FFI Forsvarets forskningsinstitutt
Norwegian Defence Research Establishment

Classification of anti-submarine warfare sonar targets using a deep neural network

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MATLAB EXPO Stockholm

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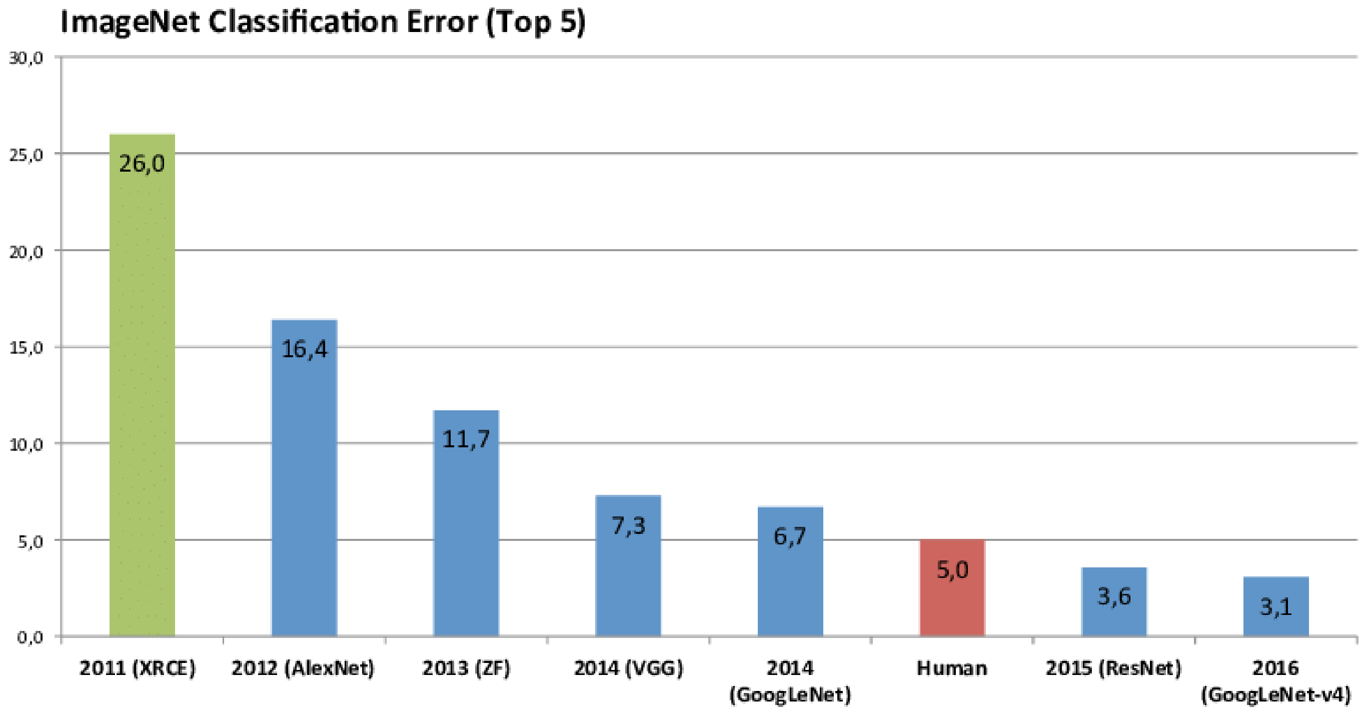
Deep learning applications

- Massive breakthrough for deep learning in recent years
- Particularly convolutional neural network for image classification applications
  - e. g. ImageNet – annual image classification competition



Deep learning applications

- Massive breakthrough for deep learning in recent years
- Particularly convolutional neural network for image classification applications
  - e. g. ImageNet – annual image classification competition
- Other fields with breakthroughs include
  - Speech processing
  - Machine translation (e.g. Google Translate)
  - Medical diagnosis systems
  - Prediction (e.g. weather, earthquakes)
  - Autonomy (e.g. self-driving cars)
  - Games (Chess, Go etc)
  - Art? (literature and paintings)

Gatys, Leon A., Alexander S. Ecker, and Matthias Bethge. "A neural algorithm of artistic style." *arXiv preprint arXiv:1508.06576* (2015).

A quick attempt at deep learning

- Bird classification
  - 11 species from the bird feeder

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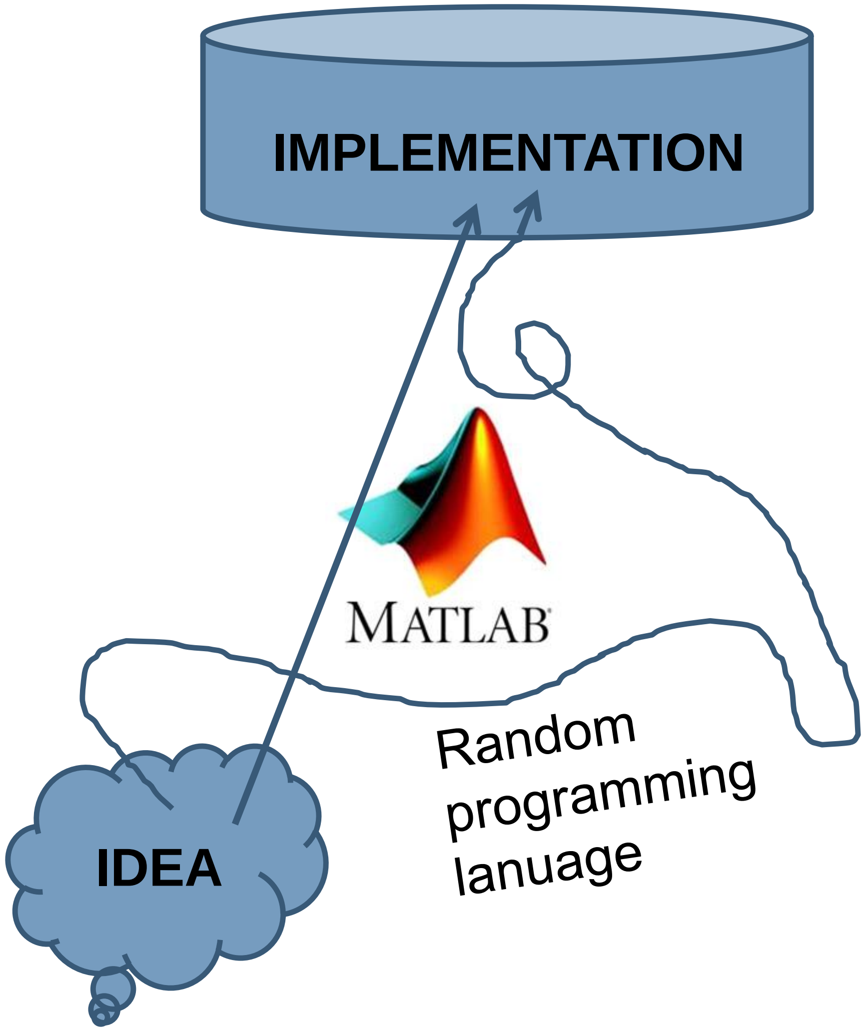
  - 11 species from the bird feeder
- Decided to go for MATLAB using
  - Deep Learning Toolbox
  - Image Processing Toolbox
  - Parallel Computing Toolbox for GPU
- Following this example:
  - https://se.mathworks.com/help/deeplearning/gs/get-started-with-transfer-learning.html
  - Using RESNET101



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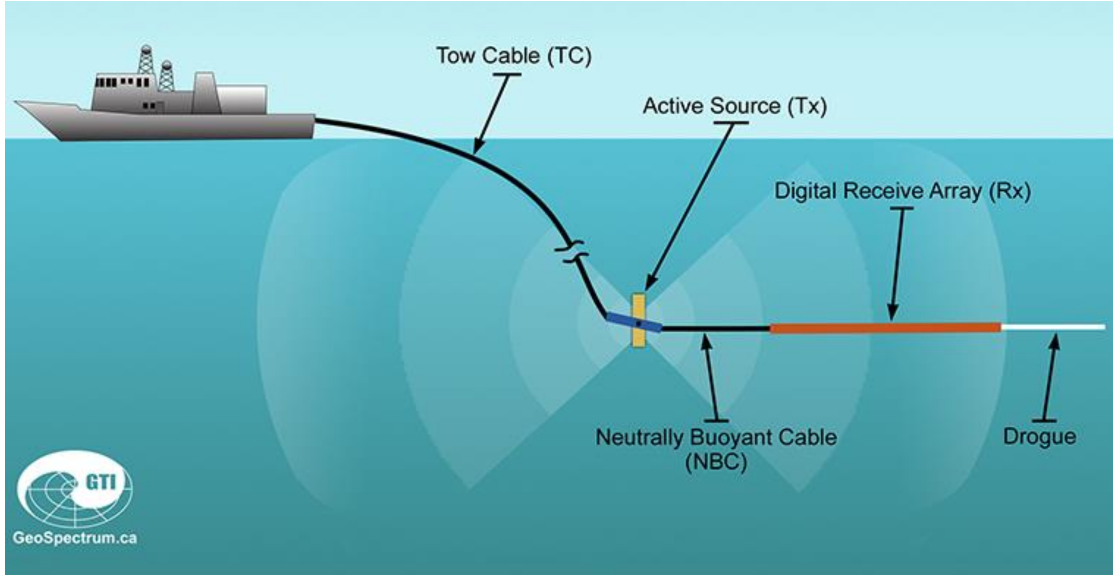
- After 10 minutes of coding and 10 hours of processing on my GPU…

