
  - Controls Interface for a Virtual Assistant;
- Anomaly Detection
- Future Projects: Polarization Optimization

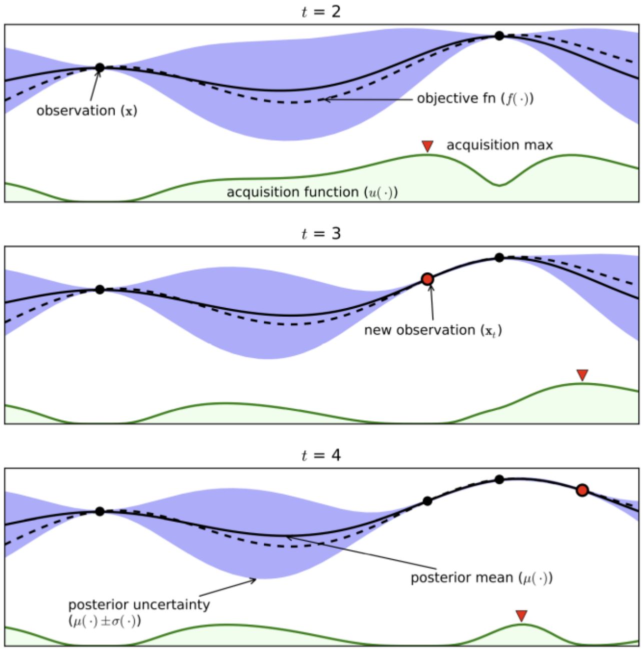
# Bayesian Optimization (BO)

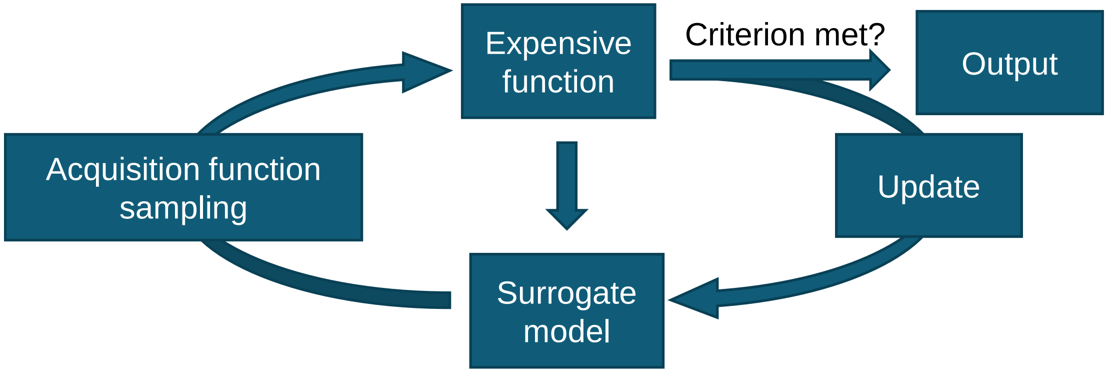
- The goal of BO is to optimize the objective function in the least number of steps; expensive samples;

- Name comes from the famous "Bayes' theorem":

$$P(f|\mathcal{D}_{1:t}) \propto P(\mathcal{D}_{1:t}|f)P(f)$$

- Surrogate model, gaussian process, acquisition function;

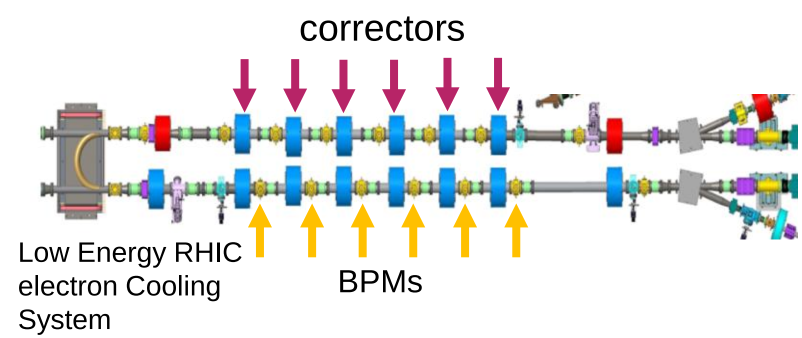


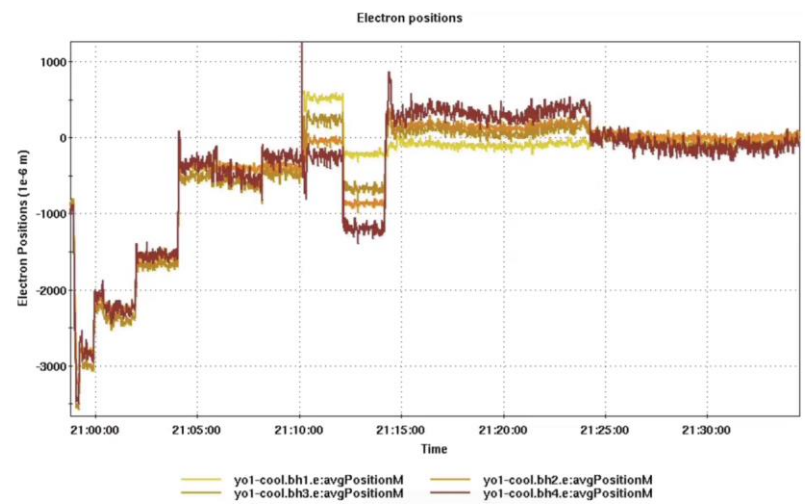

- The acquisition is high where the GP predicts a high objective (exploitation) and where the prediction uncertainty is high (exploration).

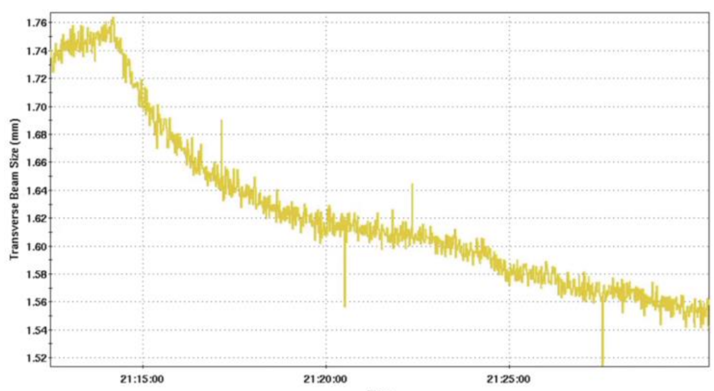
$$\mathrm{UCB}(\mathbf{x}) = \mu(\mathbf{x}) + \kappa\sigma(x)$$

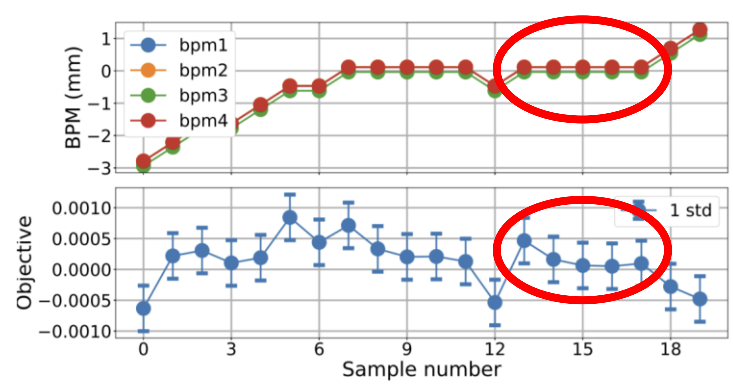
# Optimize LEReC cooling rate




- By steering the electrons in the center position, the ion's cooling rate can be maximized;
- High noise level in the objective;
- In this initial experiment, BO is used to tune electron positions as measured by BPMs; 40 initial samples; converge in 10 steps;



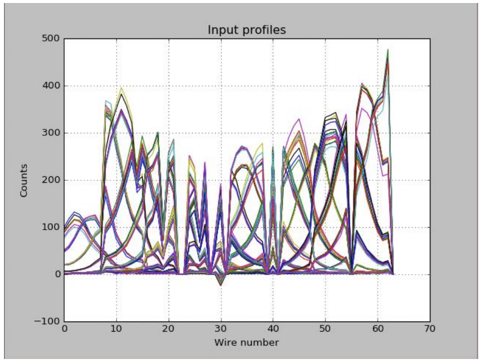



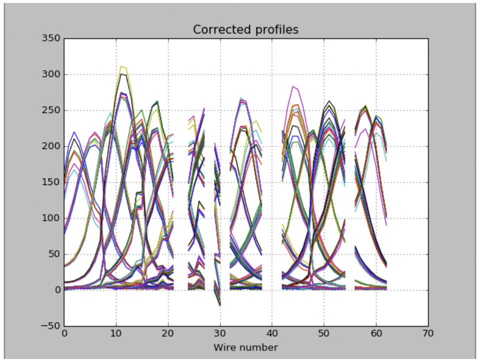



# Calibration of IPM Monitor

- Ionization Profile Monitor (IPM) measures transverse profile of the beam:
  - Circulating beam ionizes residual gas in the beampipe;
  - An electric field forces electrons onto a microchannel plate (MCP);
  - Forms a projection of the beam profile;

- Beam width measurement depends on position because of systematic errors in channel gains:
  - Initial channel-to-channel gain variation;
  - Depletion of channel gains due to aging;
  - Time response of the channel to beam signals;
  - Usually addressed with position scans and offline calibrations;



