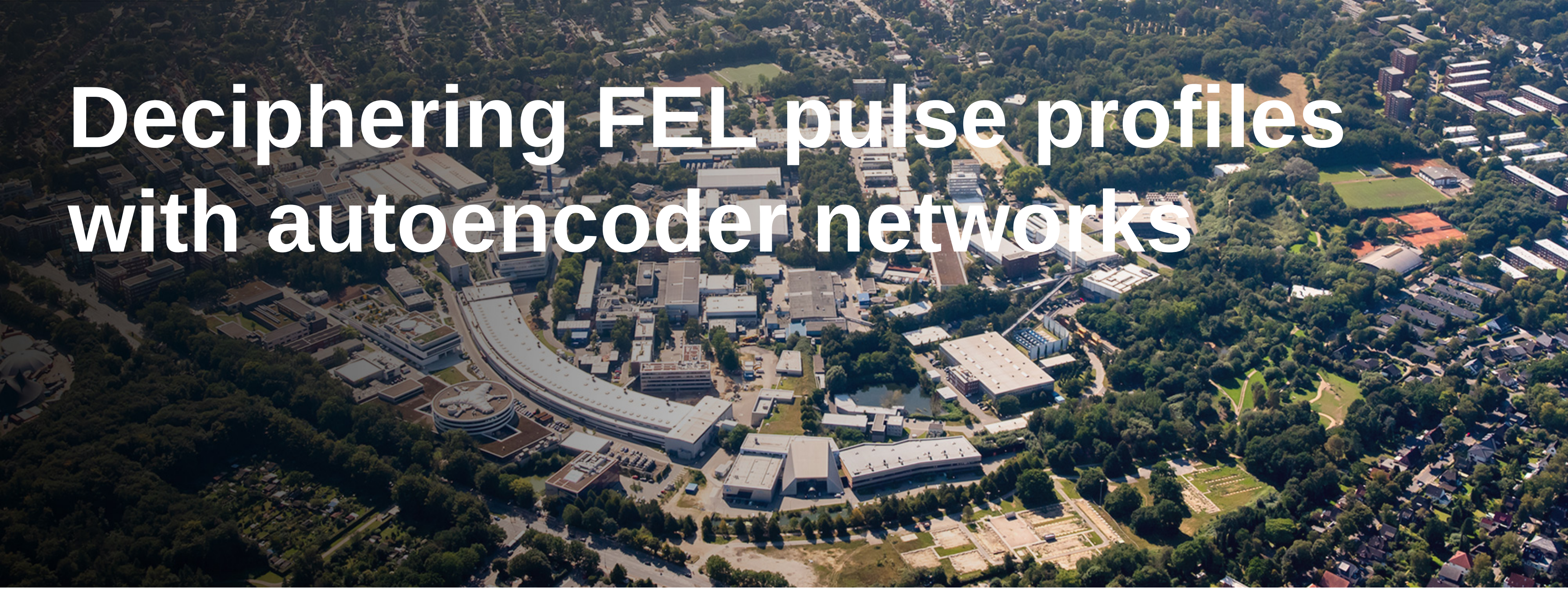
Deciphering FEL pulse profiles with autoencoder networks



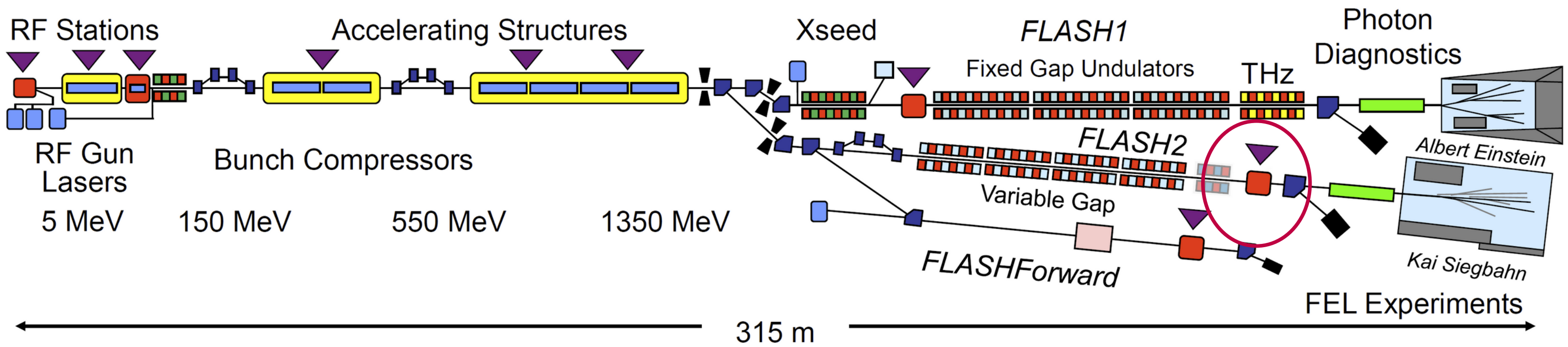
Gesa Goetzke – FLASH Photon Diagnostics

Longitudinal photon diagnostics Workshop

Gesa Goetzke[1], Rajan Plumley[2], Felix Möller[3], Thorsten Otto[1], Daniel Ratner[2], Joshua Turner[2], Stefan Düsterer[1], Gregor Hartmann[3]

[1] Deutsches Elektronen-Synchrotron DESY, Hamburg, Germany
[2] SLAC National Accelerator Laboratory, Menlo Park, CA 94025, USA
[3] Helmholtz-Zentrum Berlin für Materialien und Energie GmbH, Berlin, German

Pulse length diagnostics



https://flash.desy.de/sites2009/site_vuvfel/content/e66400/infoboxContent259146/FLASH_layout-2022.png

- We want photon pulse length information.

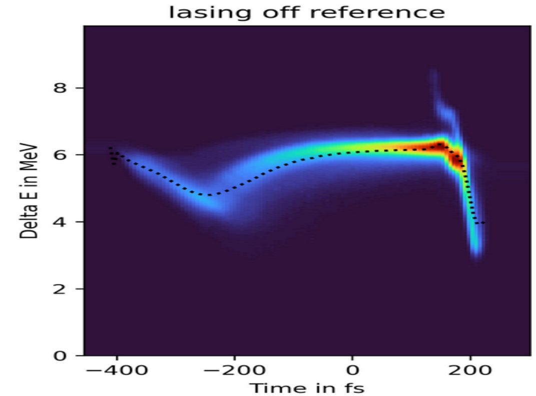
- We analyze the energy of the electrons that created this photon pulse.

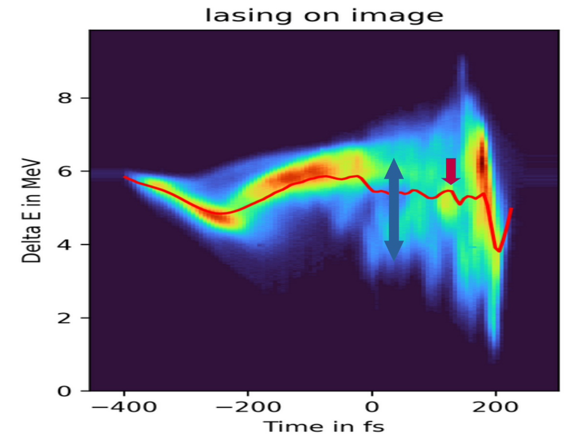
Obtaining power profiles

Few-femtosecond time-resolved measurements of X-ray free-electron lasers

C. Behrens, F.-J. Decker, Y. Ding, V. A. Dolgashev, J. Frisch, Z. Huang, P. Krejcik, H. Loos, A. Lutman, T. J. Maxwell, J. Turner, J. Wang, M.-H. Wang, J. Welch & J. Wu

Nature Communications **5**, Article number: 3762 (2014) | Cite this article

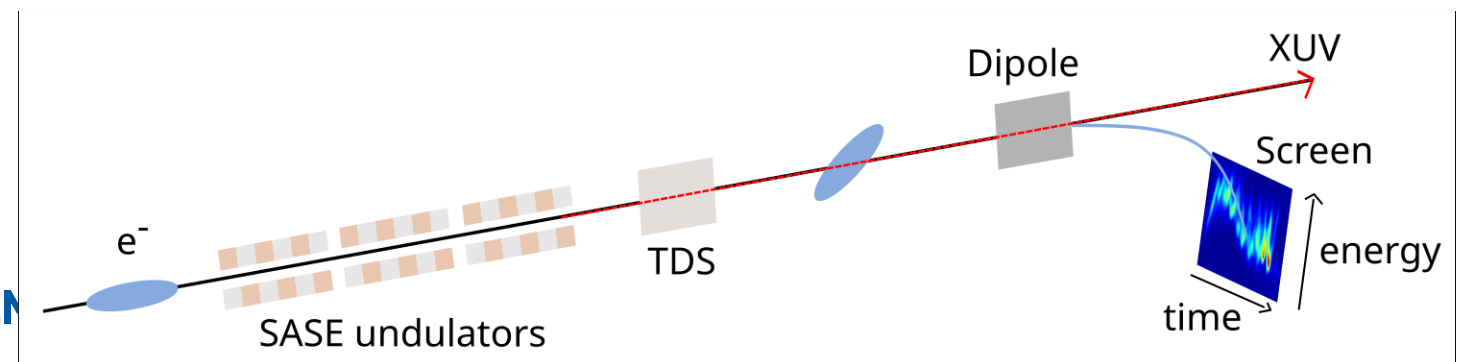




- to get a power profile you have to compare lasing on images with the matching lasing off images.
- you can compare the center of mass or the energy spread.

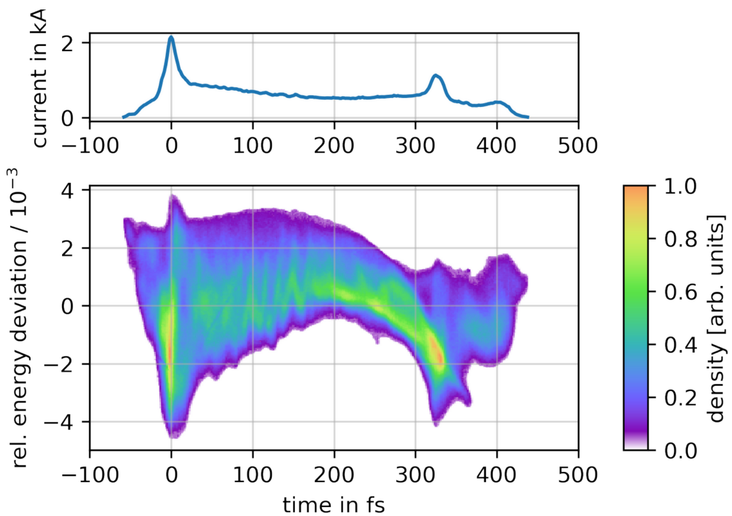
Com: $\mathrm{P} = \Delta E \cdot I/e$

Spread: $\mathrm{P} \propto I^{2/3}(\sigma^2_{E,on} - \sigma^2_{E,off})$

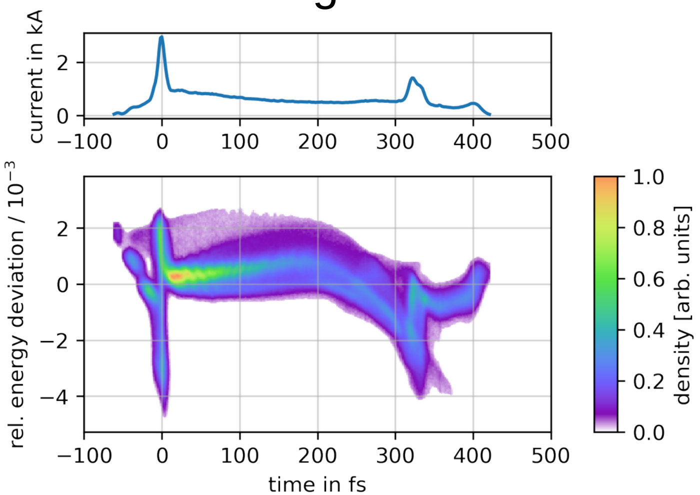


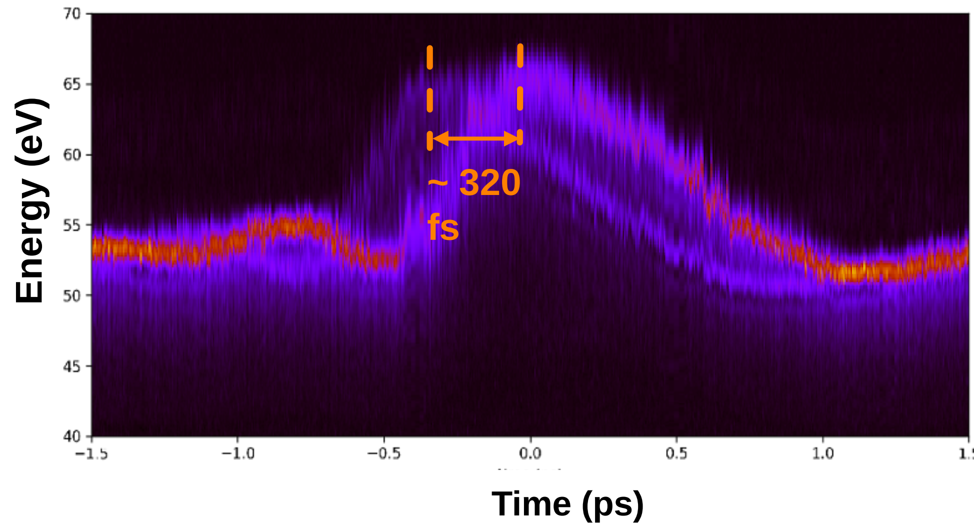
Polarix and THz streaking

Lasing on

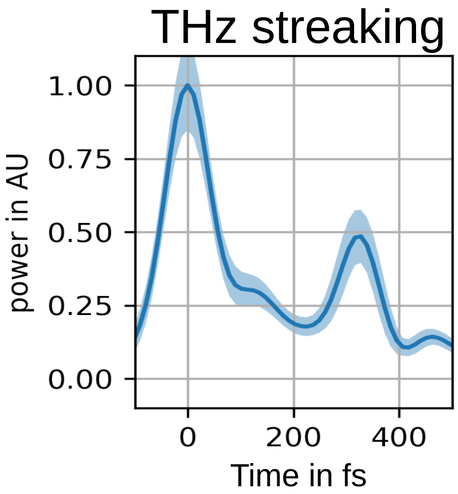


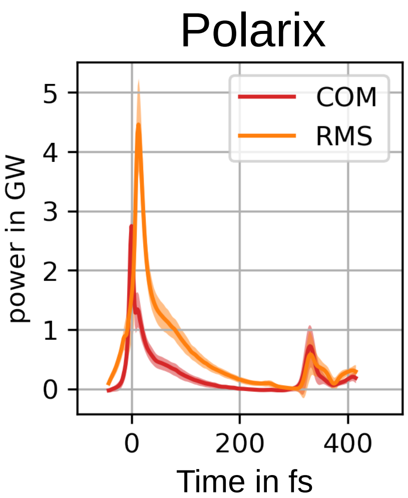
Lasing off





Polarix and THz streaking



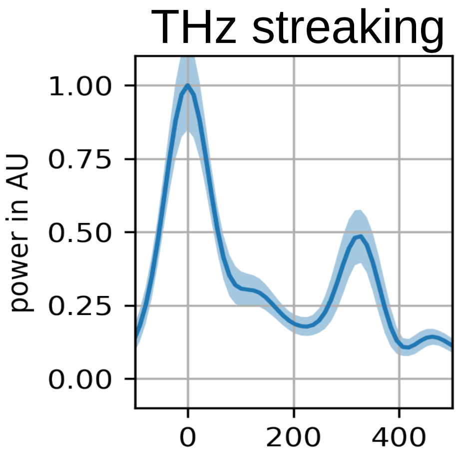


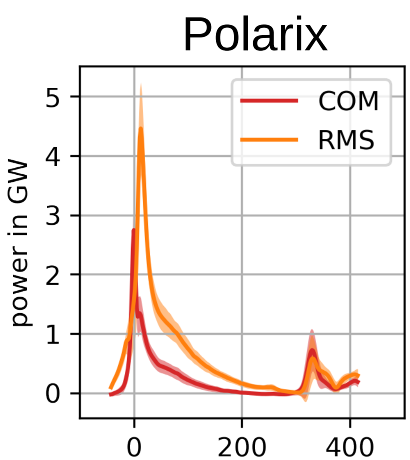
- THz pulses are much broader

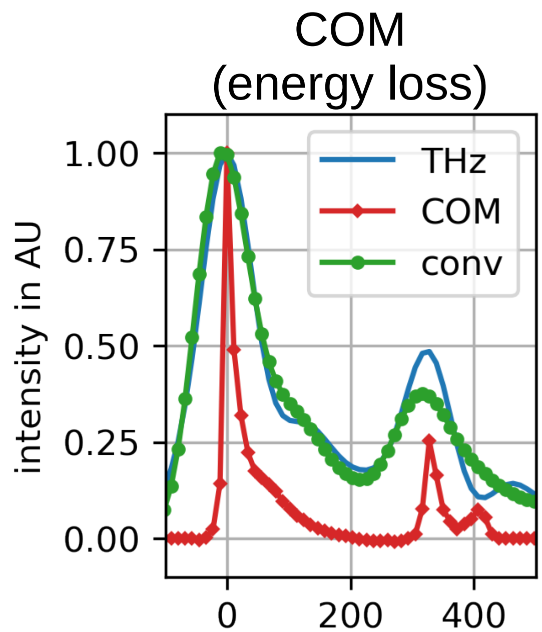
- This has to do with the long THz streaking ramp

