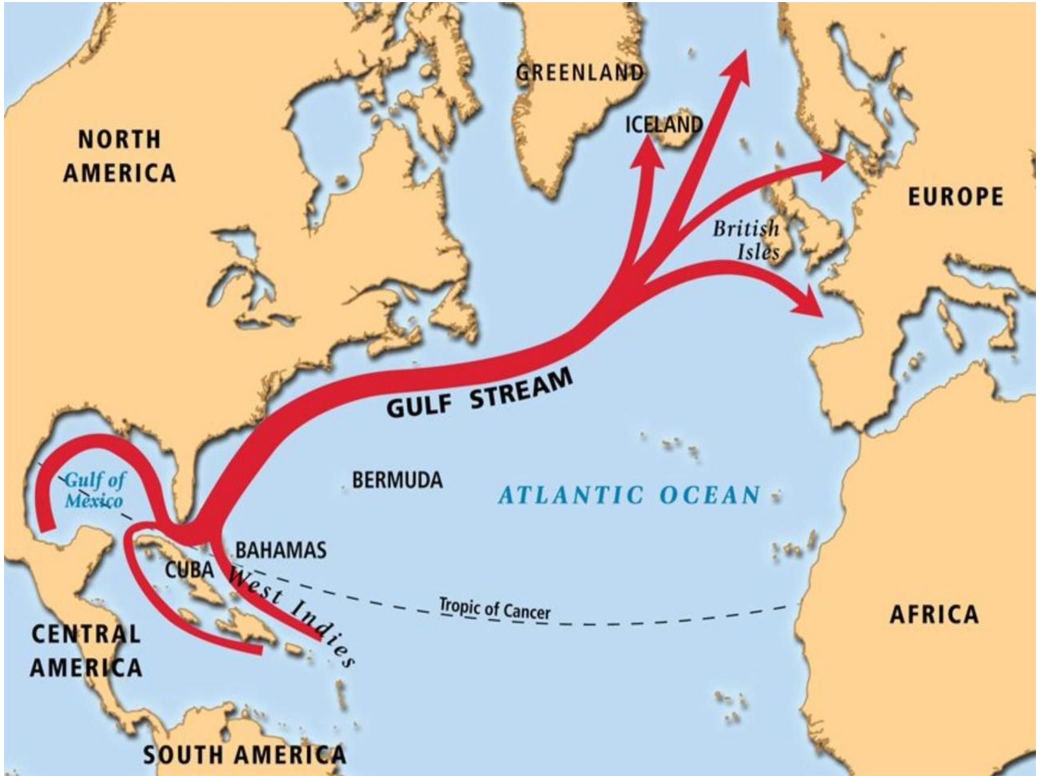
Deep Learning for Physics

Foundations of AI’s masterclass



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Past
Master in Machine Learning - Télécom ParisTech (Sophia Antipolis)
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Neural Networks for the Modeling of Ocean Surface Dynamics
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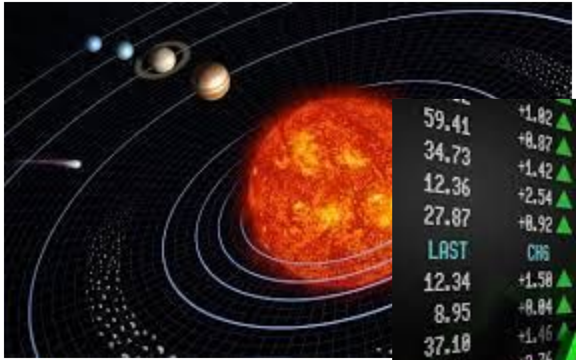
Modeling Dynamical Systems

