

MillimeterDL

Deep Learning Simulations of the Microwave Sky

Dongwon 'DW' Han

Neelima Sehgal, Francisco Villaescusa-Navarro

arXiv:2105.11444

mmDL Simulations are now public at

[NERSC] <https://portal.nersc.gov/project/cmb/data/generic/mmDL/>

[Lambda] https://lambda.gsfc.nasa.gov/simulation/tb_sim_ov.cfm

[PySM3] <https://github.com/galsci/pysm> (coming soon!)



Stony Brook
University

LSS x CMB Data Products & Experiments

LSS

Galaxies (photometric / spectroscopic), LRGs, Quasars, AGNs
Galaxy groups / clusters
Weak lensing
Lyman-alpha forest
HI maps
Other line-intensity maps



CMB

Temperature
Polarization
Lensing
tSZ
kSZ



A Slide from Chihway's Talk from CMB-S4 Summer 2020 Meeting

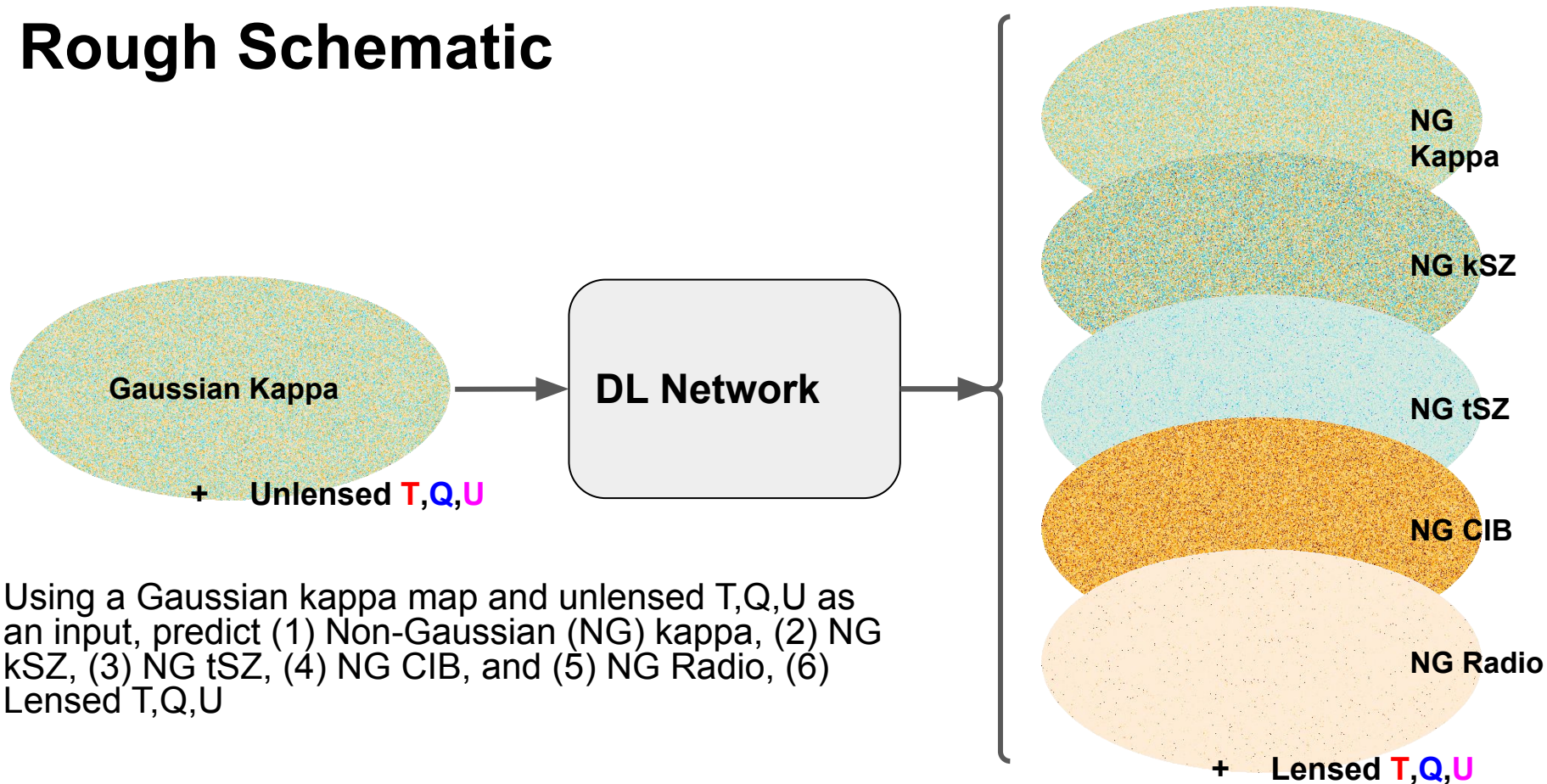
Requirements for Correlated Simulations

- Require **many realizations** (500 simulations or more) for statistical analysis
- **Full-sky, high-resolution** (half-arcminute), **multi-frequency**
- Contains **non-Gaussian Information** and **correlations** among different components.

