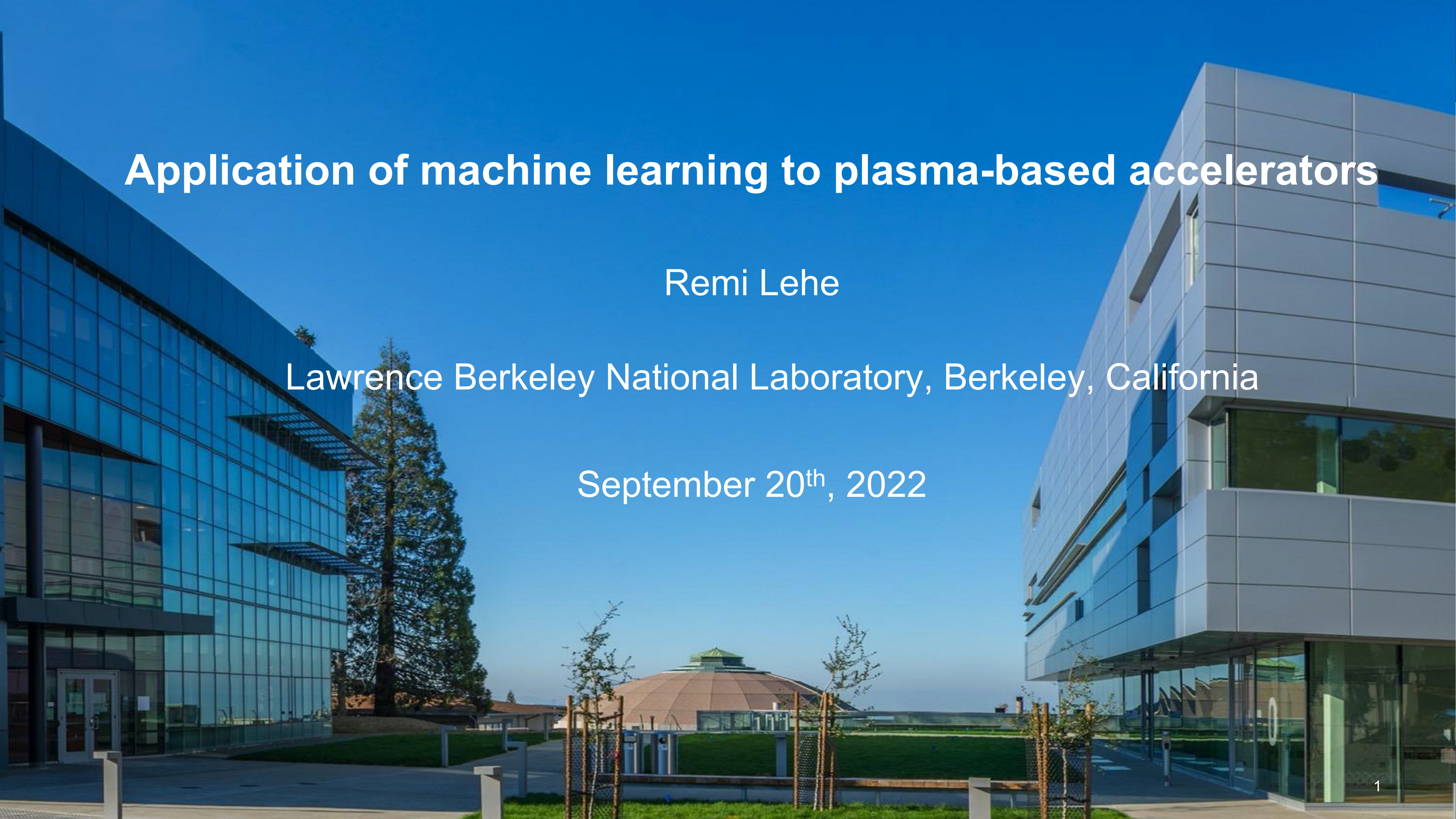

Application of machine learning to plasma-based accelerators

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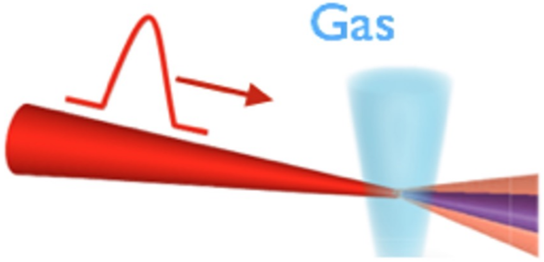
Machine Learning for control/tuning of plasma-based accelerators

Set the right **control parameters**

- Gas pressure
- Laser energy
- Laser focal position
- Laser spectral properties
- Laser waist
- …



in order to **maximize one (or several) objectives**:

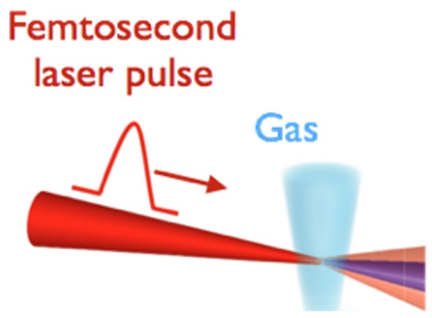
- Electron emittance
- Electron energy
- Electron energy spread
- Electron charge
- Combinations thereof
- …

In high-dimensional parameter space:

$$\boldsymbol{x} = \begin{pmatrix} \text{Laser energy} \\ \text{Gas density} \\ \text{Laser chirp} \\ \dots \end{pmatrix}$$

Find $\boldsymbol{x}_{\boldsymbol{best}}$ such that $f\left(\boldsymbol{x}_{\boldsymbol{best}}\right)$ is maximal.

Two different tuning problems: optimization and stabilization



Optimization:
The (uncontrolled) properties of the system do not change (e.g. negligible drift).

e.g.
- Design study (simulations)
- Experimental setup, over relatively short timescales

Aim: "exhaustively" search the parameter space to find $\boldsymbol{x_{best}}$.

Stabilization:
The (uncontrolled) properties of the system change in time (e.g. thermal drifts)

The previously-found optimal point $\boldsymbol{x_{best}}$ becomes obsolete after some time.

Aim: Find the correction $\Delta\boldsymbol{x}$ that recovers the optimal behavior.

Outline

- Machine Learning for **optimization** of plasma-based accelerators
- Machine Learning for **stabilization** of plasma-based accelerators
- Conclusion

High-dimensional optimization is expensive

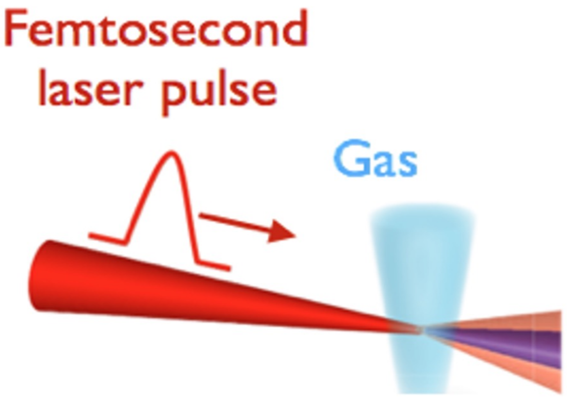
Aim:

Find $\mathbf{x}_{best}$ such that $f(\mathbf{x}_{best})$ is **maximal**, with **few** evaluations of f

Motivation: evaluations of f are usually costly

- **Design studies**:
  Evaluations of f require **computationally expensive** numerical simulations

- **Tuning in experiments:**
  Evaluations of f **take time** on the experiments
  Parameters of the machine may **drift** if it takes too long to find the minimum.



$$x = \begin{pmatrix} \text{Laser energy} \\ \text{Gas density} \\ \text{Laser chirp} \\ \dots \end{pmatrix}$$

Overview of different optimization algorithms

"Conventional" optimization algorithms:

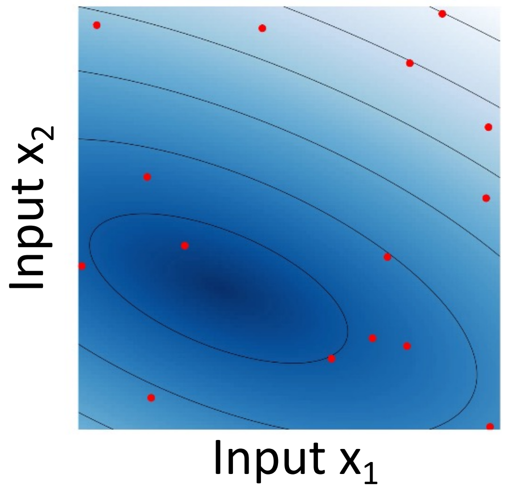
e.g.
- Gradient descent
- Genetic algorithms
- Nelder-Mead algorithm (a.k.a. simplex)
- …

The next evaluations are based on simple rules that the depend on the **last few evaluations**.

Typically require **many** evaluations of f.

Optimization algorithms based on machine learning:

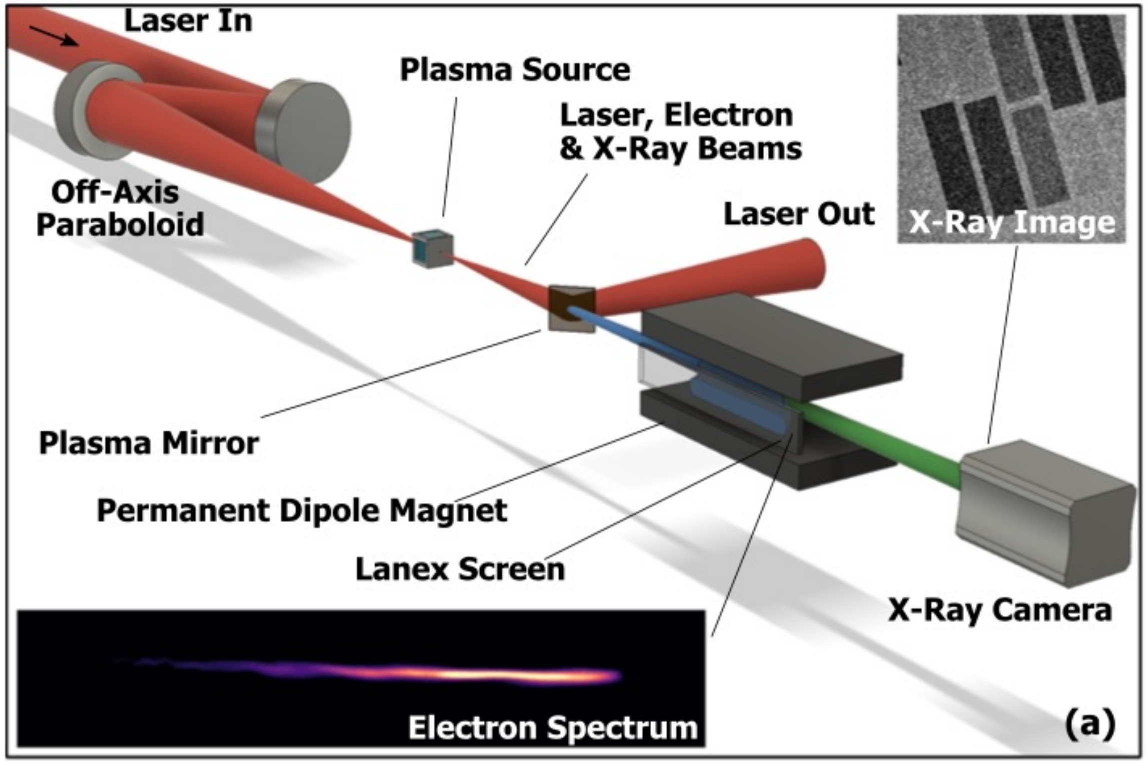
Progressively learn a **global model** of the objective function $f(\boldsymbol{x})$ over the parameter space.
Use this model to **only evaluate** the most promising $\boldsymbol{x}$.

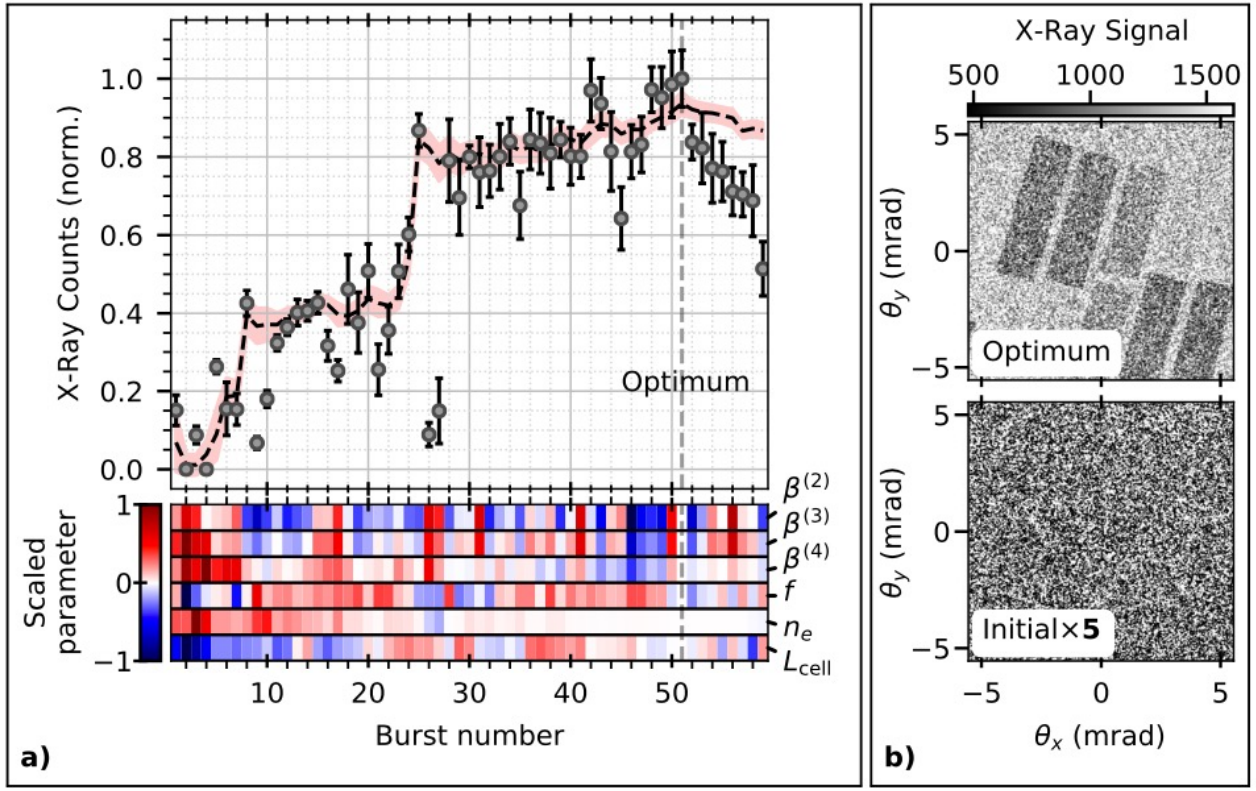


e.g. Bayesian optimization

Typically require **fewer** evaluations of f.

