A Simulator-based Autoencoder approach for Focal-Plane Wavefront Sensing using Vortex Phase Diversity

Maxime Quesnel[a,b]

Gilles Orban de Xivry[b], Olivier Absil[b], Gilles Louppe[a]

[a]Montefiore Institute of Electrical Engineering and Computer Science

[b]Space sciences, Technologies and Astrophysics Research (STAR) Institute

University of Liège

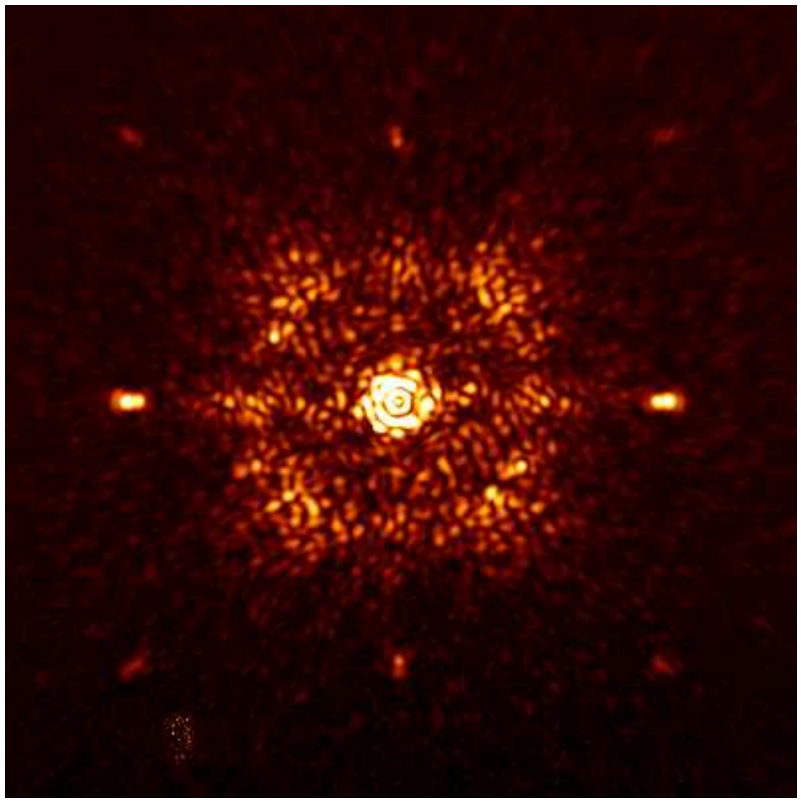
Wavefront Sensing in the VLT/ELT era VII workshop

