Course #3:

Auto-encoders and Recurrent Neural Networks

Roadmap

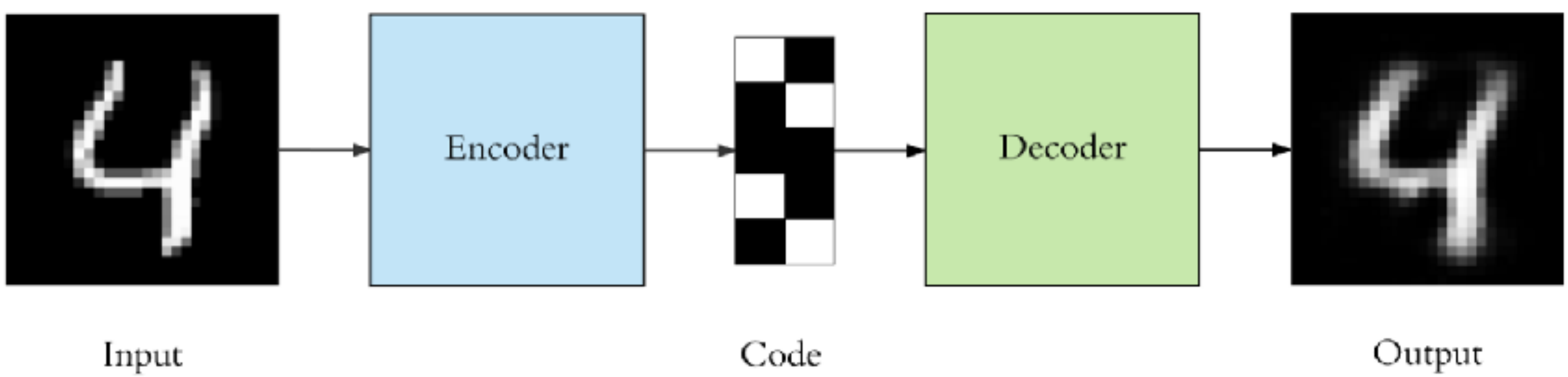
- Recap from course #2
- Auto-encoders
- Recurrents Neural Networks

