

From traditional machine learning to deep learning

**FORCE Hackathon and Advances of Machine Learning
on Subsurface Data**

Anders U. Waldeland anders@nr.no

Stavanger, 20.09.2018



Norsk Regnesentral

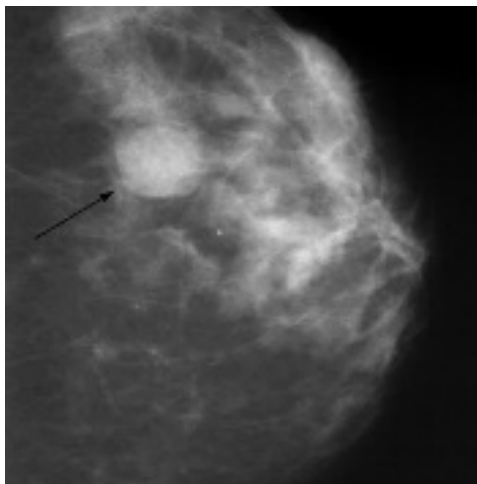


1953



- ▶ Research institute with about 80 employees, located in Oslo
- ▶ Specialize in statistical analysis, machine learning, image analysis

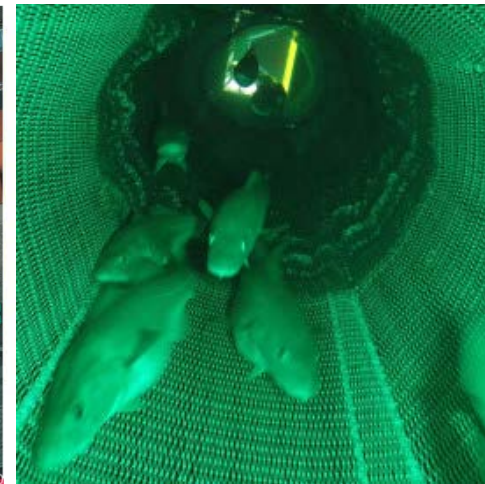
Classification



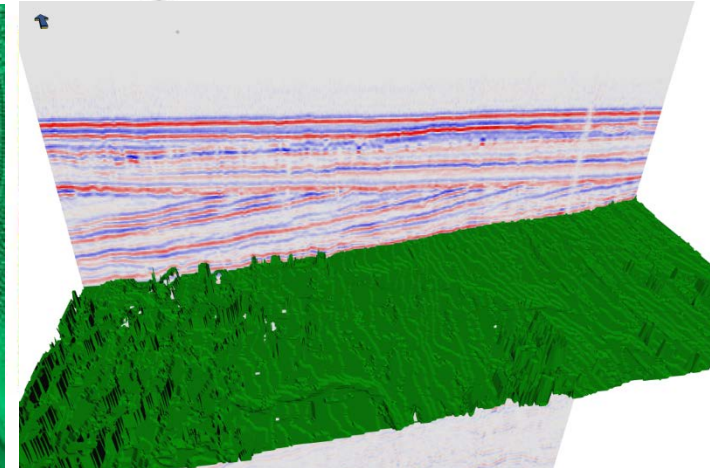
Classification + Localization



Object Detection



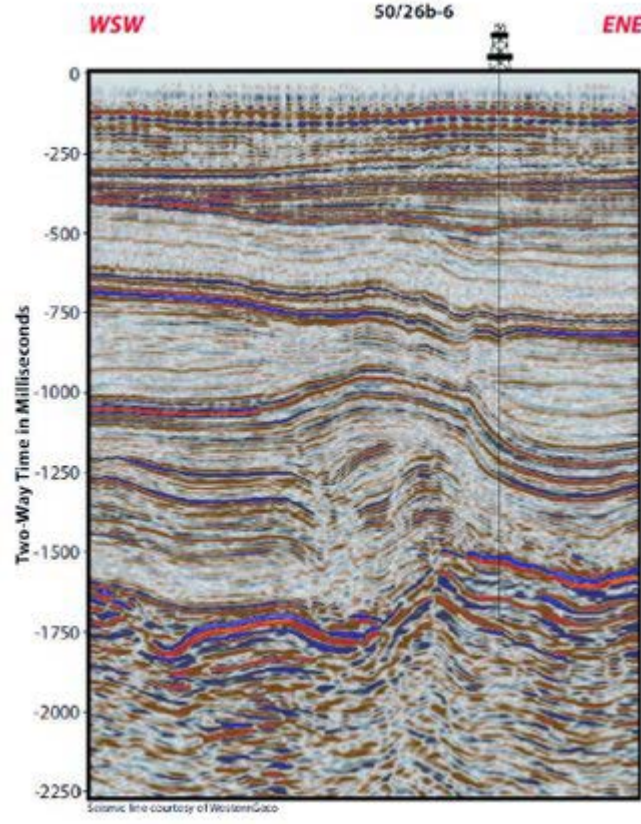
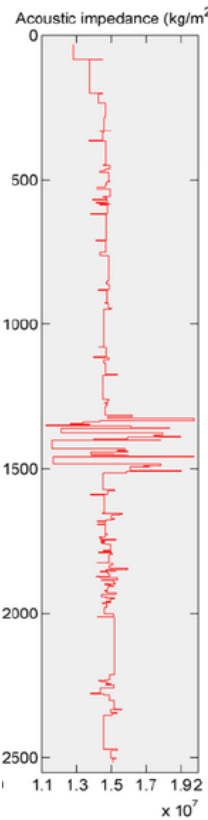
Instance Segmentation



Input data

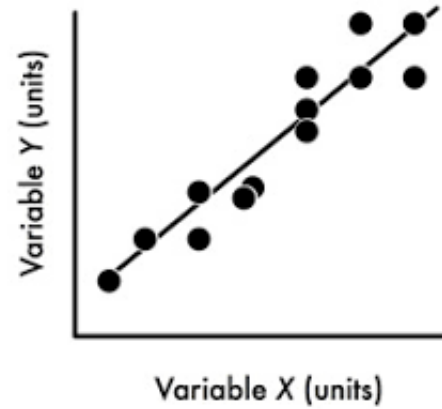


FIZZY
50/26b-6

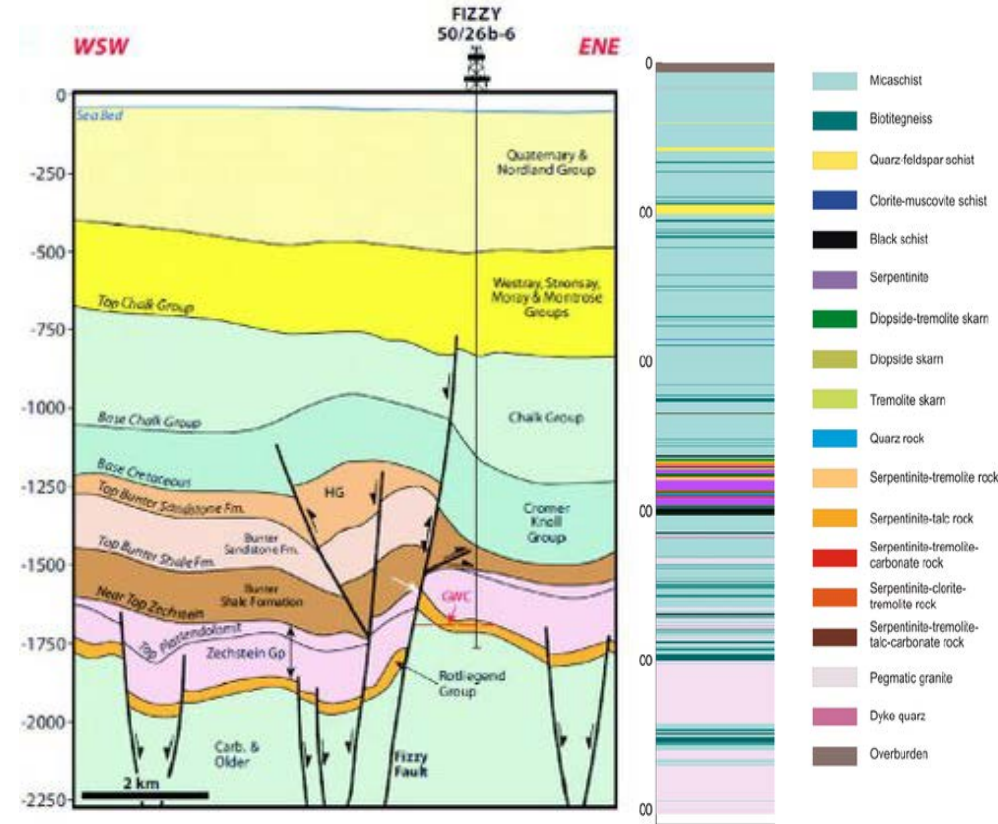
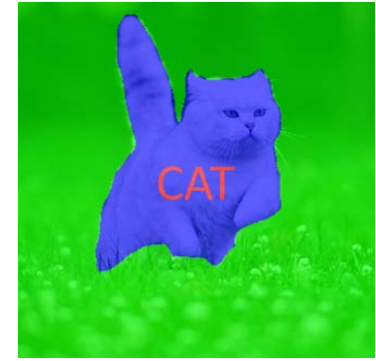


Relationship

Domain expert



Output



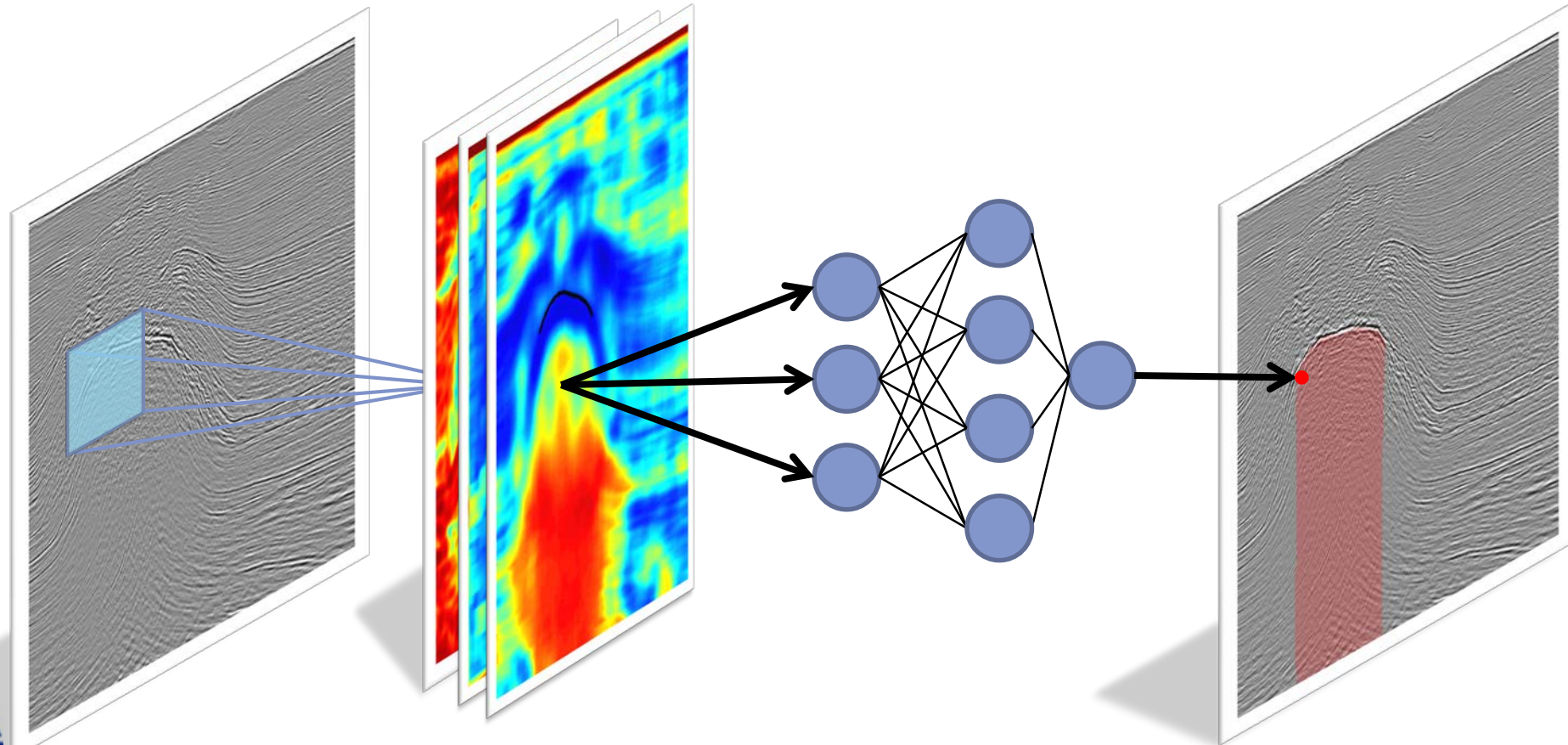
Traditional machine learning

Input

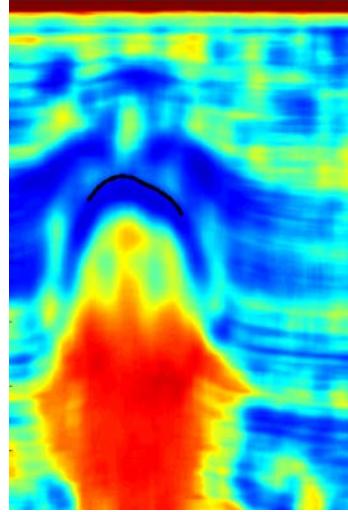
Features

Classifier

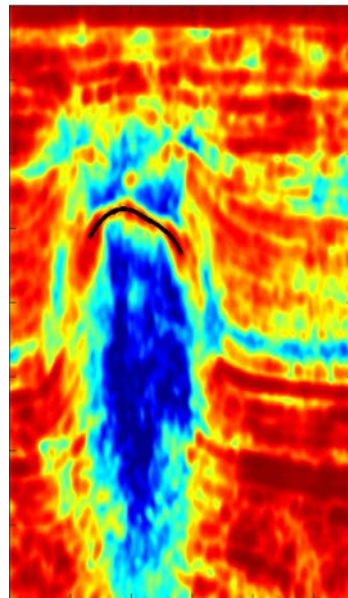
Output



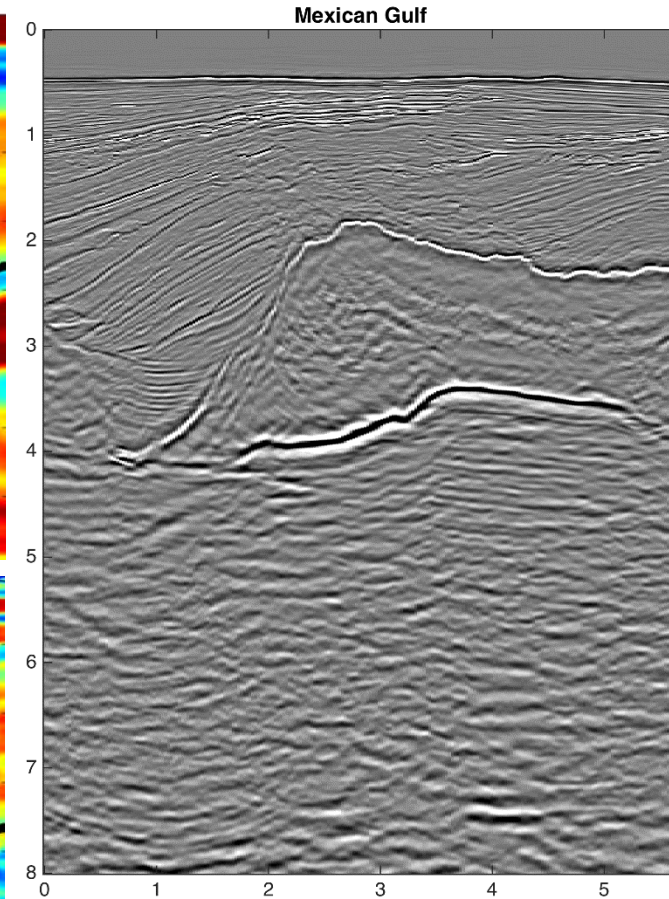
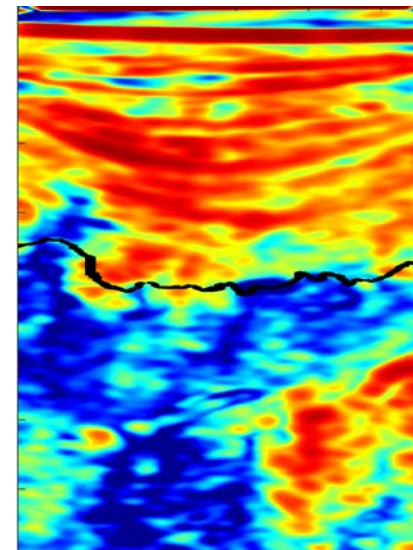
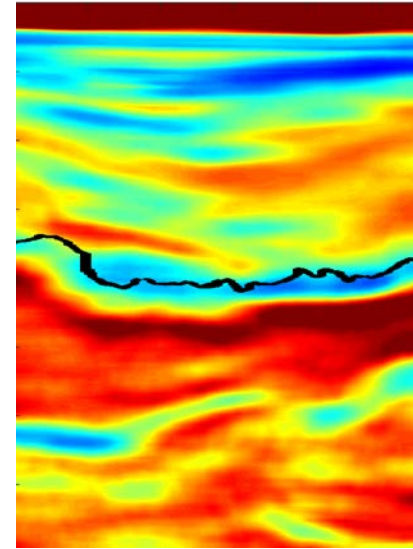
Training a classifier



