Nuclear Science and Security Consortium
Virtual Scholar Showcase 2020

Neural-net-based imager offset estimation in fieldable associated particle imaging

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NUCLEAR SCIENCE and SECURITY CONSORTIUM

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Introduction

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Nuclear Engineering

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Focus Areas: Radiation Detection | Nuclear Engineering

Crosscutting Areas: Modeling and simulation

Neutron Imaging

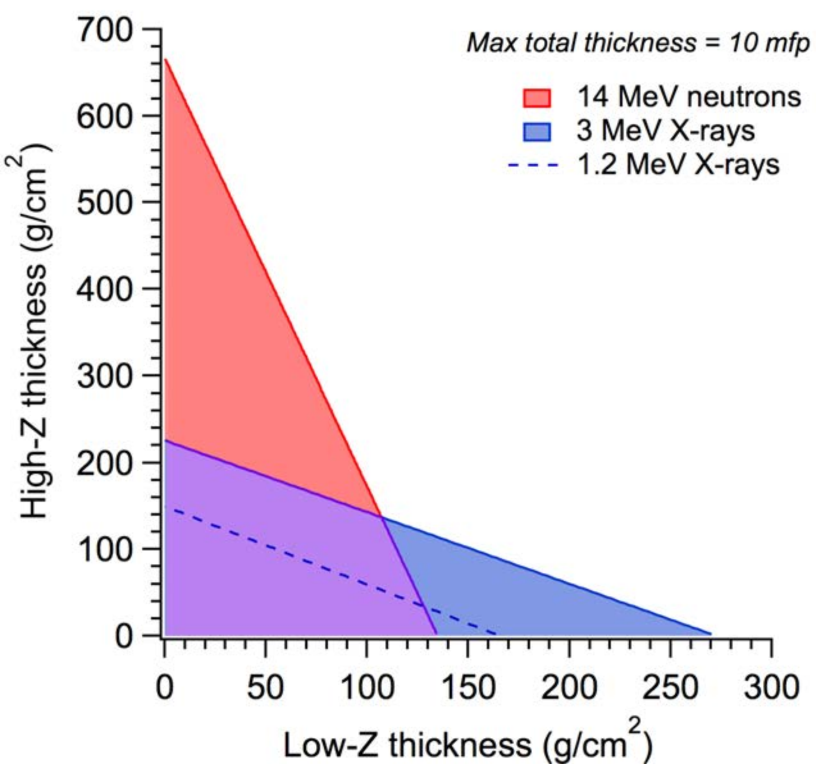
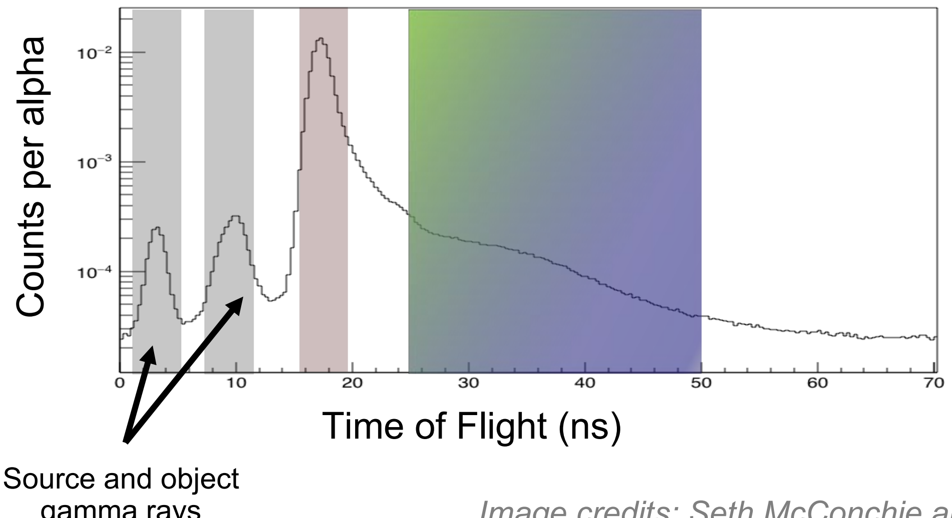


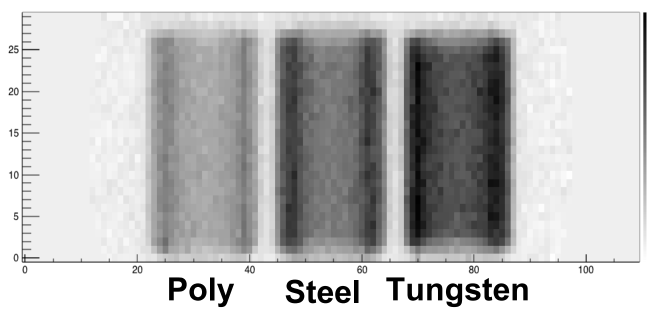
Image credit: Seth McConchie, ORNL

- **Complements X-ray imaging**
- **Nuclear interactions mean it can resolve isotopic differences**
- **Common shielding materials that are effective at attenuating X-rays do not interact as readily with neutrons**

Associated Particle Imaging

- **Method to improve signal to noise by filtering in time domain**
- **Three modes:**
  - Transmission imaging
  - Scatter imaging
  - Fission imaging
- **ORNL Nuclear Materials Identification System (NMIS) uses deuterium-tritium generator to produce α (3.54 MeV) and neutron (14 MeV) in opposite directions**