Confusion Matrix

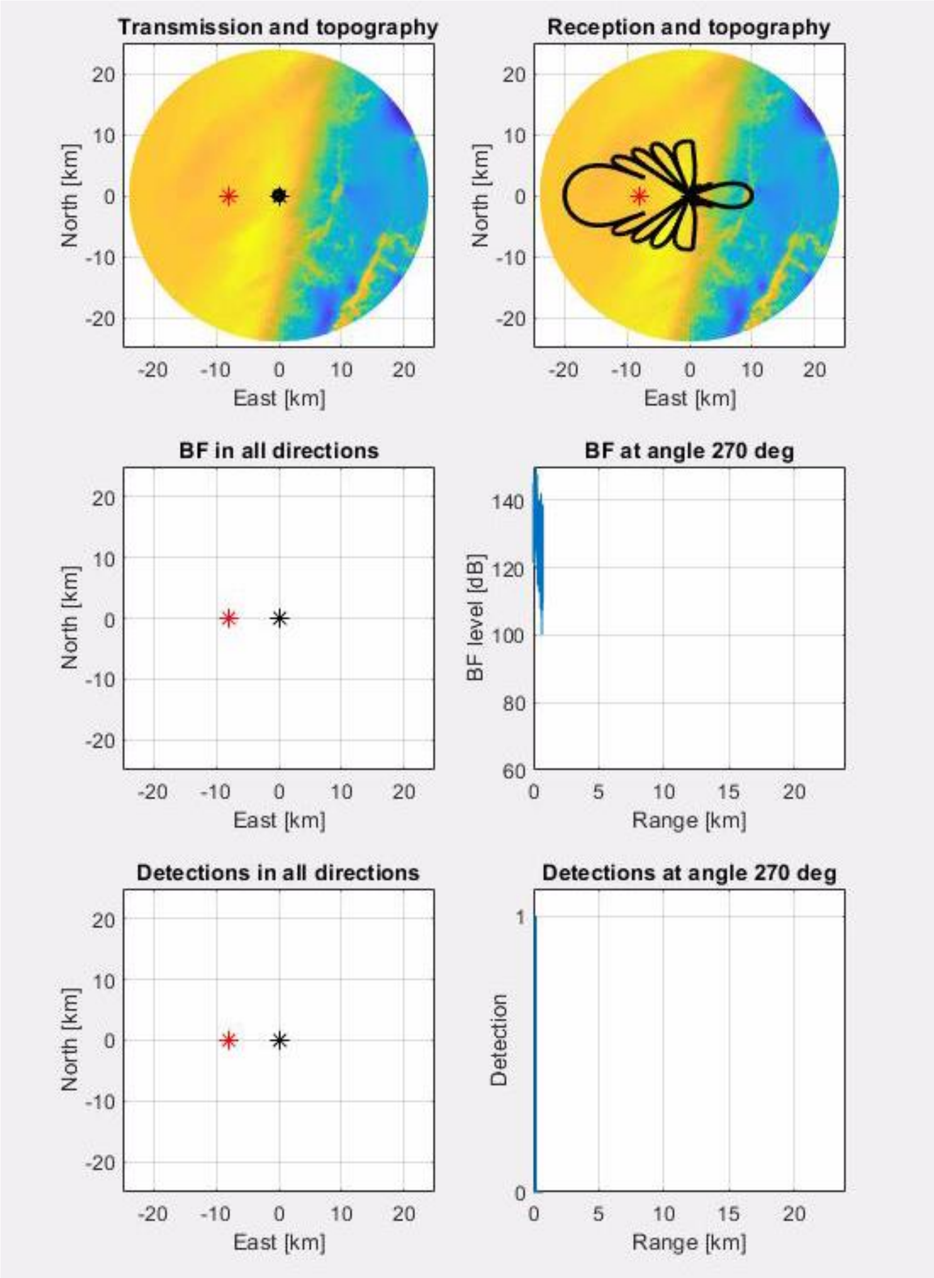
Output Class \ Target Class	blåmeis	dompap	flaggspett	gråspurv	grønnfink	gulspurv	kjøttmeis	pilfink	rødstrupe	skjære	svarttrost	
blåmeis	123 8.7%	1 0.1%	1 0.1%	2 0.1%	1 0.1%	0 0.0%	2 0.1%	1 0.1%	0 0.0%	0 0.0%	0 0.0%	93.9% 6.1%
dompap	0 0.0%	96 6.8%	1 0.1%	1 0.1%	1 0.1%	0 0.0%	0 0.0%	0 0.0%	1 0.1%	1 0.1%	0 0.0%	95.0% 5.0%
flaggspett	1 0.1%	2 0.1%	135 9.6%	2 0.1%	0 0.0%	0 0.0%	1 0.1%	1 0.1%	0 0.0%	1 0.1%	0 0.0%	94.4% 5.6%
gråspurv	2 0.1%	2 0.1%	0 0.0%	90 6.4%	5 0.4%	6 0.4%	1 0.1%	19 1.4%	1 0.1%	0 0.0%	1 0.1%	70.9% 29.1%
grønnfink	1 0.1%	1 0.1%	0 0.0%	0 0.0%	80 5.7%	5 0.4%	0 0.0%	1 0.1%	2 0.1%	0 0.0%	1 0.1%	87.9% 12.1%
gulspurv	0 0.0%	0 0.0%	0 0.0%	3 0.2%	5 0.4%	129 9.2%	0 0.0%	1 0.1%	0 0.0%	0 0.0%	0 0.0%	93.5% 6.5%
kjøttmeis	14 1.0%	1 0.1%	2 0.1%	0 0.0%	2 0.1%	0 0.0%	130 9.2%	4 0.3%	1 0.1%	0 0.0%	2 0.1%	83.3% 16.7%
pilfink	2 0.1%	3 0.2%	2 0.1%	11 0.8%	0 0.0%	2 0.1%	1 0.1%	113 8.0%	3 0.2%	0 0.0%	0 0.0%	82.5% 17.5%
rødstrupe	1 0.1%	1 0.1%	1 0.1%	1 0.1%	1 0.1%	1 0.1%	1 0.1%	1 0.1%	131 9.3%	0 0.0%	1 0.1%	93.6% 6.4%
skjære	0 0.0%	2 0.1%	2 0.1%	2 0.1%	1 0.1%	3 0.2%	0 0.0%	2 0.1%	1 0.1%	68 4.8%	4 0.3%	80.0% 20.0%
svarttrost	2 0.1%	3 0.2%	2 0.1%	1 0.1%	1 0.1%	0 0.0%	2 0.1%	3 0.2%	1 0.1%	5 0.4%	137 9.7%	87.3% 12.7%
	84.2% 15.8%	85.7% 14.3%	92.5% 7.5%	79.6% 20.4%	82.5% 17.5%	88.4% 11.6%	94.2% 5.8%	77.4% 22.6%	92.9% 7.1%	90.7% 9.3%	93.8% 6.2%	87.6% 12.4%

What about active sonar applications?

