

Testing likelihood accuracy for cluster count cosmology

Constantin Payerne

3rd year PhD student at LPSC, Grenoble

Under the supervision of Dr. Céline Combet

Talk based on:

Testing likelihood accuracy for cluster abundance cosmology

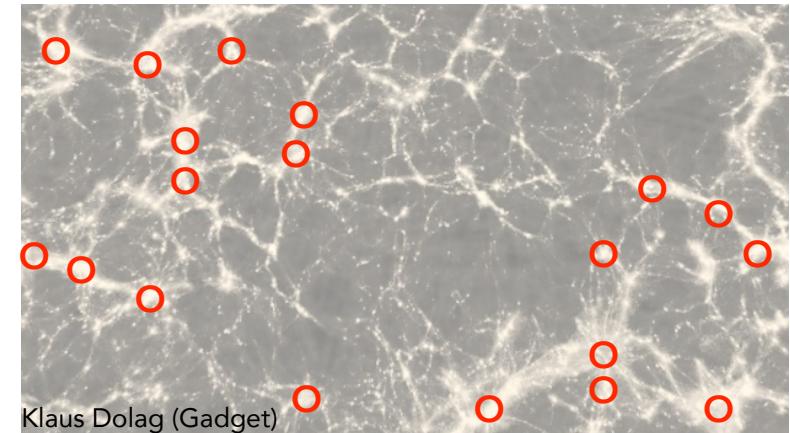
C. Payerne, C. Murray, C. Combet, C. Doux, A. Fumagalli, M. Penna-Lima, 2210.11093



Galaxy Clusters and Cosmology

Galaxy clusters: a brief introduction

- Most massive bound systems with $M \in 10^{13} - 10^{15} M_{\odot}$
- $z < 2$, last step of hierarchical structure formation process
- Densest regions in the cosmic web filaments

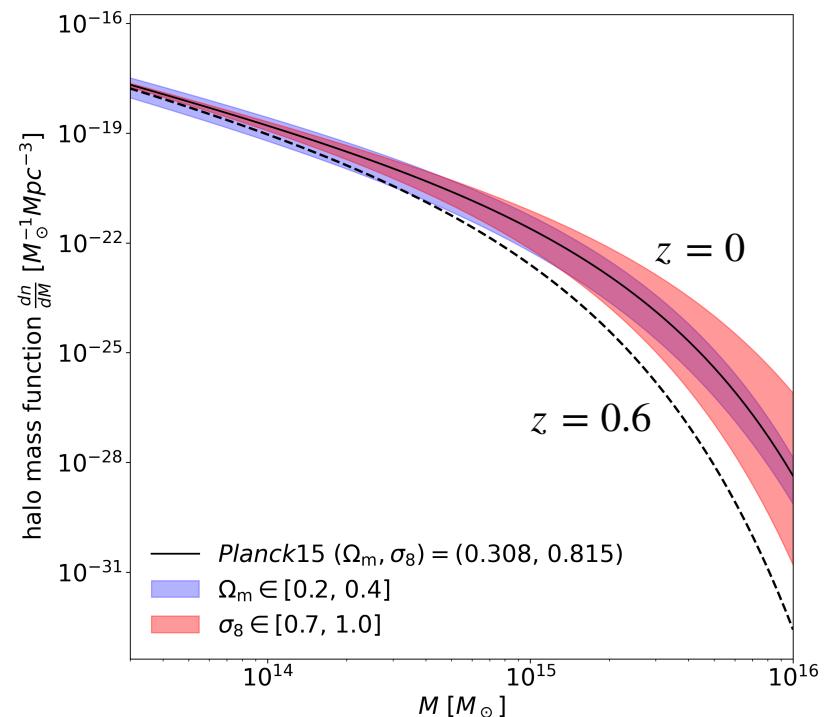


Probing cosmology with galaxy cluster abundance

- Count clusters a function of redshift and mass

$$\text{Number density } \frac{\partial^2 N_{\text{th}}}{\partial z \partial m} \propto \frac{dn(m, z)}{dm} \frac{dV(z)}{dz}$$

