21cm foreground removal with machine learning

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HI intensity mapping (IM)

- **Motivation**

  Precision cosmology, Dark Energy

  Baryon Acoustic Oscillation (BAO)

- **Keywords**

  Emission line (e.g., HI)

  Large scale structure fluctuations

  Unresolved individual galaxies

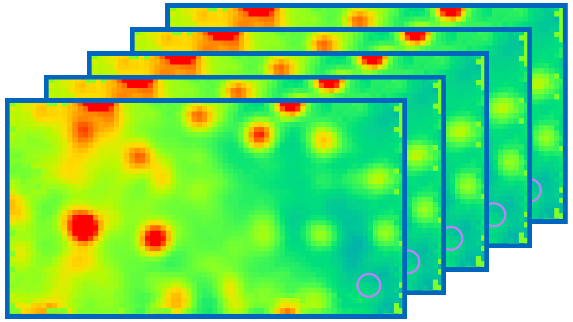
- **Benefits**

  Relatively cheap and efficient

  3D information ---

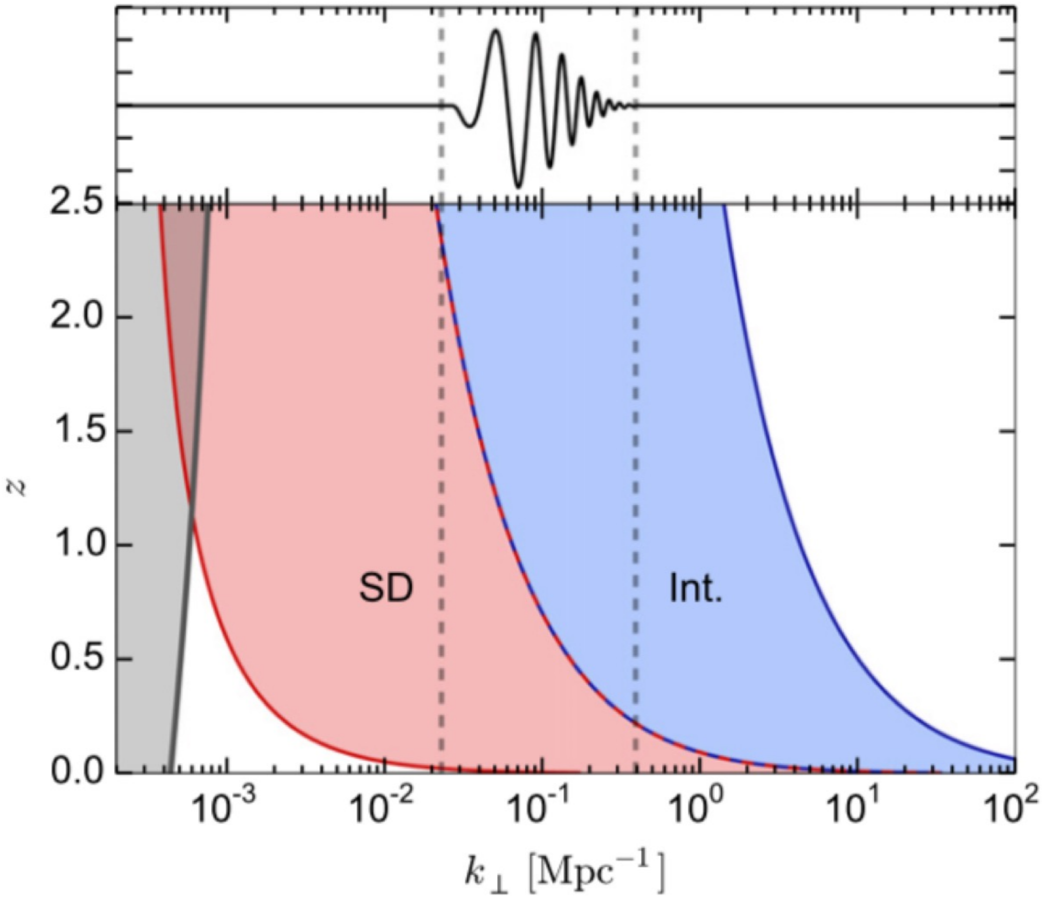
  2D angular size + 1D redshift (obs. Freq.)

