# Fundamental physics with CMB and galaxy surveys

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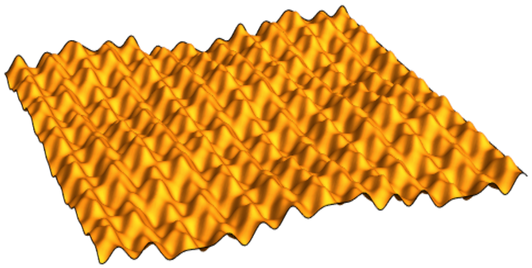
# Introduction

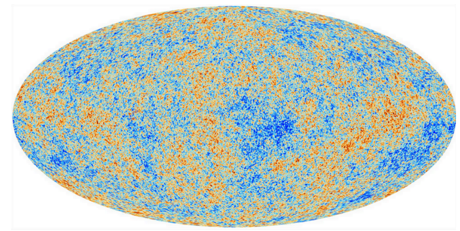
# The big picture

**Physical quantities** | **Observations**

**Inflation: Primordial quantum fields and interactions**



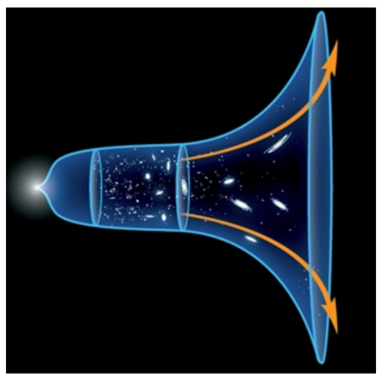
380.000 yrs



**Cosmic Microwave background**

Billions of years

**Background expansion (Dark Energy)**

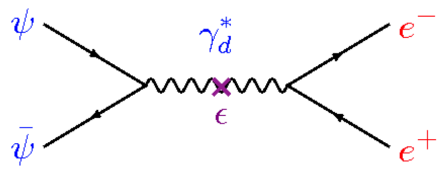


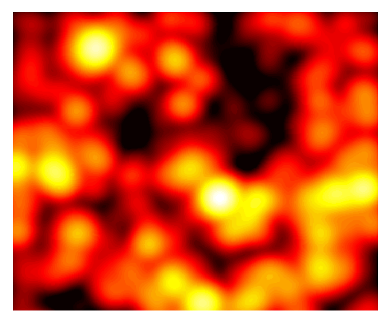
Discover magazine

NASA – Hubble deep field

**Galaxy surveys**

**Properties of matter and radiation (neutrinos, Dark Matter etc.)**



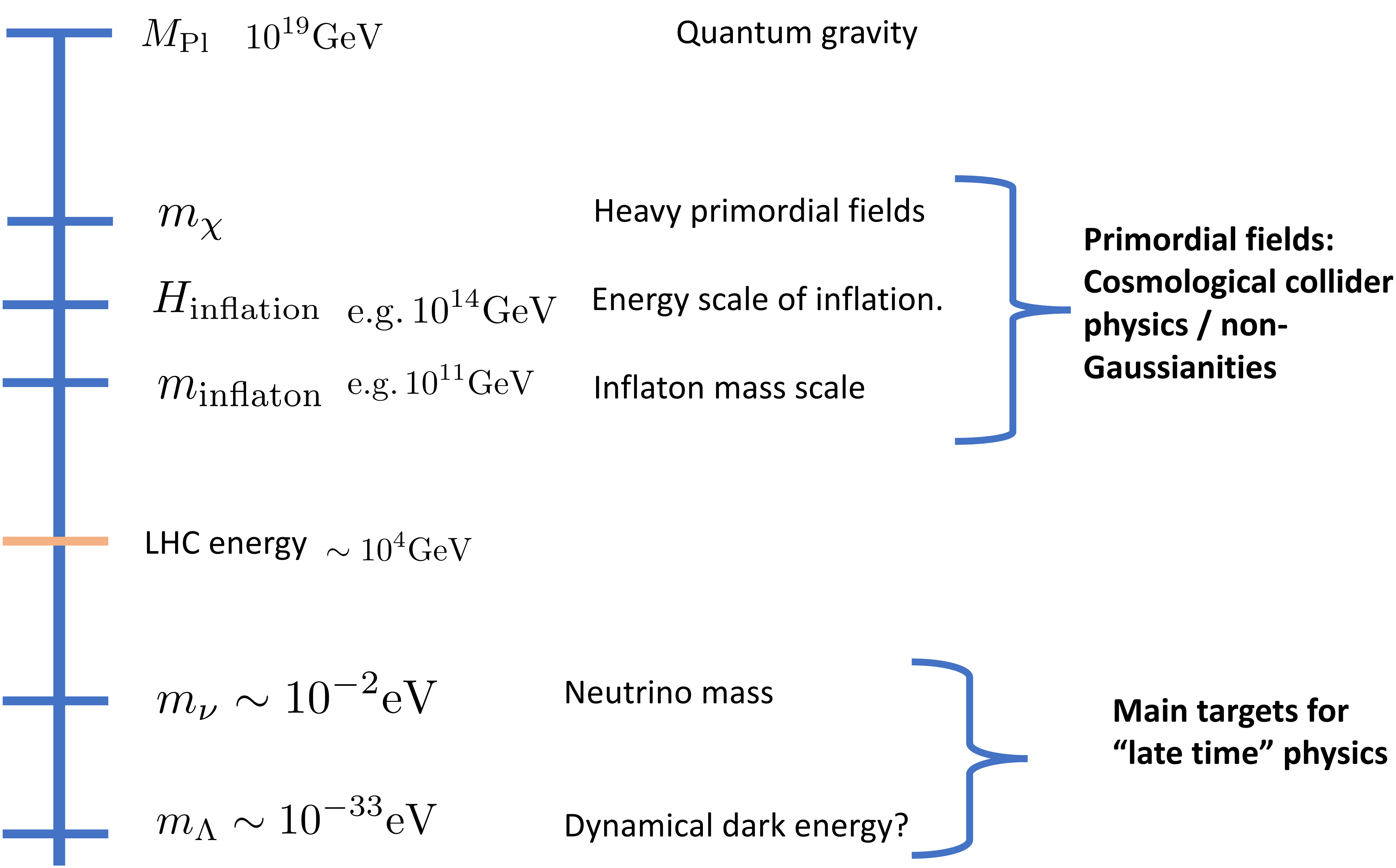
Kovetz et. al. 2017

**Spectral line intensity mapping**

**inference**

**This talk: two new methods**

# Energy scales probed by cosmology



# Cosmological collider physics

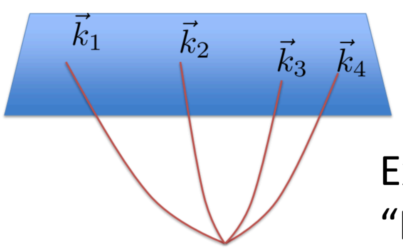
## Inflation

- Inflation Lagrangian $\mathcal{L}_{\text{infl}}(\phi, g_{\mu\nu}, m_\chi ..)$

- Calculate equal time N-point correlation functions of the primordial perturbations ϕ.

**Power spectrum** $P(k) \propto \langle \Phi(k)\Phi(k) \rangle$

**Non-Gaussianity** $\langle \Phi(k_1) ... \Phi(k_N) \rangle$




Example: 4-point function
“Feynman diagram”

- Can’t re-run the experiment.

