# Cosmological constraints from low redshift 21 cm intensity mapping with machine learning

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Based on:
CPN et al. MNRAS, 528, 2078 (2024) [arXiv:2309.07868]

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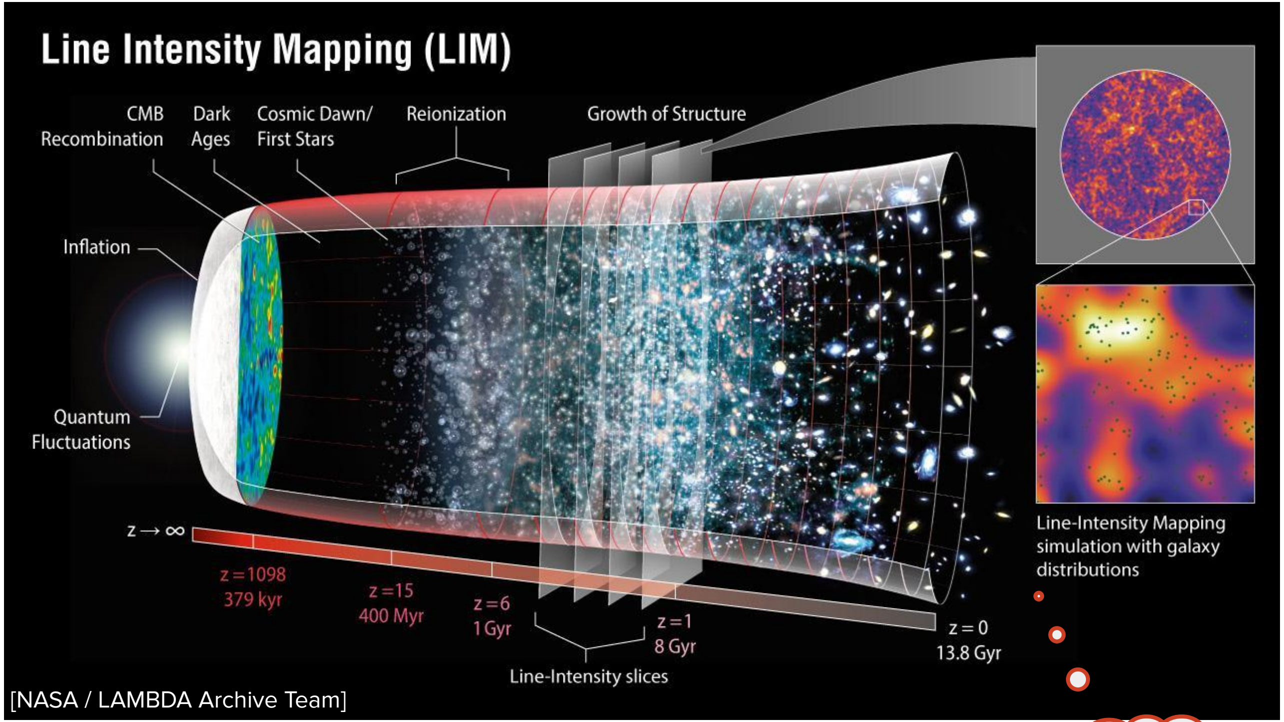
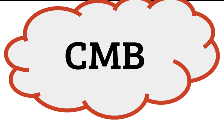
YITP long-term workshop, Gravity and Cosmology 2024

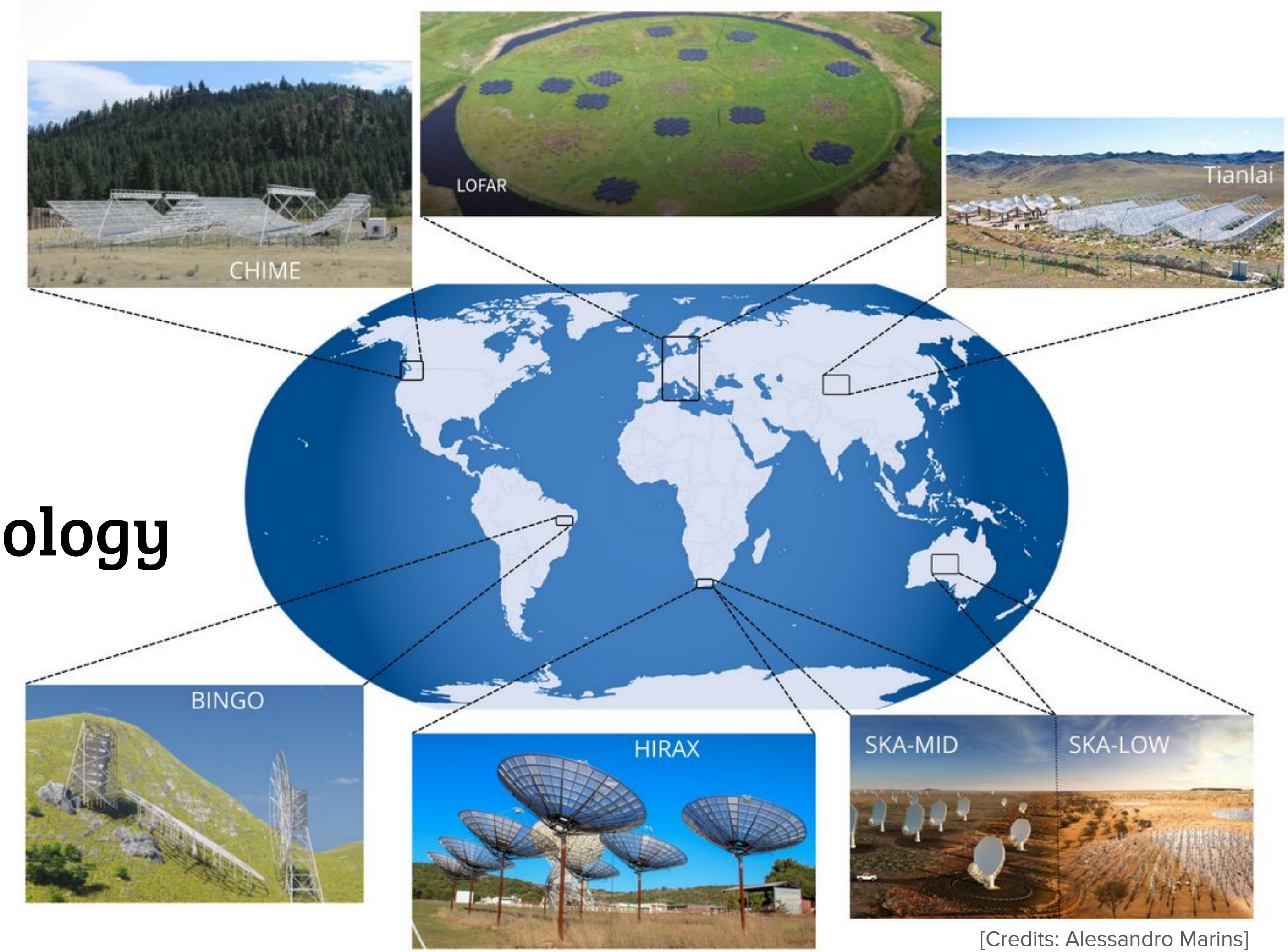
# The new observational window: 21 cm Intensity Mapping




