

Course #3:

**Auto-encoders and
Recurrent Neural Networks**

Roadmap

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

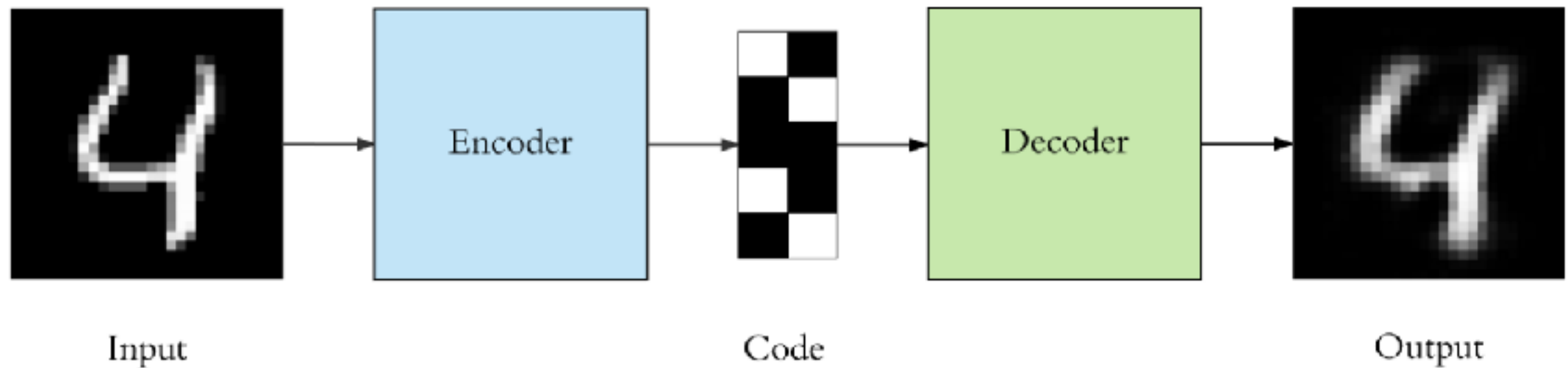
Lecture. #2

Things to know

