# Laser Wakefield Accelerator Modelling with Neural Networks

Matthew Streeter

Centre for Light Matter Interactions

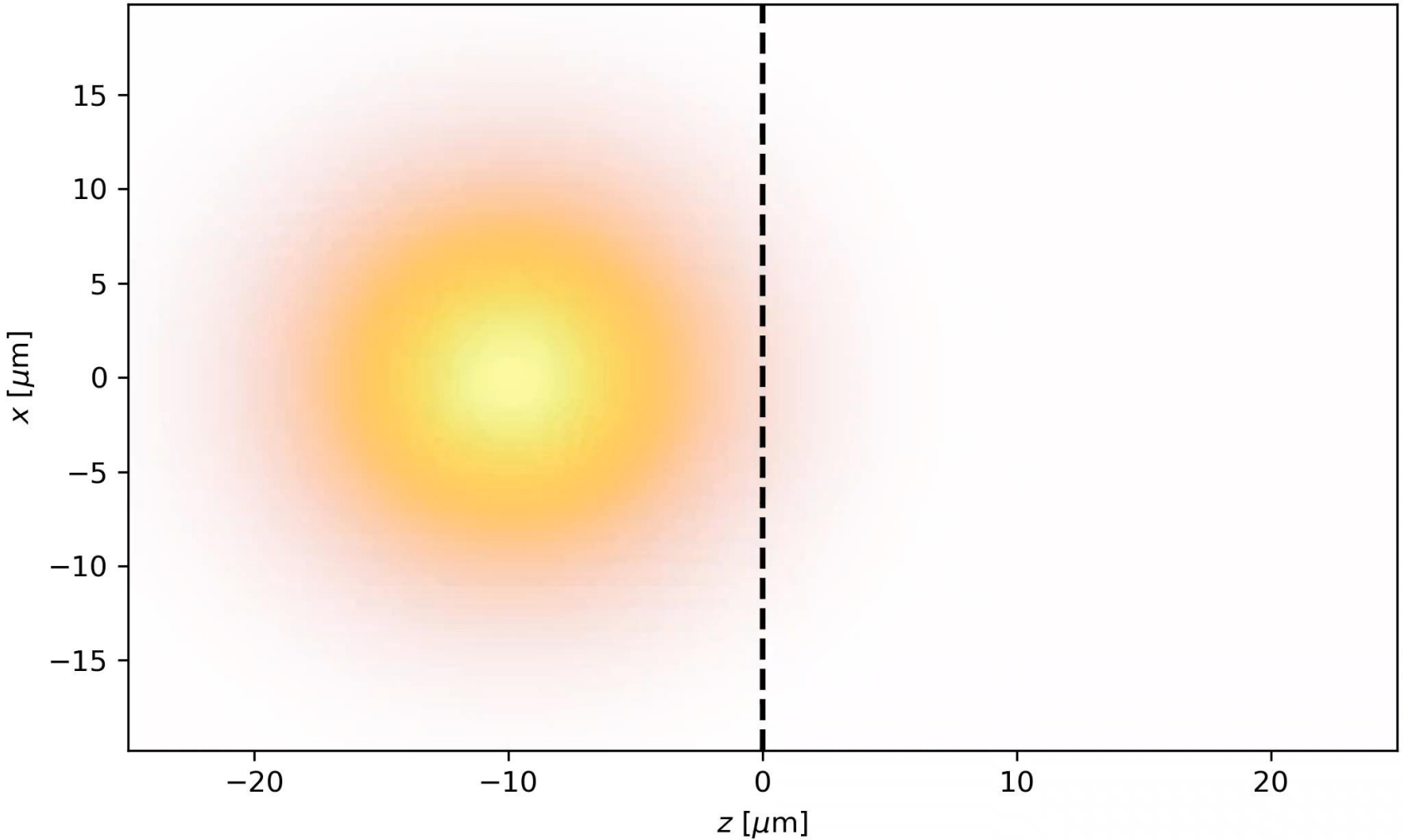
Queen's University Belfast

THE ROYAL SOCIETY URF-R1221874

QUEEN'S UNIVERSITY BELFAST

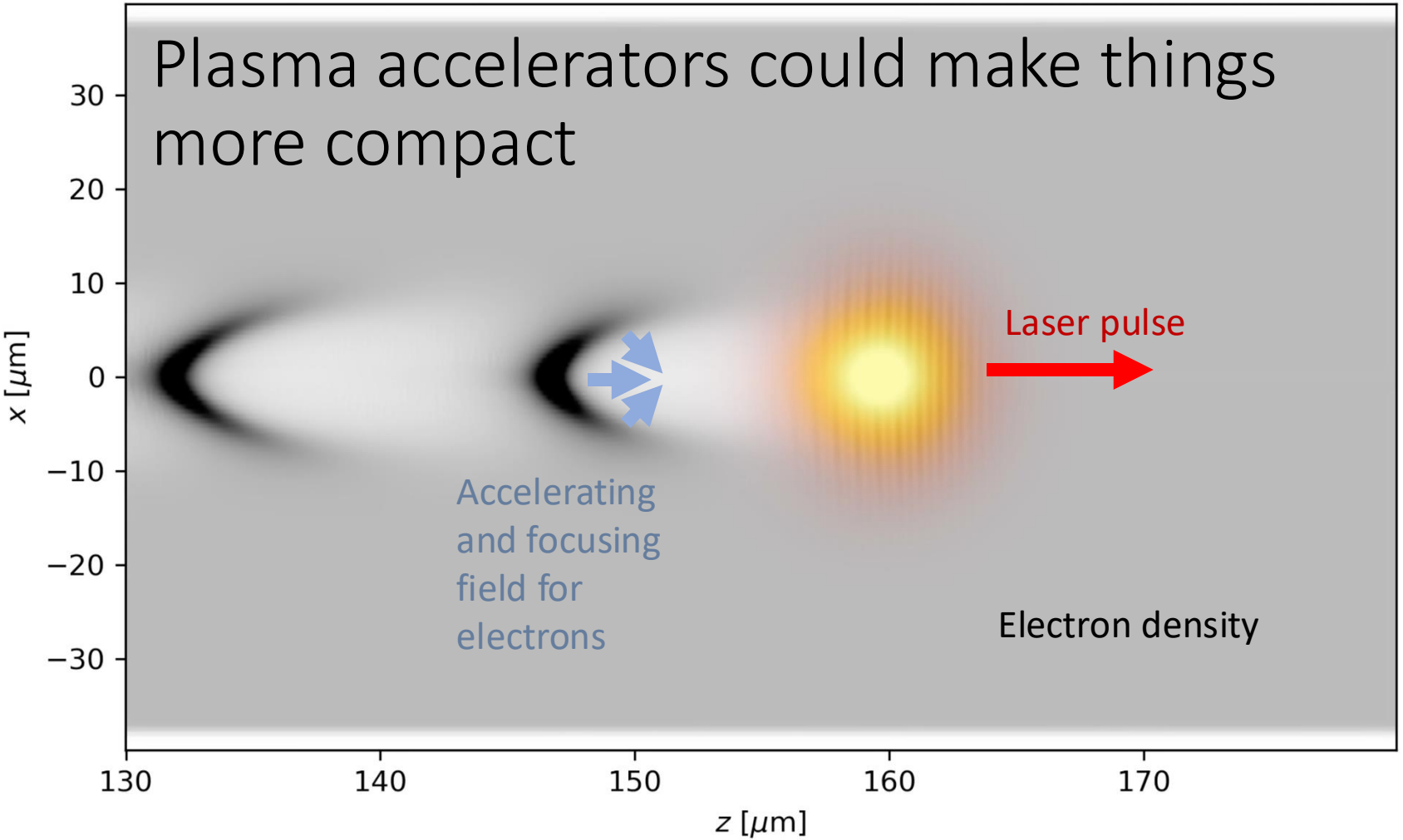
# Laser Wakefield Accelerator Modelling with Neural Networks

- A laser-plasma experiment that needed a model
- Methodology for building a predictive neural network
- Using the model as a synthetic diagnostic
- Future implementations




FBPIC: Lehe, R., Kirchen, M., Andriyash, I. A., Godfrey, B. B., & Vay, J.-L. *Computer Physics Communications*, *203*, 66–82. (2016)

# Plasma accelerators could make things more compact

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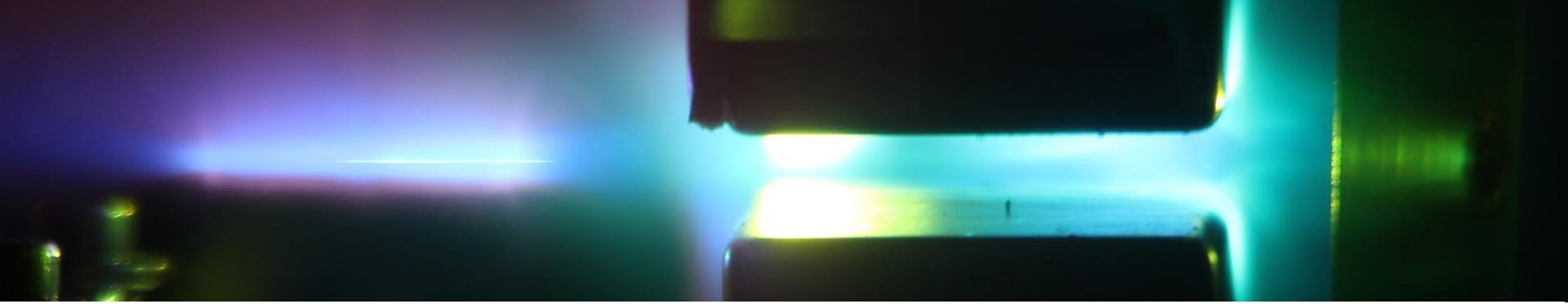
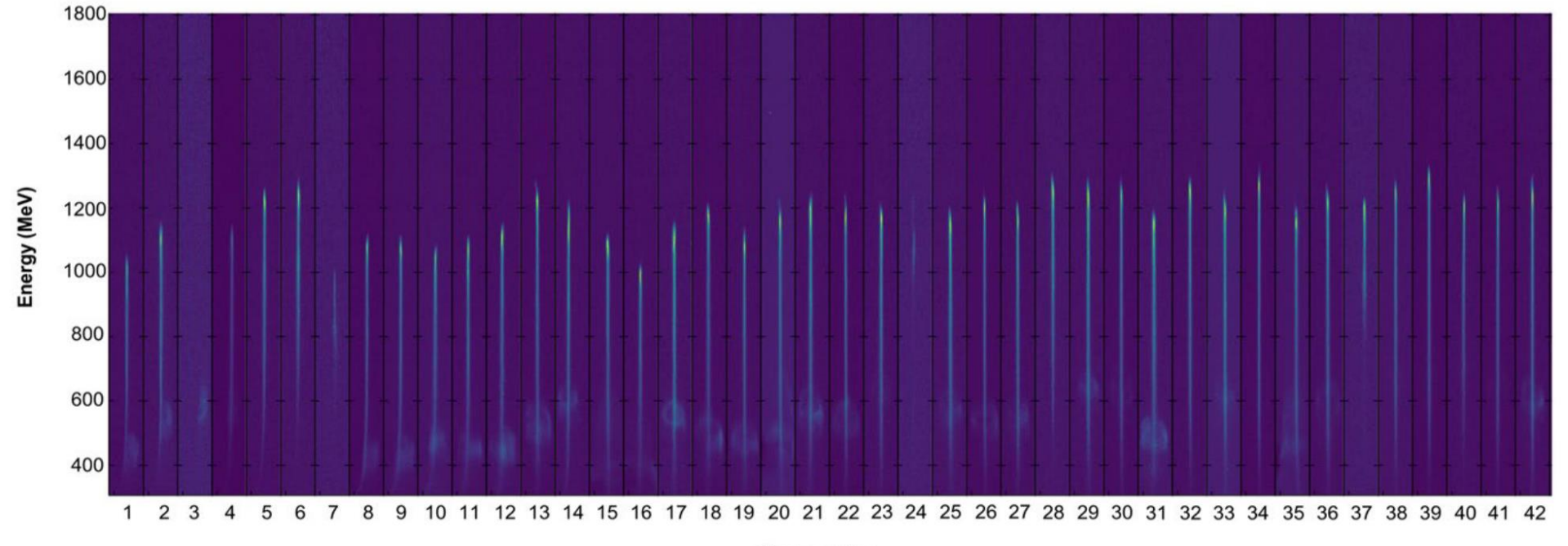
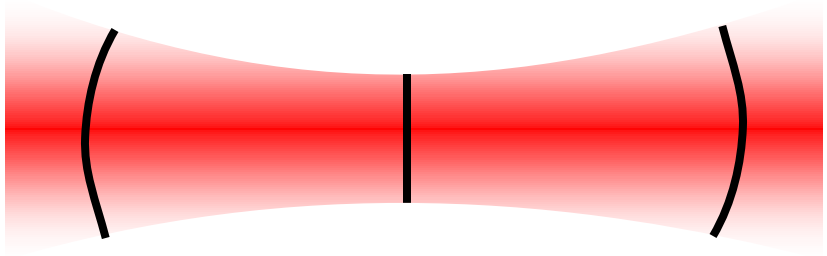