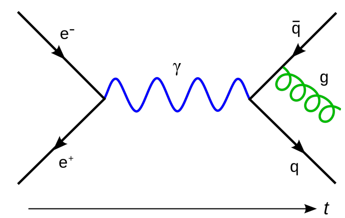
Cosmic Variance

## Particle collisions

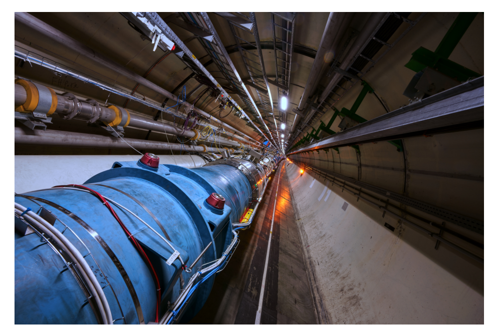
- Standard model Lagrangian

$$
\begin{aligned}
\mathcal{L} = & -\frac{1}{4} F_{\mu\nu} F^{\mu\nu} \\
& + i \bar{\Psi} \not{D} \psi \\
& + D_\mu \Phi^\dagger D^\mu \Phi - V(\Phi) \\
& + \bar{\Psi}_L \hat{Y} \Phi \Psi_R + h.c.
\end{aligned}
$$

- Calculate scattering amplitudes



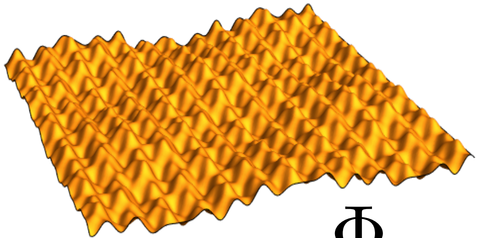

- Can get more data.



CERN

# Non-Gaussianity search with the CMB

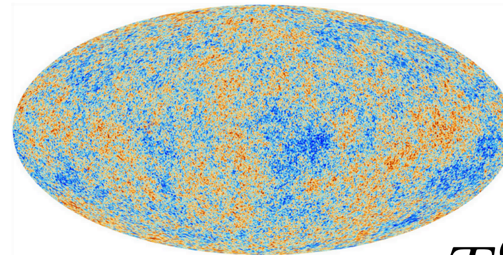
- **The “primary CMB” is a linear map of the primordial potential.**



$\Phi$

$$T^{CMB}(\mathbf{k}) = \Delta(\mathbf{k})\,\Phi(\mathbf{k})$$

“transfer function”



$T^{CMB}$

- **Planck satellite results**. **Akrami, MM et. al., 1905.05697**
  - Constrained many theoretically motivated 3-point correlation functions.

$$\langle \Phi_{\mathbf{k}_1} \Phi_{\mathbf{k}_2} \Phi_{\mathbf{k}_3} \rangle \propto f_{NL}$$

Constraints on the amplitude $f_{NL}$.

  - Roughly: Non-Gaussianity is constrained to be ~$10^{-4}$ smaller than Gaussian part. The minimum possible value is ~$10^{-7}$.

- Aside: Something new in CMB non-Gaussianities: **large-N-point function searches** **MM et. al., 1910.00596, PRD**

# The future of cosmological collider physics

- Sensitivity to primordial physics: $\sigma_{f_{NL}} \propto \dfrac{1}{\sqrt{N_{\mathrm{modes}}}}$

- O(1) fraction of all modes in the primary CMB were measured by Planck.

  Need other probes with more modes.

- Near term goal: **Probe multi-field inflation / local non-Gaussianity.**

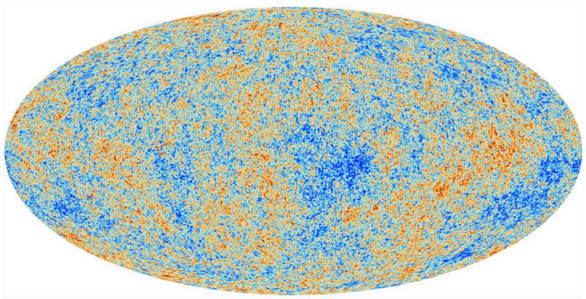
  INFLATION → single field → Gaussian fluctuations $f_{NL} \ll 1$

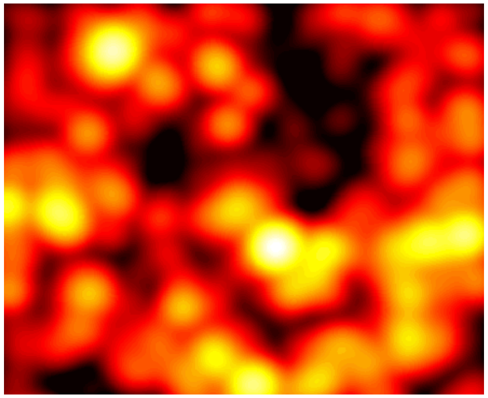
  INFLATION → multi-field → Non-Gaussian fluctuations $f_{NL} \gtrsim 1$

  **Current constraint $f_{NL}$ = -0.9 ± 5.1 (from Planck) must get 10 times tighter.**

- Long term goal: Detect **masses, couplings and spins of primordial fields**.
  - Ultimate constraints from intensity mapping of the ”dark ages”: **MM et. al., 1610.06559, JCAP**

# What data will we get next?





**Simons Observatory (2021)**

Main goals:

- Primordial B-modes (gravitational waves)
- Secondary CMB anisotropies

**DESI (spectroscopic, 2021)**
**LSST/VRO (photometric, 2022)**

Main goals:

- Expansion history / dark energy (DESI)
- Dark matter, Dark energy, Transients (VRO)

**CHIME (now), PUMA (2030)**

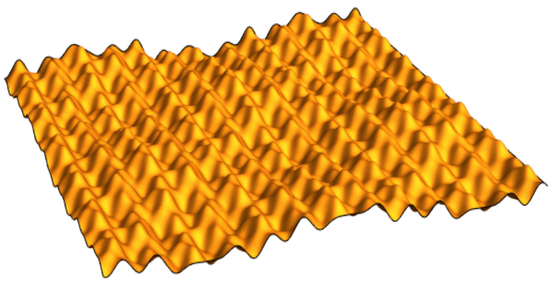
Main goals:

- Establish the technology
- Map BAO up to redshift 2 (Chime)
- Map all linear modes up to redshift 6 (Puma).

Strong synergy. Focus of my research.

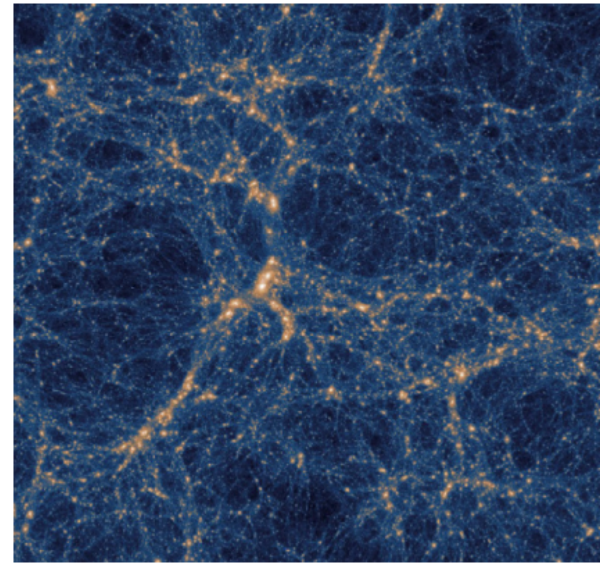
**Orange: Collaborations that I am a member of.**

# The problem of non-linearities



Non-linear gravitational evolution

Complicated astrophysics



*IllustrisTNG simulation*

- Non-linear evolution and complicated astrophysics are a major problem for cosmological collider physics!
- Generates large non-primordial N-point functions, that we can't fully calculate.

