The robustness of machine learning for 21cm foreground removal

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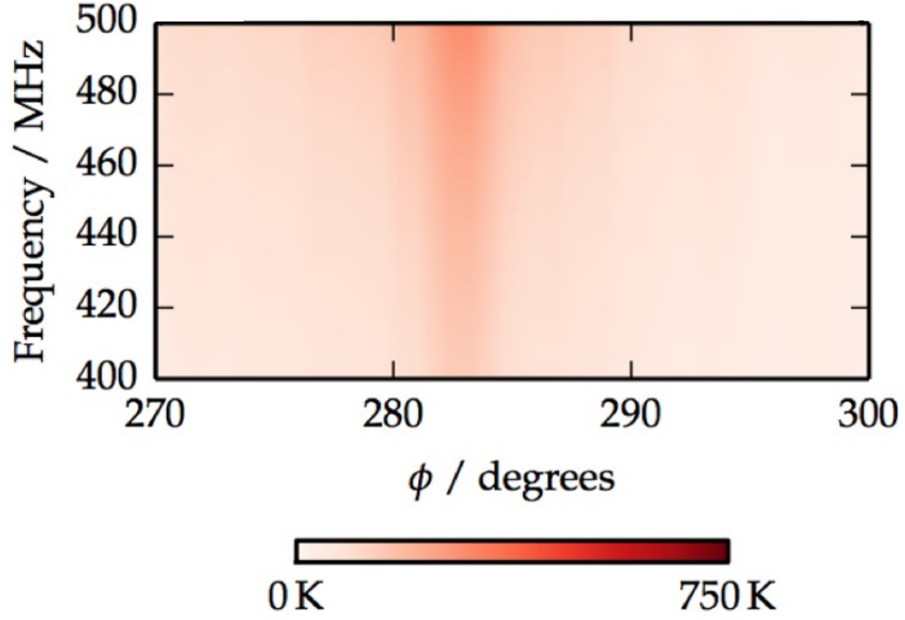
Introduction

- IM as one main goal of SKA
- Foreground critical for 21cm detection
- Large SKA dataset incoming

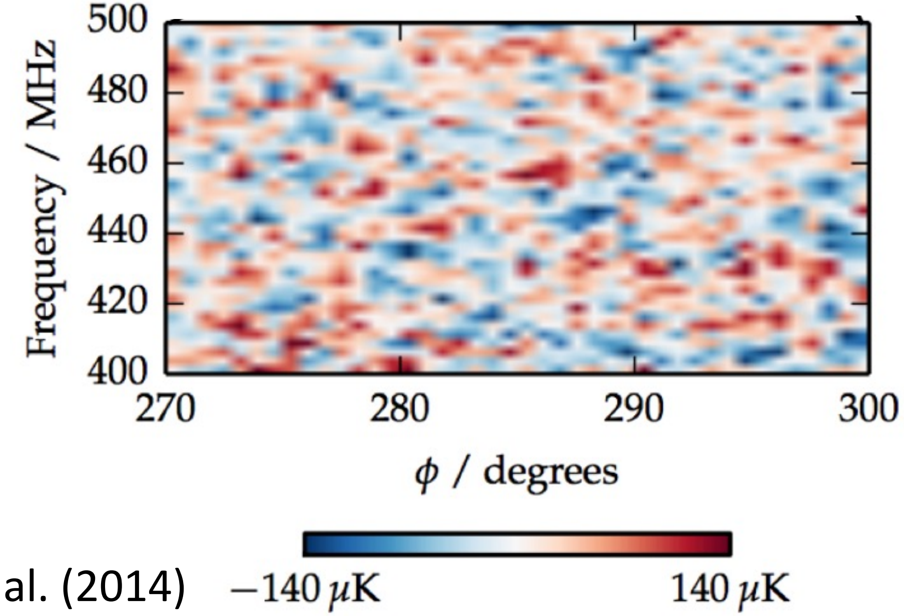
- Traditional approach:
  - Sensitive to systematics (e.g., KL filter)
  - Signal loss (e.g., PCA)

- Machine learning algorithm?
  - Comparable with mature technique?
  - Consistent under different models?
  - Robust againt systematics?

Synchrotron



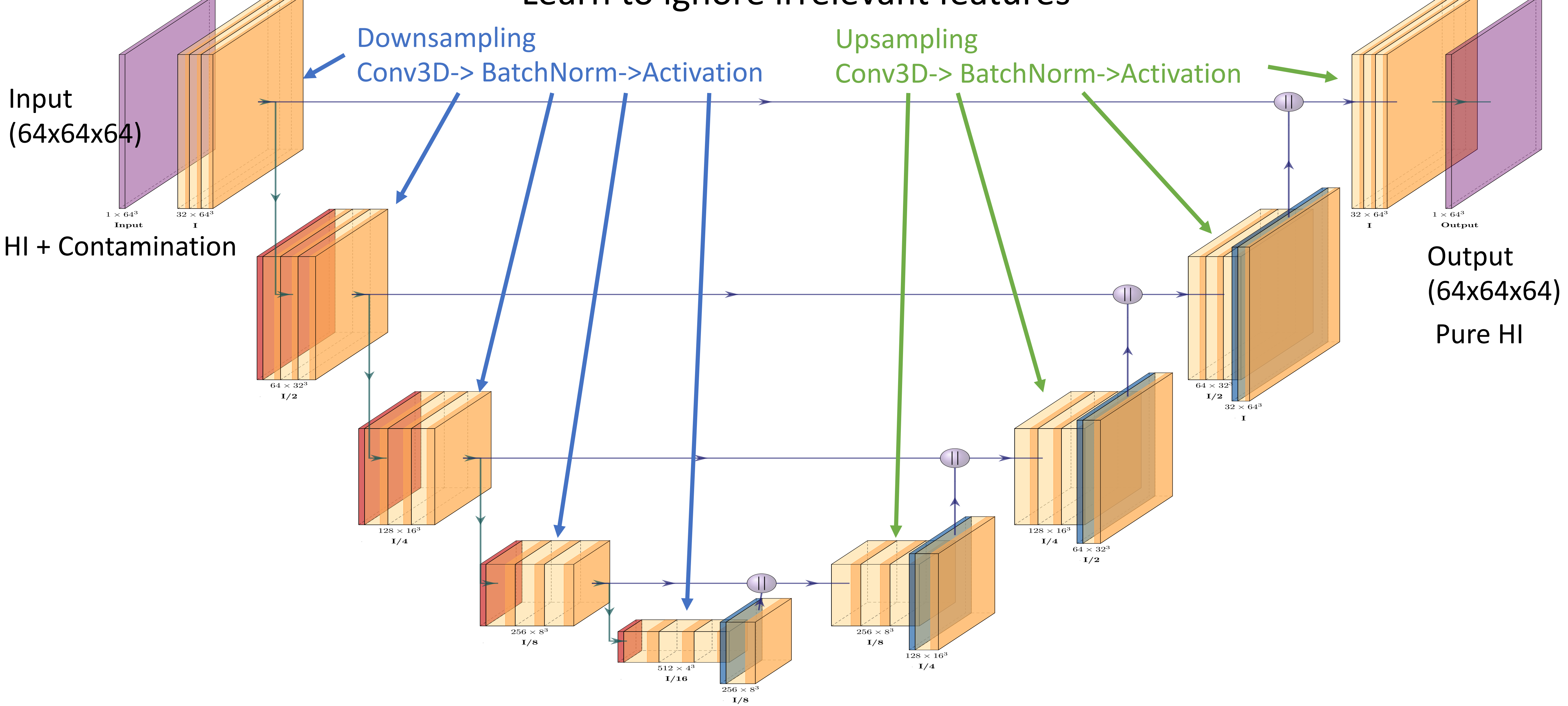
HI



Shaw et al. (2014)

