CONSTRAINING NEUTRINO MASSES WITH TOMOGRAPHIC WEAK LENSING STARLET PEAK COUNTS

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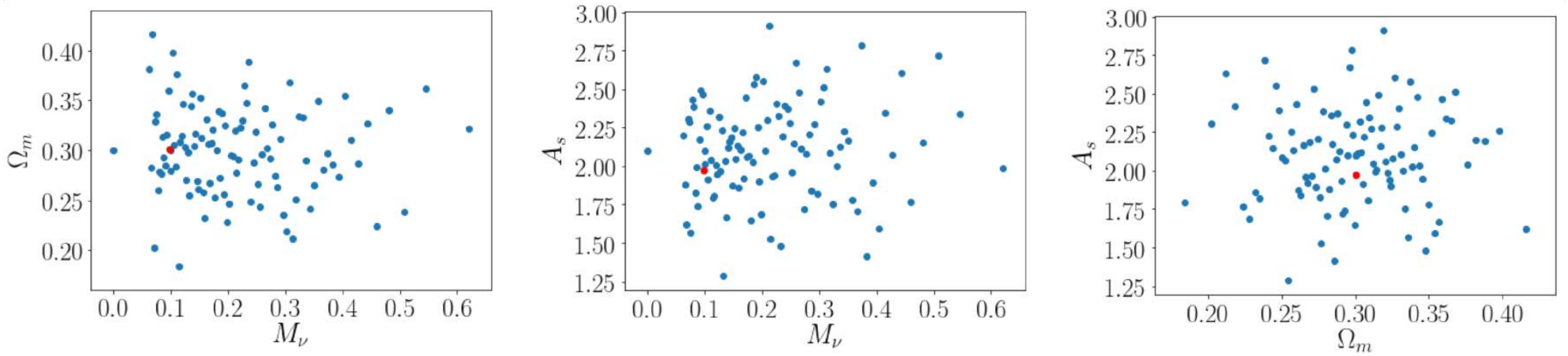
OUTLINE

- MassiveNus Simulations
- Building the pipeline
- Results for Gaussian smoothing
- Wavelet-based filtering technique
- Conclusion and Future prospects

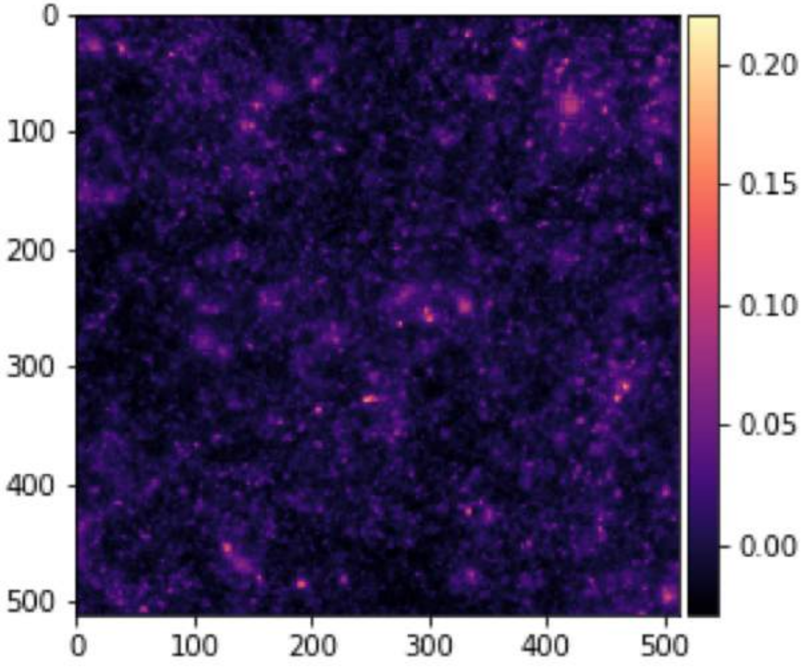
MassiveNus Simulations



- 1024^3 particles, 512 Mpc/h box size
- 101 N-body simulations
- $\sum_\nu m_\nu, \quad \Omega_m, \quad A_s$ varying
- Fiducial model $(M_\nu, \Omega_m, 10^9 A_s) = (0.1, 0.3, 2.1)$

Data publicly available on http://columbialensing.org from [Liu et al. 2018](#), [arXiv:1711.10524v1**]**

