Improving Covariance Matrices using Machine Learning

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Mathematical Physics Department
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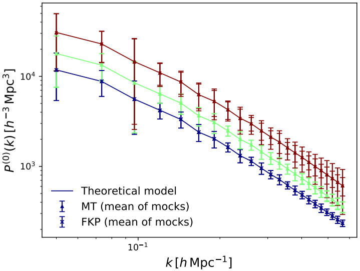
December 17, 2020

Motivation: Why improving covariance matrices?

- They reflect the propagation of the statistical errors:



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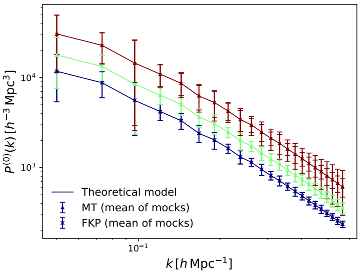
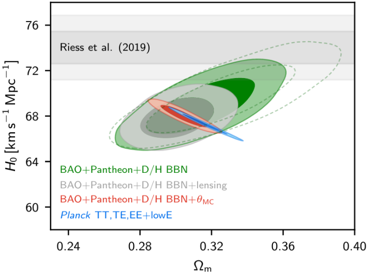
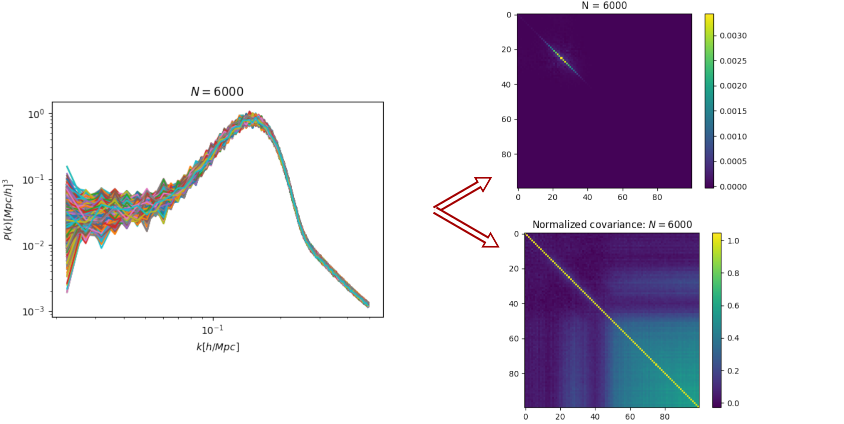




Planck 2018 results: VI Cosmological parameters.

Problem

- To represent the true statistical errors we need a lot of data to build these matrices:



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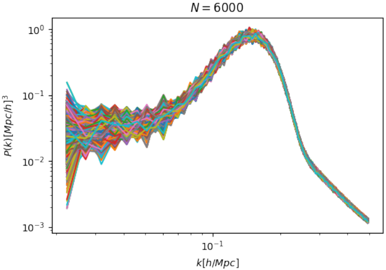
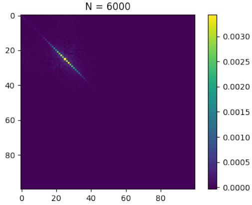
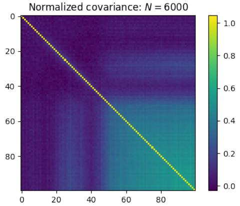
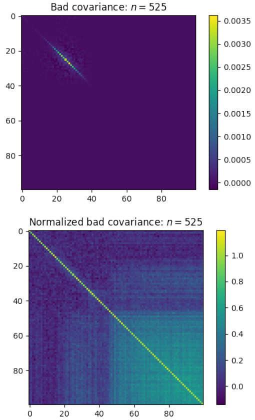


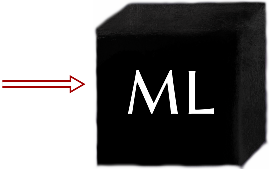




But we can not always do it in practice...

