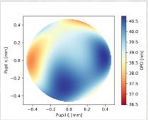
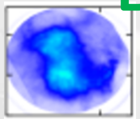
Predicted vs. measured electron beam charge



X: Laser wavefront (feature)

Dataset

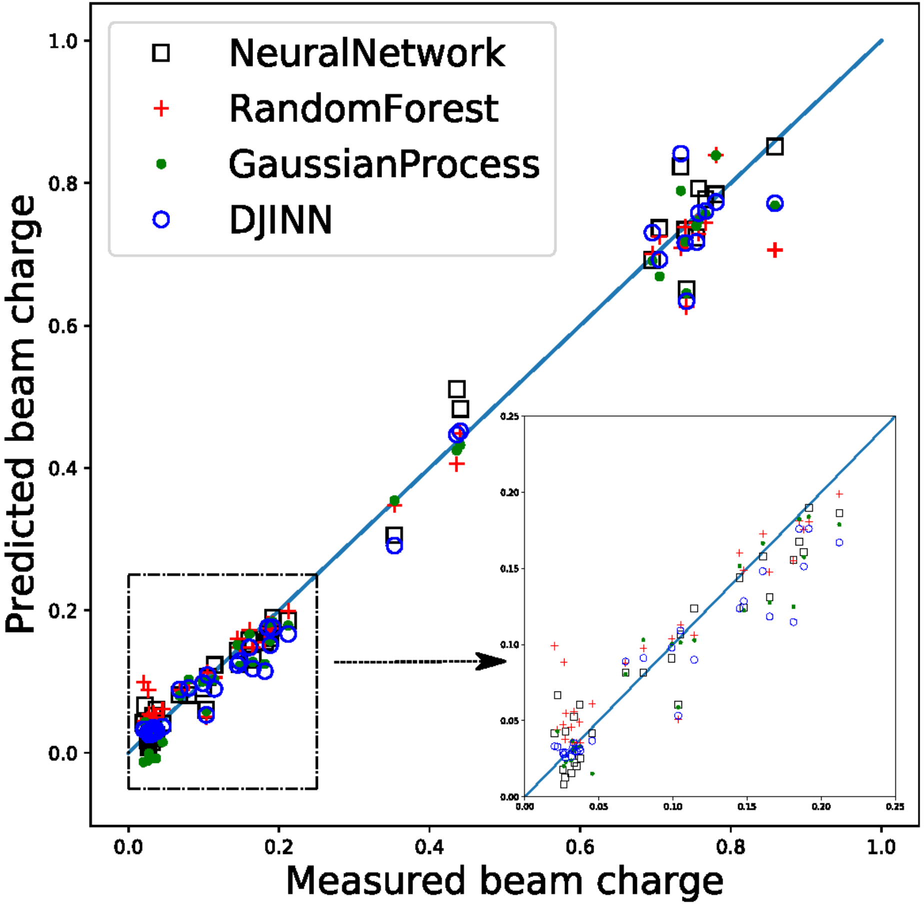


Y: Electron beam charge (label)

80% → Training dataset

20% → Test dataset

Model	MSE	MAE	R^2	ExVar
Random Forest	0.00132	0.0268	0.986	0.987
Neural network	0.00162	0.0292	0.983	0.984
DJINN	0.00154	0.02741	0.98403	0.98404
Gaussian Process	0.00185	0.0305	0.981	0.981



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Feature analysis in relativistic laser-plasma experiments utilizing machine learning methods

Jinpu Lin[1], Qian Qian[1], Jon Murphy[1], Abigail Hsu[2], Alfred Hero[3], Alexander G.R. Thomas[1], and Karl Krushelnick[1]