Lecture. #2
Things to know

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

Auto-encoders

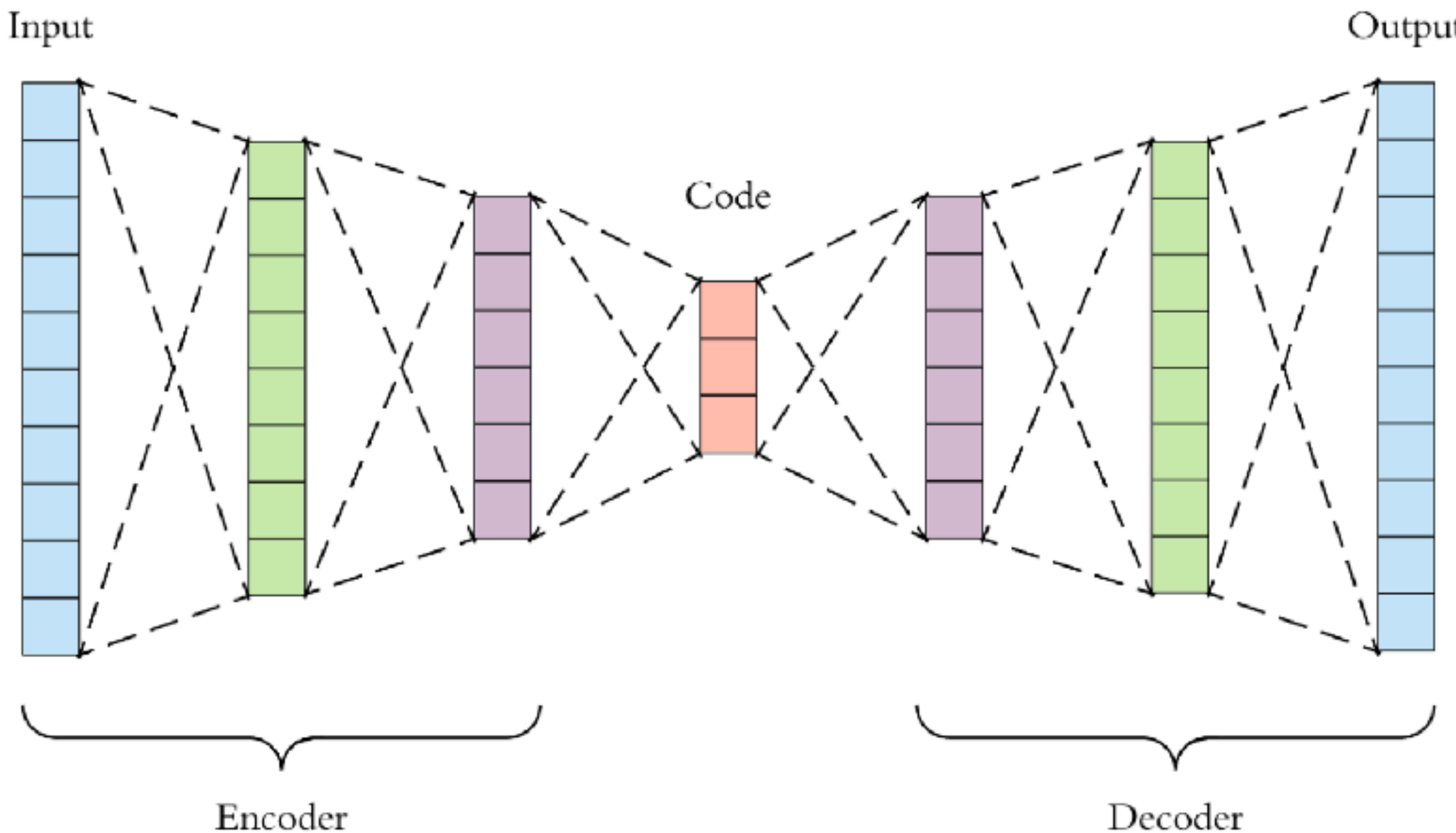
Auto-encoders



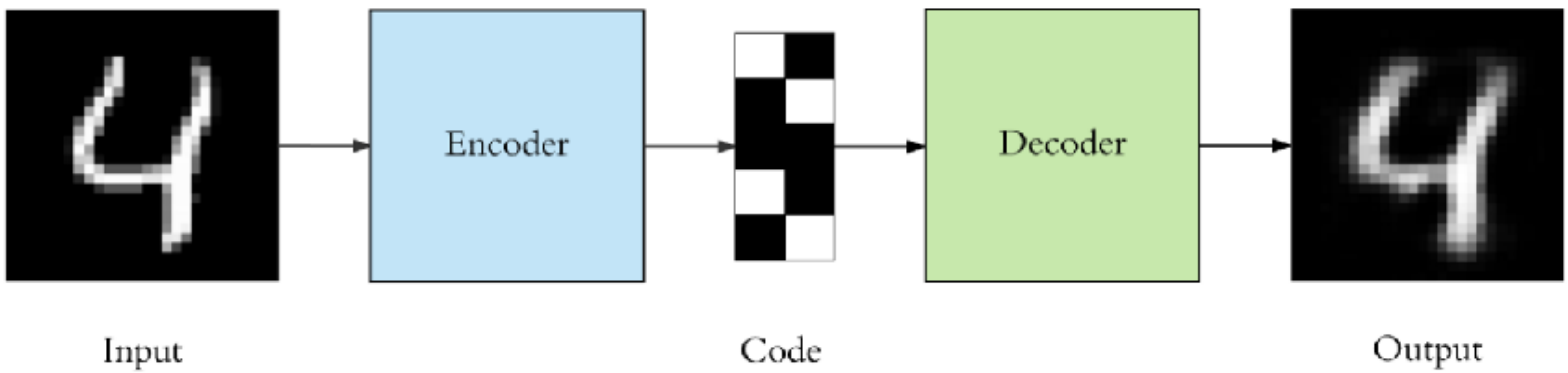
Output with the same shape as the input

Application ?