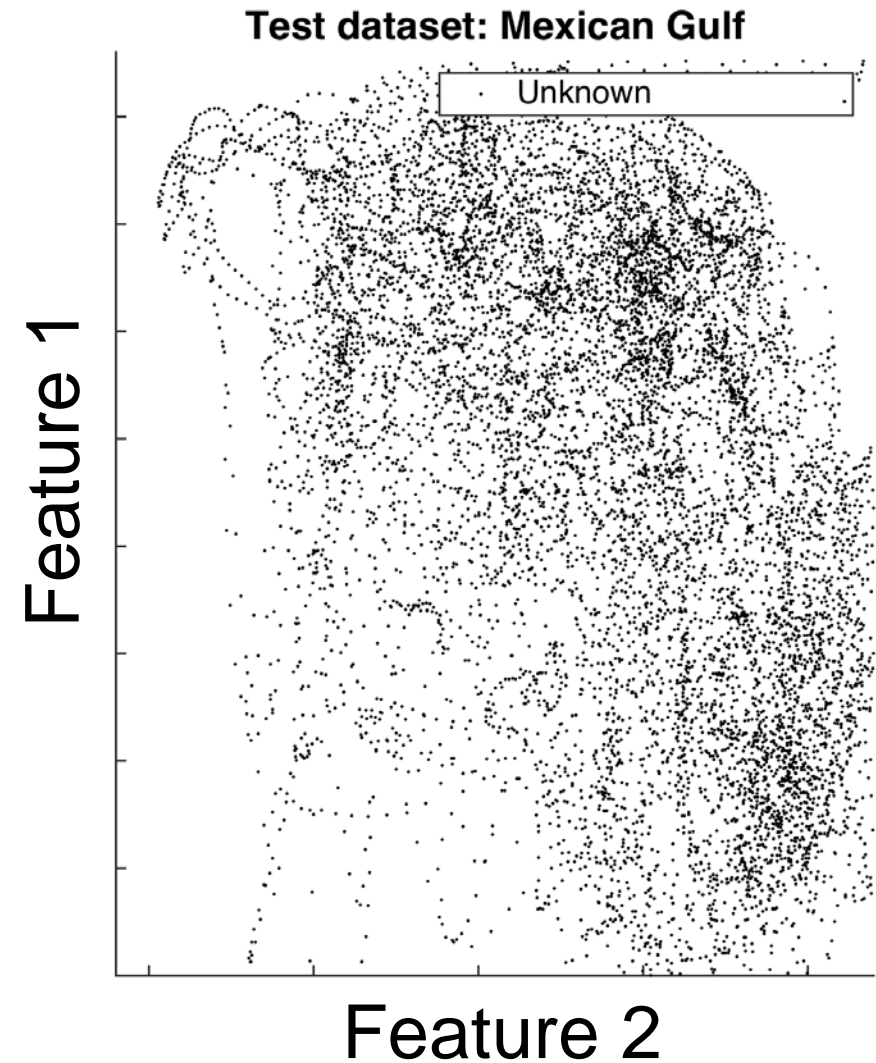
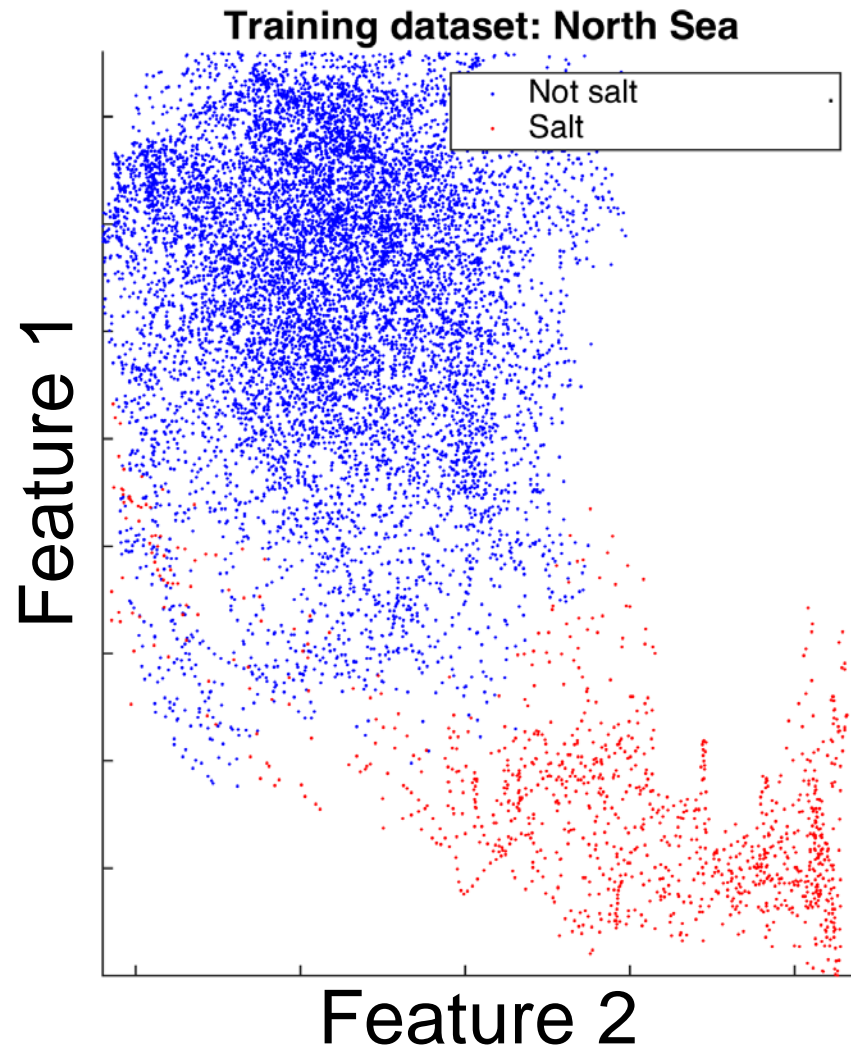
Feature 1



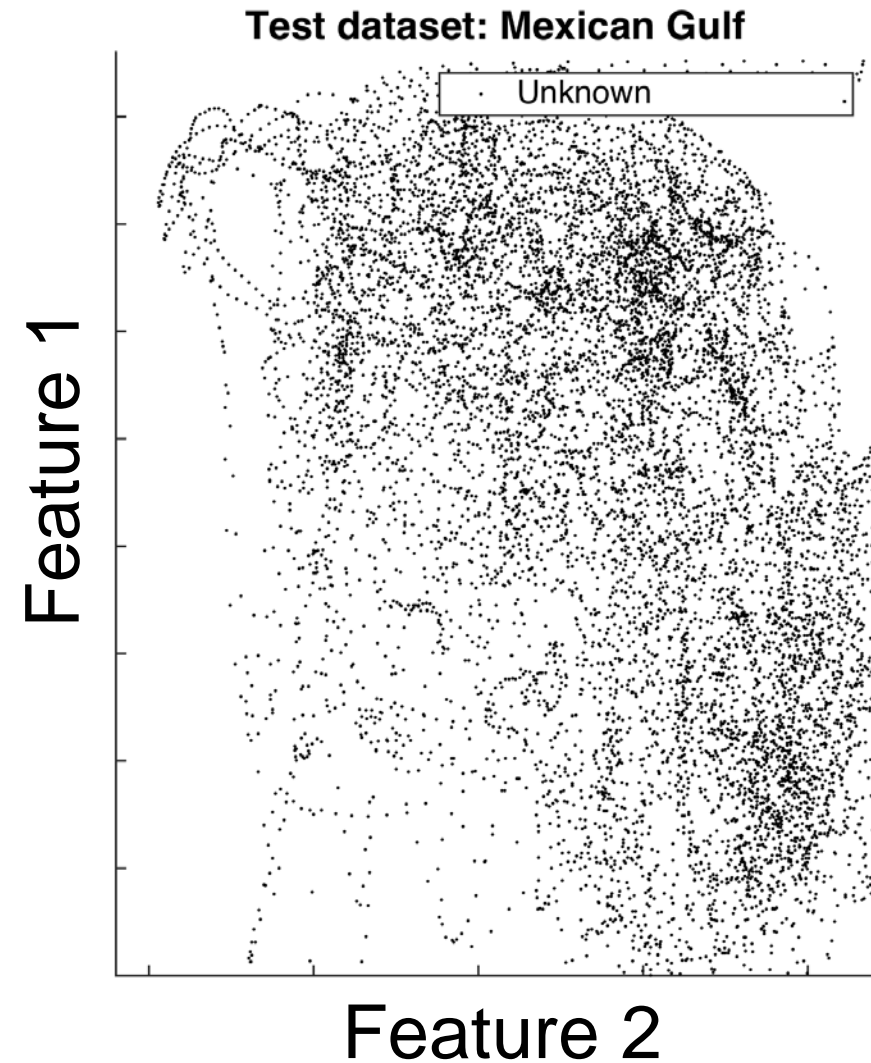
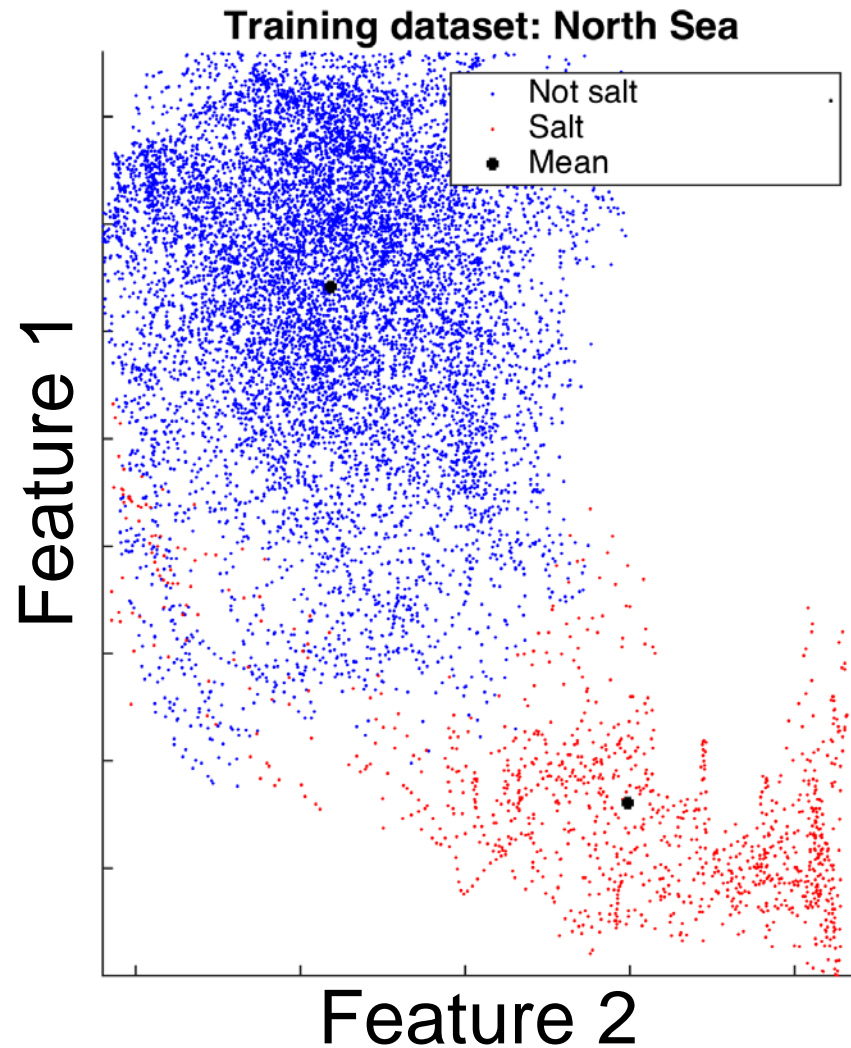
Feature 2



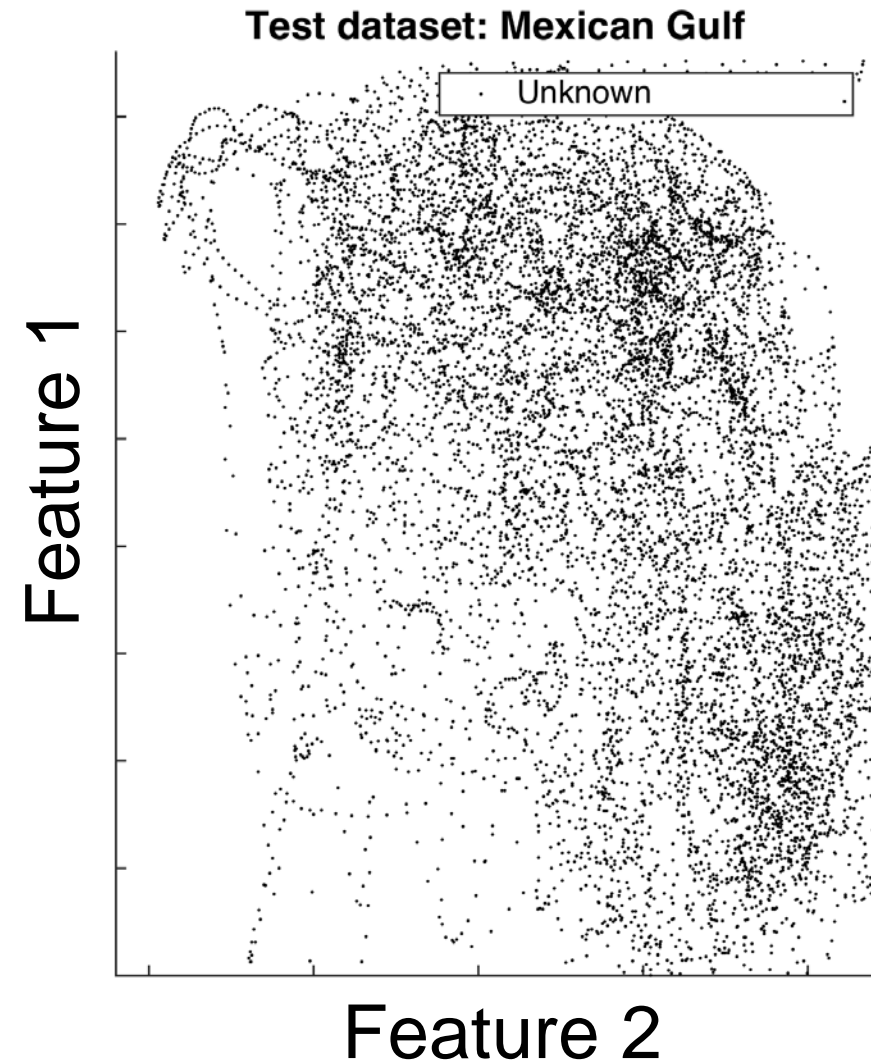
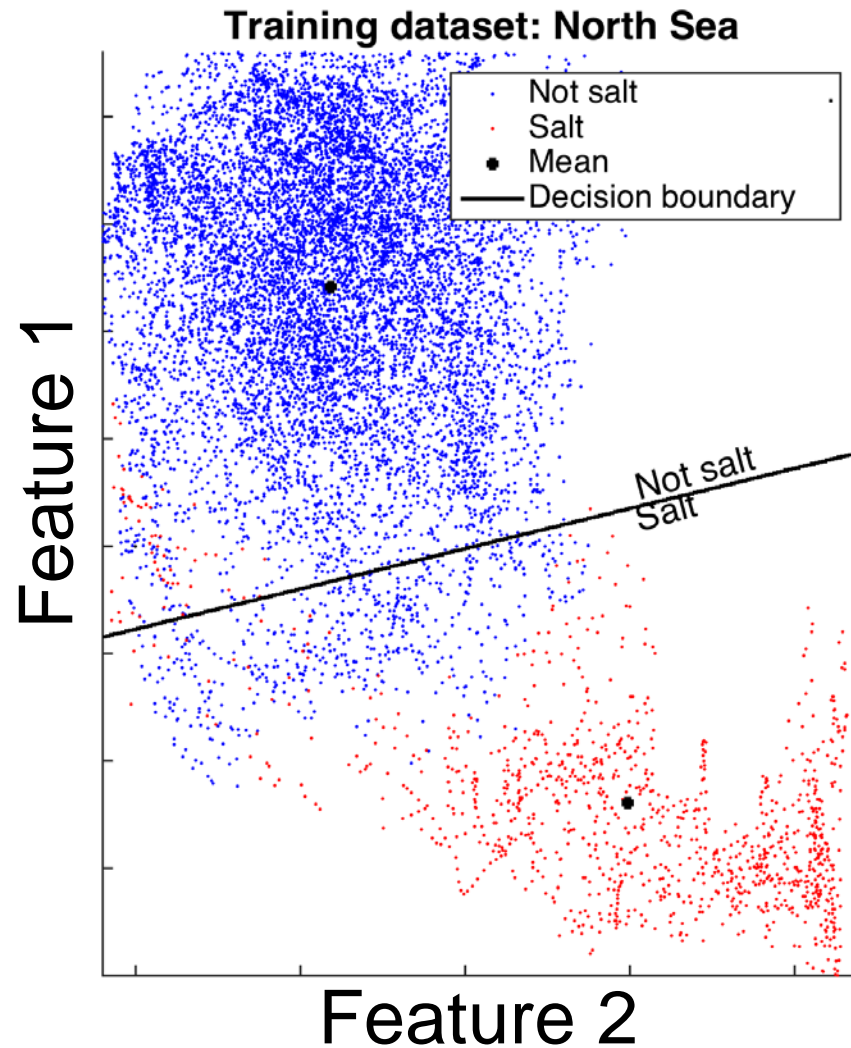
Training a classifier



