



# On the Confluence of **Data-Driven Techniques and Laser-Plasma Acceleration**

**Andreas Döpp**<sup>1,2,3</sup>, Faran Irshad<sup>1</sup>, Sunny Howard<sup>1,3</sup>, Jannik Esslinger<sup>1</sup>, Nils Weisse<sup>1</sup>,  
Christoph Eberle<sup>1</sup>, Jinpu Lin<sup>1</sup>, Robin Wang<sup>3</sup>, Peter Norreys<sup>3</sup>, Stefan Karsch<sup>1,2</sup>

<sup>1</sup> Centre for Advanced Laser Applications, Faculty of Physics, LMU Munich

<sup>2</sup> Max Planck Institute for Quantum Optics (MPQ)

<sup>3</sup> Faculty of Physics, Oxford University





An aerial photograph of a city, likely Geneva, showing the confluence of the Rhone and Arve rivers. The Rhone river flows from the left, and the Arve river flows from the right. The city is densely packed with buildings, and there are large green spaces with trees. In the background, there are mountains under a clear sky. A semi-transparent white box is overlaid on the image, containing the title text.

On the **Confluence** of  
**Data-Driven Techniques and  
Laser-Plasma Acceleration**

Rhone

Arve





Physics

Data\*

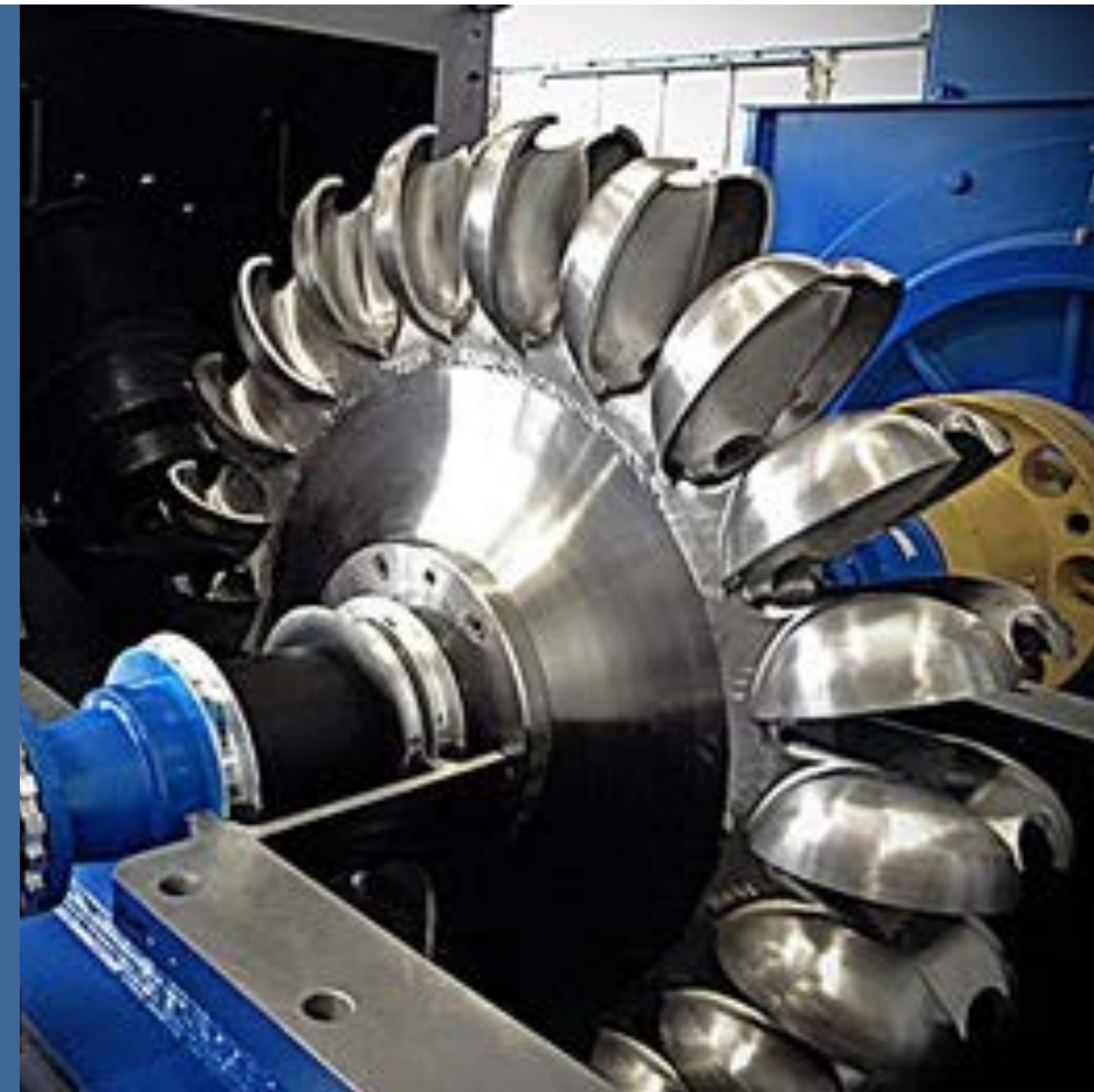
\* Here I use „data-driven techniques“ as an umbrella term that encompasses everything from traditional methods to modern AI.



# Talk outline

... maintaining data ↔ water analogies

Phase I  
Collect data



Phase III  
Custom-made solutions  
for your application

Phase II  
Let the data work using  
off-the-shelf methods



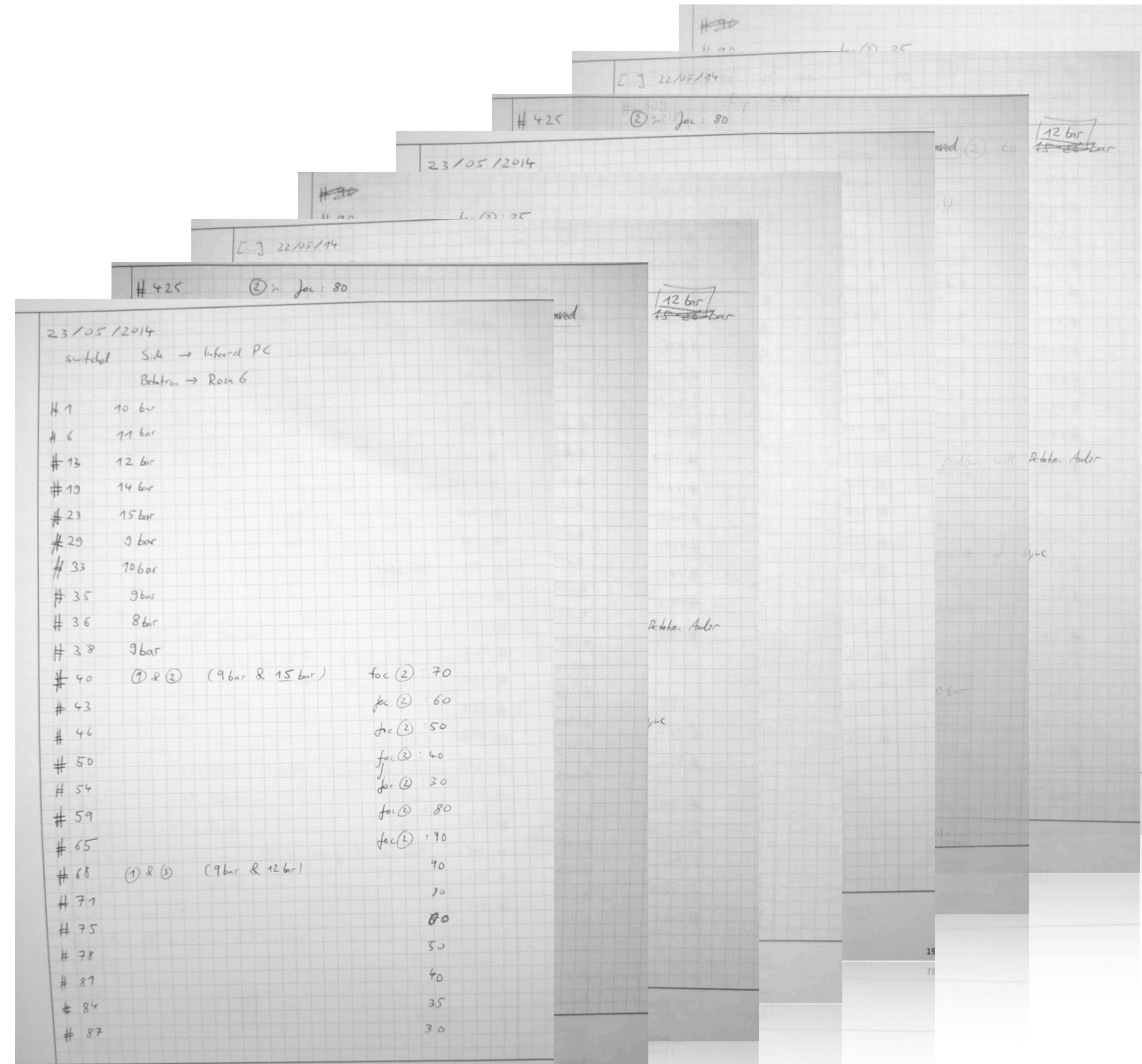


# Phase I Data collection and control systems

From manual labor ...



- Inside of vacuum chambers motorized, but gas regulation etc. manually
- Use camera manufacturer's software for data acquisition (some supported continuous sets, others have to be armed manually before each shot)
- Data logging: handwritten lab book
- Control system: Mix between proprietary software and LabView





# Phase I Data collection and control systems

... to fully automatized



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High Power Laser Science and Engineering, (2023), Vol. 11, e44, 7 pages.  
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**RESEARCH ARTICLE**

## Tango Controls and data pipeline for petawatt laser experiments

Nils Weiße, Leonard Doyle, Johannes Gebhard, Felix Balling, Florian Schweiger, Florian Haberstroh, Laura D. Geulig, Jinpu Lin, Faran Irshad, Jannik Esslinger, Sonja Gerlach, Max Gilljohann, Vignesh Vaidyanathan, Dennis Siebert, Andreas Münzer, Gregor Schilling, Jörg Schreiber, Peter G. Thirolf, Stefan Karsch, and Andreas Döpp  
Ludwig-Maximilians-Universität München, Garching, Germany  
(Received 1 December 2022; accepted 16 February 2023)

**Abstract**  
The Centre for Advanced Laser Applications in Garching, Germany, is home to the ATLAS-3000 multi-petawatt laser, dedicated to research on laser particle acceleration and its applications. A control system based on Tango Controls is implemented for both the laser and four experimental areas. The device server approach features high modularity, which, in addition to the hardware control, enables a quick extension of the system and allows for automated data acquisition of the laser parameters and experimental data for each laser shot. In this paper we present an overview of our implementation of the control system, as well as our advances in terms of experimental operation, online supervision and data processing. We also give an outlook on advanced experimental supervision and online data evaluation – where the data can be processed in a pipeline – which is being developed on the basis of this infrastructure.

**Keywords:** data processing; high-power laser experiments; laser-plasma acceleration; online diagnostics

**1. Introduction**

Petawatt laser facilities<sup>[1]</sup> enable the study of a plethora of phenomena, ranging from fundamental physics<sup>[2,3]</sup> and over laser-driven radiation sources<sup>[4–8]</sup> to applications with high societal relevance, such as medical imaging<sup>[9,10]</sup> and fusion energy<sup>[11]</sup>. However, the wide range of applications also results in a high variability of experimental configurations, and frequently shifting experimental requirements demand continuous modifications to the used technical infrastructure. The integration of new devices, such as motors, cameras or special instruments, into an experimental setup can be a time-consuming task for experimental physicists. Reliable control and supervision of all implemented devices is the first step in conducting any successful experiment. Thus, having a highly dependable and customizable server infrastructure that enables data acquisition and control of the entire experiment can be of great benefit for daily experimental work. However, this server infrastructure should still be easy to maintain and to work with because it must be used by many different employees and collaborating scientists from other facilities with specific needs and varying levels of programming experience. If these requirements are met, the server infrastructure then allows for even more advanced steps, such as online diagnostics, that enable the automation of the experiment and the implementation of safety features. In addition, a common server infrastructure standardizes the acquired data and streamlines the evaluation process into a data pipeline. The ongoing development of the data pipeline is planned to further enable advanced evaluation and control methods enabled by machine learning<sup>[12]</sup>.

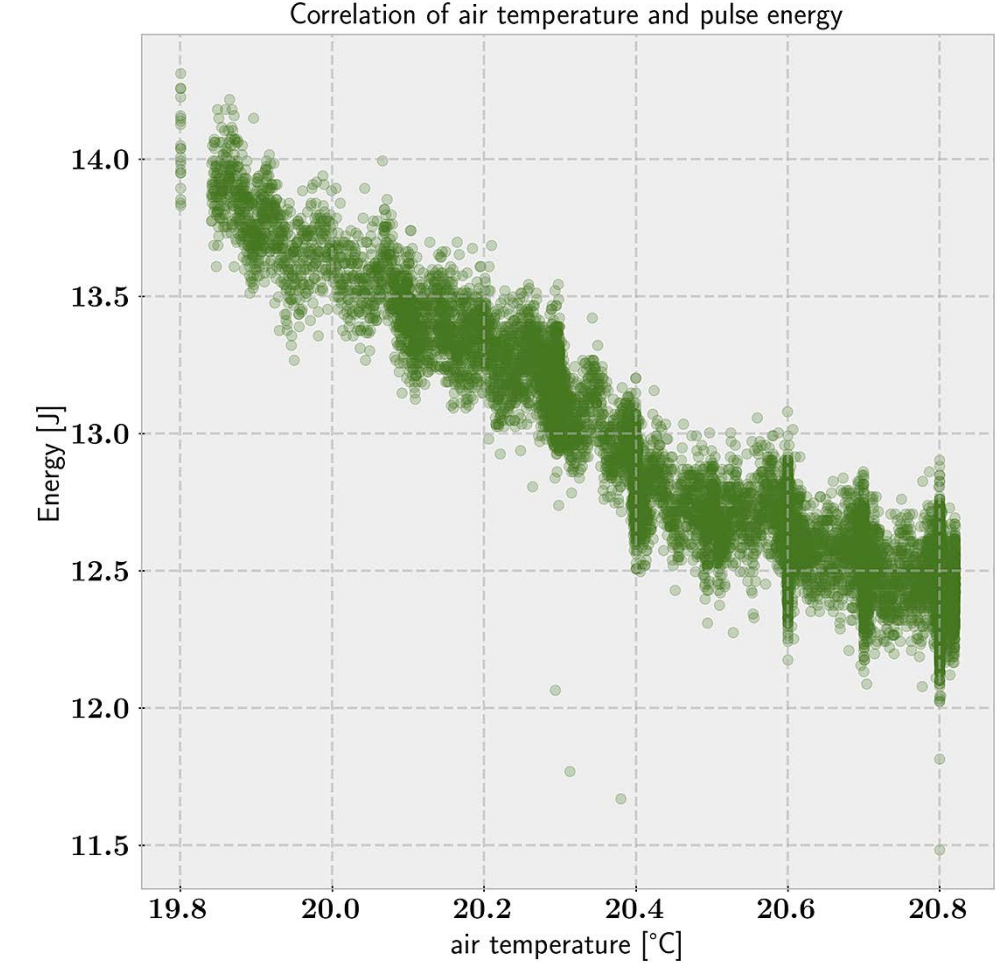
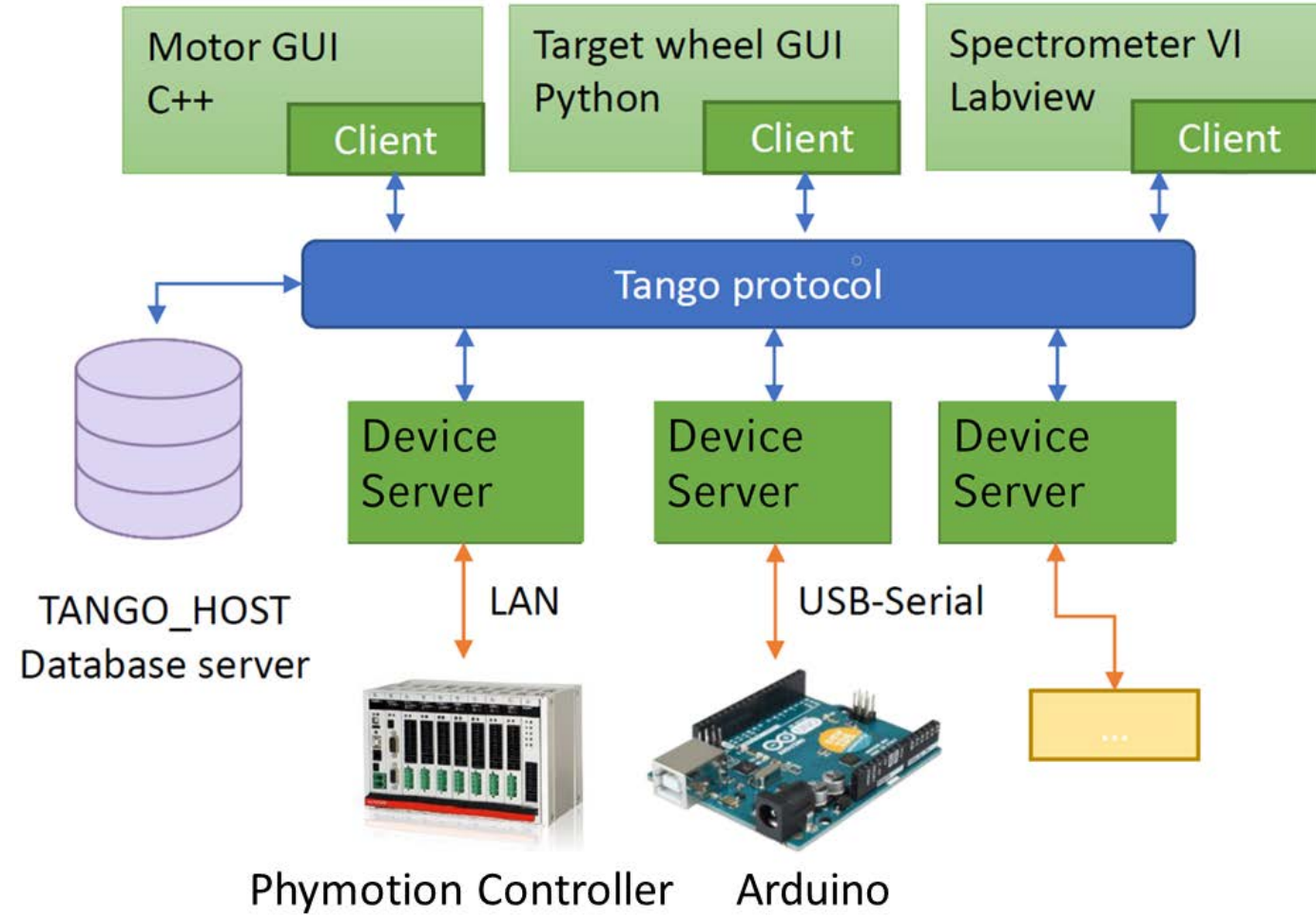
In this paper we are going to review the implementation of a control system that satisfies the requirements outlined above at the Centre for Advanced Laser Applications (CALA), its petawatt laser and experimental chambers<sup>[13,14]</sup>. The paper is structured as follows. Section 2 outlines the experimental infrastructure at CALA and the need for a common server infrastructure. An overview of the implemented control system, Tango Controls<sup>[15]</sup>, and its basic features in terms of supervision and experimental operation is given

Correspondence to: Nils Weiße, Ludwig-Maximilians-Universität München, Am Coulombwall 1, 85748 Garching, Germany. Email: nils.weiße@physik.uni-muenchen.de

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- Set up coherent acquisition and control system for both the laser and experiments based on TANGO controls
- On-going laboratory-wide effort, driven mostly by PhD students



# Phase I Data collection and control systems

## Review paper



- Overview about control systems written / coordinated by Scott Feister (California State U.) and Charlotte Palmer (QUB)
- Discusses different **design considerations**
- Case studies about
  - **LabView** at BELLA
  - **EPICS** at RAL
  - **Tango** at PALLAS

Check for updates

High Power Laser Science and Engineering, (2023), Vol. 11, e56, 25 pages.  
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**HIGH POWER LASER SCIENCE AND ENGINEERING**

**REVIEW**  
**Control systems and data management for high-power laser facilities**

Scott Feister<sup>1</sup>, Kevin Cassou<sup>2</sup>, Stephen Dann<sup>3</sup>, Andreas Döpp<sup>4</sup>, Philippe Gauron<sup>2</sup>, Anthony J. Gonsalves<sup>5</sup>, Archis Joglekar<sup>6,7</sup>, Victoria Marshall<sup>3</sup>, Olivier Neveu<sup>2</sup>, Hans-Peter Schlenvoigt<sup>8</sup>, Matthew J. V. Streeter<sup>9</sup>, and Charlotte A. J. Palmer<sup>9</sup>

<sup>1</sup>California State University Channel Islands, Camarillo, California, USA  
<sup>2</sup>Université Paris-Saclay, CNRS/IN2P3, ICLab, Orsay, France  
<sup>3</sup>Central Laser Facility, STFC Rutherford Appleton Laboratory, Didcot, UK  
<sup>4</sup>Ludwig-Maximilians-Universität München, Garching, Germany  
<sup>5</sup>BELLA Center, Lawrence Berkeley National Laboratory, Berkeley, California, USA  
<sup>6</sup>Department of Nuclear Engineering and Radiological Sciences, University of Michigan, Ann Arbor, Michigan, USA  
<sup>7</sup>Ergodic LLC, San Francisco, California, USA  
<sup>8</sup>Helmholtz-Zentrum Dresden – Rossendorf, Dresden, Germany  
<sup>9</sup>Queen's University Belfast, Belfast, UK  
(Received 23 February 2023; revised 13 May 2023; accepted 30 May 2023)

**Abstract**  
The next generation of high-power lasers enables repetition of experiments at orders of magnitude higher frequency than what was possible using the prior generation. Facilities requiring human intervention between laser repetitions need to adapt in order to keep pace with the new laser technology. A distributed networked control system can enable laboratory-wide automation and feedback control loops. These higher-repetition-rate experiments will create enormous quantities of data. A consistent approach to managing data can increase data accessibility, reduce repetitive data-software development and mitigate poorly organized metadata. An opportunity arises to share knowledge of improvements to control and data infrastructure currently being undertaken. We compare platforms and approaches to state-of-the-art control systems and data management at high-power laser facilities, and we illustrate these topics with case studies from our community.

