

Bridging Physics and Learning: application to ocean dynamics

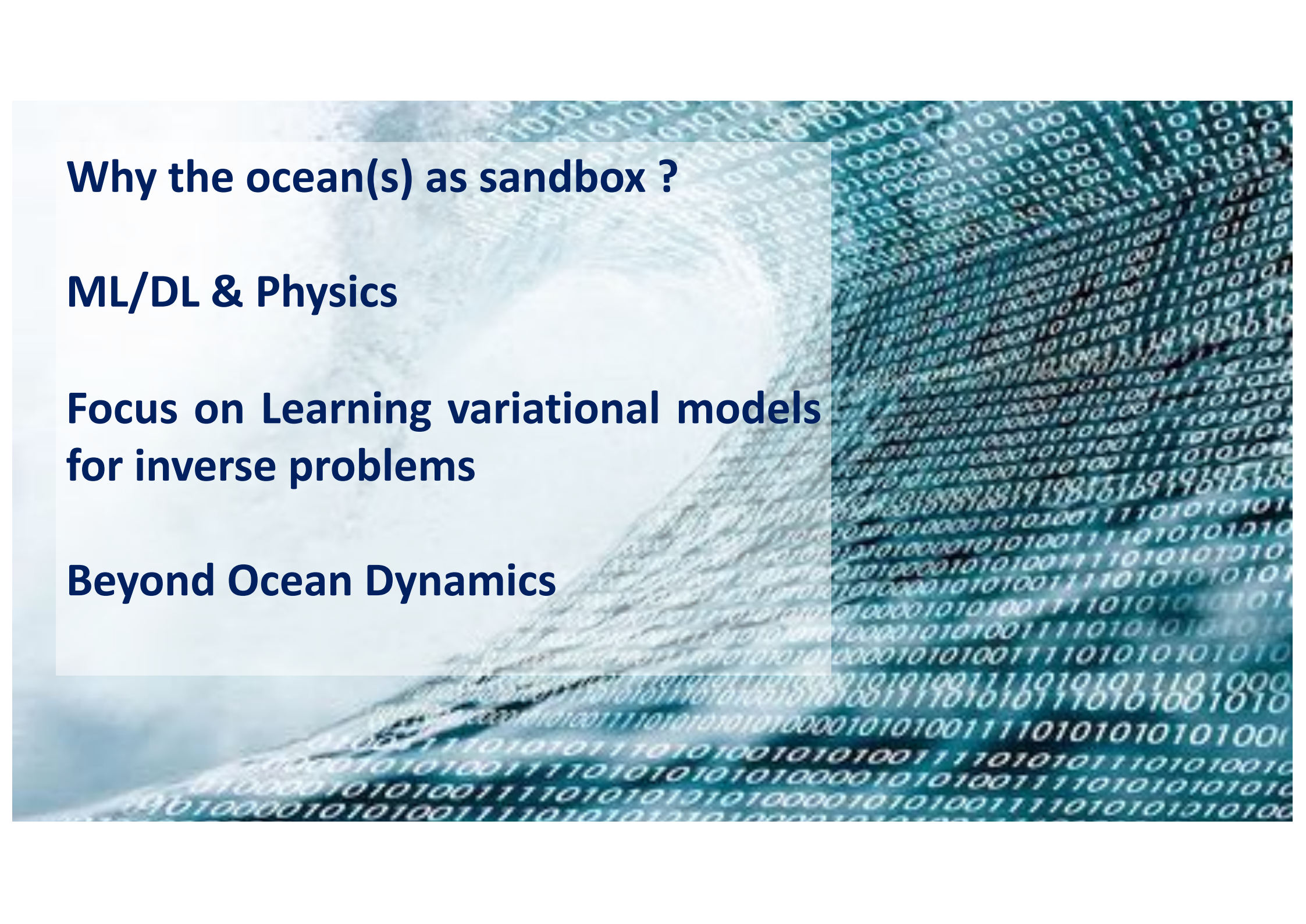
R. Fablet et al.

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[web: rfablet.github.io](https://github.com/rfablet)

Webinar IMT Data & AI, July 2020





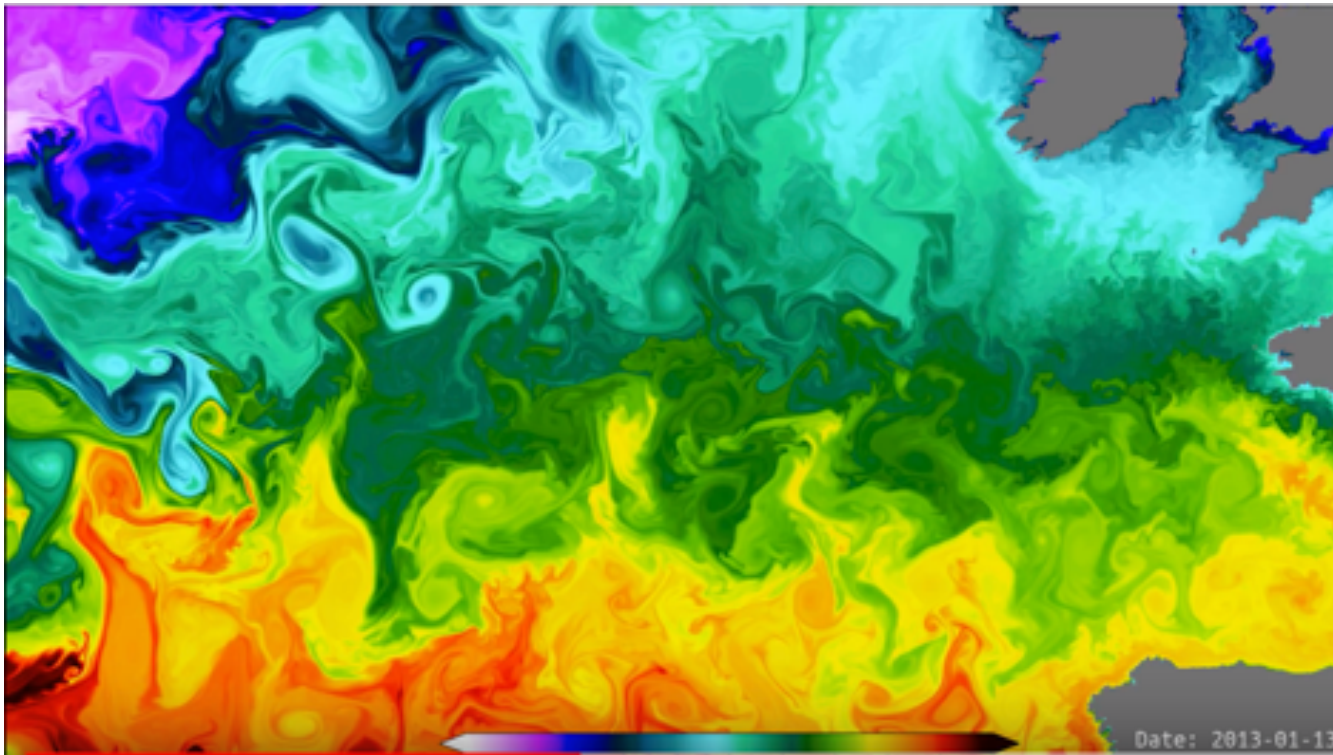
Why the ocean(s) as sandbox ?

ML/DL & Physics

**Focus on Learning variational models
for inverse problems**

Beyond Ocean Dynamics

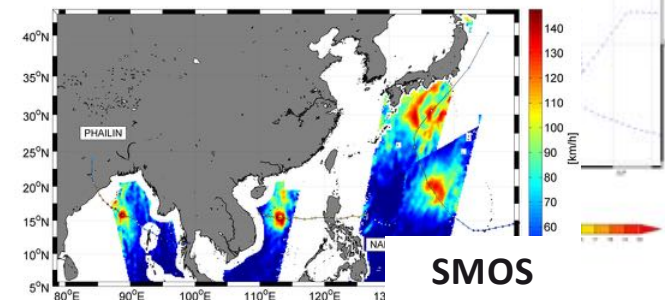
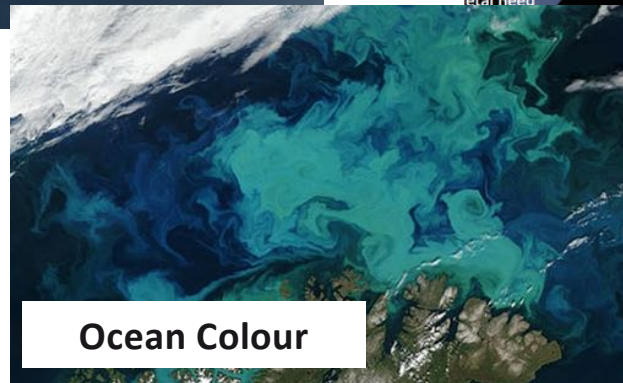
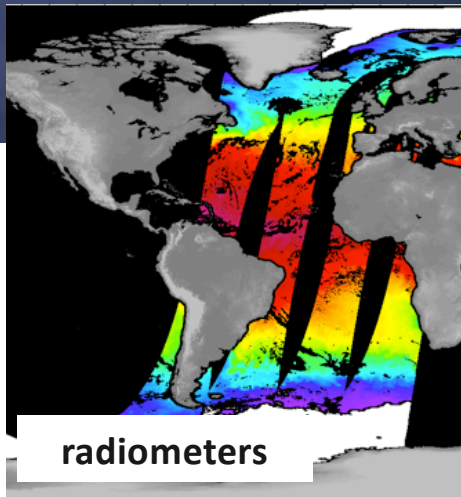
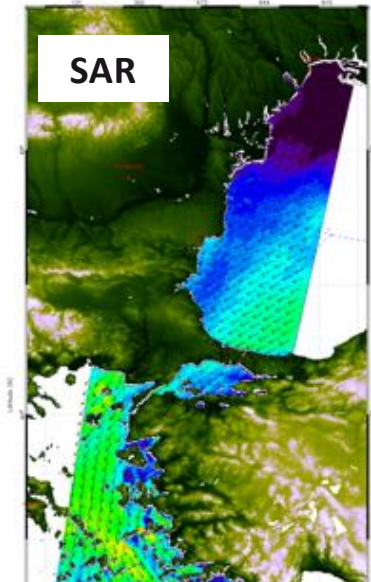
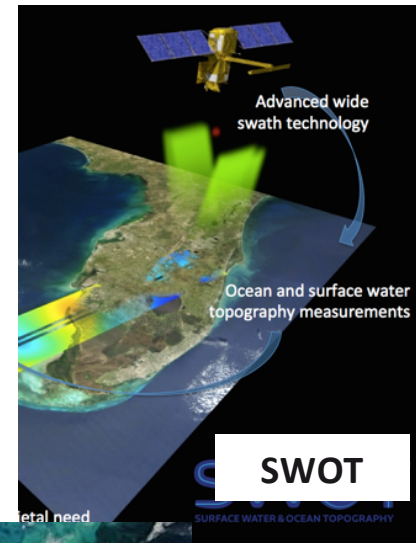
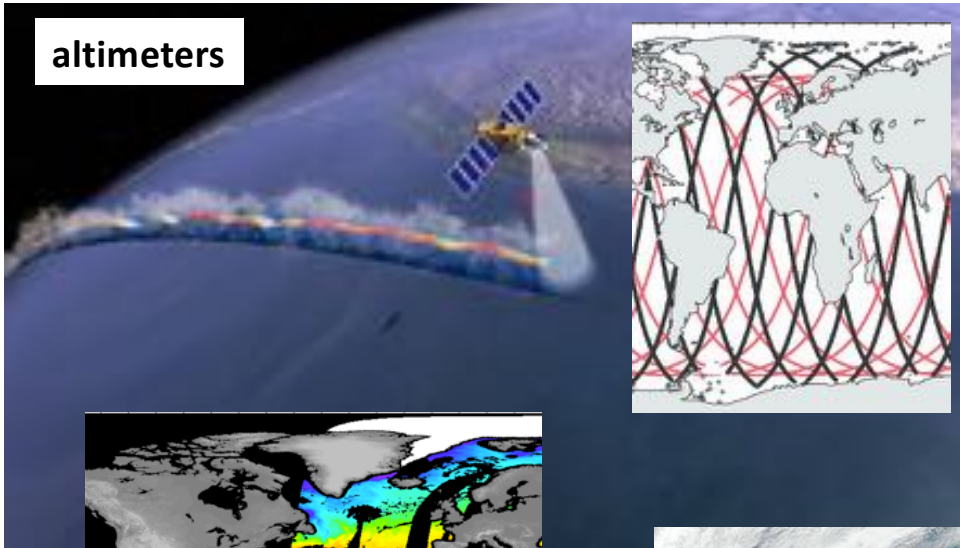
Context: No observation / simulation system to resolve all scales and processes simultaneously



