Machine Learning for Autonomous Accelerator Control and Phase Space Reconstruction

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U.S. DEPARTMENT OF ENERGY | Stanford University

SLAC NATIONAL ACCELERATOR LABORATORY

Overview

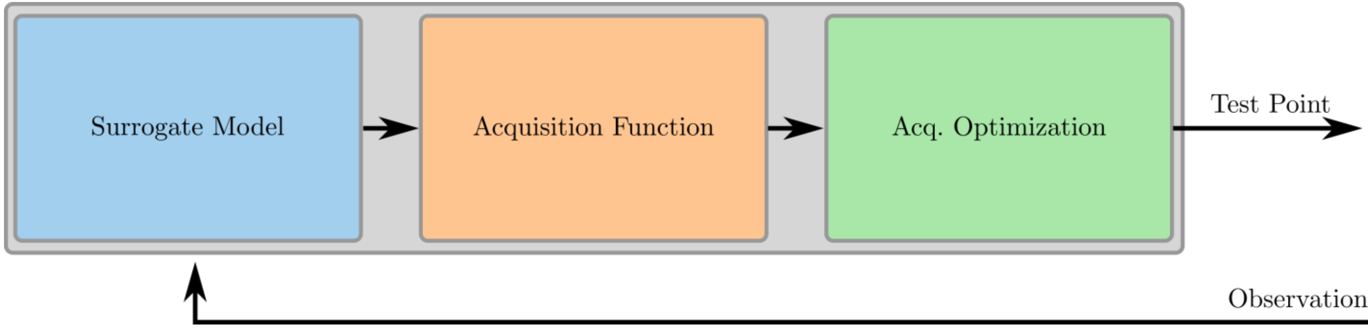
- **Autonomous Accelerator Operations @ AWA**
  - Bayesian Exploration
  - Automatic Emittance Characterization
- **Phase Space Reconstructions using Neural Networks @ AWA**
  - Reconstructions from Quadrupole Scans

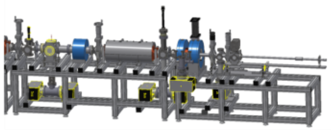
Bayesian Algorithms For Accelerator Control

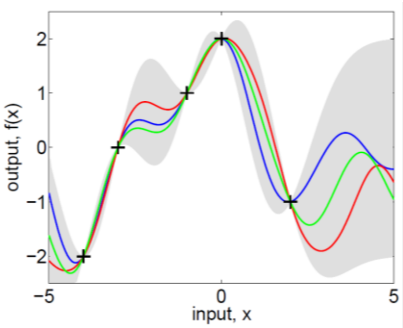
Create a computational model of the system

Determine the value of potential future measurements

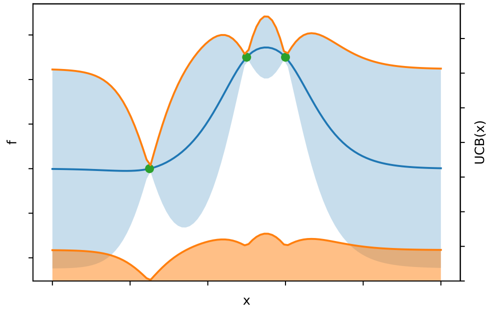
Pick the point that maximizes value







Gaussian Process Model



Acquisition function definition

Why?

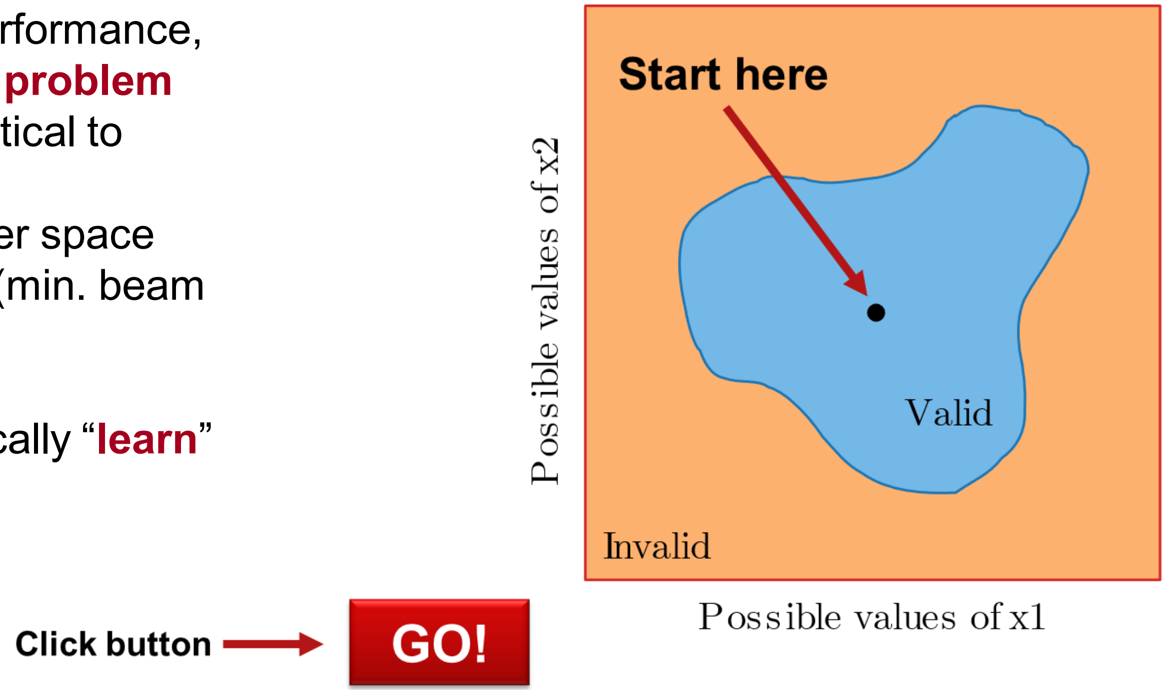
- **Extremely data efficient** → build models from scratch
- **Intrinsically incorporates measurement uncertainty** → perfect for noisy accelerator operation