Large beam on the sky (~1 deg) contains large number of galaxies



HI IM with SKA

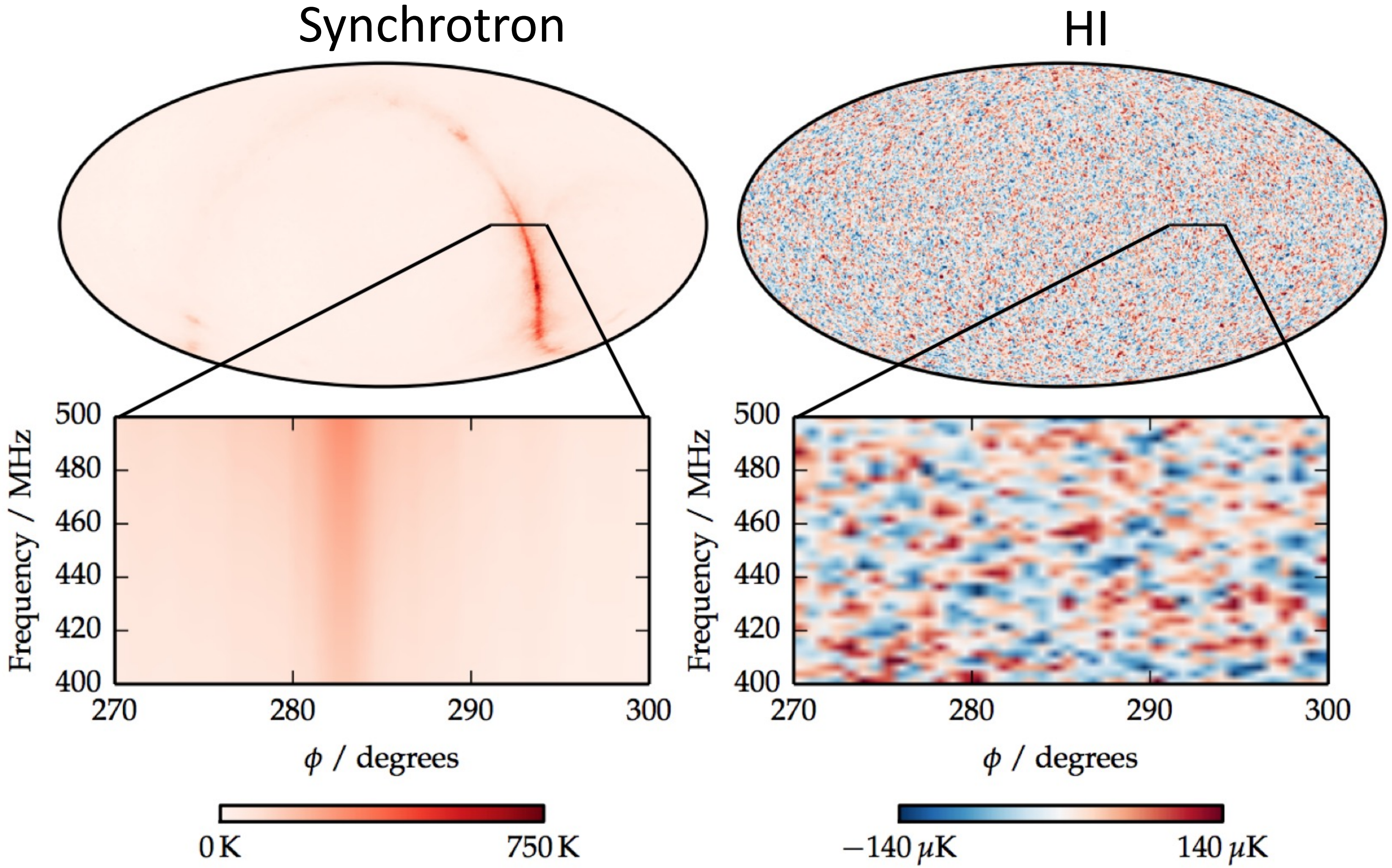
- Interferometer mode – high z (SKA-low)
- Single-dish mode (total power) – low z (SKA-mid)



