Using convolutional neural networks to classify UXO with multi-component electromagnetic induction data

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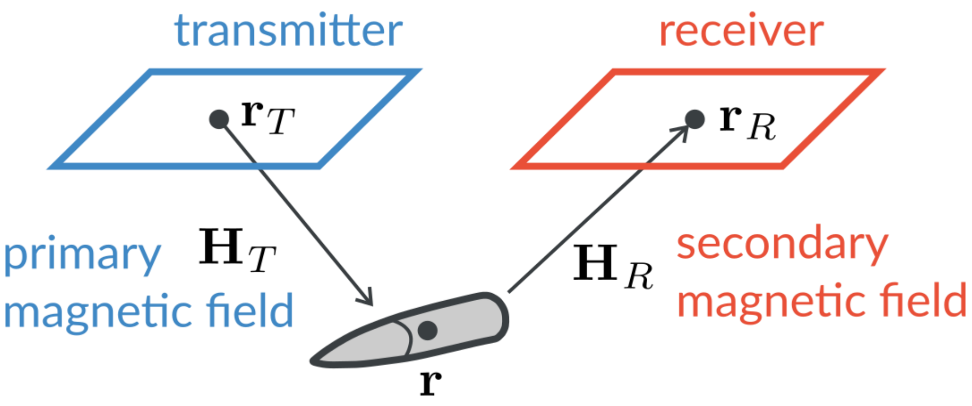
This work is supported by DoD SERDP project MR22-3487

Time-domain EM response of a UXO



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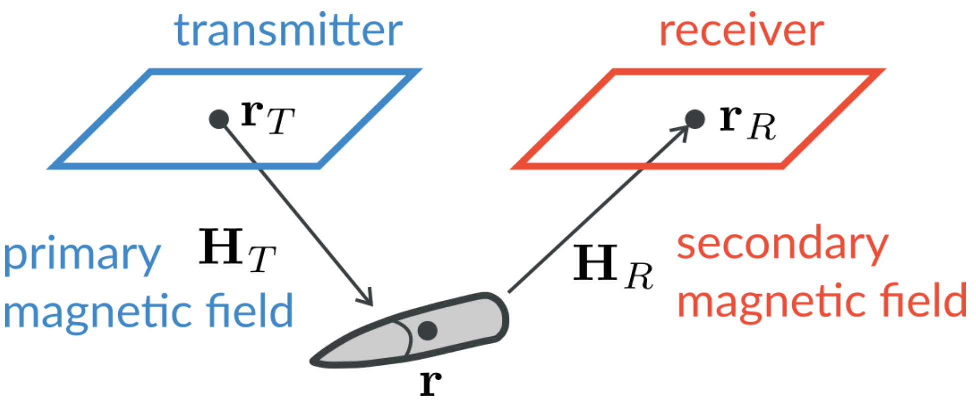
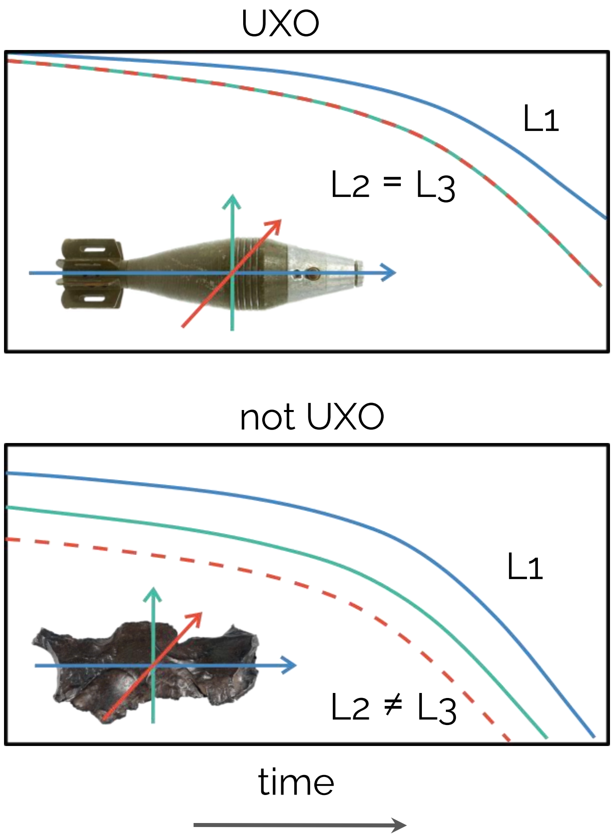


$$d(\mathbf{r}_R, t) = \mathbf{H}_R(\mathbf{r}, \mathbf{r}_R) \cdot \mathbf{P}(t) \cdot \mathbf{H}_T(\mathbf{r}, \mathbf{r}_T)$$

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

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



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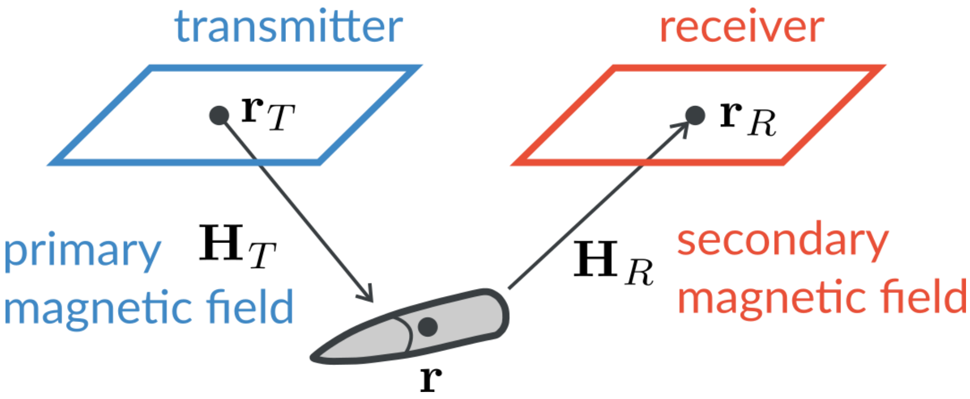

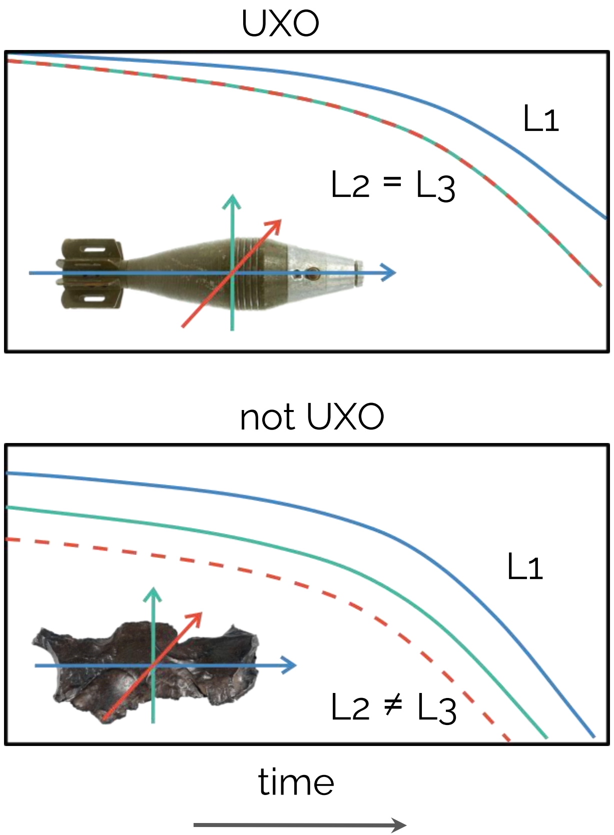

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traditional approach: use inversion to get these and then classify by comparing **L**(t) with ordnance library

Survey and system

UltraTEMA-4 system:

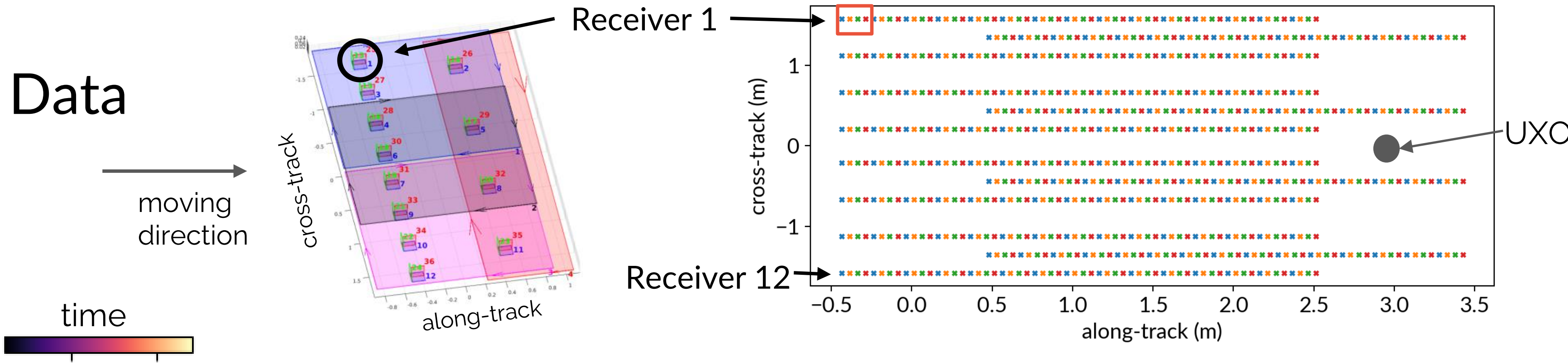
4 transmitters

12 receivers (3-component)

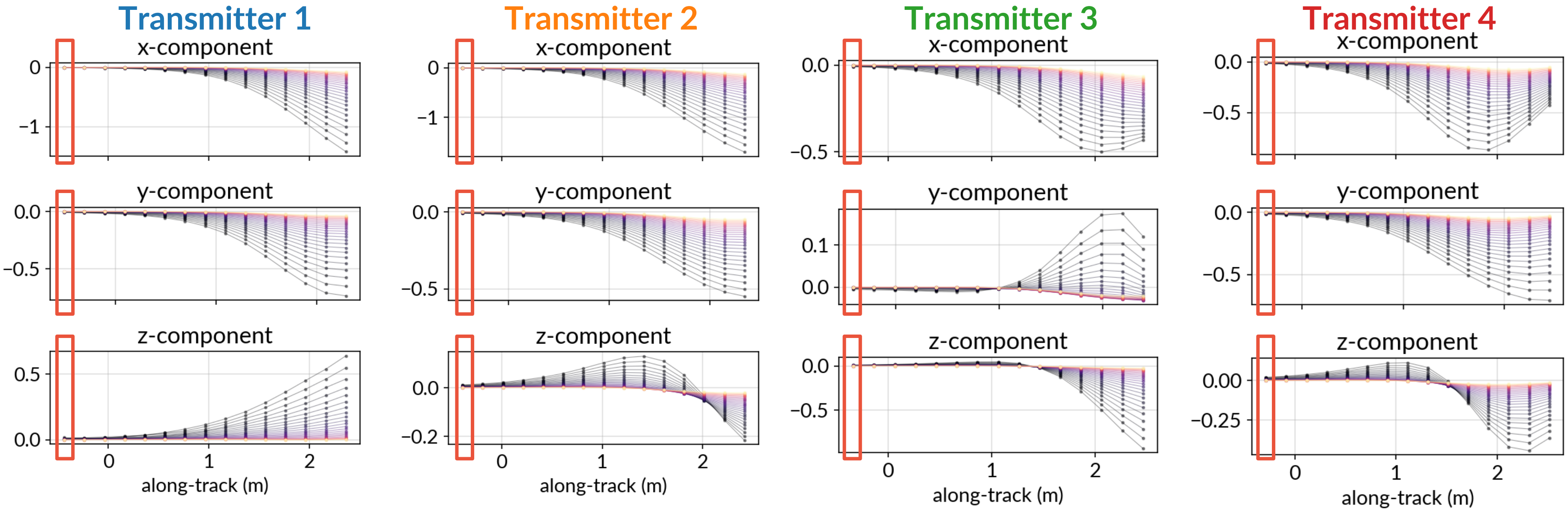
27 time channels

Height above seabed: ~1 m

Data

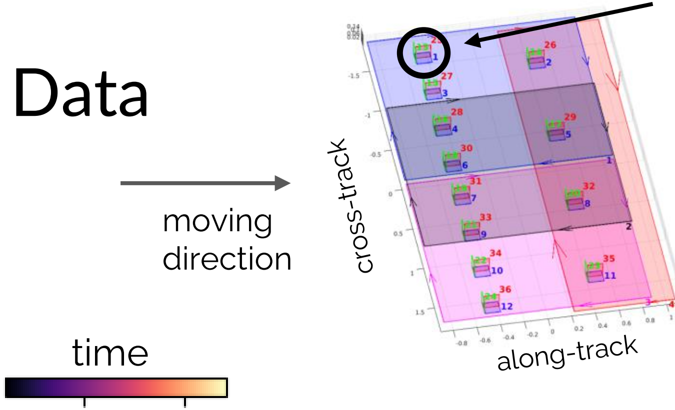


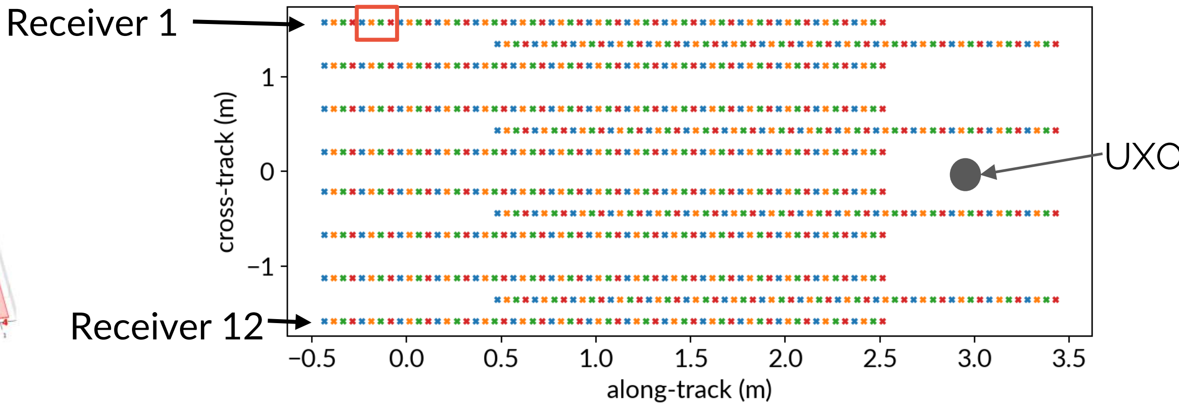
moving
direction
cross-track
along-track
Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)
time