**Keywords:** big data; community organization; control systems; data management; feedback loops; high-power lasers; high repetition rate; metadata; stabilization; standards

**1. Introduction**

*1.1. Shifts in high-power laser technology necessitate revised digital infrastructure*

High-power and high-intensity laser-plasma interactions provide a versatile experimental platform. They can produce extreme plasma environments, either for laboratory astrophysics and fundamental plasma physics, or as a unique source of secondary radiation. Secondary sources include bright, keV–MeV X-rays<sup>[1]</sup>, low-emittance and high-current electron beams<sup>[2–4]</sup>, GeV electron beams<sup>[5–8]</sup>, ultra-short MeV proton beams<sup>[9,10]</sup> and pulsed neutron sources<sup>[11]</sup>. These sources have demonstrated significant potential for applications<sup>[12]</sup> including rapid, high spatial resolution X-ray tomography<sup>[13–15]</sup>, free-electron lasing<sup>[16–18]</sup>, FLASH radiotherapy<sup>[19,20]</sup> and materials damage testing<sup>[21]</sup>. In order to develop these sources for applications (e.g., optimizing their stability and tunability), and in order for them to be competitive with alternative sources, it is necessary for the source repetition rate to drastically increase from sub-Hz to hundreds of Hz (and beyond).

Tackling the obstacles to achieving multi-Hz repetition-rate high-intensity laser-plasma interactions has been a focus of the high-power laser community in recent years. Great progress has been shown in laser technology<sup>[22]</sup>, replenishing targets<sup>[23–29]</sup> and online diagnostics<sup>[30–33]</sup>. The increasing availability of experimental facilities compatible with high repetition rates now highlights the need to adjust traditional experimental practices, and control, in order to fully exploit the opportunities offered by these systems<sup>[34]</sup>. Among these

Correspondence to: Charlotte A. J. Palmer, Queen's University Belfast, Belfast BT7 1NN, UK. Email: c.palmer@qub.ac.uk; Scott Feister, California State University Channel Islands, Camarillo, California 93012, USA. Email: scott.feister@csuci.edu

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# Phase II *Apply* established machine learning techniques



- What to do with my data?
- What are established machine learning techniques?
- Which method is suitable for my application?

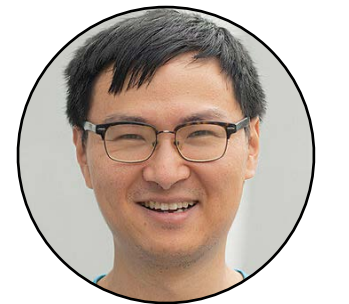


# Phase II Apply established machine learning techniques

## Review paper

- What to do with my data?
- What are established machine learning techniques?
- Which method is suitable for my application?
- Extensive **review / tutorial paper** (30+ pages) on data-driven science and machine learning methods in laser-plasma physics

- A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics**, High Power Laser Science and Engineering **11** 55 (2023) | *arXiv:2212.00026* (2022)



arXiv:submit/4626985 [physics.plasm-ph] 30 Nov 2022

### Data-driven Science and Machine Learning Methods in Laser-Plasma Physics

Andreas Döpp,<sup>1,\*</sup> Christoph Eberle,<sup>1</sup> Sunny Howard,<sup>1,2</sup> Faran Irshad,<sup>1</sup> Jinpu Lin,<sup>1</sup> and Matthew Streeter<sup>3</sup>

<sup>1</sup>Ludwig-Maximilians-Universität München, Am Coulombwall 1, 85748 Garching, Germany  
<sup>2</sup>Department of Physics, Clarendon Laboratory, University of Oxford, Parks Road, Oxford OX1 3PU, United Kingdom  
<sup>3</sup>Centre for Plasma Physics, Queens University Belfast, Belfast BT7 1NN, United Kingdom

Laser-plasma physics has developed rapidly over the past few decades as lasers have become both more powerful and more widely available. Early experimental and numerical research in this field was dominated by single-shot experiments with limited parameter exploration. However, recent technological improvements make it possible to gather data for hundreds or thousands of different settings in both experiments and simulations. This has sparked interest in using advanced techniques from mathematics, statistics and computer science to deal with, and benefit from, big data. At the same time, sophisticated modeling techniques also provide new ways for researchers to deal effectively with situation where still only sparse data are available. This paper aims to present an overview of relevant machine learning methods with focus on applicability to laser-plasma physics and its important sub-fields of laser-plasma acceleration and inertial confinement fusion.

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\* [a.doep@lmu.de](mailto:a.doep@lmu.de)



# Phase II Apply established machine learning techniques

## Review paper

- What to do with my data?
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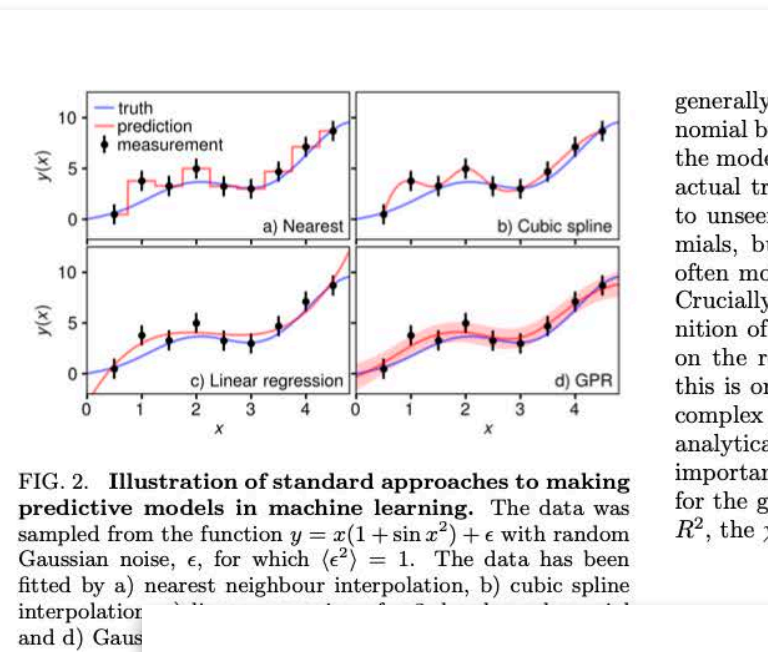


FIG. 2. Illustration of standard approaches to making predictive models in machine learning. The data was sampled from the function  $y = x(1 + \sin x^2) + \epsilon$  with random Gaussian noise,  $\epsilon$ , for which  $\langle \epsilon^2 \rangle = 1$ . The data has been fitted by a) nearest neighbour interpolation, b) cubic spline interpolator and d) Gaussian Process Regression (GPR).

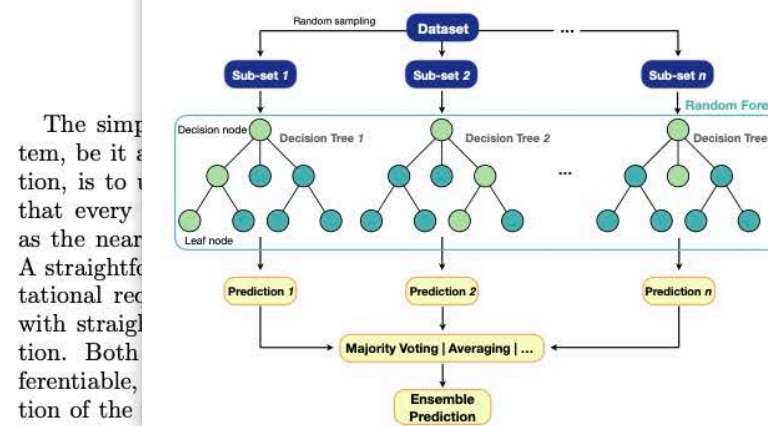


FIG. 4. Sketch of a random forest, an architecture for regression or classification consisting of multiple decision trees, whose individual predictions are combined using into an ensemble prediction e.g. via majority voting or averaging.

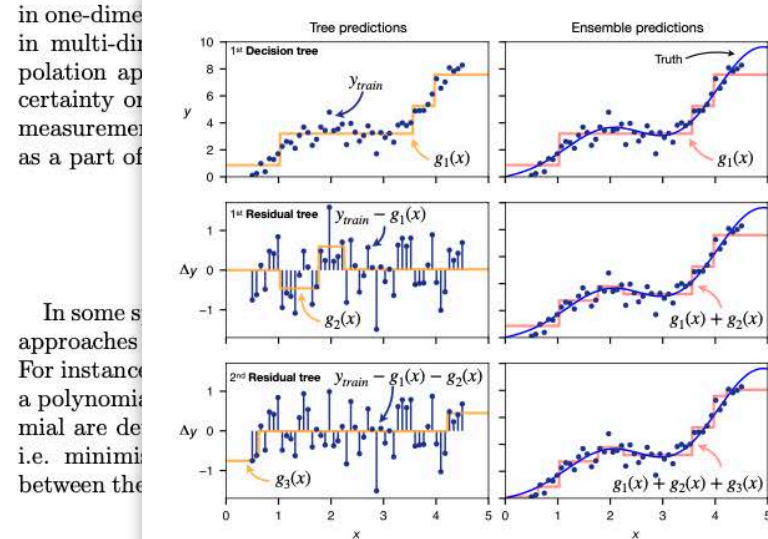


FIG. 5. Example of gradient boosting with decision trees. First, a decision tree  $g_1$  is fitted to the data. In the next step, the residual difference between training data and the prediction of this tree is calculated and used to fit a second decision tree  $g_2$ . This process is repeated  $n$  times, with each new tree  $g_n$  learning to correct only the remaining difference to the training data. Data in this example sampled from same function as in Fig. 2 and each tree has a maximum depth of two decision layers.

In regression settings or entropy and information gain in a classification setting. At each decision point the data set is split and subsequently the metric is re-evaluated for the resulting groups, generating the next layer of decision nodes. This process is repeated until the leaves are reached. The more layers decision layers are used, called the depth of the tree, the more complex relationships can

generally in nominal but the model does not capture actual trends to unseen data, but often motivated by physical intuition. Crucially, a limitation of analytical models is that this is one complex system, analytical models are important to understand the physics for the good  $R^2$ , the  $\chi^2$ .

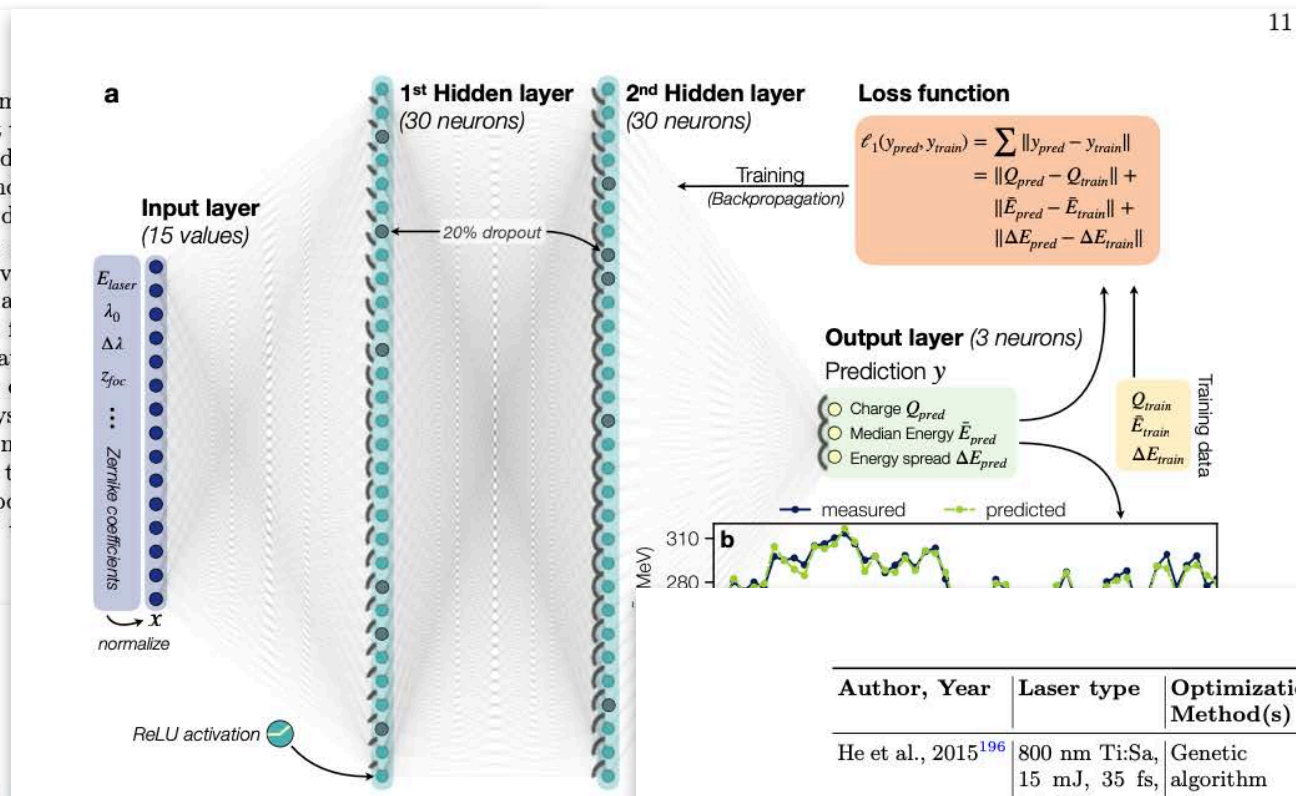


FIG. 7. Real-world example of a multilayer perceptron consists of 15 input neurons, two hidden layers with 30 neurons each, and an output layer with 3 neurons. The input is derived from parasitic laser diagnostics (laser power  $\Delta\lambda$ , longitudinal focus position  $z_{foc}$  and Zernike coefficients  $\lambda_0, \Delta\lambda, z_{foc}, \dots$ ). 20% of neurons drop out for regularization during training. We evaluate the accuracy of the model, in this case using the median energy  $\bar{E}$  and (c) measured and predicted energy spread  $\Delta E$ . b-c adapted from Kirchen *et al.*<sup>29</sup>

model incorporating a trained neural network was used to provide an additional computation package to the Geant4 particle physics platform. Neural networks are also trained to assist hohlraum design for ICF experiments by predicting the time evolution of the radiation temperature, in the recent work by McClarren *et al.*<sup>112</sup>. In the work by Simpson *et al.*<sup>113</sup>, a fully-connected neural network with three hidden layers is constructed to assist the analysis of a x-ray spectrometer, which measures the x-rays driven by MeV electrons produced from high-power laser-solid interaction.

### 7. Physics-informed machine learning models

The ultimate application of machine learning for modeling physics systems would arguably be to create an “artificial intelligence physicist”, as coined by Wu and Tegmark<sup>114</sup>. One prominent idea at the backbone of how to train a deep neural network. An example of using a decision tree as an initializer are Deep Jointly-Informed Neural Networks (DJINN) developed by Humbird *et al.*<sup>95</sup>, which have been widely applied in the high power laser community, especially in analyzing inertial confinement fusion datasets. The algorithm first constructs a tree or a random forest with tree depth set as a tunable hyperparameter. It then maps the tree to a neural network, or maps the forest to an ensemble of networks. The structure of the network (number of neurons and hidden layer, initial weights, etc.) reflects the structure of the tree. The neural network is then trained using back-propagation. The use of decision trees for initialization largely reduces the computational cost while maintaining comparable performance to optimized neural network architectures. The DJINN algorithm has been applied to several classification and regression tasks

Author, Year	Laser type	Optimization Method(s)	Free Parameters	Optimization goals
He et al., 2015 <sup>196</sup>	800 nm Ti:Sa, 15 mJ, 35 fs, 0.5 kHz	Genetic algorithm	deformable mirror (37 actuator voltages)	Electron angular profile, energy distribution & transverse emittance, optical pulse compression
Dann et al., 2019 <sup>197</sup>	800 nm Ti:Sa, 450 mJ, 40 fs, 5 Hz	Genetic & Nelder-Mead algorithms	deformable mirror or acousto-optic programmable dispersive filter	Electron beam charge, total charge within energy range, electron beam divergence
Shaloo et al., 2020 <sup>198</sup>	800 nm Ti:Sa, 0.245 J, 45 fs (bandwidth limit), 1 Hz	Bayesian optimization	Gas cell flow rate & length, laser dispersion ( $\partial_x^2 \phi$ , $\partial_z^2 \phi$ ), focus position	Total electron beam energy, Electron charge within acceptance angle, Betatron X-ray counts
Jalas et al., 2021 <sup>199</sup>	800 nm Ti:Sa, 2.6 J, 39 fs, 1 Hz	Bayesian optimization	Gas cell flow rates (H <sub>2</sub> front and back, N <sub>2</sub> ); focus position and laser energy	Spectral charge density

TABLE I. Summary of a few representative papers on machine-learning-aided optimization in the context of laser-plasma acceleration and high-power laser experiments.

distributions, in this case the electron energy distribution. While simple at first glance, these objectives need to be properly defined and there are often different ways to do so<sup>201</sup>. In the example above, energy and bandwidth are examples for the central tendency and the statistical dispersion of the energy distribution, respectively. These can be measured using different metrics such as weighted arithmetic or truncated mean, the median, mode, percentiles and so forth for the former; and full width at half maximum, median absolute deviation, standard deviation, maximum deviation, etc. for the latter. Each of these seemingly similar measures emphasises different features of the distribution they are calculated from, which can affect the outcome of optimization tasks. Sometimes one might also want to include higher order momenta as objectives, such as the skewness, or use integrals, e.g. the total beam charge.