- Depends on:
 - **Halo Mass Function** (matter content Ω_m , growth rate of structure $\sigma_8(z)$)
 - **Volume** (background cosmology)
- Geometry + growth of structures in the Universe



Cosmology with galaxy cluster abundance

Basic recipe for cluster abundance cosmology

- Observations
 - From a galaxy cluster survey with known redshifts, masses
 - Count the number \vec{N}_{obs} of galaxy clusters within bins of redshift and mass
- Cosmological analysis: define likelihood
 - \vec{N}_{th} at arbitrary cosmology
 - Statistics:
 - Count of discrete objects in bins
 - Poisson sampling
 - Intrinsic count variance: Shot noise $\text{Var}_{\text{Poiss}}(N_k) = N_k$
 - Fluctuation + clustering of the matter density field
 - Gaussian contributions: (Super) Sample Covariance
 - $\text{Corr}_{\text{SSC}}(N_k, N_l) \neq 0$
 - $\text{Var}_{\text{SSC}}(N_k) \sim b_k^2 \sim P_{\text{mm}}(k) \sim N_k^2$
 - Non-linear physics of halo formation → More complications
 - Observational systematics, ...

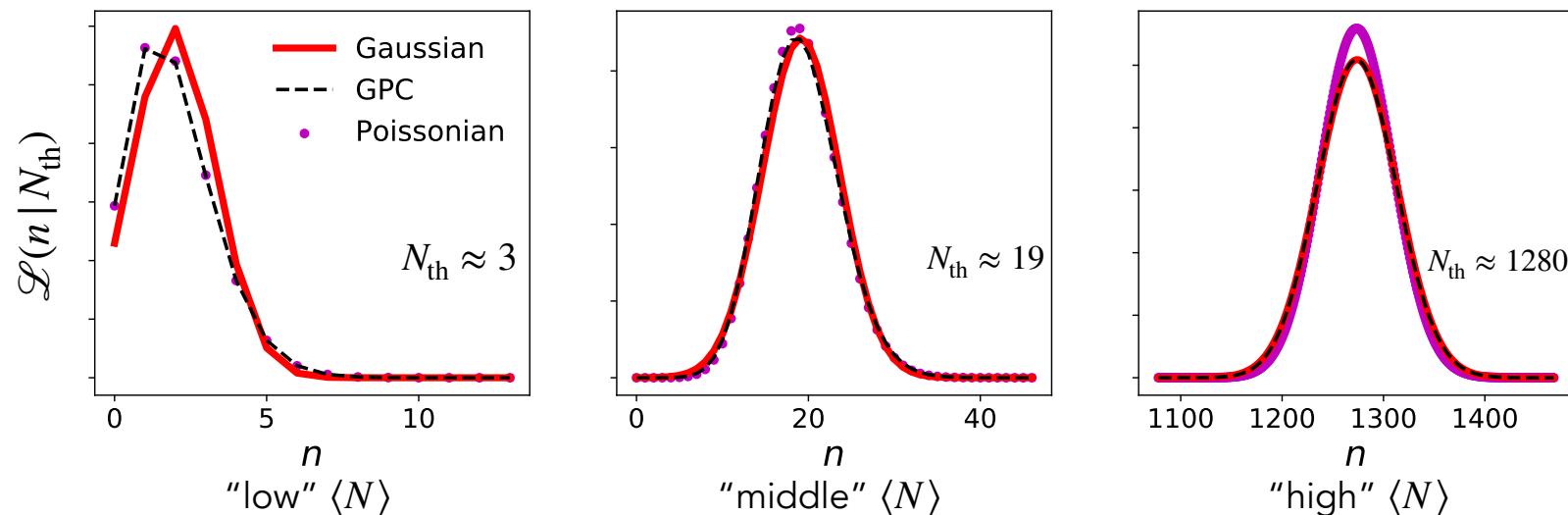
Likelihoods for cluster count cosmology

Likelihoods

- Ideally should describe completely abundance statistics
- There exist approximations
 - **Poisson likelihood** (Planck, 2015 ~ 500 clusters)
 - Accounts for Poisson sampling
 - Does not account for sample covariance
 - Valid for low number of clusters, Shot Noise >> Sample variance
 - **Gaussian likelihood** (DES, 2021 ~ 7000 clusters)
 - Sample covariance
 - Limited to continuous approximation
