$(M \cup \Phi) \cap ML$ *Seminar, June 1st, 2023*

Machine-learning strategies
in laser-plasma physics

Andreas Döpp[1,2,3], Faran Irshad[1], Sunny Howard[1,3], Jannik Esslinger[1], Nils Weisse[1], Christoph Eberle[1], Jinpu Lin[1], Robin Wang[3], Peter Norreys[3], Stefan Karsch[1,2]

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[2] *Max Planck Institute for Quantum Optics (MPQ)*

[3] *Faculty of Physics, Oxford University*

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Data-driven **O**ptimization of **L**aser **Ph**ysics and **In**teractions

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Collaborators in Oxford

Peter Norreys

Robin Wang

Machine learning in laser-plasma physics

- Held **1st online workshop on control systems and machine learning** in January 2022 (150+ registered participants)
- **Special issue** in High-Power Laser Science and Engineering.
- Pre-print of **review paper** (30+ pages) **recently published on arXiv**

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

Andreas Döpp,[1,*] Christoph Eberle,[1] Sunny Howard,[1,2] Faran Irshad,[1] Jinpu Lin,[1] and Matthew Streeter[3]
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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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1. A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics,** *arXiv:2212.00026* (2022)

Machine learning in laser-plasma physics

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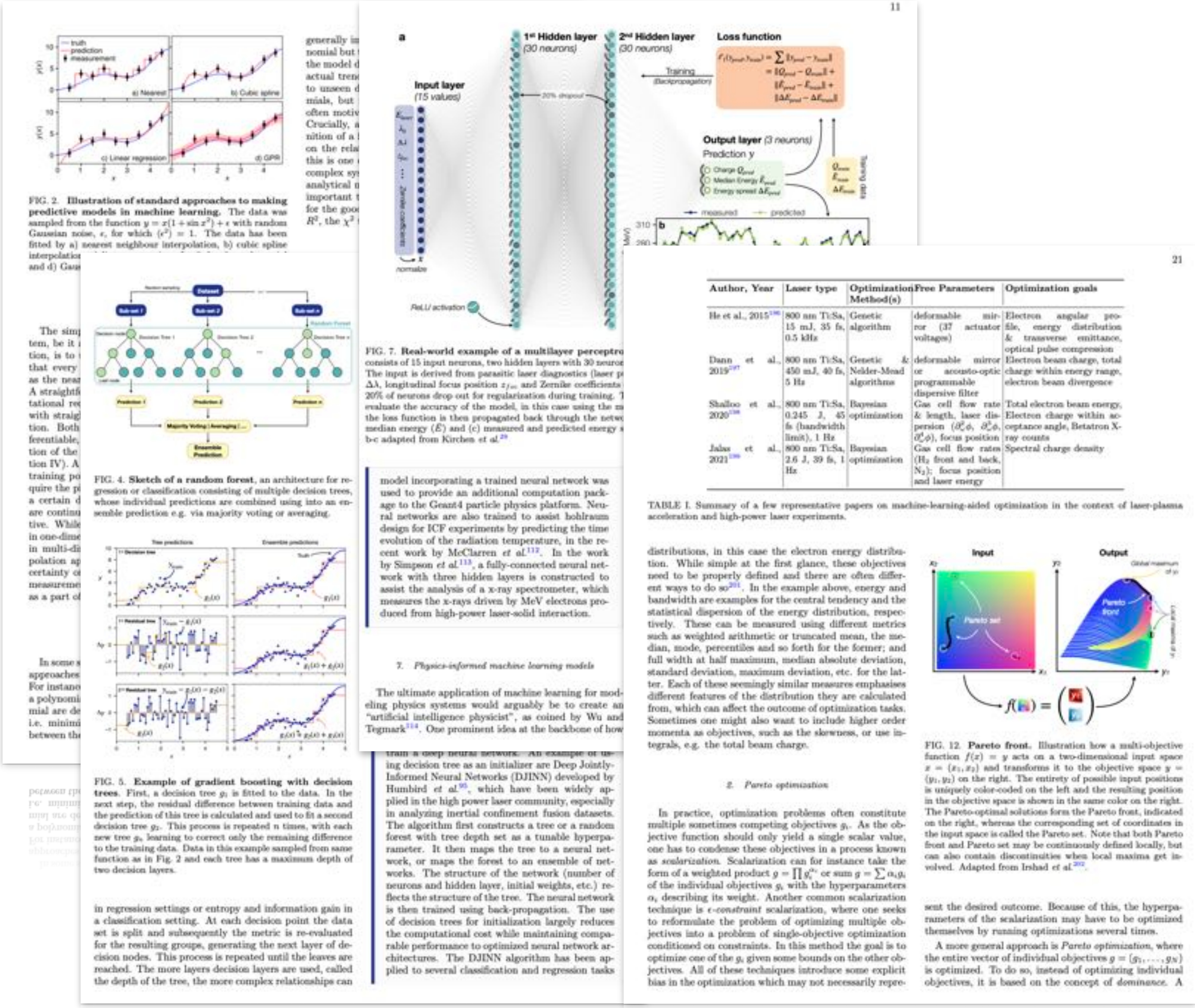
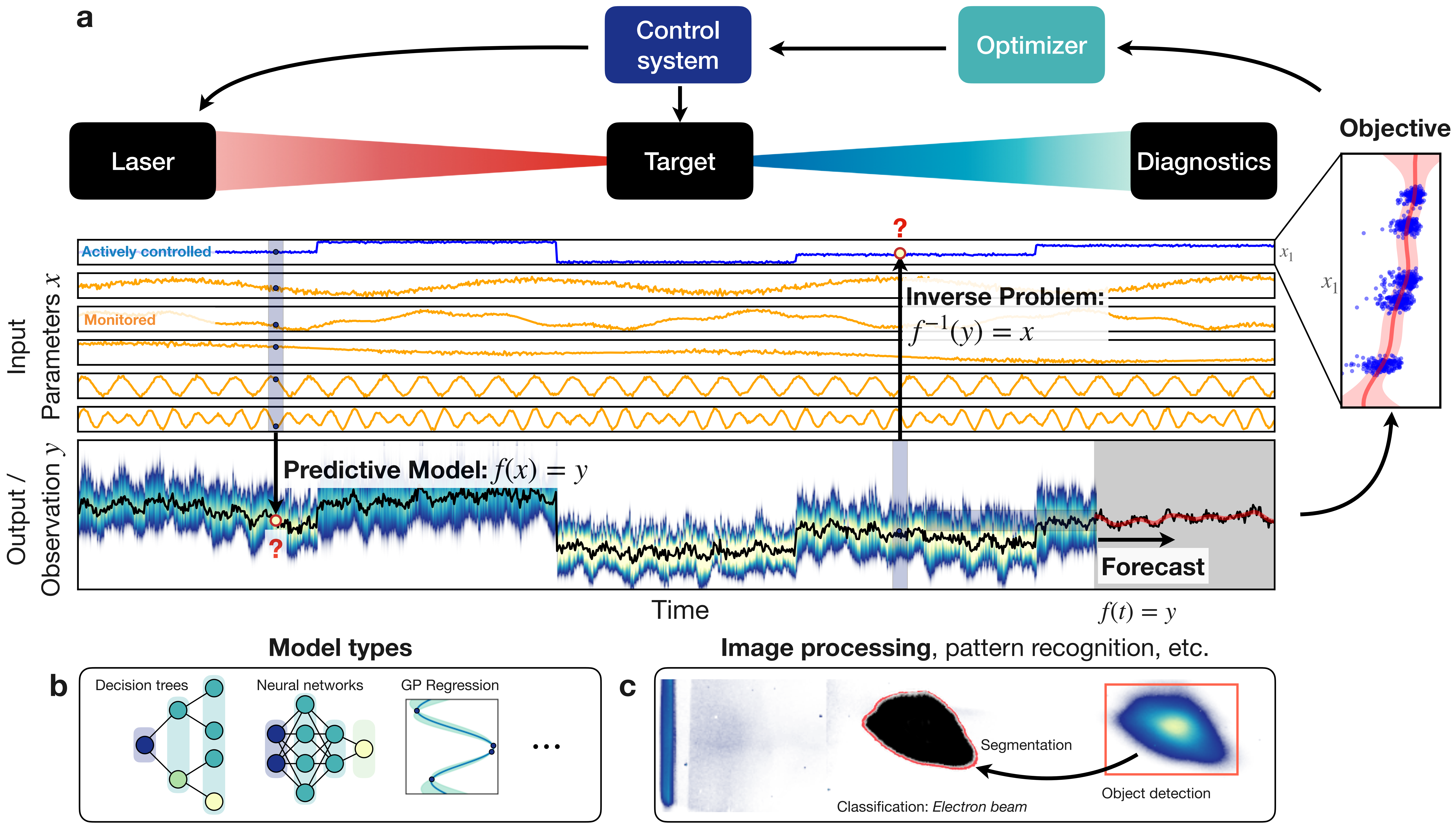


