Distributed Holographic Image Processing with Neural Networks

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Introduction

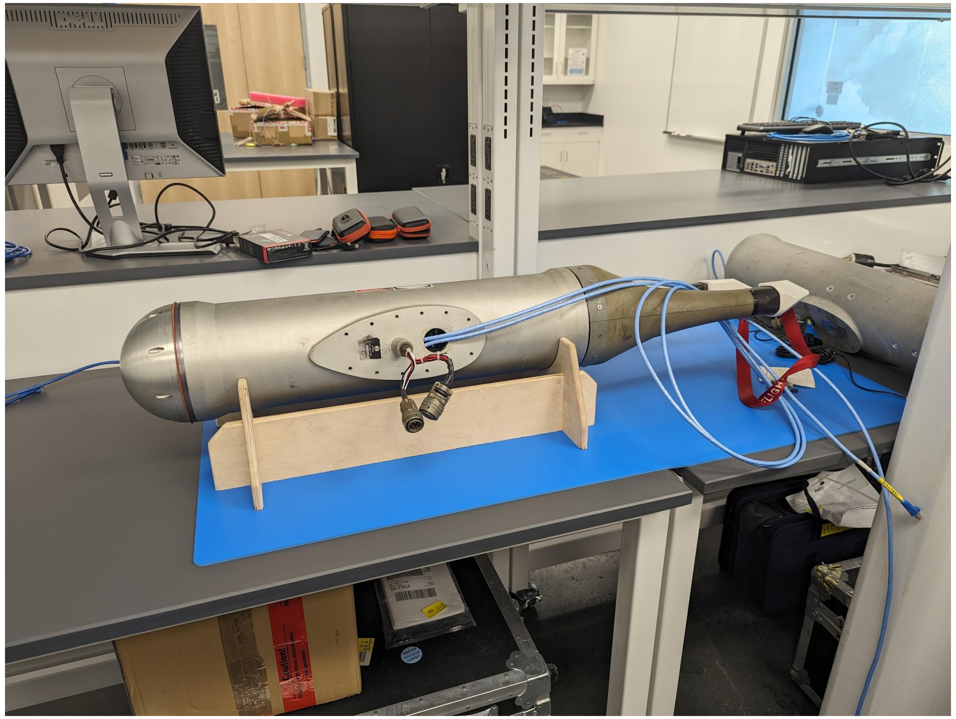
Project Goals: Improved **performance** and **scalability** of hologram processing

Hologram**:** A **three-dimensional** image of space formed by the interference of light beams

- What kinds of holograms are we interested in?
- What are we hoping to discover?
- How do we processes these holograms?
- How well are we performing?

The HOLODEC cloud particle detector

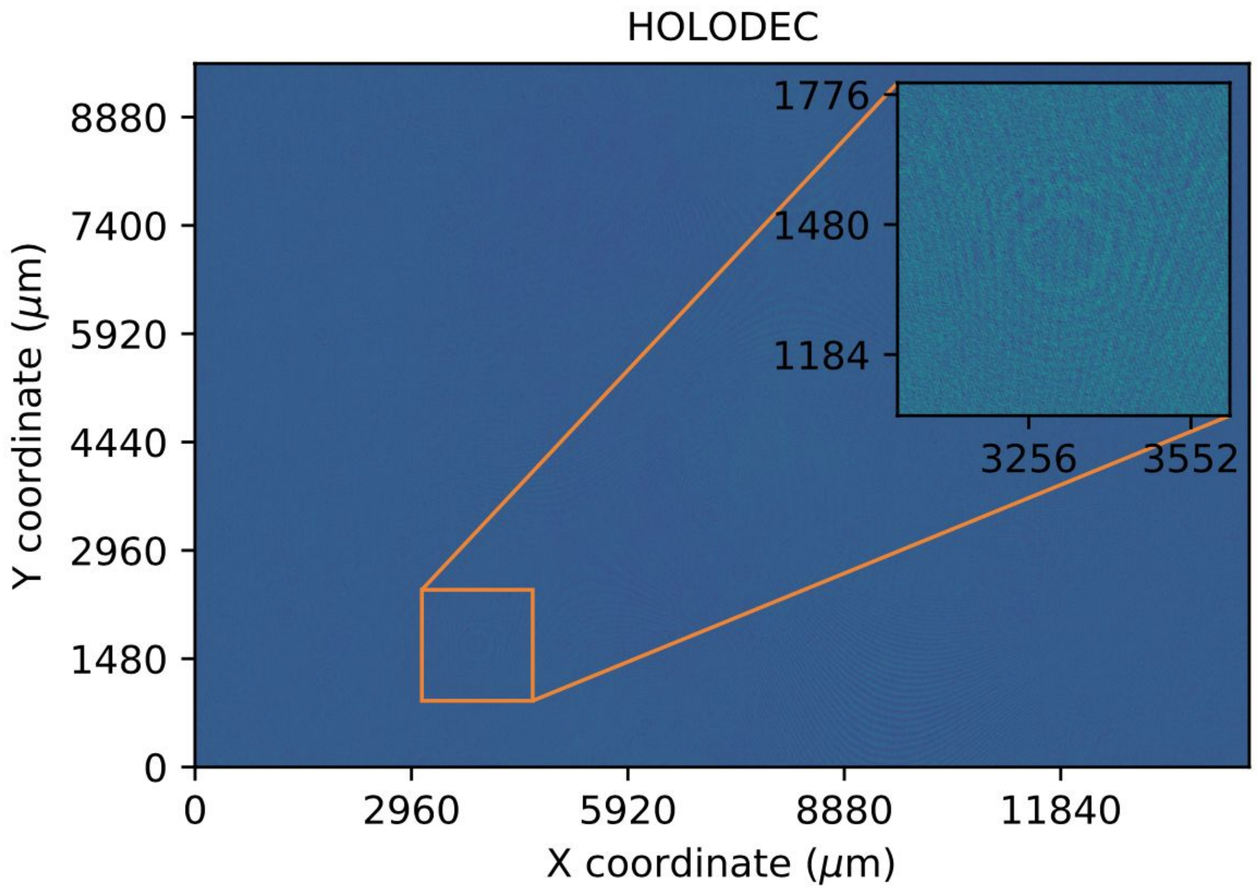
- The HOLODEC-II is a second-generation version of a holographic cloud probe [1, 2].
- Designed to determine the size, two-dimensional shape, and three-dimensional position of hydrometeors via digital in-line holography.



HOLODEC-II on workbench at RAF

HOLODEC-II installed on C-130

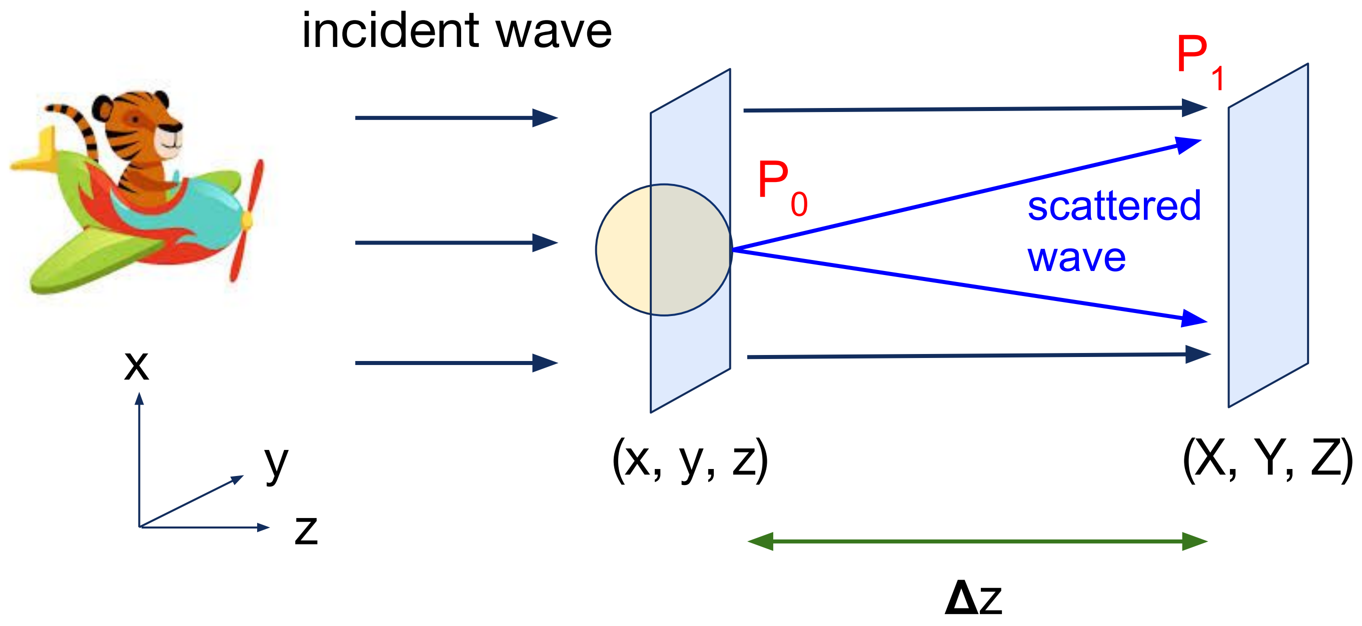
HOLODEC holograms – Cloud Systems Evolution in Trades project (CSET)