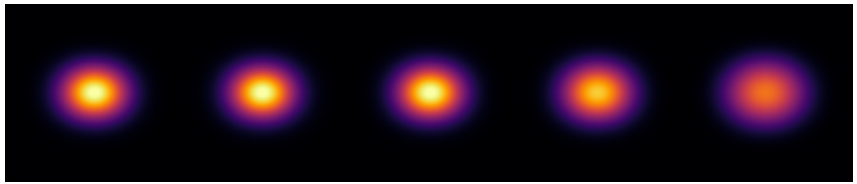



Hussein, A. E., et al. *Scientific Reports*, *9*(1), 3249. (2019)

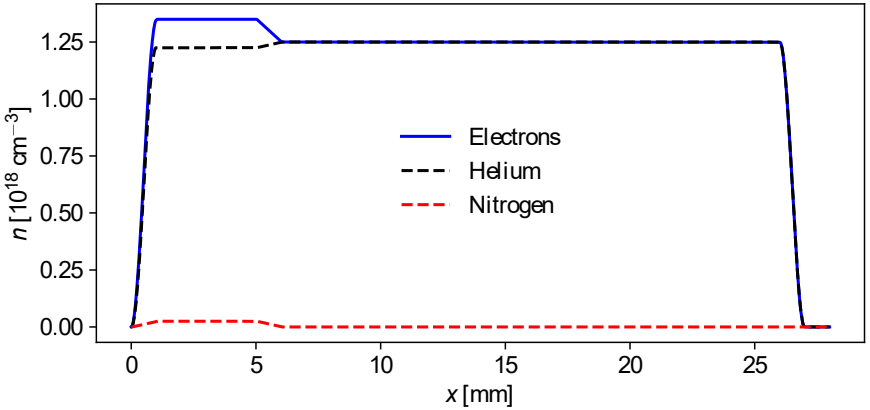
# Laser evolution depends on initial conditions

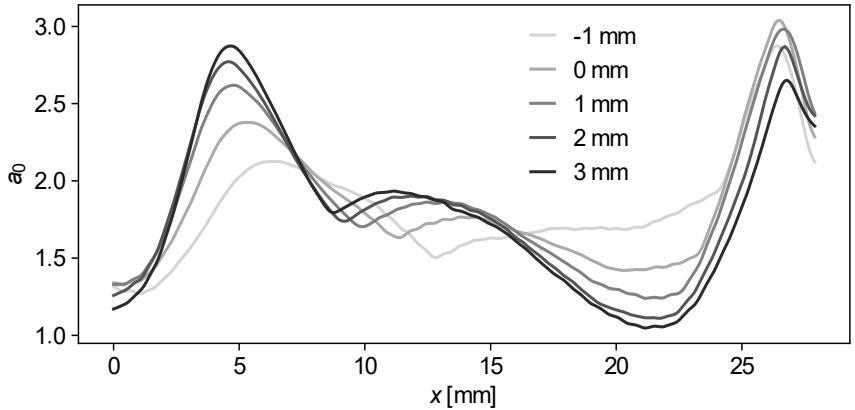
e.g. focal plane



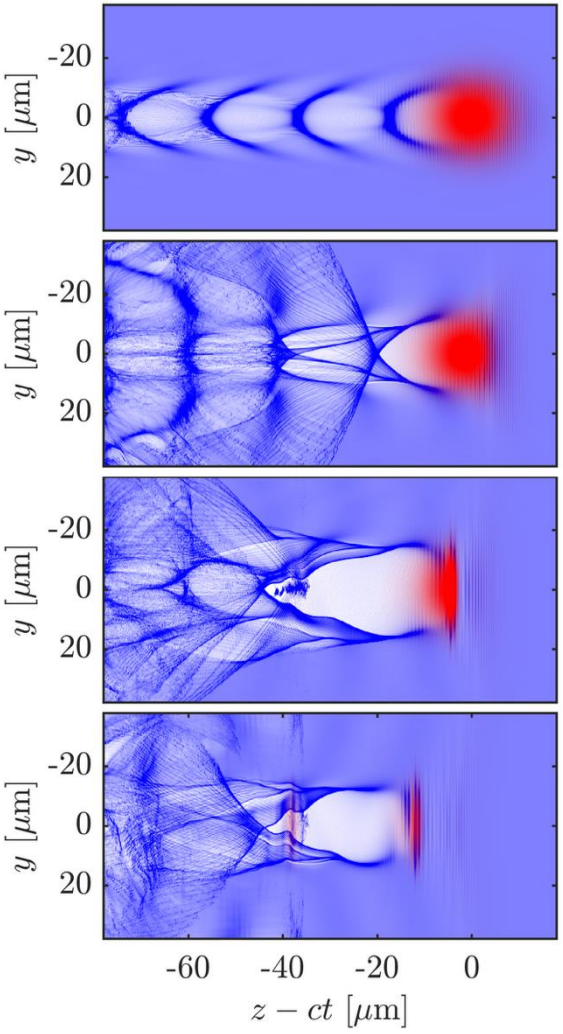


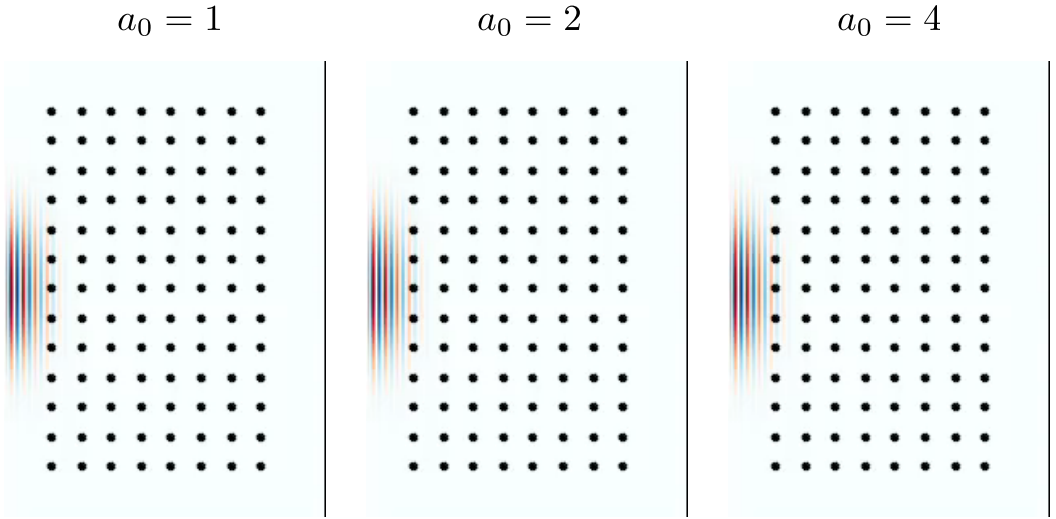
-1 mm 0 mm 1 mm 2 mm 3 mm



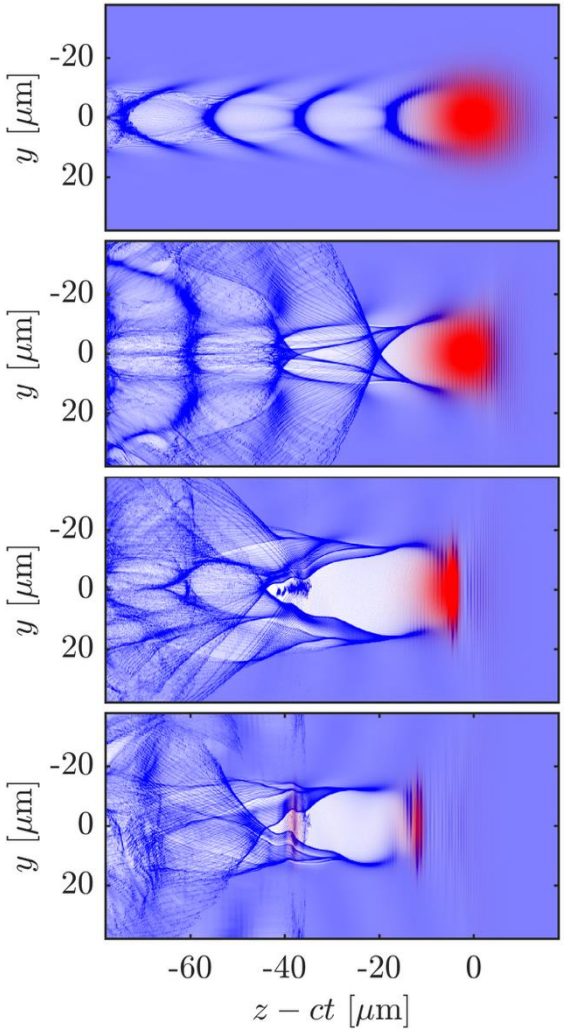
# Evolution of the laser intensity changes the nature of the plasma response

