Università di Genova | DIFI DIPARTIMENTO DI FISICA

From Redshift to Real Space

Combining Linear Theory with Convolutional Neural Networks

arXiv:2507.11462 [astro-ph.CO]

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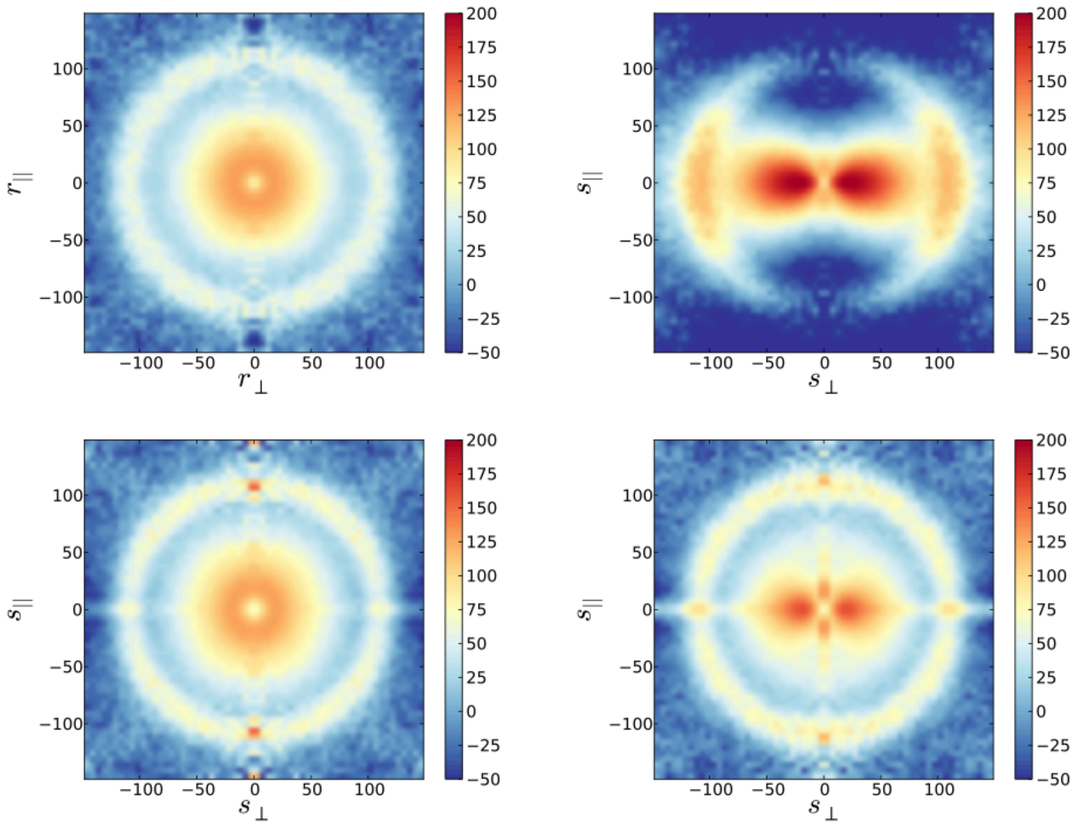
Edoardo Maragliano - Sexten - July 16th, 2025

The problem

Redshift Space Distortions

- We use redshift as distance proxy
- Distortions in the LSS mapping
- Degrade the BAO + Cosmic Voids
- Can be *partially* reversed via standard reconstruction techniques, usually based on linear theory

Padmanabhan et al. (2012), arXiv:1202.0090 **[astro-ph.CO]**



Standard reconstruction

Strenghts and room for improvement

PRO

- Based on a physically motivated framework
- Generally robust against variation of input parameters
- Large scale modes are recovered very well

CONS

- Small scale modes are not recovered very well
- Only partial RSD removal

Can we improve standard reconstruction techniques?

