Monitoring Pack-ice Seal Populations from Space with Deep Learning

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Ecology & Evolution

Outline

Introduction

- Antarctic Ecology 101
- Intro to computer vision
- Seal detection pipeline

Present work

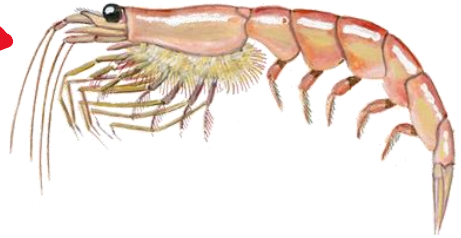
- Training set
- Haul out detection CNNs
- Counting CNNs

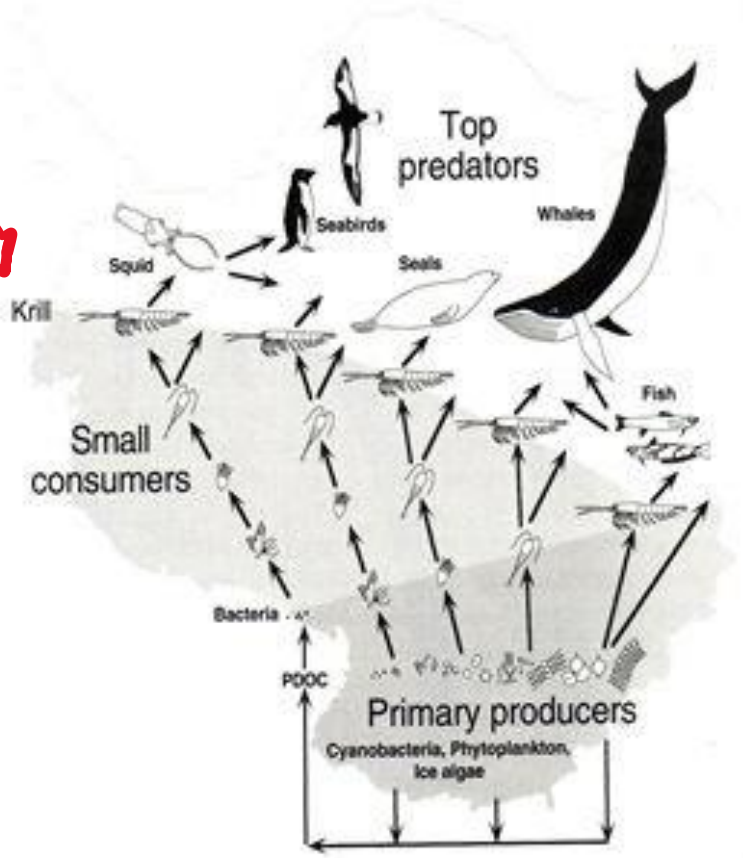
Summary and next steps

Big Picture: How many pack-ice seals are in Antarctica?

