Reconstructing the Local Universe with Neural Networks

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Cosmology from Home

Field reconstructions as a cosmological probe

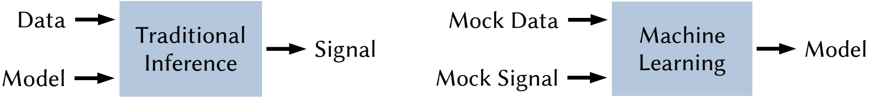
- Compare reconstructed and observed peculiar velocities to constrain the growth rate

$$-\frac{1}{H}\,\vec{\nabla}_r \cdot \vec{v}^{\,(\mathrm{lin})} = f\,\delta \qquad\qquad f \approx \Omega_\mathrm{m}^{0.55}$$

- Use reconstructed peculiar velocities to reduce errors in low-z Hubble measurement

$$z^{\mathrm{cosmo}} = \frac{1 + z^{\mathrm{observed}}}{1 + z^{\mathrm{peculiar}}} - 1$$

Why use neural nets?



- Caveats of traditional inference methods
  - Often assume simplified model for prior, likelihood, bias
  - Expensive for sophisticated model
- Neural nets (NNs) may help
  - Learn prior, likelihood, bias, selection from mock signal and data
  - Can be trained relatively cheaply on one or few GPUs
- But can we trust the neural net results?

Statistical interpretation of neural net estimators

- Mean Squared Error loss

$$\mathrm{MSE} = \sum_{S,D} P(S,D)\left(\hat{S}(D) - S\right)^2$$

- Linear NN

$$\hat{S}^{\,\mathrm{lin\,NN}}(D) = wD + b$$

- Minimize MSE

$$\frac{\partial \mathrm{MSE}}{\partial w_{ij}} = 0 = \frac{\partial \mathrm{MSE}}{\partial b_i}$$

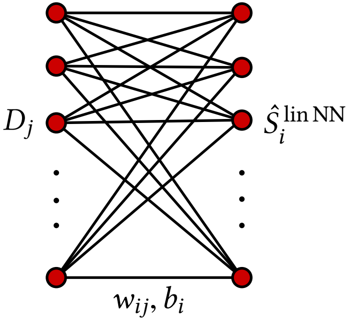
$\Longrightarrow$ Equivalent to Wiener filter

$$\hat{S}^{\,\mathrm{lin\,NN}}(D) = \langle SD \rangle \langle DD \rangle^{-1} D = \hat{S}^{\,\mathrm{WF}}(D)$$

D : data

S : signal

$\hat{S}$: signal estimate



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Statistical interpretation of neural net estimators

- Mean Squared Error loss

$$\mathrm{MSE} = \sum_{S,D} P(S,D)\left(\hat{S}(D) - S\right)^2$$

- Minimize MSE for general (nonlinear) NN

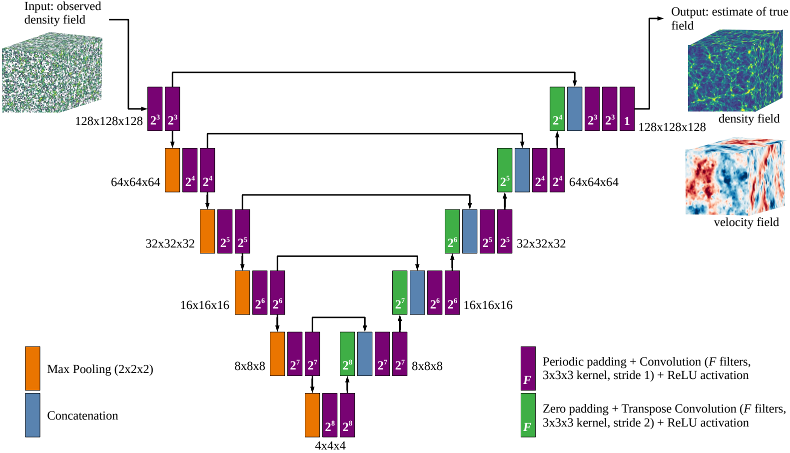
$$0 = \frac{\delta \mathrm{MSE}}{\delta \hat{S}^{\mathrm{NN}}(D)} = 2 \sum_{S} \underbrace{P(S,D)}_{P(S|D)\,P(D)} \left(\hat{S}^{\mathrm{NN}}(D) - S\right)$$

$$\Rightarrow \hat{S}^{\mathrm{NN}}(D) = \sum_{S} P(S|D)\, S = \langle S|D \rangle$$

$\Longrightarrow$ Equivalent to mean of posterior (if sufficiently expressive)

U-Net Autoencoder (AE)