Convolutional Neural Networks

A Data-Driven RSD Correction

- Leverage **large simulation** to train CNNs
- Learn the mapping **from a reconstructed density field to Real Space**
- Capture **nonlinear transformations** without explicit modelling assumptions
- **Modest computational cost**, scalable with modern hardware
- Once trained, the model can **generalise to new data**

Plan

A three-part benchmark

Linear Theory (LT):

- Estimate the displacement field using the iFFT algorithm
- Displace the tracers accordingly

Neural Network (NN):

- Feed the redshift-space density field into a Neural Network
- NN learns to map the RSDs to the real space density field

LT+NN:

- Apply LT
- Feed the partially corrected density field into a NN
- NN learns to correct the residual RSDs

Burden et al. (2015)
arXiv:1504.02591 **[astro-ph.CO]**

Dataset

Halo catalogues from the Quijote simulations

- **Simulations:** 100 halo catalogues from the Quijote High-Resolution N-body runs

- **Dataset Split:** 0-79: training set; 80-99: validation set.

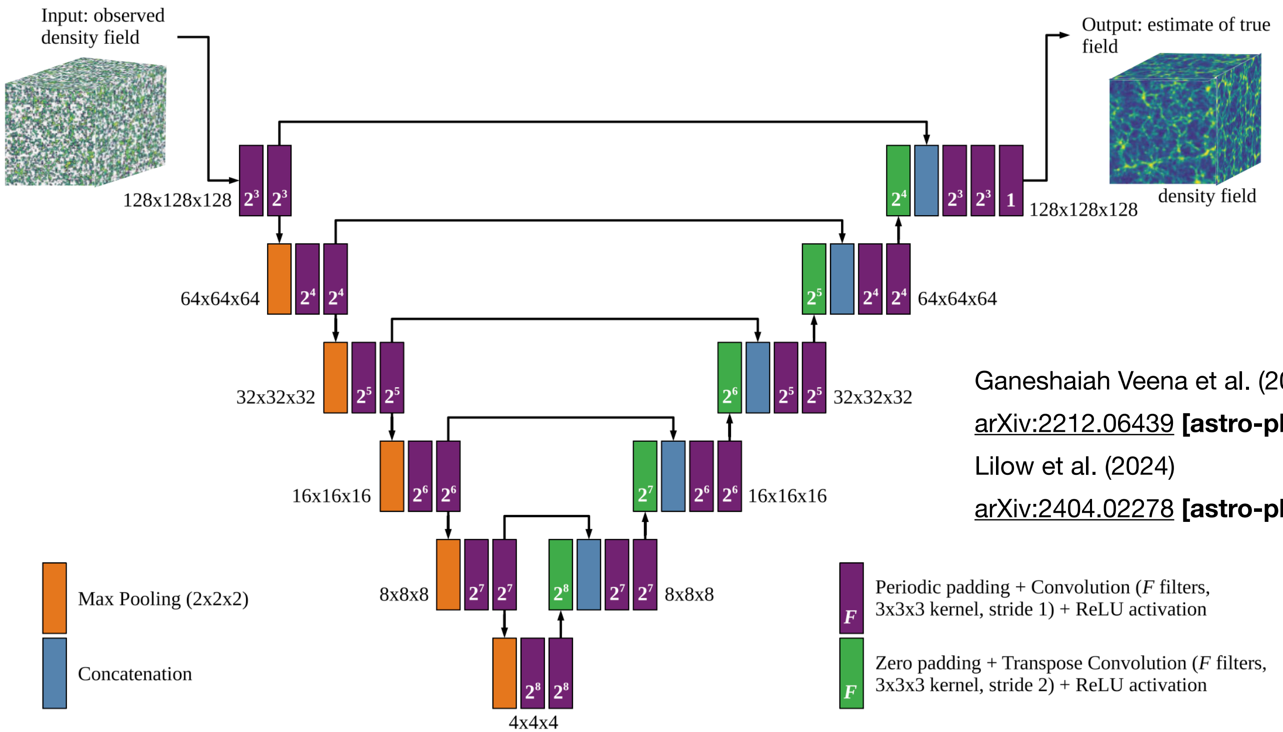
- **Snapshot:** z=1

- **Box size:** 1000 Mpc/h per side

The Neural Network step

U-Net architecture

- **Architecture:** Symmetric encoder-decoder
- **Depth:** 5 blocks, each with 2 convolutional layers + ReLu + max pooling
- **Channels:** Increasing number of convolutional kernels capture hierarchical features
- **I/O:** 128^3 gridded density field
- **Loss:** MSE between predicted and real space field



