Interactions between ocean scientists and ML scientists: timeliness and instruments in the context of SWOT ?

SWOT ST meeting
Bordeaux, 19 juin, 2019

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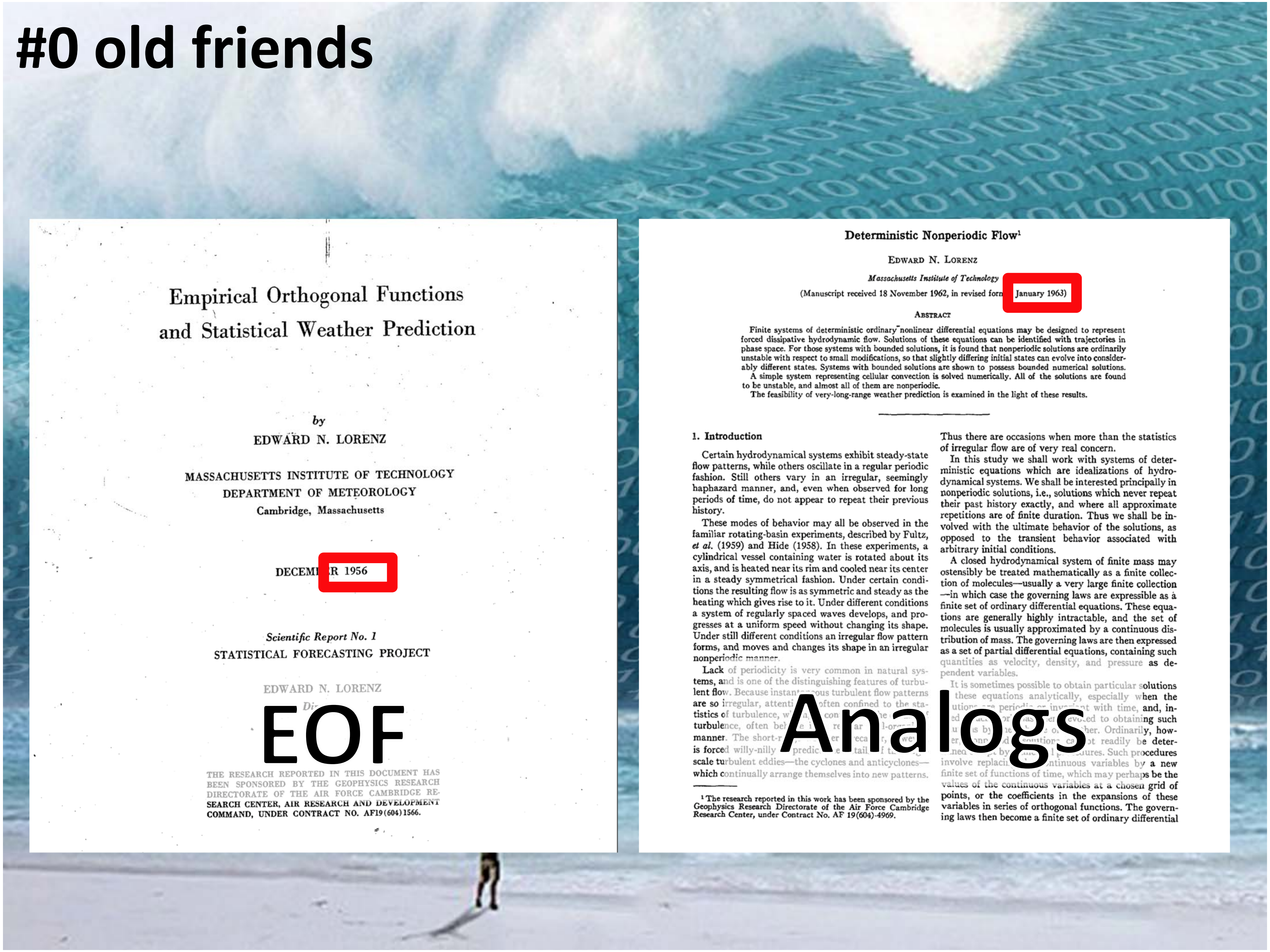
#0 old friends



Empirical Orthogonal Functions and Statistical Weather Prediction

by

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MASSACHUSETTS INSTITUTE OF TECHNOLOGY
DEPARTMENT OF METEOROLOGY
Cambridge, Massachusetts

DECEMBER 1956

Scientific Report No. 1
STATISTICAL FORECASTING PROJECT

EDWARD N. LORENZ
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Deterministic Nonperiodic Flow[1]

EDWARD N. LORENZ

Massachusetts Institute of Technology

(Manuscript received 18 November 1962, in revised form January 1963)

ABSTRACT

Finite systems of deterministic ordinary nonlinear differential equations may be designed to represent forced dissipative hydrodynamic flow. Solutions of these equations can be identified with trajectories in phase space. For those systems with bounded solutions, it is found that nonperiodic solutions are ordinarily unstable with respect to small modifications, so that slightly differing initial states can evolve into considerably different states. Systems with bounded solutions are shown to possess bounded numerical solutions.

A simple system representing cellular convection is solved numerically. All of the solutions are found to be unstable, and almost all of them are nonperiodic.

The feasibility of very-long-range weather prediction is examined in the light of these results.

1. Introduction

Certain hydrodynamical systems exhibit steady-state flow patterns, while others oscillate in a regular periodic fashion. Still others vary in an irregular, seemingly haphazard manner, and, even when observed for long periods of time, do not appear to repeat their previous history.

These modes of behavior may all be observed in the familiar rotating-basin experiments, described by Fultz, *et al.* (1959) and Hide (1958). In these experiments, a cylindrical vessel containing water is rotated about its axis, and is heated near its rim and cooled near its center in a steady symmetrical fashion. Under certain conditions the resulting flow is as symmetric and steady as the heating which gives rise to it. Under different conditions a system of regularly spaced waves develops, and progresses at a uniform speed without changing its shape. Under still different conditions an irregular flow pattern forms, and moves and changes its shape in an irregular nonperiodic manner.

Lack of periodicity is very common in natural systems, and is one of the distinguishing features of turbulent flow. Because instantaneous turbulent flow patterns are so irregular, attenti[illegible] often confined to the statistics of turbulence, [illegible] turbulence, often [illegible] manner. The short-r[illegible] is forced willy-nilly [illegible] predic[illegible] scale turbulent eddies—the cyclones and anticyclones—which continually arrange themselves into new patterns.