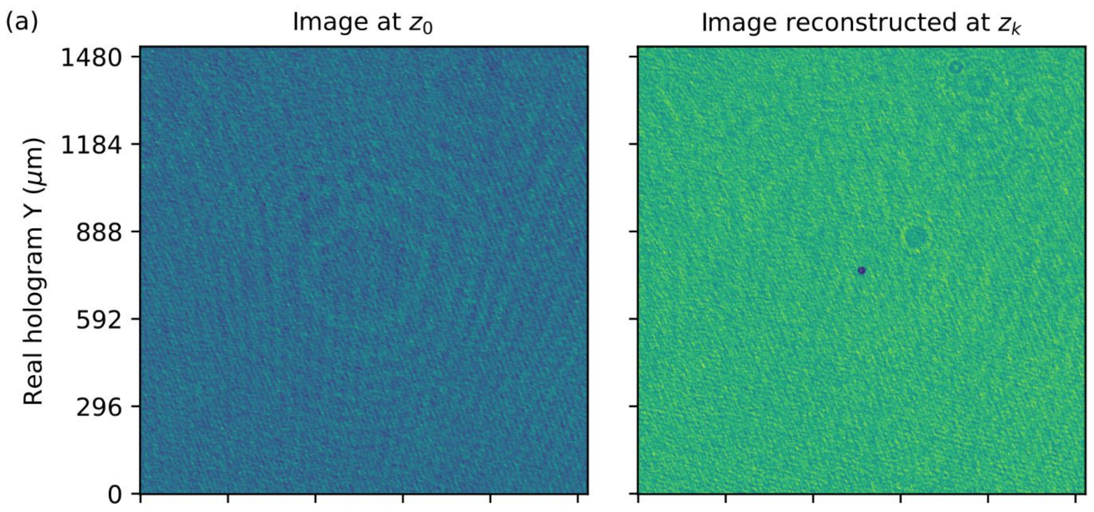


- Each is **megapixel** in size
- 14.42 mm x 9.61 mm (4872 x 3248 pixels = 2.96 μm/px)
- Other holograms in CSET may contain up to 10,000 droplet particles!

- The identification program used to process RF07 is referred to as the **standard method** [4, 5].

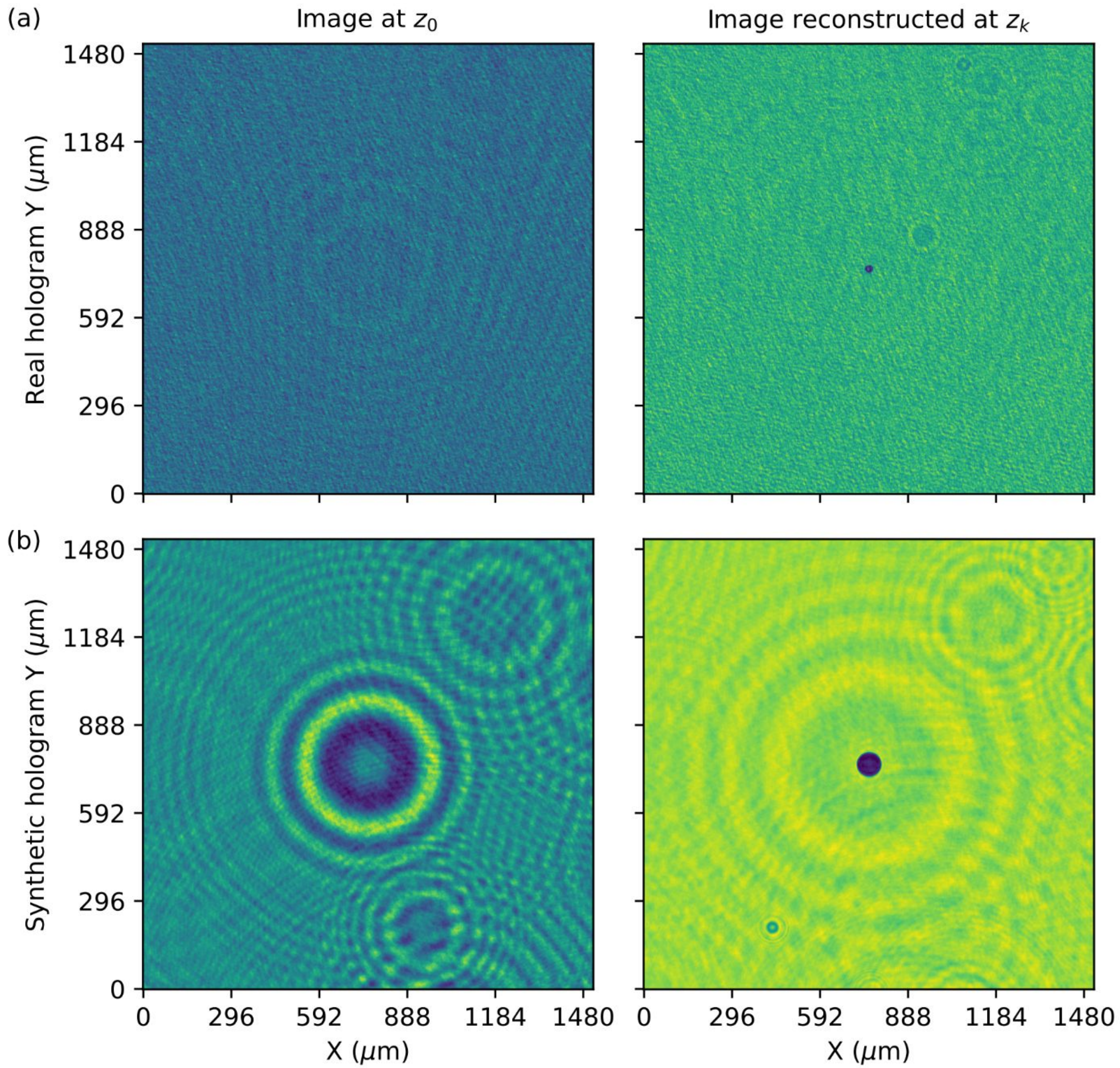
Wave-propagation to refocus holograms along the axis orthogonal to the detector arms (z)



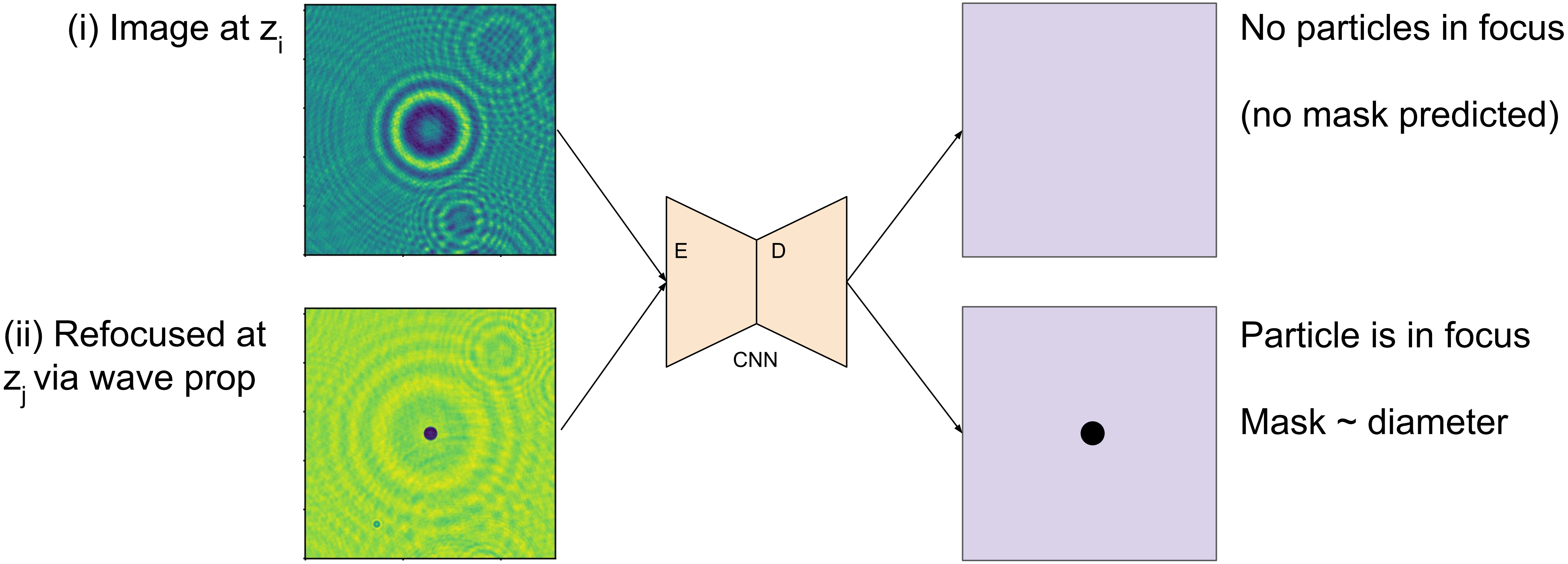


- Wave propagation takes a hologram plane at (x, y, z) and reconstructs it a distance **Δ**z away to the plane at (X, Y, Z).
- Can do this because we have the phase information.
- Don't know where particles are so we must search across all depths.

