

Towards wide-field, field-level simulation-based inference (SBI) for Euclid cosmic shear



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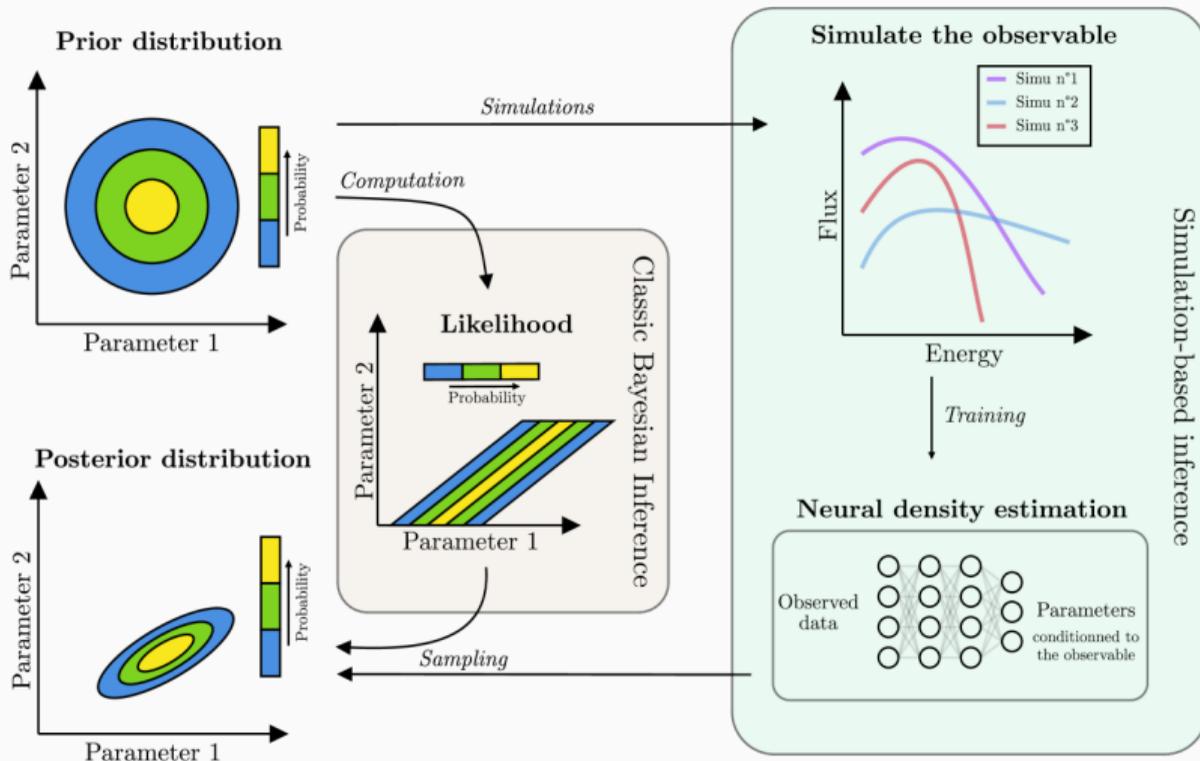
Mullard Space Science Laboratory (MSSL)
University College London (UCL)

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1. SBI: what and why
2. Towards Euclid SBI cosmic shear pipeline
 - 2.1. Wide-field mass-mapping
 - 2.2. Wide-field compression
 - 2.3. Bayesian model selection

SBI: what and why

Classical likelihood-based inference versus SBI



Simulation-based inference (SBI)

Simulation-based inference (aka. likelihood-free inference) seeks to perform Bayesian inference by **estimating the posterior** $p(\theta | x_o, M)$ of **parameters** θ for **observed data** x_o using **simulations only**.

Simulation-based inference (SBI)

Simulation-based inference (aka. likelihood-free inference) seeks to perform Bayesian inference by **estimating the posterior** $p(\theta | x_o, M)$ of **parameters** θ for **observed data** x_o using **simulations only**.

Key advantages:

- ▷ Forward modelling of complex physics, systematics, observational process.
- ▷ No assumptions on the form of the likelihood.

Three variants:

1. **Neural posterior estimation (NPE)**: learn surrogate of posterior (probability distribution over parameters).
2. **Neural likelihood estimation (NLE)**: learn surrogate of likelihood (probability distribution over data).
3. **Neural ratio estimation (NRE)**: learn surrogate of likelihood-to-evidence ratio.

