CLASSE
Cornell Laboratory for Accelerator-based ScienceS & Education

Brookhaven National Laboratory

U.S. DEPARTMENT OF ENERGY

The EIC-BeamAI Collaboration: Preparing Machine Learning for the Electron-Ion Collider

Georg Hoffstaetter de Torquat

For the EIC-BeamAI collaboration

How to prepare AI for a huge new accelerator, outside the construction project ?

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AI/ML funded projects for the EIC

AI / ML is not part of the EIC construction project
(partly because AI for accelerator operations is so now.)

Subsequent (off-project) funding:

- **Higher RHIC polarization by Physics-informed Bayesian Learning**
  BNL, Cornell, JLAB, SLAC, RPI (DOE-NP funding 2023 – 2025)
- **Toward higher brightness and polarization of hadron beams: Digital-Twin-based autonomous control of BNL's hadron accelerator chain**
  BNL, Cornell, JLAB, SLAC, FNAL, RPI (DOE-NP funding 2025 – 2027)
- **Developing AI-Ready Data Framework for DOE NP Particle Accelerators**
  Now called **NARAD =** NP AI-Ready Accelerator Data
  JLAB (lead), BNL, Cornell, LBNL, PNNL (ASCR/NP funding 2025-2027)
- **National collaboration: Multi Organization Accelerator Team (MOAT)**
  To prepare for AI/ML in accelerators funding through the US Genesis mission.

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What is the EIC-BeamAI collaboration

Growing out of funded proposals

- Higher RHIC polarization by Physics-informed Bayesian Learning
- Toward higher brightness and polarization of hadron beams: Digital-Twin-based autonomous control of BNL's hadron accelerator chain

Bi-weekly meetings focus on all AI/ML topics relevant to the EIC.
Topics have included:

- AI/ML optimization of accelerator commissioning for existing and future BNL accelerators.
- New ML-ready codes, e.g., fully differentiable SciBmad and digital twins of existing BNL accelerators
- New standards, e.g., AI-ready Accelerator Data, Particle Accelerator Lattice Standard (PALS)
- Osprey for LLM help in accelerator operations
- Topics of Multi Organization Accelerator Team (MOAT) and AI ready data standardisatiuon (NARAD)

Zoom meetings are **open to all** (Tuesdays 11am, Friday 3pm EST)

Monthy meeting for the EIC-BeamAI WG of the international EIC accelerator collaboration

Combined with workshop meetings of the **AI4EIC** Workshops for the EIC User Group

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NOTE: MODA'26, Modern Optimization of DA, ICFA mini workshop, 10/19/26 at Cornell

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The US Genesis mission

Genesis Mission is a national initiative to build the world's most powerful scientific platform to accelerate discovery science, strengthen national security, and drive energy innovation.

MOAT (9 DOE labs and universities) prepares the particle accelerator community for the Genesis Mission. It aims to build national accelerator physics knowledge into a national AI infrastructure that can be used across all platforms to inform on accelerator design and operation.

Several of the MAOT-related proposals are applicable to or focused on the EIC, e.g.,

- AI-Driven, Self-Learning Digital Twins for Robust Operation of Particle Accelerators
- AI-reform of legacy codes in Accelerator modeling and operations
- AI-driven Accelerator Operations Prototyping with Cornell’s Electron Test Beams
- Robust Diagnostic Comprehension for Facilitation of Large-Scale Digital Twins
- Robust and Safe Deep Agent for Optimization and Control of Particle Accelerators
- And more …

The EIC-BeamAI collaborations aim as part of the Genesis Mission is to build infrastructure that will benefit EIC.

The EIC will be one of the first large-scale collider-based programs in which AI/ML is integrated from the start.

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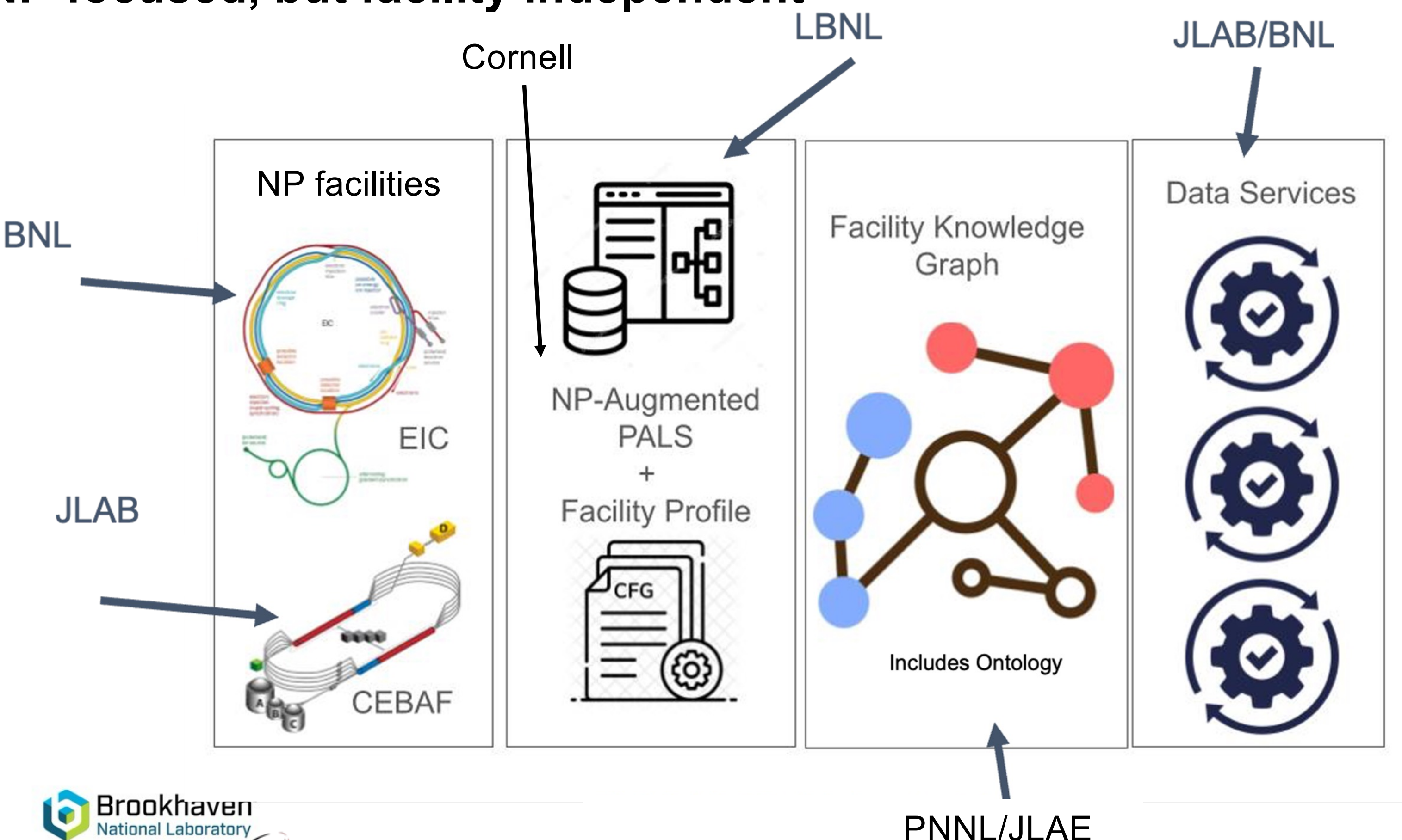
NP AI-ready Accelerator Dada (NARAD)

NP-focused, but facility independent



American Science Cloud (AmSC) integration

JLab/PNNL

- Strategic alignment of NARAD artifacts/demos with AmSC infrastructure
- Definition of AI-ready semantic contracts for NARAD data

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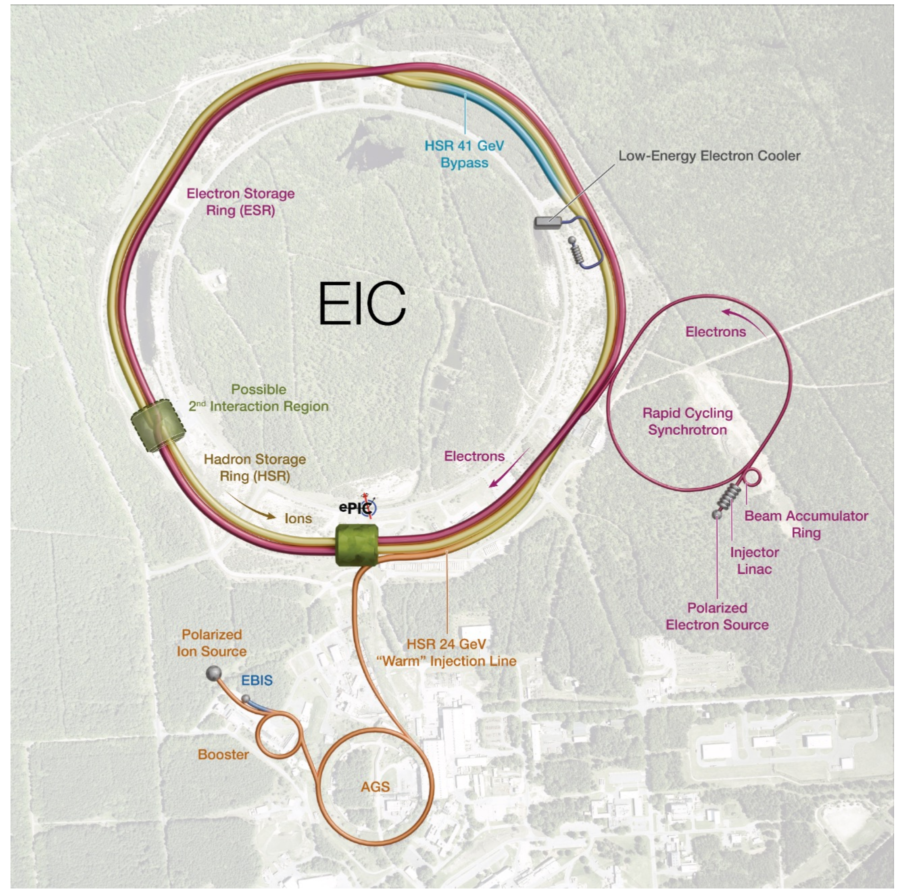
AI/ML for EIC design and operation

EIC-BeamAI

- The **Electron Ion Collider (EIC)** is designed for unprecedented precision to reveal the structure of nuclear matter.
- EIC will adopt AI/ML-native operations from the start, leveraging Genesis / MOAT AI capabilities.
- Operational complexity and data scale make AI/ML crucial for efficient control of modern particle accelerators.
- EIC design choices are increasingly analyzed with AI tools.



