

Applications of machine learning and active feedback in laser- plasma wakefield accelerators

Matthew Streeter

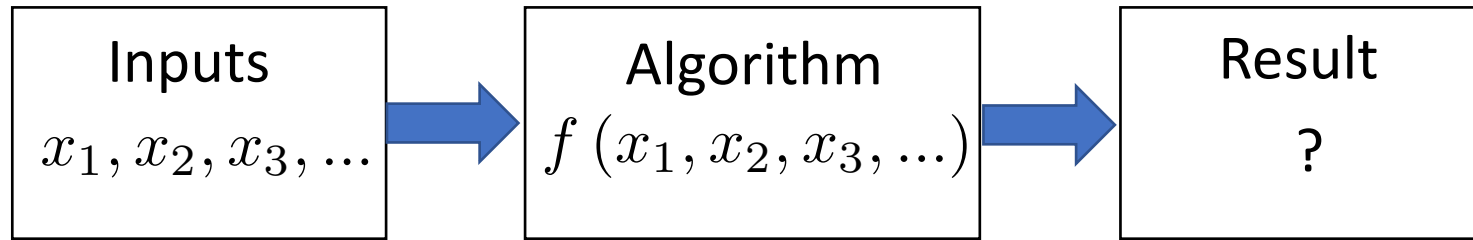
(Stuart Mangles)

John Adams Institute for Accelerator Science

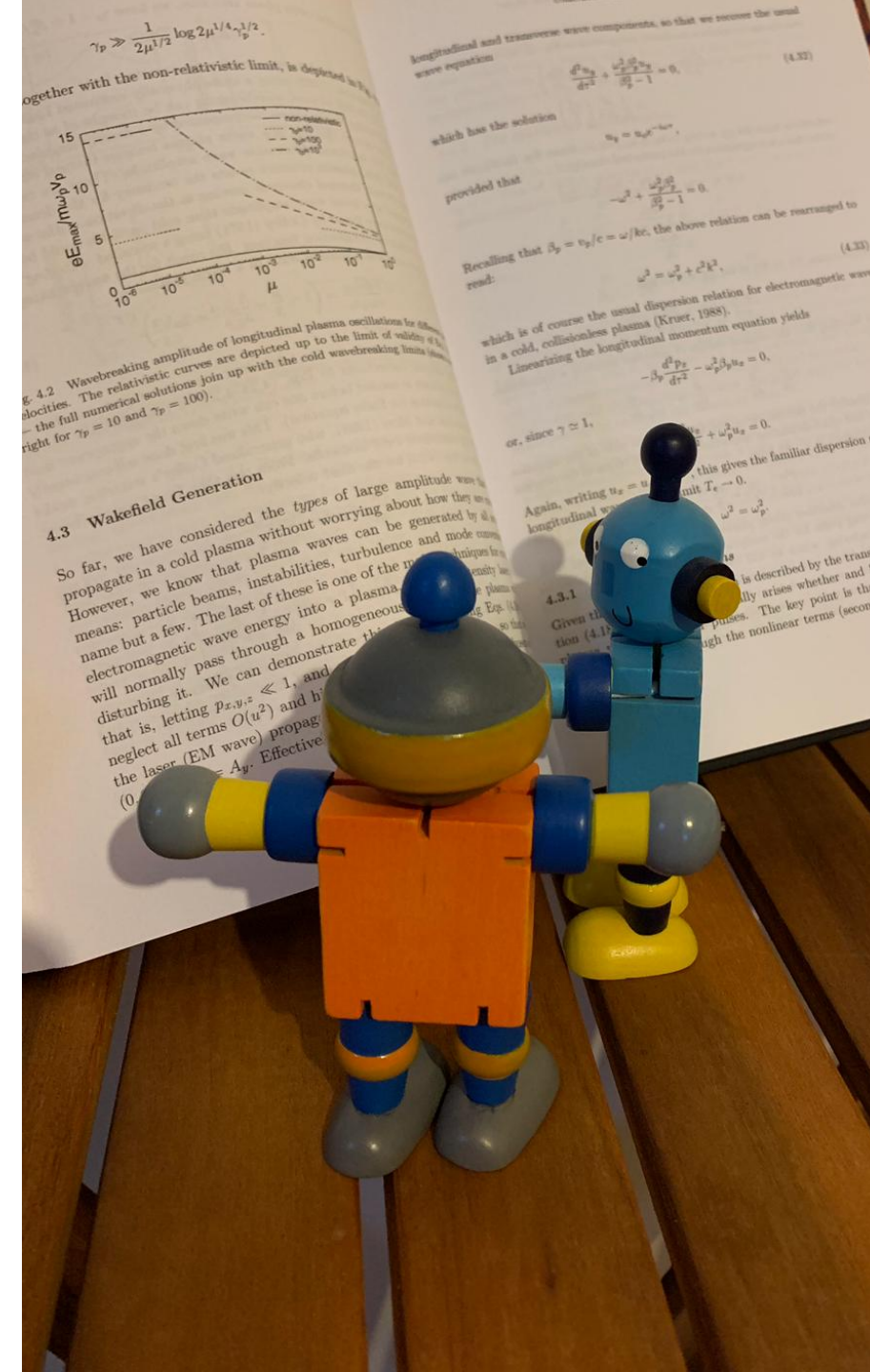
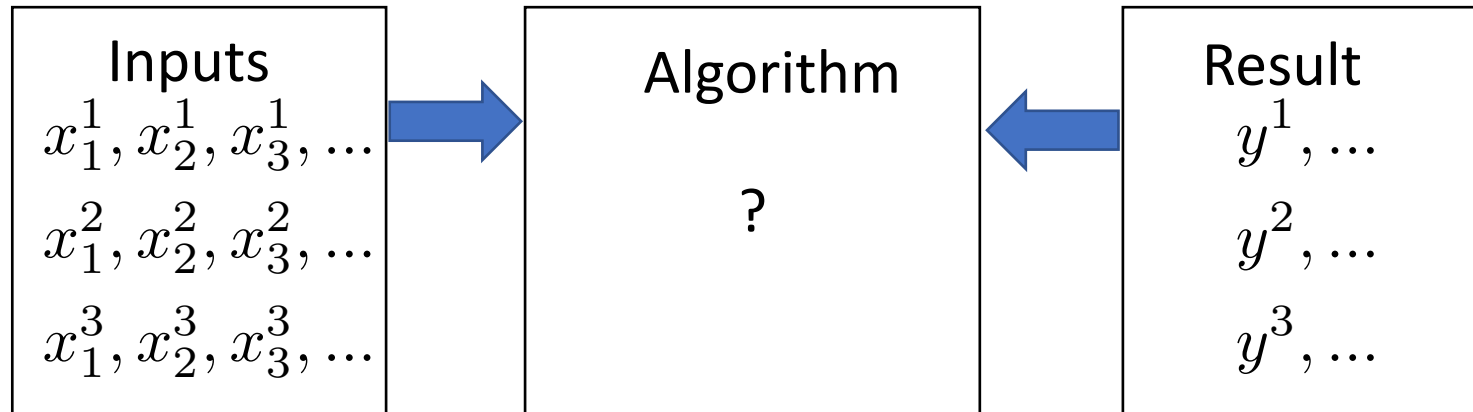
Imperial College London

How can machine learning help?

- An algorithm performs a calculation with a set of inputs to obtain a result



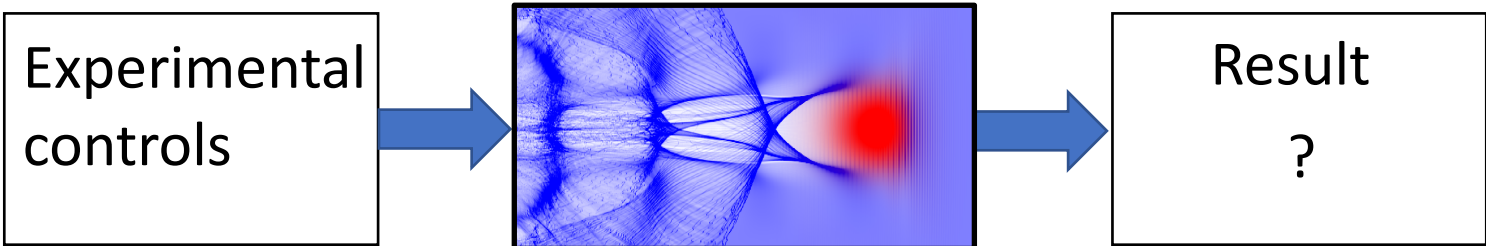
- A (supervised) 'learner' will take inputs and results and create the algorithm



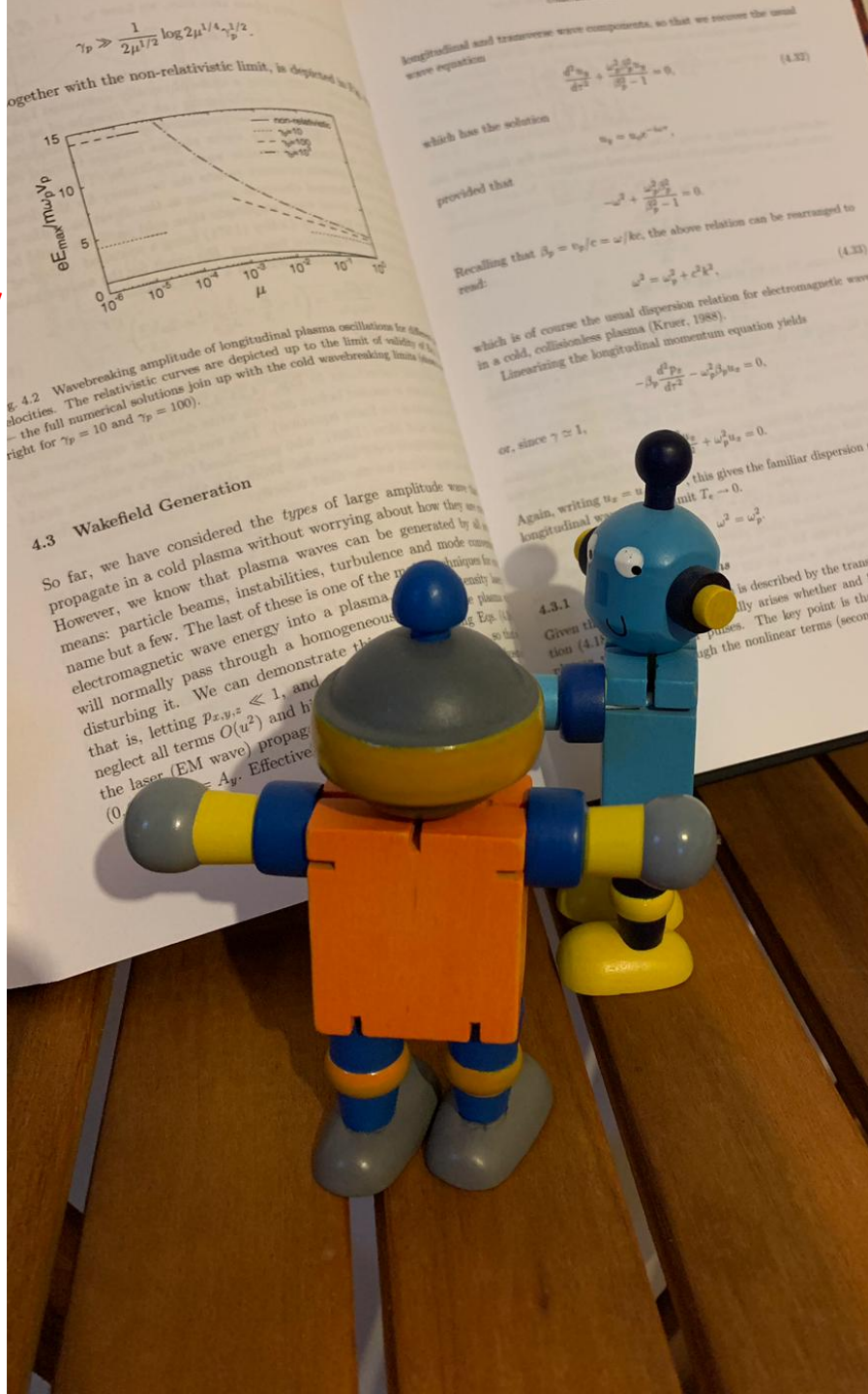
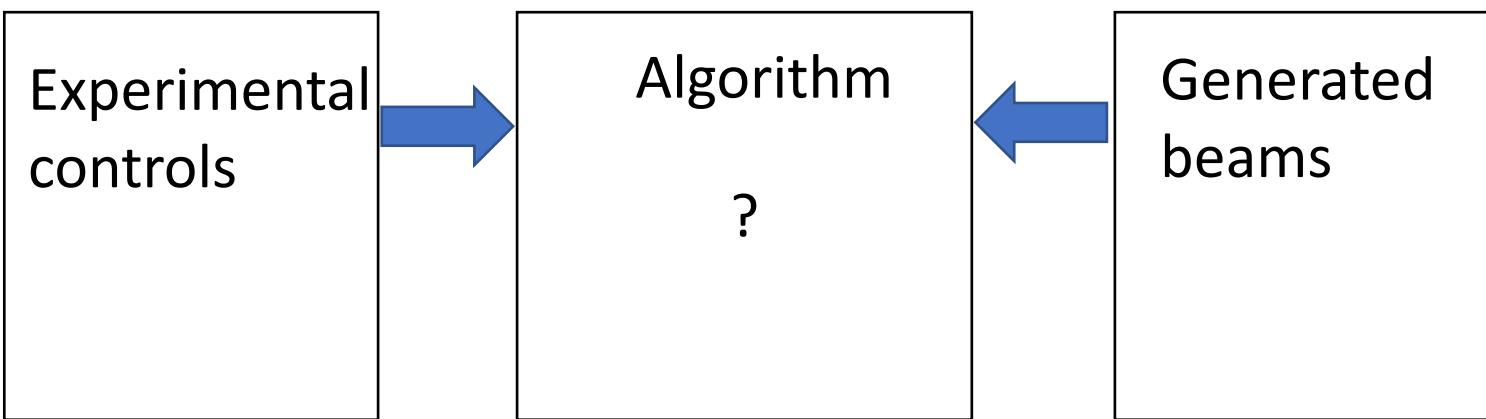
How can machine learning help?

