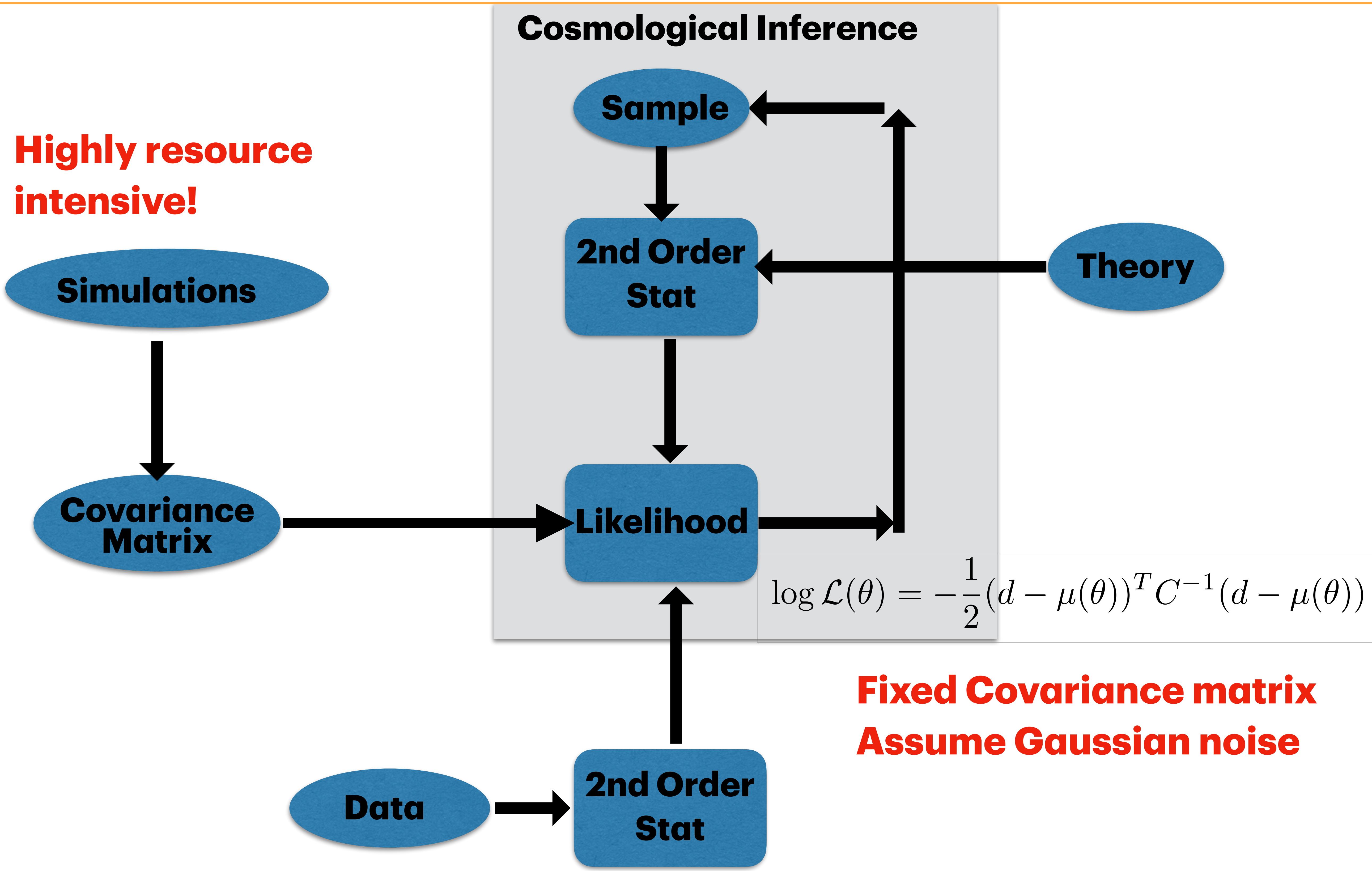
Weak Lensing High Order Statistics

Jean-Luc Starck

http://jstarck.cosmostat.org

Collaborators: Vilasini T. Sreekanth, Sandrine Codis, Alexandre Barthelemy, Virginia Ajani, Denise Lanzieri, Francois Lanusse, Valeria Pettorino

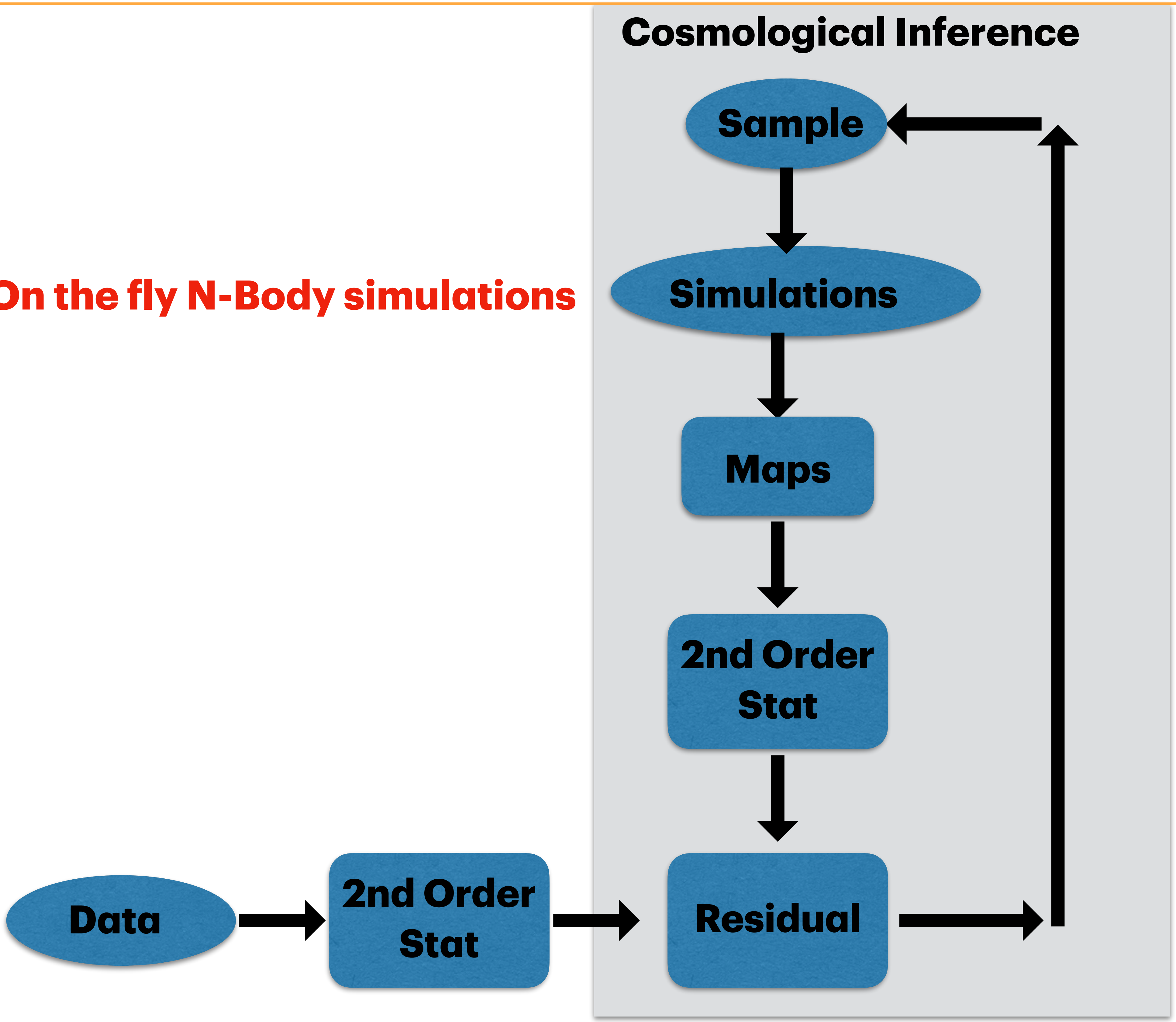
Traditional Cosmological Inference



$$\log \mathcal{L}(\theta) = -\frac{1}{2}(d - \mu(\theta))^T C^{-1}(d - \mu(\theta))$$

Forward Modeling Approach

On the fly N-Body simulations



Speed Up thanks to Automatic Diff.

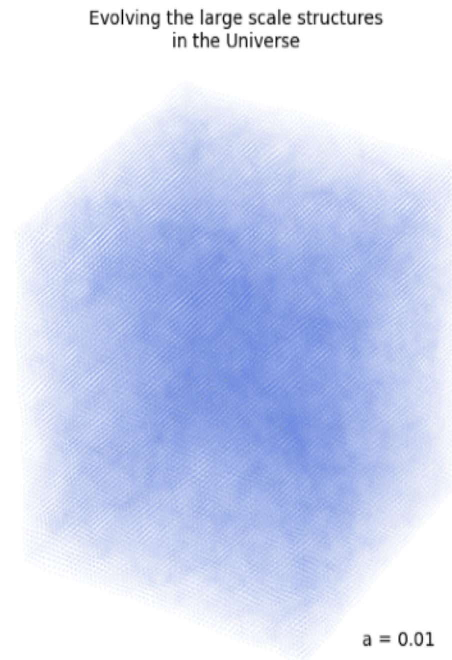
No Covariance matrix !

