A convolutional neural network for the classification of UXO in marine settings

Jorge Lopez-Alvis[1], Lindsey J. Heagy[1], Douglas W. Oldenburg[1], Stephen Billings[2], Lin-Ping Song[2]

[1]University of British Columbia, [2]Black Tusk Geophysics, Inc.

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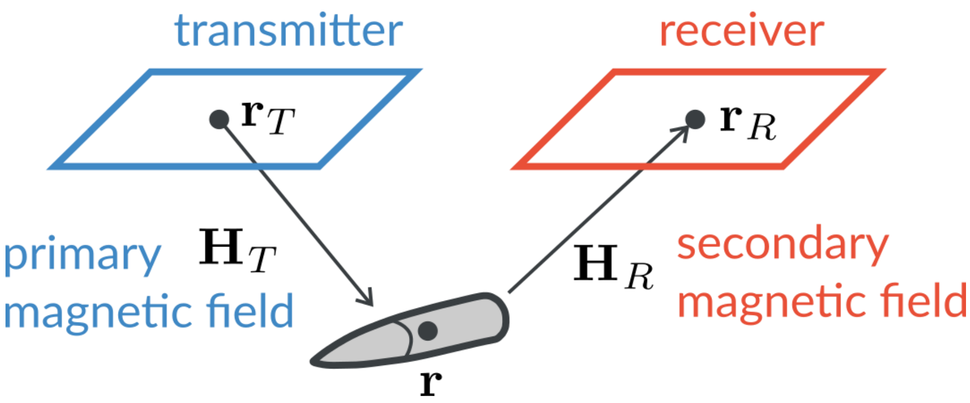
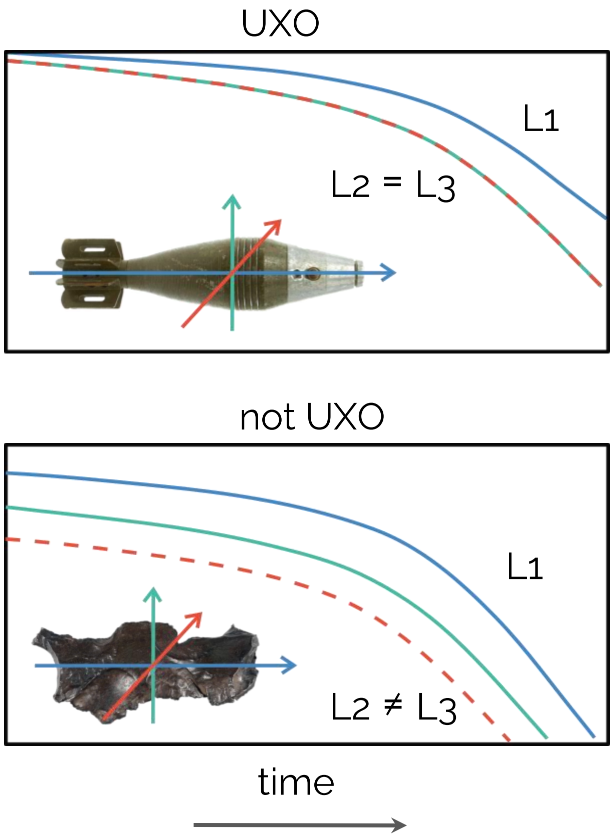
Time-domain EM response of a UXO



$$d(\mathbf{r}_R, t) = \mathbf{H}_R(\mathbf{r}, \mathbf{r}_R) \cdot \mathbf{P}(t) \cdot \mathbf{H}_T(\mathbf{r}, \mathbf{r}_T)$$

$$\mathbf{P}(t) = \mathbf{A}(\phi, \theta, \psi) \cdot \mathbf{L}(t) \cdot \mathbf{A}^\top(\phi, \theta, \psi)$$

$$\mathbf{L}(t) = \begin{pmatrix} L_1 & & \\ & L_2 & \\ & & L_3 \end{pmatrix}$$



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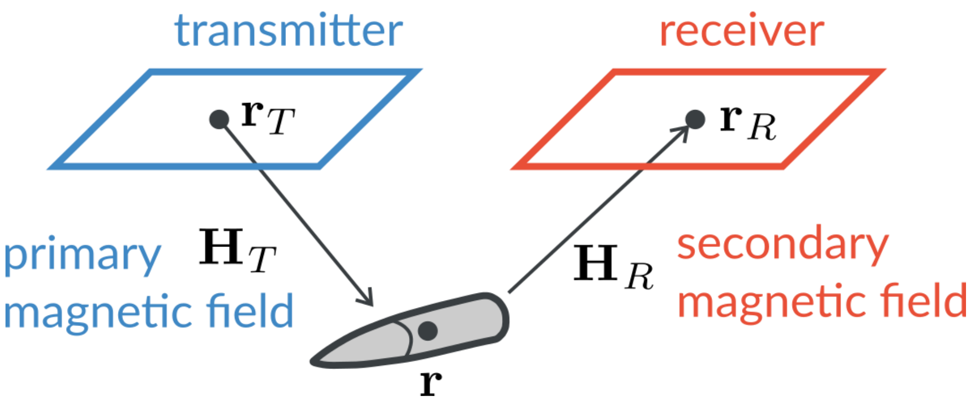
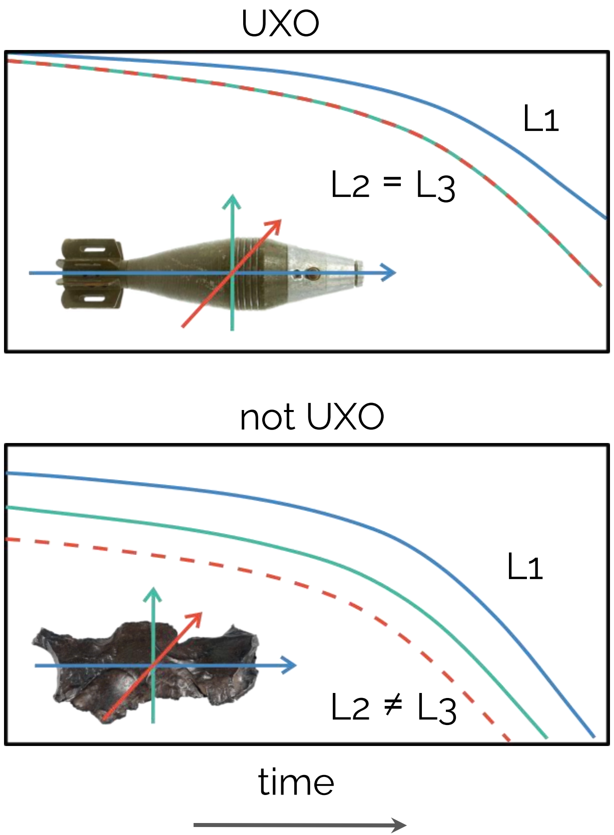


$$d(\mathbf{r}_R, t) = \mathbf{H}_R(\underbrace{\mathbf{r}}, \mathbf{r}_R) \cdot \mathbf{P}(t) \cdot \mathbf{H}_T(\mathbf{r}, \mathbf{r}_T)$$

$$\mathbf{P}(t) = \underbrace{\mathbf{A}(\phi, \theta, \psi)} \cdot \mathbf{L}(t) \cdot \mathbf{A}^\top(\phi, \theta, \psi) \qquad \mathbf{L}(t) = \underbrace{\begin{pmatrix} L_1 & & \\ & L_2 & \\ & & L_3 \end{pmatrix}}$$

traditional approach: use inversion to get these and then classify based on **L**(t)



Survey and system

UltraTEMA-4 system:

4 transmitters

12 receivers (3-component)

27 time channels

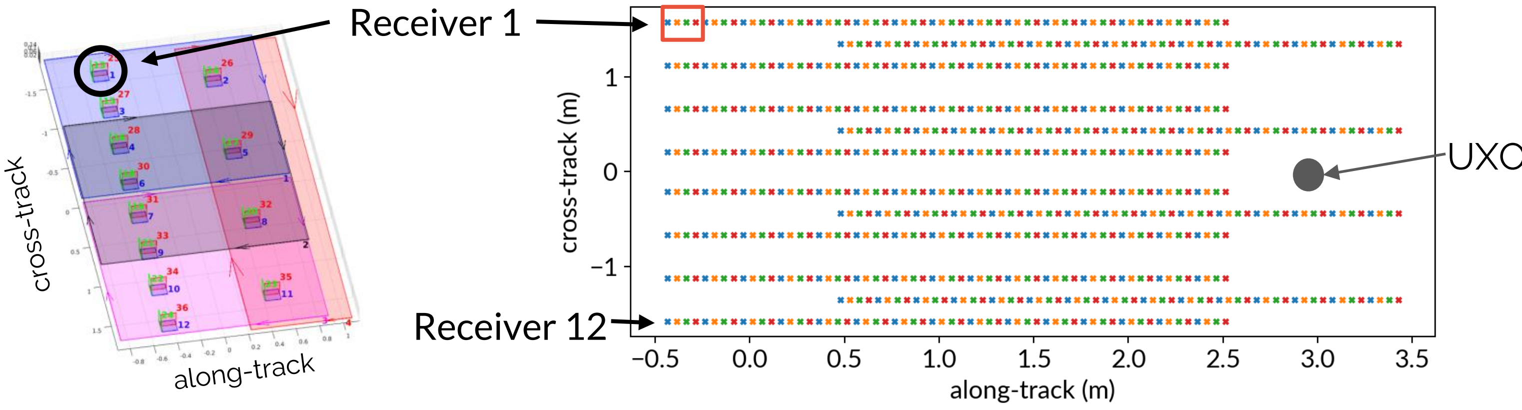
Height above sea-bottom: ~1 m

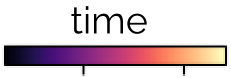
Challenges:

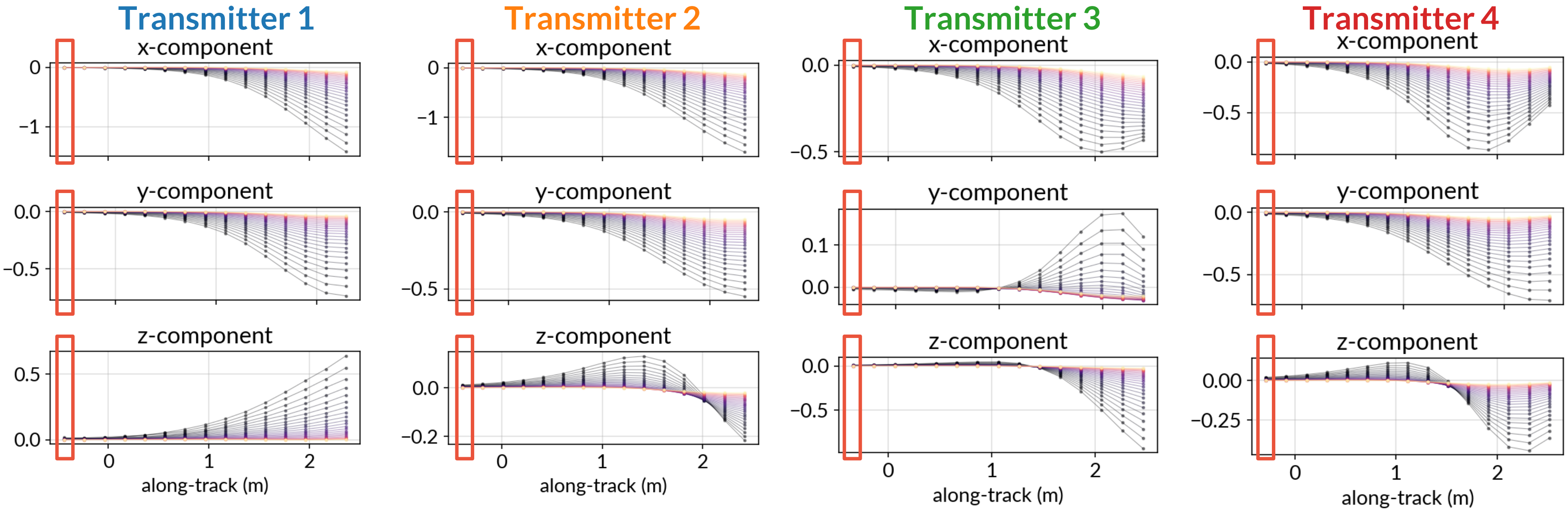
- Accuracy in location
- EM response of seawater and sediments (background)

Data

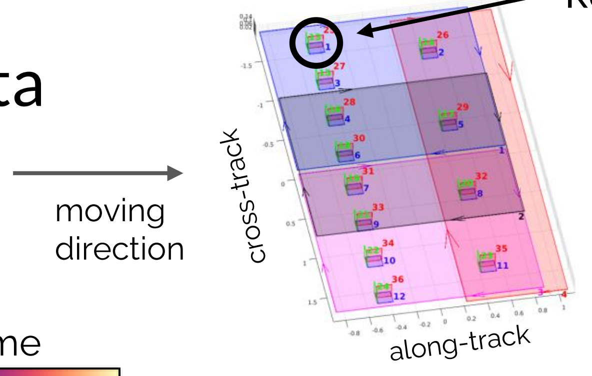

moving
direction


Receiver 1
Receiver 12
UXO
cross-track
along-track
cross-track (m)
along-track (m)

