Denoising Wavefront sensor Images with Deep Neural Networks

Bartomeu Pou

Barcelona Supercomputing Center

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Introduction

Bartomeu Pou

- PhD student in Artificial Intelligence in Barcelona Supercomputing Center and Polytechnic University of Catalonia.
- Interested in Machine Learning and its application in Adaptive Optics.

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Rising STARS

Introduction

Eduardo Quiñones

- Barcelona Supercomputing Center.

Damien Gratadour

- Australian National University.
- LESIA, Observatoire de Paris, Universite PSL, CNRS, Sorbonne Universite.
- Universite Paris Diderot.

Mario Martín

- Polytechnic University of Catalonia.

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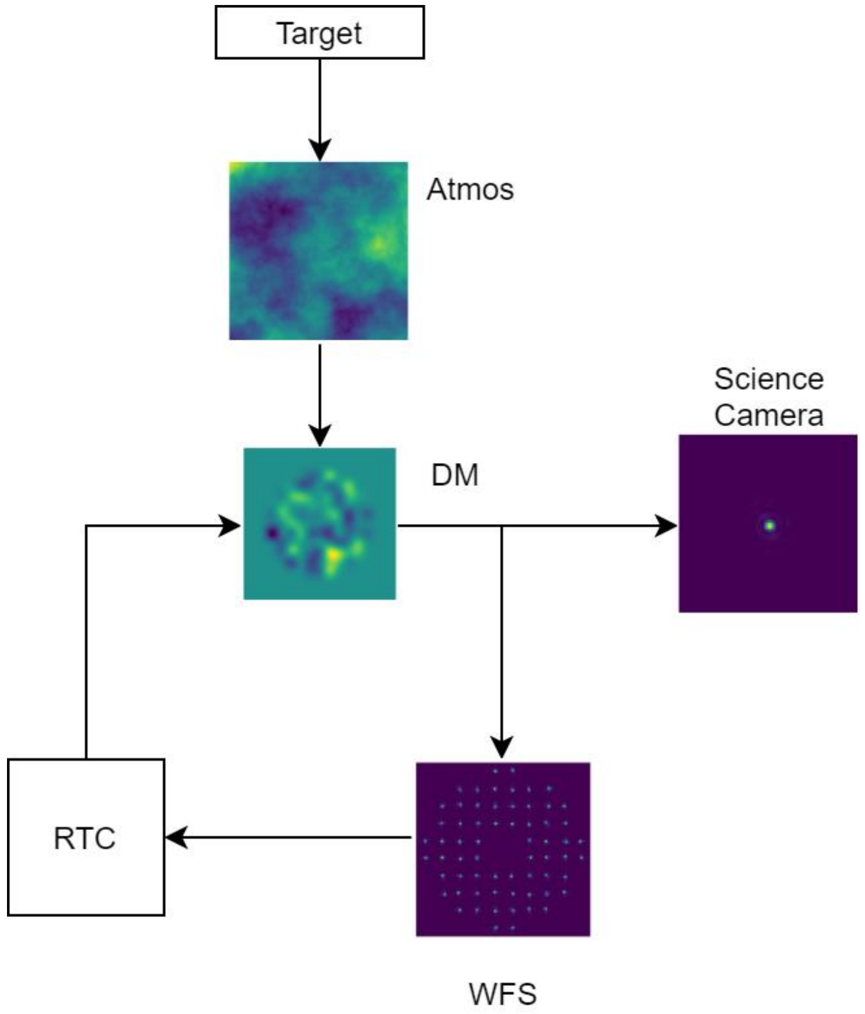
Problem: Noise in the AO Loop

Closed-loop Adaptive Optics



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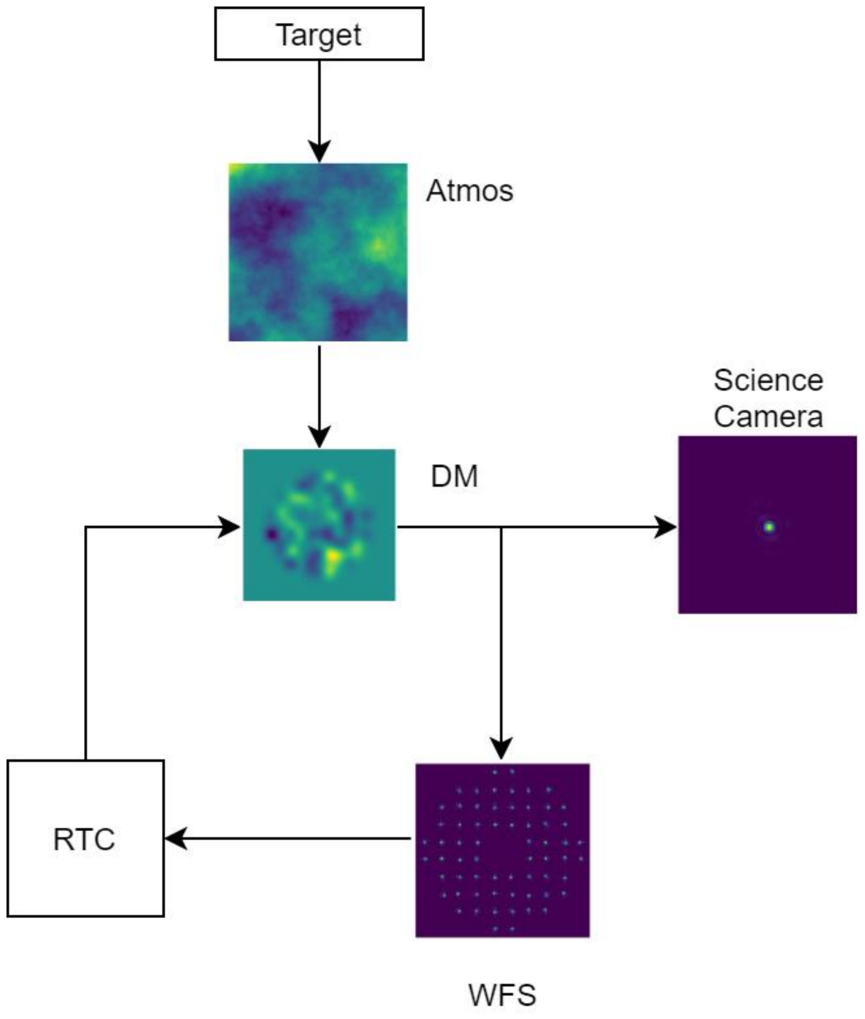
Closed-loop Adaptive Optics

1. Process WFS info with **Center of gravity (cog)** method.

$$S_x = \frac{\sum_x (\sum_y I(x,y))x}{\sum_x \sum_y I(x,y)} \; ; \; S_y = \frac{\sum_y (\sum_x I(x,y))y}{\sum_x \sum_y I(x,y)}$$

$$m = (S_{x_1}, S_{x_2}, \dots, S_{x_n}, S_{y_1}, S_{y_2}, \dots, S_{y_n})$$



Closed-loop Adaptive Optics

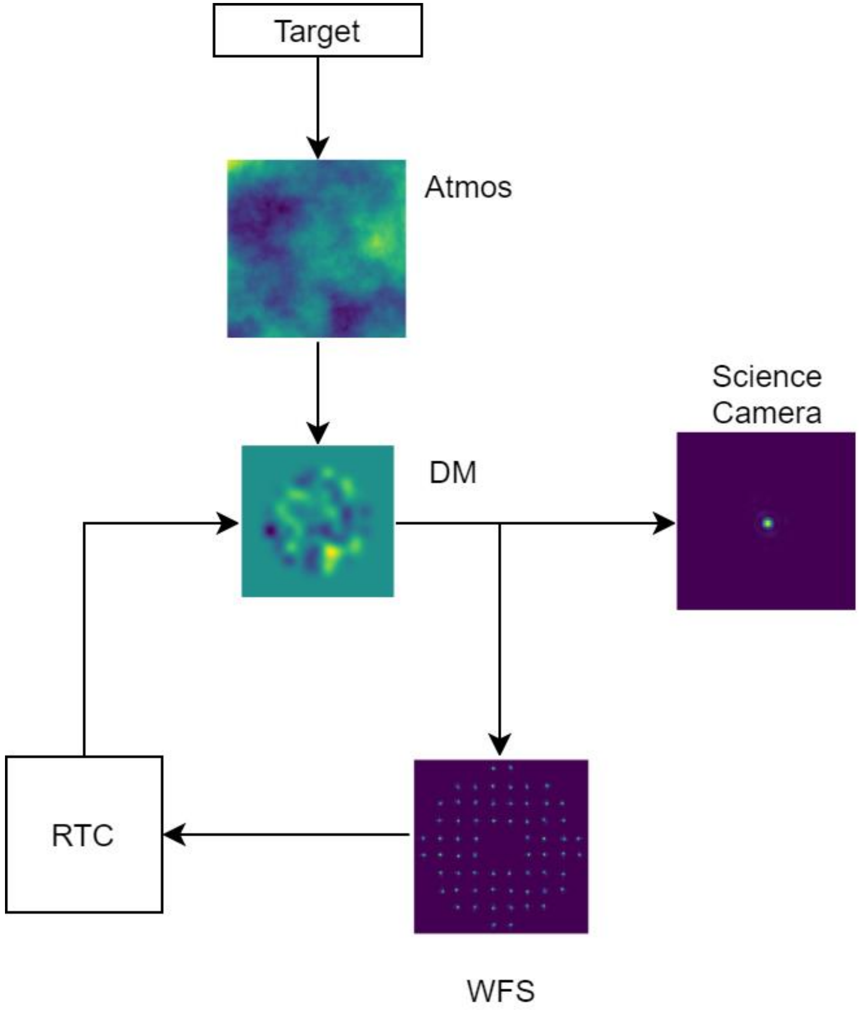
2. **Integrator with gain**

- Commands that should be applied:

$$c = R\,m$$

- Reduce error by integrating past commands:

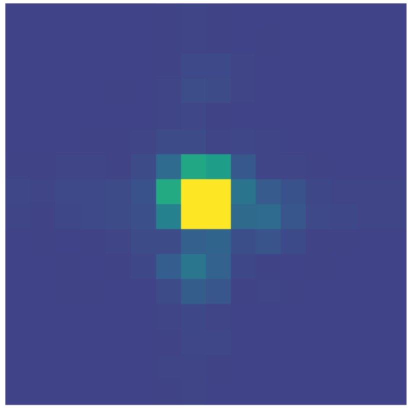
$$C_t = C_{t-1} - gc$$



Noise in wavefront sensor subapertures

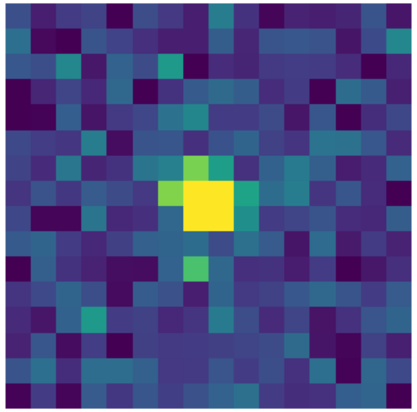
We treat the two main sources of noise in AO:

1. **Readout noise** on the subaperture detectors.
2. **Shot noise** due to photon statistics.



a) Noise free WFS subaperture image.

cog=(-0.008, -0.028)



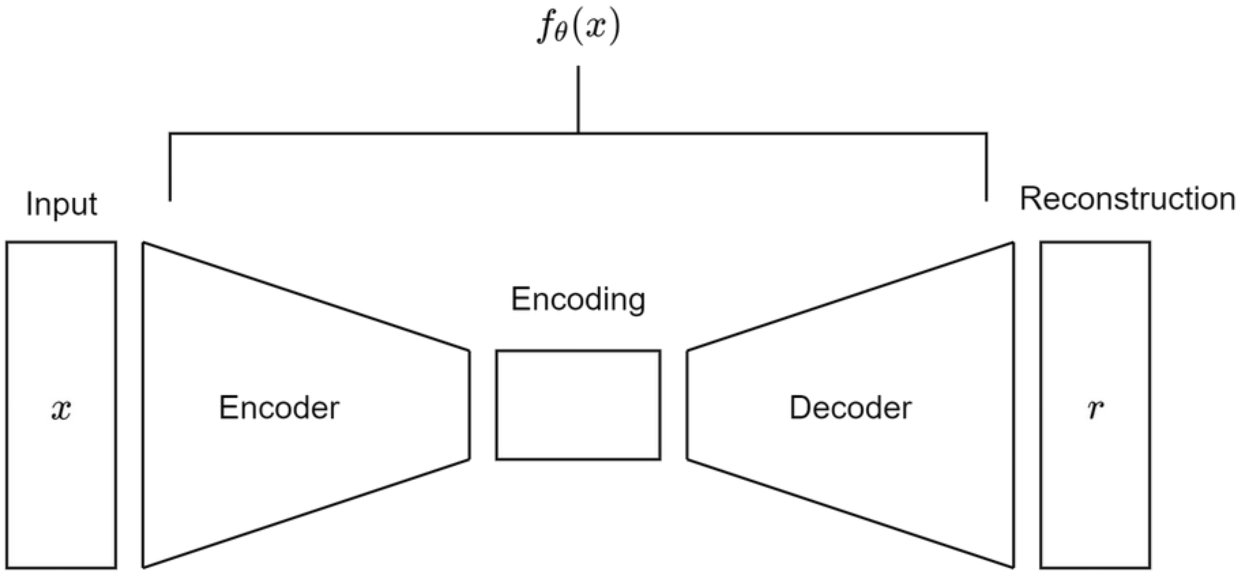
b) Noise in the subaperture image.

cog=(0.367, -0.018)

Solution: Denoising Autoencoder

Autoencoder (LeCun 1987, Bourlard and Kamp, 1988, Hinton and Zemel 1994)

1. Unsupervised learning method based on neural networks.



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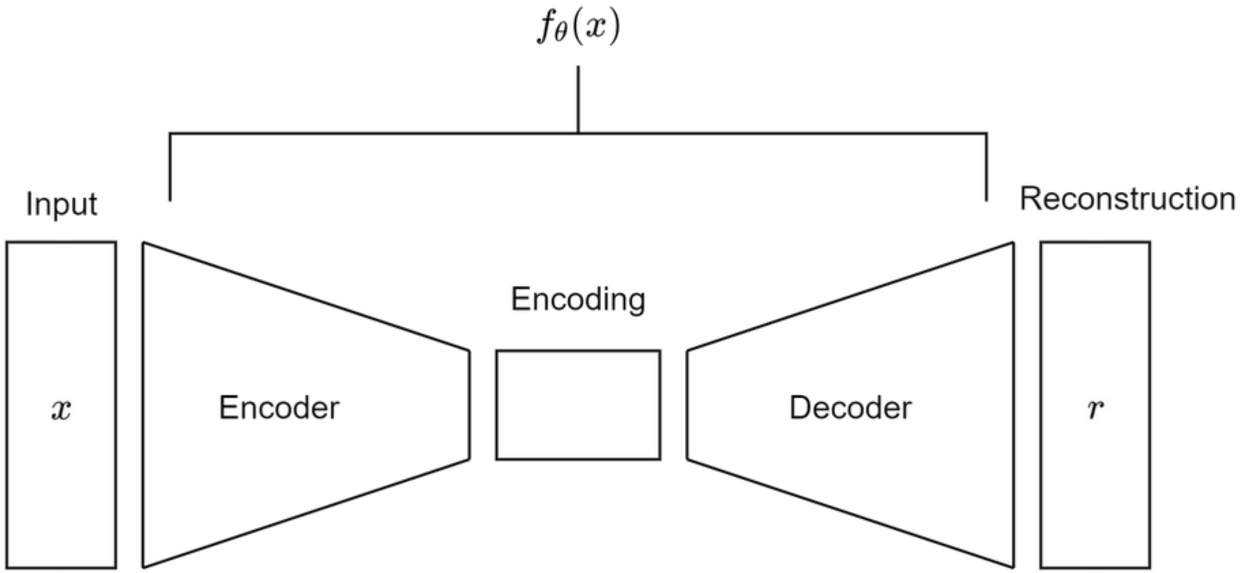
2. Learn a function f_θ with parameters θ to **reconstruct input**.