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

Auto-encoders

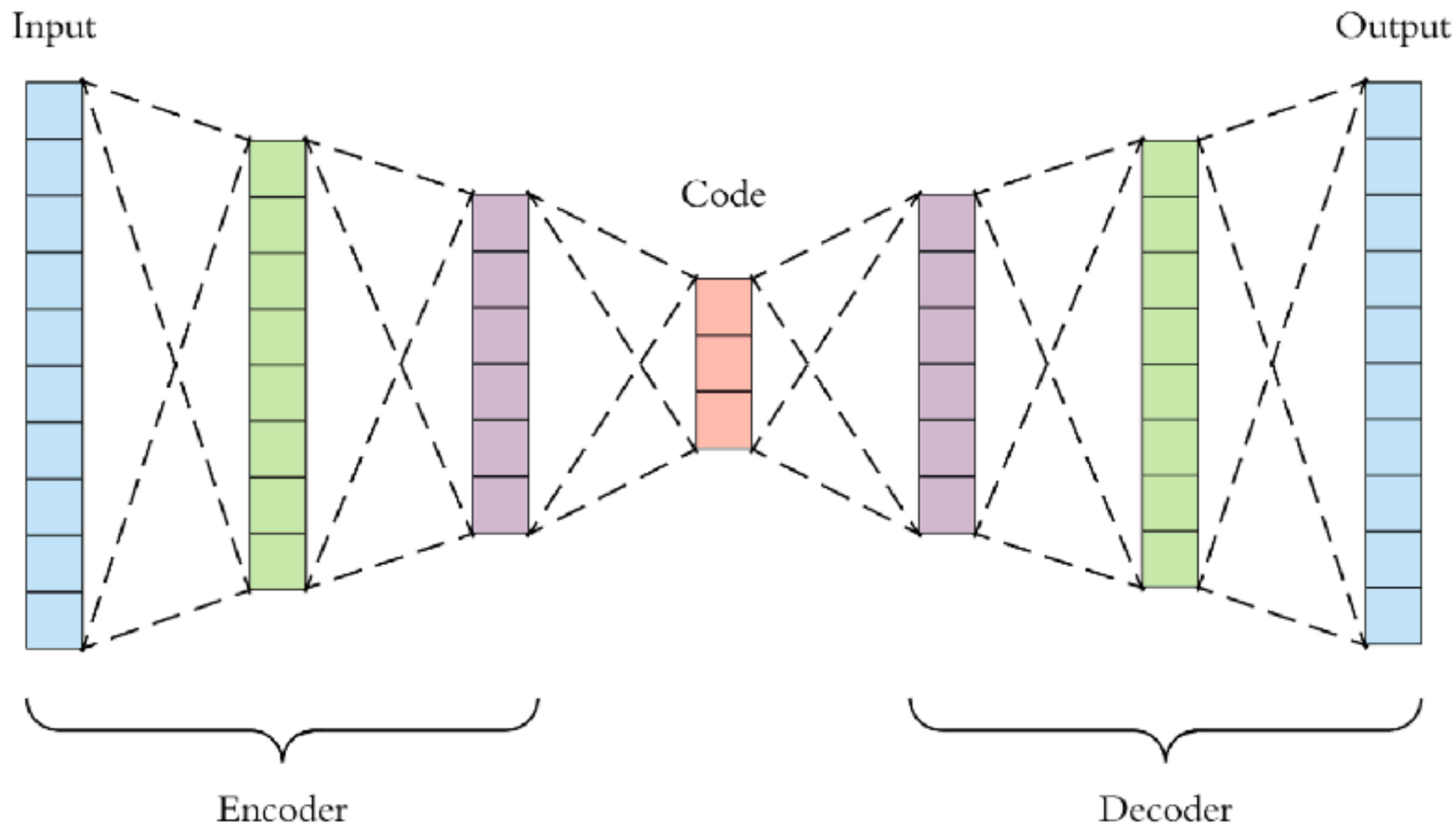
Auto-encoders



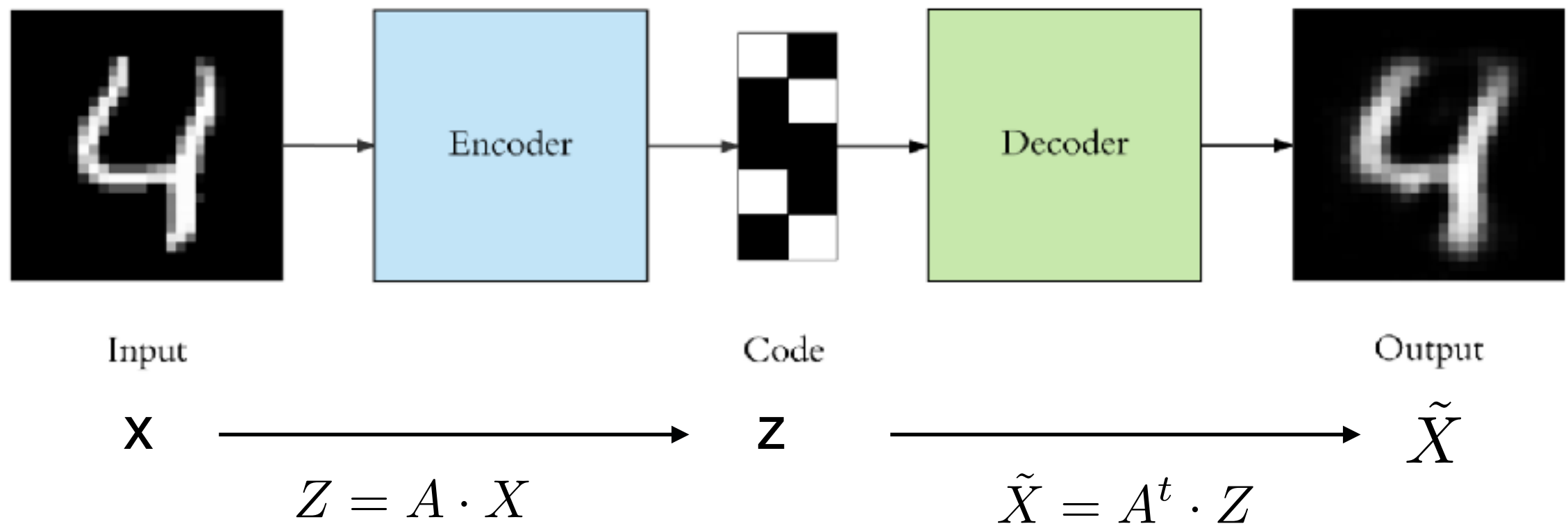
Output with the same shape as the input

Application ?

