



**dLux**

**'Derivatives Through Light'**

**A fully differentiable, open-source, optical modelling framework**

Supervisors:

Peter Tuthill & Benjamin Pope

# Where are we going?

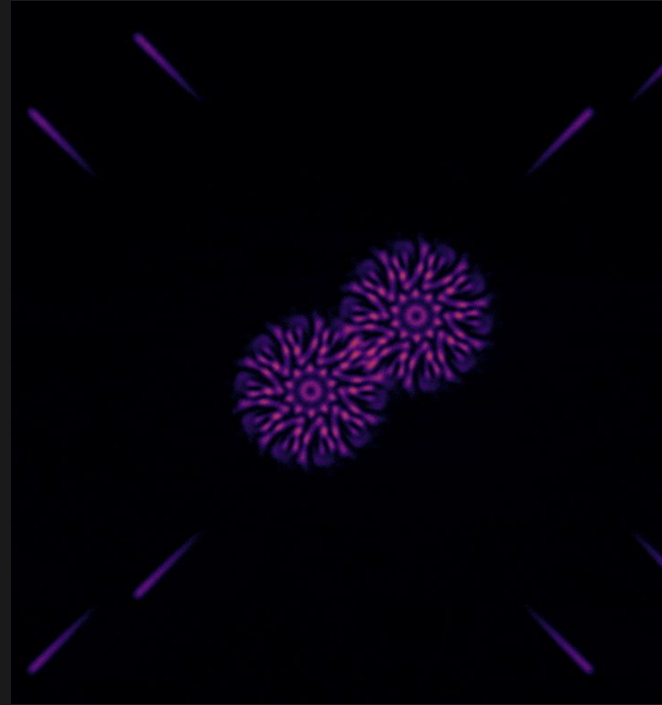
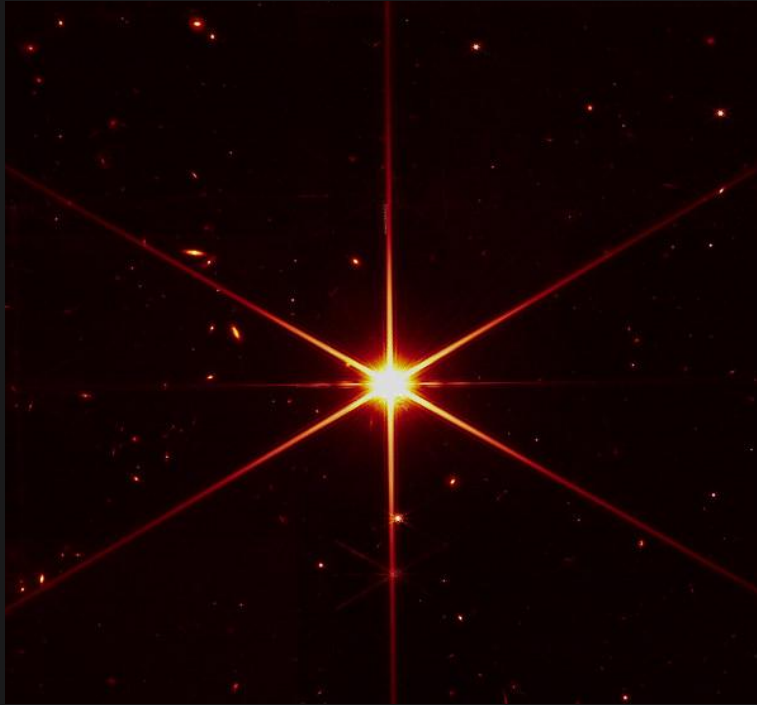
- Part 1: Context & Theory
- Part 2: Instrumental Calibration
- Part 3: Optical Analysis & Design
- Part 4: Preliminary JWST Fitting

∂ L U X



# Contex & Theory

# JWST & Toliman



# Differentiable Optics

## Optics and Neural Networks:

- Composed of the same base mathematical operations
- Defined by a series of operations on an input vector
- All operations fully differentiable

## Benefits of Jax/Autodiff

- Highly efficient optimisation and inference in high dimensions
- XLA compiled at run time
- Natively deploys across GPUs
- Integrates with machine learning optimisation packages (ie Optax)

# ∂Lux!

The logo for ALUX, featuring the letters 'a', 'L', 'U', and 'X' in a stylized, white, outlined font. The 'a' is lowercase and cursive, while 'L', 'U', and 'X' are uppercase and more geometric.