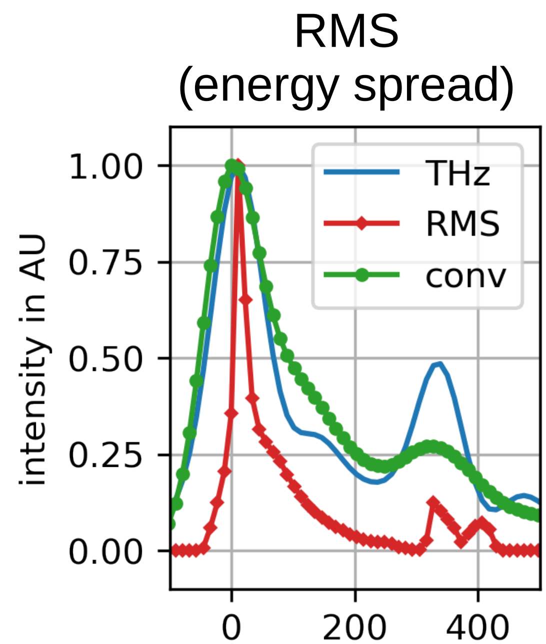
- For better comparison of the pulse shapes:
  → convolve the Polarix profiles with
  the THz streaking instrument function

Polarix and THz streaking









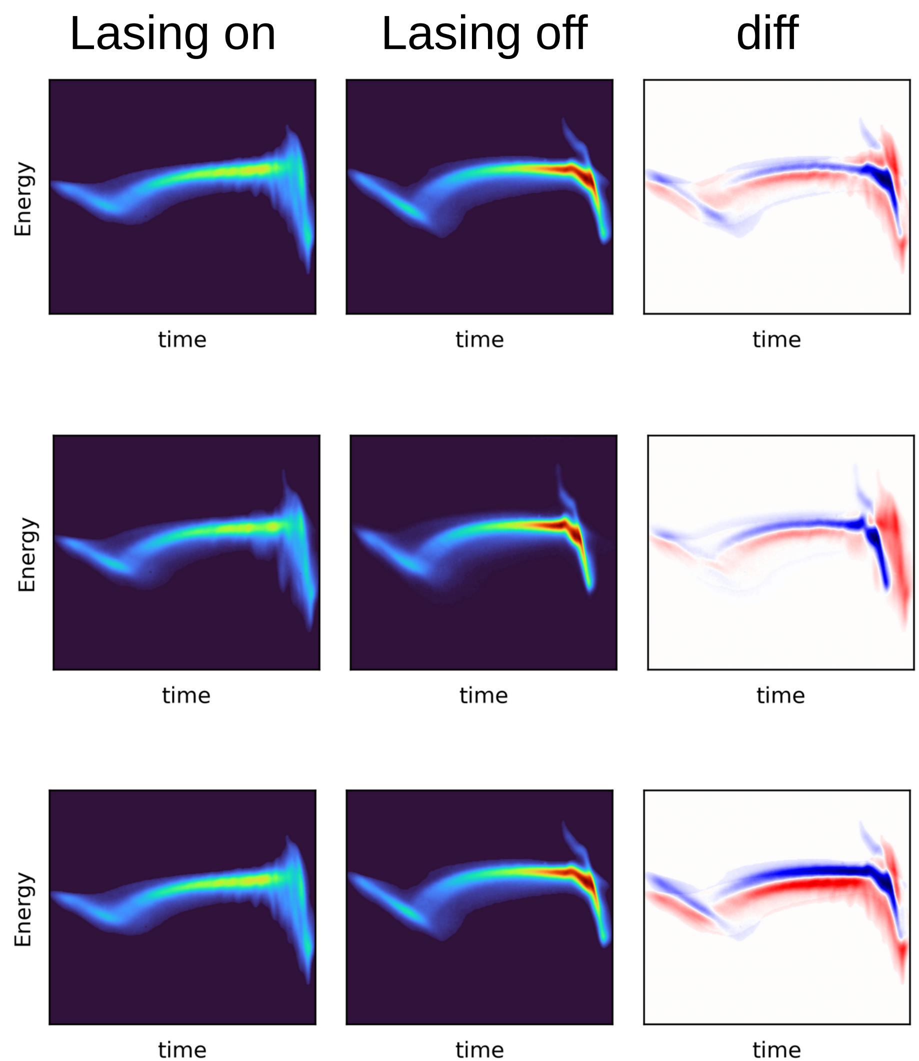
Challenges in TDS analysis

Finding matching lasing off references

Finding the ‘perfect’ reference:

Isolating the signal / matching in x:

Matching in y:



How to adress those challenges

“for foundational discoveries and inventions that

enable machine learning with artificial neural networks”

“for protein structure prediction”

Machine learning is really good in pattern recognition,
and with handling of large datasets.

HELMHOLTZ

DESY.

How to adress those challenges

“for foundational discoveries and inventions that

enable machine learning with artificial neural networks”

“for protein structure prediction”

Ich

Write a sentence that contains the letter G exactly three times.

KI

Sure! Here is a sentence that contains the letter G exactly three times: "The gentle breeze was gliding through the garden."

GPT4 omni

But sometimes fail in most basic tasks

You should never blindly trust them.

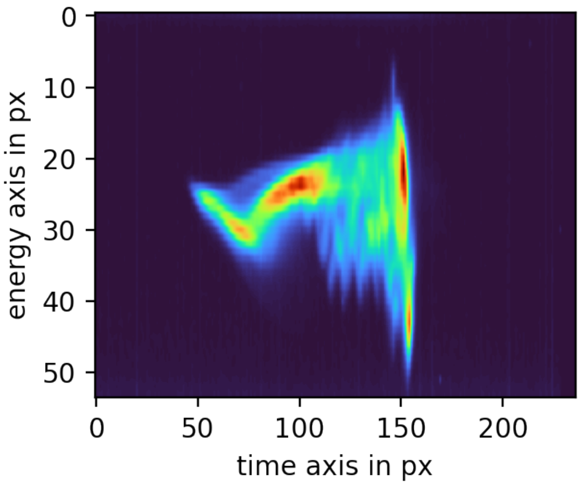
HELMHOLTZ

DESY.

Two projects with XTCAV and machine learning

@FLASH (DESY)

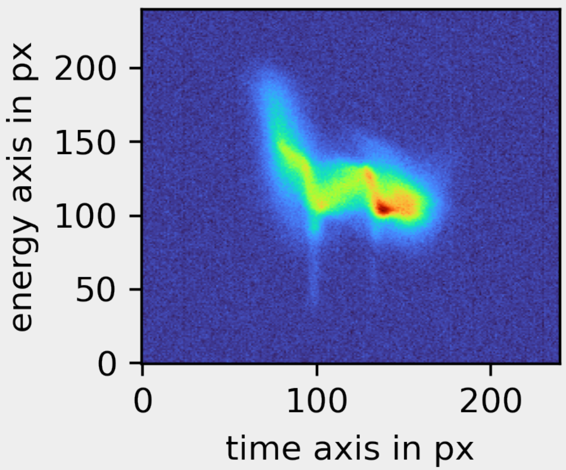
- SASE
- strong lasing
  signal



@LCLS (SLAC)

With Rajan Plumley, Daniel Ratner, Joshua Turner

- self seeded
- emittence spoiling foil
- very weak lasing signal



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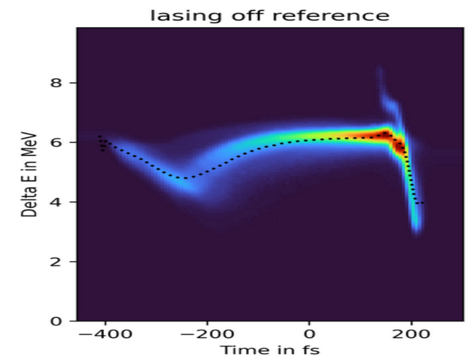
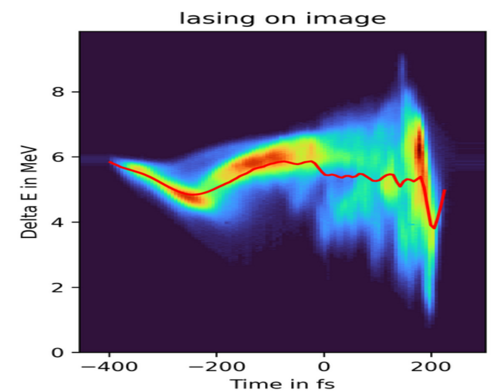
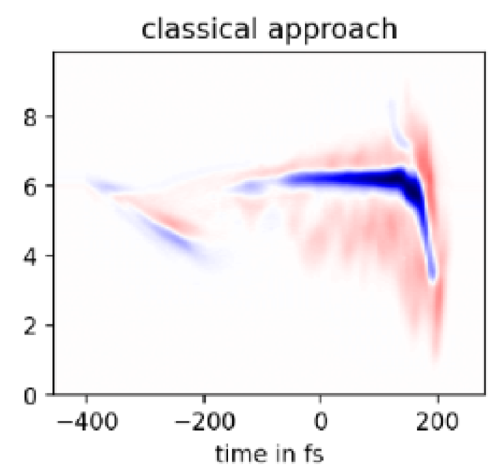
SASE Data from FLASH

- Electron energy distribution changes from shot to shot.
- We want a method that can learn lasing off representations and can interpolate between them.
- We want a method that can solve the x,y matching problem for us.

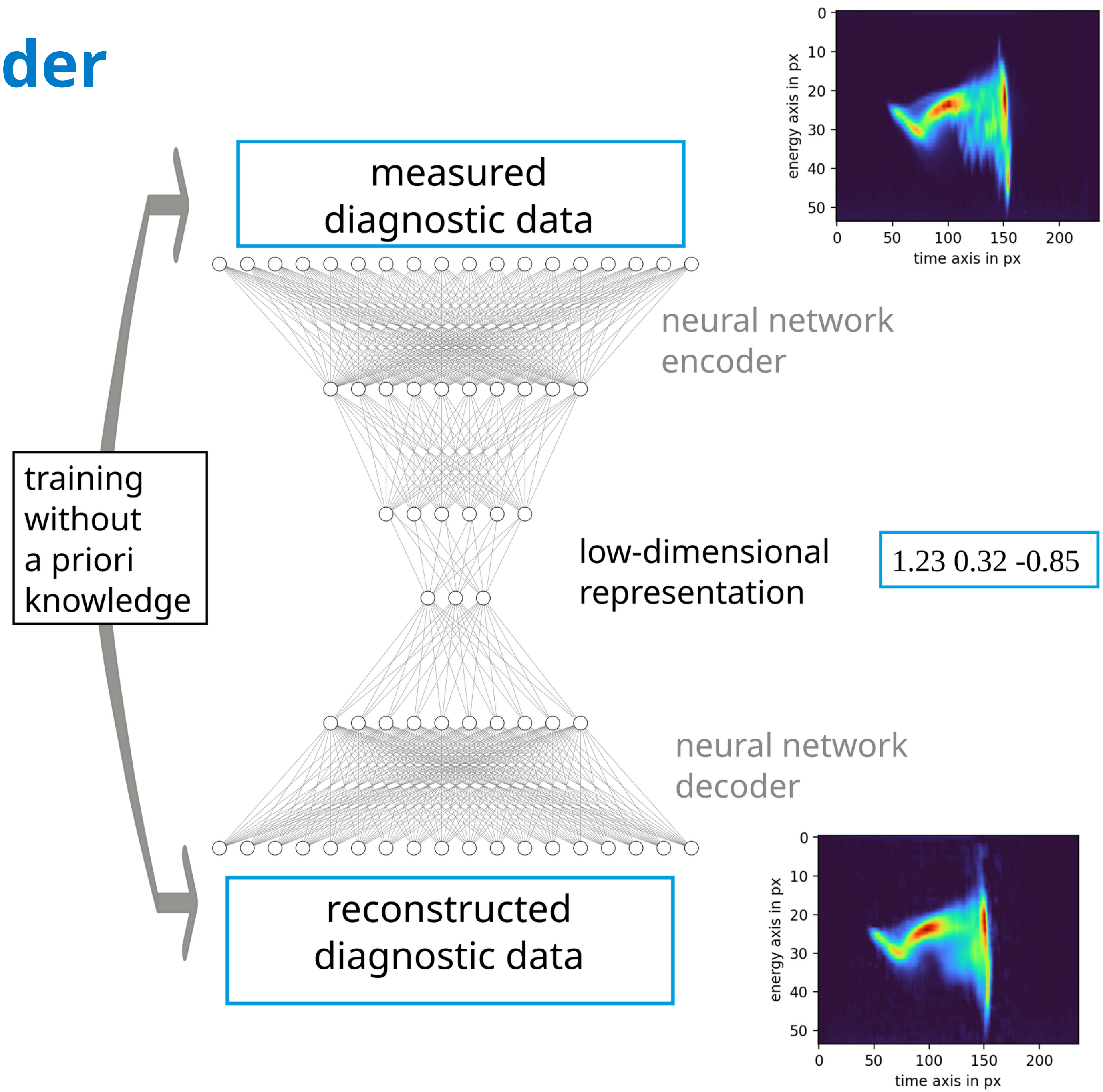
→ **Beta-Variational Convolutional Autoencoders**