- ➔ New technique to **trace large scale structure**.
- ➔ Low resolution: **temperature fluctuations**.
- ➔ We can use much of what we have learned from **CMB**.
- ➔ **Tomographic** approach.
- ➔ Precise determination in **redshift**: $\lambda = \lambda_o (1 + z)$.

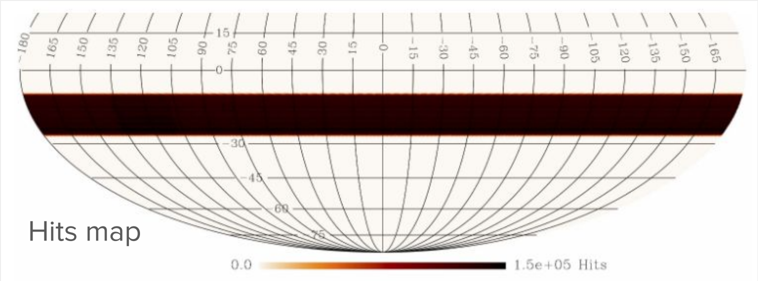
# The future:
# 21 cm Cosmology




[Credits: Alessandro Marins]

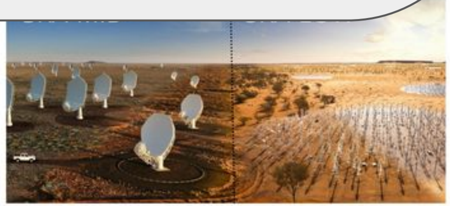
# The future:
# 21 cm Cosmology

- Sky coverage: ∼ 5324 deg$^2$ (⅛ of the sky),
- Declination: ∼ -25 deg,
- Angular resolution: 40 arcmin,
- Frequency range: 980 to 1260 MHz ($0.127 < z < 0.449$) (tomographic approach).




Celestial coordinates

BINGO
Baryon Acoustic Oscillations [BAO] from Integrated Neutral Gas Observations

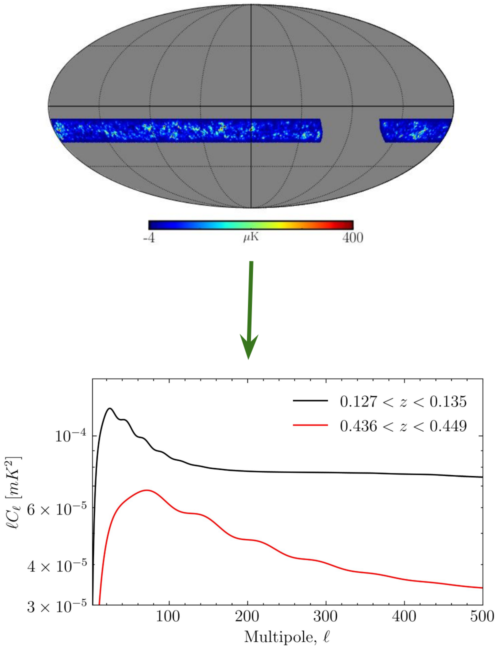
[Credits: Alessandro Marins]

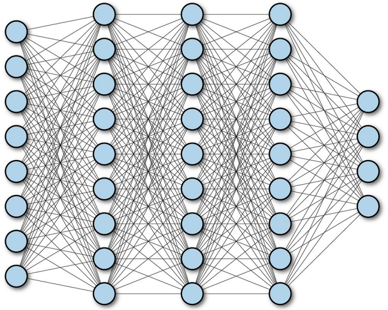
# Cosmology with 21 cm

## We investigate:

- → Performance of
  - ◆ non-Gaussian (higher order) statistics +
  - ◆ simulation based inference with machine learning.
- → Impact of contaminants and sky area.
- → Evolution with redshift.
- → Case study: BINGO telescope.