Thus there are occasions when more than the statistics of irregular flow are of very real concern.

In this study we shall work with systems of deterministic equations which are idealizations of hydrodynamical systems. We shall be interested principally in nonperiodic solutions, i.e., solutions which never repeat their past history exactly, and where all approximate repetitions are of finite duration. Thus we shall be involved with the ultimate behavior of the solutions, as opposed to the transient behavior associated with arbitrary initial conditions.

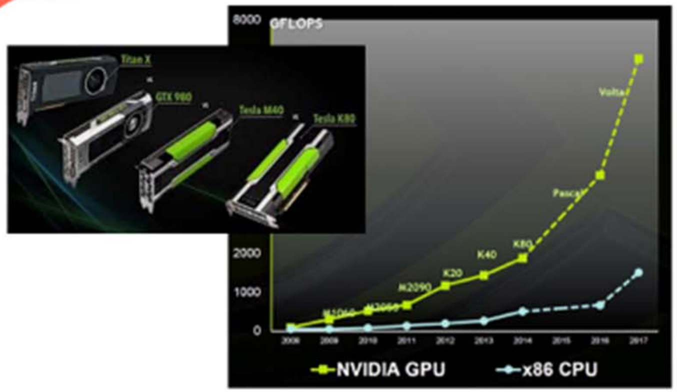
A closed hydrodynamical system of finite mass may ostensibly be treated mathematically as a finite collection of molecules—usually a very large finite collection—in which case the governing laws are expressible as a finite set of ordinary differential equations. These equations are generally highly intractable, and the set of molecules is usually approximated by a continuous distribution of mass. The governing laws are then expressed as a set of partial differential equations, containing such quantities as velocity, density, and pressure as dependent variables.

It is sometimes possible to obtain particular solutions of these equations analytically, especially when the solutions are periodic or invariant with time, and, in[illegible] [illegible] evolved to obtaining such [illegible] her. Ordinarily, how[illegible] [illegible] solutions cannot readily be determined [illegible] procedures. Such procedures involve replacing the continuous variables by a new finite set of functions of time, which may perhaps be the values of the continuous variables at a chosen grid of points, or the coefficients in the expansions of these variables in series of orthogonal functions. The governing laws then become a finite set of ordinary differential

Analogs

[1] The research reported in this work has been sponsored by the Geophysics Research Directorate of the Air Force Cambridge Research Center, under Contract No. AF 19(604)-4969.

#1 The technology is ready (and easy-to-use)



High-performance computing (GPU)

Large annotated dataset (> 1M)

+

Keras

TensorFlow

Caffe

PYTORCH

Efficient & easy-to-use libraries

End-to-end learning

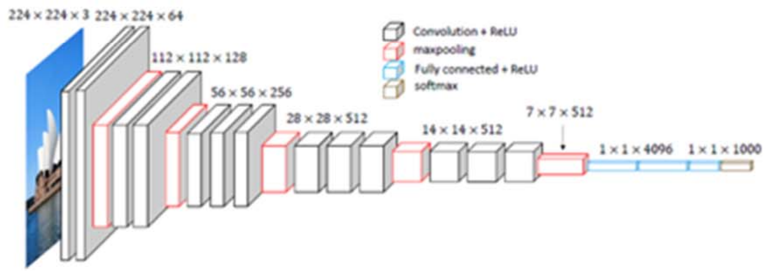


Figure 2: The architecture of VGG16 model .

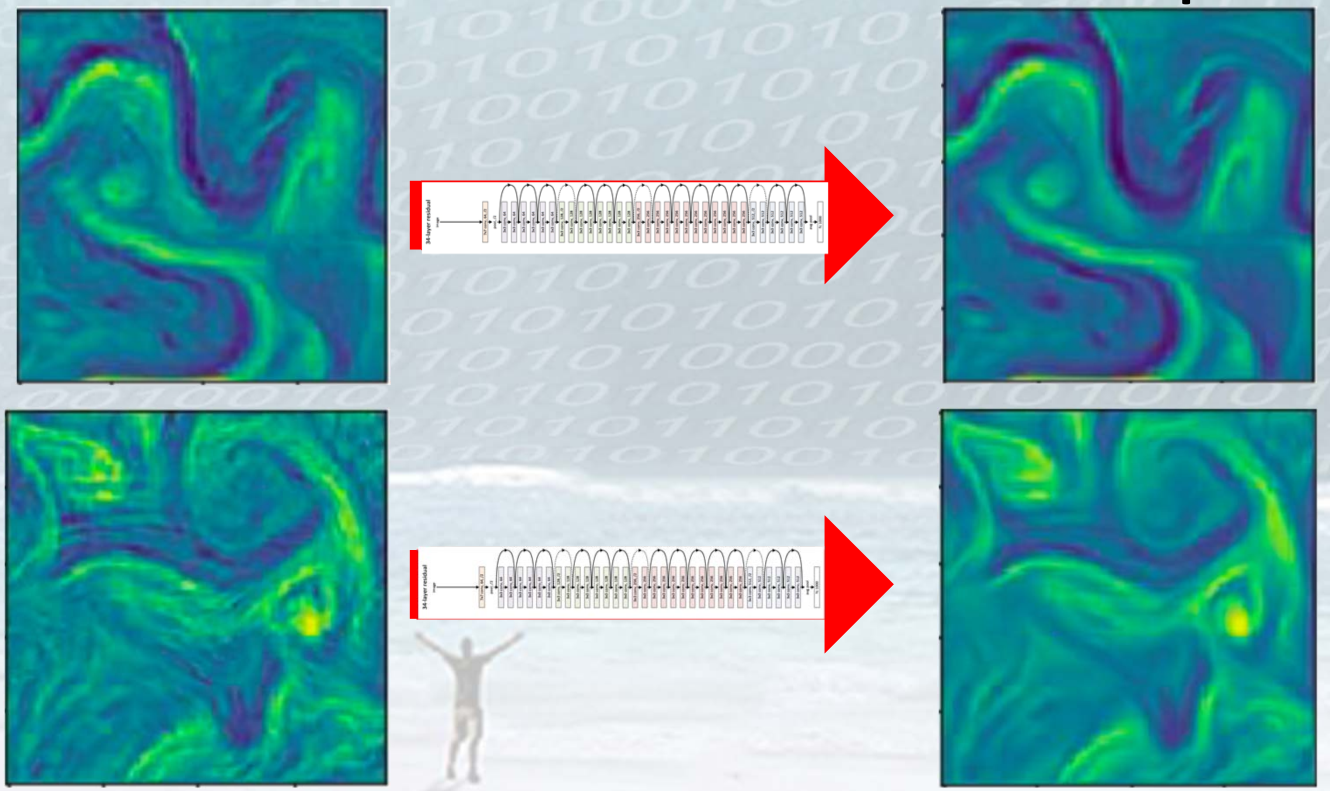
136.10^6 parameters

#2 Plug-and-play use of end-to-end learning

Learning-based «Noise» removal in HR snapshots (here, Laplacian of SSH fields, Osmosis region)

