SOCIETY OF EXPLORATION GEOPHYSICISTS

جامعة الملك عبدالله للعلوم والتقنية
King Abdullah University of Science and Technology

FWI with ML assisted low frequency extrapolation

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KAUST

SWAG
Seismic Wave Analysis Group

Seismic Modeling and Inversion (SMI)
Research Group

Problem

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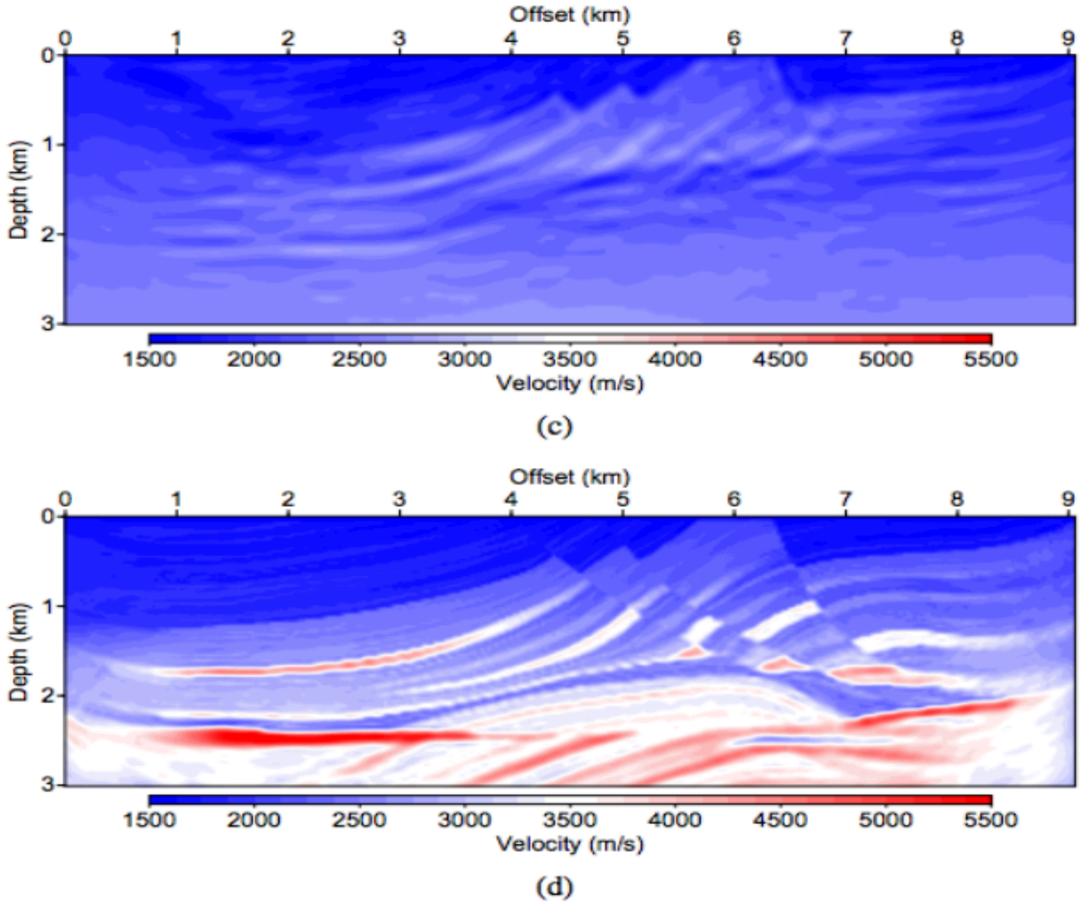
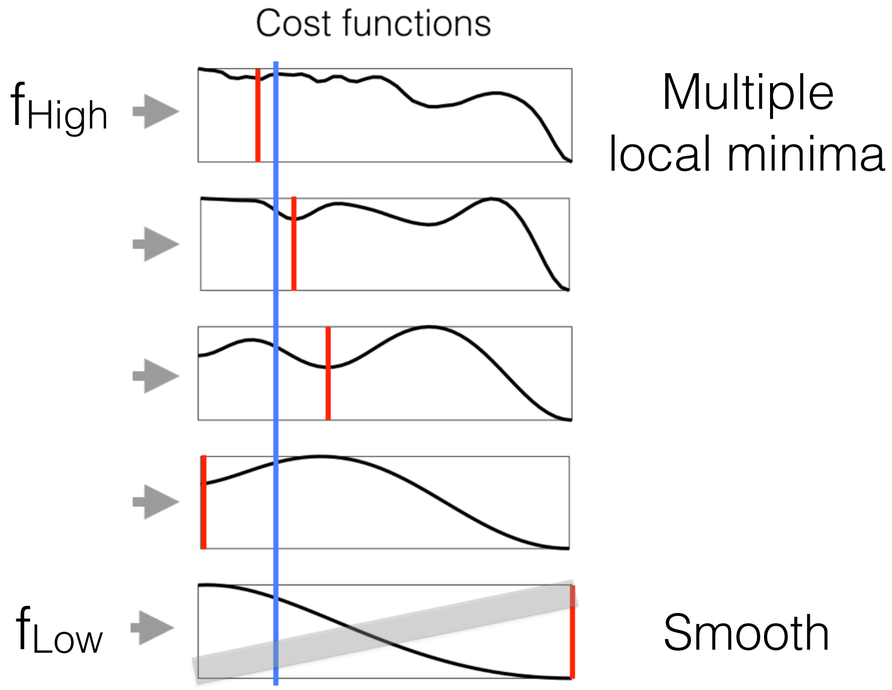
Low-frequency data in FWI



(Kazei et al., 2016)

- Inverts large-scale velocity structures
- Less chance to get stuck in local minima
- Reveals deep model structures / below salt



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Existing solutions

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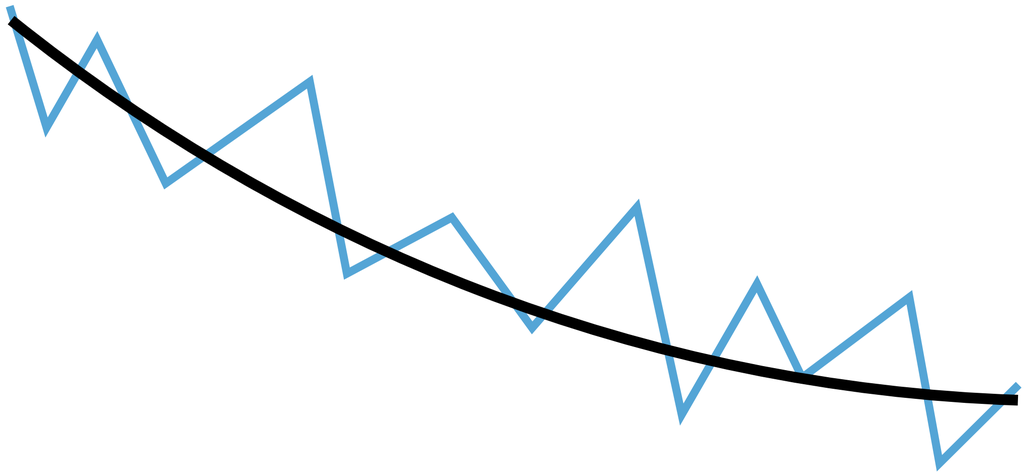
FWI with different misfits



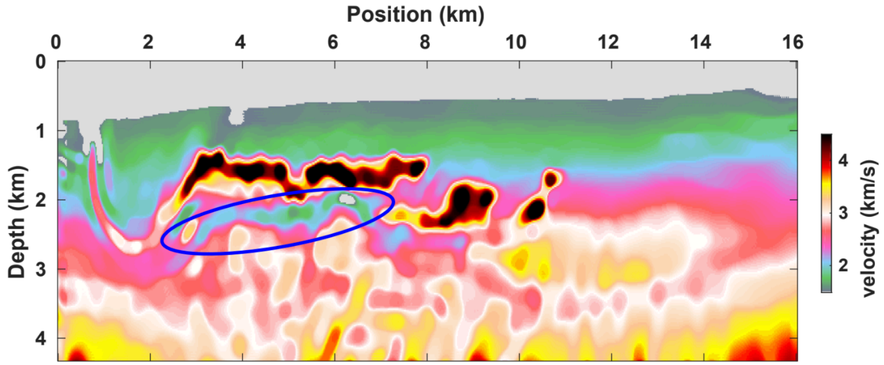
Pros:

- Established workflow
- Direct image quality control

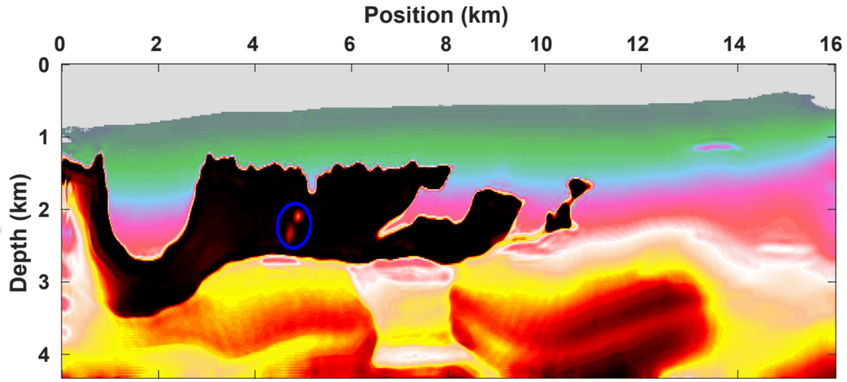
Cons:

- Computational costs
- Prone to event mismatching
- Sensitivity hard to control

(Bozdag 2011, Choi & Alkhalifah 2013, Leeuwen & Herrmann, 2014 …)



Kalita et al., 2018



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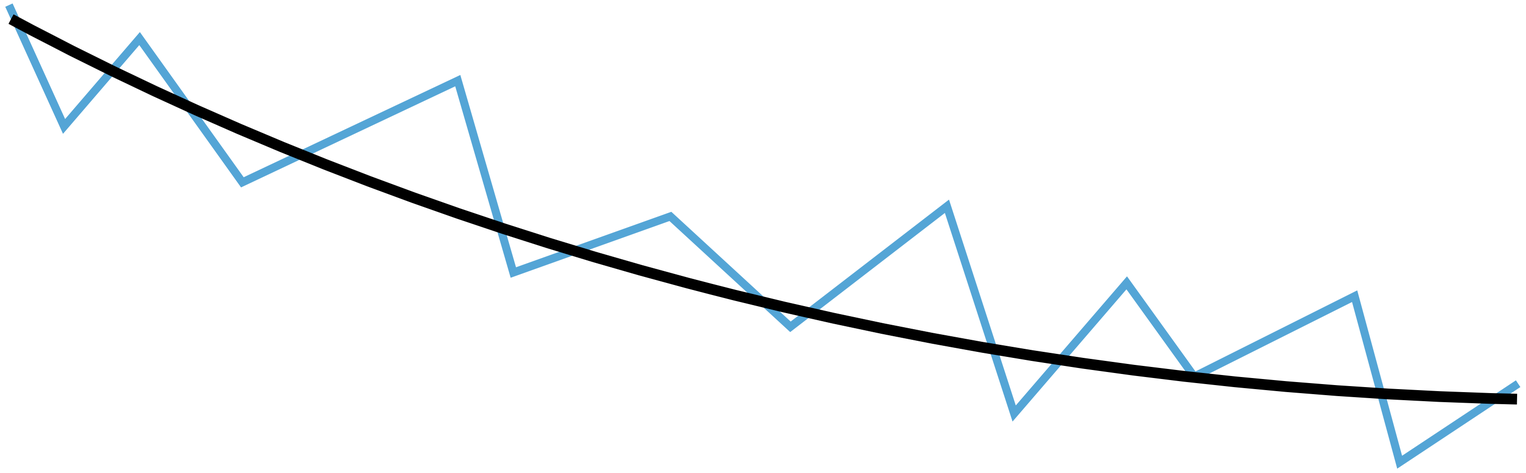
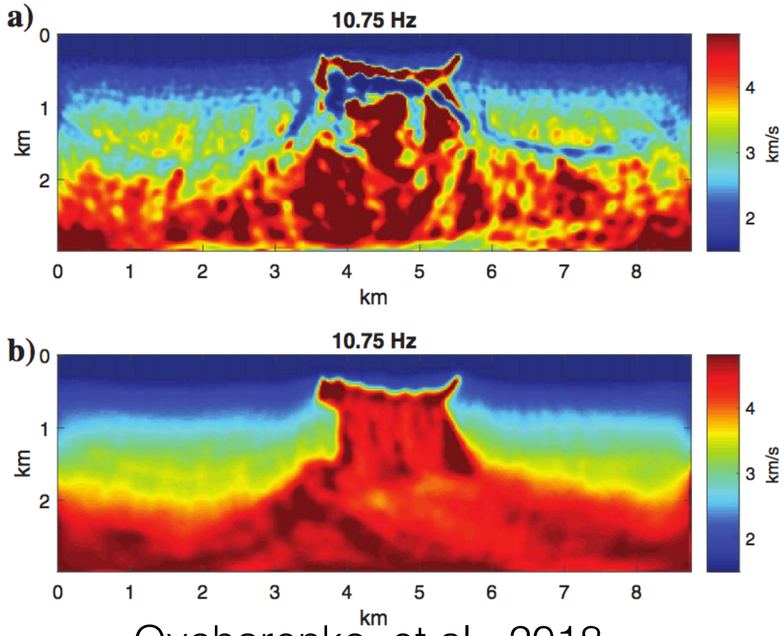
FWI with update conditioning