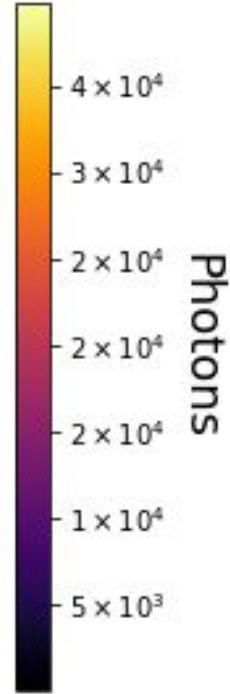
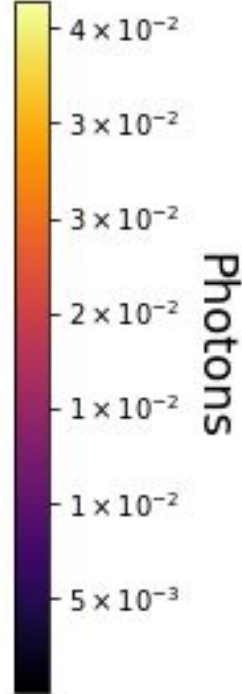
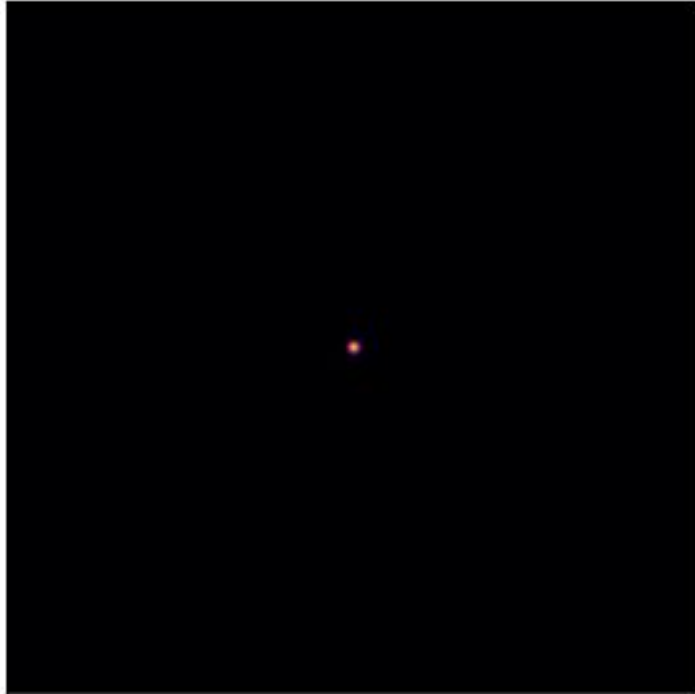
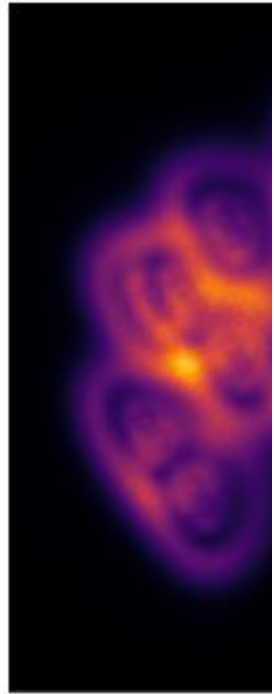
## Features

- Open source
- Built in Python with Jax (Numpy like API)
- Modular & object-oriented
- End to end differentiable
- Native multithreading across wavelengths/stars/images
- Integration with Neural Networks
- Fast, Flexible & Easy to use!
- Can faithfully reproduce poppy/webbpsf models



# Instrumental Calibration

# Modelling a Telescope





# Model optimisation

## Noise Sources:

- Photon
- Detector

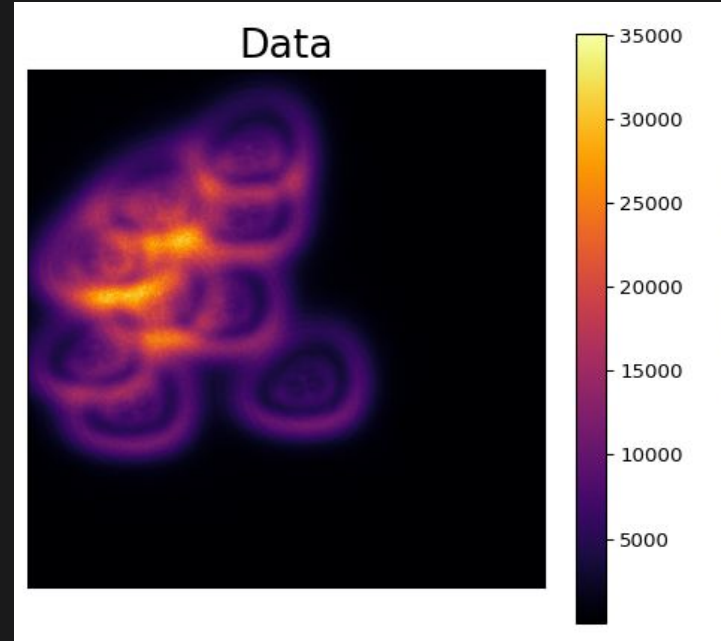
## Optimised Parameters:

- Positions
- Fluxes
- Defocus
- Zernike Aberrations
- Pixel Response

x4

**PSFs per model: 200**

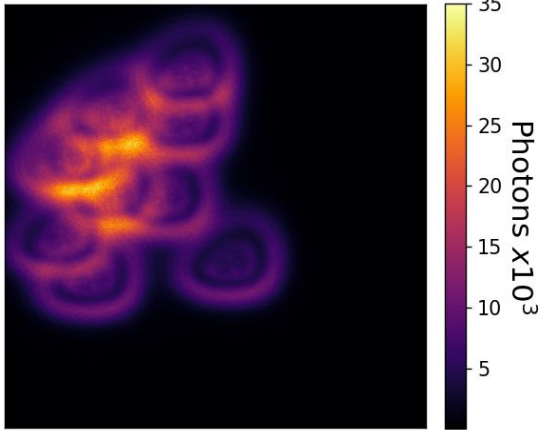
**Total parameters: 262'181**



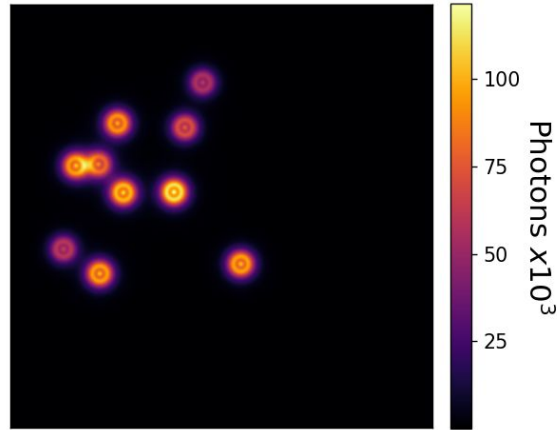
# Residuals (single image)