Dense auto-encoders



PCA/EOF

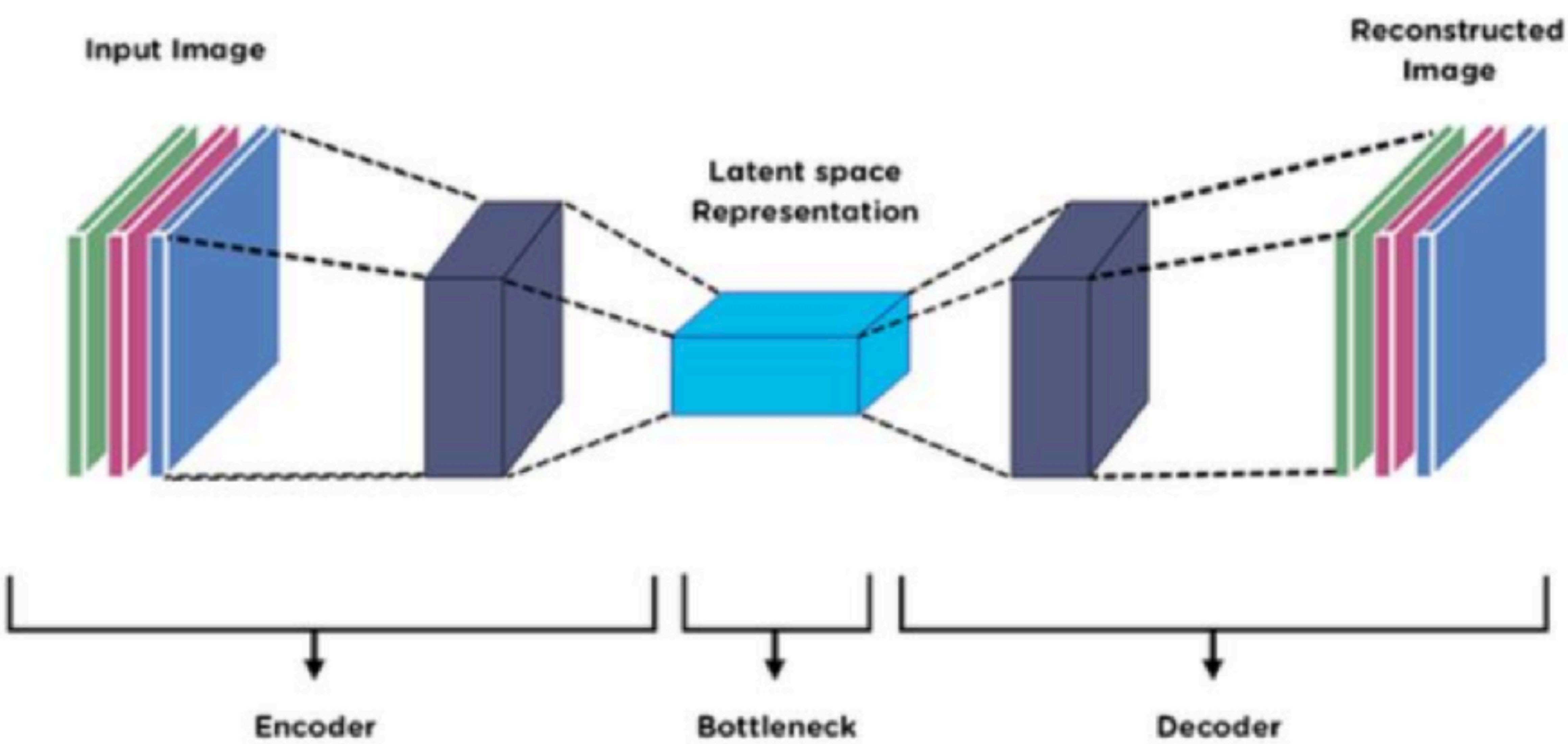


$$X \xrightarrow{Z = A \cdot X} Z \xrightarrow{\tilde{X} = A^t \cdot Z} \tilde{X}$$

PCA as a linear auto-encoder architecture.

Which additional constraint ?

