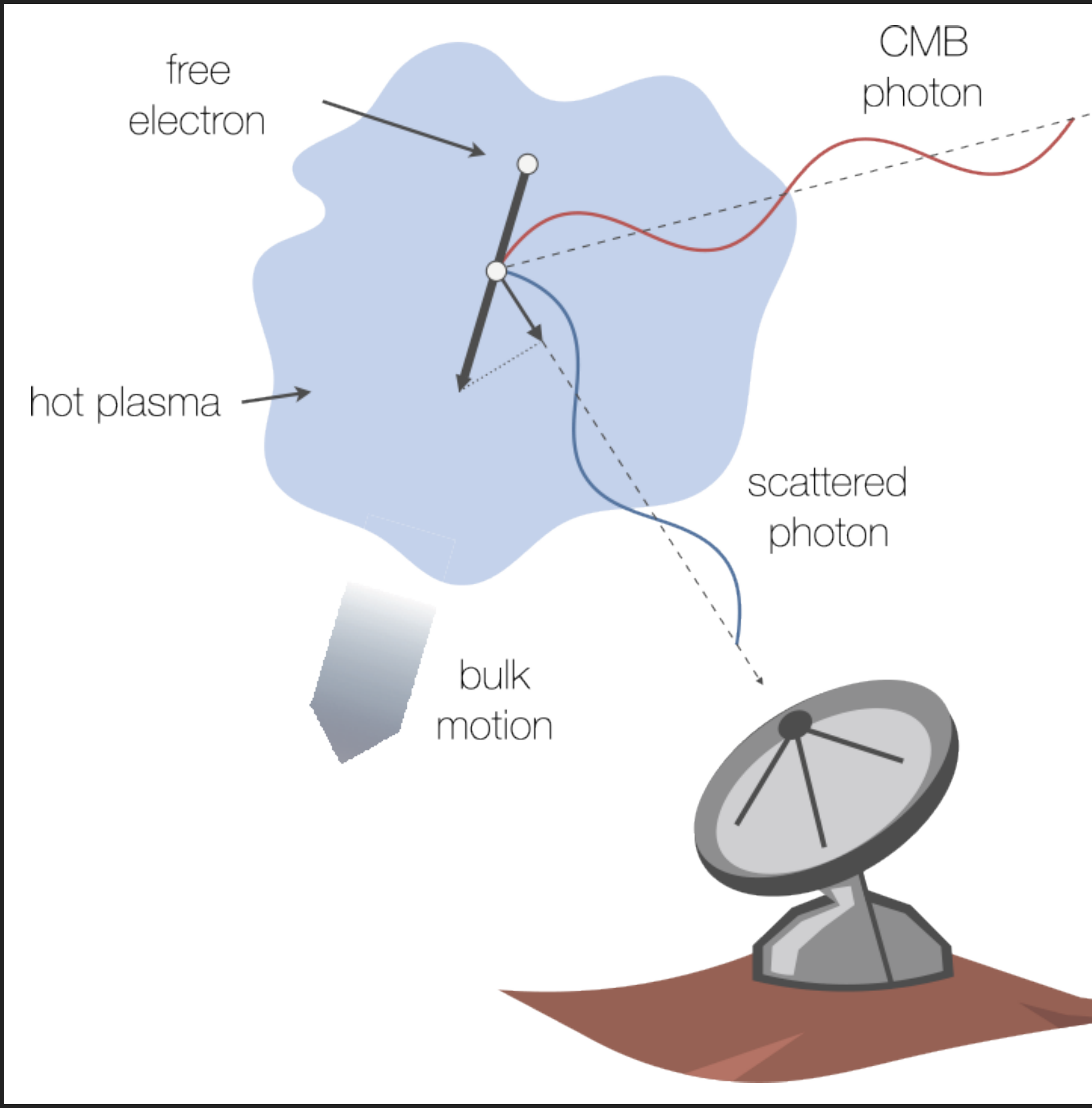
SMF (CCA, NYC) + JAA/JCH/BDW/DNS

ACT TSZ PDF LFI (WIP)