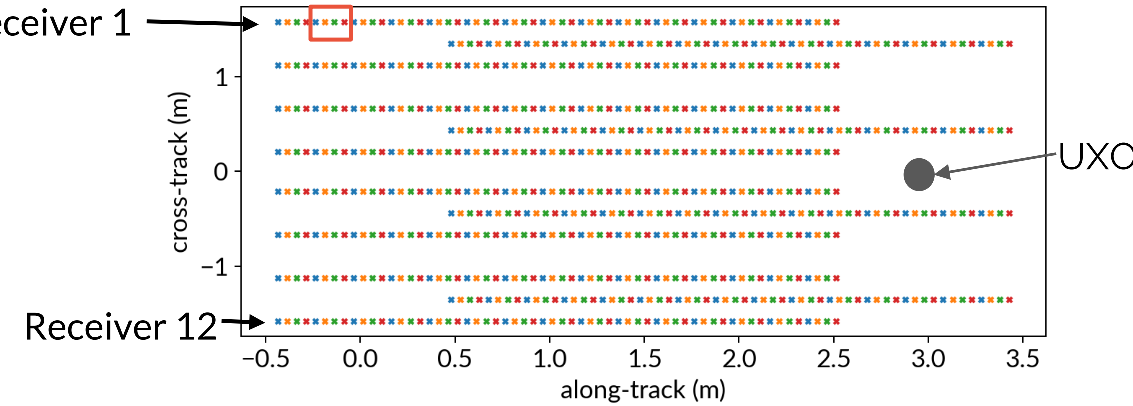

time


Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

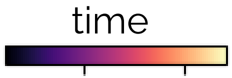
Data



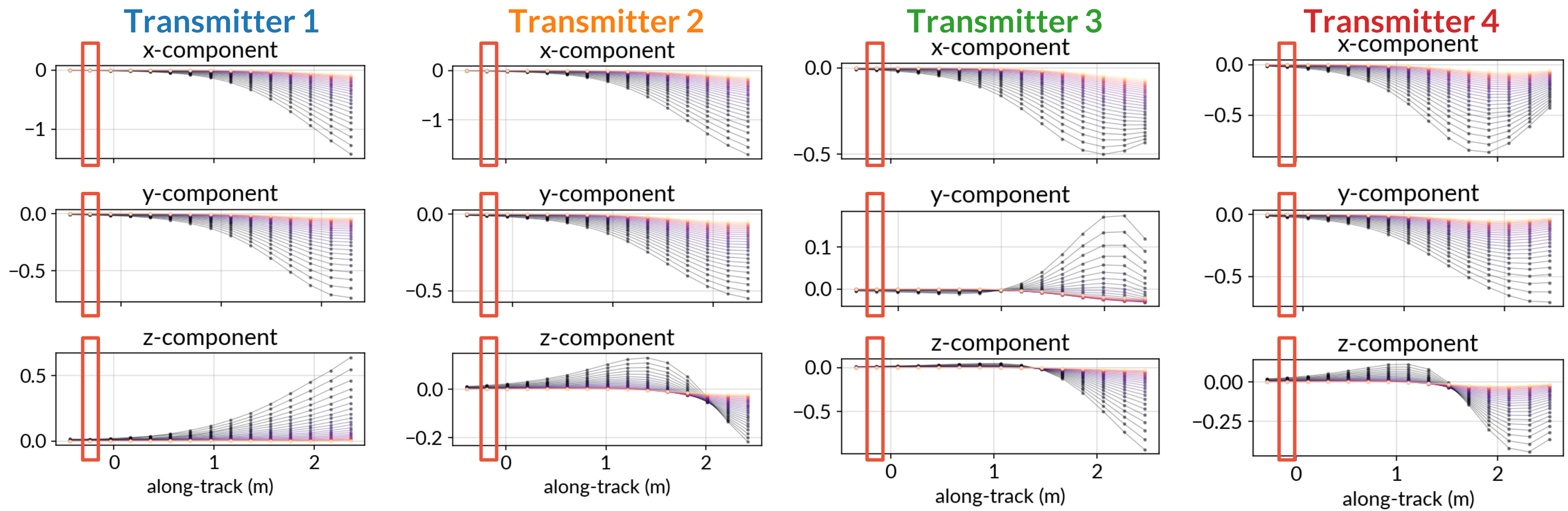
moving
direction
cross-track
along-track



Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)

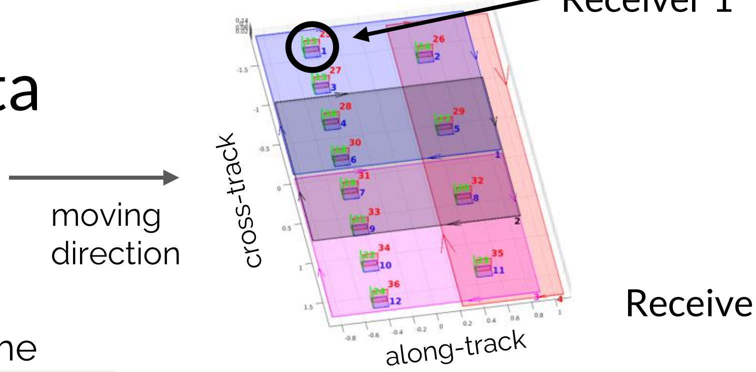


time

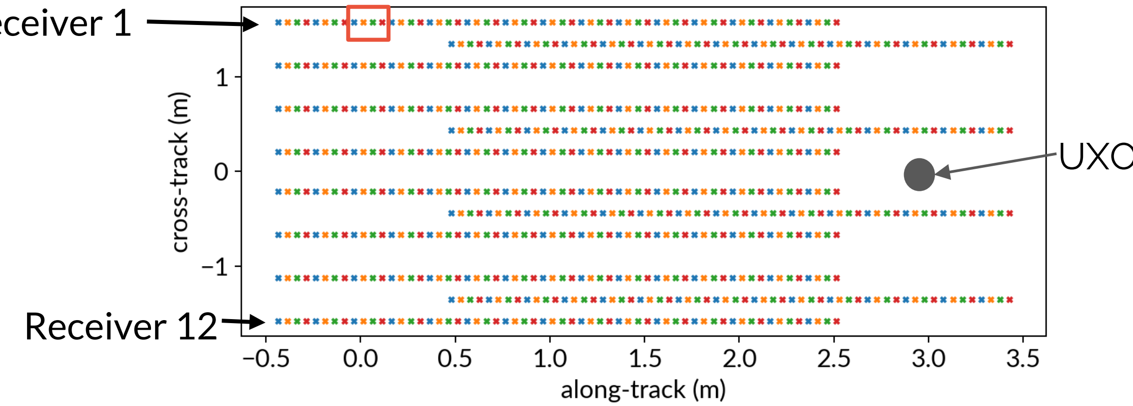


Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

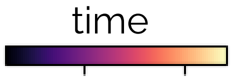
Data



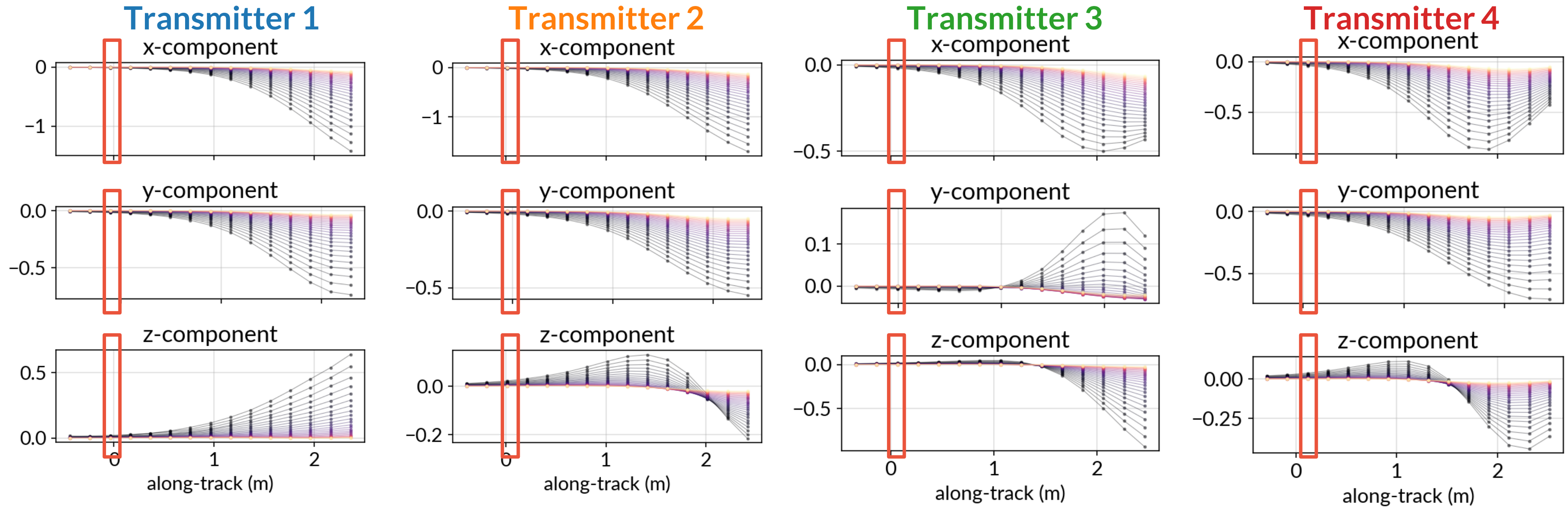
moving
direction
cross-track
along-track
Receiver 1



Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)

