Course #4:

Recurrent Neural Networks

Roadmap

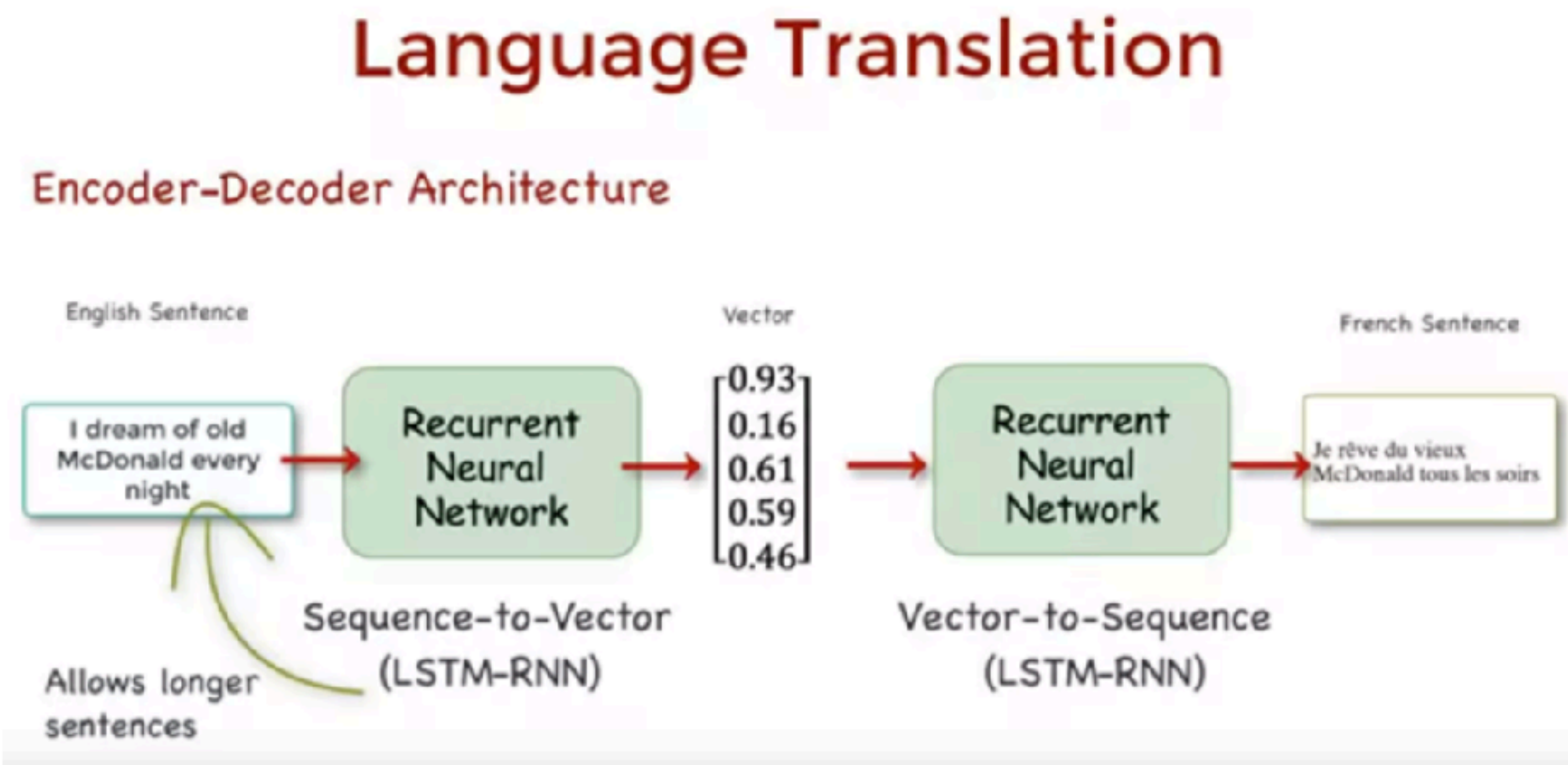
- Recap from course #3
- Auto-encoders
- Recurrents Neural Networks

Lecture. #3
Things to know (AE)

- Auto-encoder
- Latent variable
- UNet
- ResNet

Recurrent Neural Networks

Application to text data



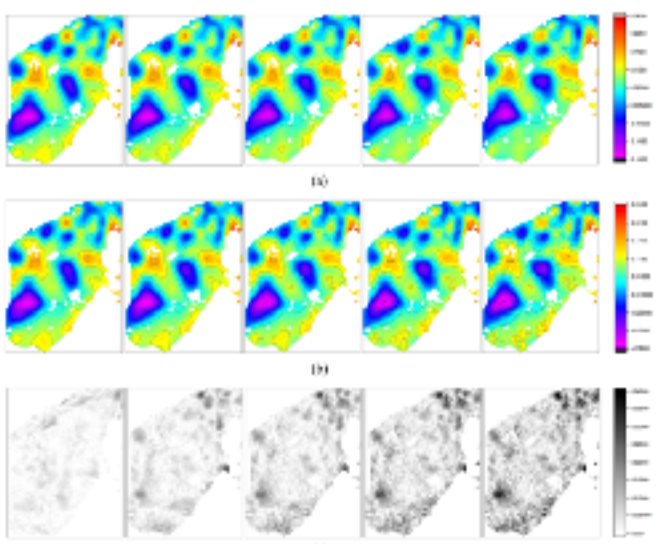
https://towardsdatascience.com/understanding-neural-machine-translation-encoder-decoder-architecture-80f205643ba4