Three variants:

1. **Neural posterior estimation (NPE)**: learn surrogate of posterior (probability distribution over parameters).
2. **Neural likelihood estimation (NLE)**: learn surrogate of likelihood (probability distribution over data).
 - ▶ NLE introduced by Papamakarios *et al.* (2019).
 - ▶ First applied to cosmology by Alsing *et al.* (2019).
 - ▶ First applied to cosmic shear by Taylor *et al.* McEwen (2019).
3. **Neural ratio estimation (NRE)**: learn surrogate of likelihood-to-evidence ratio.

Towards Euclid SBI shear pipeline

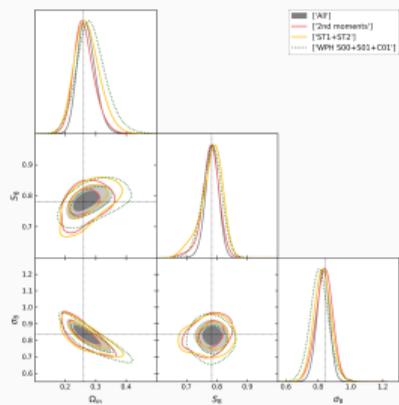
Advantages of a field-level SBI pipeline for Euclid cosmic shear

- ▷ Extract informative field-level cosmological information.
- ▷ No assumptions regarding likelihood (no need to characterize covariances).
- ▷ Capture all uncertainties.
- ▷ Accurately model systematic effects at the field-level.

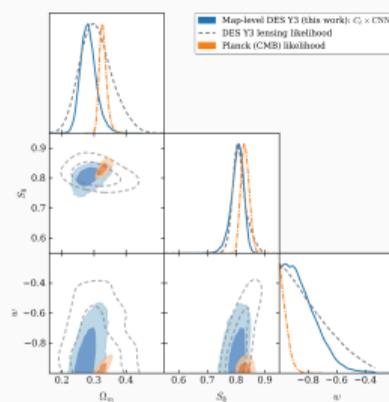
⇒ **More precise** (tighter constraints) and **more accurate** (in right place) Bayesian inference.

Effectiveness of field-level SBI for cosmic shear

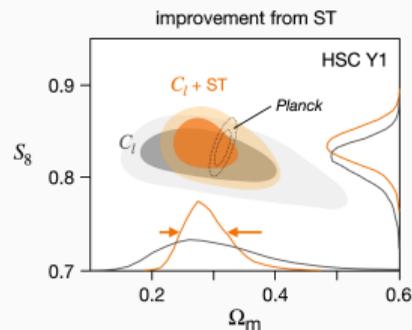
Effectiveness of field-level SBI demonstrated already in **small-field planar setting**.



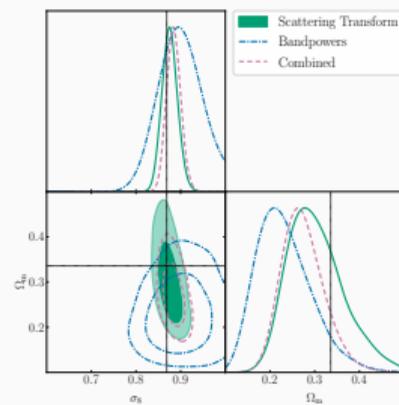
Gatti *et al.* (2023)



Jeffrey *et al.* (2024)



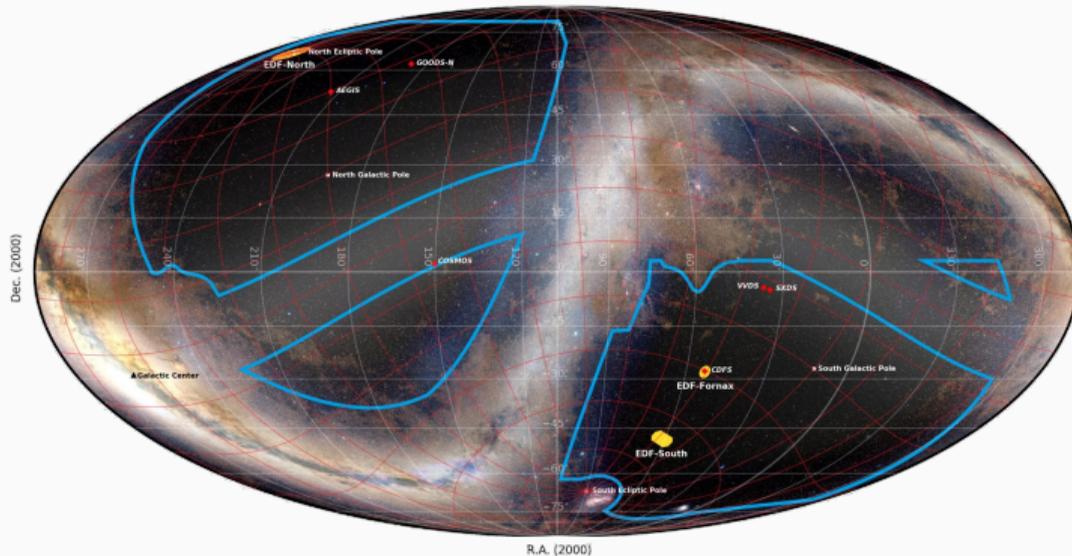
Cheng *et al.* (2024)