# Cosmology with …   machine learning



Constraints on cosmological parameters.

$$\{\Omega_c, h\}$$

$$\{\Omega_c, h, w_0, w_a\}$$

# Cosmology with alternative techniques

Standard method: Bayesian inference

Technical problems:

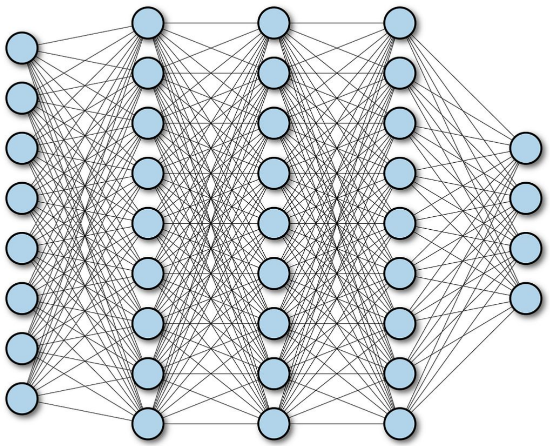
$$\chi^2(\lambda) = \sum_{i,j} [X_i - m_i(\lambda)] C_{ij}^{-1} [X_j - m_j(\lambda)]$$

$$L \propto \exp(-\chi^2/2)$$

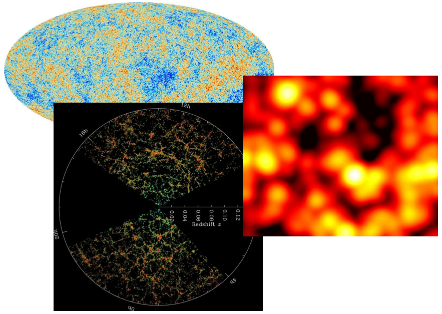
- Data modeling: signal (non-linearity), noise, systematics, ...
- Assumptions for analytical likelihood (e.g., Gaussianity)
- Non-Gaussian distributions of structures
- Higher order statistics: no analytical expression for *likelihood*.
- Covariance matrix estimate

# Cosmology with alternative techniques

Alternative method: Likelihood-free with machine learning



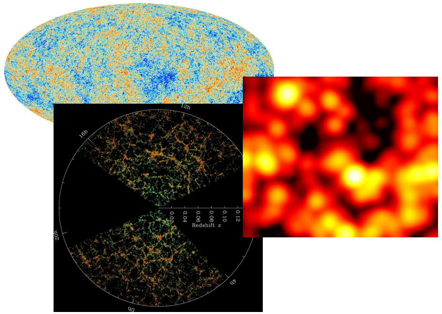
- ✓ Simulation based inference,
- ✓ No assumptions for likelihood,
- ✓ No need for data modeling,
- ✓ Able to recognise complex patterns,
- ✓ **Easier combination of different data sets!**



# Cosmology with alternative techniques

Simulation based inference

Alternative method: Likelihood-free with machine learning



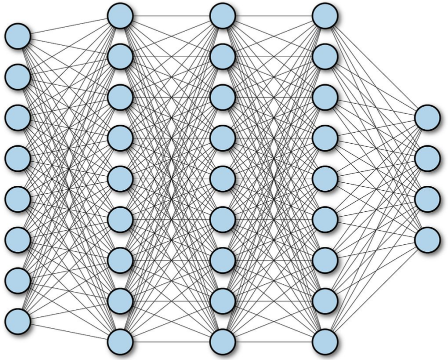
✓ Easier combination of different data sets!

[CPN et al. JCAP 2014, 2015]

Simulations → Summary statistics

Simulations

(Convolutional neural networks)

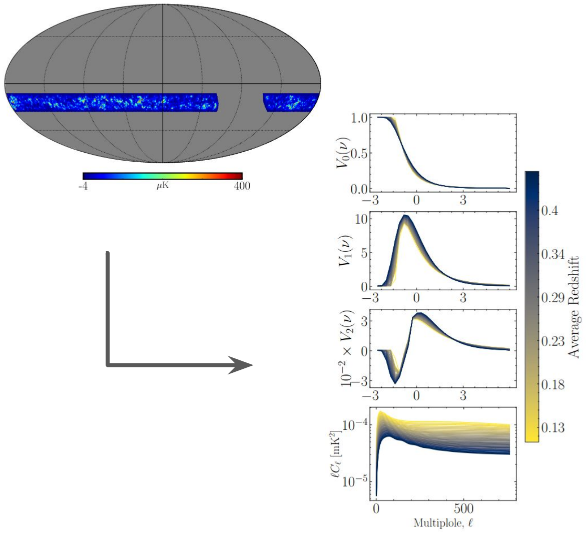


Cosmological parameters

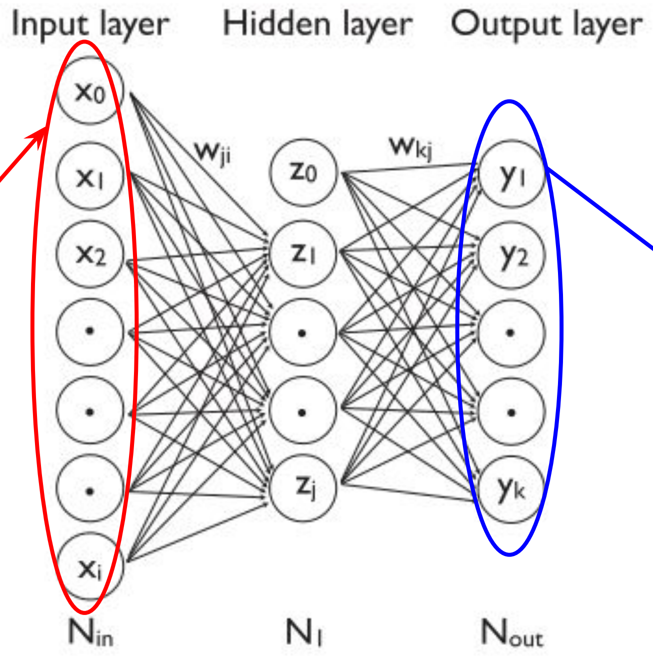
# Cosmology with machine learning

*Simulation based inference*

Features:
Summary statistic calculated from sims.




## Neural Networks




Architecture: `Optuna`

Targets:
Cosmological parameters.