Dense auto-encoders



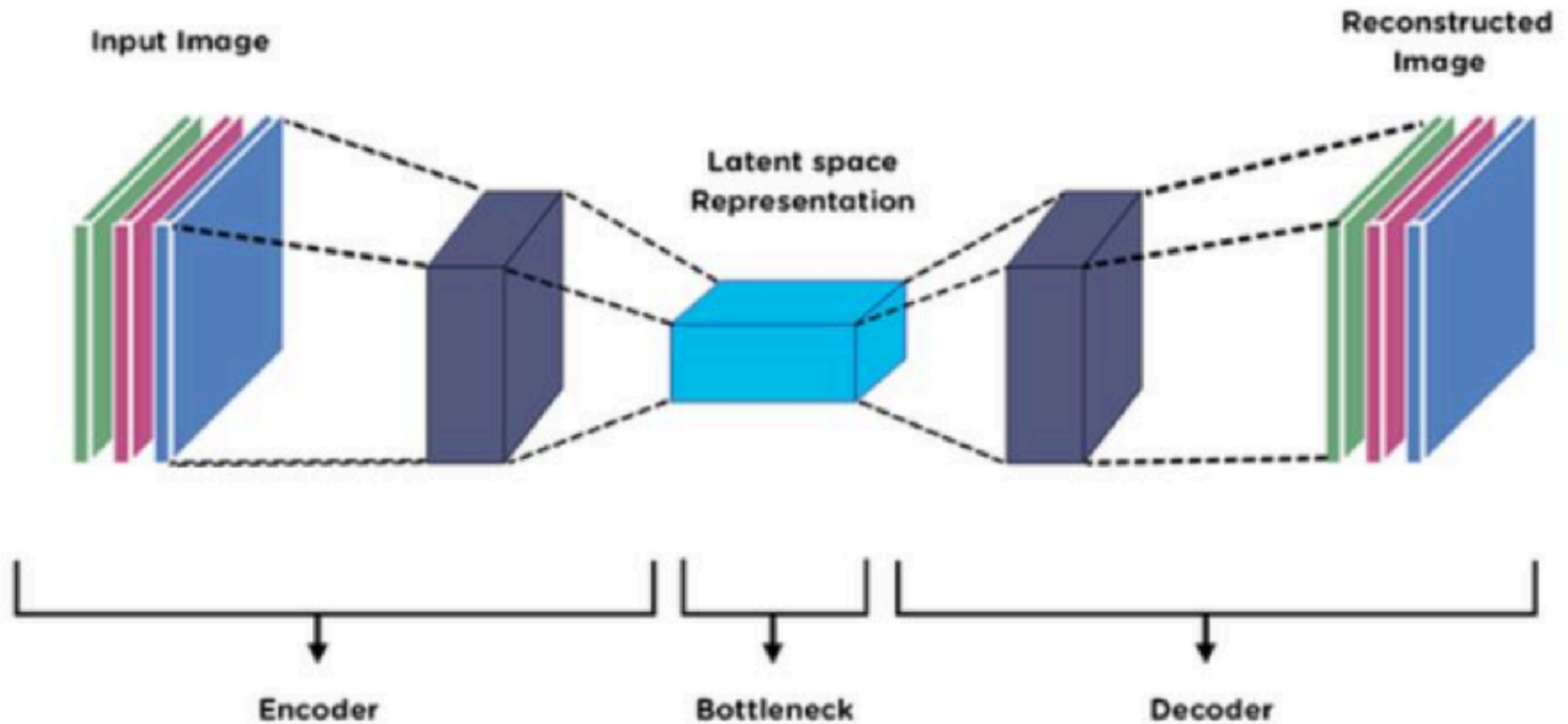
PCA/EOF



PCA as a linear