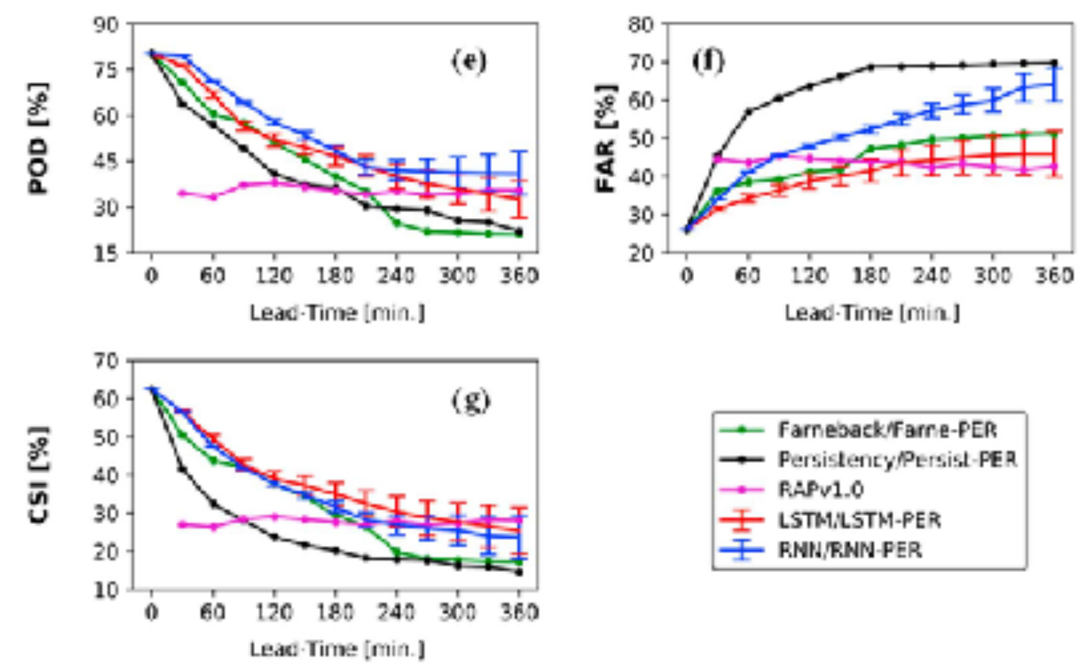
Applications to geoscience

IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 13, 2020 2853

A Deep Learning Method With Merged LSTM Neural Networks for SSHA Prediction

Tao Song, *Senior Member, IEEE*, Jingyu Jiang, Wei Li, and Danya Xu





AGU100 ADVANCING EARTH AND SPACE SCIENCE

Journal of Geophysical Research: Atmospheres

RESEARCH ARTICLE
10.1029/2018JD028375

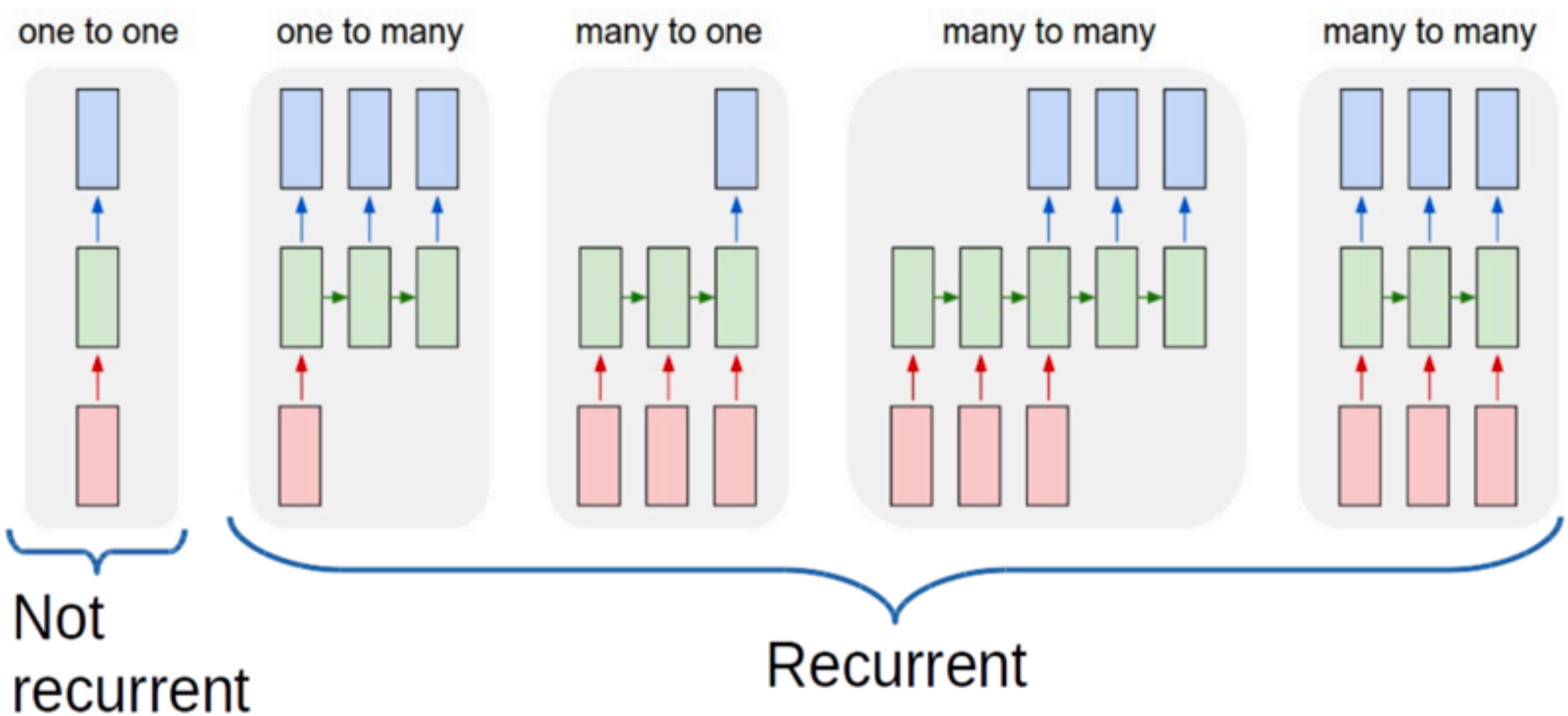
Short-Term Precipitation Forecast Based on the PERSIANN System and LSTM Recurrent Neural Networks

Ata Akbari Asanjan[1], Tiantian Yang[1,2], Kuolin Hsu[1,3], Soroosh Sorooshian[1], Junqiang Lin[4], and Qidong Peng[4]

[1]Department of Civil and Environmental Engineering, Center for Hydrometeorology and Remote Sensing, University of California, Irvine, CA, USA, [2]School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, OK, USA, [3]Center for Excellence for Ocean Engineering, National Taiwan Ocean University, Keelung, Taiwan, [4]China Institute of Water Resources and Hydropower Research, Beijing, China

Key Points:
- Artificial intelligence techniques are useful tools in support of forecasting complex precipitation in short range (0–6 hr)
- Long Short-Term Memory structure is capable of learning spatial and temporal correlations efficiently
- The framework provides accurate precipitation forecasts, especially for

Recurrent Neural Networks



Applications:
- Time-series forecasting
- Audio processing
- Translation
- ....

Do CNNs also apply ?