Epoch: 0

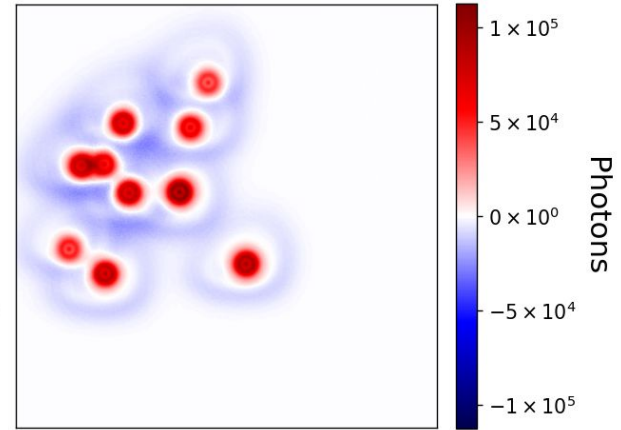
Data



Model

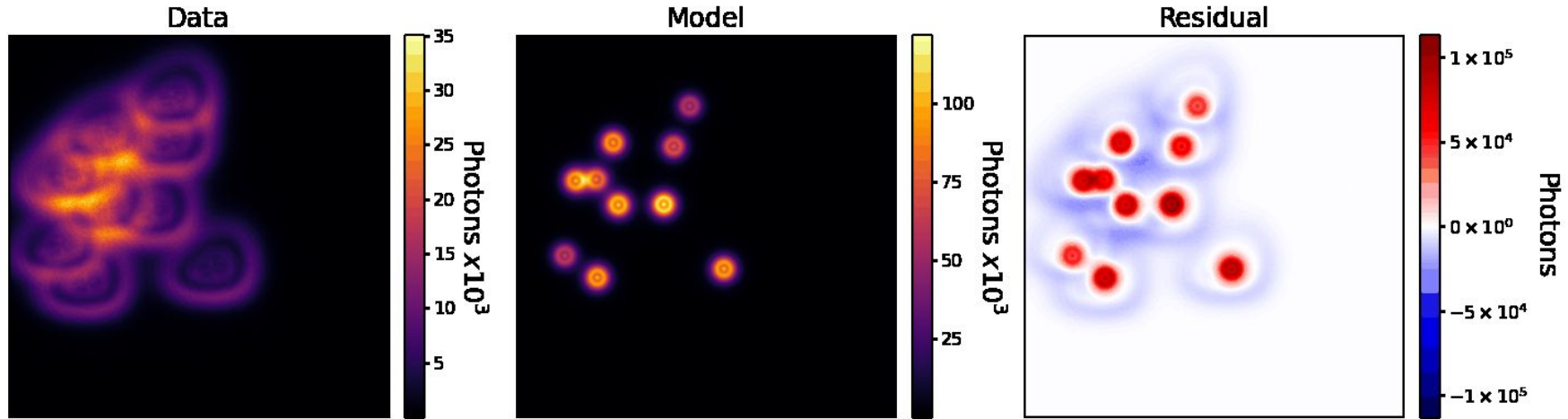


Residual

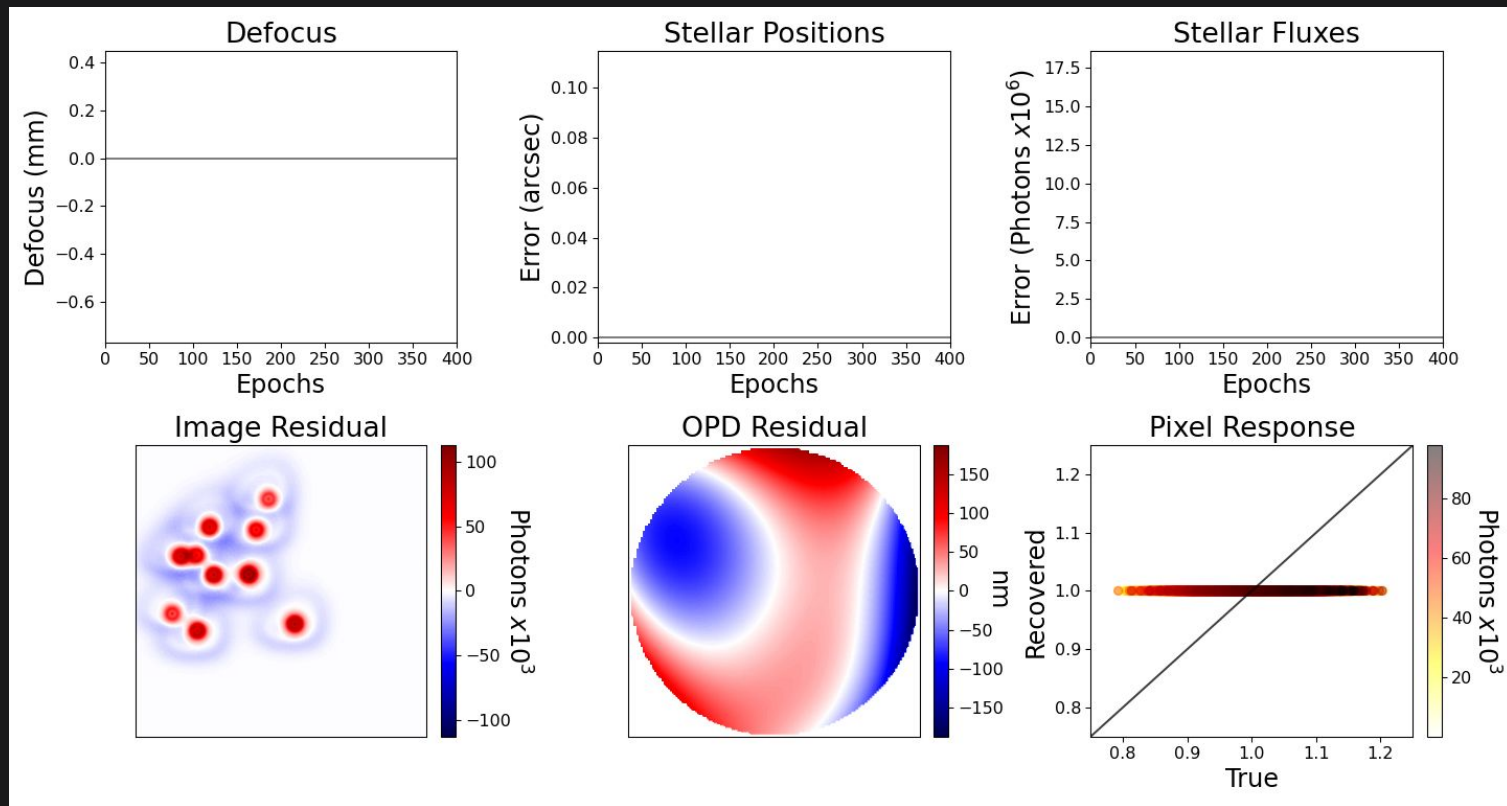


# Residuals (single image)

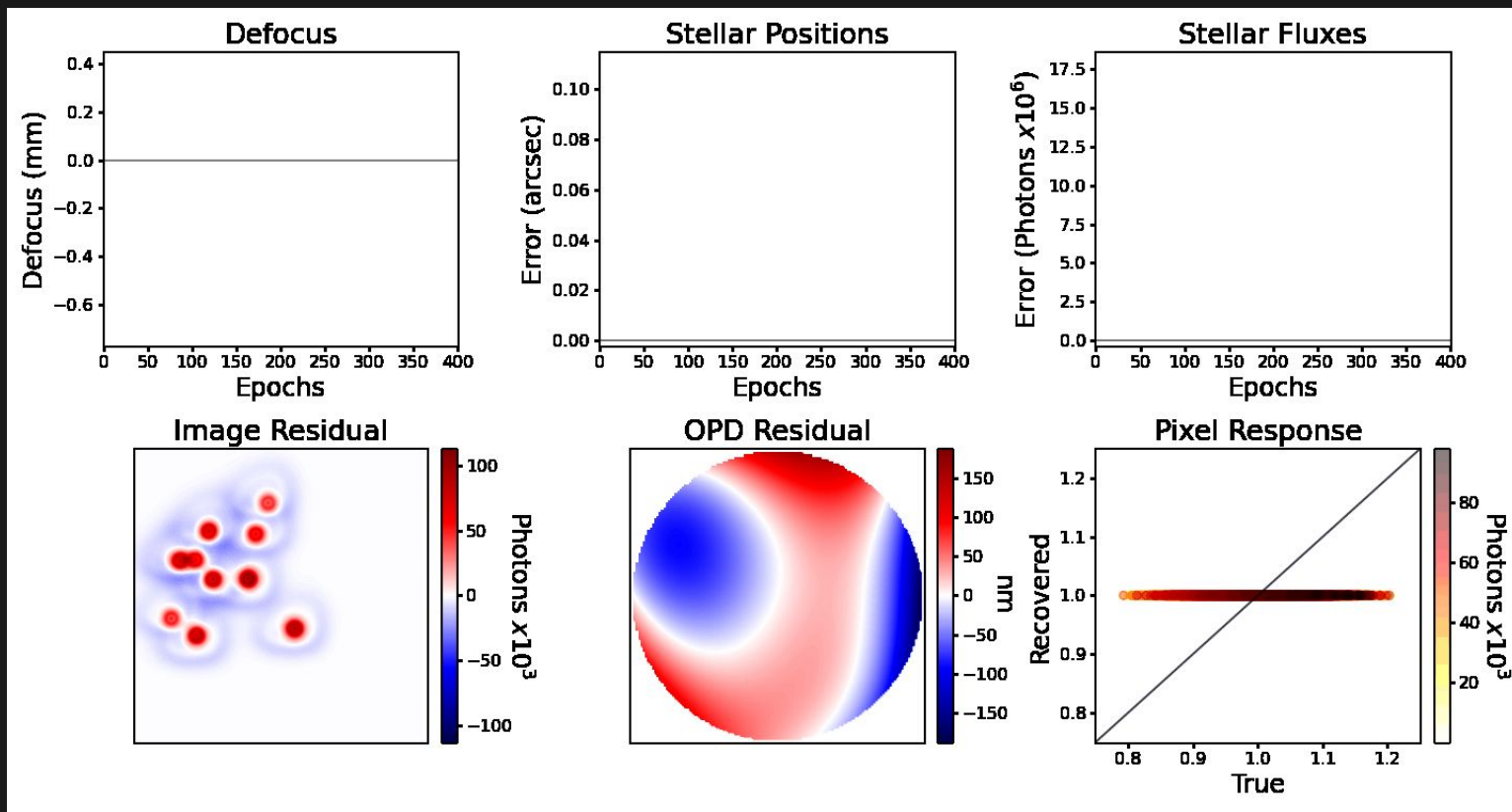
