

MEOM/IGE Group

*Implicit Neural Representations for Sea Surface Height Interpolation
(a.k.a. Modern Optimal Interpolation)*

J. Emmanuel Johnson

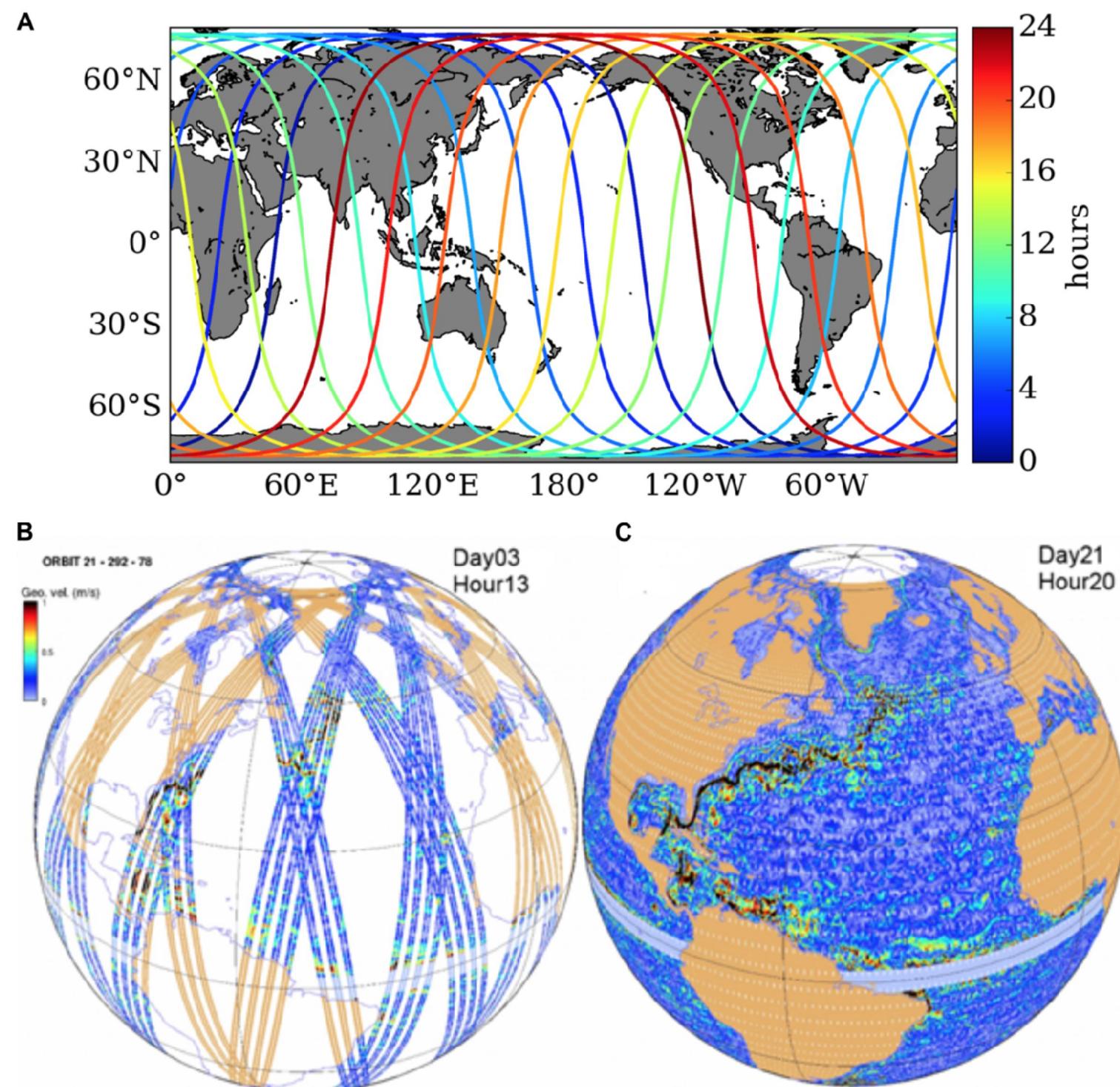
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MeLODy Project*



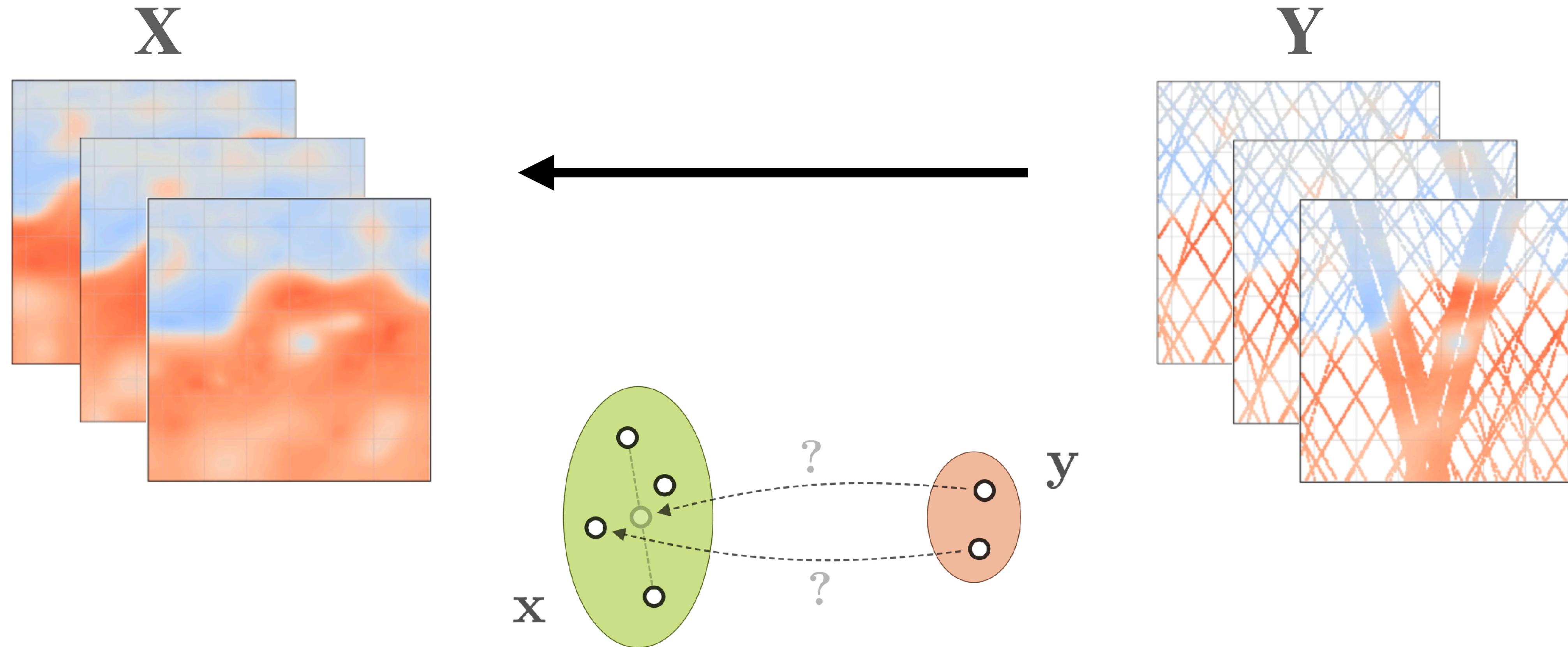
Motivation SWOT Mission (2022+)



- Sea Surface Height (SSH)
- **Gateway to the Ocean State**
- Physical Processes
- Bio-Geochemical Processes

A new influx of data with a multitude of applications!

Problem Statement



Can we interpolate the missing observations?

