Study of the LIFT focal-plane wavefront sensor for GALACSI NFM

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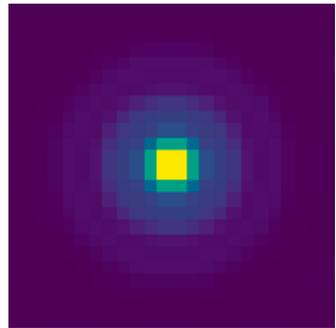
Wavefront Sensing in the VLT/ELT era VII, 2022

Objectives

■ Re-analyze the on-sky data and potentially improve the accuracy of reconstruction

■ Try Machine Learning (ML) within the scope of LIFT

■ Prepare the background for future work with ML

■ It is the side project

■ It is a playground project

■ It is a work in progress
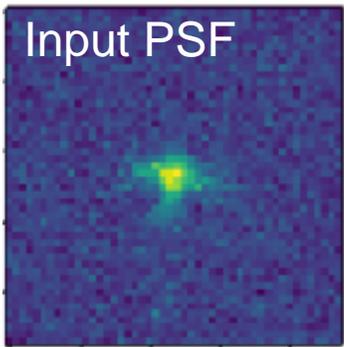
LIFT on IRLOS

Defocus sign indetermination

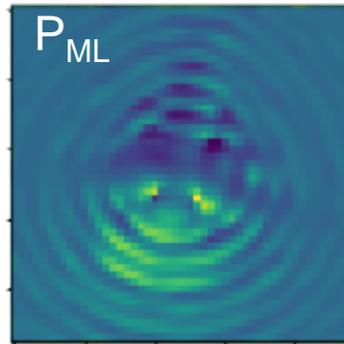Astigmatic phase diversity →
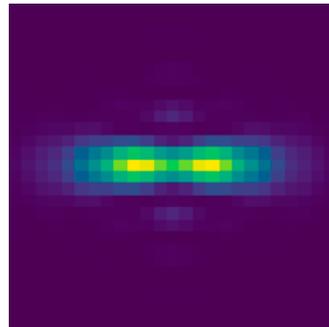
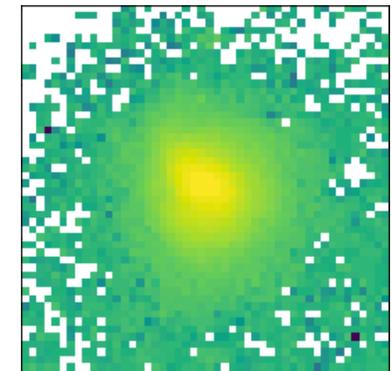LIFTed PSF resolves the sign of even modes

Input PSF → P_{ML}

By weighing with pixel variance, LIFT uses the vicinity of the PSF core in low-flux and the whole image in high-flux. **In this work we consider high flux**

- ■ Baseline was to use LIFT as a slow truth-sensor for tip/tilt, defocus (m.b. higher orders) in low-flux
- ■ LIFT is based on inserting known amount of astigmatic phase diversity into optical path
- ■ In IRLOS the cylindrical lens is inserted into the filter wheel
- ■ Therefore, acquired LIFTed PSFs are **highly polychromatic**
- ■ LIFT is model-based → an **accurate and well-calibrated model** of the focal-plane PSF in required for accurate reconstruction with LIFT
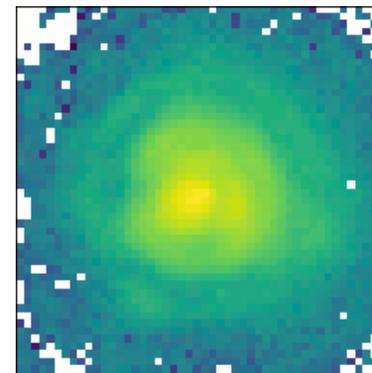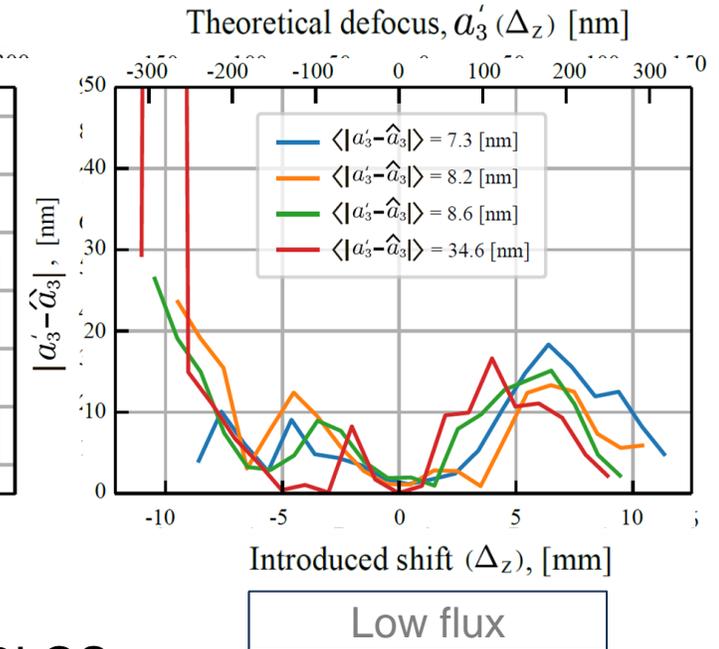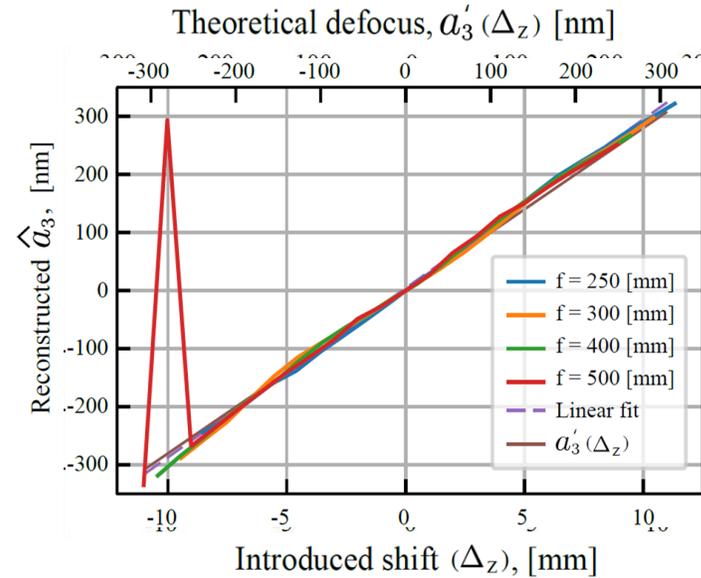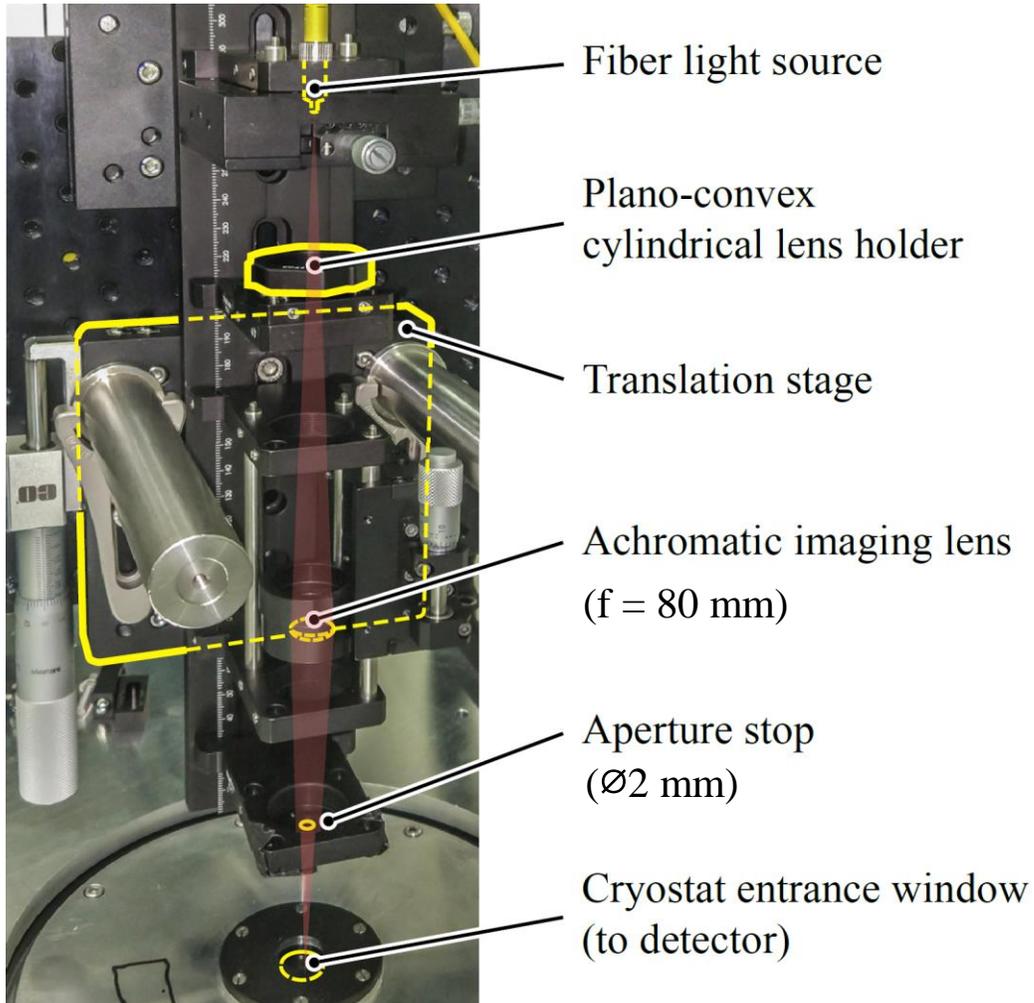