### 2. Pareto optimization

In practice, optimization problems often constitute multiple sometimes competing objectives  $g_i$ . As the objective function should only yield a single scalar value, one has to condense these objectives in a process known as *scalarization*. Scalarization can for instance take the form of a weighted product  $g = \prod g_i^{\alpha_i}$  or sum  $g = \sum \alpha_i g_i$  of the individual objectives  $g_i$ , with the hyperparameters  $\alpha_i$  describing its weight. Another common scalarization technique is  $\epsilon$ -constraint scalarization, where one seeks to reformulate the problem of optimizing multiple objectives into a problem of single-objective optimization conditioned on constraints. In this method the goal is to optimize one of the  $g_i$  given some bounds on the other objectives. All of these techniques introduce some explicit bias in the optimization which may not necessarily repre-

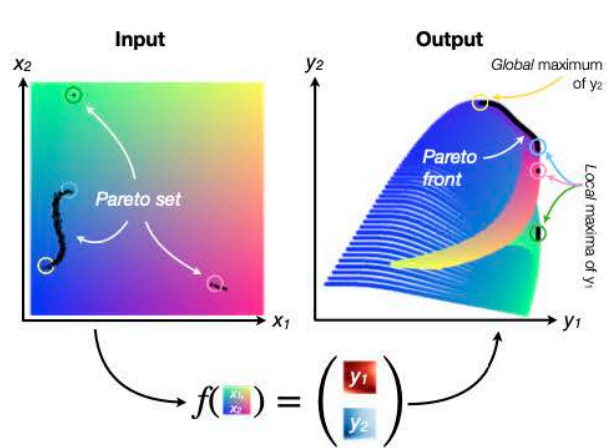


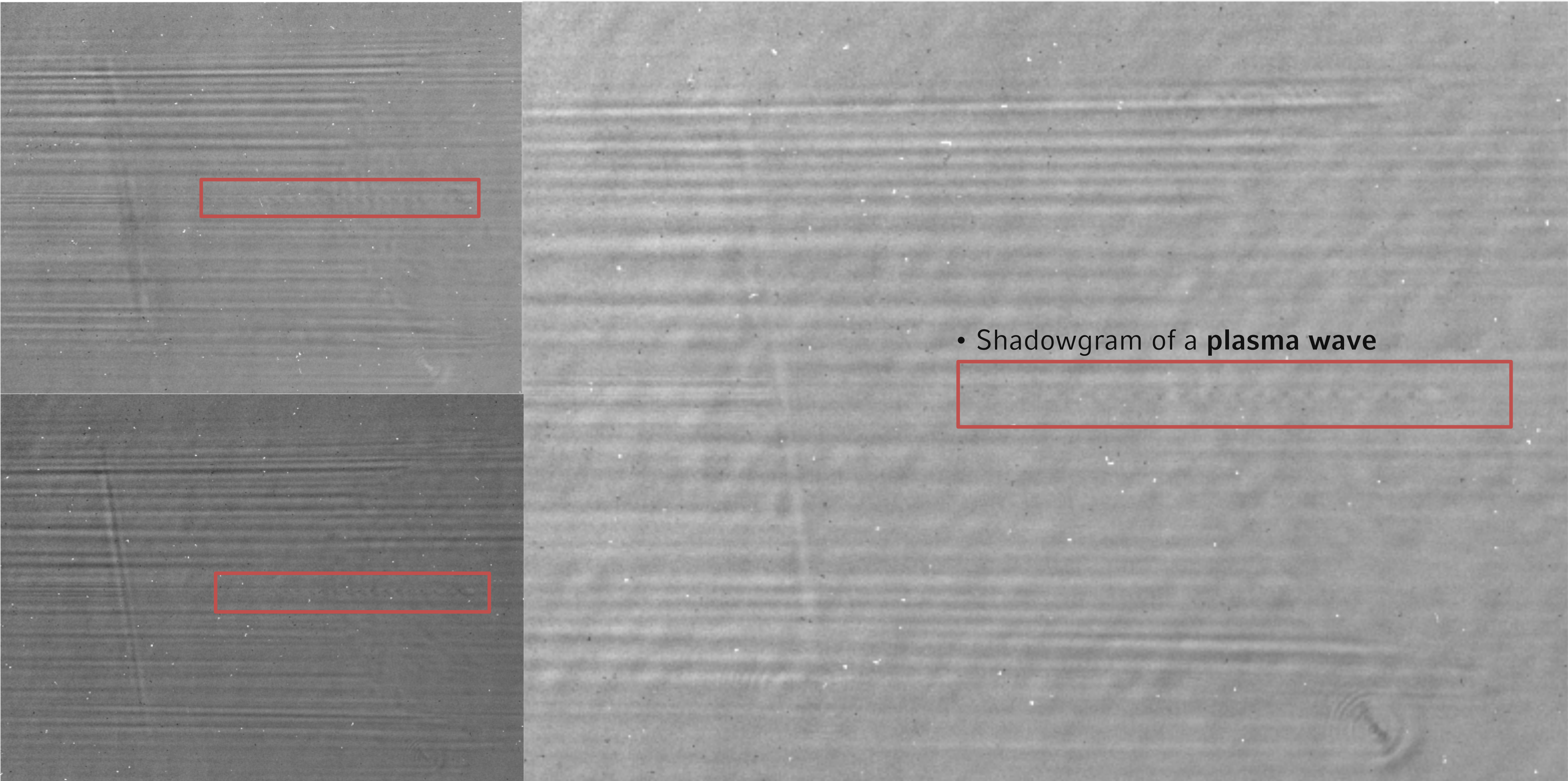
FIG. 12. Pareto front. Illustration how a multi-objective function  $f(x) = y$  acts on a two-dimensional input space  $x = (x_1, x_2)$  and transforms it to the objective space  $y = (y_1, y_2)$  on the right. The entirety of possible input positions is uniquely color-coded on the left and the resulting position in the objective space is shown in the same color on the right. The Pareto-optimal solutions form the Pareto front, indicated on the right, whereas the corresponding set of coordinates in the input space is called the Pareto set. Note that both Pareto front and Pareto set may be continuously defined locally, but can also contain discontinuities when local maxima get involved. Adapted from Irshad *et al.*<sup>202</sup>.

sent the desired outcome. Because of this, the hyperparameters of the scalarization may have to be optimized themselves by running optimizations several times. A more general approach is *Pareto optimization*, where the entire vector of individual objectives  $g = (g_1, \dots, g_N)$  is optimized. To do so, instead of optimizing individual objectives, it is based on the concept of *dominance*. A



# Phase II **Apply** established machine learning techniques

Object detection using YOLOv5



- Shadowgram of a **plasma wave**



# Phase II Apply established machine learning techniques

## Object detection using YOLOv5



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High Power Laser Science and Engineering, (2023), Vol. 11, e7, 9 pages.  
doi:10.1017/hpl.2023.1

**RESEARCH ARTICLE**

### Applications of object detection networks in high-power laser systems and experiments

Jinpu Lin<sup>1</sup>, Florian Haberstroh<sup>1</sup>, Stefan Karsch, and Andreas Döpp<sup>1</sup>  
<sup>1</sup>Ludwig-Maximilians-Universität München, Garching, Germany  
(Received 25 August 2022; revised 20 December 2022; accepted 30 December 2022)

**Abstract**  
The recent advent of deep artificial neural networks has resulted in a dramatic increase in performance for object classification and detection. While pre-trained with everyday objects, we find that a state-of-the-art object detection architecture can very efficiently be fine-tuned to work on a variety of object detection tasks in a high-power laser laboratory. In this paper, three exemplary applications are presented. We show that the plasma waves in a laser-plasma accelerator can be detected and located on the optical shadowgrams. The plasma wavelength and plasma density are estimated accordingly. Furthermore, we present the detection of all the peaks in an electron energy spectrum of the accelerated electron beam, and the beam charge of each peak is estimated accordingly. Lastly, we demonstrate the detection of optical damage in a high-power laser system. The reliability of the object detector is demonstrated over 1000 laser shots in each application. Our study shows that deep object detection networks are suitable to assist online and offline experimental analysis, even with small training sets. We believe that the presented methodology is adaptable yet robust, and we encourage further applications in Hz-level or kHz-level high-power laser facilities regarding the control and diagnostic tools, especially for those involving image data.

**Keywords:** high repetition rate; laser-plasma accelerators; machine learning; object detection; optical diagnostics

### 1. Introduction

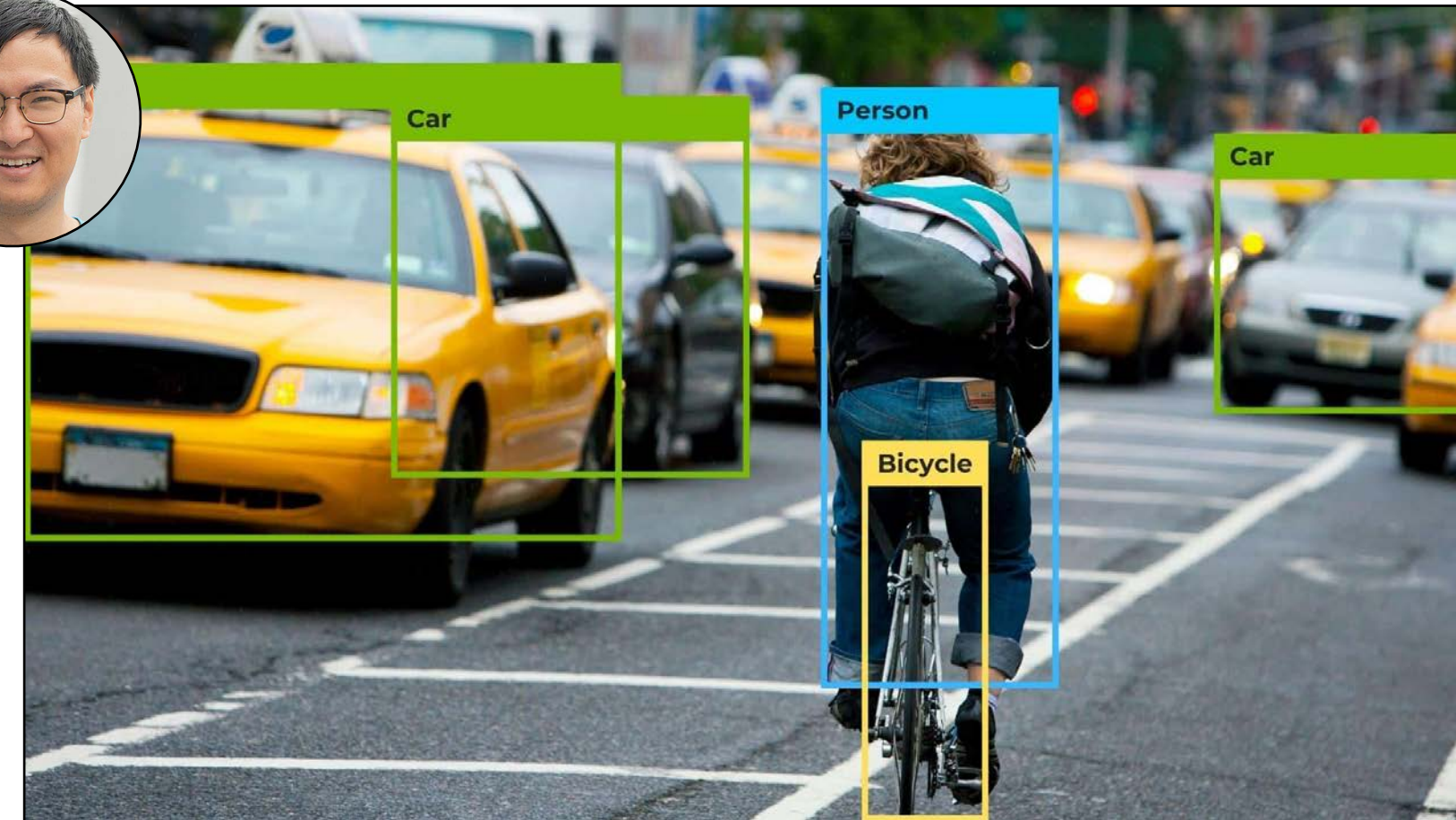
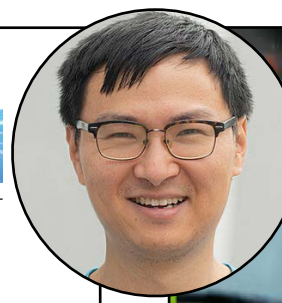
High-power laser systems with power reaching the petawatt level and repetition rate at a fraction of a hertz have emerged worldwide in the past few years<sup>1–3</sup>. With the fast development of high-repetition-rate operation capabilities in plasma targetry, high-power laser-plasma experiments can employ statistical methods that require a large number of shots. Studies for real-time optimization using evolutionary algorithms have been reported in recent years<sup>6–11</sup>. As the size of data to process has continued to increase, more advanced machine learning models have attracted increasing attention. By constructing predictive models, machine learning methods are employed to model the nonlinear, high-dimensional processes in high-power laser experiments. Various methods, including neural networks, Bayesian inference and decision trees, have been introduced for optimization tasks and physics interpretation<sup>12–17</sup>. Meanwhile, as the measurement and diagnostic tools evolve, digital imaging is playing an increasingly important role in experiments and, with it, machine learning methods to process image data.

In the case of a laser-plasma accelerator, image-based diagnostics can take a variety of forms, from the optical elements in the high-power laser facility, over shadowgraphy and interferometry of plasma dynamics, to scintillator signals generated by energetic electron or X-ray beams from the accelerator. In particular, the evolving structure of a plasma accelerator is challenging to visualize because of its microscopic size ( $\sim 10^{-5}$  m) and its high velocity (approaching the speed of light). With the latest techniques, such as few-cycle shadowgraphy, taking snapshots of the plasma wake structure is enabled in femtosecond resolution over a range of picoseconds<sup>18–20</sup>. The latest generation of laboratory diagnostics for plasma structures is reviewed by Downer *et al.*<sup>1,21</sup>.

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- Applied „off-the-shelf“ ML method
- You Only Look Once (YOLO) is an industry-standard object detection network

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# Phase II Apply established machine learning techniques

## Object detection using YOLOv5



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High Power Laser Science and Engineering, (2023), Vol. 11, e7, 9 pages.  
doi:10.1017/hpl.2023.1

**RESEARCH ARTICLE**

**Applications of object detection networks in high-power laser systems and experiments**

Jinpu Lin<sup>1</sup>, Florian Haberstroh<sup>1</sup>, Stefan Karsch, and Andreas Döpp<sup>1</sup>  
*Ludwig-Maximilians-Universität München, Garching, Germany*  
(Received 25 August 2022; revised 20 December 2022; accepted 30 December 2022)

**Abstract**  
The recent advent of deep artificial neural networks has resulted in a dramatic increase in performance for object classification and detection. While pre-trained with everyday objects, we find that a state-of-the-art object detection architecture can very efficiently be fine-tuned to work on a variety of object detection tasks in a high-power laser laboratory. In this paper, three exemplary applications are presented. We show that the plasma waves in a laser-plasma accelerator can be detected and located on the optical shadowgrams. The plasma wavelength and plasma density are estimated accordingly. Furthermore, we present the detection of all the peaks in an electron energy spectrum of the accelerated electron beam, and the beam charge of each peak is estimated accordingly. Lastly, we demonstrate the detection of optical damage in a high-power laser system. The reliability of the object detector is demonstrated over 1000 laser shots in each application. Our study shows that deep object detection networks are suitable to assist online and offline experimental analysis, even with small training sets. We believe that the presented methodology is adaptable yet robust, and we encourage further applications in Hz-level or kHz-level high-power laser facilities regarding the control and diagnostic tools, especially for those involving image data.

**Keywords:** high repetition rate; laser-plasma accelerators; machine learning; object detection; optical diagnostics

**1. Introduction**

High-power laser systems with power reaching the petawatt level and repetition rate at a fraction of a hertz have emerged worldwide in the past few years<sup>1–3</sup>. With the fast development of high-repetition-rate operation capabilities in plasma targetry, high-power laser-plasma experiments can employ statistical methods that require a large number of shots. Studies for real-time optimization using evolutionary algorithms have been reported in recent years<sup>6–11</sup>. As the size of data to process has continued to increase, more advanced machine learning models have attracted increasing attention. By constructing predictive models, machine learning methods are employed to model the nonlinear, high-dimensional processes in high-power laser experiments. Various methods, including neural networks, Bayesian inference and decision trees, have been introduced for optimization tasks and physics interpretation<sup>12–17</sup>. Meanwhile, as the measurement and diagnostic tools evolve, digital imaging is playing an increasingly important role in experiments and, with it, machine learning methods to process image data.

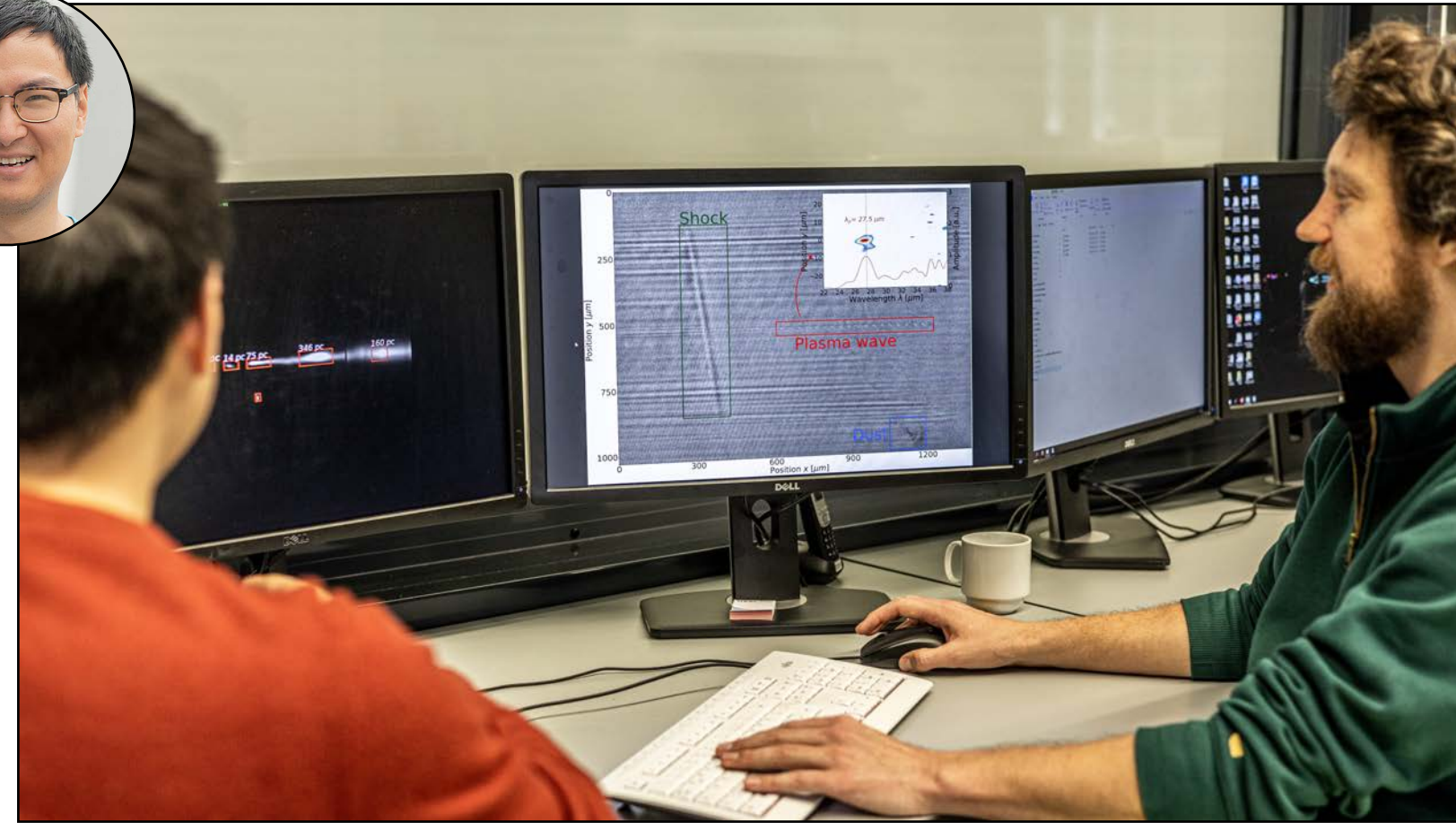
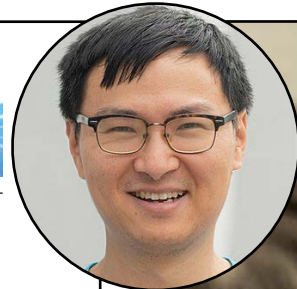
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- Accurate predictions after fine-tuning with only 30-50 samples
- Works for plasma waves, laser damage, etc.

Labelled set size	Augmented set size	Time	Inference set of 50 accuracy	Inference set of 1000 accuracy
15	35	5 min	68%	52%
30	52	8 min	98%	85%
50	124	11 min	100%	97%

1

1

1



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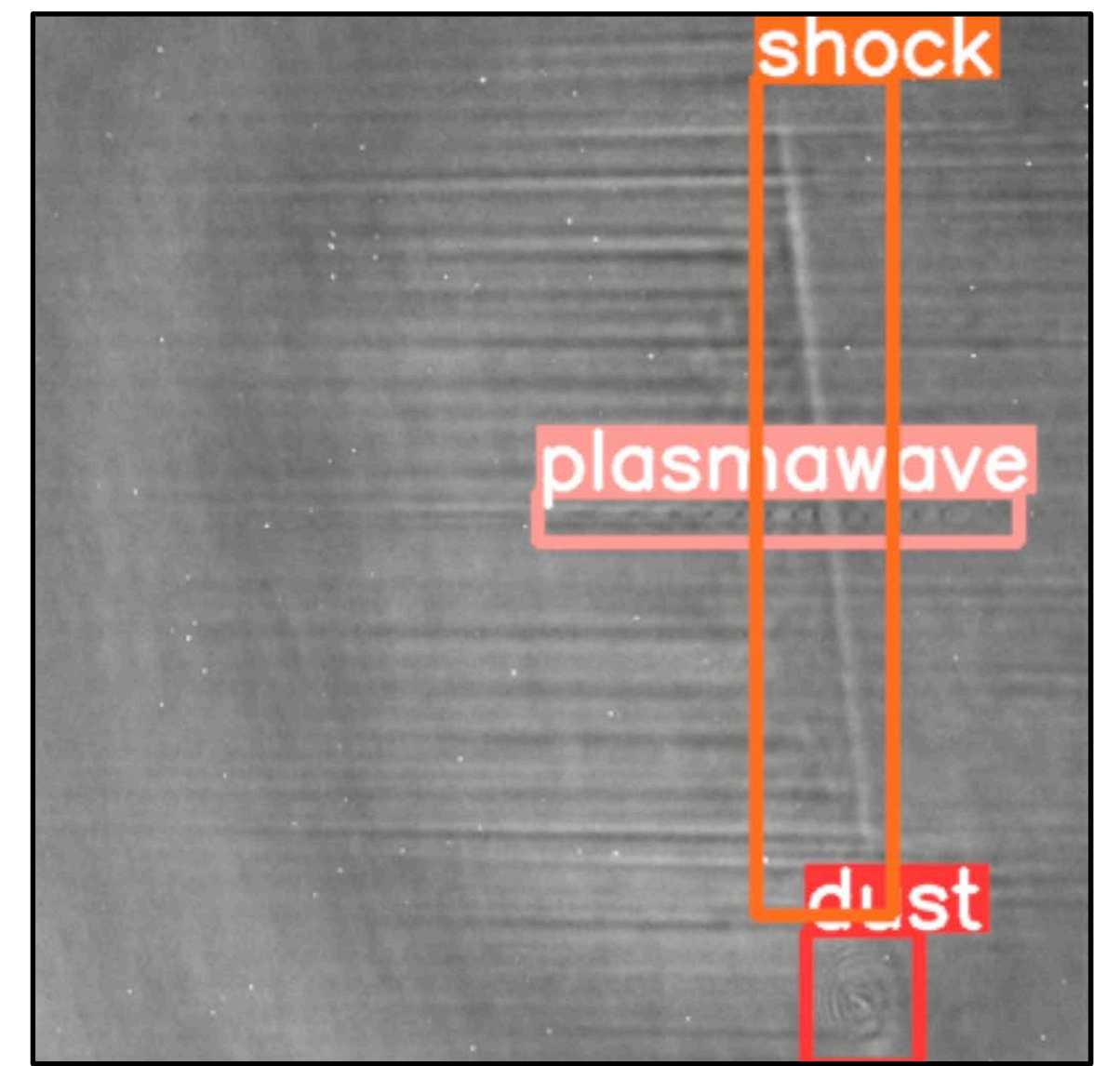
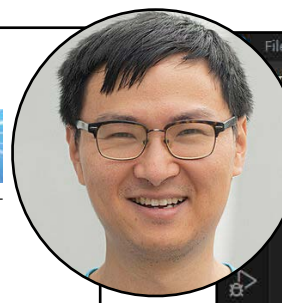
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- Implemented in TANGO  
(get image from camera, remove noise, detect features, show results)
- Allows for live analysis during experiments

https://doi.org/10.1017/hpl.2023.1 Published online by Cambridge University Press