A natural solution is to generate N-body simulations and post-process them (CrowCanyon, DC2, MDPL2, S10, Websky). Unfortunately, this approach is computationally expensive.

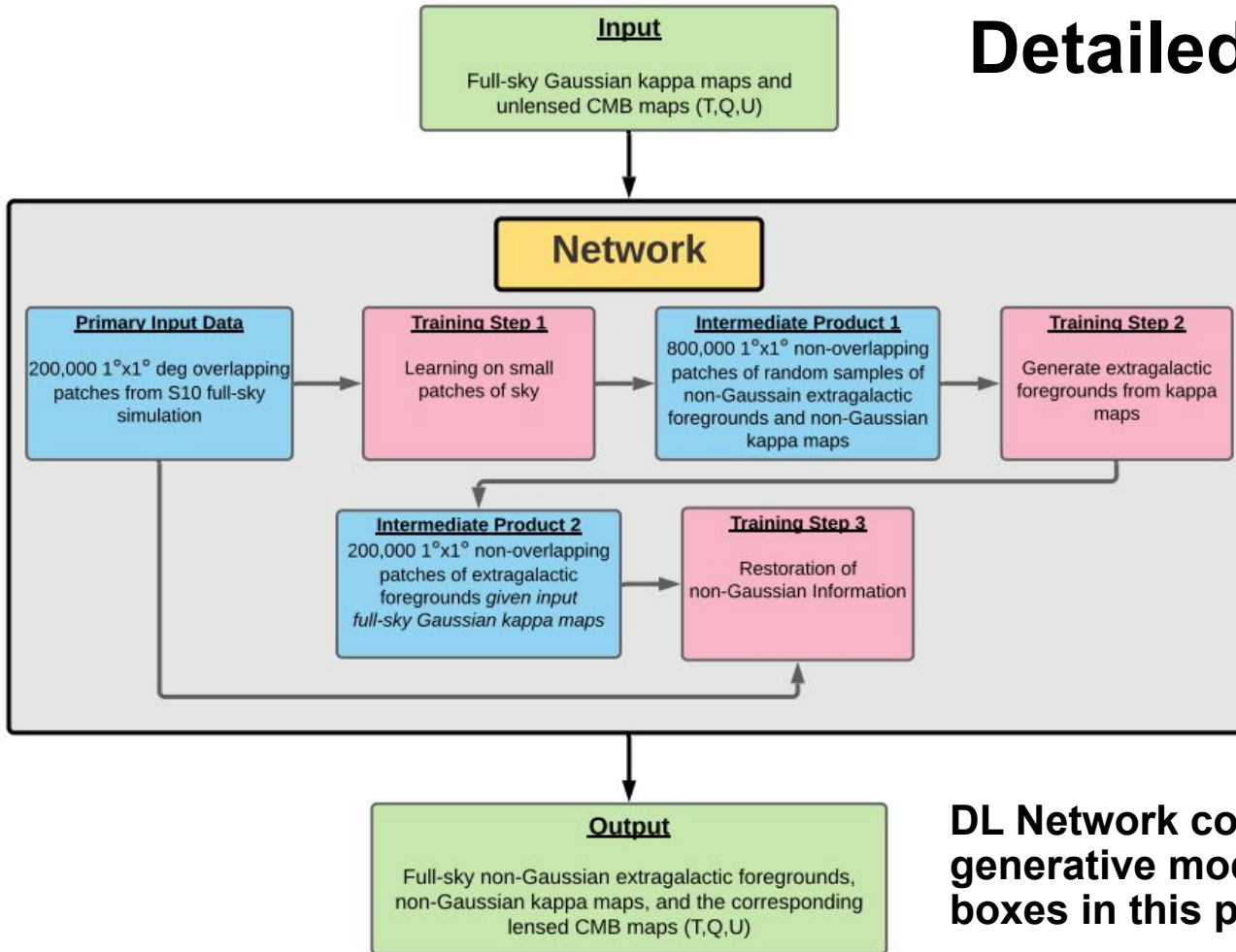
However, once you have just a single realization of such simulation, you can use a Deep Learning (DL) Generative Model to get around this restriction.