- Deep encoder + decoder NN with skip connections
- Very expressive and scalable



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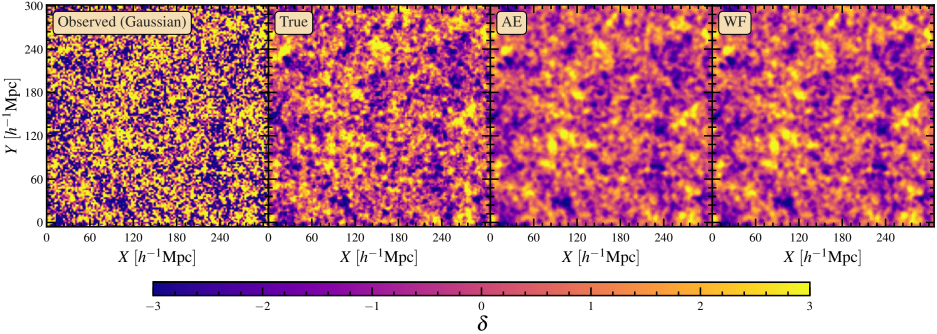
Cross-check for Gaussian fields

- Visual comparison



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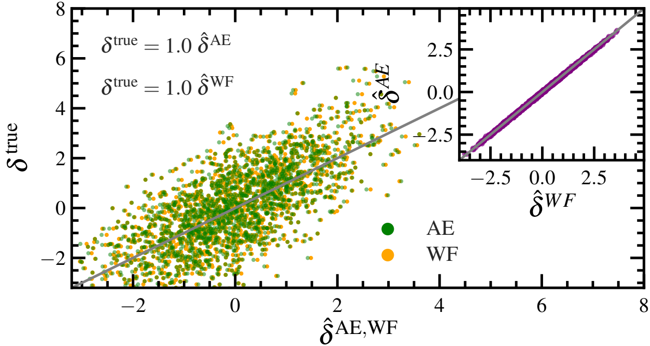
Cross-check for Gaussian fields

- Point-by-point comparison



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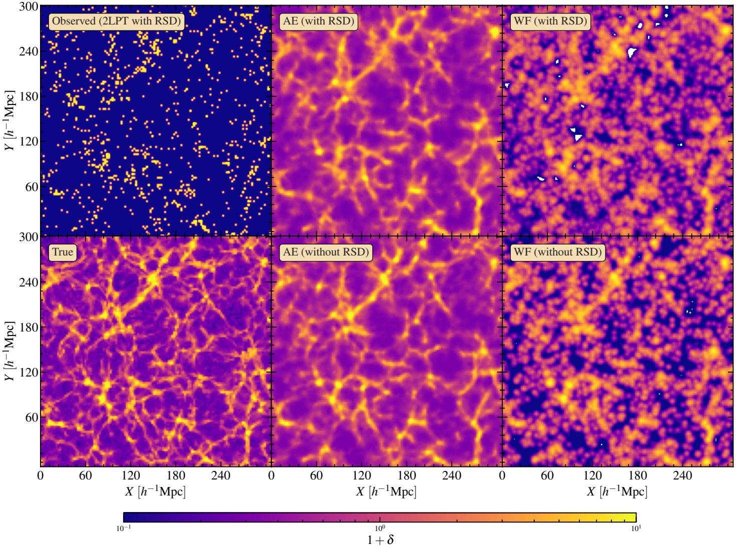
$\Longrightarrow$ AE agrees with Wiener filter for Gaussian fields

Non-Gaussian fields

- Simplified mock fields:
  - Periodic box with 300 h^{-1} Mpc side length
  - Fields on 128^3 grid
  - Signal: 2LPT density and velocity fields
  - Data: Poisson-sampled galaxies with $\bar{n} = 5 \times 10^{-3}\ h^3\,\mathrm{Mpc}^{-3}$
  - RSD along Z-axis
  - 1000 realizations

Density reconstruction



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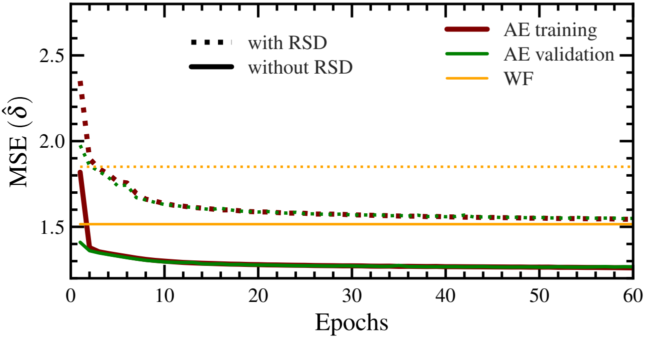
Density reconstruction