MassiveNus: Convergence Maps



- **10000 maps** realisations, **100 cosmologies, 5 redshifts**
- ray-tracing code `LensTools`
- 512^2 pixels
- 12,25 $\deg^2$, 0.4 arcmin resolution

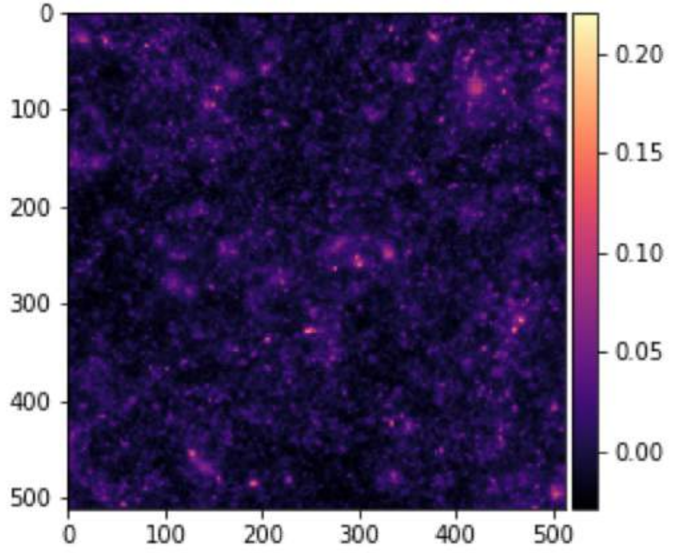
$$\kappa(\boldsymbol{\theta}) = \int_0^\infty dz W(z) \delta(\chi(z)\boldsymbol{\theta}, z), \text{ where}$$

$$W(z) = \frac{3}{2}\Omega_m H_0^2 \frac{(1+z)}{H(z)} \frac{\chi(z)}{c} \times \int_z^\infty dz_s \frac{dn(z_s)}{dz_s} \frac{\chi(z_s) - \chi(z)}{\chi(z_s)}$$

(http://columbialensing.org)

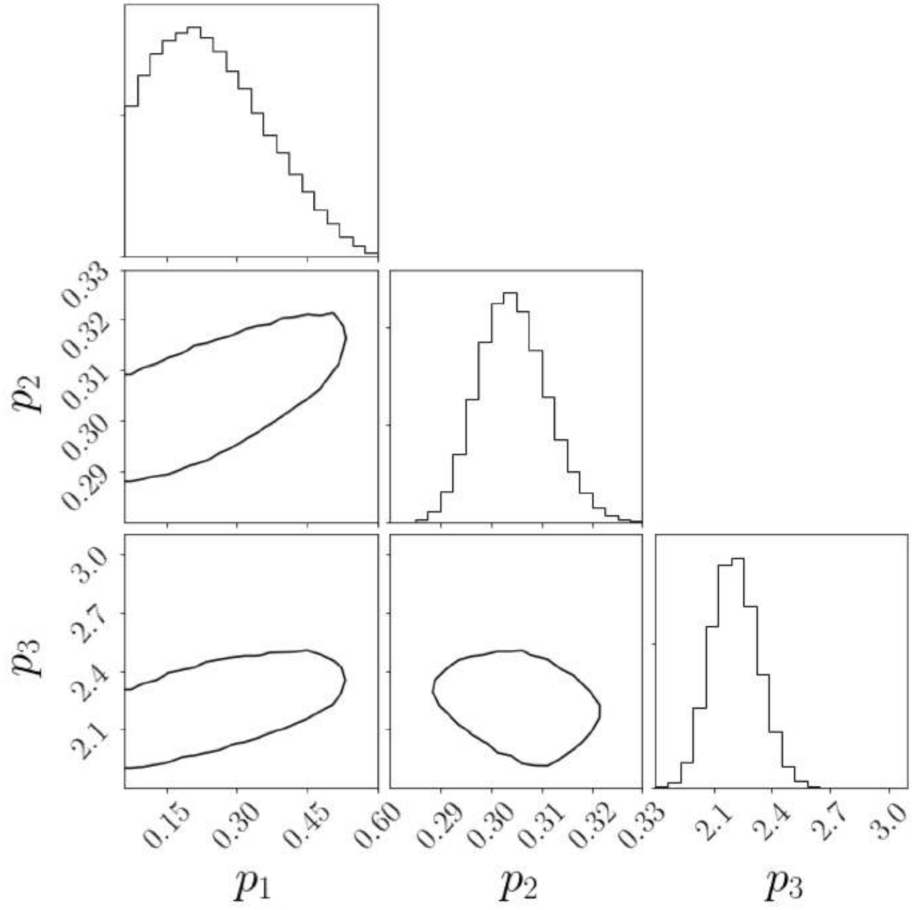
Building the Pipeline

Data (simulated)