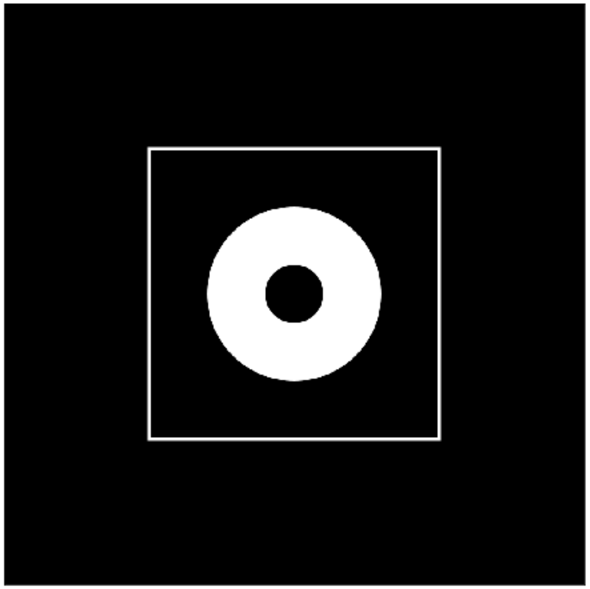




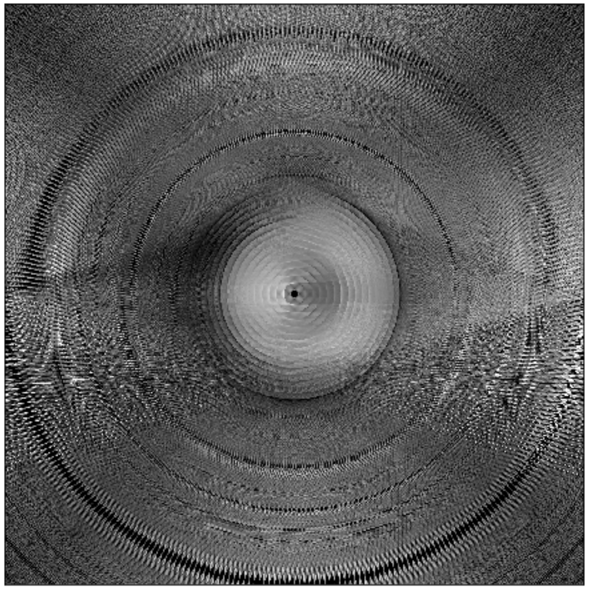
Example neutron radiograph with 2D pixelated detector. Scale is the attenuation coefficient in the material.

Image credits: Seth McConchie and Matthew Blackston, ORNL

Problem statement



Simulated imaging phantom



CT reconstruction of phantom
with 7.5cm lateral array offset

In a fully portable, fielded version of NMIS, the neutron detector array could be misaligned relative to its nominal position. This affects both scatter rejection and image reconstruction.

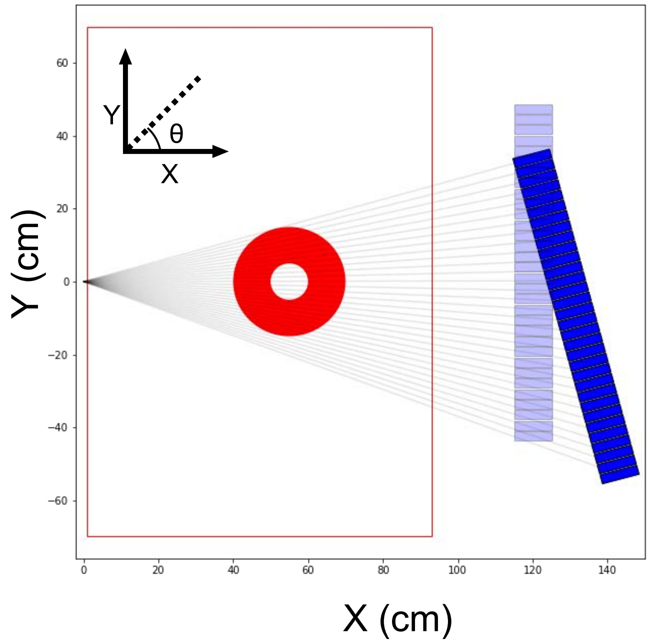
Solution: design a neural network to infer the position of a neutron array (distance, offset, and rotation) from measurement data.

