Cosmological constraints with mass maps and peak counts for Euclid

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Introduction

Peak count statistics in weak lensing (WL) mass maps provide access to non-Gaussian information contained in the large-scale distribution of matter in the universe. They are therefore a useful complementary probe to the power spectrum and other two-point statistics to constrain the parameters of our cosmological models. With its advanced optics and large survey area, the upcoming space-based Euclid telescope will measure the cosmic weak lensing signal with unprecedented precision. As a step toward forecasting for Euclid, we study the constraining power of peak counts in a simulated Euclid-like survey on the cosmological parameter set $\{\Omega_m, \sigma_8, w_0\}$.

Methodology

1. Implement a wavelet-based multiscale mass mapping technique to produce S/N maps from a galaxy shear catalogue.

2. Process a large-area mock catalogue and compute peak statistics to serve as the observation data set.

3. Use a stochastic peak count model to generate peak count data vectors as a function of cosmological parameters.

4. Explore parameter space with approx. Bayesian computation (ABC) and derive credible contours.

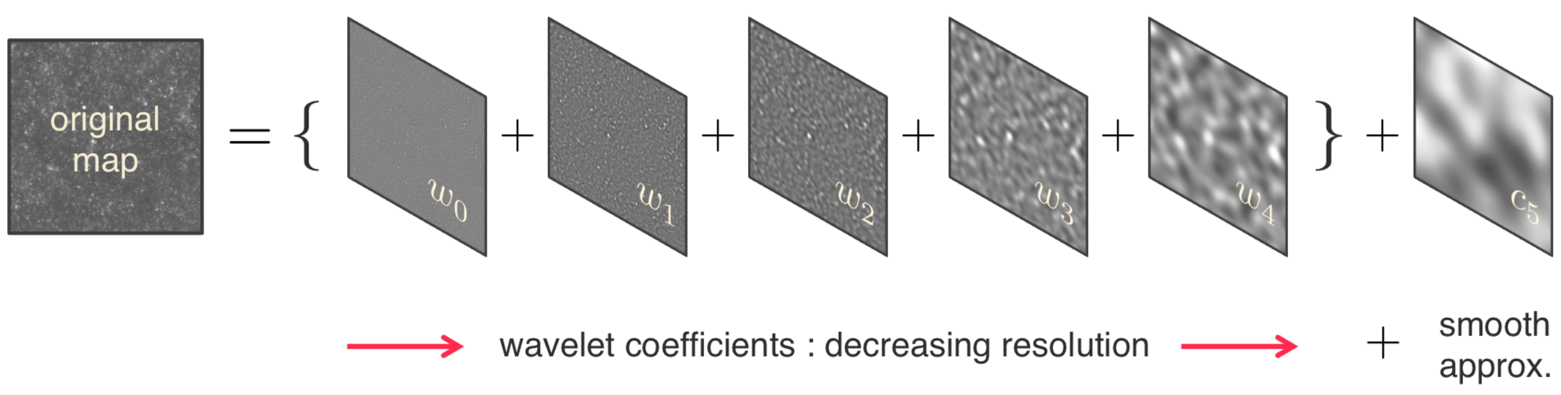
Mass mapping and peak detection

Mass mapping process

galaxy ellipticity catalogue ⇨ pixelated shear map ⇨ mass (convergence) map

Wavelet filtering / decomposition

We use the isotropic undecimated wavelet transform (*starlet*) to extract multiscale information from the noise-dominated mass maps. This transform decomposes an image into a set of J maps at a different resolutions, $\{w_j\}$ for $j = 0 \ldots J-1$, plus a smoothed approximation c_J, where the sum equals the original image.



We identify peaks in signal-to-noise (S/N) maps and compute peak abundance histograms as a function of S/N and scale j.

A peak is a pixel whose S/N value is larger than its eight neighbors.

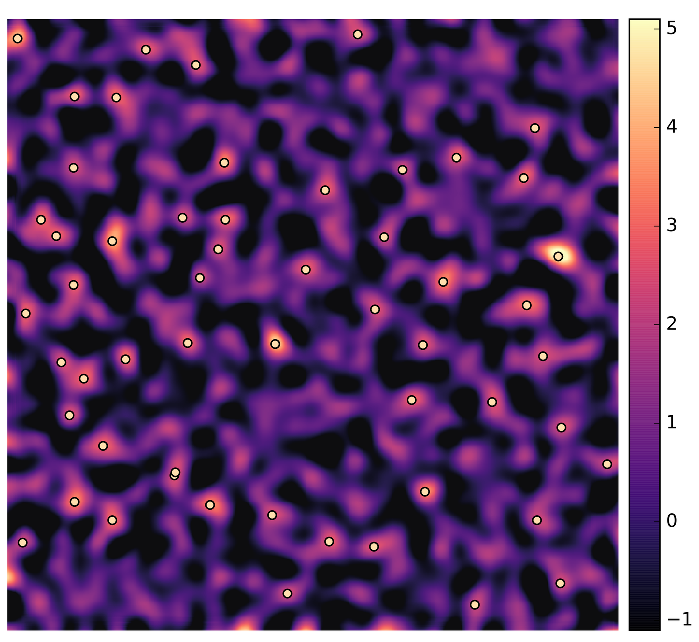


Illustration of peak detection. Color gradient indicates S/N value.