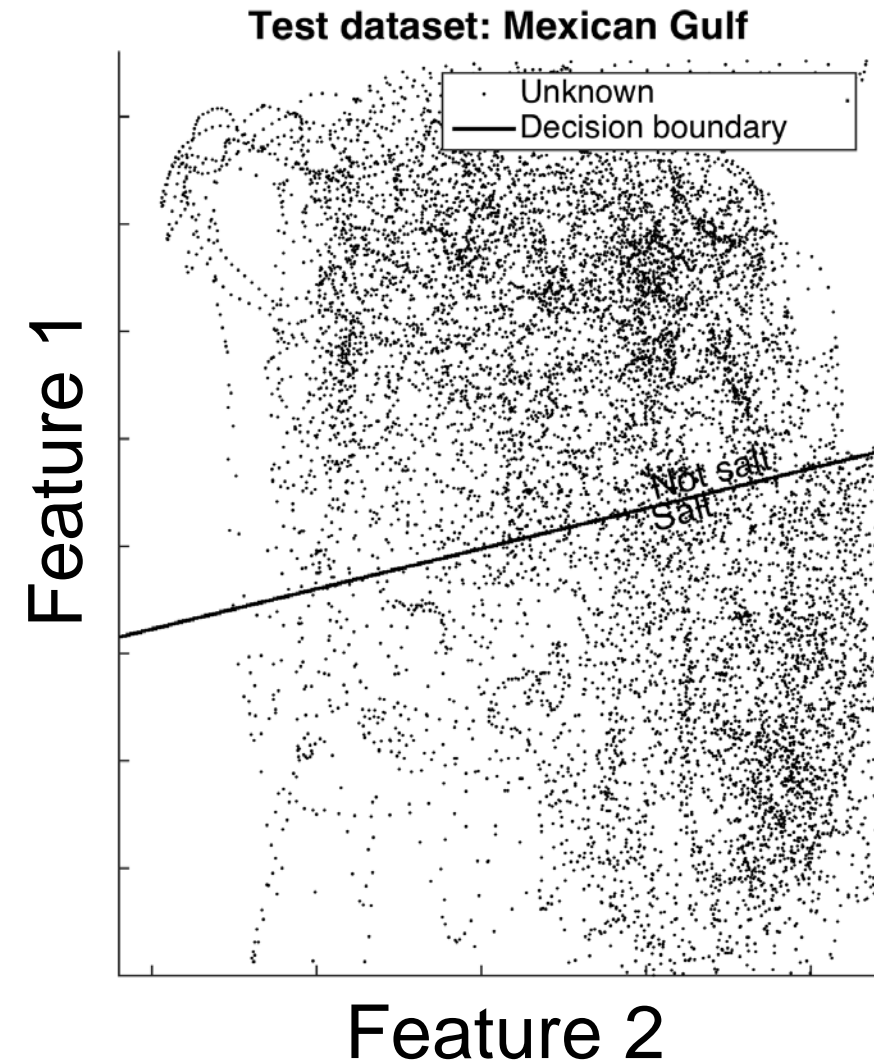
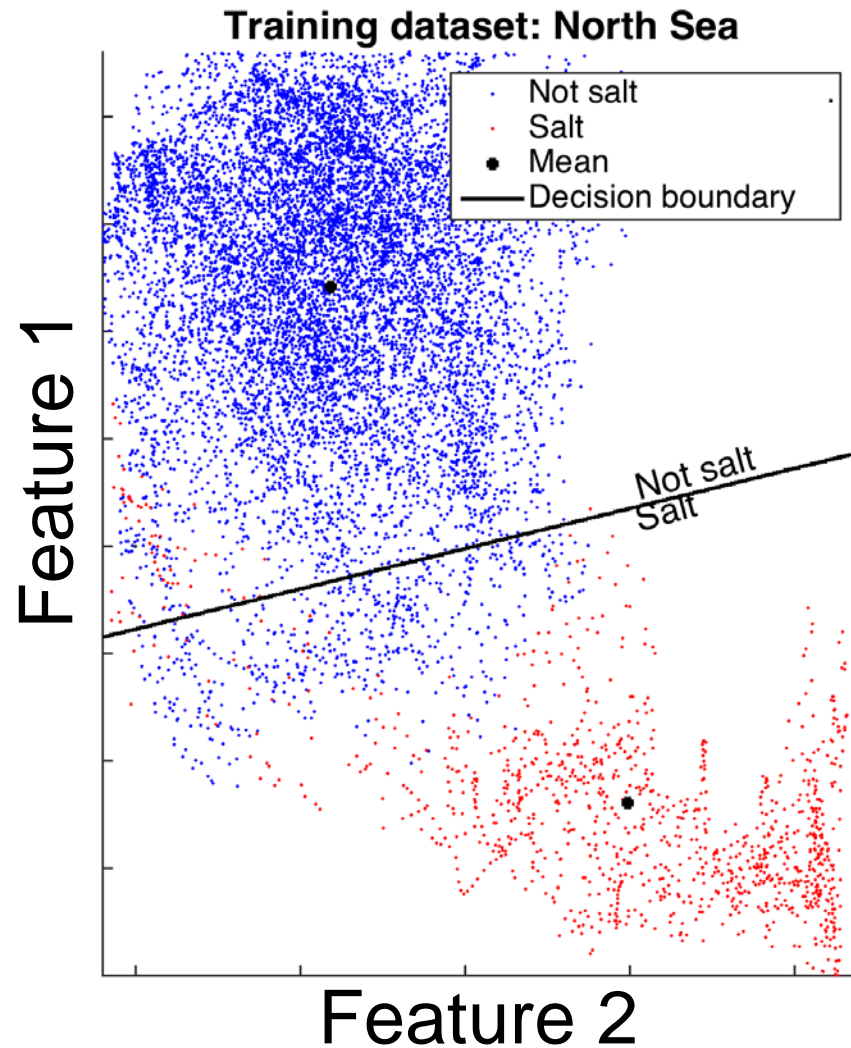
Training a classifier



Training a classifier



Training a classifier



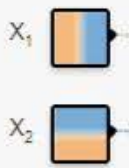
Neural network classifier

Epoch 000,000 Learning rate 0.03 Activation Sigmoid Regularization None Regularization rate 0 Problem type Classification

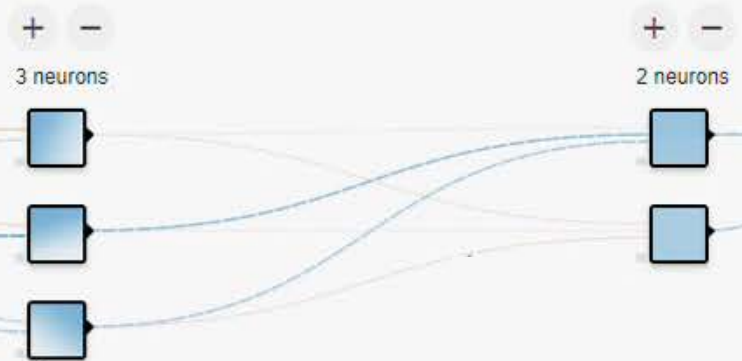
DATA



FEATURES

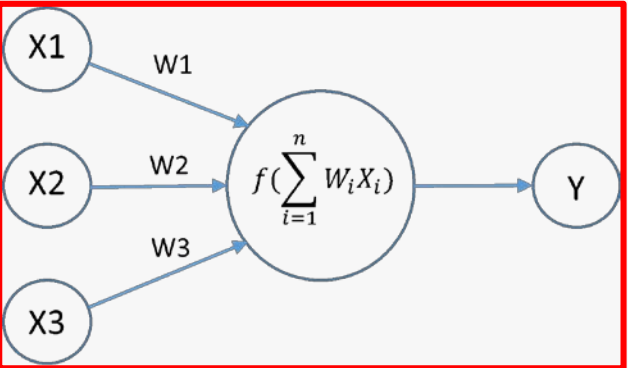
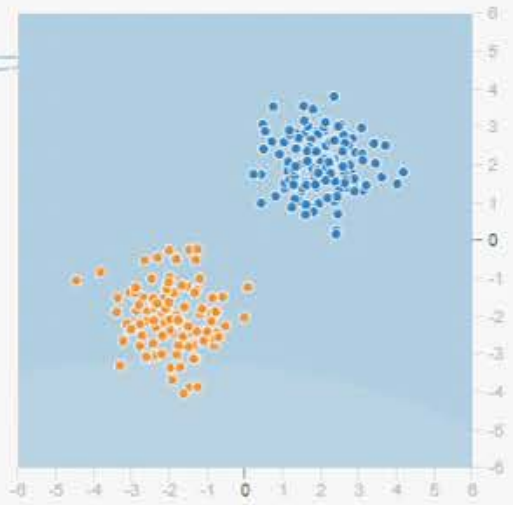


HIDDEN LAYERS



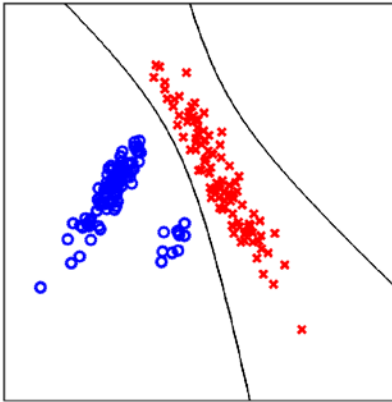
OUTPUT

Test loss 0.619
Training loss 0.551

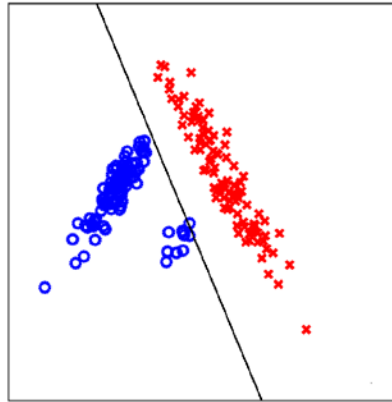


Different types of classifiers

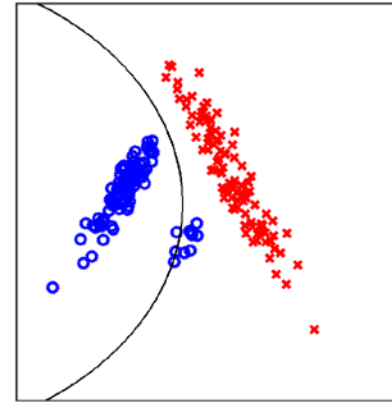
Quadratic



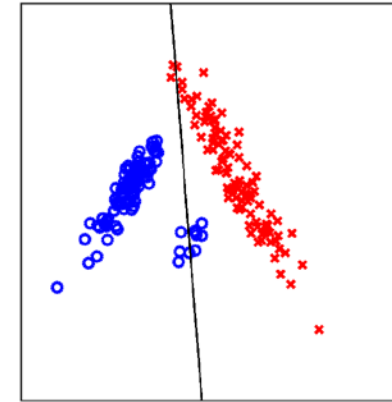
Linear



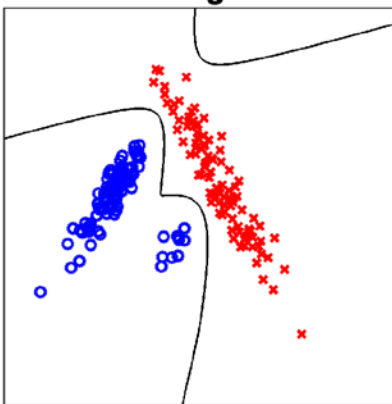
Uncorrelated



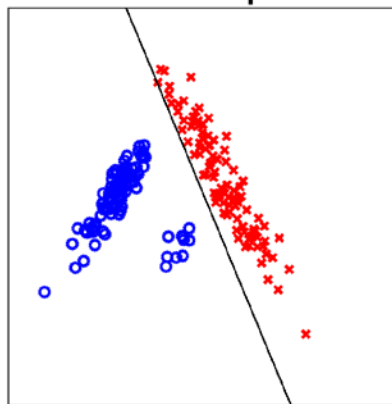
Nearest mean



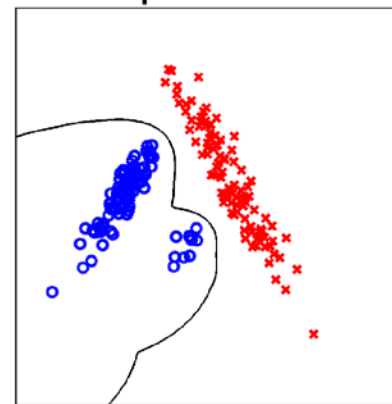
M. O. Gaussians



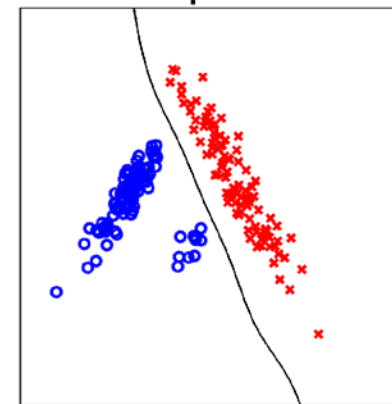
Fisher



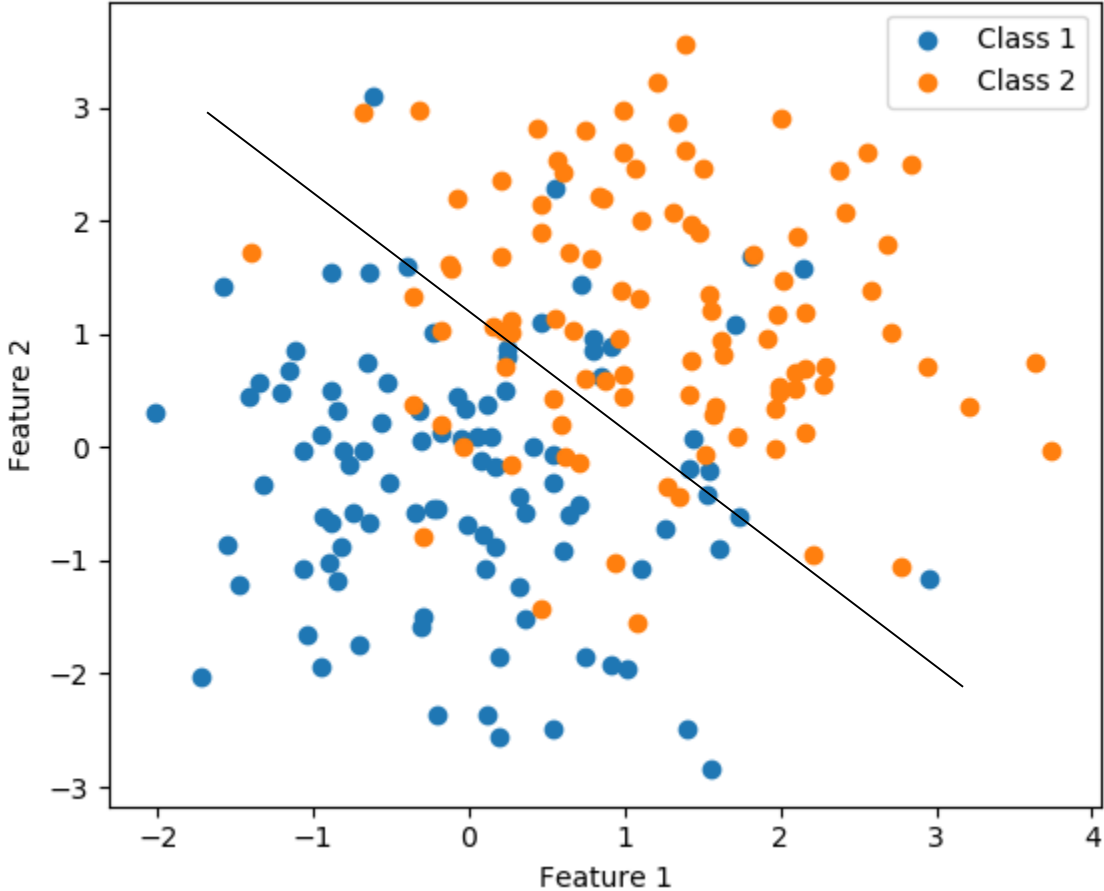
Parzen window



Neural network



What if the features are bad?