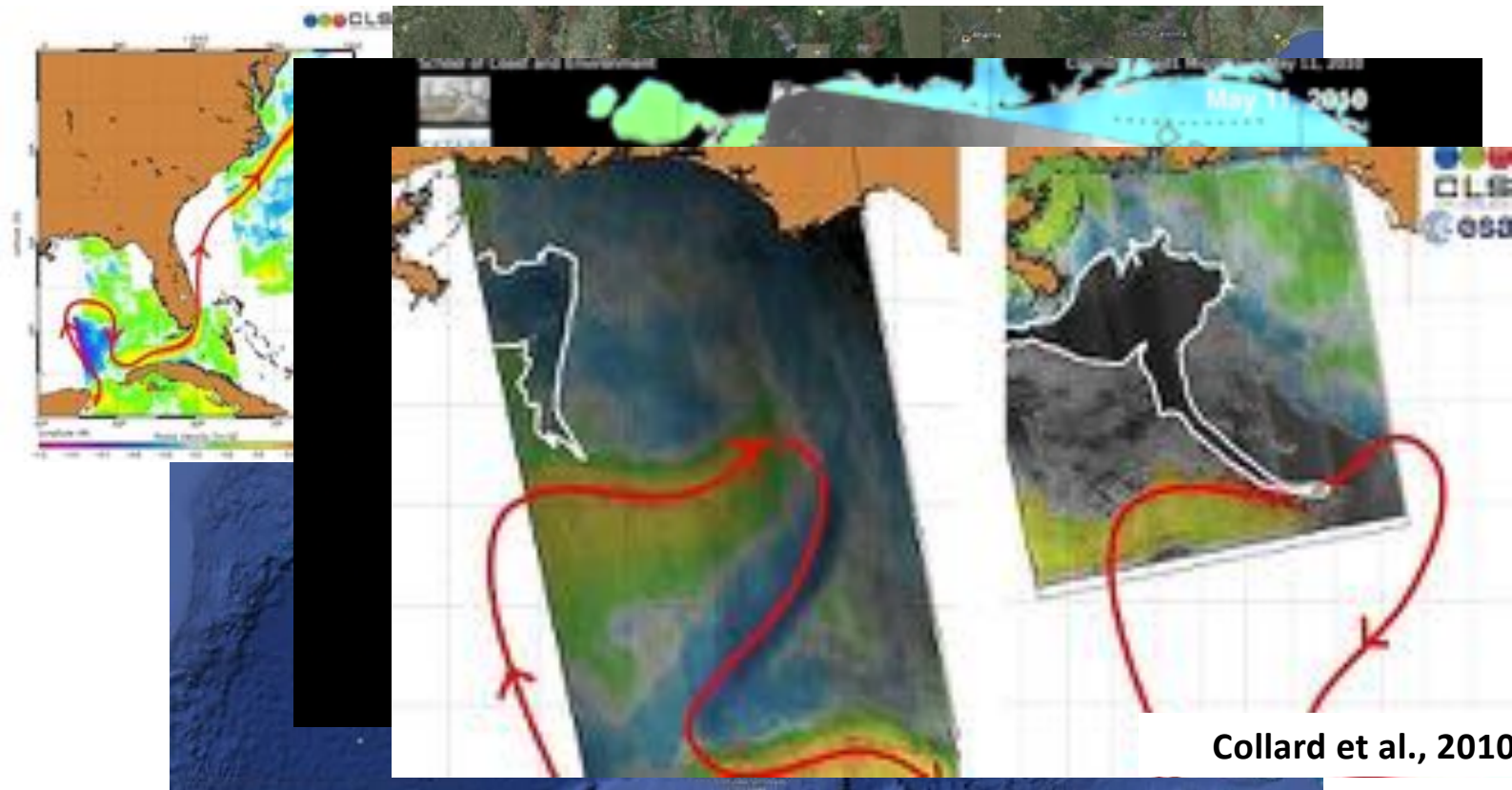
General question: how could data-driven/learning-based tools contribute to solving sampling gaps and higher-level information ?

Illustration of satellite-derived sea surface observations

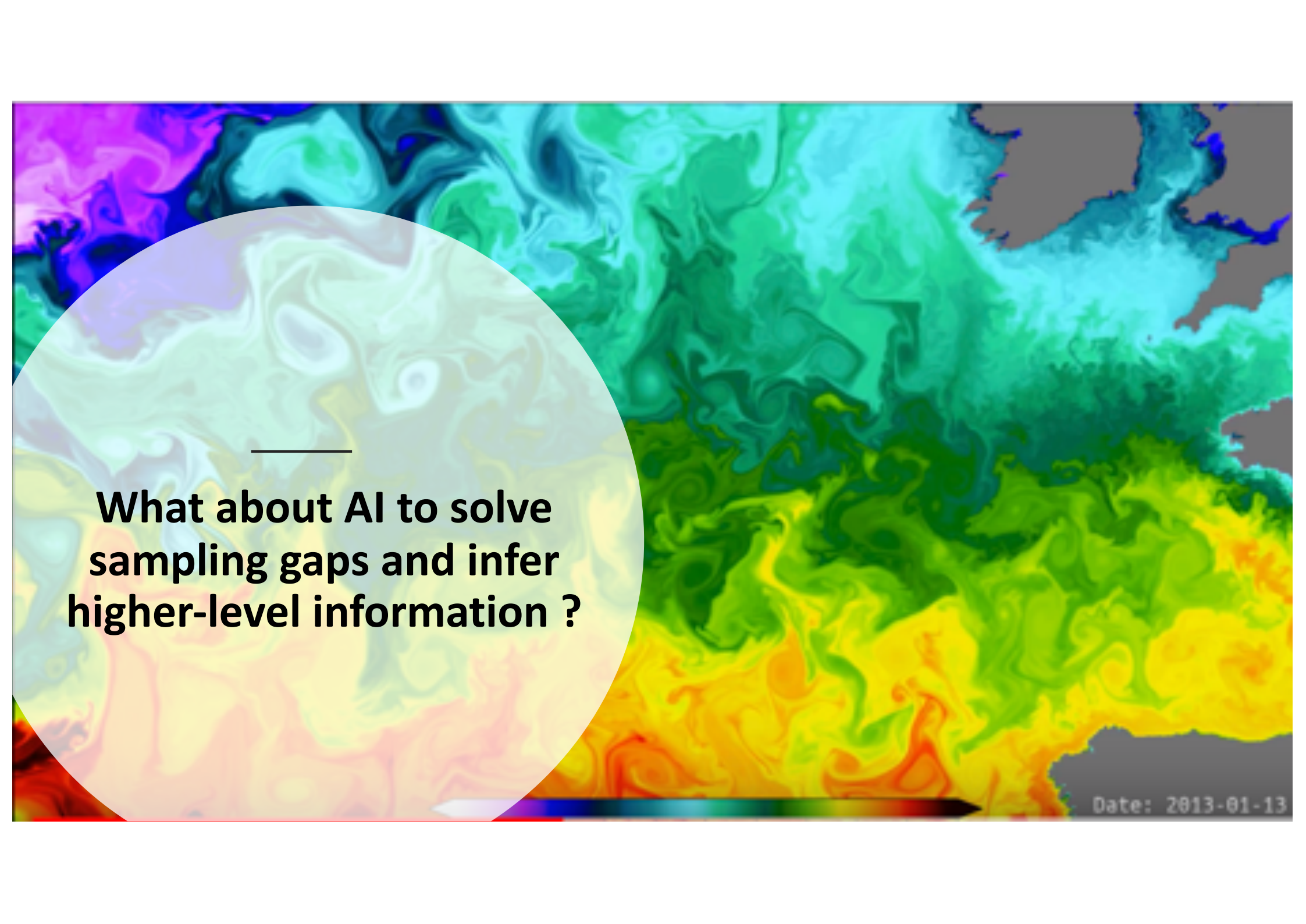
altimeters



Deepwater horizon [2010]

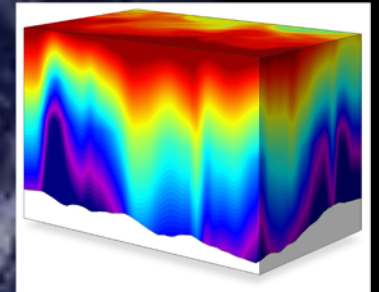
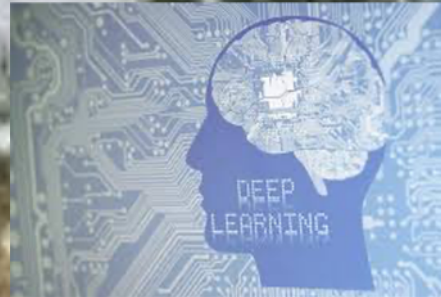


Collard et al., 2010



**What about AI to solve
sampling gaps and infer
higher-level information ?**

Date: 2013-01-13



**Context: Data-driven
and learning-based
approaches for ocean
monitoring &
surveillance**

Learning & Geoscience: nothing new ?

Empirical Orthogonal Functions and Statistical Weather Prediction

by
EDWARD N. LORENZ

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
DEPARTMENT OF METEOROLOGY
Cambridge, Massachusetts

DECEMBER 1956

Scientific Report No. 1
STATISTICAL FORECASTING PROJECT

EDWARD N. LORENZ

Directed by
EOF/PCA

THE RESEARCH REPORTS IN THIS DOCUMENT HAVE
BEEN SPONSORED BY THE GEOPHYSICS RESEARCH
DIRECTORATE OF THE AIR FORCE CAMBRIDGE RE-
SEARCH CENTER, AIR RESEARCH AND DEVELOPMENT
COMMAND, UNDER CONTRACT NO. AF19(604)1564.

Deterministic Nonperiodic Flow¹

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 have been identified in the familiar rotating flow of a liquid in a cylindrical container (e.g., Taylor 1936; Taylor and Görtler 1938). In the case of a rotating cylinder, the flow is periodic, and the motion is characterized by a regular pattern of vortices. In the case of a rotating sphere, the flow is nonperiodic, and the motion is characterized by a complex pattern of vortices. The flow is also characterized by a regular pattern of vortices, and the motion is characterized by a regular pattern of vortices. The flow is also characterized by a regular pattern of vortices, and the motion is characterized by a regular pattern of vortices.

Lack of periodicity is a distinguishing feature of turbulent flow. Because instantaneous turbulent flow patterns are so irregular, attention is often confined to the statistics of turbulence, which, in contrast to the details of turbulence, often behave in a regular well-organized manner. The short-range weather forecast, however, is forced to deal with the details of the flow, and the details of the flow are often characterized by a nonperiodic motion. The details of the flow are often characterized by a nonperiodic motion. The details of the flow are often characterized by a nonperiodic motion.

¹The research reported in this work has been supported by the Geophysics Research Directorate of the Air Force Cambridge Research Center, under Contract No. AF 19(604)1564.

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 identified with hydrodynamical systems. We shall be interested principally in nonperiodic solutions, i.e., solutions which never repeat their past history exactly, and where approximate repetitions are of finite duration. These solutions shall be identified with trajectories in phase space. The solutions shall be identified with trajectories in phase space. The solutions shall be identified with trajectories in phase space. The solutions shall be identified with trajectories in phase space. The solutions shall be identified with trajectories in phase space.

It is sometimes possible to obtain particular solutions of these equations analytically, especially when the solutions are periodic or invariant with time, and, indeed, much work has been devoted to obtaining such solutions by one scheme or another. Ordinarily, however, nonperiodic solutions cannot readily be determined by analytical procedures. The solutions are often characterized by a nonperiodic motion. The details of the flow are often characterized by a nonperiodic motion. The details of the flow are often characterized by a nonperiodic motion.