experimenter laser shot laser and plasma parameters electron/x-ray

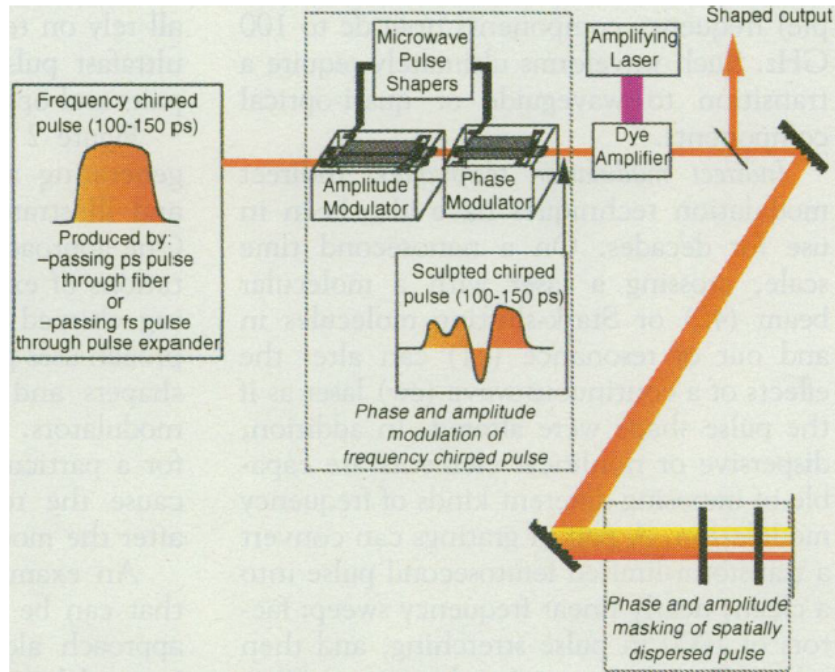
- An ~~algorithm~~ performs a ~~calculation~~ with a set of ~~inputs~~ to obtain a ~~result~~



- A (supervised) 'learner' will take inputs and results and create the algorithm



High repetition rate allows for active feedback techniques



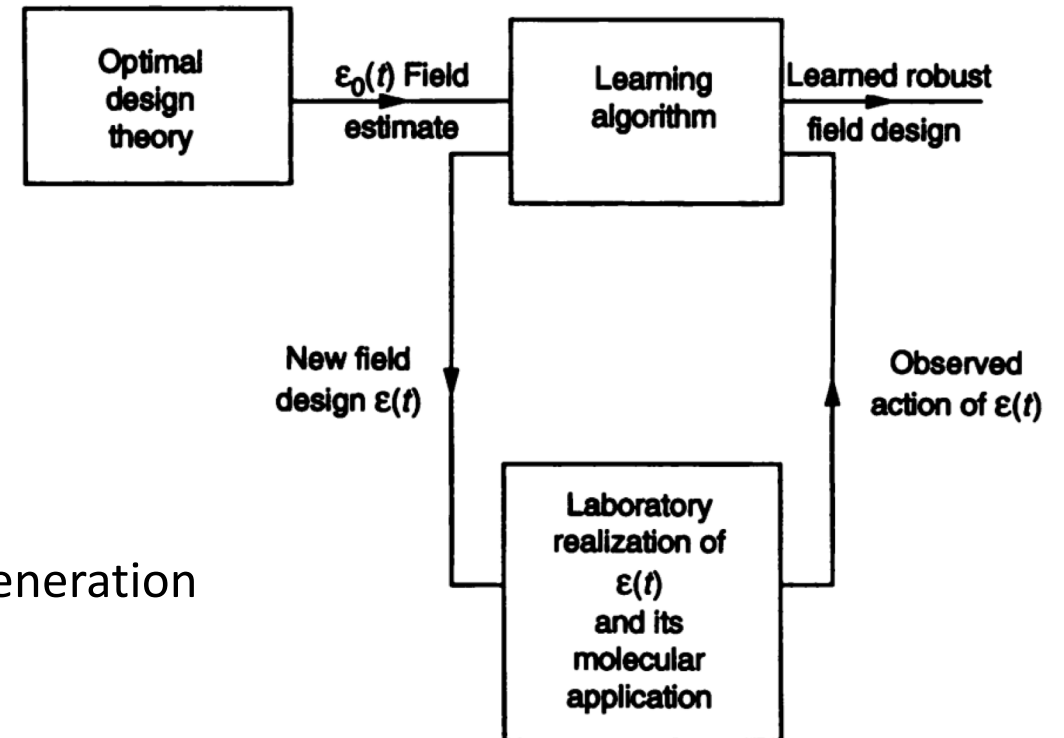
- “Fitness function” based on desired outcome defined
- Feedback loop shapes the pulse to improve output at each generation
- Commonly used on kHz (few mJ energy) lasers

Coherent Control of Quantum Dynamics: The Dream Is Alive

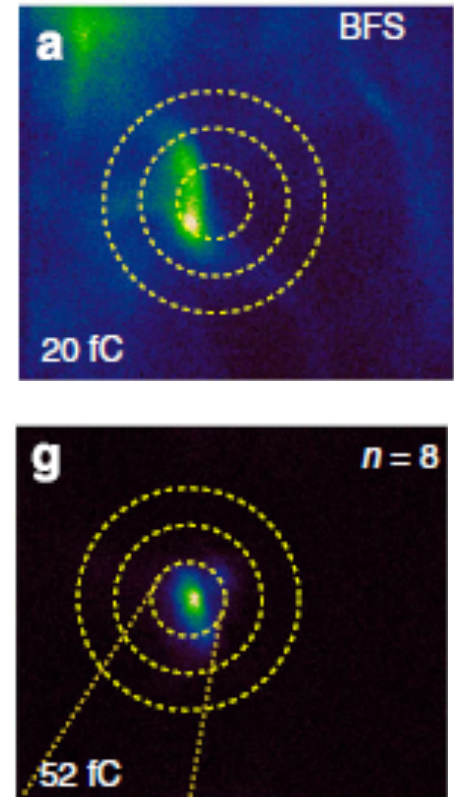
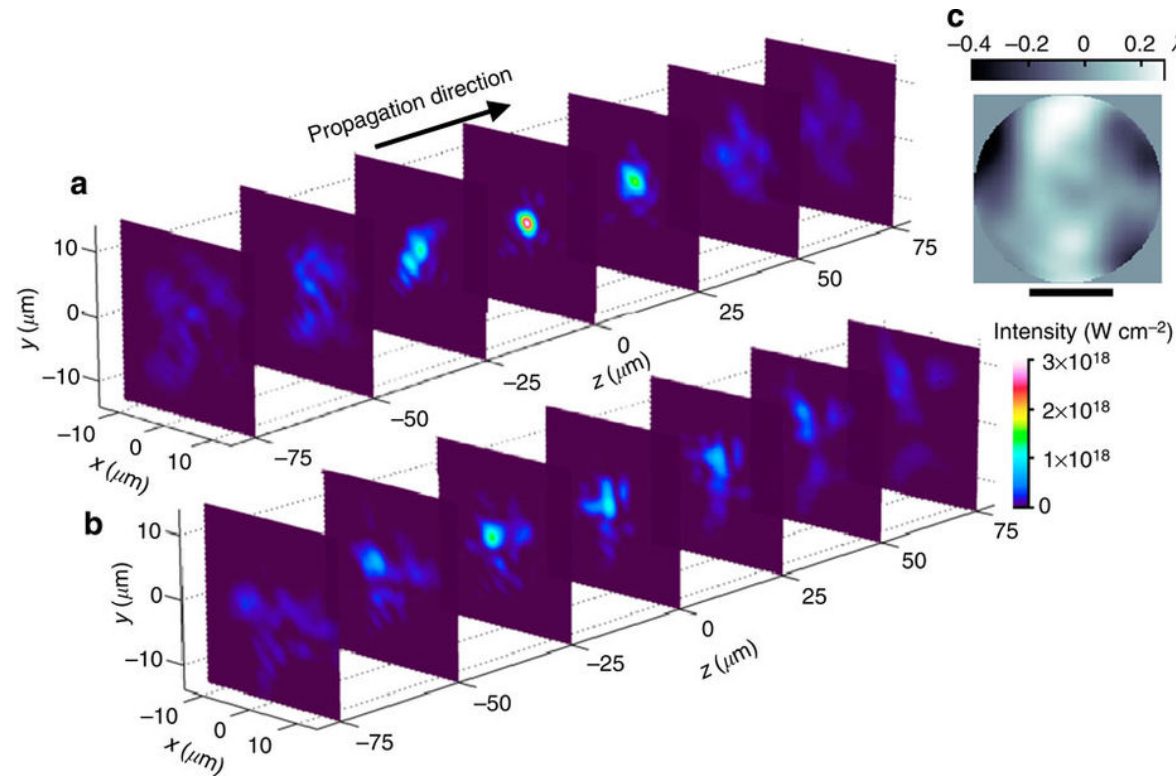
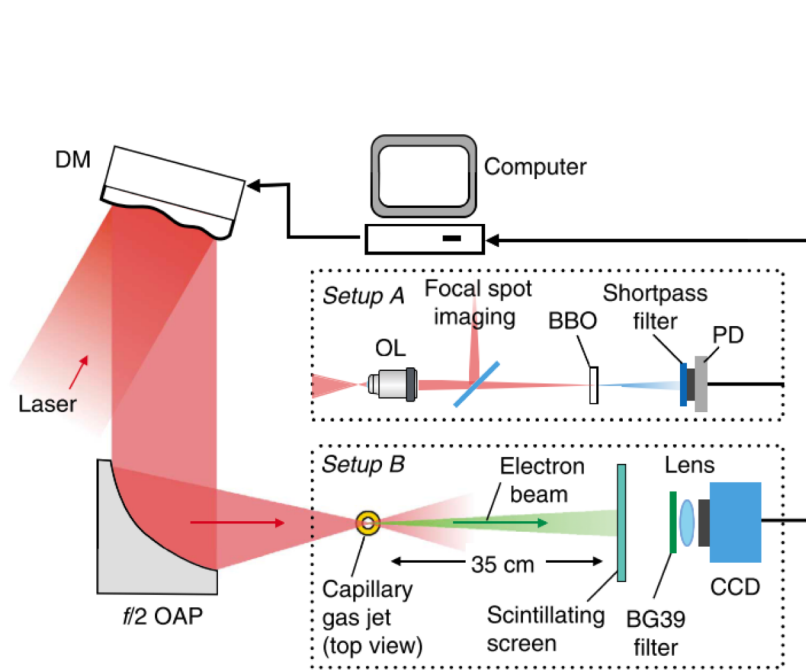
Warren S. Warren, Herschel Rabitz, Mohammed Dahleh

Current experimental and theoretical progress toward the goal of controlling quantum dynamics is summarized. Two key developments have now revitalized the field. First, appropriate ultrafast laser pulse shaping capabilities have only recently become practical. Second, the introduction of engineering control concepts has put the required theoretical framework on a rigorous foundation. Extrapolations to determine what is realistically possible are presented.

