

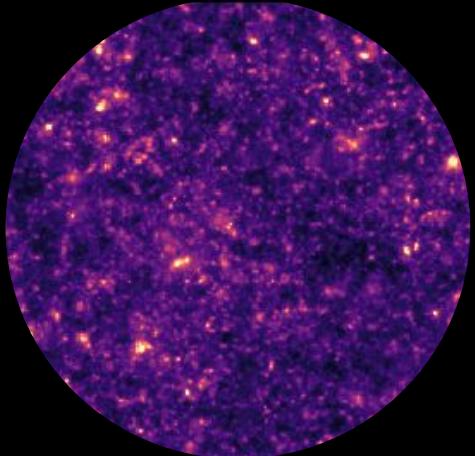
# Adaptive wavelet distillation from neural networks through interpretations



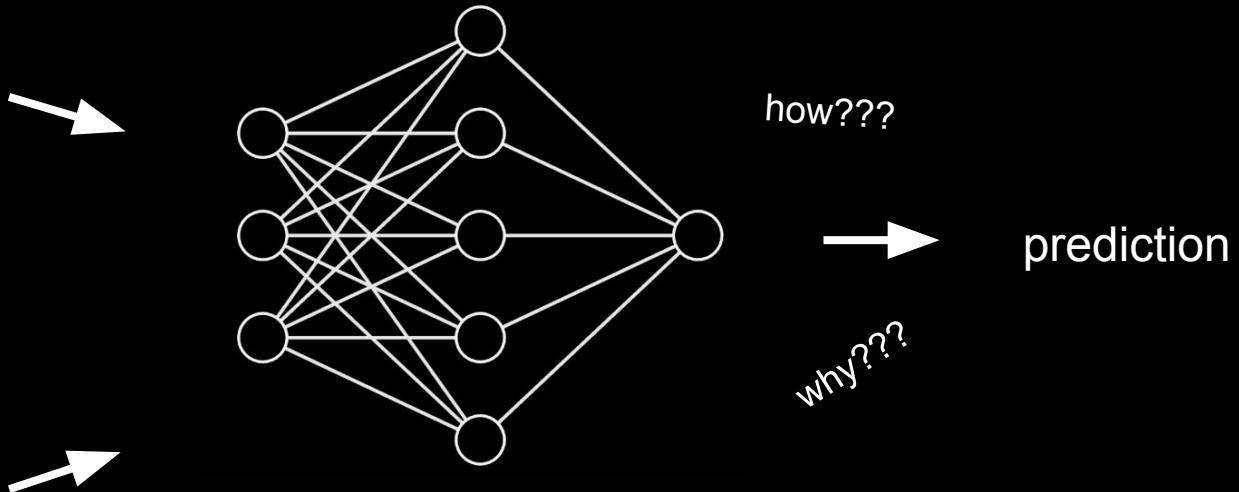
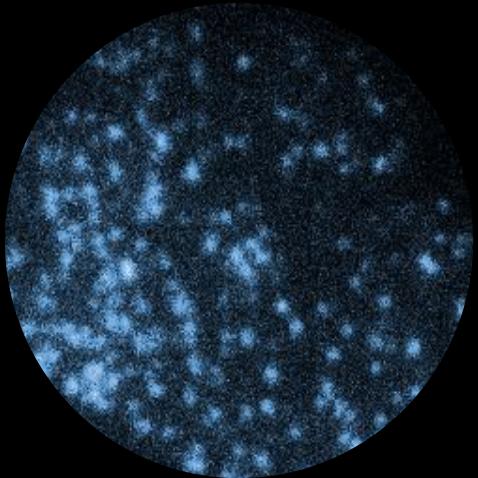
UC Berkeley

