From DARK LIGHT to dark matter: understanding the galaxy-matter connection to measure the Universe

A view from Milan

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>>> For both themes, the emphasis was on developing innovative techniques in preparation for new survey data, and first applications

RU1 (UniMI & INAF MI) original PRIN 2017 goals

- Develop advanced 2pt clustering analysis of galaxy surveys:
    - advanced RSD modelling (Bianchi, LG)
    - forward-modelling cosmology, halo-galaxy match (Granett, Carbone, LG)

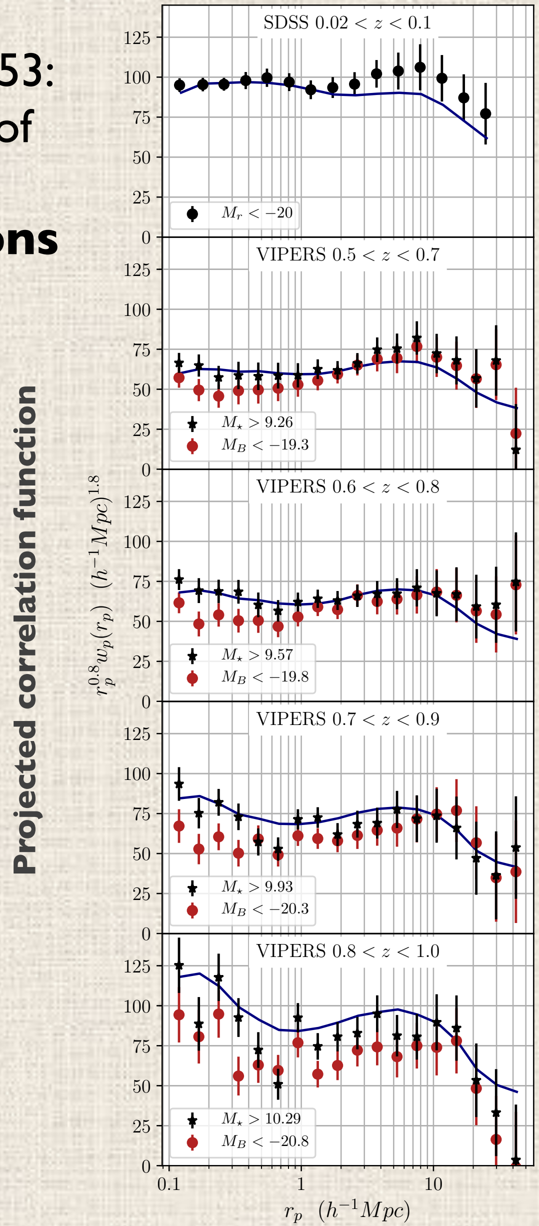
- Link to DM and particles:
    - n-body simulations in neutrino cosmologies (Carbone)

In fact, it enabled brand new directions to be explored…

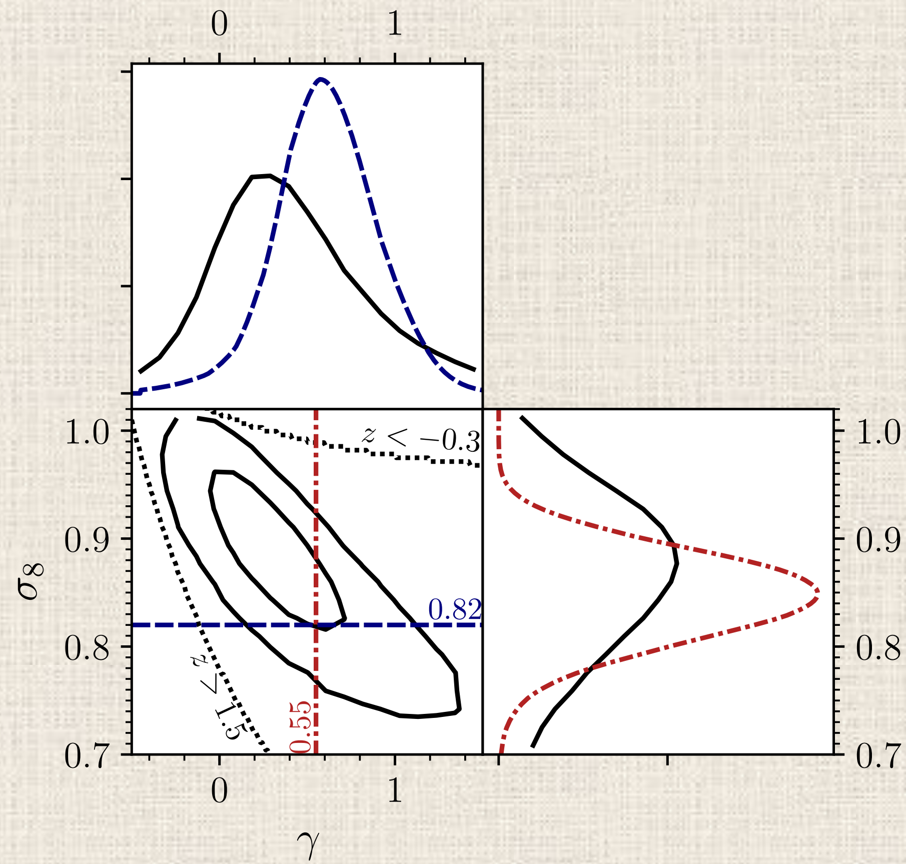
- Develop advanced 2pt clustering analysis of galaxy surveys:
  - advanced RSD modelling (Bianchi, LG)
  - forward-modelling cosmology, halo-galaxy match (Granett, Carbone, Tosone, LG)
  - Void cosmology (Carbone, Verza, Bonici,…)
  - Machine-Learning cosmological applications to data analysis and modelling (Tosone, Bonici, Cagliari, Granett, Bianchi, LG)
- Link to DM and particles:
  - n-body simulations in neutrino cosmologies (Carbone, Carella,…)
  - improved neutrino masses / "dark force" constraints from LSS (Archidiacono, Carbone, Castorina)

Connect real galaxies and DM halos using SHAM

Granett+ 2019, A&A 489, 653: simultaneous model fitting of simulation prediction to measured **2pt correlations between 0<z<1**



