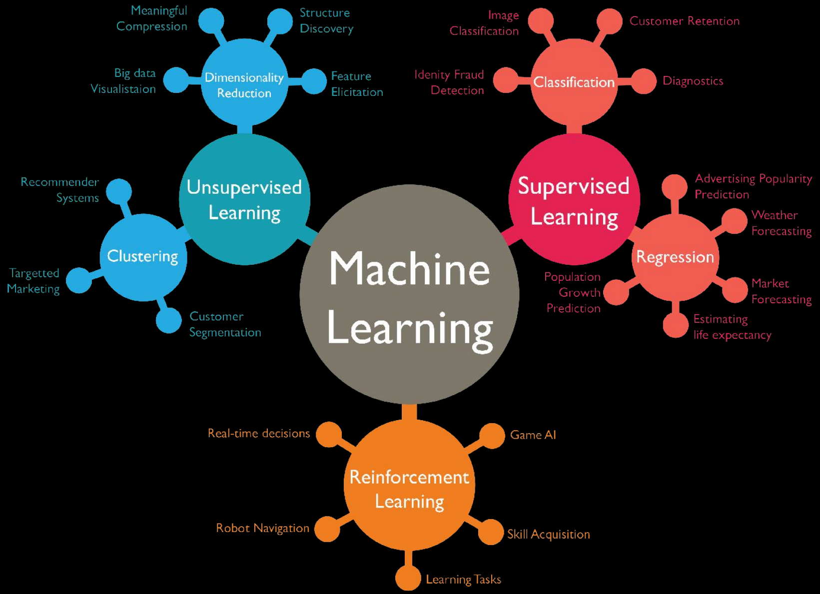
Machine learning skills useful for climate applications

Organizers:
Salva Rühling Cachay (UC San Diego, sruhlingcachay@ucsd.edu)
Lingwei Meng (Princeton University, lingweim@princeton.edu)

16th ANNUAL
GRADUATE CONFERENCE
Pack Forest, WA October 28 - 30, 2022

We will

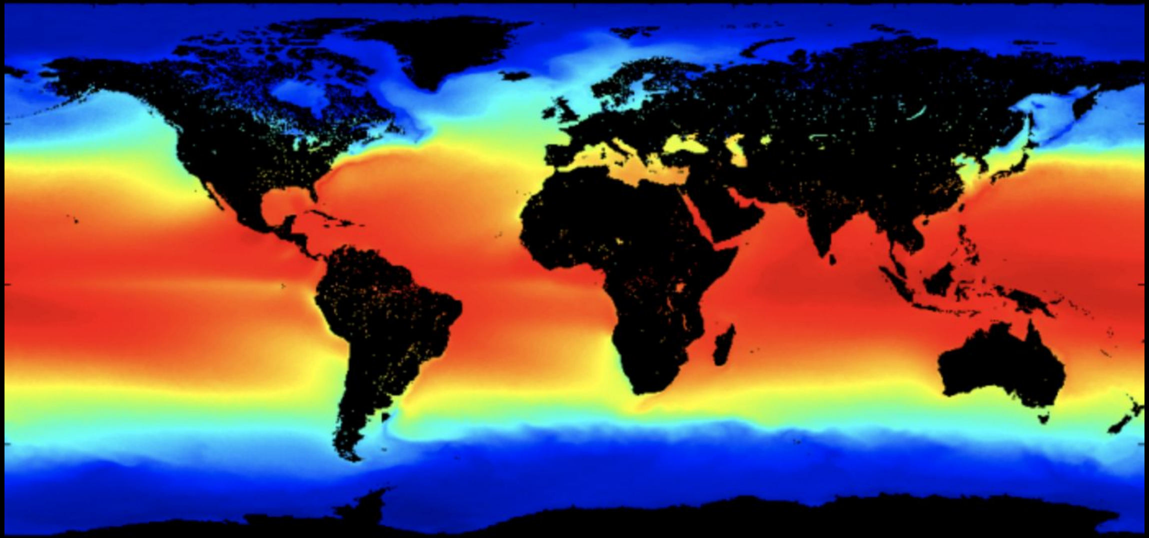
understand the basics of machine learning and some key use cases for climate problems.