WHAT'S THE TSZ

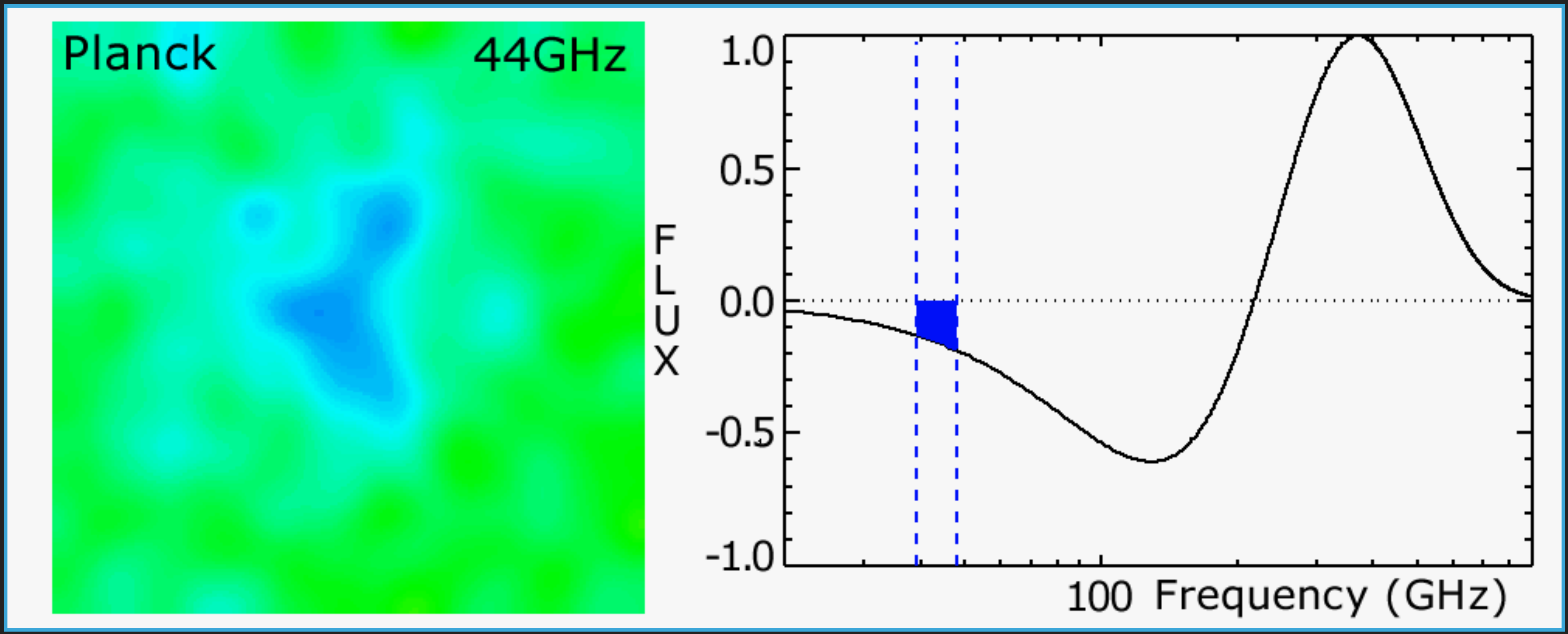
- Thermal Sunyaev-Zeldovich effect
- Scattering of cosmic microwave background (CMB) photons by hot electrons
- Sensitive to ~everything on line of sight: strongest effect from clusters

