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

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Agenda

1) Learning Representations of Pulse Shapes
2) Sampling from Pulse Shapes
3) Closing Remarks and Outlook

Learning Representations of Pulse Shapes

Data are generated through RPfiber simulations.

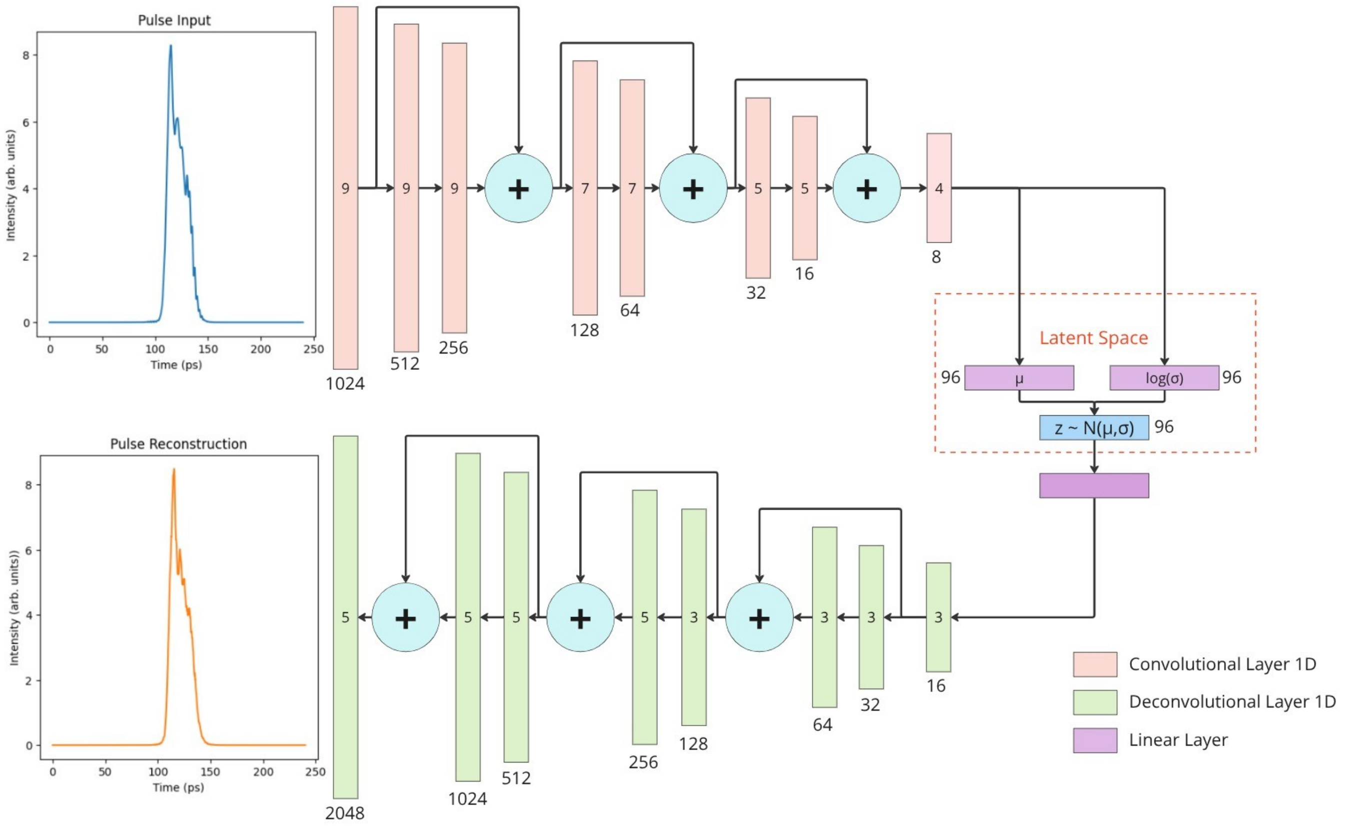
- Each simulation takes a filter setting as input and returns the complex spectrum.
- Filter settings are randomly generated by sampling different pulse shapes in time domain.
- Time domain phase is described as a 4^{th} order polynomial, whose coefficients are uniformly sampled based on FWHM.
- Data available on Zenodo [10.5281/zenodo.14906677](https://doi.org/10.5281/zenodo.14906677)