- Active sonar
  - Transmits known signal
  - Receives echo from target and environment
  - Processes contacts through beam forming, matched filtering, normalisation, and detection



https://elbitsystems.com/pr-new/geospectrum-technologies-to-showcase-their-towed-reelable-active-passive-sonar-traps-at-cansec-2018/

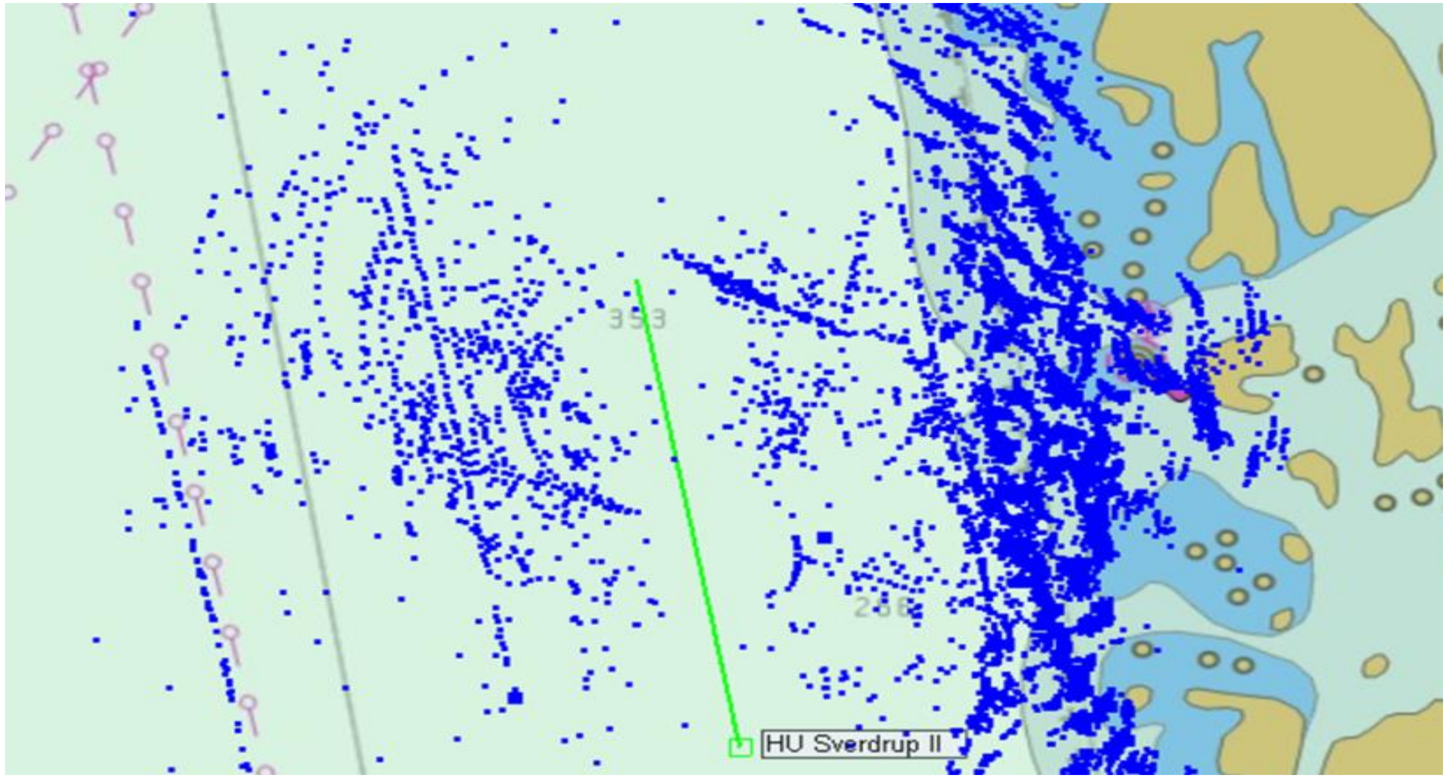


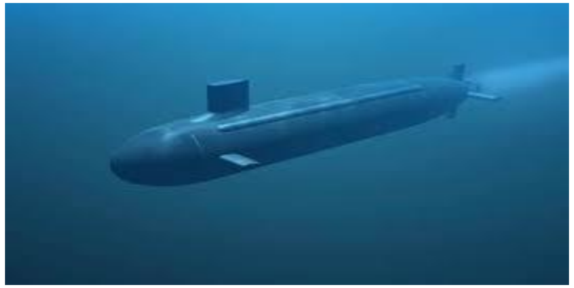
Classification problem

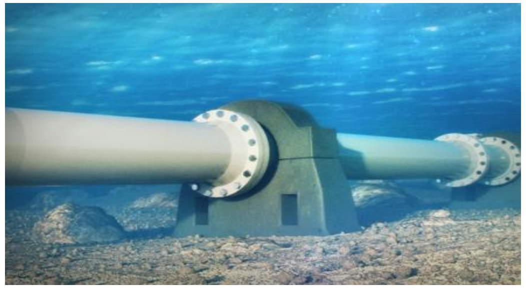
- High false alarm rates
  - Modern high resolution sonars
  - Littoral waters

- Cluttered sonar picture
  - Difficult to track targets automatically
  - Confusing picture for sonar operator

- **Conclusion**
  - **Automatic target classification**







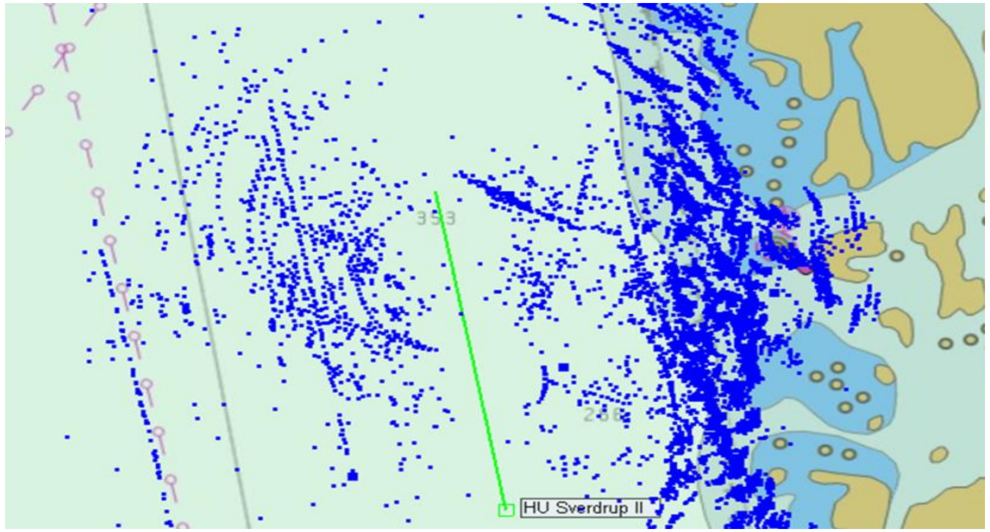
Automatic classification – Classic approach