Easy to model systematics, with marginalisation over parameters

Fast Forward Modeling with GPU Software (TensorFlow)

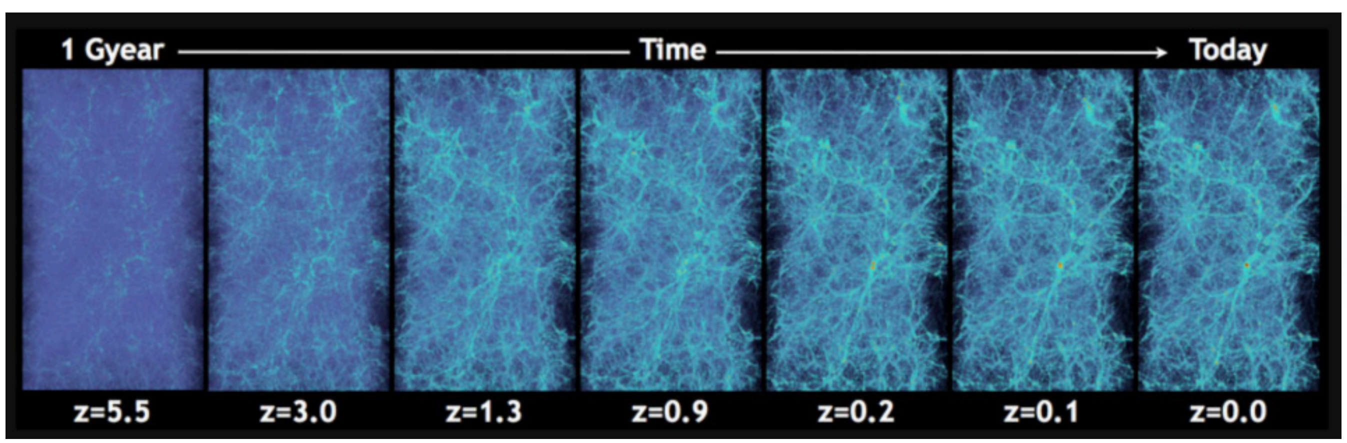
D. Lanzieri

F. Lanusse

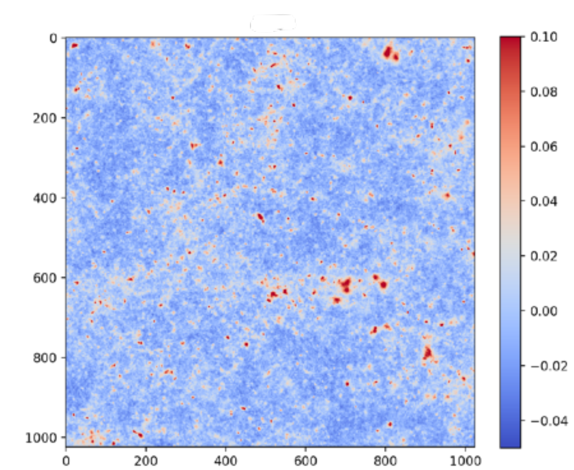


20s for a 5x5 square degrees field

Cosmological N-Body Simulations



Ray-tracing



Lensing lightcones implementing gravitational lensing ray-tracing in FlowPM framework (Born approximation)

D. Lanzieri, F. Lanusse and J.-L. Starck, “Hybrid Physical-Neural ODEs for Fast N-body Simulations”, ICML, 2022. ArXiv: 2207.05509

Forward Modeling with an Emulator

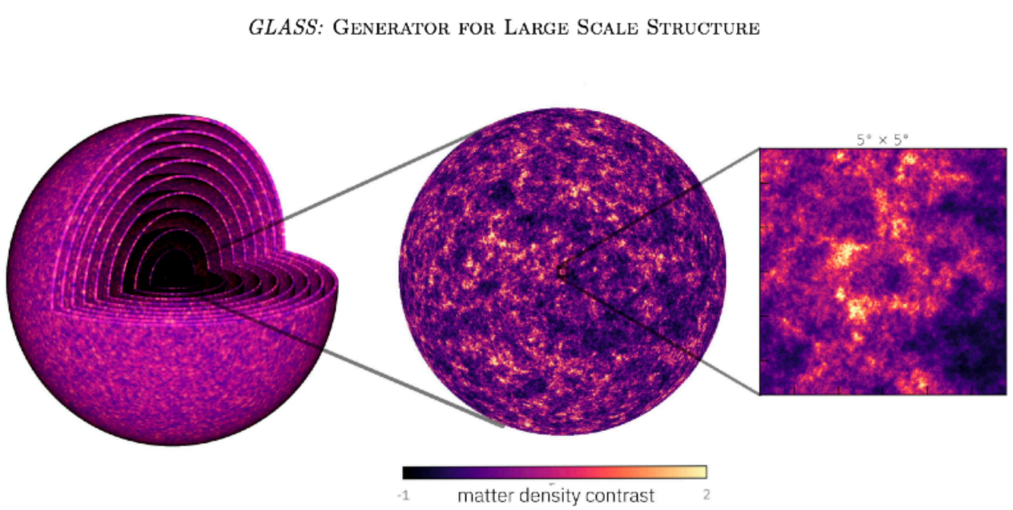
~~Ohe fly N-dy simuions~~

Cosmological Inference

Theory → Emulators

Sample → Emulators → Maps → 2nd Order Stat → Residual → Sample

Data → 2nd Order Stat → Residual



Speed Up thanks to Emulator

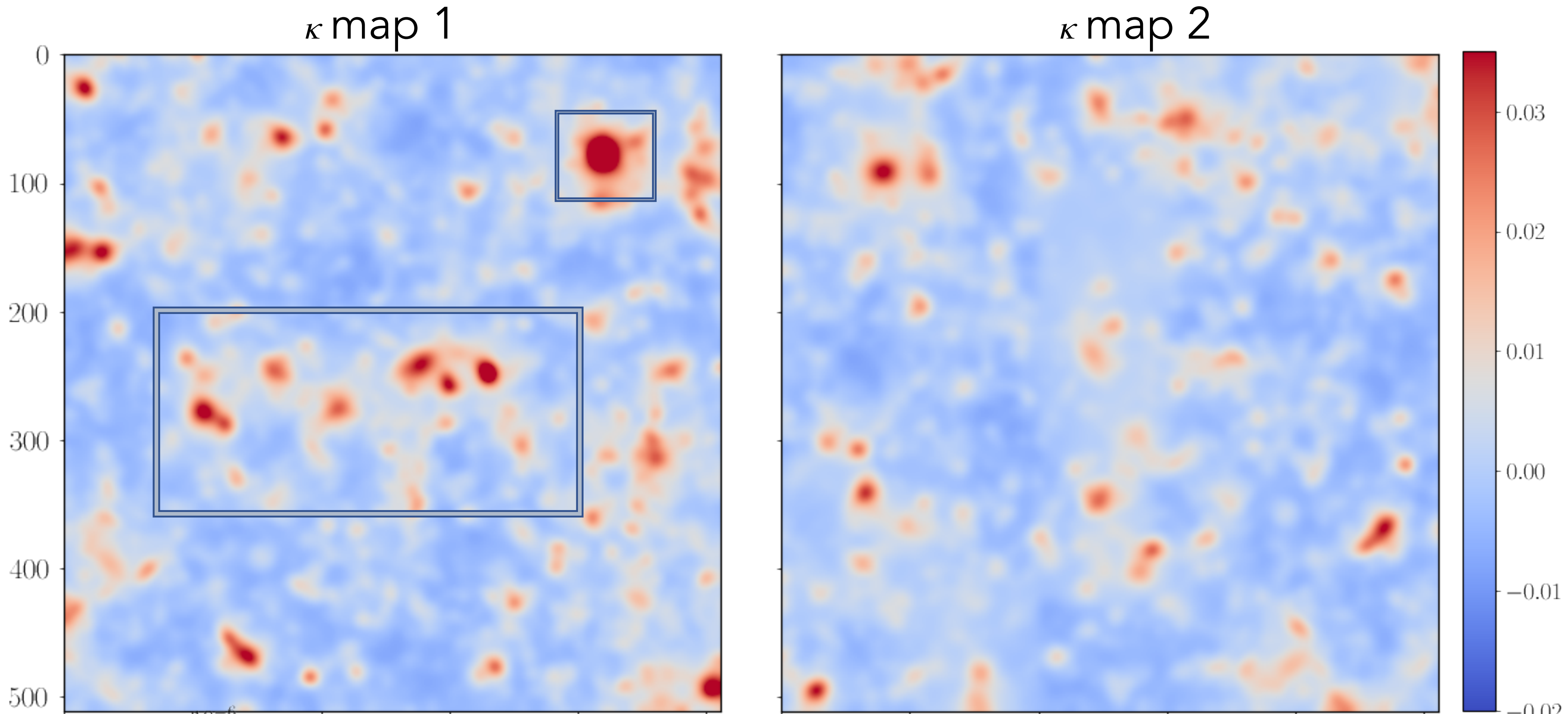
No Covariance matrix !

