Machine Learning in Laser System Optimization

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Overview of Applications and Methods

What is ML?

- ML model represents a statistically motivated heuristic for given task
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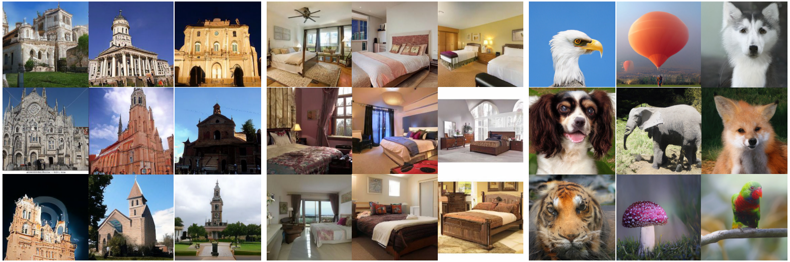

Rombach, R. et al. Proc. of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 10684, (2022)

What has ML been useful for?

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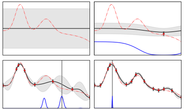
- Automation
- Generating insight into the non-linear structure of problems form a statistical perspective

ML Problem Types and Methods

Optimization

- Finding Optima in an objective fuction
  - pulse shape/spectrum optimization
  - compensating beam pointing



Shalloo, R. et al. Nat. Comm. 11(1) 6355 (2020)

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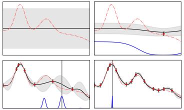

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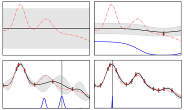

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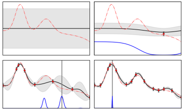

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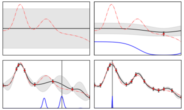

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  - Surrogate Modeling
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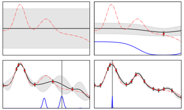

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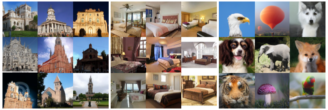

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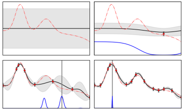

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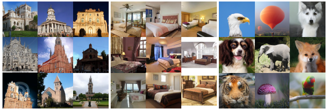

- Methods
  - GAN, VAE, Normalizing Flows, Diffusion Models, large transformer models, ...
  - Gaussian processes

Deep Learning

https://xkcd.com/1838/

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http://www.esa.int/spaceinimages/Images/2009/07/EDU_esa_exp_-_Launchers

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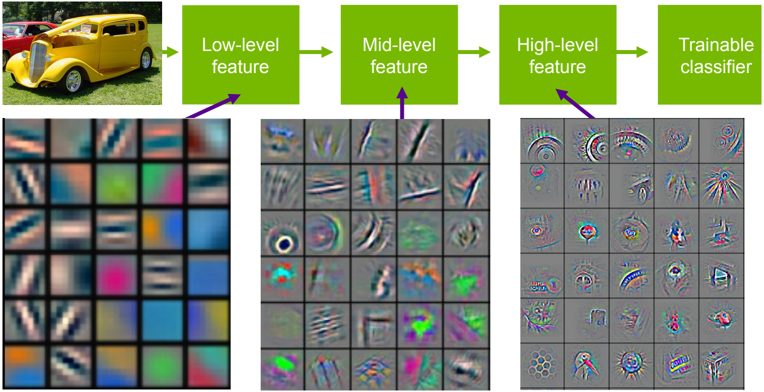
$\Leftarrow$ this is a cyle

ML vs Deep Learning?

A deep model is one which learns a hierarchy of features/concepts.



Data-Driven Digital Twins

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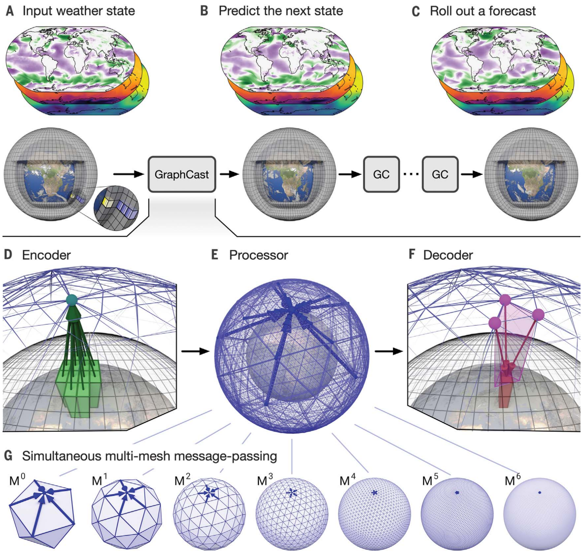
$\Rightarrow$ Data-driven digital twin can approximate system as-is.