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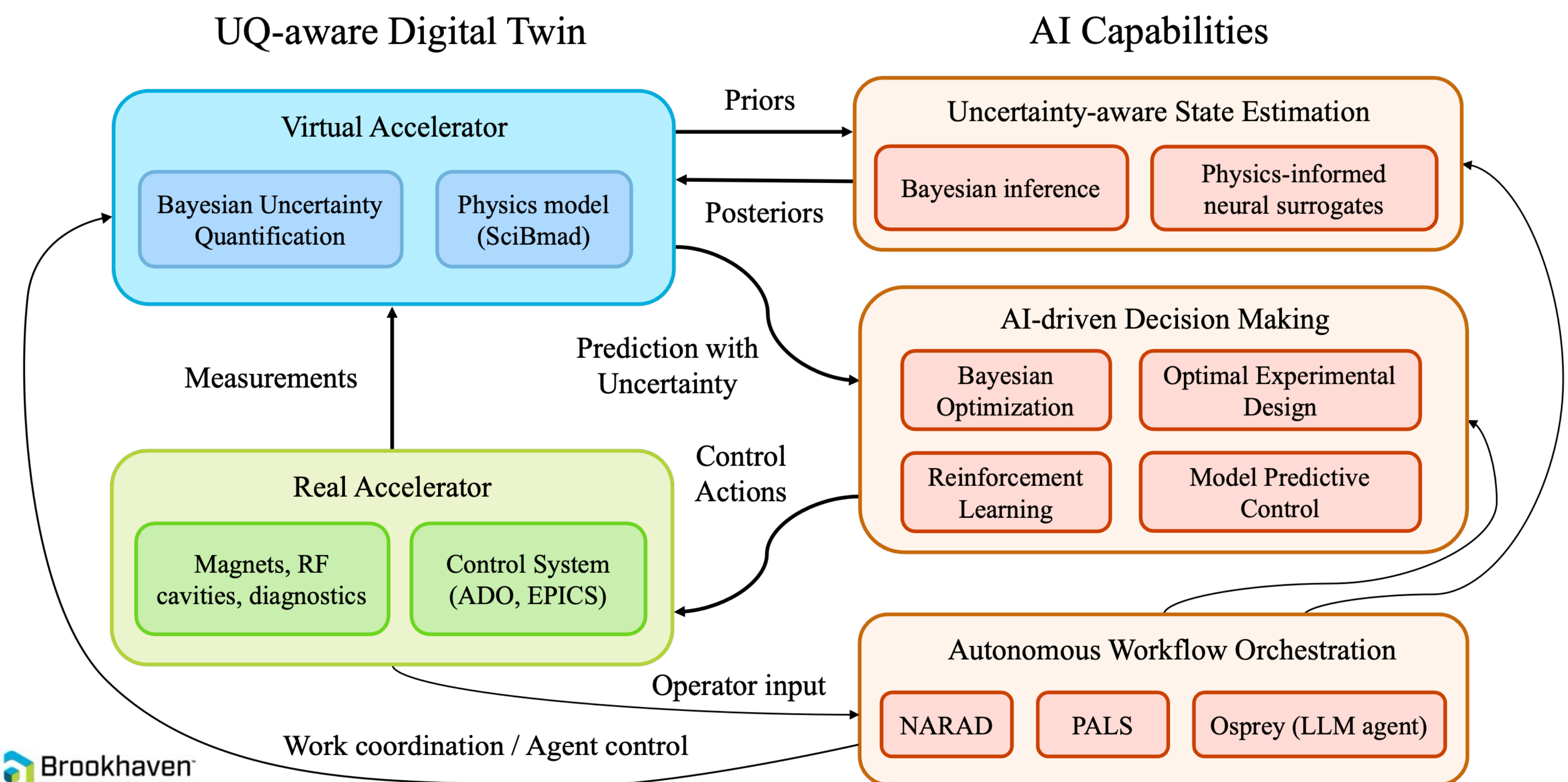
AI integration in EIC operations

Closed-Loop AI and Digital Twin Framework for Accelerator Operations



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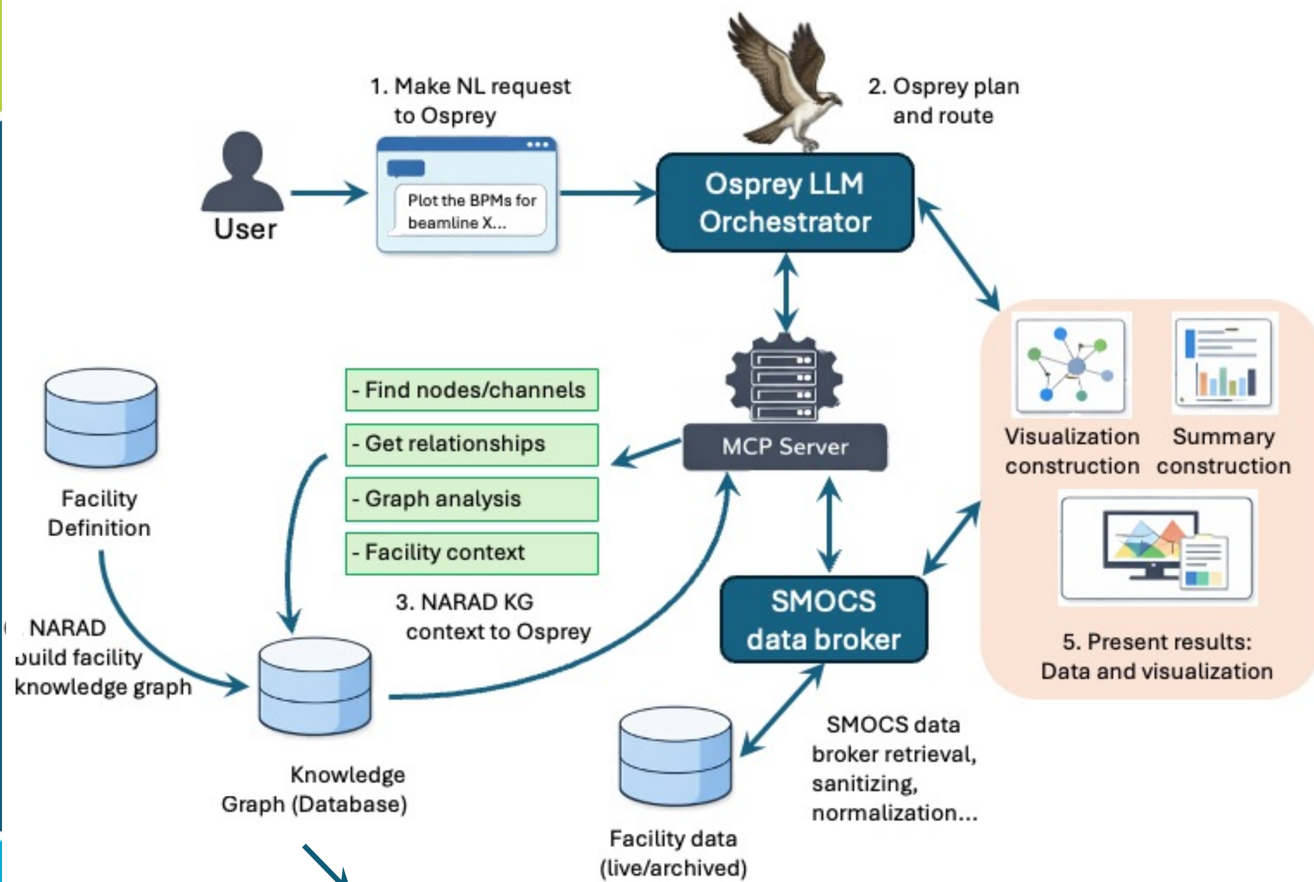
Facility-independent AI standards



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Particle Accelerator Lattice Standard (PALS)

PALS-Ext. for AI/ML, e.g., surrogates

Knowledge Graph from PALS-Ext:
- control name discoverability
- **standards based** facility ontology
- **standards based** verifiable (LinkML)