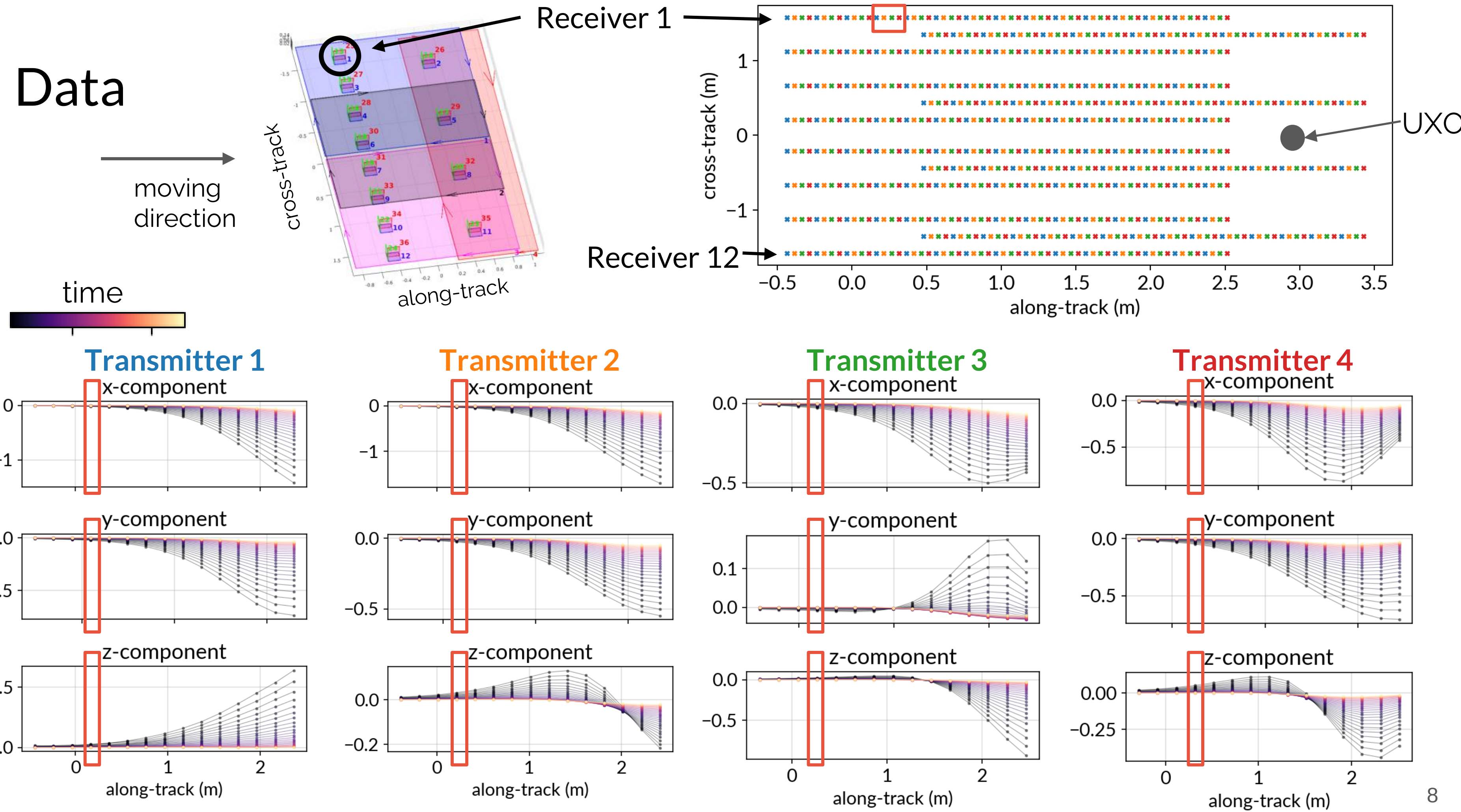


time



Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

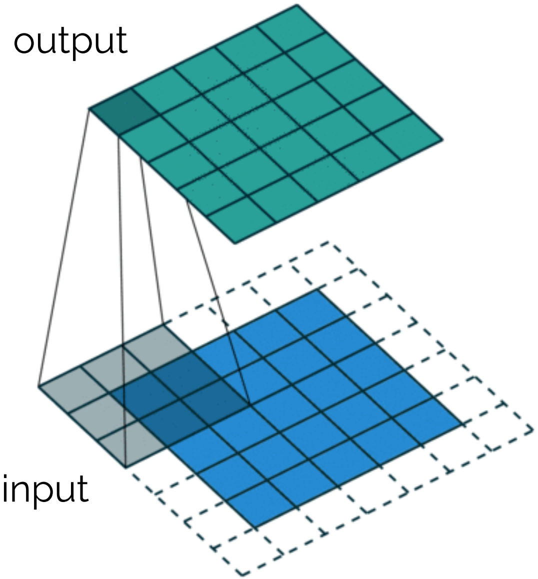
Data

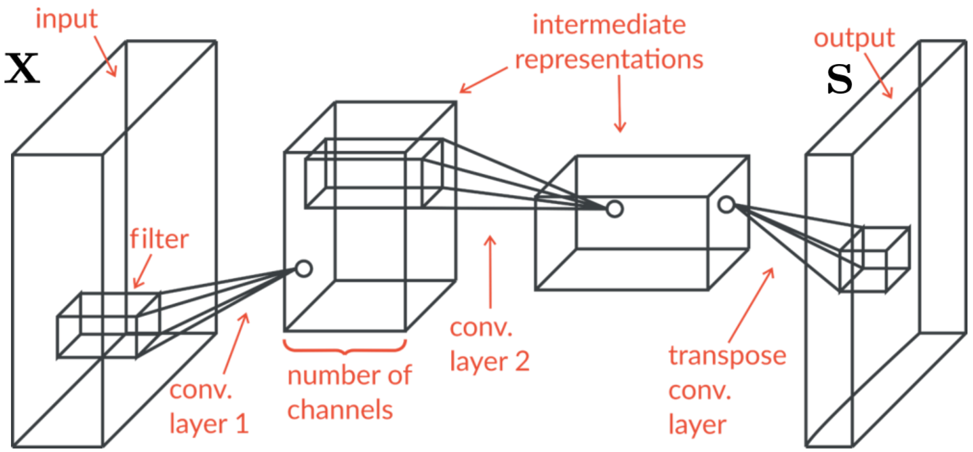


Receiver 1
Receiver 12
UXO
moving direction
cross-track
along-track
time
cross-track (m)
along-track (m)
Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

Can we classify directly from data?

Densely sampled data and correlated in space and time: a good candidate for convolutional neural networks.





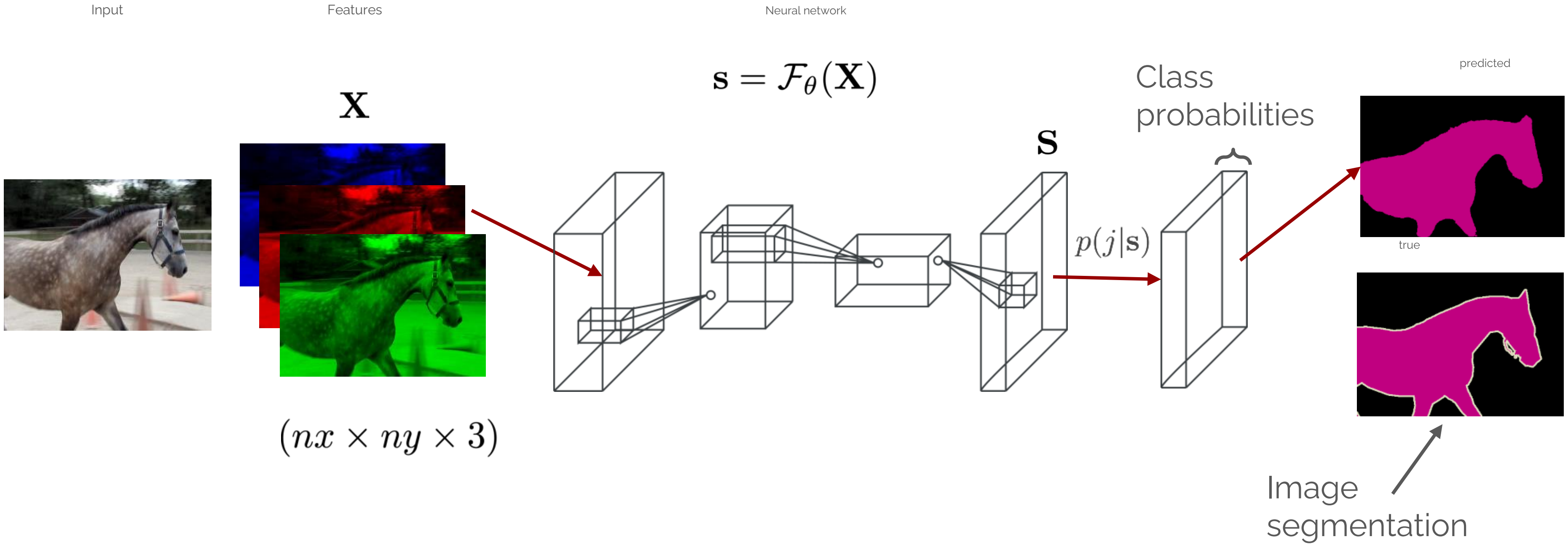
$$\mathbf{s} = \mathcal{F}_\theta(\mathbf{X})$$

https://github.com/vdumoulin/conv_arithmetic/blob/master/README.md

Convolutional Neural Networks

Supervised classification problem

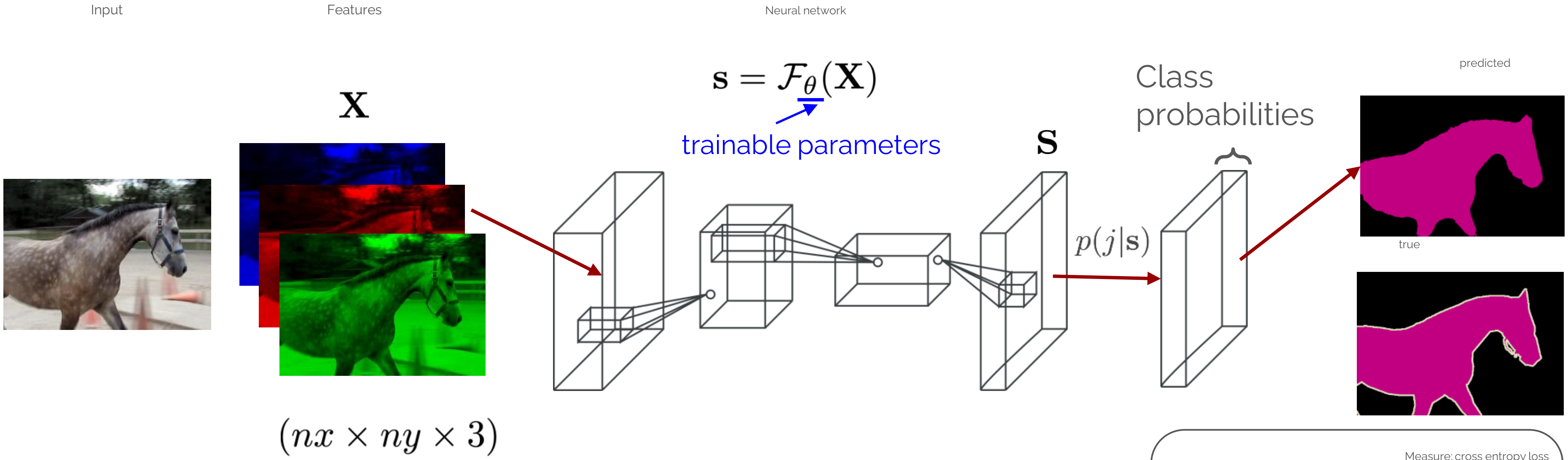
provided data with labels, construct a function (network) that outputs labels given input data



Convolutional Neural Networks

Training

define an optimization problem to estimate network parameters

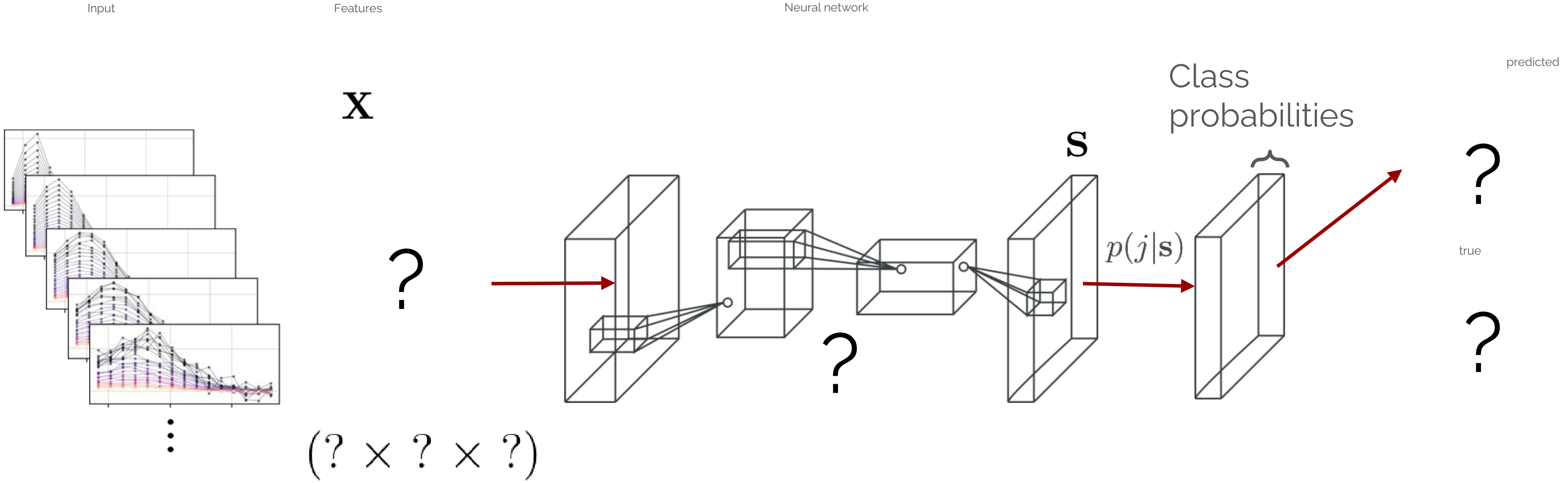


Measure: cross entropy loss

$$\min_{\theta} \phi = -\sum q_j \log(p_j)$$

Convolutional Neural Networks

How do we translate these things to the UXO classification problem?