auto-encoder architecture.

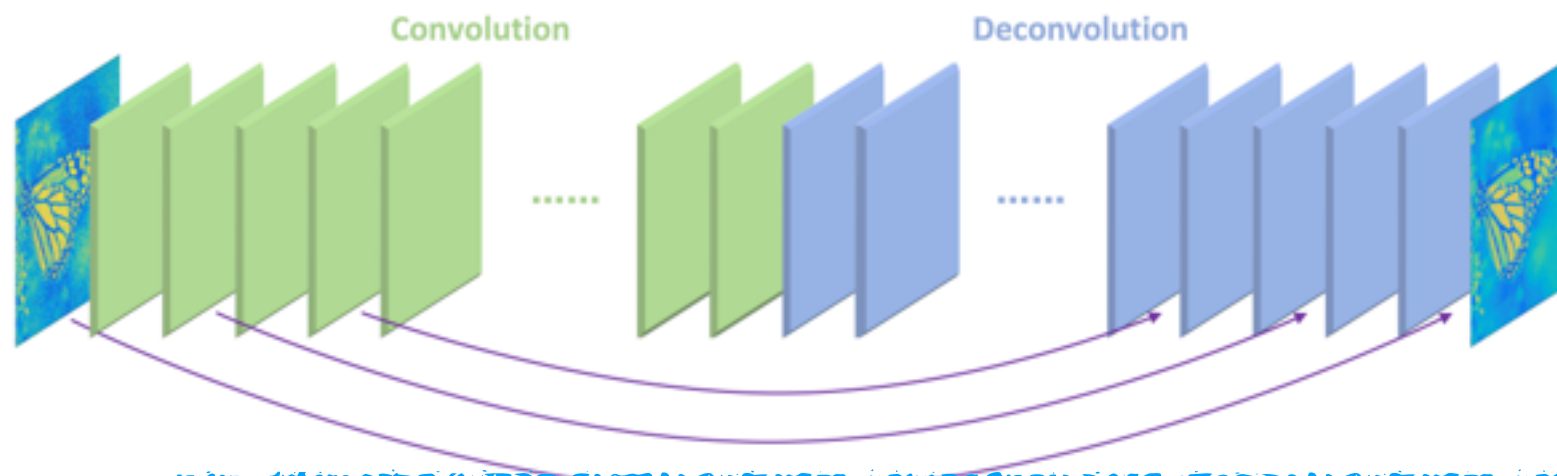
Which additional constraint ?

