# Learned Exascale Computational Imaging (LEXCI)

## ExCALIBUR Cross-Cutting Research Programme

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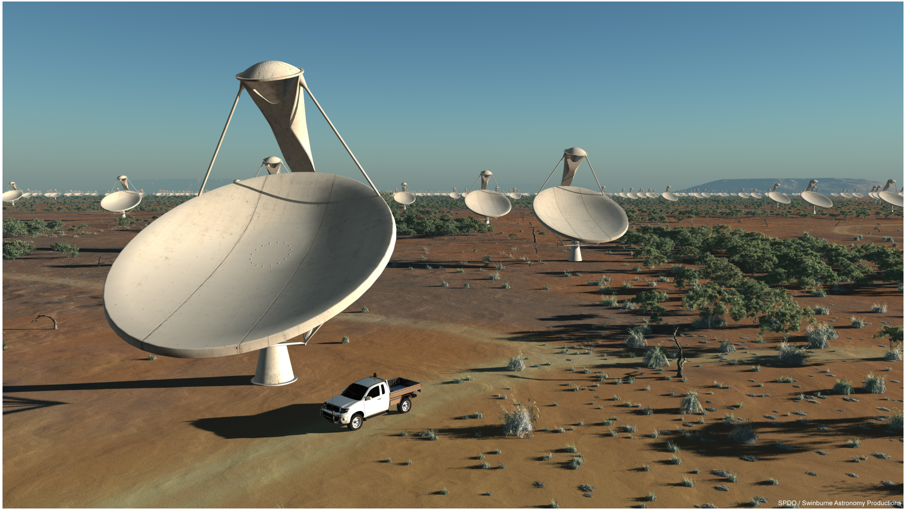
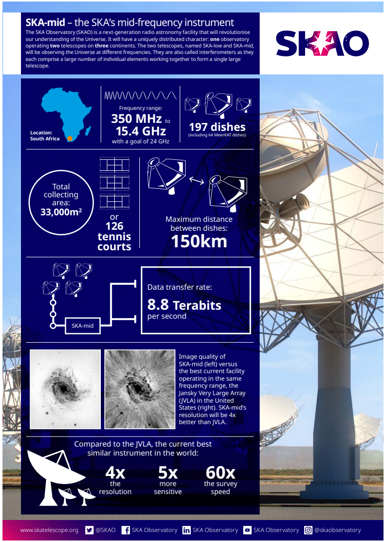
Blueprinting AI for Science At Exascale (BASE-II) Workshop
May 2023

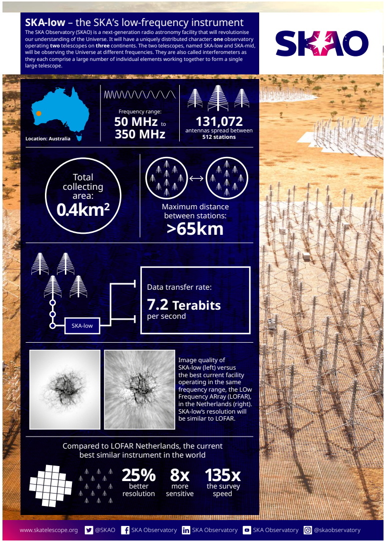
# Canonical application: Square Kilometre Array (SKA)



# SKA sites



SKA-mid – the SKA's mid-frequency instrument
The SKA Observatory (SKAO) is a next-generation radio astronomy facility that will revolutionise our understanding of the Universe. It will have a uniquely distributed character: one observatory operating two telescopes on three continents. The two telescopes, named SKA-low and SKA-mid, will be observing the Universe at different frequencies. They are also called interferometers as they each comprise a large number of individual elements working together to form a single large telescope.
SKAO
Location: South Africa
Frequency range:
350 MHz to 15.4 GHz
with a goal of 24 GHz
197 dishes
(including 64 MeerKAT dishes)
Total collecting area: 33,000m²
or 126 tennis courts
Maximum distance between dishes:
150km
SKA-mid
Data transfer rate:
8.8 Terabits
per second
Image quality of SKA-mid (left) versus the best current facility operating in the same frequency range, the Jansky Very Large Array (JVLA) in the United States (right). SKA-mid's resolution will be 4x better than JVLA.
Compared to the JVLA, the current best similar instrument in the world:
4x the resolution
5x more sensitive
60x the survey speed
www.skatelescope.org @SKAO SKA Observatory SKA Observatory SKA Observatory @skaobservatory