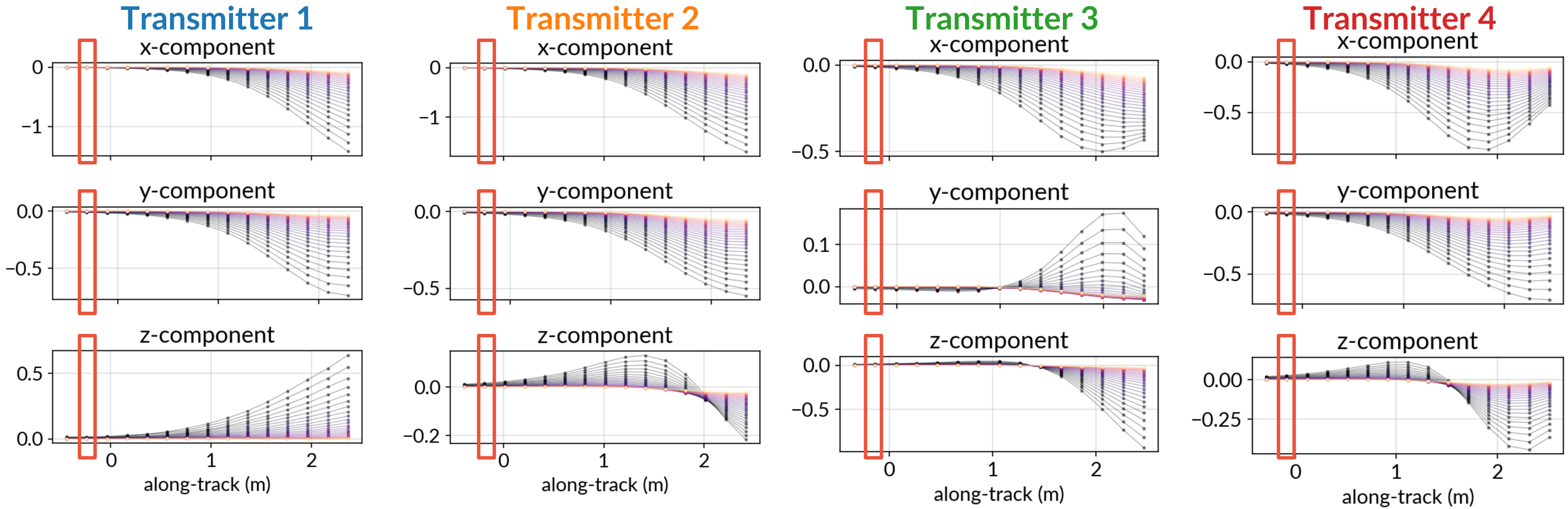


Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

Data


moving
direction
cross-track
along-track
time


Receiver 1
Receiver 12
cross-track (m)
along-track (m)
1
0
−1
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5


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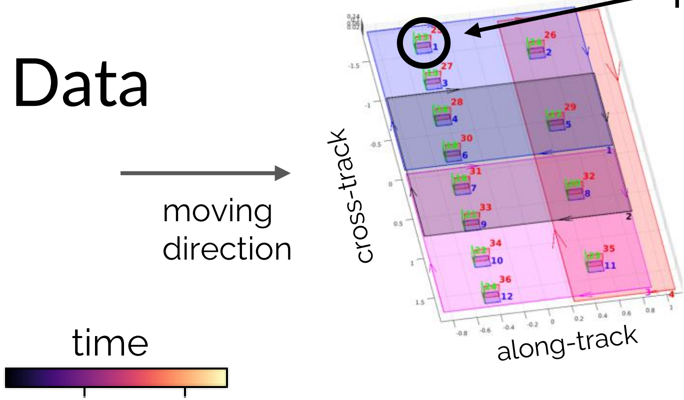
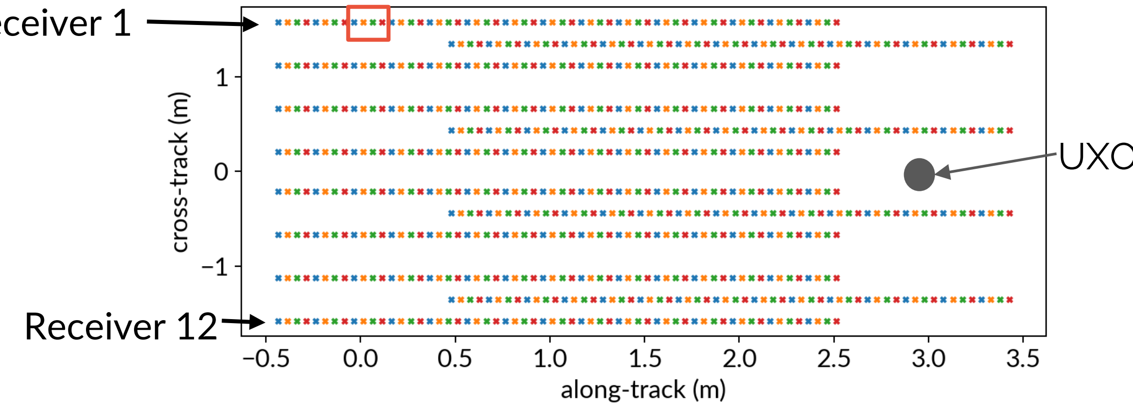
Transmitter 4
x-component
y-component
z-component
along-track (m)

Data



moving direction
cross-track
along-track
time



Receiver 1
Receiver 12
UXO
cross-track (m)
along-track (m)
1
0
−1
−0.5
0.0
0.5
1.0
1.5
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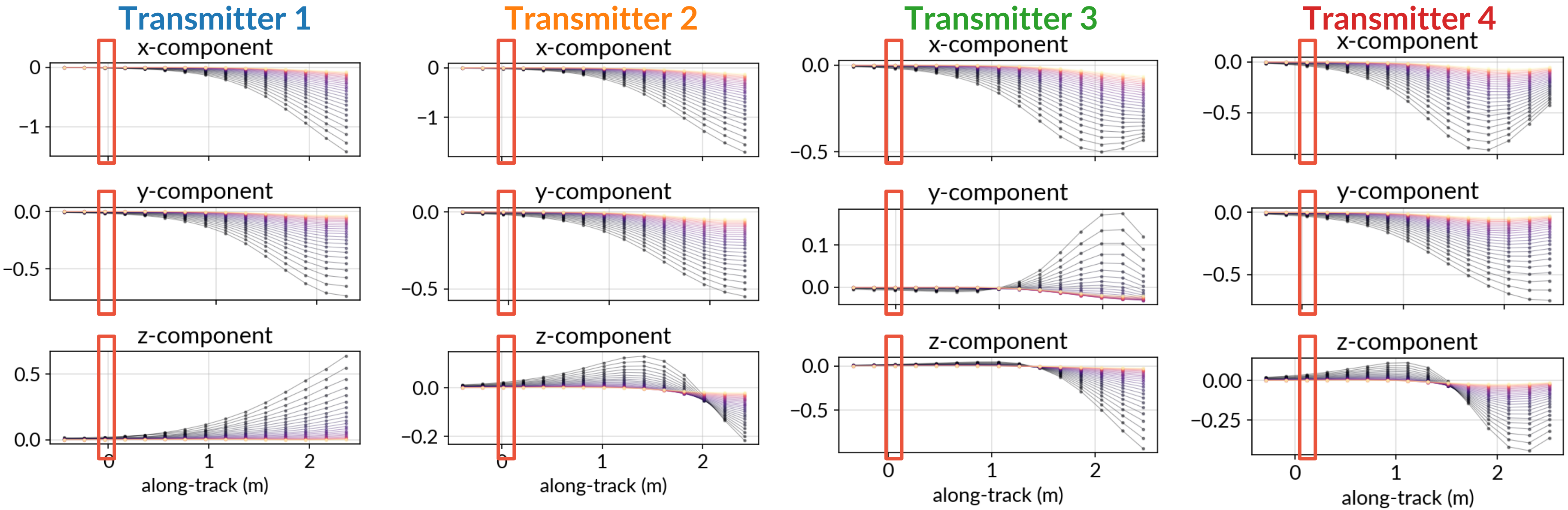
3.0
3.5



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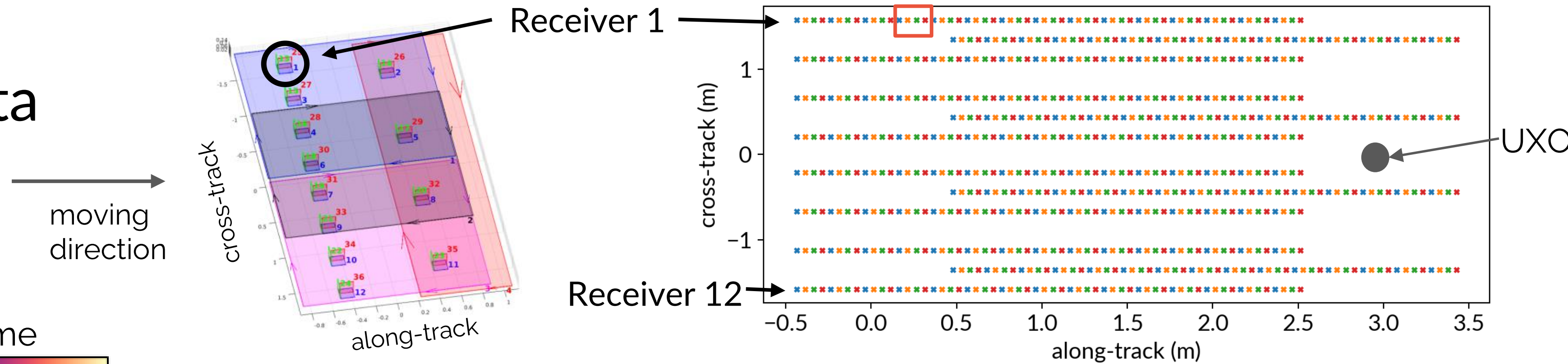
Transmitter 4
x-component
y-component
z-component
along-track (m)