 - Valid for high number of clusters, Shot Noise ~ Sample variance
 - **Gauss-Poisson Compound** (GPC) (KiDS, 2021 ~ 4000 clusters)
 - Takes into account both Poisson sampling and sample covariance (Hu & Kravtsov, 2003)
 - Computationally expansive to compute
 - Multidimensional integral $\mathcal{L}(\widehat{N} | \vec{\theta}) \propto \int d\vec{x} \mathcal{N}[\vec{x} | \vec{N}(\theta)] \times \prod_{k=1}^n \mathcal{P}[\widehat{N}_k | x_k]$
 - More precise, can we gain cosmological information?

Likelihoods for cluster count cosmology

Considering the count in 3 different mass-redshift bins



Bias on parameter inference

- Deviation of the analysis likelihood from the latent one may bias results
- Most robust constraints with analysis likelihood closest to latent one

Using simulations to test cluster abundance likelihoods

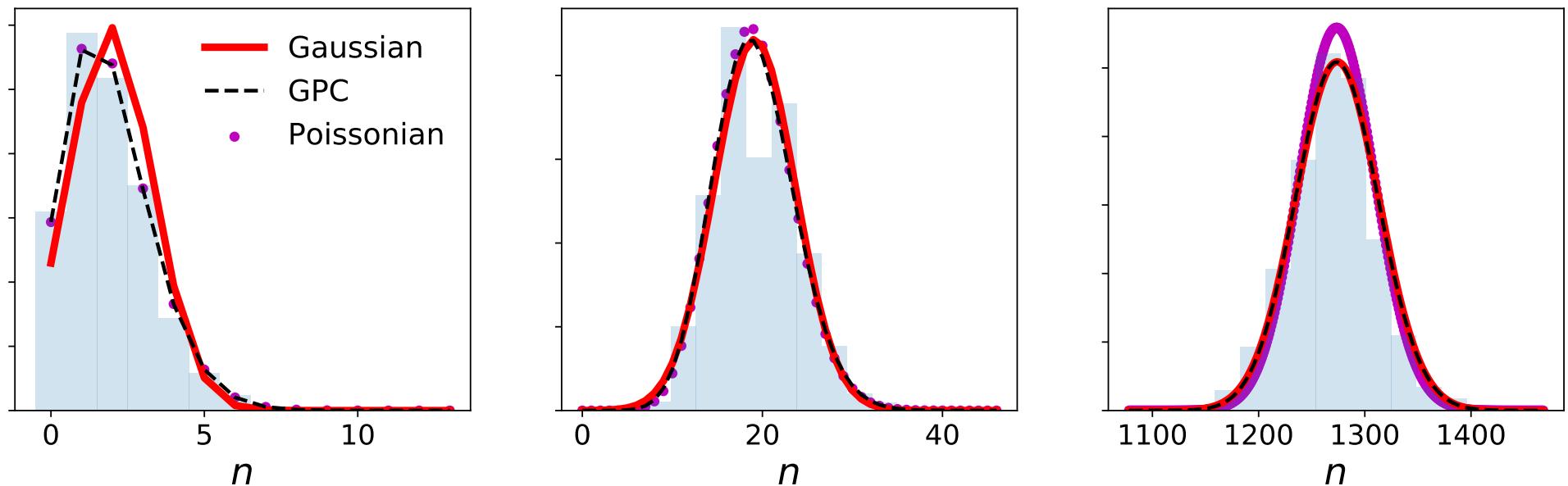
- Likelihood: statistical properties of the data at input cosmology
- With multiple simulations, can have access to "true" statistics of abundance

Framework for testing the accuracy of likelihoods

We use a set 1000 simulated dark matter halo catalogs

- PINOCCHIO algorithm (Monaco et al., 2013)
- Planck cosmology
- Masses calibrated on known halo mass function (Despali et al., 2015)
- Euclid-like sky area $\sim \frac{1}{4}$ of full-sky
- $\sim 10^5$ halos per simulation
- $M > 10^{14} M_\odot$

Abundance likelihood can be estimated from counts over the 1000 cosmological simulations



