

# Simulation-based inference pipelines for Euclid data



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In collaboration with the Aquila Consortium www.aquila-consortium.org

21 June 2023



Markov Chain Monte Carlo is 70 years old!

THE JOURNAL OF CHEMICAL PHYSICS VOLUME 21, NUMBER 6

JUNE, 1953

## Equation of State Calculations by Fast Computing Machines

NICHOLAS METROPOLIS, ARIANNA W. ROSENBLUTH, MARSHALL N. ROSENBLUTH, AND AUGUSTA H. TELLER, Los Alamos Scientific Laboratory, Los Alamos, New Mexico

AND

EDWARD TELLER,\* Department of Physics, University of Chicago, Chicago, Illinois (Received March 6, 1953)

A general method, suitable for fast computing machines, for investigating such properties as equations of state for substances consisting of interacting individual molecules is described. The method consists of a modified Monte Carlo integration over configuration space. Results for the two-dimensional rigid-sphere system have been obtained on the Los Alamos MANIAC and are presented here. These results are compared to the free volume equation of state and to a four-term virial coefficient expansion.



# Why I decided to go "likelihood-free" for galaxy clustering additional probes

Note: likelihood-free inference  $\approx$  simulation-based inference  $\approx$  implicit likelihood inference

• A question of <u>accuracy</u>: first, avoid biases.



FL & Heavens, 2103.04158

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• Some WL additional probes also have a non-Gaussian distribution.



• A question of <u>precision</u>: can numerical forward models be used to push further than  $k \gtrsim 0.15 h/Mpc$ ? The full field contains much more information.

Euclid HOWLS-KP paper 1, Ajani et al., 2301.12890Simulation-based inference pipelines for Euclid data21/06/20233

#### DELFI (Density Estimation Likelihood-Free Inference): Inference from cosmic shear log-normal forward models

#### (WL: Forward Modelling)





## BOLFI (Bayesian Optimisation for Likelihood-Free Inference): Re-analysis of the JLA supernova sample



- The number of required simulations is reduced by 2 to 3 orders of magnitude with respect to likelihood-free rejection sampling or MCMC
- Bayesian optimisation can also be applied to the "true" likelihood (if known) or to iteratively build an emulator of the data model



#### SELFI (Simulator Expansion for Likelihood-Free Inference): Euclid forecast vs BOSS data

- $V = (3780 \text{ Mpc}/h)^3$ (volume of the Euclid flagship simulation)
- Gaussian random field data model; 6,060 simulations
- 100 parameters are simultanéously inferred





0.1

0.2

0.3

 $k \, [h/{
m Mpc}]$ 

0.4

1.1

0.9

 $P(k)/P_0(k)$ 

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6

## (GC: Additional Probes)

•  $V = (3780 \text{ Mpc}/h)^3$  cubic box, covering one octant of the sky The extracted region

The extracted region of the mask for the observed octant is delimited by the orange triangle



### Systematic effects at large scales: mask and selection functions

## (GC: Additional Probes)

- Two models:
  - Model A: lognormal selection functions, luminosity-dependent galaxy bias
  - Model B: misspecified selection functions and galaxy biases



Selection functions

8

#### SELFI posterior: reconstructed initial matter power spectrum (GC: Additional Probes) Model A Reconstruction for the well specified model 1.0 $\theta_0$ (prior) 1.4 $\gamma$ (reconstruction) 1.3 $\theta_{gt}$ (groundtruth) - 0.8 1.2 $P(k)/P_0(k)$ - 0.6 1.0- 0.4 $\theta(k) = 0.9$ 0.8- 0.2 0.70.60.0 $10^{-2}$ $10^{-1}$ $k \, [h/{\rm Mpc}]$ Hoellinger & Leclercq, in prep.

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#### Simulation-based inference pipelines for Euclid data 21/06/2023 9

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## Data compression for SBI

- Good old techniques are still quite useful...
- MOPED/score compression: compresses n data points to p summaries (where p is the number of parameters).

$$\mathbf{F} \equiv -\mathbf{E}_{\boldsymbol{\theta}} \left[ \nabla \nabla^{\mathrm{T}} \mathcal{L} \right] = \mathbf{E}_{\boldsymbol{\theta}} \left[ \nabla \mathcal{L} \nabla^{\mathrm{T}} \mathcal{L} \right]$$
$$\hat{\boldsymbol{\theta}} = \boldsymbol{\theta}_{*} + \mathbf{F}_{*}^{-1} \nabla \mathcal{L}_{*}$$

 Score compression is lossless linear data compression (optimal at first-order in the log-likelihood)  Non-linear data compression: Can we saturate the information content thanks to machine learning?



 IMNN compression gives summaries that are nearly maximally informative compared to theoretical estimates

Heavens, Jimenez & Lahav 2000, astro-ph/9911102 Alsing & Wandelt 2018, 1712.00012



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Makinen et al., 2107.07405

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1.0

6 0.8

0.6

0.0

0.5