We will

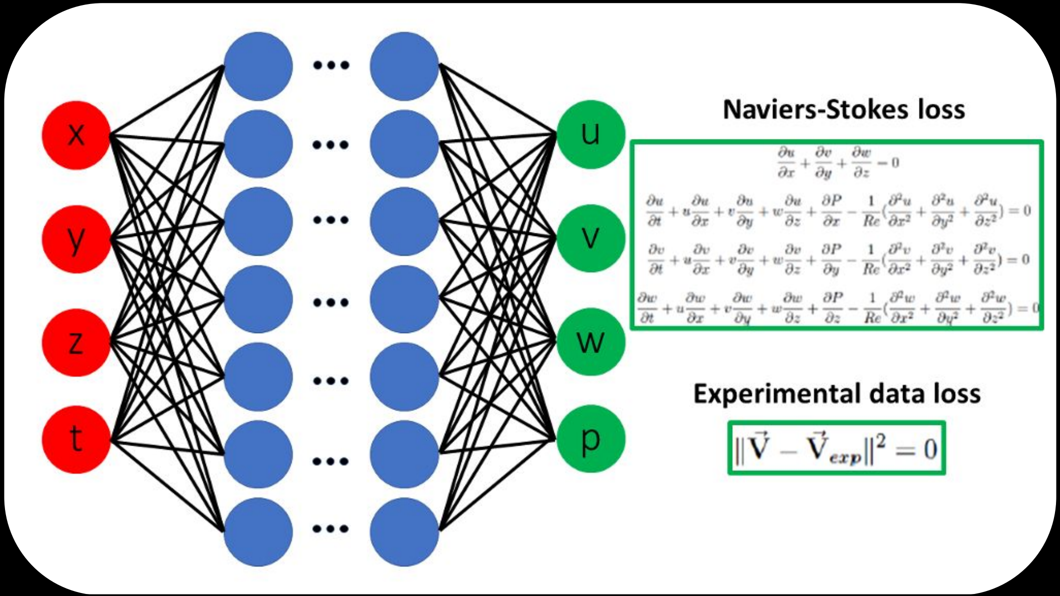
predict daily SST pattern based on PyTorch, become familiar with general idea and process of coding.

PyTorch



We will

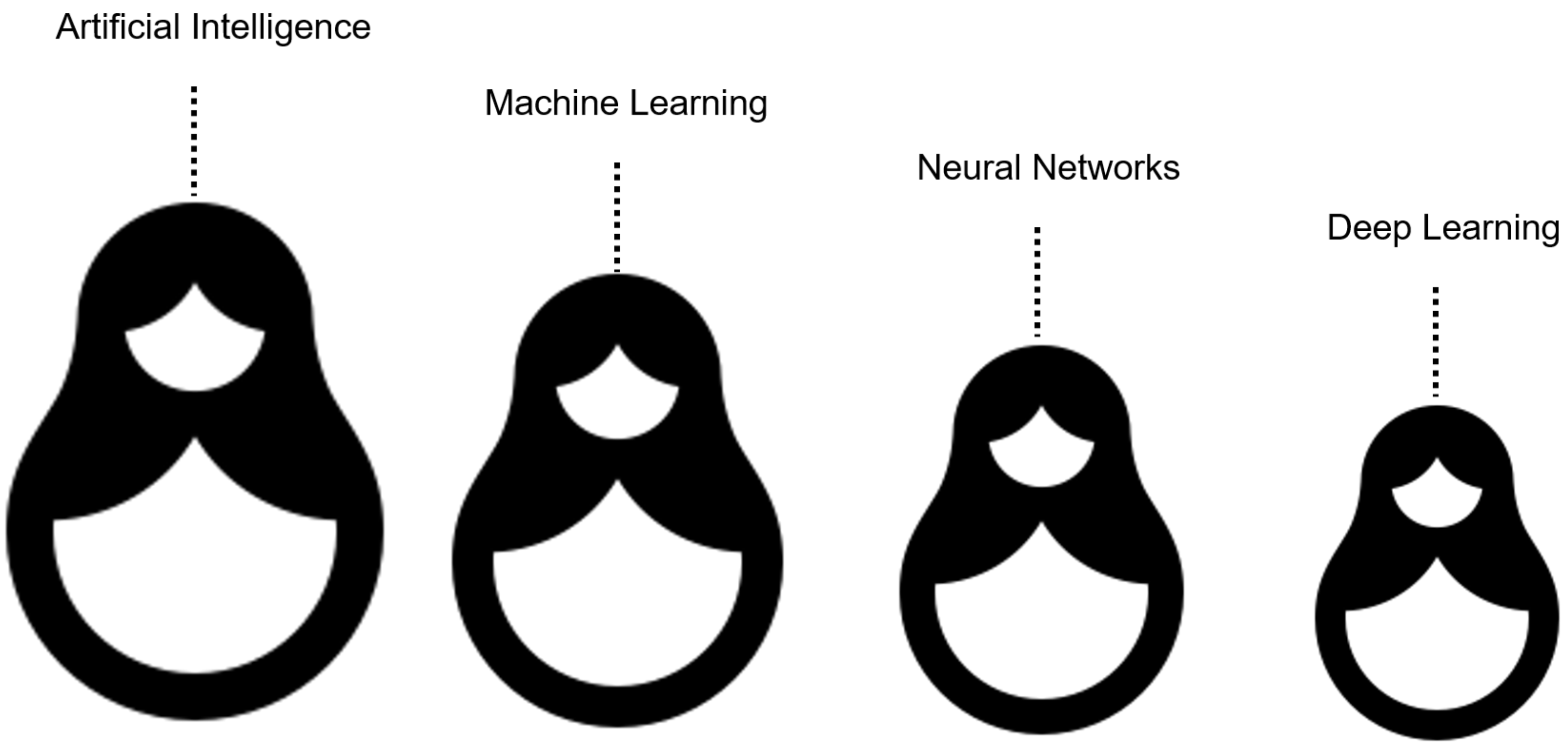
know how Neural Networks can be combined with Physics.