Data served through SMOCS
- **facility-independent** data broker
- **scalable** container-based design
- **standards-based** (Apache Kafka)
- streaming/synchronous readout
- live/archiver data source abstraction

Channel finding for LLM orchestrators
- mapping natural-language intent to actionable control-system signals
- critical tool identification

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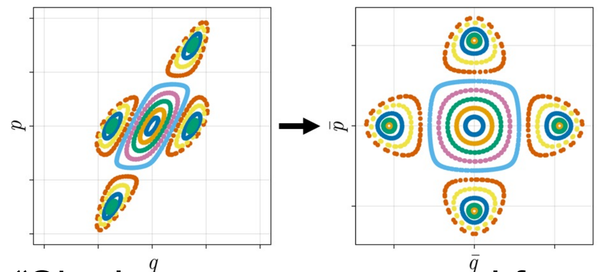
SciBmad – ML oriented beam modeling

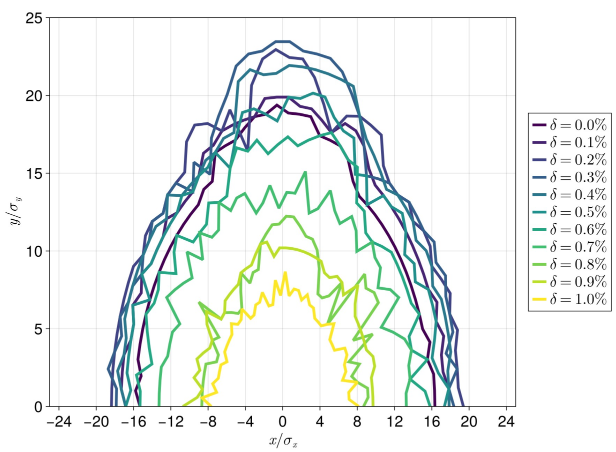
New accelerator modeling library *SciBmad* for nonlinear dynamics **simulation, analysis + optimization**:

SciBmad



"Single resonance normal form"

Optimization by GPU lattice parallelization



Dynamic aperture for the EIC

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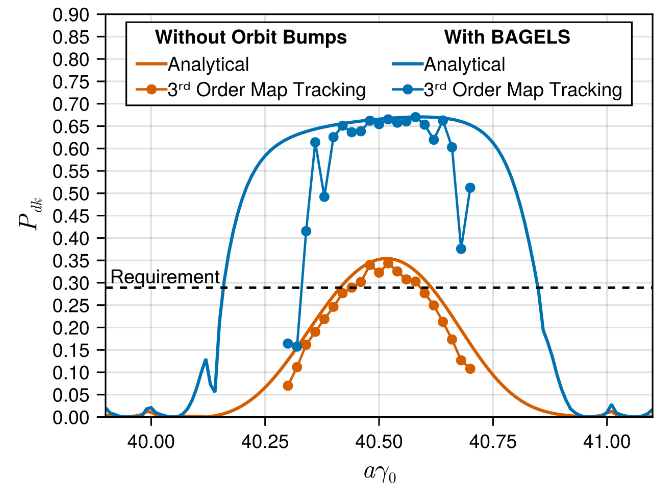
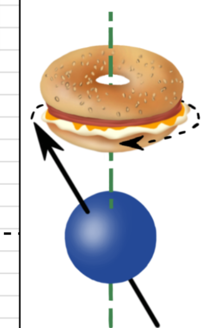
EIC-BeamAI

- **Fully forward, backward, and Taylor differentiable.**
- **Fully GPU and CPU parallelized.**
- **Spin dynamics optimized "BAGELS"**





Phys. Rev. Accel. Beams **28**, 031002, ***Editor's Suggestion***

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SciBmad – ML oriented beam modeling

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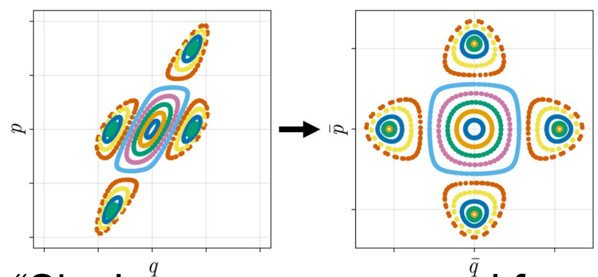
SCIBMAD



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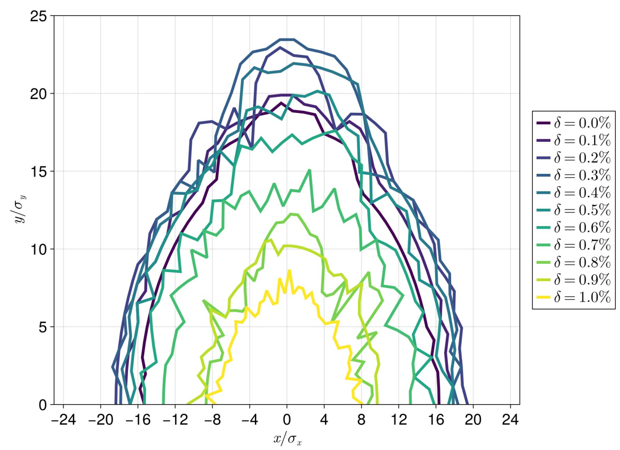

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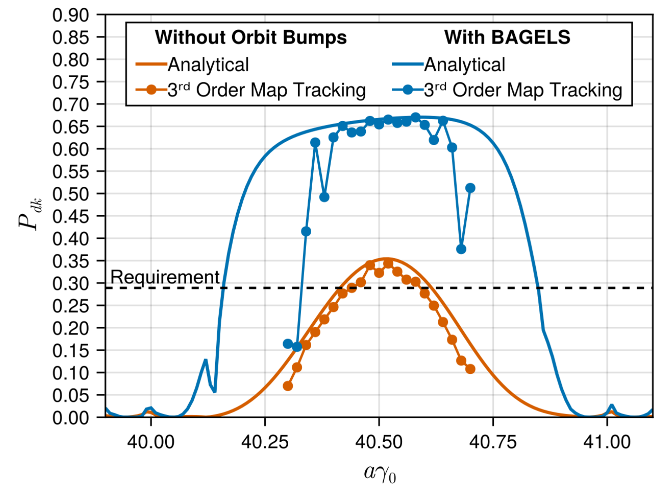

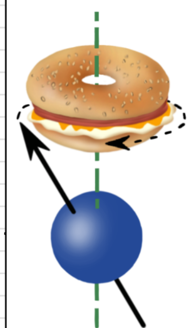

Phys. Rev. Accel. Beams **28**, 031002, ***Suggestion***

Matt Signorelli
EIC Postdoc

Cornell University

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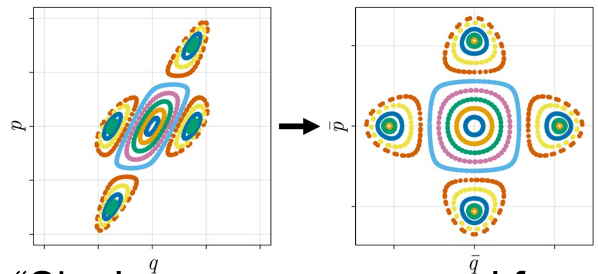
New accelerator modeling library *SciBmad* for nonlinear dynamics **simulation, analysis + optimization**:

SciBMAD



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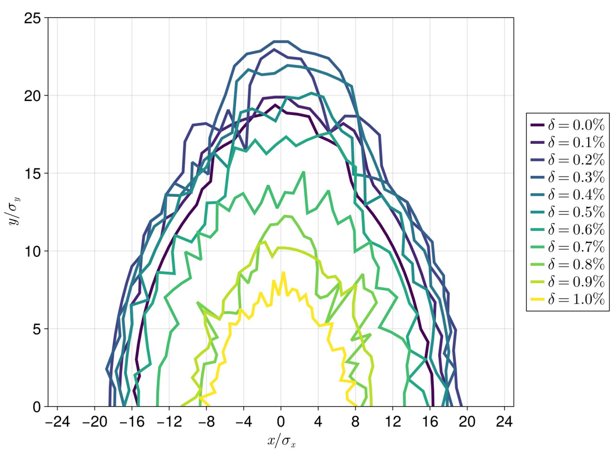

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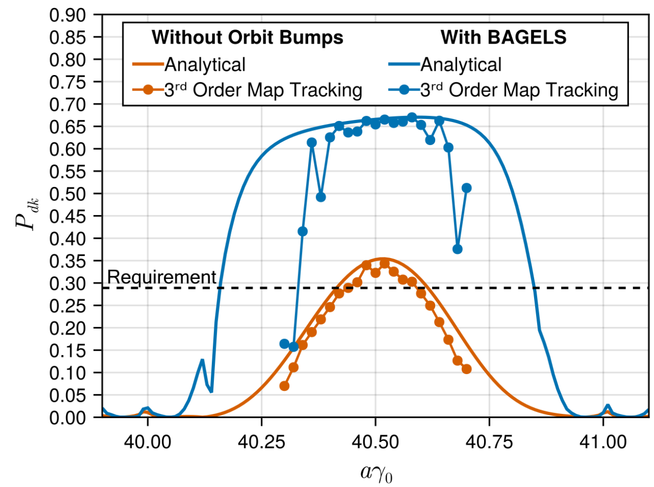