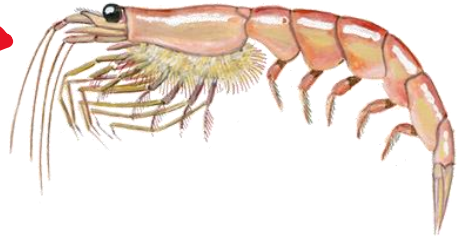
Introduction

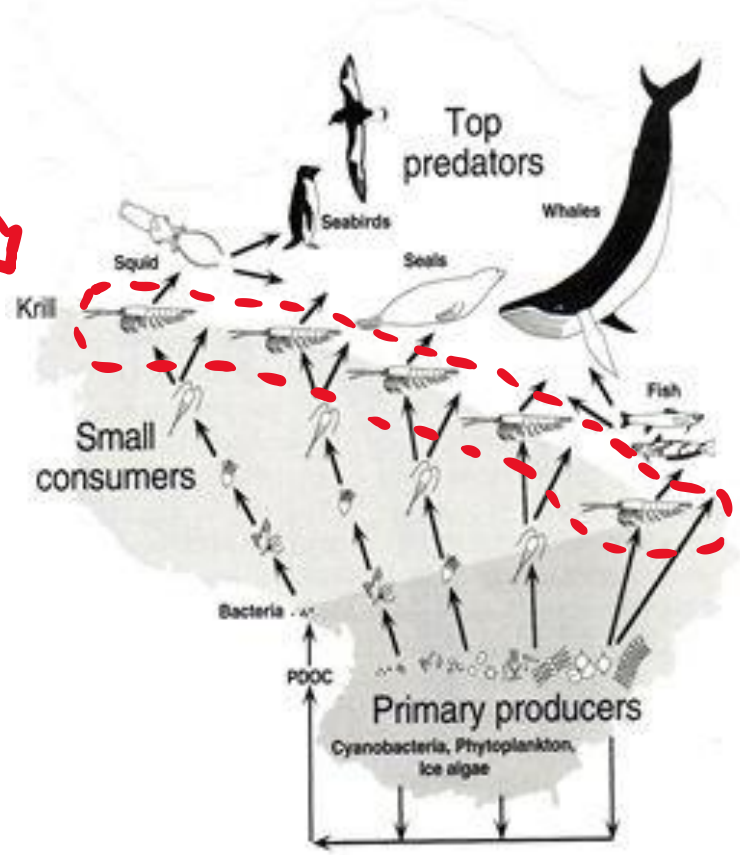
Antarctic Ecology 101





Antarctic Ecology 101