Convolutional Neural Networks

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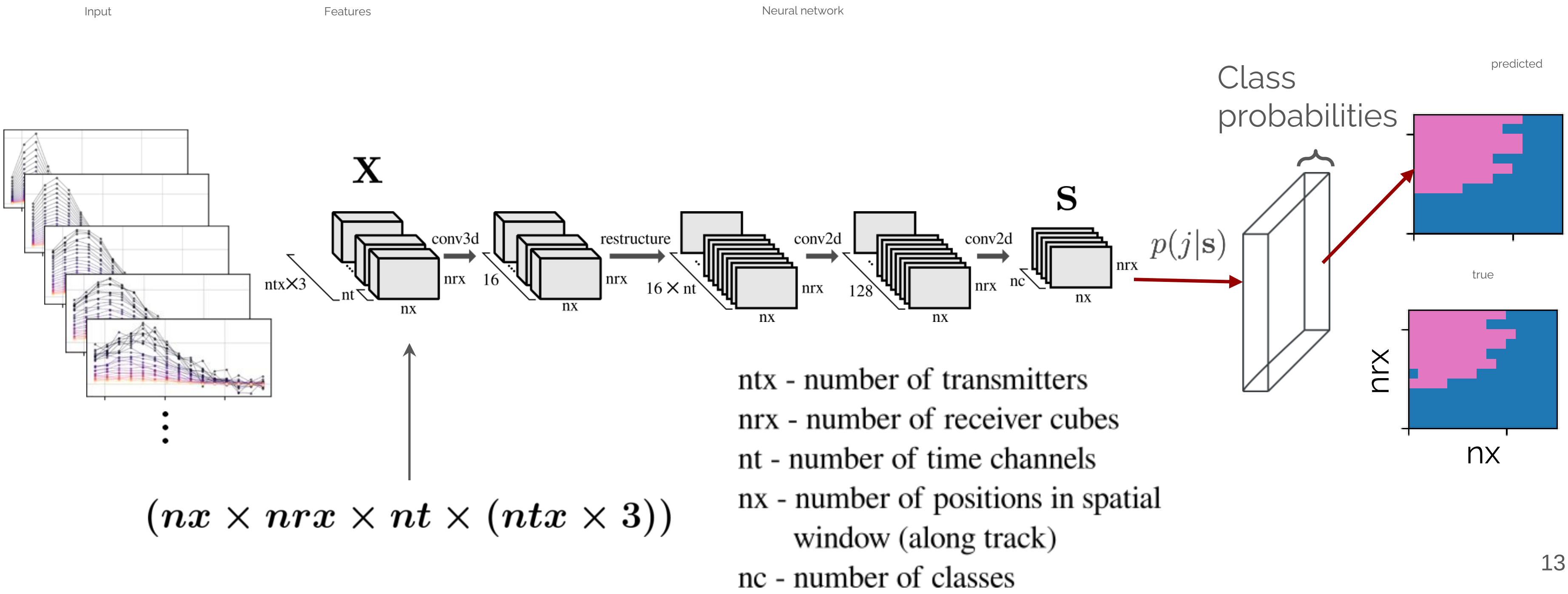
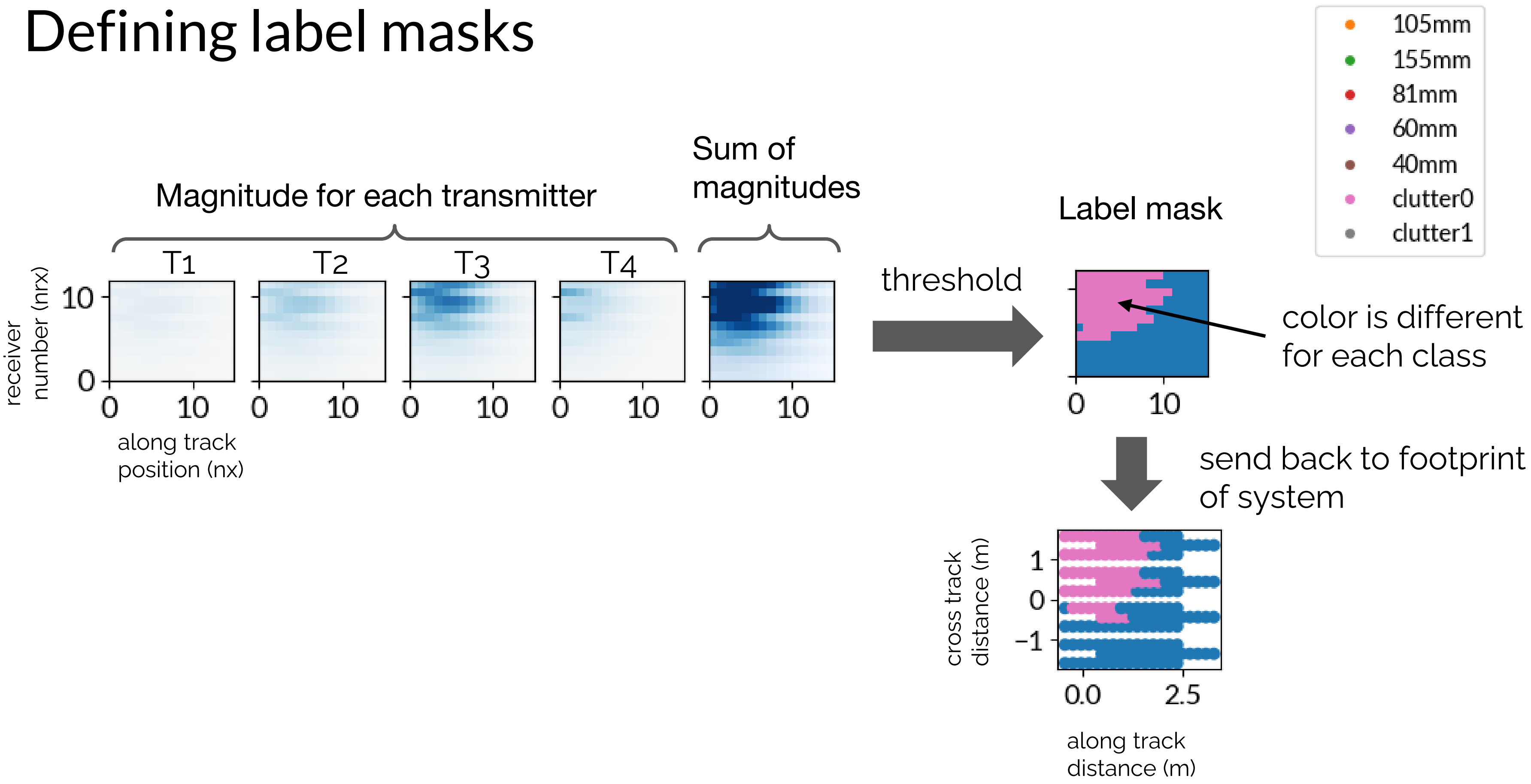


Defining label masks



Convolutional Neural Networks

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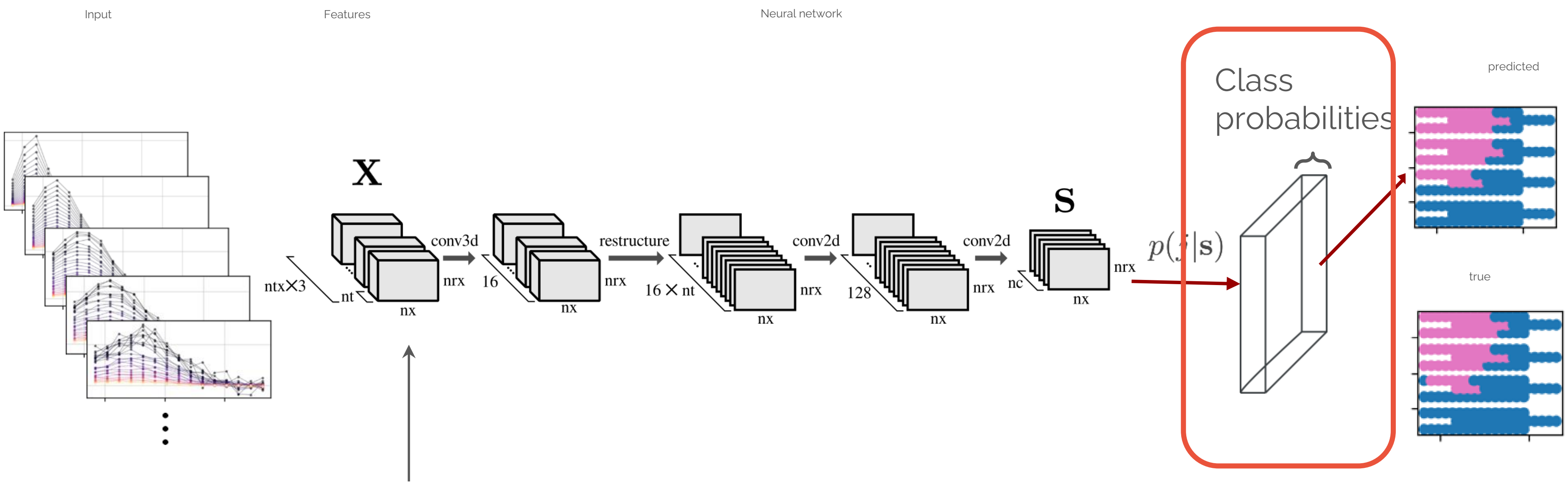
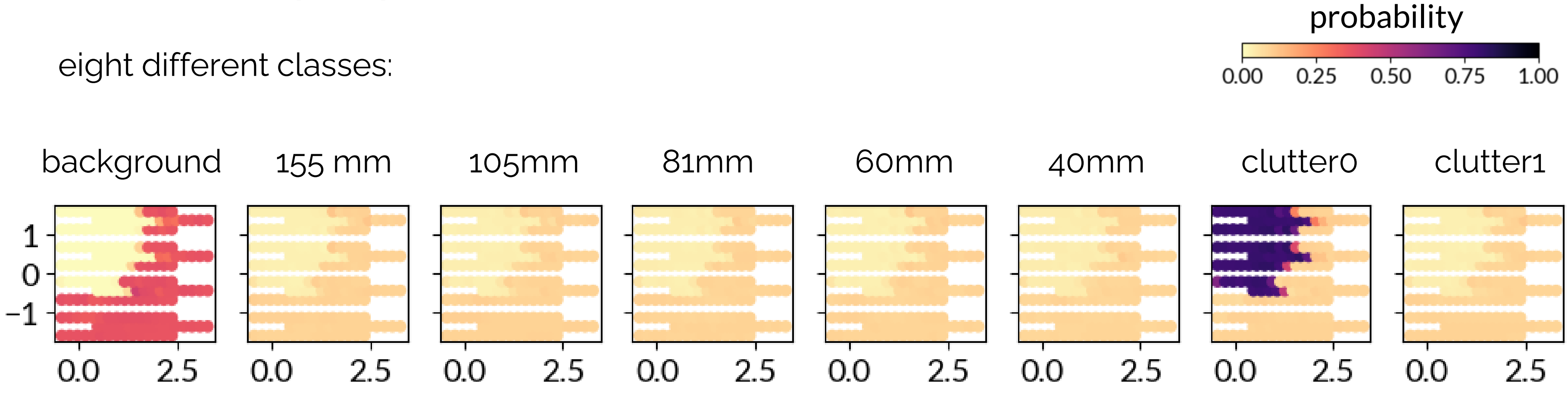
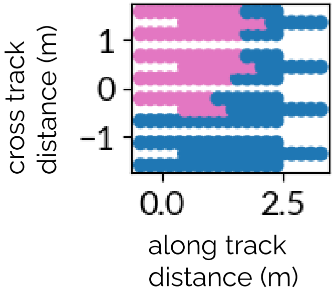


$$(nx \times nrx \times nt \times (ntx \times 3))$$

Probability layer and classification

eight different classes:

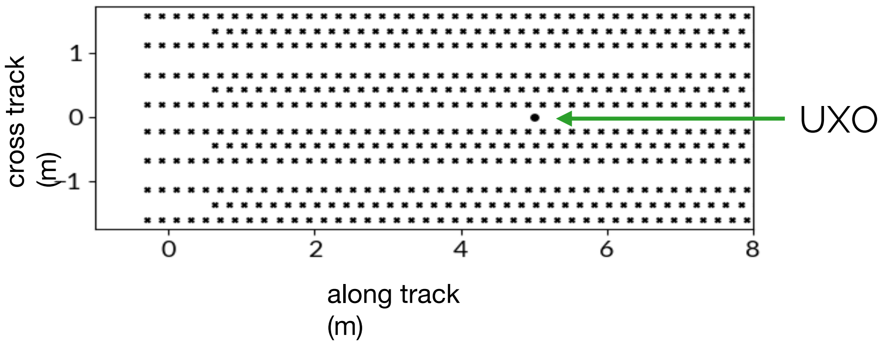




point-wise classification according to max probability

Application to a line of data

Input features are created by using a sliding window:



Application to a line of data

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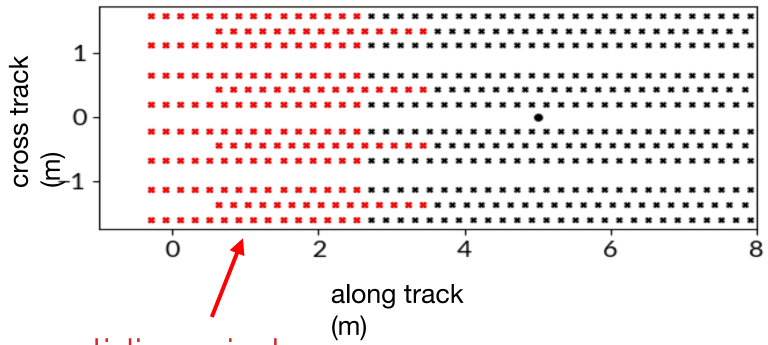

sliding window

Application to a line of data

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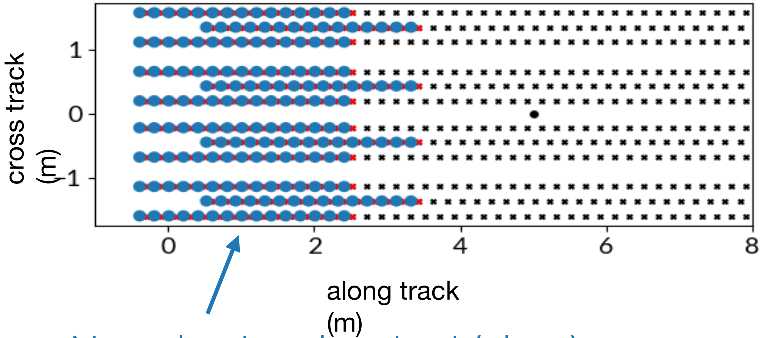
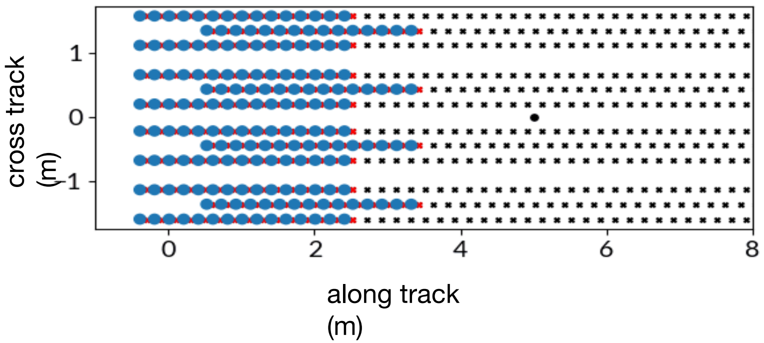