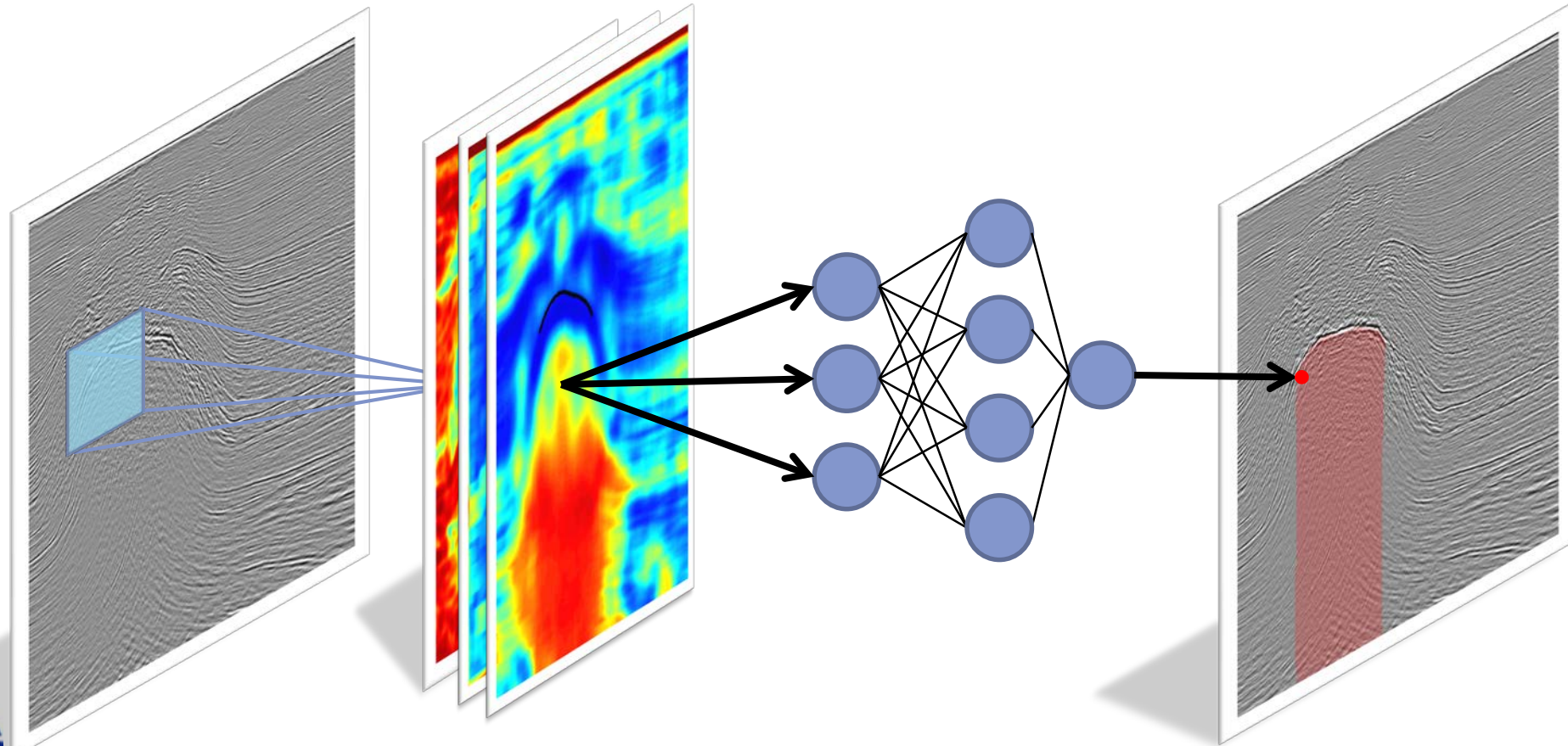
Traditional machine learning

Input

Features

Classifier

Prediction

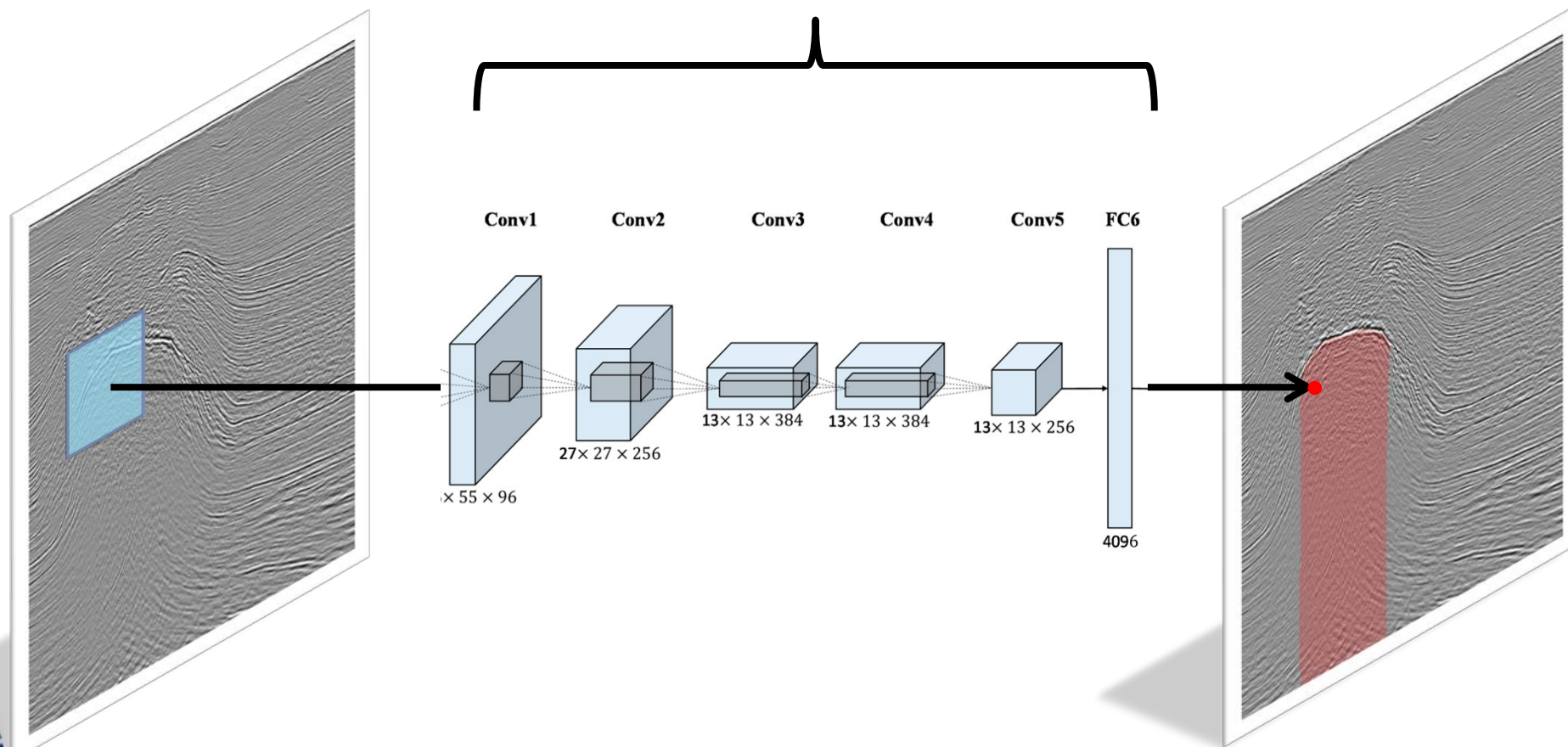


Deep Learning

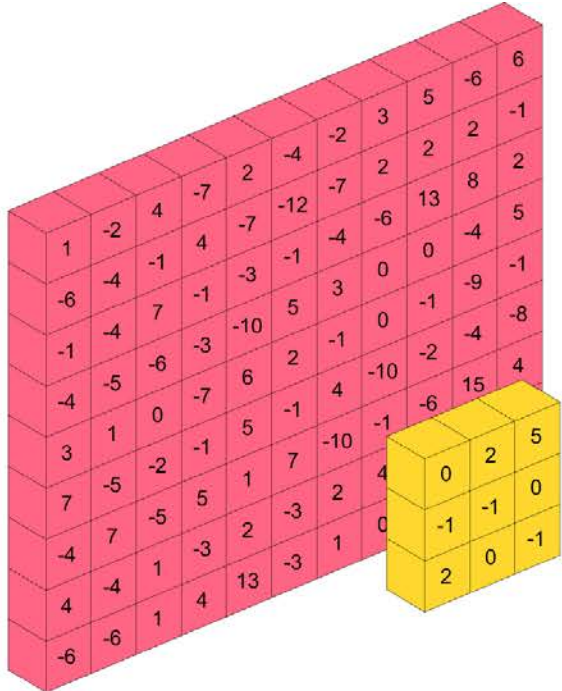
Input

Convolutional Neural Network (CNN)

Predicted salt



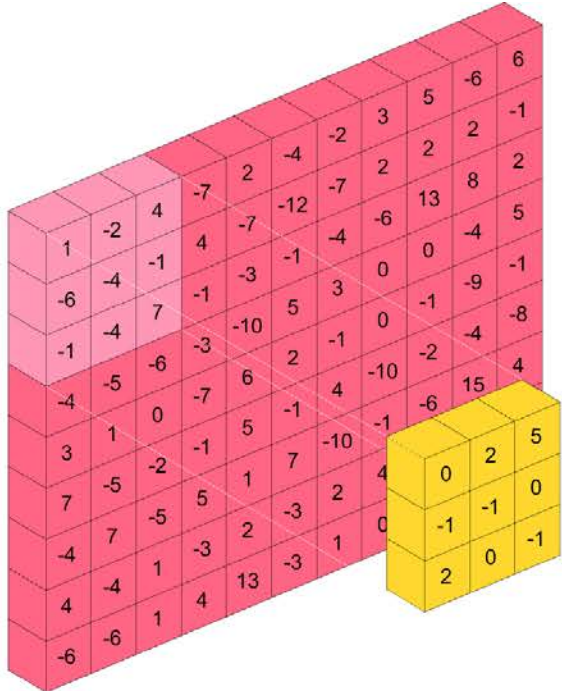
Convolution



Input

Filter

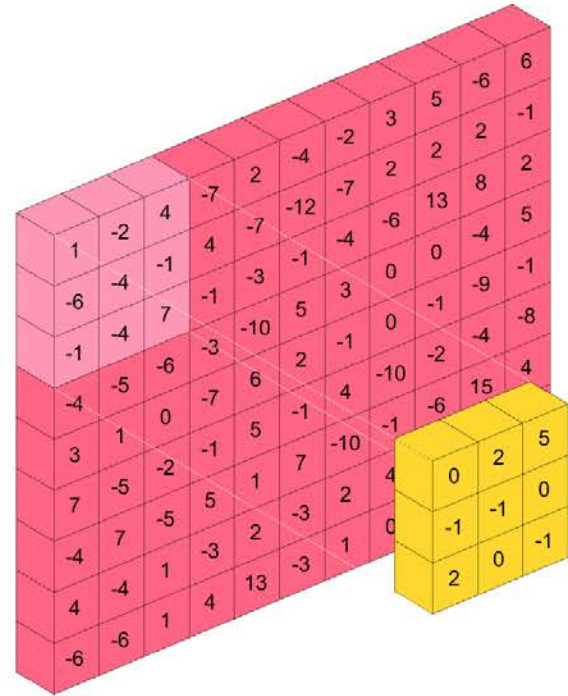
Convolution



Input

Filter

Convolution

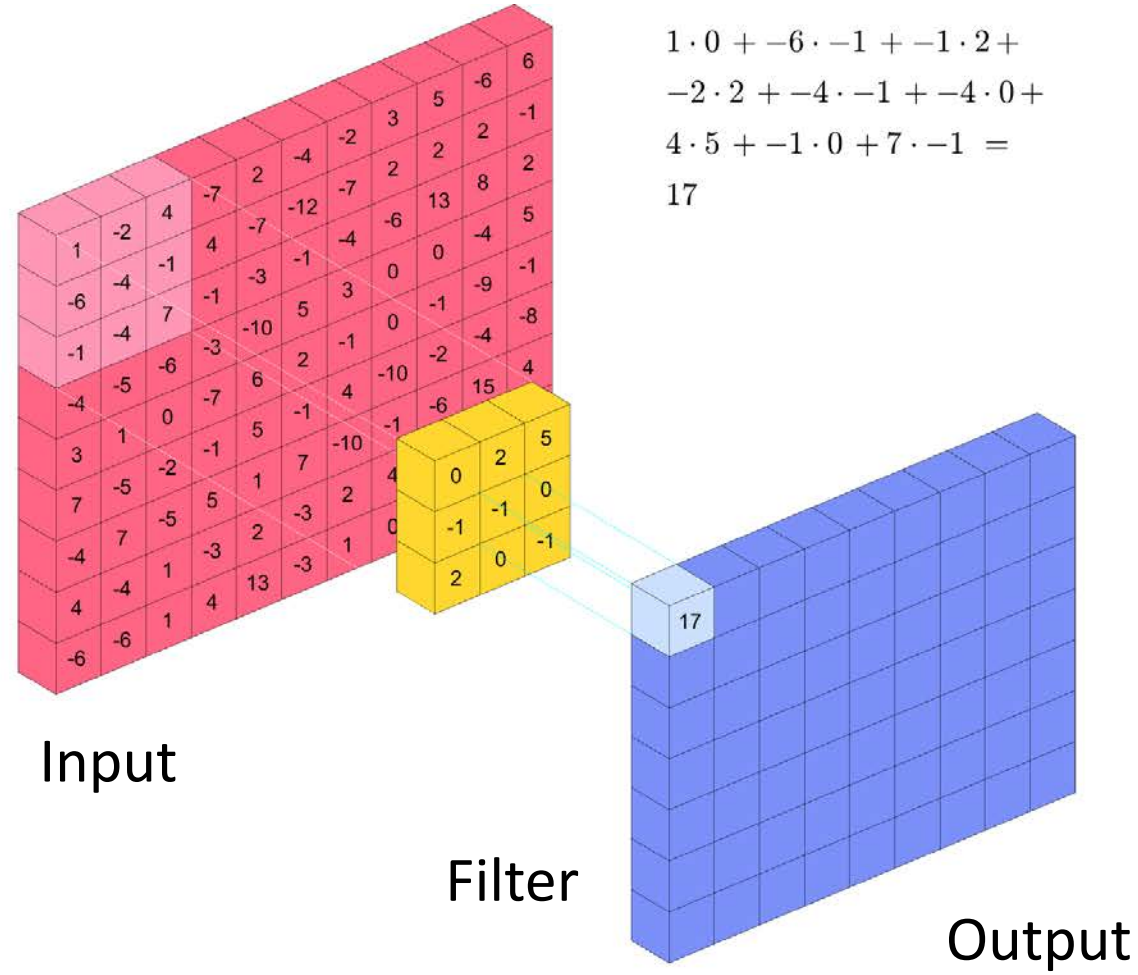


Input

Filter

$$\begin{aligned} &1 \cdot 0 + -6 \cdot -1 + -1 \cdot 2 + \\ &-2 \cdot 2 + -4 \cdot -1 + -4 \cdot 0 + \\ &4 \cdot 5 + -1 \cdot 0 + 7 \cdot -1 = \\ &17 \end{aligned}$$