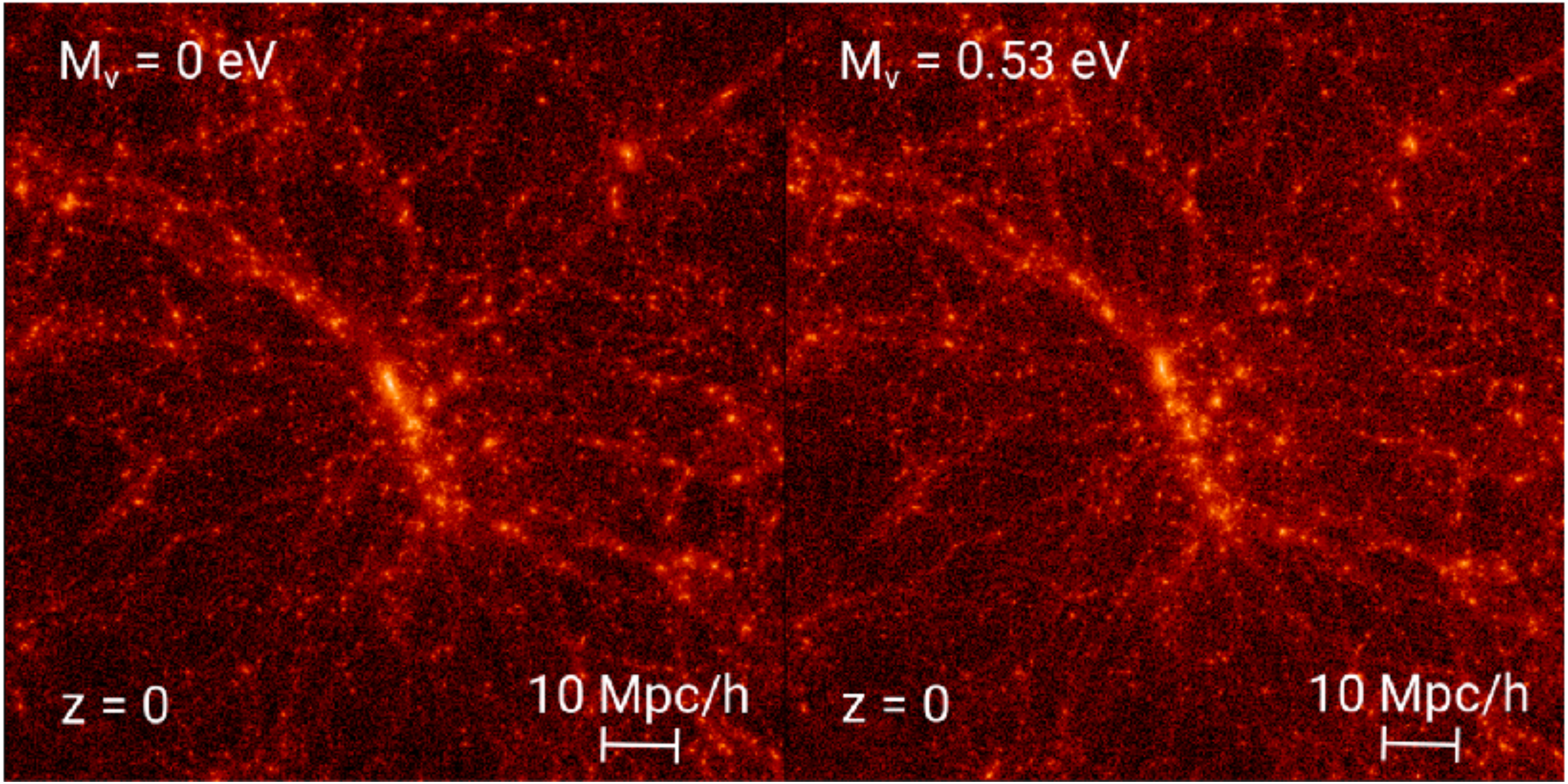
Joint analysis of SDSS and VIPERS



Predict amplitude and growth rate of clustering

Model the effect of massive neutrinos on large-scale structure

C. Carbone - DEMNUni N-body simulations in massive neutrinos and DE cosmologies: many applications and papers, including SHAM modelling vs survey data (Carella)

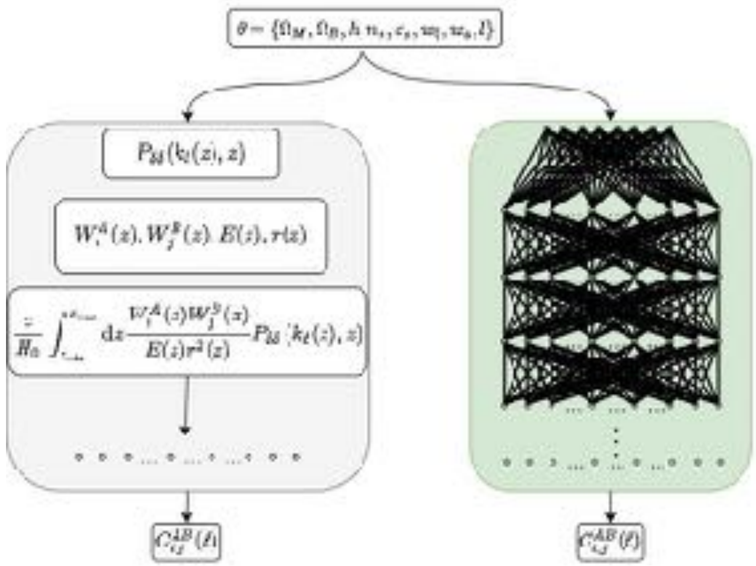


The new directions

I) Accelerate likelihood computation for summary statistics via ML emulation

(**Bonici**, Biggio, Carbone & Guzzo, 2024, MNRAS 531, 4203)

Replace expensive computations of model power spectra for the Likelihood with a trained neural network

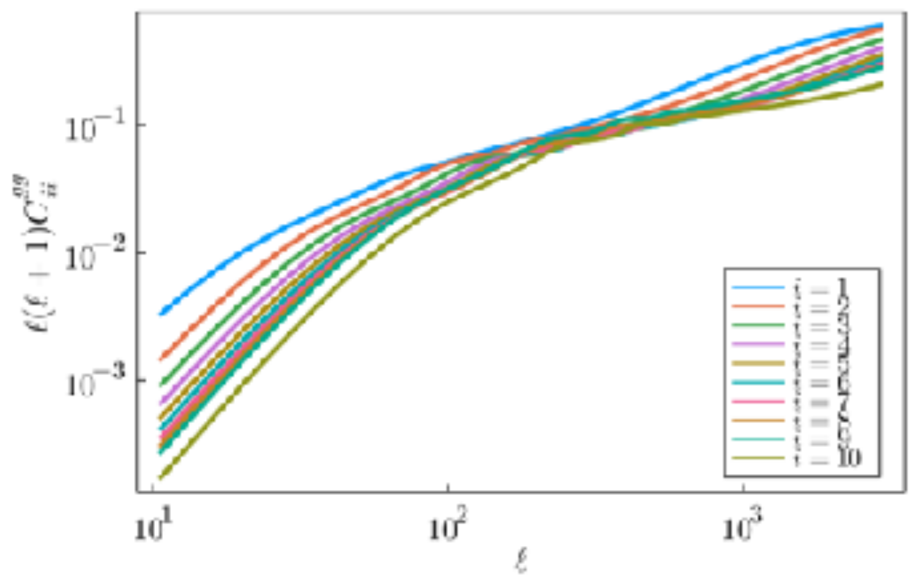


$$P(\theta \mid D) = \frac{\mathcal{L}(D|\theta)P(\theta)}{P(D)}$$

Our goal: **posterior** on data

Likelihood function, connecting **theory** and **data**

Prior on model parameters



$$\mathcal{L}(\boldsymbol{D} \mid \boldsymbol{\theta}) \propto \exp\left(-\tfrac{1}{2}\left[(\boldsymbol{D} - \boldsymbol{C}(\boldsymbol{\theta}))^{\mathrm{T}} \boldsymbol{Cov}^{-1} (\boldsymbol{D} - \boldsymbol{C}(\boldsymbol{\theta}))\right]\right)$$

- **Speed-up ~10^3 x**
- **Accuracy <0.2% on all scales**

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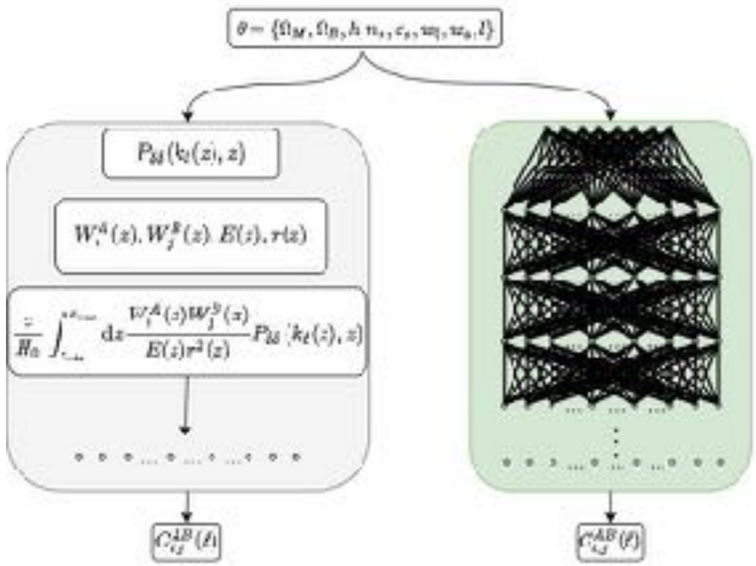

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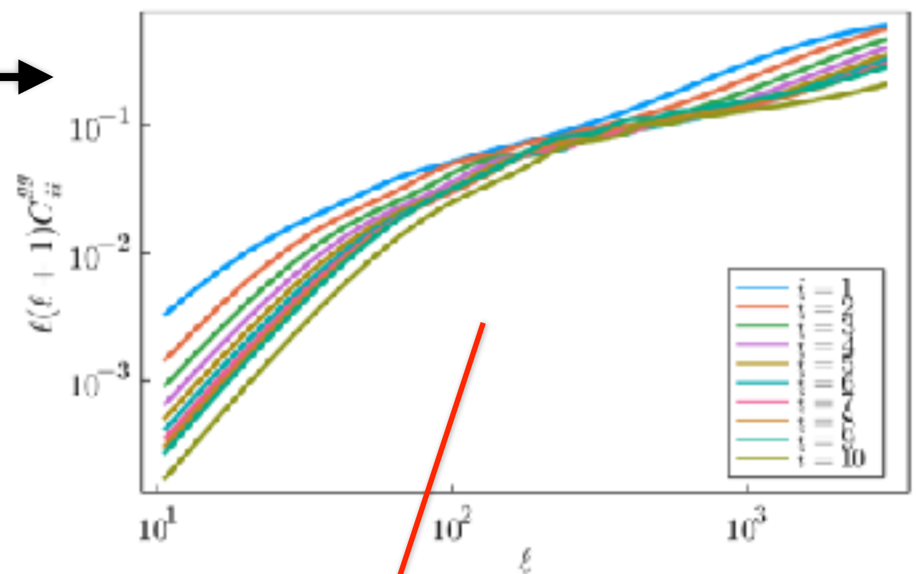

