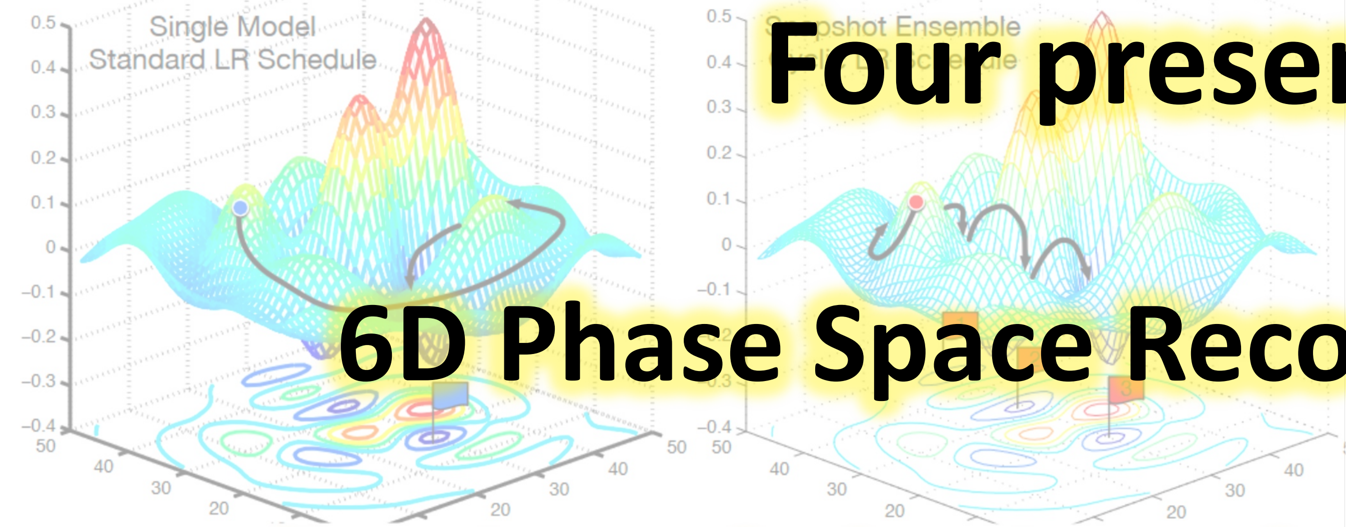
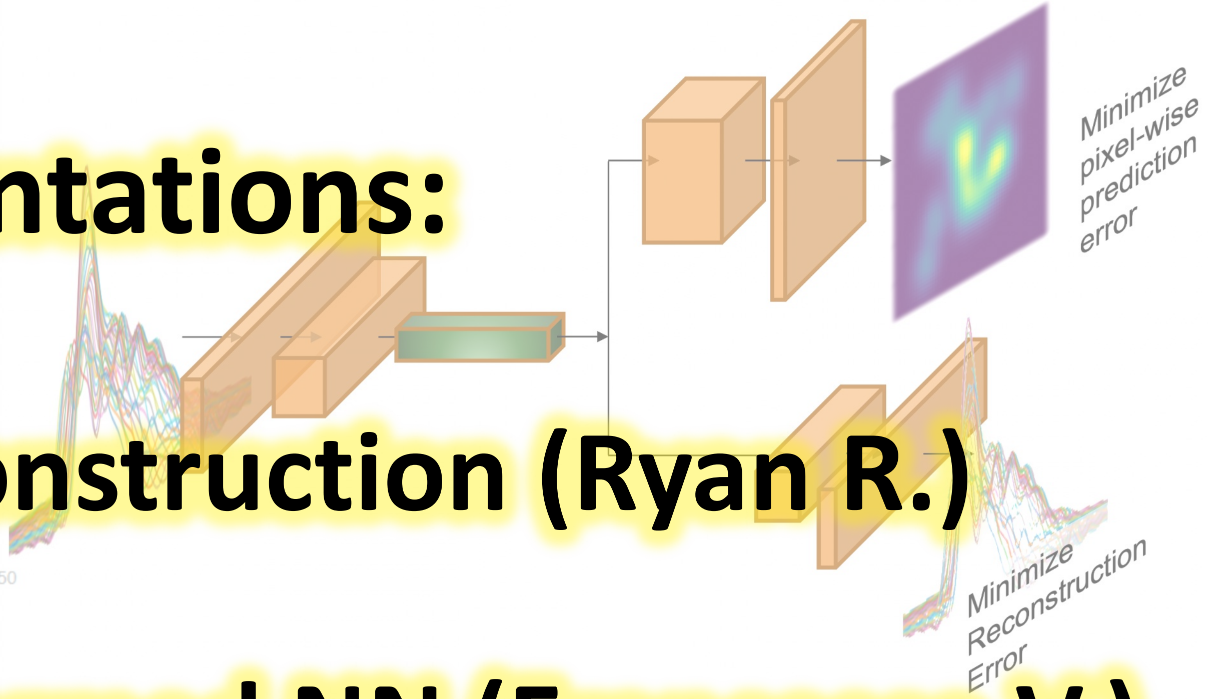
Summary Analysis Session