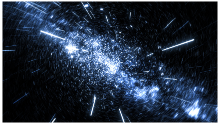



SKA-low – the SKA's low-frequency instrument
The SKA Observatory (SKAO) is a next-generation radio astronomy facility that will revolutionise our understanding of the Universe. It will have a uniquely distributed character: one observatory operating two telescopes on three continents. The two telescopes, named SKA-low and SKA-mid, will be observing the Universe at different frequencies. They are also called interferometers as they each comprise a large number of individual elements working together to form a single large telescope.
SKAO
Location: Australia
Frequency range:
50 MHz to 350 MHz
131,072
antennas spread between 512 stations
Total collecting area:
0.4km²
Maximum distance between stations:
>65km
SKA-low
Data transfer rate:
7.2 Terabits
per second
Image quality of SKA-low (left) versus the best current facility operating in the same frequency range, the LOw Frequency ARray (LOFAR), in the Netherlands (right). SKA-low's resolution will be similar to LOFAR.
Compared to LOFAR Netherlands, the current best similar instrument in the world
25% better resolution
8x more sensitive
135x the survey speed
www.skatelescope.org @SKAO SKA Observatory SKA Observatory SKA Observatory @skaobservatory

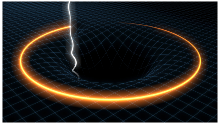
# Next-generation of radio interferometry rapidly approaching

**Next-generation of radio interferometric telescopes** will provide orders of magnitude improvement in sensitivity and resolution.

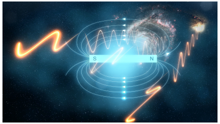
Unlock broad range of science goals.



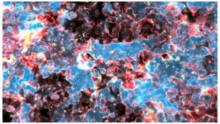
Dark energy



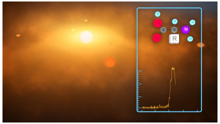
General relativity



Cosmic magnetism



Epoch of reionization

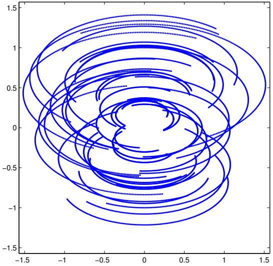


Exoplanets

# Radio interferometric telescopes acquire “Fourier” measurements

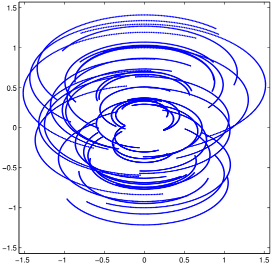
“Fourier” Measurements

$\Rightarrow$



# Radio interferometric telescopes acquire “Fourier” measurements

“Fourier”
Measurements
$\Rightarrow$



Interferometric imaging is an exascale computational inverse imaging problem:

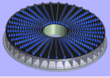
Recover an image from noisy and incomplete “Fourier” measurements.

