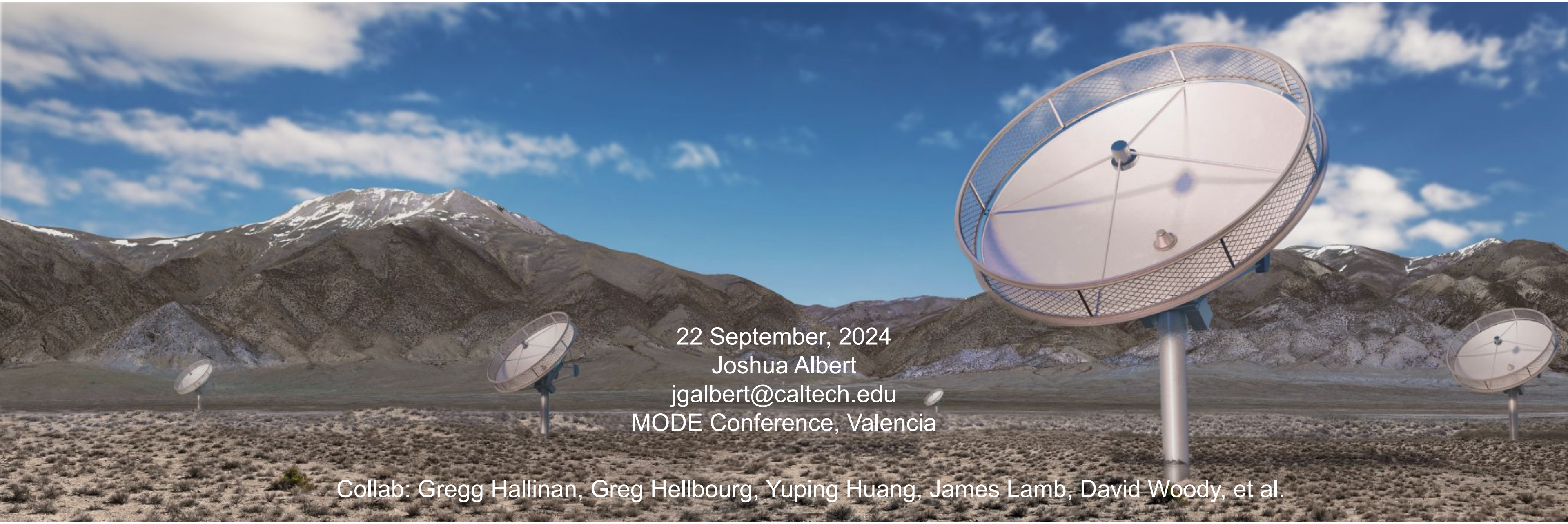
Optimising the DSA-2000



22 September, 2024

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MODE Conference, Valencia

Collab: Gregg Hallinan, Greg Hellbourg, Yuping Huang, James Lamb, David Woody, et al.

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Schmidt Sciences

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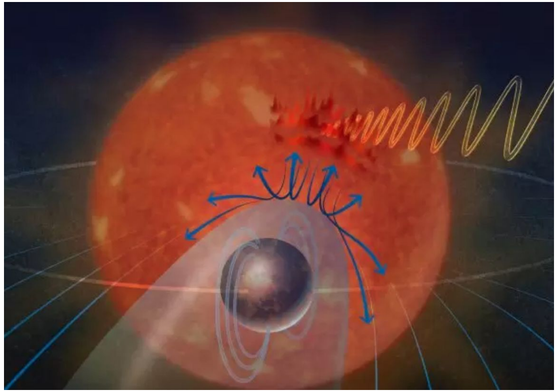
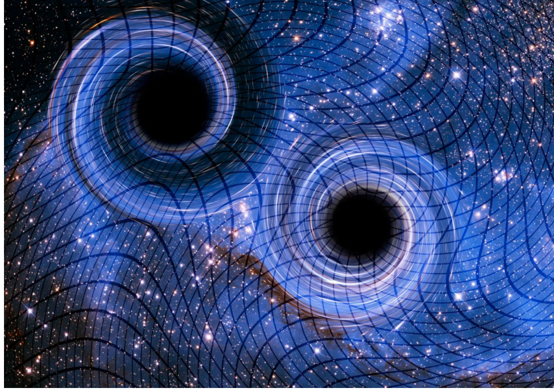
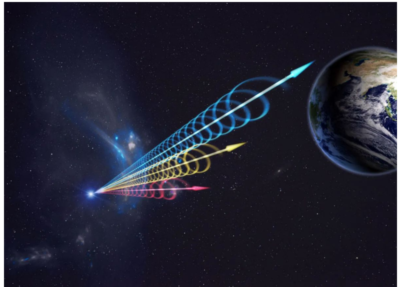
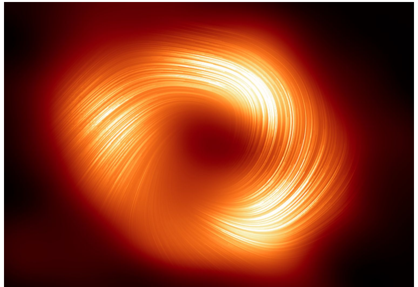




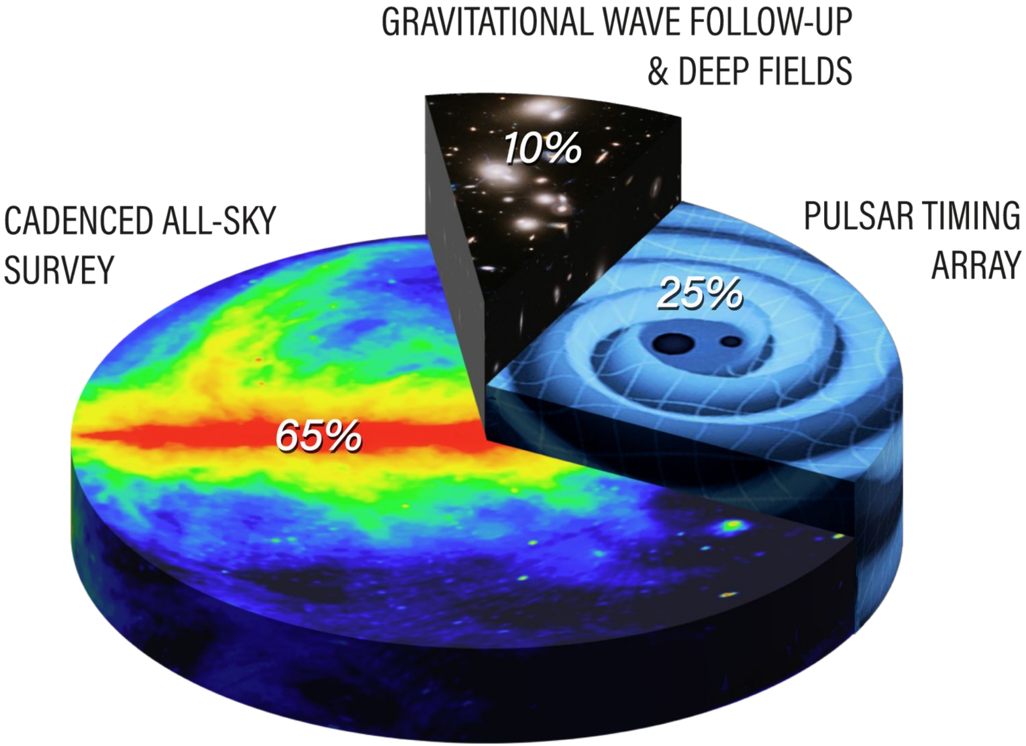
In this talk

1. Why forward modelling is key in achieving science outcomes for big experiments
2. Three examples of how it’s being used for DSA-2000