Neural network output (class)

Application to a line of data

Input features are created by using a sliding window:



Application to a line of data

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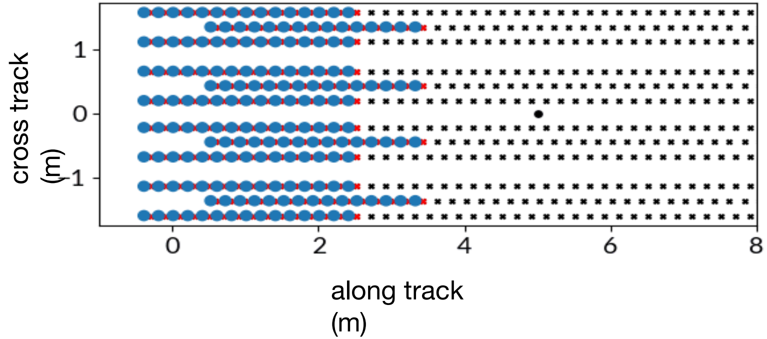
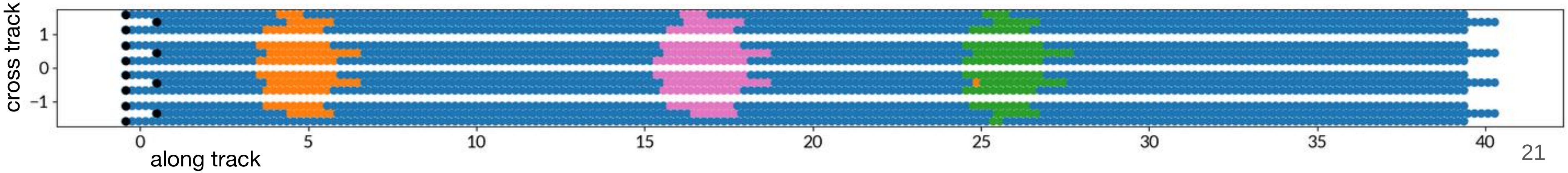


Single acquisition line with three objects (classification results)



Training for marine data

8 classes:

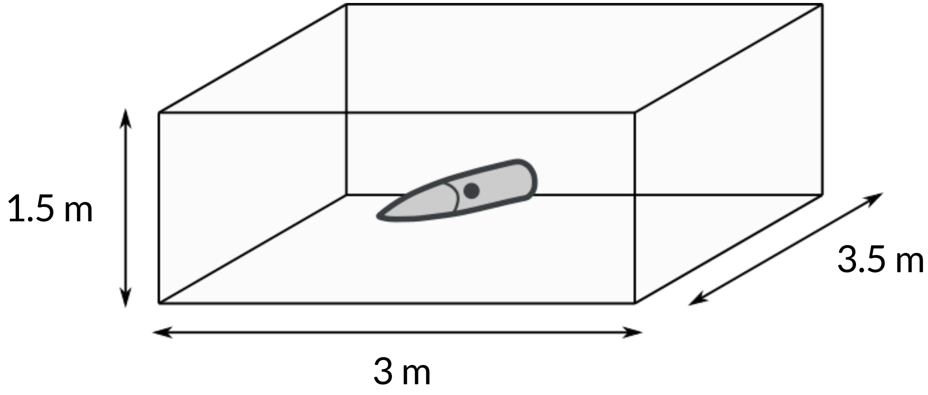
- background
- 155 mm
- 105 mm
- 81 mm
- 60 mm
- 40 mm
- Clutter0 (spheres and disks)
- Clutter1 (rods)

# of realizations:

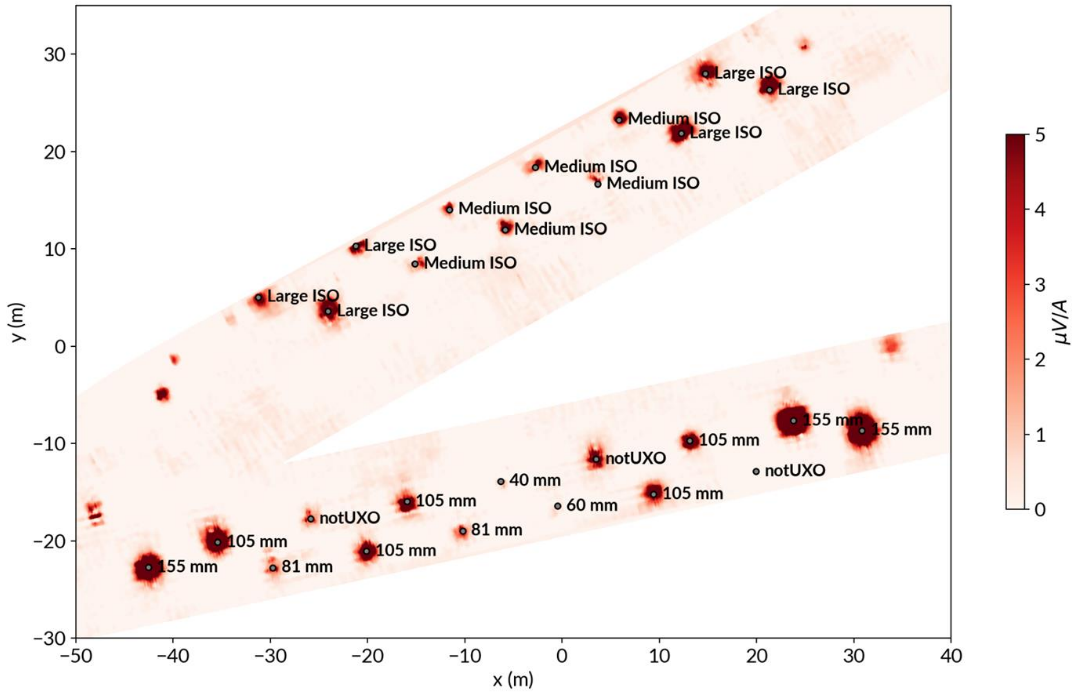
- Training: 80,000
- Validation: 10,000

Randomly assign:

- Target class
- Location (x, y, z)
- Orientation (ϕ, θ, ψ)
- Noise level: approximate from background areas in the field data

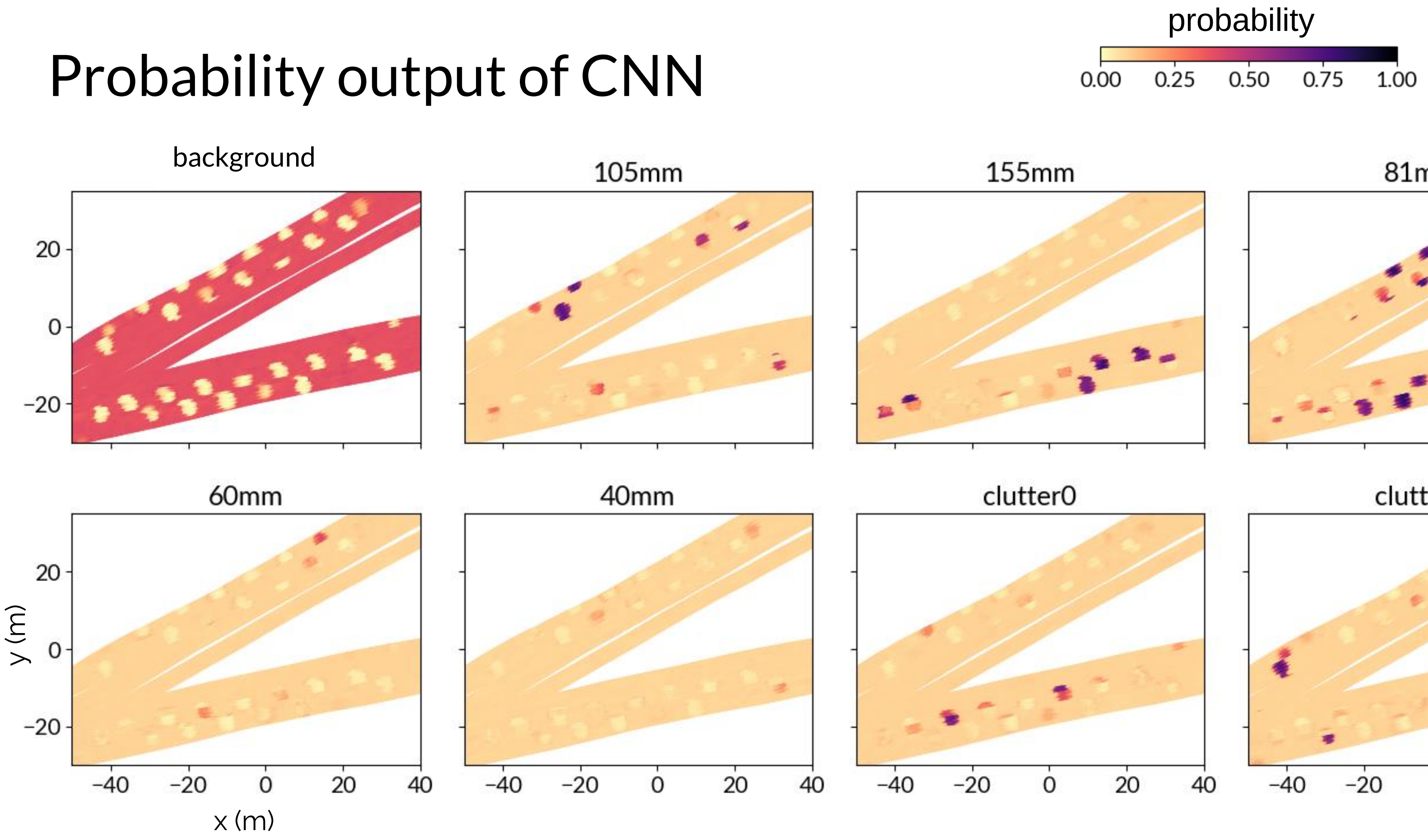


Calibration line Sequim Bay 2021

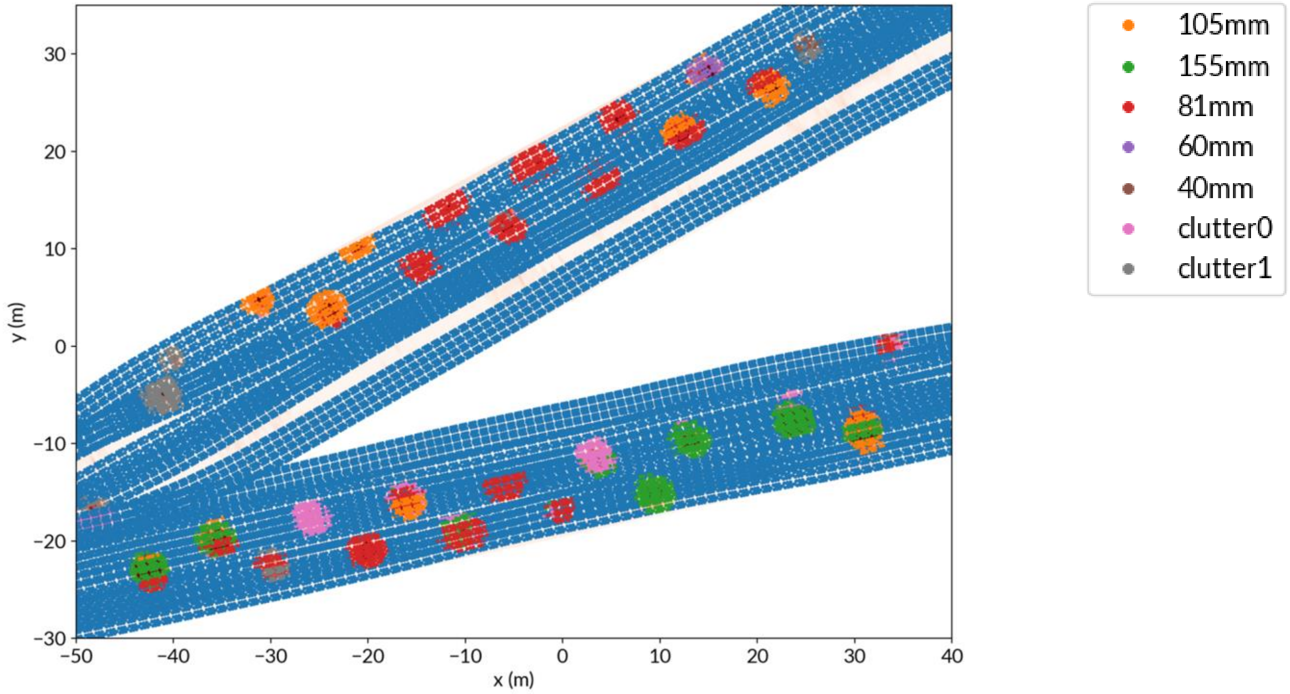


- 12 acquisition lines
- Current CNN requires background response removed
- Some ISOs present, we used only UXO objects to train (e.g. medium ISO ~ 81mm)

