PAINTING BARYONS ON DARK MATTER

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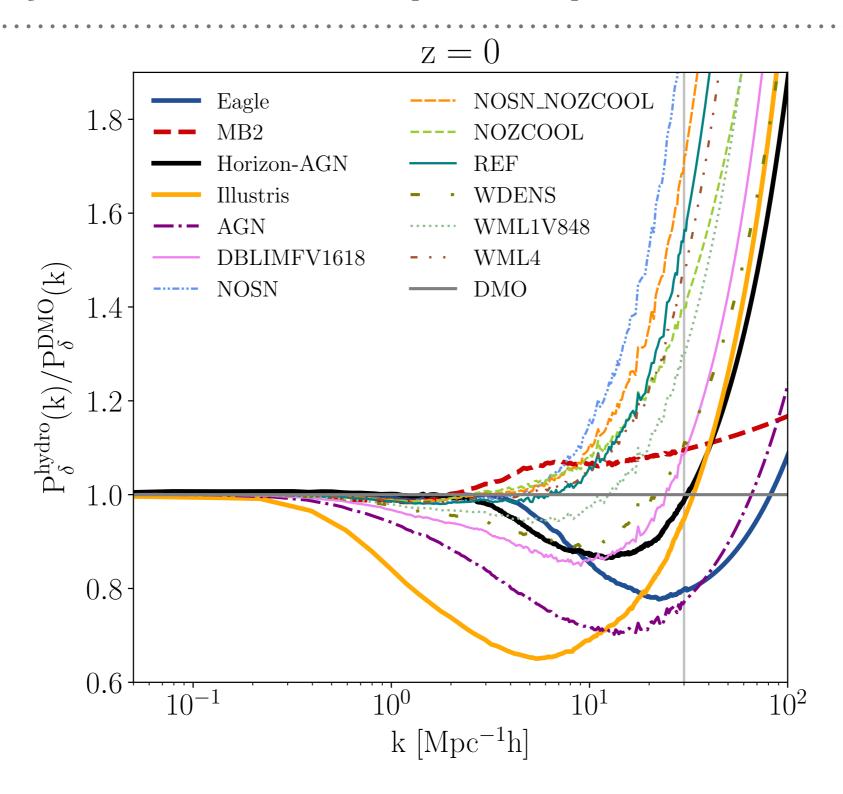
DEX XV, Edinburgh, 8 Jan 2019

Weak lensing

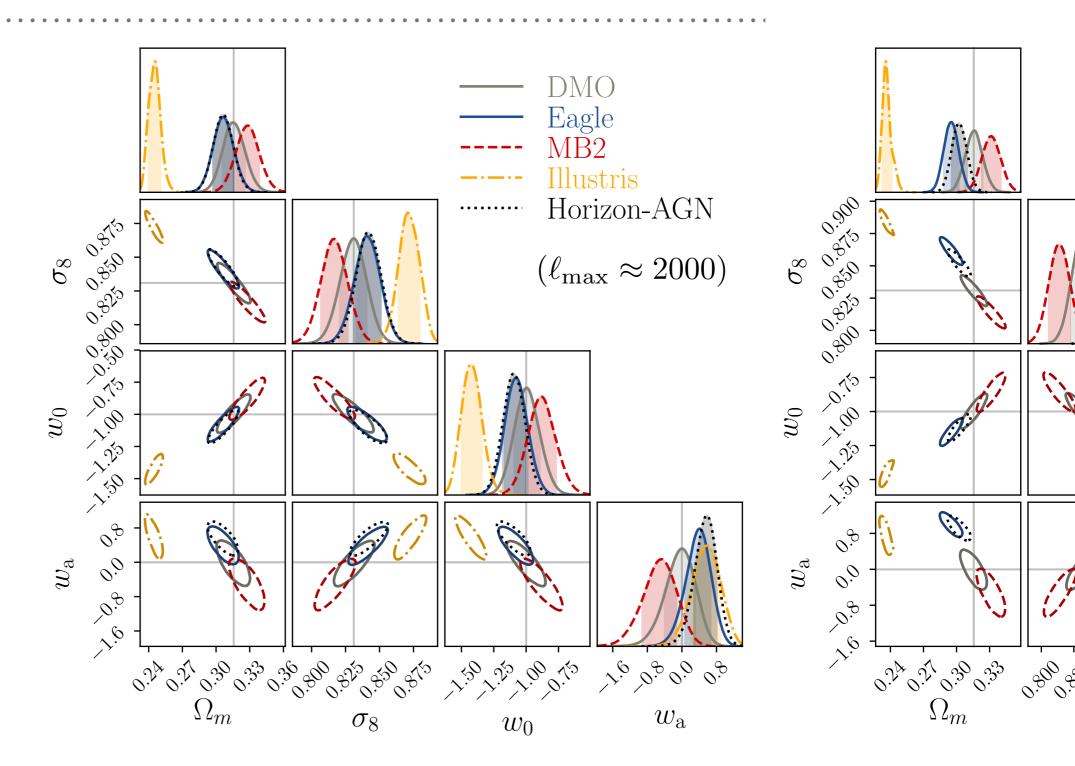
Weak lensing probes the total matter distribution

- ➤ ~80% of matter is dark matter
- ➤ If we want to constrain LCDM, we need to understand the other 20%
- Baryons are complicated!