Table of Contents

- Current Methods
- *Modern* Methods
- Experiments
- Next Steps

In Practice

Coordinate



$$\mathbf{X} \in \mathbb{R}^{N \times D_\phi}$$

$$D_\phi = [\text{Latitude}, \text{Longitude}, \dots]$$

$$N = [\star \star \star \star \star \star \star]$$

- Scalability
- Easy to Compute
- Expressive
- Take Advantage of Sparsity

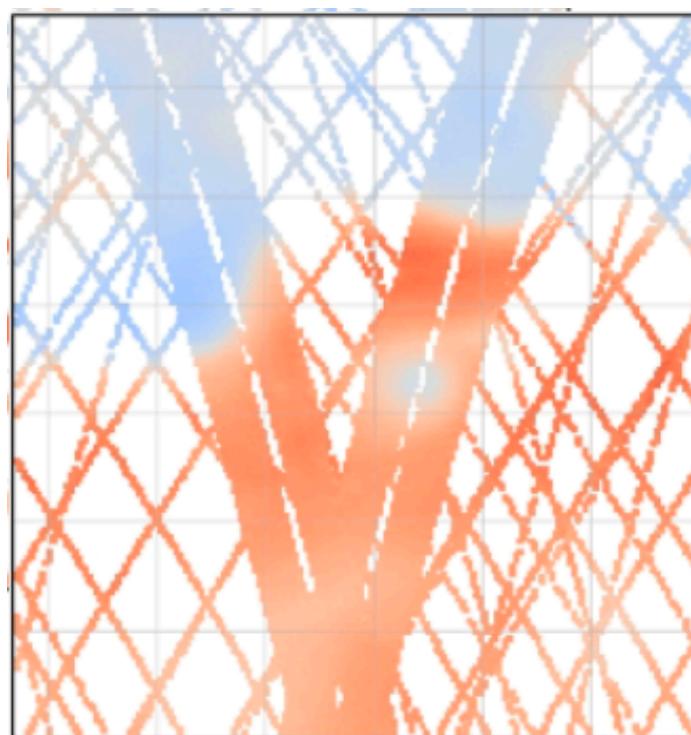
In some operational settings, coordinate-based inputs are used in practice!

A technique for objective analysis and design of oceanographic experiments applied to MODE-73 – Bretherton et. al. – 1975

A numerically efficient data analysis method with error map generation – Rixen et al – 2000

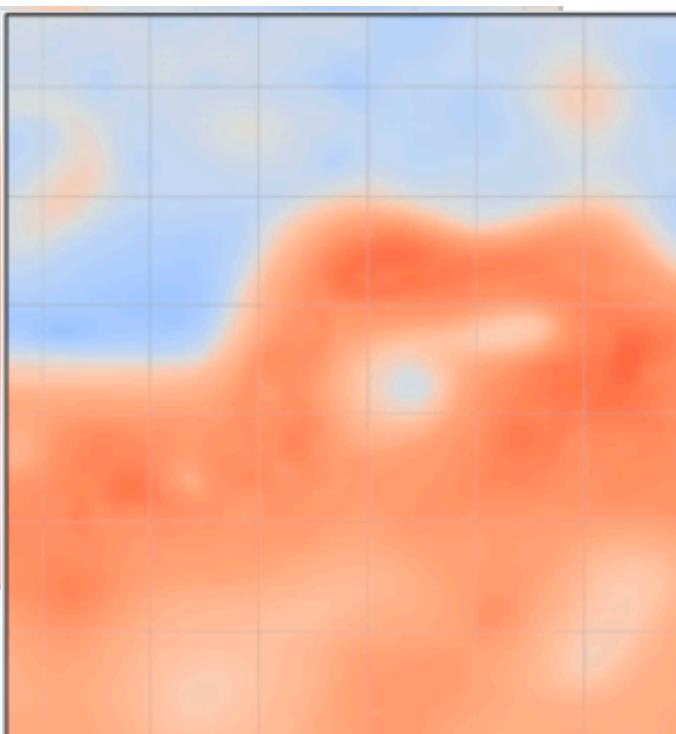
Coordinates

Training



$$\mathbf{y}_{obs} = f_{\theta}(\mathbf{X}_{\phi}) + \epsilon$$

Evaluation

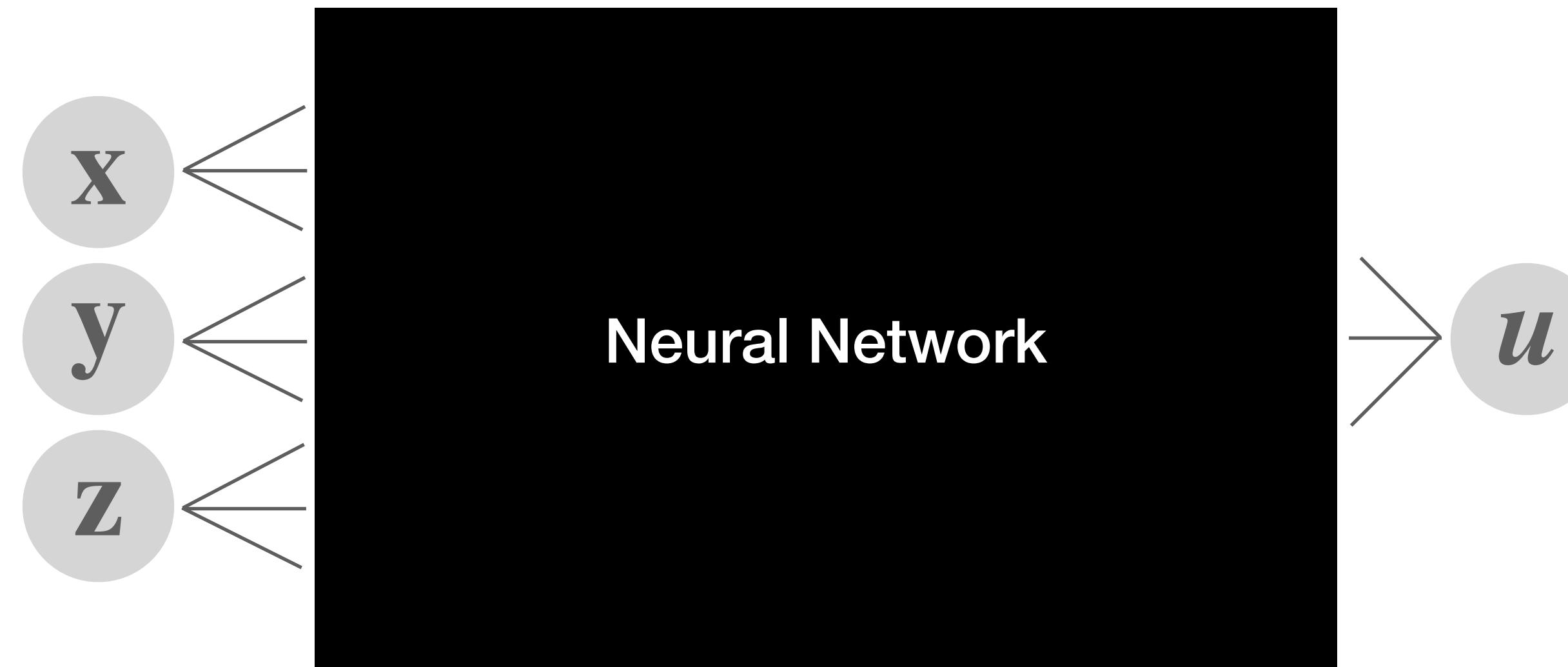


$$\mathbf{y}^* = f_{\theta}(\mathbf{X}_{\phi}^*) + \epsilon$$

$$p(\theta | \mathbf{X}_{\phi}, \mathbf{y}_{obs}) \propto p(\mathbf{y}_{obs} | \mathbf{X}_{\phi}, \theta) p(\theta)$$

What are the best parameters of our model which best fits the observations?