Mroczkowski+2019



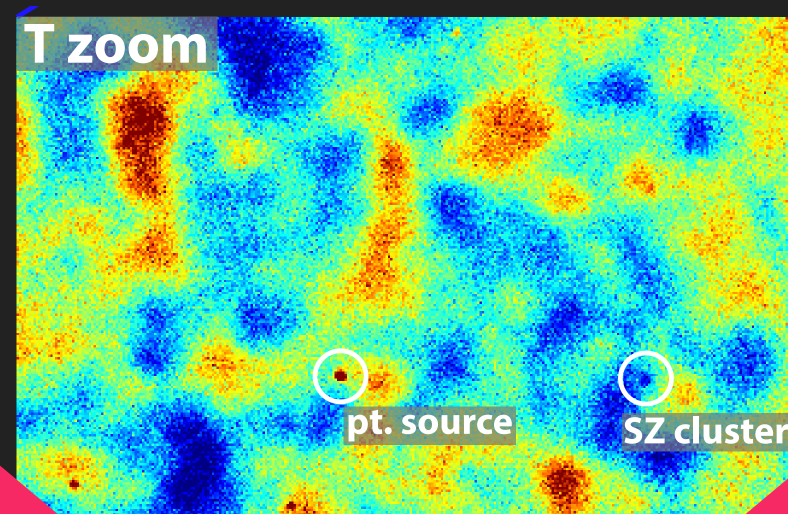
TSZ SIGNAL

ESA/Planck



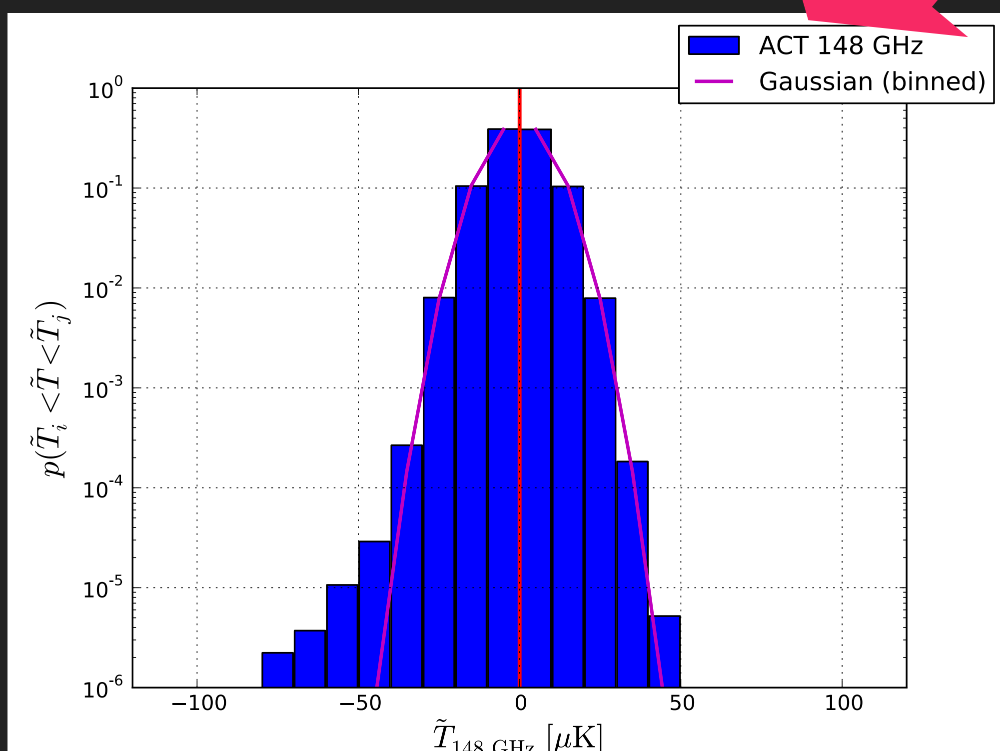
- Shifts blackbody distribution up in energy (frequency)
- Clusters: holes @ low freqs, peaks @ high, null @ 218 GHz
- Excellent probe of σ_8, Ω_m (how much clustered matter)