HR snapshots

« Denoised » tide-free output

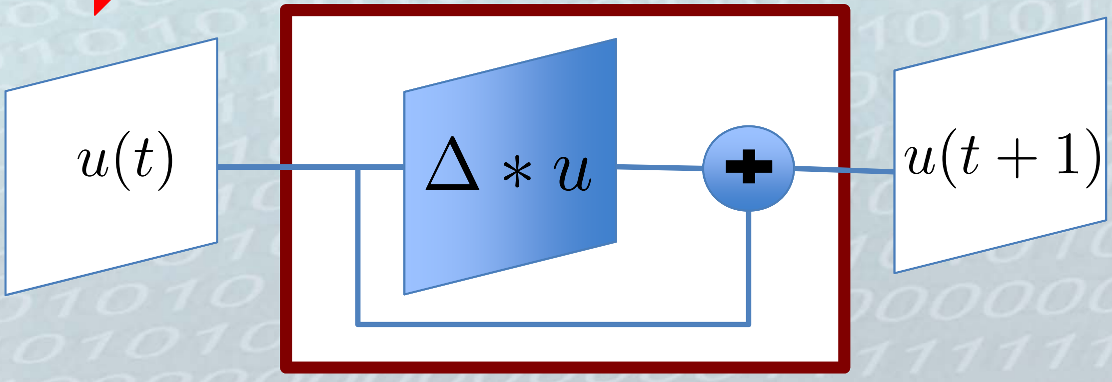


#3 Beyond black boxes: Physics-informed learning-based representations

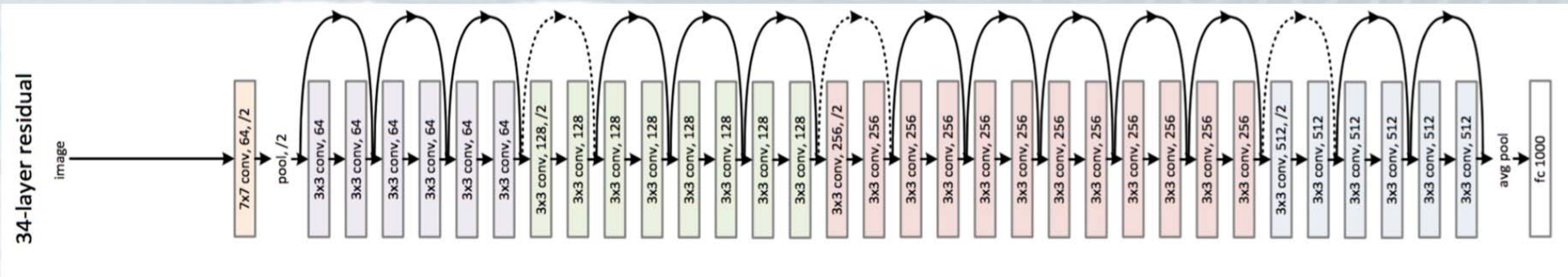
PDE/ODE

$$\frac{\partial u}{\partial t} = \kappa \Delta u$$

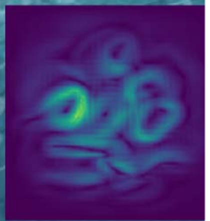
NN representation



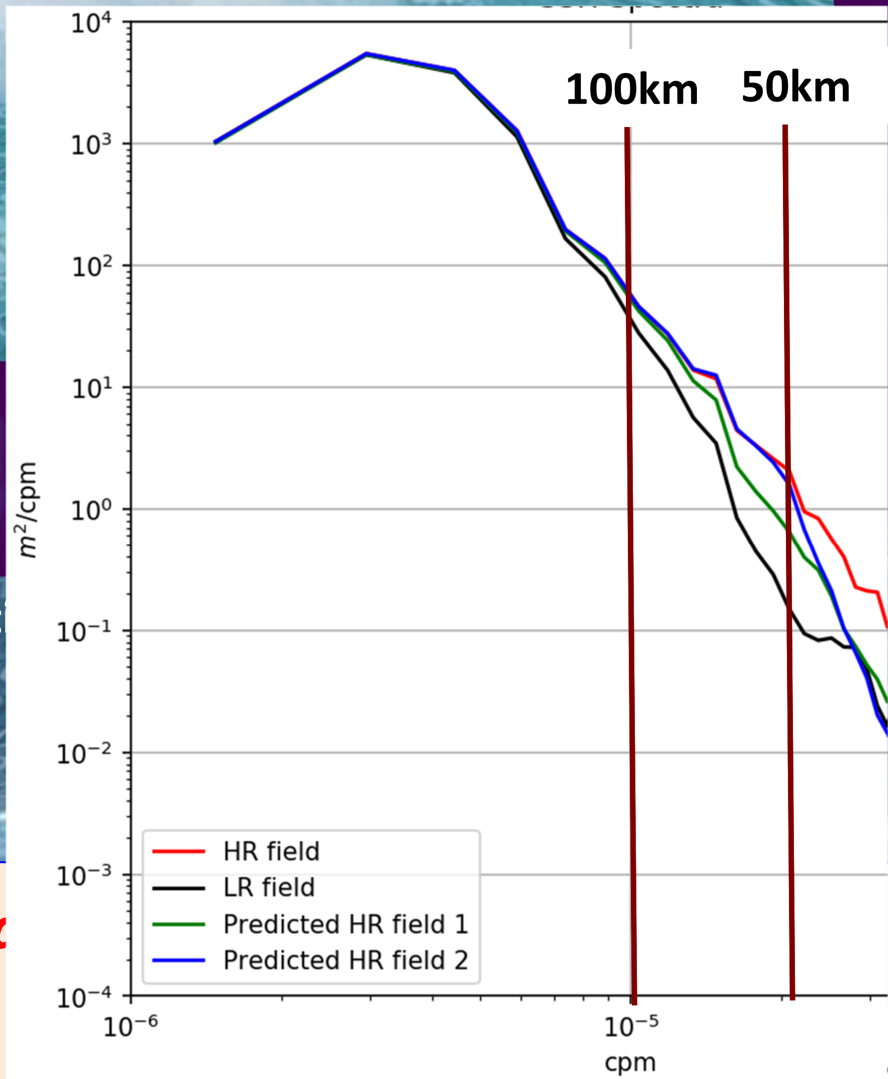
Numerical integration schemes as ResNets [He etal. 2015]