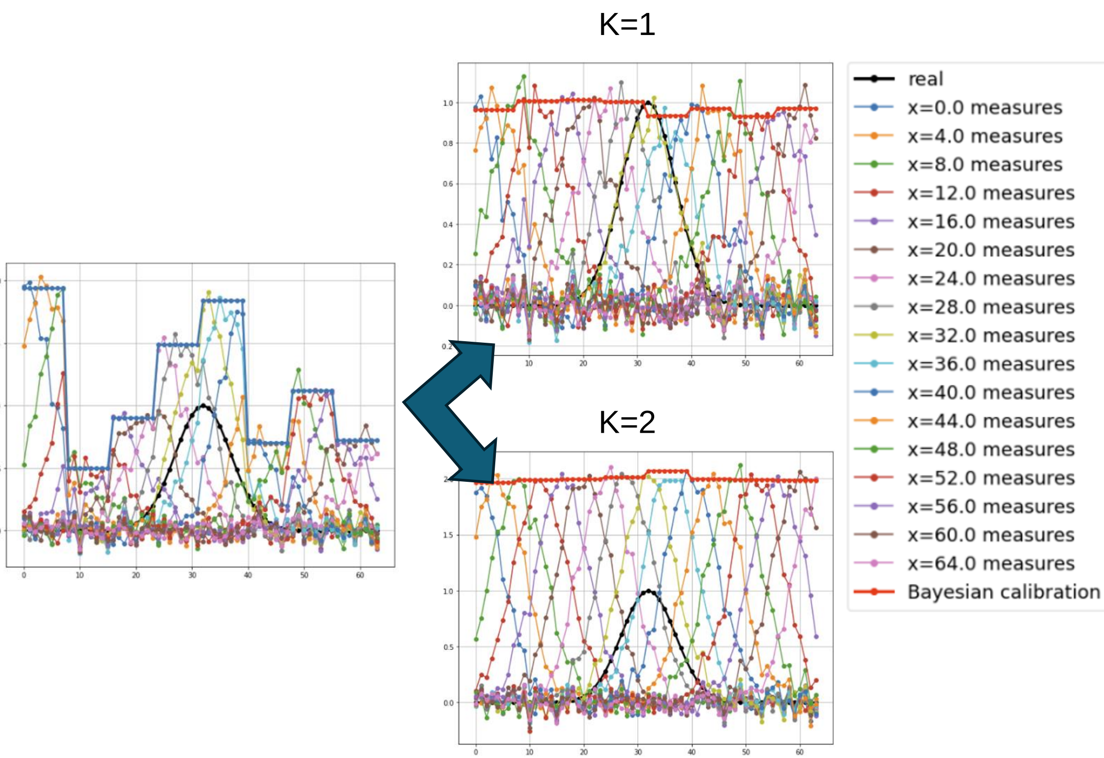



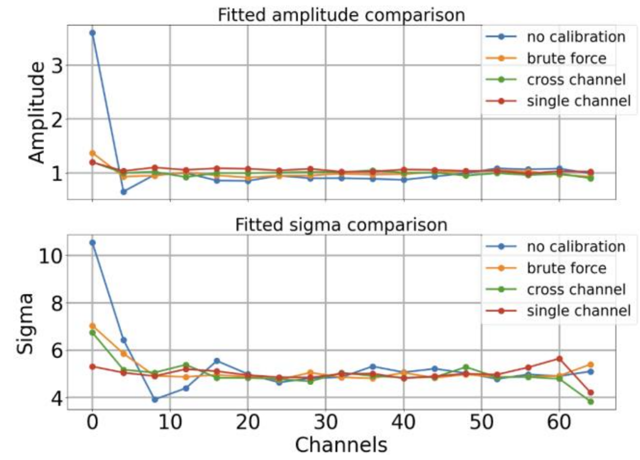

<u>IPM Signal Error Model</u>

$$y_{meas,i} = y_{real,i} \; * \; g_{cal,i} \, g_{err,i} \, F(\tau_{xfr\_delay}, \tau_{channel,i}) + \sigma_{offset,i} + \varepsilon_{noise,i}$$

$y_{meas,i}$ = 'as measured' counts for channel i
$y_{real,i}$ = ground truth signal for channel i
$g_{cal,i}$ = user supplied calibration correction for channel i
$g_{err,i}$ = error in the gain (unknown a priori) for channel i
$F(\tau_{xfr\_delay}, \tau_{channel,i})$ = time response of the channel to beam signal
$\sigma_{offset,i}$ = offset error for channel i
$\varepsilon_{noise}$ = normally distributed noise, same sigma for all channels, sampled for each measurement

# BO Error Corrections



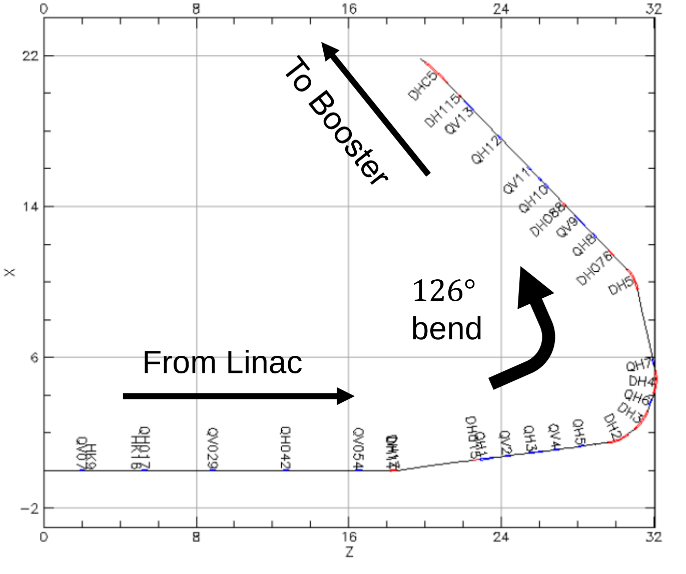




| Method | | Average | std |
|---|---|---|---|
| No calibration | amplitude | 1.09 | 0.63 |
| | sigma | 5.33 | 1.40 |
| Greedy | amplitude | 1.00 | 0.10 |
| | sigma | 5.11 | 0.55 |
| Cross-channel | amplitude | 1.00 | 0.06 |
| | sigma | 4.99 | 0.54 |
| Single-channel | amplitude | 1.06 | **0.04** |
| | sigma | 5.00 | **0.28** |

- Parallelized optimization; Monte-Carlo (MC) q-EI acquisition function;
- The algorithm can correct systematic errors efficiently;

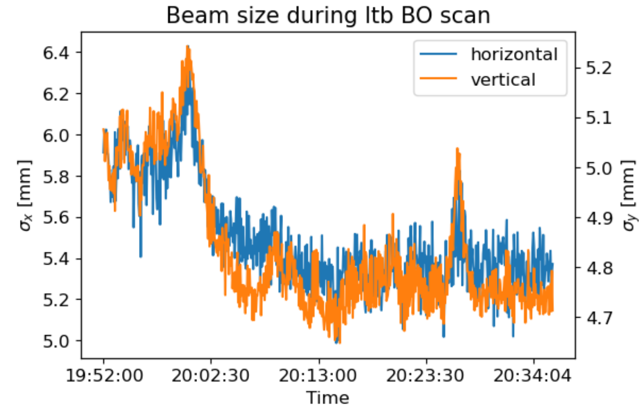
# Booster Injection Optimization*


- Booster injection/early acceleration process sets maximum beam brightness for rest of acceleration though RHIC;
- Linac pulse of 300 us, $H^-$ beam ~6-9x$10^{11}$ protons, strip through a carbon foil;
- Intentional horizontal and vertical scraping reduce emittance (and intensity) to RHIC requirements;
- Goal: minimize beam loss at scraper / maximize beam intensity after scraping
- Controls: Linac to Booster (LtB) transfer line optics
- Method: Bayesian Optimization (BO)



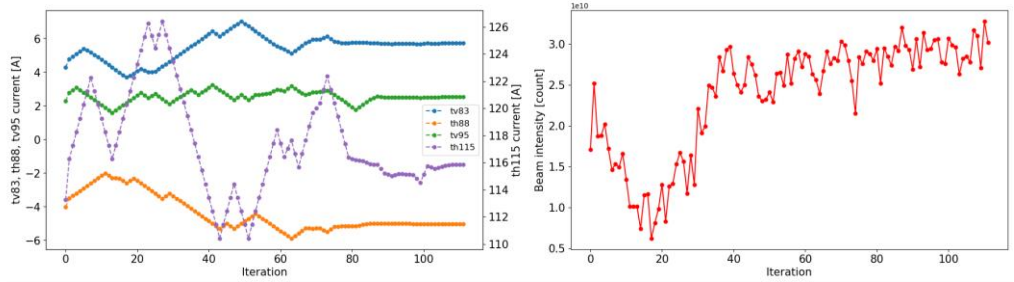

* wl674@cornell.edu

# Booster Injection Optimization

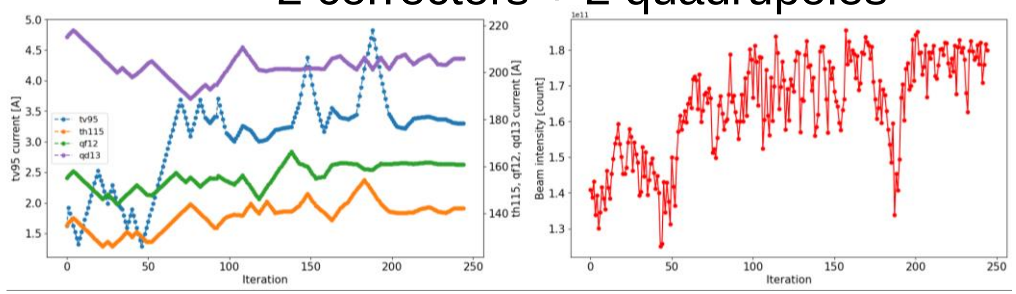



- Controls:
  - 4 correctors; 7pm – 9pm;
  - 2 correctors + 2 quadrupoles; 7pm – 9pm;
- Goal: Maximize beam intensity
- Xopt, Trust Region BO;
- 4 correctors case converges with 120 samples (20-25 min);

4 correctors

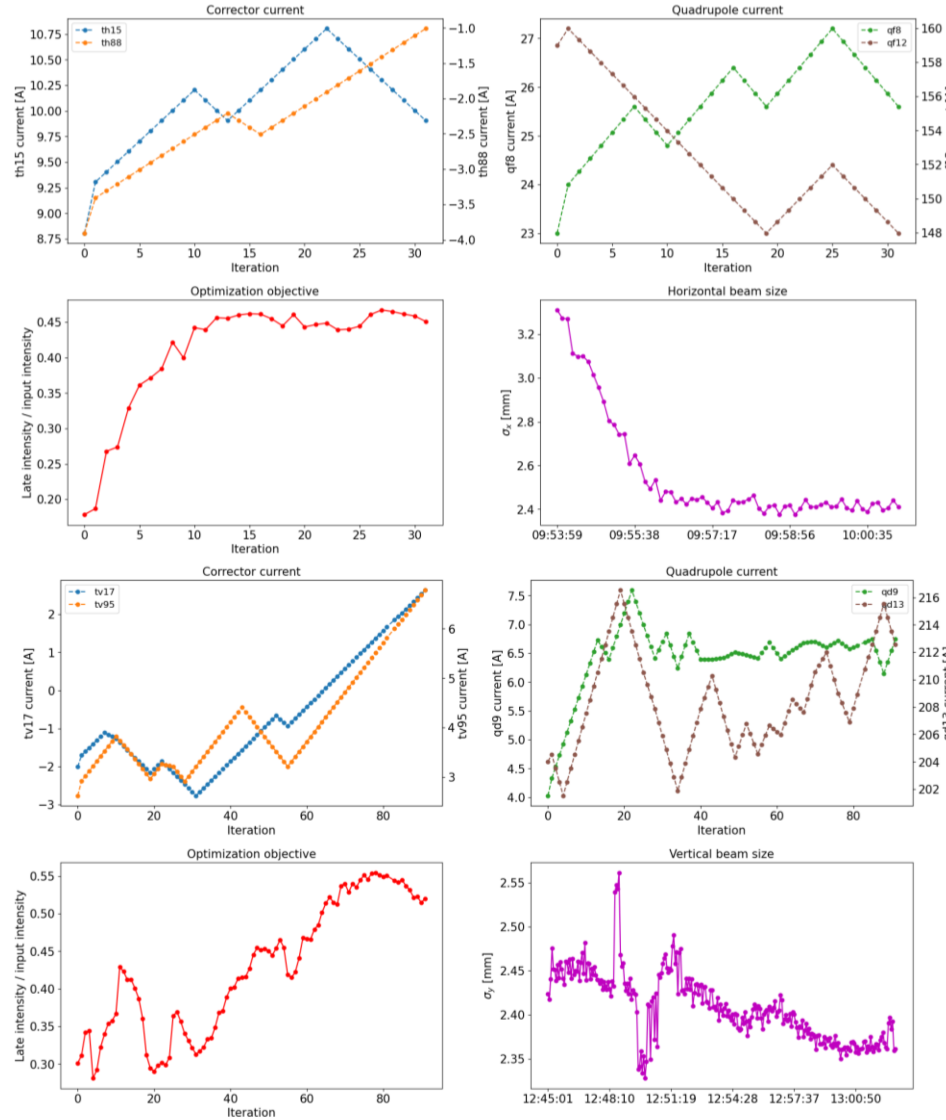



2 correctors + 2 quadrupoles



# Horizontal and Vertical

- Controls:
  - 2 H correctors + 2 H quads; 9:30am – 10am;
  - 2 V correctors + 2 V quads; 12:30pm – 1pm;
- Goals: Maximize Booster late intensity / input intensity
- Degeneracy problem: objective value converges but input values don't;