Autoencoder



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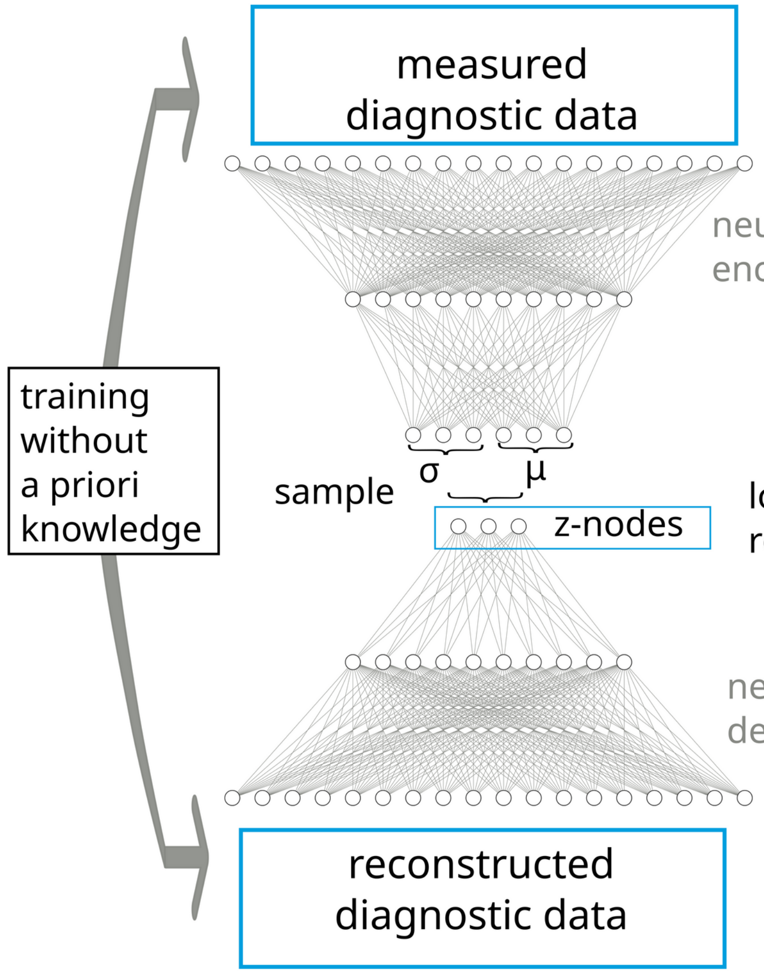
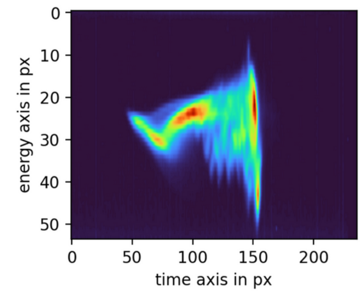
β variational autoencoder

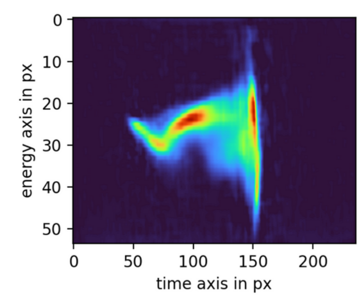


neural network
encoder

low-dimensional
representation

neural network
decoder





β-VAE: LEARNING BASIC VISUAL CONCEPTS WITH A CONSTRAINED VARIATIONAL FRAMEWORK

Irina Higgins, Loic Matthey, Arka Pal, Christopher Burgess, Xavier Glorot, Matthew Botvinick, Shakir Mohamed, Alexander Lerchner
Google DeepMind
{irinah,lmatthey,arkap,cpburgess,glorotx,
botvinick,shakir,lerchner}@google.com

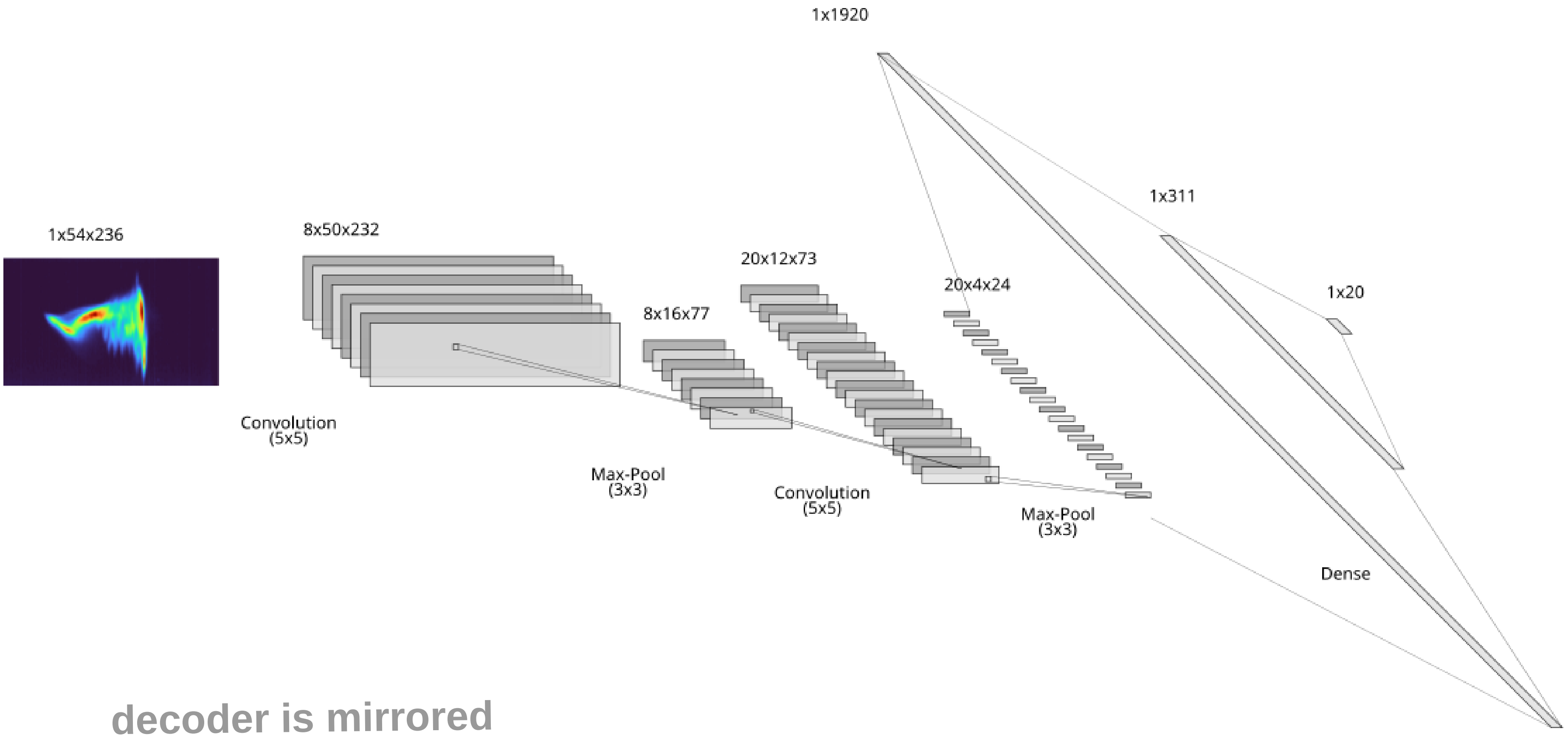
Google DeepMind

Unsupervised real-world knowledge extraction via disentangled variational autoencoders for photon diagnostics

Gregor Hartmann, Gesa Goetzke, Stefan Düsterer, Peter Feuer-Forson, Fabiano Lever, David Meier, Felix Möller, Luis Vera Ramirez, Markus Guehr, Kai Tiedtke, Jens Viefhaus & Markus Braune

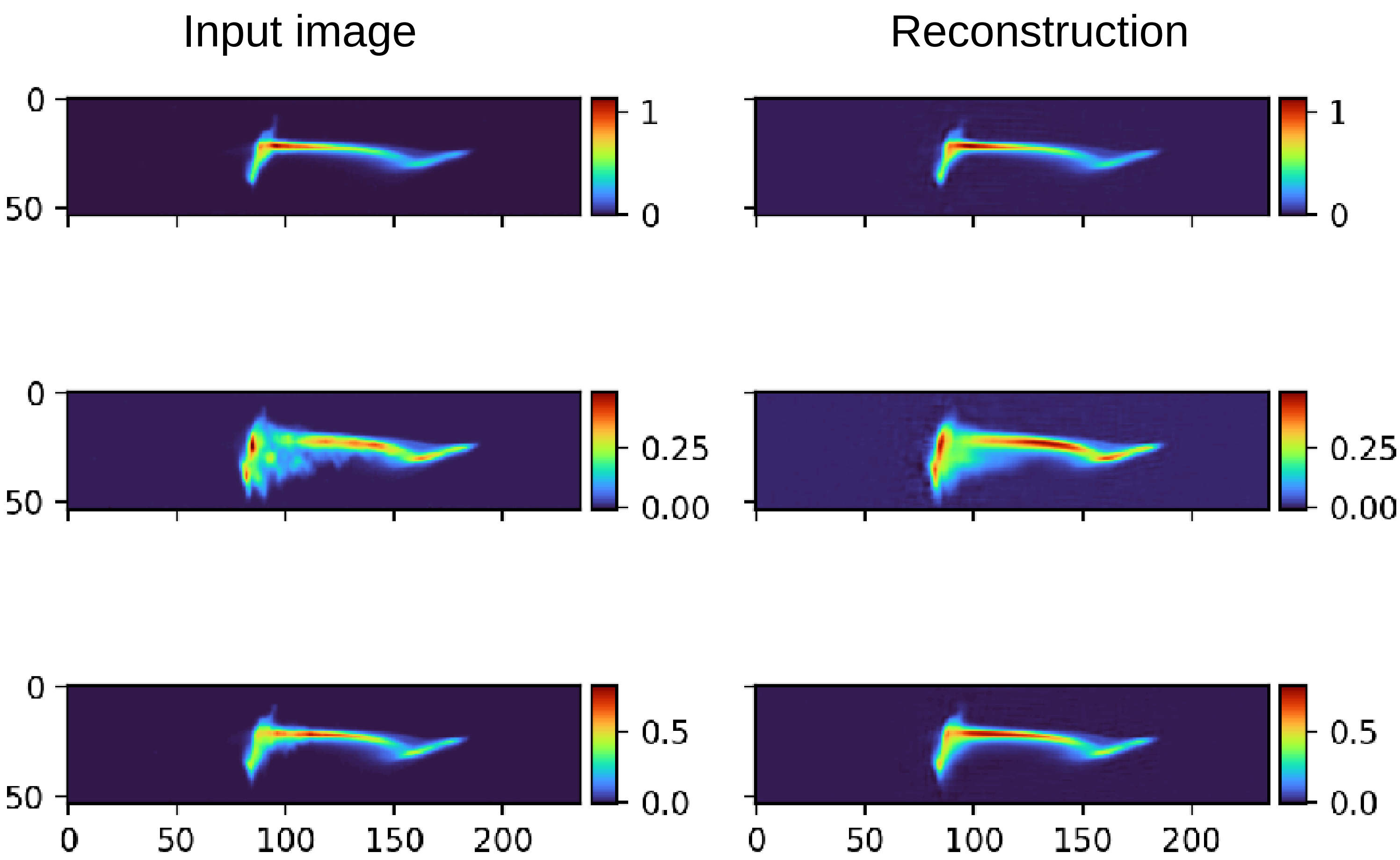
Scientific Reports **12**, Article number: 20783 (2022) | Cite this article