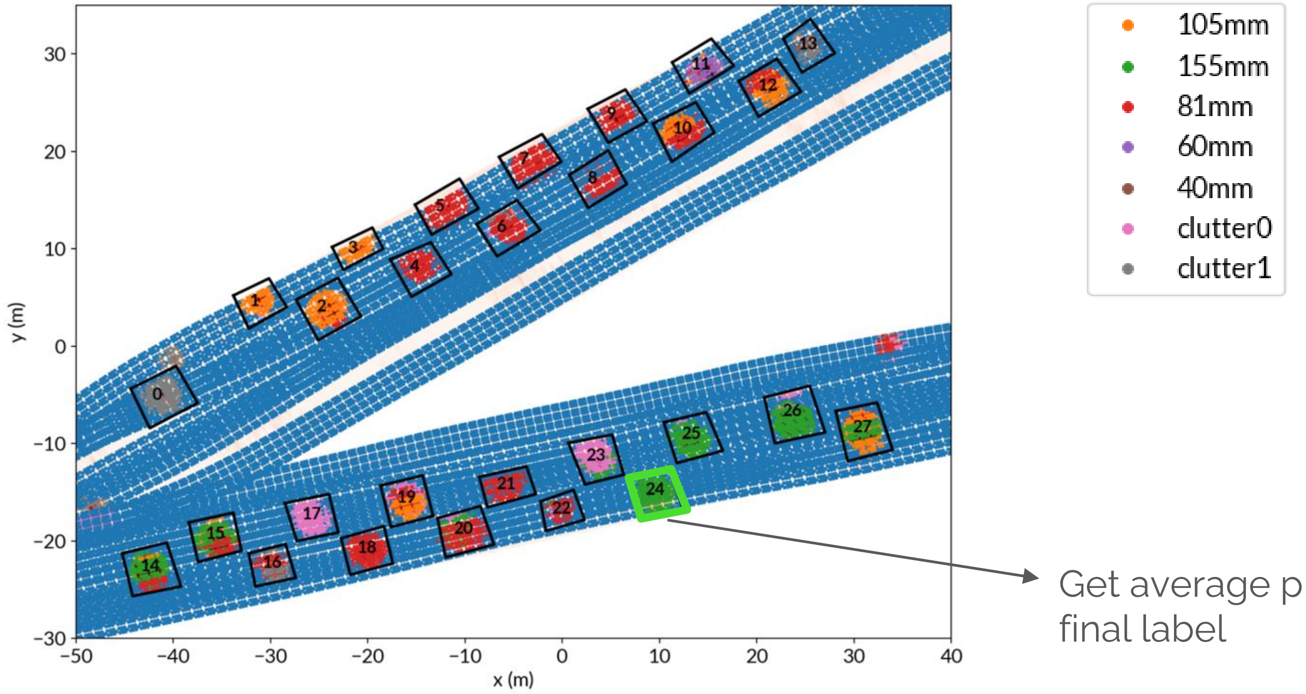
Probability output of CNN



Classification output of CNN - calibration line 2021

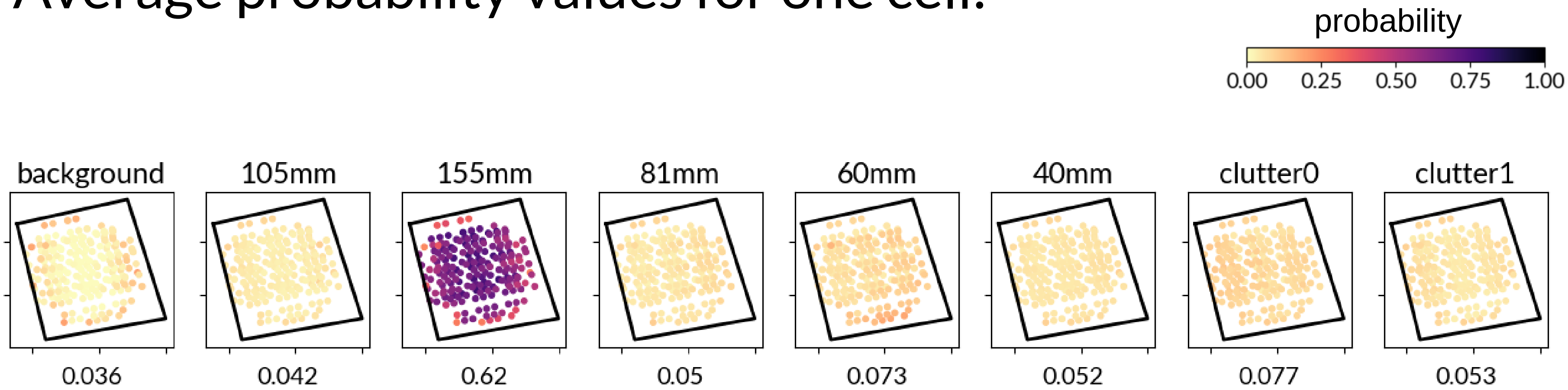


Divide in cells to get a single probability value per cell:



Get average probability for cell and assign final label

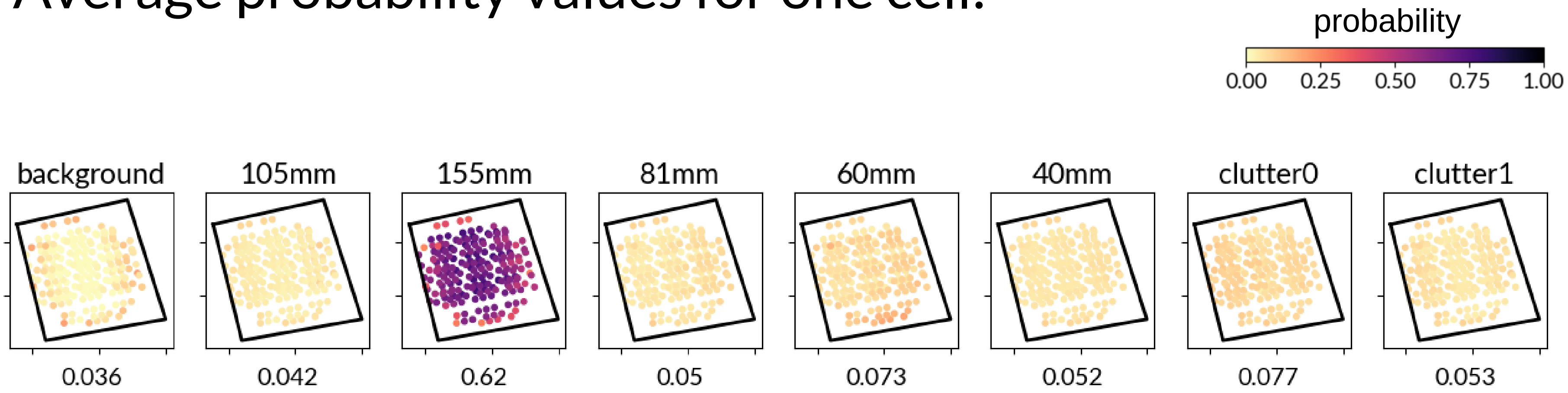
Average probability values for one cell:



average probabilities (using all points not classified as background)

Assign label with highest probability: “155 mm”

Average probability values for one cell:



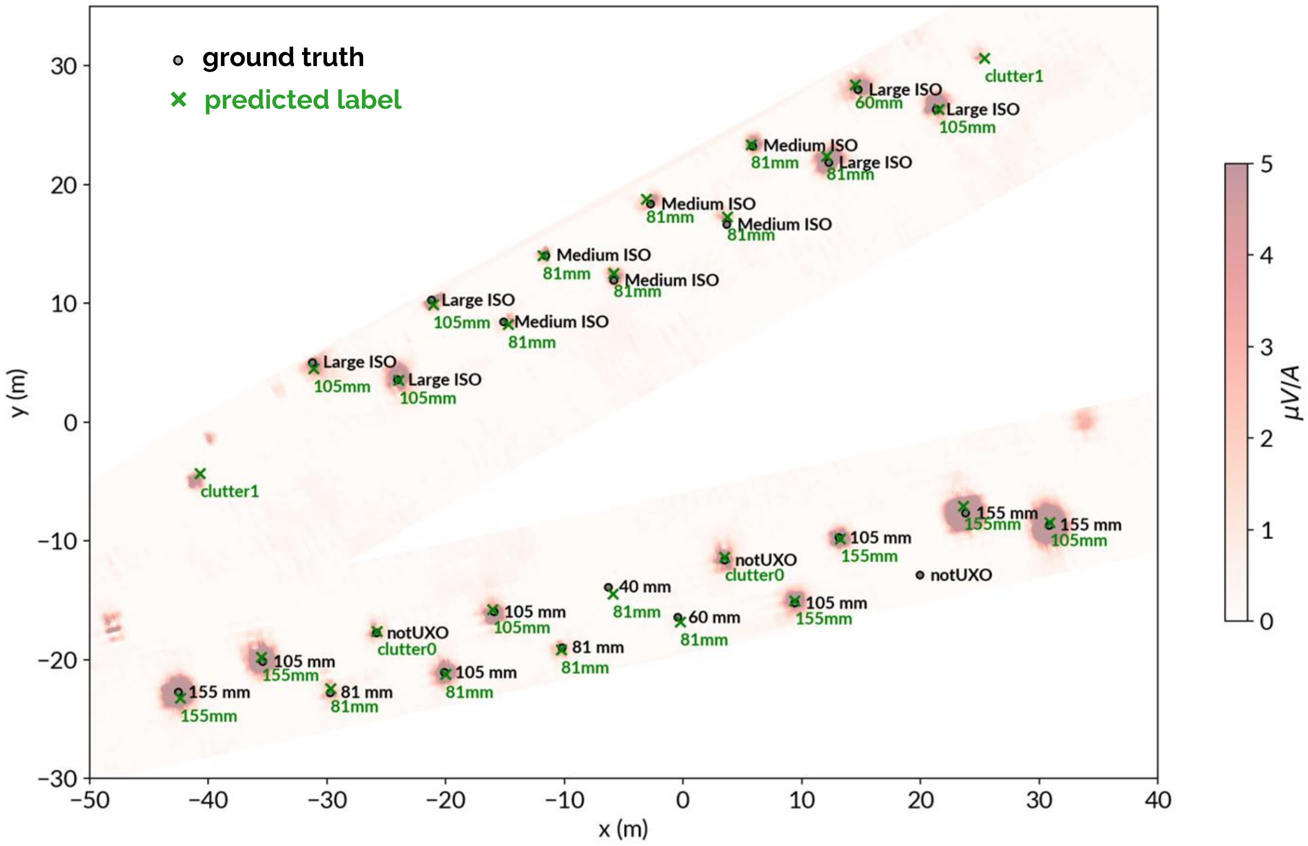
average probabilities (using all points not classified as background)

Assign label with highest probability: “155 mm”

If object is classified as “clutter”, apply “safety” rule.