Applications of Bayesian optimization in laser-plasma acceleration

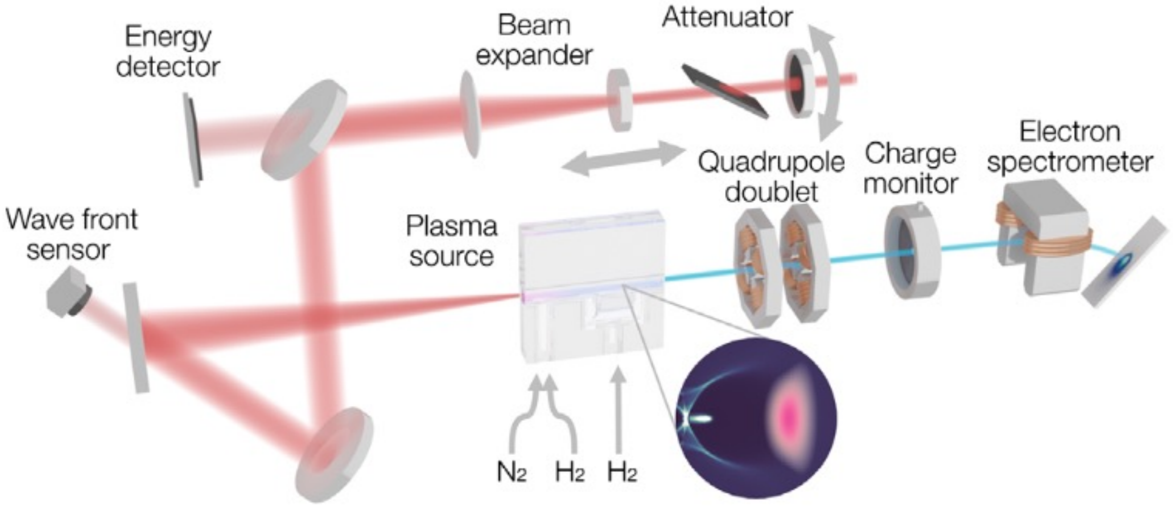


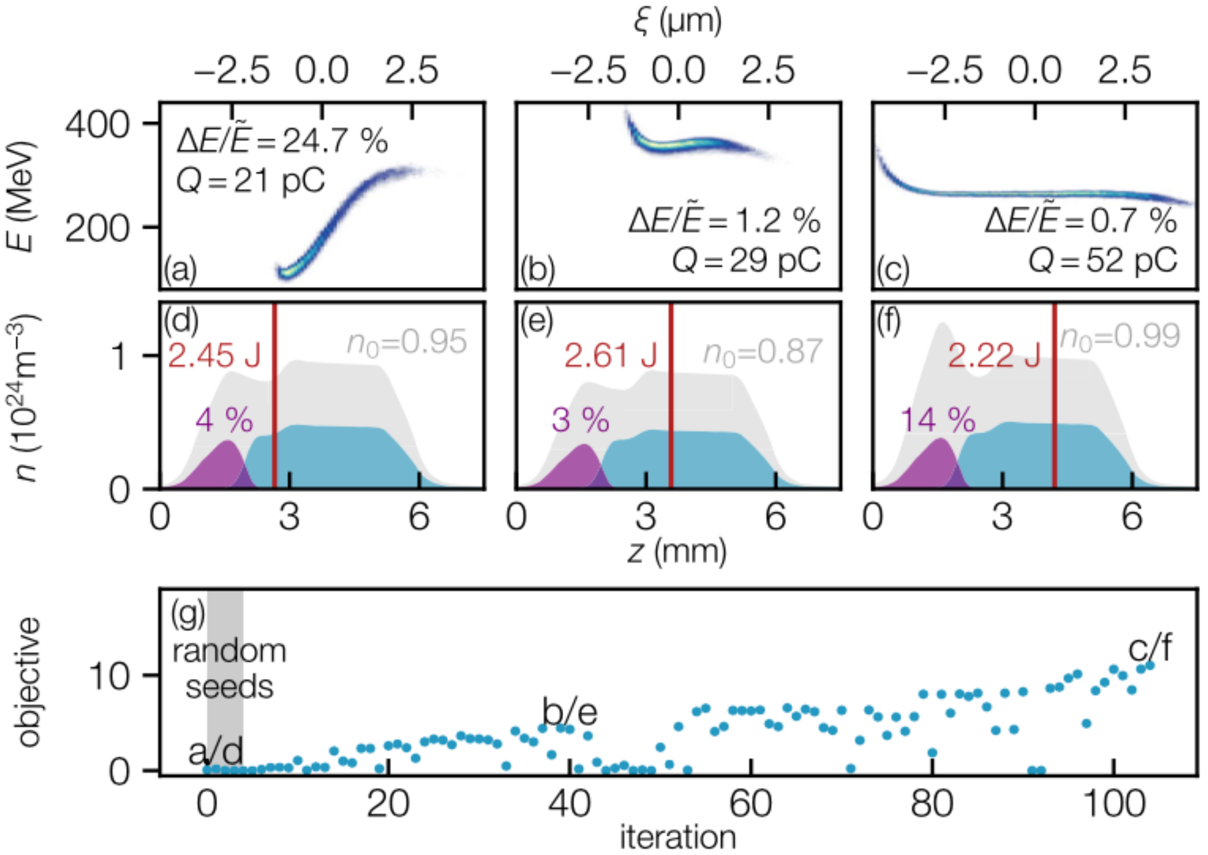


6 control parameters tuned simultaneously, to maximize the betatron X-ray yield.

R. Shalloo et al., Nature Communications (2020)

Applications of Bayesian optimization in laser-plasma acceleration





Tuning:

- background density
- amount of N2 injected
- laser energy
- laser focal position

in order to maximize **beam quality** in ionization injection

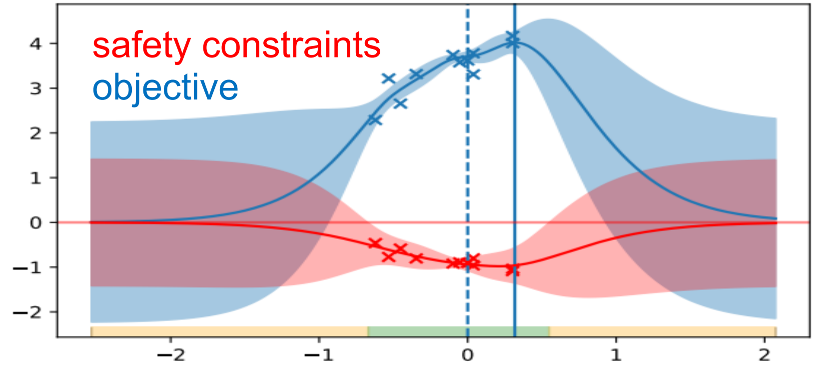
$$f = \sqrt{Q}\,\frac{\bar{E}}{\Delta E}$$

S. Jalas et al., PRL (2021)

Some areas of current research

F. Irshad et al., arXiv:2112.13901 (2021)
A. Ferran-Pousa et al., IPAC 2022
F. Irshad et al., arXiv:2011.01542 (2022)

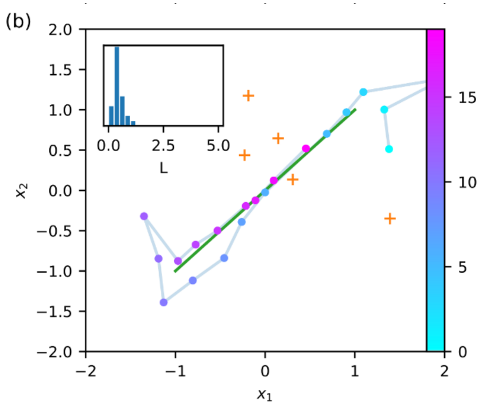
- **Multi-fidelity Bayesian optimization**
  Using low-fidelity simulations to rapidly scan the parameter space and high-fidelity simulations when focusing on the optimal point



Kirschner et al., arxiv: 1902.03229 (2019)

- **How to satisfy safety constraints**
  esp. for quantities that are difficult to predict
  and require simulation / experiments (e.g. beam loss)

- **Proximal optimization**
  For experiments: how to avoid repeated,
  large jumps in input parameters



R. Roussel et al.,
arxiv:2010.09824 (2021)

Outline

- Machine Learning for **optimization** of plasma-based accelerators
- Machine Learning for **stabilization** of plasma-based accelerators
- Conclusion

Overview of different stabilization algorithms

“Conventional” stabilization algorithms:

e.g.
- PID
- Stochastic gradient descent
- Extremum seeking
- …

Often require relatively slow feedback loops.

Stabilization algorithm based on machine learning:

Can recognize “patterns” in the system and directly apply the right correction.