Convolution



Convolution

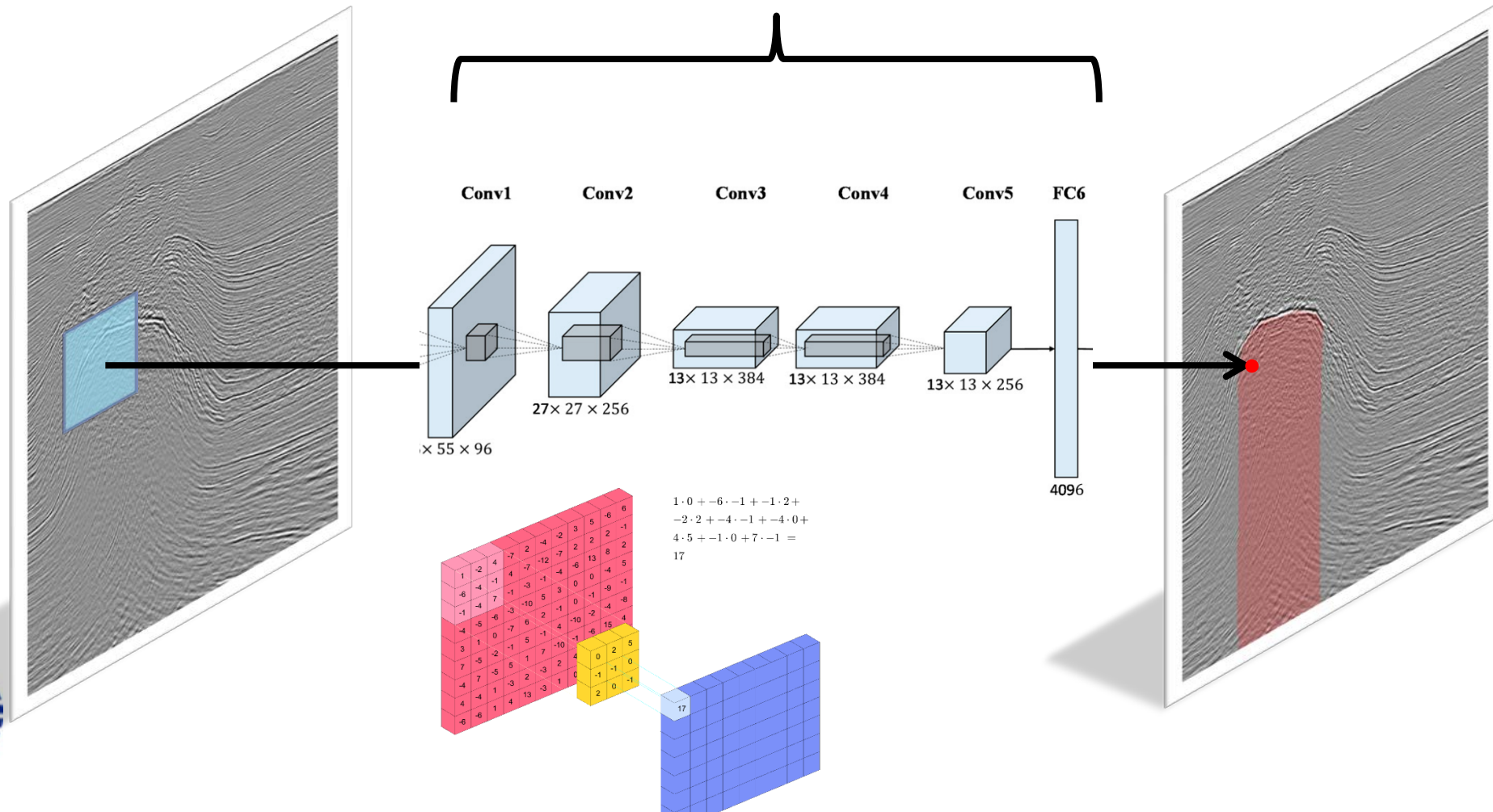


Deep Learning

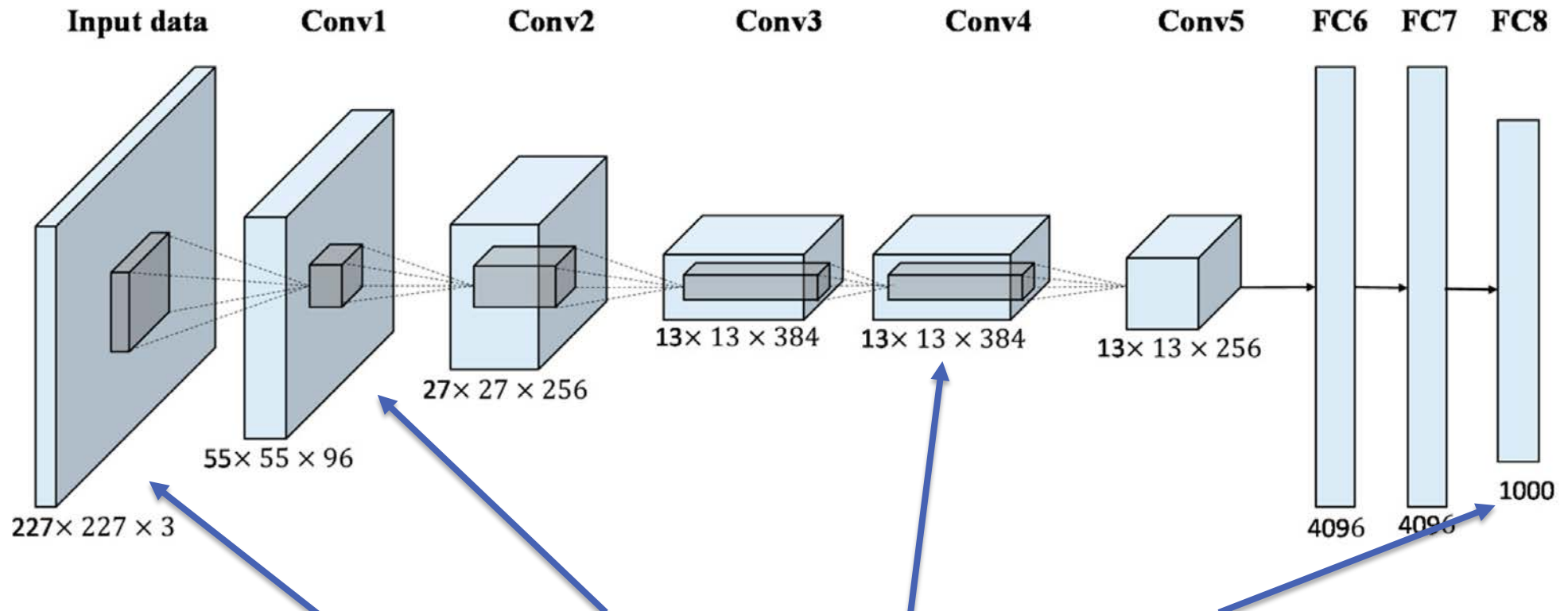
Input

Convolutional Neural Network (CNN)

Predicted salt



CNNs learns high level features

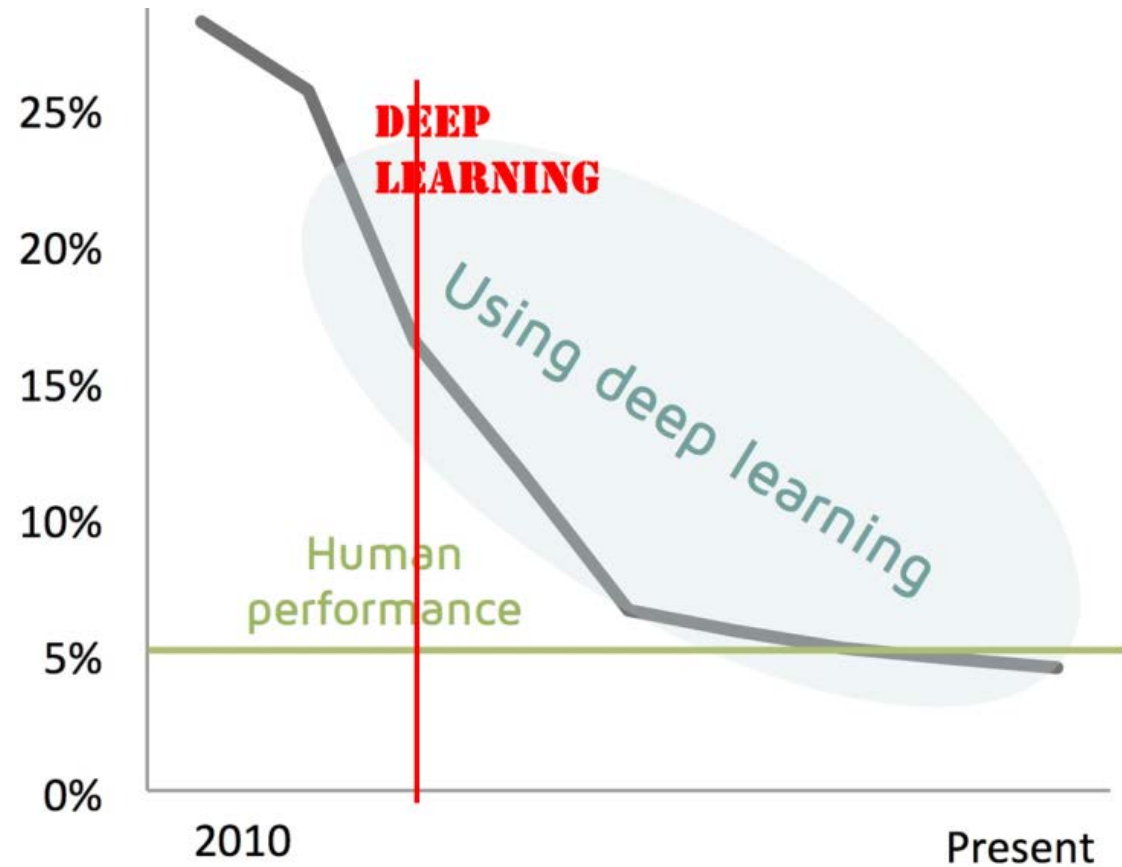


Deep learning

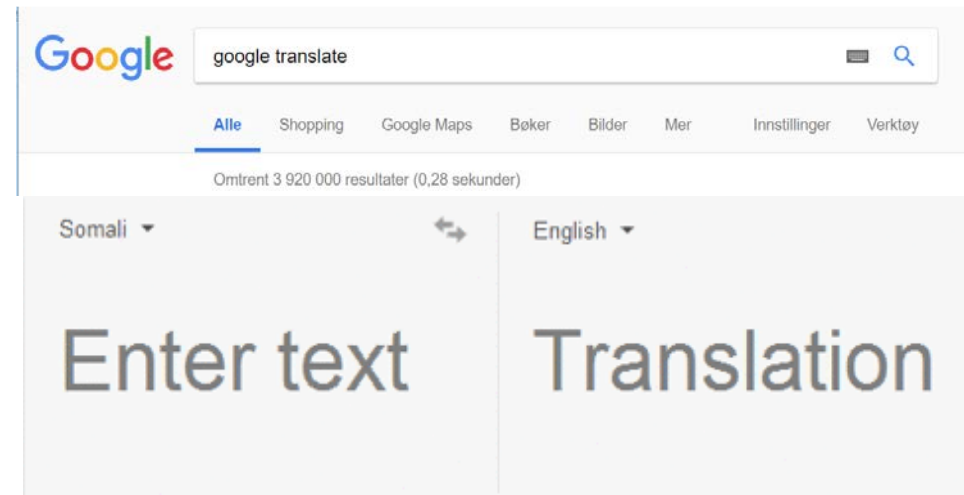
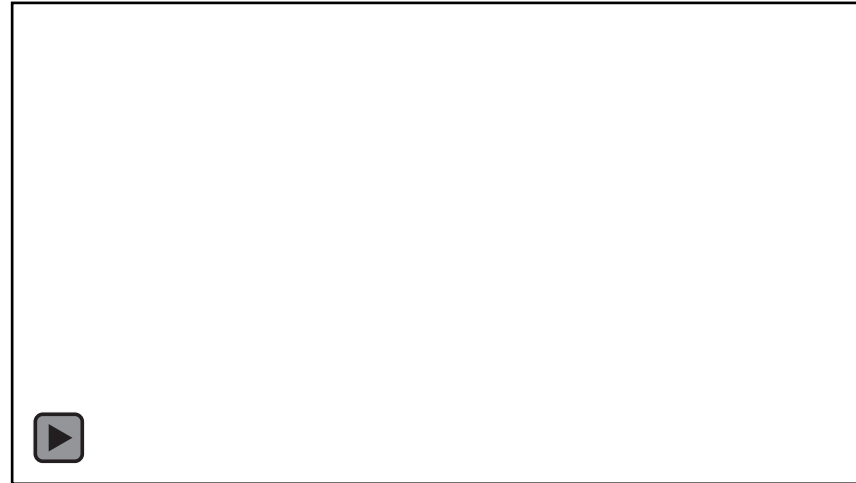
- a revolution in computer vision



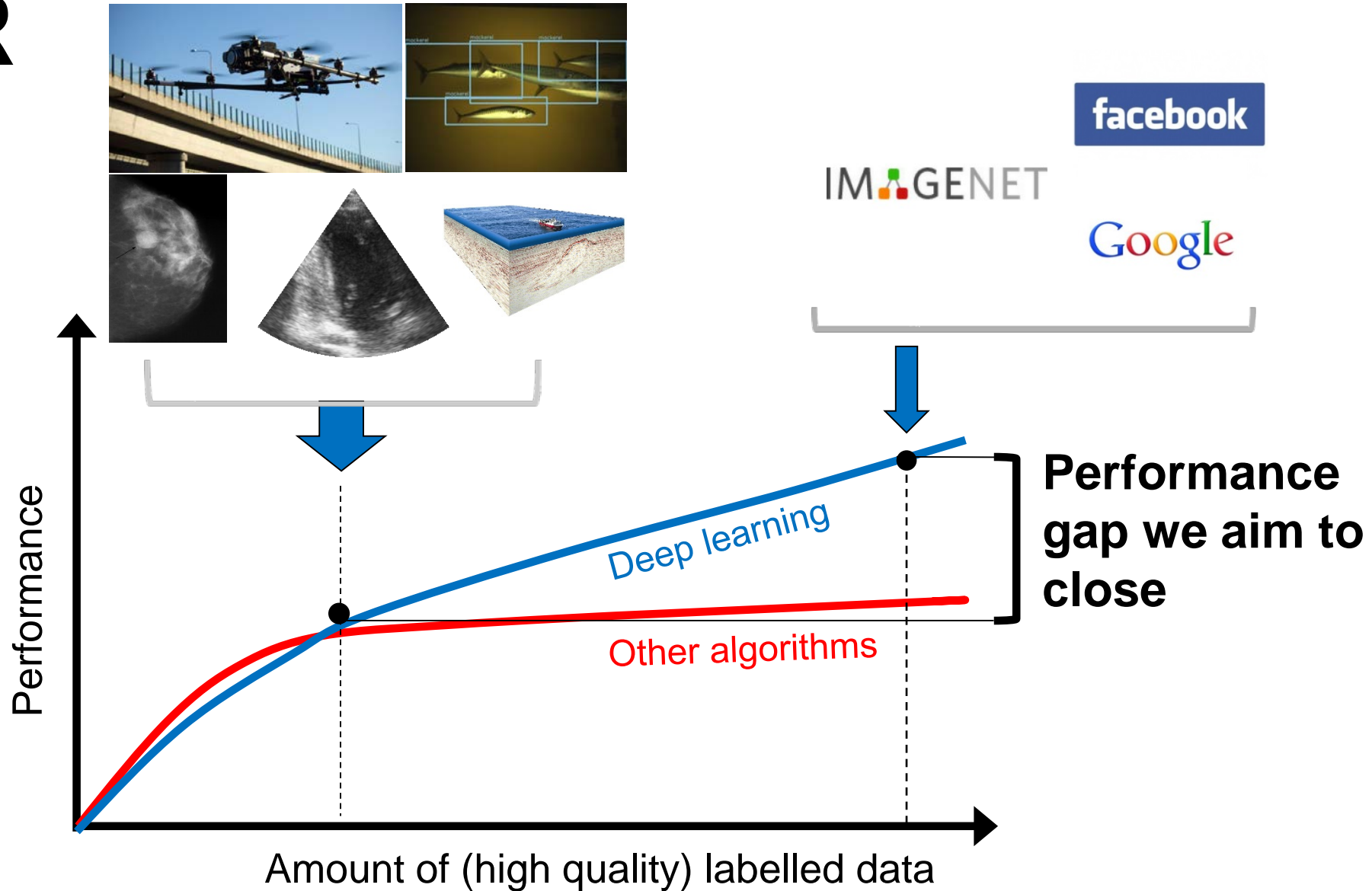
- ▶ Much higher accuracy
- ▶ Much more training data