Wave-propagation to refocus holograms along the axis orthogonal to the detector arms (z)

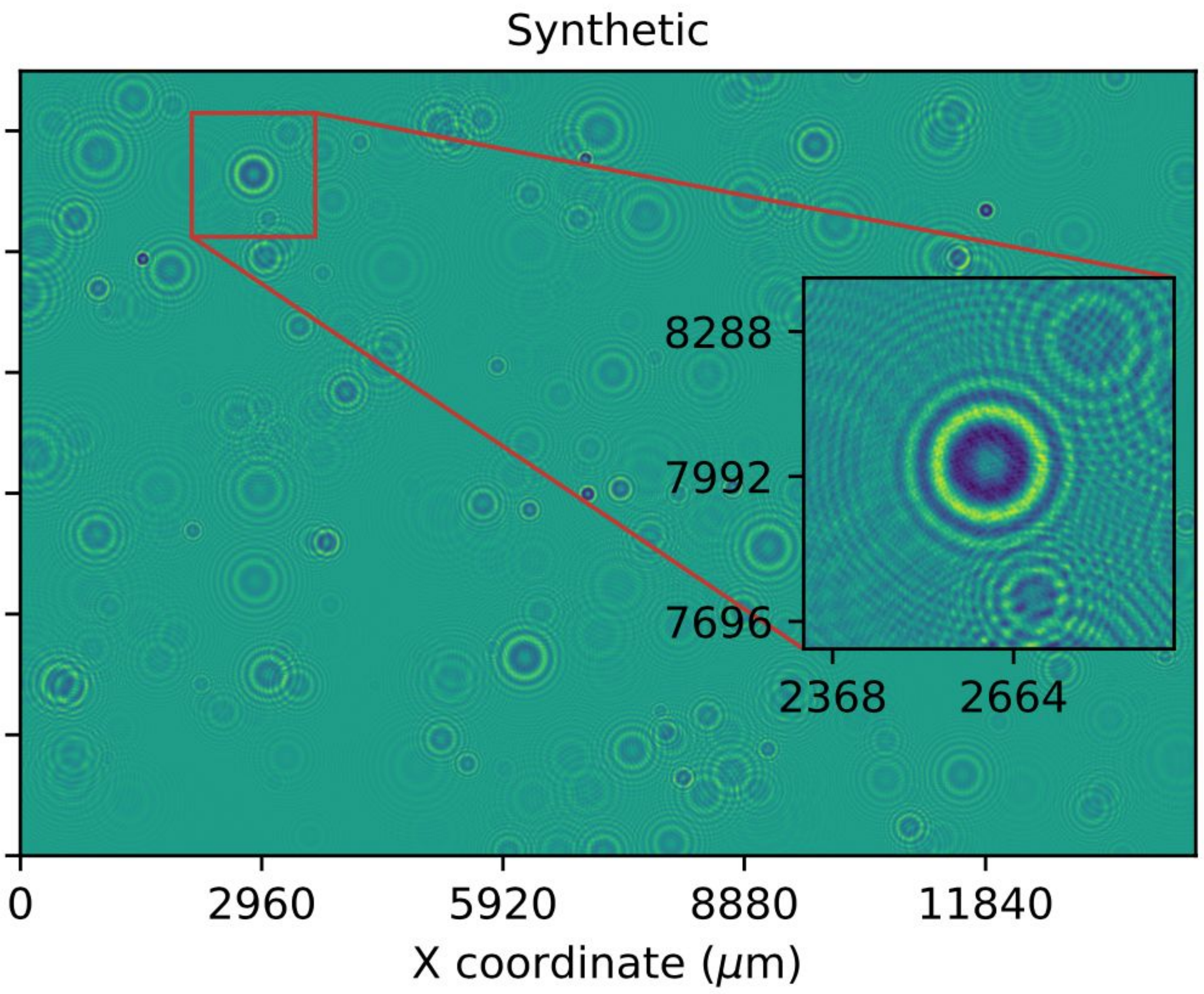


Using a neural network to predict particle position and shape



- Convolutional neural network (CNN) model to predict “masks” over in-focus particles [6]
- From a predicted mask, can estimate (x, y, z_j, d)
- CNN can predict arbitrary number of particles per image

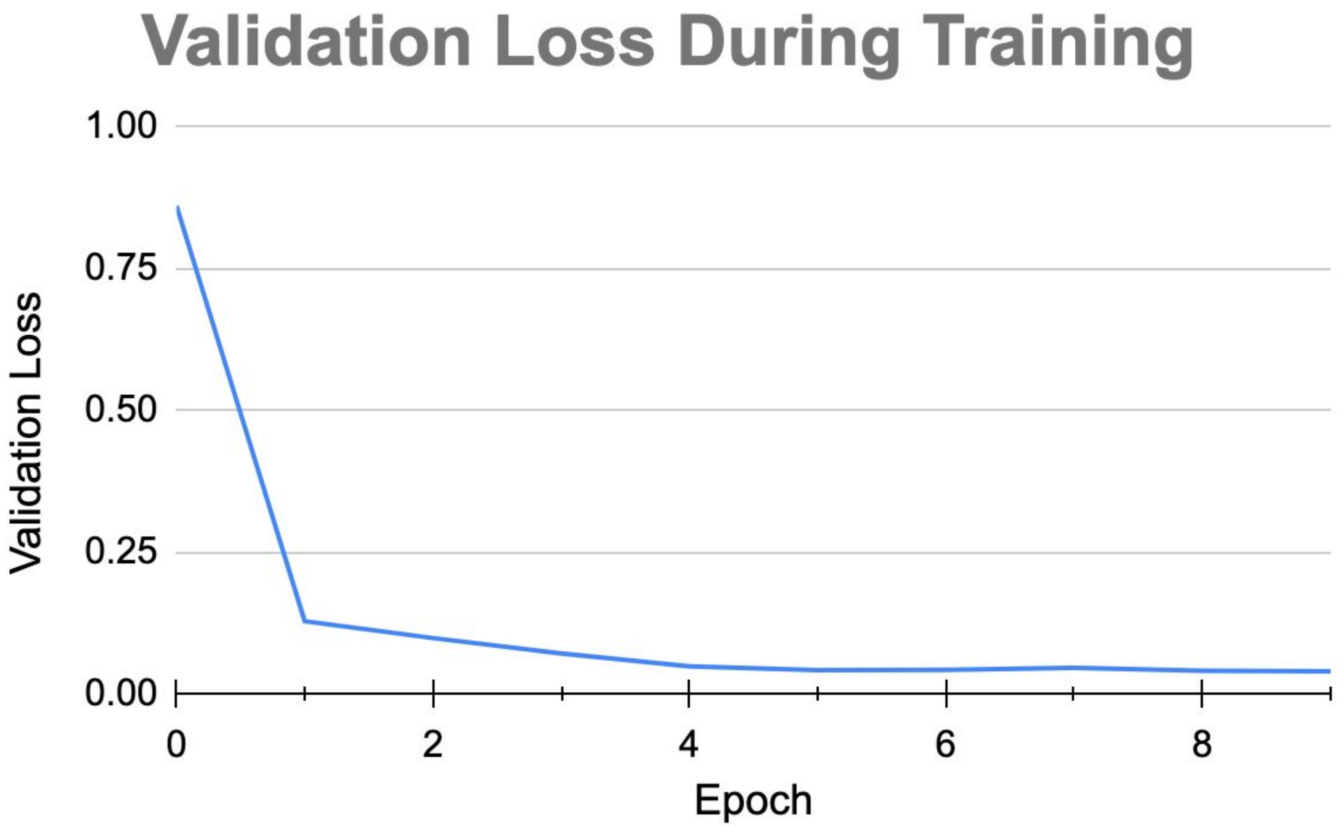
Simulated (synthetic) holograms because no truth labels for the real data



- Same optical settings as physical instrument
- 500 particles per hologram positioned along z
- Train (100 holograms), validation (20), and testing (10) sets produced
- Truth masks easily created for synthetic images
- Noise can be applied to mimic holograms from CSET