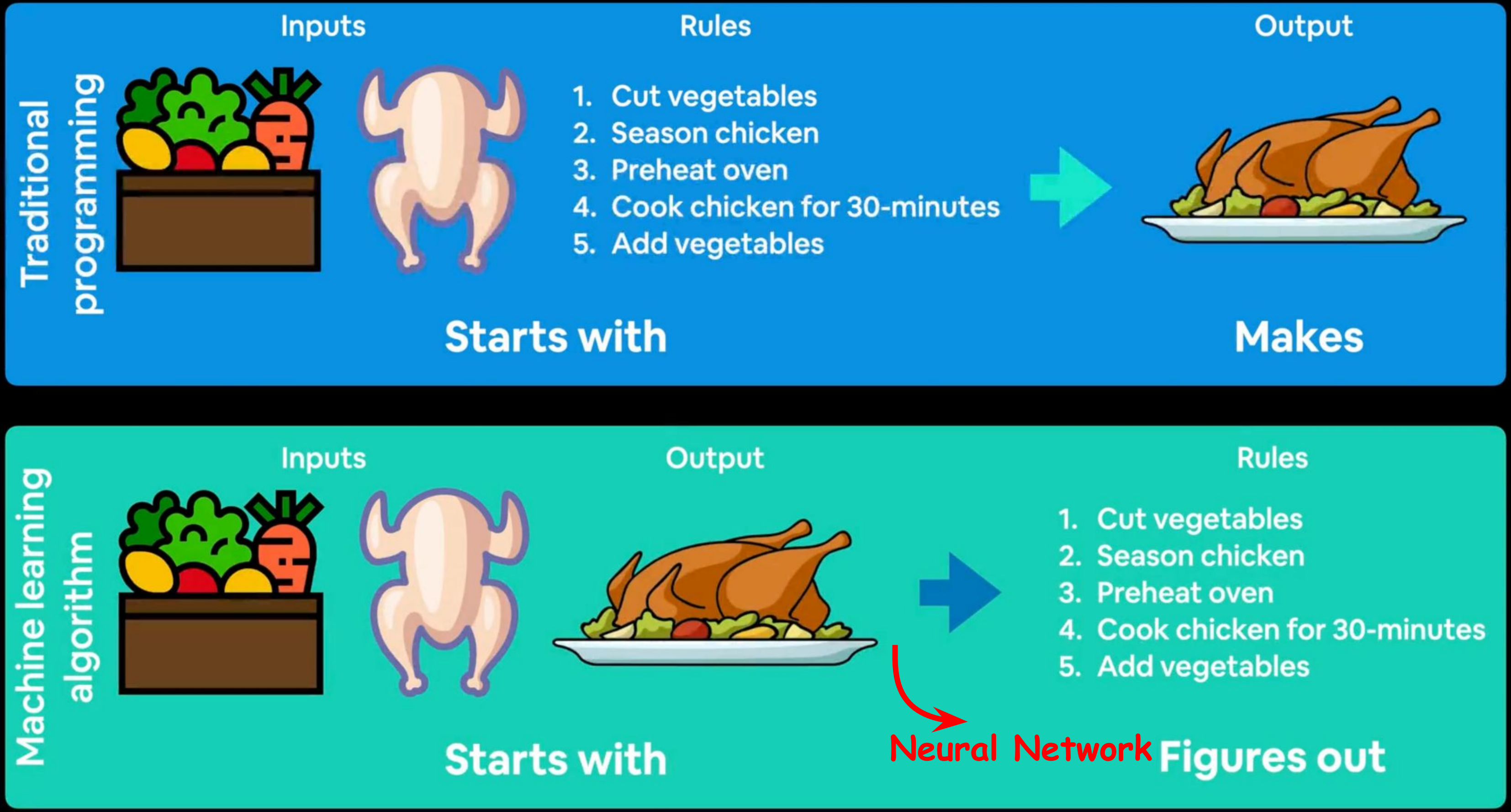


Agenda

• Intro	5 min
• What is / why / when to use Machine learning?	15 min
• Coding: Daily SST prediction with PyTorch.	30 min
• Intro to Physical Informed Neural Network (PINN).	10 min