Ovcharenko, et al., 2018

(Alkhalifah, 2015; Kazei, et al., 2016;
Yao et al., 2018; Ovcharenko, et al., 2018) etc…

Pros:

- Easily accessible sensitivity
- Direct image quality control
- Can be used together with any misfit

Cons:

- Computational costs
- Prone to event mismatching

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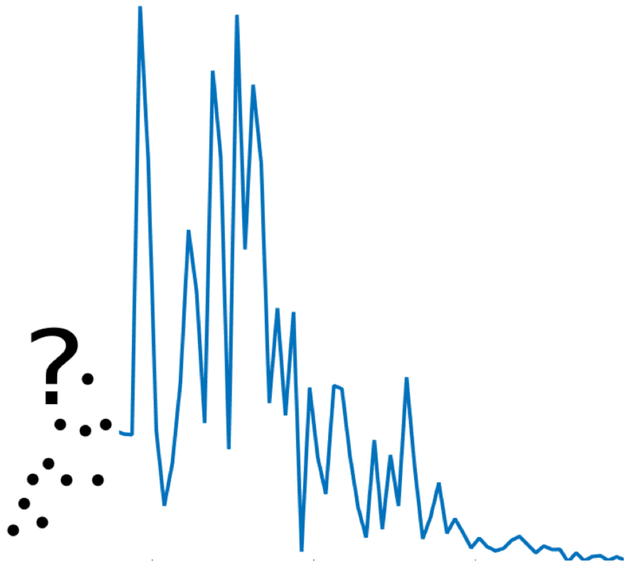
FWI with bandwidth extrapolation

Extrapolation of low-frequency data



Pros:

- Cheaper computations

Cons:

- Not well explored robustness
- Wavefield approximations

Hu et al., 2014; Li & Demanet, 2015, 2016, Ovcharenko et al., 2018)
etc…

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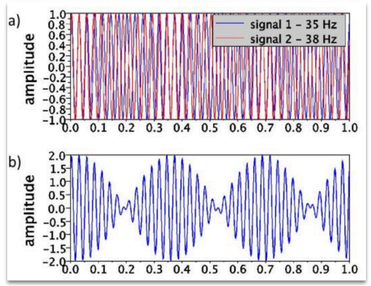
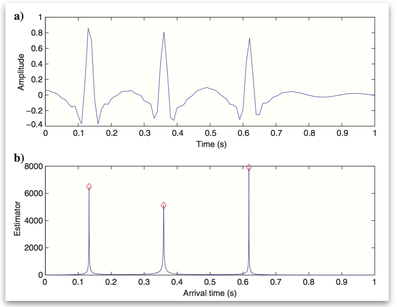
Low-frequency extrapolation

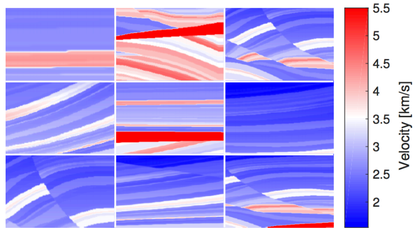
Beat tone inversion
(Hu et al., 2014)



Bandwidth extension for atomic events
(Li & Demanet, 2015, 2016)



Deep learning freq domain for CSG – Ovcharenko et al., 2017
Trace to trace deep learning – Sun & Demanet, 2018



This work: Low-frequency data extrapolation for a CSG using a CNN

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Our solution

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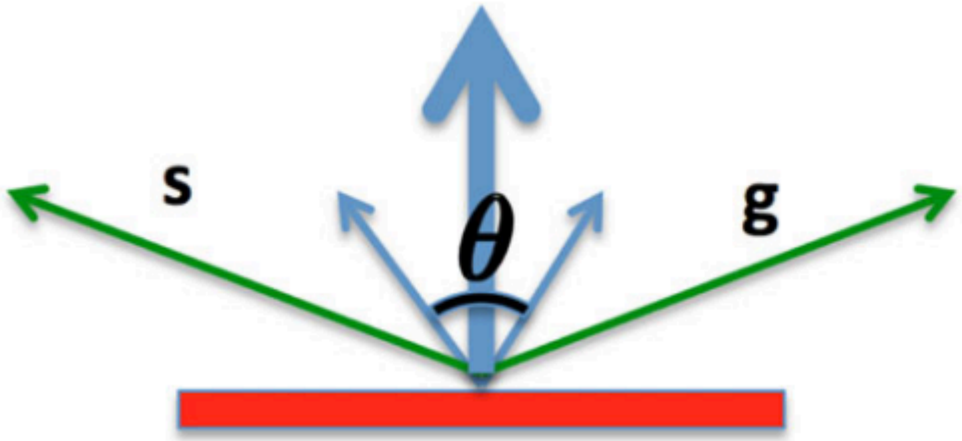
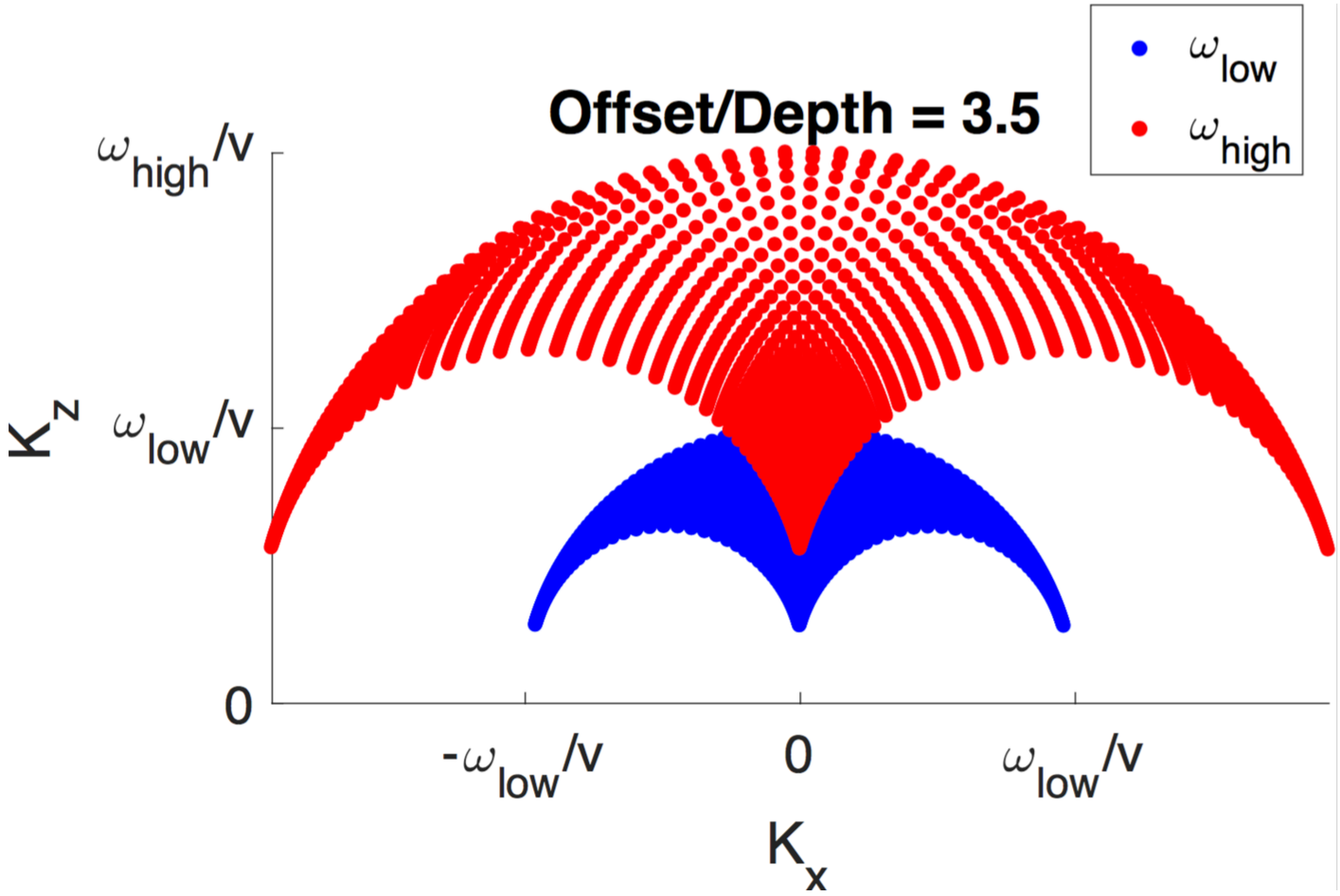
Data – model – data connection