Lin, Joachimi, McEwen in prep. (preliminary)

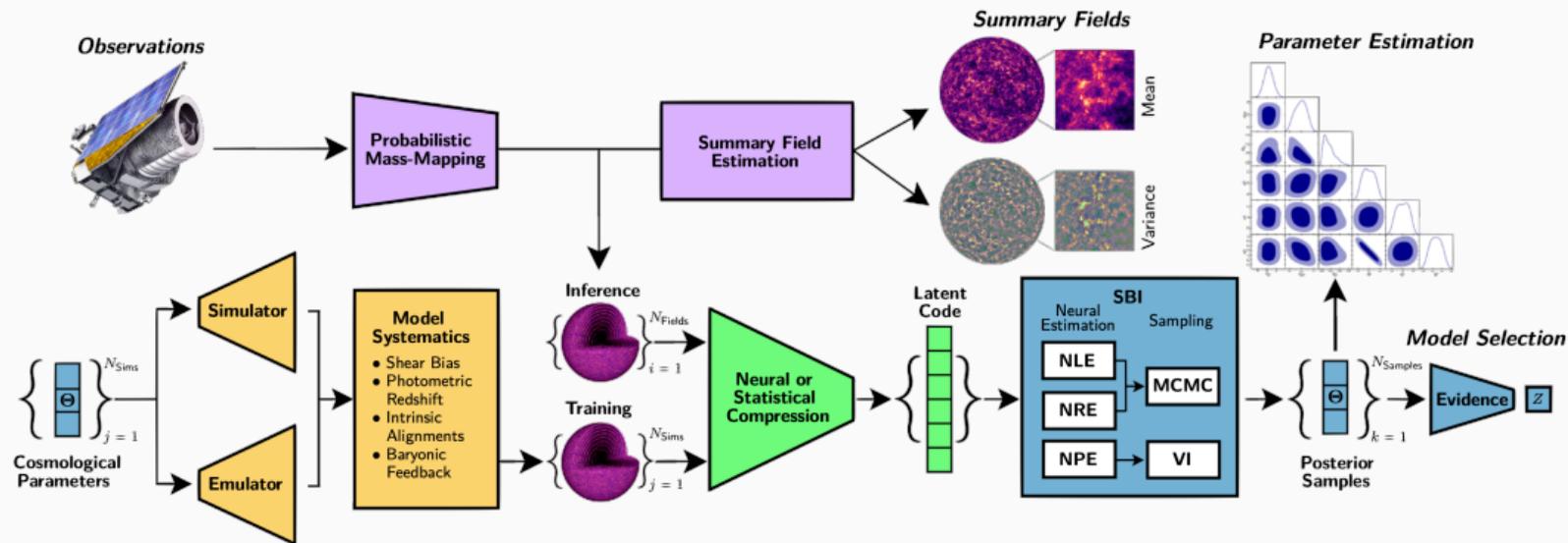
⇒ Tightest cosmic shear constraints to date from SBI.

Euclid wide-field survey



Field-level SBI techniques must be extended to support wide-fields, requiring spherical methods defined on the curved sky.

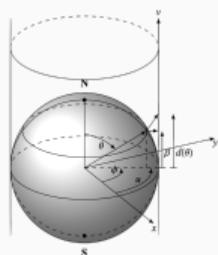
Wide-field, field-level SBI pipeline



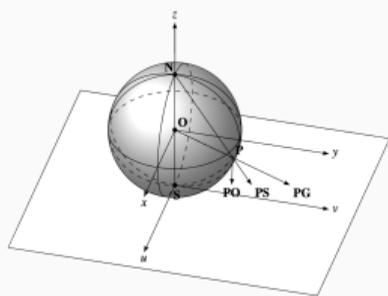
Wide-field mass-mapping

Spherical Kaiser Squires mass-mapping

Spherical Kaiser Squires mass-mapping introduced by Wallis *et al.* McEwen (2017) to avoid planar approximations.