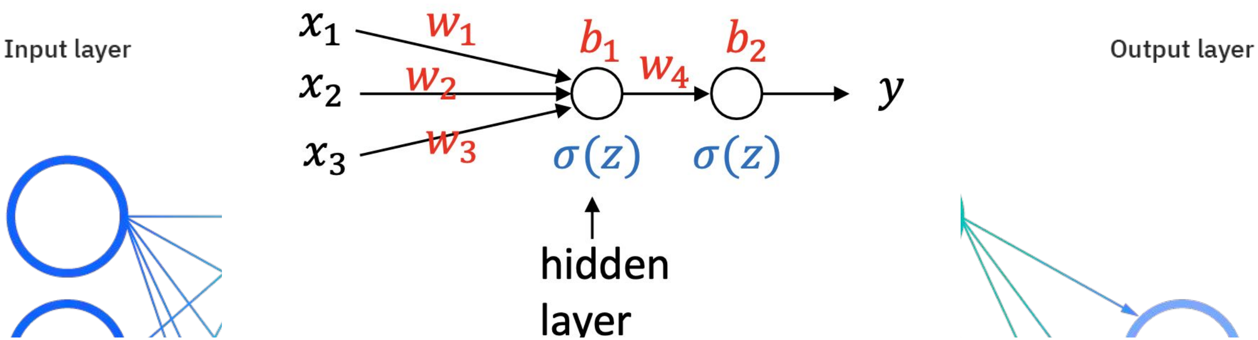
What is Machine learning?


Artificial Intelligence
Machine Learning
Neural Networks
Deep Learning



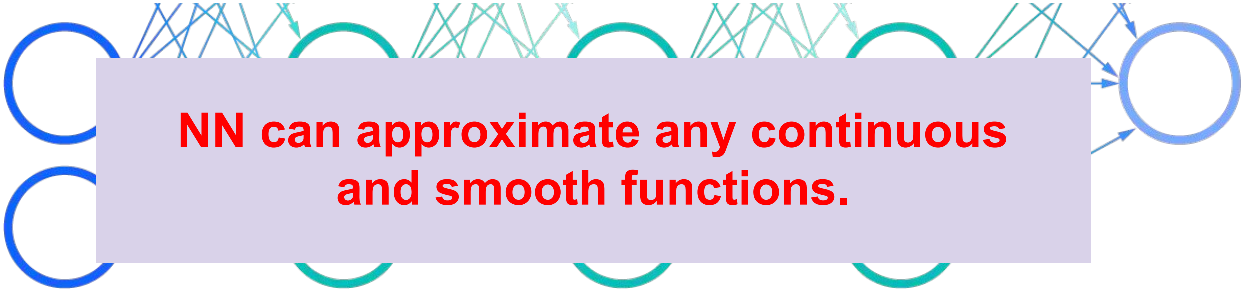
https://zerotomastery.io/courses/learn-pytorch/