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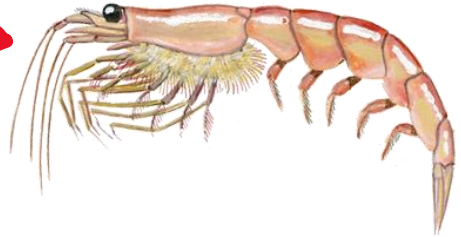
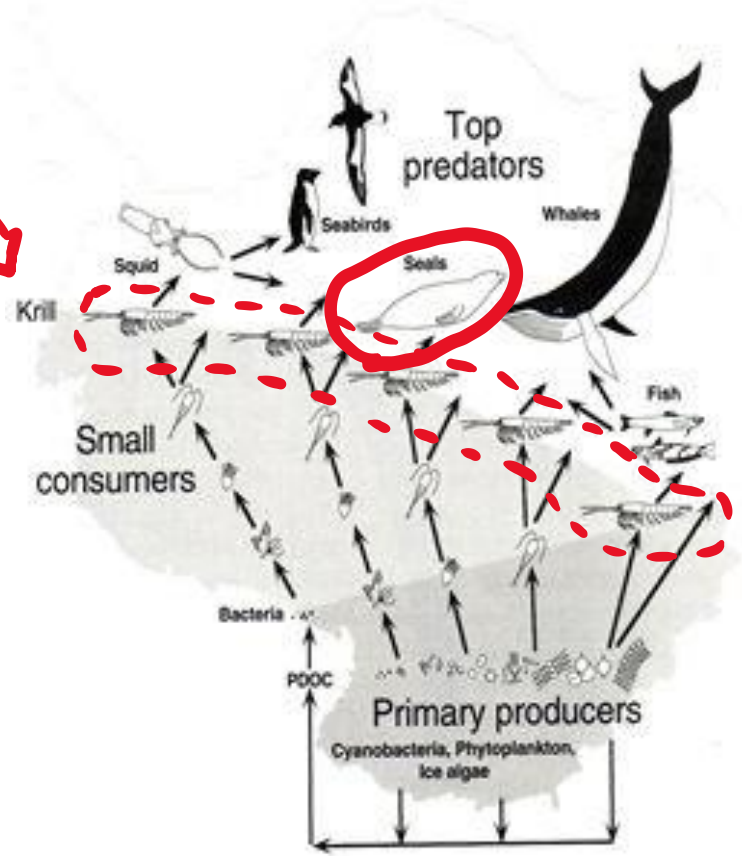
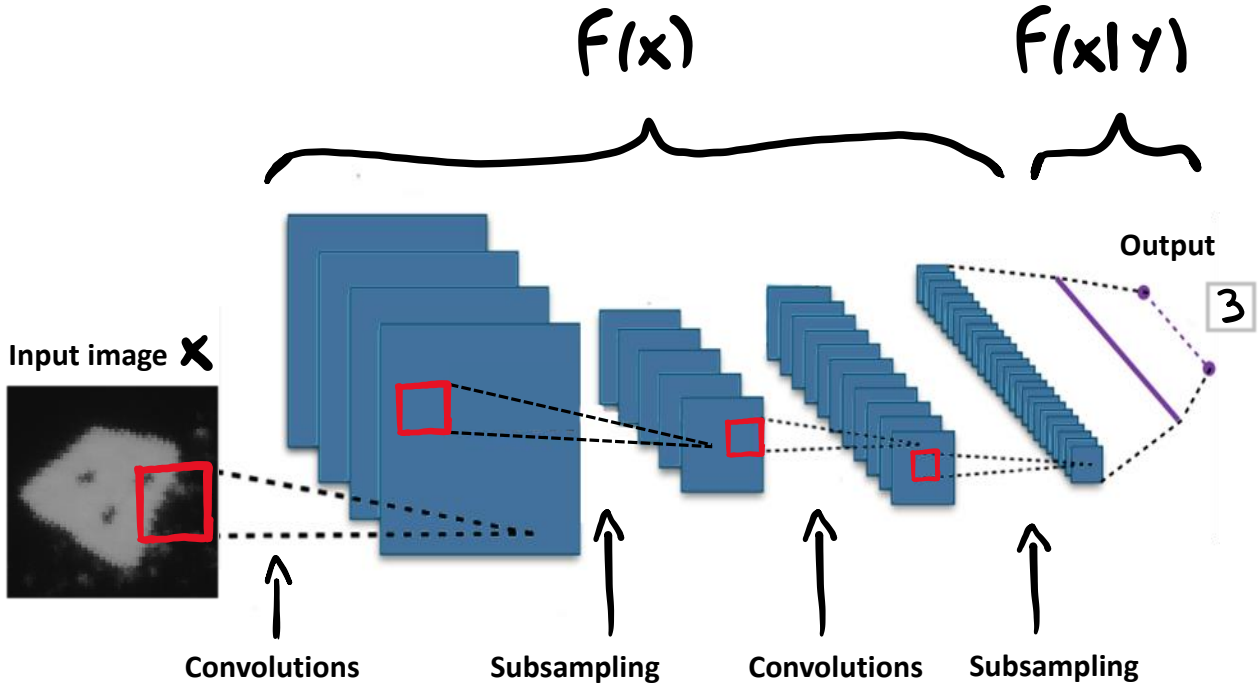