Approach

- Simulate neutron physics with Monte Carlo (MCNP)
- Use measured data to incorporate detector response
- Train neural network on generated data

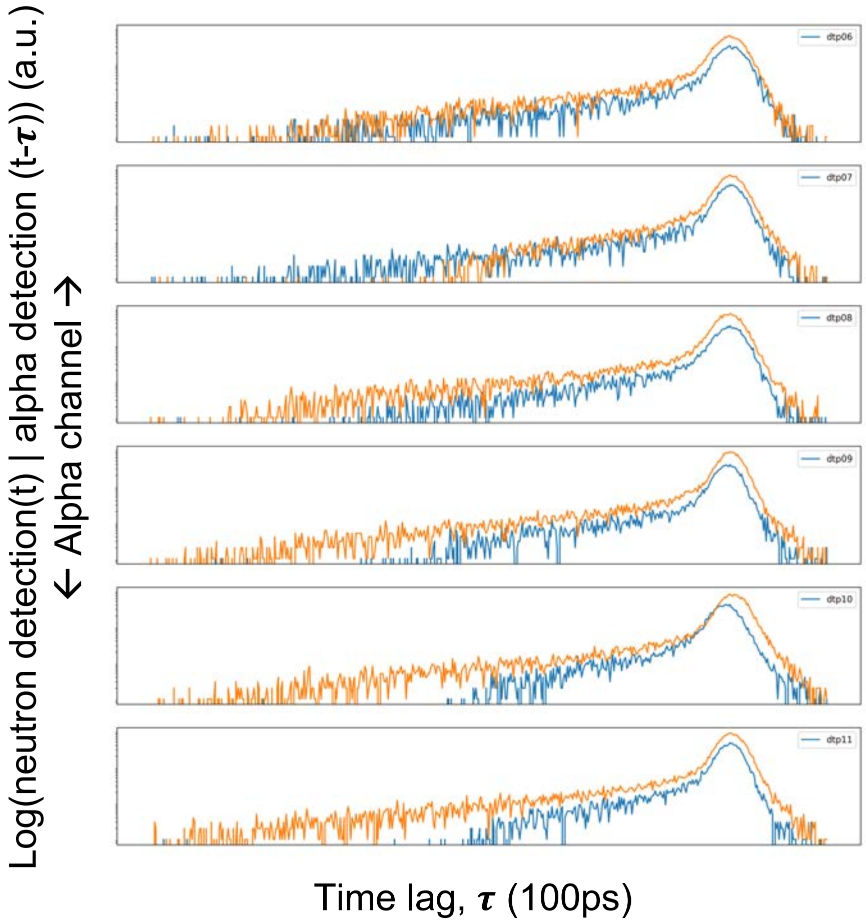
Monte Carlo (MCNP) Workspace

- No line of sight assumed between source and detector due to steel box
- Annulus materials selected from plastic, steel, aluminum, tungsten, DU, or explosive
- MCNP source distribution based on curves fit to measured data from generator → separate “source” for each alpha pixel matching correlated emission cone
- Neutron pixels: PVT, 1” x 1” x 4” based on existing NMIS design
- Train / Test: 842 / 157 simulations



	ΔX (cm)	ΔY (cm)	ΔΘ (°)	Outer radius (cm)	Inner radius (cm)
Min	-15	-15	-7.5	0	0
Max	15	15	7.5	25	24.35

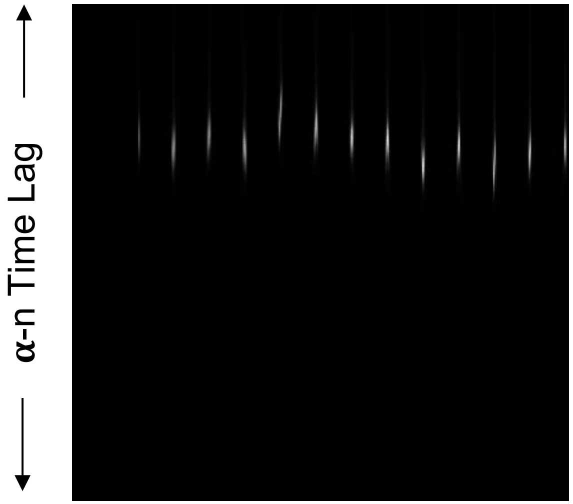
Accounting for detector timing response



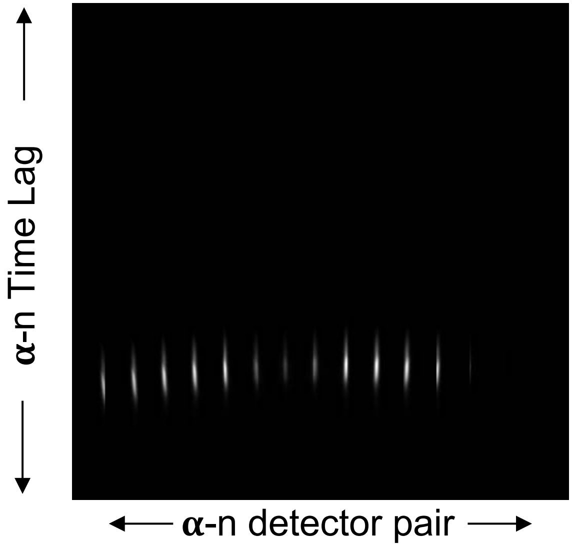
- MCNP does not model light/charge collection in neutron/alpha detectors
- Timing is assigned using constant fraction discriminators (CFD)
- Measured 1000 pulses per channel and simulated CFD to find timing variability
- Created approximated distribution alpha times-> combined with MCNP simulations of alpha to blur measurements

Final Simulation

Measured data



Monte Carlo simulation



- MCNP gives the probability of a neutron scatter in pixel *n* at time *t* after source event given detection in alpha pixel *a*
- That probability is blurred/delayed based on detector timing response
- Probabilities converted into counts by binomial sampling based on generator output and time