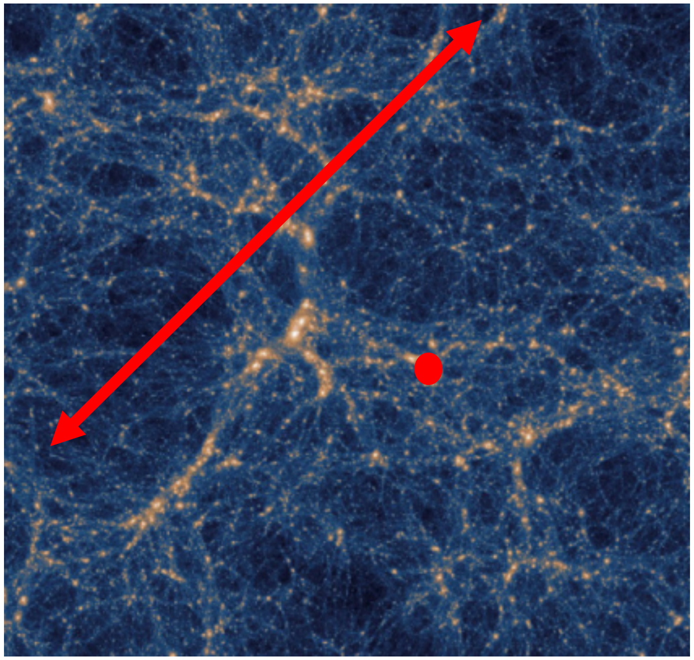
How do we use this data for fundamental physics?

**Theory. Part 1 of this talk.**

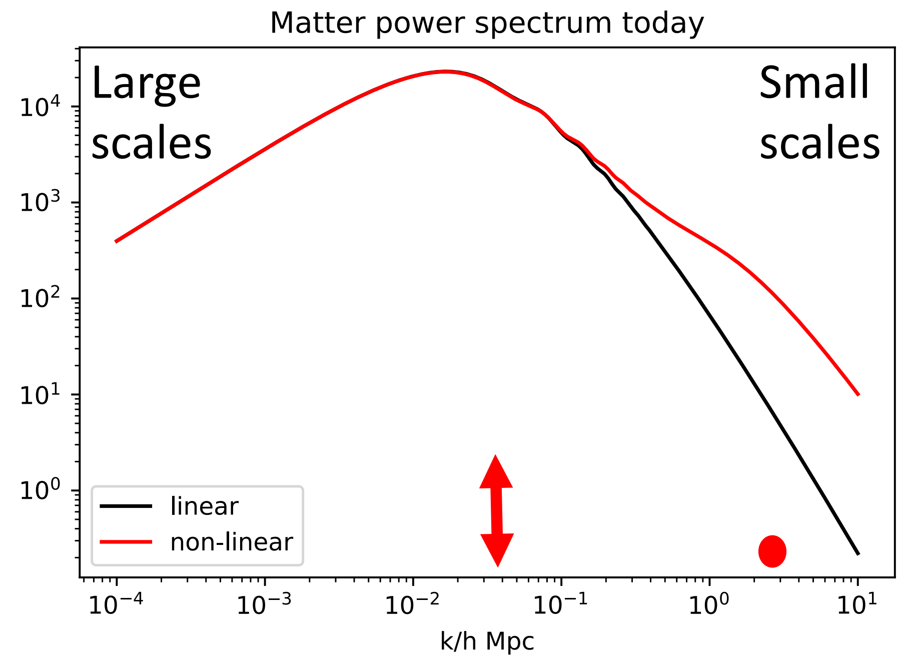
**Computation. Part 2 of this talk.**

# (Non-)linearities at different scales

The all important matter power spectrum plot!



Fourier space



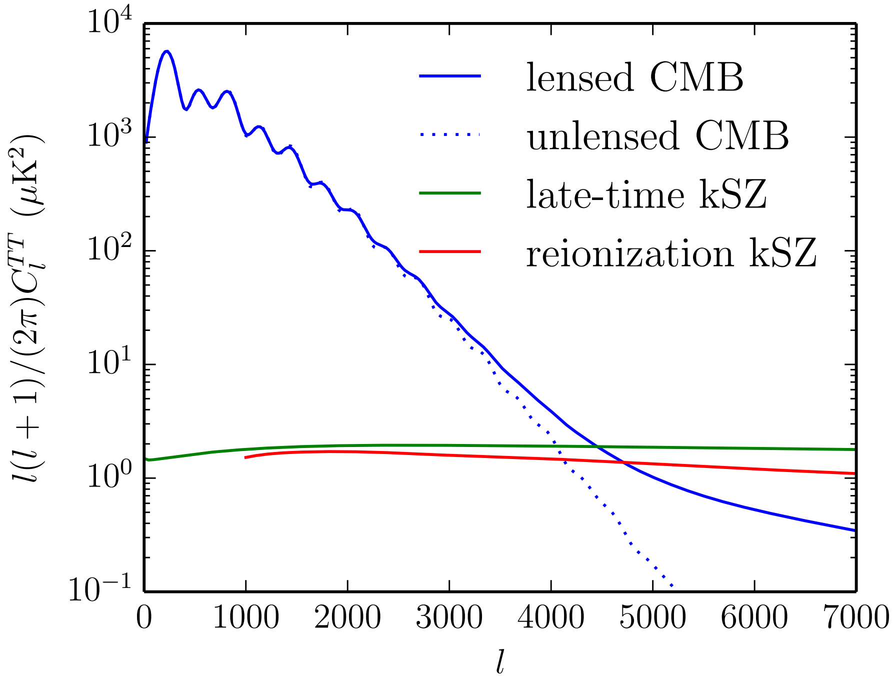

- Large scales evolve linearly. → Easy to use for cosmology.
- Small scales have very complicated astrophysics. → Hard to use for cosmology, but MUCH more information.

Approach 1: Theory – A new way to map the universe

Approach 2: Computation – Cosmology with machine learning

# CMB anisotropies overview

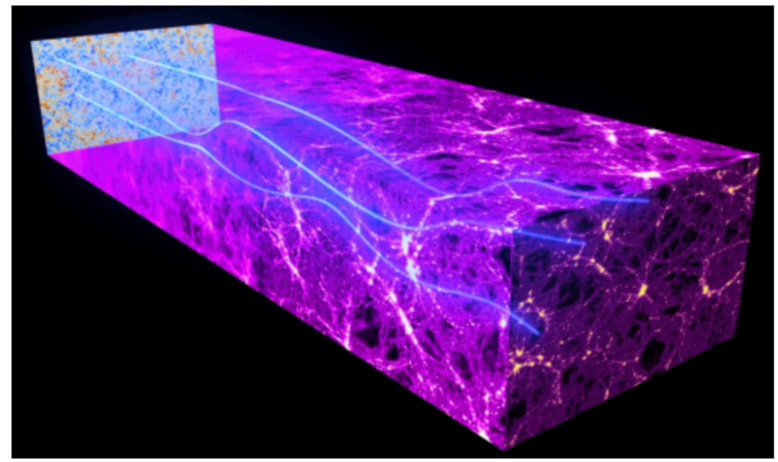
## CMB power spectrum




Planck satellite,
Primary anisotropies,
Linear physics

Upcoming experiments,
Secondary anisotropies,
non-linear physics

## Primary vs secondary anisotropies



Planck collaboration

- Primary anisotropies from early universe (when electrons and protons combine).
- Secondary anisotropies from gravitational lensing and photon scattering on electrons.

