AUTOENCODERS

Week 10

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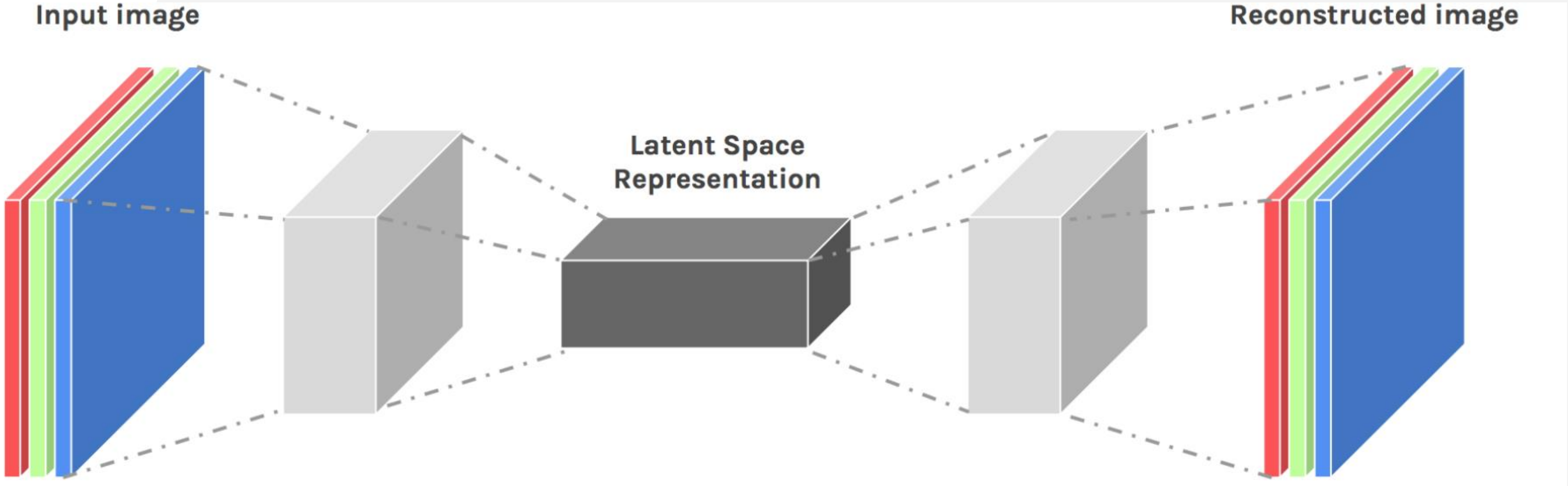
OVERVIEW

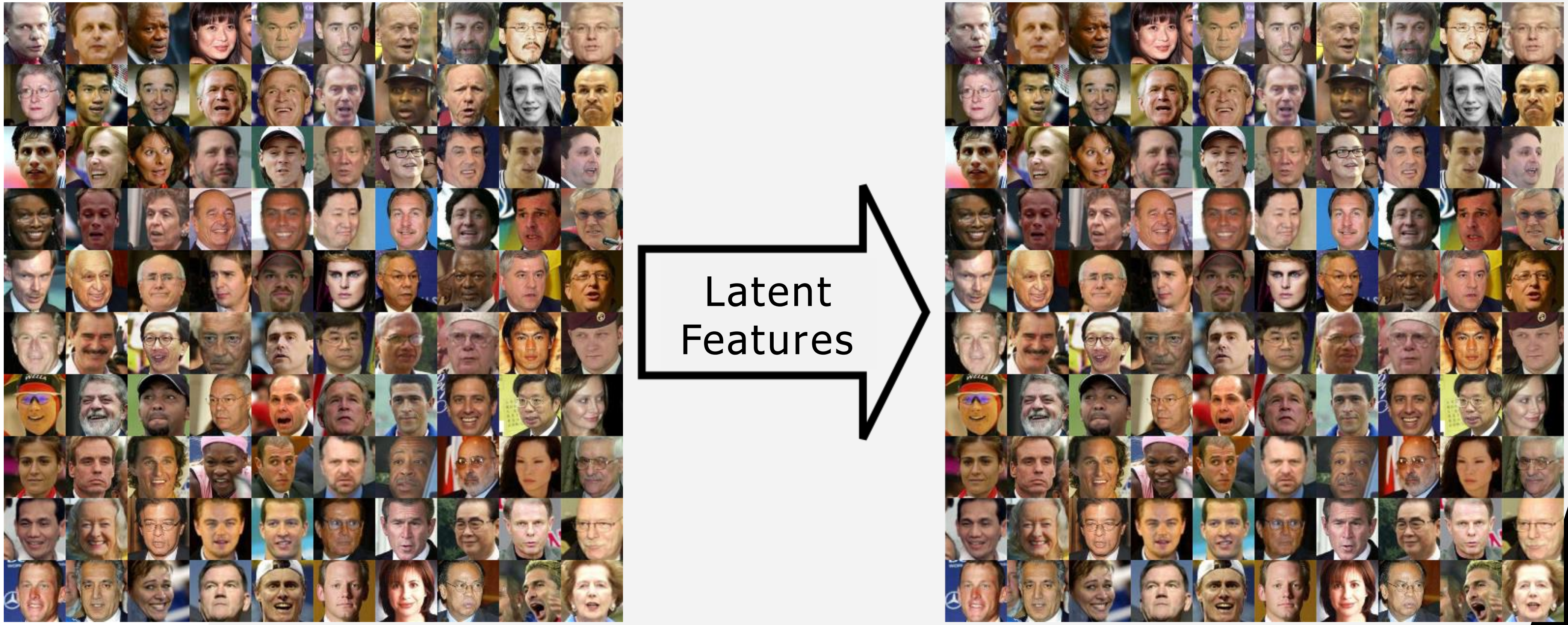
- AutoEncoders
  - Basics
  - Applications
  - Architecture
  - Hands-on Example