NN: An analytical model of output y as a function of input x, containing some fitting parameters.



$$y = \sigma(w_4\sigma(w_1x_1 + w_2x_2 + w_3x_3 + b_1) + b_2),$$

where $\sigma(z)$ is a nonlinear activation function



NN can approximate any continuous and smooth functions.

Why Machine learning?

What ML is good for:

Problems with poorly understood mechanisms — when the traditional approach fails.

Discovering insights within large amounts of data

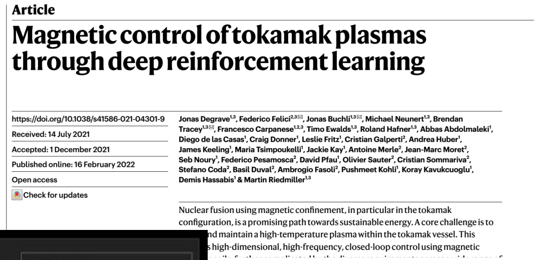
What ML is NOT good at:

When you need explainability — the patterns learned by ML are typically uninterpretable by a human.

When the input data are bad or overly limited — important for data to be clean and ensure it represents what you want

Generalization to out-of-distribution data — (e.g. trained on present-day data to predict on data heavily affected by climate change)

Overview - Some ML applications

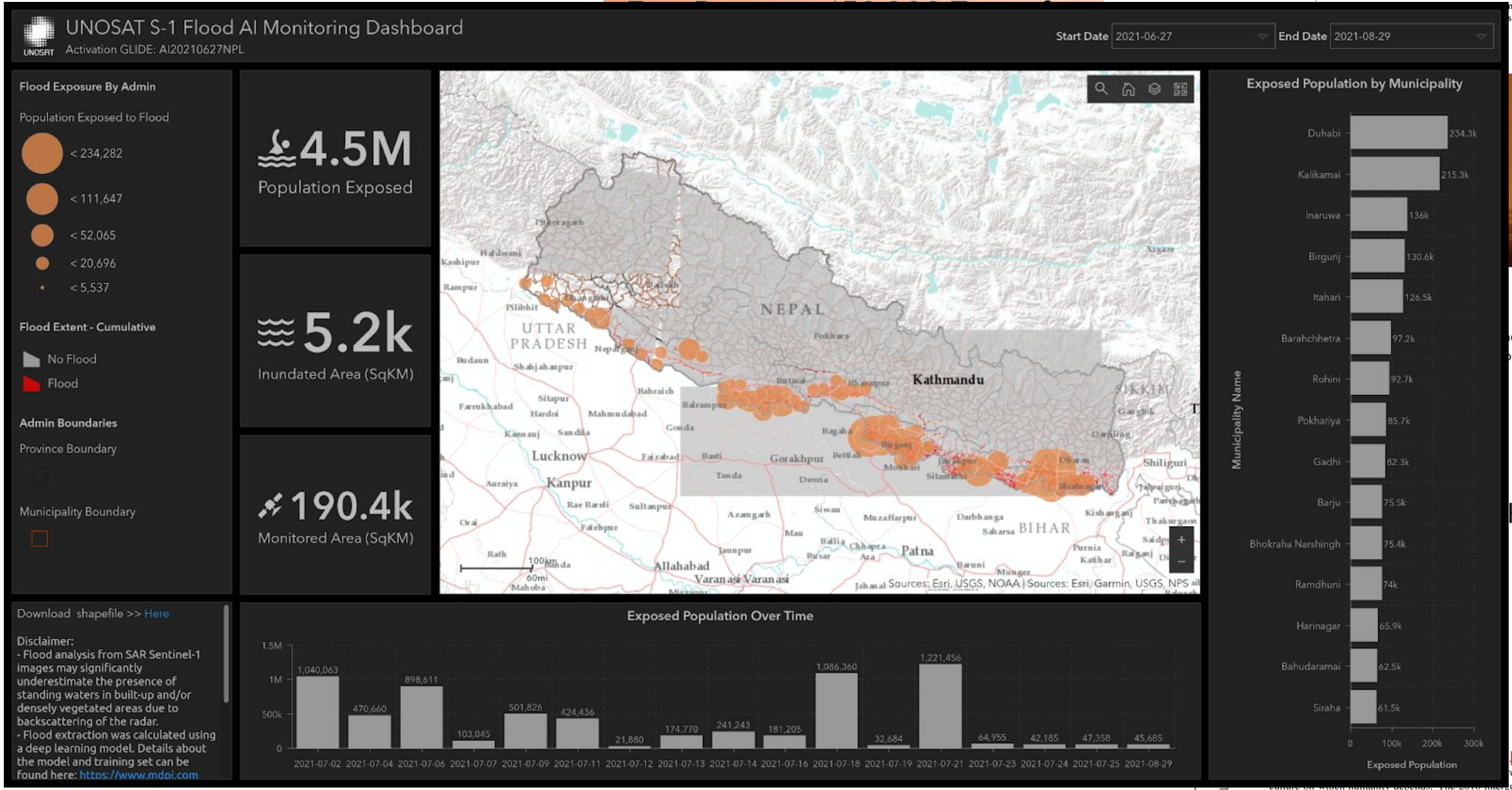

Article

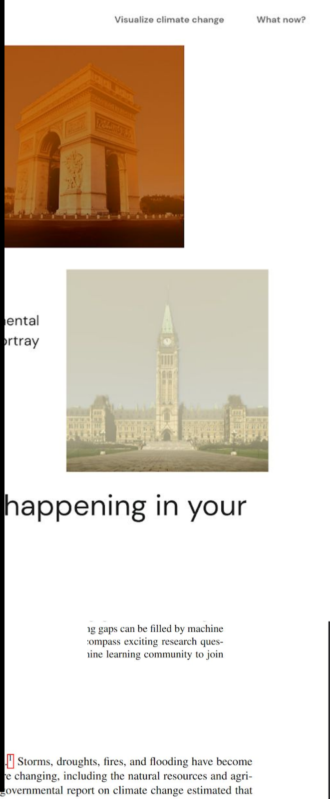
Magnetic control of tokamak plasmas through deep reinforcement learning

https://doi.org/10.1038/s41586-021-04301-9