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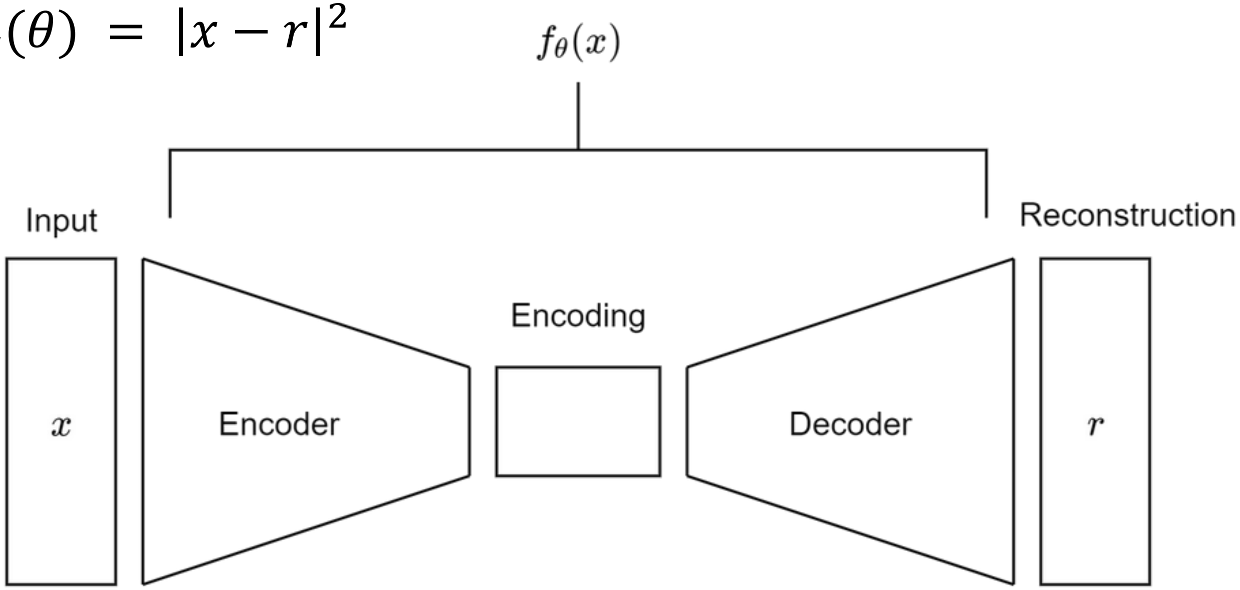

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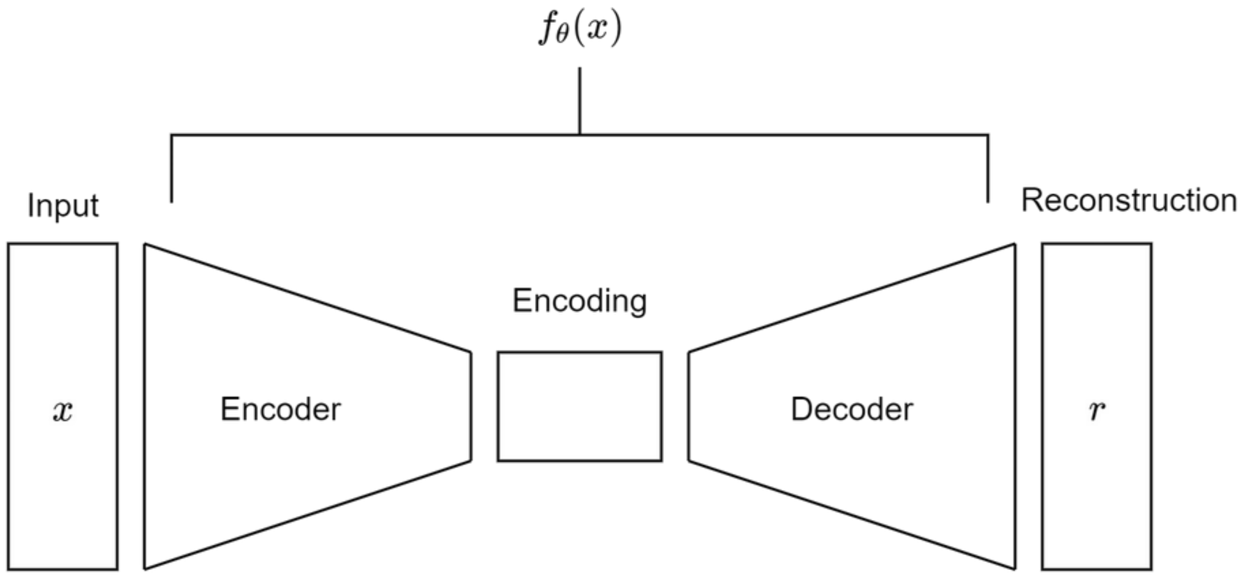
4. Applications:

- Dimensionality reduction.
- Pretraining other networks.
- Denoising.
- Anomaly detection.



Denoising Autoencoder (Vincent et al. 2008)

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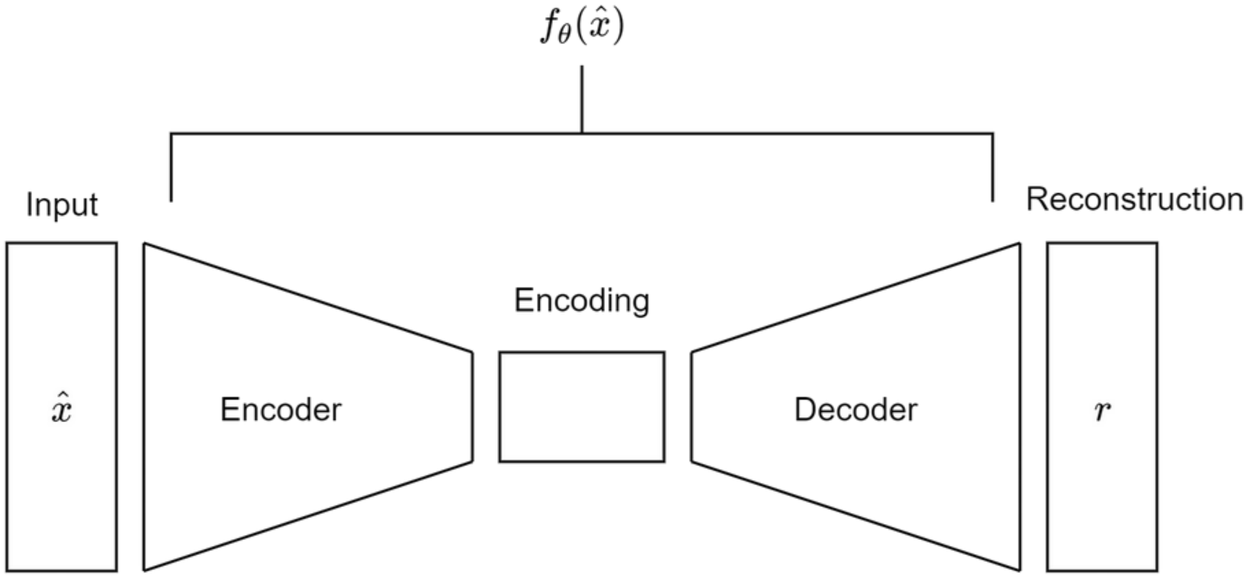

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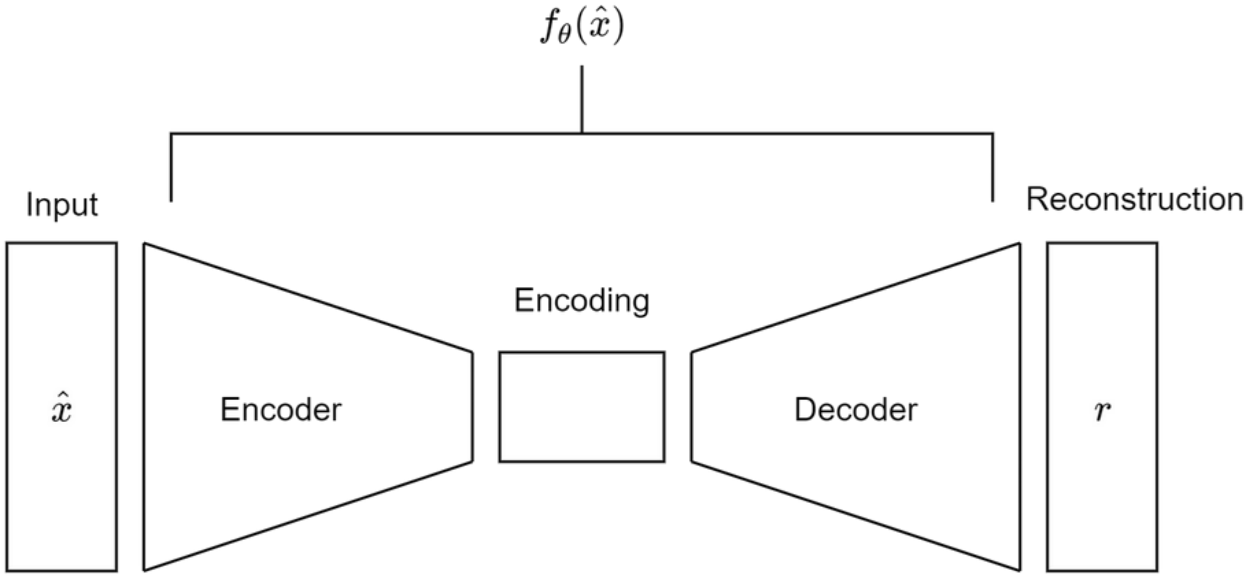
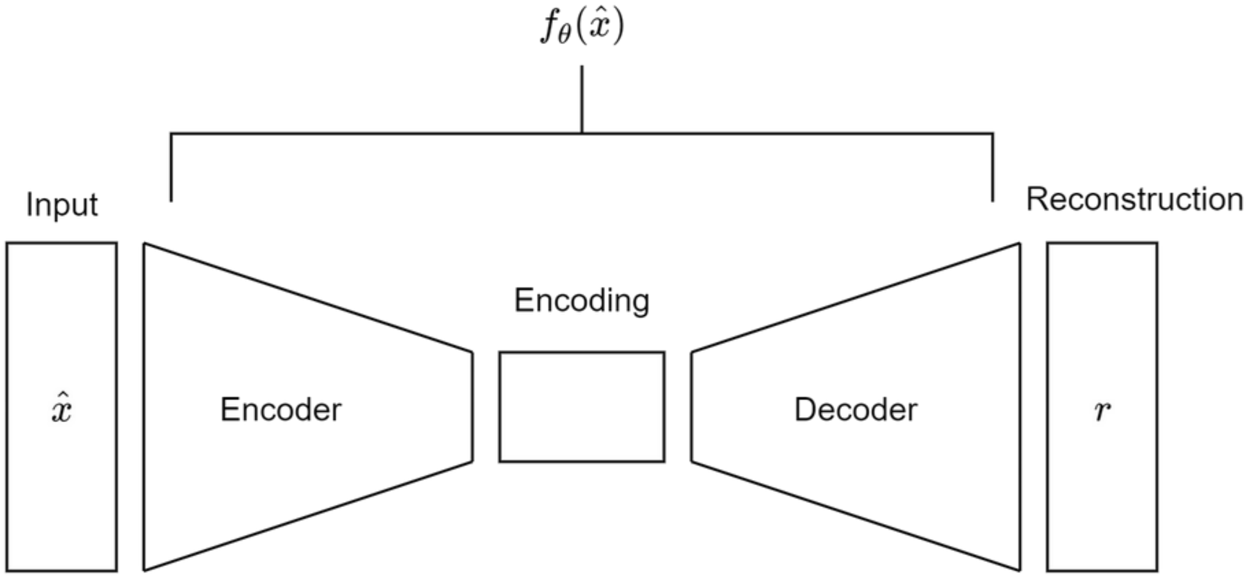
1. Problem of Autoencoder: f_θ can just **become the identity** function.
2. Solution: **corrupt the input**, $x \sim \hat{x}$, so it learns a map to noise corrupted input to noise free reconstructed output.
3. In Vincent et al. 2008, Denoising Autoencoder used the learned encoding as the initial weights of a neural network classification network and obtained better results as if not using them.