Implicit Neural Representations



Optimal Interpolation with a different Model...

Problem

Neural Networks have problems with high frequency signals...!

Example: Interpolating an Image



<https://wandb.ai/wandb/nerf-jax/reports/Implementing-NeRF-in-JAX--VmIldzoxODA2NDk2?galleryTag=jax>

Problem

Neural Networks have problems with high frequency signals...!

Solutions

Basis Function Transformations

Sinusoidal Activation Functions

Fourier Features Mapping

Basis Transformation

Basis Function

$$\phi(\mathbf{x}) = \begin{bmatrix} \sin(2\pi\Omega\mathbf{x}) \\ \cos(2\pi\Omega\mathbf{x}) \end{bmatrix}$$

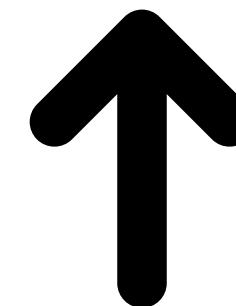
$$\Omega \sim \mathcal{N}(0, \gamma^2 I)$$

$$\phi(\mathbf{x}) = \begin{bmatrix} \sin(2\pi\Omega\mathbf{x}) \\ \cos(2\pi\Omega\mathbf{x}) \end{bmatrix}$$

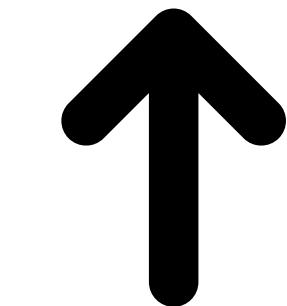
Fourier Features Mapping

Basis Transformation

$$f_\theta(\phi(\mathbf{x})) := \text{NN}_\theta \circ \phi(\mathbf{x})$$



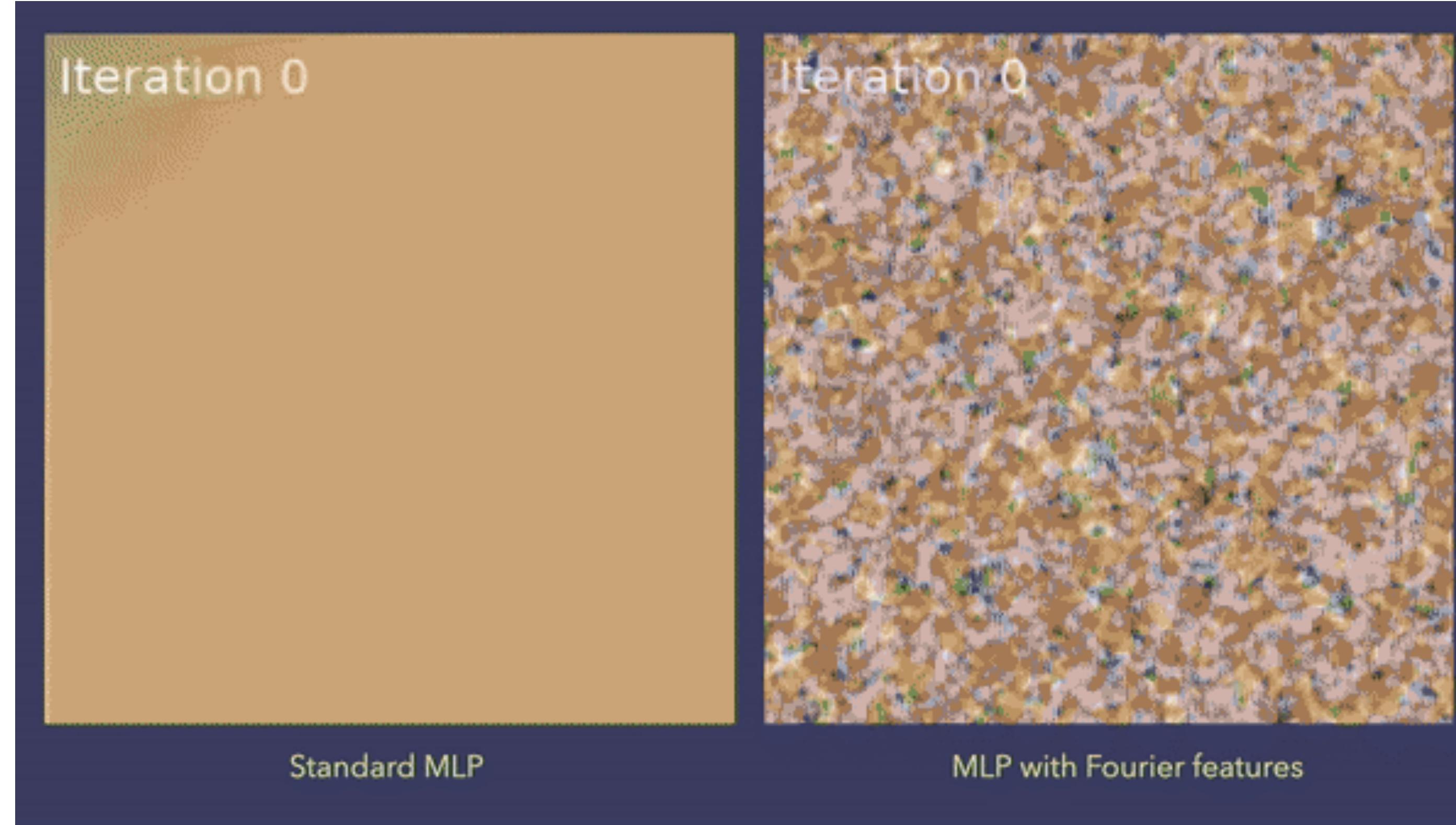
Standard NN



RFF Transformation

Transform using Fourier Features, then use any Neural Network...

Example: Interpolating an Image Revisited



Problem

Neural Networks have problems with high frequency signals...!

Solutions

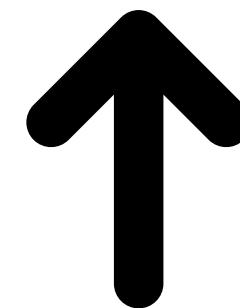
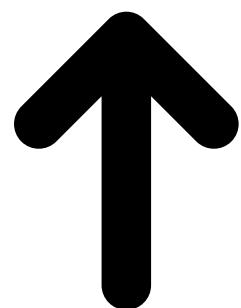
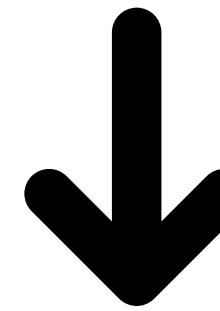
Basis Function Transformations