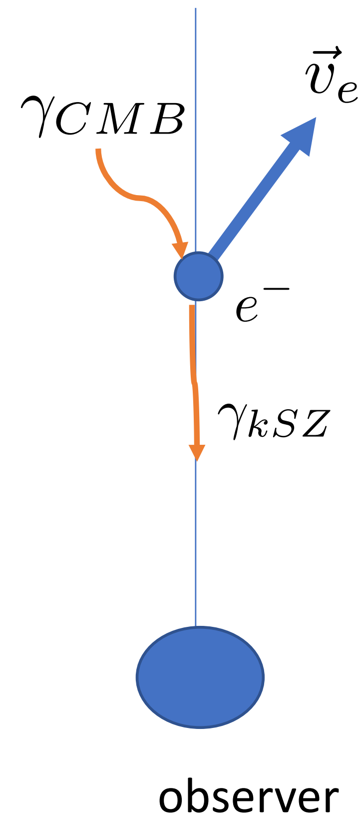
# Kinetic Sunyaev-Zeldovich effect

- Thompson scattering of CMB photons on free electrons

$$T_{kSZ}^{CMB} \sim \int dr \;\; \rho_e(r) \;\; v_r(r)$$

Electron density

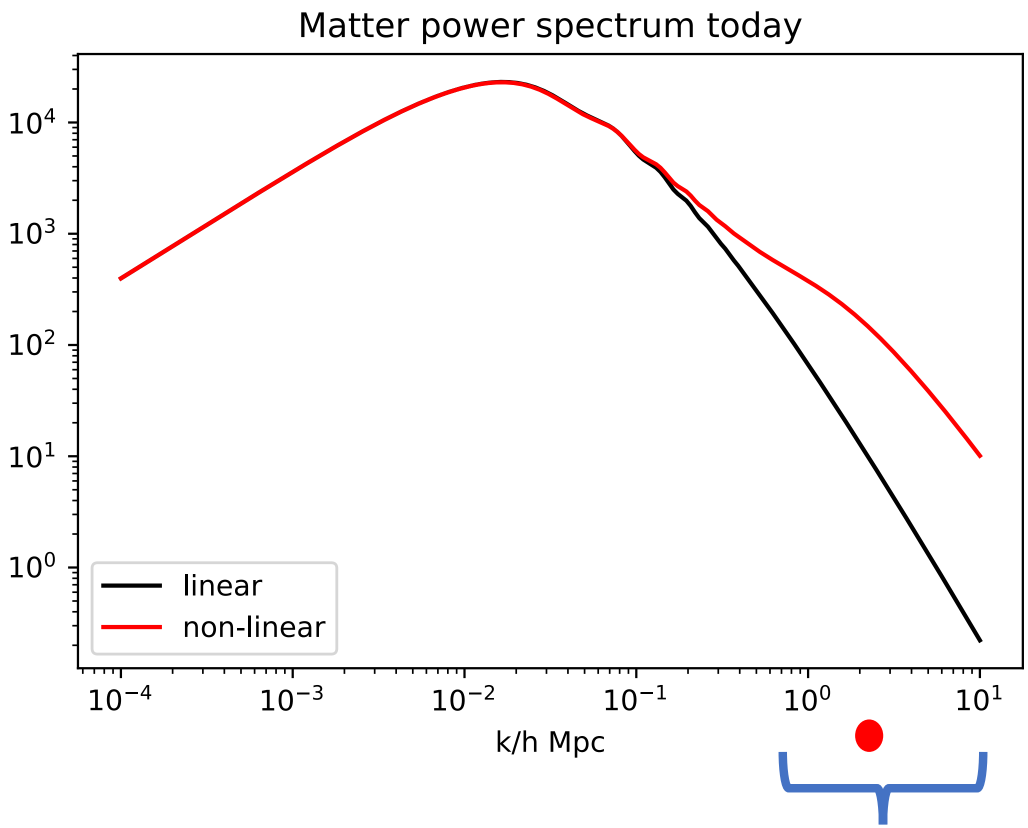
Radial velocity

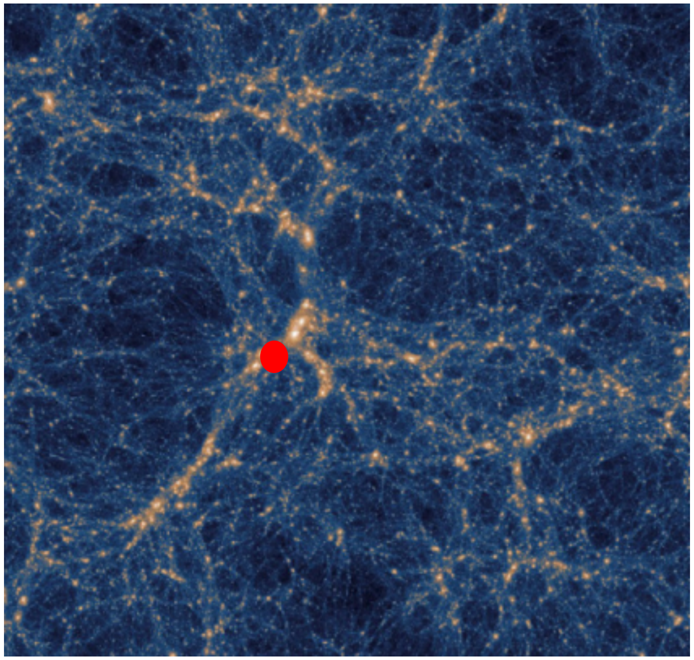



- Doppler shift interpretation:
  - For $v_r > 0$ CMB photons are red shifted (cold spot)
  - For $v_r < 0$ CMB photons are blue shifted (hot spot)

# What is the kSZ good for?

- Prior to my work: kSZ signal was **widely believed to be interesting only for small scale astrophysics (many papers)**, not cosmology.

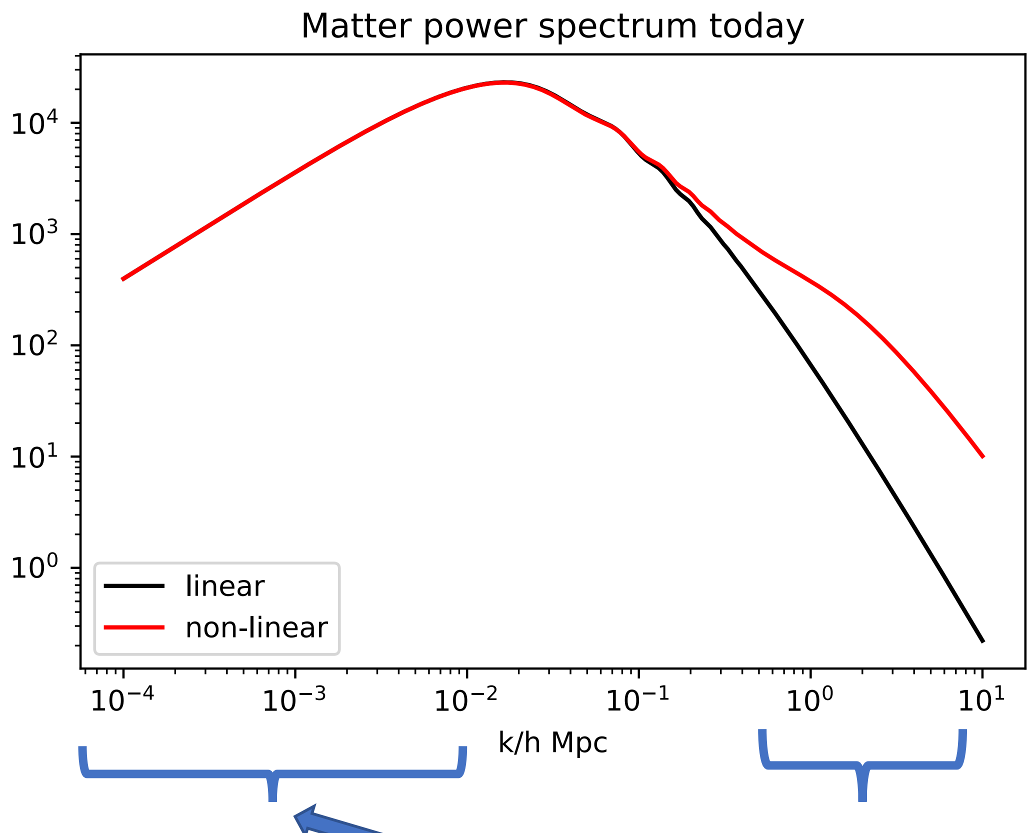


Domain of astrophysics,
kSZ anisotropy scales,
Length scale of galaxy clusters

# What is the kSZ good for?

**Now we will see: the kSZ can be used as the best tracer of matter on large scales!**



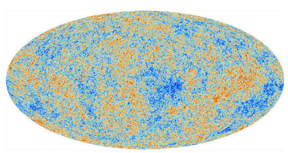

**We will use this information to measure the matter distribution over there!**

# Overview of the method

- **Step 1**: estimate the radial velocity field from kSZ

**Idea:** $$T_{kSZ}^{CMB} \sim \int dr\ \rho_e(r)\ v_r(r)$$

From CMB



From galaxy survey

Estimate!