Effect of baryons on the matter power spectrum



Effect on cosmological parameters

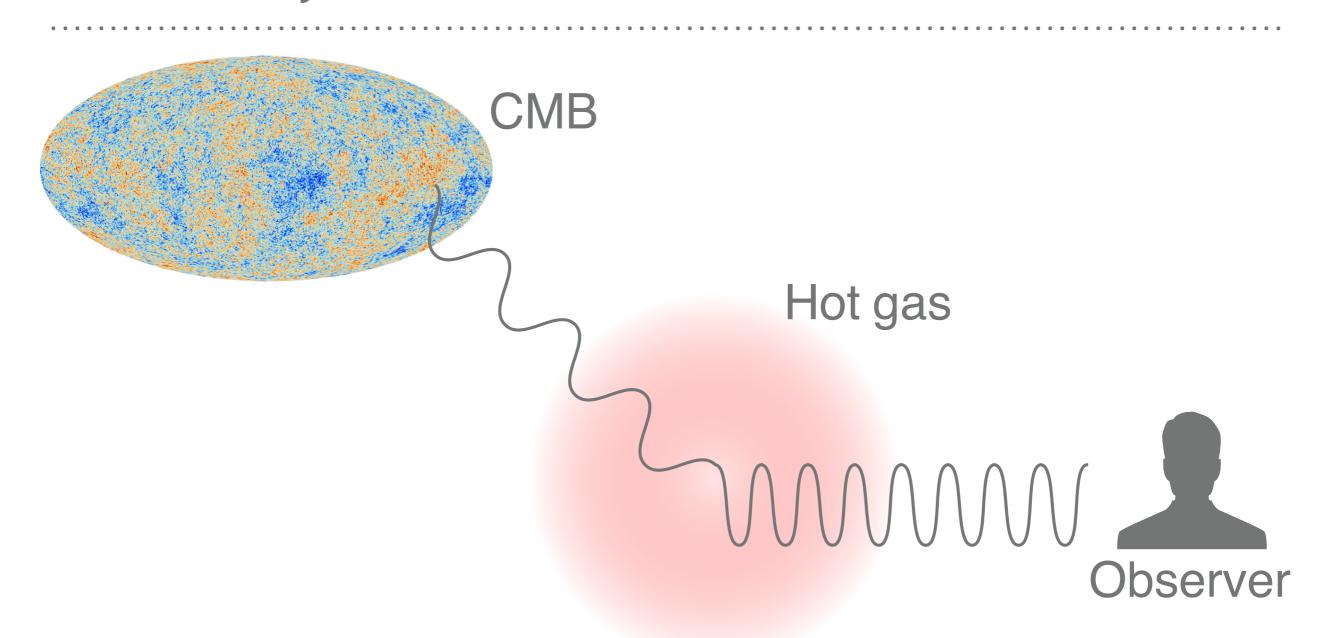


Effect on cosmological parameters

Account for baryons

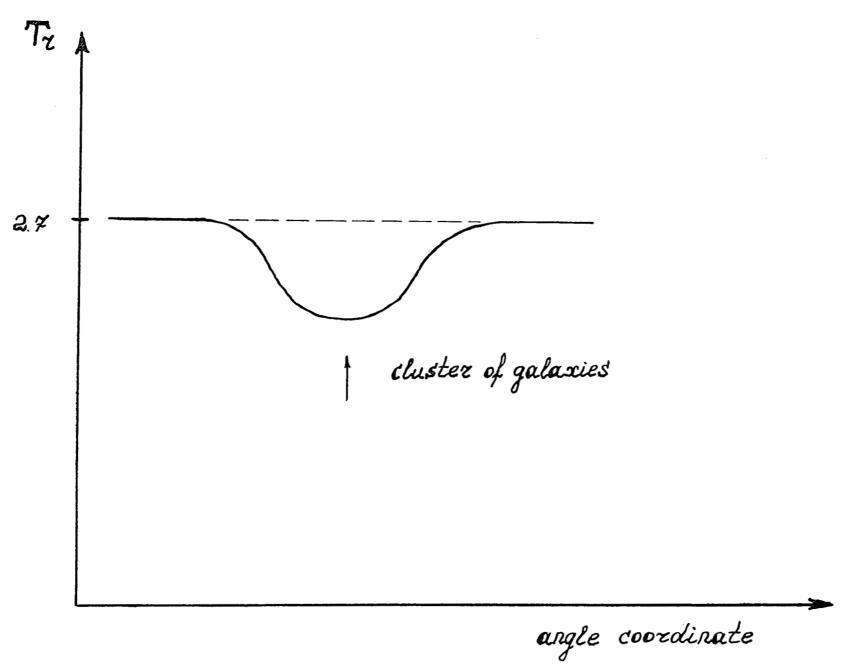
- ➤ Model
- ➤ Marginalise
- Need priors
 - ➤ Need observations