BASICS

- Neural Network that copies input to output (trivial task?)
- Self-supervised learning
- Used mainly for data compression / dimension reduction

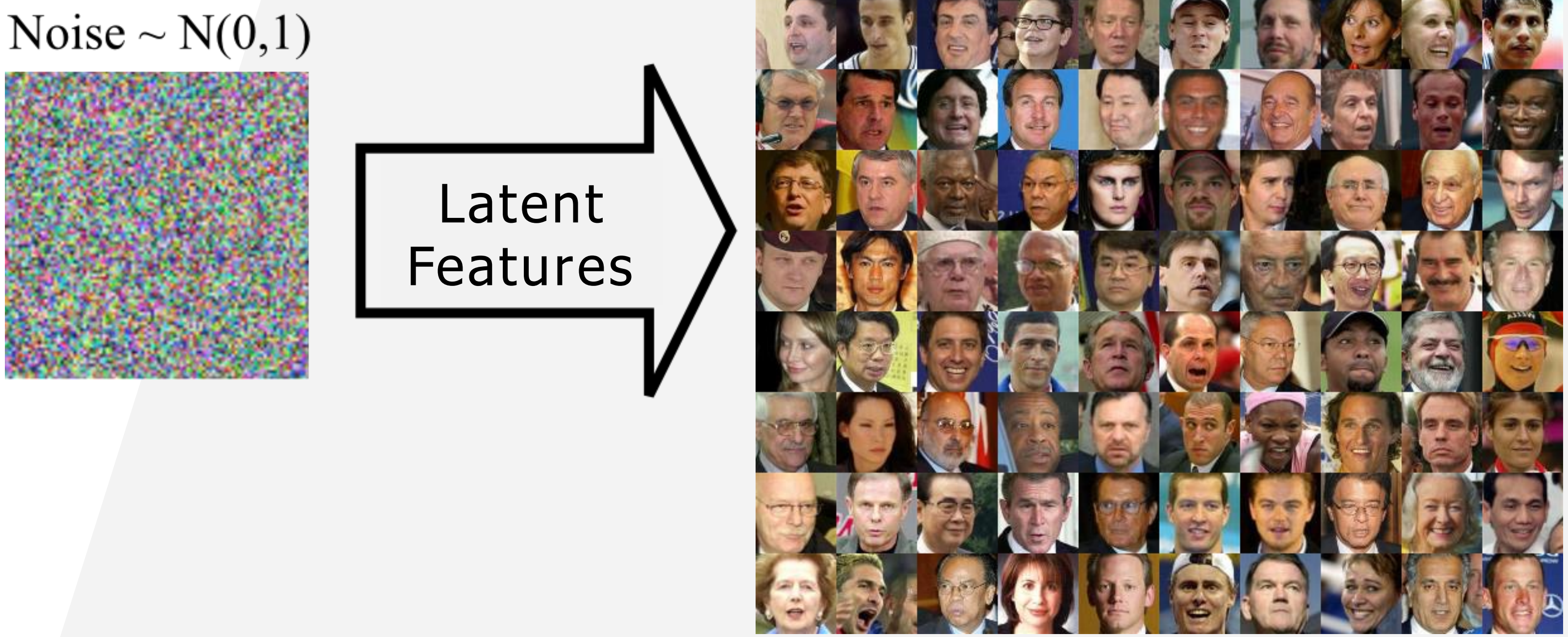


GENERATIVE ADVERSARIAL NETWORKS



https://thispersondoesnotexist.com/

GENERATIVE ADVERSARIAL NETWORKS

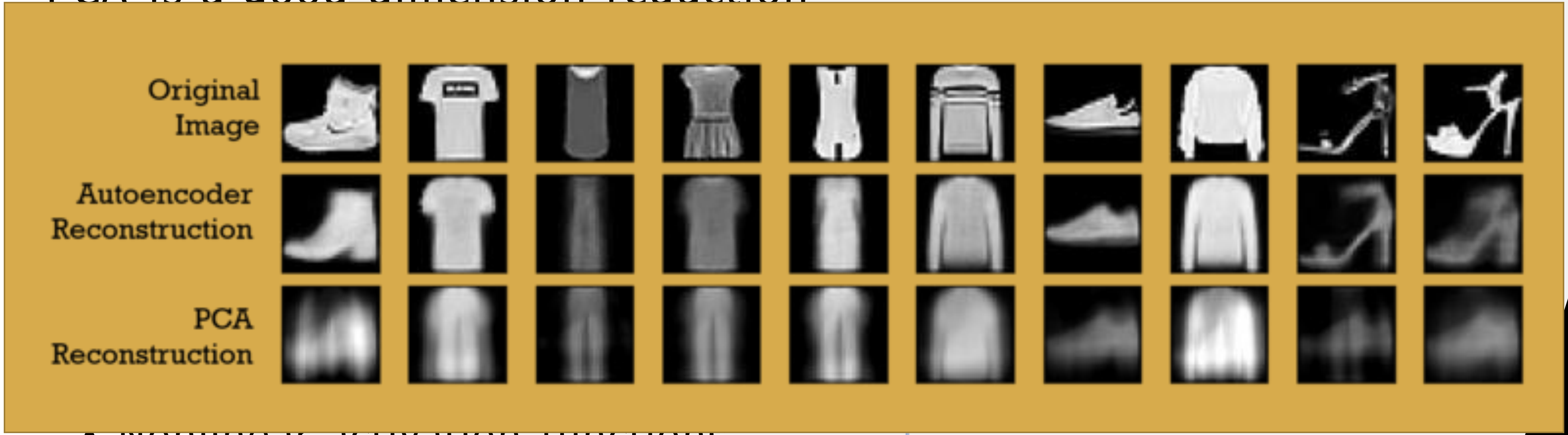


https://thispersondoesnotexist.com/

WHY DO WE NEED AUTOENCODERS?