Framework for testing the accuracy of likelihoods

Frequentist Covariance of Bayesian Estimators

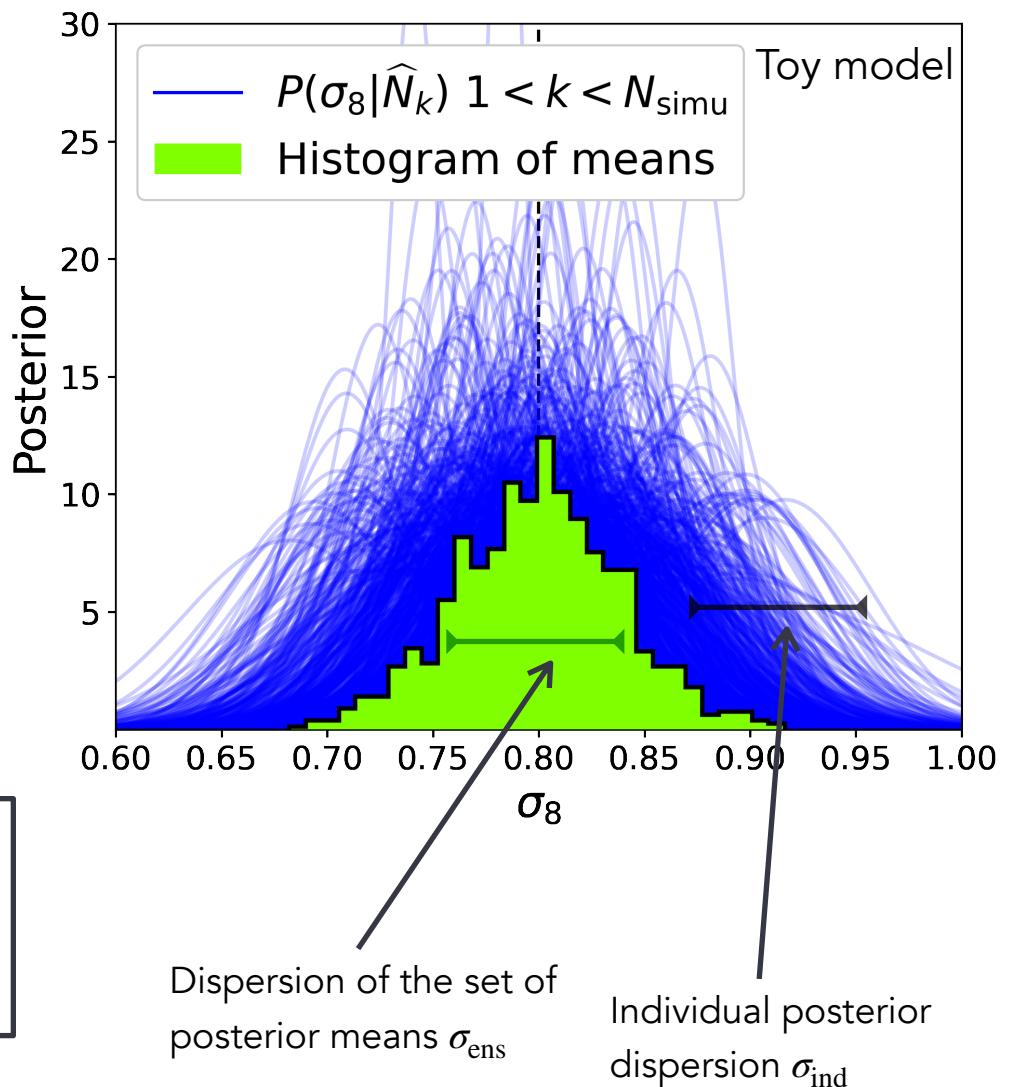
Methodology

- Estimate the posterior for each of the 1000 Pinocchio mocks
- Biases ? Compare the mean of each posterior to input cosmology
- Robustness of errors ? Compare individual posterior dispersion σ_{ind} to the spread of posterior means σ_{ens} (ensemble dispersion)

More than 1 parameter: compare covariances

$$\sigma_{\text{ind}}^2 \rightarrow C^{\text{ind}} \text{ Individual parameter covariance}$$

$$\sigma_{\text{ens}}^2 \rightarrow C^{\text{ens}} \text{ Ensemble parameter covariance}$$



Why comparing individual errors to the spread of means ?