Sinusoidal Activation Functions

Sinusoidal Layer

$$\phi(\mathbf{x}) = \sin(\omega_0(\mathbf{w} \cdot \mathbf{x} + \mathbf{b}))$$

Frequency
Parameter

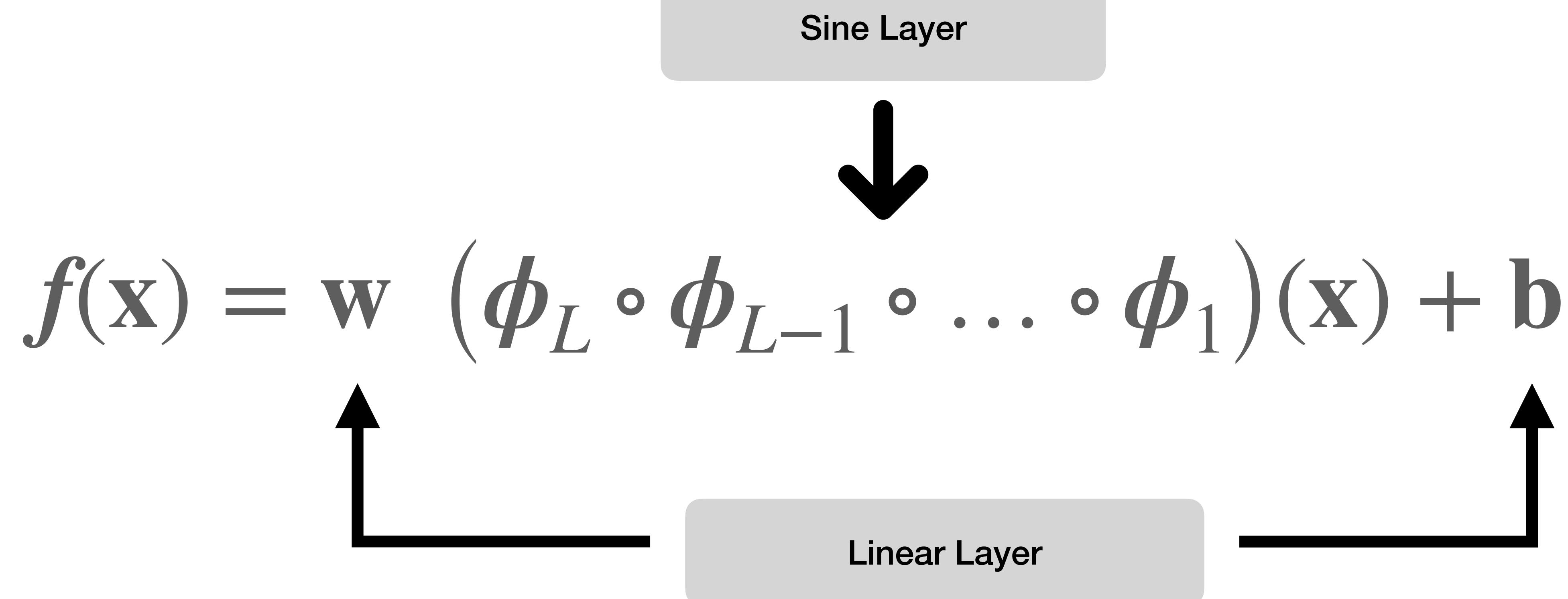


Sine function

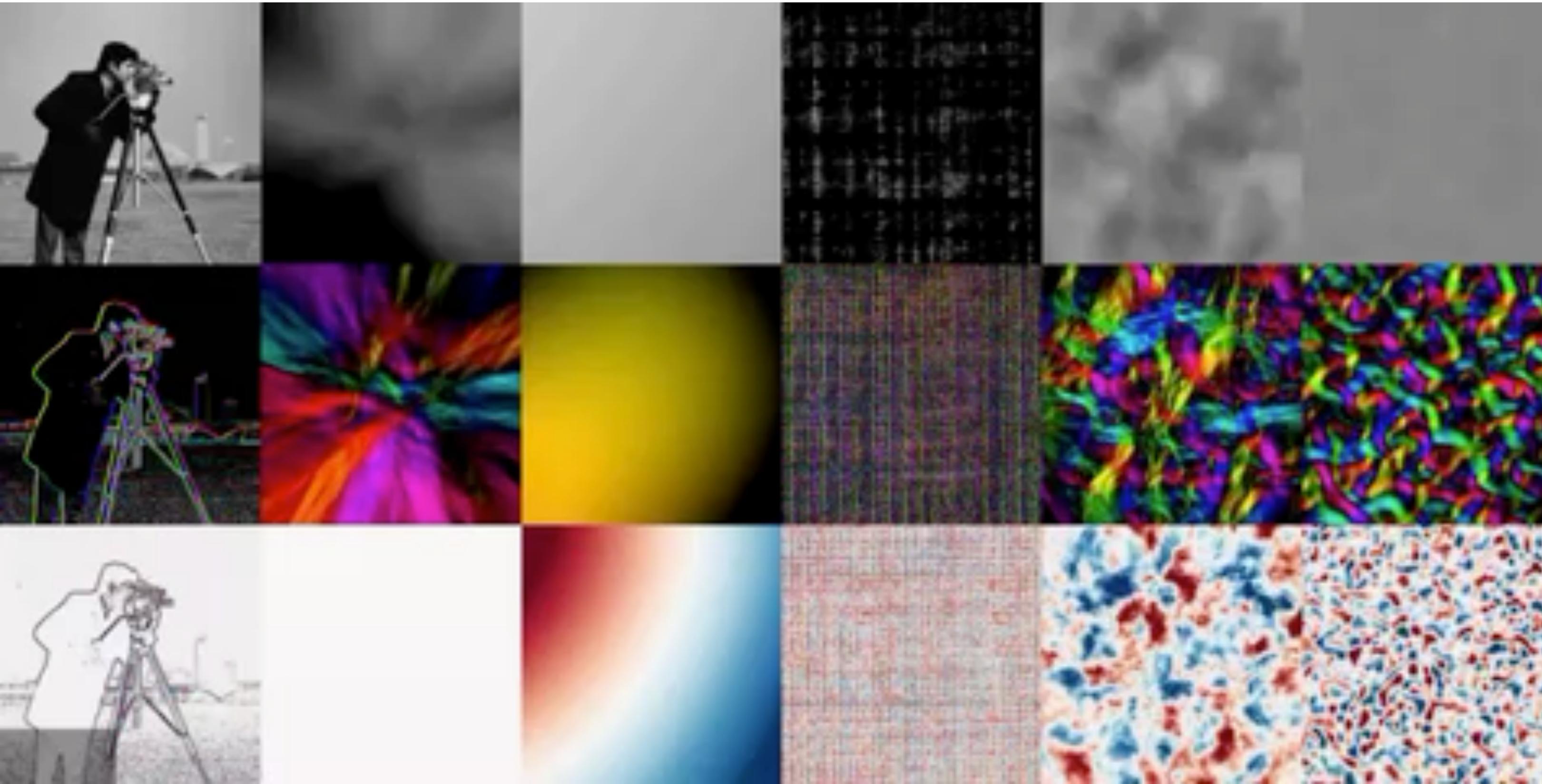
Linear Layer

$$\phi_\ell(\mathbf{x}) = \sin(\omega_0(\mathbf{w}\mathbf{x} + \mathbf{b}))$$

SIREN Model



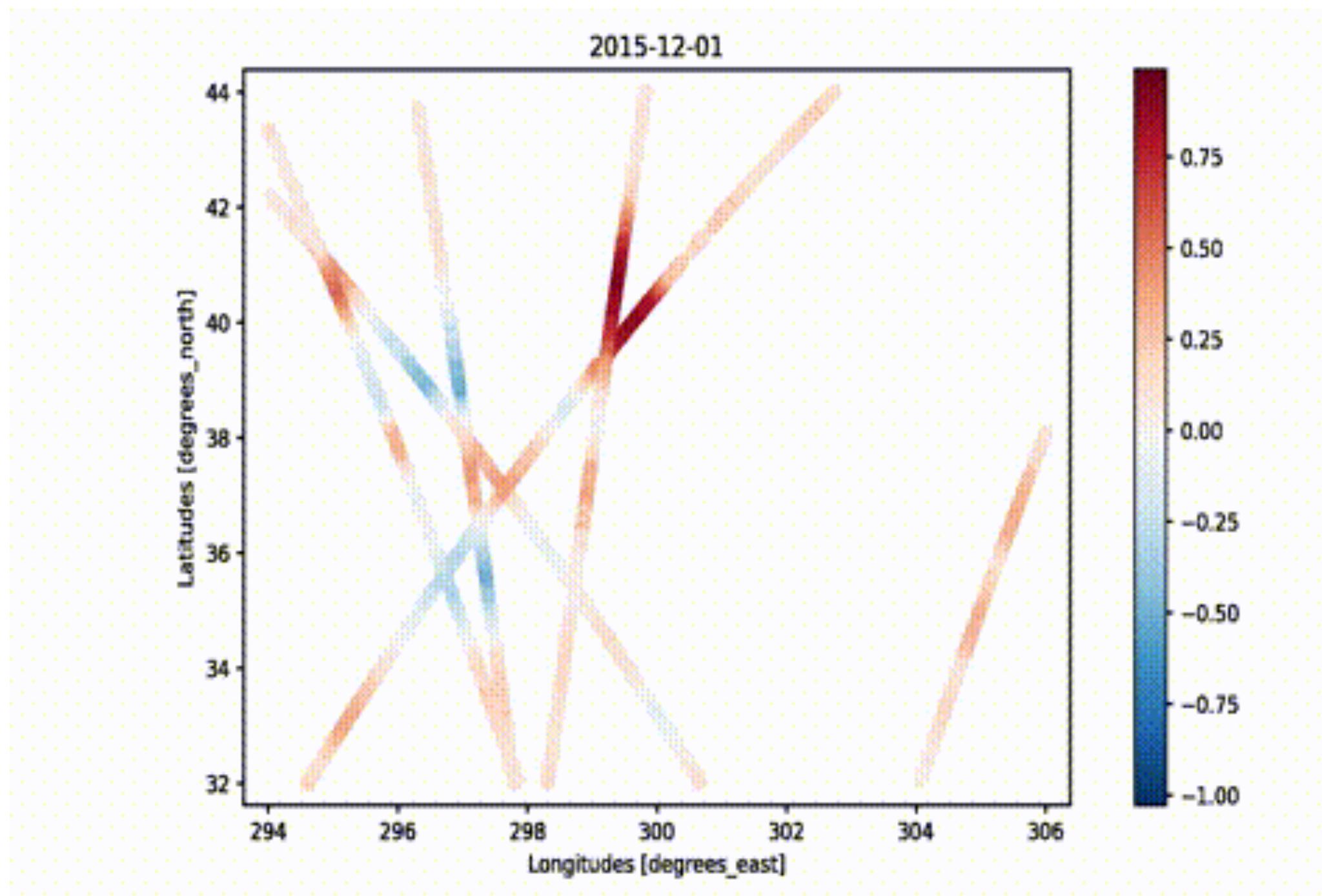
Result - Better Gradient Representation



Preliminary Results