Thermal Sunyaev-Zel'dovich Effect

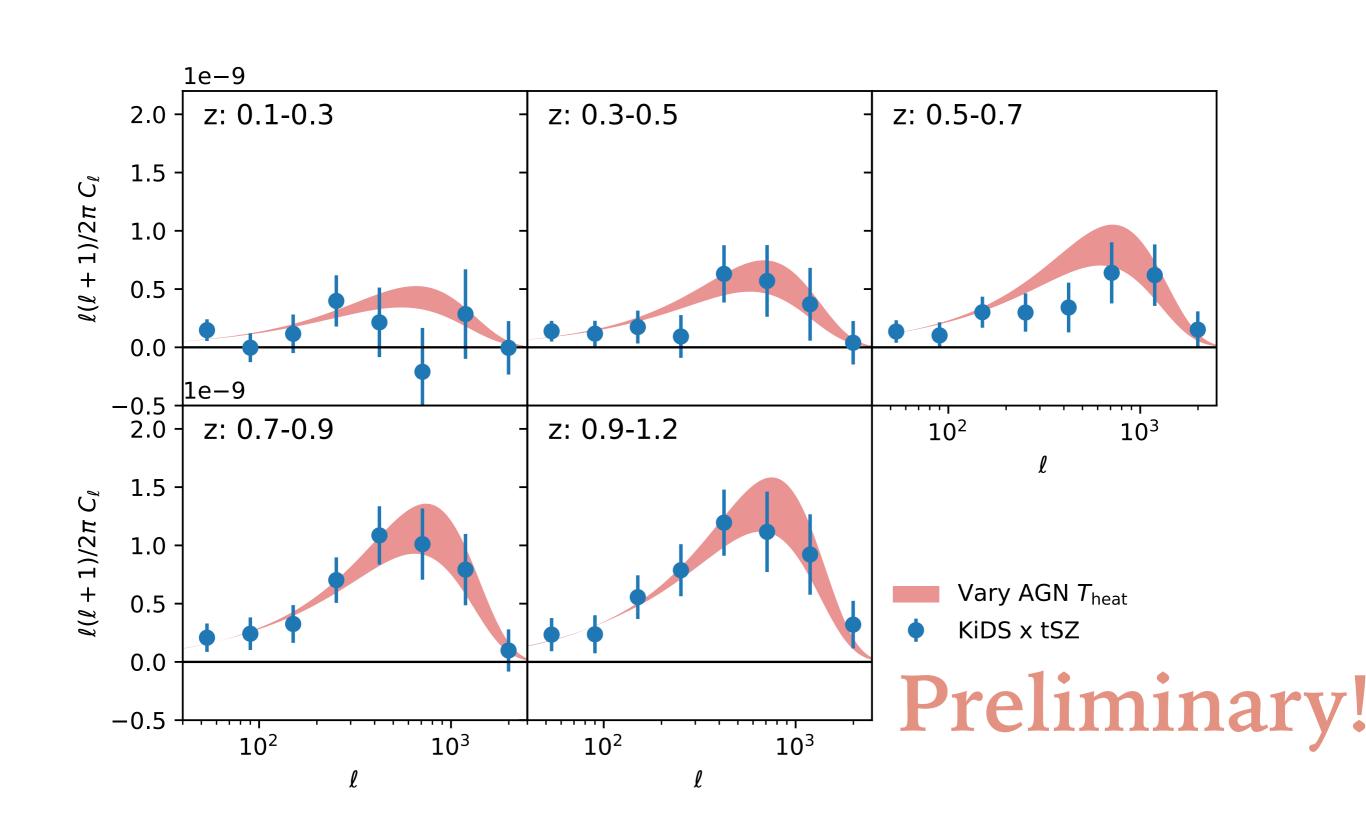


tSZ effect

"Shadow" on the CMB



Cross-correlate tSZ with lensing



Covariances

Analytic

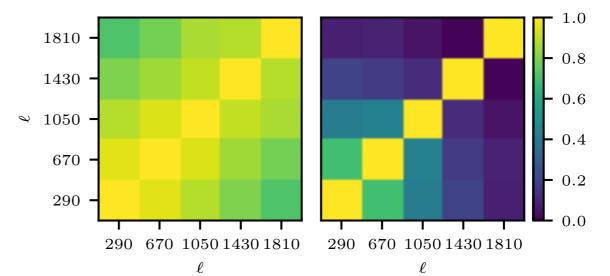
- ➤ Gaussian insufficient
- Modelling uncertain

Simulations



Internal

➤ Non-trivial to do correctly



Covariances

Analytic

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Simulations

➤ Know anyone with 10³ lensing + tSZ lightcones?