Bull et al (2015)

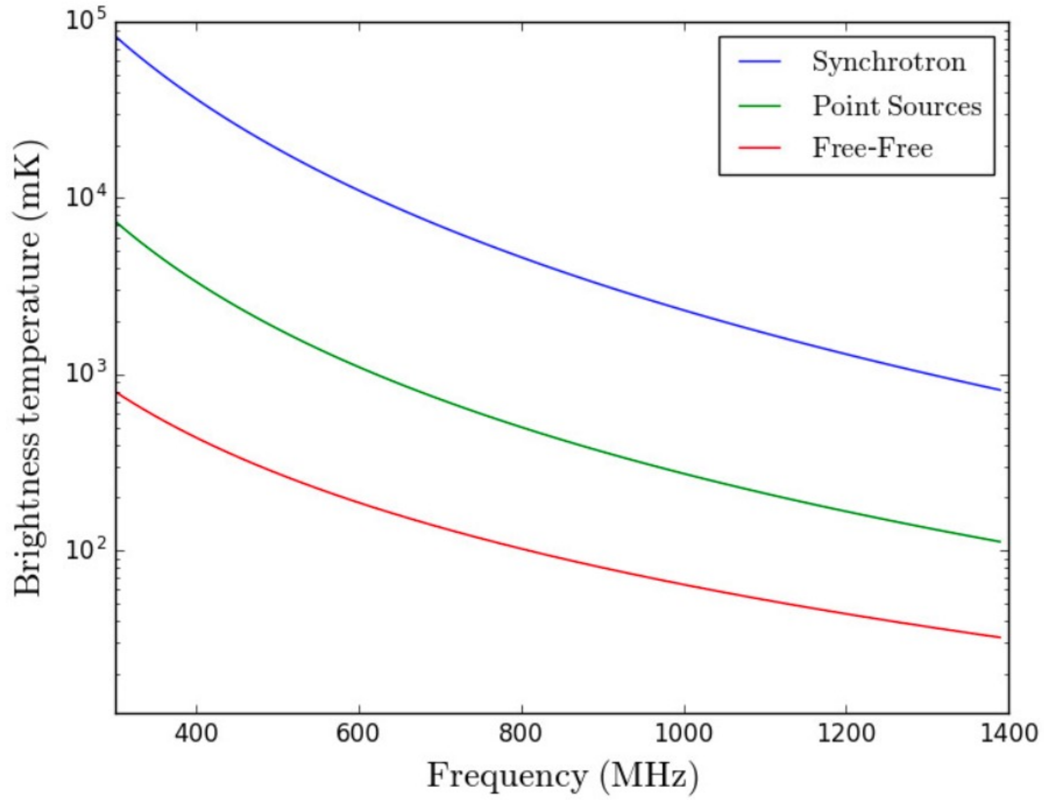
IM challenges - foregrounds

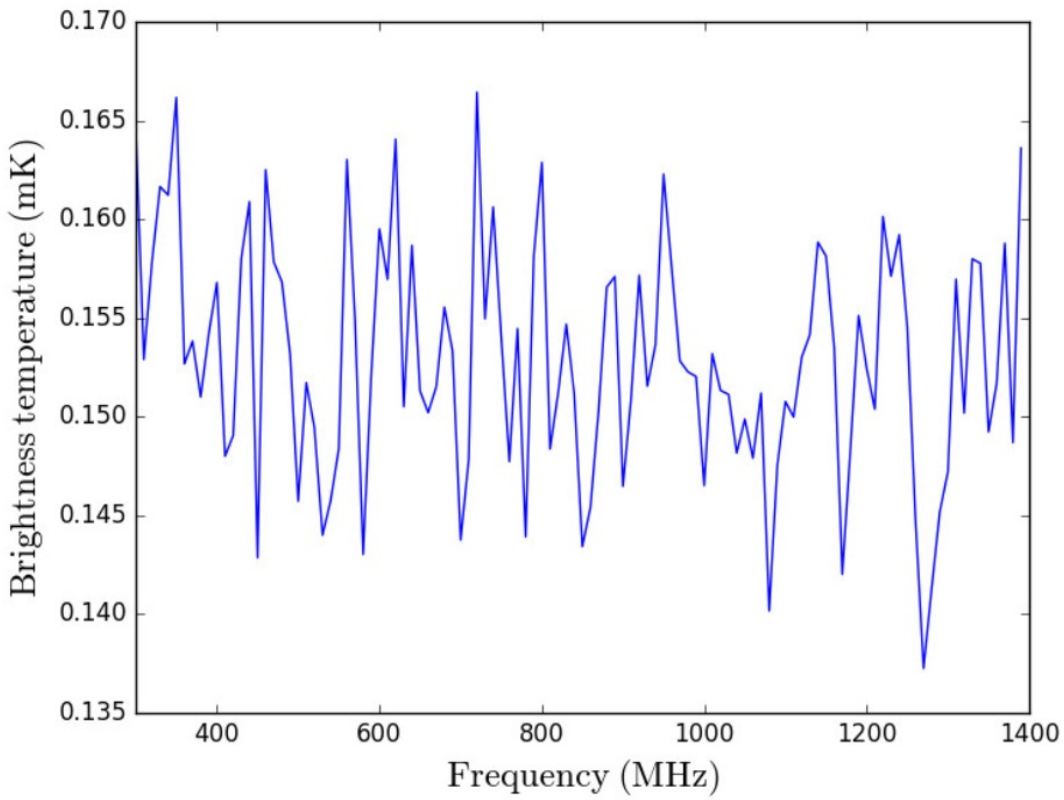
- Foreground >> HI



Simulations, Shaw et al. (2014)