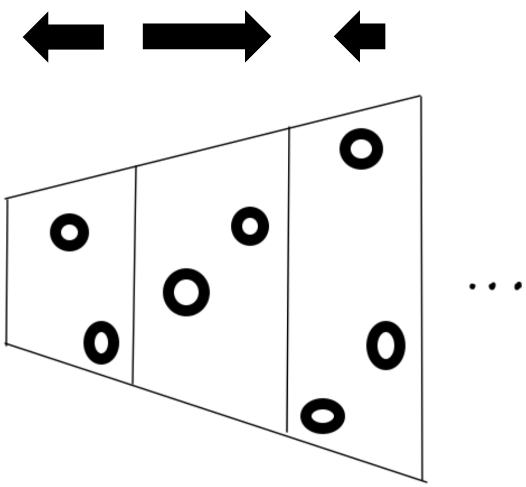
- **Step 2**: From reconstructed velocities, we can calculate the matter density perturbations (continuity equation).

$$\hat{v}_r(\mathbf{k}) \xrightarrow{\mathbf{v} \propto \frac{\delta_m}{k}} \hat{\delta}_r(\mathbf{k})$$

# Velocity estimator (in pictures)

Observer

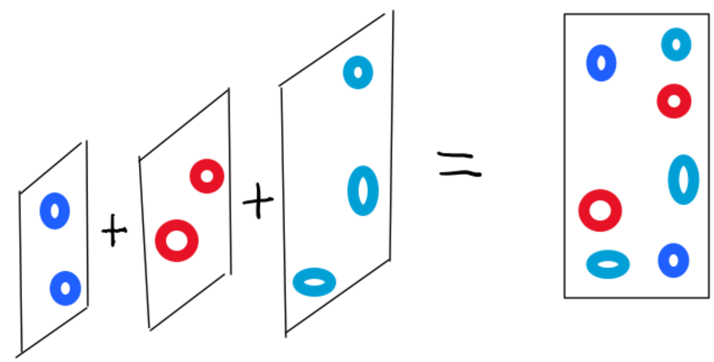
**Large-scale radial velocity** $v_r$



**Matter density** $\delta_m$

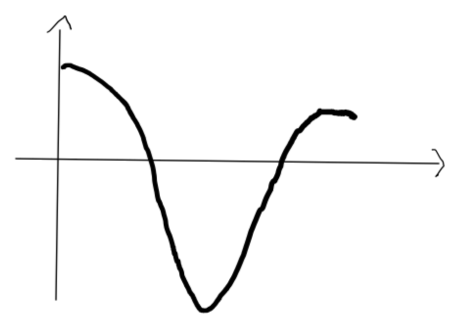
**Resulting kSZ temperature**

$$T_{kSZ} \sim v_r \times \delta_m$$



**Cross correlation estimator**

$$\hat{v}_r \sim \langle \delta_m T_{kSZ} \rangle$$



# Velocity estimator (in math)

- Optimal quadratic estimator for large scale velocity field:

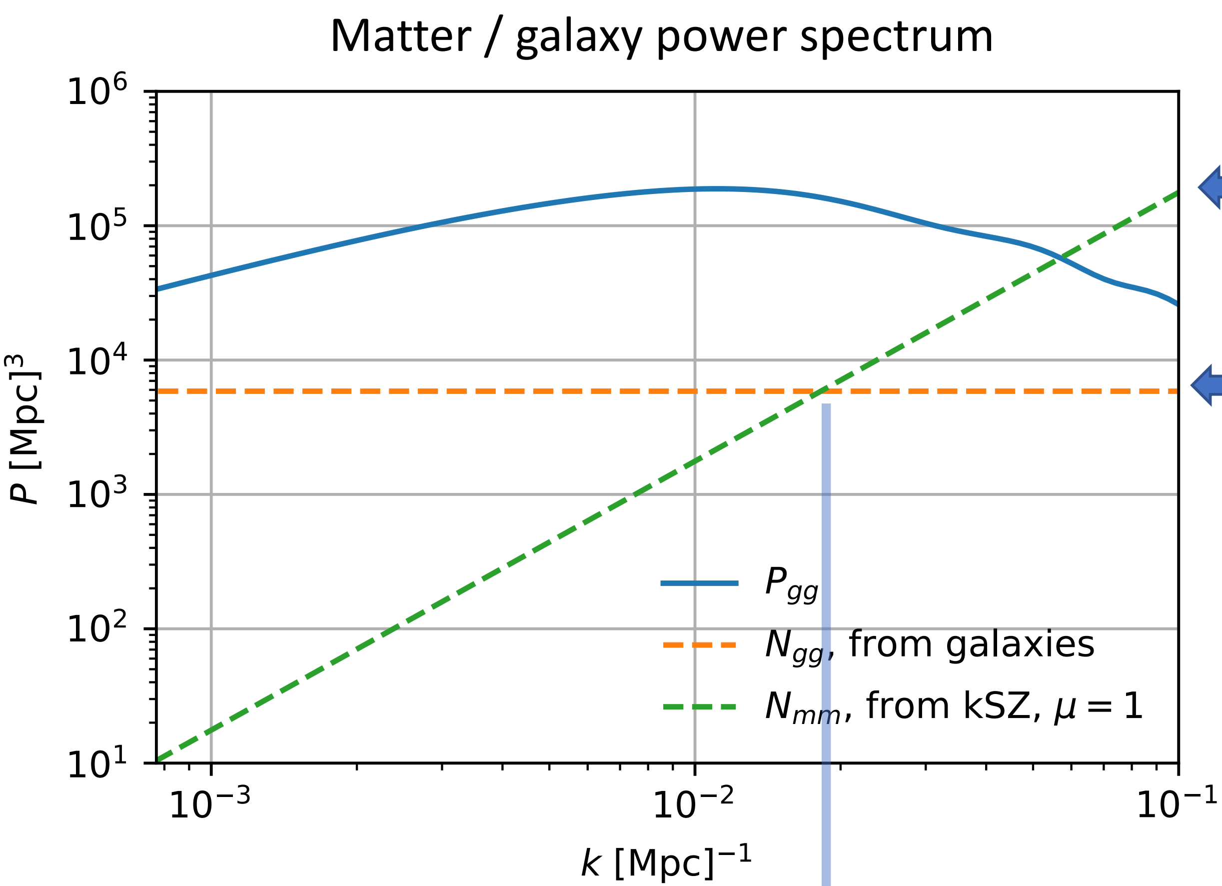
$$\hat{v}_r(\mathbf{k}_L) = \int \frac{d^3\mathbf{k}_S}{(2\pi)^3} \frac{d^2\mathbf{l}}{(2\pi)^2} W(\mathbf{k}_S, \mathbf{l}) \underbrace{\delta_g^*(\mathbf{k}_S) T^*(\mathbf{l})}_{\text{quadratic combinations of CMB and galaxy data}} (2\pi)^3 \delta^3\left(\mathbf{k}_L + \mathbf{k}_S + \frac{\mathbf{l}}{\chi_*}\right)$$

optimal weights

**Deutsch, MM et. al., 1707.08129, PRD**

- From the estimator we calculate its noise depending on the experimental parameters.