$$\mathbf{K}_{PP} = \frac{\omega}{v_p}(\mathbf{s} + \mathbf{g})$$

low frequency – small theta

high frequency – large theta



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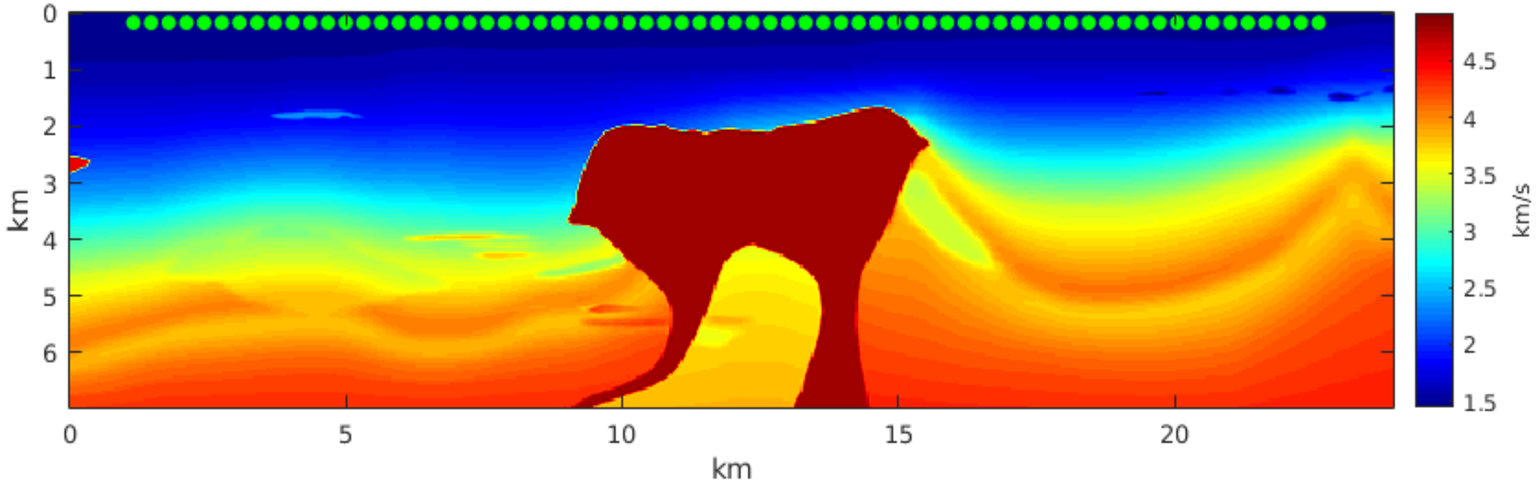
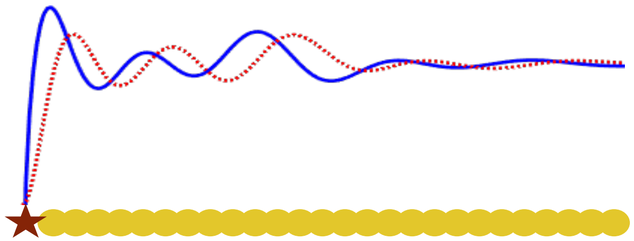
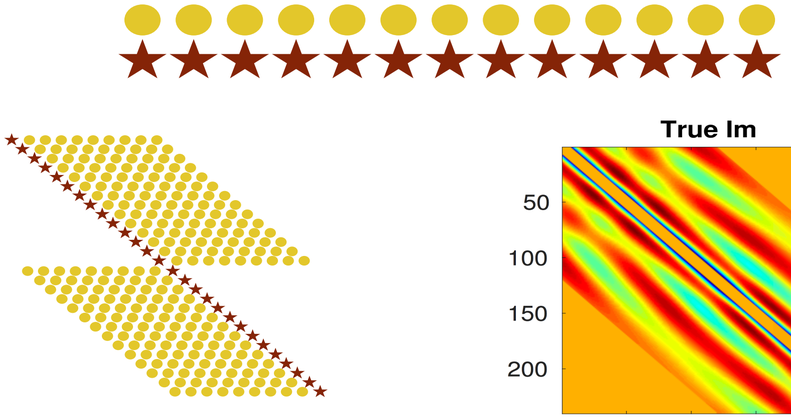
Setup and data in frequency domain



Mono-frequency wavefield





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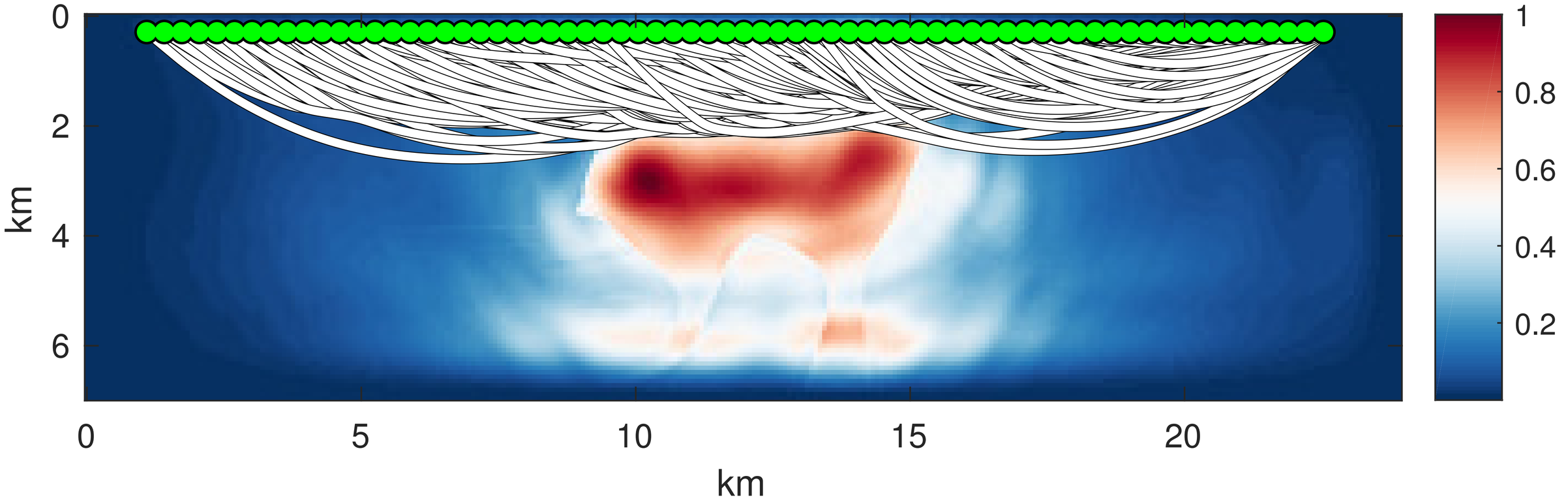
Illumination map



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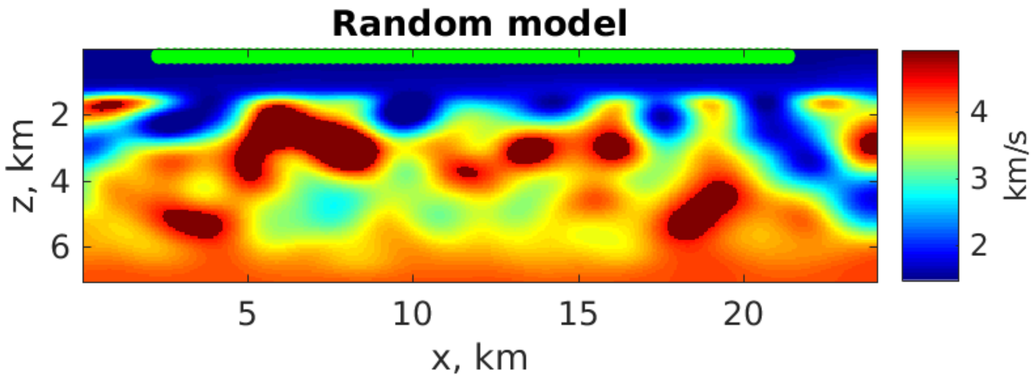
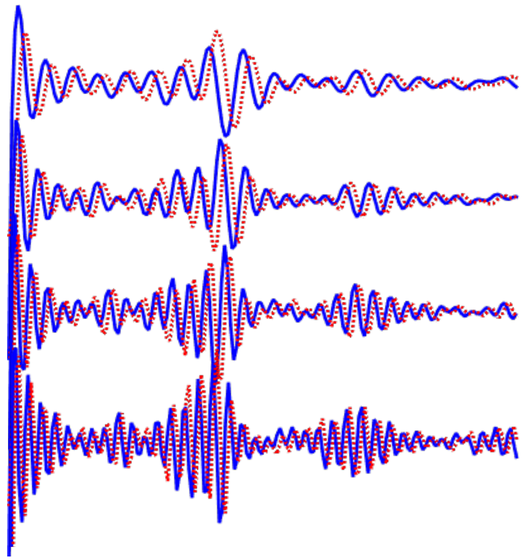
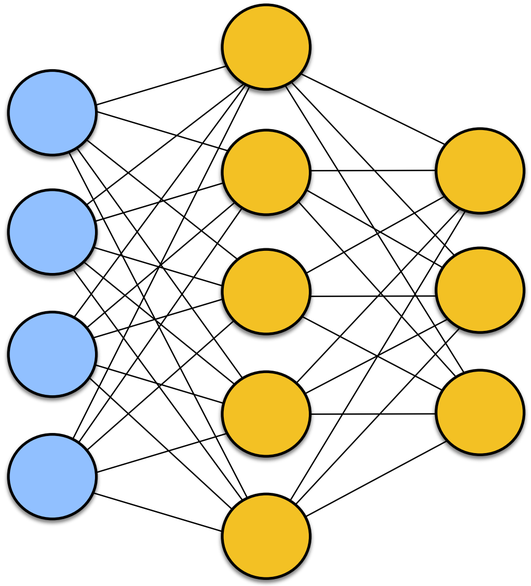
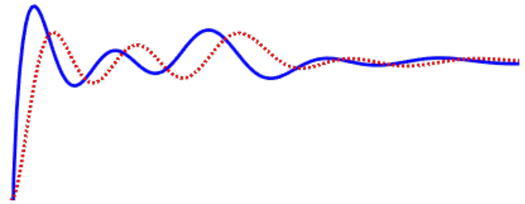
Single low-frequency from multiple high-frequency data









High-frequency data

Neural network

Low frequency data

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Random model generation

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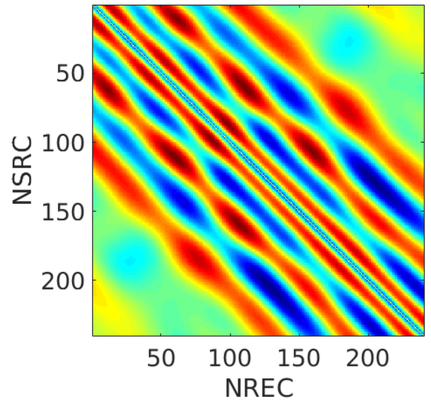
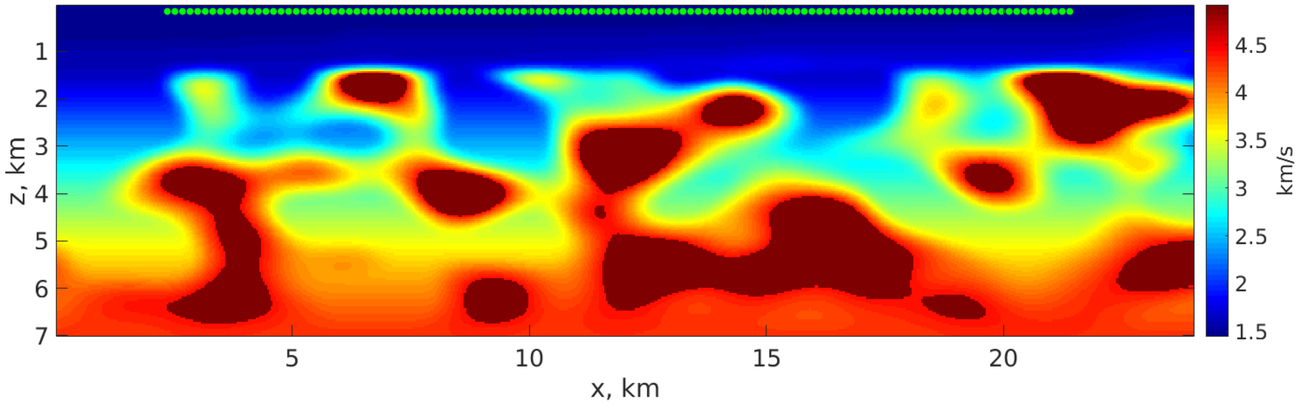
Random model generation





- Random Gaussian field
- Flat bathymetry
- Fixed model size
- Permissible velocity range
- Use data for each src-rec pair