Proposed solution





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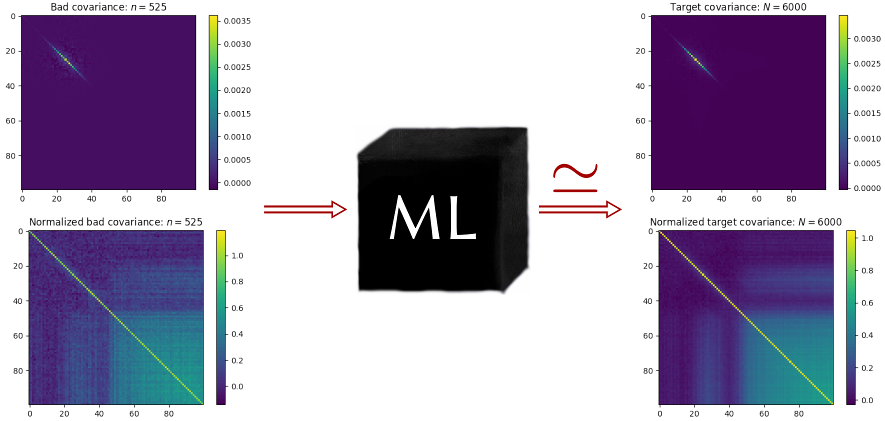

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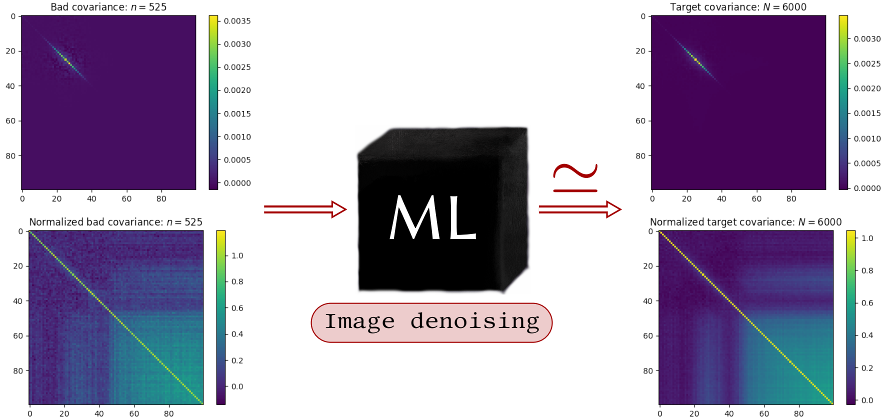

Methodology - Toy project simulation

- The simulations followed the theoretical function:

$$P(k) = P_0 \exp\left[-\frac{(k-k_0)^2}{2\sigma_0^2}\right]$$

	Value
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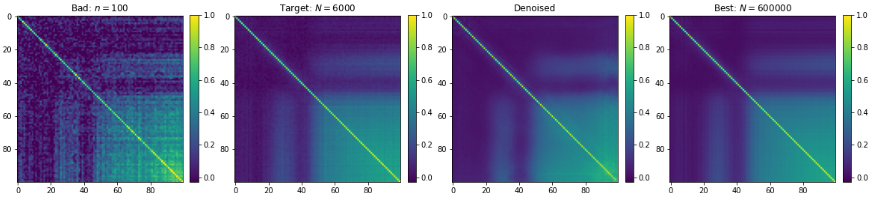
- Then, we test the each **denoiser** with:
  - `input_test`: **bad cov. matrices** (hundreds of spectra) $\Rightarrow n$.

Results - Visual Results



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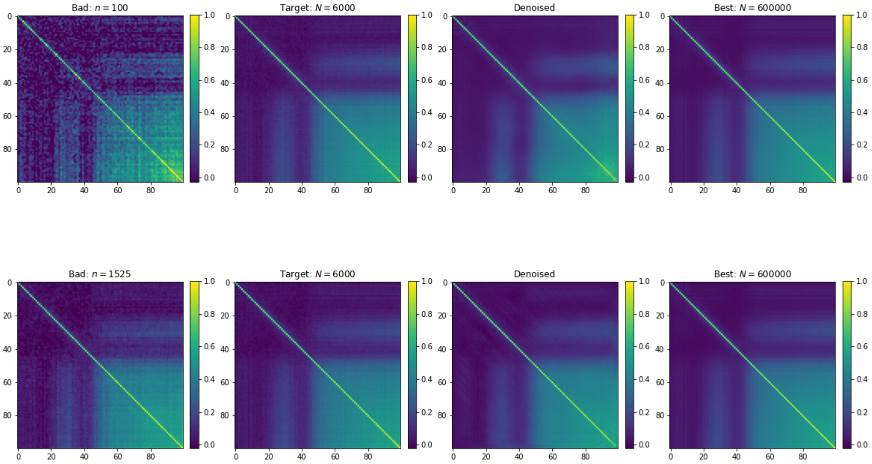
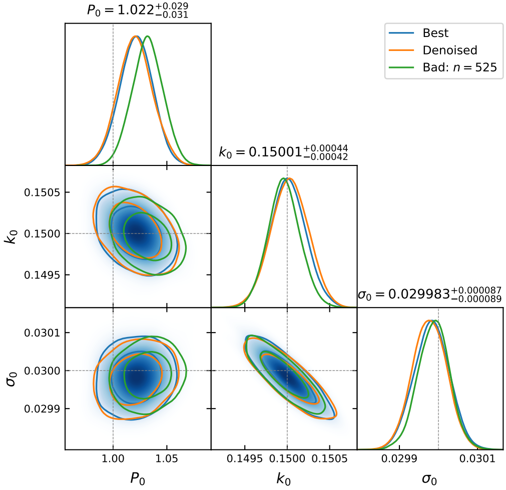