Rough Schematic



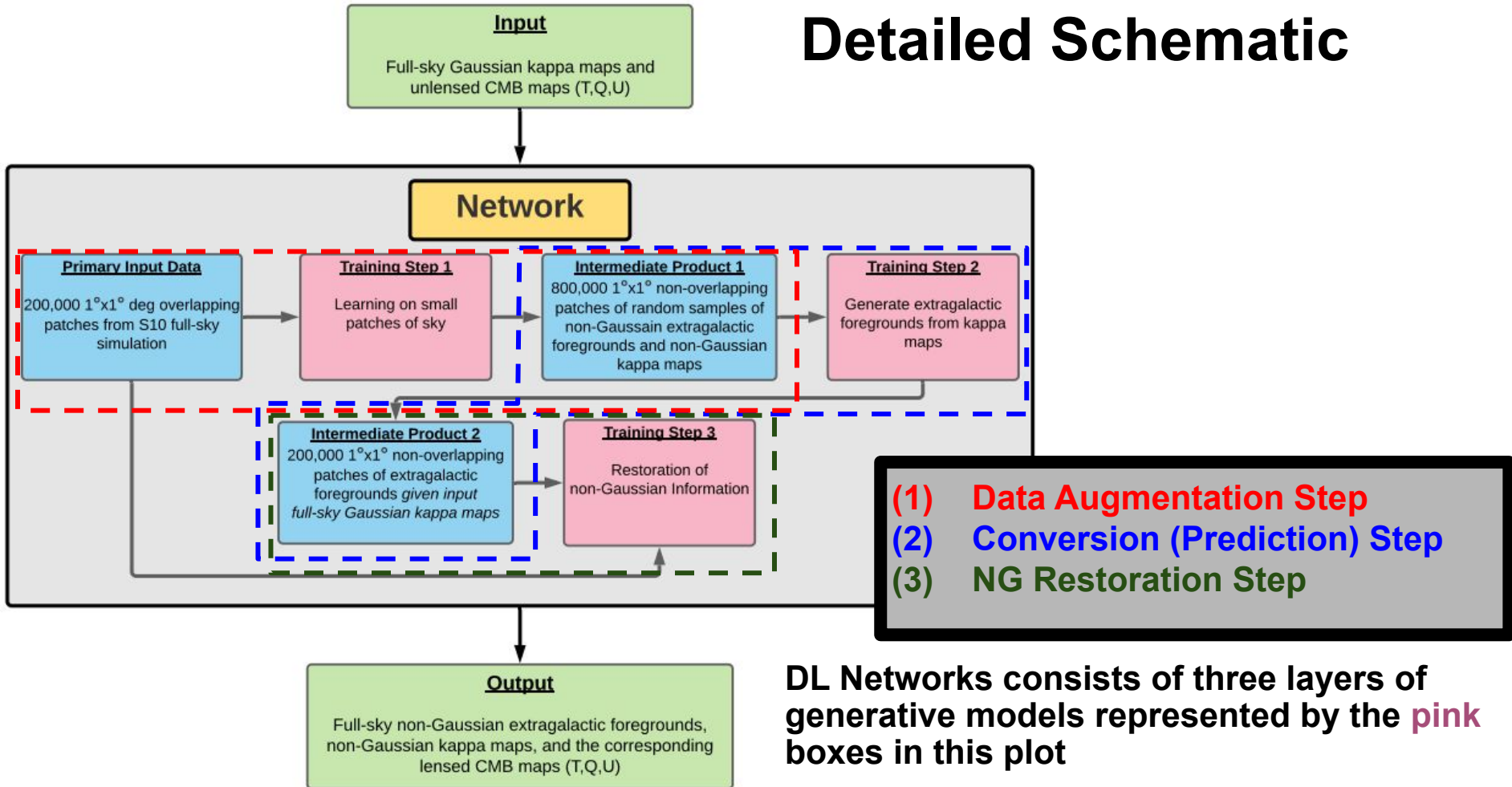
Using a Gaussian kappa map and unlensed T,Q,U as an input, predict (1) Non-Gaussian (NG) kappa, (2) NG kSZ, (3) NG tSZ, (4) NG CIB, and (5) NG Radio, (6) Lensed T,Q,U

Detailed Schematic

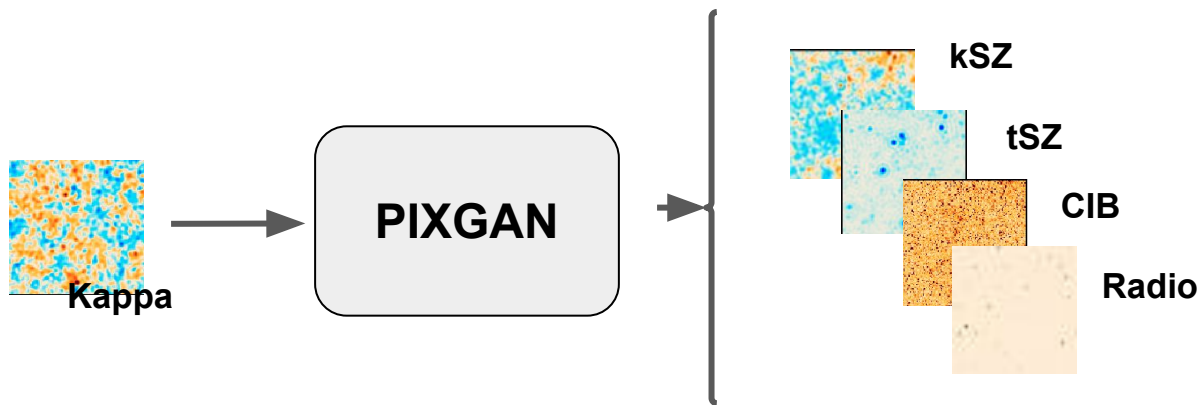


DL Network consists of three layers of generative models represented by the pink boxes in this plot