20 October 2022

maxime.quesnel@uliege.be

Exoplanet imaging: Limitation

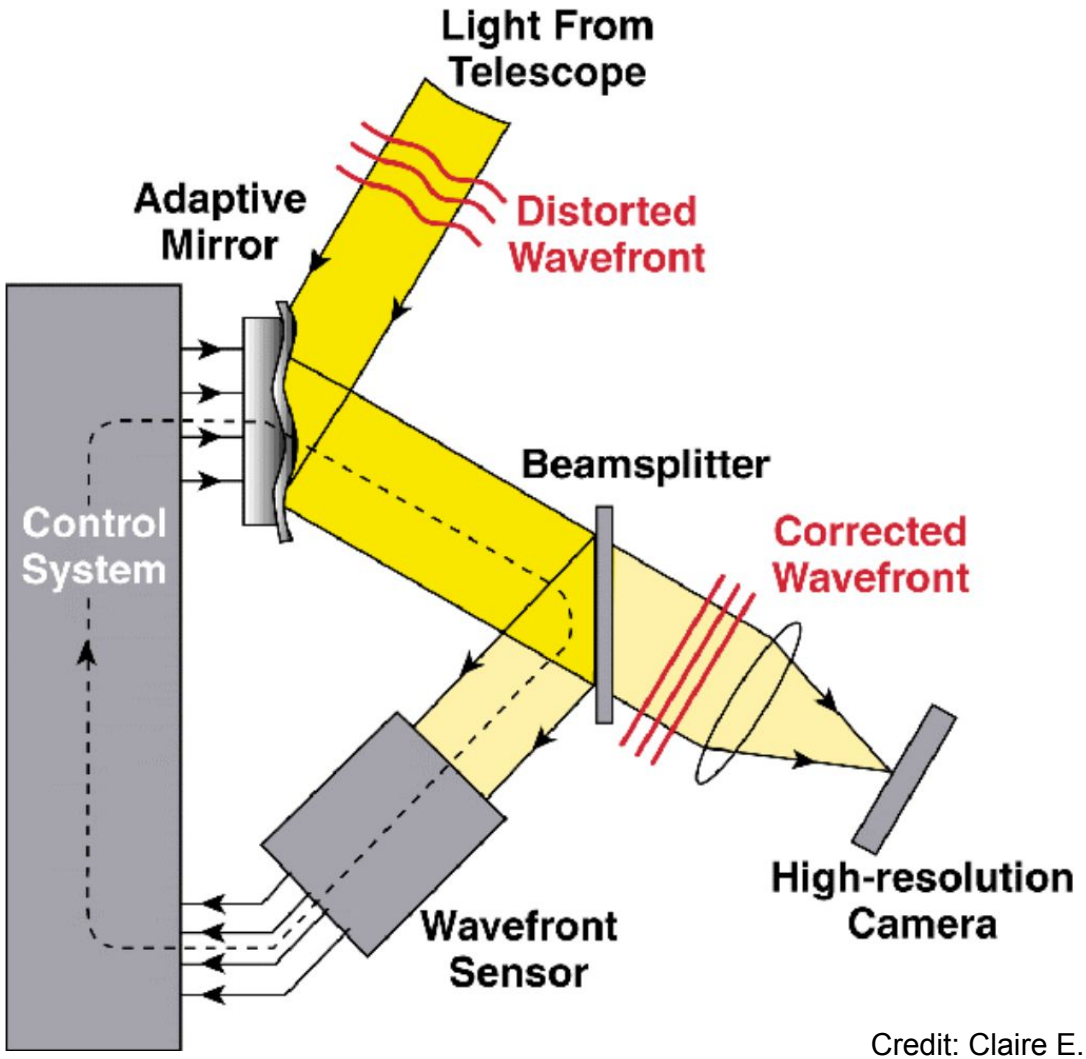
The problem: **SPECKLES**



Martinez et al. 2013

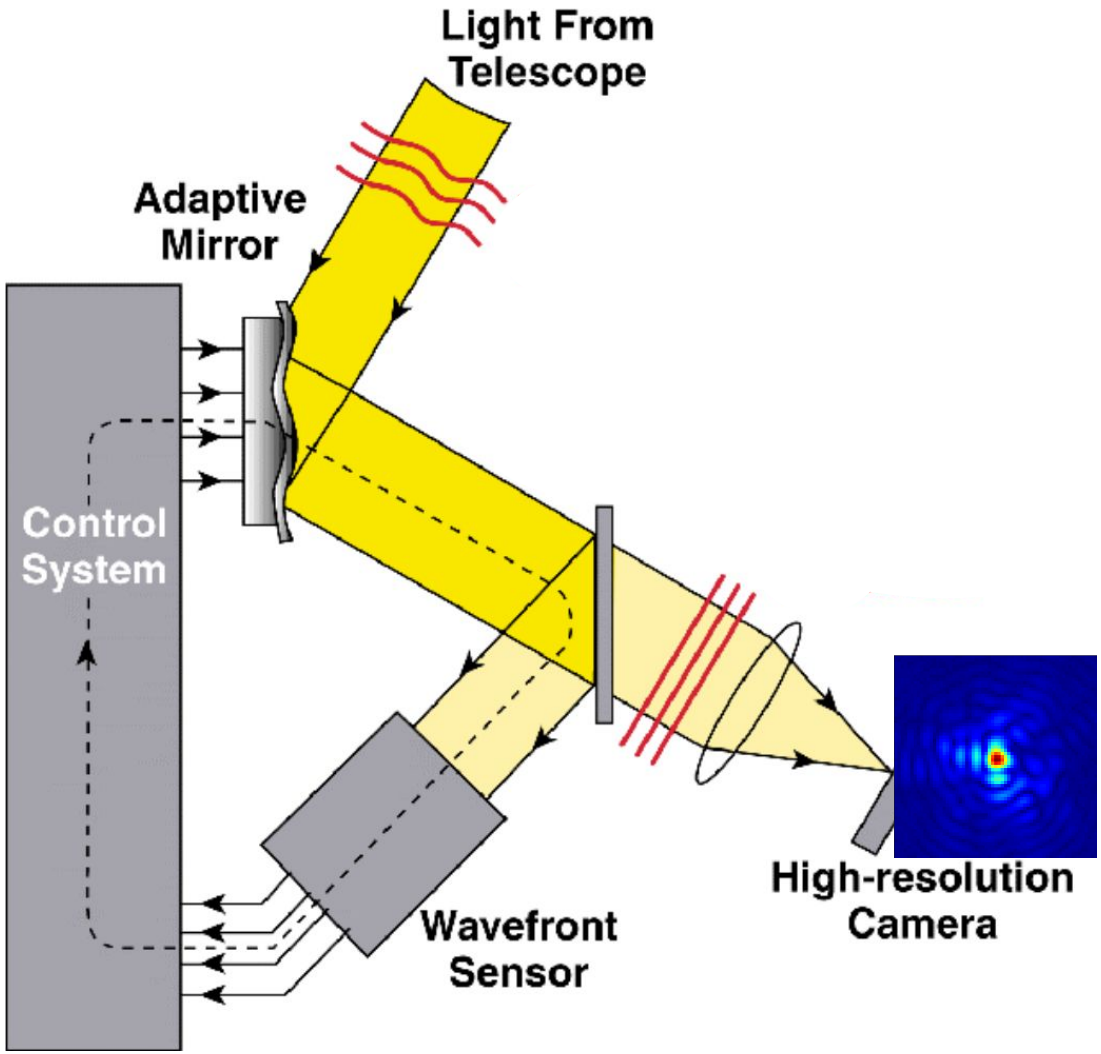
Especially the **quasi-static** ones

Non-common path aberrations



Credit: Claire E. Max, UCSC

Focal-plane wavefront sensing



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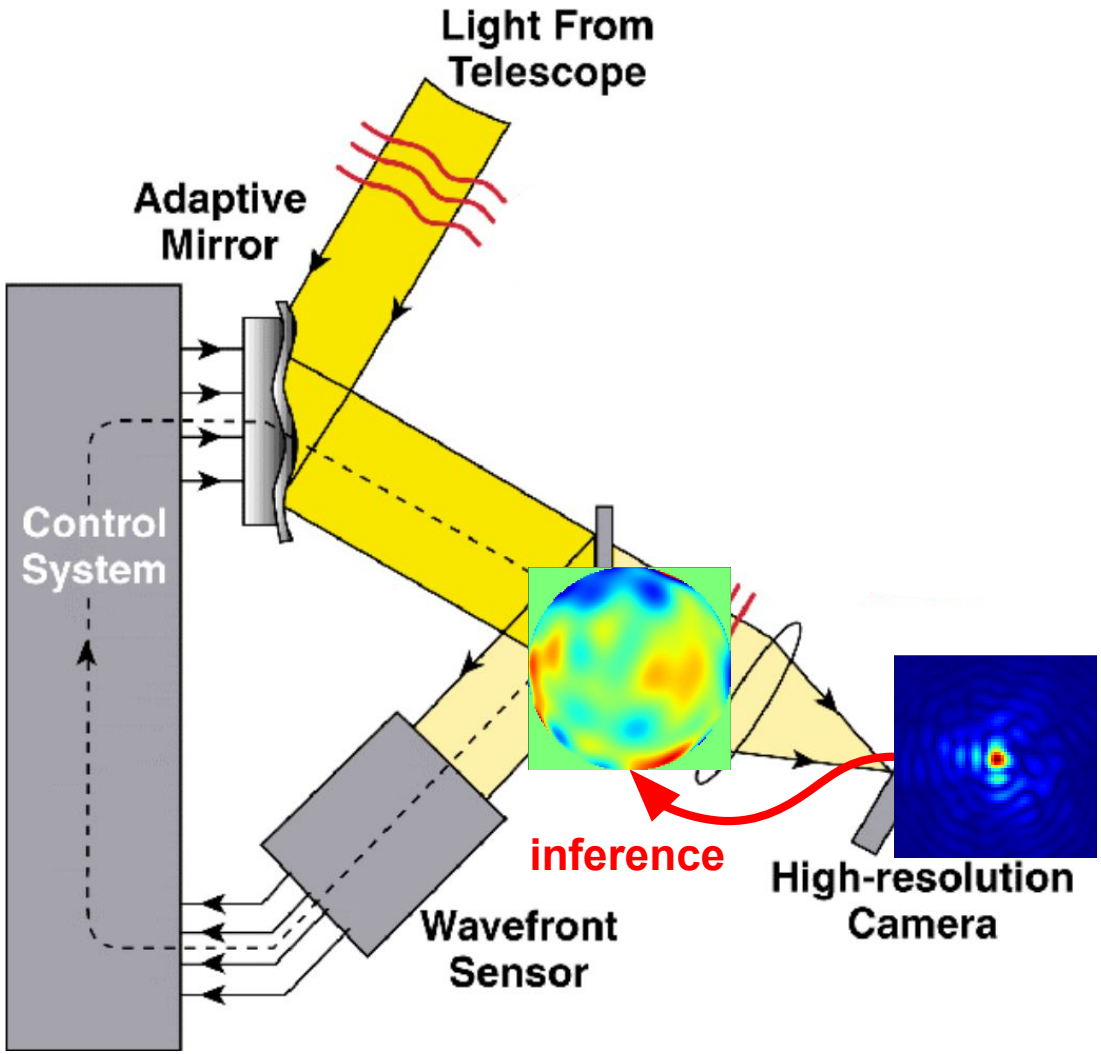

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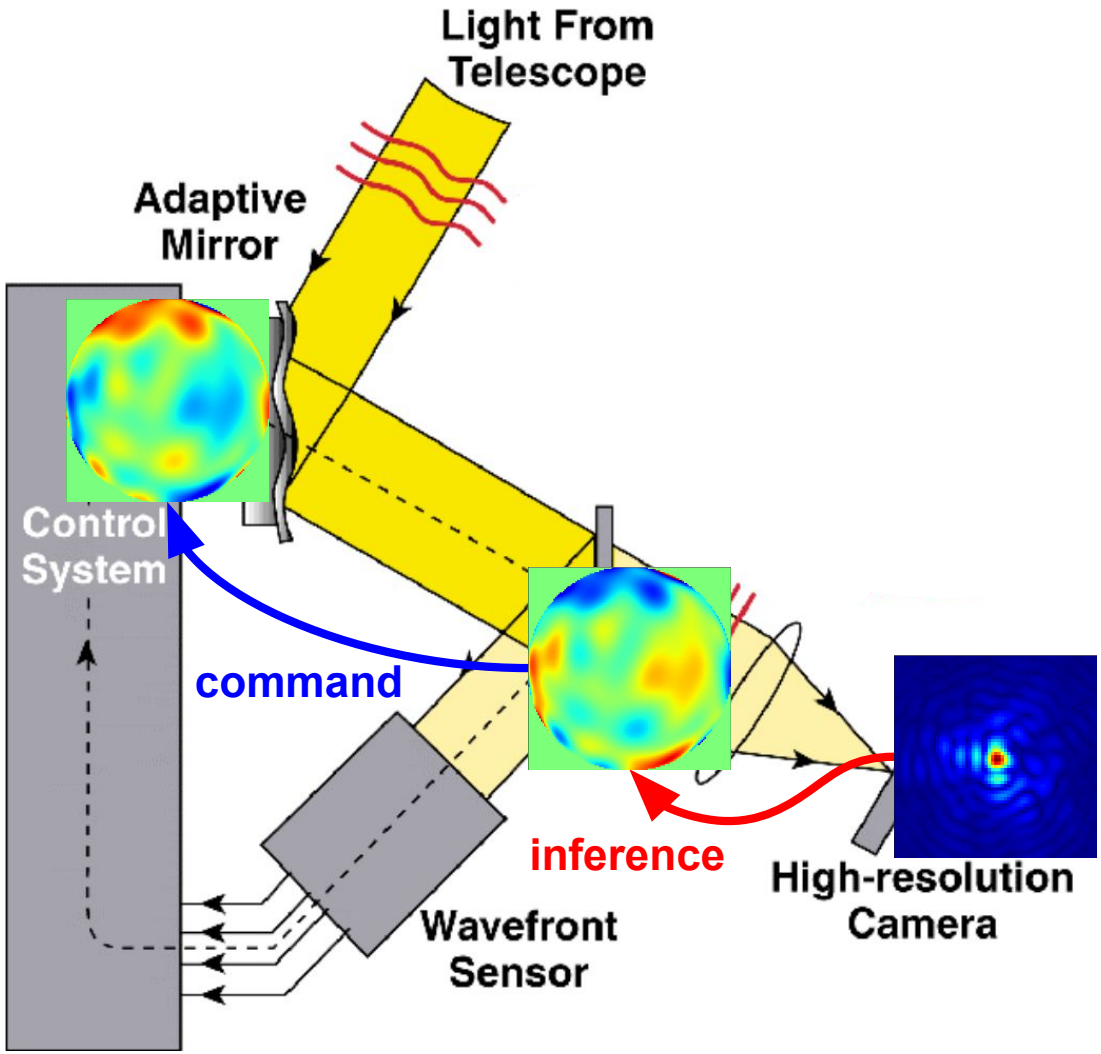