The more diverse data - the better

Sampling multidimensional model space

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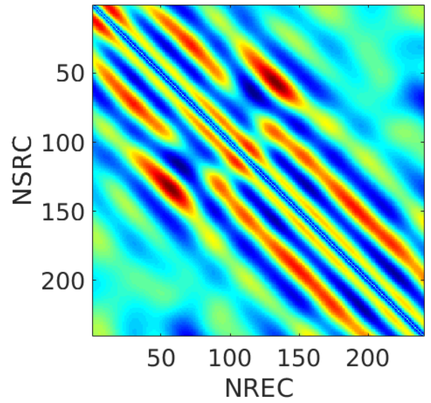
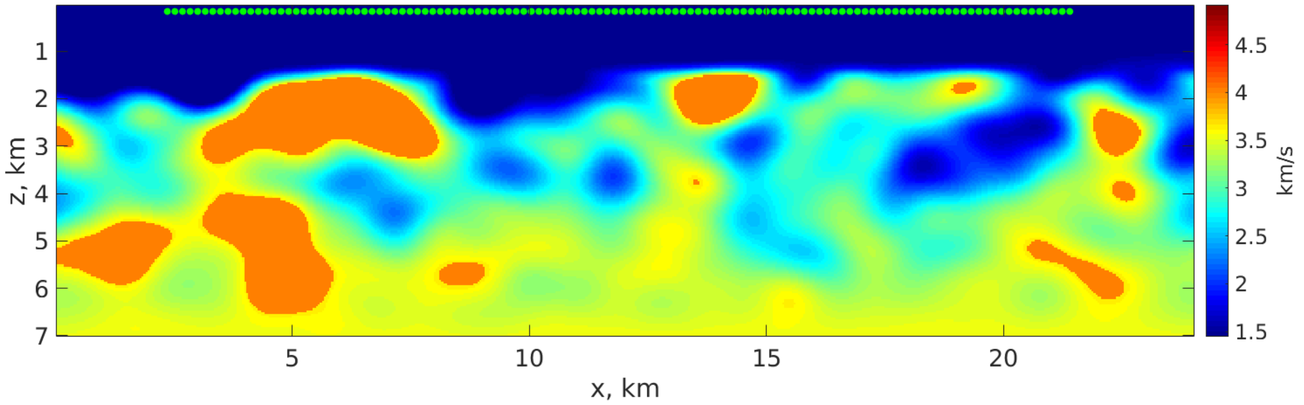
Random model generation





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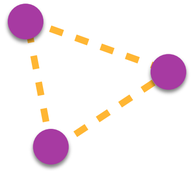

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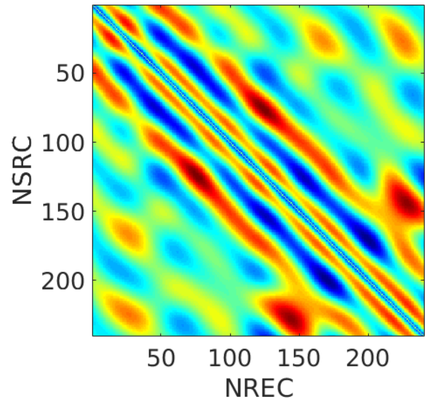
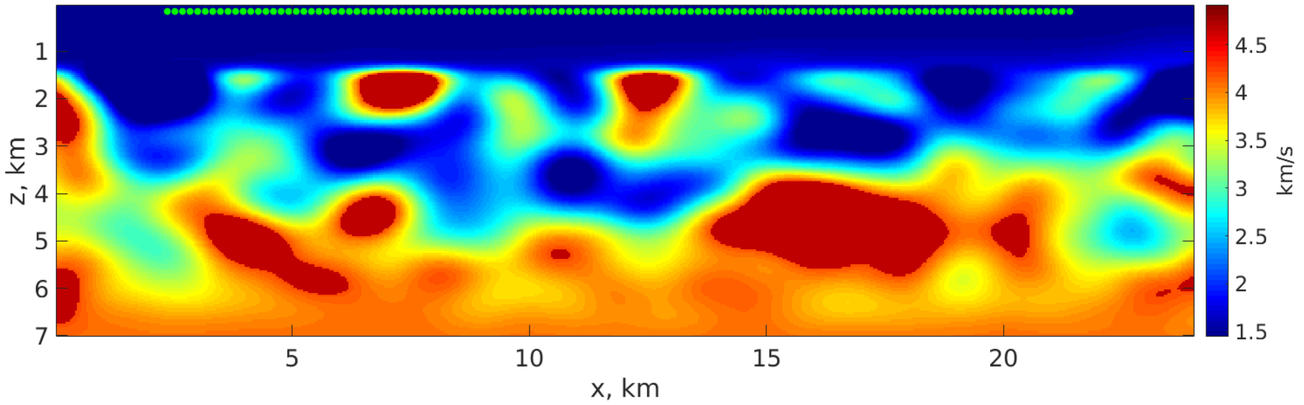
Random model generation





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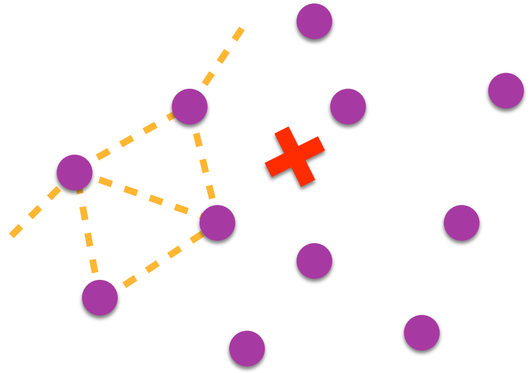

Sampling multidimensional model space

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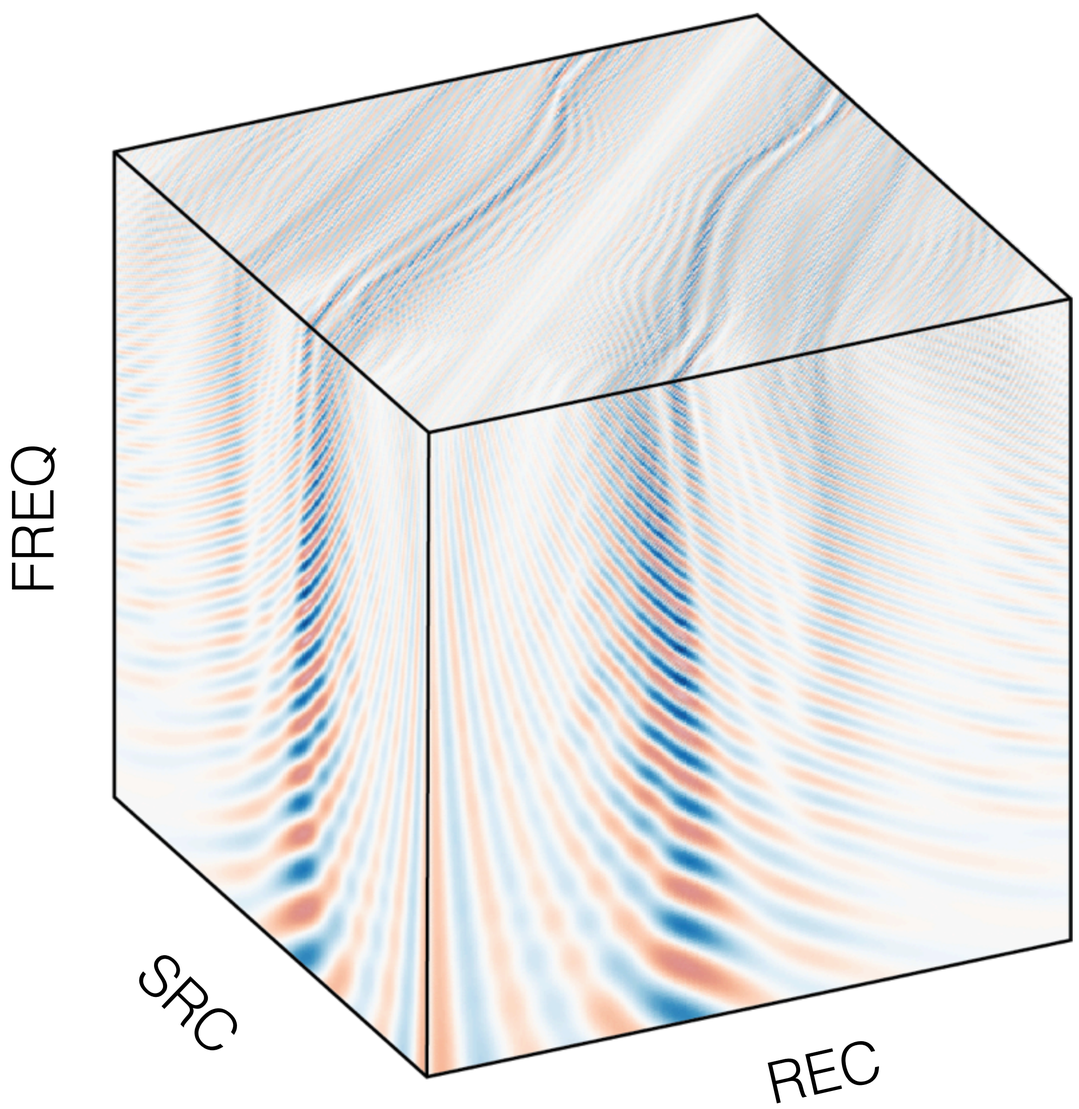
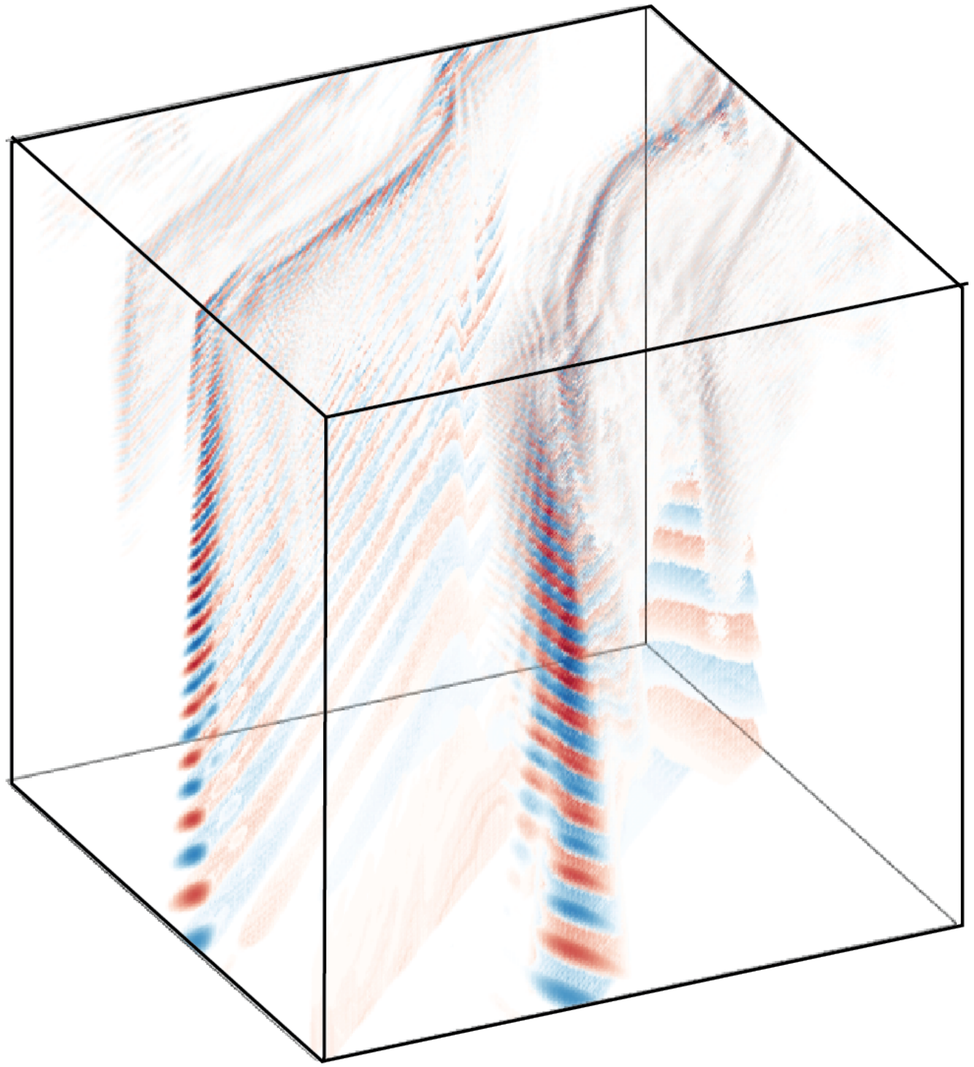
Data cube patterns