Detailed Schematic



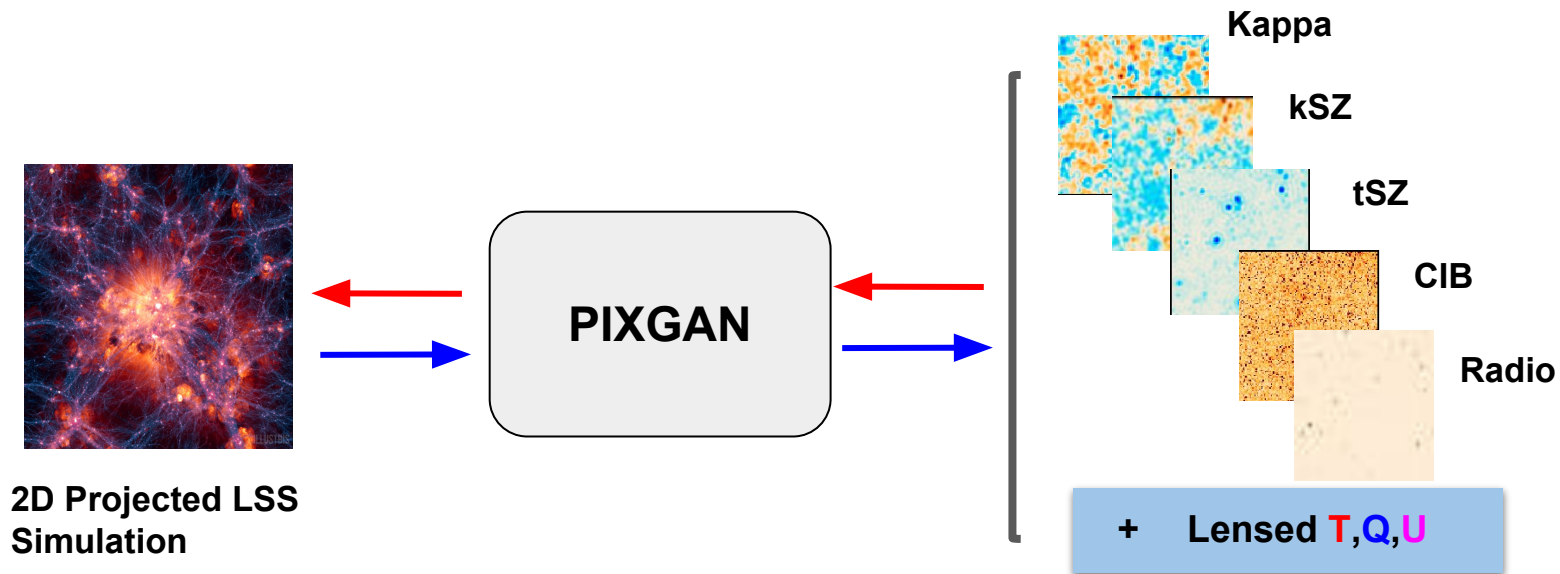
Prediction Step (Step#2 on the schematic)



We train a conditional GAN (PIXGAN) to predict multiple fields (kSZ, tSZ, CIB, Radio maps) from kappa maps.