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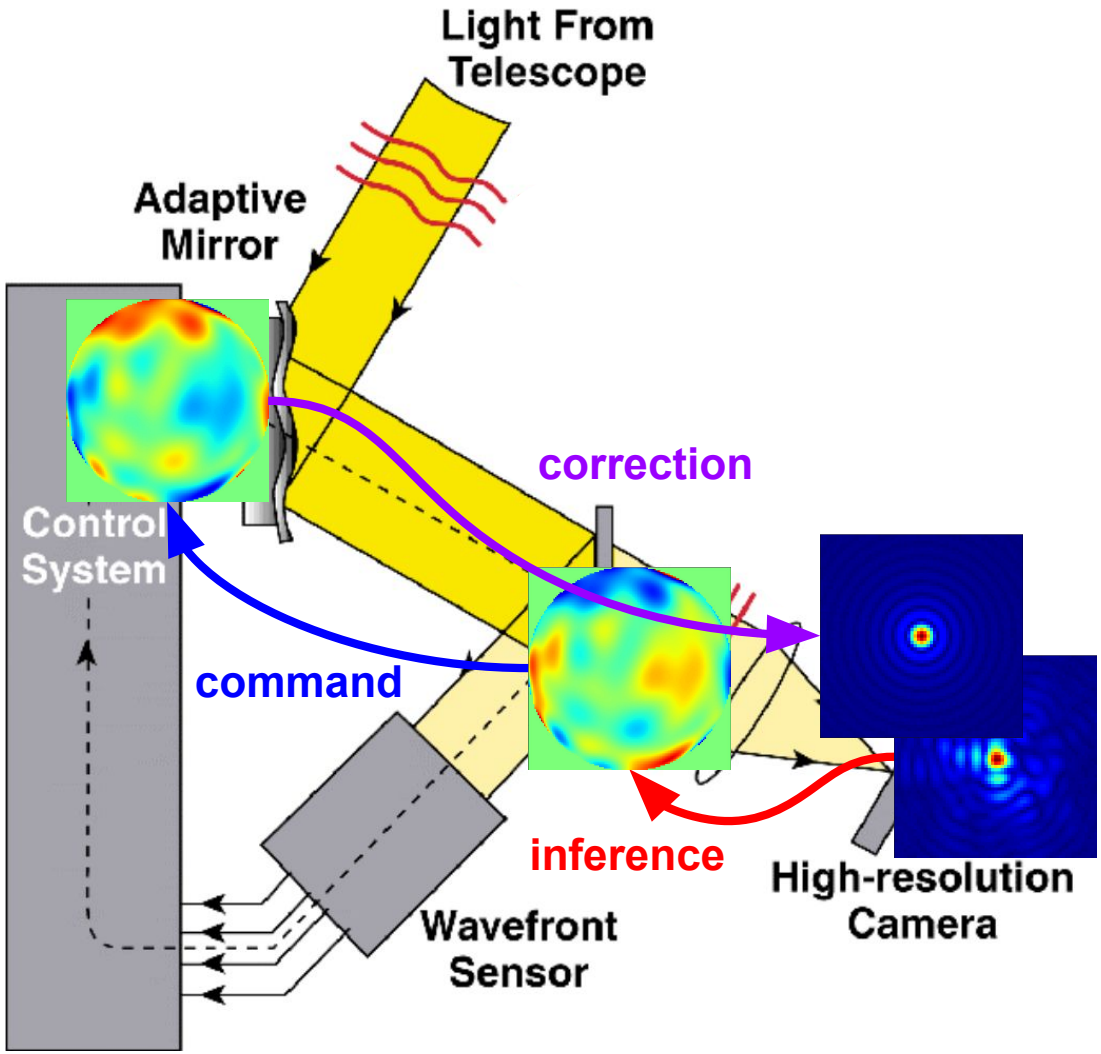
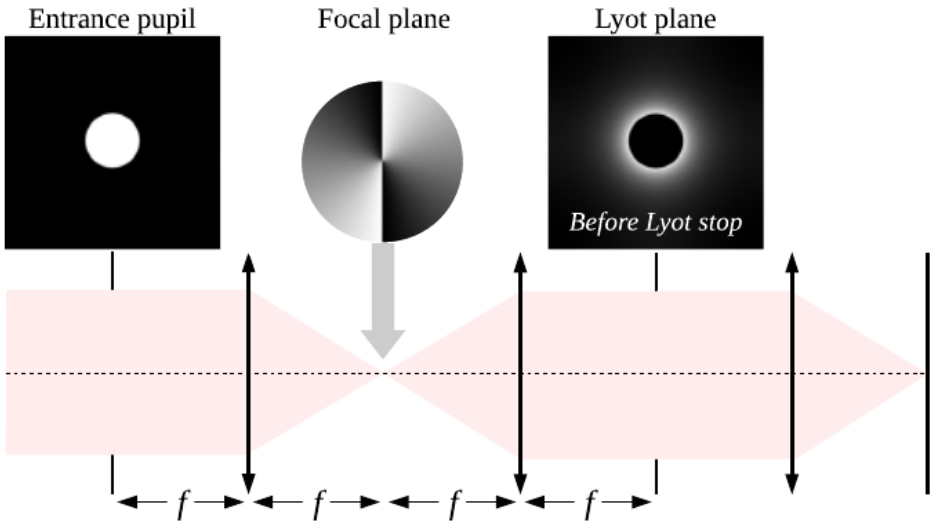
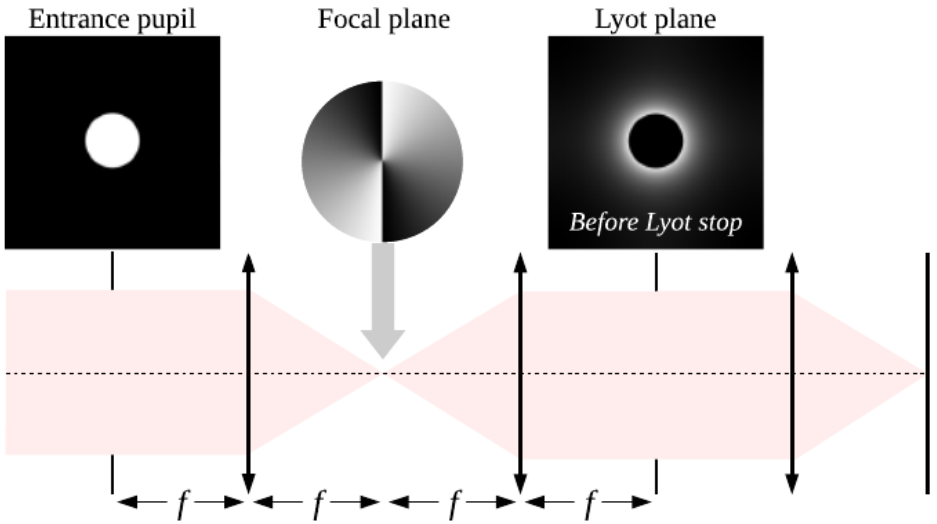


Vortex coronagraphs



Huby et al. 2015

Vortex coronagraphs



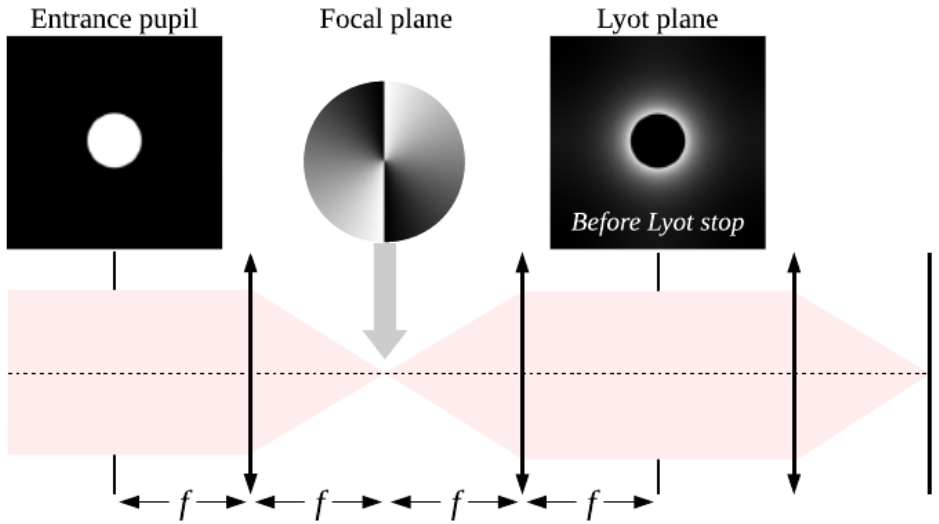
Huby et al. 2015

Vector Vortex coronagraph (VVC):

(Mawet et al. 2005)

- Conjugated phase ramps $e^{i \pm \ell_p \theta}$.
- Split circular polarization states and use two in-focus PSFs.

Vortex coronagraphs



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Vector Vortex coronagraph (VVC):

(Mawet et al. 2005)

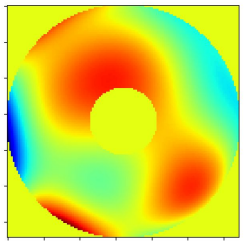
- Conjugated phase ramps $e^{i \pm \ell_p \theta}$.
- Split circular polarization states and use two in-focus PSFs.

Scalar Vortex coronagraph (SVC):

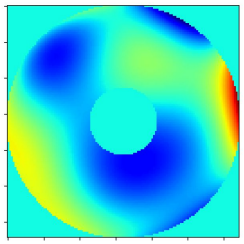
(Ruane et al. 2019)

- Same phase ramp $e^{i \ell_p \theta}$ for both circular polarization states.
- Use one in-focus PSF.

Phase sign ambiguity: Vortex phase diversity

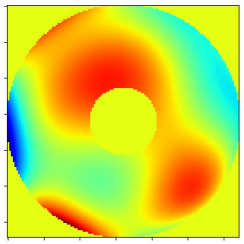


Φ



$\Phi'_{even} = -\Phi_{even}$

Phase sign ambiguity: Vortex phase diversity



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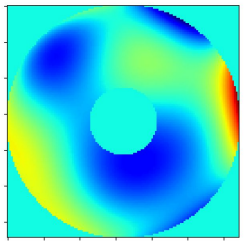

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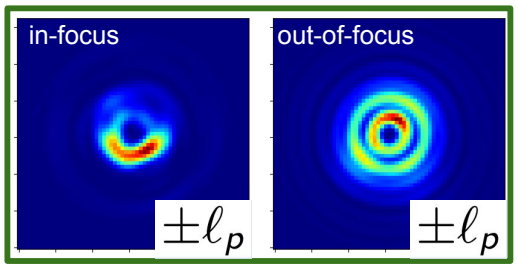
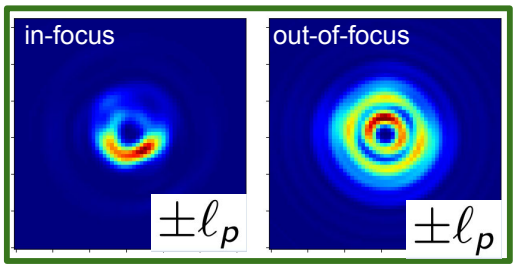
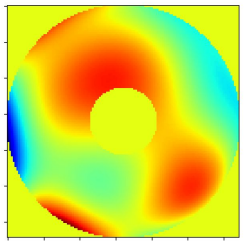




Vector VC
classical phase diversity

Phase sign ambiguity: Vortex phase diversity



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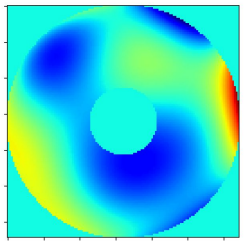

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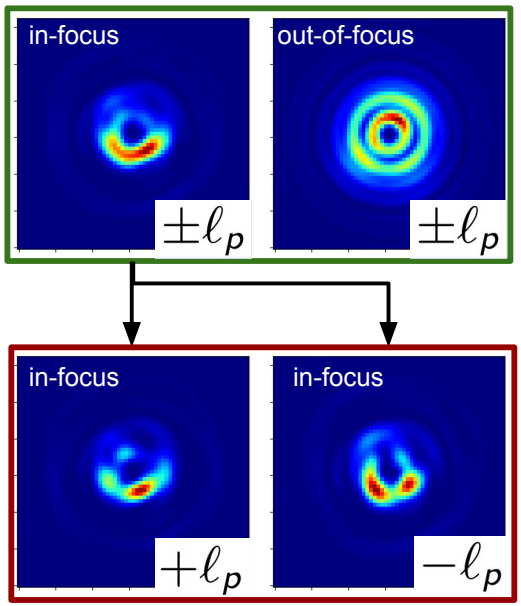
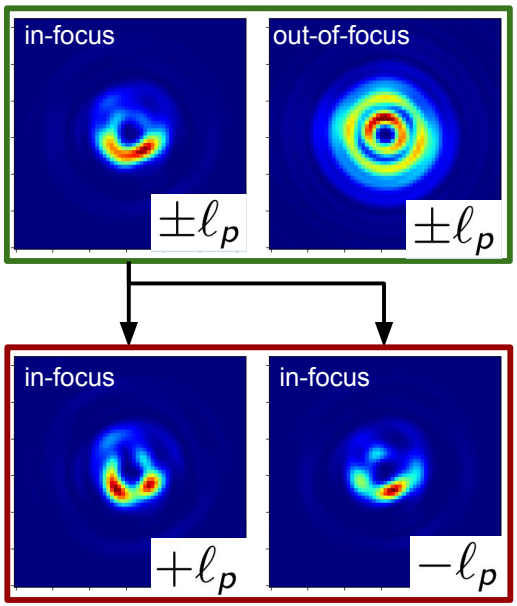
Concept introduced by
Riaud et al. 2012