Epoch: 0



# Parameter Recovery



# Parameter Recovery





# Optical Design & Analysis

# Diffraction Pupil Design

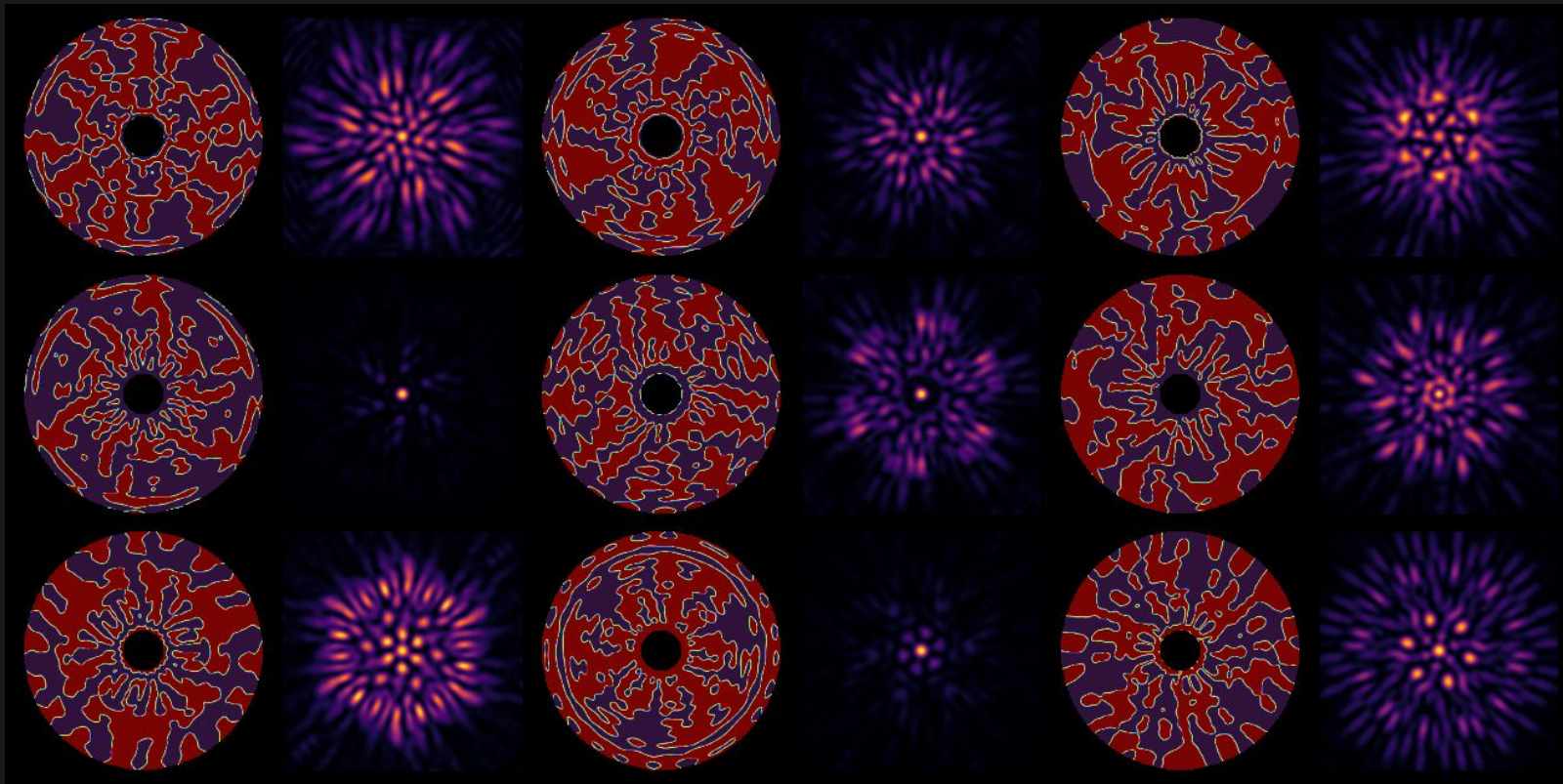
Toliman Design Goals:

- Spread PSF into dense peaks of similar amplitude
- Overlap PSFs of at  $\sim 10$  arcseconds
- Maximise positional registration of a single PSF
- Maximally constrain state of telescope

-> Maximise the PSF gradient energy!

