Neural networks for FEL diffraction image separation

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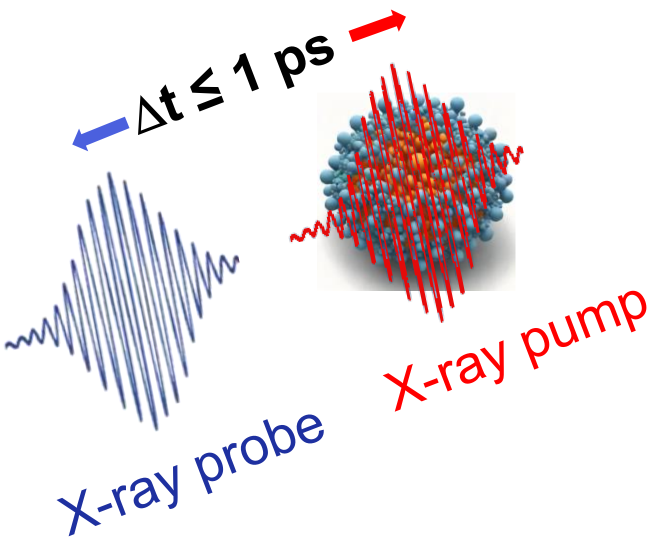
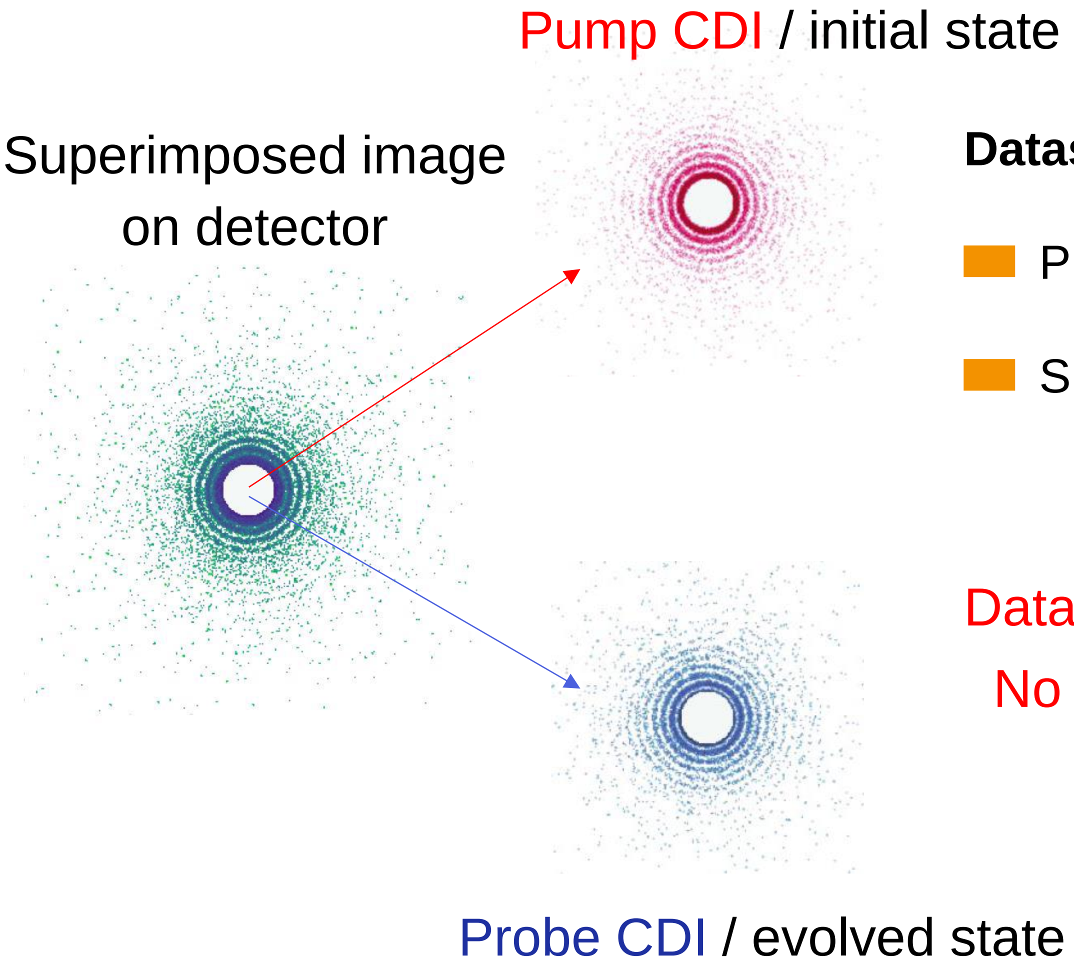
Problem setting