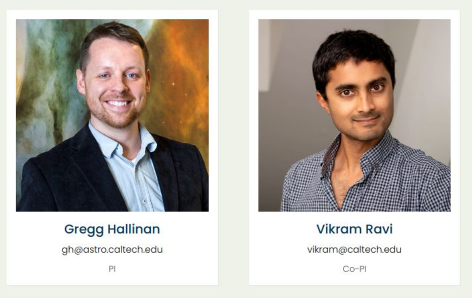


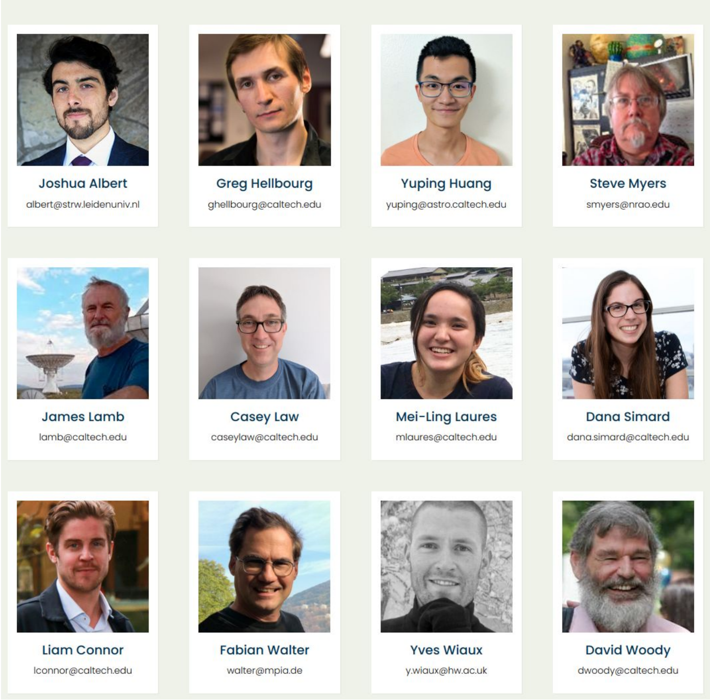


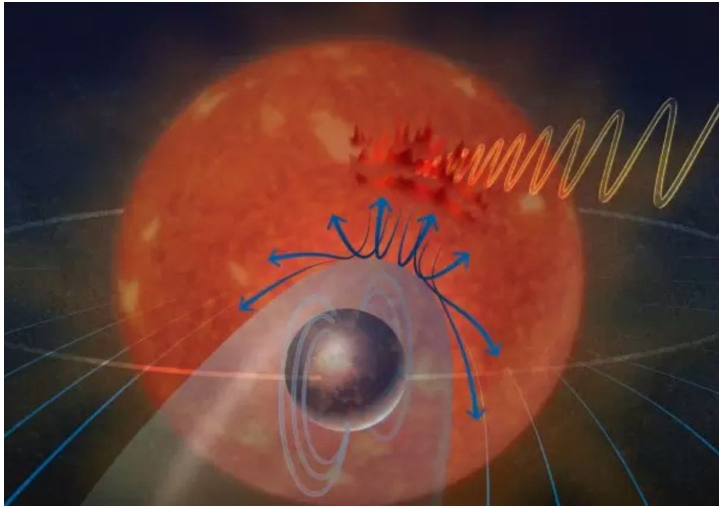
DSA-2000 Science and Team

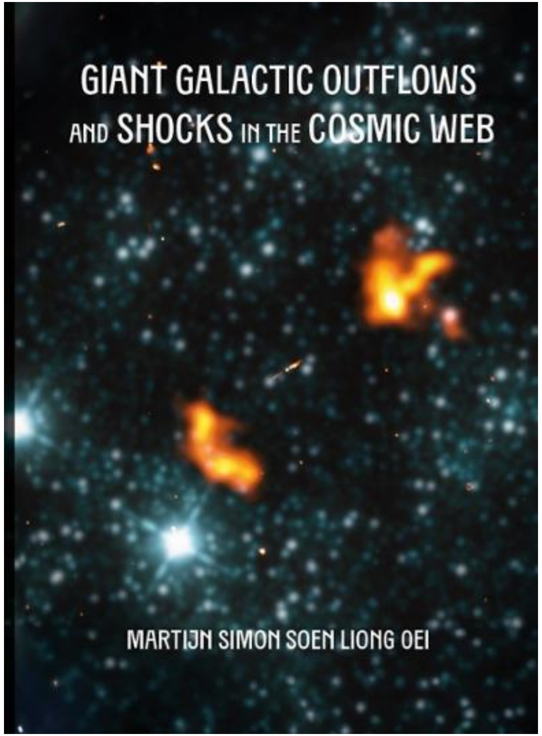


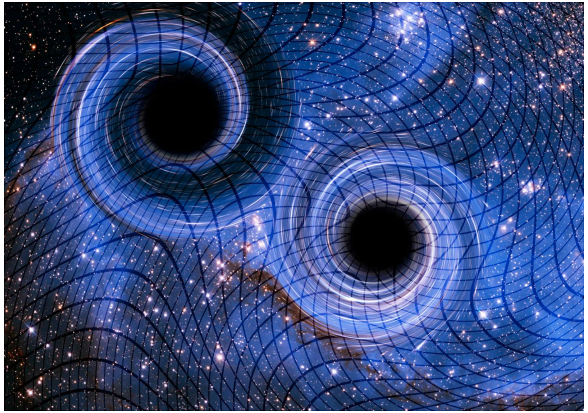
> 100x known sources, and a novel gravitational wave observatory!