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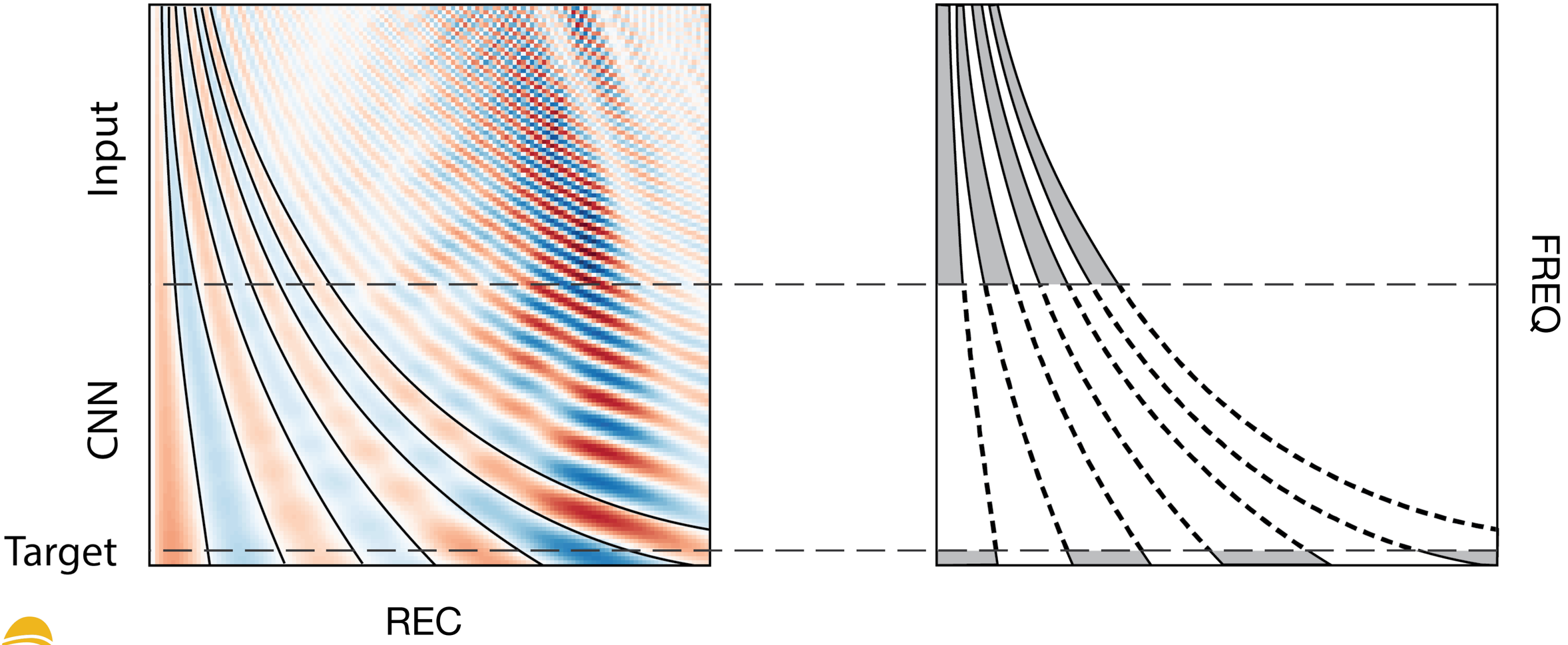
Single shot gather



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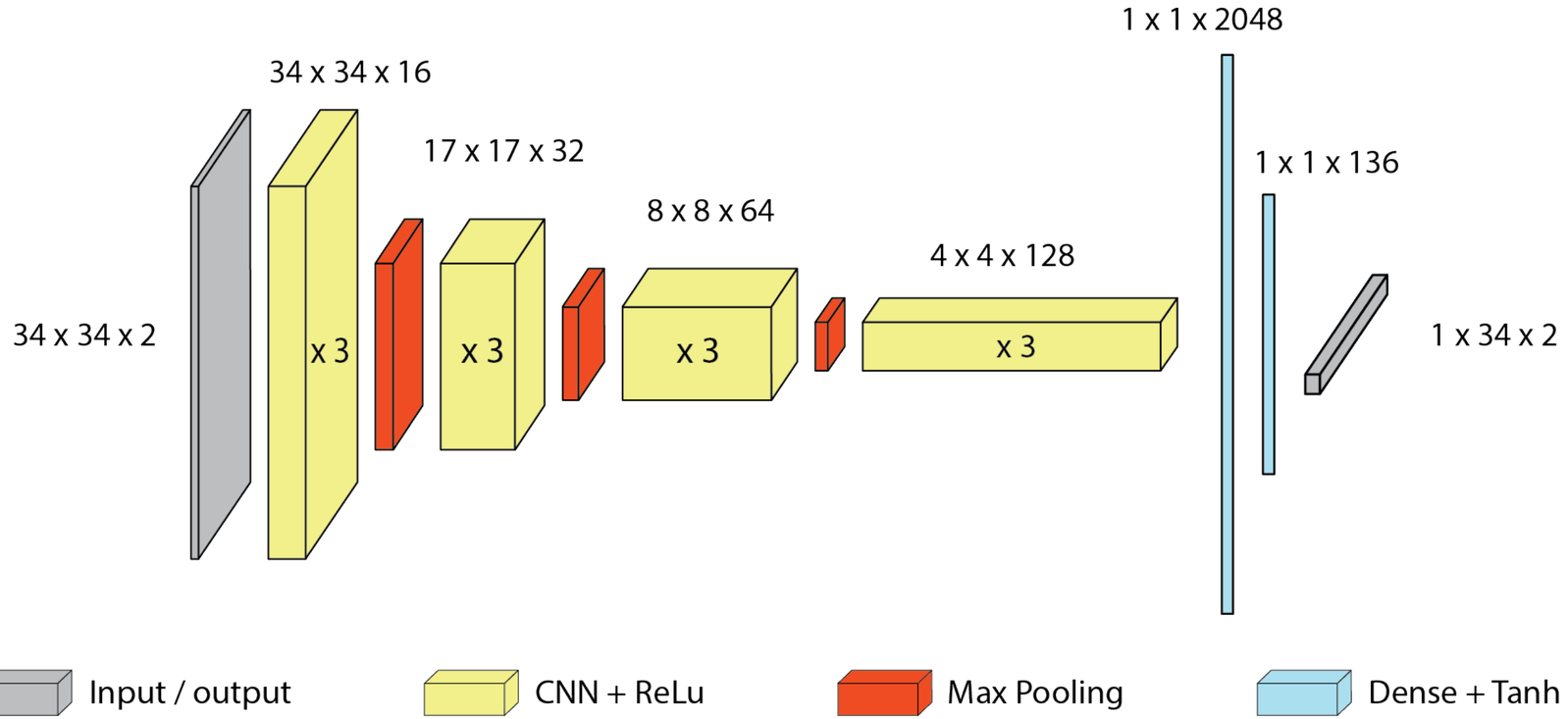
CNN design



Python 3.6

TensorFlow 1.3.0

Keras 2.0.5

NVIDIA Titan V

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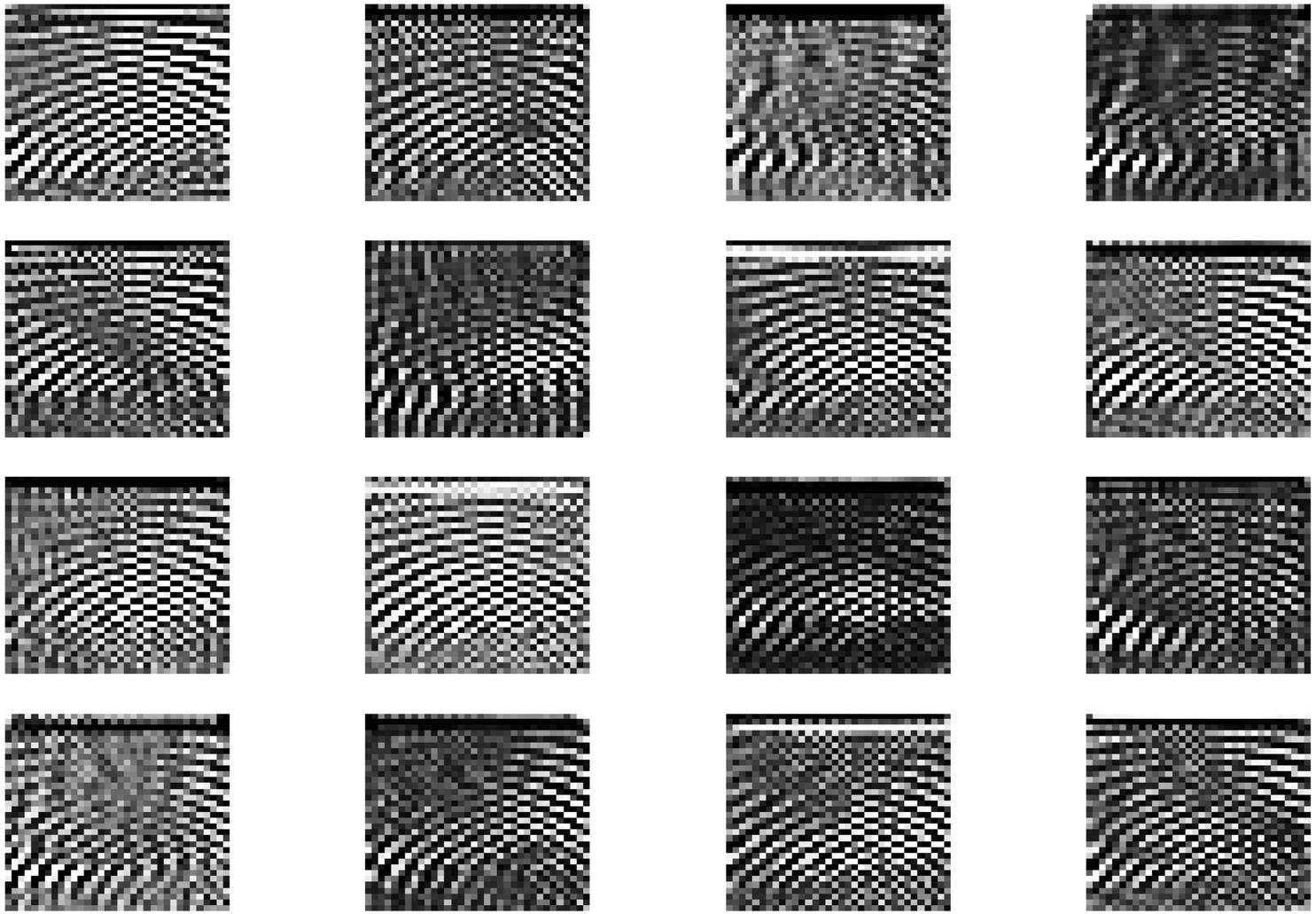
Feature maps 34 x 34 x 16