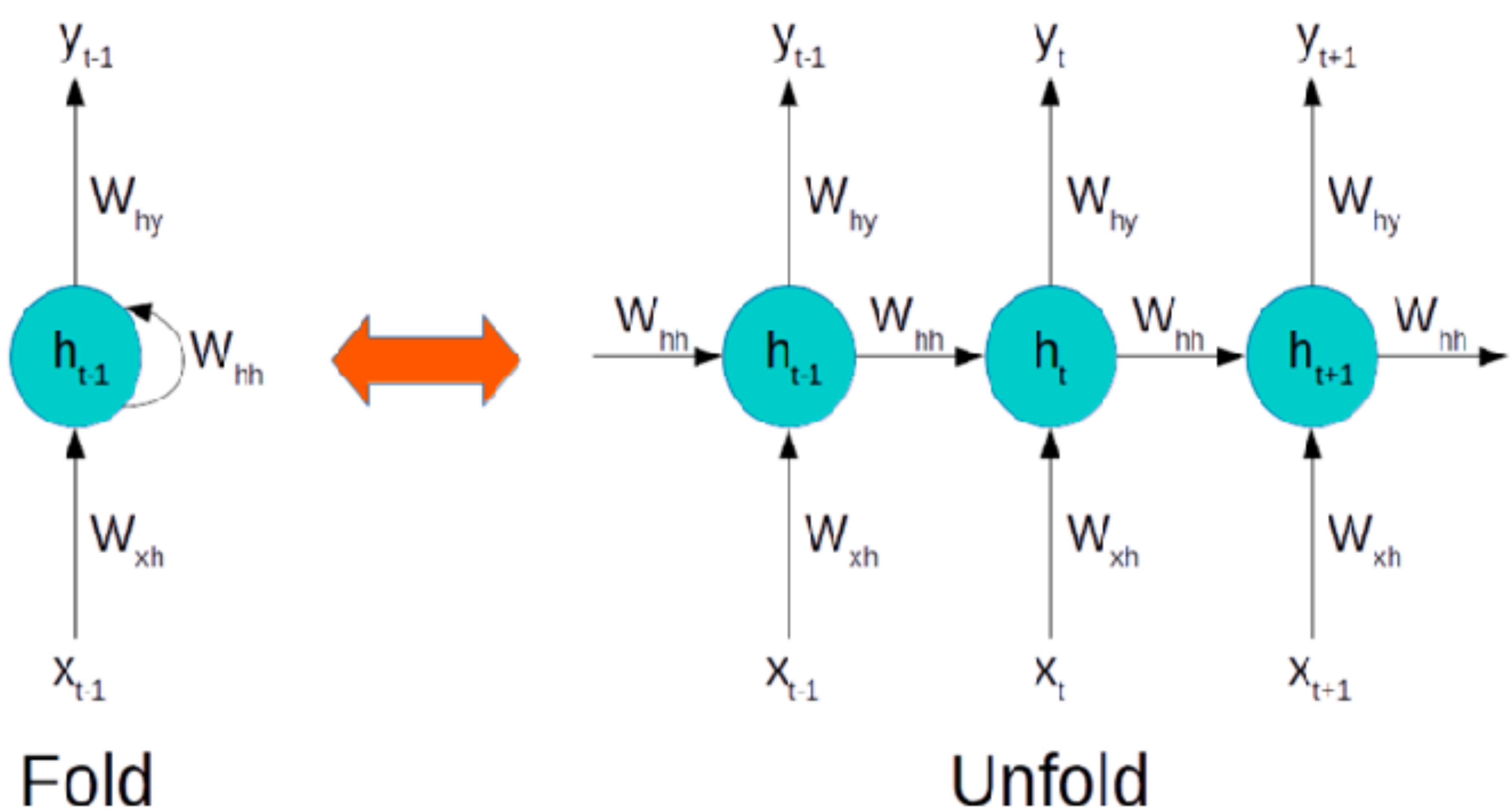
RNN: Underlying formulation (similar to state-space representation)

$x \rightarrow$ input vector

$y \rightarrow$ output vector

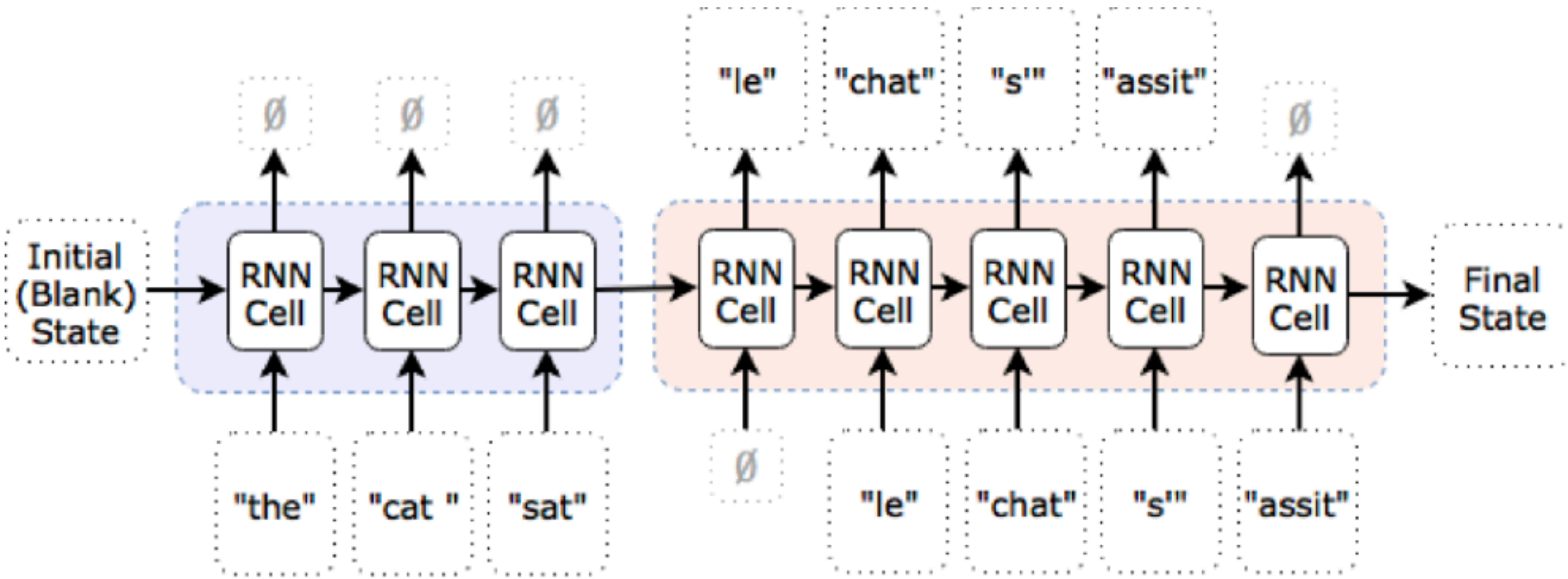
$h \rightarrow$ hidden state

$t \rightarrow$ index (time, index, etc...)



