Scientific AI for Imaging

Jason D. McEwen

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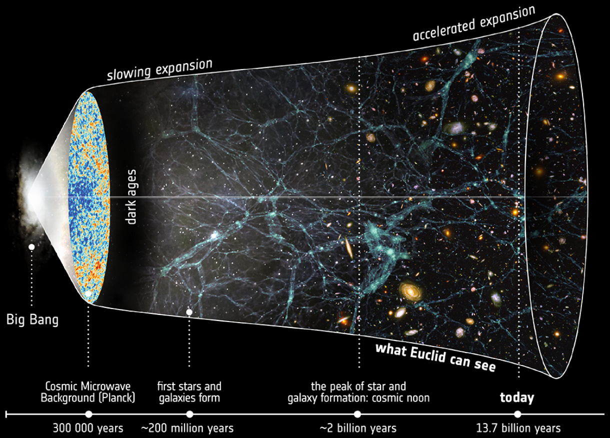
Scientific AI (SciAI) Group
Mullard Space Science Laboratory (MSSL), University College London (UCL)

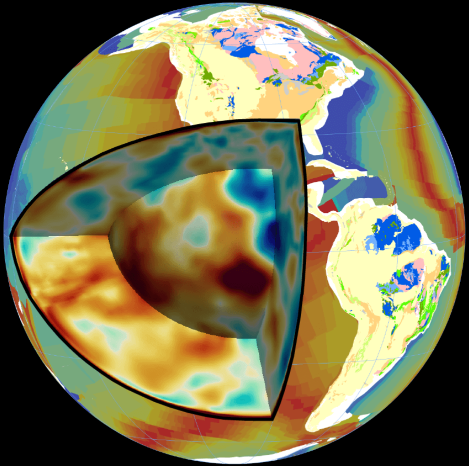
Collaborative Computational Modelling at the Interface (CCMI)
Centre for Doctoral Training (CDT)
Open Day, November 2024

Cosmic evolution

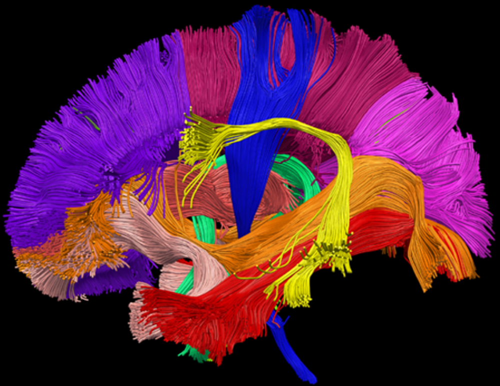


Global climate and weather prediction

Seismic imaging of the Earth's deep interior



Diffusion MRI of the brain



Many scientific inference tasks involve solving inverse problems

Consider model $\mathbf{\Phi}$ mapping underlying quantity of interest x to observed data y in the presence of noise n:

$$y = \mathbf{\Phi}(x) + n$$

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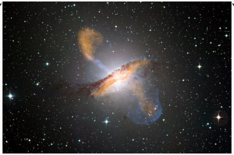

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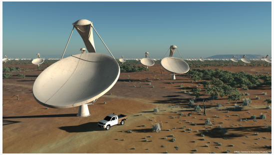
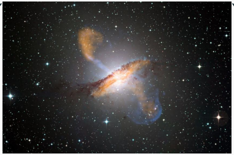
$=$  $\Bigg($  $\Bigg)$

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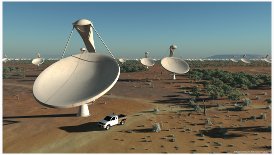
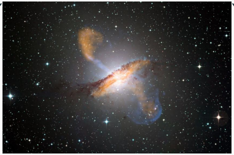
$=$  $\Bigg($  $\Bigg) + n$

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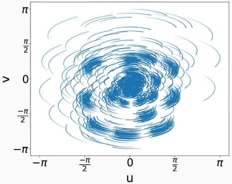

