Wide-field, field-level compression for simulation-based inference (SBI)

for Euclid cosmic shear

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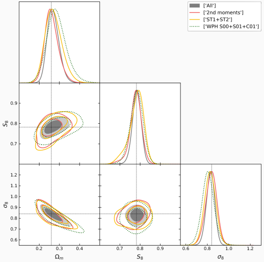
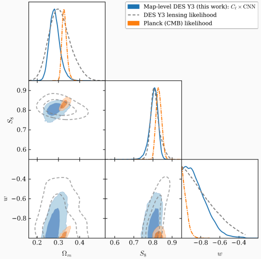
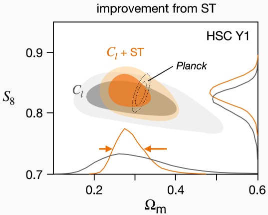
Effectiveness of field-level SBI



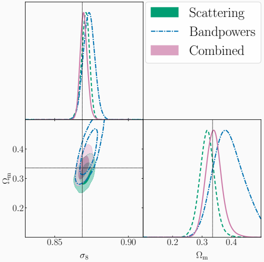
Gatti *et al.* (2023)



Jeffrey *et al.* (2024)

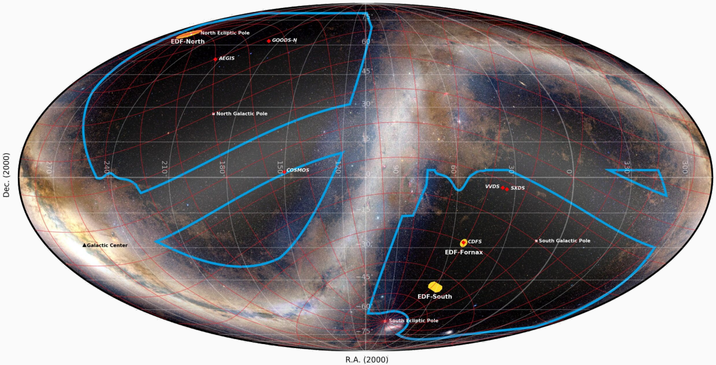


Cheng *et al.* (2024)



Lin, Joachimi, McEwen in prep. (preliminary)

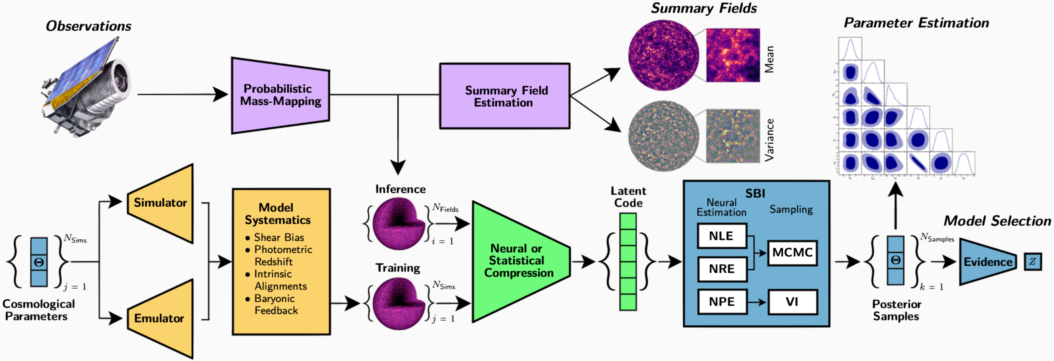
Euclid wide-field survey



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

Jason McEwen

Wide-field, field-level SBI pipeline



Aside: Learned harmonic mean estimator for Bayesian evidence

Enhanced Bayesian model selection with **learned harmonic mean**

(McEwen *et al.* 2021, Spurio Mancini *et al.* 2022, Polanska *et al.* 2024, Piras *et al.* 2024)

- 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

Accelerated Bayesian inference (Piras *et al.* 2024)

37 parameter cosmic shear analysis of LCDM vs $w_0 w_a$CDM

- CAMB + PolyChord ⇝ 8 months on 48 CPU cores
- CosmoPower-JAX + NumPyro/NUTS + **Harmonic**
  ⇝ 2 days on 3 GPUs

157 parameter 3x2pt analysis of LCDM vs $w_0 w_a$CDM

- CAMB + PolyChord ⇝ 12 years on 48 CPUs (projected)
- CosmoPower-JAX + NumPyro/NUTS + **Harmonic**
  ⇝ 8 days on 24 GPUs

`harmonic`: Learnt harmonic mean estimator of Bayesian evidence

`https://github.com/astro-informatics/harmonic`

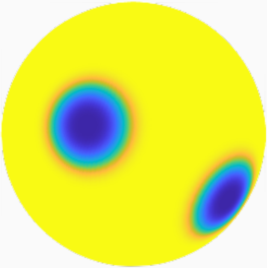
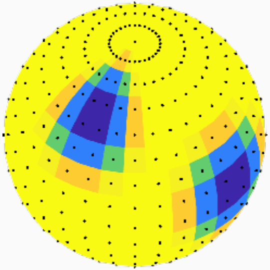
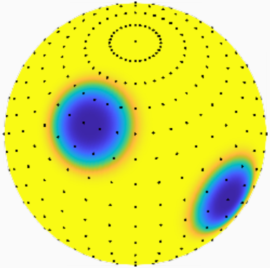
Wide-field compression

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** (Ocampo, Price, McEwen 2023, Cobb *et al.* 2021) and **spherical scattering transforms** (McEwen *et al.* 2022, Mouset *et al.* in prep.) defined on the curved sky.

