

# 21cm foreground removal with machine learning

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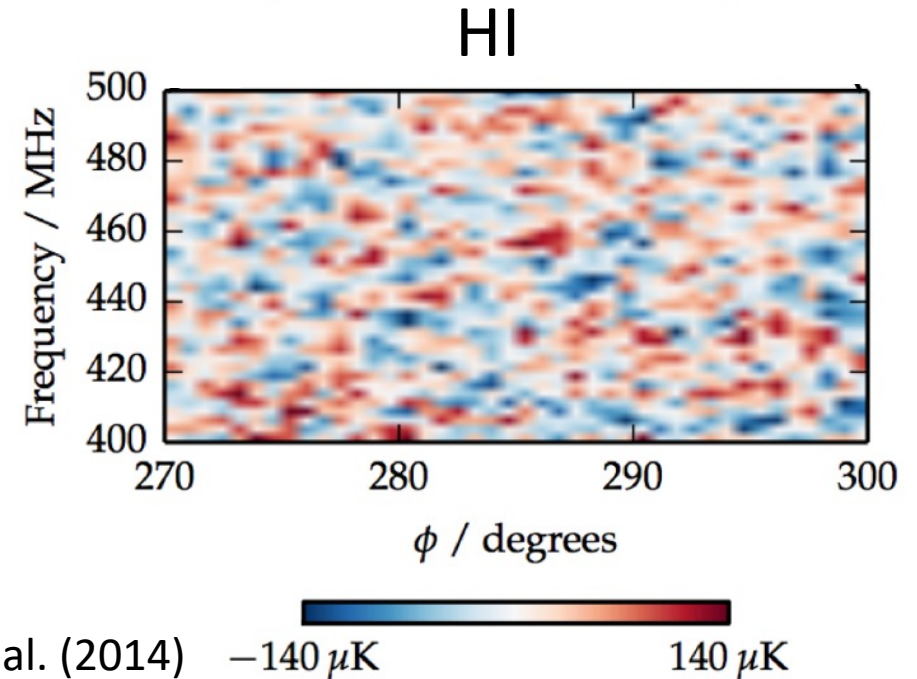
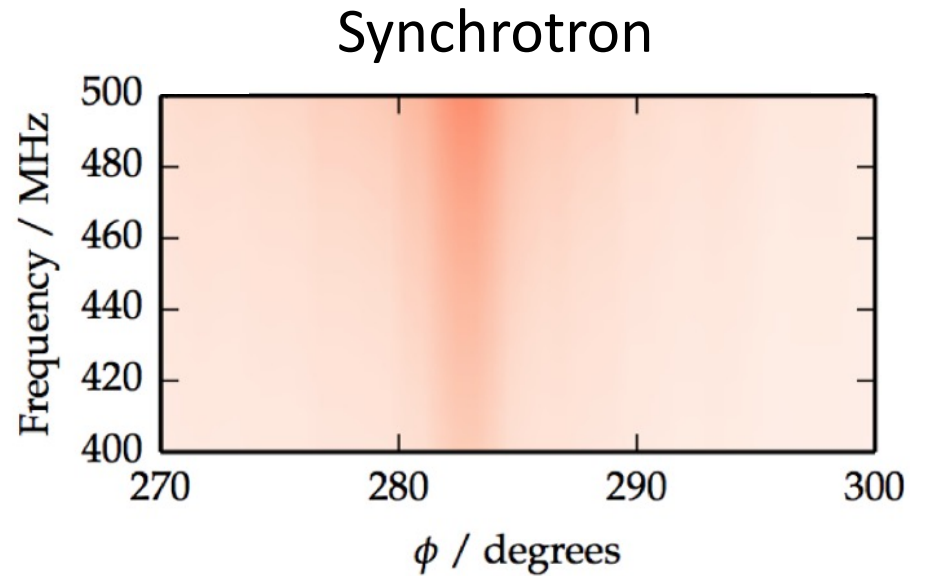
Ecole Polytechnique Fédérale de Lausanne (EPFL)