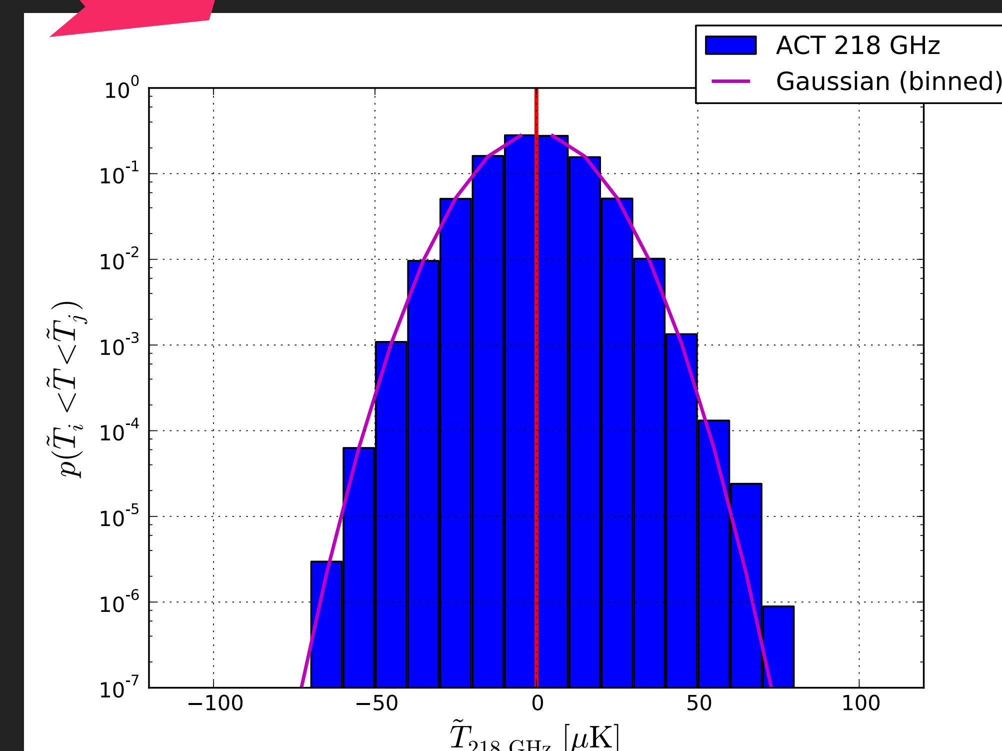
WHAT ARE THE DATA?



