Update on data-driven emittance optimization (OPAL-FEL)

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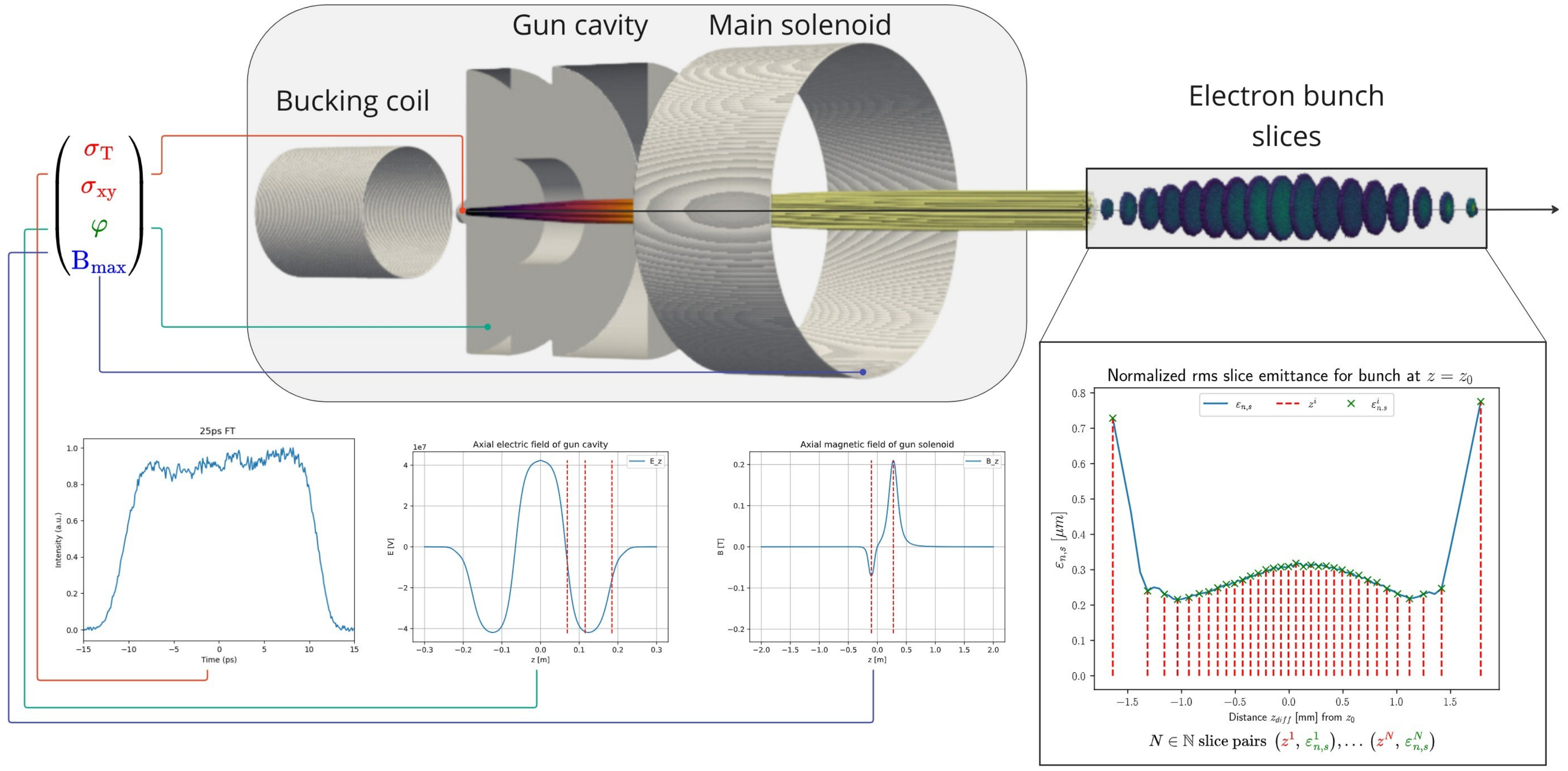