System = a set of things working together as parts of a mechanism

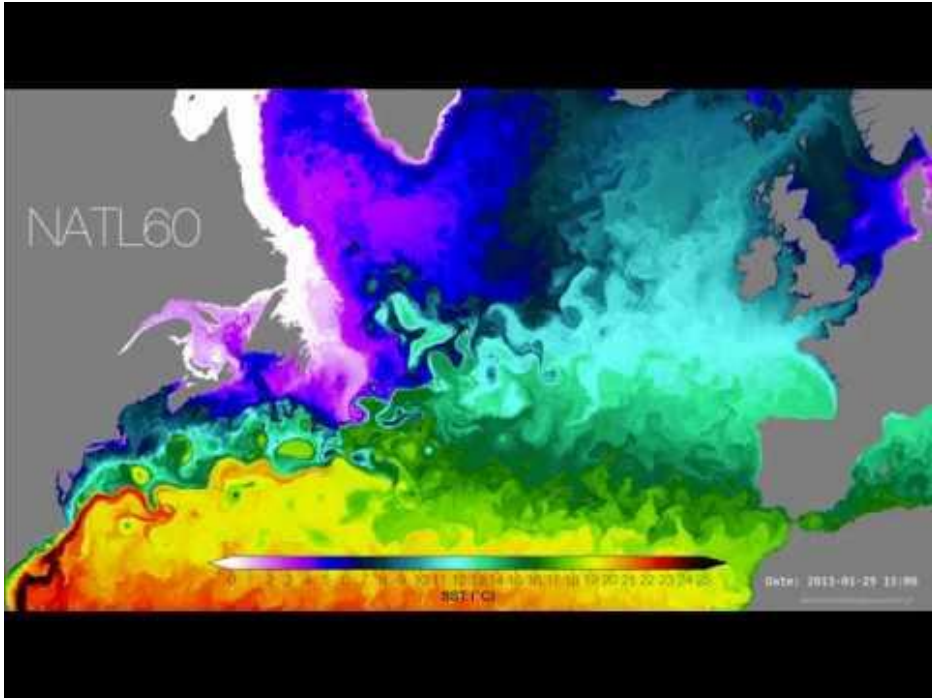
Dynamical system = system and a law describing the evolution of the system

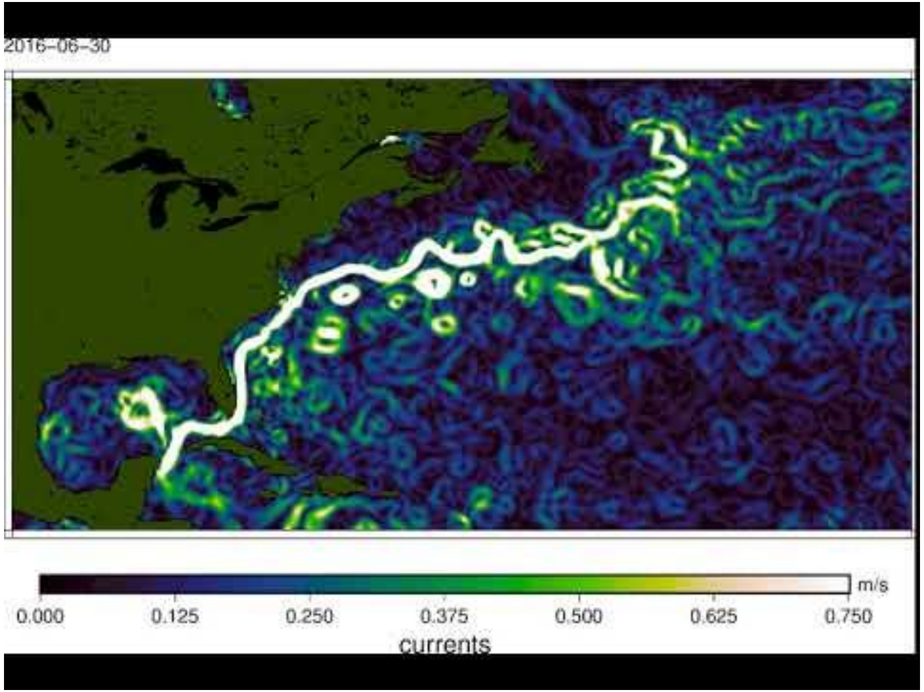


We are interested in predicting the evolution of the system of interest.