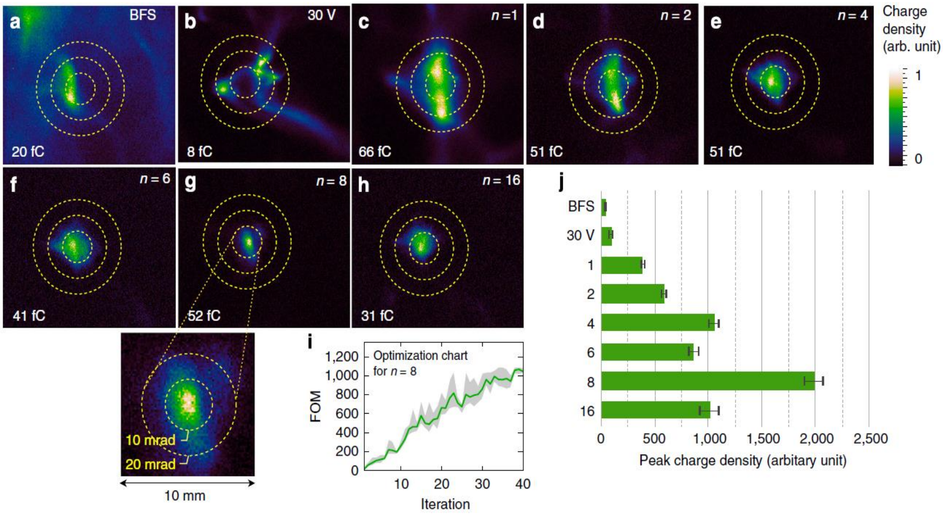
1) Center for Ultrafast Optical Science, University of Michigan

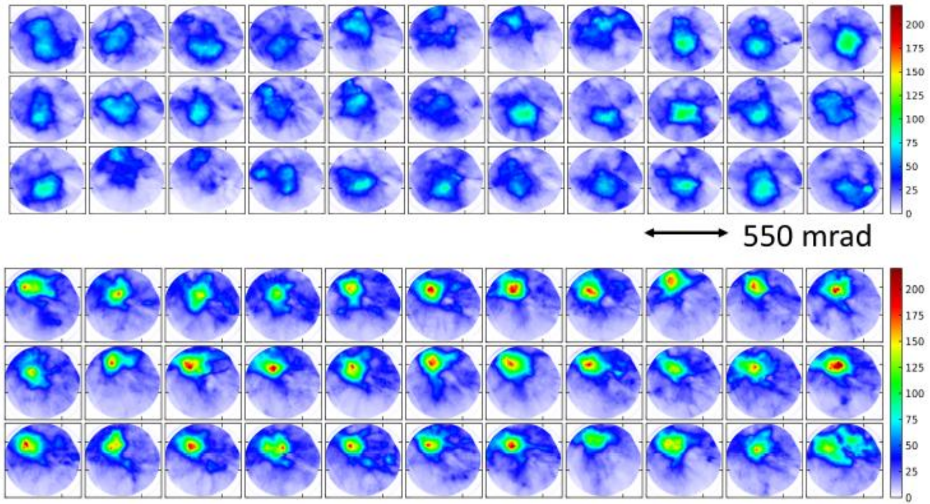
2) Department of Applied Mathematics and Statistics, Stoney Brook University

3) Department of Electrical Engineering and Computer Science, University of Michigan

November 12, 2020, 62nd Annual Meeting of the APS Division of Plasma Physics

Statistical methods in high-rep-rate LWFA – genetic algorithm



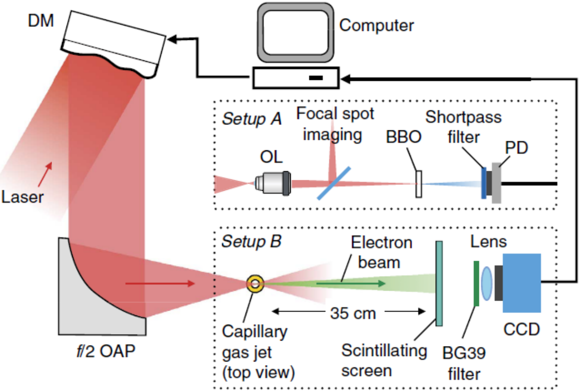


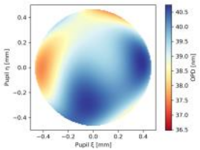
He, Z-H., et al. "Coherent control of plasma dynamics." *Nature communications* 6.1 (2015): 1-7.

Lin, J., et al. "Adaptive control of laser-wakefield accelerators driven by mid-IR laser pulses." *Optics express* 27.8 (2019): 10912-10923.