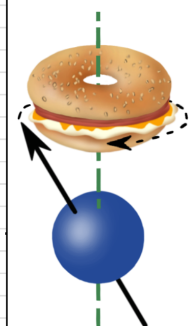

Phys. Rev. Accel. Beams **28**, 031002, ***Suggestion***

Matt Signorelli
EIC Postdoc

Arrow,
Matt's puppy

PALS => Julia ; SciBmad => PALS

```julia
@elements D2ER_6 = LineElement(kind = SBend, L = 5.50007539103, g_ref = -3.2977170394029E-3, e1 = -9.0688461675E-3, e2 = -9.0688461675E-3)
@elements EDGE3_002__1 = LineElement(kind = Multipole, Kn1L = -4.78133619569E-6)
@elements RF0__1 = LineElement(kind = RFCavity, L = 4.01667, voltage = 3.3210942126011E6, harmon_master = false, rate = 5.9114268014977E8)
ring = Beamline([D2ER_6, EDGE3_002__1, RF0__1], species_ref = Species("proton"), E_ref = 70)
```

```yaml
PALS:
  facility:
    - BEGELE:
        kind: BeginningEle
        ReferenceP:
          species_ref: proton
          E_tot_ref: 70
          time_ref: 2E-3
          location: UPSTREAM_END
    - D2ER_6:
        kind: SBend
        length: L = 5.50007539103
        BendP:
          g: -3.2977170394029E-3
          e1: -9.0688461675E-3
          e2: -9.0688461675E-3
    - EDGE3_002__1:
        kind: Multipole
        MagneticMultipoleP:
          Kn1L: -4.78133619569E-6
    - RF0__1:
        kind: RFCavity
        length: 4.01667
        RFP:
          voltage: 3.3210942126011E6
          frequency: 5.9114268014977E8
    - ring:
        kind: BeamLine
        line:
          - BEGELE
          - D2ER_6
          - EDGE3_002__1
          - RF0__1
```

mini_esr.pals.yaml

pals-cpp

pals-julia

any compatible code

scibmad_to_pals

```yaml
PALS:
  version: null
  notes:
    - "This file was generated by the `scibmad_to_pals()` function."
    - "Elements that have no `TrackingP` dictionary have `SciBmadStandard`
    as their tracking method with all parameters equal to false."
  extension_names:
    names:
      - SciBmad
    prefixes:
      - SciBmad_
  facility:
    - BEGELE1:
        kind: BeginningEle
        ReferenceP:
          species_ref: proton
          E_tot_ref: 70
    - D2ER_6:
        kind: SBend
        length: 5.50007539103
        BendP:
          g: -0.0032977170394029
          e1: -0.0090688461675
          e2: -0.0090688461675
    - EDGE3_002__1:
        kind: Multipole
        MagneticMultipoleP:
          Kn1L: -4.78133619569e-6
    - RF0__1:
        kind: RFCavity
        length: 4.01667
        RFP:
          voltage: 3.3210942126011e6
          frequency: 5.9114268014977e8
    - beamline1:
        kind: Beamline
        line:
          - BEGELE1
          - D2ER_6
          - EDGE3_002__1
          - RF0__1
    - lattice:
        kind: Lattice
        branches:
          - beamline1
    - use: lattice
```

new_mini_esr.pals.yaml

Differences Explained:

- ReferenceP does not yet store `time_ref` or `location` on the SciBmad side.
- Beamlines do not yet support names in SciBmad; instead they get named “Beamline`N`”
- The `scibmad_to_pals` translator adds Lattice information in addition to Beamline information.

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LUME to integrate controls and DTs

Standardized interfaces provide flexibility for controls and DTs

Open to different control systems

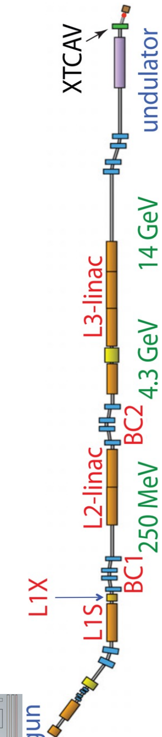
Users

Applications

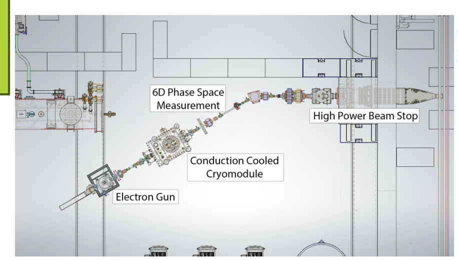
Virtual accelerator

Digital twin

Open to applications, e.g., SciBmad, Bmad, Mad-X, Impact, Cheeta, etc.



LCLS for AI-developments



Cornell AI-test Beamline from xLight inc & Genesis

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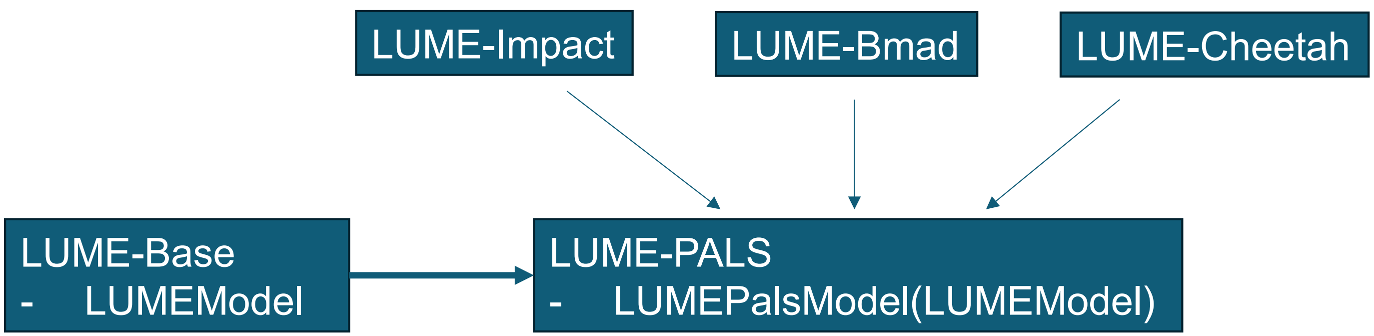
LUME – PALS connection

- Ultimately PALS will aim to handle a lot of this, future LUME-PALS may look like:



LUME-PALS allows for the selection of different simulator backends

Courtesy Ryan Roussel

Cornell University

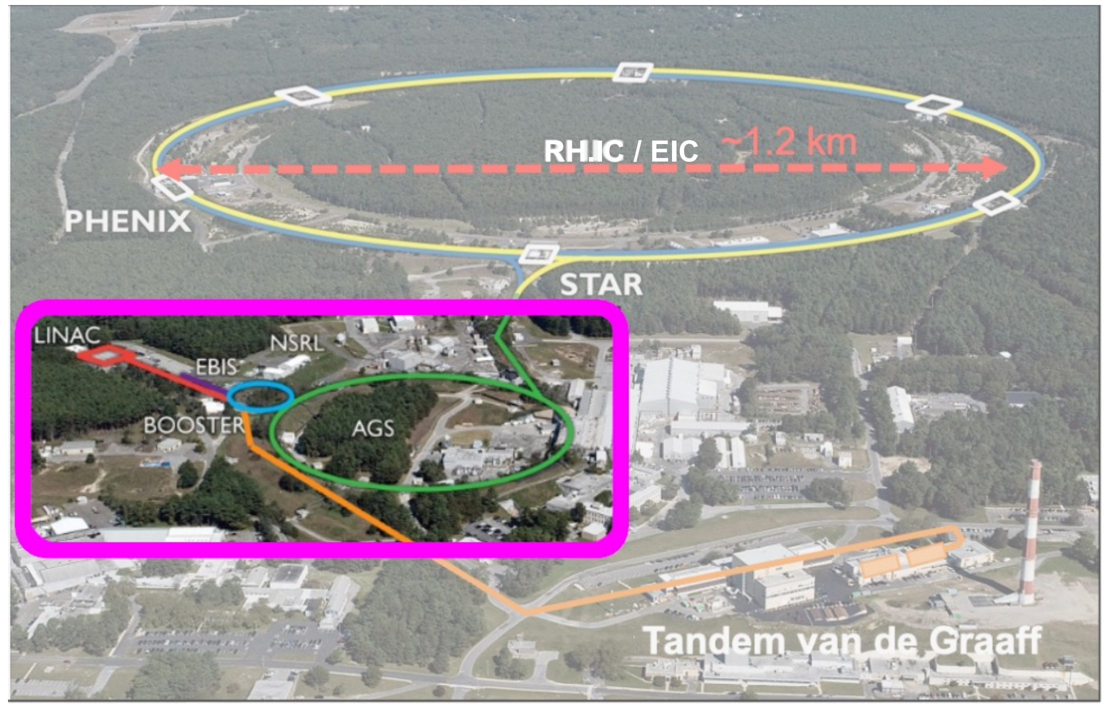
Development at existing EIC systems

Accelerator Rings

	Circumference [m]
Booster	201
AGS	807
RHIC	3833

Typical Top Energies [Total, GeV/N]