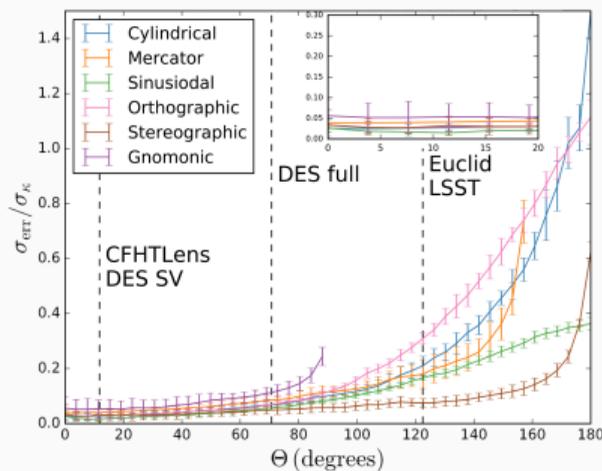


Equitorial



Polar

Projections of sphere to plane.



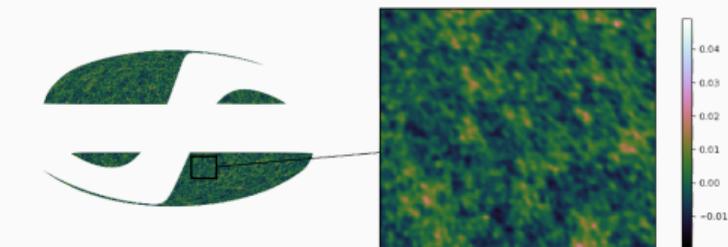
Planar projections introduce **significant error** in mass-mapping.

Enhanced spherical mass-mapping

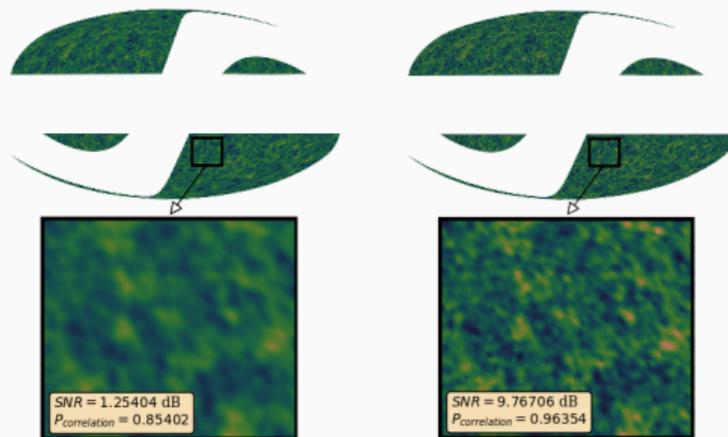
Spherical wavelet mass-mapping

introduced by Price, McEwen *et al.* 2021.

Spherical AI mass-mapping techniques
in preparation...



Ground truth



Spherical Kaiser-Squires

Spherical wavelet regularization

Wide-field compression

Wide-field compression

1. Neural compression

- ▶ CNNs: Convolutional neural networks (*e.g.* Jeffrey *et al.* 2024)

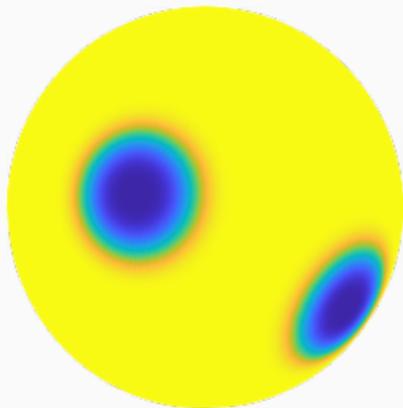
2. Statistical compression

- ▶ Scattering transforms (*e.g.* Cheng *et al.* 2024, Gatti *et al.* 2023)

Require **spherical CNNs** and **spherical scattering transforms** defined on the curved sky.

Categorization of spherical CNN frameworks

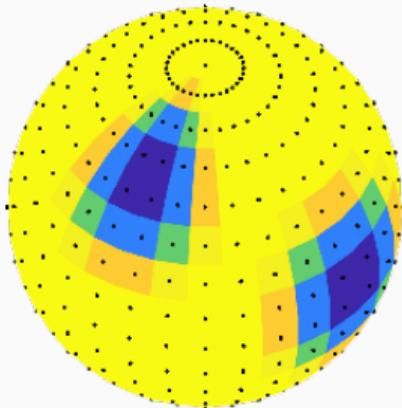
Continuous



- ✓ Equivariant
- ✗ Not Scalable

(Cohen et al. 2018, Esteves et al. 2018, Kondor et al. 2018, Cobb et al. 2021, McEwen et al. 2022, ...)