Convolutional Denoising Autoencoder (Masci et al. 2011).

1. **Convolutional neural networks (CNN)** state of the art in image processing tasks since the breakthrough of Alexnet (Krizhevsky et al. 2017).



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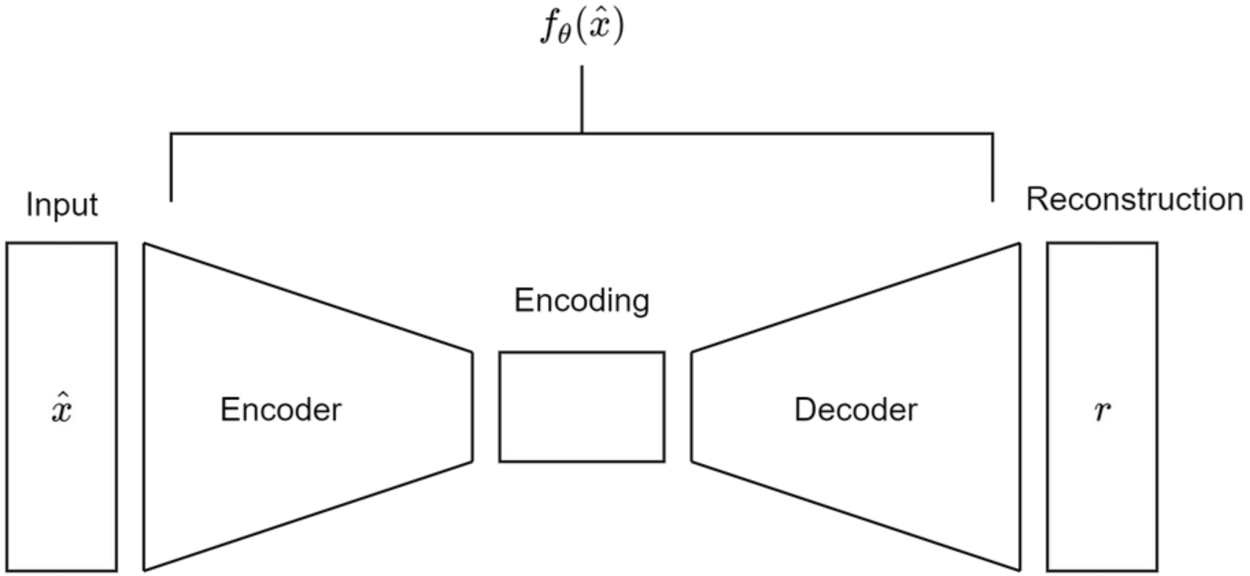
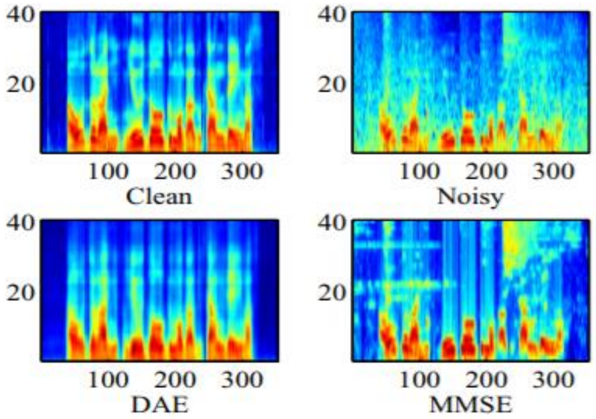
1. **Convolutional neural networks (CNN)** state of the art in image processing tasks since the breakthrough of Alexnet (Krizhevsky et al. 2017).
2. In Masci et al. 2011, CNN were used as the layers in a denoising autoencoder and use it as a pretraining step for a classification network and reported improvements on the classification task.



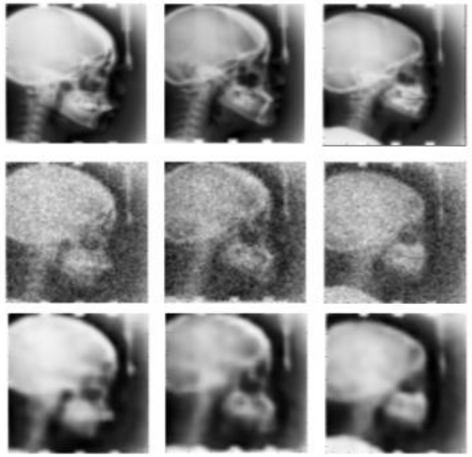
Some denoising applications

1. **Speech**: *Lu et al. "Speech enhancement based on deep denoising autoencoder" (2013)*

2. **Medical images**: *Gondara et al. "Medical image denoising using convolutional denoising autoencoder" (2016)*



Source: Lu et al.



a) Noise-free.

b) Noisy

c) Convolutional DAE

Source: Gondara et al.

Solution: Autoencoder for WFS Images

Autoencoder for WFS Images

1. We change from a Unsupervised Learning problem to a Supervised Learning one:
   1. **Input**, x: noisy WFS subaperture pixel value.
   2. **Reconstruction**, r: denoised input $r = f_\theta(x)$
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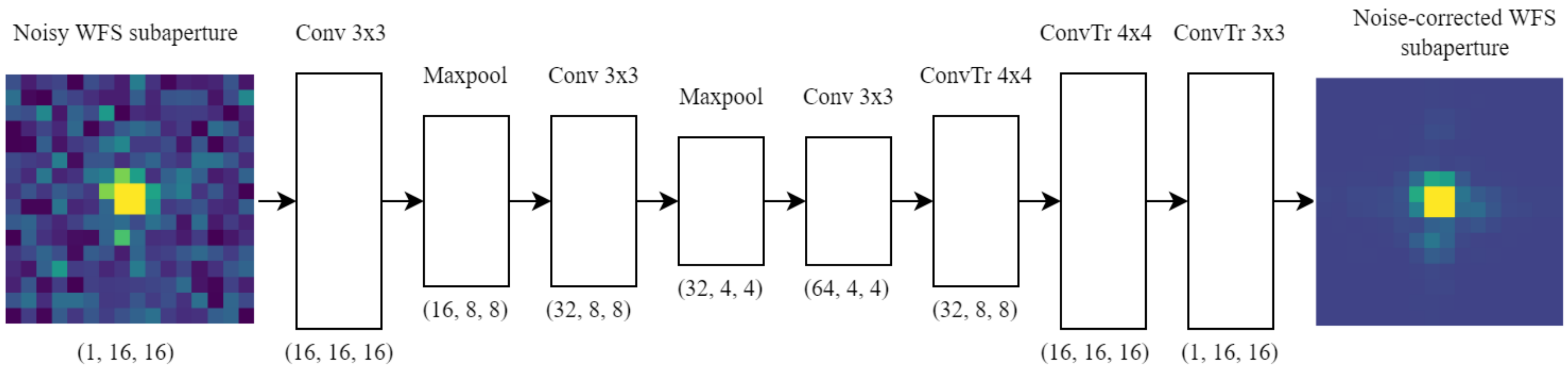
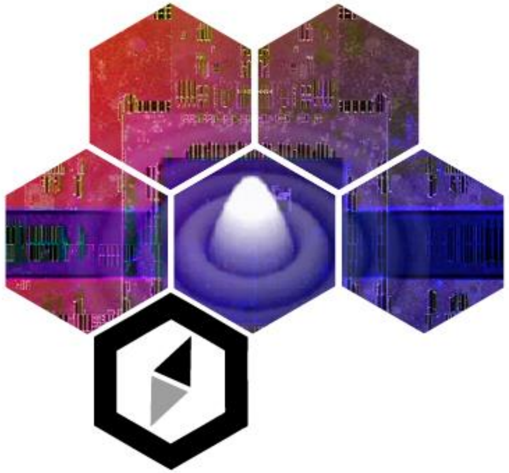
2. Loss MSE: $L(\theta) = |r - y|^2$