U-net for IM

- One type of artificial neutral network
- Learn to ignore irrelevant features



Sky models

- MS model (Gaussian model):
  - Santos et al. (2005)
  - FG: $$C_\ell(\nu_i, \nu_j) = A\left(\frac{1000}{\ell}\right)^\beta \left(\frac{\nu_{\rm ref}^2}{\nu_i \nu_j}\right)^\alpha I_\ell^{ij}$$
  - HI: Battye et al. 2013 $$\bar{T}_{\rm obs}(z) = 44\mu{\rm K}\left(\frac{\Omega_{\rm HI}h}{2.45^{-4}}\right)\frac{(1+z)^2}{E(z)} \qquad C_\ell = \frac{H_0 b^2}{c}\int {\rm d}z E(z)\left[\frac{W(z)\bar{T}(z)D(z)}{r(z)}\right]^2 P_{\rm cdm}\left(\frac{\ell+\frac{1}{2}}{r}\right)$$
- CoLoRe model (non-Gaussian HI):
  - HI: Lagrangian perturbation theory
- Planck Sky Model (non-Gaussian FG):
  - Synchrotron : Haslam 408 map;
  - Free-free : Hα template;
  - Point source: NVSS catalogue;

Instrumental systematics

- Instrumental parameters:
  - Beam: SKA-mid single dish Gaussian beam
  - Frequency range: 700-1020 MHz, 64 channels

- Instrumental systematics:
  - Frequency-dependent beam $\theta_{\mathrm{B}}(z_i) = \theta_{\mathrm{FWHM}}(\nu_{\mathrm{mid}}) \frac{\nu_{\mathrm{mid}}}{\nu_i}$
  - Gain drift G_{υ} = 1+ΔG_{υ} $\Delta G(\nu) = G_0 \sin(G_1 \nu + G_2) + 1$

- Format:
  - Healpix full sky maps → 192 equal-size patches (64x64x64)

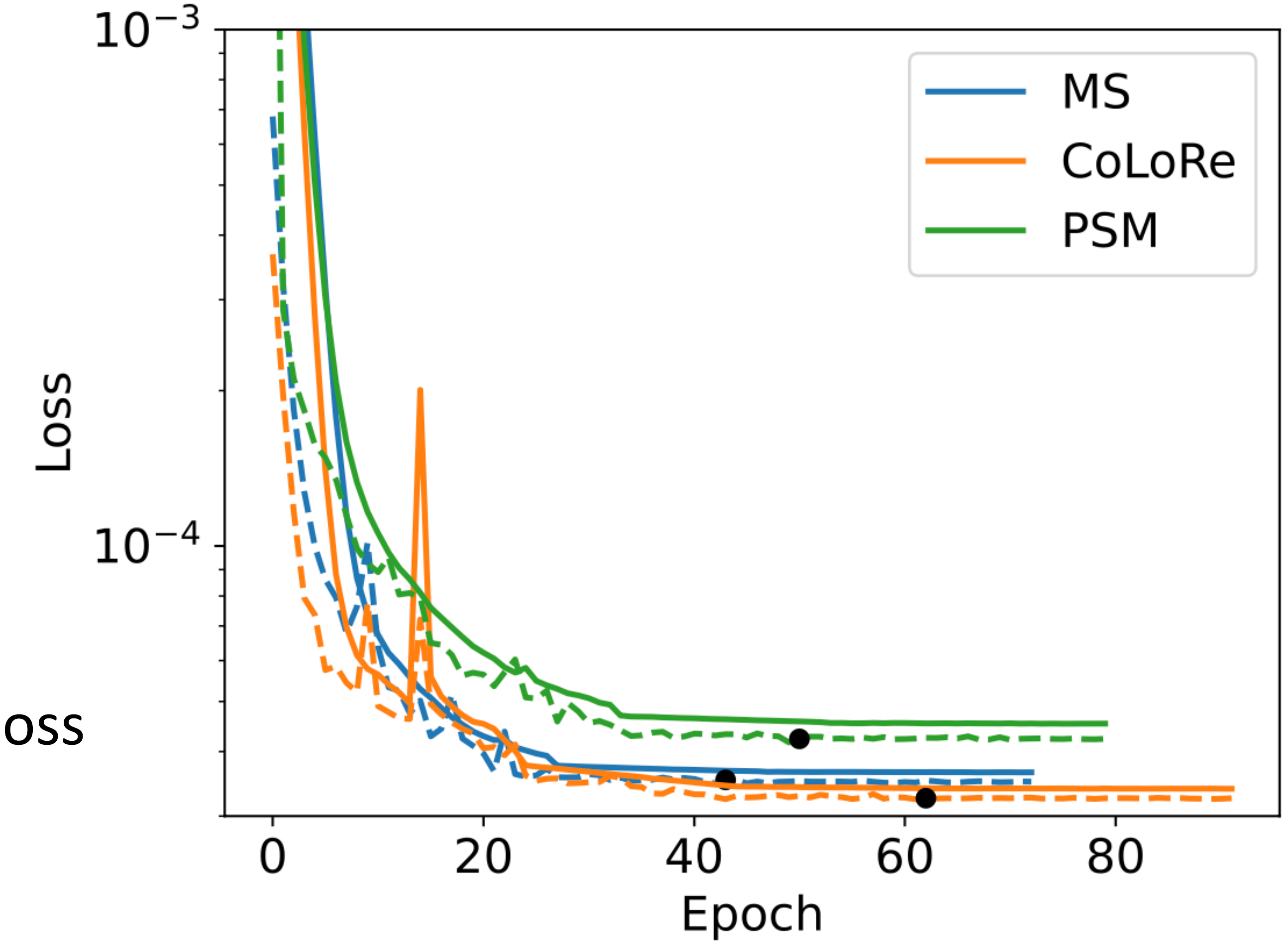
Loss function

Minimise reconstruction errors (loss)

$$\mathcal{L}(\mathbf{x}, \mathbf{x}') = \|\mathbf{x} - \mathbf{x}'\|^2$$

Train loss: how model fits the training data
Validation loss: how model performs

- Training: 40 healpix maps (7680 samples)
- Validation: 10 healpix maps (1920 samples)
- Test: 10 healpix maps (1920 samples)