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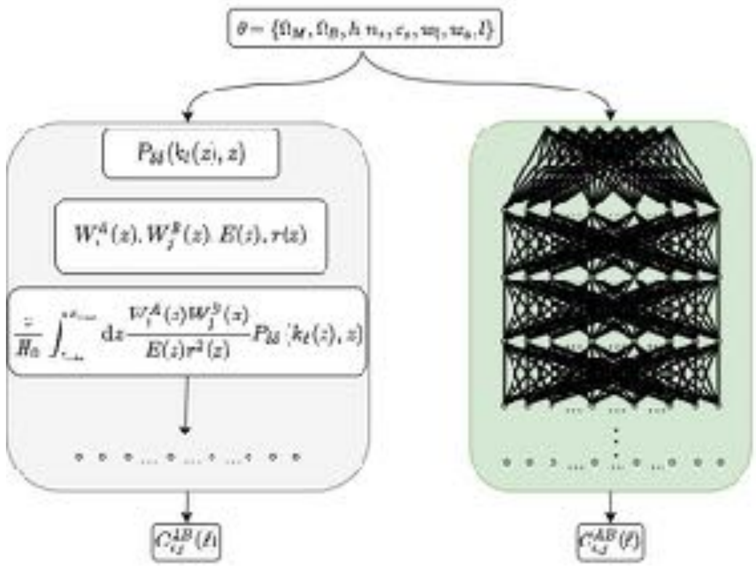

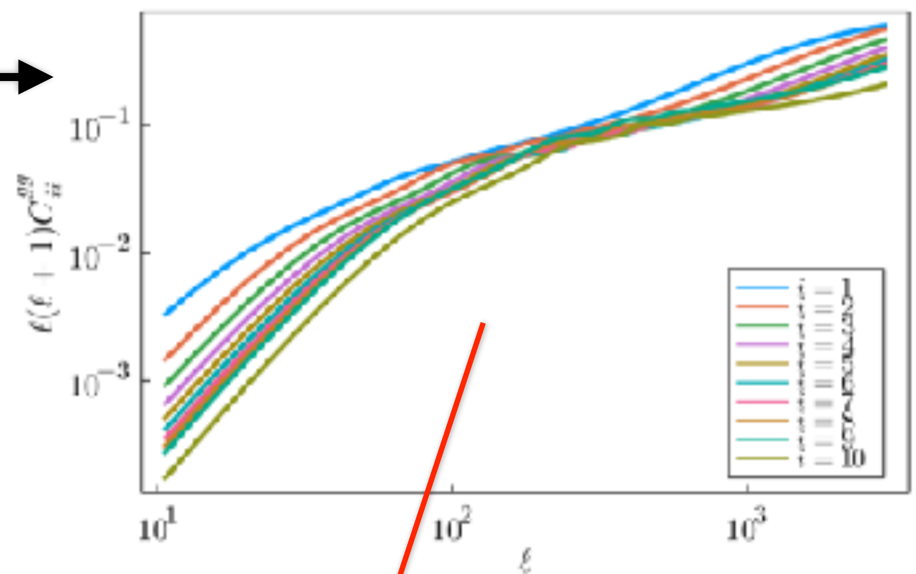

>>> Alternative route: ***symbolic regression***

BSc theses of F. Farinelli and S. Carturan (2023, 2/ Bonici)

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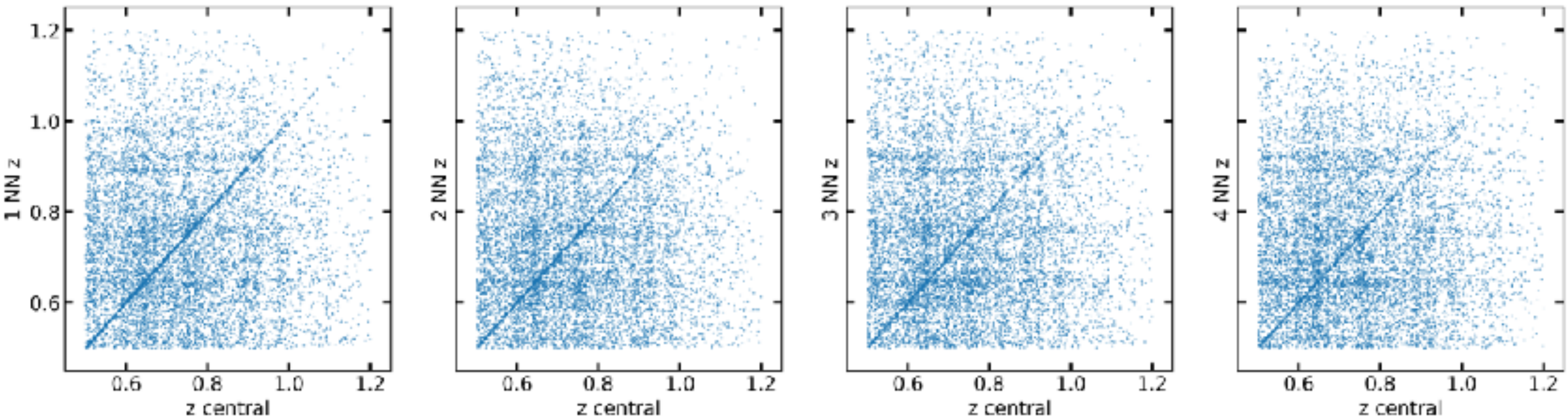
2) Improving photo-z accuracy by exploiting galaxy spatial correlations via Graph Neural Networks (GNN)

(**Tosone**, Cagliari, LG, + 2023)



- Angular pairs on the sky have a **higher-than-random probability to be also at similar redshift**: galaxies are correlated!
- **We can train a GNN to learn the link of colours and redshifts among neighbouring galaxies**

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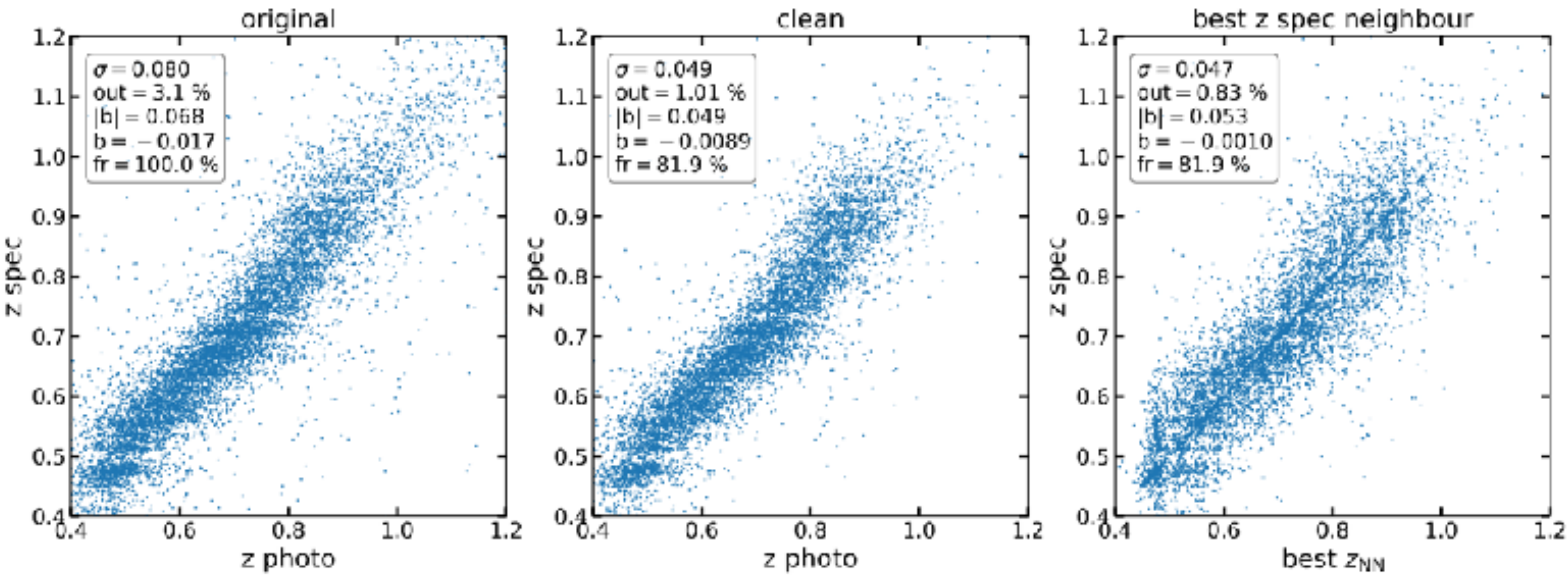