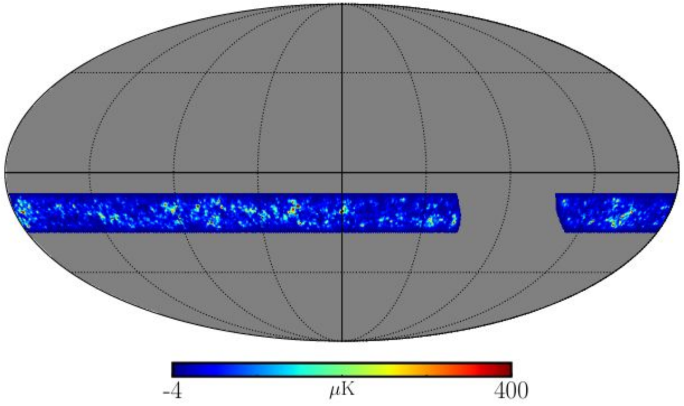
$\{\Omega_c, h\}$

$\{\Omega_c, h, w_0, w_a\}$

# Simulations

Case study: BINGO telescope

- 21 cm IM: **30 frequency bins** [$0.127 < z < 0.449$],
- Foreground contamination,
- Beam size (~40 arcmin),
- Instrumental noise (white noise).
- Foreground cleaning.




z-bin 1
(*0.127< z < 0.138*)

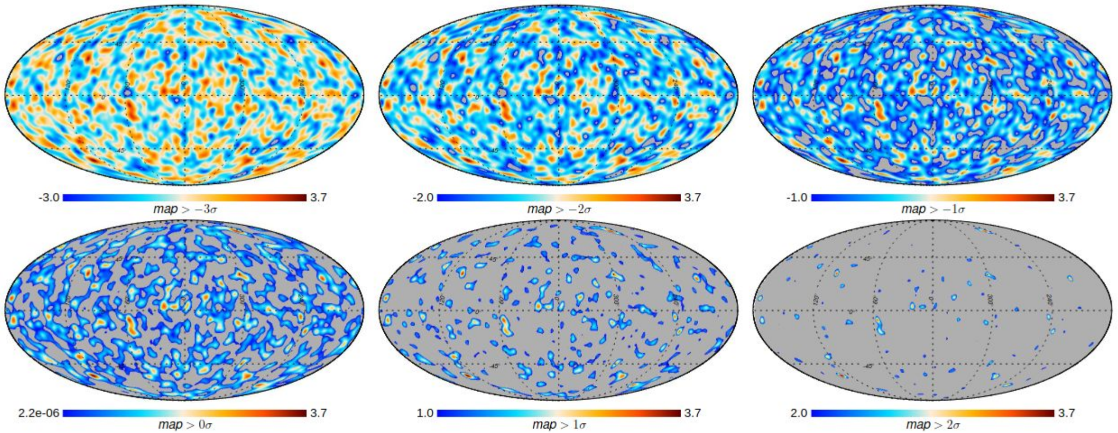
# Methodology

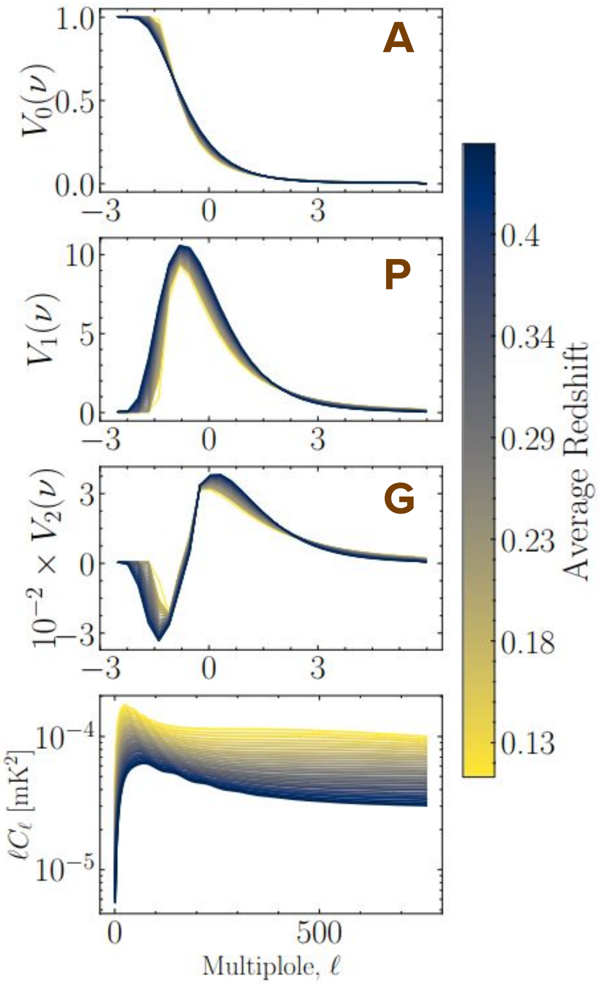
Features - Summary statistics:

**Why NG statistics?**

- Minkowski functionals (MF):
  - Area ($V_0$)
  - Perimeter ($V_1$)
  - Genus ($V_2$)

[CPN et al. MNRAS 2016]
[CPN et al. MNRAS 2018]



# Methodology

Features - Summary statistics:

**Why NG statistics?**

- Minkowski functionals (MF):
  - Area ($V_0$)
  - Perimeter ($V_1$)
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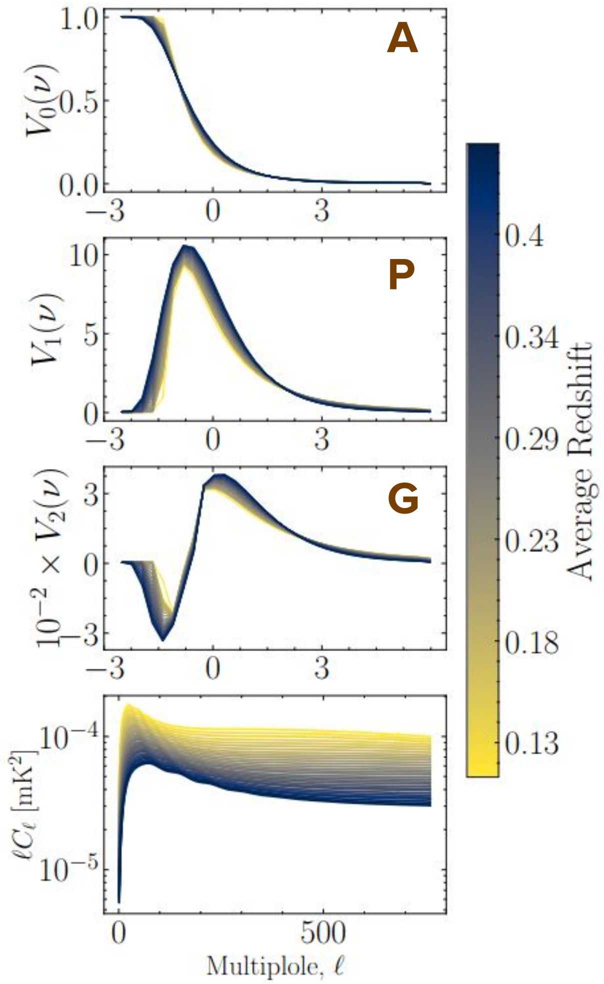
[CPN et al. MNRAS 2016]
[CPN et al. MNRAS 2018]