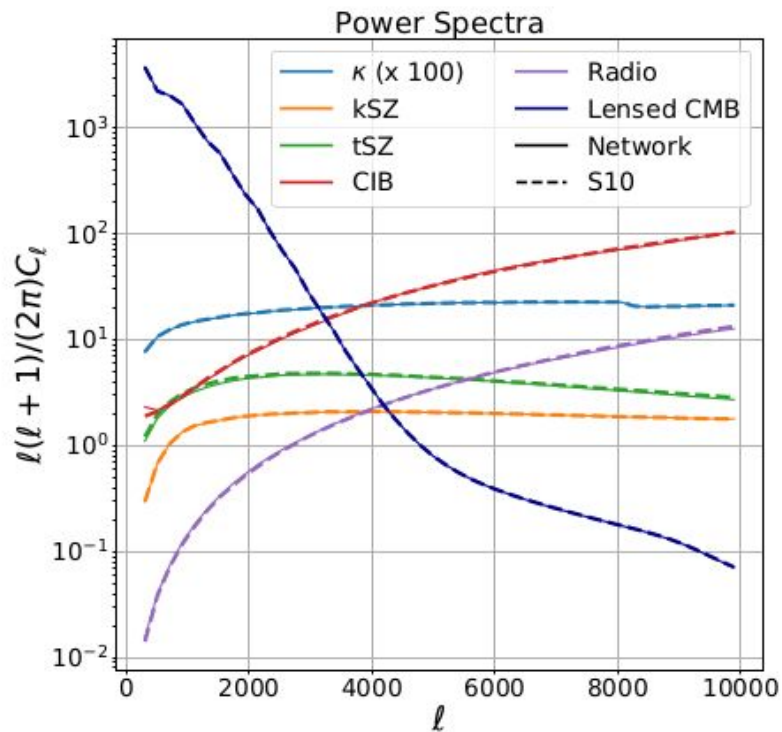
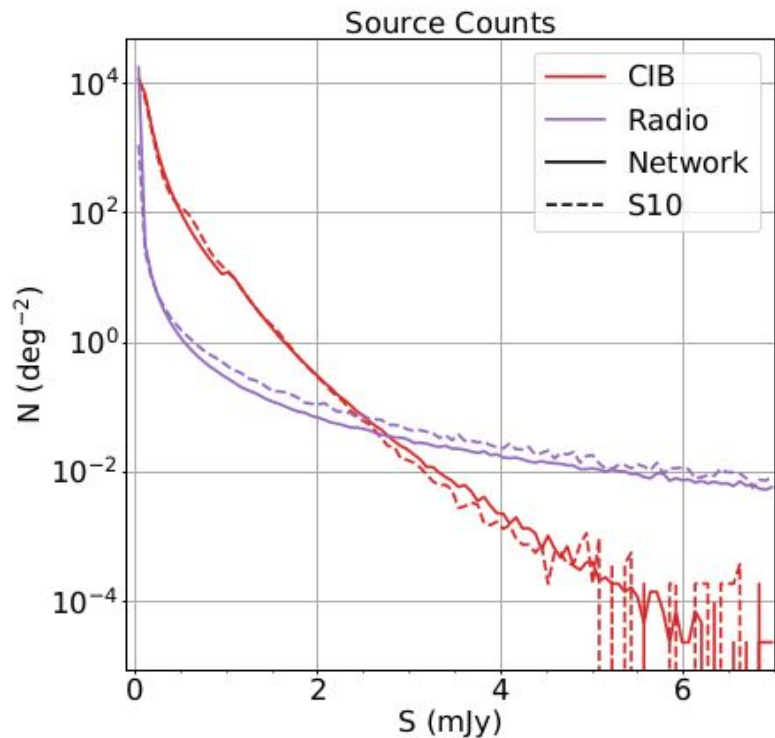
In principle, you can predict any field(s) from any input field(s) using this network.

For Example: LSS Simulation to Correlated CMB Sims (Or the other way around)

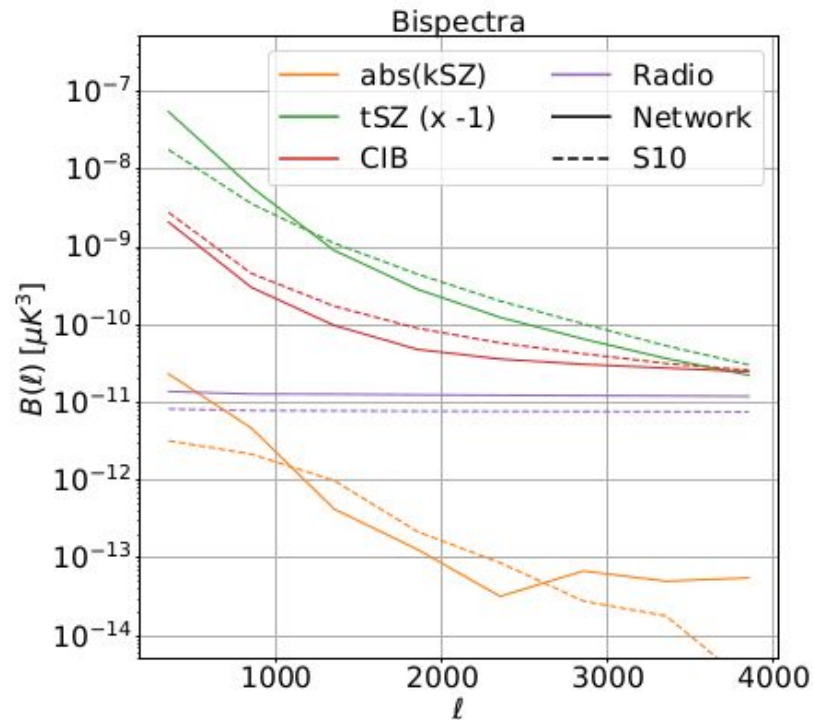
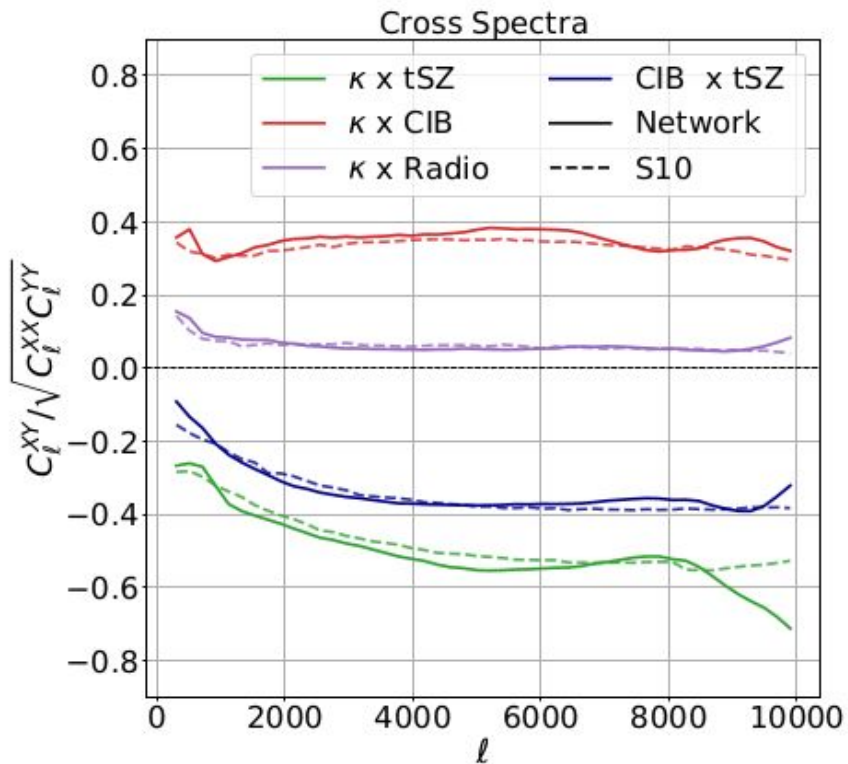