Data


moving
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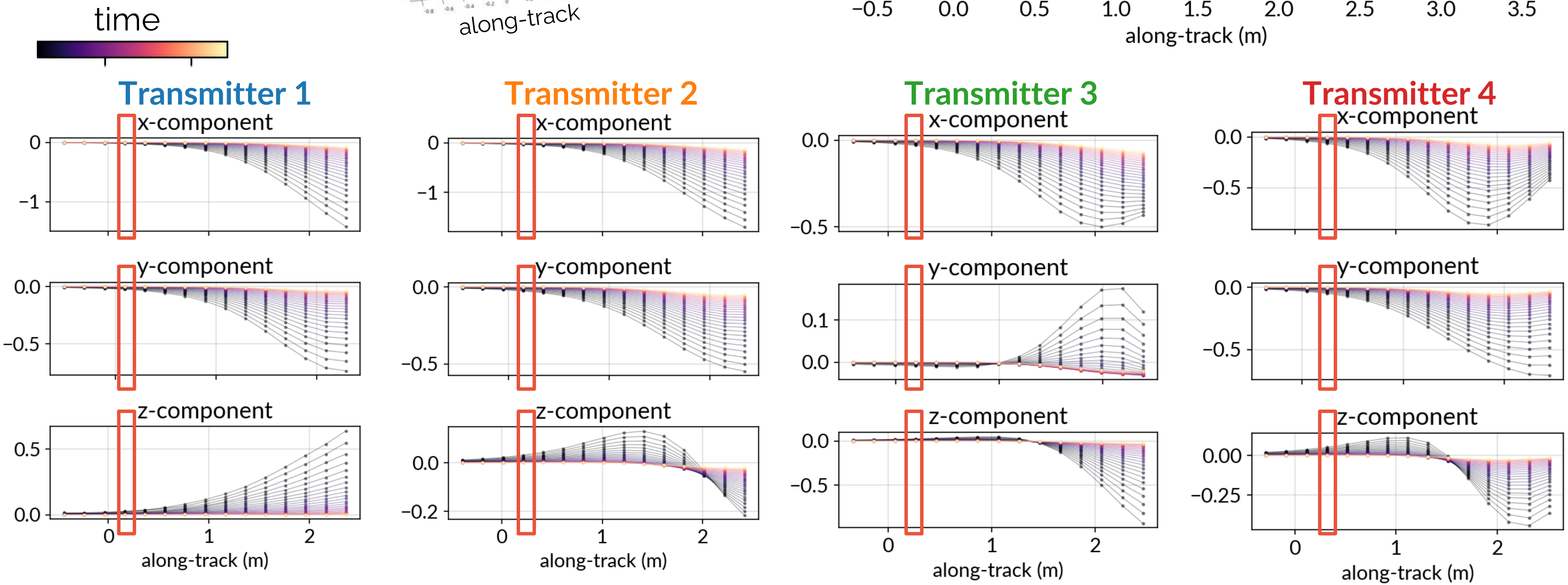

time
Transmitter 1
Transmitter 2
Transmitter 3
Transmitter 4
x-component
y-component
z-component
along-track (m)

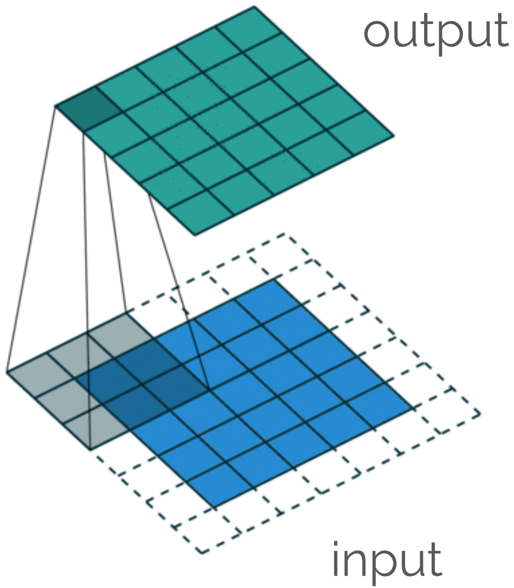
Can we classify directly from EM data?

Convolutional neural networks (CNNs)

- Convolutional filters look at spatial / temporal features in the data

Training EM data for UXO classification:

- Available library of ordnance objects with polarizations
- Fast geophysical simulations

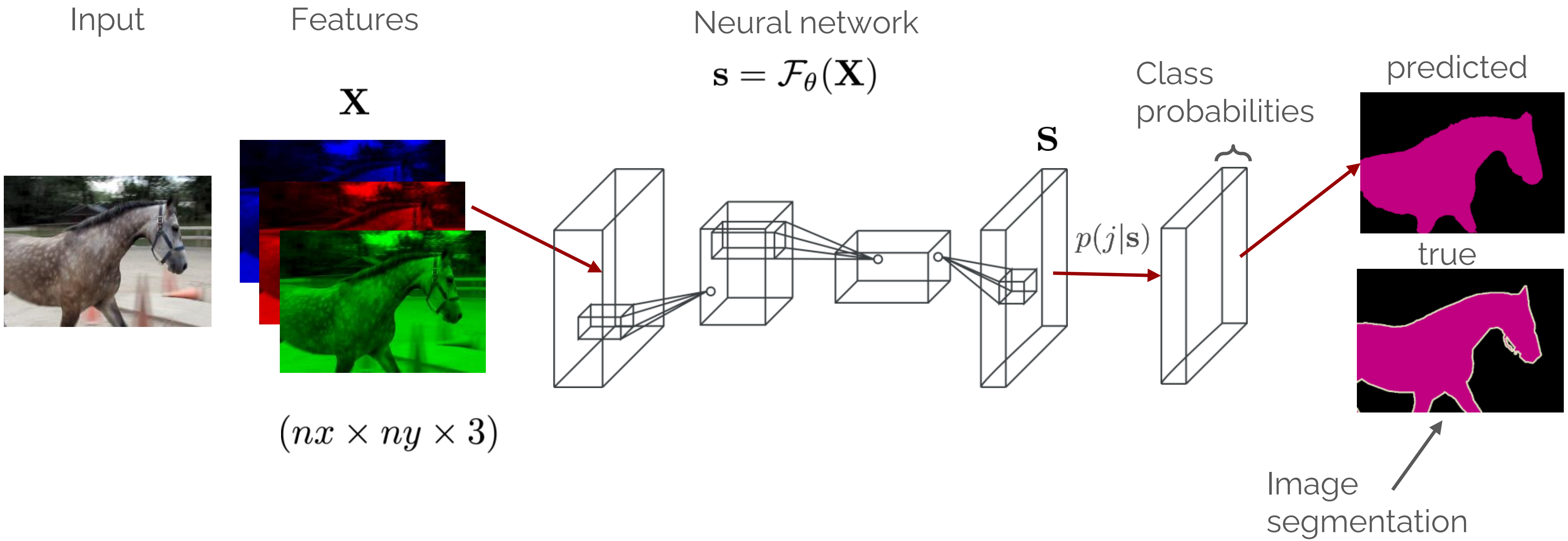


https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

Convolutional Neural Networks (CNNs)

Supervised classification problem

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



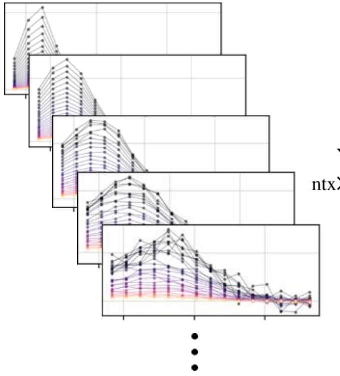
Convolutional Neural Networks (CNNs)

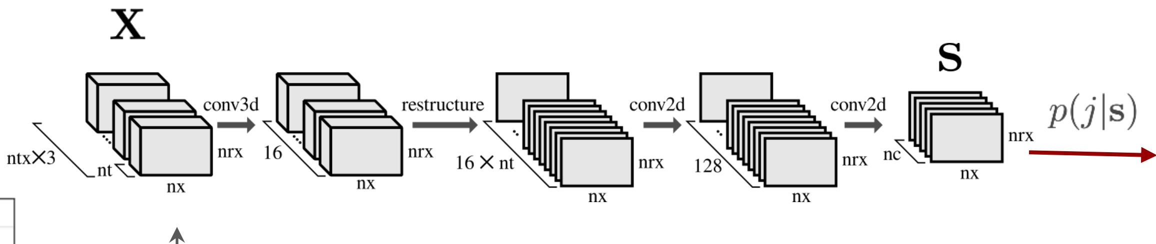
How do we translate these things to the UXO classification problem?