Intro to computer vision

- Artificial neural networks – Deep learning
- Convolutional neural networks (CNN)
  - Data hungry
  - Computationally expensive



Intro to computer vision

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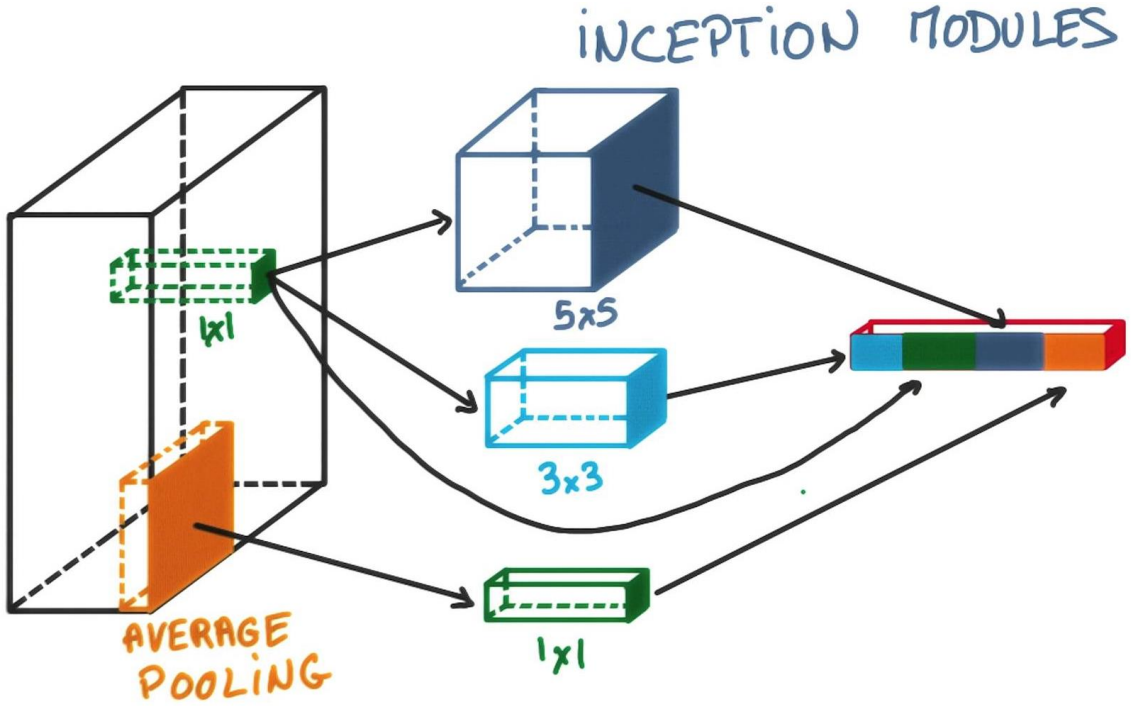
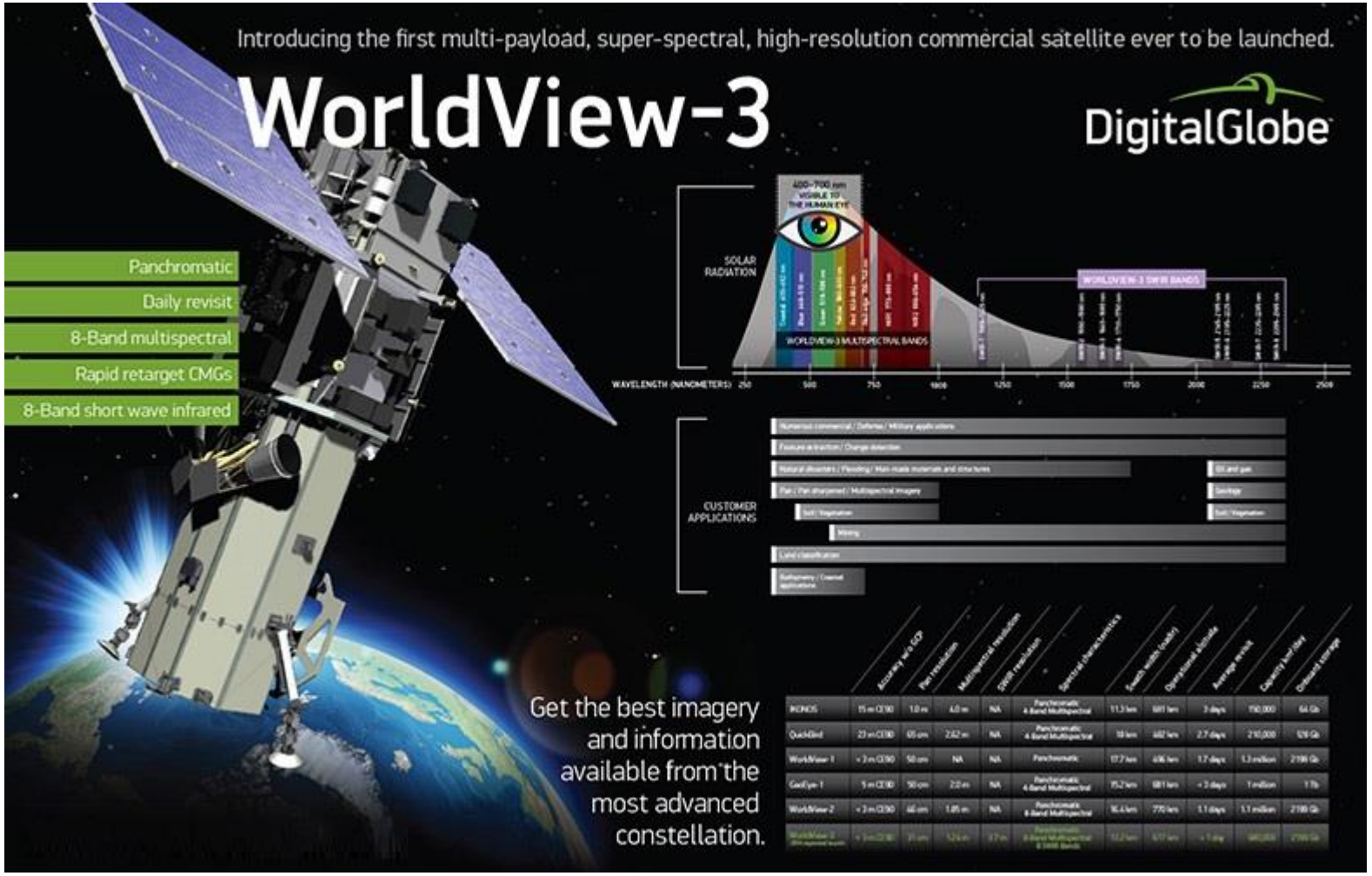
  - Computationally expensive
- CNN Architectures:
  - VGG16
  - Resnet
  - Inception

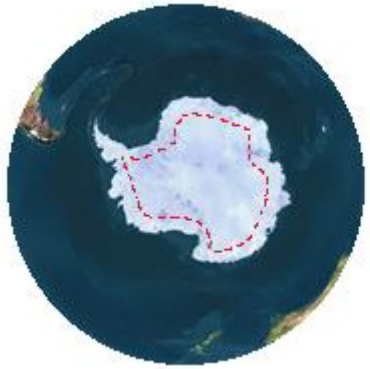


High-resolution satellite imagery

- WorldView-3
- 31cm resolution at nadir
- Coverage is not as good as low-res sensors (e.g. MODIS)
- Scene (~ 300 km^2) vs. Patch (1 ha)



Model framework – pipeline



STEP 1: Buffer out scenes that are too far from the coastline or with too much cloud cover, split remaining scenes into patches