You can predict CMB fields from any 2D projected LSS simulation, and vice versa.

mmDL Results: Source Counts & Power Spectra

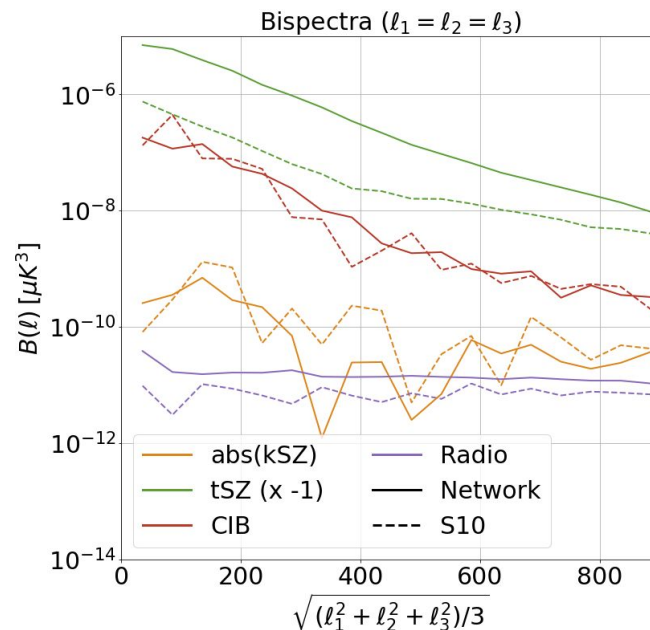
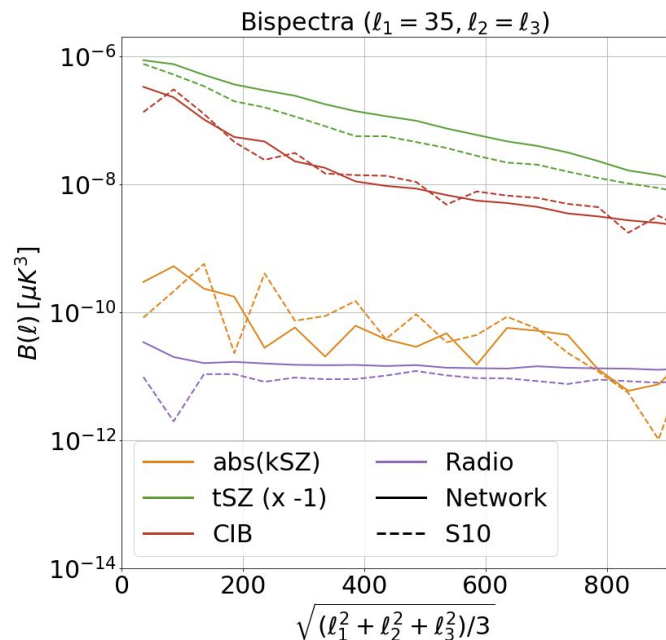