Ganeshaiah Veena et al. (2023)
arXiv:2212.06439 **[astro-ph.CO]**
Lilow et al. (2024)
arXiv:2404.02278 **[astro-ph.CO]**

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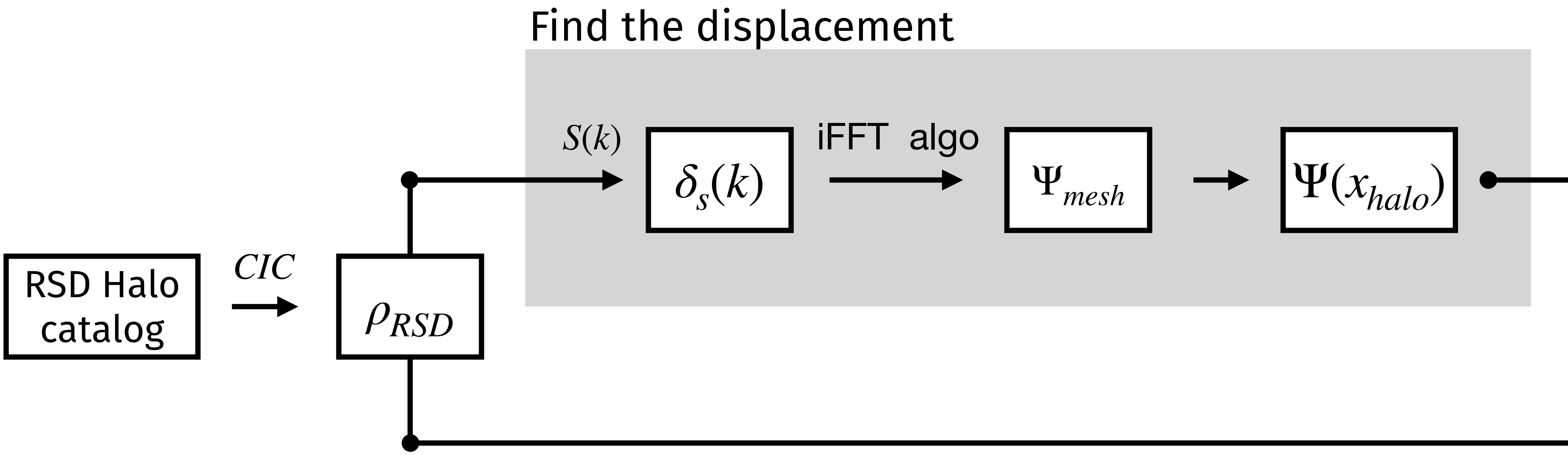
Pipeline