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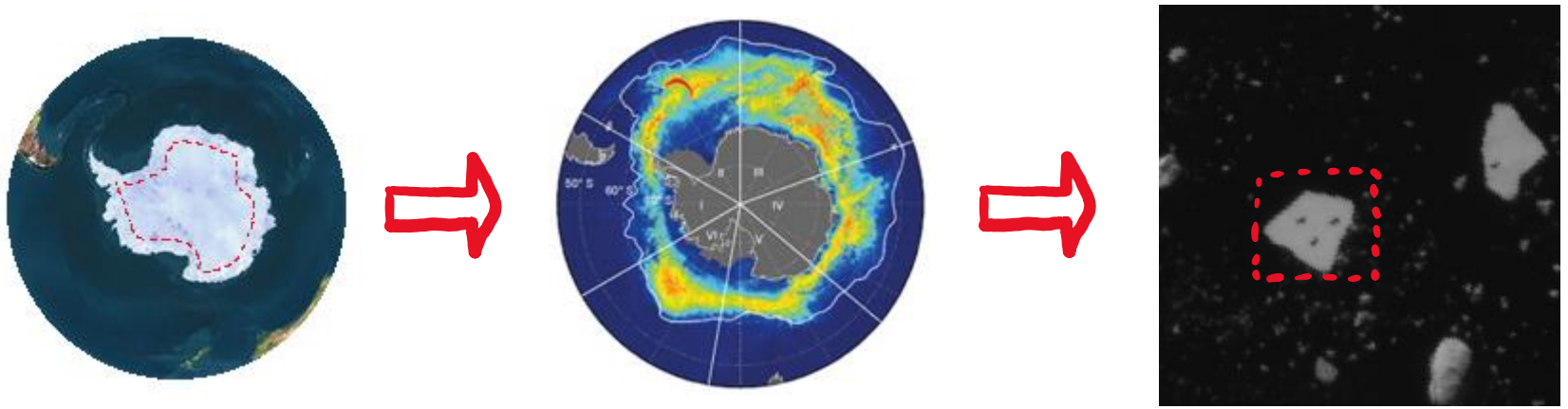

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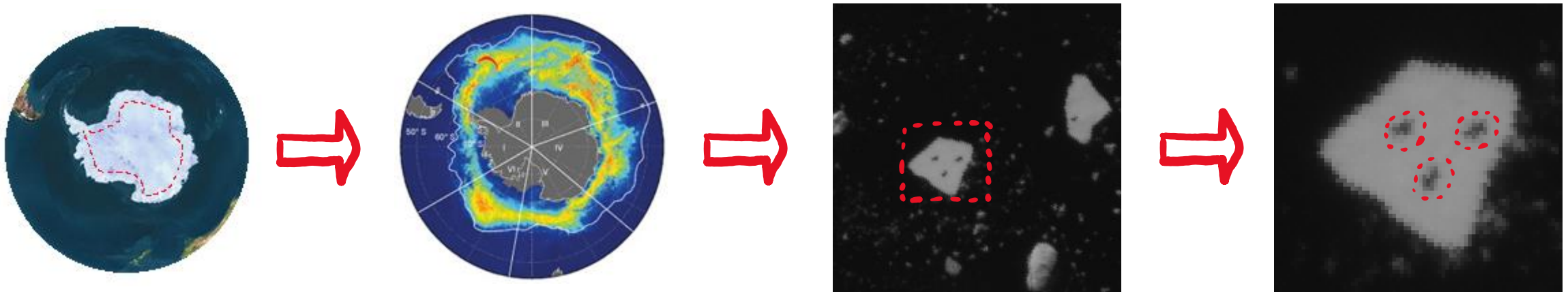

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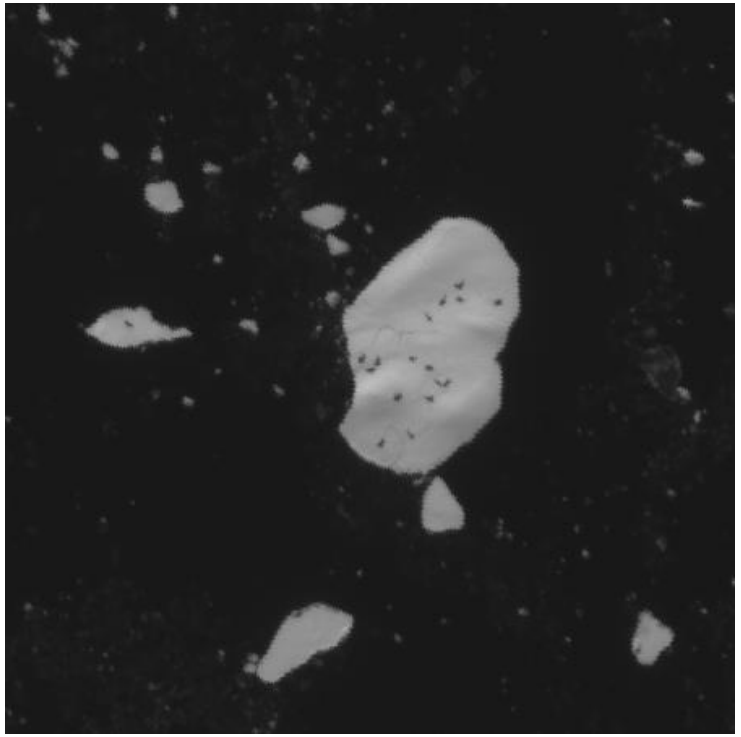
STEP 2: Extract environmental data at input locations