Map parameters

Number of wavelet scales	5
Map area [deg^2]	25
Pixel size [arcmin]	0.5
Number of pixels	600×600

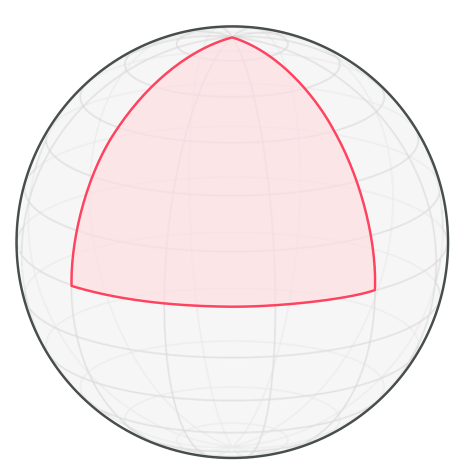
Mock observations

MICE–GC : The Marenostrum Institut de Ciències de l'Espai Grand Challenge simulation

`http://www.ice.cat/mice`

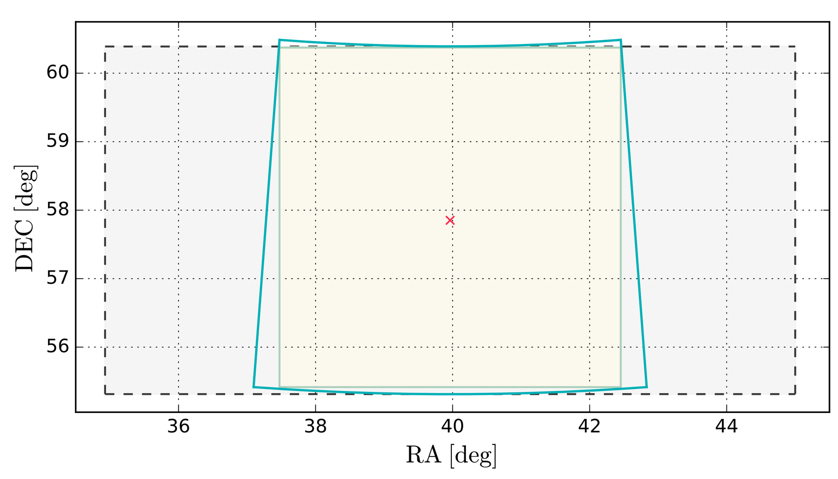
- Large-volume N-body simulation of ~ 70 billion dark matter particles
- Evolves a flat ΛCDM model in a box of side length $3\ h^{-1}$ Gpc
- Lensing information for ~ 500 million galaxies out to $z = 1.4$

Lensing catalogue coverage



The MICEv2.0 lensing catalogue spans one octant of the sky. There is no repetition of the simulation box, and the area is about one-third of what Euclid's wide-field survey will cover.

Patch extraction example



We cut rectangular patches in RA/DEC space and project them to the tangent plane about their center point. We extract 186 patches from the octant, giving a total area of $4,650\ \mathrm{deg}^2$ for our peak count analysis.

Peak count model

We use the stochastic CAMELUS code (`http://www.cosmostat.org/software/camelus/`) to model peak counts as a function of input cosmological parameters. The algorithm's final step has been modified to include our mass mapping technique.

CAMELUS algorithm

1. Sample dark matter halo masses from a mass function within the range $5 \times 10^{12} \leq M \leq 10^{17} M_\odot/h$.
2. Assign density profiles, and distribute halos randomly in a $25\ \mathrm{deg}^2$ field.
3. Generate a galaxy shear catalogue for sources by ray-tracing.
4. Make maps, detect peaks, and compute peak count abundances.

We repeat this process to obtain peak count statistics for a cumulative area matching MICE.

Parameter settings for CAMELUS

Description	Symbol	Value
Dimensionless Hubble param.	h_{100}	0.70
Baryon density	Ω_b	0.044
Spectral index	n_s	0.95
DE linear EOS param.	w_1	0.0
NFW inner slope	α	1.0
M–c relation param.	c_0	9.0
M–c relation param.	β	0.13
Galaxy density [arcmin^{-2}]	n_{gal}	27
Source ellipticity st. dev.	σ_ϵ	0.43