Convolutional β-Variational Autoencoder

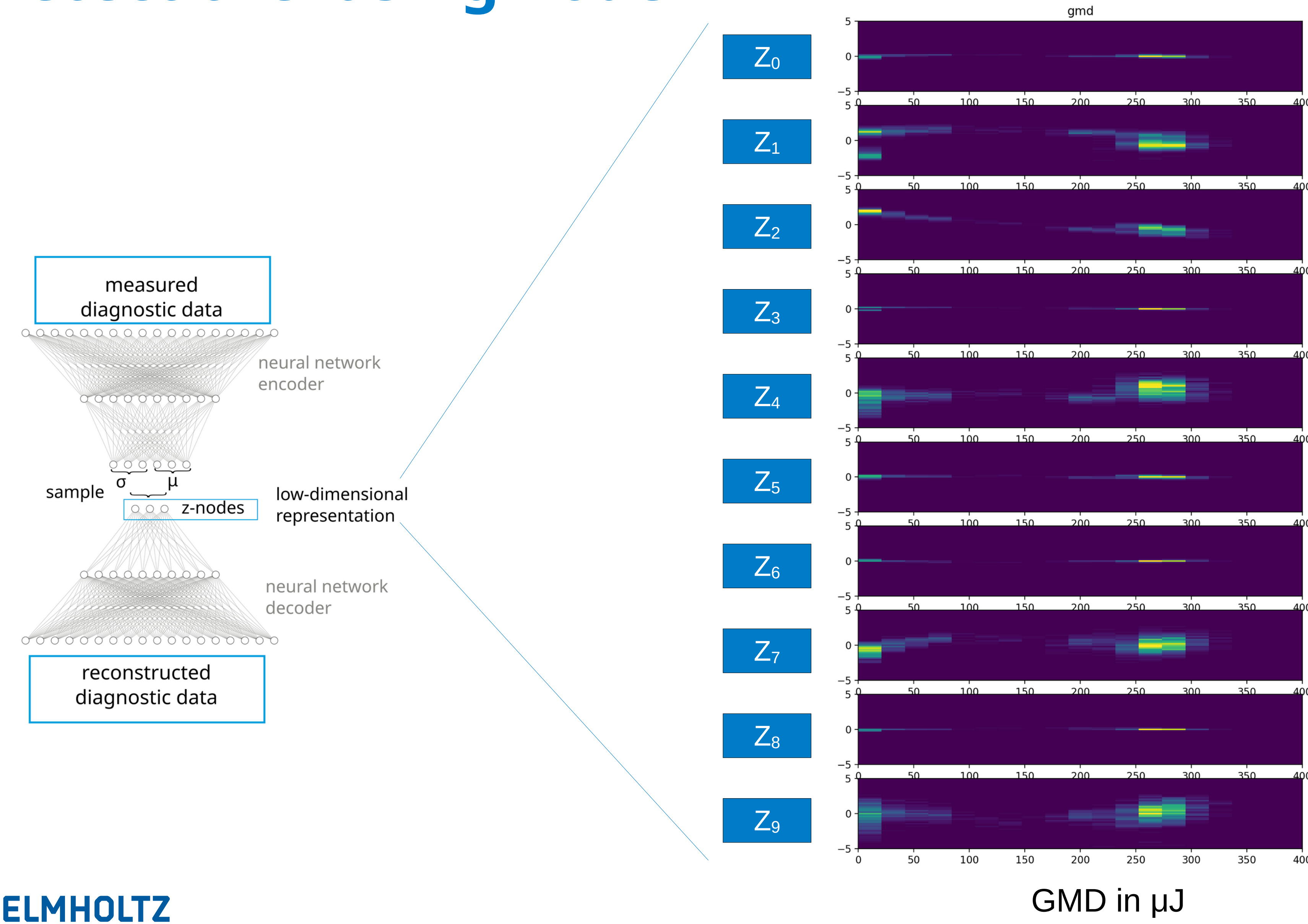


decoder is mirrored

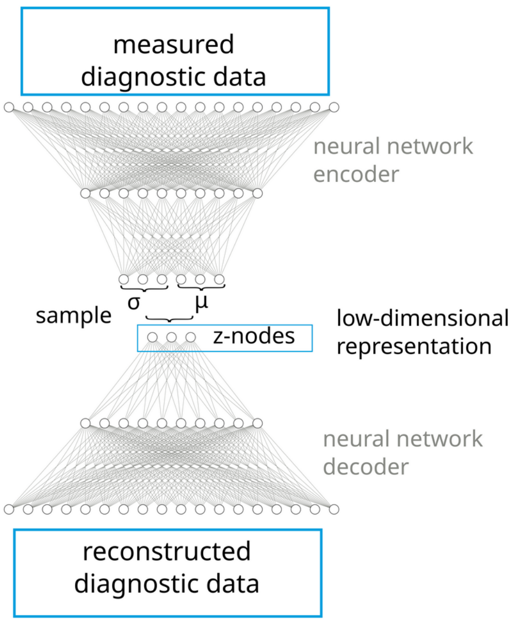
Some reconstructions

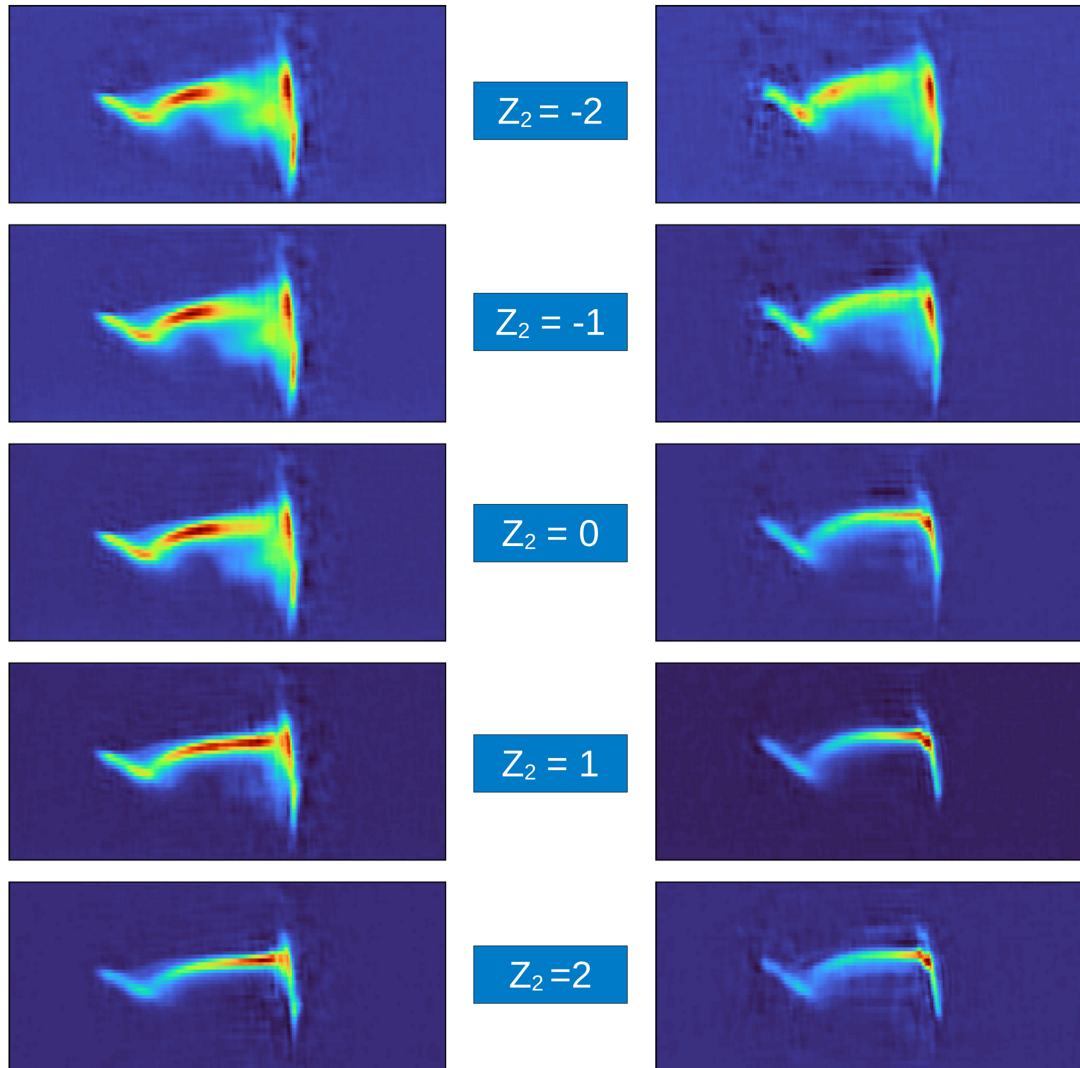


Detect the lasing node

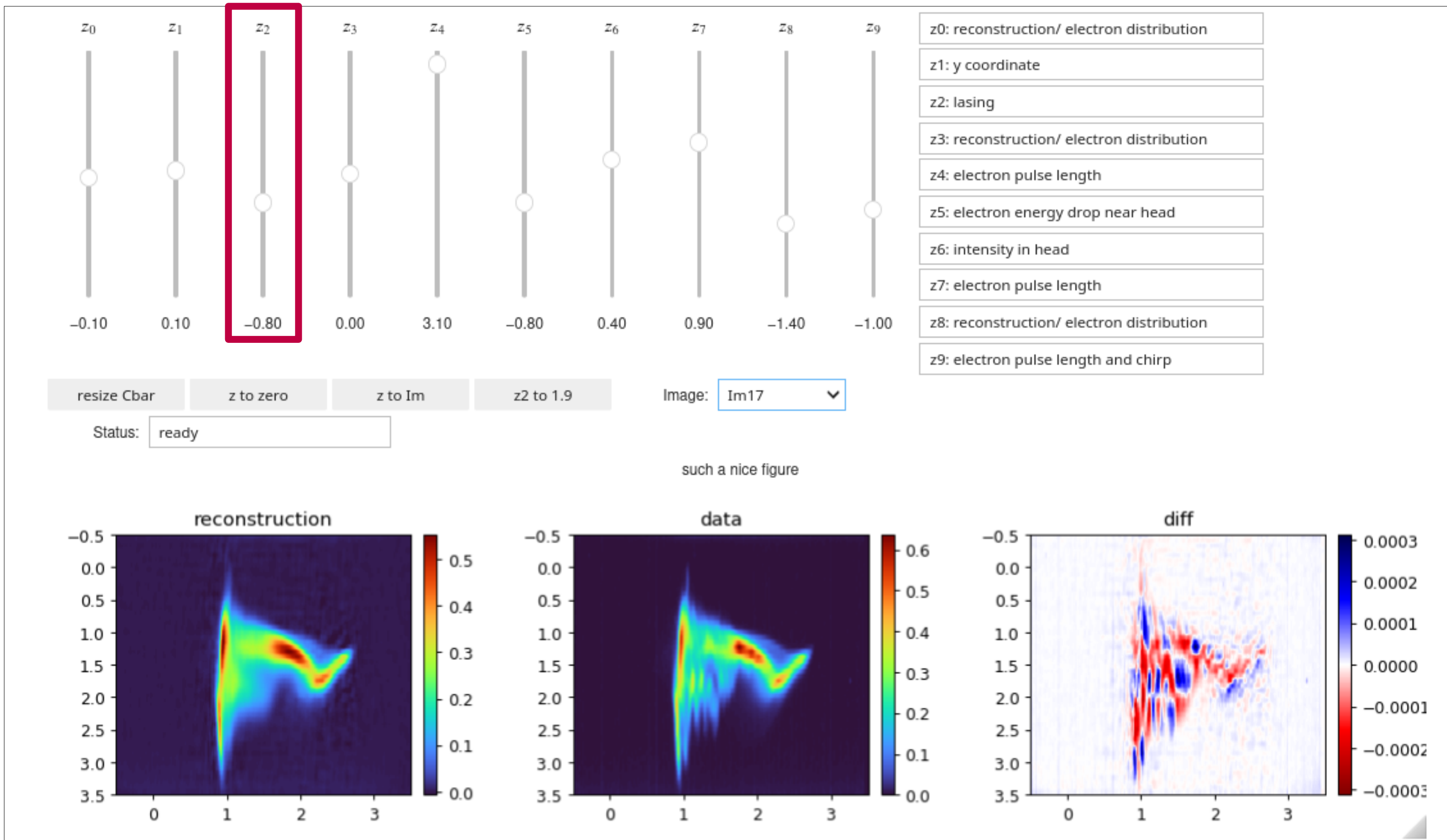


POLARIX: Traversing the latent space





POLARIX: Traversing the latent space



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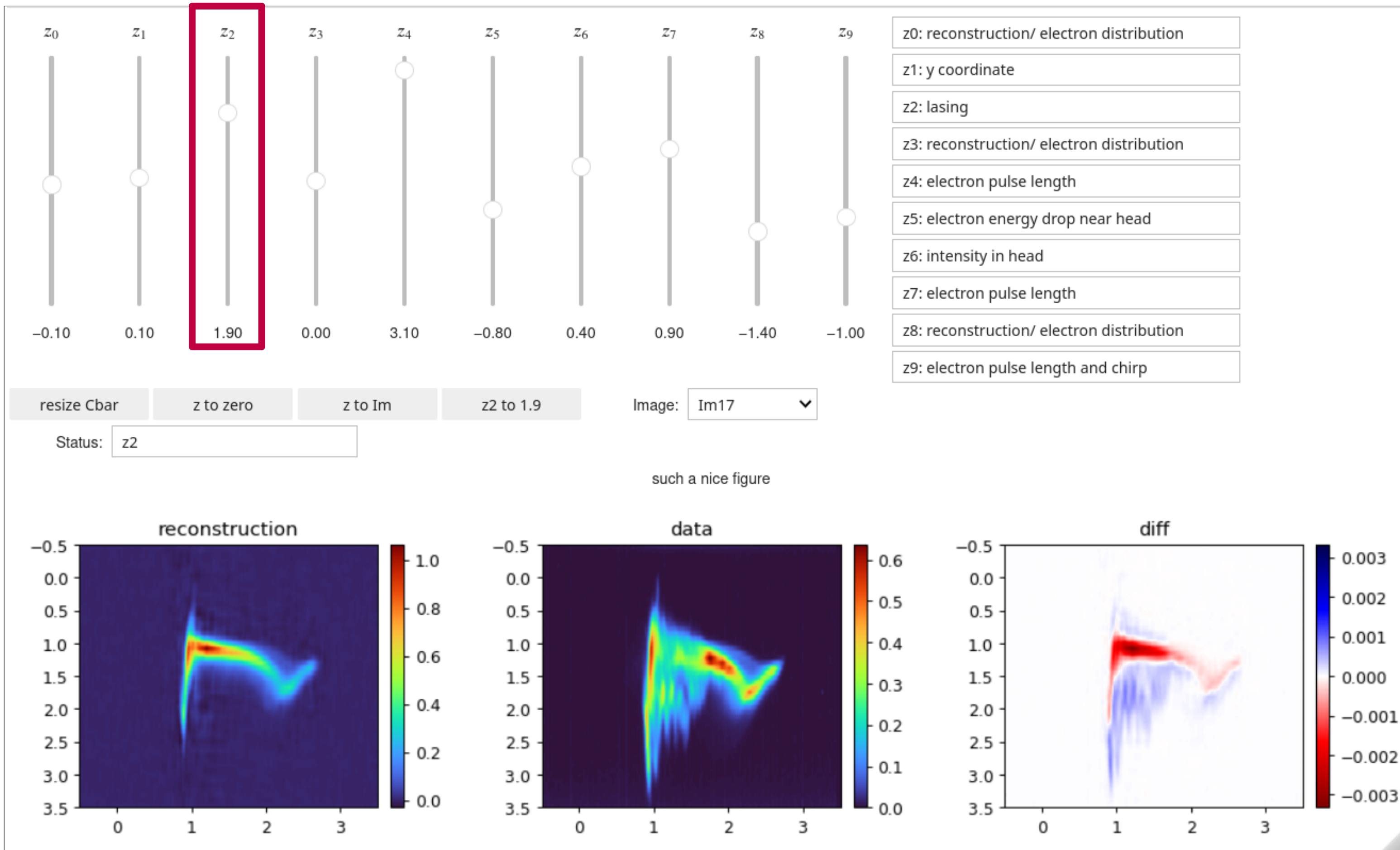
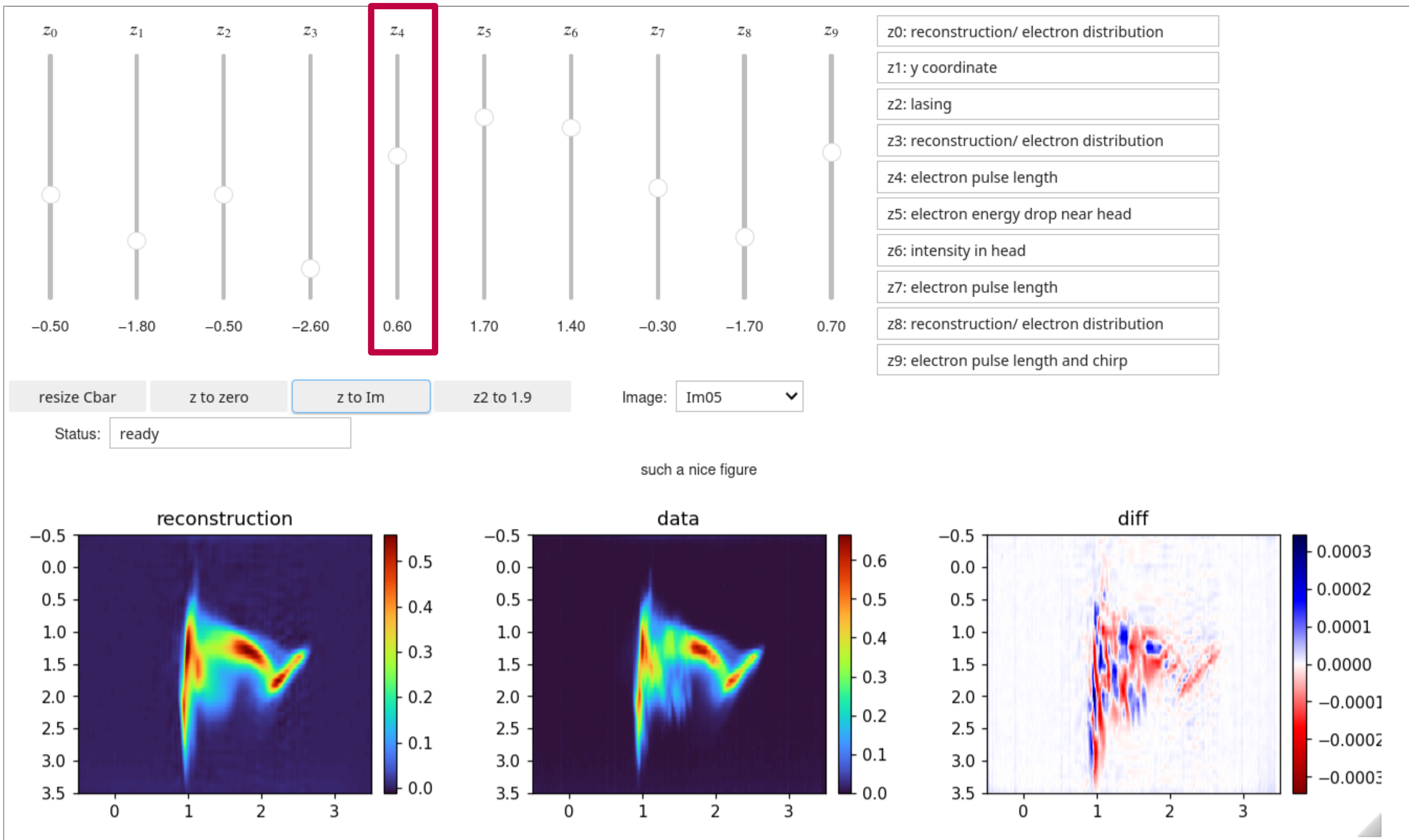
DESY.

