BERKELEY CENTER *for* COSMOLOGICAL PHYSICS

AI-assisted emulator for cosmological simulations

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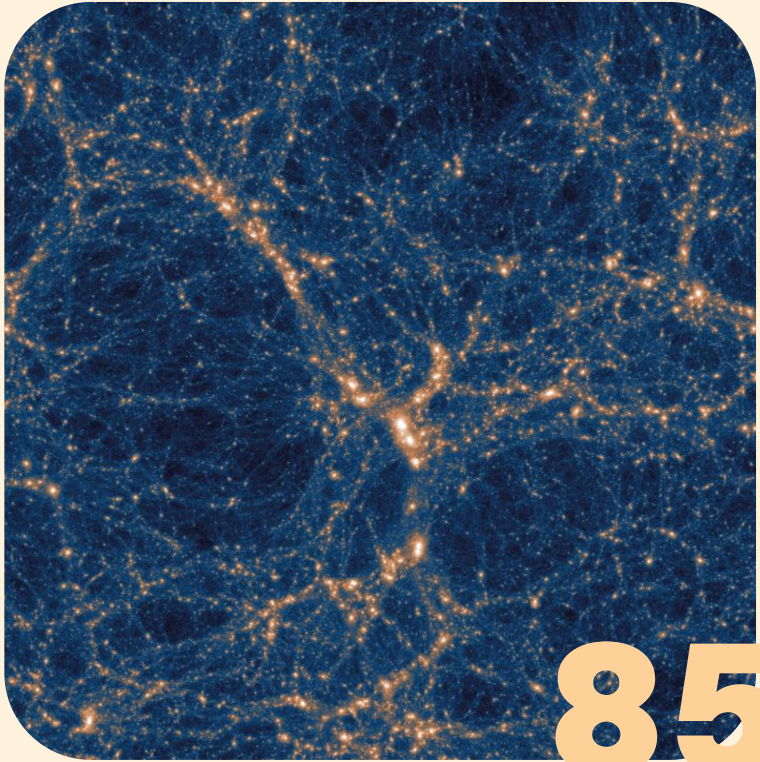
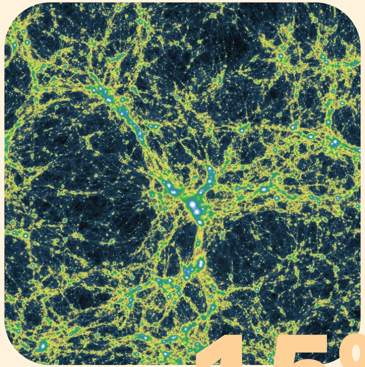
Computational challenge of simulating

Universe(s)



Dark matter density map from a N-body simulation at z=0.0 (TNG300-1-Dark from TNG website).



Gas density map for a hydrodynamical simulation with the same random seed (TNG300-1 from TNG website).

15%

Gas and stellar particles (baryons) are physics we don't know – unfeasibly expensive*

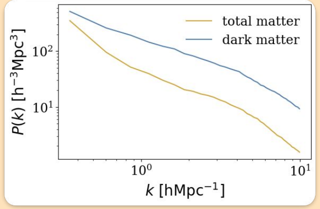
(Magneto)hydrodynamic simulations

~20M node-hours for a reasonable scale to study the large scale structure (100 Mpc)

this work!

Modeling baryonic process

An HPC solution to paint gas and stellar properties onto the dark matter field from N-body simulations.



We observe suppression in power spectra that comes from baryons.

