# Machine Learning in Heavy-ion Accelerators

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# AI/ML for accelerators

Accelerator Design

Construction

Commissioning

Operation

Maintenance

AI/ML can find hidden data structures and build surrogate models for:

- Machine tuning
- Anomaly Detection
- Tomography
- Model predictive control

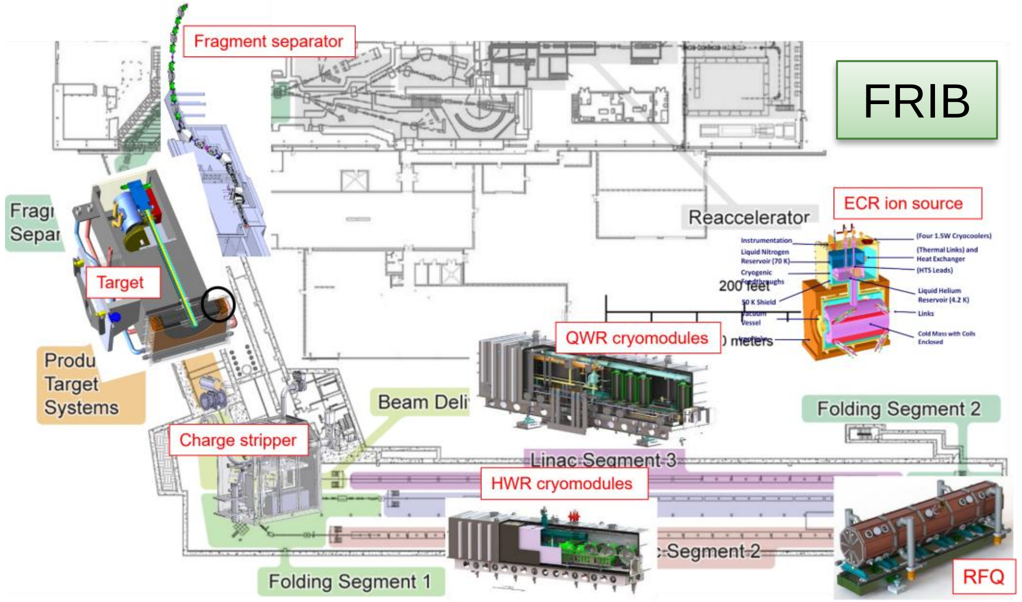
GP+BO

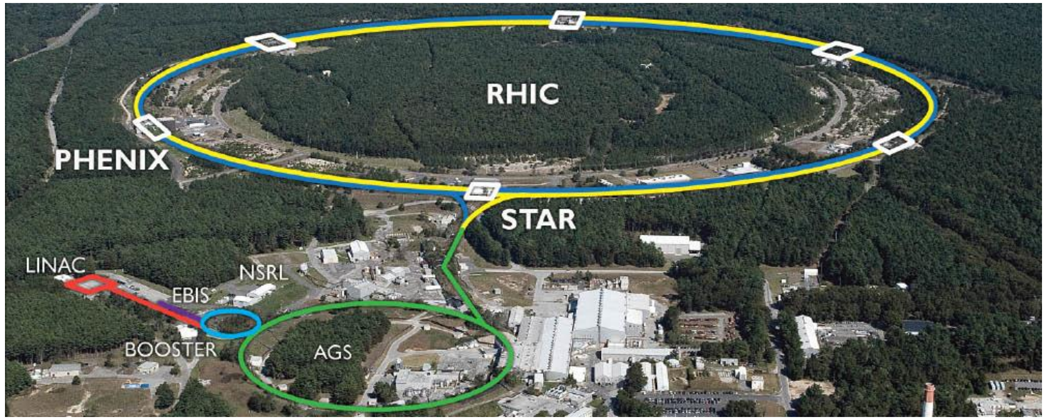
xNN

RL

Auto-Encoder

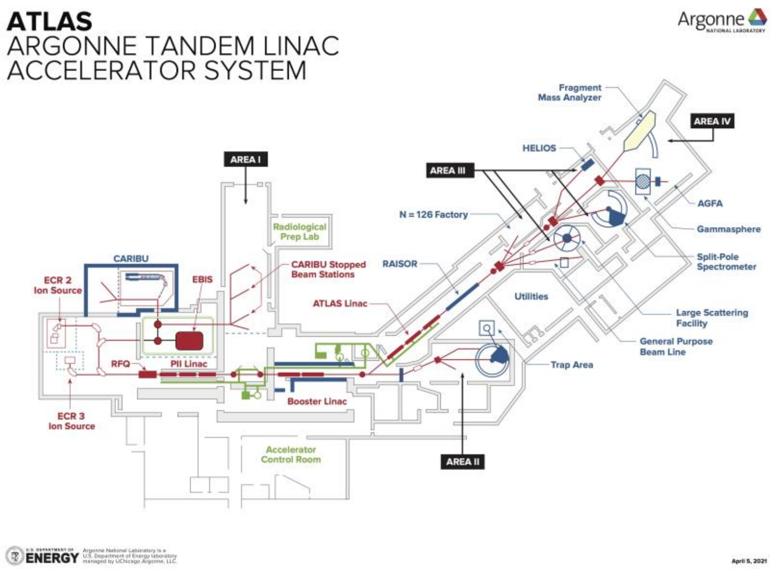

# Heavy-ion Accelerators




Goal of NP Heavy-ion Accelerator

- High power primary beam (FRIB, ATLAS)
- High Luminosity (RHIC)
- Various ion species (ALL)
- high availability/Reliability (ALL)



# Outline

- A brief survey of the AI/ML applications in heavy ion accelerator
  - AI/ML based Machine tuning in FRIB, ATLAS and RHIC
    - Various of Bayesian Optimization applications
  - Retrieving beam profiles with AI/ML method
    - Connecting with beam loss
    - Towards Tomography of phase space
- Summary

# Machine Tuning

# AI/ML Methods for Machine Tuning

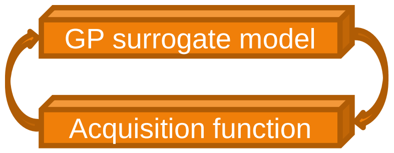
- (model independent) Reinforcement Learning (RL) vs Gaussian Process + Bayesian Optimization (BO)
  - RL can adapt to time variation (e.g. drift), and scales well to large data but sample *in*efficient.


  - BO with Gaussian Process is very sample efficient but is for static problem and scales terribly to large data

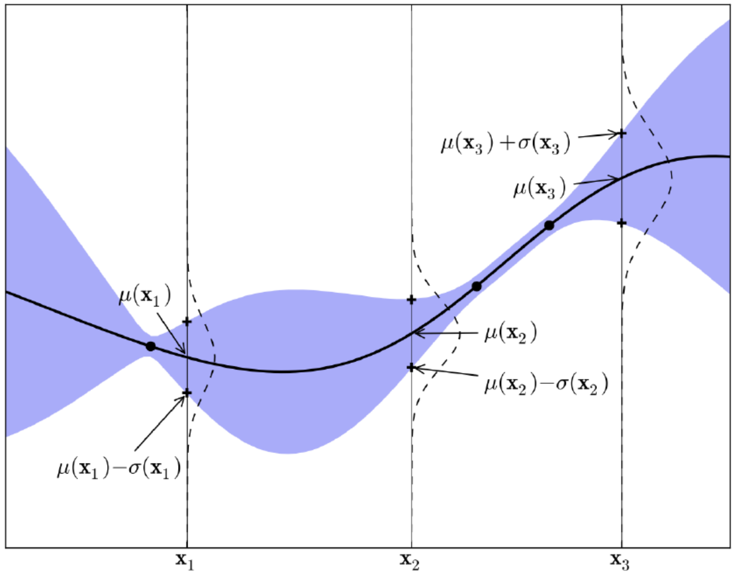
$$p(f\,|\,\mathbf{x},\mathcal{D},\boldsymbol{\theta}) = \mathcal{N}(f\,|\,\mu(\mathbf{x}),\sigma^2(\mathbf{x}))$$

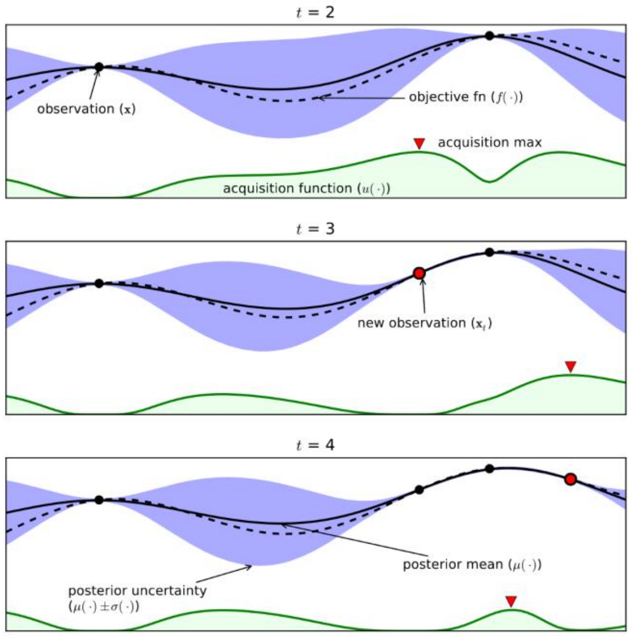
$$\mu(\mathbf{x}\,|\,\mathcal{D},\boldsymbol{\theta}) = m(\mathbf{x}) + \boldsymbol{\kappa}(\mathbf{x},X)K^{-1}(\mathbf{f}-\mathbf{m})$$

$$\sigma^2(\mathbf{x}\,|\,\mathcal{D},\boldsymbol{\theta}) = \kappa(\mathbf{x},\mathbf{x}) - \boldsymbol{\kappa}(\mathbf{x},X)^\top K^{-1}\kappa(X,\mathbf{x})$$