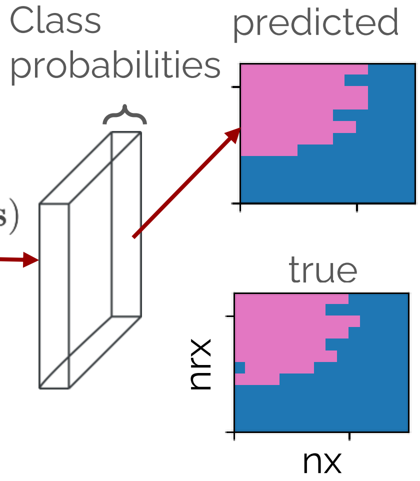
Input

Features

Neural network



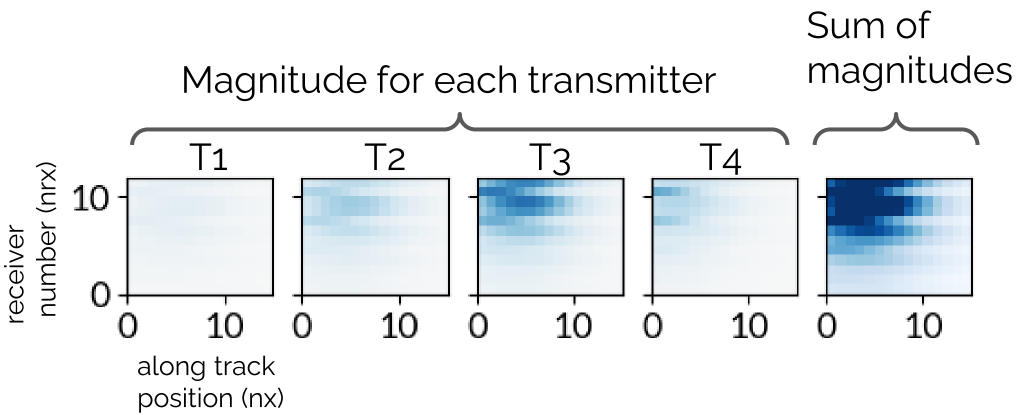


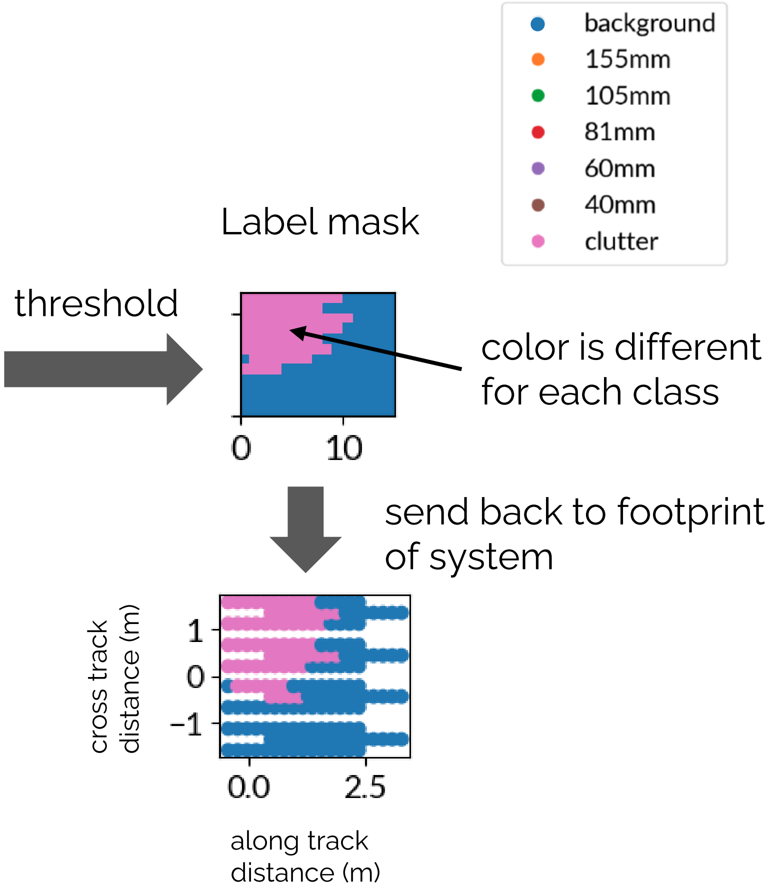


$$(\boldsymbol{nx} \times \boldsymbol{nrx} \times \boldsymbol{nt} \times (\boldsymbol{ntx} \times \boldsymbol{3}))$$

$ntx = 4,$ number of transmitters
$nrx = 12,$ number of receiver cubes
$nt = 27,$ number of time channels
$nx = 15,$ number of positions in spatial window (along track)
$nc = 8,$ number of classes

Defining label masks

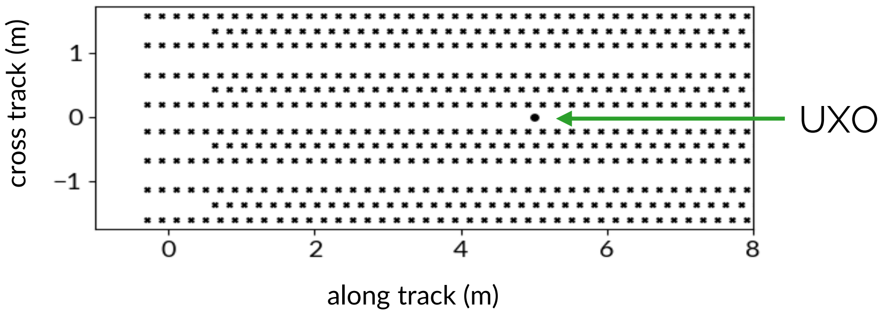




For time channel #5

Application to a line of data

Input features are created by using a sliding window:



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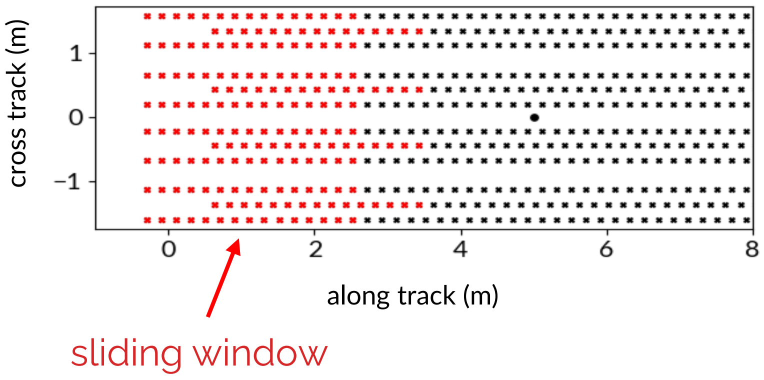