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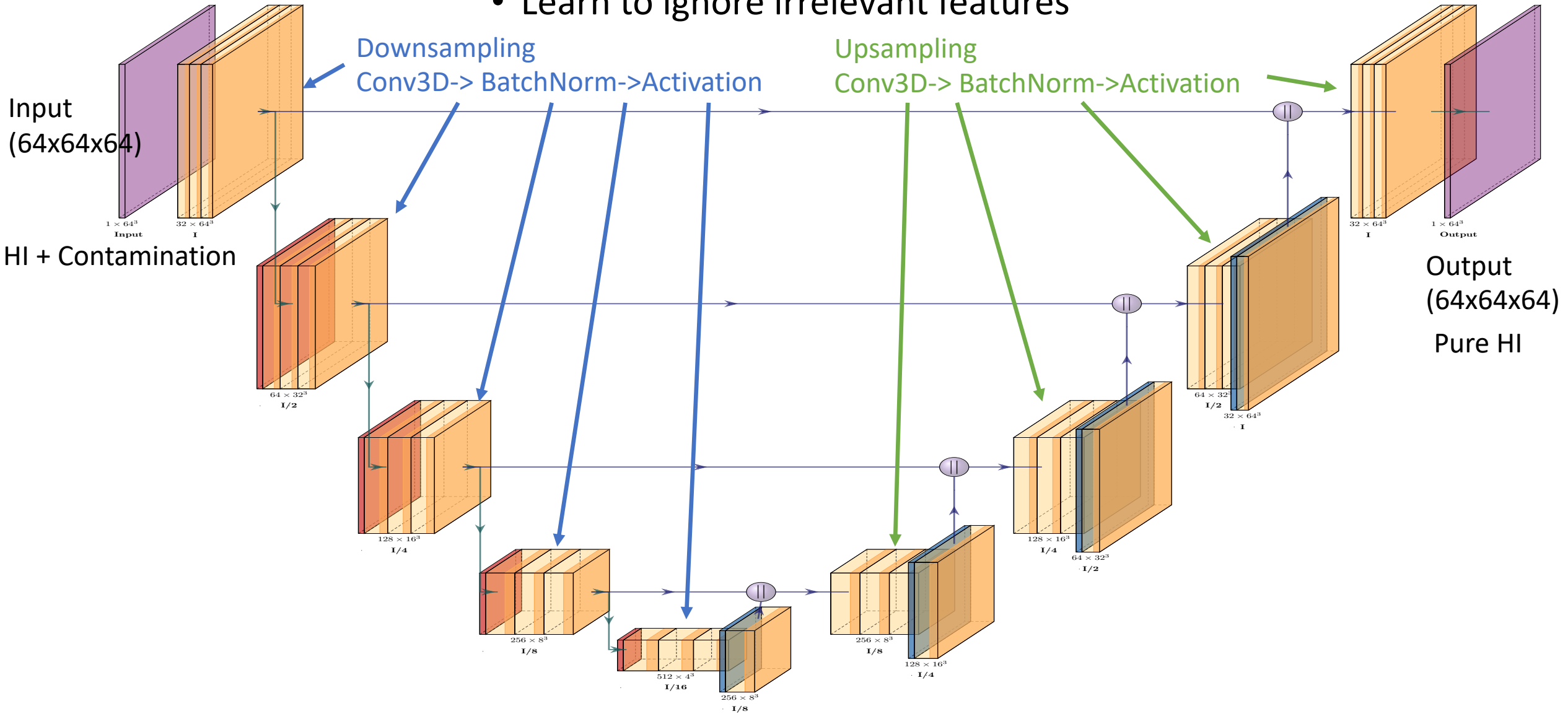
# Introduction

- 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)
- Can we design a machine learning algorithm?
  - Effectively remove FG
  - Robust against systematics
  - Handle large dataset



# U-net for IM

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



# Sky models

- Foreground models:

- Santos et al. (2005)

$$C_\ell(\nu_i, \nu_j) = A \left( \frac{1000}{\ell} \right)^\beta \left( \frac{\nu_{\text{ref}}^2}{\nu_i \nu_j} \right)^\alpha I_\ell^{ij}$$

- Planck Sky Model: Synchrotron → Haslam 408 map; Free-free → H $\alpha$  template

- HI model:

- Battye et al. 2013

$$\bar{T}_{\text{obs}}(z) = 44 \mu\text{K} \left( \frac{\Omega_{\text{HI}} h}{2.45^{-4}} \right) \frac{(1+z)^2}{E(z)}$$