Deep learning is pushing AI



Research challenges we aim to solve at NR



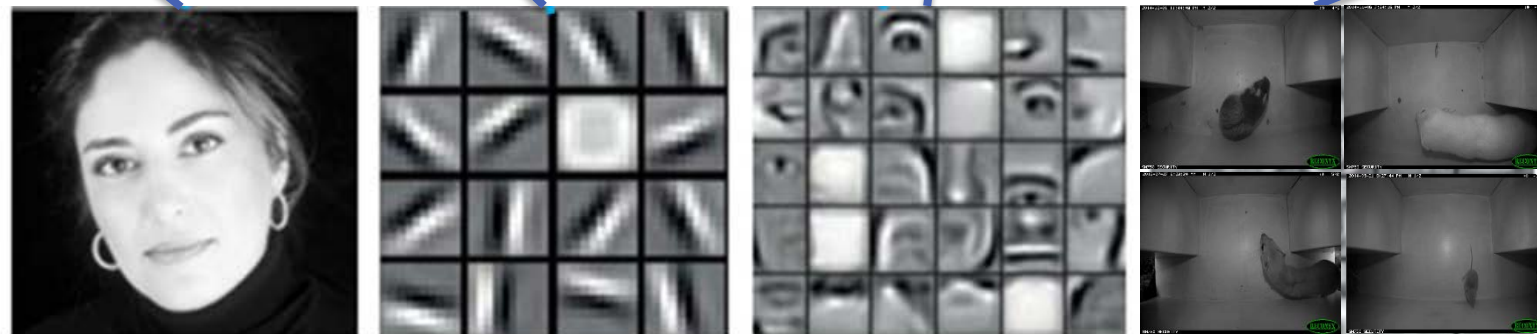
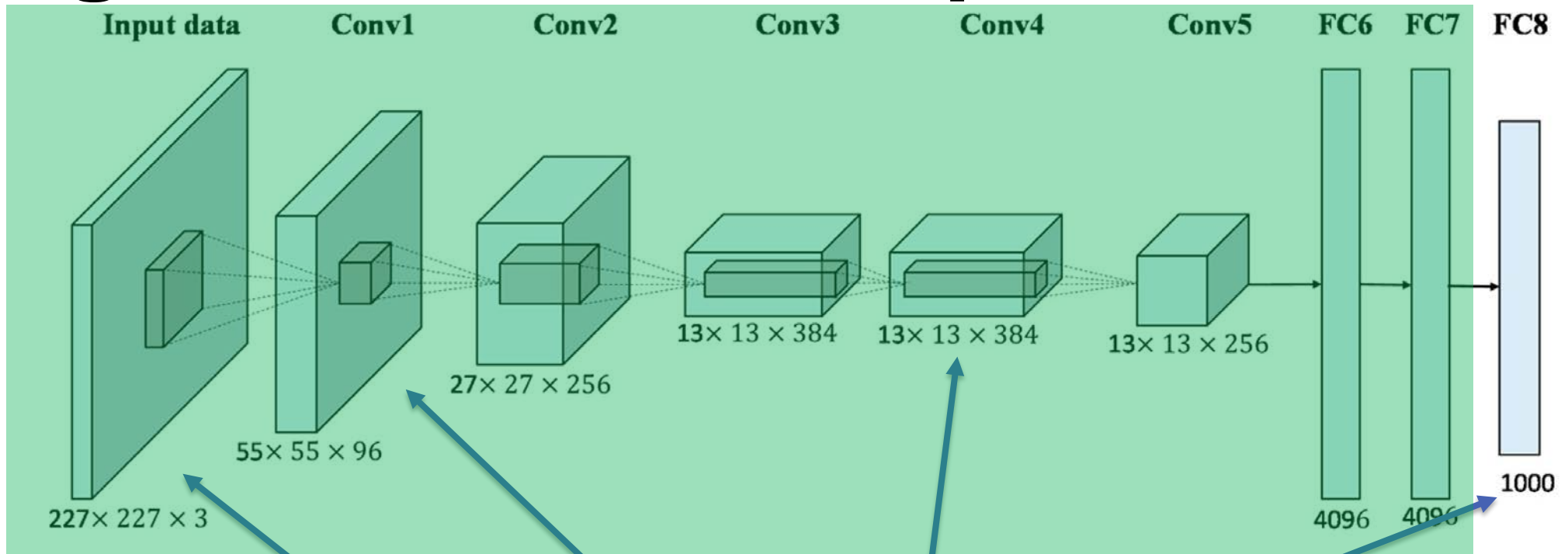
NR experiment: Recognition of animal species

Goal: Predict the species in the box

Challenge: around 1500 labelled images



NR experiment: Recognition of animal species



NR experiment: Recognition of animal species



NR experiment: Recognition of animal species

Confusion table:

	Predicted									
True	1	2	3	4	5	6	7	8	9	10
1: Røyskatt (192)	188.	0.	2.	1.	0.	1.	0.	0.	0.	0.
2: Fugl (120)	0.	120.	0.	0.	0.	0.	0.	0.	0.	0.
3: Spissmus (191)	0.	0.	186.	0.	2.	0.	0.	0.	0.	3.
4: Snømus (60)	3.	0.	1.	56.	0.	0.	0.	0.	0.	0.
5: Snø (196)	0.	0.	2.	0.	192.	0.	0.	0.	2.	0.
6: Lemen (212)	0.	0.	0.	0.	0.	211.	0.	1.	0.	0.
7: Rusk (223)	0.	0.	3.	0.	0.	0.	217.	1.	1.	1.
8: Vole (254)	1.	0.	1.	0.	0.	0.	3.	249.	0.	0.
9: Vann (157)	0.	0.	0.	0.	0.	0.	0.	0.	157.	0.
10: Tomt (211)	0.	0.	0.	0.	0.	0.	1.	0.	0.	210.

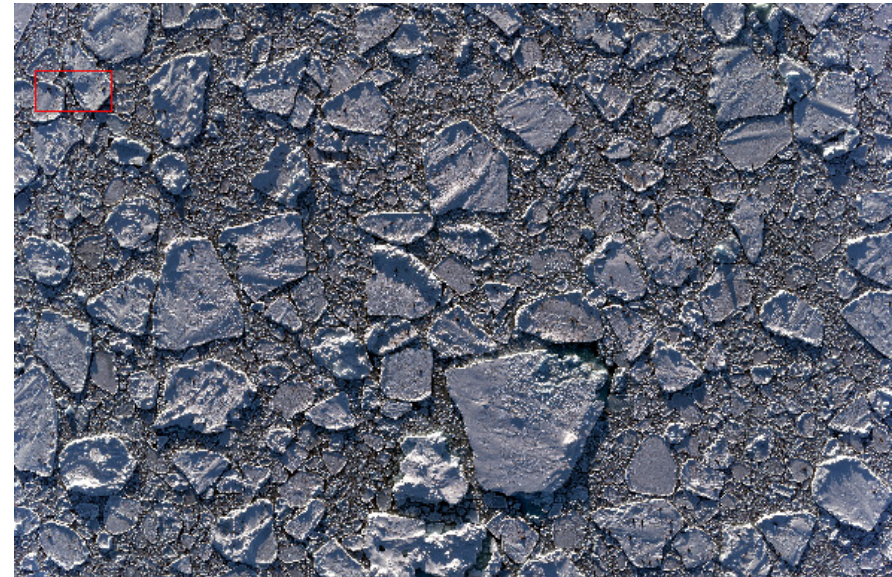
Correct recognition rate = **98.3%**

NR experiment: Recognition of animal species

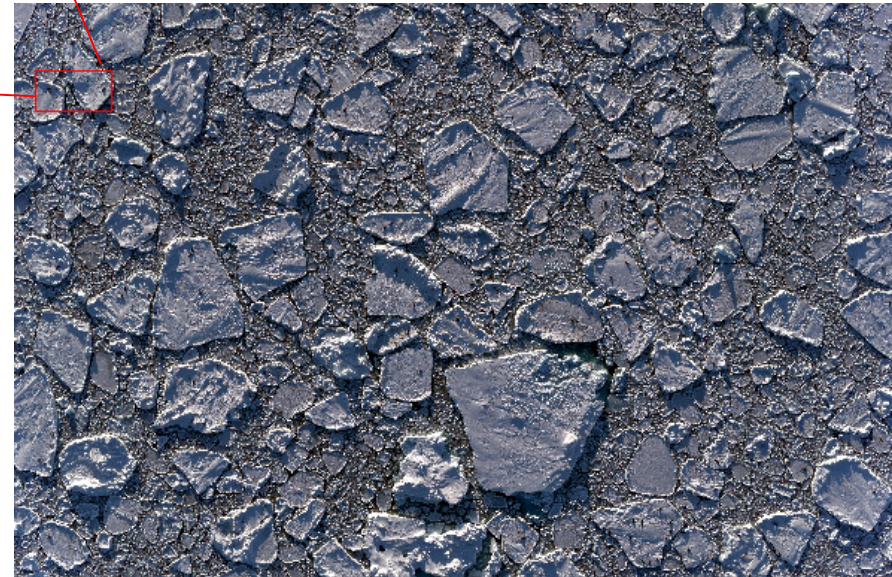
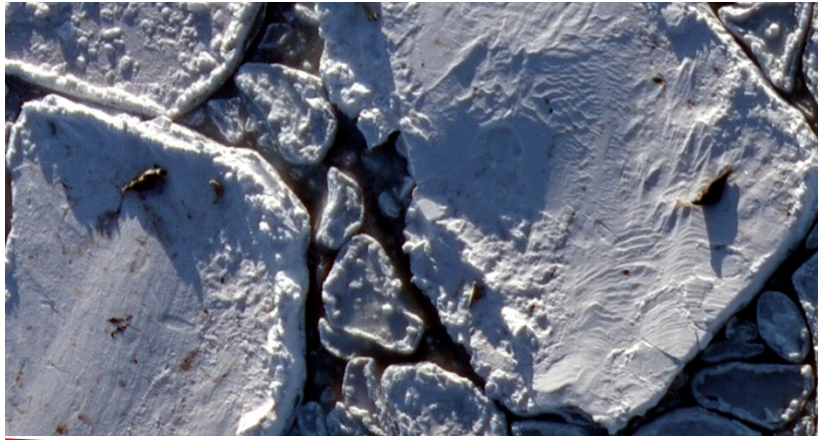


NR-project: Seal detection

Havforsknings Instituttet – Marine Research Institute



NR-project: Seal detection



The challenge is that we have several thousands of large images covering sea ice.

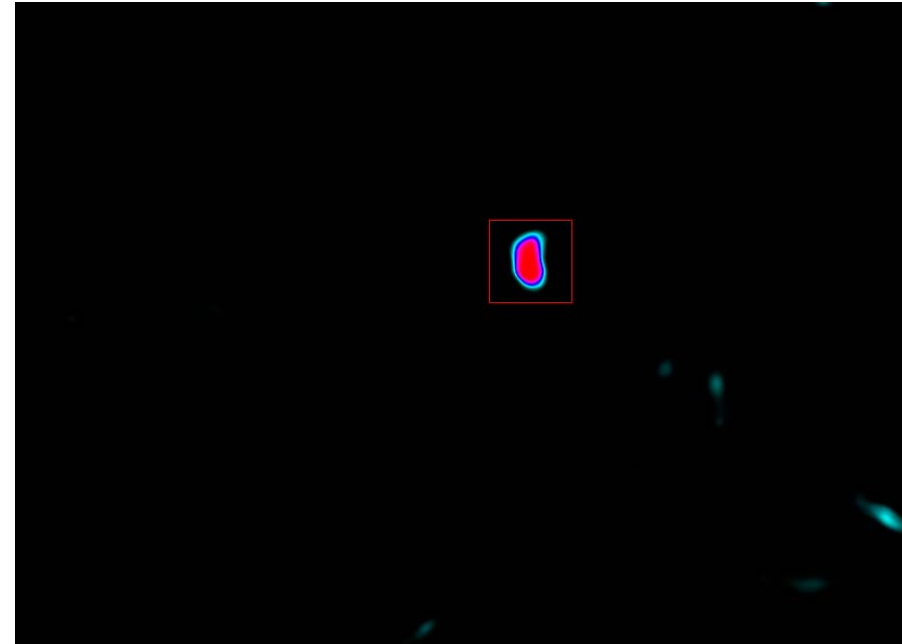
NR-project: Seal detection

- ▶ Dataset from the West Ice 2007 & 2012 and Canada 2012
- ▶ About 10000 seal pups (9000 harp seals and 1000 hooded seals) have been identified.
- ▶ About 90000 background images



Some results

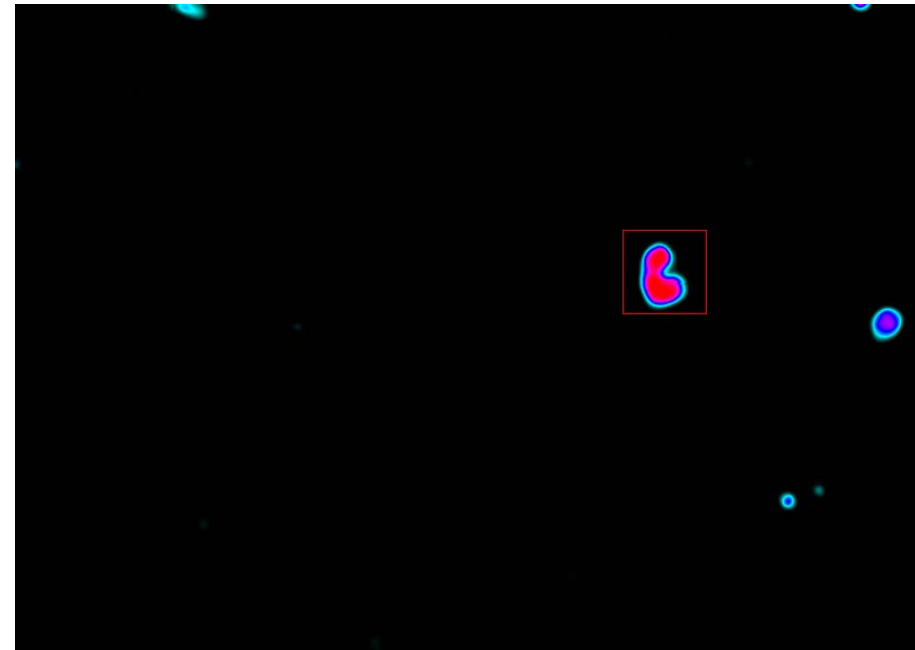
Accuracy 3 classes (background, harp, hood): **99.7%**