Gaussian:

Latent likelihood $\mathcal{L}_X(\Sigma_X)$

Analysis likelihood $\mathcal{L}_Y(\Sigma_Y)$

$$C^{\text{ens}} - C^{\text{ind}} = ?$$

$$= 0 \text{ if } \Sigma_X = \Sigma_Y$$

- Parameter errors are "robust"
- And can be forecasted (Fisher formalism)

$$[(C^{\text{Fisher}})^{-1}]_{\alpha\beta} = N_{,\alpha}^T \Sigma_Y^{-1} N_{,\beta}$$

$$\neq 0 \text{ if } \Sigma_X \neq \Sigma_Y$$

- C^{Fisher} is not sufficient
- C^{ens} can be forecasted

$$C_{\alpha\beta}^{\text{ens}} = (C^{\text{Fisher}} N)_{\alpha}^T \Sigma_Y^{-1} \Sigma_X \Sigma_Y^{-1} (C^{\text{Fisher}} N)_{\beta} \neq C_{\alpha\beta}^{\text{Fisher}}$$

- Example:

$$\Sigma_{Yii} < \Sigma_{Xii} \text{ then we have } C^{\text{ind}}_{\alpha\alpha} < C^{\text{correct}}_{\alpha\alpha} < C^{\text{ens}}_{\alpha\alpha}$$

- Metric: Using correct likelihood gives $C^{\text{ens}} = C^{\text{ind}}$
- Likelihood and posterior are not always gaussians
- Rather closeness between individual errors and ensemble error
- Used as a metric to test likelihood accuracy $C^{\text{ind}} + \text{robustness } C^{\text{ens}} - C^{\text{ind}} = ?$

Cosmological inference setup

- The Poisson, Gaussian and GPC likelihood are approximations
- Valid at linear scales (clusters are biased tracers of the density field)
- For given count magnitude N_k + for SSV/SN ratio $\sim N_k$
- These quantities can vary by changing the binning the mass-redshift plane

Methodology: Test accuracy of likelihoods for various regimes

For each likelihood

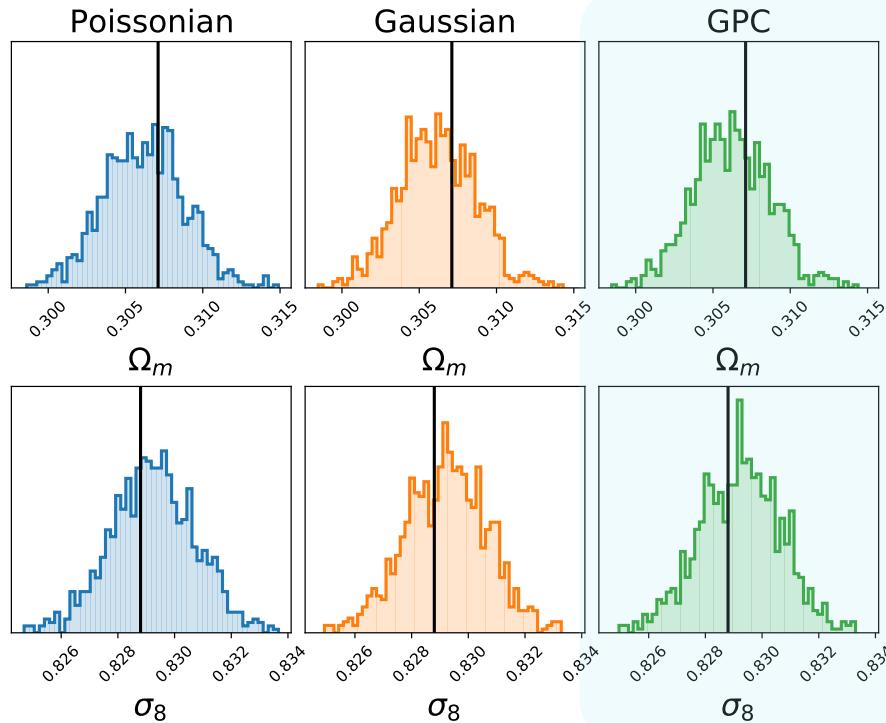
1. Compare C^{ens} , C^{ind} for the overall 1000 PINOCCHIO mocks
2. For 3 binning schemes

