Deep Neural Networks for Black Hole Imaging

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Introduction

Very long baseline interferometry (VLBI) uses an array of physically disconnected telescopes to image astronomical objects. In VLBI imaging, a hidden astronomical image is recovered using measurements taken between pairs of telescopes, known as *complex visibilities*.

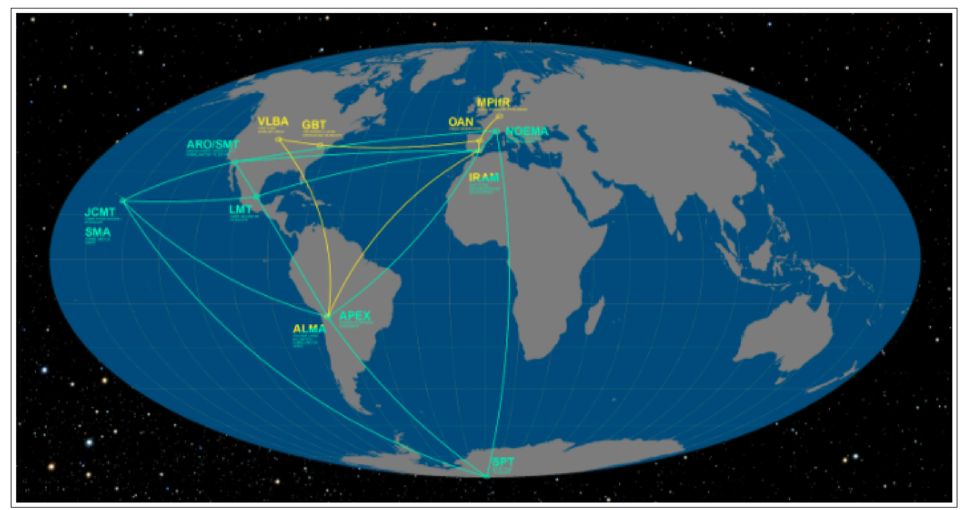


Figure 1:The Event Horizon Telescope.

A state-of-the-art approach for VLBI imaging is the *regularized maximum likelihood* method, which solves for an image that jointly maximizes the measured data log-likelihood and a hand-selected image regularizer.

We propose an alternative, data-driven approach that uses a convolutional neural network to reconstruct the hidden image from measurement data.

Background

The **regularized maximum likelihood (RML) method** minimizes:

$$\hat{x} = \arg\min_{x} \quad [\chi^2(y, f(x)) + \beta\mathcal{R}(x)] \qquad (1)$$

- $\hat{x}$: the reconstructed image
- $\chi^2(y, f(x))$: distance measure between measured visibilities y and visibilities $f(x)$ of reconstructed image x
- $\mathcal{R}(x)$: image regularization functions
- β: hand-selected constant coefficient for regularization

Qualitative Reconstruction Examples

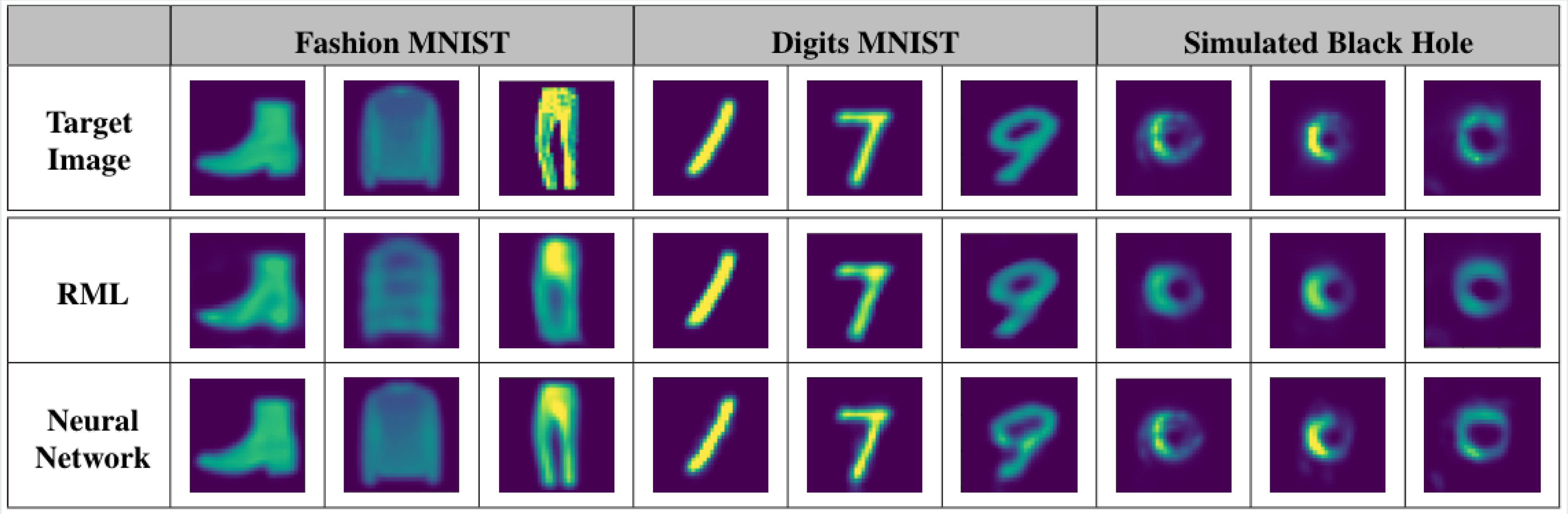
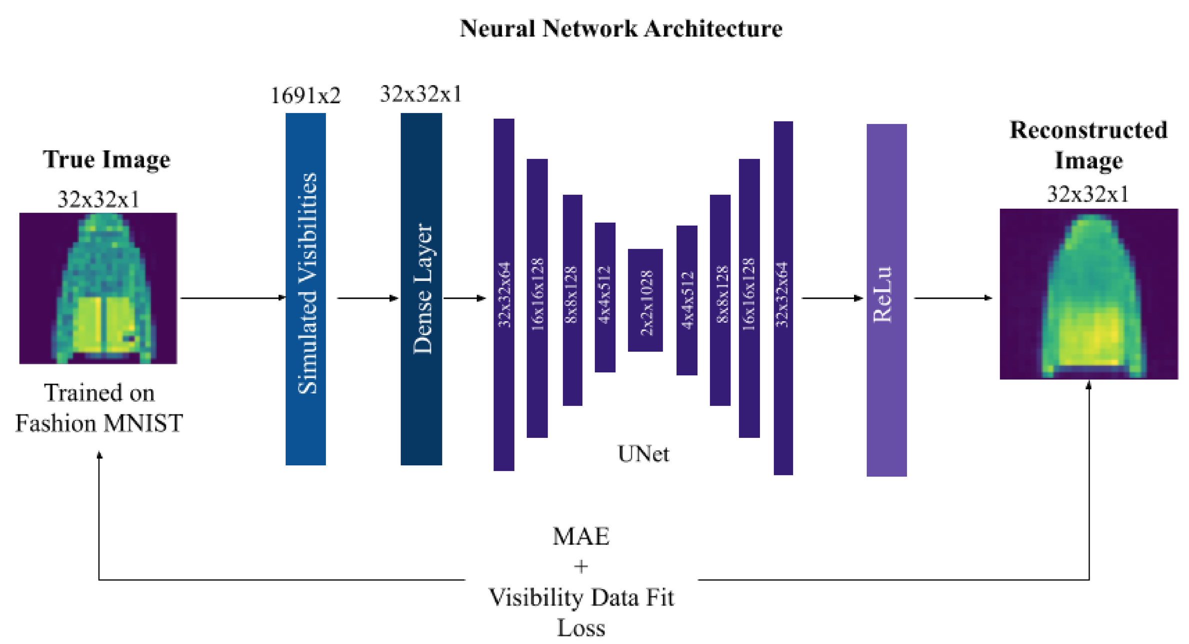