$$P(H|M) = \frac{P(M|H)P(H)}{P(M)} \sim P(M|H)P(H)$$

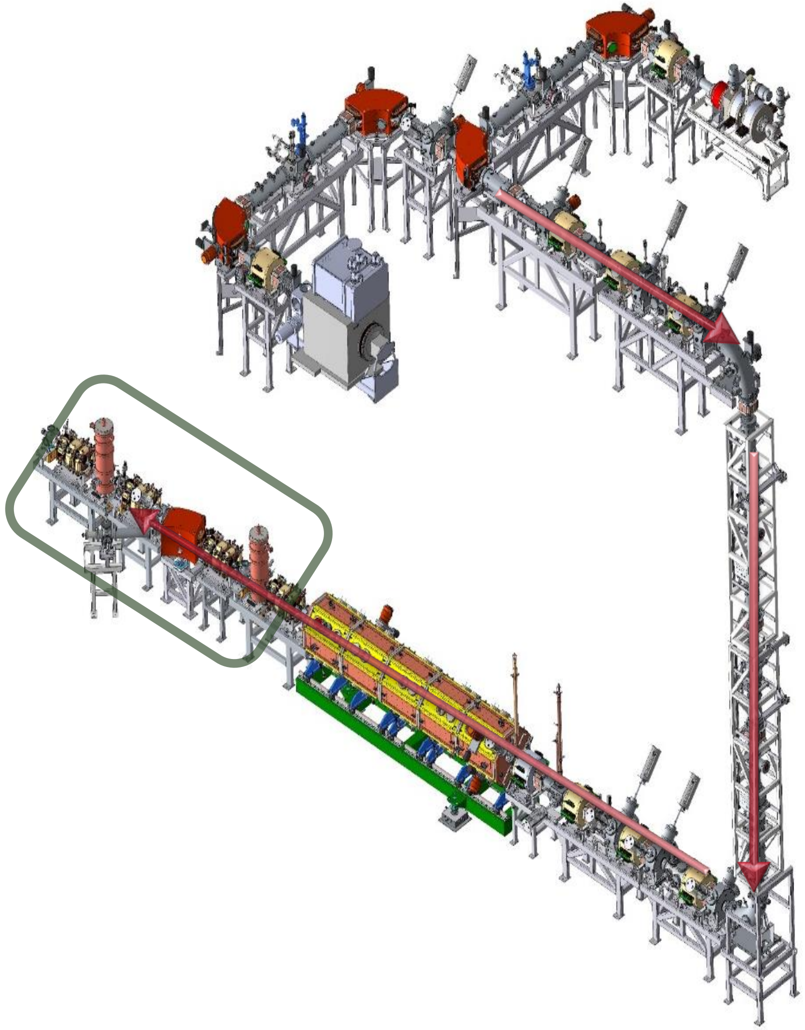



@ Brochu et al, 2010

# FRIB Beam Tuning: Problem

- Goals
  - Minimization 3D beam centroid deviations at 3 MEBT BPMs
  - Maximize beam current ratio $\frac{I_{\text{afterRFQ}}}{I_{\text{beforeRFQ}}}$ at two BCMs
  - Maximize beam current at two BCMs and 3 BPMs
- 6 Decision Knobs:
  - electric currents for magnetic correctors
- Goal Budget: <10 min
- Cost
  - $2\ sec$ for BPM reading
  - $1A/sec$ (max $\pm5A$) for electric current ramping of correctors
  - Additional $15\ sec$ for the electric current polarity change



# FRIB Beam Tuning: Strategy

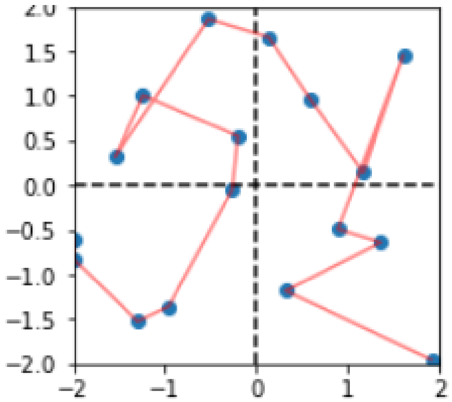
- Asynchronous evaluation
  - Evaluate objective of a candidate solution on machine while computing BO step (model training and candidate query with penalization on currently evaluating candidate)
- Penalize and favor
  - On the currently evaluating candidate one need to penalize for asynchronous BO while at the same need to favor to reduce ramping time.
    - » need careful choice of length scale and weight for the penalize / favor
  - Favor current polarity

$$f_{penal} = -C_{penal} e^{-(x-x_{penal})^2/L_{penal}^2}$$

$$f_{favor} = +C_{favor} e^{-(x-x_{favor})^2/L_{favor}^2}$$

$$f_{polarity} = \begin{cases} +C_{polaity} & \text{if } sign(x) = sign(x_{current}) \\ 0 & \text{else} \end{cases}$$

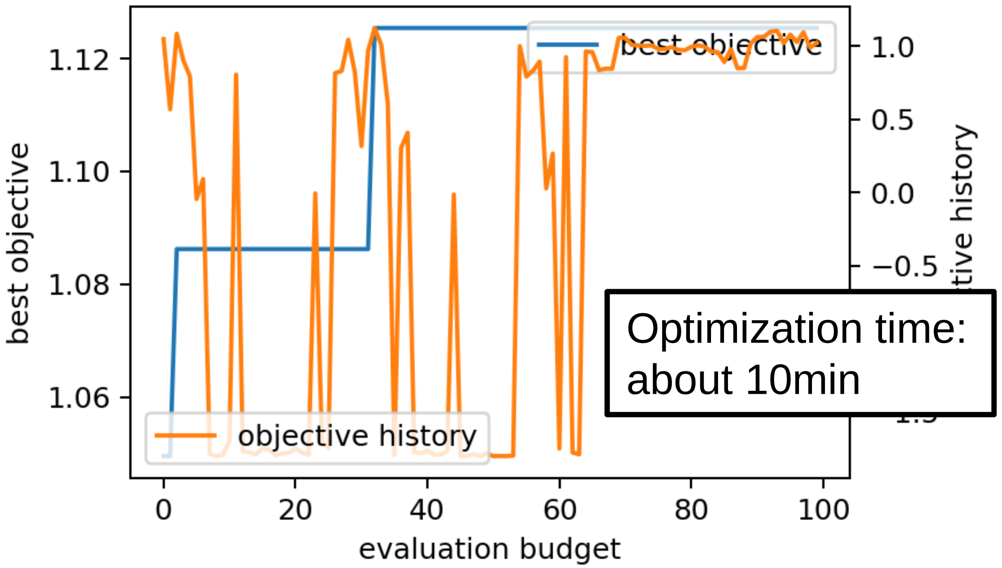
- Minimize ramping path of initial training samples



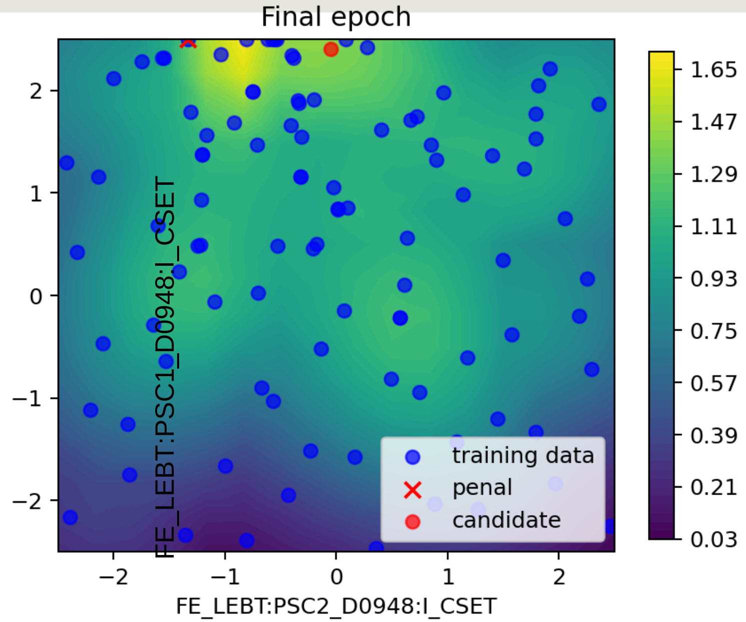

example shows 16 initial samples in 2D decision parameter domain.

