Teaching neural networks to generate Fast Sunyaev Zel'dovich Maps

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Motivation

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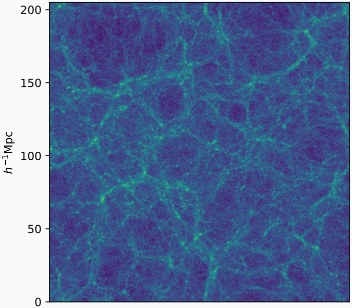
- possible simplification: astrophysical processes are more local than gravity, baryons trace dark matter distribution fairly well $\rightarrow$ machine-learning approach
- allows much faster generation of mock maps, from cheaper N-body simulations

Idea

dark matter-only simulation



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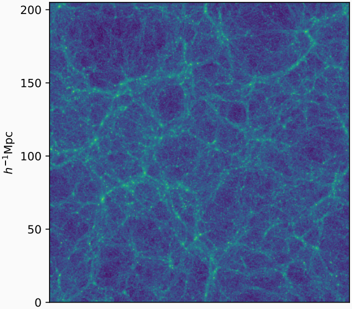
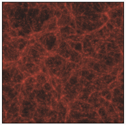
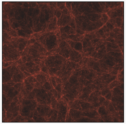
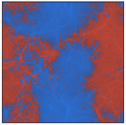




electron
pressure P_e
($\rightarrow$ tSZ effect)



electron
density ρ_e
($\rightarrow$ optical depth)



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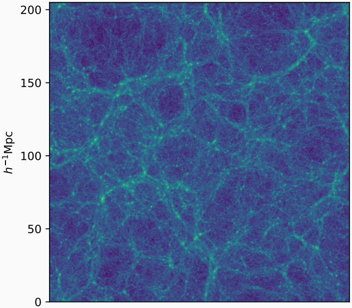
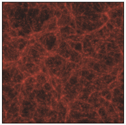
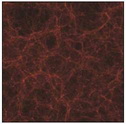


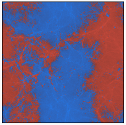
semi-analytic models



electron pressure P_e ($\rightarrow$ tSZ effect)



electron density ρ_e ($\rightarrow$ optical depth)



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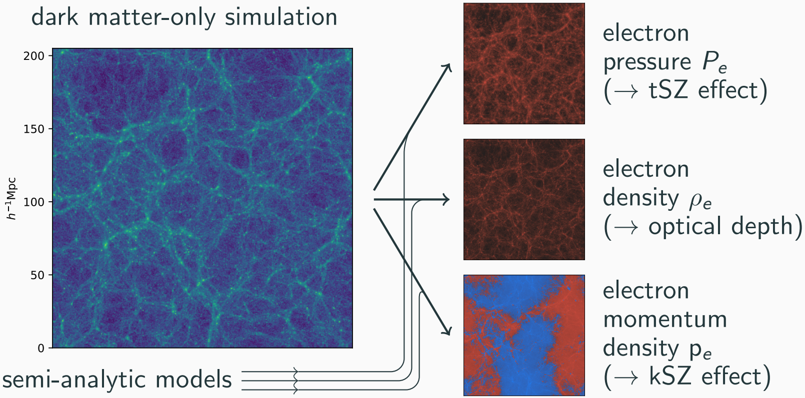
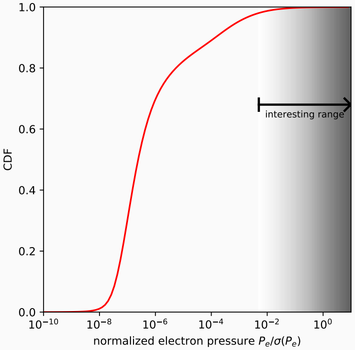


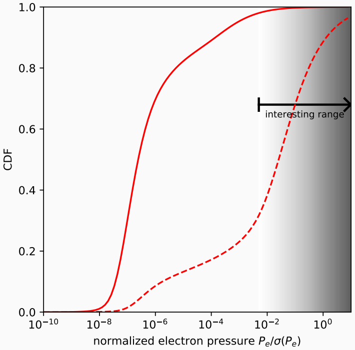
- simulation data mostly from IllustrisTNG300
- work directly with 3-dimensional field
- only $z = 0$ so far

Sparsity



1.0
0.8
0.6
0.4
0.2
0.0
CDF
interesting range
10^{-10}
10^{-8}
10^{-6}
10^{-4}
10^{-2}
10^{0}
normalized electron pressure $P_e/\sigma(P_e)$

Sparsity



Few interesting voxels

$\rightarrow$ biased training samples:

zoom-ins for tSZ,

mass biases o/wise

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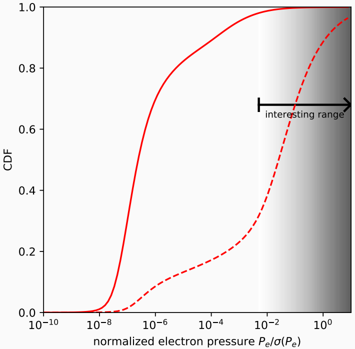

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Tailed distributions

$\rightarrow$ input transformation

$\rightarrow$ epoch-dependent loss function

$\rightarrow$ semi-analytic models

Network & Training

Tune hyperparameters & network architecture on electron pressure, then apply to density & momentum.