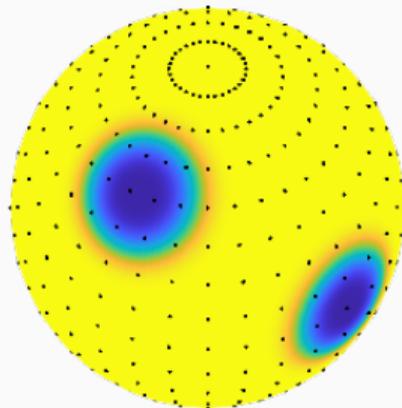
Discrete



- ✗ Not Equivariant
- ✓ Scalable

(Jiang et al. 2019, Zhang et al. 2019, Perraudin et al. 2019, Cohen et al. 2019, ...)

Discrete-Continuous (DISCO)



- ✓ Equivariant
- ✓ Scalable

(Ocampo, Price & McEwen 2023)

Efficient Generalized Spherical CNNs

(Cobb *et al.* McEwen 2021)

Scalable and Equivariant Spherical CNNs by Discrete-Continuous (DISCO) Convolutions

(Ocampo, Price & McEwen 2023)

Equivariance \Rightarrow **state-of-the-art performance** on all problems considered to date.

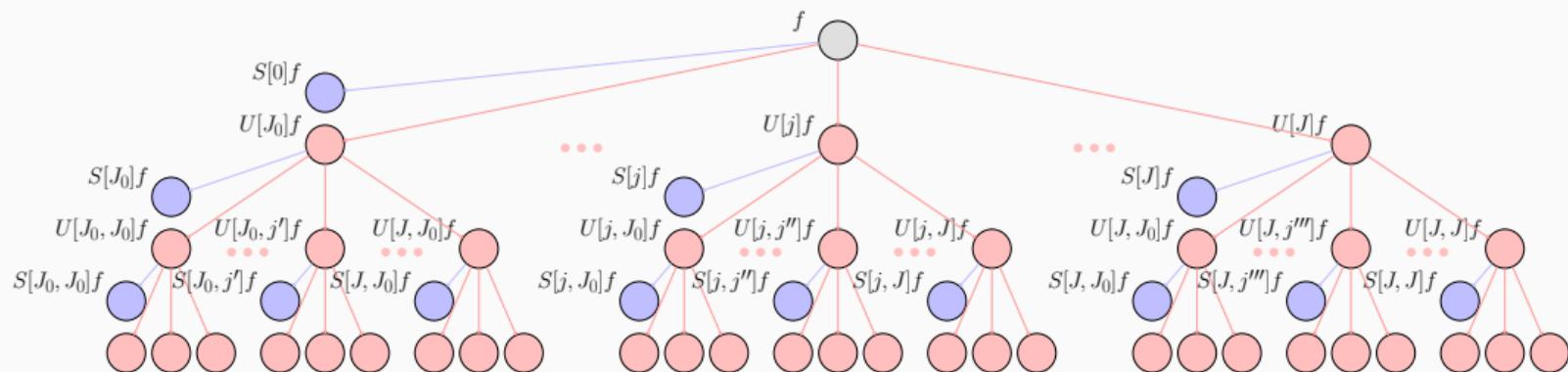
Spherical scattering networks (first generation)

Scattering networks inspired by CNNs but designed rather than learned filters (Mallat 2012).

Scattering networks on the sphere

(McEwen et al. 2022)

Cascade of **spherical wavelet transforms** (McEwen et al. 2018) and non-linearities (modulus).



Spherical scattering covariance (third generation)

Generative models of astrophysical fields with scattering transforms on the sphere