Monochromatic full-pupil PSF

Chromatic J+H full-pupil PSF → challenging!

LIFT, verification in the lab

- Fiber light source
- Plano-convex cylindrical lens holder
- Translation stage
- Achromatic imaging lens (f = 80 mm)
- Aperture stop (Ø2 mm)
- Cryostat entrance window (to detector)

Theoretical defocus, $a_3'(\Delta_z)$ [nm]

Reconstructed $\hat{a}_3$, [nm]

Introduced shift (Δ_z), [mm]

- f = 250 [mm]
- f = 300 [mm]
- f = 400 [mm]
- f = 500 [mm]
- Linear fit
- $a_3'(\Delta_z)$

Theoretical defocus, $a_3'(\Delta_z)$ [nm]

$|a_3' - \hat{a}_3|$, [nm]

Introduced shift (Δ_z), [mm]

- $\langle |a_3' - \hat{a}_3| \rangle$ = 7.3 [nm]
- $\langle |a_3' - \hat{a}_3| \rangle$ = 8.2 [nm]
- $\langle |a_3' - \hat{a}_3| \rangle$ = 8.6 [nm]
- $\langle |a_3' - \hat{a}_3| \rangle$ = 34.6 [nm]

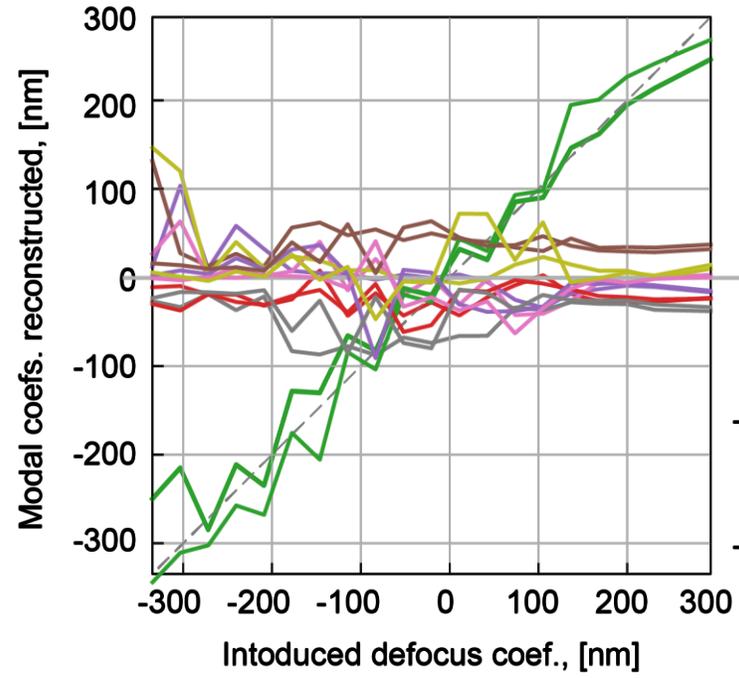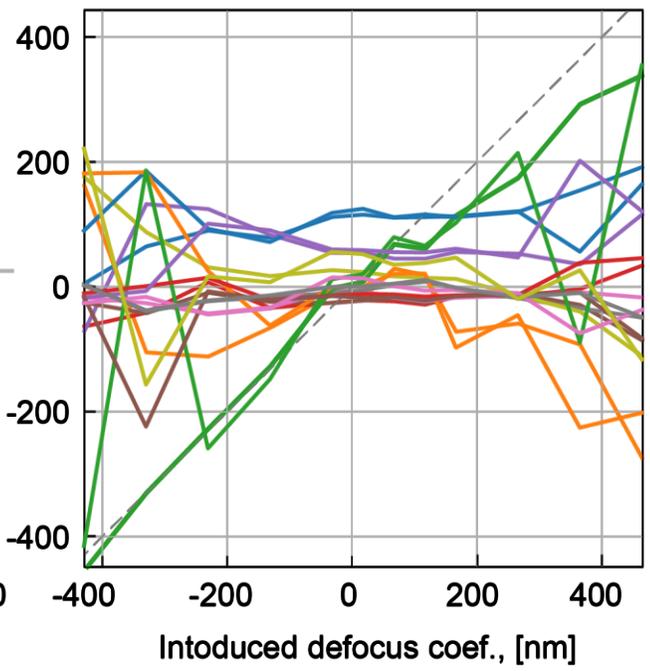Low flux