mmDL Results: Cross-spectra and 3pt functions



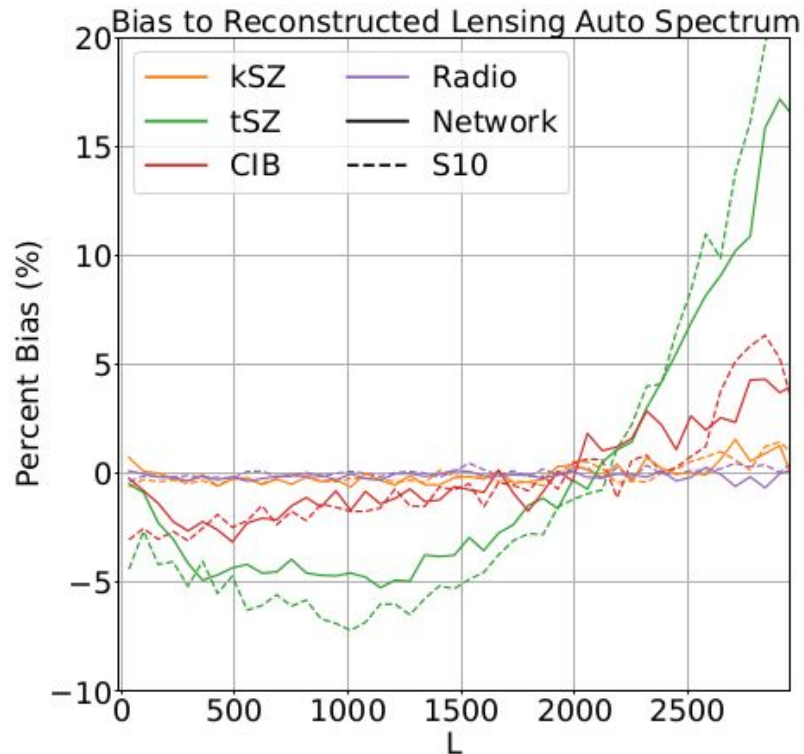
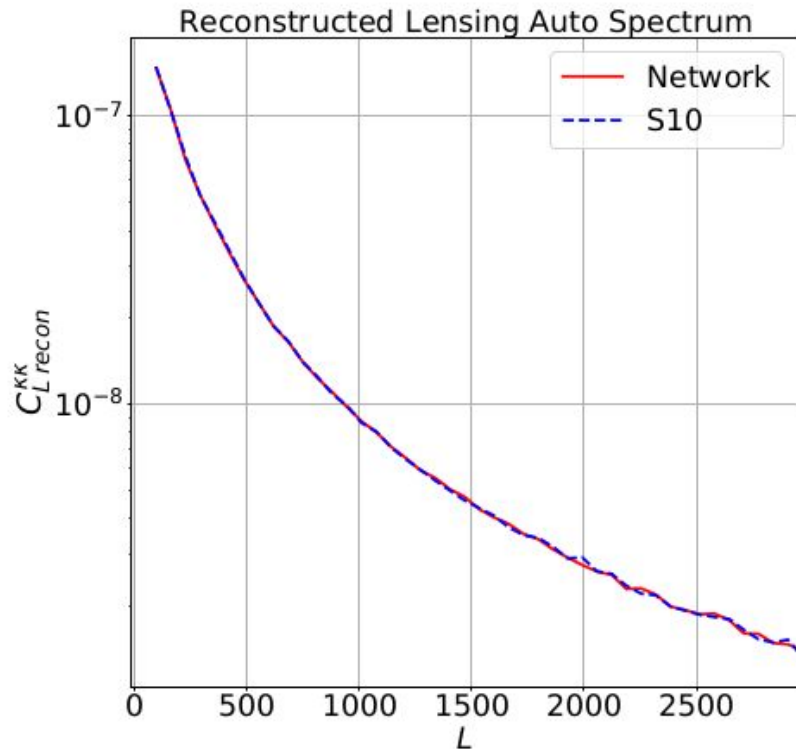
mmDL Results: 3pt functions