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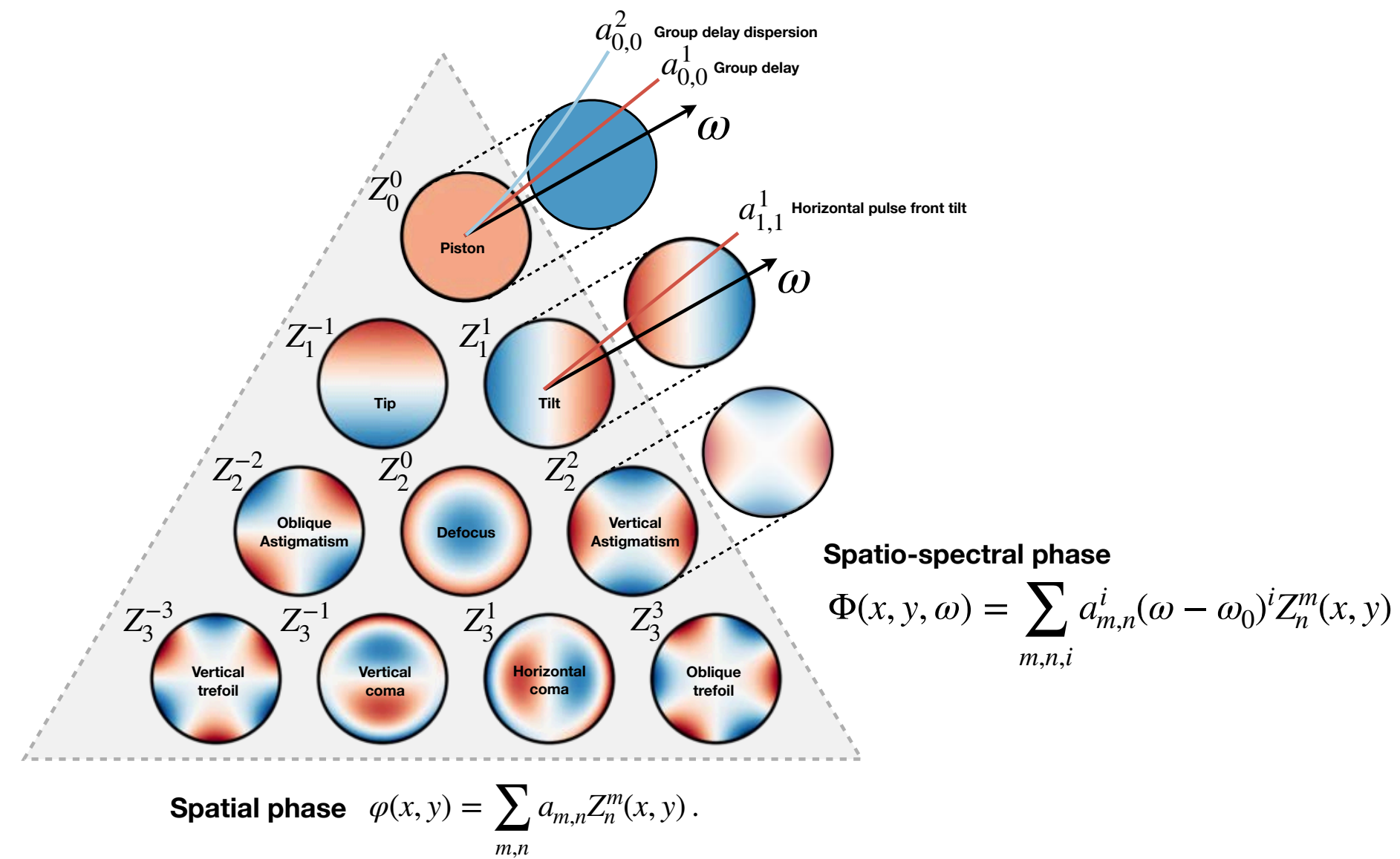
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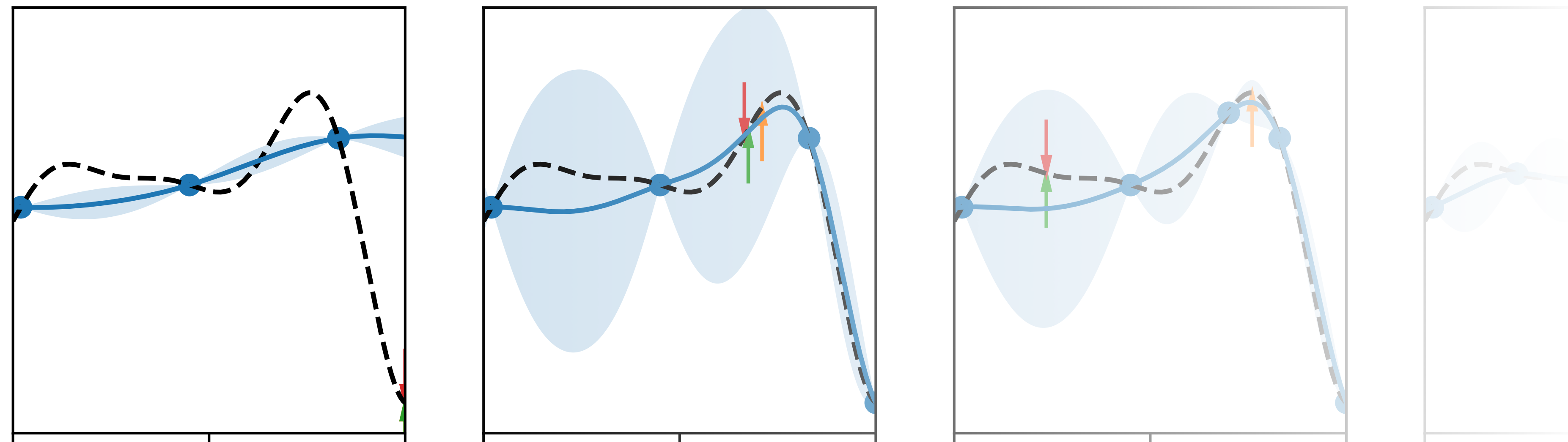


# Phase III Custom-built methods

## Example I Spatio-Temporal Laser Pulse Characterization



## Example II Laser-Accelerator Optimization





# Ultra-intense laser characterization

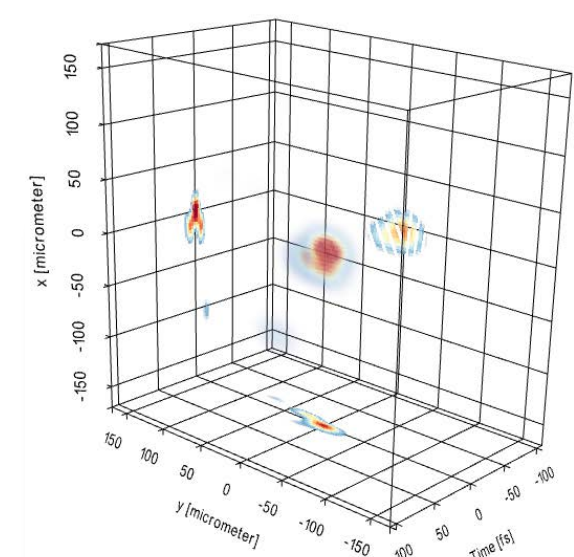
$$f(\text{cube}) = \text{square}$$

Take measurements with 2D camera sensor

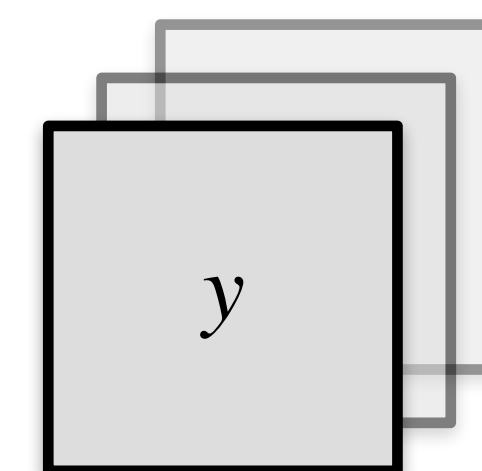
## 3-D intensity distribution in time

Knowledge necessary for

- Highest peak-intensity
- Accurate simulations
- Spatio-temporal shaping (flying focus etc.)
- ...



$$I(x, y, t)$$

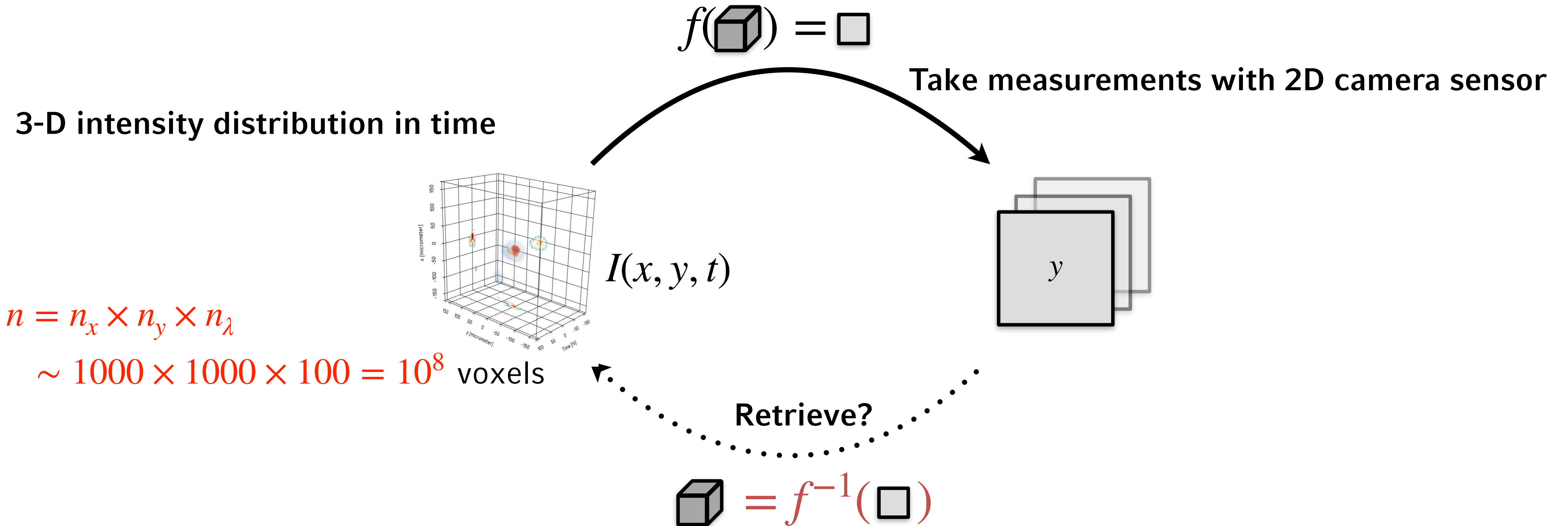


Retrieve?

$$\text{cube} = f^{-1}(\text{square})$$



# Ultra-intense laser characterization



**100 million voxels / parameters:** Need many measurements (e.g. Fourier transform spectroscopy with >1000 2D measurements)

**But are voxels really a good base function choice?**

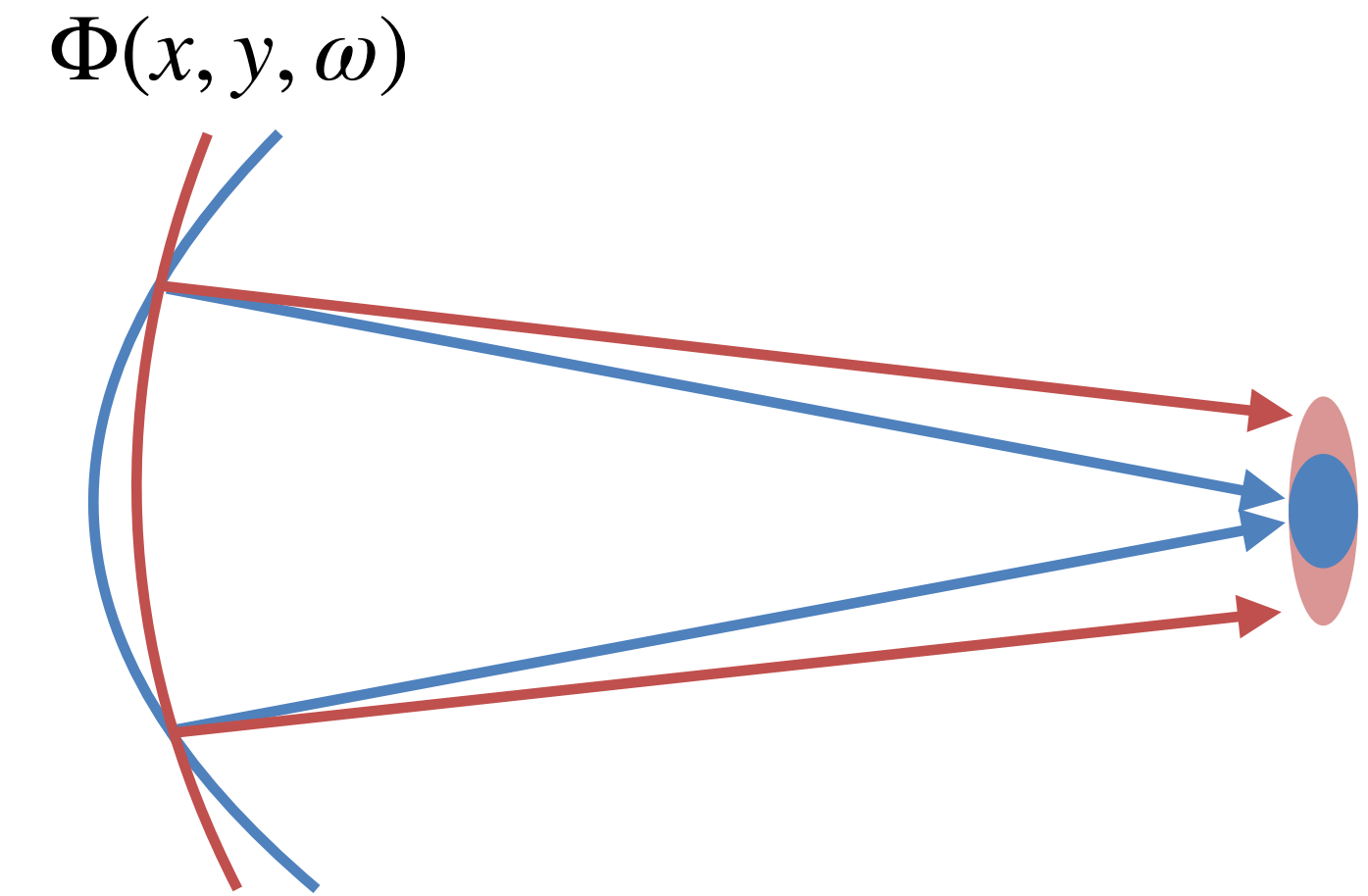


# Ultra-intense laser characterization

Multi-spectral, modal reconstruction

$$I(x, y, t) = \left\| \mathcal{F} \left[ \sqrt{I(x, y, \omega)} \cdot \exp(i\Phi(x, y, \omega)) \right] \right\|^2$$

↑  
This is the important part,  
describing how light of  
different color is focused!

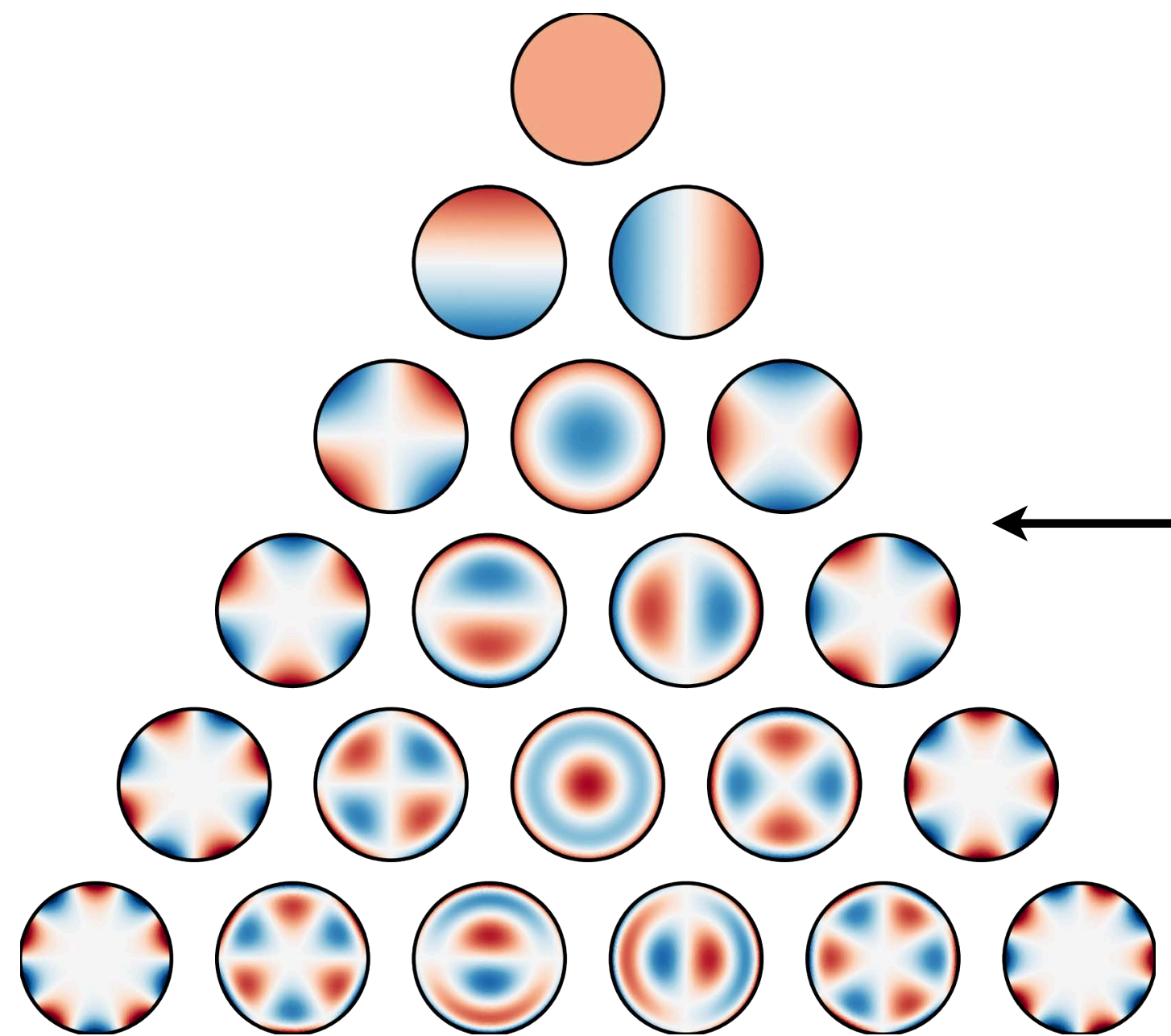




# Ultra-intense laser characterization

Multi-spectral, modal reconstruction

$$I(x, y, t) = \left\| \mathcal{F} \left[ \sqrt{I(x, y, \omega)} \cdot \exp(i\Phi(x, y, \omega)) \right] \right\|^2$$



We know there is a very good base to describe phase:

**Zernike polynomials**

$$Z_n^m(\rho, \varphi) = R_n^m(\rho) \cos(m \varphi)$$

$$Z_n^{-m}(\rho, \varphi) = R_n^m(\rho) \sin(m \varphi),$$



# Ultra-intense laser characterization

Multi-spectral, modal reconstruction



$$I(x, y, t) = \left\| \mathcal{F} \left[ \sqrt{I(x, y, \omega)} \cdot \exp(i\Phi(x, y, \omega)) \right] \right\|^2$$

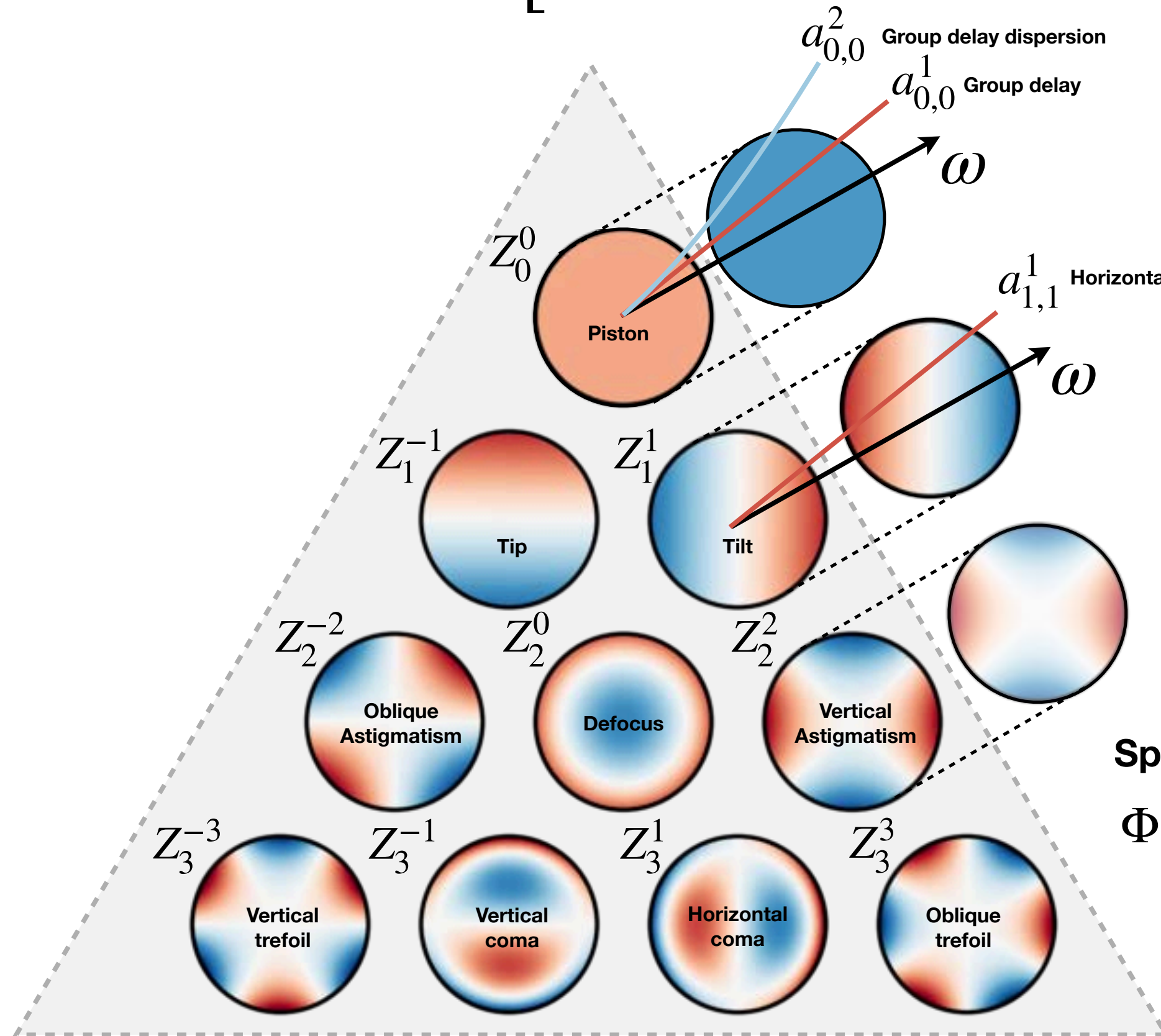
We also know there is a very good way to describe spectral phase: **Taylor expansion** (group delay, group delay dispersion, etc.)