	Au	Pol. Protons
Linac (H^-)	--	1.1
Booster	1	2.3
AGS	10	23.8
RHIC	100	255



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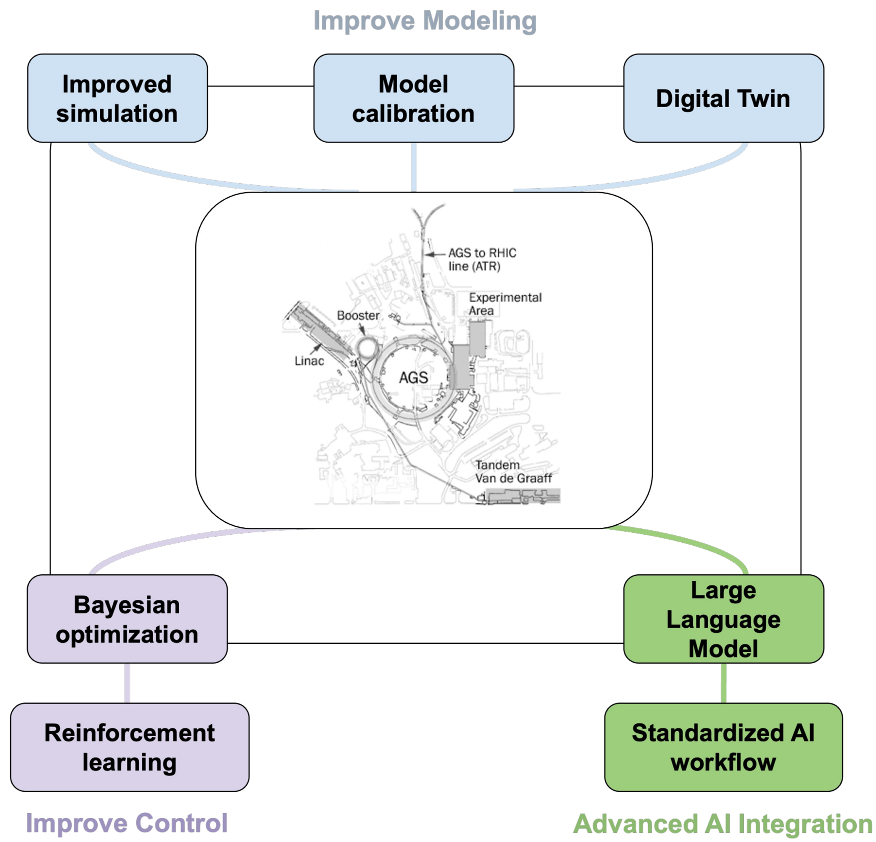
Preparation of AI for the EIC

Goal: Improve beam quality (brightness and polarization) and operational efficiency.

- Automated beam tuning
- Operational Digital Twin
- Data-driven model calibration
- Fast adaptive control

Case studies: BNL hadron injector complex



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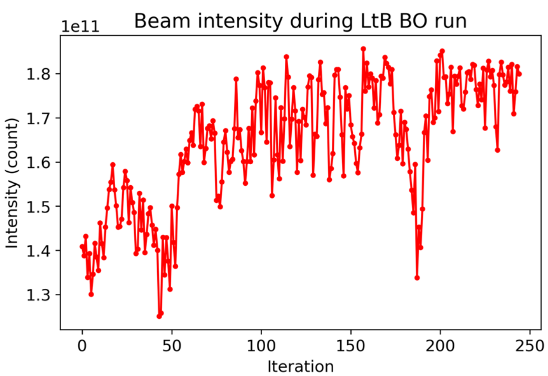
Booster injection optimization with BO

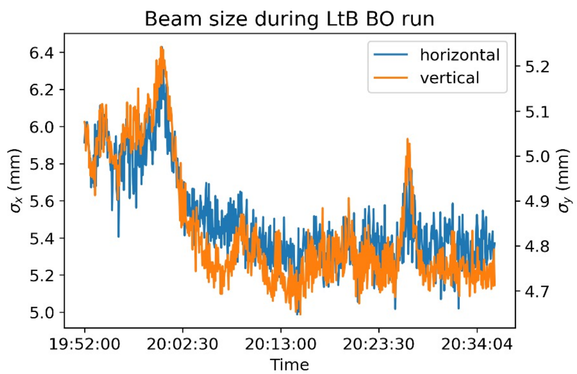
LtB Injection Optimization

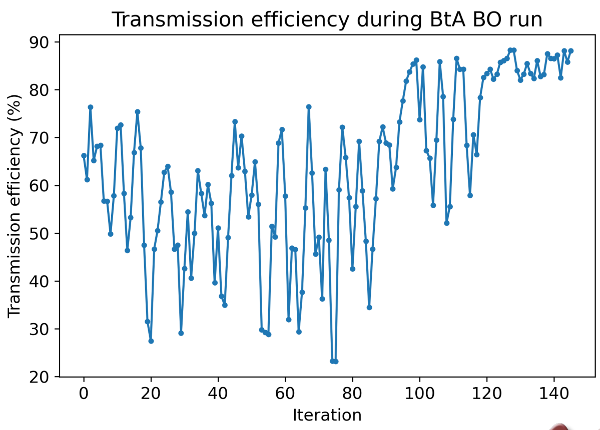
- BO maximizes Booster beam intensity using LtB optics.
- Beam size decrease in both planes during LtB optimization.

BtA Injection Optimization

- BO maximizes beam transmission efficiency using using BtA optics.
- 20% improvement from operational settings.







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Xopt

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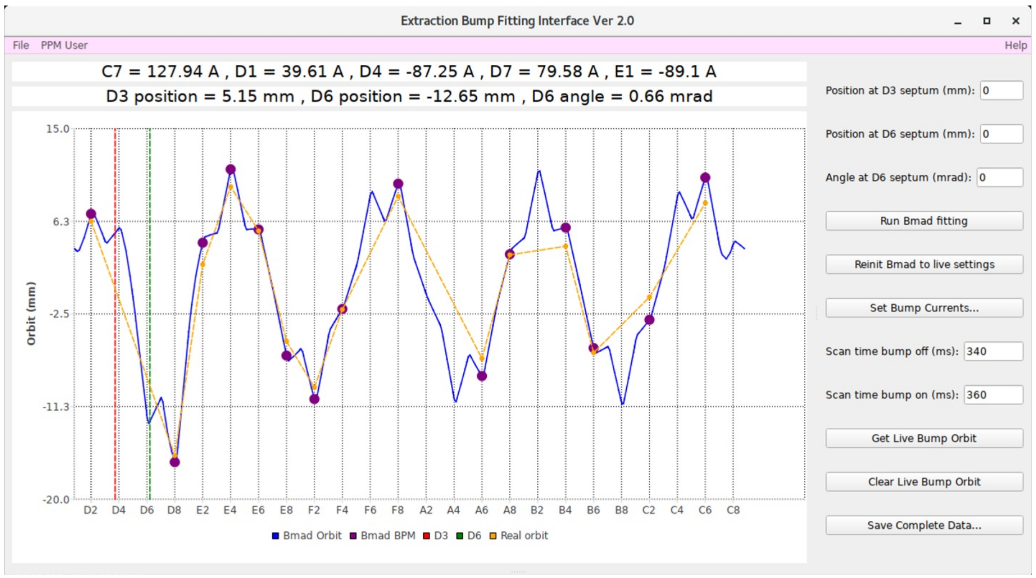
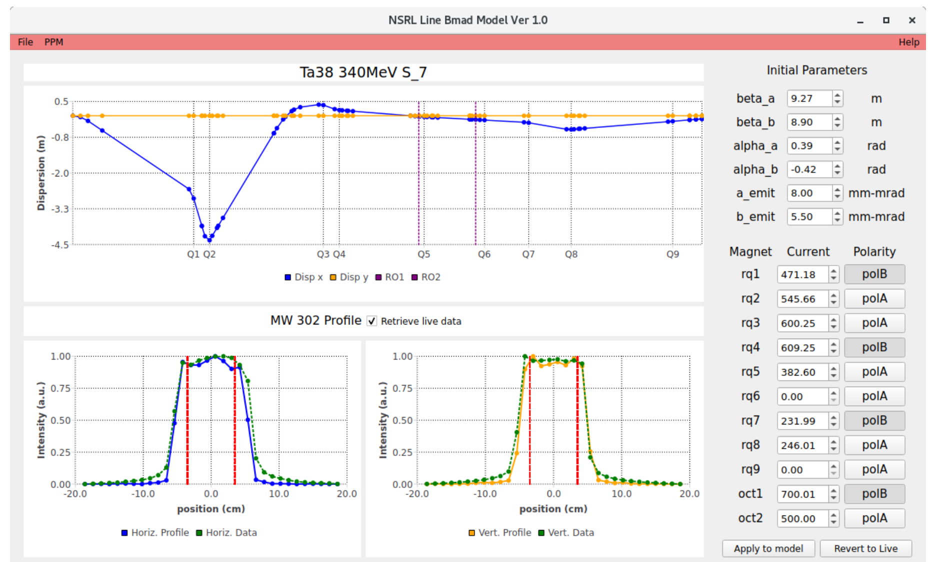
Digital Twin for NSRL

Goal: Operational digital twin framework with **bidirectional interaction** between the physical and virtual machines.

Outcome: Enable non-interruptive, model-based routine tuning for NSRL operations.