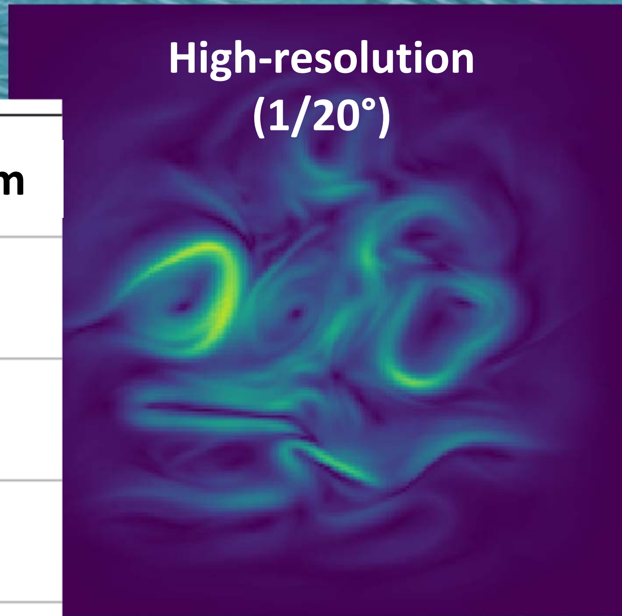


Learning-based Downscaling for Ocean Currents [Fablet et al., 2019]



Low-resoluti
(~1/4°)



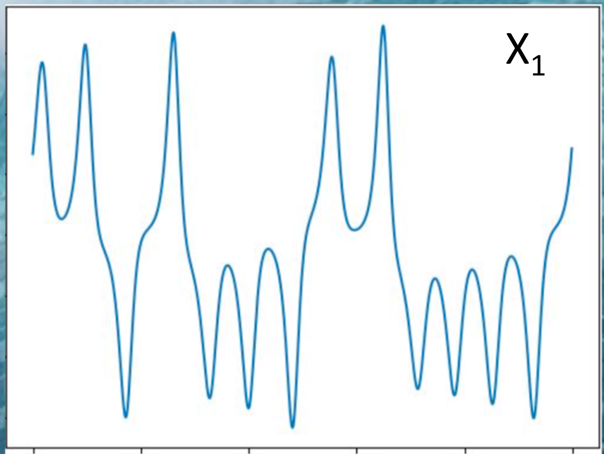


Subgrid-scale

Can we lea

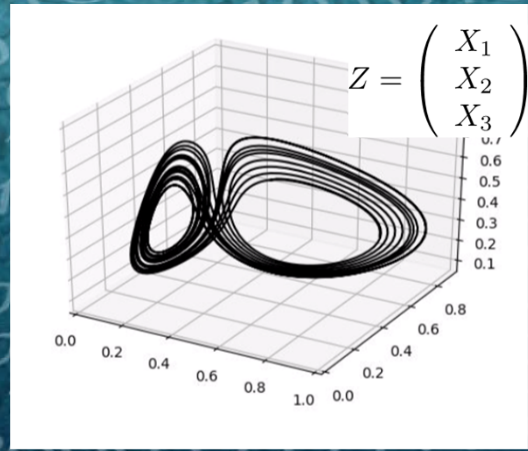
$$, \psi(X)\rangle$$

Learning latent dynamics for partially-observed systems [Ouala et al., 2019]