Received: 14 July 2021
Accepted: 1 December 2021
Published online: 16 February 2022
Open access
Check for updates

Jonas Degrave, Federico Felici, Jonas Buchli, Michael Neunert, Brendan Tracey, Francesco Carpanese, Timo Ewalds, Roland Hafner, Abbas Abdolmaleki, Diego de las Casas, Craig Donner, Leslie Fritz, Cristian Galperti, Andrea Huber, James Keeling, Maria Tsimpoukelli, Jackie Kay, Antoine Merle, Jean-Marc Moret, Seb Noury, Federico Pesamosca, David Pfau, Olivier Sauter, Cristian Sommariva, Stefano Coda, Basil Duval, Ambrogio Fasoli, Pushmeet Kohli, Koray Kavukcuoglu, Demis Hassabis & Martin Riedmiller

Nuclear fusion using magnetic confinement, in particular in the tokamak configuration, is a promising path towards sustainable energy. A core challenge is to ...nd maintain a high-temperature plasma within the tokamak vessel. This ...s high-dimensional, high-frequency, closed-loop control using magnetic





Coding: Daily SST prediction with PyTorch

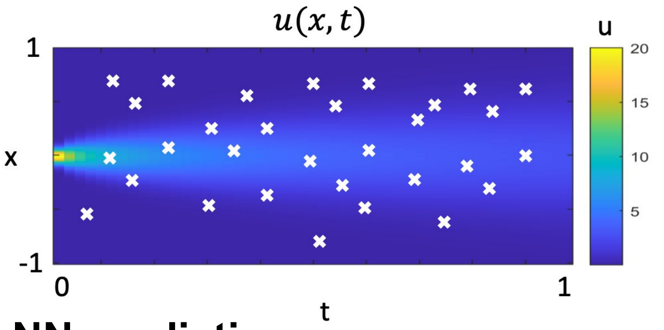
- **Github:** github.com/salvaRC/GCC2022-climate-machine-learning-workshop
- **Run it yourself on google colab**