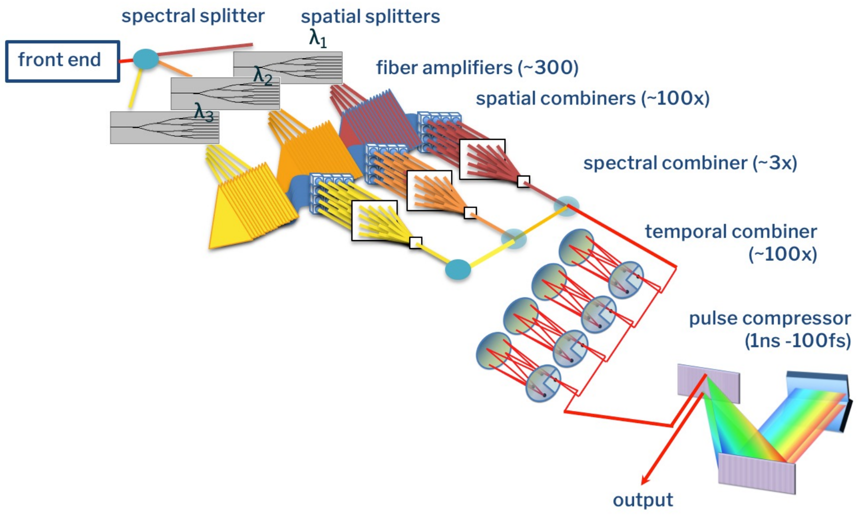
Measured pattern

Correction Δx

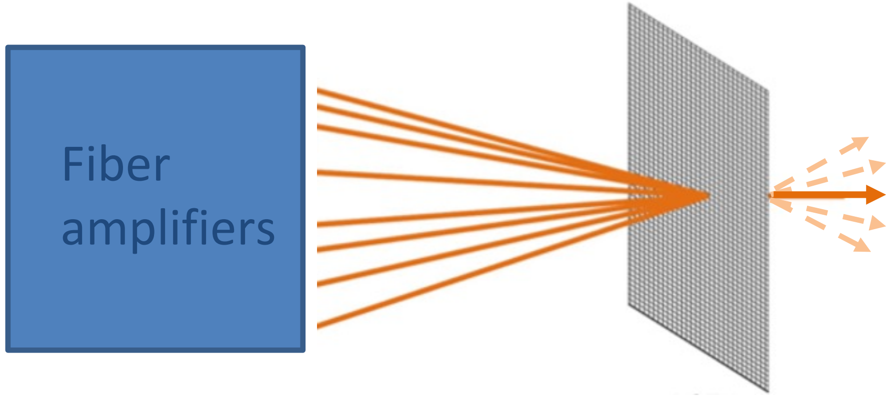
Neural network

(other solutions: reinforcement learning, …)

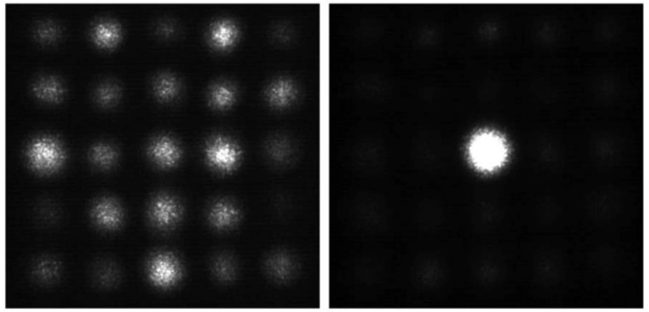
Example: coherent laser combining



Spatial combiner

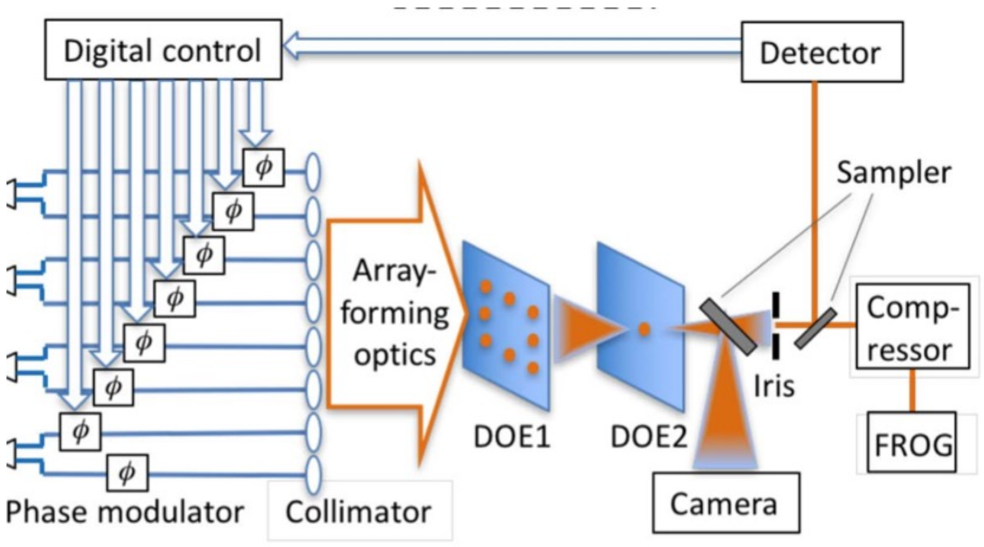


The phases of the incident laser beams need to be such that they **interfere destructively** in **all but the forward direction**.