Data-Driven Earth-Weather Twin: GraphCast



Lam et al., Science 382, 1416 (2023)

- Graph neural netork (GNN)
- message-passing on multimesh

- 10-day weather forecast in $< 1\,\mathrm{min}$
- accuracy $\gtrsim$ ECMWF-IFS HRES

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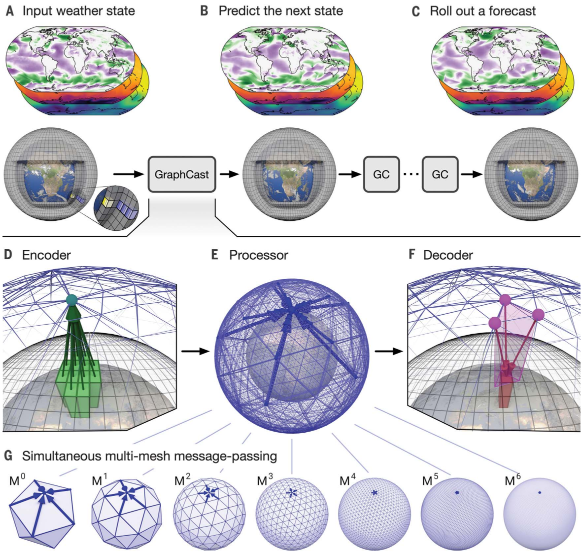

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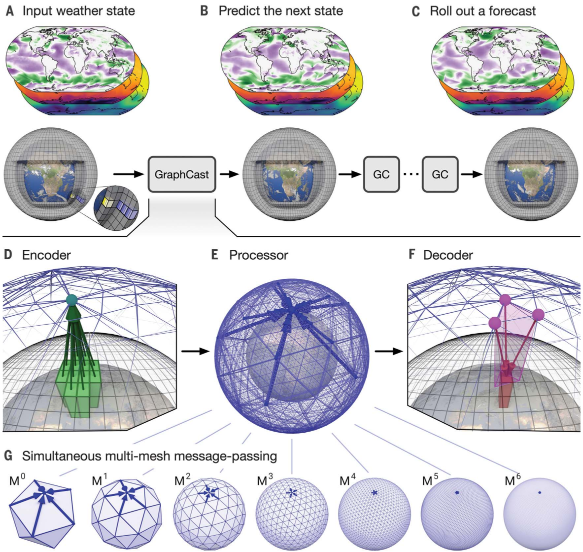

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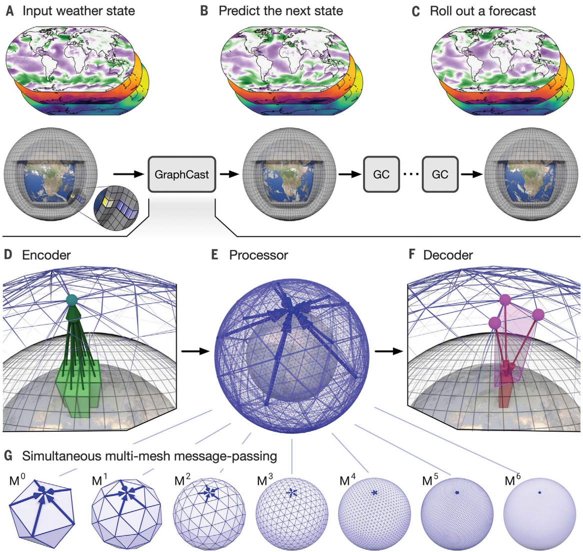

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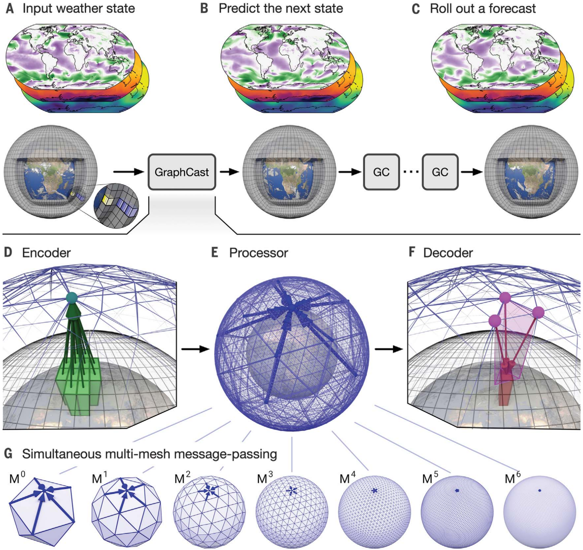

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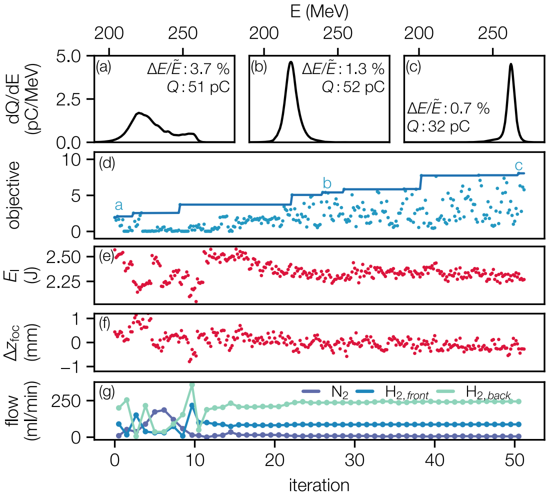
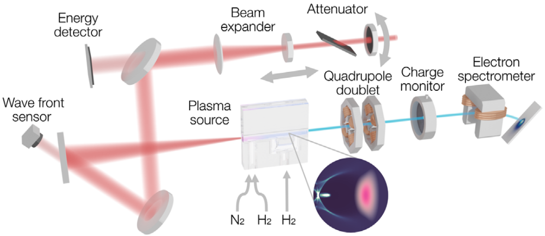
! trained on $\gtrsim 39\,\mathrm{y}$ of data (1979-2017) evaluated on following year