Interpretability

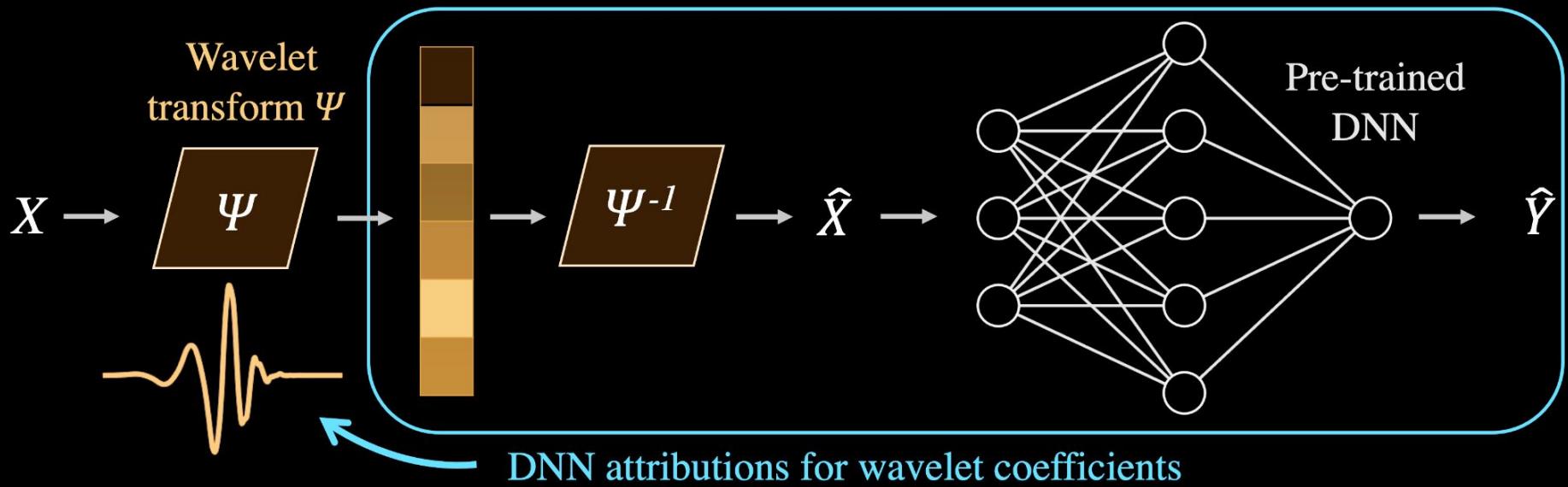




# a deep problem: interpretability

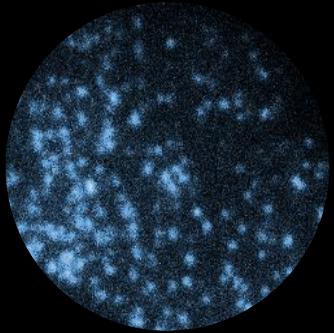


# a shallow solution: wavelets



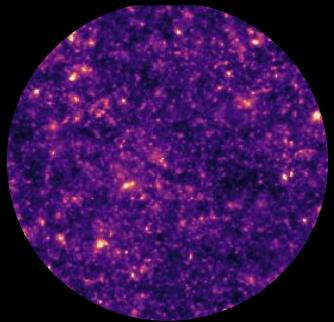
$$\underset{h,g}{\text{minimize}} \mathcal{L}(h,g) = \underbrace{\frac{1}{m} \sum_i \|x_i - \hat{x}_i\|_2^2}_{\text{Reconstruction loss}} + \underbrace{\frac{1}{m} \sum_i W(h, g, x_i; \lambda)}_{\text{Wavelet loss}} + \underbrace{\gamma \sum_i \|\text{TRIM}_{\Psi,f}(\Psi x_i)\|_1}_{\text{Interpretation loss}}$$