Characterization Before Optimization

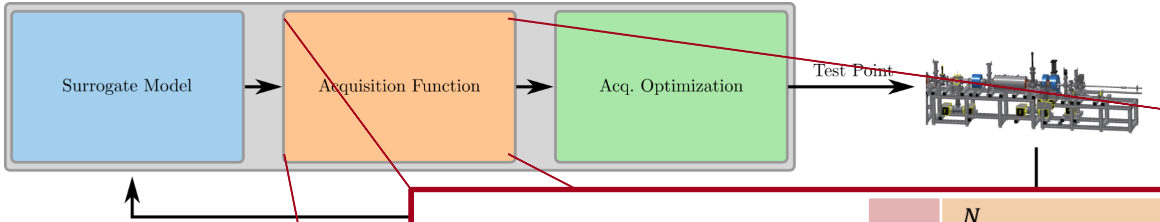
To maximize optimization performance, we want to **understand our problem**

- Which parameters are critical to optimization?
- What regions of parameter space produce valid conditions (min. beam transition, etc.)?

Can we use BO to automatically "**learn**" about our objective?

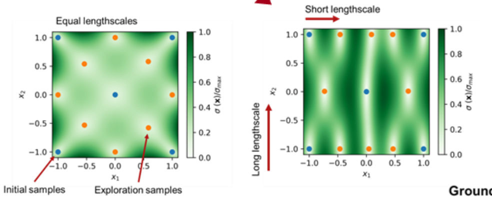


Bayesian Exploration

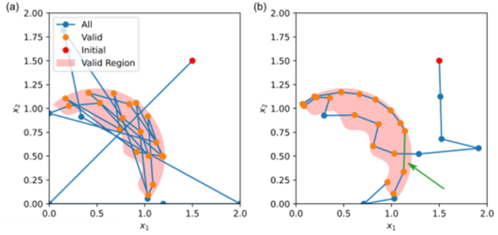


$$\alpha(\boldsymbol{x}) = \sigma(\boldsymbol{x}) \prod_{i=1}^{N} p(g_i(\boldsymbol{x}) \geq h_i)\, \Psi(\boldsymbol{x}, \boldsymbol{x_0})$$

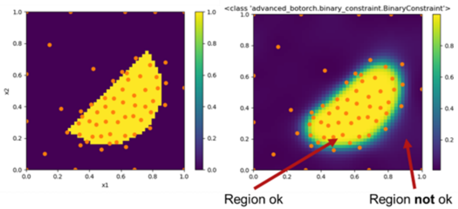
Adaptive sampling



Proximal biasing

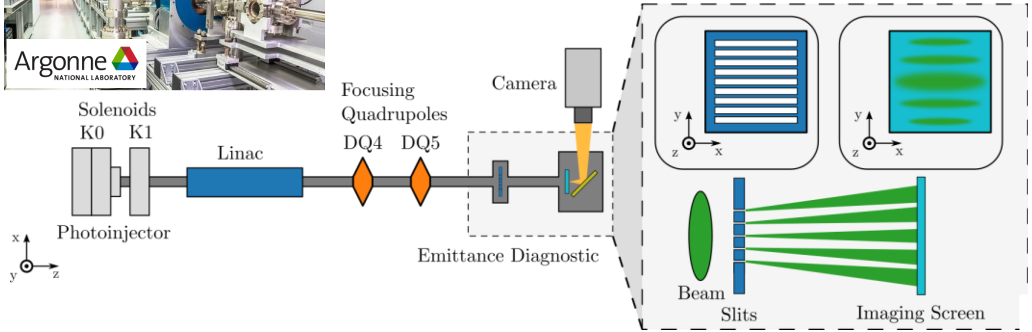


Unknown constraints



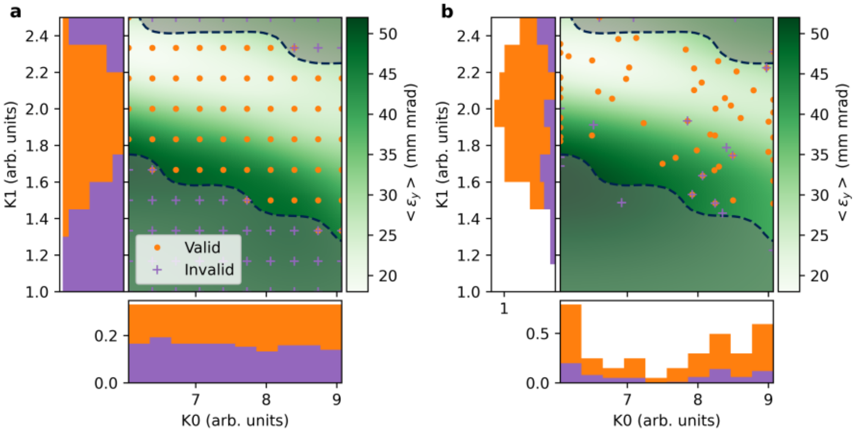
Roussel et. Al. *Nat. Comm.* **2021**

Characterizing Photoinjector Emittance at AWA



Determine beam emittance as a function of:

- 2 solenoids
- 2 quadrupoles



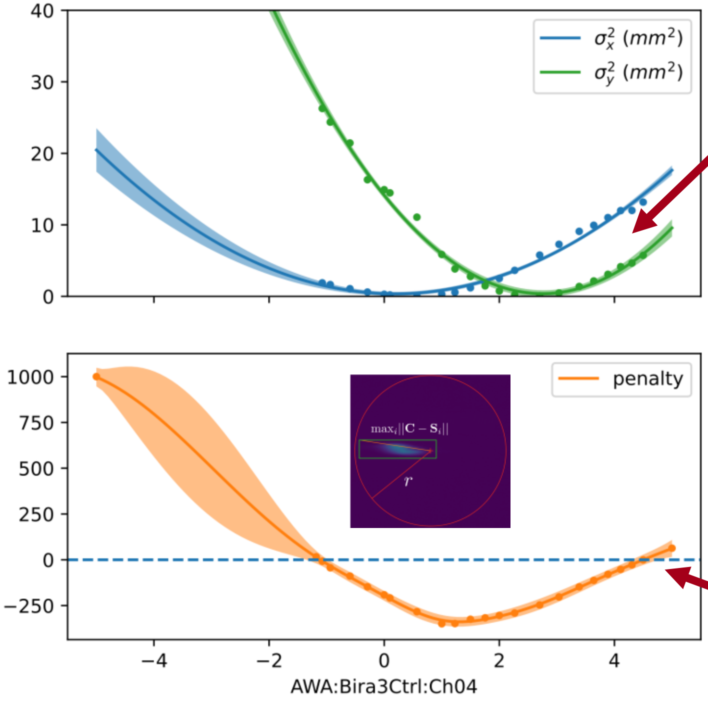
- Able to characterize emittance dependance in **~70 measurements** with **no prior information**
- Equivalent 4D grid scan uses **~1000 measurements**
- **14x** characterization speed-up

Roussel et. Al. *Nat. Comm.* **2021**

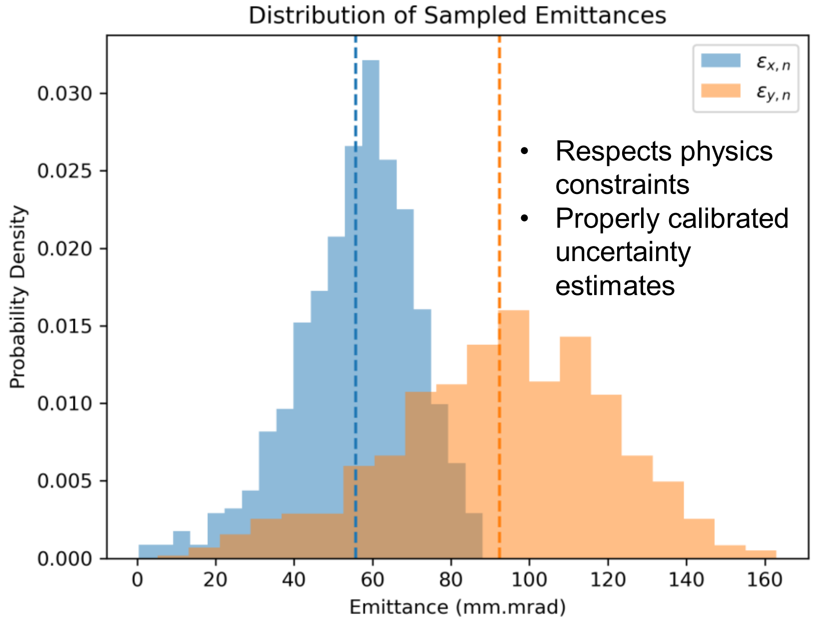
Automatic Emittance Measurements

Click button → **GO!**

2nd order Bayesian fits to data



Respects bounding box penalty



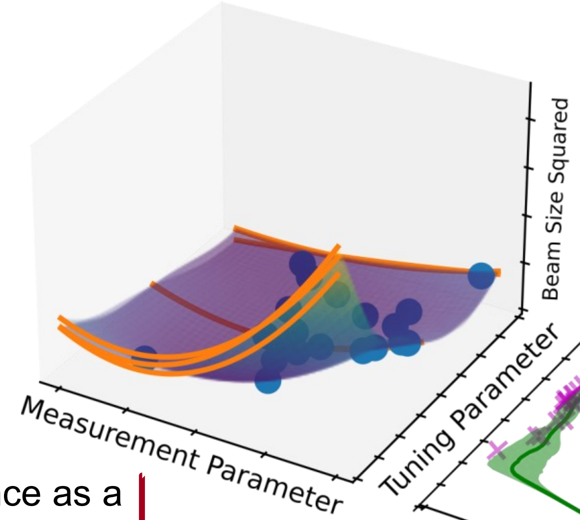
- Respects physics constraints
- Properly calibrated uncertainty estimates

Future Work: Bayesian Algorithm Execution (BAX)

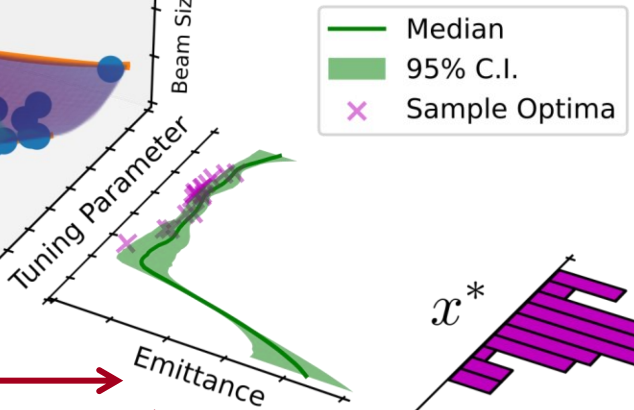
SLAC

Our goal:
Use **virtual measurements** to optimize beam parameters (alignment, emittance, etc.)