85%

of the total matter content in the Universe is dark matter

Gravity-only N-body simulations

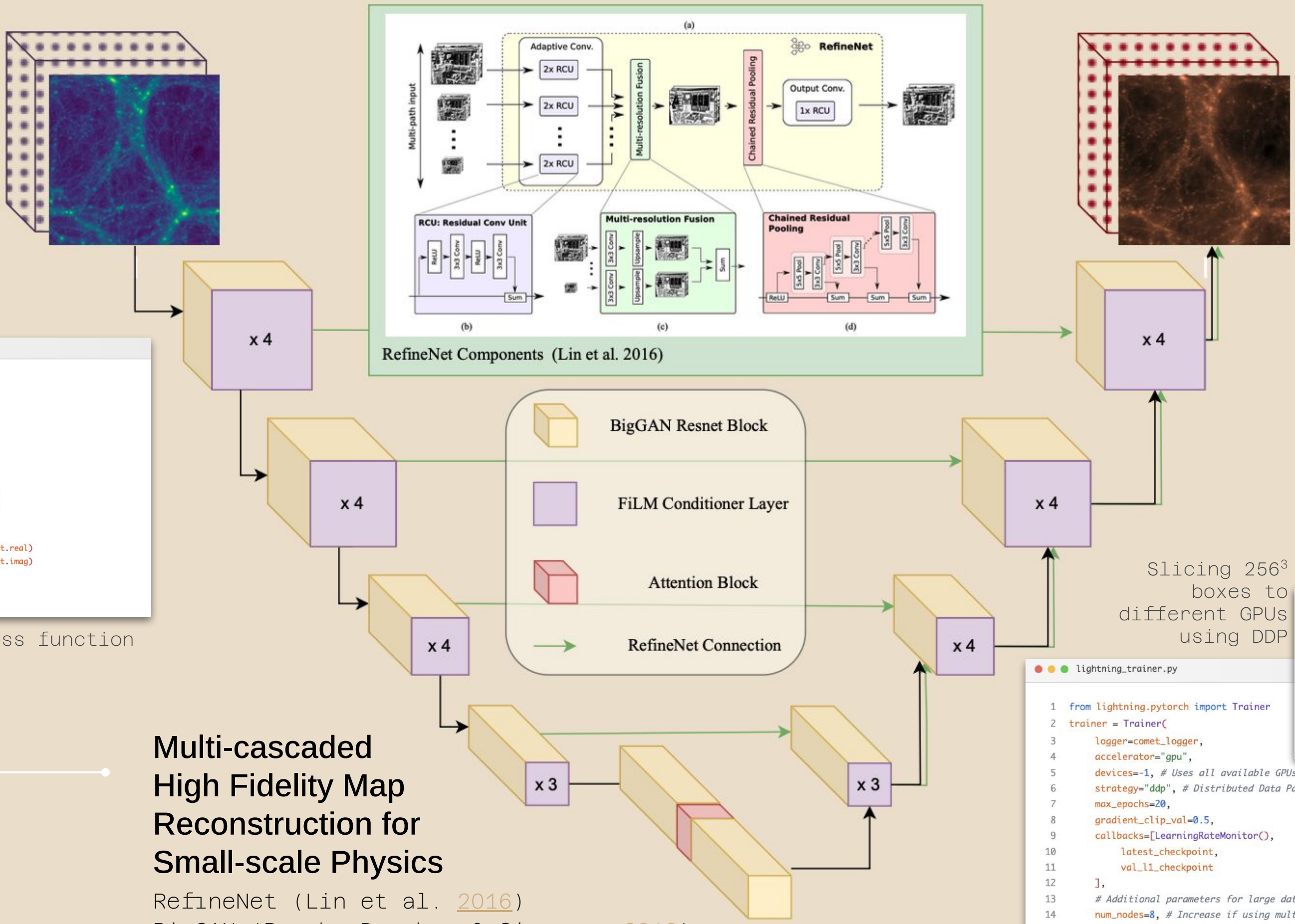
~1M node-hours

*For full simulations over gigaparsec volume with a reasonable resolution.

fourier_loss.py

```python
loss_fn = fourier_loss

def fourier_loss(output, target):
  # Progressive frequency scaling during training
  progress = current_epoch / trainer.max_epochs
  low, high = get_current_min_max_freq(progress)

  # Apply frequency-domain filtering
  filtered_output = fourier_filter(output, low, high)
  filtered_target = fourier_filter(target, low, high)

  # Complex-valued MSE loss
  real_loss = MSE(filtered_output.real, filtered_target.real)
  imag_loss = MSE(filtered_output.imag, filtered_target.imag)

  return real_loss + imag_loss
```

Scale-attentive loss function

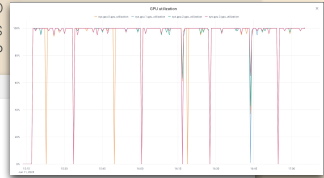


CNN

Multi-cascaded High Fidelity Map Reconstruction for Small-scale Physics

RefineNet (Lin et al. 2016)
BigGAN (Brock, Donahue & Simonyan 2018)