Han et al 2021, arXiv:2105.11444

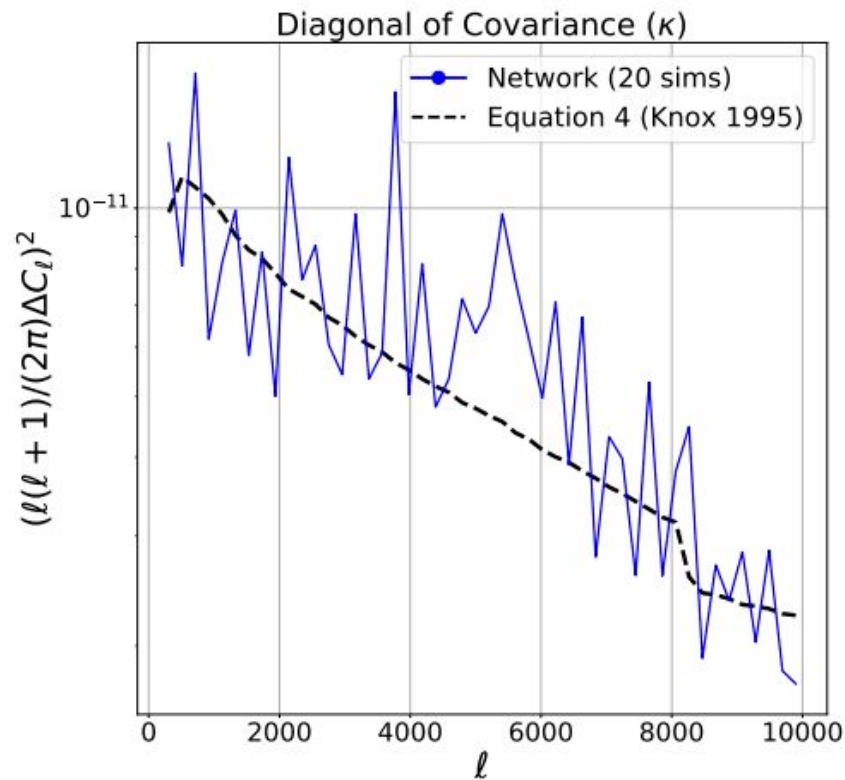
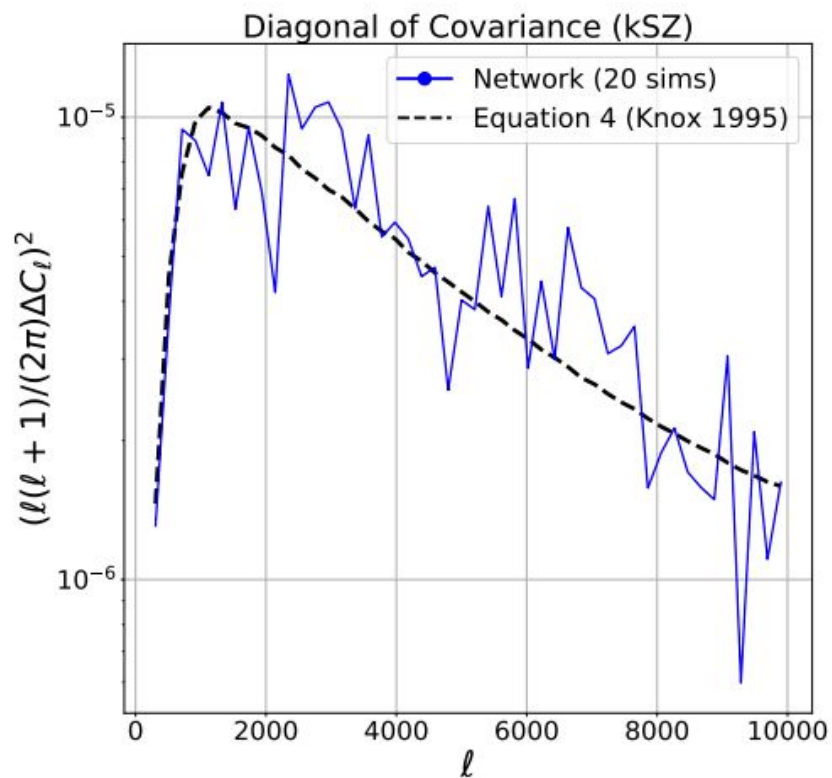


Since we “stitch” up 1x1 sq deg tiles to full-sky maps, you don’t necessarily expect the network to preserve the correlations between large super-sample modes ($l < 200$) and small scale modes ($l > 200$). But our network can recover them.

mmDL Results: 4pt functions



mmDL Results: Variance of mmDL sims



mmDL Data Product Release

We have generated 500 mmDL realizations using our network. These are fullsky simulations at half-arcminute resolution at six different frequencies (30, 90, 148, 219, 277, and 350 GHz),

which include:

- the lensing convergence map (κ),
- the kinetic Sunyaev-Zeldovich effect (kSZ),
- the thermal Sunyaev-Zeldovich effect (tSZ),
- the Cosmic Infrared Background (CIB)
- the radio galaxies (Radio), and
- the lensed CMB (T,Q,U)

The simulations are available publicly at:

- [NERSC] <https://portal.nersc.gov/project/cmb/data/generic/mmDL/>
- [Lambda] https://lambda.gsfc.nasa.gov/simulation/tb_sim_ov.cfm
- [PySM3] <https://github.com/galsci/pysm> (coming soon!)

Takeaways from mmDL project

- MillimeterDL (mmDL) can reproduce a wide range of non-Gaussian summary statistics.
- We can mass produce independent full-sky realizations from a single expensive full-sky simulation.
- We can “stitch” small patches up to make a full-sky realization that reproduces all the NG statistics.
- **Using our methods, we can take a full-sky lensing convergence map from any large-scale structure (LSS) simulation and generate the corresponding lensed CMB and correlated foreground components at millimeter wavelengths.**
- We can also adopt our procedure to quickly generate FG maps for forward-modelling.

Deep Learning for Correlated Simulations (Cont.)

- ❖ Network is trained at a particular fiducial cosmology and with a particular baryonic model.
- ❖ Missing associated catalogues.
- ❖ In order to generate the simulations, the network must have learned all the relevant statistics from the fields (one-point, two-points, three-points, ...). Can we use this information to make “optimal” summary statistics?

Deep Learning for Correlated Simulations (Cont.)

- ❖ Network is trained at a particular fiducial cosmology and with a particular baryonic model.
 - Given few simulations at different cosmology and byronic models (i.e. CAMELS simulations), one might be able to train a network to generate simulations at new cosmology.
- ❖ Missing associated catalogues.
 - A variation of our model can generate an associated catalogues along with fields.
- ❖ In order to generate the simulations, the network must have learned all the relevant statistics from the fields (one-point, two-points, three-points, ...). Can we use this information to make “optimal” summary statistics?
 - Bayesian NN for rescue? (Villaescusa-Navarro 2021, [astro-ph/2011.05992](#))