Important features in common:
- ✓ Each blur represents one alpha detector in coincidence with 3-5 neutron pixels
- ✓ Intensity (number of counts) matches to within range defined by generator power
- ✓ Length of blur matches detector response in time

Neural network training

- **First convolutional layer incorporates regions of pixels into intermediate representations (“features”)**
- **“ResNet” architecture employed for feature development**
  - Each block predicts residuals from previous block through “skip connections,” allowing for iterative function approximation
- **Dropout used to promote orthogonality at feature layer**
  - During training each output value could be temporarily set to zero→ forces network to match neurons to features
- **Network depth determined by training with single output layer:**

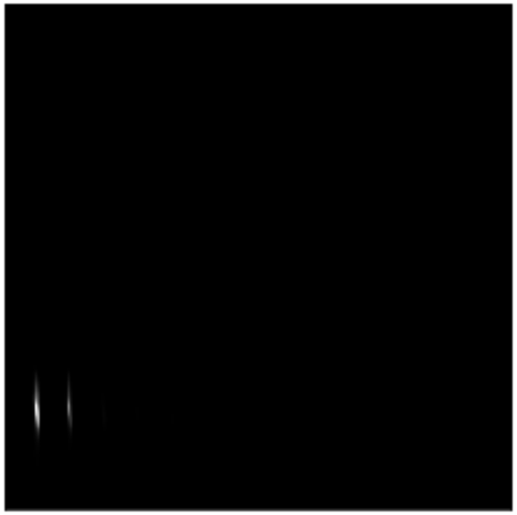
Depth	Training time (s/500epoch)	Time to stability (epochs)	Loss		Parameters	RMSE (test)
			Training	Validation		
101	21032	93	0.0009	0.023	43013633	1.34
50	3050	>500*	0.0062	0.023	2560000	1.35
10	2010	152	0.0226	0.051	547633	1.328
8	2103	100	0.0662	0.1638	1160433	2.108
6	2108	30	0.3989	0.4118	3724997	4.3767

[1] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.
[2] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A Simple Way to Prevent Neural Networks from Overfitting,” *J. Mach. Learn. Res.*, vol. 15, pp. 1929–1958, 2014.

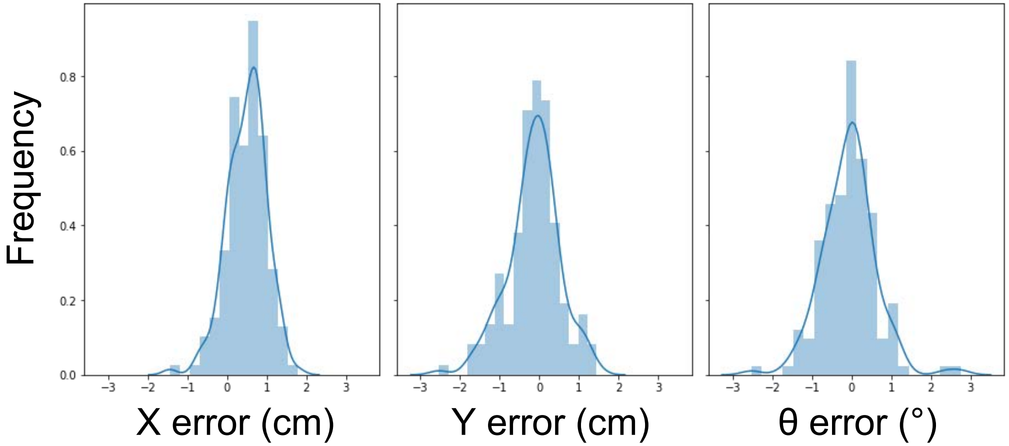
Results

RMSE: 0.49cm (X), 0.65cm (Y), 0.68° (θ)

Representative high-error prediction



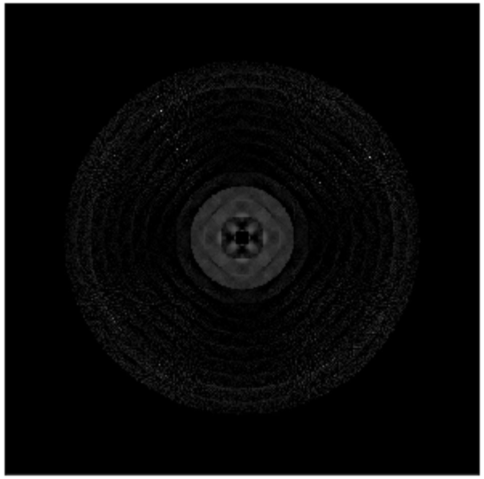
Maximum errors corresponded to nearly complete obstruction of neutron pixels



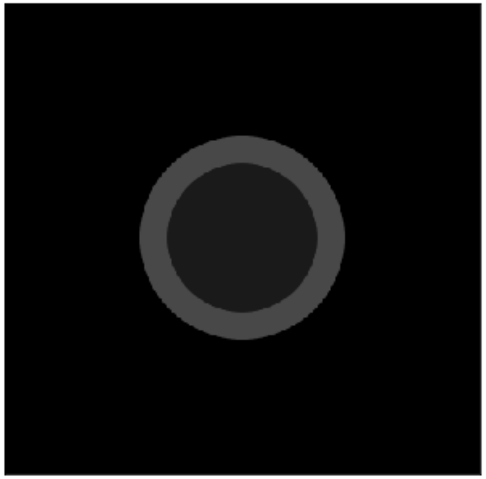
Measurement time (s)	dX RMSE (cm)	dY RMSE (cm)	dθ RMSE (°)
600	0.4912	0.6479	0.6776
300	0.4904	0.6485	0.6774
120	0.4904	0.6485	0.6774
60	0.4904	0.6485	0.6774
30	0.4904	0.6485	0.6774