@ K. Hwang

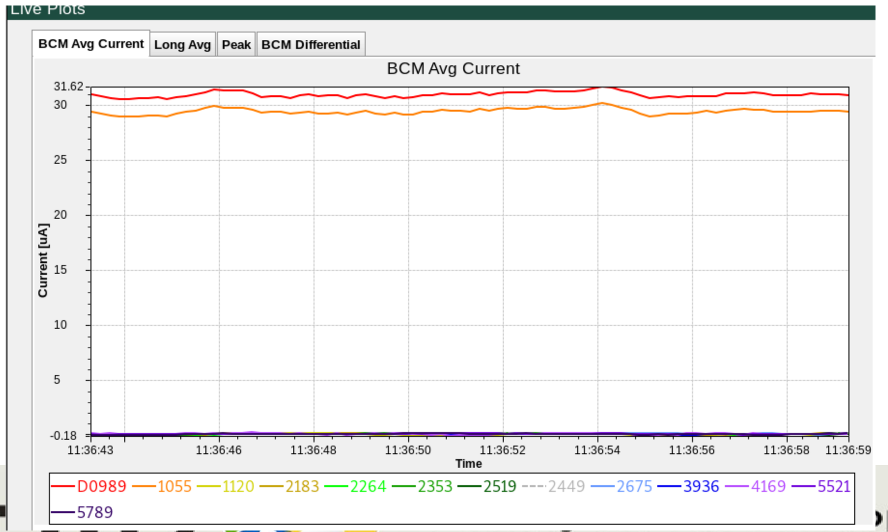
# FRIB Beam Tuning: Results

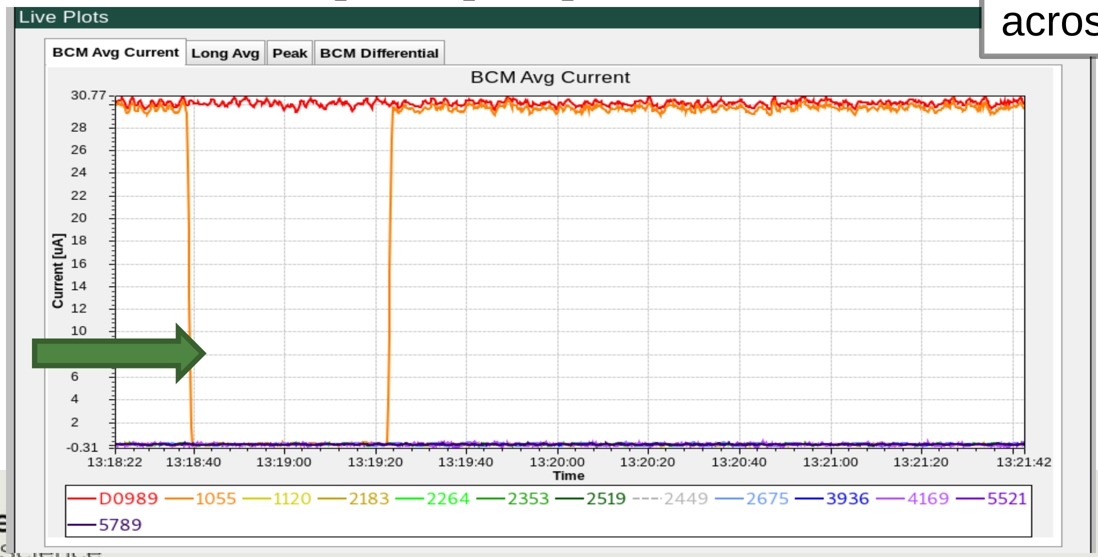



Optimization time:
about 10min




GP mean visualized by projecting maximum across projection axes

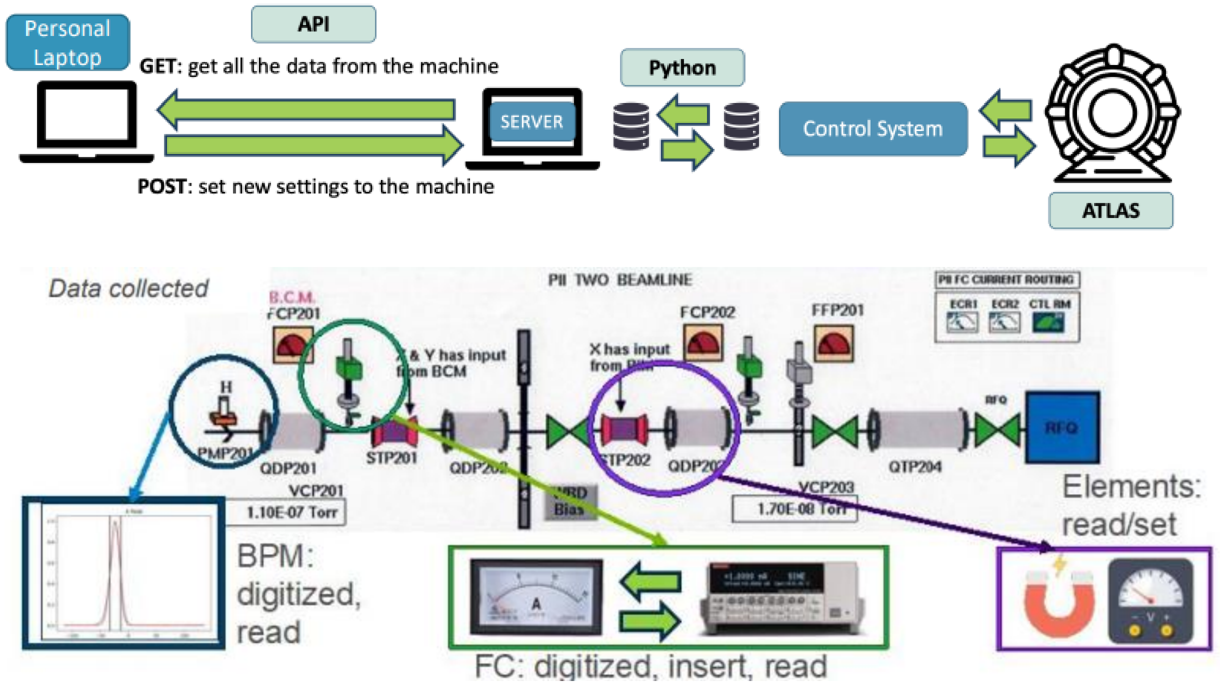


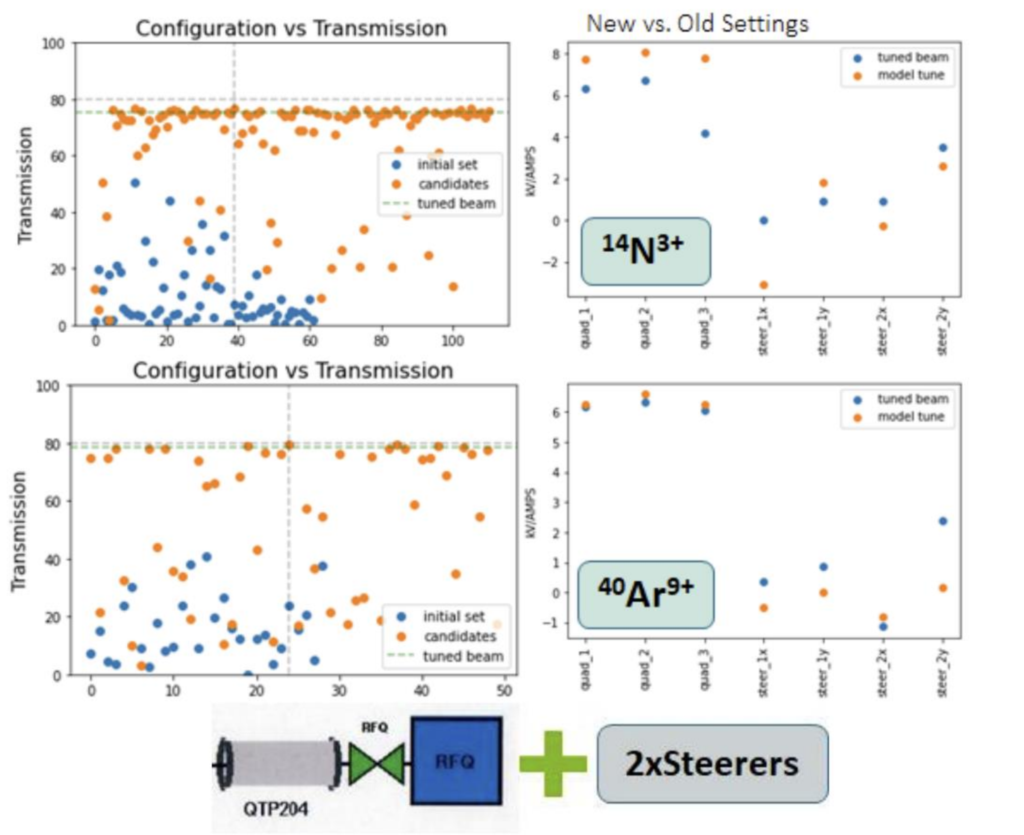

@ K. Hwang

# ATLAS Tuning: Optimize Beam Transmission

- Digitize the Legacy System
  - New Python API for machine tuning
  - Offline modeling: Track code



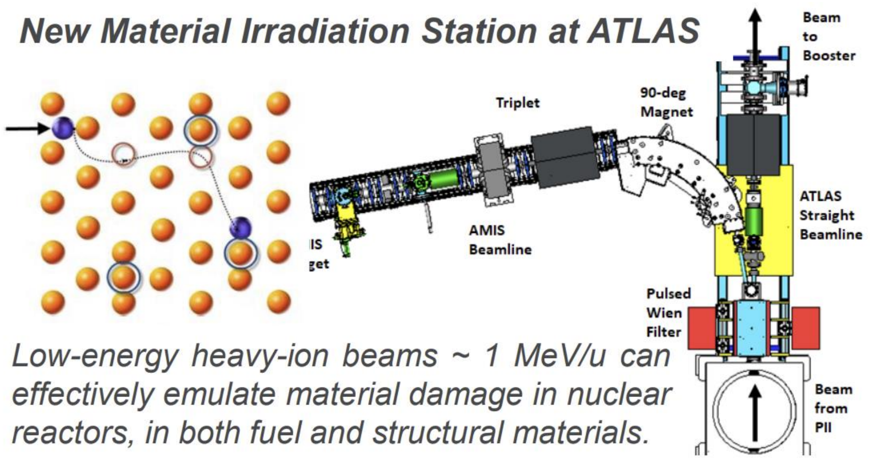

@ B. Mustapha



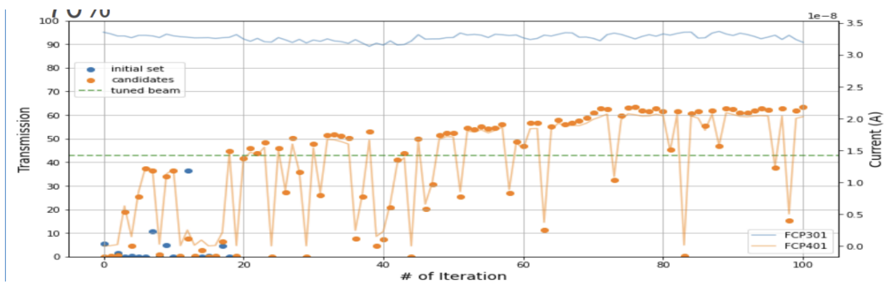

- 7 varied parameters (3 quads + 2 steerers)
- Optimization of beam transmission
- Case of $^{14}N^{3+}$ : 29 historical + 33 random tunes
- Case of $^{40}Ar^{9+}$ : 29 historical tunes