# LEXCI application domains more broadly

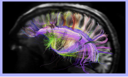
## Learned Exascale Computational Imaging (LEXCI)

**Radio Interferometry**
*e.g.* MWA, SKA

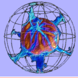
**Optical Interferometry**
*e.g.* SPIDER



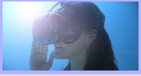
**Medical Imaging**
*e.g.* Diffusion MRI



**Seismic Imaging**
*e.g.* Mantle Plumes



**Computer Graphics**
*e.g.* Inverse Rendering



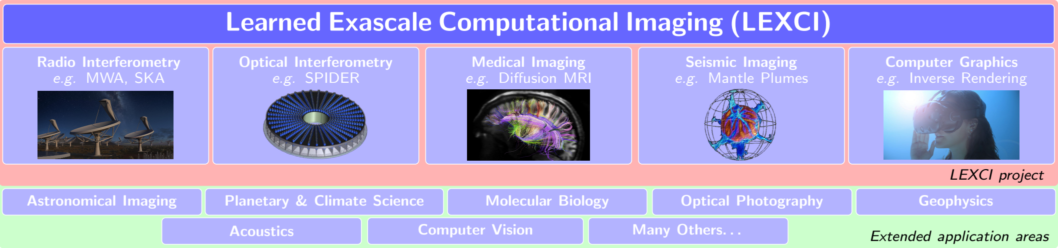
*LEXCI project*

**Astronomical Imaging** | **Planetary & Climate Science** | **Molecular Biology** | **Optical Photography** | **Geophysics**

**Acoustics** | **Computer Vision** | **Many Others...**

*Extended application areas*

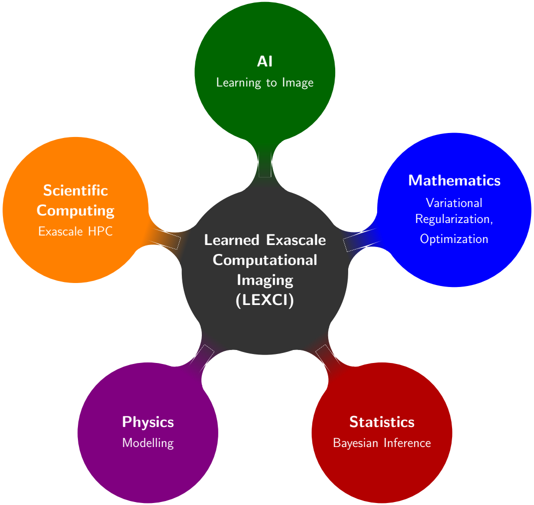
# LEXCI application domains more broadly




## Partners

- Radio interferometry: Prof. Melanie Johnston-Hollitt (Curtin), Dr Luke Pratley (Toronto)
- SPIDER: Prof. Ben Yoo (UC Davis)
- Medical Imaging: Prof. Gary Zhang (CMIC, UCL)
- Seismic Imaging: Prof. Ana Ferreira (Earth Sciences, UCL)
- Computer Graphics & Virtual Reality: Copernic AI
- (ExCALIBUR Benchmarking for AI for Science at Exascale; BASE-II)

# Cross-cutting research areas

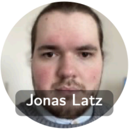


# LEXCI team

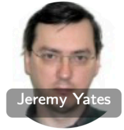

PI
Astrostatistics


Co-I
Mathematics


Co-I
Statistics



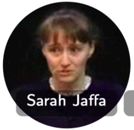

Co-I
Mathematics




Co-I
Scientific
Computing


KE Co-ordinator
Scientific
Computing


RSE
Scientific
Computing




RSE
Scientific
Computing


RSE
Scientific
Computing


MSSL-RA
Astrostatistics


MSSL-PhD
Astrostatistics


CS-RA
Astrostatistics

# Classical approach to computational inverse imaging

Classically, inverse imaging problems solved by **variational regularization**, where an optimization problem is posed that includes data fidelity and regularization terms:

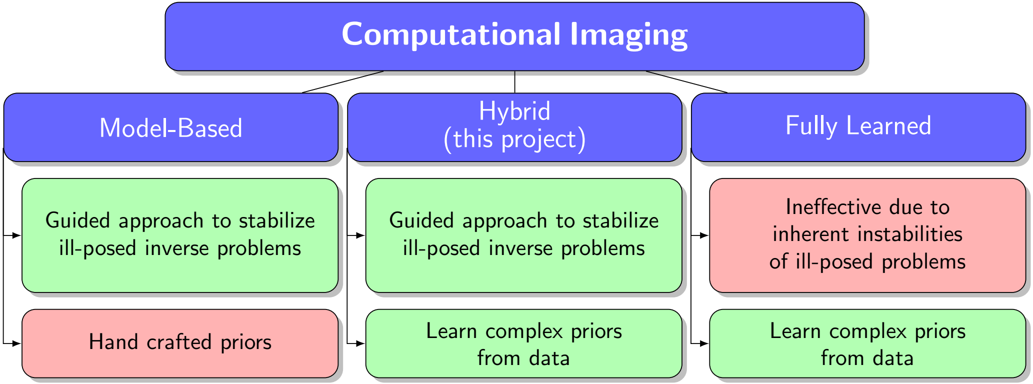
$$\arg\min_{\boldsymbol{x}} \|\boldsymbol{y} - \boldsymbol{\Phi}\boldsymbol{x}\|_2^2 + \lambda f(\boldsymbol{x}).$$

for observational model $\boldsymbol{\Phi} : \mathbb{R}^N \rightarrow \mathbb{R}^M$, data $\boldsymbol{y}$ and underlying image $\boldsymbol{x}$.

**Regularization functional** $f : \mathbb{R}^N \rightarrow \mathbb{R}$ encodes prior knowledge.

Typically **model-based regularizers** are used, *e.g.* $f(\boldsymbol{x}) = \|\boldsymbol{\Psi}^\dagger \boldsymbol{x}\|_1$ to promote sparsity in some dictionary $\boldsymbol{\Psi} : \mathbb{R}^D \rightarrow \mathbb{R}^N$.

# LEXCI hybrid approach

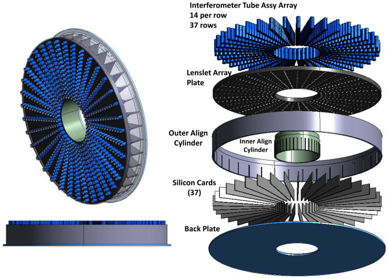


# Computational strategy

- **Hybrid** deep learning (data-driven) and model-based approach.
- **Big data** and **big compute** BUT moderate size learned models.
- Training with full telescope model may **not always possible computationally**.
    - Multiscale telescope models
    - Deep learning models (priors) that are agnostic to telescope model
    - Computational challenge of training and inference sometimes inverted (training $\downarrow$, inference $\uparrow$)
- **Computing paradigms**:
    - Data partitioning algorithms
    - Distributed compute, storage & memory
    - Stochastic distributed algorithms
    - Parallelized & distributed uncertainty quantification

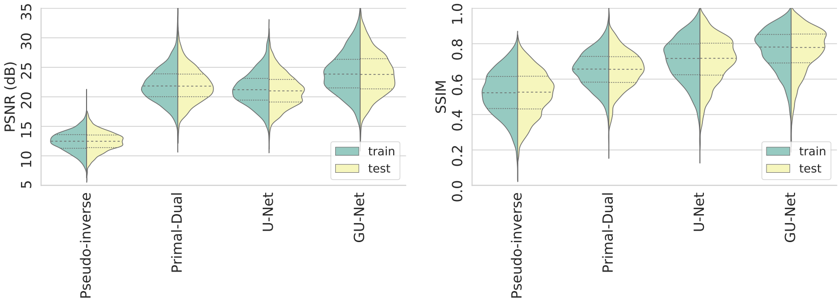
# Initial results: learned SPIDER imaging

- ▷ SPIDER is new interferometric optical imaging device developed by UC Davis and Lockheed Martin.
- ▷ Lenslet array to measure multiple interferometric baselines and photonic integrated circuits (PICs) for miniaturization.
- ▷ Reduces weight, cost and power consumption of optical telescopes.