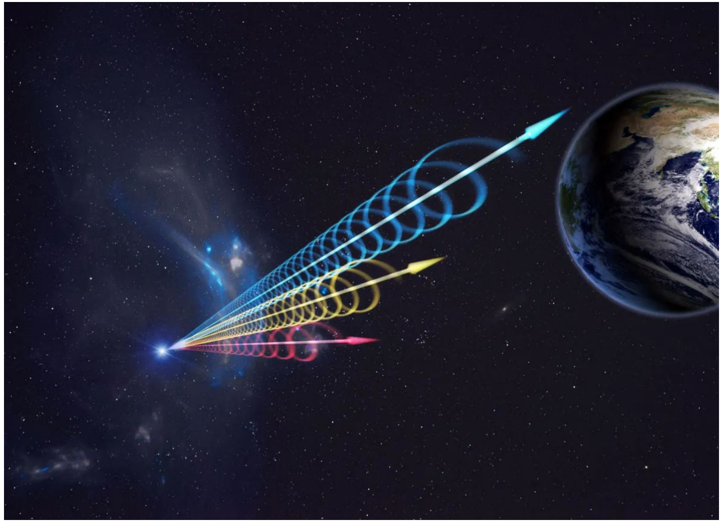


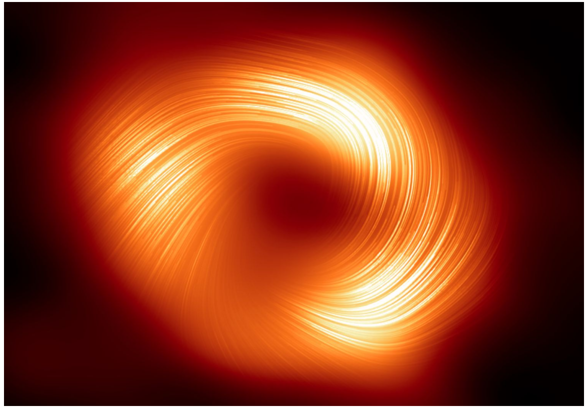




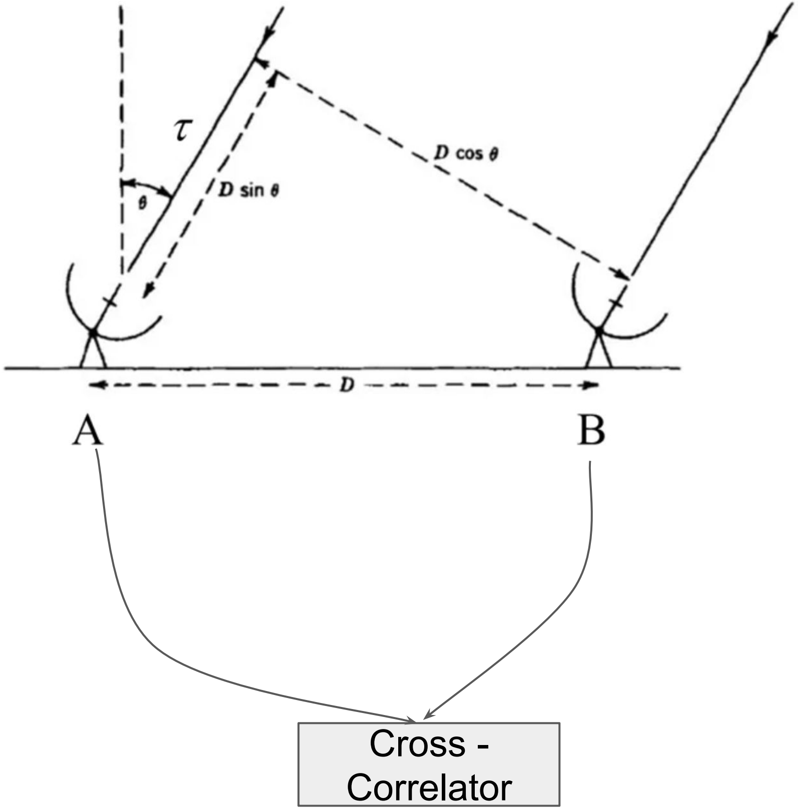

GIANT GALACTIC OUTFLOWS
AND SHOCKS IN THE COSMIC WEB
MARTIJN SIMON SOEN LIONG OEI

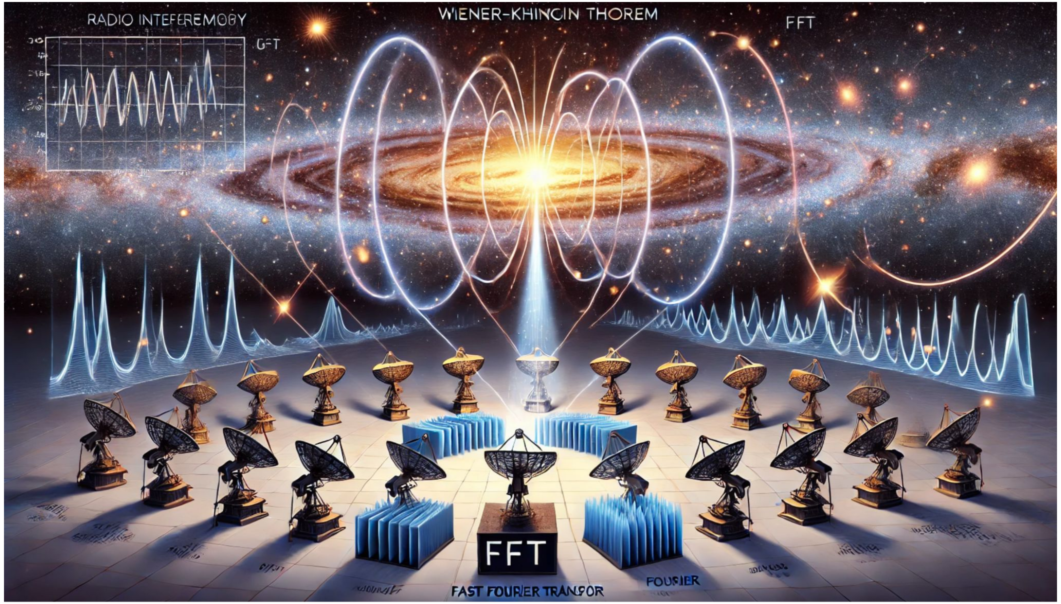






What is radio interferometry? Some basics…

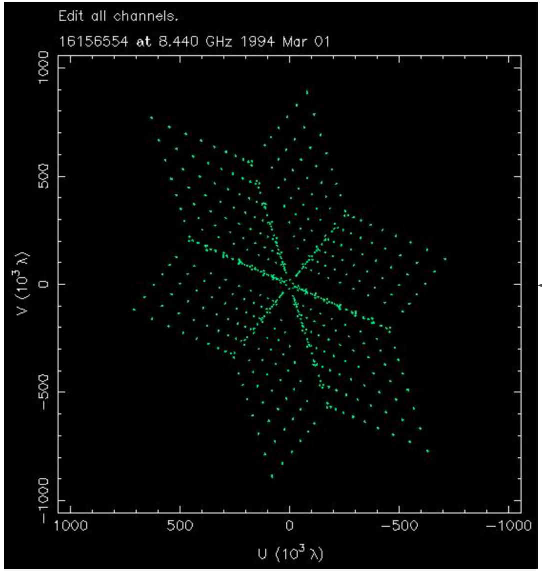




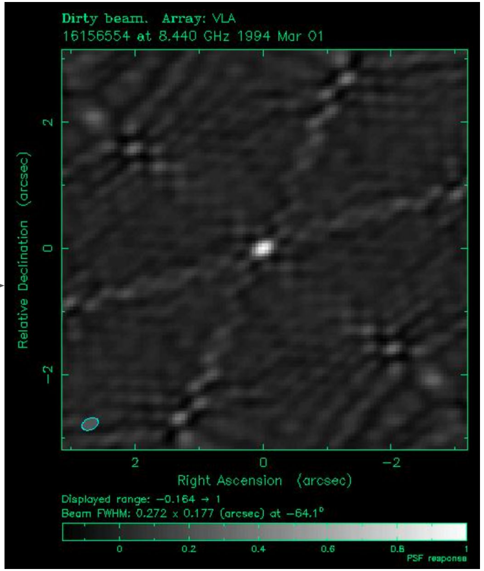
Wiener-Khinchin theorem states:
Sky Brightness = FFT(Electric field coherence)

Traditional radio imaging problem

Sampled aperture leads to complex **Point Spread Function (PSF)** that necessitates some form of inference