# results (spoilers!)



cell-biology: CME event prediction

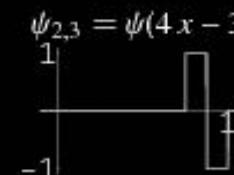
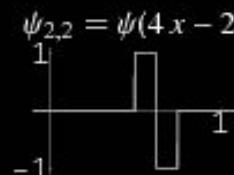
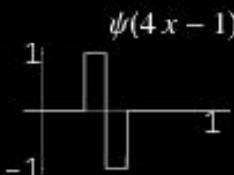
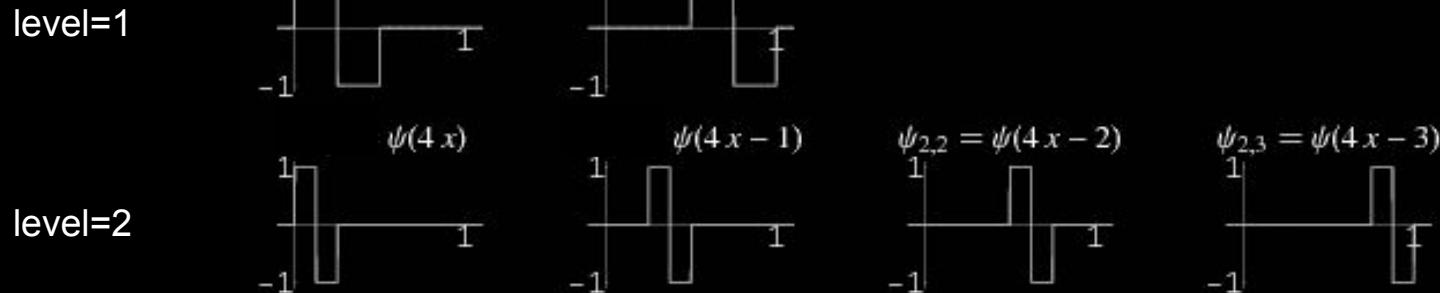
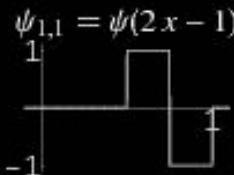
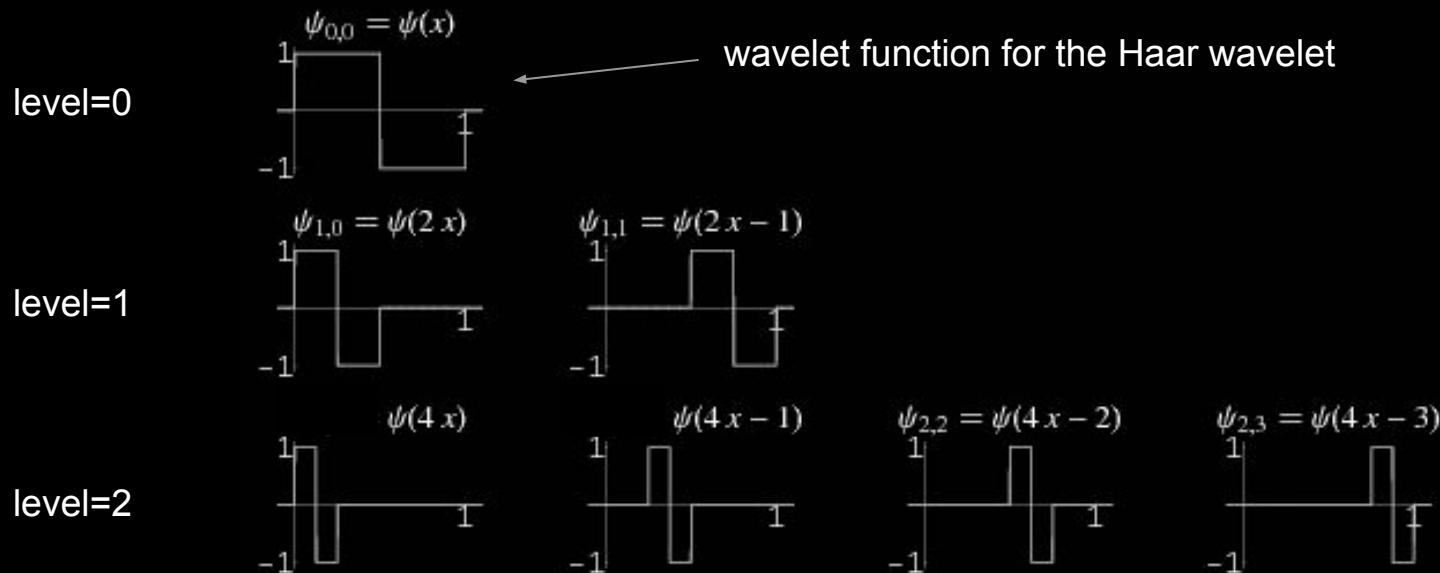
LSTM	SOA Baseline	
0.237	0.197	$R^2$ (higher is better)