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Optimisation of electron beams with spatial feedback with CUOS I³ laser

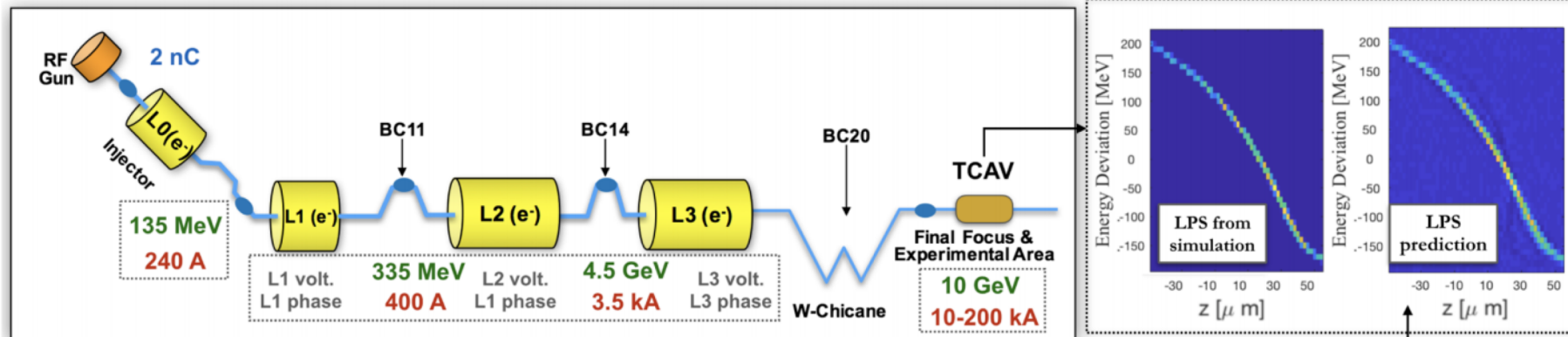


Non-ideal focus gave **higher charge** and **better divergence**.

Z. H. He *et al*, Nat. Comm 2015

Neural networks used for prediction of beam properties in large accelerators

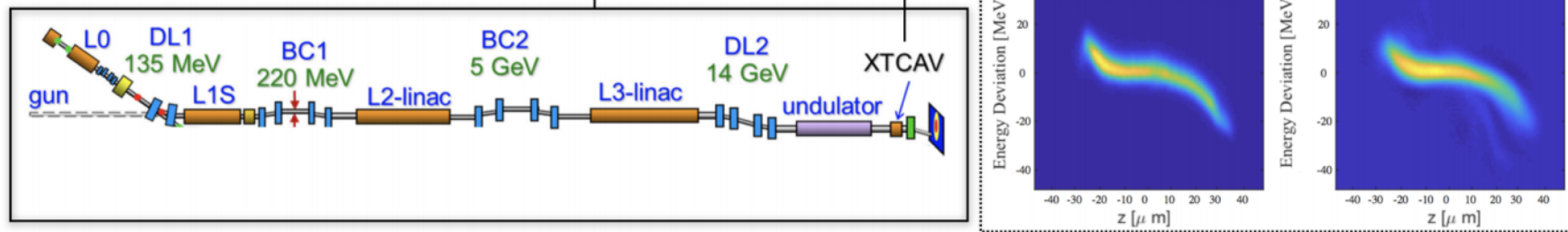
FACET-II electron accelerator schematic



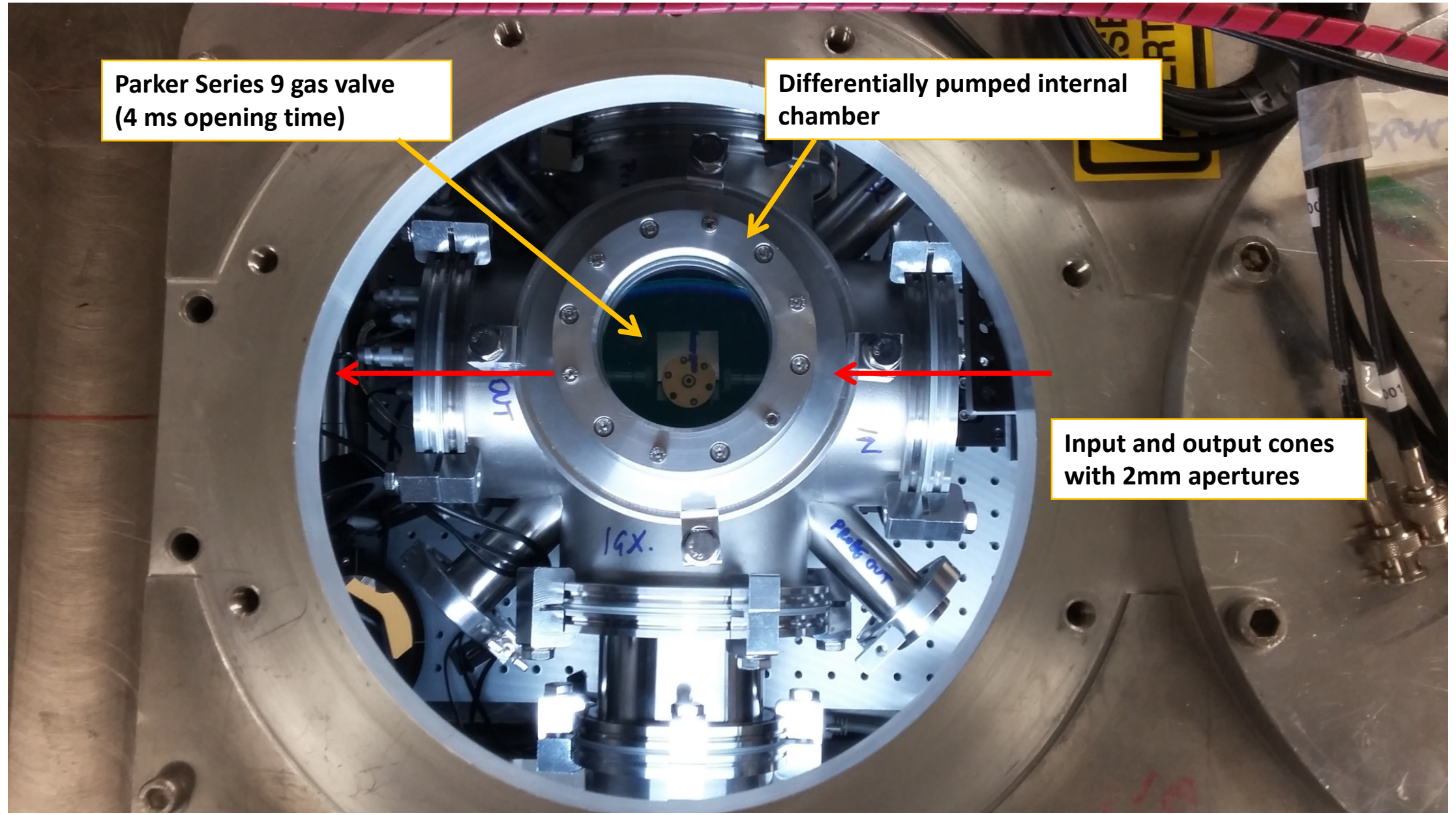
Non-destructive measurements of e-beam and linac parameters

ML based virtual diagnostic

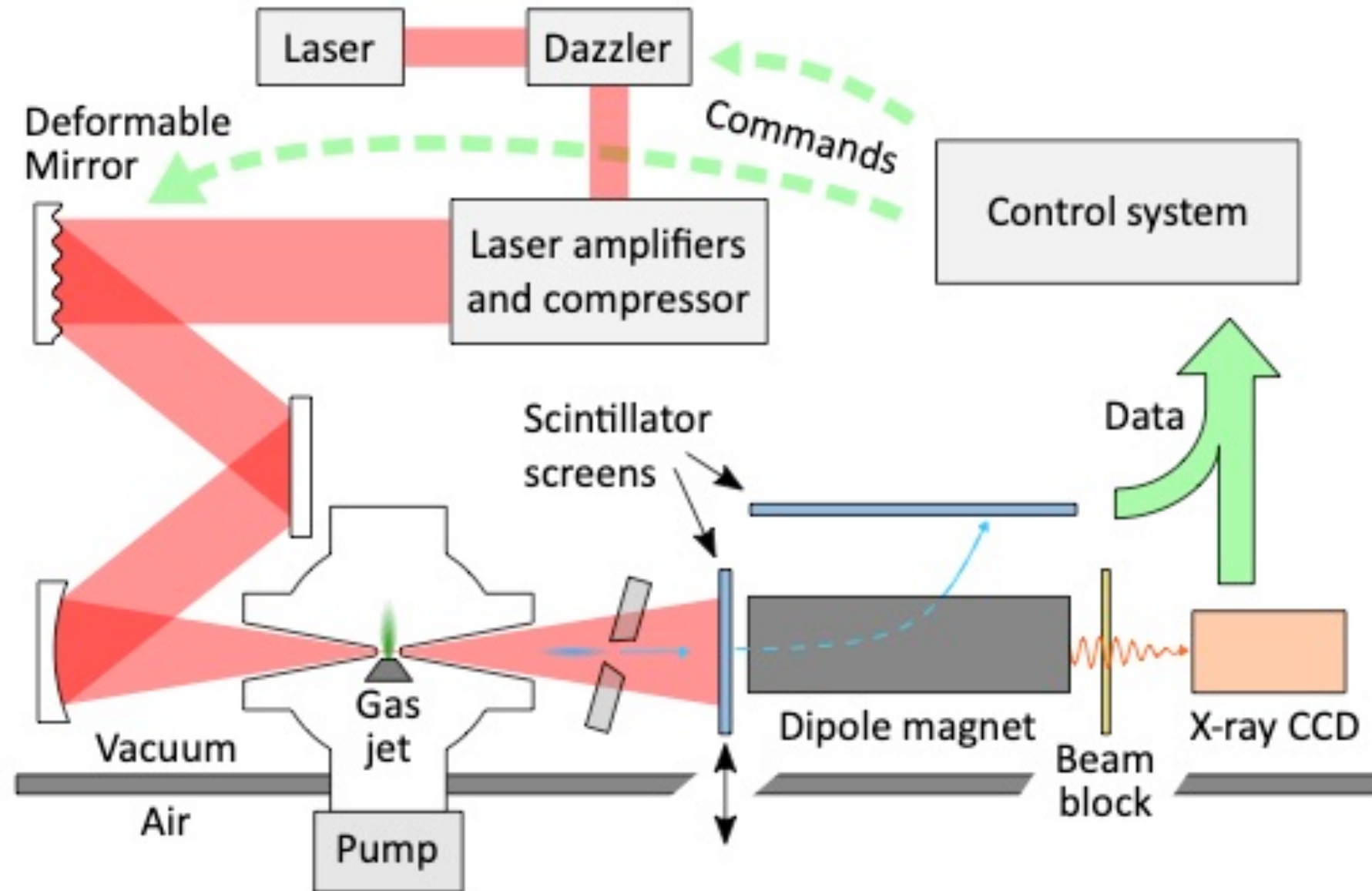
LCLS accelerator schematic



2017 Experiment in 20 TW Gemini TA2 at the CLF



2017 Experiment in Astra Gemini at the CLF



Optimisation loop with a genetic algorithm

Test the population

Parameters

1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4

Evaluation

S
S
S
S
S
S

Creating the next generation

Ranking

S
S
S
S
S
S

Selection and breeding

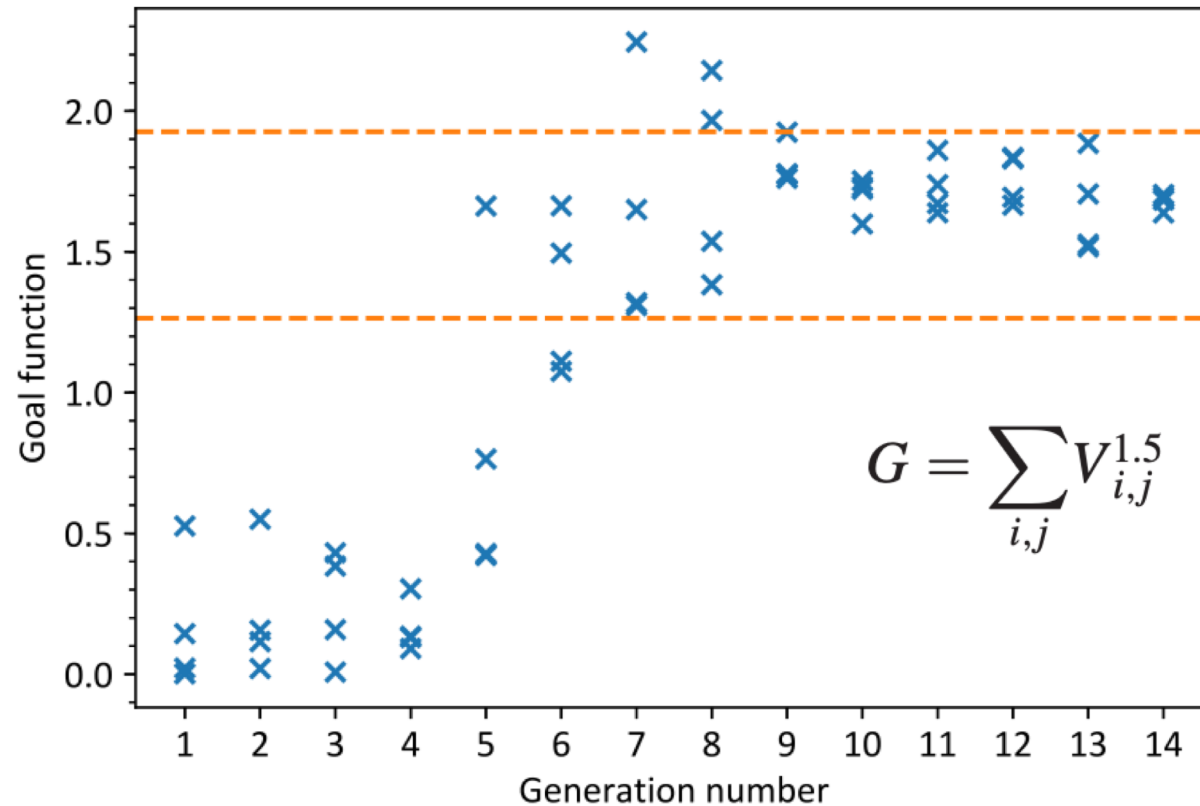
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4