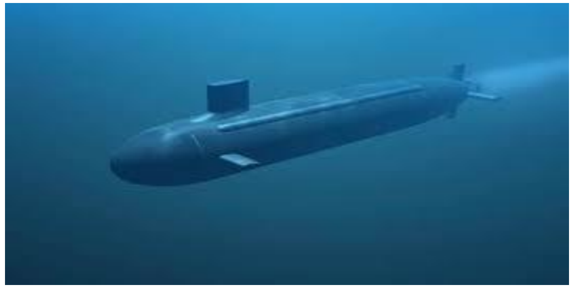
Sensor data → Processing → Features

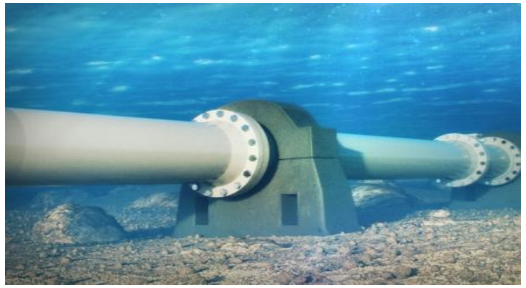
Test

Training

Machine Learning → Classifier → Classification







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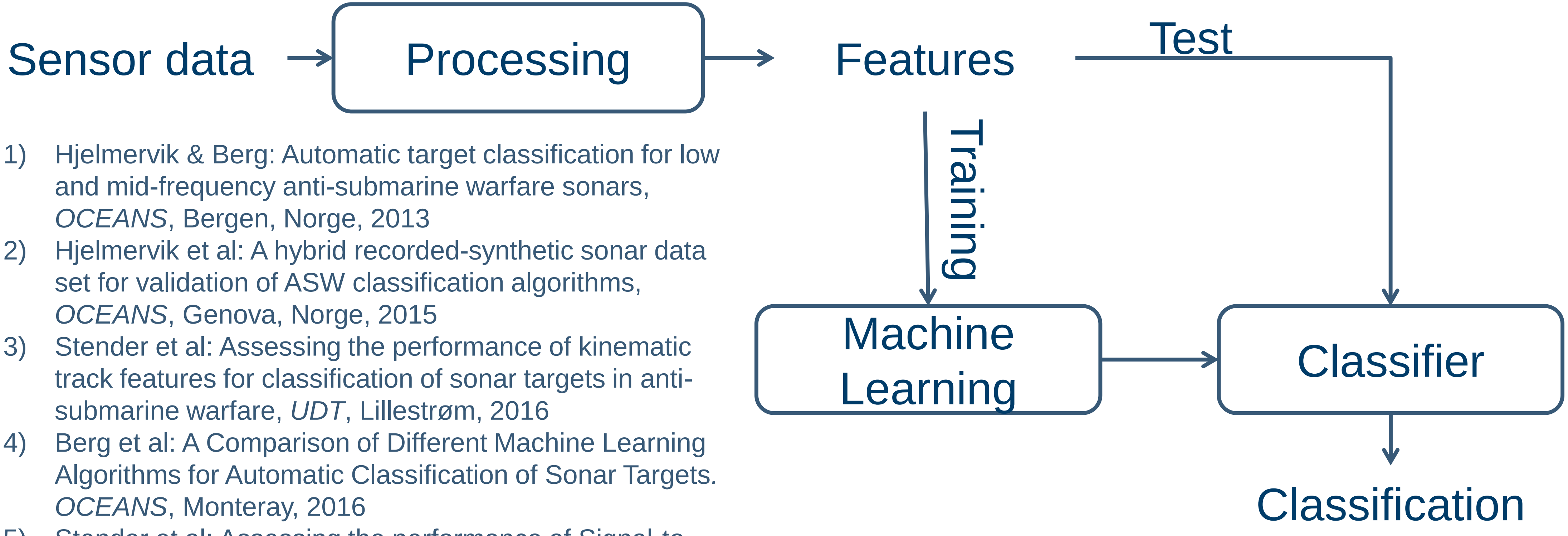


1) Hjelmervik & Berg: Automatic target classification for low and mid-frequency anti-submarine warfare sonars, *OCEANS*, Bergen, Norge, 2013
2) Hjelmervik et al: A hybrid recorded-synthetic sonar data set for validation of ASW classification algorithms, *OCEANS*, Genova, Norge, 2015
3) Stender et al: Assessing the performance of kinematic track features for classification of sonar targets in anti-submarine warfare, *UDT*, Lillestrøm, 2016
4) Berg et al: A Comparison of Different Machine Learning Algorithms for Automatic Classification of Sonar Targets. *OCEANS*, Monteray, 2016
5) Stender et al: Assessing the performance of Signal-to-noise ratio and kinematic features in varying environments. *OCEANS*, Aberdeen, 2017
6) Stender et al: Sensitivity to target behaviour in automatic classification on kinematic track features. *OCEANS,* Kobe, Japan, 2018

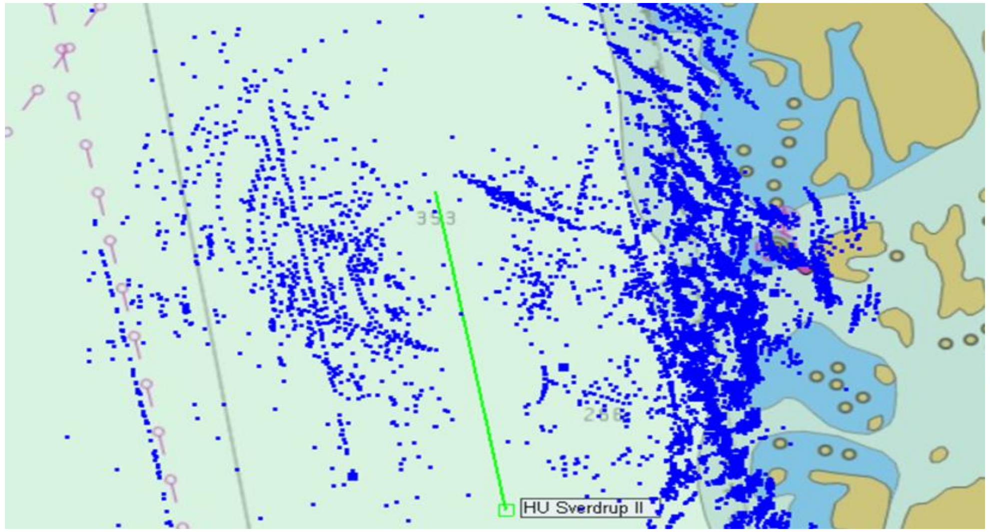
Automatic classification – Deep learning

Sensor data → Processing → Instances

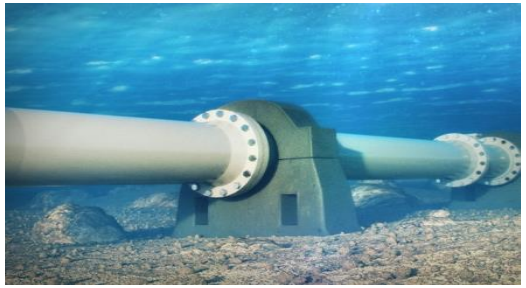
Instances → Test → Classifier

Instances → Training → Machine Learning → Classifier

Classifier → Classification



Berg & Hjelmervik: Classification of anti-submarine warfare sonar targets using a deep neural network. OCEANS, Charleston, USA, 2018



NATIII - Sonar Clutter Experiment 2002

- Collaboration between
  - FFI (N)
  - TNO (NL)
  - Thales Underwater Systems (F)
  - The navies of NL, F and N

- Performed off the west coast of Norway (in the Norwegian Trench)
- Active, Low frequency Towed Array Sonar