# Initial results: learned SPIDER imaging

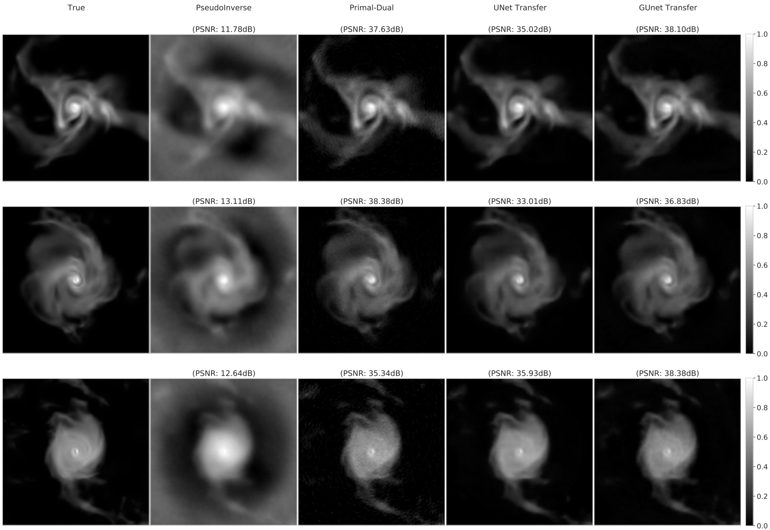
- **Differentiable implementation** of SPIDER measurement operator integrated in architecture of learned model (Mars et al. 2023; arXiv:2301.10260).




Imaging time reduced from $\sim$**1 min** $\rightarrow$ $\sim$**10 ms**

$\Rightarrow$ **Real-time imaging**

# Initial results: learned SPIDER imaging

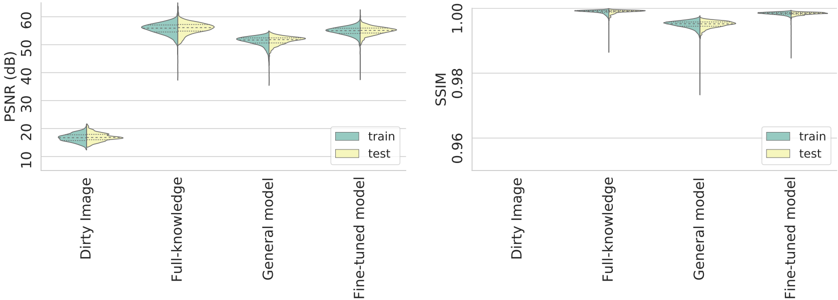


# Initial results: learned radio interferometric imaging

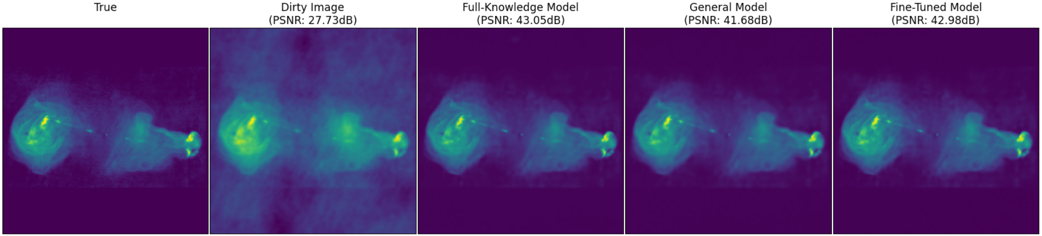
- Telescope measurement **operator changes for each observation**
  (since observing different point on sky, over different duration, with potentially different telescope configuration).
- **Integrate knowledge of measurement operator** form into model architecture (Mars et al., in prep.).

# Initial results: learned radio interferometric imaging

▷ Train on general form of operator and then (potentially) fine-tune.