# Xopt Overview

https://christophermayes.github.io/Xopt/

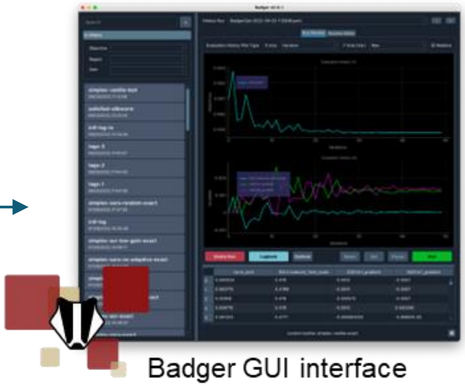
Text input

YAML file

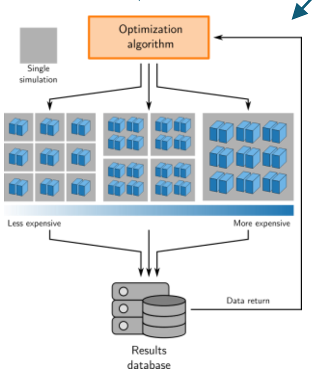
```yaml
xopt:
    max_evaluations: 6400

generator:
    name: cnsga
    population_size: 64
    population_file: test.csv
    output_path: .

evaluator:
    function: xopt.resources.test_functions.tnk.evaluate_TNK
    function_kwargs:
      raise_probability: 0.1

vocs:
    variables:
        x1: [0, 3.14159]
        x2: [0, 3.14159]
    objectives: {y1: MINIMIZE, y2: MINIMIZE}
    constraints:
        c1: [GREATER_THAN, 0]
        c2: [LESS_THAN, 0.5]
    linked_variables: {x9: x1}
    constants: {a: dummy_constant}
```

Python API

```python
# create Xopt object.
X = Xopt(YAML)

# take 10 steps and view data
for _ in range(10):
    X.step()

X.data
```



Badger GUI interface




Accelerator simulation

Online Control R&D

Experiment facility

Xopt implements a number of different algorithms:

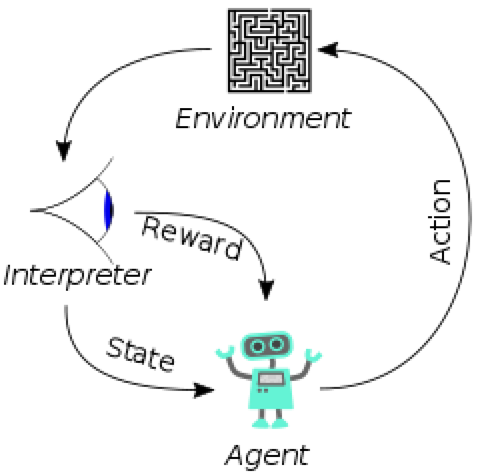
- Various Bayesian optimizations:
  - Single/Multi-objective BO, Trust Region BO, Bayesian Algorithm Execution, custom model priors, etc.
- Genetic optimization (CNSGA), RCDS, Nelder-Mead Simplex, Extremum seeking;

# Reinforcement Learning

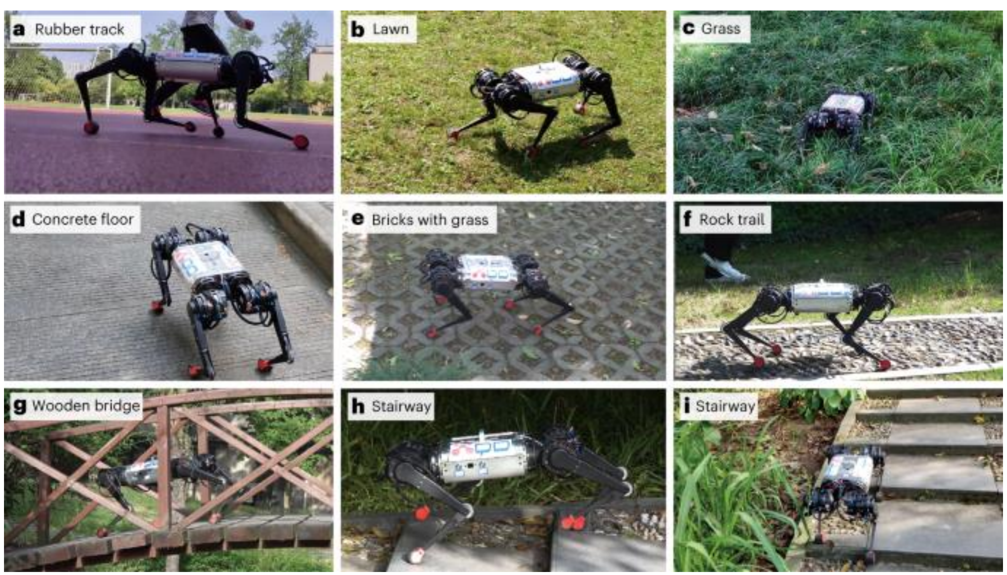
Problems involving an **agent** interacting with an **environment**, which provides numeric **rewards**

**Goal**: Learn how to take actions in order to maximize reward

**Markov property**: Current state completely characterizes the state of the world

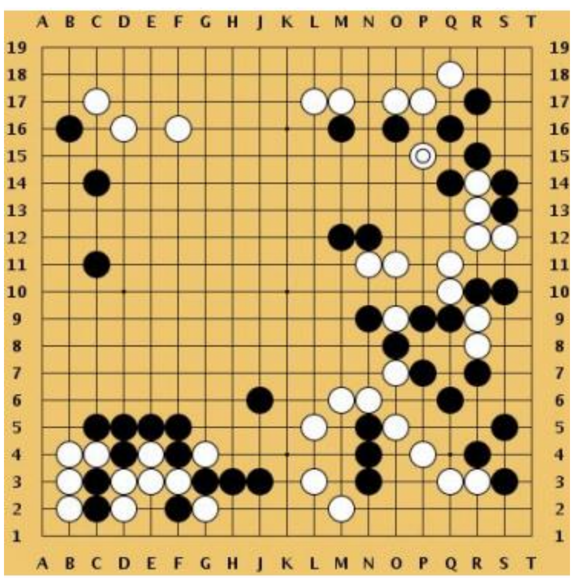



Atari Games




Robot Locomotion

Go

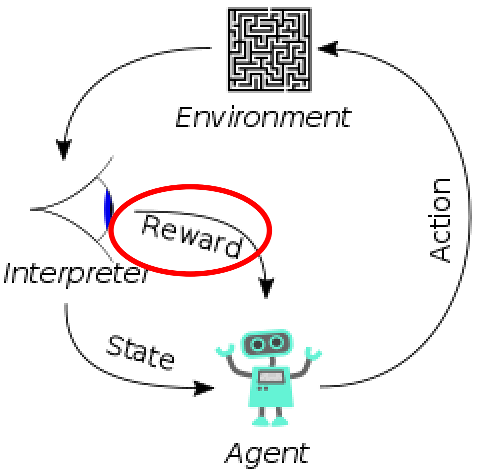


# Designing a good reward function can be hard

- Recall that the reward function is the only incentive for the agent to learn;

- Designing a reward function is sometimes straightforward, but can get hard:
  - Complicate objectives;
  - Sparse or delayed rewards;

- Several ways to improve the reward function:
  - Learning from demonstrations:
    - Learn the policy directly (imitation learning)
    - Learn the reward function first, then learn the policy (IRL)
  - Incorporate human feedback (in an interactive manner);
  - Curriculum learning;
  - Transfer learning;
  - Reward shaping:
    - Incorporate domain knowledge;
    - Potential-based reward shaping, can slow down learning if not design well;

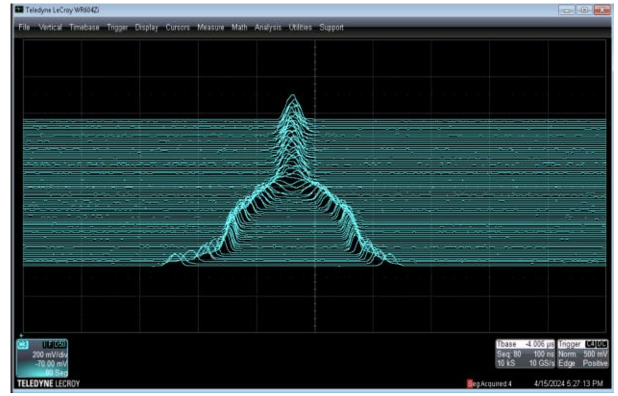




Reward design can go wrong

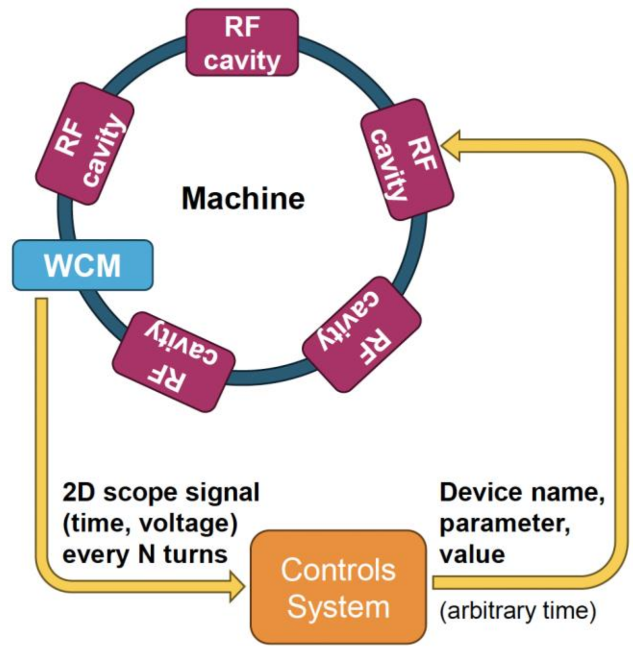
# AGS Bunch Merging

- Before transferring to AGS, beam bunch is split into 2 longitudinally to reduce the space charge effect
  -> reduce emittance -> improve polarization
- Bunches are later merged before AGS extraction;
- Requires expert tuning of many parameters:
  - Prone to drift over time;
  - Time consuming;
- Controls: RF voltages, phases
- Goal: Obtain a “good” merged bunch profile:
  - Emittance preservation:
    - No particle lost;
    - Gaussian shape;
    - No “baby” bunches;
  - Stable final bunch profile:
    - Not shifting left to right;
    - Not bouncing up and down;
    - Merged in the center;