Processing

Hydrophone data

Beamforming

Matched filtering

Normalisation

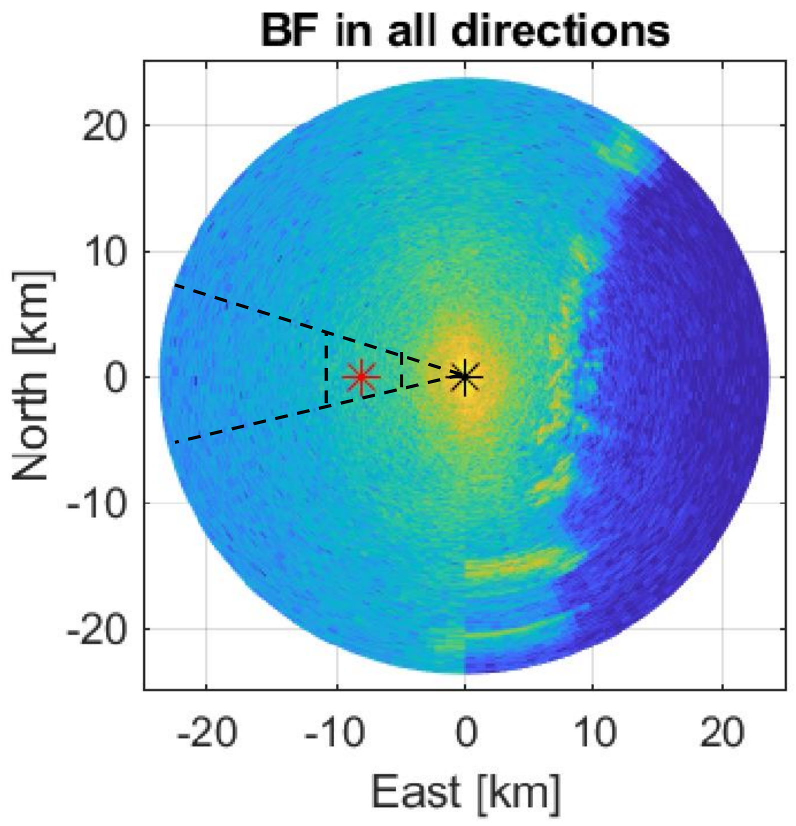
Detection

Clustering

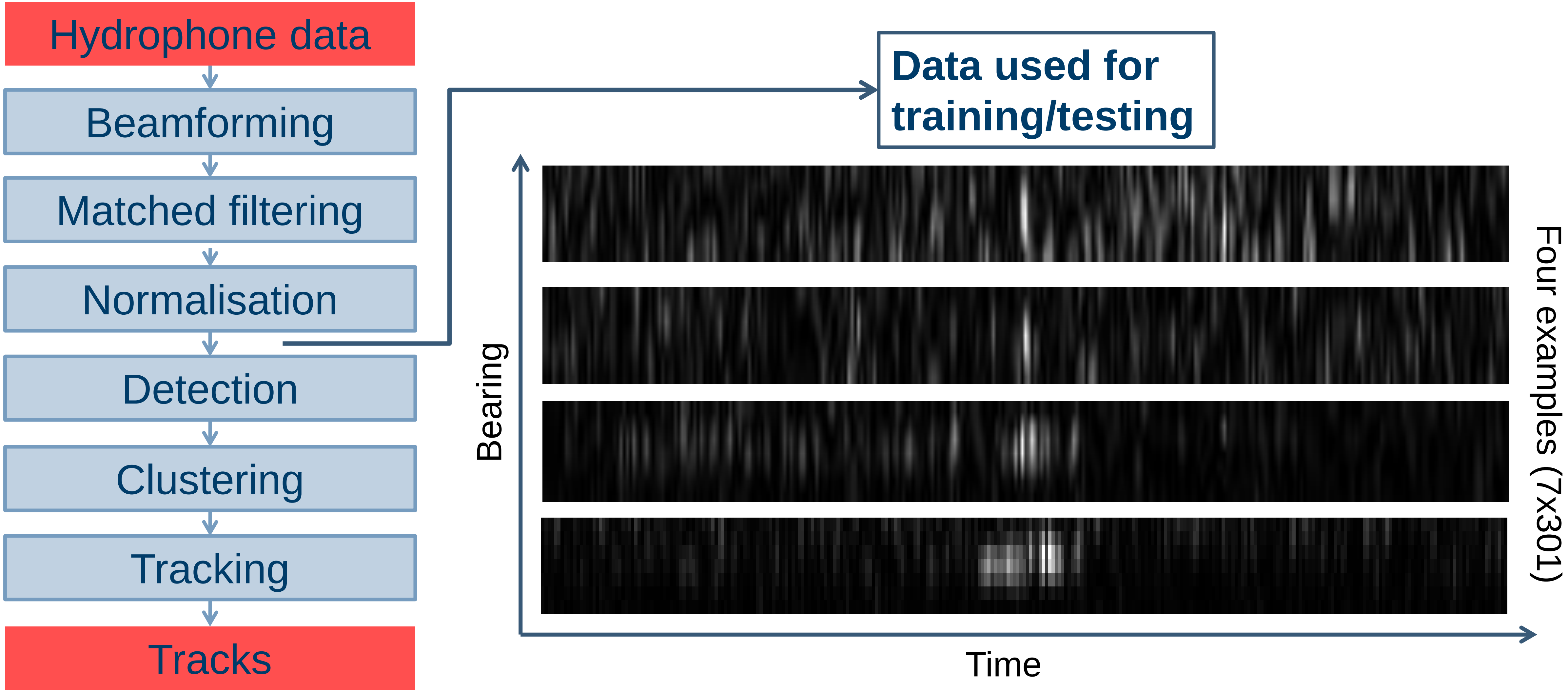
Tracking

Tracks

Data used for training/testing



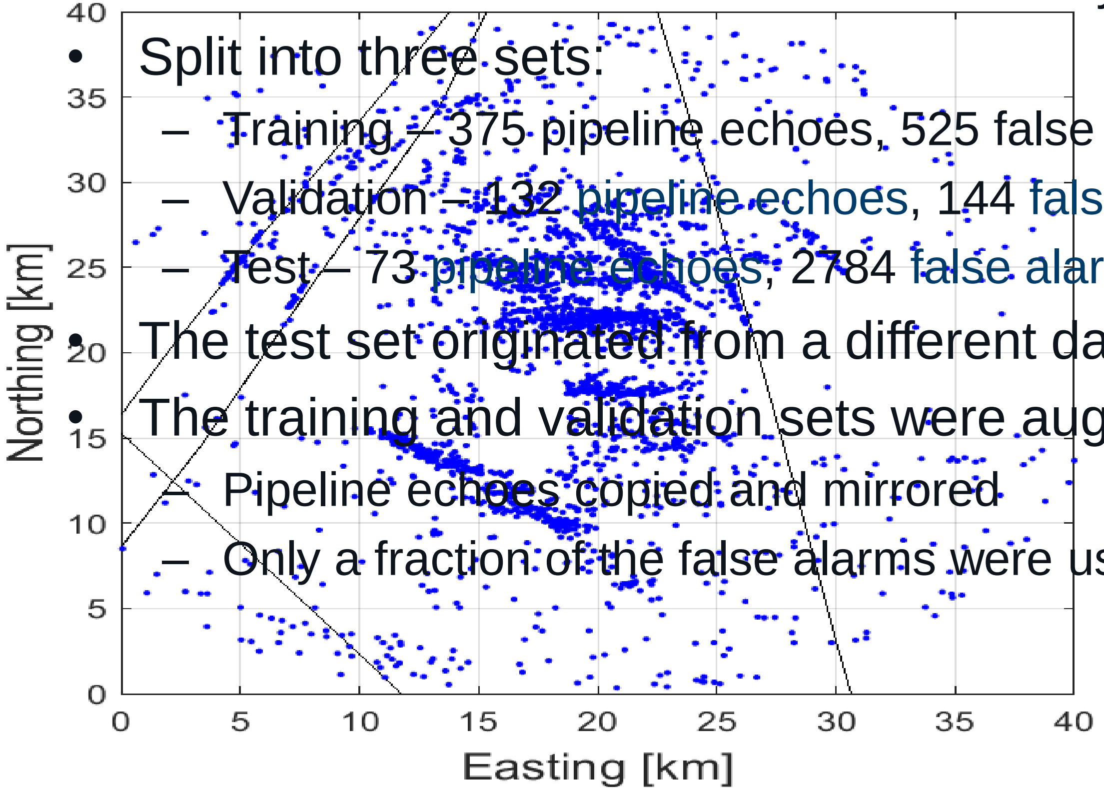
Processing

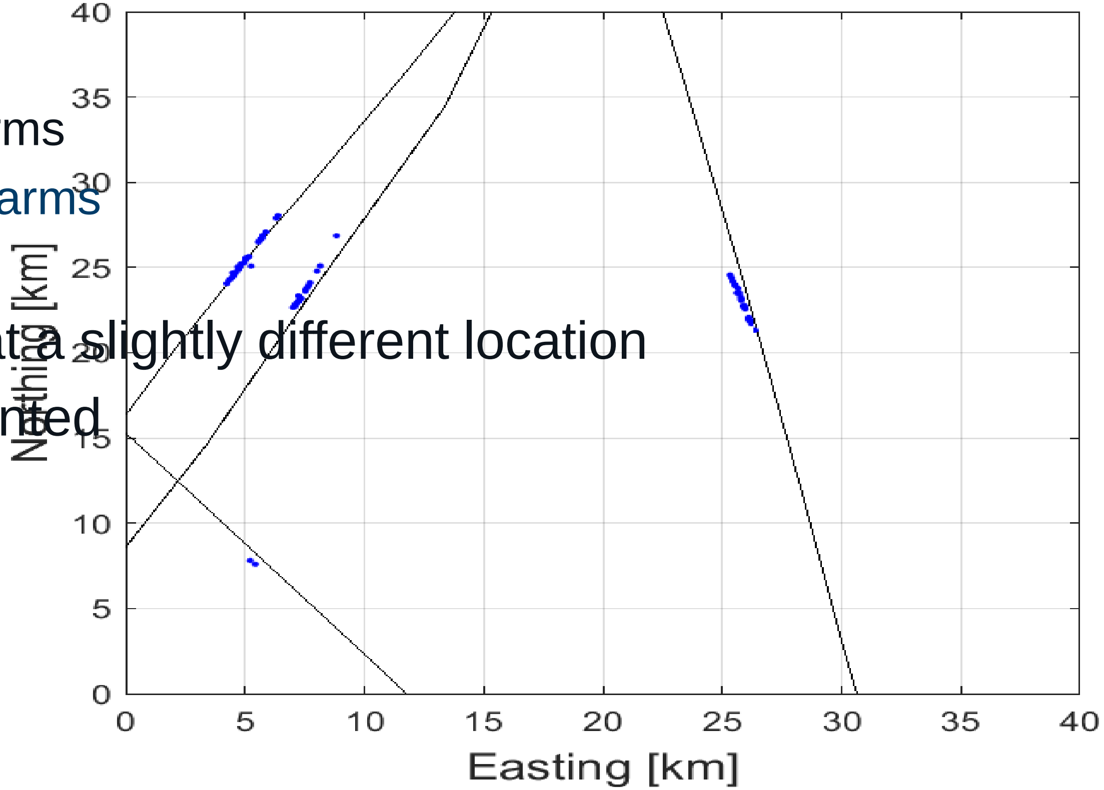


Hydrophone data
Beamforming
Matched filtering
Normalisation
Detection
Clustering
Tracking
Tracks
Data used for training/testing
Bearing
Time
Four examples (7x301)