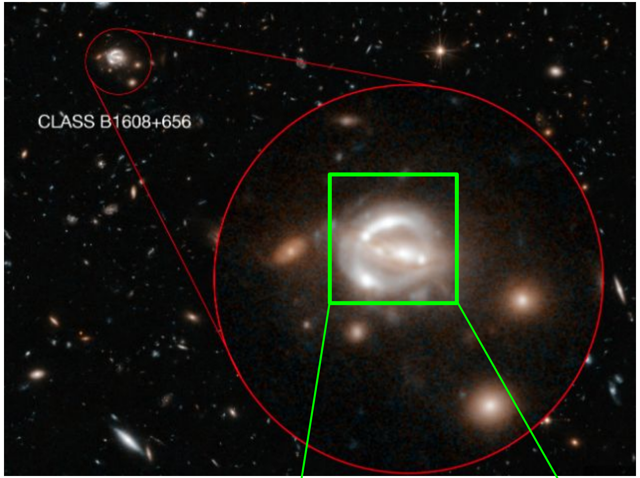


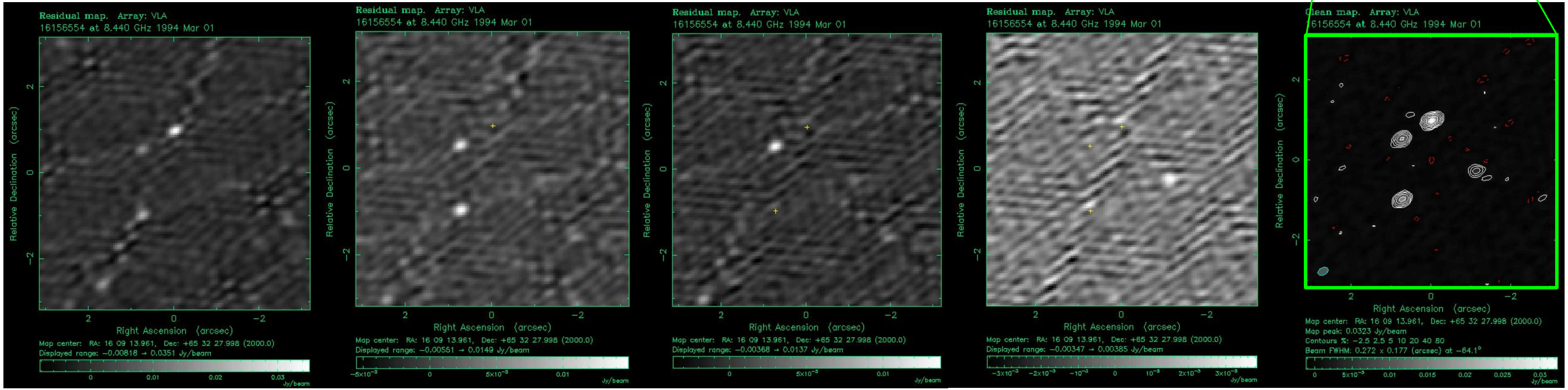
FFT



Traditional radio imaging problem

Classic iterative solution can takes days/weeks to analyse a single modern large dataset!





Traditional radio imaging problem

As the number of antennas (N) grows, we get better images but longer processing times and more data volume.

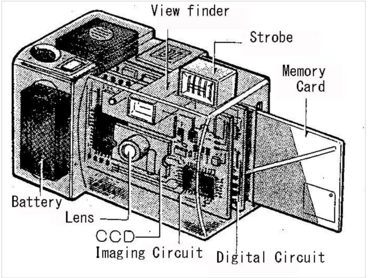
Traditionally (small N)	**Radio Camera (large N)**
Data volume $\propto N^2$	$\Rightarrow$ **Data volume $\propto N^2$**
Thermal Noise $\propto N^{-1}$	$\Rightarrow$ **Thermal Noise $\propto N^{-1}$**
Survey Speed $\propto N^2$	$\Rightarrow$ **Survey Speed $\propto N^2$**
Dynamic Range $\propto N$	$\Rightarrow$ **Dynamic Range $\propto N$**
Processing $\propto N^2\log(N)$	$\Rightarrow$ **Processing $\propto N^2\log(N)$**

The Challenge

To go where no one has gone before.

Schmidt Sciences

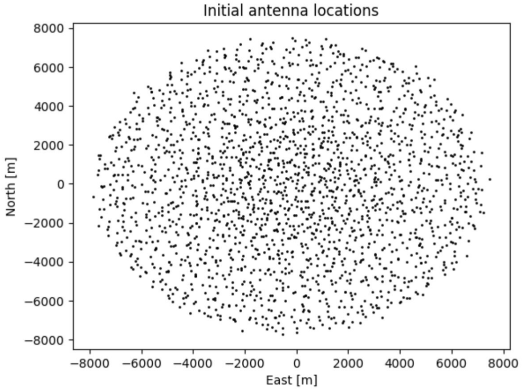
DSA-2000 the first point-and-shoot radio camera: revolutionising radio astronomy



Caltech OVRO NANOGrav

What makes a radio camera?

1. **Large N** fills in the aperture, “approaching a CCD”
2. **Real-time** capability, “don’t need to wait for imaging”



Radio Camera (large N)

⇒ **Data volume $\propto N^2$**

⇒ **Thermal Noise $\propto N^{-1}$**

⇒ **Survey Speed $\propto N^2$**

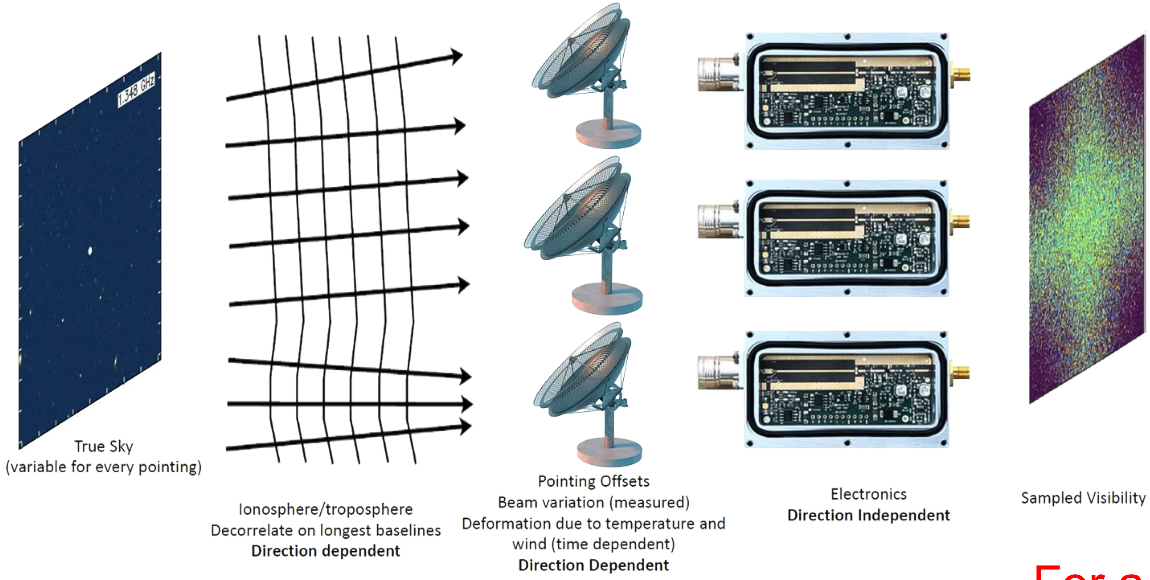
⇒ **Dynamic Range $\propto N$**

⇒ **Processing $\propto N^2 \log(N)$**

The Challenge

To make a streaming radio interferometer with thousands of antennas.

What is forward modelling?



Enables

Validating requirements

Design optimisation

Generating infinite datasets

For a 10.3min observation

Signal Simulation → Instrument Simulation → Data Simulation → Calibration → Imaging

~1GB | 12.6 PB | 200 TB | 800 TB | 16.7 GB

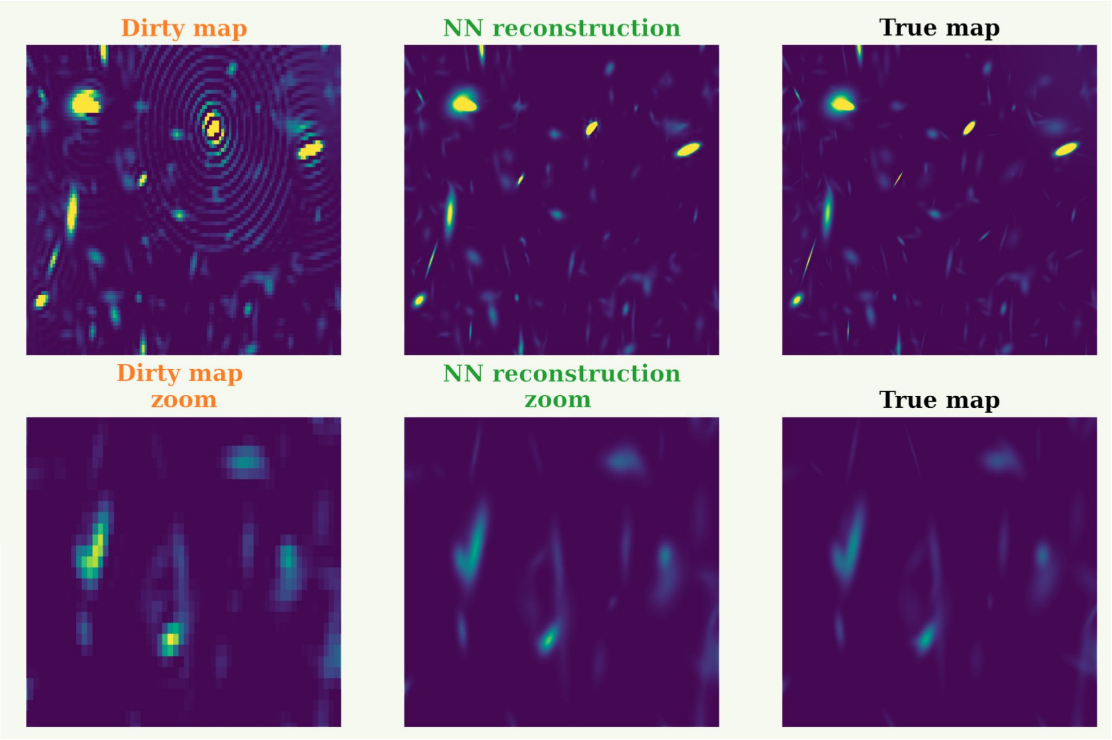
Generative data useful for surrogate ML components