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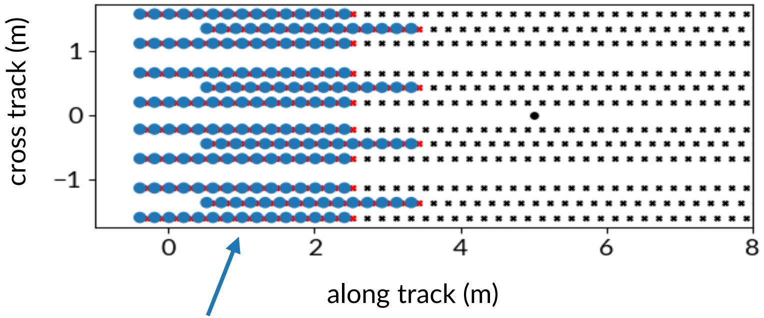

Neural network output (class)

Application to a line of data

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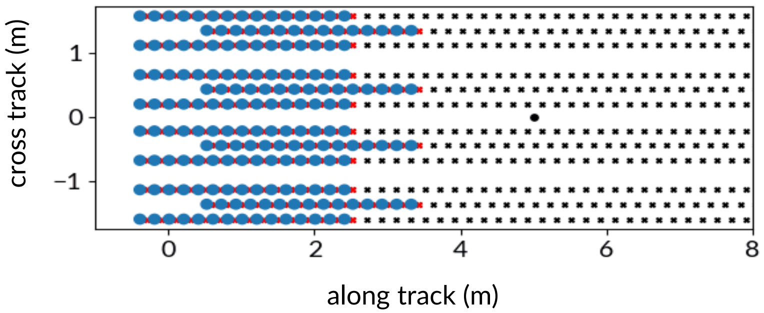

Application to a line of data

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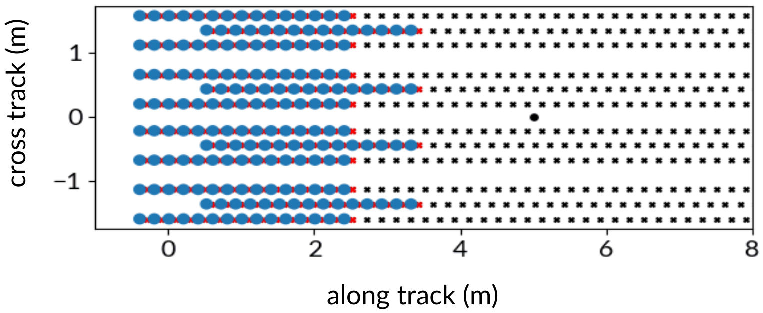
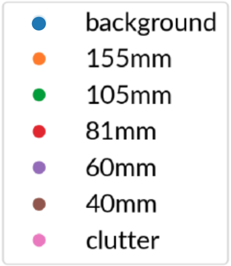
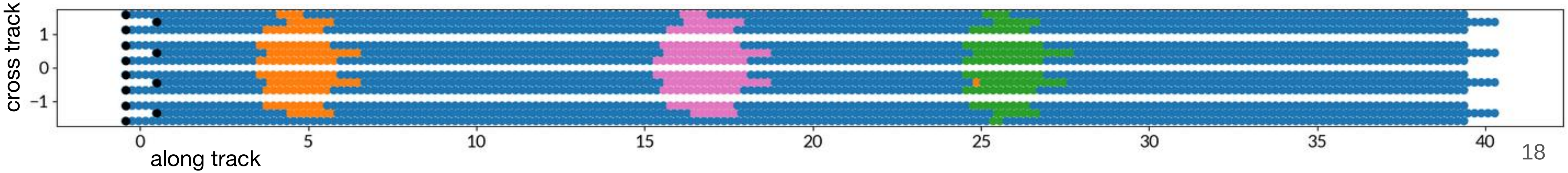


Single acquisition line with three objects (classification results)





Training dataset: dipole forward model

7 classes:

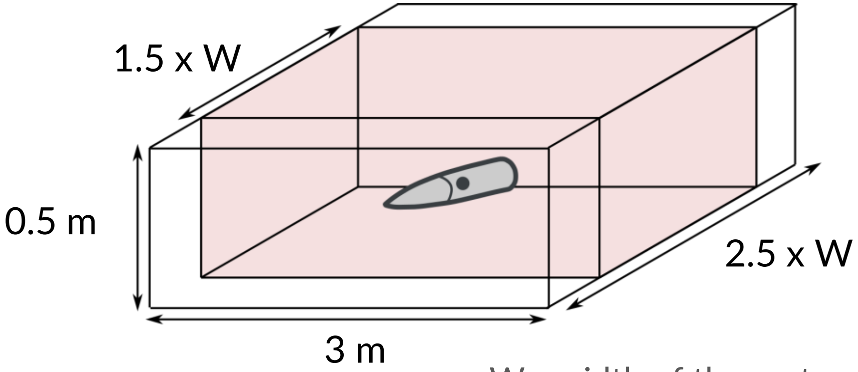
- background
- 155 mm
- 105 mm
- 81 mm
- 60 mm
- 40 mm
- clutter

# of realizations:

- Training (multi-class): 400,000
- 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



W - width of the system

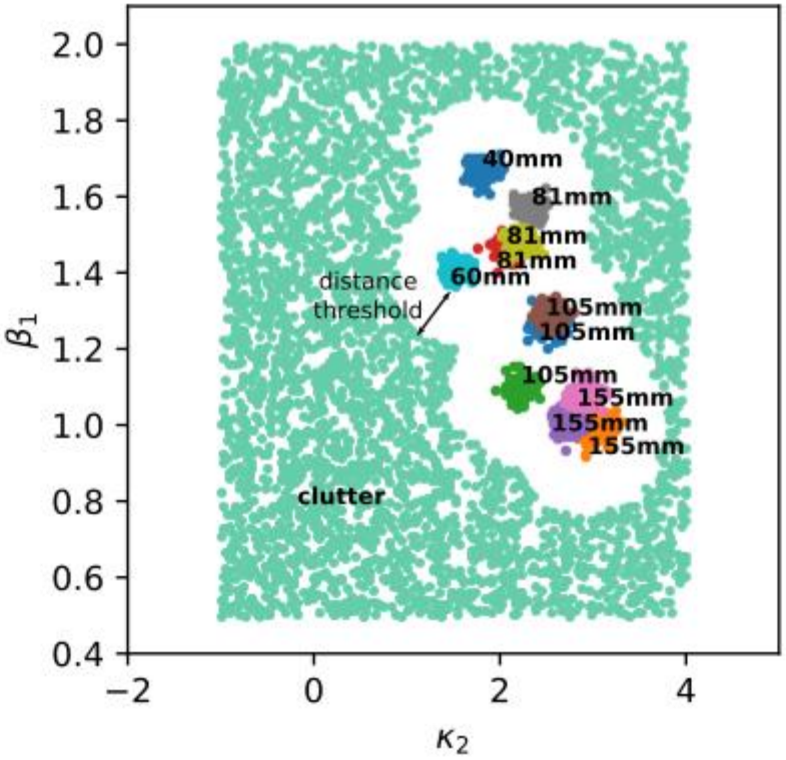
Clutter design

Physics-based parameterization of EM decay:

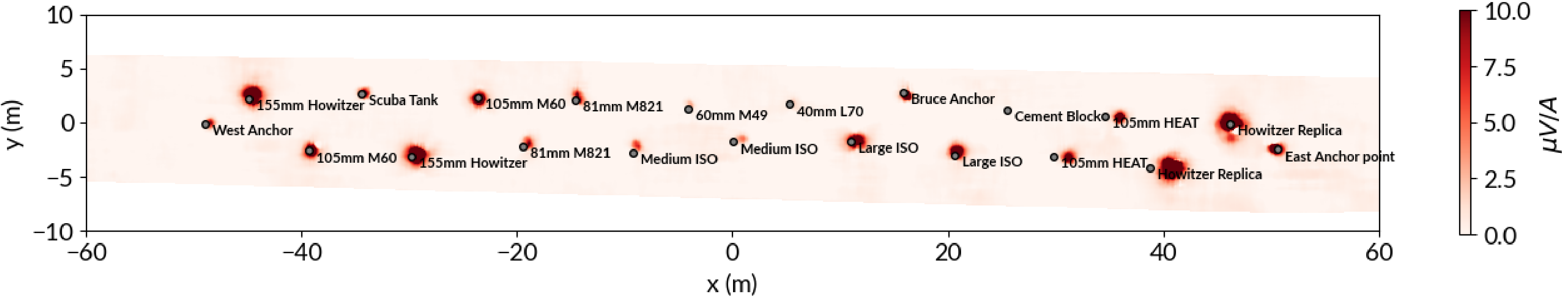
$$L(t) = kt^{-\beta}exp(-t/\gamma)$$

9 parameters in total:

1. Estimate values for UXOs in ordnance library
2. Define a distance threshold
3. Fill the remaining space with clutter objects

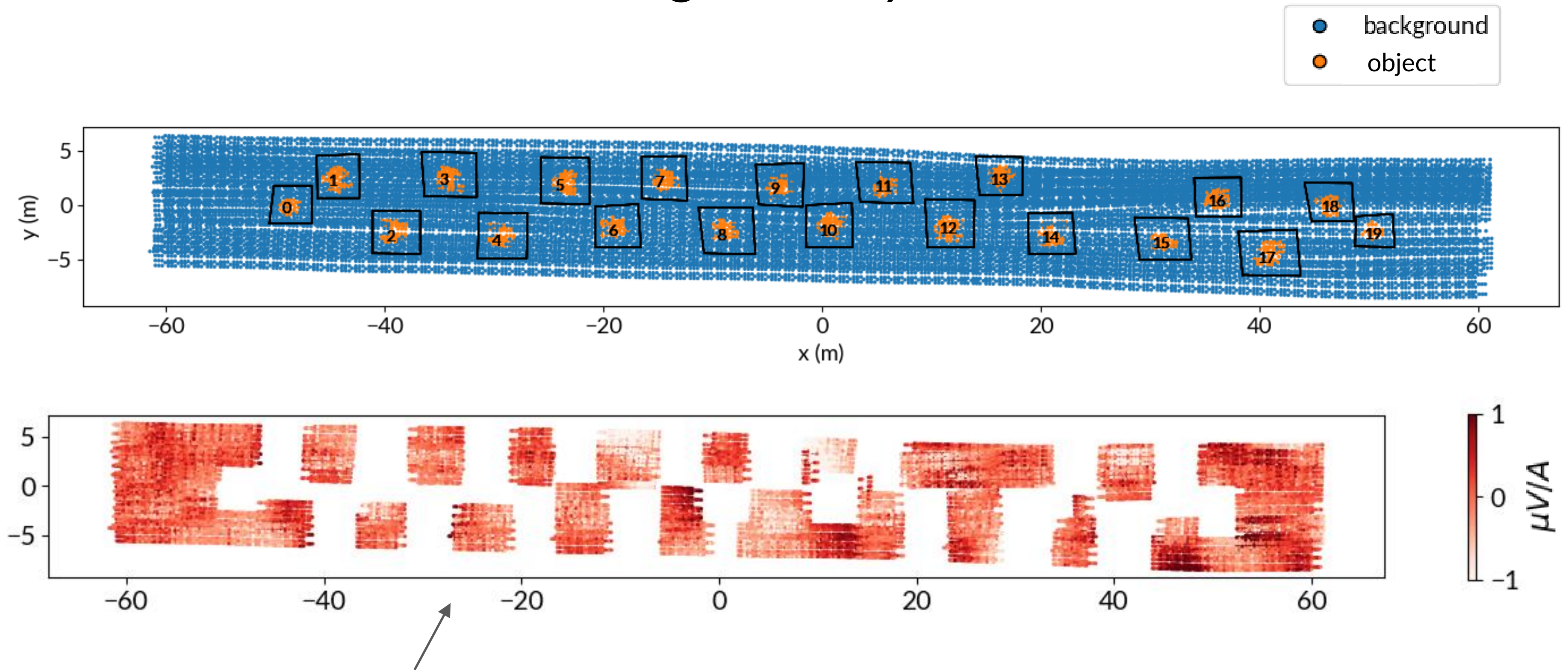


Field data - Sequim Bay test site (2022)



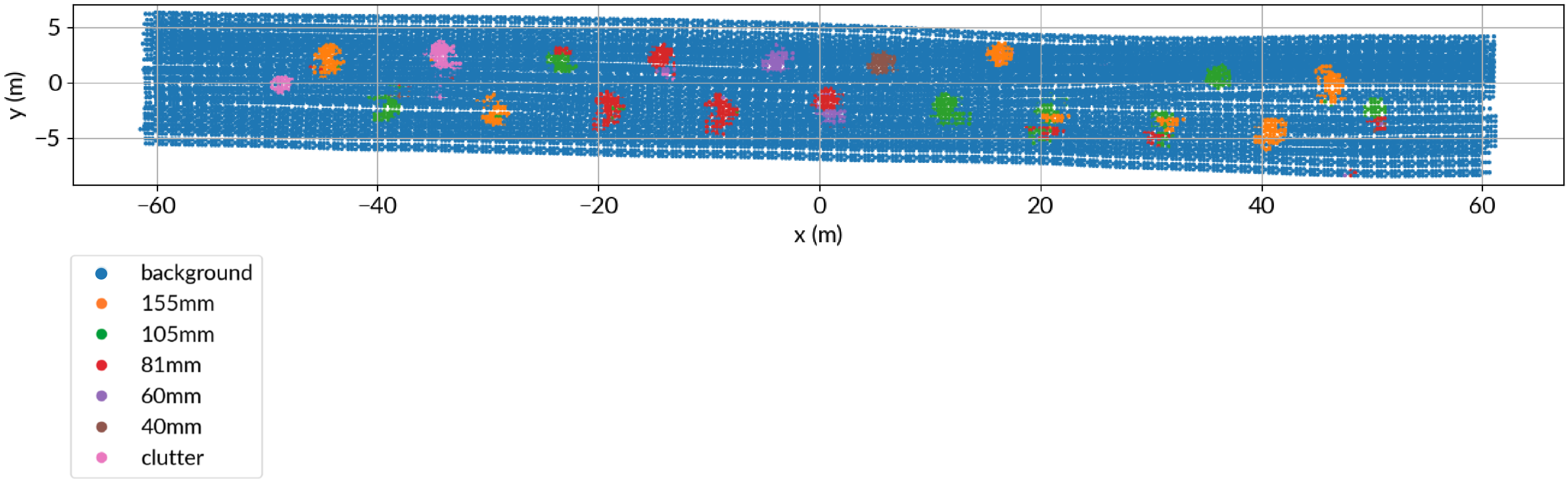
- 7 acquisition lines
- Current workflow requires seawater response removed
- Some ISOs present, we used only UXO objects to train (e.g. medium ISO ~ 81mm)

Get correlated noise using a binary classifier

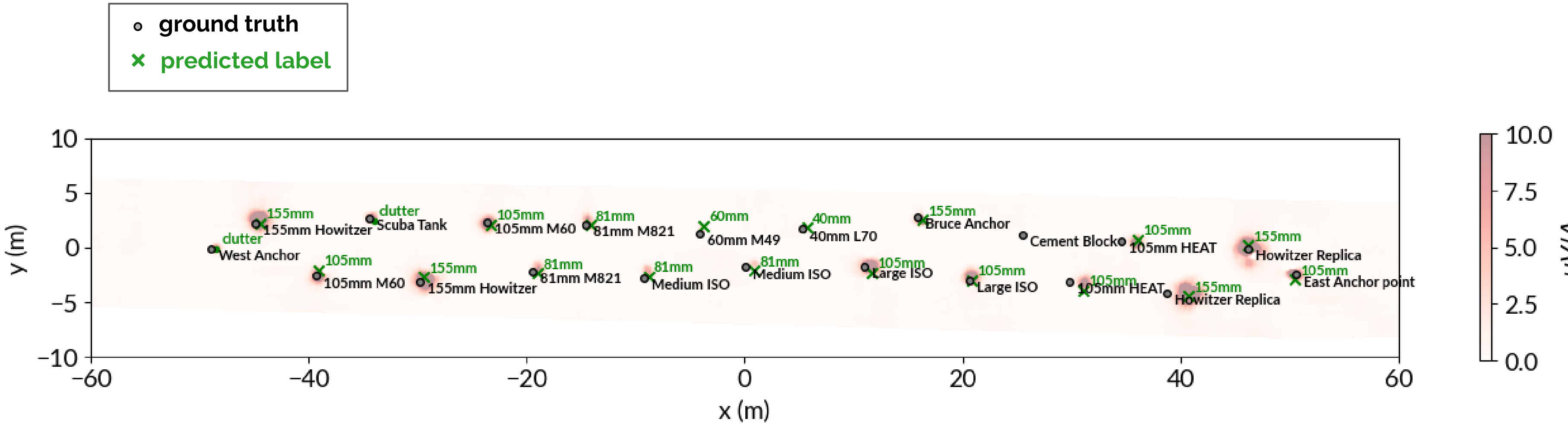


get spatially correlated noise from this subset of field data

Classification map (output of CNN)