1. A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics,** *arXiv:2212.00026* (2022), *HPLSE* (2023)

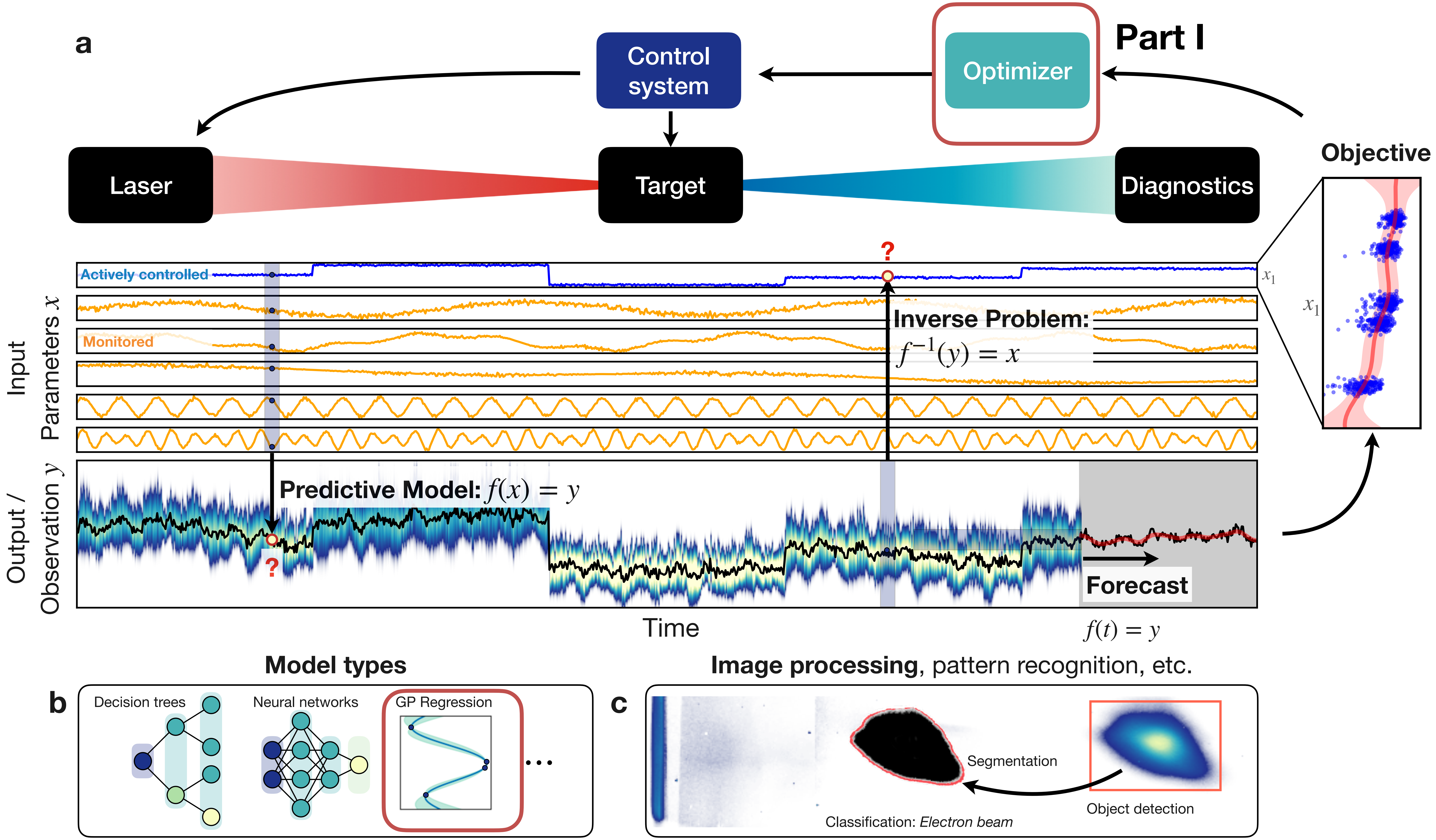
Machine learning strategies

General use cases



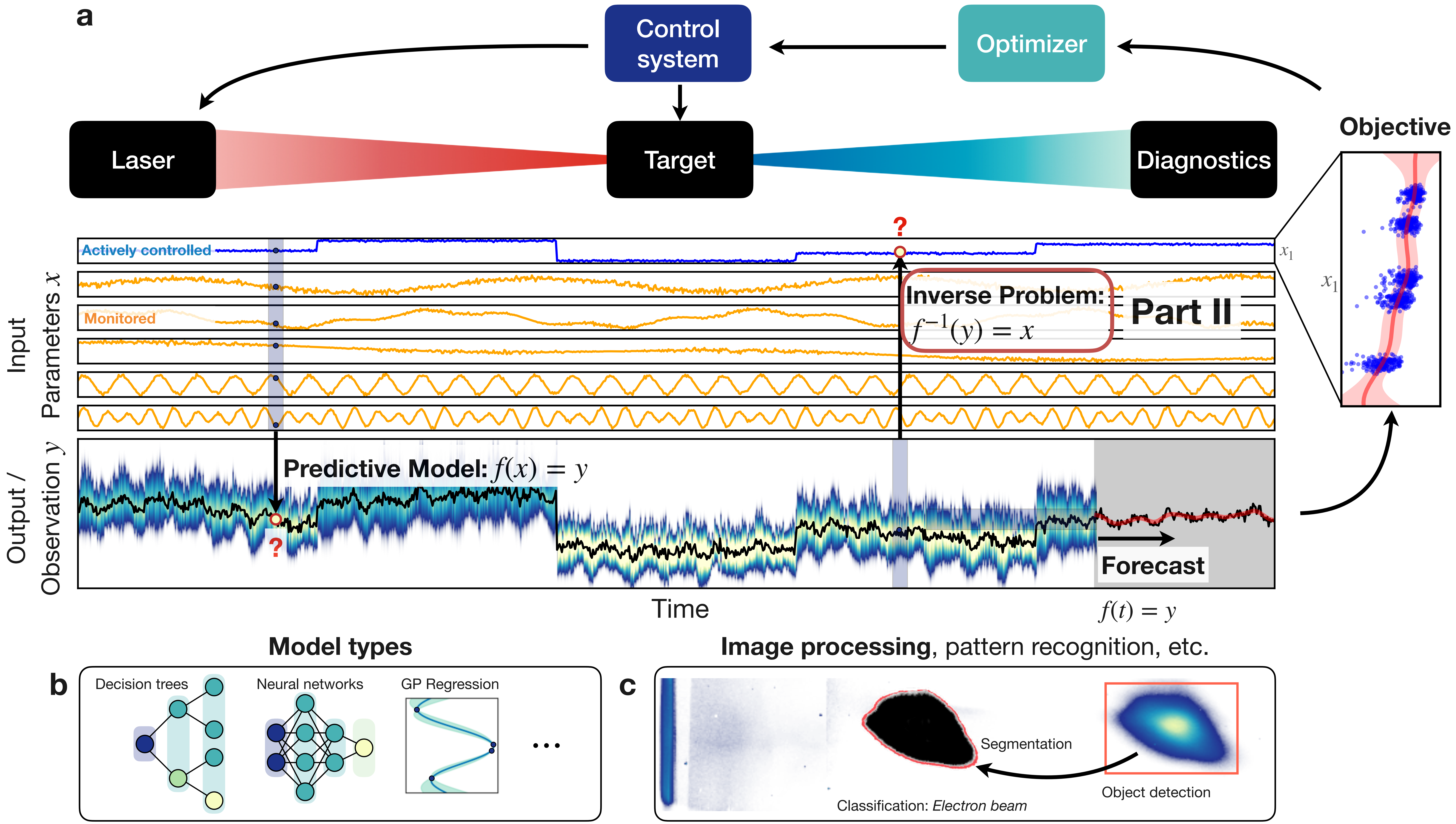
Machine learning strategies

General use cases



Machine learning strategies

General use cases



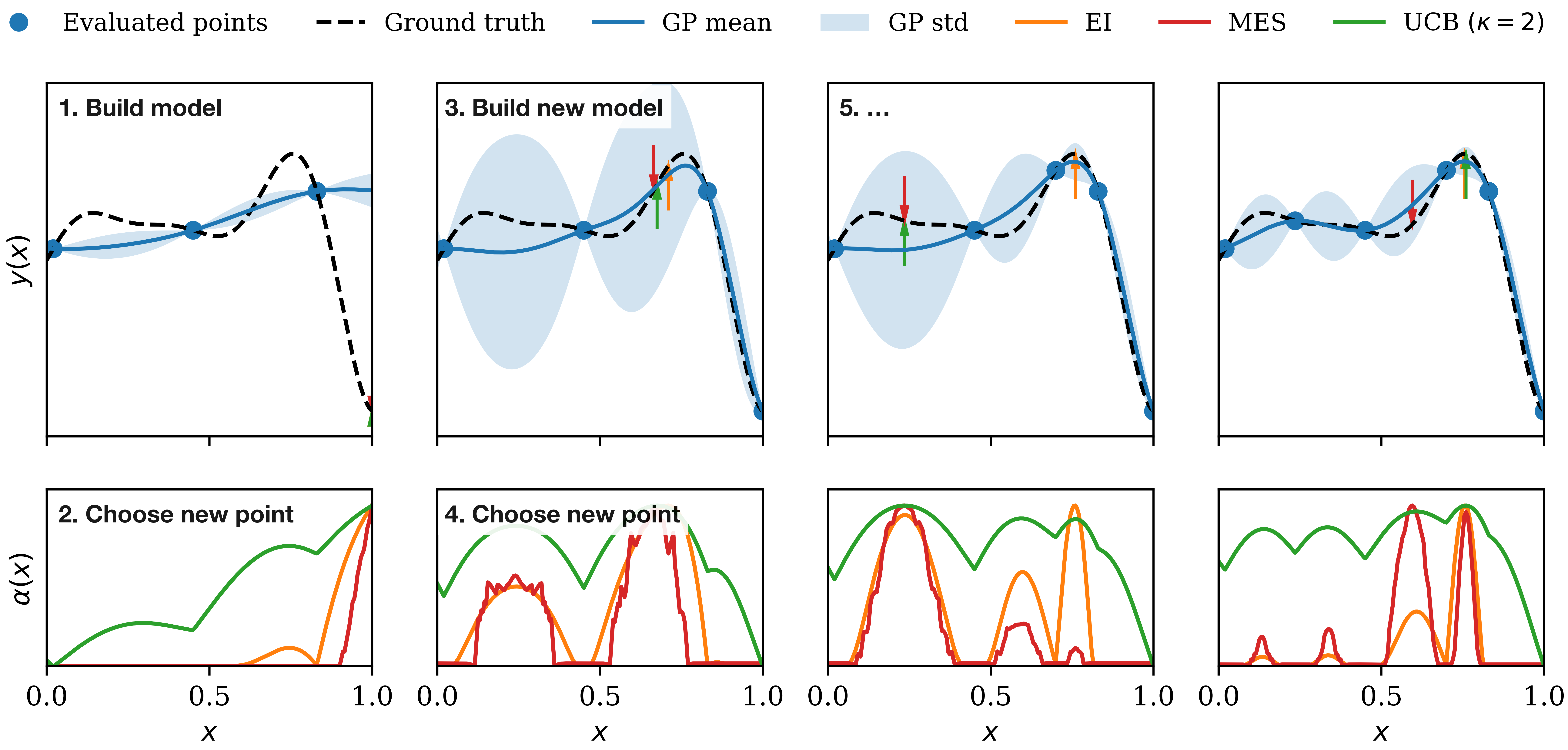
Part 1

Multi-objective, multi-fidelity

Bayesian optimization

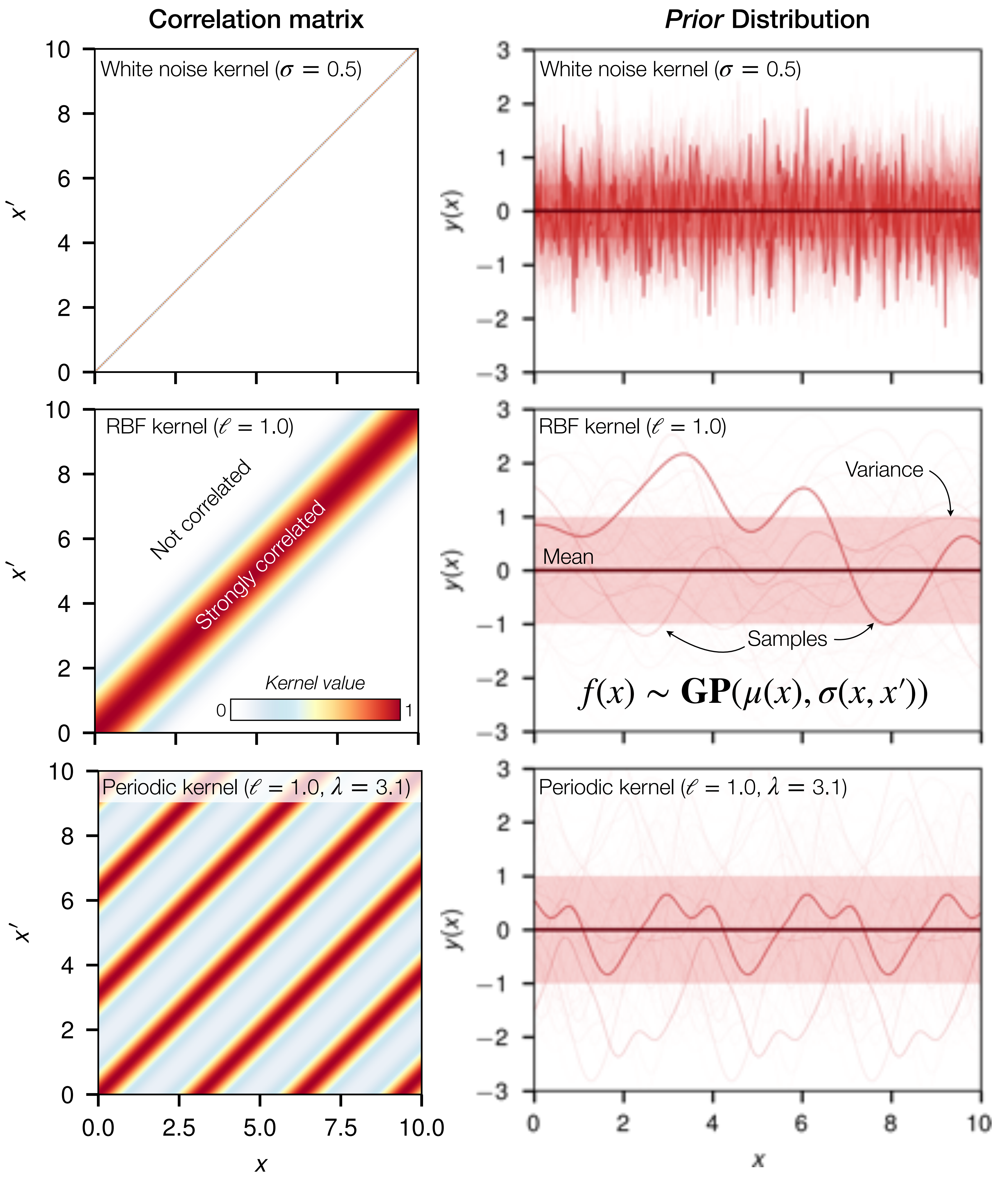
Bayesian optimization

Sequential surrogate-based optimization



Gaussian process regression

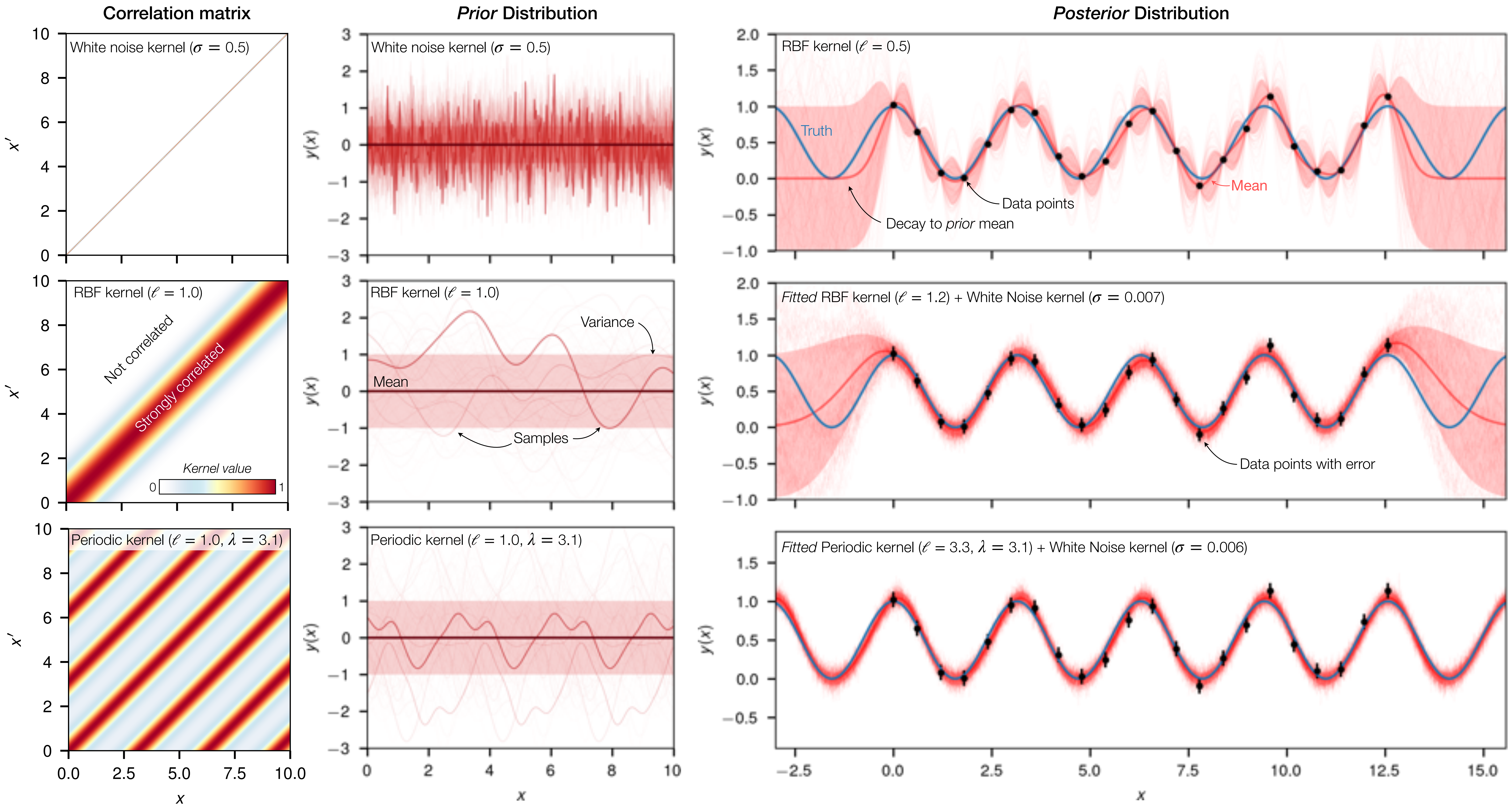
Modeling functions via correlations



- **Non-parametric method:** Predicts function values based on observed data without a predetermined model.
- **Covariance function/Kernel:** Defines the relationship between points, capturing their correlations.
- **Probabilistic description:** Provides a full description of the function, including mean and uncertainty.

Gaussian process regression

Modeling functions via correlations



Bayesian optimization

First experimental results in laser-plasma acceleration

- R. J. Shalloo et al. Automation and control of laser wakefield accelerators using Bayesian optimization, Nature Communications 11, 6355 (2020)

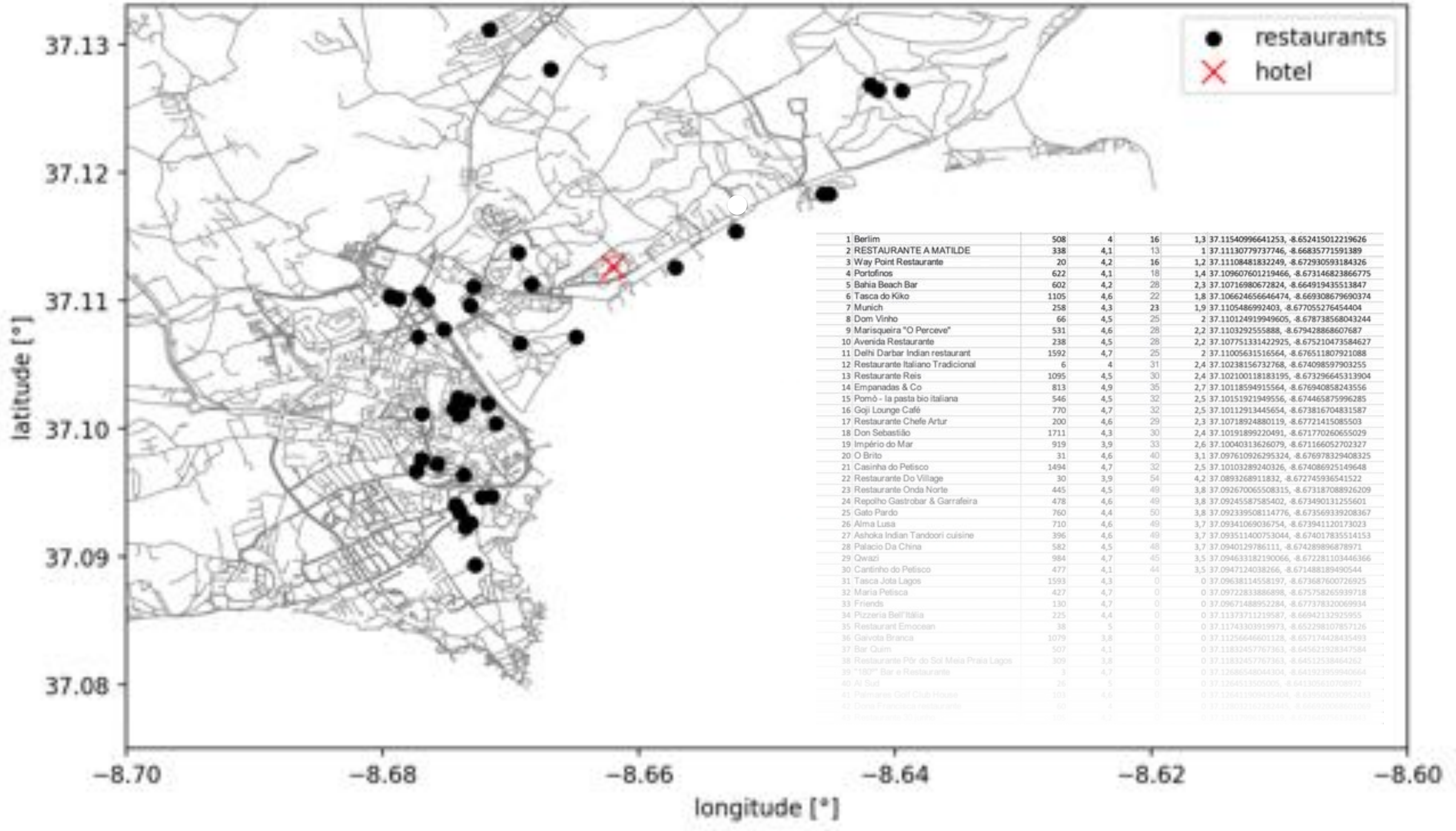
Multi-objective, multi-fidelity

Bayesian optimization

The dinner problem

Multi-objective optimization

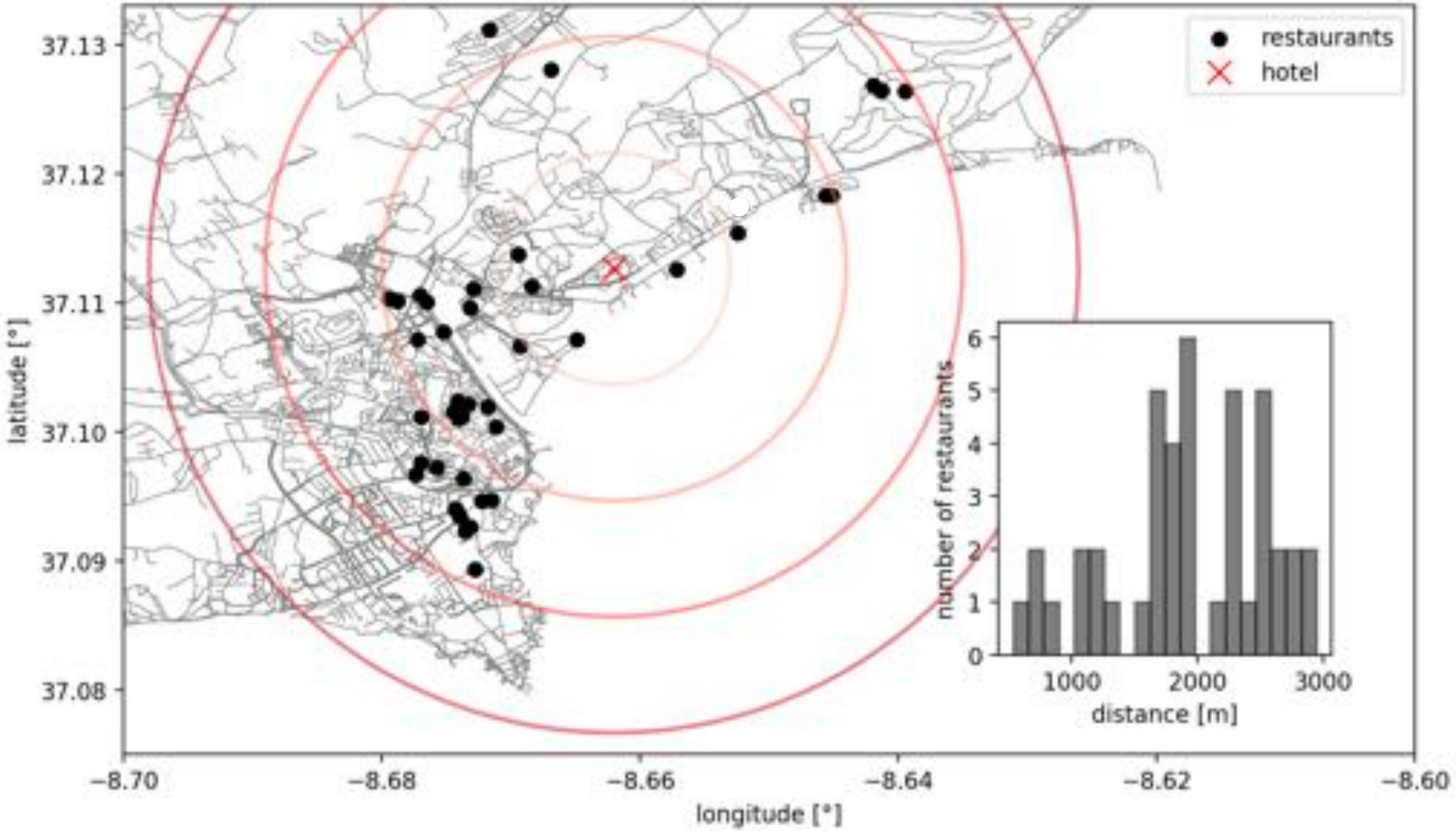
The dinner problem



1	Berlim	508	4	16	1,3	37.11540996641253, -8.652415012219626
2	RESTAURANTE A MATILDE	338	4,1	13	1	37.11130779737746, -8.66835771591389
3	Way Point Restaurante	20	4,2	16	1,2	37.11108481832249, -8.672930593184326
4	Portofinos	622	4,1	18	1,4	37.109607601219466, -8.673146823866775
5	Bahia Beach Bar	602	4,2	28	2,3	37.10716980672824, -8.664919435513847
6	Tasca do Kiko	1105	4,6	22	1,8	37.106624656646474, -8.669308679690374
7	Munich	258	4,3	23	1,9	37.1105486992403, -8.677055276454404
8	Dom Vinho	66	4,5	25	2	37.110124919949605, -8.678738568043244
9	Marisqueira "O Perceve"	531	4,6	28	2,2	37.1103292555888, -8.679428868607687
10	Avenida Restaurante	238	4,5	28	2,2	37.107751331422925, -8.675210473584627
11	Delhi Darbar Indian restaurant	1592	4,7	25	2	37.11005631516564, -8.676511807921088
12	Restaurante Italiano Tradicional	6	4	31	2,4	37.10238156732768, -8.674098597903255
13	Restaurante Reis	1095	4,5	30	2,4	37.102100118183195, -8.673296645313904
14	Empanadas & Co	813	4,9	35	2,7	37.10118594915564, -8.676940858243556
15	Pomò - la pasta bio italiana	546	4,5	32	2,5	37.10151921949556, -8.674465875996285
16	Goji Lounge Café	770	4,7	32	2,5	37.10112913445654, -8.673816704831587
17	Restaurante Chefe Artur	200	4,6	29	2,3	37.10718924880119, -8.6772141508503
18	Don Sebastião	1711	4,3	30	2,4	37.10191899220491, -8.671770260655029
19	Império do Mar	919	3,9	33	2,6	37.10040313626079, -8.671166052702327
20	O Brito	31	4,6	40	3,1	37.097610926295324, -8.676978329408325
21	Casinha do Petisco	1494	4,7	32	2,5	37.10103289240326, -8.674086925149648
22	Restaurante Do Village	30	3,9	54	4,2	37.0893268911832, -8.672745936541522
23	Restaurante Onda Norte	445	4,5	49	3,8	37.092670065508315, -8.673187088926209
24	Repolho Gastrobar & Garrafeira	478	4,6	49	3,8	37.09245587585402, -8.673490131255601
25	Gato Pardo	760	4,4	50	3,8	37.092339508114776, -8.673569339208367
26	Alma Lusa	710	4,6	49	3,7	37.09341069036754, -8.673941120173023
27	Ashoka Indian Tandoori cuisine	396	4,6	49	3,7	37.093511400753044, -8.674017835514153
28	Palacio Da China	582	4,5	48	3,7	37.0940129786111, -8.674289896878971
29	Qwazi	984	4,7	45	3,5	37.094633182190066, -8.672281103446366
30	Cantinho do Petisco	477	4,1	44	3,5	37.0947124038266, -8.67148818949054
31	Tasca Jota Lagos	1593	4,3	0	0	37.09638114558197, -8.673687600726925
32	Maria Petisca	427	4,7	0	0	37.09722833886898, -8.675758265939718
33	Friends	130	4,7	0	0	37.09671488952284, -8.677378320069934
34	Pizzeria Bell'Itália	225	4,4	0	0	37.11373711219587, -8.6694213292595
35	Restaurant Emocean	38	5	0	0	37.11743303919973, -8.652298107857126
36	Gaivota Branca	1079	3,8	0	0	37.11256646601128, -8.657174428435493
37	Bar Quim	507	4,1	0	0	37.11832457767363, -8.645621928347584
38	Restaurante Pôr do Sol Meia Praia Lagos	309	3,8	0	0	37.11832457767363, -8.6451253864262
39	"180°" Bar e Restaurante	3	4,7	0	0	37.12686548044304, -8.641923959940664
40	Al Sud	26	5	0	0	37.1264513505005, -8.641305610708972