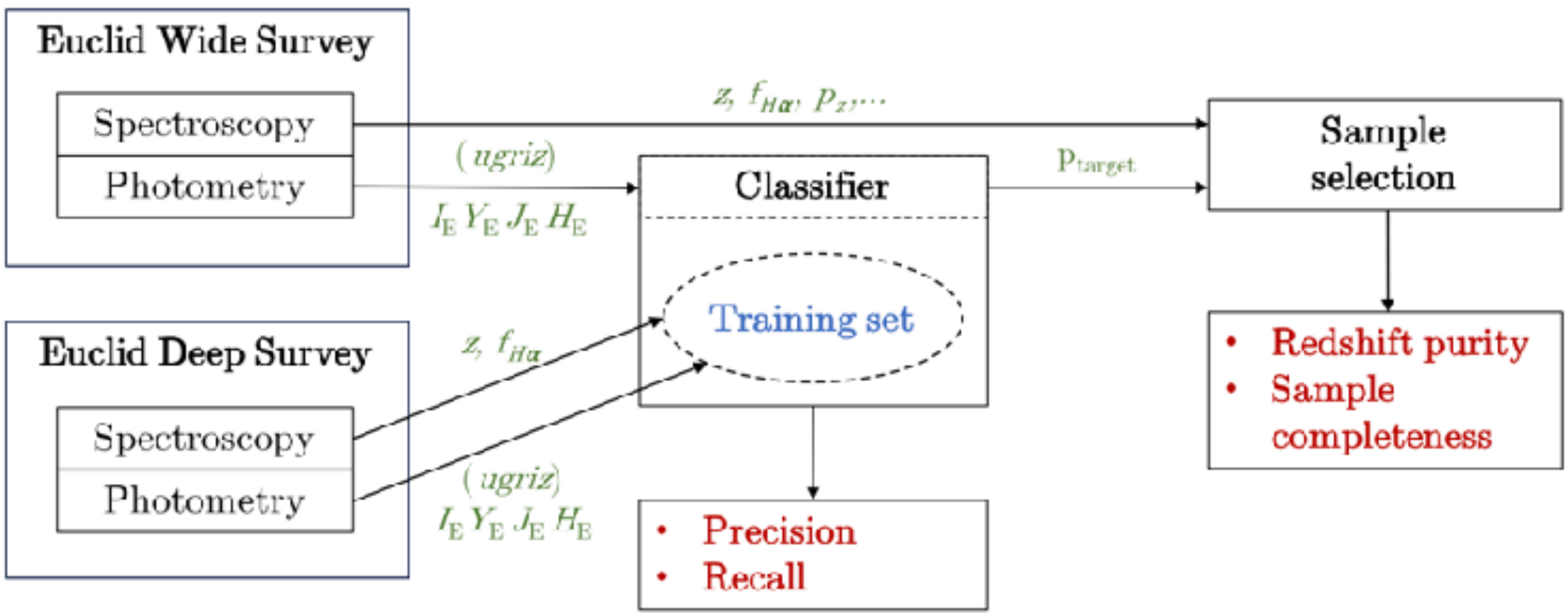
- Probability threshold for a galaxy to be classified as neighbour can be tuned to select (smaller and smaller) samples with increasingly precise redshifts
- **Redshift of a highly confident neighbour is typically more precise than original photo-z** (3d panel)

3) Improving purity & completeness of (Euclid) spectroscopic samples

Photometric selection for Euclid

Cagliari et al. (2024)

Due to **false detection** and **line mis-identification** the redshift purity of Euclid galaxy clustering sample is low.



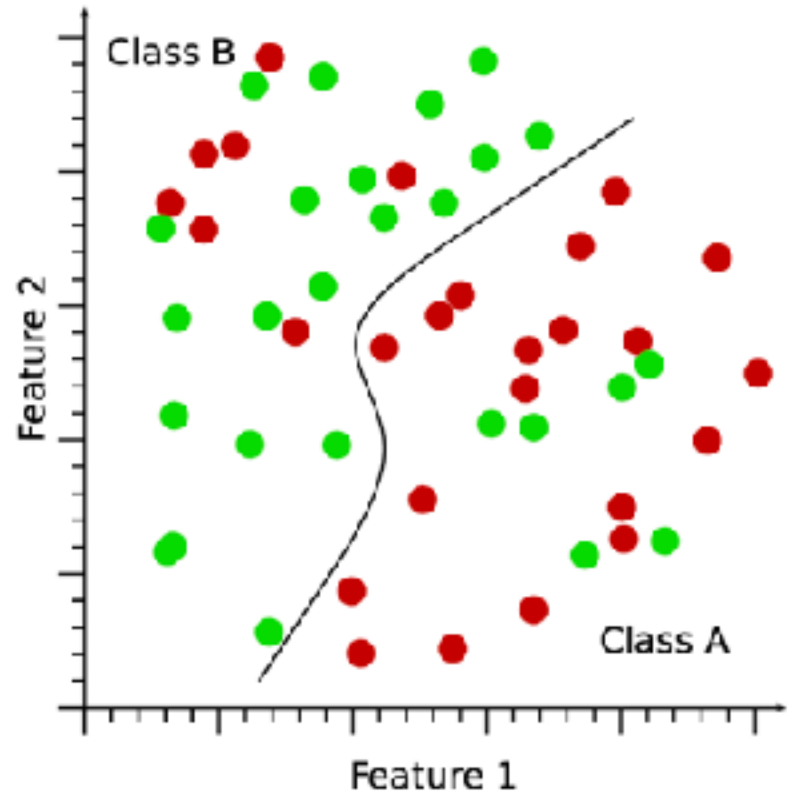
3) Improving purity & completeness of (Euclid) spectroscopic samples

Classifiers

- A classifier output is the probability of an object of being part of a class.
- Metrics of interest:

$$\text{precision} = \frac{TP}{TP + FP},$$
$$\text{recall} = \frac{TP}{TP + FN}.$$

- We tested six different ML-based classifiers.



3) Improving purity & completeness of Euclid spectroscopic samples

(**Cagliari**, Granett, LG, + 2024)

Mock data

$$\text{Targets:} \begin{cases} 0.9 < z < 1.8 \\ f_{\mathrm{H}\alpha}^{\mathrm{gal}} > 2 \times 10^{-16}\,\mathrm{erg\,s^{-1}\,cm^{-2}} \end{cases}$$

We test the algorithms with **EL-COSMOS** and **Flagship2** data.

Euclid

EL-COSMOS & Flagship

- $I_{\mathrm{E}} - Y_{\mathrm{E}}$,
- $Y_{\mathrm{E}} - J_{\mathrm{E}}$,
- $J_{\mathrm{E}} - H_{\mathrm{E}}$,
- H_{E}.

Euclid + ground

EL-COSMOS & Flagship

- $u - g$,
- $g - r$,
- $r - i$,
- $i - z$,
- $z - Y_{\mathrm{E}}$,
- $Y_{\mathrm{E}} - J_{\mathrm{E}}$,
- $J_{\mathrm{E}} - H_{\mathrm{E}}$,
- H_{E}.