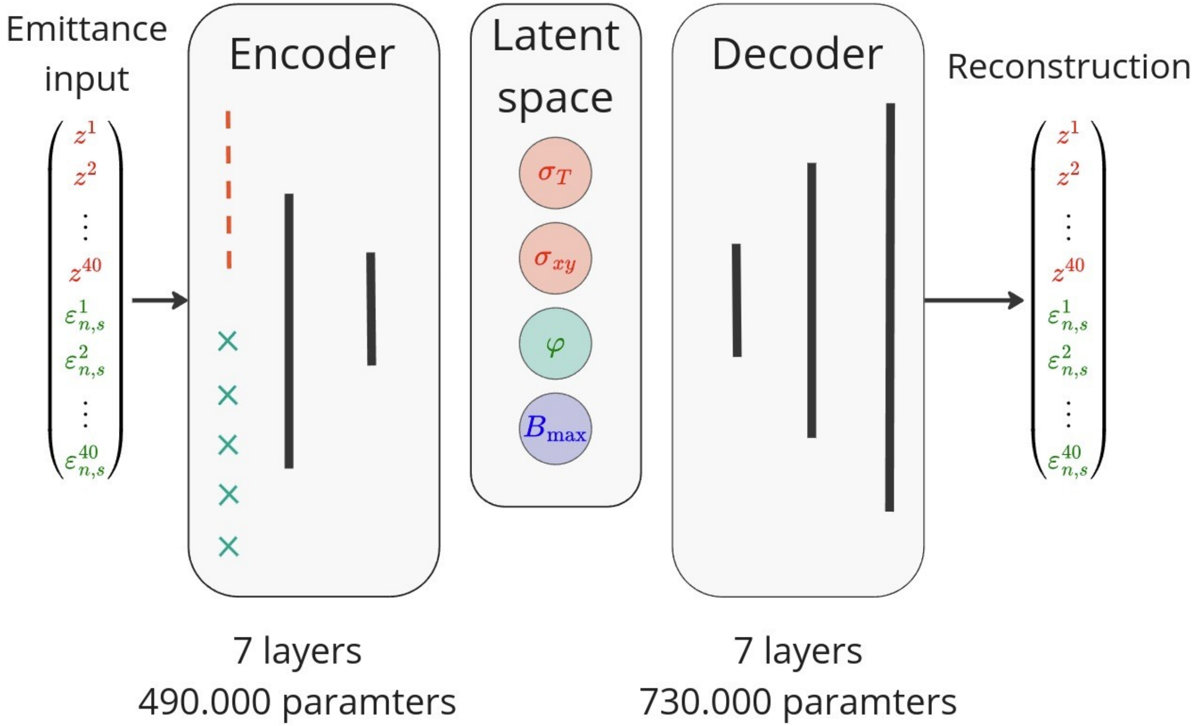
Gun cavity
Main solenoid
Bucking coil
Electron bunch slices
z
σ_T
σ_{xy}
φ
B_{max}
25ps FT
Intensity (a.u.)
Time (ps)
Axial electric field of gun cavity
E_z
E [V]
z [m]
Axial magnetic field of gun solenoid
B_z
B [T]
z [m]
Normalized rms slice emittance for bunch at $z = z_0$
$\varepsilon_{n,s}$
z^i
$\varepsilon^i_{n,s}$
$\varepsilon_{n,s}$ [μm]
Distance z_{diff} [mm] from z_0
$N \in \mathbb{N}$ slice pairs $(z^1, \varepsilon^1_{n,s}), \dots (z^N, \varepsilon^N_{n,s})$

Data sampling

- Sampling of in total 40.000 simulations using ASTRA with the parameters in the table below
- Bold parameters are varied within given ranges
- Code published on Zenodo

Parameter	Value/Range
Laser pulse length FWHM	5 to 15 ps
Transverse rms beam spot size	0.18 to 0.30 mm
Gun phase	-10 to 10 deg
Gun solenoid strength	0.15 to 0.3 T
Temporal laser pulse shape	Flattop
Transverse laser profile	Radial uniform
Gun gradient	57.6 MV/m
Bunch charge	250 pC

First Model: AutoEncoder



Input-Output pairs:

$$n\text{-batches } \{(\mathbf{x_i}, \mathbf{y_i})\}_{i=1}^n \subset \mathbb{R}^{80} \times \mathbb{R}^4$$

$$\mathbf{x_i} := (z^1, \ldots, z^N, \varepsilon^1, \ldots, \varepsilon^N)$$

$$\mathbf{y_i} := (\sigma_T, \sigma_{XY}, \varphi, B_{\max})$$

Normalized slice charge densities:

$$\mathbf{w_i} := (d^1, \ldots, d^N)$$

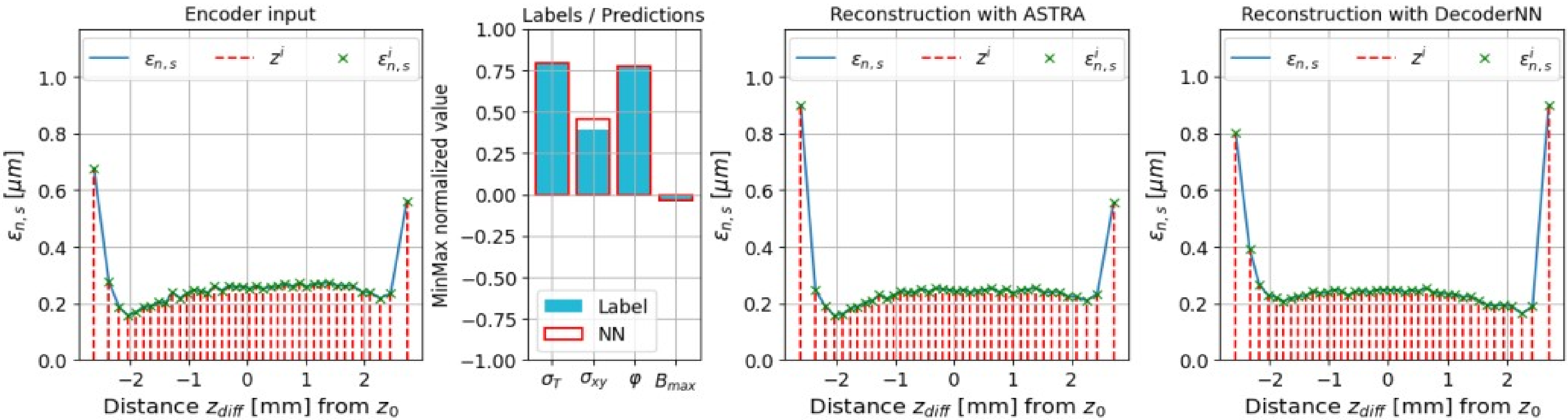
Loss:

$$\mathcal{L}_E(\mathbf{x}, \mathbf{y}) = \frac{1}{n} \sum_{i=1}^{n} ||\mathbf{y_i} - E(\mathbf{x_i})||_2^2$$