- PCA is a good dimension reduction

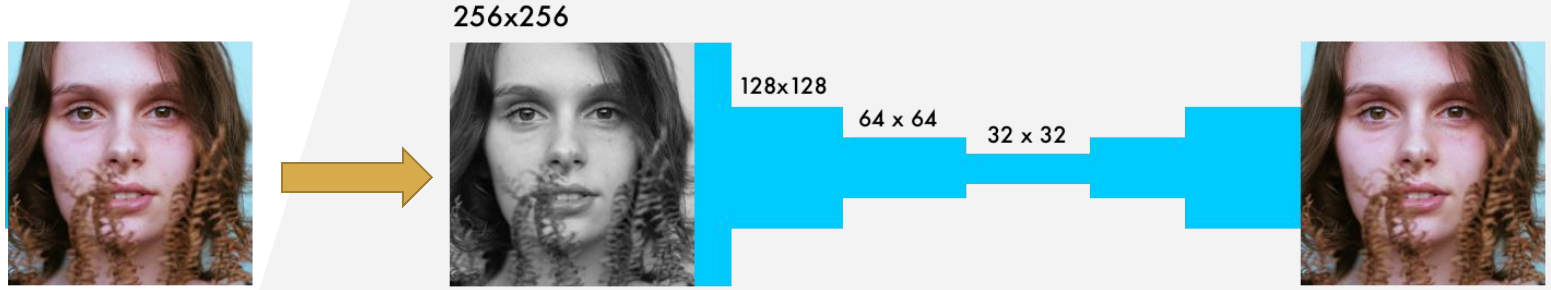
Linear vs nonlinear dimensionality reduction



  - Nonlinear activation functions
  - More efficient for training and testing for big datasets

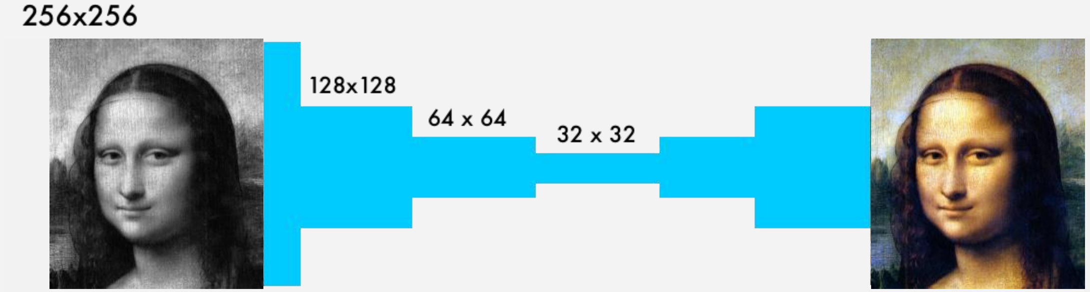
PRACTICAL USE CASES
COLORING IMAGES

Training Time



Ground Truth   BW   Reconstruction

Testing Time



BW   Reconstruction

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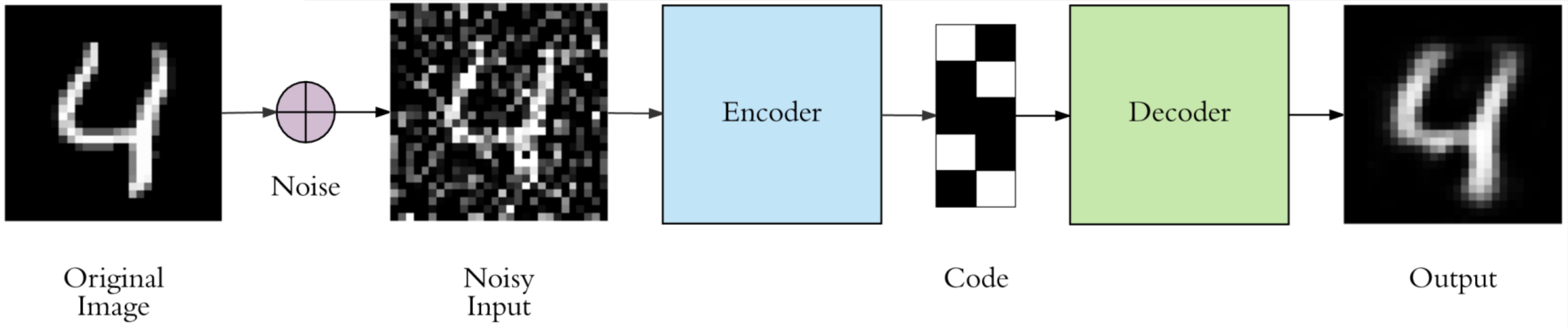
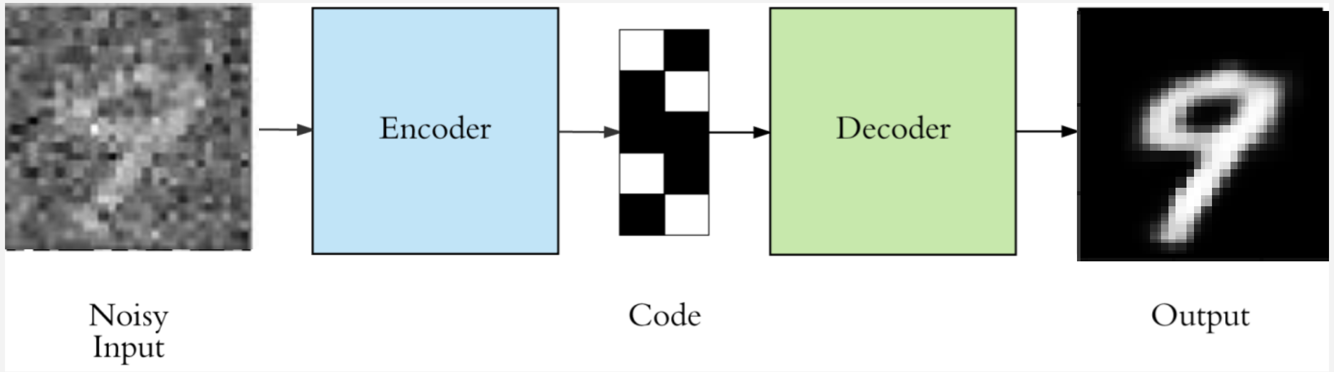
PRACTICAL USE CASES
DENOISING IMAGES