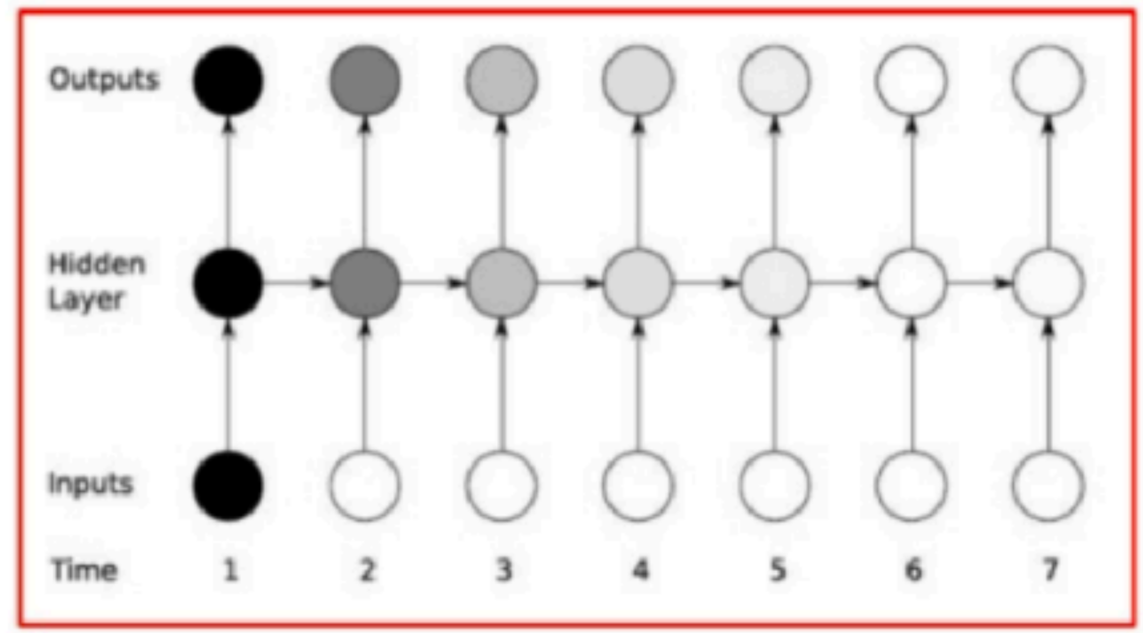
$$h_t = f\left(W_{hh}h_{t-1} + W_{xh}x_t\right) \text{ and } y_t = g\left(W_{hy}h_t\right)$$

RNN: Underlying formulation (similar to state-space representation)

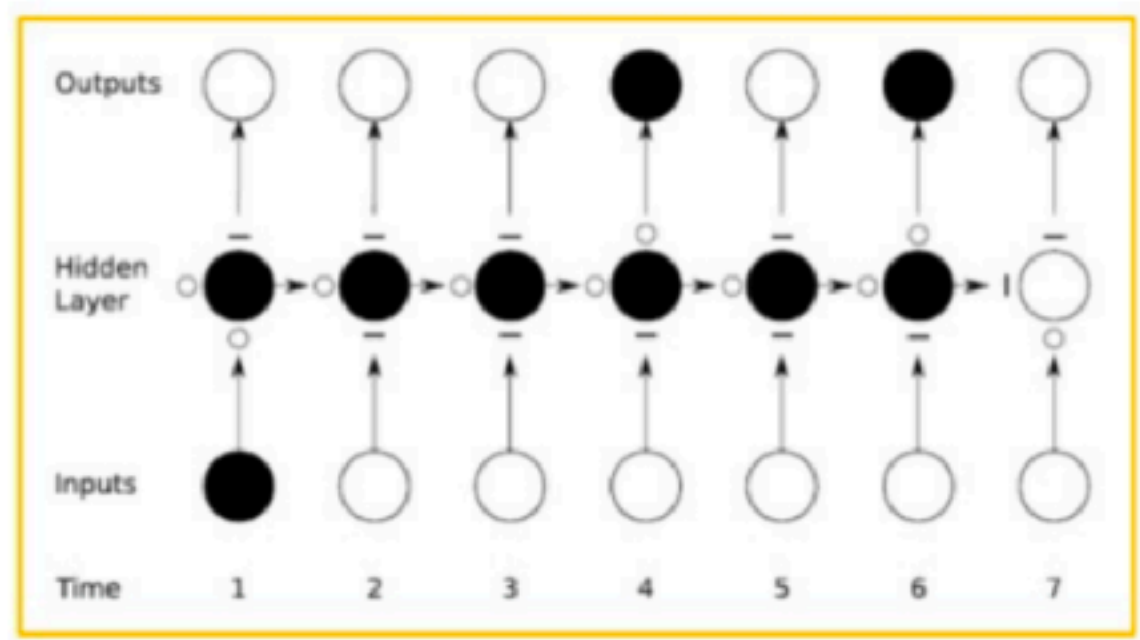


Classic RNN Architectures

- **Conventional RNN with sigmoid**
  - The sensitivity of the input values decays over time
  - The network forgets the previous input



- **Long-Short Term Memory (LSTM)** [2]
  - The cell remember the input as long as it wants
  - The output can be used anytime it wants



Dense and convolutional versions of LSTM and GRU exist (depending on the structure of the hidden state)

Short-term forecasting application (L63 case-study)

https://github.com/CIA-Oceanix/DLCourse_MOi_2022/blob/main/notebooks/notebook_PytorchLightning_Forecasting_L63_students.ipynb

Lecture. #3
Things to know (RNN)

- Recurrent Neural Network
- LSTM
- Unfloded and folded representations

Physics-informed/theory-guided networks

General question

How to exploit physical knowledge in the design of neural networks ?

Bridging physics & AI: a broader picture

Representation learning

Physical model

$$\frac{\partial u}{\partial t} + \langle \nabla u, v \rangle = \kappa \Delta u$$

Trainable representation

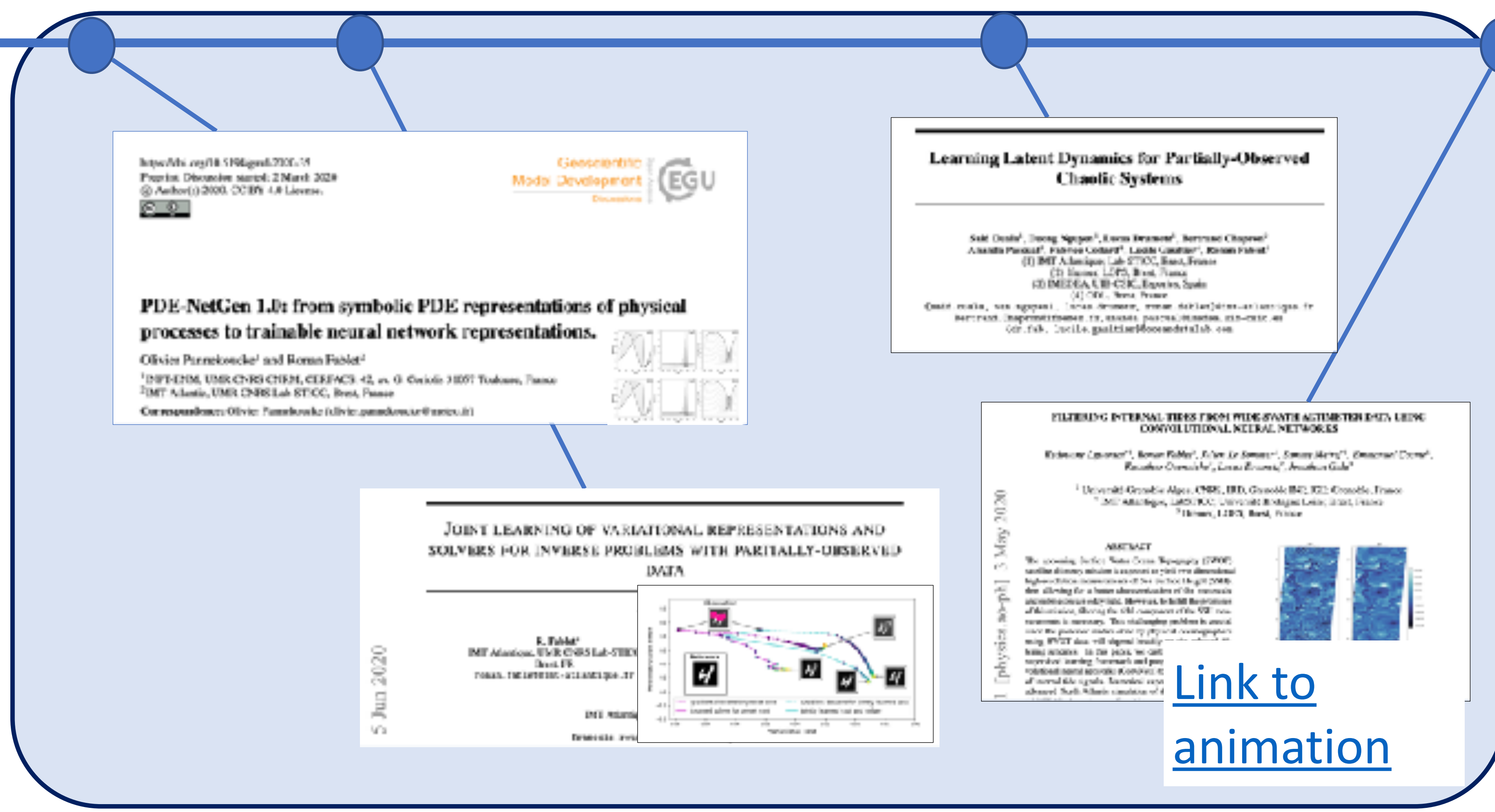
Making the most of AI and Physics Theory