Neural Network Training

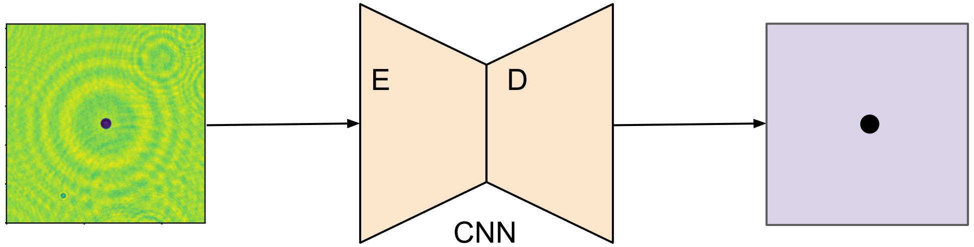
- Plot of **Dice Loss** on validation data per epoch of best-performing model
- Trained using **Pytorch DDP** across 4-NVIDIA A100 GPUs on Derecho
- Trained on 512x512 tiles of **synthetic holograms** and associated truth masks
- Inference speed:
  - 7 holograms/hr per NVIDIA A100
  - ~1500 GPU-hours per campaign



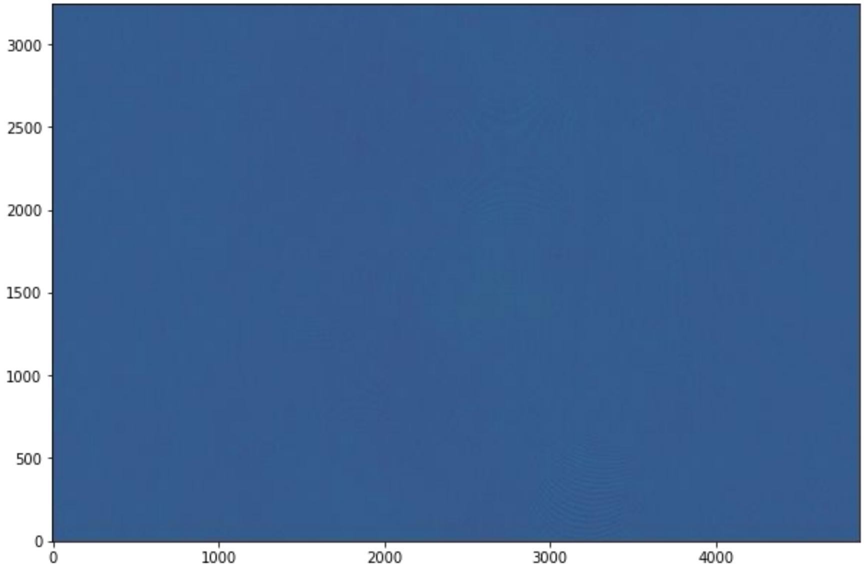
PyTorch Lightning

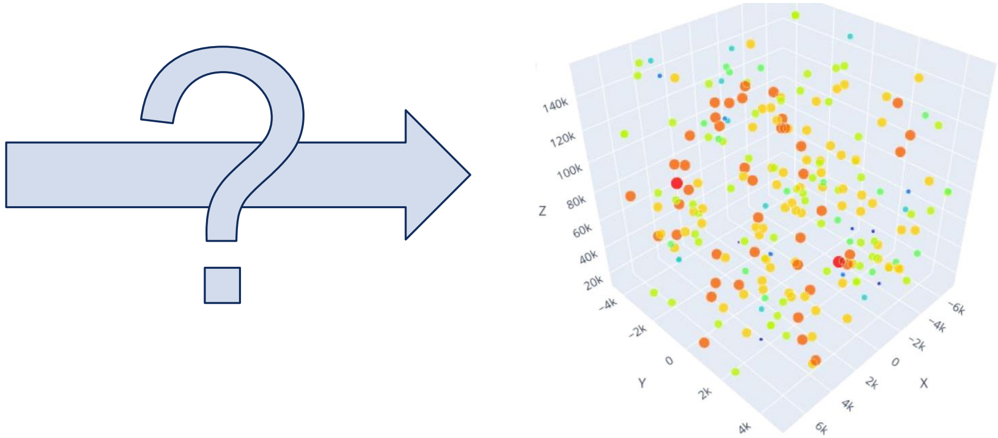
Post-processing: How can we extract meaning from masks?

So we can accept an image slice and generate a mask with ML:



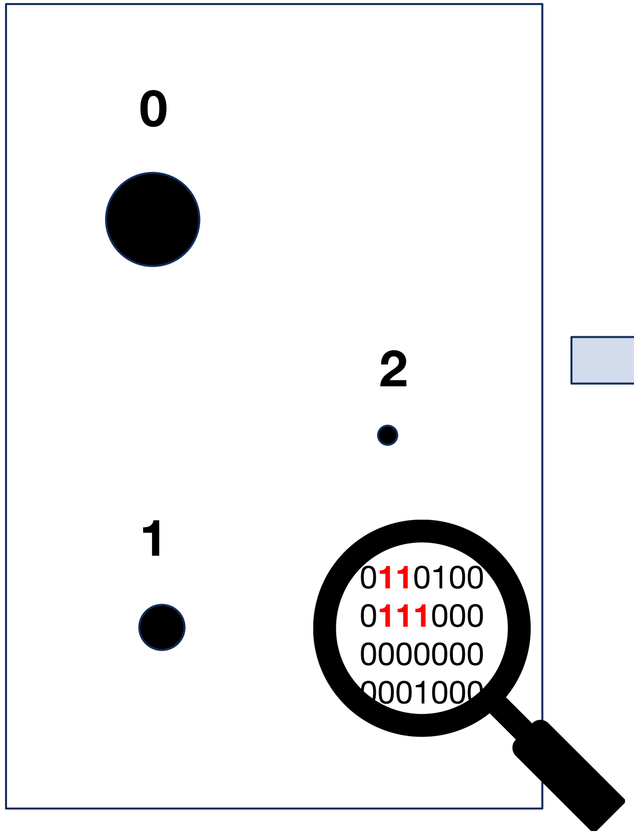
How can we actually process full holograms for hydrometeor properties?





Results: 2D Clustering of Predicted Masks

- Need to cluster predicted pixels in mask to obtain (x, y, z, d) data
- Neighboring 1-labeled pixels are grouped together
- Clusters are approximated to a circle and diameter is calculated
- Grouping is done on predicted masks of each plane for all z