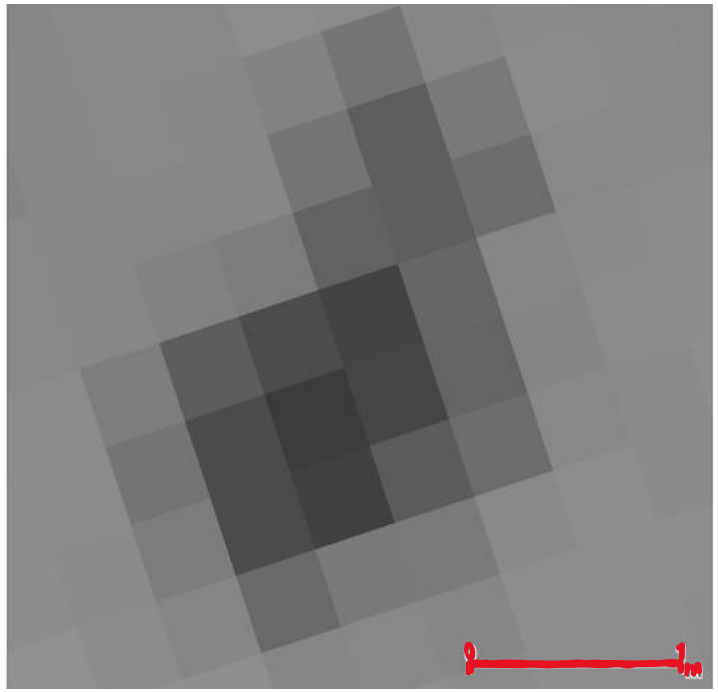
STEP 3: Sweep through patches with a classification CNN trained on groups of seals

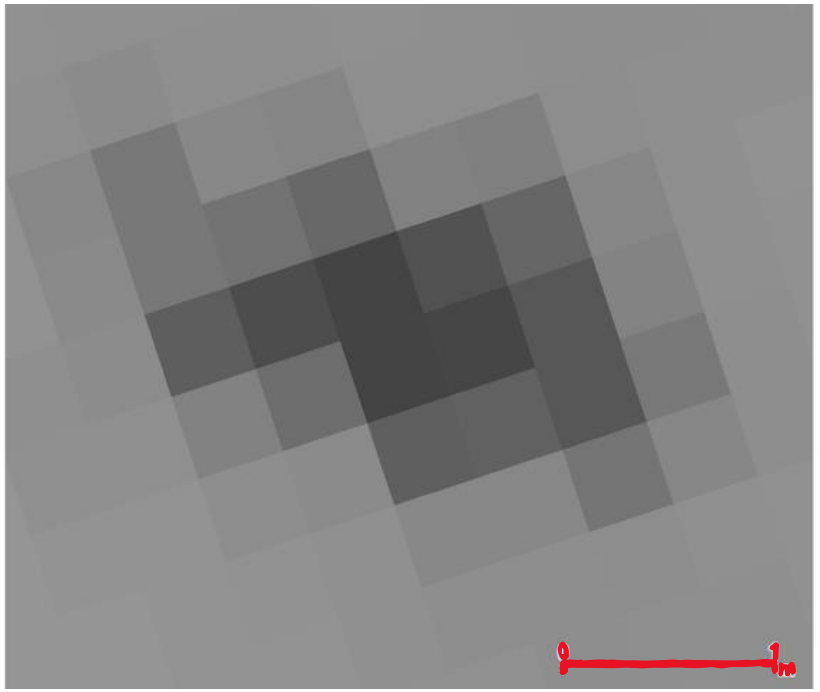
STEP 4: Locate and count individual seals inside flagged patches with a detection CNN