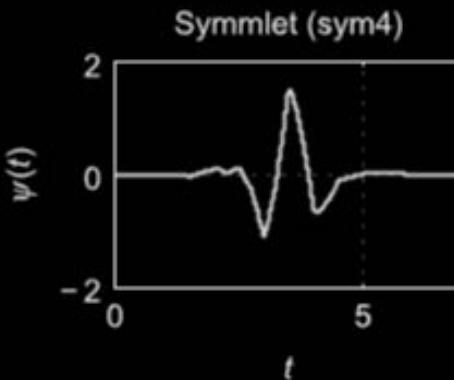
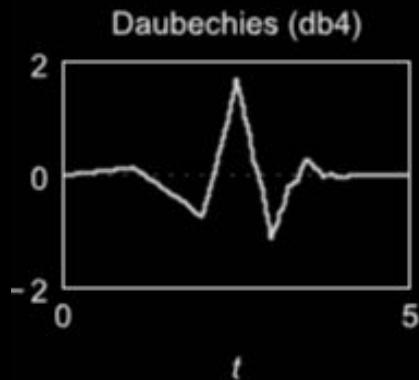
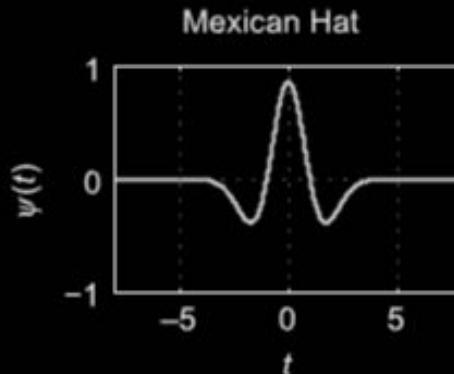
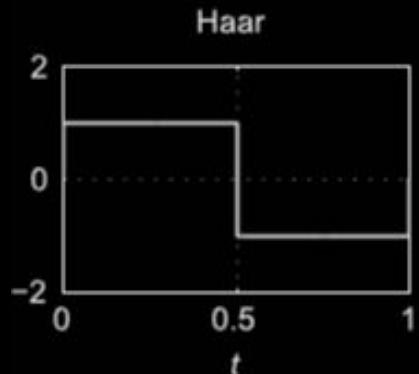
cosmological parameter prediction

Resnet	SOA Baseline	
1.156	1.259	RMSE (lower is better)

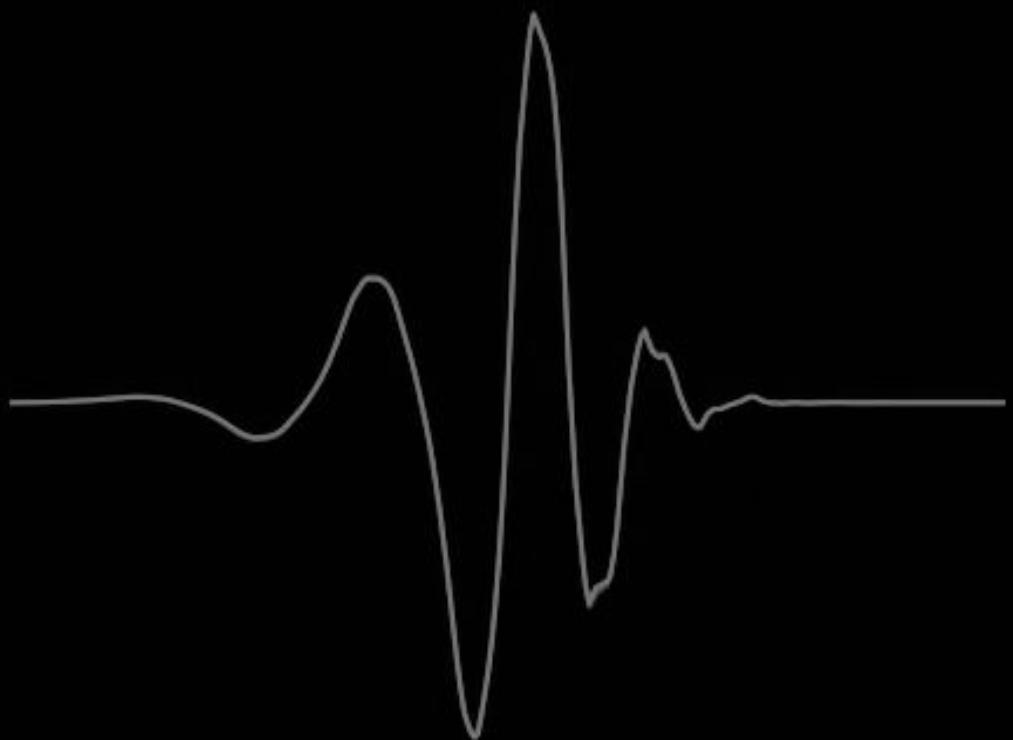
# wavelet transform: multi-scale, spatially localized