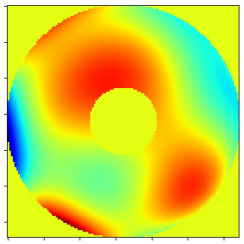




Vector VC
classical phase diversity

Vector VC
polarization separation

Phase sign ambiguity: Vortex phase diversity



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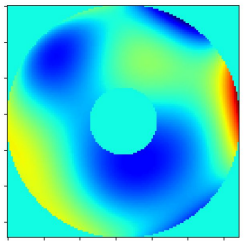

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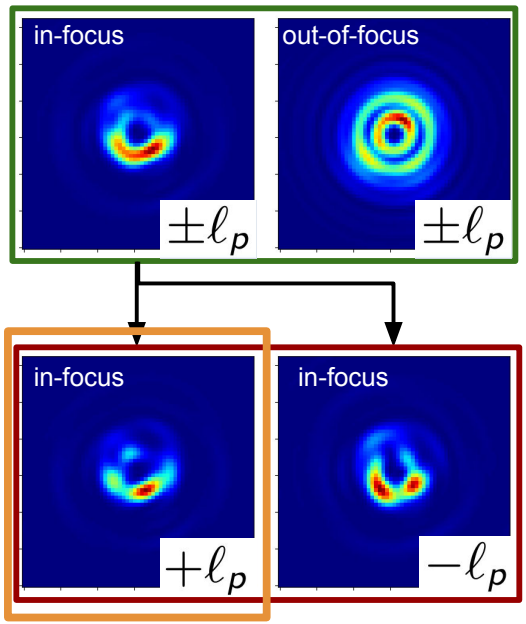
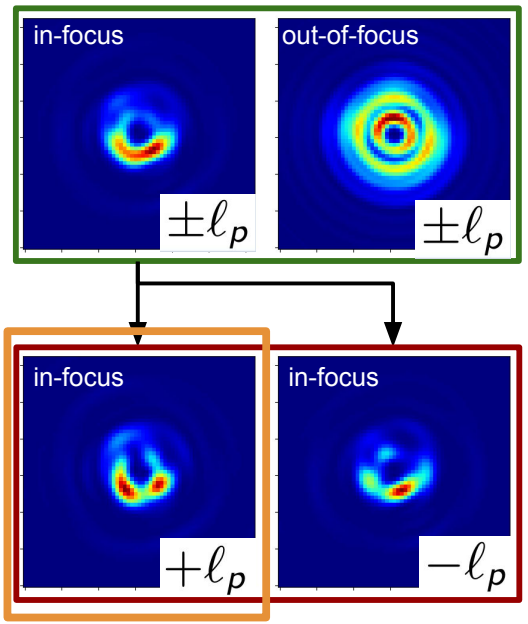




Vector VC
classical phase diversity

Vector VC
polarization separation

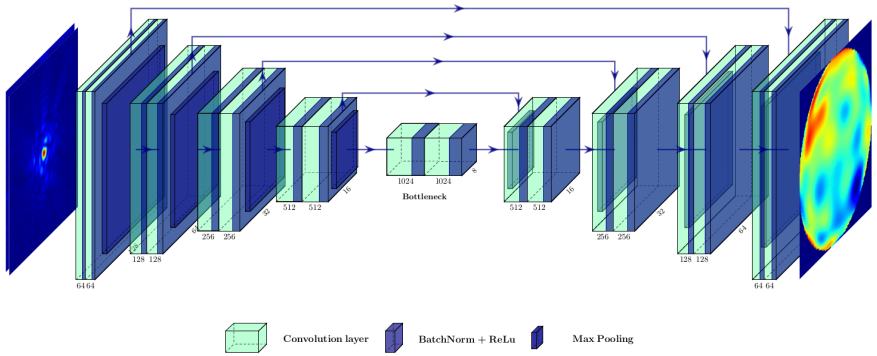
or

Scalar VC

Deep Convolutional Neural Networks

→ Motivation: fast predictions, higher performance, better robustness.

U-Net (Ronneberger et al. 2015):



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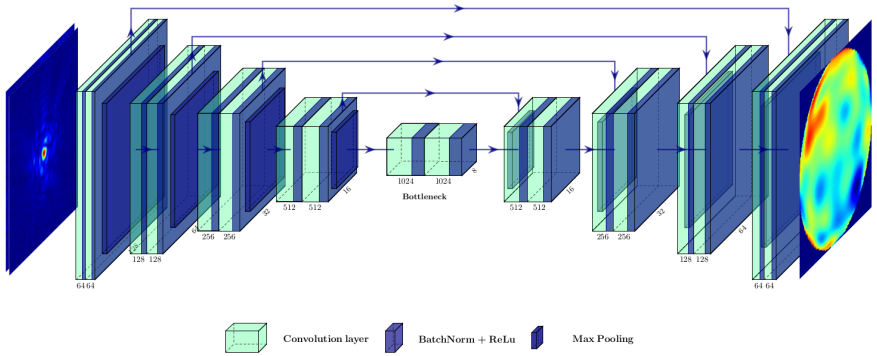
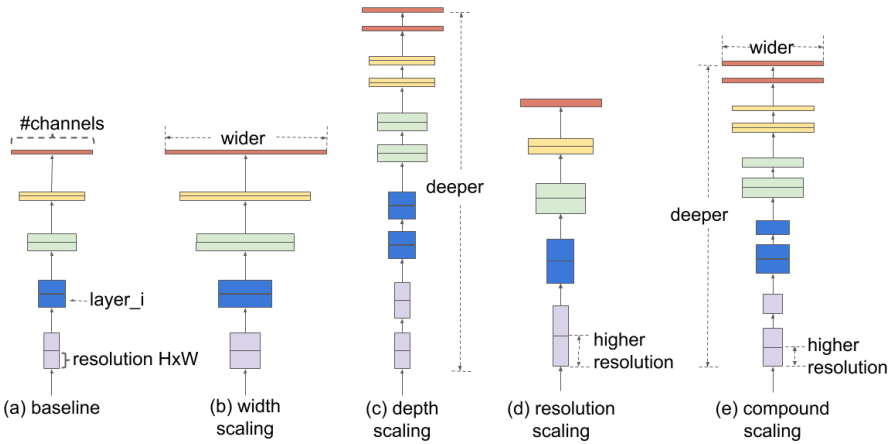
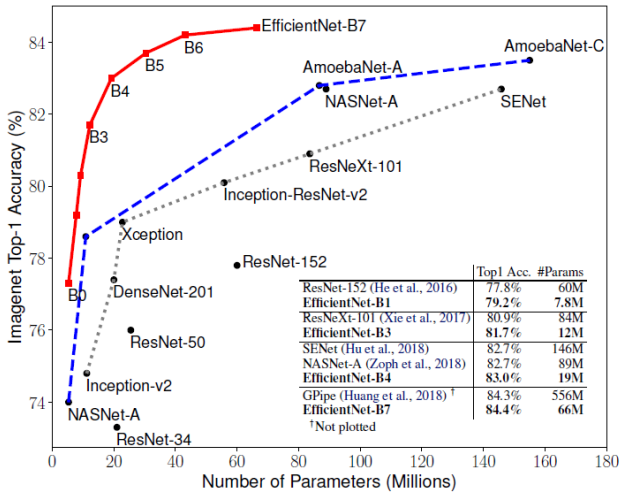
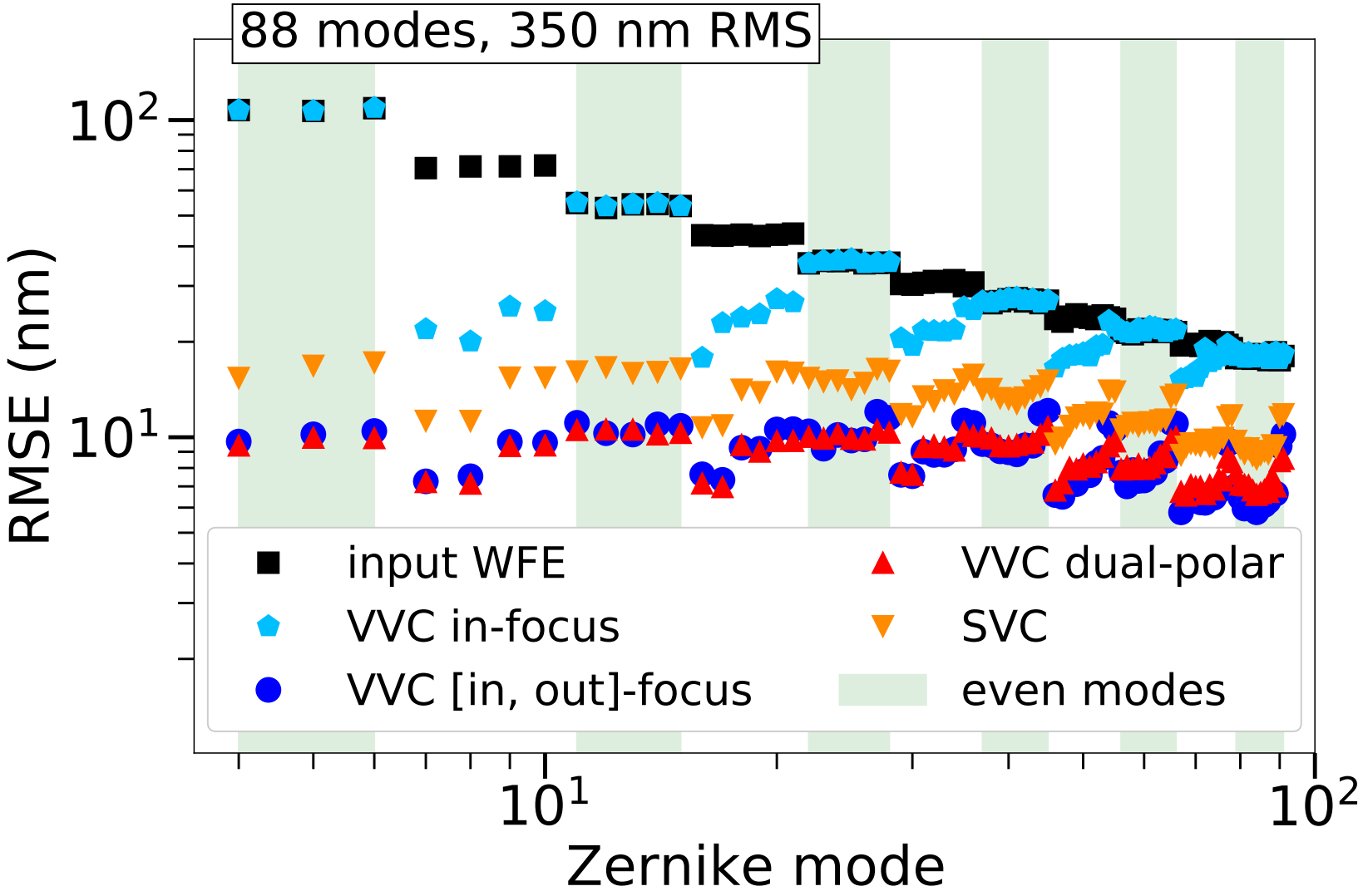