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

Bridging Physics & AI: a broader picture

Model-driven

ODEs/PDEs
Variational models
State-space models
Data Assimilation
….



Data-driven

Analog methods
Kernel methods
Neural Networks
…..

Physics-informed & Data-constrained

Data-driven & Physics-aware

Bridging physics & AI: a broader picture

Representation learning

Physical model

$$\frac{\partial u}{\partial t} + \langle \nabla u, v \rangle = \kappa \Delta u$$

Trainable representation

Making the most of AI and Physics Theory

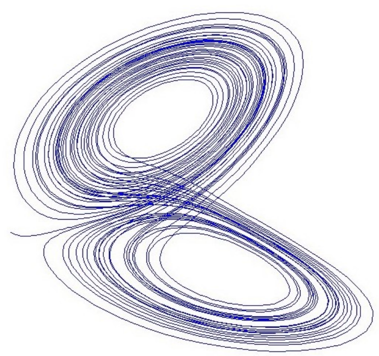
- **Model-Driven/Theory-Guided & Data-Constrained schemes**
- Data-Driven & Physics-Aware schemes (eg, Ouala et al., 2019)

How to embed physics-driven priors in DL models ?

An illustration through L63 dynamics: numerical experiments (Fablet et al., 2018)

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = \sigma\left(y(t) - x(t)\right)$$
$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = x(t)\left(\rho - z(t)\right) - y(t)$$
$$\frac{\mathrm{d}z(t)}{\mathrm{d}t} = x(t)\,y(t) - \beta\, z(t)$$

Lorenz-63 equations

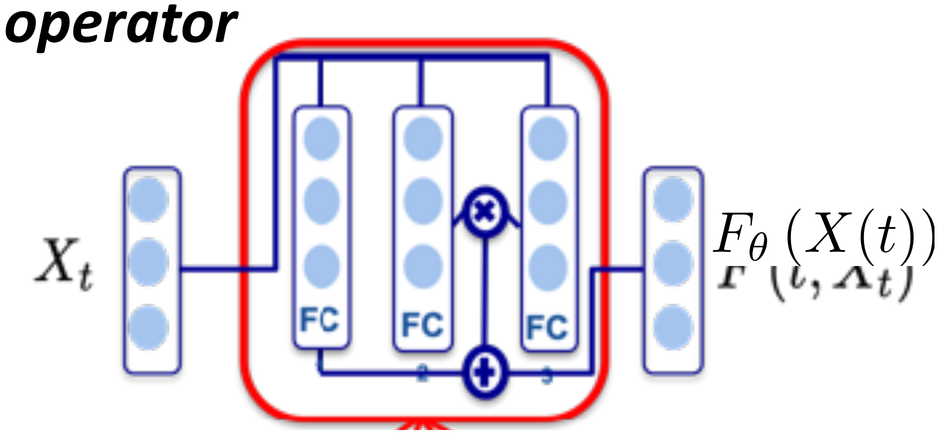


Associated Euler integration scheme

$$d_t X(t) = F_\theta\left(X(t)\right)$$

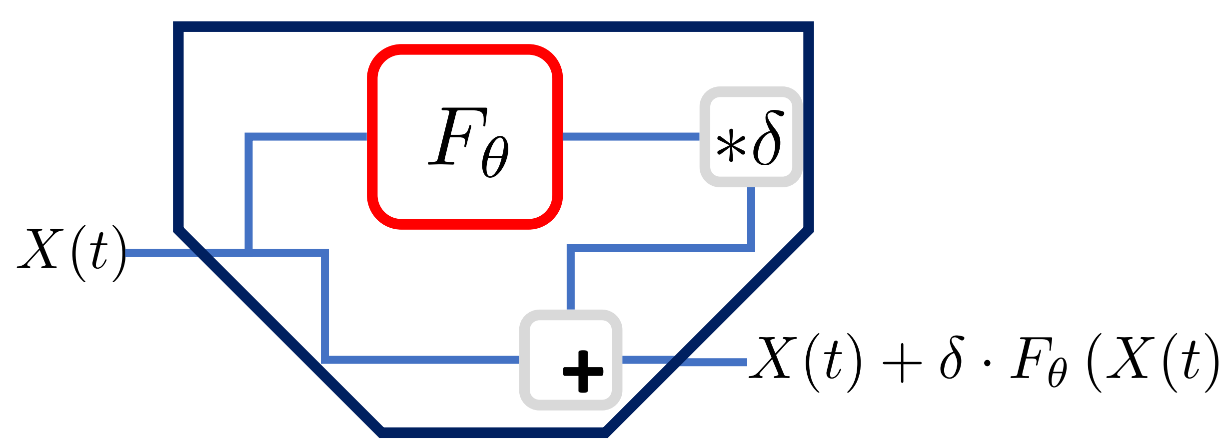
$$X(t+\delta) = X(t) + \delta \cdot F_\theta\left(X(t)\right)$$

NN architecture for differential operator



Bilinear architecture

NN architecture for integration scheme



ResNet architecture (Residual Network)

How to embed physics-driven priors in DL models ?