How does this work on oceanographic-like datasets?

Data Challenge 2021a



- Gulf Stream
- 7 Altimetry Sources
- 1 Left out for validation

DOI [10.5281/zenodo.5511905](https://doi.org/10.5281/zenodo.5511905)

SSH Mapping Data Challenge 2021a

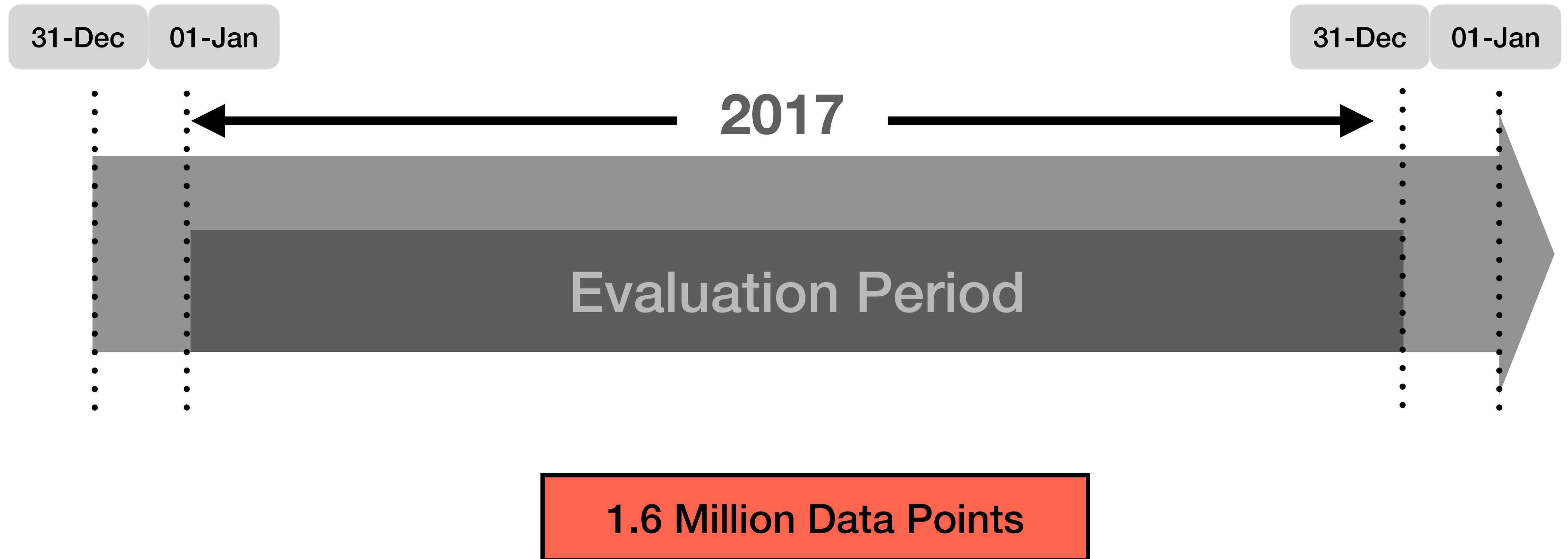
This repository contains codes and sample notebooks for downloading and processing the SSH mapping data challenge.

The quickstart can be run online by clicking here: [?](#)