Dataset available:

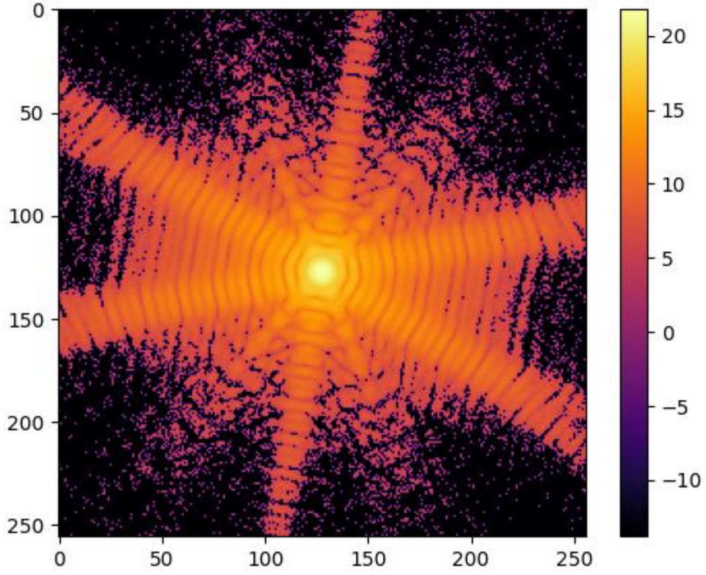
- Pump
- Superimposed images

Datasets are unpaired

No probe dataset

Challenge ⇒ Separate superimposed images

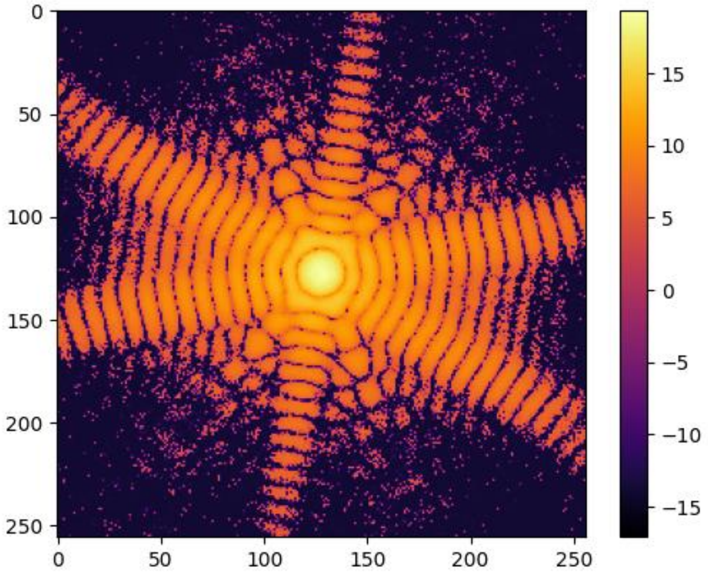