Predicted labels vs truth labels - field data



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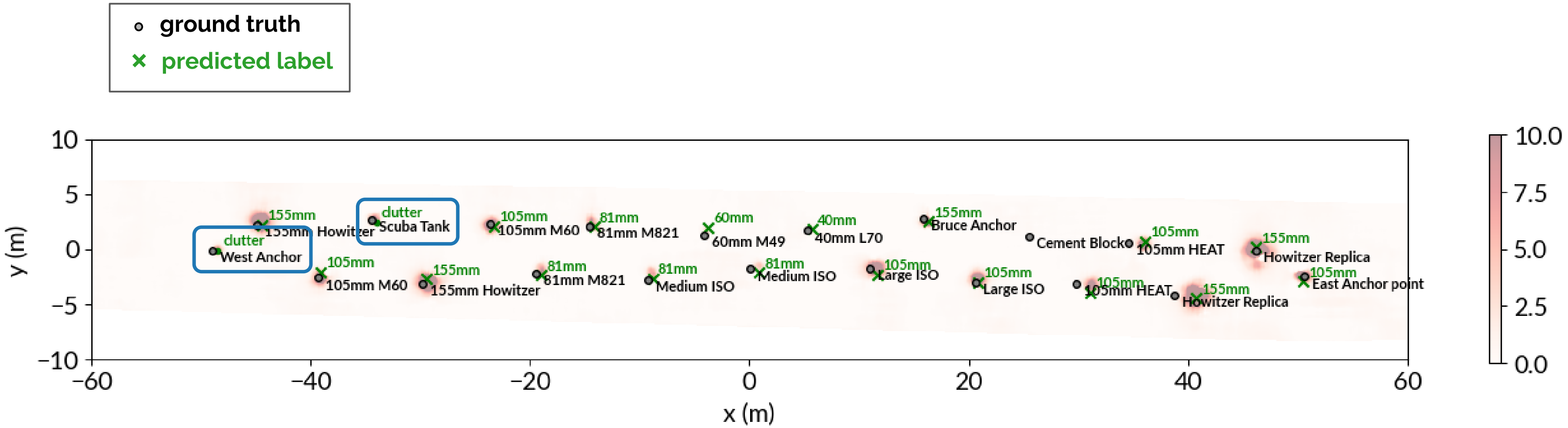
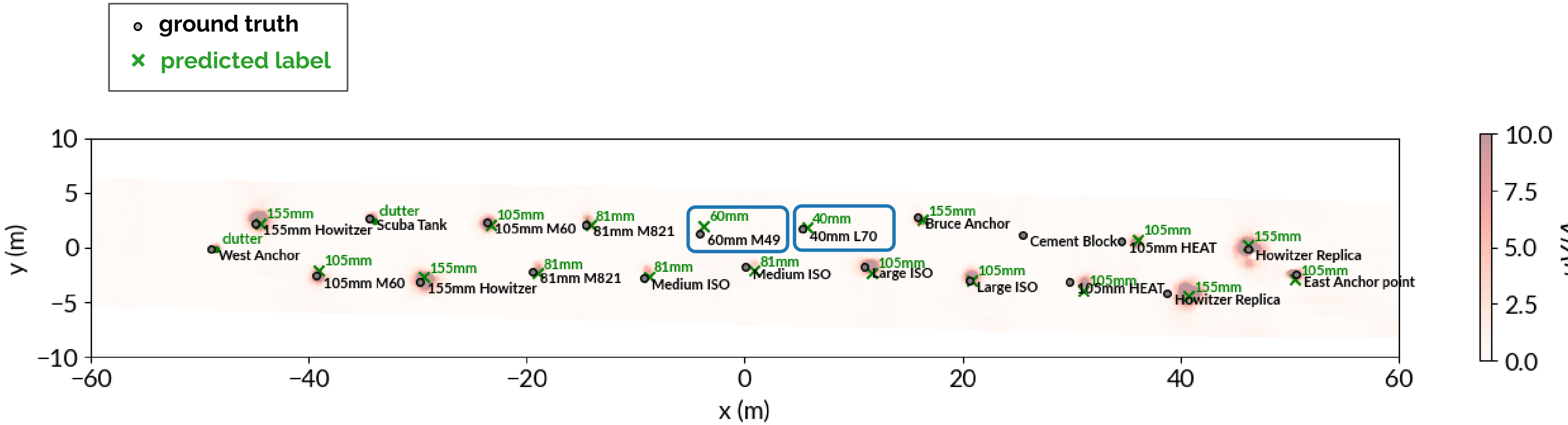


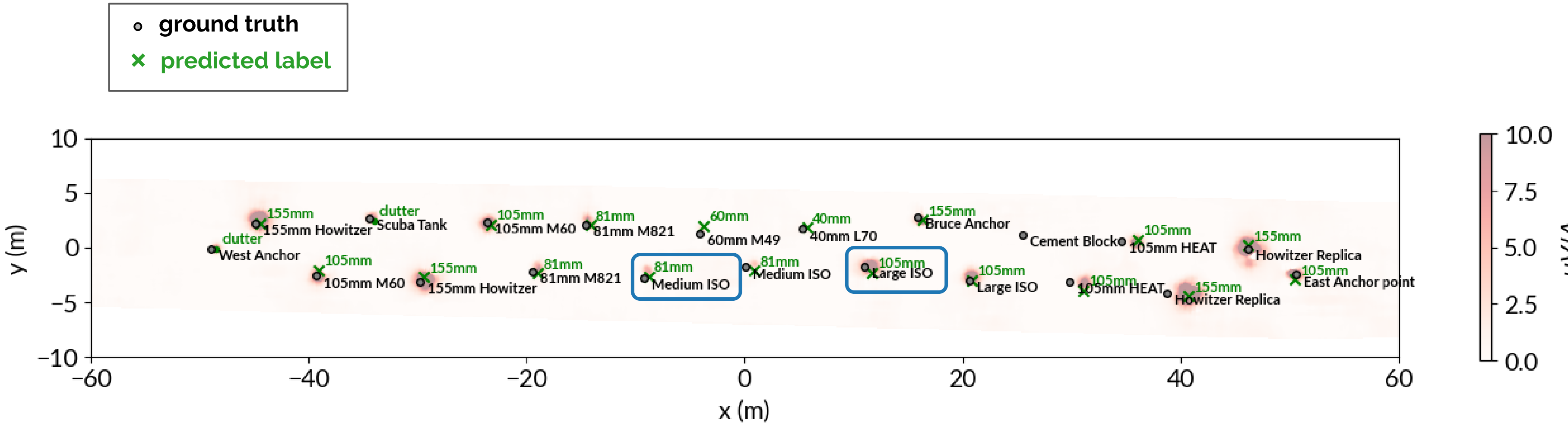
- Discriminated clutter

Predicted labels vs truth labels - field data



- Discriminated clutter
- Did not miss any UXO

Predicted labels vs truth labels - field data



- Discriminated clutter
- Did not miss any UXO
- Classified to closest object in training dataset

Concluding remarks:

- Key points:
  - image-segmentation architecture
  - clutter design and correlated noise are important
- Some limitations:
  - not trained to handle multiple objects in the same window
  - objects used to generate synthetic data should be close to the objects on the field
- Future work:
  - explore multi-target scenario (maybe instance segmentation)
  - combining with traditional approach

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