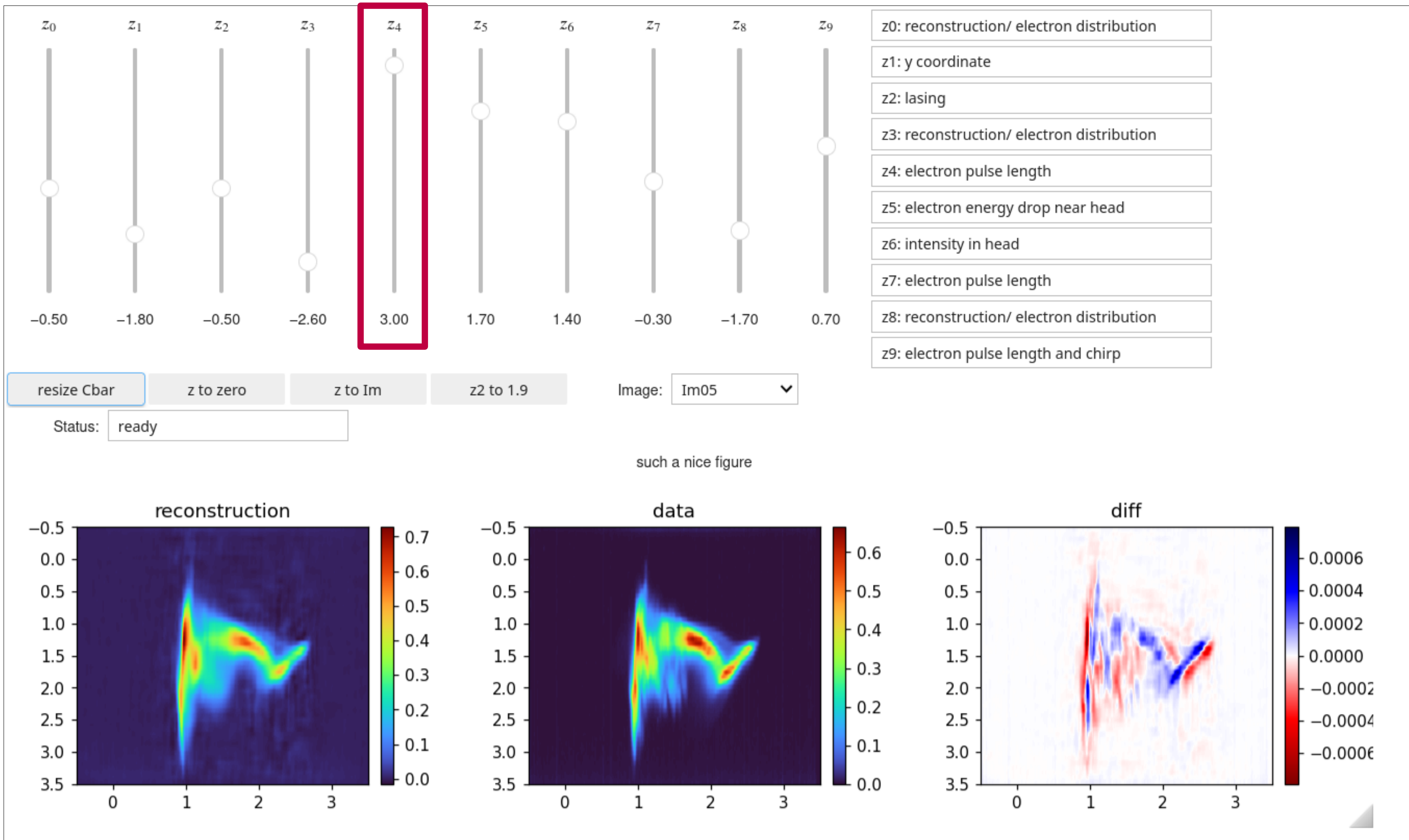
POLARIX: Traversing the latent space



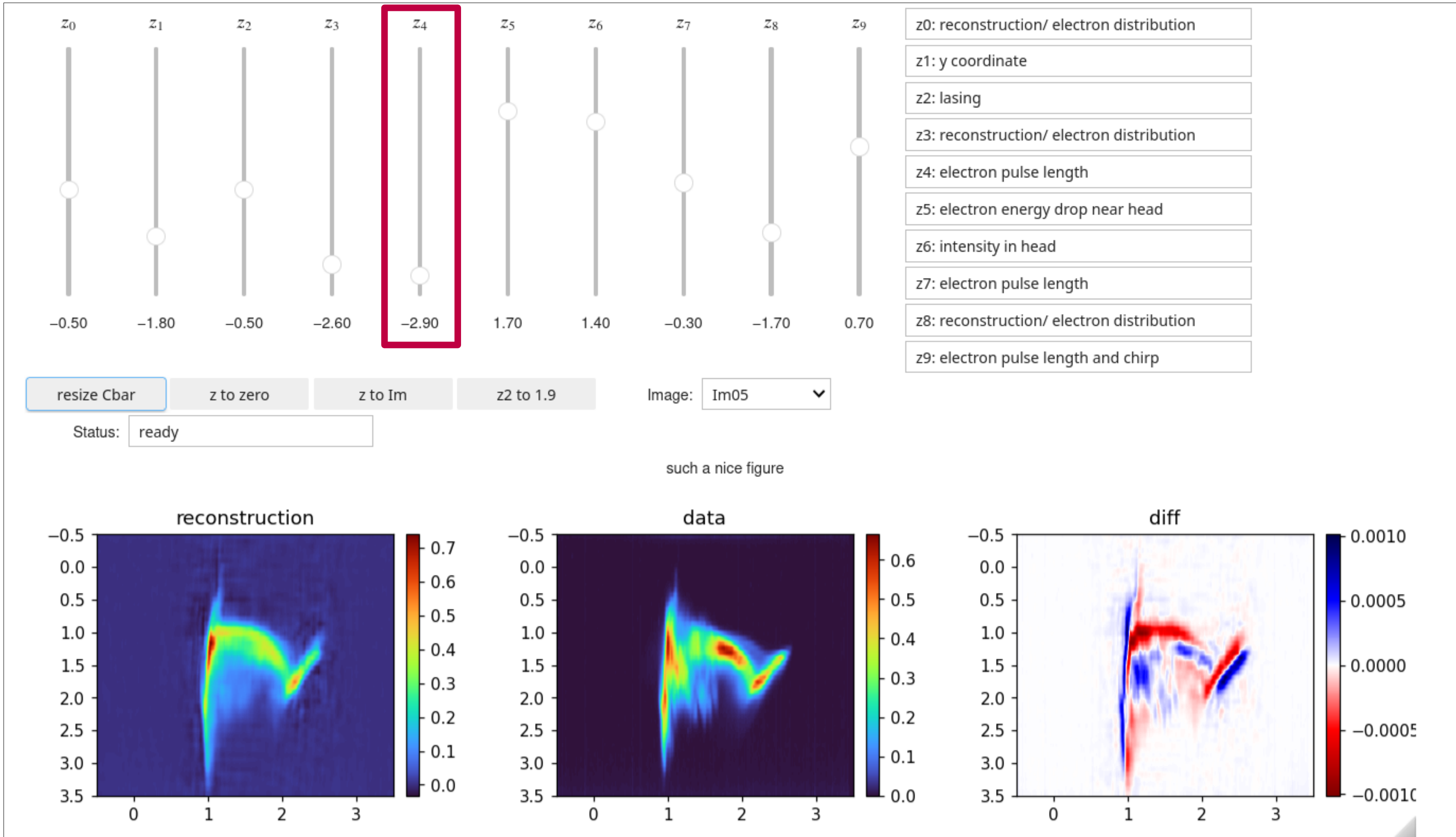
POLARIX: Traversing the latent space



POLARIX: Traversing the latent space



POLARIX: Traversing the latent space



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Traversing the latent space: web app

1) Permanent link, start it and grab a coffee

https://mybinder.org/v2/gh/Goetzkeg/betaVAEDemo/HEAD?urlpath=voila%2Frender%2FvisLS_lowCompute.ipynb

update recons...

2) Just today, run it at my personal computer at home

https://8f7c-2a02-3100-8b01-8900-6611-aedc-7c73-d7f0.ngrok-free.app

You are about to visit:

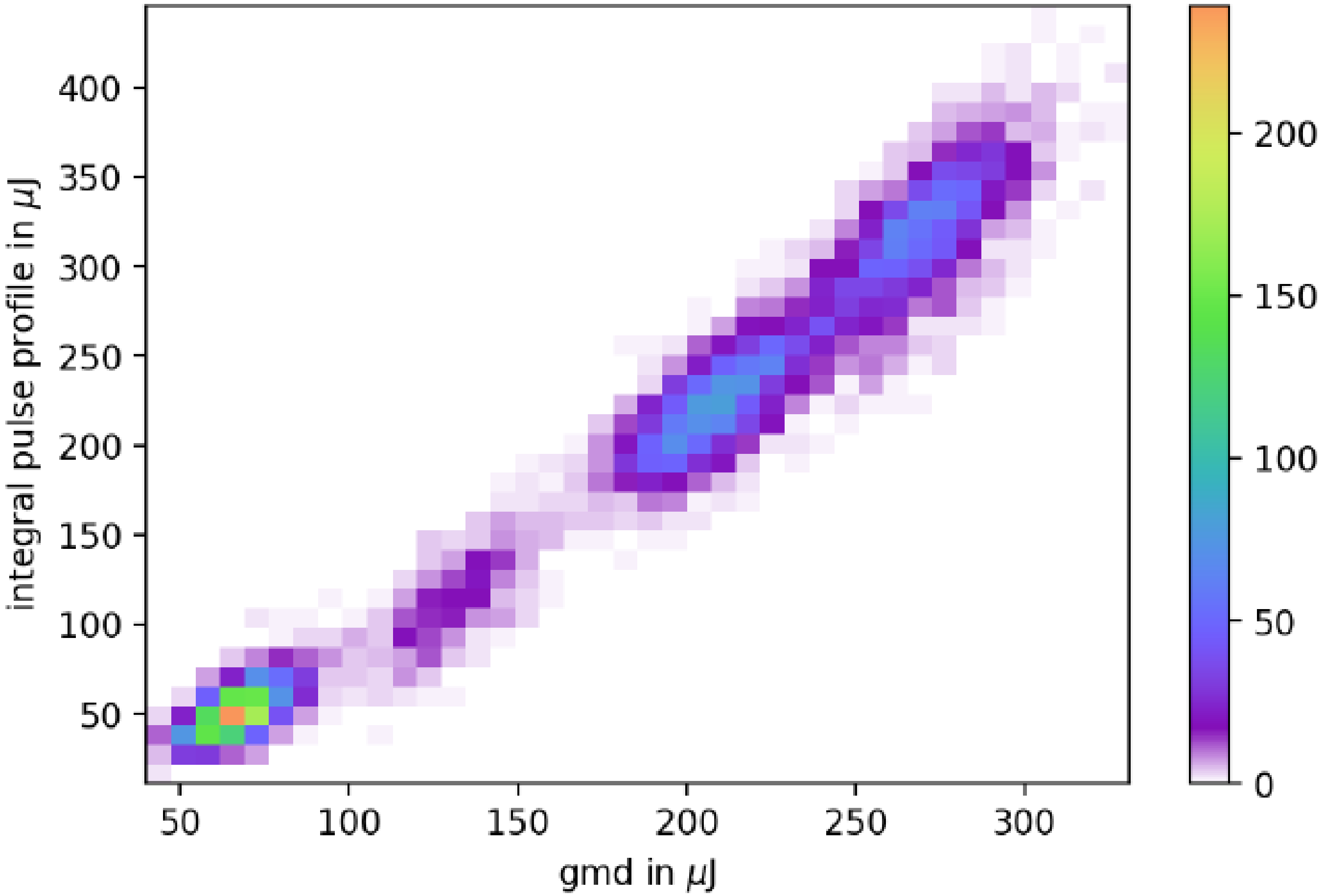
8f7c-2a02-3100-8b01-8900-6611-aedc-7c73-d7f0.ngrok-free.app

Website IP: 2a02:3100:8b01:8900:6611:aedc:7c73:d7f0

- This website is served for free through ngrok.com.
- You should only visit this website if you trust whoever sent the link to you.
- Be careful about disclosing personal or financial information like passwords, phone numbers, or credit cards.

Visit Site

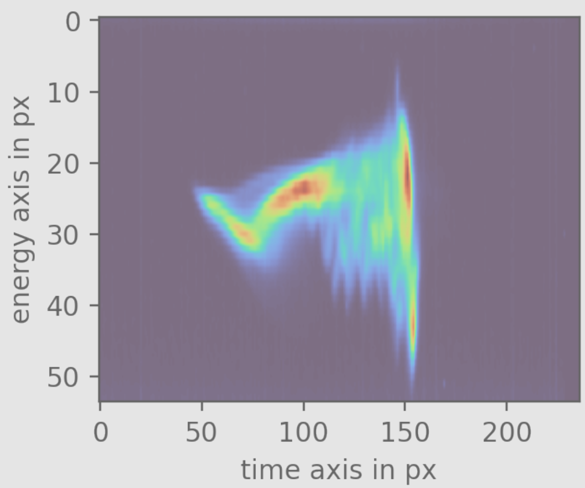
Correlation with the GMD



Two projects with XTCAV and machine learning

@FLASH (DESY)

- SASE
- strong lasing signal



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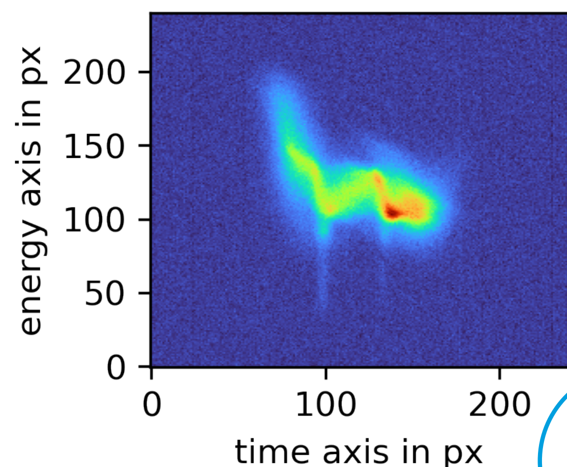
@LCLS (SLAC)

With Rajan Plumley, Daniel Ratner, Joshua Turner

- self seeded
- emittence spoiling foil
- very weak lasing signal

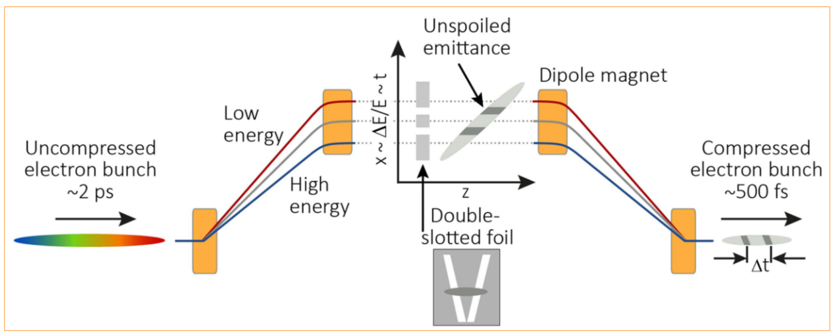


Requirements and Setup

2 pulses with few fs distance, monochromatic (8.5 keV), known intensity ratio

TDS

Emittence spoiling foil



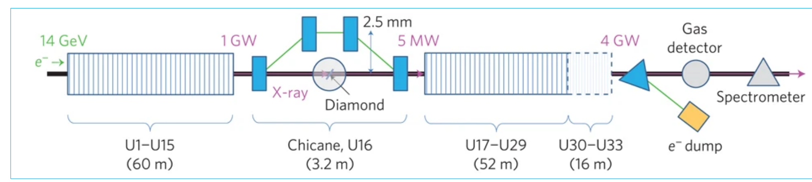
Femtosecond profiling of shaped x-ray pulses

