EuPRAXIA-DN School on Plasma Accelerators
April 25, 2024

Modeling & Optimizing Plasma Accelerators

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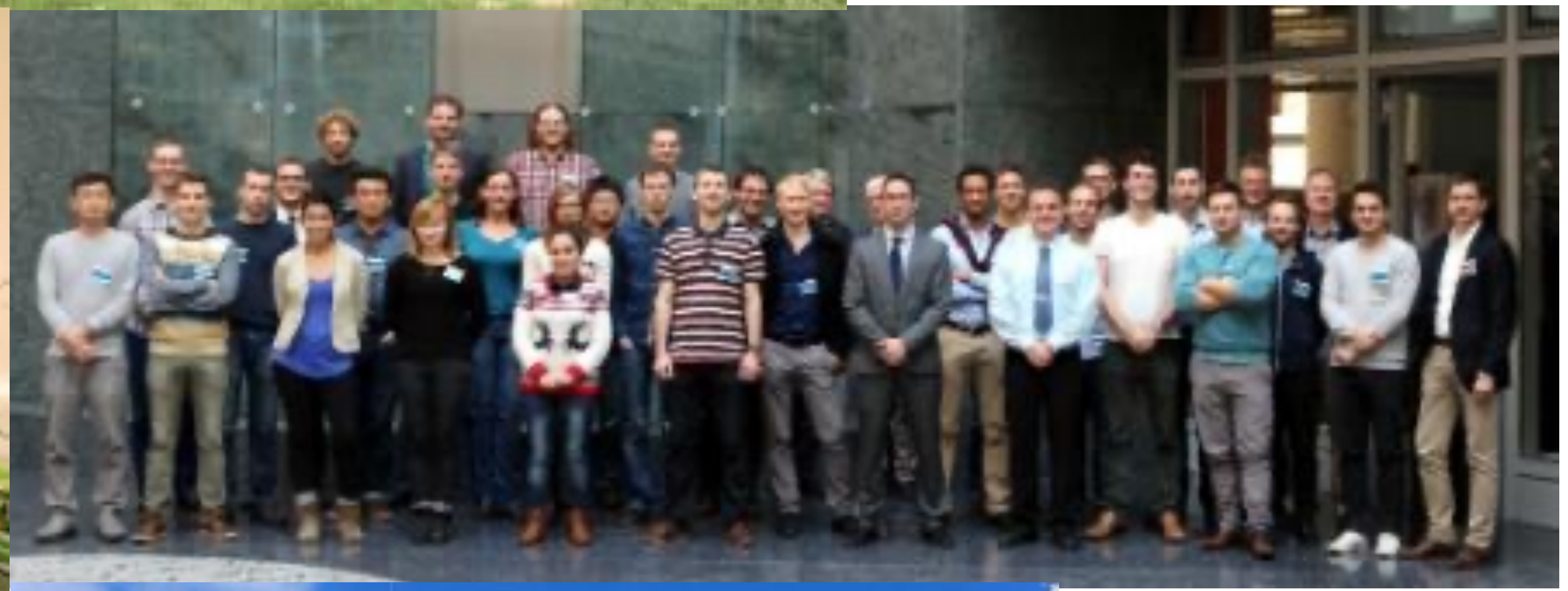
It's a pleasure to be here!

PULSE CALA

LA³NET



I also used to be a Marie-Curie fellow … almost a decade ago 😅

Team DOLPHIN

Data-driven Optimization of Laser Physics and Interactions

PhD students

Sunny

Jannik

Chris

Jakob

Collaborators

in CALA

Stefan Karsch, Jörg Schreiber

Faran, Nils, Jinpu

in Oxford

Peter Norreys,

Robin Wang

in Salamanca

Iñigo Sola,

Benjamin Alonso

Modeling & Optimizing

Plasma Accelerators

Modeling

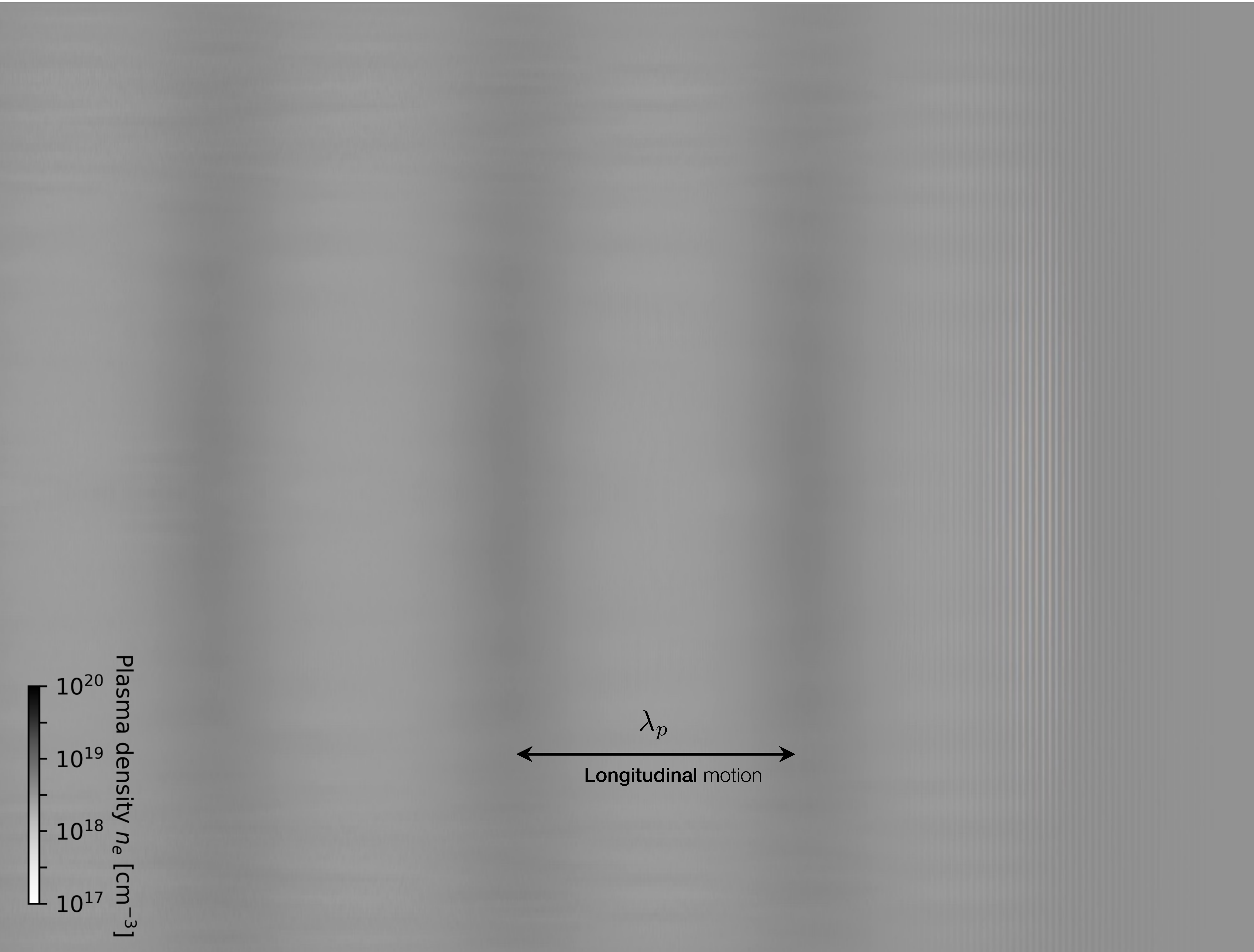
- Analytical Models
- Particle-In-Cell Models
- Machine-learning Models

Optimization

- Objective functions
- Multi-objective optimization

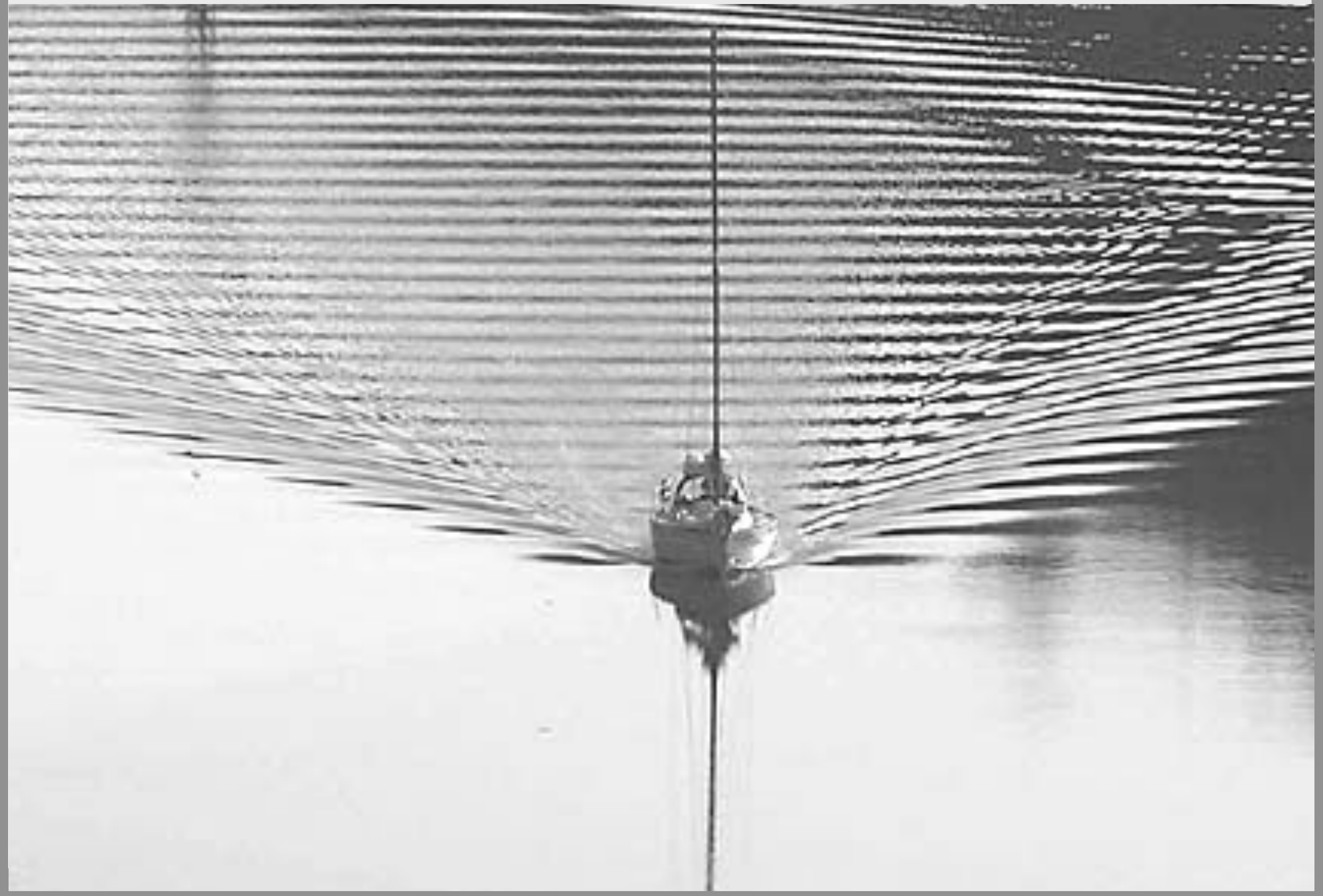
Modeling laser-plasma interaction

The linear wakefield regime



$a_0 \sim E_0$ [TV/m] / 4

$$\left(\frac{\partial^2}{\partial \xi^2} + k_p^2\right)\phi = k_p^2 \frac{\langle a^2 \rangle}{2}$$



- H. Ding, A. Döpp et al. Phys. Rev. E 101, 023209

Modeling laser-plasma interaction

The linear wakefield regime

Consider impulse response:

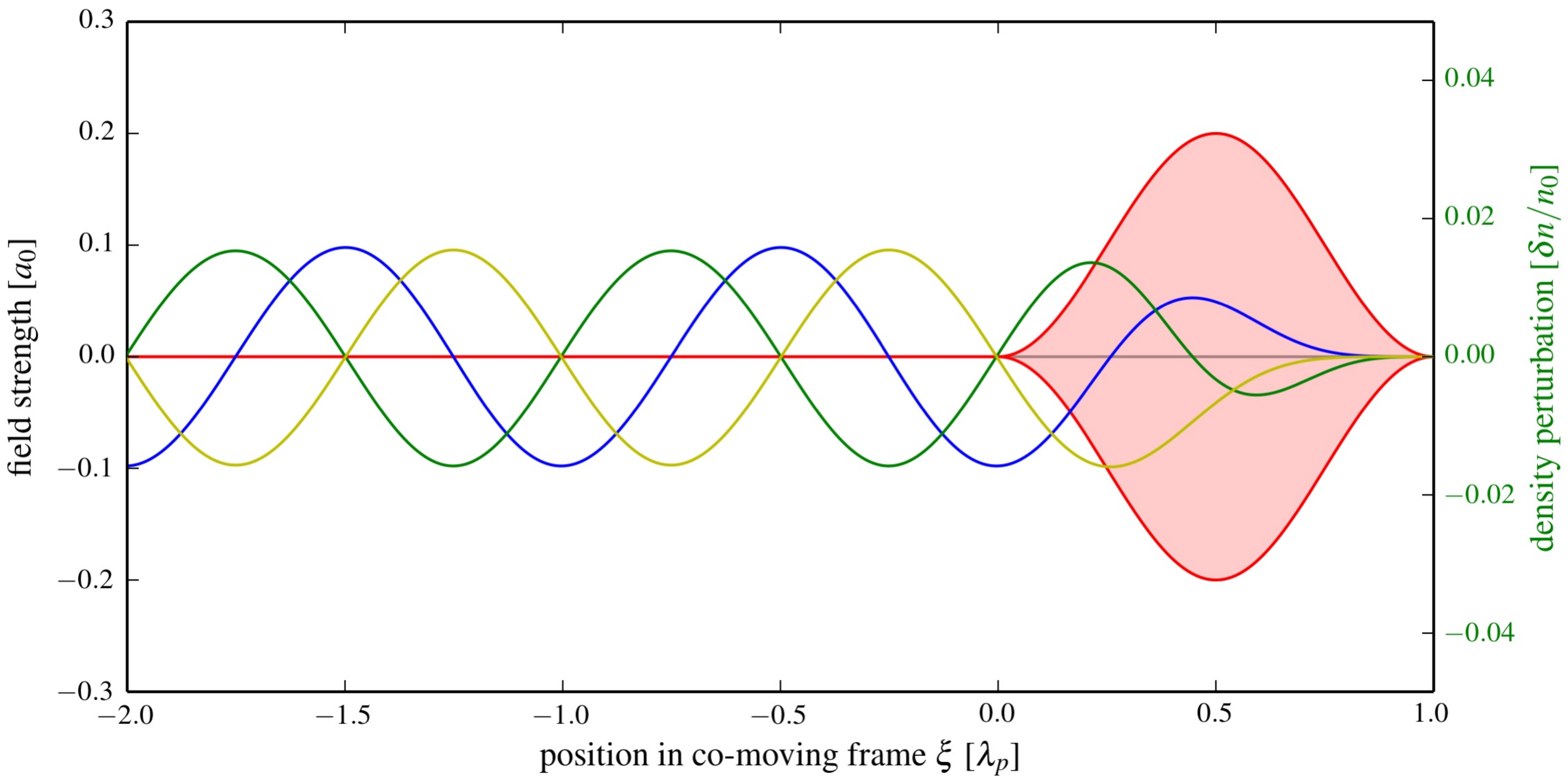
$$\left(\frac{\partial^2}{\partial \xi^2} + k_p^2\right)\phi = \delta(\xi)$$

Find the Green's function

$$G(\xi) = \frac{1}{2}\sin[k_p(\xi - \xi')]$$

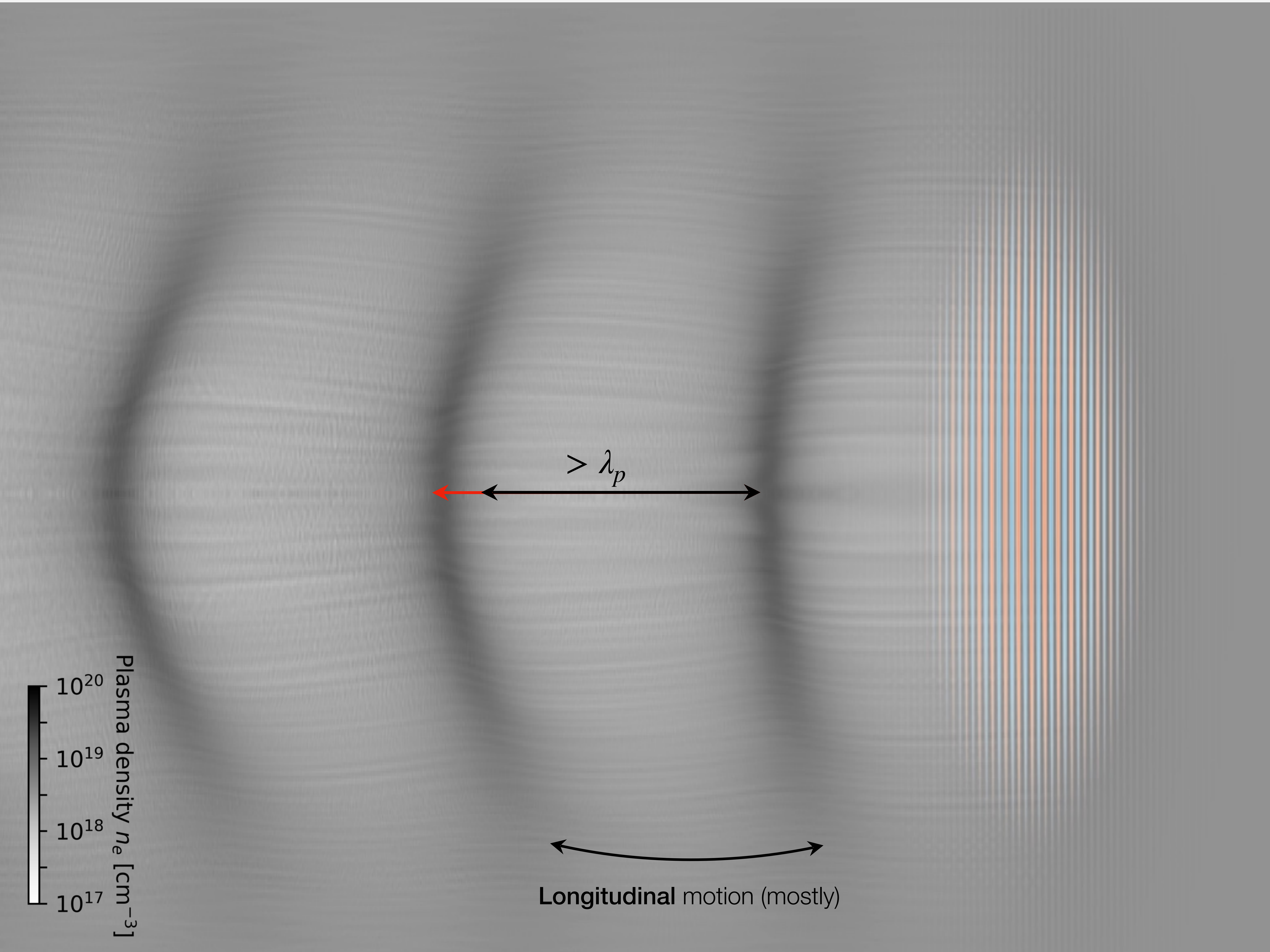
Convolve the actual excitation with the Green's function:

$$\phi = \int_{-\infty}^{\xi} f(\xi')G(\xi - \xi')d\xi'$$

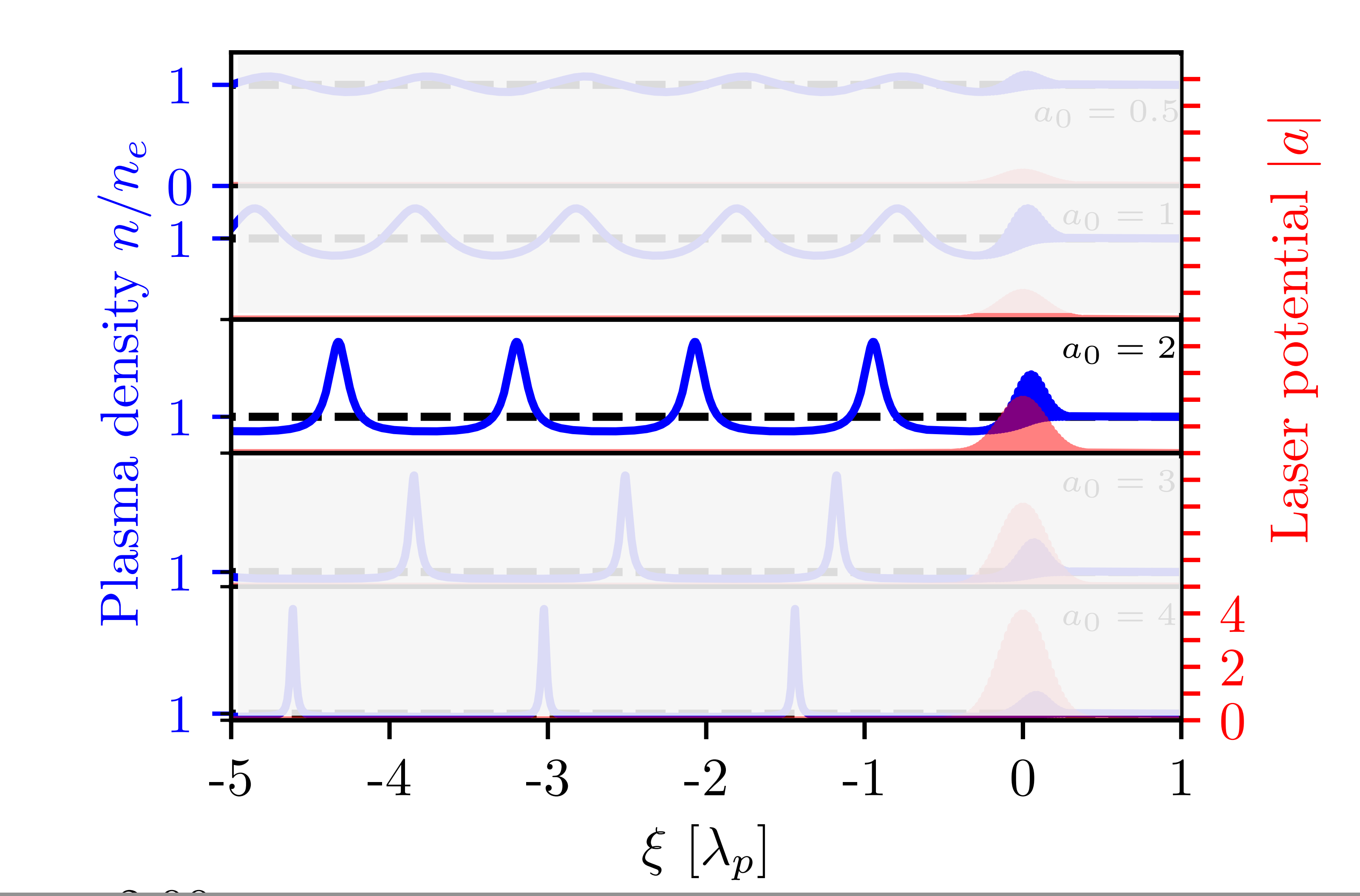


Modeling laser-plasma interaction

The non-linear wakefield regime



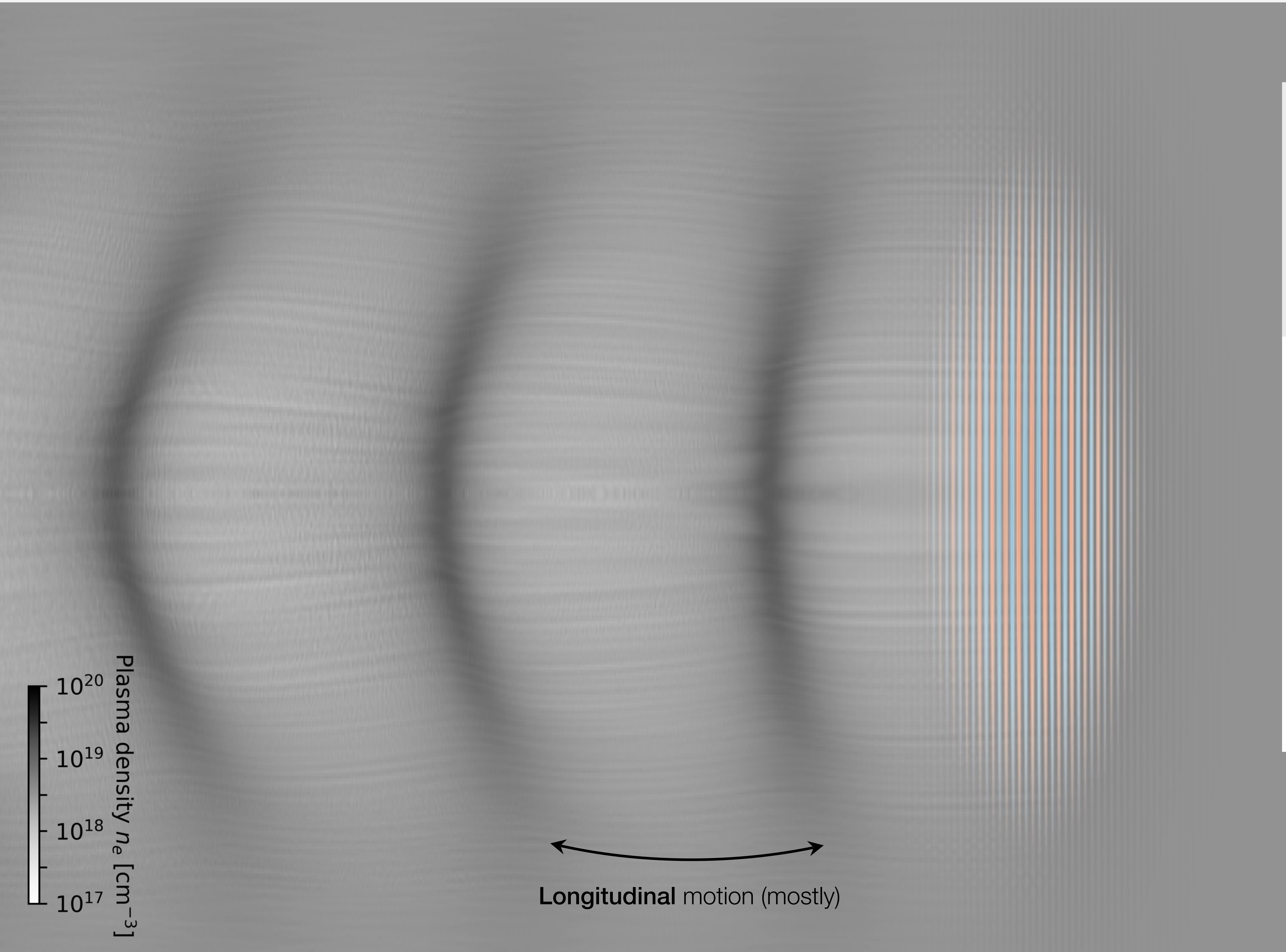
$$\frac{\partial^2}{\partial \xi^2}\Phi = \frac{1}{2}\left(\frac{1+a^2}{(1+\Phi)^2} - 1\right)k_p^2$$



- H. Ding, A. Döpp et al. Phys. Rev. E 101, 023209

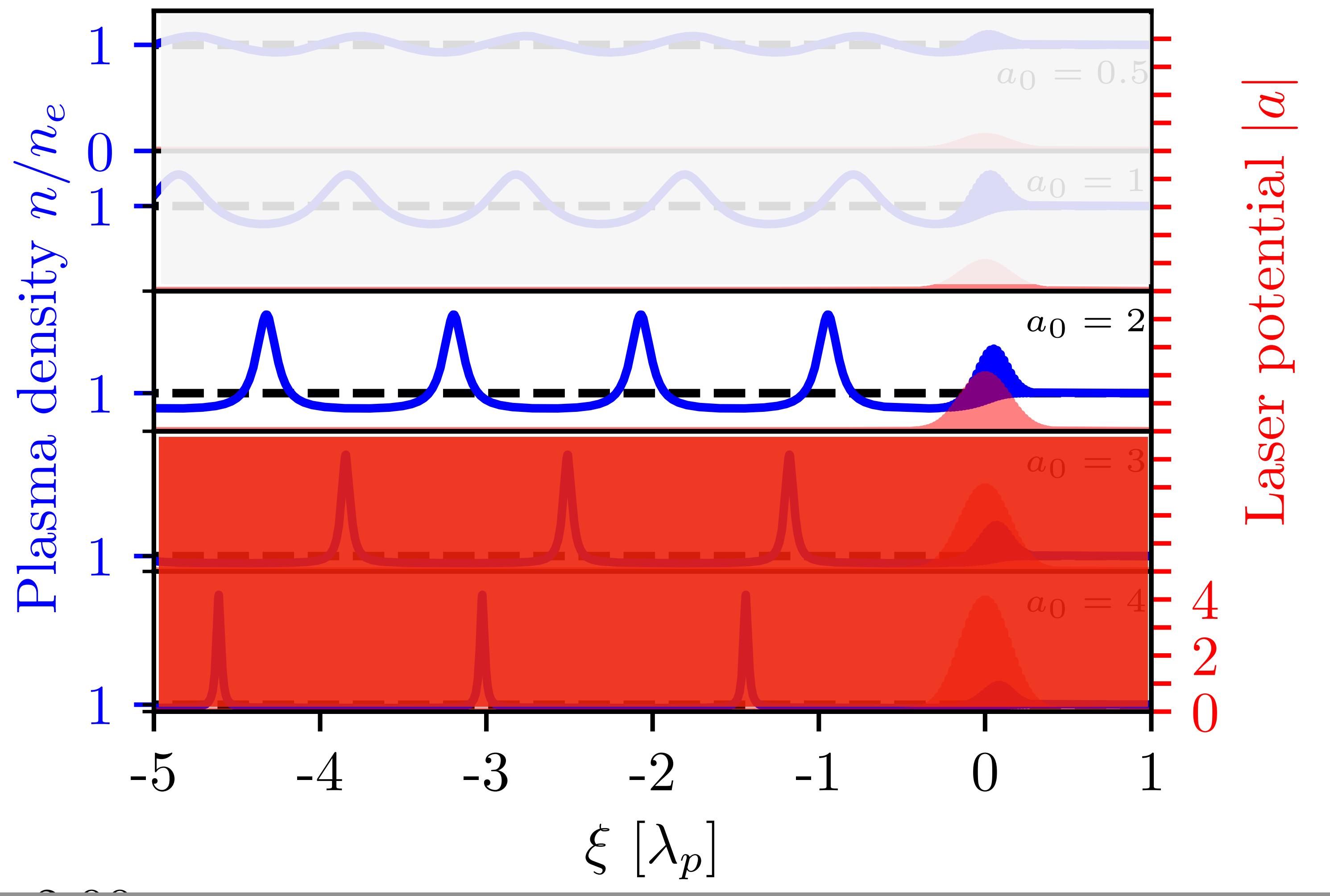
Modeling laser-plasma interaction

The non-linear wakefield regime



$$\frac{\partial^2}{\partial \xi^2}\Phi = \frac{1}{2}\left(\frac{1+a^2}{(1+\Phi)^2} - 1\right) k_p^2$$

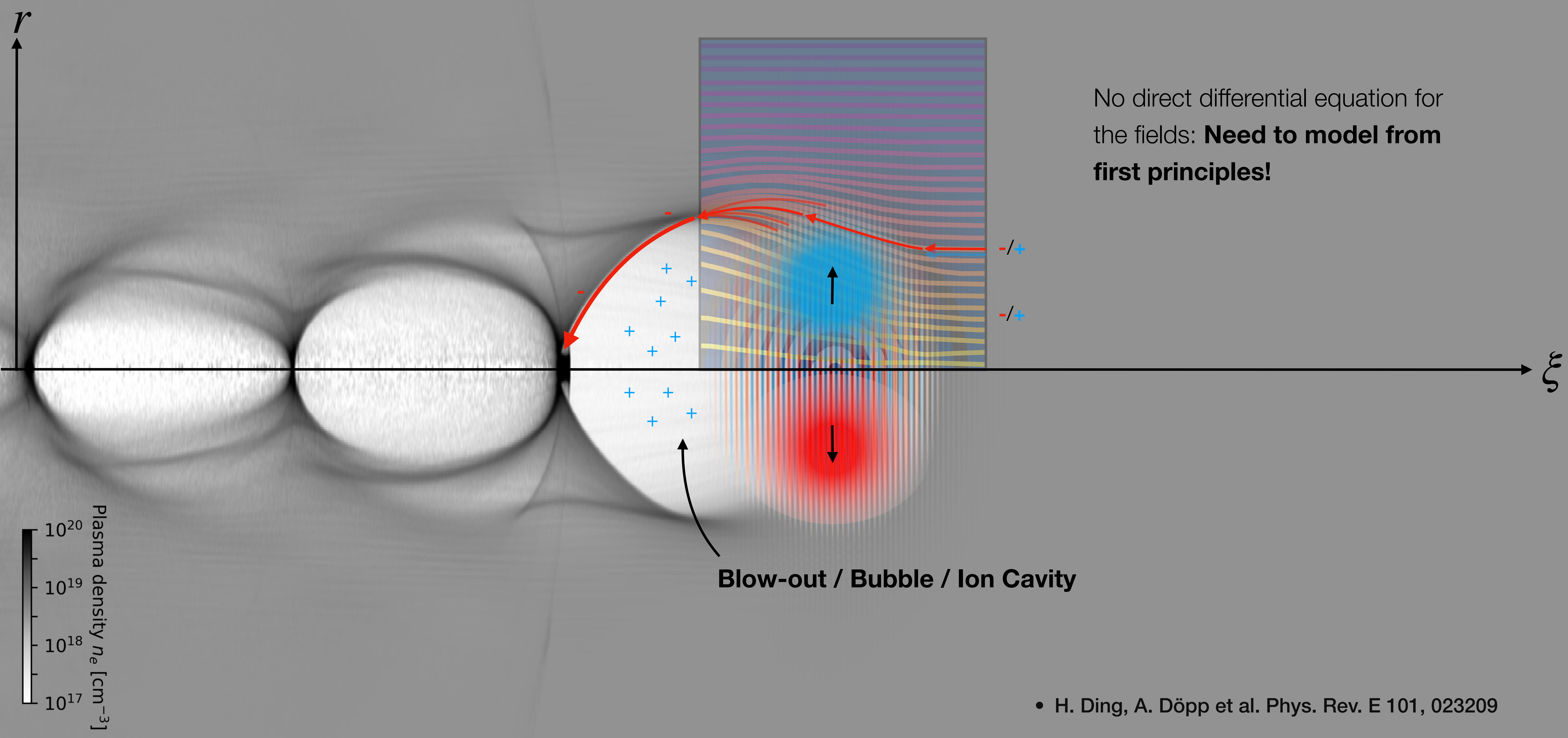
Approximation only valid if **mainly longitudinal motion**! This is the case for large focus when the transverse ponderomotive force is small.



- H. Ding, A. Döpp et al. Phys. Rev. E 101, 023209

Modeling laser-plasma interaction

The highly non-linear “blow-out” regime



No direct differential equation for the fields: **Need to model from first principles!**

- H. Ding, A. Döpp et al. Phys. Rev. E 101, 023209

Modeling laser-plasma interaction

The Vlasov equation

- We are interested in the evolution of a particle distribution in space, velocity and time $\rho(\vec{x}, \vec{v}, t)$
- In a collisionless system, where particles are neither created nor destroyed, the continuity equation is valid:

$$\frac{df}{dt} = \frac{\partial f}{\partial t} + \vec{v}_x \cdot \left(\nabla_x f \right) + \vec{v}_p \cdot \left(\frac{\vec{v}}{c} \nabla_p f \right) = 0$$

How does distribution change to movement of particles?

How does distribution change due to momentum changes (forces)?

Electrons

$$\frac{\partial f_e}{\partial t} + \vec{v}_e \cdot \nabla_x f_e - e \left(\overrightarrow{E} + \frac{\vec{v}_e}{c} \times \overrightarrow{B} \right) \cdot \nabla_p f_e = 0$$

Ions

$$\frac{\partial f_i}{\partial t} + \vec{v}_i \cdot \nabla_x f_i + Z_i e \left(\overrightarrow{E} + \frac{\vec{v}_i}{c} \times \overrightarrow{B} \right) \cdot \nabla_p f_i = 0$$

Modeling laser-plasma interaction

The Maxwell equations

- At the same time we need to fulfill the Maxwell equations

$$\nabla \times \overrightarrow{B} = \frac{4\pi}{c}\vec{j} + \frac{1}{c}\frac{\partial \overrightarrow{E}}{\partial t} \qquad \nabla \times \overrightarrow{E} = -\frac{1}{c}\frac{\partial \overrightarrow{B}}{\partial t}$$

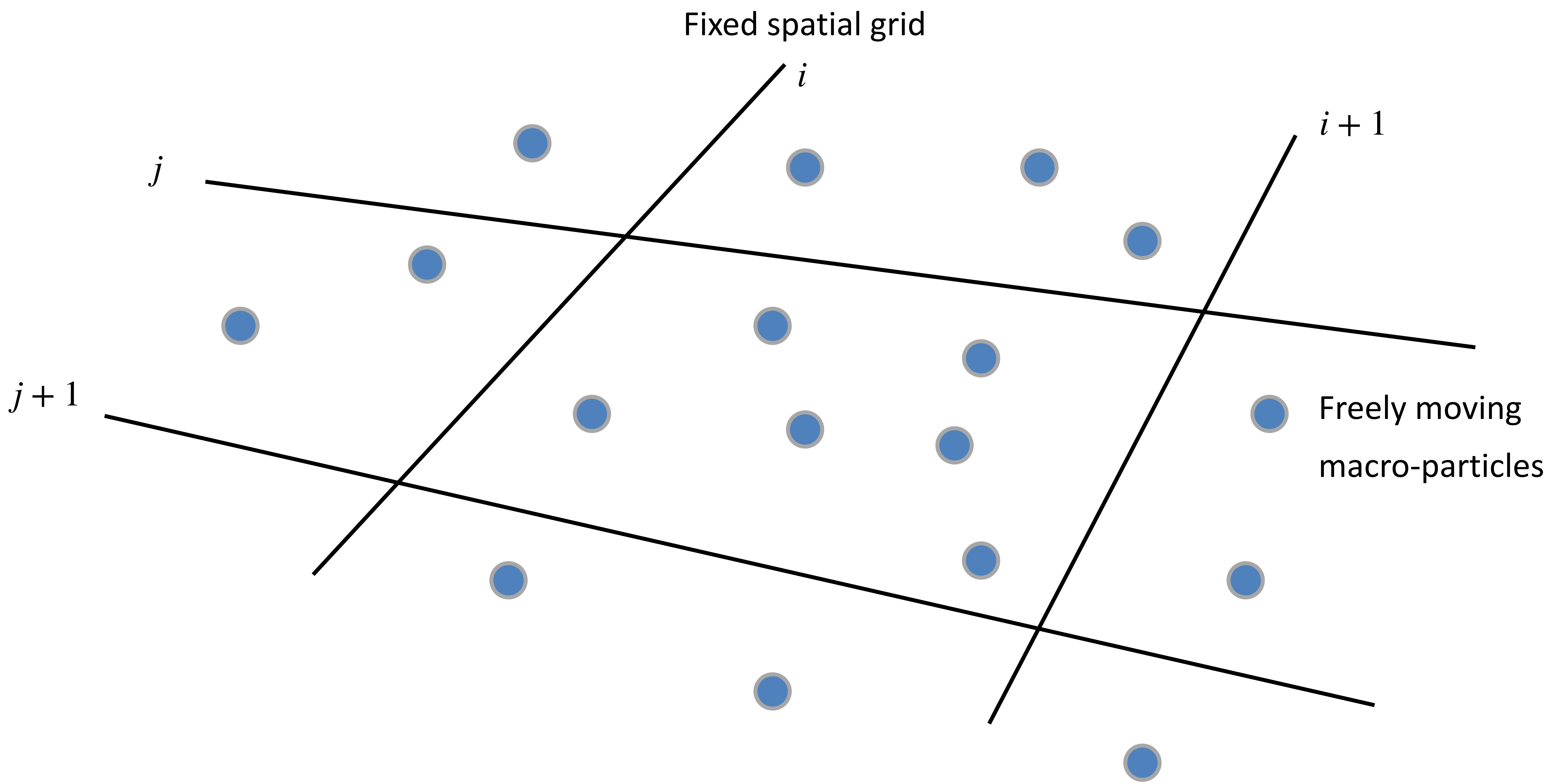
$$\nabla \cdot \overrightarrow{B} = 0 \qquad \nabla \cdot \overrightarrow{E} = 4\pi\rho$$

- With the charge density ρ and current j defined as

$$\rho = e\int (Z_i f_i - f_e) d^3p \qquad \vec{j} = e\int (Z_i \vec{v}_i f_i - \vec{v}_e f_e) d^3p$$

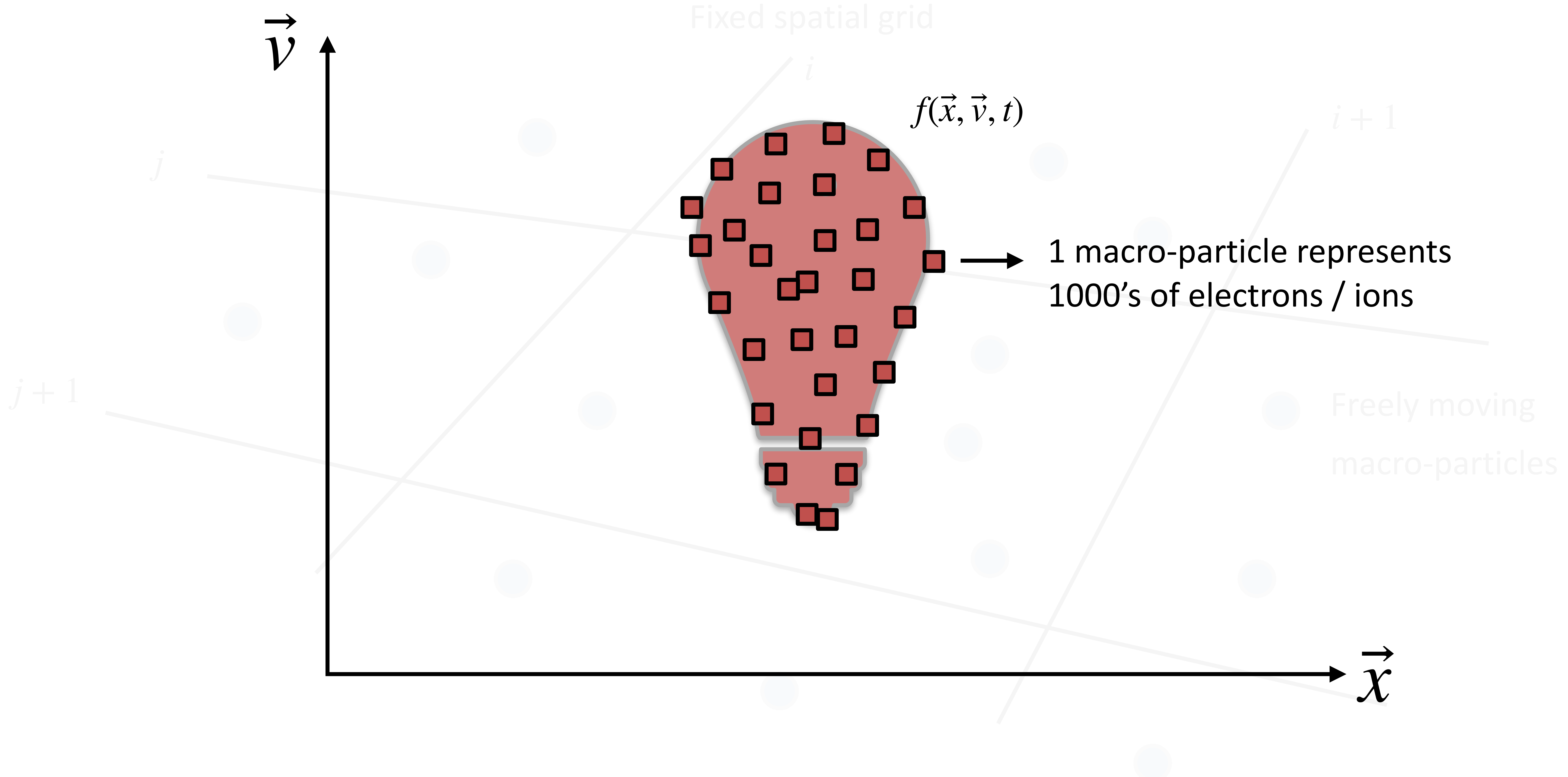
Modeling laser-plasma interaction

The Particle-In-Cell Method



Modeling laser-plasma interaction

The Particle-In-Cell Method

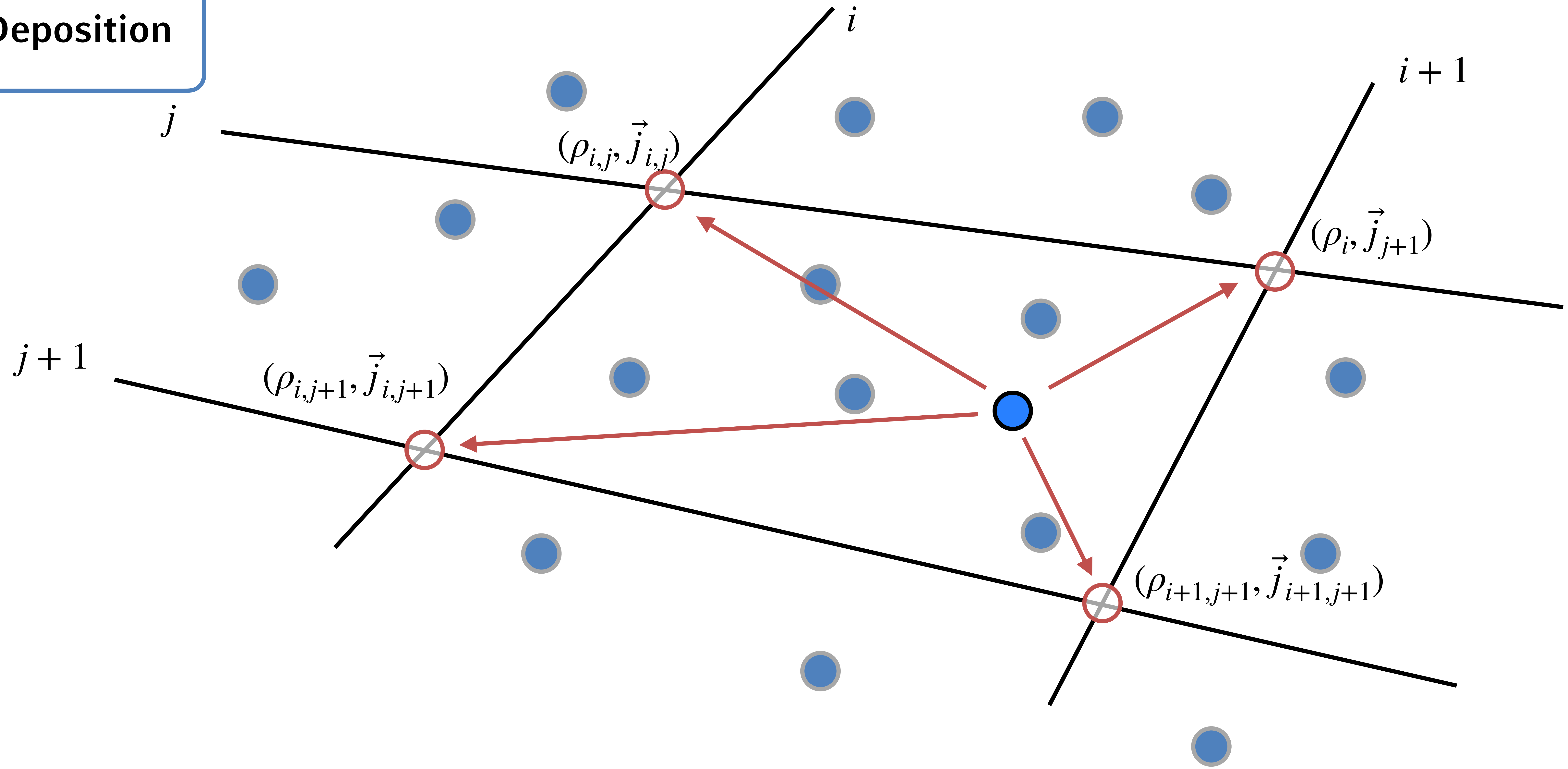


The PIC assumption is basically that particles initially close to another stay close to another