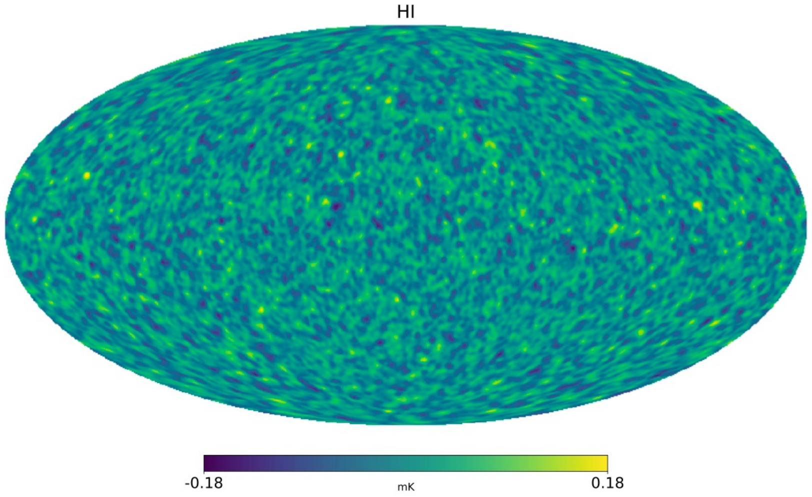


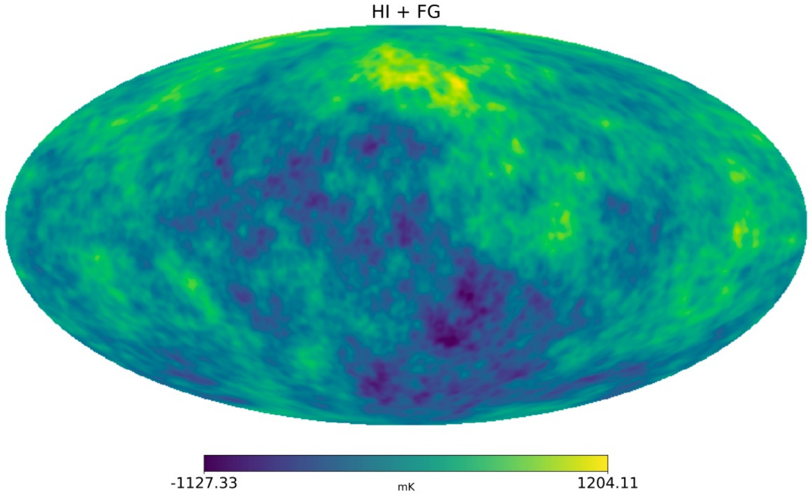
- Comparable under different models
- PSM: more complicated feature -> higher loss

MS model - maps

- Network can’t handle large dynamic range
- Apply PCA to pre-process the data (mode = 2), use ML for fine tuning