Apply machine learning to LWFA experimental data

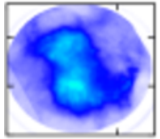
- Machine learning vs. genetic algorithms?
  - GA provides only local optimum while ML allows feature analysis
  - GA throws away 90% of the data while ML utilizes all





X: Laser wavefront (feature)

Dataset



Y: Electron beam charge (label)

Training dataset

Build

Test dataset

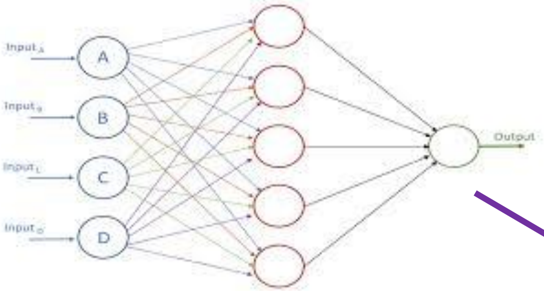
Validate

Model function f(X) For LWFA

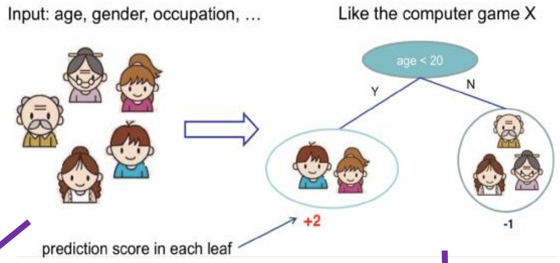
He, Z-H., et al. "Coherent control of plasma dynamics." *Nature communications* 6.1 (2015): 1-7.

Maris, A. D., et al. *Finding Correlations in Inertial Confinement Fusion Experimental Data Using Machine Learning*. No. LLNL-PROC-791967. Lawrence Livermore National Lab.(LLNL), Livermore, CA (United States), 2019.

Supervised learning architectures

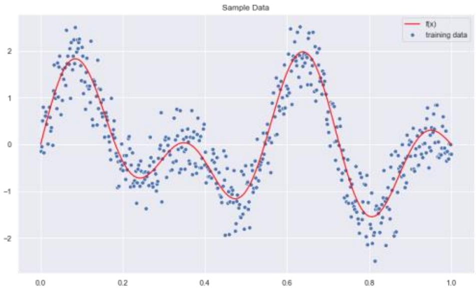


Neural network

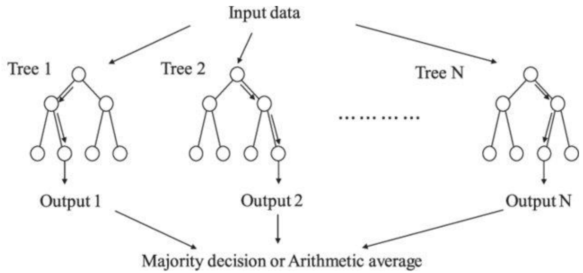


Decision tree

Deep Jointly-Informed Neural Networks[1]



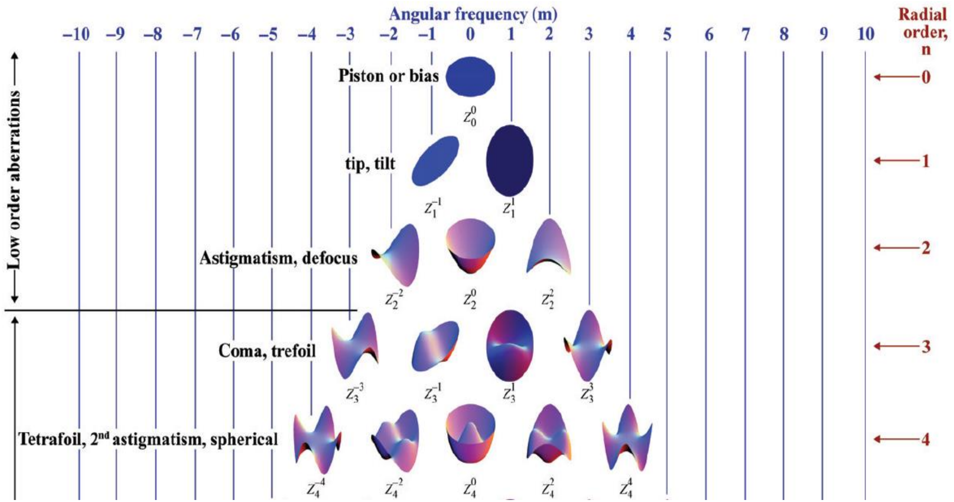
Gaussian process regression with kernels