Learning & Geoscience: Data-driven approaches for data assimilation

OCTOBER 2017 LGUENSAT ET AL. 4093

The Analog Data Assimilation[®]

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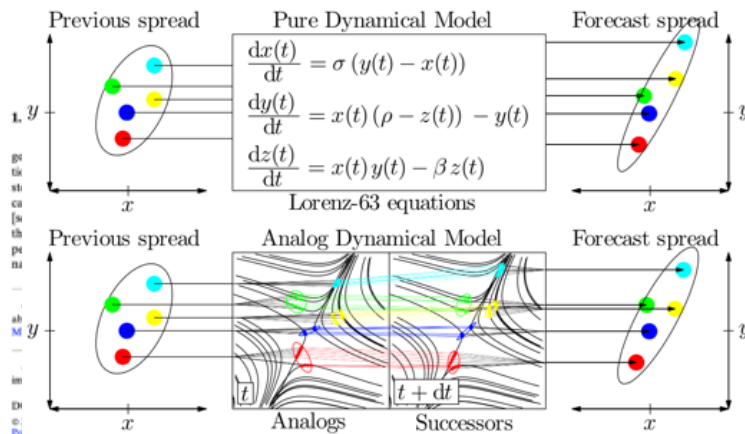
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(Manuscript received 23 November 2016, in final form 31 July 2017)

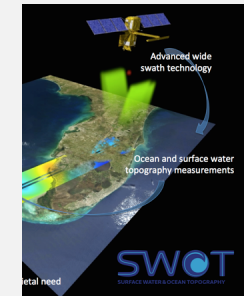
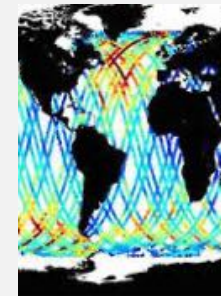
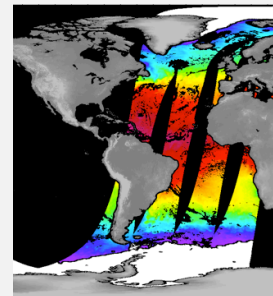
ABSTRACT

In light of growing interest in data-driven methods for oceanic, atmospheric, and climate sciences, this work focuses on the field of data assimilation and presents the analog data assimilation (AdDA). The proposed framework produces a reconstruction of the system dynamics in a fully data-driven manner where no explicit knowledge of the dynamical model is required. Instead, a representative catalog of trajectories of the system is assumed to be available. Based on this catalog, the analog data assimilation combines the nonparametric



The analog data assimilation [Lguensat et al., 2017]

- Combination of analog forecasting strategies and EnKF assimilation schemes
- Extension to 2D+t geophysical dynamics



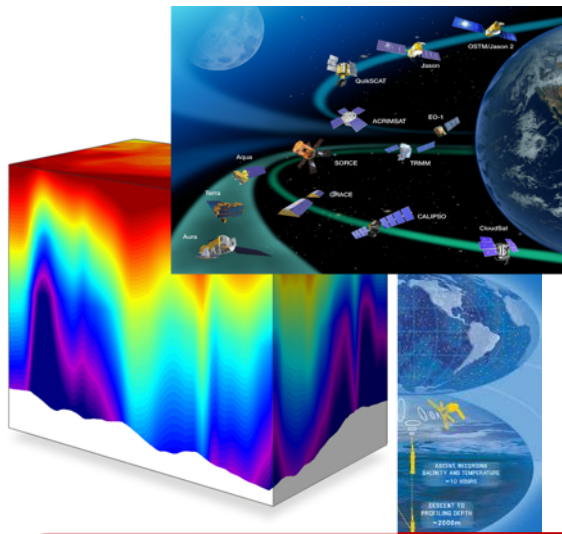
Open questions

- Bridging model-driven and data-driven paradigms
- Learning data-driven representations from real observation data

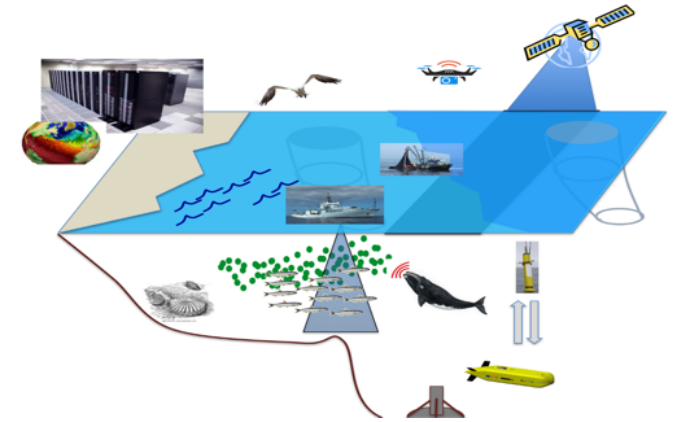
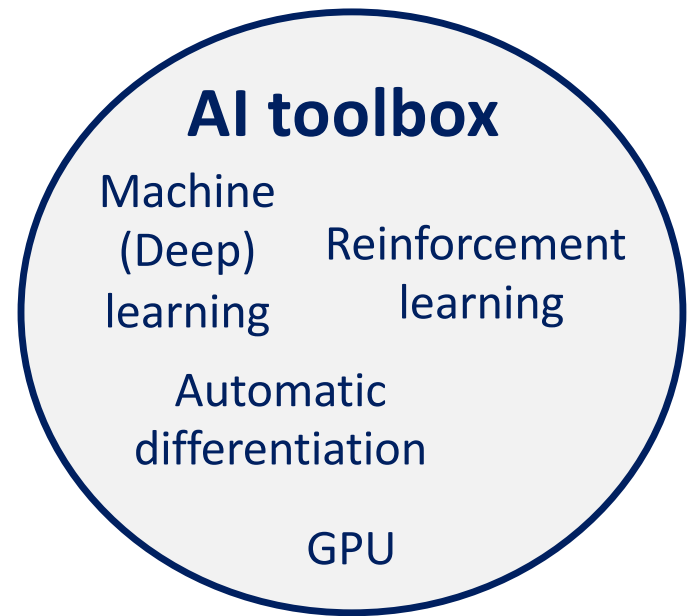
Bridging ML/DL paradigms and Physics ?

Lab-STICC

Bridging Physics & AI: Expected breakthroughs

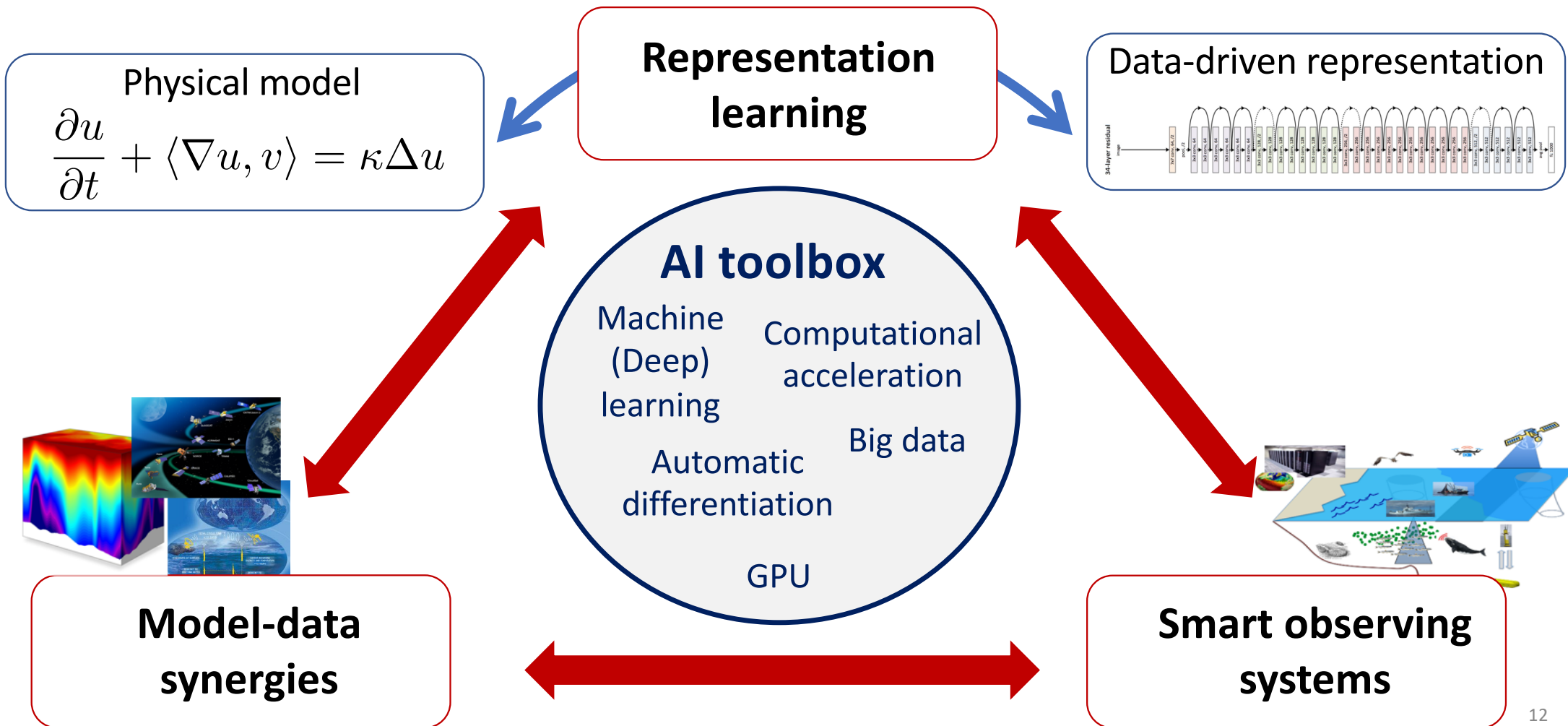


**Model-data
synergies**



**Smart observing
systems**

Bridging Physics & AI: Expected breakthroughs

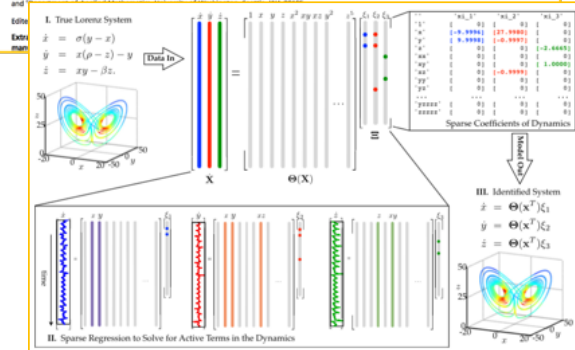


Direct applications of DL schemes to physics-related issues

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

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^aDepartment of Mechanical Engineering, University of Washington, Seattle, WA 98195; ^bInstitute for Disease Modeling, Bellevue, WA 98005

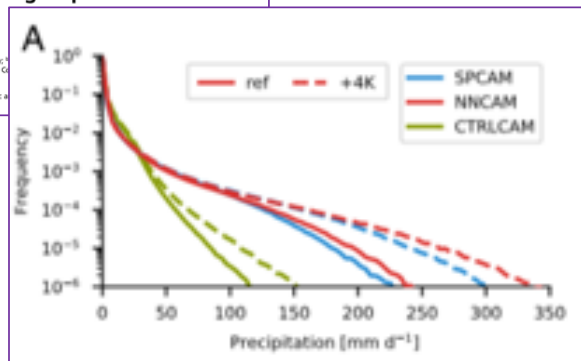


Deep learning to represent subgrid processes in climate models

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^aMeteorological Institute, Ludwig-Maximilians-University, 80333 Munich, Germany; ^bCA 50087; ^cDepartment of Earth and Environmental Engineering, Earth Institute, Columbia University, New York, NY 10027

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



Deep learning at scale for the construction of galaxy catalogs in the Dark Energy Survey

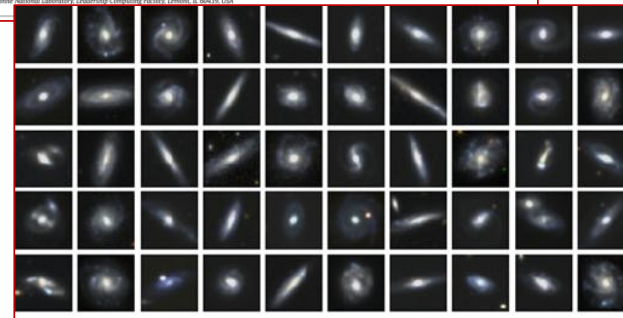
Asad Khan^{a,b,c,d}, E.A. Huerta^{a,c}, Sibor Wang^a, Robert Gruendl^{a,c}, Elise Jennings^d, Huihuo Zheng^d

^aNational Center for Supercomputing Applications, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA

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Classification of the global Sentinel-1 SAR vignettes for ocean surface process studies

