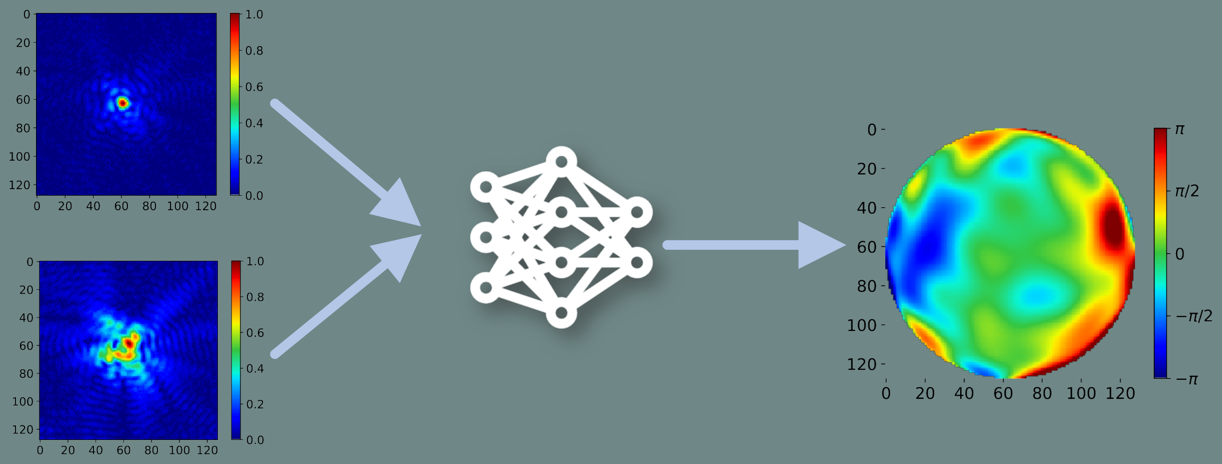
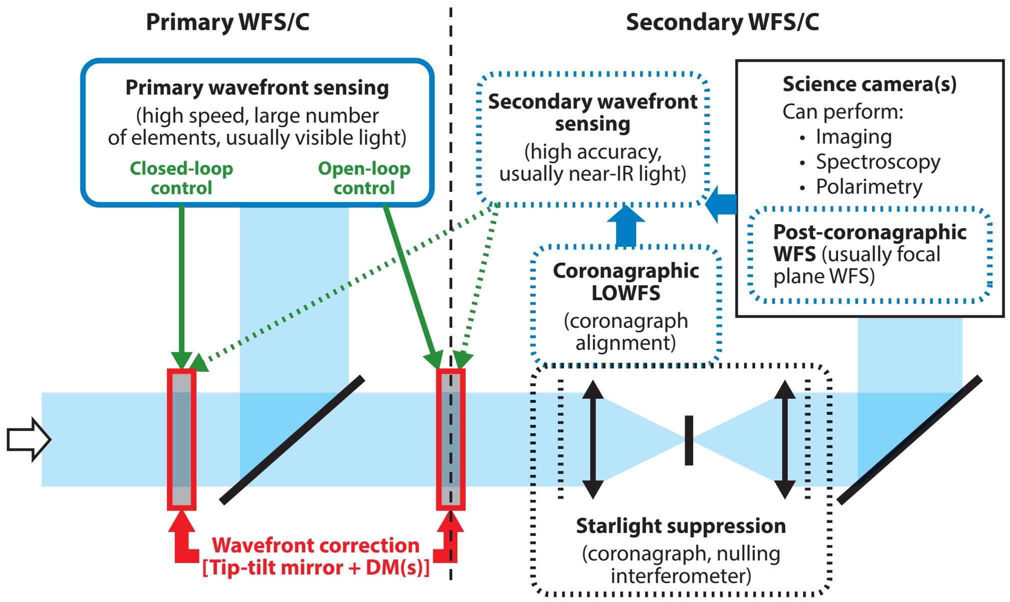



# FOCAL PLANE WAVEFRONT MEASUREMENT WITH CNN

G. Orban de Xivry
P.-O. Vanberg, O. Absil, G. Louppe

Firenze 2019
WFS in the ELT/VLT ERA

# CONTEXT




Guyon 2018

Focal plane wavefront sensing:

- Particular interest for coronography: measuring aberrations where it matters most
- Optically simple (but computationally challenging)
- Focal plane intensity <-> pupil complex amplitude: non-linear and degenerate

# FOCAL PLANE WFS CHALLENGES

Twin image problem:

*h(x), h(-x)* have the same* $|\mathcal{F}\{.\}|$

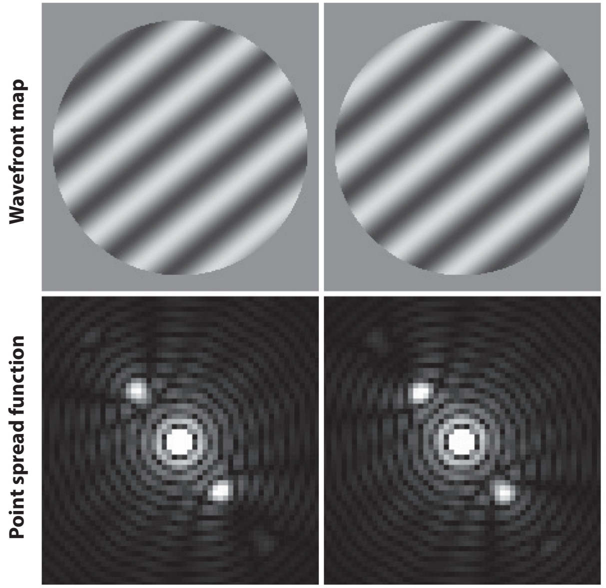
➢ sign ambiguity of Zernike even mode

Capture range problem (likelihood of stagnating in local minima)

probability decreases as ~ 1 / $R^{n+1}$

$R \propto$ *RMS WFE*

n $\propto$ number of coefficients




➢What can Convolutional Neural Network do for us?

➢And is it a promising avenue for high-contrast imaging?