Naess+2014

Hill+2014

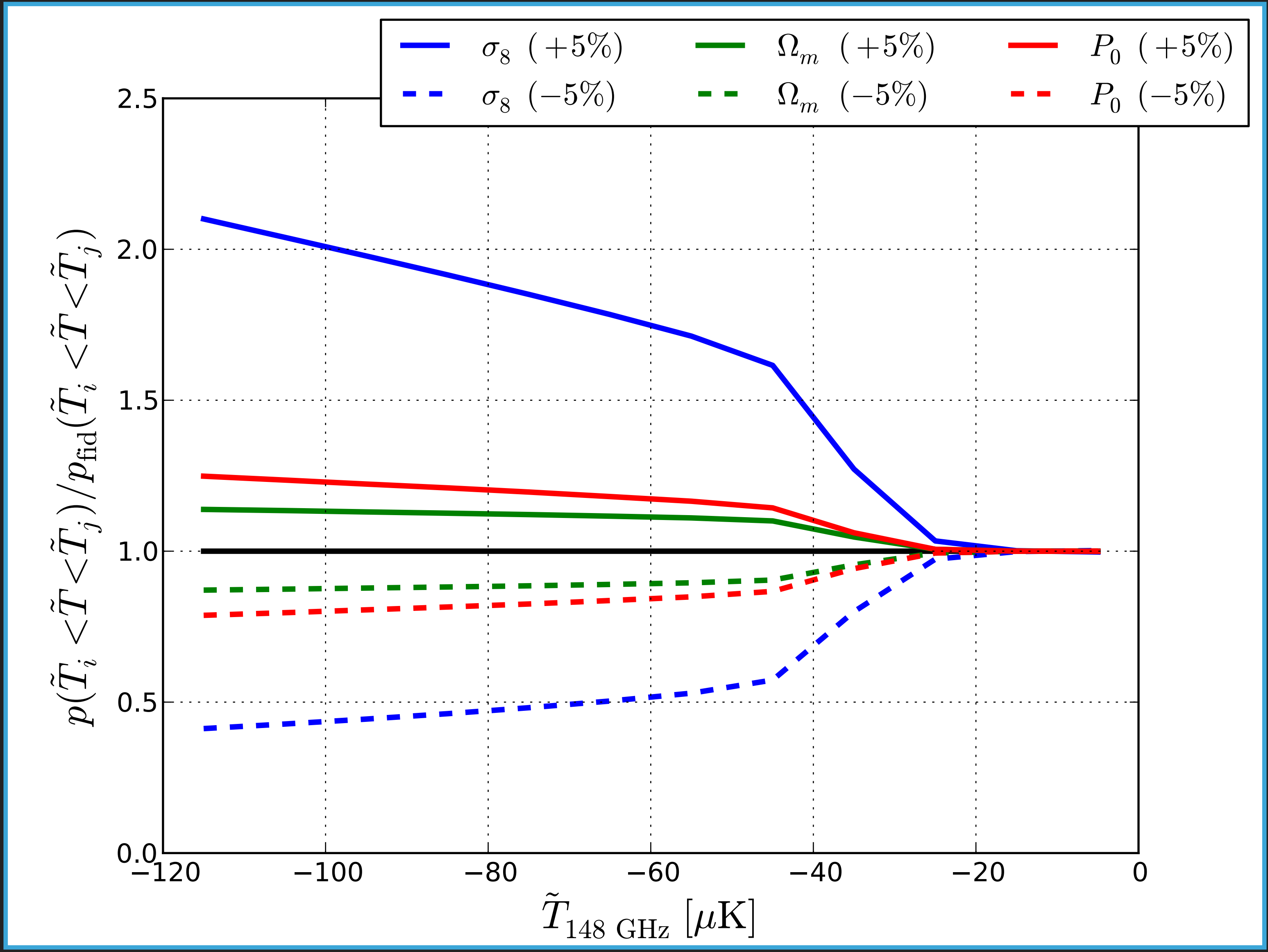




- Multi-frequency CMB observations from Atacama Cosmology Telescope (ACT)
- Histogram 148 GHz map, discard positive bins