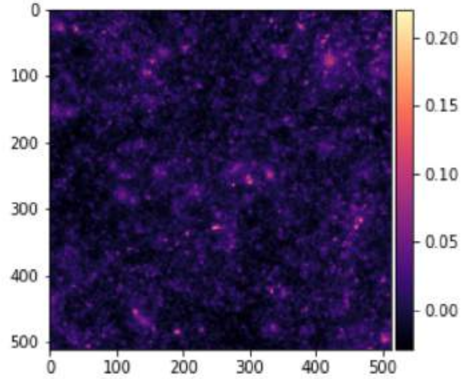
$$\log \mathcal{L}(\theta) = -\frac{1}{2}(d-\mu(\theta))^T C^{-1}(d-\mu(\theta))$$

Cosmological constraints



Based on Z. Li et al 2018, [**1810.01781**]

Noiseless convergence map



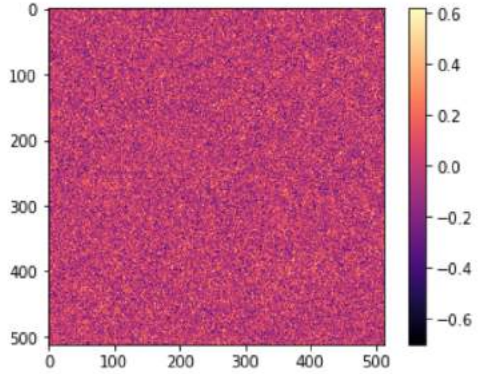
+

$$\sigma_{noise} = \frac{< \sigma_{\lambda}^2 >}{n_{gal} \Delta\Omega}$$