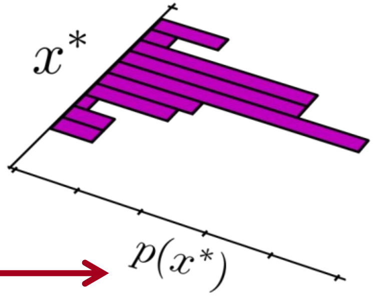
Beam size model



Predict beam emittance as a function of tuning config. (with uncertainty)



Predict optimal tuning config. (with uncertainty)

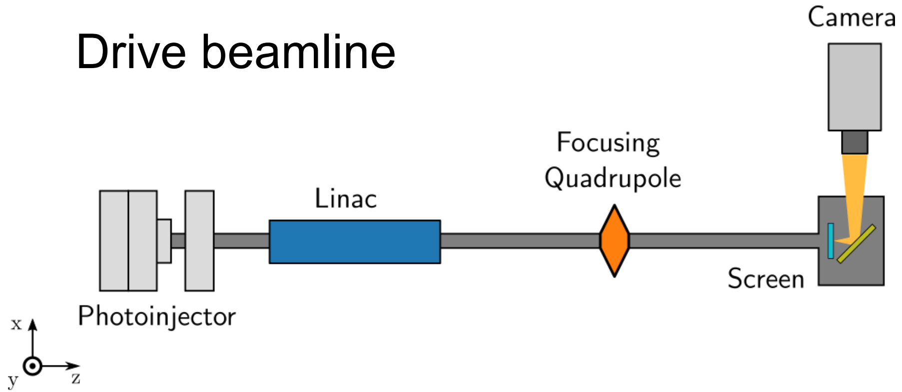


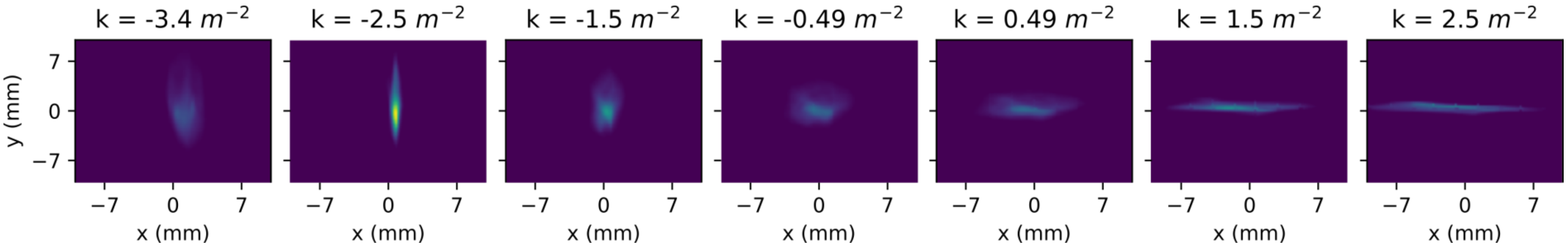
The BAX algorithm chooses beam size measurements that reduce uncertainty in x^* **without measuring emittance directly → 20x speed up for LCLS**

Miskovich, et. al., arXiv:2209.04587

Phase Space Reconstructions using Neural Networks

Quadrupole Scan @ AWA

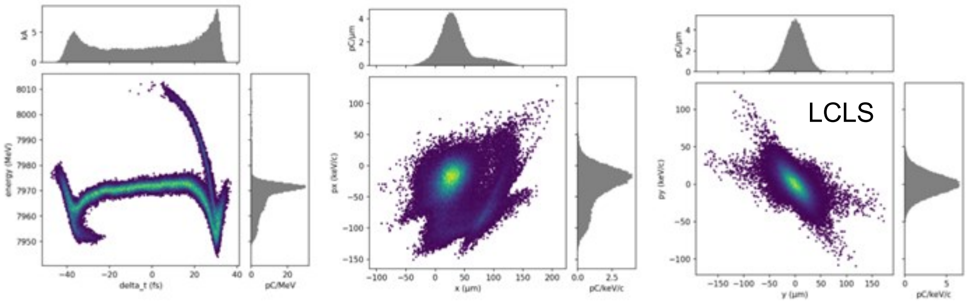


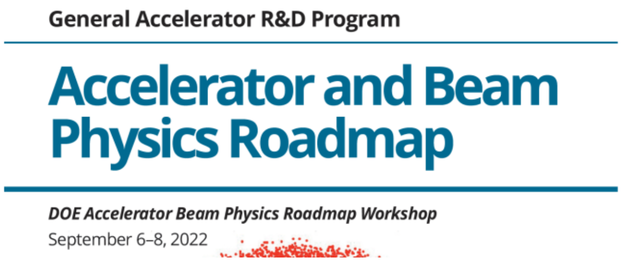


Conventional analysis of measurements loses **A LOT** of beam information

Phase Space Reconstruction Challenges

Simple phase space distribution representations are **insufficient** to describe real beams w/ needed detail