Plane reconstructed at z_j

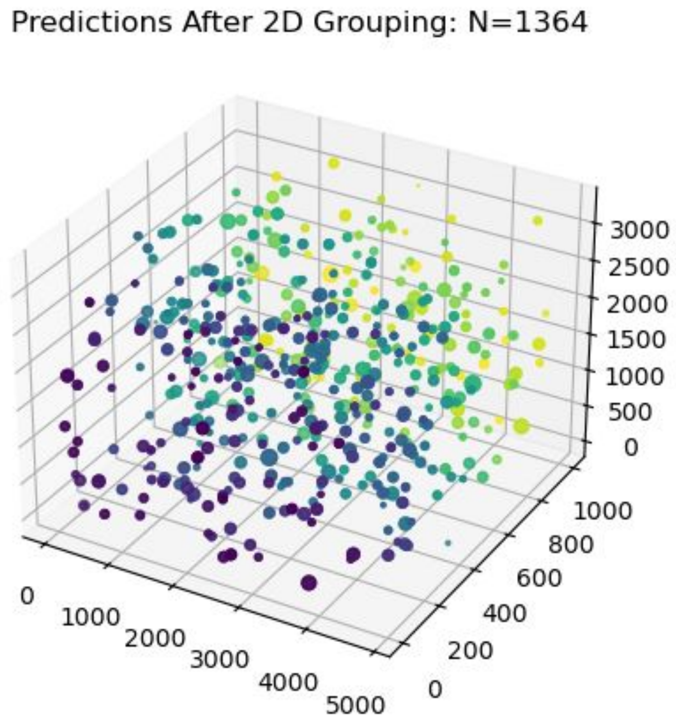
Result

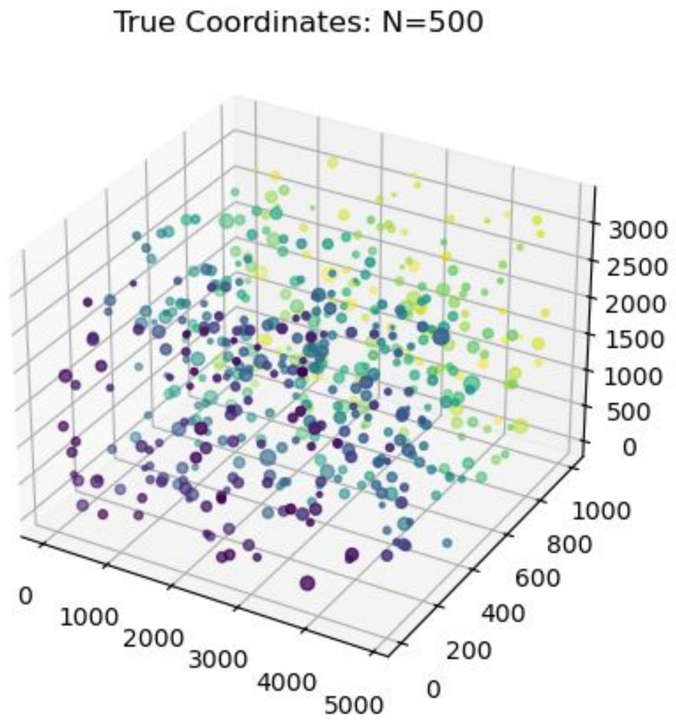
0: x_0, y_0, z_j, d_0

1: x_1, y_1, z_j, d_1

2: x_2, y_2, z_j, d_2

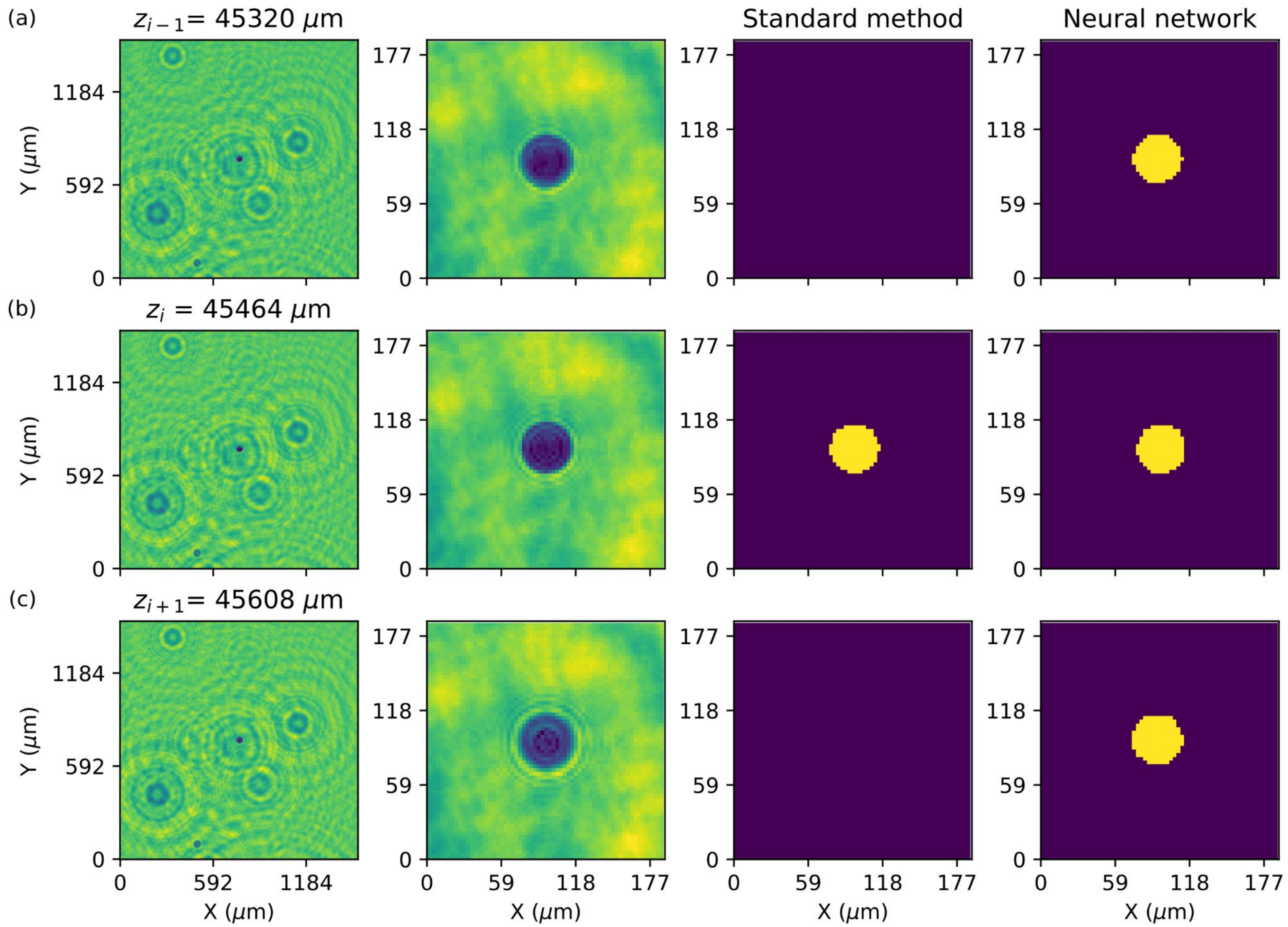
Results: 2D Clustering of Predicted Masks





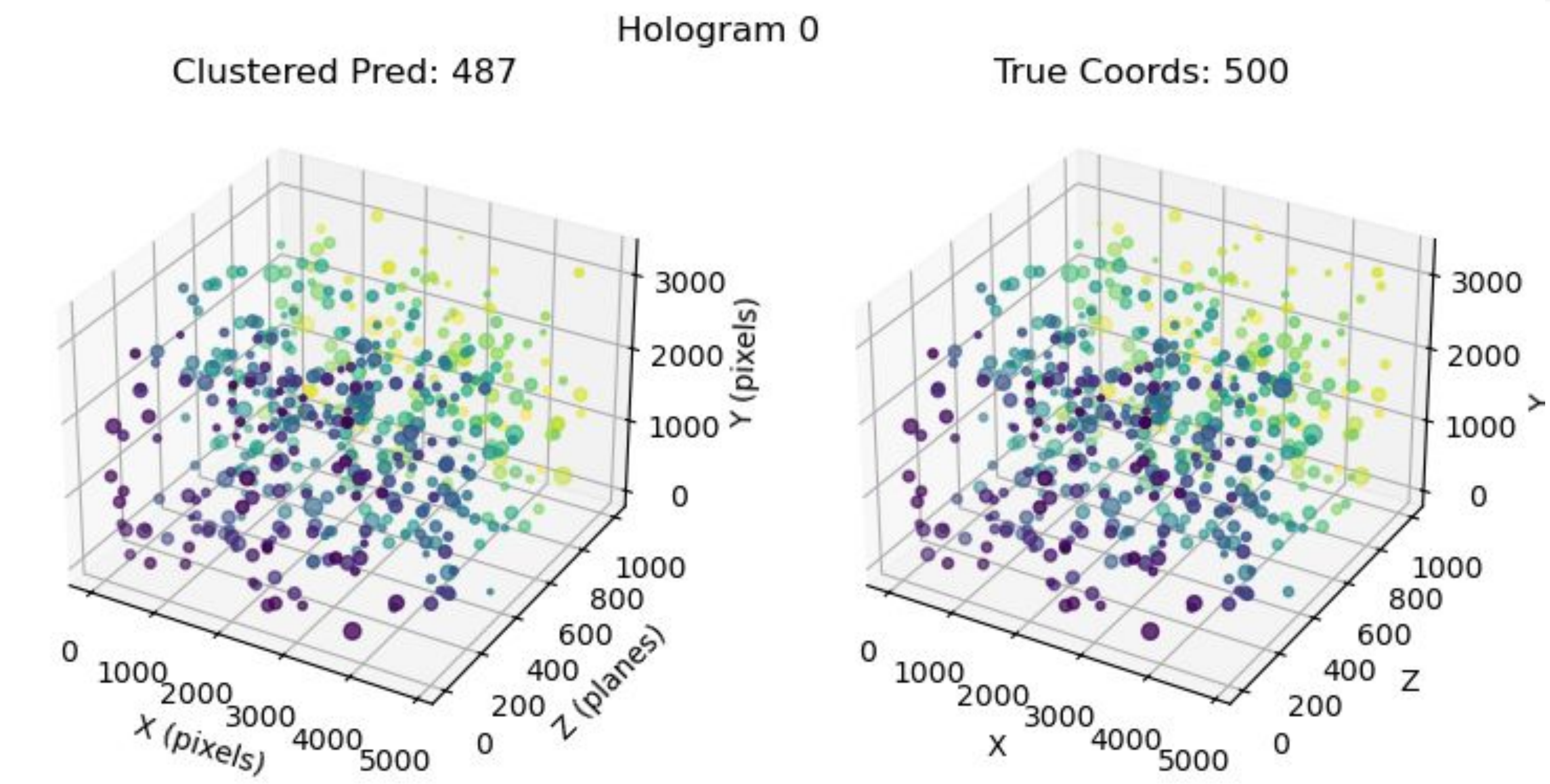
- At first glance, results look quite similar to truth
- However, have significantly overpredicted the number of particles