Chen Wang^{a,b,c}, Pierre Tandoe^a, Nicolas Longepe^a, Douglas Van

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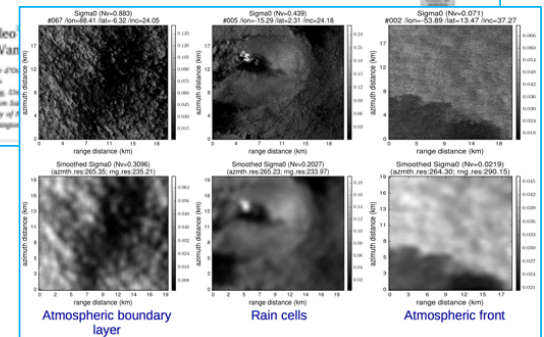
^cIMF Atlantique, Lab-STIC, CNRS, Brest, France

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^eSpace and Ground Systems, College of Aeronautics, U

^fOcean Processes Analysis Laboratory, University of W

^gApplied Physics Laboratory, University of Washington



FILTERING INTERNAL TIDES FROM WIDE-SWATH ALTIMETER DATA USING CONVOLUTIONAL NEURAL NETWORKS

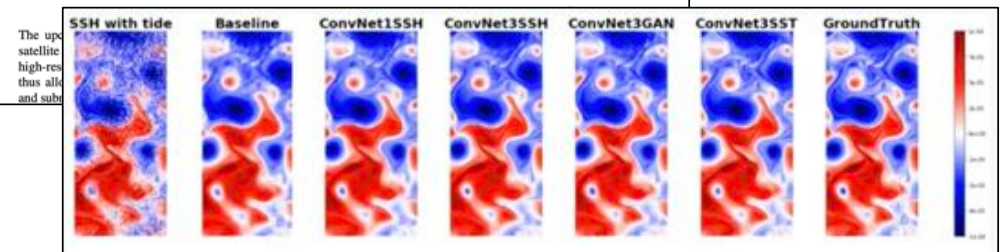
Redouane Lguensar¹, Ronan Fablet², Julien Le Sommer¹, Sammy Metref¹, Emmanuel Cosme¹, Kaouther Ouenniche², Lucas Drumetz², Jonathan Gula³

¹ Université Grenoble Alpes, CNRS, IRD, Grenoble INP, IGE; Grenoble, France

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[ph] 3 May 2020



Bridging physics & AI: Expected breakthroughs



Making the most of AI and Physics Theory

- Model-Driven/Theory-Guided & Data-Constrained schemes
- Data-Driven & Physically-Sound schemes (eg, Ouala et al., 2019)

Bridging physics & AI: Expected breakthroughs

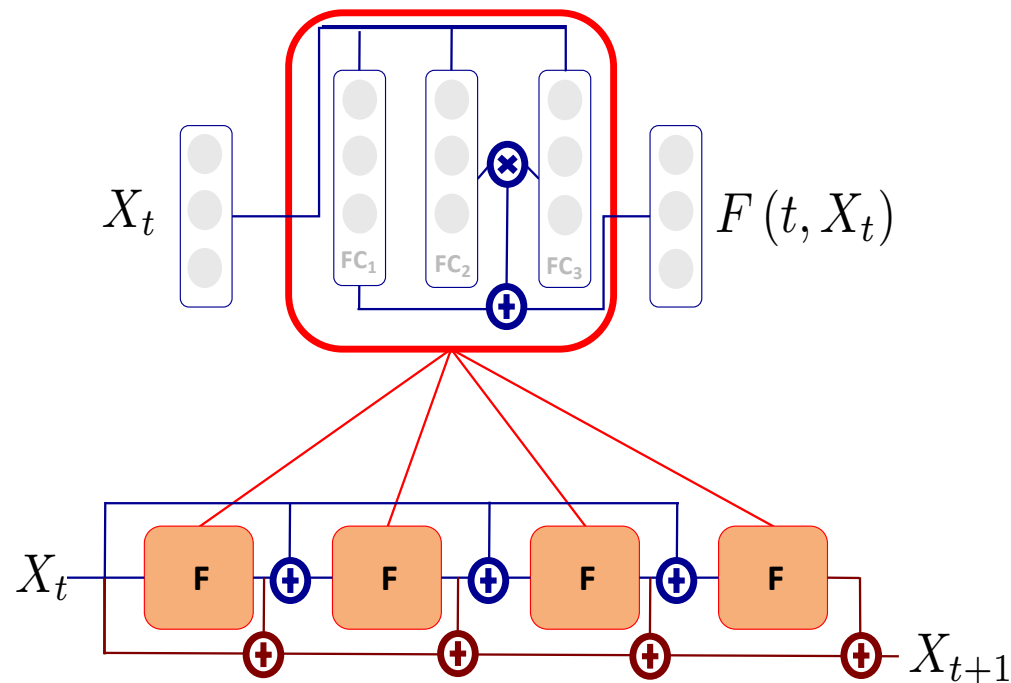


Making the most of AI and Physics Theory

- **Model-Driven/Theory-Guided & Data-Constrained schemes**
- Data-Driven & Physically-Sound schemes (eg, Ouala et al., 2019)

DL representations for ODEs/PDEs (Neural ODE)

An example: Residual RK4 Bilinear Network [Fablet et al., 2018]



$$\begin{aligned}\frac{dx(t)}{dt} &= \sigma(y(t) - x(t)) \\ \frac{dy(t)}{dt} &= x(t)(\rho - z(t)) - y(t) \\ \frac{dz(t)}{dt} &= x(t)y(t) - \beta z(t)\end{aligned}$$

Lorenz-63 equations

Noise-free training data

Forecasting time step	t_0+h	t_0+4h	t_0+8h
Analog forecasting	$<10^{-6}$	0.002	0.005
Sparse regression	$<10^{-6}$	0.002	0.006
MLP	$<10^{-6}$	0.018	0.044
Bi-NN(4)	$<10^{-6}$	$<10^{-6}$	$<10^{-6}$

NN Generator from Symbolic PDEs (Pannekoucke et al., 2020)

$$\partial_t u + u \partial_x u = \kappa \partial_x^2 u$$

**Symbolic calculus
(SymPy)**

**PDE-GenNet
(keras)**

ResNet

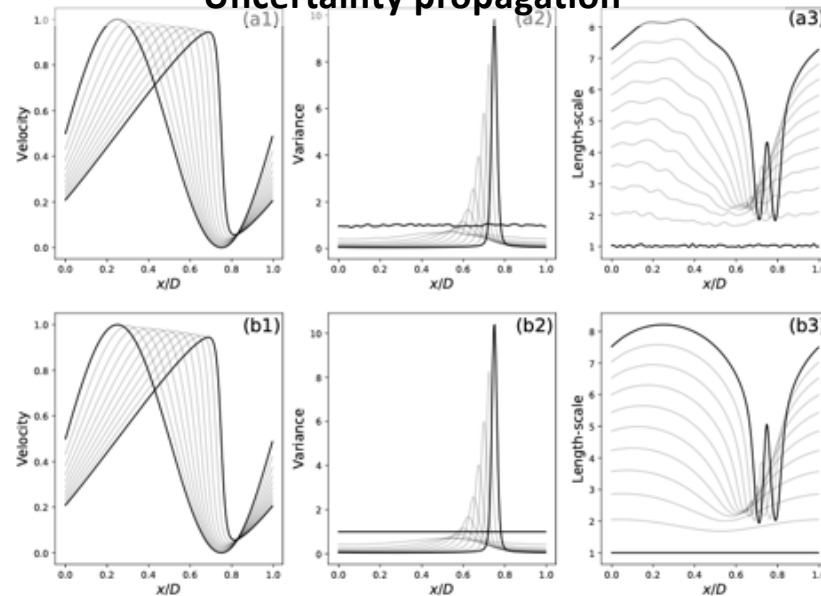
$$\begin{pmatrix} \mu_u(t) \\ \Sigma_u(t) \end{pmatrix} \rightarrow \begin{pmatrix} \mu_u(t+1) \\ \Sigma_u(t+1) \end{pmatrix}$$

Generated code

```
# Example of computation of a derivative
kernel_Du_x_o1 = np.asarray([[0.0, 0.0, 0.0], [0.0, 0.0, 0.0], [0.0, 0.0, 0.0]], dtype=float)
kernel_Du_x_o1 = kernel_Du_x_o1.reshape((3, 3) + (1, 1))
Du_x_o1 = DerivativeFactory((3, 3), kernel=kernel_Du_x_o1, name='Du_x_o1')(u)

# Computation of trend_u
mul_1 = keras.layers.multiply([Dkappa_11_x_o1, Du_x_o1], name='MulLayer_1')
mul_2 = keras.layers.multiply([Dkappa_12_x_o1, Du_y_o1], name='MulLayer_2')
mul_3 = keras.layers.multiply([Dkappa_12_y_o1, Du_x_o1], name='MulLayer_3')
mul_4 = keras.layers.multiply([Dkappa_22_y_o1, Du_y_o1], name='MulLayer_4')
mul_5 = keras.layers.multiply([Du_x_o2, kappa_11], name='MulLayer_5')
mul_6 = keras.layers.multiply([Du_y_o2, kappa_22], name='MulLayer_6')
mul_7 = keras.layers.multiply([Du_x_o1_y_o1, kappa_12], name='MulLayer_7')
sc_mul_1 = keras.layers.Lambda(lambda x: 2.0*x, name='ScalarMulLayer_1')(mul_7)
trend_u = mul_1 + mul_2 + mul_3 + mul_4 + mul_5 + mul_6 + sc_mul_1
```

Uncertainty propagation



**Ensemble-based
prediction**

NN prediction

Bridging physics & AI: Expected breakthroughs



Making the most of AI and Physics Theory

- Model-Driven/Theory-Guided & Data-Constrained schemes
- **Data-Driven & Physically-Sound schemes (eg, Ouala et al., 2019)**

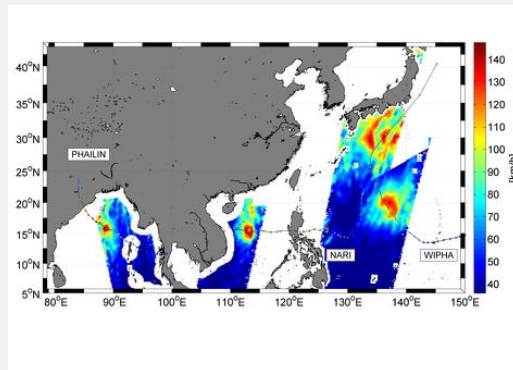
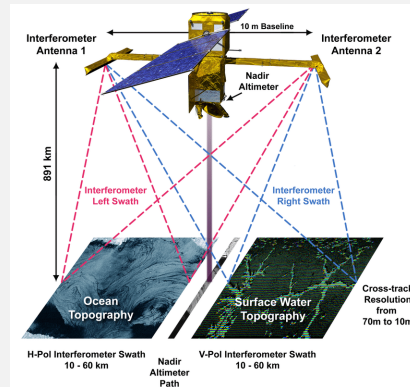
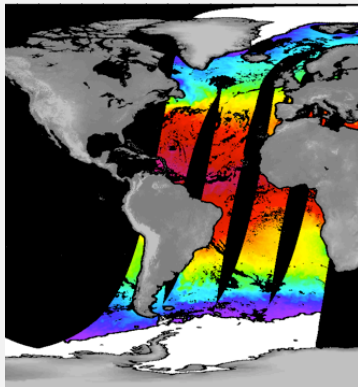
The background of the slide features a blurred, high-angle view of a city skyline, likely San Francisco, with the Golden Gate Bridge visible. Overlaid on this image is a dense pattern of green and blue binary code (0s and 1s) that appears to be flowing or falling from the top right towards the bottom left, creating a sense of digital rain or data flow.

**Dealing with real systems, including
Irregularly-sampled, noisy and/or
partially-observed systems ?**

End-to-end learning from irregularly-sampled data

[Nguyen et al., 2019; Fablet et al., 2019]

Can we learn directly from observation data ?