→ we seek for the law describing the evolution of the system

Ocean Surface Dynamics





Ocean Modeling

Necessary to model climate.

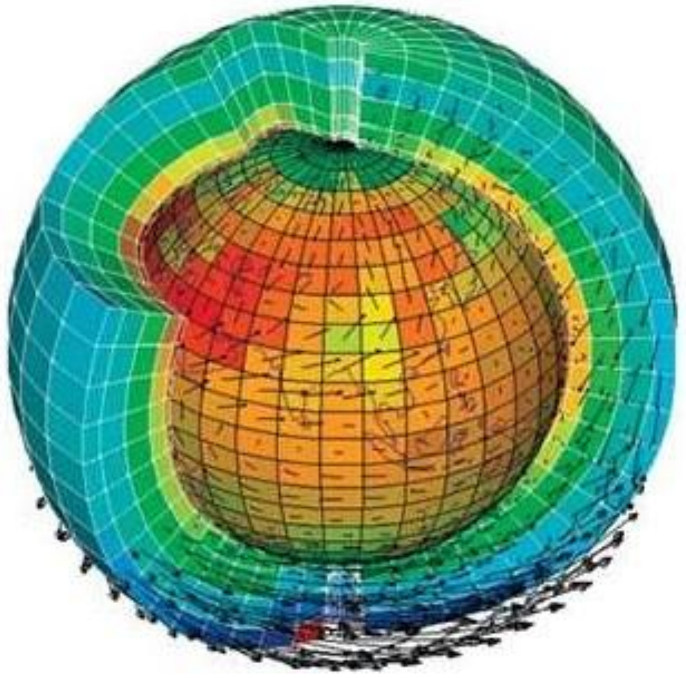
Rely on a very old knowledge…
Claude-Louis Navier (1822) and George Gabriel Stokes (1840s) described the motion of viscous fluid substances with **differential equations**:

$$\frac{\partial X_t}{\partial t} = f(X_t, t)$$

where X_t stands for temperature, pressure, currents velocity, salinity, heat exchanges,...

Traditional approach : we know f and use it to predict X_t at future timesteps.

Ocean Modeling



- Ocean models are based on a 3D grid representing the entire ocean
- Each variable is constant for each grid point.
- Current model : grid points with 100km-sides

Problems still unsolved…
- Computationally infeasible to run models at fine resolution in space and time
- Processes which are not completely understood
- Uncertainty Quantification

Data-driven models and physics

- Success of machine learning (ML) for multiple tasks in computer vision, NLP,...
- Available data (satellites, floats,...)
- How could ML help for physics ?

$$\frac{\partial X_t}{\partial t} = f(X_t, t)$$

Models rely on a new approach : we learn f to predict X_{t+1}

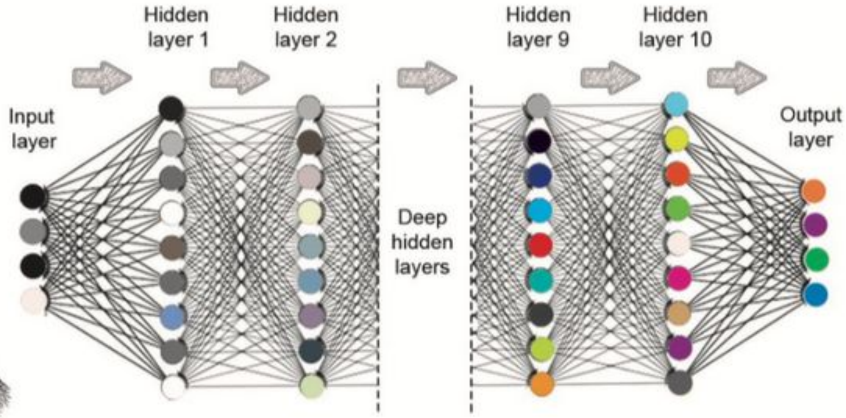
Note the paradigm shift : such models don't rely on physical knowledge !