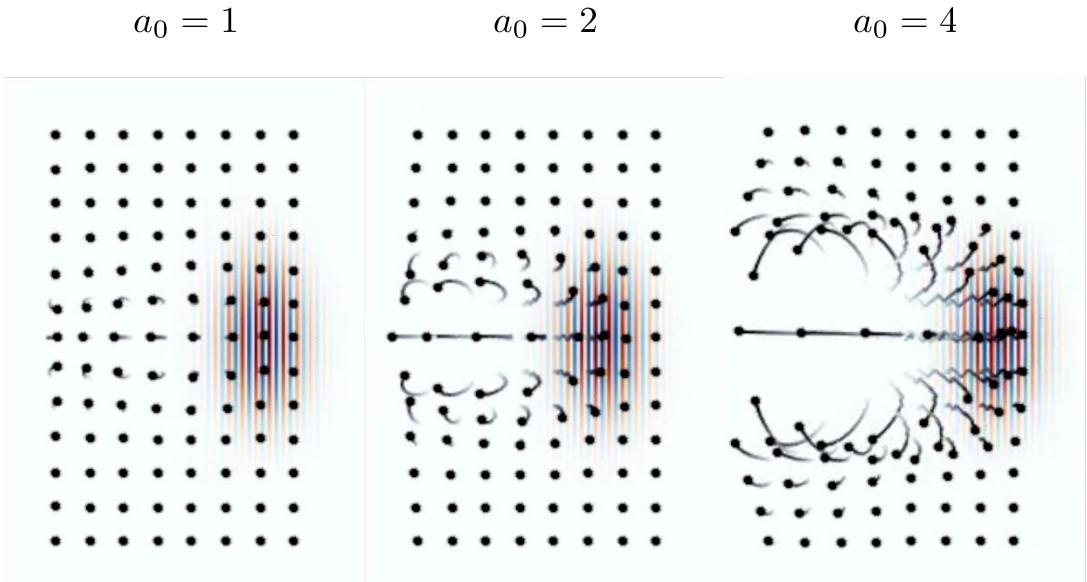



OSIRIS simulations: Fonseca, R. A., et al *Computational Science — ICCS 2002 SE - 36* (Vol. 2331, pp. 342–351). (2002)

# Evolution of the laser intensity changes the nature of the plasma response

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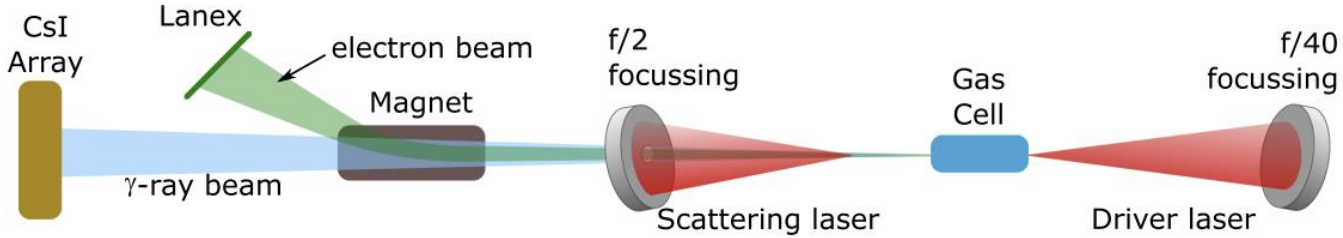
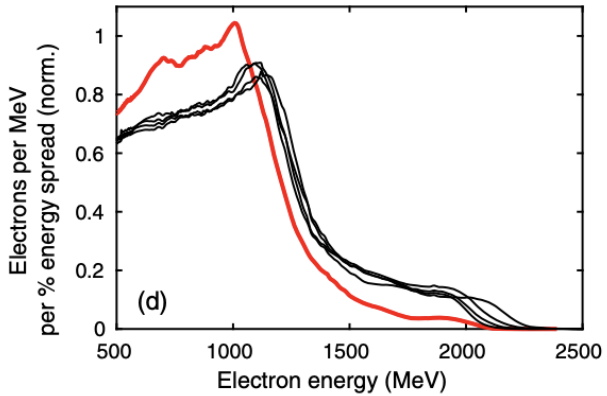
# Inferring electron beam spectrum for destructive processes

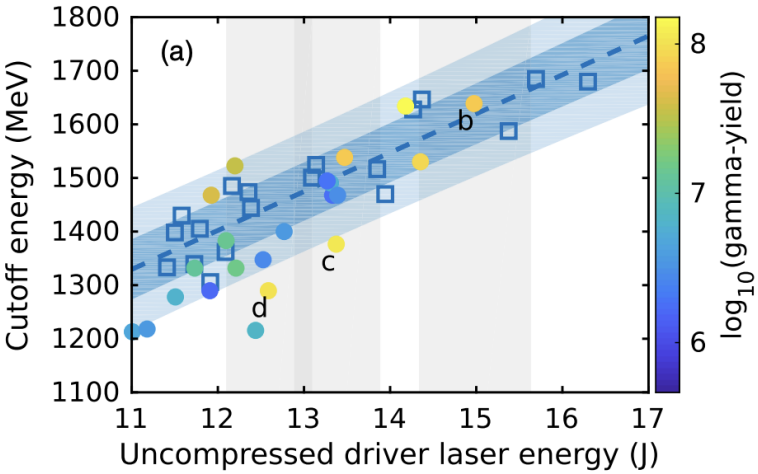


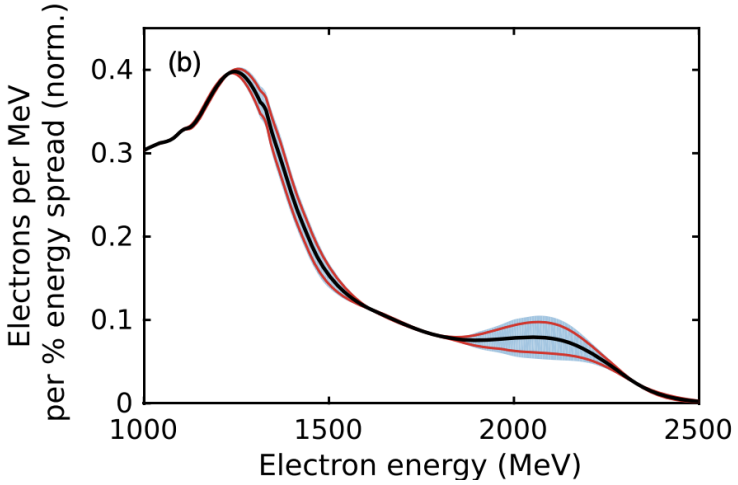

- Quantitative studies of radiation reaction require knowledge of the pre-interaction electron spectrum
- Can we use secondary diagnostics to predict the electron spectrum?



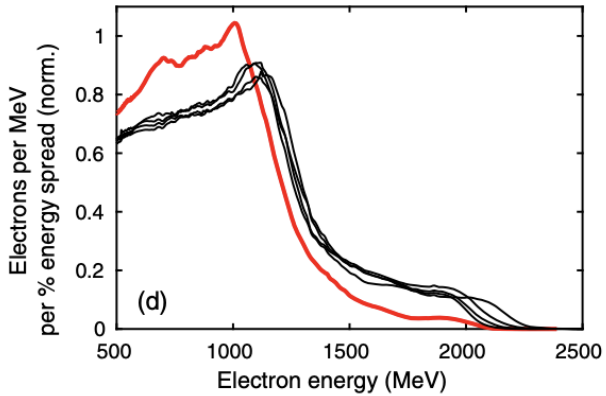

K. Poder et al. Phys. Rev. X 8, 031004 (2018)

# Inferring electron beam spectrum for destructive processes




- Poder *et al.* correlated laser energy with 'cut-off energy' in electron spectra
- Can we use more information to obtain full spectrum?
- Follow synthetic diagnostic approach shown by C. Emma *et al.* PRAB 21, 112802 (2018)