M C Hoffmann[16,1], I Grguraš[16,2,3], C Behrens[4], C Bostedt[1,5], J Bozek[1,6], H Bromberger[2,3], R Coffee[1], J T Costello[7], L F DiMauro[8], Y Ding[1] + Show full author list

Published 26 March 2018 • © 2018 The Author(s). Published by IOP Publishing Ltd on behalf of Deutsche Physikalische Gesellschaft

New Journal of Physics, Volume 20, March 2018

Self-seeding



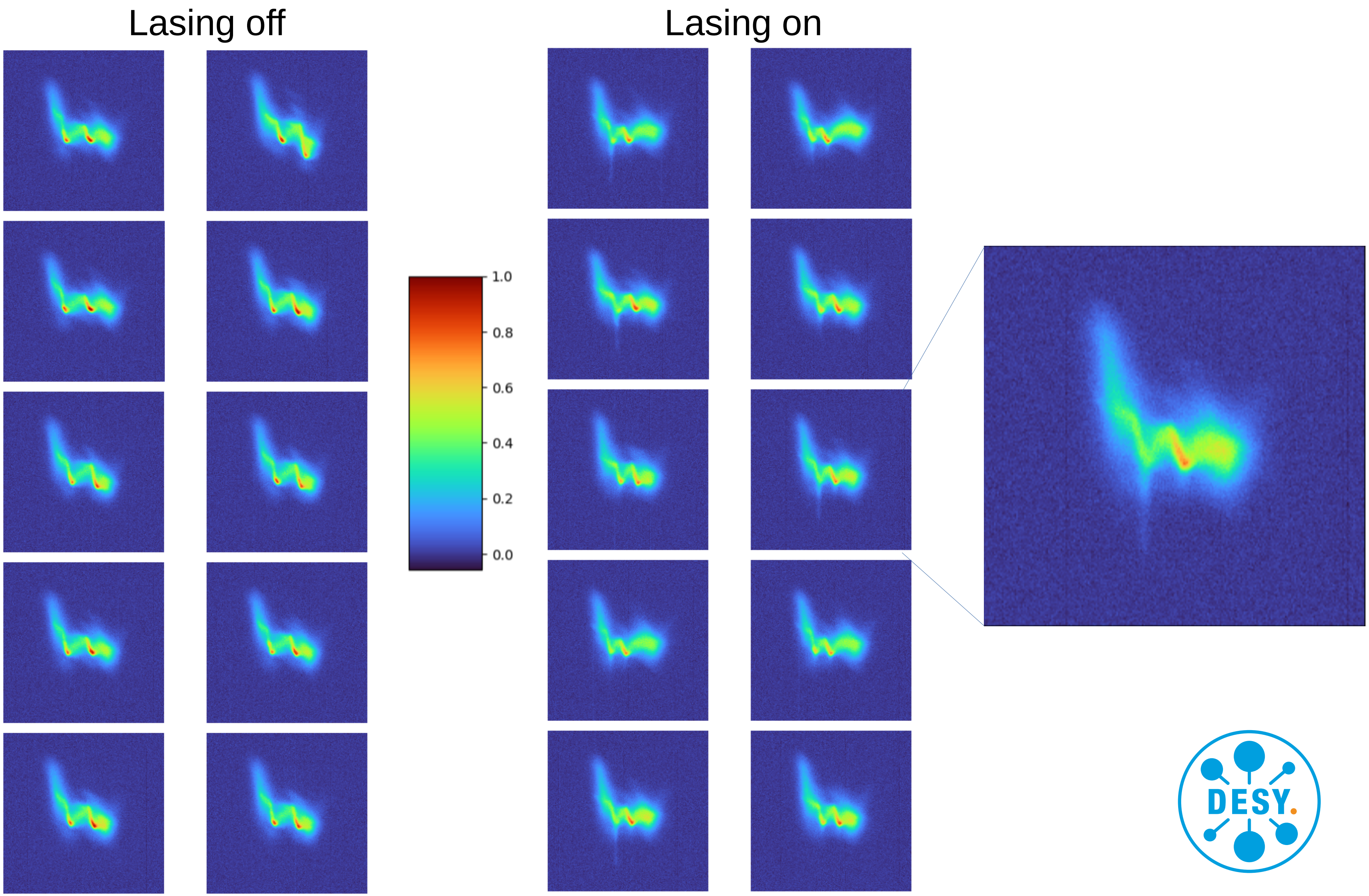
Article | Published: 12 August 2012

Demonstration of self-seeding in a hard-X-ray free-electron laser

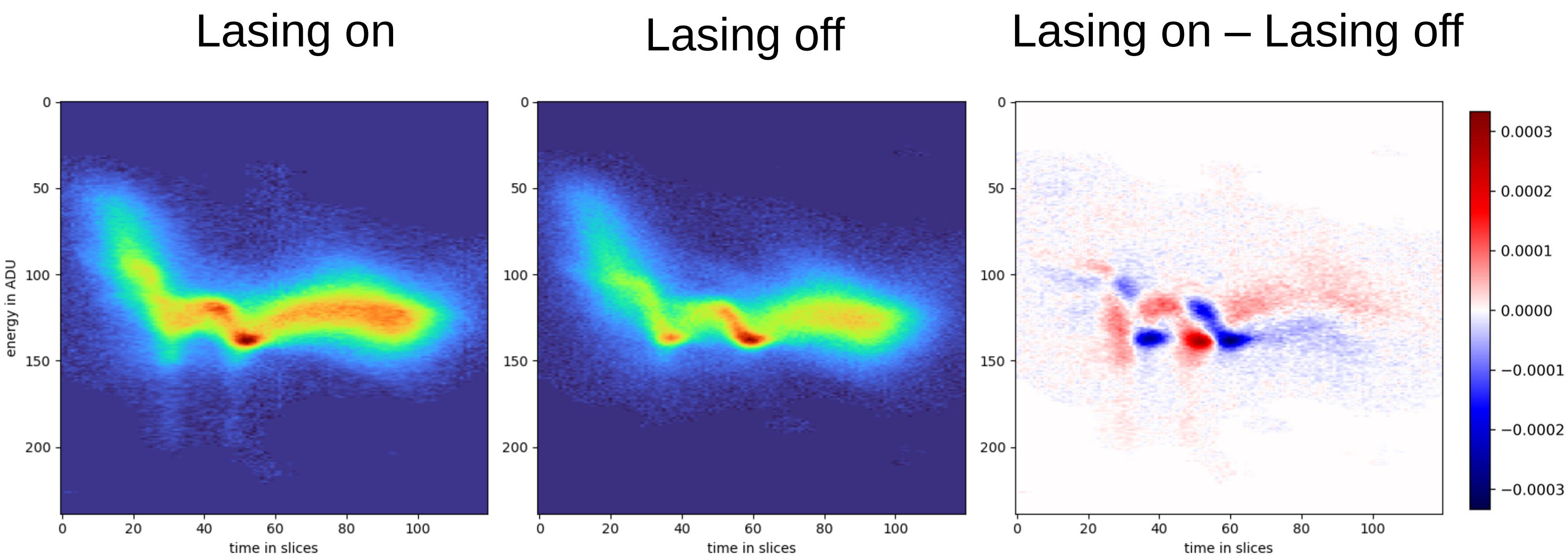
J. Amann, W. Berg, V. Blank, F.-J. Decker, Y. Ding, P. Emma, Y. Feng, J. Frisch, D. Fritz, J. Hastings, Z. Huang, J. Krzywinski, R. Lindberg, H. Loos, A. Lutman, H.-D. Nuhn, D. Ratner, J. Rzepiela, D. Shu, Yu. Shvyd'ko, S. Spampinati, S. Stoupin, S. Terentyev, E. Trakhtenberg, ... D. Zhu + Show authors

Nature Photonics **6**, 693–698 (2012) | Cite this article

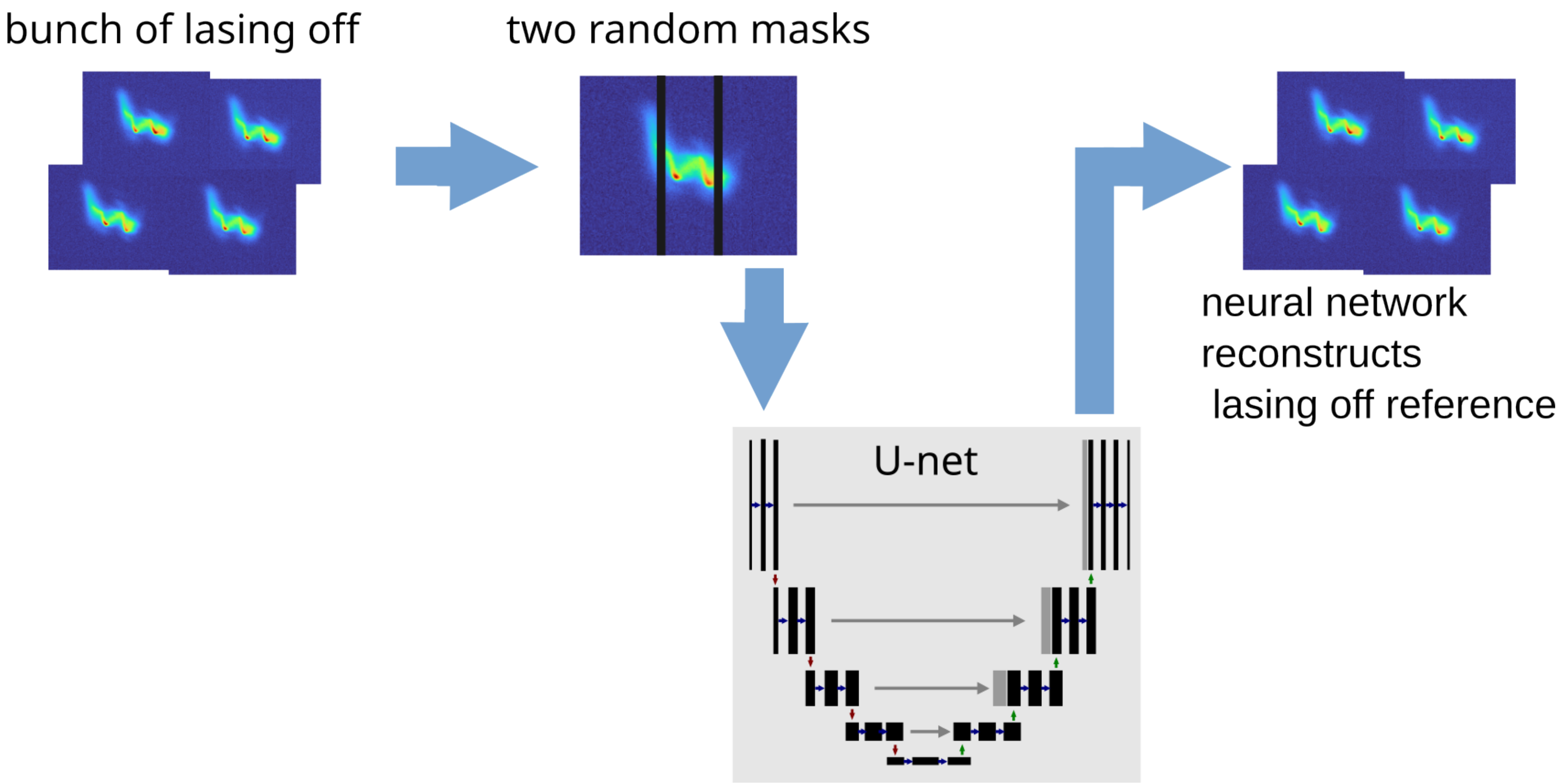
Lasing on and lasing off examples



Classical evaluation fails



Network approach: training phase

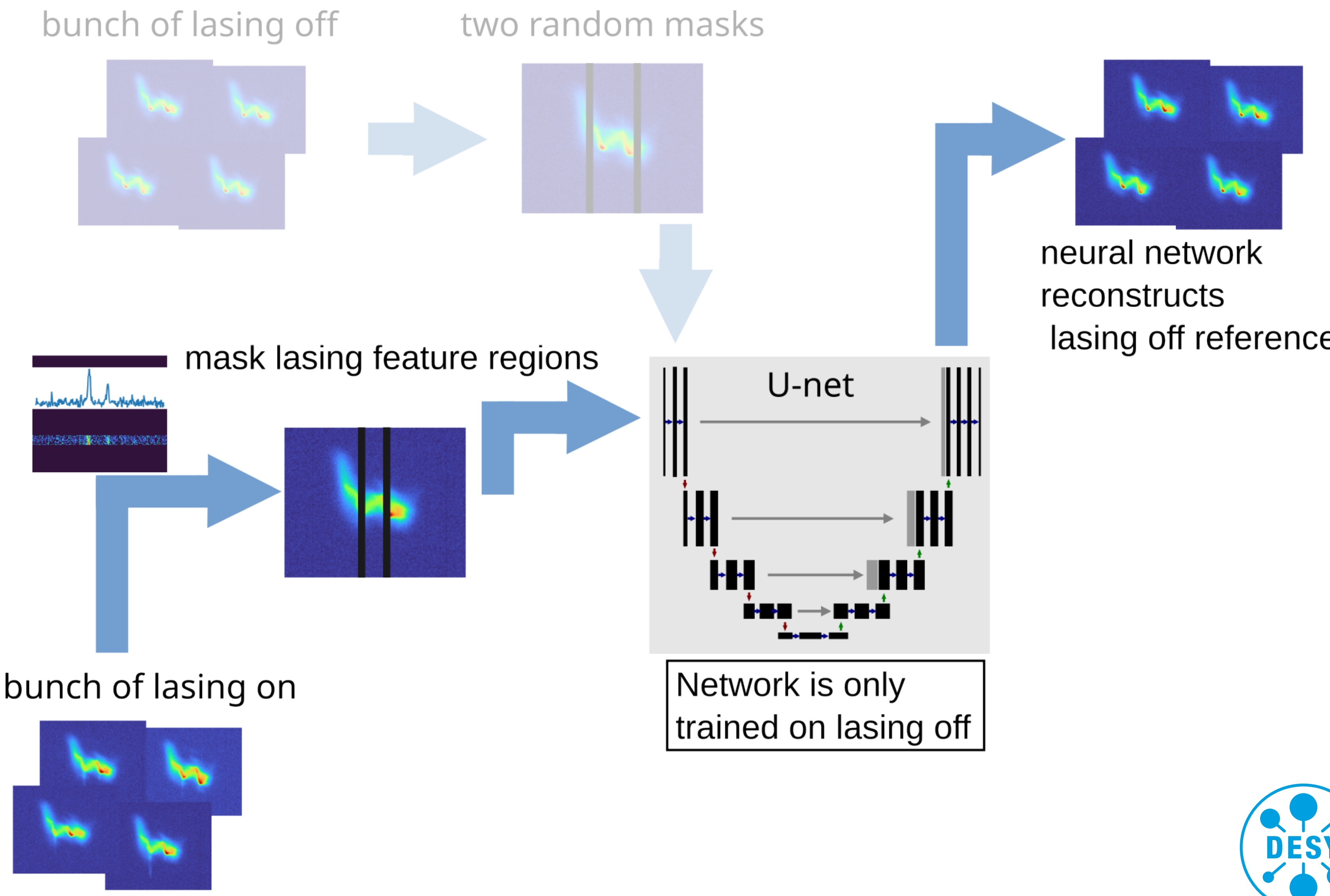


[Submitted on 18 May 2015]