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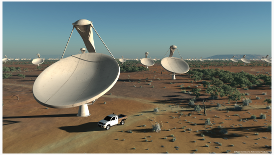

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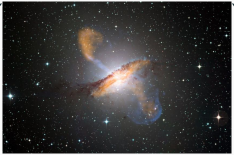

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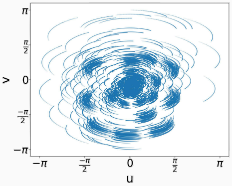

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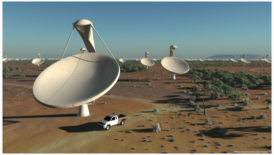

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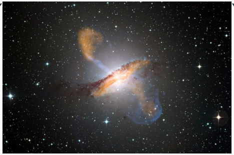

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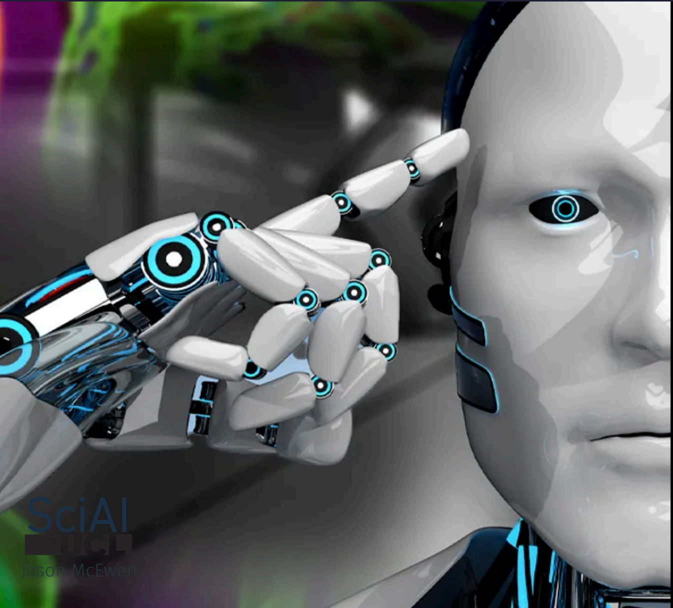
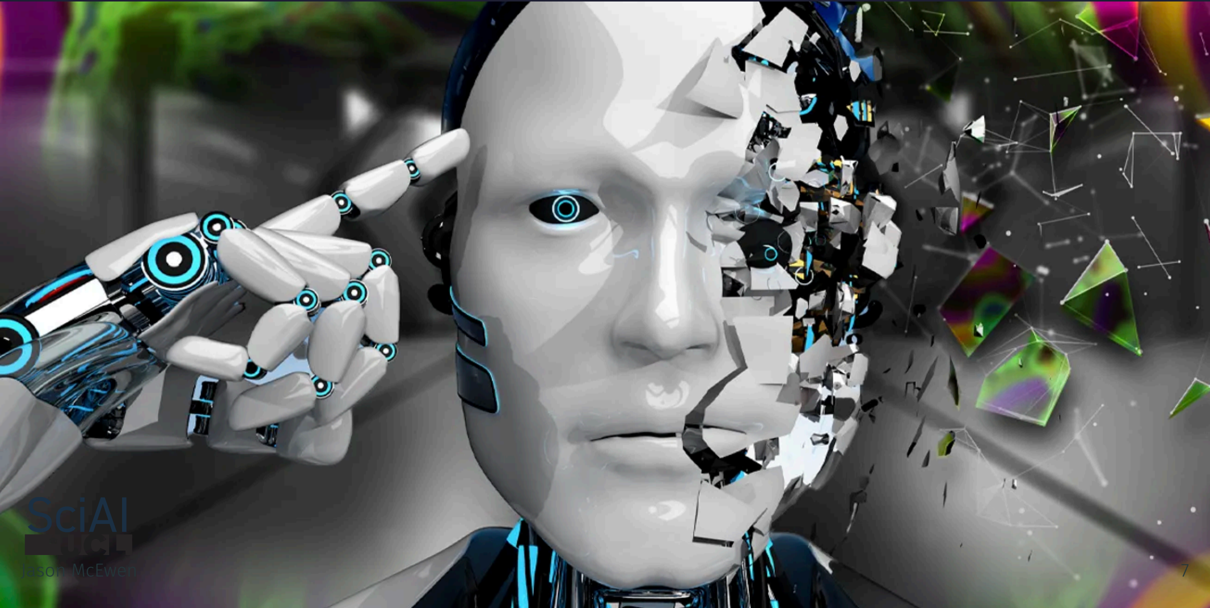
$$y \xrightarrow[\text{inverse inference}]{} x$$