- Test setup very similar to IRLOS
- Same SAPHIRA detector as on real IRLOS (RON < 1e⁻)
- Varying defocus by translating the setup relative to the focal plane to scan linearity range
- Fiber point source with λ ≈ 1.2…1.6 μm
- → LIFT performed well, even in very faint conditions

LIFT, verification on-sky

Target #1, J+H$_{mag}$ ≈ 13
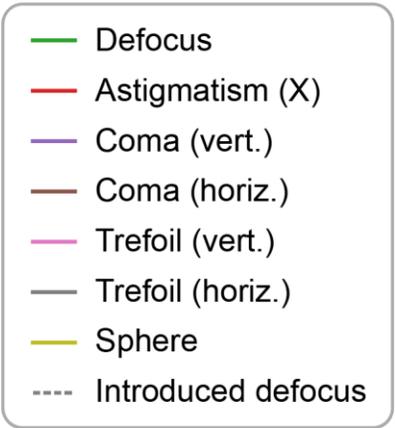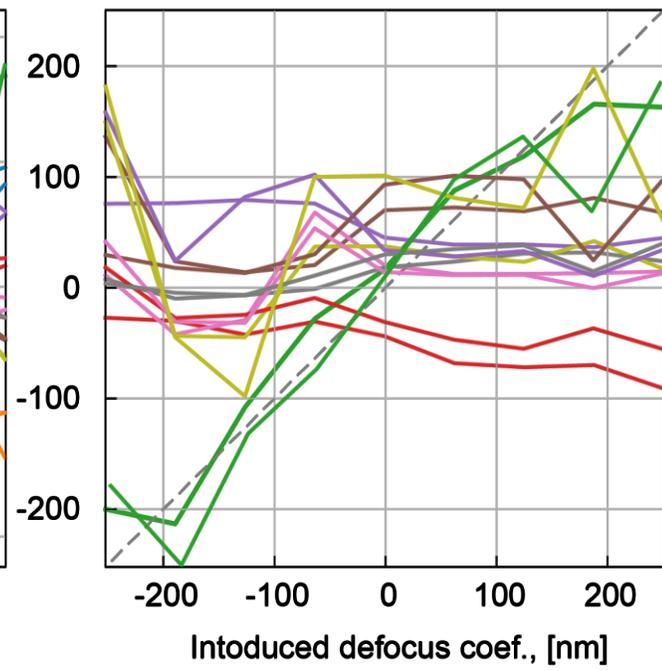
Target #2, J+H$_{mag}$ ≈ 9

Target #3, J+H$_{mag}$ ≈ 9

Legend:
- Defocus (green)
- Astigmatism (X) (red)
- Coma (vert.) (purple)
- Coma (horiz.) (brown)
- Trefoil (vert.) (pink)
- Trefoil (horiz.) (gray)
- Sphere (yellow)
- Introduced defocus (dashed)

The assumption for the convolution kernel is turned off.
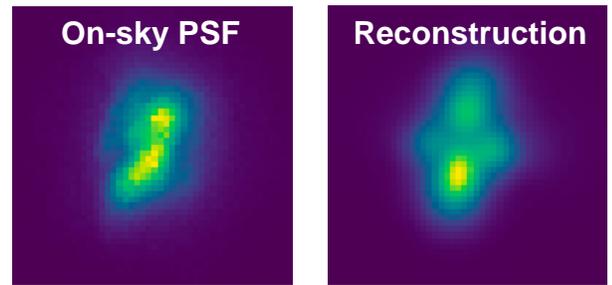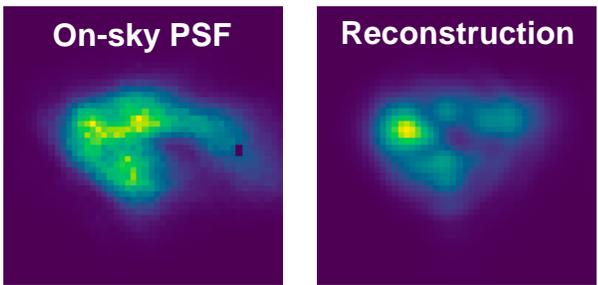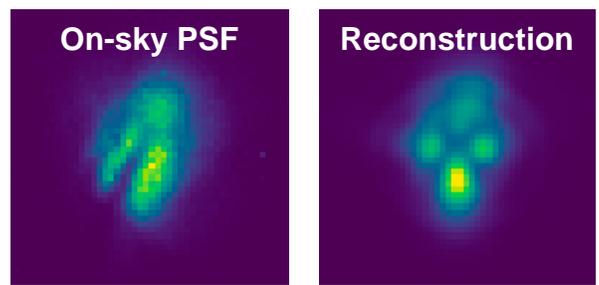
This kernel is a way to account for the uncharacterized effects

On-sky PSF   Reconstruction   On-sky PSF   Reconstruction   On-sky PSF   Reconstruction

So, on-sky PSFs…

■ Highly chromatic

■ Affected by NCPAs (possibly chromatic)

■ Affected by uncharacterized effects

■ Only one image is used for the reconstruction

■ Long exposure (several seconds)

→ Real PSFs have a complex morphology
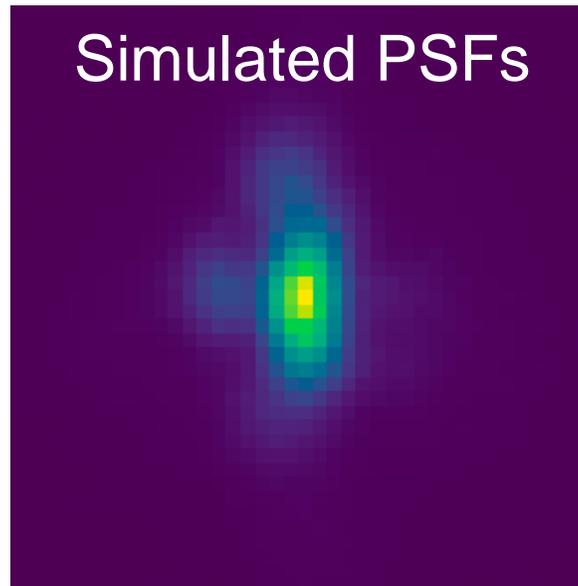
→ Very challenging case!