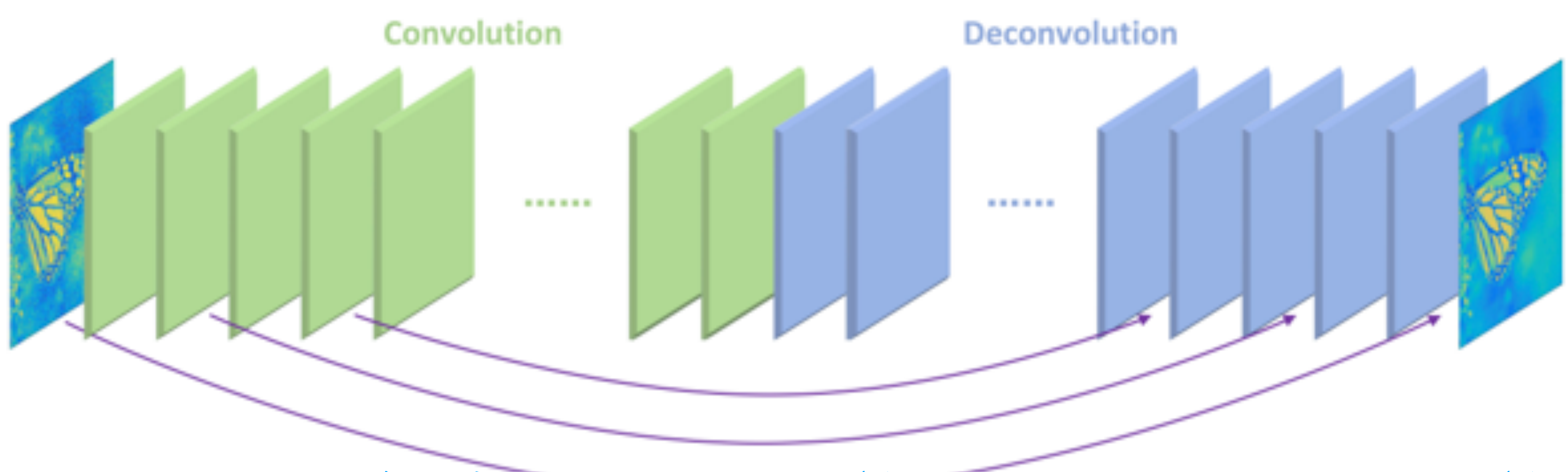
Convolutional auto-encoders



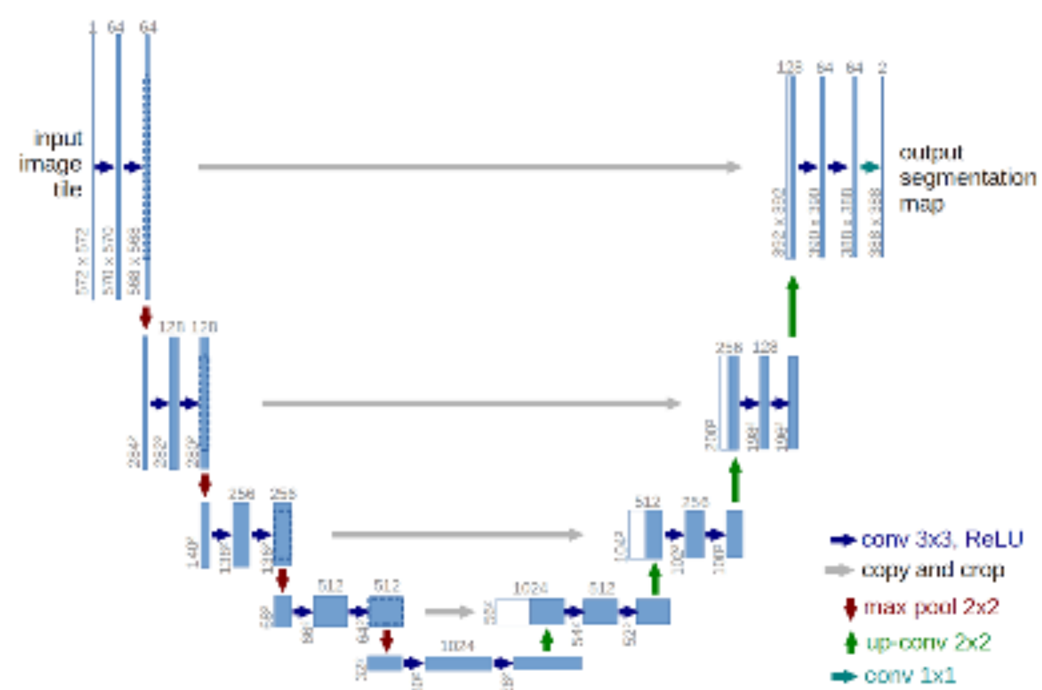
Source: https://www.analyticsvidhya.com/

