Course #3:

Auto-encoders and Recurrent Neural Networks

Roadmap

- Recap from course #2
- Auto-encoders
- Recurrents Neural Networks

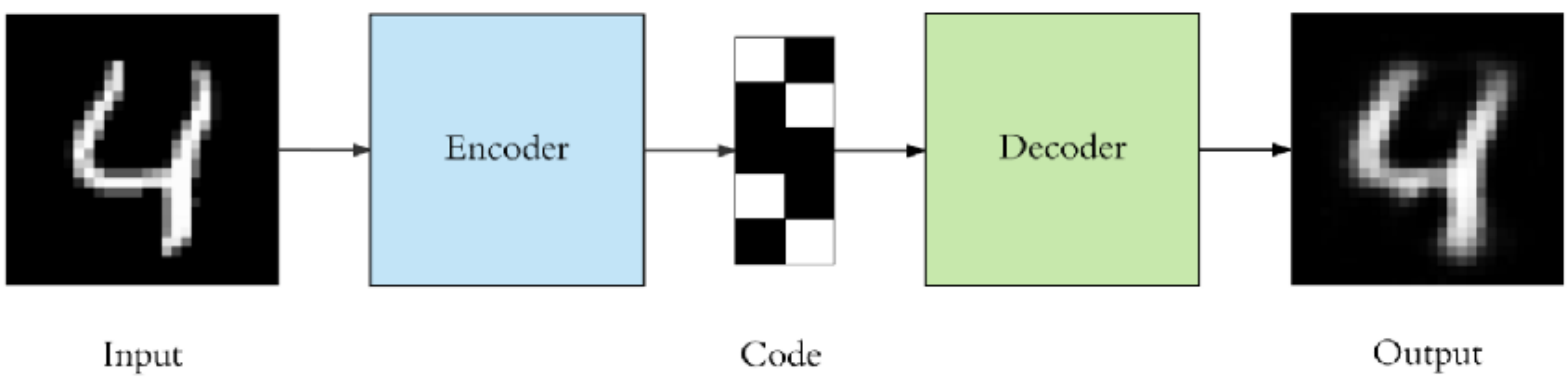
Lecture. #2
Things to know

- Convolution layers
- Pooling layers
- Activation layers
- Dropout layers
- Padding and stride
- Fine-tuning
- Over-fitting
- Data augmentation
-