Mutation

1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4
1	2	3	4

To the next loop

Electron beam charge density increased by a factor of 2 by automatic control of the spatial phase

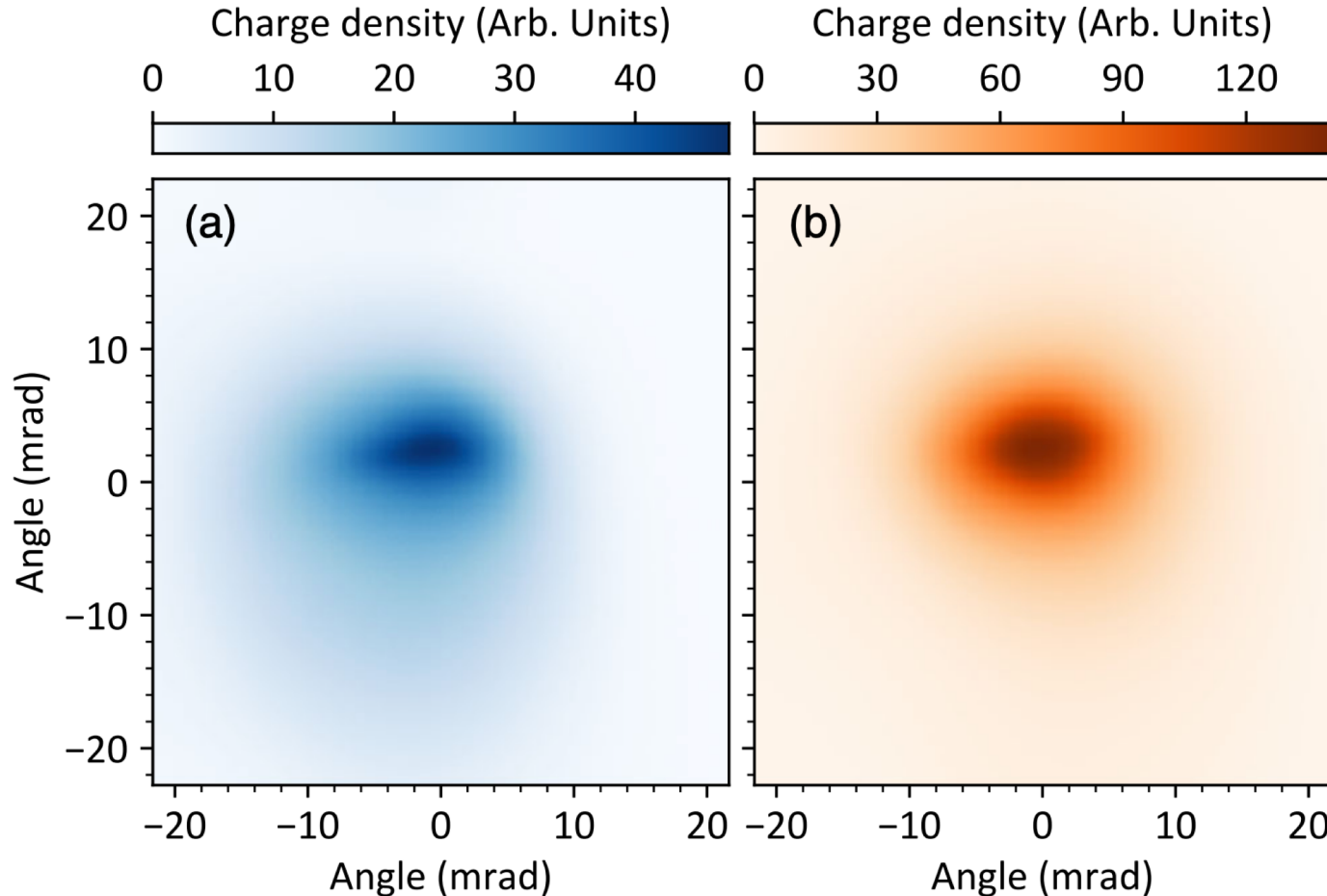


- Started from 'flat' deformable mirror position with some random fluctuations
- Optimised the actuator voltages so no need for measurements or calibrations
- Reached equivalent level of performance when the spot was optimised with a focal spot camera

Streeter, M. J. V., et al. *Applied Physics Letters*, 112(24), 244101 (2018).

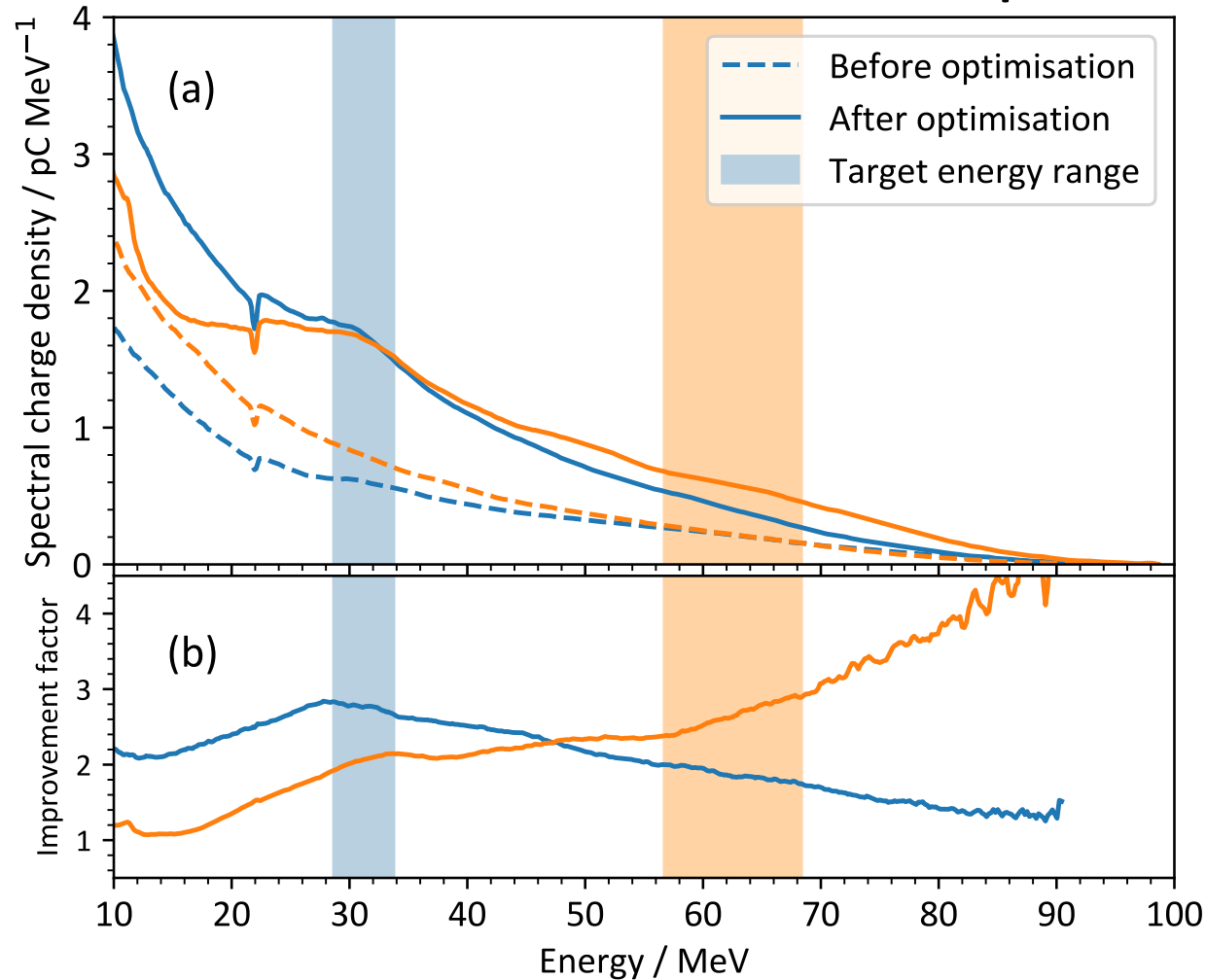
Dann, S. J. D. et al *Physical Review Accelerators and Beams*, 22(4), 041303 (2019).

Electron beam charge density optimised by a factor of 3 by automatic control of the spectral phase

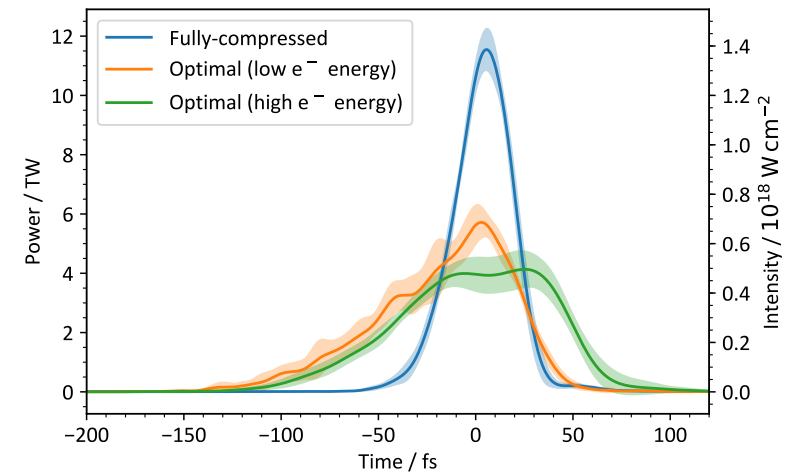


- Started from compressed pulse with some random variations
- Optimal pulse for electron generation was not the most compressed

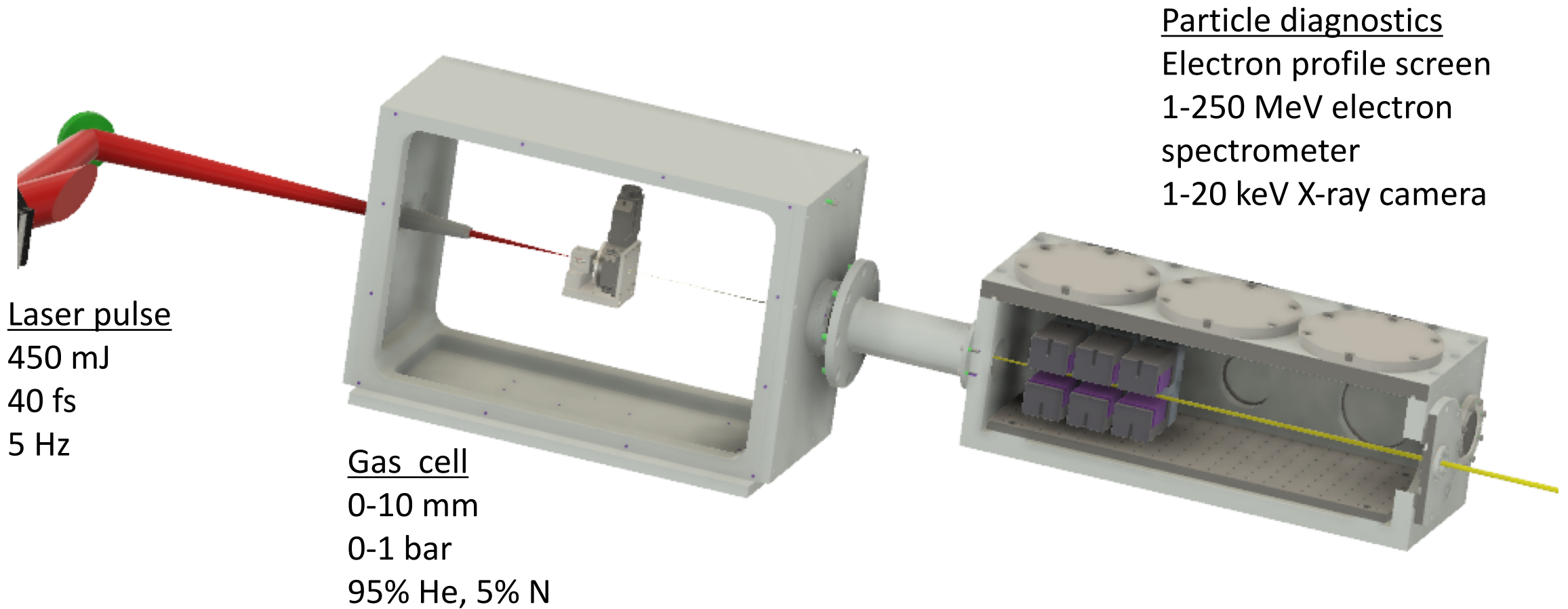
Optimising different parts of the spectrum required different pulse shapes



