Optimizing Beamlines with Image-to-Image surrogates

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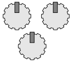
Major research questions

- How to use artificially generated data in order to improve learning?
- How to fix the gap between simulations and reality?
  - How to deal with noisy or missing data?
  - How to determine deviations of alignment?

What is a beamline?

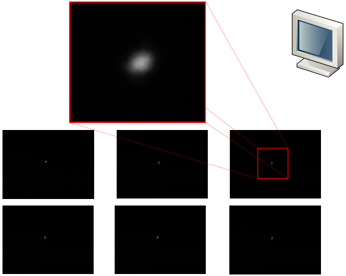
METRIX: What we have



34 parameters of

Undulator
ASBL Slit
Cylindrical Mirror
Spherical Grating
Exit Slit

→

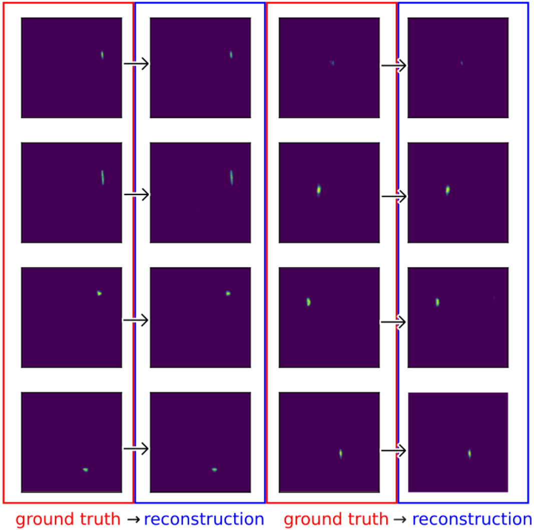


… 10 images at
different positions

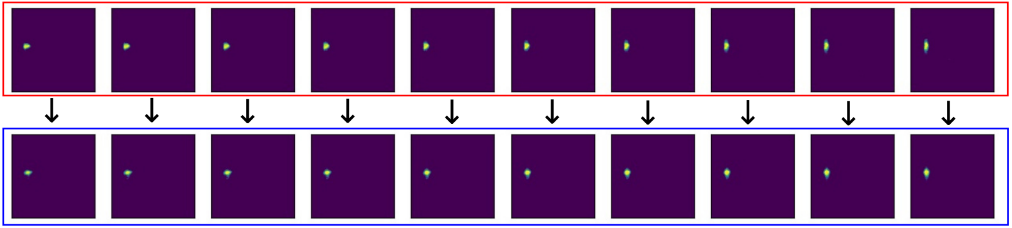
Knobs to turn

Fluorescence screen

METRIX Beamline Inversion: Autoencoder



METRIX Beamline Inversion: Surrogate



simulation (ground truth) surrogate model

METRIX Beamline Inversion: Decoded image with offsets

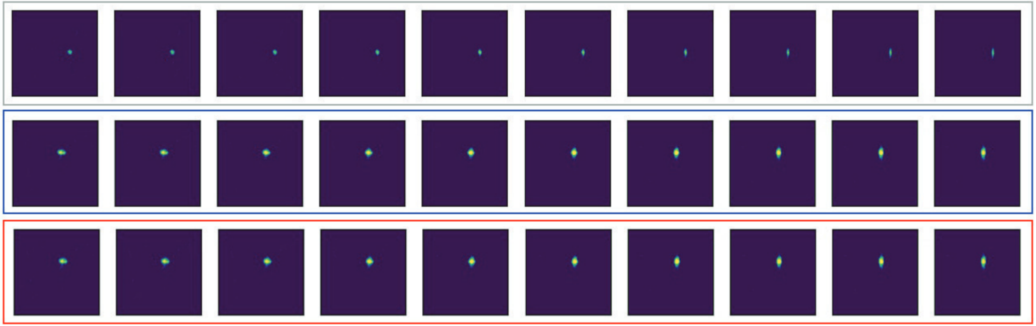


Figure: without offset with real offset with approximated offset by BO

Problems

- Center of mass is well reconstructed
- But: The shapes are poorly reconstructed

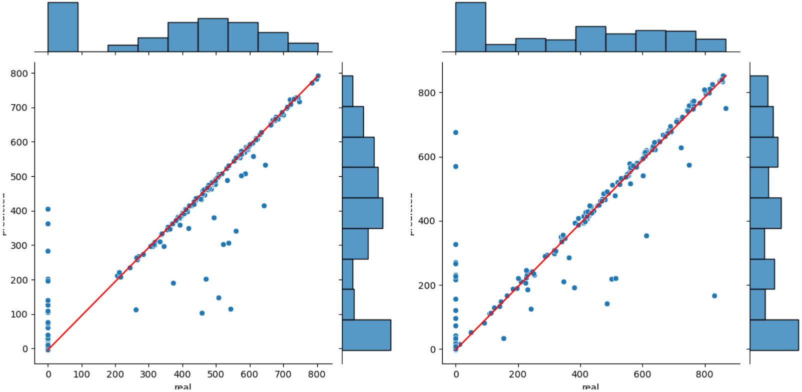


Figure: Determination of center of mass x and y

Solution 1: Image2Image surrogates

- Use small surrogates for all componentes of a beamline separately
- Use ConvMixer for learning image to image transformations
- Experiments for now with MNIST-Data

Figure: Example of rotation with ConvMixer

Solution 2: Fast approximates of small simulation

- Omit surrogate by density estimation of e.g. 1000 or 10000 rays $\Rightarrow$ computationally feasable
- Apply e.g. Bayesian Optimization or global optimizer directly

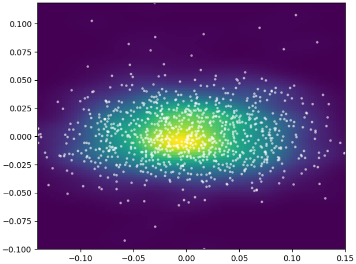


Figure: Kernel density estimation of beam footprint (white points)

Outlook

- Test surrogates to learn output density estimation representation
- Try on real data
- Experiment with different metrics, e.g. EMD or Sinkhorn
- Transfer to another beamline