Real mountain range data showing 2-to-1 bunch merge in AGS

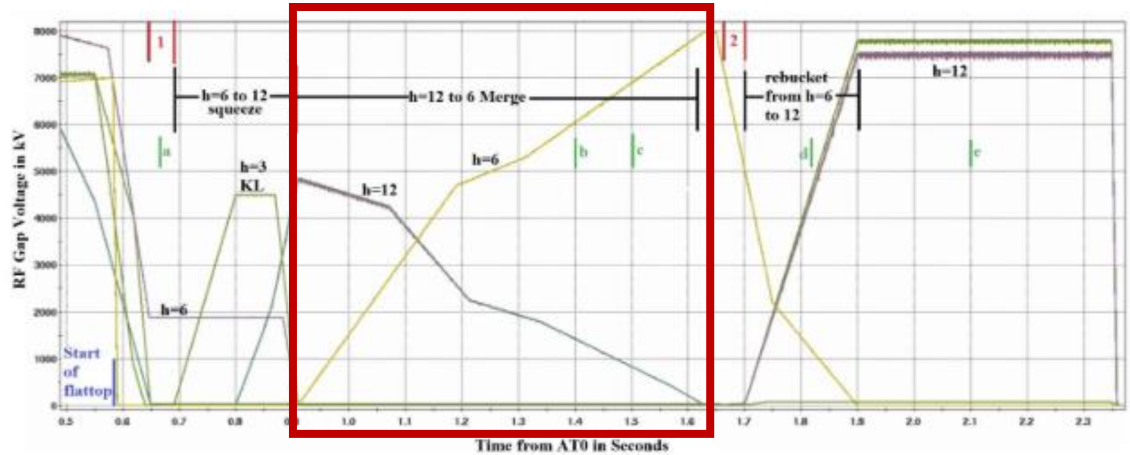
Wall current monitor (WCM) generates voltage vs time signal. Each separated in time by N turns (N accelerator periods)



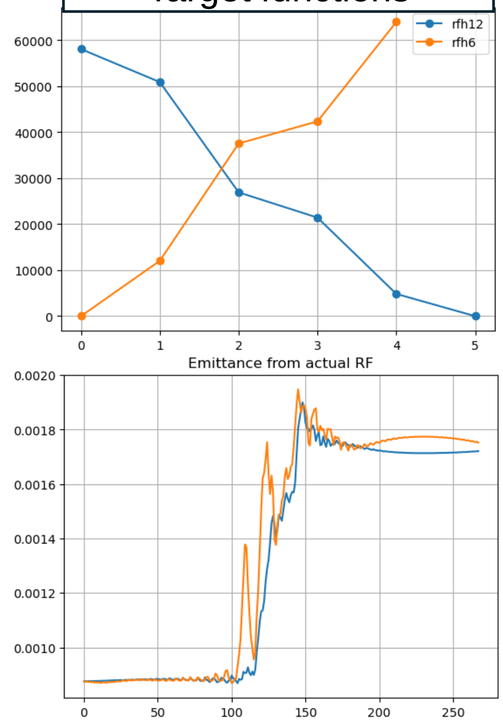

Cartoon representation of accelerator with WCM, RF cavities (arbitrary number), and input/output

# Simulation Results

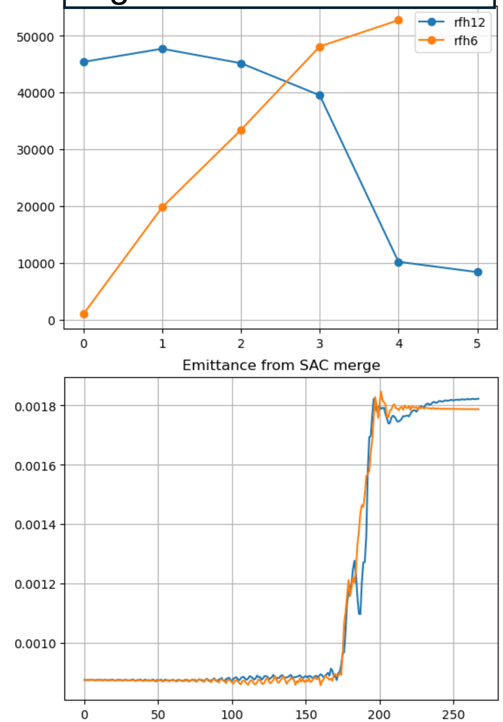
- Bmad simulator; Speed problem; Mountain range plots;
- SAC agent: 10,000 initial samples + 4,000 training steps;
- 3% emittance growth;



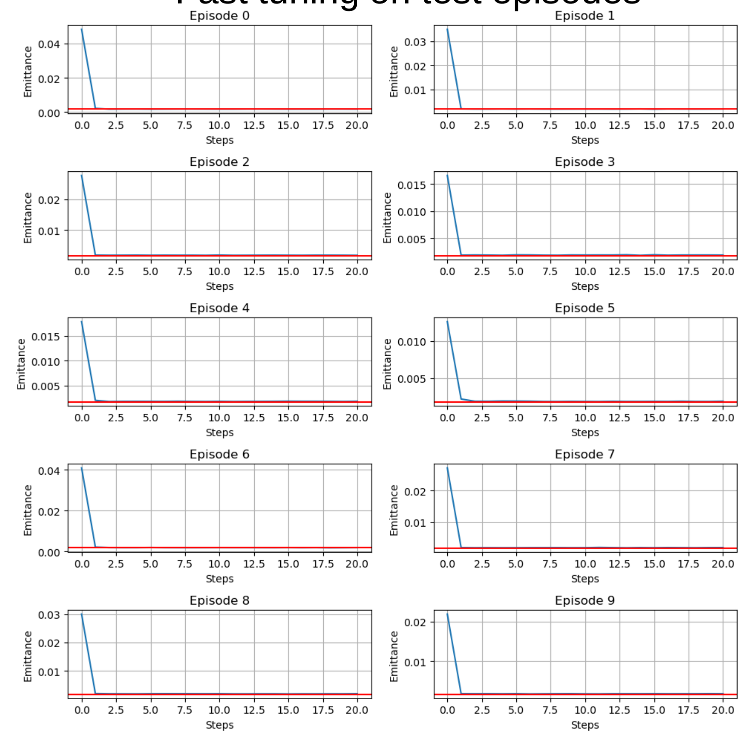

## Target functions



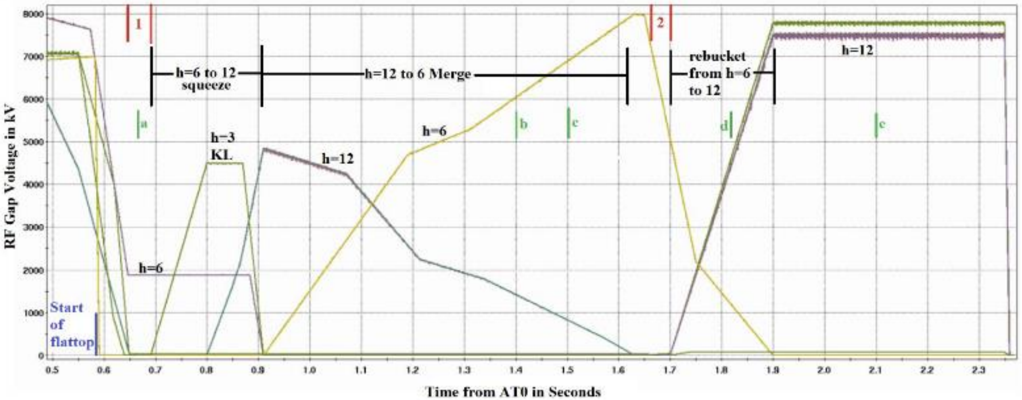

## Agent learned functions




## Fast tuning on test episodes



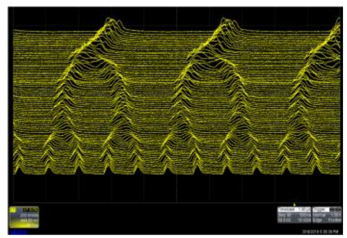
# Workflow




RL Agent

RF settings
[6+5 numbers]

Accelerator system



Process &
Feedback

Mountain range
readings

- Actual system considerations:
  - How good is the simulator? How to get enough training data (random sampling)?
  - Safety constraints; Setting step size;
  - Log historical merge data;

- Data pipeline to process the mountain range plots data:
  - Scope settings;
  - Emittance; area of curve;
  - Center oscillations; number of traces;
  - Bunch center positions;

# System Side Preparations

- We can now do a basic demonstration code to acquire input signals from wall current monitors (offloading oscilloscope data) and show results in a Jupyter notebook.

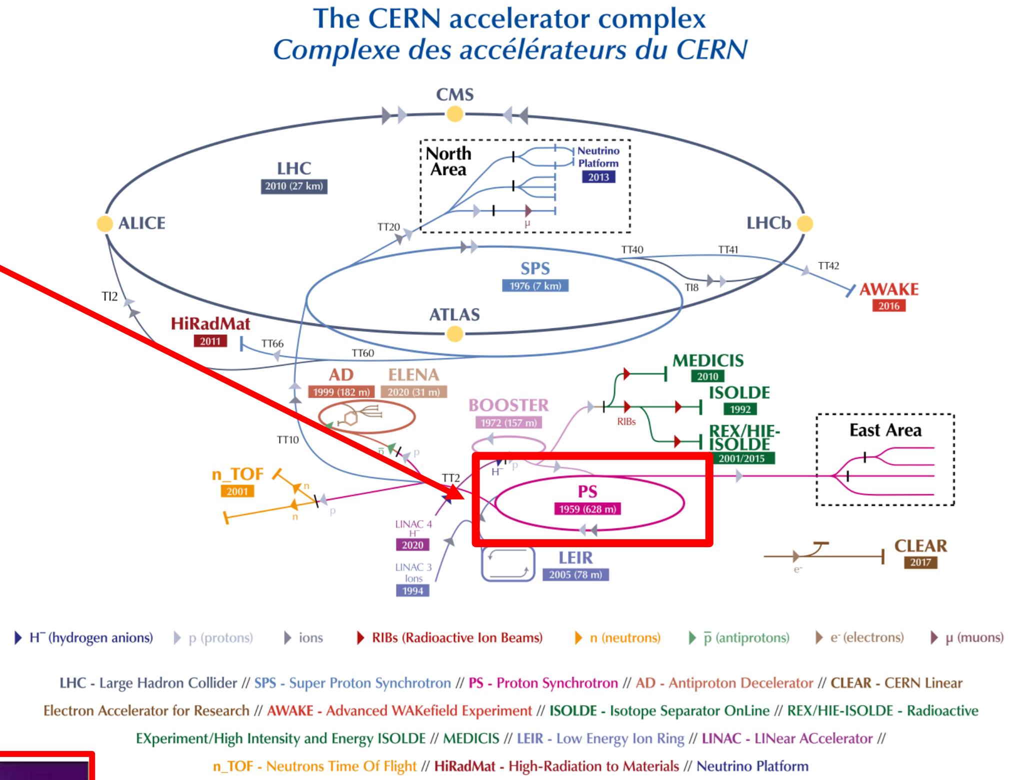
- We have a Zynq Ultrascale FPGA evaluation board and an FMC expansion card to digitize the WCM signals:
  - 12-bit conversion at 1,000 Megasamples per second, with an analog range of +=2.5V