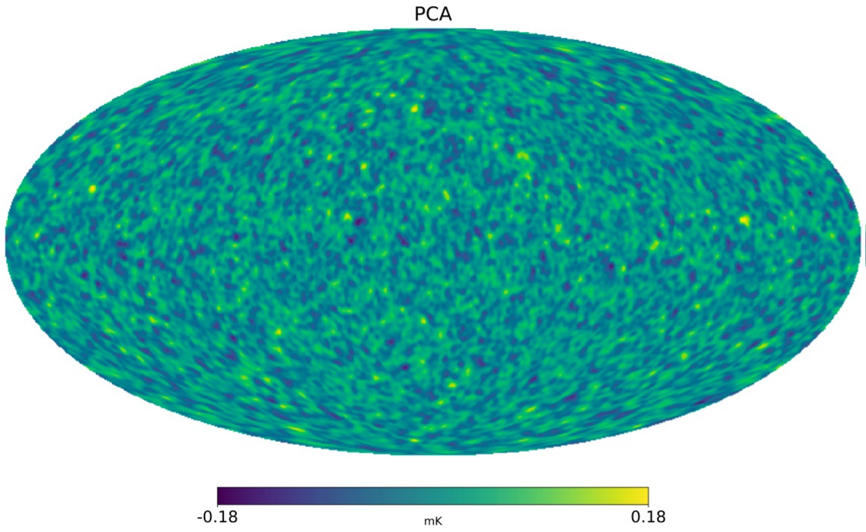
HI

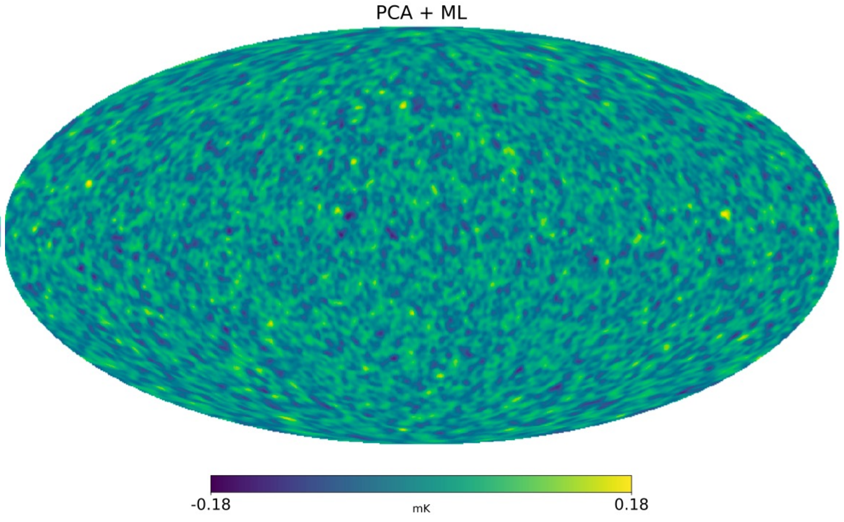




HI + FG

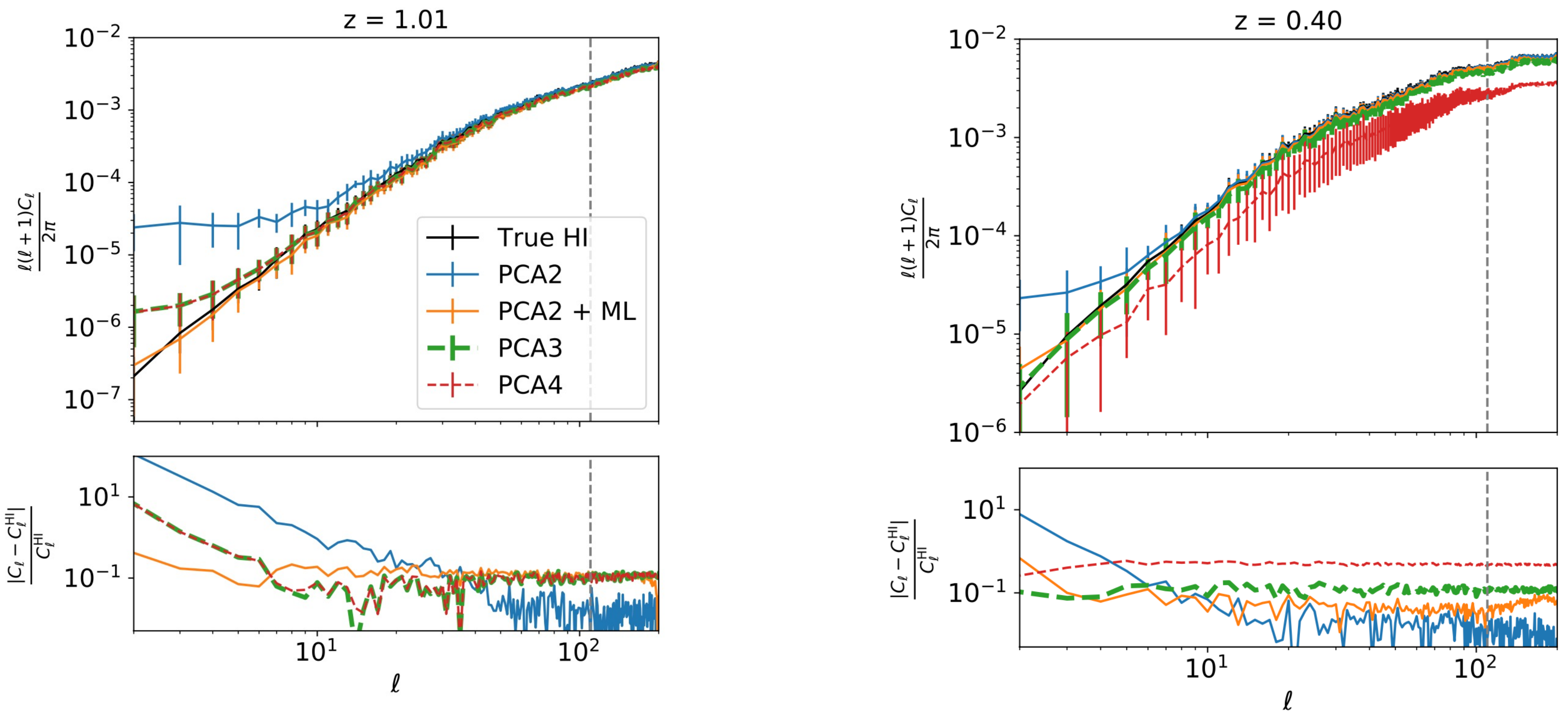
PCA





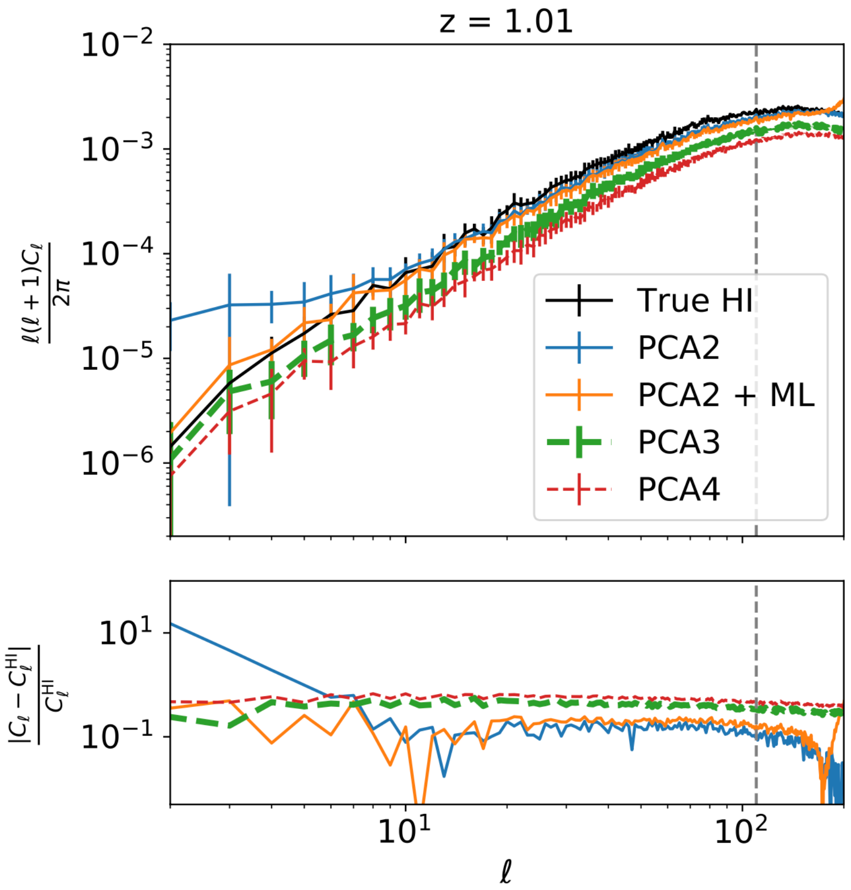
PCA + ML

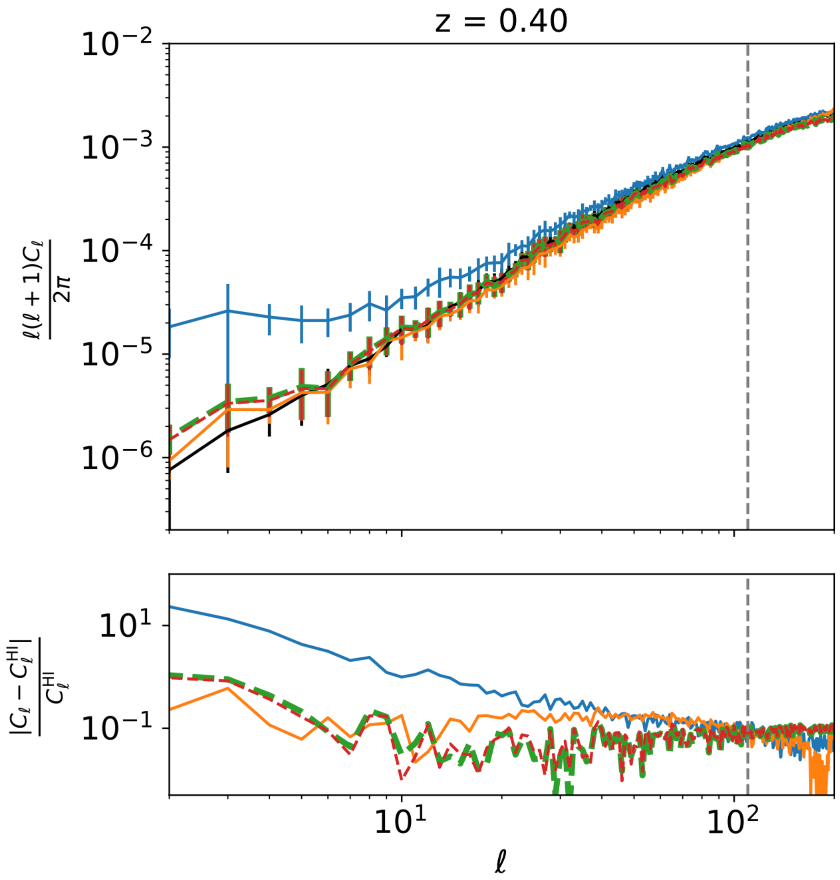
MS model – Power Spectrum



ML particularly effective at reducing large-scale FG residuals
ML comparable with PCA 3 alone
ML less sensitive to redshift
On average, fractional residual of 10% signal over all scales

