

# Some insights into the LSS likelihood from N-body simulations?

F. Elsner, F. Schmidt, M. Nguyen, J. Jasche

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## Recent developments

Since our last meeting, we have implemented into BORG

- the LSS bias model to second order
- the negative binomial likelihood

Analyzing N-body simulations, we failed to reproduce bias parameter measurements obtained from the 2-point statistics.<sup>1</sup>

To do tests much more quickly, we developed a simplified MLE outside of BORG.

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<sup>1</sup>Now understood as not necessarily being equivalent

## A simplified maximum likelihood estimator

To quickly test different bias models and likelihoods, we compute maximum likelihood estimates for a fixed density field,

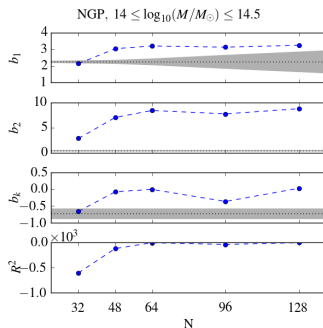
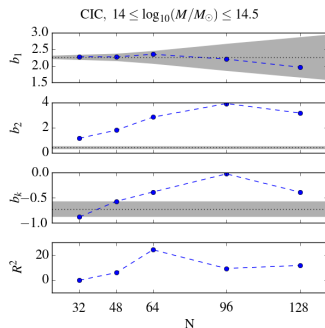
$$\begin{aligned} &P(\{b_i\}, \delta_m | \delta_h^{\text{N-body}}) \\ &\quad \downarrow \\ &P(\{b_i\} | \delta_h^{\text{N-body}}, \delta_m^{\text{N-body}}) \\ &\quad \downarrow \\ &\underset{\{b_i\}}{\operatorname{argmax}}[P(\{b_i\} | \delta_h^{\text{N-body}}, \delta_m^{\text{N-body}})], \end{aligned}$$

where we used a halo catalog as input data ( $\delta_h^{\text{N-body}}$ ), computed from a given dark matter density field ( $\delta_m^{\text{N-body}}$ ).

# MLE results vs. previous measurements I

Results from  $> 500$  test are quite discouraging, e.g.,

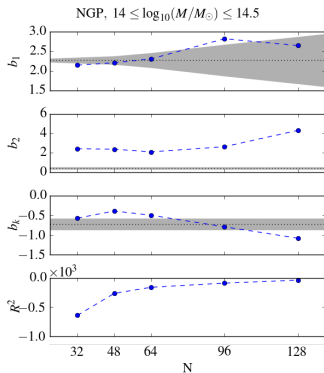
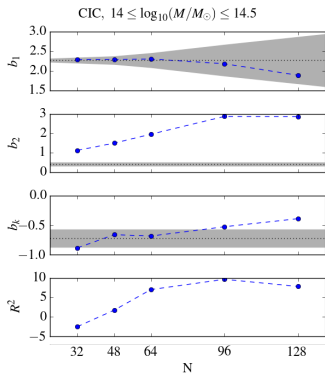
Negative binomial likelihood:



# MLE results vs. previous measurements II

Results from  $> 500$  test are quite discouraging, e.g.,

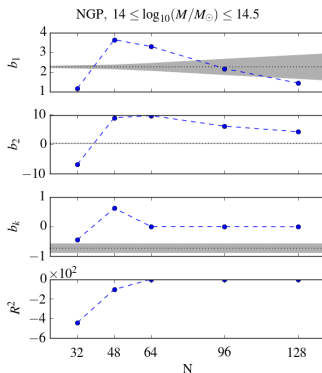
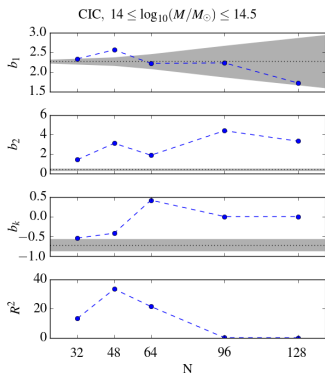
Gaussian likelihood:



# MLE results vs. previous measurements III

Results from  $> 500$  test are quite discouraging, e.g.,

Log-normal likelihood:



# MLE results summary

We find evidence for

- systematically different results of NGP and CIC data projections
- disagreement in the recovered parameters even at the lowest resolution runs – in particular for  $b_2$
- a noticeable dependence of the MLE on the likelihood used

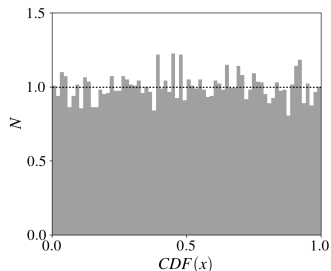
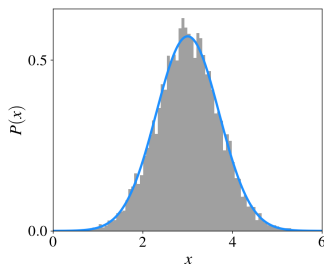
Can we assess the shortcomings of the likelihood quantitatively?

# Quantile analysis I

We start by observing that

- we have a large data vector, with many entries
- the likelihood is different in every pixel, dependent on  $\delta_m, \dots$

For any given likelihood, we can compute the quantile at each grid point. Its distribution should be flat:



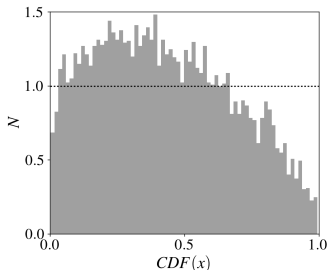
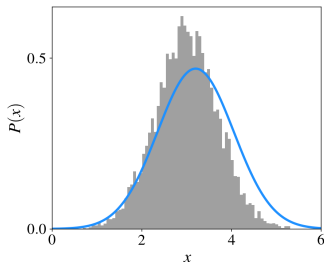


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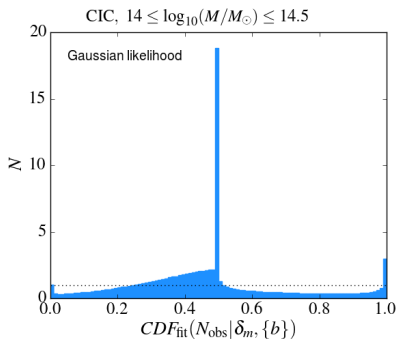
For any given likelihood, we can compute the quantile at each grid point. Its distribution should be flat:



## Quantile analysis II

How does the LSS quantile distribution look like if we fit the data with a simple Gaussian?

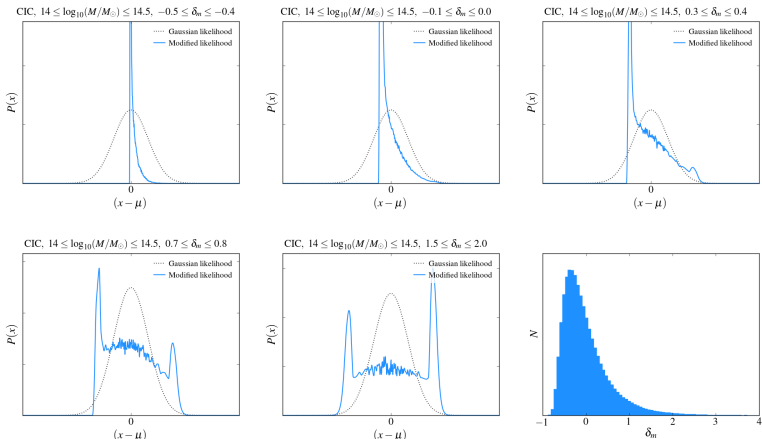
It's not flat at all:



How do we have to modify the shape of the likelihood for the quantiles to become flat?

# LSS likelihood reconstruction

Since we expect the likelihood to be a function of matter density, we should do this analysis in bins in  $\delta_m$ :



## Current status

In our tests, we have found that

- typical LSS likelihoods proposed in literature fail to capture “second order” effects
- a quantile analysis can provide us with insights into the actual shape of the likelihood – it is very complex

Important questions remain open:

- How well do we have to reproduce the likelihood shape?
- Can we recover unbiased *cosmological* parameters using more standard analytical likelihoods?