# Forecast for upcoming experiments (SO+DESI)




kSZ method noise.
DESI galaxies + SO

Galaxy "shot noise"
DESI galaxies

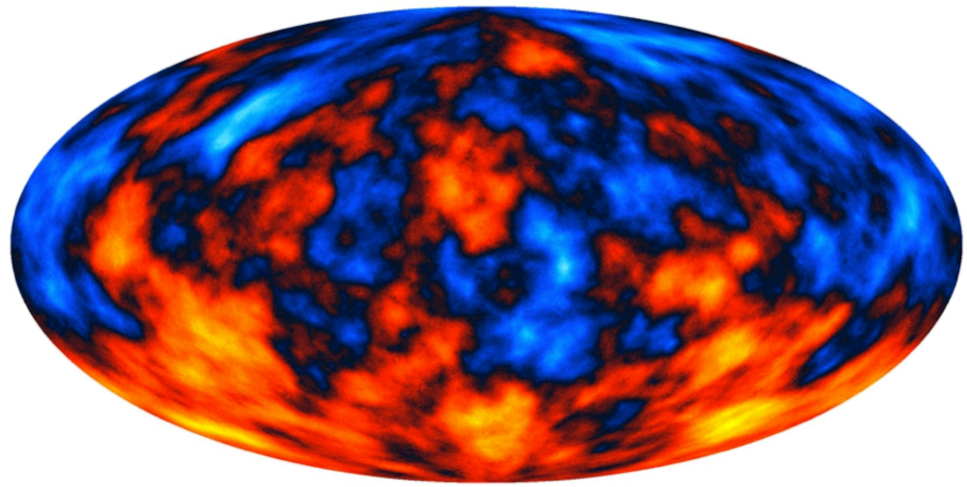
**Region of improvement**
**Lower noise than galaxies themselves!**

**Smith, MM et. al., 1810.13423**

The lowest noise known probe of matter at large scales! Will be done with experiments in 2022.

# What can we do with it?

A totally new probe of the universe on large scales, with high signal-to-noise for upcoming experiments!



Simulation from Cayuso et. al. 2018.

What is it good for? Lots of possibilities are being explored.
e.g.: Neutrino masses, dark energy, statistical anisotropies.

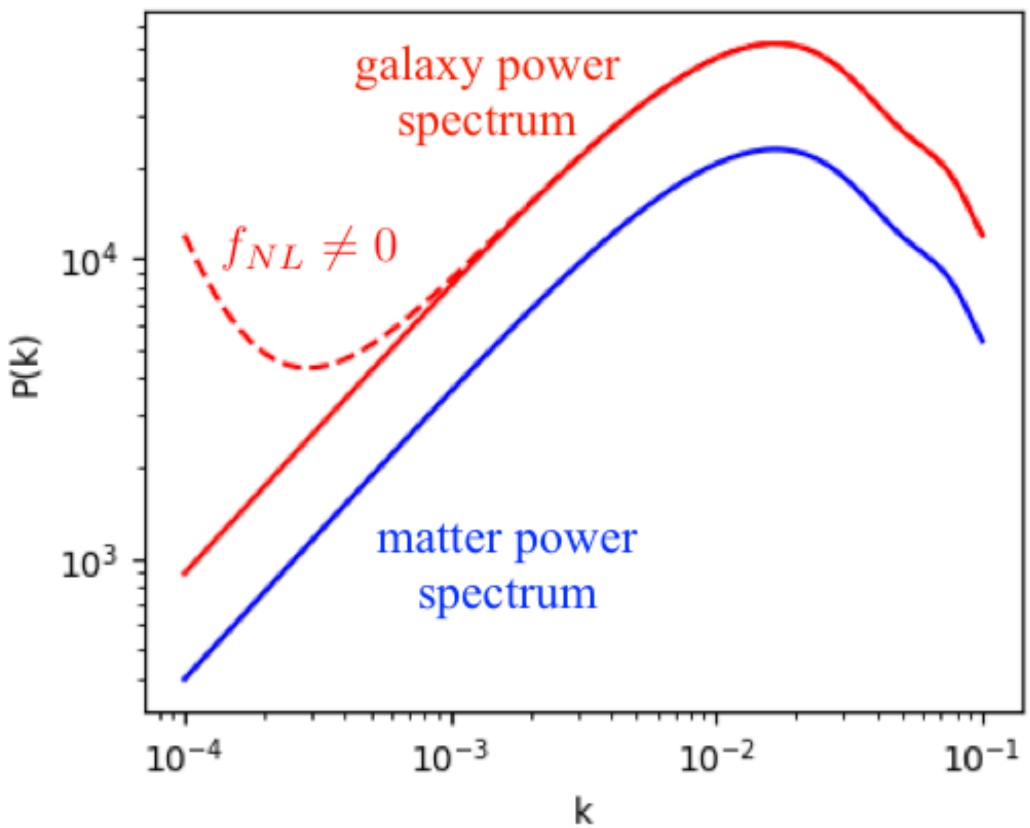
- The ”killer application” (so far): primordial non-Gaussianity

$f_{NL}^{\mathrm{local}}$ “multifield inflation target”

# Application to non-Gaussianities

**Basic idea**: use low-noise kSZ measurement to measure power spectrum kink induced by $f_{NL.}$ ("scale dependent bias", Dalal et. al. 2008).

**Full story**: more subtle, involving "sample variance cancellation".



# Application to non-Gaussianities

- **Forecast (included in SO and CMB S4 science books):**

SO mission + DESI
combined $\sigma_{fnl} = 1.0$
Improvement factor 1.6

CMB S4 mission + LSST
combined $\sigma_{fnl} = 0.4$
Improvement factor 3!

- **Comparison: Planck CMB** $\sigma_{fnl} = 5.1$

- Multifield inflation target $f_{NL}<1$ reachable!
- Improvement factor 3 just from smarter analysis (kSZ)!
- Safe from auto-calibration problems.

**(MM et. al., 1810.13424, PRD editors suggestion)**

# What did we learn and where to go next?

- **Entirely new, powerful and unexpected probe of the universe on large scales.**

- Combining secondary CMB and galaxies will likely lead to **the best constraints on primordial non-Gaussianity**.

- **Highly non-linear scales used for primordial physics**, in a reliable way.

- What needs to be done to apply this method on real data?
  - Study masked sky estimators and foregrounds *(with I. Holst).*
  - **Apply this method to Simons Observatory + DESI (with my group).**

- Similar approaches with other secondary CMB effects, e.g. moving lens effect **(Hotinli, MM et. al., 1812.03167, PRL)**

Approach 1: Theory – A new way to map the universe

Approach 2: Computation – Cosmology with machine learning

# We need more help from the machines!

- We will get huge amounts of correlated and highly non-Gaussian data. Impossible to understand everything with theory.

→ **Simulation based inference will dominate.**

- Even today almost all cosmology analysis uses simulations.
- Problems:
  - Simulations become forbiddingly expensive (computationally).
  - Estimators need to be developed manually. Often also impossibly expensive.