Motivation

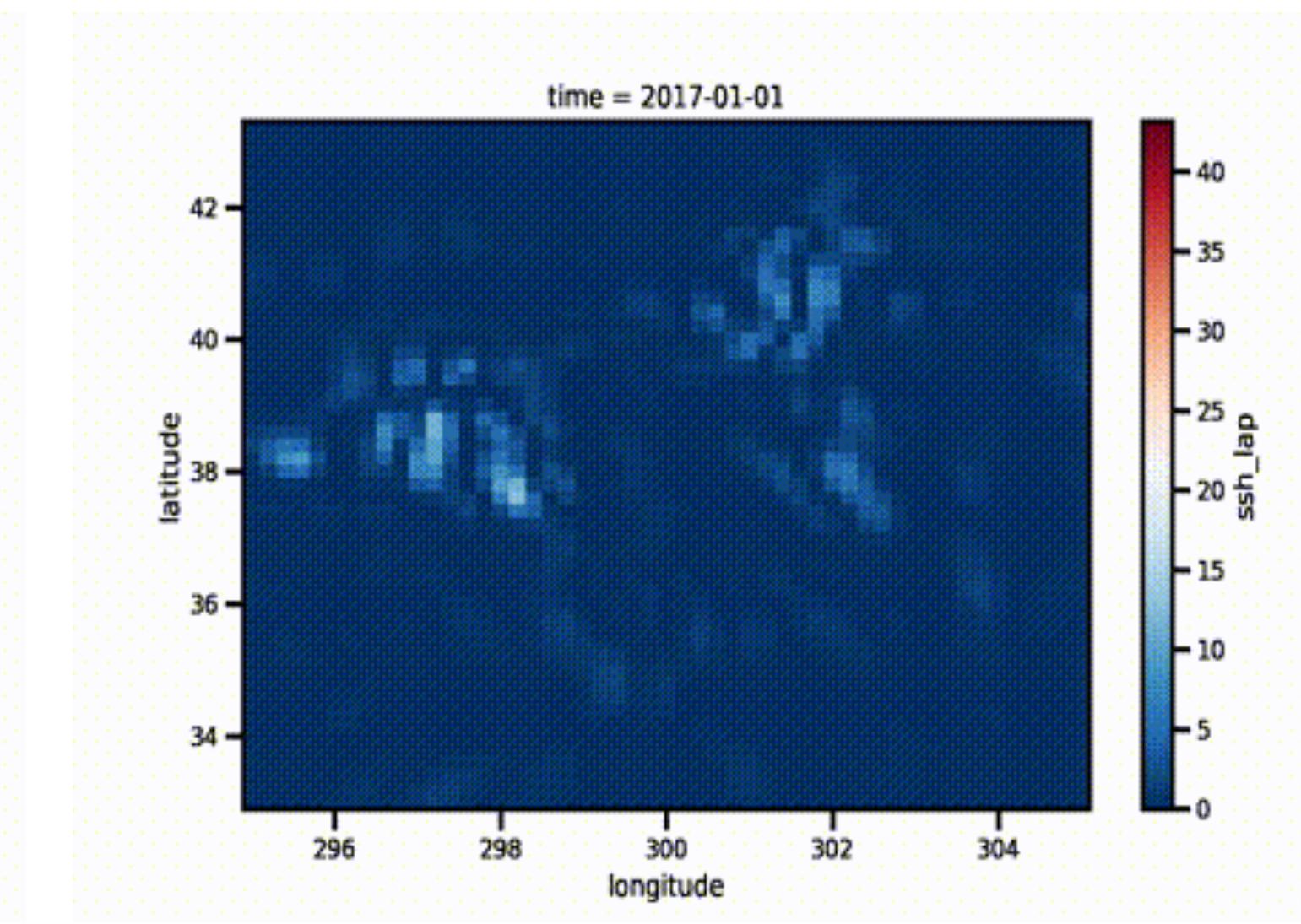
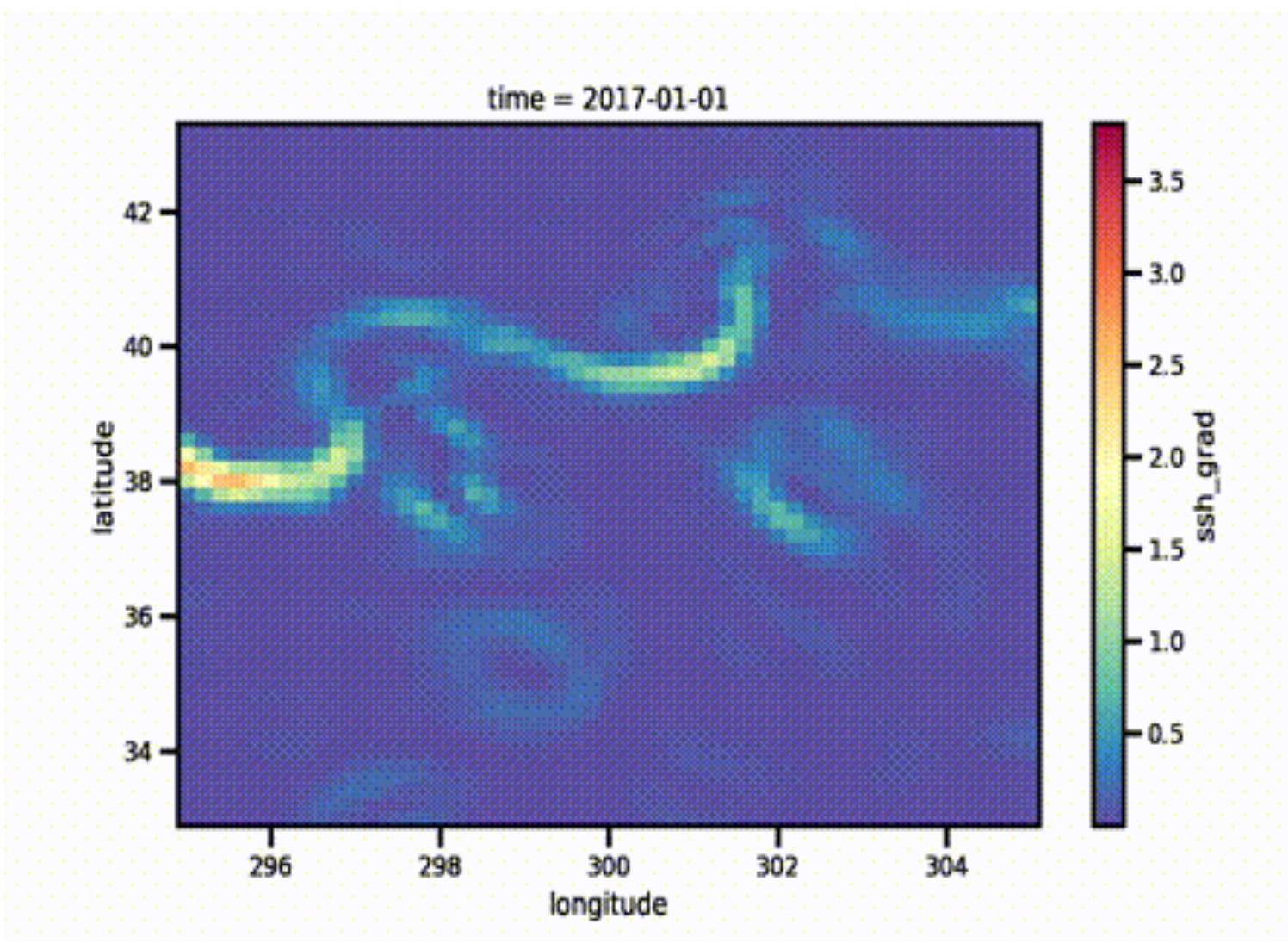
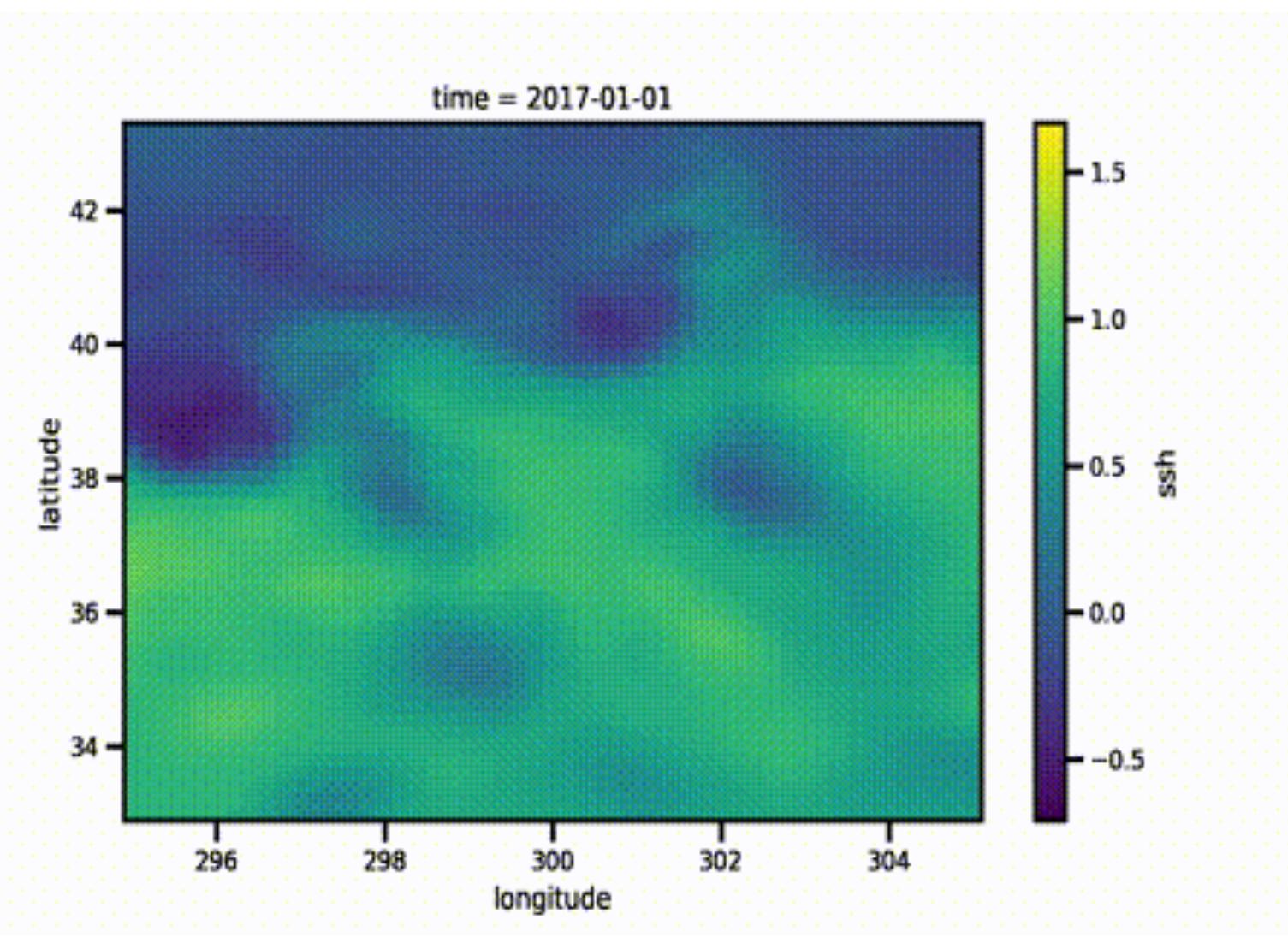
The goal is to investigate how to best reconstruct sequences of Sea Surface Height (SSH) maps from partial satellite altimetry observations. This data challenge follows an *Observation System Experiment* framework: Satellite observations are from real sea surface height data from altimeter. The practical goal of the challenge is to investigate the best mapping method according to scores described below and in Jupyter notebooks.