Figure 2:Reconstructed images from three different data sets and two different reconstruction methods: (1) regularized maximum likelihood (RML) and (2) a neural network trained with data generated from "Fashion MNIST" images with thermal noise in the measurements. Note that images in a column share the same color bar. Neural network reconstructed images are higher quality for both in-sample (Fashion MNIST) and out-of-sample (Simulated Black Hole) images.

Experimental Methodology



Our proposed neural network approach reconstructs images from complex visibilities. As shown above, the neural network model architecture consists of a single dense layer and UNet.

Our network is trained and validated entirely on "Fashion MNIST" dataset images. The **objective function** for training the reconstruction neural network aims to minimize the summation of the mean absolute error (MAE) between the true and reconstructed images and the χ^2 between the true and predicted visibilities.

$$\theta^* = \arg\min_{\theta} \mathrm{MAE}(x, \hat{x}) + \chi^2(f(\hat{x})), y) \qquad (2)$$

- θ^*: optimal network parameters
- $\hat{x}$: predicted image
- x: true image
- y: measured visibilities
- $f(\hat{x})$: visibilities of the reconstructed image

Results

	Fashion MNIST		Digits MNIST		Simulated Black Hole	
	No Noise	Th. Noise	No Noise	Th. Noise	No Noise	Th. Noise
RML	1.396e-4	1.463e-4	1.554e-4	1.623e-4	1.898e-4	2.024e-4
Neural Network w/ No Noise	4.320e-5	4.528e-5	1.036e-4	1.042e-4	1.196e-4	1.201e-4
Neural Network w/ Th. Noise	2.046e-5	3.304e-5	4.957e-5	5.032e-5	1.010e-4	1.012e-4

Above we show the averaged MAE values from over 100 different test images from three different datasets for RML and two neural network models. One neural network was trained with no noise and the other was trained with thermal noise in the training measurements. Each dataset was tested using measurements generated with and without random thermal noise in the measurements.

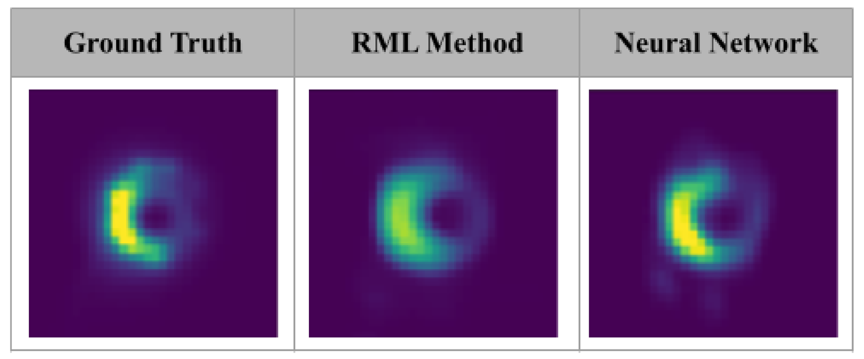


Figure 3:Comparison of RML and Neural Network reconstructions on an out-of-sample, simulated black hole image.

Discussion

Key Findings:

- Our neural network reconstructions achieve lower average mean absolute error than RML reconstructions
- Our neural network approach is more robust to thermal noise

Future Work:

- Analyze robustness to other kinds of noise, such as amplitude gain error and phase error
- Train network using closure quantities, such as closure phases and closure amplitudes