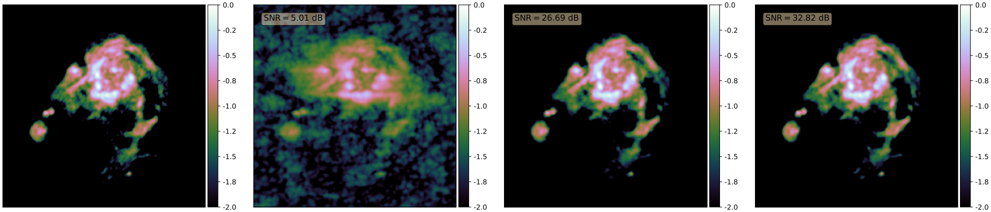
# Initial results: learned radio interferometric imaging




$\Rightarrow$ Reconstruction quality (almost) reaches oracle
(case where train with full knowledge of operator).

# Preliminary results: scalable learned imaging with uncertainty quantification

- ▷ Uncertainty quantification for learned exascale imaging previously not feasible.
- ▷ Exploit learned convex regulariser to support **data-driven prior** and **scalable uncertainty quantification** (Liaudat et al., in prep.).

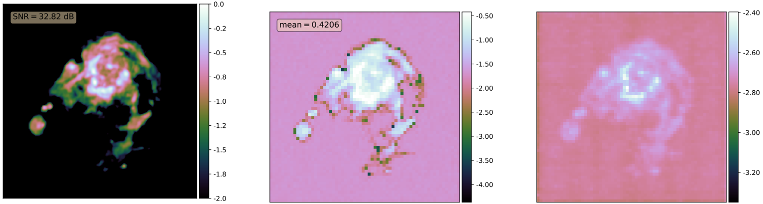



Ground Truth | Dirty Image | Wavelet Reconstruction | Learned Reconstruction

$\Rightarrow$ Superior reconstruction quality.

# Preliminary results: scalable learned imaging with uncertainty quantification

▷ Compute approximate **local credible intervals** (LCIs) to capture local measure of uncertainty.

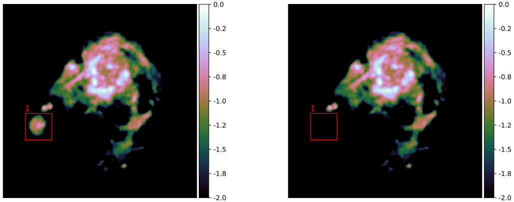



Learned Reconstruction | MAP LCI ($4 \times 4$ pixels) | MCMC Std ($4 \times 4$ pixels)

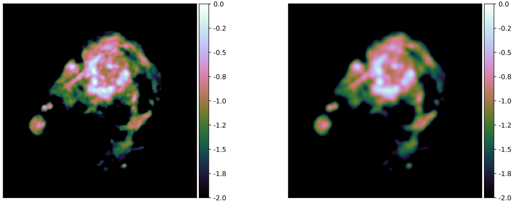
$\Rightarrow$ **Computation time reduced by factor of $10^3$.**

# Preliminary results: scalable learned imaging with uncertainty quantification

- ▷ Perform **scalable hypothesis testing** to assess whether structure physical or artifact.




$\Rightarrow$ Blob physical




$\Rightarrow$ Substructure physical

# Public open-source codes

## PURIFY code

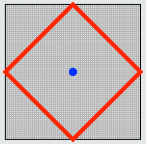
https://github.com/astro-informatics/purify

### Next-generation radio interferometric imaging

PURIFY is a highly distributed and parallelized open-source C++ code for radio interferometric imaging, leveraging recent developments in the field of variational regularization, convex optimisation, and learned imaging.

## SOPT code

https://github.com/astro-informatics/sopt



### Sparse OPTimisation

SOPT is a highly distributed and parallelized open-source C++ code for variational regularization and convex optimisation, with learned data-driven priors.