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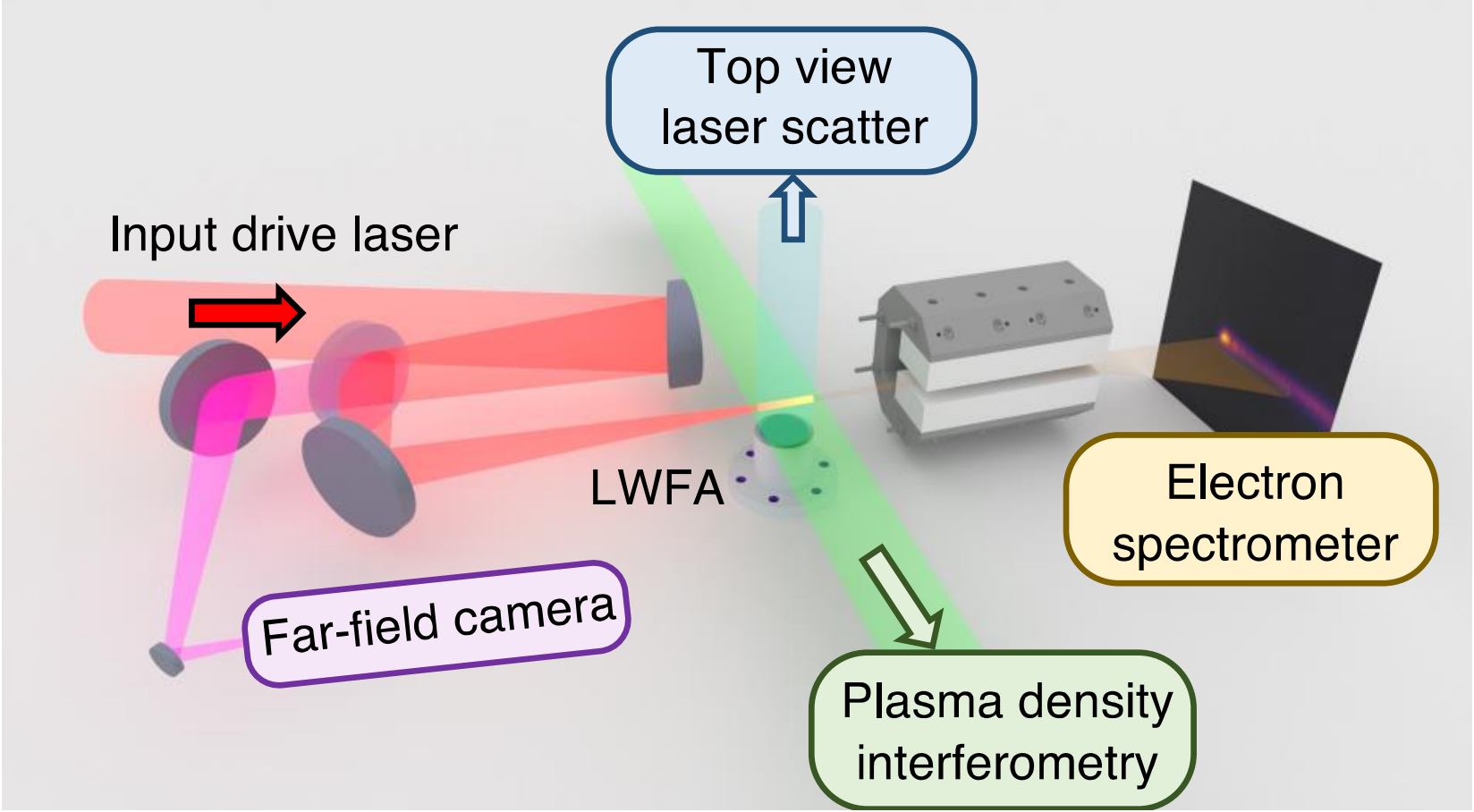
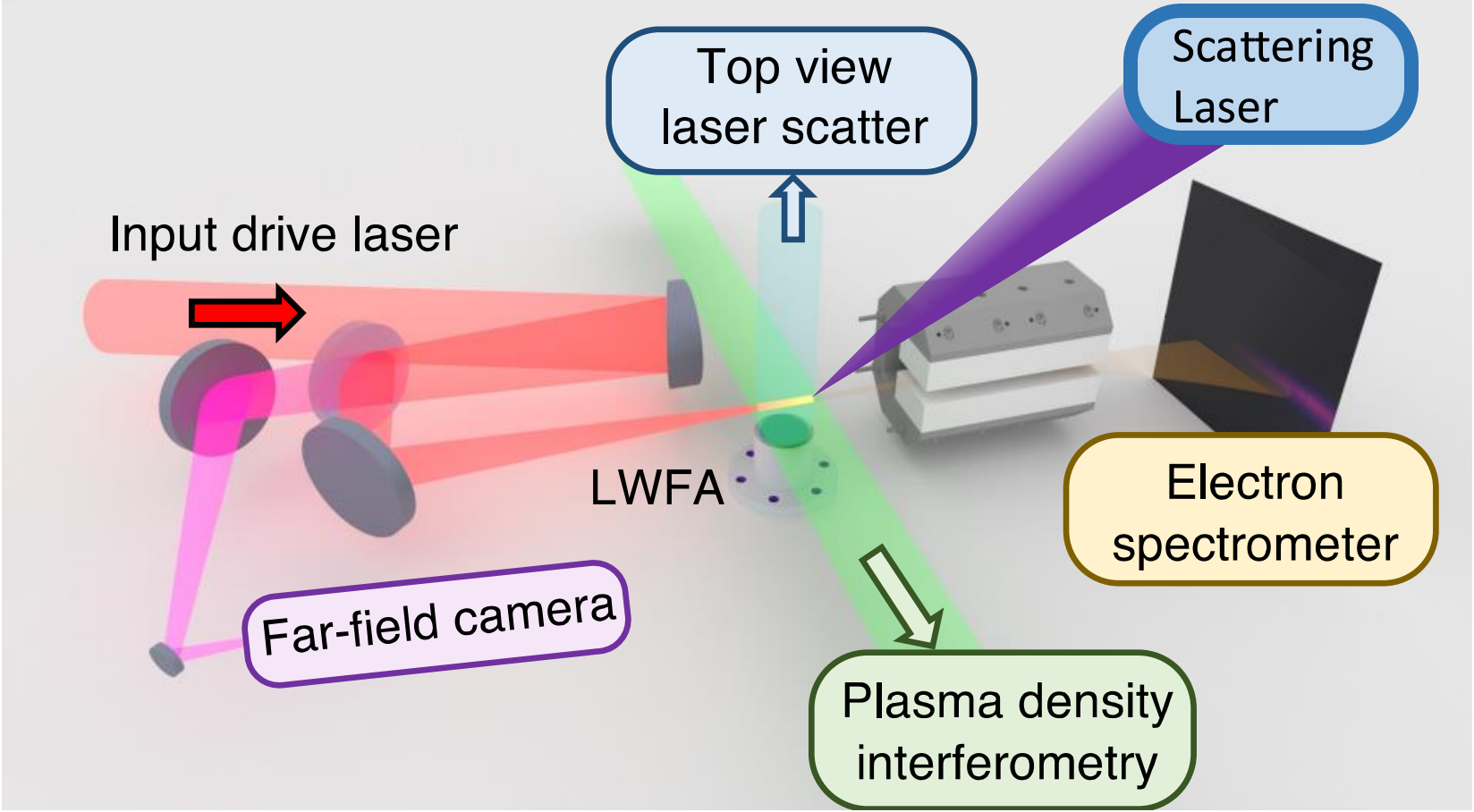
# Inferring electron beam spectrum for destructive processes

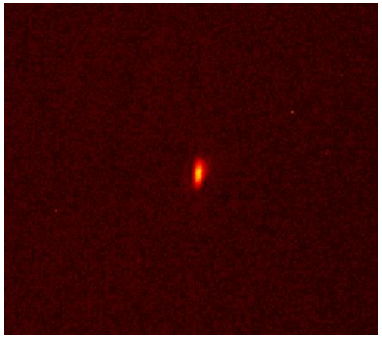


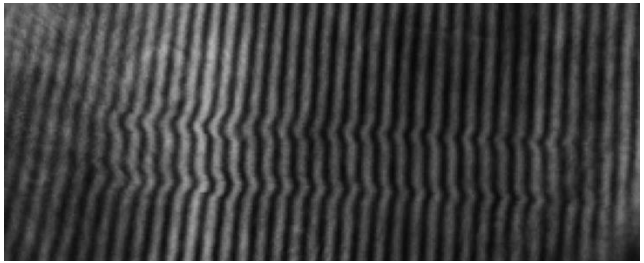
# Inferring electron beam spectrum for destructive processes

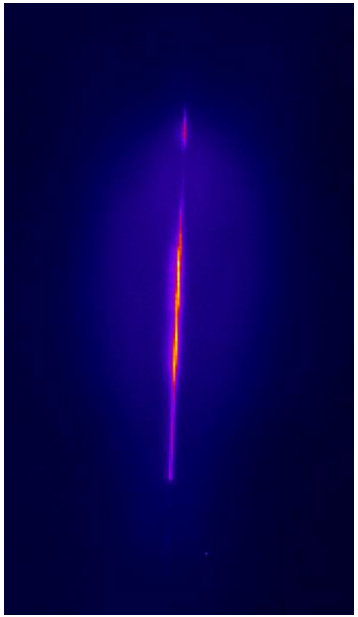


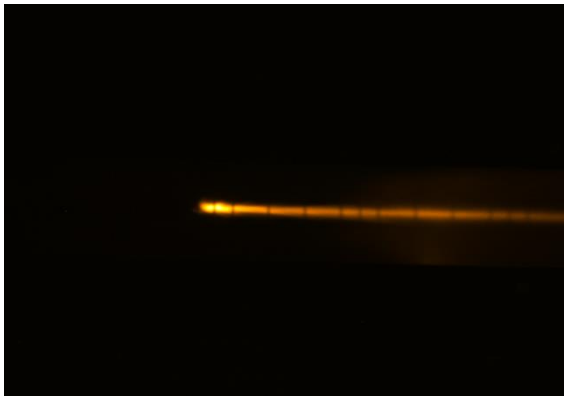
# Raw data is multi-modal and with many parameters

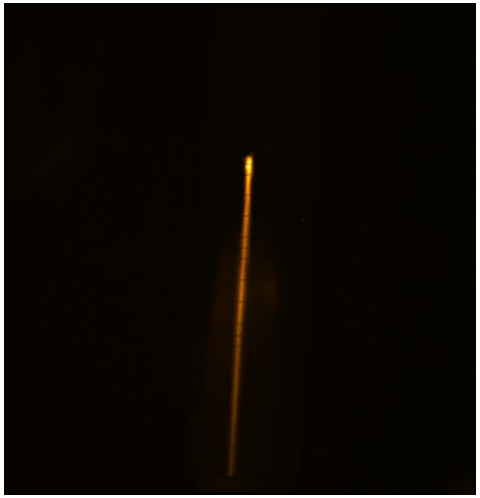
- Making a fully connected layer between raw diagnostic data would be an extremely large number (>$10^{12}$) of free parameters