- MSE loss



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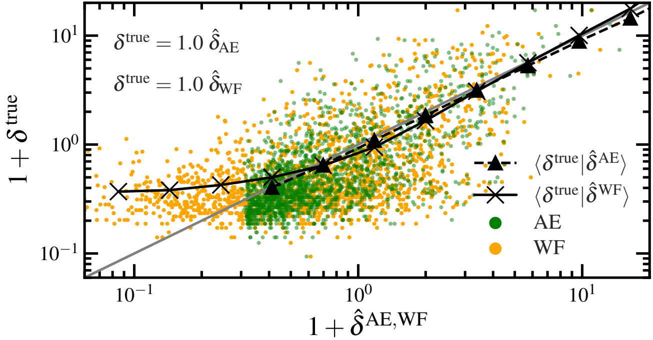
$\Rightarrow$ AE more accurate than WF

Density reconstruction

- Point-by-point and binned comparisons



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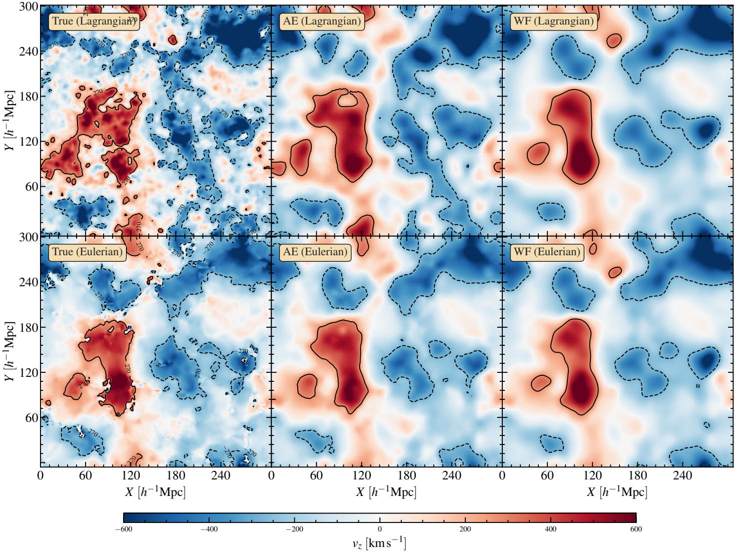
$\Rightarrow$ AE matches behaviour of mean posterior estimate

Velocity reconstruction



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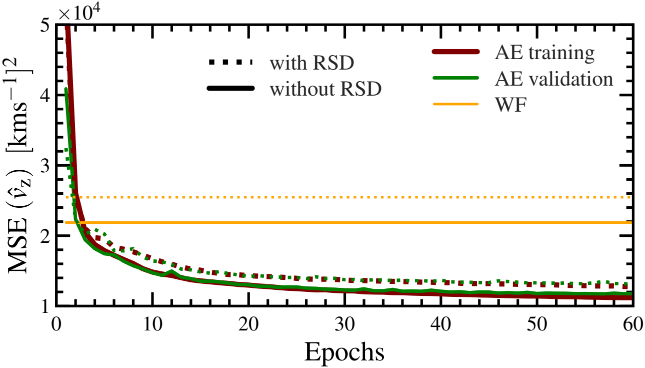
Velocity reconstruction

- Lagrangian velocity MSE loss



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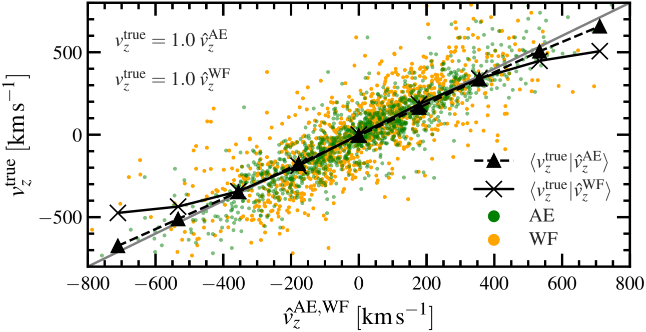
$\Rightarrow$ AE more accurate than WF