With infinite datasets and realistic systematics you can explore ML surrogates.

E.g. deconvolving the PSF with CNNs.

(POLISH; Connor et al. 2021)

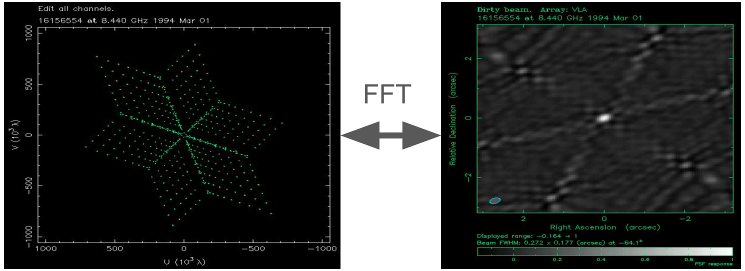

Liam Connor

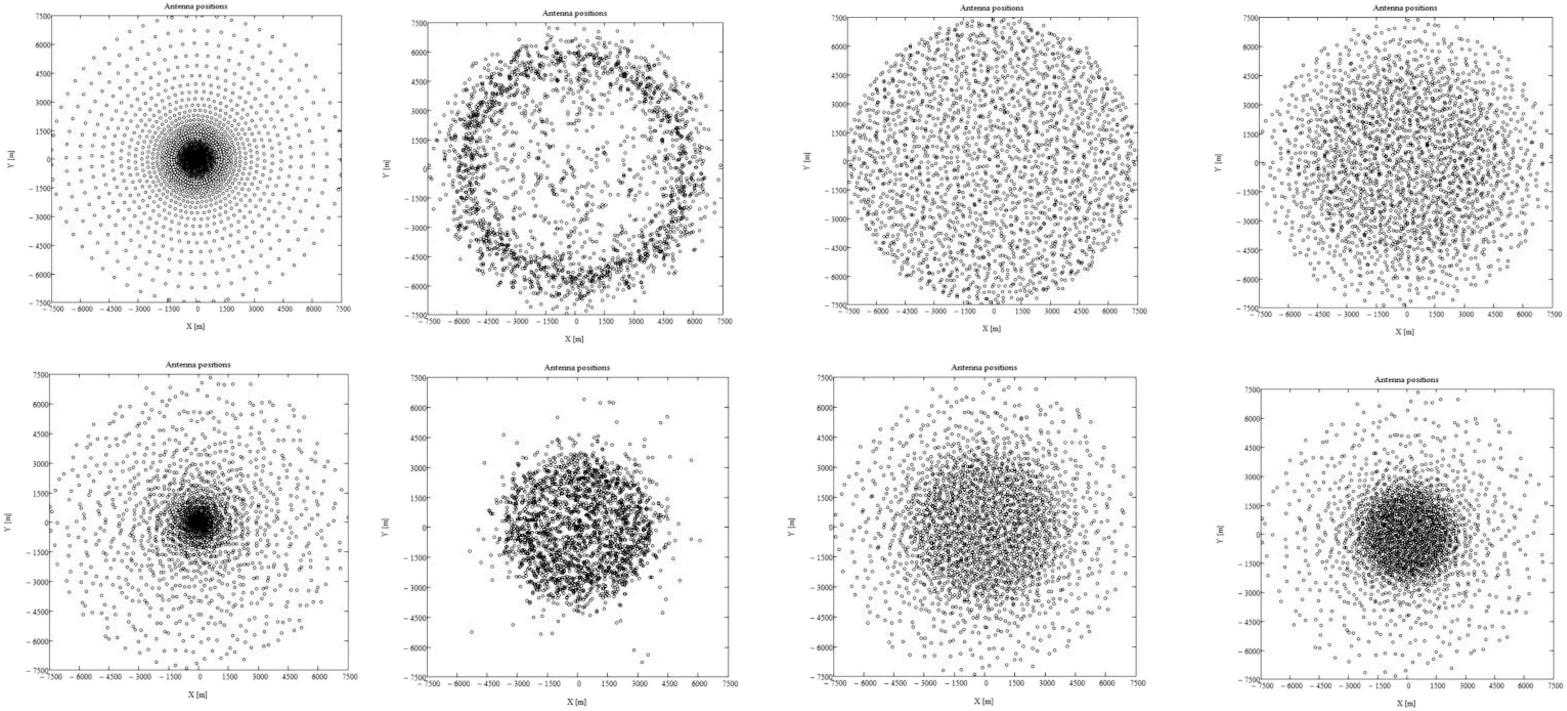


Three examples of optimising DSA-2000

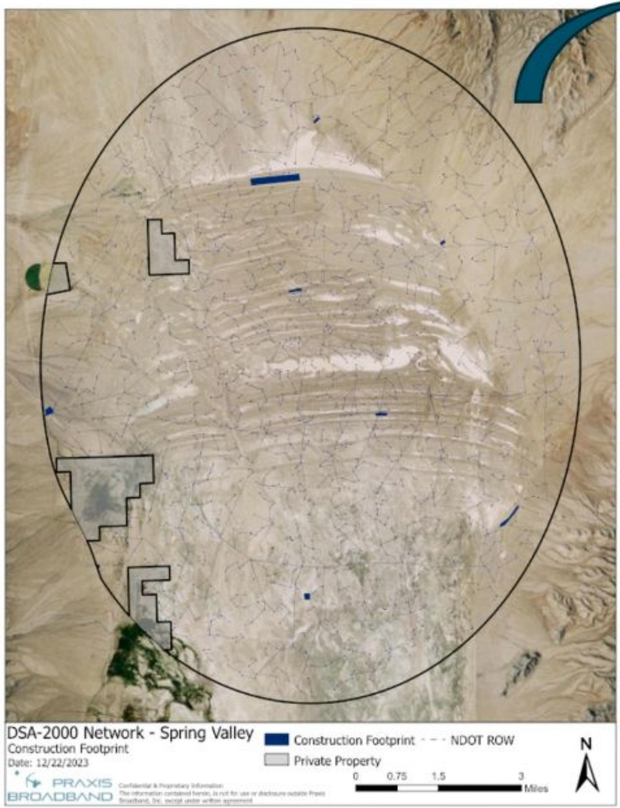
1. Array layout, subject to land allotment constraints.
2. Dish design, subject to manufacturing constraints.
3. Calibration hyper-parameters, subject to real-time.