- PINOCCHIO light cone (Spinelli et al. 2022)
- CoLoRe (lognormal fields)

- Beam: SKA-mid single dish beam

- Frequency range: 700-1020 MHz, 64 channels

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

# Instrumental systematics

- Bandpass error  $G_\nu = 1 + \Delta G_\nu$ 
  - $\Delta G_\nu$  - Gaussian random of Nfreq

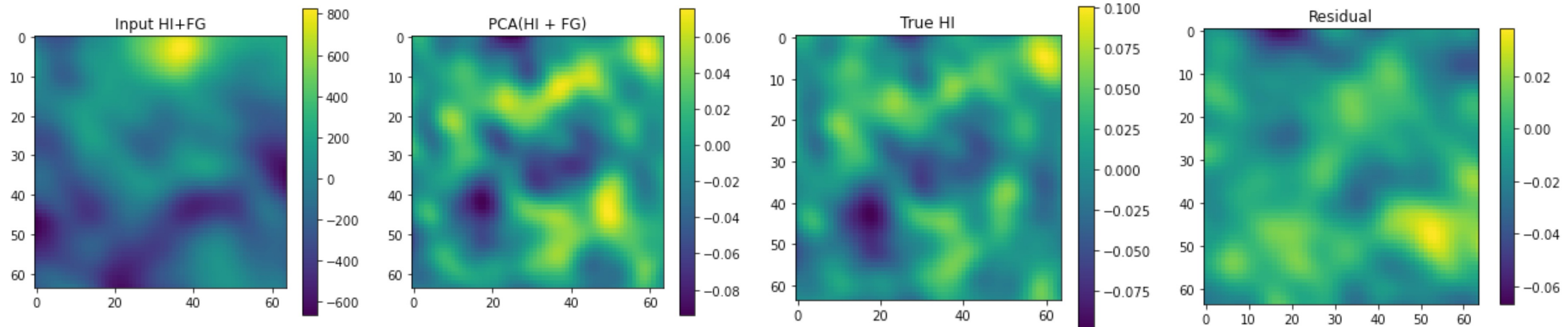
- Frequency-dependent beam

$$\theta_B(z_i) = \theta_{\text{FWHM}}(\nu_{\text{mid}}) \frac{\nu_{\text{mid}}}{\nu_i}$$