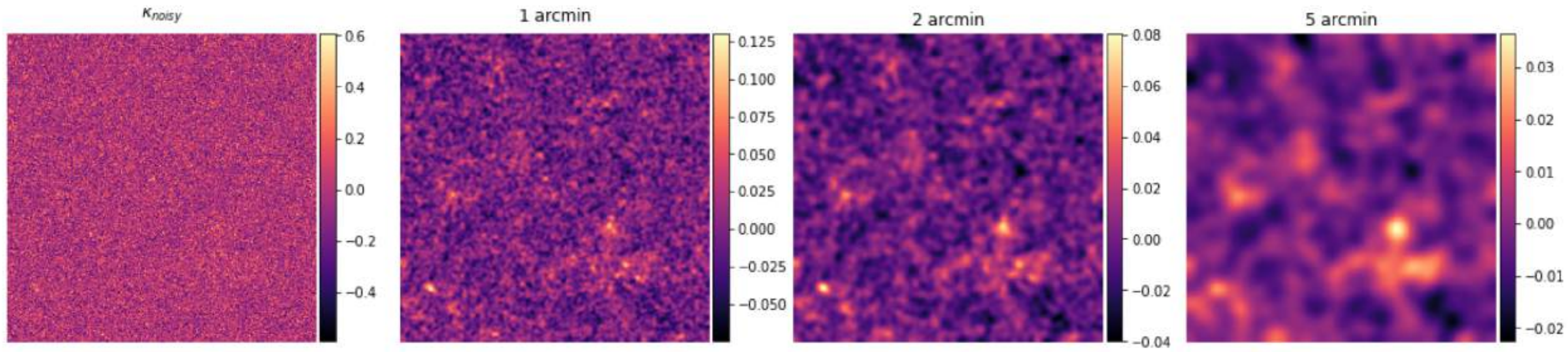
=

Euclid-like noise

Noisy convergence map

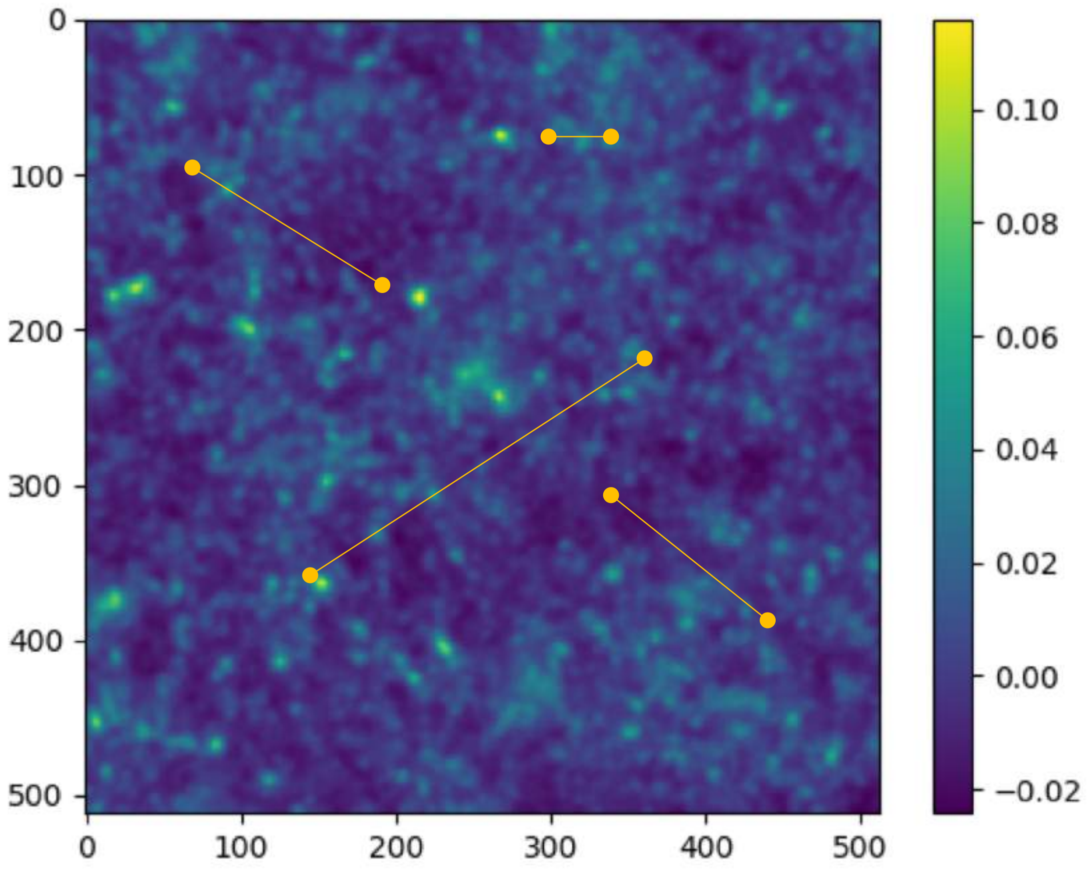


Filtering noise with Gaussian kernel



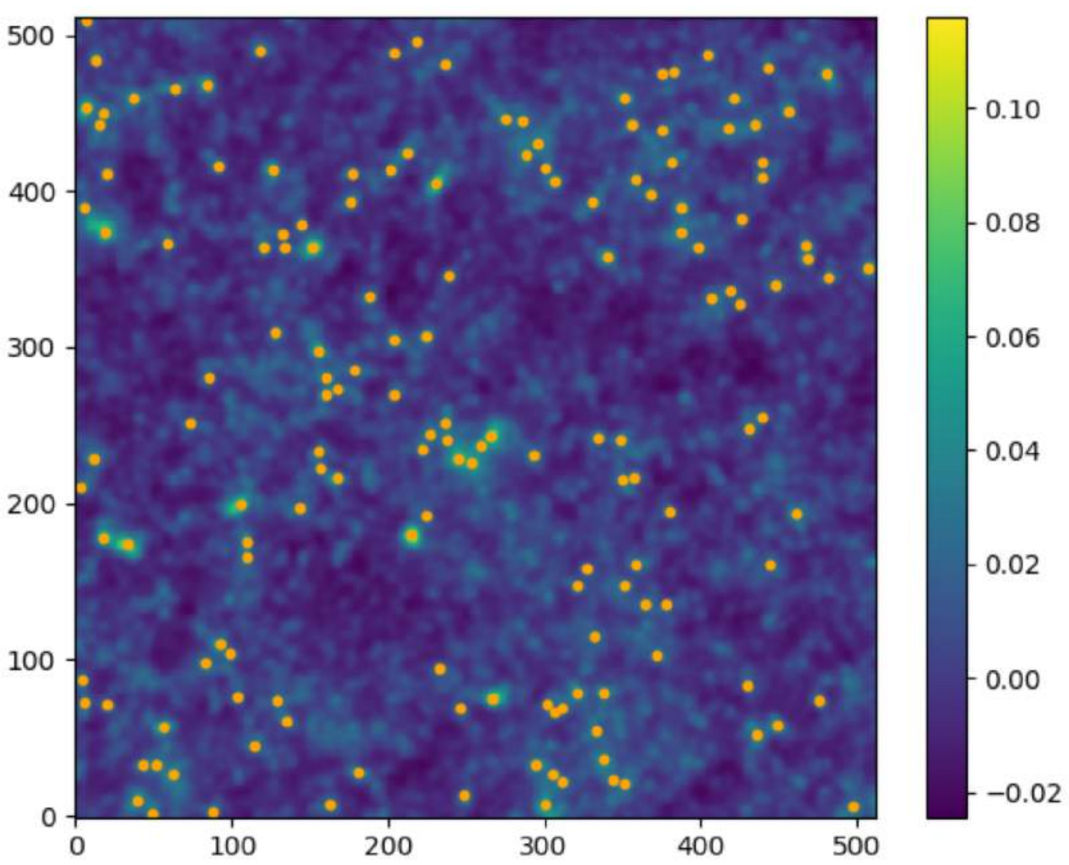
SUMMARY STATISTICS

Second Order Statistics



Power spectrum

Higher Order Statistics



