

Identification of Field Errors with Machine Learning Techniques

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- ▶ GSI/FAIR hosts variety of ring accelerators
- ▶ SIS100 central accelerator of future FAIR facility
- ▶ existing SIS18 will be used as injector

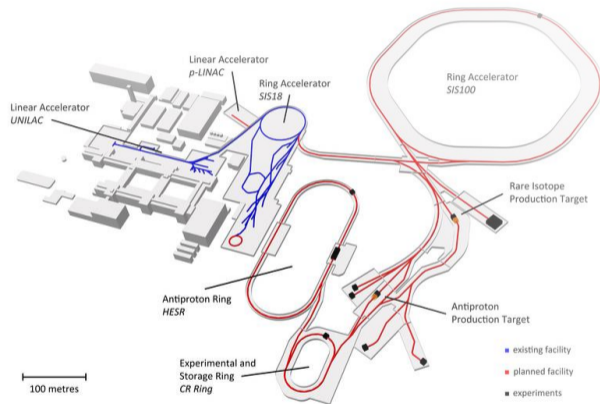
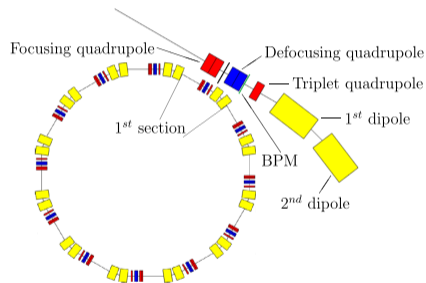


Figure: GSI/FAIR facility.

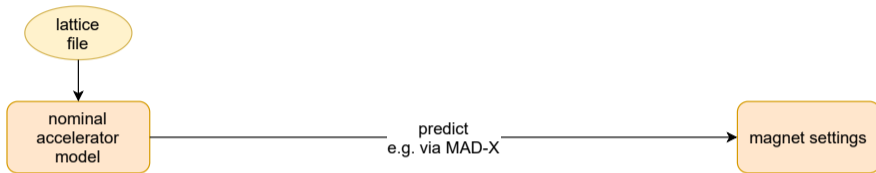
[Courtesy of Dr. Rahul Singh]

Field Errors

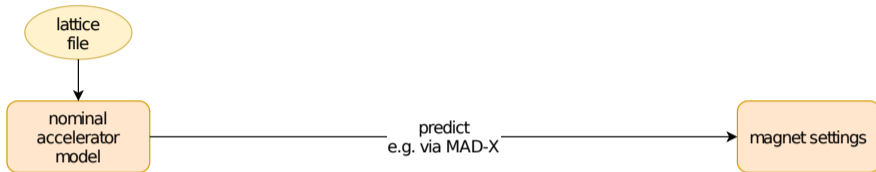
- ▶ unwanted multipoles
 - ▶ excite resonances
 - ▶ reduce dynamic aperture
 - ▶ cause beam loss
- ▶ mitigation and correction
 - ▶ requires type, location and strength
 - ▶ compute from accurate model
 - ▶ dedicated beam time necessary to find them
 - LOCO-algorithm, non-linear tune response matrix