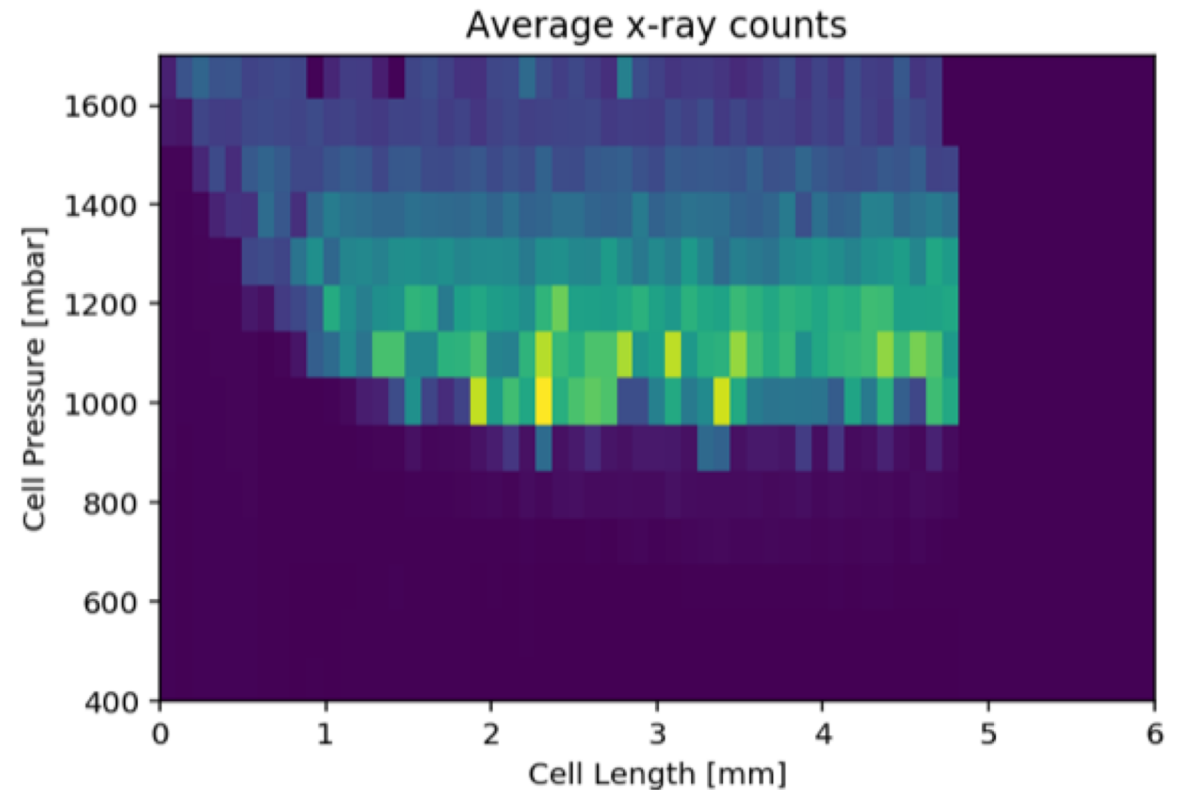
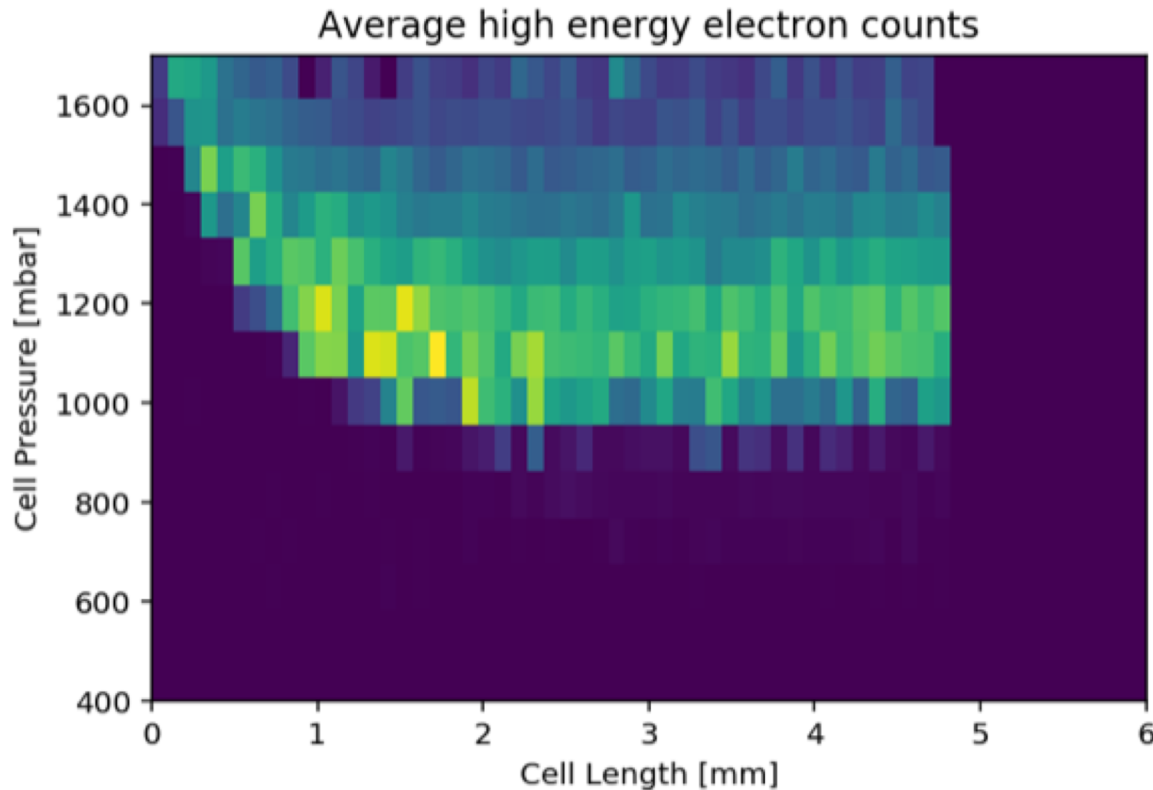
Fully compressed pulse shape and optimized cases



Ongoing experiment in 20 TW Gemini TA2



Big(ish) data allows for high quality parameter scans

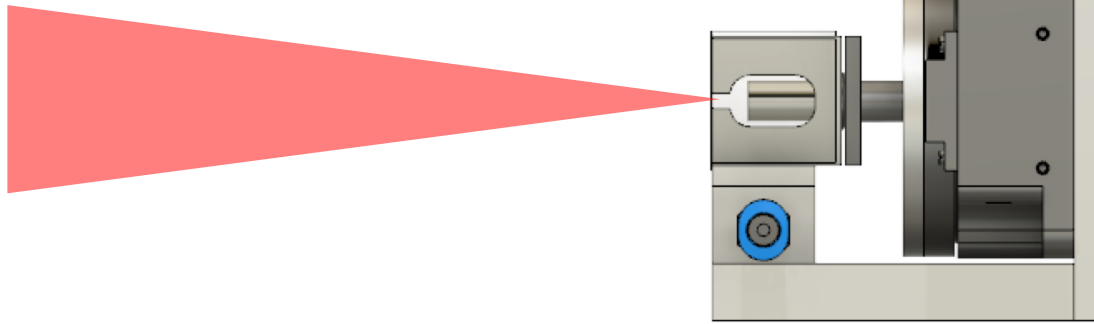


Scan time = time per point $\times$ (points per dimension)^{number of dimensions}

- Time for 2D scan was approx. 2 hours
- 3D scan would take >40 hours

Curse of dimensionality!

Control



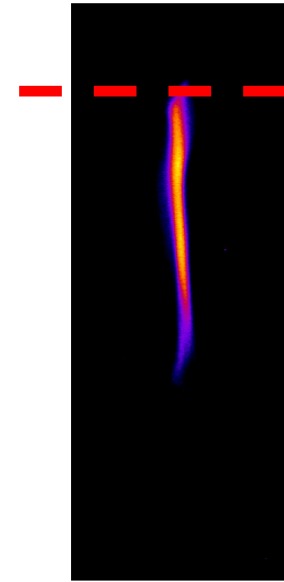
Laser

Energy
Spectral phase
(temporal pulse shape)
Spatial phase
(focal spot shape)

Plasma

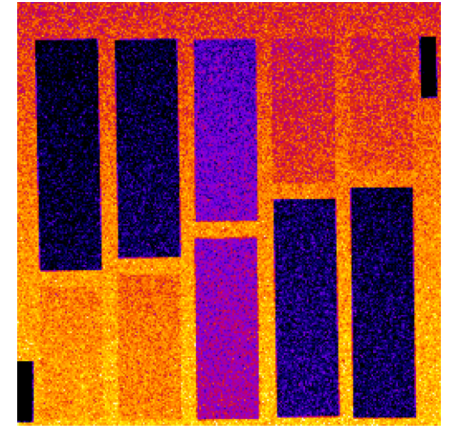
Density
Length
Longitudinal profile

Feedback



Electrons

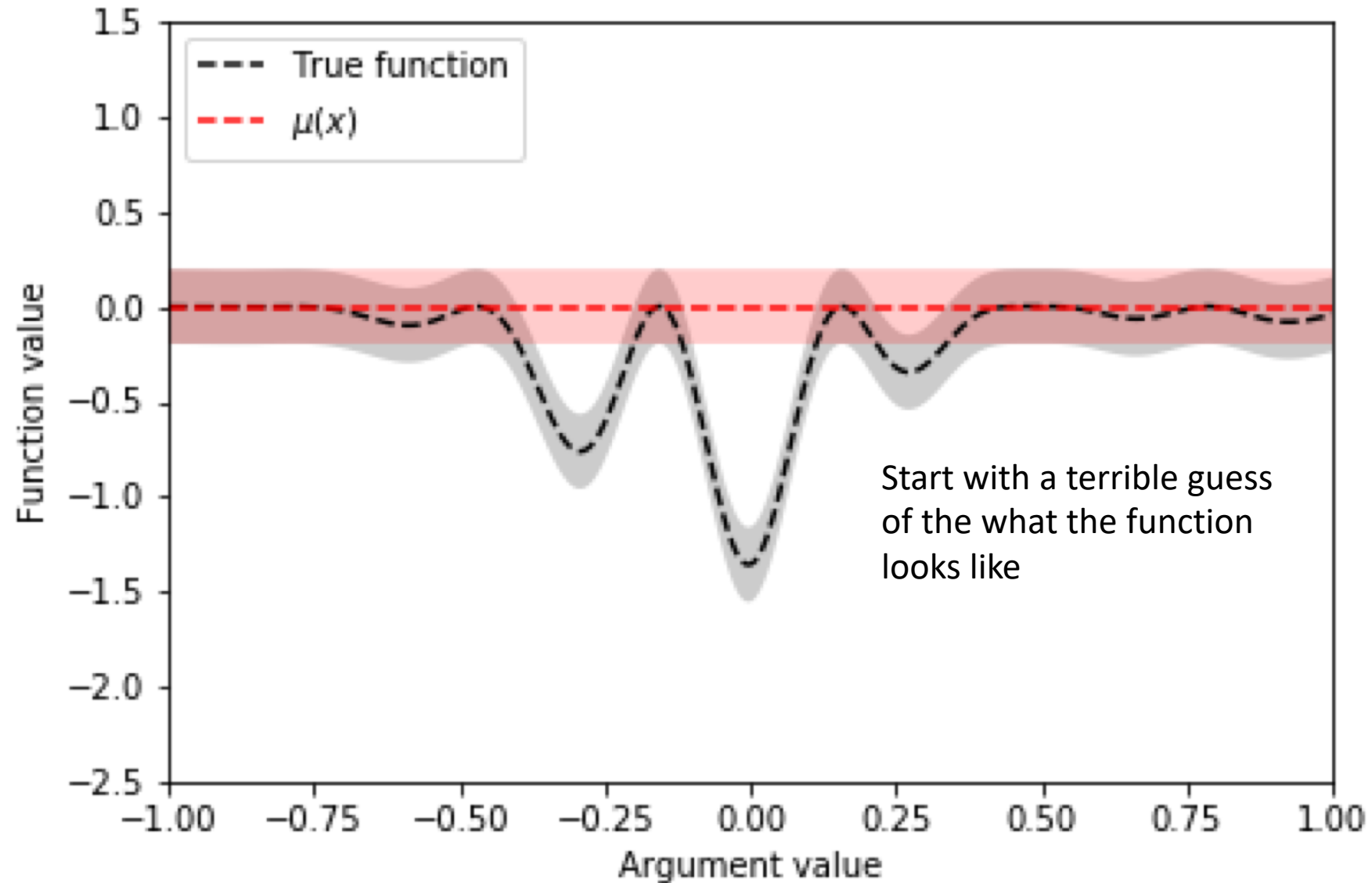
Maximum energy
Charge
Spectrum
Divergence