# ATLAS Tuning: Multi-Object BO

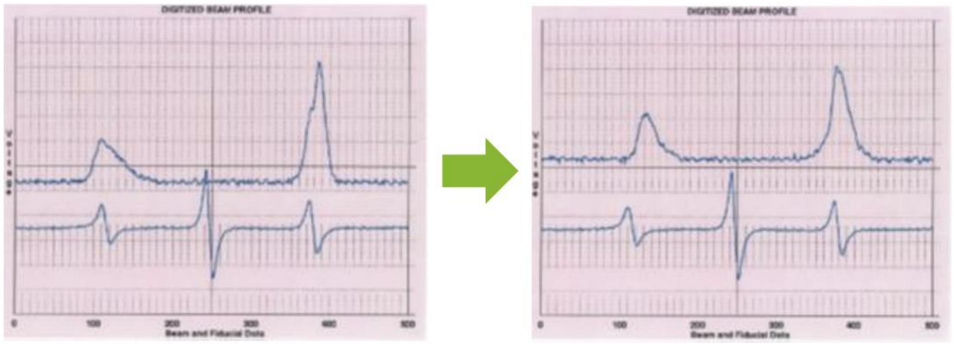
Use Bayesian Optimization for dual objections

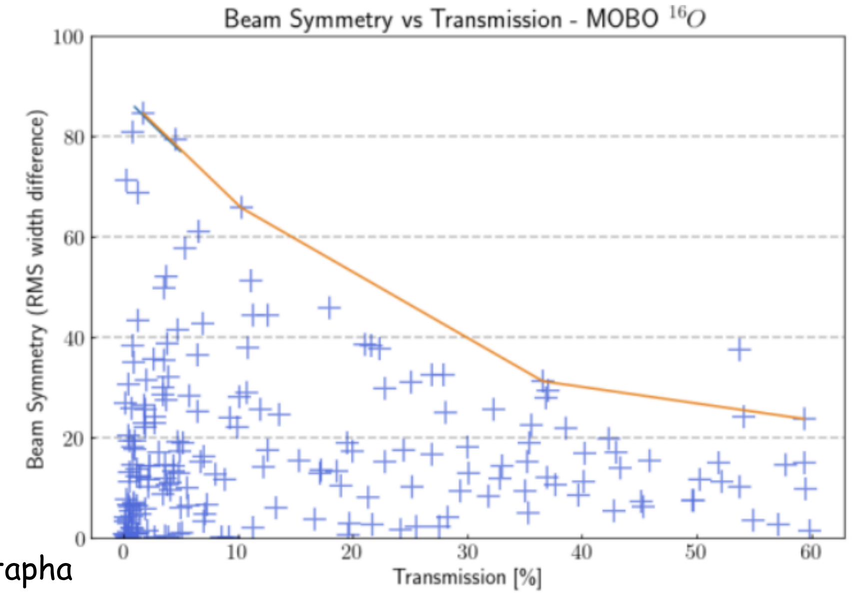



Optimizing transmission




Optimizing Profile, symmetric

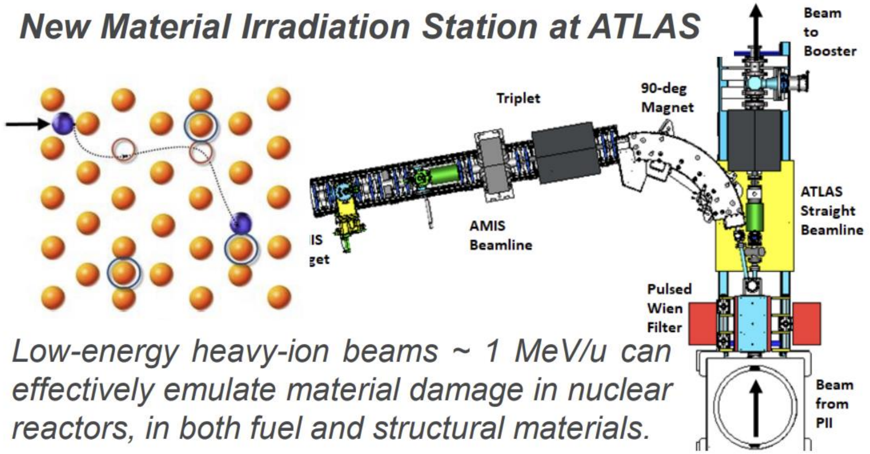


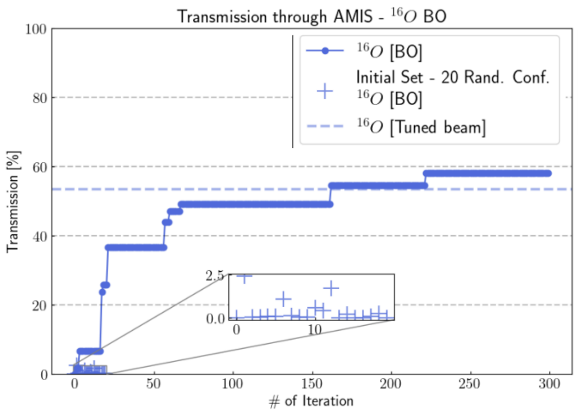

@ B. Mustapha

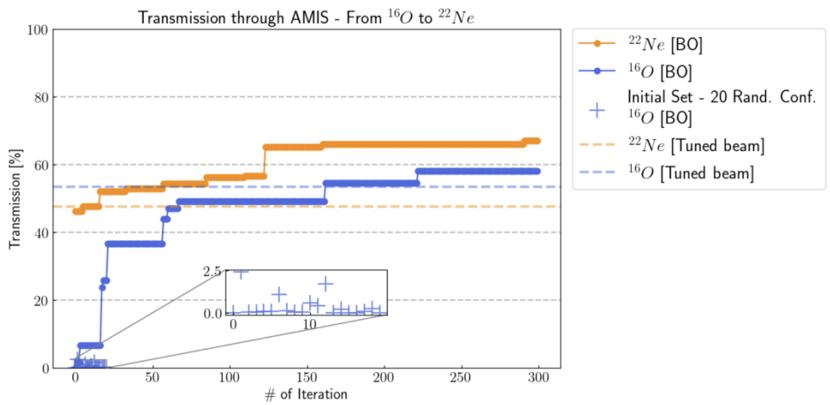
Pareto front of two objects.