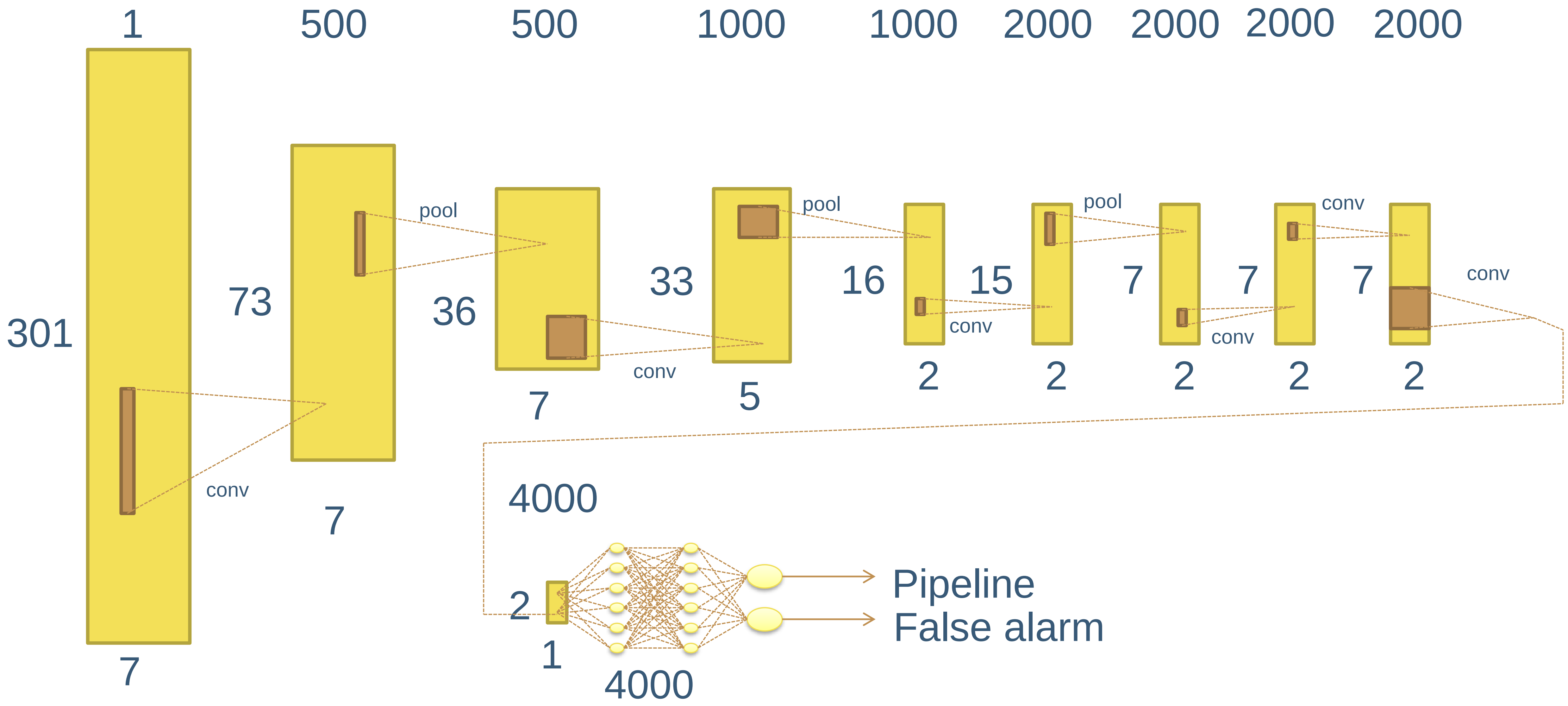
Data

- A few thousand echoes recorded during three different experiments
- The area contained four pipelines (with a total of 242 echoes)
- The echoes were classified semimanually
- Split into three sets:
  - Training – 375 pipeline echoes, 525 false alarms
  - Validation – 132 pipeline echoes, 144 false alarms
  - Test – 73 pipeline echoes, 2784 false alarms
- The test set originated from a different day, at a slightly different location
- The training and validation sets were augmented
  - Pipeline echoes copied and mirrored
  - Only a fraction of the false alarms were used





