Precision cosmology: myth or reality? A theoretical perspective

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Context

Precision cosmology allows us to perform Bayesian inference on the standard model parameters, and may be discover exotic dark matter particles or modified gravity models.

Precision cosmology with the CMB sky



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Non-linear dark matter dynamics plays an important role in various cosmology probes of the dark sector.

- galaxy clustering: non-linear BAO shifts
- weak lensing: non-linear boost.

Large scale structures: towards precision cosmology?



Context

Precision cosmology allows us to perform Bayesian inference on the standard model parameters, and may be discover exotic dark matter particles or modified gravity models.

Non-linear dark matter dynamics plays an important role in various cosmology probes of the dark sector.

- galaxy clustering: non-linear BAO shifts
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Non-linear dynamics can be described analytically using high-order perturbation theories on relatively large scales.

Small scales are affected by baryonic effects.

N-body models are the only viable alternative at intermediate scales.

How accurate are N-body simulations ? Can we use them to perform include non-linear corrections in expensive Monte Carlo Markov Chains and compute the Likelihood of the best fit parameters ?



N body codes solve the Vlasov-Poisson equations using a Lagrangian sampling of phase space. So far, the most competitive approach, but for how long ?

Main numerical limitations are:

- 1. Finite box size
- 2. Finite number of particles
- 3. Finite force resolution

Popular techniques are, in chronological order:

- 1. Direct N body, scaling as N²
- 2. PM: Fast Fourier Transform solvers, N log N, low resolution
- 3. P3M (PP + PM): order N log N if large box, N² if small box, low resolution
- 4. Tree codes, O(N log N), high resolution, see also Tree-PM
- 5. Adaptive Mesh Refinement (AMR) and Multigrid solver, O(N), high resolution
- 6. Fast Multipole Method (FMM), O(N), high resolution

Performance of N body codes



Systematic errors in N body codes ?









Evolution of GR corrections over time



N-body gauge with photons, neutrinos and metric linear fluctuations generated with CLASS Tram *et al.* 2018





Particle discreteness effects



Particle linear theory can be used to rescale the initial conditions and correct from discreteness effects.

Sub-percent accuracy down to the Nyquist frequency

Garrison et al. 2018 1.02 z=1 1.00 $P(k)/P_{\rm ref}(k)$ 0.98 ΖA ZA-PLT 0.96 2LPT-PLT ZA-PLTR $z_{\text{target}} = 5$ 2LPT-PLTR $z_{\text{target}} = 5$ 0.94 2LPT-PLTR $z_{\text{target}} = 12$ 2LPT-PLTR $z_{\text{target}} = 5$, Oversampled (Reference) 0.92 10⁻² 10⁻¹ $k \,[h\,{
m Mpc}^{-1}]$ 10⁰ 10^{1} $k_{\rm Nv}$

simple cubic lattice

Designing the optimal N body simulation for P(k)



- 1. Box size larger than 2000 Mpc/h
- 2. N larger than 4096^3 particles
- 3. For each parameter set, use 2 simulations with pairing and fixing (Angulo and Pontzen 2016) to suppress variance on large scale

Emulating the power spectrum for Euclid

In order to fit galaxy survey data using non-linear corrections, one needs to explore the 6-dimensional parameter space to perform the likelihood analysis.



Each individual simulation is very expensive.

Goal: replace N body simulations by a surrogate model with the same subpercent accuracy.

Uncertainty quantification techniques used routinely in engineering.

First implementation for cosmology by Heitmann et al. (2010): CosmicEmu.

This work: used the platform UQLab developed at ETH Zurich by Sudret and collaborators to design new, more accurate emulators for the Euclid mission. The Euclid collaboration, Knabenhans *et al.* (2018), arXiv:1809.04695: The EuclidEmulator Knabenhans et al. (2020) EuclidEmulator2, under review

New approach: emulate the non-linear boost



Optimising the experimental design

How many simulations do we need to perform ?

How do we sample the parameter space ?

How do we interpolate the power spectrum in between the sampling points ?

Monte Carlo Sampling

(Some shared rows or columns.)