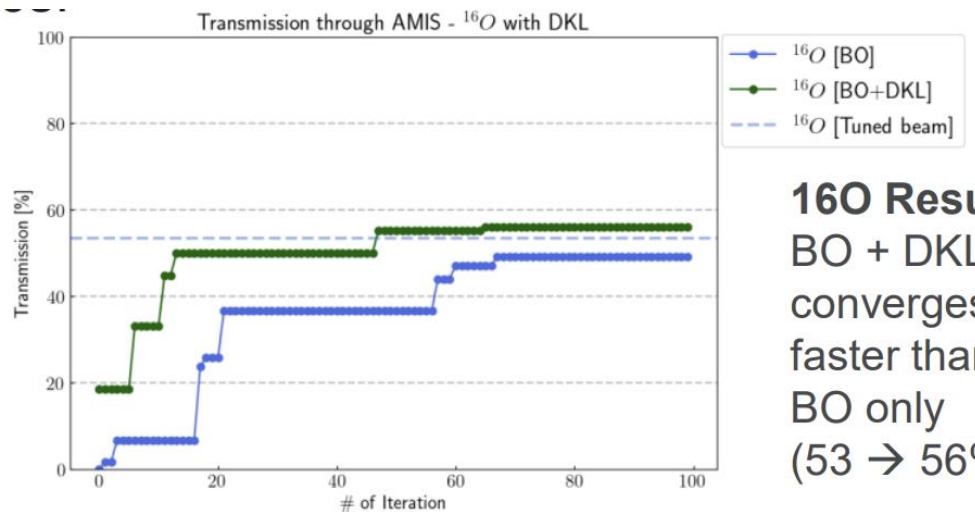
# ATLAS Tuning: Transfer learning




Establish model using $^{16}$O then use on $^{22}$Ne, with scaling

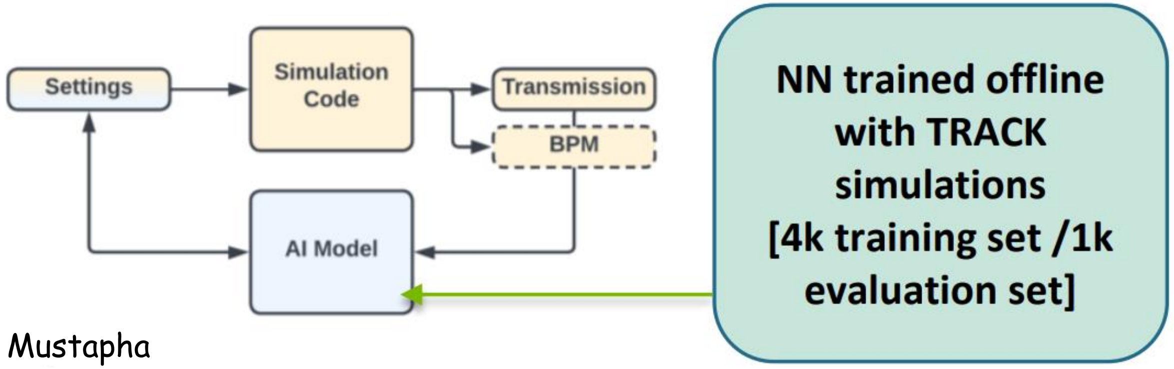


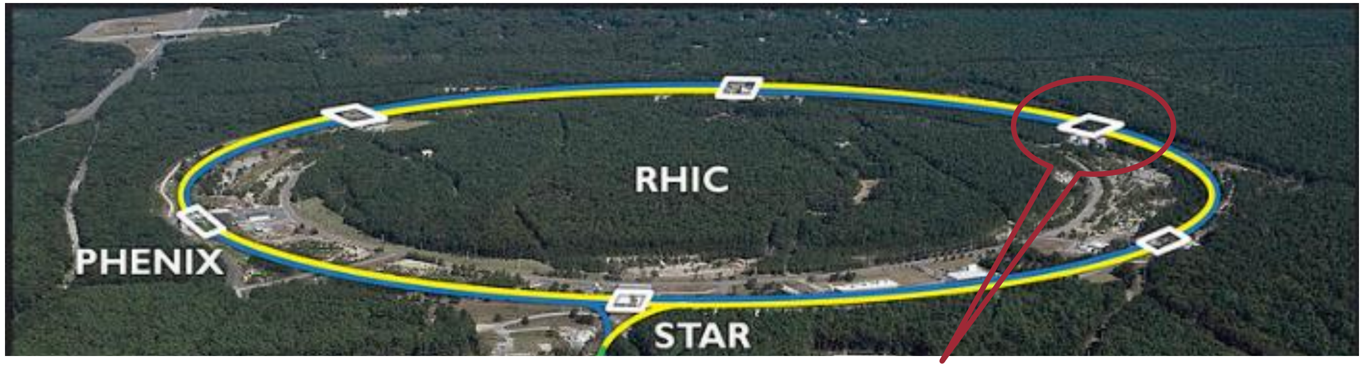

**16O Results**:
BO + DKL converges faster than BO only
(53 → 56%)

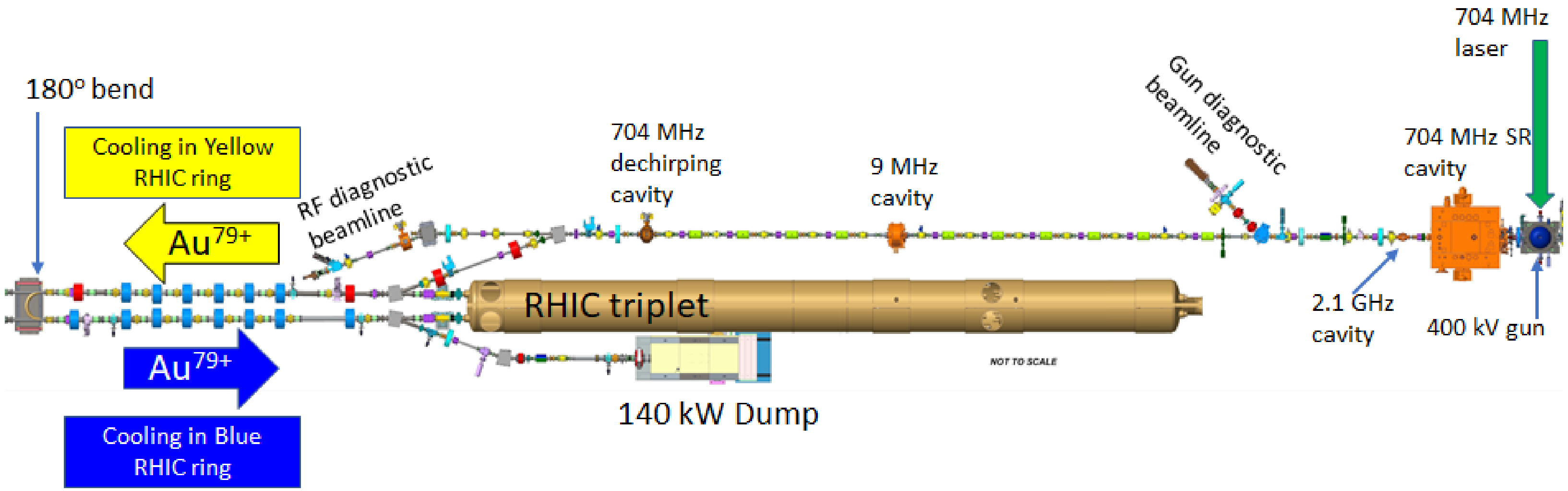
Transfer simulation knowledge using Deep Kernel Learning



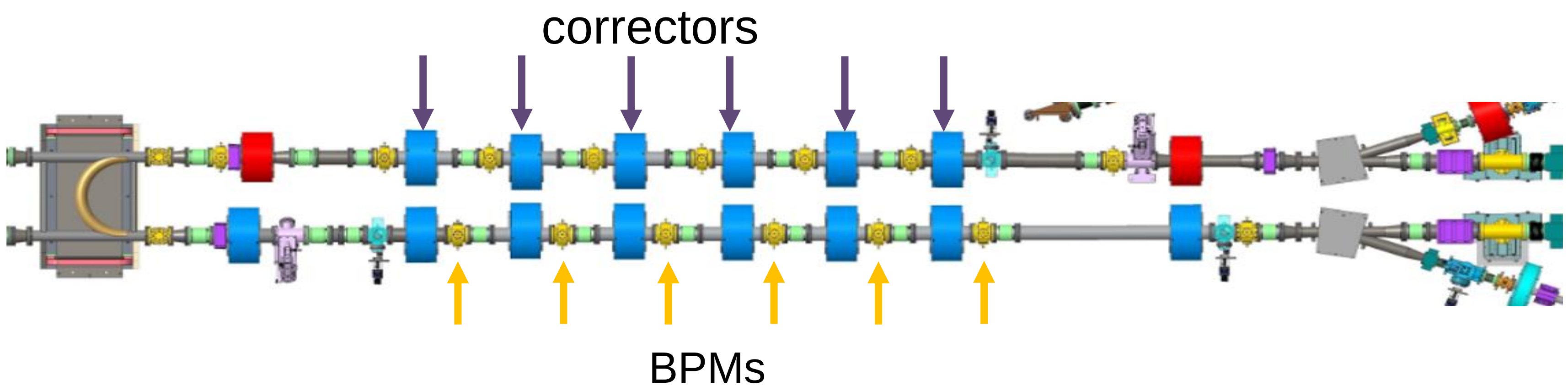

@ B. Mustapha

# AI/ML application in Cooling Exp at RHIC



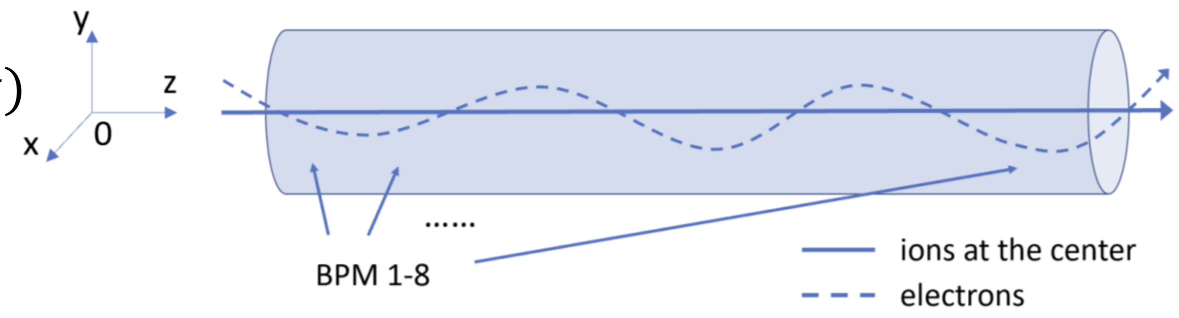
# RHIC: BO to optimize cooling rate




- Only the first 4 BPMs are considered;
- Cooling performance is measured by the cooling rate;
- Decreasing speed of transverse ion beam size:

$$\lambda = (1/\delta)(d\delta/dt)$$

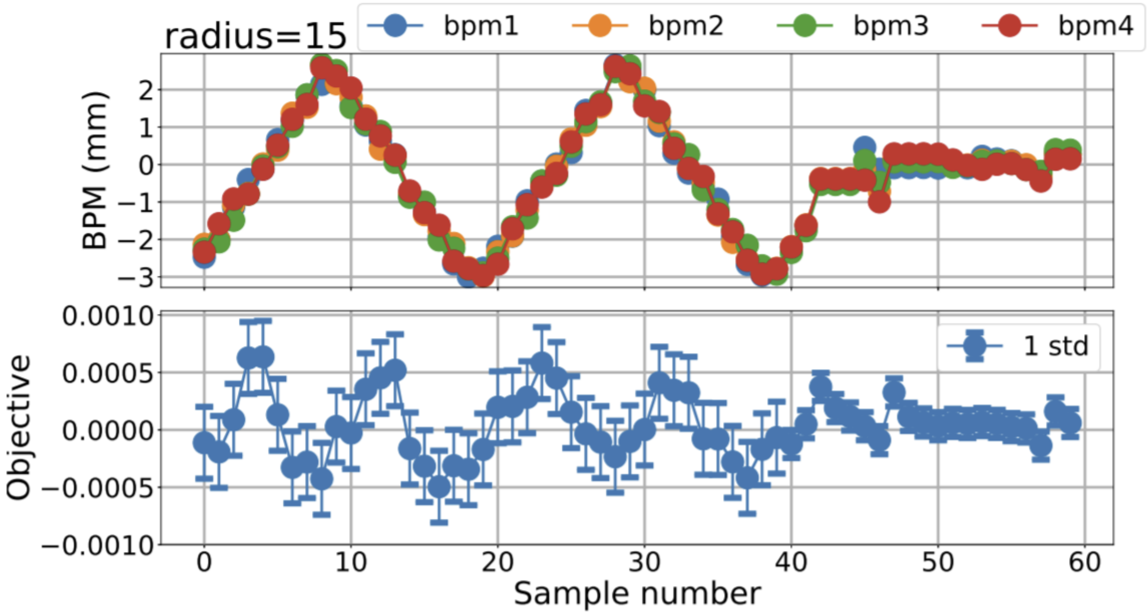
- A more negative $\lambda$ means a faster cooling rate;
- Ions are assumed in the center position (x=0, y=0).