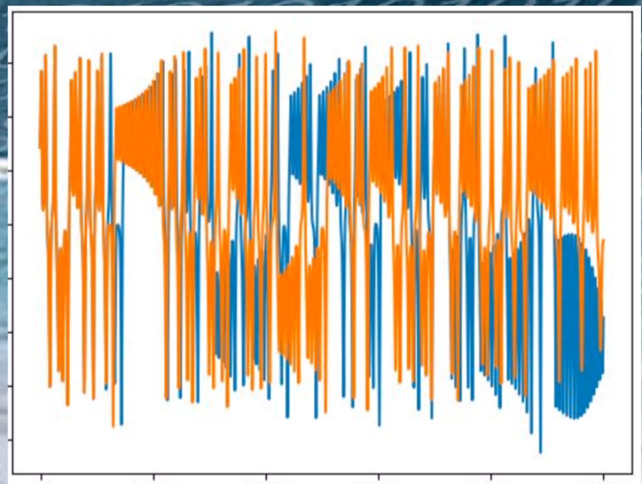


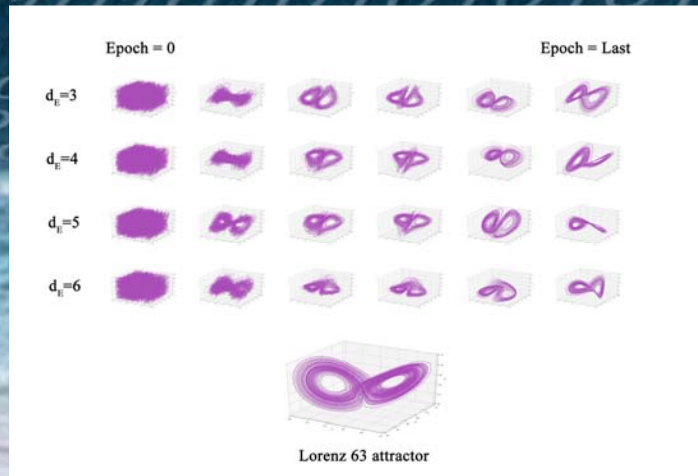
Latent (unobserved) dynamics

$$d_t Z_t = \Phi_\theta(Z_t)$$



Realistic « long-term » simulations

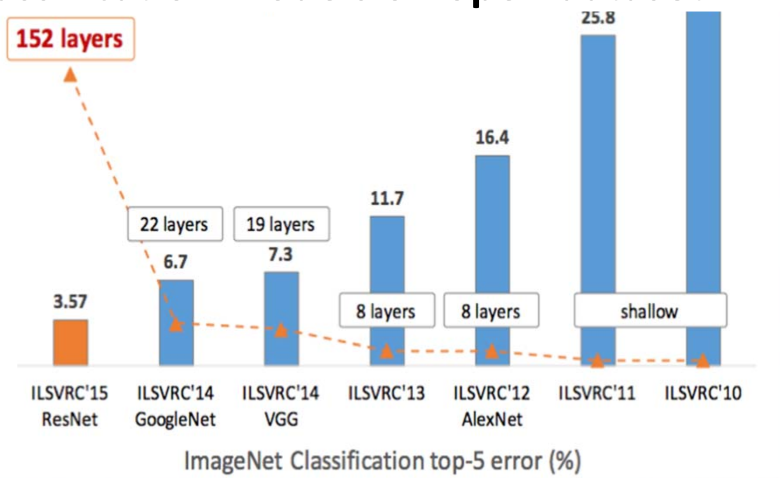




Bridging ocean science & DL/ML: Data challenges as a key instrument ?

Shared benchmarking datasets/platforms to accelerate ML/DL breakthroughs

Benchmarking expriments for image classification models on open dataset



Open (training) dataset

+

Evaluation framework

+

Data challenge workshop /platform

(eg, codalab, ramp, kaggle**)**

Relevant for ocean/swot challenges ?

Means to draw data scientists' interest ?

Thank you.

Lopez Radcenco et al., Analog Data Assimilation of Along-Track Nadir and Wide-Swath SWOT Altimetry Observations in the Western Mediterranean Sea. IEEE JSTARS, 2019.

Ouala et al. Neural Network Based Kalman Filters for the Spatio-Temporal Interpolation of Satellite-Derived Sea Surface Temperature. RS, 2018.

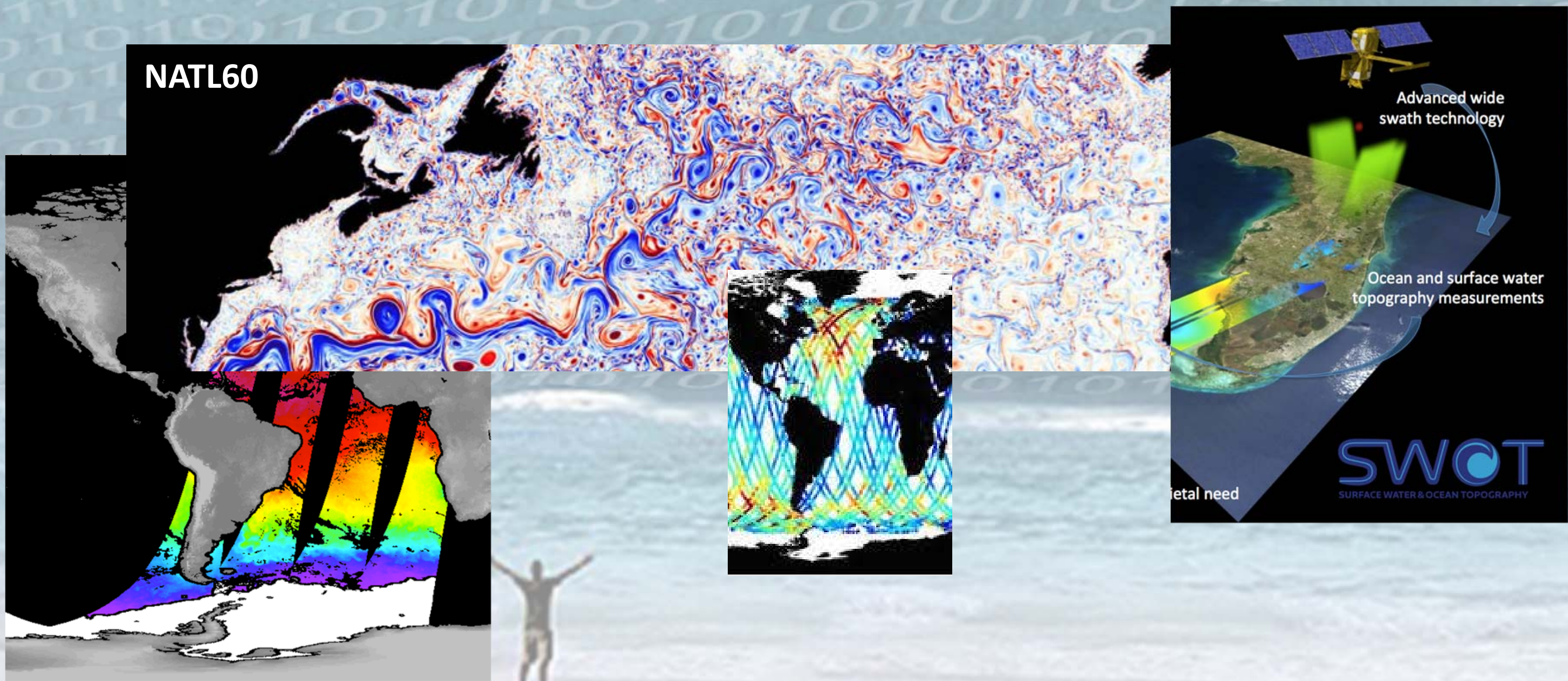
Ouala et al., Learning Latent Dynamics for Partially Observed Systems. Preprint, 2019.

More at https://www.researchgate.net/profile/Ronan_Fablet

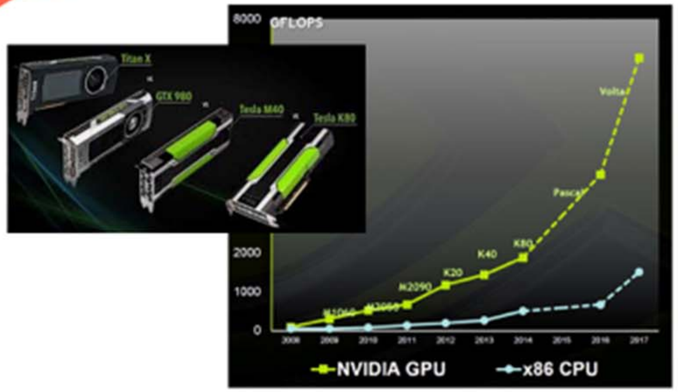
The example of analog methods. Nothing new?