Simulated dataset

- Question: can we do more with these data using Machine Learning?
- Problem: only 41 samples of on-sky PSFs available → too few for training
- Solution: simulate realistic synthetic dataset for pre-training

J_{mag} = 12
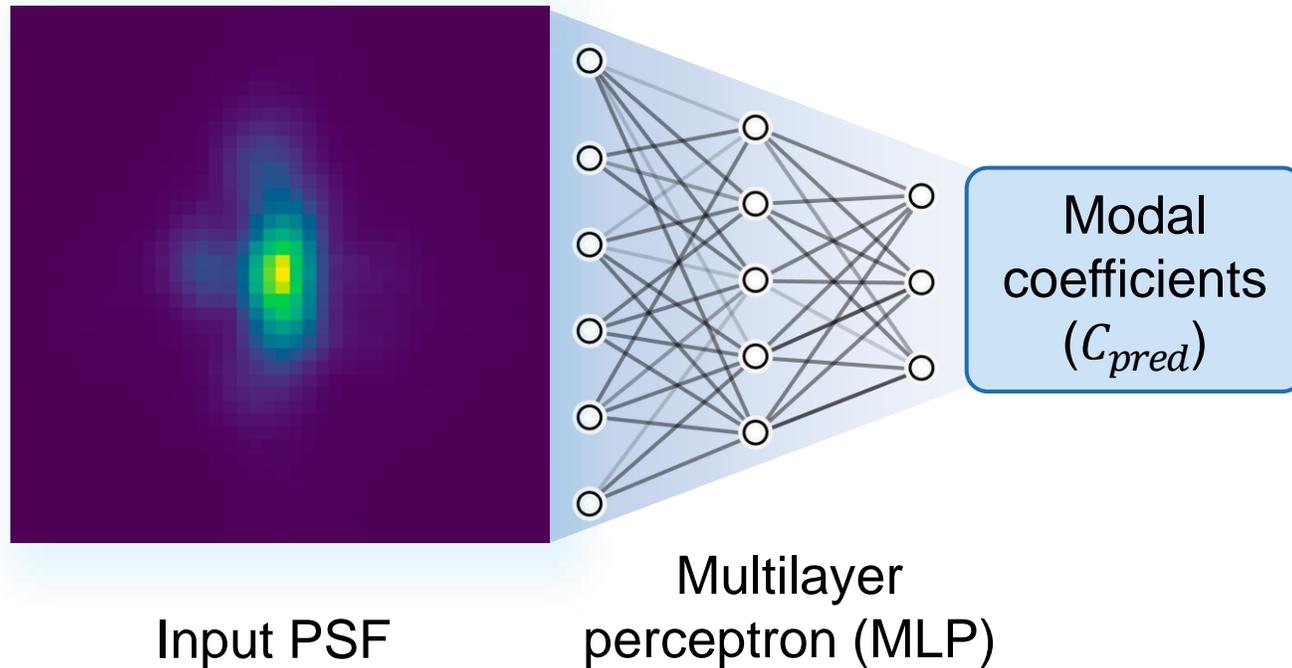
Polychromatic (J+H)

Convolution with a random kernel

Simulated PSFs

AO residuals

20 Zernike modes as NCPAs

Photon + electron noise

Proposed architecture

Input PSF

Multilayer perceptron (MLP)
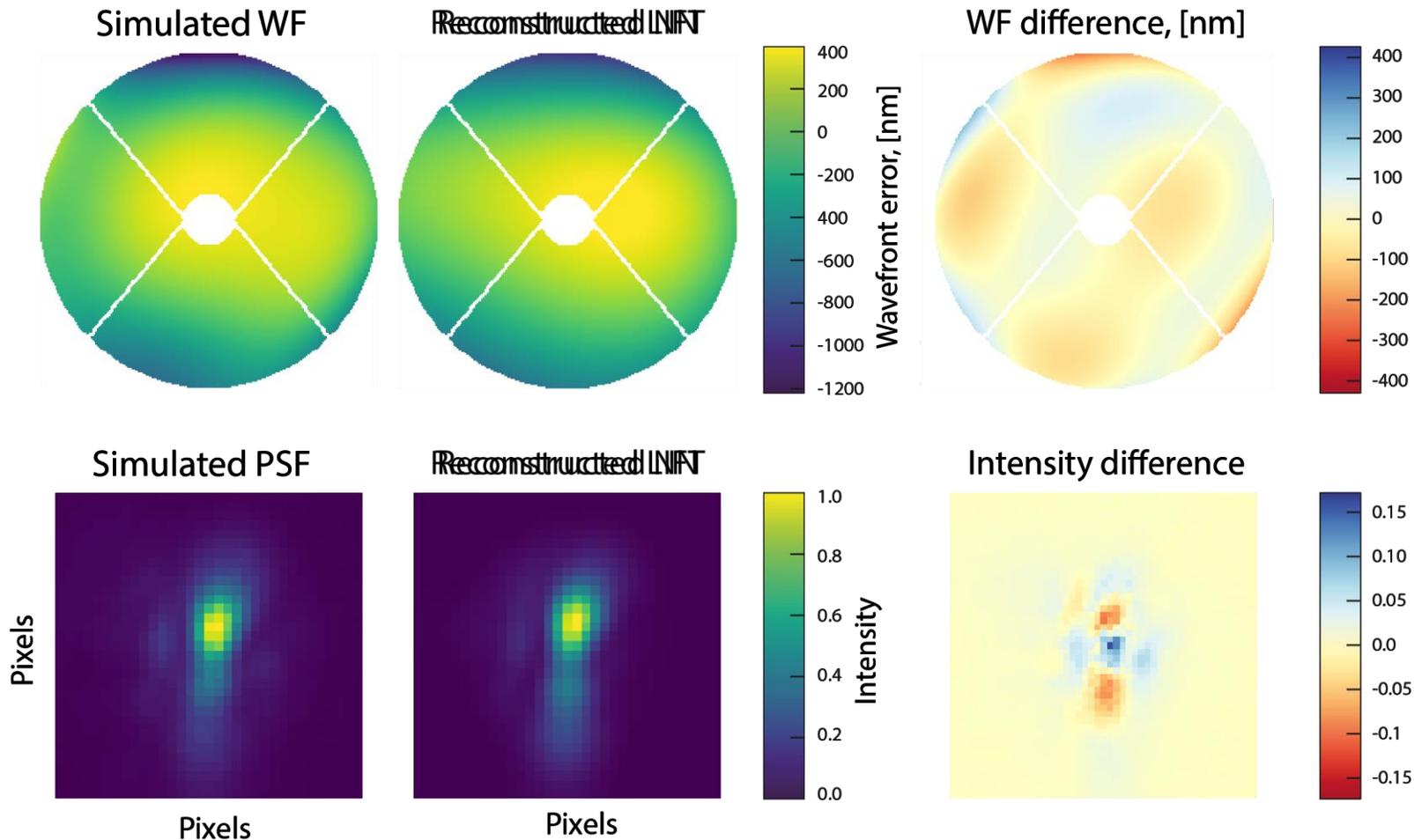
Modal coefficients (C_{pred})