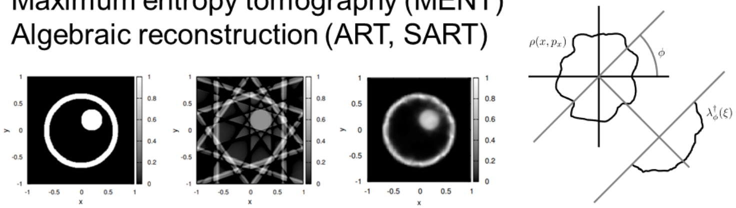


5 Grand Challenge Three

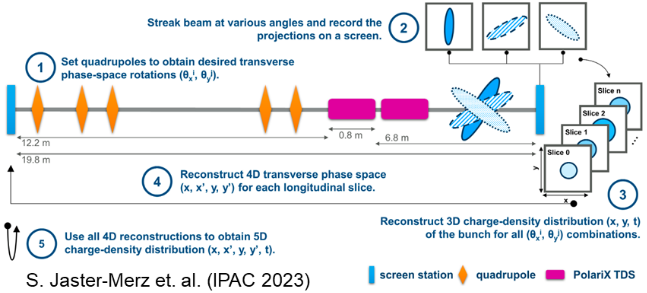
Beam Control: How do we control and diagnose the beam distribution at all scales—from its macroscopic properties down to the level of individual particles?

Advanced tomographic methods:

- Maximum entropy tomography (MENT)
- Algebraic reconstruction (ART, SART)



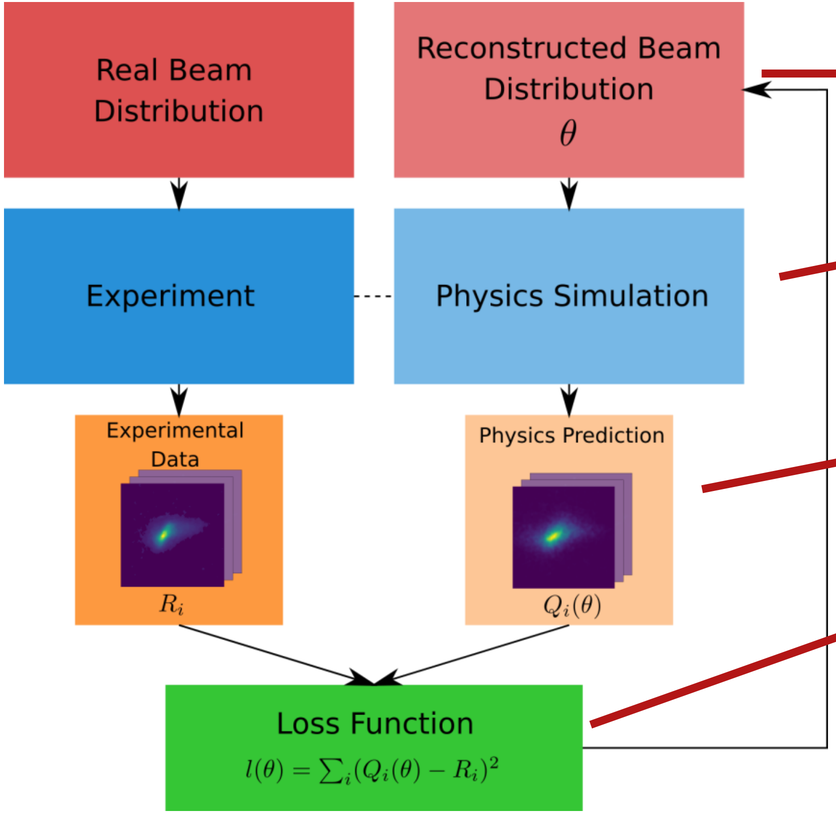
Hock K. and Ibison M., JINST, 2013



S. Jaster-Merz et. al. (IPAC 2023)

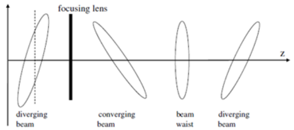
Tomographic methods need many measurements, **~28 hrs. for 5D reconstruction**

Phase Space Reconstruction Using Optimization



Simple quad scan:

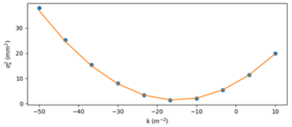
- Beam distribution is assumed to be elliptical. Fully parametrized by σ_{xx}, σ_{xp_x}, $\sigma_{p_xp_x}$
- Assume linear transport of elliptical beam



- Beam sizes from screen downstream

$$\sigma_x^2 = (1 + dlk)^2 \boldsymbol{\sigma_{11}} + 2(1 + dlk)\boldsymbol{\sigma_{12}} + d^2 \boldsymbol{\sigma_{22}}$$