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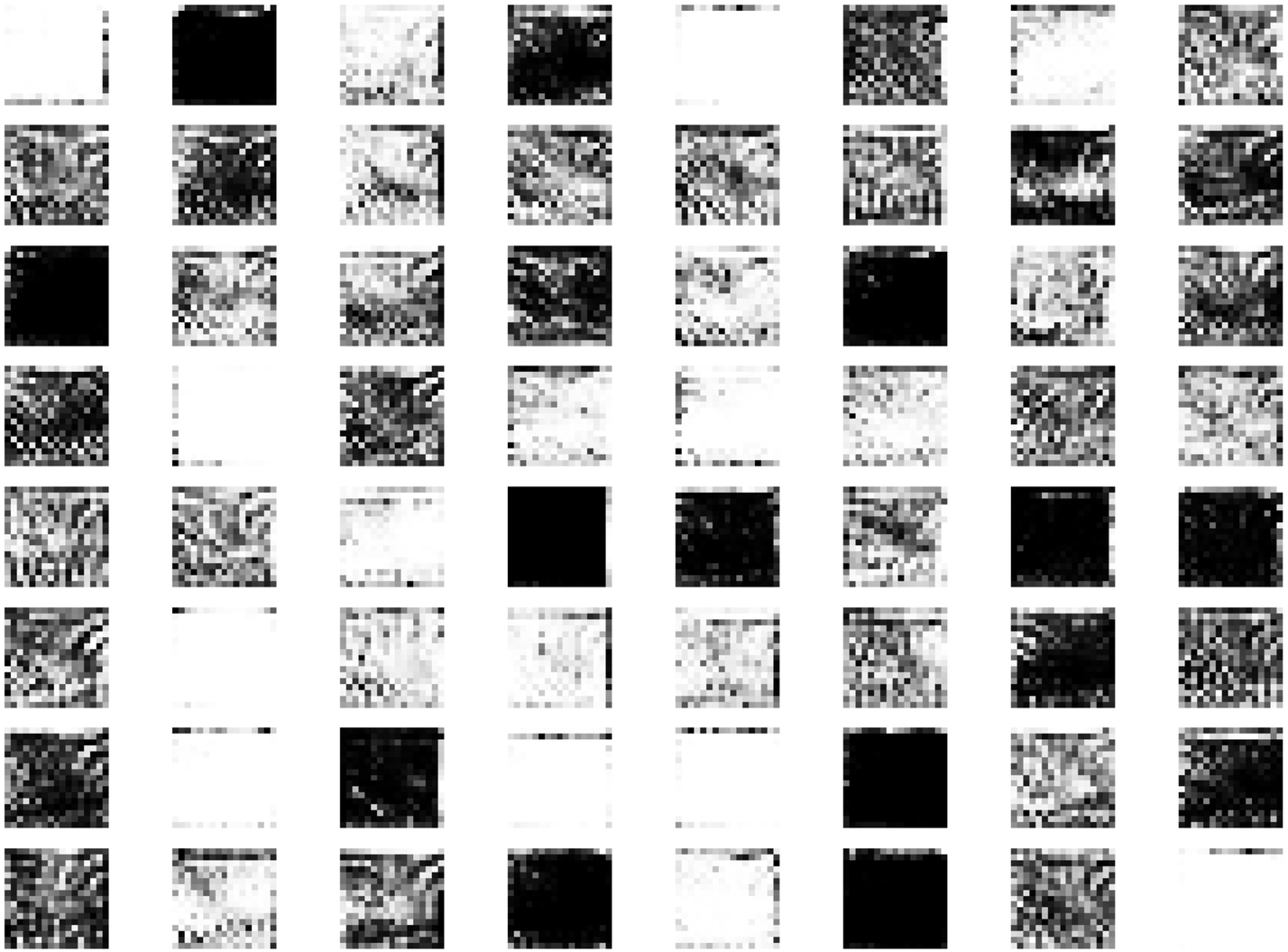
Feature maps 16 x 16 x 64



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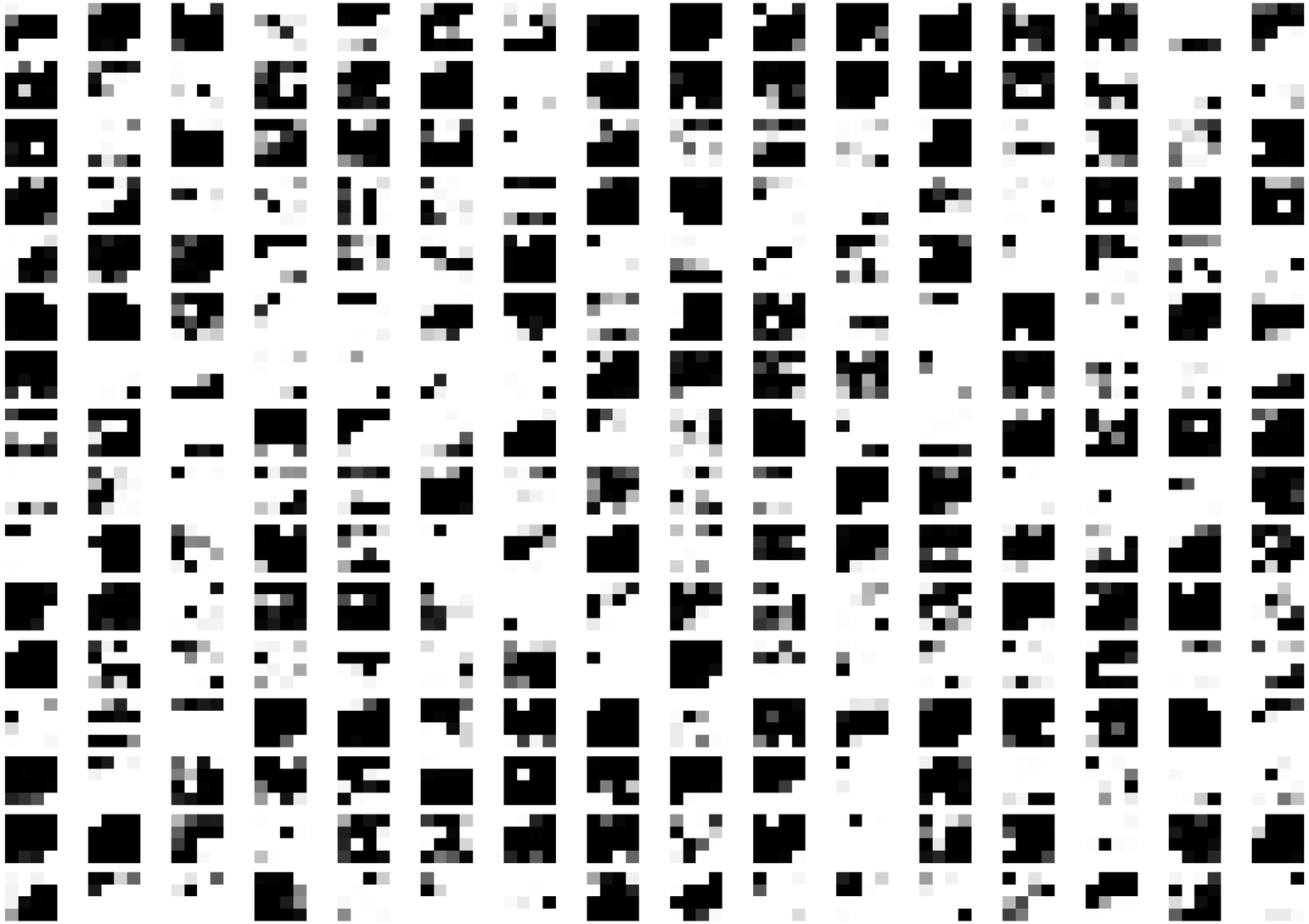
Feature maps 4 x 4 x 128



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Examples of low-frequency extrapolation

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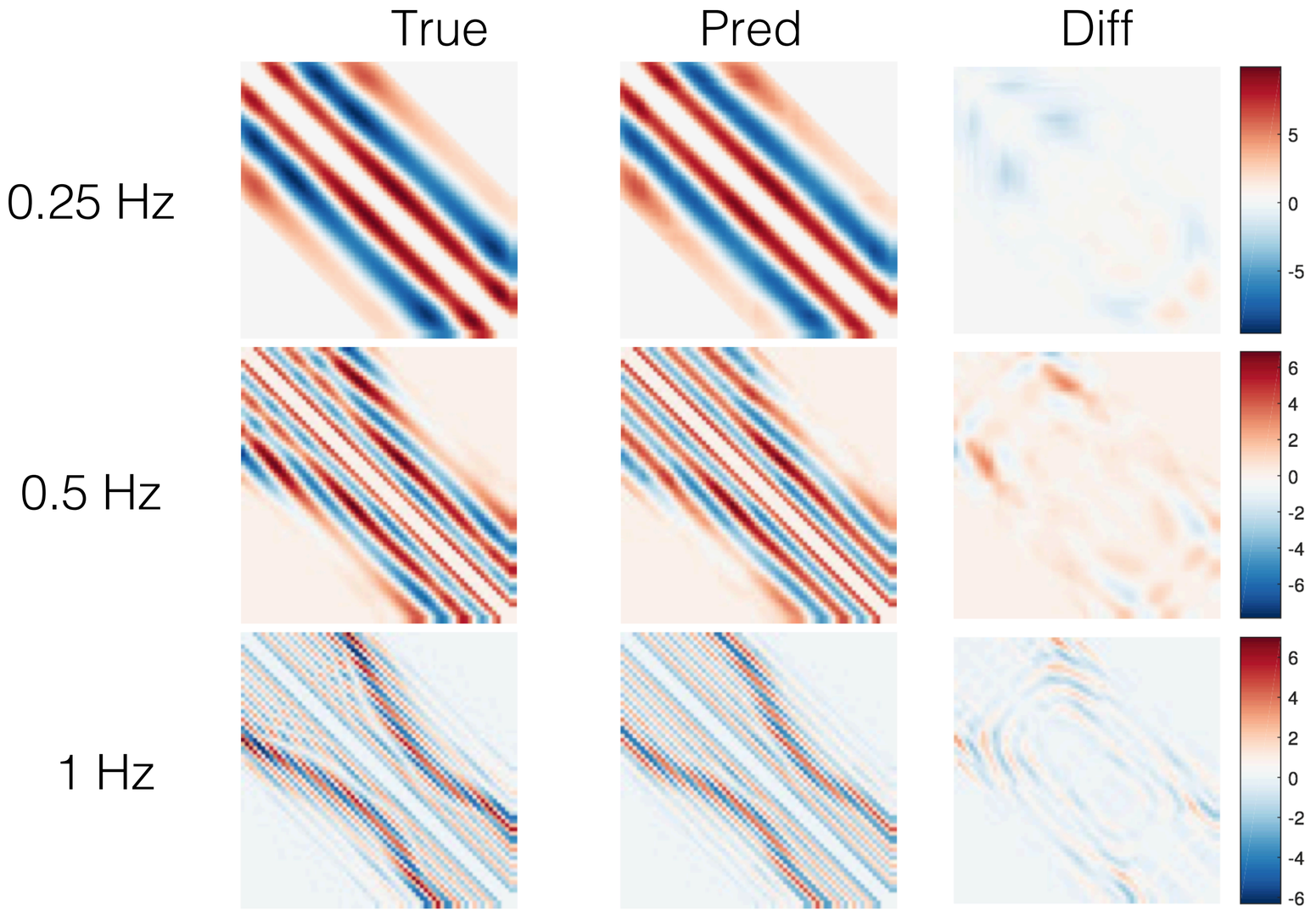
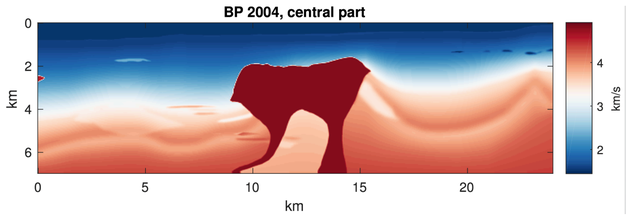
BP 2004 Central section