Improving purity & completeness of Euclid spectroscopic samples

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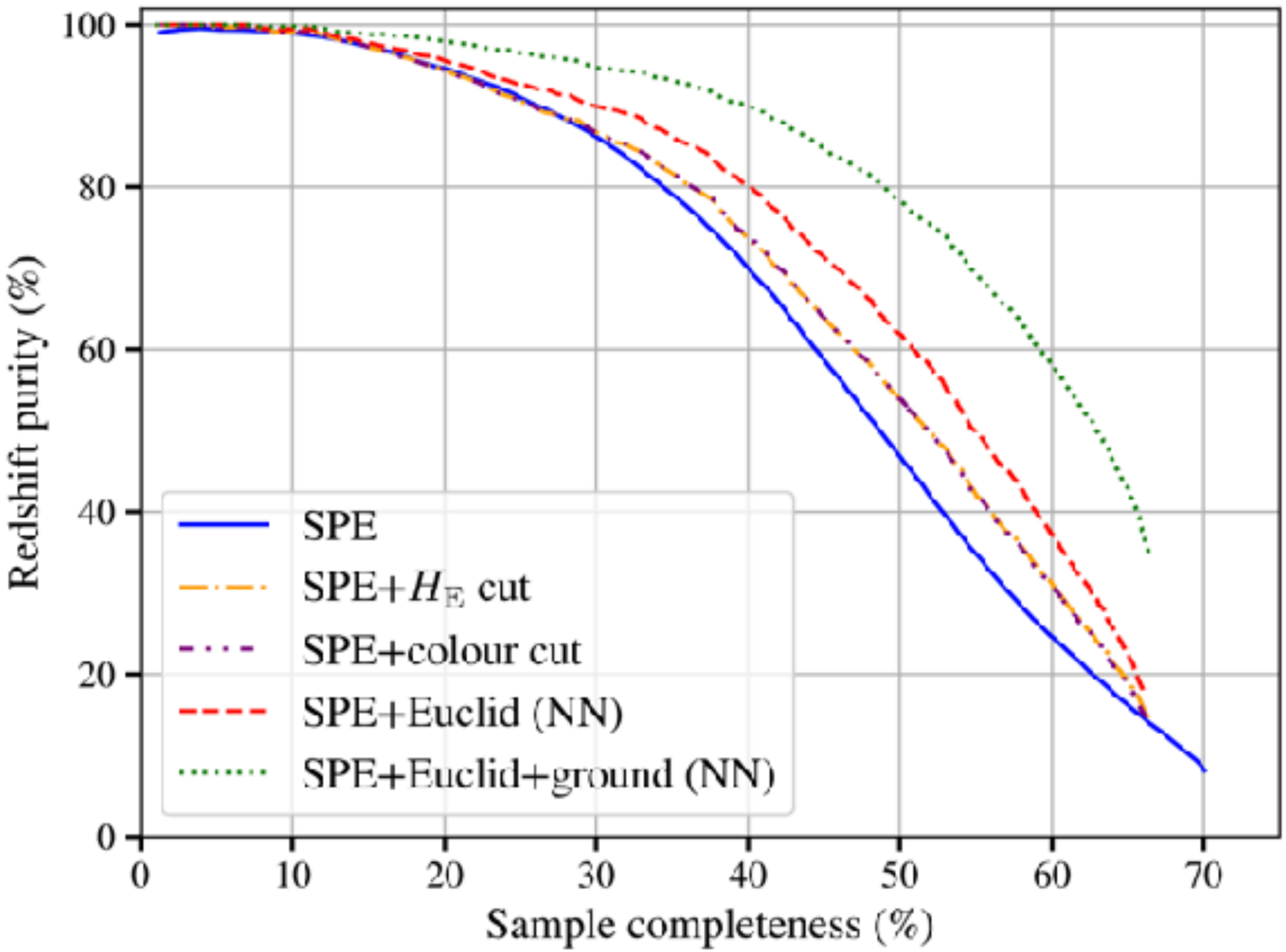
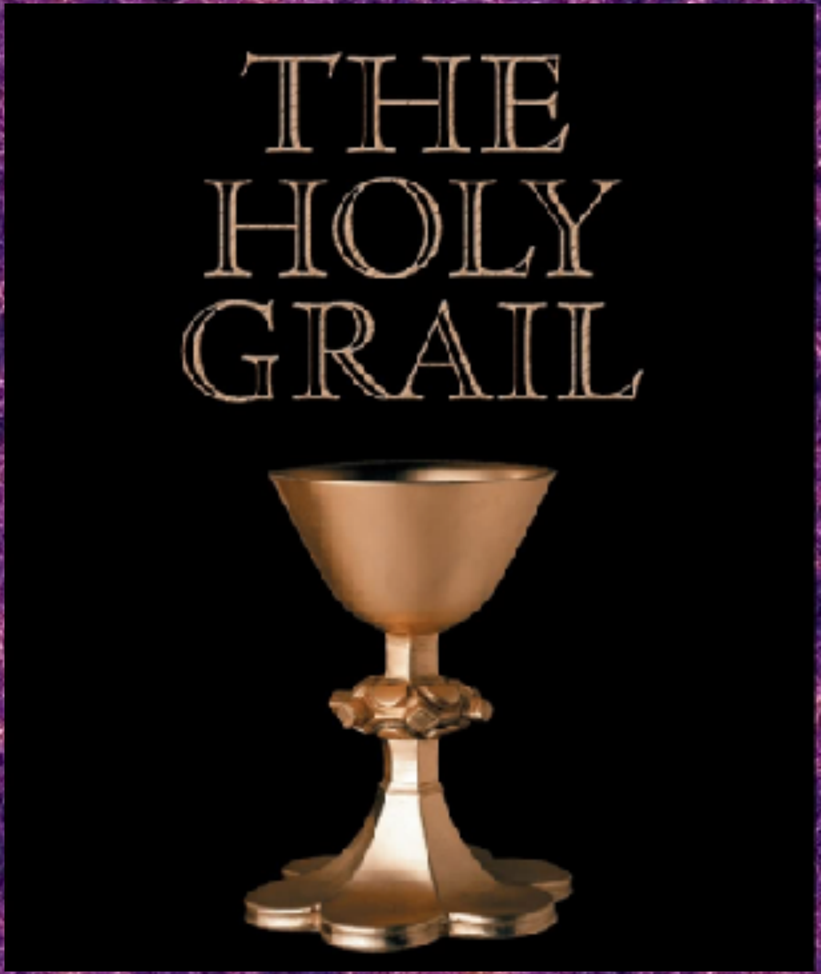
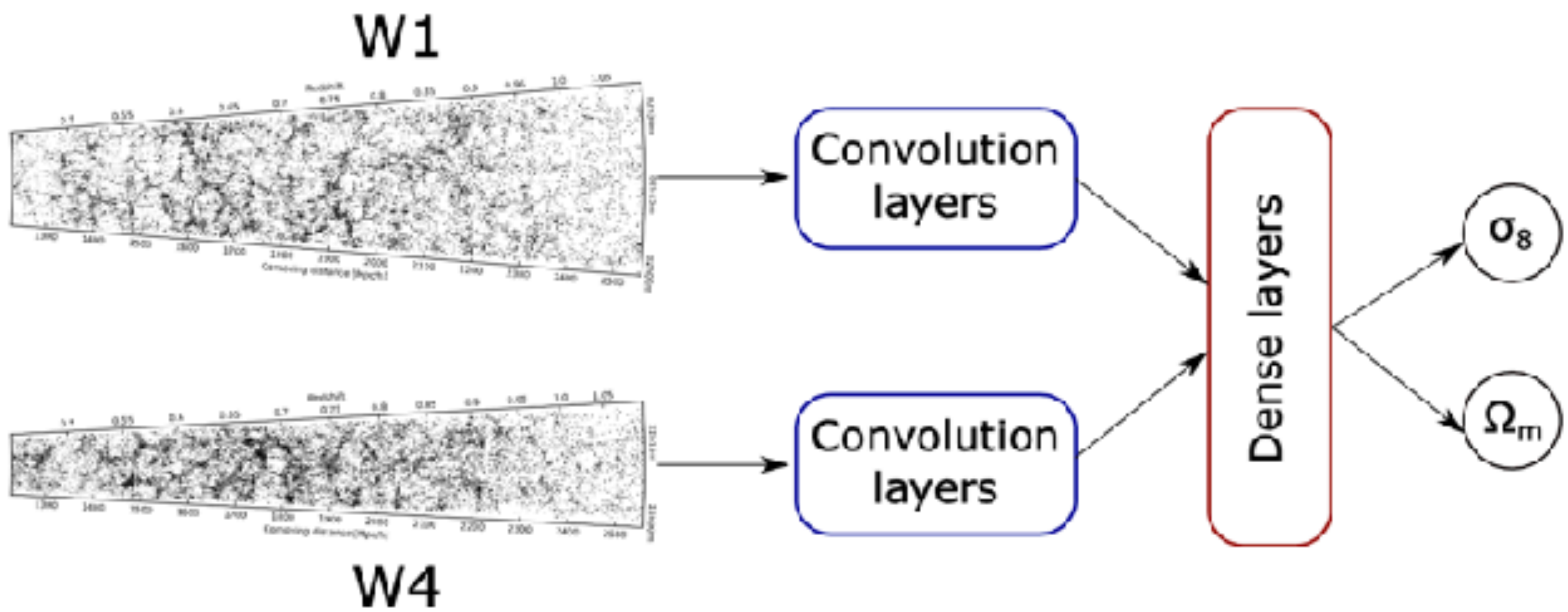


The future: bypass summary statistics and measure parameters directly from the galaxy field?



