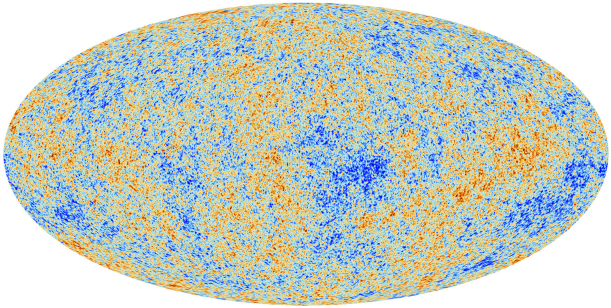
CosmicNet II

Emulating extended cosmologies with efficient and accurate neural networks [2207.05707]



Sven Günther, Julien Lesgourgues, Georgios Samaras, Nils Schöneberg, Florian Stadtmann, Christian Fidler and Jesús Torrado

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What we learned from CMB

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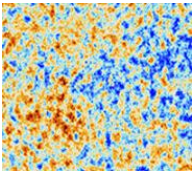

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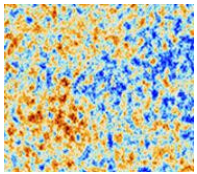
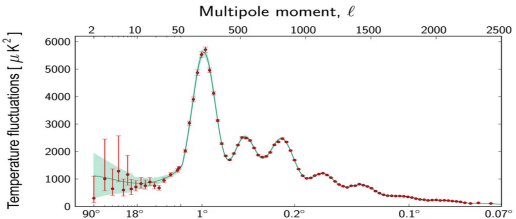
What we learned from CMB

- 1960s: isotropic temperature of 2.7 K
  $\Rightarrow$ Big Bang origin
- 1990s: anisotropic at $\delta T/T \sim 10^{-5}$
  $\Rightarrow$ correlation on all scales
- 2010s: observation show Gaussian fluctuations
  $\Rightarrow$ support model of inflation





Calculating the power spectrum

- CMB power spectrum:

$$C_\ell = 4\pi \int \frac{dk}{k} \Theta_\ell^2(k) \mathcal{P}_\mathcal{R}(k)$$

$\rightarrow$ transfer function Θ_ℓ^2
$\rightarrow$ prim. power spectrum $\mathcal{P}_\mathcal{R}$

Einstein Boltzmann Solver (EBS)

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  2. lin. Einstein-Boltzmann equation $\sim \mathcal{O}(20s)$
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  3. calc. line-of-sight integral $\sim \mathcal{O}(5s)$

$\Rightarrow$ inference: $\mathcal{O}(10^5)$ calls

$\Rightarrow$ accelerate bottleneck!

Source function S_{T_0}

Idea: predict source functions (6 in total)

- untangle different physically effects:

$$\begin{aligned} S_{T_0} &= S_{T_0,\mathrm{ISW}} + S_{T_0,\mathrm{reco}} + S_{T_0,\mathrm{reio}} \\ &= e^{-\kappa} \underbrace{2\phi'}_{[\mathrm{N1}]} + \underbrace{g_{\mathrm{reco}} \cdot (F_0 + \phi) + (g_{\mathrm{reco}} \theta_b / k^2)'}_{[\mathrm{N2}]} + \underbrace{g_{\mathrm{reio}} \cdot (F_0 + \phi) + (g_{\mathrm{reio}} \theta_b / k^2)'}_{[\mathrm{N3}]} \end{aligned}$$

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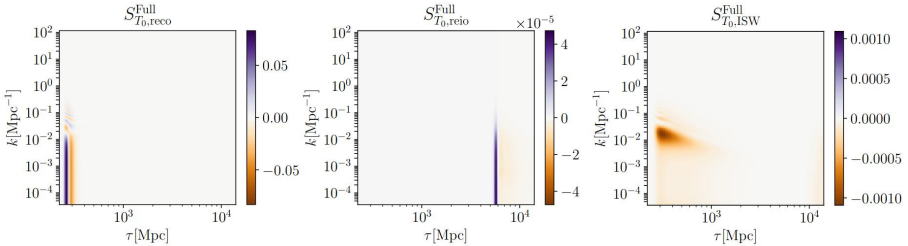

Network ideas

Conceptional ideas:

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$$H_0, \Omega_\mathrm{b} h^2, \Omega_\mathrm{m} h^2, \kappa_\mathrm{reio}, \left(\triangle N_\mathrm{eff}, \Omega_k, \Omega_\nu h^2, w_0, w_a\right)$$