Results: 2D Clustering of Predicted Masks



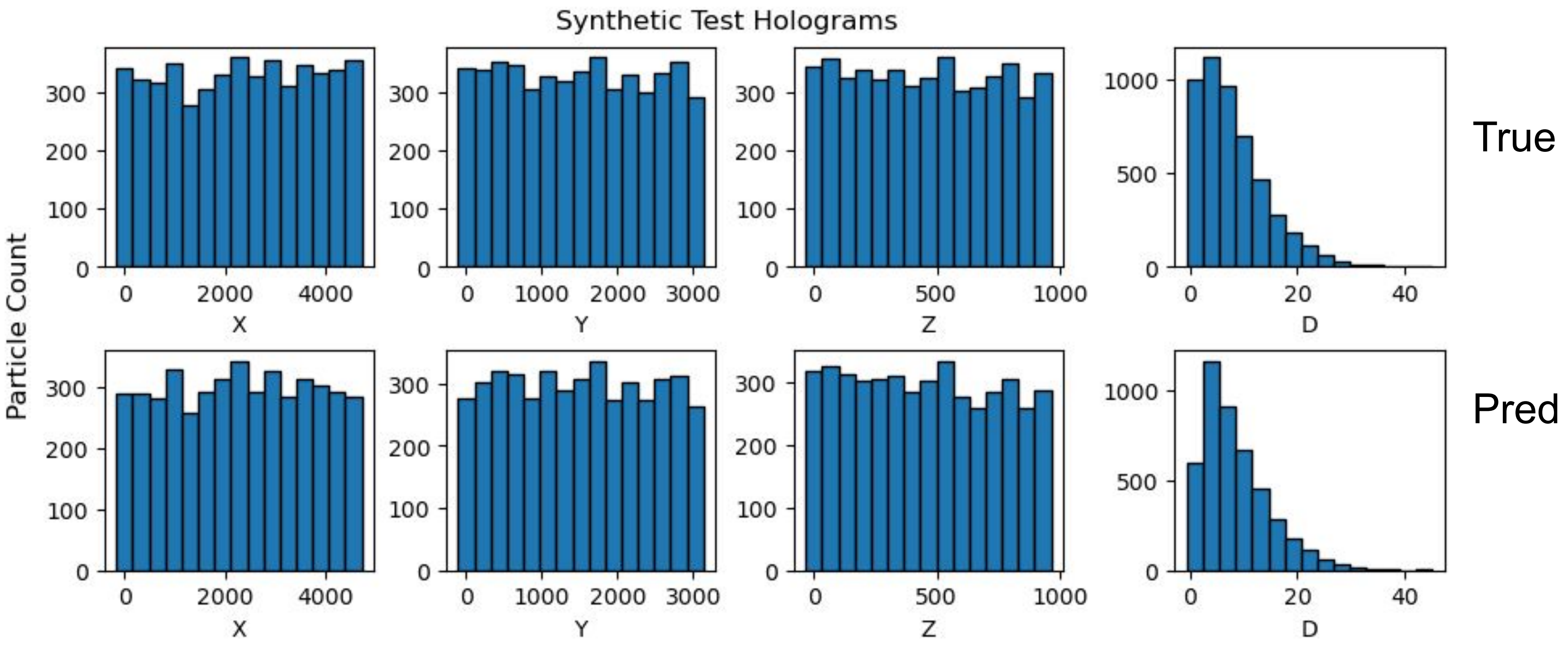
- Model has high False Positive rate in adjacent depths to true particle
- With N = 1,000, particles with large diameters most affected.
- Smaller particles increasingly affected as N grows
- Partially due to training, as images with in-focus particles were upsampled 1-to-1

Results: 3D Clustering of Predicted Coordinates



- Each (x, y, z, d) represents 3D coordinates of a predicted sphere
- Cluster these coordinates again in all
  3 dimensions to remove depth-adjacent over predictions
- Use OPTICS algorithm to perform spatial clustering

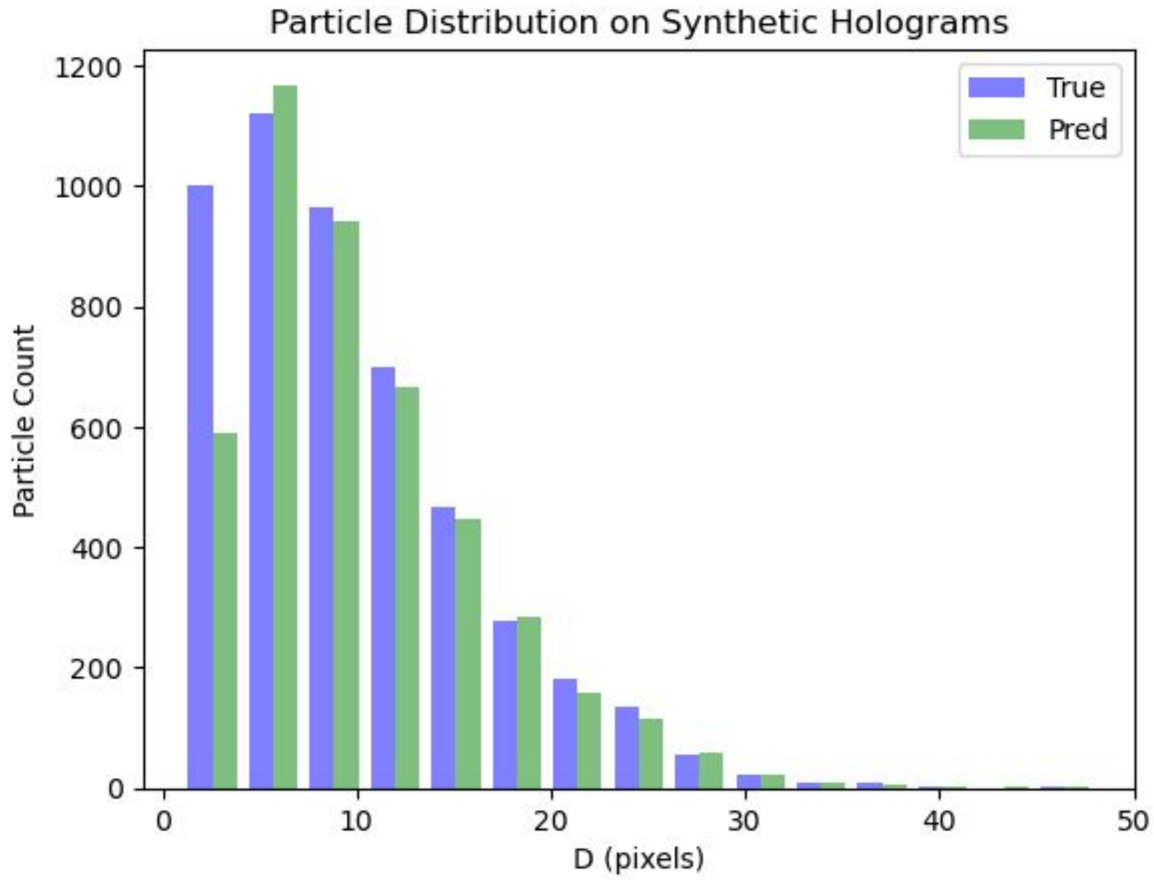
Results: Synthetic Test Hologram Predictions



- Under-predicting extremely small particles (False Negatives)
- Larger errors around image edges in X and Y