Problems:

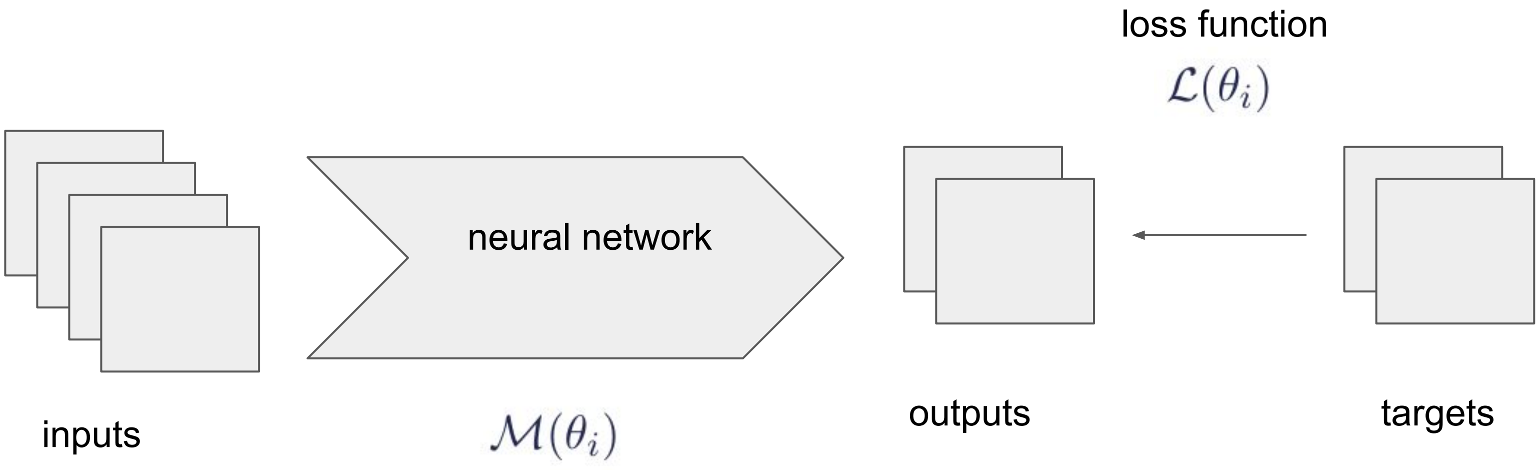
- Complex systems : lots of interactions, lots of variables
- Interpretability : we want our model to respect the underlying physics
- Learning may be unsupervised

Best of both worlds ?

Physics-guided learning is a very recent topic…
2 publications in 2017, 8 in 2018, 27 in 2019, 63 in 2020 !