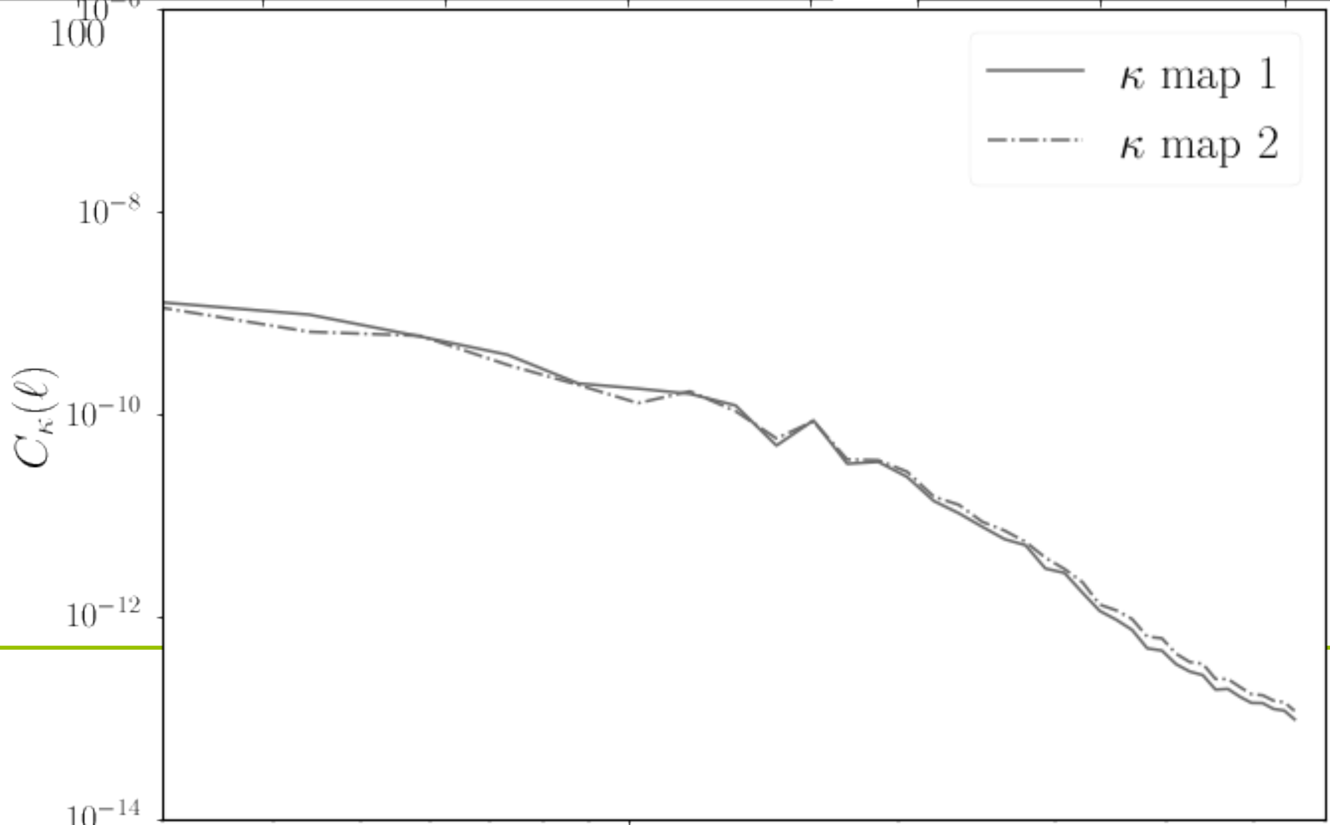
Easy to model systematics, with marginalisation over parameters