Binning setup					Poisson sampling ↑ ↓ Sample Variance
Redshift bins	Mass bins	# of bins	Average # N/bin		
#1	4	4	16	5000	
#2	20	30	600	150	
#3	100	100	10 000	10	

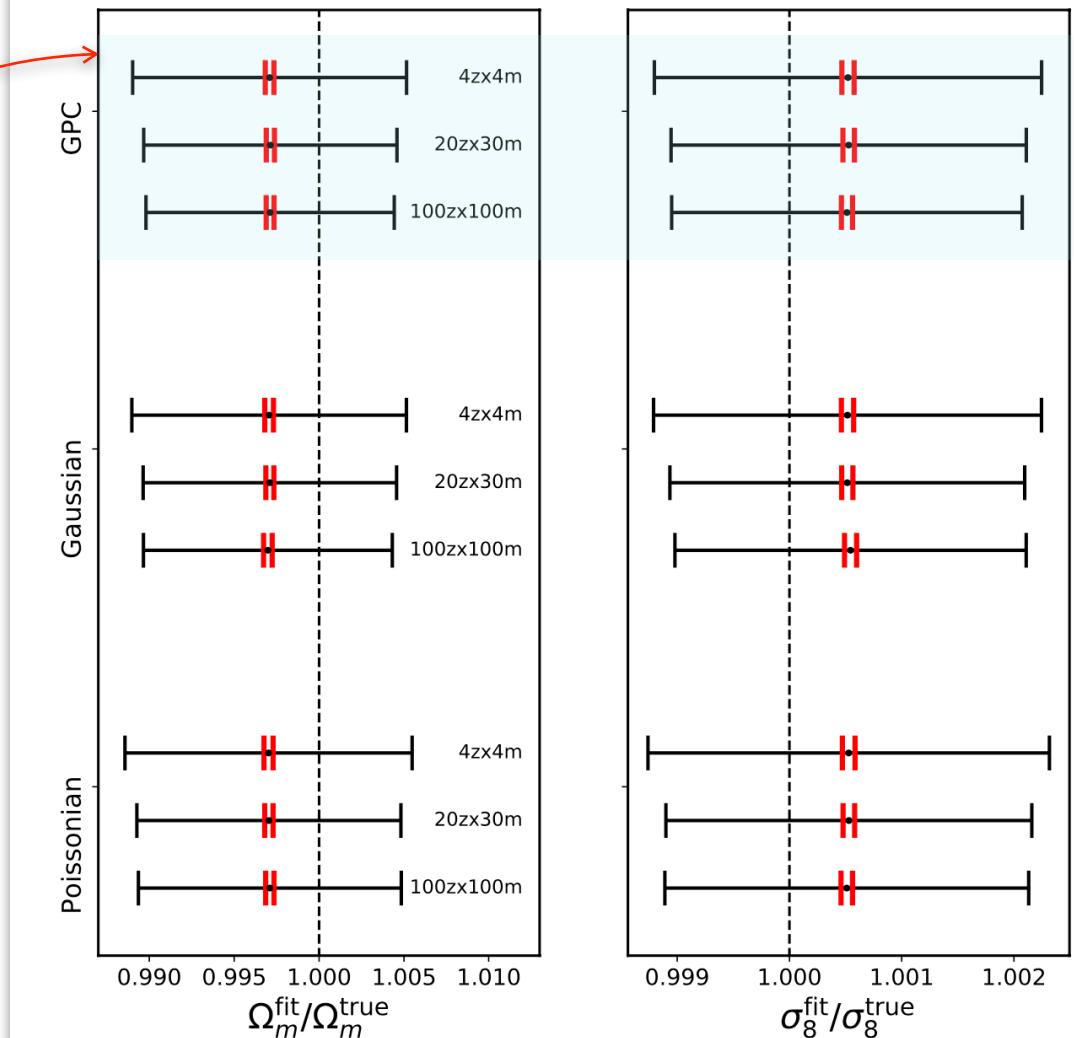
$\sim 10^4$ cosmological constraints ! **Importance sampling (efficient for 2 parameters)**

Results: Bias to input cosmology ?