Internal

Might work but WIP

Covariances

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Simulations

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Simulation data

SLICS

- ➤ N-body simulation
- ➤ 505 Mpc/h box size
- ➤ ~1000 independent volumes

BAHAMAS

- ➤ Hydrodynamical simulation
- ➤ 400 Mpc/h box size
- ➤ 3 independent volumes

Why are hydro sims hard?

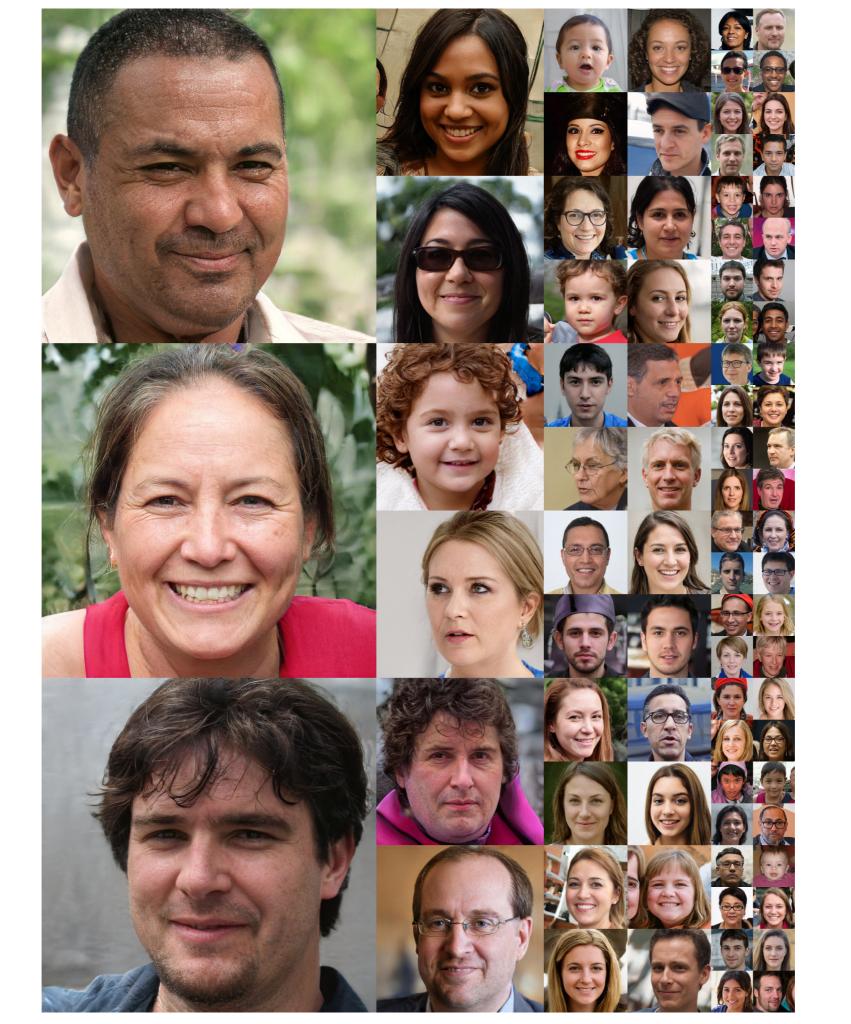
Feedback couples large and small scales

- ➤ Simulating large and small scales at the same time is hard
- ➤ (for lensing) we don't care about the small scales
- ➤ "small scales":
 - Galaxy properties
 - > SFR
 - > etc

Use machine learning?

Gas Temperature Dark Matter







Generative models

Conditional variational auto-encoder (CVAE)

- Probabilistic description
- ➤ Easy to train
- ➤ Can predict variance of output

Generative adversarial network (GAN)

- ➤ Tends to give better results
- ➤ Training is harder; often unstable

Conditional Variational Auto-Encoder (CVAE)

Sample x, given y:

- $\rightarrow x \sim p_{\theta}(x|y)$
- ➤ E.g., x is pressure, y is dark matter

Introduce latent variable z

$$p_{\theta}(x|y) = \int dz \ p_{\theta}(x,z|y) = \int dz \ p_{\theta}(x|y,z)p(z)$$

Infinite mixture model

Conditional Variational Auto-Encoder (CVAE)