Peak counts

(Non-Gaussian information)

Gaussian Likelihood

$(M_\nu, \Omega_m, 10^9 A_s) = (0.1, 0.3, 2.1)$

Gaussian Processes

$$\boxed{\log \mathcal{L}(\theta) = -\frac{1}{2}(d - \mu(\theta))^T C^{-1}(d - \mu(\theta))}$$

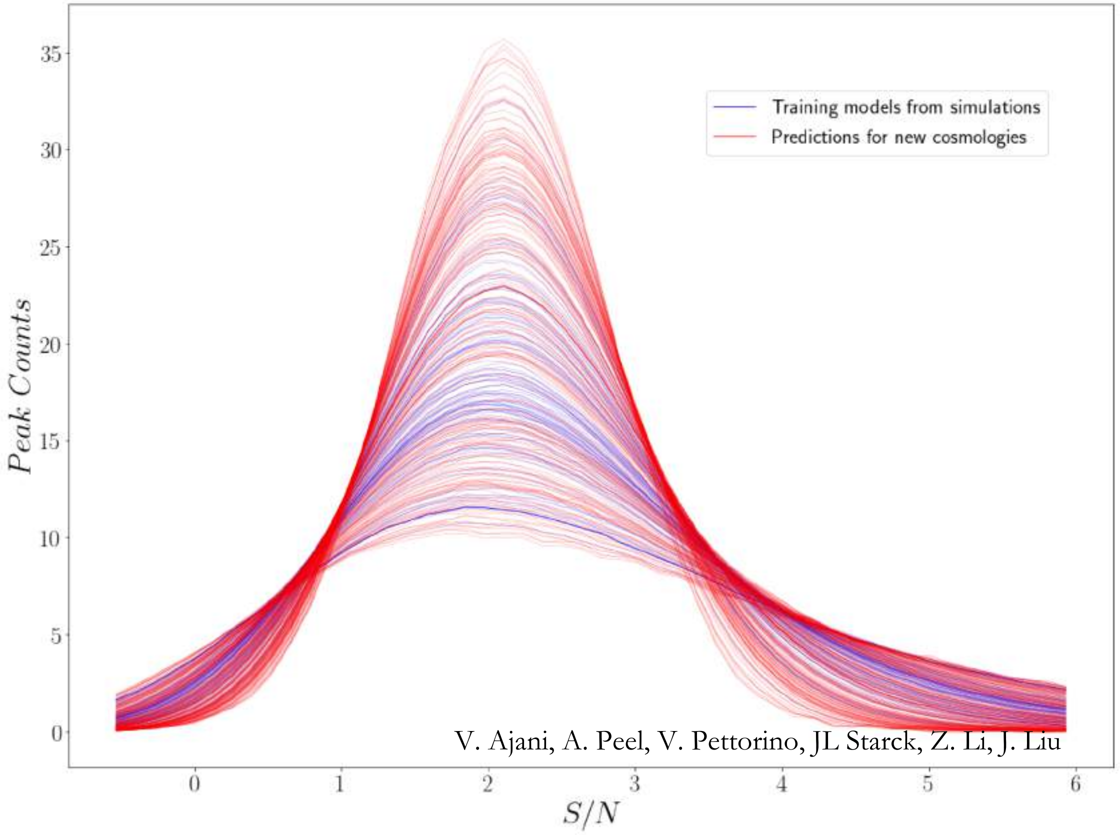
- build the model (Gaussian Processes)