Because they were trained using scaled data, network predictions are robust to measurement time/Poisson noise

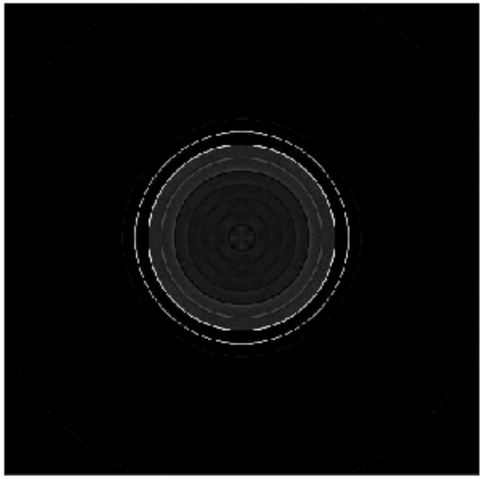
Reconstruction after algorithm



Before correction



Actual object



After correction

Network Accuracy

	dx (cm)	dy (cm)	dθ (°)
Actual offsets	12.2	-13.3	-1.46
Network output	11.5	-13.4	-1.69
Error (%)	5.7	0.8	16

Dimension error after reconstruction

	Outer diameter (cm)	Inner diameter (cm)
Object	17.2	13.2
Reconstruction	15.8	11.4
Error (%)	8.3	13.8

Conclusions

- Neural networks are a good tool to recover array position information in NMIS system
- Accuracy is sufficient to allow tomographic image reconstruction

Future work

- **Incorporate uncertainty in neural network predictions: network should raise flag if prediction is low confidence.**
- **Sensitivity study for portable NMIS: is there a better configuration of number/size of detectors that provides better information?**

NSSC Experience Highlights

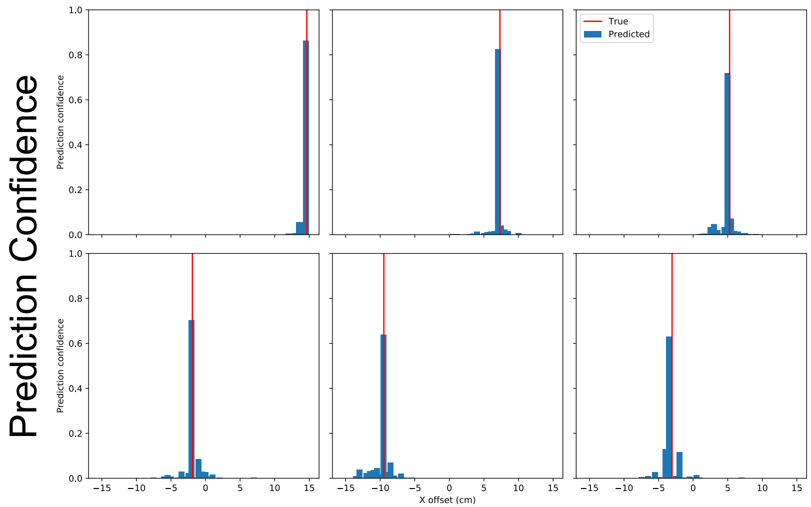
Hiking in Muir Woods following 2017
UPR in Walnut Creek

Data Science Summer Institute 2019

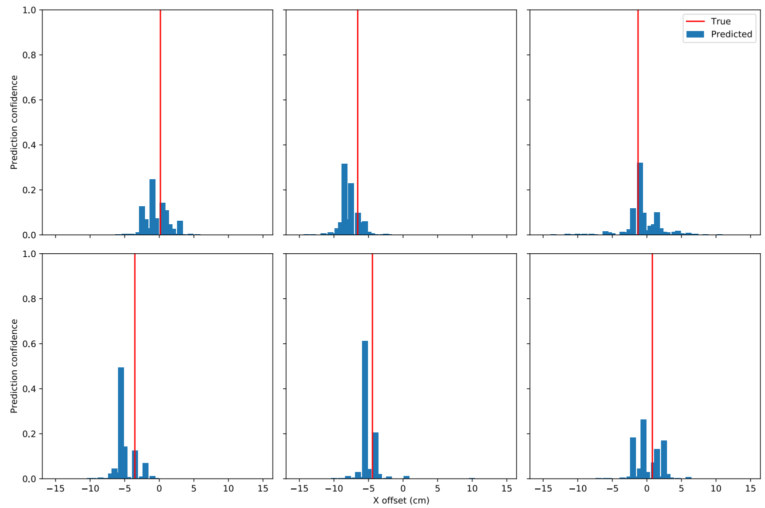
Acknowledgements

This material is based upon work supported by the Department of Energy National Nuclear Security Administration under Award Number DE-NA0003180.