# wavelet function can vary



# adaptive wavelet



$$\underset{h,g}{\text{minimize}} \mathcal{L}(h,g) = \underbrace{\frac{1}{m} \sum_i \|x_i - \hat{x}_i\|_2^2}_{\text{Reconstruction loss}} + \underbrace{\frac{1}{m} \sum_i W(h,g, x_i; \lambda)}_{\text{Wavelet loss}}$$

**orthonormal basis** under following conditions (mallat, 1998):

$$|\hat{h}(w)|^2 + |\hat{h}(w + \pi)|^2 = 2 \quad \forall w$$

$$\sum h_i = \sqrt{2}$$

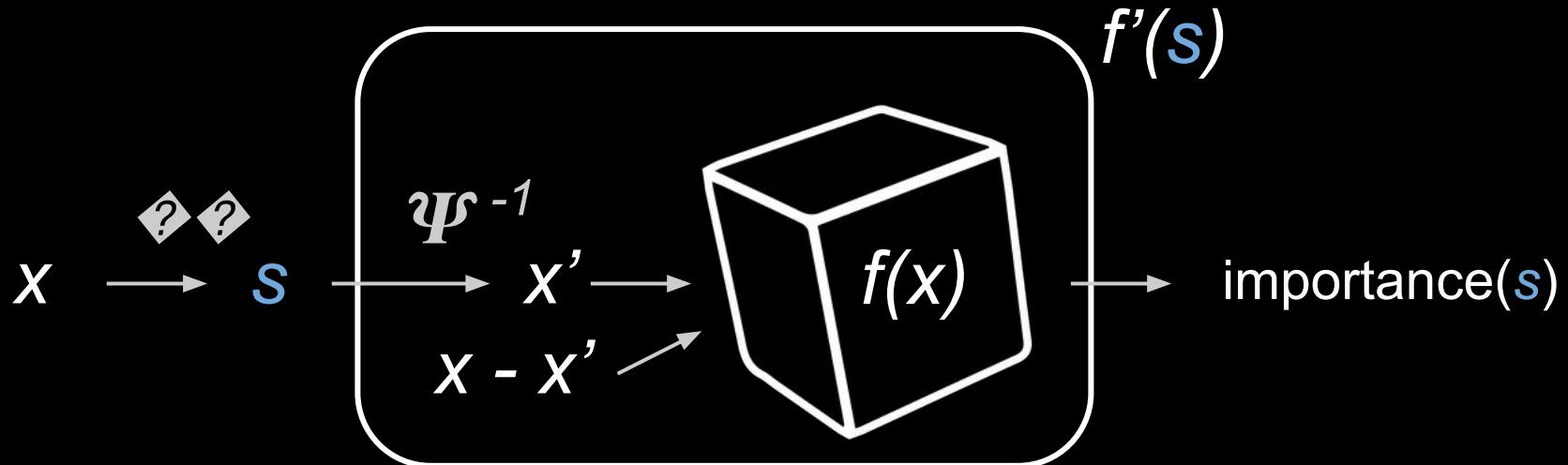
$$g(n) = (-1)^n h(N - 1 - n)$$

$$\|\Phi f\|_1 \text{ small}$$

## adaptive wavelet + distillation

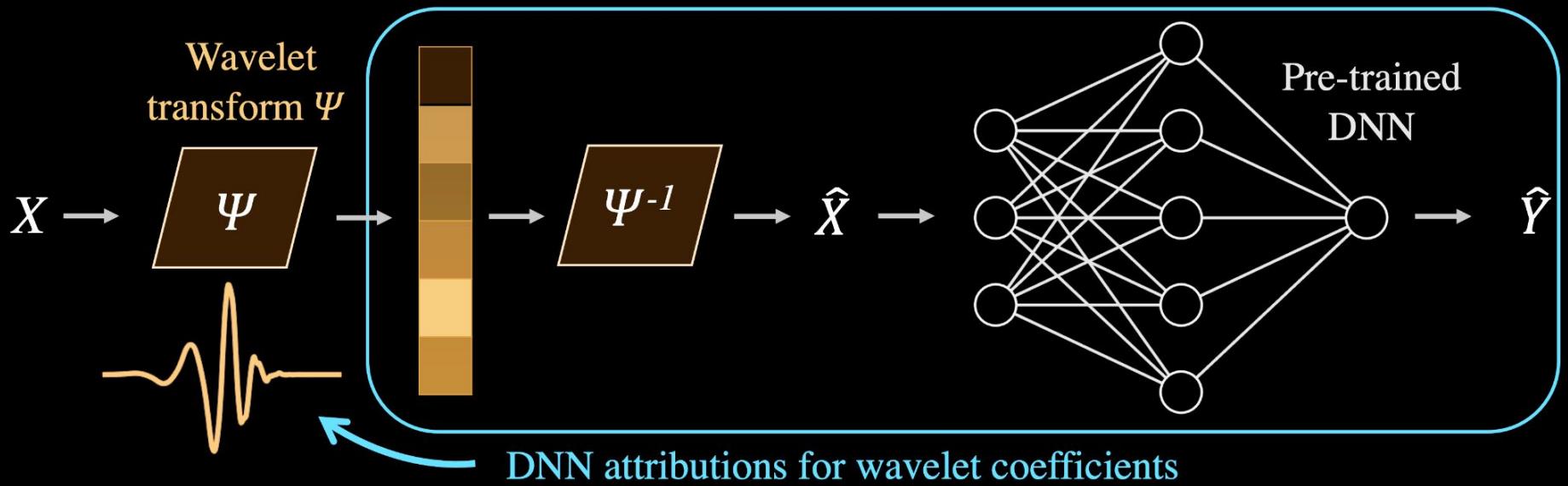