$\Rightarrow$ faster, more accurate, but less generalizable

Optimization

Bayesian Optimization



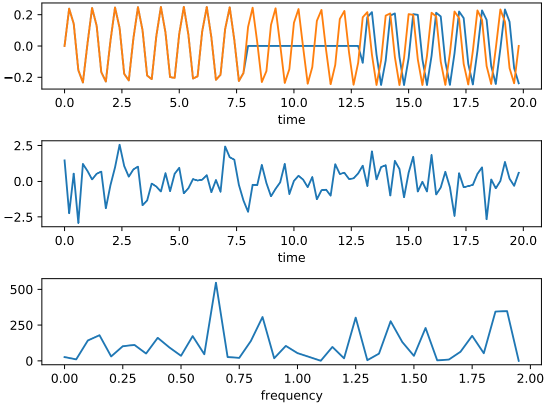


Jalas S. et al. PRL 126 104801 (2021)

Data

Getting a Signal from Samples

$n = 20$



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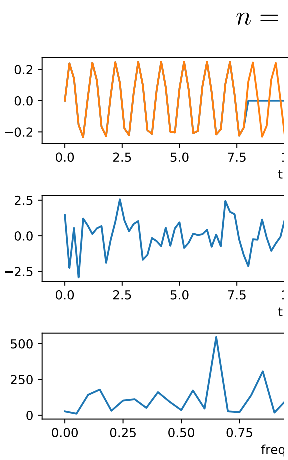

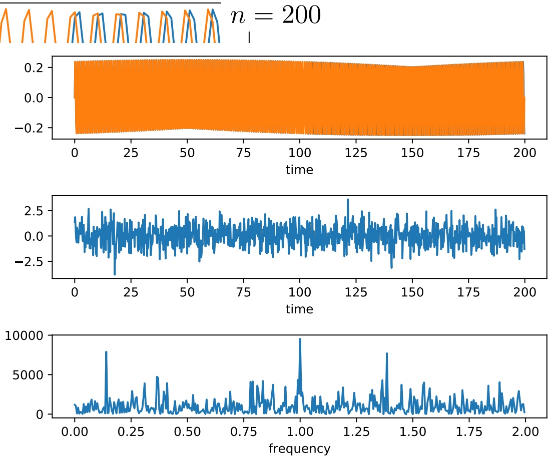

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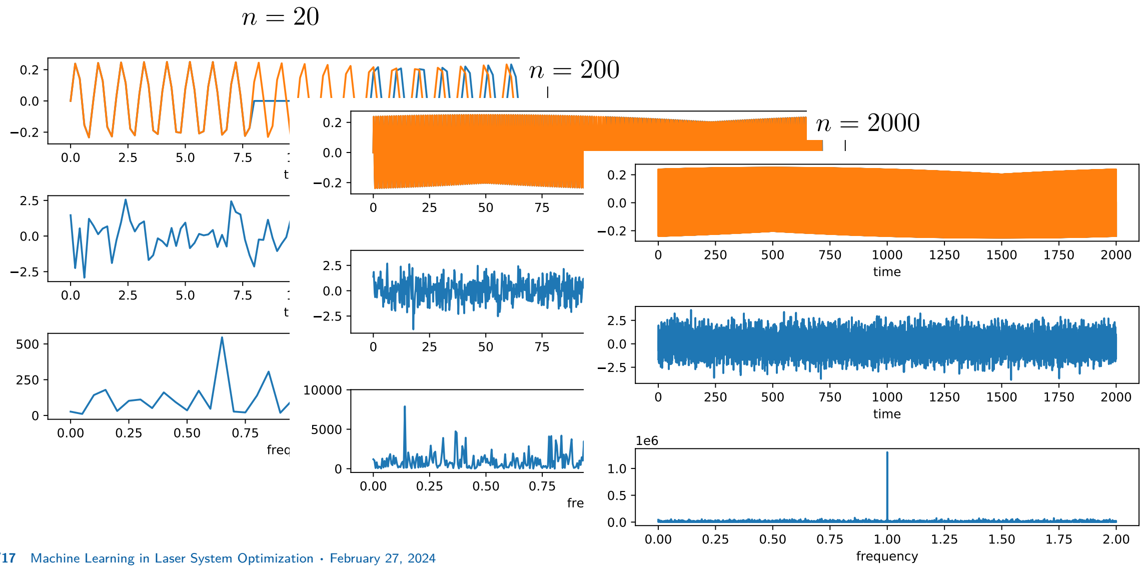

Summary

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  $\Rightarrow$ more data better statistics
- There is ahost of methods
  $\Rightarrow$ try basic analysis first to estimate what is in the data