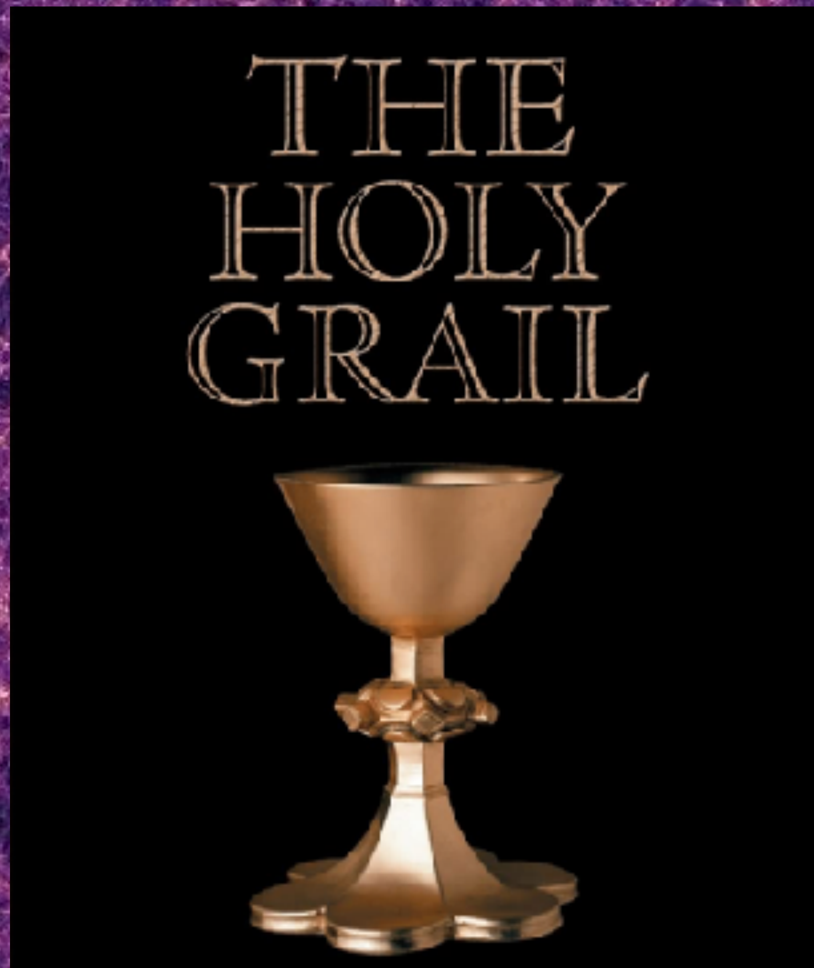
A field-level analysis with observational information



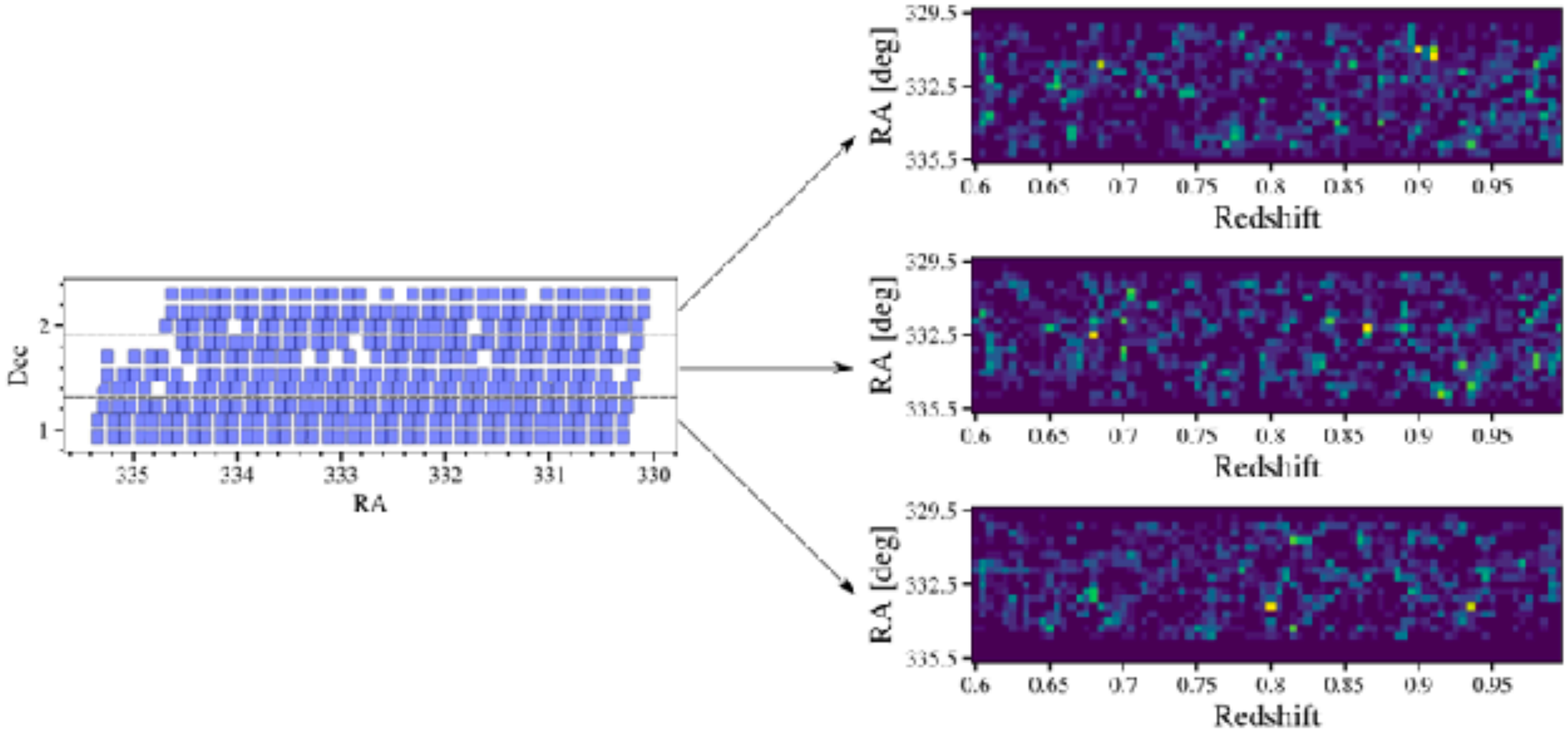
- The ambitious plan is a field-level analysis of VIPERS with a convolutional neural network.
- We use only observational information: the angular position and the redshift of the objects.

Cagliari, PhD thesis, 2024 - project idea by B. Granett)

Central problem: training samples.
We do not have “example Universes”



My current setup

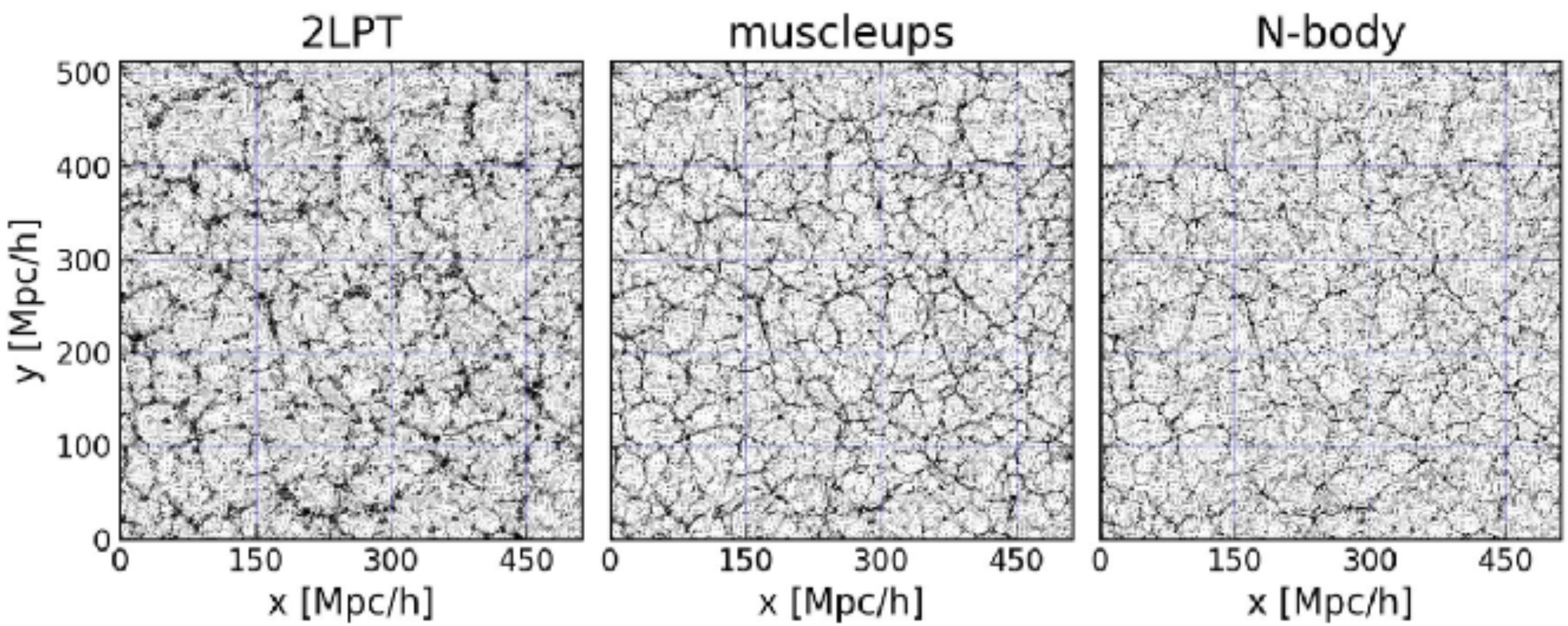


- I am working with DM halos in redshift space and real space.
- I am training the CNN with **3LPT** simulations and testing with an **N-body**.