Combine Physics and Machine Learning



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Pipeline

Combine Physics and Machine Learning

Use the displacement

Displace halos by $-f(\Psi \cdot \hat{z})\,\hat{z}$ → ρ_{LT} →

Apply the Neural Network

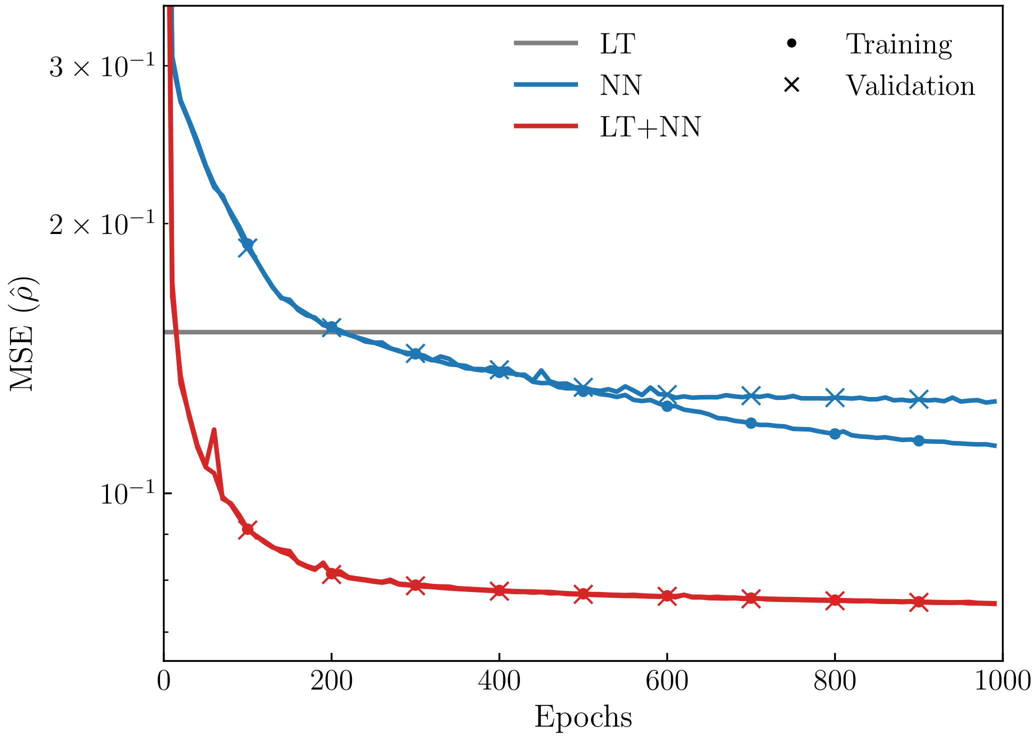
NN trained on LT reconstructed field Target: ρ_{real} → ρ_{LT+NN}