Modeling laser-plasma interaction

The Particle-In-Cell Method

Deposition



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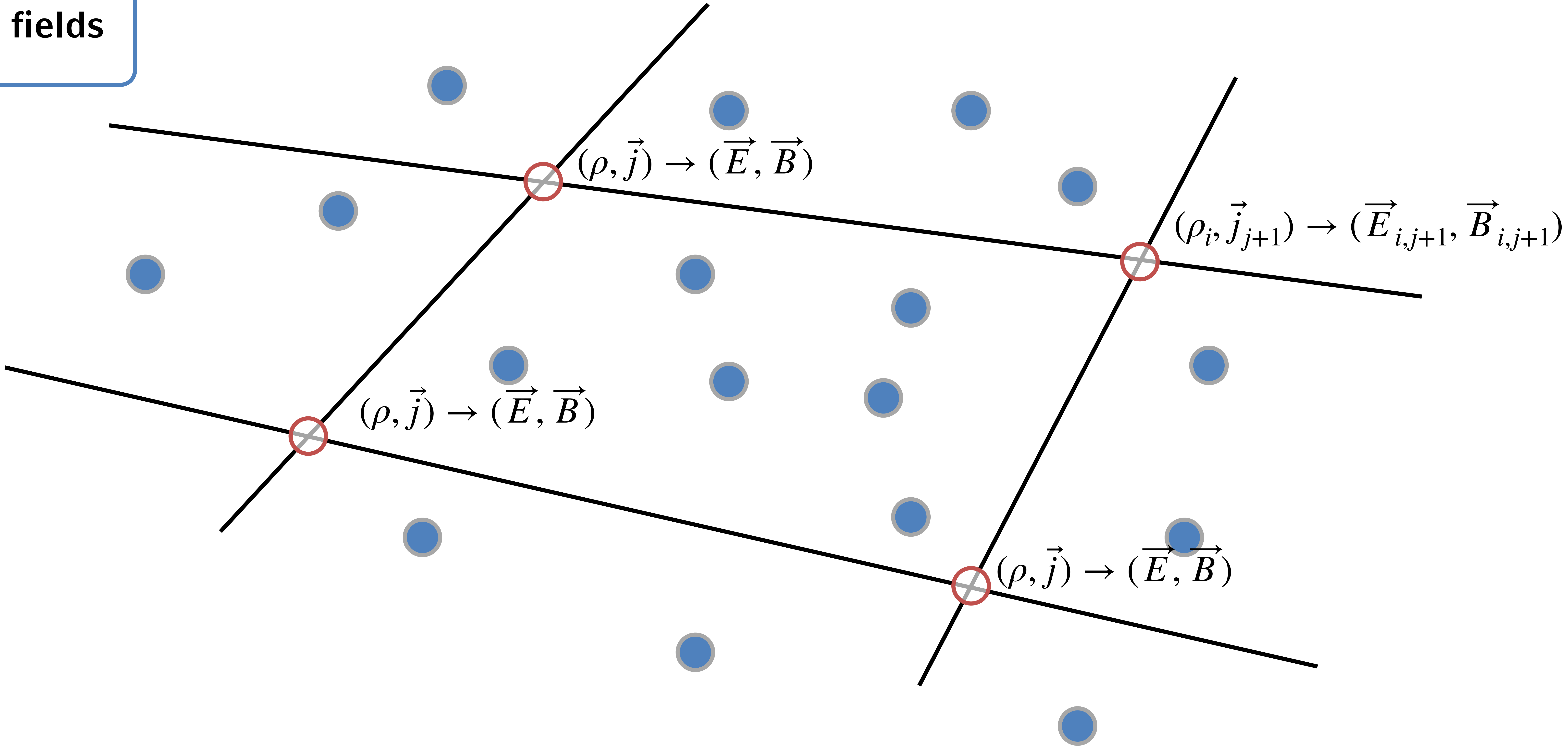
The Particle-In-Cell Method

Update fields



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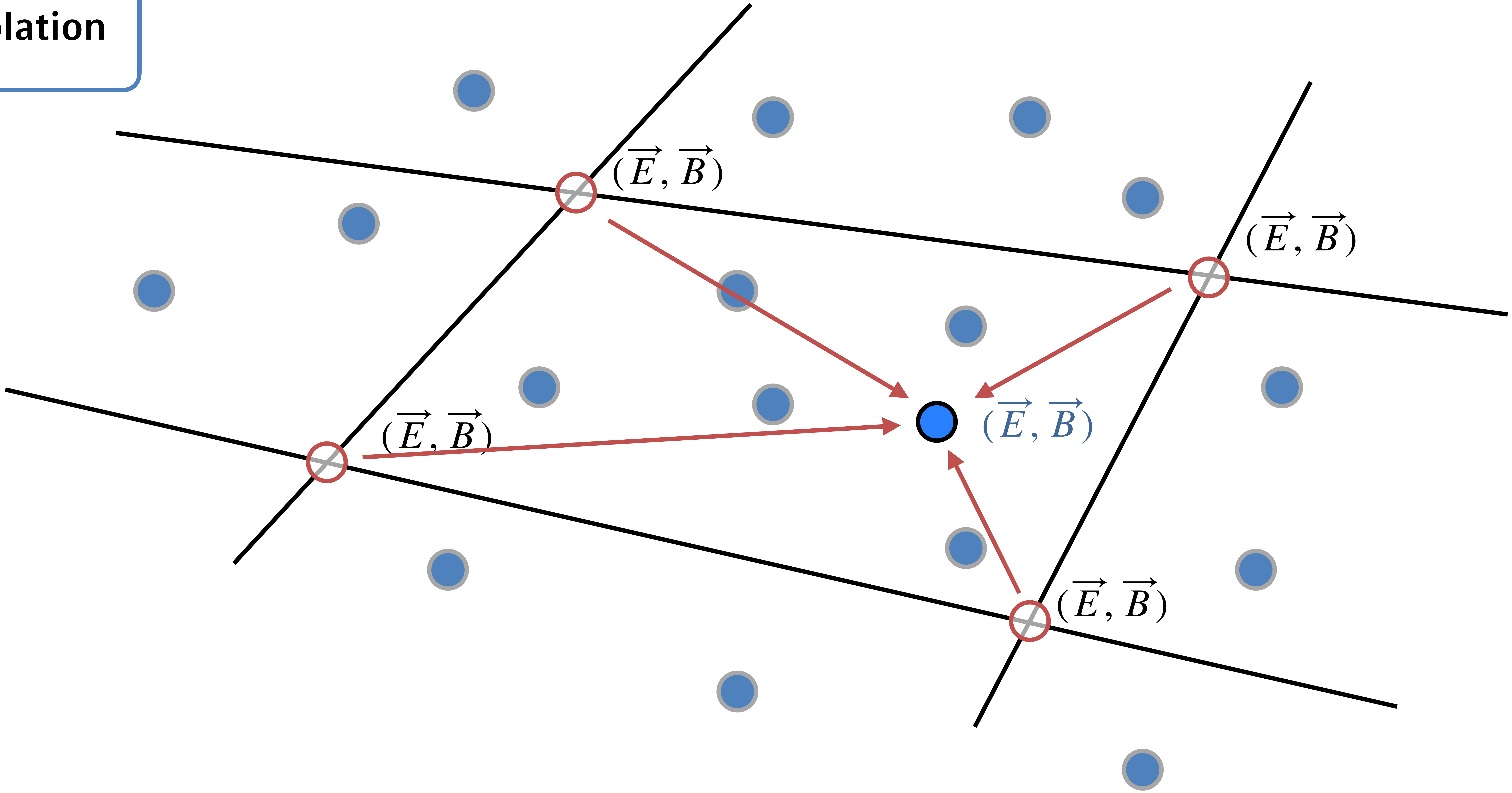
The Particle-In-Cell Method

Interpolation



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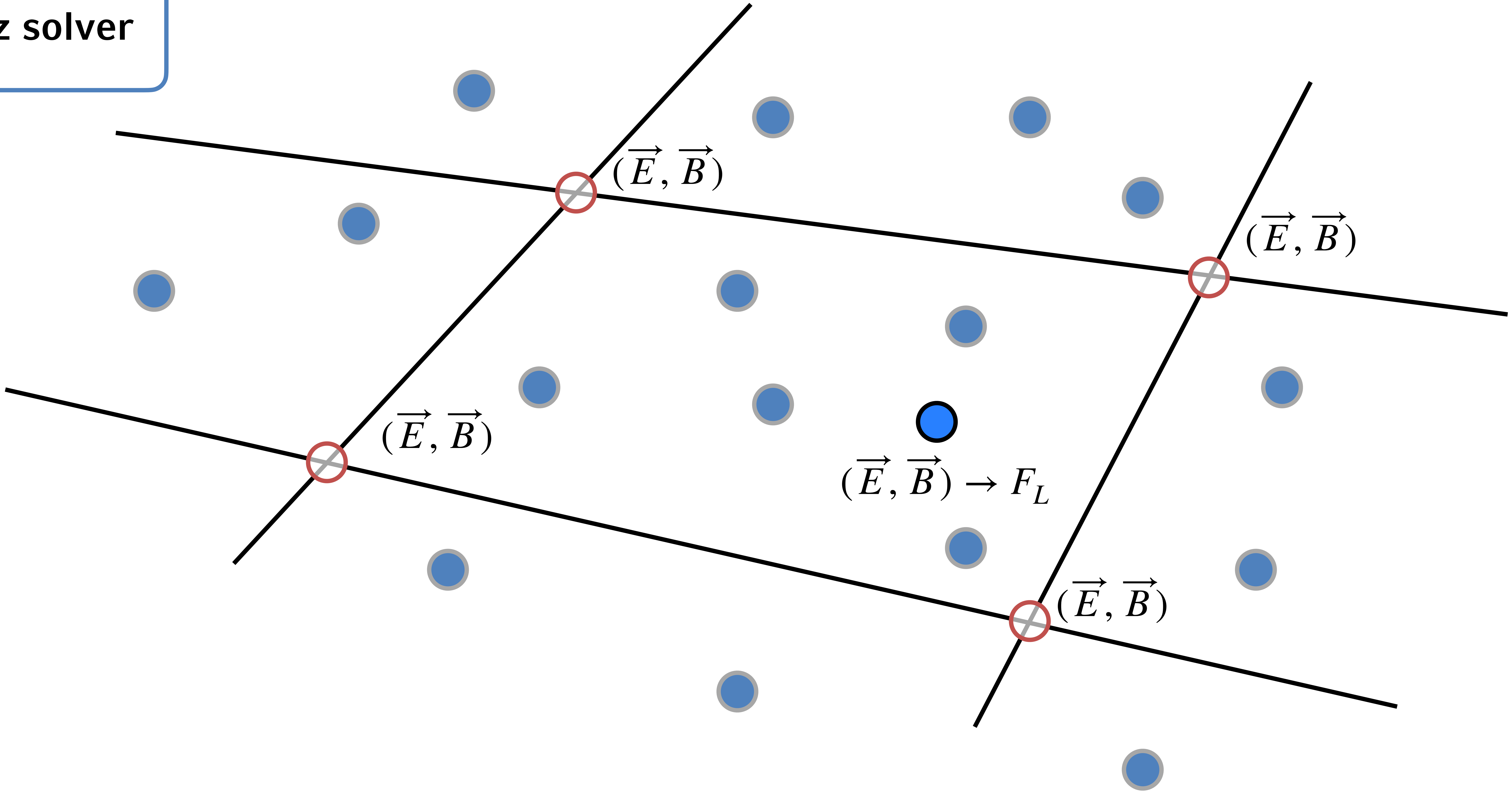
The Particle-In-Cell Method

Lorentz solver



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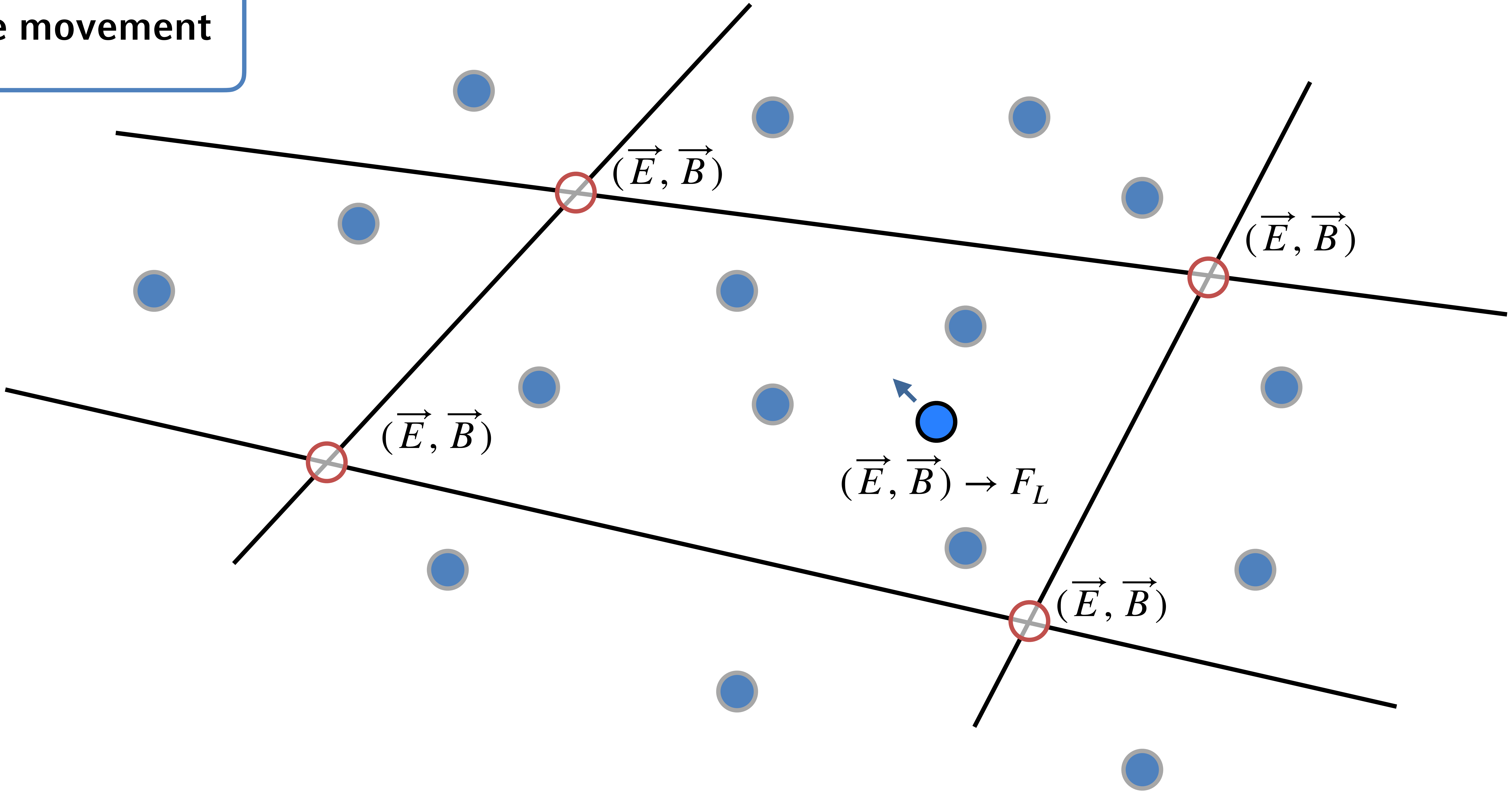
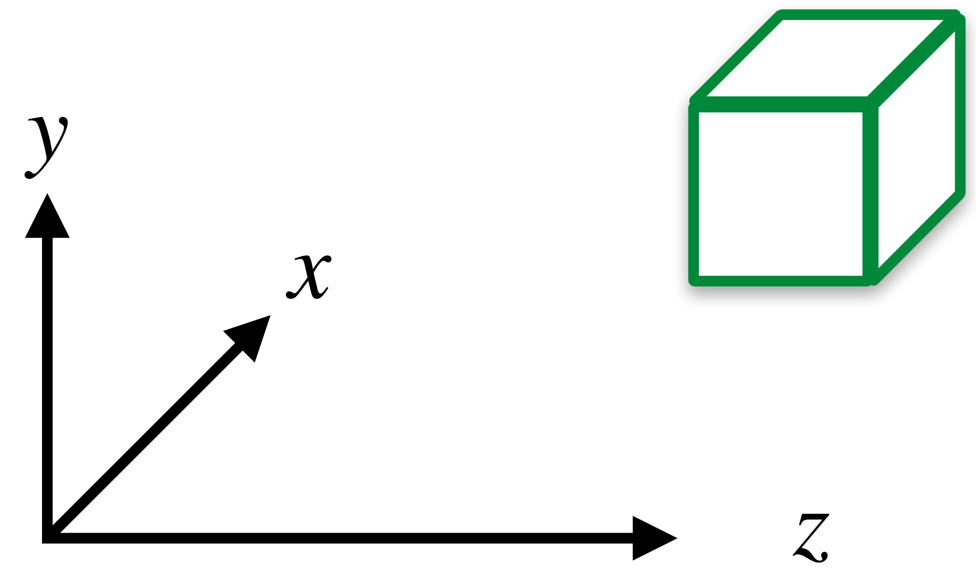
The Particle-In-Cell Method