Component separation



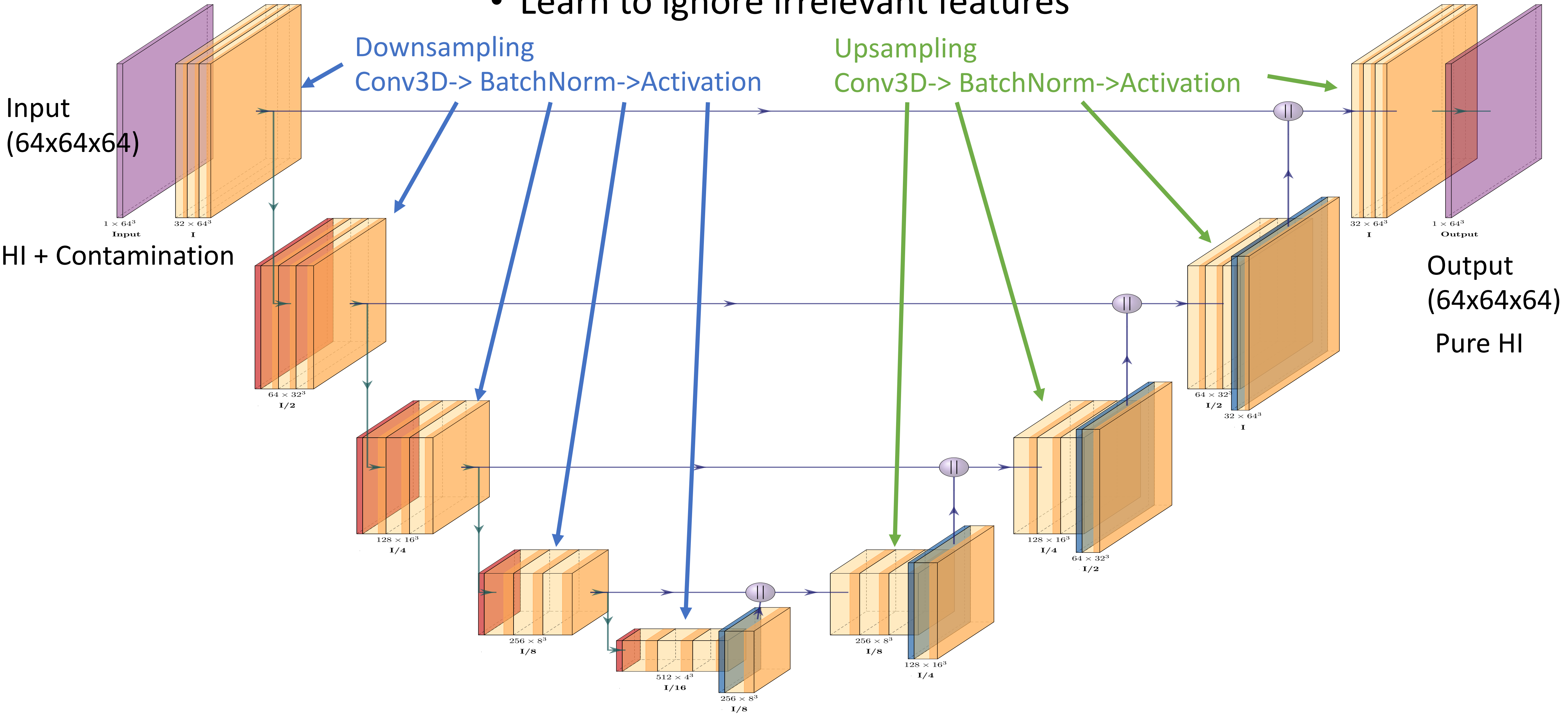


- Traditional approach:
  - Rely on spectral smoothness
  - Sensitive to systematics
  - Signal loss