Loss: $MSE(C_{GT} - C_{pred})$

- Naïve approach: simple MLP

- Trained to correspond PSF images to modal coefficients directly

- Trained on the synthetic dataset with the ground-truth (GT) modal coefficients available

- Small model (~55K params) → very fast training/inference

Simulated WF

Reconstructed LIFT

WF difference, [nm]

Simulated PSF

Reconstructed LIFT

Intensity difference

- LIFT tries to reconstruct the PSF accurately, though the WF is not always accurate

- But the Neural network (NN) reconstructs WF with higher accuracy

- Makes sense: LIFT tries to fit to PSF image at any cost → modes can cross-couple, while the NN was trained to predict the coefficients
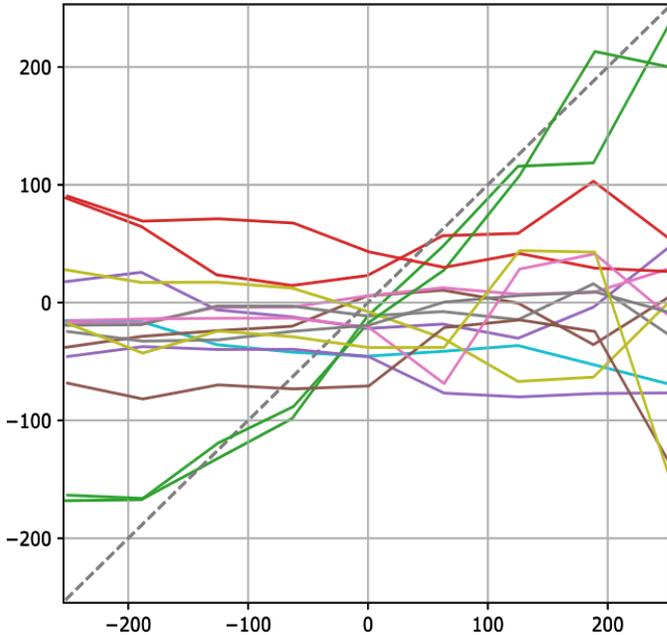
Results (synthetic data)
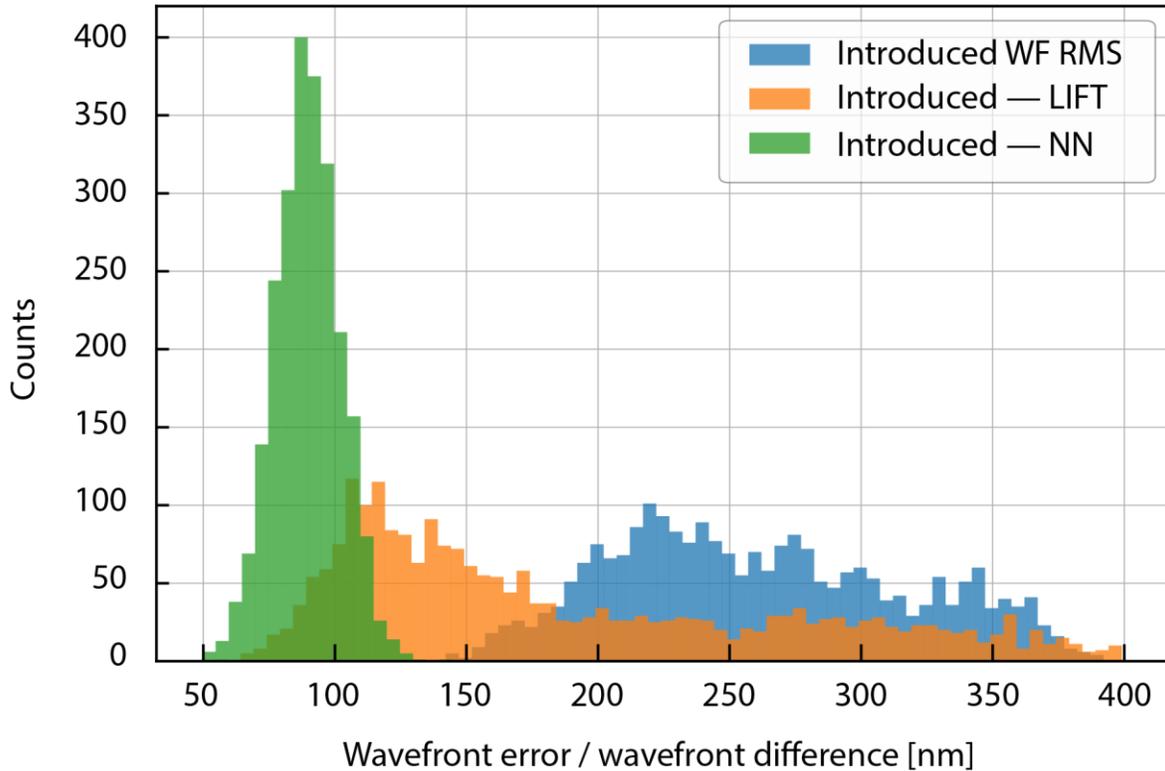
Median WFE, [nm]	
Introduced WF RMS	256
LIFT WF error	160
NN WF error	89

- NN is better than LIFT
- No convolution kernel prior is needed, unlike for LIFT
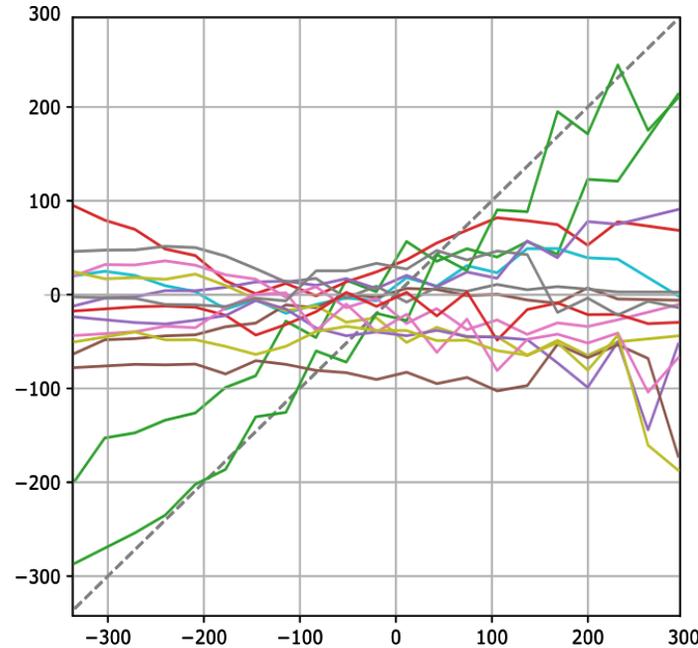- Very fast: direct inference of the modal coefficients

But these tests were made using the synthetic dataset. Will it perform as well with the real data?