Generic issue:
Joint identification and inversion

Dynamical model

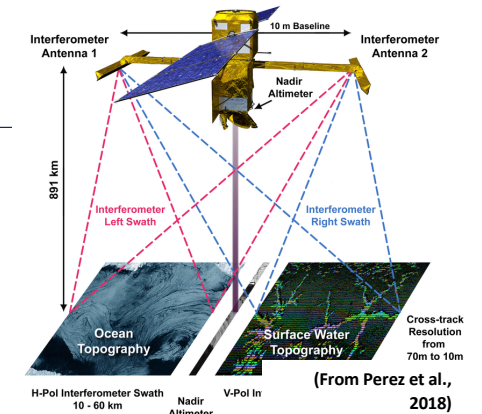
$$X_t \rightarrow \partial_t X = F(X, \xi, t, \theta) \rightarrow X_{t+1}$$

+

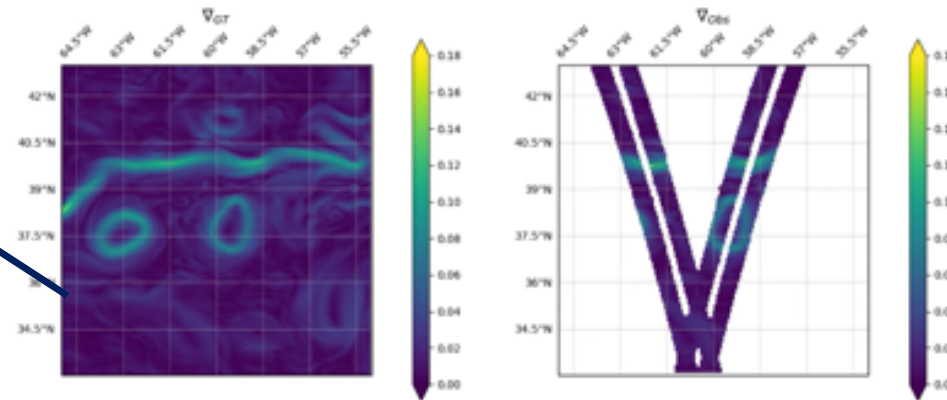
Observation model

$$Y_t = H(X, \zeta, t, \phi)$$

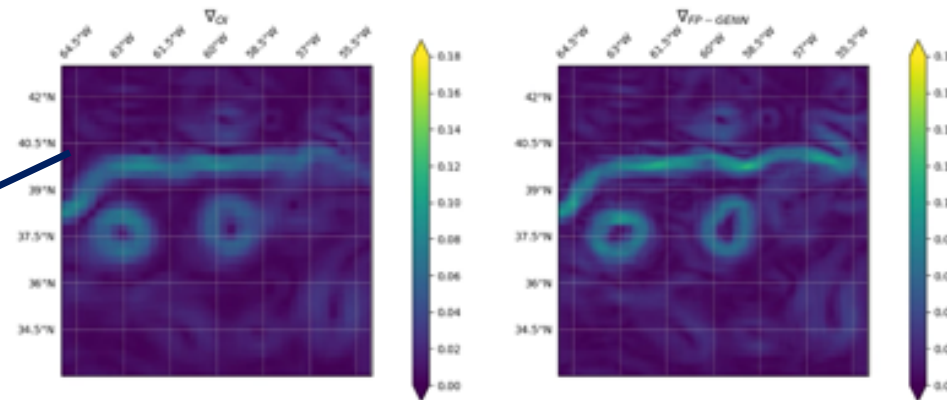
An example for upcoming SWOT mission



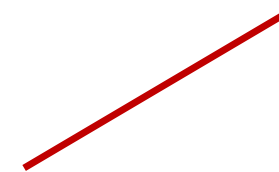
Groundtruth



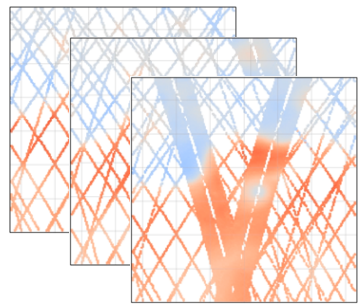
State-of-the-art
operational processing



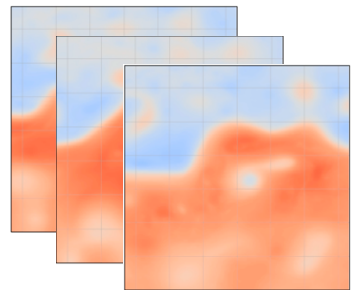
Proposed NN framework
(Fablet et al., 2019)



End-to-end learning for inverse problems (Fablet et al., 2020)



Partial observations y



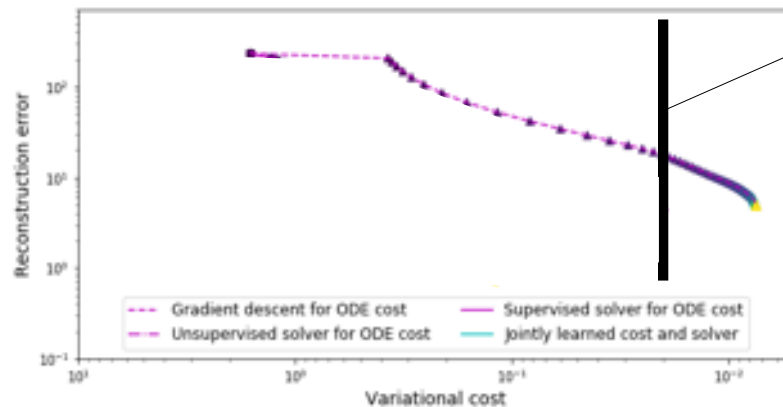
True states x

Model-driven schemes: $\hat{x} = \arg \min_x \underbrace{\lambda_1 \|x - y\|_\Omega^2 + \lambda_2 \Phi(x)}_{U_\Phi(x^{(k)}, y, \Omega)}$

Gradient-based solver (adjoint/Euler-Lagrange method):

$$x^{(k+1)} = x^{(k)} - \alpha \nabla_x U_\Phi(x^{(k)}, y, \Omega)$$

No control on the reconstruction error $x^{true} \neq \arg \min_x U_\Phi(x^{(k)}, y, \Omega)$

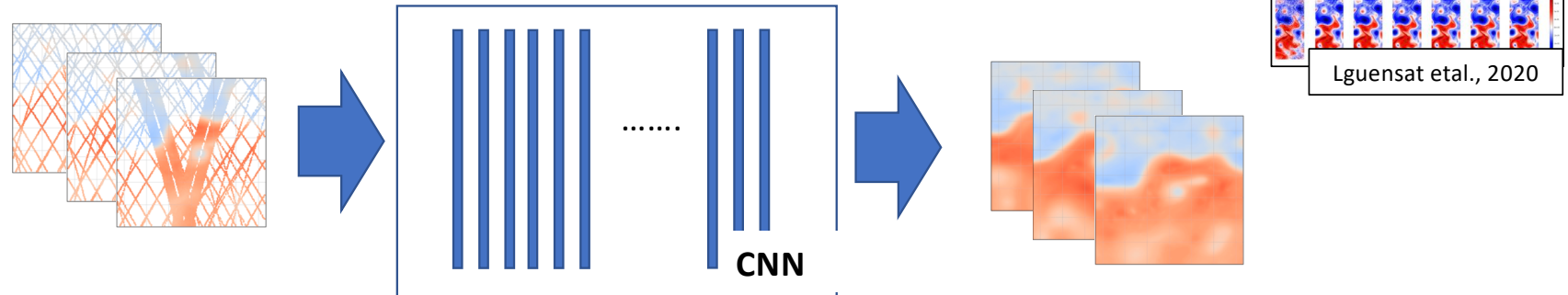
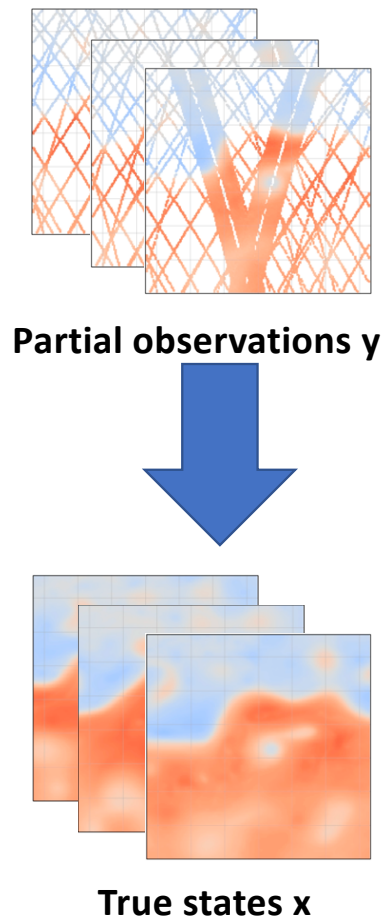


Variational cost for the true state

End-to-end learning for inverse problems (Fablet et al., 2020)

Model-driven schemes: $\hat{x} = \arg \min_x \lambda_1 \|x - y\|_{\Omega}^2 + \lambda_2 \Phi(x)$

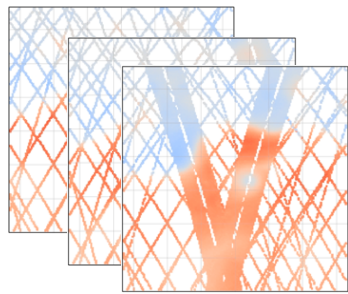
Direct learning for inverse problems: $\hat{x} = \Psi(y)$ $y \rightarrow \text{CNN} \rightarrow x$



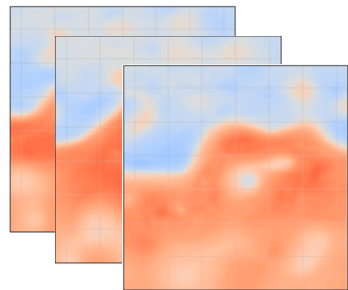
Examples of CNN architectures: Reaction-Diffusion architectures, ADMM-inspired architectures,...

Good performance but possibly weak interpretability/generalization capacities of the solution beyond the training cases

End-to-end learning for inverse problems (Fablet et al., 2020)



Partial observations y



True states x

Model-driven schemes: $\hat{x} = \arg \min_x \lambda_1 \|x - y\|_{\Omega}^2 + \lambda_2 \Phi(x)$

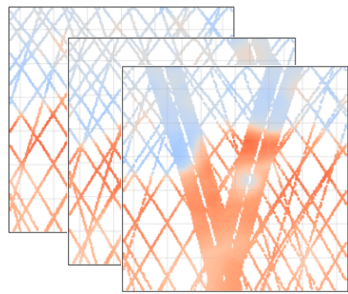
Direct learning for inverse problems: $\hat{x} = \Psi(y)$ $y \rightarrow \text{CNN} \rightarrow x$

Proposed scheme: joint learning of the variational model and solver

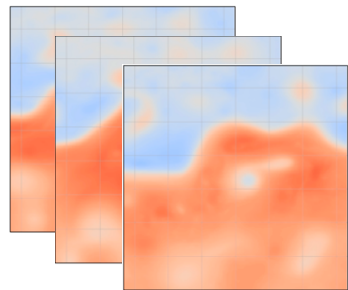
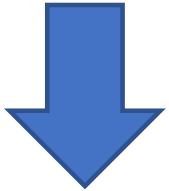
- Theoretical bi-level optimization

$$\arg \min_{\Phi} \sum_n \|x_n - \tilde{x}_n\|^2 \text{ s.t. } \tilde{x}_n = \arg \min_{x_n} U_{\Phi}(x_n, y_n, \Omega_n)$$

End-to-end learning for inverse problems (Fablet et al., 2020)



Partial observations y



True states x

Model-driven schemes: $\hat{x} = \arg \min_x \lambda_1 \|x - y\|_{\Omega}^2 + \lambda_2 \Phi(x)$

Direct learning for inverse problems: $\hat{x} = \Psi(y)$ $y \rightarrow \text{CNN} \rightarrow x$

Proposed scheme: joint learning of the variational model and solver

- Theoretical bi-level optimization

$$\arg \min_{\Phi} \sum_n \|x_n - \tilde{x}_n\|^2 \text{ s.t. } \tilde{x}_n = \arg \min_{x_n} U_{\Phi}(x_n, y_n, \Omega_n)$$