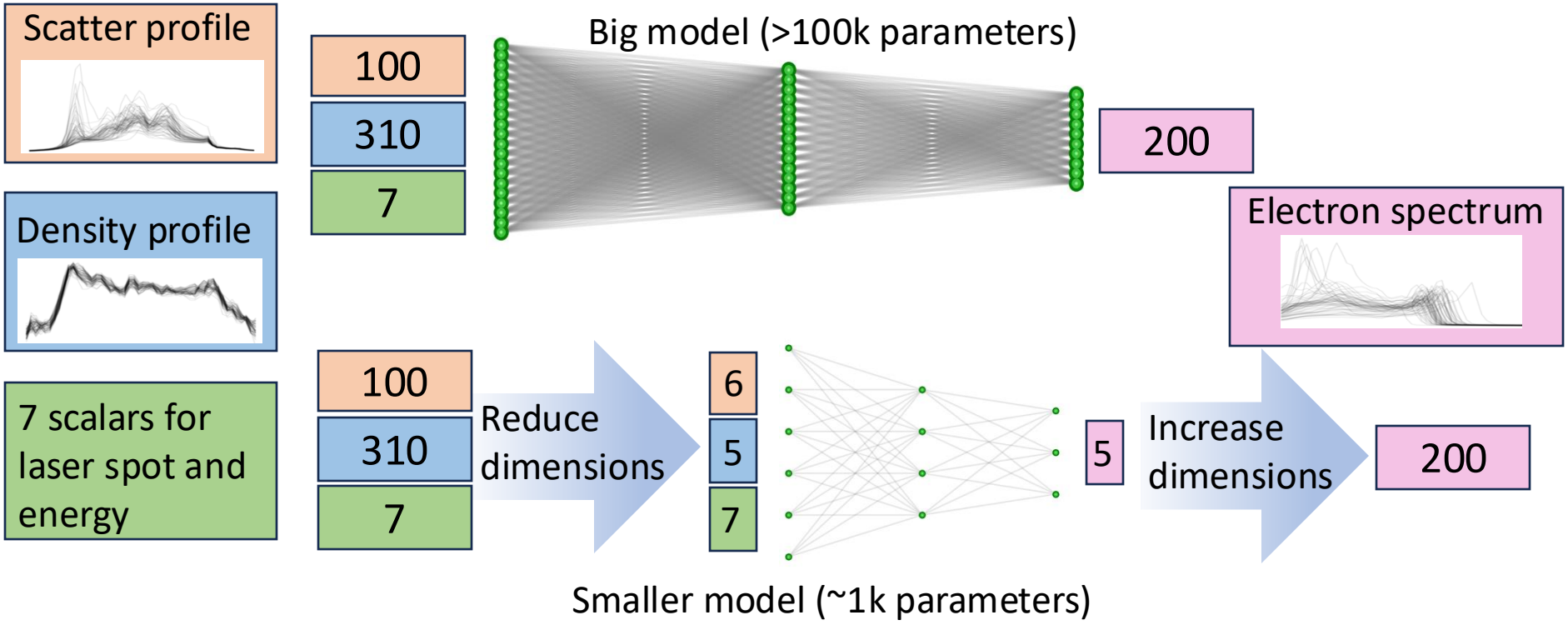






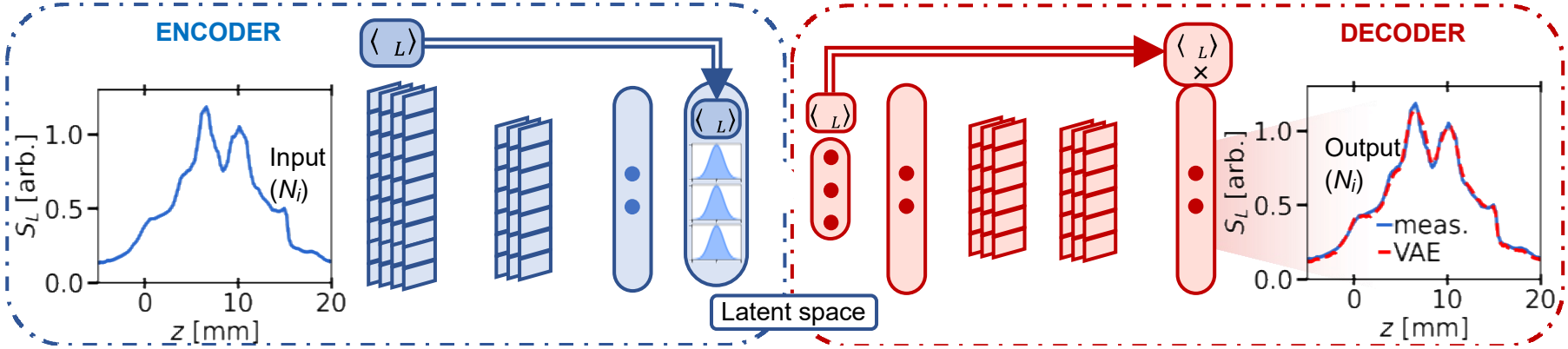


# Simplification and separation of tasks reduces free parameters




- With <1000 shots, we need something that can learn the important relationships efficiently

# Variational Autoencoders trained on individual diagnostics

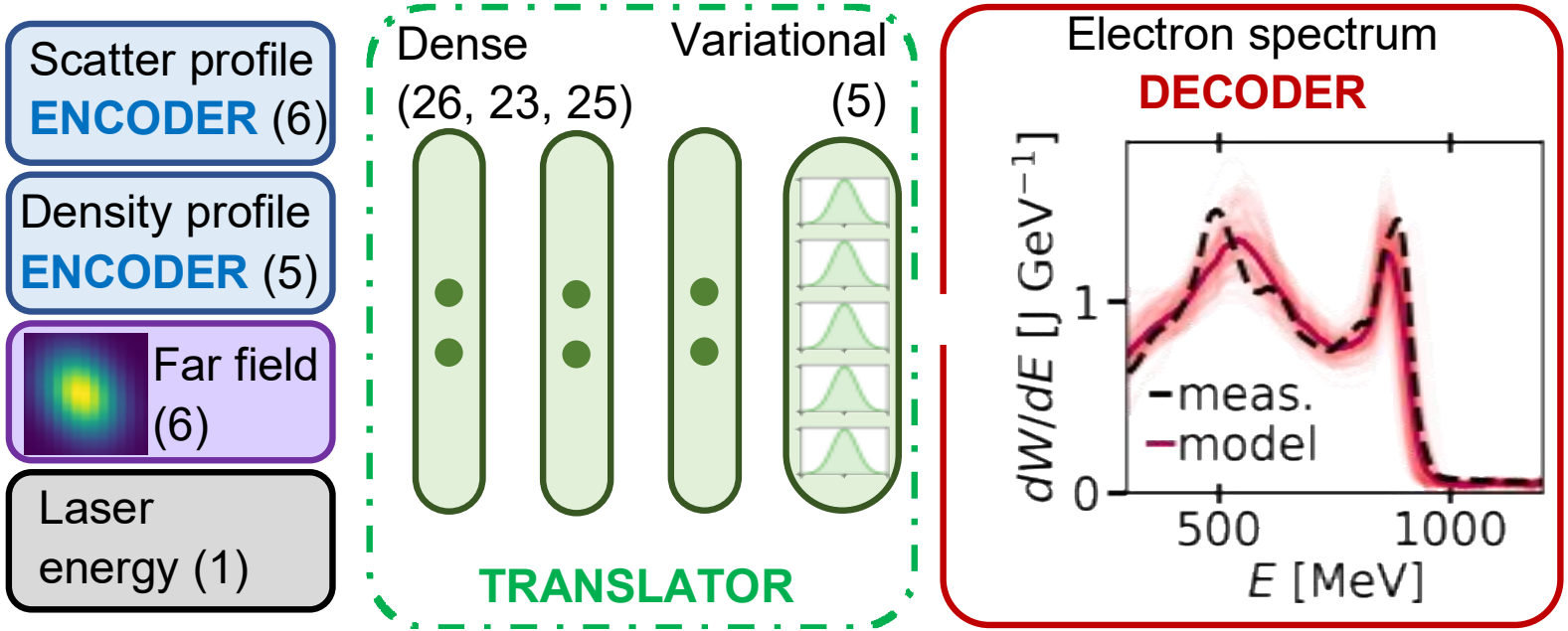



1D diagnostic data → Few representative parameters → 1D diagnostic data

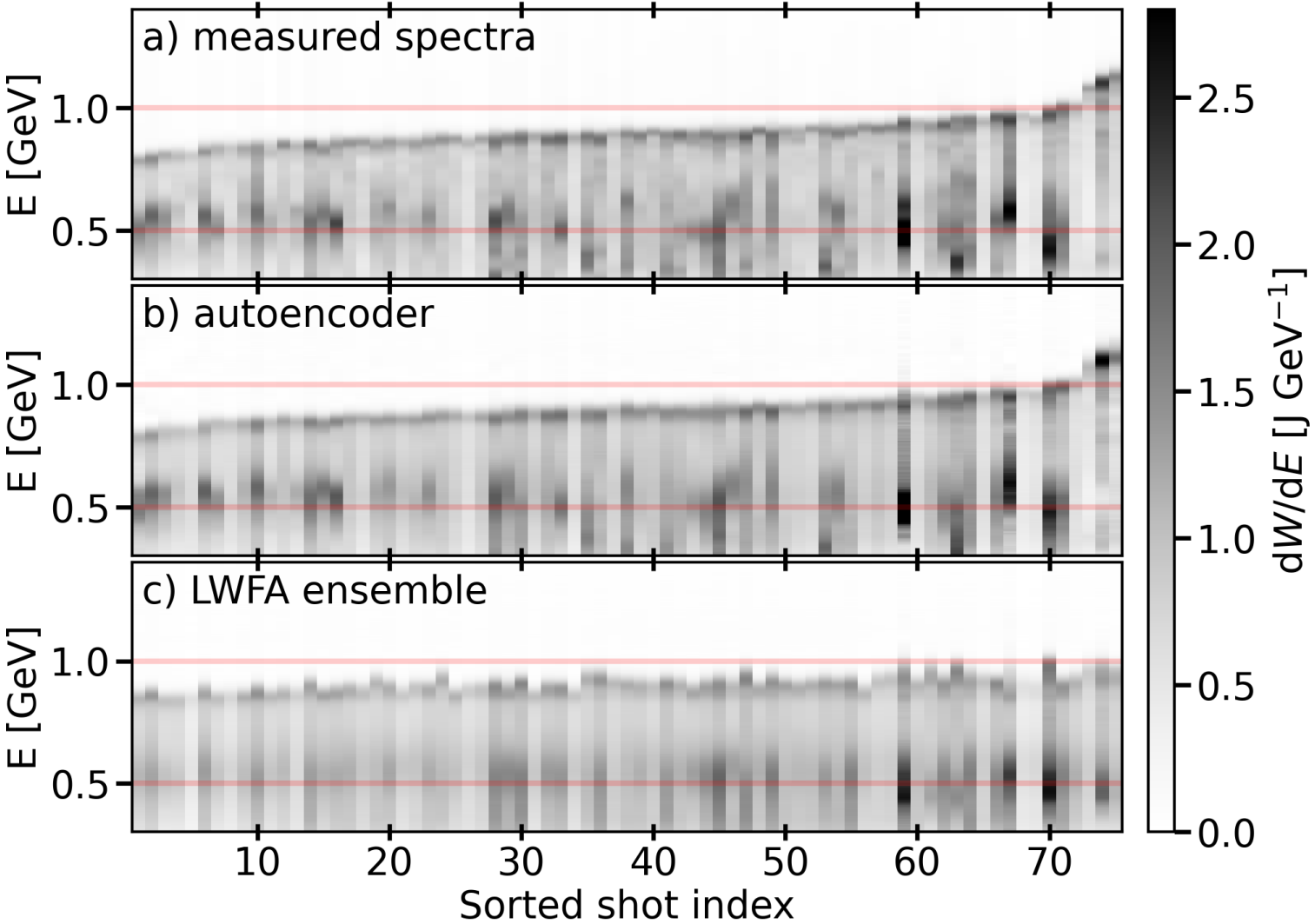
- Learned a reduced representation of the experimental diagnostic measurements

Streeter, MJV *et al.* (2023). Laser wakefield accelerator modelling with variational neural networks. *High Power Laser Science and Engineering, 11*, E9.