But the phase of each beam is drifting and is not measured directly (only the resulting intensity pattern is).

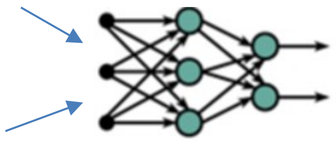
Solution for stabilization: pattern recognition with neural network



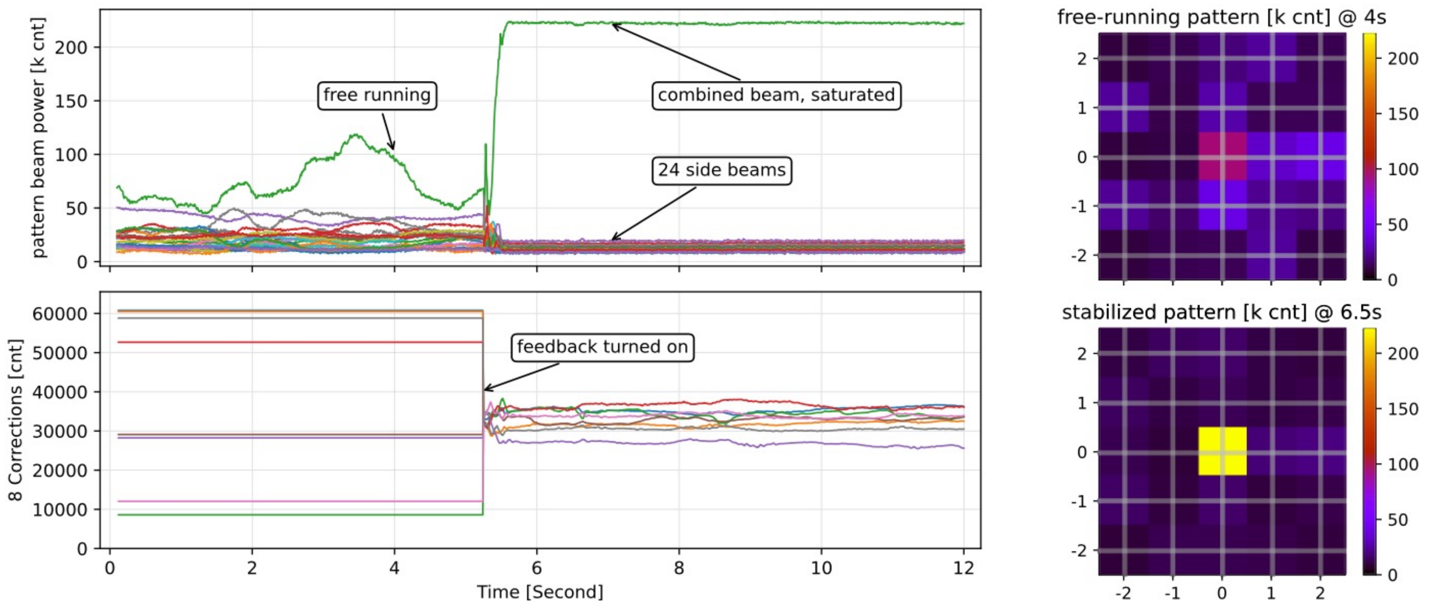
Training set:
Apply **known** changes in phases and record the intensity pattern before and after the change.