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

U-net for IM

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



Sky models

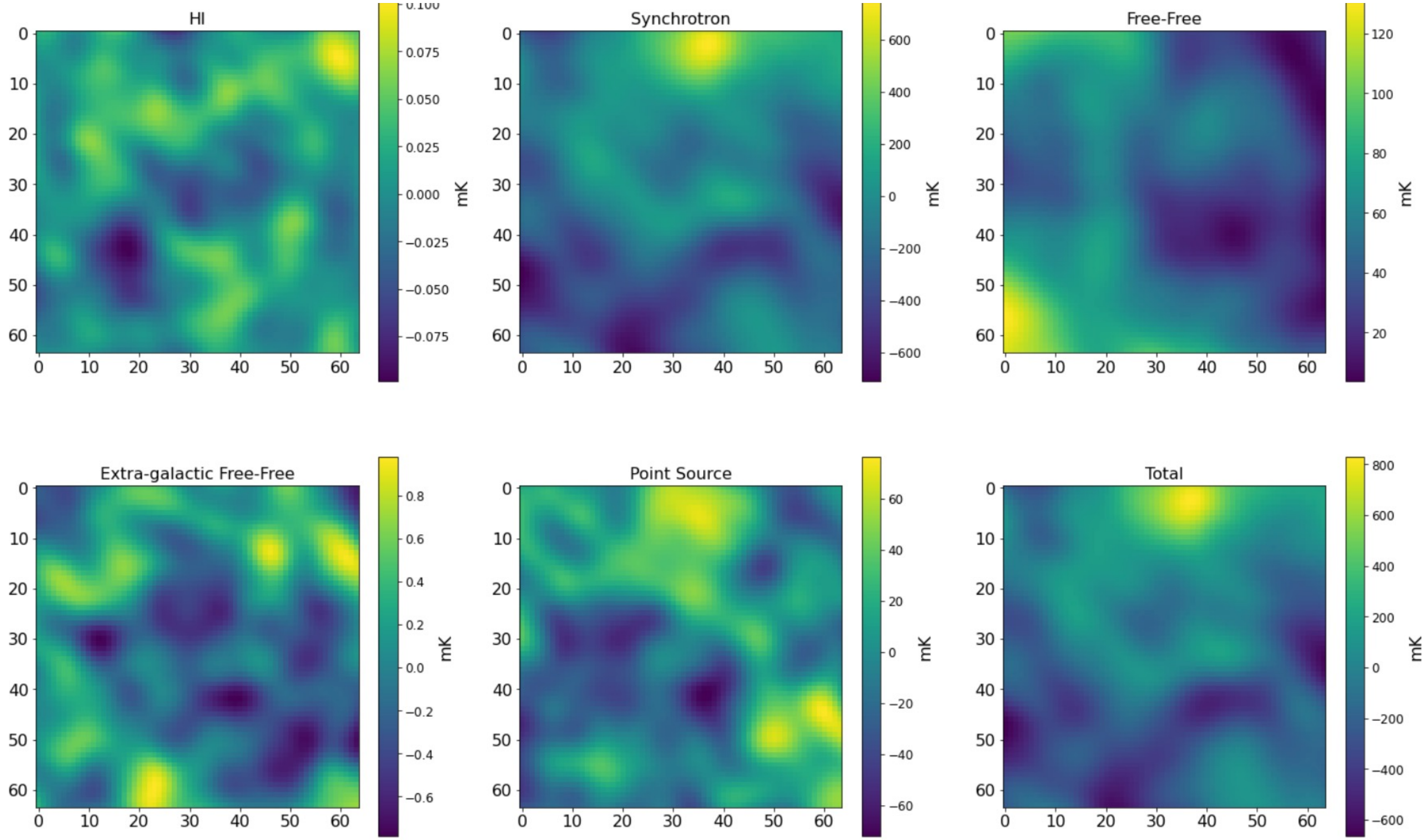
Foreground: (Santos et al. 2005)