Training Time

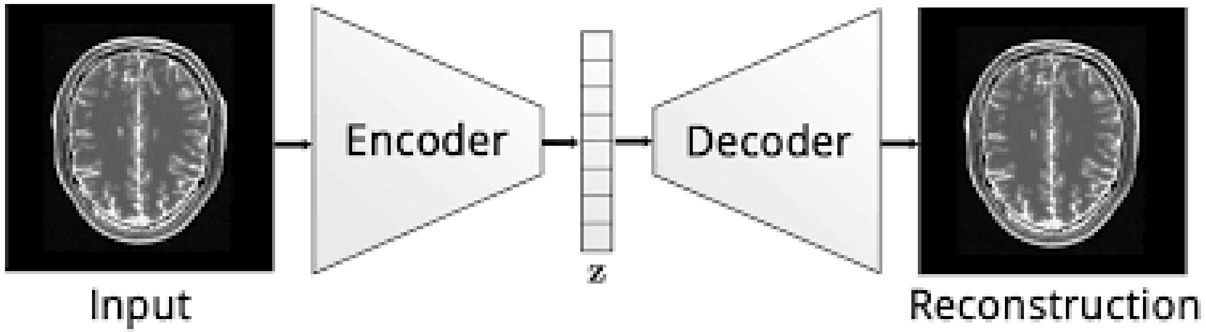


Testing Time



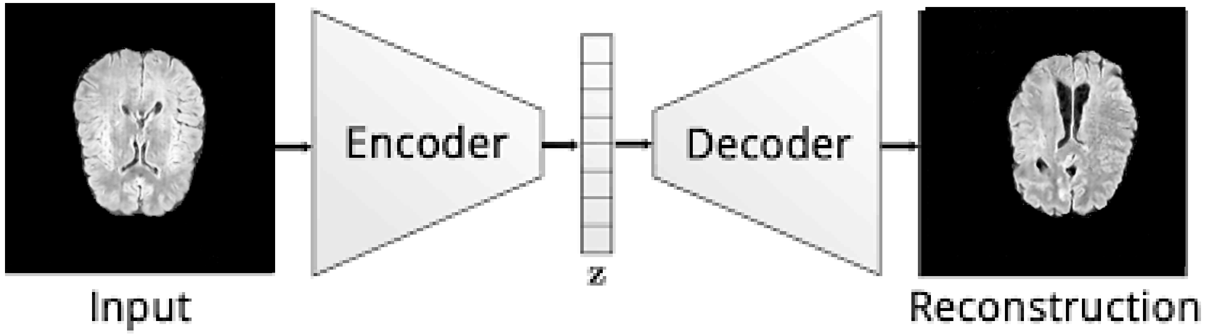
PRACTICAL USE CASES
NOVELTY DETECTION

Training Time



$$E = \left|X - \hat{X}\right|$$
$$E > T?$$

Testing Time



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MORE INTO AE AND ARCHITECTURE