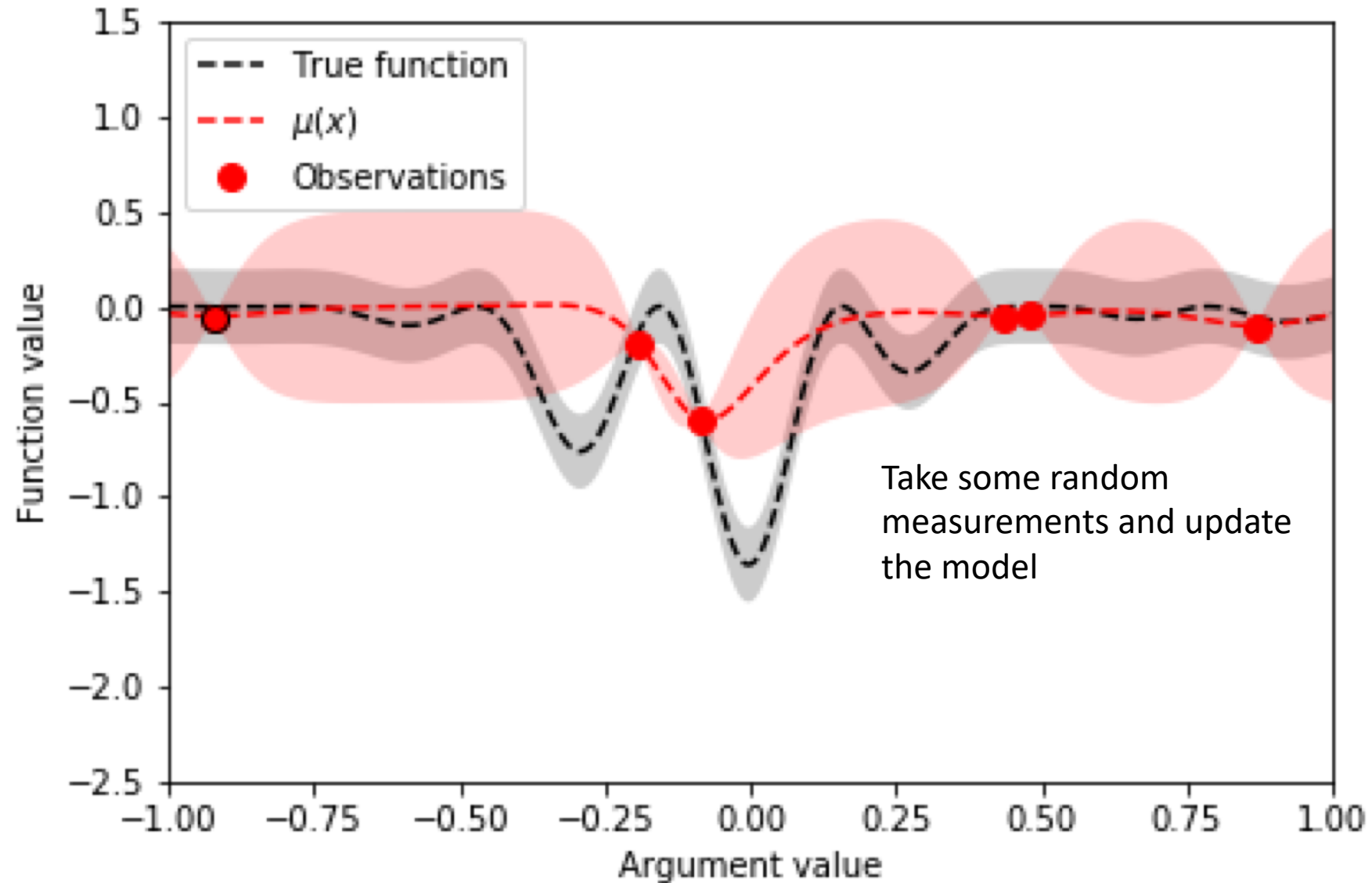
X-rays

Flux
Critical energy

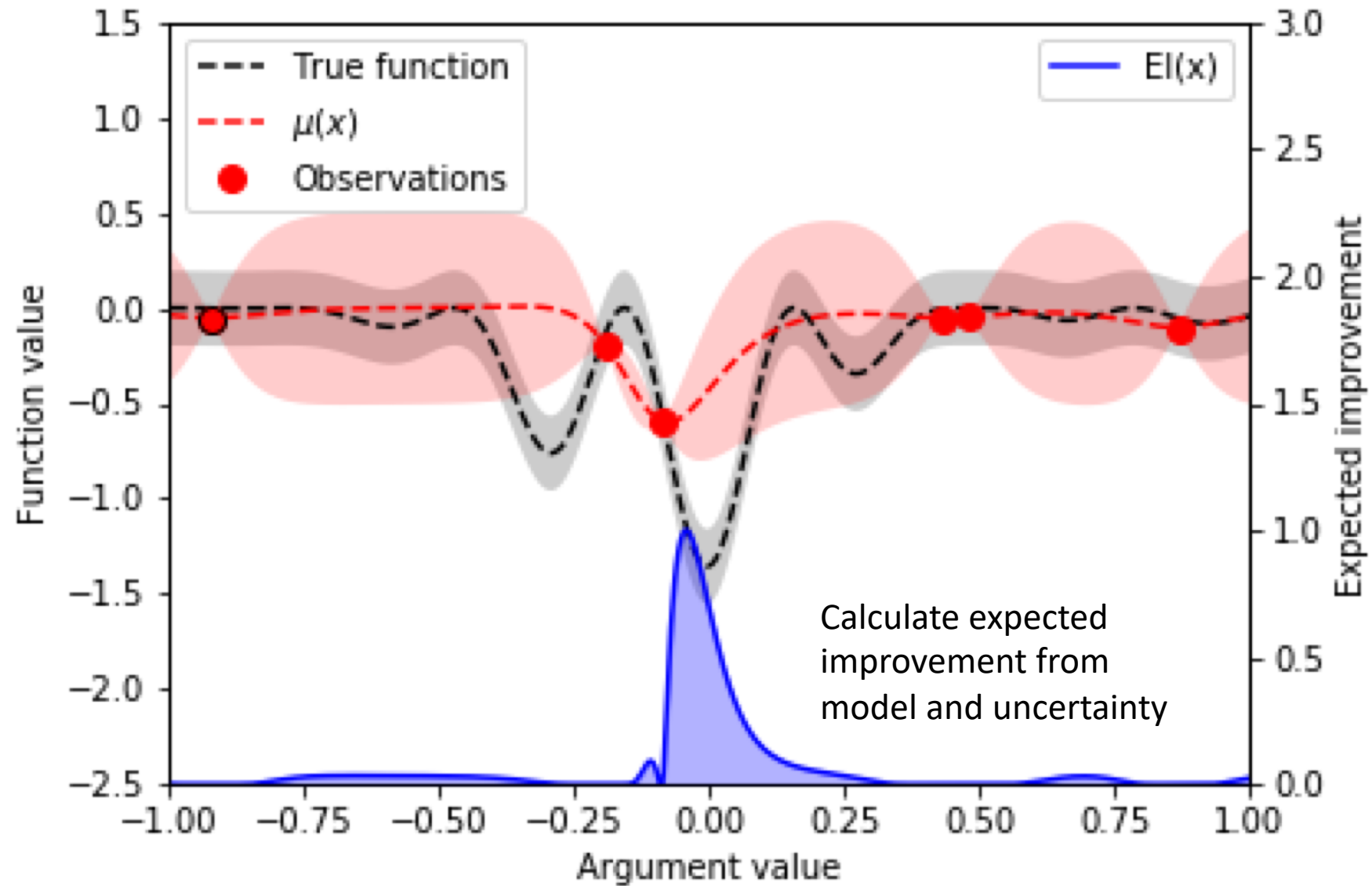
Bayesian optimisation with gaussian process regression



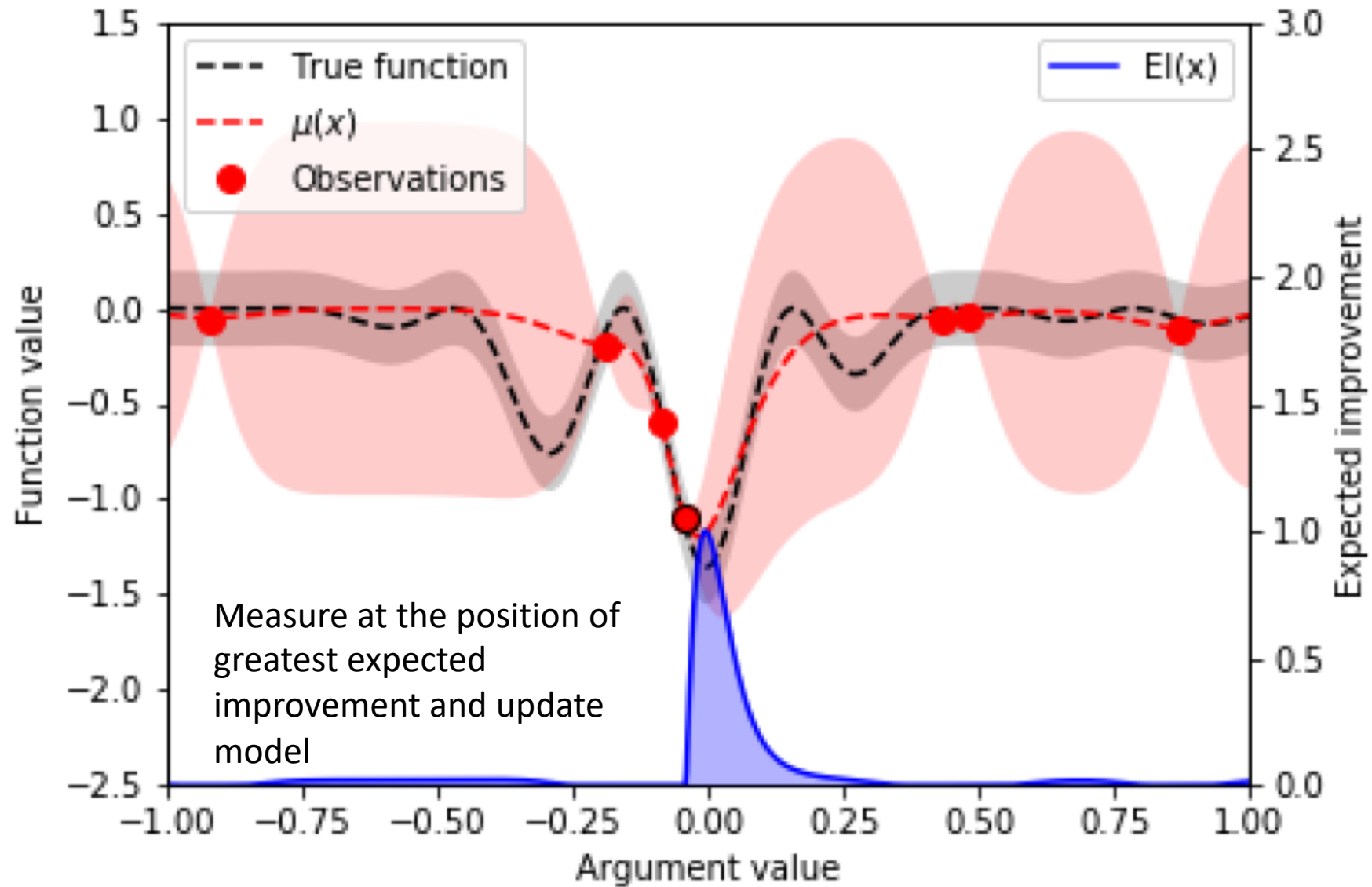
Bayesian optimisation with gaussian process regression