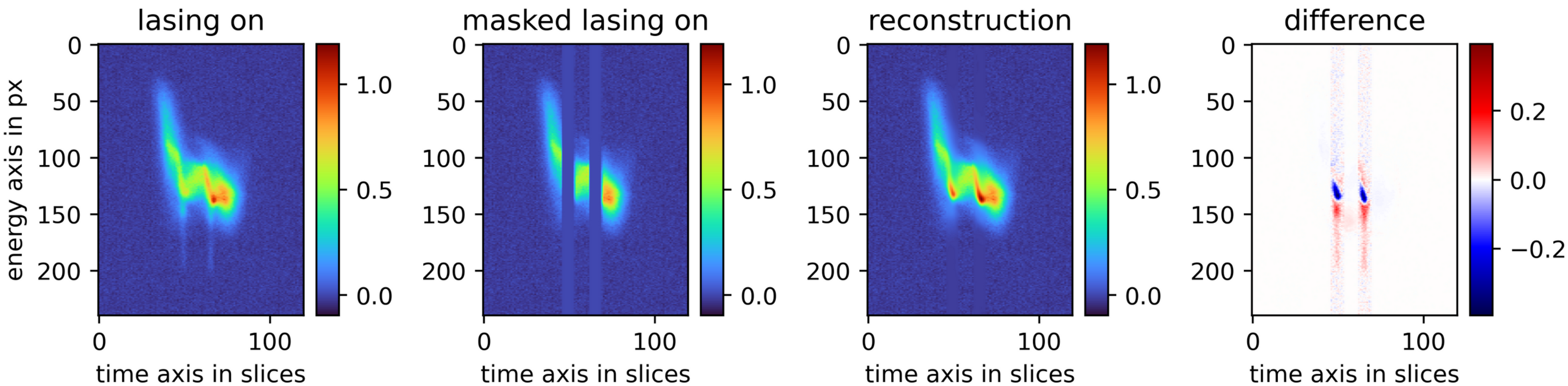
U-Net: Convolutional Networks for Biomedical Image Segmentation

Olaf Ronneberger, Philipp Fischer, Thomas Brox

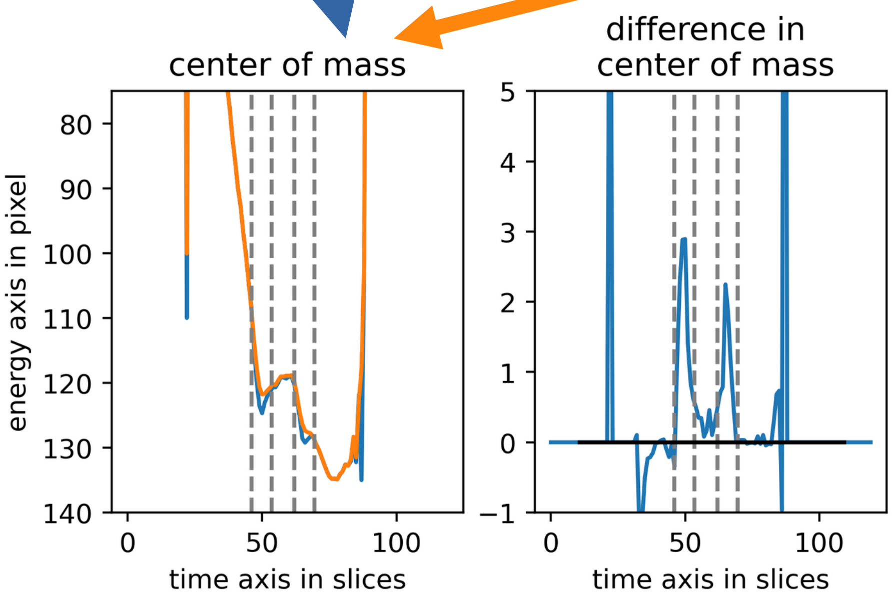
Network approach: evaluation phase



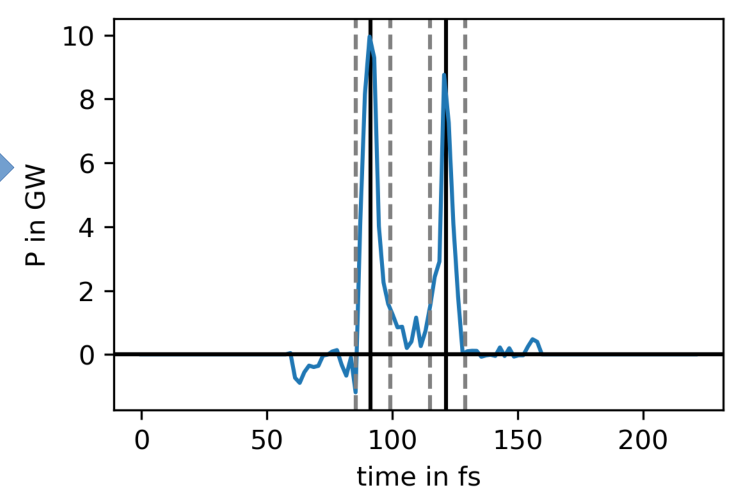
Results: one reconstruction in detail



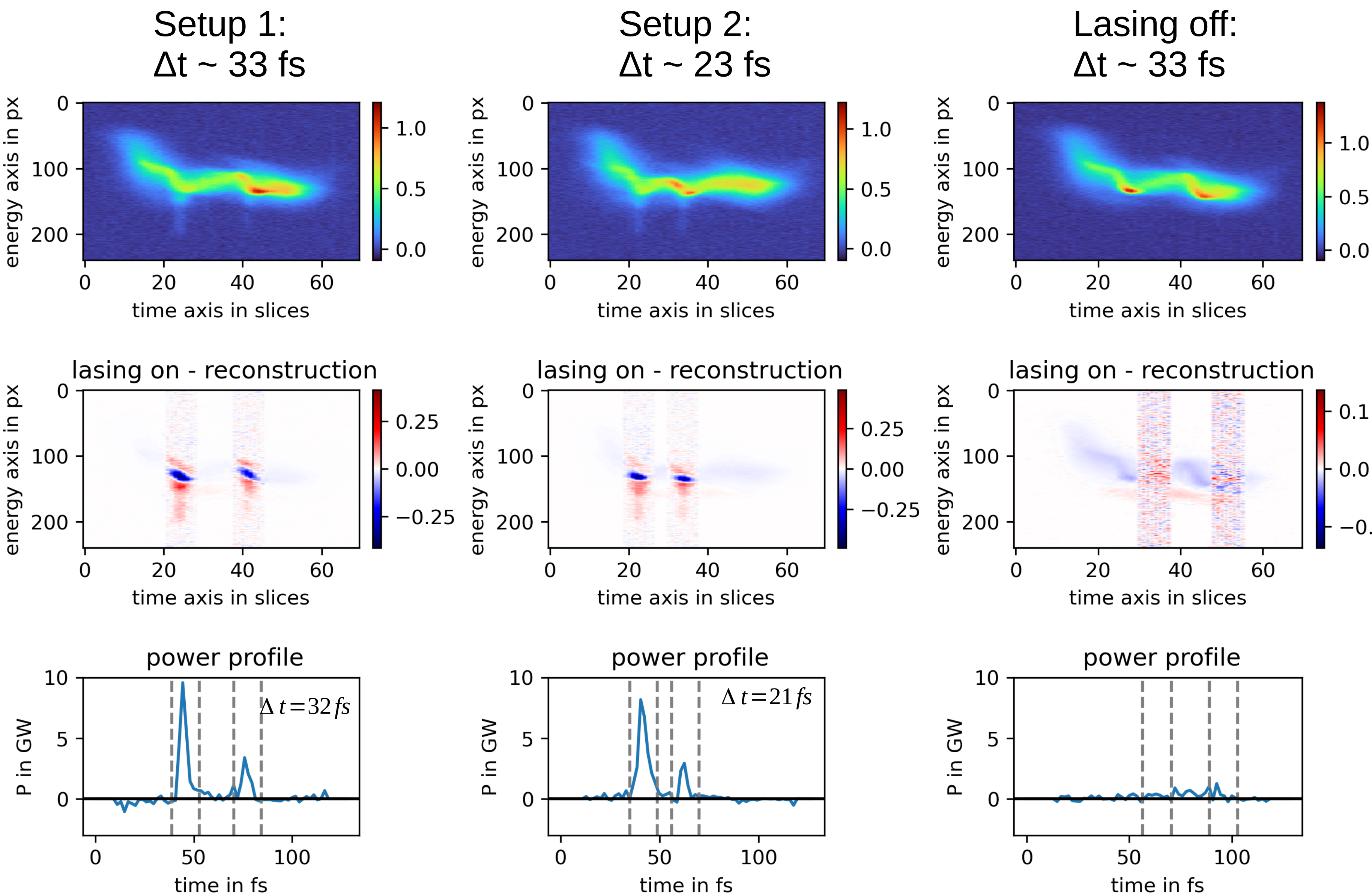
Calculate center of mass for each slice



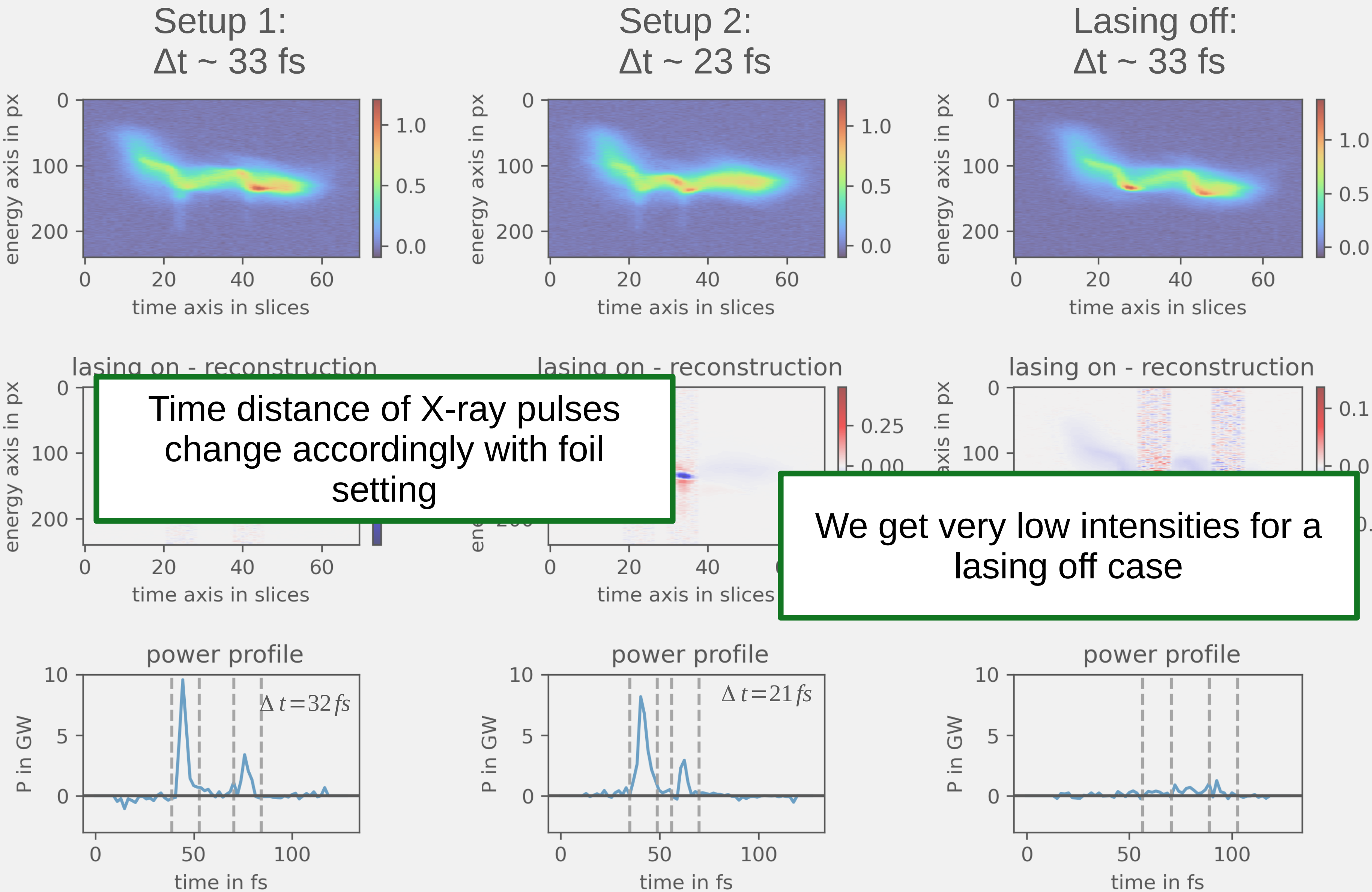
Power profile: $P(t) = \Delta E(t) I(t) / e$



Results: power profiles for different setups



Results: power profiles for different setups

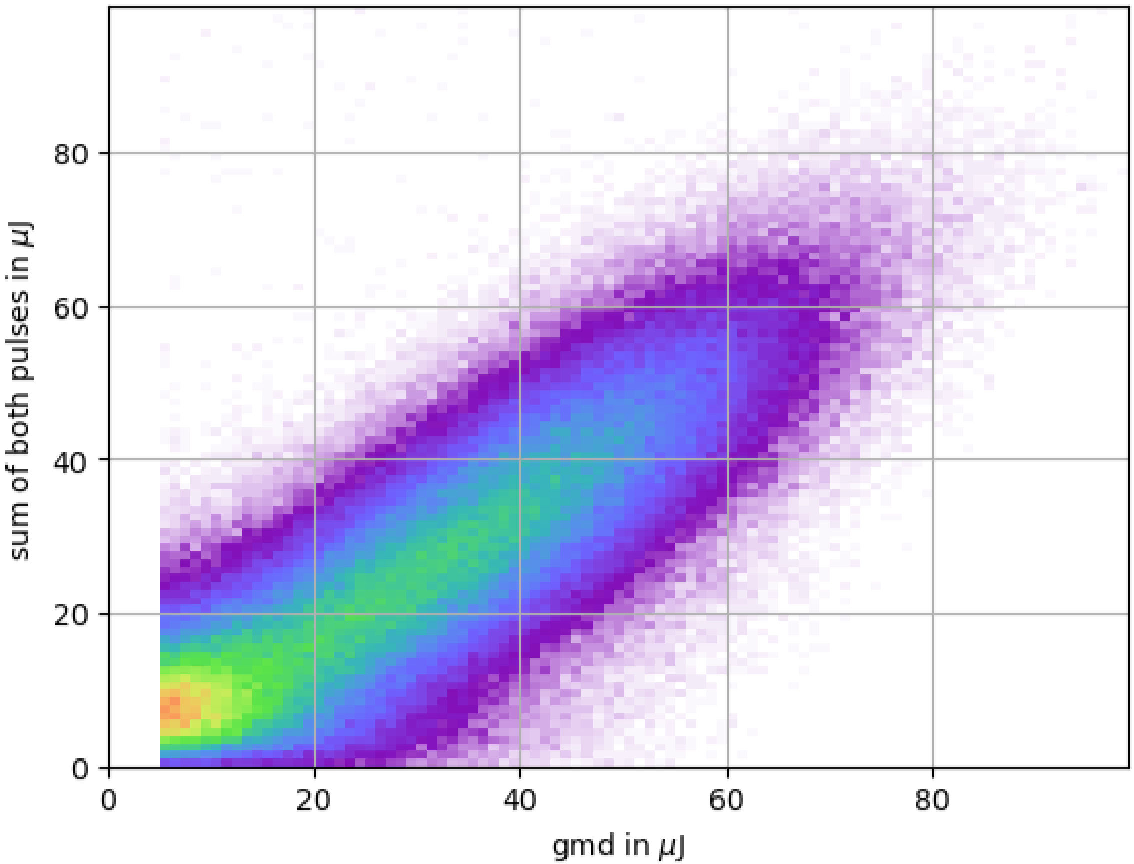


Time distance of X-ray pulses change accordingly with foil setting

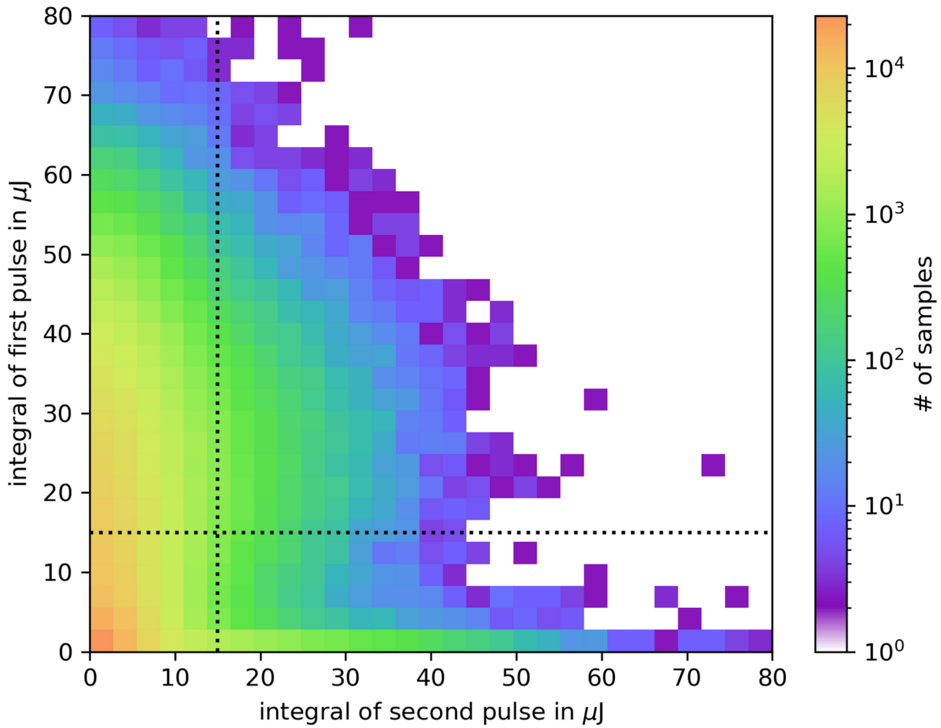
We get very low intensities for a lasing off case