- Error of the quadratic fit

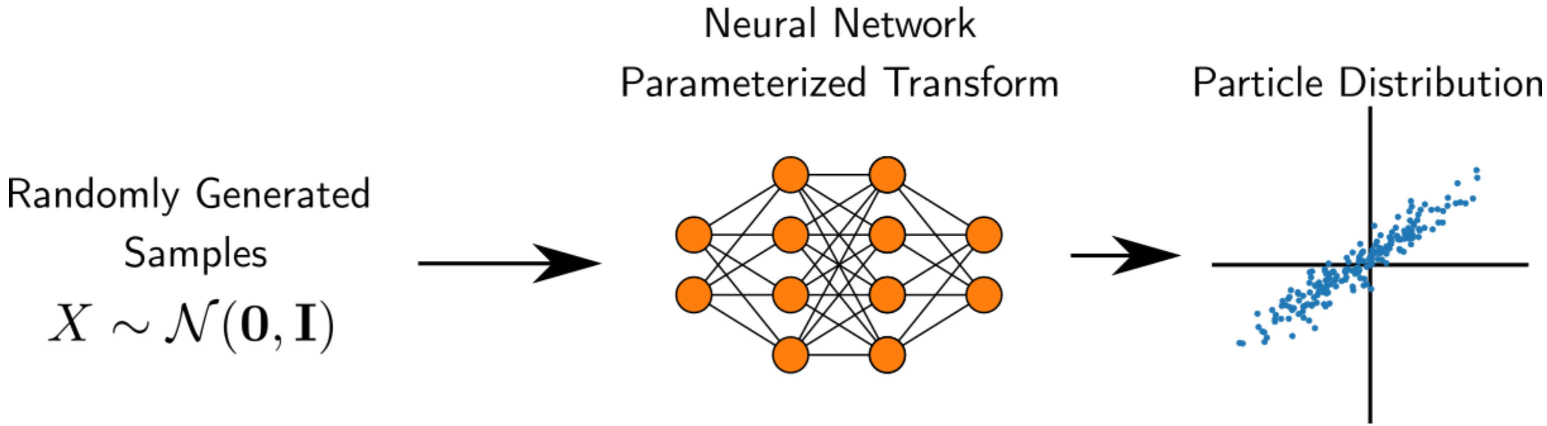


Result:

- Elliptical 2D phase space consistent with beam size measurements.

Machine Learning Based Beam Representations

Use a **generative** machine learning model to create **arbitrary beam distributions**



O(~1000) parameters of the neural network control the distribution of particles in 6D phase space

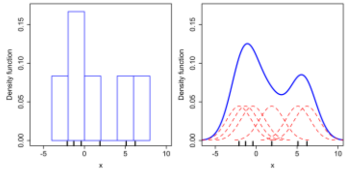
Learn the NN parameters → learn the beam distribution

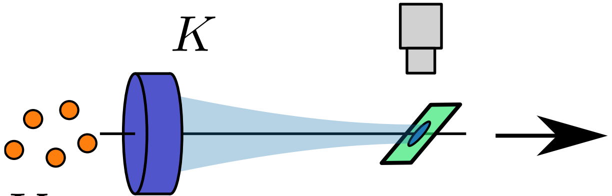
Differentiable Beam Physics Simulations

Differentiable sims keep track of derivative information during **every** calculation step.

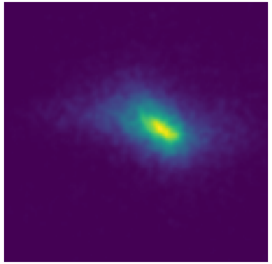
Enables **cheap gradient evaluations** which enable optimization of >10k free parameters.

Allows us to extract information from the **individual pixels** of an image.





$$Z = f(Y; K)$$

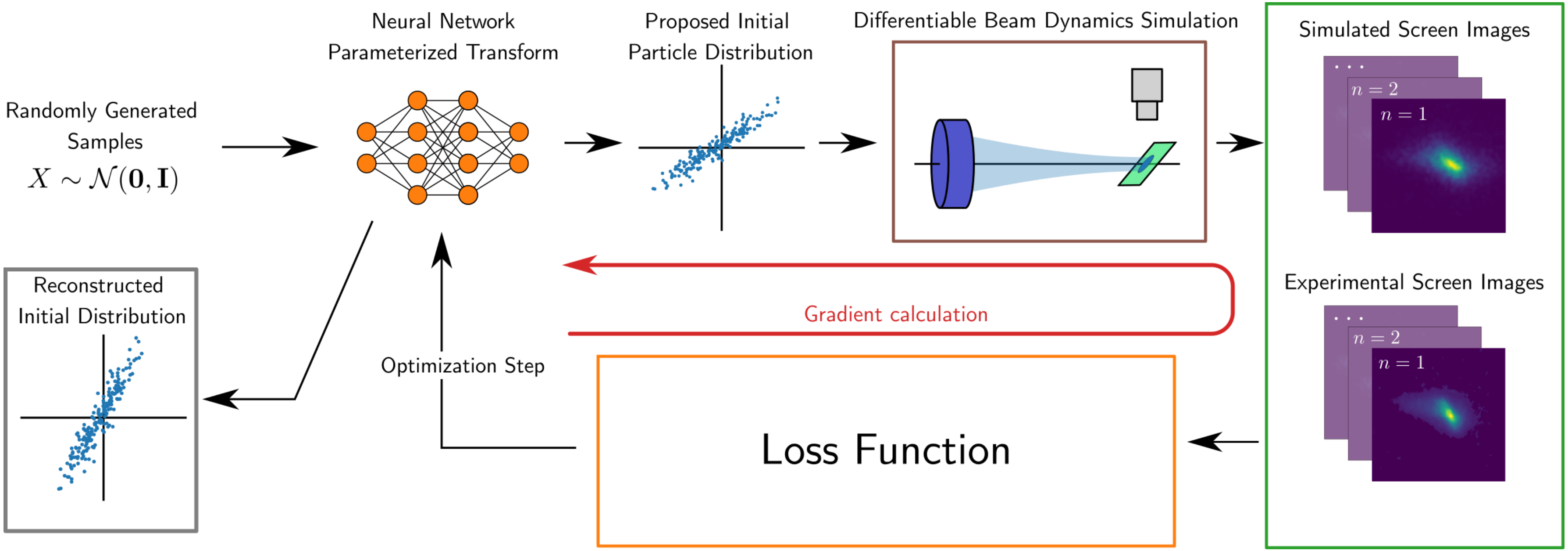


$$Q^{(i,j)} = \mathrm{KDE}(Z)$$

$$\frac{\partial Z}{\partial Y}, \frac{\partial Z}{\partial K}, \frac{\partial \sigma_Z}{\partial K}, \cdots$$