# Ultra-intense laser characterization

Multi-spectral, modal reconstruction

$$I(x, y, t) = \left\| \mathcal{F} \left[ \sqrt{I(x, y, \omega)} \cdot \exp \left( i\Phi(x, y, \omega) \right) \right] \right\|^2$$



Can describe the **hyperspectral wavefront** using **Zernike-modes and Taylor-expansion in frequency**

Instead of  $> 1,000,000$  voxels we only need to reconstruct dominant mode coefficients: Need less measurements

**Spatio-spectral phase**

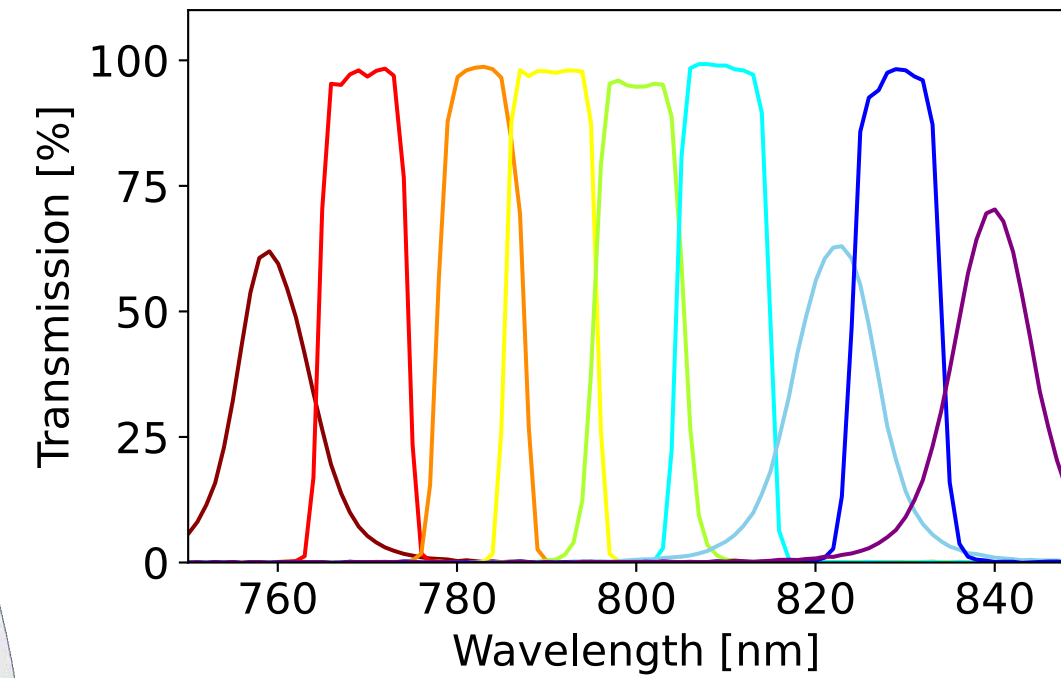
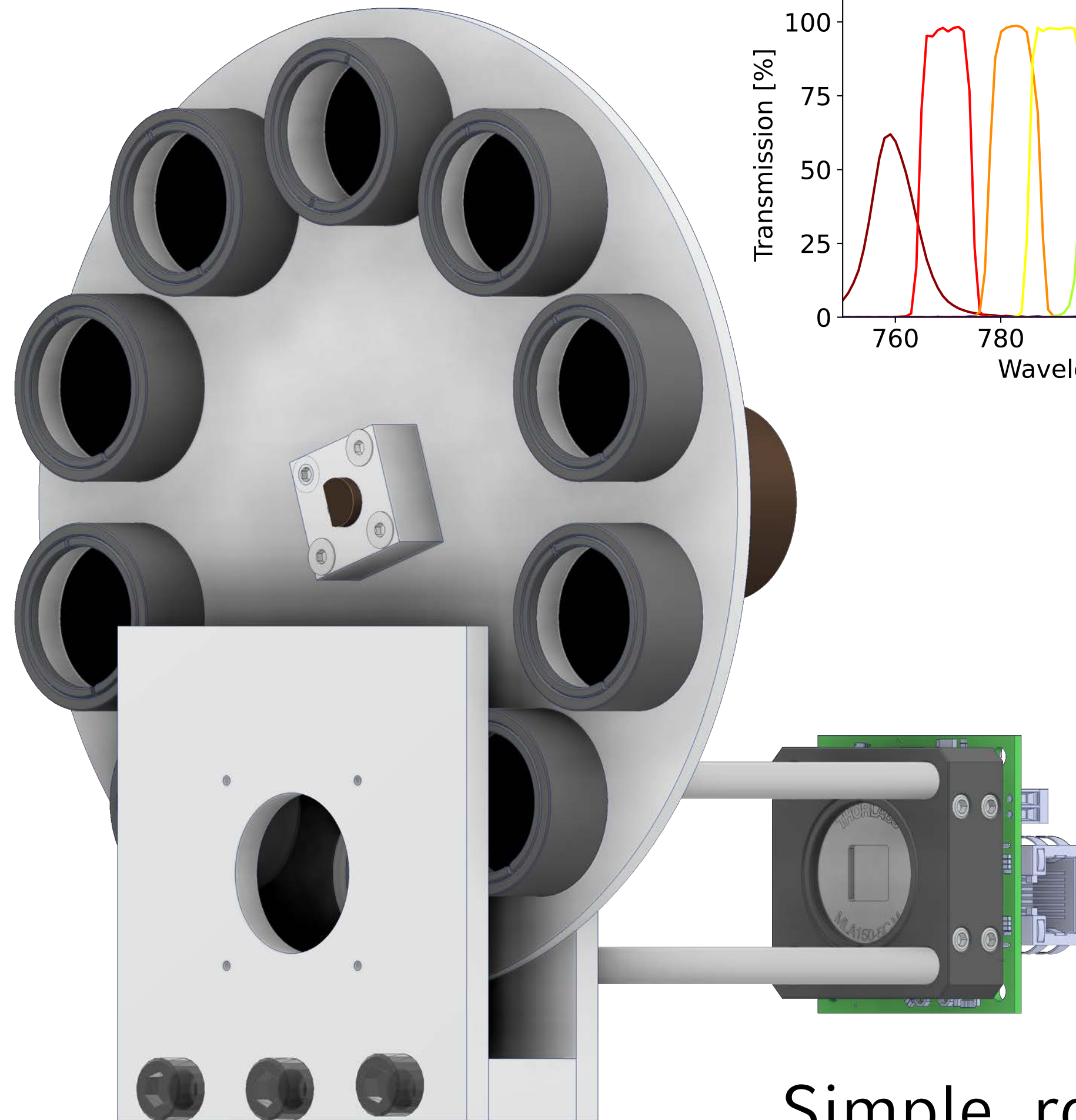
$$\Phi(x, y, \omega) = \sum_{m,n,i} a_{m,n}^i (\omega - \omega_0)^i Z_n^m(x, y)$$

**Spatial phase**  $\varphi(x, y) = \sum_{m,n} a_{m,n} Z_n^m(x, y).$



# Ultra-intense laser characterization

**FALCON** - Fast Acquisition of Laser Couplings using Narrowband Filters



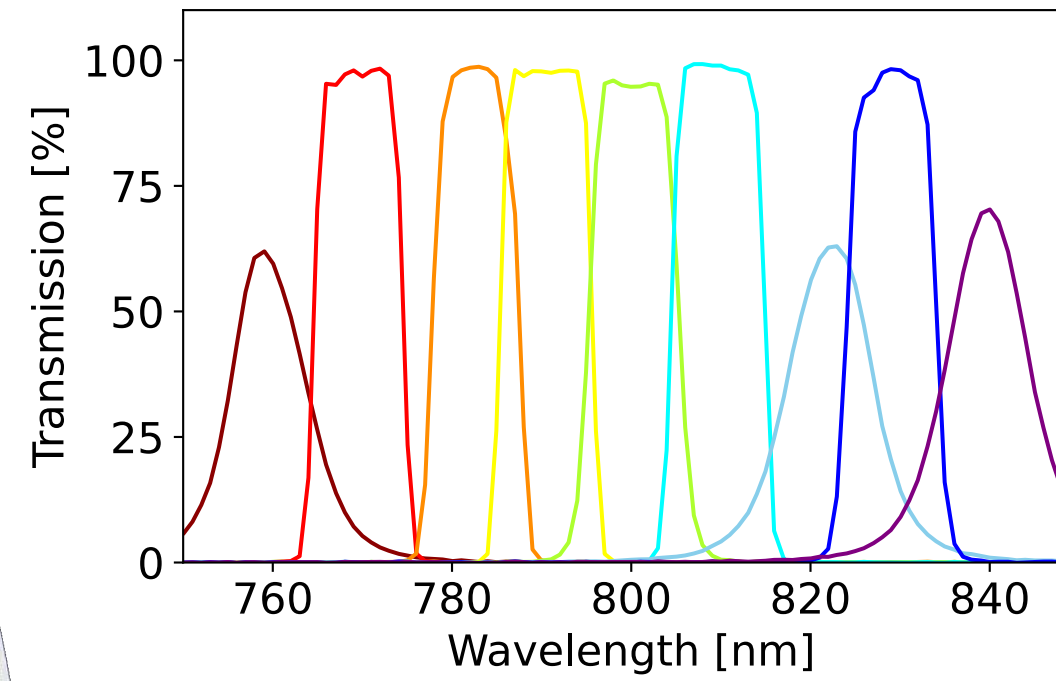
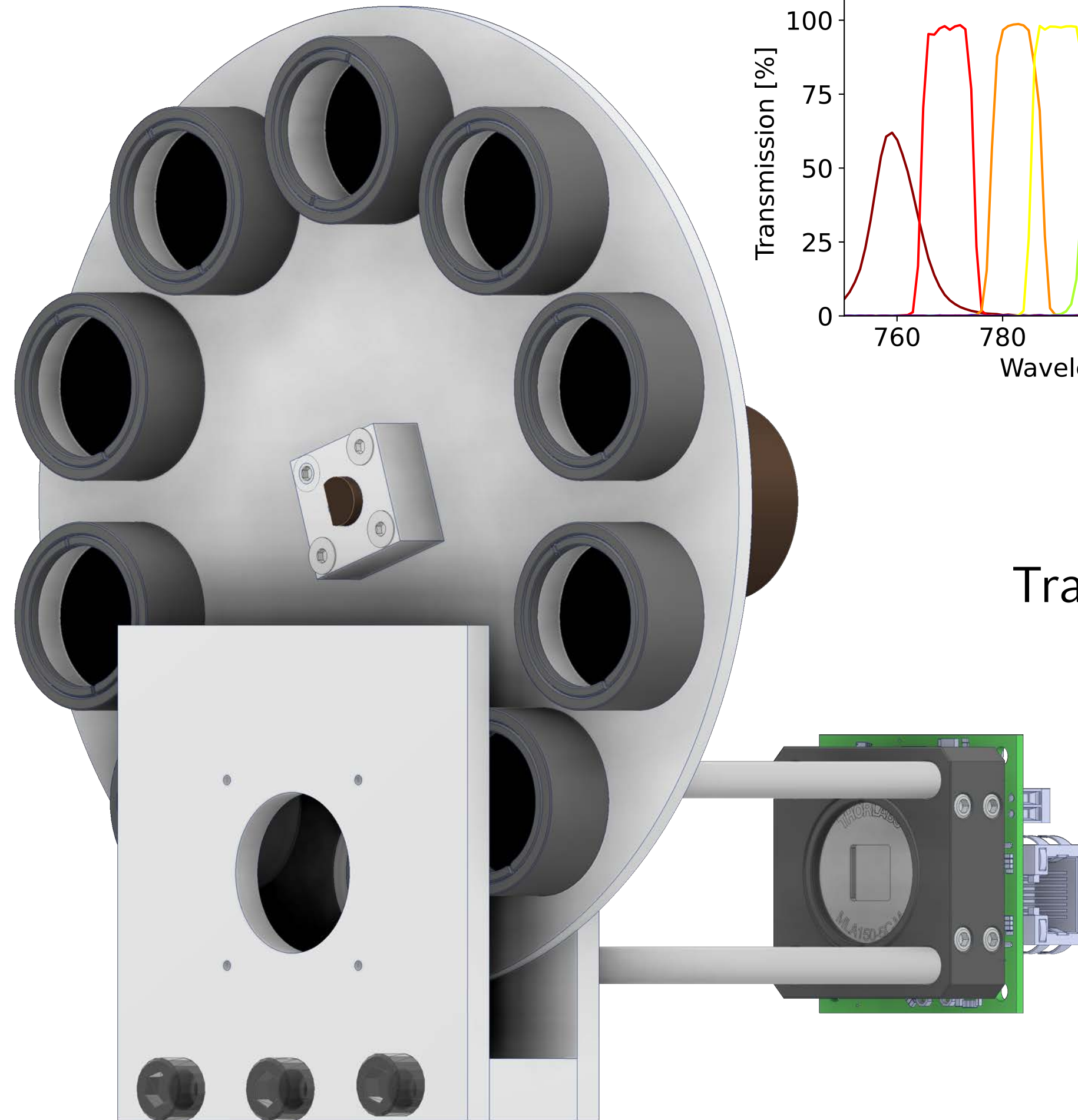
Simple, robust device

- N. Weiße, J. Esslinger et al. Measuring spatial-temporal couplings using modal multi-spectral wavefront reconstruction, Opt. Express 31, 19733-19745 (2023)



# Ultra-intense laser characterization

## FALCON - Fast Acquisition of Laser Couplings using Narrowband Filters



This is for a simple 2x2 lenslet SH detector

$$\begin{pmatrix}
 s_{x,\omega_1}(0,0) \\
 s_{x,\omega_1}(0,1) \\
 s_{x,\omega_1}(1,0) \\
 s_{x,\omega_1}(1,1) \\
 s_{y,\omega_1}(0,0) \\
 s_{y,\omega_1}(0,1) \\
 s_{y,\omega_1}(1,0) \\
 s_{y,\omega_1}(1,1) \\
 s_{x,\omega_2}(0,0) \\
 s_{x,\omega_2}(0,1) \\
 s_{x,\omega_2}(1,0) \\
 s_{x,\omega_2}(1,1) \\
 s_{y,\omega_2}(0,0) \\
 s_{y,\omega_2}(0,1) \\
 s_{y,\omega_2}(1,0) \\
 s_{y,\omega_2}(1,1)
 \end{pmatrix}
 =
 \begin{pmatrix}
 \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1^1 \\
 \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1^1 \\
 \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1^1 \\
 \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1^1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1^1 \\
 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1^1 \\
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 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1^1 \\
 \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_2^1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_2^1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_2^1 \\
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 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2^1 \\
 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2^1 \\
 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2^1 \\
 \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2^1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2^1
 \end{pmatrix}
 \begin{pmatrix}
 a_{0,0}^0 \\
 a_{1,-1}^0 \\
 a_{1,1}^0 \\
 a_{0,0}^1 \\
 a_{1,-1}^1 \\
 a_{1,1}^1
 \end{pmatrix}$$

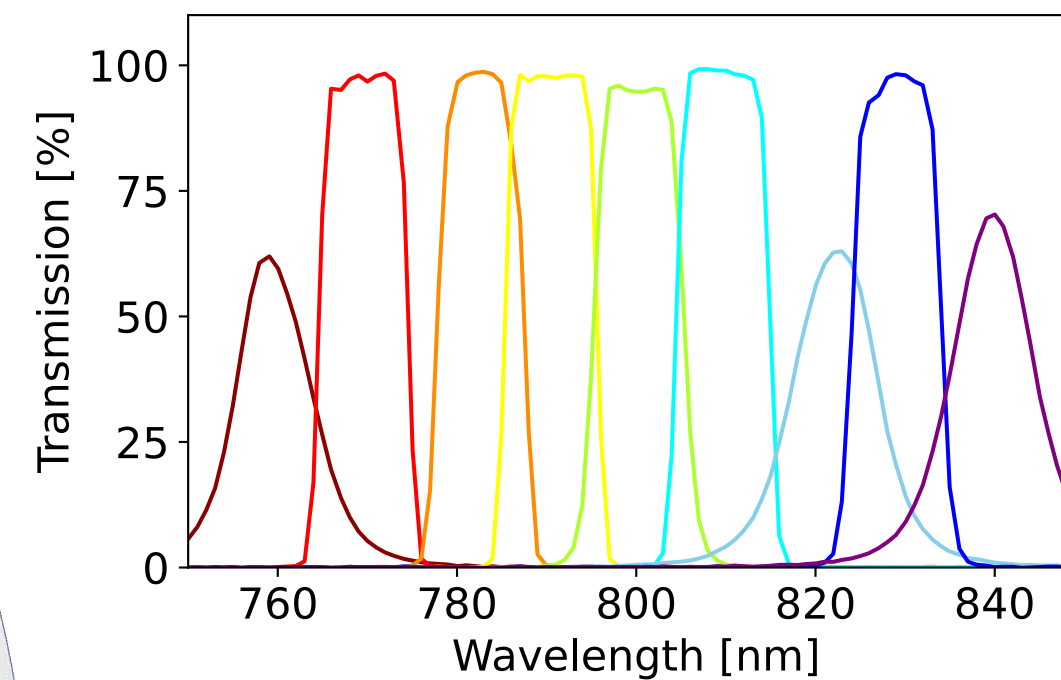
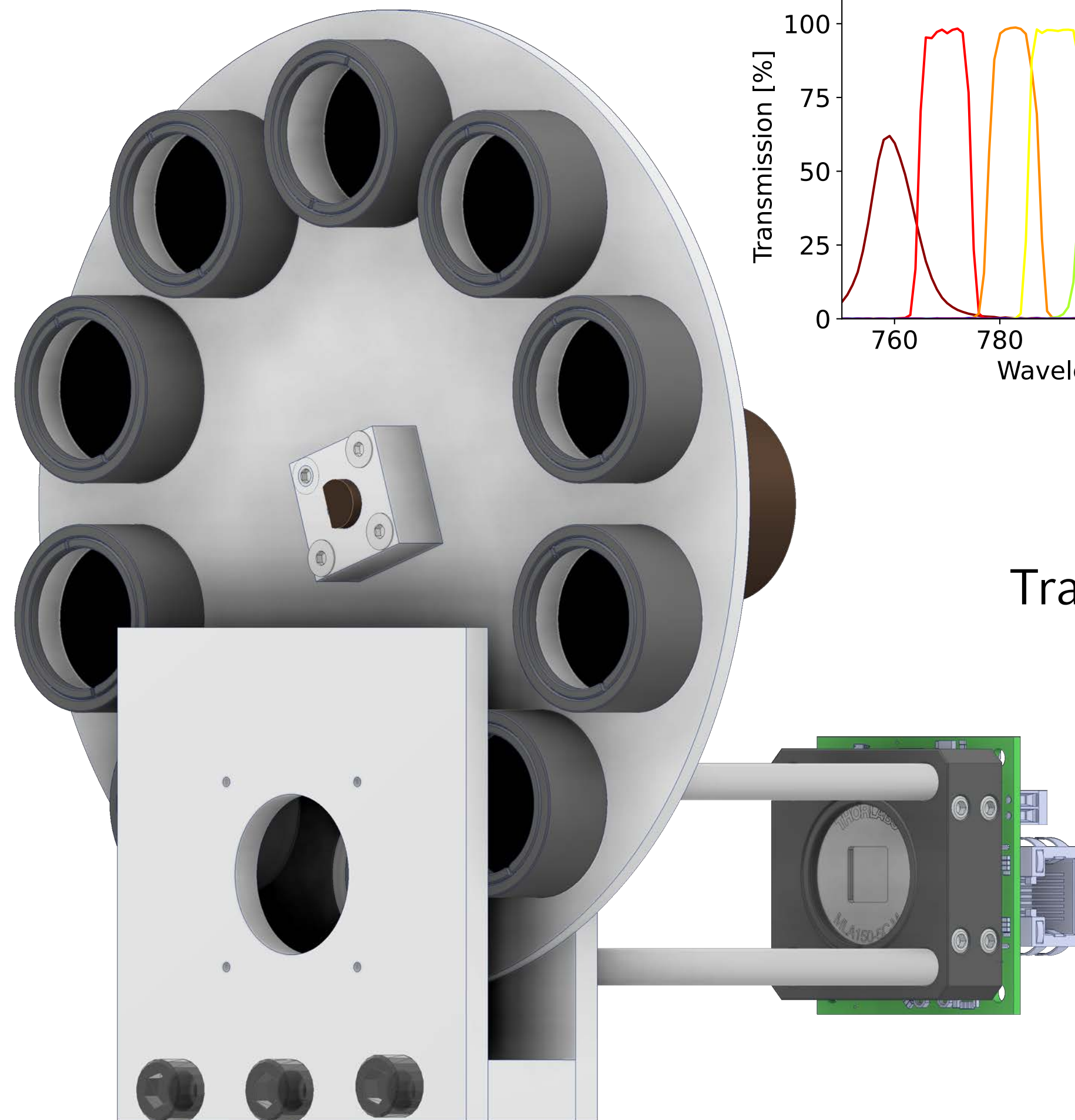
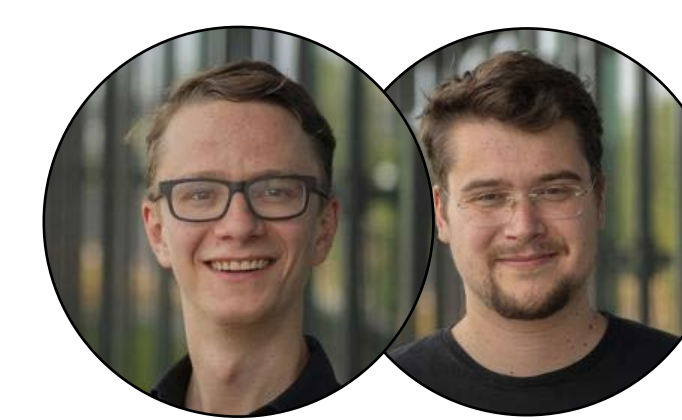
Translate into a forward problem