# Models connected via translation network to produce predictions

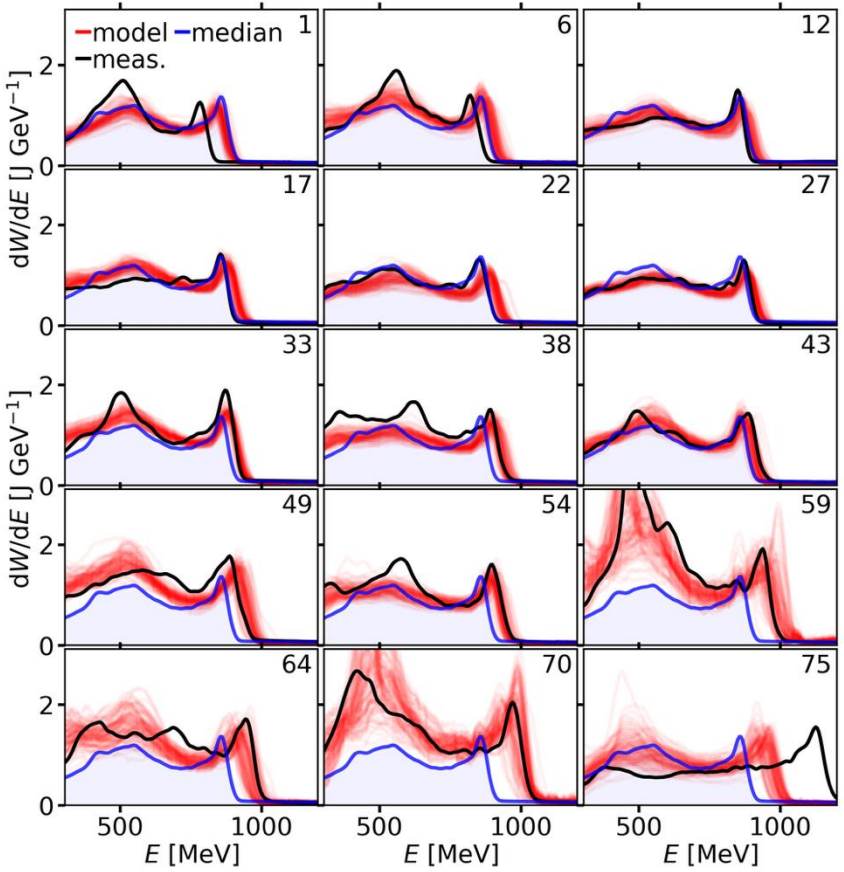



- Secondary diagnostic **encoders** used to produce 18 inputs to **translator**
- **Translator** outputs passed to electron spectrum **decoder** to generate spectrum prediction

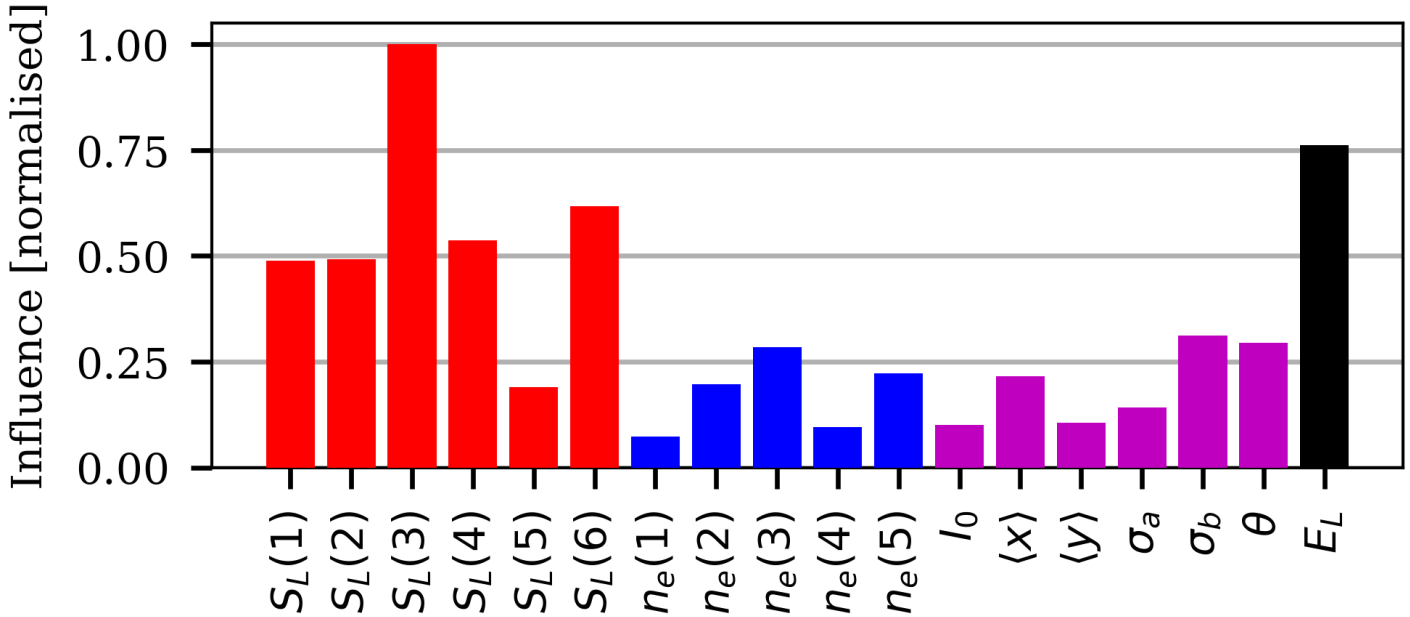

a) measured spectra
b) autoencoder
c) LWFA ensemble
E [GeV]
1.0
0.5
10
20
30
40
50
60
70
Sorted shot index
2.5
2.0
1.5
1.0
0.5
0.0
dW/dE [J GeV$^{-1}$]

# Model predictions compared to measured spectra

- Able to give useful predictions for most electron spectra
- Model performs significantly better than taking the median spectrum
- Ensemble of models trained with different data subsets provides some uncertainty quantification
- Increase dataset size and additional diagnostics (temporal pulse shape, spatial phase) should improve predictive power

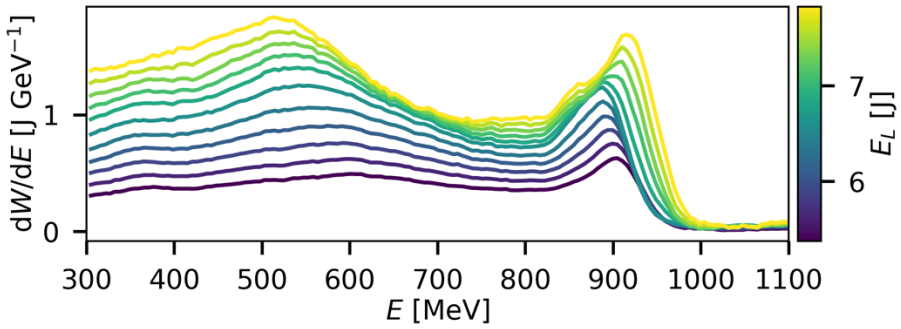


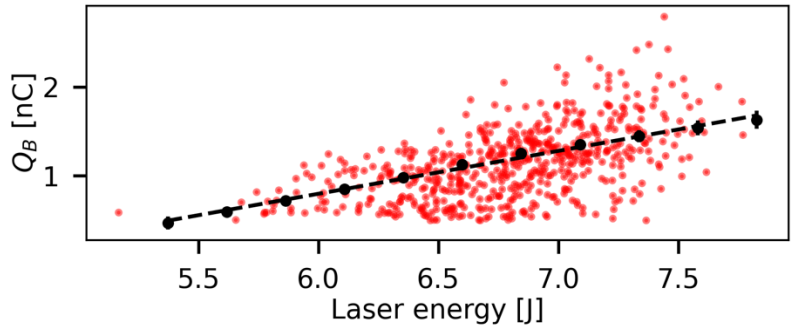
# The influence of each parameter can be examined by seeing its effect on the predicted electron spectrum

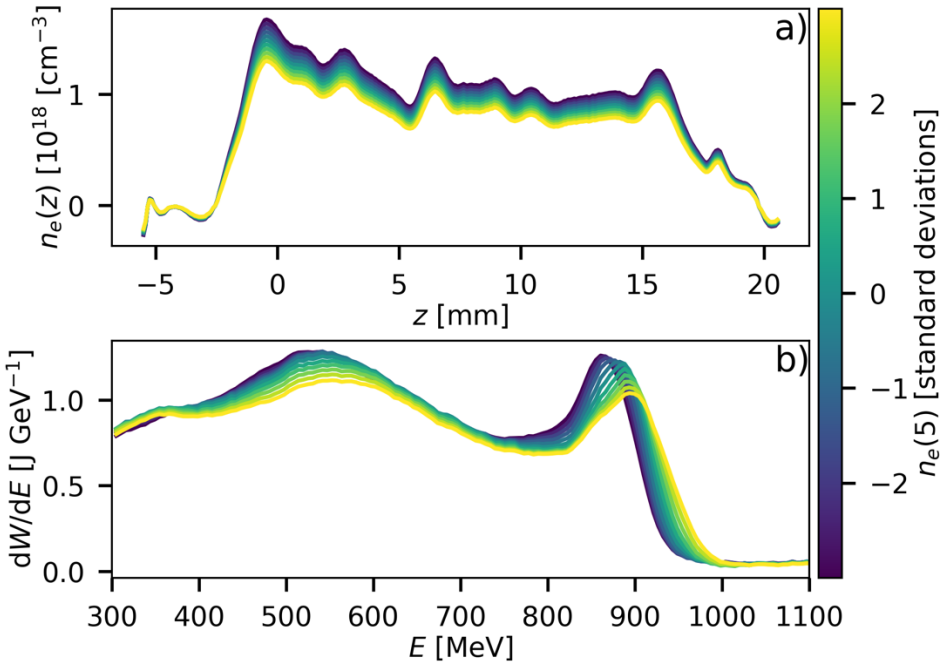



- Laser energy variation (rms 7.5%) was more of an issue than the density variation (rms 4%) for this data
- Scatter diagnostic is not an “input” but very strongly correlated to electron beam

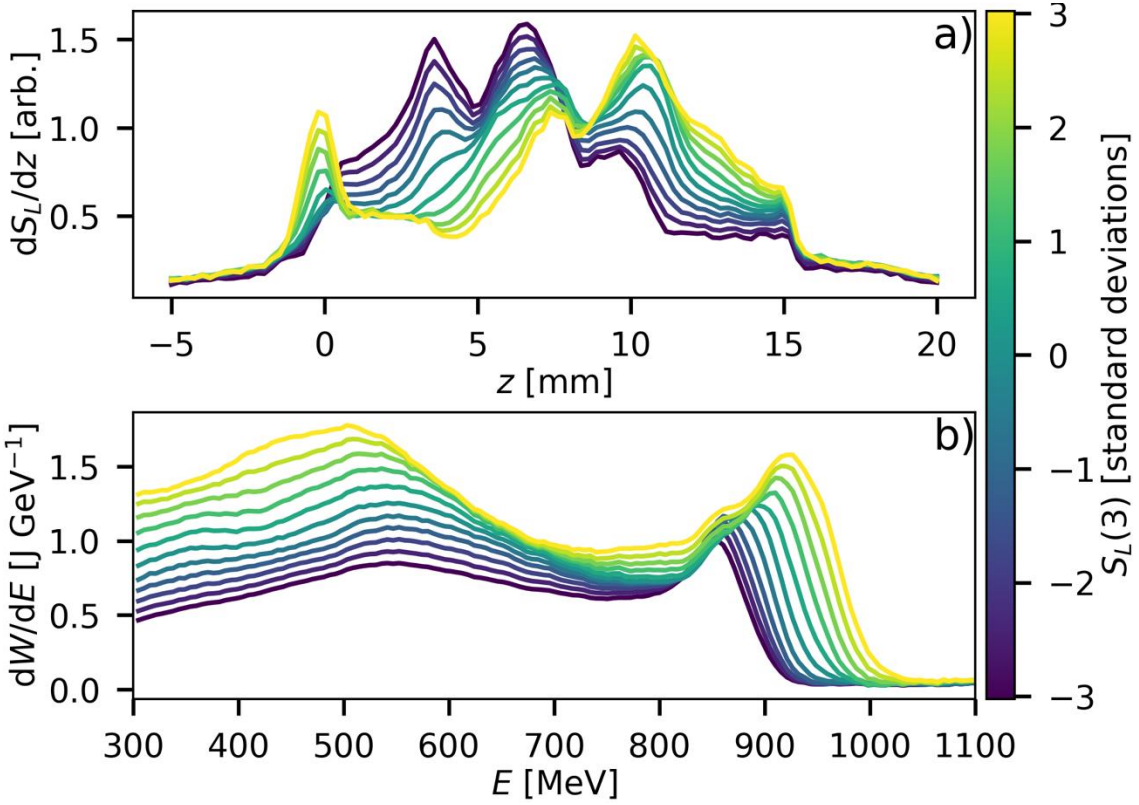
# Model can be used to predict the average effect of changing parameters