Recent revival and extension of analog methods:

- ***Downscaling, forecasting (eg, Shenk & Zorita, 2012)***
- ***Analog data assimilation (Lguensat et al., 2017)***
- ***Extension to geophysical fields (Fablet et al., 2017)***



Deep learning models



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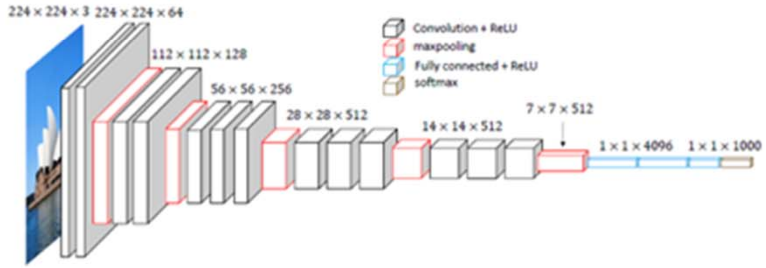

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136.10^6 parameters

DL representations for ODEs/PDEs

PDE/ODE

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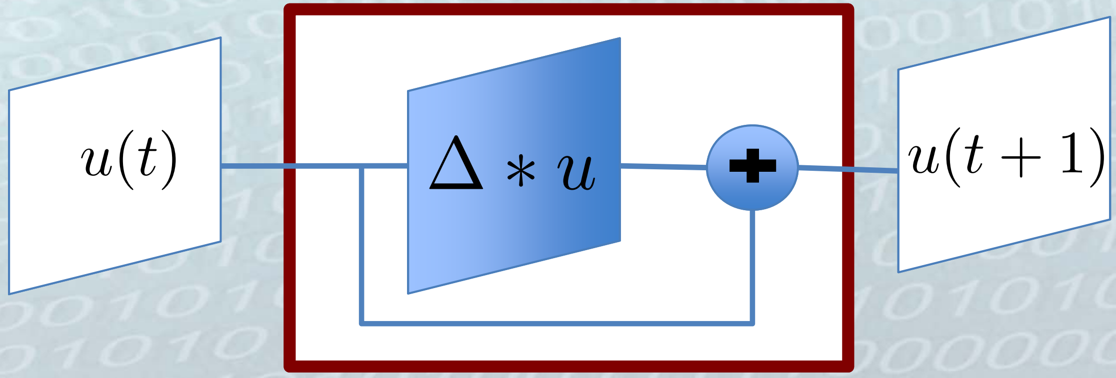
NN representation



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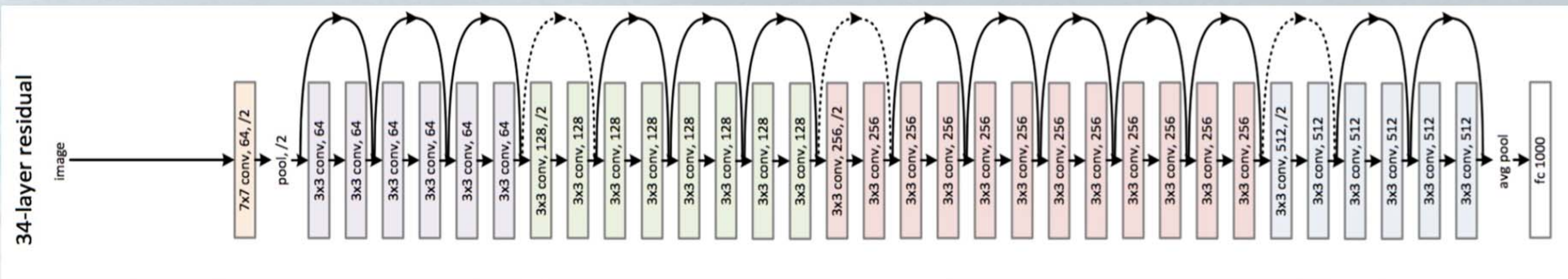


So what ? Exploring open and new challenges from a AI viewpoint

- **Identification of governing equations**
- **Computationally-efficient models**
- **Improved forecasting & reconstruction**
- **Autonomous/adaptive observing systems**

PNAS

CrossMark

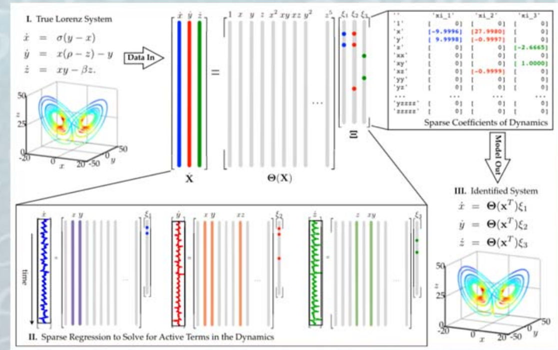
Discovering governing equations from data by sparse identification of nonlinear dynamical systems

Steven L. Brunton[a,1], Joshua L. Proctor[b], and J. Nathan Kutz[c]

[a]Department of Mechanical Engineering, University of Washington, Seattle, WA 98195; [b]Institute for Disease Modeling, Bellevue, WA 98005; and [c]Department of Applied Mathematics, University of Washington, Seattle, WA 98195

Edited by William Bialek, Princeton University, Princeton, NJ, and approved March 1, 2016 (received for review August 31, 2015)

Extracting governing equations from data is a central challenge in many diverse areas of science and engineering. Data are abundant ... dynamical systems from data. However, symbolic regression is expensive, does not scale well to large systems of interest, and