N. Tessore et al, "GLASS: Generator for Large Scale Structure", Open Journal of Astrophysics, vol. 6, 2023

NEED FOR HIGHER ORDER STATISTICS

V. Ajani

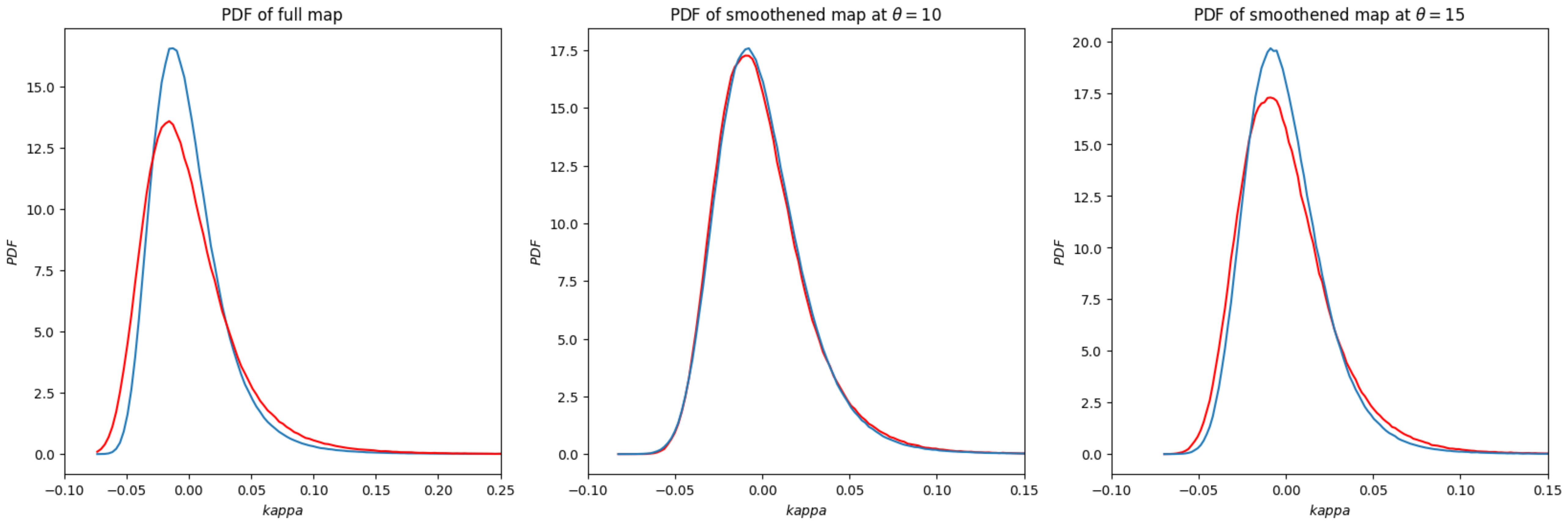




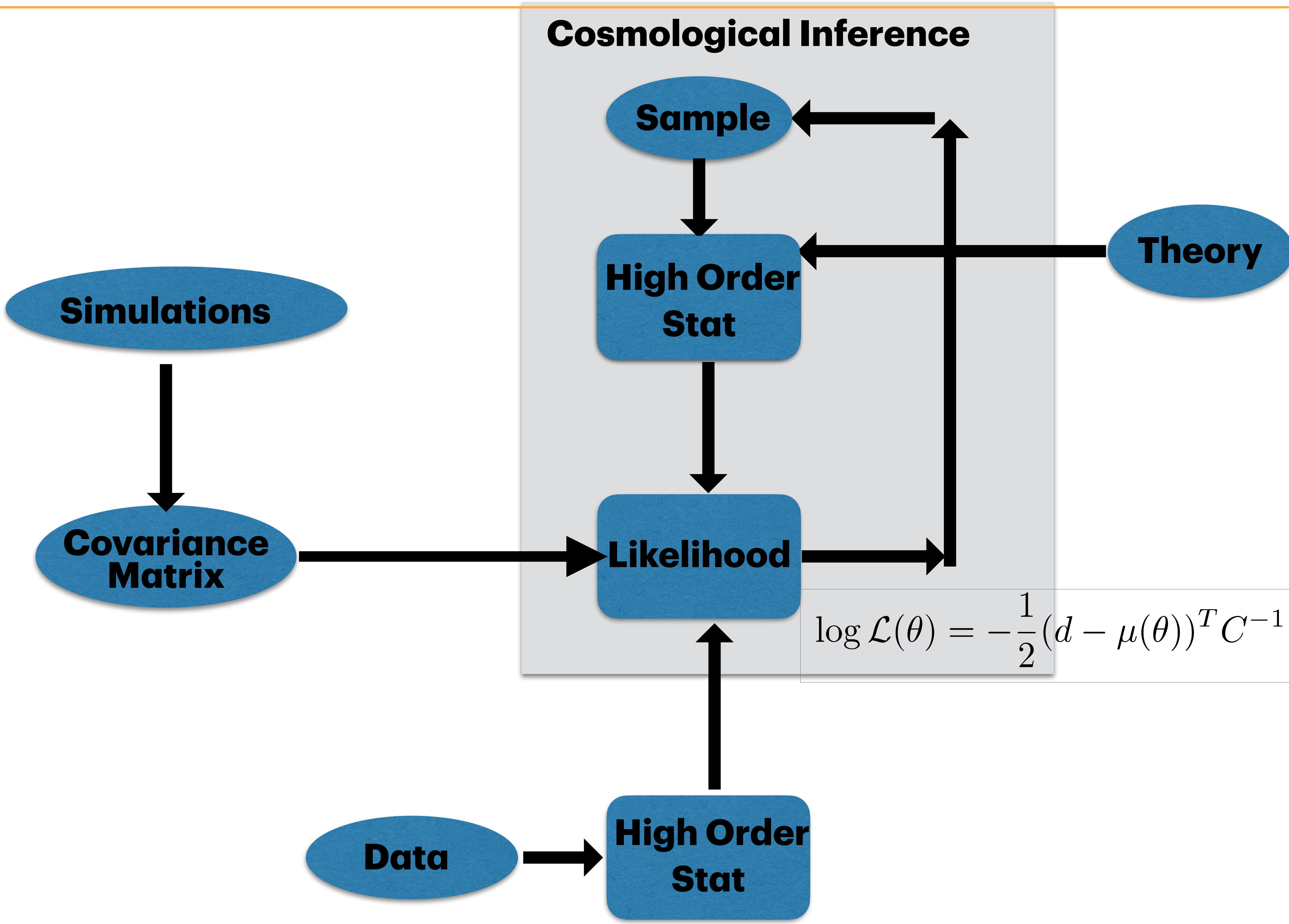
HIGH ORDER STATISTICS

Statistics	Tomo	Systematics	Params	Forecasts (with II order)	Real data	Survey	References
Summary statistics employed in the analysis	If a tomographic analysis was performed	m = multiplicative bias c = additive bias photo-z = photometric redshifts bar = baryonic effects IA = intrinsic alignment	The cosmological parameters that are constrained	Improvement w.r.t 2PCF %=single parameter Number = 2D FoM	Constraining power > = better ~ = similar < = worst	Survey specs, name or sky coverage + galaxy number density	First author + year.
PDF	no yes no	m, c no no	Ω_m, σ_8 M_ν, A_s M_ν, w_0	2 35%, 61% 27%,40%+Planck		DES-Y1 LSST Euclid	Patton + 2017 Liu, J.+ 2018 Boyle+ 2020
Bispectrum	yes yes yes	no no no	$\sigma_8, w_a, w_0, \Omega_\Lambda$ Ω_m, σ_8 M_ν, Ω_m, A_s	3 2 32%, 13%, 57%		4000 deg^2, 100 arcmin^{-2} Euclid LSST	Takada+ 2005 Bergé+ 2010 Coulton+ 2019
MF	yes no yes yes	no photo-z, m, c no IA, photo-z, m	Ω_m, σ_8, w_0 Ω_m, σ_8 M_ν, Ω_m, A_s Ω_m, σ_8	11%, 14%, 14% 4 4.2	biased (syst.)	LSST CFHTLenS LSST DES	Kratochvil+ 2012 Petri+2015 Marques+2018 Zürcher+ 2021
Moments	no yes yes	photo-z, m, c m, c bar, IA, photo-z, m	Ω_m, σ_8 Ω_m, σ_8 S_8	 2 20%	$>$ 2PCF	CFHTLenS 3500 deg^2, 27 arcmin^{-2} DES-Y3	Petri+ 2015 Vicinanza+ 2018 Gatti+ 2019
Peaks	yes yes no yes yes yes	photo-z, m, c photo-z, m, c m,c, IA, boost, photo-z m,c, IA, photo-z, bar no no	Ω_m, σ_8 Ω_m, σ_8 Ω_m, σ_8 S_8 M_ν, Ω_m, A_s M_ν, Ω_m, A_s	 39%, 32%, 60% 63%, 40%, 72%	~ 2PCF $>$ 2PCF (2) ~ 2PCF $>$ 2PCF (20%)	CS82 CFHTLenS DES-Y1 KiDS-450 LSST Euclid	Liu X.+ 2015 Liu J.+ 2015 Kacprzak+ 2016 Martinet+ 2017 Li Z.+ 2018 Ajani+ 2020
Minima **Minima+Peaks** **Voids** **1D M_{ap}**	yes yes no yes	IA, photo-z, m bar no no	Ω_m, σ_8 M_ν, Ω_m, A_s Ω_m, S_8, h, w_0 Ω_m, S_8, w_0	2.8 44%, 11%, 63% $\gtrsim$ 2PCF 57%, 46%, 68%		DE LSST LSST Euclid	Zürcher+ 2021 Coulton+ 2020 Davies+ 2020 Martinet+2020
M. Learning	no no yes	no no photo-z, m, c, IA	Ω_m, σ_8 Ω_m, σ_8 S_8	5 ~45% (dep. noise) 	 $>$ 2PCF (30%)	3500 deg^2, no noise KiDS-450 KiDS-450	Gupta+ 2018 Fluri 2018 Fluri 2019
Scattering T. **Starlet ℓ_1- norm**	yes yes	no no	M_ν, Ω_m, w_0 M_ν, Ω_m, A_s	40%, $>$ 2PCF 72%, 60%, 75%		LSST Euclid	Cheng S.+ 2021 Ajani+ 2021

PDF of Log-normal map

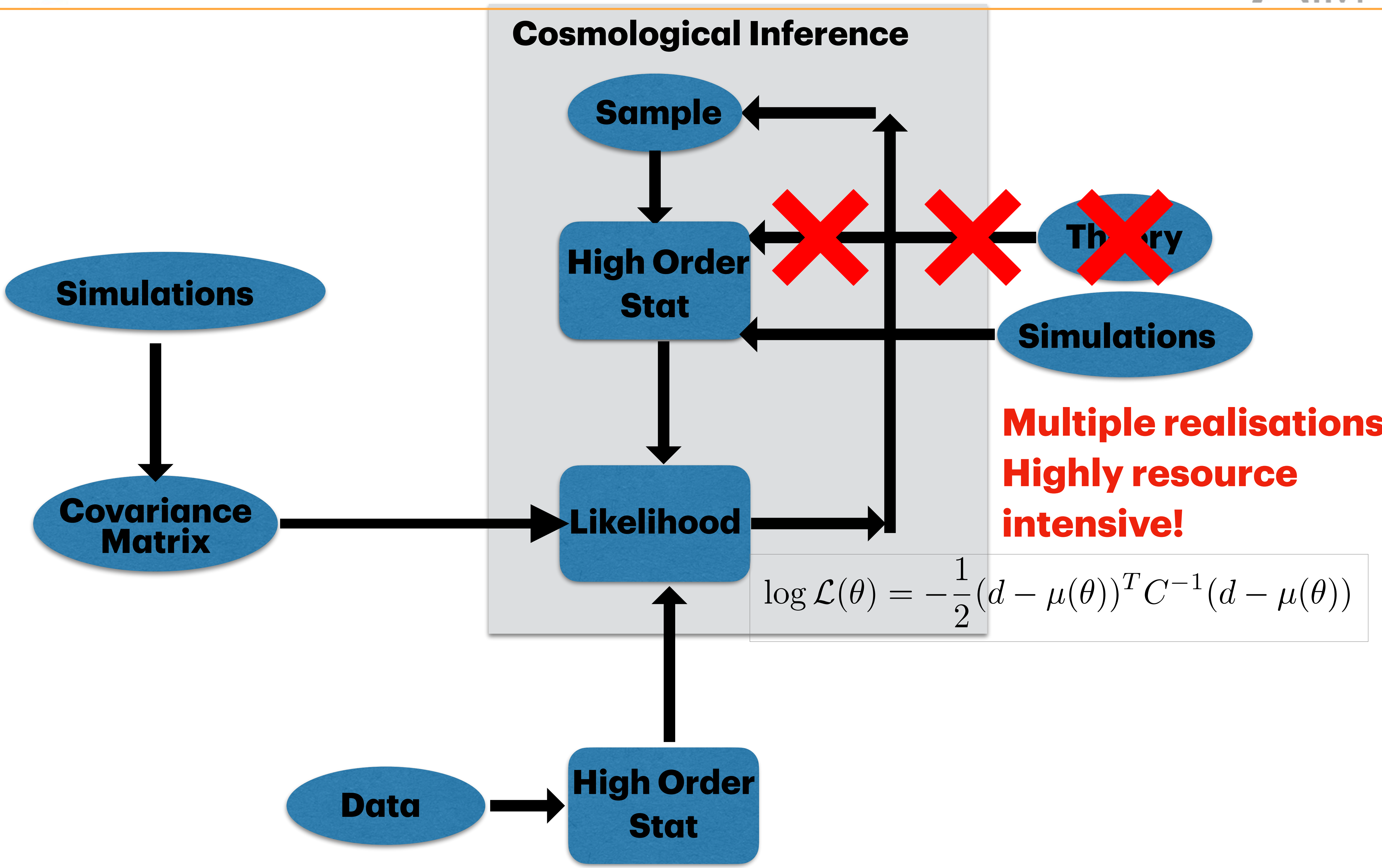


Back to Traditional Cosmological Inference



$$\log \mathcal{L}(\theta) = -\frac{1}{2}(d - \mu(\theta))^T C^{-1}(d - \mu(\theta))$$