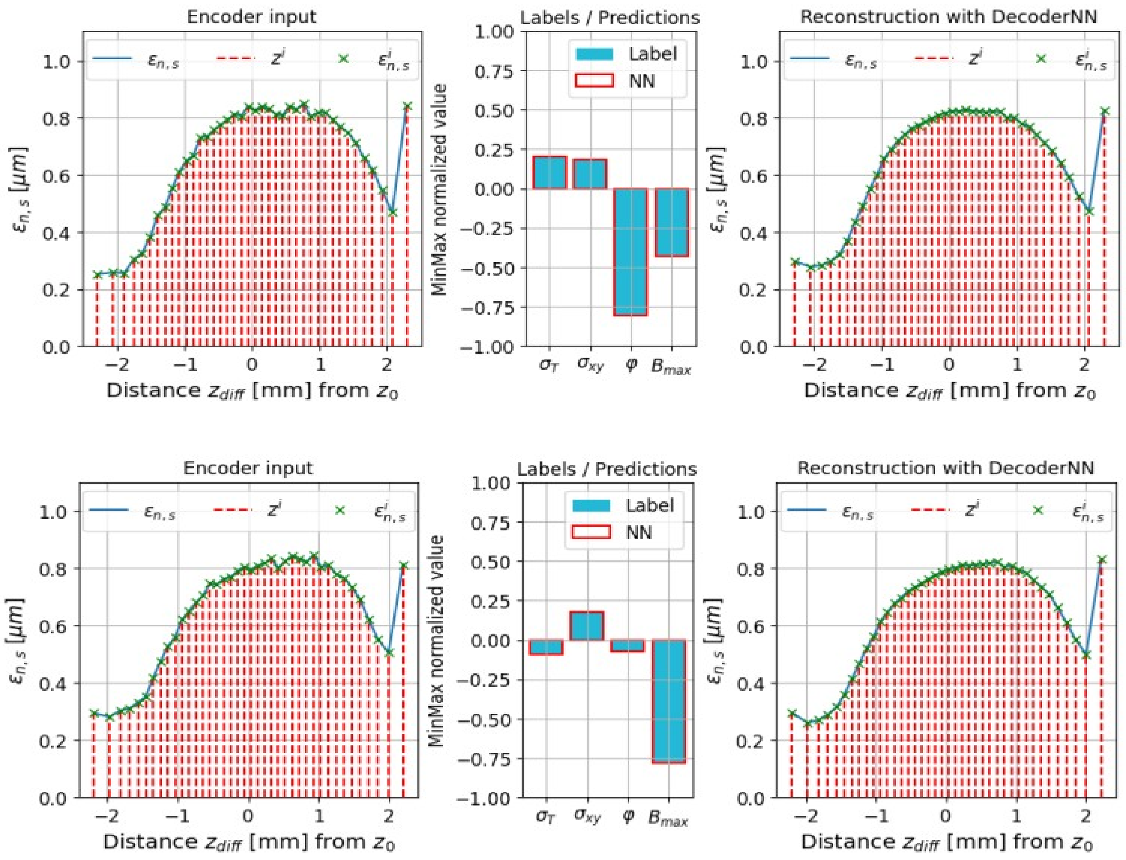
$$\mathcal{L}_D(\mathbf{x}) = \frac{1}{n} \sum_{i=1}^{n} ||\mathbf{w} * (\mathbf{x_i} - D(E(\mathbf{x_i})))||_2^2$$

$$\mathcal{L}(\mathbf{x}, \mathbf{y}) = \mathcal{L}_E(\mathbf{x}, \mathbf{y}) + \beta \cdot \mathcal{L}_D(\mathbf{x}), \ \beta > 0$$

AutoEncoder: Evaluation



Problem,: Similar samples



Similar samples

We might need more phase space information

Idea*: slice emittance alone is insufficient to fully describe the slice phase spaces. So the data needs to be enriched with more information, which can be done by

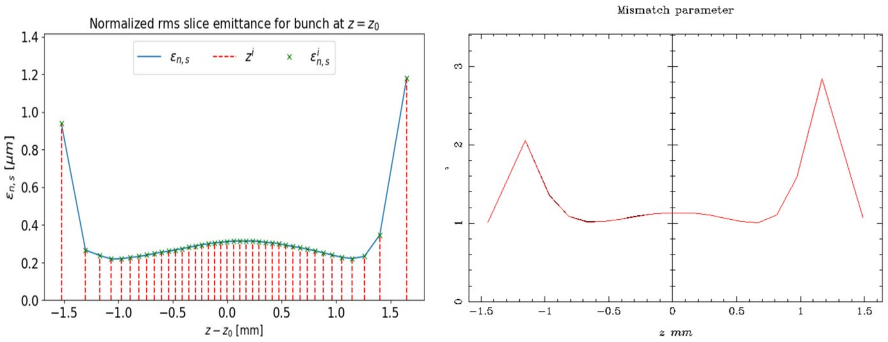
(1) adding 2 out of three twiss parameters per slice