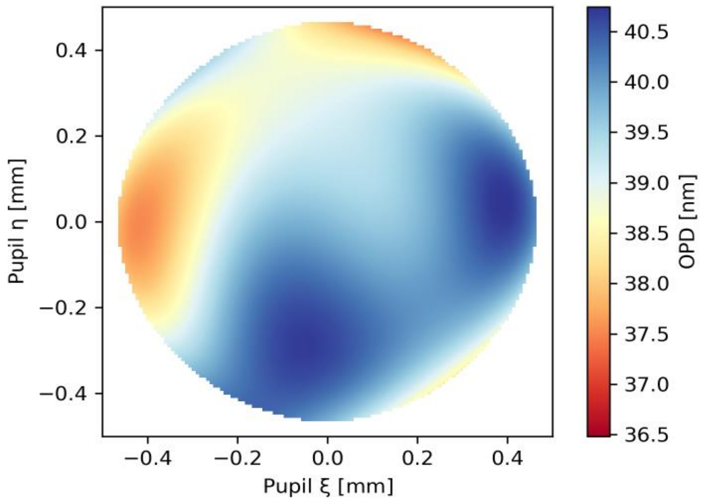
Random forest

[1]Humbird, Kelli D., et al. "Deep neural network initialization with decision trees." *IEEE trans. on neural networks and learning systems* 30.5 (2018): 1286-1295.

Feature dimensionality reduction



Zernike expansion



Reproduced laser wavefront

Reduced feature (X) dimension = 15,
Label dimension = 1

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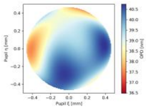
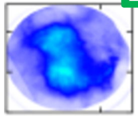
Predicted vs. measured electron beam charge



X: Laser wavefront (feature)

Dataset



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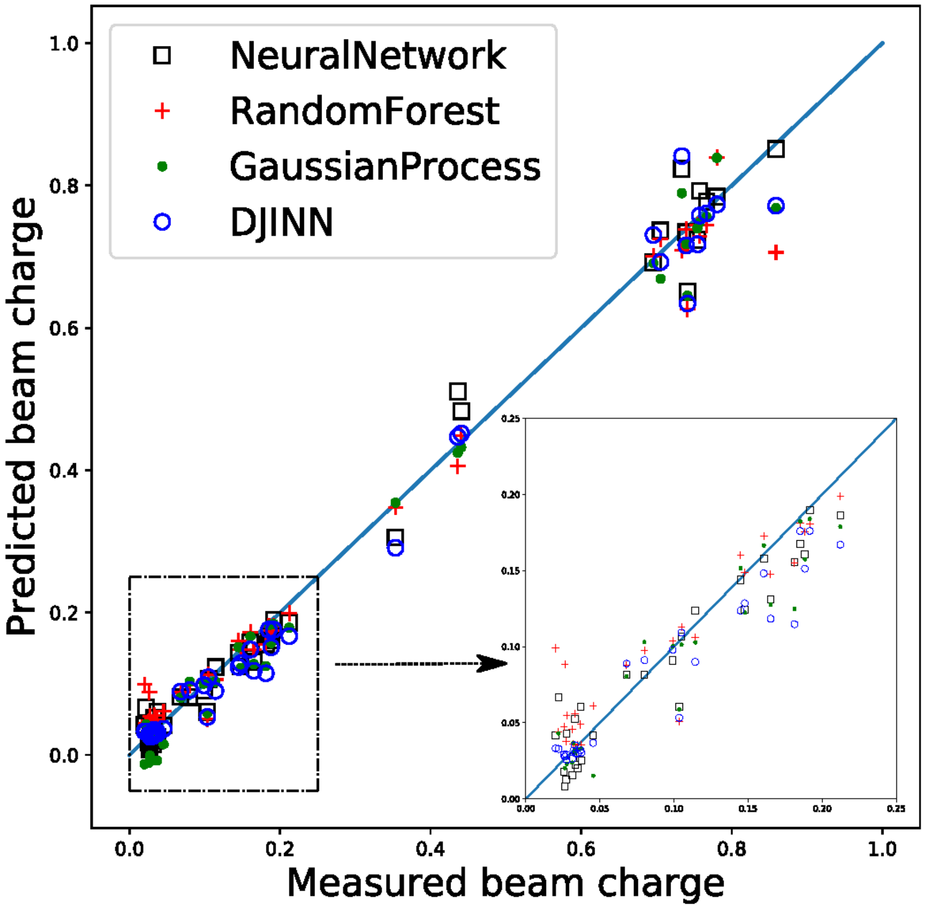