Chicago 4. November 2022

Raimund Kammering

Four presentations:



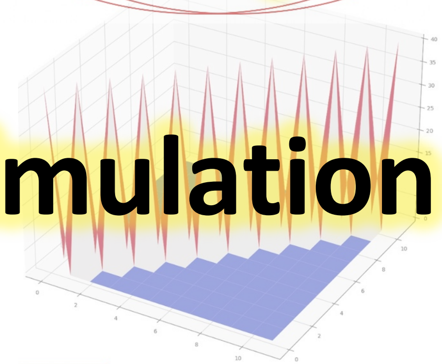


6D Phase Space Reconstruction (Ryan R.)

Application of Physics Informed NN (Francesco V.)

Phase Space Tomography Using BPMs (Kilean H.)

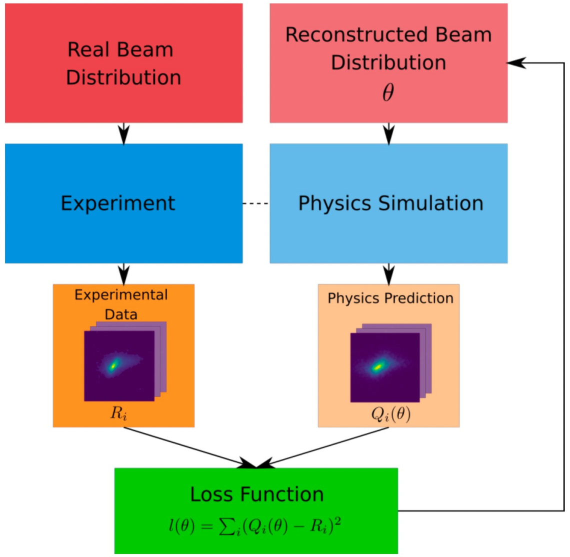
Simulation Studies for Orbit Correction (Lucy L.)

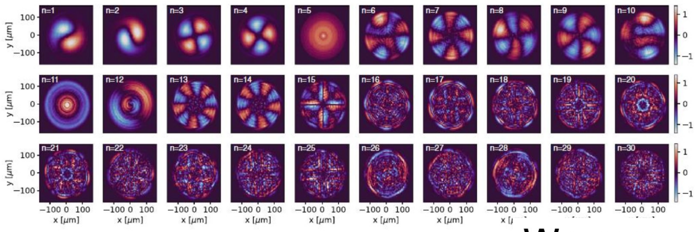


Ryan R.

Phase Space Reconstruction Using Neural Networks and Differentiable Simulations

Inferring Beam Distributions Using Optimization





Scheinker, Alexander, et al *Scient*

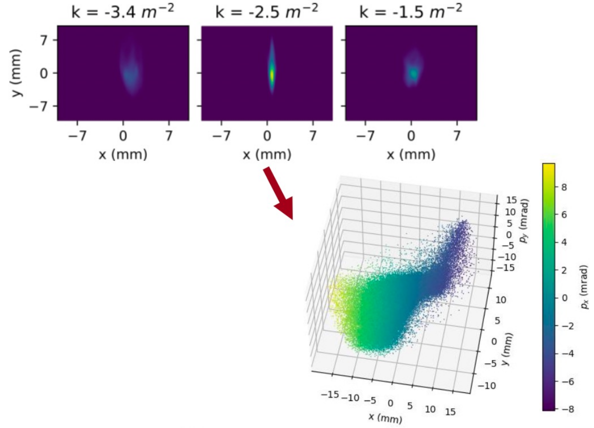
Represent beam distributi
with principal component
analysis (PCA) and optimi
weights to fit experimental
measurements