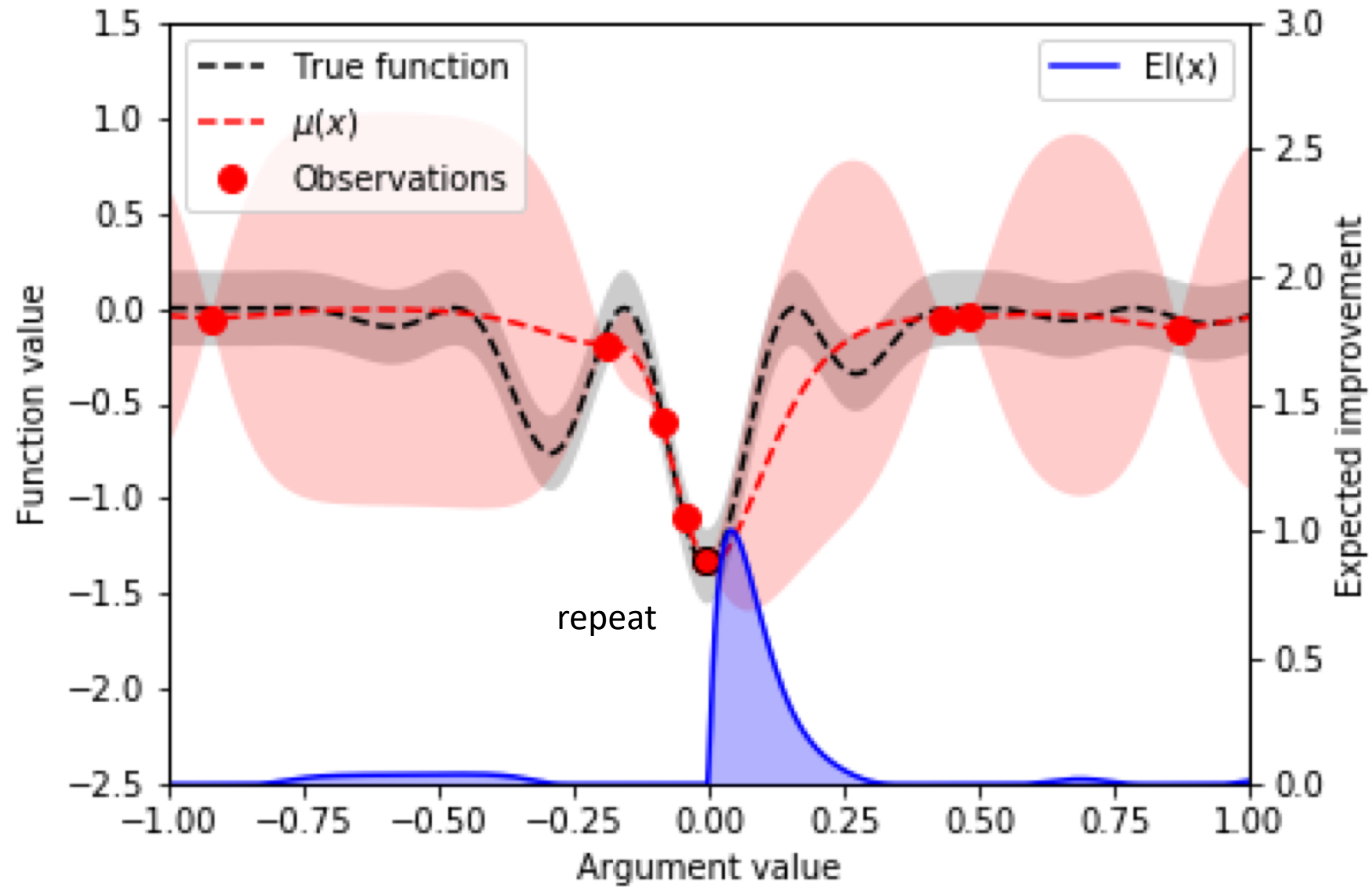
Bayesian optimisation with gaussian process regression



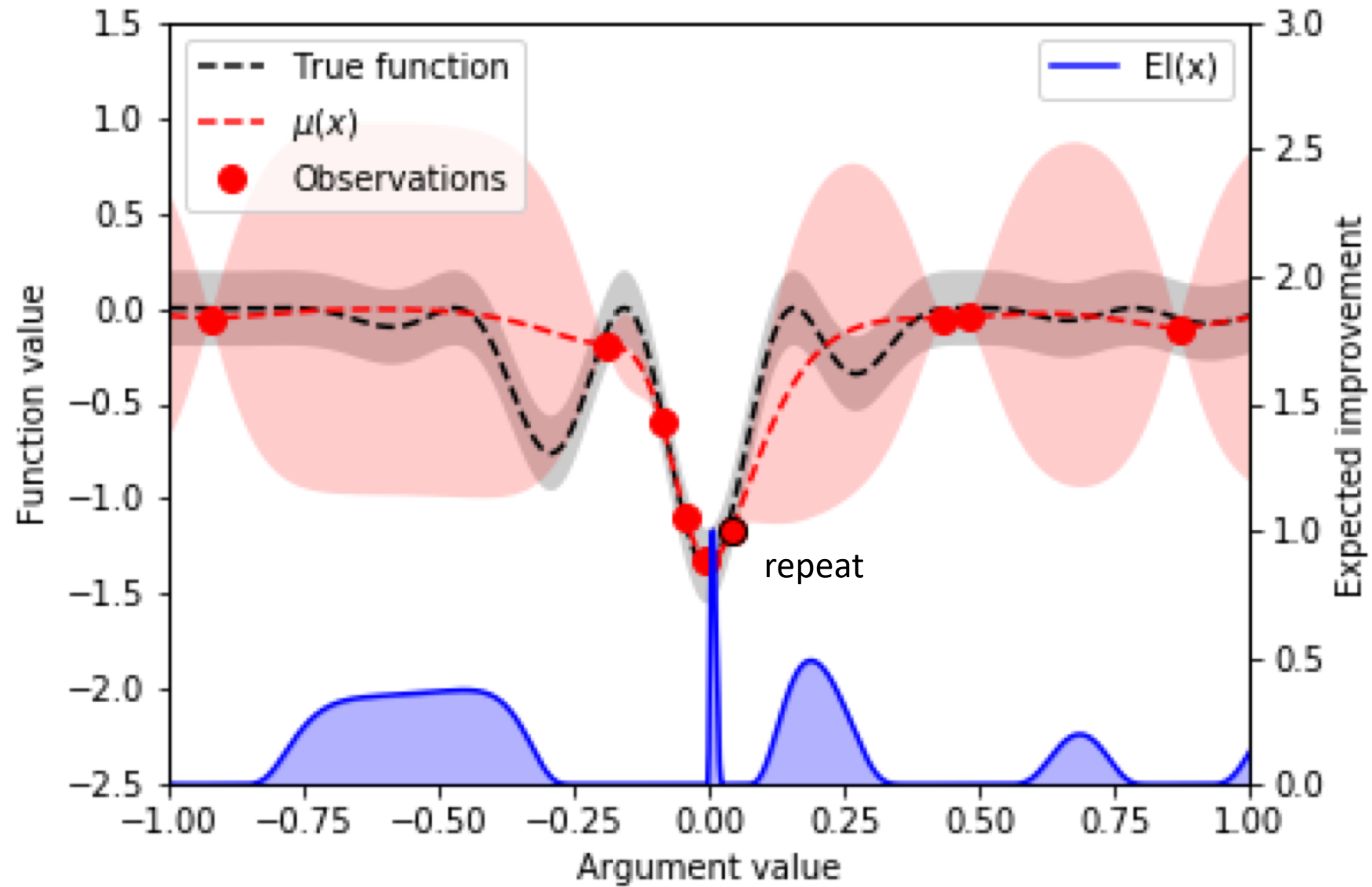
Bayesian optimisation with gaussian process regression



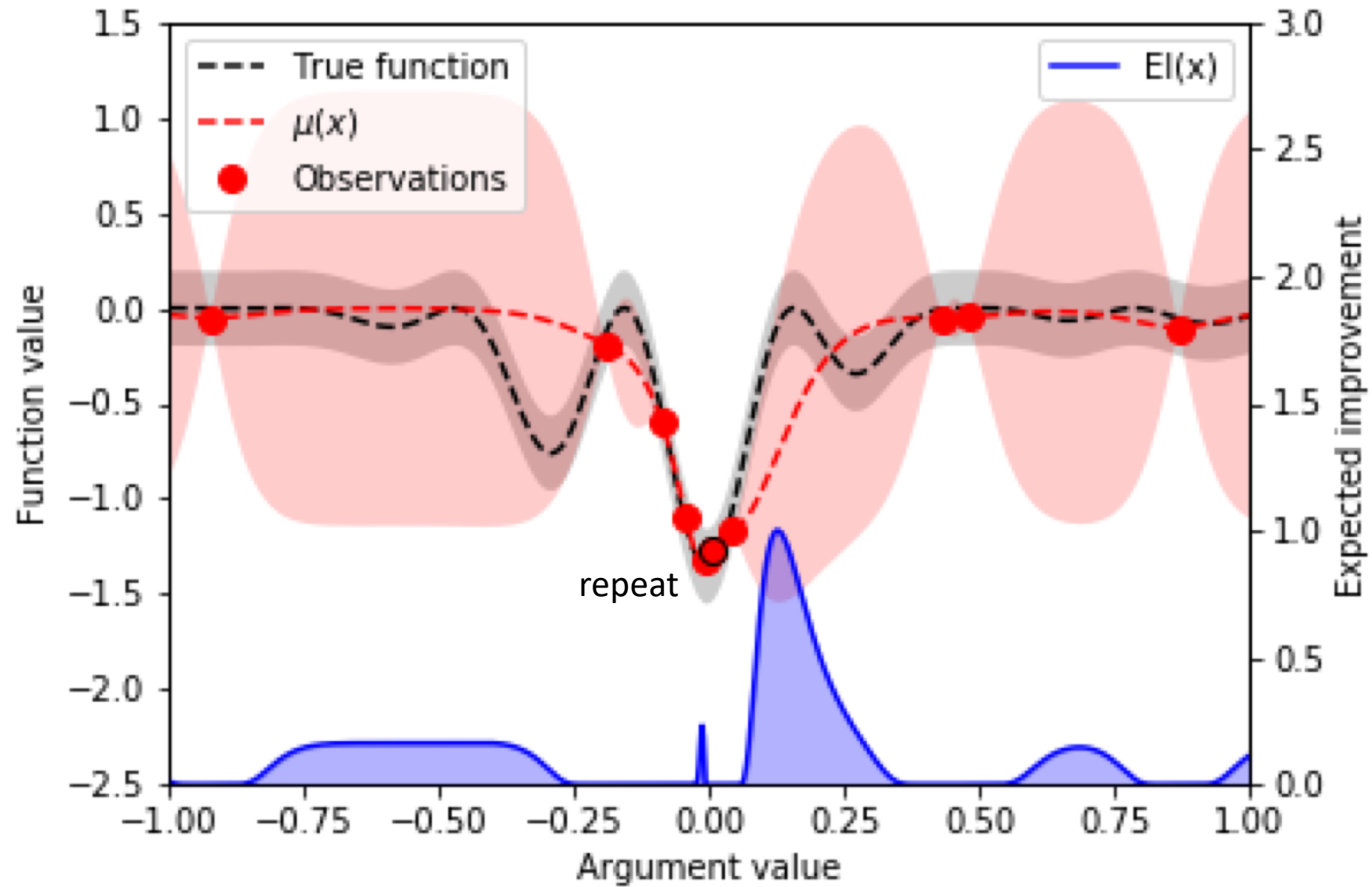
Bayesian optimisation with gaussian process regression



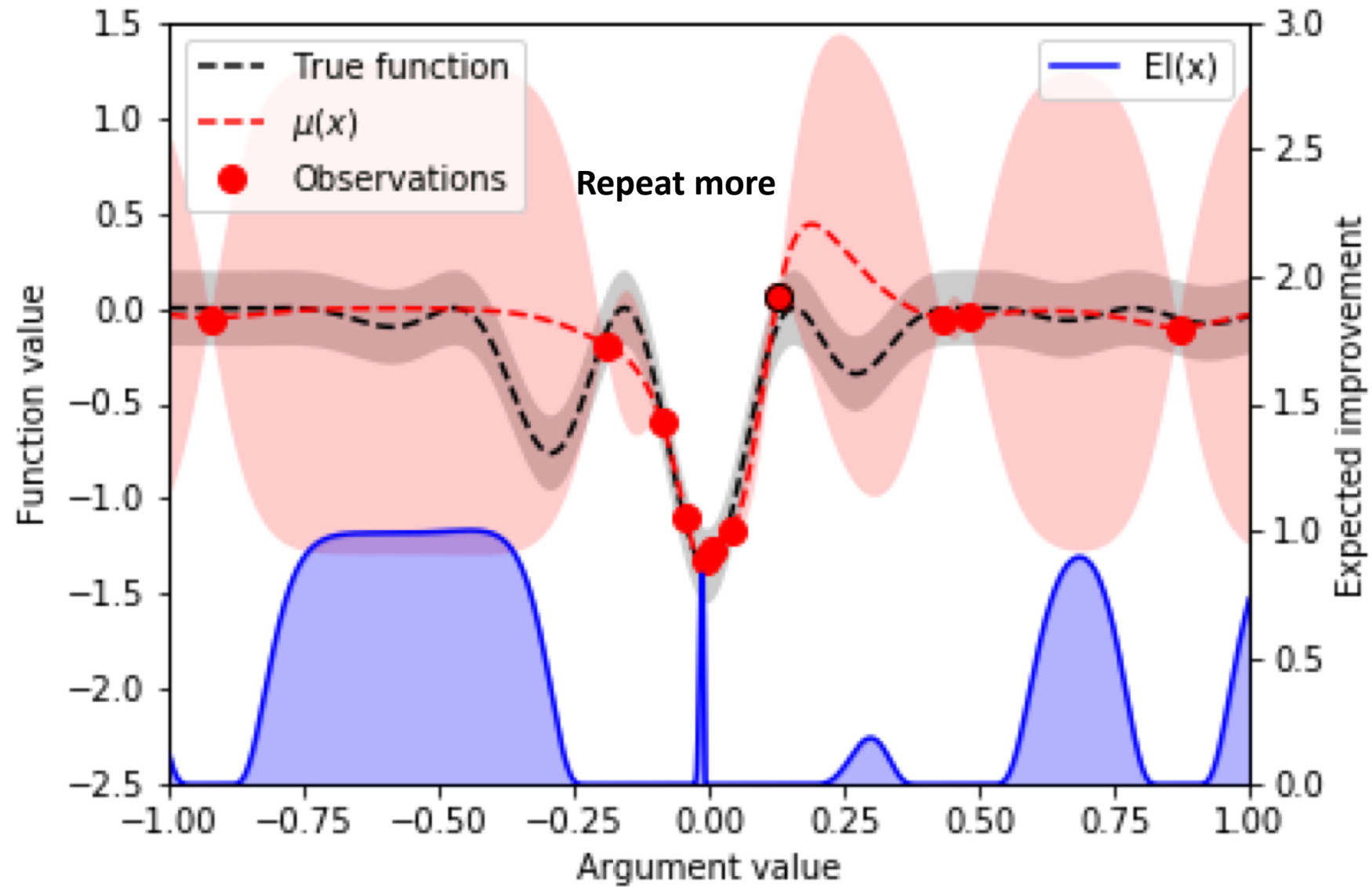
Bayesian optimisation with gaussian process regression