Results - Markov Monte Carlo Chain (MCMC)[1]: Recovering Parameters



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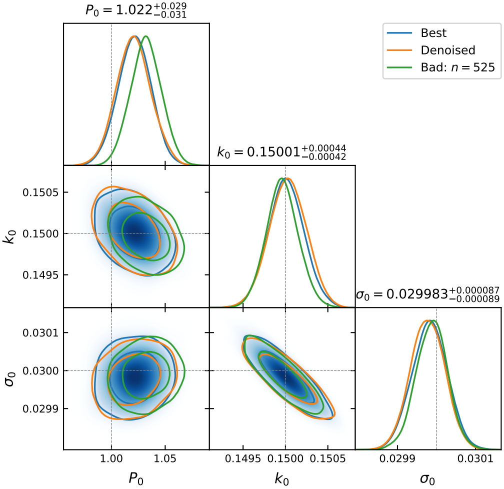

$$\frac{\Delta\mu}{\sigma_{Best}} = \frac{\mu_X - \mu_{Best}}{\sigma_{Best}}$$

$\Delta\mu/\sigma_{Best}$	**Bad**	**Denoised**
P_0	0.685	0.054
k_0	0.218	0.092
σ_0	0.118	0.120

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Results - Sigma fraction: σ_X/σ_{Best}

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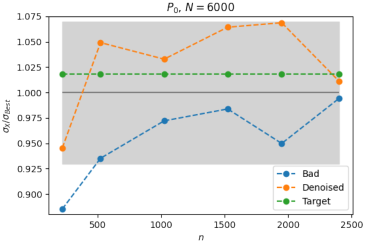

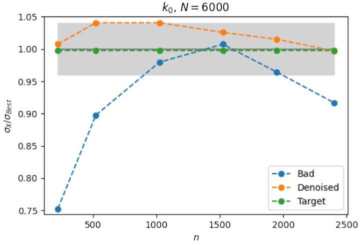

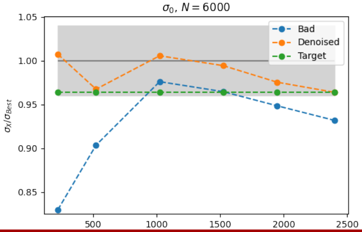

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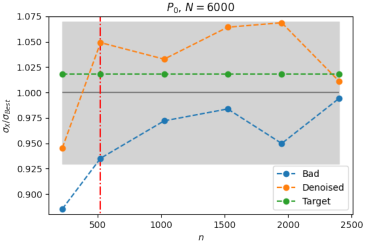

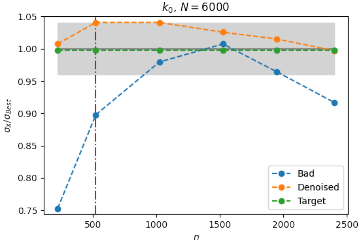

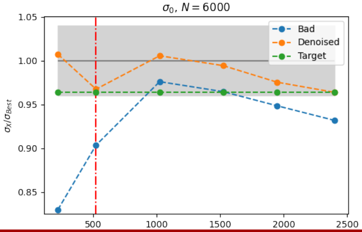

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- We have achieved great results using **image denoising** techniques to improve the *covariance matrices*;
- We showed that even with a **low** number of simulations, we can achieve the same results as a **higher** number of them;
- Once all this work is a really controlled "toy project", we want to apply the same method in **realistic simulations** (e.g., `ExSHalos`, `LogNormals`, `N-body`).