Convolutional auto-encoders

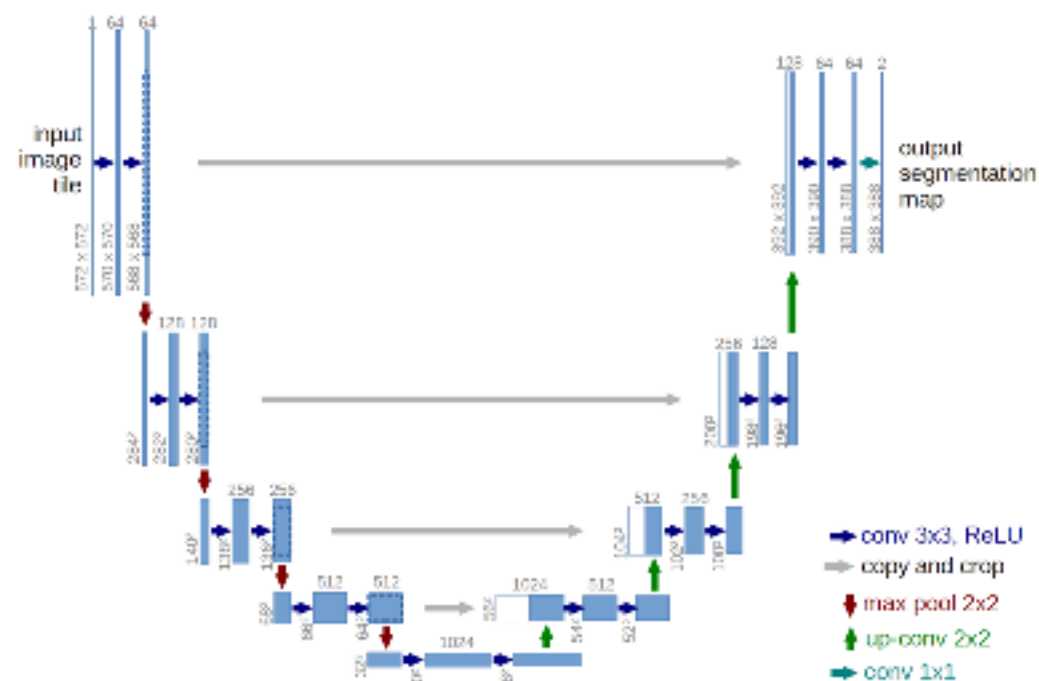


Convolutional AE Zoo

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



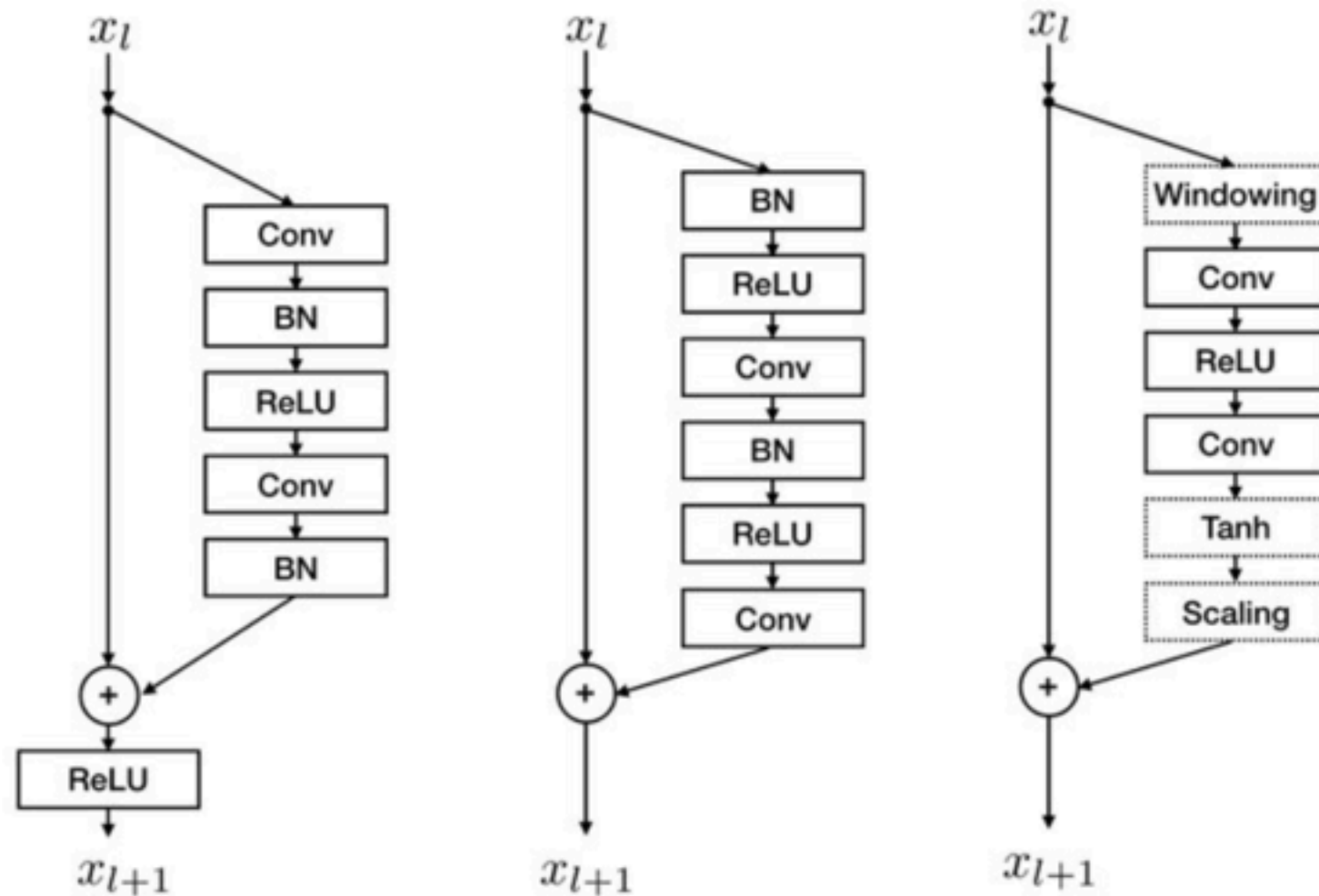
<https://arxiv.org/pdf/1606.08921.pdf>



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

Pytorch version

https://github.com/CIA-Oceanix/DLOA2023/blob/main/lectures/notebooks/corrections/notebook_MNIST_AutoEncoder_with_correction.ipynb

Lightning version

https://github.com/CIA-Oceanix/DLOA2023/blob/main/lectures/notebooks/notebook_PytorchLightning_MNIST_AutoEncoder_students.ipynb

Question 1. Fill in the architecture of the convolutional block of the encoder module to train a convolutional auto-encoder

Question 2. Modify the code to test a linear auto-encoder (cf. AE and PCA)