Dataset

1. Dataset: simulator

COMPASS: COMputing Platform for Adaptive optics SystemS.



[5] High performance simulations using GPU.

2. Dataset: simulation parameters

Simulation parameters.

- Telescope: 2m 10x10/8m 40x40
- GS Magnitude 9/9.2
- Fried parameter value: 0.08, 0.16, 0.24 m

Atmospheric parameters		**Telescope Parameters**	
L_0 (m)	10^5	λ_{target} (µm)	1.65
r_0(m)	0.08/0.16/0.24 @ 0.5 µm		
Wind speed (m/s)	20	**WFS parameters**	
Wind direction (°)	45	Number of subapertures	10x10/40x40
AO loop parameters		Number of valid subapertures	64/1200
Loop frequency (Hz)	500	Pixels per subaperture	16
Delay	0/2	Pixel size (arcsec)	0.25
DM parameters		λ_{wfs} (µm)	0.5
Mirrors	Pzt and TT	GS Magnitude	9/9.2
Coupling (pzt)	0.2	Read Out Noise (e- RMS)	3

(n=3)

Table 2: Simulation parameters. Symbol "/" indicates that different values for that parameter are used.

3. Dataset: obtaining x-y pairs

1. Optimise the integrator gain, g, in the presence of noise.

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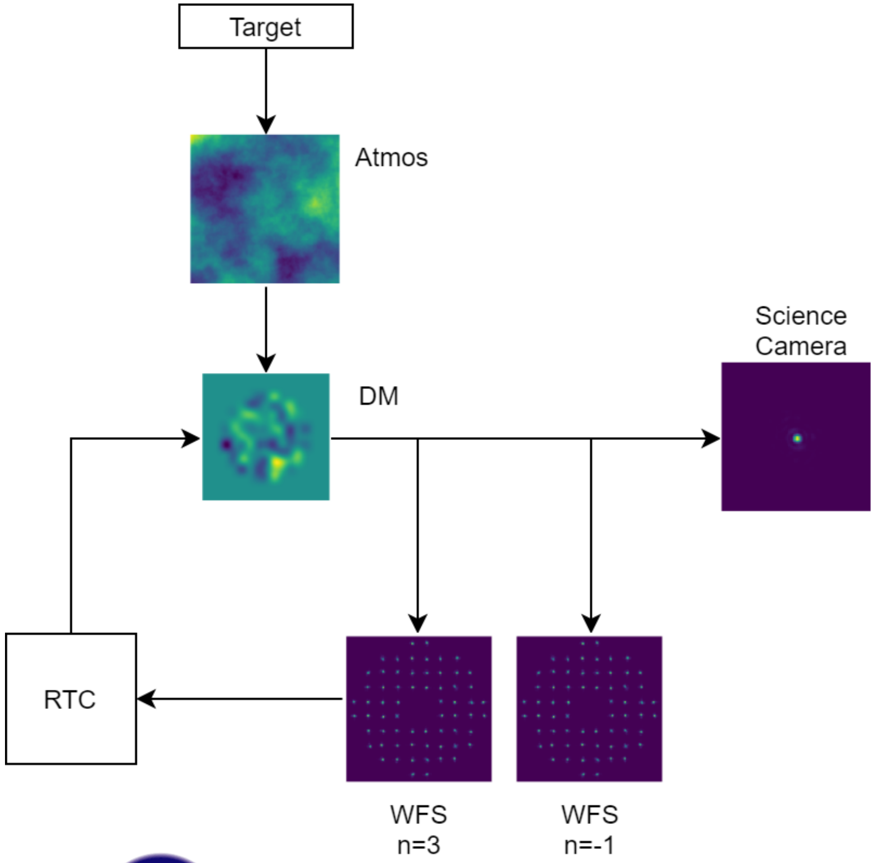
2. Then run a simulation with two wavefront sensors, one with readout (3 e- RMS) and photon noise, n=3, and one without noise, n=-1.



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    - WFS (n=3) will provide the input to train our network.
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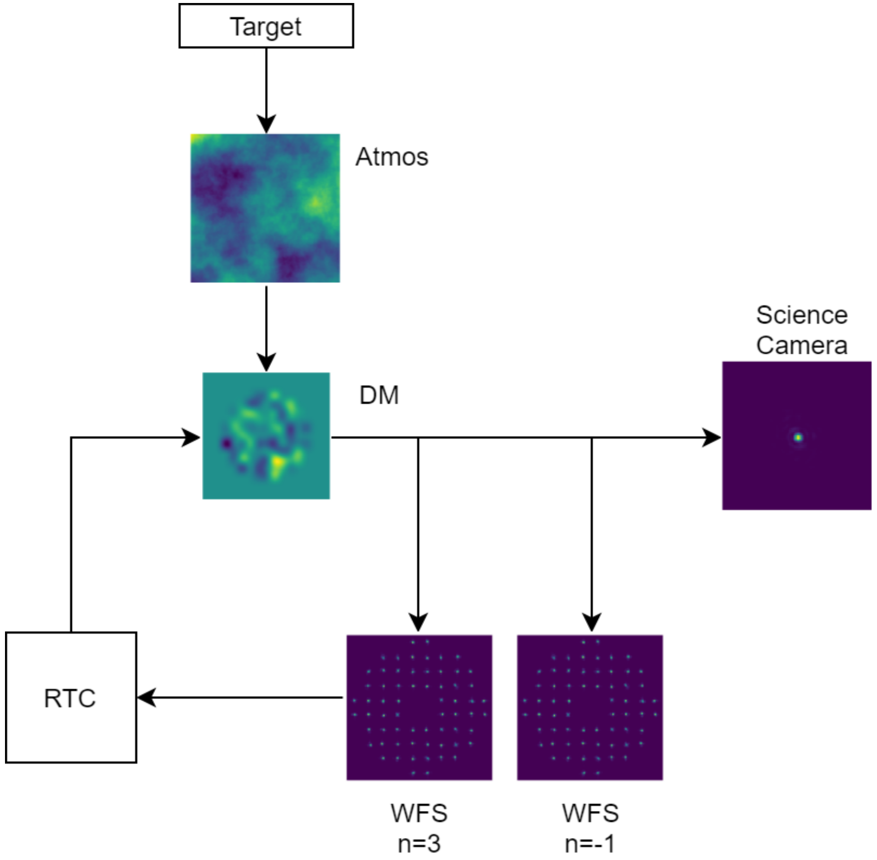

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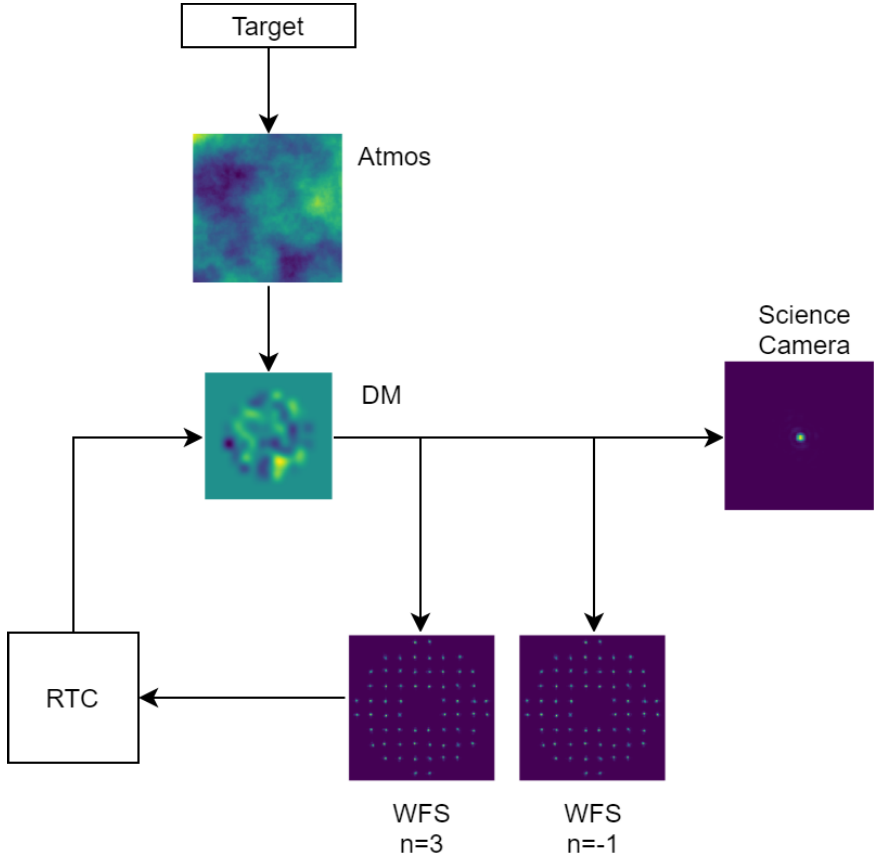
3. 10000 WFS images obtained.