# Diffractive Pupil Design

ALUX

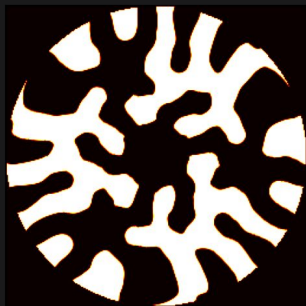




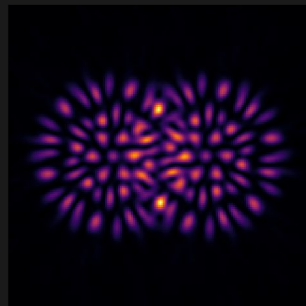
# Posterior Analysis

aLUX

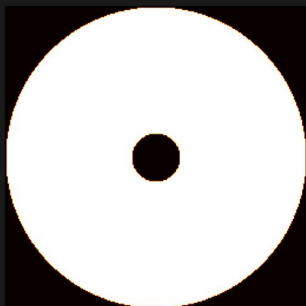
$\partial$ Lux-optimised Pupil



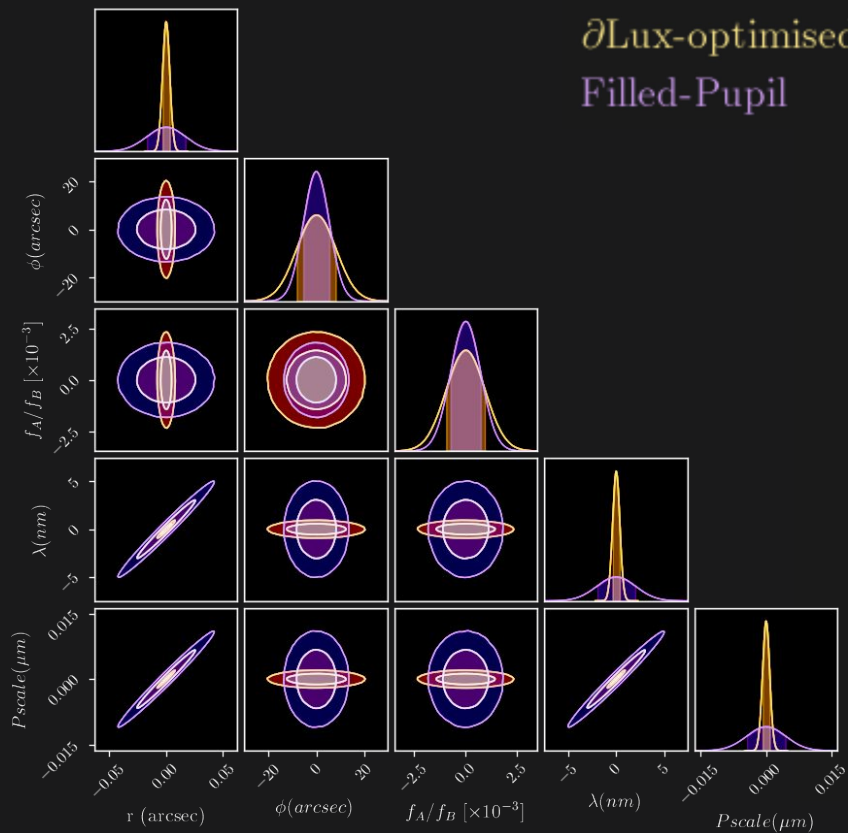
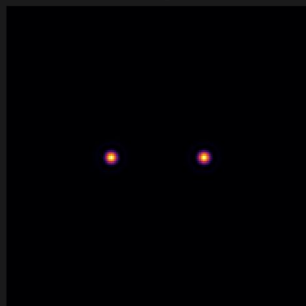
$\partial$ Lux-optimised PSF