Exploring parameter space with ABC

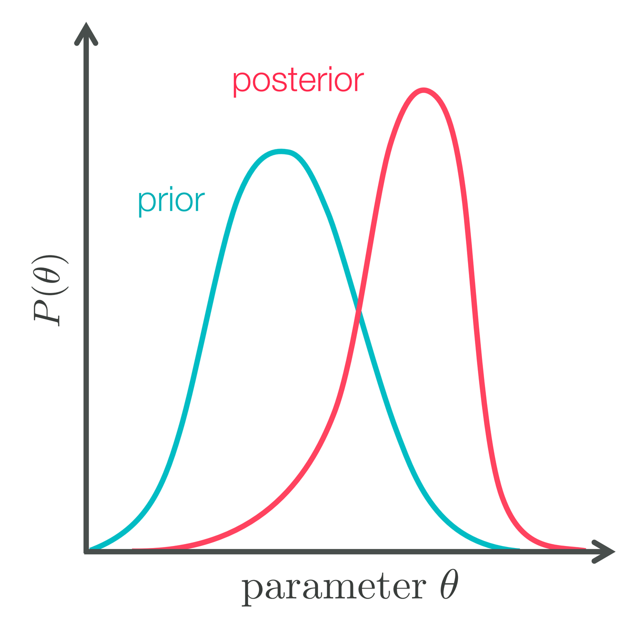
Approximate Bayesian computation (ABC) is an approach to constraining model parameters that avoids the evaluation of a likelihood function. With ABC, statistics of the observed data are compared to the corresponding statistics derived from simulations, which are assumed to model the process that generated the observations. Parameter space is probed via accept–reject sampling of trial parameter sets, giving a fast and accurate estimate of the true parameter posterior distributions.

General requirements

- **Data** : MICE peak abundance data vector
- **Generative model** : CAMELUS algorithm
- **Priors** : uniform for Ω_m, σ_8, and w_0
- **Summary statistic** : concatenated histograms of S/N values at all scales

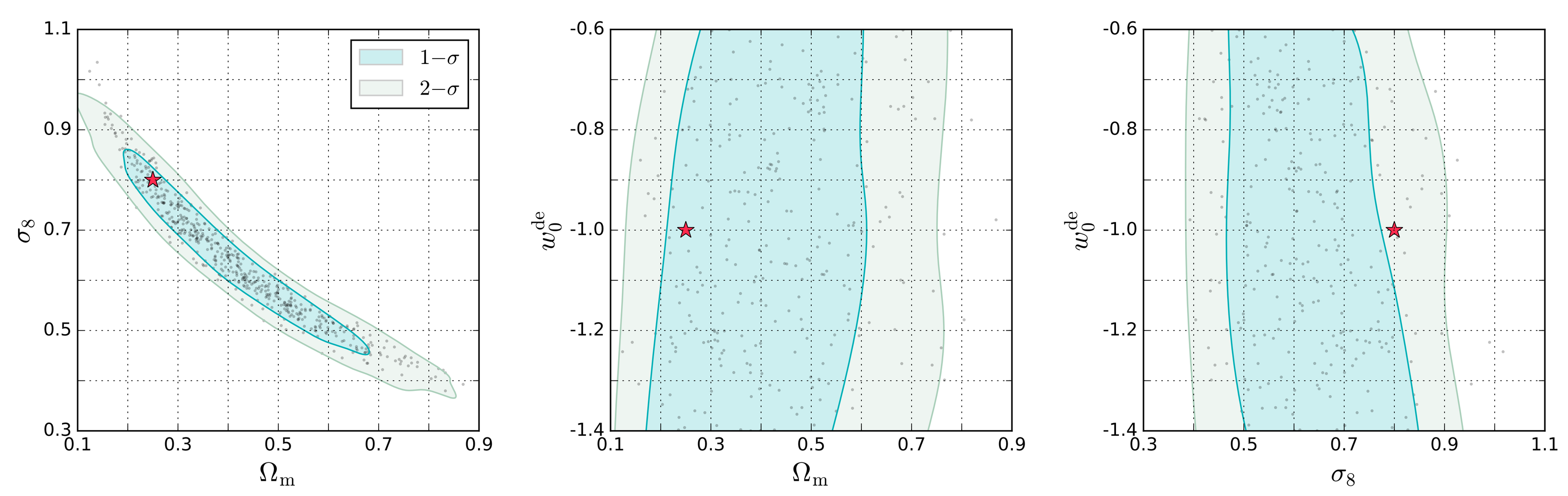
- **Matching criterion**, or distance :

$$d = \left[\sum_i \frac{(x_i^{\mathrm{model}} - x_i^{\mathrm{obs}})^2}{C_{ii}} \right]^{1/2} \leq \epsilon$$



Results

Credible contours : 9[th] iteration of ABC



We recover the typical WL degeneracy between σ_8 and Ω_m, and the MICE cosmology (red star) lies within the 1-σ region. We measure the derived parameter $\Sigma_8 := \sigma_8(\Omega_m/0.27)^{0.67} = 0.844^{+0.015}_{-0.044}$, which represents the width of the contour. Without tomography, we cannot yet constrain w_0.

Summary and outlook

With wavelet filtering and a probabilistic peak count model, we show that we can use peak count statistics in weak lensing mass maps to constrain cosmological parameters.

Extensions and further work

- Tomographic analysis
- Test on real data
- Comparison with power spectrum results and joint analysis
- More realistic survey conditions (masks, weights, etc.)

References

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