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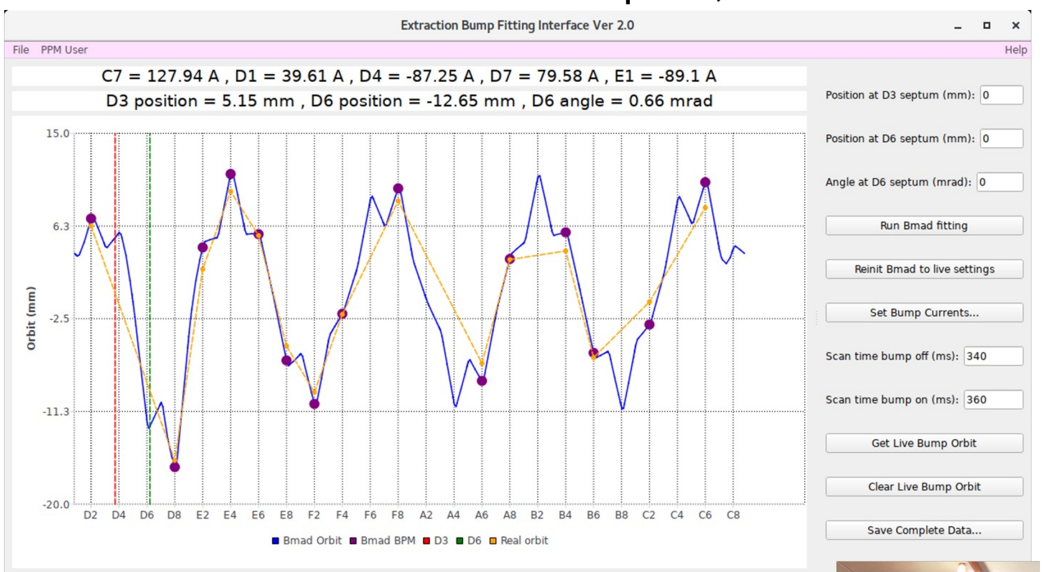

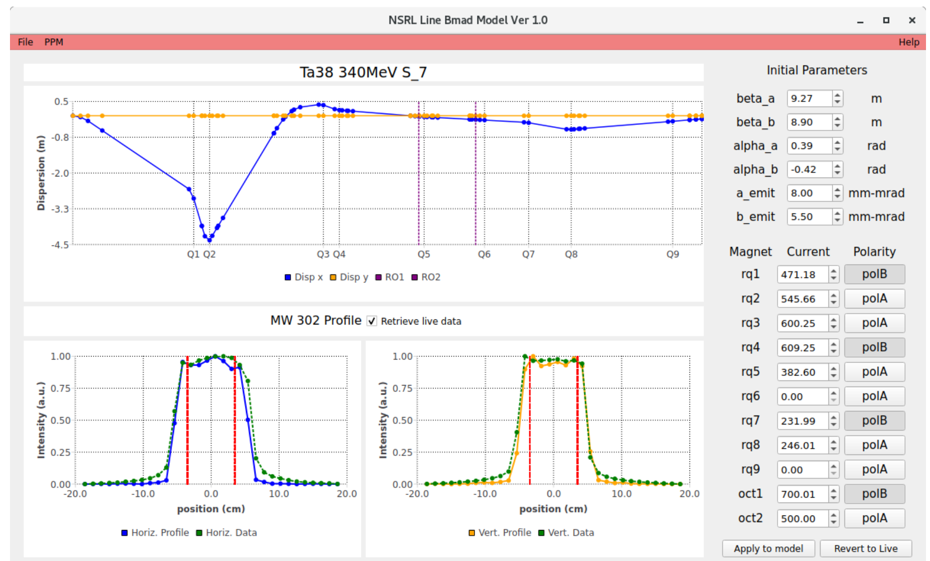

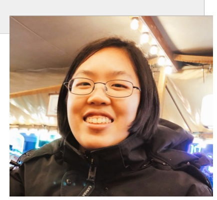

Weijian (Lucy) Lin
BNL postdoc

Brookhaven National Laboratory
EIC-Beam AI

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UQ to improve the Booster Model

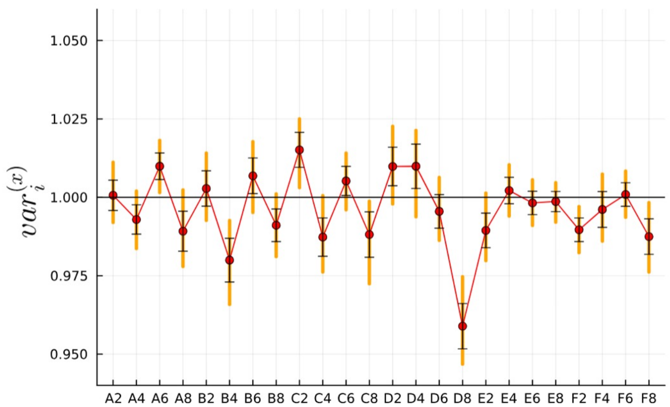
Goal: Use Bayesian Uncertainty Quantification (UQ) to characterize and reduce model-data mismatches, assisting Digital Twin development.

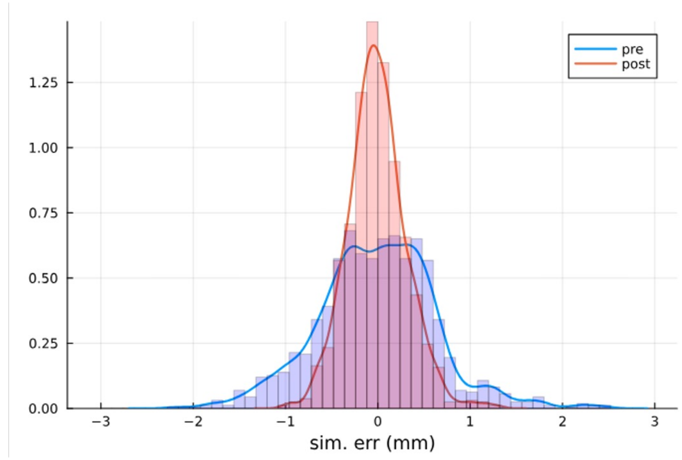
Approach

- Bayesian UQ analyzes orbit response discrepancies.
- Neural network surrogate model accelerates UQ process.

Outcome

- UQ analysis investigates quadrupole field errors as possible sources of errors.
- Incorporating UQ results improves agreement between simulation and measurement.





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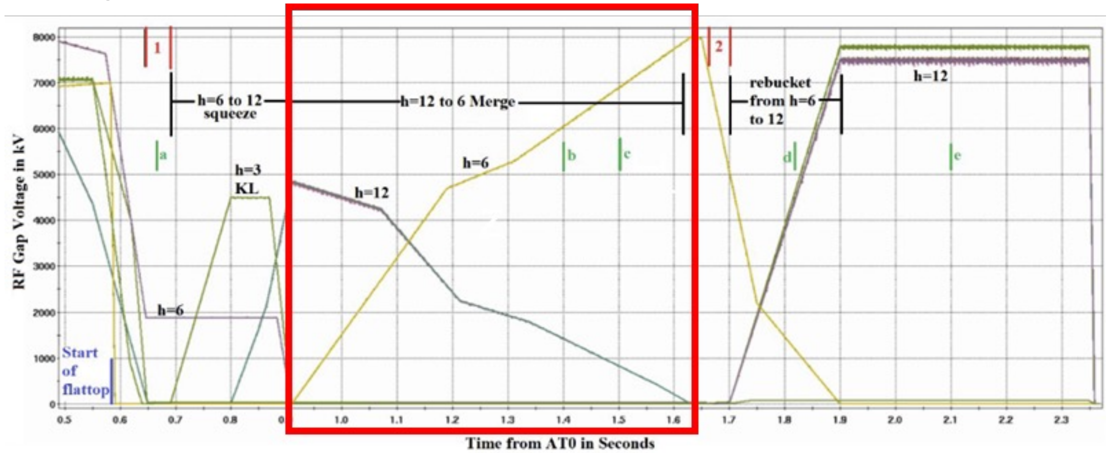
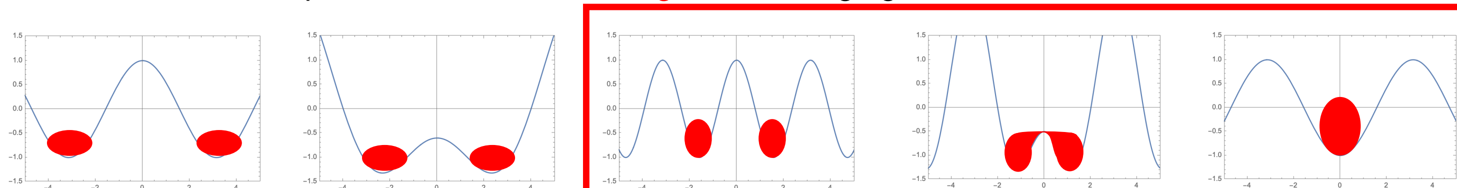
Bunch splitting and merging at BNL

Splitting in the Booster and merging after AGS accelerator reduces space charge and emittance growth ➔ more polarization



Three RF amplitudes (h=3, 6, 12) in the AGS during bucket manipulation and merging.

➔ We have set up Reinforcement Learning for the merging section.