Intro to Physical Informed Neural Network (PINN)

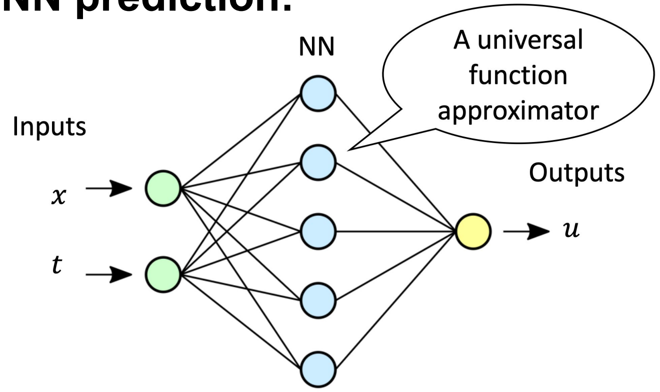
governing equations

Option 2: Find u(x,t) with a NN empirically

Training data (ground truth):



NN prediction:



GOAL: Find NN that minimizes the difference between groud truth and prediction (the loss function)

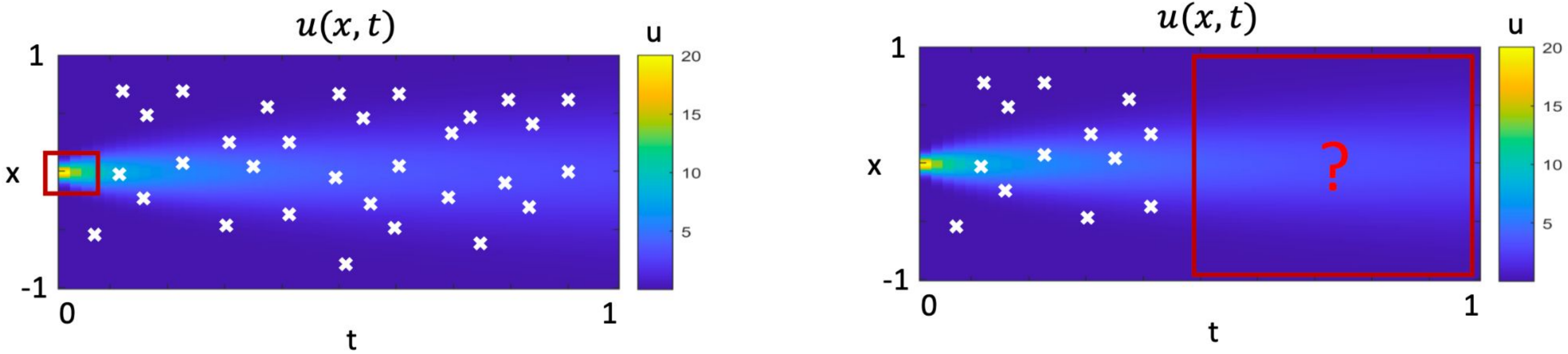
Loss function:

Data loss:

$$\text{minimize} \quad \frac{1}{N}\sum_{i}^{N}\left|u_i - u_{pred}(t_i, x_i)\right|^2$$

