Holographic image reconstruction using variational inference with limited experimental data.

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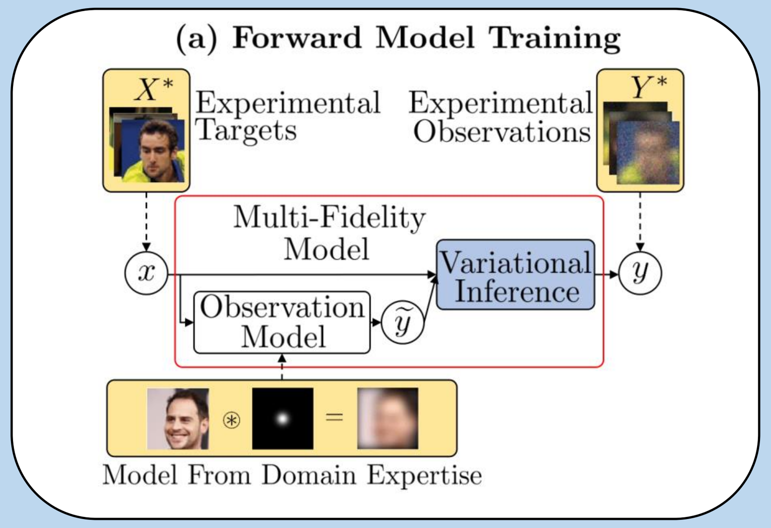
INTRO:

- Machine Learning **predictions** are **not always accurate.**
- Using machine learning for applications such as **medical imaging** and **self-driving cars** it is crucial to consider **uncertainty of predictions**.

METHODS:

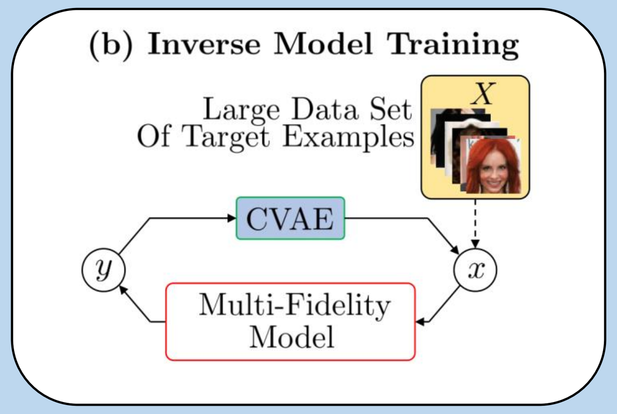
STEP 1:

Create a "Multi-Fidelity" forward model which can generate large realistic datasets by combining measured data with simple simulations based on domain expertise (e.g. blur kernel or Fourier transform).



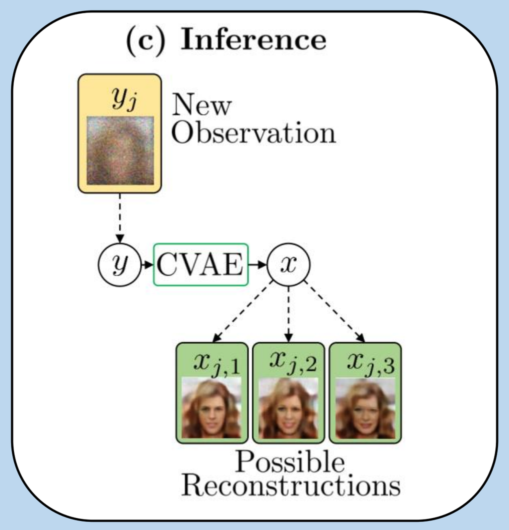
STEP 2:

Train an inverse model with large generated dataset using a Conditional Variational Autoencoder (CVAE). The latent space learns a probability distribution conditioned on the input.



STEP 3:

Make a prediction for a given test observation by sampling the learned latent distribution. The most likely image (Pmax) is generated using the maxima of latent space, whereas multiple random samples can be used to approximate the marginal mean and variance of the prediction.