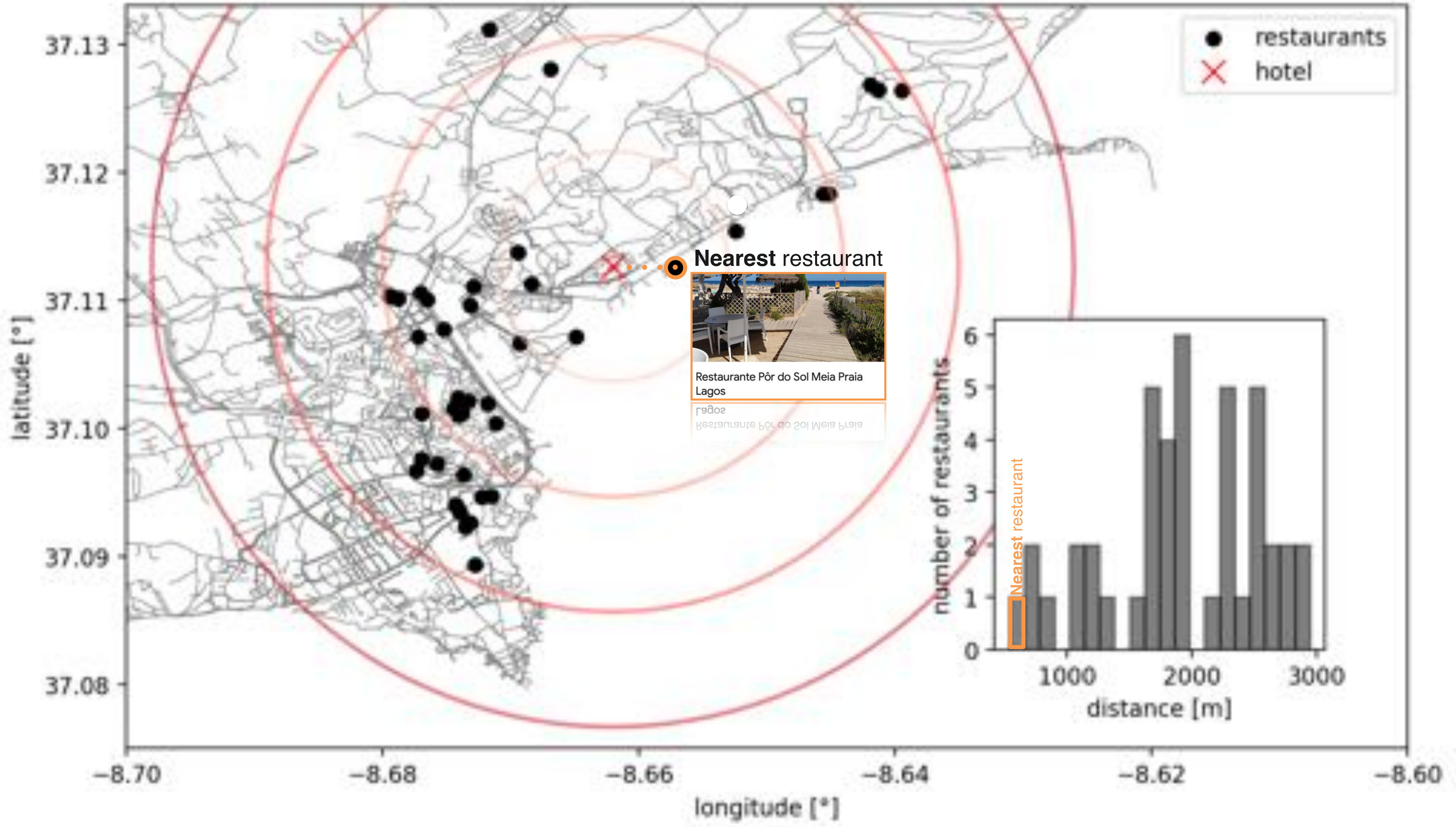
Multi-objective optimization

The dinner problem



Multi-objective optimization

The dinner problem



Multi-objective optimization

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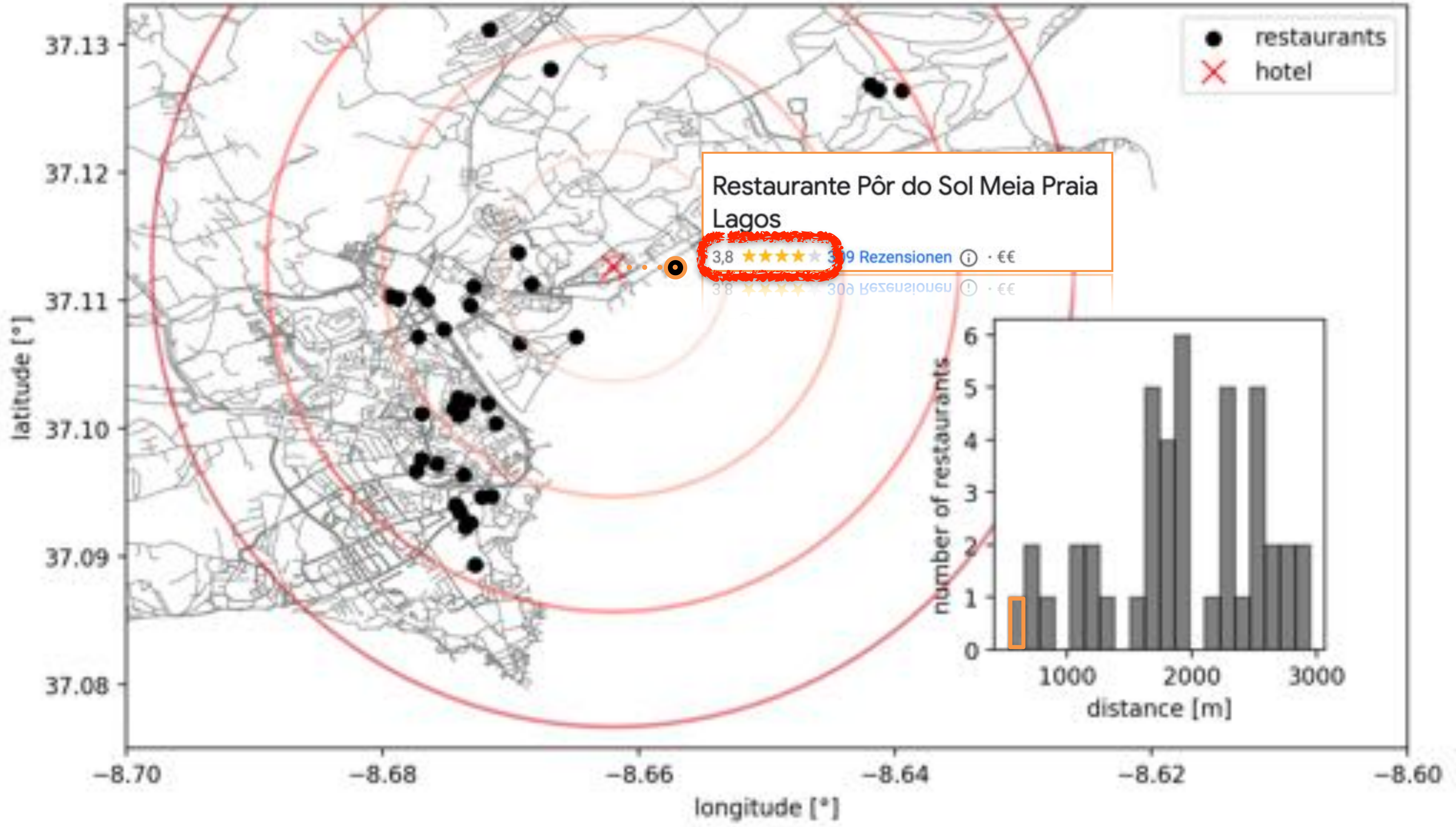

Multi-objective optimization

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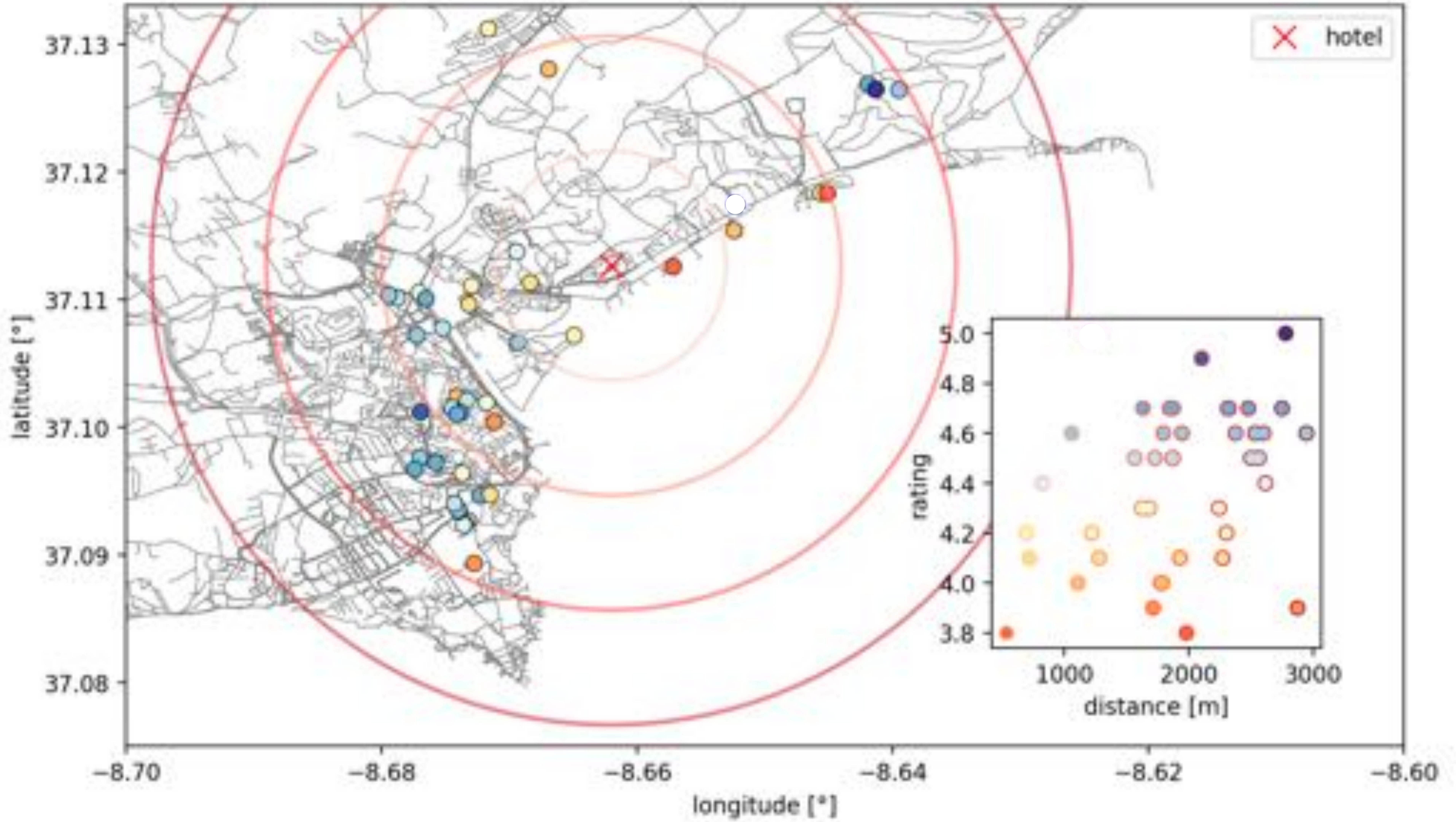
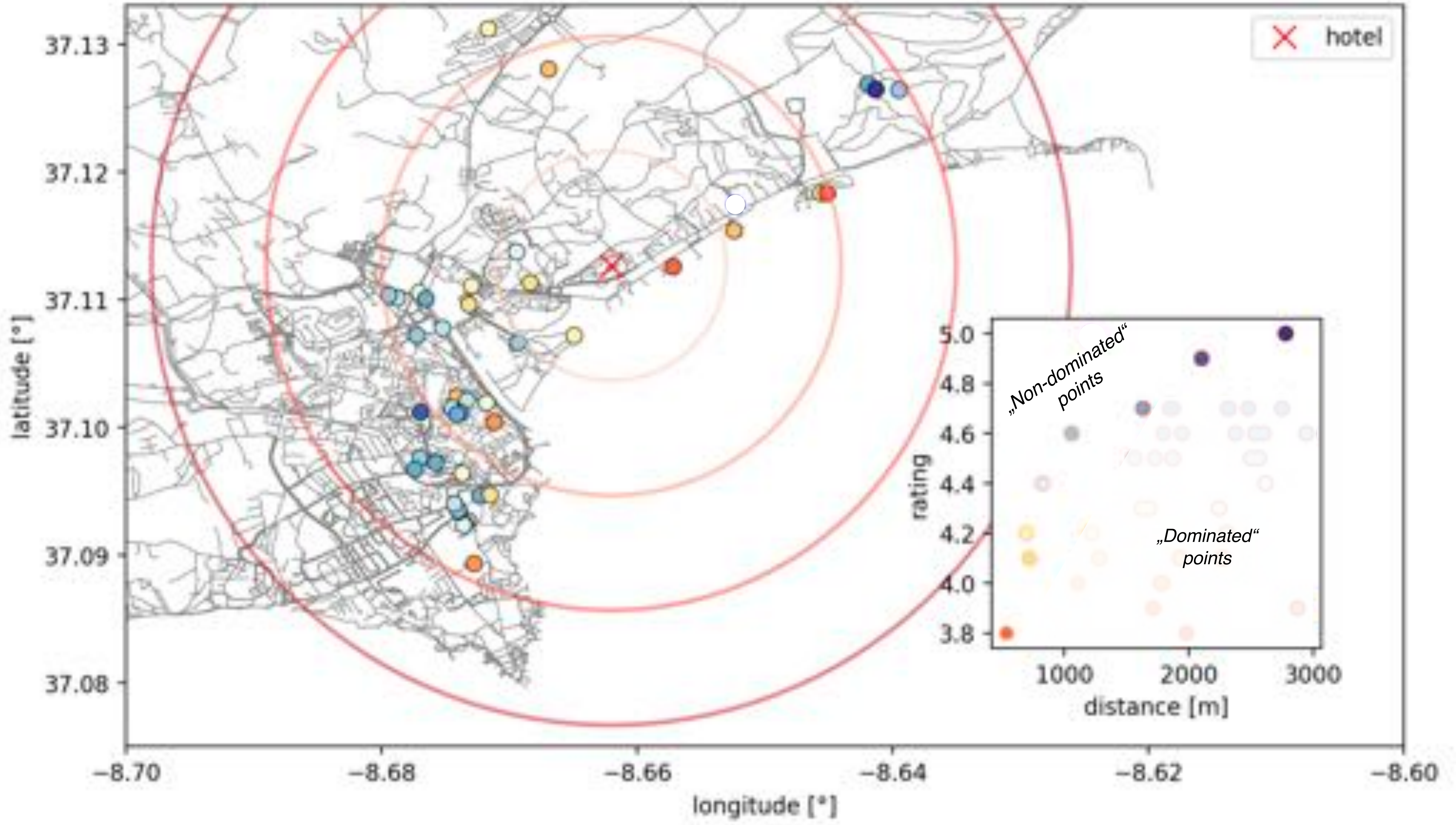


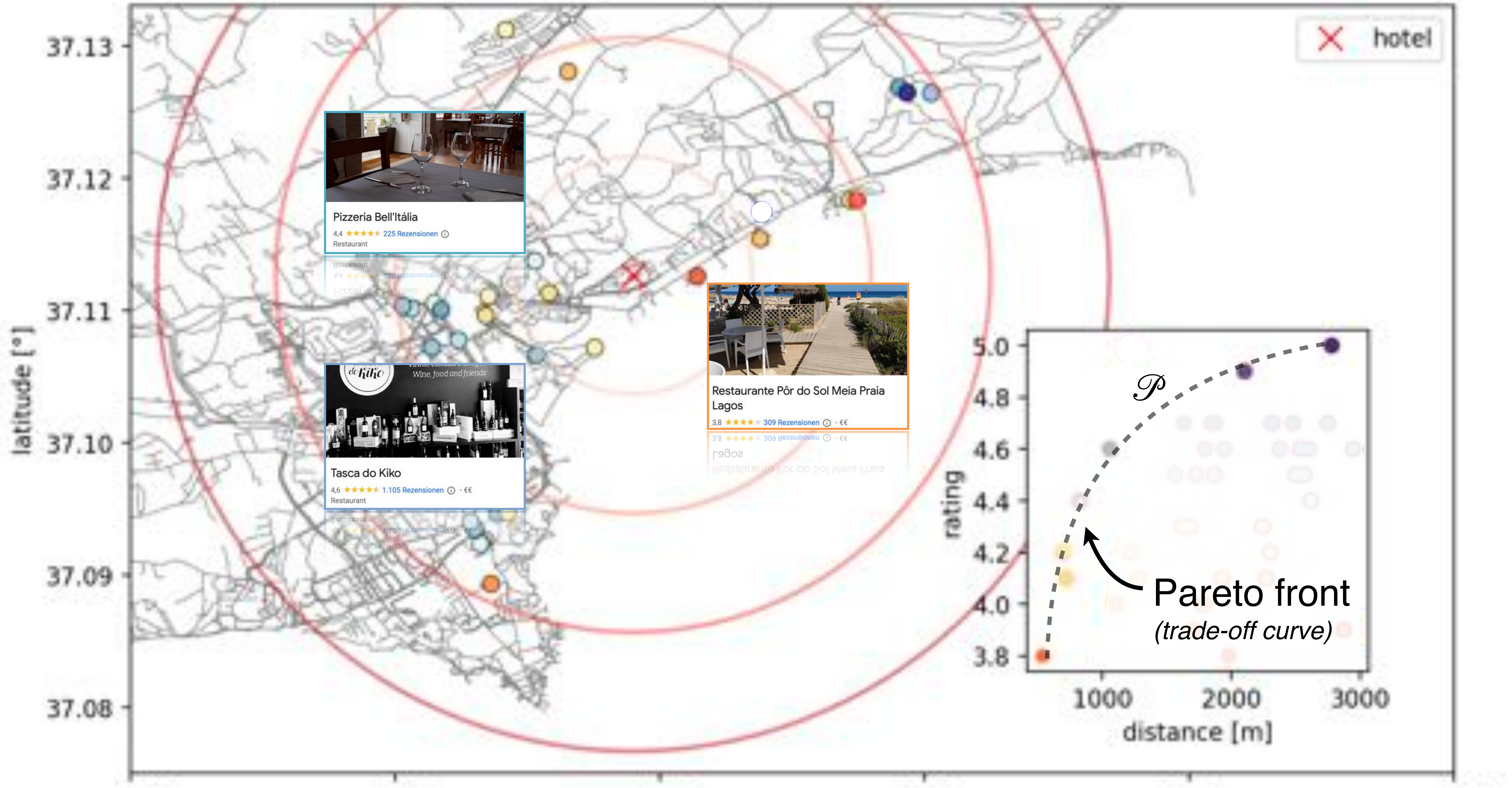
Multi-objective optimization

The dinner problem



Multi-objective optimization

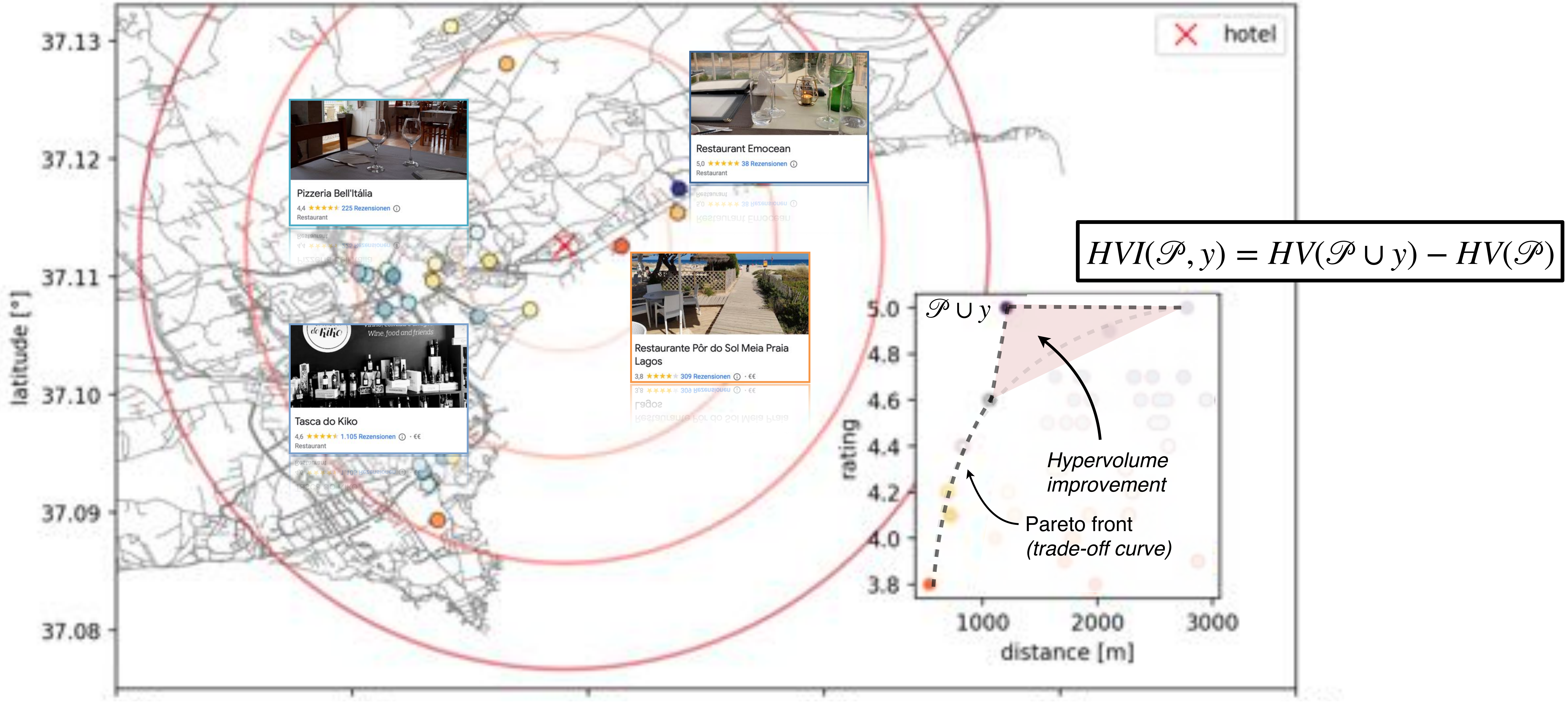
The dinner problem



In *multi-objective* optimization we have **multiple (competing) goals** with **different trade-offs**.

Multi-objective optimization

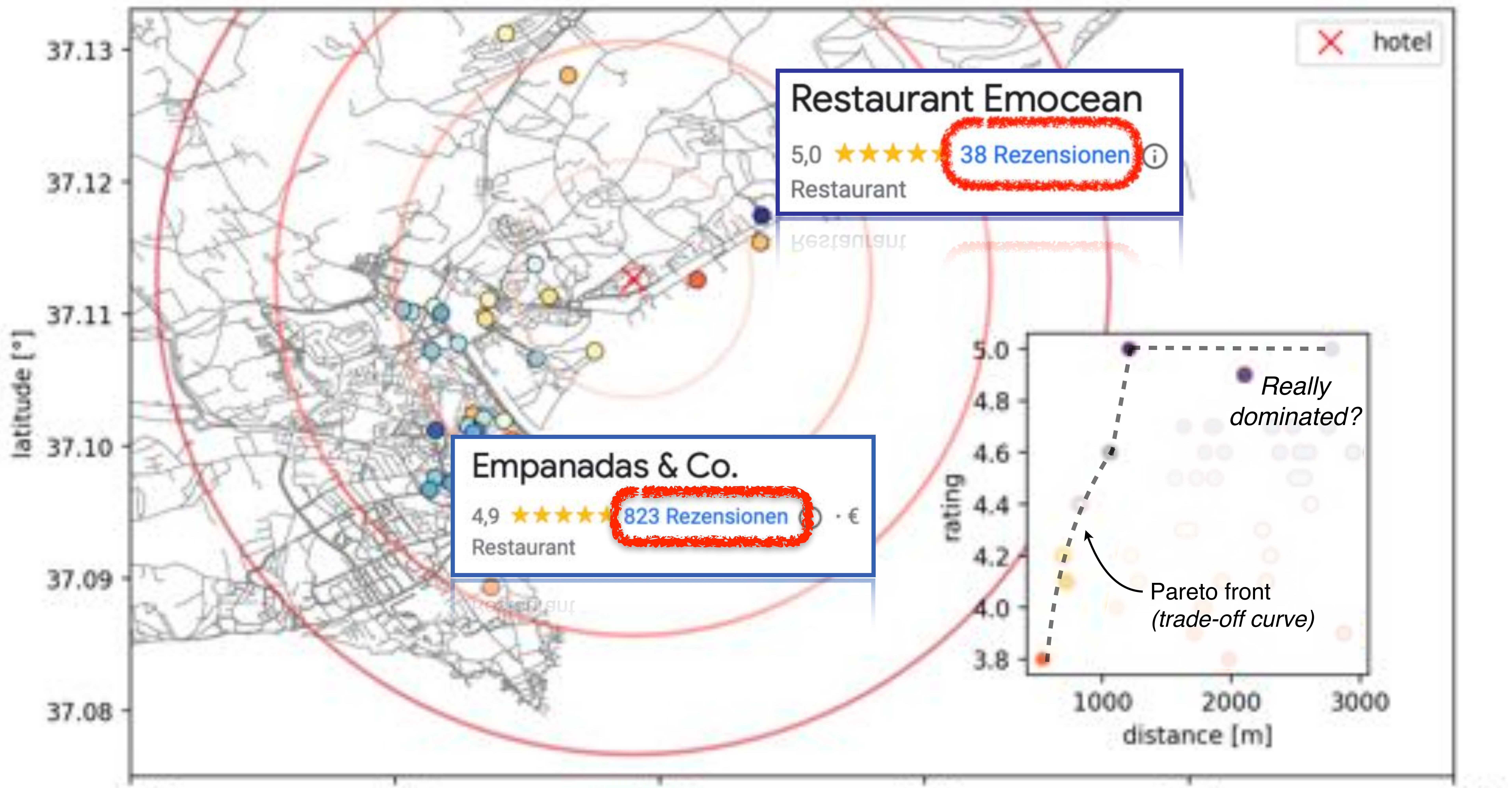
The dinner problem



In *multi-objective* optimization we have **multiple (competing) goals with different trade-offs**.