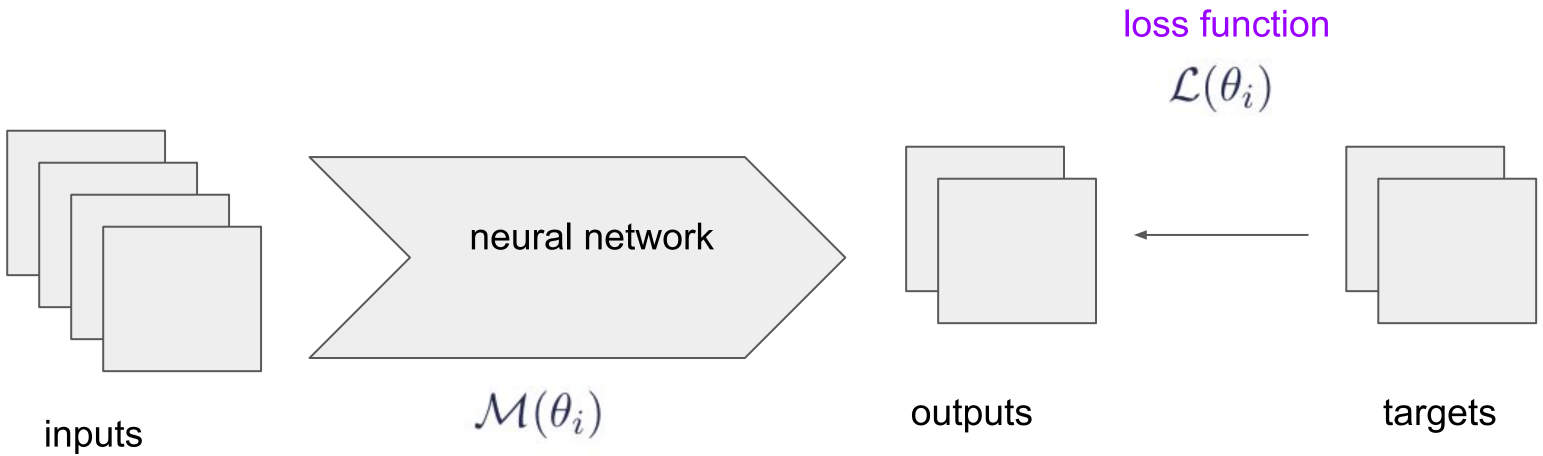
Physics-guided learning



Inputs: coordinates (latitude, longitude), variable of interest (ex: temperature), …
Outputs: variable at coordinates, prediction, ...

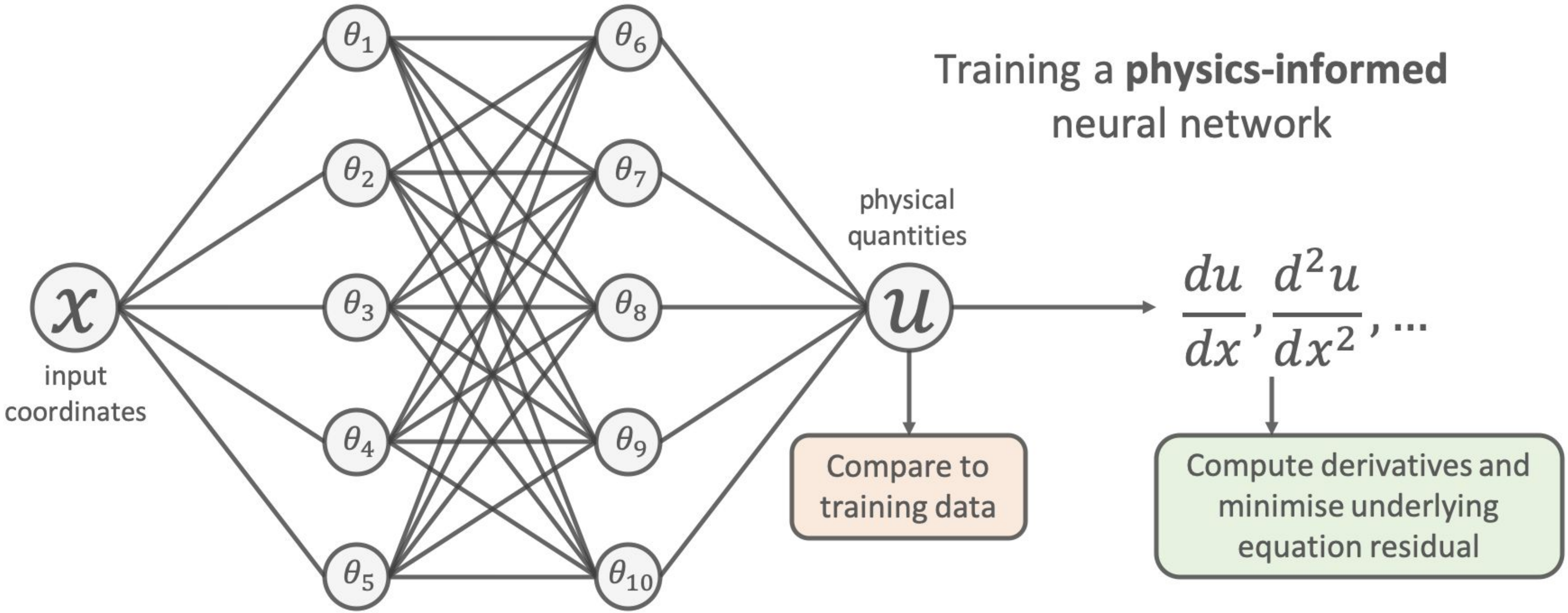
How to integrate scientific knowledge into the ML framework ?