NN trained on RSD field Target: ρ_{real} → ρ_{NN}

Training and validation performance

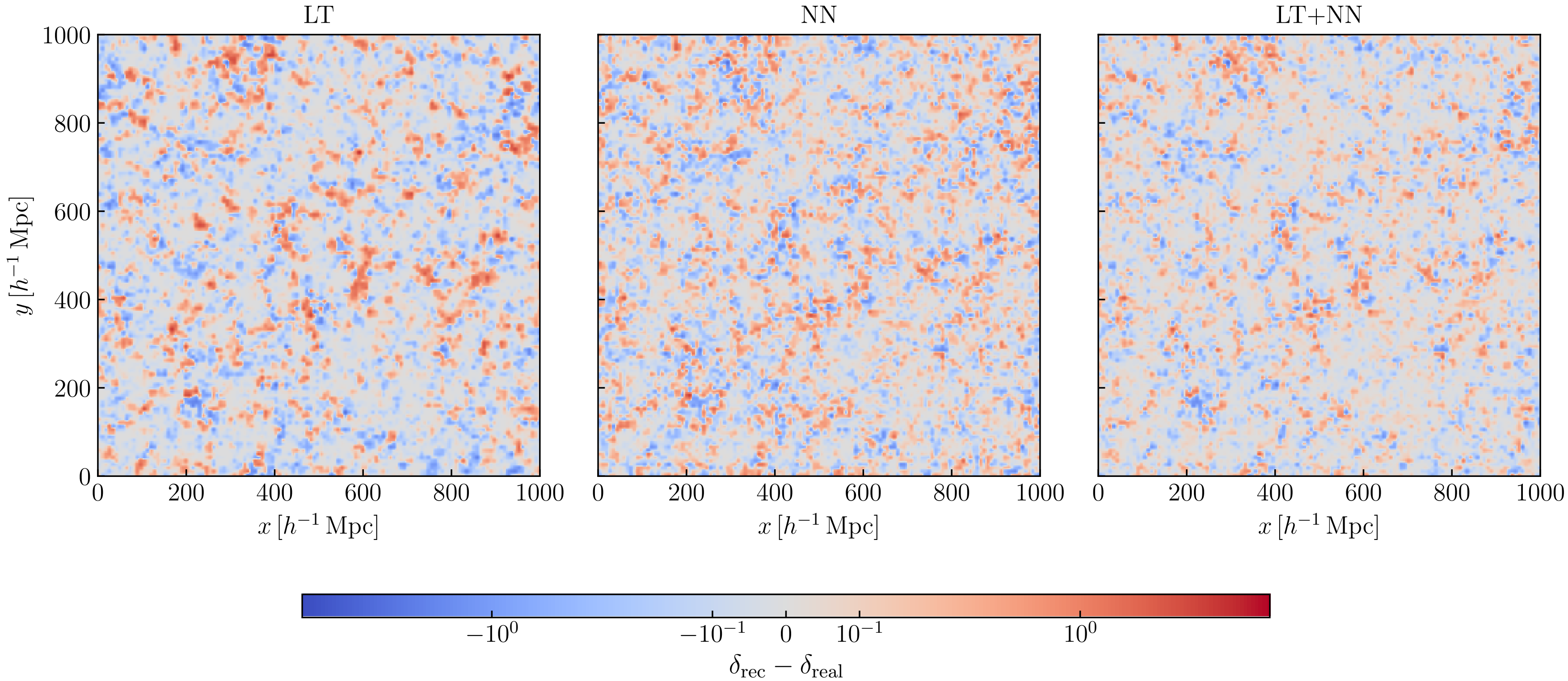
Loss function

- NN improves $\sim 13\,\%$ over LT
- NN converges slowly and starts overfitting after 500 epochs
- LT+NN improves $\sim 50\,\%$ over LT
- LT+NN converges much faster and does not overfit up to 1000 epochs



Results

Residuals on a slice



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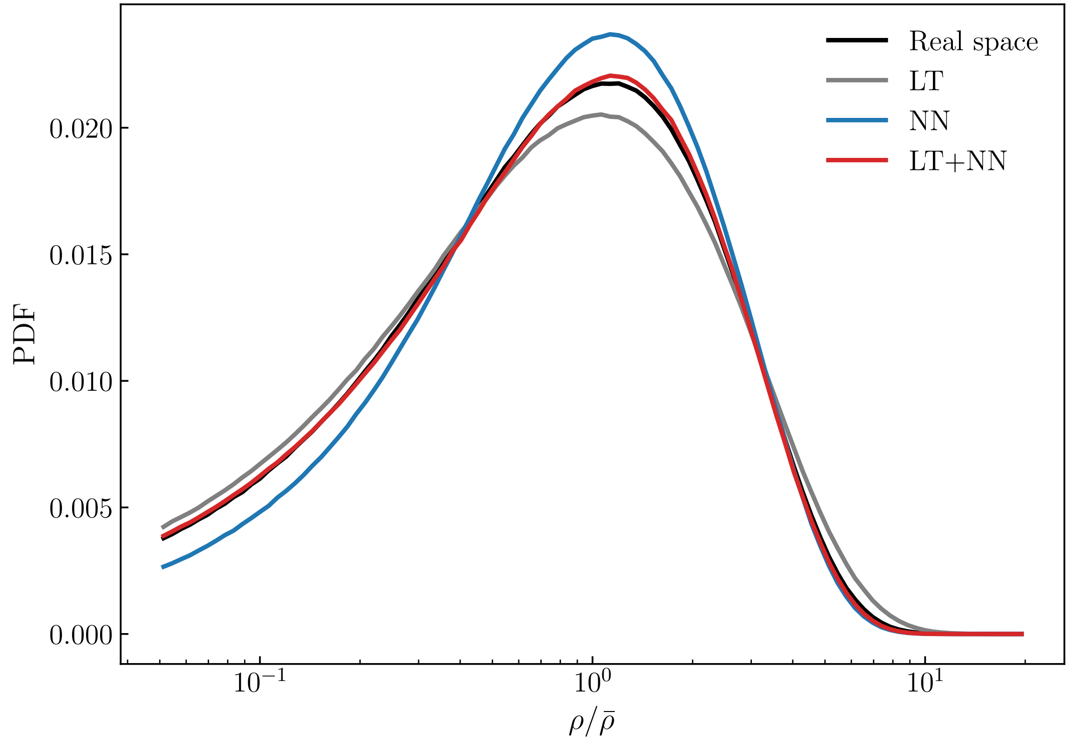
Results