Particle movement

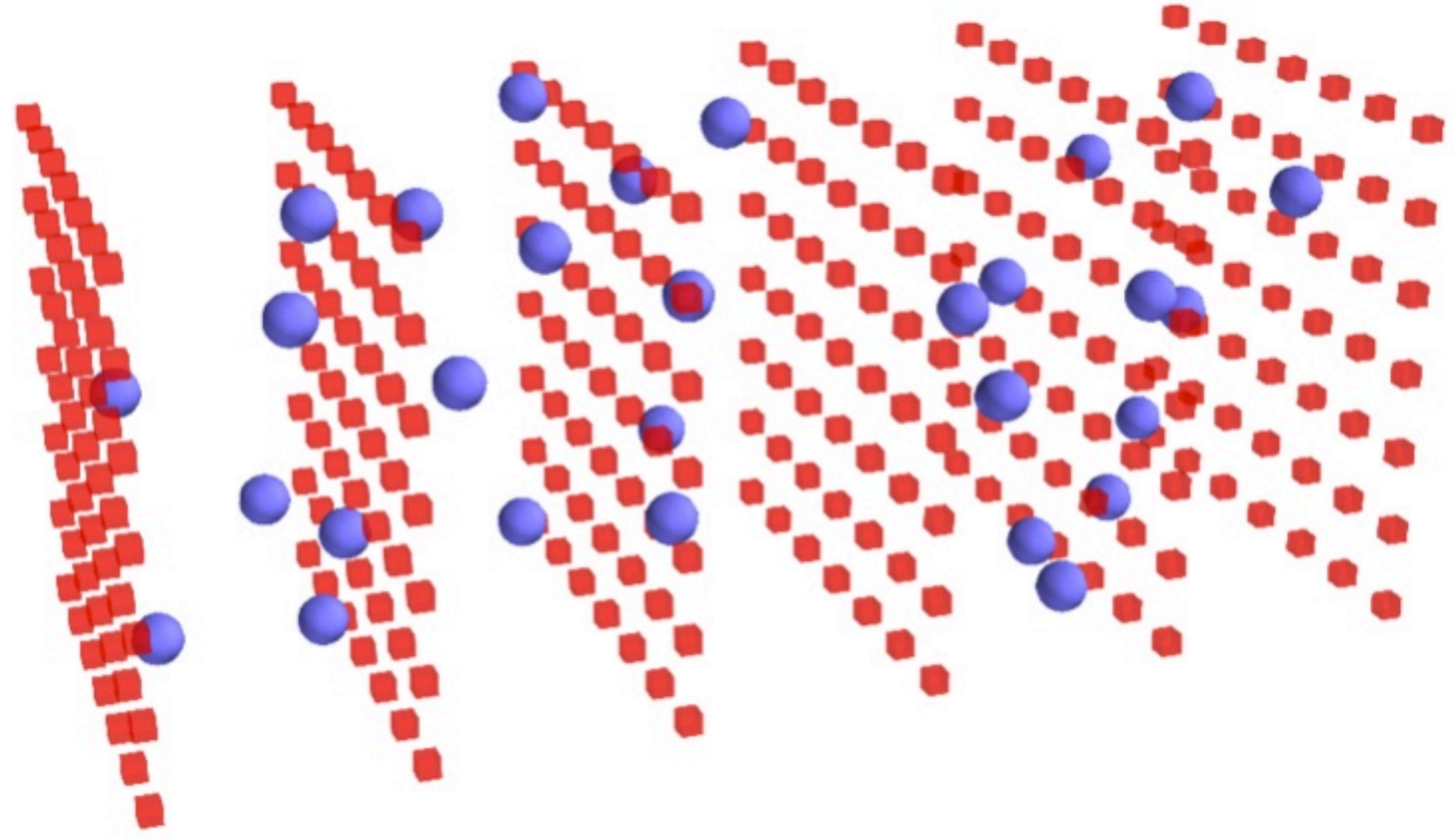


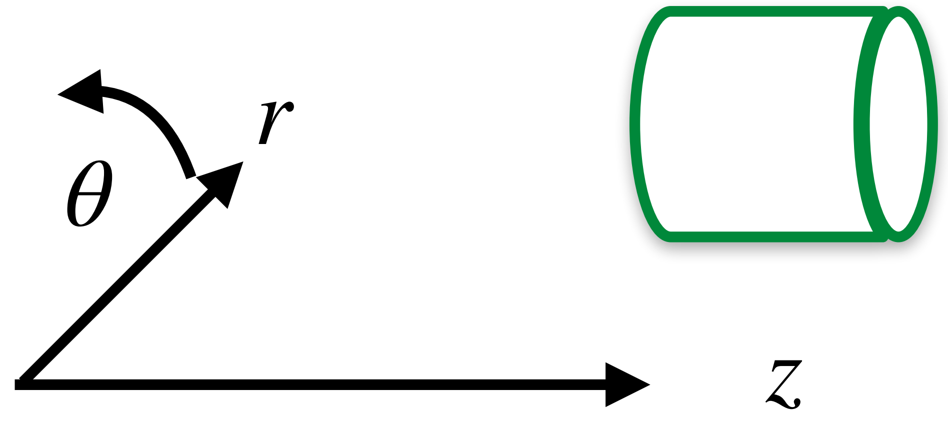
Modeling laser-plasma interaction

The Particle-In-Cell Method | Geometries

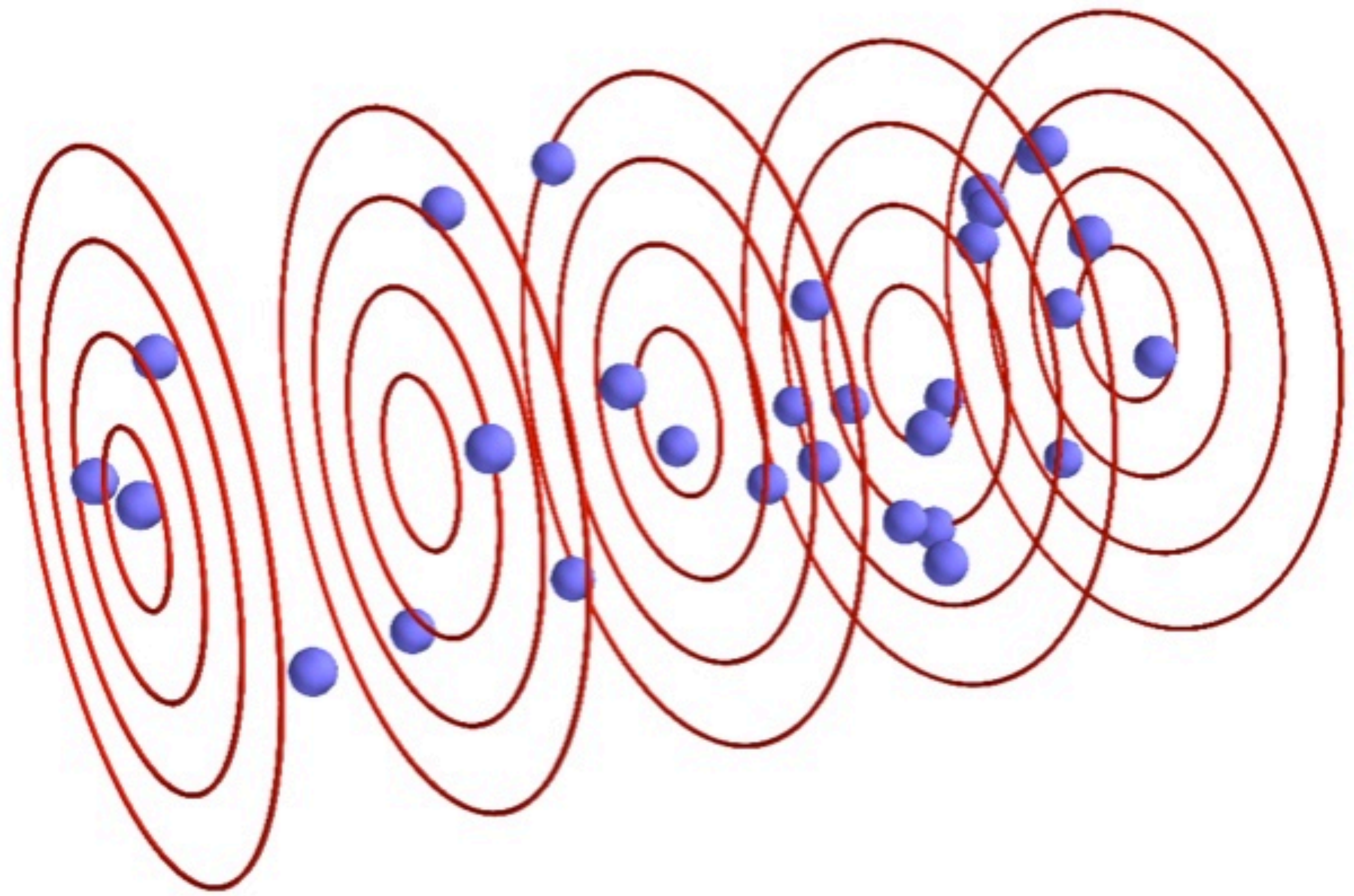


Cartesian





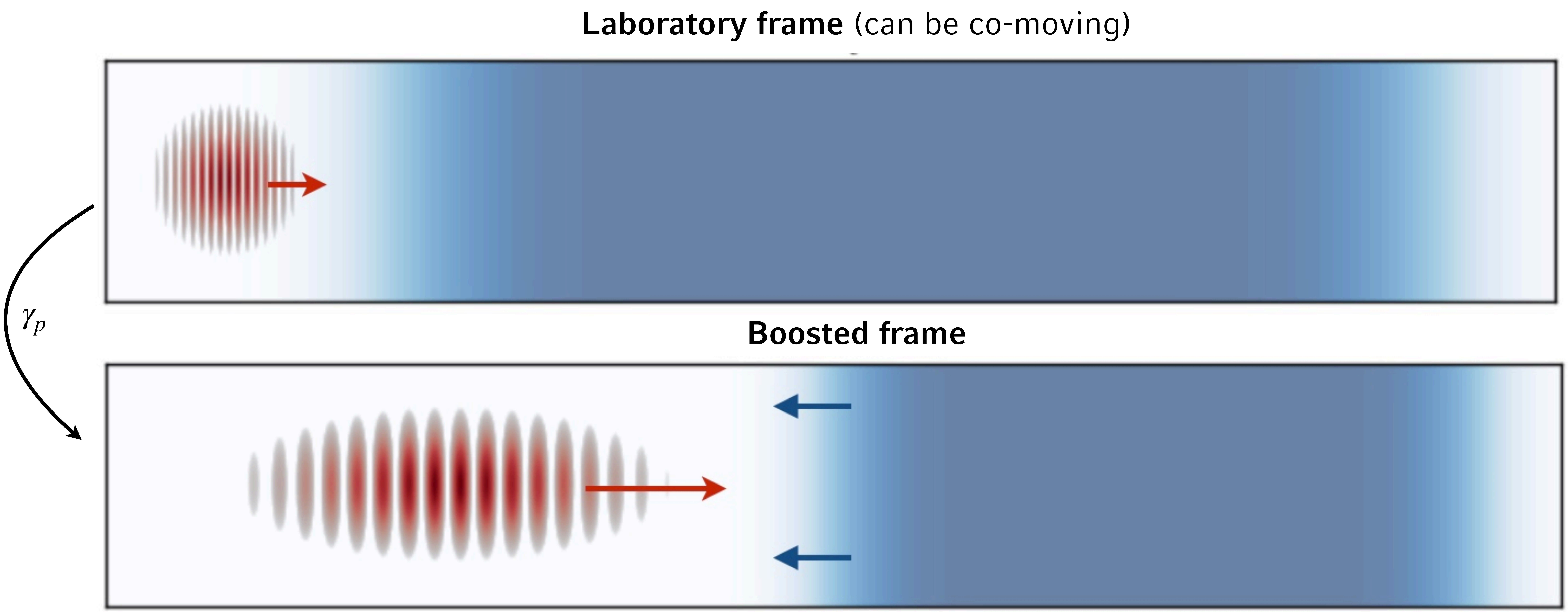
Cylindrical



Figures from FBPIC documentation

Modeling laser-plasma interaction

The Particle-In-Cell Method | Reference frames



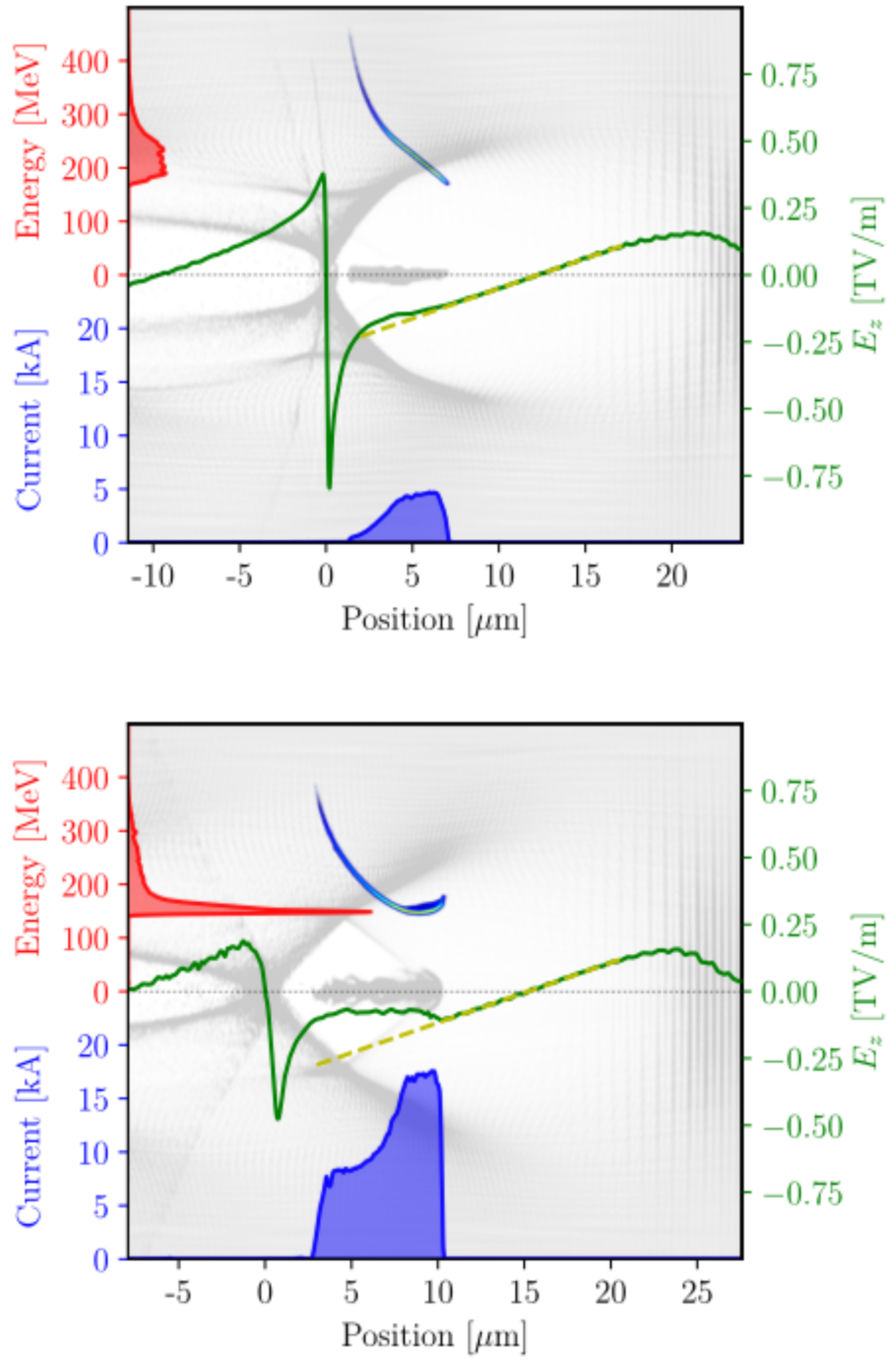
Figures from FBPIC documentation

Modeling laser-plasma interaction

The Particle-In-Cell Method | The Output

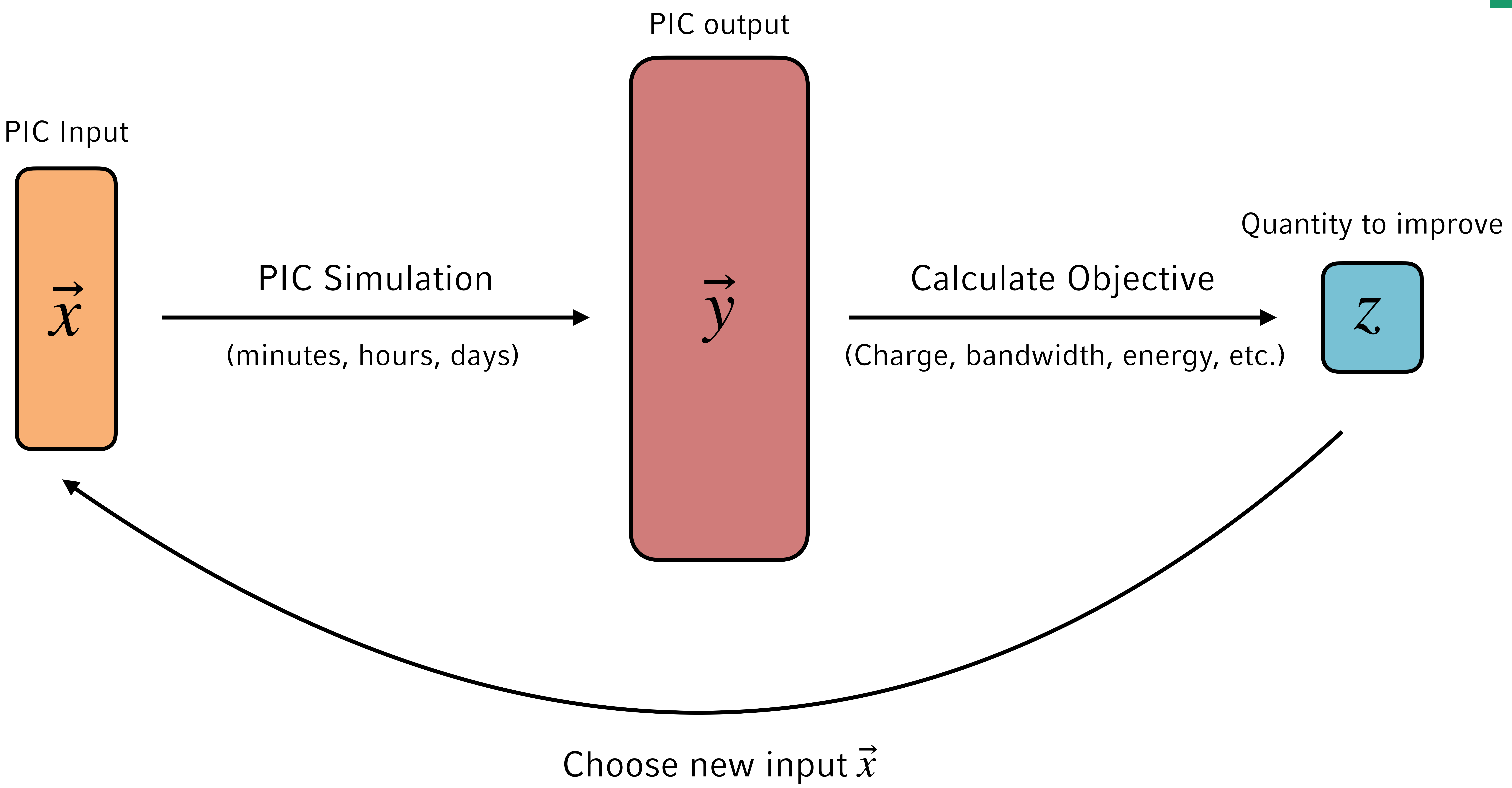
- **Field data:** Meshes of all fields, as well as the deposited density and currents
- **Particle data:** List of macro particles with their individual weights and the phase space values (position, momentum).

- **We are talking about GBs of data.** But often we are actually **only interested in a single number that we can optimize.**
- We do this via an **objective function** that **reduces the entire distribution function to a single scalar number** $O[f(\vec{x}, \vec{v}, t)] = z$.



Modeling laser-plasma interaction

Towards optimization



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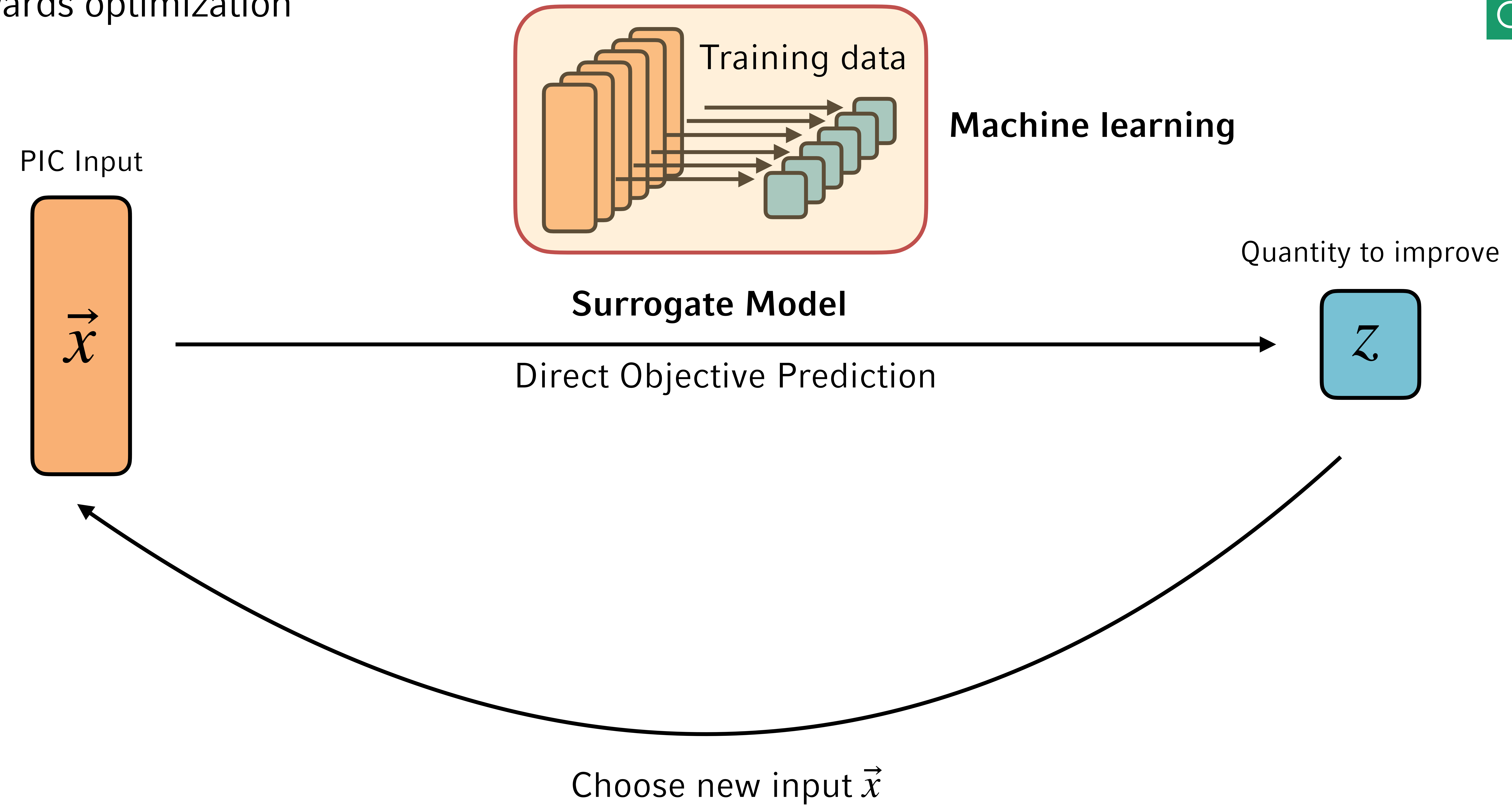
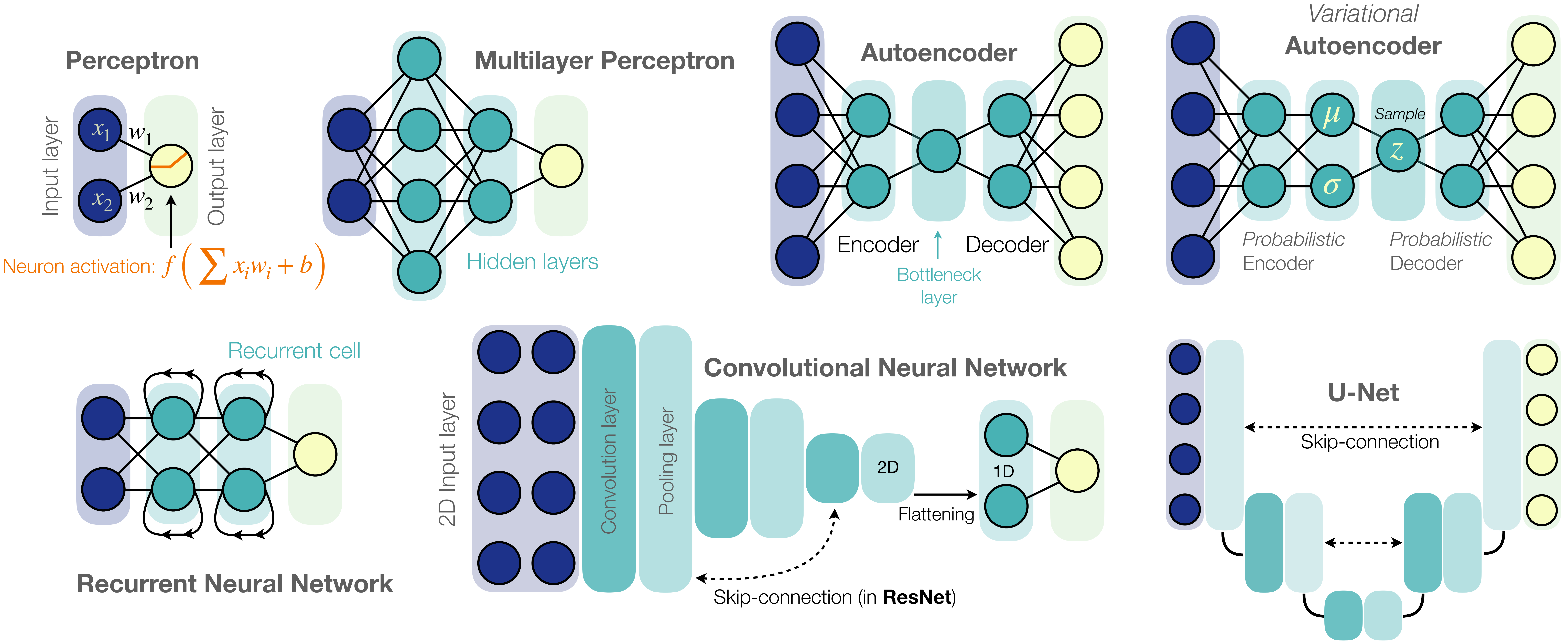
Towards optimization