PyTorch Lightning

Auto-encoders

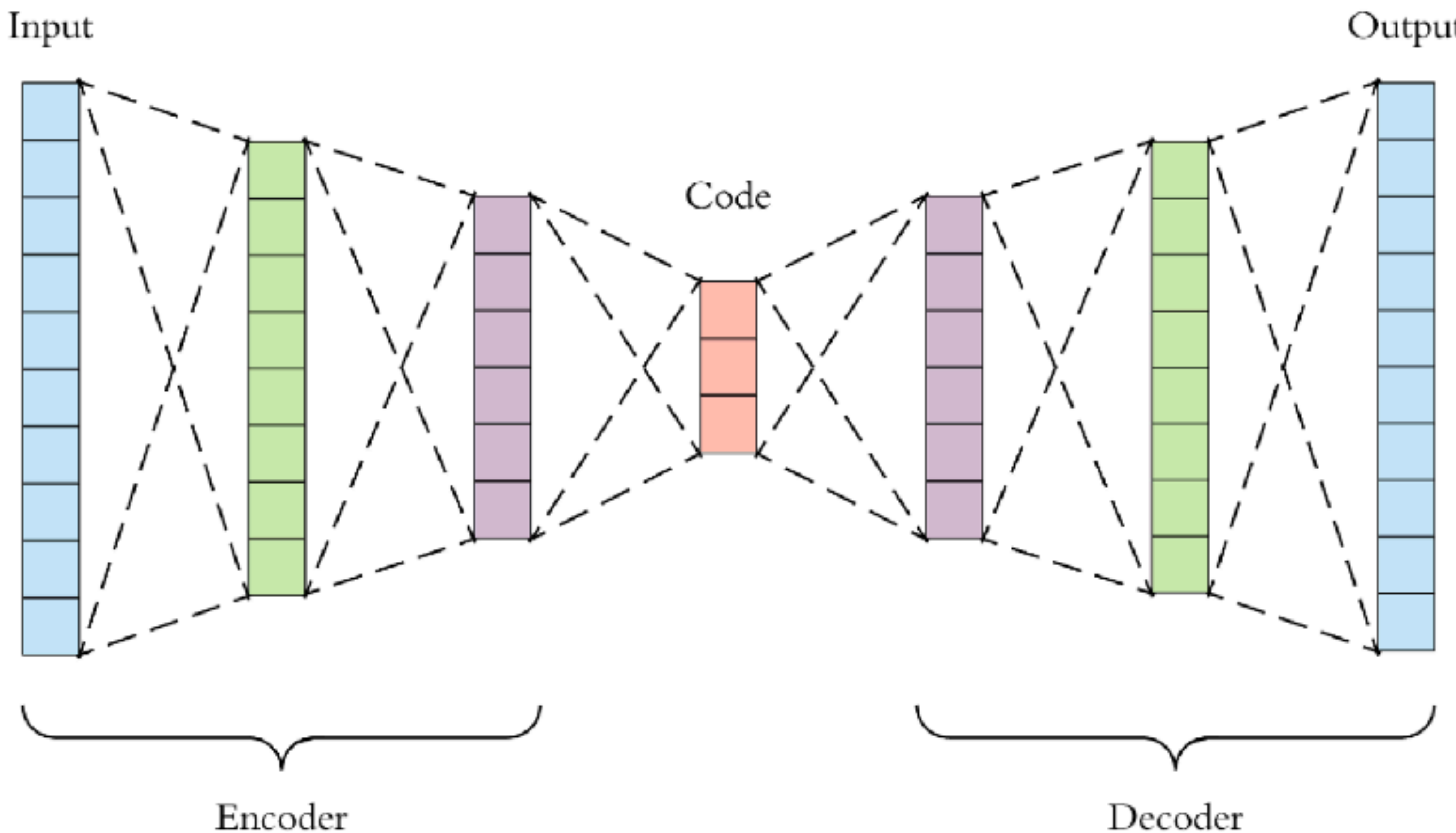
Auto-encoders



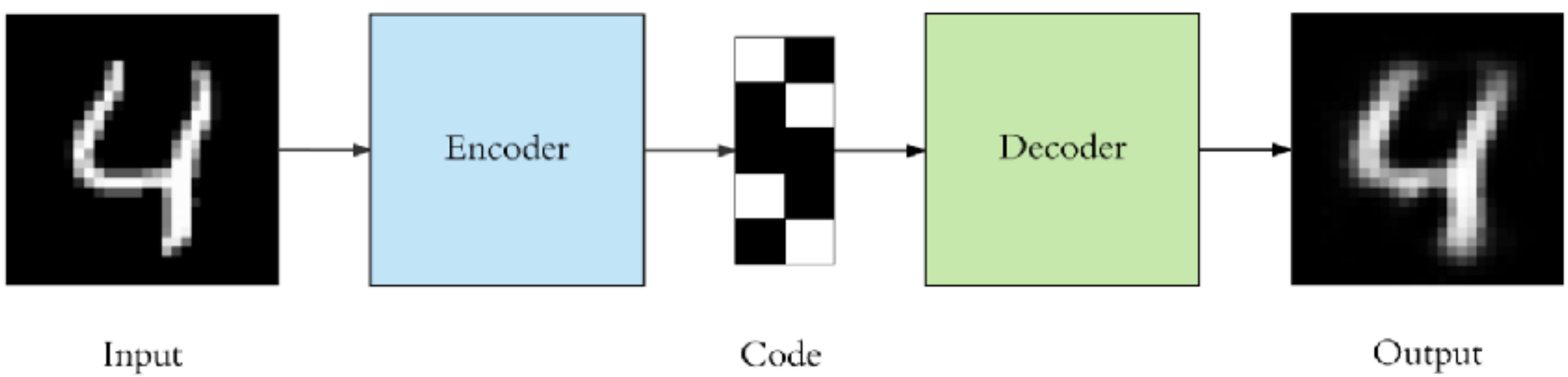
Output with the same shape as the input

Application ?

Dense auto-encoders



PCA/EOF



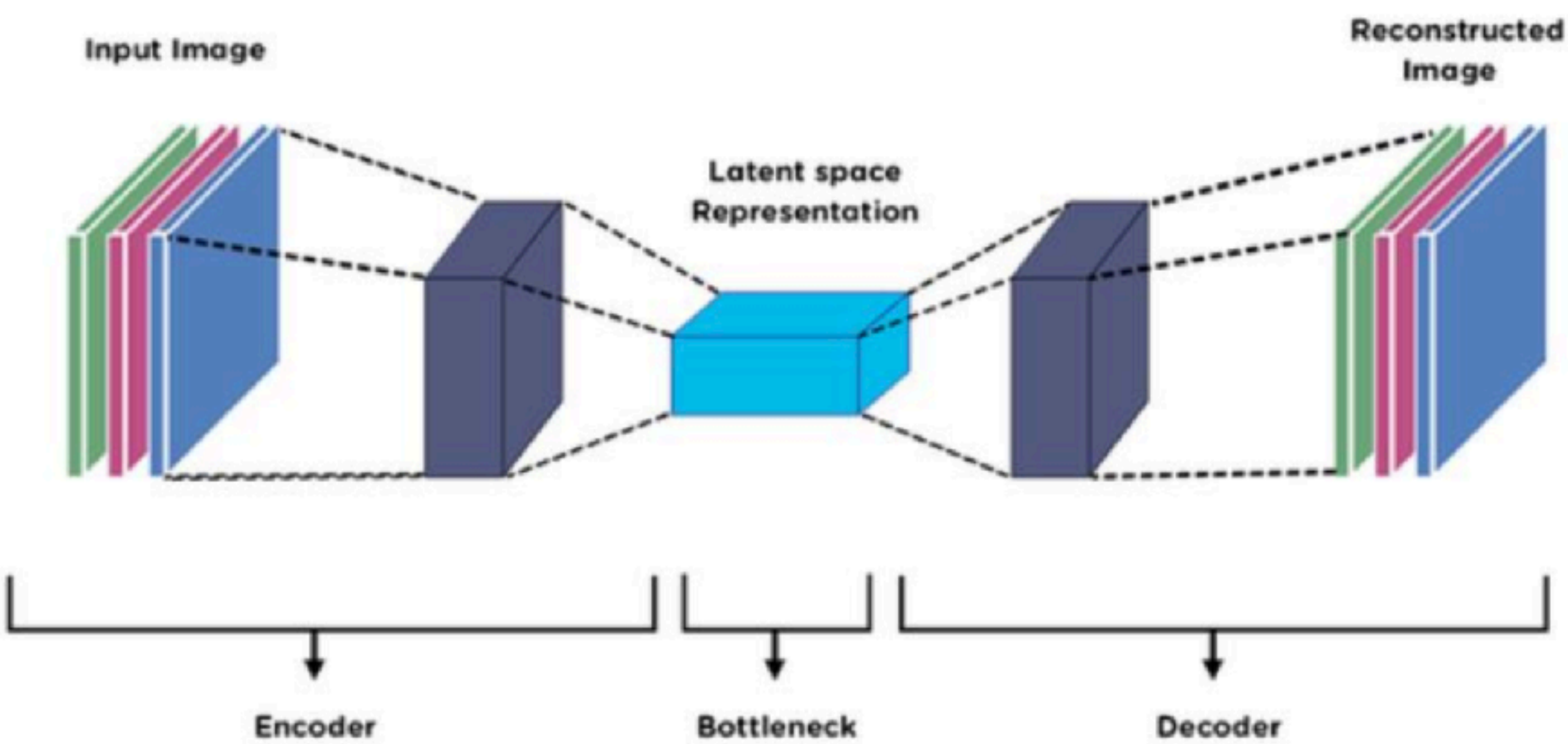
X $\longrightarrow$ Z $\longrightarrow$ $\tilde{X}$