Pinocchio (Monaco+ 2002)

Training sets from Lagrangian PT:

- State of the art: **Pinocchio** (Monaco+ 2002; Monaco 2016), extensively used in Euclid.
- **PRIN2017** contribution: **MUSCLE-UPS** (2021, w/ Neyrinck, Granett, LG - publicly available),
- Builds upon and improves prev. ALPT (Neyrinck 2013), PATCHY (Kitaura+ 2016) and MUSCLE (Neyrinck 2016)



Training sets from n-body ML Emulators? 2D tests

(**Sofia Chiarenza**, BSc 2021; **Marco Chiarenza**, BSc 2022 — supervisors **F. Tosone, LG**)

- **Emulate Lagrangian displacement field against N-body output**
- **Use CNN-UNET (Sofia C.) or Gen. Adversarial Networks (GAN, Marco C.)**

- q –> initial positions
- x –> final positions
- Ψ –> displacement

$$x = q + \Psi \tag{2}$$

- provide to the network $\nabla \cdot \Psi_{\text{approx}}$
- the Unet outputs $\nabla \cdot \Psi_{\text{unet}}$
- pixel-wise MSE loss

$$\mathcal{L} = \frac{1}{N} \sum_{\text{pixels}} (\nabla \cdot \Psi_{\text{N-body}} - \nabla \cdot \Psi_{\text{unet}})^2 \tag{3}$$

References: (He et al., 2019; Alves de Oliveira et al., 2020)

(courtesy F. Tosone)

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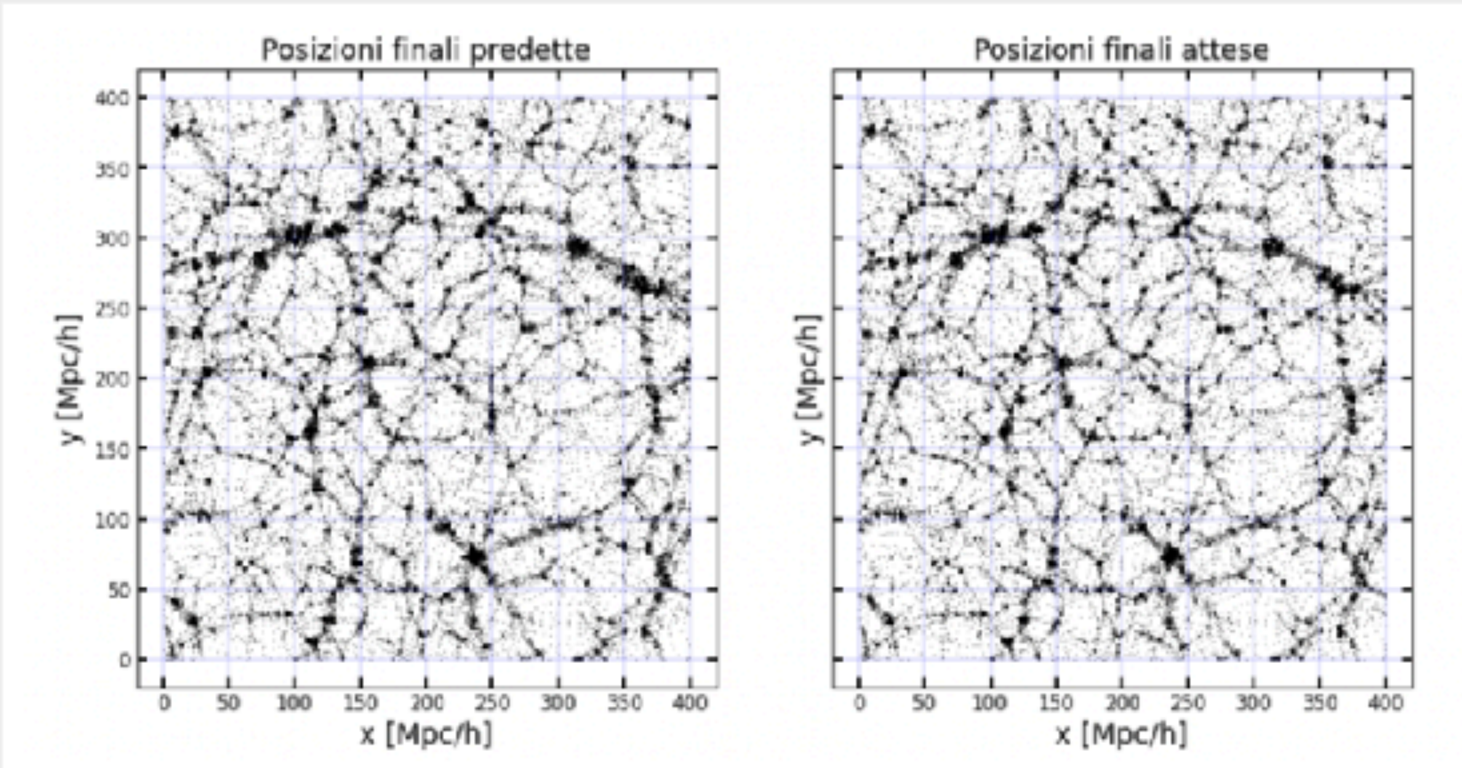
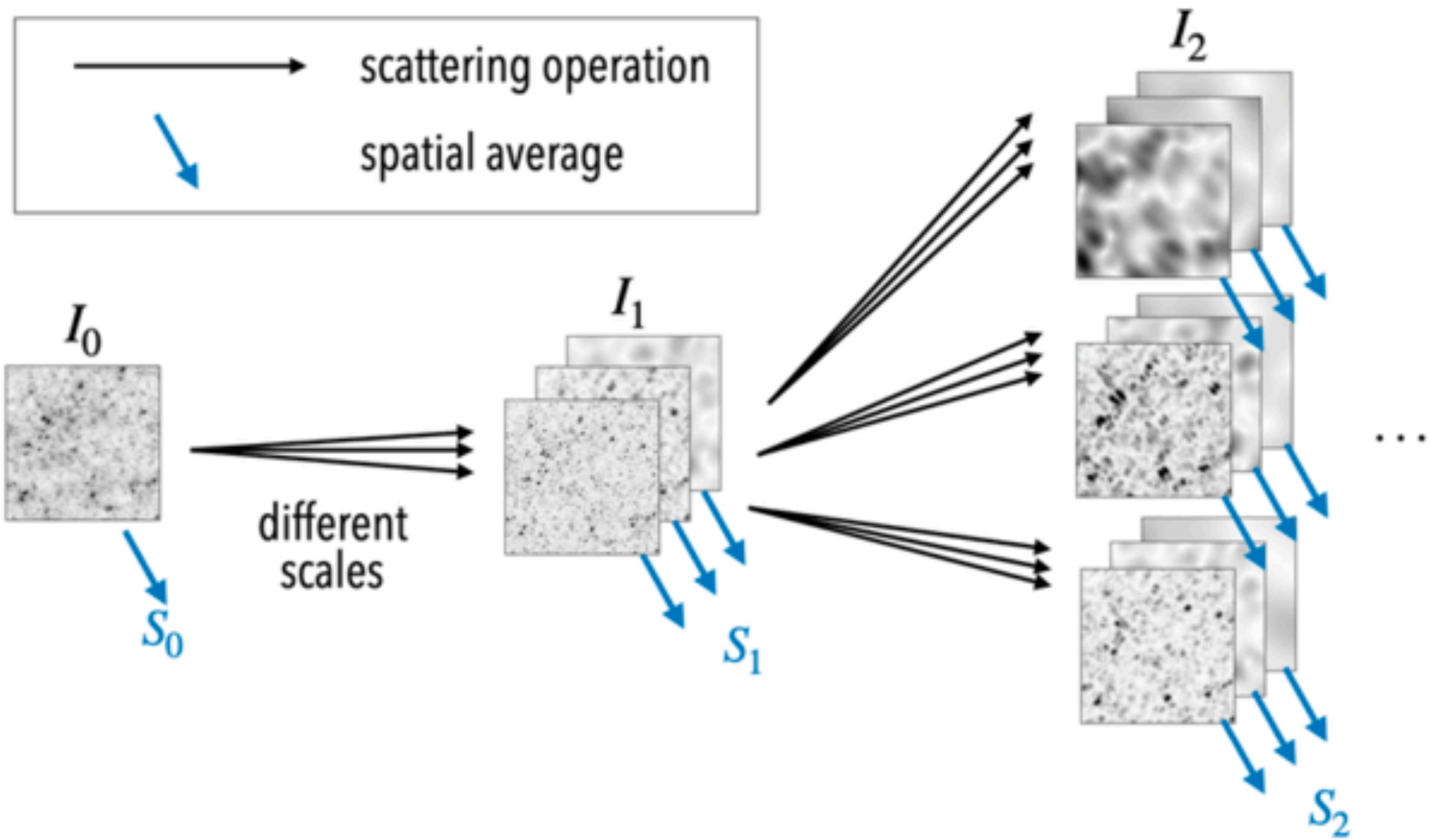


from Sofia Chiarenza bachelor thesis

Pseudo-CNN: the Wavelet Scattering Trasform

(**S. Chiarenza, MSc thesis**, /w D. Bianchi)