- define and compute the covariance

Interpolation with Gaussian Processes

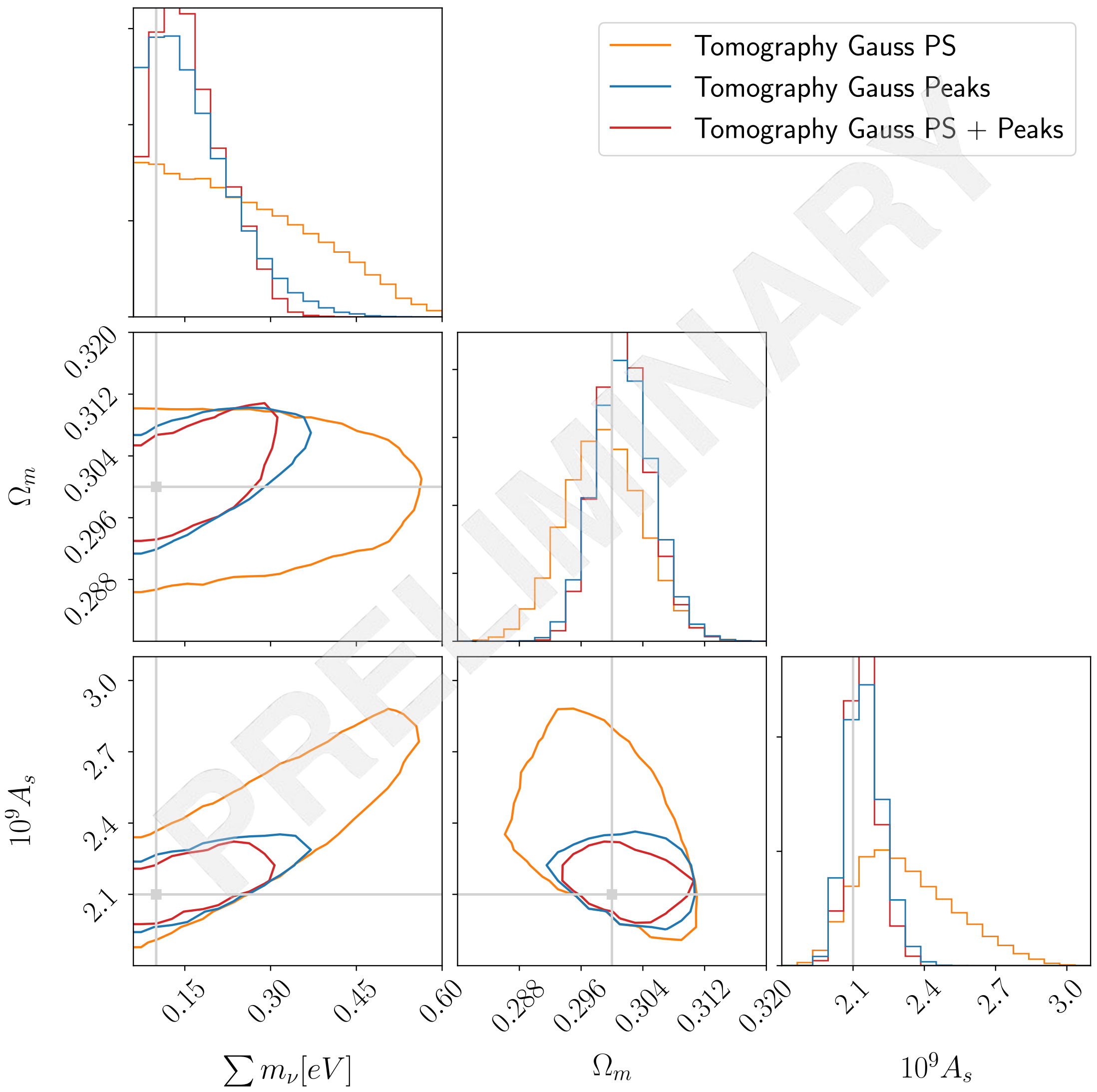
$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}'))$$