- Angular power spectrum ($C_\ell$)

$$\hat{C}_\ell = \sum_{\ell'} \mathcal{M}_{\ell\ell'} C_{\ell'}$$

Observed
$\hat{C}_\ell = \langle a_{\ell m} a^*_{\ell m} \rangle$

True



# Methodology

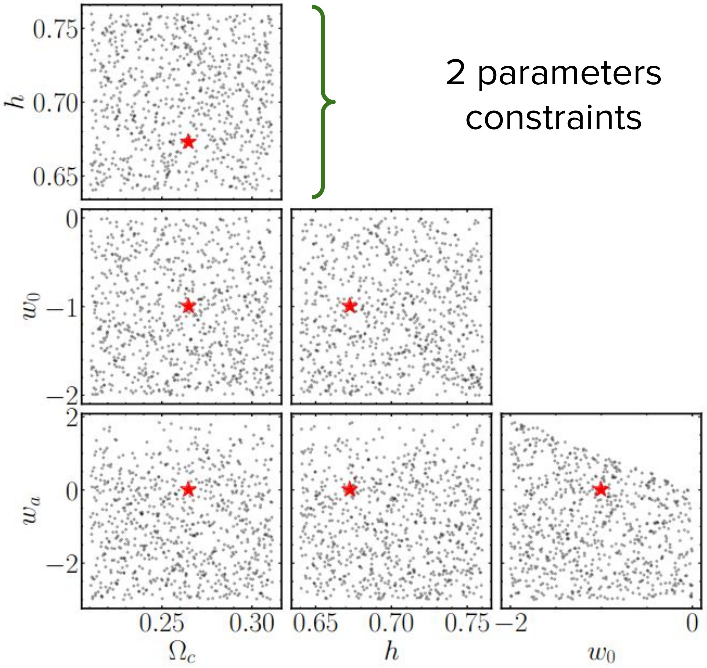
## Targets - Cosmological parameters:

2 parameters constraints

$$\{\theta_p\} \longrightarrow \{\Omega_c, h\}$$

4 parameters constraints

$$\{\theta_p\} \longrightarrow \{\Omega_c, h, w_0, w_a\}$$




CPL parameterization [Chevallier & Polarski 2001; Linder 2003]

**650** + **150** cosmologies
12 simulations for each

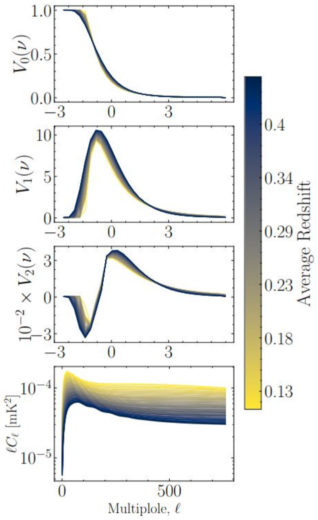
*+ $\Omega_b$, $n_s$, $A_s$ varying inside Planck constraints*

# Cosmology with machine learning

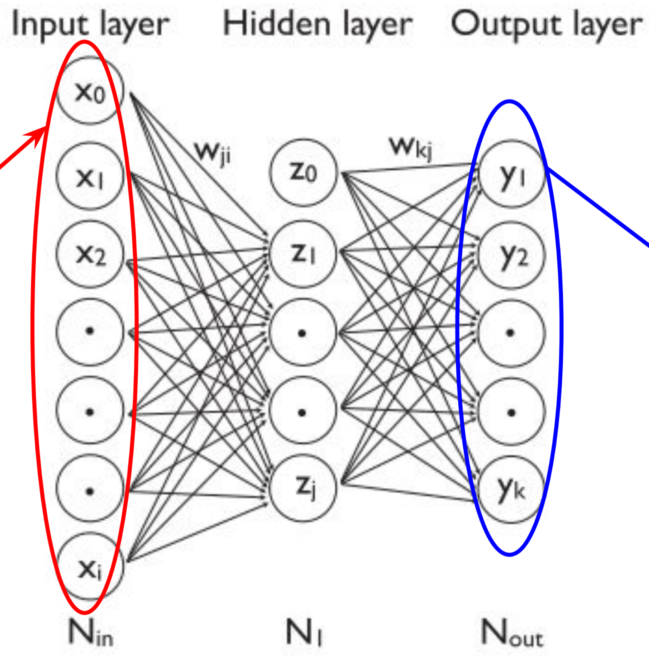
*Simulation based inference*

Features: MFs and $C_\ell$.

Data vector




## Neural Networks




Targets: Cosmological parameters.