An illustration through L63 dynamics: numerical experiments (Fablet et al., 2018)

$$\frac{\mathrm{d}x(t)}{\mathrm{d}t} = \sigma\left(y(t) - x(t)\right)$$
$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = x(t)\left(\rho - z(t)\right) - y(t)$$
$$\frac{\mathrm{d}z(t)}{\mathrm{d}t} = x(t)\,y(t) - \beta\,z(t)$$

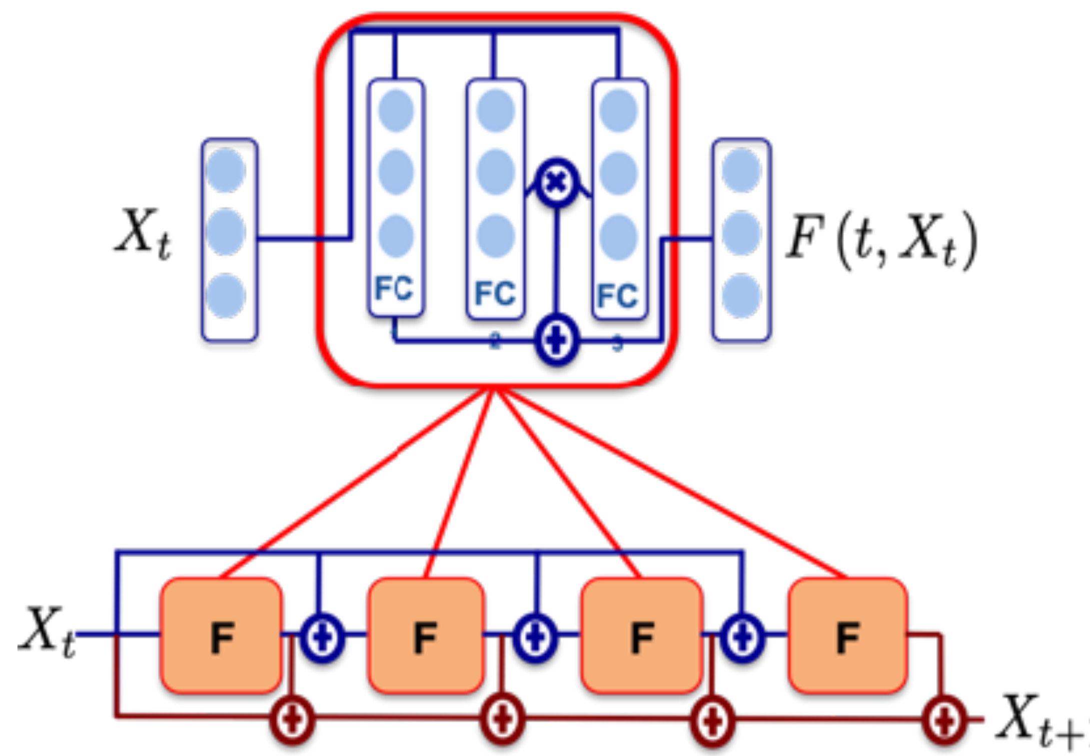
Lorenz-63 equations

Generalization to higher-order integration schemes (eg, RK4)

$$d_t X(t) = F_\theta\left(X(t)\right)$$

$$X(t+\delta) = X(t) + \sum_i \beta_i k_i$$

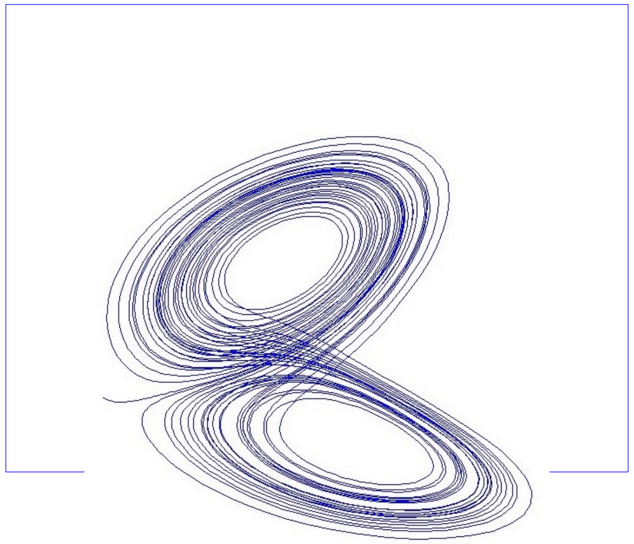
with $k_i = F_\theta\left(X(t) + \delta \alpha_i k_{i-1}\right)$



NB: Same number of trainable model parameters as the Euler-based architecture

How to embed physics-driven priors in DL models ?

An illustration through L63 dynamics: numerical experiments (Fablet et al., 2018)



Forecasting experiments

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}***

Noisy training data (σ=0.5)

Forecasting time step	**t_0+h**	**t_0+4h**	**t_0+8h**
Analog forecasting	<10^{-6}	2.01	2.2
Bi-NN(4)	***<10^{-6}***	***0.054***	***0.14***

Assimilation experiment

(1 obs. every 8 time steps**)**

Noise standard deviation in training data	**0**	**0.25**	**1**
True model	*0.50*	-	-
Analog forecasting	0.65	1.17	1.81
Bi-NN(4)	***0.60***	***0.75***	***0.86***

NN Generator from Symbolic PDEs

(Pannekoucke et al., 2020)

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

Symbolic calculus (Simpy)

PDE-GenNet (keras)

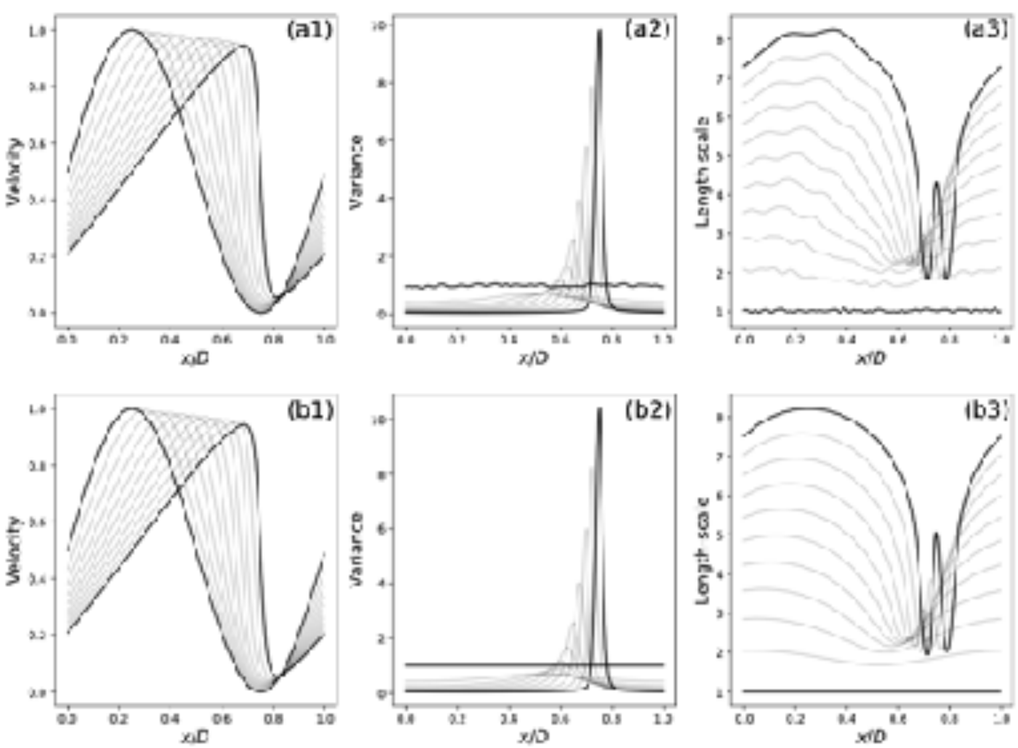
$$\begin{pmatrix} \mu_u(t) \\ \Sigma_u(t) \end{pmatrix} \longrightarrow \boxed{\textit{ResNet}} \longrightarrow \begin{pmatrix} \mu_u(t+1) \\ \Sigma_u(t+1) \end{pmatrix}$$