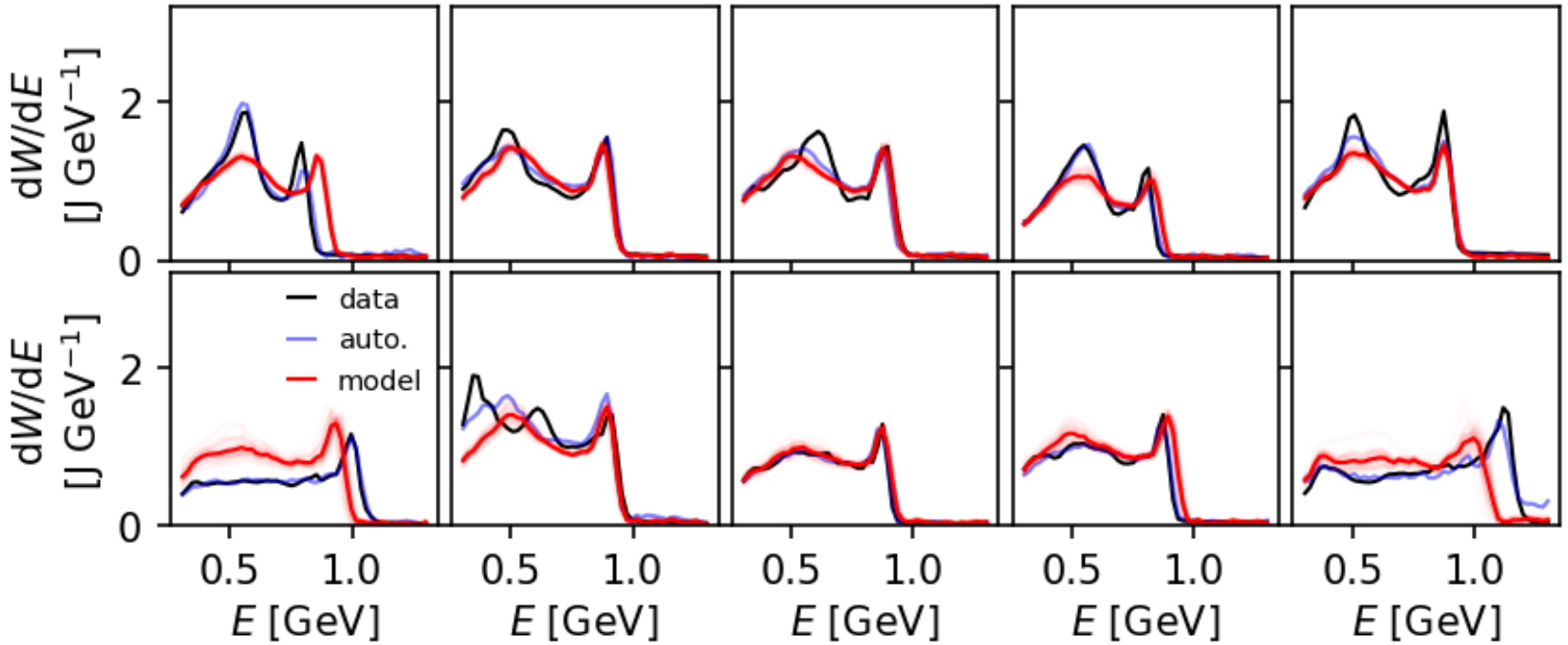
# Model can be used to predict the average effect of changing parameters




Top view signal indicates where self-focusing occurs – linked to injection

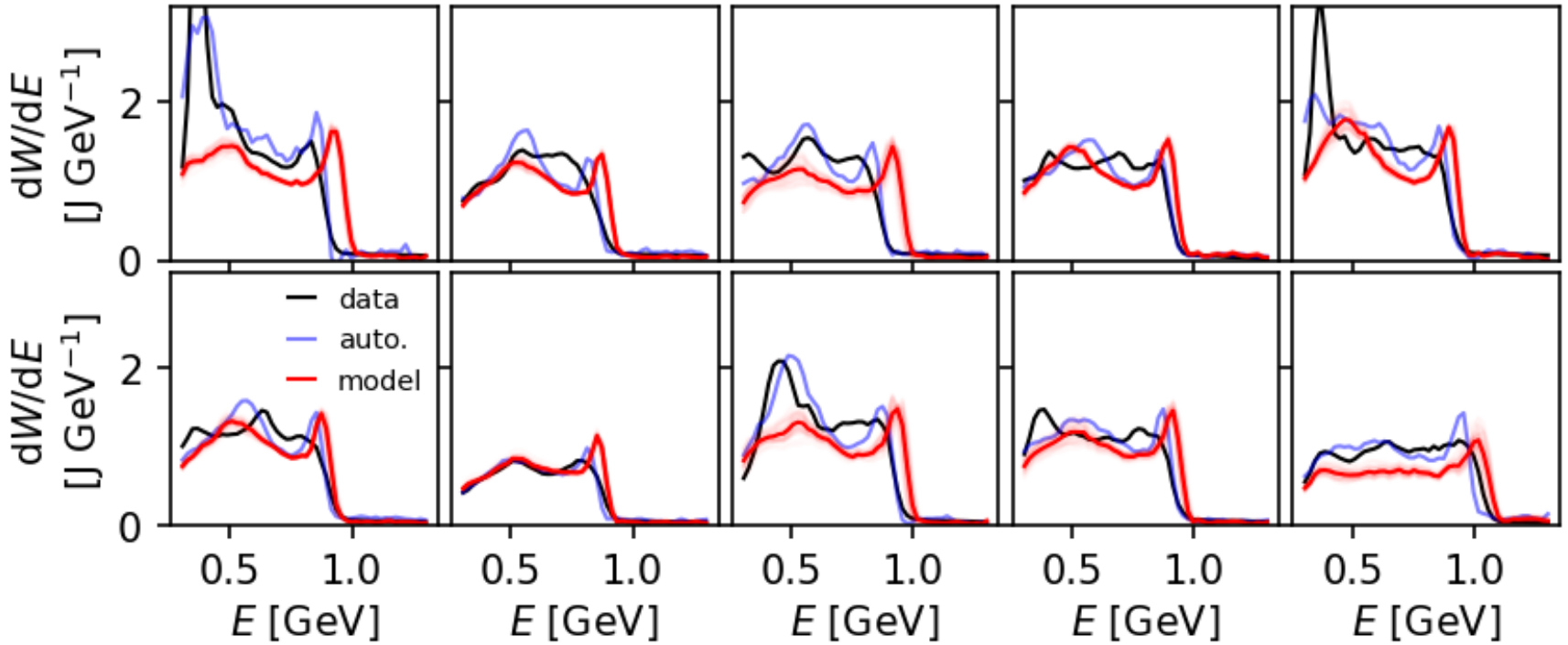
# Model predictions for 10 null shots (scattering laser off)

- Autoencoder pretty accurate in returning shape as matches training data
- Predictive network accurate in most cases



# Model predictions for 10 ‘hot’ shots (scattering laser on)

- Autoencoder fails to return shape due to qualitative change to spectrum
- Predictive network provides estimate of pre-interaction spectrum