• N. Weiße, J. Esslinger et al. Measuring spatial-temporal couplings using modal multi-spectral wavefront reconstruction, Opt. Express 31, 19733-19745 (2023)



# Ultra-intense laser characterization

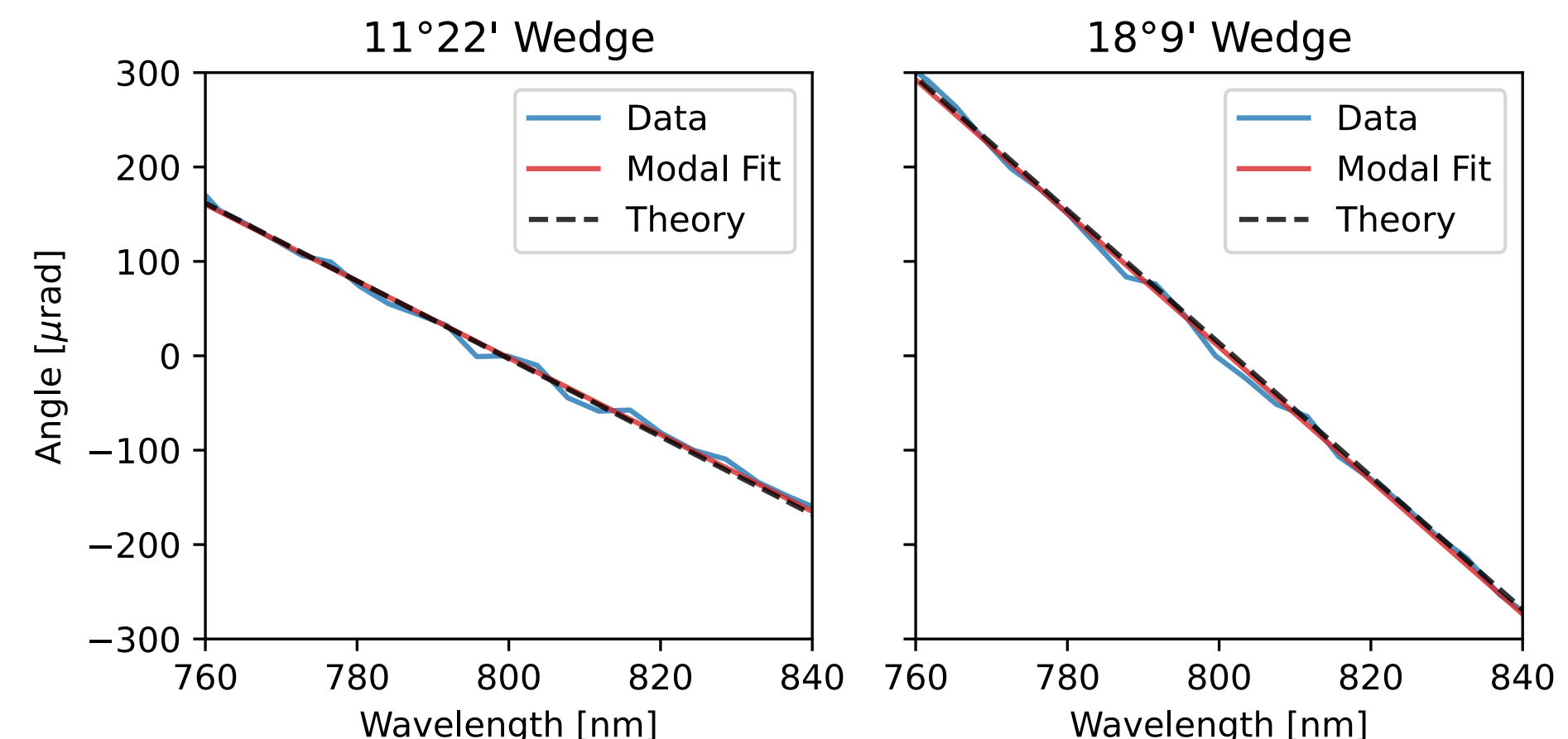
## FALCON - Fast Acquisition of Laser Couplings using Narrowband Filters



$$\begin{pmatrix} s_{x,\omega_1}(0,0) \\ s_{x,\omega_1}(0,1) \\ s_{x,\omega_1}(1,0) \\ s_{x,\omega_1}(1,1) \\ s_{y,\omega_1}(0,0) \\ s_{y,\omega_1}(0,1) \\ s_{y,\omega_1}(1,0) \\ s_{y,\omega_1}(1,1) \\ s_{x,\omega_2}(0,0) \\ s_{x,\omega_2}(0,1) \\ s_{x,\omega_2}(1,0) \\ s_{x,\omega_2}(1,1) \\ s_{y,\omega_2}(0,0) \\ s_{y,\omega_2}(0,1) \\ s_{y,\omega_2}(1,0) \\ s_{y,\omega_2}(1,1) \end{pmatrix} =$$

$$\begin{pmatrix} \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_1 & \frac{dZ_1^1}{dx} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_1 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_1 & \frac{dZ_2^2}{dy} & \tilde{\omega}_1 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_2 & \frac{dZ_1^1}{dx} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_2 & \frac{dZ_1^1}{dx} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_2 & \frac{dZ_1^1}{dx} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dx} & \frac{dZ_1^1}{dx} & \frac{dZ_0^0}{dx} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dx} & \tilde{\omega}_2 & \frac{dZ_1^1}{dx} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2 \\ \frac{dZ_1^{-1}}{dy} & \frac{dZ_1^1}{dy} & \frac{dZ_2^{-2}}{dy} & \tilde{\omega}_2 & \frac{dZ_1^{-1}}{dy} & \tilde{\omega}_2 & \frac{dZ_2^2}{dy} & \tilde{\omega}_2 \end{pmatrix} \begin{pmatrix} a_{0,0}^0 \\ a_{1,-1}^0 \\ a_{1,1}^0 \\ a_{0,0}^1 \\ a_{1,-1}^1 \\ a_{1,1}^1 \end{pmatrix}$$

Translate into a forward problem



Penrose pseudo-inverse calculation (basically realtime)

• N. Weiße, J. Esslinger et al. Measuring spatial-temporal couplings using modal multi-spectral wavefront reconstruction, Opt. Express 31, 19733-19745 (2023)

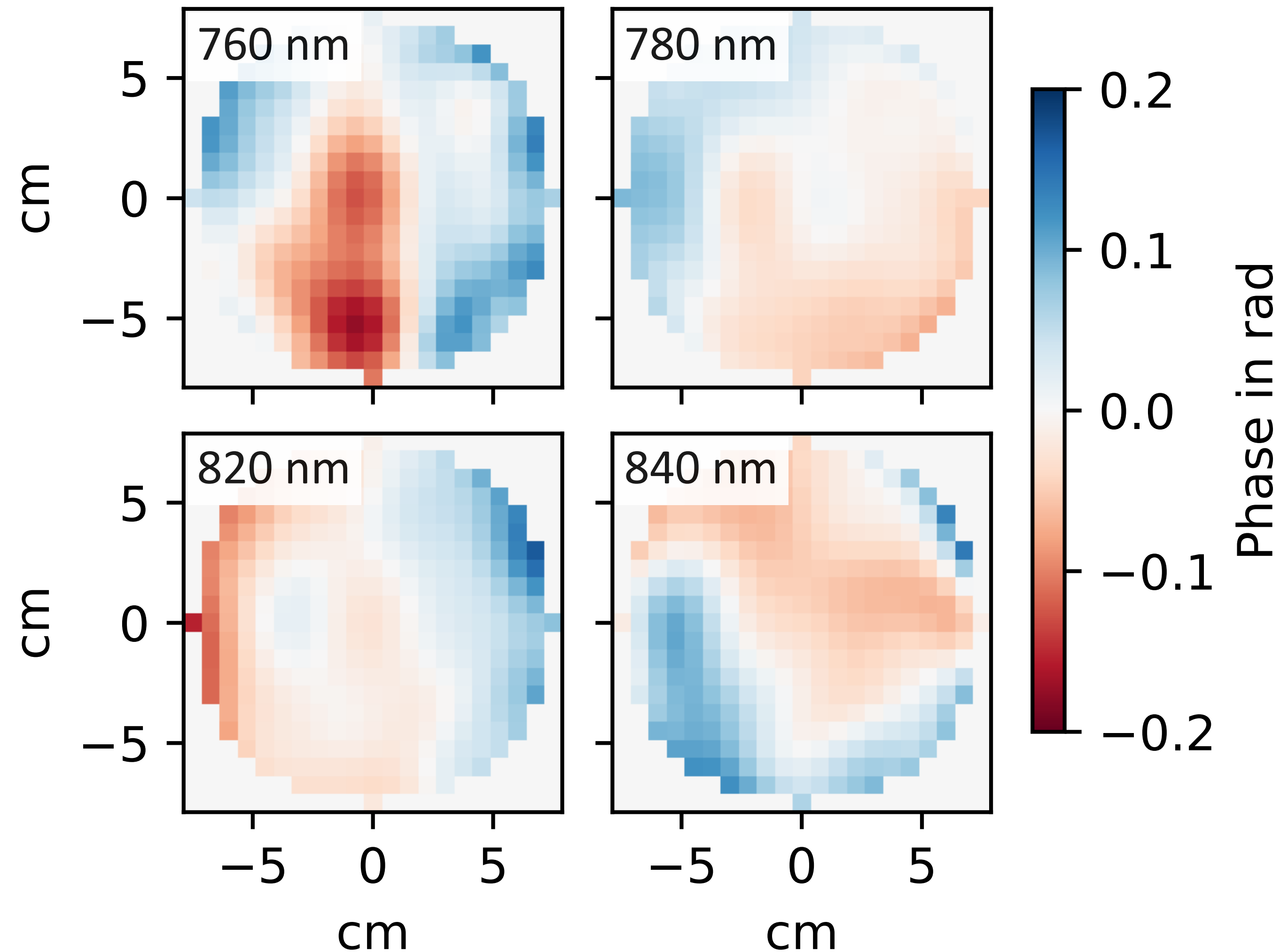


# Ultra-intense laser characterization

Measurement of STCs of the ATLAS petawatt laser



- Full measurement takes  $\sim 1$  minute (9 wavelengths, 5 shots each)
- Measurement shows couplings in ATLAS are  $< \lambda/10$  between 780 - 820 nm
- FALCON measurement now routinely performed every day after focus measurements

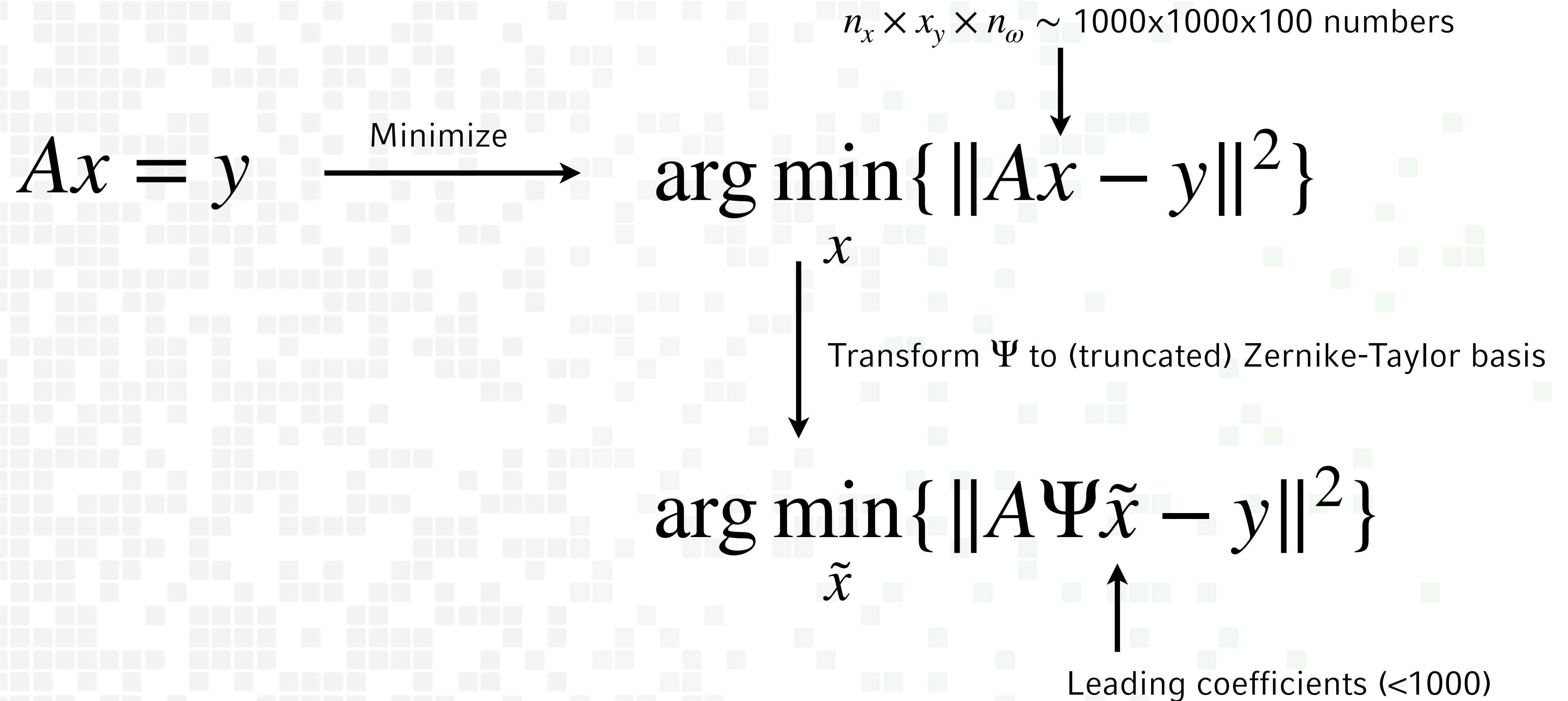


- N. Weiße, J. Esslinger et al. Measuring spatial-temporal couplings using modal multi-spectral wavefront reconstruction, Opt. Express 31, 19733-19745 (2023)