Accelerating RF h=6 | Attracting RF h=3 | Close bucketing h=12 | Combining h=6 | Final bucketing h=6

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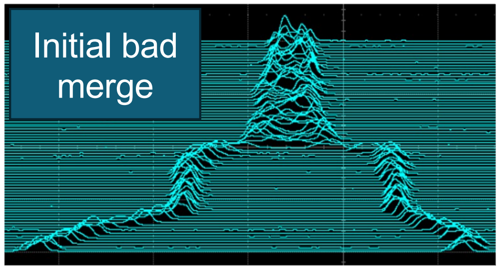
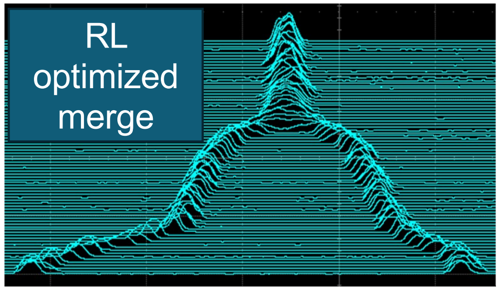
Optimal AGS Bunch Merging by RL

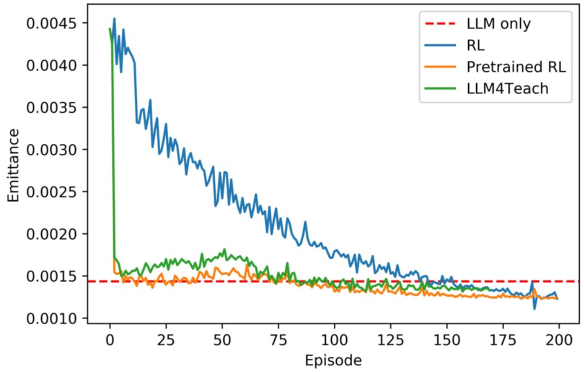
Goal: Obtain a good merged bunch profile – low emittance growth, no loss, centered and stable.



RL Optimization

- RL agent trained to minimize emittance growth.
- Begins from poor merge conditions; finds good RF settings after one step.
- Comparable performance to operational settings.
- LLM-based policy teacher for RL agent in development, leads to faster convergence and better performance.





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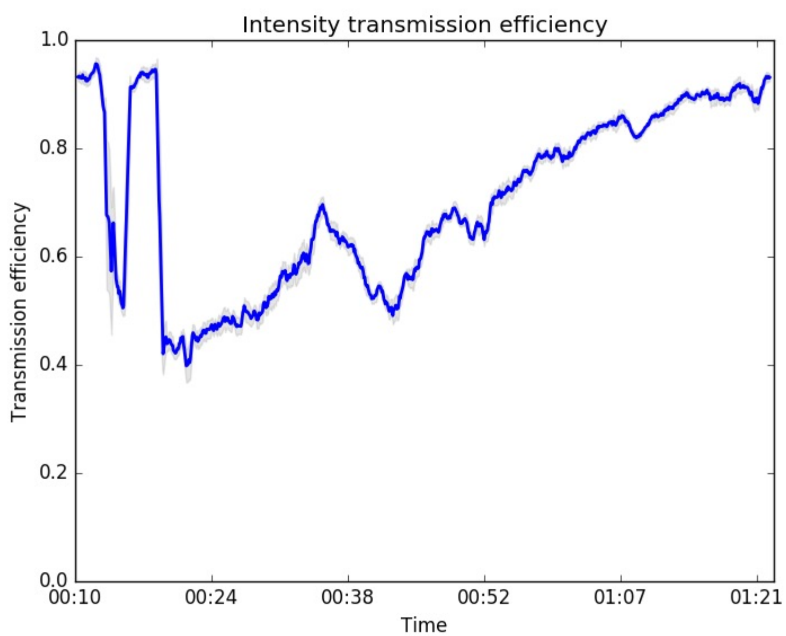
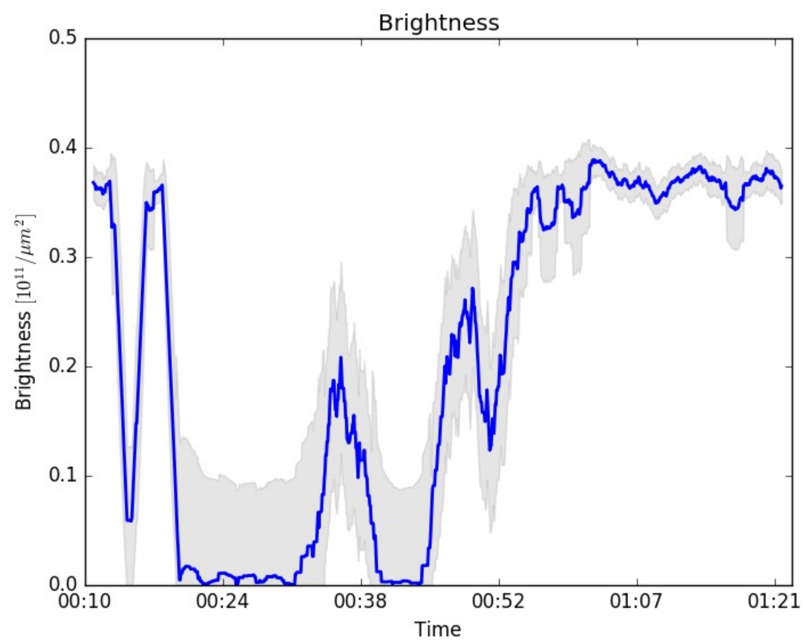
Automated AGS injection by BO

Algorithm efficiently found settings that were different, but at least as good as the previously optimized ones, automatically maintain the AGS injection at optimal performance without human intervention.





➔ Optimization of current while observing the brightness.

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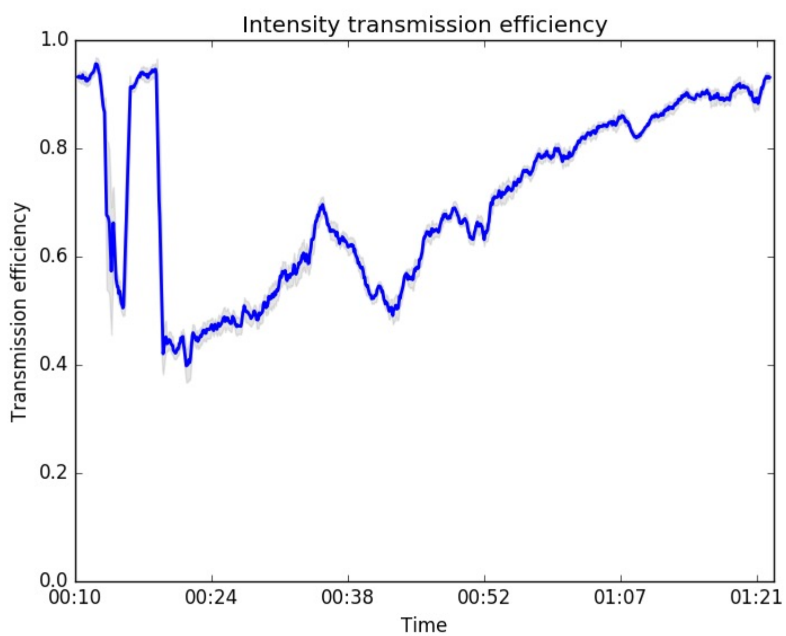
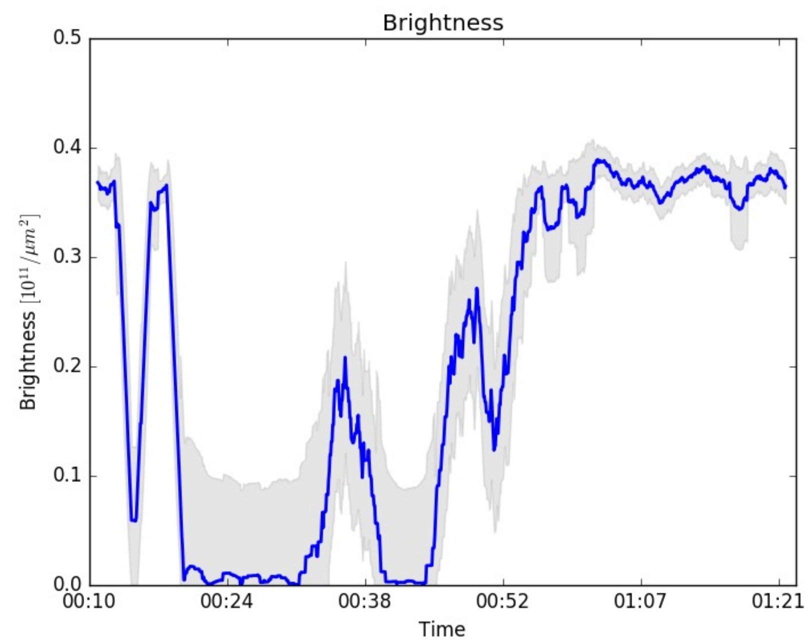
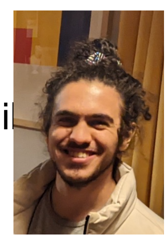
Automated AGS injection by BO

Algorithm efficiently found settings that were different, but at least as good as the previously optimized ones, automatically maintain the AGS injection at optimal performance without human intervention.





➔ Optimization of current whi observing the brightness.