Modeling laser-plasma accelerators

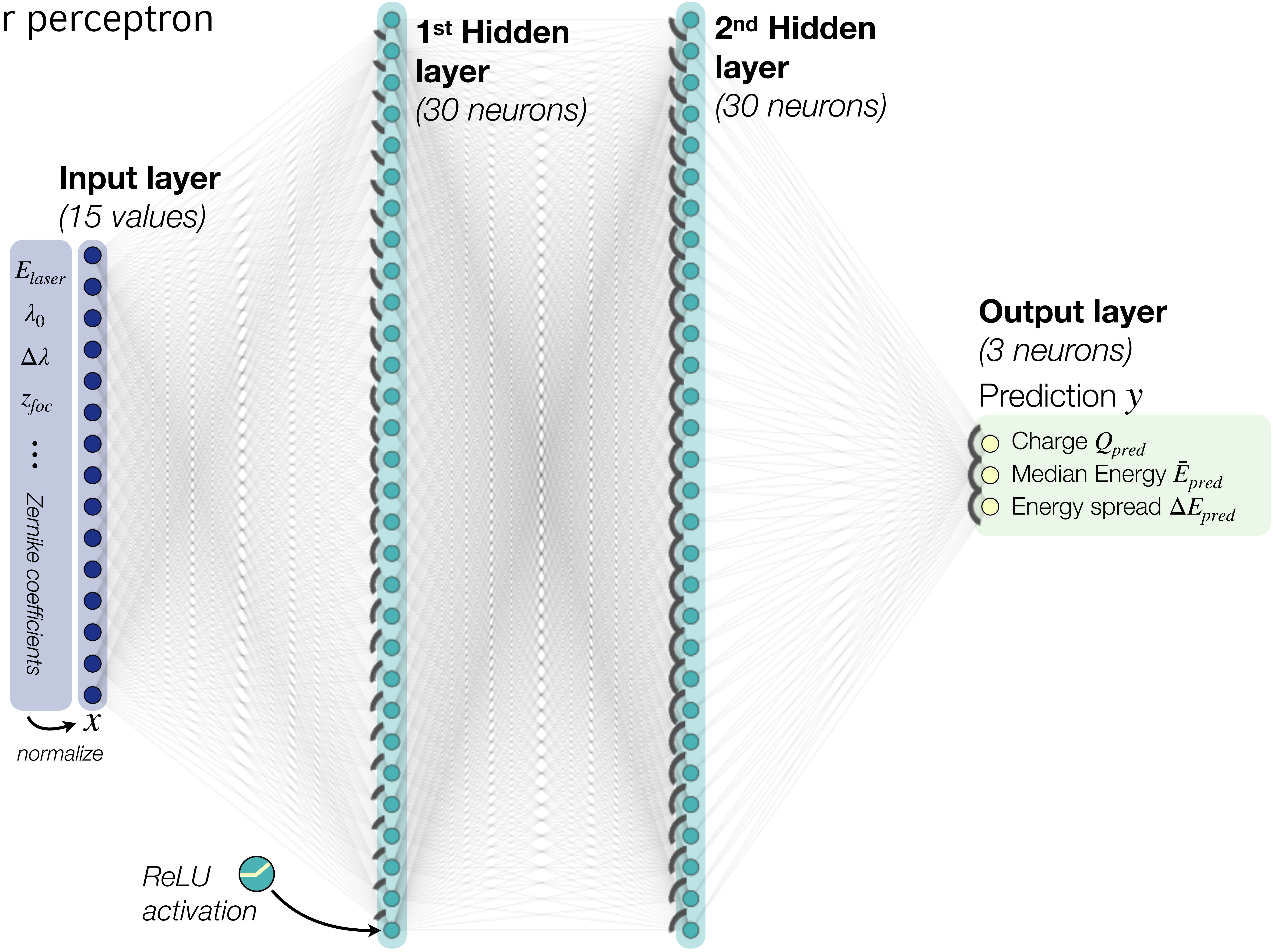
Which neural network architecture to choose?



- 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)

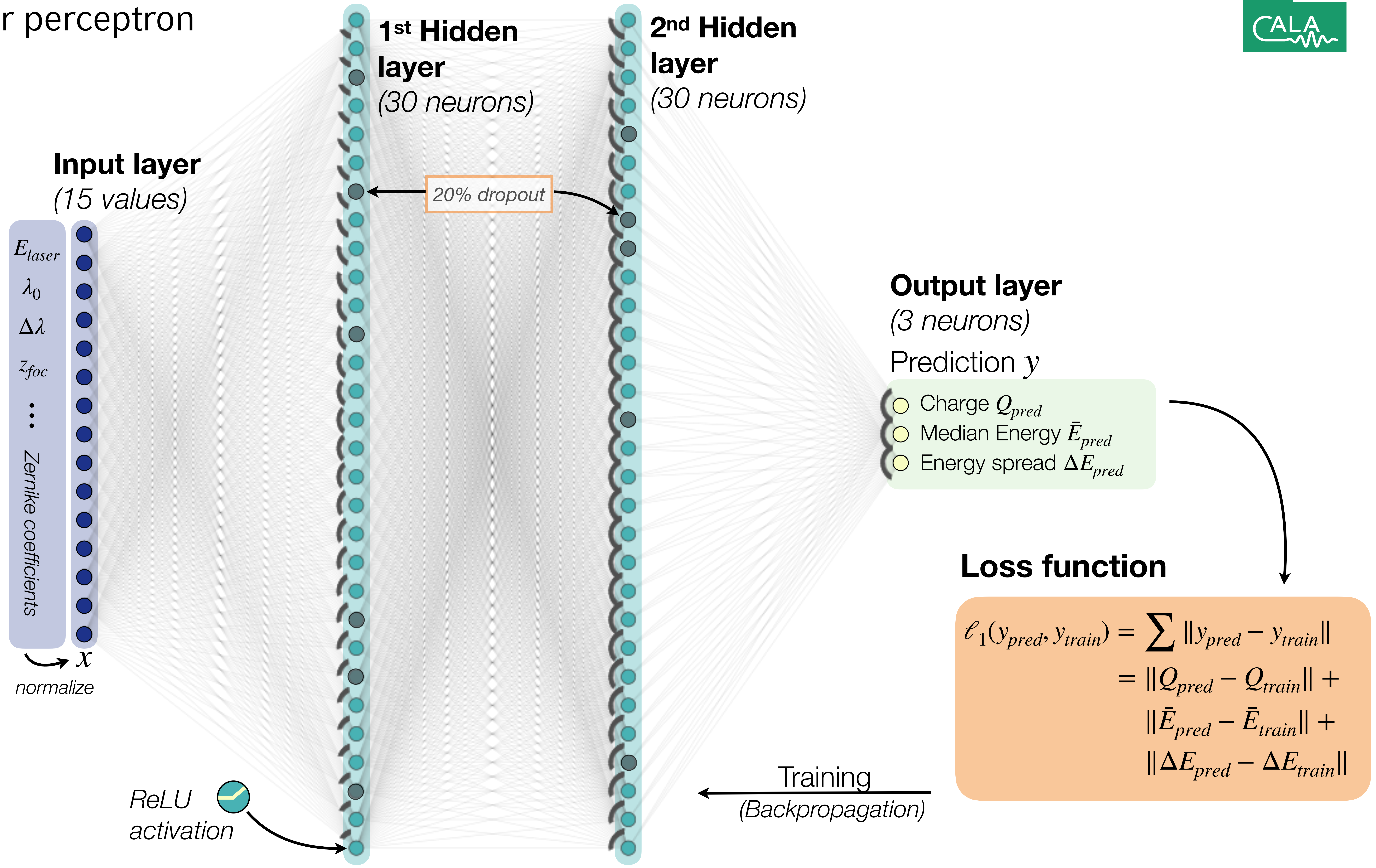
Modeling laser-plasma accelerators

The multilayer perceptron



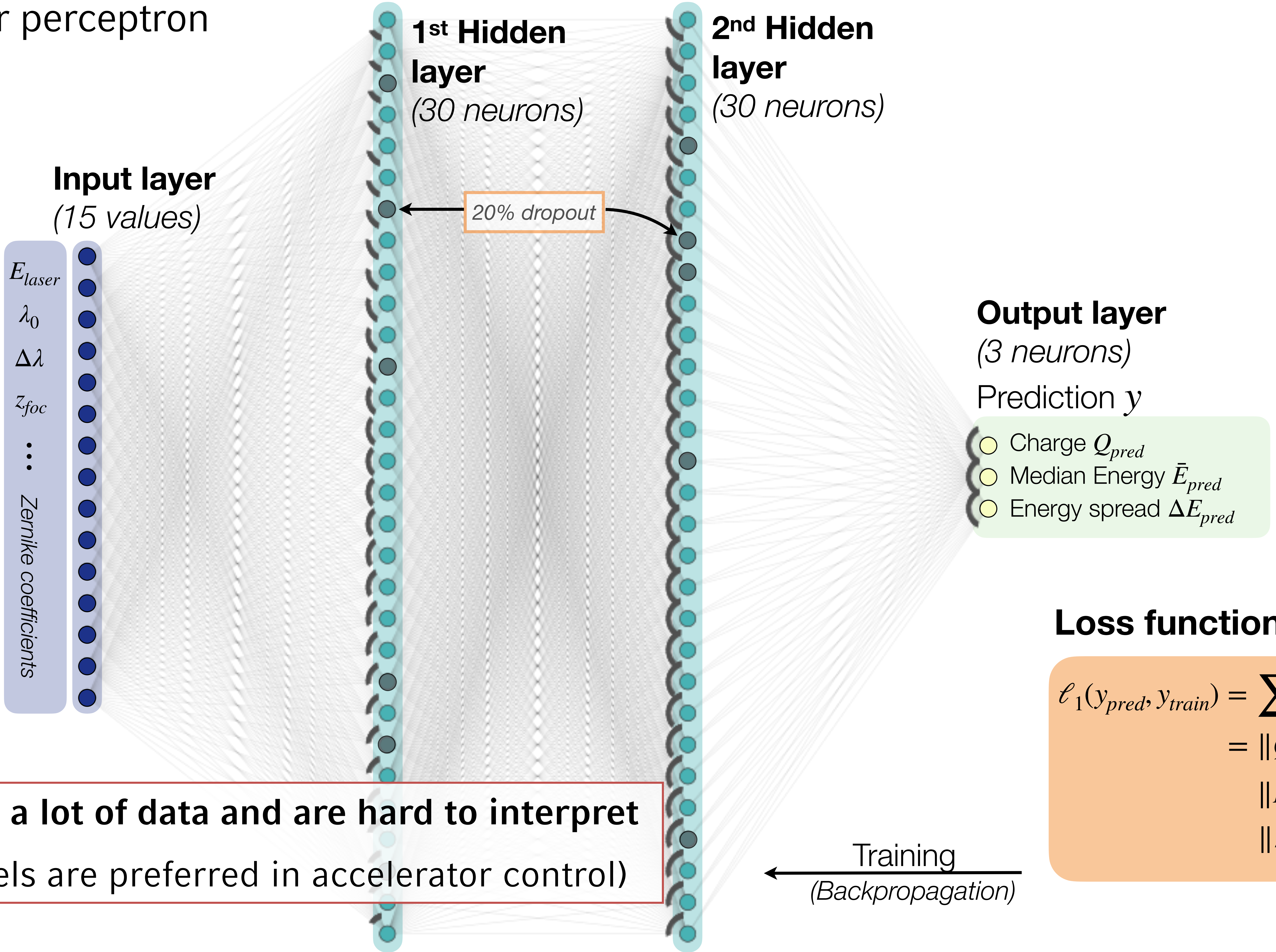
Modeling laser-plasma accelerators

The multilayer perceptron



Modeling laser-plasma accelerators

The multilayer perceptron



Loss function

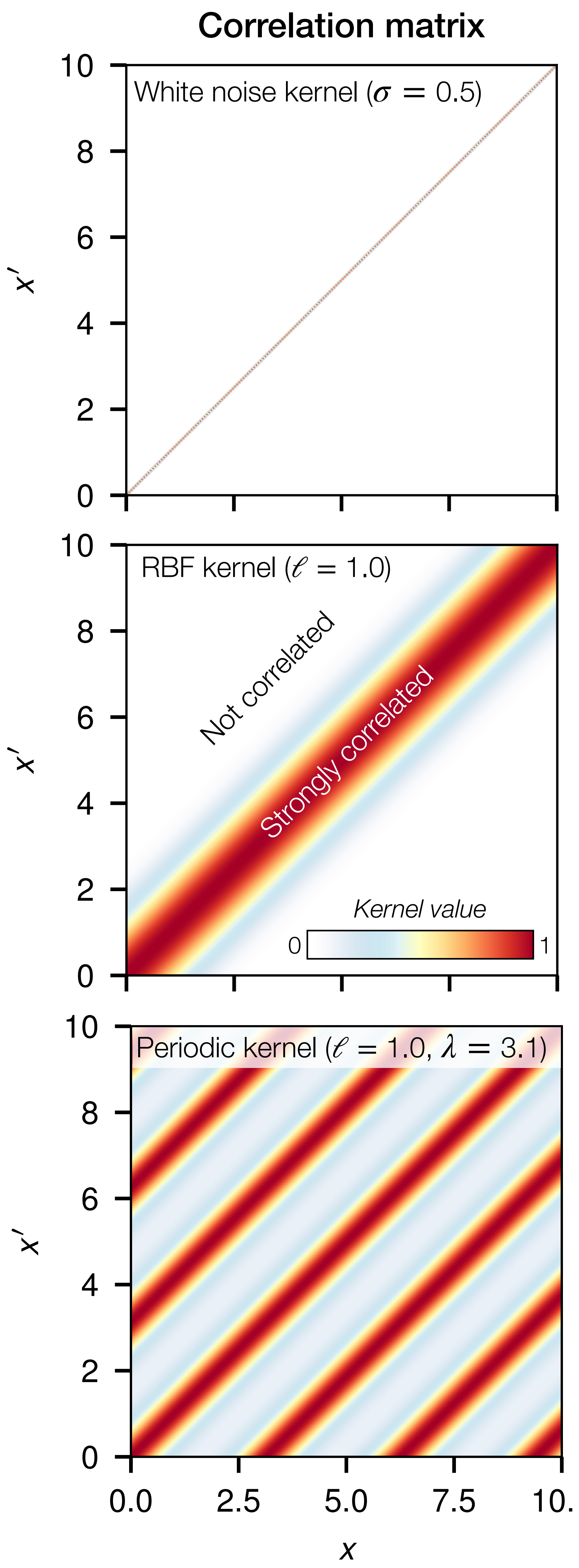
$$\ell_1(y_{pred}, y_{train}) = \sum \|y_{pred} - y_{train}\| = \|Q_{pred} - Q_{train}\| + \|\bar{E}_{pred} - \bar{E}_{train}\| + \|\Delta E_{pred} - \Delta E_{train}\|$$

Neural nets need a lot of data and are hard to interpret

(explainable models are preferred in accelerator control)

Modeling laser-plasma accelerators

Gaussian Process Regression

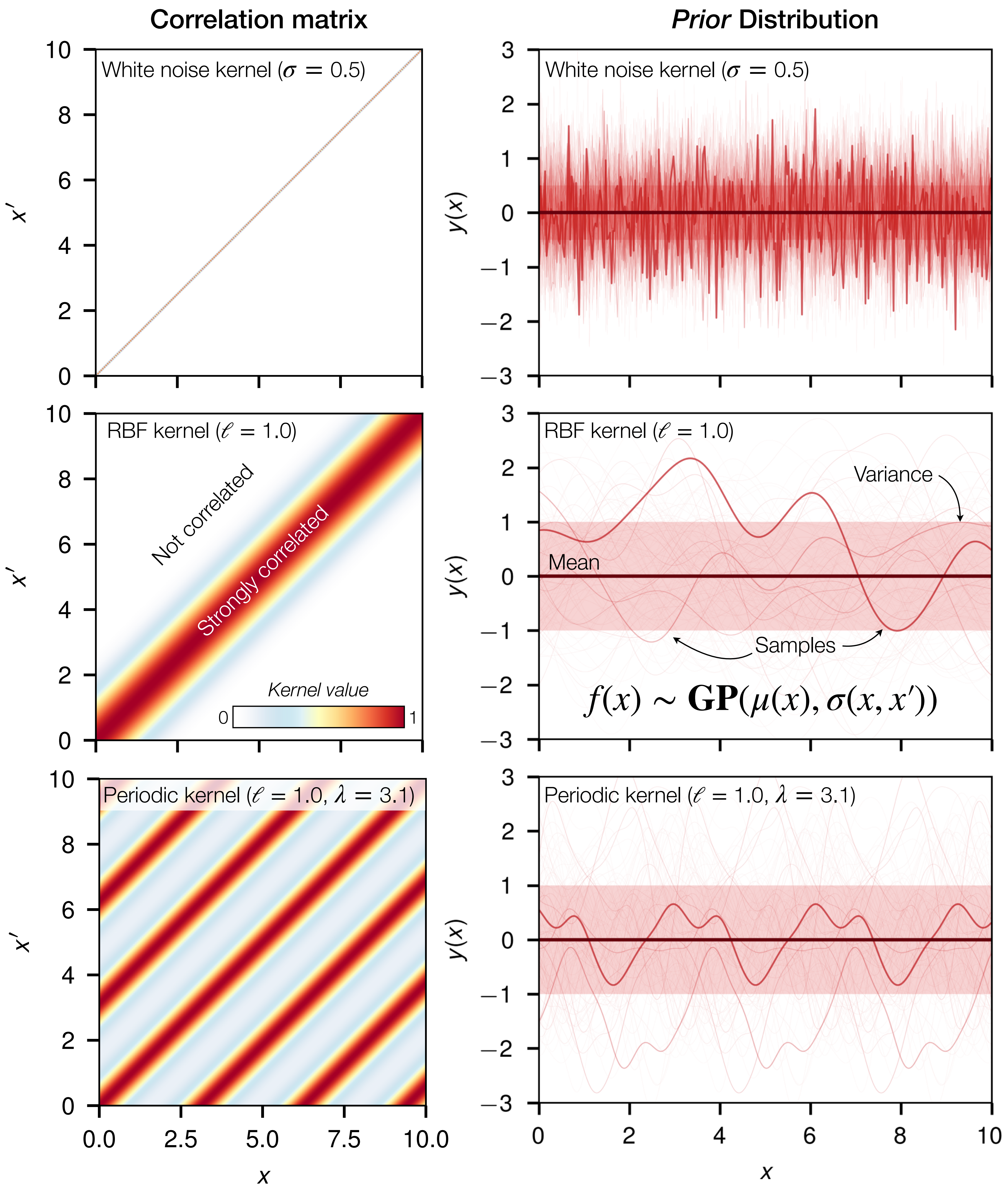


- **Non-parametric method:** Predicts function values based on observed data without a predetermined model.
- **Covariance function/Kernel:** Defines the relationship between points, capturing their correlations.
- **Probabilistic description:** Provides a full description of the function, including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

- 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)

Modeling laser-plasma accelerators

Gaussian Process Regression



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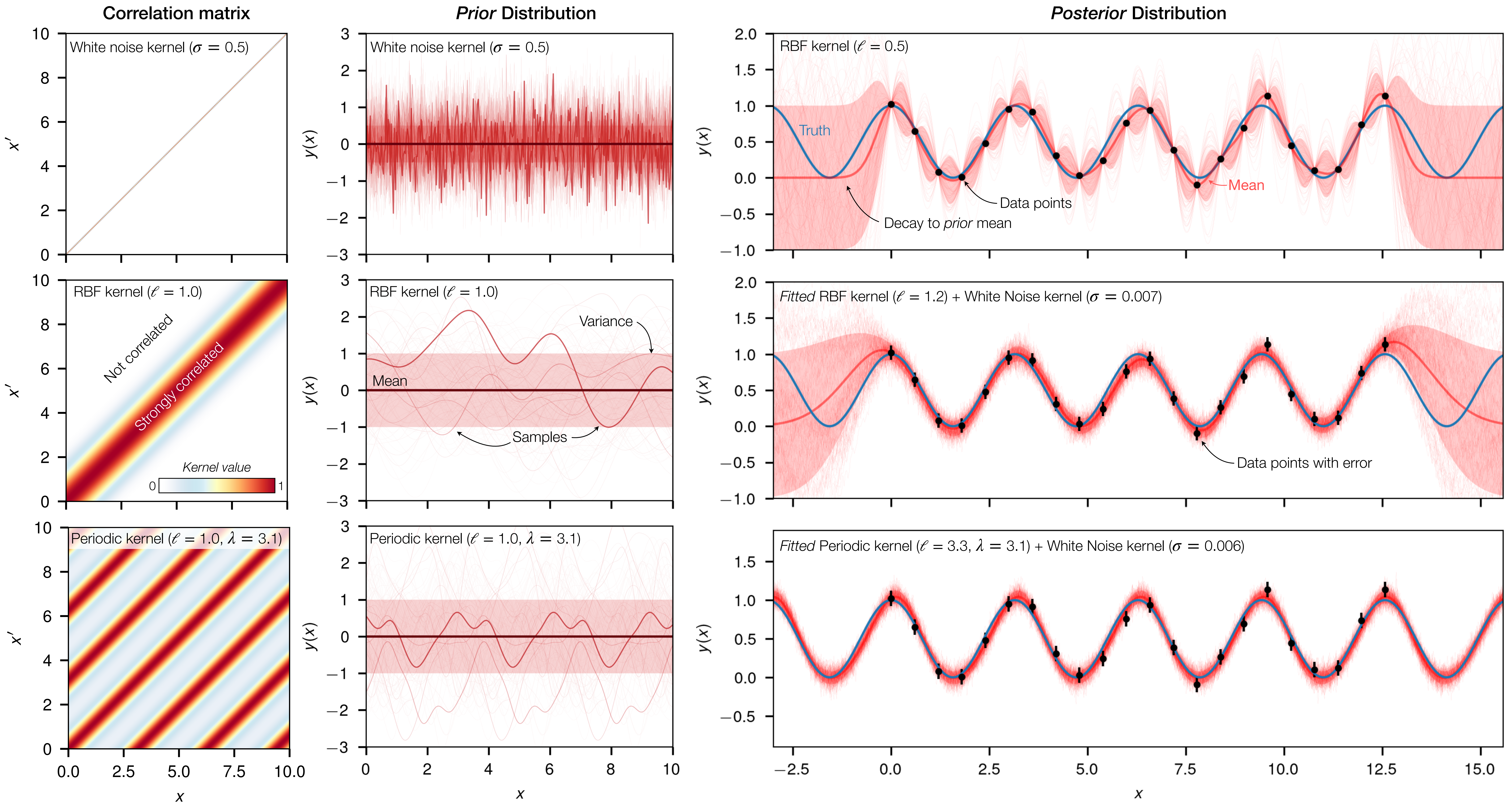
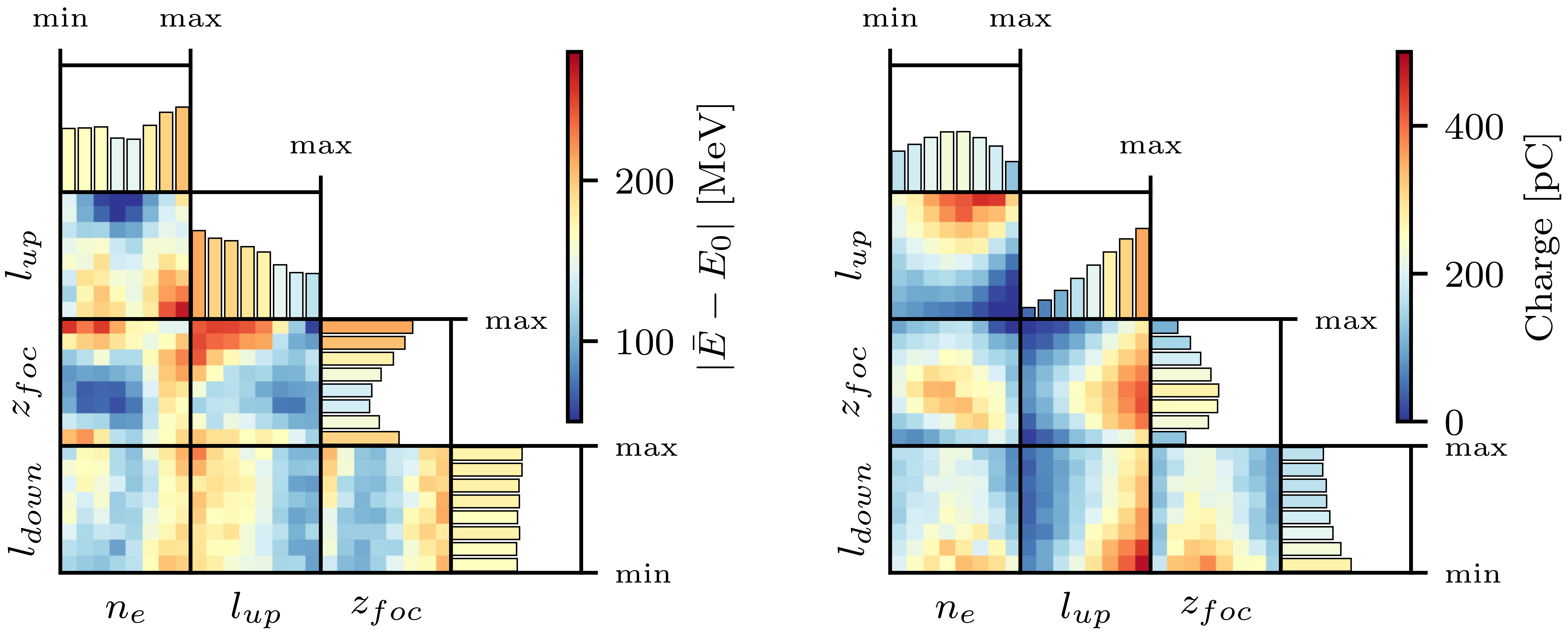
Modeling laser-plasma accelerators