Physics-guided learning

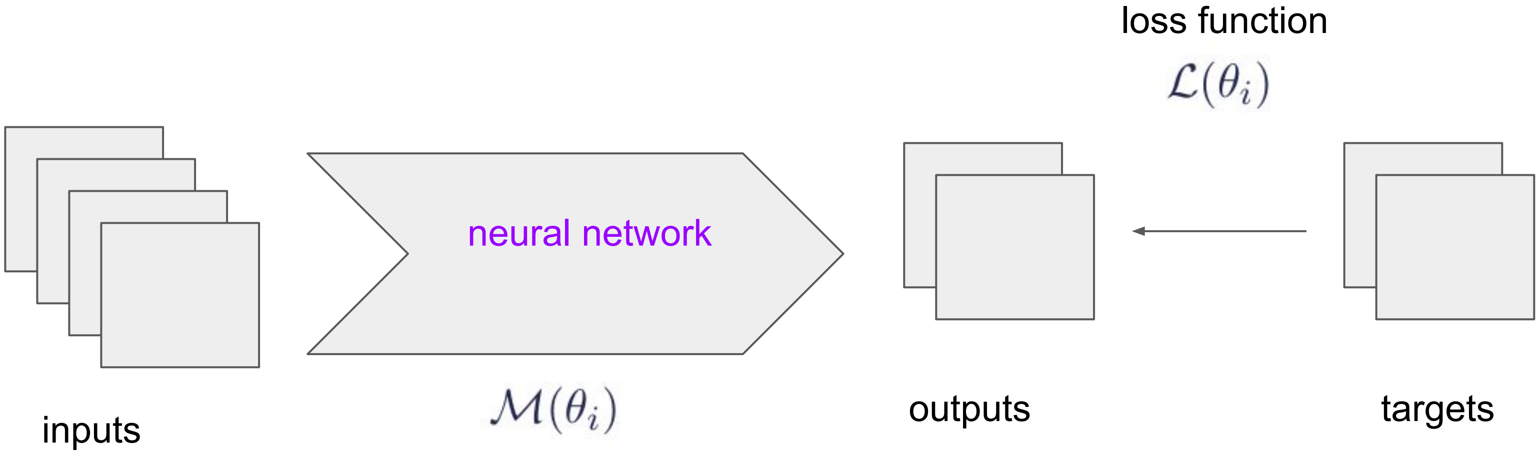


Physics-guided learning

Physics-informed neural network



Physics-guided learning



New area of research : hybrid physics-ML modeling

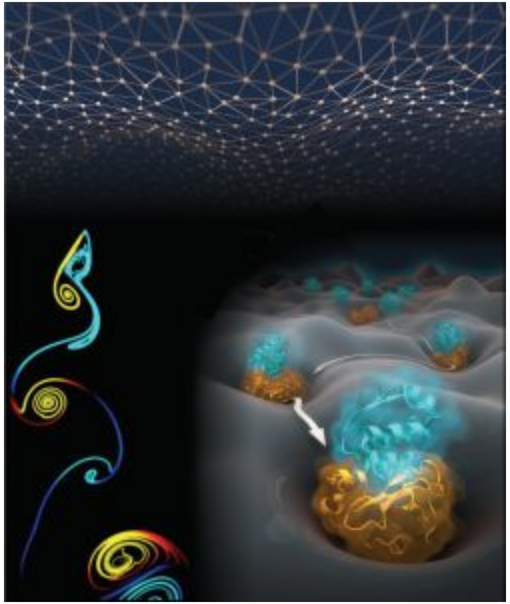
$$\frac{\partial X_t}{\partial t} = f(X_t, t) = (f_p + f_d)(X_t, t)$$

the known part of the dynamics (physical knowledge)

the unknown part of the dynamics (to be learnt)

Conclusion

- Two paradigms to model dynamical systems : knowledge-based and data-driven
- Physics-guided learning : how to integrate knowledge into the ML framework ?
- Lots of possible applications…



Thank you very much !

Hybrid Physics-ML models

$$\frac{\partial X_t}{\partial t} = f(X_t, t) = (f_p + f_d)(X_t, t)$$

where f is the dynamics associated to X_t

which we decompose into

f_p the known part of the dynamics (physical knowledge)
it relies on physical knowledge, but still depends on unknown parameters θ_p such that

$$f_p = f_p(\theta_p)$$

f_d the unknown part of the dynamics (to be learnt)

Hybrid Physics-ML models

$$\frac{\partial X_t}{\partial t} = f(X_t, t) = (f_p + f_d)(X_t, t)$$