$$Z = A \cdot X \qquad \tilde{X} = A^t \cdot Z$$

PCA as a linear auto-encoder architecture.

Which additional constraint ?

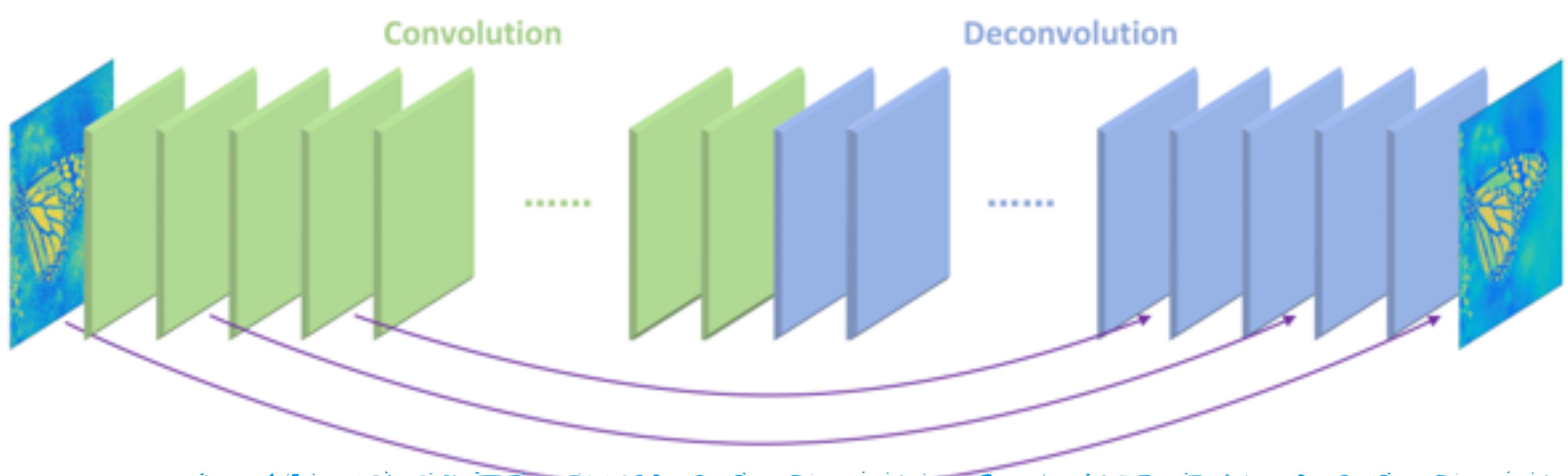
Convolutional auto-encoders



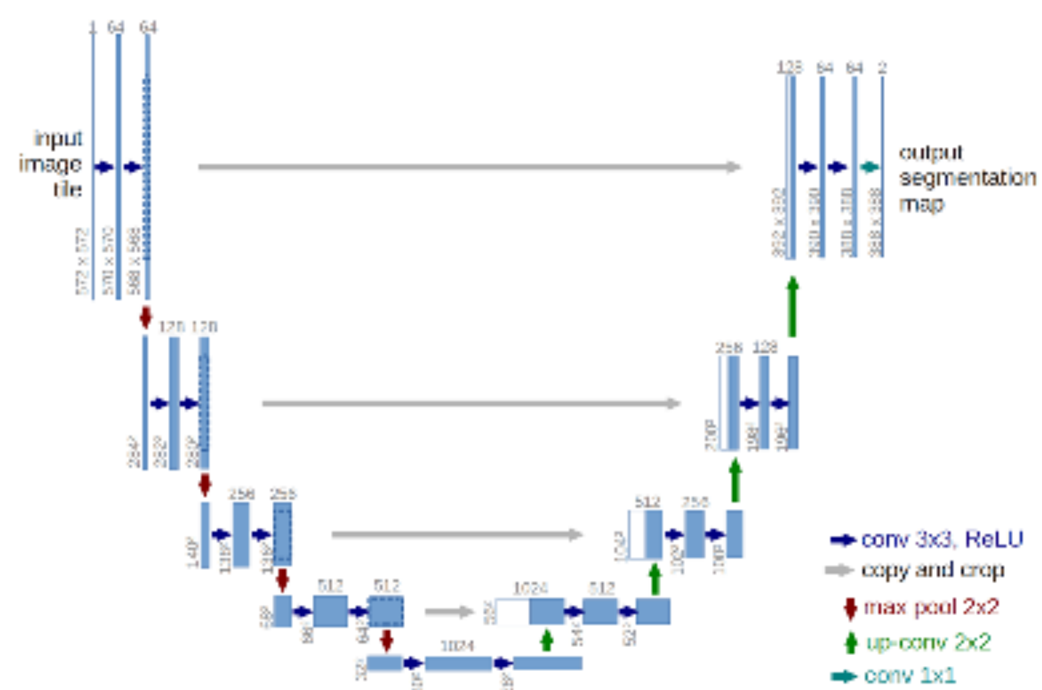
Source: https://www.analyticsvidhya.com/