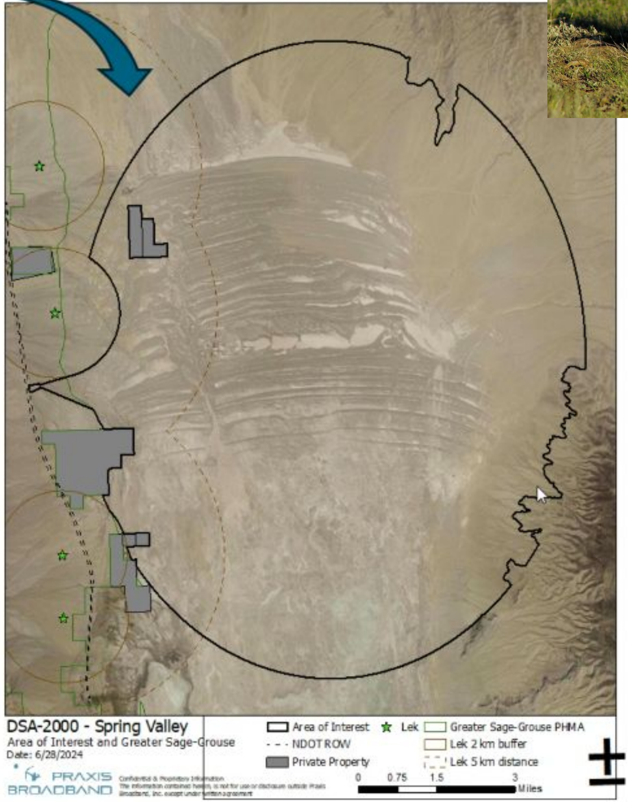
Optimising array layout





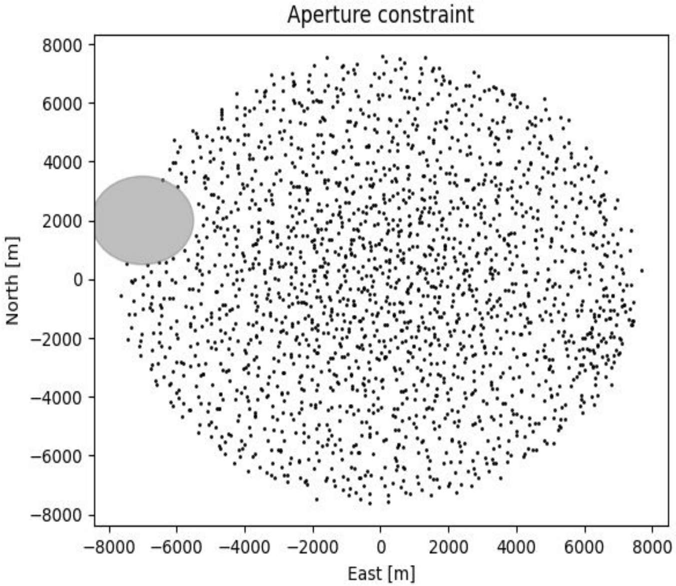
Choosing a site can be a challenge…

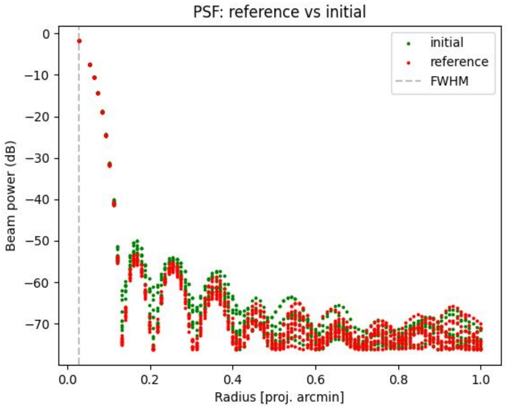


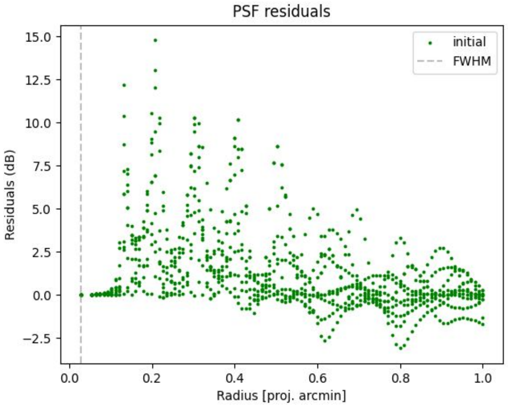


Optimisation objective is reference PSF

Science requirements have already be verified with reference PSF





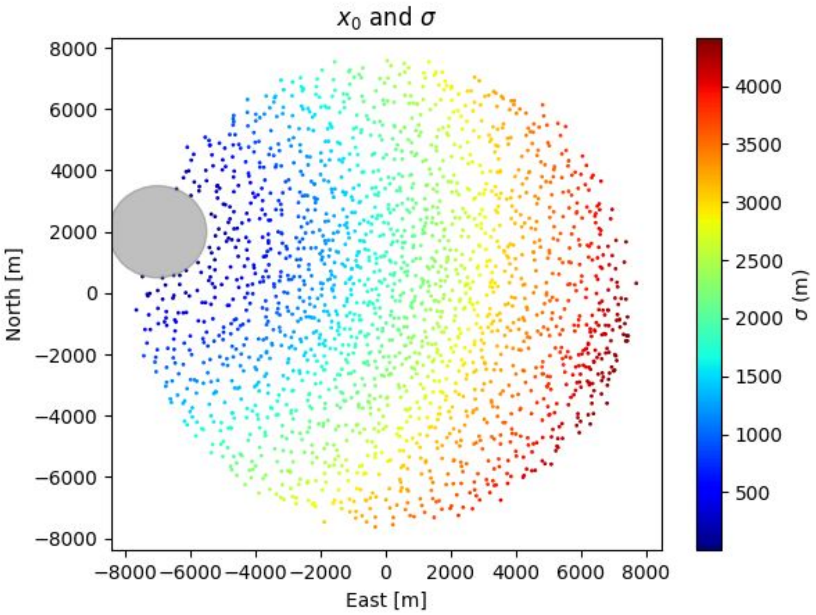


Defining problem with probabilistic programming

Formulate as a maximum likelihood problem.

Constraints defined via setting per-antenna $\mathbf{x}_0$ and σ

$$\begin{aligned}
\mathbf{x} &\sim \mathcal{N}[\mathbf{x}_0, \sigma^2 \mathbf{I}] \\
\mathbf{y} &= f_{\mathrm{PSF}}(\mathbf{x}) \\
p(\mathbf{y} \mid \mathbf{x}) &= \mathcal{N}[f_{\mathrm{PFS}}(\mathbf{x}_{\mathrm{ref}}), \epsilon^2 \mathbf{I}]
\end{aligned}$$



Implement probabilistic program with JAXNS

Formulate as a maximum a-posteriori problem.