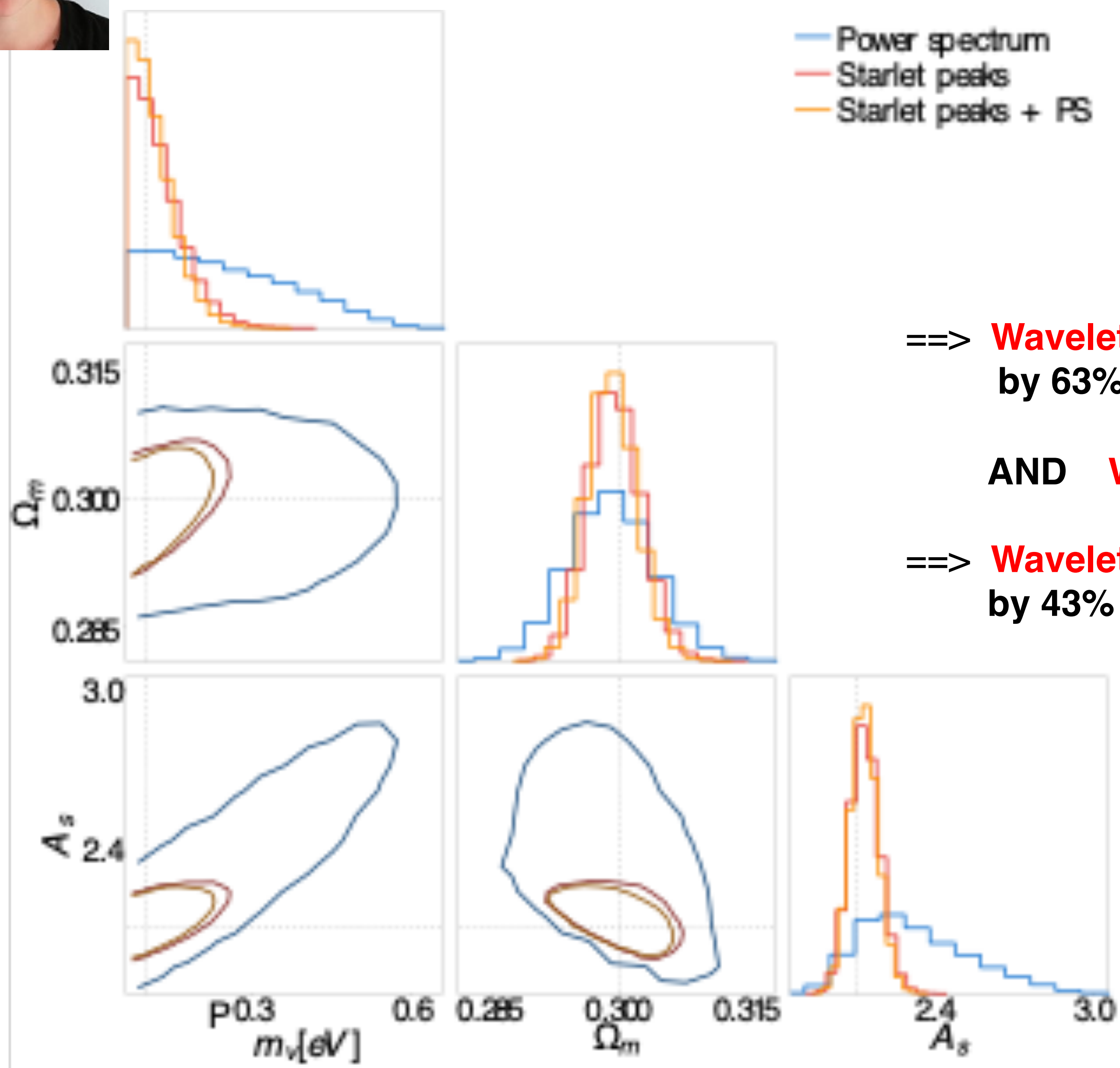
Cosmological Inference



$$\log \mathcal{L}(\theta) = -\frac{1}{2}(d - \mu(\theta))^T C^{-1} (d - \mu(\theta))$$

Wavelet Peaks: RESULTS

V. Ajani, A. Peel, V. Pettorino, J.-L. Starck, Z. Li, J. Liu, "**Constraining neutrino masses with weak-lensing starlet peak counts**", Physical Review D, 102, 103531, 2020, DOI: 10.1103/PhysRevD.102.103531, [arXiv:2001.10993].



Convergence Map from **MassiveNus** simulations

==> **Wavelet peak count > power spectrum,**
by 63% on M_ν, 40% on Ω_m, 72% on A_s.

AND Wavelet peak count + power spectrum = Wavelet peak count

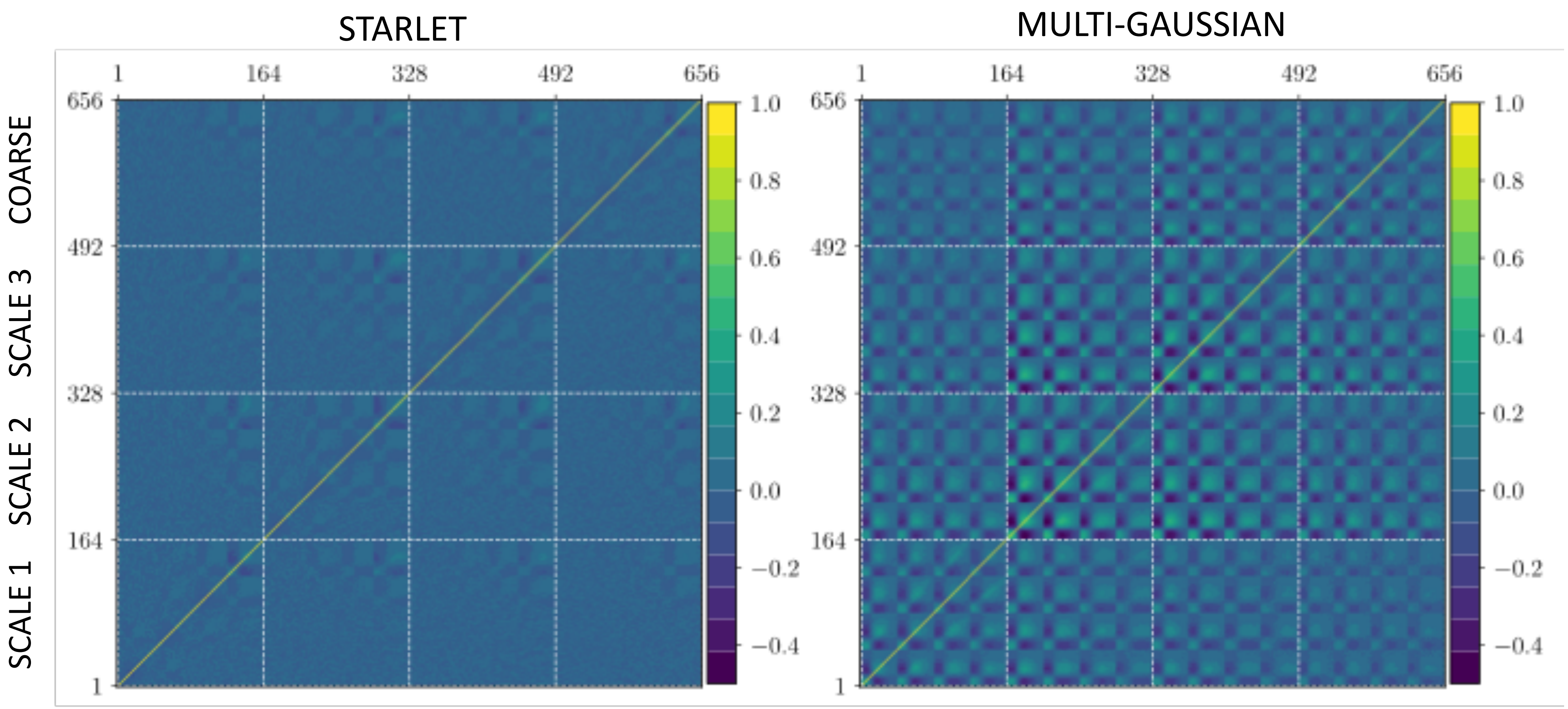
==> **Wavelet peak count > mono-scale peaks,**
by 43% on M_ν, 25% on Ω_m, 34% on A_s.