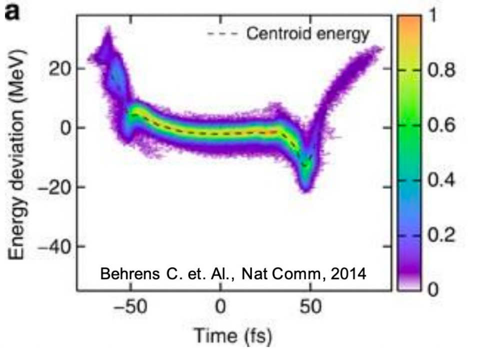
We can create **detailed reconstructions of beam phase spaces** from simple tomographic accelerator measurements without special diagnostics

Reconstructions from differentiable simulations **are not limited** by analytical tractability, number of free parameters

Theoretically we are only limited by model detail and accuracy, **need further investment in differentiable simulations**

Need to expand our idea of what can be used as a diagnostic





Behrens C. et. Al., Nat Comm, 2014

ails https://arxiv.org/abs/2209.04505

Francesco V.

Improving Neural Networks Predictions using Physics - PINN for the CERN Accelerators

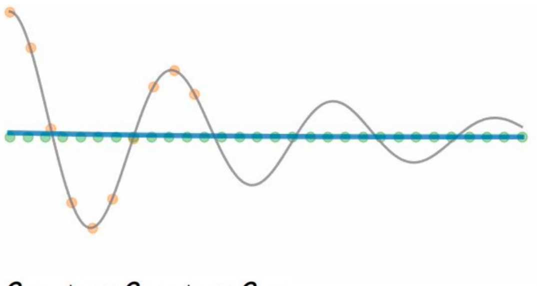
min(Loss) => Loss = Mean(data - prediction)^2
+ Additional_info(prediction)

$$\mathcal{L}_1 = 1/N \sum_i^N (u(x_i) - \hat{u}(x_i, \theta))^2$$

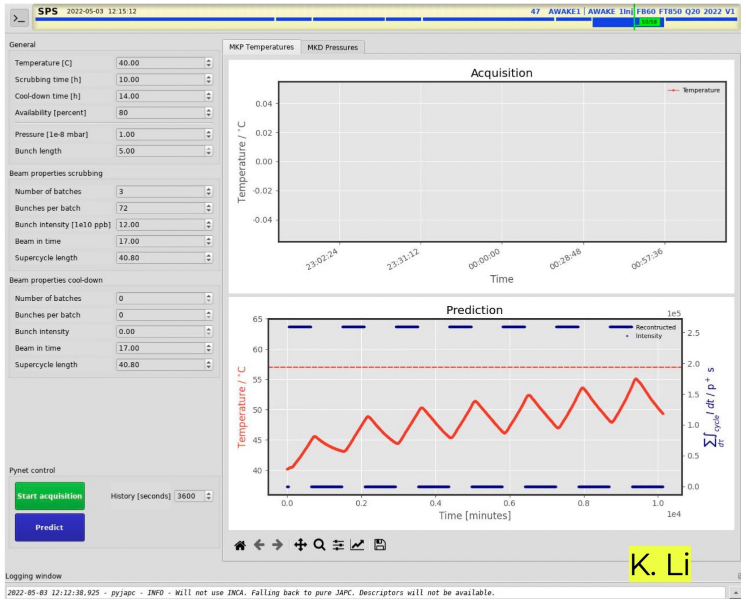
$$\mathcal{L}_2 = 1/M \sum_j^M (\frac{\partial^2 \hat{u}}{\partial x^2} - \frac{\partial \hat{u}}{\partial t})^2$$

$$\mathcal{L}_3 = \hat{u}(x, t=0) - f(x)$$

$$\mathcal{L}_4 = \hat{u}(x=0, t) - u_0$$



$$\mathcal{L}_{tot} = \alpha\mathcal{L}_1 + \beta\mathcal{L}_2 + \gamma\mathcal{L}_3 + \eta\mathcal{L}_4$$