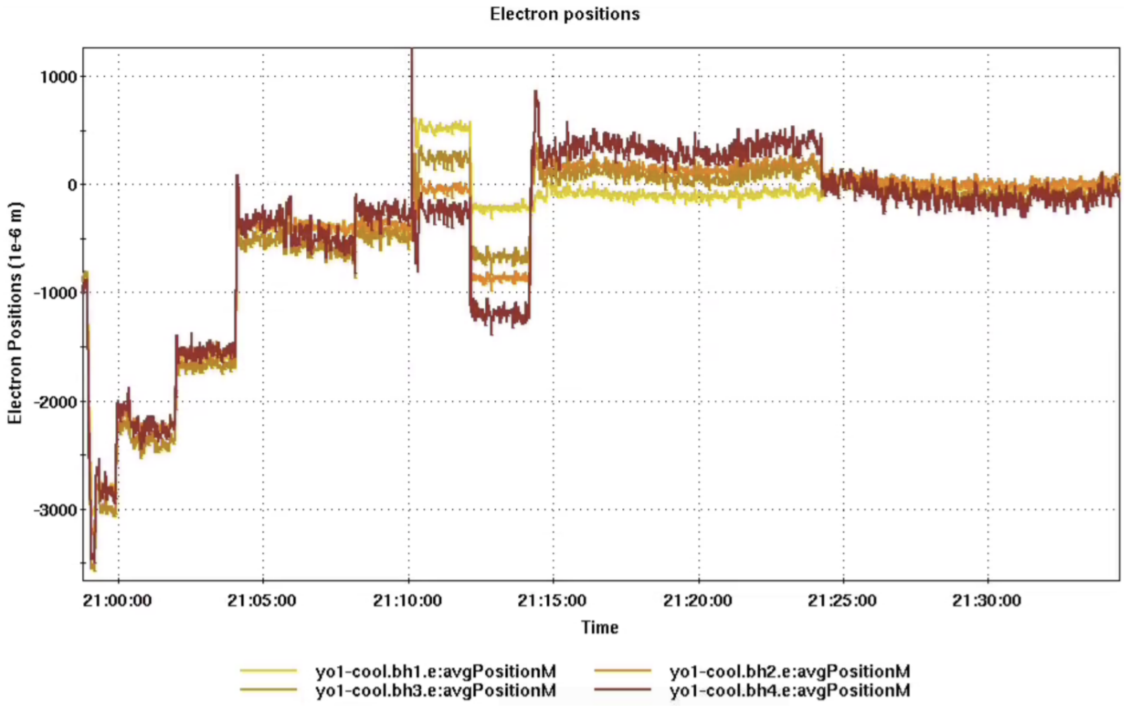



@ Y. Gao and W. Lin

# RHIC: BO to optimize cooling rate

- 4 BPMs are used to optimize the cooling rate.  Cooling rate is observed to be optimized with zero BPM offsets.

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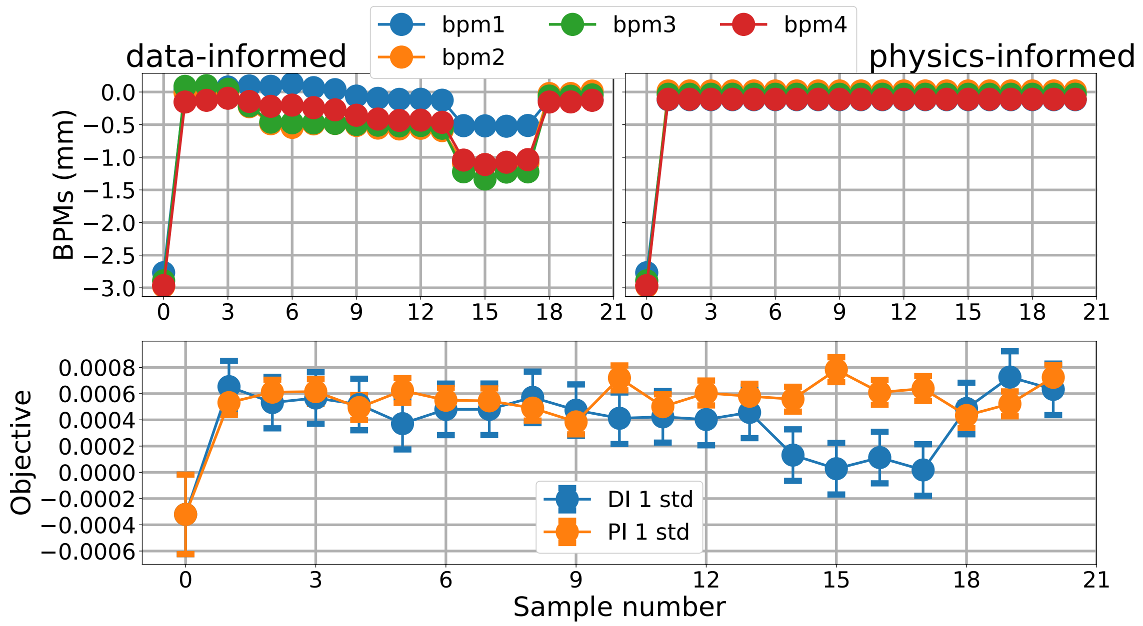
# RHIC: Physics informed and Contextual GP

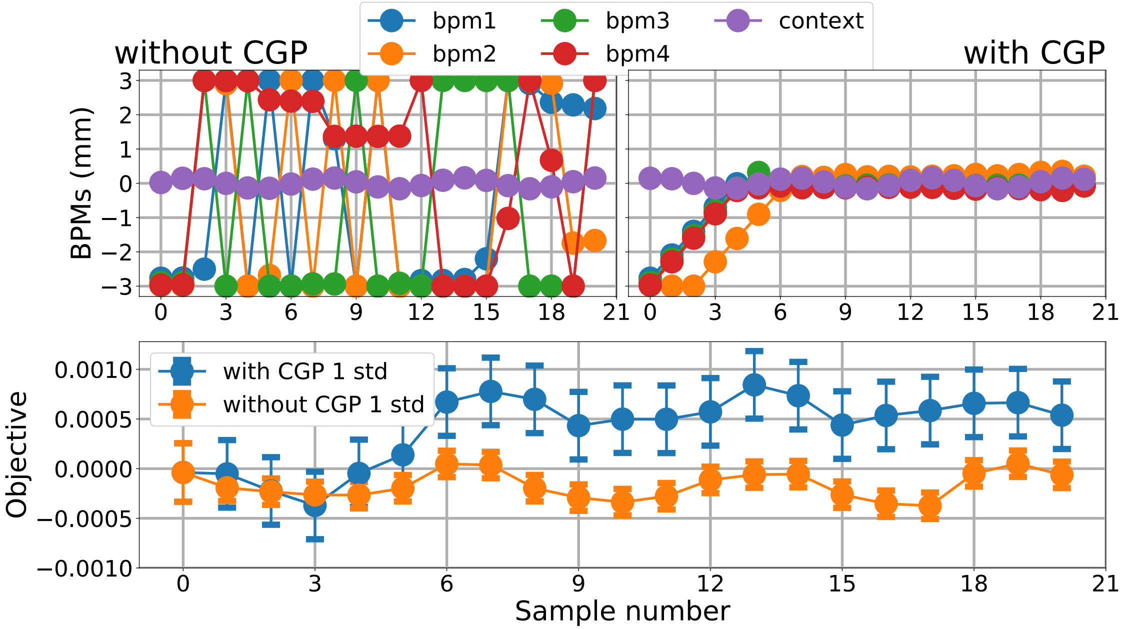
## Physics-Informed GP

Replace the kernel (RBF) with the Hessian from the simulation data near the optimum point




## Contextual GP

Handel the environmental change, such as the intensity change during one ‘store’, using Contextual-UCB