Results

Validation curves

- Training (80%) and validation (20 %) sets.

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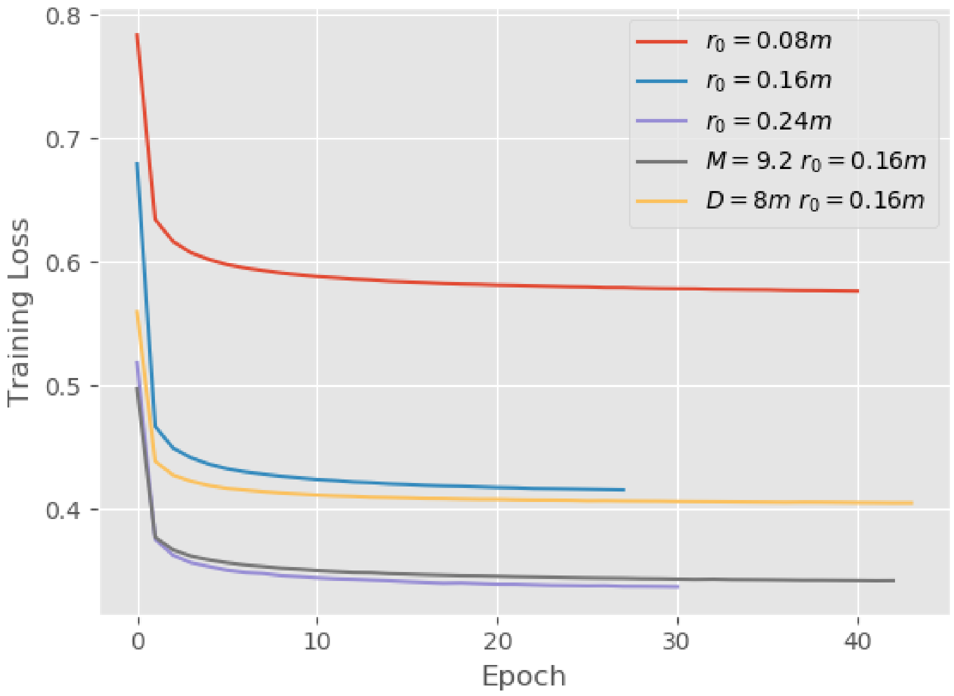

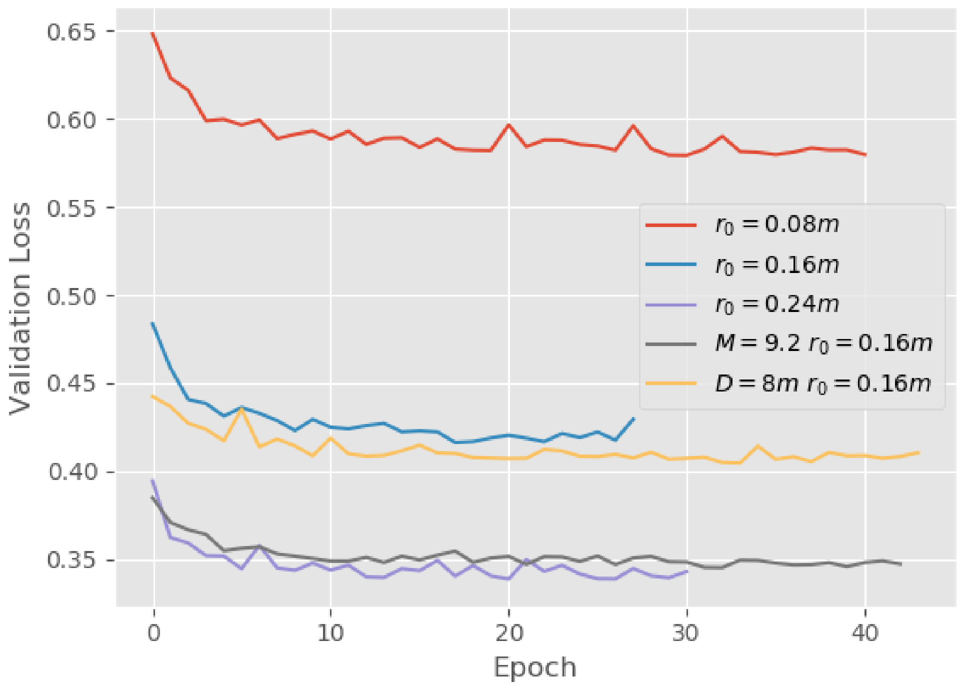

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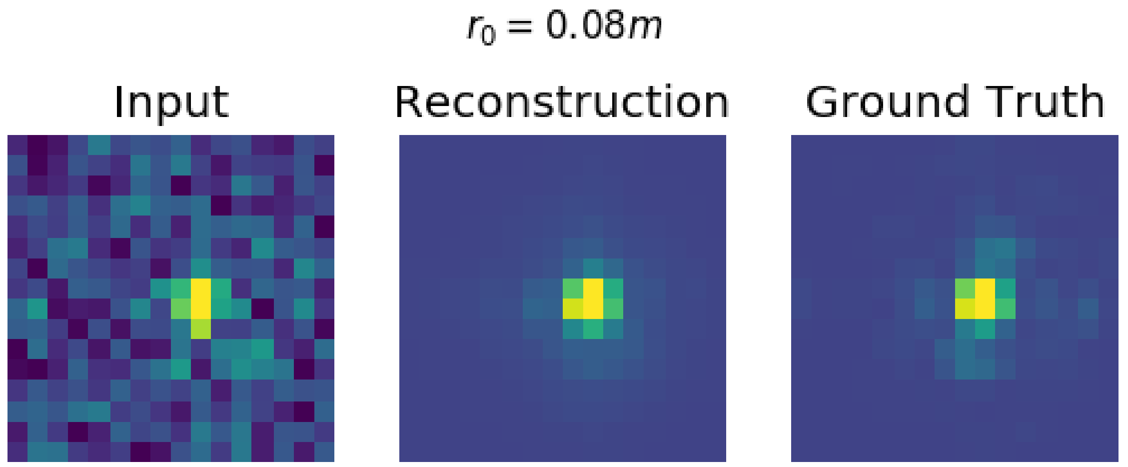
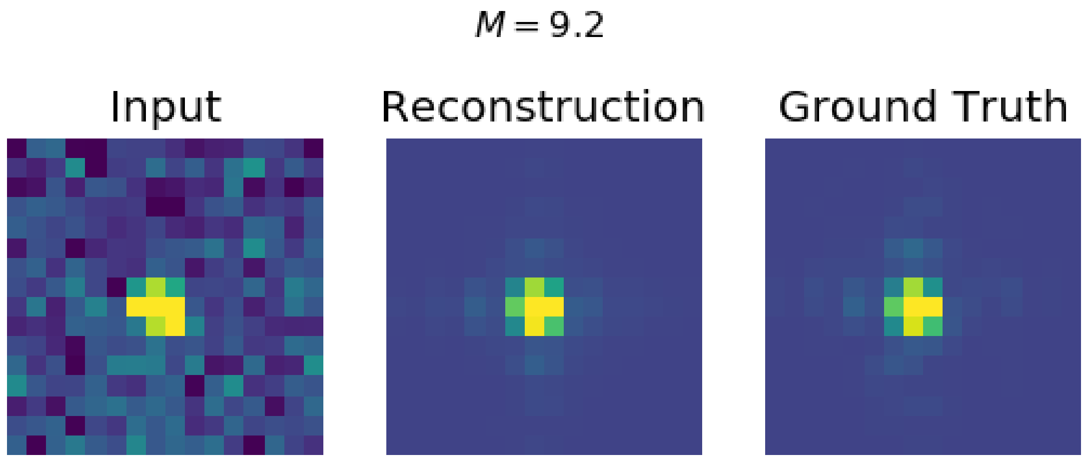
Reconstruction example I

- $r_0 = 0.08\,m$
- Guide star magnitude, $M = 9$



Reconstruction example II

- $r_0 = 0.16\, m$
- Guide star magnitude, $M = 9.2$



Testing Autoencoder on a simulation

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- Plug Autoencoder into a simulation.
- After obtaining a WFS image, denoise each subaperture with the denoising autoencoder.