Approximate prior on z

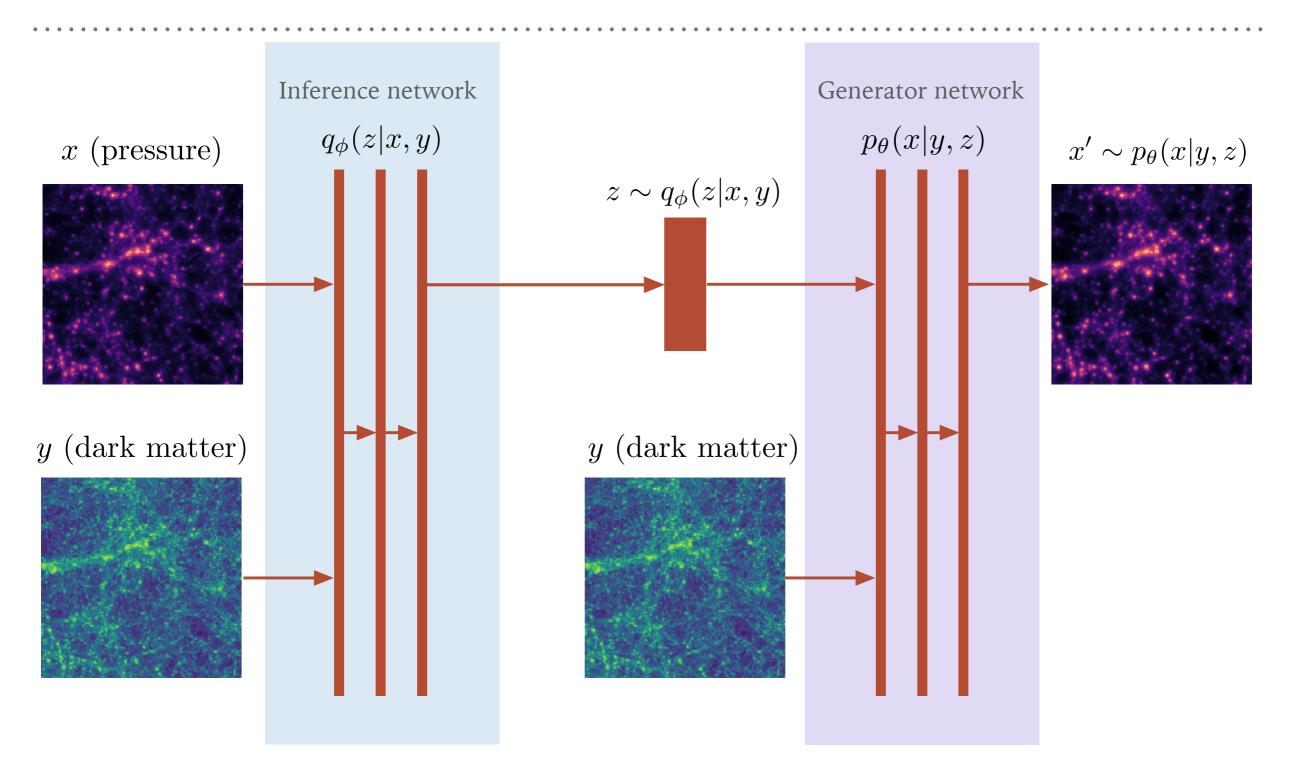
 $ightharpoonup q_{\phi}(z|x,y) \approx p(z)$

Variational lower bound

$$\log p_{\theta}(x|y) \ge -\mathbb{D}_{KL}(q_{\phi}(z|x,y)||p(z)) + \mathbb{E}_{z \sim q_{\phi}(z|x,y)}[\log p_{\theta}(x|y,z)]$$
KL-term
Reconstruction loss

- $ightharpoonup p_{\theta}(x|y,z)$ and $q_{\phi}(z|x,y)$ can be expressed as neural networks
- Can be efficiently optimised

Conditional Variational Auto-Encoder (CVAE)