$$\underset{h,g}{\text{minimize}} \quad \mathcal{L}(h, g) = \underbrace{\frac{1}{m} \sum_i \|x_i - \hat{x}_i\|_2^2}_{\text{Reconstruction loss}} + \underbrace{\frac{1}{m} \sum_i W(h, g, x_i; \lambda)}_{\text{Wavelet loss}} + \underbrace{\gamma \sum_i \|\text{TRIM}_{\Psi,f}(\Psi x_i)\|_1}_{\text{Interpretation loss}}$$

# transformation importance



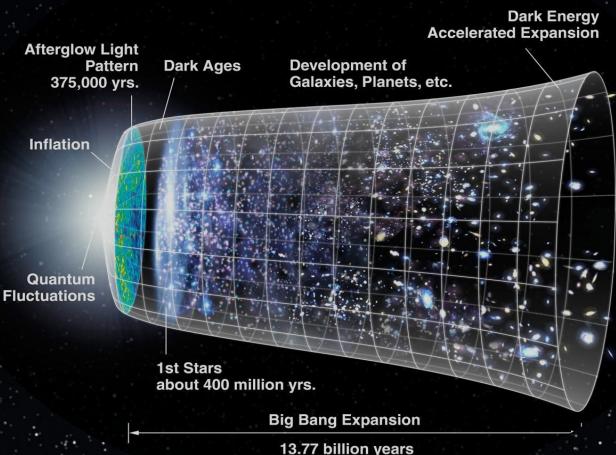
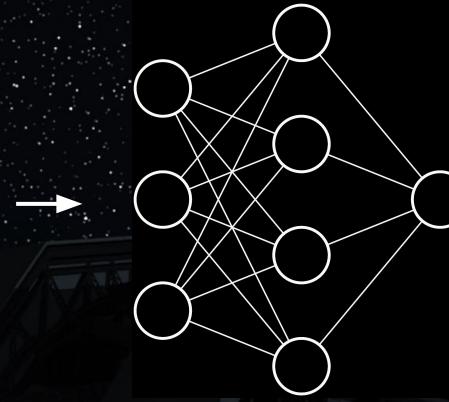
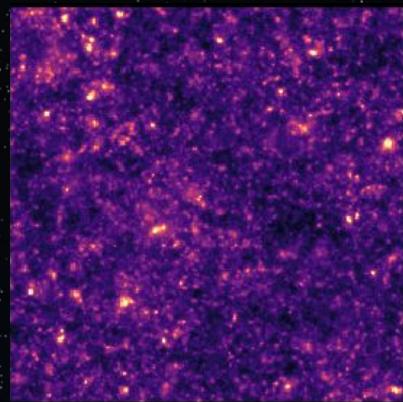
singh, ha, lanusse, boehm, liu, & yu, 2019  
“transformation importance with applications to cosmology”