CoLoRe model – Power Spectrum



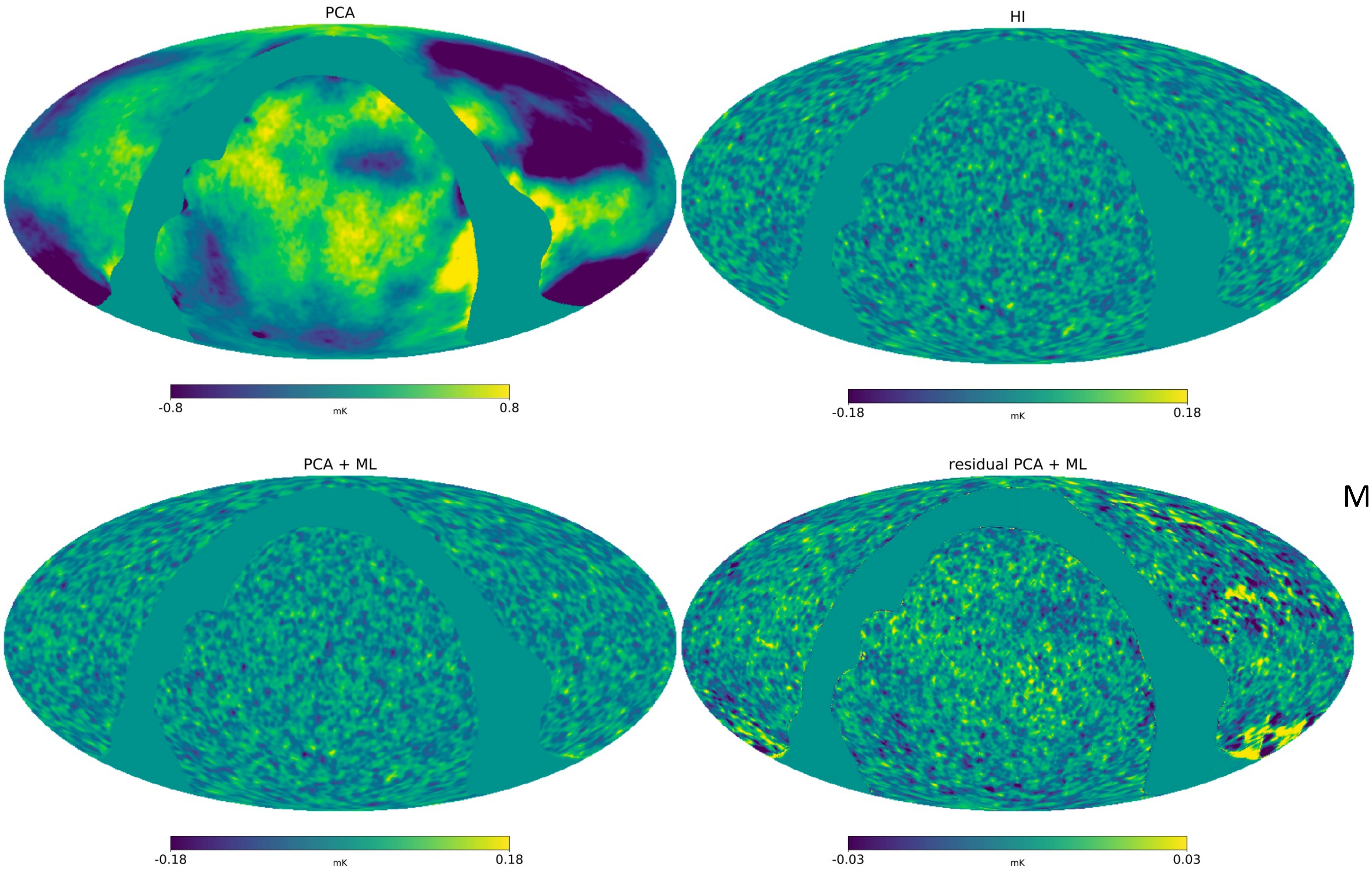


Consistent with MS model

Comparable with PCA 3,4 alone

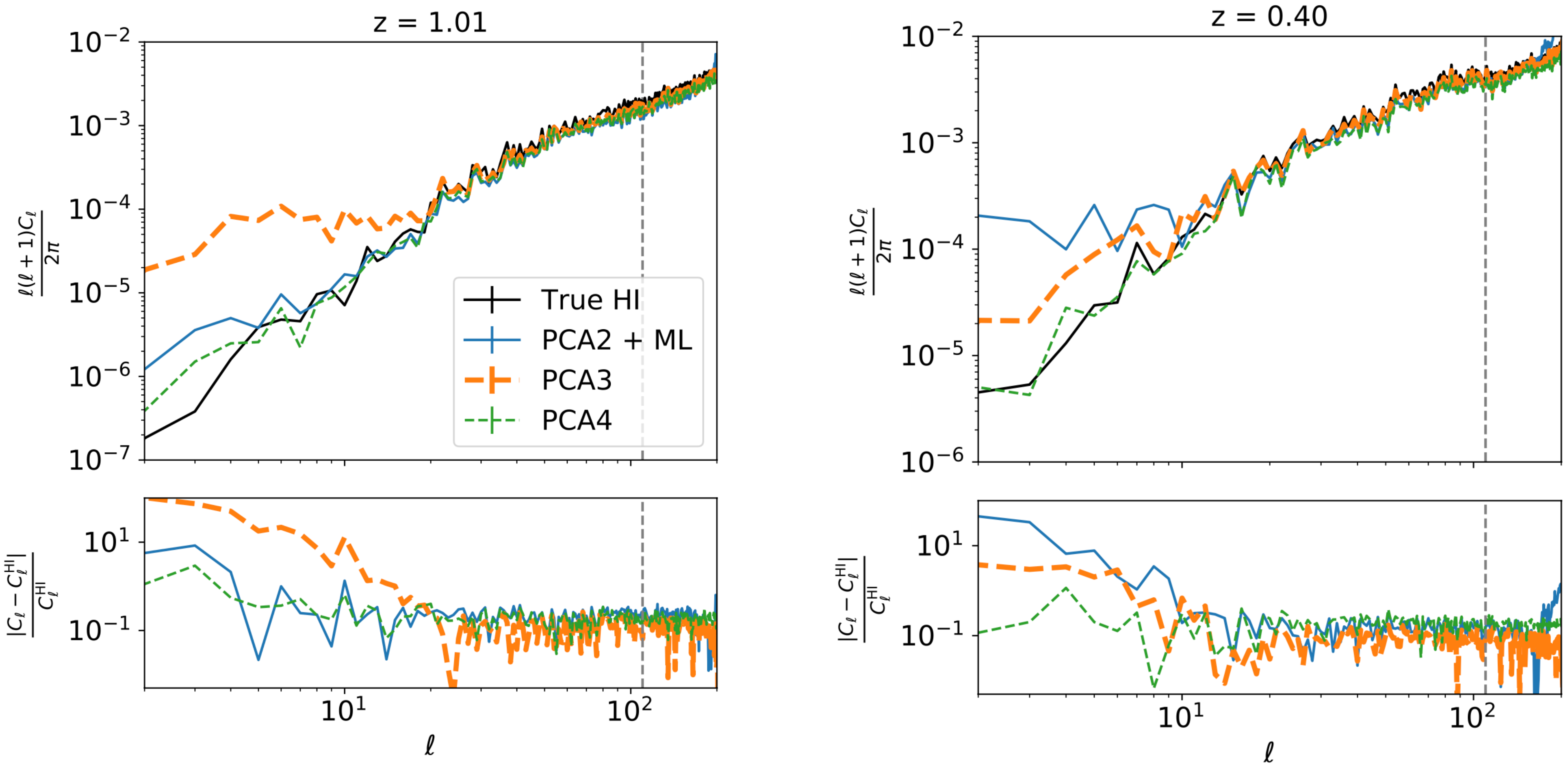
On average, fractional residual of 10% signal over all scales