Filled-Pupil



Filled-Pupil PSF

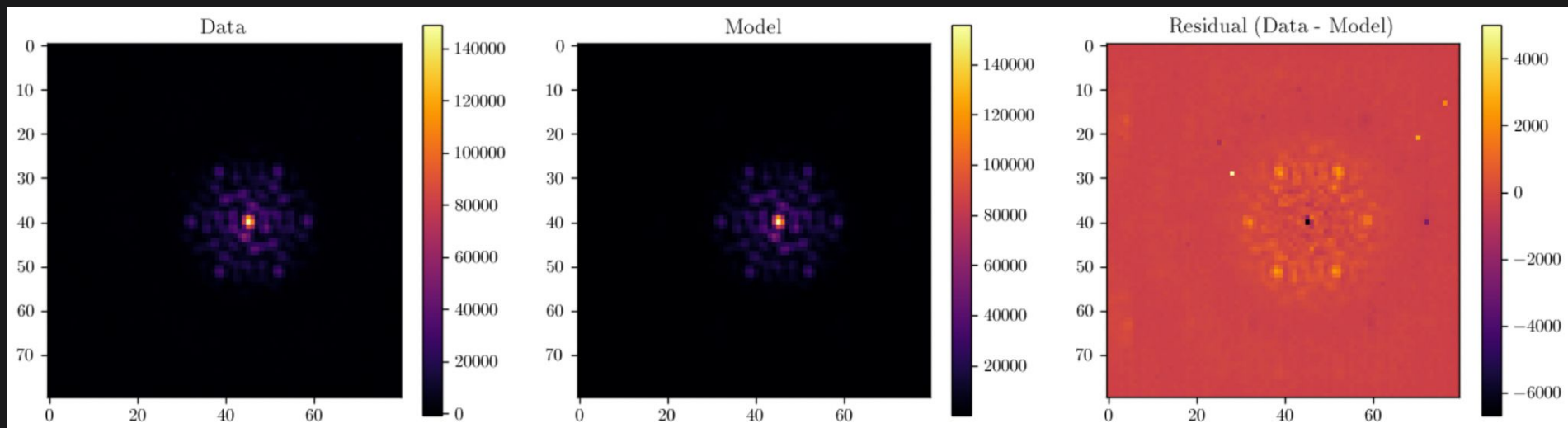




# Preliminary JWST Fitting

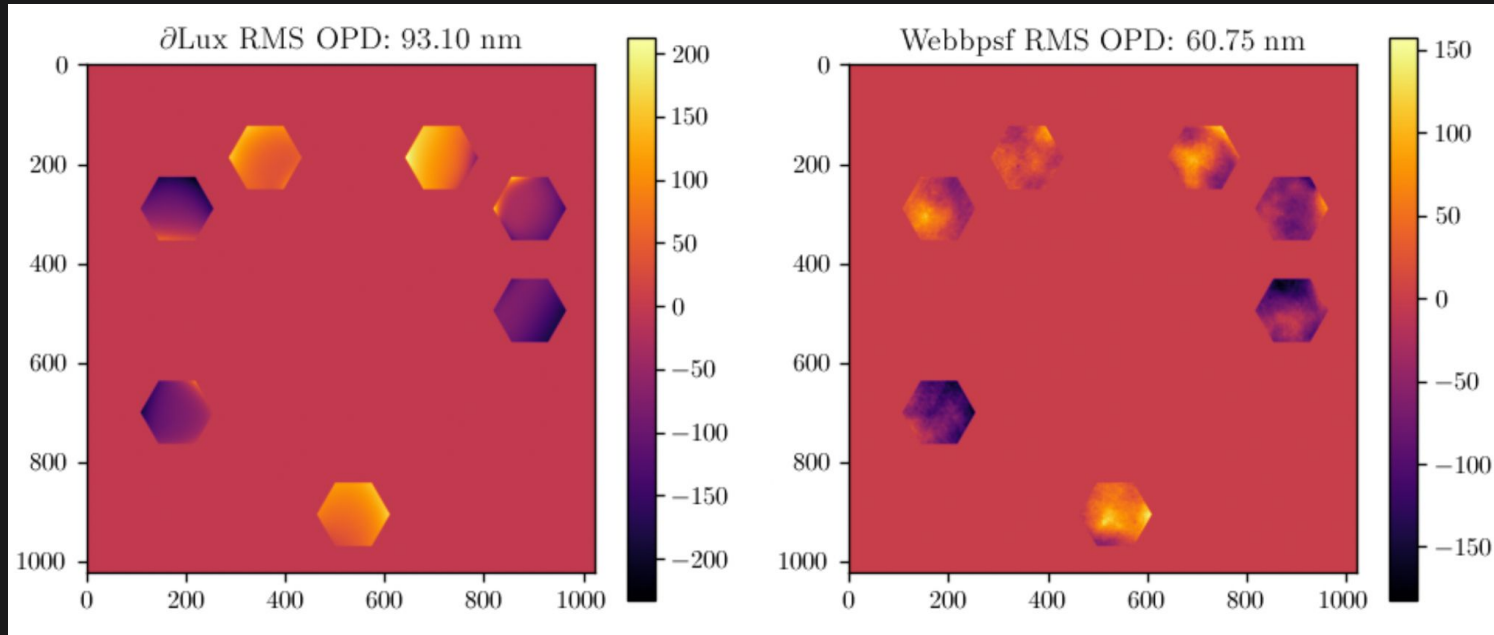
# Preliminary JWST Fitting

## PSF Residuals



# Preliminary JWST Fitting

## Phase retrieval



# Questions

## Contributors:

- Louis Desdoigts
- Jordan Dennis
- Benjamin Pope
- Peter Tuthill



## Documentation and git:

- 'dLux'
- Documentation: <https://louisesdesdoigts.github.io/dLux/>
- Github: <https://github.com/LouisDesdoigts/dLux>
- Contact: [Louis.Desdoigts@sydney.edu.au](mailto:Louis.Desdoigts@sydney.edu.au)

**As open-source software, we invite all to both use and collaborate on this project!**

# ∂Lux - Optimising a Model

## 1. Define Loss Function:

```
@eqx.filter_jit
@eqx.filter_value_and_grad
def loss_func(model, data):
    psfs = model[0]()
    return np.mean((psfs - data)**2)
```

## 2. Set Learning Rates:

```
optim = optax.multi_transform(
    {"null":      optax.adam(0.0),
     "positions": optax.adam(2.5e-8),
     "fluxes":    optax.adam(2.5e6),
     "prop_dist": optax.adam(5e-5),
     "coeffs":    optax.adam(5e-9),
     "FF":        optax.adam(FF_sched)},
    param_spec)
```

## 3. Optimise!

```
for i in tqdm(range(250)):
    loss, grads = loss_func(model_out, data)
    updates, opt_state = optim.update(grads, opt_state)
    model_out = eqx.apply_updates(model_out, updates)
```