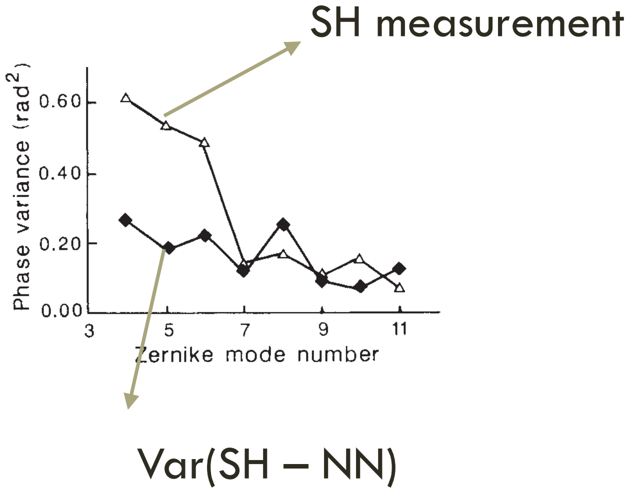
# NEURAL NETWORK IN WAVEFRONT ESTIMATION

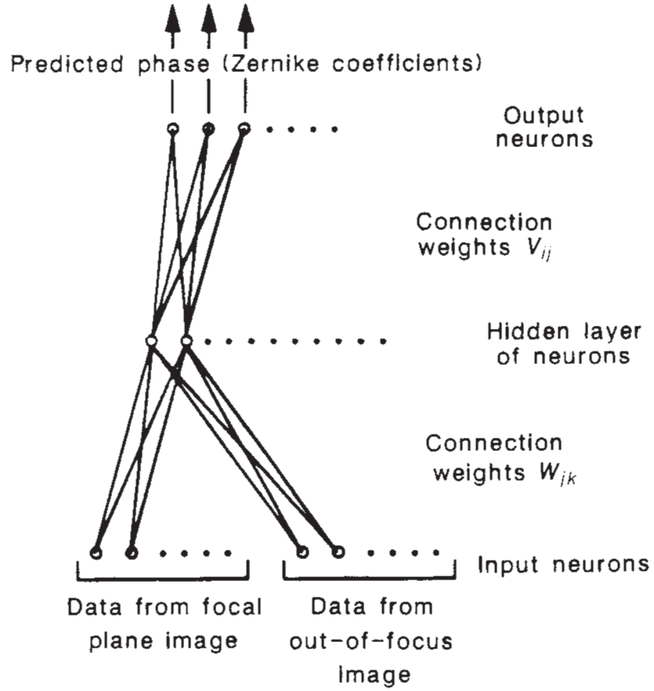
Angel et al. 1990 :

- ANN to correct piston and tip-tilt of the 6 MMT segments
- Single layer of hidden nodes; input: in- & out-focus

Sandler et al. 1991

- Successful test on a real star at 1.5m SOR
- Agreement to SH-WFS




Barrett and Sandler 1993

- Apply to HST
- Good agreement with phase retrieval algo

But also used for:

- Prediction (e.g. Jorgenson & Aitken 1992, McGuire et al. 1999)
- Slope measurements (Montera et al. 1996)

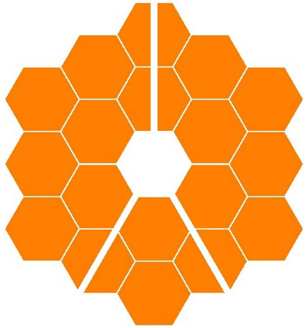
More recently

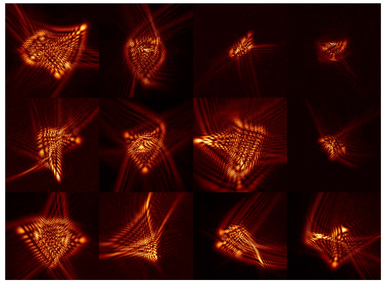
- MOAO : use MLP with WFS signal as input (e.g. Osborn et al. 2011on CANARY)
- CNN for WF reconstruction from slopese and prediction (Swanson et al. 2018)

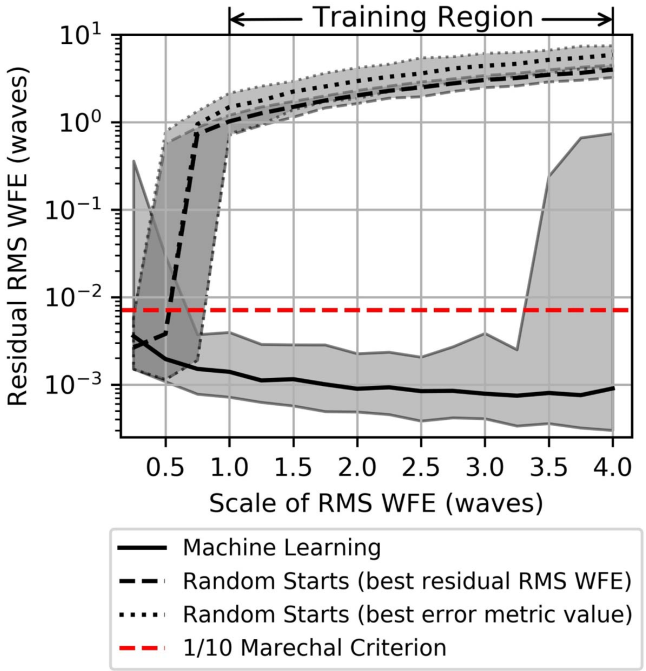
# NEURAL NETWORK IN WAVEFRONT ESTIMATION

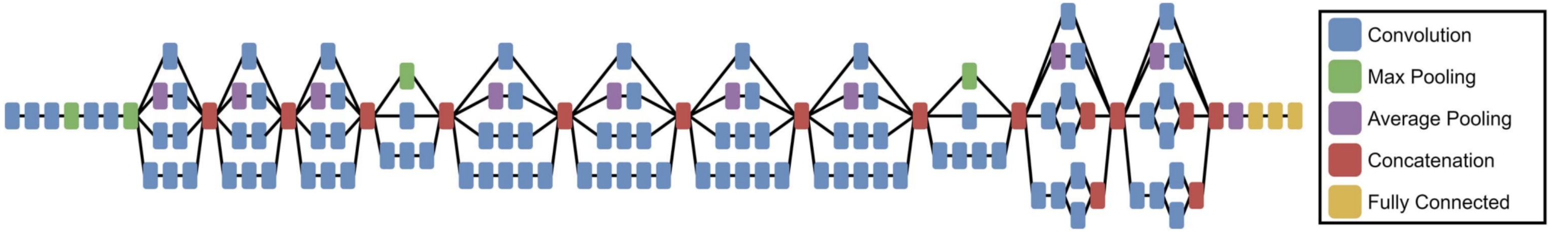
Improved image-based wavefront sensing for JWST (**Paine & Fienup 2018**)

- Aim: generate starting estimate with CNN within the capture range







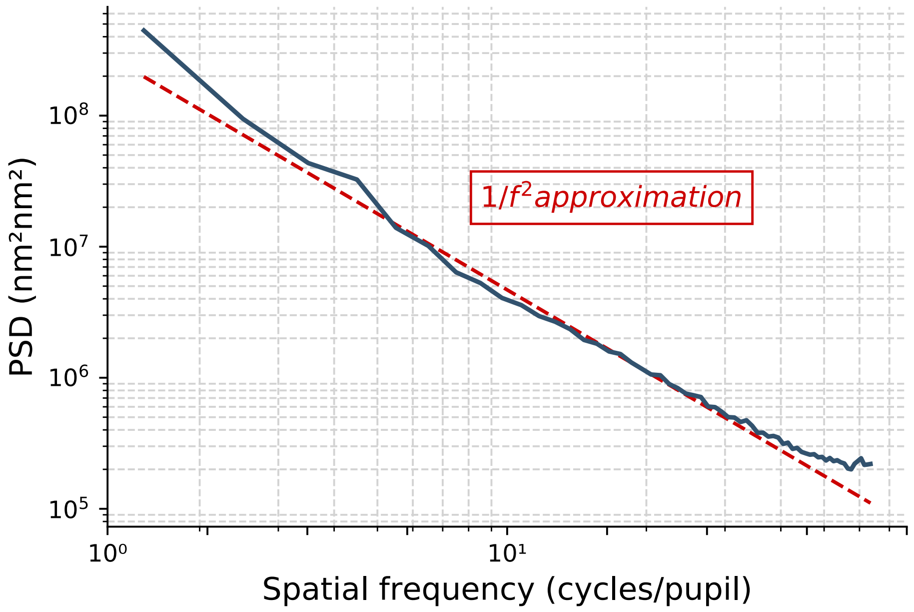



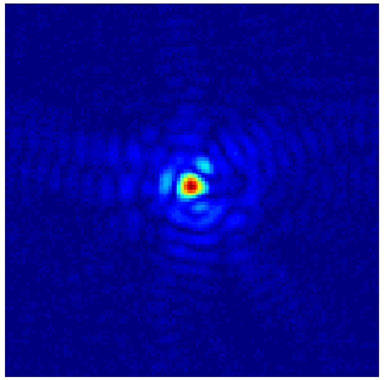

Inception v3

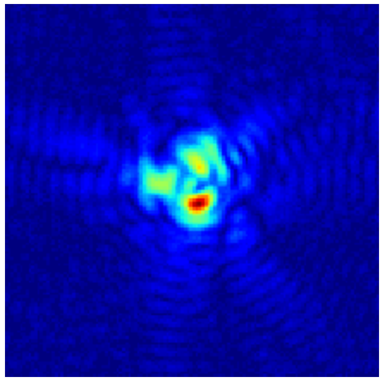
# METHOD

Two datasets are created:

- Distributed on 20 or 100 Zernike modes
- Spatial PSD ∝ 1/f^2 (typical of good optics)
- Average of 350nm RMS WFE (~1rad)
- Dataset of 100,000 images
- λ=2.2µm, sampling similar to NIRC2-Keck
- Defocus (for out-of-focus image) = λ/4
- Circular aperture; 128x128 px images
- Photon noise (SNR=100)



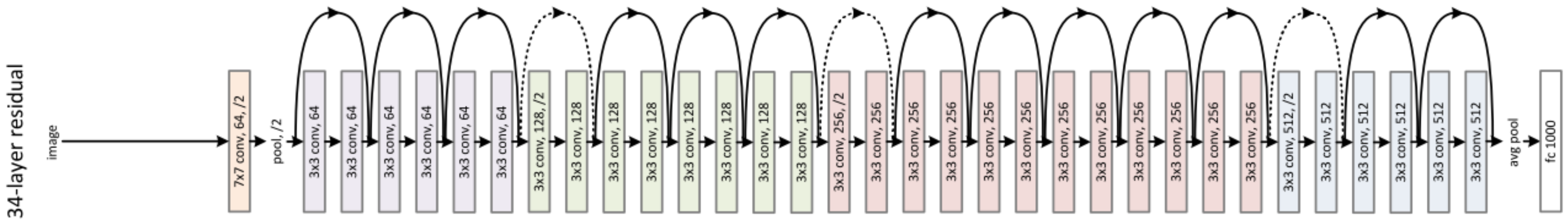


# CNN ARCHITECTURES

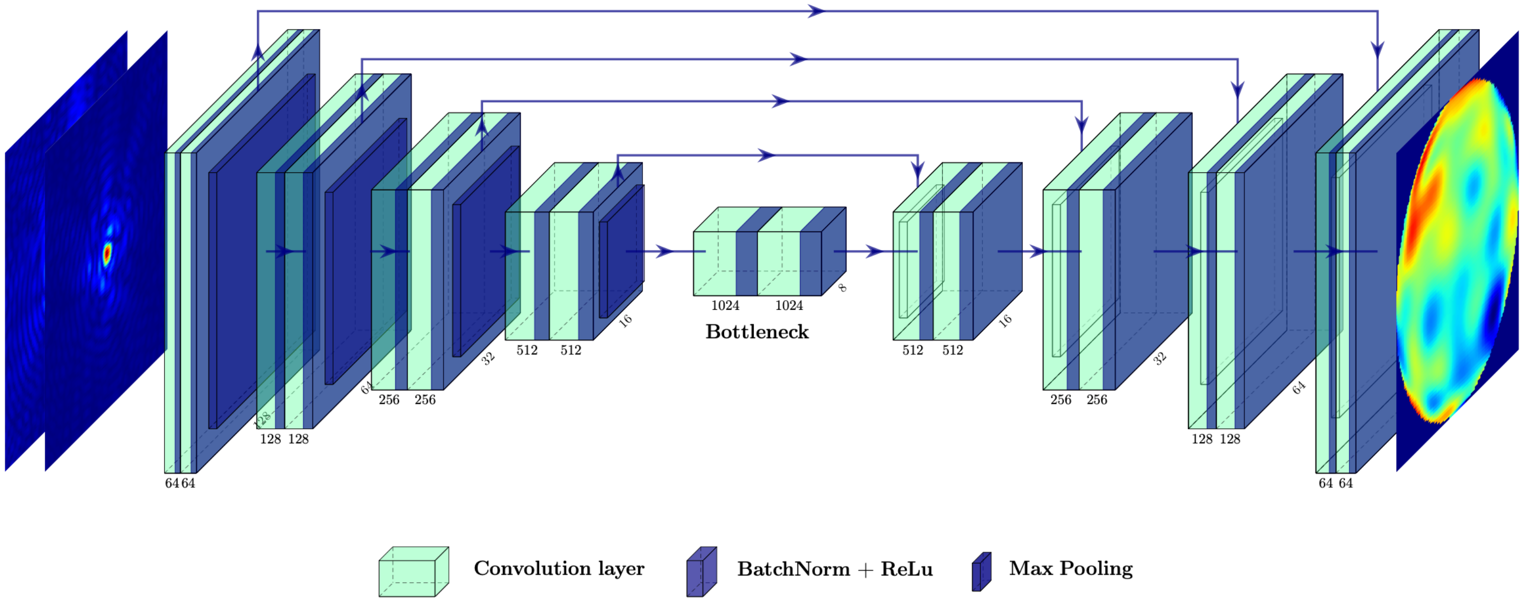
We compare several architectures

| | |
|---|---|
| VGG-16 | Zernike coefficients |
| Inception v3 | Zernike coefficients |
| ResNet - 50 | Zernike coefficients |
| U-Net / U-Net++ | Direct phase map |

ResNet-34:

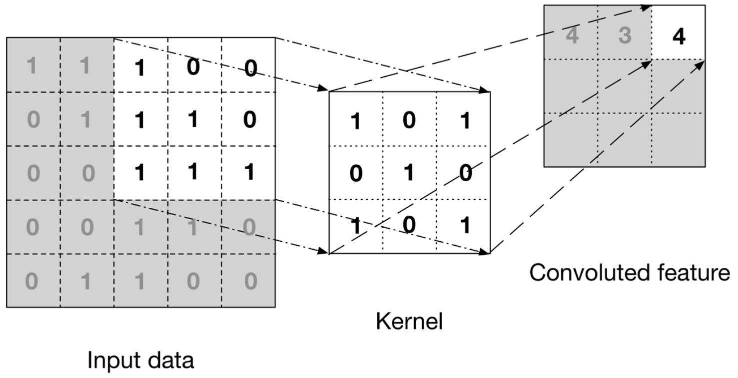


# CNN ARCHITECTURES

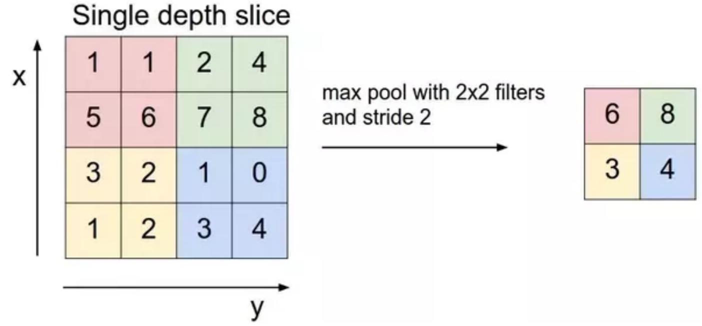



10 - 30 Millions of parameters

Convolution:

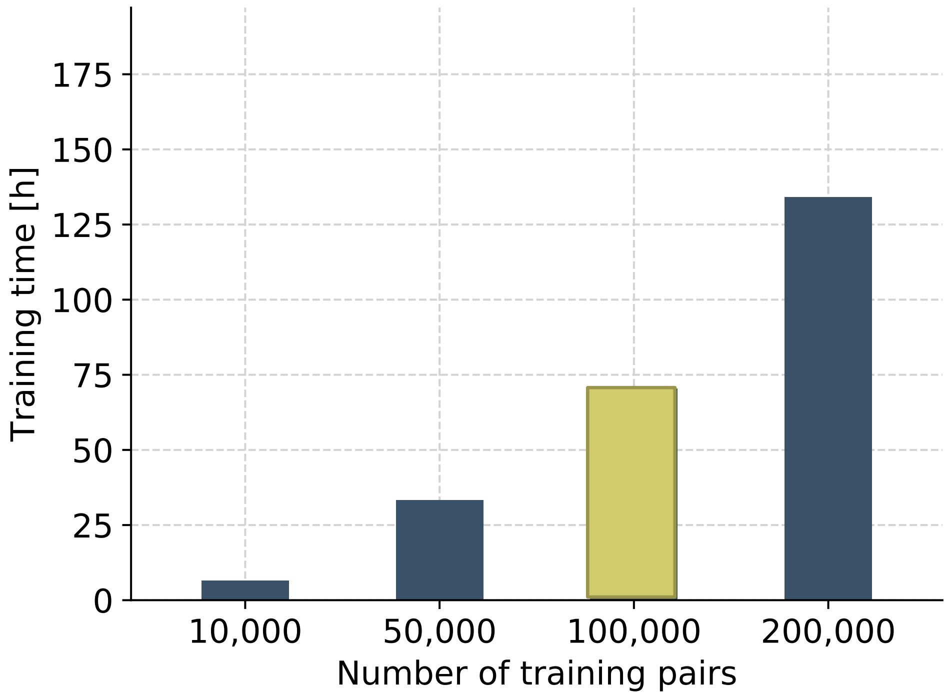



Max pooling:

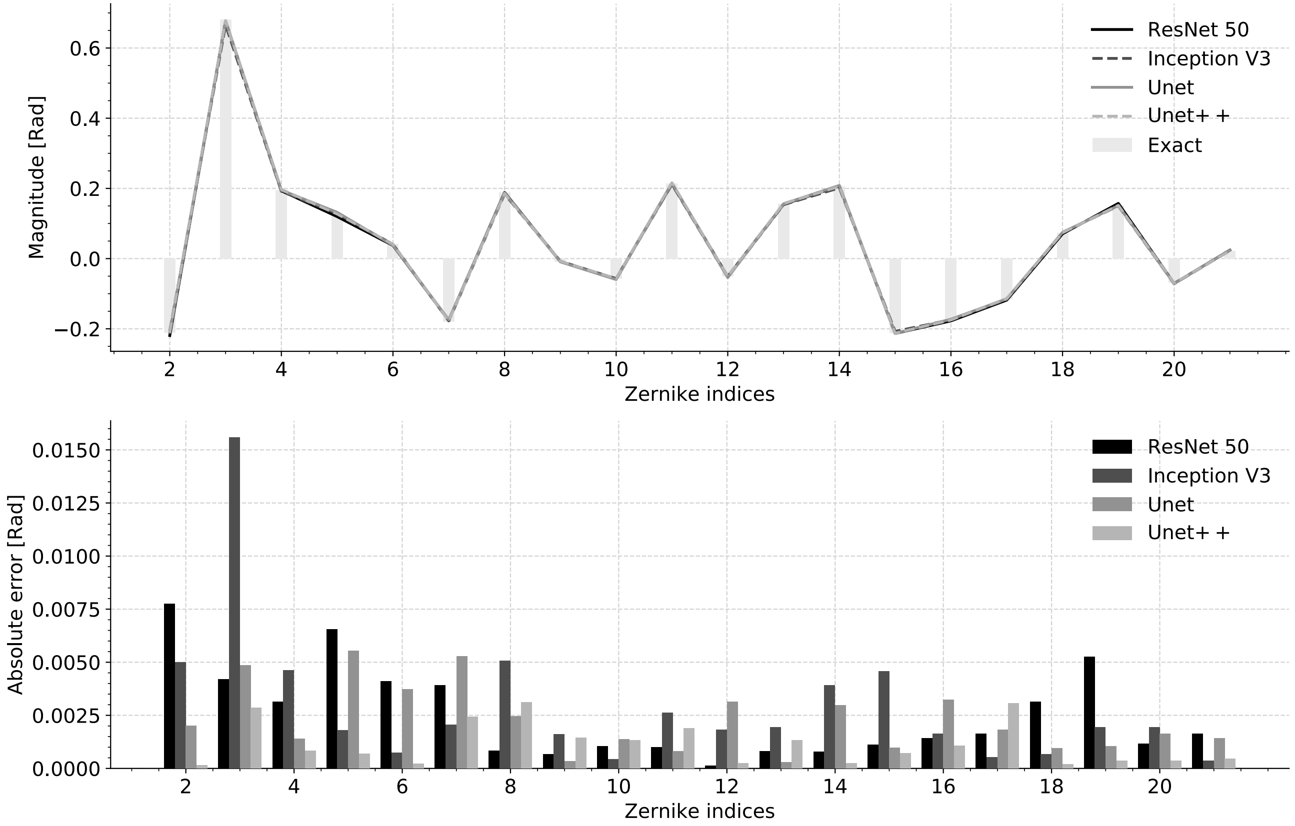


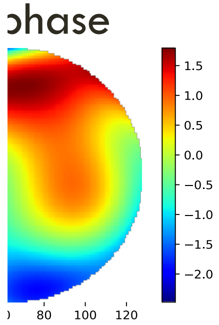
# TRAINING AND FIRST RESULTS

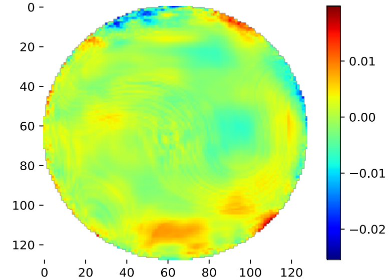
First you wait…



# RESULTS



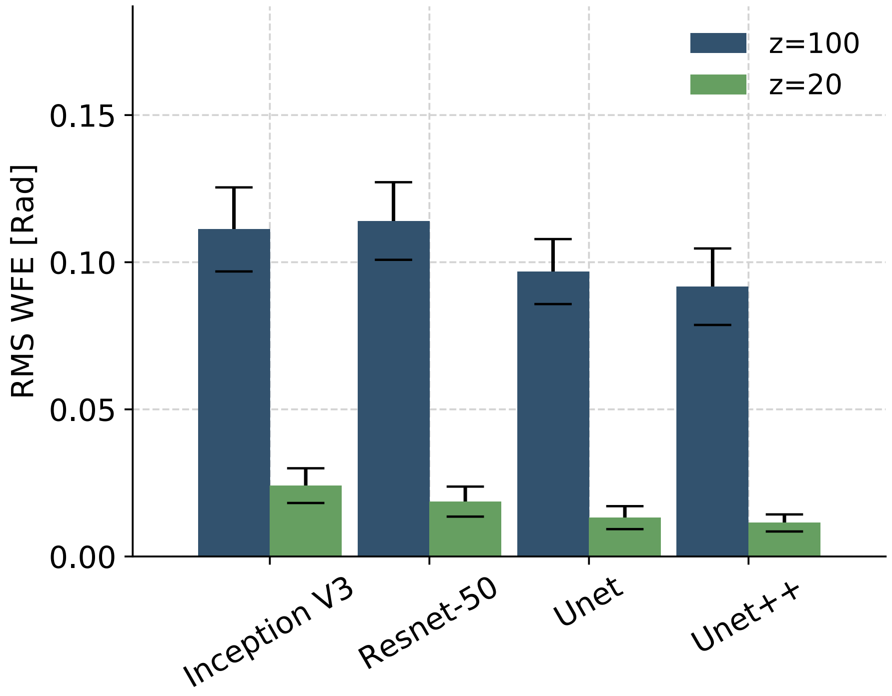



U-Net
Residual phase

# RESULTS

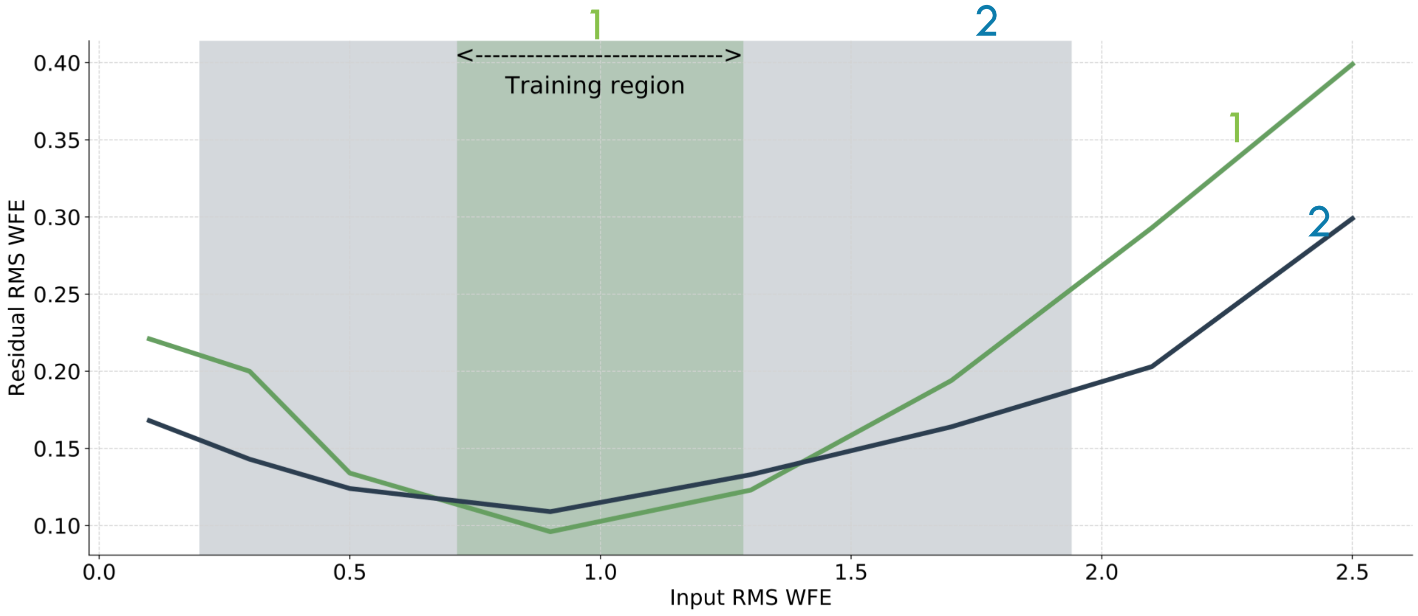
Input WFE ~1rad



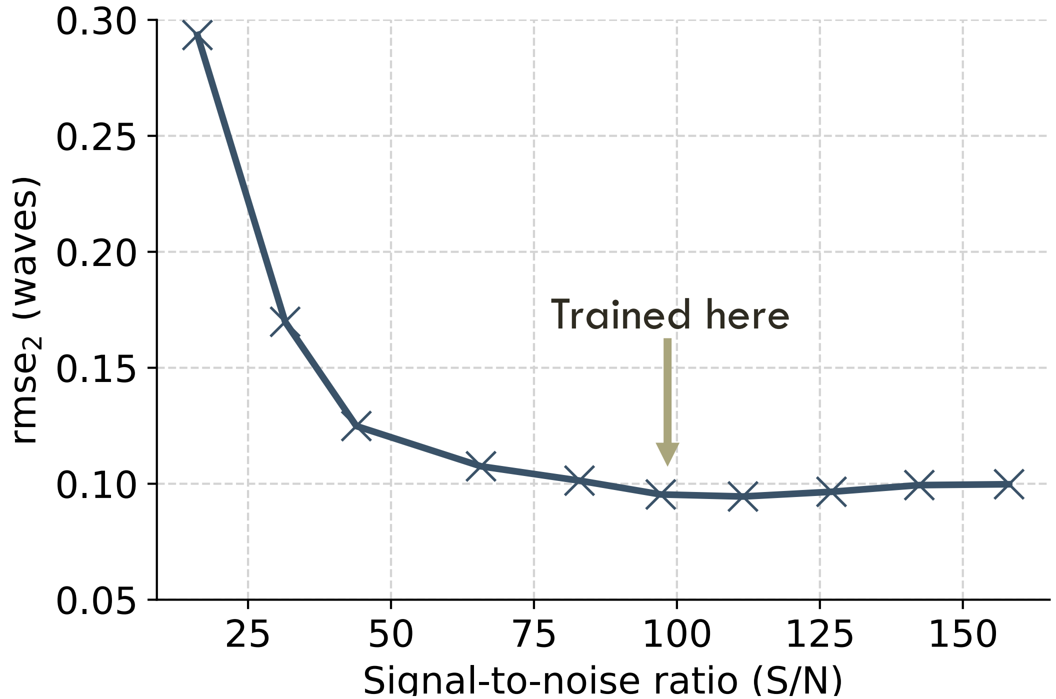

| Architectures | Inference time |
|---|---|
| Inception v3 | 0.1182s |
| ResNet 50 | 0.1090s |
| U-Net | 0.1102s |
| U-Net++ | 0.1358s |

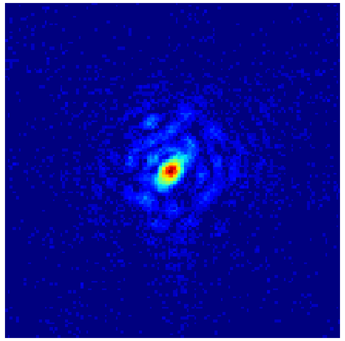
# ROBUSTNESS

- CNN works best within training range
- Narrow training region gives better estimates