$$k(x, x') = \sigma_f^2 exp[\frac{-(x - x')^2}{2l^2}]$$



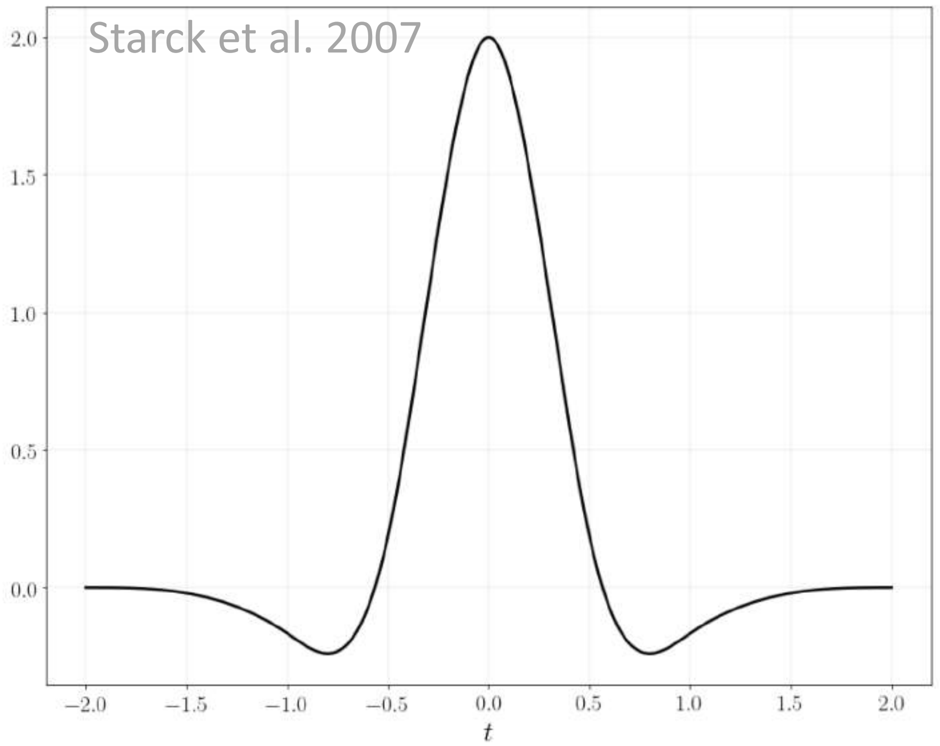
- **INPUT**: (training params, training obs)
- interpolate weighting for different bins and cosmologies (`scikit-learn`)
- **OUTPUT**: predictions for the observables

RESULTS: GAUSSIAN SMOOTHING

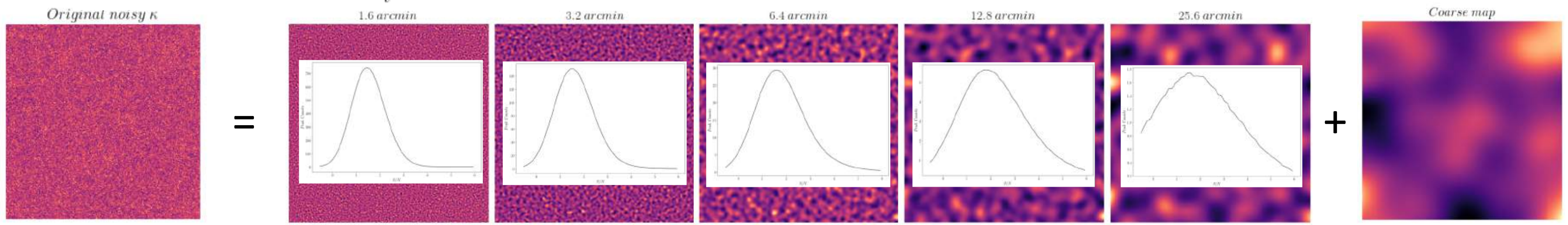


- 95 % confidence contours
- `emcee` package for MCMC
- flat prior
- gaussian likelihood
- **tighter constraints with peaks**