→ **Need to bring the Machine Learning revolution to cosmology.**

# Machine Learning for precision science

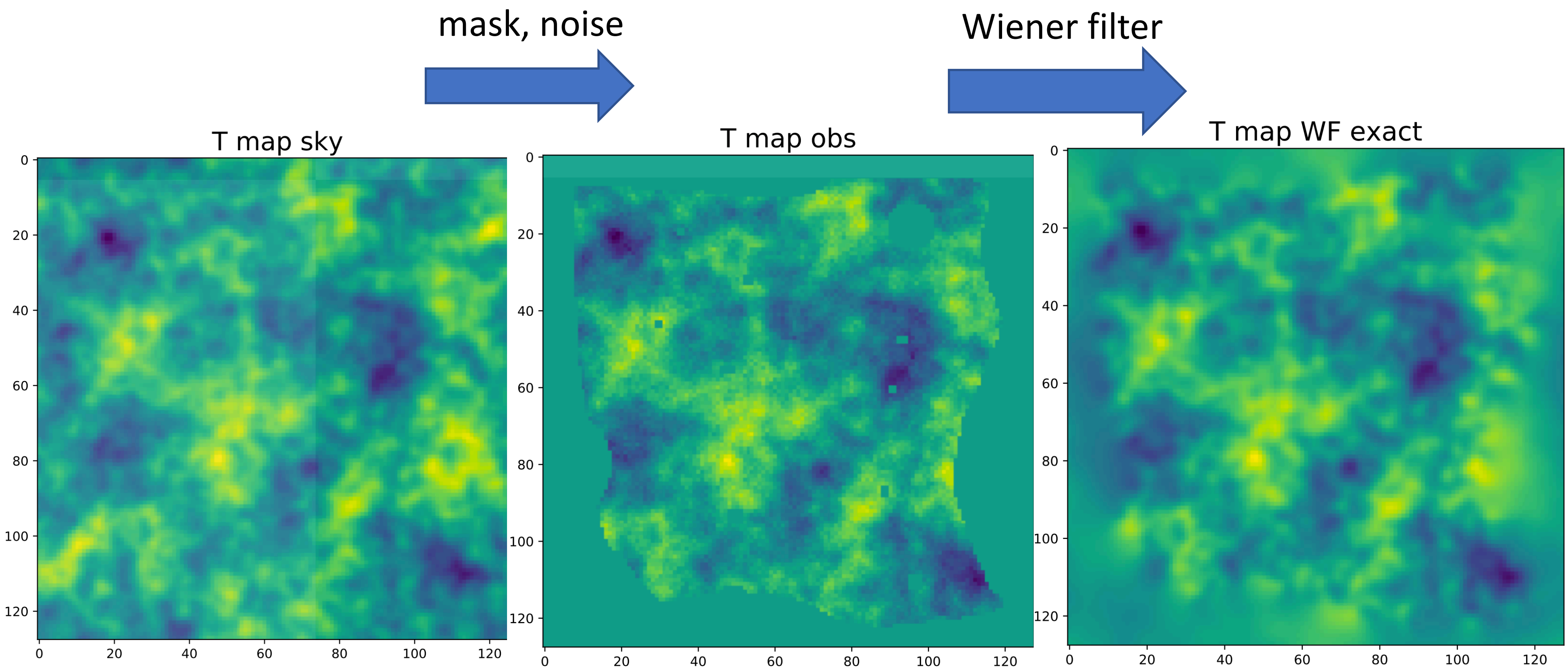
- generic “black box” neural network trained on unreliable simulations
- “parameter estimates” without error bars.
- no idea where the information comes from.

- incremental approach building on established methods
- specific steps in the analysis chain are replaced by specialized machine learning methods
- methods need to incorporate our physics understanding.

**My contribution**

- A key element of this program: Neural Network Wiener Filtering.
- Both practically important and interesting methodology.

# Wiener Filtering (in pictures)




**true CMB**

**measurement**

**Best possible reconstruction of the true CMB**

**Very important method! First step for any optimal statistical analysis.**

# Wiener Filtering (in math)

- **Common situation:** $$d = s + n$$

data signal noise

- **Wiener filter:** $$d_{WF} = S(S+N)^{-1}d$$

Signal covariance matrix. Noise covariance matrix.

- **Optimal reconstruction** of s given d.
- Data d can have $10^8$ elements. Direct matrix inversion impossible.
- Standard approach: **conjugate gradient method**. But too slow! **Most Planck CMB analysis is suboptimal for this reason.**

➡ **Neural network approach**

# Neural networks / Supervised learning

**Neural network:** hierarchical function with many parameters **w**.

$$\text{data}: \ \mathbf{x} \rightarrow \boxed{\begin{array}{c}\textbf{Neural network}\\ \mathbf{y} = f_{\mathbf{w}}(\mathbf{x})\end{array}} \rightarrow \text{result}: \ \mathbf{y}$$

**Training:**

$$\begin{array}{r}\text{training data}:\\ (\mathbf{x}_i, \mathbf{y}_i)\end{array} \rightarrow \boxed{\begin{array}{c}\textbf{Loss function minimization}\\ \dfrac{\partial J}{\partial w}\end{array}} \rightarrow \text{best weights}: \ \mathbf{w}$$

**We adapt both network and loss function to the physical task at hand.**

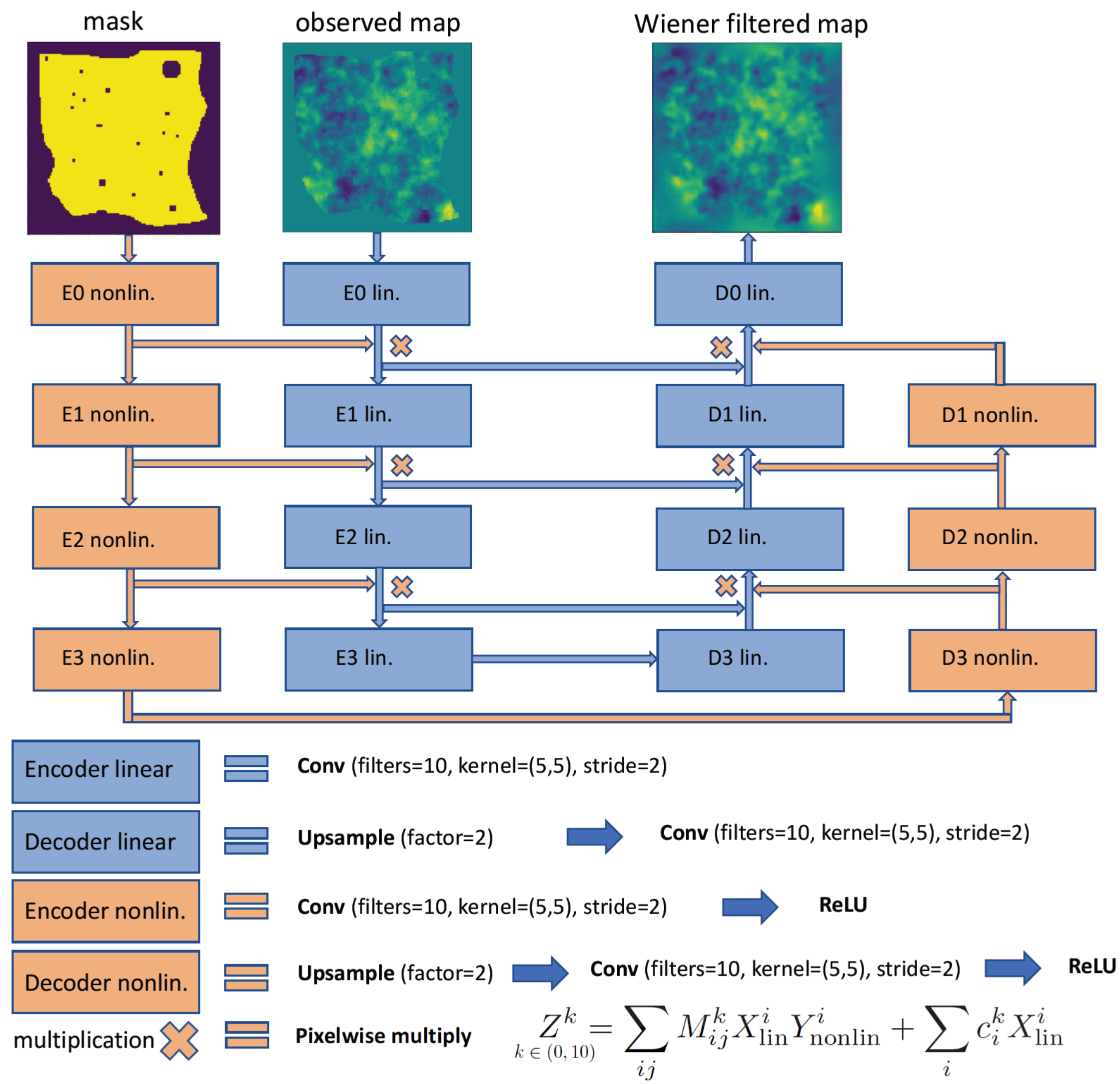
# WienerNet: neural network architecture