Neural network

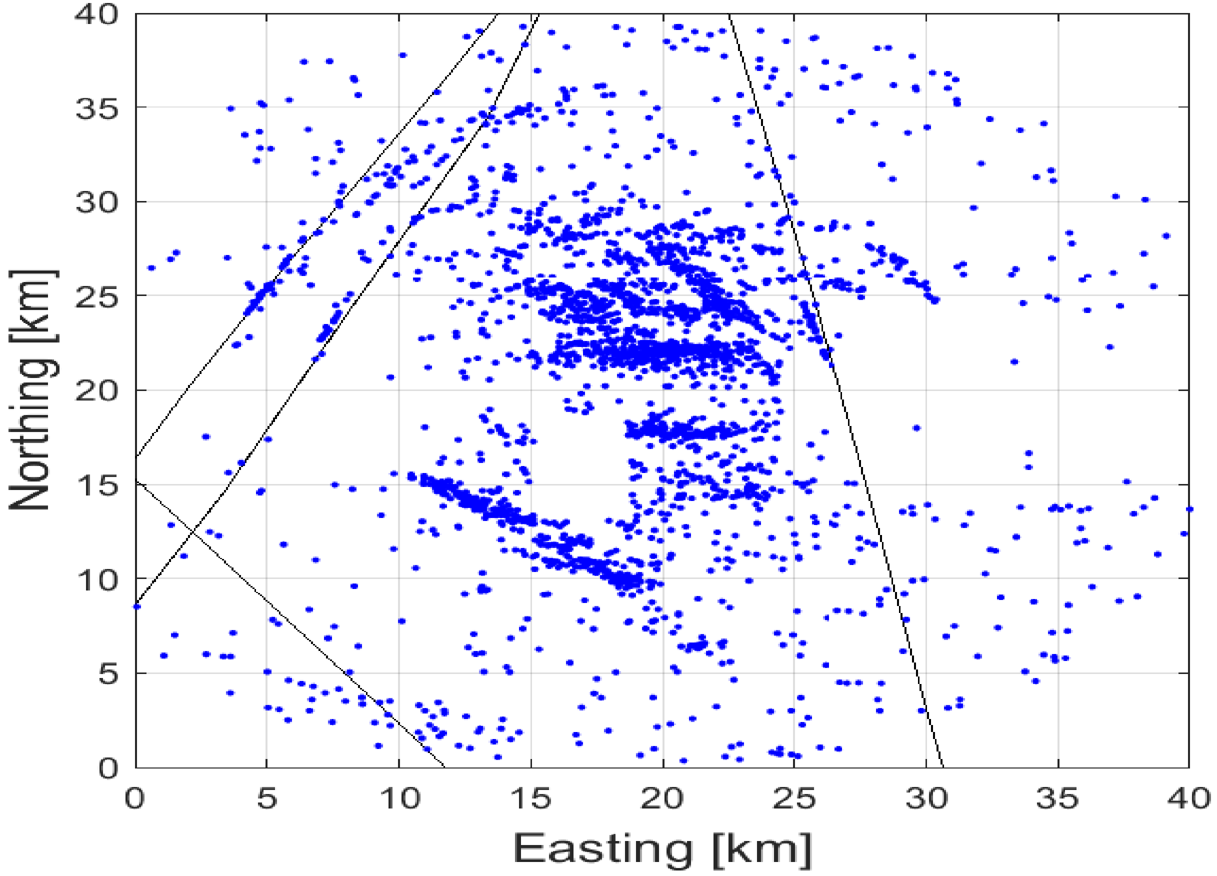


Traning and validation

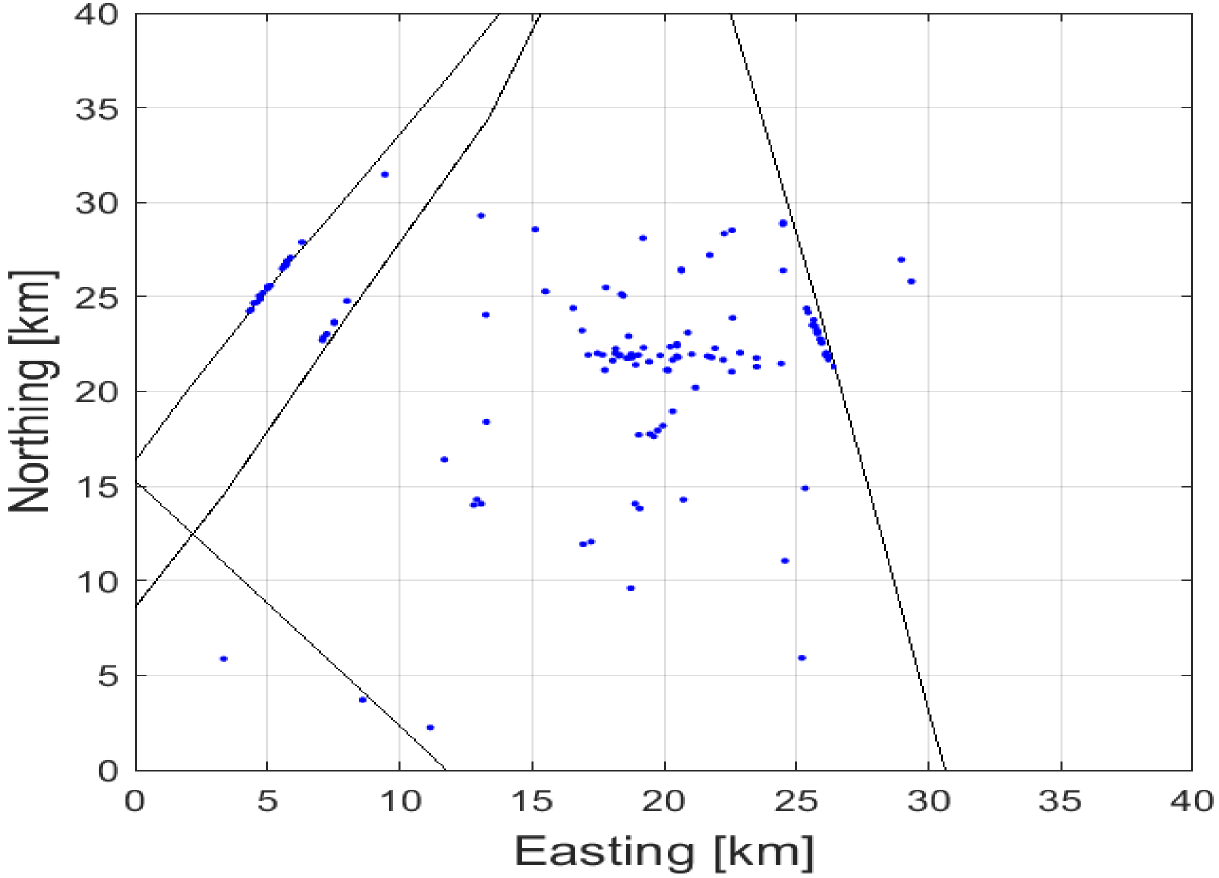
- Implemented i MATLAB Deep learning Toolbox
- Executed on a Nvidia Geforce 980 GPU
- Learning rate 0.01, minibatch size 10
- Stop condition: Performance on validation set decreased
- 10 runs, 7-12 minutes per run
- Results combined by weighted averaging

- Finally: Tested on test set
  - Not used in any way during training

Results



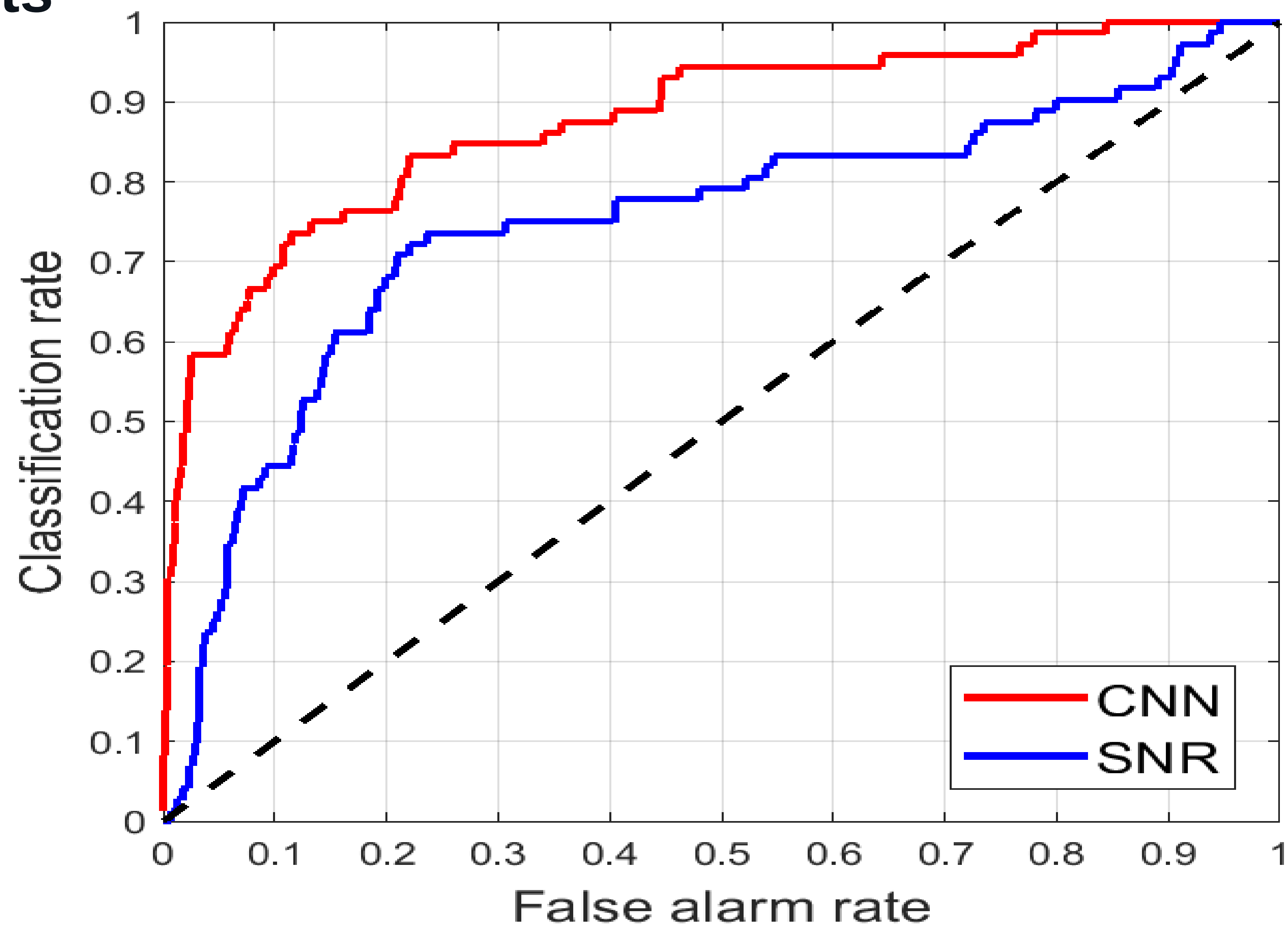
Test set



Classified by the trained network

Manually classified

Results



1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Classification rate
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
False alarm rate
CNN
SNR

Conclusions

- Deep learning for active sonar target classification shows promise
  - Easy to implement in MATLAB
  - Too small data set. More augmentation?
  - Significantly better results than simply raising the threshold in the detector

- Current/future work:
  - We need more training data
    - New augmentation techniques
    - Synthetic data
  - Investigate using data from different levels of processing
    - Beam formed
    - Multiple pings