K. Li

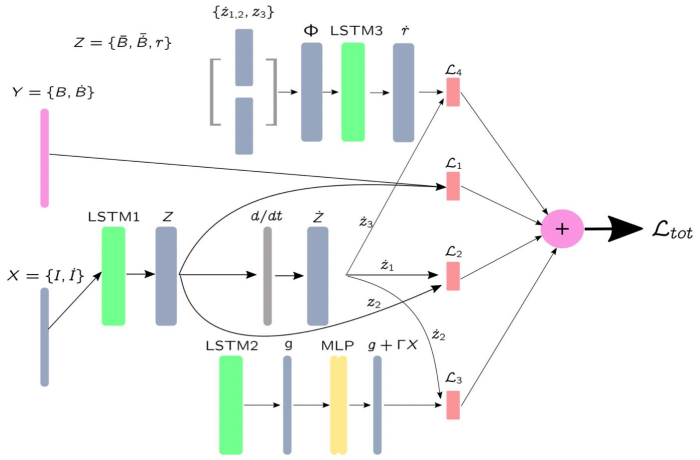
➔ A generic hysteretic model can be written as [5]:

$$a\ddot{y}(t) + b(y, \dot{y}) + r(y, \dot{y}, y(\tau)) = \Gamma x(t) \qquad \ddot{y} + g = \Gamma x$$

➔ Using input x = {I, dI/dt} and output y = {B, dB/dt}, we wrote our model and loss:

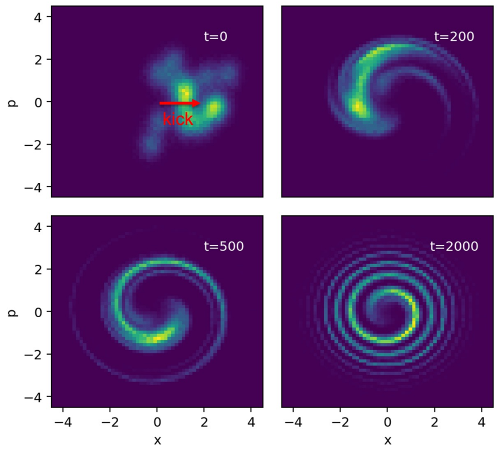
$$\mathcal{L}_1 = MSE(z_1(\theta_1) - y_1) + MSE(z_2(\theta_1) - y_2)$$
$$\mathcal{L}_2 = MSE(\dot{z}_1(\theta_1) - z_2(\theta_1))$$
$$\mathcal{L}_3 = MSE(\dot{z}_2(\theta_1) + MLP(g(\theta_1, \theta_2), x_1))$$
$$\mathcal{L}_4 = MSE(\dot{r}(\theta_1, \theta_3) - \dot{z}_3(\theta_1)); \dot{r} = f(\Phi); \Phi = \{\Delta z_2, r\}$$

$$\mathcal{L}_{tot} = \alpha\mathcal{L}_1 + \beta\mathcal{L}_2 + \gamma\mathcal{L}_3 + \eta\mathcal{L}_4$$



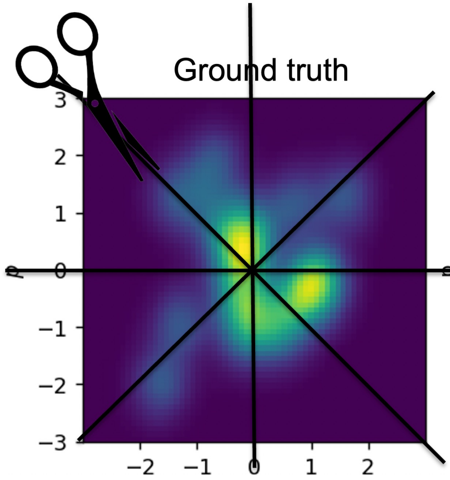
Kilean H.