Parameter	Distribution	
Shape	Gaussian, Parabolic, Sech, Triangular, Flat-top	
Order parameter (gaussian | triangle)	1, 2, 3, 4, 5, 10	1, 2, 4
FWHM	Uniform: 2 – 40 ps	
SOC	Gaussian: μ = 0 , σ = 50 * 2 / 3*(FWHM**2)	
TOC	Gaussian: μ = 0 , σ = 50 * 2 / (FWHM**3)	
FOC	Gaussian: μ = 0 , σ = 50 * 8 / (FWHM**4)	

Learning Representations of Pulse Shapes

Idea: Find a lower dimensional latent representation of pulse shapes by leveraging VAEs

Idea^2: Can the dynamics mapping input to output pulses be replicated in a learnt latent space?



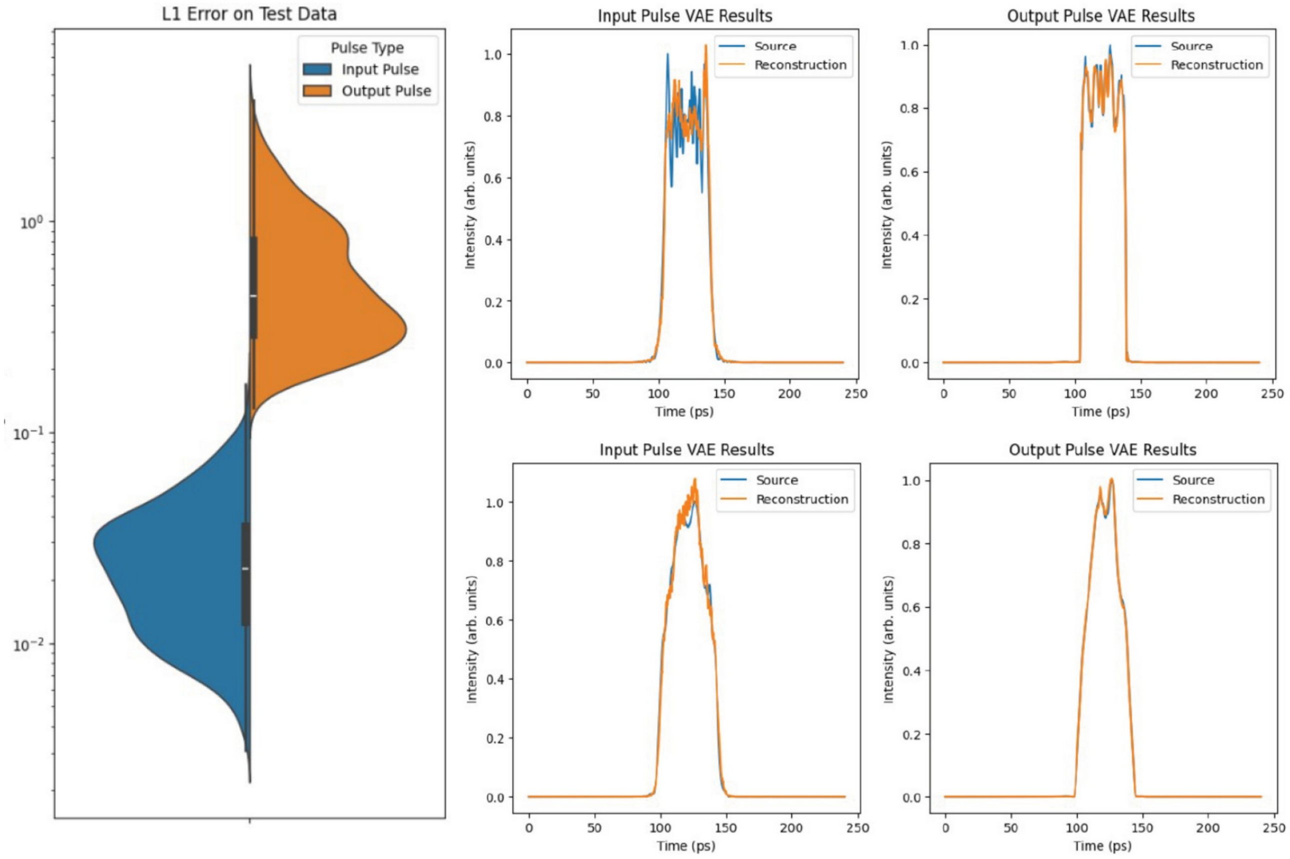
Used network architecture in pulse shape representation learning.