Multi-fidelity optimization

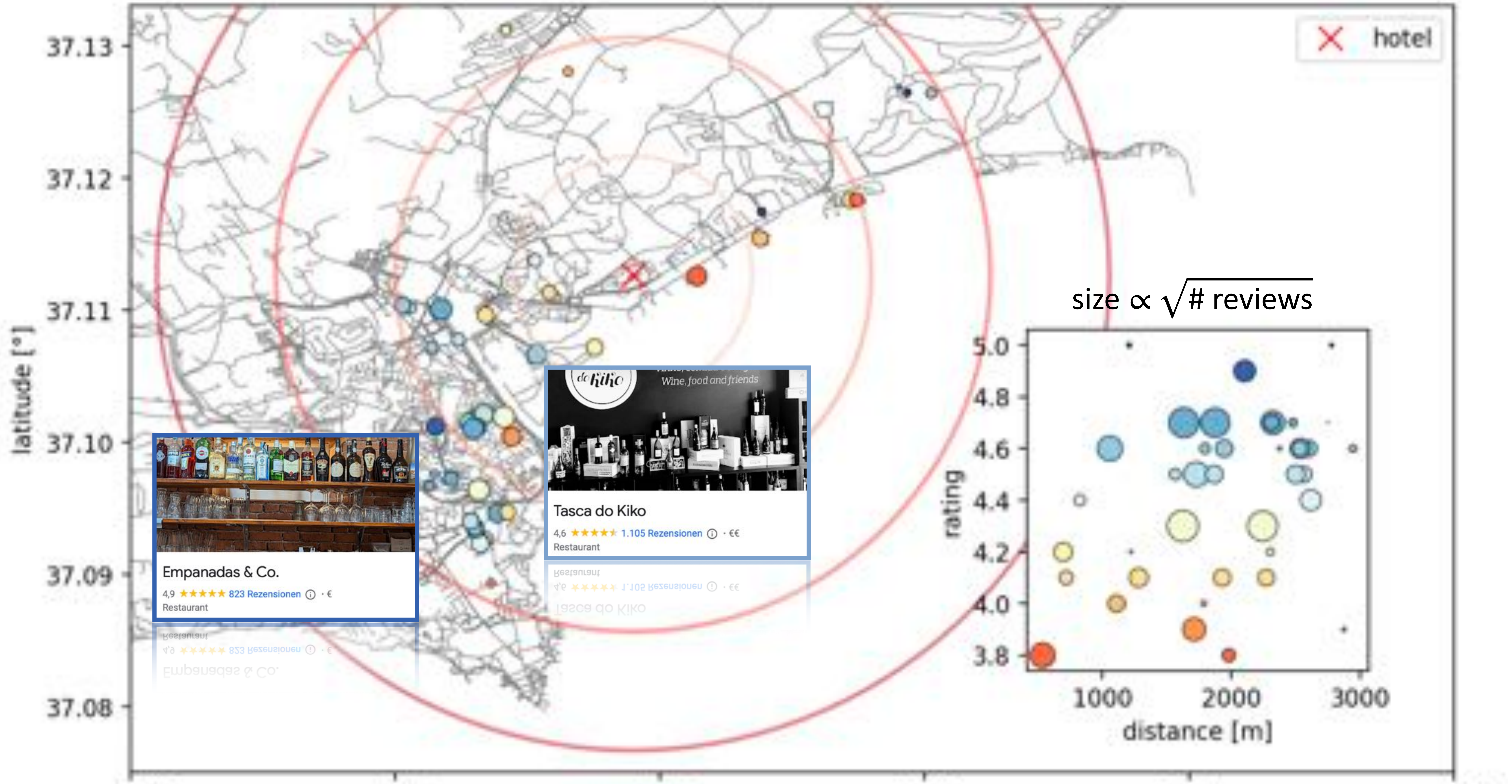
The dinner problem



In *multi-fidelity* optimization we have **different confidence in measurements.**

Multi-fidelity optimization

The dinner problem



In *multi-fidelity* optimization we have **different confidence in measurements,** thus **spanning another dimension** that represents how much we *trust* the point.

Multi-objective, multi-fidelity

Bayesian optimization

applied to laser-plasma acceleration

Multi-objective multi-fidelity optimization

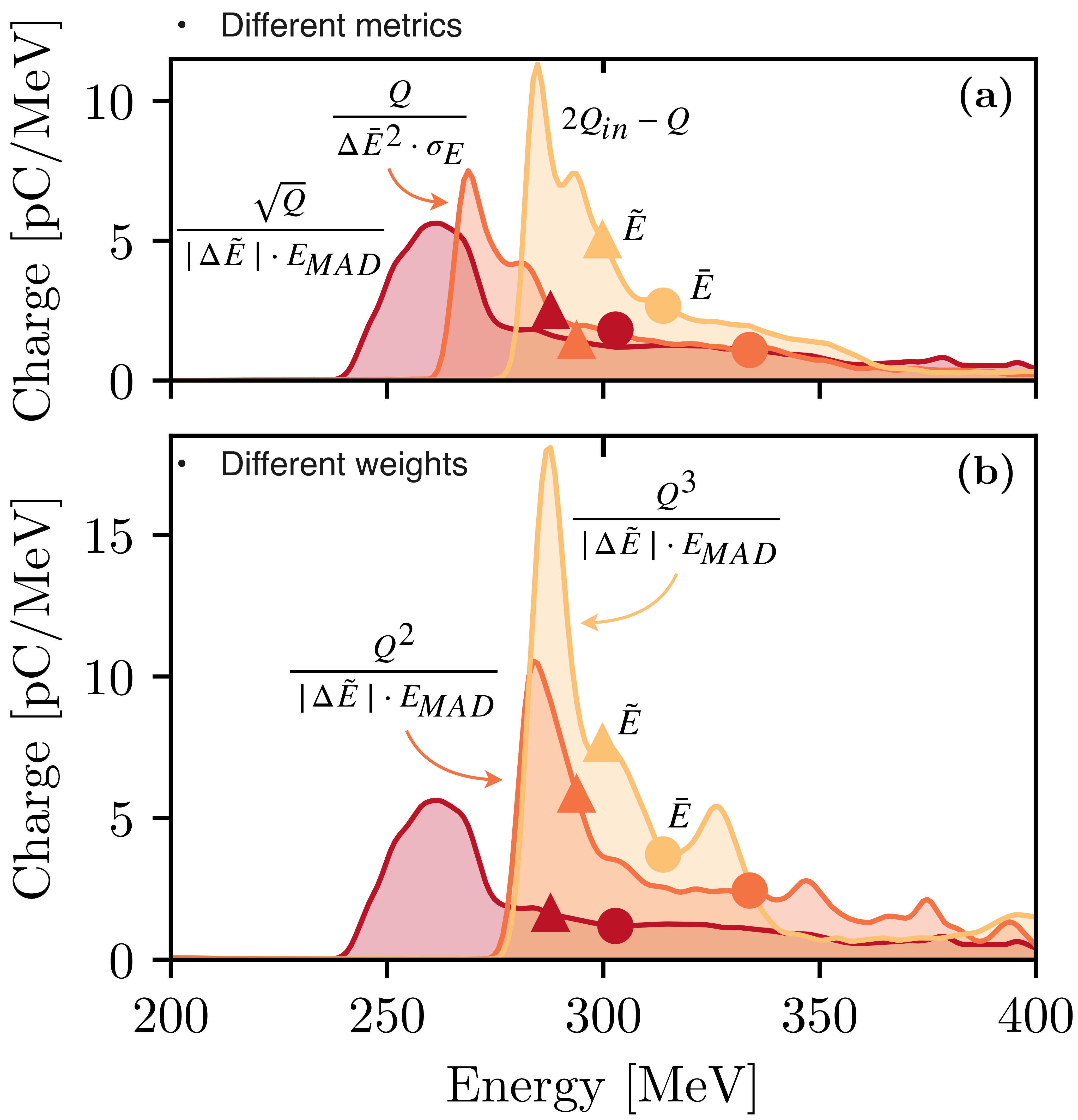
Optimization of electron beam properties *(FBPIC simulations)*

- We want to optimize three electron beam parameters:
  - Charge Q (total charge, charge within FWHM, etc.)
  - Bandwidth (standard deviation σ_E, median absolute deviation E_{MAD}, etc.)
  - Distance to a target energy $|E_{target} - E|$ (using mean energy, median energy, peak energy, etc.)

Multi-objective multi-fidelity optimization

Optimization of electron beam properties *(FBPIC simulations)*

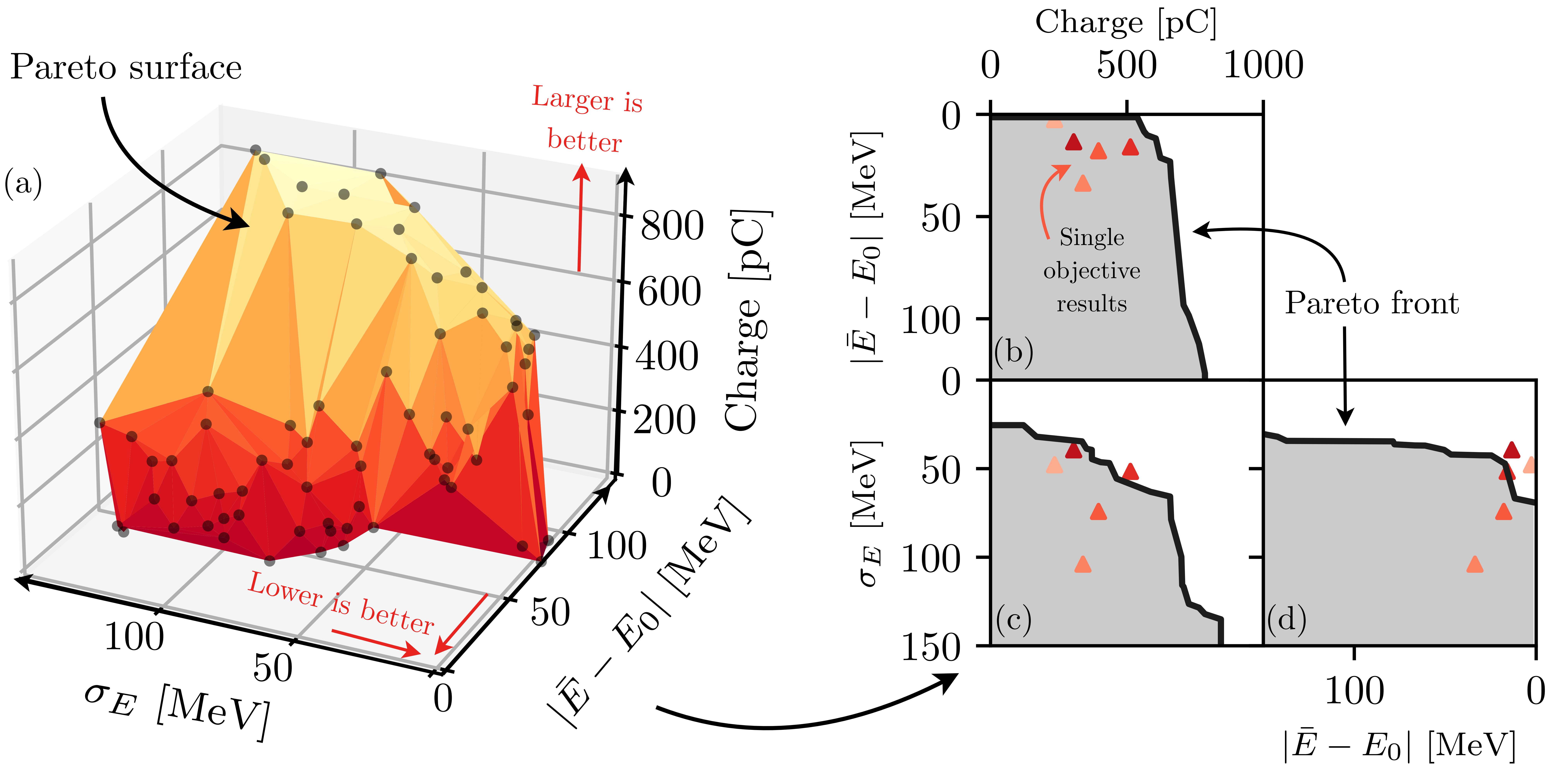
- We want to optimize three electron beam parameters:
  - Charge Q (total charge, charge within FWHM, etc.)
  - Bandwidth (standard deviation σ_E, median absolute deviation E_{MAD}, etc.)
  - Distance to a target energy $|E_{target} - E|$ (using mean energy, median energy, peak energy, etc.)
- We can use the simulation resolution as our fidelity, i.e. we trust a high-resolution simulation more than a low-resolution simulation *(including low-res gives one order of magnitude speed-up)*
- Choosing **different metrics or weights** for each objective **changes the outcome in an *a priori* unknown way**!



- 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 *(FBPIC simulations)*



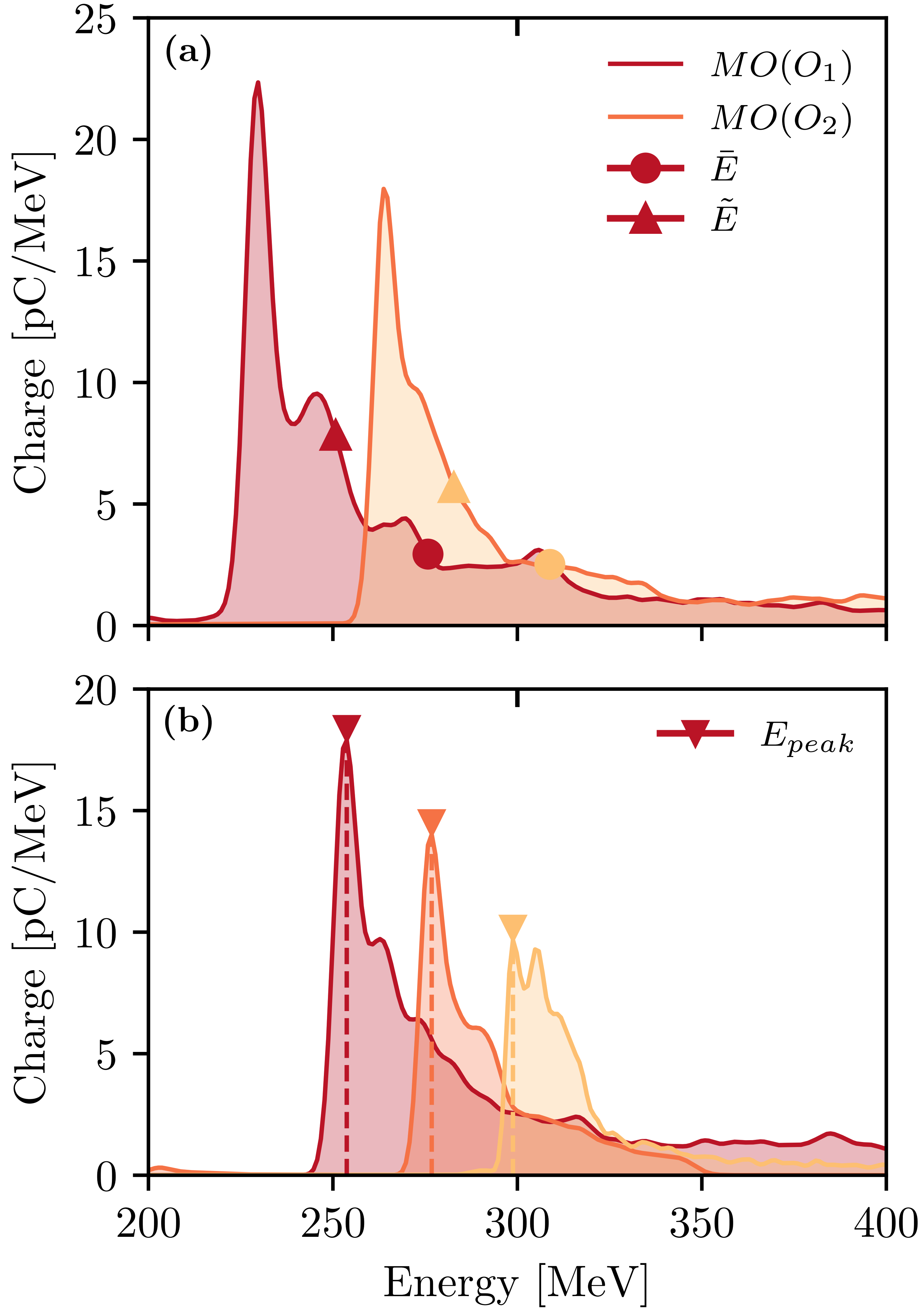
1. Irshad, F., Karsch, S., & Döpp, A. **EHVI for simultaneous multi-objective and multi-fidelity optimization**. *arXiv preprint arXiv:2112.13901 (2021)*
2. Irshad, F., Karsch, S., & Döpp, A. **Multi-objective and multi-fidelity Bayesian optimization of laser-plasma acceleration**. *Phys. Rev. Research 5, 013063 (2023)*

Multi-objective multi-fidelity optimization

Optimization of electron beam properties *(FBPIC simulations)*

- Once the Pareto-optimal solutions are identified, we can choose from them what kind of beam we want.

- We can also use the model's data to **change parameters** *a posteriori*, e.g. to **tune the beam energy**.