Generated code

```
# Example of computation of a derivative
kernel_Du_x_o1 = np.asarray([[0.0,-1/(2*self.dx[self.coordinates.index('x')]),0.0],
        [0.0,0.0,0.0],
        [0.0,1/(2*self.dx[self.coordinates.index('x')]),0.0]]).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 = k
```

Uncertainty propagation

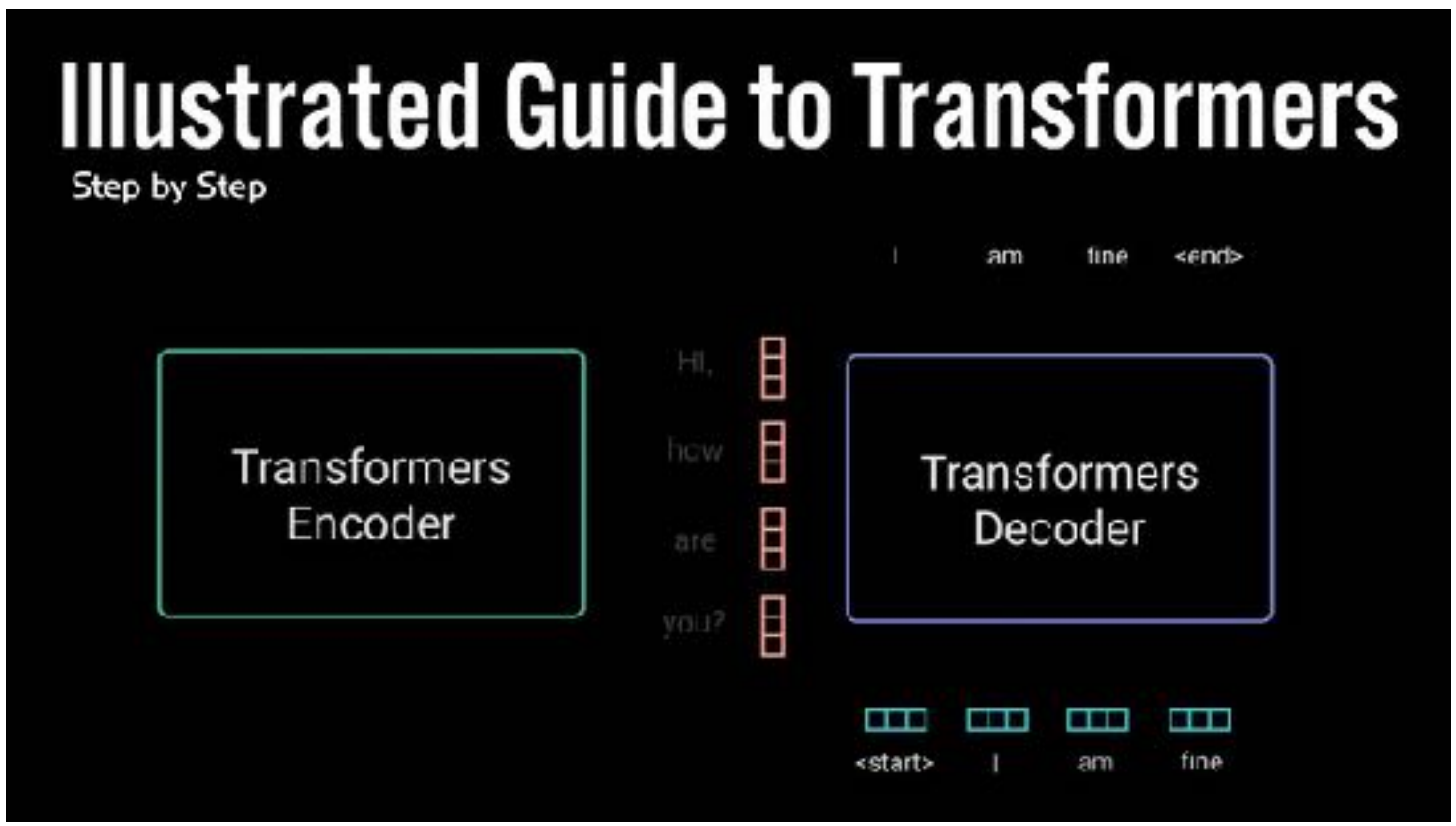


Ensemble-based prediction

NN prediction

Transformer Networks
Some links

https://towardsdatascience.com/illustrated-guide-to-transformers-step-by-step-explanation-f74876522bc0