Feature Importance of Zernike coefficients

- ❑ Calculate prediction error of model f:
  $e = L\big(y, f(X)\big)$
- ❑ For each feature i:
  - ❑ Permute data values in feature i
  - ❑ Generate permuted feature matrix x^{perm}
  - ❑ Calculate prediction error of model f:
    $e^{perm} = L\big(y, f(X^{perm})\big)$
  - ❑ Obtain importance of the i^{th} feature = $e^{perm} - e$
- ❑ Sort importance of features in descending order

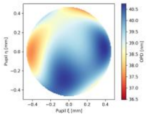
Importance

Model	1^{st}	2^{nd}	3^{rd}	4^{th}
Random Forest	0	6	1	10
Gaussian Process	1	10	0	6
Neural Network	0	10	1	3
DJINN	1	10	0	6
Correlation	0	10	1	13

Order of Zernike polynomials

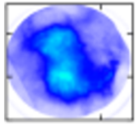
Molnar, Christoph. Interpretable Machine Learning. Lulu. com, 2020.

Evaluate model performance on every datapoint



X: Laser wavefront (feature)

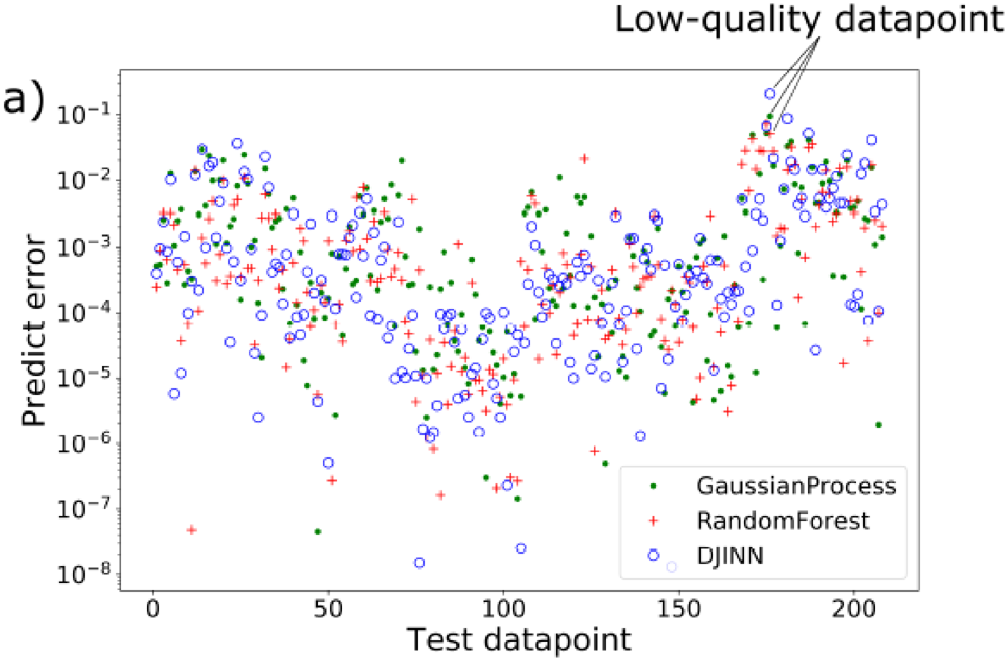
Dataset



Y: Electron beam charge (label)