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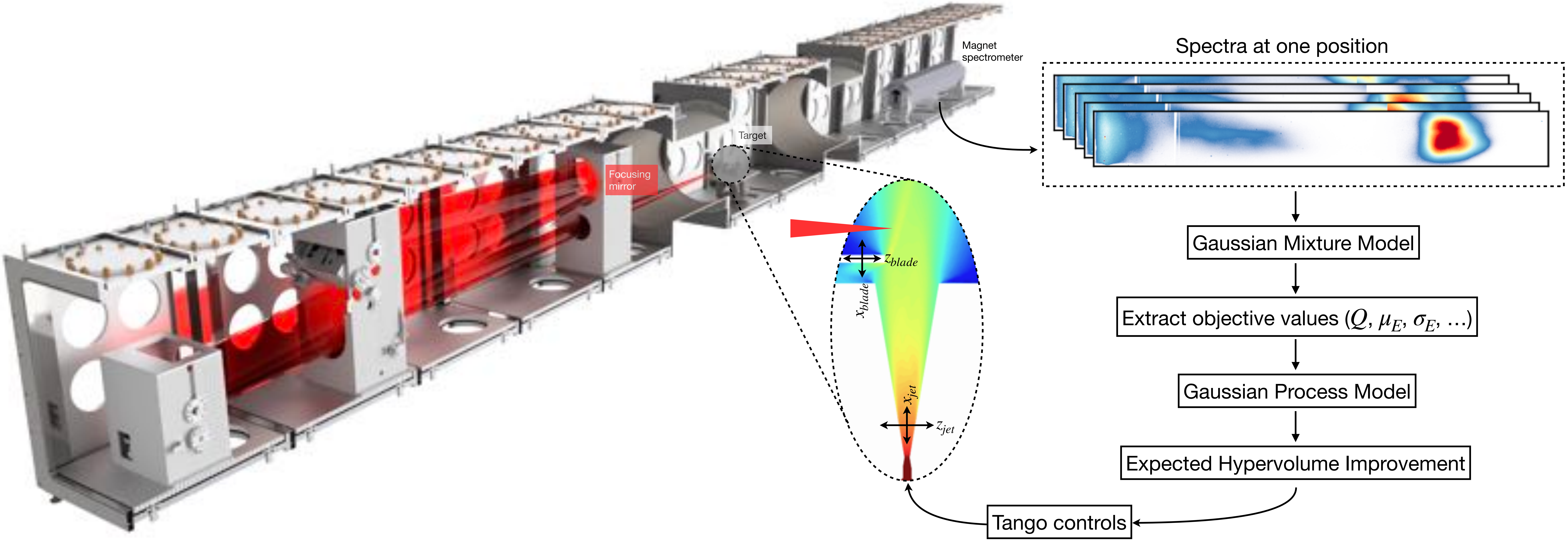
Multi-objective multi-fidelity optimization

Optimization of electron beam properties *(Experiment)*

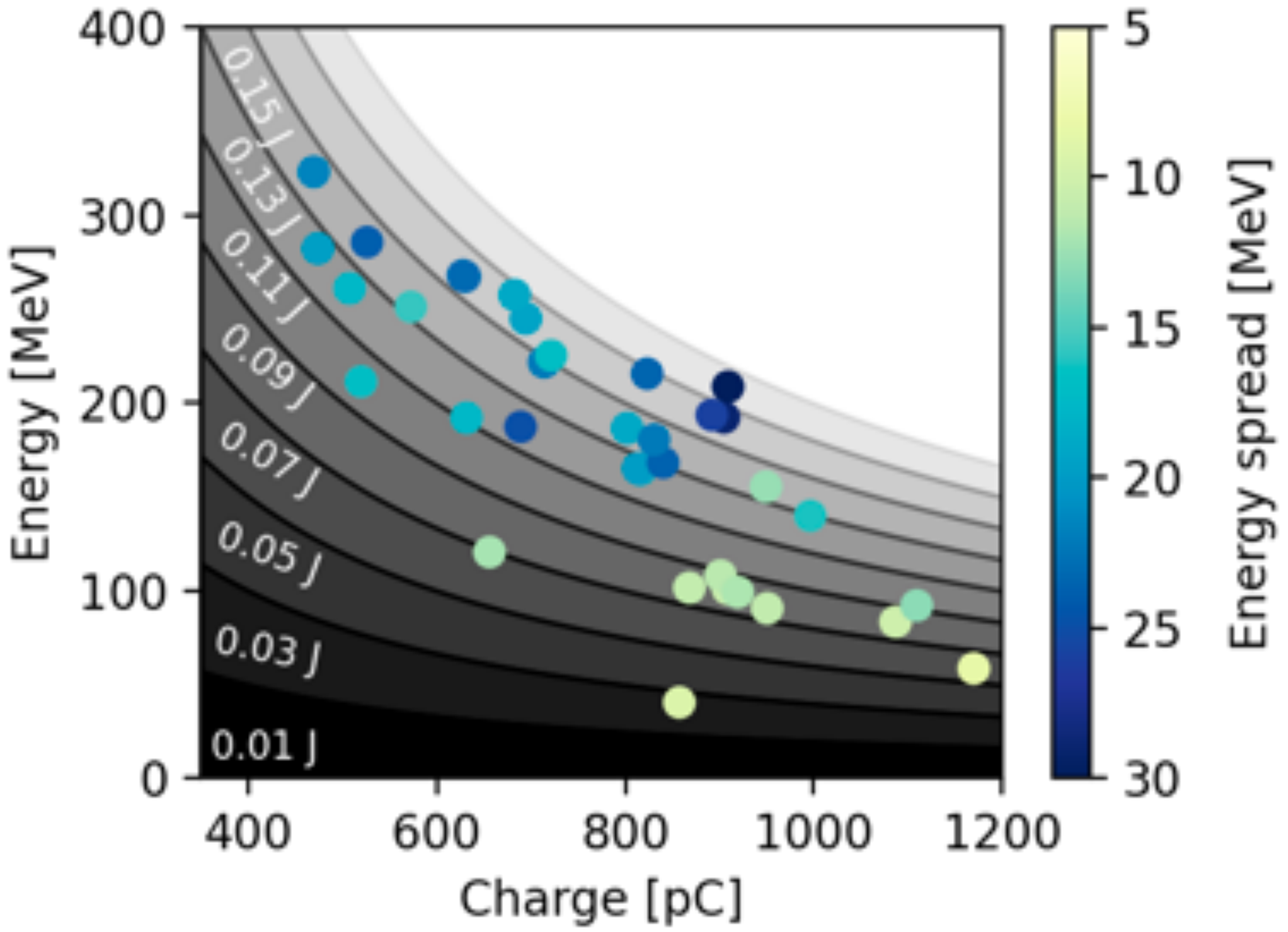


- N. Weiße et al. **Tango Controls and Data Pipeline for Petawatt Laser Experiments**, HPLSE, 10.1017/hpl.2023.17 (2023)
- F. Irshad, et al. **Pareto Optimization of a Laser Wakefield Accelerator** *(under review)*

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**.



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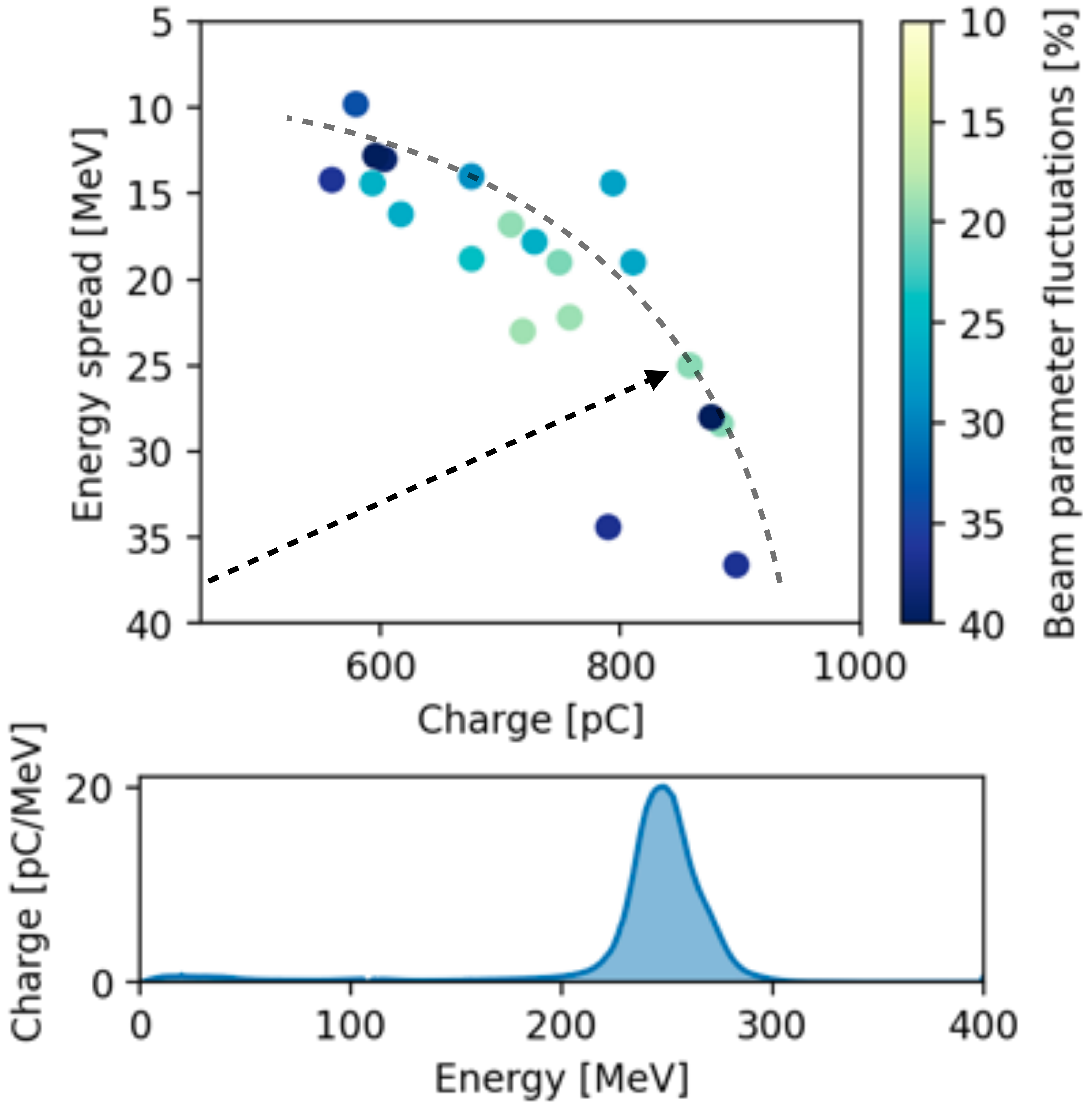
Multi-objective multi-fidelity optimization

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 can **select and exploit one particular solution** within the Pareto-optimal solutions by fitting $O_{select} = a_1 Q + a_2 \sigma_E + a_3 |E_{target} - E|$ such that it is maximized for the selected point.



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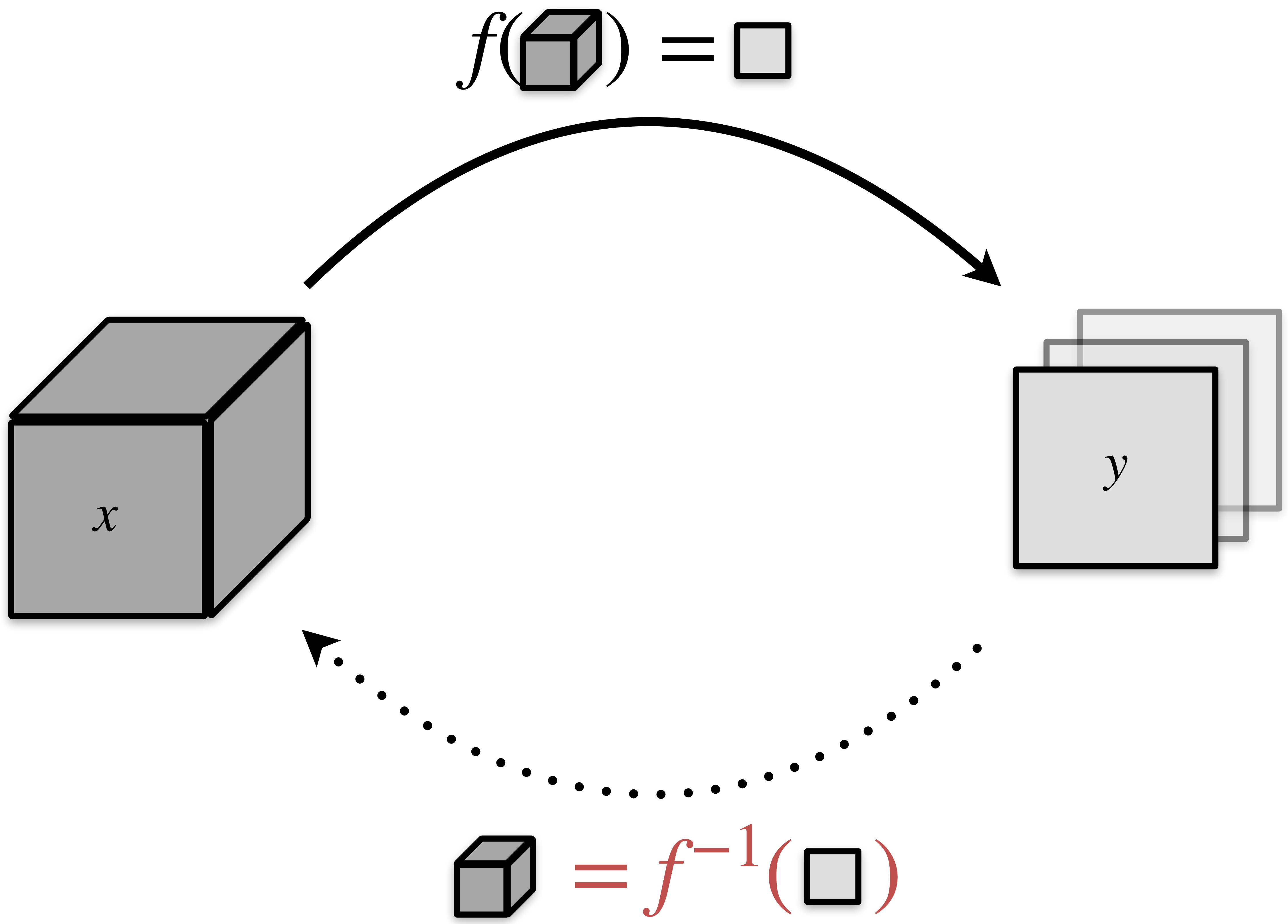
Part 2

Inverse problems

Inverse Problems

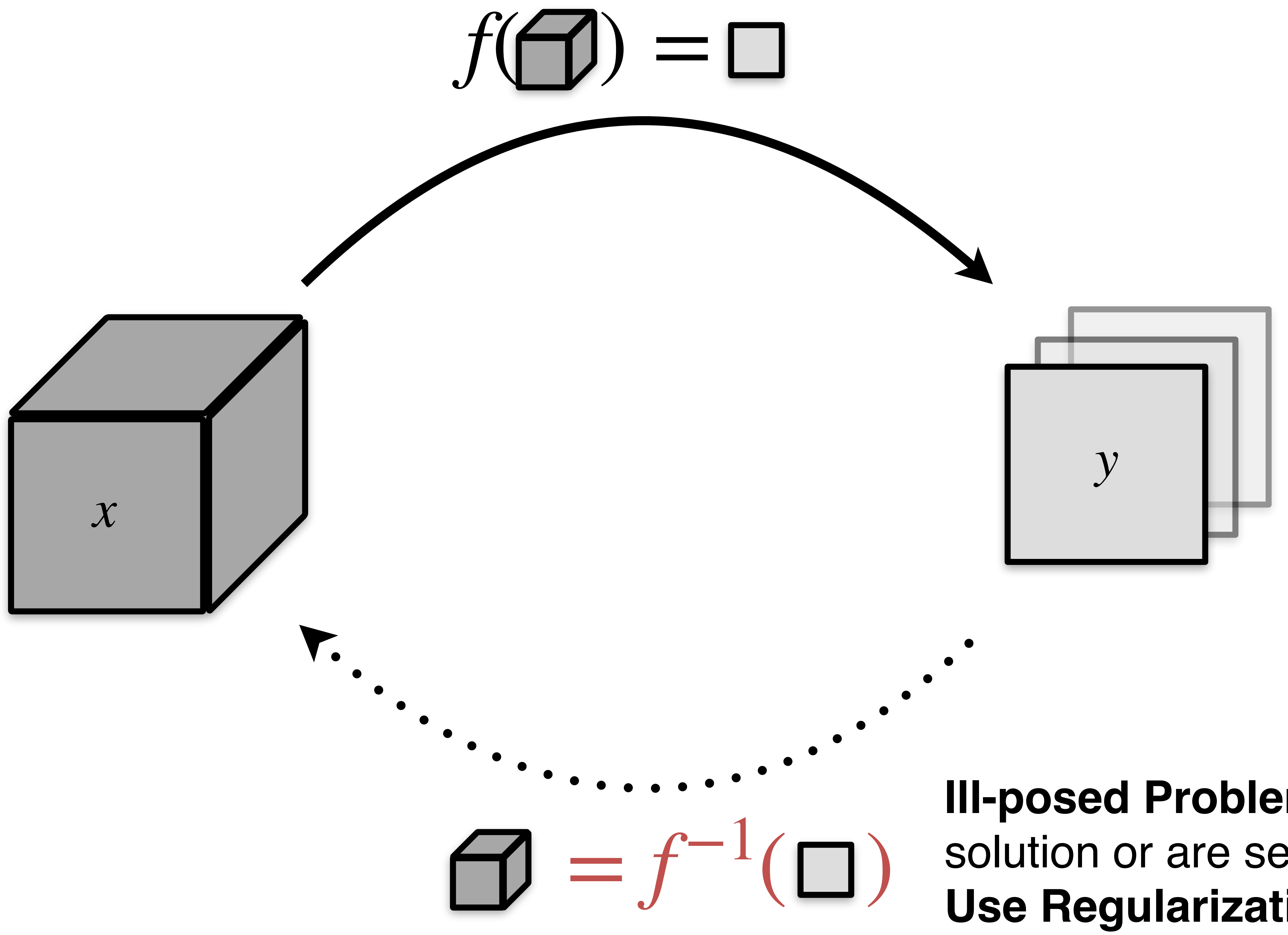
Determining cause from effect



Cause and Effect: Inverse problems involve determining the cause (e.g. 3D structure) from the observed effect (e.g. 2D projections).

Inverse Problems

Determining cause from effect



Ill-posed Problems: Inverse problems often lack a unique solution or are sensitive to input data.
Use Regularization to stabilize the solution by introducing additional information or assumptions.

Cause and Effect: Inverse problems involve determining the cause (e.g. 3D structure) from the observed effect (e.g. 2D projections).