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Simulation data

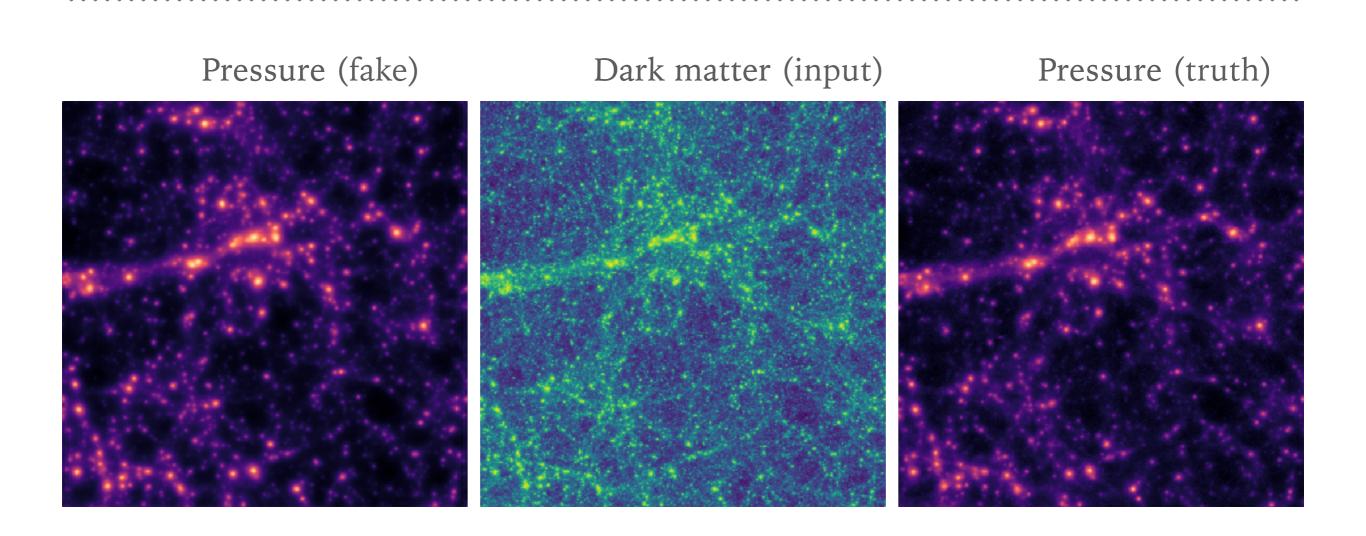
SLICS

- ➤ No particle snapshots
- ➤ Mass sheets corresponding to 252 Mpc/h thick slices
- ➤ Not a problem; lensing and tSZ are projected quantities

BAHAMAS

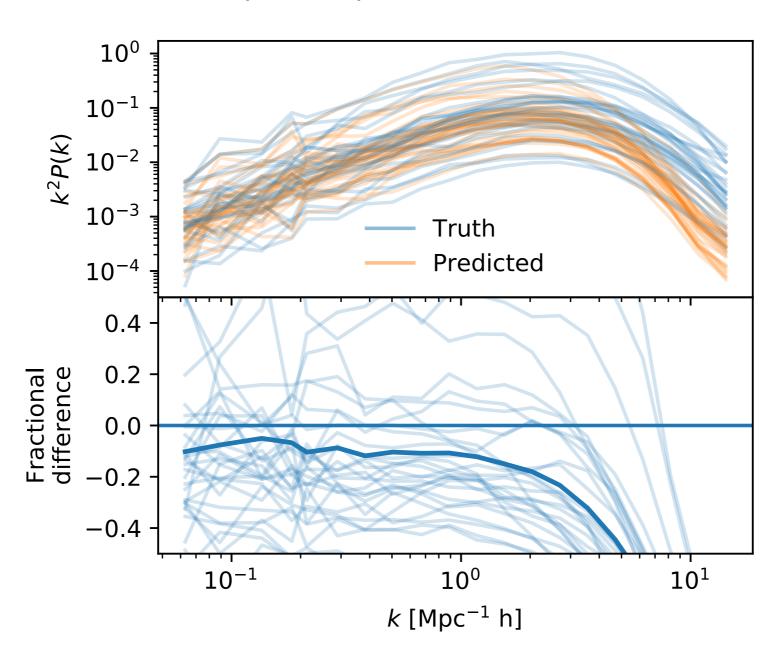
- ➤ Create 250 Mpc/h thick slices
- ➤ Form combinations of 150 Mpc/h and 100 Mpc/h slices
- ➤ 16 tiles per slice
 - ➤ ~50k combinations per redshift