All but 1 → Training dataset

1 → Test dataset



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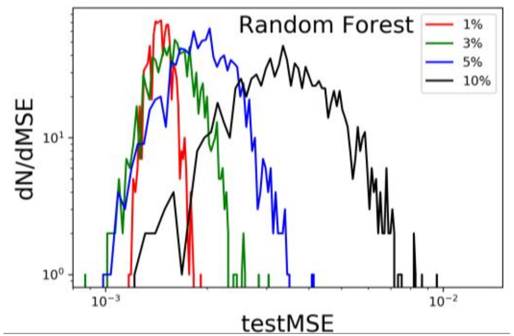
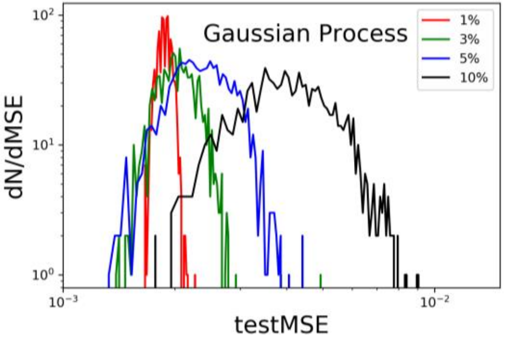
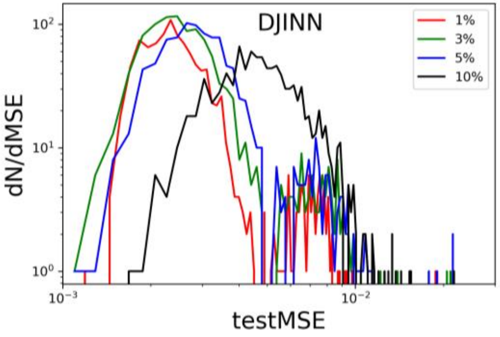
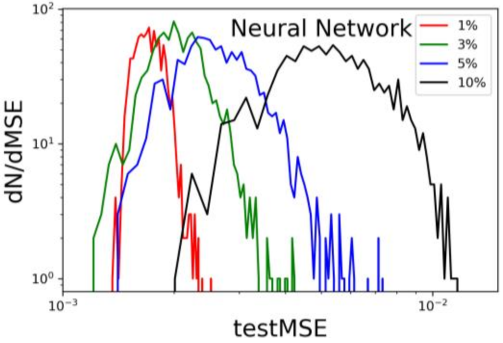
Model performance against virtual measurement errors









RF

Measure. Error	Mean	σ	Within σ	Within 2σ	Within 3σ
1%	1.47E-03	1.11E-04	67.8%	95.2%	99.6%
3%	1.64E-03	2.65E-04	69.8%	95.9%	99.3%
5%	2.04E-03	4.40E-04	70.8%	95.1%	99.2%
10%	3.83E-03	1.21E-03	70.2%	95.7%	99.4%

GP

Measure. Error	Mean	σ	Within σ	Within 2σ	Within 3σ
1%	1.88E-03	8.34E-05	69.0%	96.1%	99.5%
3%	2.07E-03	2.72E-04	70.4%	97.0%	99.6%
5%	2.46E-03	4.67E-04	68.5%	95.5%	99.5%
10%	4.37E-03	1.22E-03	69.6%	95.6%	99.5%

DJINN

Measure. Error	Mean	σ	Within σ	Within 2σ	Within 3σ
1%	2.9E-03	1.6E-03	91.3%	93.2%	97.4%
3%	3.2E-03	2.0E-03	90.1%	94.1%	98.3%
5%	3.6E-03	2.0E-03	88.3%	94.8%	98.4%
10%	5.3E-03	2.0E-03	74.6%	96.6%	98.7%

NN

Measure. Error	Mean	σ	Within σ	Within 2σ	Within 3σ
1%	1.73E-03	1.60E-04	69.8%	96.3%	98.9%
3%	2.14E-03	4.15E-04	74.1%	95.8%	98.9%
5%	2.83E-03	8.05E-04	75.2%	96.0%	98.2%
10%	5.93E-03	2.00E-03	70.9%	96.8%	98.9%

Summary

- Built four supervised learning regression models to predict the electron beam charge from the laser wavefront change
  - Evaluated model prediction : $MSE < 2 * 10^{-3}$ for all models
  - Random Forest fit our dataset better considering performances and computational cost
- ML enables feature analysis beyond just optimizing a target
  - Ranked the importance of Zernike coefficients in this LWFA process
- Analyzed data quality by evaluating models on every datapoint
- Included virtual measurement error

http://arxiv.org/abs/2011.05866

linjinp@umich.edu