  $\rightarrow$ additional derived quantities

$$D(\tau), g(\tau), g'(\tau), \tau_\mathrm{reio}, \tau_\mathrm{reco}, e^{-\kappa(\tau)}$$

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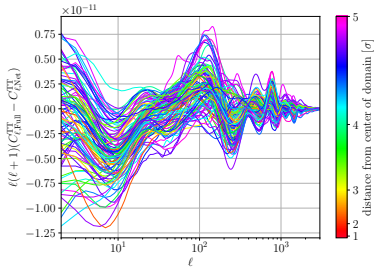
- use analytical (Hu & Eisenstein) approximation

$\Rightarrow$ use **understanding** of the underlying physics to allow for **small and fast network** designs

Training

- LHS sample 10.000 training cosmologies in 5 σ hypersphere around best-fit model
  - $\rightarrow$ ensures sufficient domain coverage
  - $\rightarrow$ considerably less samples than MCMC sampling



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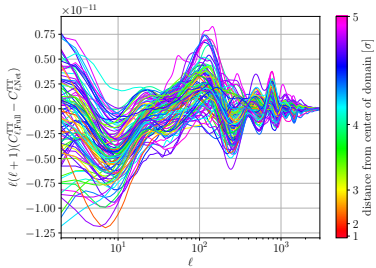
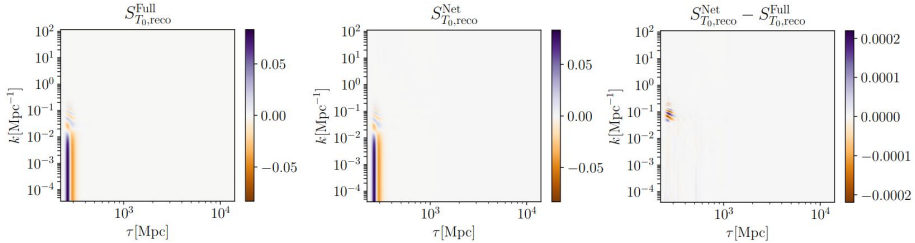
- train for 30-40 epochs (network dependent)



Predictions



Prediction accuracy

- residual of the source function below $\sim 1\%$

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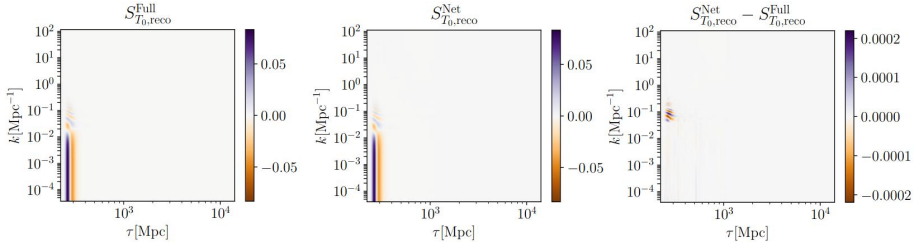
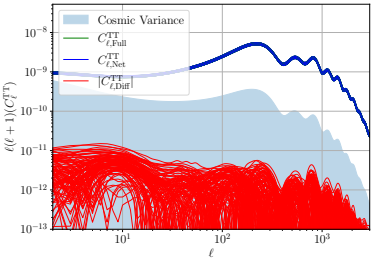


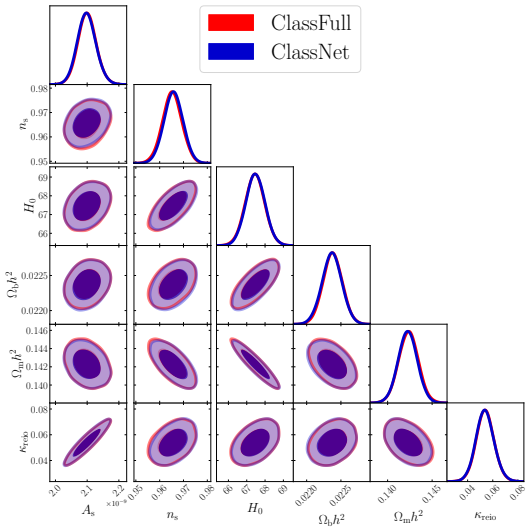
Prediction accuracy

- residual of the source function below $\sim 1\%$
- accuracy on CMB temperature power spectrum well above cosmic variance