# Ultra-intense laser characterization

Least-squares in Zernike-Taylor basis



**Much more robust reconstruction!**

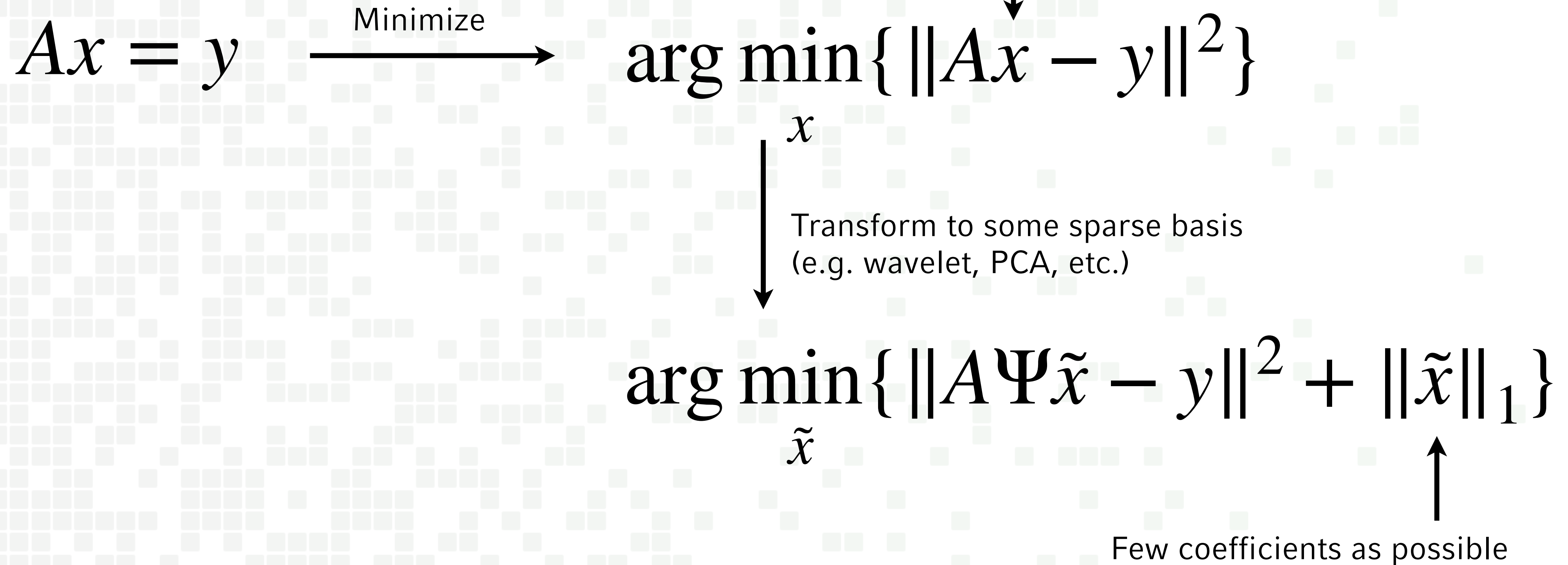


# Ultra-intense laser characterization

Compressed sensing



$n_x \times x_y \times n_\omega \sim 1000 \times 1000 \times 100$  numbers



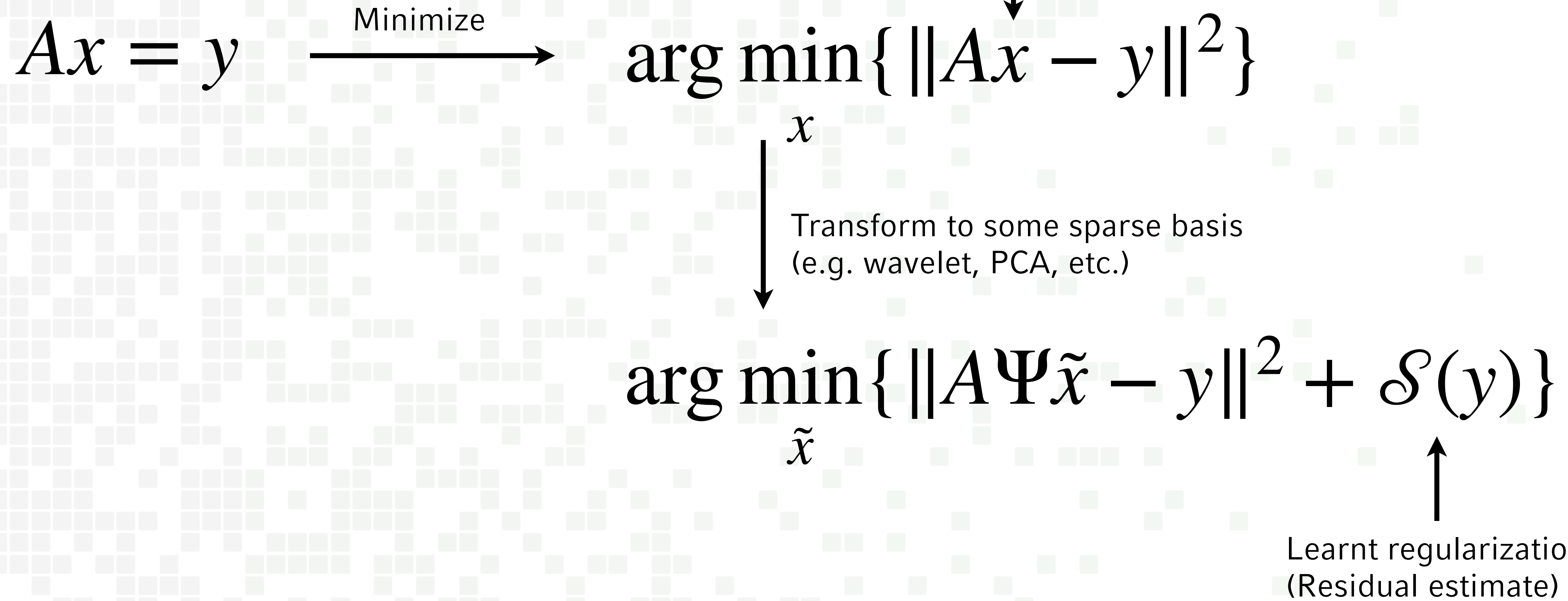


# Ultra-intense laser characterization

Deep compressed sensing



$n_x \times x_y \times n_\omega \sim 1000 \times 1000 \times 100$  numbers





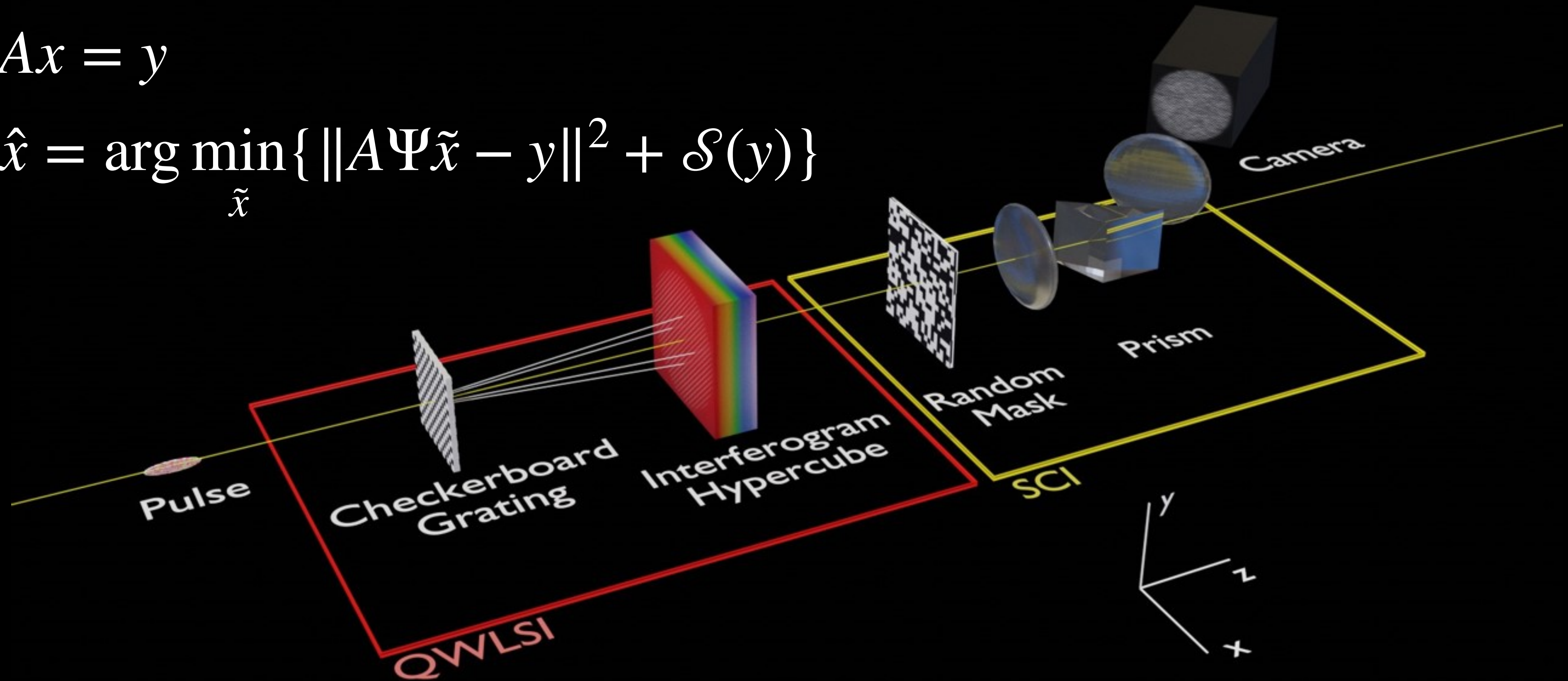
# Ultra-intense laser characterization

Deep compressed sensing



$$Ax = y$$

$$\hat{x} = \arg \min_{\tilde{x}} \{ \|A\Psi\tilde{x} - y\|^2 + \mathcal{S}(y) \}$$





# Bayesian optimization

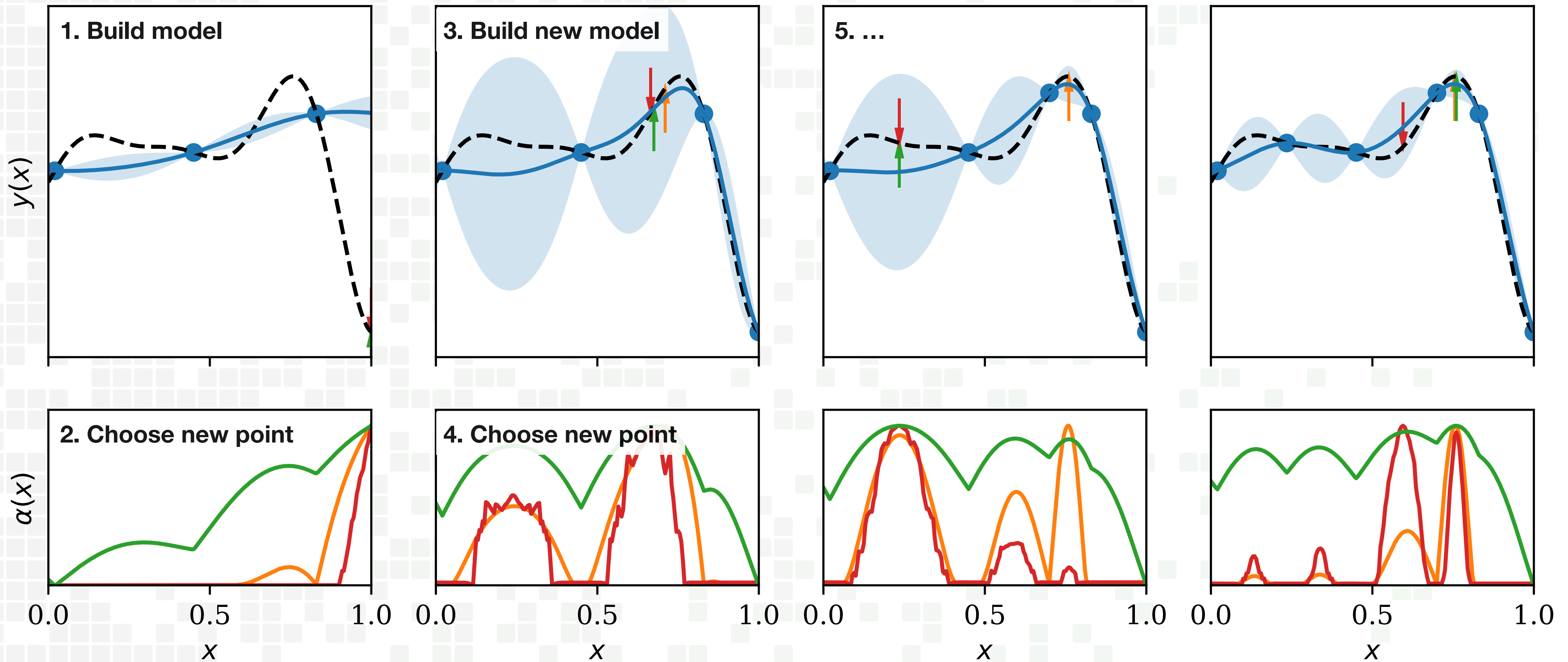
## Sequential model-based optimization

More on Bayesian optimization tomorrow in WG7!

PULSE

CALA

● Evaluated points    - - - Ground truth    — GP mean    GP std    EI    MES    UCB ( $\kappa = 2$ )



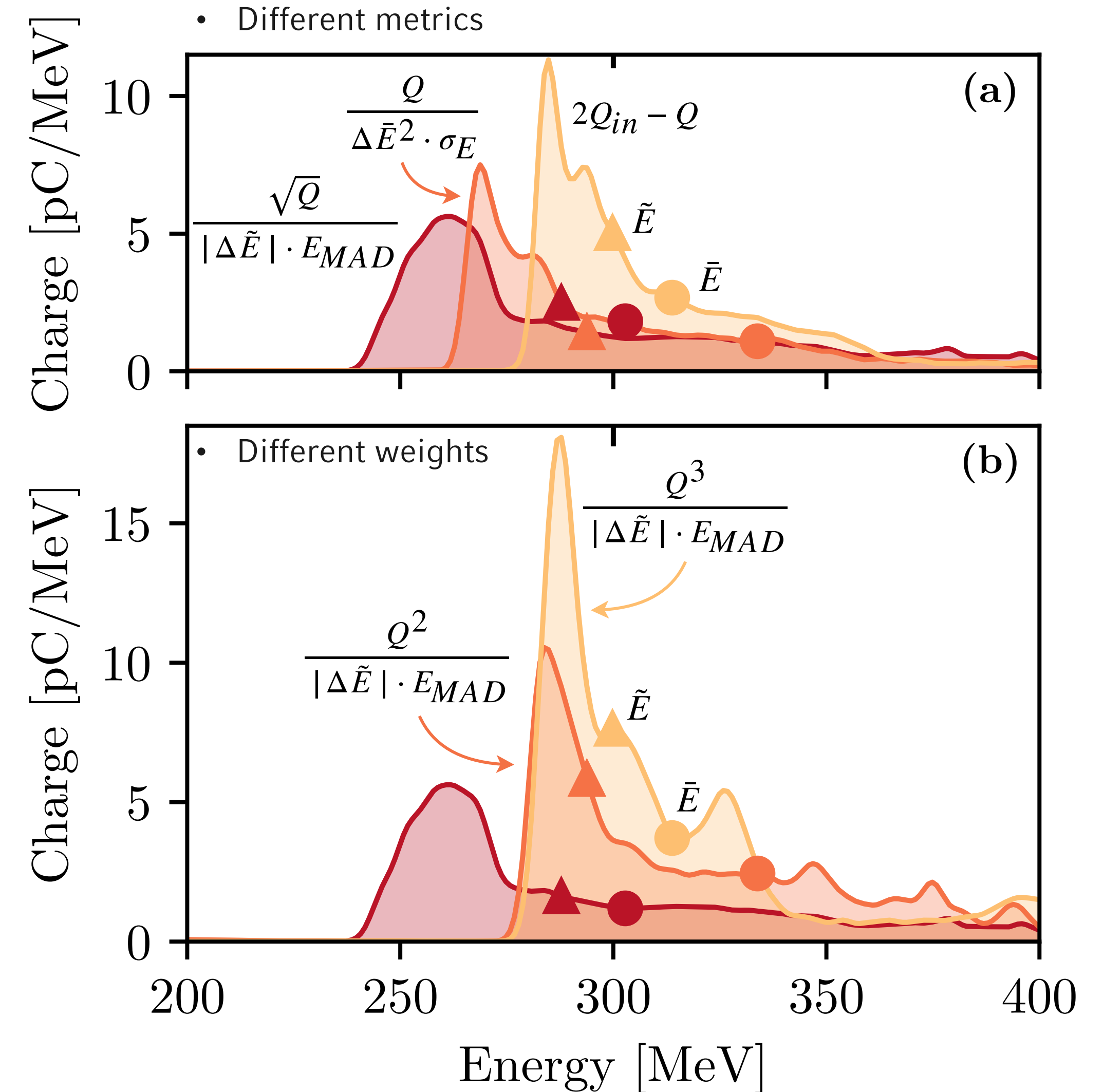


# Multi-objective multi-fidelity optimization

Optimization of electron beam properties (FBPIC simulations)



- We want to optimize three electron beam parameters:
  - Charge  $Q$  (total charge, charge within FWHM, etc.)
  - Bandwidth (standard deviation  $\sigma_E$ , median absolute deviation  $E_{MAD}$ , etc.)
  - Distance to a target energy  $|E_{target} - E|$  (using mean energy, median energy, peak energy, etc.)
- Choosing **different metrics or weights** for each objective **changes the outcome in an a priori unknown way!**
- Instead we want to make a survey and **learn the trade-offs** between all objectives (Pareto optimization)



• Irshad, F., Karsch, S., & Döpp, A. Multi-objective and multi-fidelity Bayesian optimization of laser-plasma acceleration. *Phys. Rev. Research* 5, 013063 (2023)



# Multi-objective multi-fidelity optimization

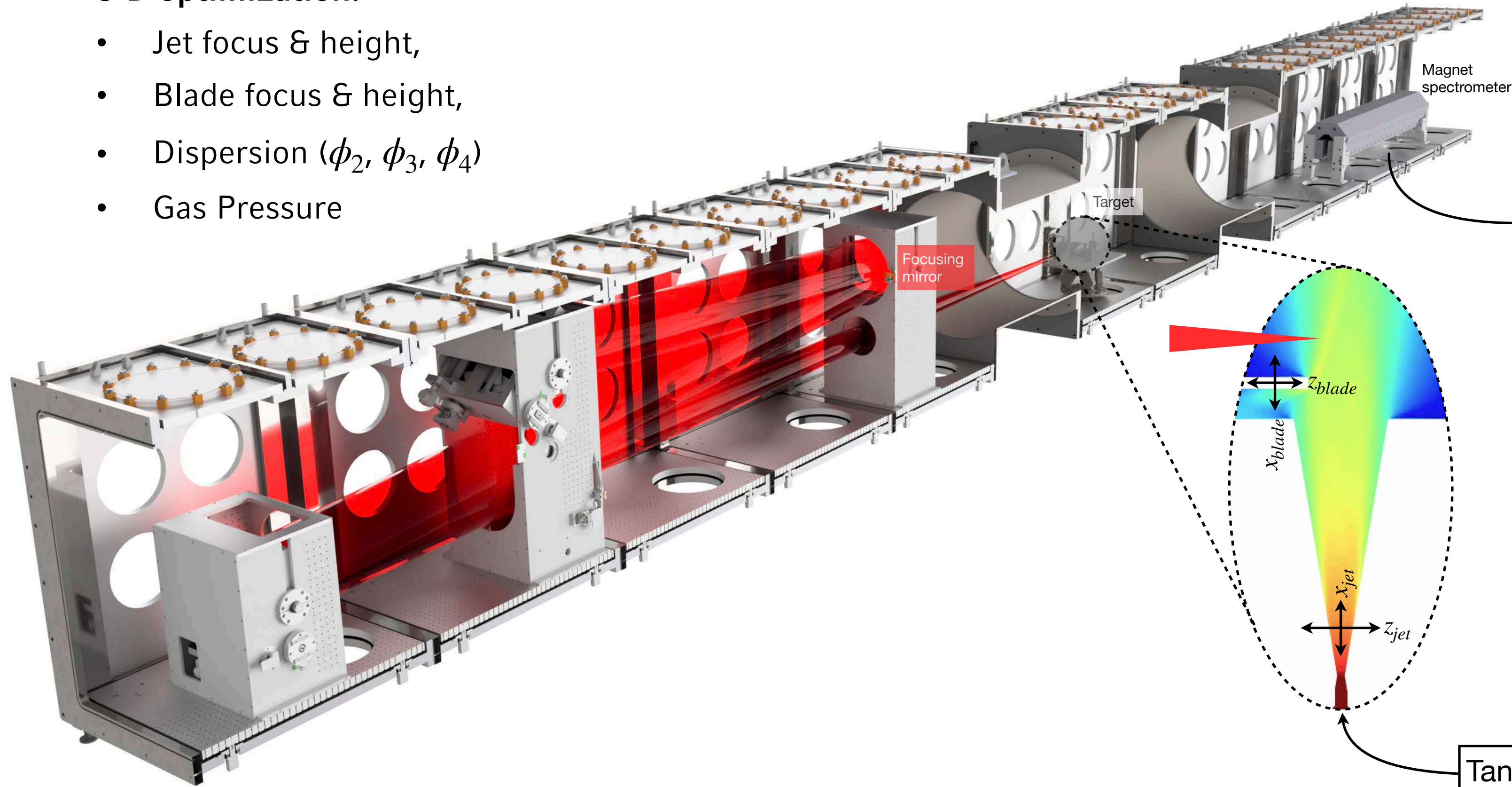
## Optimization of electron beam properties (Experiment)

See Faran's talk tomorrow  
at 17:40 in WG7

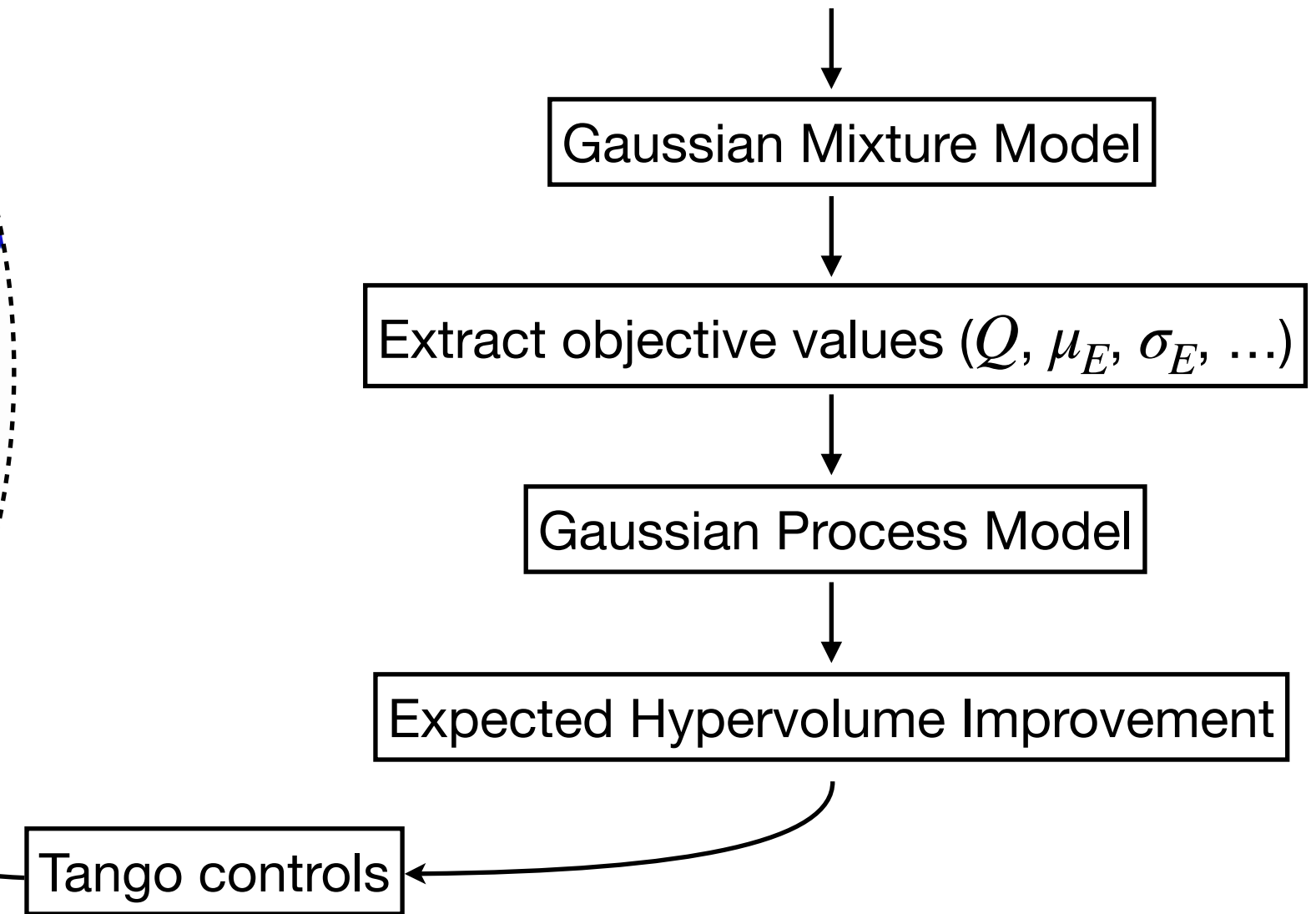
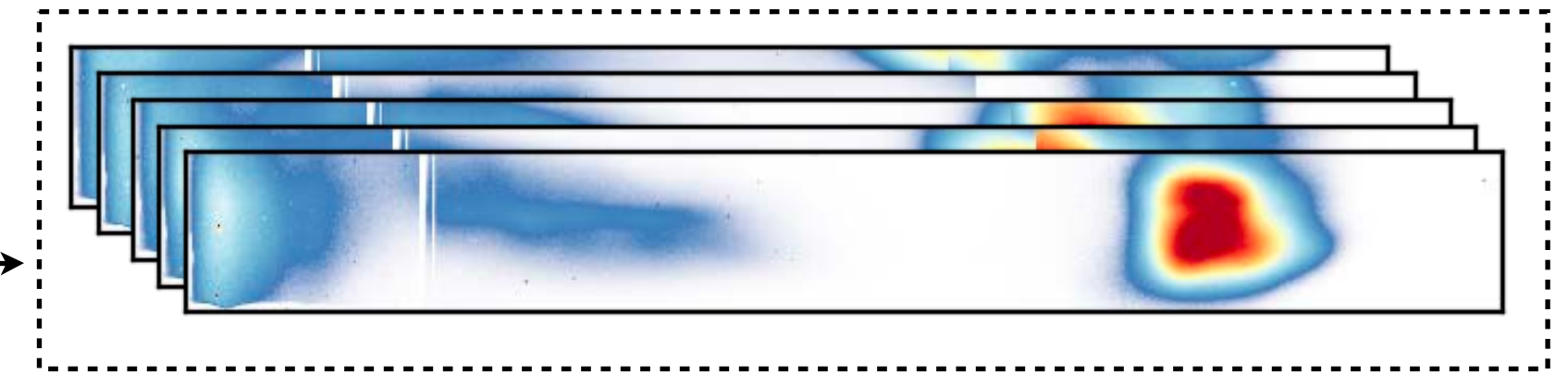