Feed-forward CNN



Mixture image

U-Net

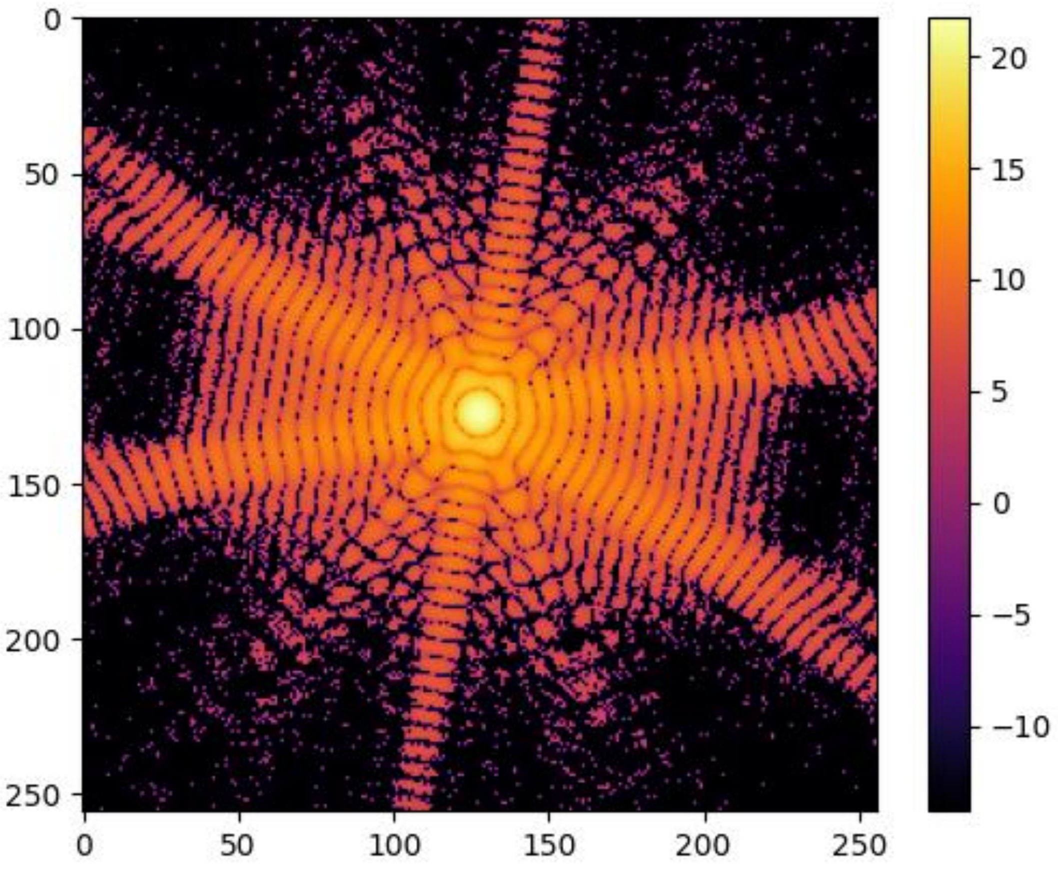
Possible likelihood:
- Normal
- Poisson



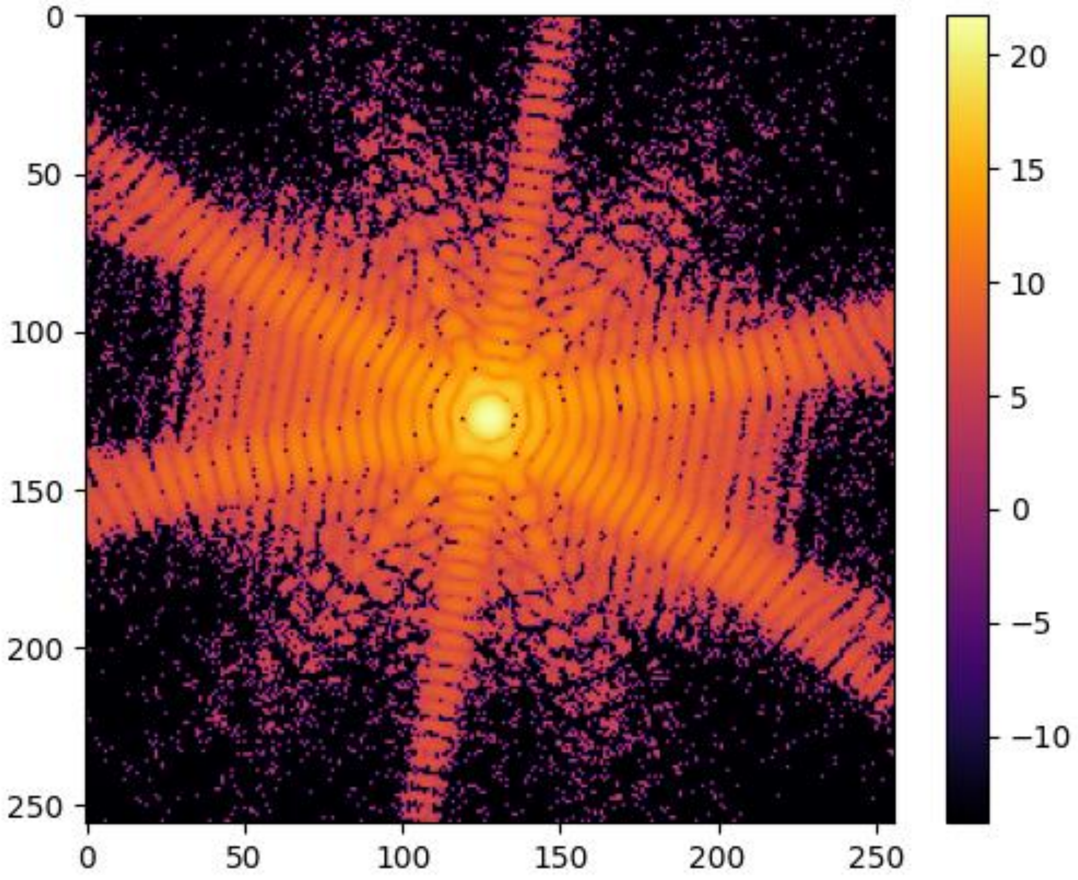
Pump image

Trained with realistic pulse simulations