$$\frac{\partial Q^{(i,j)}}{\partial Y}, \frac{\partial Q^{(i,j)}}{\partial K}$$

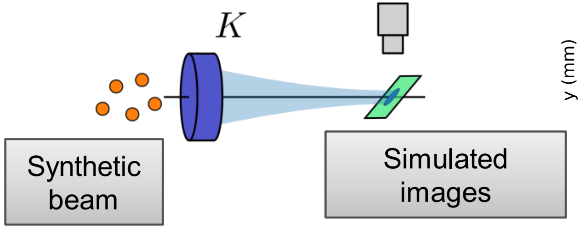
High Fidelity Phase Space Reconstructions

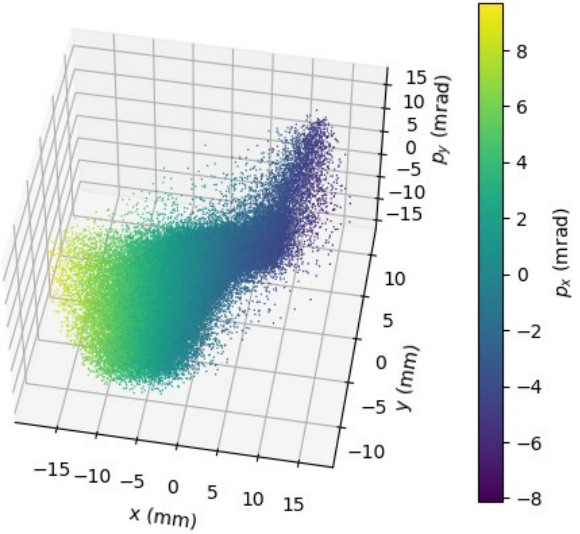


Roussel, Ryan, et al. PRL (2023)

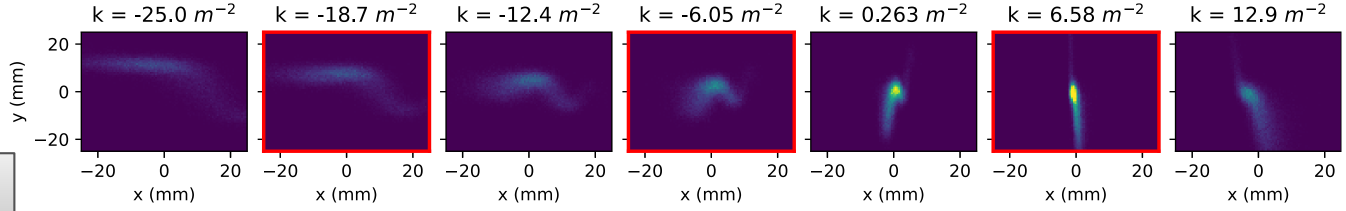
Synthetic Example Reconstruction

Beamline





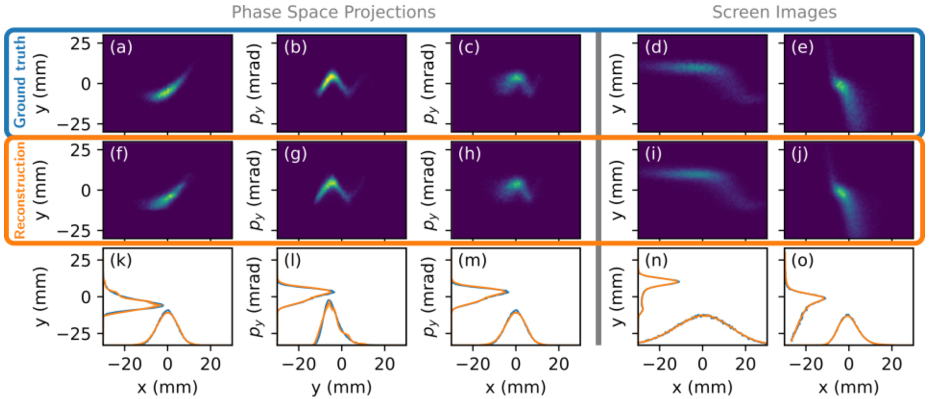
Screen images



Accurate **4D reconstructions** using **10 measurements!**

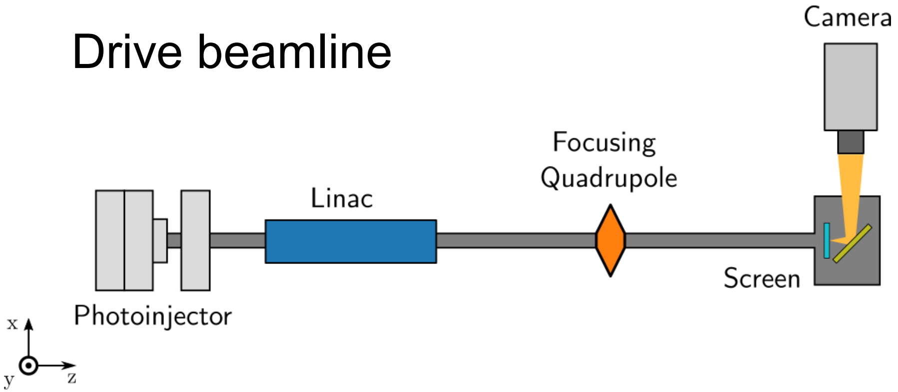
Reconstruction (training) time **< 5 mins**