Tuning NN on real data

Scan #1   Scan #2   Scan #3

Legend:
- Defocus
- Astigmatism (X)
- Astigmatism (+)
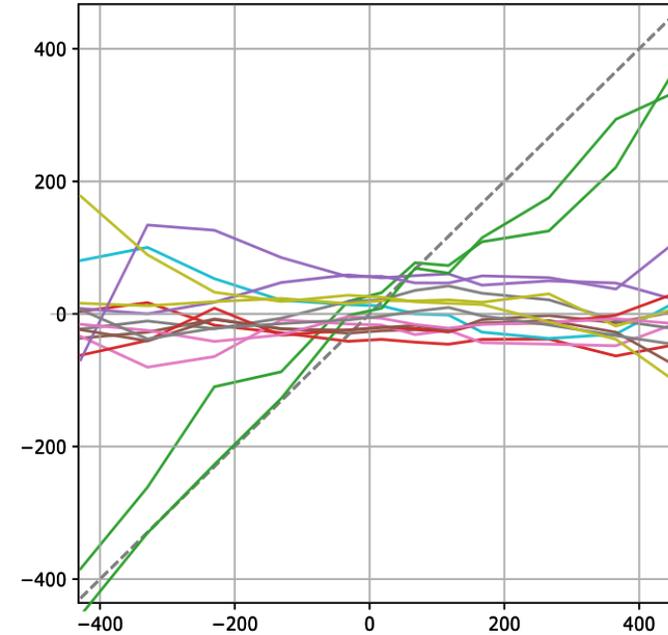- Coma vert
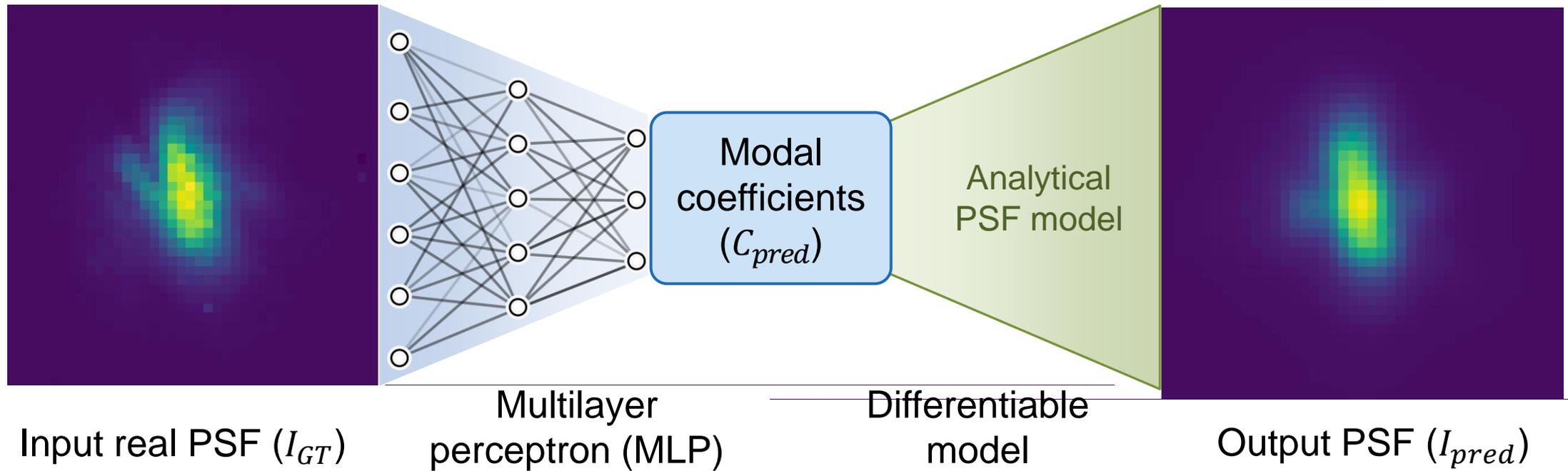- Coma horiz
- Trefoil vert
- Trefoil horiz
- Sphere
- Introduced def.

LIFT
NN

■ *Trained on synthetic data only*

■ The NN maybe shows smoother results, though accuracy is not so good

■ Can we do it better?

Input real PSF (I_{GT})   Multilayer perceptron (MLP)   Differentiable model   Output PSF (I_{pred})
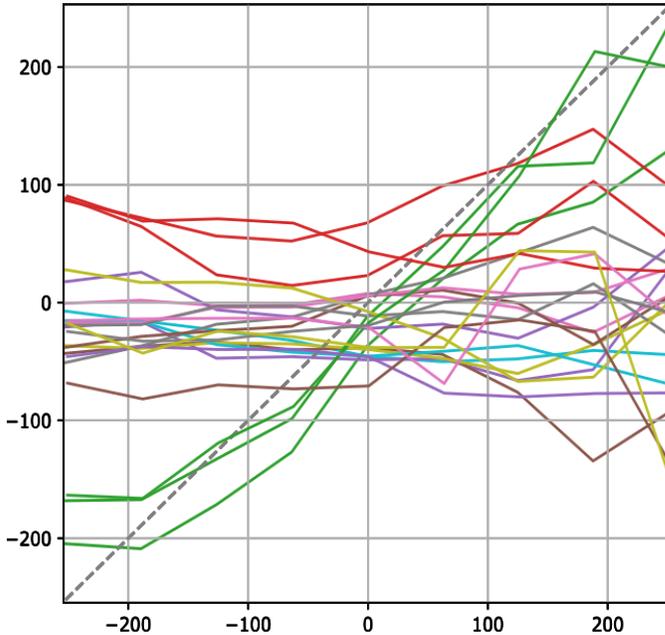
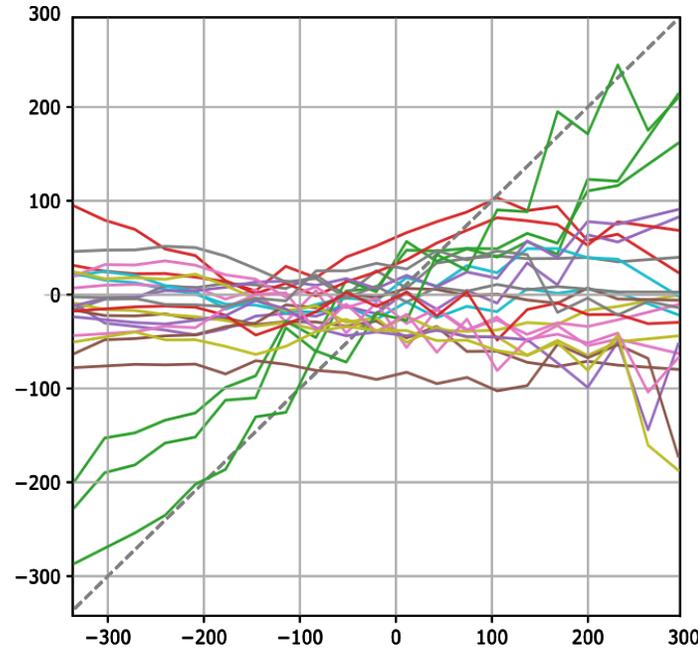Loss: $MAE(I_{GT} - I_{pred}) + \cancel{MSE(C_{GT} - C_{pred})} + MSE(Defoc_{GT} - Defoc_{pred})$