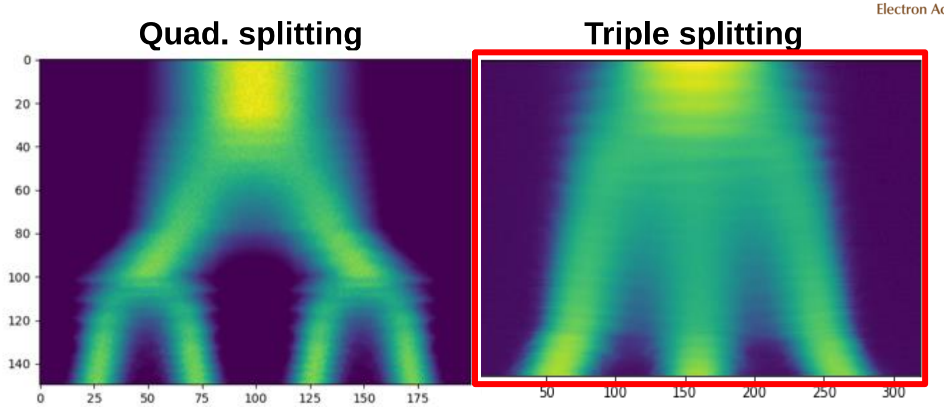
- Next steps after this is completed:
  - Evaluating multiple commercially available digitizer products for performance comparison to FPGA-based system;
  - Work on buffer memory implementation (to store multiple turns);
  - Work on the hardware configurations to match the actual system specifications;

# Bunch Manipulations in the CERN PS[1]

- A complex consisting a cascade of four separate accelerators before injection.
  - The nominal bunch spacing of 25 ns is created in the PS through RF manipulations;
  - Those manipulations need to be carefully optimized;
  - The relevant parameters are the **RF amplitude** and **phase;**

- Current tuning relies on operators, which takes time and suffers performance lost due to qualitative judgement errors.



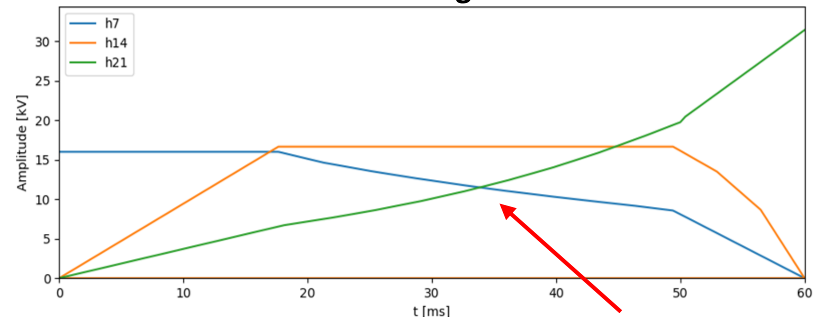

Results for both cases are promising
Triple splitting is used as an illustration

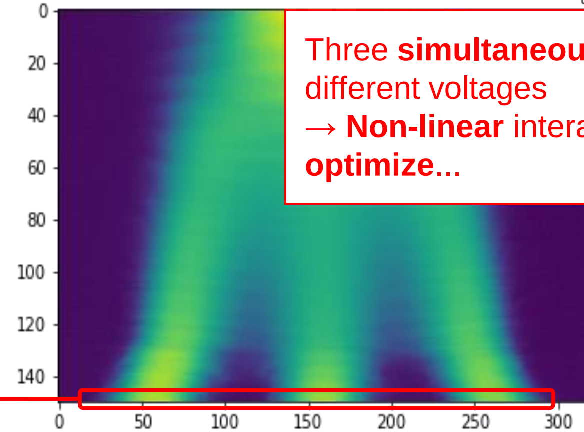
1. Reinforcement Learning applied to Optimization of LHC beams in the CERN Proton Synchrotron, J. Wulff

# Triple Splitting: Parameters and Objectives

- Three main parameters to optimize:
  - Phases and voltages
    $\Phi_{14}$, $\Phi_{21,}$ and $V_{14}$
- Objectives:
  - Final bunch profile observables: **bunch width** & **intensity**, equal after splitting;
  - Quality measured through Mean Square Error (MSE) between bunches after splitting.

***RF voltages***

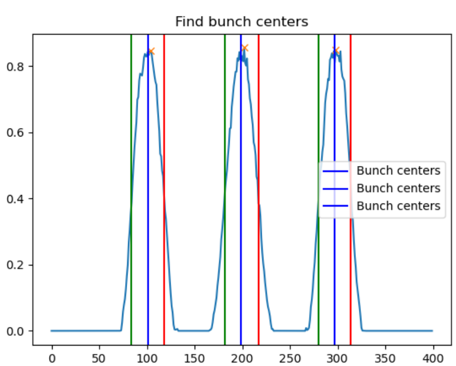


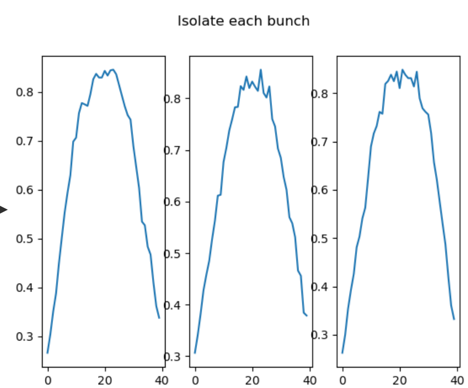



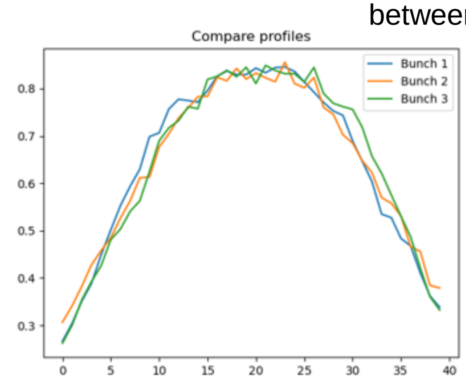
Three **simultaneously** active cavities with different voltages
→ **Non-linear** interactions, **difficult to optimize**...

The final profile after the triple split is extracted

All bunch profiles are compared and the MSE between them is calculated



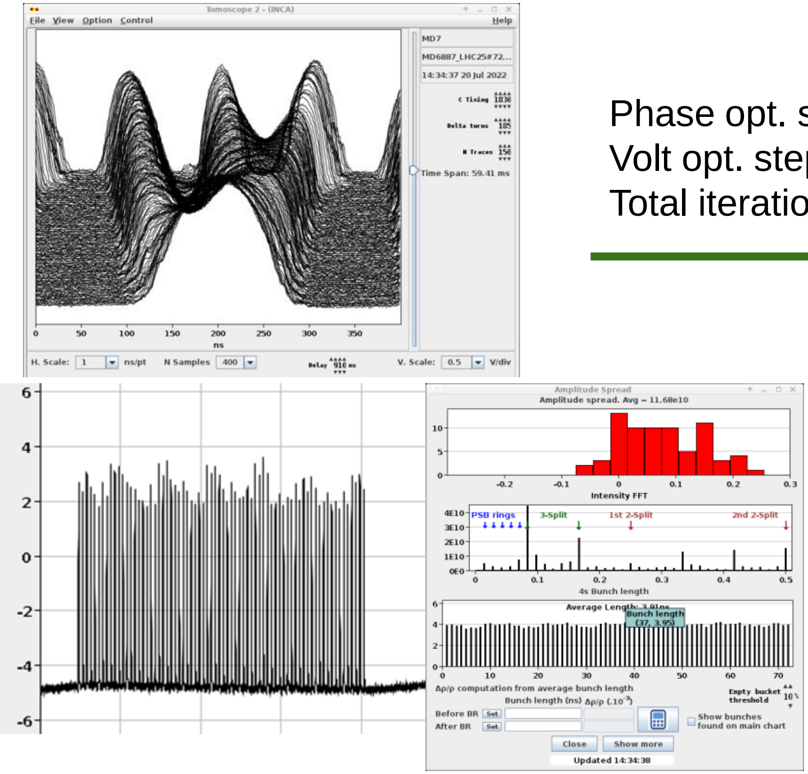



# Segmented RL and Machine Test Results

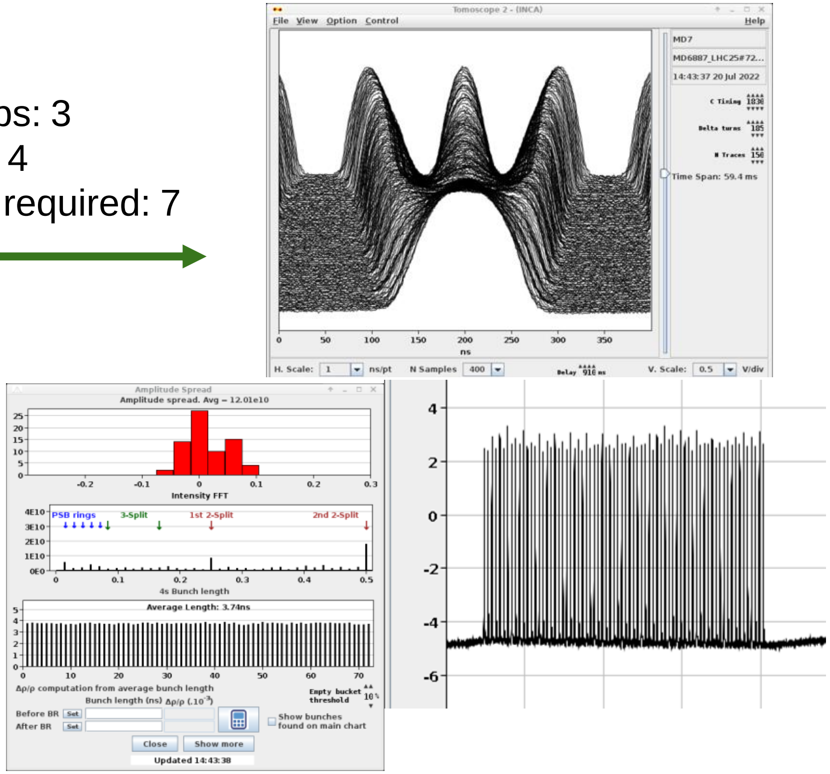
Init

Example episode

Final




Phase opt. steps: 3
Volt opt. steps: 4
Total iterations required: 7




- Segmented SAC agent: Phase → Voltage;
- Bootstrapping from a feature extractor built by CNN to leverage more information from the tomoscope structure.
- The extracted information will put the RL agents in a decent place to start the optimization.