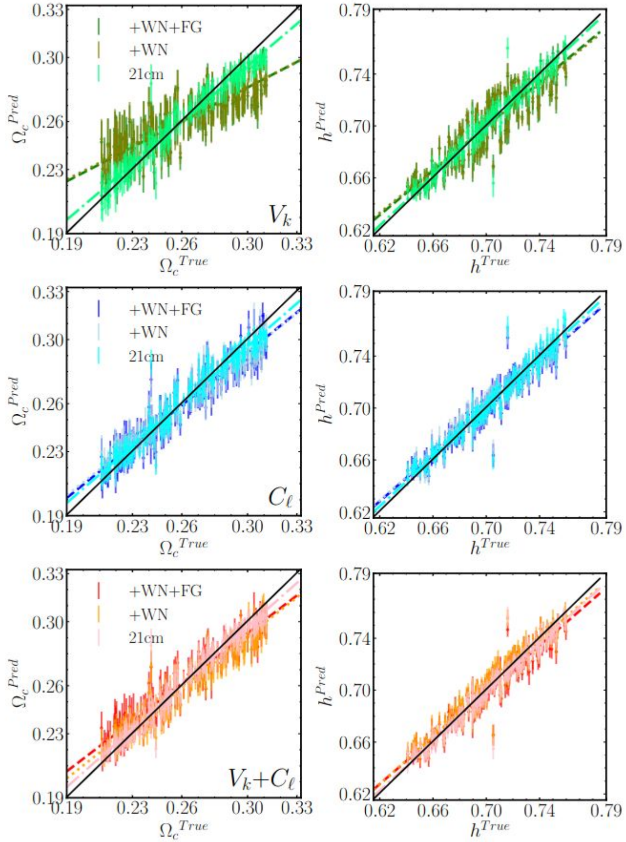
$\{\Omega_c, h\}$

$\{\Omega_c, h, w_0, w_a\}$

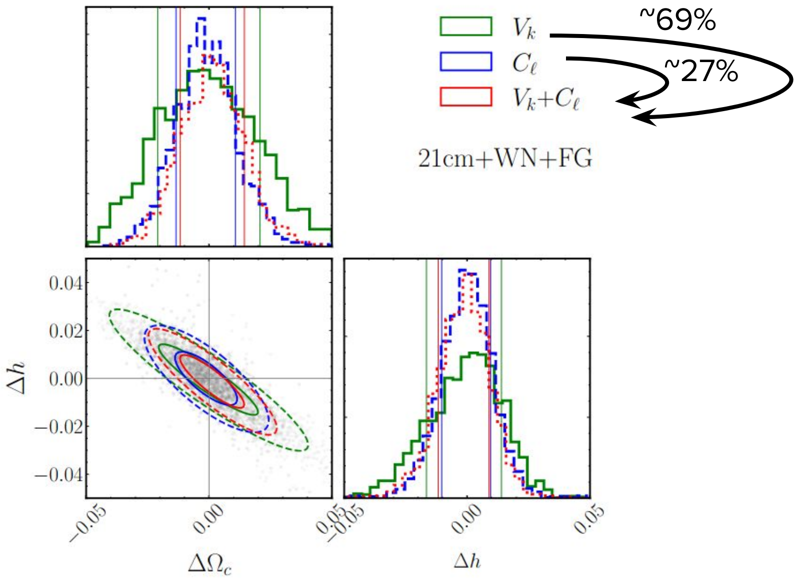
Architecture: `Optuna` [Akiba et al. 2019]

# Results (2 parameters)

frac. error:4.9%



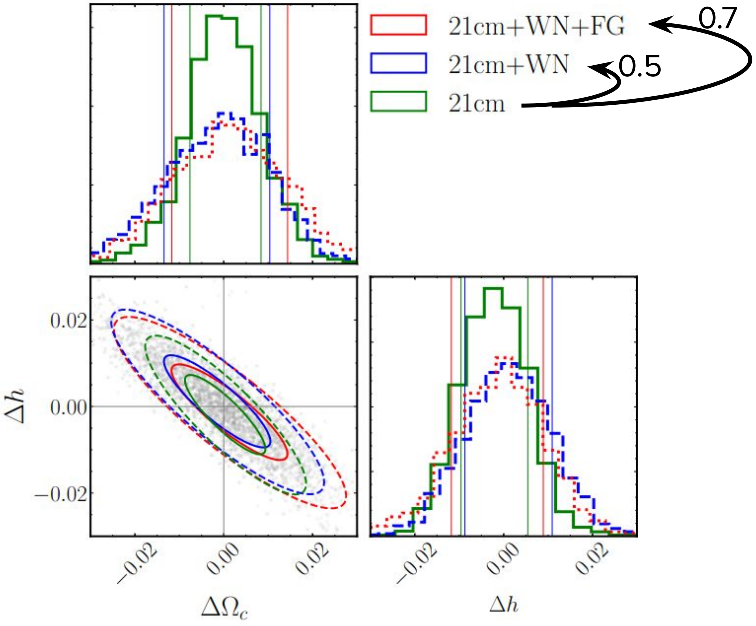

frac. error: 1.6%

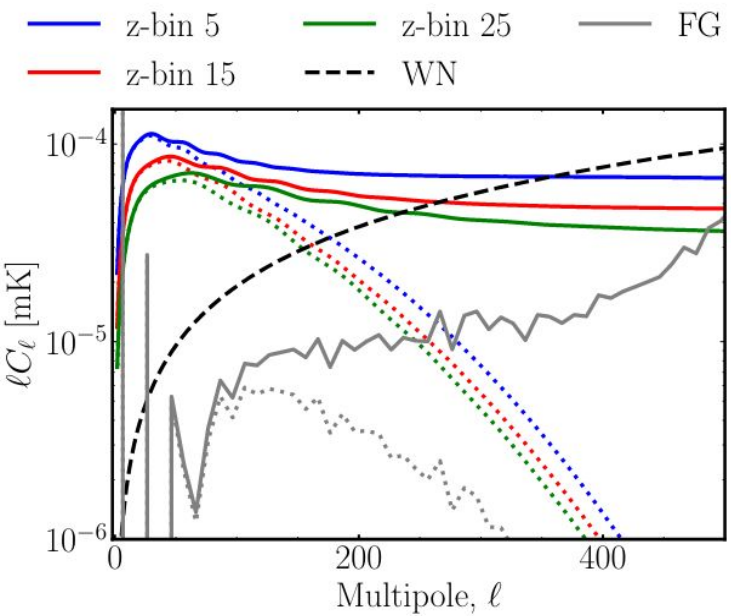



| Parameter space | 21 cm | | | 21 cm+WN+FG | | |
|---|---|---|---|---|---|---|
| | $V_k$+$C_\ell$ | $C_\ell$ | $V_k$ | $V_k$+$C_\ell$ | $C_\ell$ | $V_k$ |
| 2 parameters constraint | | | | | | |
| $\Omega_c - h$ | 1 | 1.194 | 1.188 | 1 | 1.267 | 1.686 |