EfficientNet (Tan et al. 2019):

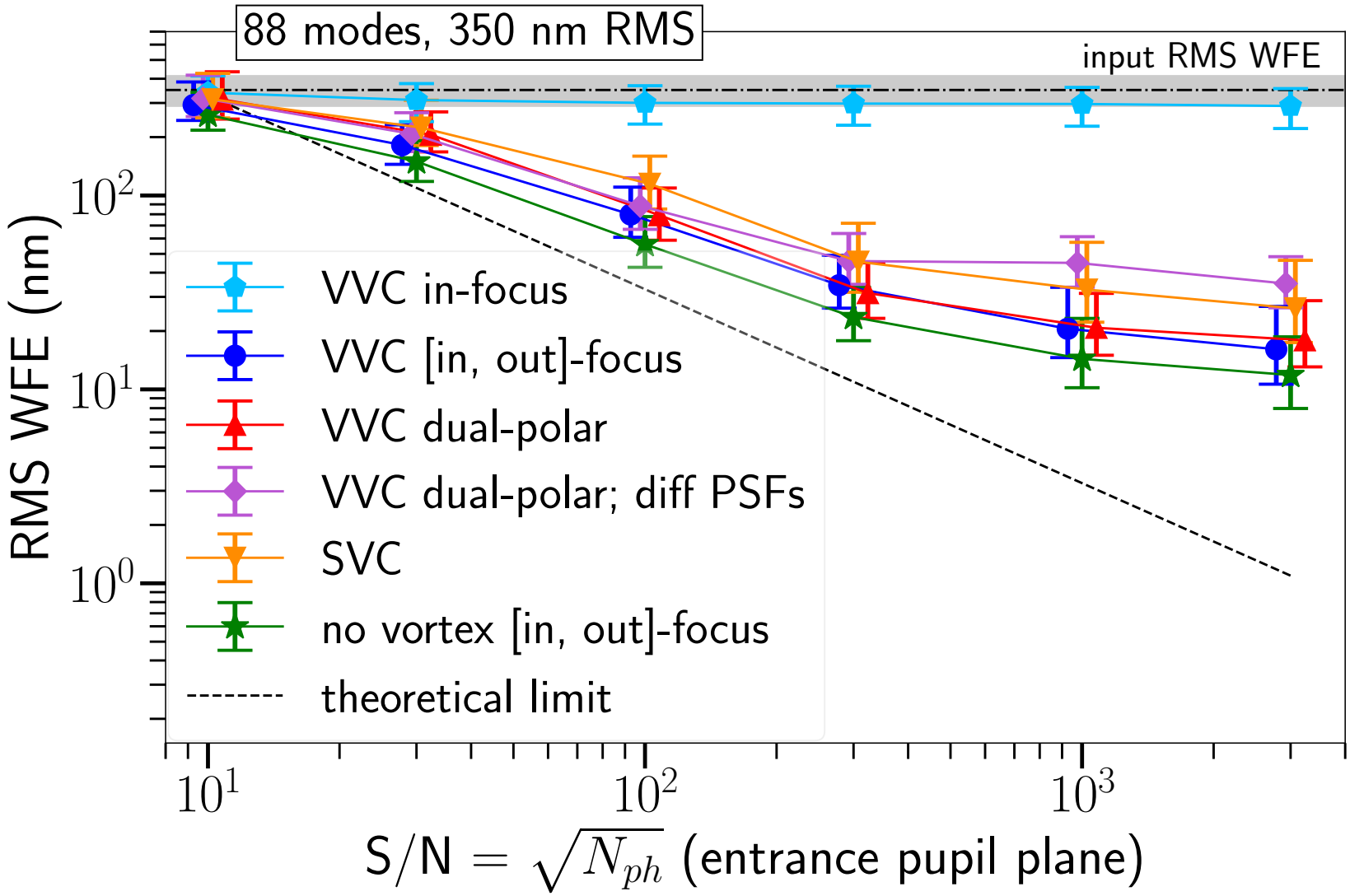




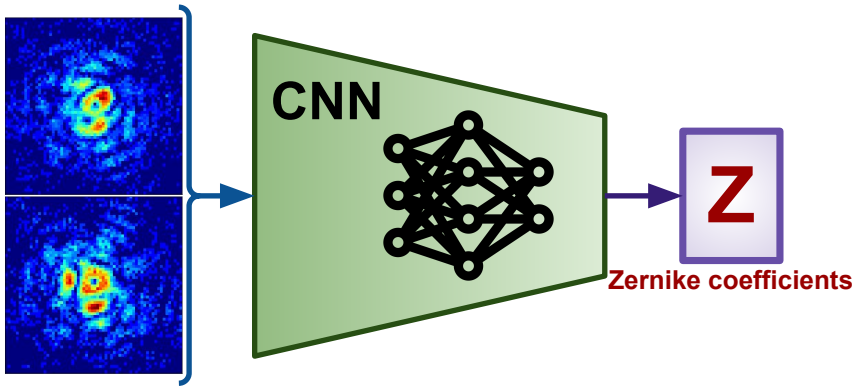
Zernike modes reconstruction



Phase retrieval performance



Simulator-based Autoencoder (SimAE)



CNN loss function (supervised):

$$\mathcal{L}_{CNN}(z, \hat{z}(x;\phi)) = \sqrt{\frac{1}{N}\sum_{i}^{N}(z_i - \hat{z}_i(x;\phi))^2))}$$

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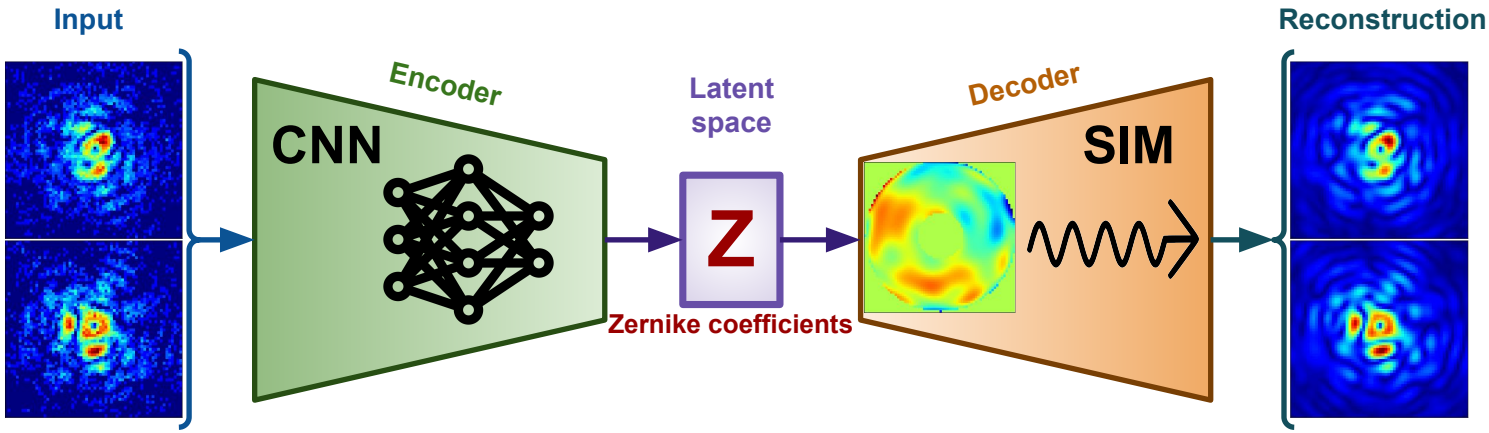