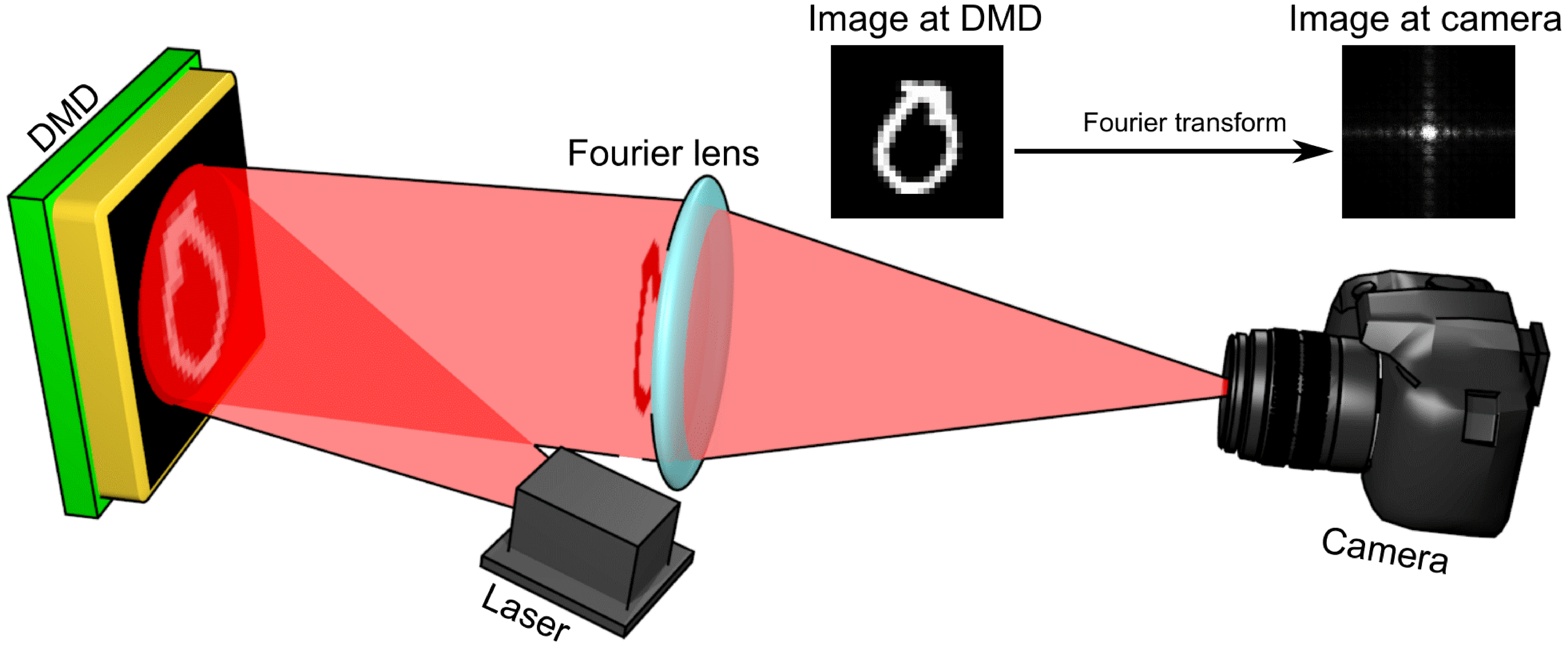


HOLOGRAPHY EXPERIMENT (Top Figure):