Convolutional AE Zoo

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



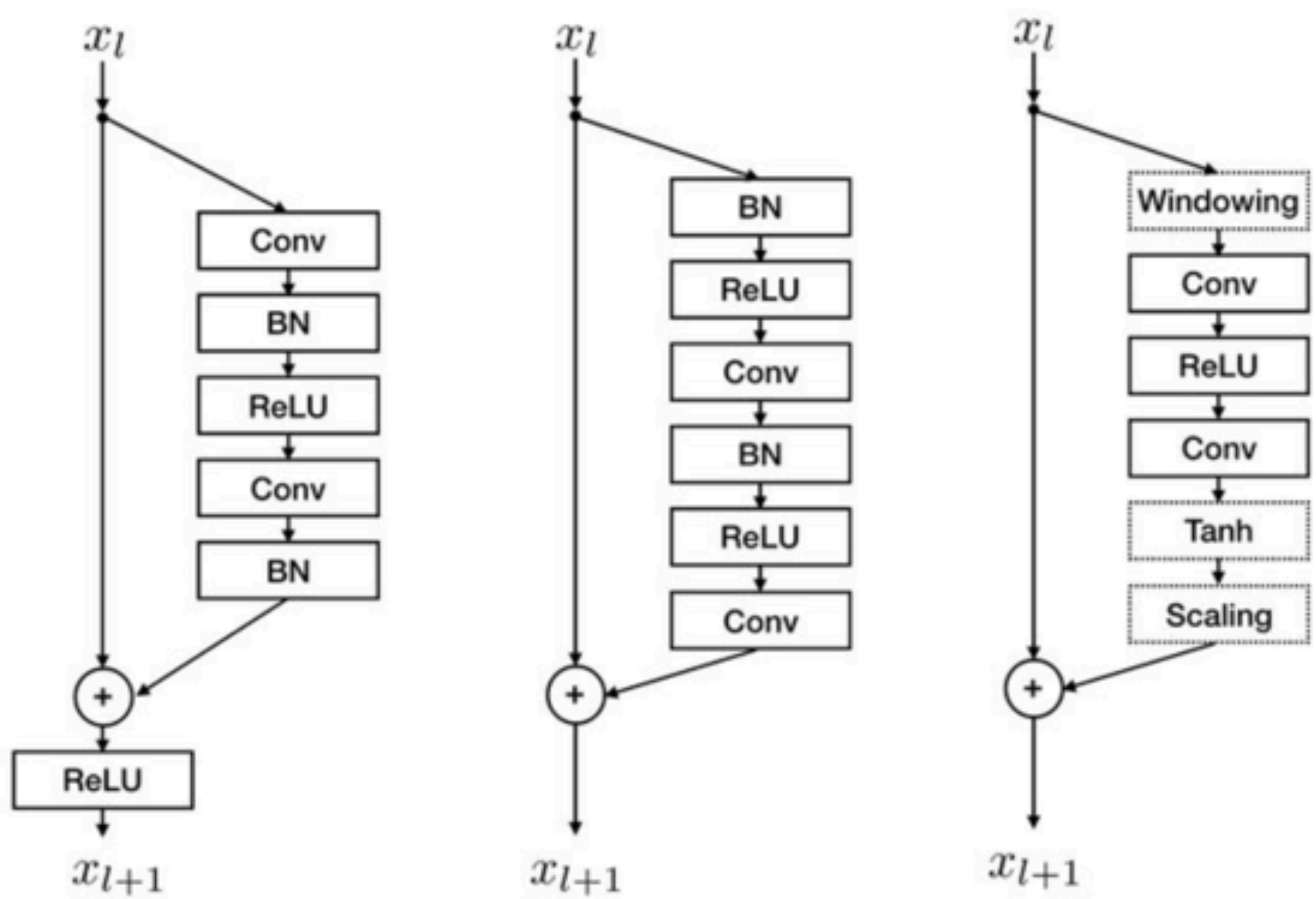
https://arxiv.org/pdf/1606.08921.pdf



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

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 dense encoder module to train a dense auto-encoder