Leading architectures for image classification and natural language processing

https://arxiv.org/abs/1706.03762

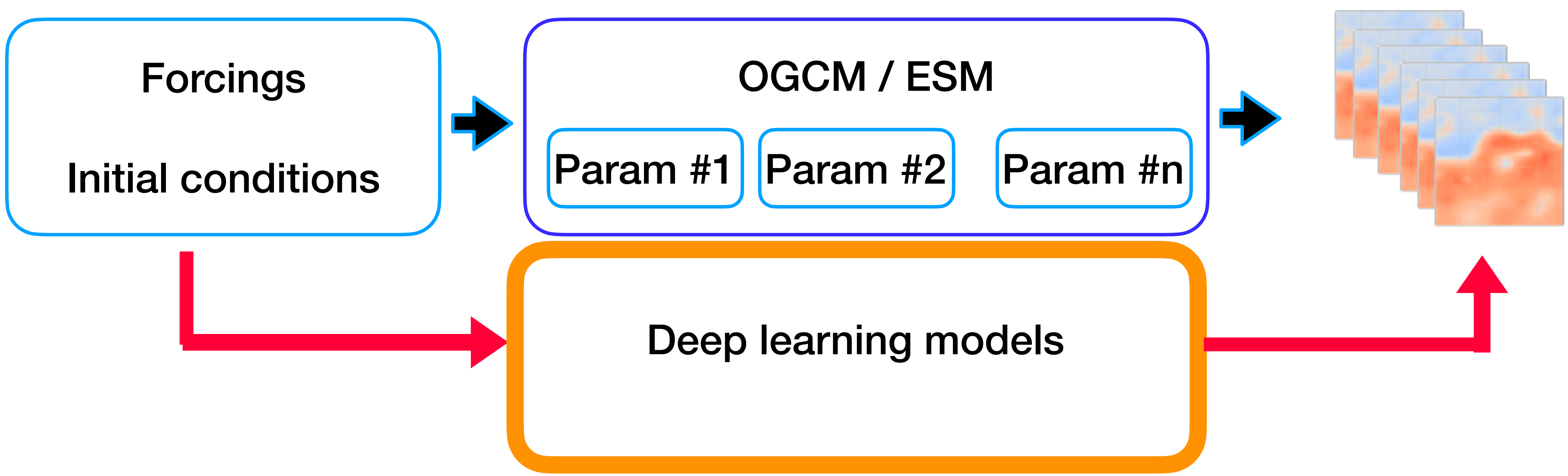
Deep Learning & DTO

Deep Learning and EDITO Model Lab

Deep Learning and EDITO Model Lab

WP2. Deep Differentiable Emulators for Ocean Modeling and Forecasting

WP2.2 DDE for ocean forecasting/simulation

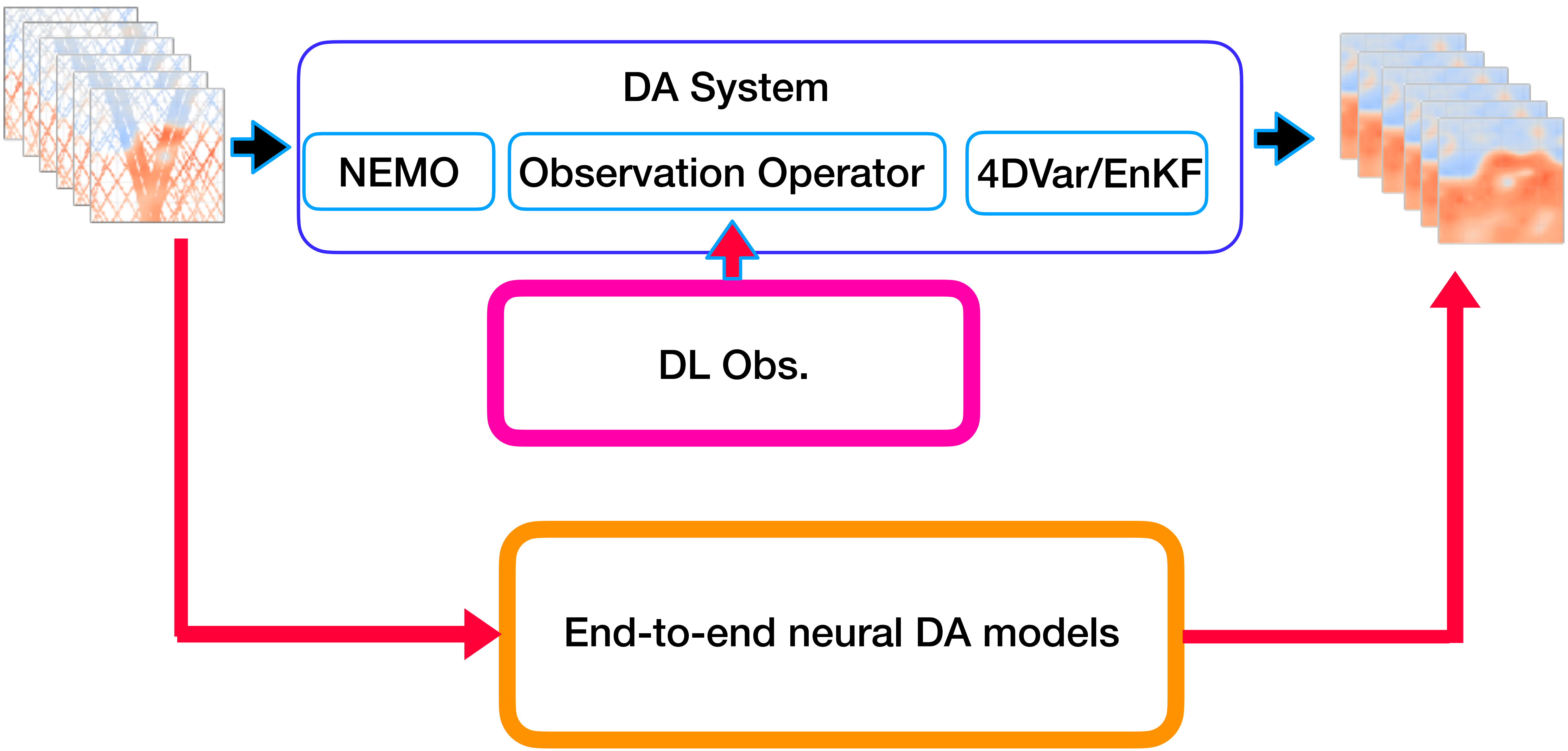


Objective: Deep learning models to emulate the simulation of specific variables

Deep Learning and EDITO Model Lab

WP2. Deep Differentiable Emulators for Ocean Modeling and Forecasting

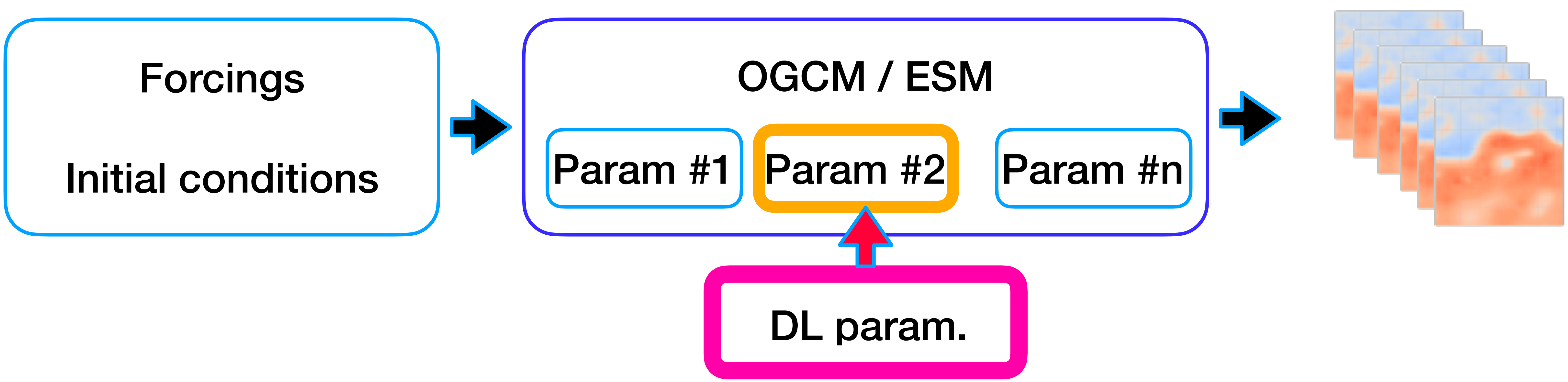
WP2.3 DDE for ocean data assimilation



Deep Learning and EDITO Model Lab

WP2. Deep Differentiable Emulators for Ocean Modeling and Forecasting

WP2.1 DDE for the calibration of OGCM components



Approach: learning a DL architecture to emulate the system to calibrate param#2 while accounting to impact/interactions with other components of the system