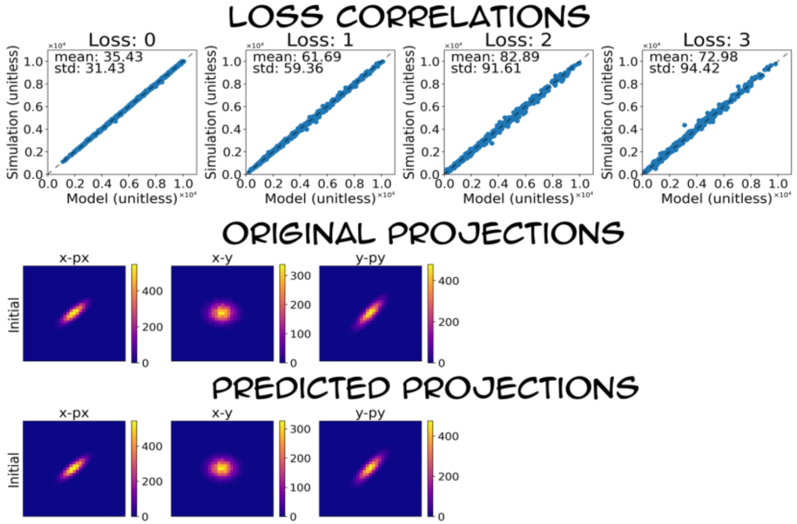


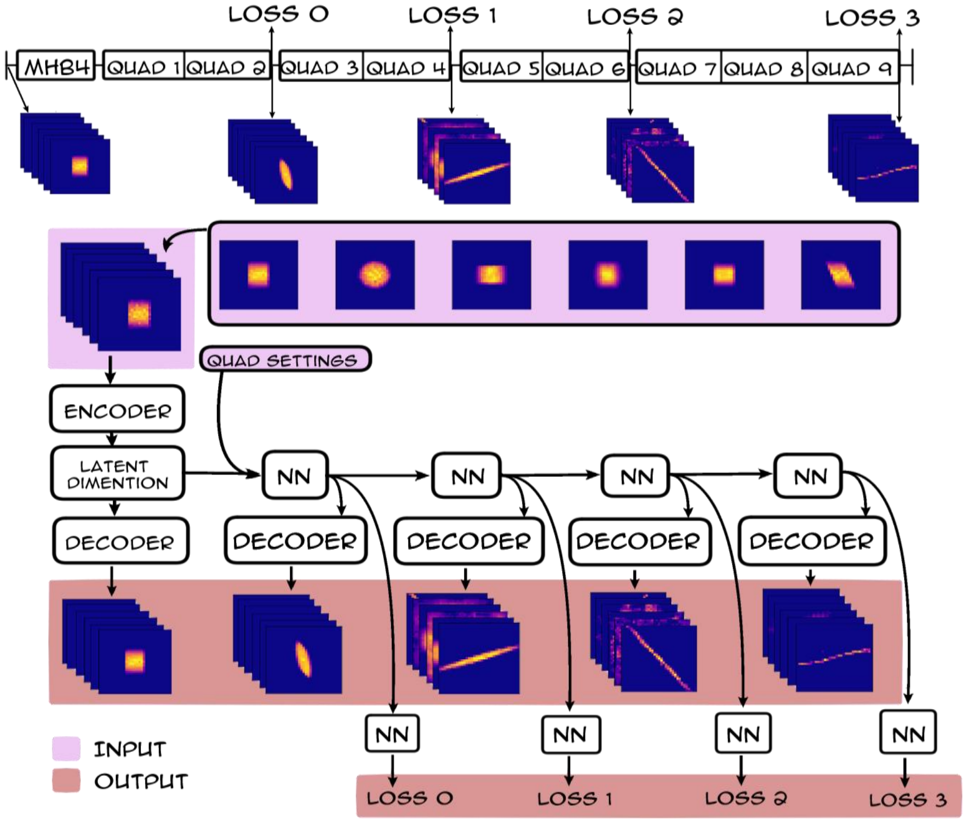

@ Y. Gao and W. Lin

# Beam Loss, Beam Profile, and Tomography

# Beam distribution in NP accelerators

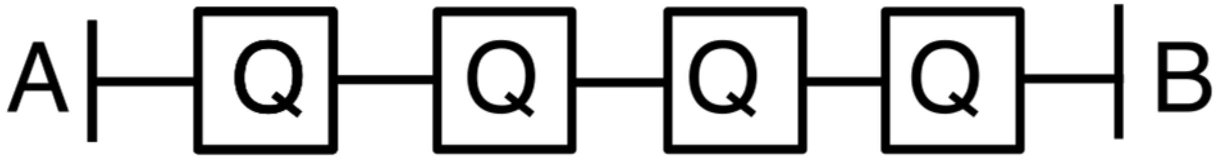
- Unlike light sources, for NP accelerators, the knowledge of beam distribution (other than the 2nd order moments) are used to provide **better beam matching** and **minimize the uncontrolled losses**.
- Beam distribution inferred from a series of 2-D profiles in latent space.
- Associate latent space with beam loss.
- No accelerator physics is used.



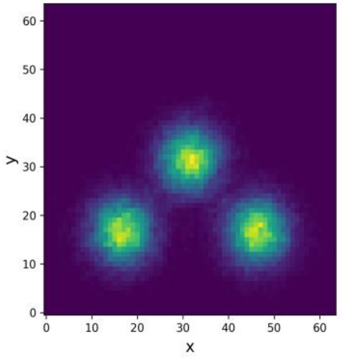




~1% accuracy achieved in this simulation demonstration, with aggressive data needs

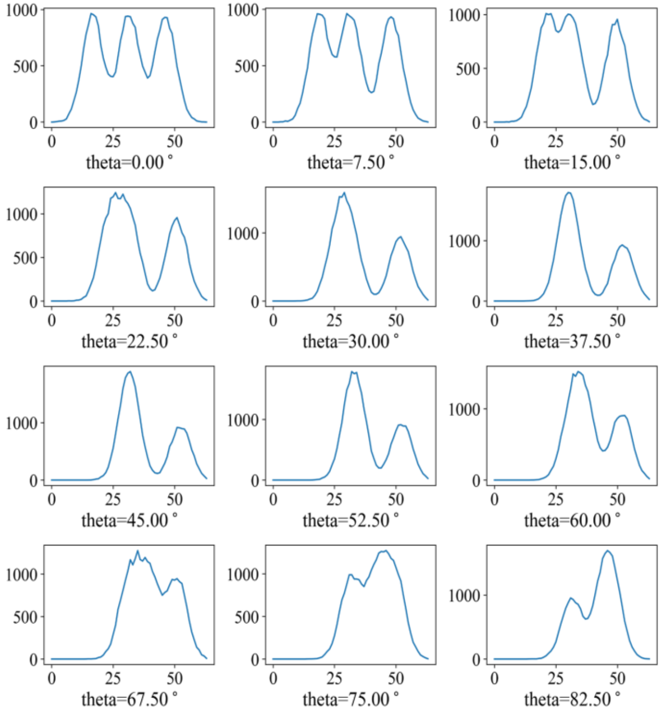
# Tomography




Ground Truth

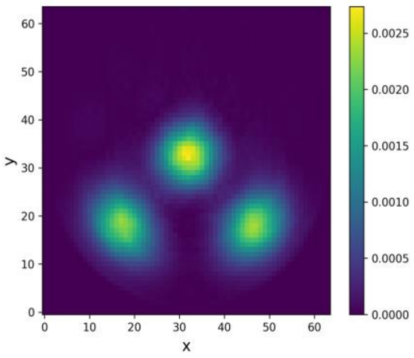


$M(A \rightarrow B)$, Projection

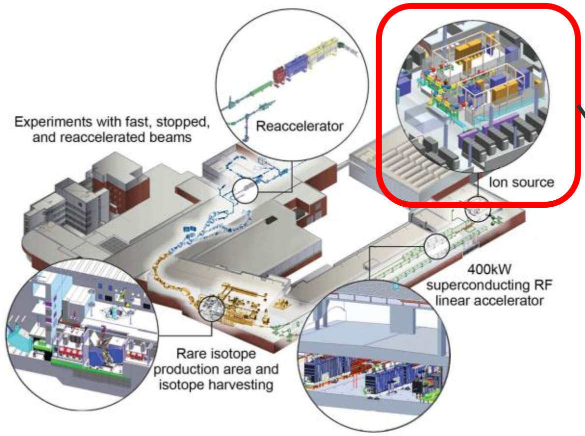



$M^{-1}(A \rightarrow B)$, Infer

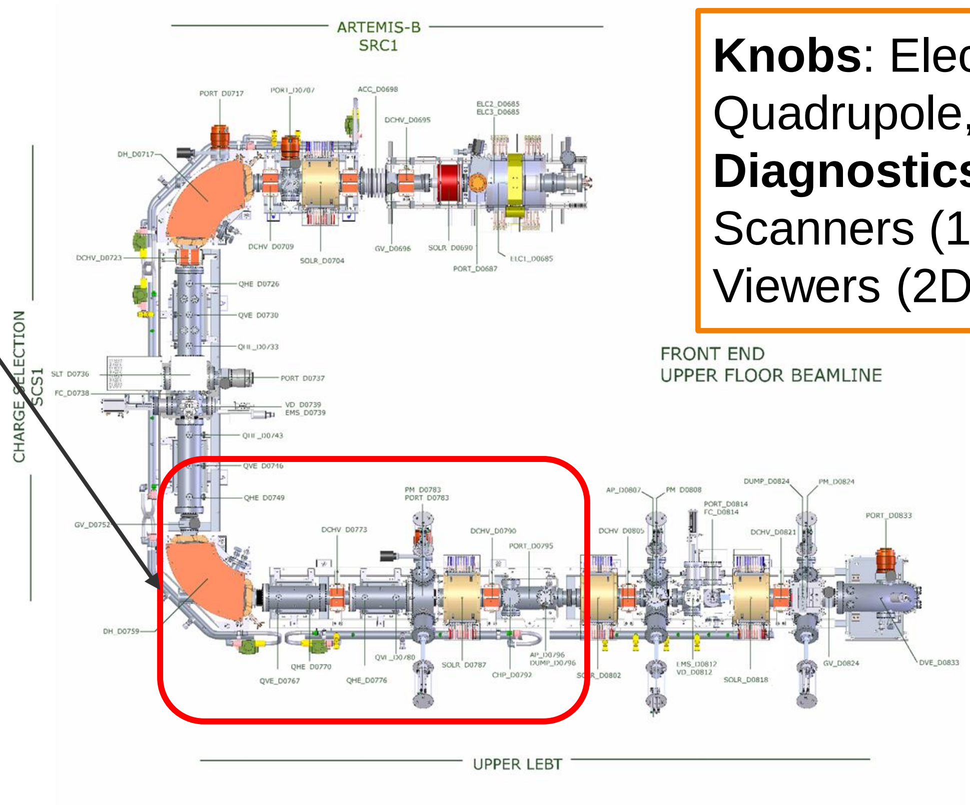
Reconstruction



# Tomography at FRIB - Simulation




- Linear accelerator
- Rare isotope production with primary beams up to 400 kW, 200 MeV/u uranium
- Understanding the beam will help control beam loss at high intensity

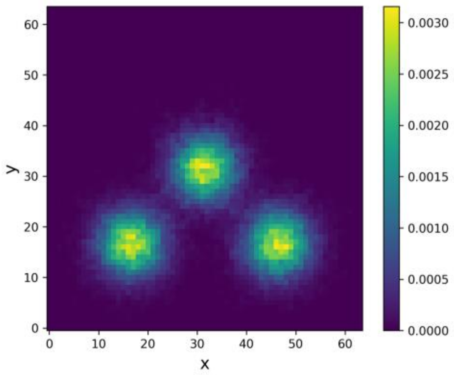



**Knobs**: Electric Quadrupole, Solenoids
**Diagnostics**: Wire Scanners (1D), Viewers (2D)

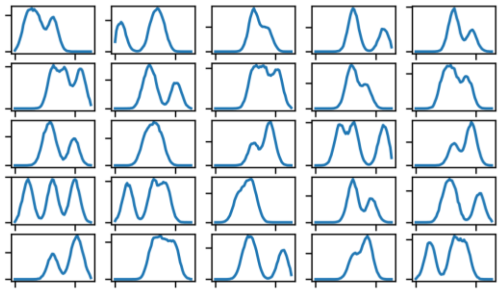
Fox, https://www.fox47news.com/neighborhoods/msu-campus/after-13-years-and-close-to-1-billion-msus-facility-for-rare-isotope-beams-is-up-and-running

# Maximum Entropy (MENT) method

Distributions:




Measurements Projections



The entropy of a beam distribution:

$$H(f) = -\int\int dxdy f(x,y)\ln f(x,y)$$

Constrains are the profile measurement (projections) down stream, denoted p(s). Using Lagrange multiplier:

$$\psi(f,\lambda) = H(f) + \sum_{n=1}^{N}\int ds\lambda_n(s)\left[\int dt f(x_n,y_n) - p_n(s)\right]$$

$$\frac{\partial\psi}{\partial f} = 0, \qquad \frac{\partial\psi}{\partial\lambda} = 0$$