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

HI: (Battye et al. 2013)

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

$$C_\ell = \frac{H_0 b_{\rm HI}^2}{c} \int dz E(z) \left[\frac{\bar{T}_{\rm obs}(z) D(z)}{r(z)}\right]^2 P_{\rm cdm}\left(\frac{\ell+0.5}{r}\right)$$



Full sky maps (healpix)

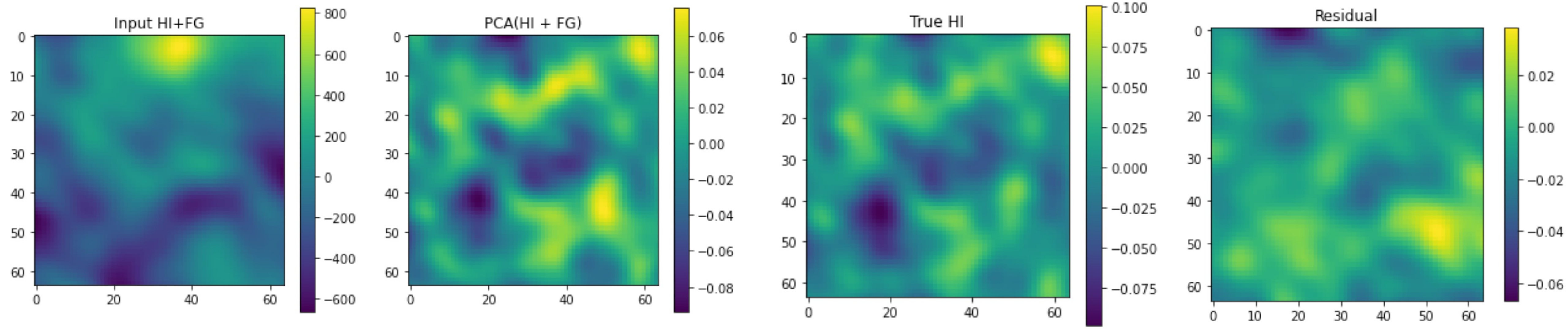
SKA-mid single-dish beam

192 equal-size patches

(64x64x64)