STARLET KERNEL

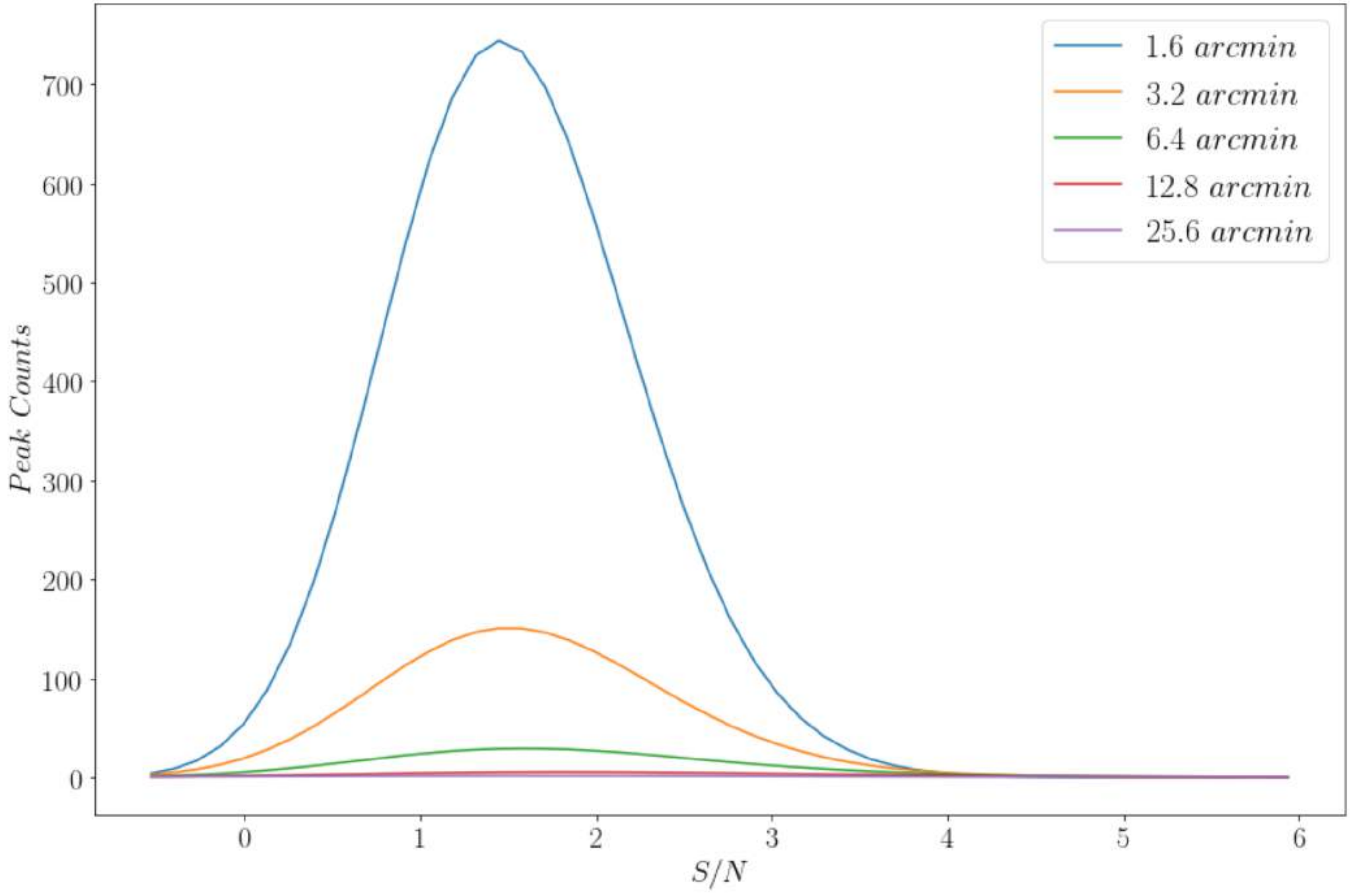


- wavelet transform
- $c_0 = c_p + \sum_{j=1}^{p} w_j$
- multi-scale approach



c_0 w_1 w_2 w_3 w_4 w_5

STARLET PEAK COUNTS



- **estimate the noise level at each scale**

$$\mathbf{S/N} = \nu_j(\boldsymbol{\theta}) = \frac{\kappa_j(\boldsymbol{\theta})}{\sigma_j}$$

CONCLUSIONS

- Tomography outperforms single redshift case
- Gaussian Joints statistics (Power Spectrum + Peaks) tighter constraints than PS alone
- **Starlet Joints statistics (Power Spectrum + Peaks) ~ Peaks alone**
- **Central scales seem to encode almost all information**

Next:

- Real data, other simulations, systematics …