Eiad Hamwi, BNL postdoc

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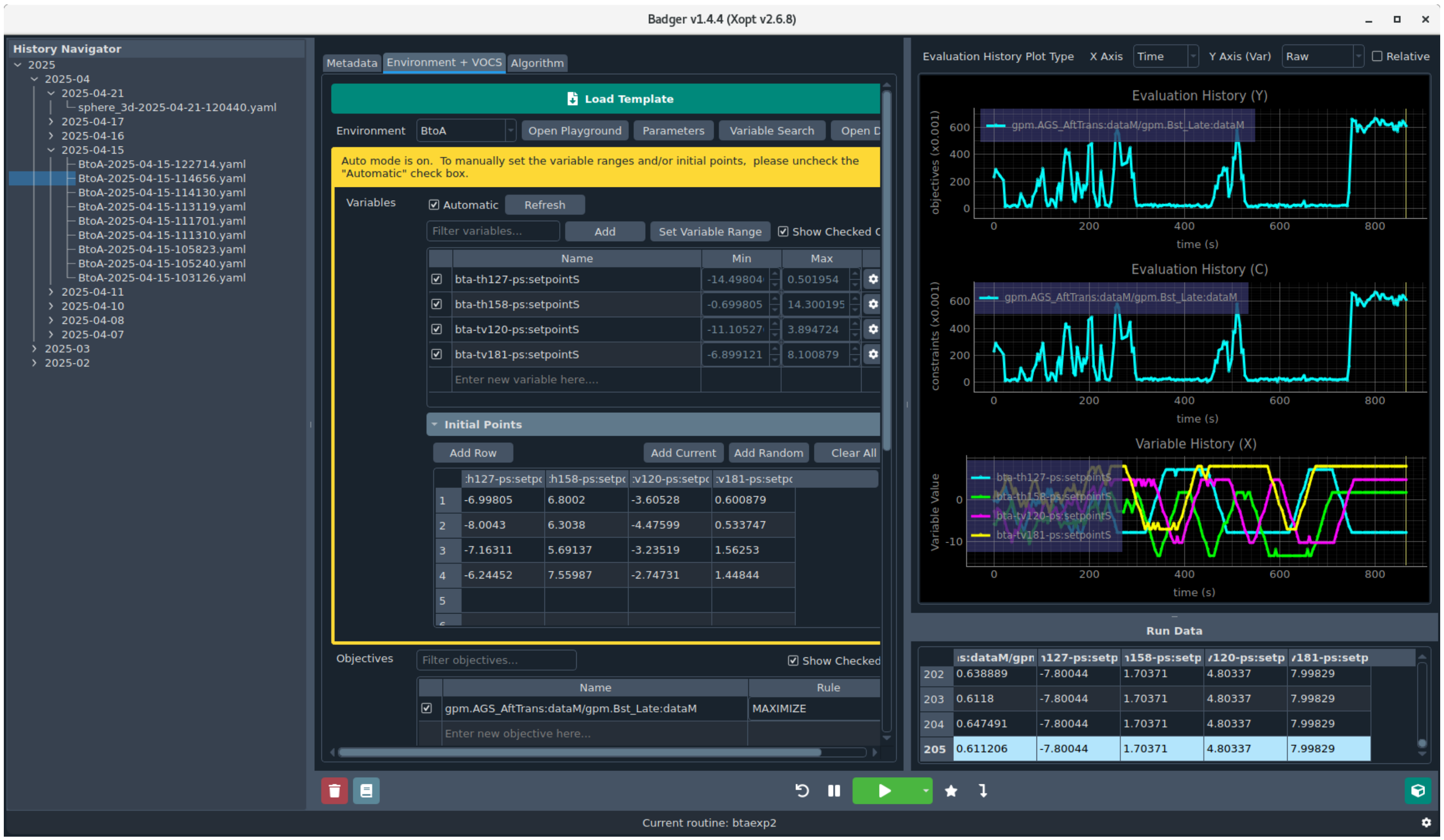
Badger: GUI for Bayesian Optimization



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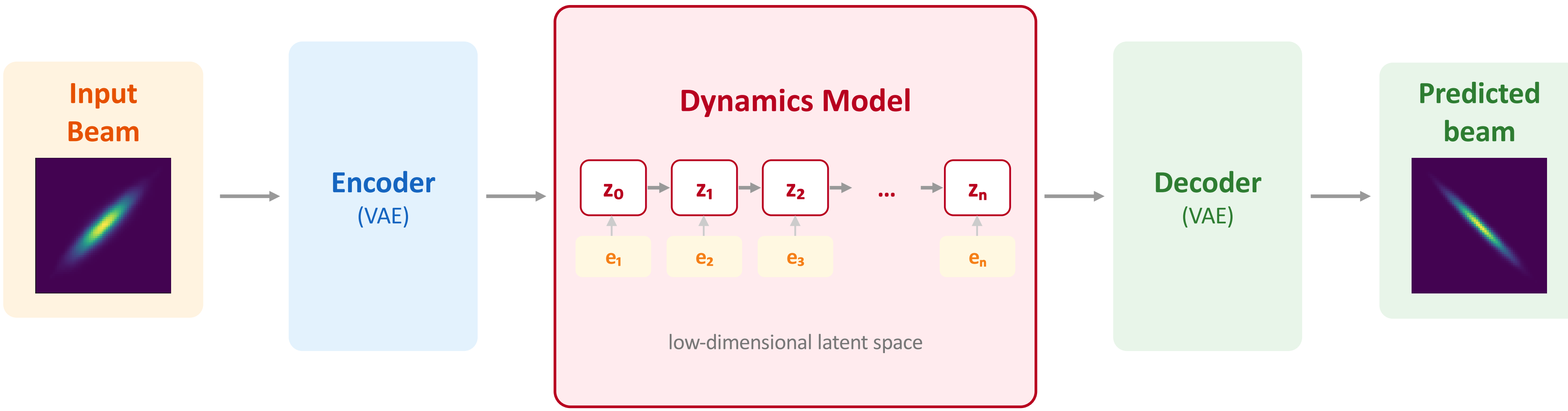
Beam Propagation in Latent Space

Compress beam distributions into a learned latent space, then predict dynamics there.



Fast: dynamics in low-dimensional latent space, not full beam.

Application: collective effect (space charge, etc.) dominated regimes where tracking is computationally expensive.

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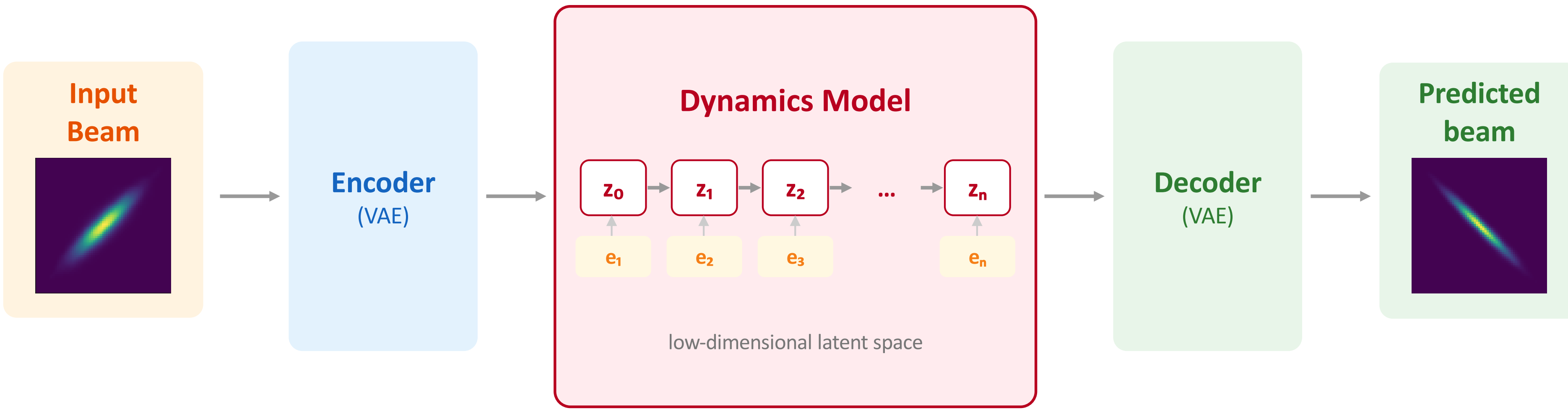

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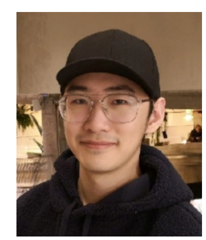

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Publications

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- [2] W. Lin et al., “Simulation Studies and Machine Learning Applications at the Coherent electron Cooling experiment at RHIC”, in *Proc. IPAC'22*, Bangkok, Thailand, Jun. 2022, pp. 2387-2390.
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- [13] L. Hajdu et al., “Image processing with ML for automated tuning of the NASA Space Radiation Laboratory beam line”, in *Proc. ICALEPCS2025*, Chicago, Sep. 2025, pp. 1008-1011.
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Summary

The EIC-BeamAI collaboration connects the EIC and DOE AI missions

- Genesis Mission building a unified AI platform for accelerator science
- Injector ML experience enables AI-assisted operation for EIC
- NARAD developing cross-facility AI-ready workflow

Key Outcomes of Injector ML incorporation

- Automated beam-tuning routines
- Operational bidirectional Digital Twin
- Streamlined model calibration
- Robust anomaly detection and diagnostics

Community & infrastructure efforts

- DOE-funded projects and collaborations: NARAD, MOAT, AmSC
- Intent to strengthen international buy-in to **EIC-BeamAI** through the **Int. EIC accel. Collaboration**

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