Density PDF

- LT tends to underestimate densities around the mean and overestimate the tails

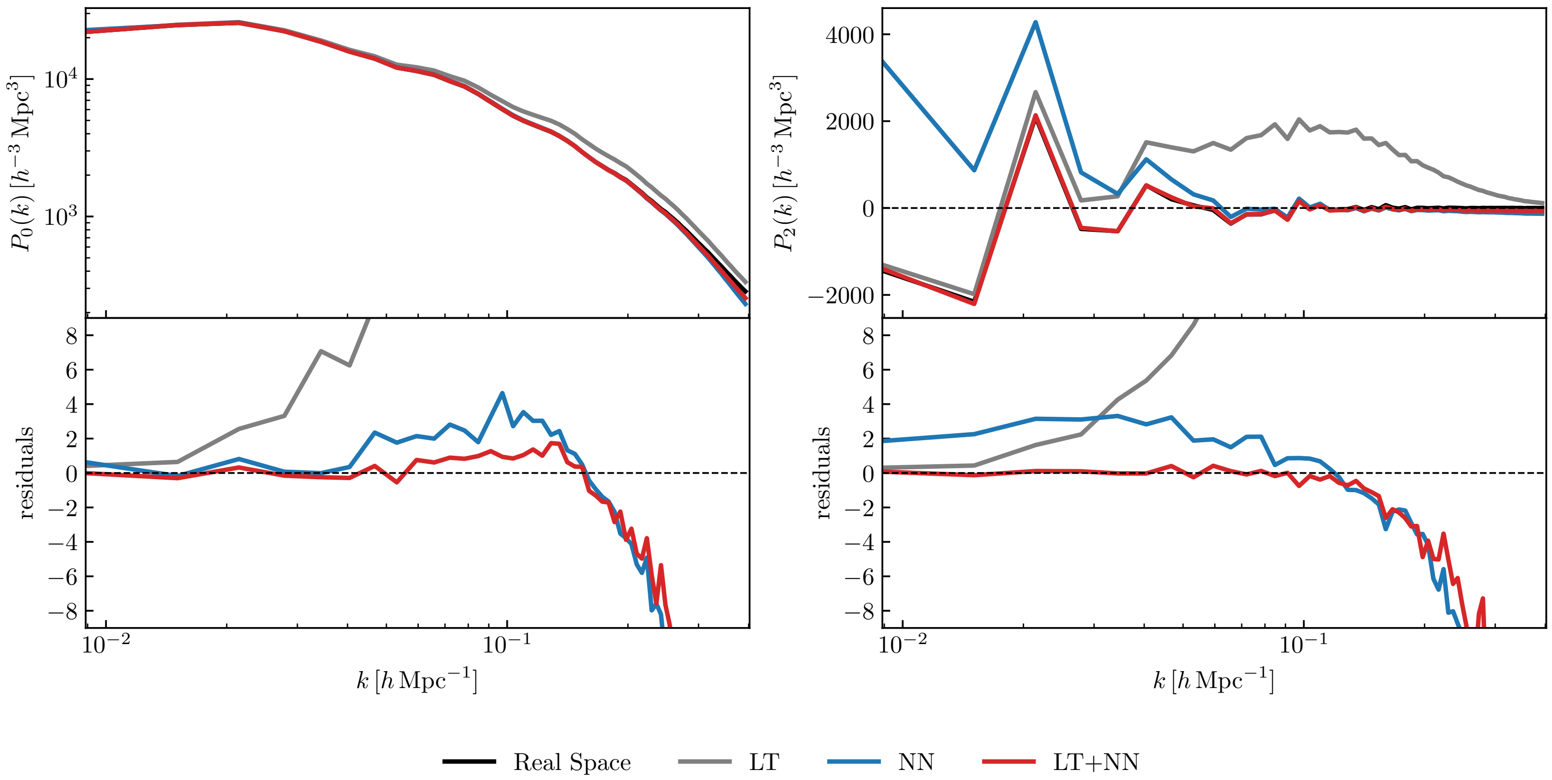
- NN tends to assign densities close to the mean in underdense and overdense regions