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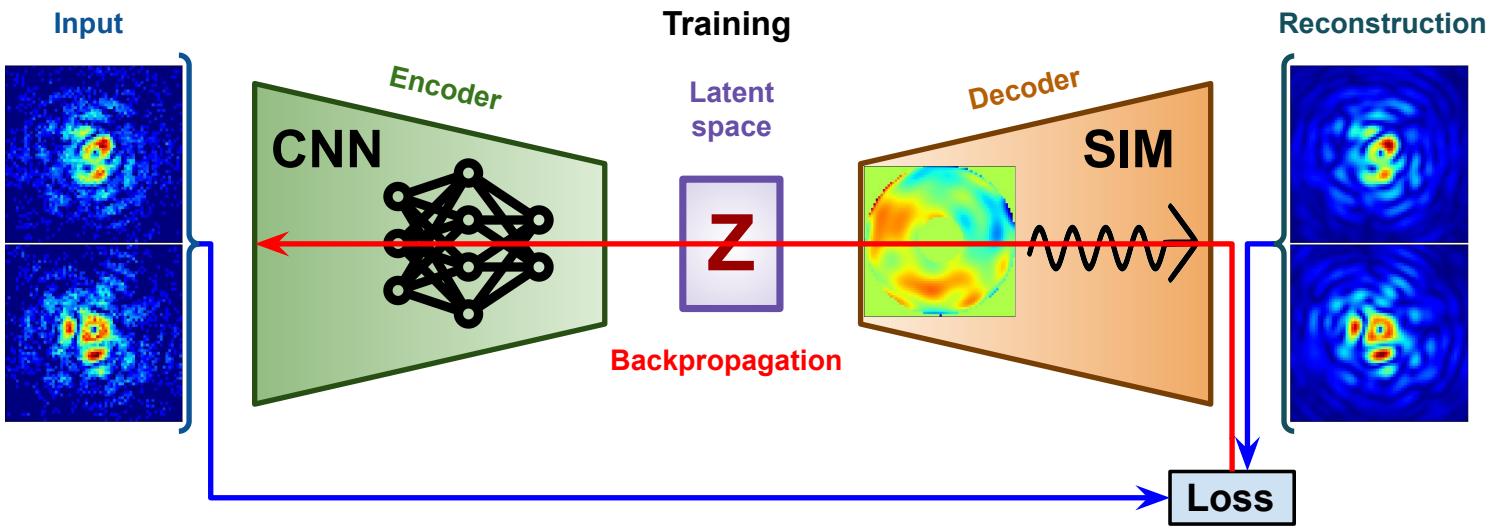

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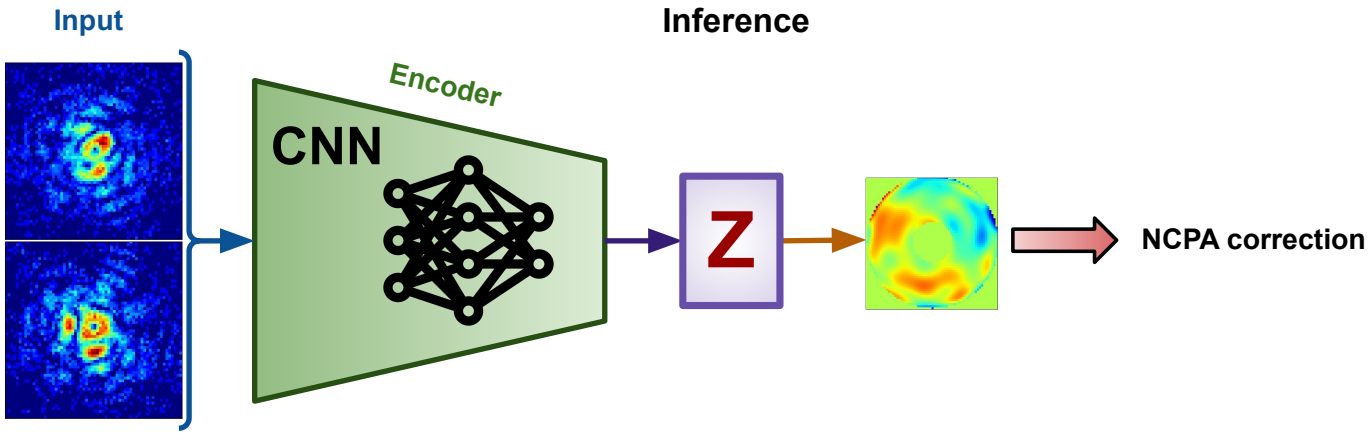
SimAE loss function (unsupervised) $\rightarrow$ Poisson distributions:

$$\mathcal{L}_{SimAE}(x;\phi) = -\mathbb{E}_{x\sim p(x)}\left[\log\left(\frac{\lambda(x;\phi)^x}{x!}\exp(-\lambda(x;\phi))\right)\right]$$

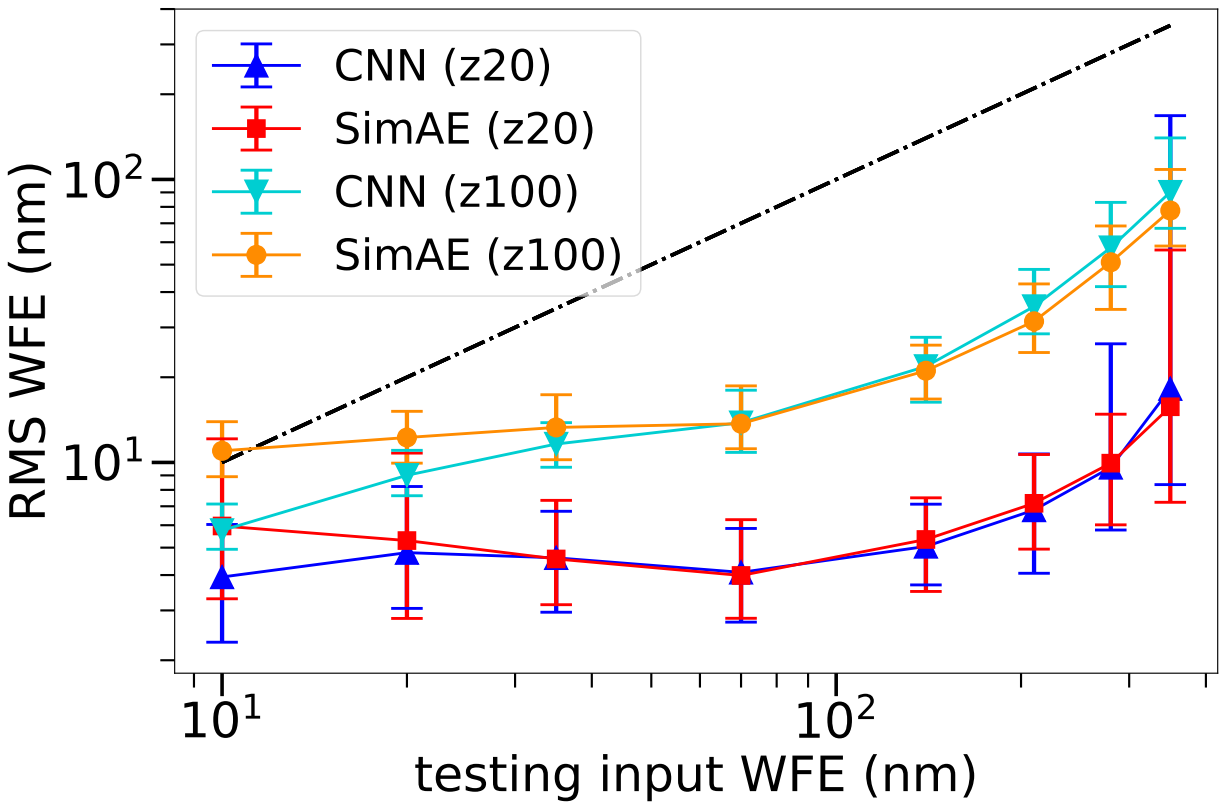
Simulator-based Autoencoder (SimAE)



SimAE: Performance

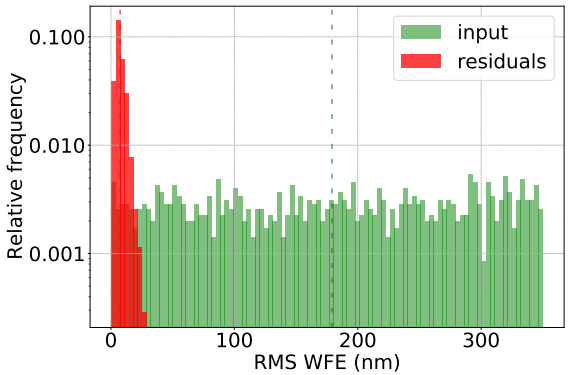
- WFE $\in$ [0, 350] nm rms
- SNR $\simeq$ 100
- 10^5 training & 10^2 test samples

Evaluated on specific WFE distributions:

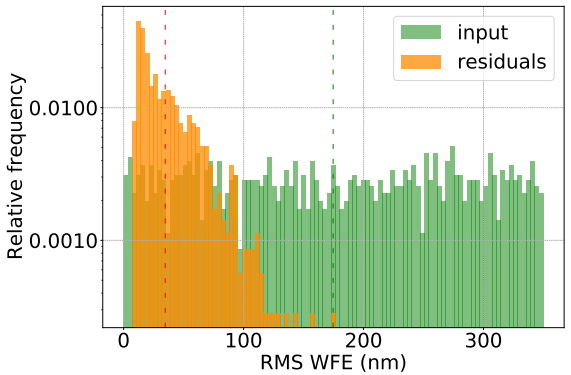


Entire WFE distribution:

20 Zernike modes:

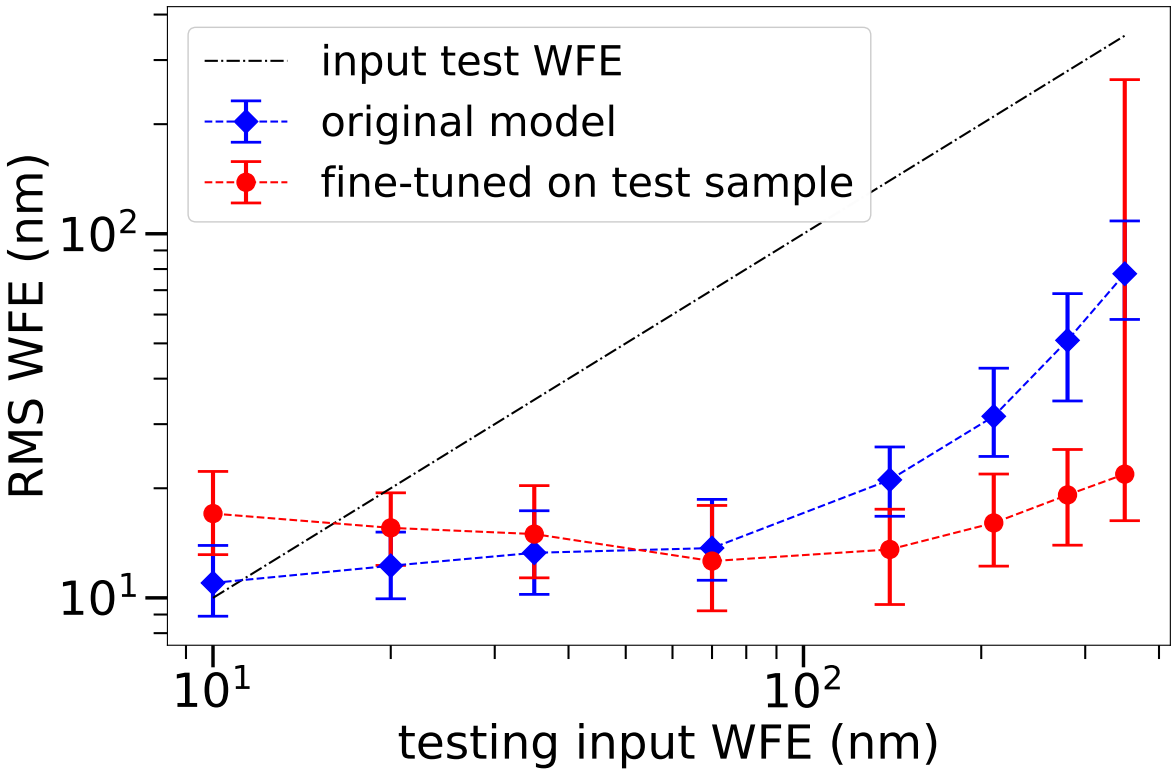


100 Zernike modes:



SimAE: fit on-the-fly

- Pre-trained on 10^5 samples
- Fine-tuned on 1 test sample
- Convergence time: $\sim$ 10 seconds



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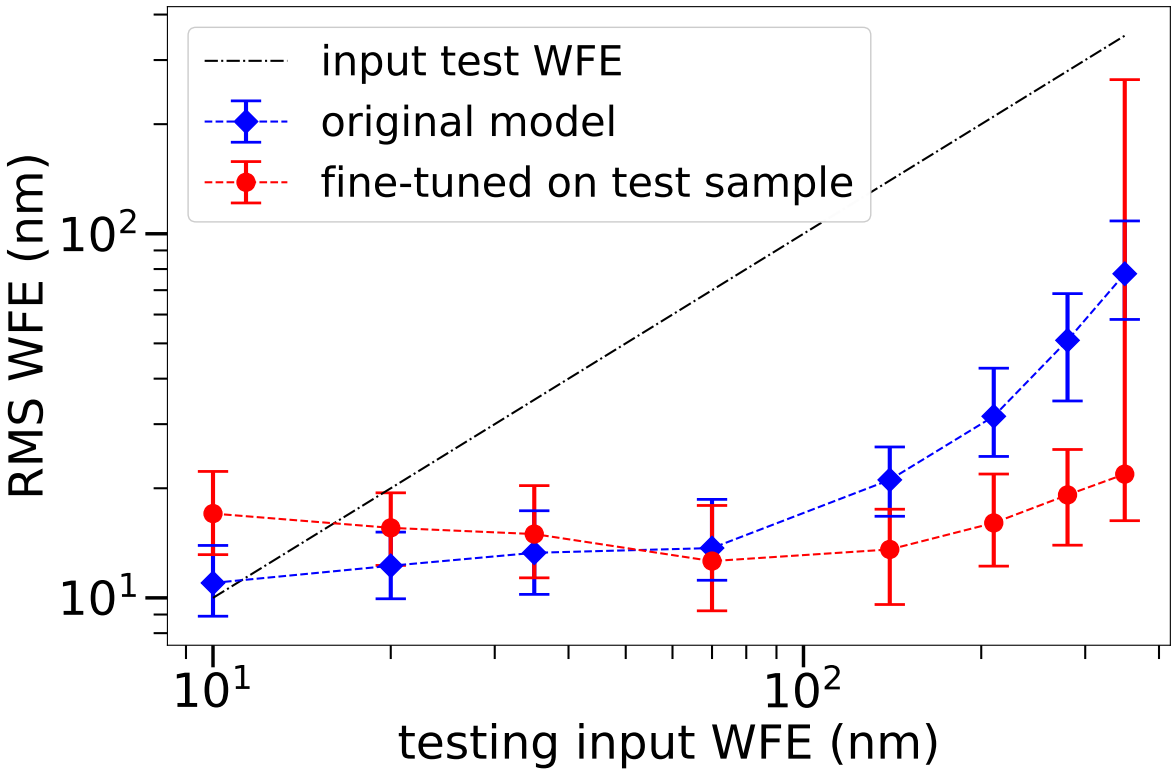
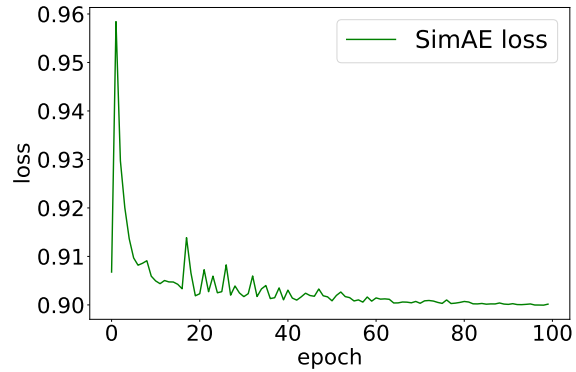
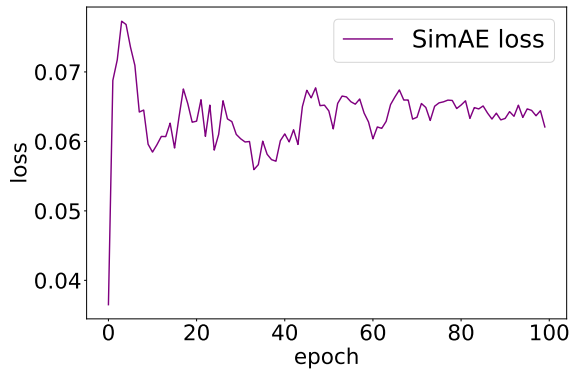


Fine-tune at 10 nm rms:





Current developments

- Improving the simulator:
  - ⋆ Learnable instrumental parameters: e.g., Vortex rejection factor
  - ⋆ Including AO telemetry
  - ⋆ Use optical propagation package, e.g., dLux (github.com/LouisDesdoigts/dLux)

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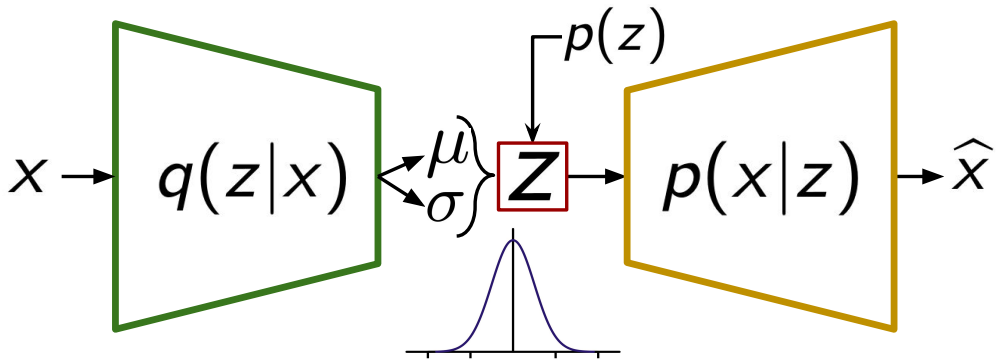
- Variational Autoencoder:
  - ⋆ Add Posterior $q(z|x)$ and Prior distributions $p(z)$



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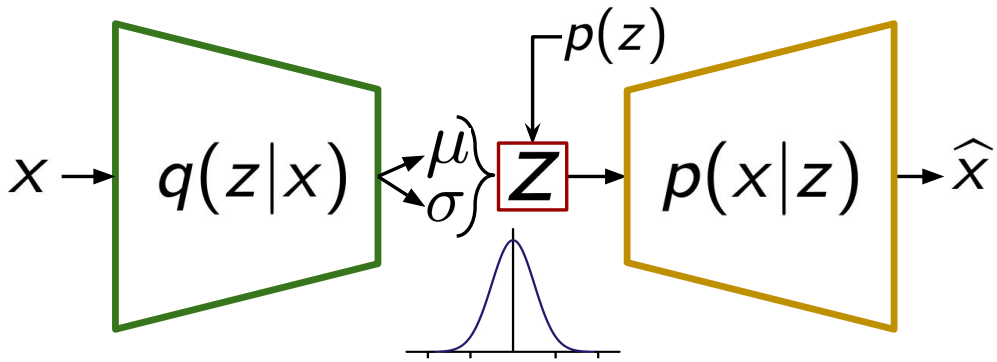
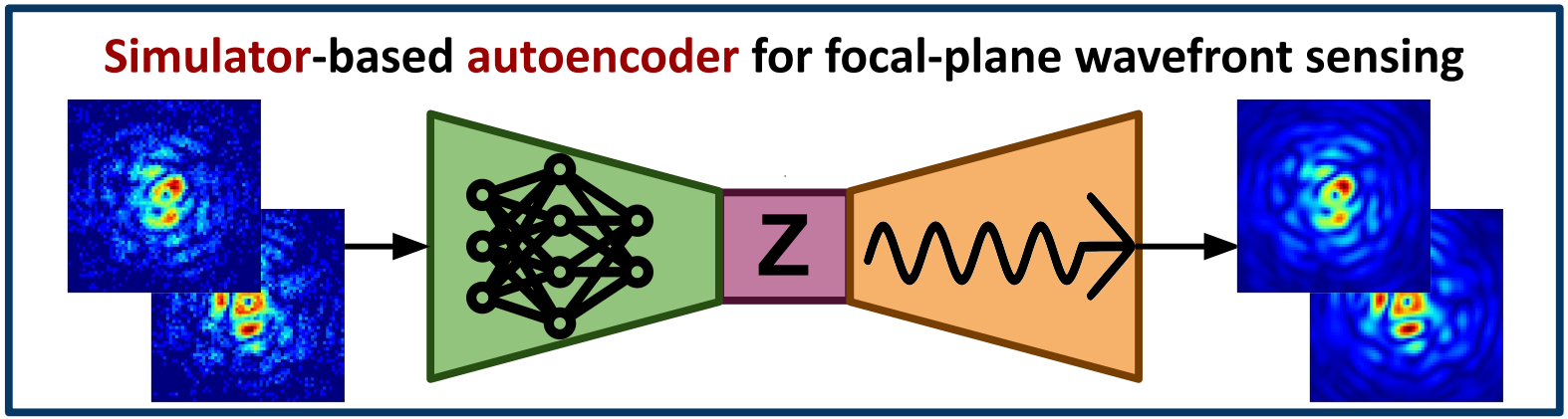