# putting it all together



$$\underset{h,g}{\text{minimize}} \mathcal{L}(h,g) = \underbrace{\frac{1}{m} \sum_i \|x_i - \hat{x}_i\|_2^2}_{\text{Reconstruction loss}} + \underbrace{\frac{1}{m} \sum_i W(h, g, x_i; \lambda)}_{\text{Wavelet loss}} + \underbrace{\gamma \sum_i \|\text{TRIM}_{\Psi,f}(\Psi x_i)\|_1}_{\text{Interpretation loss}}$$

cosmology problem  
(more in the paper)

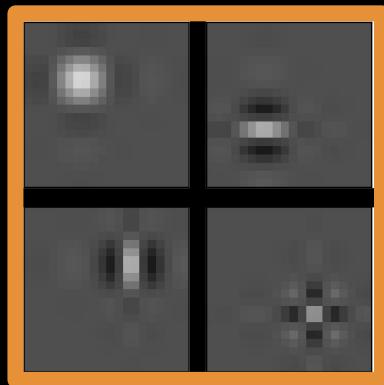

 $\Omega_m \rightarrow$ 

 $\hat{\Omega}_m \rightarrow$ 


Increasing attribution penalty  $\gamma \rightarrow$

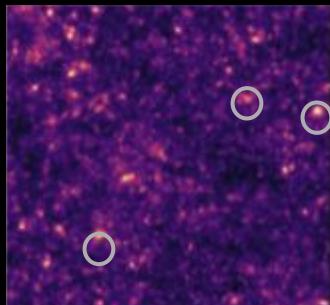
← Increasing sparsity penalty  $\lambda$



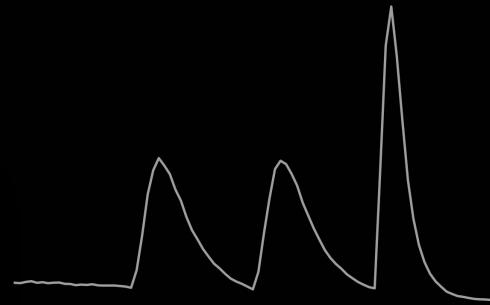
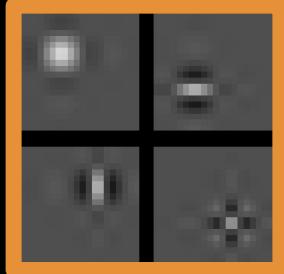
Recon loss = 0.0089  
Wavelet loss = 0.0013



# Predicting via peak counts



Filtered values  
at the local maxima



Binning into histogram

Predict using  
nearest-neighbor

$\widehat{\Omega}_m$

## Prediction error for $\Omega_m$ (RMSE)

AWD	Resnet	AWD no interp. loss	x 10 <sup>-4</sup>
<b>1.029</b>	1.156	1.354	

Peak Height   Laplace\*   Roberts-Cross\*   DB5

1.609	1.369	1.259	1.569	x 10 <sup>-4</sup>
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\*Ribli et al (2019) Nature Astronomy