Encoder

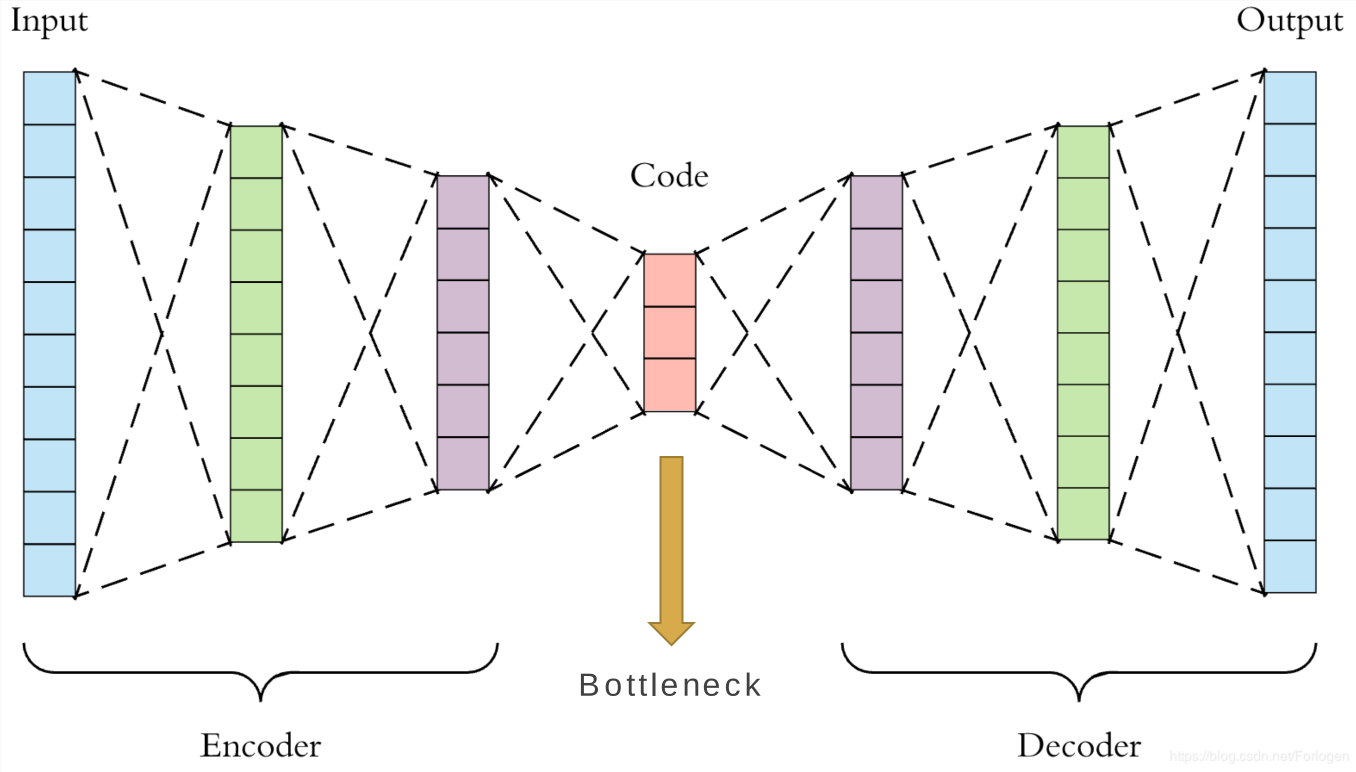
Compresses the input

Code - Bottleneck

Represents latent features

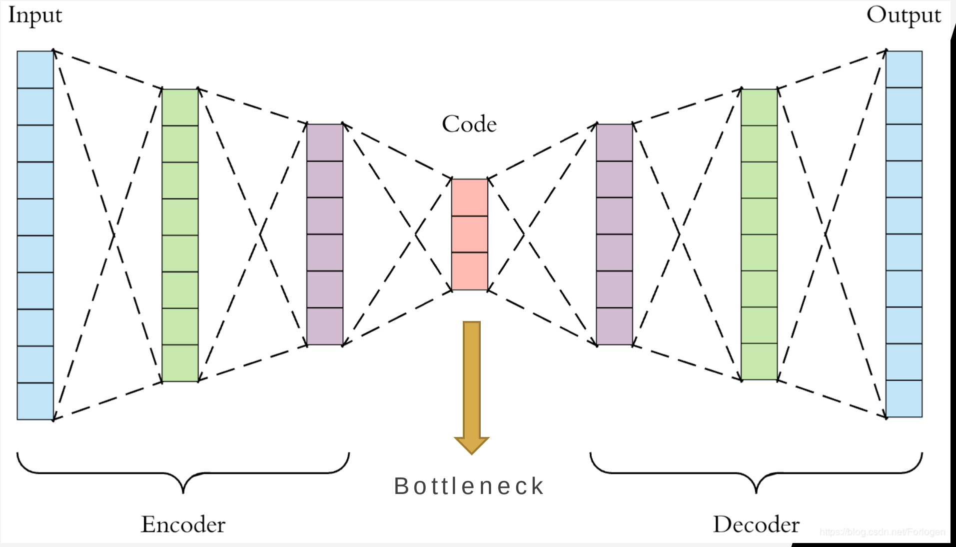
Decoder

Reconstructs the input



ARCHITECTURE CONT'D

- # of neurons per layer reduce towards Code and grows away from Code (hourglass)
- The less layers and neurons means less representation
- Loss function AKA Reconstruction Error
  - MSE or Binary Cross Entropy