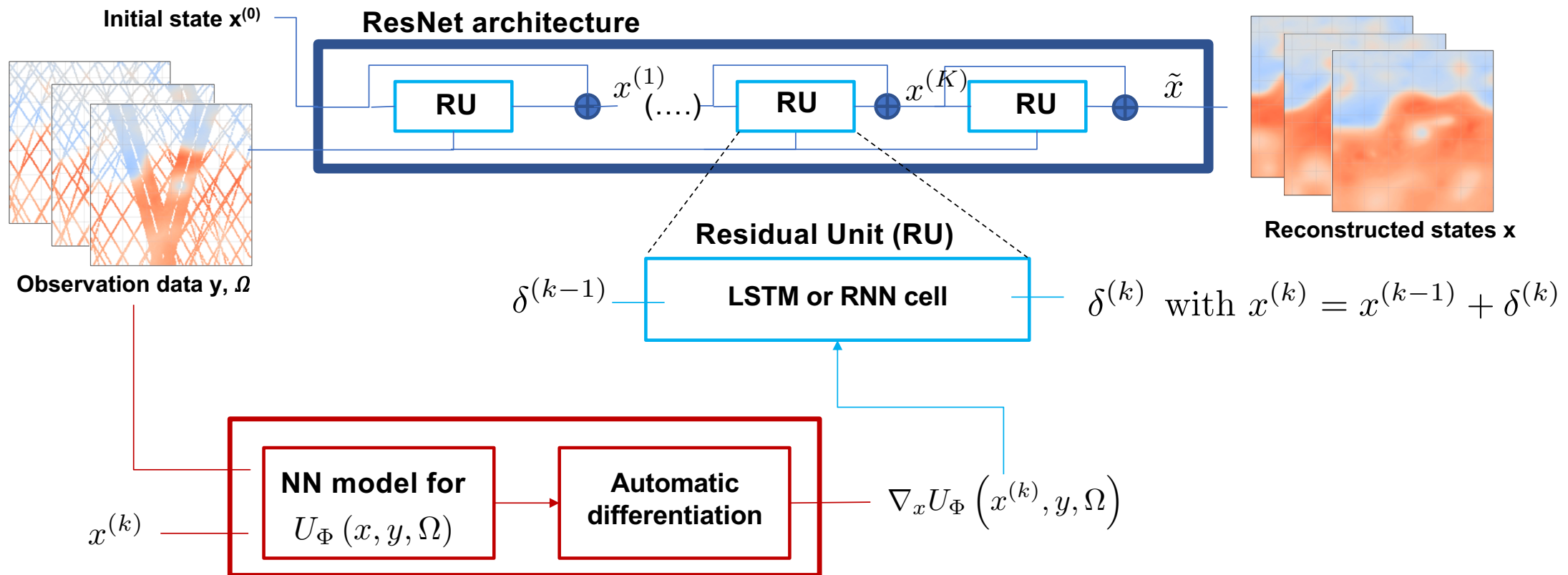
- Restated with a gradient-based NN solver for inner minimization

$$\arg \min_{\Phi, \Gamma} \sum_n \|x_n - \tilde{x}_n\|^2 \text{ s.t. } \tilde{x}_n = \Psi_{\Phi, \Gamma}(x_n^{(0)}, y_n, \Omega_n)$$

Iterative NN solver using automatic differentiation to compute gradient $\nabla_x U_{\Phi}(x^{(k)}, y, \Omega)$

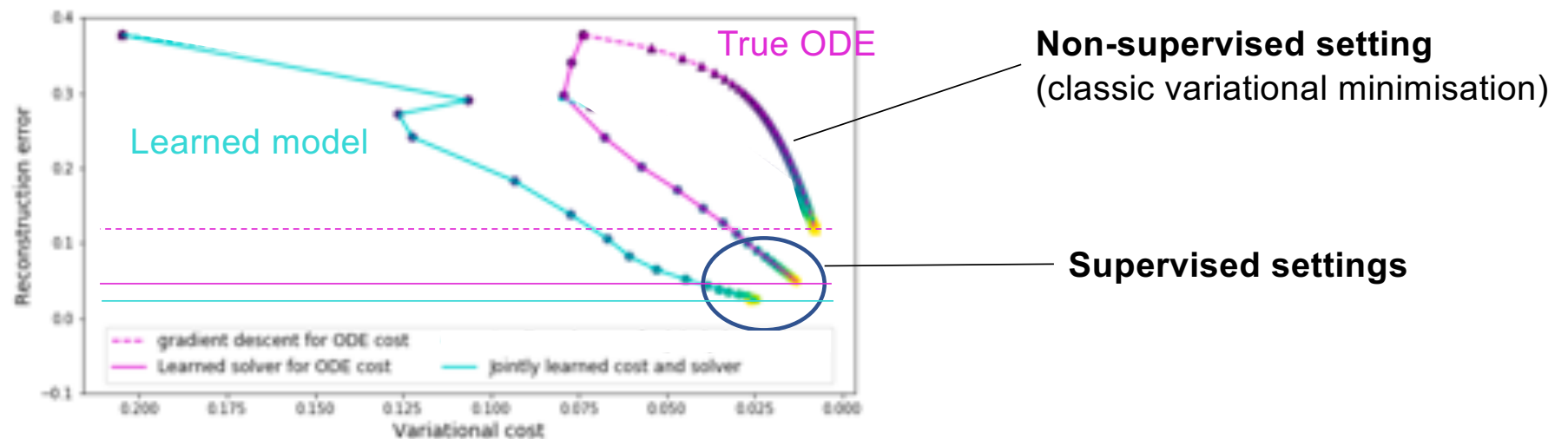
End-to-end learning for inverse problems (Fablet et al., 2020)

Proposed scheme: **associated NN architecture**

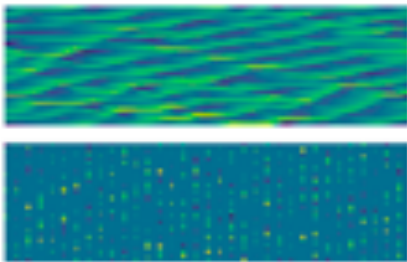


End-to-end learning for inverse problems (Fablet et al., 2020)

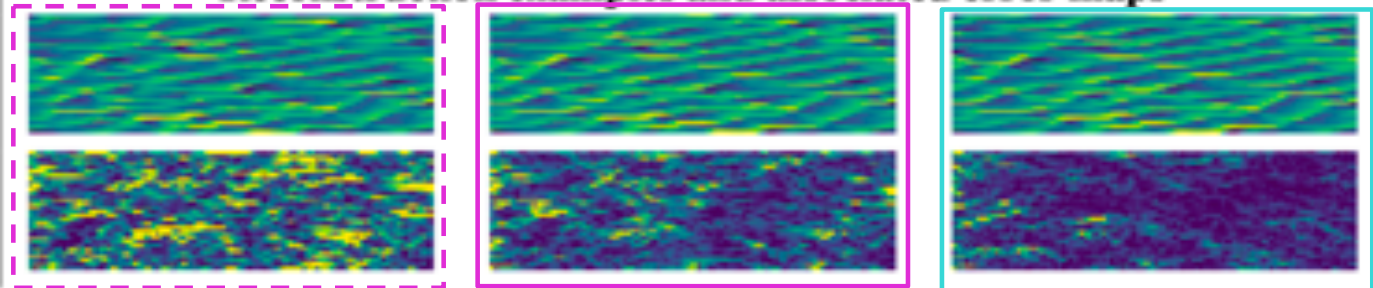
Illustration on Lorenz-96 dynamics (Bilinear ODE)



True and observed states



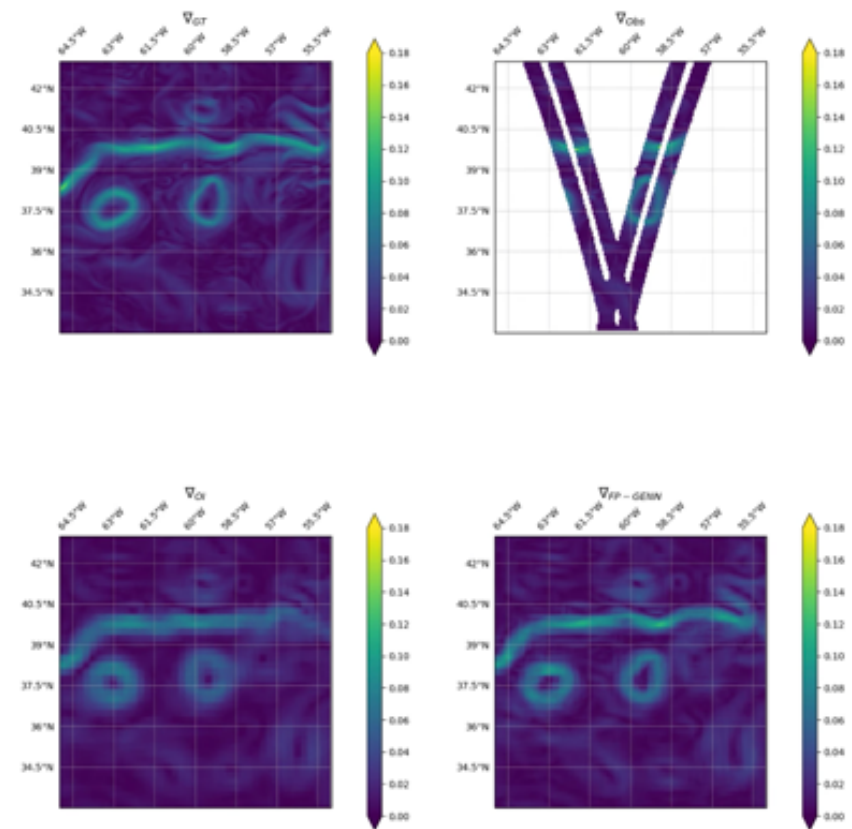
Reconstruction examples and associated error maps



End-to-end learning for inverse problems (Fablet et al., 2020)

Applications to the reconstruction of sea surface current from SWOT data

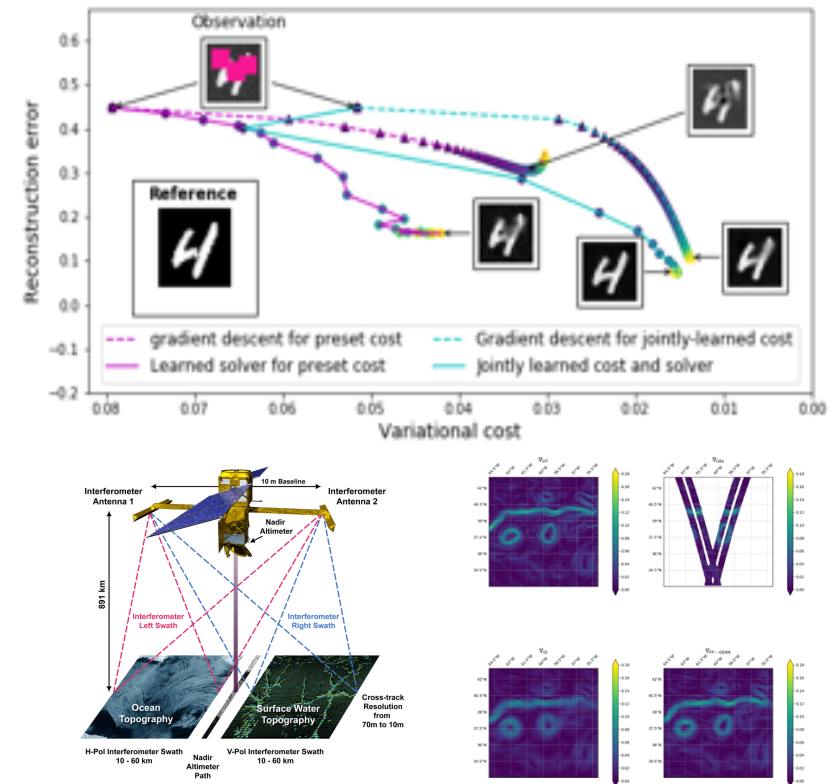
NB: preliminary results with a fixed-point Solver rather than a gradient-based solver



End-to-end learning for inverse problems (Fablet et al., 2020)

Key messages

- We can bridge DNN and variational models to solve inverse problems
- Learning both variational priors and solvers using groundtruthed (simulation) or observation-only data
- The best model may not be the TRUE one for inverse problems
- Generic formulation/architecture beyond space-time dynamics