Learning Representations of Pulse Shapes

Results

- Representations for pulse intensity profiles can be learnt suffciently accurate and reconstructed from for both kinds of pulses (before and after propagation).

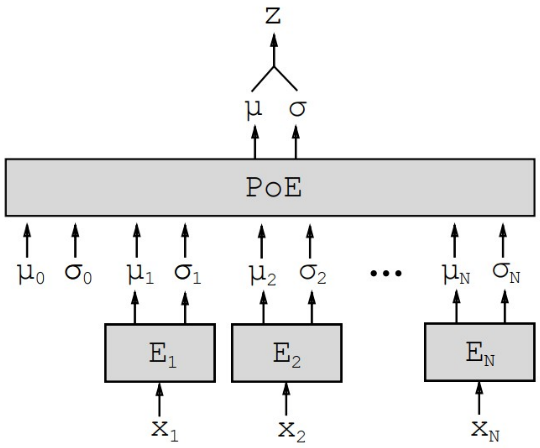
- Problems occur for learning representations for the phase profiles involved due to periodicity.



Learning Representations of Pulse Shapes

Introducing Multimodality

Instead of training distinct models for representing input and output pulse intensities, intensities and phases shall be **encoded jointly** using **Multimodal VAEs.**



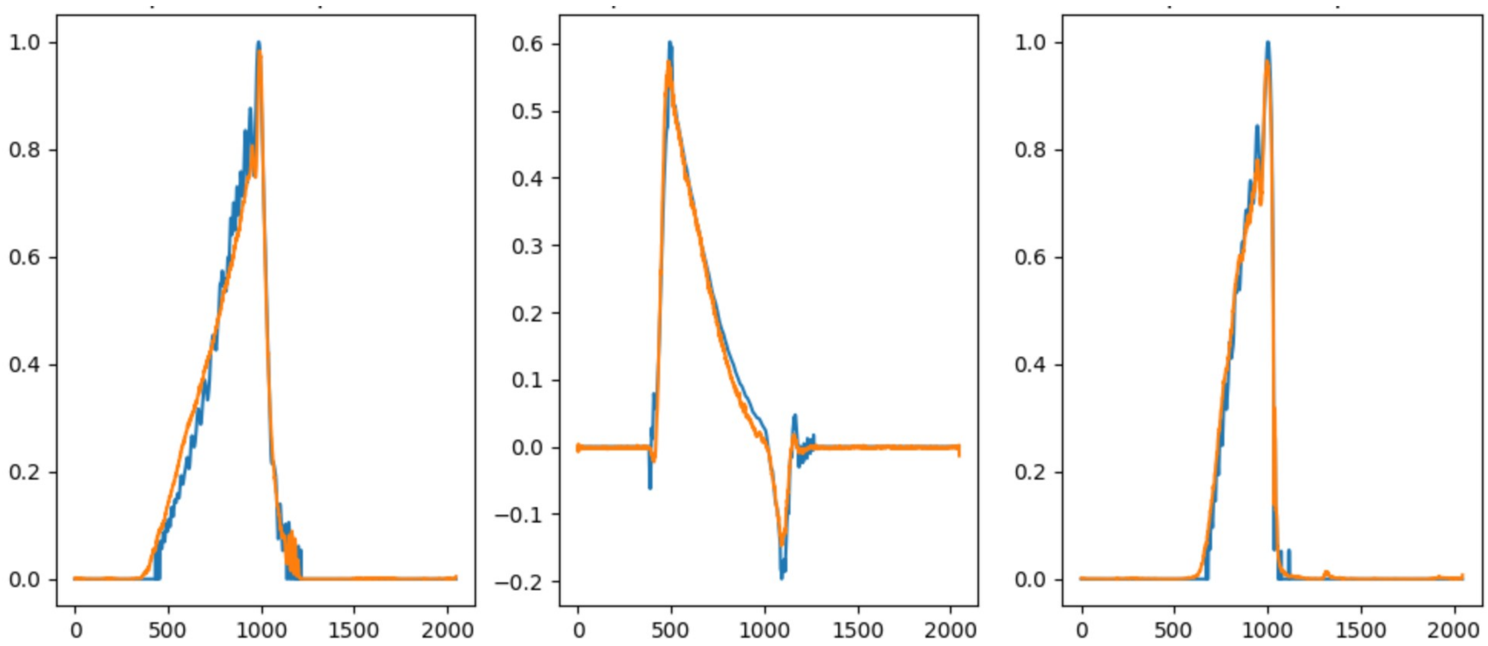
$$\begin{tikzcd} x \arrow[r, "\varphi_X"] \arrow[d, "h_\Phi"'] & y \arrow[d, "h_\Phi"] \\ z_x \arrow[r, "\varphi_Z"] & z_y \end{tikzcd}$$