Possible pitfall:

- f_d may learn all the dynamics f
- In this case, the hybrid model has no physical sense anymore !

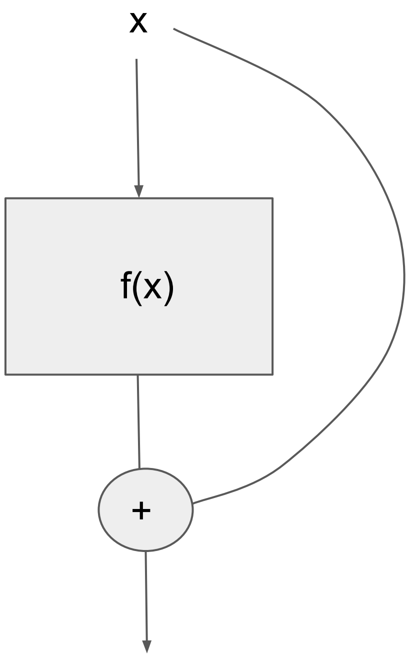
→ We have to constrain both f_p and f_d

Physics-guided learning

Physics-guided design of architecture
Established link between residual networks and

$$\frac{\partial X_t}{\partial t} = f(X_t, t)$$

$$X_{t+\Delta t} = X_t + \Delta t f(X_t, t)$$



Hybrid Physics-ML ocean models

$$\frac{\partial T}{\partial t} = -\nabla.(TU) + D^T + F^T$$
$$= f_p(T,U) + f_d(T)$$

where T is the surface temperature. It is observed with satellites.
U is the surface velocity. It is unobserved !

f_p the known part of the dynamics (physical knowledge)
it relies on physical knowledge, but still depends on unknown parameters U

f_d the unknown part of the dynamics (to be learnt)

Hybrid Physics-ML ocean models

$$\frac{\partial T}{\partial t} = -\nabla.(TU) + D^T + F^T$$
$$= f_p(T, U) + f_d(T)$$

We have to learn both U and f_d

Possible pitfall:

- f_d may learn all the dynamics
- In this case, the hybrid model has no physical sense anymore !

→ We have to constrain both f_p and f_d