Results: Synthetic Test Hologram Predictions

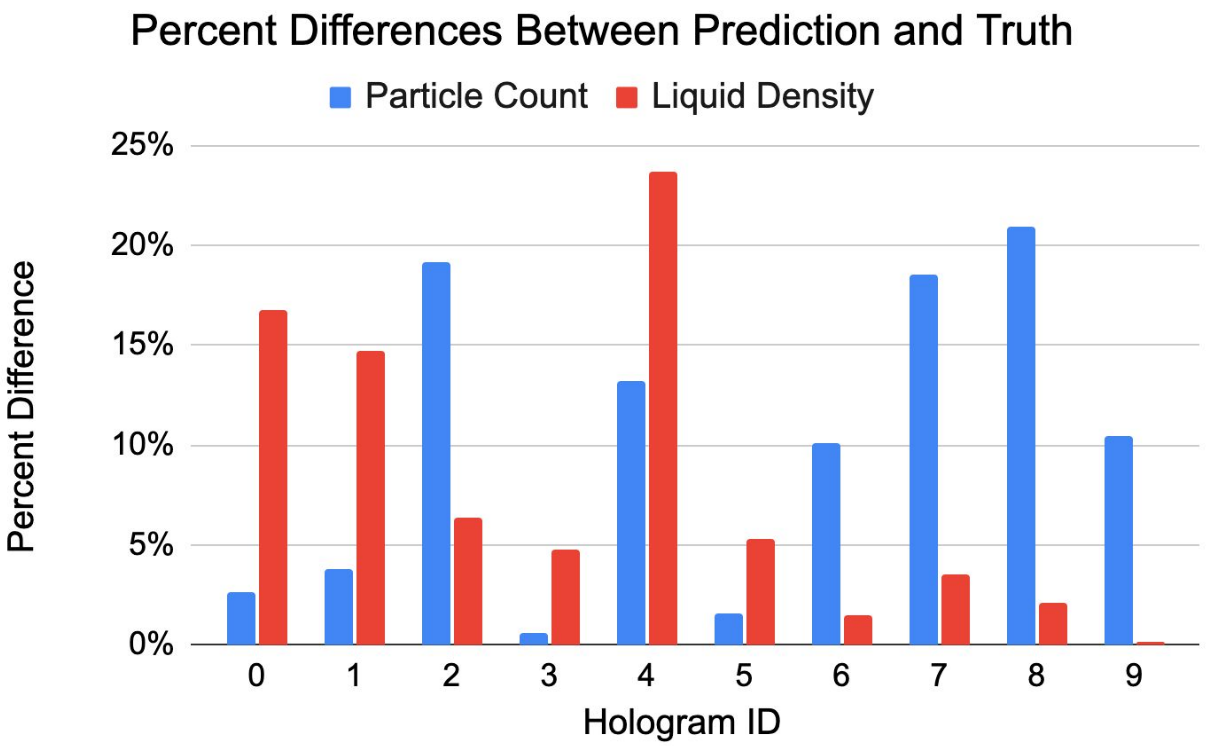
- Closer look at the prediction difference on test set by particle diameter
- Significantly more accurate for particles at least 3 pixels in diameter



Results: Synthetic Test Hologram Predictions

- Accurately predicting the number of particles does not guarantee accurate liquid density measurements

- Mean particle count difference: 10.0%
- Mean liquid density difference: 7.89%
- Mean effective radius difference: 6.52%



Lower is better

Conclusions and Future Work

- Successfully detect ~90% of particles in synthetic test set
- More accurately predict physical properties, including liquid density and radius
- Efficient, scalable inference across arbitrary number of GPUs for campaign data processing

Possible Improvements:

- The **model accuracy** is not perfect, missing many small particles
  - Currently working on a more **complex model** that takes advantage of phase data and multiple depth planes
  - Potential for a **3D-UNET** model that has found success in other fields
  - A more diverse **training dataset** could also improve performance
- Gathering and comparing results on CSET dataset against **standard method**

References

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Questions

Thank you!

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Appendix

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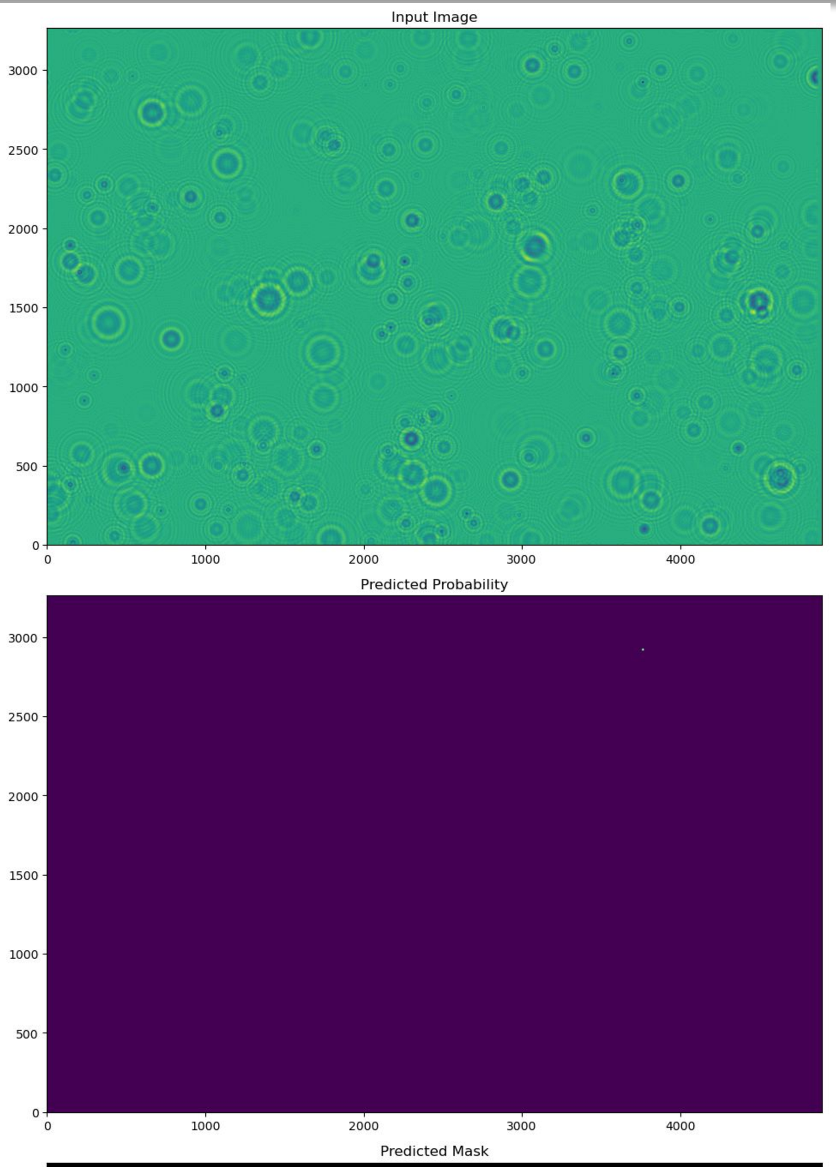
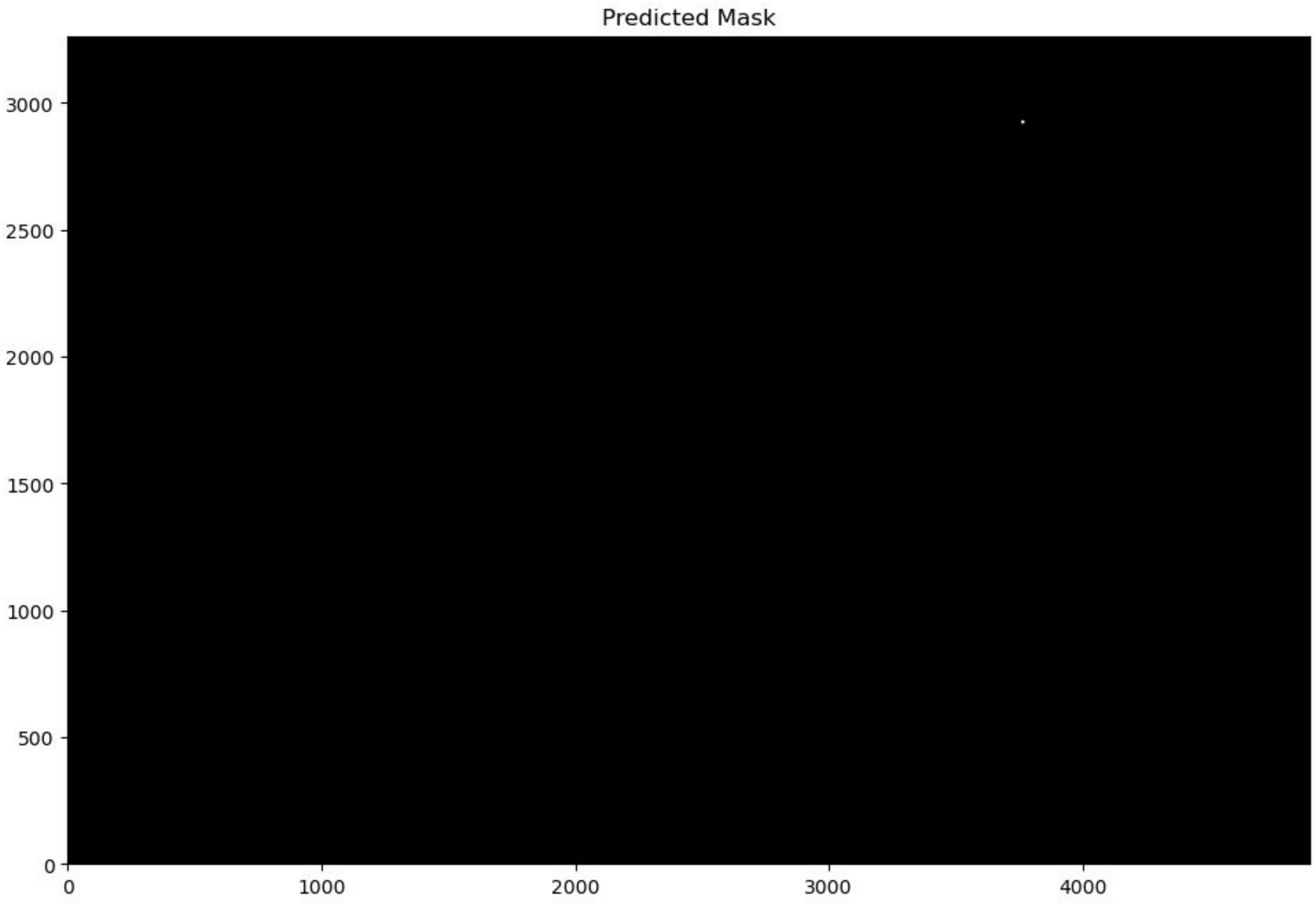
Appendix