PyTorch Lightning

ConvAE & Ocean Dynamics

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JAMES Journal of Advances in Modeling Earth Systems

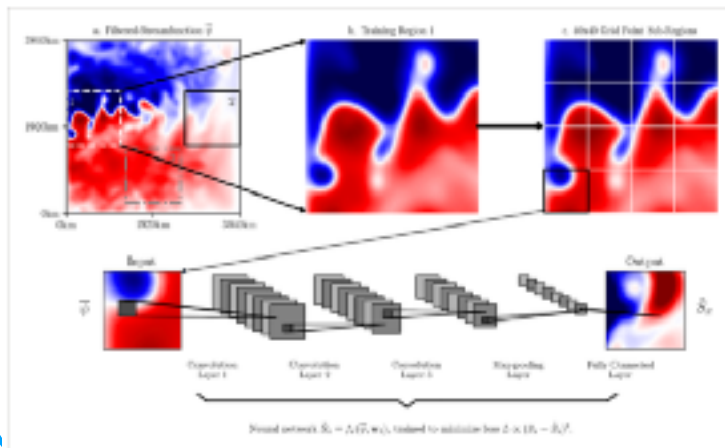
RESEARCH ARTICLE
10.1029/2018MS001472

Applications of Deep Learning to Ocean Data Inference and Subgrid Parameterization

Thomas Bolton¹ and Laure Zanna¹

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

Key Points:
• We successfully use convolutional neural networks to predict unresolved turbulent processes and subsurface velocities.
• The neural networks generalize to



[https://
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10.1029/2018MS001472](https://agupubs.onlinelibrary.wiley.com/doi/epdf/10.1029/2018MS001472)