Probe U-Net Retrieval Results



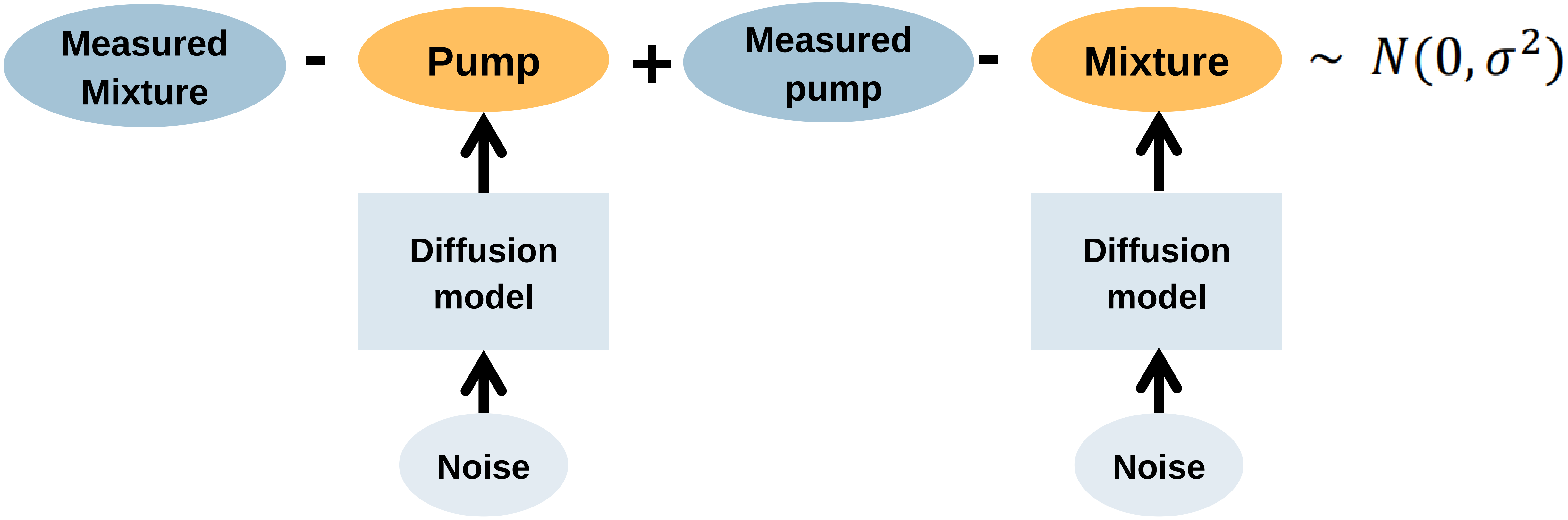
Ground Truth



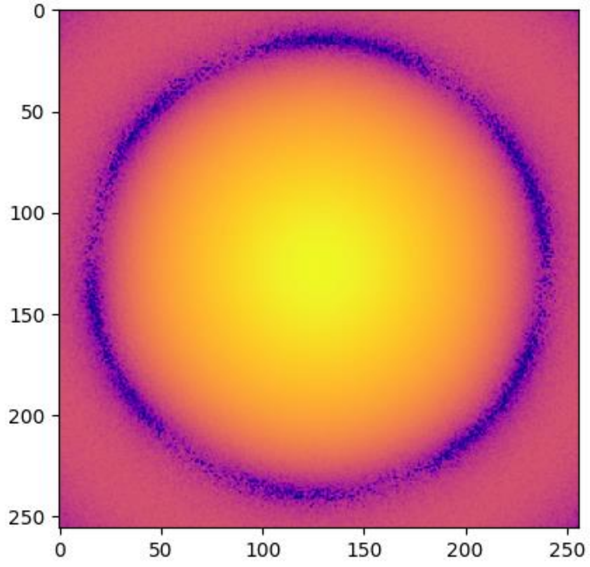
Retrieved probe

Diffusion model pipeline

- How to handle missing pairing and unrealistic simulations?