Categorical approximation for uncertainty



Six best predictions

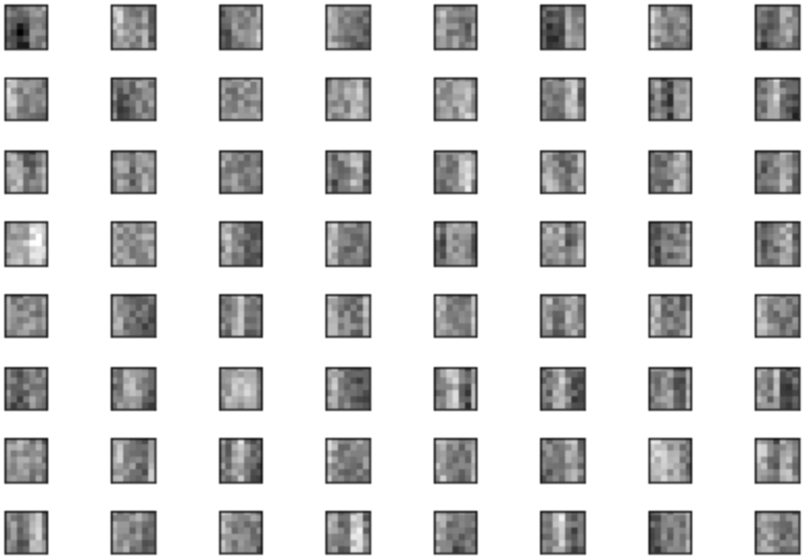


Six worst predictions

Neural networks* as classifiers converge to the Bayesian posterior distribution conditioned on the inputs as priors

[1] C. M. Bishop and others, *Neural networks for pattern recognition*. Oxford university press, 1995.

Network feature examination

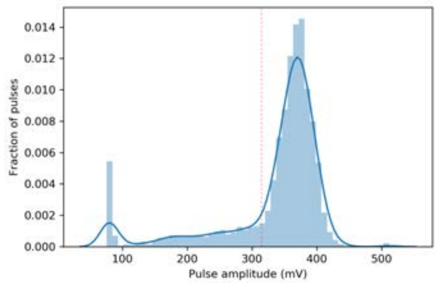


Weights for first convolution layer. Vertical white areas next to darker areas indicate that these neurons respond to vertically oriented edges

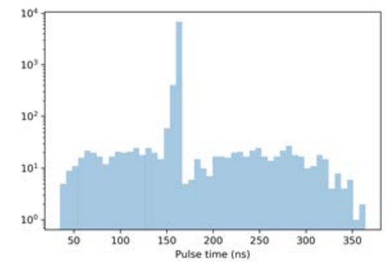
- **Primarily vertical lines of varying width**
- **Network learning to identify coincident neutron pixels→ how many neutron pixels are in each alpha cone**
- **Suggests improvement possible by using narrower neutron pixels**