PSM model – maps



ML can safely handle masks

PSM model – Power Spectrum



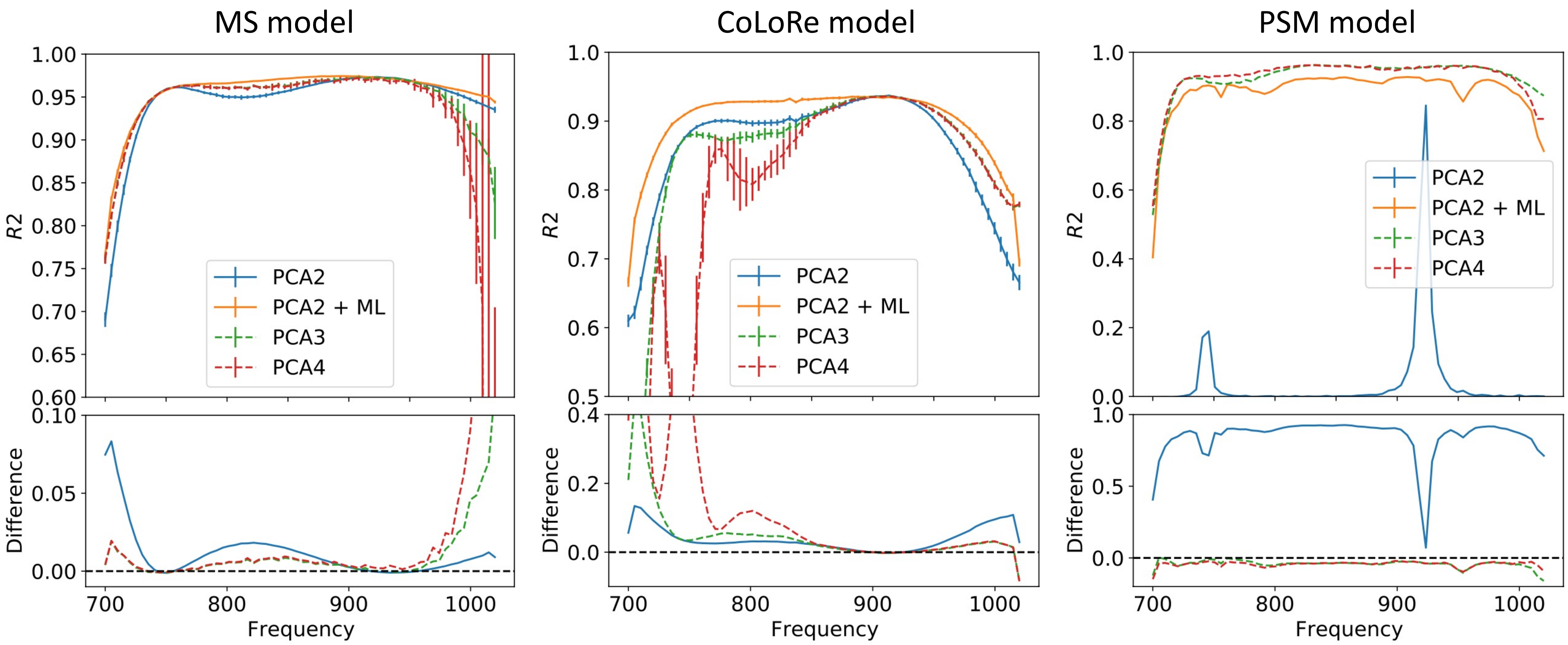
Affected by large residuals after PCA2 removal
Overall comparable with MS, CoLoRe model
Lack of signal-to-noise revolution information along redshift

R^2 score comparison

Coefficient of determination

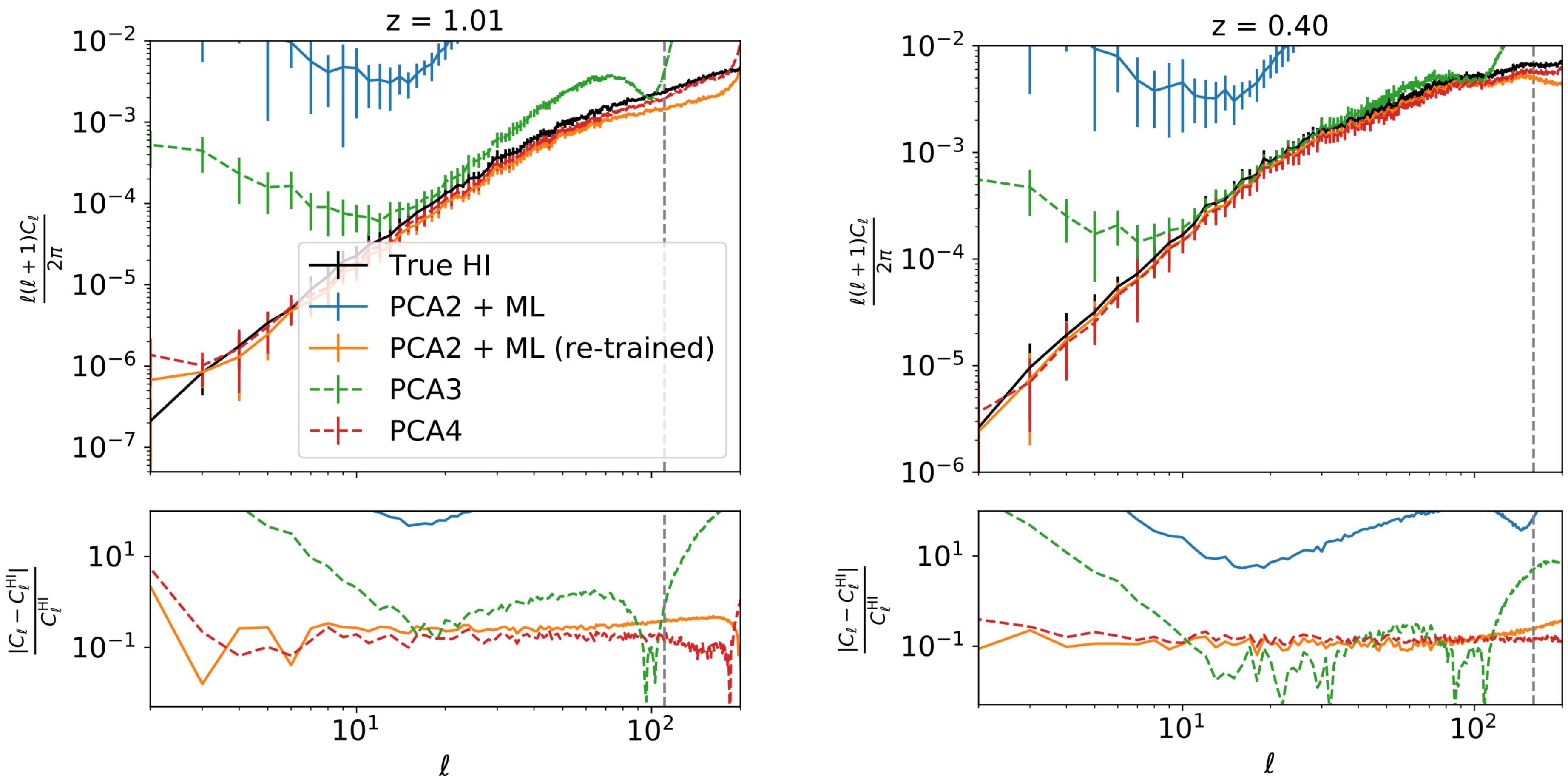
Evaluate the performance of the ML model
Accuracy measurement of predictions v.s. target