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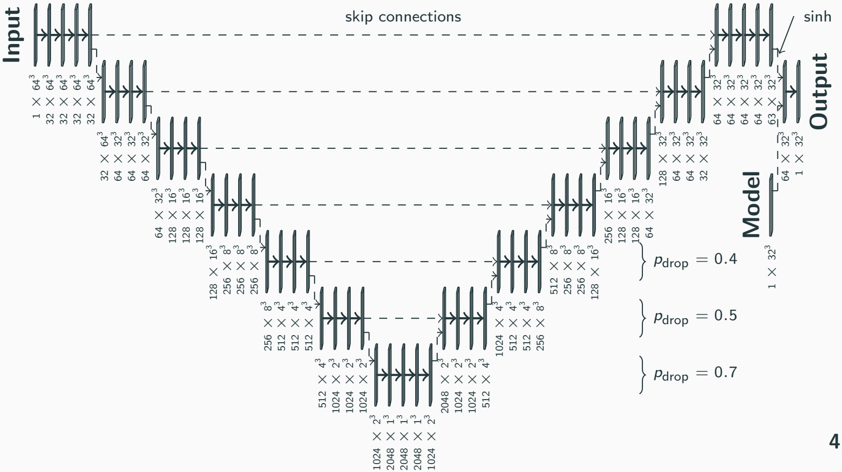
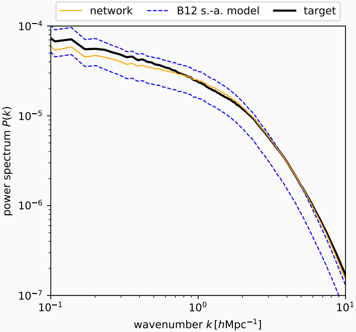


Results: electron pressure (tSZ)



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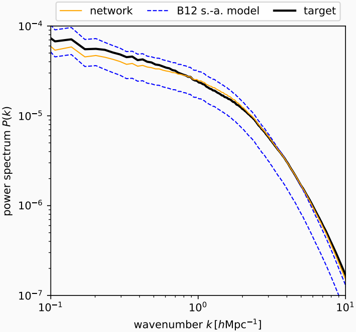

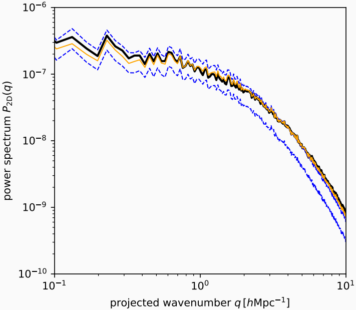

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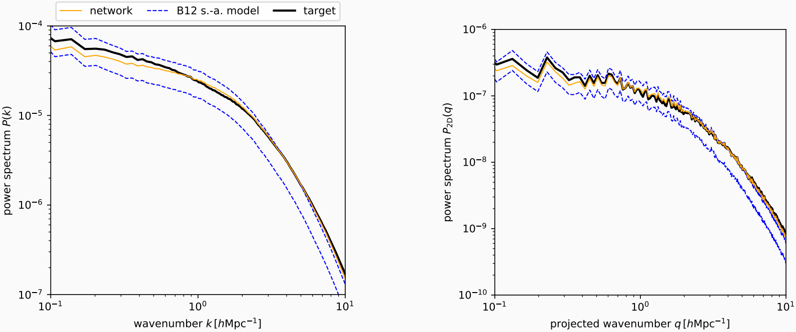
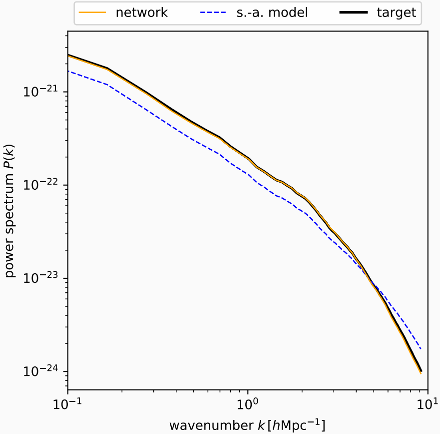


$\rightarrow$ projection improves network-fiducial agreement

Results: electron density (optical depth)