Heat map

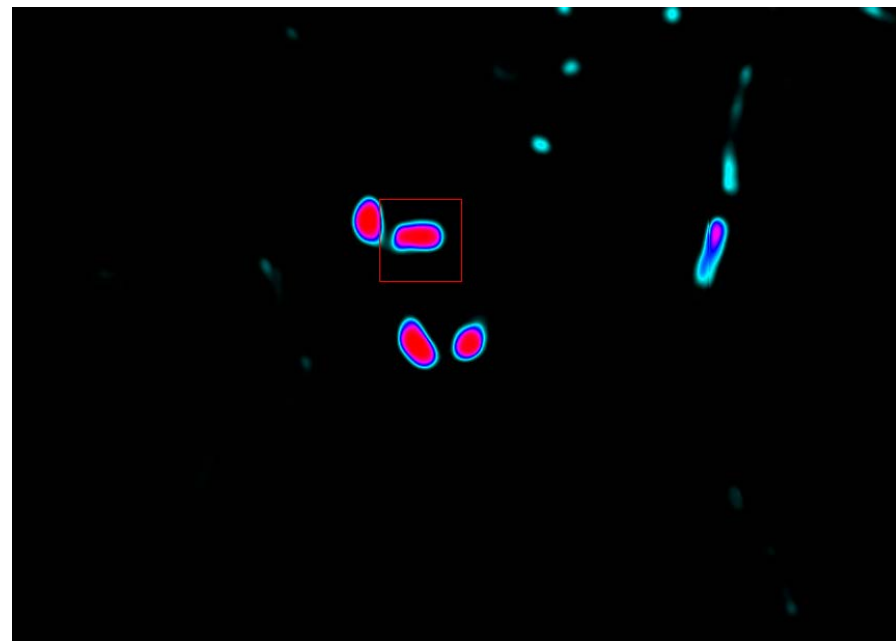
Some results

Accuracy 3 classes (background, harp, hood): **99.7%**



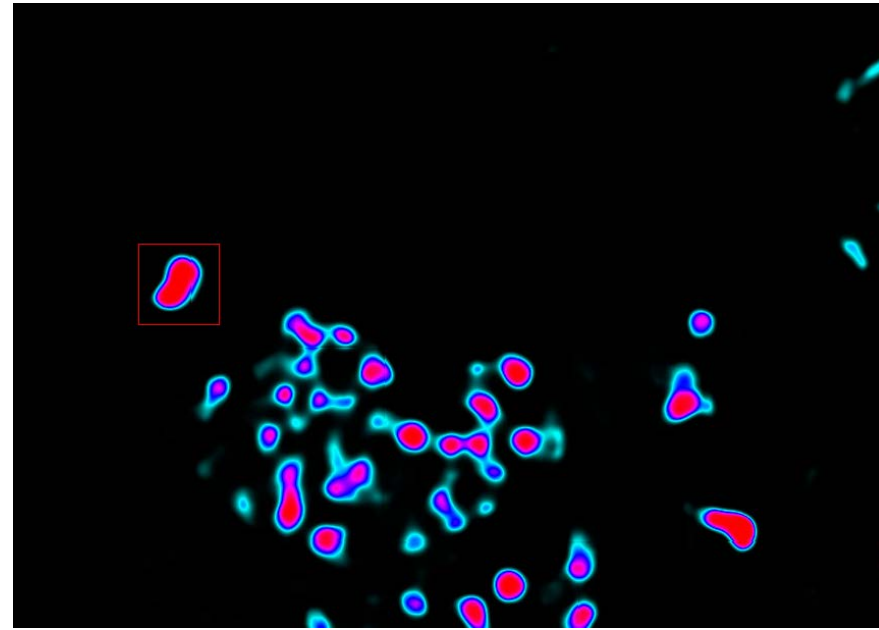
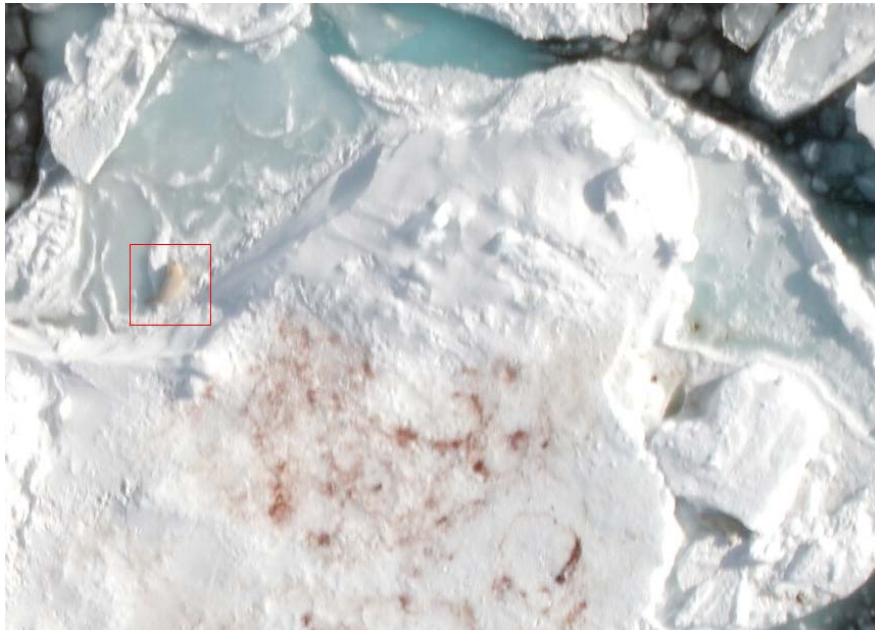
Some results

Accuracy 3 classes (background, harp, hood): **99.7%**

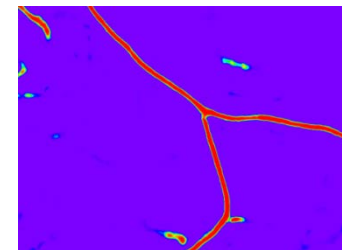
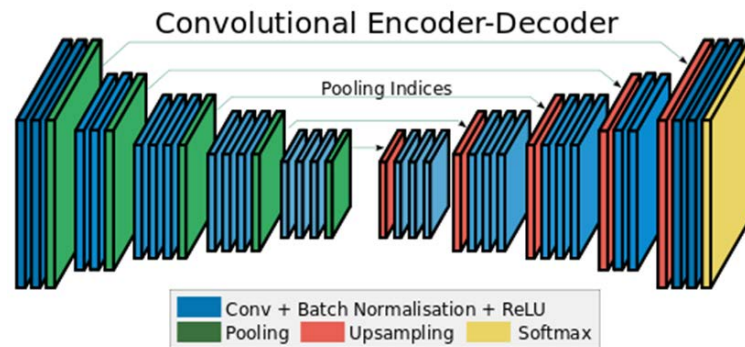
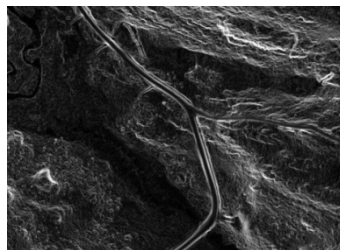
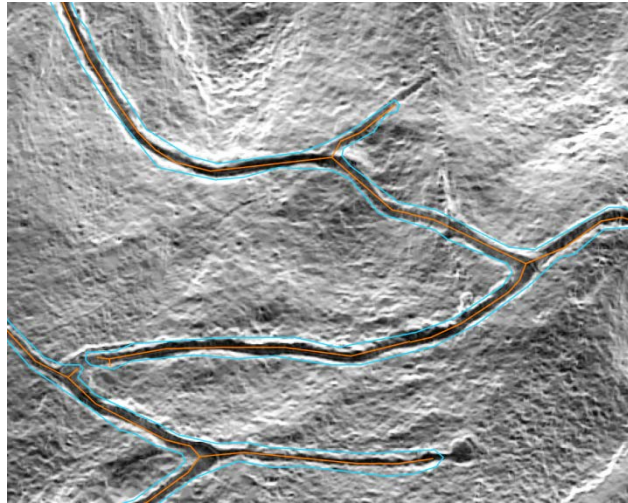


Some results

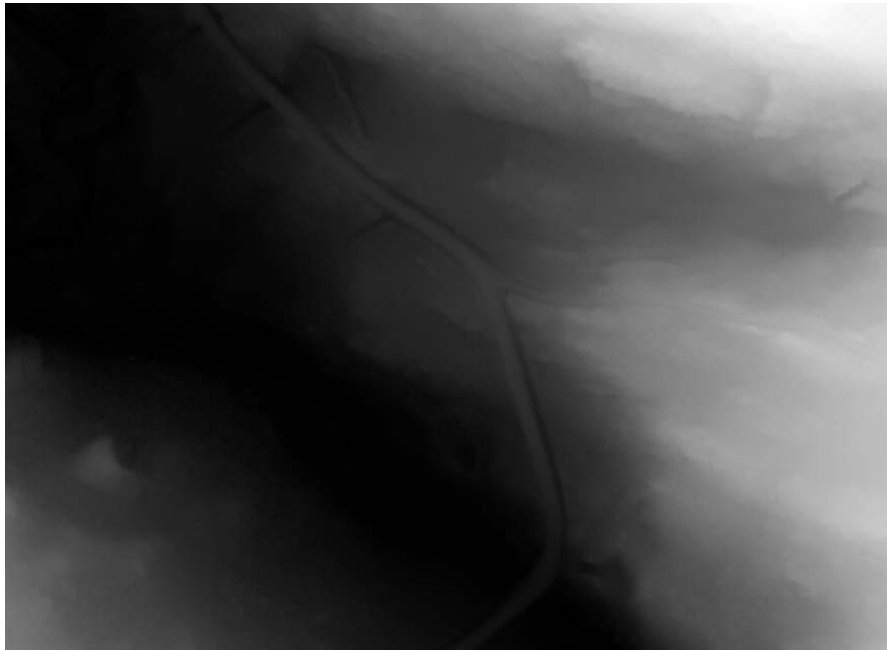
Accuracy 3 classes (background, harp, hood): **99.7%**



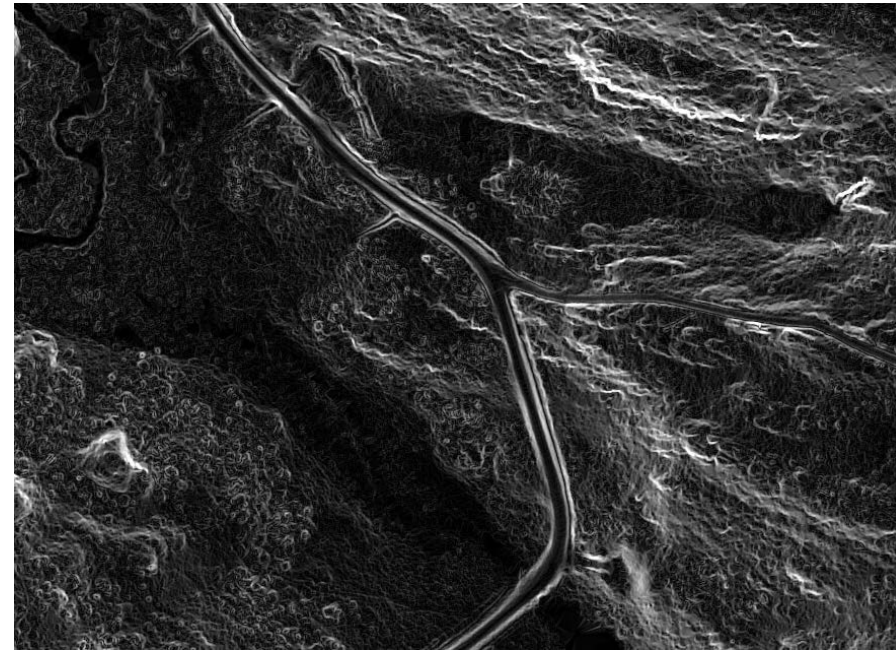
Mapping of roads from airborne laser scanning data



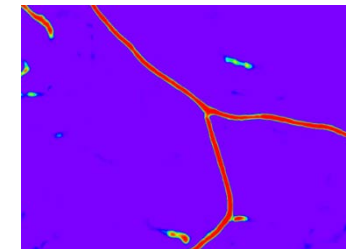
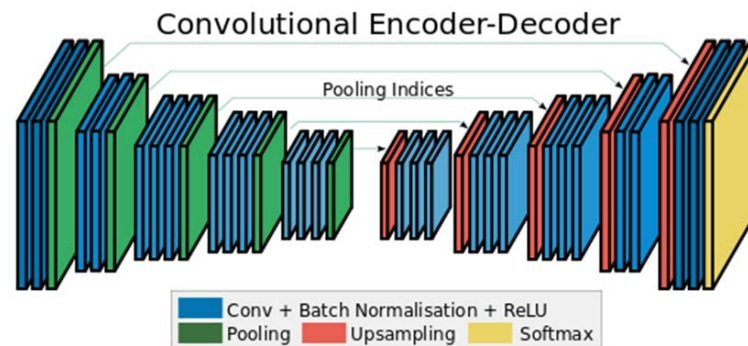
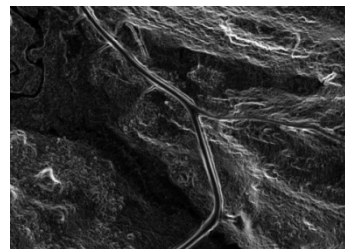
NR-project: Mapping of roads from airborne laser scanning data



Digital elevation model (DEM)