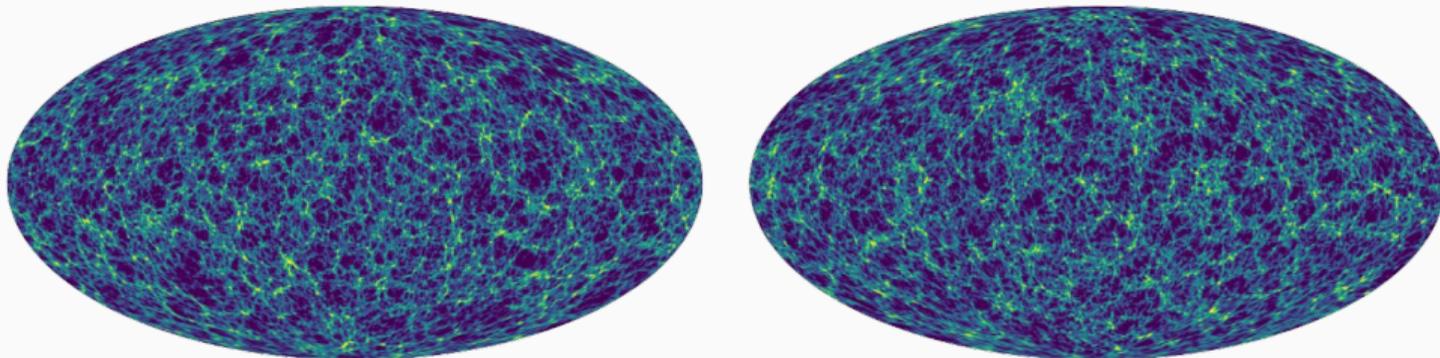
(Mousset, Allys, Price, *et al.* McEwen 2024)

Scattering covariance statistics considered:

1. $S_1[\lambda] f = \mathbb{E} [|f \star \psi_\lambda|]$.
2. $S_2[\lambda] f = \mathbb{E} [|f \star \psi_\lambda|^2]$.
3. $S_3[\lambda_1, \lambda_2] f = \text{Cov} [f \star \psi_{\lambda_2}, |f \star \psi_{\lambda_1}| \star \psi_{\lambda_2}]$.
4. $S_4[\lambda_1, \lambda_2, \lambda_3] f = \text{Cov} [|f \star \psi_{\lambda_1}| \star \psi_{\lambda_3}, |f \star \psi_{\lambda_2}| \star \psi_{\lambda_3}]$.

Emulation: Generative modelling with scattering covariances

Which field is emulated and which simulated?



Logarithm (for visualization) of weak lensing field

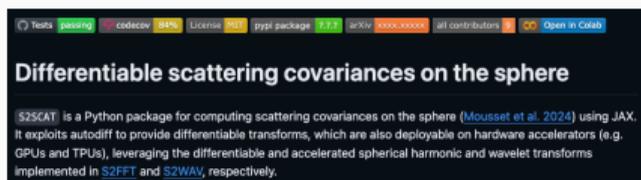
Differentiable and GPU-accelerated spherical transform codes (in JAX)



The screenshot shows the GitHub repository for 'Differentiable and accelerated spherical transforms'. At the top, there are status indicators: 'Tests passing', 'codecov 93%', 'License MIT', 'pypi package 1.1.1', 'arXiv 2023.14870', 'all contributors', and 'Open in Colab'. The repository title is 'Differentiable and accelerated spherical transforms'. Below the title is a description: 'S2FFT is a Python package for computing Fourier transforms on the sphere and rotation group (Price & McEwen 2023) using JAX or PyTorch. It leverages autodiff to provide differentiable transforms, which are also deployable on hardware accelerators (e.g. GPUs and TPUs).

s2fft: Spherical harmonic transforms

<https://github.com/astro-informatics/s2fft>



The screenshot shows the GitHub repository for 'Differentiable scattering covariances on the sphere'. At the top, there are status indicators: 'Tests passing', 'codecov 94%', 'License MIT', 'pypi package 1.0.1', 'arXiv 2023.14870', 'all contributors', and 'Open in Colab'. The repository title is 'Differentiable scattering covariances on the sphere'. Below the title is a description: 'S2SCAT is a Python package for computing scattering covariances on the sphere (Mousset et al. 2024) using JAX. It exploits autodiff to provide differentiable transforms, which are also deployable on hardware accelerators (e.g. GPUs and TPUs), leveraging the differentiable and accelerated spherical harmonic and wavelet transforms implemented in S2FFT and S2WAV, respectively.

s2scat: Spherical scattering transforms

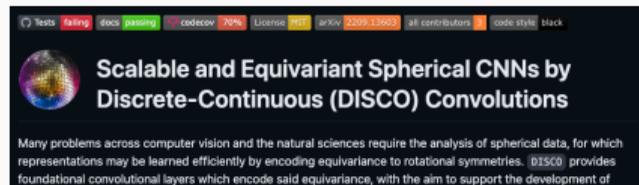
<https://github.com/astro-informatics/s2scat>