Categorization of spherical CNN frameworks

Continuous	Discrete	Discrete-Continuous (DISCO)
		
✔ Equivariant ✖ Not Scalable	✖ Not Equivariant ✔ Scalable	✔ Equivariant ✔ Scalable
(Cohen et al. 2018, Esteves et al. 2018, Kondor et al. 2018, Cobb et al. 2021, McEwen et al. 2022, ...)	(Jiang et al. 2019, Zhang et al. 2019, Perraudin et al. 2019, Cohen et al. 2019, ...)	(Ocampo, Price & McEwen 2023)

Scalable and equivariant spherical CNNS

Efficient Generalized Spherical CNNs
(Cobb *et al.* McEwen 2021, ICLR, arXiv:2010.11661)

Scalable and Equivariant Spherical CNNs by Discrete-Continuous (DISCO) Convolutions
(Ocampo, Price & McEwen 2023, ICLR, arXiv:2209.13603)

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

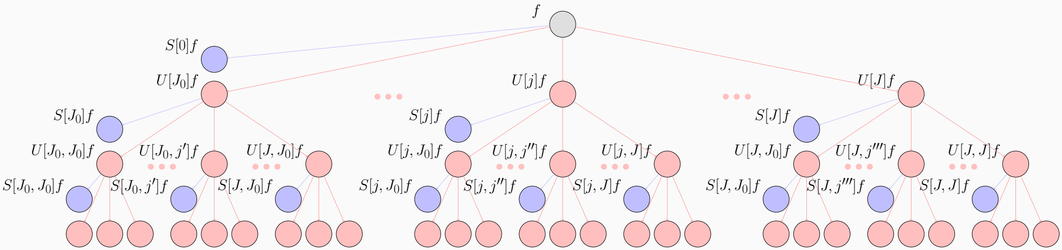
Spherical scattering networks (first generation)

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

Scattering networks on the sphere

(McEwen et al. 2022, ICLR, arXiv:2102.02828)

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, in prep.)

Scattering covariance statistics considered:

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

Emulation: Generative modelling with scattering covariances

Which field is emulated and which simulated?

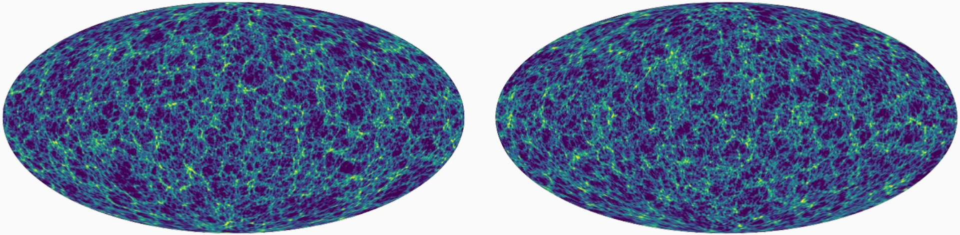
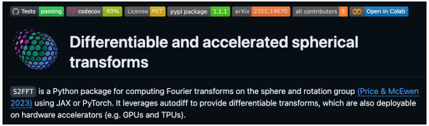


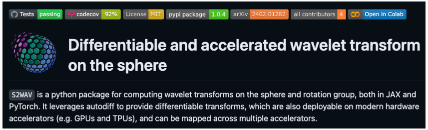
Figure 2: Logarithm (for visualization) of weak lensing field

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



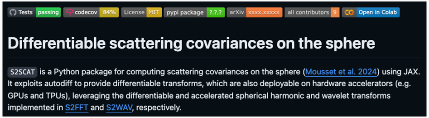
`s2fft`: Spherical harmonic transforms

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



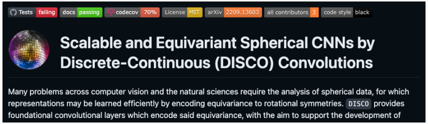
`s2wav`: Spherical wavelet transforms

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



`s2scat`: Spherical scattering transforms

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



`s2ai`: Spherical AI

Coming very soon! Contact us for early access.

Summary

- Field-level SBI highly effective.
- For Euclid, require spherical methods defined on the curved sky.
- **Neural compression**:
  - Spherical CNNs (Cobb *et al.* McEwen 2021, Ocampo, Price & McEwen 2023)
- **Statistical compression**:
  - Spherical scattering transforms (McEwen et al. 2022)
  - Spherical scattering covariances (Mousset, Allys, Price, *et al.* McEwen, in prep.)
- Can also be used to develop **spherical emulators**.

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