Problems of empirical learning

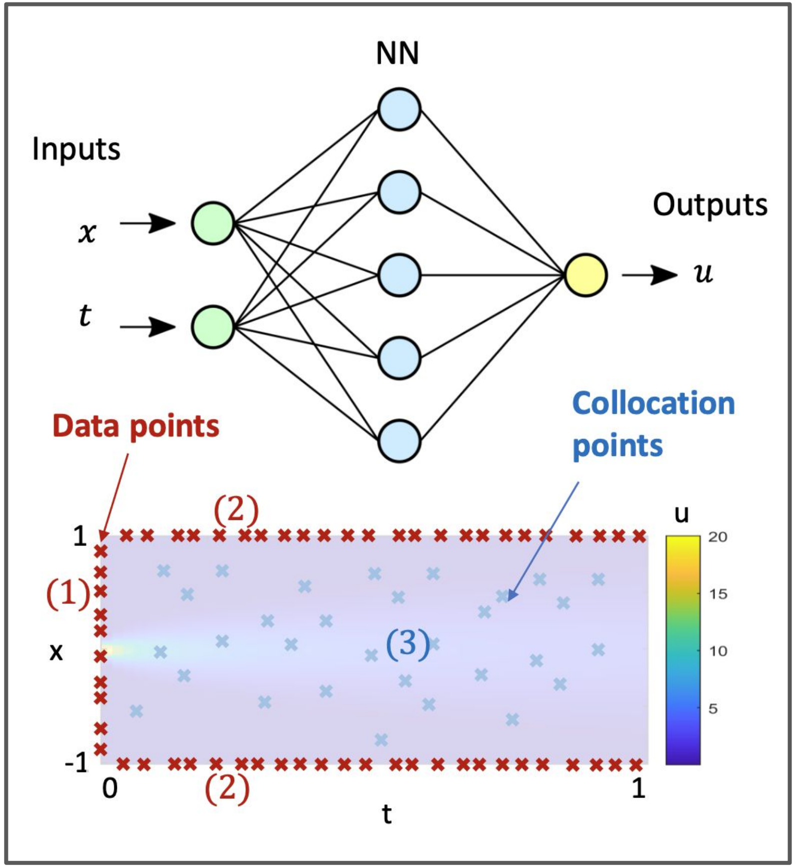
- NN will need lots of u training data to well approximate u(x,t).
- The learnt u(x,t) cannot be generalized to new t and x domains!



Can we use physical constraints to solve these problems?

$$\frac{\partial u}{\partial t} = a\frac{\partial^2 u}{\partial x^2}$$

Option 3: NN + (1) ICs + (2) BCs + (3) physics equation



$$\frac{\partial u}{\partial t} = a\frac{\partial^2 u}{\partial x^2} \qquad \boldsymbol{f} = \left[\frac{\partial u}{\partial t} - a\frac{\partial^2 u}{\partial x^2}\right] = \mathbf{0}$$

Equation loss:

minimize $\displaystyle \frac{1}{N_f}\sum_{k}^{N_f}\left|\frac{\partial u^k_{pred}}{\partial t} - a\frac{\partial^2 u^k_{pred}}{\partial x^2}\right|^2$ (3) Eqn

Cost function: (MSE: mean squared error)

$$MSE = \underbrace{MSE_u}_{\text{Data loss}} + \underbrace{MSE_f}_{\text{Equation loss}},$$

$$\frac{1}{N_u}\sum_{i=1}^{N_u}|u(t_u^i, x_u^i) - u^i|^2, \qquad \frac{1}{N_f}\sum_{i=1}^{N_f}|f(t_f^i, x_f^i)|^2$$

Data points

Collocation points

Some Climate+AI communities, groups, institutes..

- Climate Change AI - great community, social hours, conference workshops, summer school & more
- NOAA Center for AI
- NSF AI Institute on Trustworthy AI in Weather, Climate, and Coastal Oceanography (AI2ES)
- Berkeley AI Climate Initiative & seminar
- LEAP (NSF Center at Columbia)
- Some groups at MIT: https://github.com/blutjens/awesome-MIT-ai-for-climate-change
- Community at the European AI research network ELLIS: https://ellis.eu/programs/machine-learning-for-earth-and-climate-sciences
- Ongoing AI for Global Climate Cooperation competition by Salesforce & Mila
- Strong AI focus at the digital twin initiatives at ECMWF and NVIDIA
- Weather/Climate teams also at Google, Microsoft, IBM … & many start-ups in the area!
- Climate modeling team at the Allen Institute for AI (AI2) – in Seattle!

Some Pointers – Papers

- *Tackling Climate Change with Machine Learning*, in ACM Computing Surveys
- *Machine-learning-based evidence and attribution mapping of 100,000 climate impact studies*, in Nature Climate Change, 2021
- *Shipping regulations lead to large reduction in cloud perturbations*, in PNAS 2022
- *Skilful precipitation nowcasting using deep generative models of radar*, in Nature, 2021
- *Deep learning for multi-year ENSO forecasts*, in Nature, 2019
- *Deep learning and process understanding for data-driven Earth system science*, in Nature perspectives, 2019