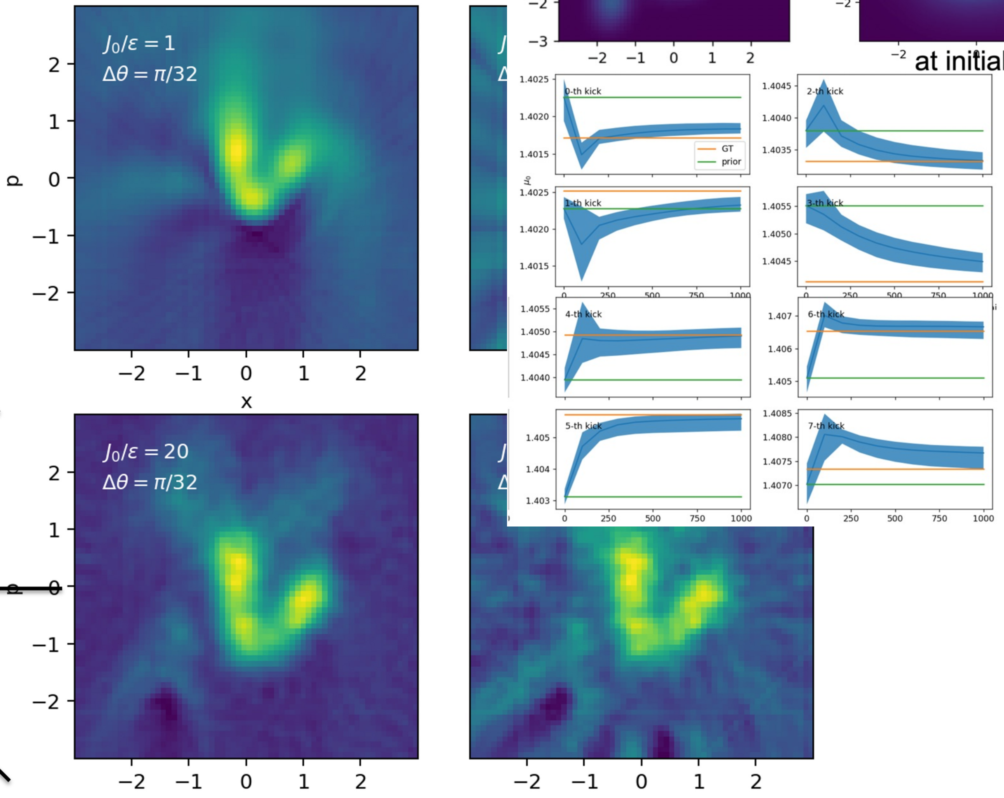
Transverse 2D Phase-Space Tomography Using BPMs

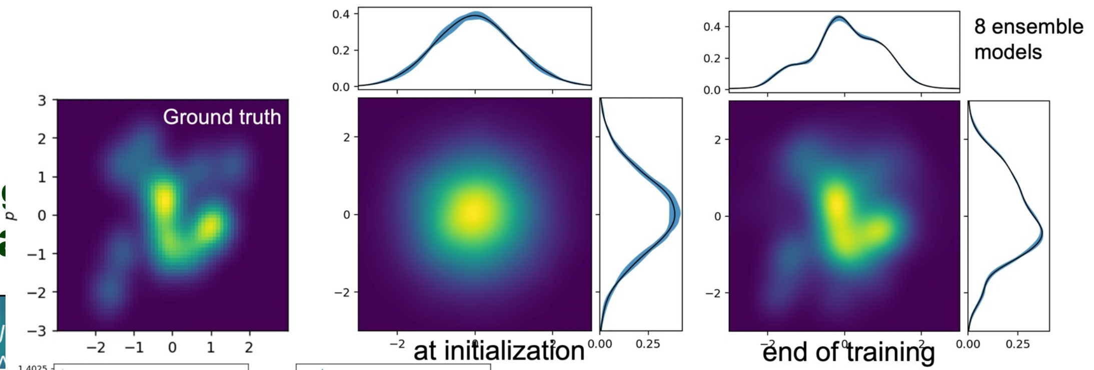


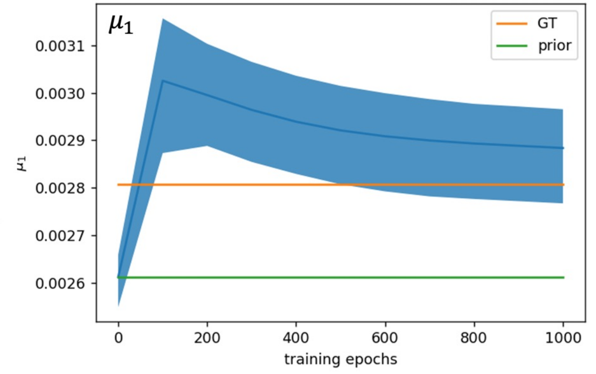
Inverse Radon transformation (an al
using theoretically estimated margina

- Reconstruction of 2D phase-space via inverse Radon transform using beam profiles estimated theoretically on (virtual) BPM data of kicked beam at various kick angles









Lucy Lin

Simulation Studies and Machine Learning Applications for Orbit Correction at the Alternating Gradient Synchrotron