Leveraging AI...



Leveraging AI... without hallucinations

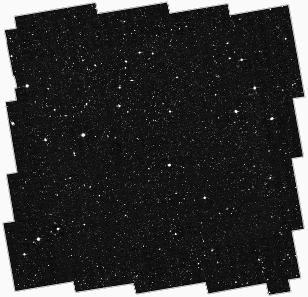


Scientific AI framework

Scientific AI

- Physical
  - Physical Properties
  - Physical Models
- Statistical
  - Statistical Uncertainties
  - Statistical Validity
- Interpretable
  - AI Priors
  - AI Models

Example: mapping the invisible dark matter of the Universe



Visible matter

Generative modelling for mass-mapping with fast uncertainty quantification
(Whitney et al. 2024; arXiv:2410.24197)

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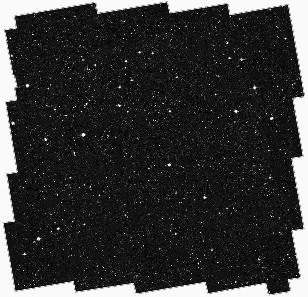

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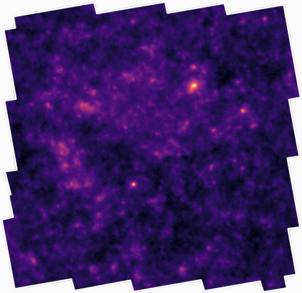

Dark matter

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SciAI UCL
Jason McEwen

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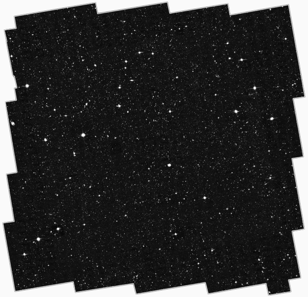

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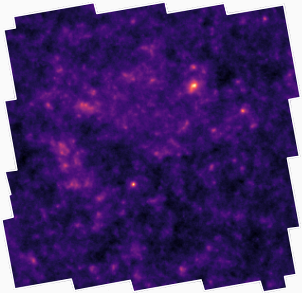

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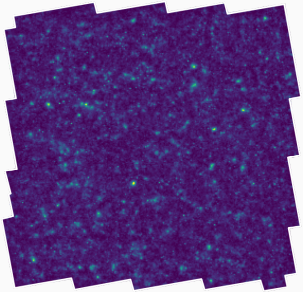

Dark matter uncertainty

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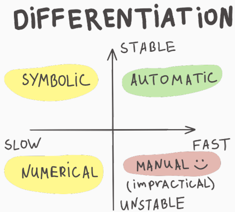
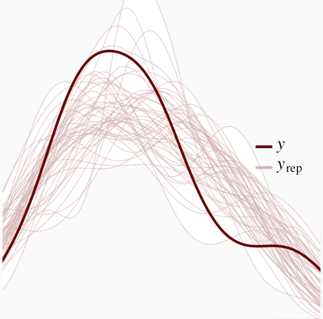
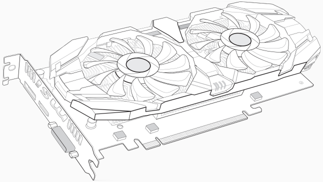


Differentiable programming



Probabilistic programming



GPU acceleration

Open-source codes

DarkMappy: Mapping the dark universe

A lightweight python package that implements hybrid sparse-Bayesian dark-matter reconstruction techniques.