Evaluation Period



Results

Visual Maps



Predictions

Gradient (Norm)

Laplacian (Norm)

No crazy looking structures...

Poor Laplacian...

Results

Metrics

Algorithm	Normalised RMSE (Mean)	Normalised RMSE (Standard Dev)	Resolved Spatial Resolution (km)
Optimal Interpolation	0.85	0.09	140
Optimal Interpolation (Production - DUACS)	0.88	0.07	152
SIREN (Ours)	0.88	0.08	146

All metrics are comparable.

Results

Inference Times - (~1 million data points)

Algorithm	CPU (10 cores)	GPU	Multi-GPU
Optimal Interpolation	1 hour	-- --	-- --
Optimal Interpolation (Production - DUACS)	-- --	-- --	-- --
SIREN (Ours)	30 secs	5 secs	-- --

Predictions are fast...really fast.

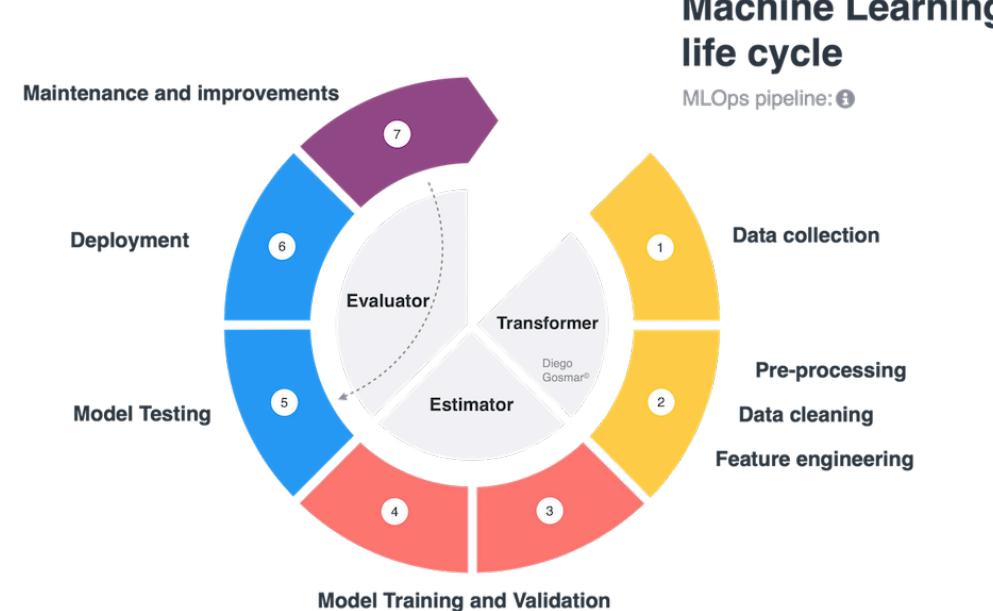
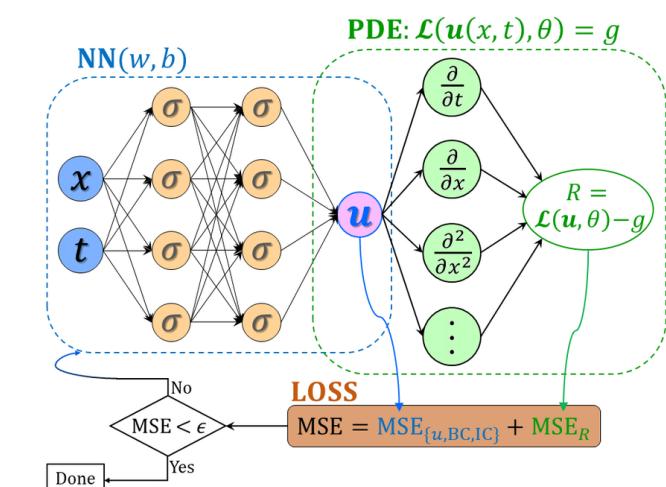
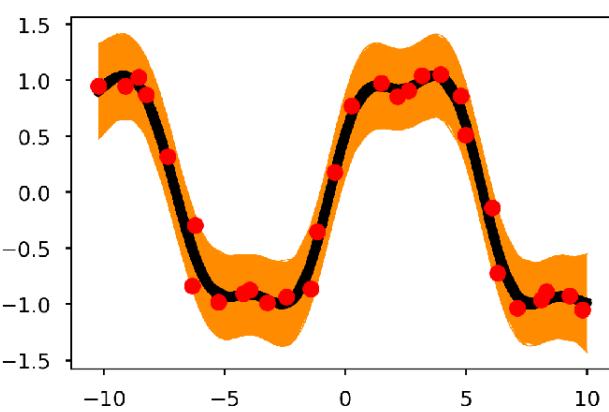
The Next Steps

Wish List

My Potential Contributions



- Data (Easy)
- Pragmatic Bayesian (Medium)
- Physics Informed Loss Function (Hard)
- MLOps + Reproducibility (**Easy**)



Thank You

Any Questions?