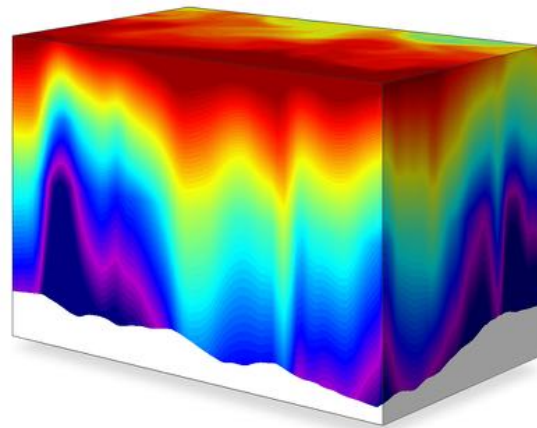
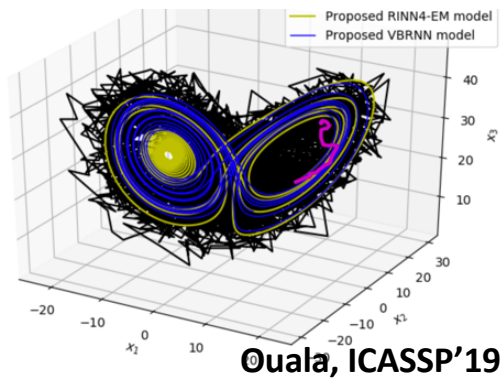


Preprint: <https://arxiv.org/abs/2006.03653>

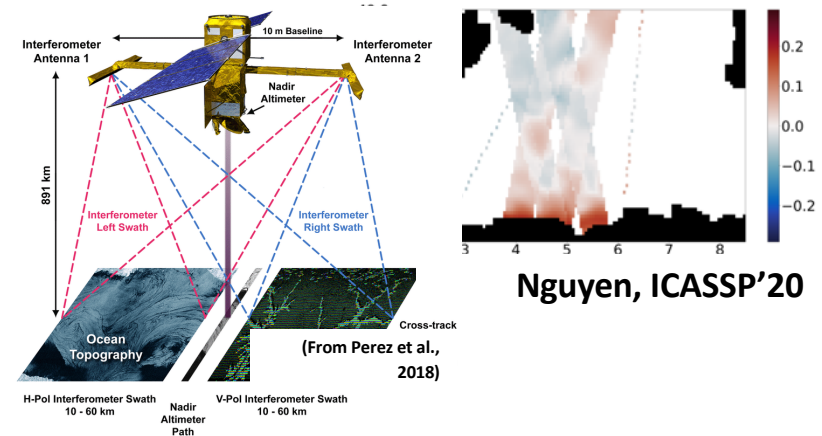
Code: <https://github.com/CIA-Oceanix>

End-to-end learning from real observation data ?

Scarce time sampling



Noisy and irregular sampling



Partially-observed system

Ouala, preprint 2019

Summary

- ***NNs as numerical schemes for ODE/PDE/energy-based representations of geophysical flows***
- ***Embedding geophysical priors in NN representations*** (e.g., Lguensat et al., 2019; Ouala et al., 2019)
- ***End-to-end architecture for jointly learning a representation (eg, ODE) and a solver*** (e.g., Fablet et al., 2020)
- ***Towards stochastic representations embedded in NN architectures*** (e.g., Pannekoucke et al., 2020, Nguyen et al., 2020)

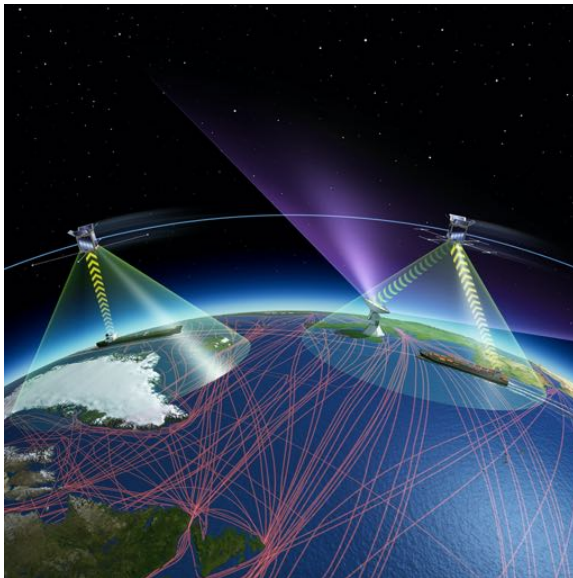
Beyond Ocean Dynamics

Learning stochastic hidden dynamics

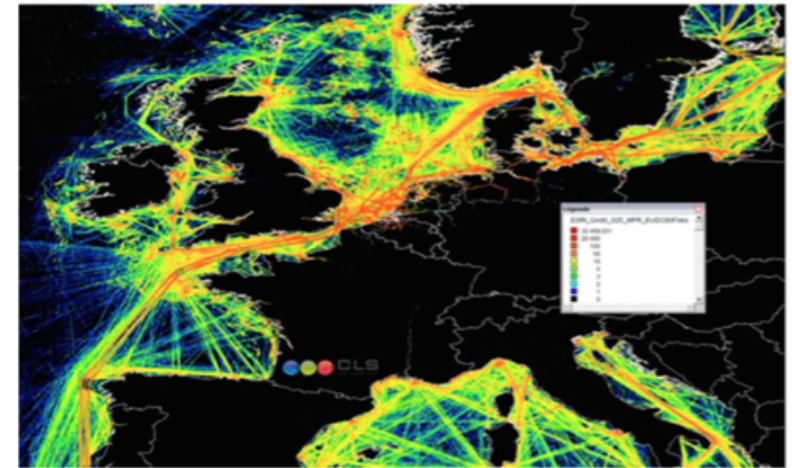
Lab-STICC

Learning stochastic hidden dynamics [Nguyen et al., 2018]

The example of AIS Vessel trajectory data

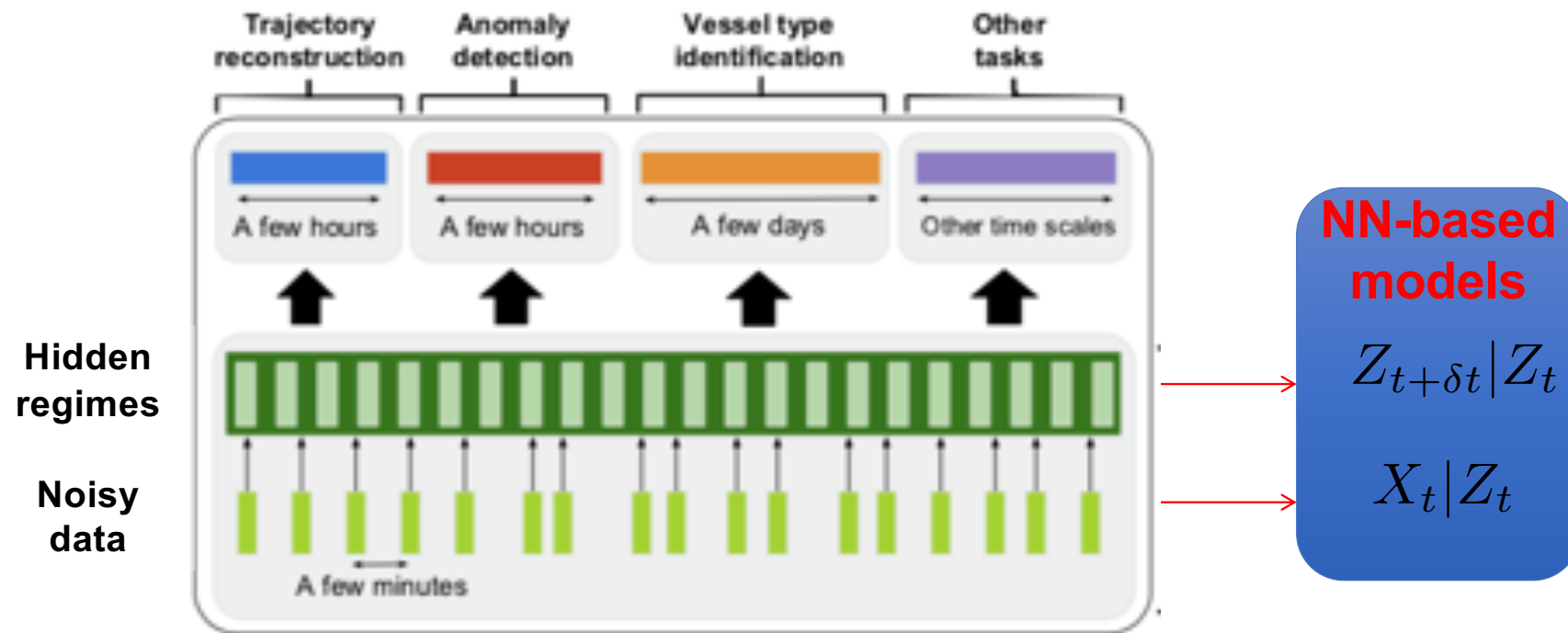


- Millions of AIS positions daily
- Noisy data: irregular sampling, corrupted data



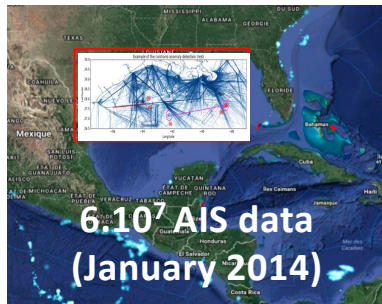
How can we learn from AIS data streams ?

Learning stochastic hidden dynamics [Nguyen et al., 2018]



Model training from noisy AIS streams using variational Bayesian approximation

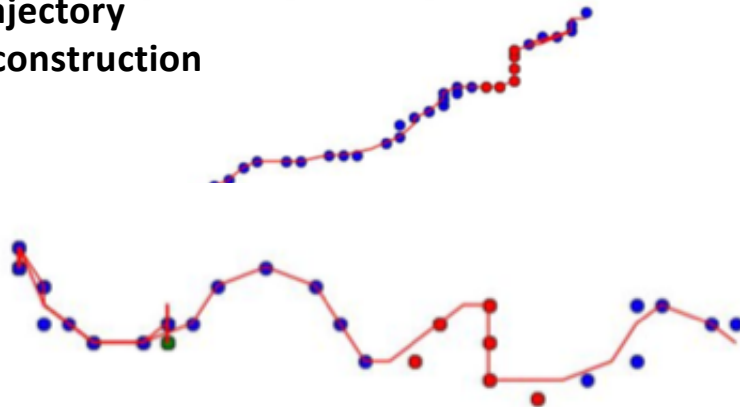
Learning stochastic hidden dynamics [Nguyen et al., 2018]



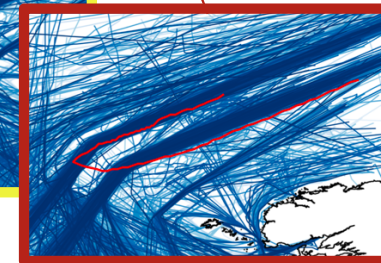
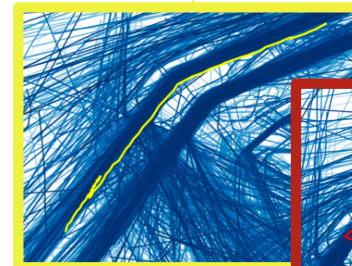
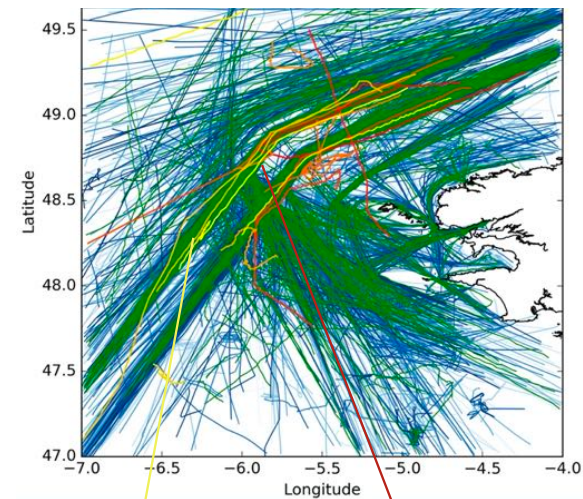
Vessel type
recognition