Web Github

harmonic: Learnt harmonic mean estimator for Bayesian model selection

Compute the Bayesian evidence (marginal likelihood) from posterior samples generated by any sampling approach.

Web Github

LeAI: Learned image reconstruction in astronomy

Reconstruct interferometric observations using learned post-processing and learned unrolled methods.

Github

OptimusPrimal: A lightweight primal-dual solver

A lightweight proximal splitting Forward Backward Primal Dual based solver for convex optimization problems.

Github

ProxNest: Proximal nested sampling for high-dimensional Bayesian model selection

Compute the Bayesian evidence for high-dimensional log-convex problems by proximal nested sampling.

Web Github

PURIFY: Next generation radio interferometric imaging

PURIFY provides functionality to perform radio interferometric imaging, i.e. to recover images from the Fourier measurements taken by ...

Web Github

QuantifAI: Scalable Bayesian uncertainty quantification with data-driven (learned) priors

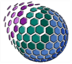
Scalable Bayesian uncertainty quantification with data-driven (learned) priors for radio interferometric imaging.

Github

S2BALL: Differentiable and accelerated wavelets on the ball

S2BALL is a JAX package for computing the scale-discretised wavelet transform on the ball and rotational ball. It leverages autodiff to ...

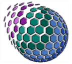
Web Github



S2FFT: Differentiable and accelerated spherical transforms

S2FFT is a JAX package for computing Fourier transforms on the sphere and rotation group. It leverages autodiff to provide ...

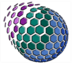
Web Github



S2SCAT: Differentiable and accelerated spherical scattering transforms

S2SCAT is a Python package for computing scattering covariances on the sphere using JAX. It exploits autodiff to provide differentiable ...

Web Github



S2WAV: Differentiable and accelerated spherical wavelets

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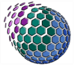
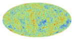
Web Github



SILC: Scale-discretised directional wavelet ILC

SILC provides functionality to perform a novel internal linear combination (ILC) algorithm for foreground separation using directional, ...

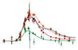
Web Github



snmachine: Classifying supernovae light curves

Classify supernovae based on their photometric light curves.

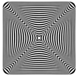
Web Github



SOPT: Sparse optimisation

SOPT provides functionality to perform sparse optimisation using state-of-the-art convex optimisation algorithms.

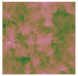
Web Github



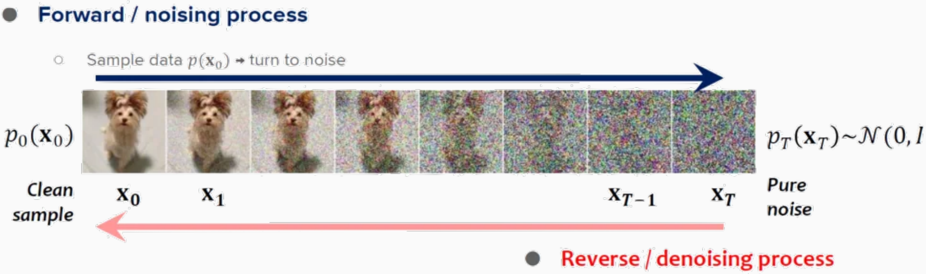
stringgen: Fast emulation of cosmic string signatures

Emulate CMB cosmic string maps.

Github



PhD project: Differentiable probabilistic deep learning with generative denoising diffusion models



Further details