- Crucial: **must not induce non-linearities.**
- Construct a neural network that is **explicitly linear in the data!**

$$y = M(\text{mask})d$$

- **Nonlinear in mask/noise**

**Machine learning does not need to be based on “generic functions”!**




**MM et. al., 1905.05846, NeurIPS 2019**

# WienerNet: loss functions and training

- **3 possible loss functions** (training objectives) with very different properties:

**"naïve loss"** $$J_1(d, y) = \frac{1}{2}(y - y_{\mathrm{WF}})^T A (y - y_{\mathrm{WF}})$$ Not useful in practice.

**"supervised loss"** $$J_2(s, y) = \frac{1}{2}(y - s)^T A (y - s)$$ Works well in S/N>1 regime.

**"physical loss"** $$J_3(d, y) = \frac{1}{2}(y - d)^T N^{-1} (y - d) + \frac{1}{2} y^T S^{-1} y$$ Works well everywhere.

$$J_3(d, y) = -\log P(s|d)_{s=y} + \mathrm{const.}$$

- All can be analytically shown to be minimized by WF solution, i.e.

$$\frac{\partial \langle J \rangle}{\partial M} \stackrel{!}{=} 0 \quad \Longrightarrow \quad M = S(S+N)^{-1}$$

**Neural networks can be used in low signal-to-noise situations!**

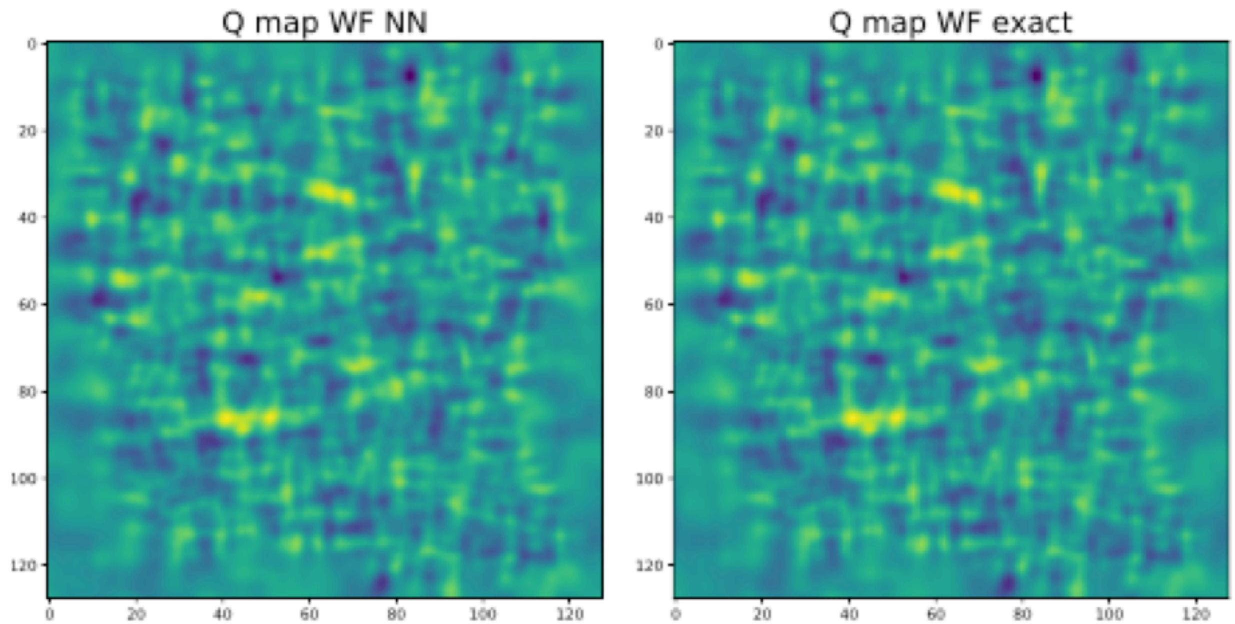
# Results: Very good and very fast!

Neural network output maps are at least 99% Wiener filtered.

Neural Network Wiener filtering is **1000 times** faster than the exact method!

- Works independent of mask and noise levels.
- Plug into standard analysis pipelines in cosmology.

**CMB polarization example:**



# What did we learn and where to go next?

- We developed a tool to **speed up many cosmological analyses massively, using machine learning.**

- The generic black box approach does not work here. **Need physical architecture and loss**!

- Current goal:
  - Use this method for power spectrum analysis (with A. Dimitrou).
  - **Bring the WienerNet to Simons Observatory,** potentially lowering error bars in cosmological analyses.

- Other maximum likelihood problem in cosmology include:
  - **CMB lensing potential estimation (uses a "delensing Wiener filter").**
  - **Reconstructing the initial conditions from large-scale structure observations.**

# Conclusion

# Outlook: Interplay of theory and computation

- **Need to combine physical theory with machine learning methods** to fully exploit upcoming data.

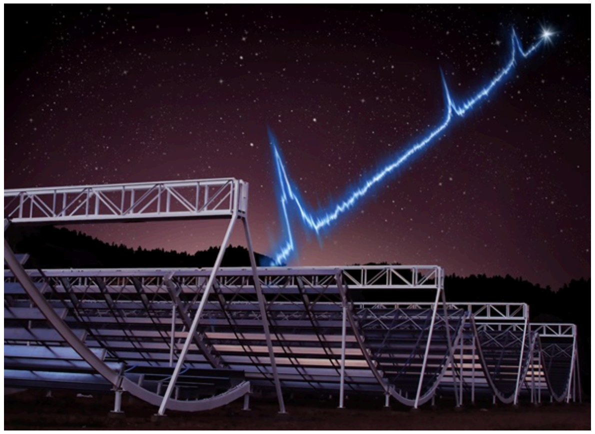
**Wide open to exciting research!**

- **Could machine learning discover the kSZ non-Gaussianities method** in simulations in explainable form?

- Machine Learning will help **automate model testing for high energy theory.**

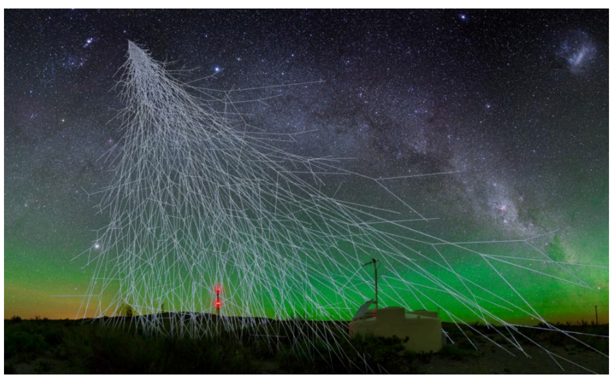
- **Learn from ML community**: well-documented tools, compiled algebraic expressions for large-scale deployment etc.

# Other things I'm interested in include



Astronomy.com

- Physics **with Fast Radio Bursts** (FRB)
  - FRB are coherent light sources at cosmological distances.
  - My main role in CHIME: machine learning for FRB population studies.
  - Some exciting applications have been proposed and more are to be found!



Eurekalert.org

- **Astroparticle physics**
  - My PhD thesis: measuring and theoretically interpreting large-scale anisotropies of Cosmic Rays with the Pierre Auger Observatory.