PCA Pre-processing

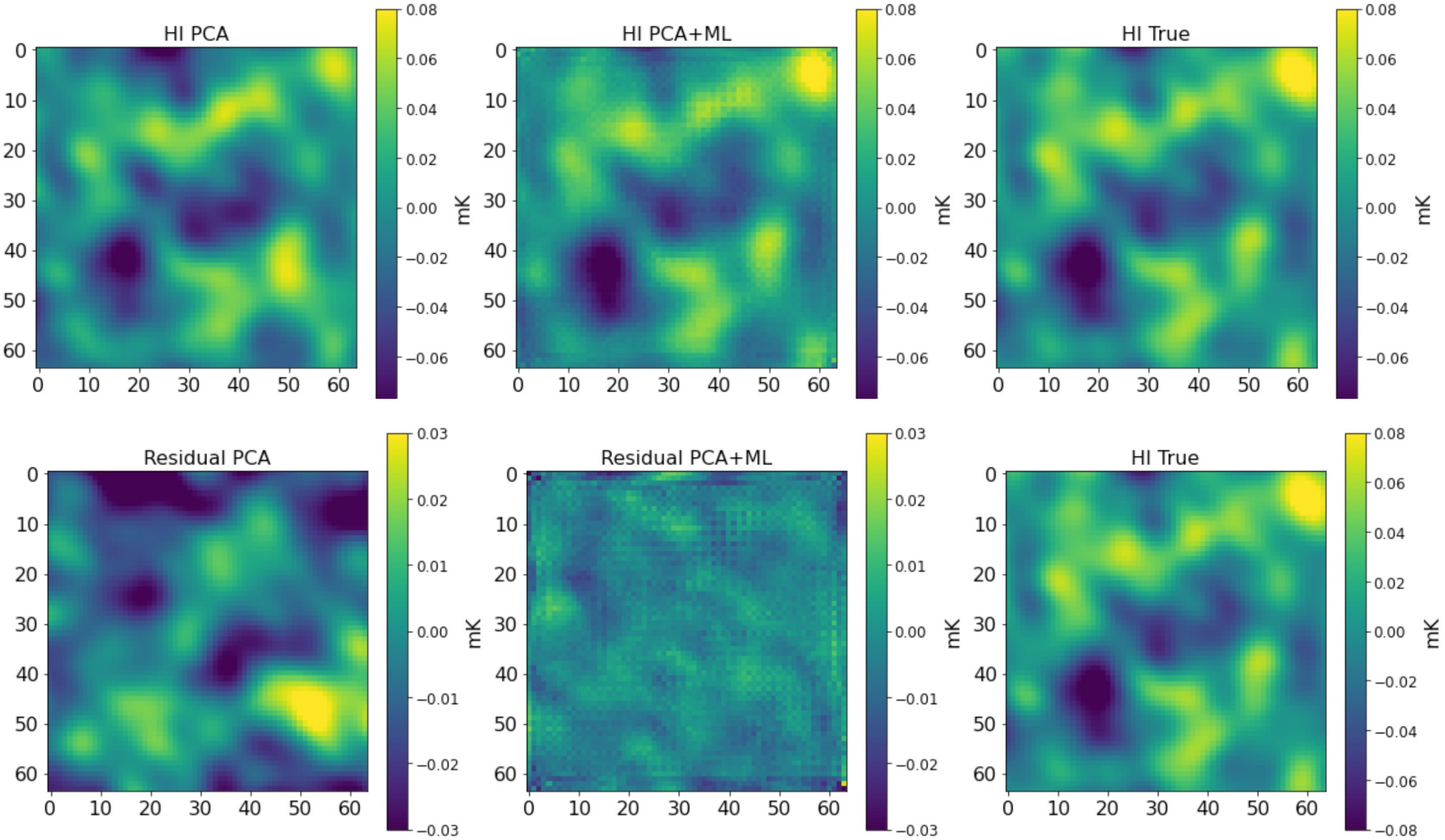
- Network can't handle large dynamic range
- Apply PCA to pre-process the data (mode = 2)
- Use ML for fine tuning