→ Would triple input dimensionality

(2) adding the mismatch parameter for the i-th slice

$$\zeta_i := \frac{1}{2}[\beta_0\gamma_i - 2\alpha_0\alpha_i + \gamma_0\beta_i] \geq 1$$

→ Would double input dimensionality



Mismatch parameter

*Credits to Xiangkun from PITZ for the idea

Improvements with misalignment

Conditions:

- Encoder architecture fixed
- Data with and without misalignment parameter
- Input dimension 80 vs 120/60

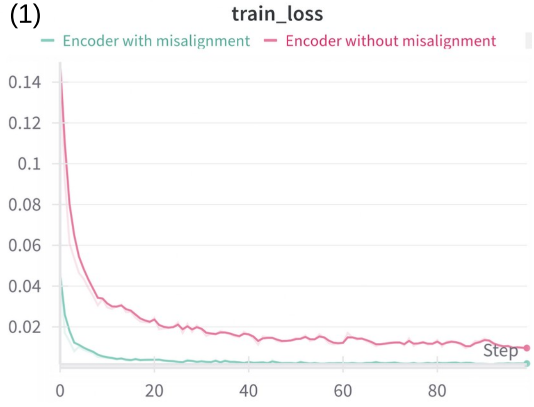
(1) Faster convergence in training and final MSE train error reduced by 1 order (~10^{-4})

(2) Neglectable error difference between results on 20 and 40 slices

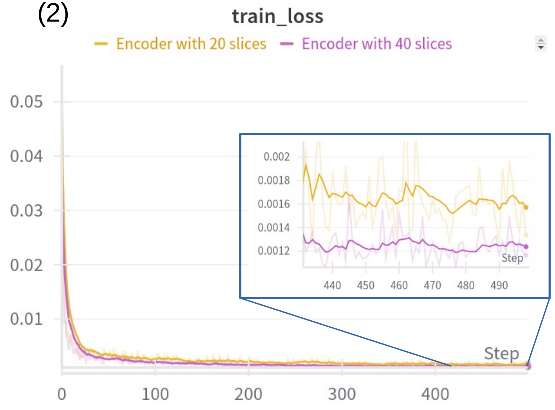
(3) Improved parameter predictions

(4) Reduction of encoder complexity
Before: 488.900 parameters
Now: 235.364 parameters

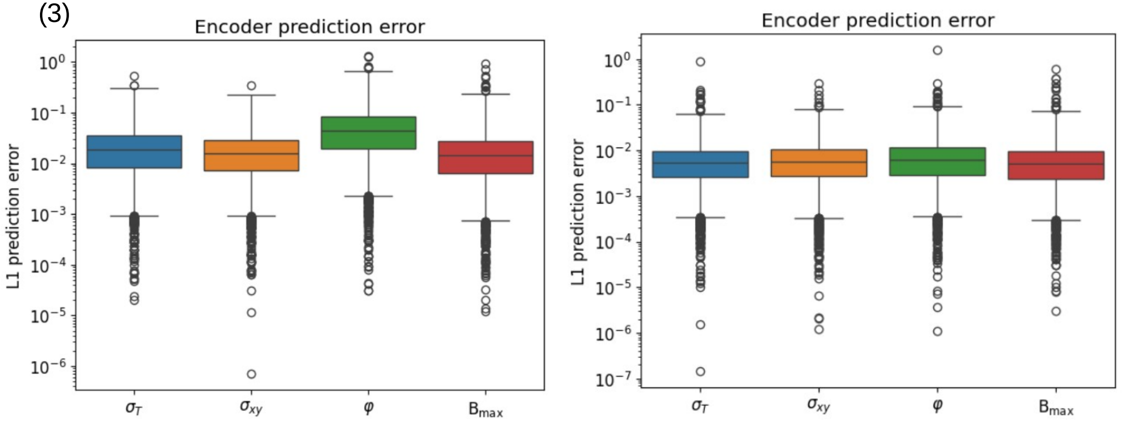
(1)



(2)