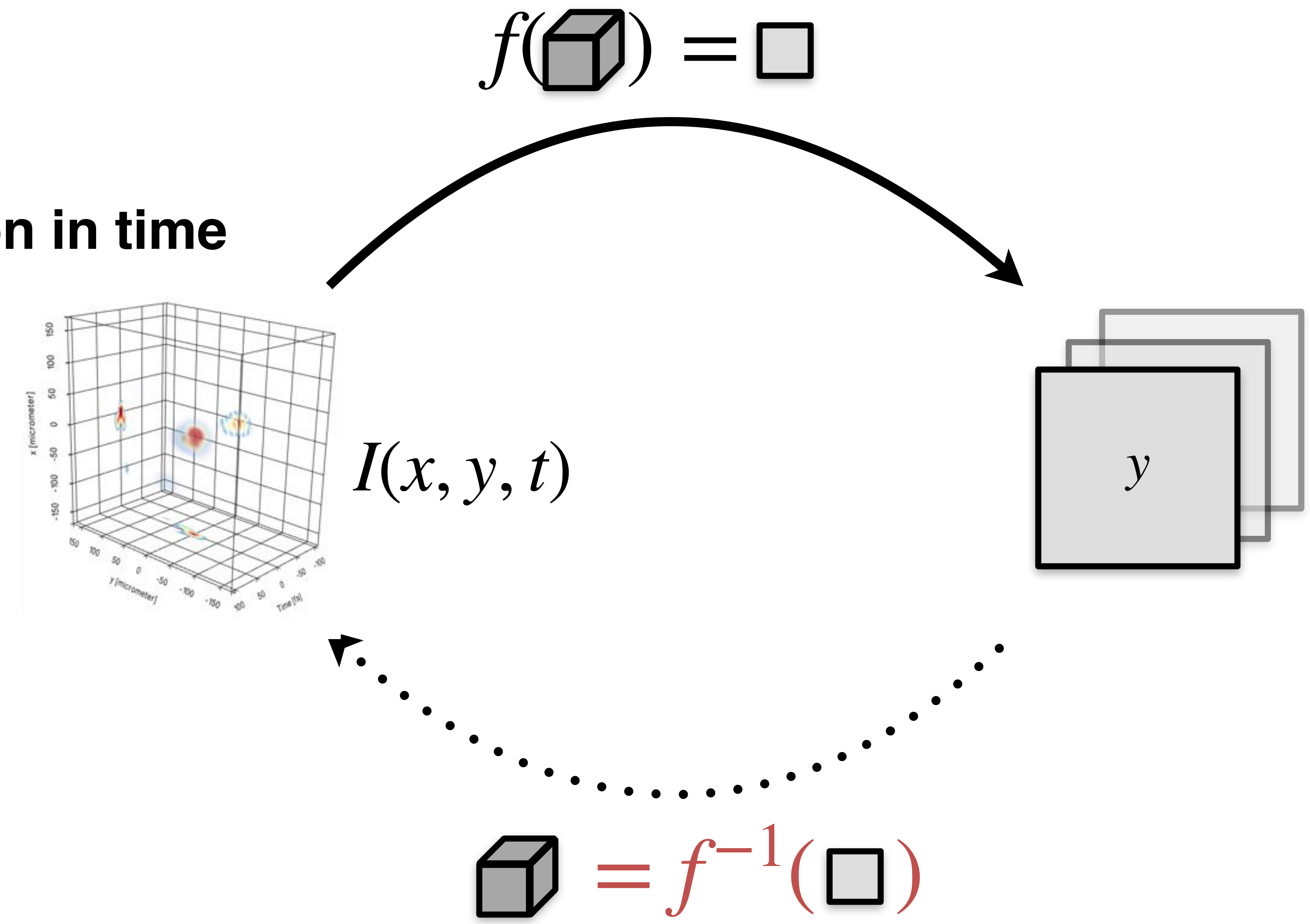
Inverse Problems

An example

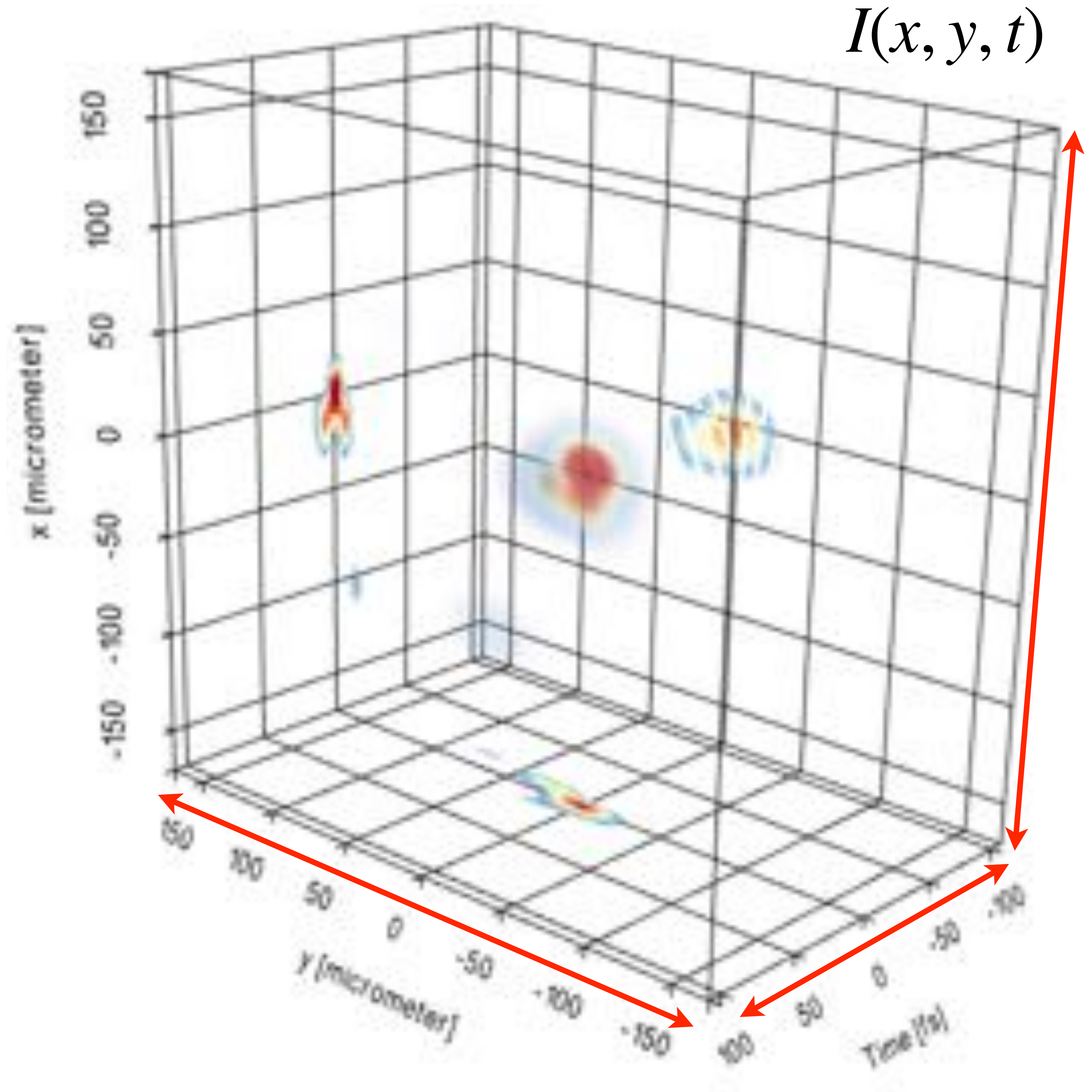
3-D intensity distribution in time

Knowledge necessary for

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



Ultra-intense laser characterization



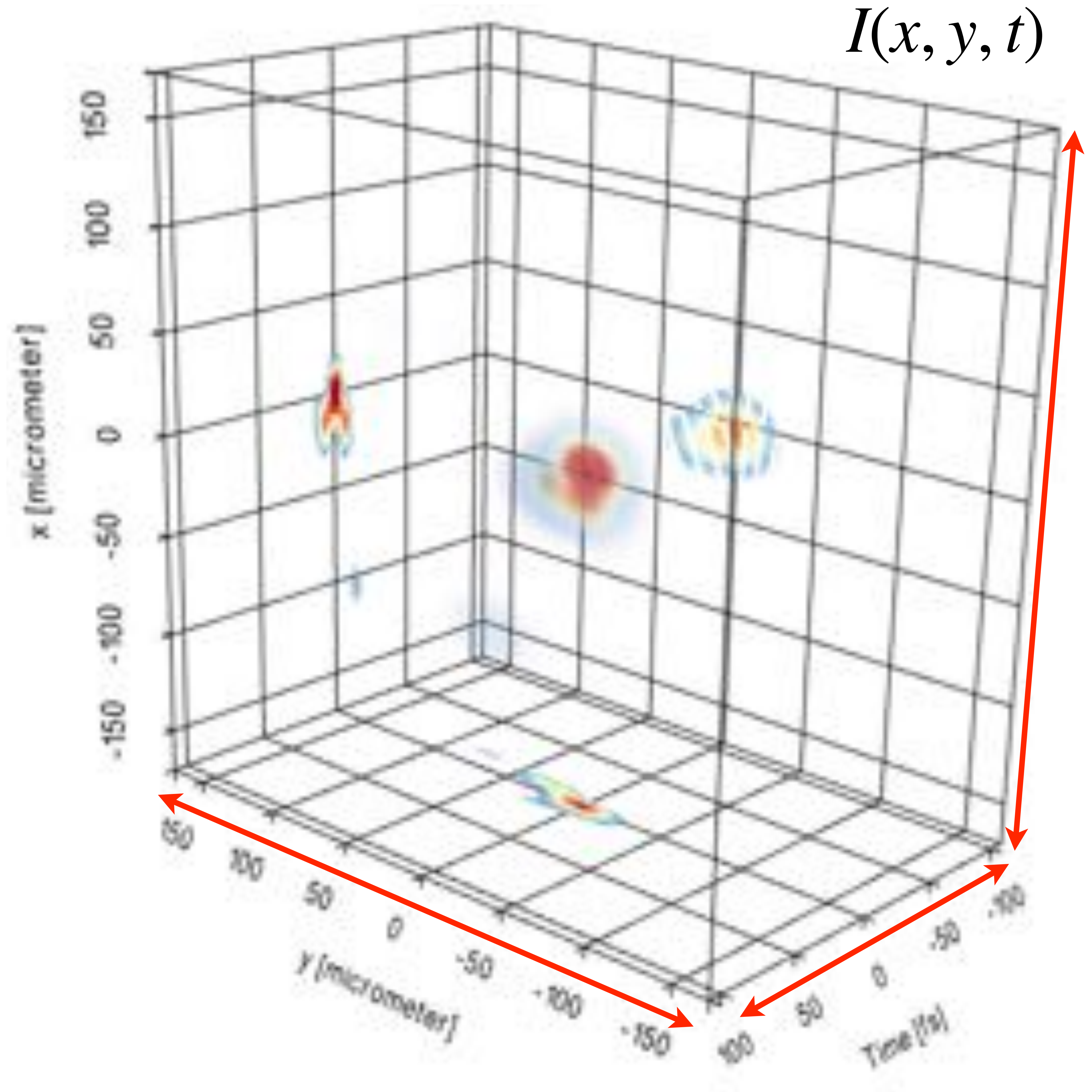
3-D intensity distribution in time

$n = n_x \times n_y \times n_\lambda \sim 1000 \times 1000 \times 100 = 10^8$ voxels

100 million parameters: Need many measurements

Common solution: Fourier transform spectroscopy (INSIGHT, TERMITES) with >1000 2D measurements at 1 MP

Ultra-intense laser characterization



3-D intensity distribution in time

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100 million parameters: Need many measurements

Common solution: Fourier transform spectroscopy (INSIGHT, TERMITES) with >1000 2D measurements at 1 MP

But are voxels really a good base function choice?

Ultra-intense laser characterization

Multi-spectral, modal reconstruction

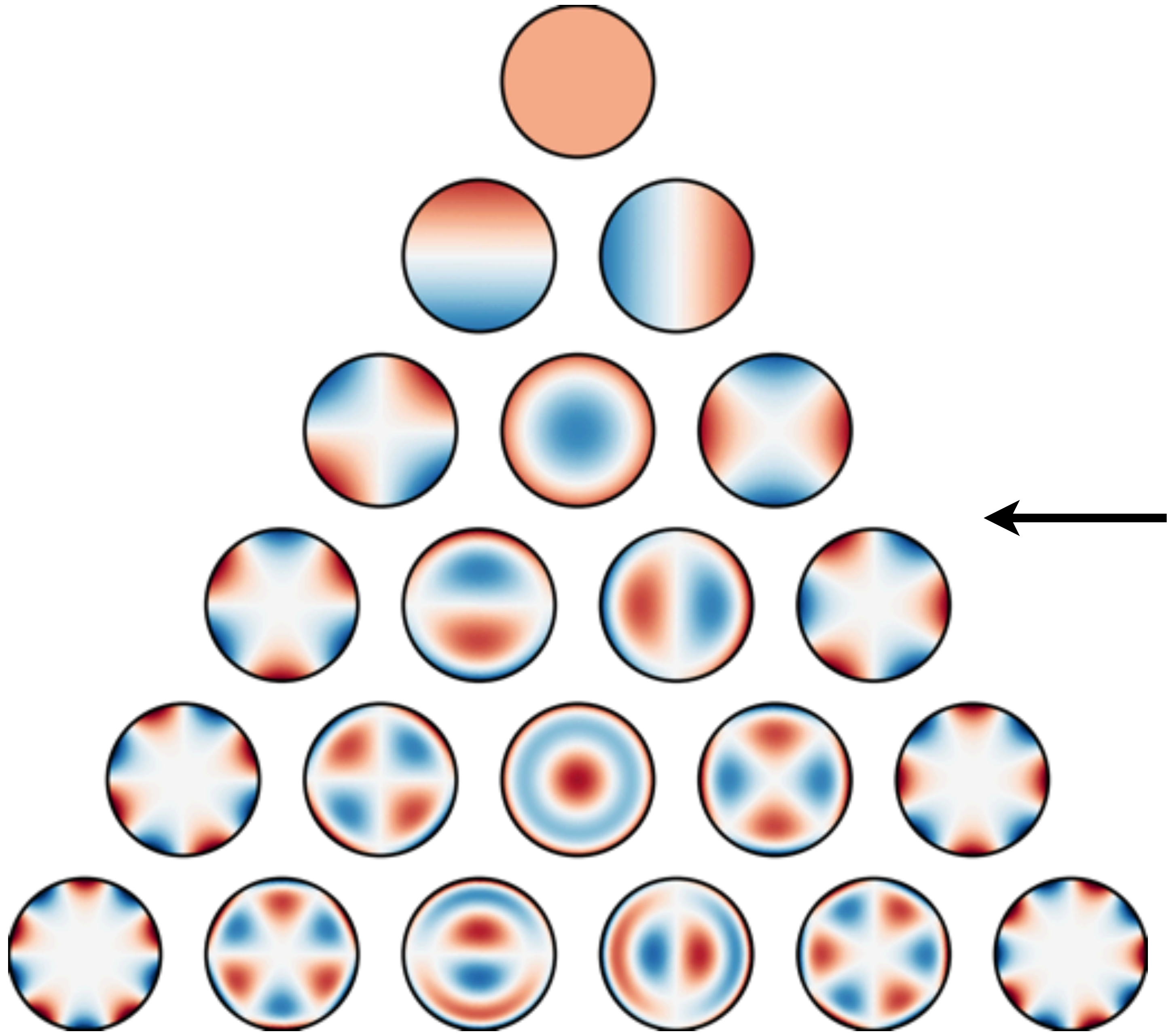
$$I(x,y,t) = \|\mathscr{F}\left[\sqrt{I(x,y,\omega)} \cdot \exp\left(i\Phi(x,y,\omega)\right)\right]\|^2$$

This is the important part,
describing the focused intensity!

Ultra-intense laser characterization

Multi-spectral, modal reconstruction

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



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

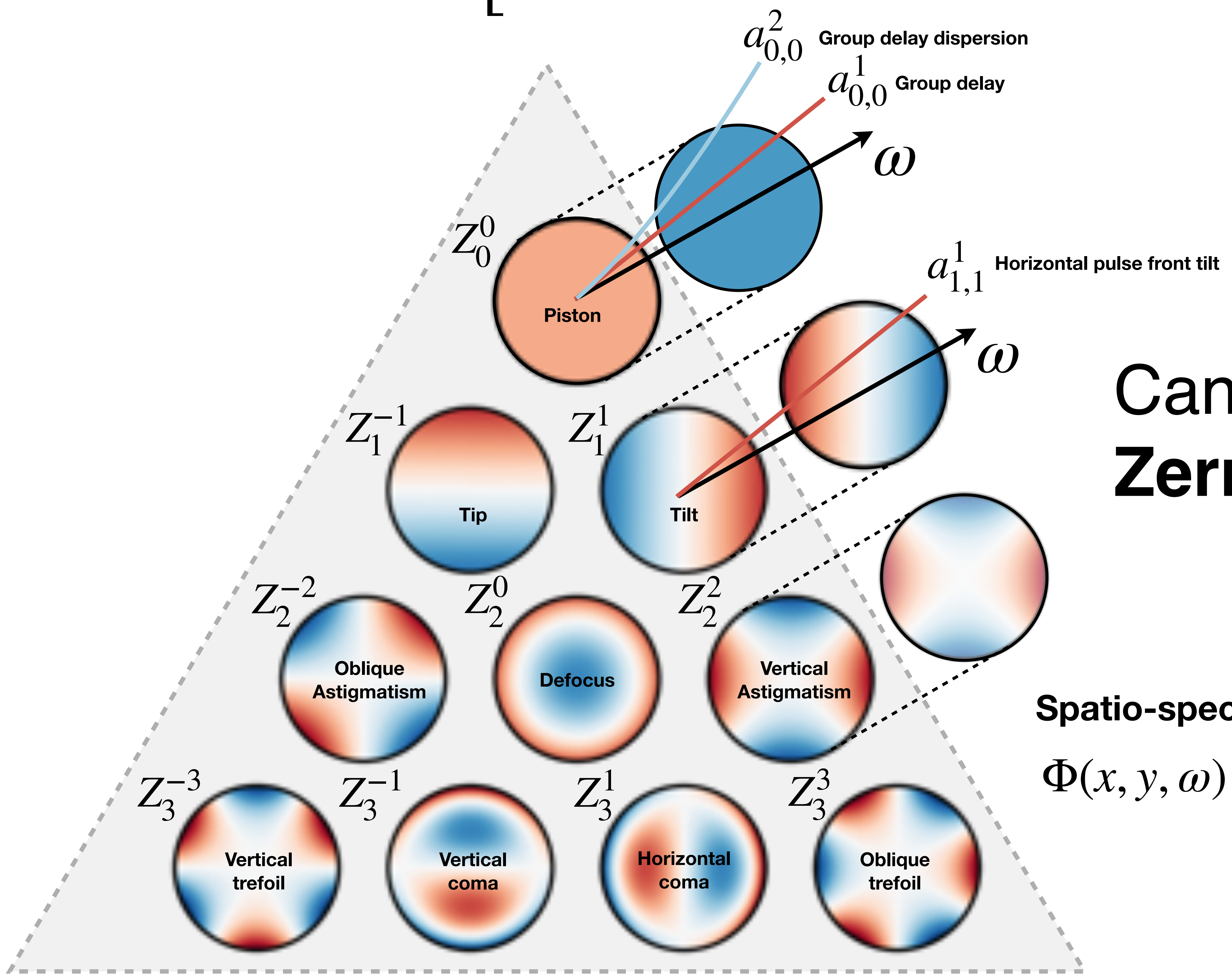
$$I(x,y,t) = \|\mathscr{F}\left[\sqrt{I(x,y,\omega)} \cdot \exp\left(i\Phi(x,y,\omega)\right)\right]\|^2$$

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

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



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

Spatio-spectral phase

$$\Phi(x,y,\omega) = \sum_{m,n,i} a^i_{m,n}(\omega-\omega_0)^i Z^m_n(x,y)$$

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

Ultra-intense laser characterization

Multi-spectral, modal reconstruction

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

↑

$$\Phi(x, y, \omega) = \sum_{m,n,i} a^i_{m,n}(\omega - \omega_0)^i Z^m_n(x, y)$$

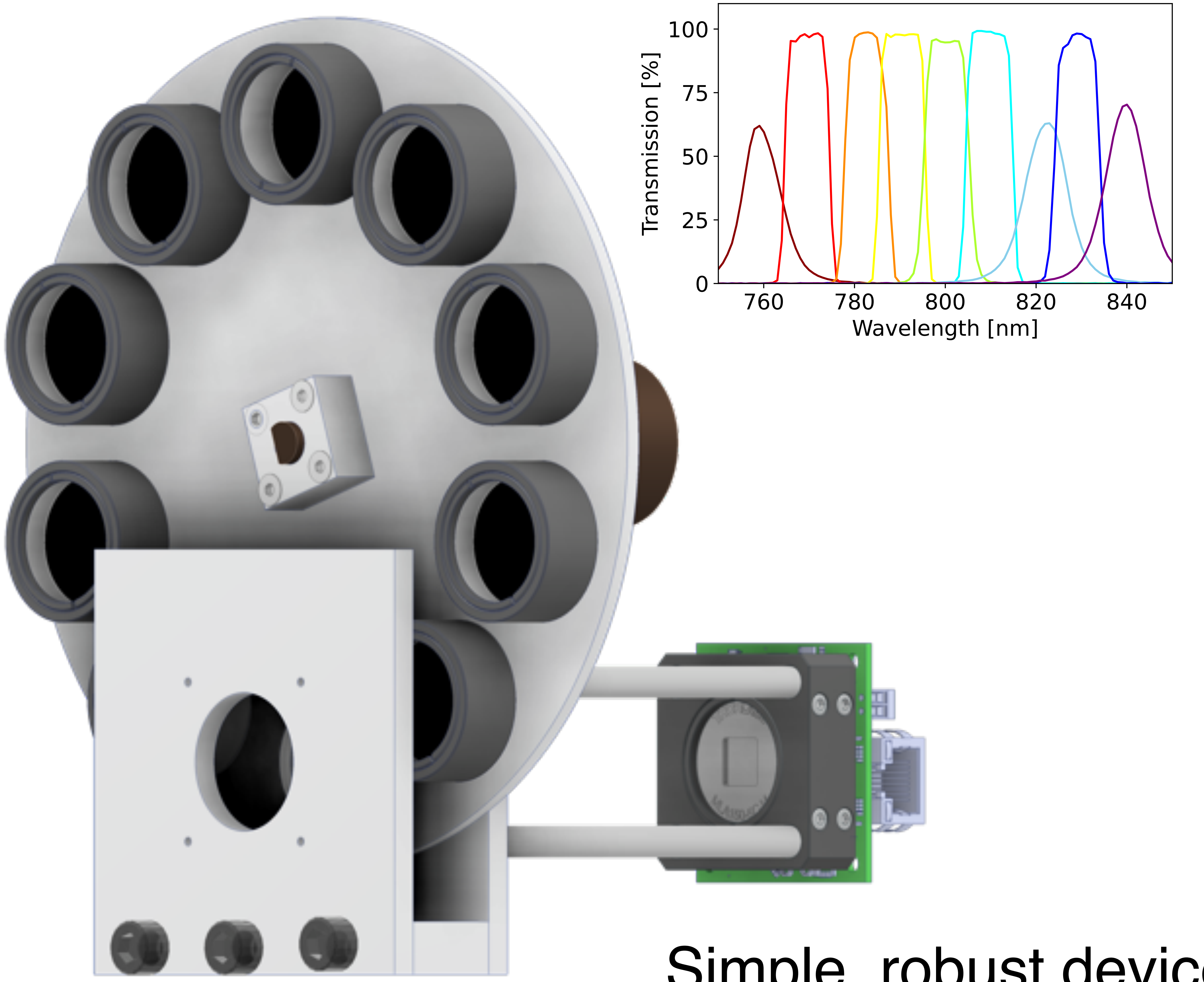
Can describe the **hyperspectral wavefront** using **Zernike-modes and Taylor-expansion in frequency**

Instead of > 1,000,000 voxels we only need to *reconstruct dominant mode coefficients*