- Training: 154 patches
- Validation: 38 patches
- Test: 10 patches

Map results

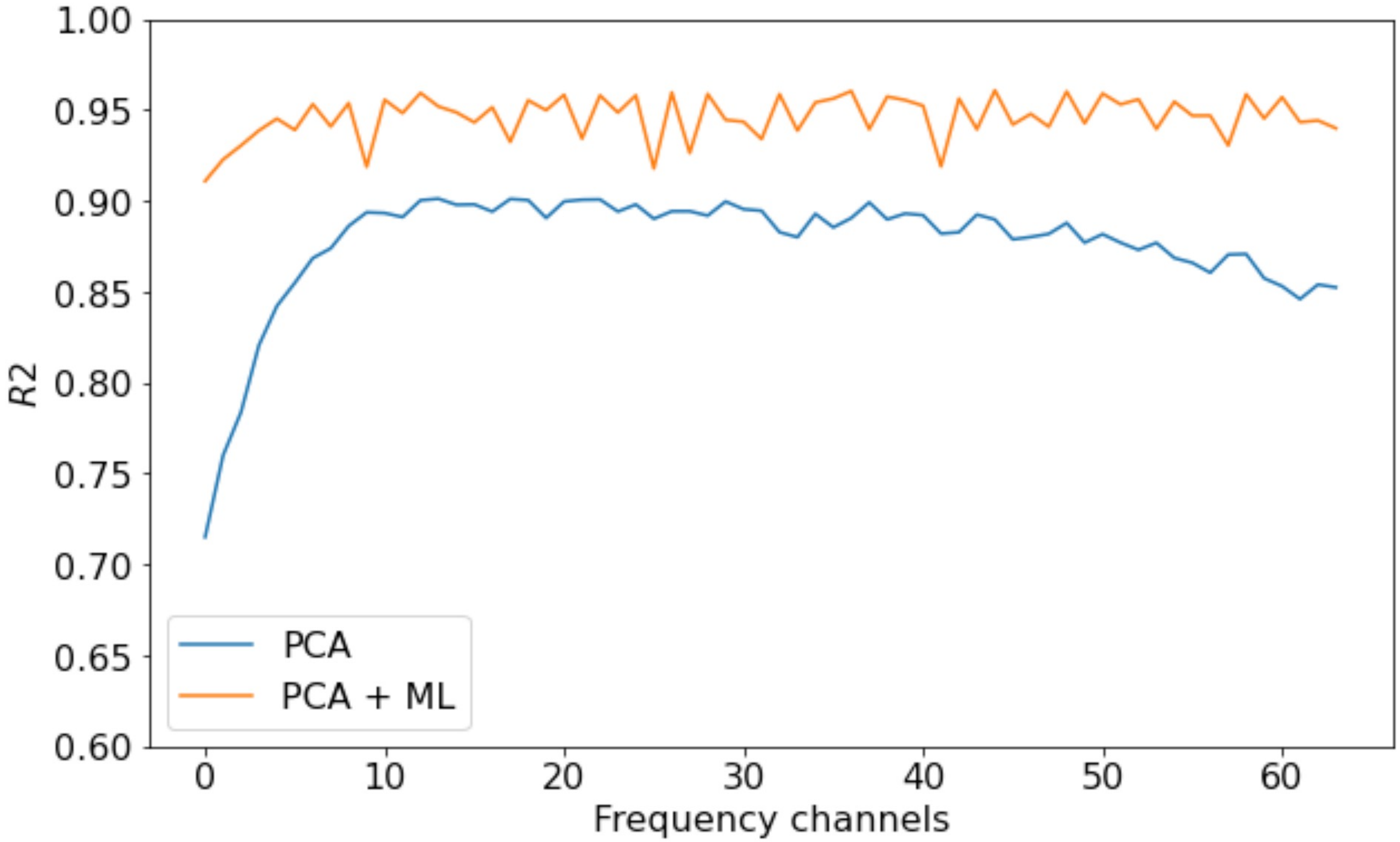
- Training: 154 patches
- Validation: 38 patches
- Test: 10 patches



R^2 Score

Coefficient of determination

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



Conclusions

- The U-net outperforms PCA alone
  - Reduced map residual
  - Better R2 score
- Next step:
  - Introduce systematics
  - ML robust agains systematics?