Gaussian Process Regression



Modeling laser-plasma accelerators

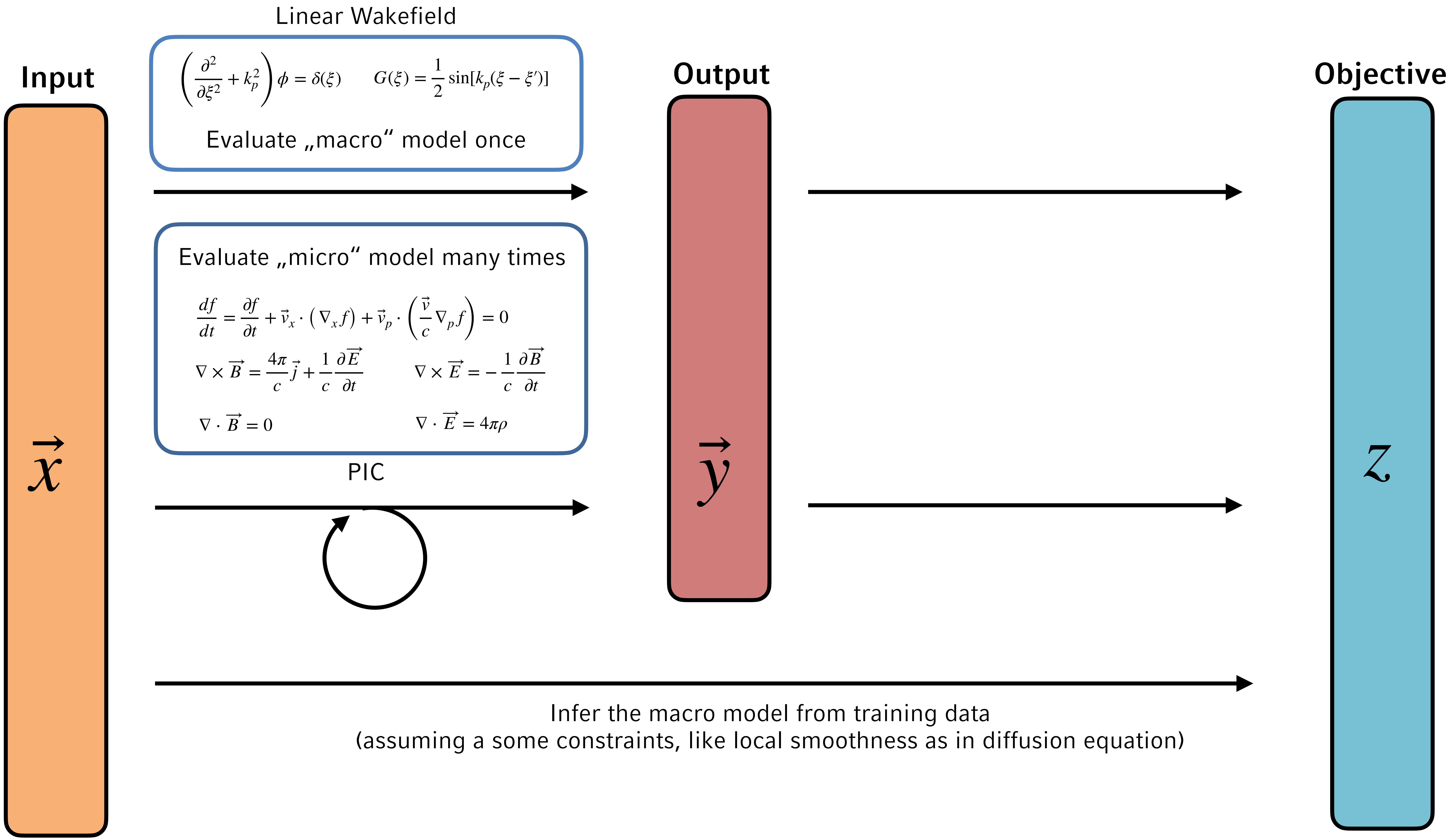
Gaussian Process Regression



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

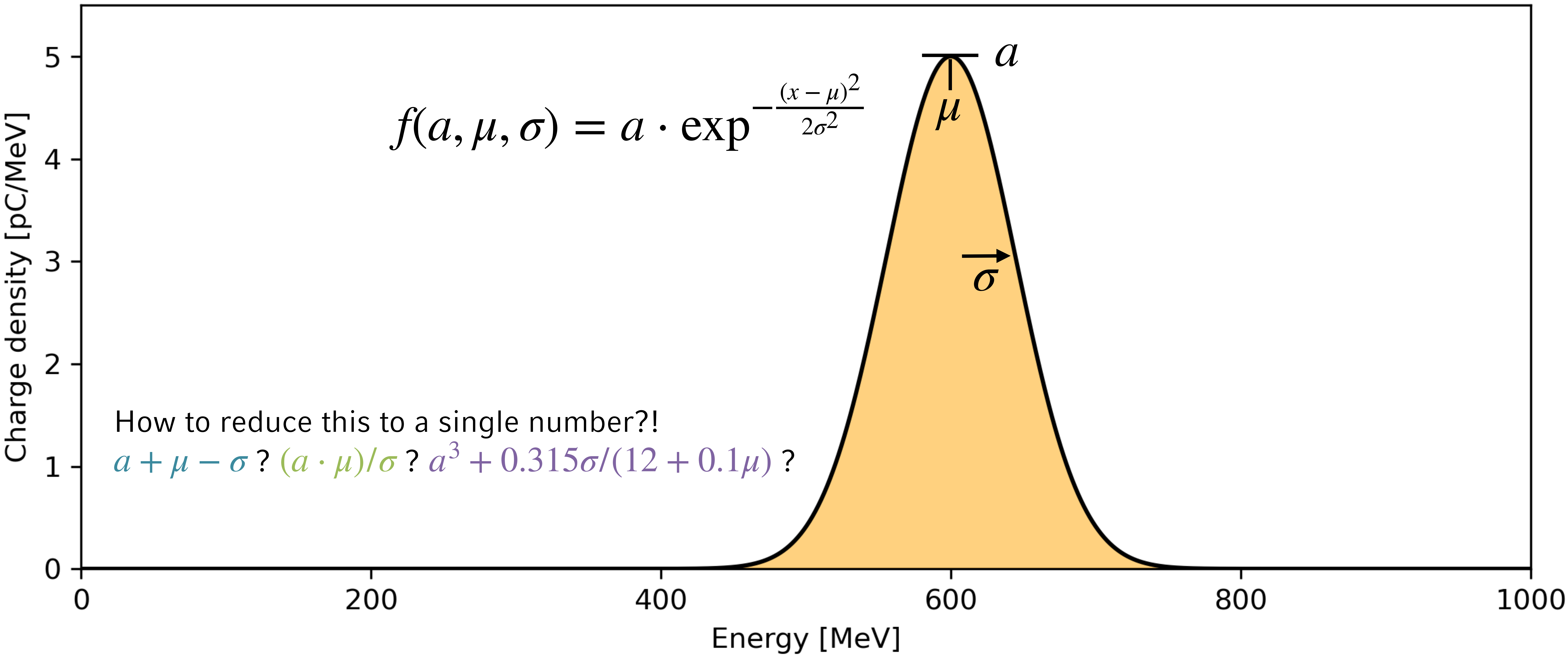
Modeling laser-plasma accelerators

Summarizing the different approaches



Optimizing laser-plasma accelerators

Choosing the right objective



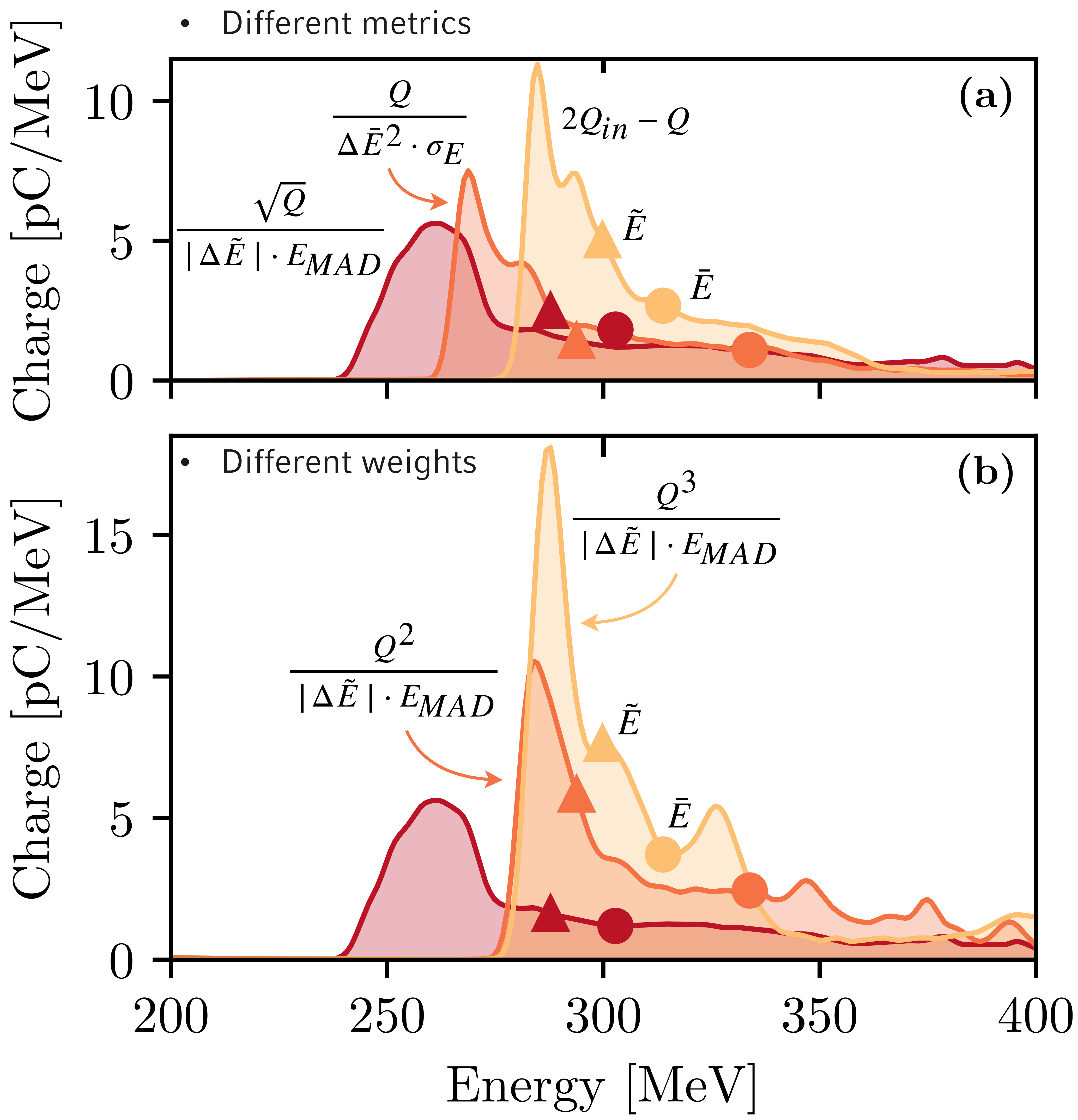
Optimizing laser-plasma accelerators

Choosing the right objective

- Say 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.)

- Choosing **different metrics or weights** for each objective **changes the outcome in an a priori unknown way**!

- How to solve this problem?



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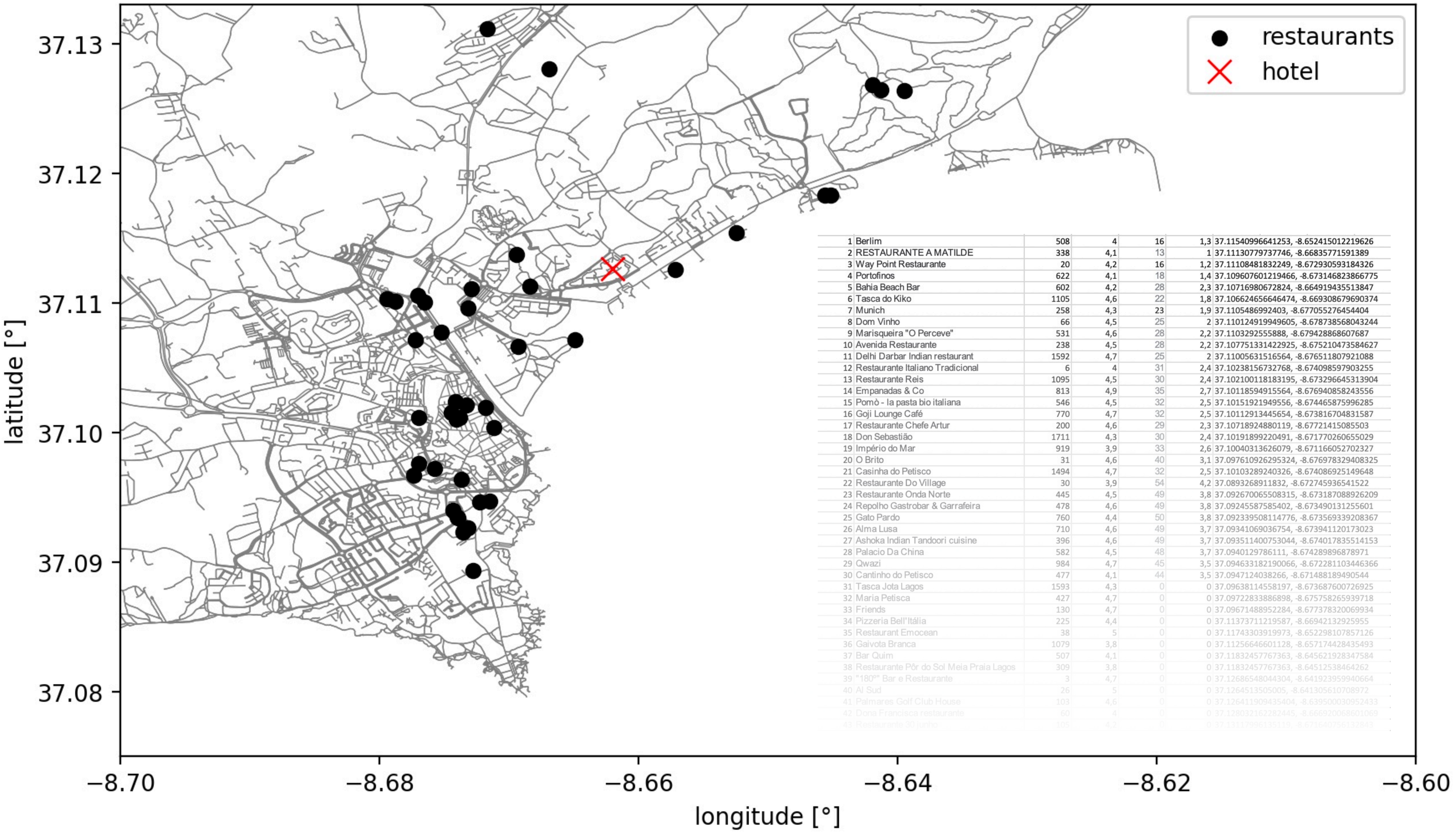
Optimizing laser-plasma accelerators

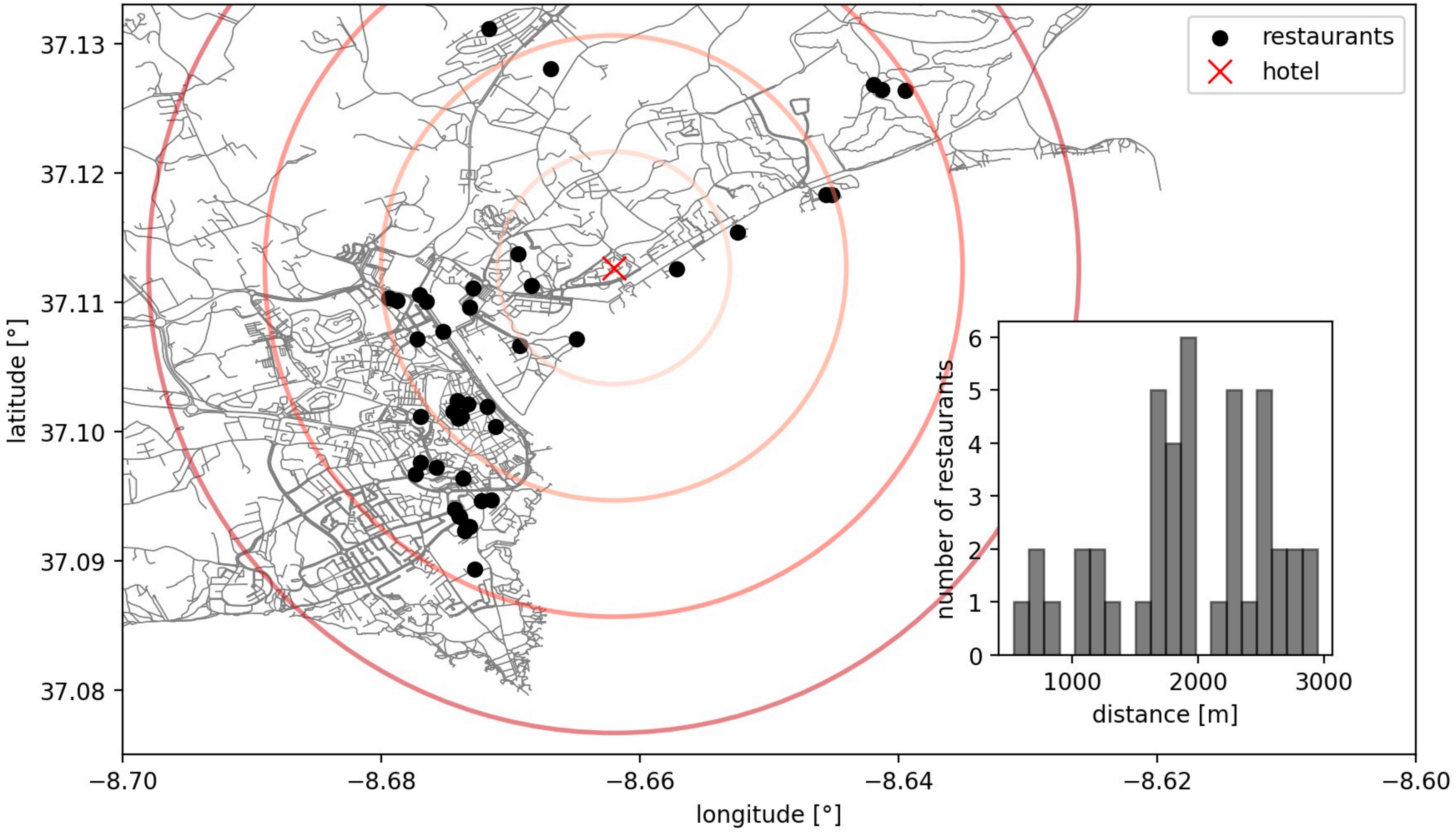
Multi-objective optimization | The conference dinner problem



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, -8.6772141508550З
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, -8.671488189490544
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, -8.66942132925955
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, -8.64512538464262
39	"180º" Bar e Restaurante	3	4,7	0	0	37.12686548044304, -8.641923959940664
40	Al Sud	26	5	0	0	37.1264513505005, -8.641305610708972
41	Palmares Golf Club House	103	4,6	0	0	37.126411909435404, -8.639500030952433
42	Dona Francisca restaurante	60	4	0	0	37.128032162282445, -8.666920068601069
43	Restaurante 30 junho	105	4,2	0	0	37.13117996135119, -8.671640756132843