Gradient (slope) of the DEM



Results



Results

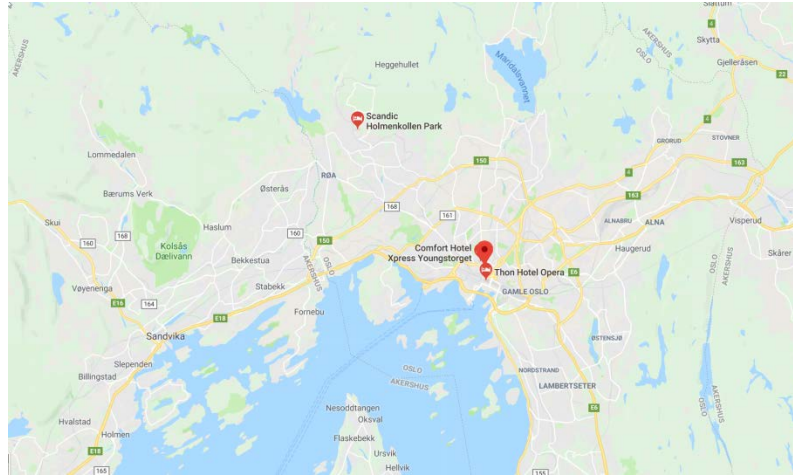


Results

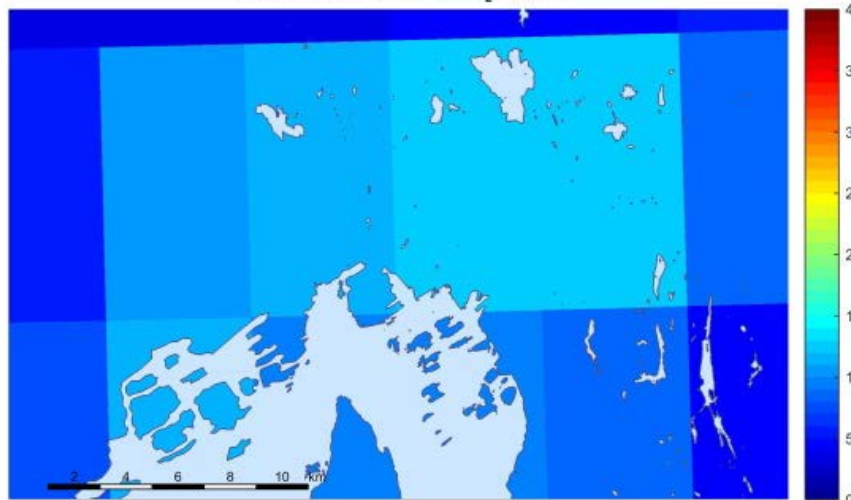


Airquip – Counting cars from satellites

Metrologisk institutt

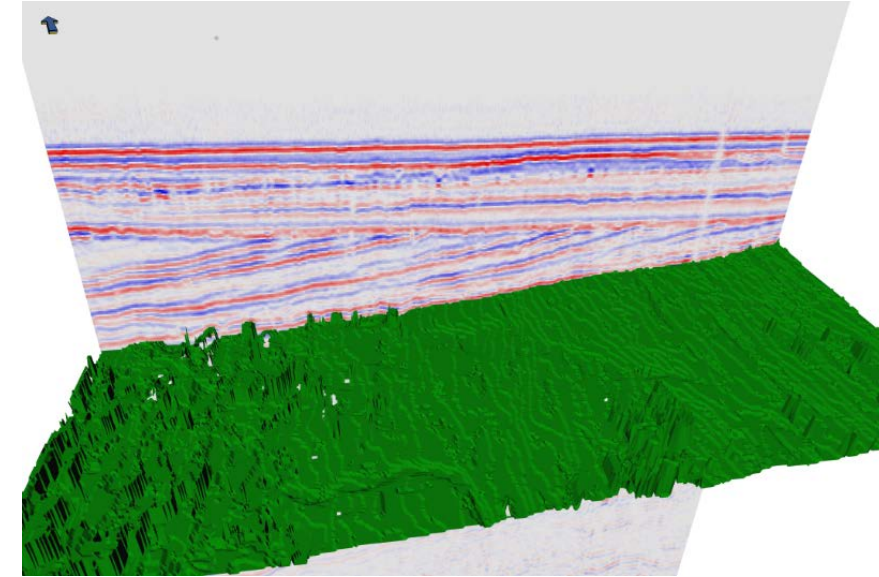
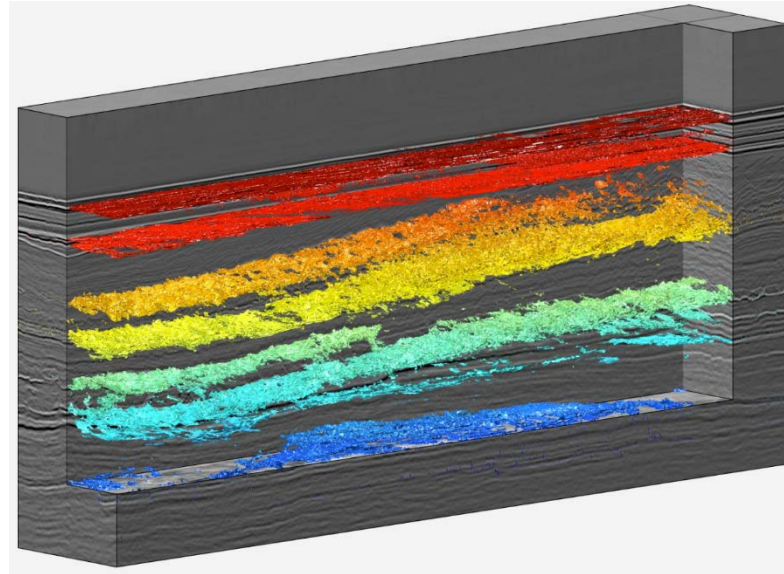
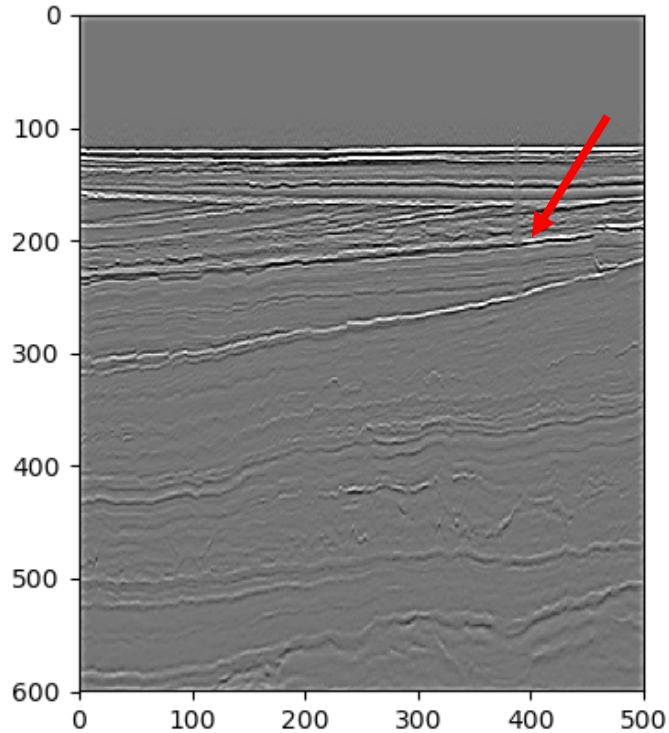


Oslo EMEP annual mean NO₂ (µg/m³)

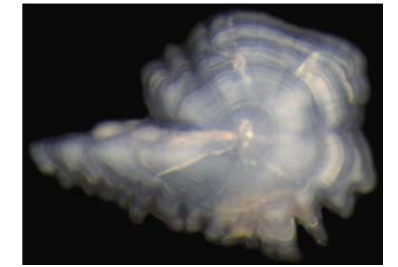
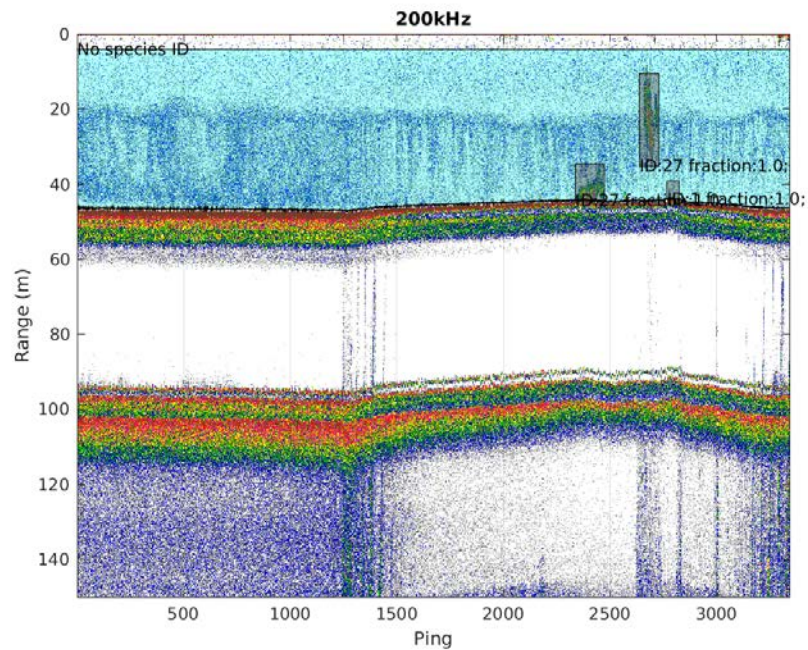
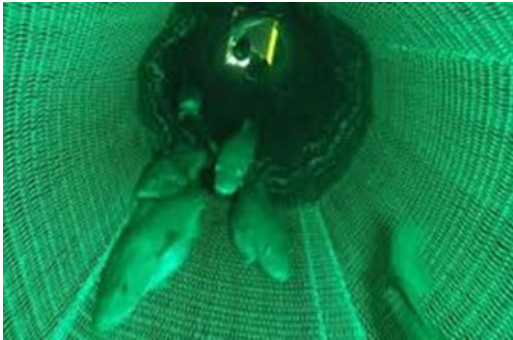


Meteorologisk institutt

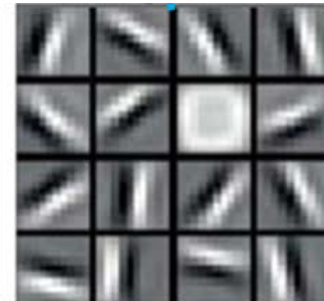
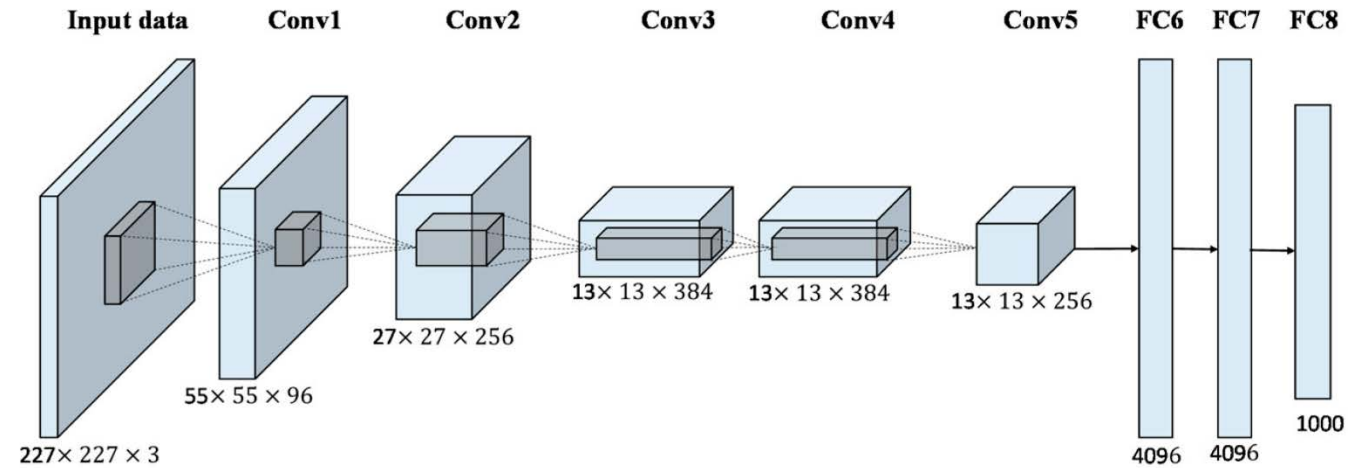
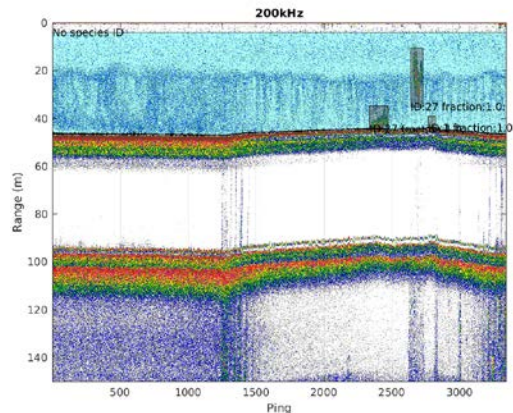
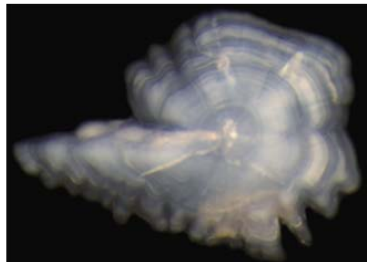
Extracting key horizons



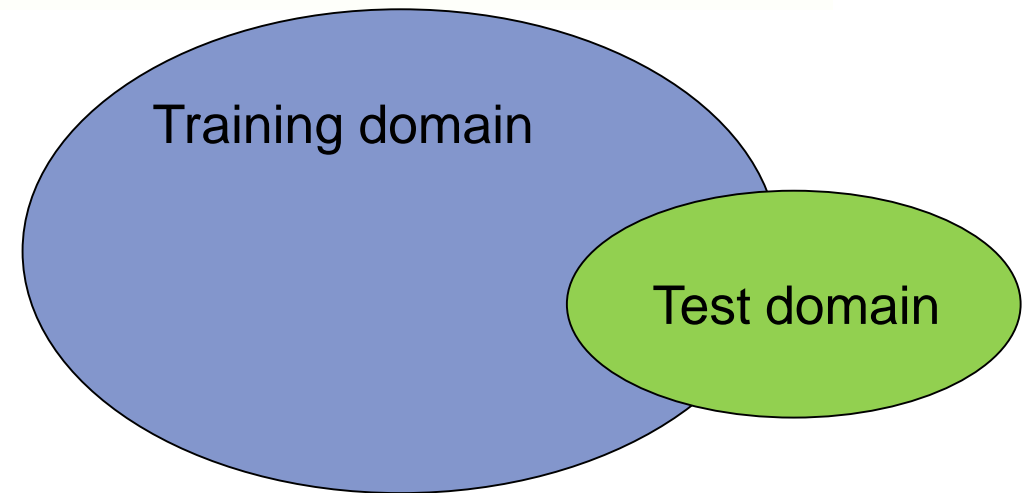
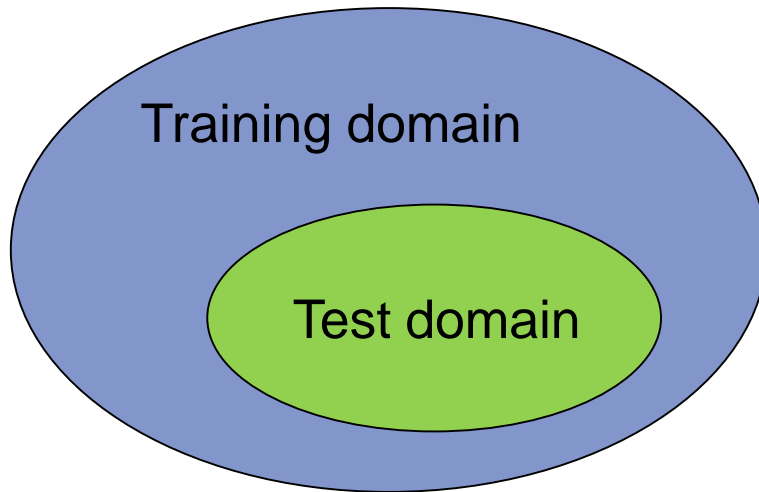
COGMAR: Image analysis for marine data



Problem: Transfer learning



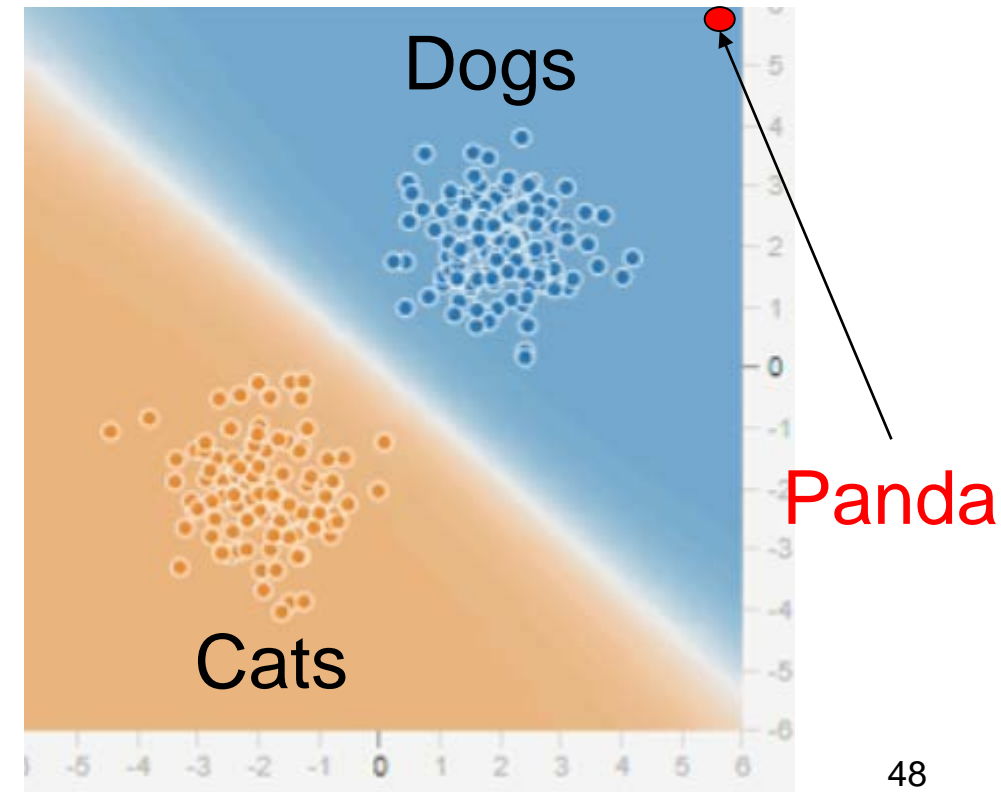
Problem: Domain shift



Problem:

No uncertainty estimates

No out-of-distribution detection



Problem: Confounding variables



Thank you for the attention.

Questions?