$$\varphi_X \circ h_\Phi = h_\Phi \circ \varphi_Z$$

In order to recover the original dynamics from latent representations, the diagram needs to commute.

Multimodal Generative Models for Scalable Weakly-Supervised Learning, https://arxiv.org/pdf/1802.05335

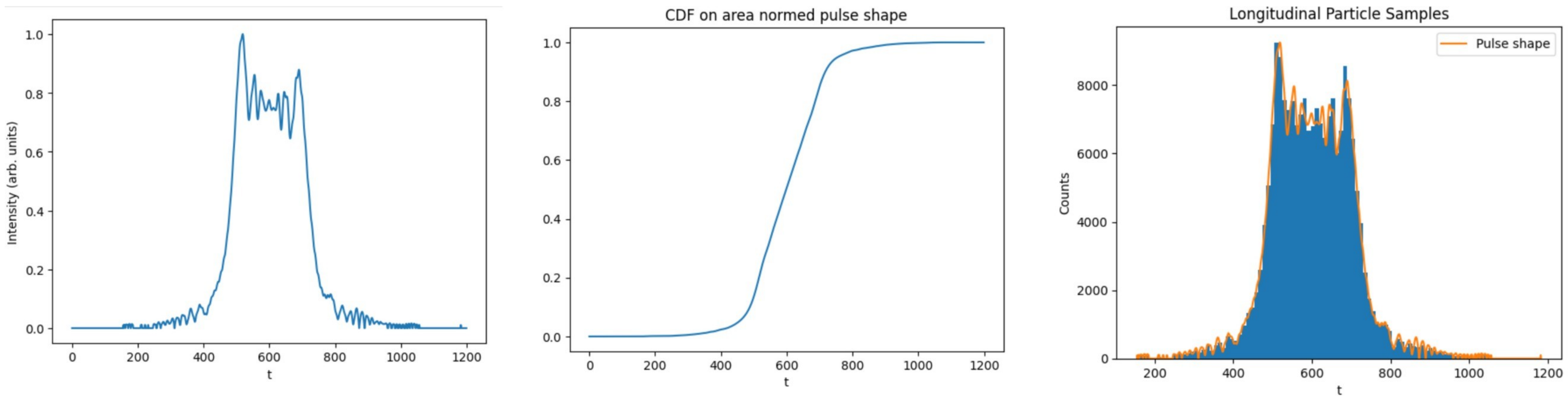
Learning Representations of Pulse Shapes



Multimodal VAE inference results, ground truth in blue, reconstructions in orange. From l.t.r.: Input pulse intensity profile, first derivative of the unwrapped input phase, output pulse intensity profile.