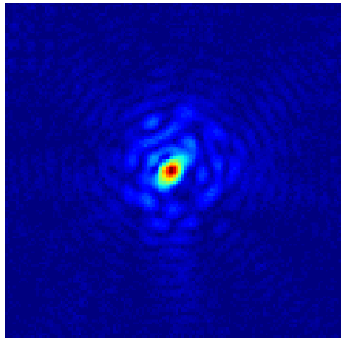


# ROBUSTNESS : NOISE



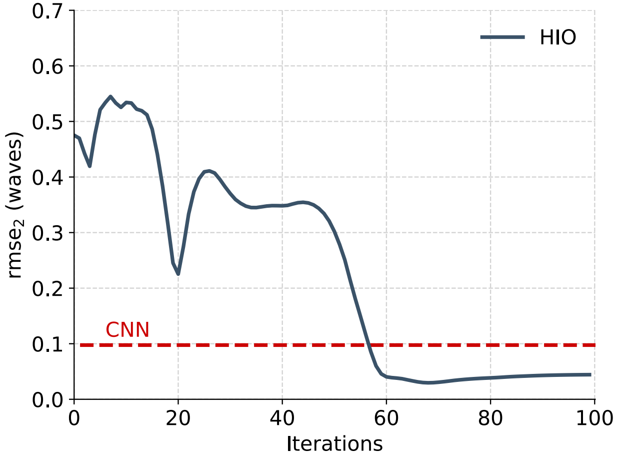



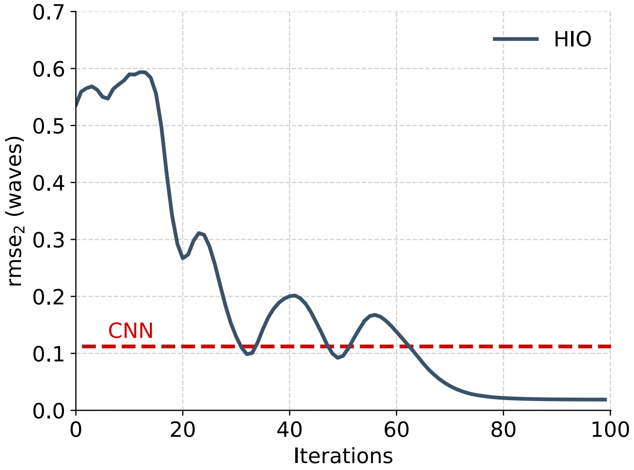
SNR=25

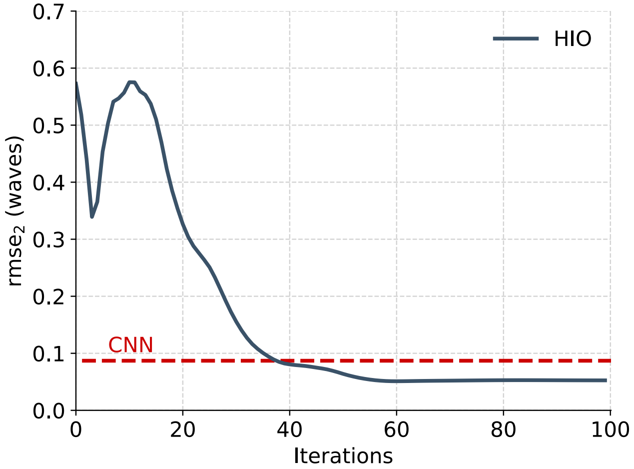


SNR=100

# COMPARISON TO HYBRID INPUT-OUTPUT



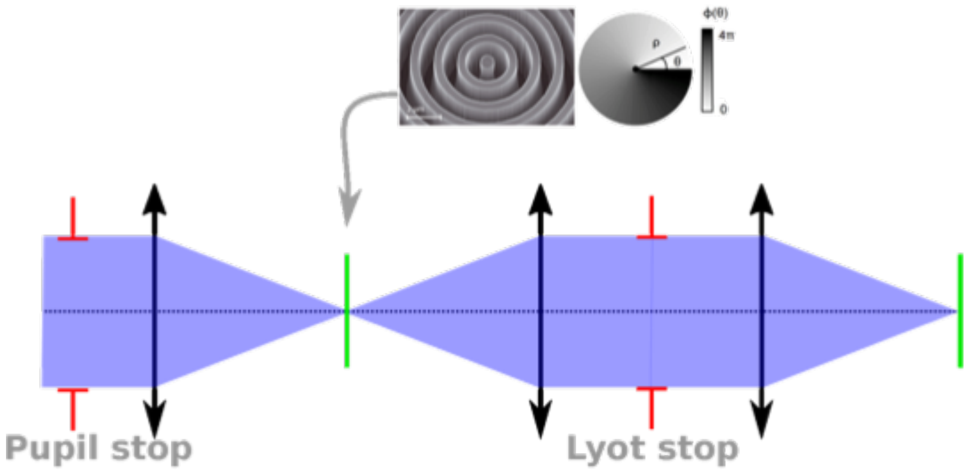



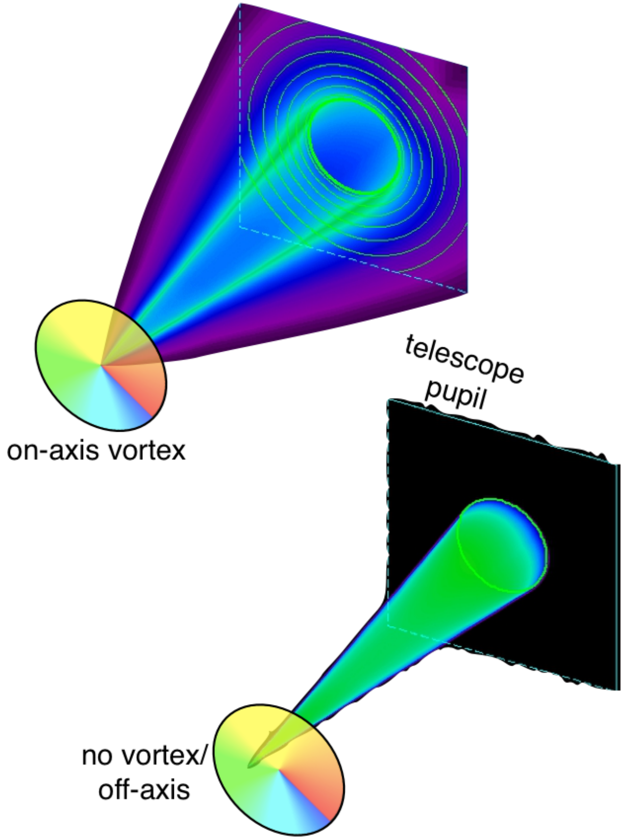




| | 20 Zernike | 100 Zernike | Inference time |
|---|---|---|---|
| U-Net | 0.0132+-0.0019 | 0.0976+-0.0133 | 0.1102s |
| HIO | 0.0036+-0.0047 | 0.0231+-0.0276 | 13.654s |