The screenshot shows the GitHub repository for 'Differentiable and accelerated wavelet transform on the sphere'. At the top, there are status indicators: 'Tests passing', 'codecov 92%', 'License MIT', 'pypi package 1.0.4', 'arXiv 2022.01254', 'all contributors', and 'Open in Colab'. The repository title is 'Differentiable and accelerated wavelet transform on the sphere'. Below the title is a description: 'S2WAV is a python package for computing wavelet transforms on the sphere and rotation group, both in JAX and PyTorch. It leverages autodiff to provide differentiable transforms, which are also deployable on modern hardware accelerators (e.g. GPUs and TPUs), and can be mapped across multiple accelerators.

s2wav: Spherical wavelet transforms

<https://github.com/astro-informatics/s2wav>



The screenshot shows the GitHub repository for 'Scalable and Equivariant Spherical CNNs by Discrete-Continuous (DISCO) Convolutions'. At the top, there are status indicators: 'Tests failing', 'docs passing', 'codecov 70%', 'License MIT', 'arXiv 2023.13663', 'all contributors', and 'code style black'. The repository title is 'Scalable and Equivariant Spherical CNNs by Discrete-Continuous (DISCO) Convolutions'. Below the title is a description: 'Many problems across computer vision and the natural sciences require the analysis of spherical data, for which representations may be learned efficiently by encoding equivariance to rotational symmetries. DISCO provides foundational convolutional layers which encode said equivariance, with the aim to support the development of

s2ai: Spherical AI

Coming very soon! Contact us for early access.

Bayesian model selection

Learned harmonic mean estimation of the Bayesian evidence

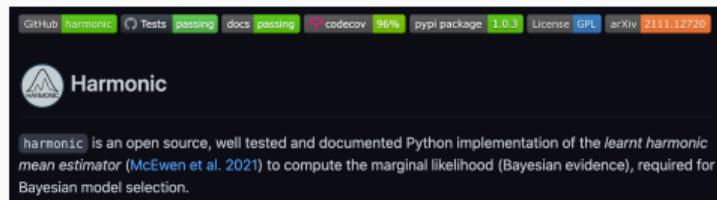
Learned harmonic mean estimator (McEwen et al. 2021)

$$z^{-1} = \rho = \mathbb{E}_{p(\theta|x)} \left[\frac{\varphi(\theta)}{\mathcal{L}(\theta)\pi(\theta)} \right]$$

where

$$\varphi(\theta) \stackrel{\text{ML}}{\simeq} \varphi^{\text{optimal}}(\theta) = \frac{\mathcal{L}(\theta)\pi(\theta)}{z}$$

- ▷ Requires **posterior samples only**
 - ↪ Evidence almost for free
- ▷ **Agnostic to sampling technique**
 - ↪ Leverage efficient samplers
 - ↪ **Simulation-based inference (SBI)**
 - ↪ Variational inference
- ▷ Scale to **high-dimensions**
 - ↪ Normalizing flows (Polanska et al. McEwen 2024)



harmonic: Learned harmonic mean

<https://github.com/astro-informatics/harmonic>

The future of cosmological (likelihood-based) inference

(Piras, Polanska, Spurio Mancini, Price, McEwen 2024)