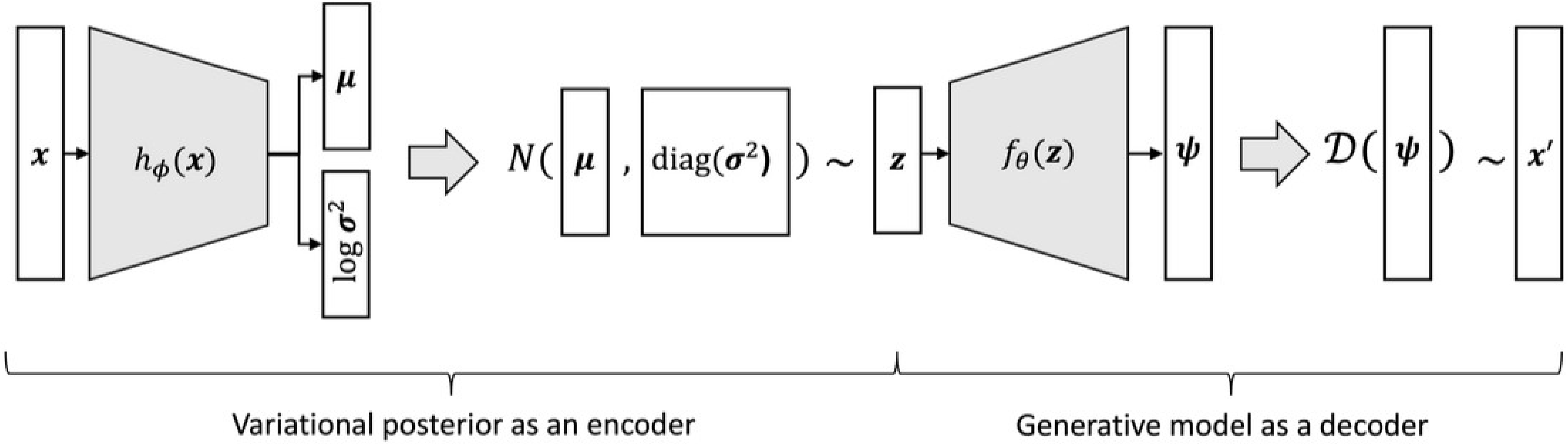


(3)



L1 encoding error per input parameter on test set.
Left: without misalignment (N=40). Right: with misalignment (N=20)

Ansatz: Experiment with Variational Auto Encoder (VAE) models



β-VAE Objective:

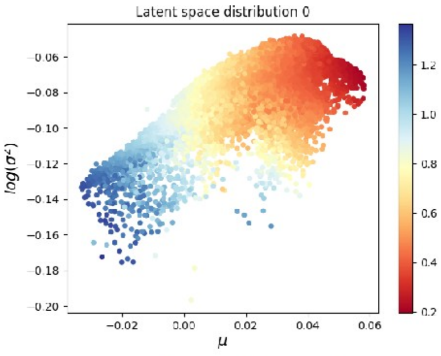
$$\mathrm{loss}_{\mathrm{VAE}}(\phi, \theta) = -\sum_{i=1}^{n} E_{z_i \sim q_\phi(z_i | x_i)} [\log p_\theta(x_i \mid z_i)] - KL(q_\phi(z_i \mid x_i) \,||\, p(z_i)) \cdot \beta$$

Figures from https://mbernste.github.io/posts/vae/

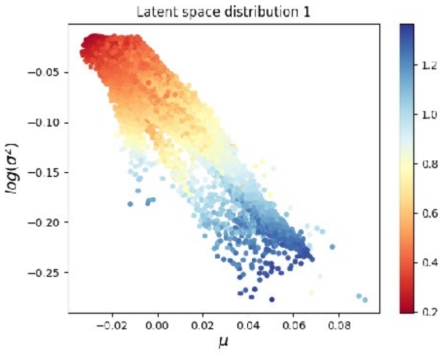
My December


SCHOOL BUS
VAE APPROACH
PULSE SHAPING
EXPERIMENTAL DATA
SOME
PROPJECT
PROPOSAL
imgflip.com

VAE Experiments – Latent Space



Beta: 1.953125e-06



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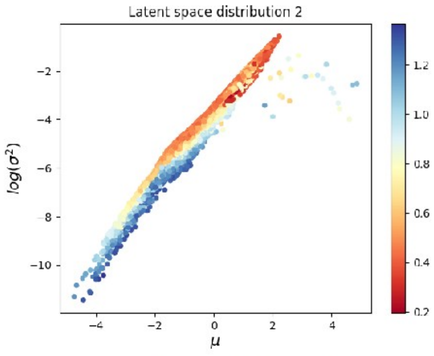

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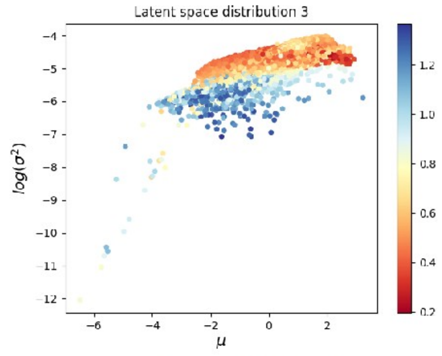

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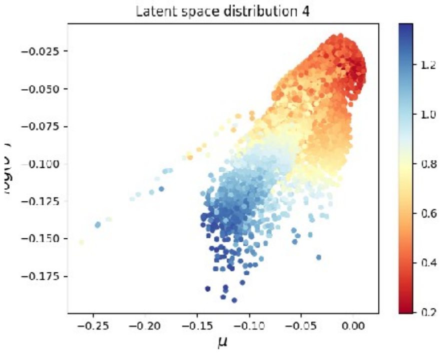

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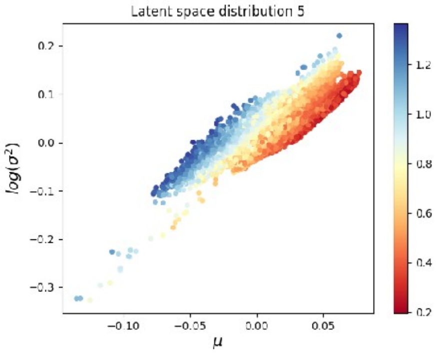