Latin Hypercube Sampling

(Monte Carlo Sampling with no shared rows or columns.)



Optimal Space-Filling Design Sampling

(Latin Hypercube sampling with even distribution of points)



Interpolation strategy

First, define the parameter space

Second, define n_{ED} , the number of points in the experimental design.

Third, perform a Principal Component Analysis

$$\mathbf{D} = \sum_{i=1}^{n_{\text{ED}}} \lambda_i(\omega_{\text{b}}, \omega_{\text{m}}, n_{\text{s}}, h, w_0, \sigma_8) \text{PC}_i(k, z)$$

 $\omega_{b} \in [0.0215, 0.0235]$ $\omega_{m} \in [0.1306, 0.1546]$ $n_{s} \in [0.9283, 1.0027]$ $h \in [0.6155, 0.7307]$ $w_{0} \in [-1.30, -0.70]$ $\sigma_{8} \in [0.7591, 0.8707]$

Fourth, interpolate the eigenvalues with Legendre polynomials of degree p.

$$\lambda_i(\omega_{\rm b}, \omega_{\rm m}, n_{\rm s}, h, w_0, \sigma_8) \approx \sum_{\alpha \in \mathcal{A}} \eta_\alpha \Psi_\alpha(\mathbf{x})$$

Polynomial coefficients are computed by regression.

Key parameters:

- Number of points in the experimental design n_{ED}
- Number of PCs N_{PC} or accuracy parameter a
- Polynomials degree p

Defining the emulation parameters

We use Takahashi's Halofit (THM) to mock N body simulations. We estimate the Emulation-Only-Error (EOE).

Required number of simulations depends on the PCA truncation parameter.



Characterising the final strategy

We set the polynomial degree to p=2, the size of the experimental design to 100 points and the number of PC to 11 ($a=1-10^{-5}$).

We test the corresponding emulator using Halofit in 2D cuts through the parameter space.



Testing the final Euclid Emulator



6 first PC in the final emulator



Comparison with previous work

Use the CLASS code to generate the linear power spectrum, then multiply by the non-linear correction (boost).



Galaxy formation in groups and clusters



Teyssier et al. (2011)

The Baryonic Correction Model (Schneider & Teyssier 2015)



Encoding baryonic effects on the power spectrum

$$\rho_{\text{gas}}(r) = \frac{\rho_{\text{gas},0}}{(1+u)^{\beta}(1+v^2)^{(7-\beta)/2}}$$
$$u \equiv r/r_{\text{co}} \text{ and } v \equiv r/r_{\text{ej}}.$$
$$r_{\text{co}} \equiv \theta_{\text{co}}r_{\text{vir}}, \qquad r_{\text{ej}} \equiv \theta_{\text{ej}}r_{\text{vir}},$$
$$\beta(M_{200}) = 3 - \left(\frac{M_{\text{c}}}{M_{200}}\right)^{\mu}$$

For each halo, we use an analytical spherically symmetric model for the total mass distribution. Particle are displaced according to the mapping from pure NFW to BCM. We then compute the baryonic correction on the power spectrum.



Matching the OWLS simulation (McCarthy et al. 2010)





Romain Teyssier



Matching real X-ray data with the BCM



Interpreting current weak lensing surveys



Forecasting future weak lensing surveys



Weak-lensing as a probe of galaxy formation physics



Combining everything



Baryonic physics or new physics?



Conclusions

Systematic errors due to N body simulation below 1% at k<10 h/Mpc (Schneider *et al.* 2016, Garrison *et al.* 2018).

Given a reasonably sized parameter space, we can design an emulator for the nonlinear boost of the matter power spectrum with « emulation-only-errors » as low as 0.2% (The EuclidEmulator, Knabenhans *et al.* 2019).

For weak lensing, baryonic effects kick in at k=1 h/Mpc (pessimistic scenario). They can be encoded as a baryonic boost with additional parameters, and marginalised over (Schneider *et al.* 2019, 2020).

Forecast including baryonic effects show that combining CMB, X-ray and galaxy survey data would deliver maximum constraining power.