# Pros & Cons of RL Approaches

Advantages:

- It can better handle giant search space:
  - AlphaGo essentially has search space of all permutations in the Go Game;
  - Accelerator control tasks may involve a large number of control points;
- Learning can be swiftly transferred or adapted to novel scenarios:
  - What RL learned is stored by the model weights in the Neural Networks; transfer learning
- Online decision-making:
  - After training, RL can be applied in an online manner;

Limitations:

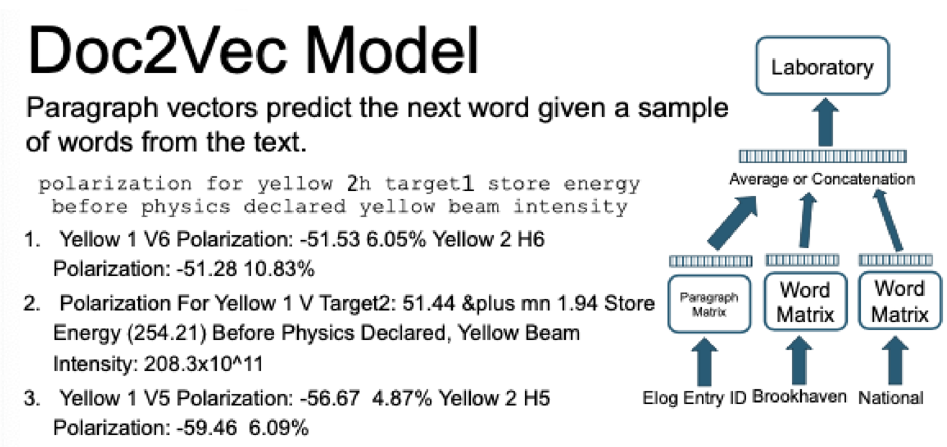
- Training requires lots of data, usually need a high-fidelity simulator;
- Not easy to make it work;
- Problem should be frameable as an MDP (or partial):
  - All decisions are based on the current state of the world;

# Enhancing Electronic Logbooks Using Machine Learning*

- **Natural Language Processing** techniques are applied to all user entries in the elog database
    - Processing data, removing stop words, lemmatizing
- Doc2Vec and Multinomial Naïve Bayes
- Web Based Search Engine
    - Connected to the model class

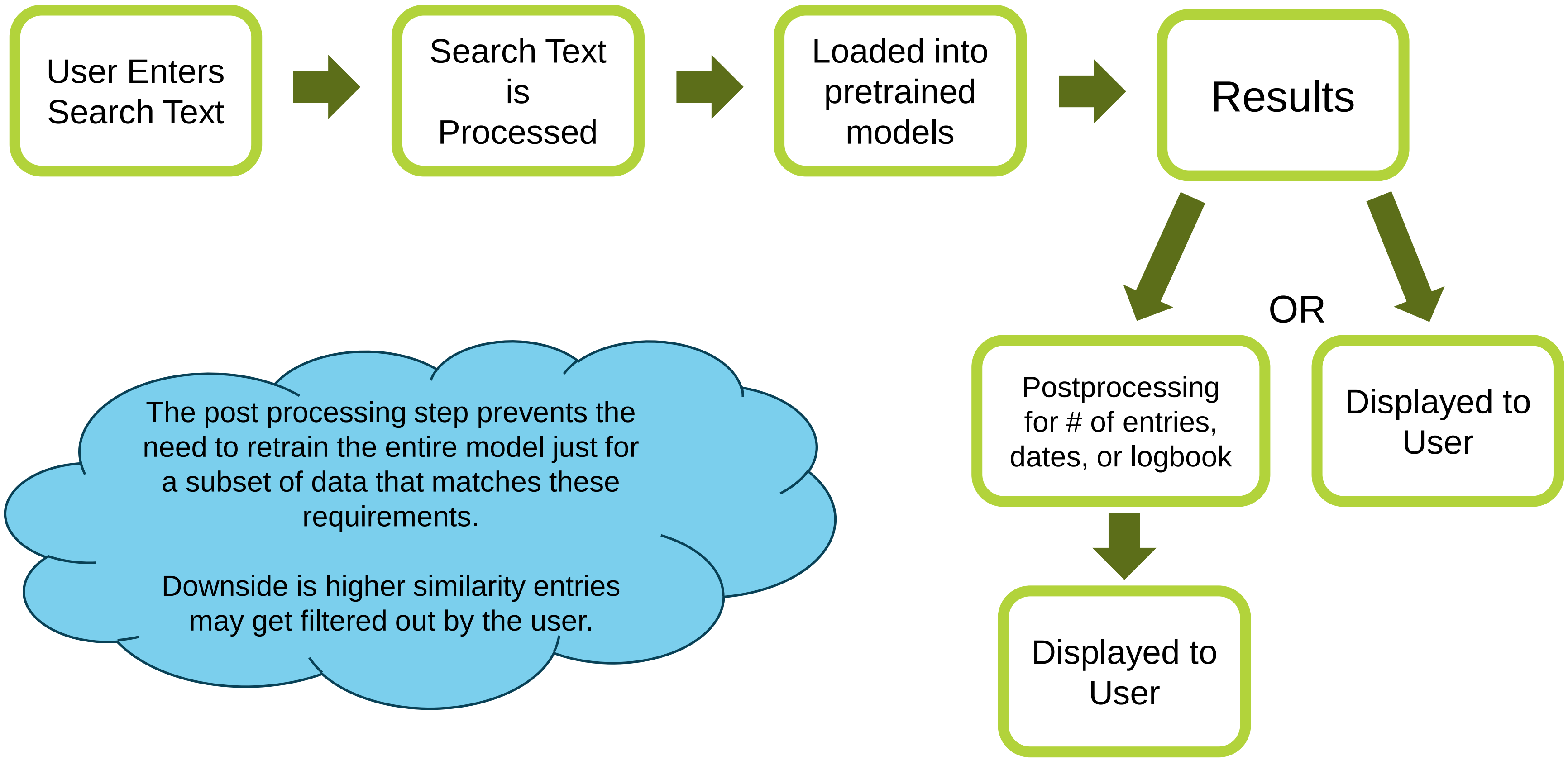
```
Service, building, and equipment tour complete.
```

```
[service, building, equipment, tour, complete]
```



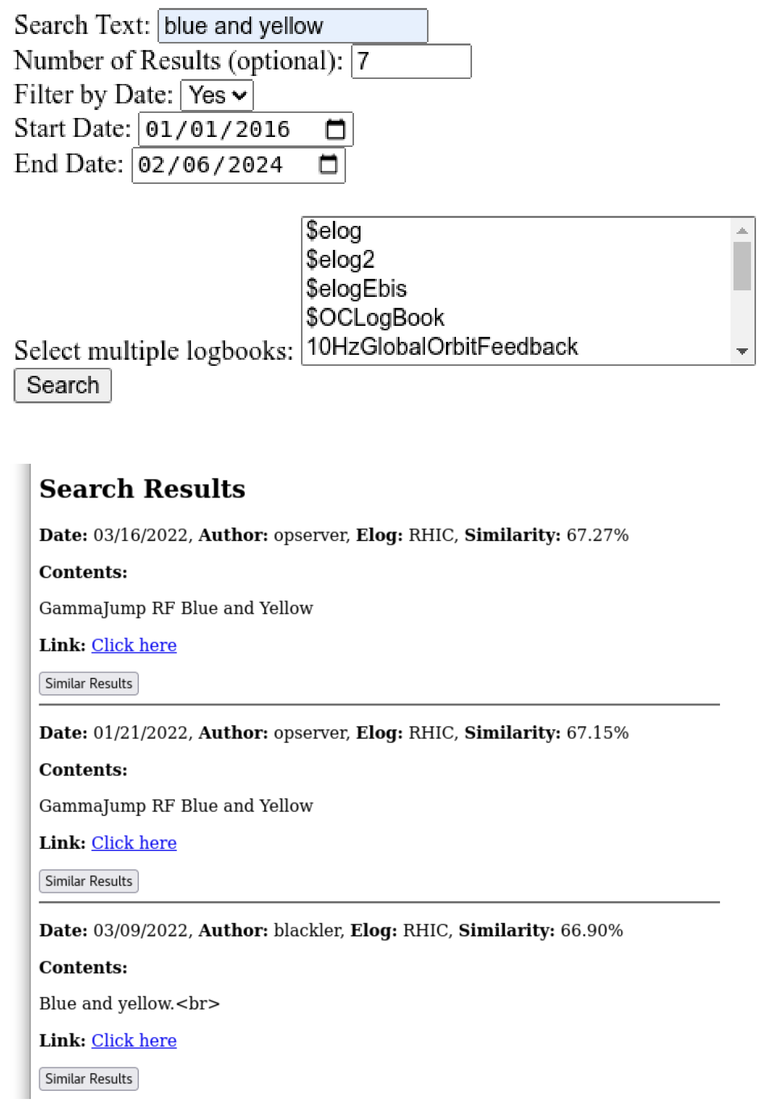

*jmaldonad@bnl.gov

# Web Interface Workflow



# Web Interface

- User’s can search by elog and date;
- Filter number of responses;
- The current elog system will be evaluated for EIC to see if this functionality will be added to the elog or another tool;



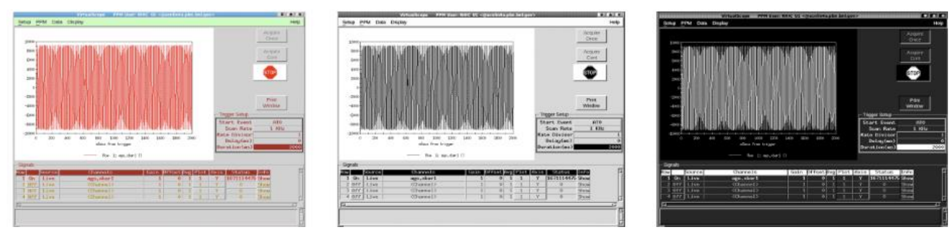
# What's Next?

- Link this demo webpage into the elog system to allow users to test thoroughly
    - Currently live on apps.pbn.bnl.gov/SearchElog
- Then decide how to implement directly into the elog (or another tool)
- Develop new ML tools to help with faster model deployment
- Summer Intern Jennipher Day
    - Reinforcement Learning model development for improved search tasks

# Controls Interface for a Virtual Assistant (CIVA)*

- There are many resources to use to troubleshoot an issue: eLogs, documents, monitoring apps, databases, alarm system, etc.
- CIVA consolidates information from various resources into a central repository;
- Search vectors for words; Image pre-processing + OCR;