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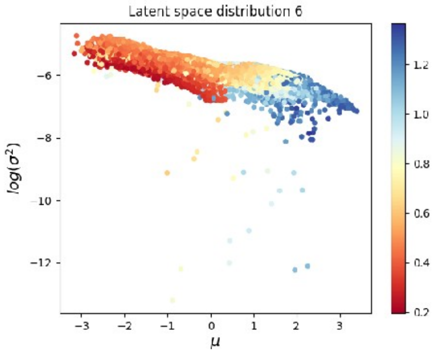

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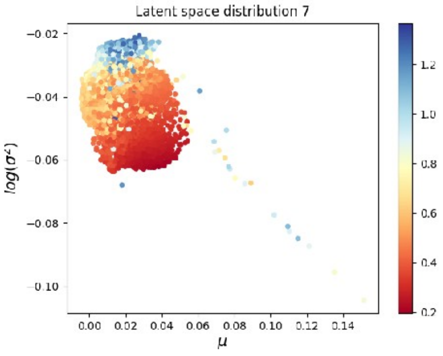

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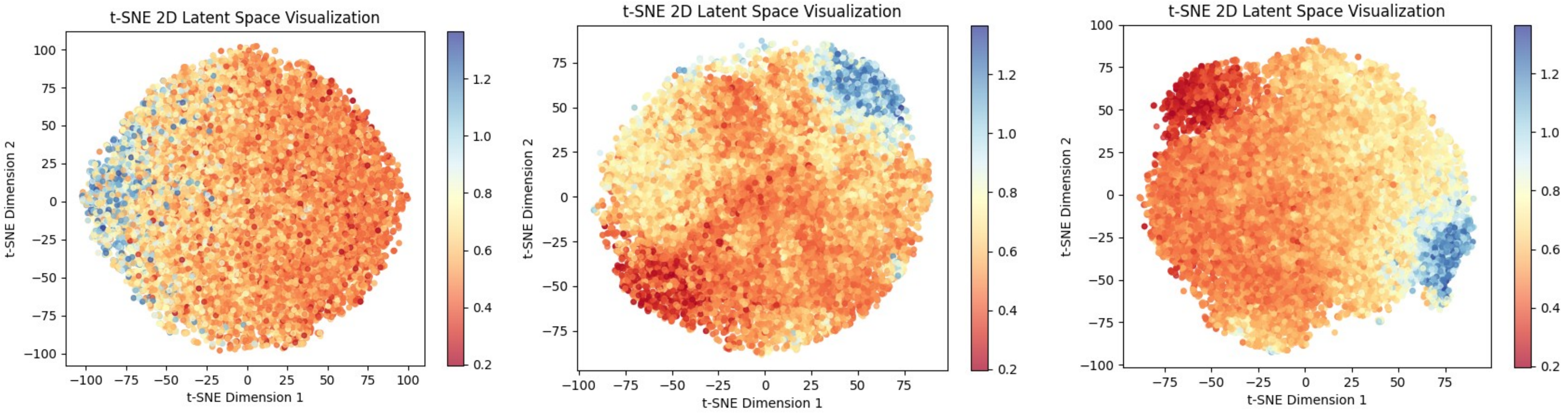
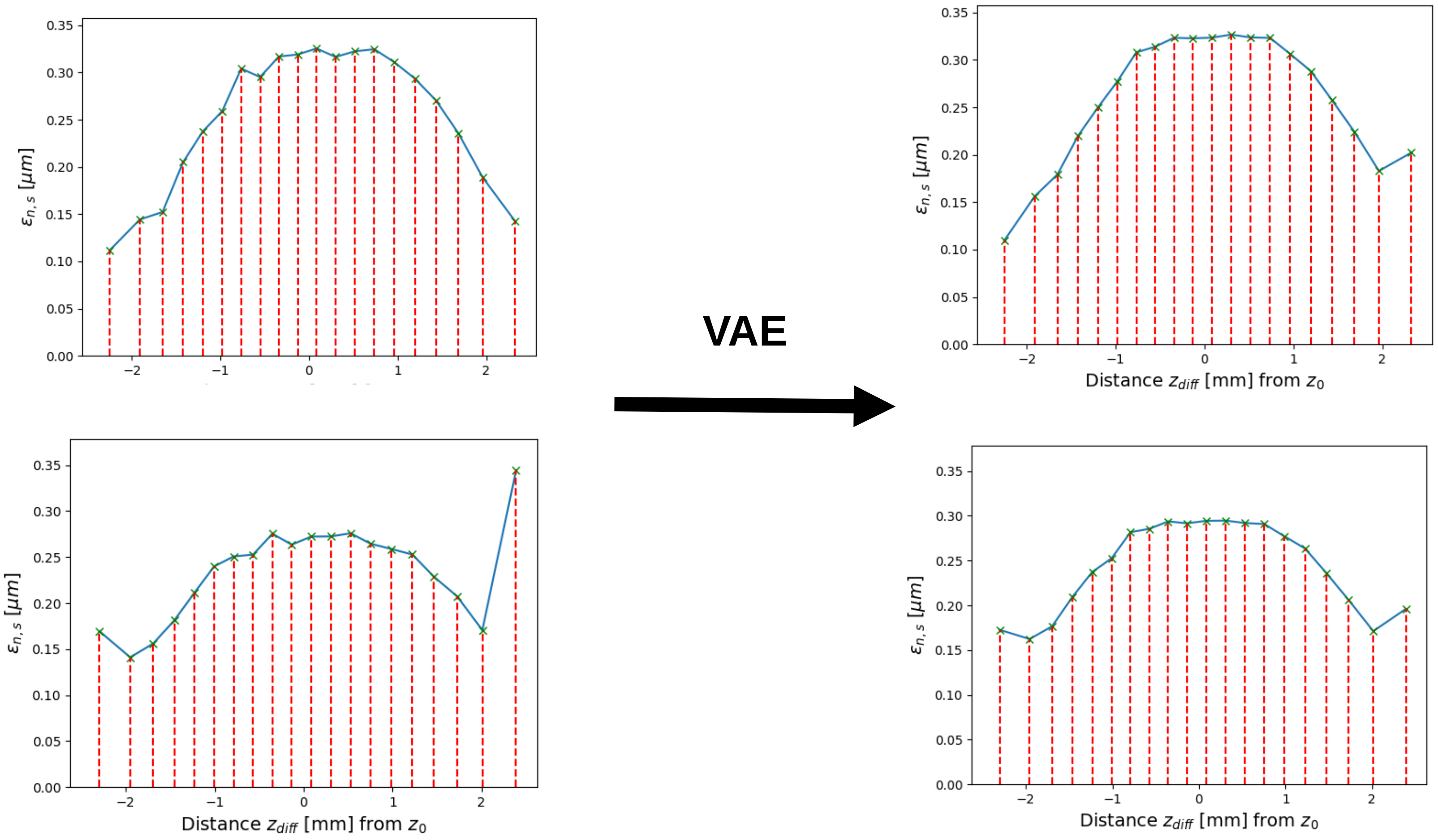
VAE Experiments – Latent Space