- Radio Frequency Interference
  - Flaging random channels

# PCA Pre-processing

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



Based on Santos (FG) + Battye (HI) model  
No systematics

# Loss function

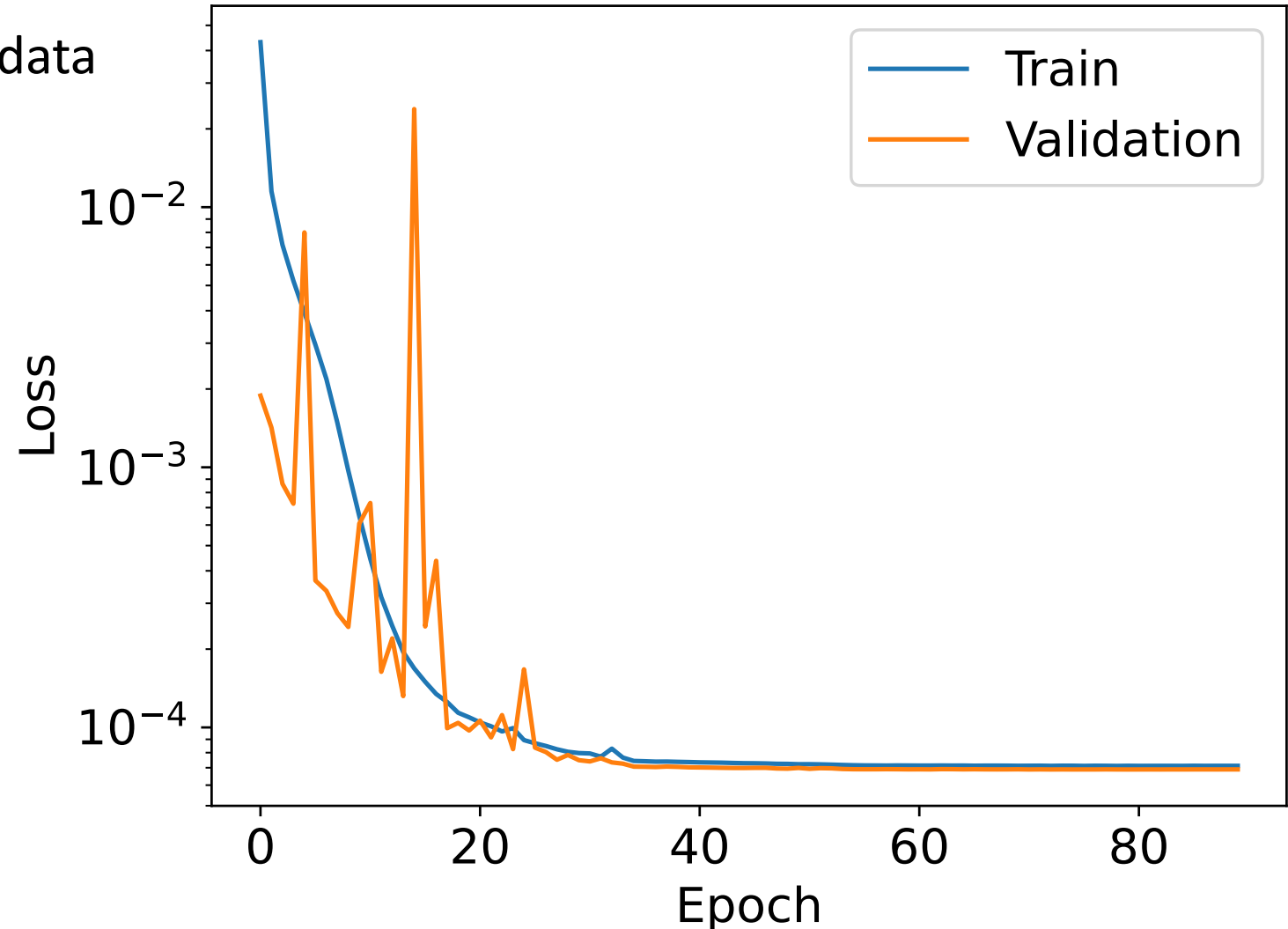
Minimise reconstruction errors (loss)

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

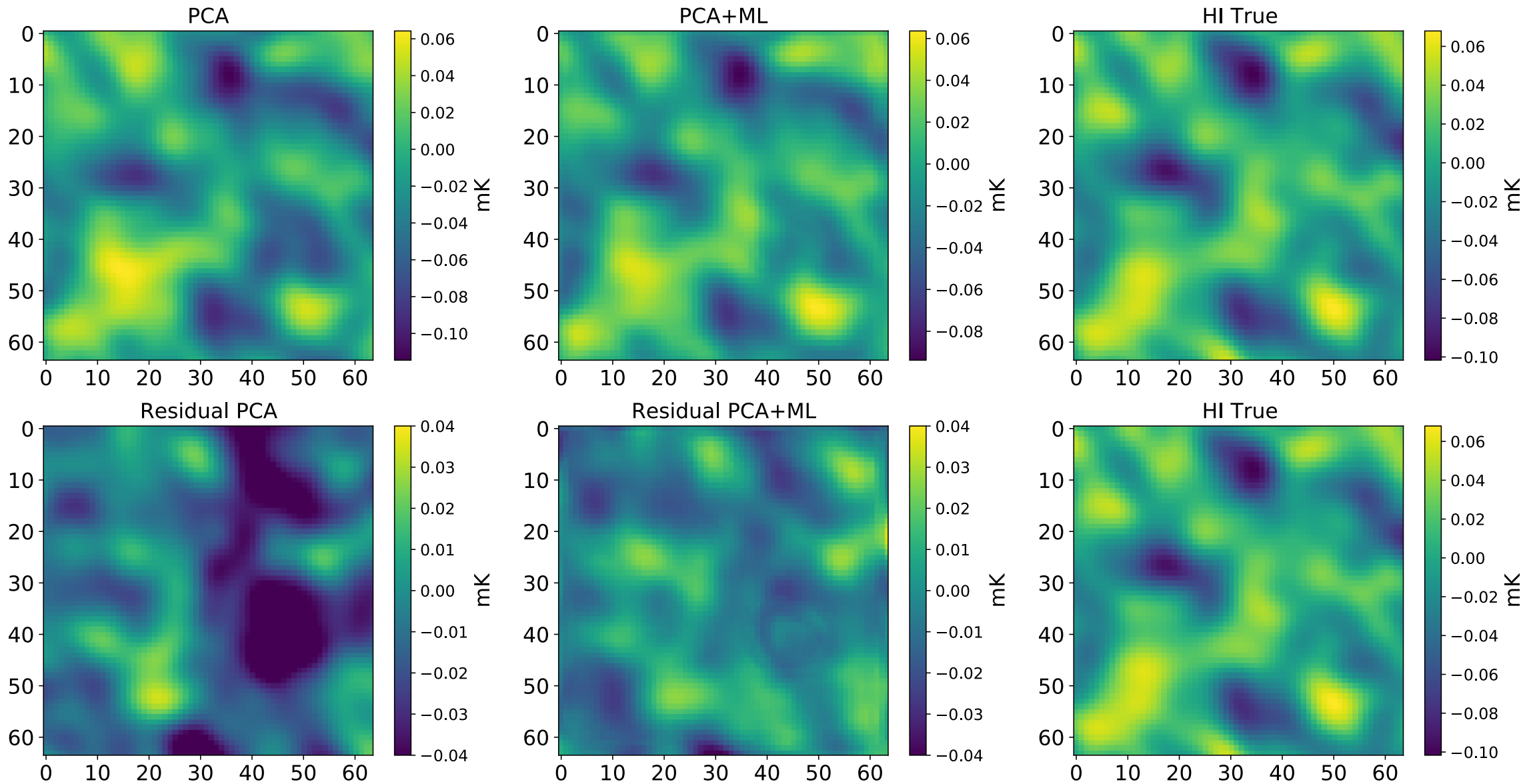
Train loss: how model fits the training data