Convolutional AE Zoo

Many applications do not require a low-dimensional representation
(e.g., densoising, interpolation, super-resolution,….)



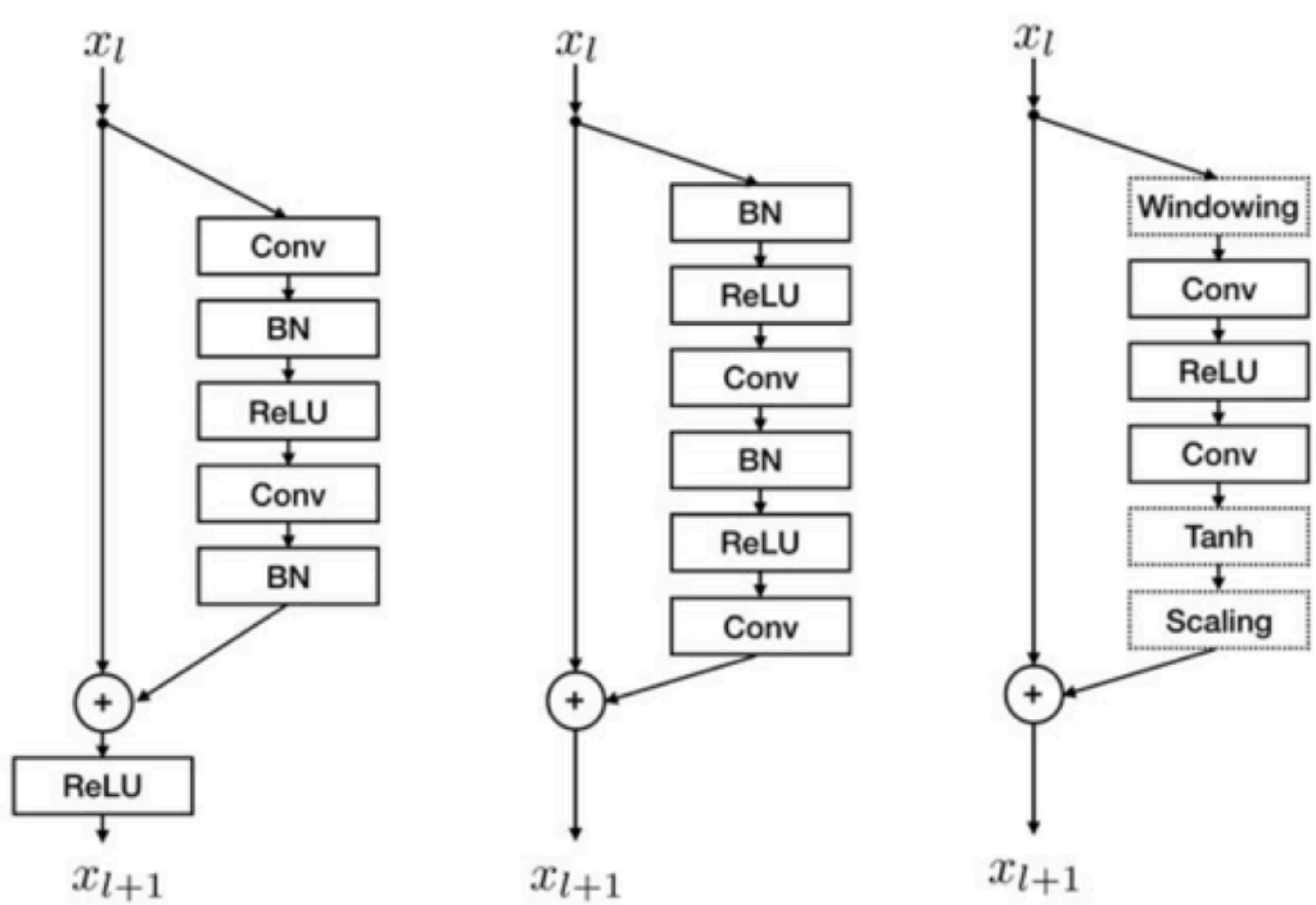
https://arxiv.org/pdf/1606.08921.pdf



UNet

Ronneberger et al., 2015

Convolutional AE Zoo



Residual Block (ResNet)

Rousseau et al., 2019

Often used to address vanishing gradients (“very” deep networks)

Auto-encoders for image denoising and image generation

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

Question 2. Fill in the architecture of the convolutional block of the encoder module to train a convolutional auto-encoder

Question 2. Modify the Conv. AE code to address image demonising and/or image interpolation

Question 3. Modify the code to test a linear auto-encoder (cf. AE and PCA)

ConvAE architectures for Ocean Dynamics ?