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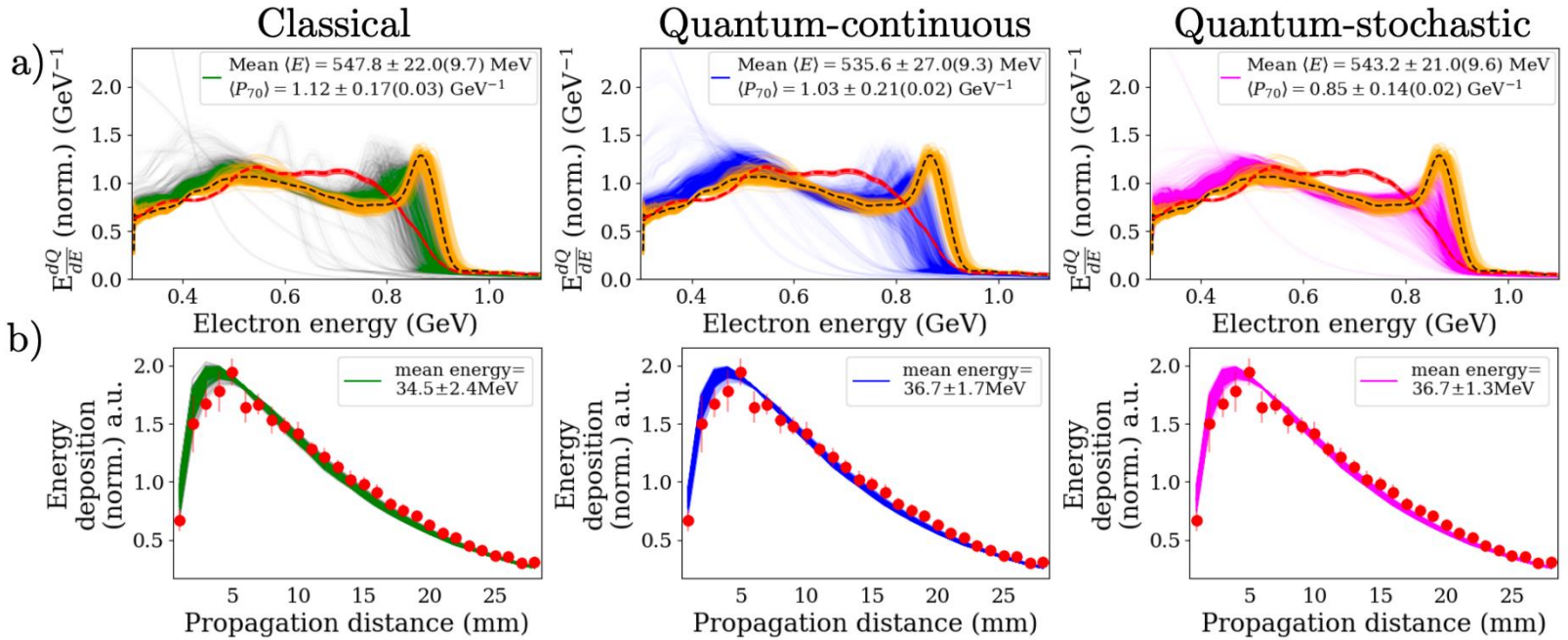
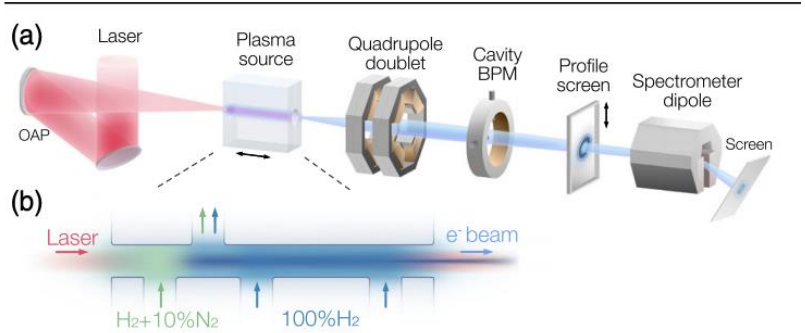
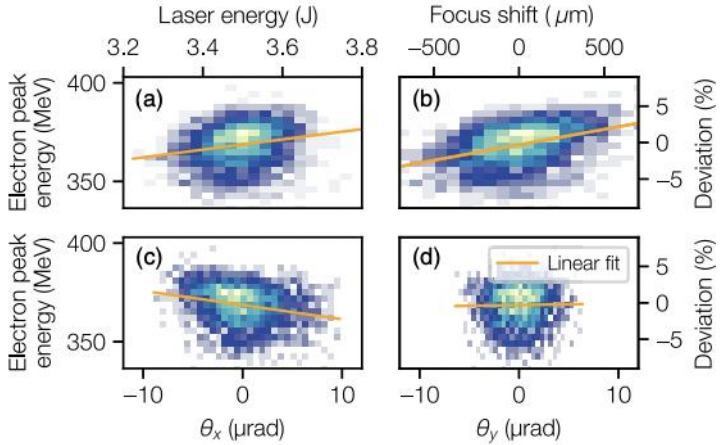


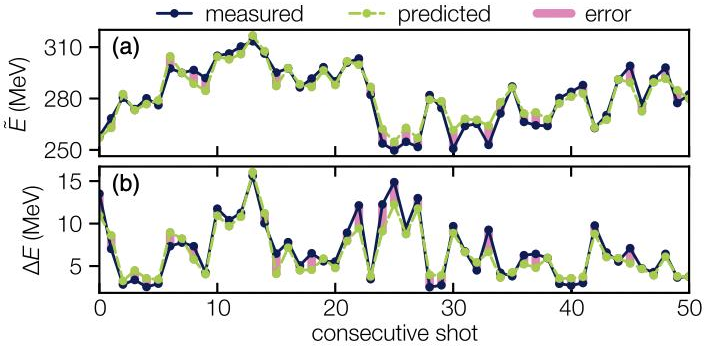

E.E. Los *et al.* HPLSE 2025;13:e25
https://arxiv.org/abs/2407.12071

# Measured laser parameters used to predict electron properties

- The variation of the electron beam is largely due to the variation in the laser
- With good diagnostics of the inputs can be known well enough to predict performance
- Indicates how to improve/stabilise experiment



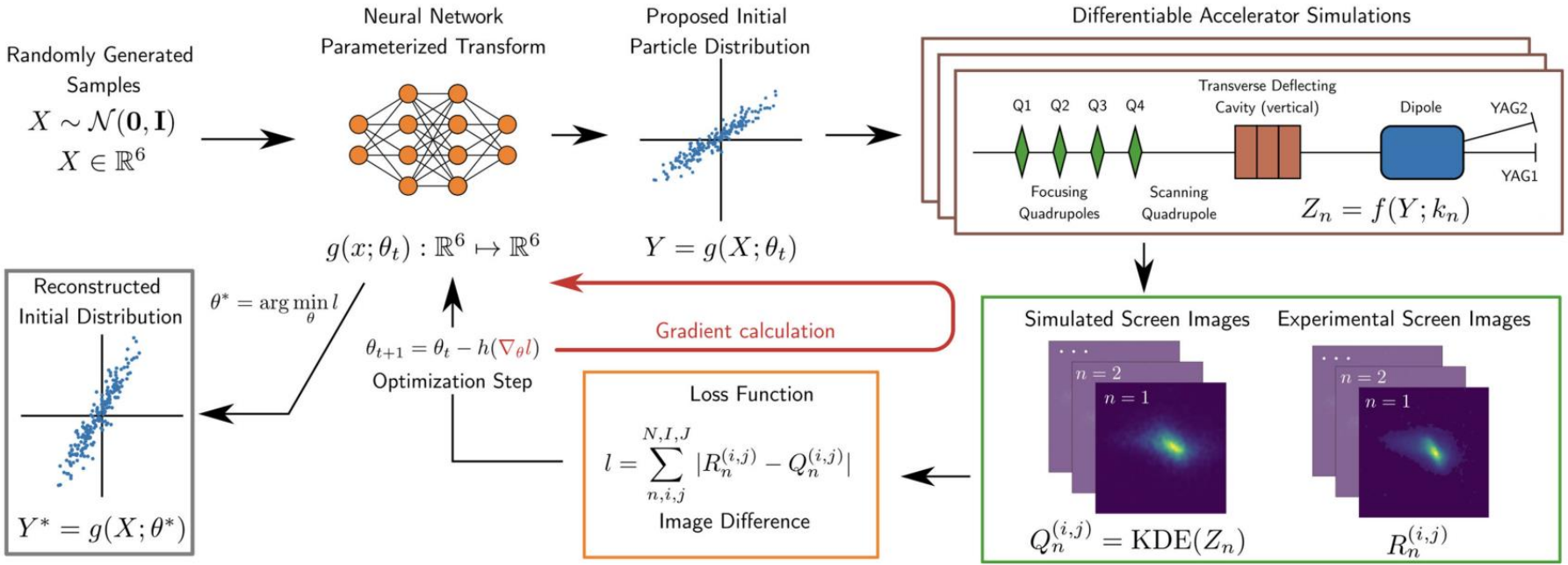




A. Maier, et al. Phys. Rev. X 10, 031039 (2020)

M. Kirchen, et al. Phys. Rev. Lett. 126, 174801 (2021)

# The combination of generative ML and differential simulations offer new possibilities

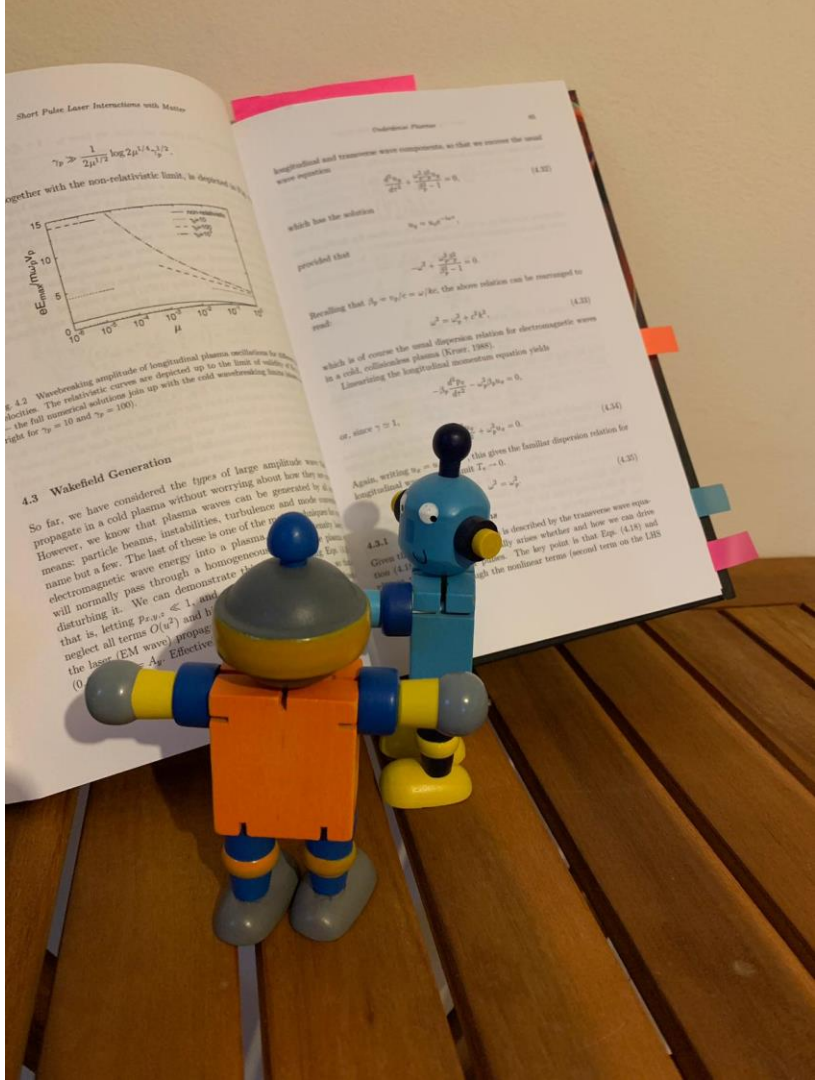



R. Roussel, et al. PRAB 27, 094601 (2024)

# EPAC: New LPA Facility embracing ML from the start

## Large-scale purpose built £100m laser plasma facility

- 1PW at 10 Hz repetition rate
- Development of secondary sources
- Dedicated beamlines for applications

# Thank you!

**L. Calvin, N. Cavanagh, E. Gerstmayr, P. Parsons, G. Sarri**
*Queen's University Belfast*
**C. Colgan, E. Los, B. Kettle, S.P.D. Mangles, R. Watt, Z. Najmudin**
*JAI, Imperial College London*
**N. Bourgeois, S.J.D. Dann, P.P. Rajeev, D.R. Symes**
*Central Laser Facility, RAL*
**C. Arran, C.C. Cobo, C.D. Murphy, C.P. Ridgers,**
*York Plasma Institute, University of York*
**J.A. Cardarelli, R. Fitzgarrald, A.S. Joglekar, Q. Qian, A.G.R. Thomas**
*University of Michigan*