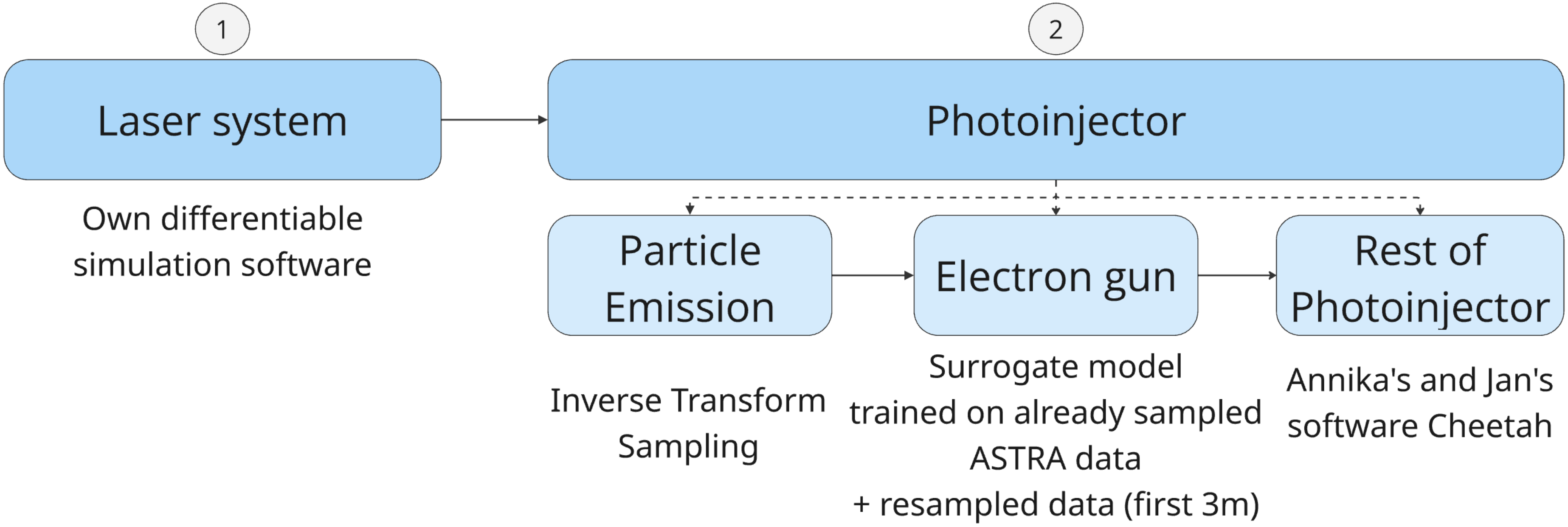
Inverse Transform Sampling from Pulse Shapes

Idea: View pulse intensity profile as pdf and sample by transforming samples from a uniform distribution on [0,1] by virtue of the corresponding cdf. Implemented in PyTorch.



Inverse Transform Sampling from pulse shapes. From l.t.r.: laser intensity profile, cumulative distribution function of laser intensity profile, histogram of electron emission times sampled from intensity profile.

Closing Remarks and Outlook



Possible way to model the whole system by interfacing the subsystems (1) and (2), derived from a discussion with Henrik.

Closing Remarks and Outlook

- Training of a gun surrogate model
  - learn the evolution of simulated of bunch states from simulated state sequences
  - Reshape already existing simulation data for XFEL and PITZ
  - resample data with varying pulse shapes
- Benchmark Cheetah vs ASTRA for beam simulations beyond 3.2m