- LT+NN provides the best matching of the real space PDF



Results

Power Spectrum



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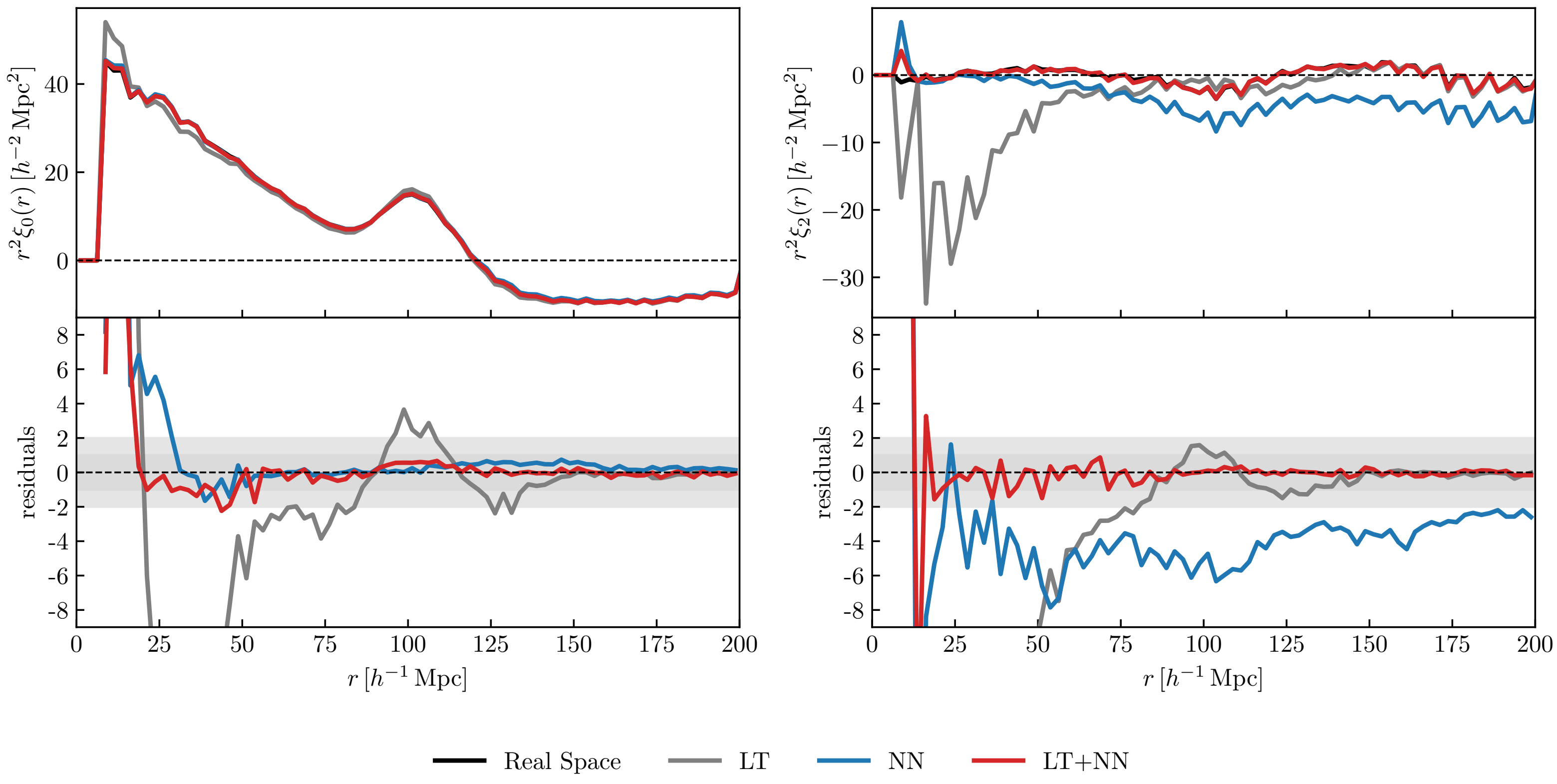
Results