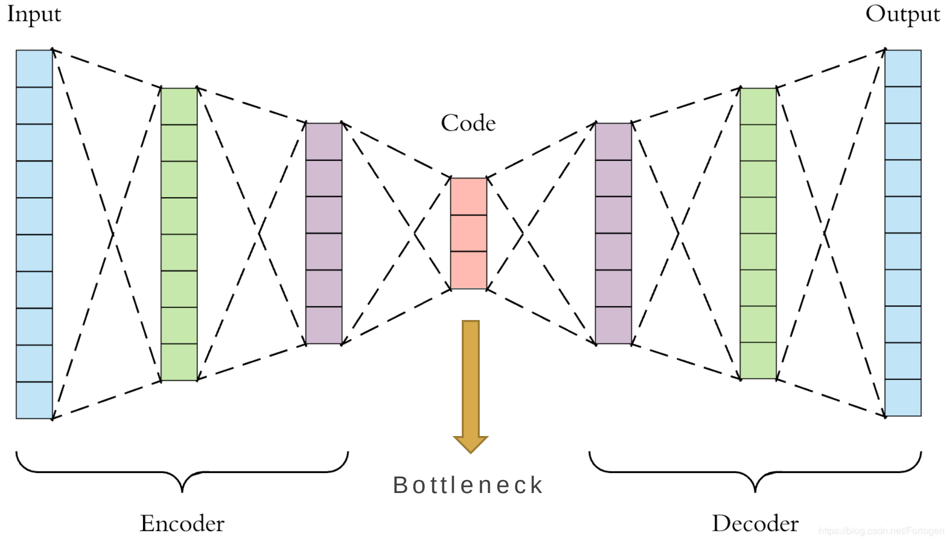


FORMAL REPRESENTATION

Encoder $\phi : \mathcal{X} \rightarrow \mathcal{F}$

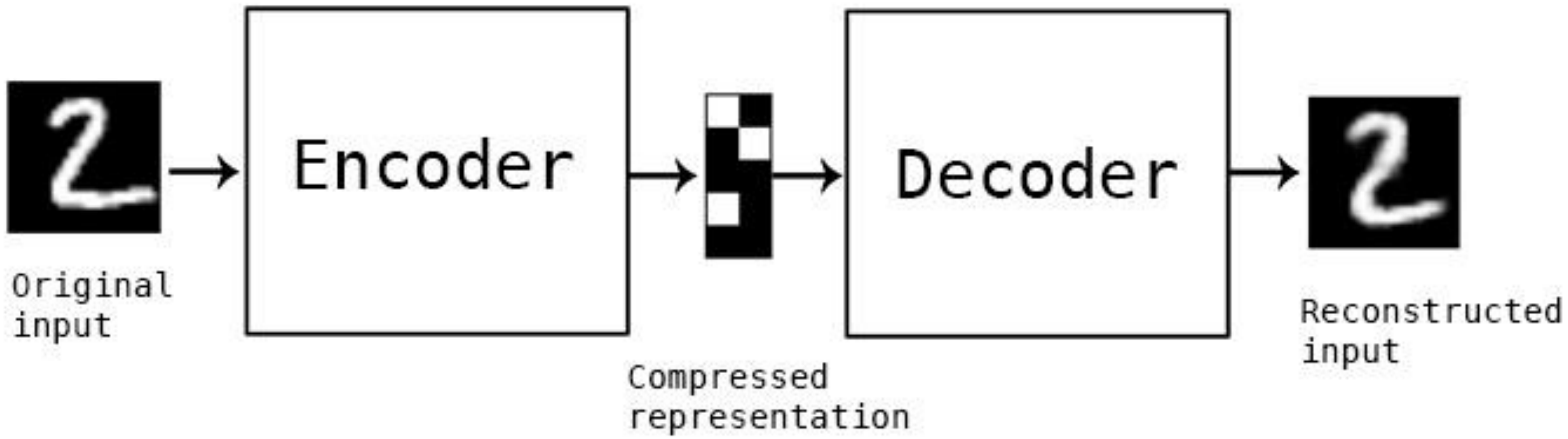
Decoder $\psi : \mathcal{F} \rightarrow \mathcal{X}$

Task $\phi, \psi = \underset{\phi,\psi}{\arg\min} \, \|X - (\psi \circ \phi)X\|^2$