Alpha channel timing distributions

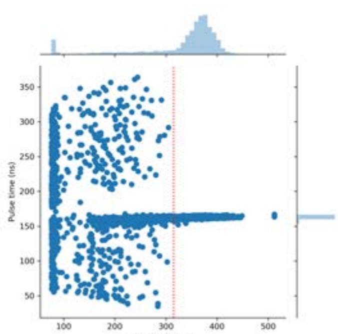
A



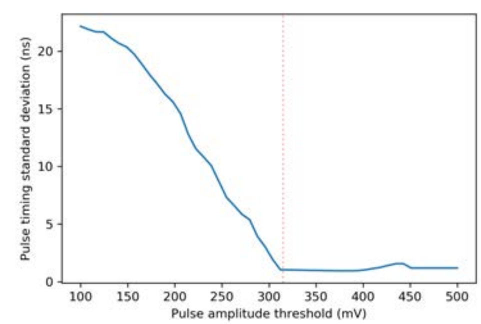
B



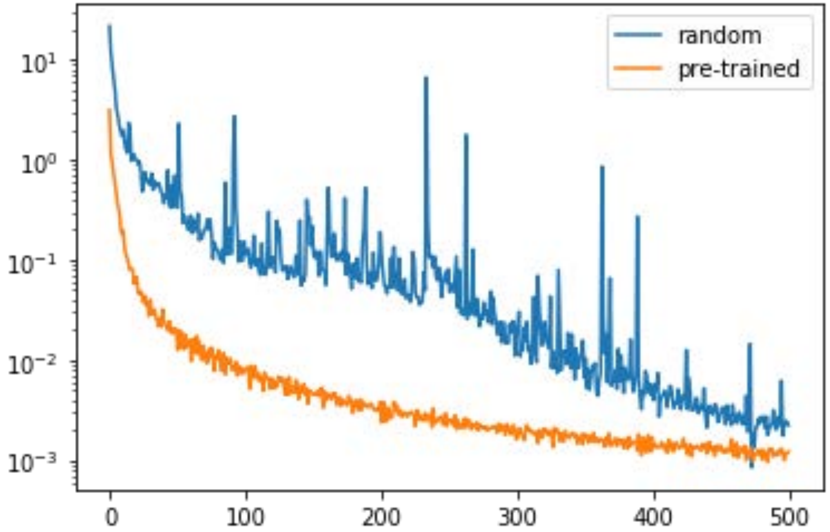
C



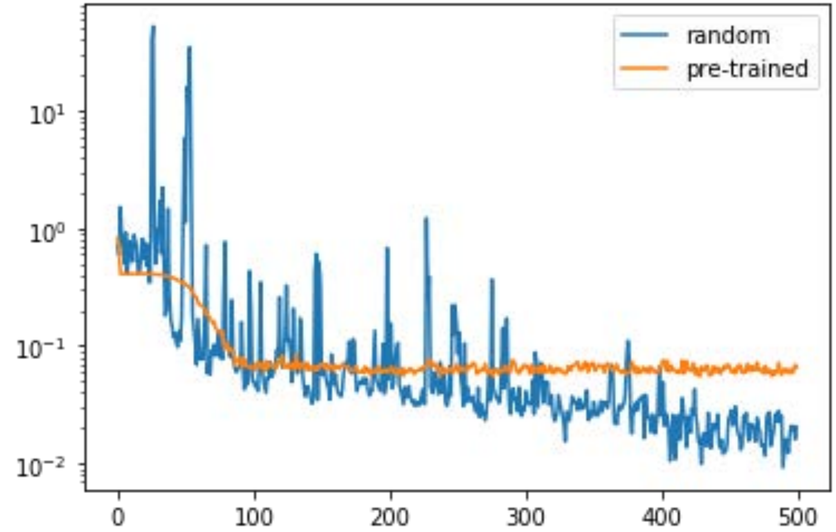
D



Pre-trained network weights

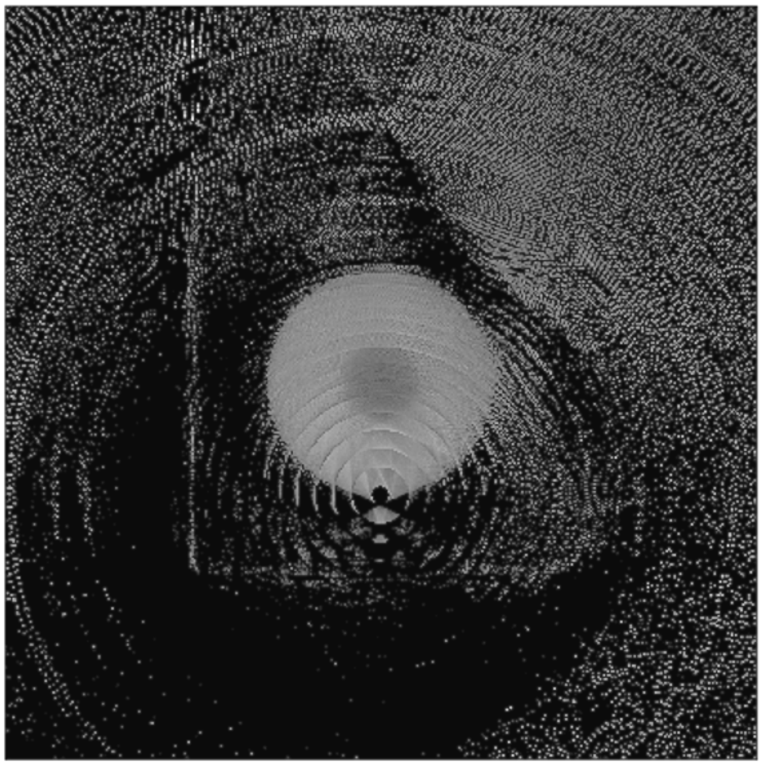


Training

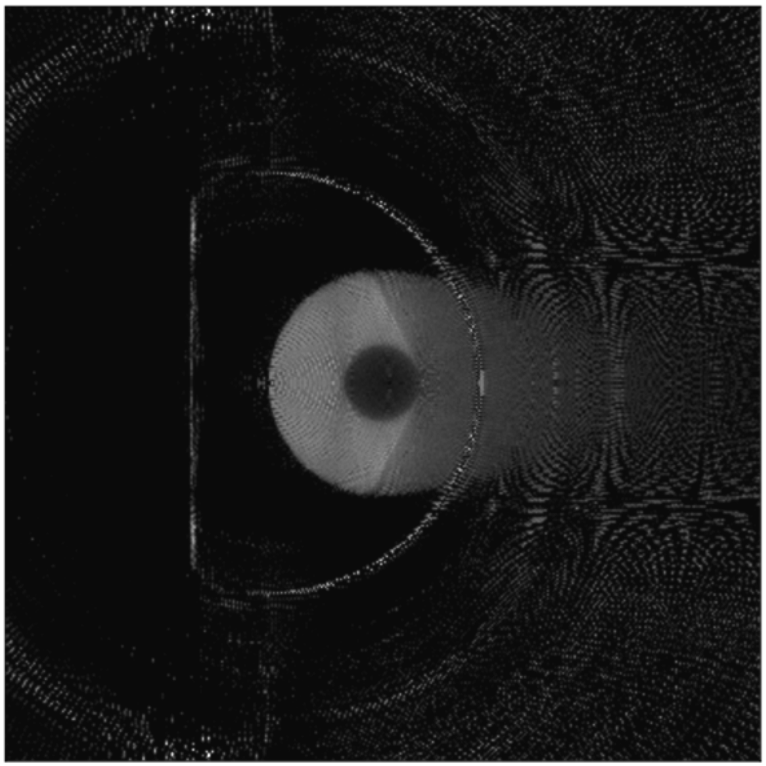


Validation

New array design trade space