Allows us to retrieve spatio-temporal couplings within a few measurements

Ultra-intense laser characterization

FALCON - Fast Acquisition of Laser Couplings using Narrowband Filters

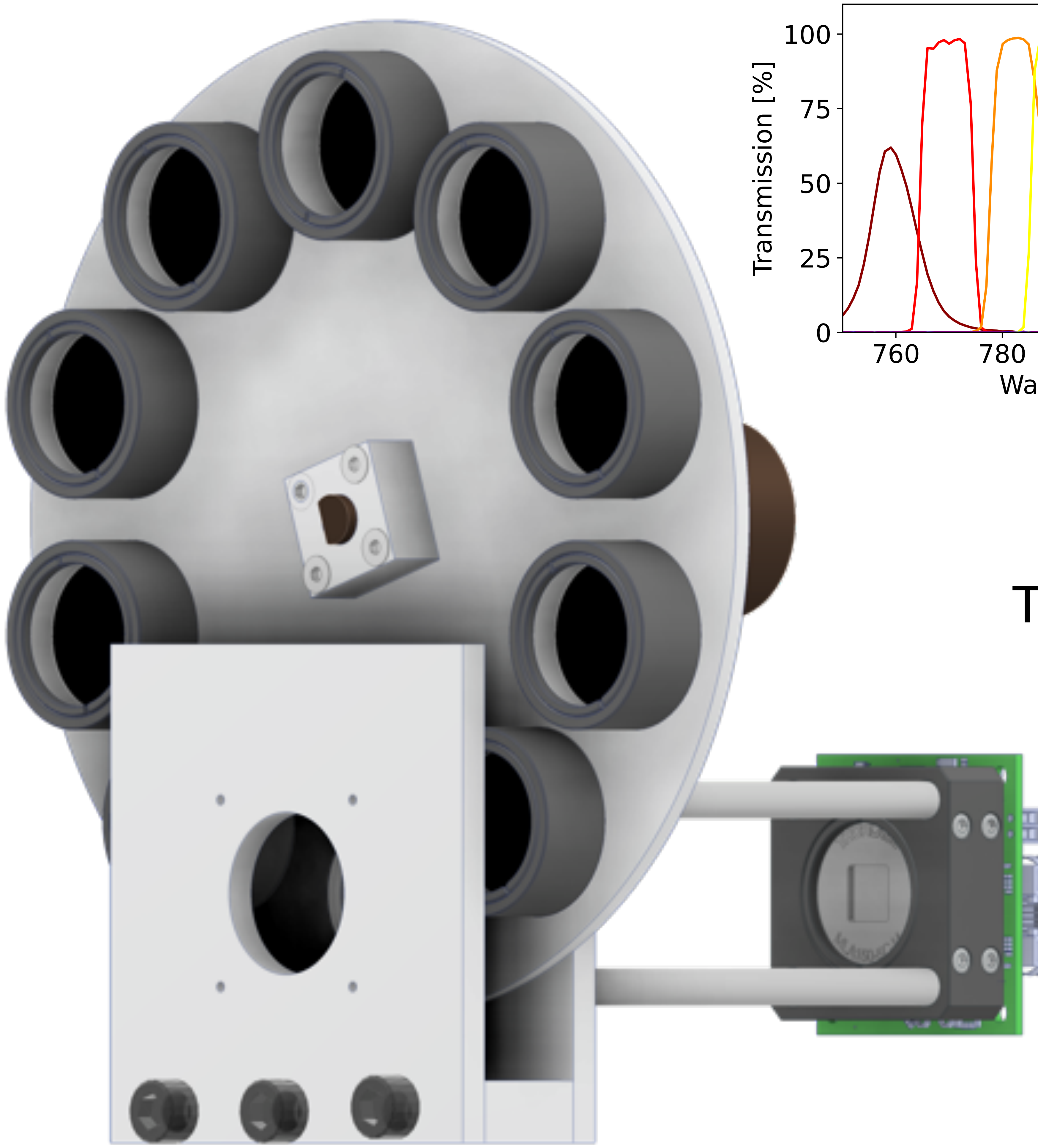


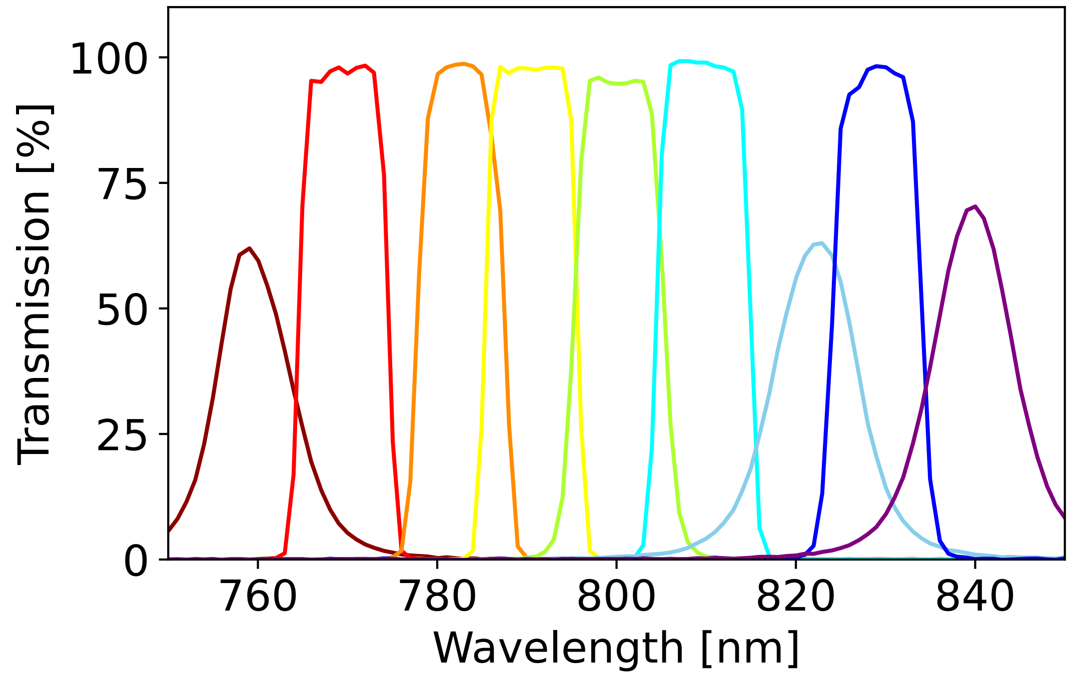
Simple, robust device

- *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

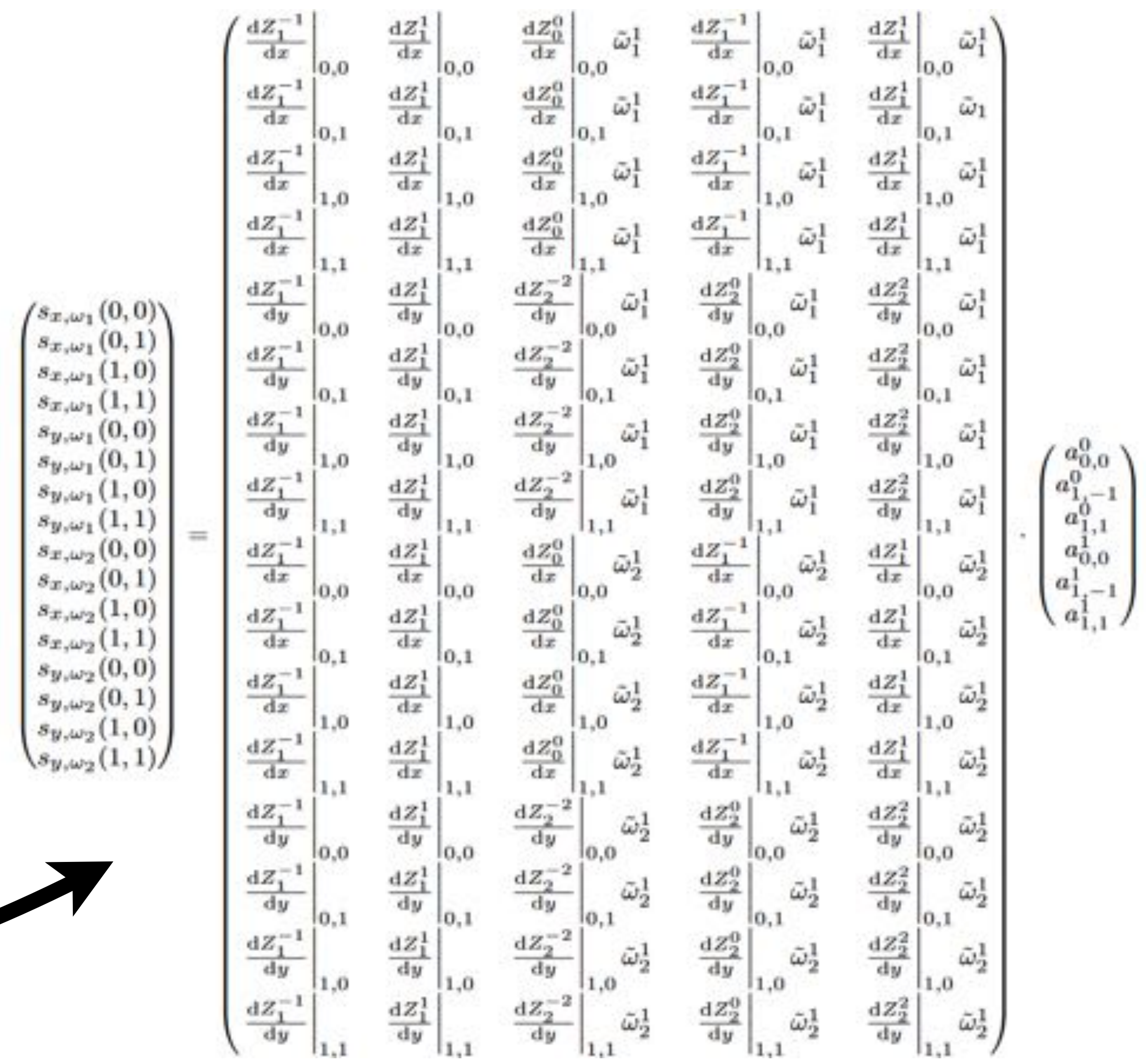
FALCON - Fast Acquisition of Laser Couplings using Narrowband Filters





Translate into an inverse problem

This is for a simple 2x2 lenslet SH detector



- *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

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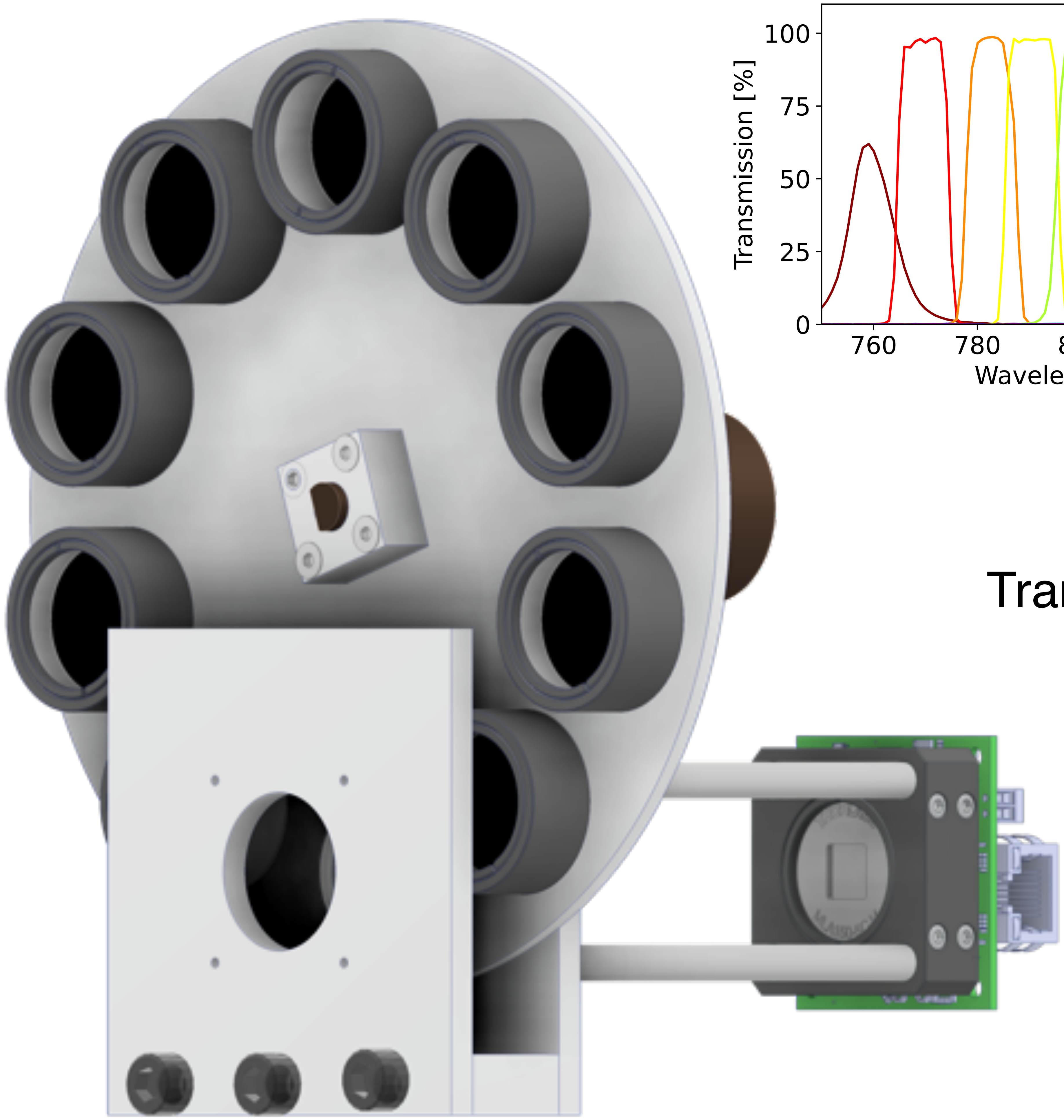
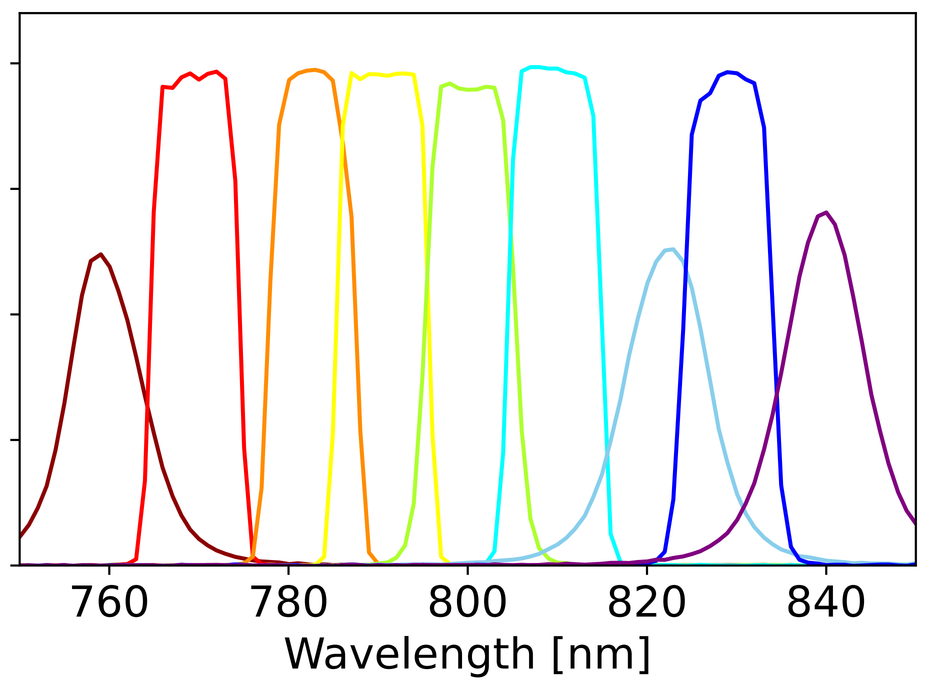
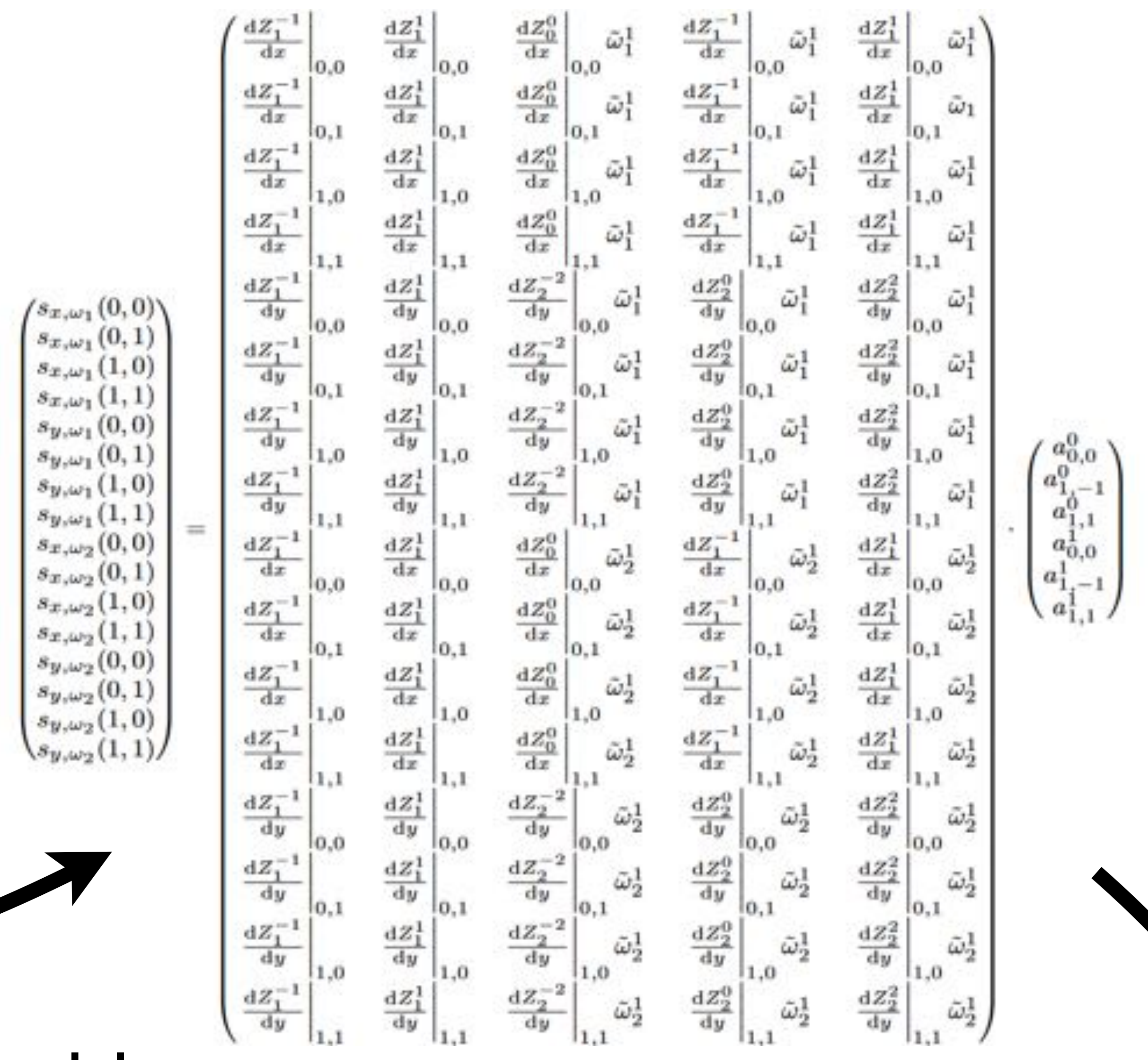
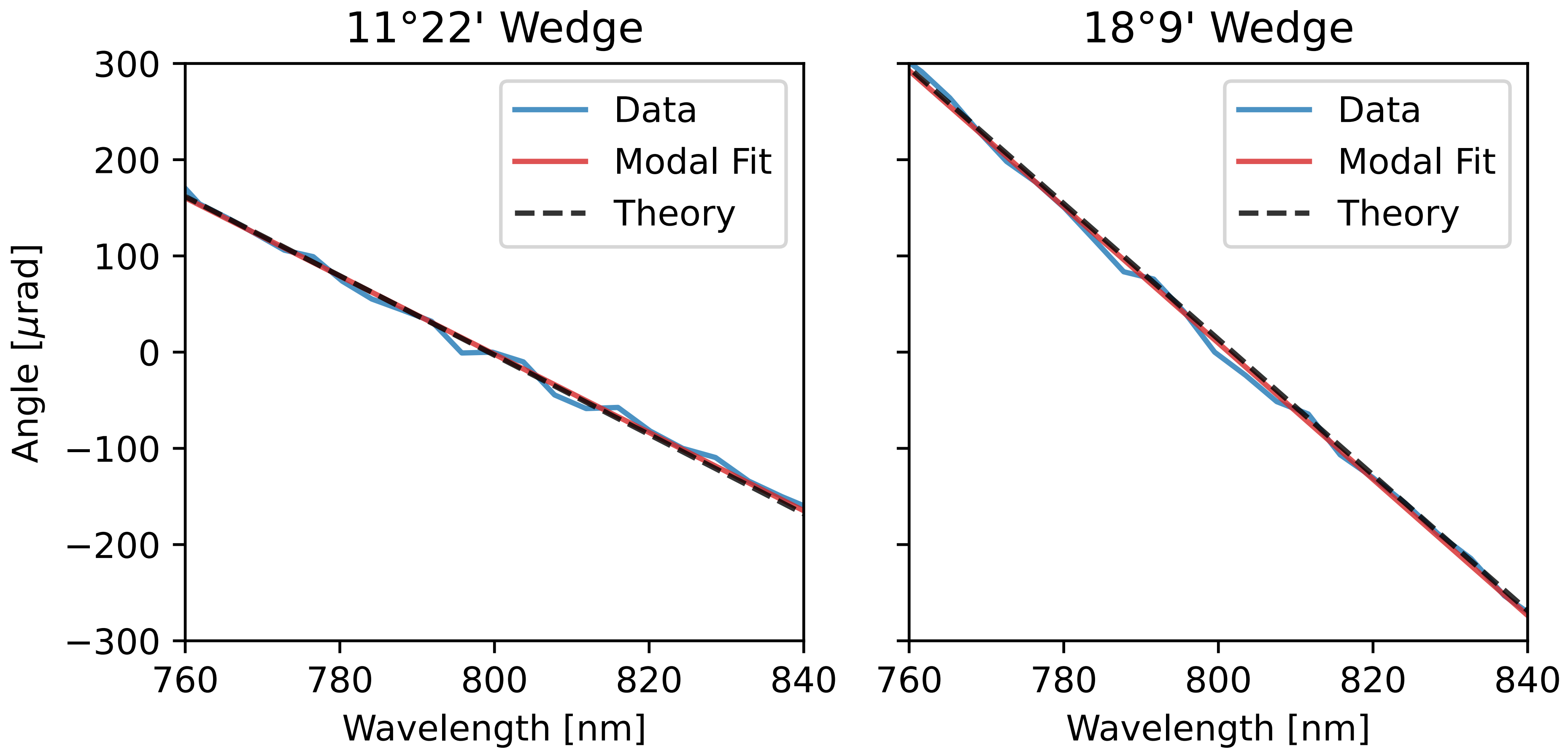






Translate into an inverse problem

Penrose pseudo-inverse calculation *(basically realtime)*

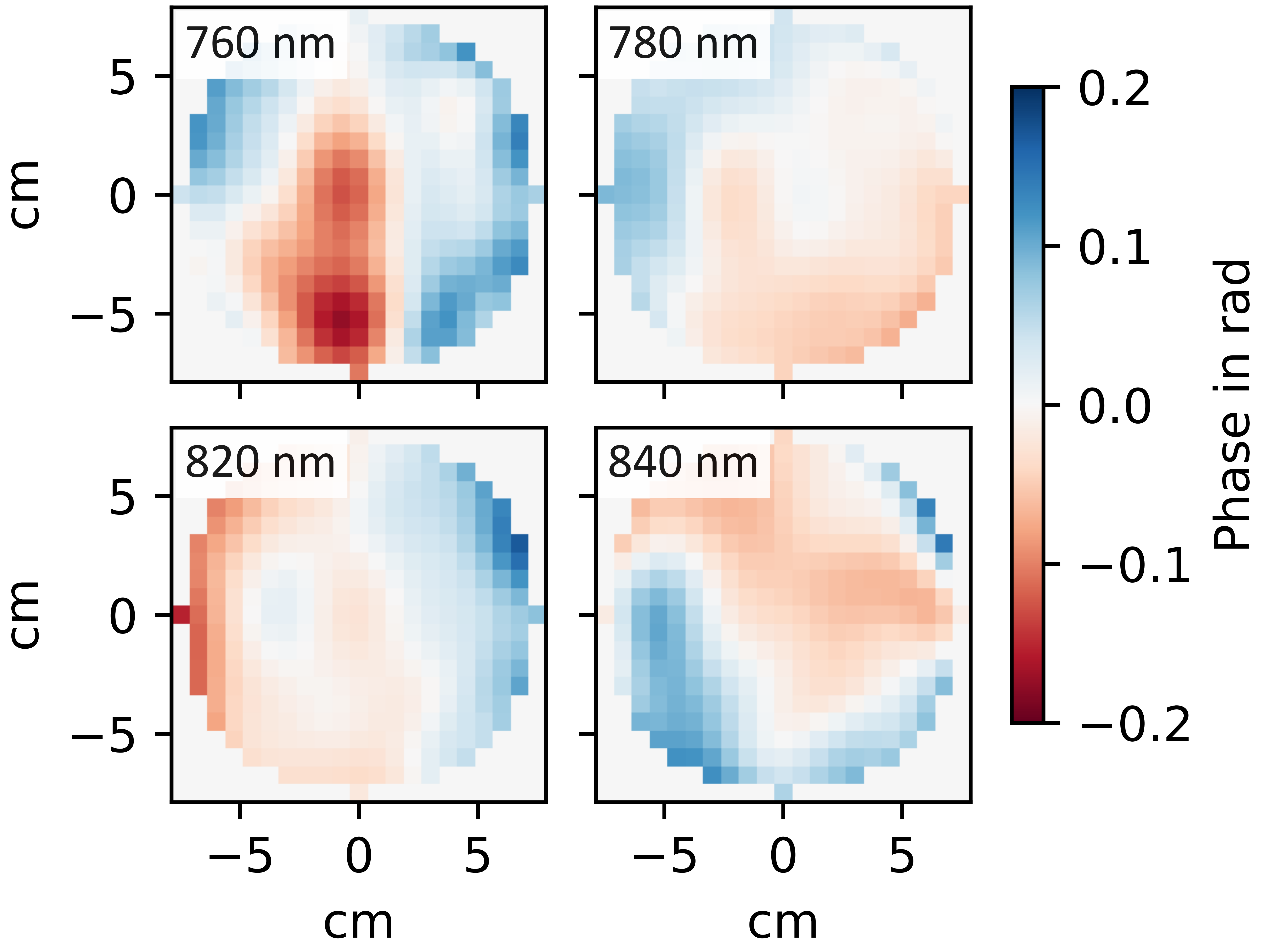


- *N. Weiße, J. Esslinger et al. Measuring spatial-temporal couplings using modal multi-spectral wavefront reconstruction, Opt. Express 31, 19733-19745 (2023)*
-

Ultra-intense laser characterization

Measurement of STCs of the ATLAS petawatt laser

- Full measurement takes ~ 1 minute (9 wavelengths, 5 shots each)
- Measurement shows couplings in ATLAS are < λ/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

$n_x \times x_y \times n_\omega \sim$ 1000x1000x100 numbers

$$Ax = y$$

Minimize →

$$\arg\min_{x} \{ ||Ax - y||^2 \}$$

↓ Transform Ψ to (truncated) *Zernike-Taylor basis*

$$\arg\min_{\tilde{x}} \{ ||A\Psi\tilde{x} - y||^2 \}$$

Leading coefficients (<1000)

Much more robust reconstruction!