### 8-D optimization:

- Jet focus & height,
- Blade focus & height,
- Dispersion ( $\phi_2, \phi_3, \phi_4$ )
- Gas Pressure



(Model chooses shot number dynamically)  
Spectra at one position



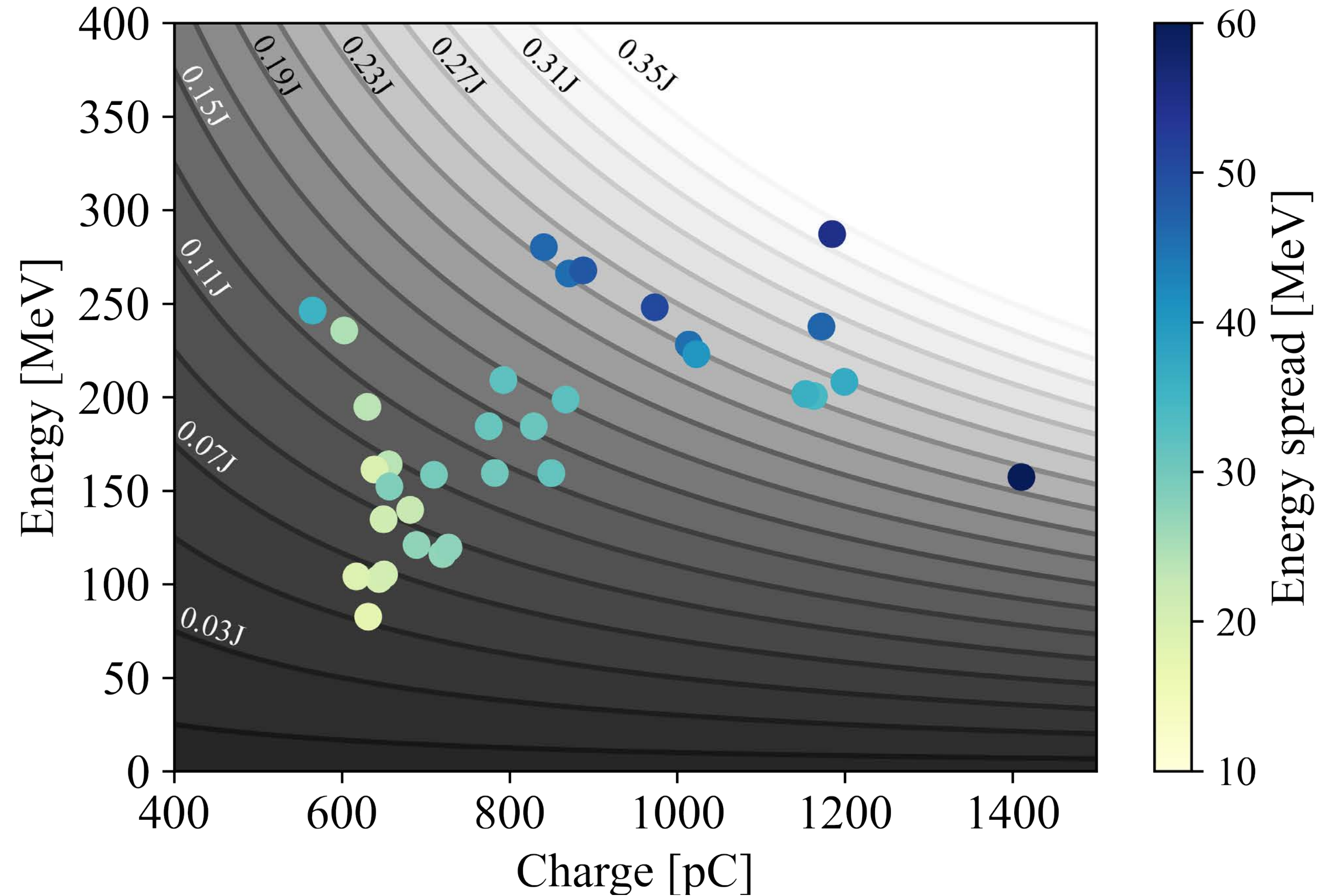


# Multi-objective multi-fidelity optimization

## Optimization of electron beam properties (Experiment)



- Once the Pareto-optimal solutions are identified, we can choose from them what kind of beam we want.
- We observe that many of the Pareto-optimal solutions yield the **same laser-to-beam efficiency**.
- Lower energy spread results in lower efficiency, i.e. is mostly a filtering effect

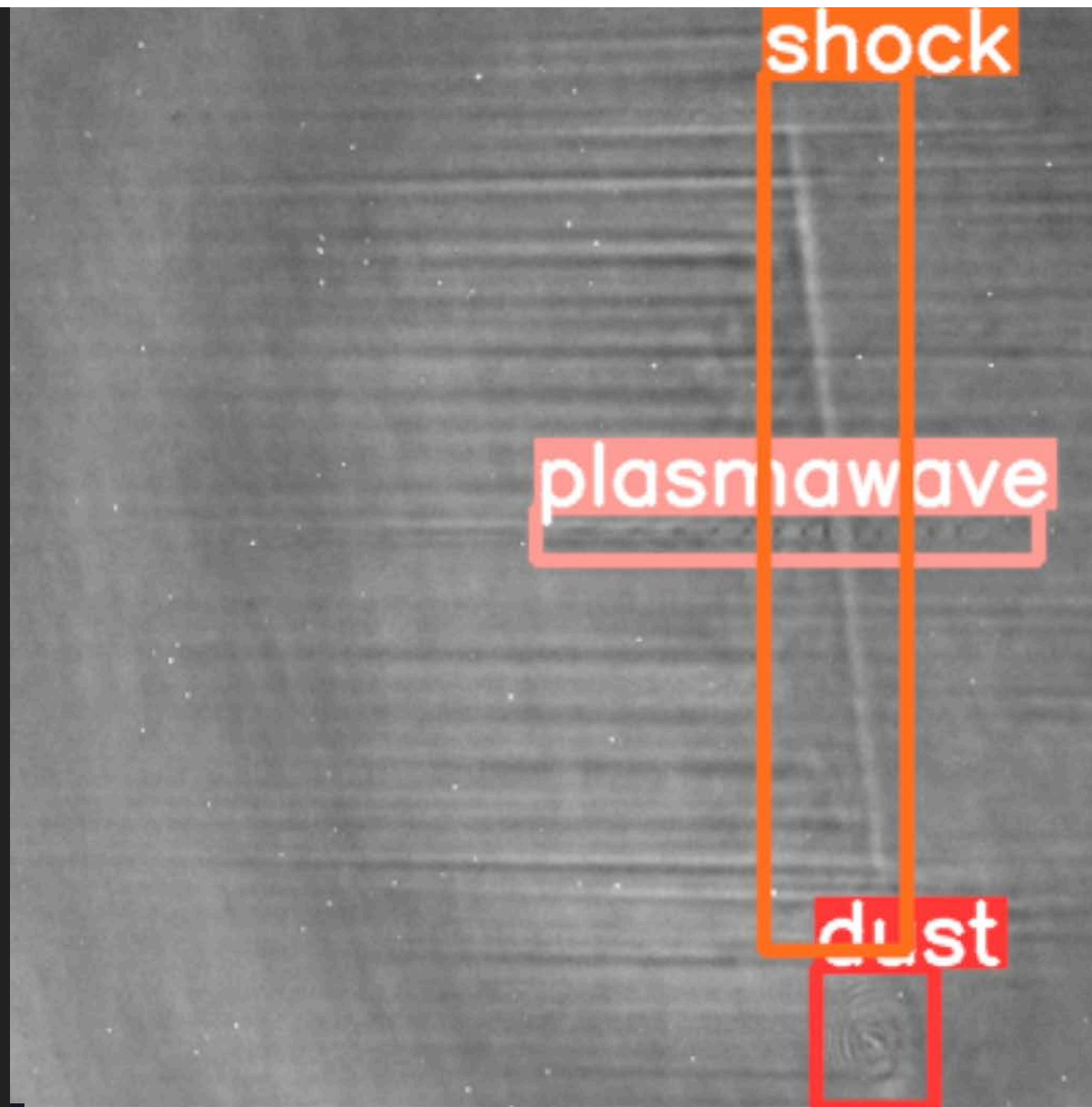




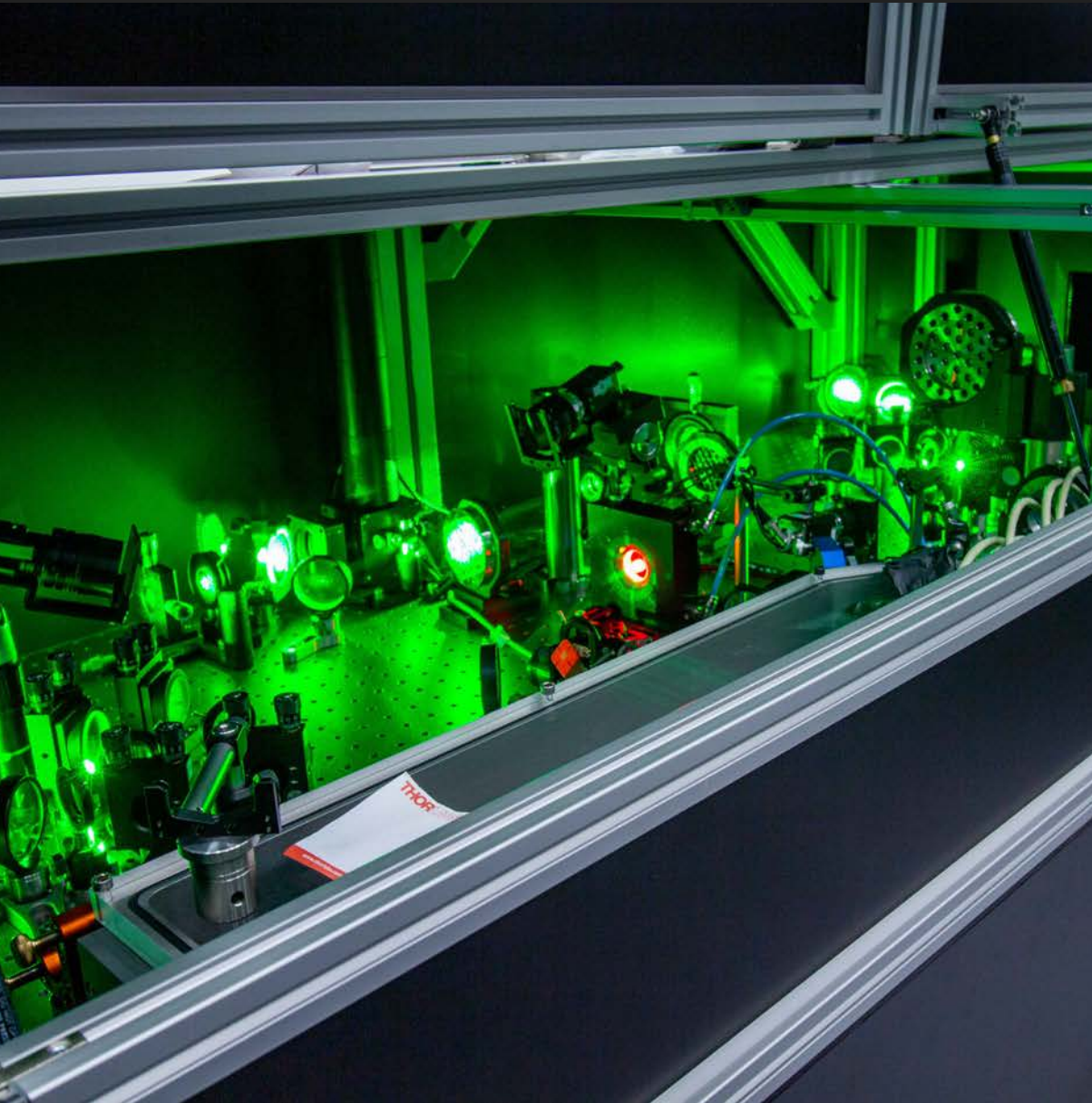
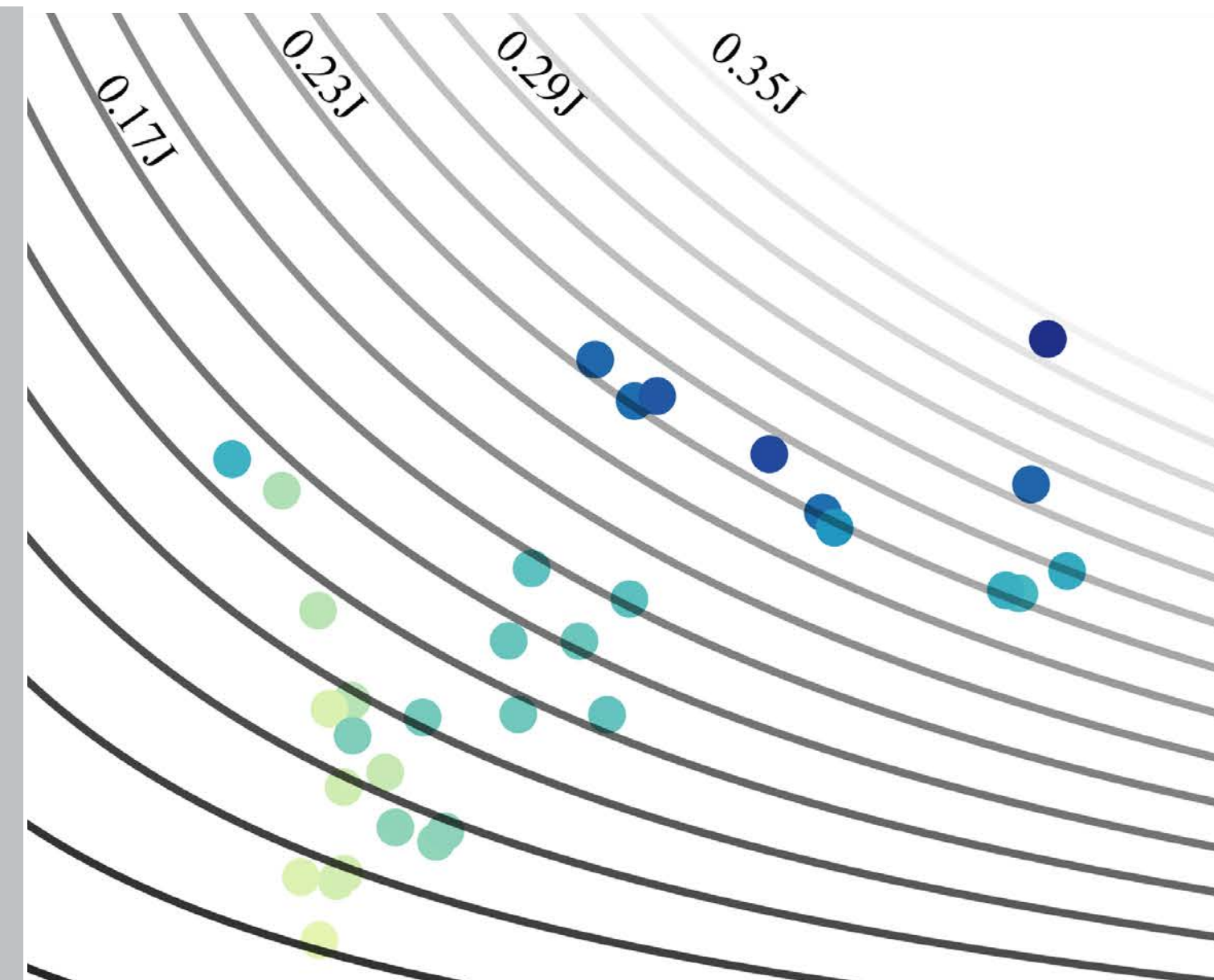
# Summary



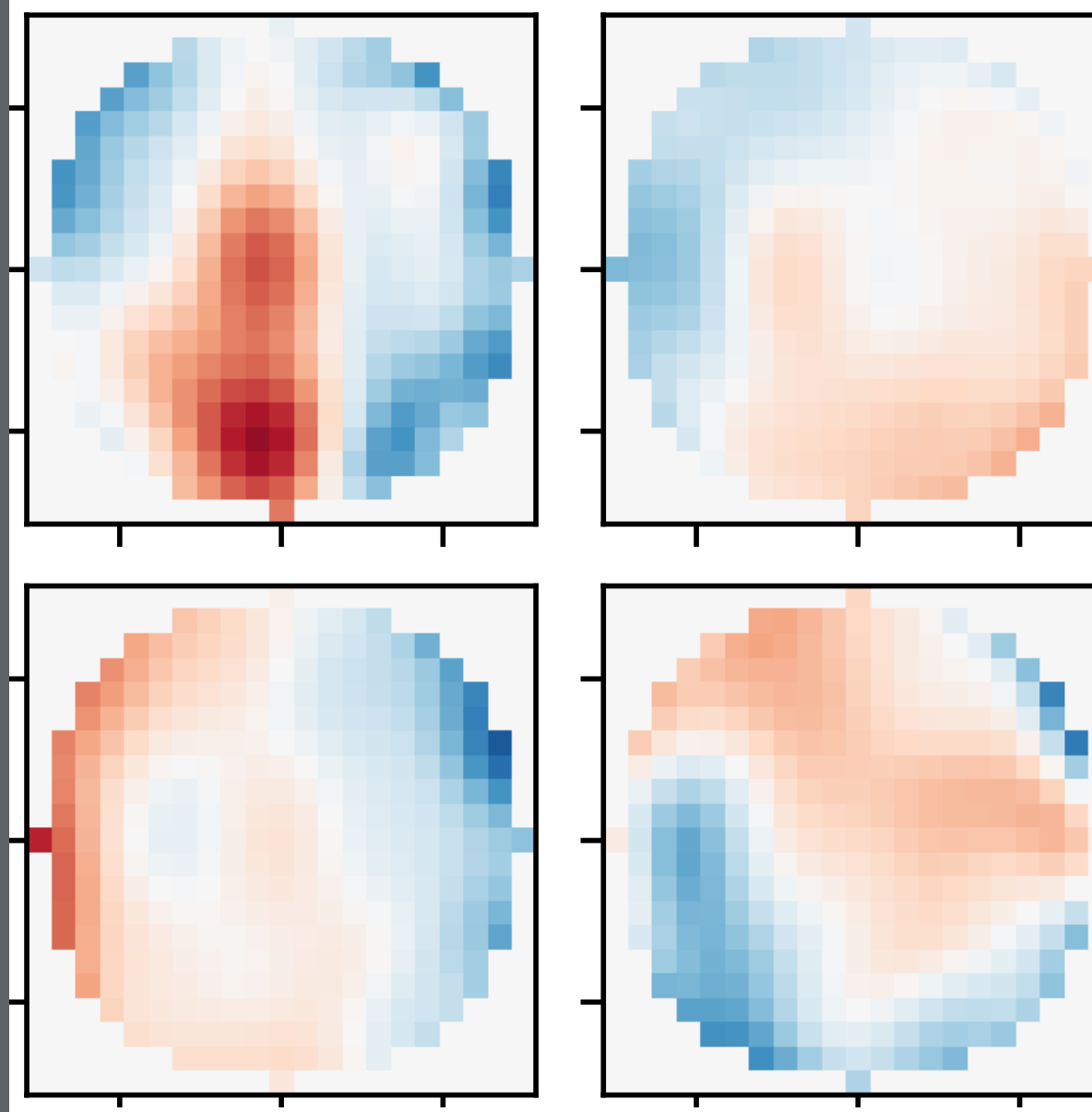
Implemented a coherent control system based on TANGO controls in CALA



Demonstrated Few-Shot Spatio-Temporal Characterization in a Zernike-Taylor Basis



„Off-the-shelf“ ML: Fine-tuned YOLO Object Detection to work with data from experiments



Demonstrated tuning of a laser-plasma accelerator with Bayesian optimization



# Thank you for your attention!

**Dr. Andreas Döpp**  
Am Coulombwall 1 · 85748 Garching · Germany  
a.doepp@lmu.de · [www.pulse.physik.lmu.de](http://www.pulse.physik.lmu.de)