Slicing 256^3 boxes to different GPUs using DDP

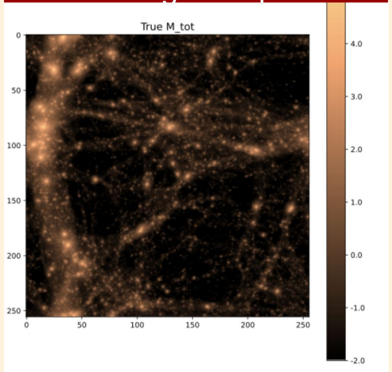


lightning_trainer.py

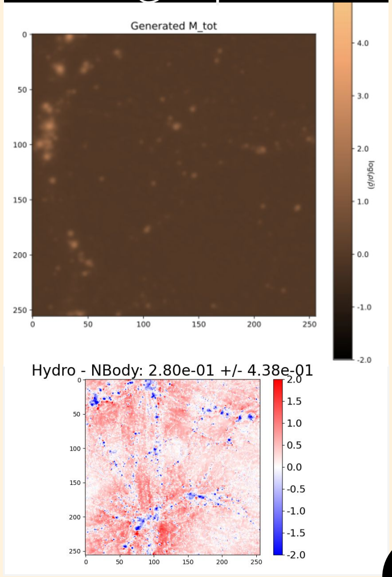
```python
from lightning.pytorch import Trainer
trainer = Trainer(
    logger=comet_logger,
    accelerator="gpu",
    devices=-1, # Uses all available GPUs
    strategy="ddp", # Distributed Data Parallel
    max_epochs=20,
    gradient_clip_val=0.5,
    callbacks=[LearningRateMonitor(),
        latest_checkpoint,
        val_l1_checkpoint
    ],
    # Additional parameters for large dataset handling
    num_nodes=8, # Increase if using multiple nodes
    precision=16, # Mixed precision for memory efficiency
    accumulate_grad_batches=2 # Gradient accumulation for larger effective batch
size
)
```

CNN generative results

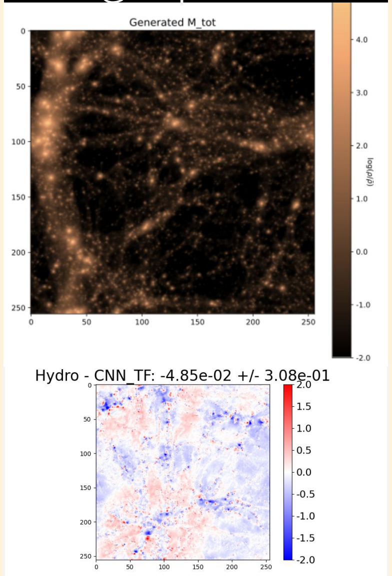
Target map



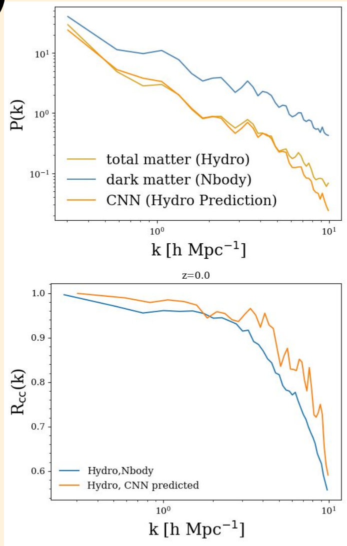
@Step 0



@Step 10500



2

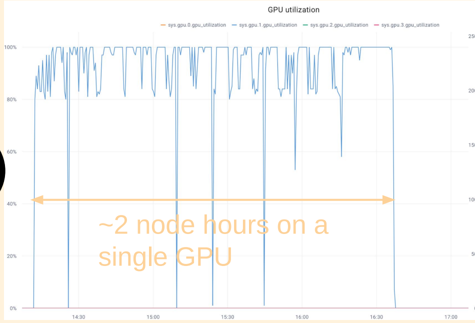


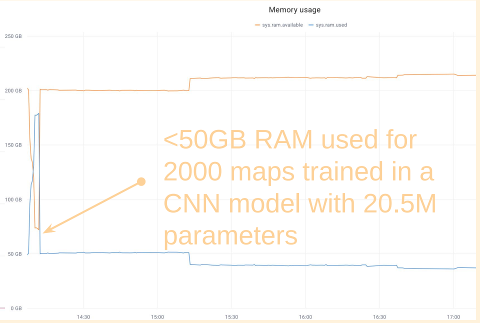
(Prelim.)Results

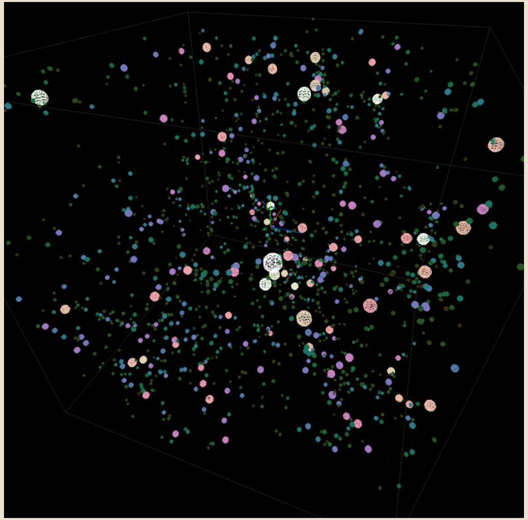
1

1. Field-level map generation.
2. Performance in fourier space – power spectrum, cross-correlation coefficient with the target hydrodynamical simulation.
3. System metrics – GPU utilization (training for 2D), RAM usage during training.

3







Cool 3D Universe Explorer (TNG website)

Questions? Comments?
Please reach out to
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Thank you!