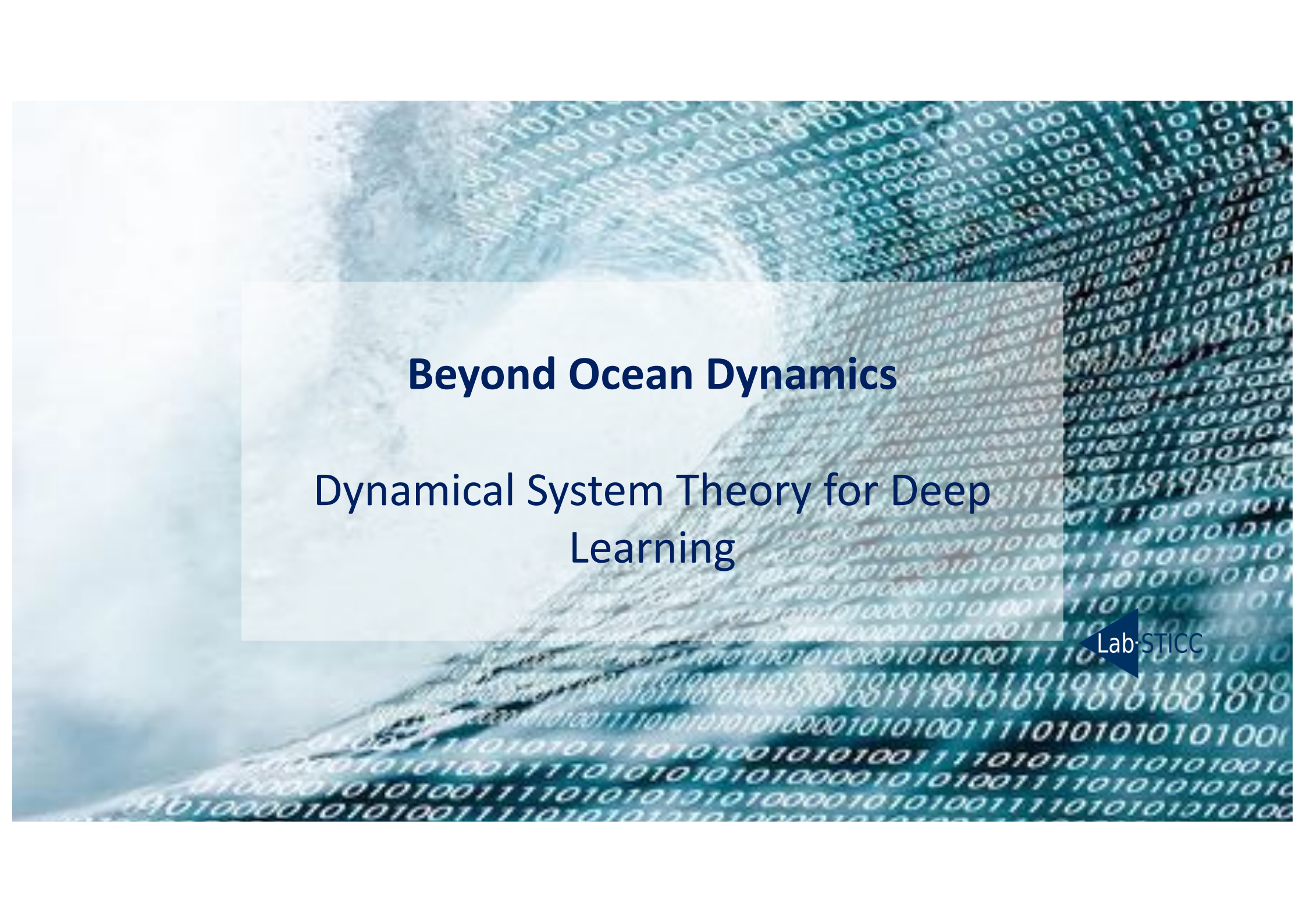
~88% of correct
recognition

Trajectory
reconstruction



Abnormal behaviour detection



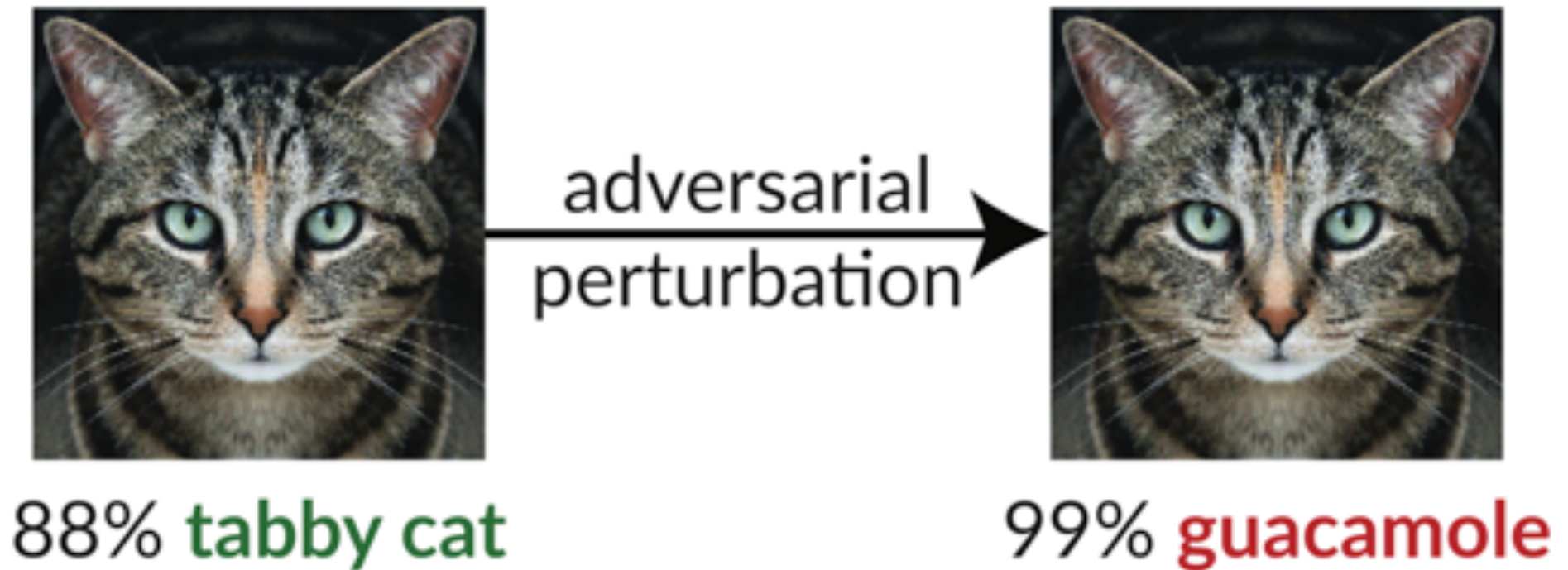


Beyond Ocean Dynamics

Dynamical System Theory for Deep Learning

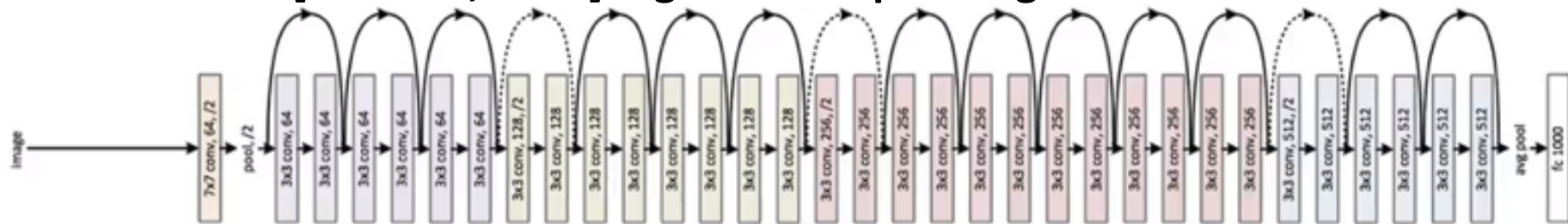
Lab-STICC

Understanding DL models ?



Understanding ResNets [Rousseau et al., 2019]

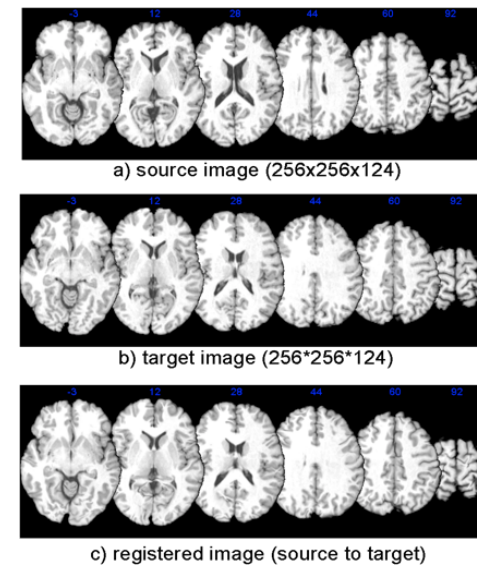
ResNet [He et al., 2015] regarded as space registration machines



- Image registration examples



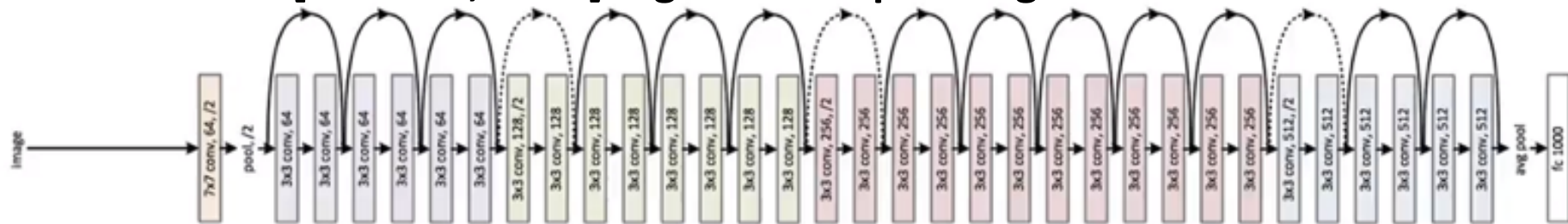
[Matlab tutorial]



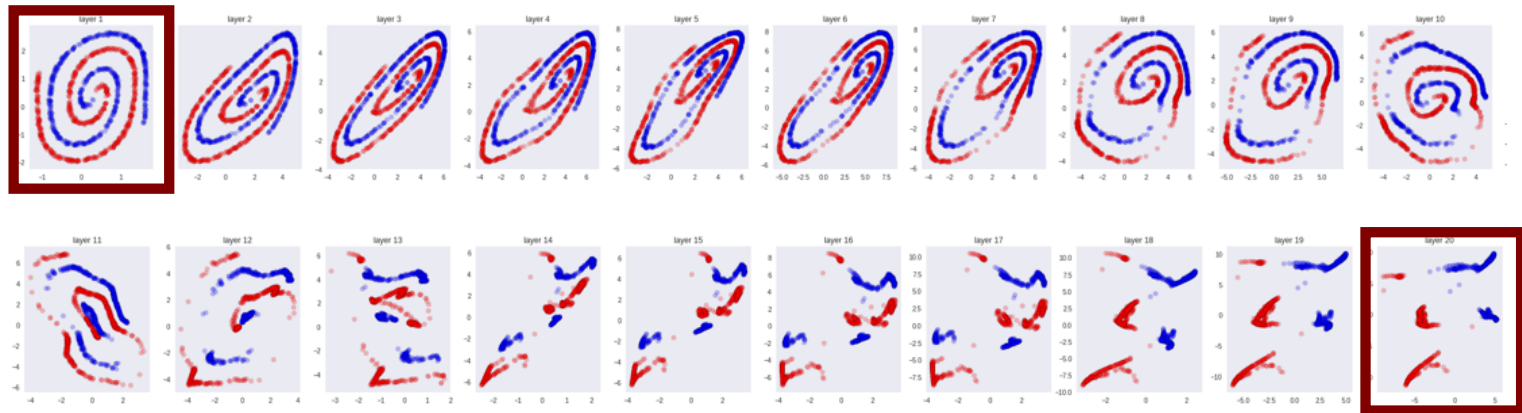
[Dramms tutorial]

Understanding ResNets [Rousseau et al., 2019]

ResNet [He et al., 2015] regarded as space registration machines



Original
feature
space



Registered space to make feasible a linear
separation between classes

AI Chair OceaniX 2020-2024

Physics-informed AI
for Observation-Driven Ocean AnalytiX

PI: R. Fablet, Prof. IMT Atlantique, Brest

Internship, PhD and
postdoc opportunities

(<https://rfablet.github.io/>)



Thank you.

Joint work with B. Chapron, F. Collard, L. Drumetz, J. Le Sommer, R. Lguensat, D. Nguyen, S. Ouala, A. Pascual, F. Rousseau, P. Tandeo, J. Verron, O. Pannekoucke, ...

More:

- Webpage: <https://rfablet.github.io/>
- Preprints: https://www.researchgate.net/profile/Ronan_Fablet