Performance within MCMC

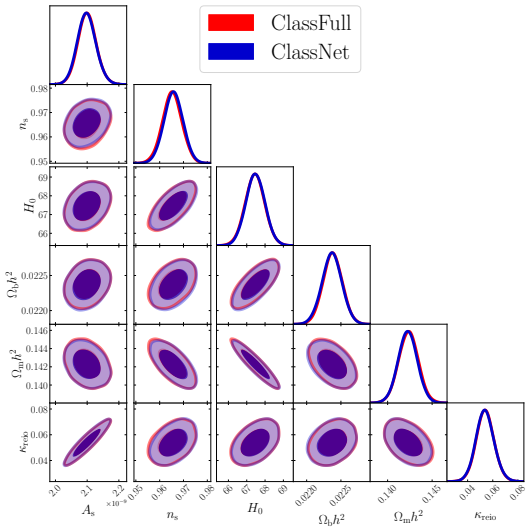
- overhaul agreement in constraints



Comparison within MCMC

Performance within MCMC

- overhaul agreement in constraints
- less than 0.1% of sampled points outside validation domain



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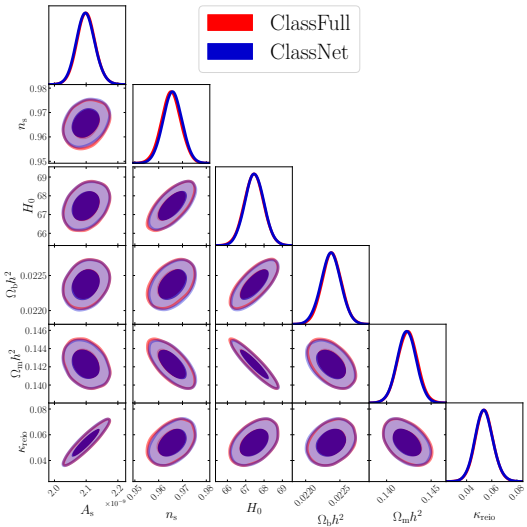

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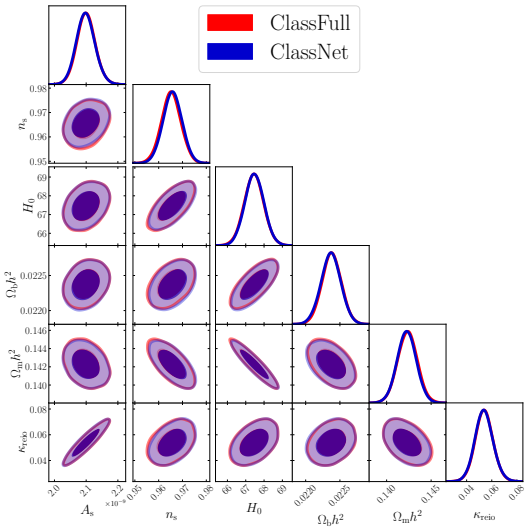
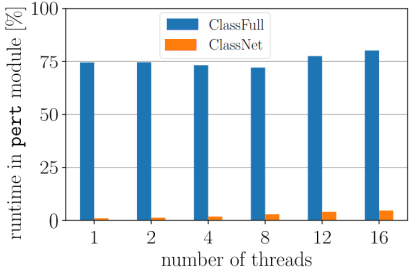
$\Rightarrow$ applicable in parameter inference

$\Rightarrow$ investigate on parameter biases



Achievable Speedup



Speedup

- removed major bottleneck

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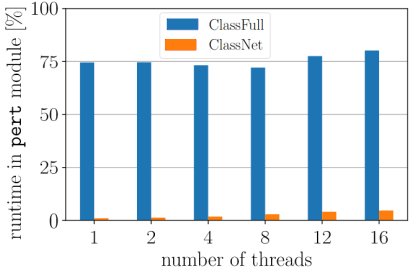

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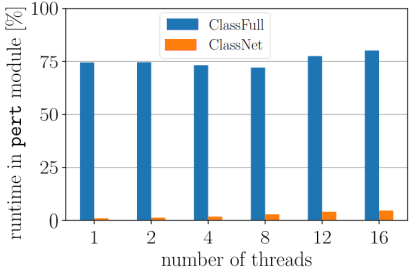

Speedup

- removed major bottleneck
- minor speedup ~ 3 for CMB power spectra
  $\rightarrow$ limited by line-of-sight integral
- major speedup $\mathcal{O}(50)$ for matter power spectrum

$\Rightarrow$ **removed EBS as bottleneck** for matter power spectrum
$\Rightarrow$ further investigation to **accelerate l.o.s. integral**

Conclusion

In this paper

- ✓ use small networks and cosmological intuition to predict source functions
- ✓ remove solving of the lin. Einstein-Boltzmann equation as bottleneck
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In the future

- accelerate the line-of-sight integral
- share trained networks for varieties of cosmologies
- investigate on biases and training process

BACK-UP