Two-point correlation function



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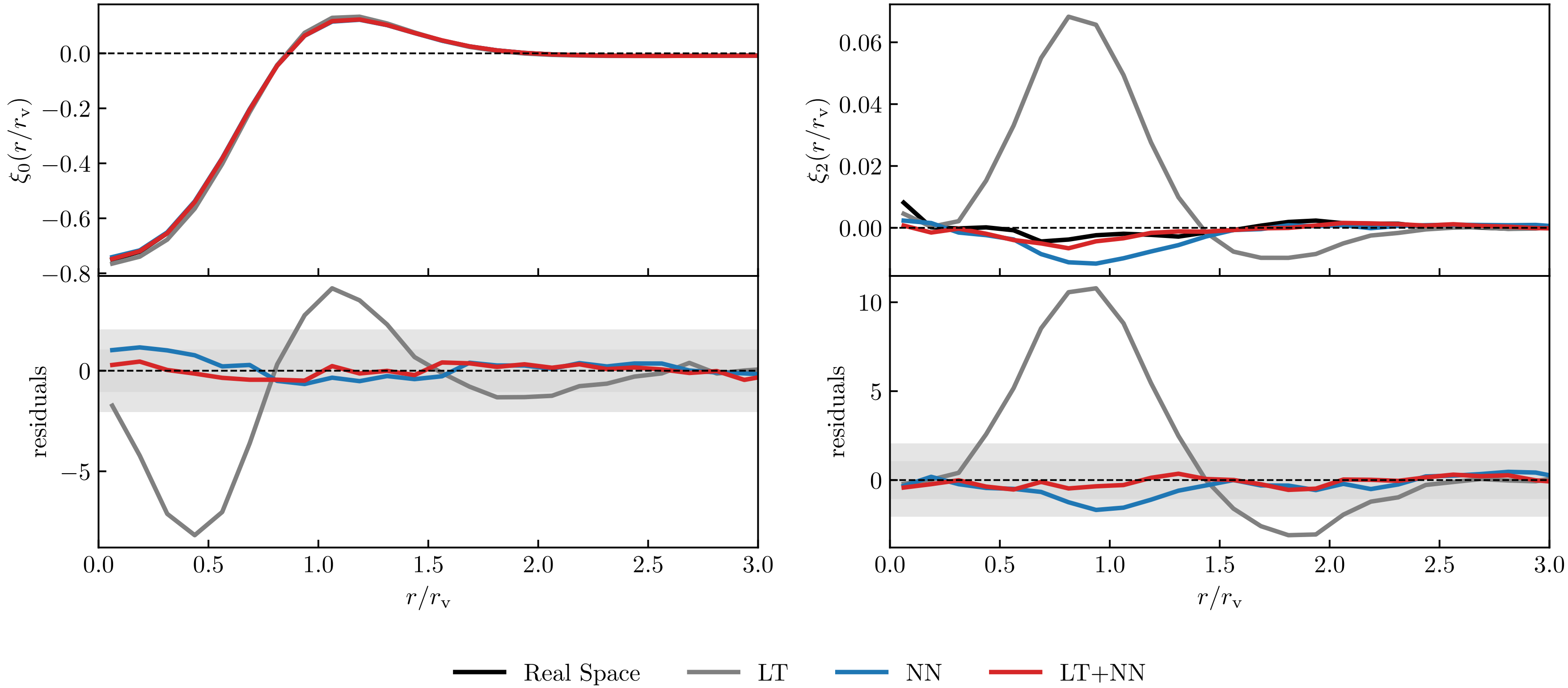
Results

Void-Halo cross correlation function



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Conclusions

Limitations of the analysis

- Network architecture must be adapted if the number of grid points changes. This can be improved (e.g. Parker et al. (2025), arXiv:2504.01092 **[astro-ph.CO]**).
- Using a finer grid (256^3) worsened MSE and 2PCF/PS residuals, likely due to insufficient training data for the increased network complexity.
- Cell size fixed at 7.8 Mpc/h limits resolution for power spectrum and correlation function measurements.
- Robustness against biases, incorrect fiducial cosmology, selection functions still needs thorough testing.

Conclusions

Recap and future work

- Combines LT’s large-scale accuracy with NN’s small-scale strengths, outperforming each individually.
- Hybrid LT+NN method reduces MSE by 50%, with excellent recovery of density PDFs and two-point statistics on scales >20 Mpc/h.
- Excels in removing redshift-space distortions in halos and cosmic voids; more robust than LT to smoothing choices.

Future Directions

- Include treatment of galaxy bias.
- Test on realistic mocks and real survey data, including complex footprints and selection effects.
- Explore advanced hybrid architectures and robustness across cosmologies.

Thank you!