- Attach the analytical PSF model after the predicted coefficients
- Now train NN PSF to PSF, feed with real data this time
- Ground-truth coefs. are not accessible anymore (except for defocus)

Tuning NN on real data

Scan #1   Scan #2   Scan #3

Legend:
- Defocus
- Astigmatism (X)
- Astigmatism (+)
- Coma vert
- Coma horiz
- Trefoil vert
- Trefoil horiz
- Sphere
- Introduced def.

LIFT
NN
NN (tuned)
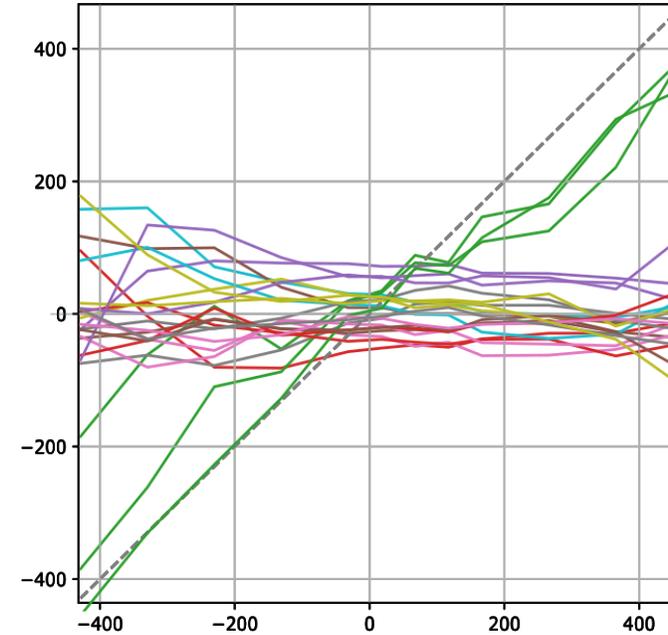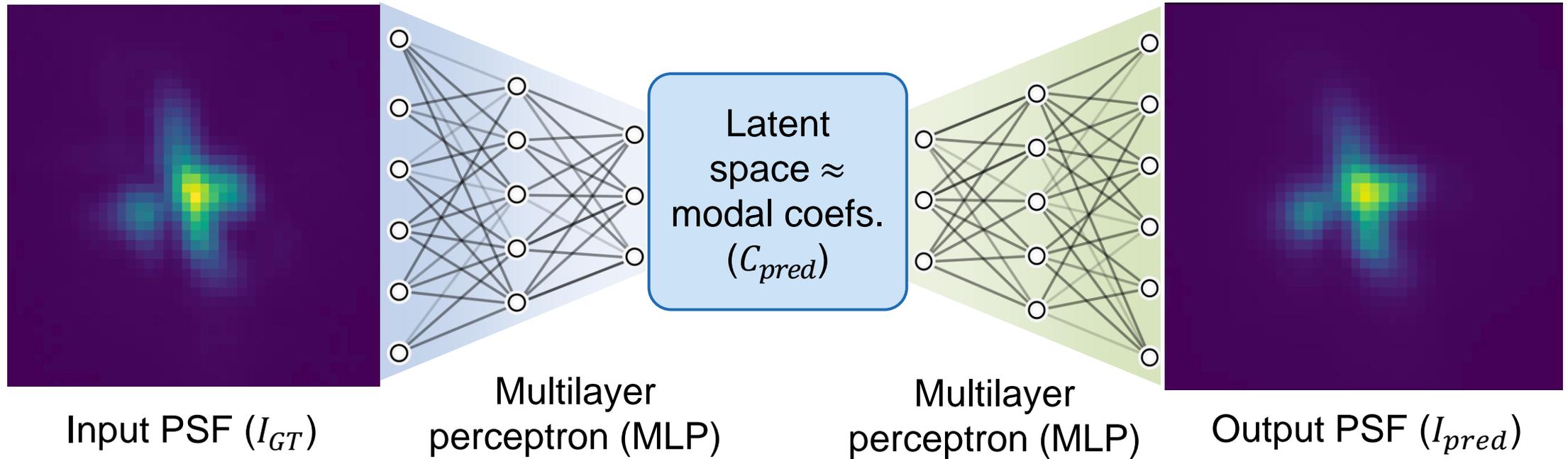
- Tuning did not help much