Results



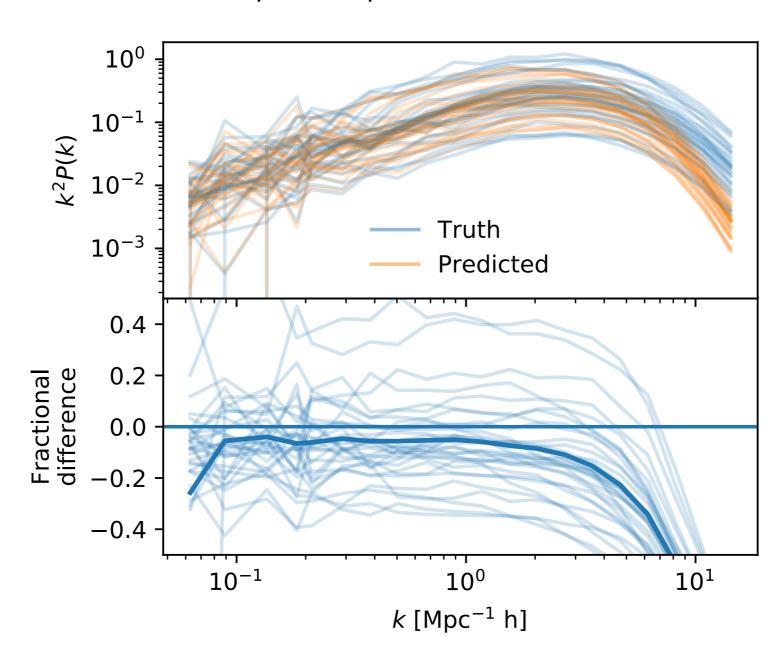
Auto-power spectra

Auto-power spectrum z = 0.0 - 1.0

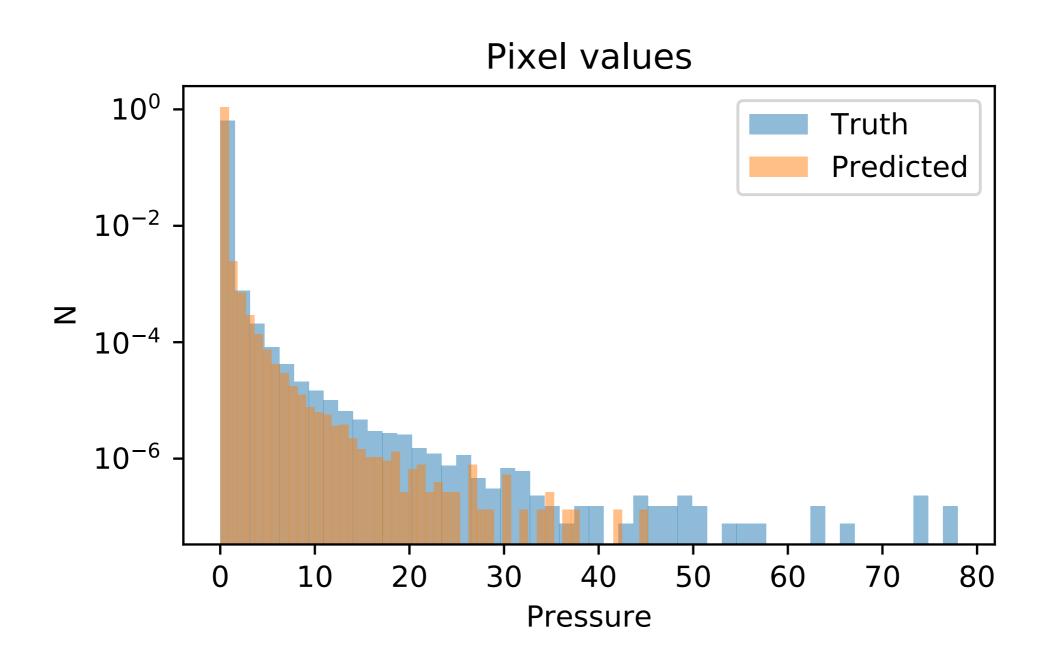


Cross-power spectra

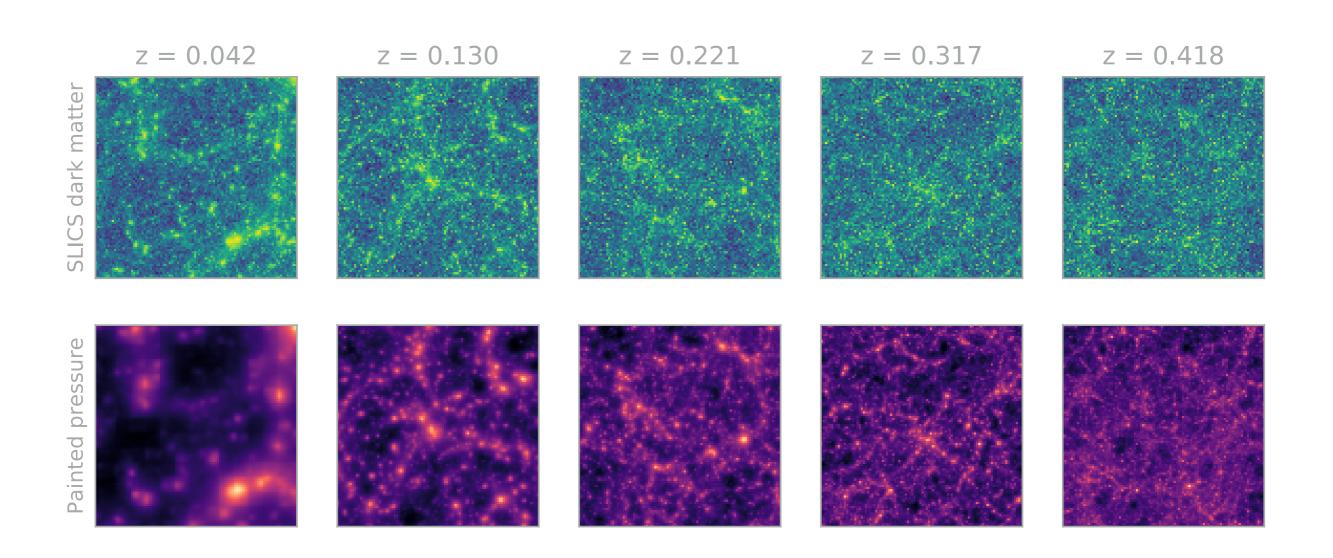
Cross-power spectrum z = 0.0 - 1.0



Pixel distribution

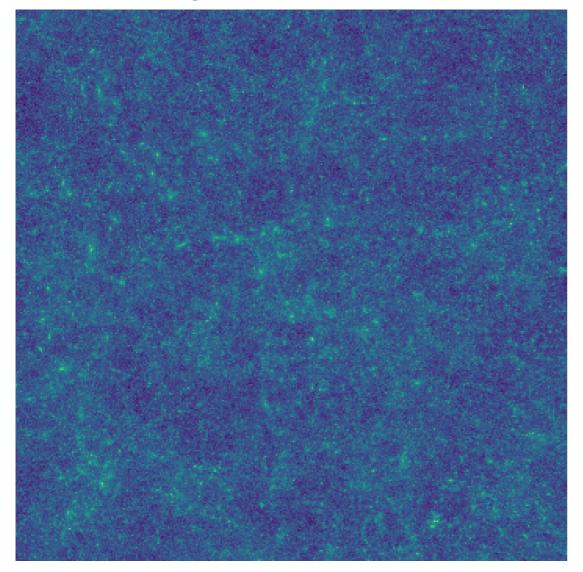


Paint on SLICS

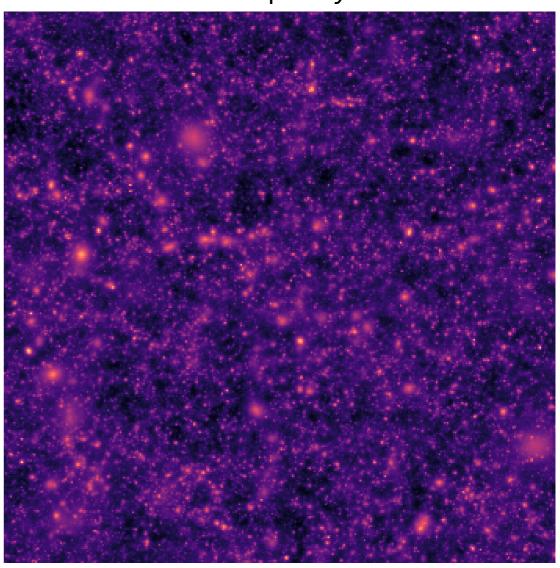


Convergence vs Compton-y