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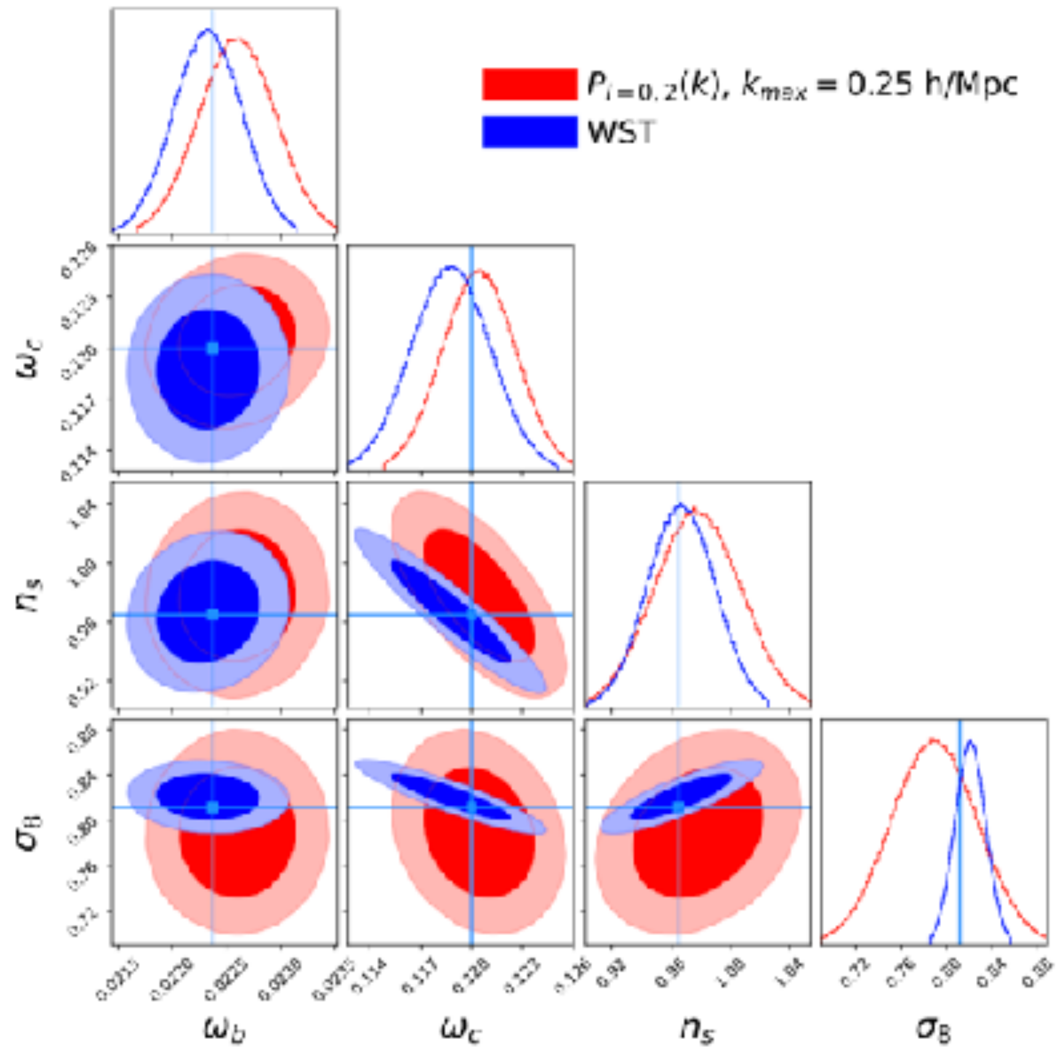
- **Re-analysis of BOSS survey data: comparison of WST vs. P(k) monopole+quadrupole fit**



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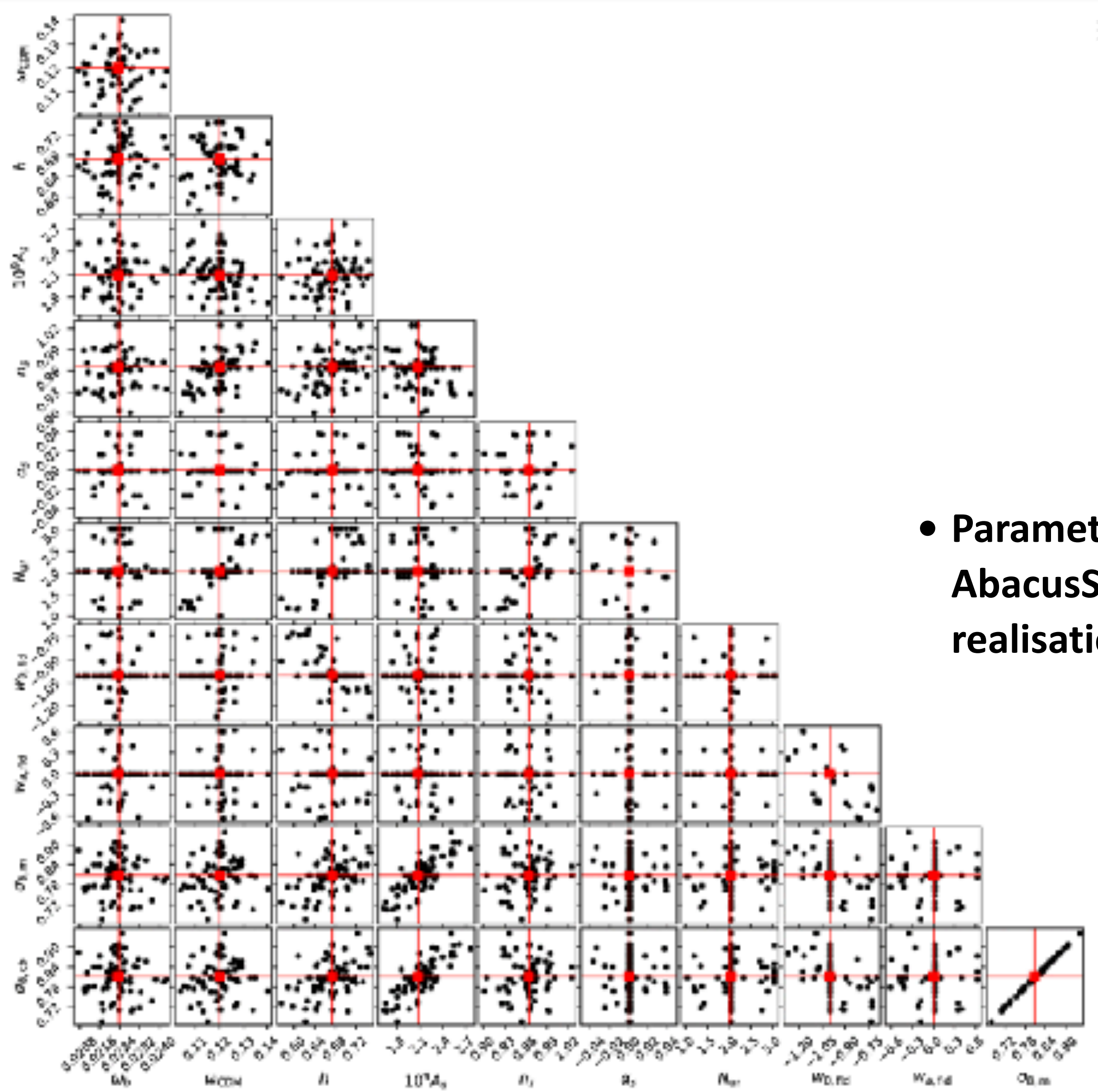

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- **Parameter space for the 96 AbacusSummit n-body realisations**

THE END