- The same problem as with LIFT → now NN is trained to accurately infer the intensity pattern, not the modal coefficients
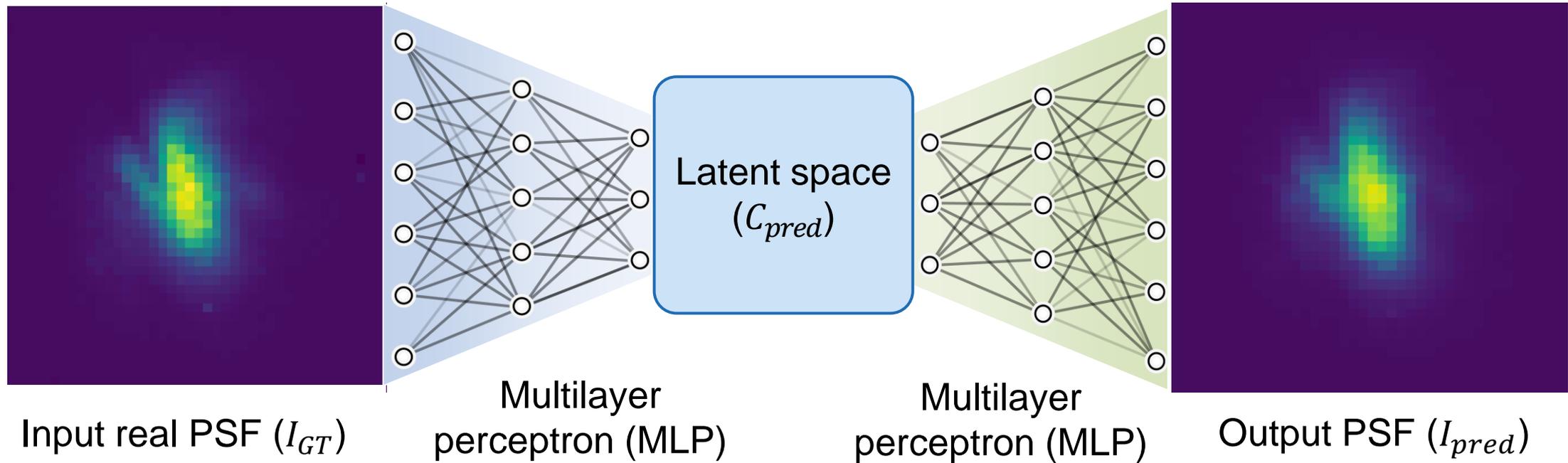
Non-analytical approach

Input PSF (I_{GT})   Multilayer perceptron (MLP)   Multilayer perceptron (MLP)   Output PSF (I_{pred})

Latent space $\approx$ modal coefs. (C_{pred})

Loss: $MAE\left(I_{GT} - I_{pred}\right) + MSE\left(C_{GT} - C_{pred}\right)$

- Pre-train variational autoencoder on simulations to tune it on real data later
- Additionally, force latent space to be equal to Zernike modal coefficients (when trained on simulated data)
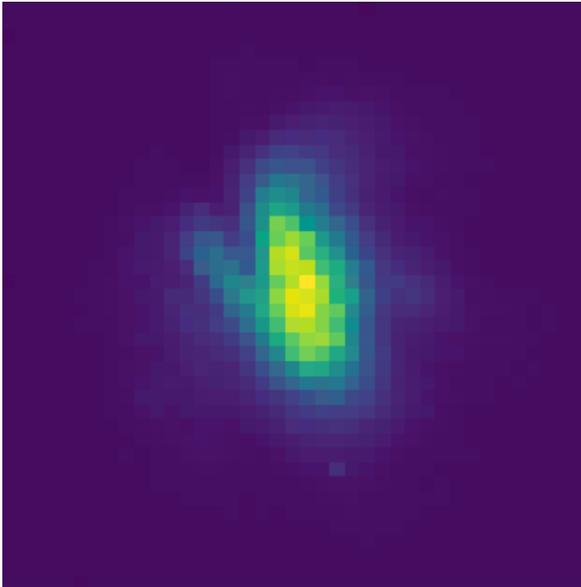
Non-analytical approach

Input real PSF (I_{GT})   Multilayer perceptron (MLP)   Multilayer perceptron (MLP)   Output PSF (I_{pred})

$$\text{Loss: } MAE\left(I_{GT} - I_{pred}\right) + \cancel{MSE\left(C_{GT} - C_{pred}\right)} + MSE\left(Defoc_{GT} - Defoc_{pred}\right)$$
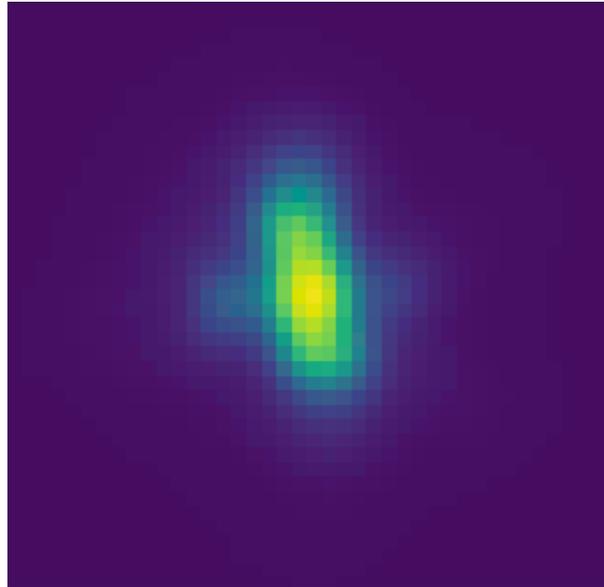
- Ground-truth coefs. are not accessible anymore (except for defocus)
- VAE trained on synthetic data and tuned on real PSFs

Tuned VAE

On-sky PSF	VAE (synth. only)	VAE (tuned on real)
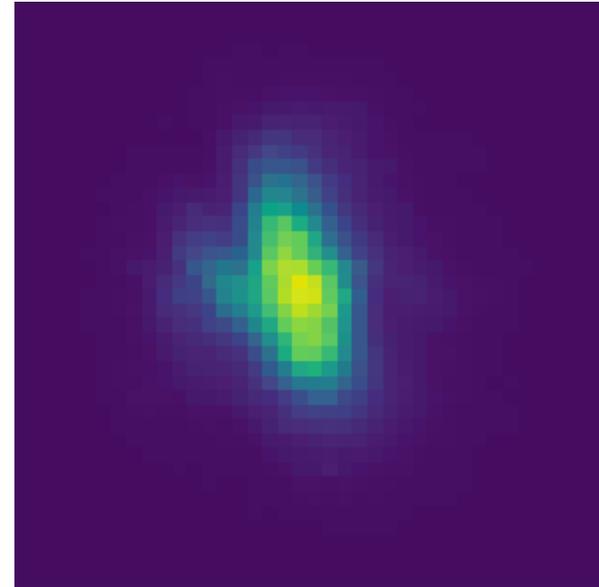
■ Tuned VAE absorbed an understanding of realistic PSF morphology
■ But what the decoder learned is a black box → it cannot be analytically expressed
→ opened the question how to interpret the decoder

Conclusion

- Although LIFT is simple, *it still performs well* (provided an appropriate convolutional kernel is assumed)

- Even though the simulated PSFs account for many realistic contributors, the bitter reality is *still much more complex*

- Nevertheless, NN is capable of "absorbing" the morphological complexity from just a few real PSFs, provided it was pretrained on the synthetic model. But it cannot tell us what it learned

- *More on-sky samples are needed* to tune the neural network adequately

Future work

■ Train a PSF to wavefront predictor

■ Bench experiments?

■ Collect more on-sky data (heh, not likely for LIFT…)

■ Use more advanced PSF models to generate a dataset?

■ LIFT is a toy project. Meanwhile, I am

■ working on PSF reconstruction/

■ prediction using the more advanced

■ PSF models.

New results are coming, stay tuned!