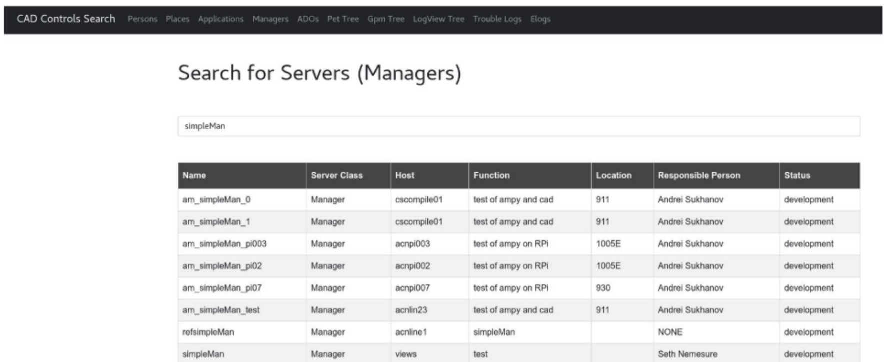
| subject | description | work_group | reported_by | search_vector |
|---|---|---|---|---|
| NX servers acnlin8 | Michiko Minty sent this | System Administration | INSTRUMENTATION | 'acnlin86':3 'acnlin87':5 'app':9 'busi':6 'nx':1 'runaway':8 'serve |
| MCR reported that | Looked into the probler | Application | William Jackson | 'agslossman':4 'cannot':5 'mcr':1 'report':2 'start':7 'startup':9 |
| DNS Reverse Zone | DNS servers could not | System Administration | Roger Katz | 'dns':1 'fecnet':4 'revers':2 'work':6 'zone':3 |
| Many alarms in MC | Tried to start servers - | System Administration | Nicholas Kling | 'alarm':2 'cdev':10 'controlsnameserv':8 'everyth':5 'mani':1 'm |
| profileDisplay and I | Two calls came in on di | Application | Nicholas Kling | 'bert':3 'data':8 'get':7 'profiledisplay':1 'unabl':5 |
| firefox process han | this has happened seve | System Administration | John Morris | 'acnlinb5':7 'desktop':6 'firefox':1 'hang':3 'process':2 |
| Operations called t | fit indicated that a rese | FEC | Seth Nemesure | '3':4 'ag':9 'alarm':10 'call':2 'messag':15 'oper':1 'report':14 'scr |
| Getting "Trigger Ov | I don't think that I can r | FEC | David Maffei | 'alarm':4 'basi':16 'control':10 'get':1 'intermitt':15 'line':8 'overl |
| CST-957-INST1 no | CST-957-INST1 was re | FEC | John Morris | '-957':2 'cst':1 'inst1':3 'work':5 |
| qpaCtrl alarm goinç | qpaFanFaultAlarmer pu | FEC | Don Bruno | 'alarm':2 'go':3 'qpactrl':1 |
| Tandem isn't gettin | Data for all of the affec | Hardware | unassigned | '-21':15 '19':14 'cup':10 'data':5 'faraday':9 'get':4 'harp':7 'isn':2 |




*kabir@bnl.gov

# Multiple GUI Supports

Web GUI



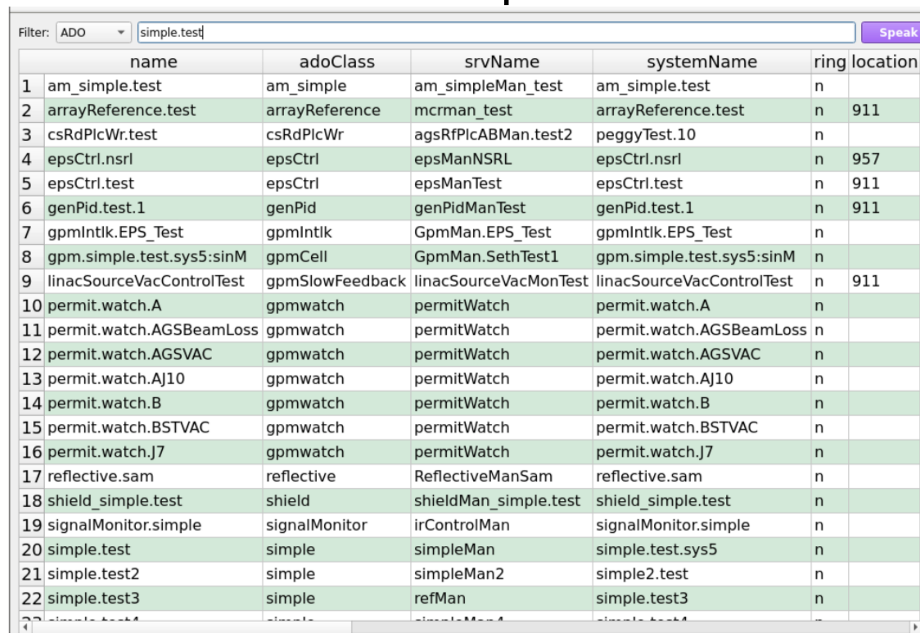
CAD Controls Search | Persons | Places | Applications | Managers | ADOs | Pet Tree | Gpm Tree | LogView Tree | Trouble Logs | Elogs

Search for Servers (Managers)

simpleMan

| Name | Server Class | Host | Function | Location | Responsible Person | Status |
| --- | --- | --- | --- | --- | --- | --- |
| am_simpleMan_0 | Manager | cscompile01 | test of ampy and cad | 911 | Andrei Sukhanov | development |
| am_simpleMan_1 | Manager | cscompile01 | test of ampy and cad | 911 | Andrei Sukhanov | development |
| am_simpleMan_pi003 | Manager | acnpi003 | test of ampy on RPi | 1005E | Andrei Sukhanov | development |
| am_simpleMan_pi02 | Manager | acnpi002 | test of ampy on RPi | 1005E | Andrei Sukhanov | development |
| am_simpleMan_pi07 | Manager | acnpi007 | test of ampy on RPi | 930 | Andrei Sukhanov | development |
| am_simpleMan_test | Manager | acnlin23 | test of ampy and cad | 911 | Andrei Sukhanov | development |
| refsimpleMan | Manager | acnline1 | simpleMan |  | NONE | development |
| simpleMan | Manager | views | test |  | Seth Nemesure | development |

Desktop GUI



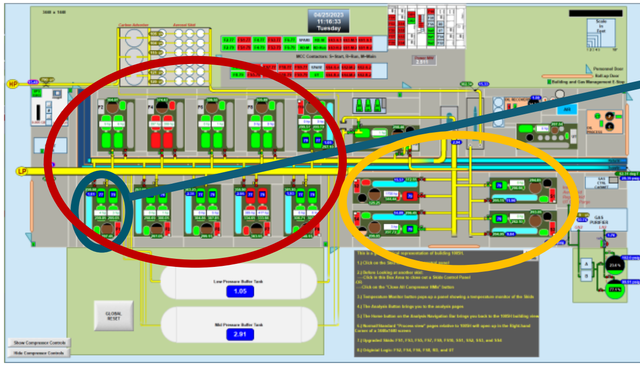
Filter: ADO | simple.test | Speak

|  | name | adoClass | srvName | systemName | ring | location |
| --- | --- | --- | --- | --- | --- | --- |
| 1 | am_simple.test | am_simple | am_simpleMan_test | am_simple.test | n |  |
| 2 | arrayReference.test | arrayReference | mcrman_test | arrayReference.test | n | 911 |
| 3 | csRdPlcWr.test | csRdPlcWr | agsRfPlcABMan.test2 | peggyTest.10 | n |  |
| 4 | epsCtrl.nsrl | epsCtrl | epsManNSRL | epsCtrl.nsrl | n | 957 |
| 5 | epsCtrl.test | epsCtrl | epsManTest | epsCtrl.test | n | 911 |
| 6 | genPid.test.1 | genPid | genPidManTest | genPid.test.1 | n | 911 |
| 7 | gpmIntlk.EPS_Test | gpmIntlk | GpmMan.EPS_Test | gpmIntlk.EPS_Test | n |  |
| 8 | gpm.simple.test.sys5:sinM | gpmCell | GpmMan.SethTest1 | gpm.simple.test.sys5:sinM | n |  |
| 9 | linacSourceVacControlTest | gpmSlowFeedback | linacSourceVacMonTest | linacSourceVacControlTest | n | 911 |
| 10 | permit.watch.A | gpmwatch | permitWatch | permit.watch.A | n |  |
| 11 | permit.watch.AGSBeamLoss | gpmwatch | permitWatch | permit.watch.AGSBeamLoss | n |  |
| 12 | permit.watch.AGSVAC | gpmwatch | permitWatch | permit.watch.AGSVAC | n |  |
| 13 | permit.watch.AJ10 | gpmwatch | permitWatch | permit.watch.AJ10 | n |  |
| 14 | permit.watch.B | gpmwatch | permitWatch | permit.watch.B | n |  |
| 15 | permit.watch.BSTVAC | gpmwatch | permitWatch | permit.watch.BSTVAC | n |  |
| 16 | permit.watch.J7 | gpmwatch | permitWatch | permit.watch.J7 | n |  |
| 17 | reflective.sam | reflective | ReflectiveManSam | reflective.sam | n |  |
| 18 | shield_simple.test | shield | shieldMan_simple.test | shield_simple.test | n |  |
| 19 | signalMonitor.simple | signalMonitor | irControlMan | signalMonitor.simple | n |  |
| 20 | simple.test | simple | simpleMan | simple.test.sys5 | n |  |
| 21 | simple.test2 | simple | simpleMan2 | simple2.test | n |  |
| 22 | simple.test3 | simple | refMan | simple.test3 | n |  |

Next step:

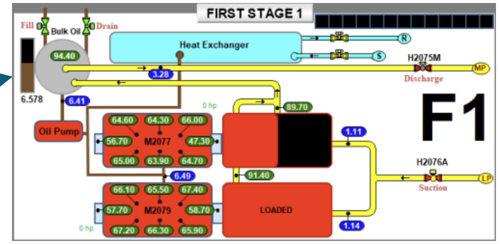
- Natural Language Querying using generative AI;
- Adding more data sources;