Safety rule:
if prob(clutter) < 0.3 then change label to next likely UXO

Predicted labels vs truth labels - calibration line 2021



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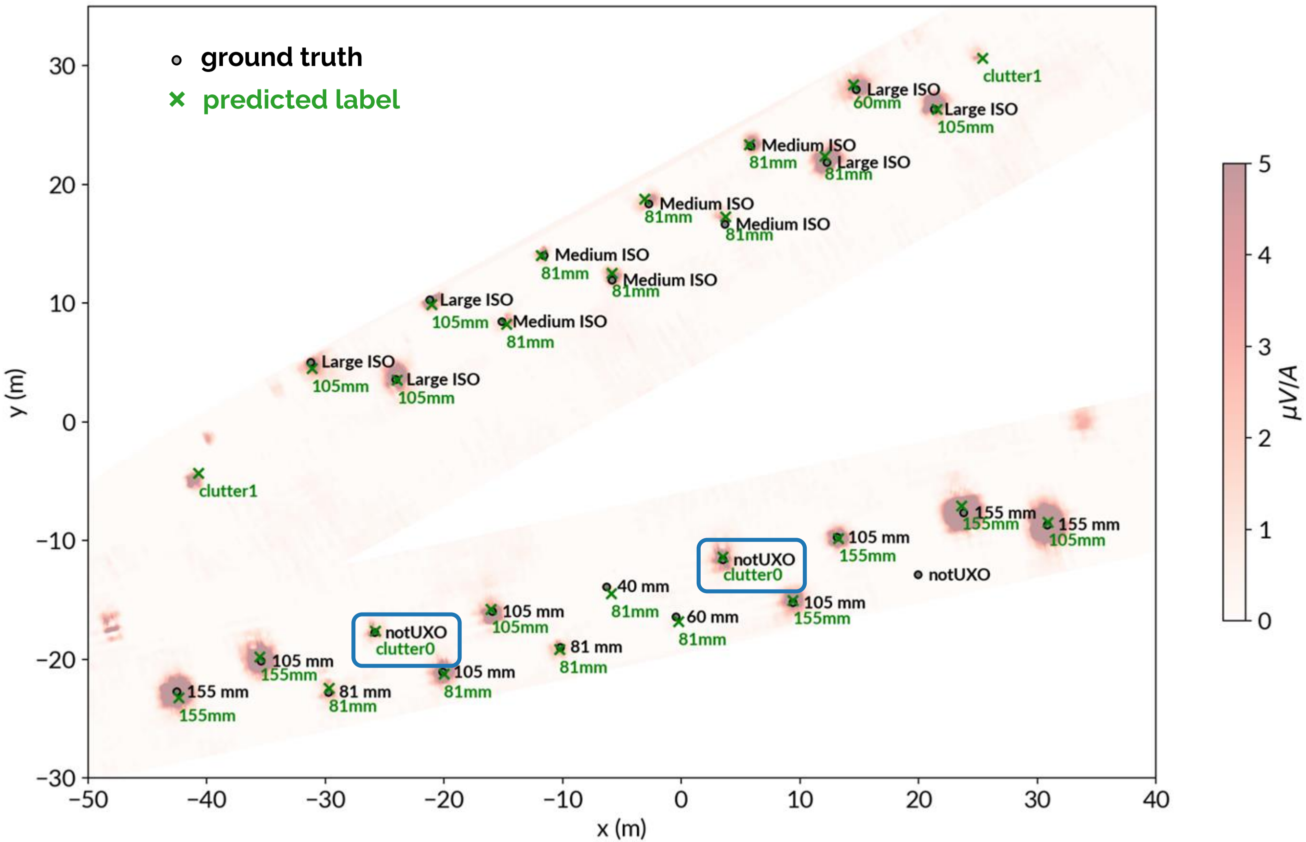

- Correctly predicted clutter

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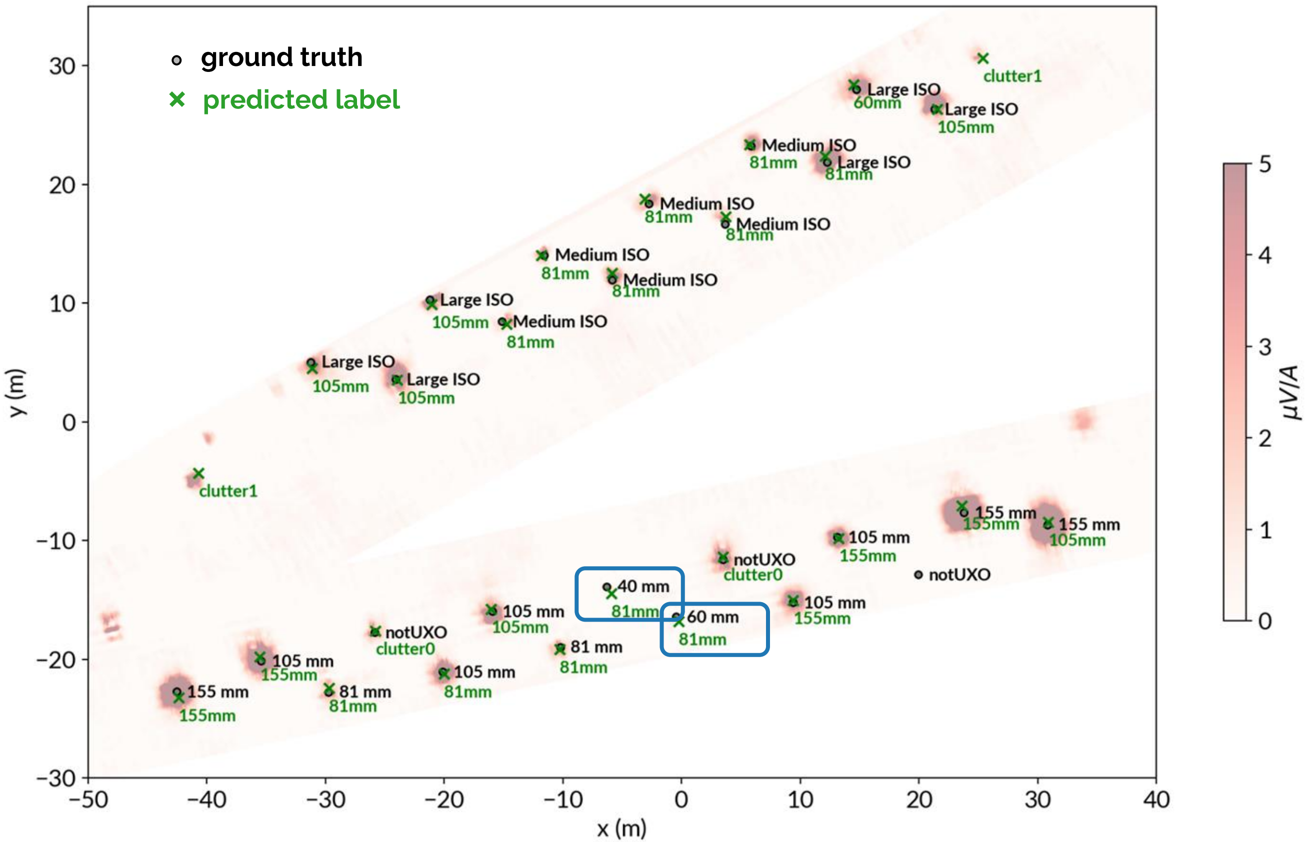
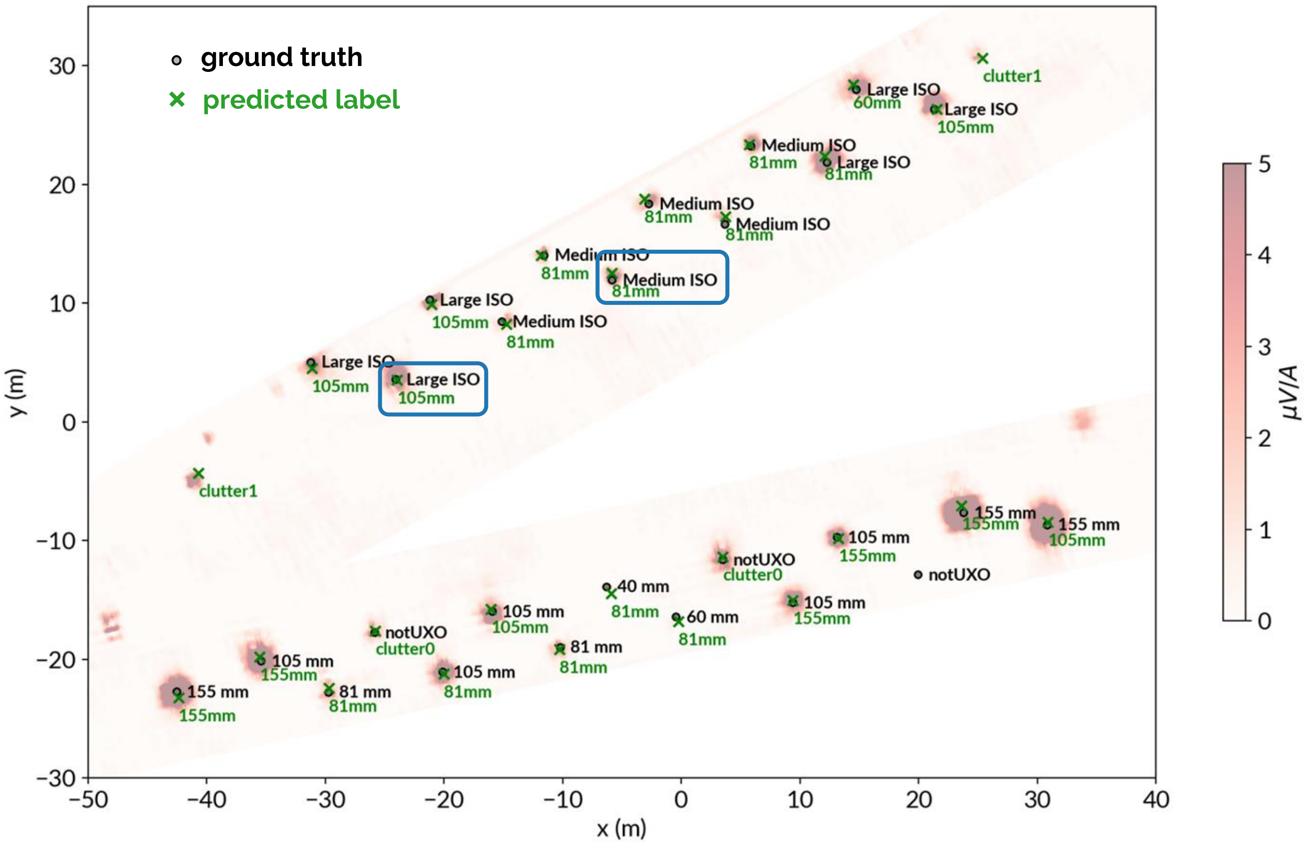


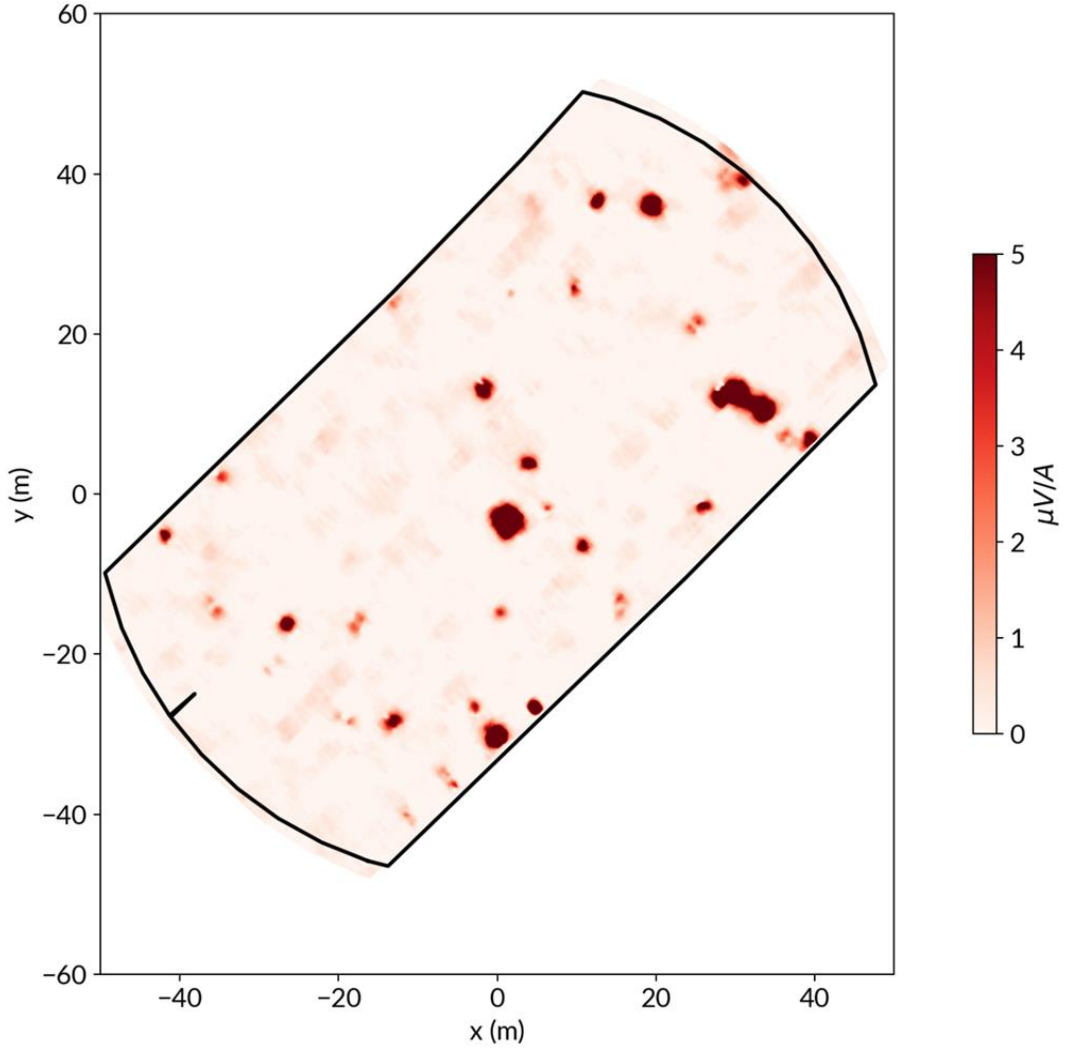
- Correctly predicted clutter
- Did not miss any UXO