Question 2. Add dropout layers in the convolutional encoder and decoder

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

PyTorch Lightning

ConvAE & Ocean Dynamics

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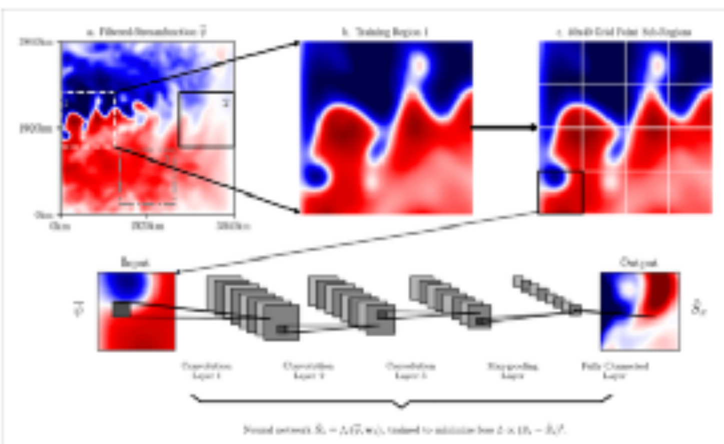
AGU100 ADVANCING EARTH AND SPACE SCIENCE
RESEARCH ARTICLE
10.1029/2018MS001472

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

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



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

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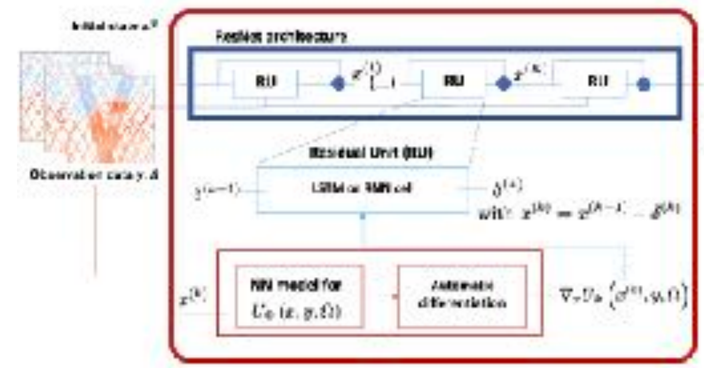
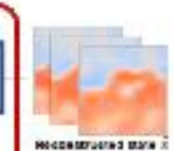
RESEARCH ARTICLE
10.1029/2021MS002572

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]
[1]IMT Atlantique, UMR CNRS Lab-STICC, Brest, France, [2]Ifremer, UMR CNRS LOPS, Brest, France, [3]INRIA Rennes, UMR CNRS IRMAR, Rennes, France, [4]INPT-ENM, UMR CNRS CNRM, CERFACS, Toulouse, France, [5]IMT 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 may jointly calibrate all the trainable components of the proposed scheme to optimize a data





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

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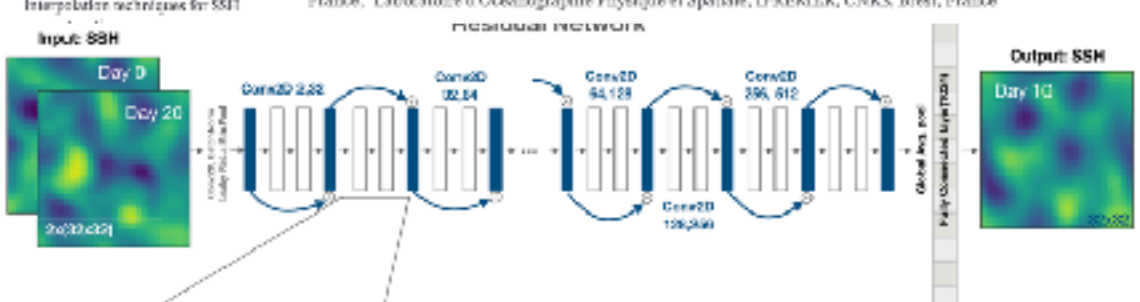
RESEARCH ARTICLE
10.1029/2019MS001965

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

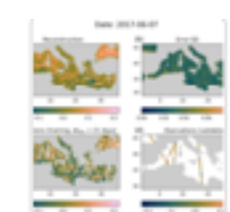
Georgy E. Manucharyan[1], Lia Siegelman[2], and Patrice Klein[2,3,4]
[1]School of Oceanography, University of Washington, Seattle, WA, USA, [2]Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA, USA, [3]Laboratoire de Météorologie Dynamique, Ecole Normale Supérieure, CNRS, Paris, France, [4]Laboratoire 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

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
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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 ?

ConvAE architectures for Ocean Dynamics ?

Lecture. #3
Things to know (AE)

- Auto-encoder
- Latent variable
- UNet
- ResNet