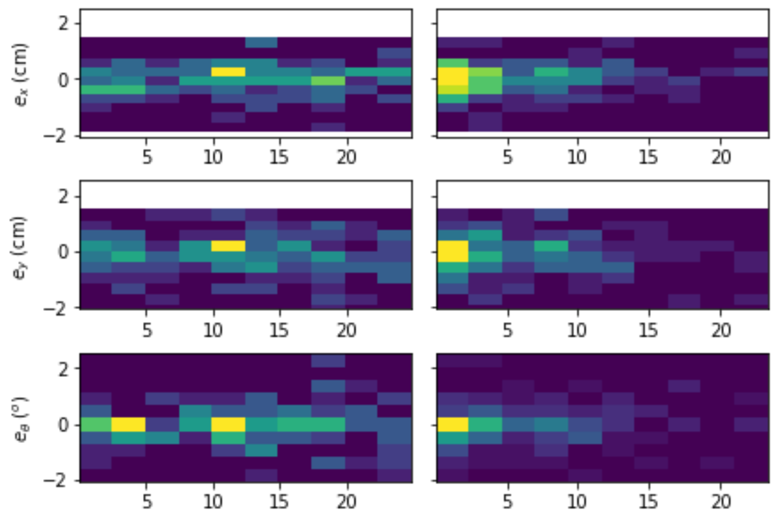


1inch pixels, 78° arc

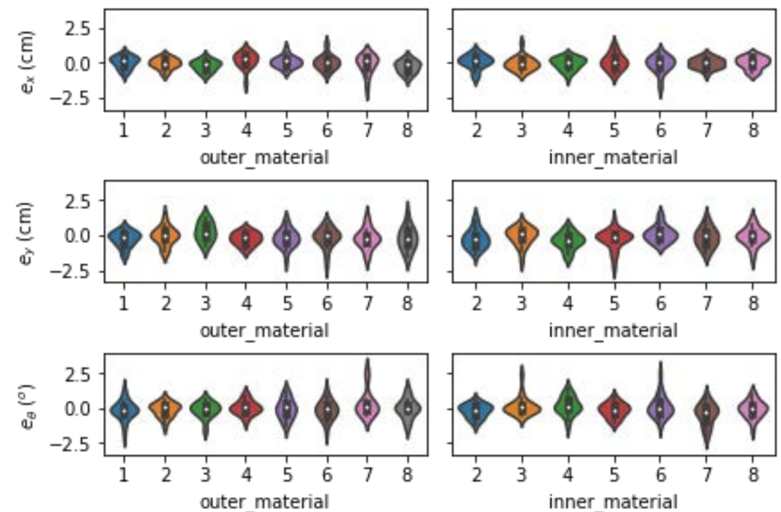


½ inch pixels, 44° arc

Analysis of residuals



A



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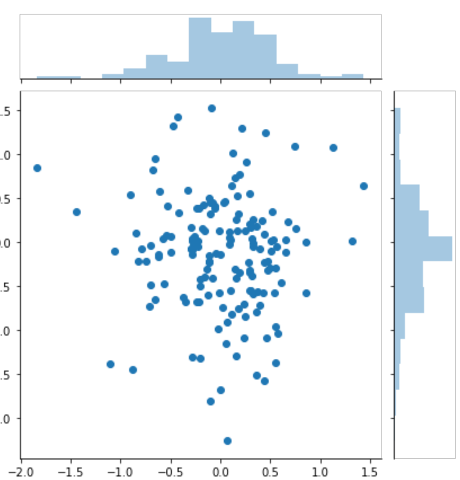

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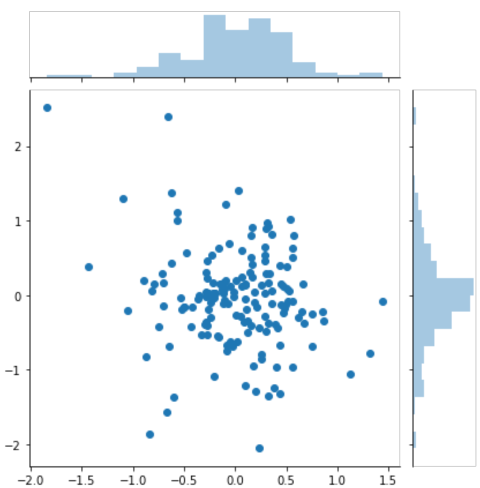
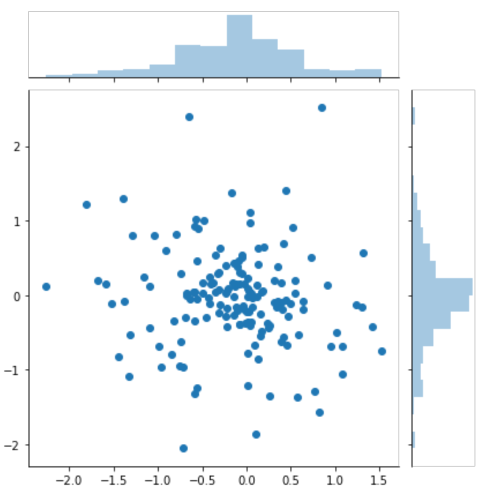


D



E