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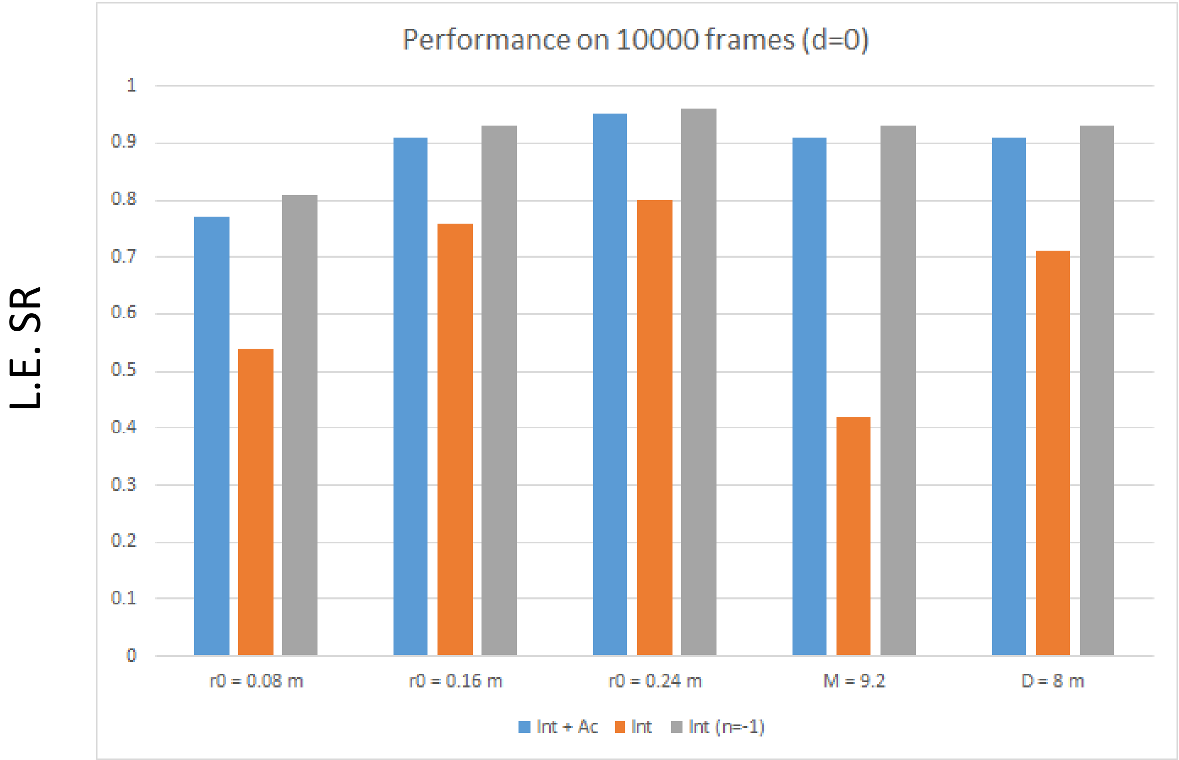
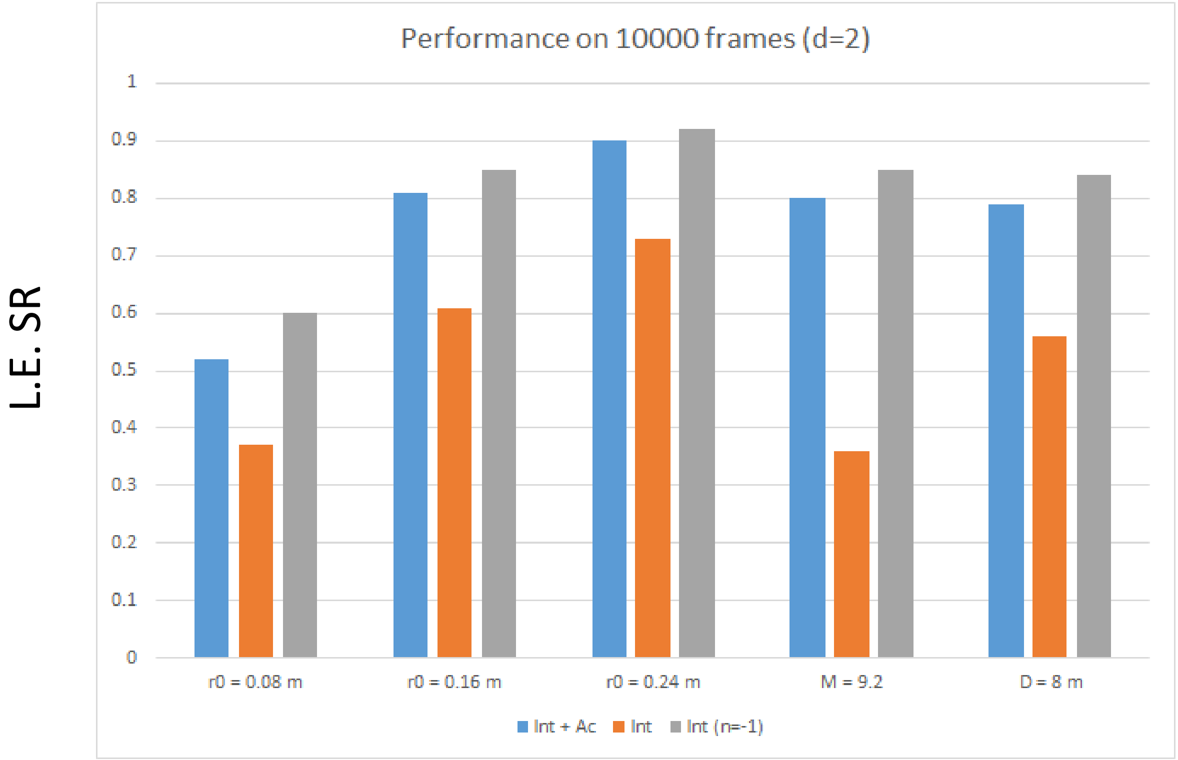
- Delay 0.



Testing Autoencoder on a simulation II

- Plug Autoencoder into a simulation.
- After obtaining a WFS image, denoise each subaperture with the denoising autoencoder.
- Delay 2.



Other Results

Comparison with other methods

- Comparison between brightest pixel [8] selection and denoising autoencoder.
- Noise (n=3) and different value of guide star magnitudes.
- Best number of brightest pixel is selected.
- For each magnitude an autoencoder is trained with data from data magnitude.

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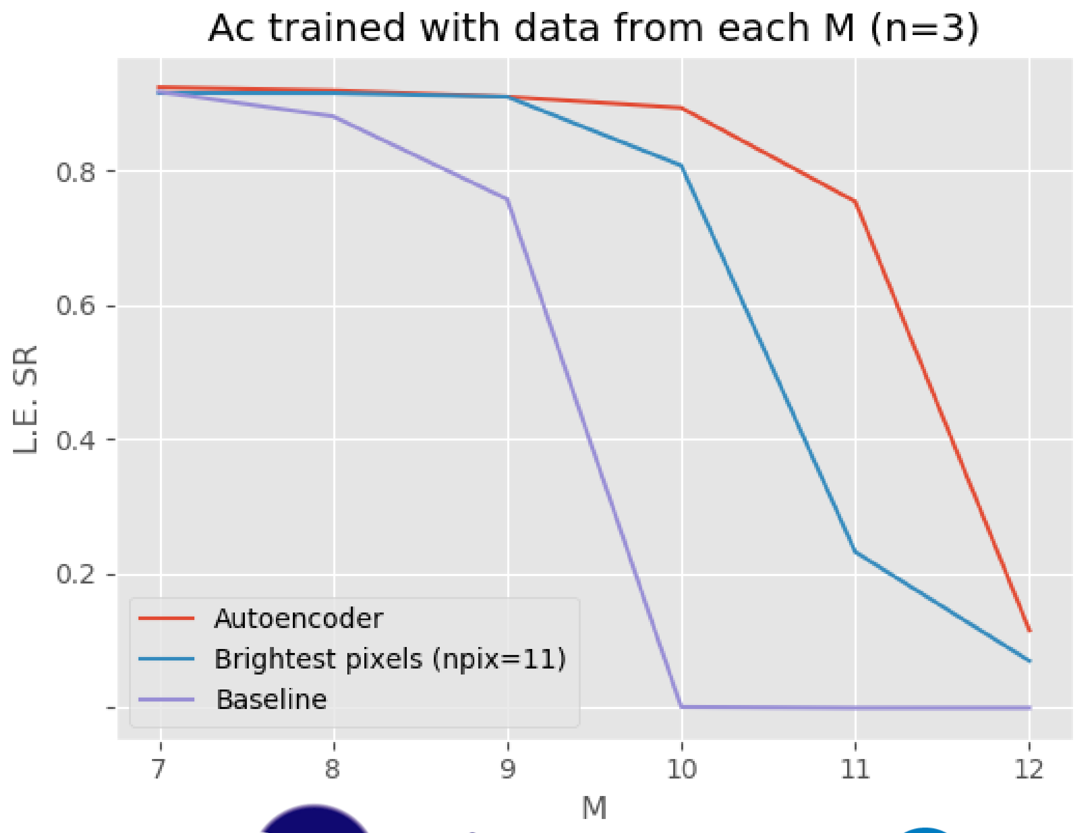