Deep learning with synthetic data

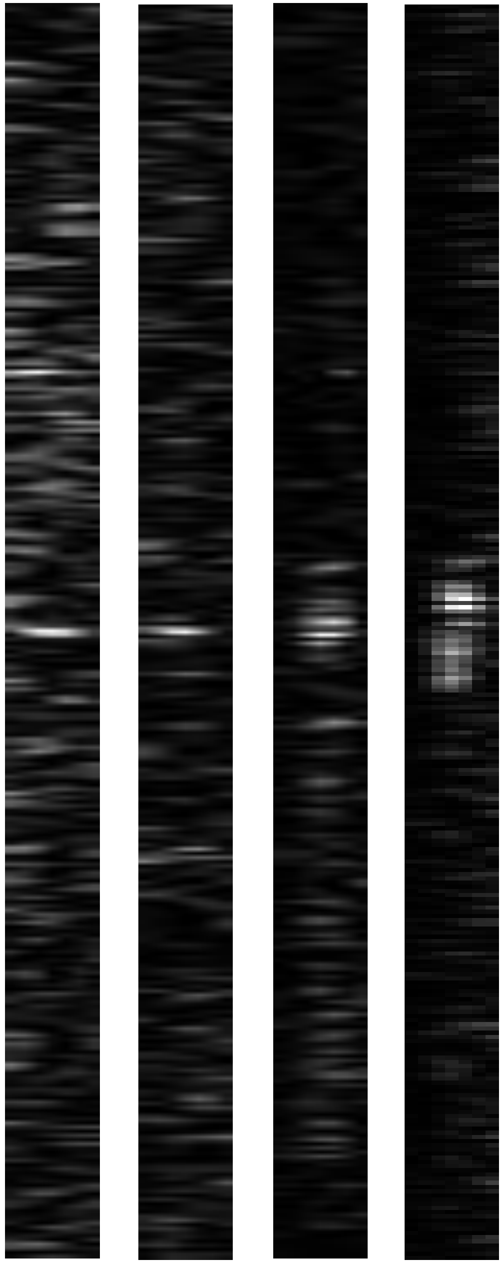
Case 1

- Data from NAT3 2002
  - Training data set
    - 167 false
    - 164 true
  - Validation data set
    - 44 false
    - 63 true
  - Test data set
    - 96 false
    - 38 true

Test

- Augmented with synthetic data
  - Ca 54000 instances (50% true)

Train



Deep learning with synthetic data

Case 2

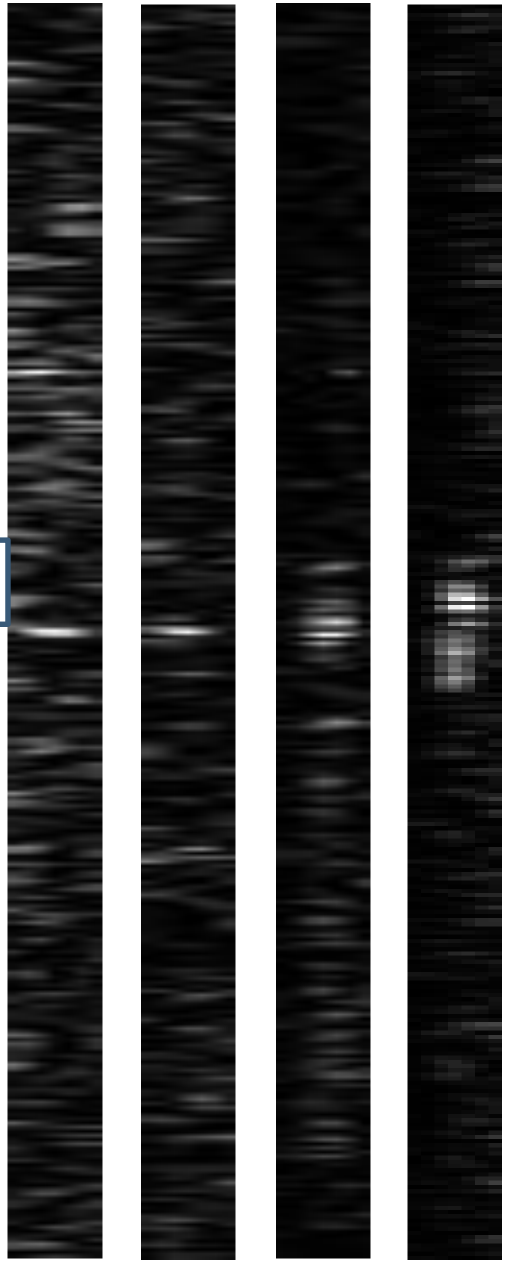
- Data from NAT3 2002
  - Training data set
    - 167 false
    - 164 true
  - Validation data set
    - 44 false
    - 63 true
  - Test data set
    - 96 false
    - 38 true

- Augmented with synthetic data
  - Ca 54000 instances (50% true)

Transfer

Test

Train



Deep learning with synthetic data

Case 3

- Data from NAT3 2002
  - Training data set
    - 167 false
    - 164 true
  - Validation data set
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    - 63 true
  - Test data set
    - 96 false
    - 38 true

- Augmented with synthetic data
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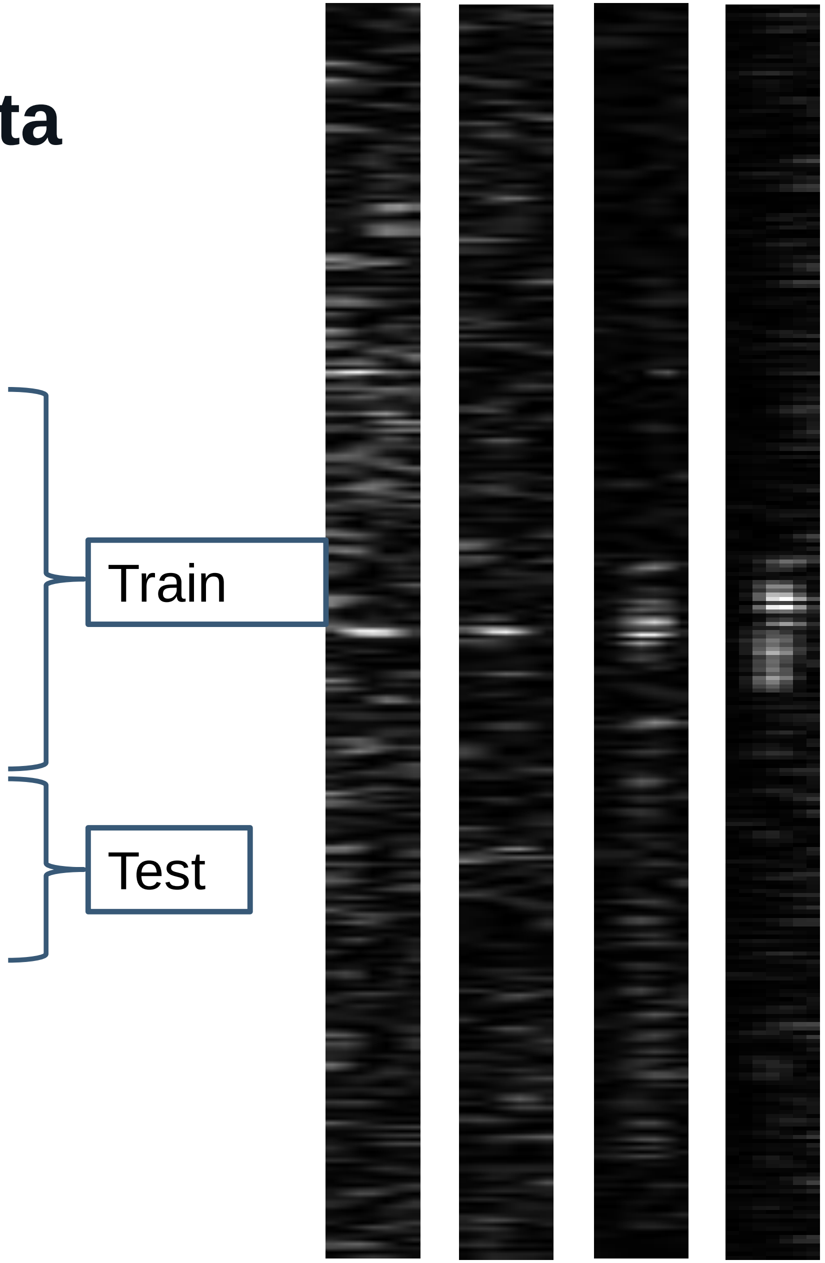
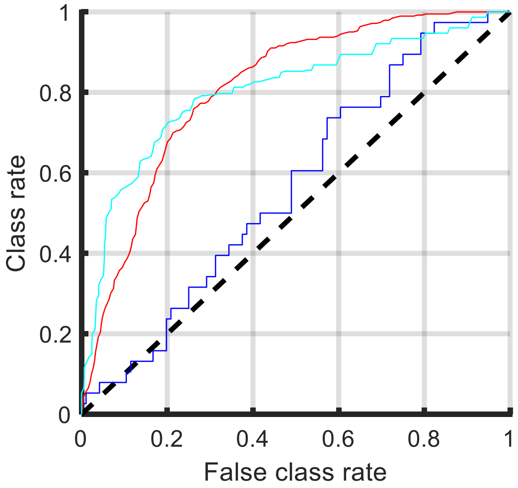


Deep learning with synthetic data



Farge	Trening	Transfer	Test
Blue	Synthetic	N/A	Recorded
Red	Synthetic	Recorded	Recorded
Cyan	Recorded	N/A	Recorded