Velocity reconstruction

- Lagrangian velocity point-by-point and binned comparisons



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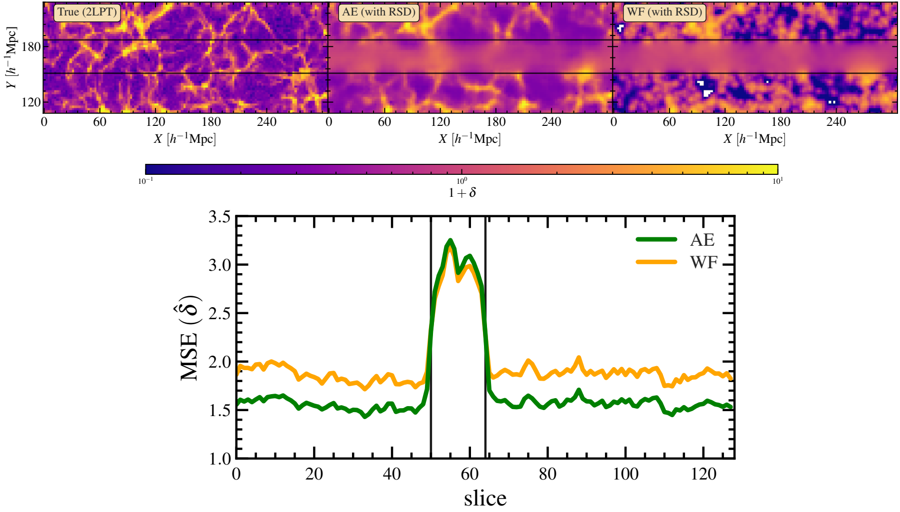
$\Longrightarrow$ AE matches behaviour of mean posterior estimate

Density reconstruction with mask



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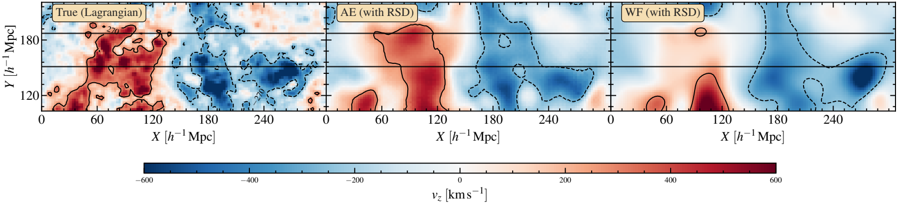
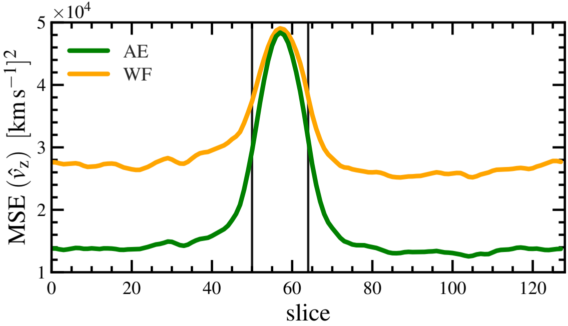
Velocity reconstruction with mask





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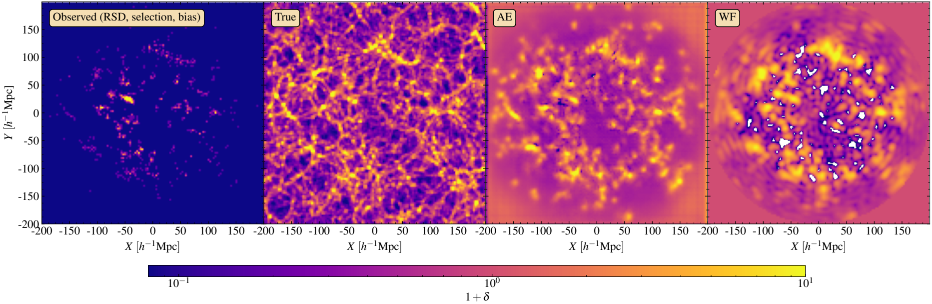
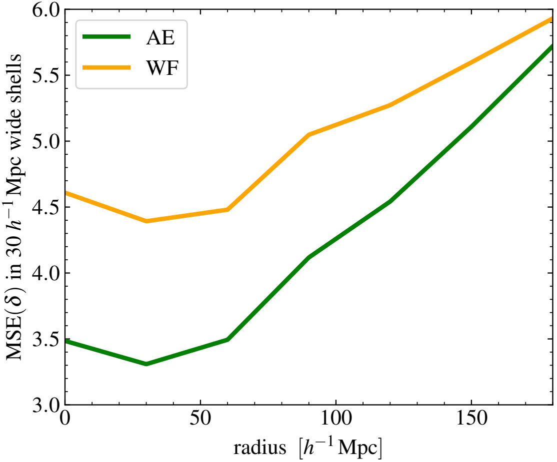
Preliminary: Reconstruction from realistic mocks

- Mocks from Quijote simulations (Villaescusa-Navarro+ 2020)
- RSD in radial direction
- Radial selection function
- Galaxy bias



Preliminary: Reconstruction from realistic mocks



$\Rightarrow$ AE handles realistic RSD, selection and bias

$\Rightarrow$ AE is consistently more accurate than WF

Conclusion

- Traditional reconstruction methods often with simplified model and/or expensive
- Neural net learns statistics, selection, bias from mocks
- Neural net with MSE loss yields efficient mean posterior estimate
- Mean posterior reconstruction consistently improves over Wiener filter
- Next step: apply to surveys