$$R^2 = 1 - \frac{\sum_i (t_i - o_i)^2}{\sum_i (t_i - \bar{t})^2}$$



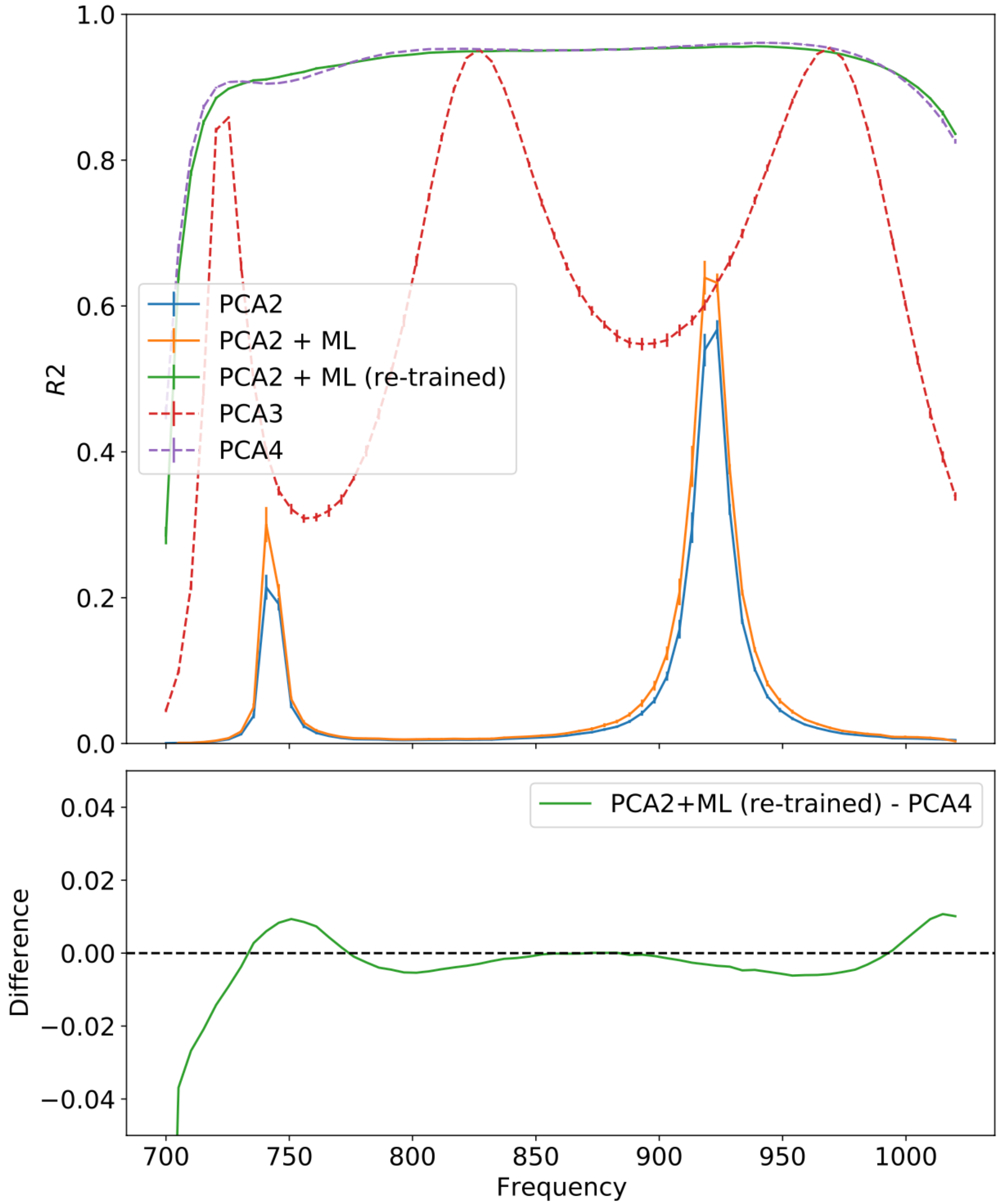
Frequency Beam – Power Spectrum

$$\theta_{\rm B}(z_i) = \theta_{\rm FWHM}(\nu_{\rm mid})\frac{\nu_{\rm mid}}{\nu_i}$$



ML doesn't handle surprise
Beam info during re-training is critical
Consistent with fixed-beam after re-training (residual ~ 10% signal)
Comparable to PCA4 alone