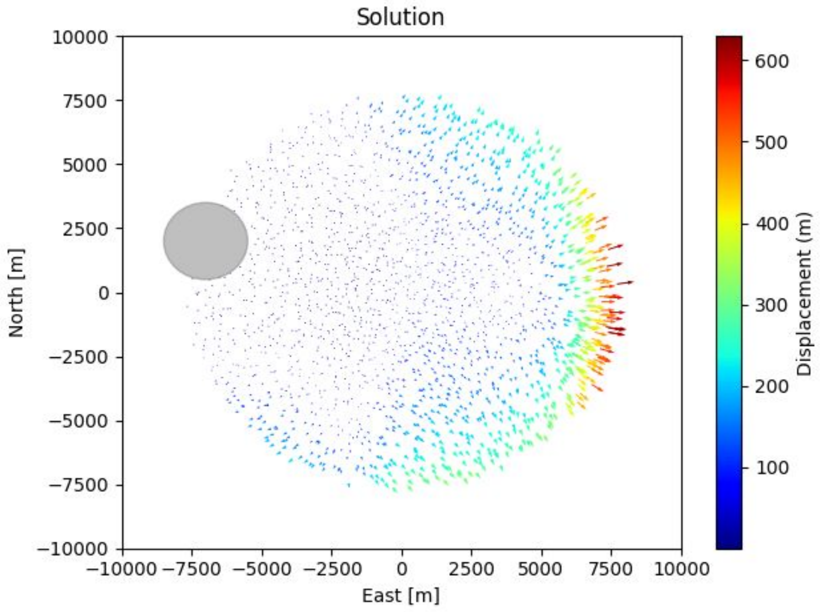
Constraints defined via setting per-antenna $\mathbf{x}_0$ and σ

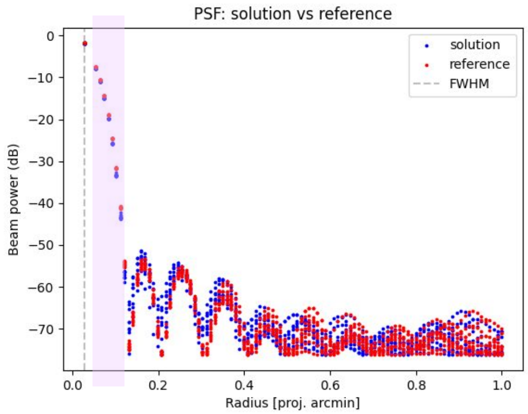
$$
\begin{aligned}
\mathbf{x} &\sim \mathcal{N}[\mathbf{x}_0, \sigma^2 \mathbf{I}] \\
\mathbf{y} &= f_{\mathrm{PSF}}(\mathbf{x}) \\
p(\mathbf{y} \mid \mathbf{x}) &= \mathcal{N}[f_{\mathrm{PFS}}(\mathbf{x}_{\mathrm{ref}}), \epsilon^2 \mathbf{I}]
\end{aligned}
$$

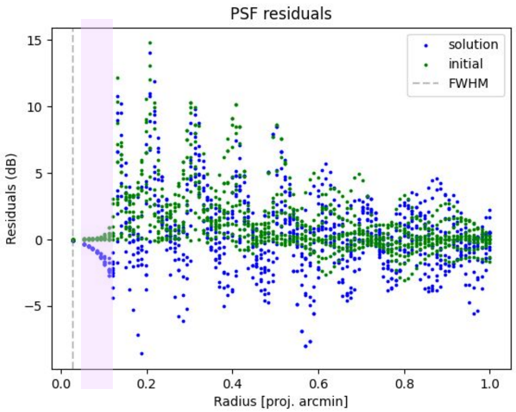
```python
from jaxns import Model, Prior
from jax.scipy import optimize
import tensorflow_probability.substrates.jax  as tfp

tfpd = tfp.distributions
x0 = ... # [n, 2]
sigma = ... # [n, 2]
ref_psf = ... # [m]

def prior_model():
    x = yield Prior(tfpd.Normal(x0, sigma),
                    'x').parametrised()
    y = compute_psf(x)
    return y

def log_likelihood(y):
    return tfpd.Normal(ref_psf, epsilon).log_prob(y)

model = Model(prior_model, log_likelihood)
result = optimize.minimize(
    lambda params: -model(params).log_prob_joint(),
    x0=model.params,
    method='BFGS'
)
print(result.x)
```

Optimised PSF vs Reference PSF

We are able to maintain the FWHM, while also decreasing sidelobes.





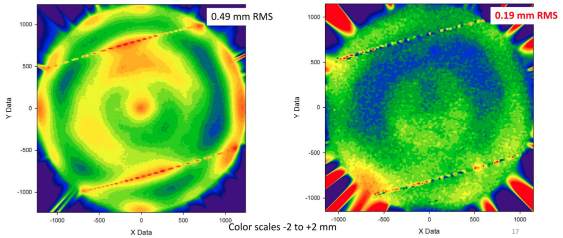


A similar application: Optimising dish manufacturing

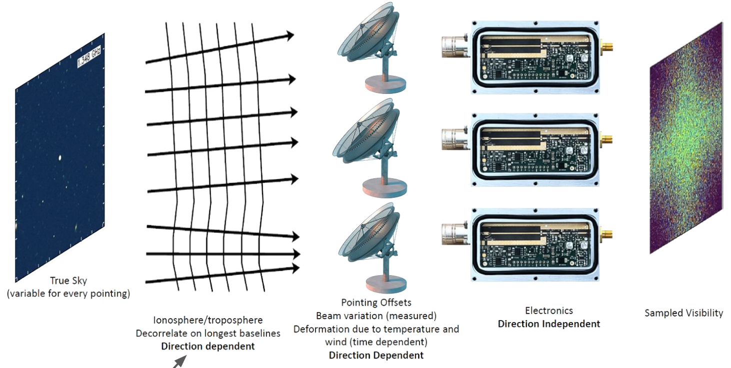
Systematics:

- Pointing errors
- Feed offsets
- Elevation-dependent gravitational deformations
- Surface RMS

Each has an impact on the signal path.



Optimising Calibration



Calibration involves fixed point solvers

$$\mathbf{g}^{n+1} = F(\mathbf{g}^{n}; \theta)$$

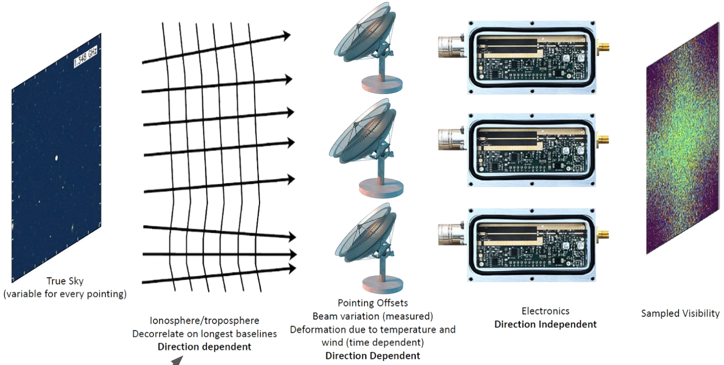
However, there are many parameters θ that affect performance.

1. Number of *approximate* vs *exact* steps
2. Damping parameters
3. Improvement threshold parameters
4. Metric p-norm

Adaptive Multi-step Levenberg-Marquardt (Fan et al. 2019) has **11 total parameters** that define the algorithm.

Question: Can we choose θ *to solve in real-time?*

Optimising Calibration



Question: Can we choose θ to solve in real-time?

$$\mathbf{g}^{n+1} = F(\mathbf{g}^n; \theta)$$

Options:

1. Implicit differentiation
2. Gradient-free optimisation

$$G(\mathbf{g};\theta) = F(\mathbf{g};\theta) - \mathbf{g} \quad (G(\mathbf{g}_*) = \mathbf{0})$$

$$\mathrm{JVP}_G(\mathbf{v};\mathbf{g}_*) = \nabla_\theta G(\mathbf{g}_*)\cdot\mathbf{v} \quad (\text{Implicit diff})$$

$$\delta > \mathbb{E}\left[||F(\mathbf{g}^n;\theta) - \mathbf{g}_*||\right] \quad \text{for small } n$$

Optimising Calibration: gradient-free global optimisation (JAXNS)