ConvAE & Ocean Dynamics

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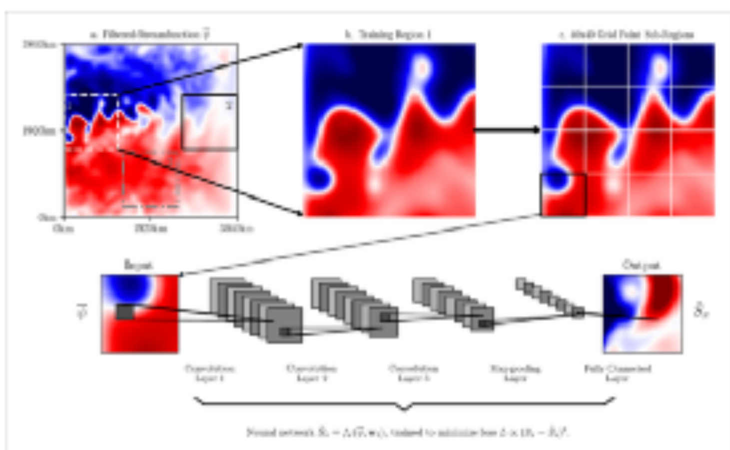
RESEARCH ARTICLE

10.1029/2018MS001472

Applications of Deep Learning to Ocean Data Inference and Subgrid Parameterization

Thomas Bolton[1] and Laure Zanna[1]

[1]Department of Physics, University of Oxford, Oxford, UK



https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2018MS001472

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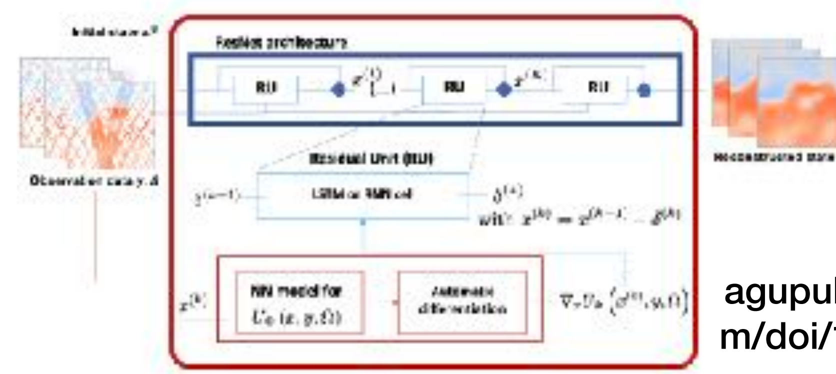
RESEARCH ARTICLE

10.1029/2021MS002572

Learning Variational Data Assimilation Models and Solvers

R. Fablet[1], B. Chapron[2], L. Drumetz[1], E. Mémin[3], O. Pannekoucke[4], and F. Rousseau[5]



https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021MS002572

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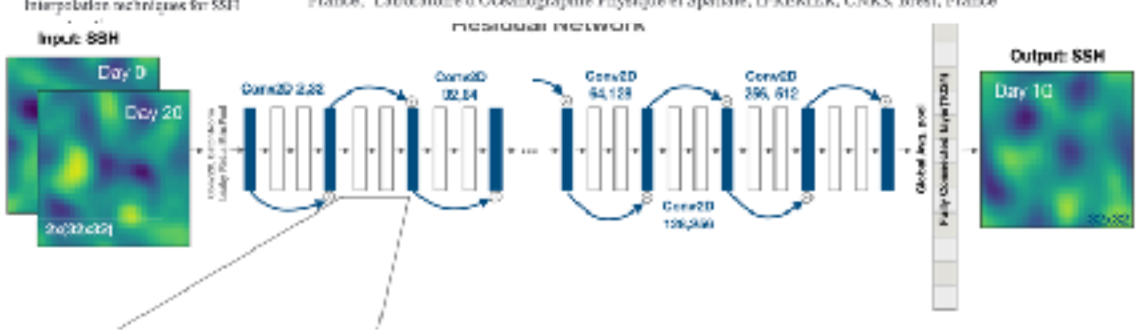
RESEARCH ARTICLE

10.1029/2019MS001965

A Deep Learning Approach to Spatiotemporal Sea Surface Height Interpolation and Estimation of Deep Currents in Geostrophic Ocean Turbulence

Georgy E. Manucharyan[1], Lia Siegelman[2], and Patrice Klein[2,3,4]



https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS001965

DINCAE 2.0: multivariate convolutional neural network with error estimates to reconstruct sea surface temperature satellite and altimetry observations

Alexander Barth, Aida Alvera-Azcárate, Charles Troupin, and Jean-Marie Beckers

GHER, University of Liège, Liège, Belgium

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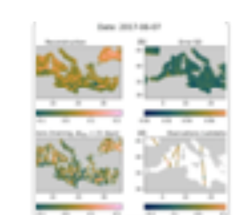
Received: 18 Oct 2021 – Discussion started: 15 Nov 2021 – Revised: 10 Feb 2022 – Accepted: 17 Feb 2022 – Published: 15 Mar 2022



https://gmd.copernicus.org/articles/15/2183/2022/

ConvAE & Ocean Dynamics
Literature review

Considered papers:
Topic#1 https://gmd.copernicus.org/articles/15/2183/2022/
Topic#2 https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2018MS001472
Topic#3 https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2019MS001965
Topic#4 https://arxiv.org/abs/2010.04663