PARAMETER SENSITIVITY

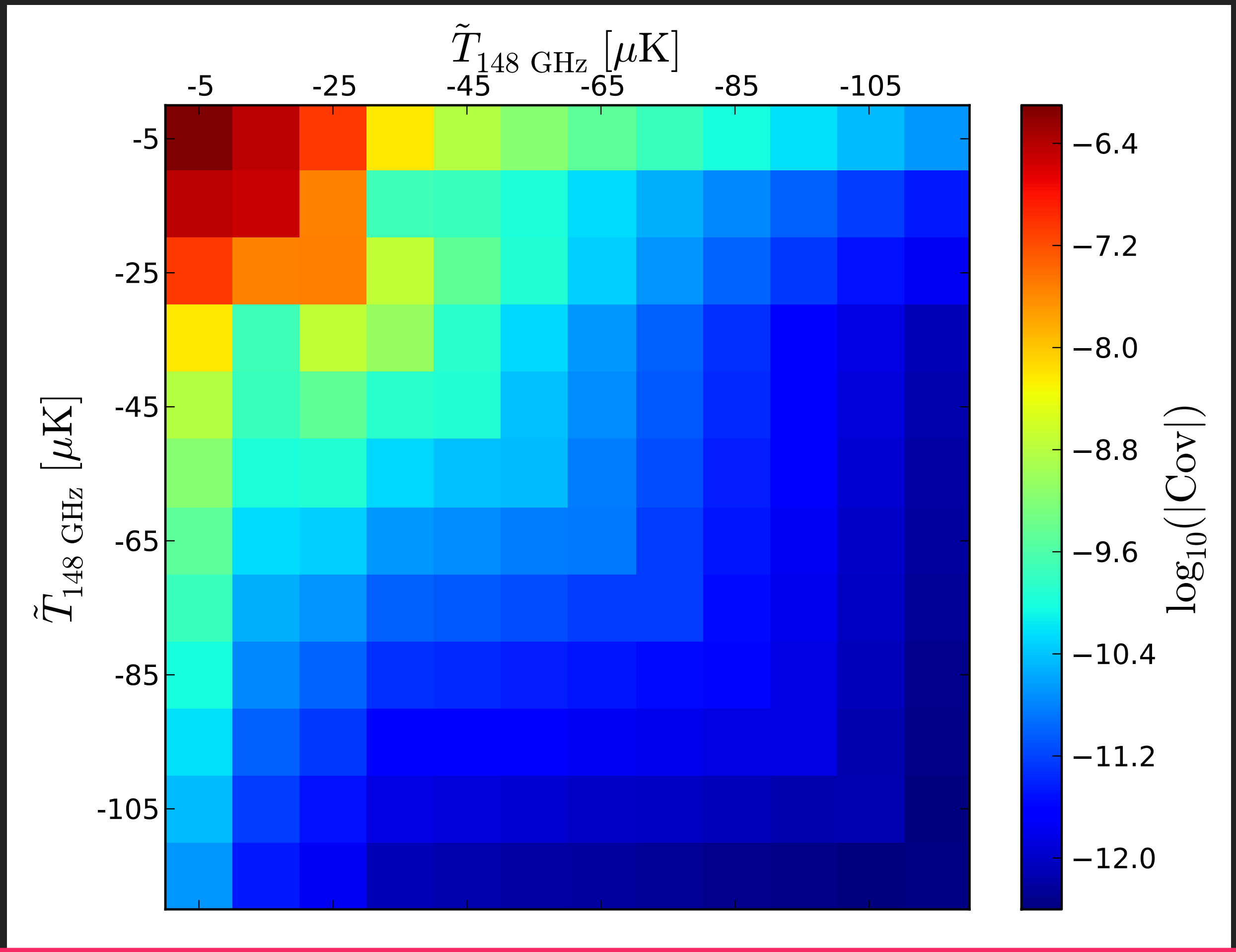
Hill+2014



- Simplest model described by σ_8, Ω_m, P_0 (astrophysics) and T_0 (noise std dev: CMB + instrument)

WHERE THE PROVERBIALS DO WE GO FROM HERE?

Hill+2014



$$\sigma_8 = 0.783 \pm 0.018 \quad (P_0 = 1, \Omega_m = 0.282).$$
$$\sigma_8 = 0.781 \pm 0.025 \quad (P_0\ \mathrm{marg.}, \Omega_m = 0.282).$$

- What's the likelihood of a histogram with inter-bin correlations?!
- ACT: Assume bin counts MV normal, but extreme bins are
  - most informative
  - almost empty
- Solution: combine extreme bins to Gaussianize
- Consequence: limiting degeneracy with nuisances

LFI TO THE RESCUE!

- LFI: likelihood, schmikelihood
- Need to compress 400,000 datapoints to 4ish parameters
- Assume multinomial likelihood:
  - counts in bins = rolling k-sided dice n times
  - no correlations but only affects optimality, no bias
- Then use score to compress & pyDELFI to process

PYDELFI TO THE RESCUE!

README.md

pydelfi

Density Estimation Likelihood-Free Inference with neural density estimators and adaptive acquisition of simulations. The implemented methods are described in detail in Alsing, Charnock, Feeney and Wandelt 2019, and are based closely on Papamakarios, Sterratt and Murray 2018, Lueckmann et al 2018 and Alsing, Wandelt and Feeney, 2018. Please cite these papers if you use this code!

Dependencies: tensorflow, getdist, emcee, mpi4py.

Usage: Once everything is installed, try out either `cosmic_shear.ipynb` or `jla_sne.ipynb` as example templates for how to use the code; plugging in your own simulator and letting pydelfi do it's thing.

If you have a set of pre-run simulations you'd like to throw in rather than allowing pydelfi to run simulations on-the-fly, look at `cosmic_shear_prerun_sims.ipynb` as a template for how to do this.

If you are interested in using pydelfi with nuisance hardened data compression to project out nuisances (Alsing & Wandelt 2019), take a look at `jla_sne_marginalized.ipynb`.

The code is not documented yet (documentation coming imminently), but if you are interested in applying it to your problem please get in touch with us (at justin.alsing@fysik.su.se) - we welcome collaboration!

- Public code! https://github.com/justinalsing/pydelfi

ANALYTIC LIKELIHOOD EXAMPLE

- Simple test: multinomial data, fixed Ω_m
- Input values [0.817, 1, 2.60]
- What about realistic simulations? See notebook!