Validation loss: how model performs

- Training: 50 healpix maps
- Validation: 10 healpix maps
- Test: 10 healpix maps



# Map results



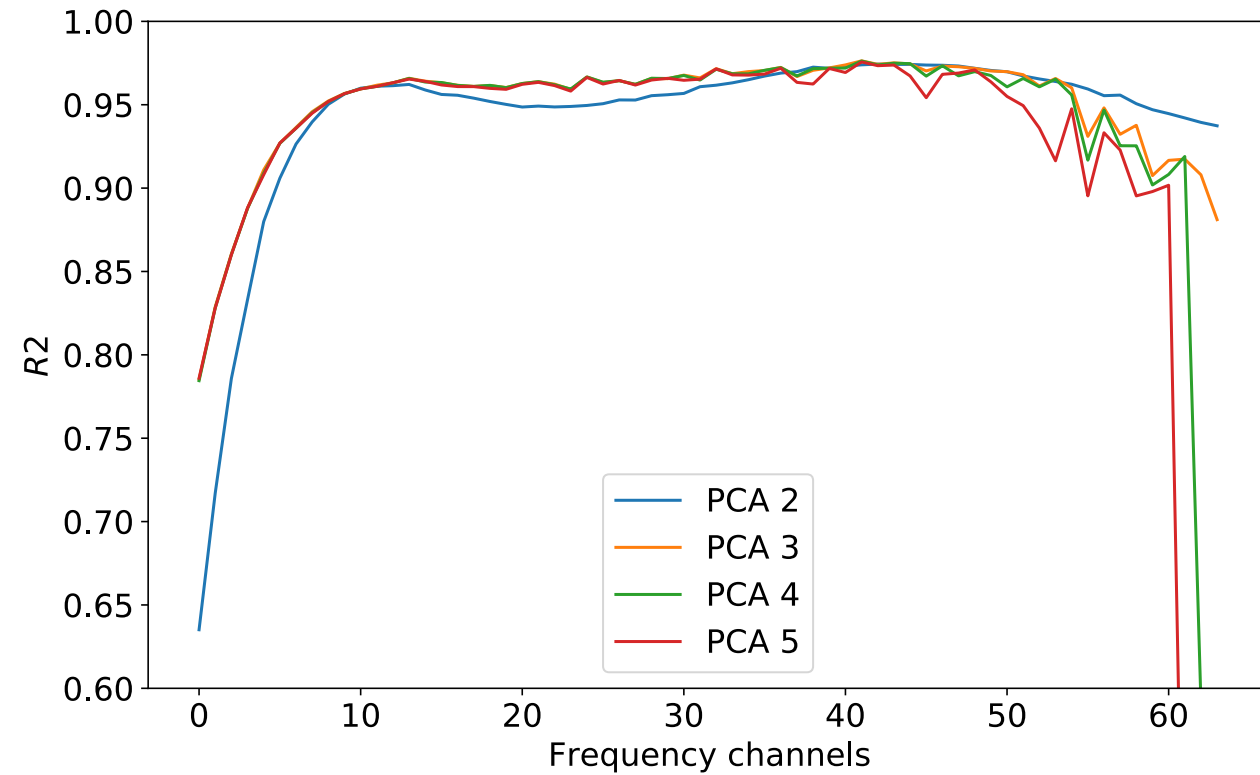
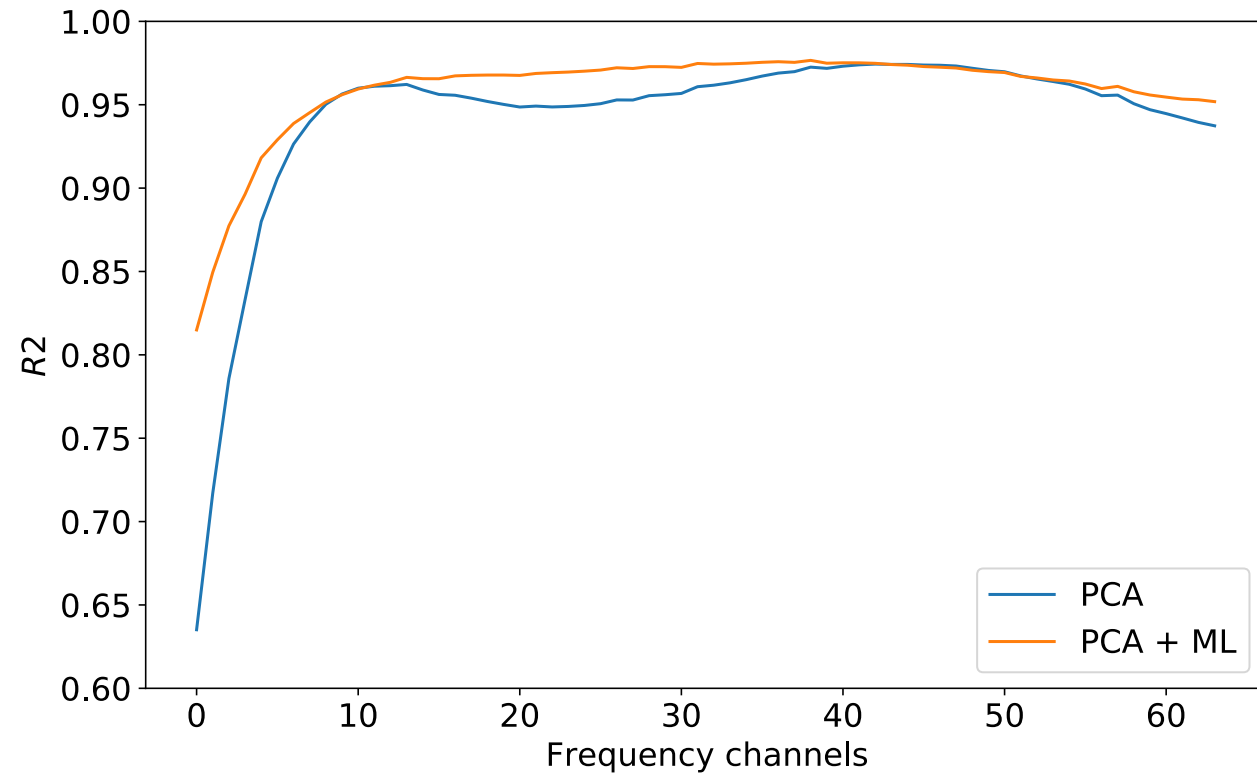


# R<sup>2</sup> Score

**Coefficient of determination**

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}}$$

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



# Conclusions and ongoing work

- Consistent results with traditional methods
- Test the network on different simulation models
  - Reliable performance independent of sky models
- Introduce systematics in the data
  - Robust against systematics