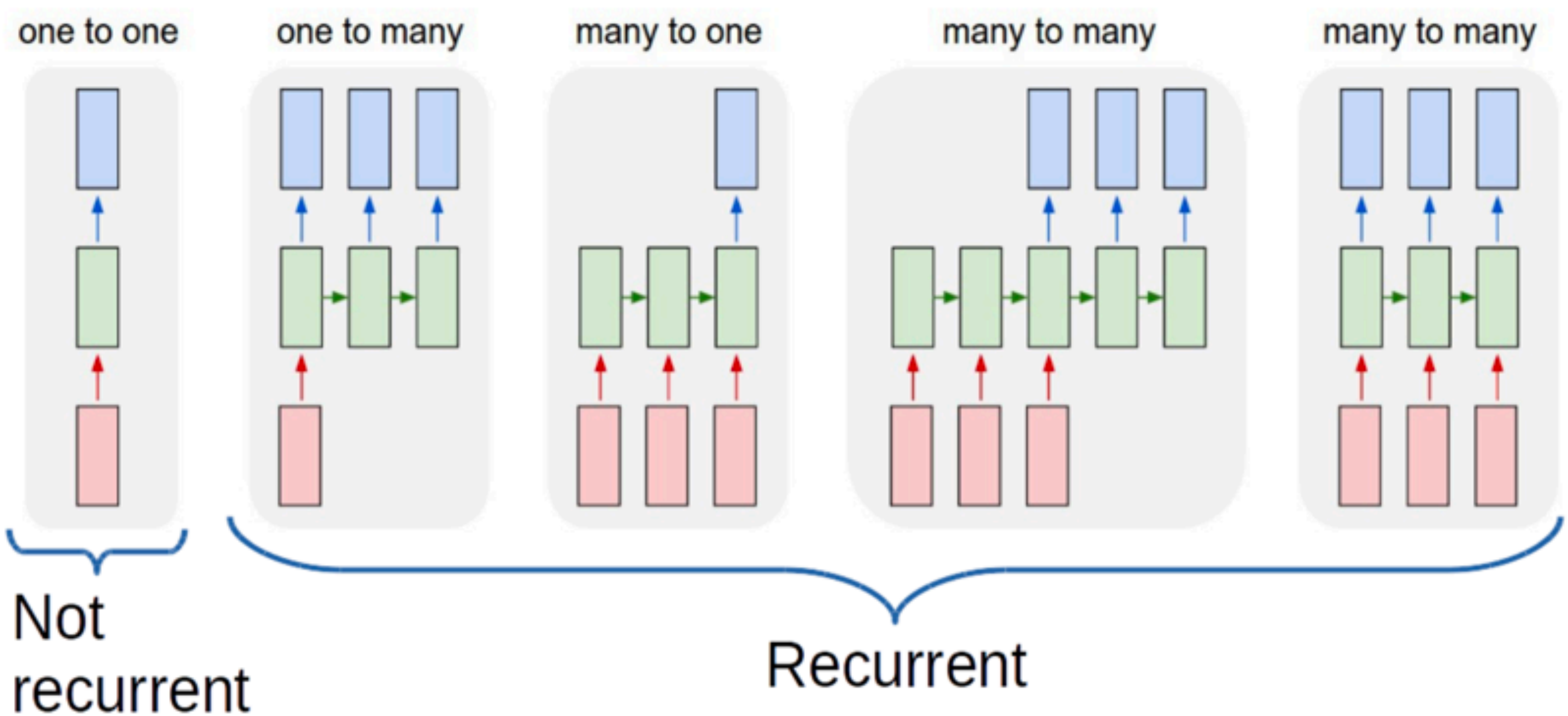
Questions:
- Which problem ?
- Which convolutional architecture ?
- Comments ?

Lecture. #3
Things to know (AE)

- Auto-encoder
- Latent variable
- UNet
- ResNet

Recurrent Neural Networks

Recurrent Neural Networks



Applications:

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

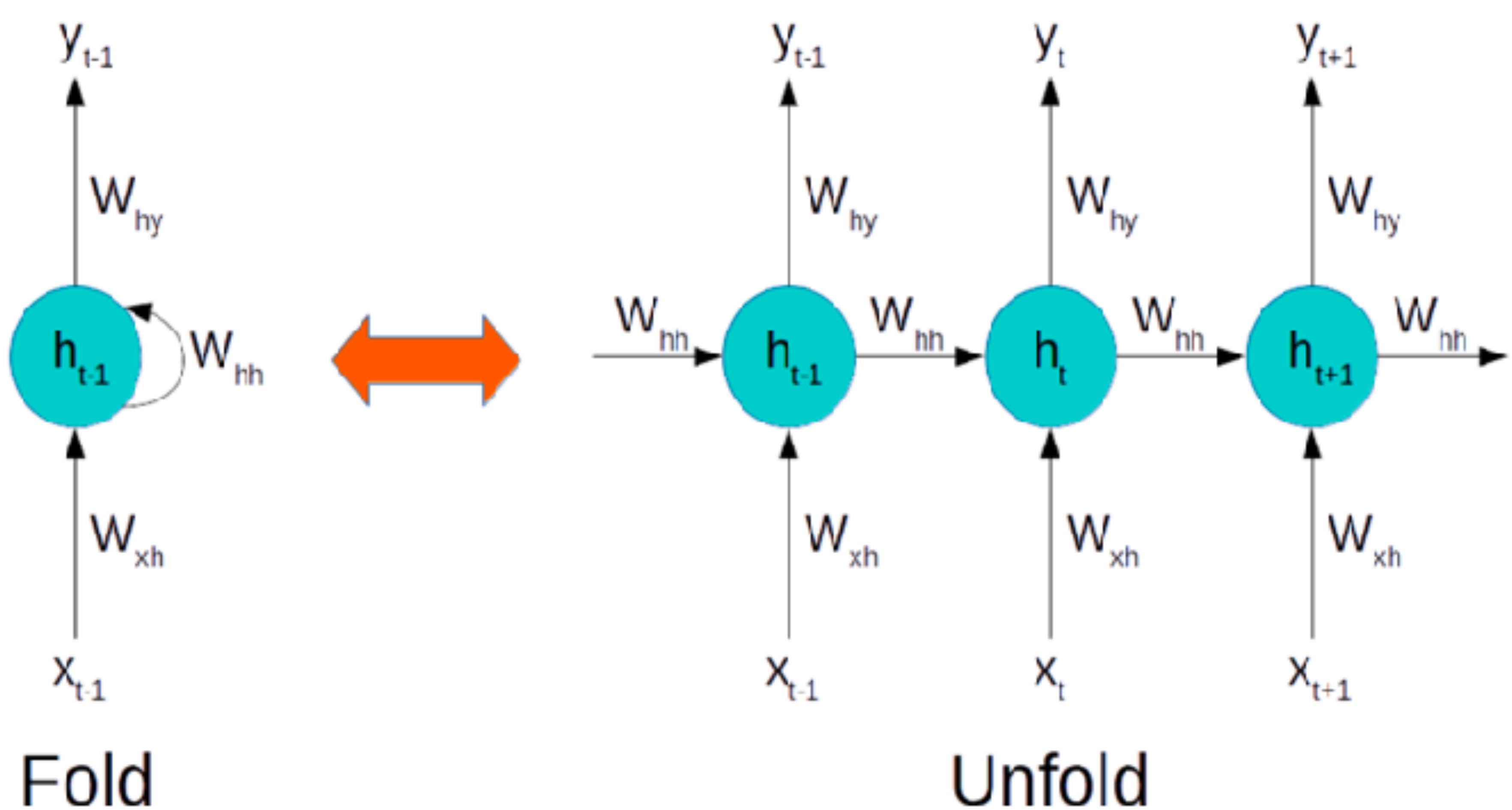
RNN: Underlying formulation (similar to state-space representation)