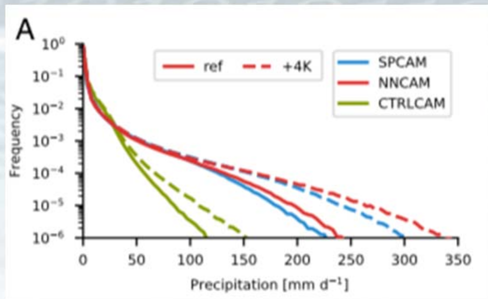
PNAS

Deep learning to represent subgrid processes in climate models

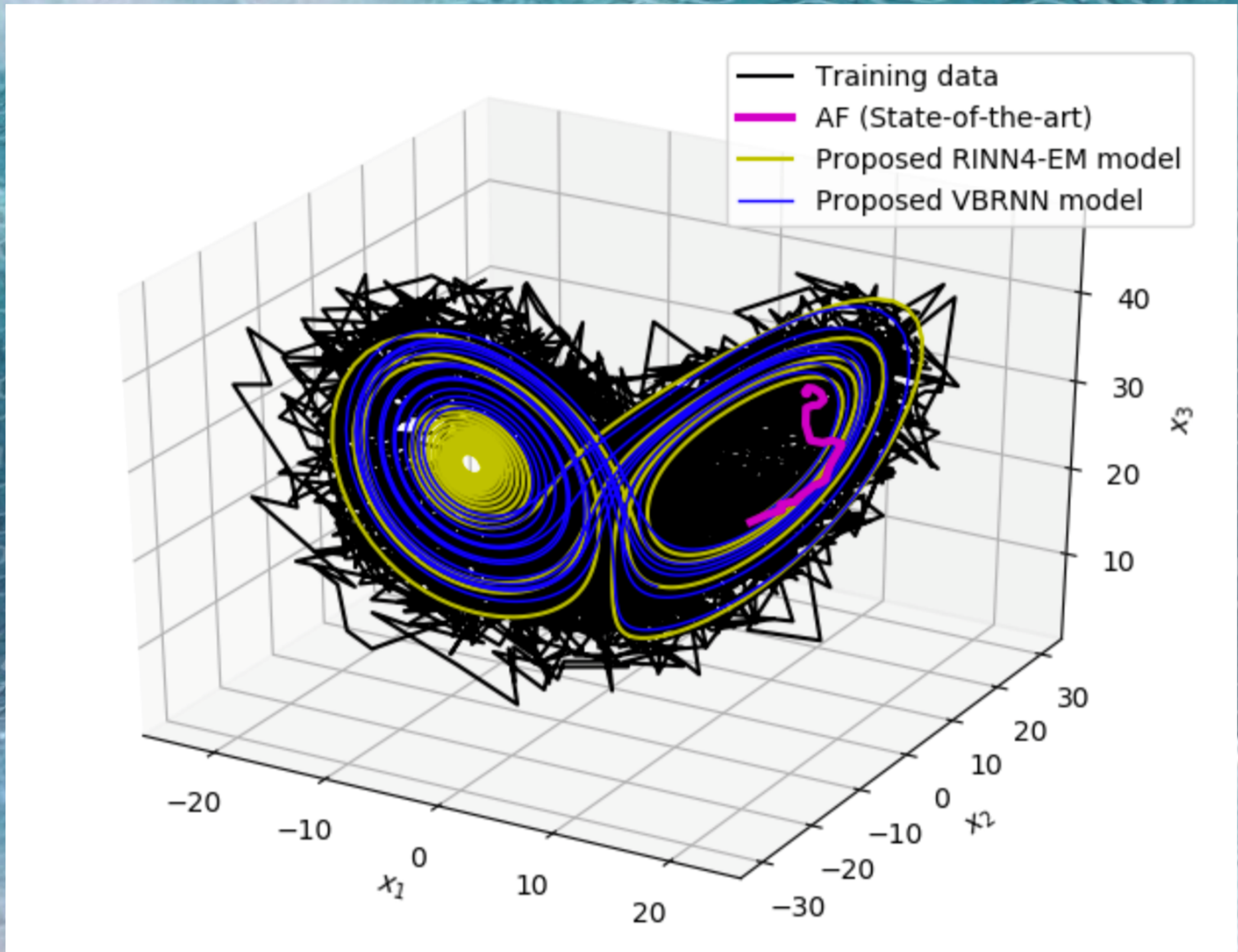
Stephan Rasp[a,b,1], Michael S. Pritchard[b], and Pierre Gentine[c,d]

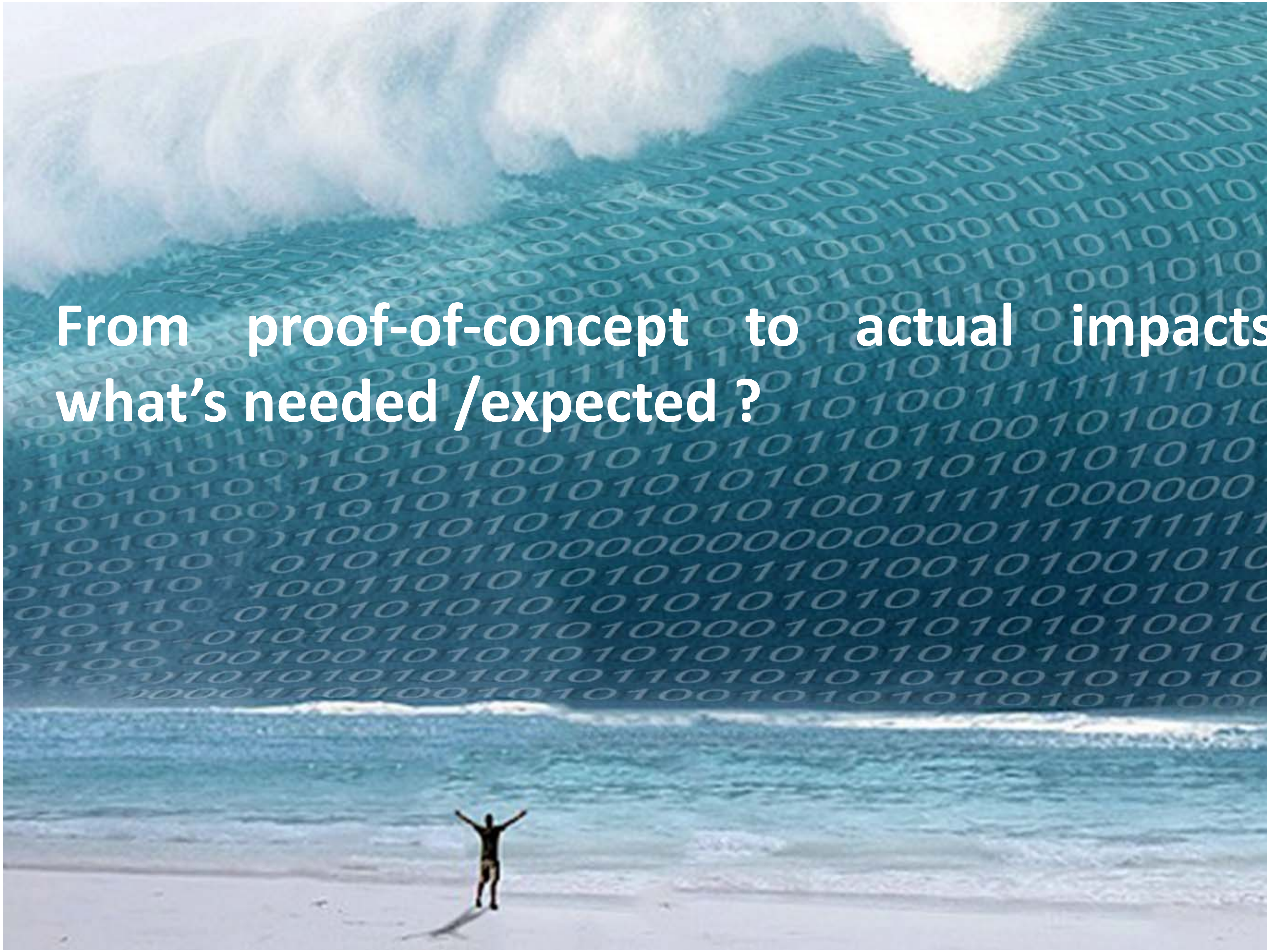
[a]Meteorological Institute, Ludwig-Maximilian-University, 80333 Munich, Germany; [b]Department of Earth System Science, University of California, Irvine, CA 92697; [c]Department of Earth and Environmental Engineering, Earth Institute, Columbia University, New York, NY 10027; and [d]Data Science Institute, Columbia University, New York, NY 10027