Test case: reconstruct errors with J_{model}

- Reconstructed error = quadrupole power supply current

Case 1: One quadrupole 1% (4A) error

```
# Quad A17 +4 Amp
np.dot(V, np.dot(S_inv, np.dot(UT, dr1)))
```

```
array([ 4.04152292e+00, -4.15488269e-05,  2.17313140e-05,  6.45374239e-05,
        4.03913733e-05,  3.09693635e-05,  2.76558248e-05, -4.31669566e-05,
       -1.36249941e-05,  4.91338661e-05, -6.14294896e-05,  3.19703471e-05])
```

Case 2: Two quadrupoles 0.5% (2A), 0.18% (0.7A) error

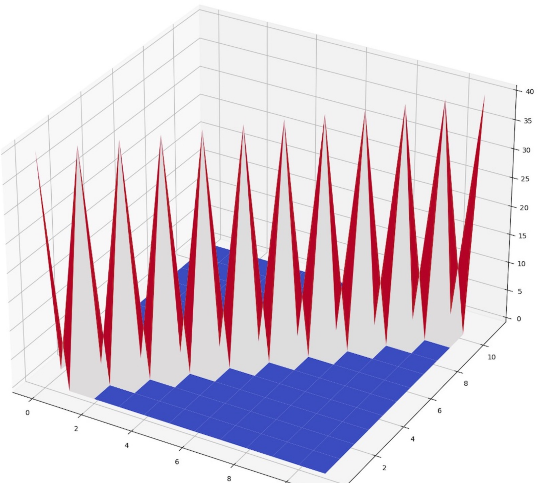
```
# Quad C17 +2 Amp, H17 +0.7 Amp
np.dot(V, np.dot(S_inv, np.dot(UT, dr2)))
```

```
array([ 3.50482558e-05, -5.54479409e-05,  2.02147800e+00,  7.69381741e-05,
        5.06832047e-05,  4.13148646e-05,  4.02598848e-05,  7.07636616e-01,
       -2.78341654e-05,  4.27531143e-05, -6.90270247e-05,  2.50657000e-05])
```

Case 3: Three quadrupoles 0.75% (3A), 0.02% (0.08A), 0.25% (1A) error

```
# Quad B17 +3 Amp, F17 +0.08 Amp, J17 +1 Amp
np.dot(V, np.dot(S_inv, np.dot(UT, dr3)))
```

```
array([ 6.97595445e-05,  3.03074518e+00, -1.42673230e-05,  8.18292016e-06,
        6.05175589e-05,  8.07700864e-02,  4.40237777e-05, -8.92267806e-05,
       -4.99647748e-05,  1.01013295e+00, -2.99336376e-05, -2.01460387e-04])
```

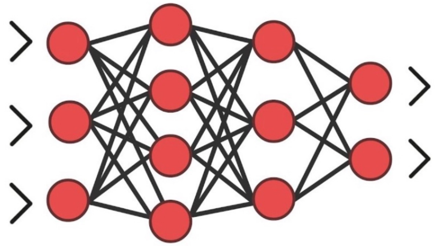


Satisfactory reconstruction r

Sensitivity studies for ORM

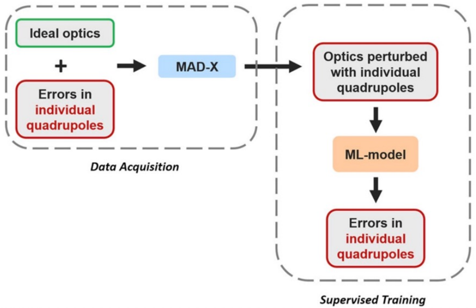
- Scan through some common sources of error to see how much ORM changes
- Find relevant parameters to include for building error-detecting model
- **Goal**: establish a neural network that identify error source given a measured ORM

$$\begin{pmatrix} \Delta\nu_1 \\ \Delta\nu_2 \\ \cdots \\ \Delta\nu_{N-1} \\ \Delta\nu_N \end{pmatrix} = J^{+}_{model} \begin{pmatrix} \Delta R_{11} \\ \Delta R_{12} \\ \cdots \\ \Delta R_{n(m-1)} \\ \Delta R_{nm} \end{pmatrix}$$



Future work

- Finish sensitivity scan to determine relevant error sources: snake magnet incorporation to Bmad using field maps in progress
- Make simulation more realistic: add Gaussian noises to both magnets and BPMs
- Establish a dynamic retraining routine to keep model updated during operation



[4]

Thanks for a very productive and informative workshop!

Our community speeded up enormously in terms of adapting up-to-date ML techniques

Looking forward to the next workshop