Multi-scale peaks alone perform as well as multi-scale peaks + power spectrum

CosmoStat

Wavelet Peaks Covariance Matrix

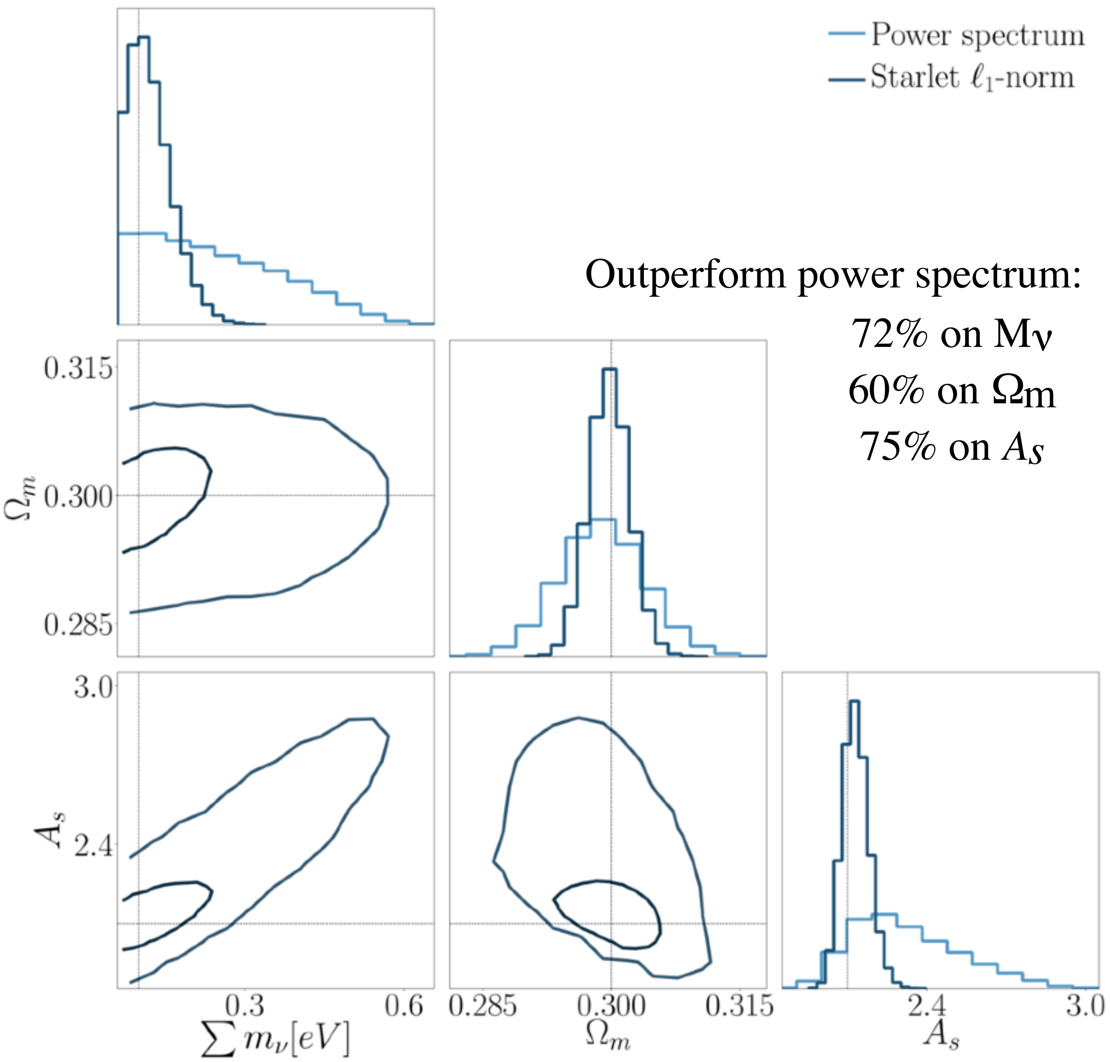
V. Ajani



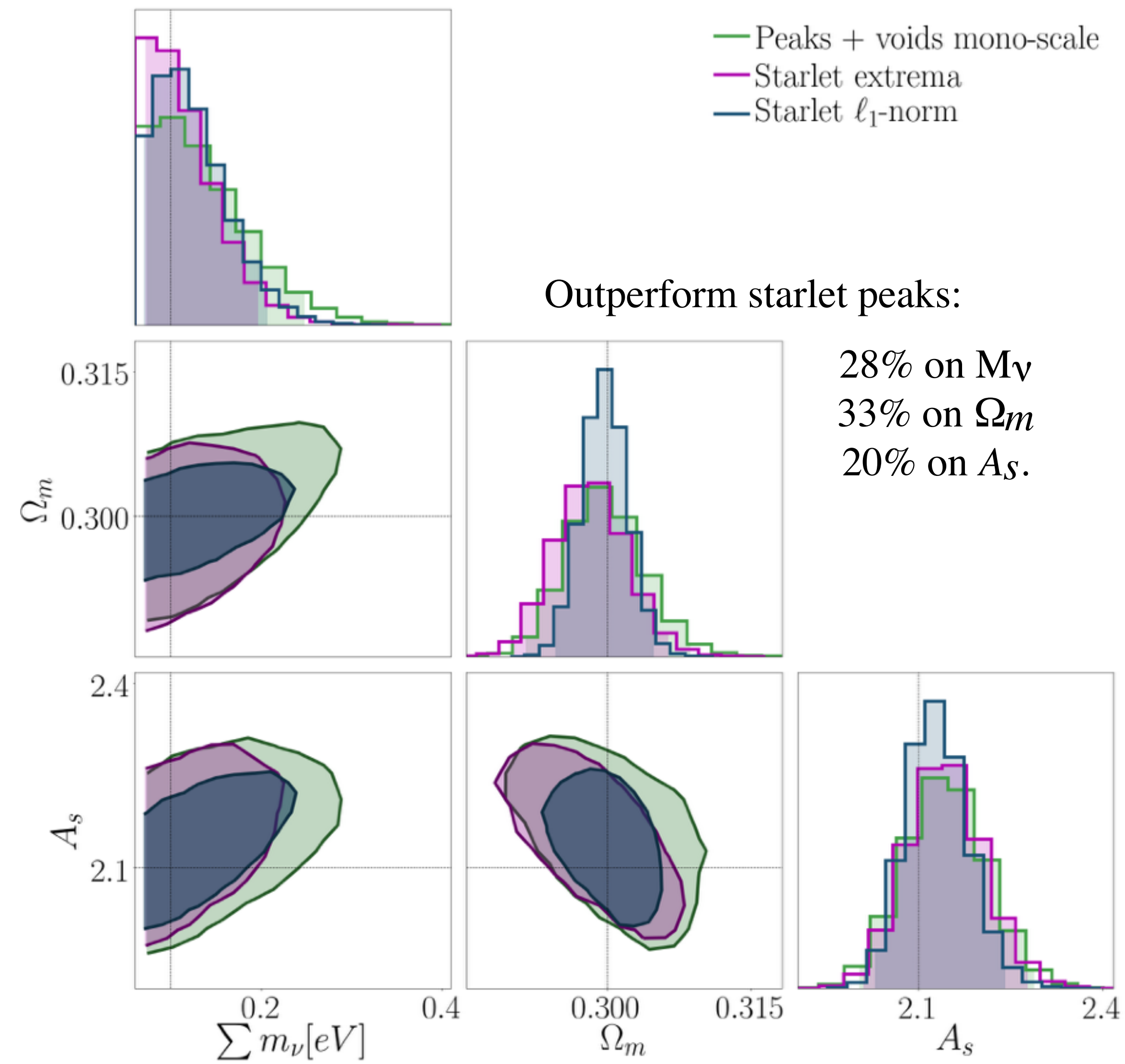
Starlet filter tends to make the covariance matrix more diagonal

https://arxiv.org/abs/2001.10993 Ajani et al, Phys. Rev. D 102, 103531, (2020)

V. Ajani, J.-L. Starck, V. Pettorino, J. Liu, **"Starlet ℓ_1- norm for weak lensing cosmology", A&A, 645, L11, 2021,** [arXiv:2101.01542](https://arxiv.org/abs/2101.01542)



Outperform power spectrum:
72% on Mν
60% on Ωm
75% on A_s



Outperform starlet peaks:
28% on Mν
33% on Ωm
20% on As.

==> unified framework to simultaneously account for peaks+voids , and **outperforms power spectrum and state of the art peaks and void statistics**

Wavelet l1-norm theoretical prediction

V. Tinnaneri Sreekanth

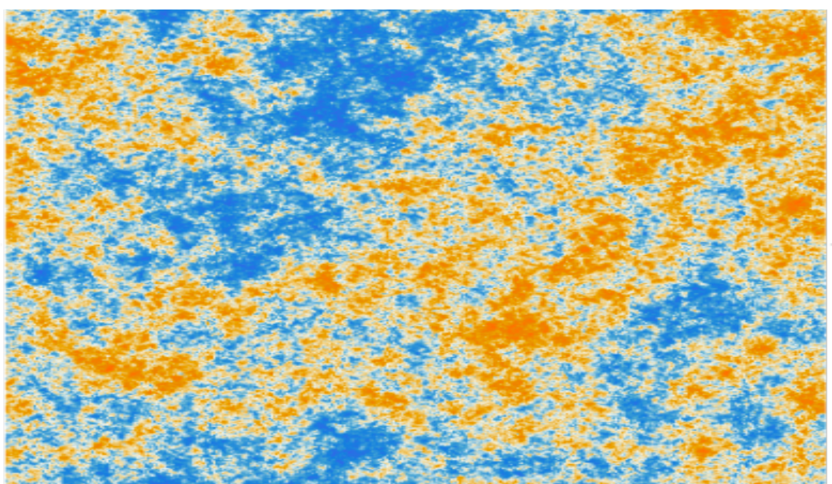
- A. Bartelemy, S. Codis, F. Bernadeau, Probability distribution function of the aperture mass field with large deviation theory, MNRAS 2021

Theoretical wavelet ℓ_1-norm from one-point PDF prediction

Vilasini Tinanneri.S[1], Sandrine Codis[1], Alexandre Barthelemy[3], and Jean-Luc Starck[1,2]

arXiv:2406.10033 , A&A, 691, Nov 2024.