Reformulate as MAP problem

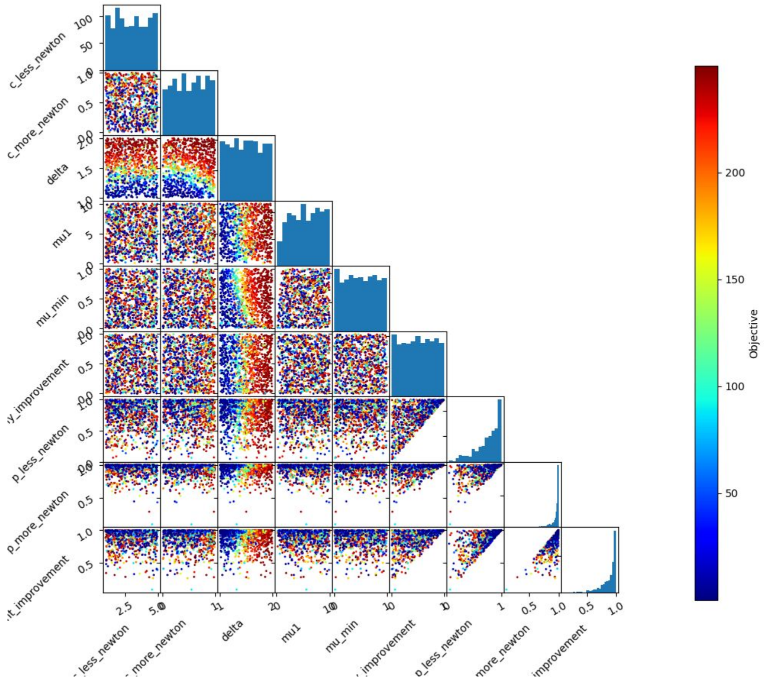
$$\mathbf{g}_* = \arg\max_{\mathbf{g}} p(\mathbf{y} \mid \mathbf{g}) p(\mathbf{g})$$

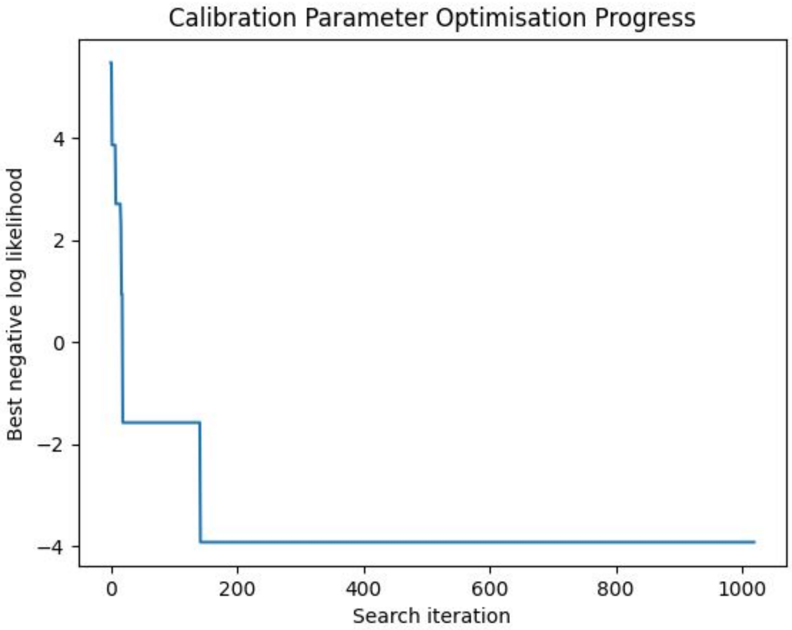
Use generative data and JAXNS for global optimisation,

$$\delta > \mathbb{E}\left[|| F(\mathbf{g}^{n}; \theta) - \mathbf{g}_* || \right] \quad \text{for small } n$$

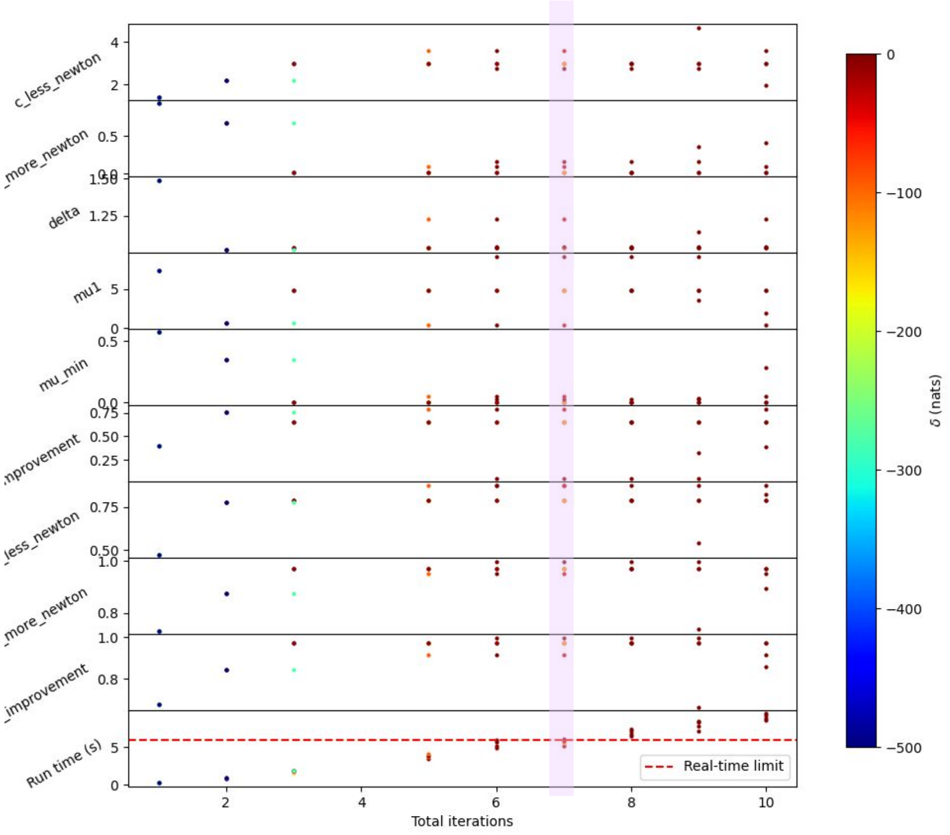
```python
from jaxns.experimental import (
    GlobalOptimisation,
    TerminationCondition
)

def prior_model() -> CalibrationParams:
    ...

def log_likelihood(params: CalibrationParams):
    ...

model = Model(
    prior_model=prior_model,
    log_likelihood=log_likelihood
)

go = GlobalOptimisation(model)
term_cond = TerminationCondition(
    max_likelihood_evaluations=1024
)
results = go.run(jax.random.PRNGKey(42), term_cond)
```

Optimising Calibration: global optimisation using JAXNS





Optimising Calibration: selecting optimal real-time parameters



Optimal **Adaptive Multi-step Levenberg-Marquardt** (Fan et al. 2019) parameters *for this particular dataset*, such that we are real-time.

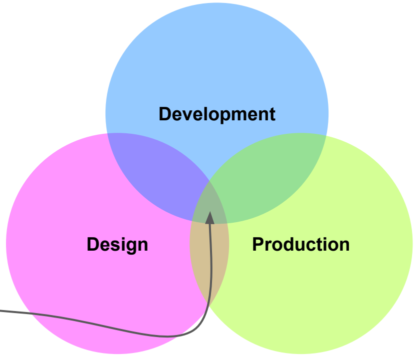
$$
\begin{aligned}
c_{\text{lessNewton}} &= 2.78 \\
c_{\text{moreNewton}} &= 0.16 \\
\delta &= 1.04 \\
\mu_1 &= 9.28 \\
\mu_{\min} &= 0.02 \\
p_0 &= 0.06 \\
p_{\text{lessNewton}} &= 0.88 \\
p_{\text{moreNewton}} = p_{\text{sufficient}} &= 1
\end{aligned}
$$

Summarising the importance of forward modelling

In today's science de-risking science outcomes is crucial to success,

- Science outcomes are de-risked via detailed forward modelling, and design optimisation (enabled by auto-diff etc.).
- The feasibility of analysis can be assessed via realistic generative models.
- High-level frameworks, e.g. JAX, enable a self-consistent platform to merge design, development, *and production.*

That's where you want your team focused.



Thank you