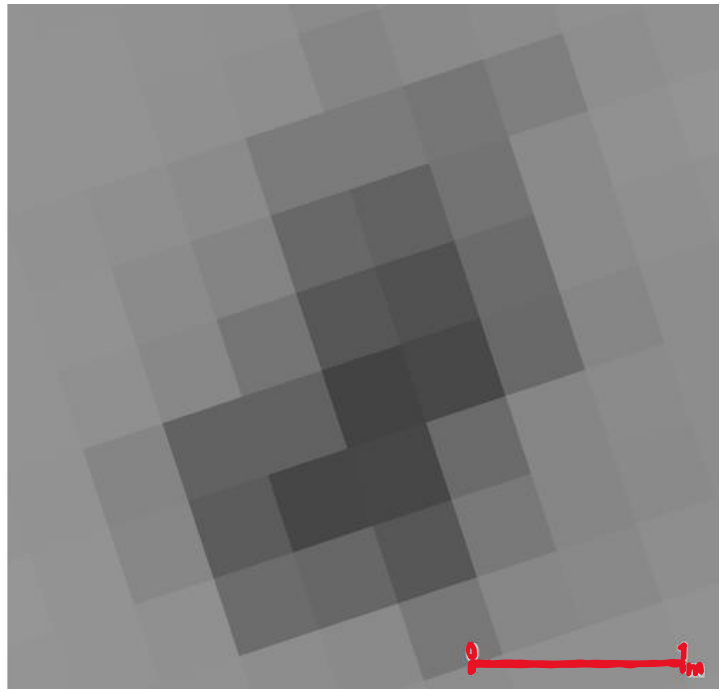
Groups of seals – crabeaters



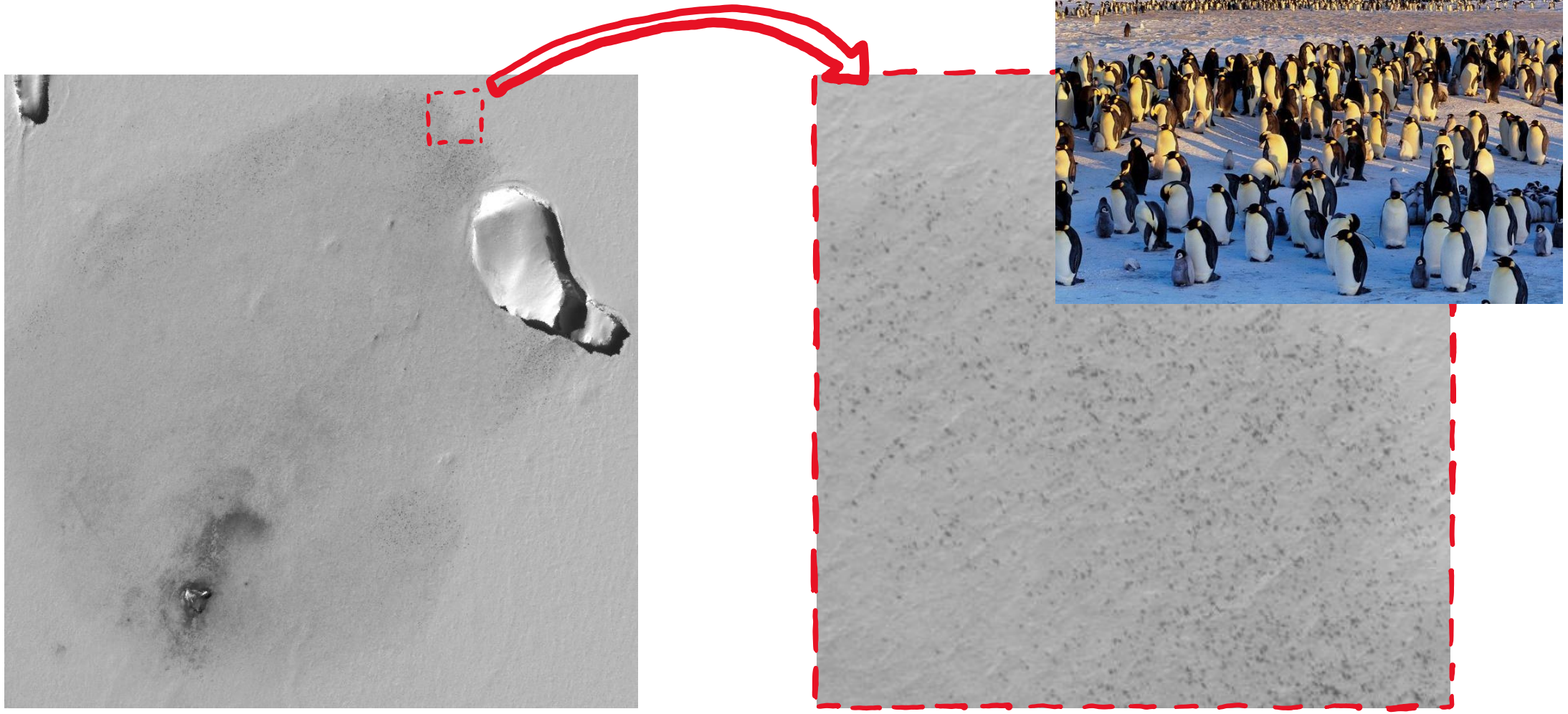