37 parameter cosmic shear analysis of Λ CDM vs w_0w_a CDM

▷ CAMB + PolyChord

↪ **8 months on 48 CPU cores**

▷ CosmoPower-JAX + NumPyro/NUTS + Harmonic

↪ **2 days on 12 GPUs**

157 parameter 3x2pt analysis of Λ CDM vs w_0w_a CDM

▷ CAMB + PolyChord

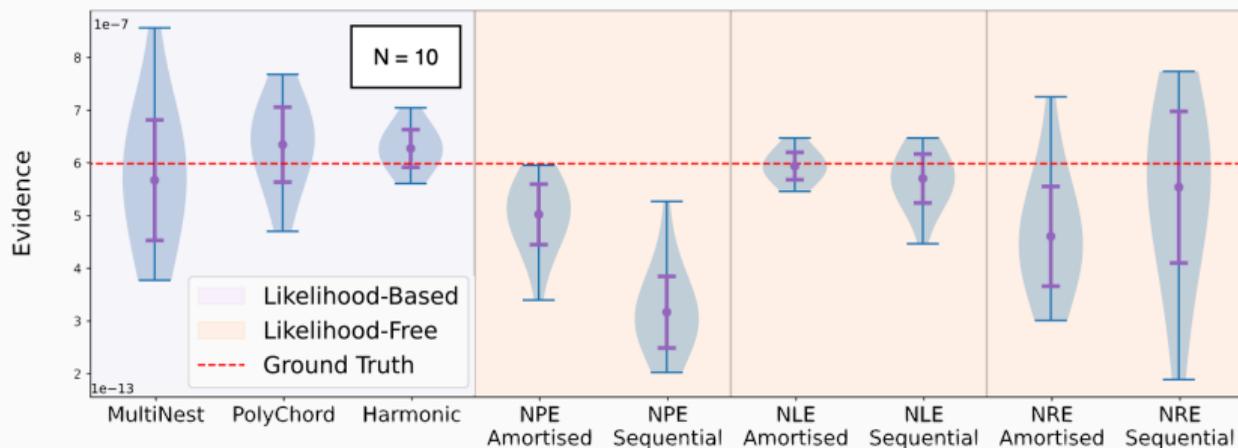
↪ **12 years on 48 CPUs (projected)**

▷ CosmoPower-JAX + NumPyro/NUTS + Harmonic

↪ **8 days on 24 GPUs**

Bayesian model selection for SBI

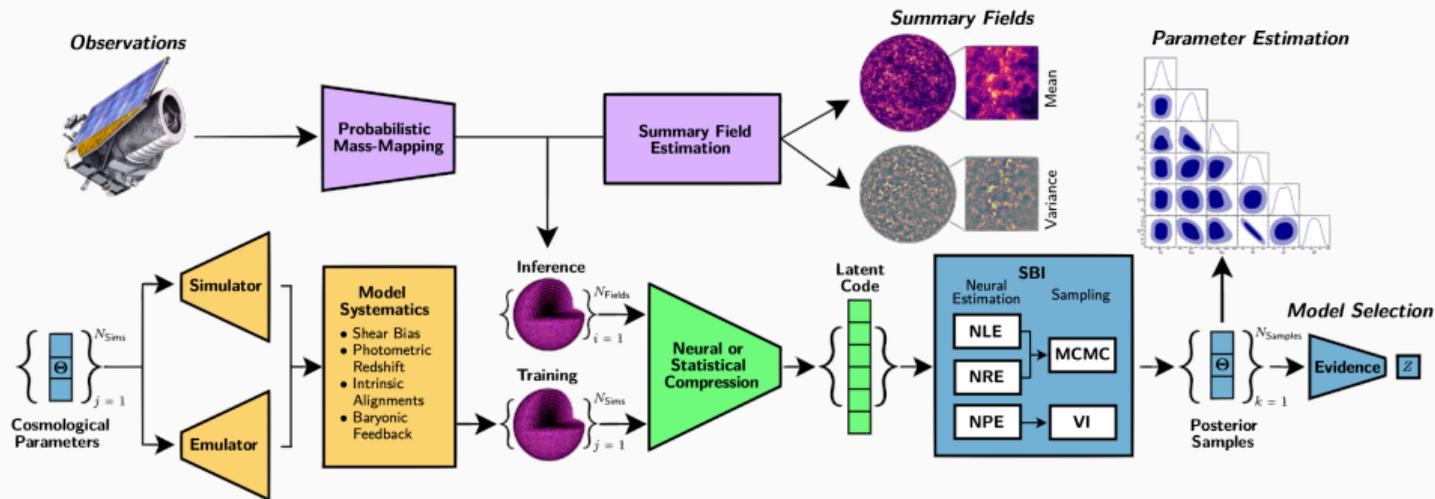
Bayesian model selection for SBI first introduced by Spurio Mancini *et al.* McEwen (2023).



Summary

Summary

- ▷ Field-level SBI highly effective.
- ▷ For Euclid, require spherical methods defined on the curved sky.



Have the methods and codes needed to develop a highly effective wide-field, field-level SBI pipeline for Euclid cosmic shear.

Extra slides

Neural likelihood estimation

Construct **training data** $\{(\theta_i, x_i)\}$ where parameter drawn from proposal prior $\theta_i \sim \tilde{p}(\theta | M)$ and then generate simulation $x_i \sim p(x | \theta_i) \Rightarrow$ joint distribution $\tilde{p}(\theta, x) = p(x | \theta, M)\tilde{p}(\theta, M)$.

Learn likelihood

$$q_\psi(x | \theta, M) \simeq p(x | \theta, M) ,$$

where ψ are the parameters of the learned model.

Train by maximum likelihood, *i.e.* by maximising

$$\mathbb{E}_{\tilde{p}(\theta, x)}[\log q_\psi(x | \theta, M)] = -\mathbb{E}_{\tilde{p}(\theta)}[D_{\text{KL}}(p(x | \theta, M), q_\psi(x | \theta, M))] + \text{const.} ,$$

where D_{KL} is the Kullback-Leibler divergence.

Sample from approximate posterior by **MCMC sampling**.

Conditional normalizing flow as density estimator