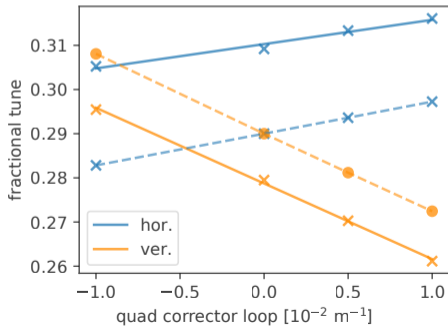
Accelerator Set Up



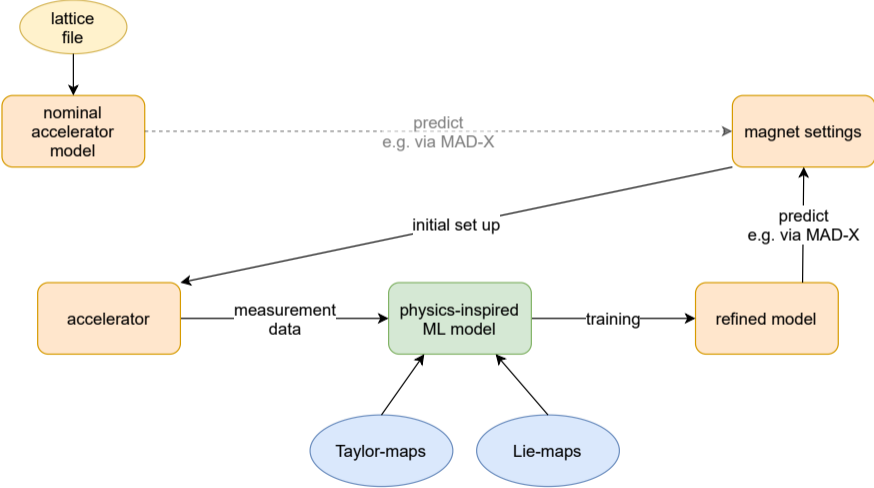
Accelerator Set Up



SIS18 measurements
-> tunes show systematic shift
-> quadrupole error present in accelerator



Accelerator Set Up

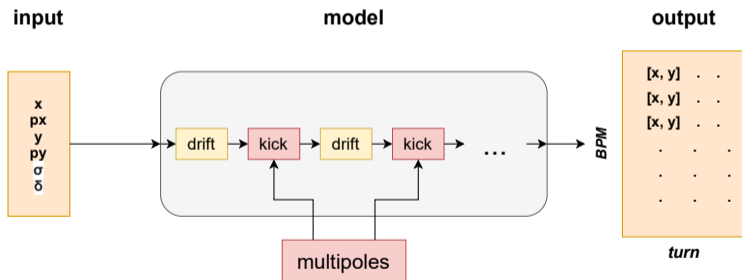


Thin-Lens Model

- ▶ treat separable Hamiltonians $H = T + V$ with Lie-algebra
- ▶ express phase-space transformations \mathcal{M} via canonical integrators
 - ▶ drift-kick scheme, symplectic by design
- ▶ maps derived for all major accelerator elements [MF15]

Thin-Lens Model

- ▶ understand accelerator model as map $\mathbb{R}^6 \rightarrow \mathbb{R}^{2 \times K \times M}$
 - ▶ map initial conditions to K BPM readings for M turns
 - ▶ non-linear multi-dimensional optimization problem like artificial neural networks
 - ▶ degrees of freedom during training: multipole strengths

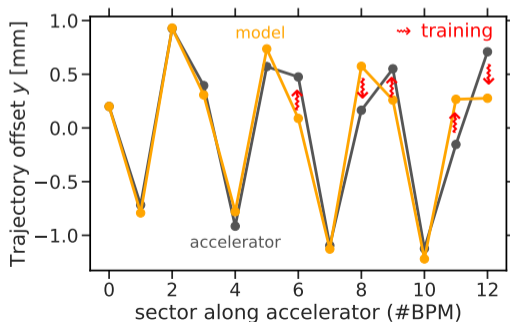


Training Procedure

- ▶ minimize discrepancy between prediction and measurement
- ▶ compare N trajectories by loss \mathcal{L}

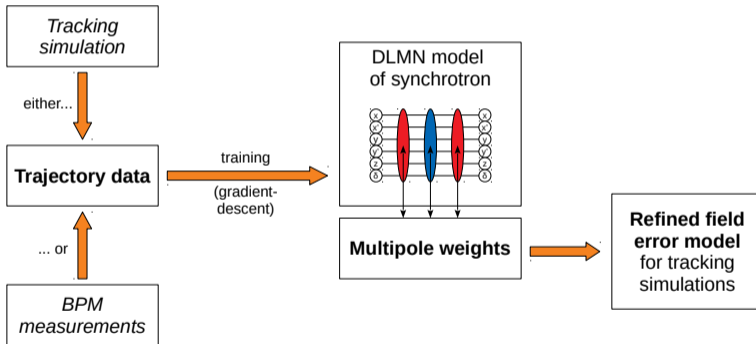
$$\mathcal{L} = \frac{1}{N} \sum_n^N \sum_m^{M_{\text{turns}}} \sum_k^K \left(\begin{bmatrix} x \\ y \end{bmatrix}_{\text{model}} - \begin{bmatrix} x \\ y \end{bmatrix}_{\text{accelerator}} \right)_{m,n,k}^2$$