Predicted labels vs truth labels - calibration line 2021



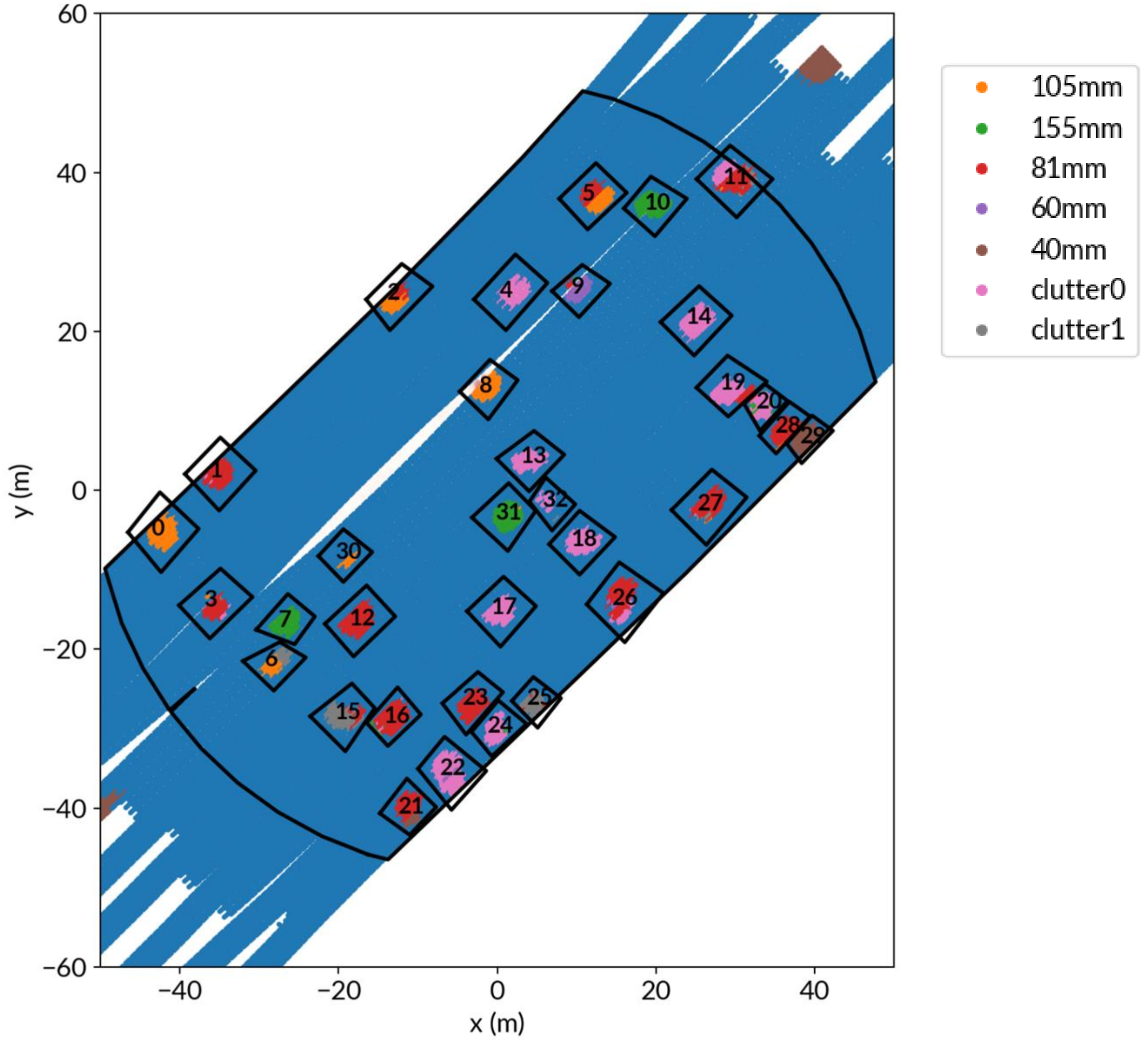
- Correctly predicted clutter
- Did not miss any UXO
- Classified to closest object included in training set

Blindgrid 2021
Sequim Bay



Blindgrid 2021
Sequim Bay

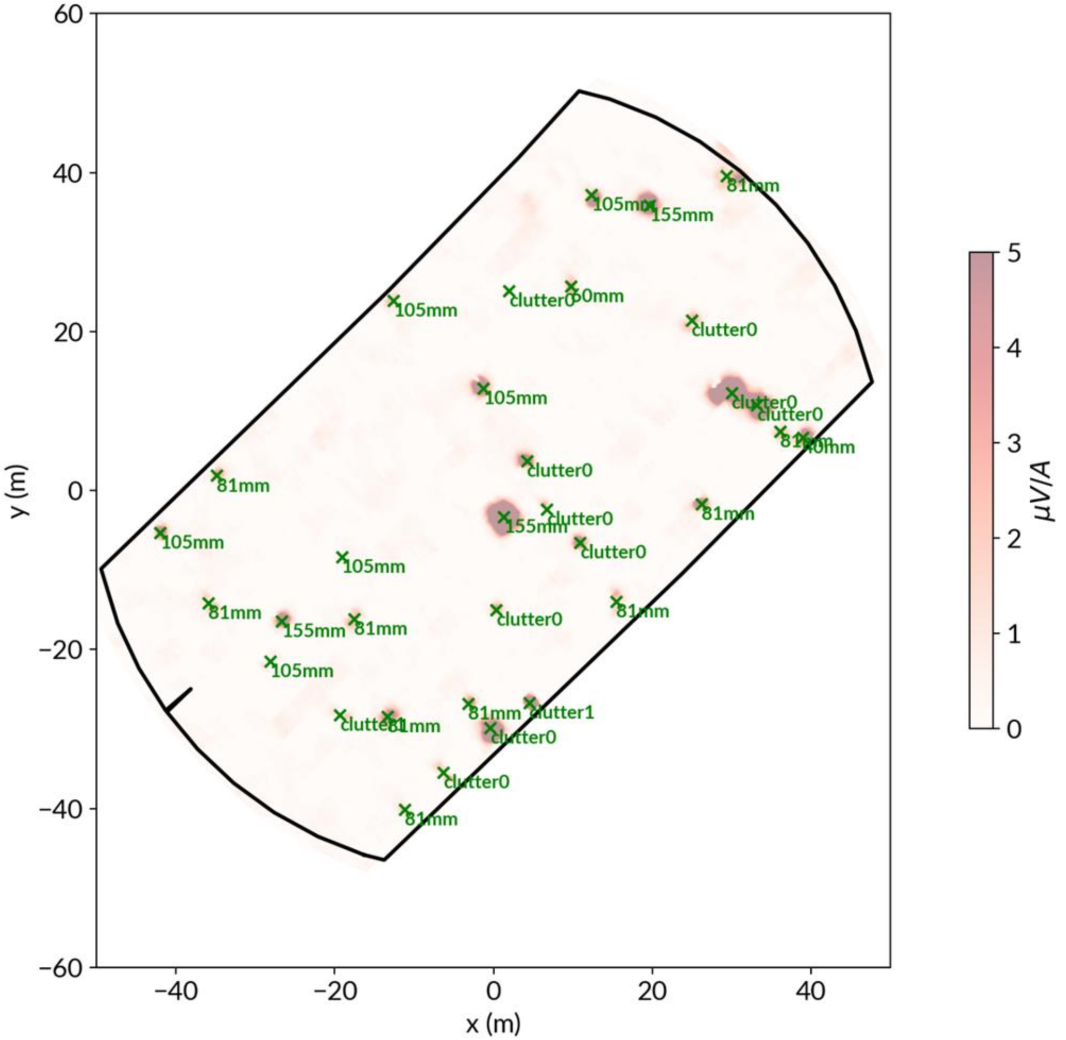
CNN classification output



Blindgrid 2021
Sequim Bay

Predicted labels

rank	label	prob.	dig
1	40mm	0.74	1
2	105mm	0.66	1
3	81mm	0.60	1
⋮			
32	clutter0	0.55	0
33	clutter0	0.61	0



Concluding remarks:

- A CNN with image segmentation architecture was successfully used to classify UXOs from marine EM data
- Some limitations:
  - CNN is relatively sensitive to effectiveness of background response removal
  - Objects used to generate synthetic data should be close to the objects on the field
  - Full inputs needed (if one receiver or transmitter is missing, we skip that window)
- Future work:
  - Training with background response included
  - Explore ways to share information between different acquisition lines

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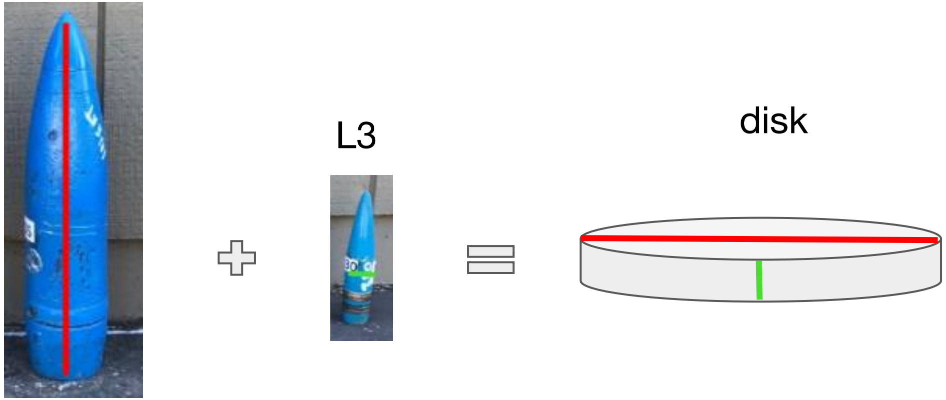
- Future work:
    - Training with background response included
    - Explore ways to share information between different acquisition lines

Thank you!

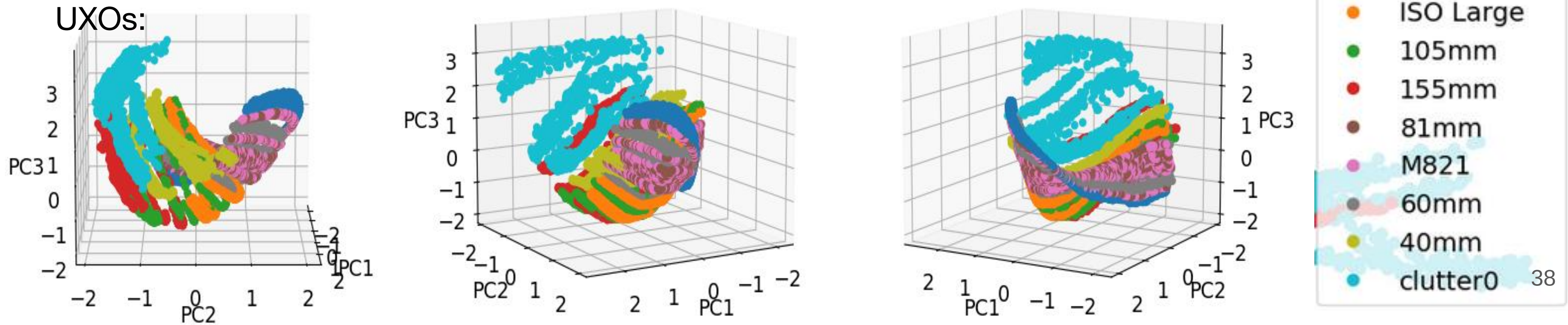
Jorge Lopez-Alvis jlalvis@eoas.ubc.ca

Clutter design

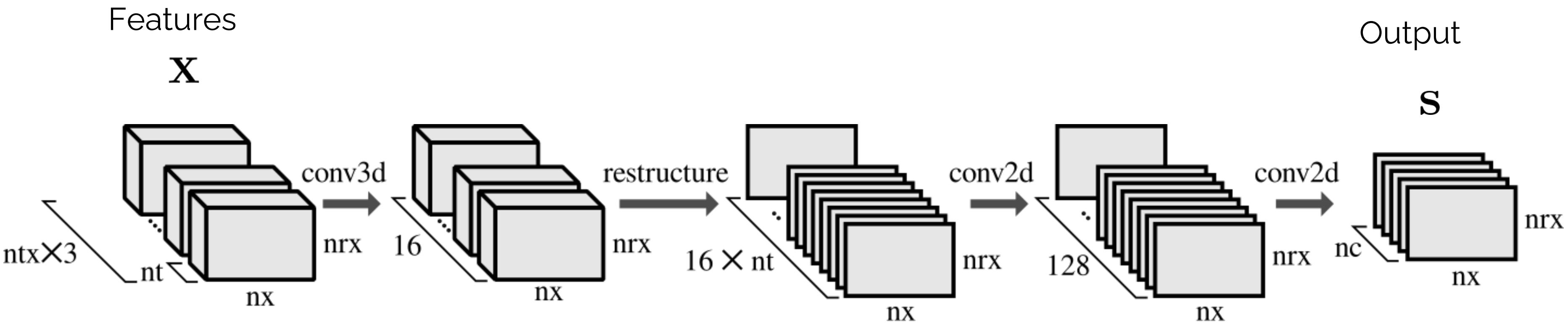
L1 and L2



PCA was helpful to decide whether clutter objects are very close to UXOs:



CNN - image segmentation architecture



ntx - number of transmitters
nrx - number of receiver cubes
nt - number of time channels
nx - number of positions in window
nc - number of classes