Success rate of the HIO algorithm is 78% wrt to 0.2rad

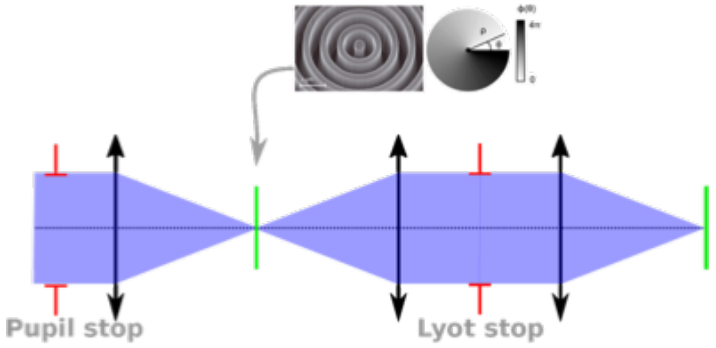
# CNN FOR POST-CORONO IMAGES

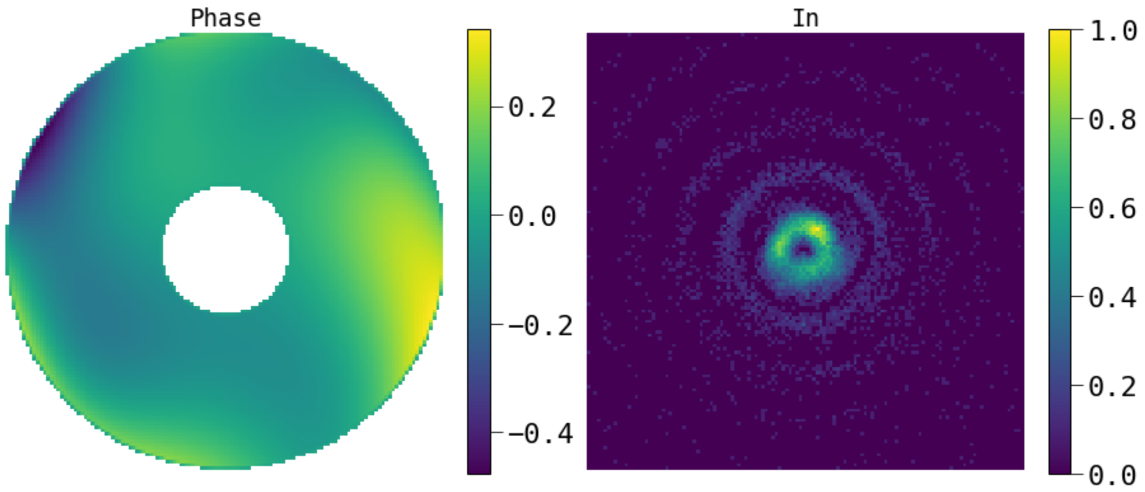


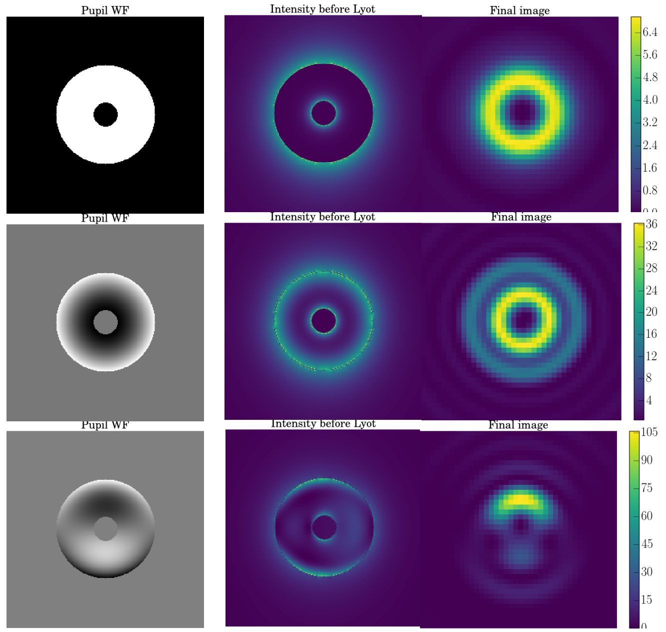




- Vortex charge-2 removes Airy pattern for circular aperture

# CNN FOR POST-CORONO IMAGES




- *Does our CNN works with post-vortex image(s)?*
- *How does it performs compared to PSF-images?*

*Analysis with*

- Low aberrations regime: λ/44, or 50nm @ 2.2µm
- *Annular aperture*
- *Single in-focus images*

# ONLY IN-FOCUS IMAGES : RESIDUAL VS NOISE

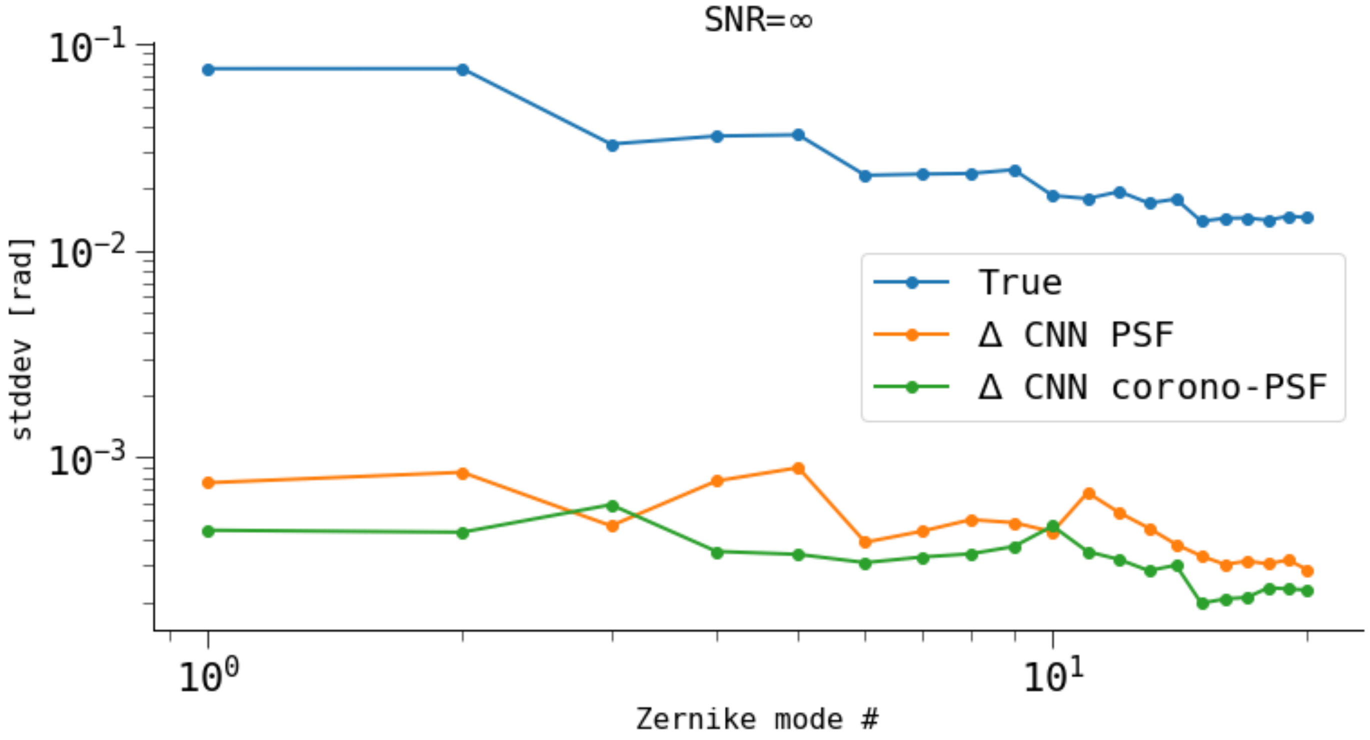
Training sample:

100,000

RMS:

PSF: 1nm +- 0.3

Cor: 0.6 +-0.1



# ONLY IN-FOCUS IMAGES : RESIDUAL VS NOISE

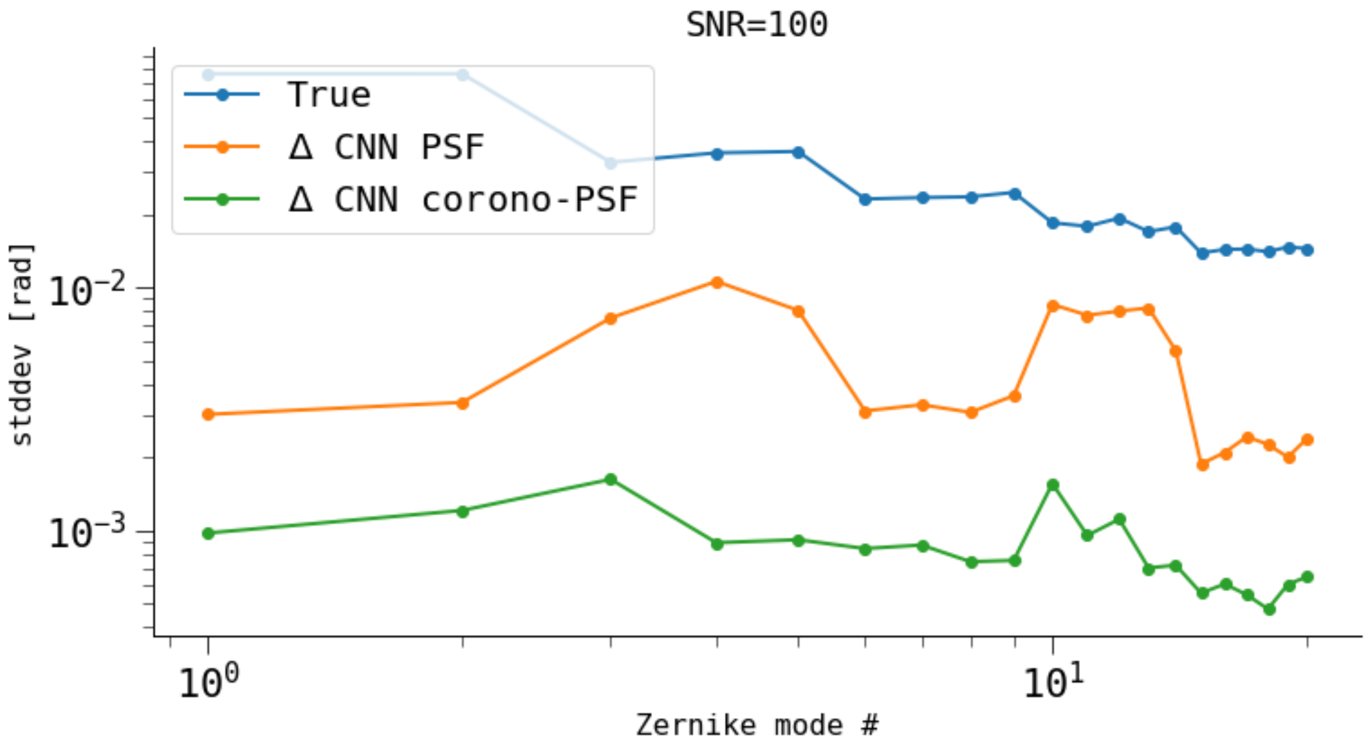
Training sample:

20,000

RMS:

PSF: 6.4nm +- 4.4

Cor: 1.4 +-0.4



# ONLY IN-FOCUS IMAGES : RESIDUAL VS NOISE

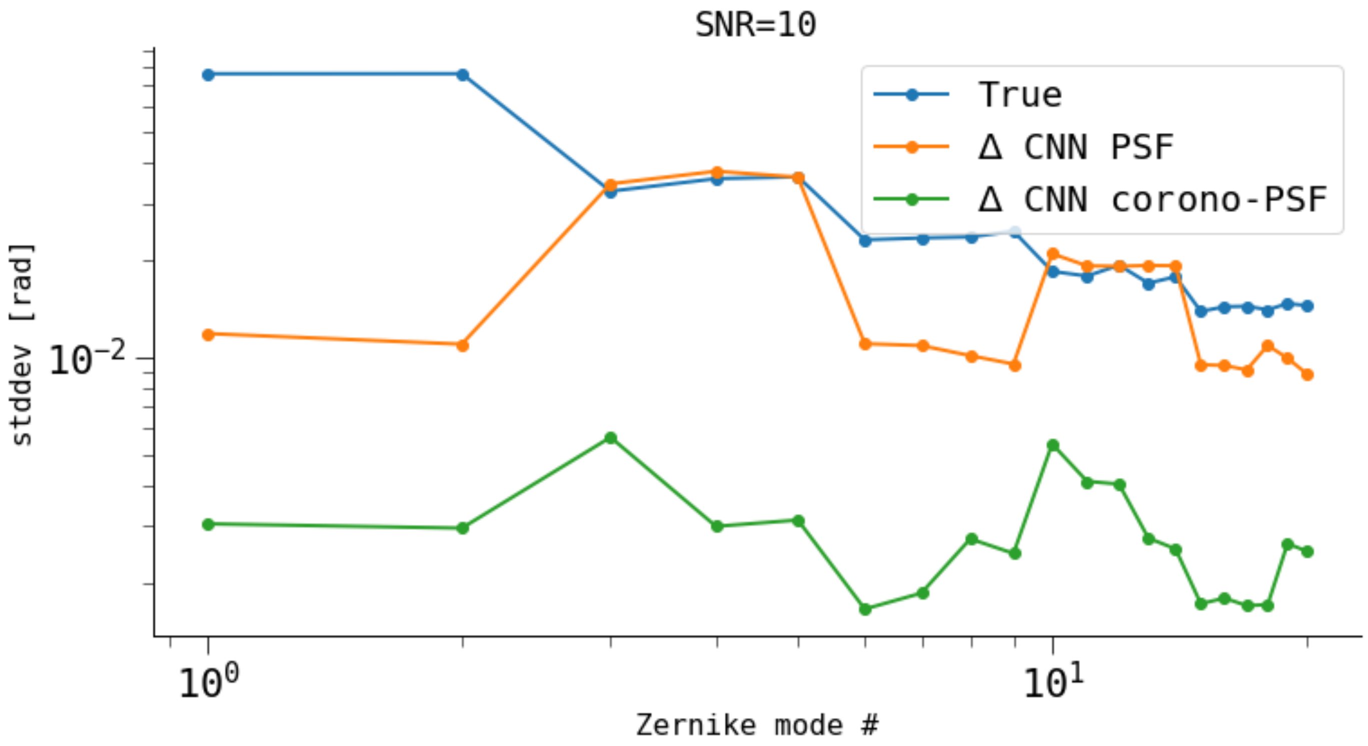
Training sample:

20,000

RMS:

PSF: 29nm +- 5

Cor: 4.5 +-1



# A FASHIONABLE TREND

- Torben et al., *Neural networks for image-based wavefront sensing for astronomy*

  "We trained the well-known "Inception" network using the artificial data sets and found that although the accuracy does not permit diffraction-limited correction, the potential improvement in the residual phase error is promising for a telescope in the 2–4 m class"

Outside astronomy and very recently

- Nishizaki et al. 2019, *Deep learning wavefront sensing*
- Guo et al. 2019, *Improved Machine Learning Approach for Wavefront Sensing*
- Möckl et al. 2019, *Accurate phase retrieval of complex point spread functions with deep residual neural networks*
- Ișil et al. 2019, *Deep Iterative Reconstruction for Phase Retrieval*
- Hu et al. 2019, *Self-learning control for wavefront sensorless adaptive optics system through deep reinforcement learning*

… *and more* …

# CONCLUSIONS

CNN is another tool for focal plane wavefront sensing which may be worth considering

Perspectives:

- Combination of CNN with other techniques
- Post-coronographic PSF; twin-image problem and stagnation behavior

Future

- Robustness (noise regimes, residual atmospheric turbulence, phase diversity, etc.)
- Lab experiment
- Beyond CNN

See also Vanberg et al., *in prep.*