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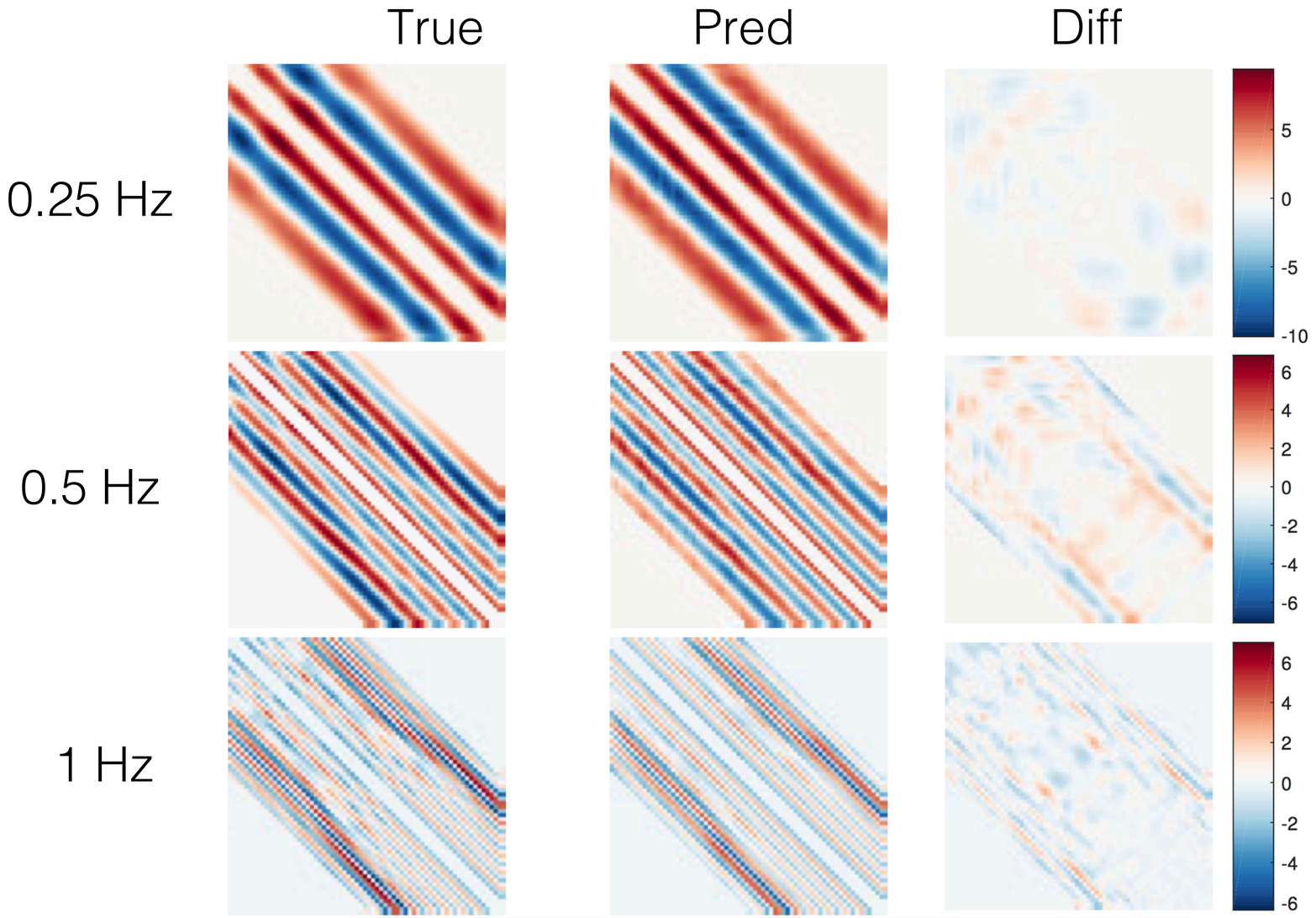
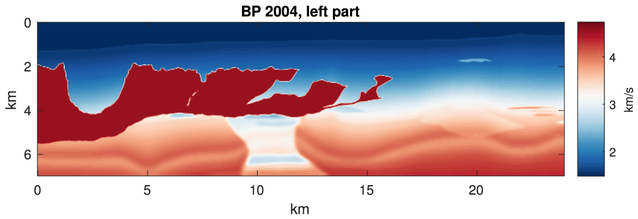
BP 2004 Left section





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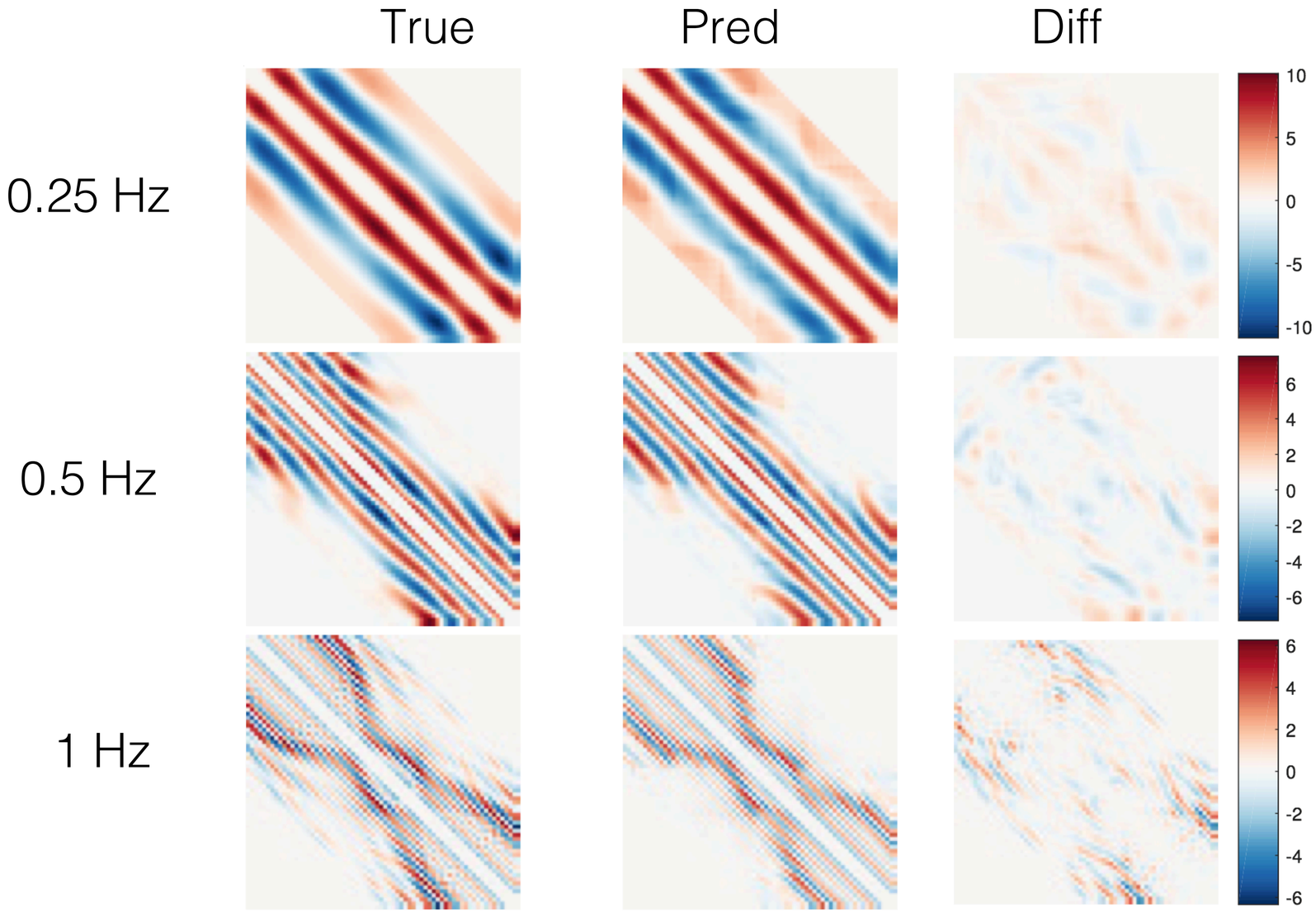
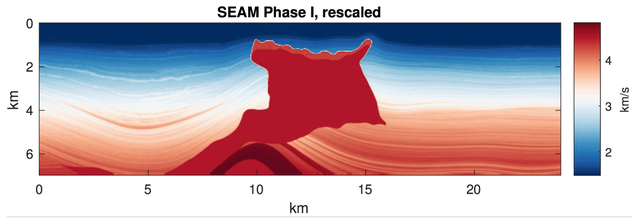
SEAM Phase I





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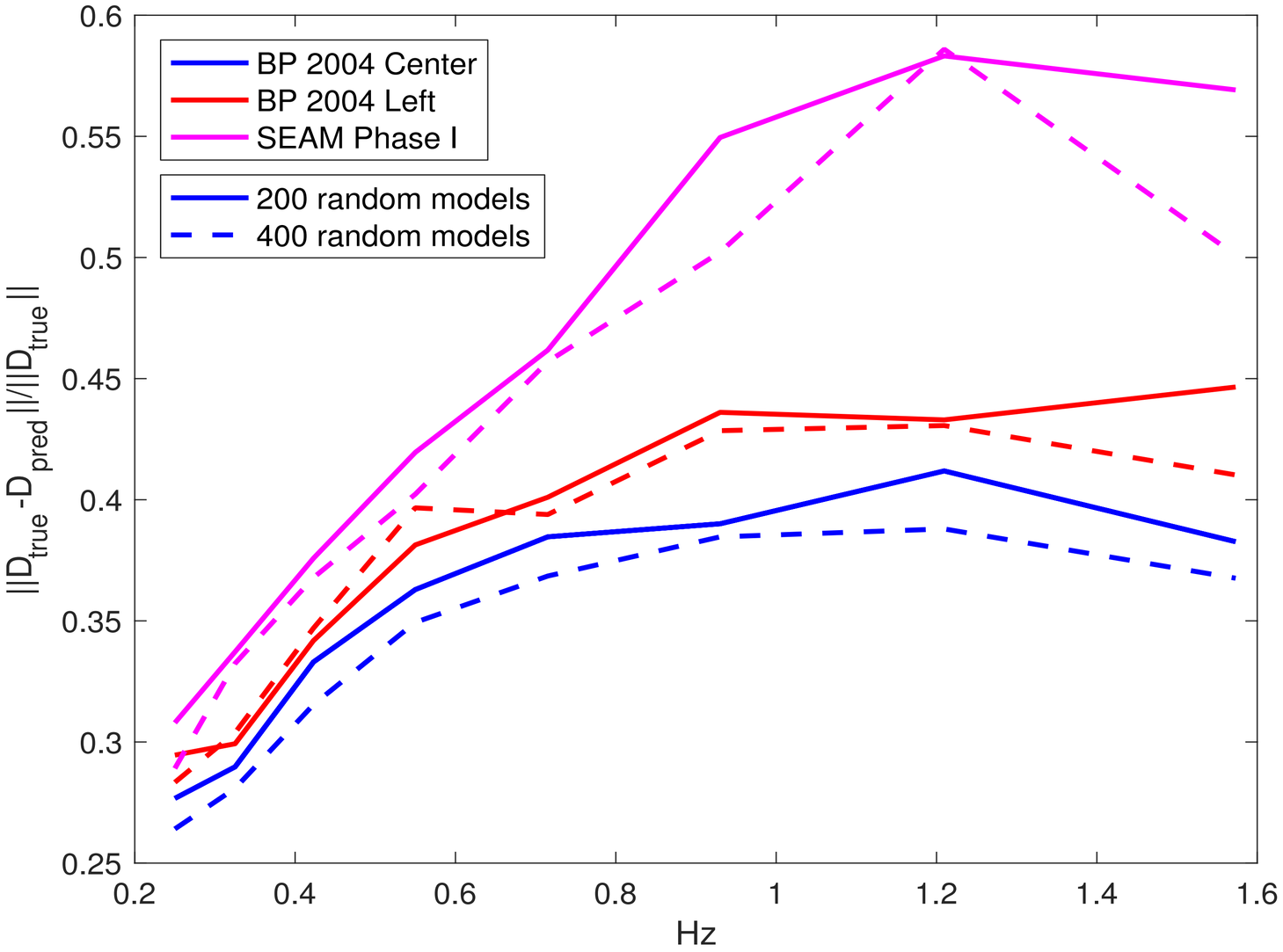
Accuracy of data extrapolation