TSNE projections of the trained VAE's latent space for betas (l.t.r.)
1.9E-4, 3.9E-6, 3.9E-7

Reconstruction Results



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ACCELERATOR SYSTEM PARAMETER ESTIMATION USING VARIATIONAL AUTOENCODED LATENT REGRESSION *

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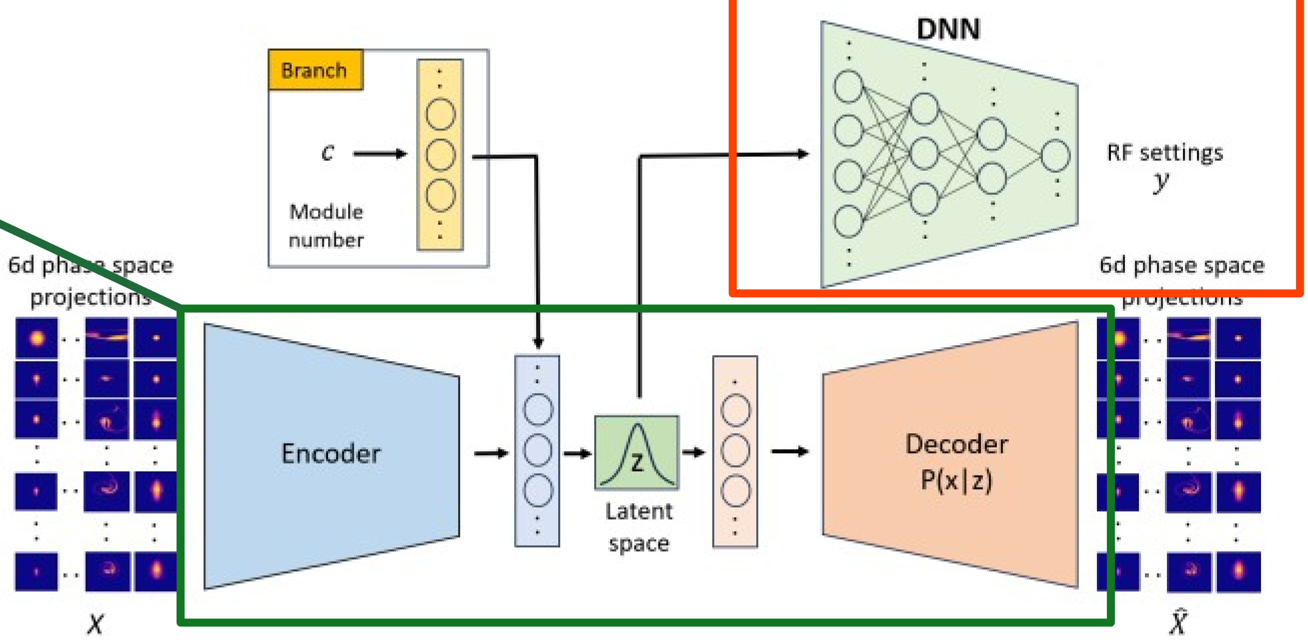
My VAE experiment covers this



To be done still

Next Steps (1)

Pulse shaping in close collaboration with Denis

ML starting point:

Artificial neural networks for nonlinear pulse shaping in optical fibers

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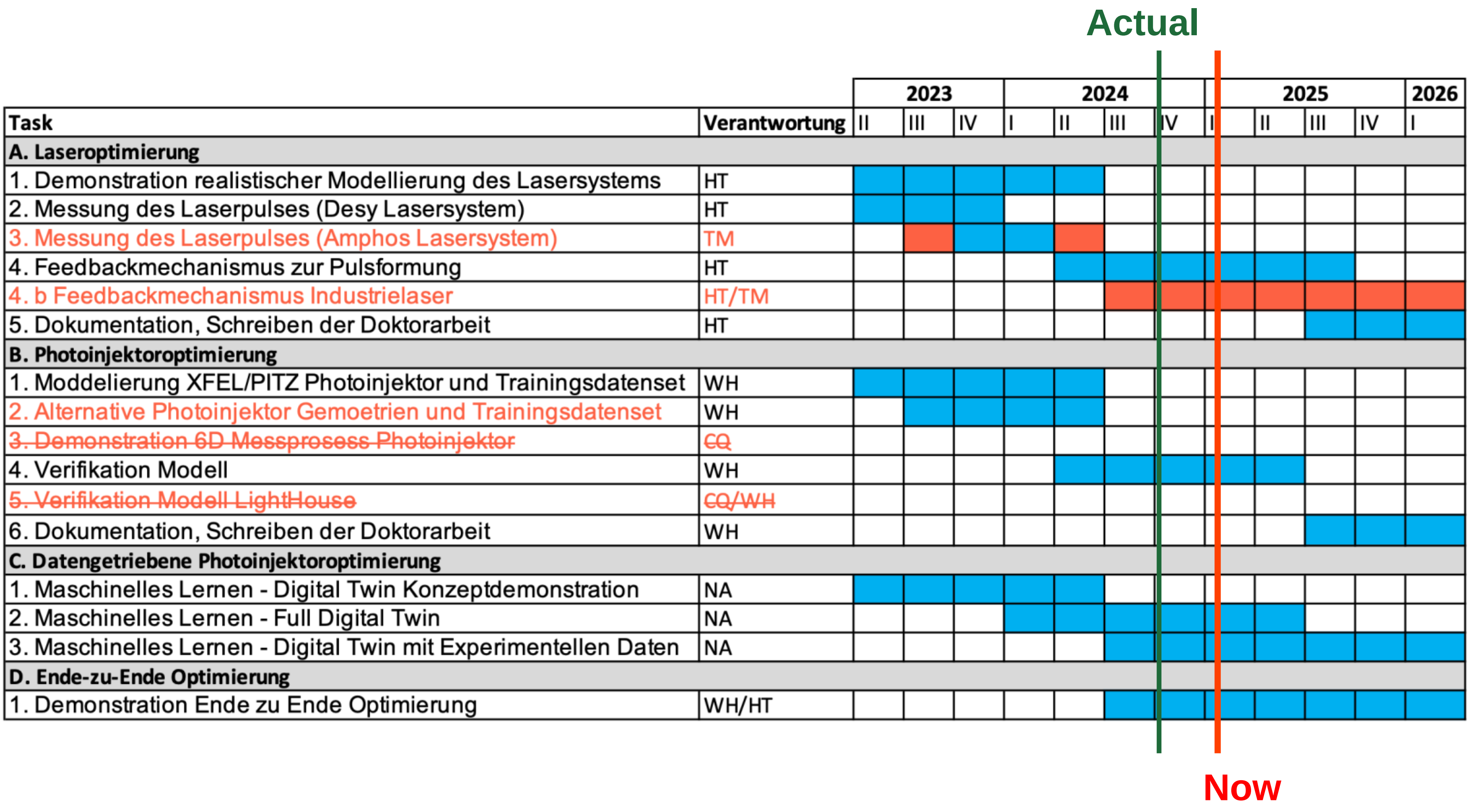
Next Steps (2)

- Preprocessing of experimental data by student assistant (starting tomorrow)
- Some experimental data samples available already
- Start with benchmarking on exp. data


Actual
Now
2023
2024
2025
2026
Task
Verantwortung
II
III
IV
I
II
III
IV
I
II
III
IV
I
A. Laseroptimierung
1. Demonstration realistischer Modellierung des Lasersystems
HT
2. Messung des Laserpulses (Desy Lasersystem)
HT
3. Messung des Laserpulses (Amphos Lasersystem)
TM
4. Feedbackmechanismus zur Pulsformung
HT
4. b Feedbackmechanismus Industrielaser
HT/TM
5. Dokumentation, Schreiben der Doktorarbeit
HT
B. Photoinjektoroptimierung
1. Moddelierung XFEL/PITZ Photoinjektor und Trainingsdatenset
WH
2. Alternative Photoinjektor Gemoetrien und Trainingsdatenset
WH
~~3. Demonstration 6D Messprosess Photoinjektor~~
~~CQ~~
4. Verifikation Modell
WH
~~5. Verifikation Modell LightHouse~~
~~CQ/WH~~
6. Dokumentation, Schreiben der Doktorarbeit
WH
C. Datengetriebene Photoinjektoroptimierung
1. Maschinelles Lernen - Digital Twin Konzeptdemonstration
NA
2. Maschinelles Lernen - Full Digital Twin
NA
3. Maschinelles Lernen - Digital Twin mit Experimentellen Daten
NA
D. Ende-zu-Ende Optimierung
1. Demonstration Ende zu Ende Optimierung
WH/HT