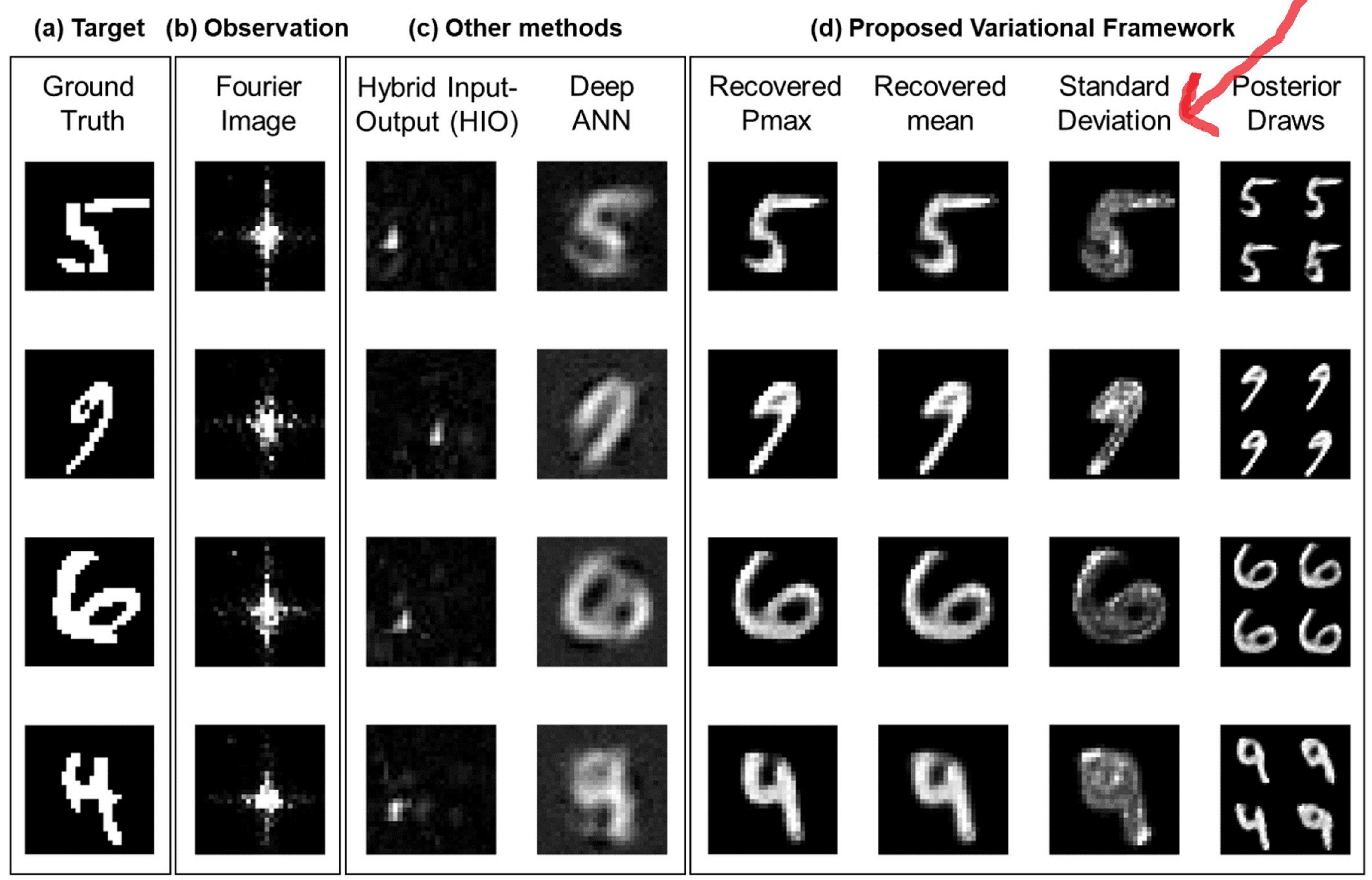
1. A collimated laser beam projects an image to a single lens.
2. A digital camera is placed at the focal distance from the lens captures the intensity of the Fourier plane.
3. Reconstructing the original image from the Fourier plane requires information about both amplitude and phase.
4. We use machine learning to predict the original image with only a noisy intensity image.

HOLOGRAPHY RESULTS (Bottom Figure):

- The proposed framework reconstructs images with higher accuracy than a state-of-the-art Hybrid Input-Output (HIO) algorithm and a Deep Artificial Neural Network (Deep ANN).
- The mean, variance and other likely predictions are also accessible.



How certain is a machine learning model about its predictions?



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MORE INFORMATION:

F.Tonolini, J. Radford, A.Turpin, D. Faccio and R. Murray-Smith, *"Variational Inference for Computational Imaging Inverse Problems,"* JMLR **21** (2020) 1-46

Included in the published article:

- *Mathematical foundations*
- *Simulated experiments*
- *Additional real-world experiment: Imaging through scattering media*
- *Performance when increasing the noise in data*

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Take home messages:

- Predictions are influenced by **domain expertise** (i.e. physical equations).
- We know about the **certainty** of the prediction.
- We have access to the **most probable** solution.
- We can access **many other** likely solutions.
- Ideal for when only a **small** amount of **real-world data** is available.

What do I need to apply this method?

- A rough **simulation model** of the experiment
- Some **experimental measurements**
- Lots of **example targets**

ACKNOWLEDGEMENTS:

Francesco Tonolini, Alex Turpin, Prof. Roderick Murray-Smith, Prof. Daniele Faccio.