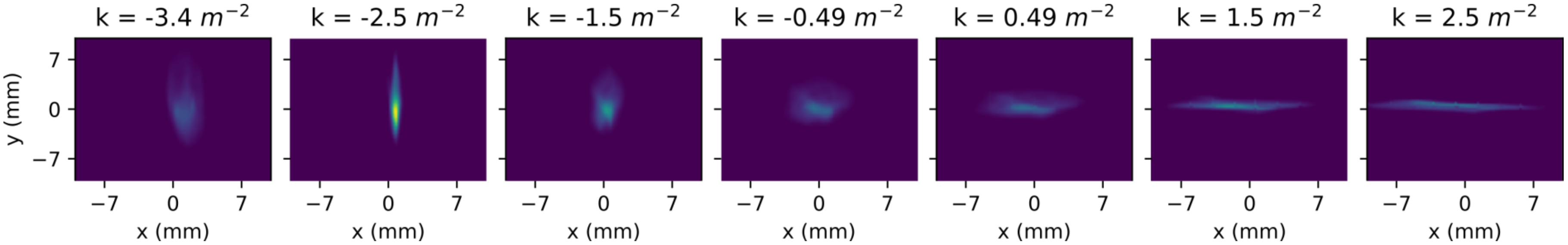
No prior training data needed!!



Experimental Demonstration @ AWA

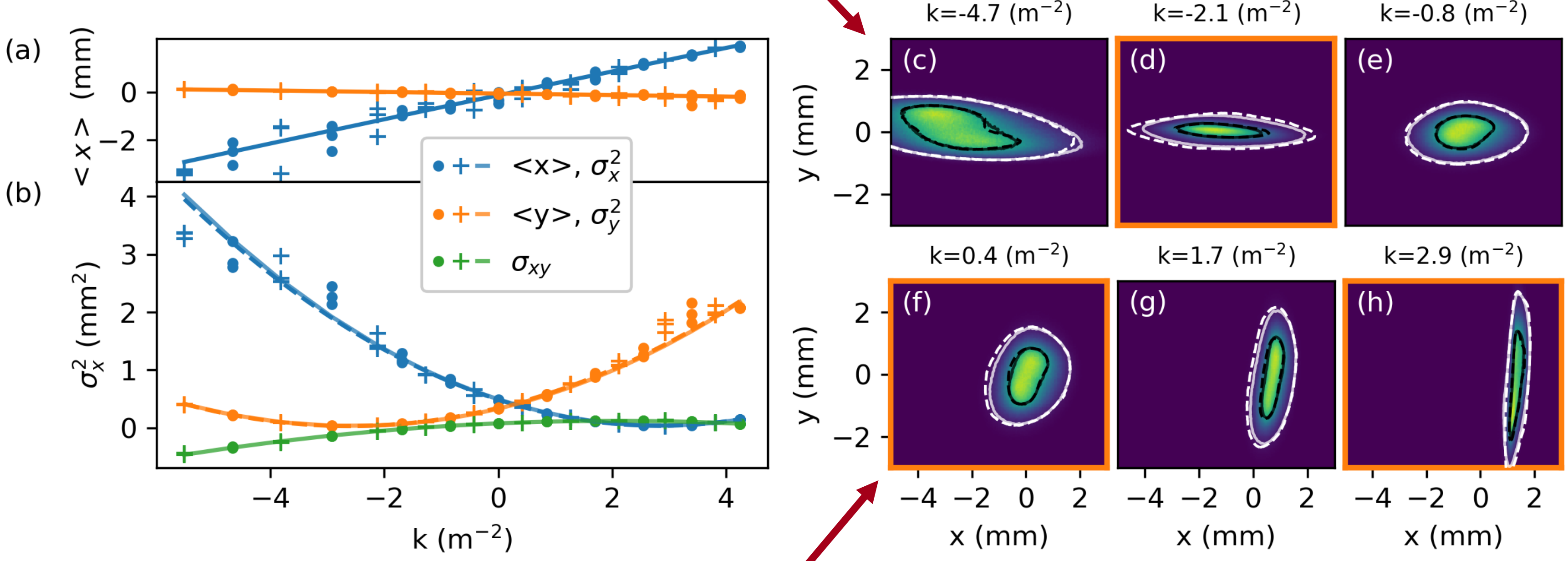
Drive beamline





AWA Reconstruction Results

Reproduces **detailed** beam features



See also: Seongyeol's talk tomorrow morning RE: flat beams

Accurately predicts beam distributions **outside the training set**

Roussel, R, et al. PRL (2023)

Conclusions

- **Major efforts in ML @ AWA** as part of collaborations with SLAC and U. Chicago

Questions?

SLAC

- Auralee Edelen
- Chris Mayes
- Daniel Ratner

U. Chicago

- Juan Pablo Gonzalez-Aguilera

Argonne Wakefield Accelerator

- Seongyeol Kim
- John Power
- Eric Wisniewski
- Wanming Liu

Thanks to the team!

Backup