Only binning 4zx4m



All binning scheme



Small constant bias between input and recovered cosmology

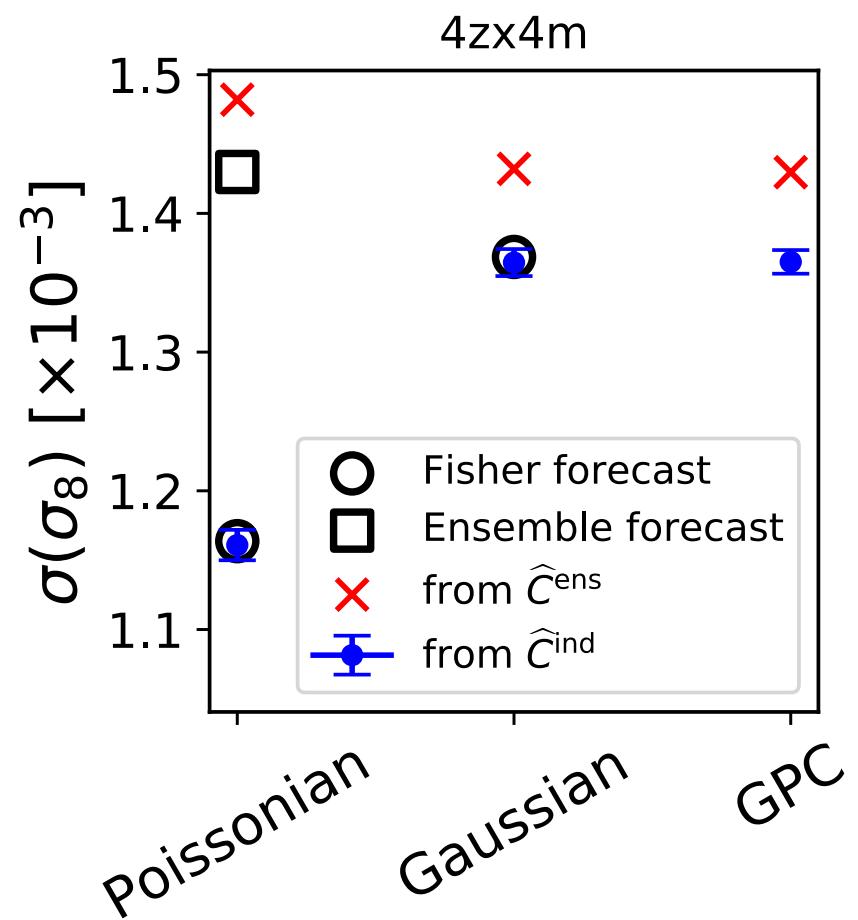
- Accuracy of the underlying halo model
- Numerical error

Results: (4 redshift bins)x(4 mass bins) case

- Individual errors on each simulation (blue)
- Spread of best fits (red)

Parameter error

- Poisson underestimates the errors, since it not takes account of sample variance
- Gaussian = Gauss-Poisson Compound
 - Slightly underestimate errors, likely due to approximations made for the 2-pt statistics
 - The same level of constraints
- Fisher forecasts (circle) in agreement with individual errors
- Ensemble forecast (square) for the spread of posterior means