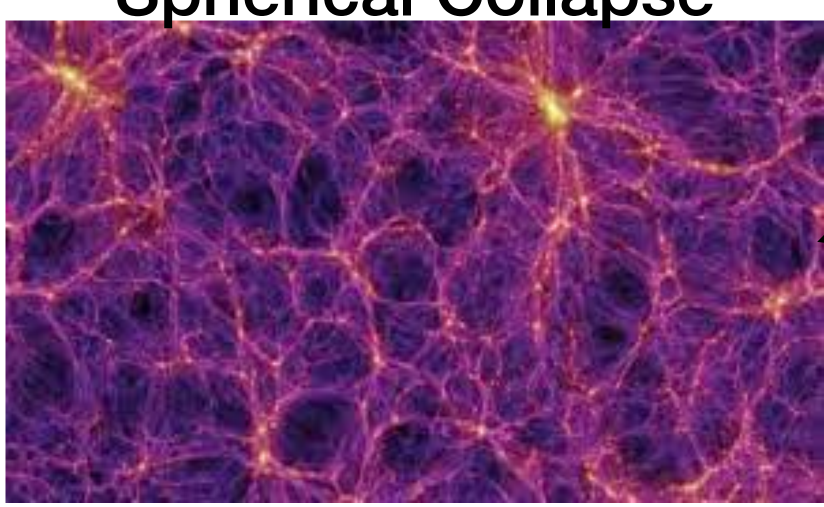
Based on previous work on **Large Deviation Theory:** A framework to predict one-PDF in mildly non-linear regime



We know the PDF

Rate Function

Spherical Collapse



Probability Density Function

Deriving wavelet ℓ_1-norm LDT

V. Tinnaneri Sreekanth

Theoretical wavelet ℓ_1-norm from one-point PDF prediction

Vilasini Tinanneri.S[1], Sandrine Codis[1], Alexandre Barthelemy[3], and Jean-Luc Starck[1,2]

$$w_j = < \kappa, \varphi_{j+1} > - < \kappa, \varphi_j >$$

Apply this in the LDT framework to get the wavelet ℓ_1-norm of the wavelet coefficients

$P(w_j)$

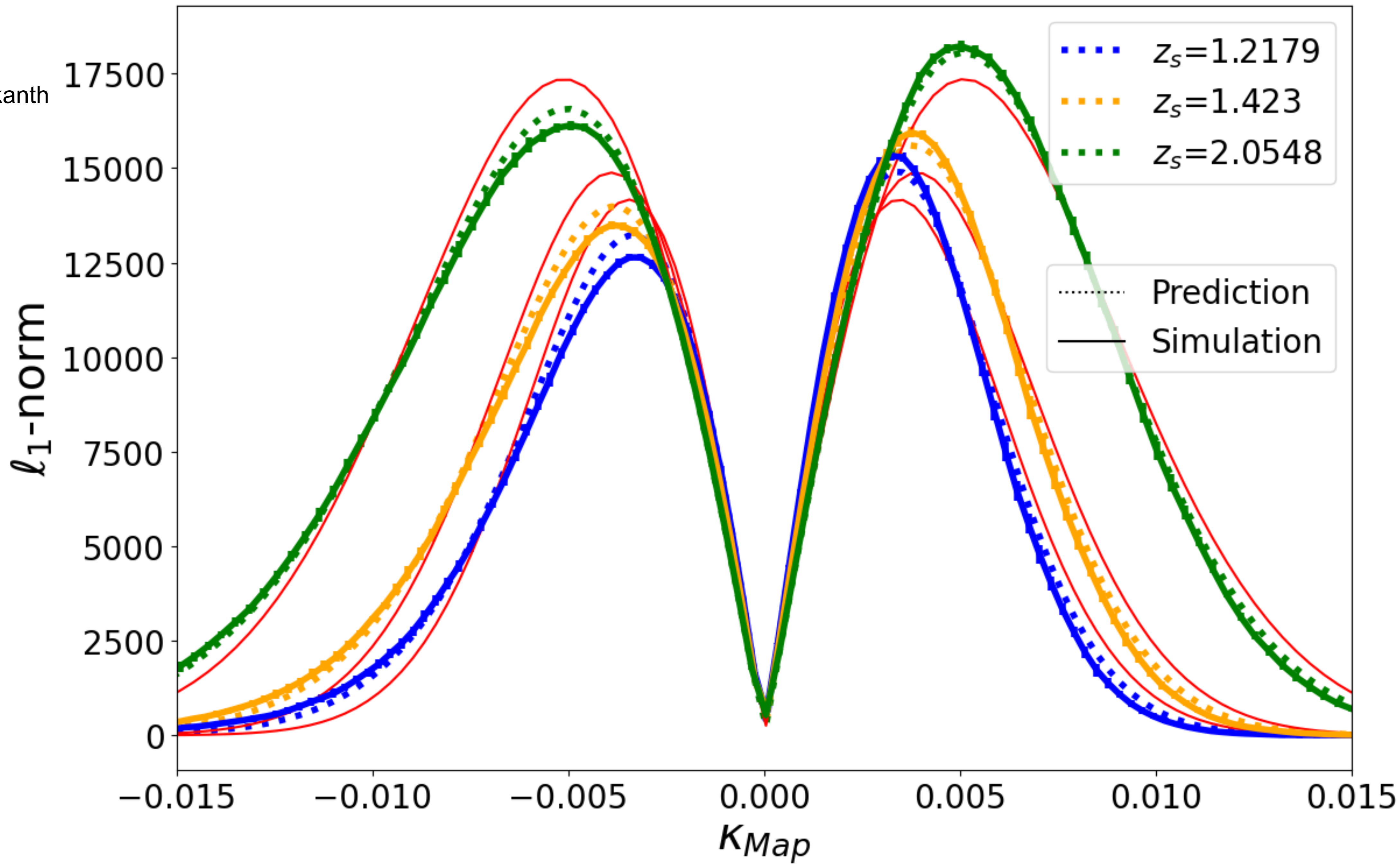
Using LDT first to get the

- **Theory** $$l_1(\Theta_j, \mathrm{B}_{j,i}) = B_i \mathbf{Prob}^{\mathrm{LDT}}_{\Theta_j}(w_j)$$
- **Data** $$l_1(\Theta_j, \mathrm{B}_{j,i}) = \sum_{k=1}^{\#\mathrm{coef}(B_{j,i})} \mid w_{j,k} \mid$$