5x5 **current** intensity pattern

5x5 **desired** intensity pattern

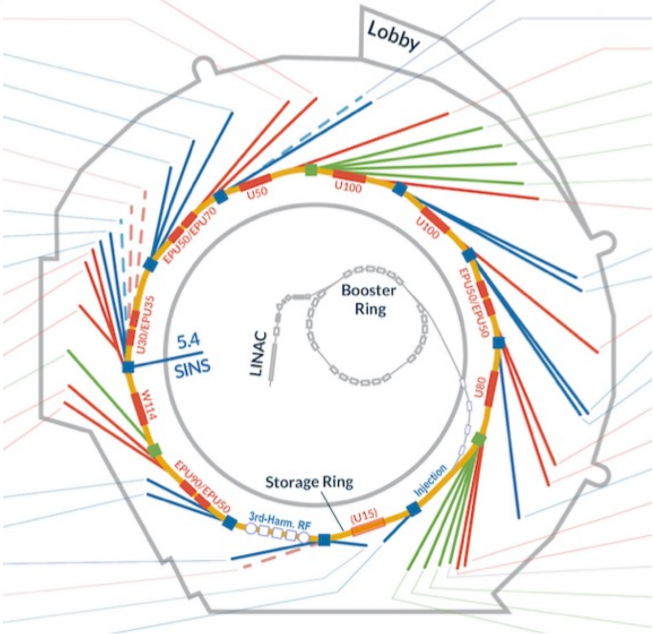


Change in phase to apply to each of the 9(-1) beams

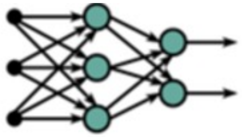


D. Wang et al., Optics Express, 30(8) 12639, 2022

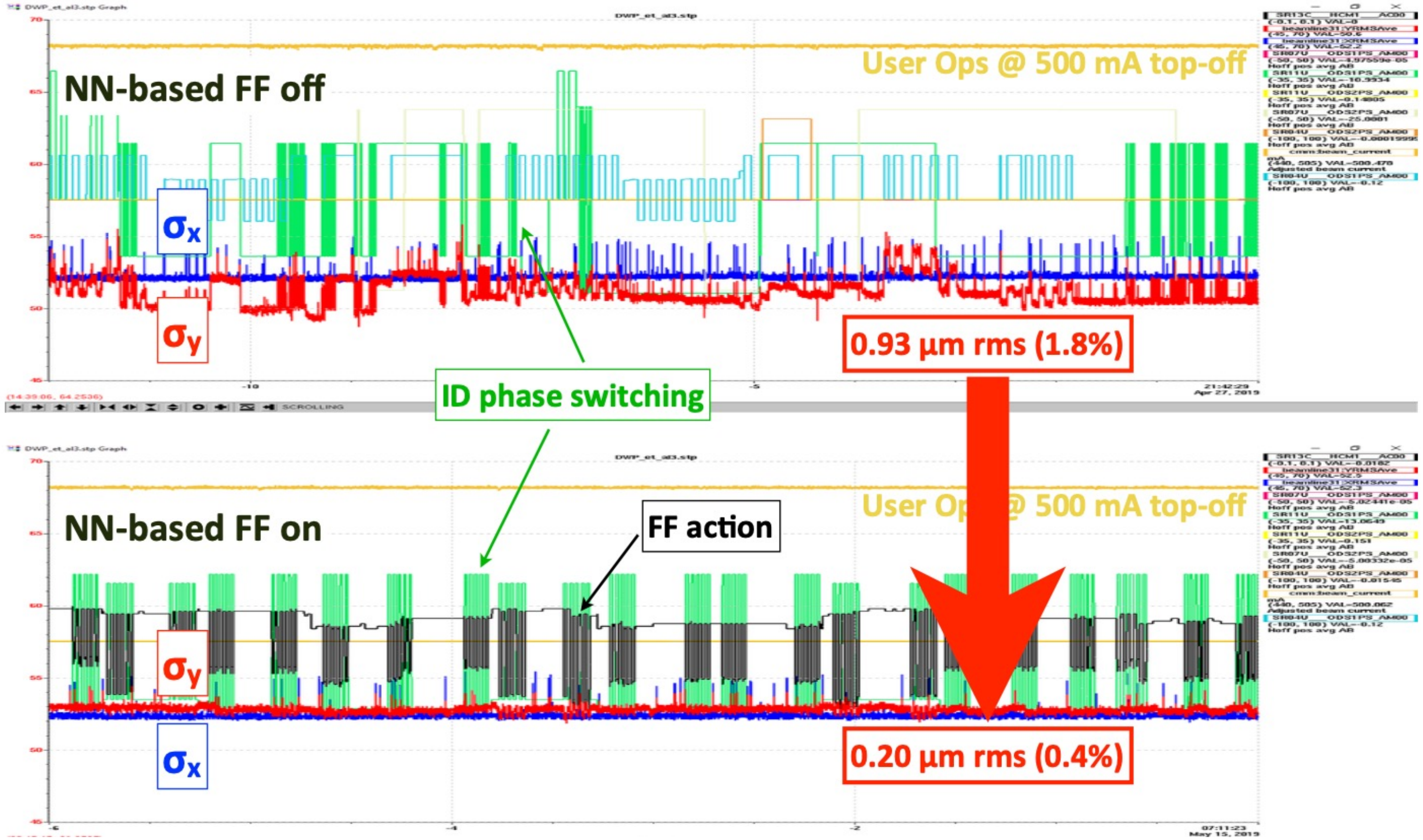
Another example: stabilizing beam size at the Advanced Light Source



Parameters of insertion devices (ID)



Beam size



S. C. Leemann et al., Phys. Rev. Let,194801 (2019)

Conclusion

Recent work showed that ML methods can be applied in practical cases, of interest for LPA

- Optimization of a static setup
  (**Bayesian optimization**, genetic algorithms + neural network, …)

- Stabilization against drifts
  (**Pattern recognition with neural networks**, reinforcement learning, …)

Conclusion

1) Future developments needed and planned as seen from the speakers and their groups

- More applications of ML for stabilization of in experiments
- Better evaluation of uncertainty from ML methods
- Combine simulations of different fidelities for design optimization

2) Do the planned activities address the requirements from funded projects (AWAKE, EuPRAXIA, …) and from various roadmaps for plasma accelerators? Are there urgent holes?

There is sometimes a gap between **proof-of-concept machine learning application** and robust solution that can run autonomously at the right rep. rate.