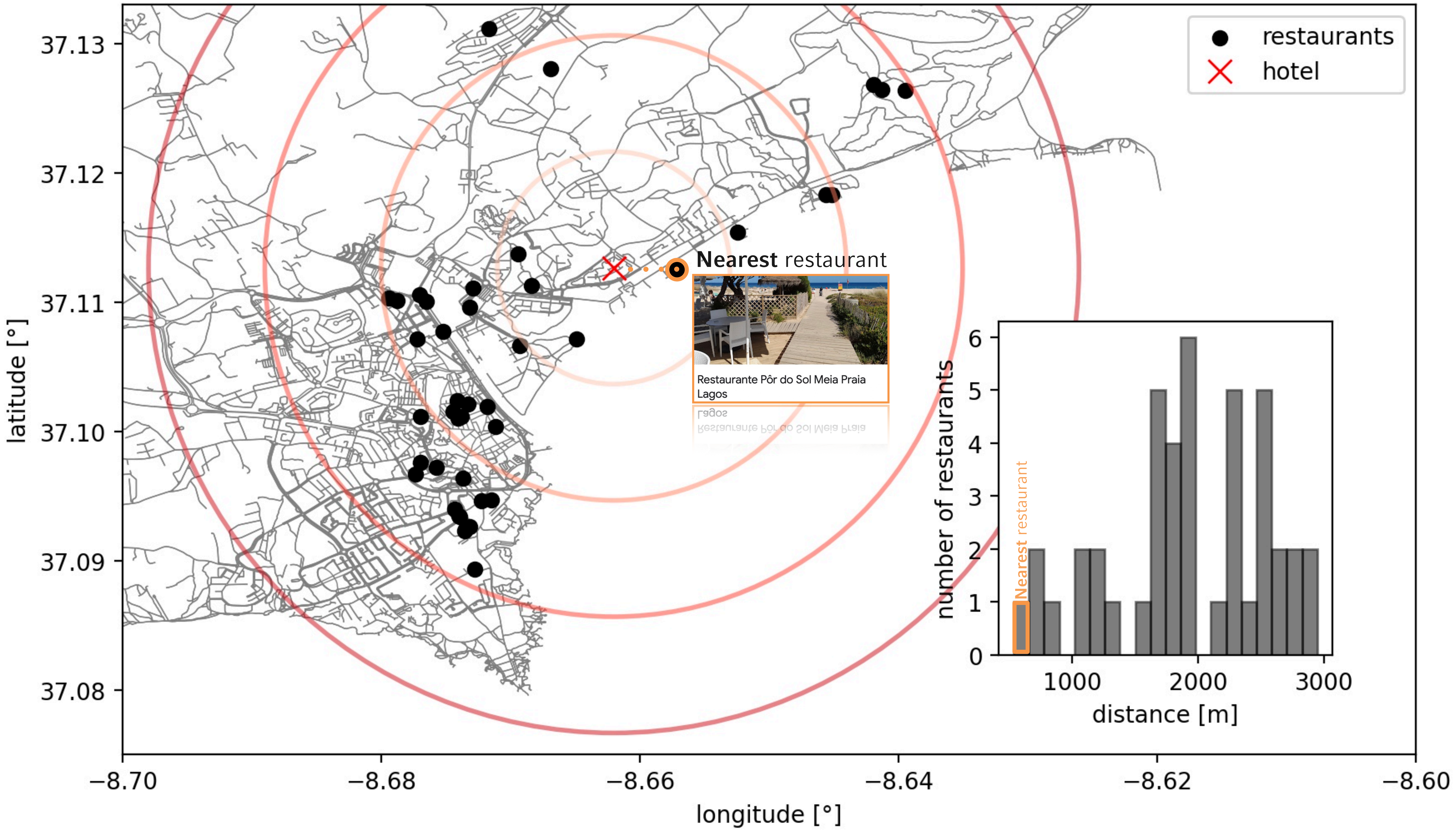
Optimizing laser-plasma accelerators

Multi-objective optimization | The conference dinner problem



Optimizing laser-plasma accelerators

Multi-objective optimization | The conference dinner problem



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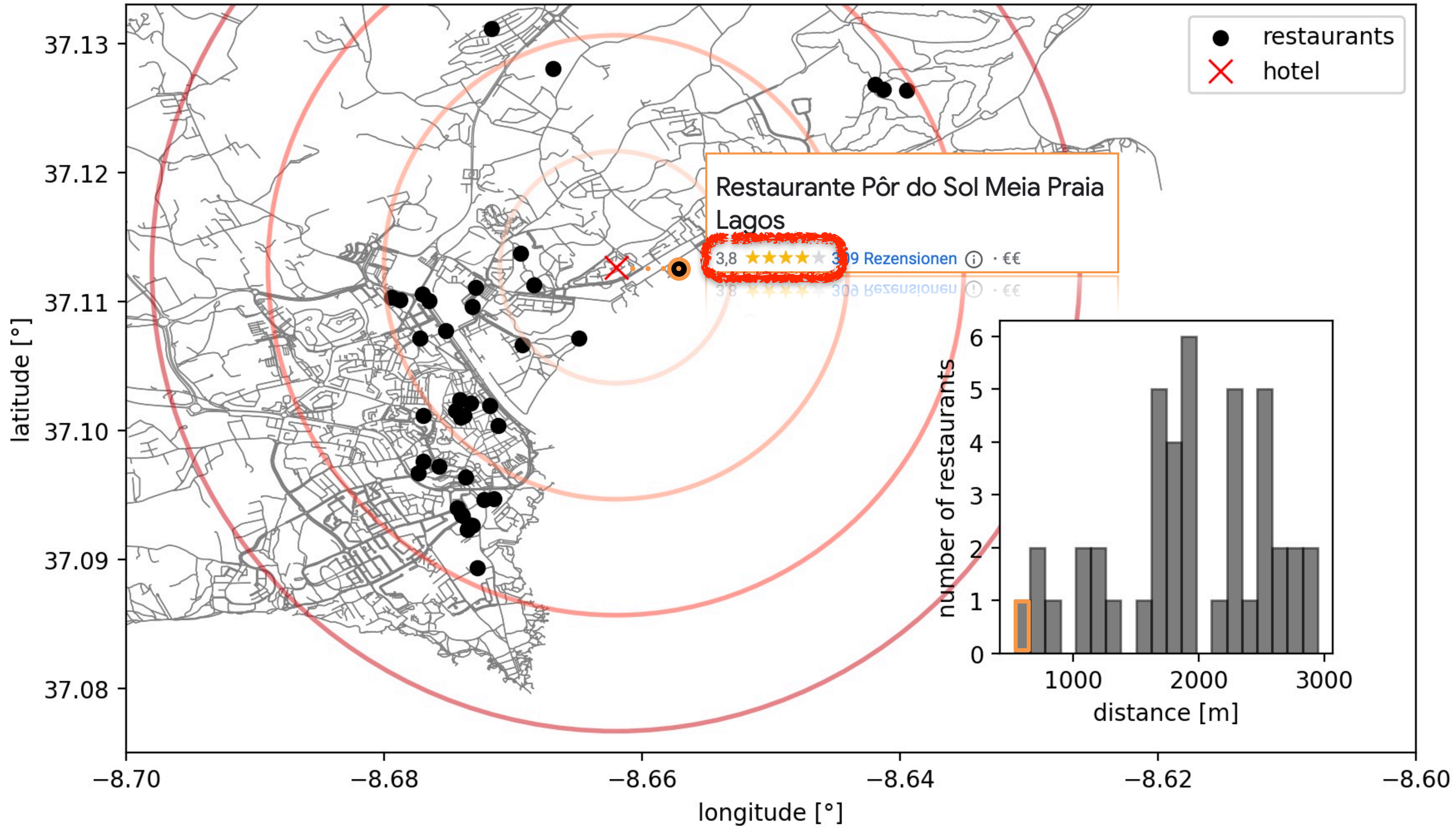

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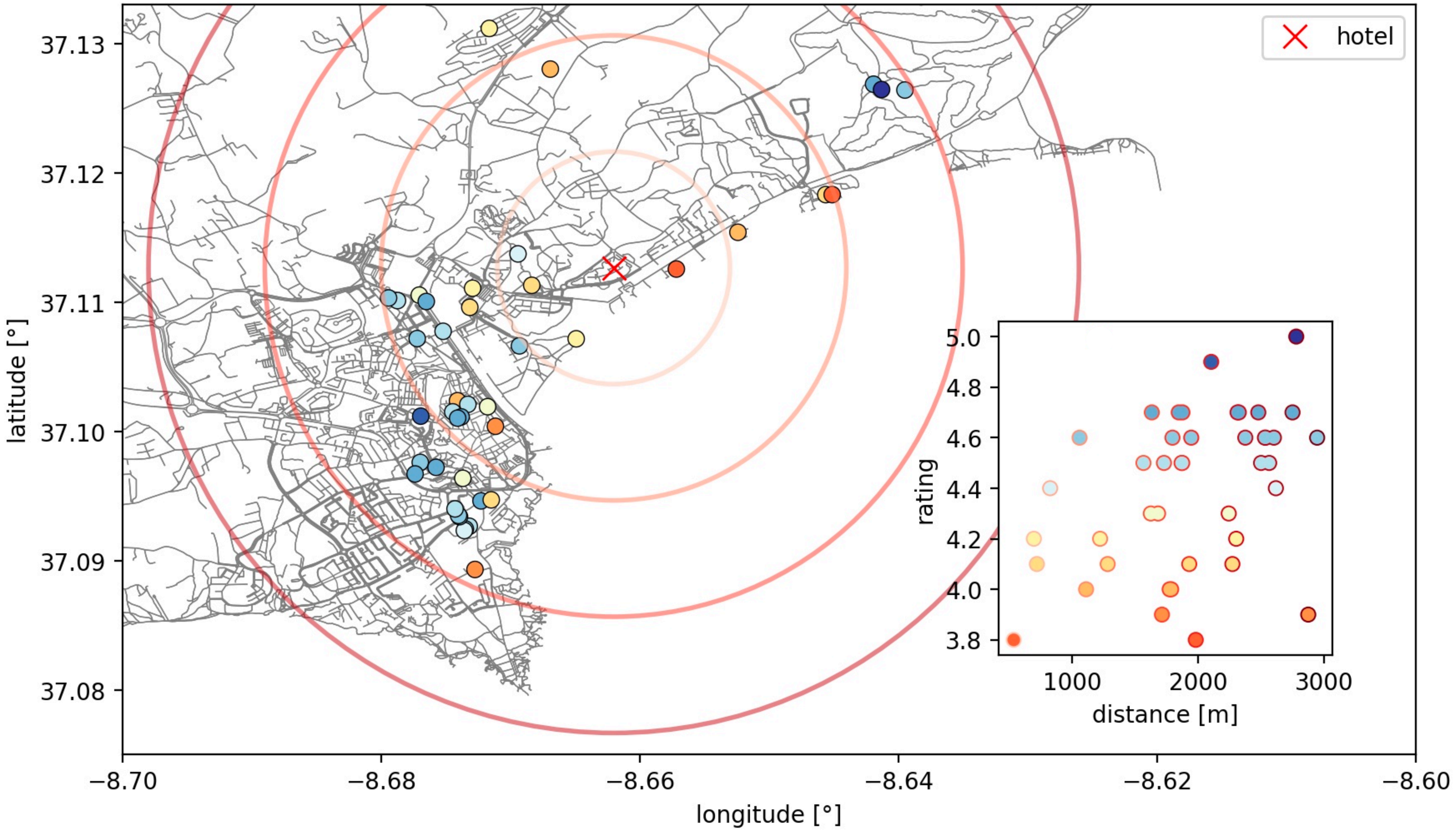

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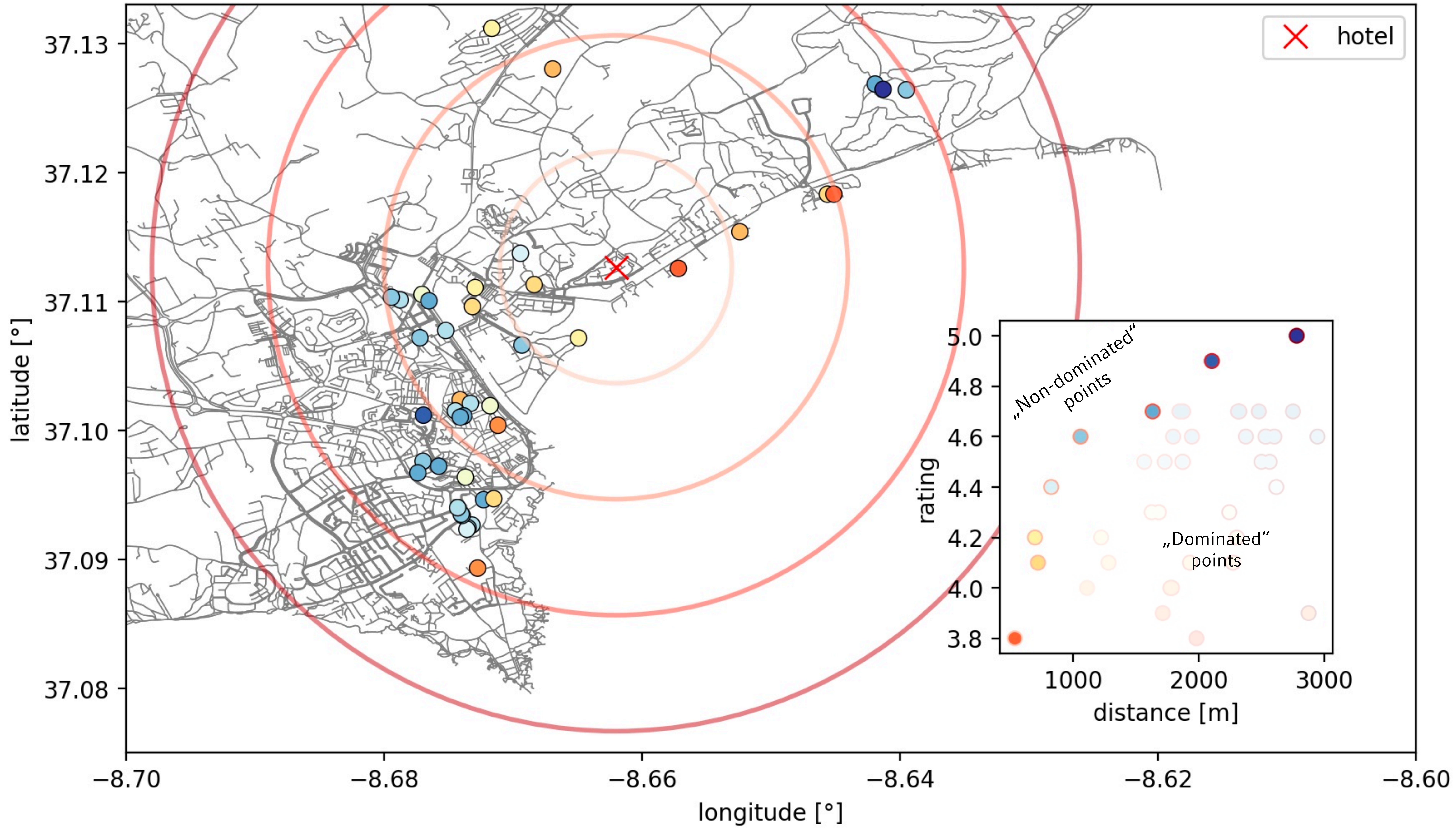

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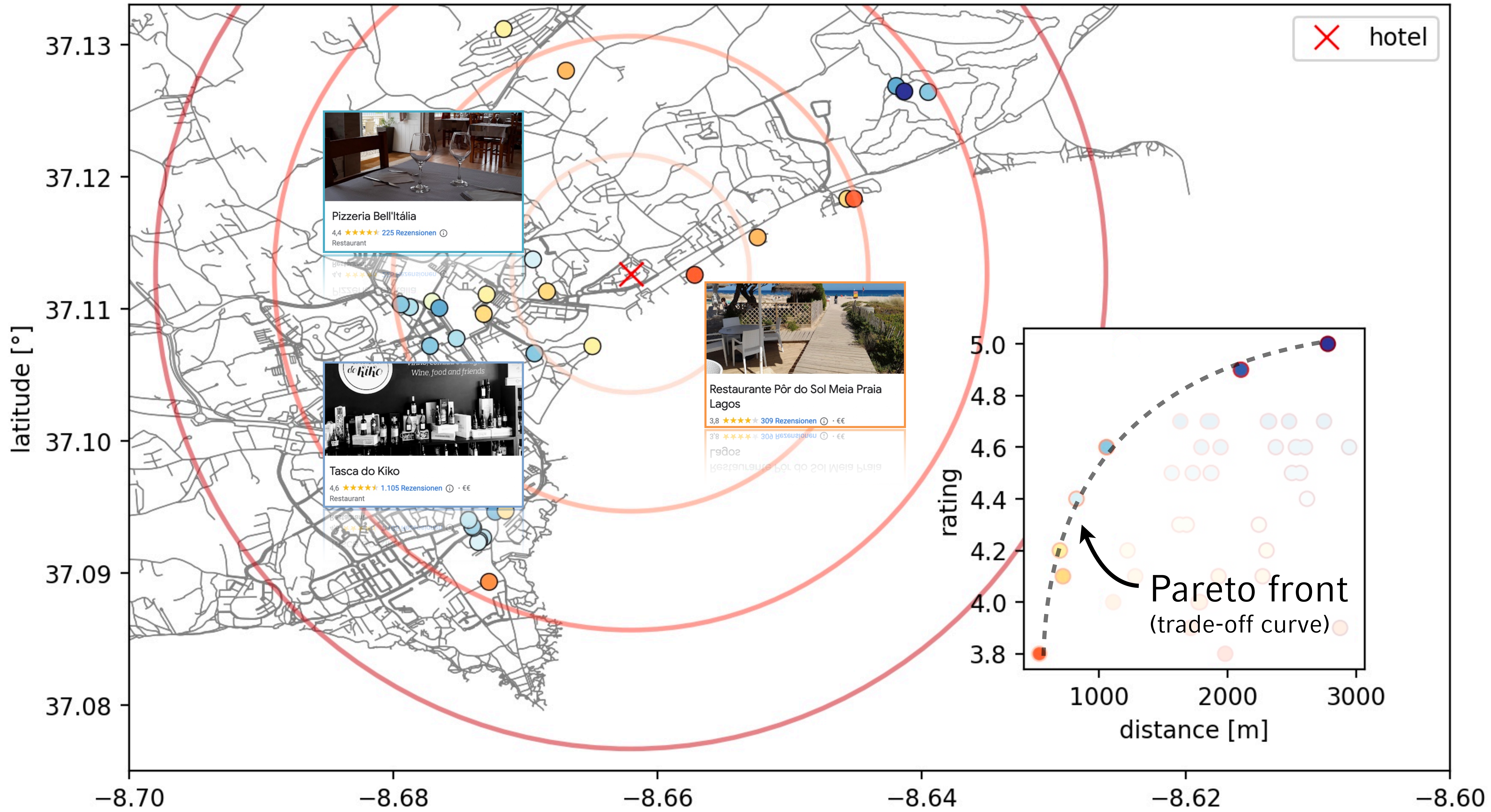

In multi-objective optimization we have **multiple (competing) goals** with **different trade-offs**.

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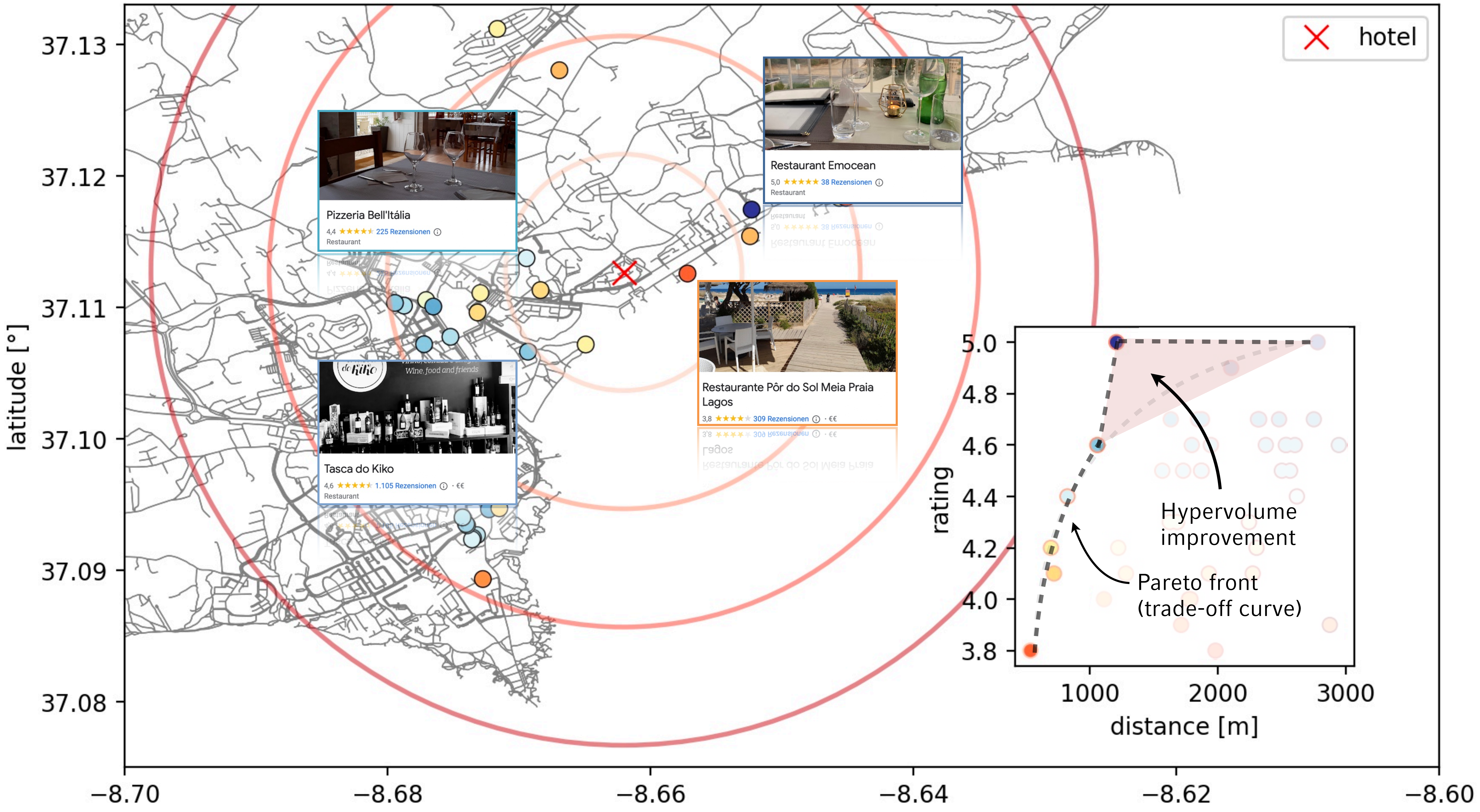