# Results (2 parameters)

Impact of individual **systematics**

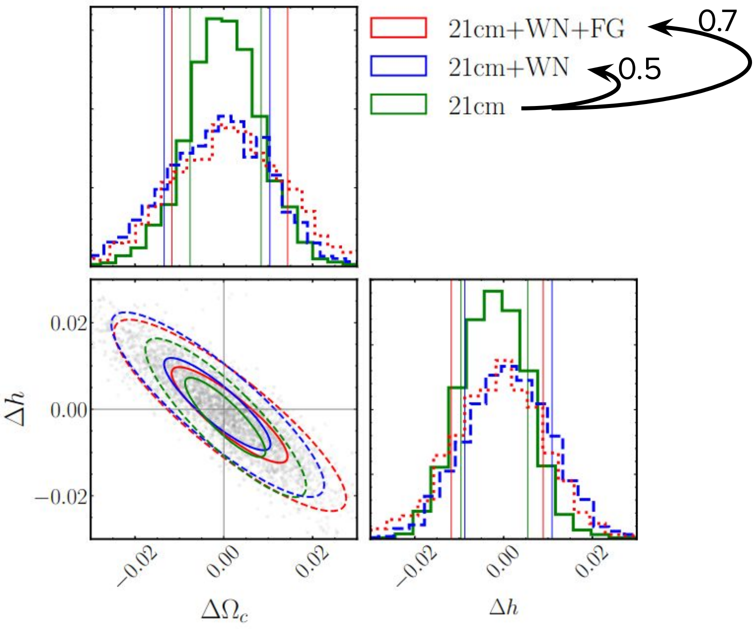



Main impact: **noise**

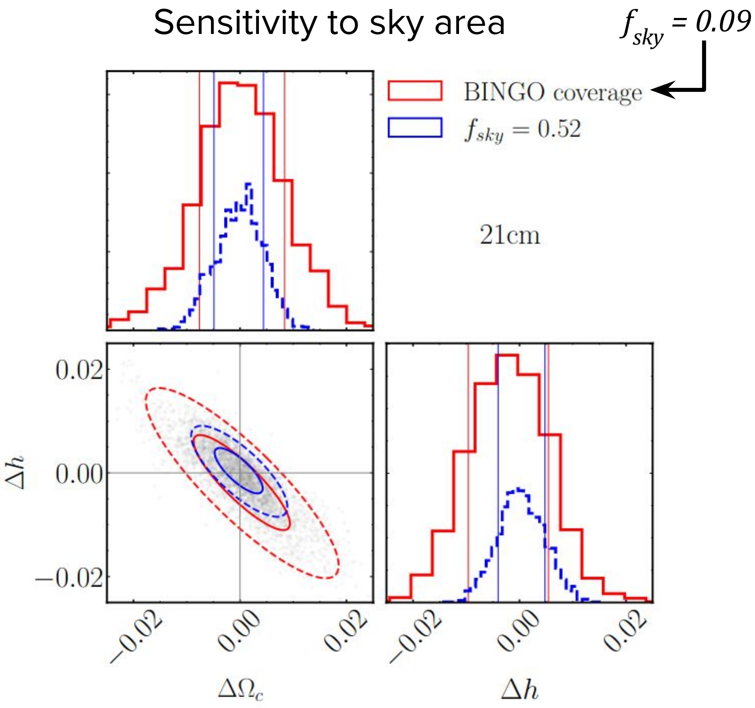
# Results (2 parameters)