- ▶ tracking implemented in PyTorch [PGM⁺19]
 - ▶ tools for automatic differentiation
 - ▶ implementation of optimization algorithms
 - ▶ access to CPUs & GPUs



Identification of Field Errors

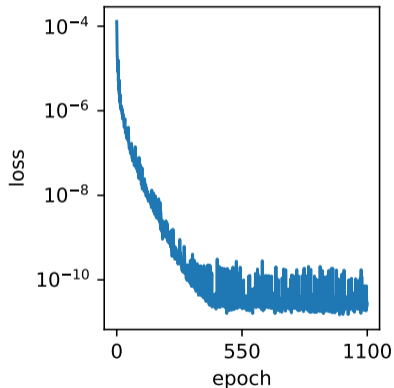
Workflow



Identification of Field Errors

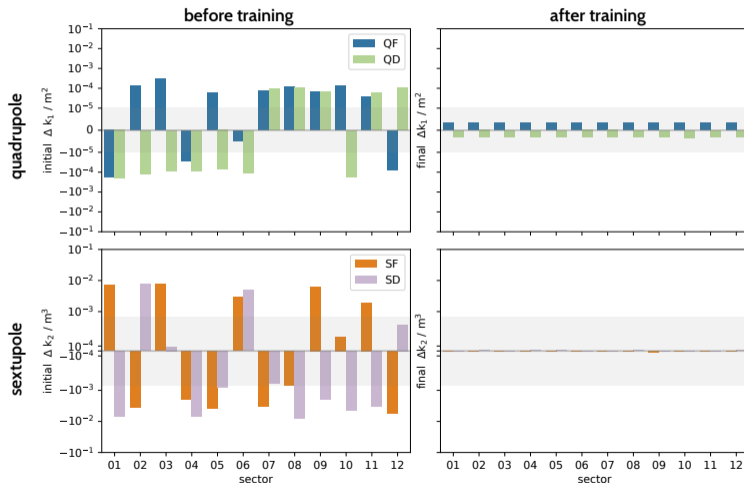
Training Procedure

- ▶ 500 simulated trajectories compared over 3 turns
- ▶ randomly group training data into mini-batches
- ▶ ADAM optimizer, hyperparameters optimized by Gaussian Process



Identification of Field Errors

Results



Identification of Field Errors

Results

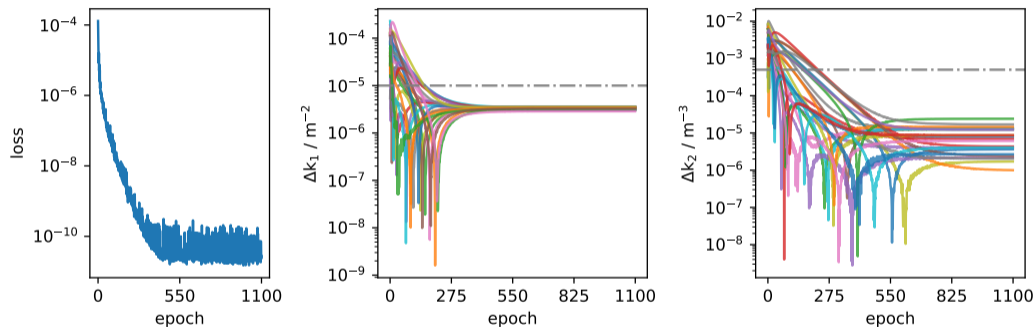
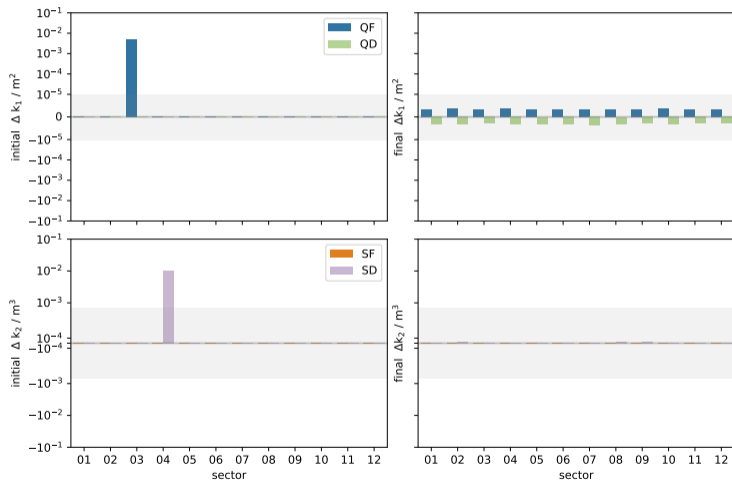