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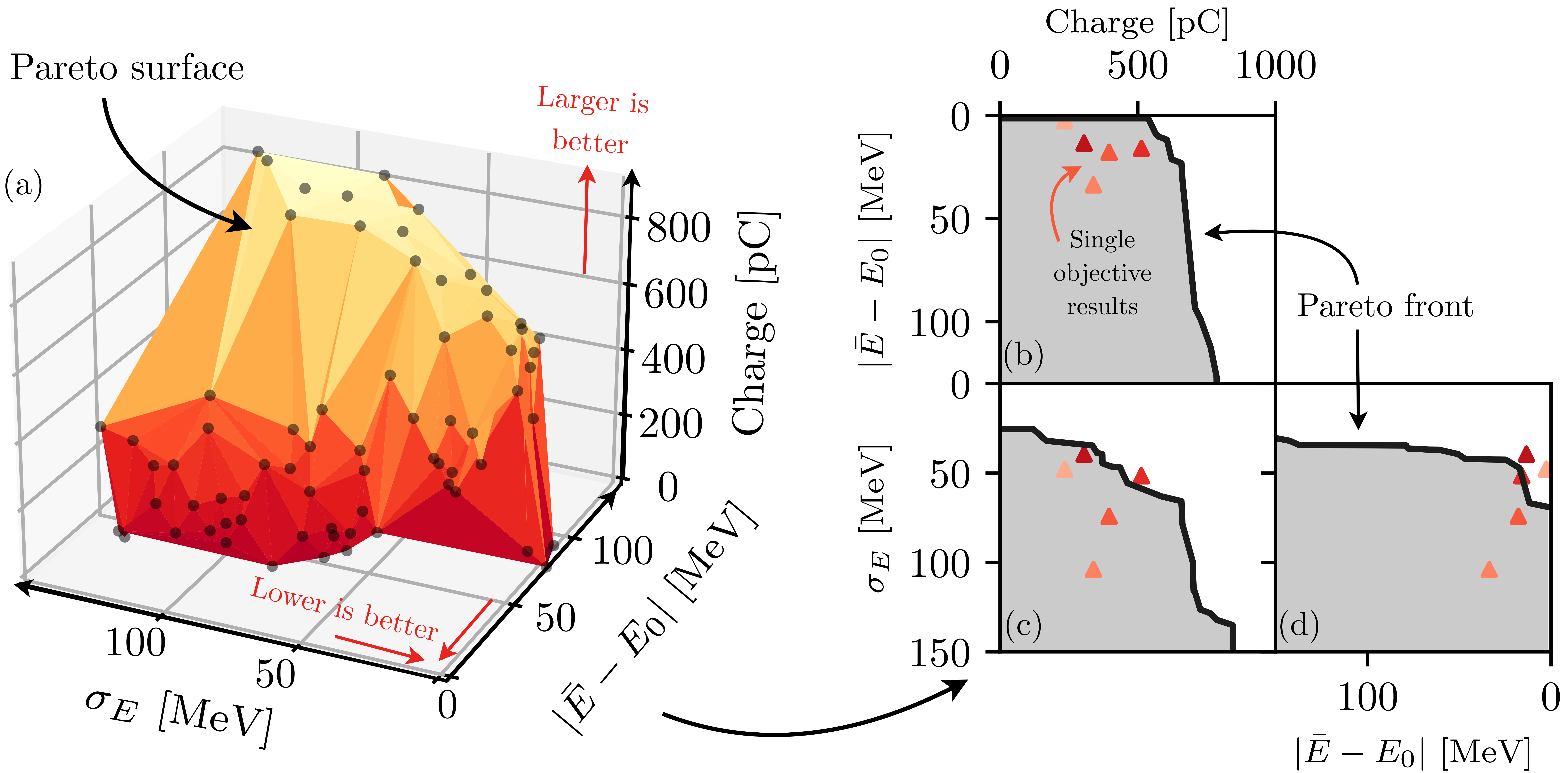
Optimizing laser-plasma accelerators

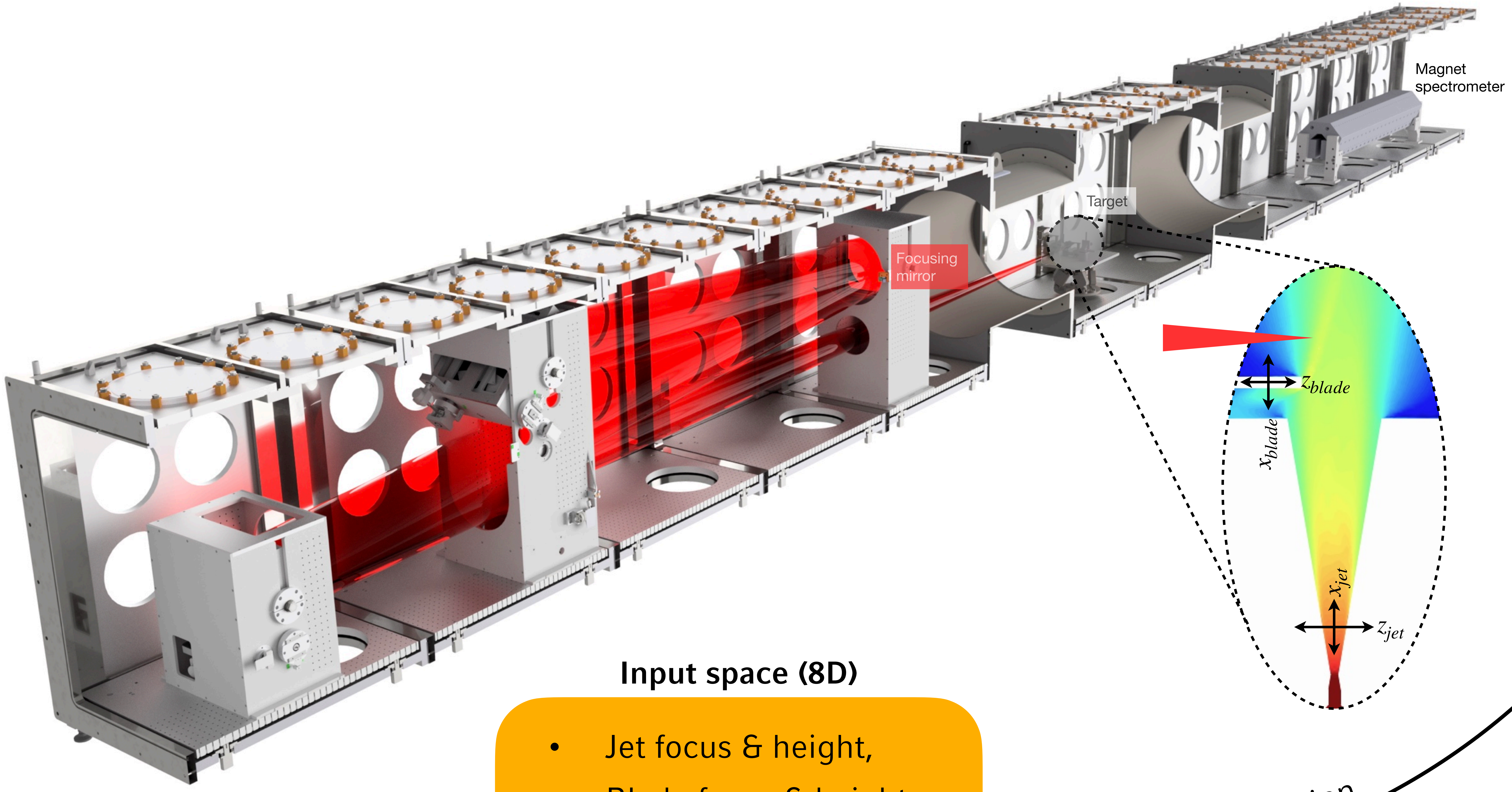
Multi-objective optimization | PIC simulations



1. Irshad, F., Karsch, S., & Döpp, A. **Leveraging trust for joint multi-objective and multi-fidelity optimization**. *Machine Learning: Science and Technology 5 (1), 015056 (2024)*
2. Irshad, F., Karsch, S., & Döpp, A. **Multi-objective and multi-fidelity Bayesian optimization of laser-plasma acceleration**. *Phys. Rev. Research 5, 013063 (2023)*

Optimizing laser-plasma accelerators

Multi-objective optimization | Experiments



Input space (8D)

- Jet focus & height,
- Blade focus & height,
- Dispersion (ϕ_2, ϕ_3, ϕ_4)
- Gas Pressure

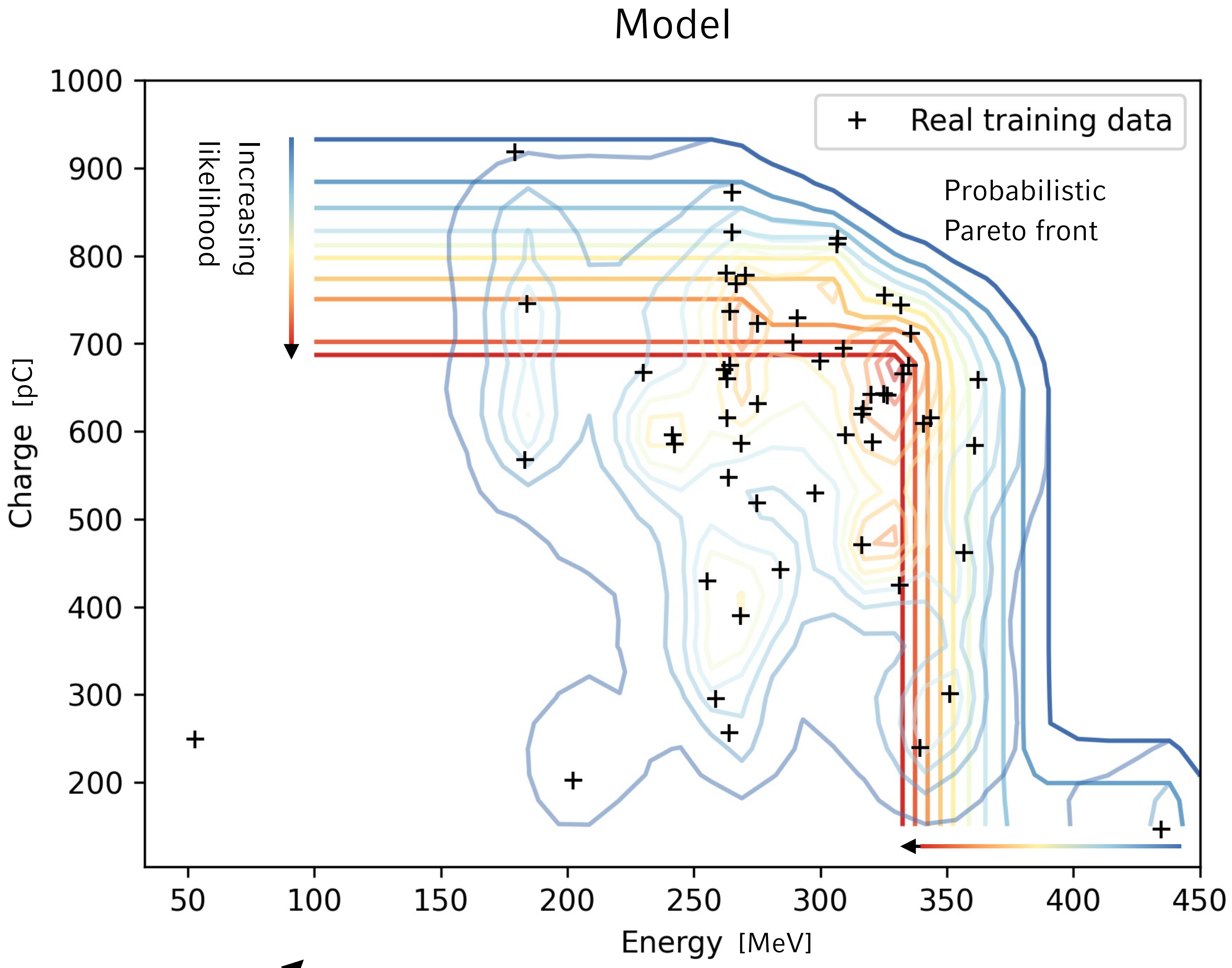
Observation

Output space (3D)

- Charge
- Energy
- Bandwidth

Optimizing laser-plasma accelerators

Multi-objective optimization | Experiments



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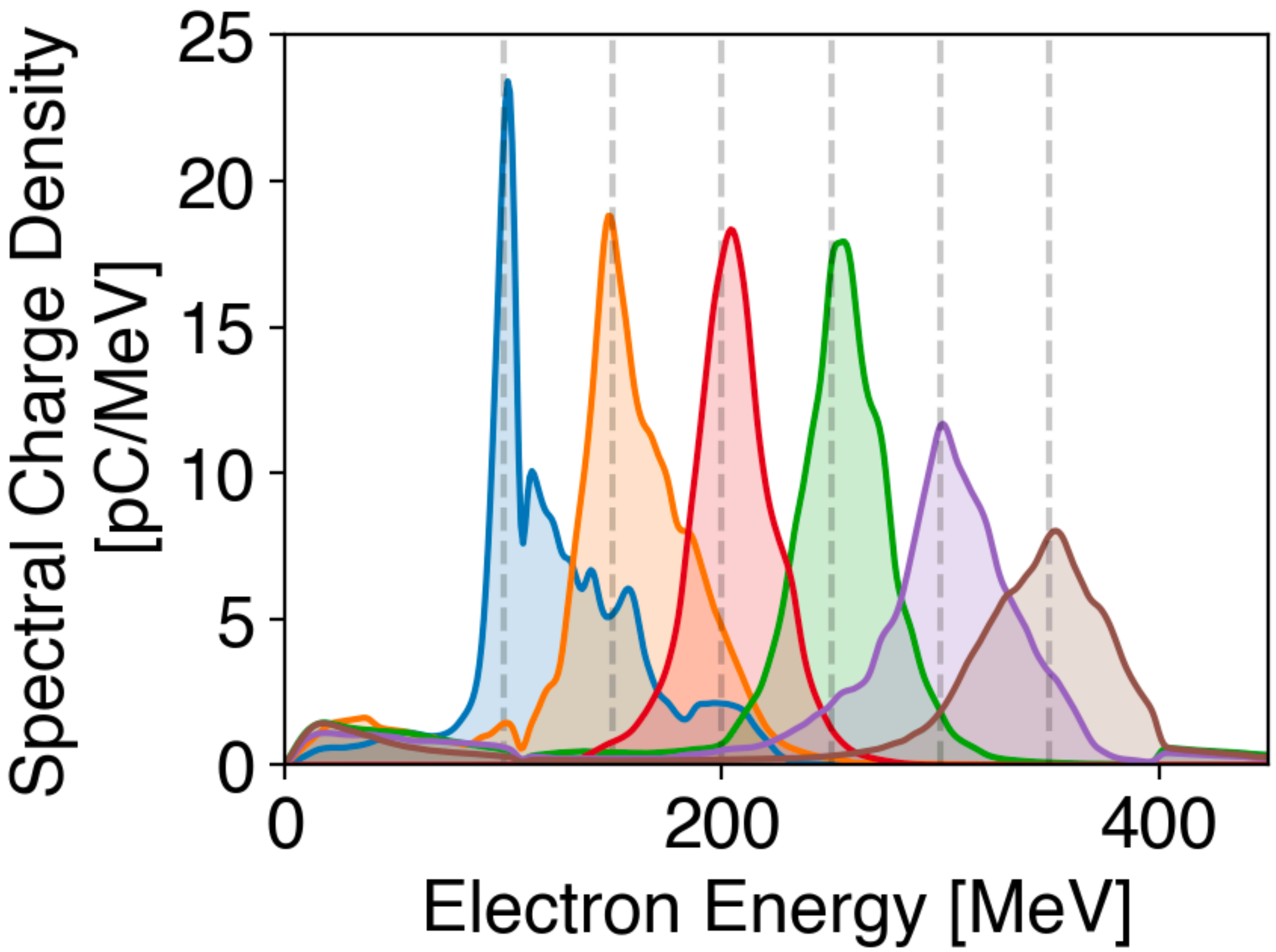
Optimizing laser-plasma accelerators

Multi-objective optimization | Experiments

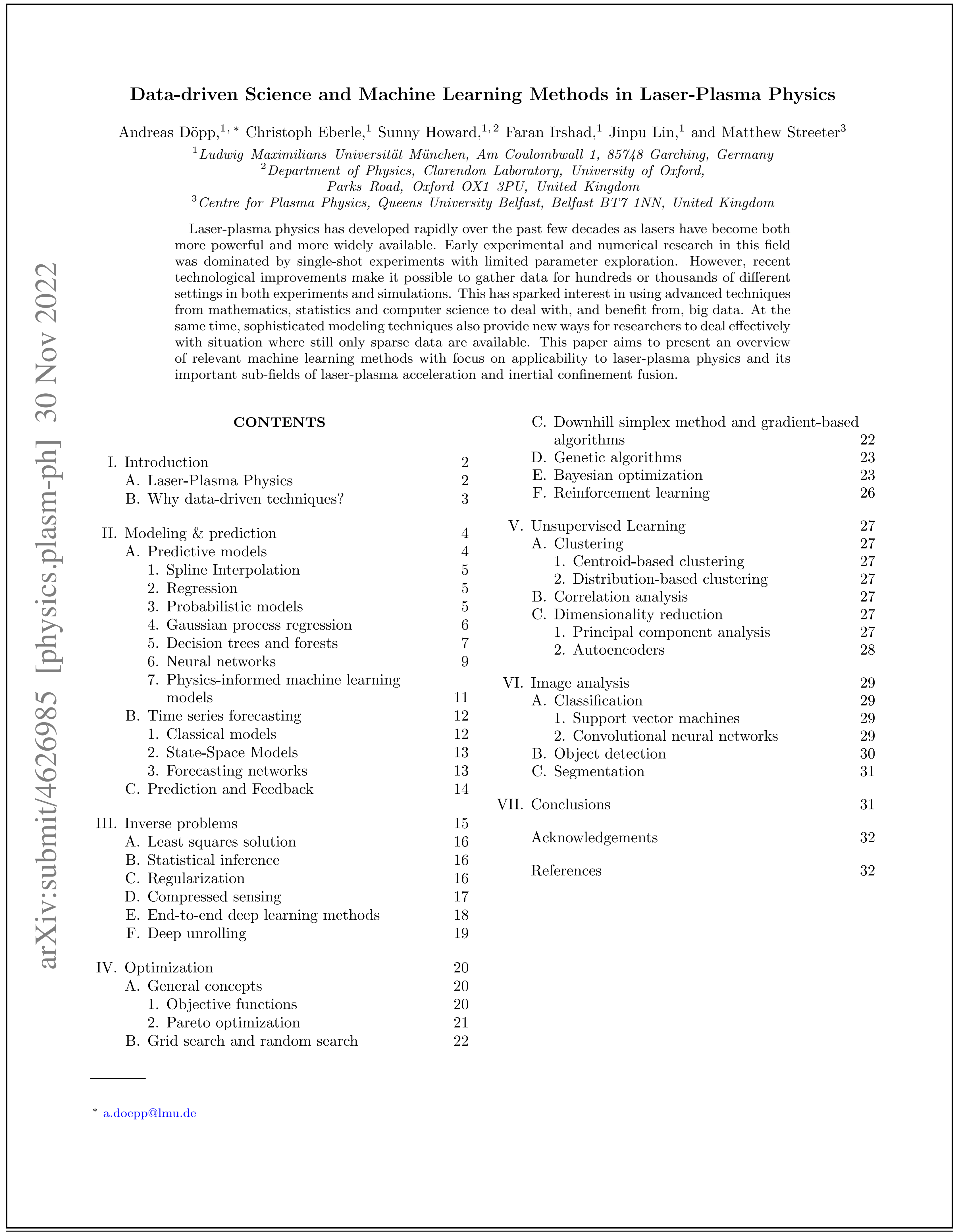
- **Inverse Optimization**: Given a target (e.g. energy), we can search the model for most likely positions in input space.
- Tricky part: Inverse from 1D to 8D has no unique solution. Use **Gaussian Mixture Network** to **predict tuning curves**.
- **Tuning also works in experiments!**



Further reading

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



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

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]
[1] *Ludwig–Maximilians–Universität München, Am Coulombwall 1, 85748 Garching, Germany*
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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.

CONTENTS

* a.doepp@lmu.de






- 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)

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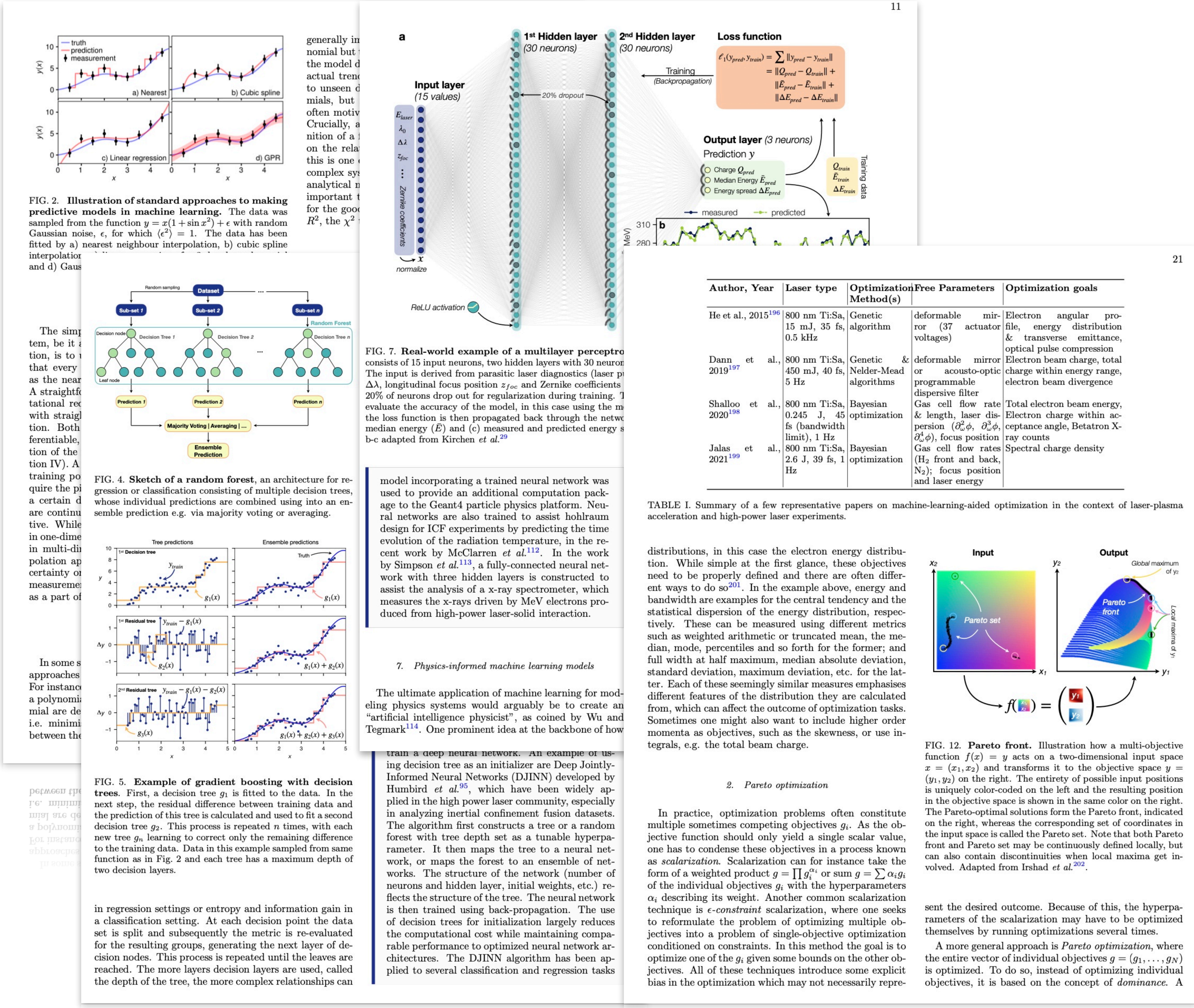

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Thank you for your attention!

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