$x \rightarrow$ input vector

$y \rightarrow$ output vector

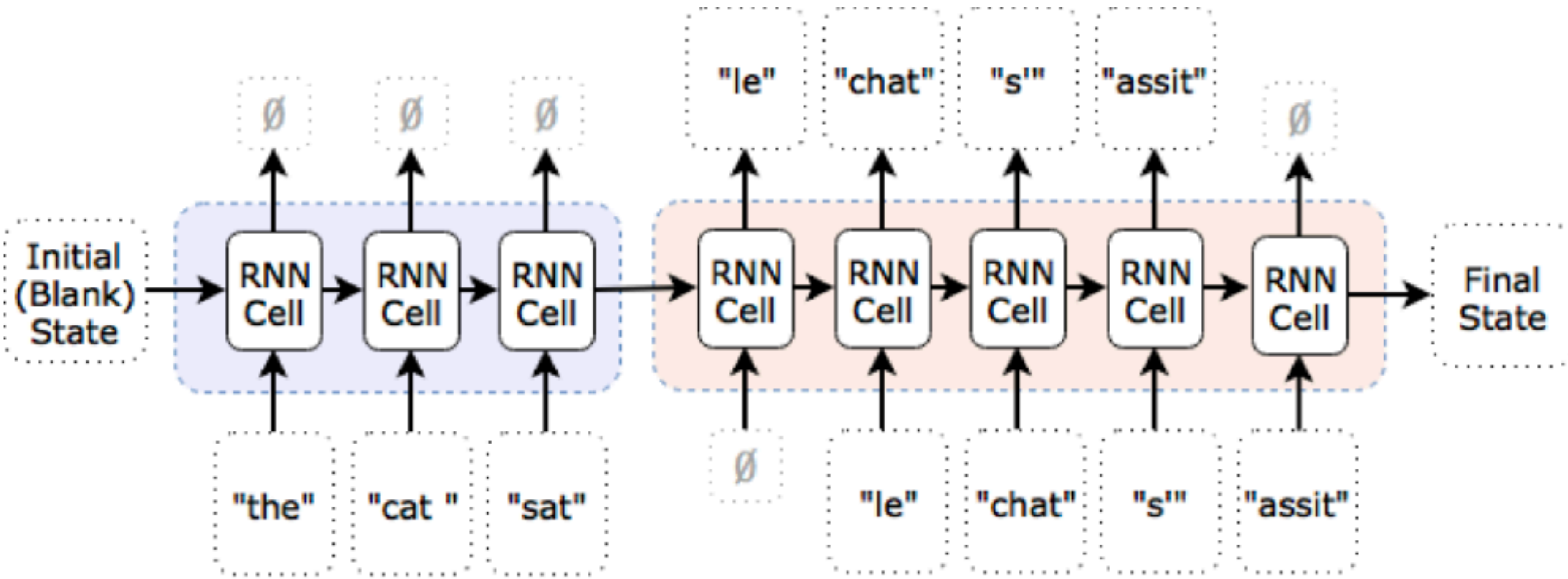
$h \rightarrow$ hidden state

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



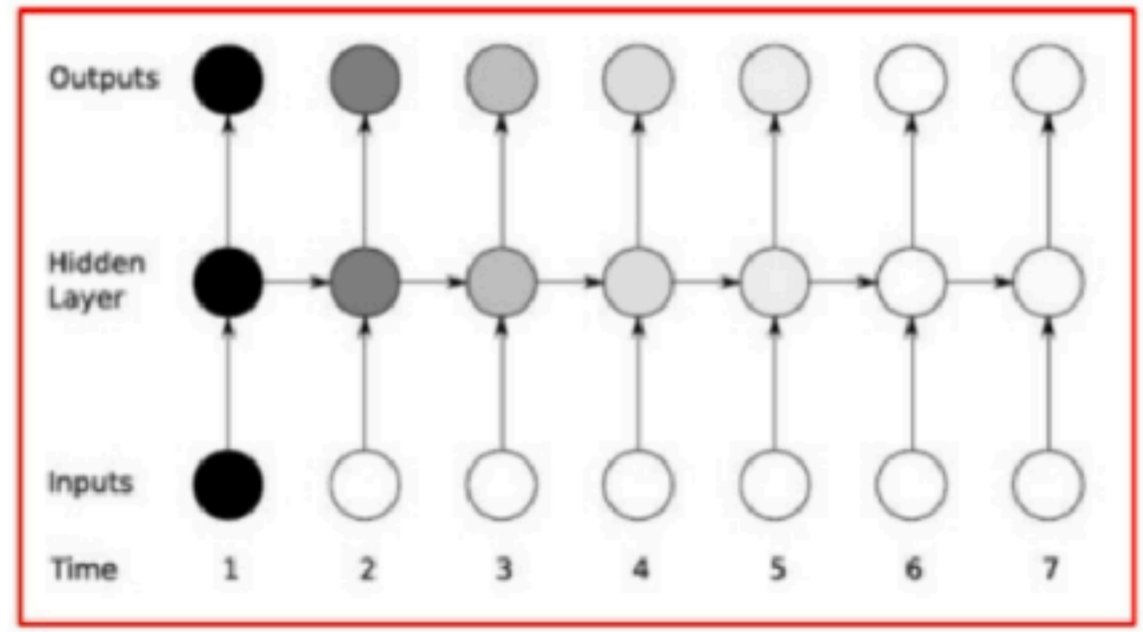
$$h_t = f\left(W_{hh}h_{t-1} + W_{xh}x_t\right) \text{ and } y_t = g\left(W_{hy}h_t\right)$$

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

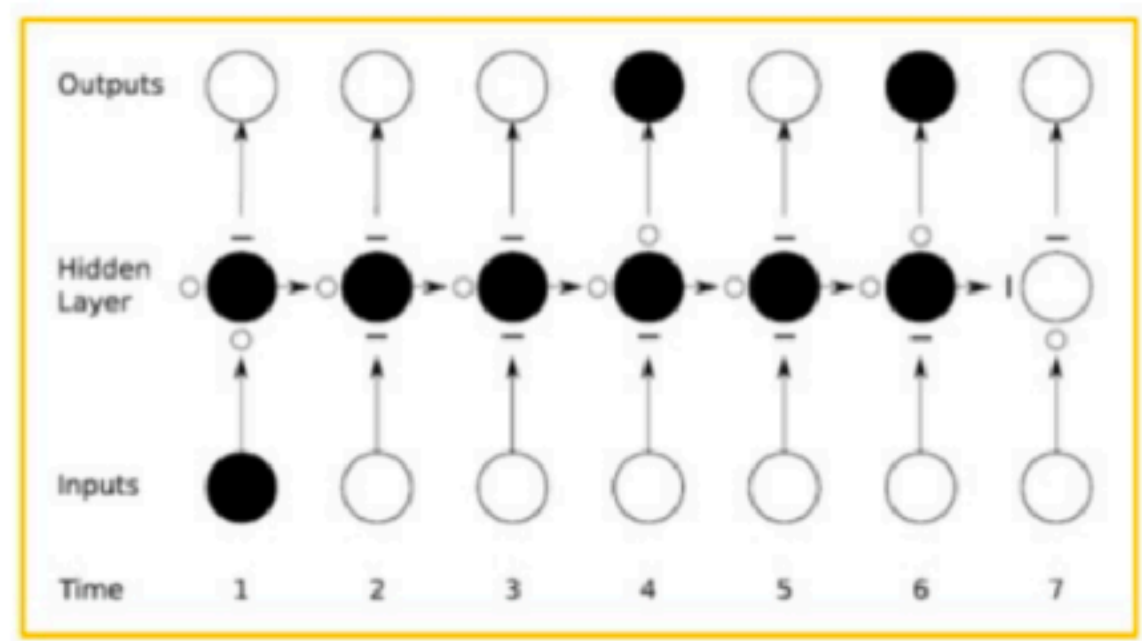


Classic RNN Architectures

- **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_Forecasting_L63_students.ipynb

Lecture. #3
Things to know (RNN)

- Recurrent Neural Network
- LSTM
- Unfloded and folded representations