JAMES Journal of Advances in Modeling Earth Systems

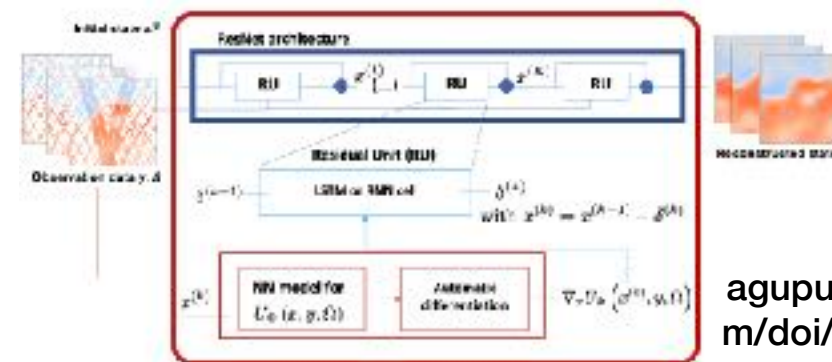
RESEARCH ARTICLE
10.1029/2021MS002572

Learning Variational Data Assimilation Models and Solvers

R. Fablet¹, B. Chapron², L. Drumetz¹, E. Mémin³, O. Pannetier⁴, and F. Rousseau⁵

¹IMT Atlantique, UMR CNRS Lab-STICC, Brest, France, ²IFREMER, UMR CNRS LOPS, Brest, France, ³INRIA Rennes, UMR CNRS IRMAR, Rennes, France, ⁴INRIA-ENM, UMR CNRS CNRM, CERFACS, Toulouse, France, ⁵IMT Atlantique, UMR INSERM Latim, Brest, France

Key Points:
• We develop a end-to-end neural architecture to design variational data assimilation models and solvers.
• We jointly calibrate all the trainable components of the proposed scheme to optimize a data



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m/doi/10.1029/2021MS002572](https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2021MS002572)

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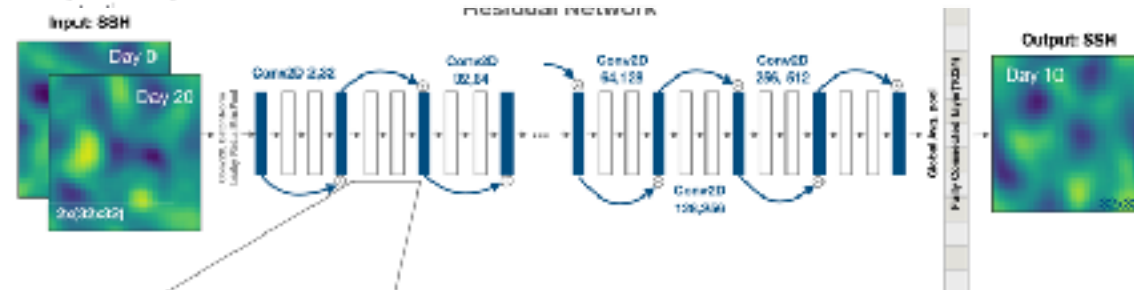
RESEARCH ARTICLE
10.1029/2019MS001965

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

Georgy E. Manucharyan¹, Lia Siegelman², and Patrice Klein^{3,4}

¹School of Oceanography, University of Washington, Seattle, WA, USA, ²The Population Laboratory, California Institute of Technology, Pasadena, CA, USA, ³Laboratoire du Mécanisme Dynamique, Ecole Normale Supérieure, CNRS, Paris, France, ⁴Laboratoire d'Océanographie Physique et Spatiale, IFREMER, CNRS, Brest, France

Key Points:
• The efficacy of Deep Learning in exploiting sparse sea surface height (SSH) data is demonstrated in a quasigeostrophic model.
• Residual Neural Networks are superior to linear and dynamical interpolation techniques for SSH



[https://agupubs.onlinelibrary.wiley.com/
doi/epdf/10.1029/2019MS001965](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 Barth¹, Aida Alvera-Azcárate¹, Charles Troupin¹, and Jean-Marie Beckers¹

GHEF, University of Liège, Liège, Belgium

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 ?

ConvAE architectures for Ocean Dynamics ?

Lecture. #3

Things to know (AE)

- Auto-encoder
- Latent variable
- UNet
- ResNet