# Anomaly Detection on the RHIC Cryogenics System



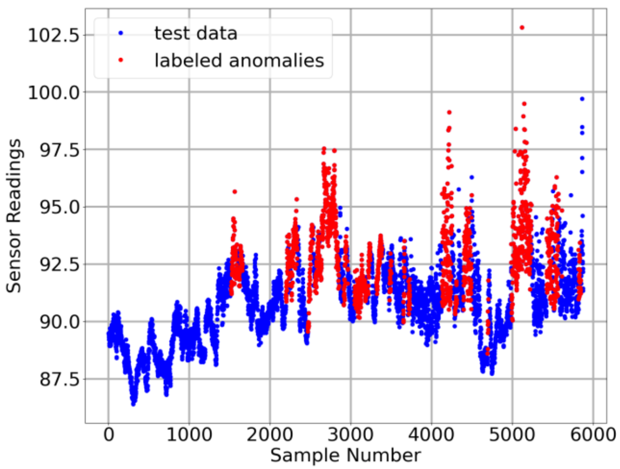
10 first stage compressors

4 second stage compressors




Our focus is one set/pair of the First Stage Compressors: FS1

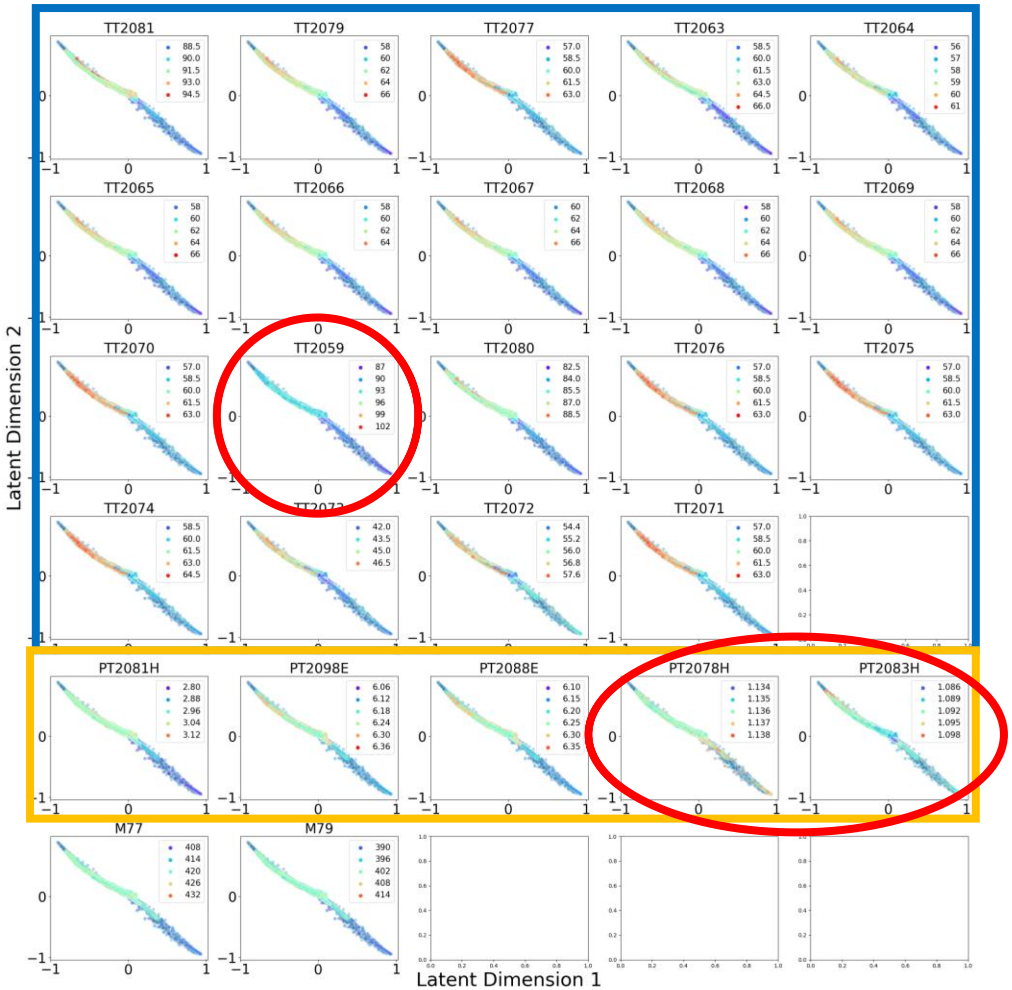
We focus on 26 analog sensors for a first-stage compressor: 19 Temperature (TT), 5 Pressure (PT), 2 horsepower (M77, M79) sensors.



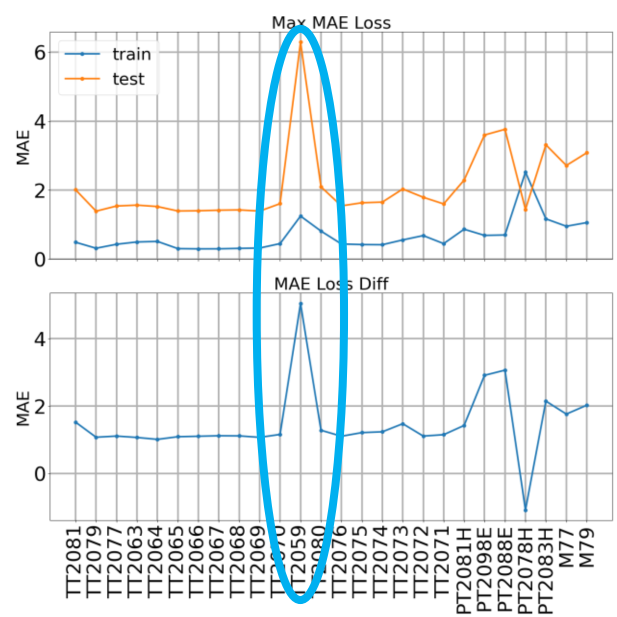

- The compressor has a documented trip which happened on Apr. 7th, 2022, due to the discharge temperature sensor TT2059 interlocking the FS1 compressor after it breached a high limit of 125 degrees C for 3 seconds. Technicians found a loose crimp on the sensor, and the compressor was returned to service after repairs.
- The LSTM autoencoder was trained on data from Jan. 15th to Mar.5th, 2022, and tested on data from Mar. 6th to Apr. 5th, 2022, to see if it is able to detect any anomaly precursors.
- Anomaly detection on sensor TT2059 demonstrates the LSTM autoencoder is able to detect early precursors so proactive actions can be taken to prevent machine failure.

# Latent Space Data Analysis

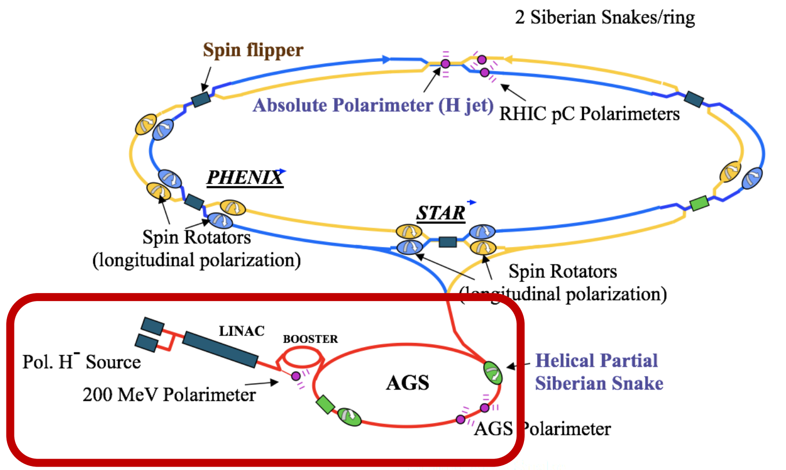
Latent space visualization for each variable




1. TT2059 has a different pattern with other TT temperature sensors;
2. PT2078H and PT2083H don't have obvious data patterns, can be omitted for analysis;
3. The sensor TT2059, which is the actual cause of the machine trip, gets the highest error value.



# Future Projects:
# Polarization Optimization




Focus on the injector compound for RHIC and future EIC

Loss in polarization along the chain

| | Max Energy [GeV] | Pol. at Max Energy [%] |
|---|---|---|
| Source + Linac | 1.1 | 82-84 |
| Booster | 2.5 | ~80-84 |
| AGS | 23.8 | 67-70 |
| RHIC | 255 | 55-60 |

- Maximize beam polarization:
  1. Preserve beam density;
  2. Synchronize accelerator components at depolarizing resonance crossings;
  3. Minimize depolarizing resonance strengths;

- Goal is to increase polarization by 5%;

# Several places to maximize polarization

- Booster injection optimization:
  - The main objectives for optimization of the Booster injection and capture process are to maximize the intensity and minimize the transverse and longitudinal emittances.
- AGS bunch splitting and merging:
  - Optimization of these processes is currently done by expert “by eye”;
  - A ML approach would help to optimize and maintain relevant outputs (longitudinal emittance and intensity) and free up valuable expert resources.
- AGS Energy vs. Time calibration;
- Depolarizing resonance strength;

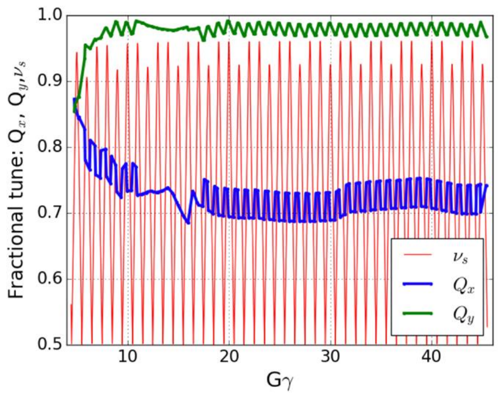
# AGS Energy vs. Time Calibration

$$\gamma = \left[1 - \frac{1}{c^2}(2\pi f_{rev})^2 (R_0 + dR)^2\right]^{-\frac{1}{2}} \quad (a)$$

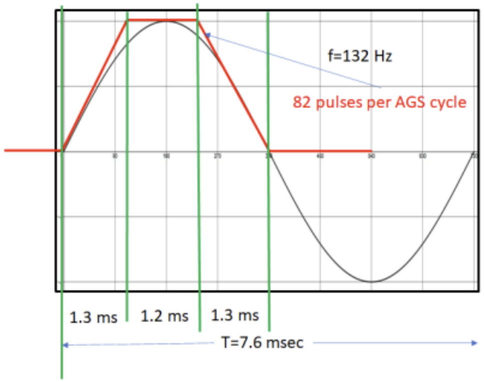
$$= \left(\left[\frac{(1+\gamma_{tr}^2\, dR/R)\rho_0 c\left(B_{inj} + B_{clock}/C_{scal}\right)}{M_0}\right]^2 + 1\right)^{\frac{1}{2}} \quad (b)$$

- Spin depolarizing resonances occur at very specific energies; determining the beam energy as a function of time is therefore crucial for optimizing any compensatory efforts, such as tune jumps or spin matching;
- In the AGS the largest identified source of depolarization remaining occurs when the proton beam passes through 82 resonances;
- Determining the energy at this precision currently relies on a calibration procedure between two formulas, one using the frequency (a) and the other using the magnetic field (b);
- The two formulae result in different calculations of the energy as a function of time. The “unknown” parameters are fit to minimize the difference between the calculation methods;
- A complimentary energy measurement comes from the polarimetry. The objective of the proposed optimization is to combine the three energy measurements into one to reduce uncertainty at all energies;

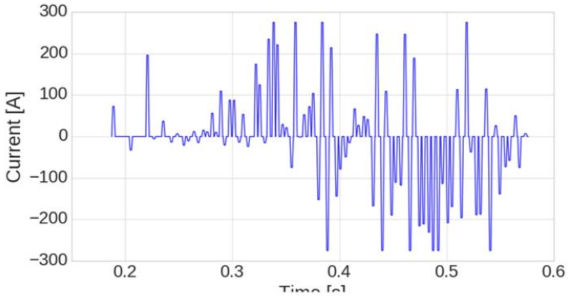
# Depolarizing Resonance Strength

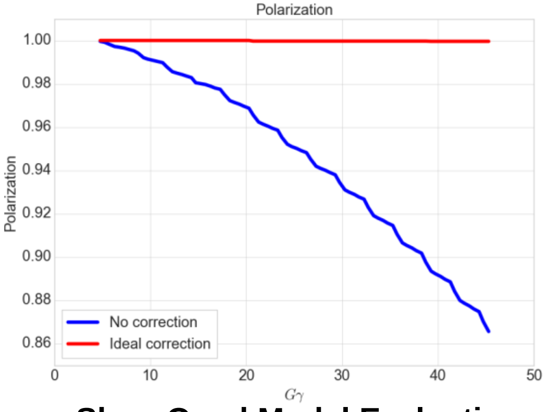



- A proposed approach to minimizing the depolarization due to horizontal resonances is to compensate for them using 15 independently powered skew quadrupoles to correct each of the 82 resonances;
- A full optimization of the system involves many knobs (15 for each of 82 resonances). Due to the time of the polarization measurement, a brute-force scanning of each individual parameters is generally not possible;
- The direct objective of the optimization is to maximize the polarization as measured at the end of the AGS acceleration process. The total number of control variables can be reduced by arranging the strengths into correlated families;




*Skew Quadrupole Current*




**Skew Quad Model Evaluation**

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Thank you for your attention!