Impact of individual systematics



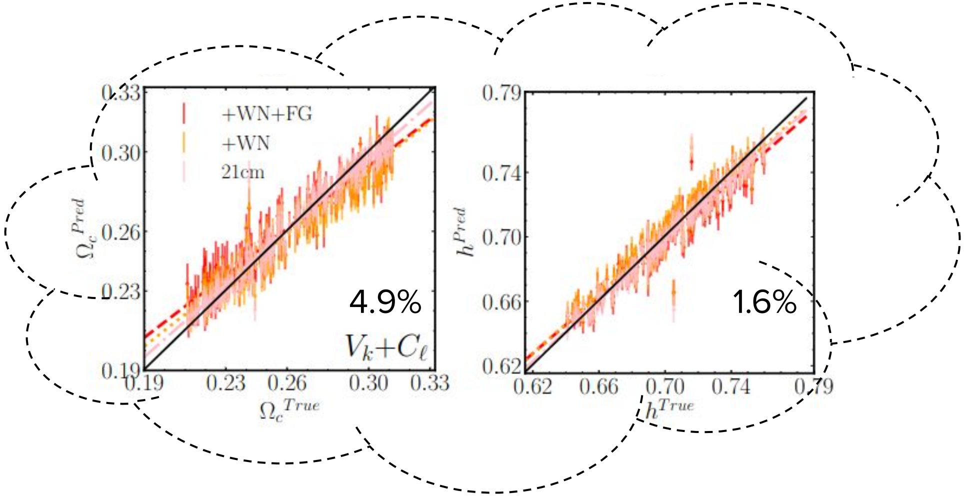

Main impact: noise

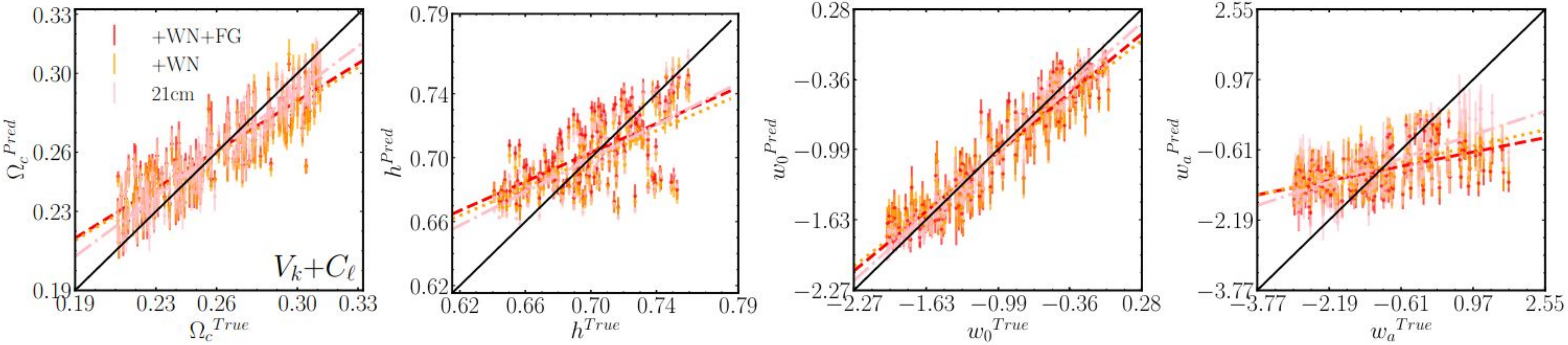
Sensitivity to sky area




> 3 times tighter constraints

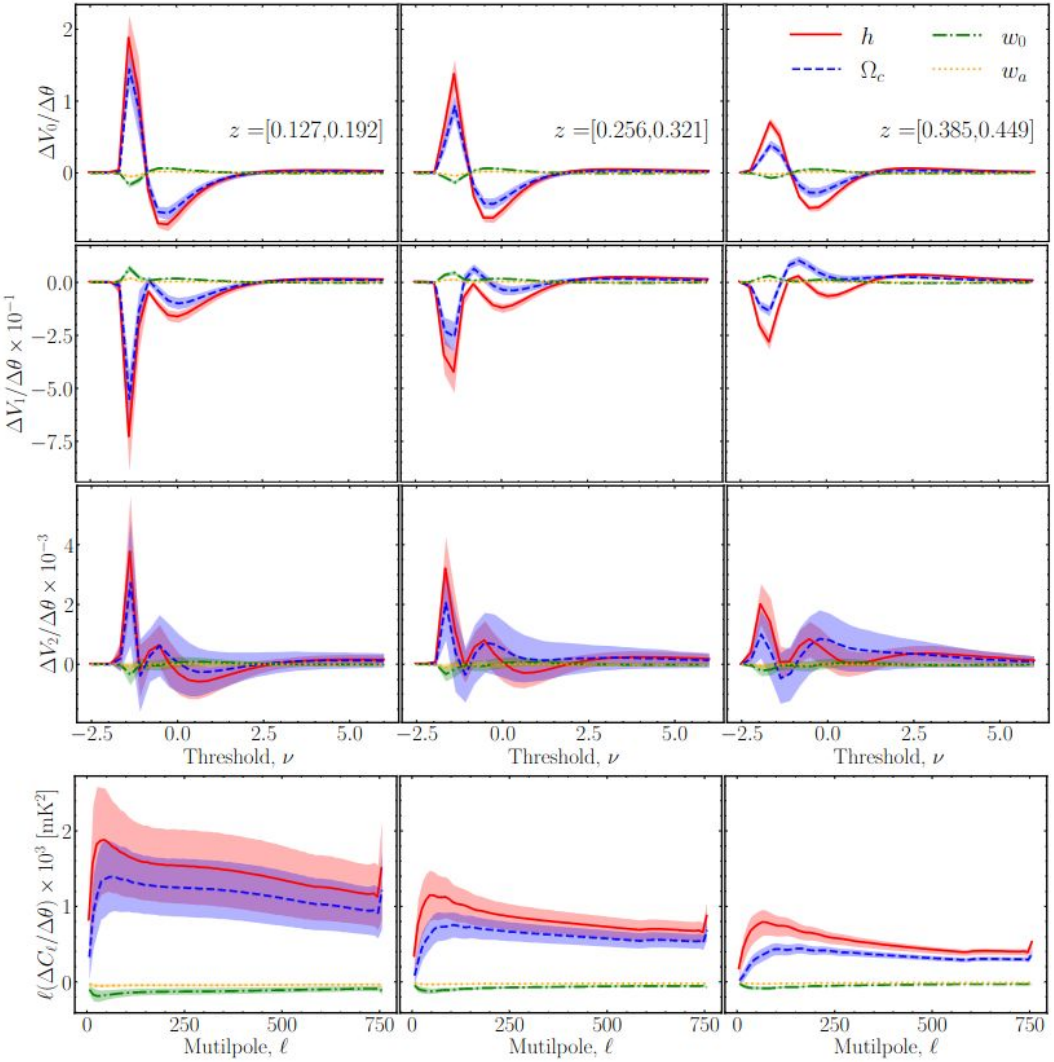
# Results (4 parameters)




frac. error: 6.4% 3.7% 24.3%

# Dependence with Cosmological parameters



# Summary of results and conclusions

- ✓ Promising results for 2 and 4 params constraints: $\{\Omega_c, h\}$ and $\{\Omega_c, h, w_0, w_a\}$.
- ✓ Larger sky coverage: significant improvements (SKA).
- ✓ Robustness to foreground contamination: method can be used outside the training set*.
- ○ To be improved:
  - Simulations,
  - Instruments characteristics,
  - Foregrounds,
  - …

→ Easy combination of different data sets.

→ Several possibilities for applications.

**Thank you!**