Figure: Evolution of loss (left), quadrupole (middle) and sextupole components (right) during training.

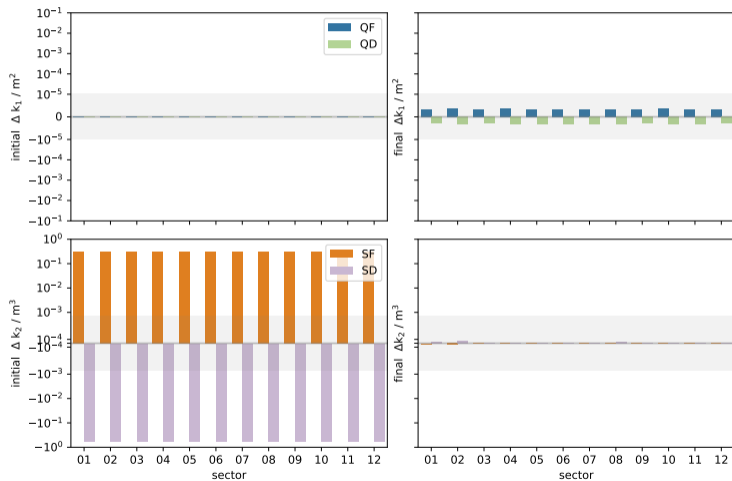
Thin-lens Model

Results



Thin-lens Model

Results

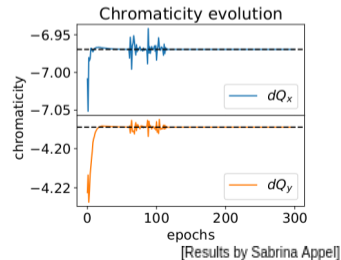
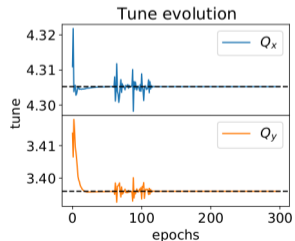
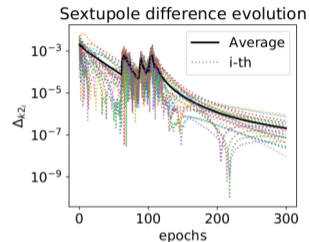
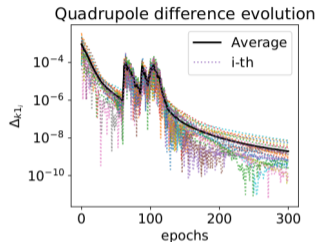


Identification of Field Errors

Results

training successfully applied to

- ▶ isolated gradient / sextupole errors
- ▶ distributed errors
- ▶ chromaticity correction scheme