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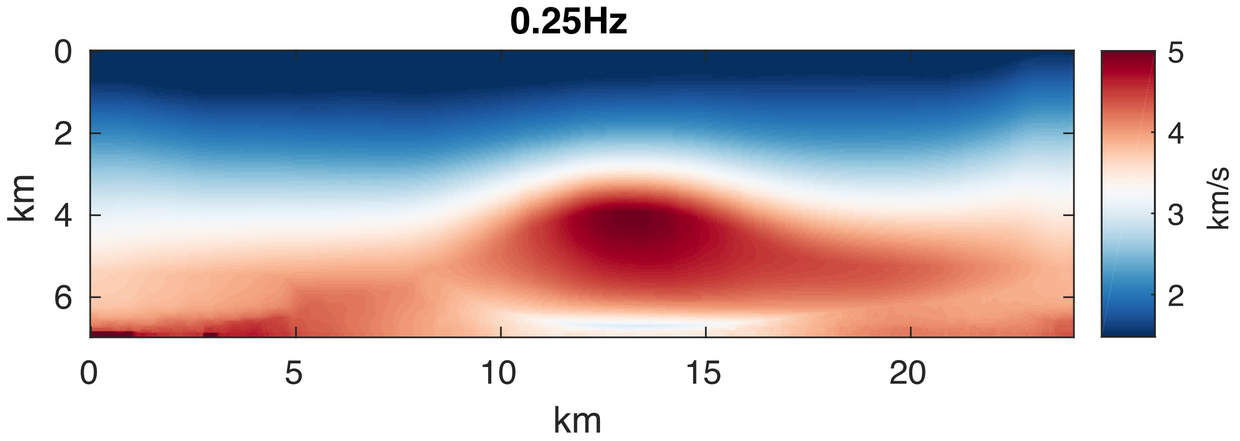
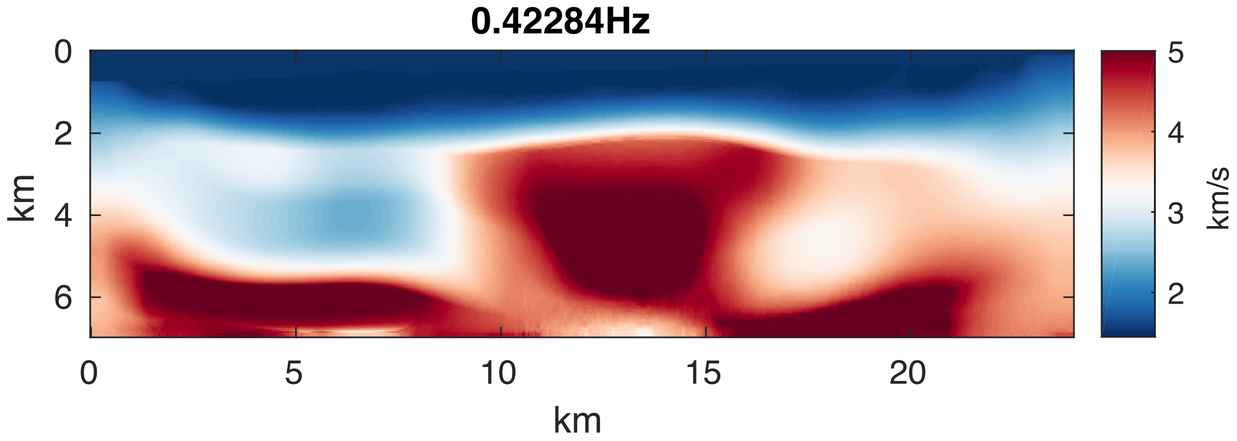
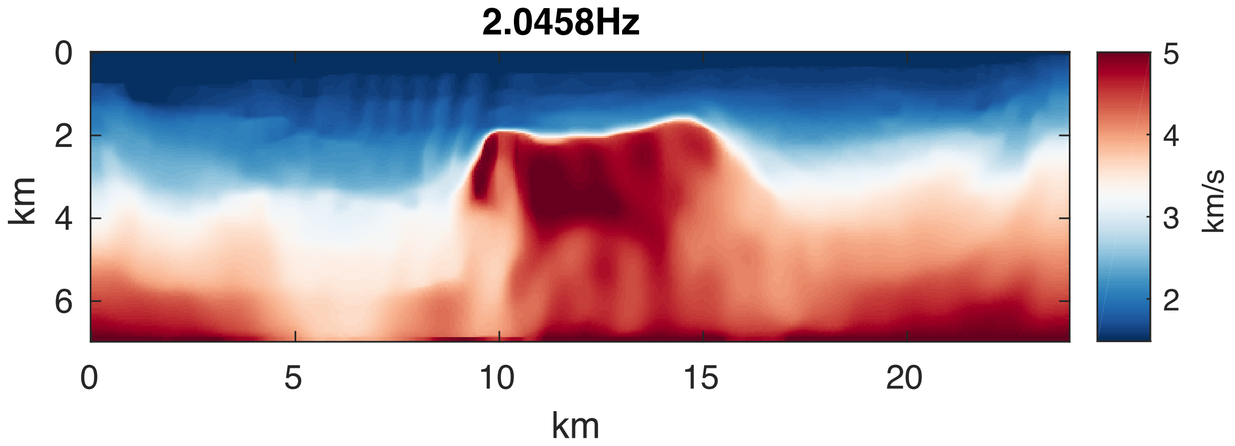
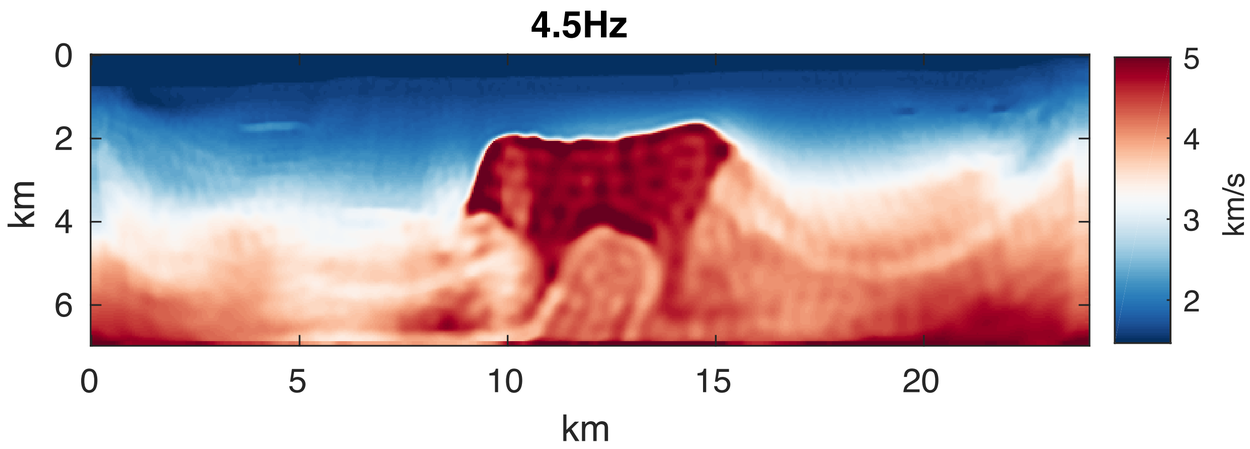
Multiscale FWI









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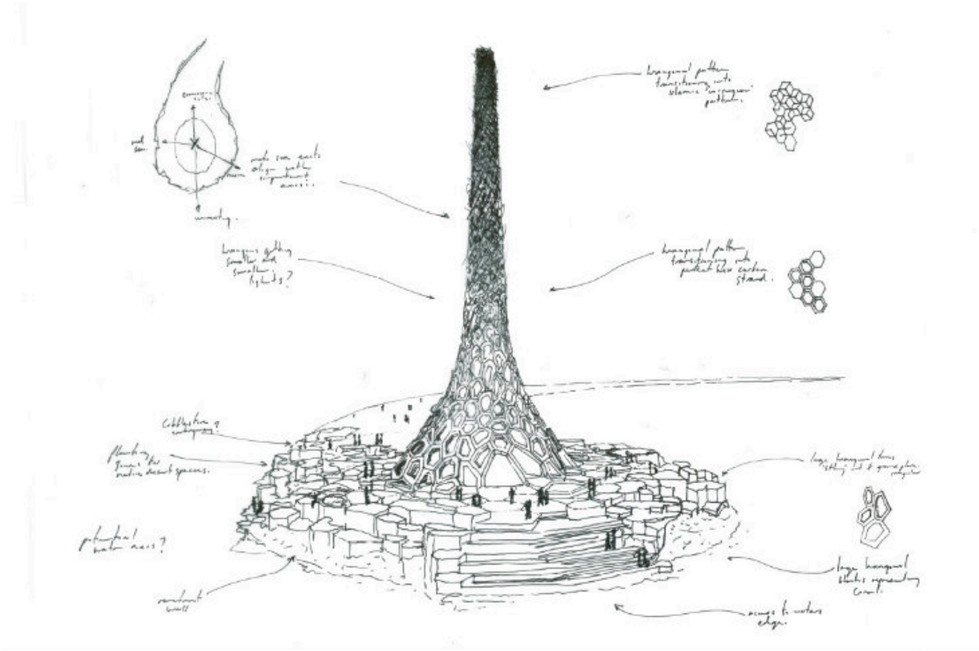
Acknowledgements



SWAG

Seismic Wave Analysis Group

Xiangliang Zhang

Gerhart Pratt

Frederik Simons

Seismic Modeling and Inversion (SMI)

Research Group

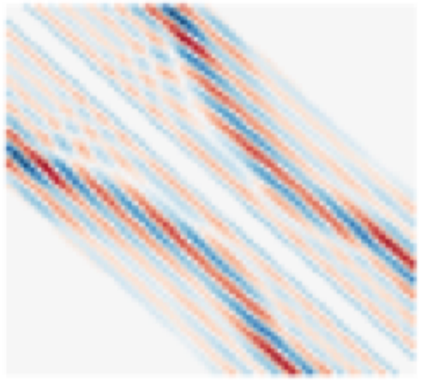
Conclusions

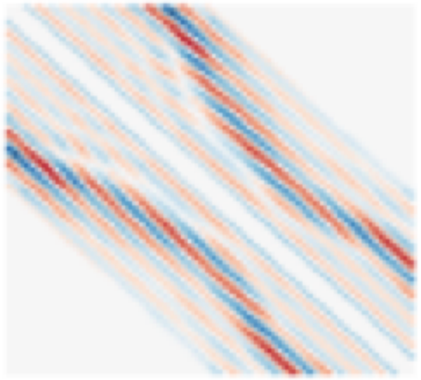
CSG to CSG extrapolation

Deep CNN learns mapping from high to low frequencies

Model generation matters

Lower frequencies are better extrapolated





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