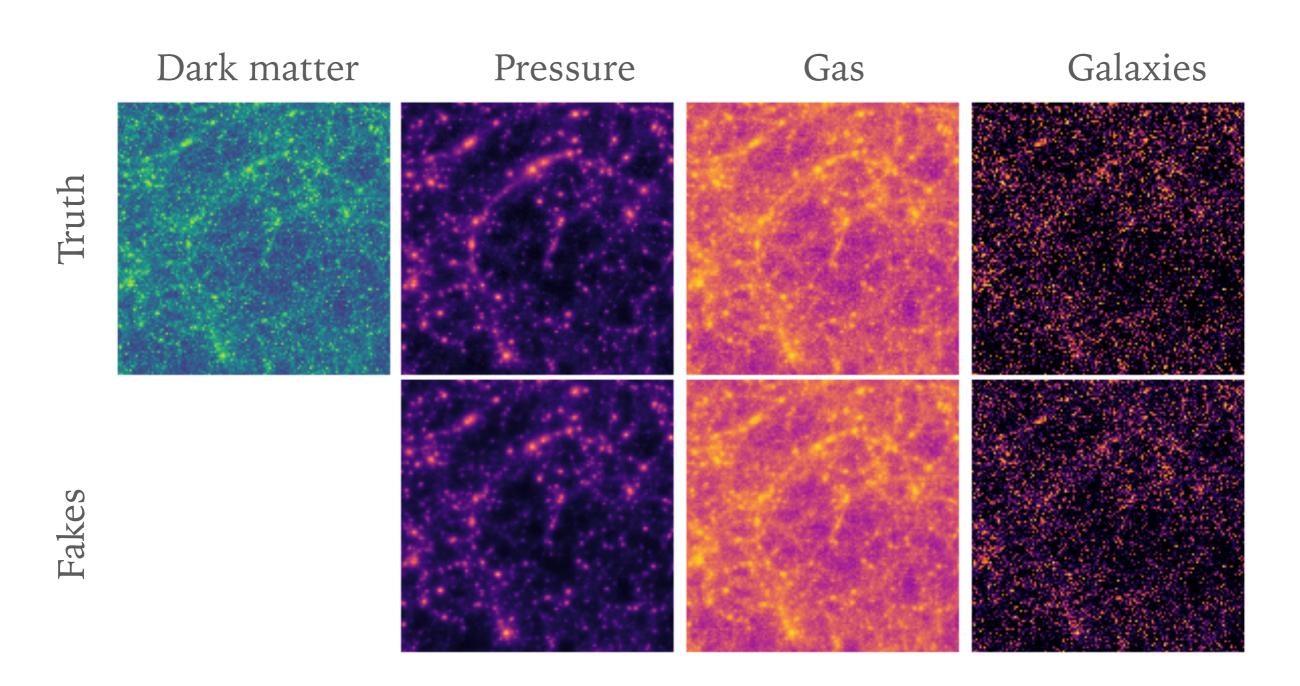
Convergence κ , KiDS-450 n(z)



Compton *y*



Paint baryons on dark matter



Summary

Deep generative models are powerful tools to bridge the gap between N-body and hydrosims

Even simple models give promising results

More sophisticated models (e.g., GANs) WIP, stay tuned!



This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 797794