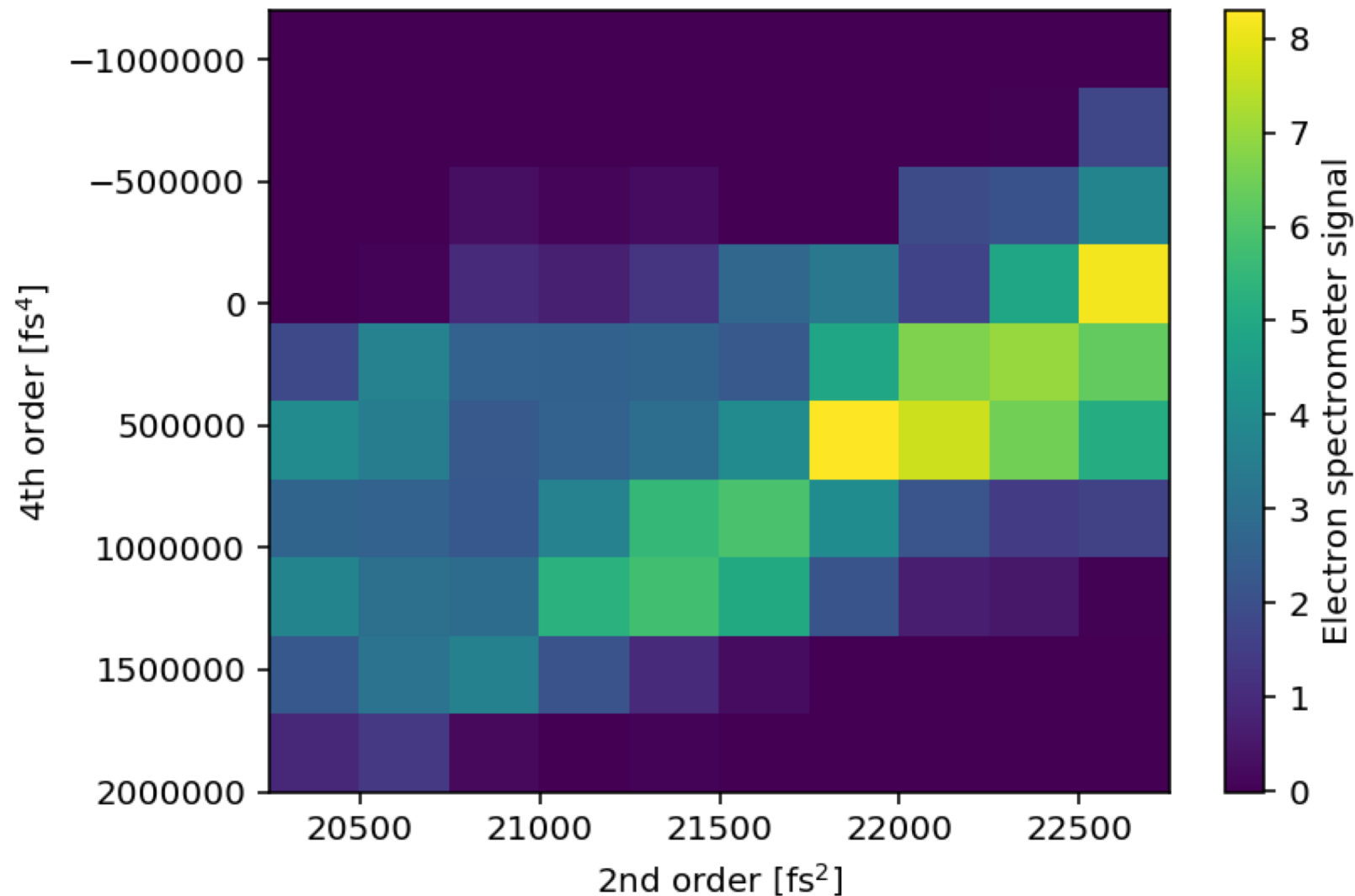
Bayesian optimisation with gaussian process regression



Bayesian optimisation with gaussian process regression

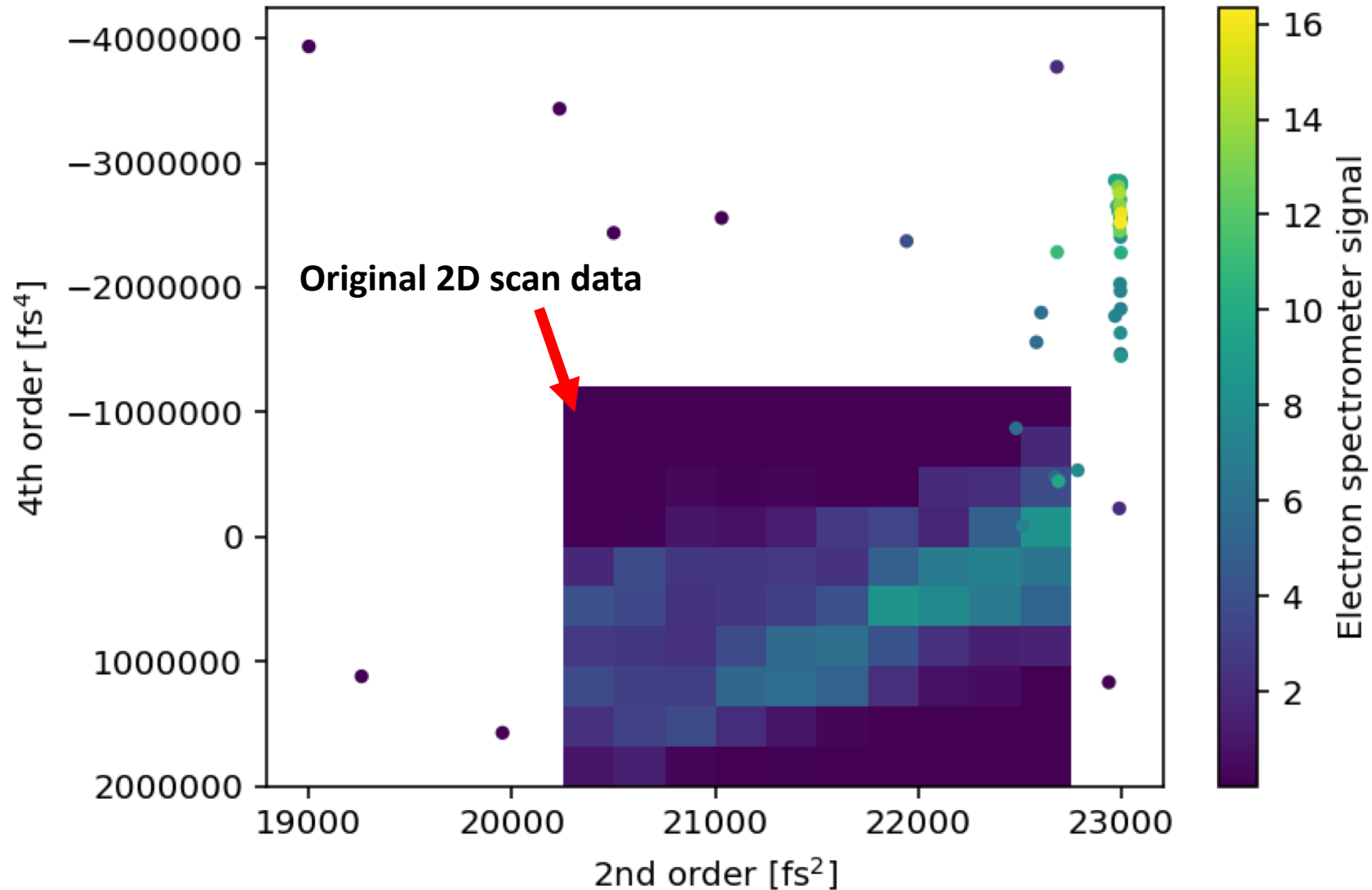


Application of gaussian process regression to optimisation of spectral phase

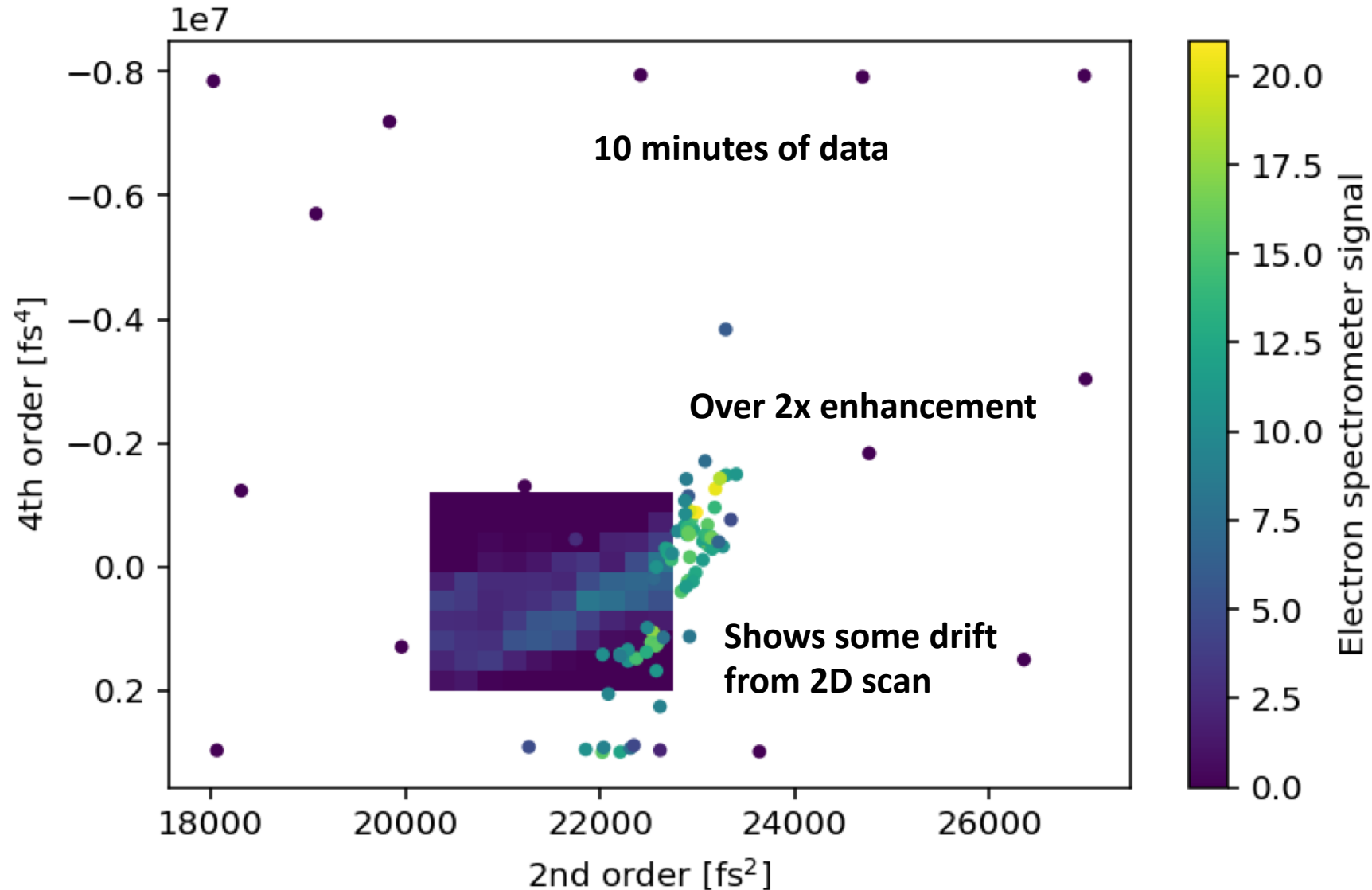


- Incomplete and coarse scan of parameter space taking 20 minutes
- Due to correlated nature of the space, you could not just optimise by 2x 1D scans

First optimisation showed a better maximum near a coded parameter limit



Second optimisation found a maximum outside of our original search region



Summary

- Machine learning techniques can be readily applied in LWFA for:
 - Optimisation: quicker than grid search and capable of more dimensions
 - Active feedback: can adjust for unseen drift in laser parameters
 - Analysis: once you have the data, you can always use it to train predictive models
- Experiment ongoing to apply these techniques to a 5 Hz LWFA
 - Will expand to higher dimensions and include plasma controls
- Machine learning will be even more beneficial in higher rep-rate systems

Acknowledgements

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