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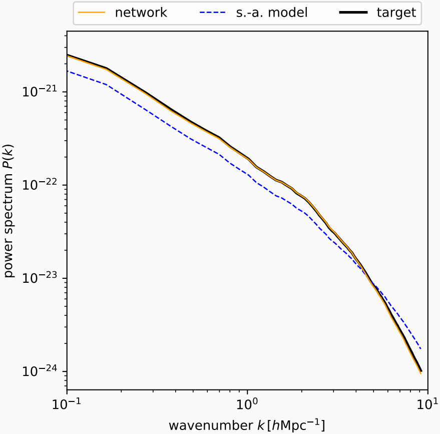
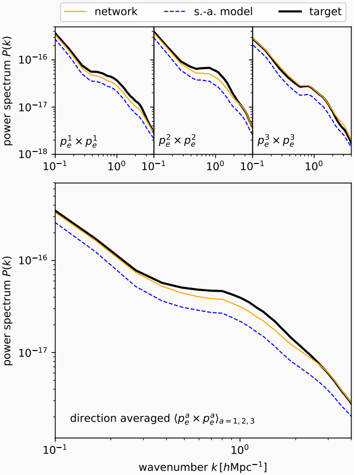


$\rightarrow$ ρ_e easier target than P_e: $P_e \sim \rho_e T_e$

Results: electron momentum density (kSZ)



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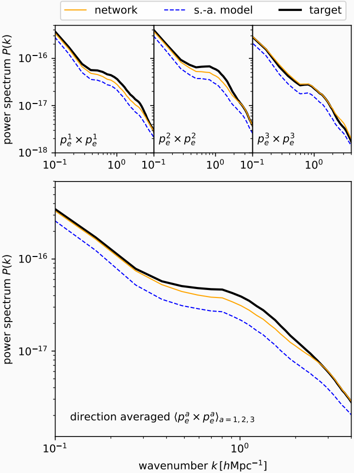

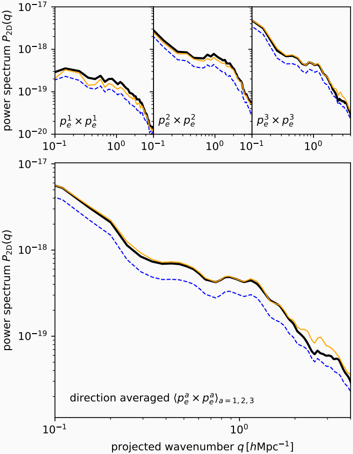

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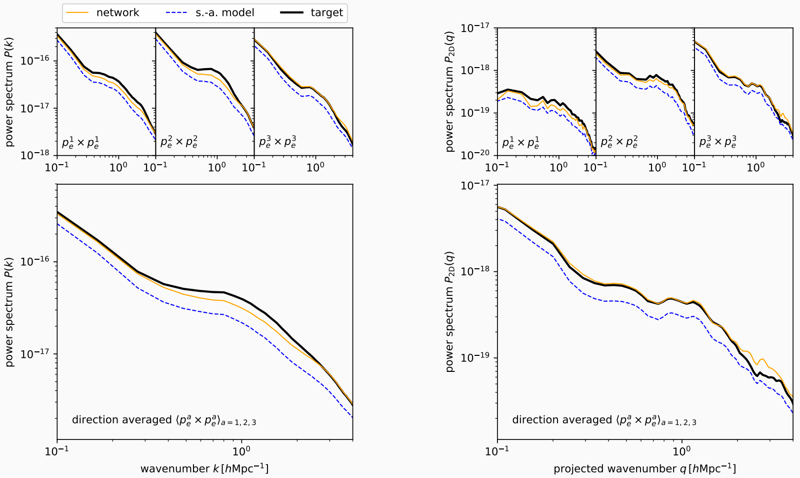
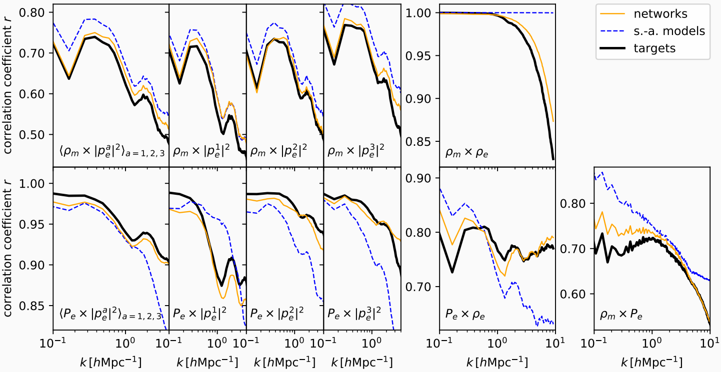
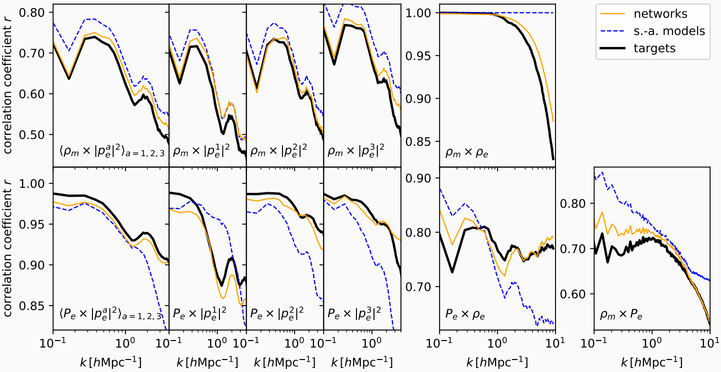