$q_\phi(f|x)$ $p_\psi(x|f)$

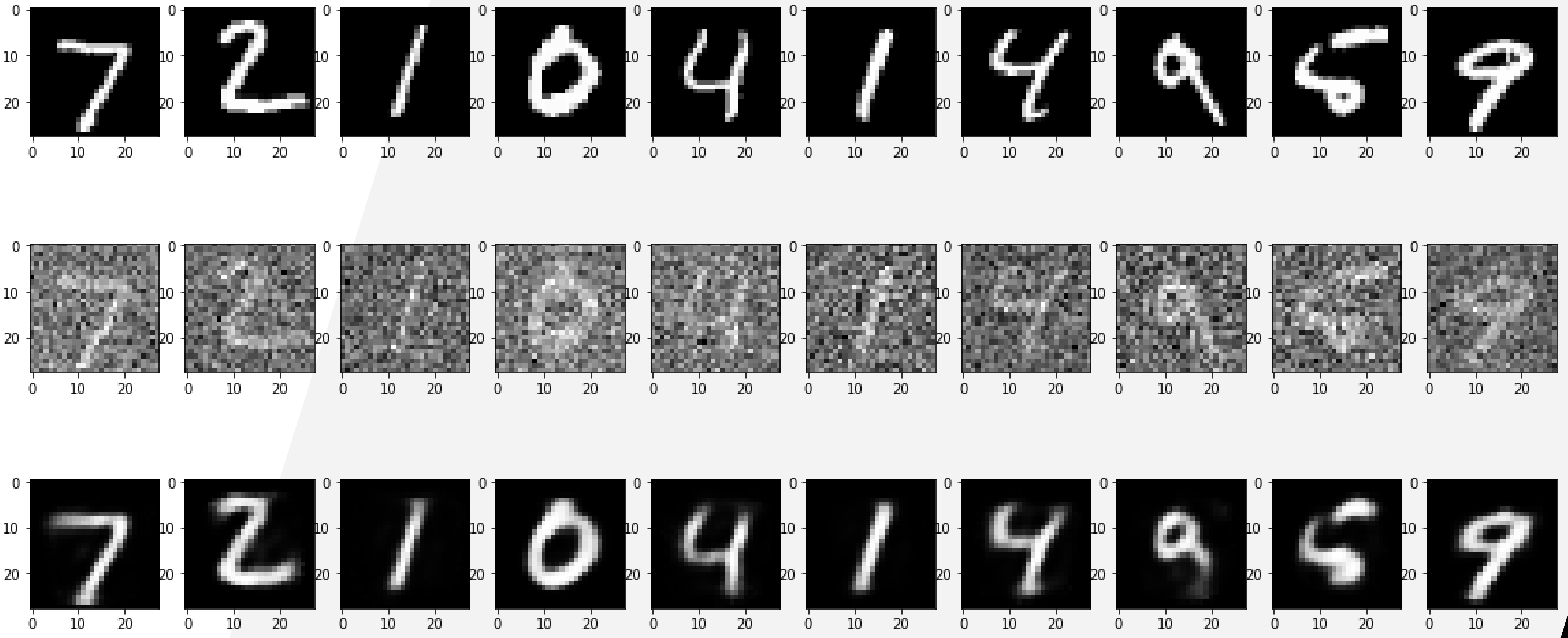
HAND-ON PART
AE EXAMPLE



Input Dimension
784
(flattened)

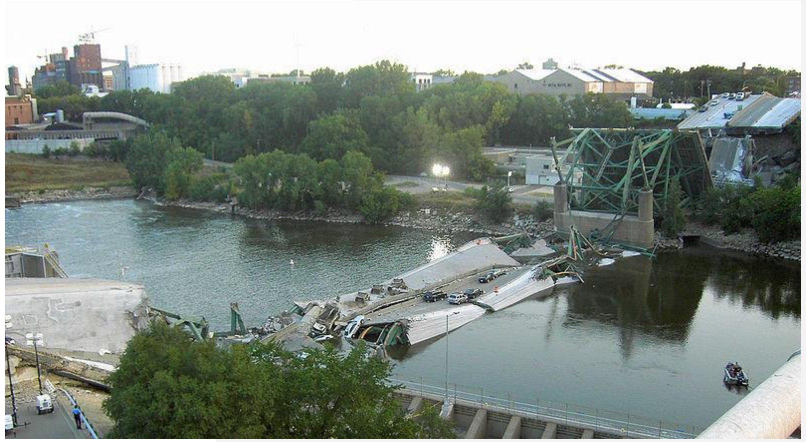
Code Dimension
32

Recons. Dimension
784
(flattened)



50% noise, 50 epochs, Dense network

NOVELTY DETECTION



- Structures get old
  - Require maintenance
- Inspections are costly
  - Early damage detection by sensors
- Dynamic characteristics
  - Natural Freqs and Mode Shapes
- Environmental effects
  - Can be nonlinear

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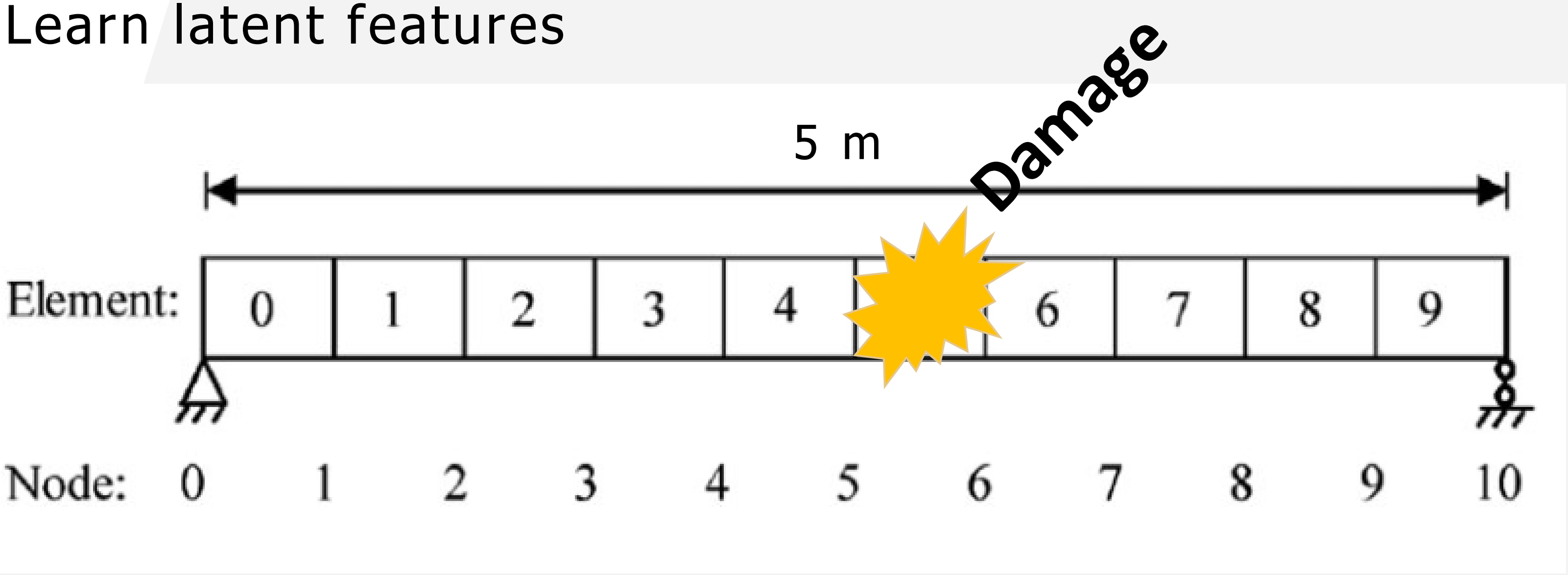
AE FOR DAMAGE DETECTION