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Reinforcement Learning in Adaptive Optics

- We are developing a controller based on “Reinforcement Learning”, learning by trial and error to optimize a reward function.
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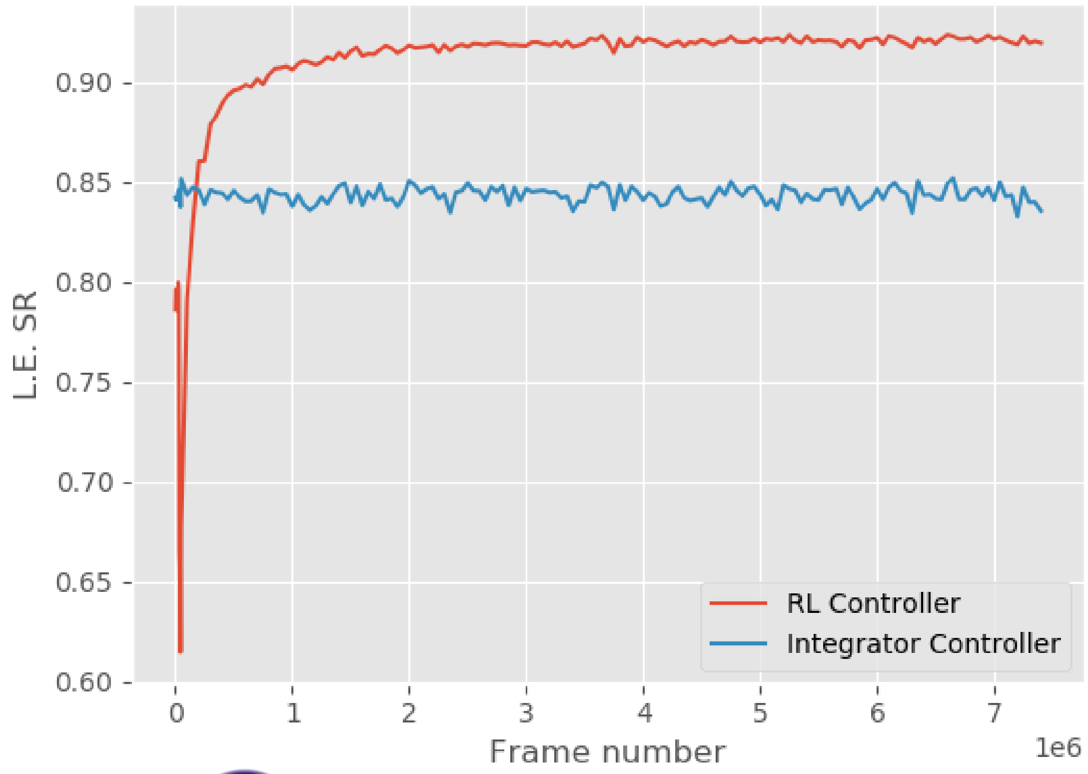

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Future work

- Test the inference time.
  - Improve inference time with network distillation or its implementation in a high performance frameworks (e.g. tensorRT).

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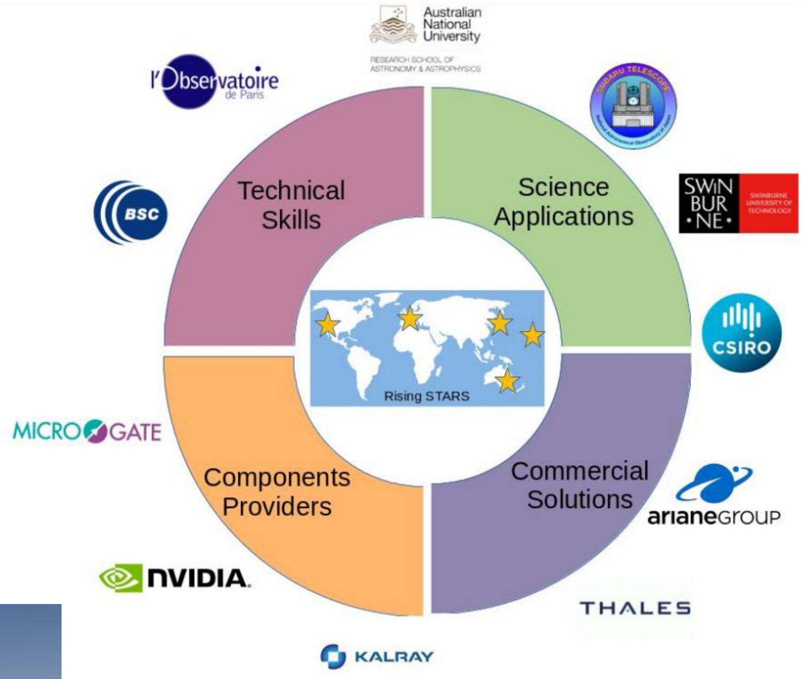
- Test the inference time.
  - Improve inference time with network distillation or its implementation in a high performance frameworks (e.g. tensorRT).
- Real life experiment.
  - It appears to be robust to seeing conditions.
  - Train several networks with the calibration source, on the bench during day-time.
  - Brightness of the calibration source will dictate the different SNR.
  - On night-time, evaluate the target brightness and load the appropriate network.

MSCA H2020 Rising STARS project

48-month mobility-oriented project across a network of 11 partners worldwide (on hold due to Covid-19)

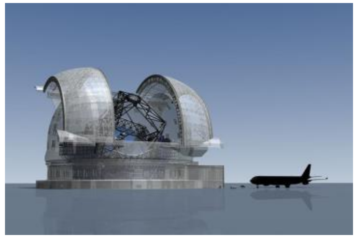
- Coordinated by OdP (A/Prof. Damien Gratadour)
- Right mix of academia & industry
- Started collaborating remotely



Facilitate the development of advanced Cyber-Physical Systems (CPS) with HPC and real-time requirements

Two astronomic use-cases (among others):

- Adaptive Optics on the European Extremely Large Telescope (ELT)
- Square Kilometer Array (SKA)



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RISE International Network for Solutions Technologies and Applications of Real-time Systems.
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Bibliography

[1] Pou, B., et al. "Denoising wavefront sensor image with deep neural networks." *Adaptive Optics Systems VII*. Vol. 11448. International Society for Optics and Photonics, 2020.

[2] Hinton, Geoffrey E., and Richard S. Zemel. "Autoencoders, minimum description length, and Helmholtz free energy." *Advances in neural information processing systems* 6 (1994): 3-10.

[3] Bourlard, Hervé, and Yves Kamp. "Auto-association by multilayer perceptrons and singular value decomposition." *Biological cybernetics* 59.4 (1988): 291-294.

[4] Yann, L. *Modeles connexionnistes de lapprentissage*. Diss. These de Doctorat, Universite Paris, 1987.

[5] Vincent, Pascal, et al. "Extracting and composing robust features with denoising autoencoders." *Proceedings of the 25th international conference on Machine learning*. 2008.

[6] Masci, Jonathan, et al. "Stacked convolutional auto-encoders for hierarchical feature extraction." *International conference on artificial neural networks*. Springer, Berlin, Heidelberg, 2011.

[7] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Communications of the ACM* 60.6 (2017): 84-90.

[8] Lu, Xugang, et al. "Speech enhancement based on deep denoising autoencoder." *Interspeech*. Vol. 2013. 2013.

[9] Gondara, Lovedeep. "Medical image denoising using convolutional denoising autoencoders." *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*. IEEE, 2016.

[10] https://anr-compass.github.io/compass/

[11] Basden, A. G., R. M. Myers, and Eric Gendron. "Wavefront sensing with a brightest pixel selection algorithm." *Monthly Notices of the Royal Astronomical Society* 419.2 (2012): 1628-1636.