  - ⋆ KL divergence loss term: $-\beta\, KL(q(z|x;\phi)||p(z))$
    $\rightarrow$ training unstable
- Application in-lab and on-sky

Conclusions



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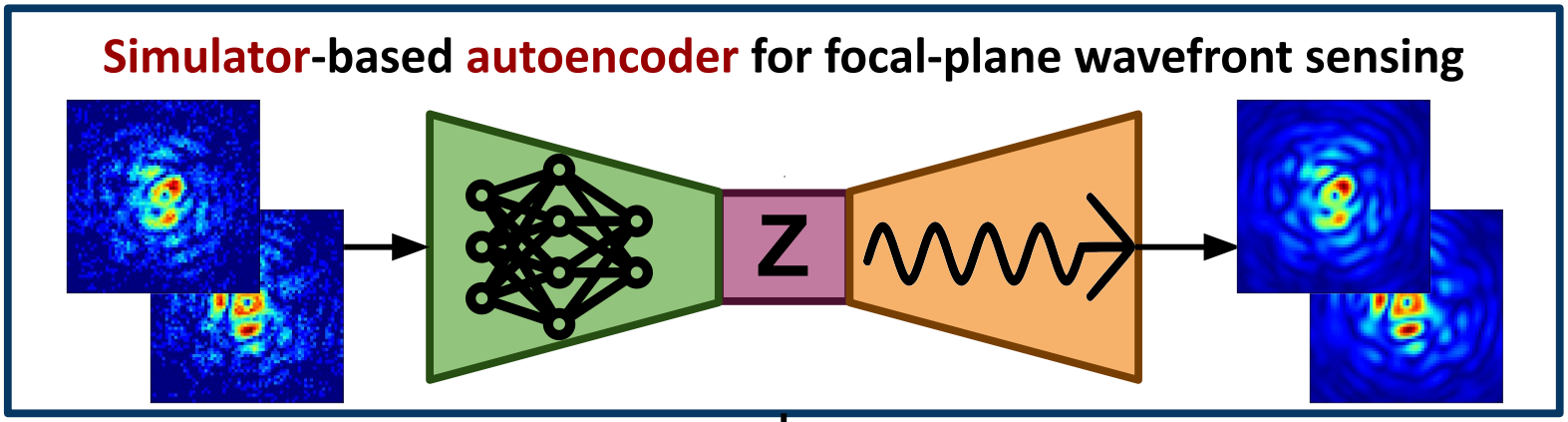
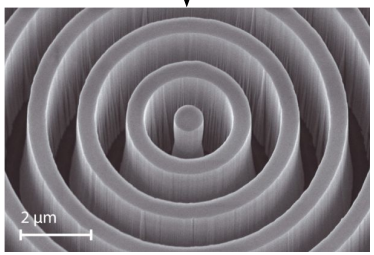
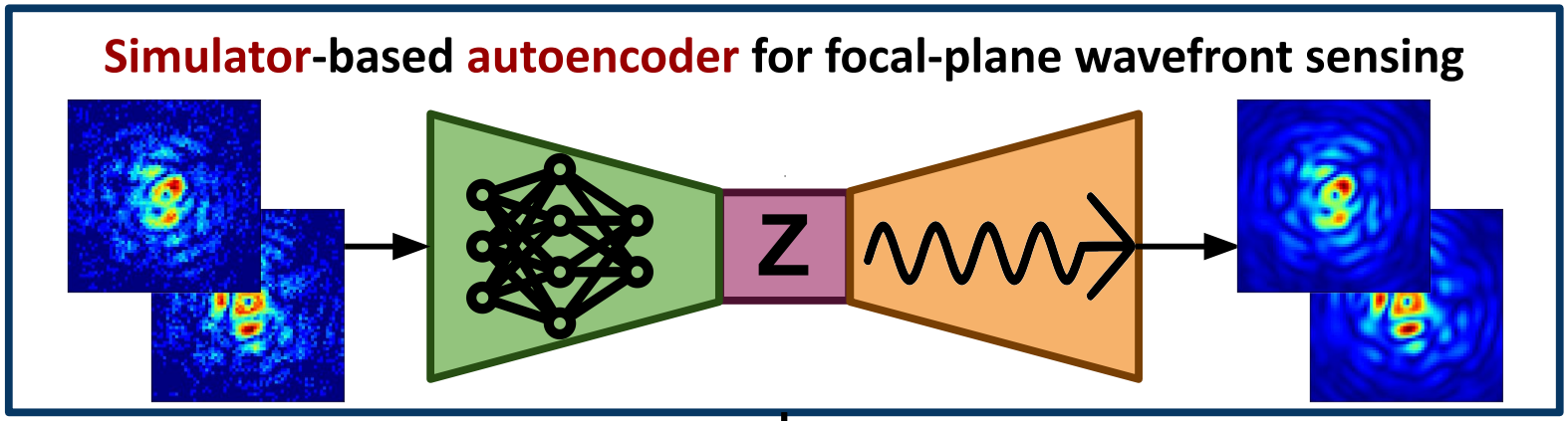


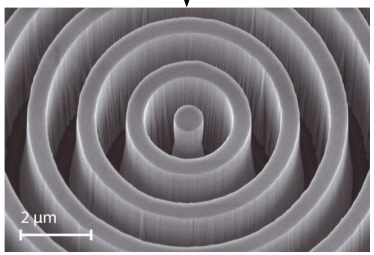


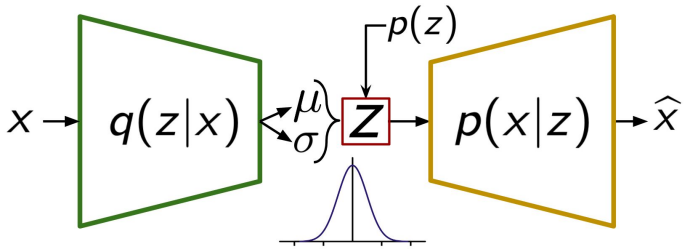
Vortex Phase diversity

Quesnel et al. 2022
(A&A, accepted)

Conclusions







Vortex Phase diversity

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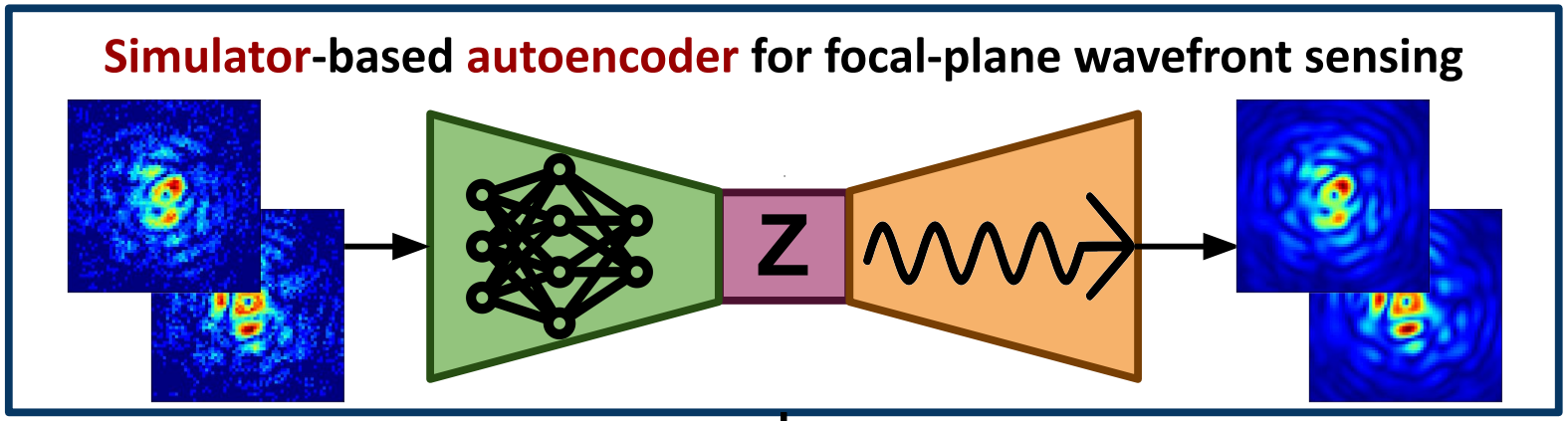
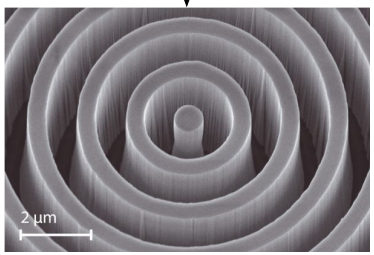
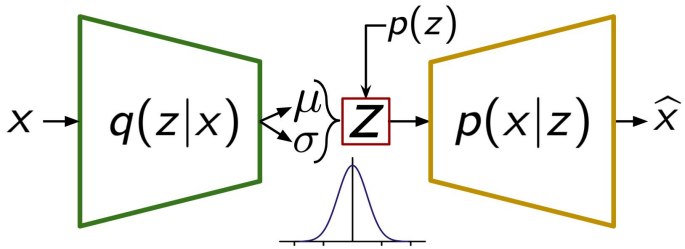
Improving the autoencoder

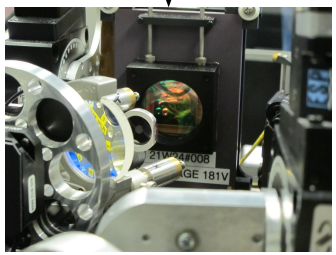
- Variational approach
- Complete simulator

Conclusions









Vortex Phase diversity

Quesnel et al. 2022
(A&A, accepted)

Improving the autoencoder

- Variational approach
- Complete simulator

Application to real data

- Subaru/SCExAO
- ULiège/VODCA bench