$\rightarrow$ sub-optimal network architecture (?)

Results: cross-correlations





→ model quality is important

Conclusions

- developed strategies to learn sparse 3-dimensional fields

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- promising results (with limitations)
- next steps:
  - construct light cones
  - marginalize over sub-grid physics
  - improvements: better semi-analytic models, more training data, better network architecture (kSZ)

Backup Sparsity

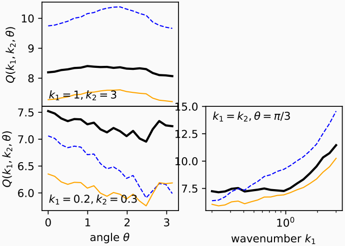
- biasing of samples: by halo mass (& zoom-in simulations)
- input transformation: $x'_{\mathrm{DM}} = a[\log(1 + bx_{\mathrm{DM}}) + c]$
- loss function:

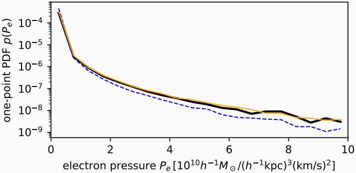
$$
\begin{aligned}
L_\tau(p,t) &= (f_\tau(p) - f_\tau(t))^2 \\
f_\tau(x) &\sim e^{-\tau/\tau_0}\log(1+x) + (1 - e^{-\tau/\tau_0})x
\end{aligned}
$$

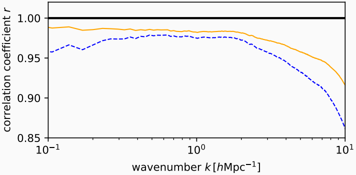
- semi-analytic models:

$$
\begin{aligned}
P_e^{\mathrm{model}} &= \sum_{\text{halos } h} \text{Battaglia+2012}(M_h, |\mathrm{x} - \mathrm{x}_h|) \\
\rho_e^{\mathrm{model}} &\propto \text{Gaussian} \circledast \rho_m \\
\mathrm{p}_e^{\mathrm{model}} &= \rho_e^{\mathrm{model}} \mathrm{v}_{\mathrm{DM}}
\end{aligned}
$$

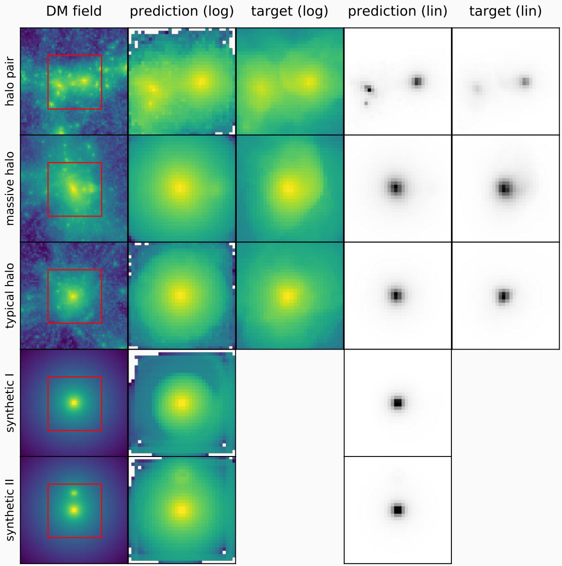
Backup electron pressure (tSZ) I



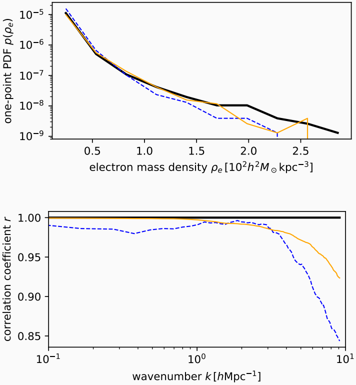




Backup electron pressure (tSZ) II



Backup electron density (optical depth)



Backup electron momentum density (kSZ)