Results: all binning schemes

Parameter error

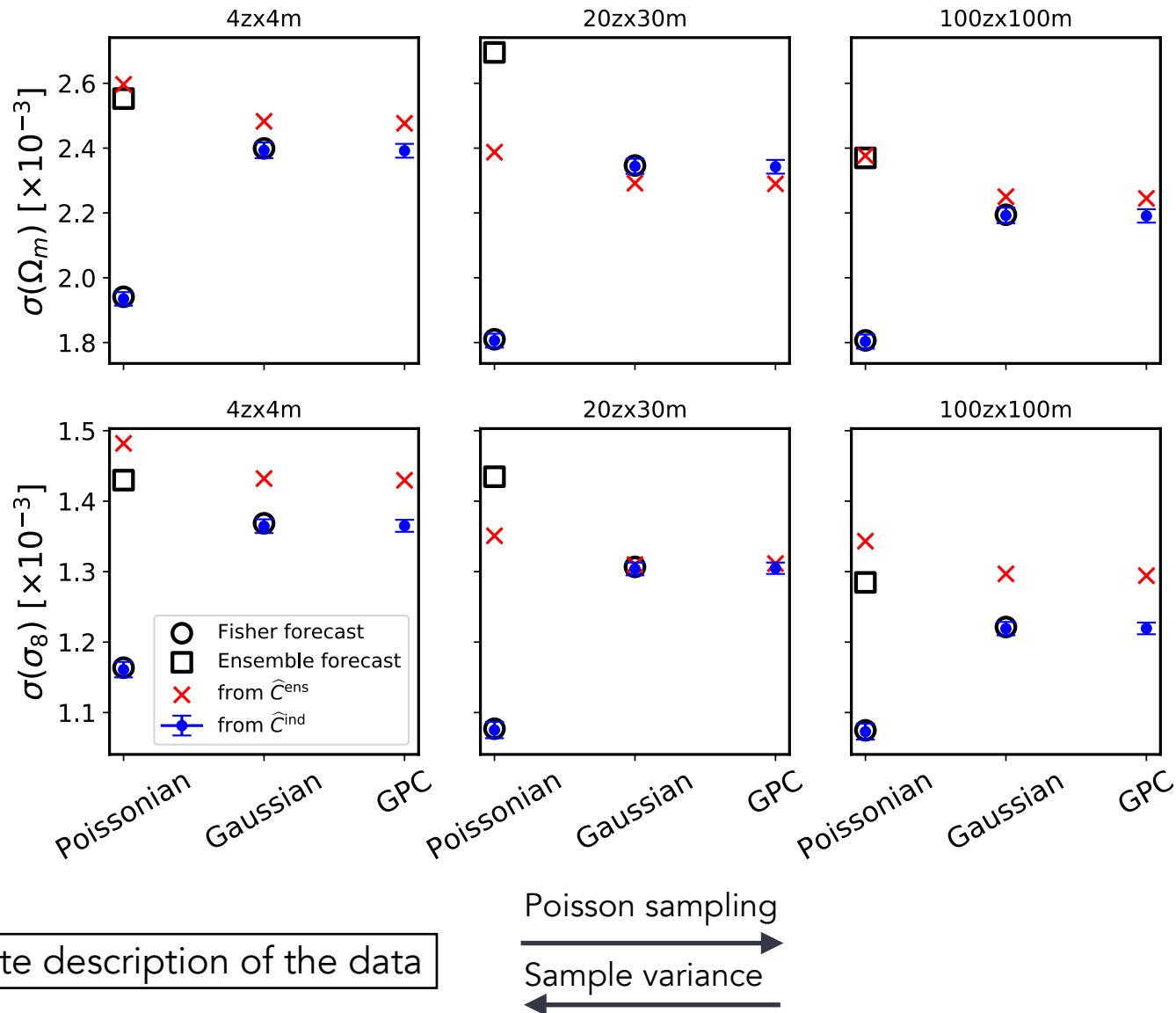
- Errors decreases with the number of bins (10% improvement from 16 to 10^4 bins)

- Poisson

- Underestimates the error, even for fine binning, does not account for sample variance

- Gaussian = Gauss-Poisson Comp.

- Over/under estimate constraints (approximation for computing the covariance matrix)
- The same level of constraints



Gaussian likelihood remains an accurate description of the data

Conclusions

Recap:

- Tested accuracy of cluster likelihoods with
 - 1000 simulated dark matter halo catalogs
 - By comparing posterior variances to spread of means over the 1000 simulations
 - Sensitive to both analysis and latent likelihood properties

Conclusions: For future Euclid or Rubin-like surveys

- Gaussian gives robust constraints over a wide range of inference setup
- No gain in using Gauss-Poisson Compound (same level of constraints but computationally expansive)
- Gauss-Poisson Compound = Gaussian (under/overestimating errors at most 5%)
- Poisson likelihood always underestimates errors