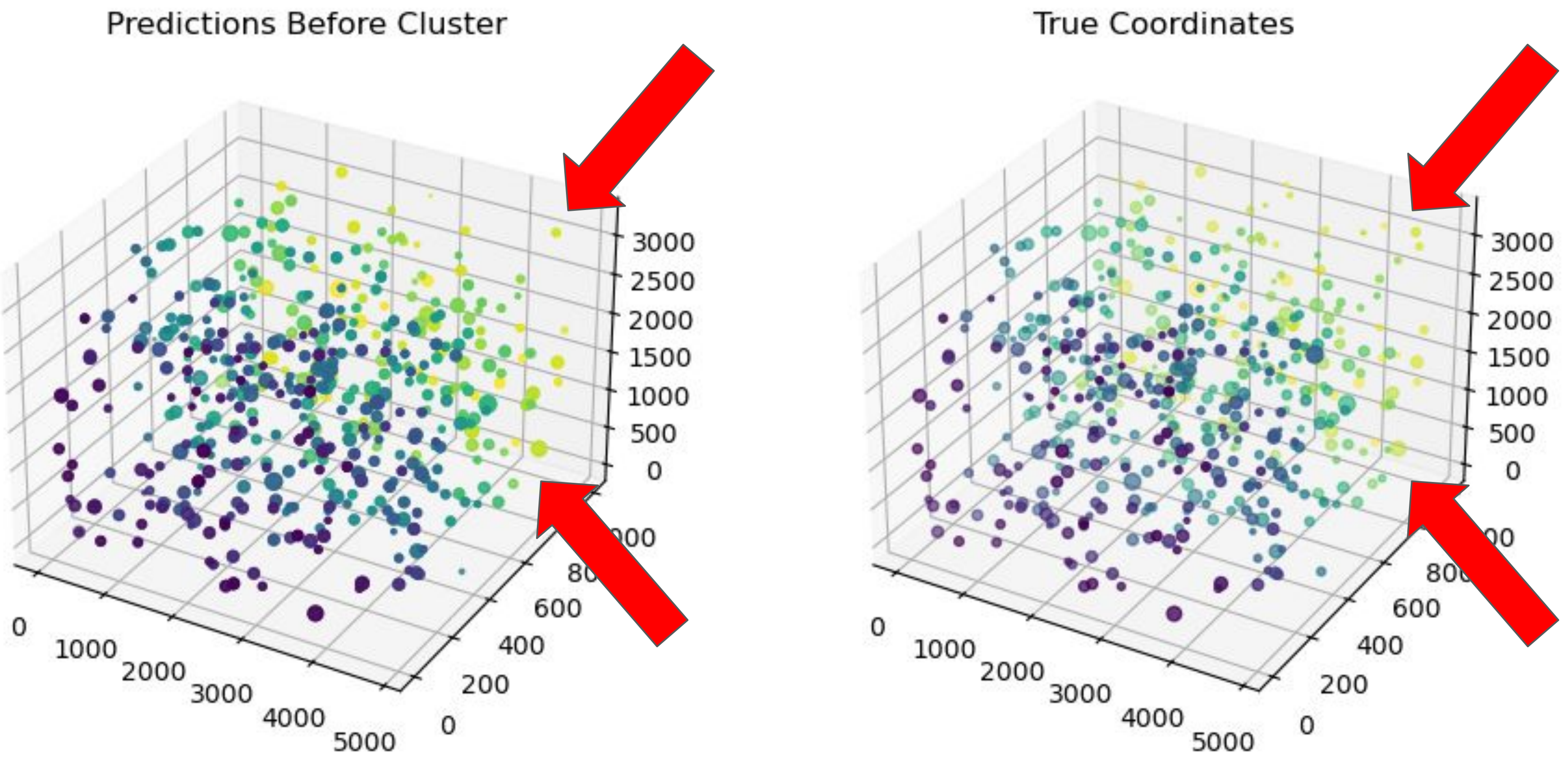


Input Image
Predicted Probability
Predicted Mask



Predicted Mask

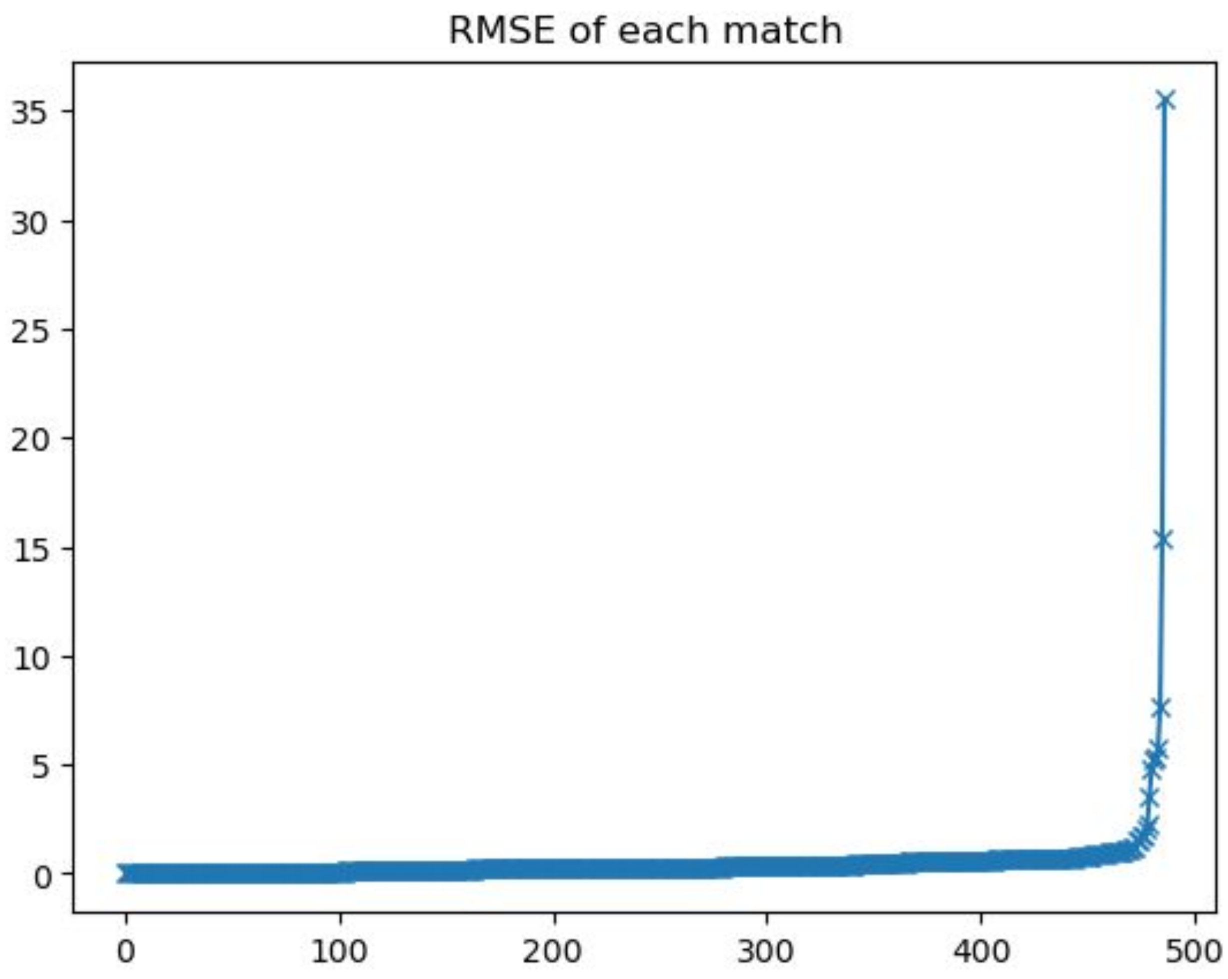
Appendix



Not getting all particles after clustering, because the model did not predict all particles in the first place

Appendix

- Matches are determined using a KDTree between pred and truth coordinates
- Only X, Y, and Z are used in matching
- Not all predictions are ‘good’ ones



Appendix

No seemingly obvious correlation between any feature and poor matches