It can be solved, albeit with computational difficulties

$$f(x,y) = \prod_{n=1}^{N} h_n[s_n(x,y)] \qquad h_n(s) = \frac{p_n(s)}{\int dt \prod_{k\neq n} h_k[s_k(x_n,y_n)]}$$

# MENT example for 4-D Distribution

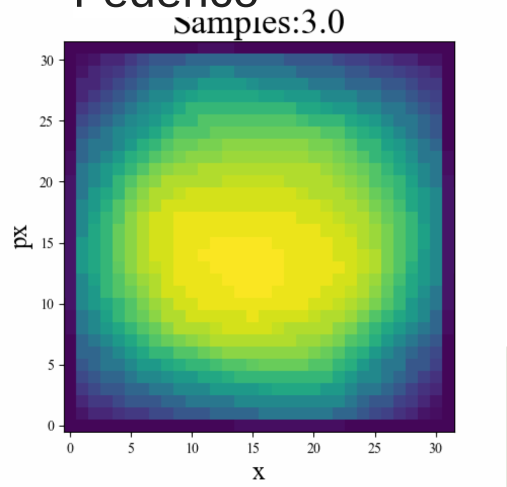
$$\vec{x}_s = R_{4\times 4}\vec{x_{s0}}$$

$$R_{4\times 4} = \prod_{i\neq j} R_{ij},$$

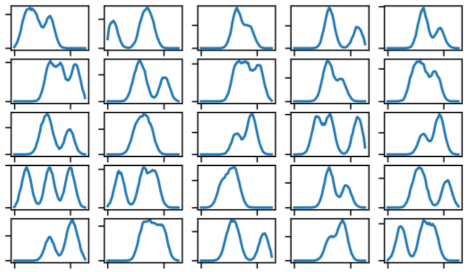
$$i, j \in (x, x', y, y')$$

$$R_{4\times 4} \to \begin{bmatrix} R(\alpha_1) & 0 \\ 0 & R(\alpha_2) \end{bmatrix}$$

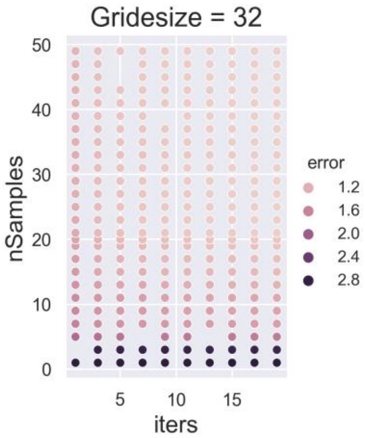
Change in reference frame [6] T. Federico



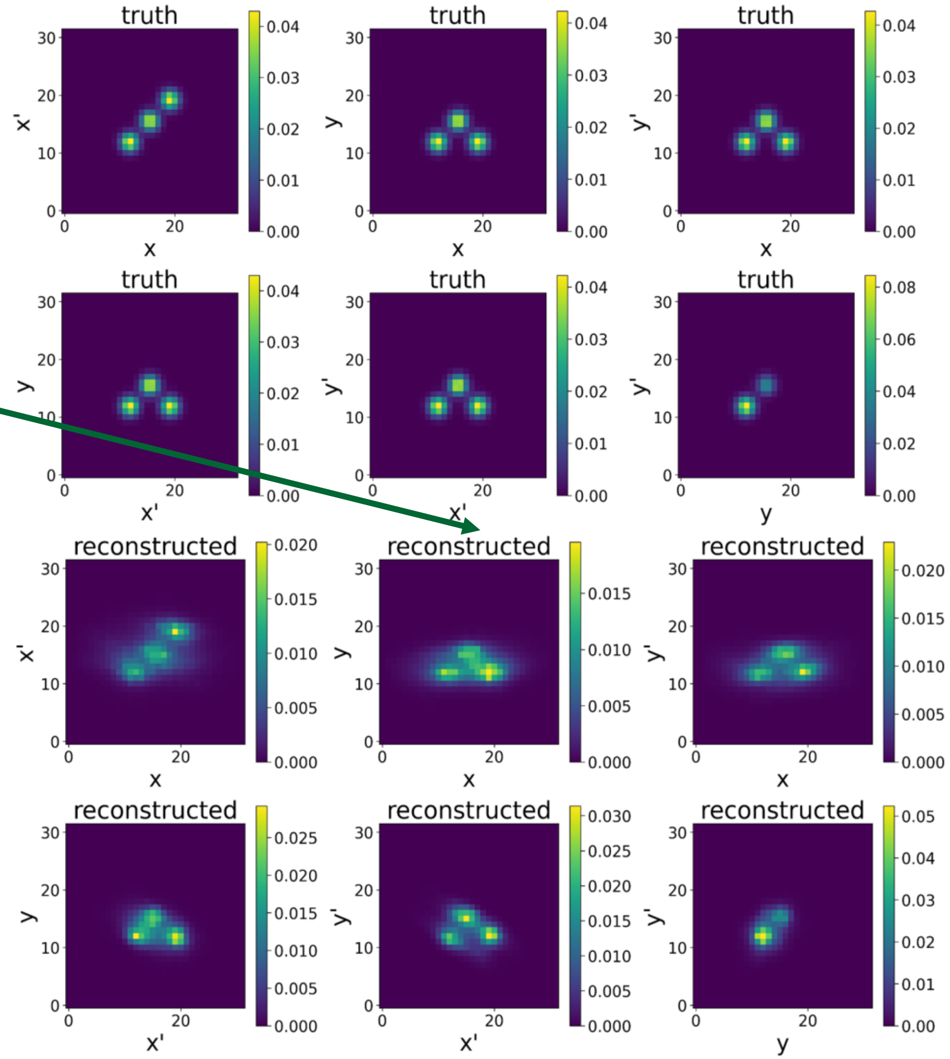

Conditions for “trick 2” to work?



Ground Truth



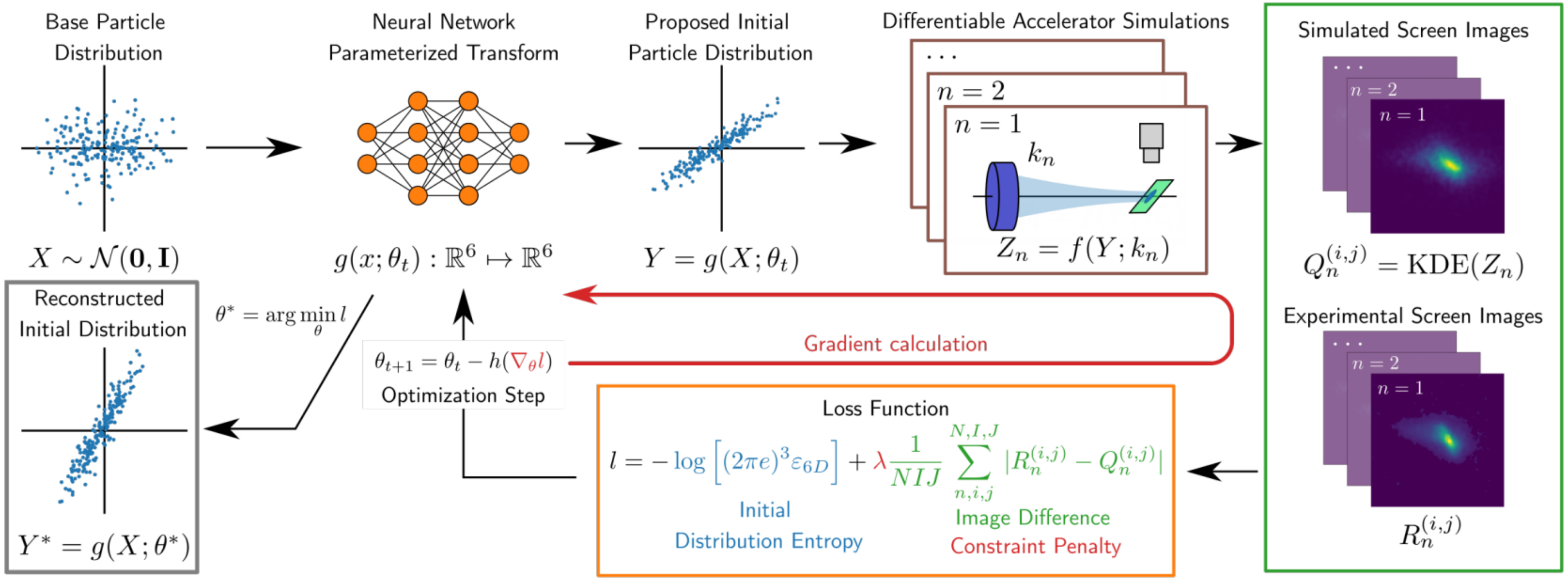

Reconstruct - 45 1D samples



# ML based MENT

Recent paper has demonstrated that MENT is ML friendly:

@ R. Roussel, et.al. PRL 130 145001, 2023




- ML approach bypasses the challenging iteration process.
- Predict the core of the beam well.
- ➢ Is finite number of measurement good enough for the beam tail 's information?

# Summary

- Machine Learning techniques are powerful tools to boost accelerator performance.
- Currently the demonstrated ML application is limited to 10 knob/feature, order of magnitudes less than number of control knobs in accelerator complex (~10K knobs)
- Problem Isolation and dimension reduction are the key.
- Beam matching and loss/background control is a challenging topic for NP accelerators.
- The link of beam distribution and losses is a challenging problem even for ML methods.
- A combination of data-driven and physics-based approach seems the promising way to proceed.

# Acknowledgement

- The materials are provided by colleagues working on ATLAS, RHIC and FRIB
  - Brahim Mustapha, Jose Martinez (ATLAS, ANL)
  - Yuan Gao, Kevin Brown (RHIC, BNL); Weijian (Lucy) Lin, Georg Hoffstaetter (Cornell U)
  - Kilean Hwang, Anthony Tran (FRIB, MSU)

*Thank you.*