github.com/jejjohnson



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Coordinate Representation



$$\mathbf{x} \in \mathbb{R}^{D_\phi}$$

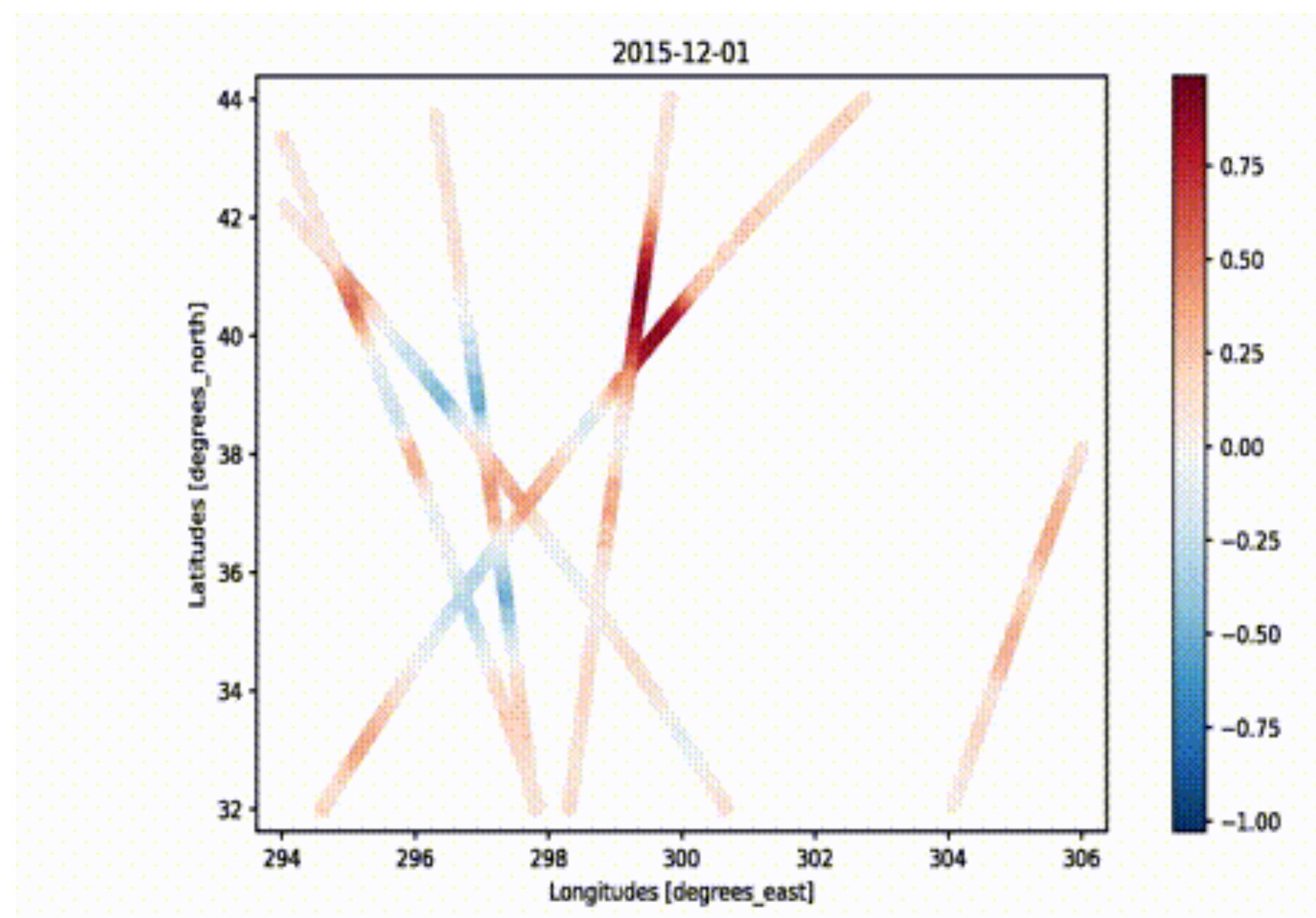
Coordinate

$$D_\phi = [\text{Latitude}, \text{Longitude}, \dots]$$

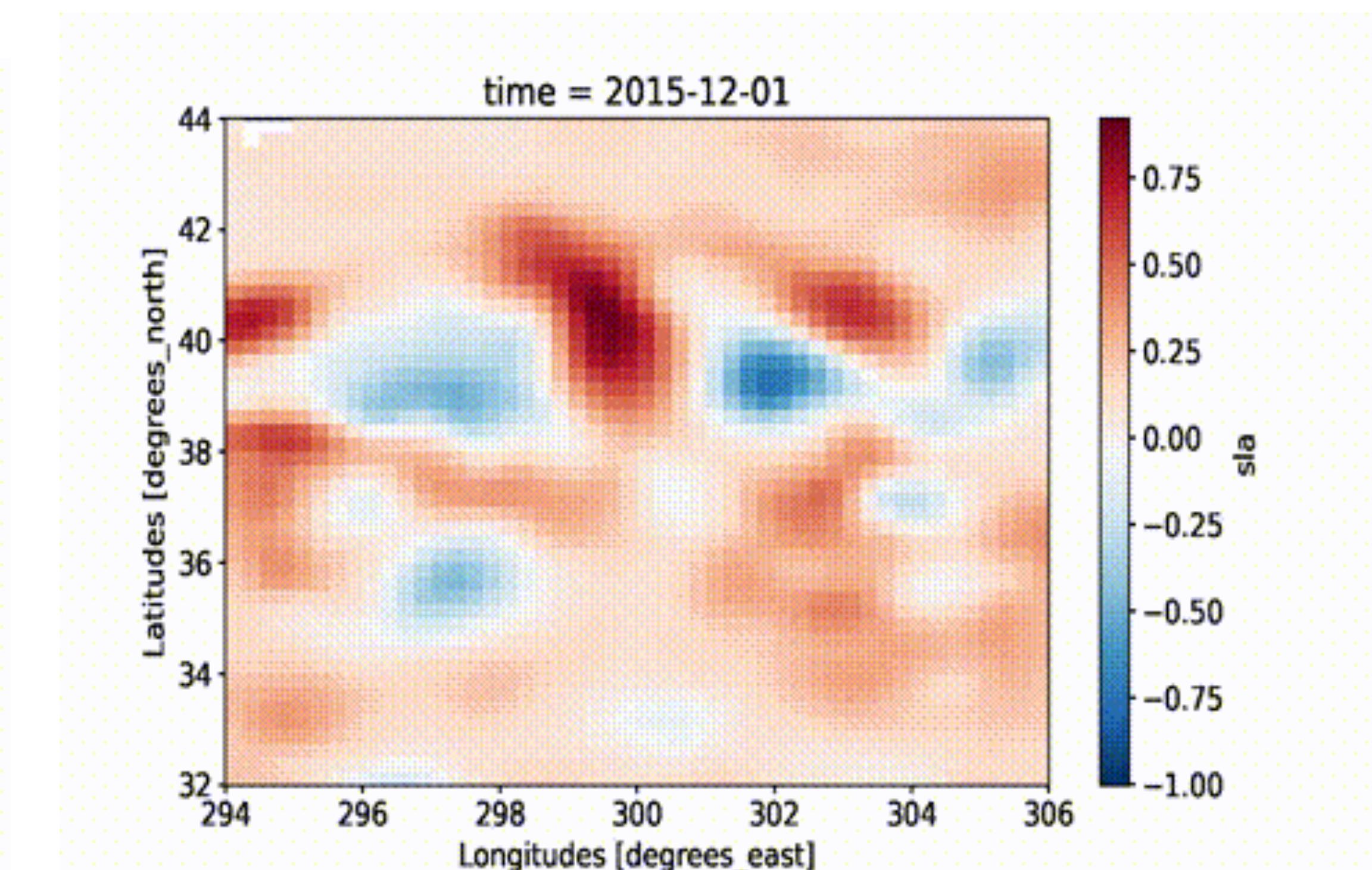


$$N = [\star \star \star \star \star \star \star]$$

Baseline



Observations



Optimal Interpolation
(Production)