- Aim: Detect damage (anomaly) in the system
- AutoEncoder: Minimize the error between input and the reconstruction
  - Input: Natural Frequencies and Mode Shapes collected under various temperatures
  - Learn latent features



NOVELTY INDEX

- Learn the latent feature space of *undamaged structure*
  - Objective function: $min\left|X - \hat{X}\right|$
  - For undamaged structure $\left|X - \hat{X}\right| \approx 0$

- Novelty Index: $NI = \left|X - \hat{X}\right|$
  - Undamaged Structure: $NI \approx 0$
  - Damaged Structure: $NI \gg 0$

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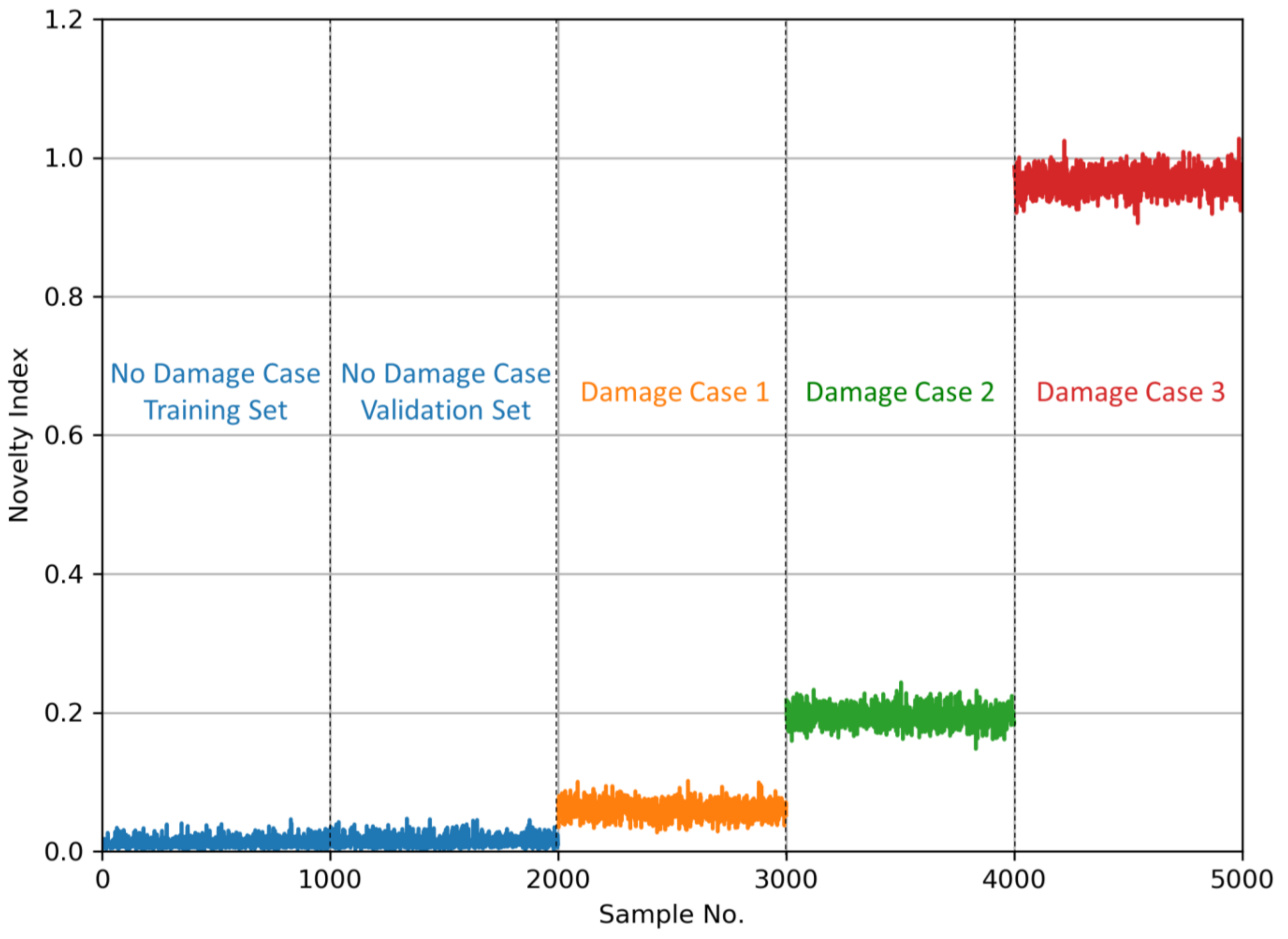
EVALUATION



- Damage Case 1:
  - 5% stiffness reduction
- Damage Case 2:
  - 10% stiffness reduction
- Damage Case 3:
  - 50% stiffness reduction

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THANK YOU!

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HANDS-ON REFERENCES

First demo

- https://blog.keras.io/building-autoencoders-in-keras.html

Denoising

- http://www.opendeep.org/v0.0.5/docs/tutorial-your-first-model

Coloring

- https://blog.floydhub.com/colorizing-b-w-photos-with-neural-networks/
- https://lukemelas.github.io/image-colorization.html

Novelty index

- https://github.com/aliirmak/ML-SHM

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REFERENCES I USED FOR GENERATING SLIDES

- Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep learning. MIT press, 2016
- https://www.jeremyjordan.me/autoencoders/
- https://www.edureka.co/blog/autoencoders-tutorial/
- https://towardsdatascience.com/art-of-generative-adversarial-networks-gan-62e96a21bc35
- https://towardsdatascience.com/generating-images-with-autoencoders-77fd3a8dd368

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