Edited by Isaac M. Held, Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Princeton, NJ, and approved August 8, 2018 (received for review June 14, 2018)



Learning from observation data [Ouala et al., 2019]




From proof-of-concept to actual impacts
what’s needed /expected ?

From proof-of-concept to actual impacts: Panel session «JT IA-OAC, 06/02/2019»

Supporting the emergence of a scientific community Applied Math. - Data Science - OA Science

- Workshops, Data challenges, … (e.g., AI4GeoDyn)
- Joint projects (e.g., LEFE-MANU IA-OAC, **ANR MeLODY**)

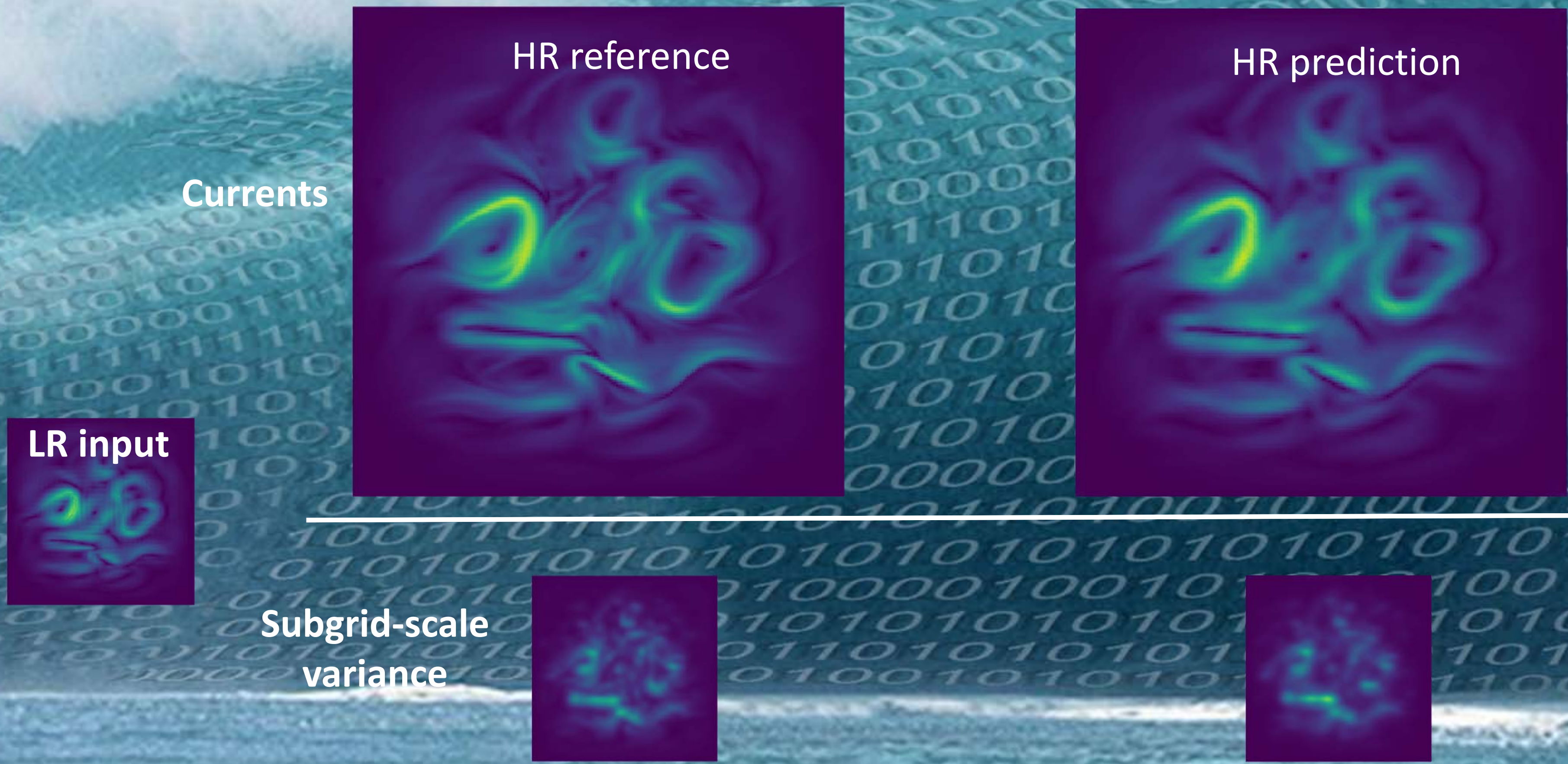
Computational resources and data management issues

- *GPUs with data storage* (e.g., Azure/Google, Jean Zay,…)
- *Hosting reference datasets/data challenges*

Supporting training initiatives

- Training course (e.g., Data Science for Geoscience)
- PhD/postdoc programs

Learning-based Downscaling for Ocean Currents [Fablet et al., 2019]



Learnt differential operators

$$\partial_s X = \phi\left(X\right) + \left\langle \nabla X, \psi\left(X\right)\right\rangle$$