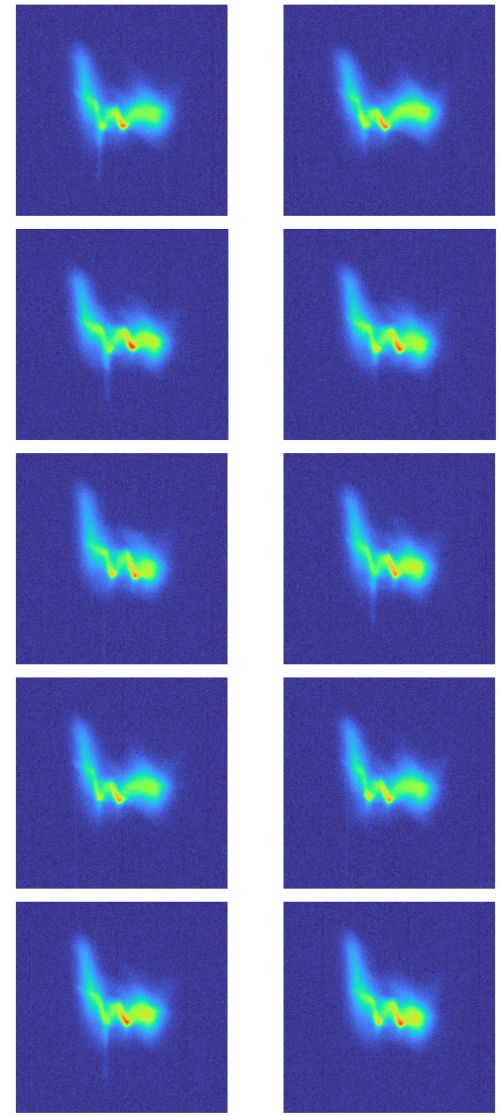
Results: how to cross check

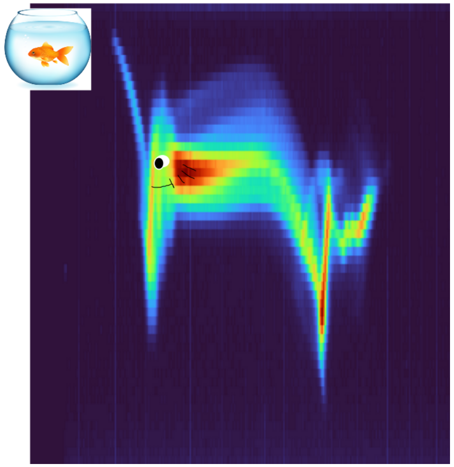
- Check if integral of both pulses match with GMD

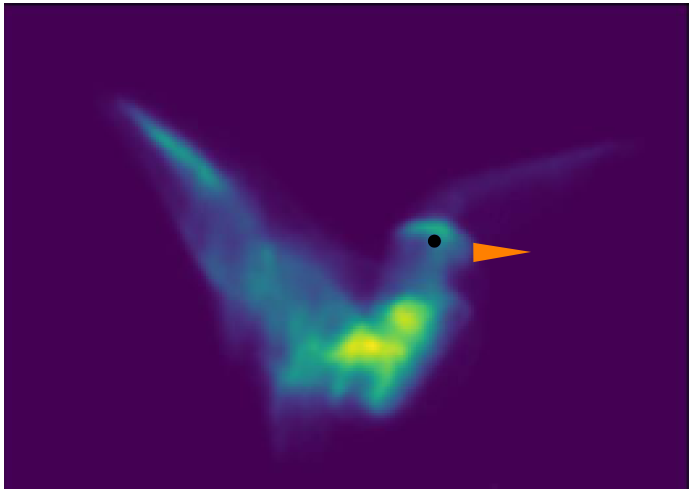


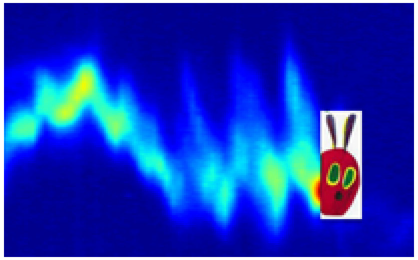
Results: find the relevant pulses



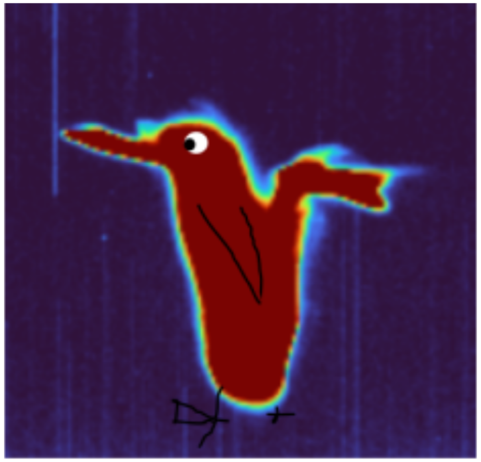


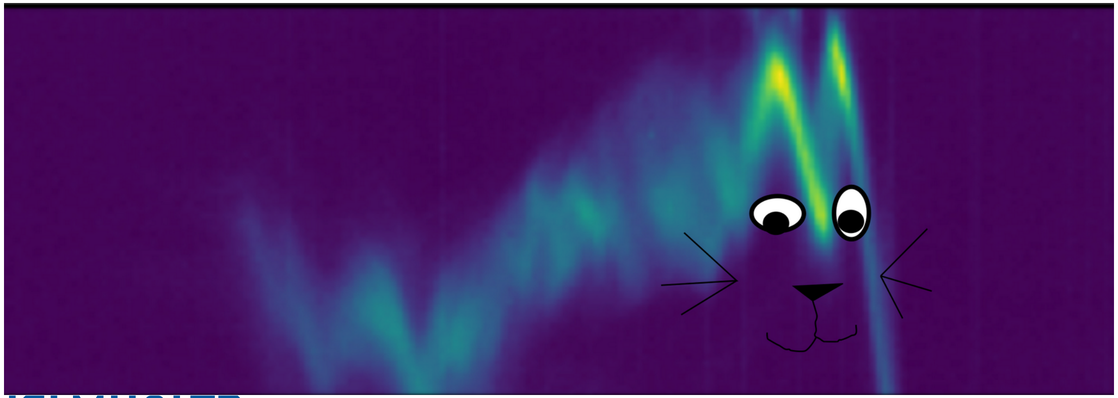






Questions?





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DESY.

Finding the right reference image

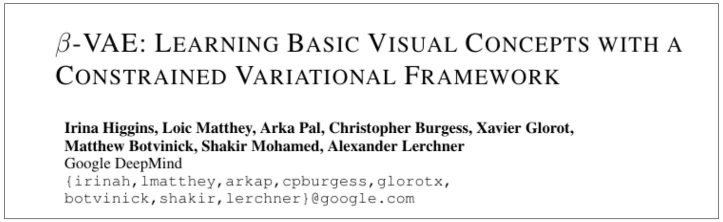
‘classical approach’

- 1) clean lasing on/off images.
- 2) slice them in n slices.
- 3) calculate the x-Projection.
- 4) nr_clusters manually or with gap_statistics.
- 5) sklearn.cluster.AgglomerativeClustering with euclidean distance to cluster them in a group, calculate mean and spread of the group, average them.
- 6) use np.corrcoef to find the best reference group (Pearson product-moment correlation coefficients).
- 7) compare com and spread of lasing on with the averaged con / spread of the best matching group.
- 8) use a different detector to find the matching total power / y offset.

$$\mathrm{R}_{ij} = \frac{C_{ij}}{\sqrt{C_{ii}C_{jj}}}$$

Beta-Variational Autoencoder

Basic principle

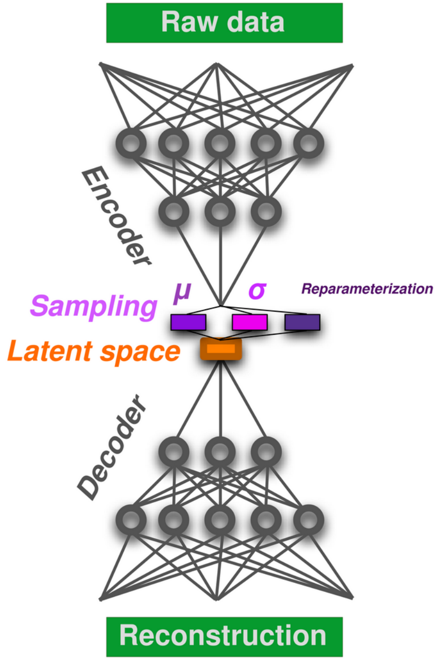

β-VAE: LEARNING BASIC VISUAL CONCEPTS WITH A CONSTRAINED VARIATIONAL FRAMEWORK

Irina Higgins, Loic Matthey, Arka Pal, Christopher Burgess, Xavier Glorot, Matthew Botvinick, Shakir Mohamed, Alexander Lerchner
Google DeepMind
{irinah,lmatthey,arkap,cpburgess,glorotx, botvinick,shakir,lerchner}@google.com

- Variational autoencoder: learn a distribution in the latent space
- Loss includes the deviation from a Gaussian normal distribution (KL divergence)

$$\mathrm{D}_{KL} = \frac{1}{2}\sum_{i=1}^{k}(\sigma_i^2 + \mu_i^2 - 1 - ln(\sigma_i^2))$$

- Reparameterization trick for backpropagation
- Beta controls the disentanglement

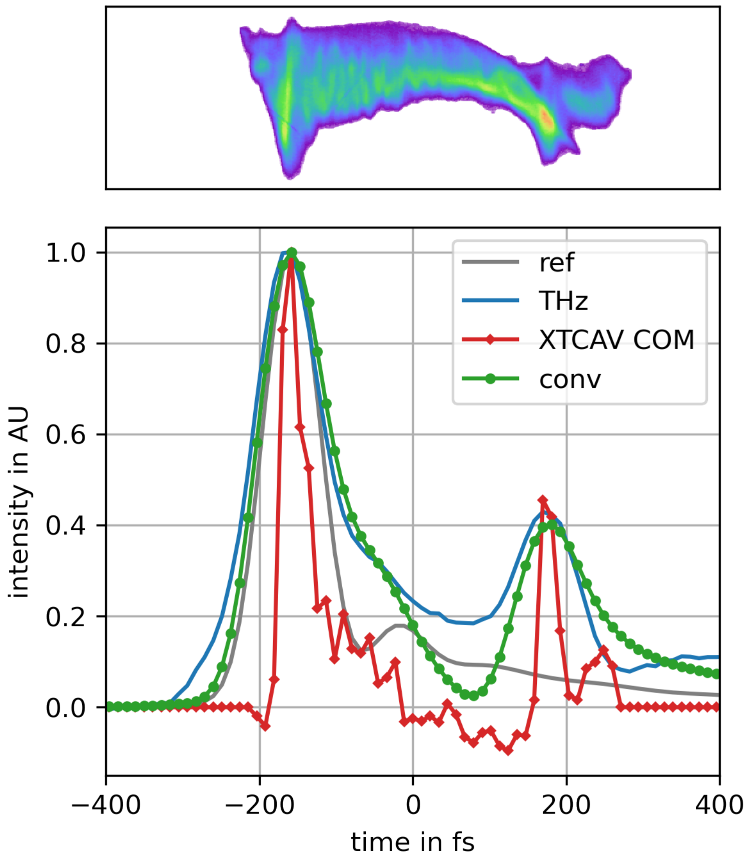


Loss =
ReconstructionError + β*DisentaglementError

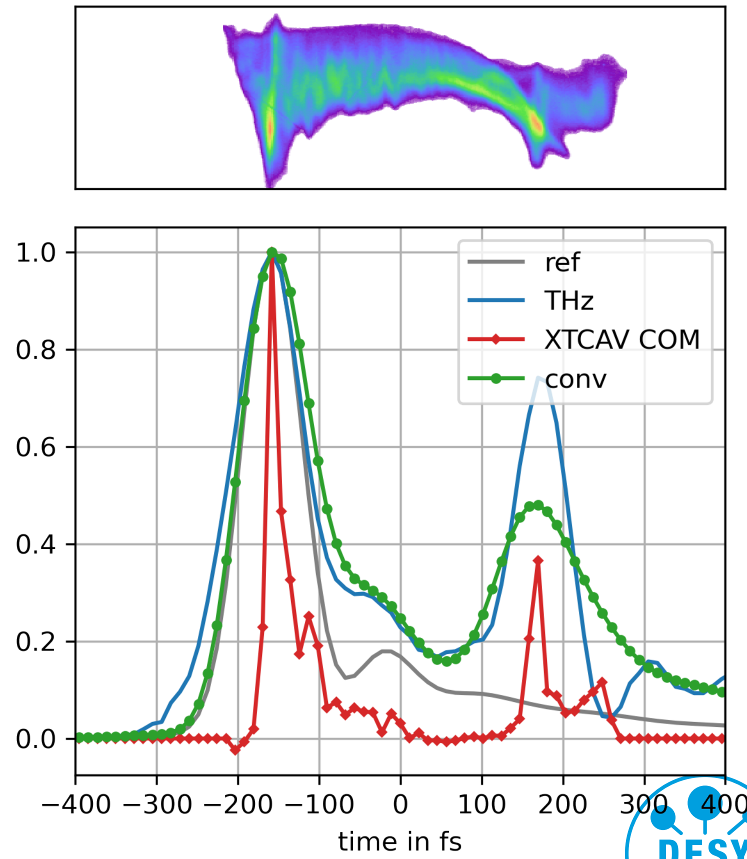
Polarix and THz streaking

Two single shot examples

Good agreement



Different intensity ratios



HELMHOLTZ