Conclusion

approach

- ▶ model accelerator based on thin-lens approximation & Lie-algebras
- ▶ canonical integrators expressed in terms of automatic differentiation
- ▶ 6D particle tracking implemented in PyTorch ML framework

outcome

- ▶ identify isolated & distributed multipole errors
- ▶ correctly reproduce physical observables
like beta-functions, tunes, chromaticities
- ▶ physical interpretation of model parameters as multipole strengths at any stage

Outlook

- ▶ train on SIS18 experimental data
 - ▶ study influence w.r.t. BPM measurement noise
 - ▶ compare to results obtained by Non-linear Tune Response Matrix [PF11]
 - ▶ leverage for resonance compensation
- ▶ study hyper-parameter optimization
 - ▶ speed
 - ▶ meta-learning
- ▶ investigate uniqueness of solution
- ▶ extend loss by additional quantities like phase advance

End

Thank you for your attention!

References I

- [Gra08] Paul Grannis. Particle accelerators - herding and hurrying cats, 2008.
- [IA20] Andrei Ivanov and Ilya Agapov. Physics-based deep neural networks for beam dynamics in charged particle accelerators. *Physical Review Accelerators and Beams*, 23(7):074601, 2020.
- [Lat20] Andrea Latina. Transverse beam dynamics, 2020.
- [MF15] R De Maria and M Fjellstrom. Sixtrack physics manual (draft), 2015.
- [PF11] A Parfenova and G Franchetti. Experimental benchmarking of nonlinear tune response matrix with several controlled sextupolar errors. *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment*, 646(1):7–11, 2011.

References II

- [PGM⁺19] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *arXiv preprint arXiv:1912.01703*, 2019.
- [Sca95] Walter Scandale. Dynamic aperture. In *AIP Conference Proceedings*, volume 326, pages 52–97. American Institute of Physics, 1995.

Physics-inspired Neural Networks

Physics-inspired Neural Networks

- ▶ exploit domain knowledge to construct network architecture
- ▶ replace layers by Taylor-maps $\mathcal{M}(\vec{z}) = \vec{z} + W_1\vec{z} + W_2\vec{z}^2 + \dots$

$$\vec{z} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}; \quad \vec{z}^2 = \begin{bmatrix} z_1^2 \\ z_1 z_2 \\ z_2^2 \end{bmatrix}; \quad \vec{z}^3 = \begin{bmatrix} z_1^3 \\ z_1^2 z_2 \\ z_1 z_2^2 \\ z_2^3 \end{bmatrix}$$

- ▶ describe accelerator as concatenation

$$\mathcal{M}_{\text{accelerator}} = M_k \circ M_{k-1} \circ \dots \circ M_1$$

Physics-inspired Neural Networks

Taylor-maps

Taylor-maps

- ▶ represent transformations in 6D-phase space
- ▶ weight matrices W_k can be calculated by Truncated-Power-Series-Algebra
- ▶ or be obtained beam dynamics, e.g. affiliated from MAD-X, elegant, ...
- ▶ Quadrupole

$$\mathcal{M}_{\text{quad}} = W_1 \vec{z} = \begin{bmatrix} \cos(\sqrt{|k|}L) & \frac{\sin(\sqrt{|k|}L)}{\sqrt{|k|}} \\ \sqrt{|k|} \sin(\sqrt{|k|}L) & \cos(\sqrt{|k|}L) \end{bmatrix} \quad (1)$$

Thin-Lens Model

thin-lens approximation

- ▶ treat separable Hamiltonians $H = T + V$ with Lie-algebra
- ▶ express phase-space transformations \mathcal{M} via canonical integrators

$$\begin{aligned}\mathcal{M}(\vec{z}) &= e^{-L:H:} = e^{-L:T+V:} \approx \prod_{i=0}^n e^{-Lc_i:T:} e^{-Ld_i:V:} + \mathcal{O}(L^{n+1}) \\ &= \prod_{i=0}^n (1 + c_i L : -T :) (1 + d_i L : -V :) + \mathcal{O}(L^{n+1})\end{aligned}$$

- ▶ symplectic by design
- ▶ maps derived for all major accelerator elements [MF15]