Deriving wavelet ℓ_1-norm LDT

V. Tinnaneri Sreekanth

Simulation used: Takahashi's



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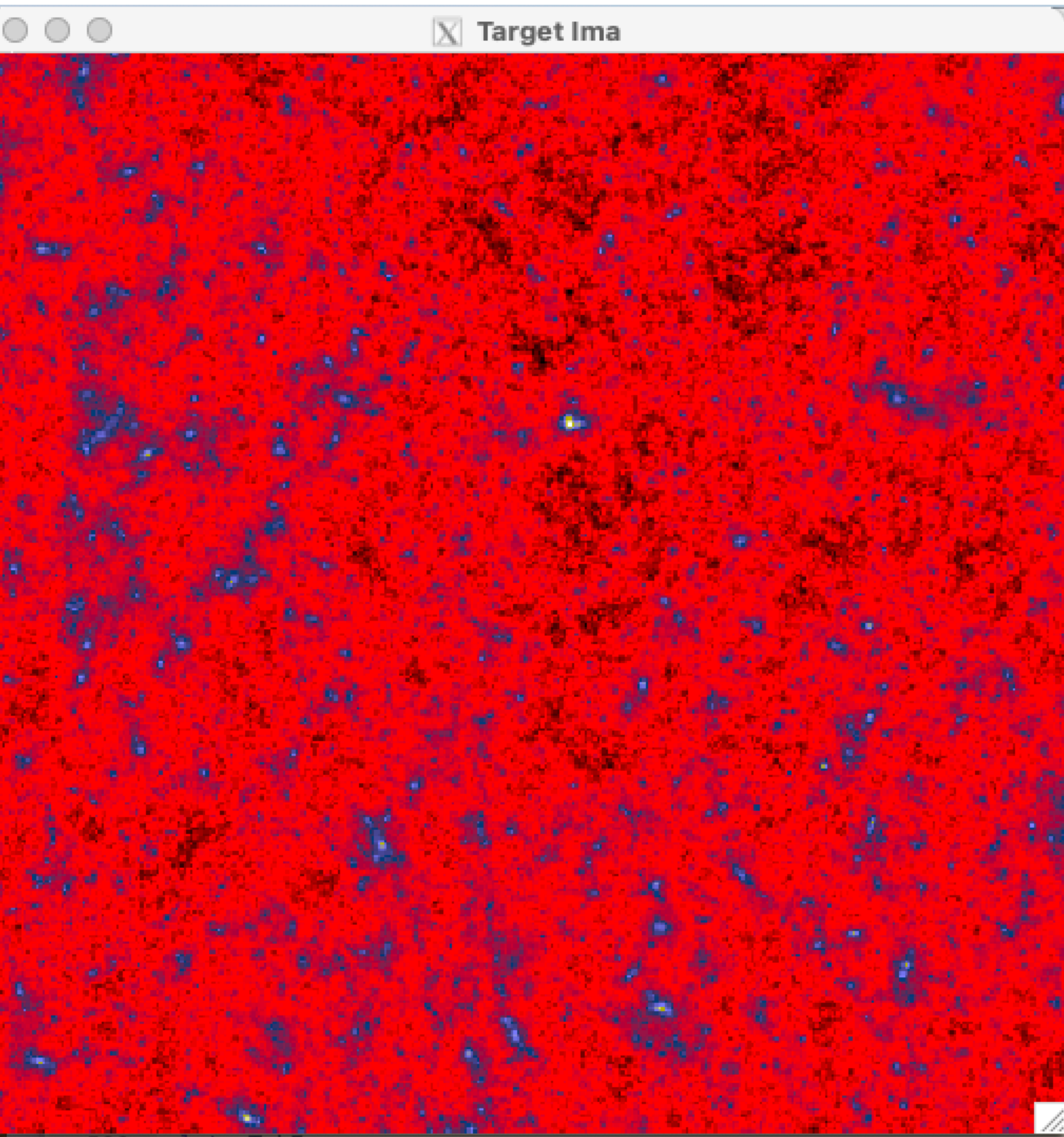
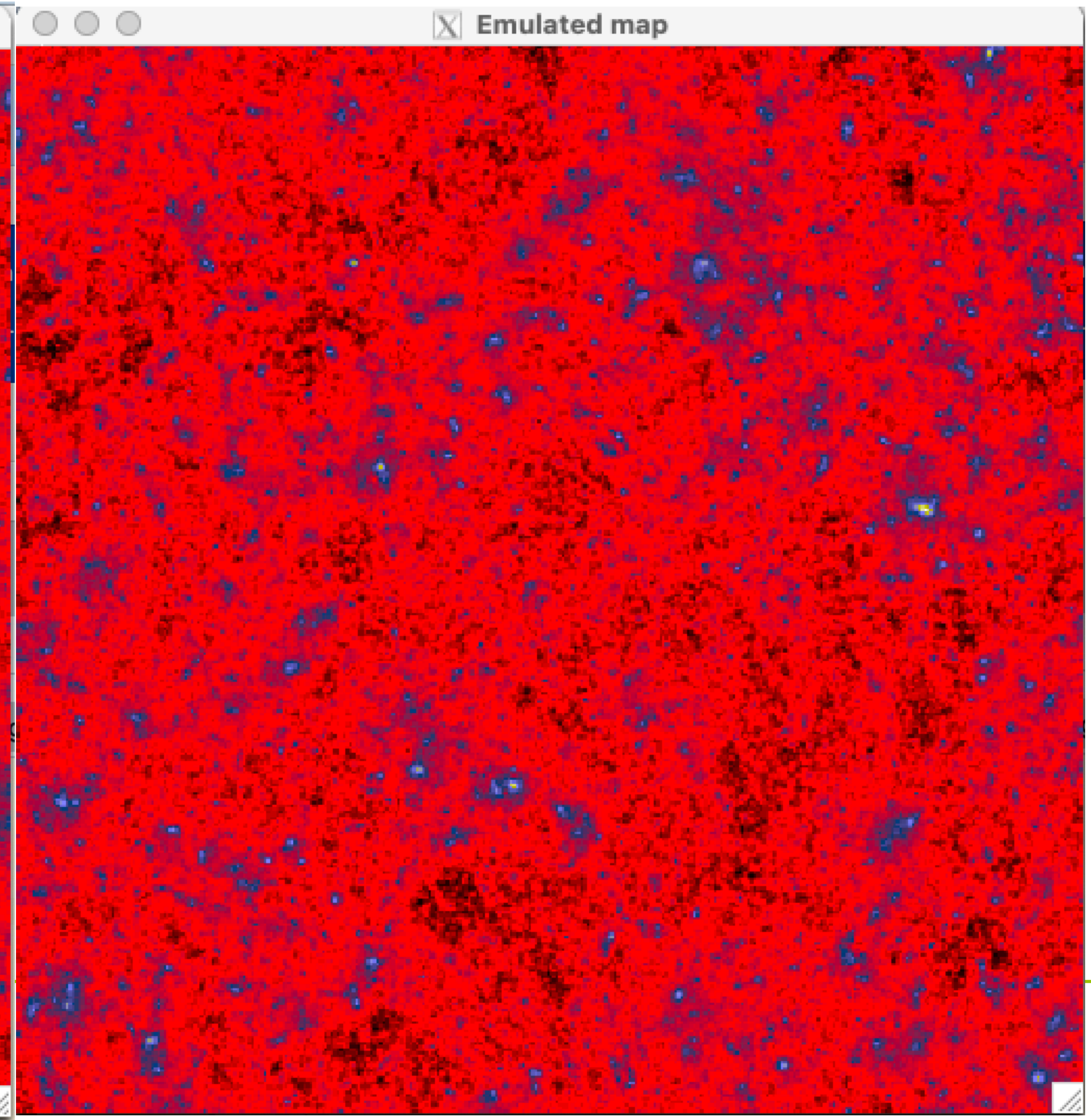
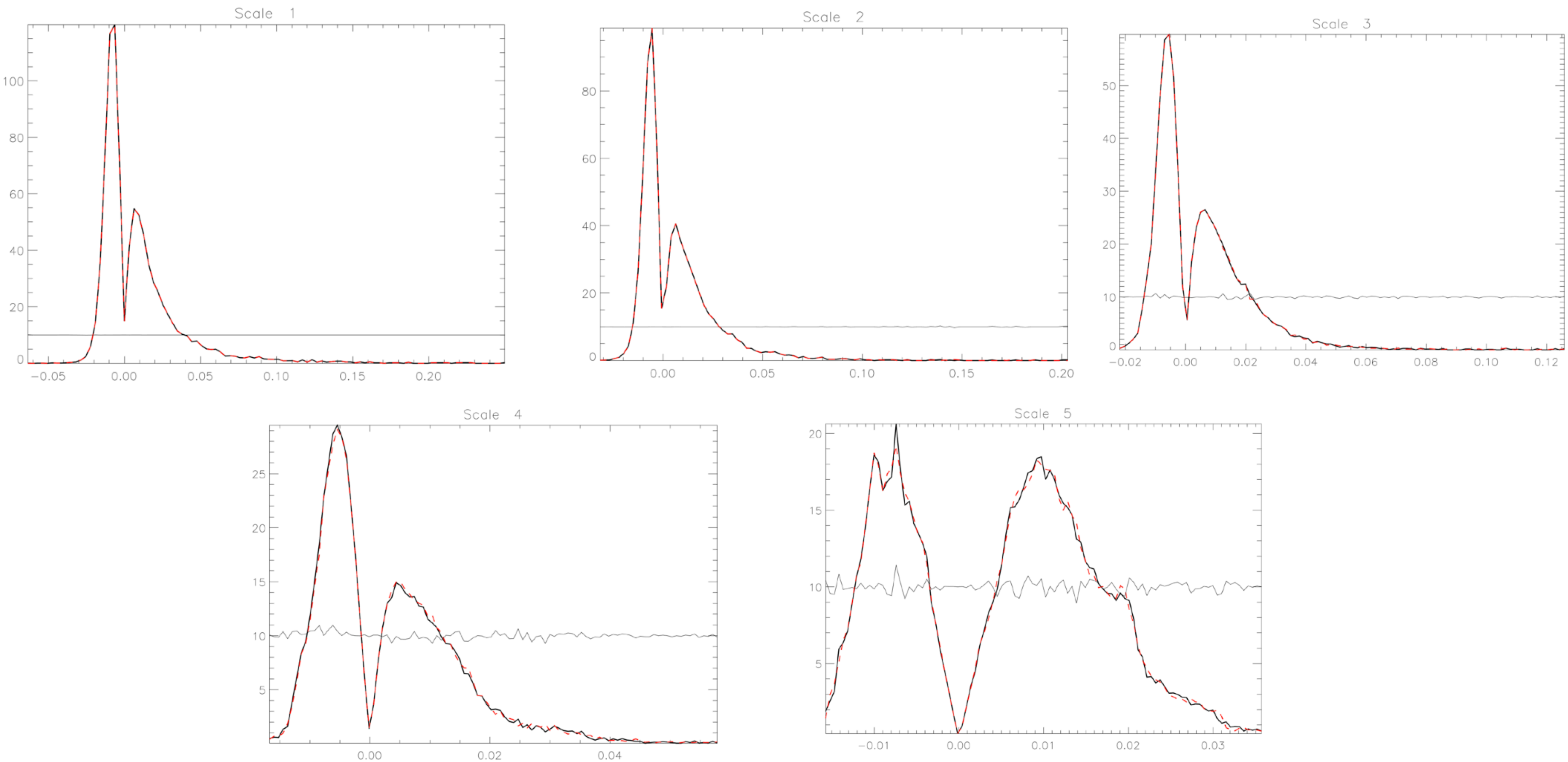
On-going Work: Wavelet l1-norm emulator

Emulation of a map with the same l1-norm and pdf as another N-body simulated map





Wavelet l1-norm for both prediction and emulated map



Conclusions

- We need different analytical methods to extract non-Gaussianities
    - Using Higher-Order statistics
    - Wavelet ℓ_1-norm is shown to be a better estimator in comparison to power spectrum, [multi-scales] peaks and void statistics

- Current methods use simulations based approach —> **Highly resource intensive**
    - Need theoretical modelling

- Use LDT based approach to obtain the PDF for mass maps
    - Derived wavelet ℓ_1-norm from PDF

- Future work: **Develop a forward modelling inference approach based on the wavelet l1-norm emulator.**