Frequency Beam – R^2 score



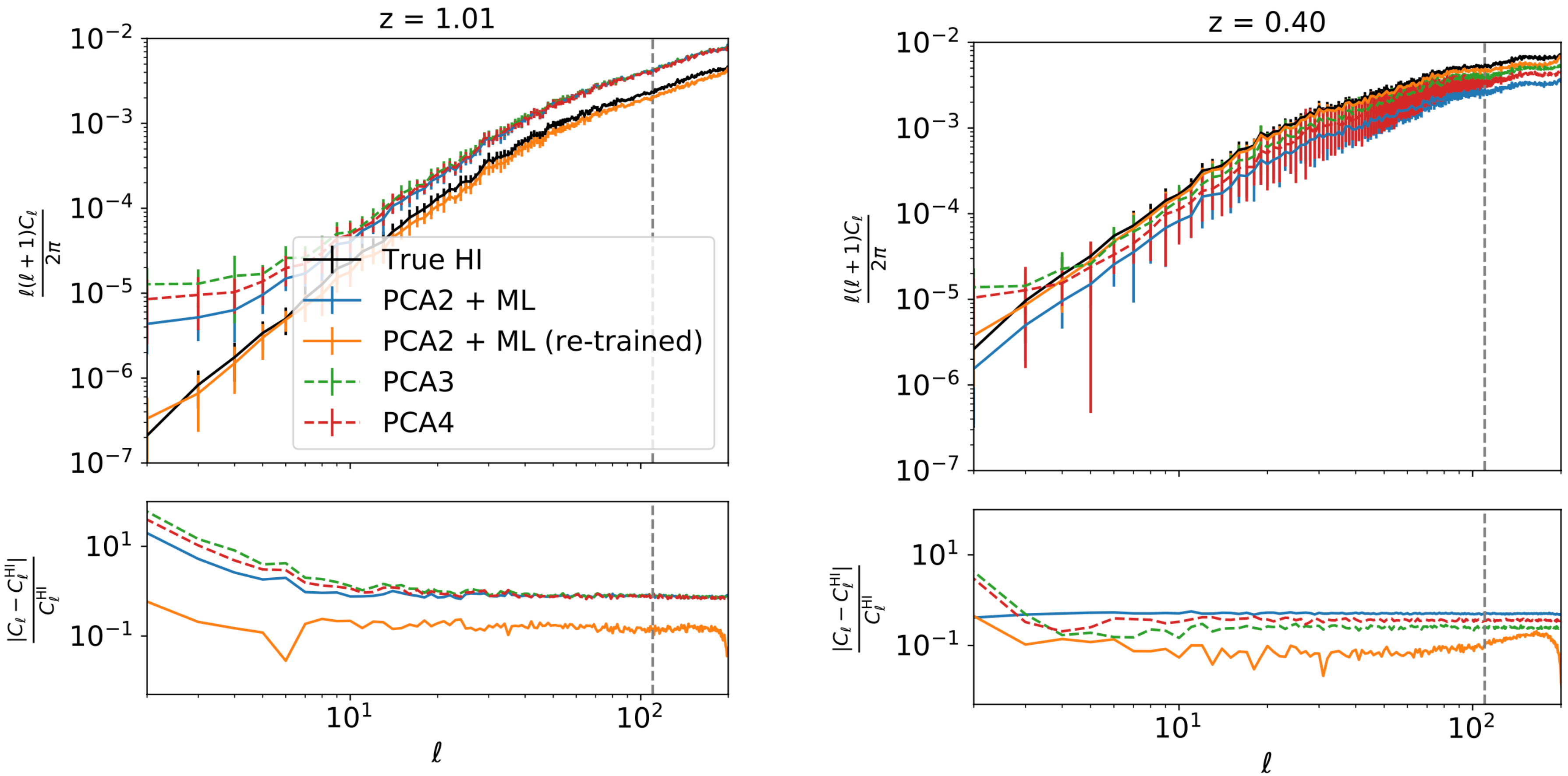
ML doesn’t handle surprise

Beam info during re-training is critical

Comparable to PCA4 alone

Gain drift – Power Spectrum

$$\Delta G(\nu) = G_0 \sin(G_1 \nu + G_2) + 1$$



ML doesn't handle surprise

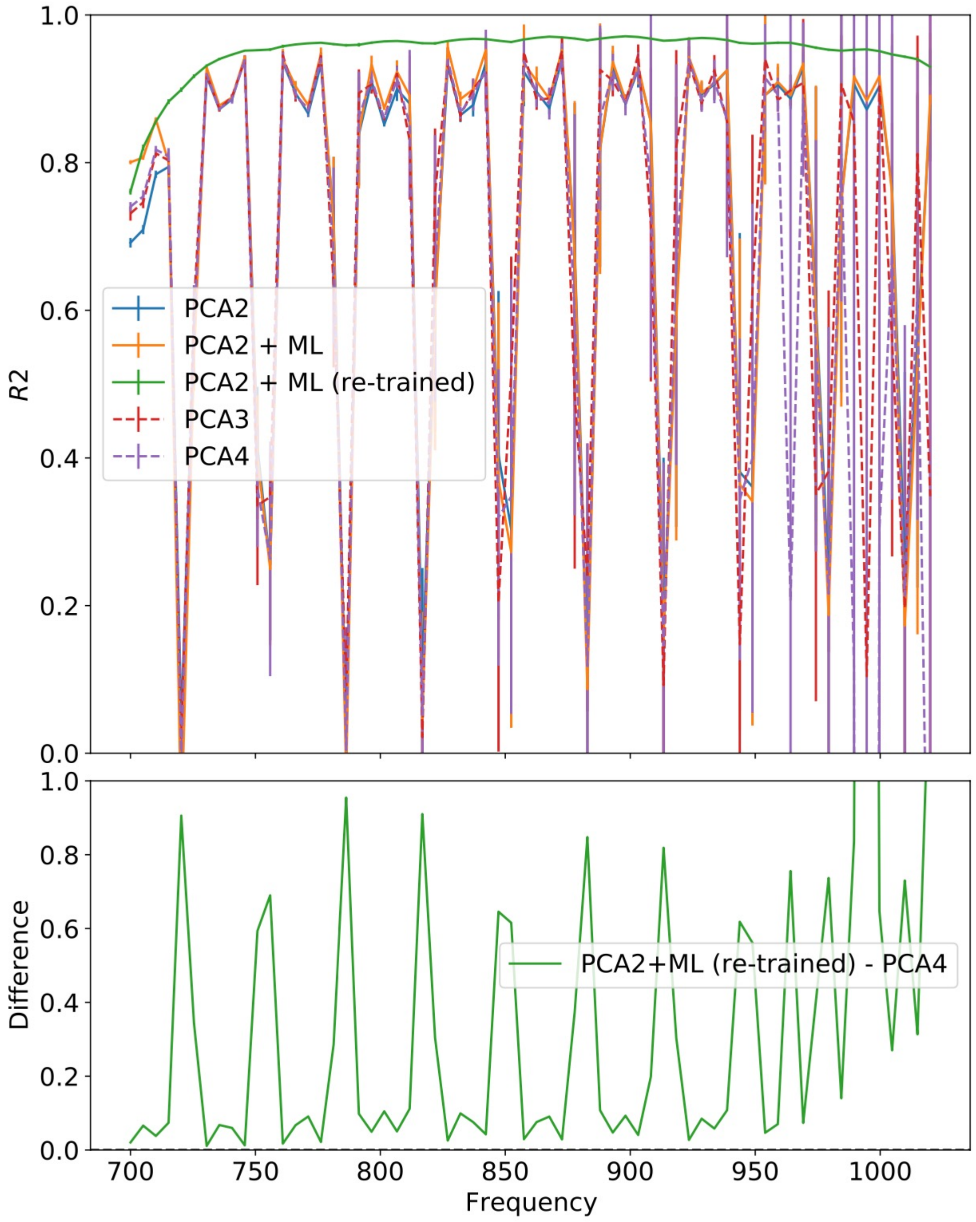
Gain info during re-training is critical

Consistent with unit gain after re-training (residual ~ 10% signal)

Advantage over PCA alone

Gain drift – R^2 score

$$\Delta G(\nu) = G_0 \sin(G_1 \nu + G_2) + 1$$



Beam info during re-training is critical
PCA alone shows sinusoidal pattern due to gain drift

Conclusions

- ML has consistent performance under different simulations
- ML returns comparable results with traditional methods
- ML requires knowledge of the data – blind usage doesn’t work
- ML can’t handle well systematics without prior knowledge
- Prior systematics knowledge significantly improves ML performance
- In real data:
  - ML provides complementary method for 21cm foreground removal
  - One should estimate the potential systematics before applying ML
- Limitations:
  - Depends on pre-process
  - Lack of redshift information