Diffusion Retrieval Results

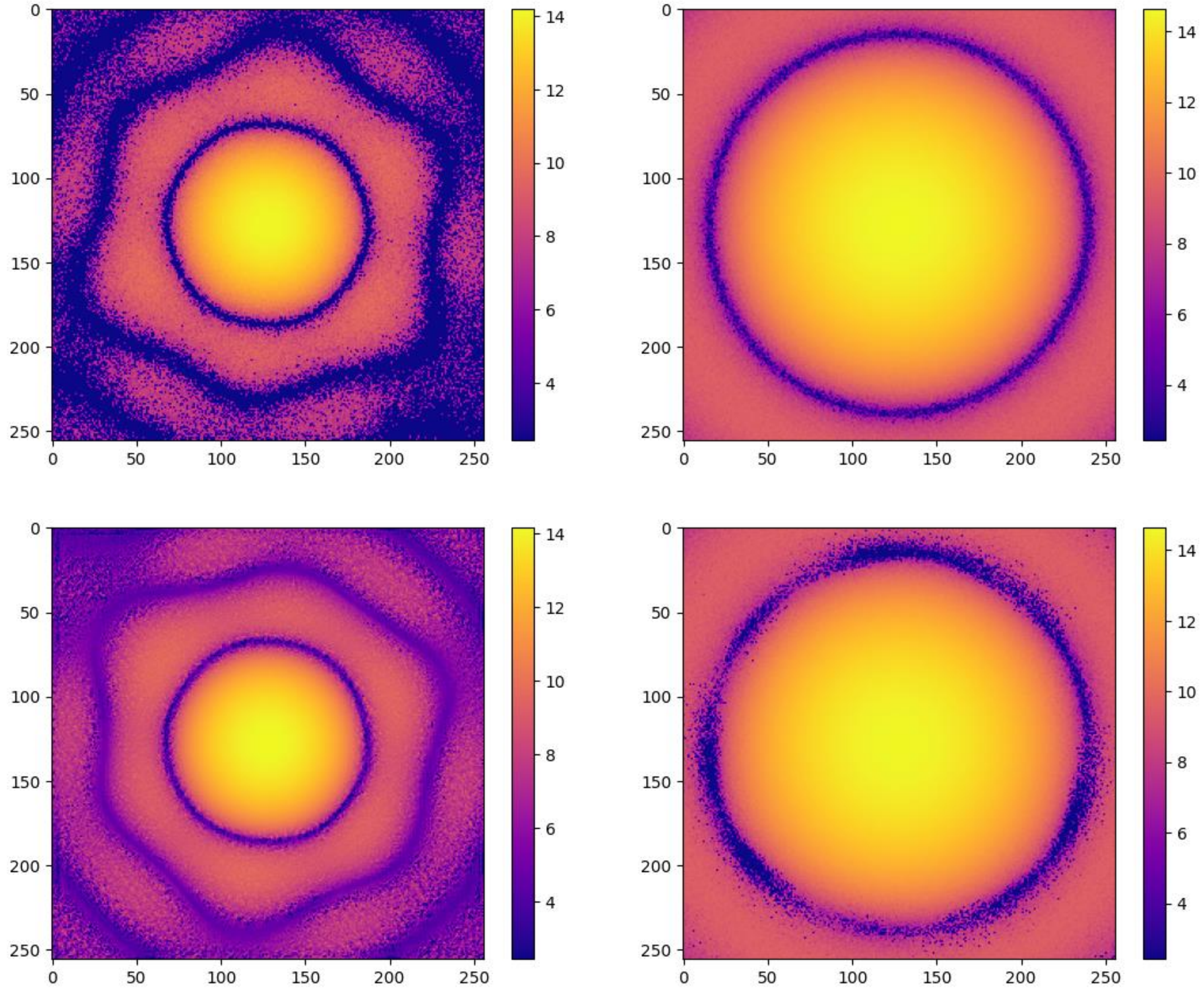


Mixture image

Pump pulse

Probe pulse

Ground Truth



Retrieved pulses

Summary and outlook

- Developed two strategies: feed-forward NN (validation) and diffusion model approach
- Results display high uncertainty around diffraction minima
- **Plans**: Improve loss function and preprocessing scheme

Acknowledgements

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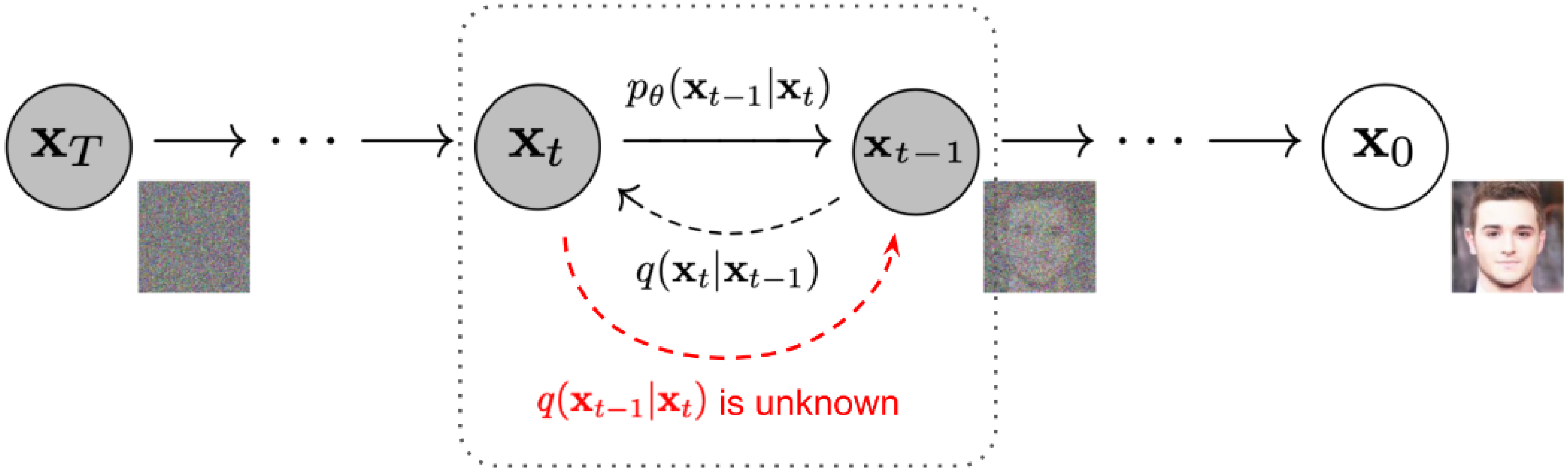
Thank you for your attention!

Diffusion model



- Capable of modeling pump and mixture distributions
- We use U-Net model (5M params) to estimate the parameters of an unknown distribution
- It takes the noisified image and a timestamp to predict parameters

Guidance at timestep t: idea

- Train pump diffusion model and mixture diffusion model
- Compute probe pulse in two different ways
- Difference between these results is a Gaussian with zero mean
- Update conditional distribution parameters for samples at timestep $t-1$