1. A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics,** *arXiv:2212.00026* (2022)

Ultra-intense laser characterization

Compressed sensing

$n_x \times x_y \times n_\omega \sim$ 1000x1000x100 numbers

$$Ax = y \xrightarrow{\text{Minimize}} \underset{x}{\arg\min}\{\|Ax - y\|^2\}$$

Transform to *some sparse* basis
(e.g. wavelet, PCA, etc.)

$$\underset{\tilde{x}}{\arg\min}\{\|A\Psi\tilde{x} - y\|^2 + \|\tilde{x}\|_1\}$$

Few coefficients as possible

1. A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics,** *arXiv:2212.00026* (2022)

Ultra-intense laser characterization

Deep compressed sensing

$n_x \times x_y \times n_\omega \sim$ 1000x1000x100 numbers

$$Ax = y \xrightarrow{\text{Minimize}} \arg\min_x \{ ||Ax - y||^2 \}$$

Transform to *some sparse* basis
(e.g. wavelet, PCA, etc.)

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

Learnt regularization
(Residual estimate)

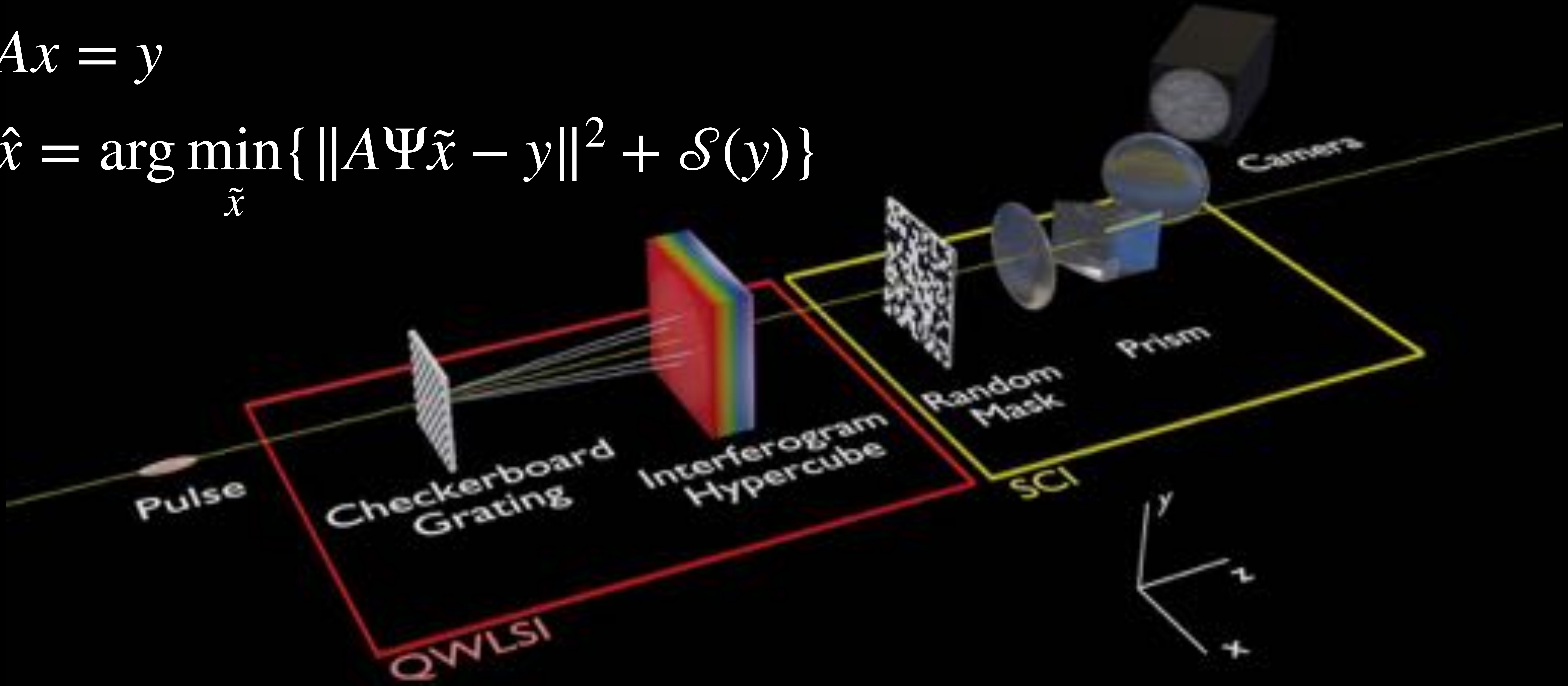
1. A. Döpp et al. **Data-driven Science and Machine Learning Methods in Laser-Plasma Physics,** *arXiv:2212.00026* (2022)

Ultra-intense laser characterization

Deep compressed sensing

$$Ax = y$$

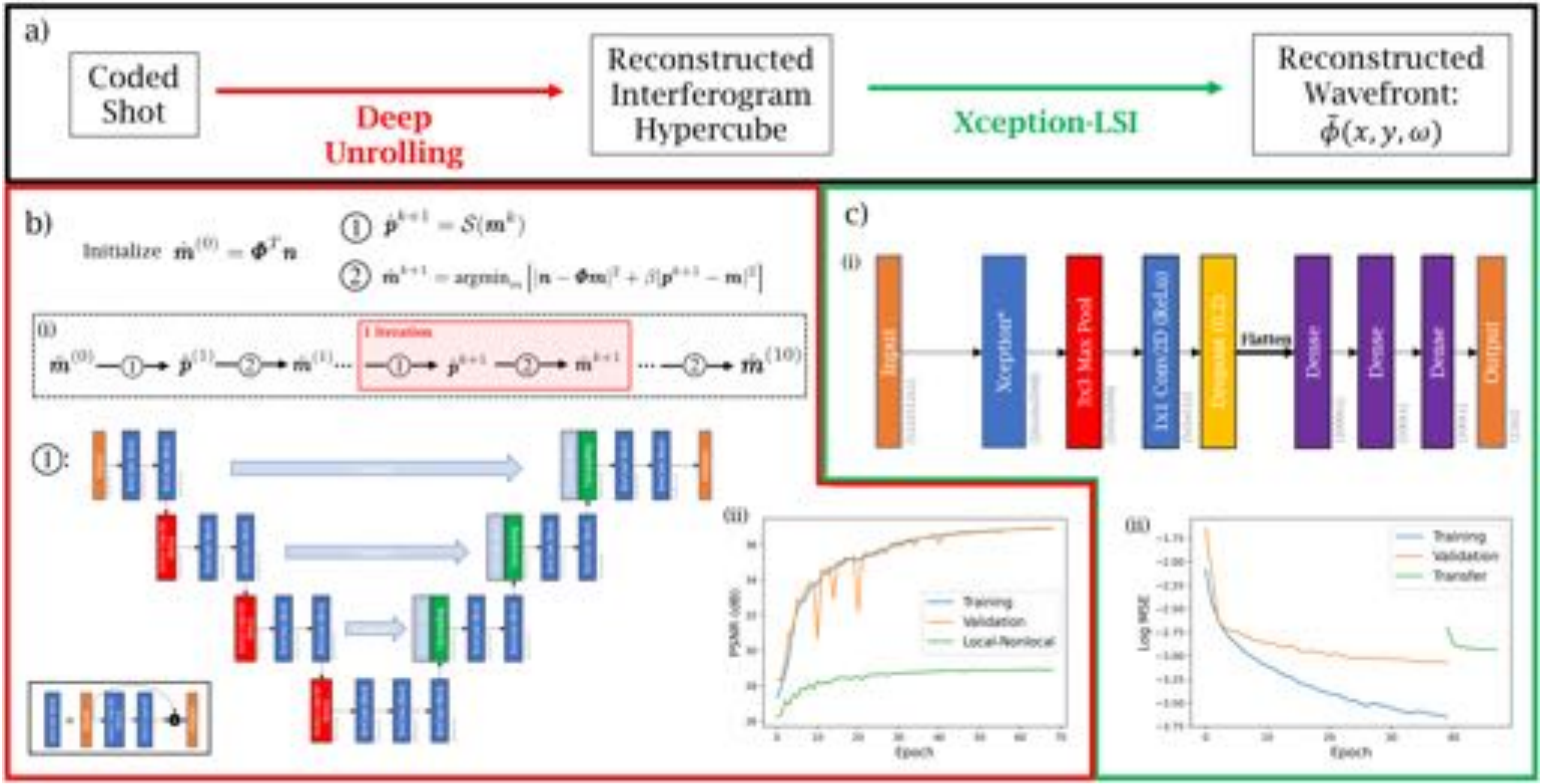
$$\hat{x} = \arg\min_{\tilde{x}}\{\,||A\Psi\tilde{x} - y||^2 + \mathcal{S}(y)\,\}$$



1. S. Howard et al. **Hyperspectral Compressive Wavefront Sensing**, *High Power Laser Science and Engineering, 2023, 11(3):32*

Ultra-intense laser characterization

Deep compressed algorithm unrolling



1. S. Howard et al. **Hyperspectral Compressive Wavefront Sensing**, *High Power Laser Science and Engineering, 2023, 11(3):32*

Ultra-intense laser characterization

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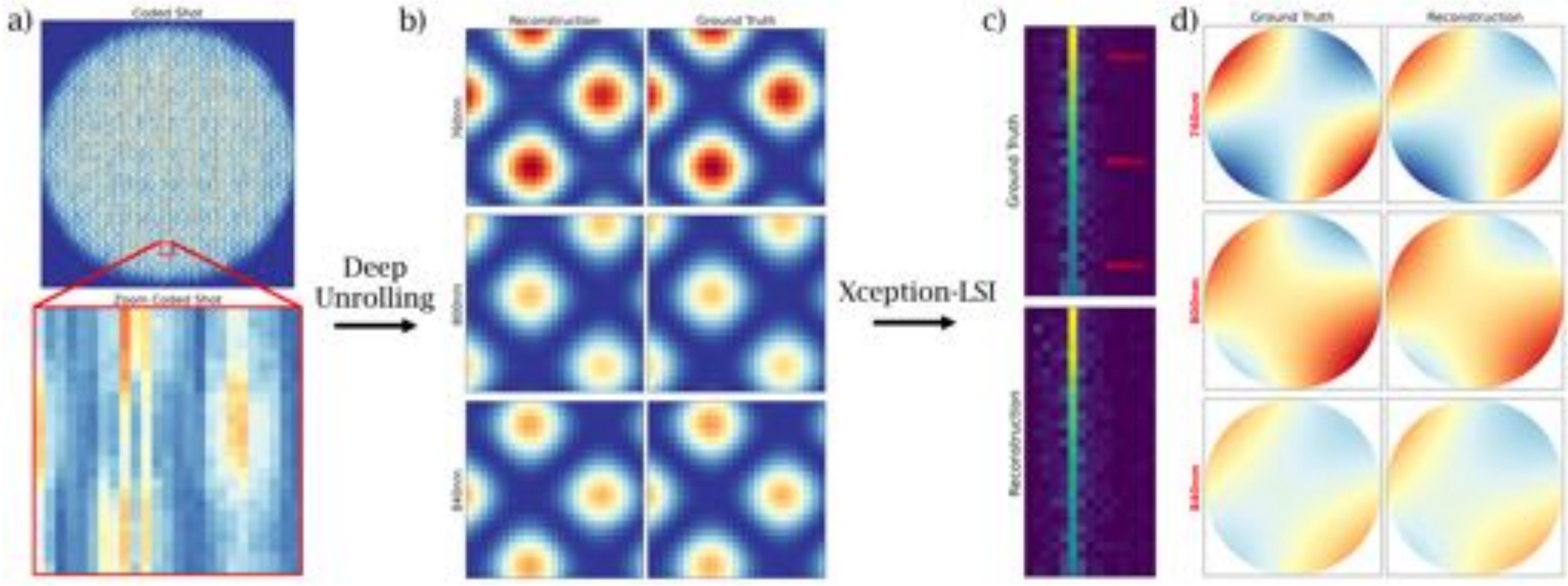
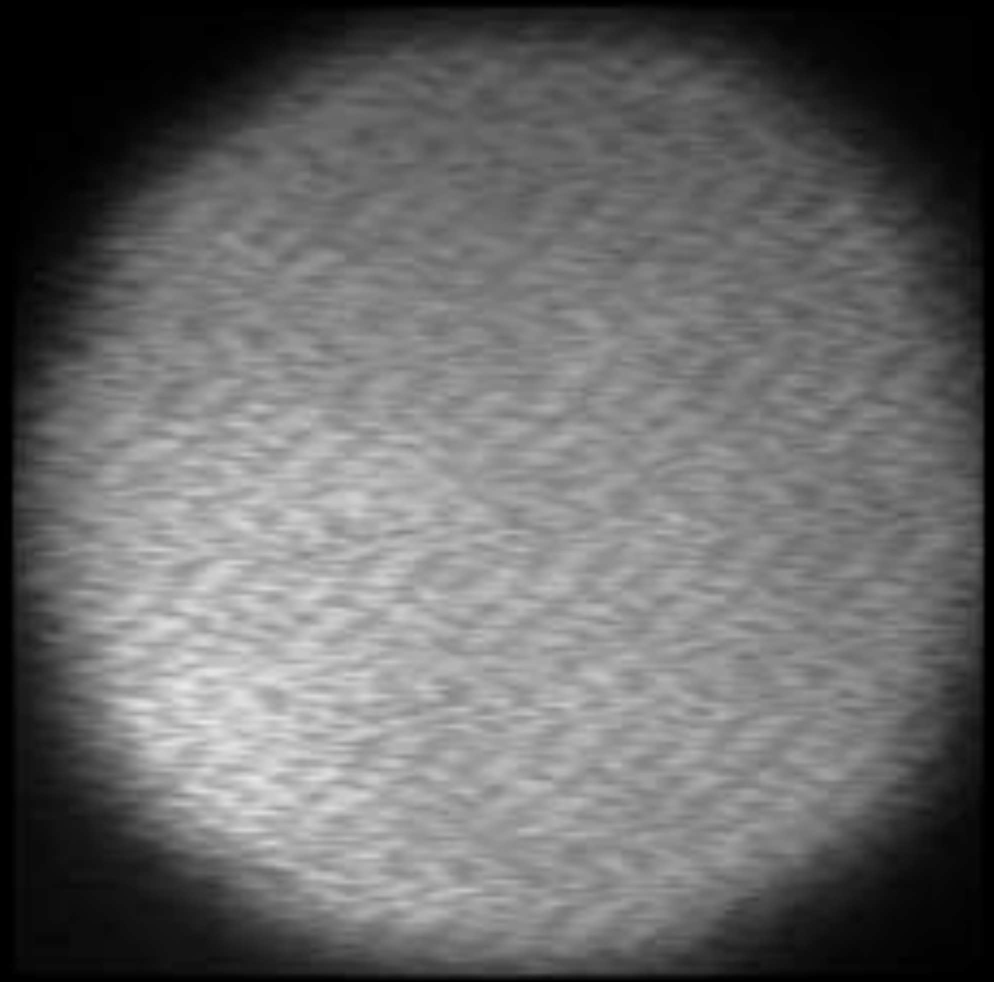


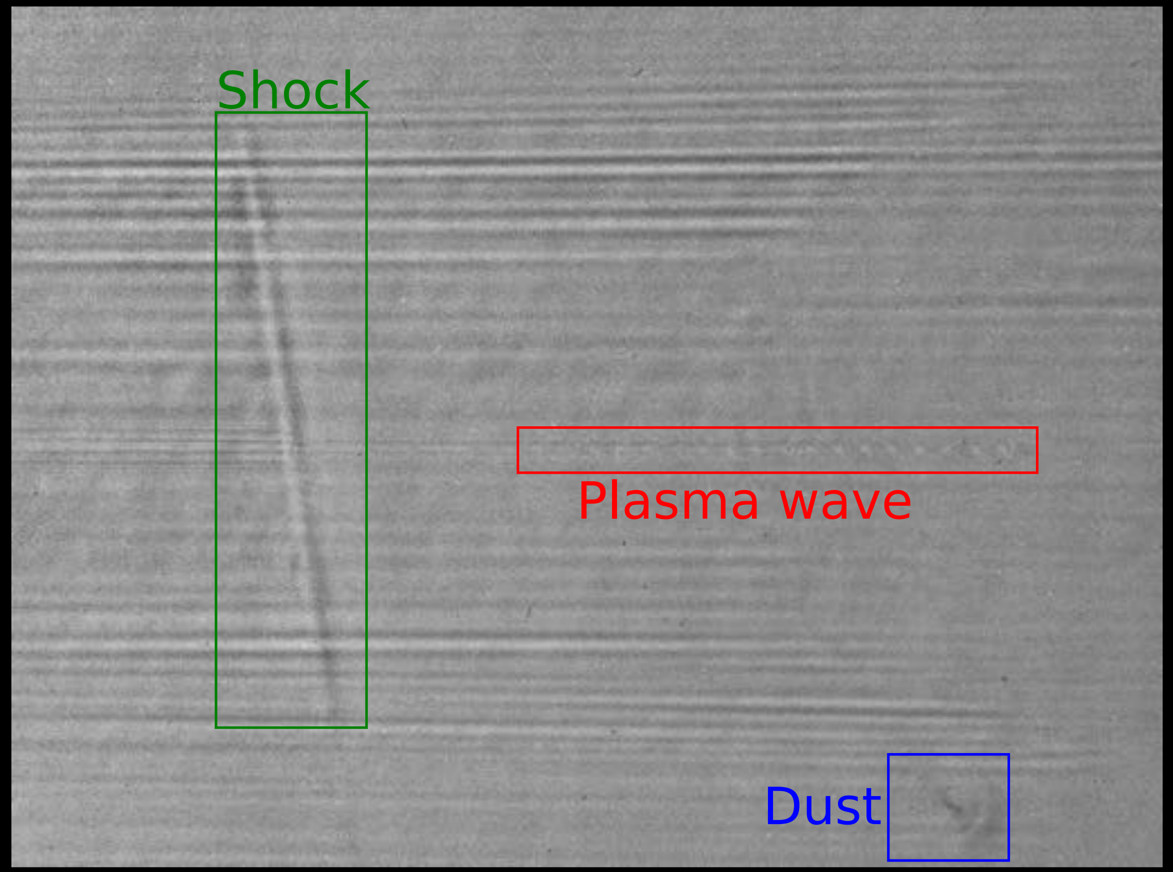
1. S. Howard et al. **Hyperspectral Compressive Wavefront Sensing**, *High Power Laser Science and Engineering, 2023, 11(3):32*

Conclusions and Outlook

- Machine learning is quickly advancing in laser-plasma physics community
- Physics-driven developments can improve essential building blocks of machine-learning
- Presented new Bayesian optimization approaches using multiple objectives and fidelities
- Presented new approaches to measuring spatio-temporal couplings; single-shot diagnostic under development

- Many other applications in development, e.g. object detection, etc.





Thank you for your attention!

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