Single seals







BONUS: emperor penguins

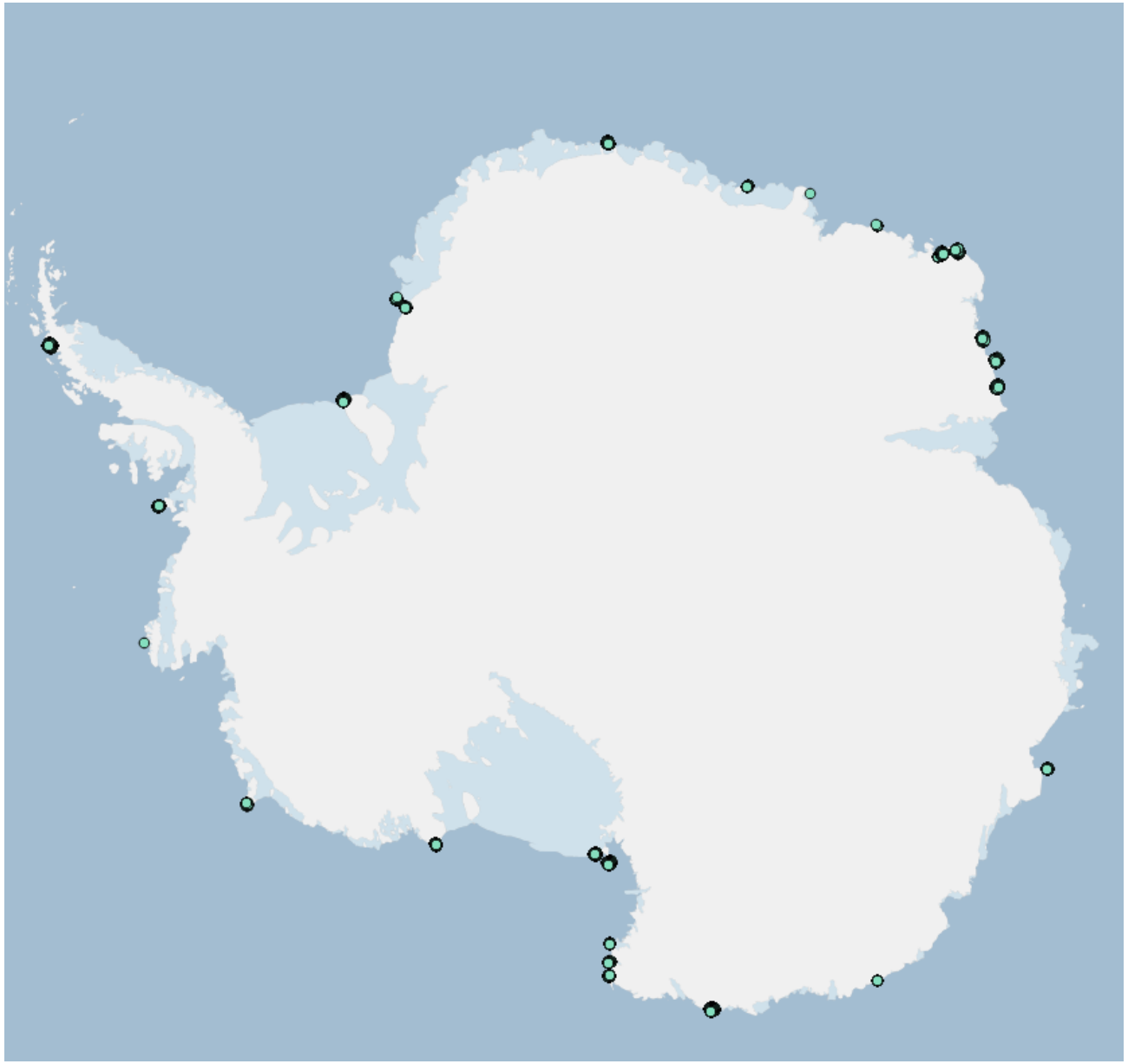


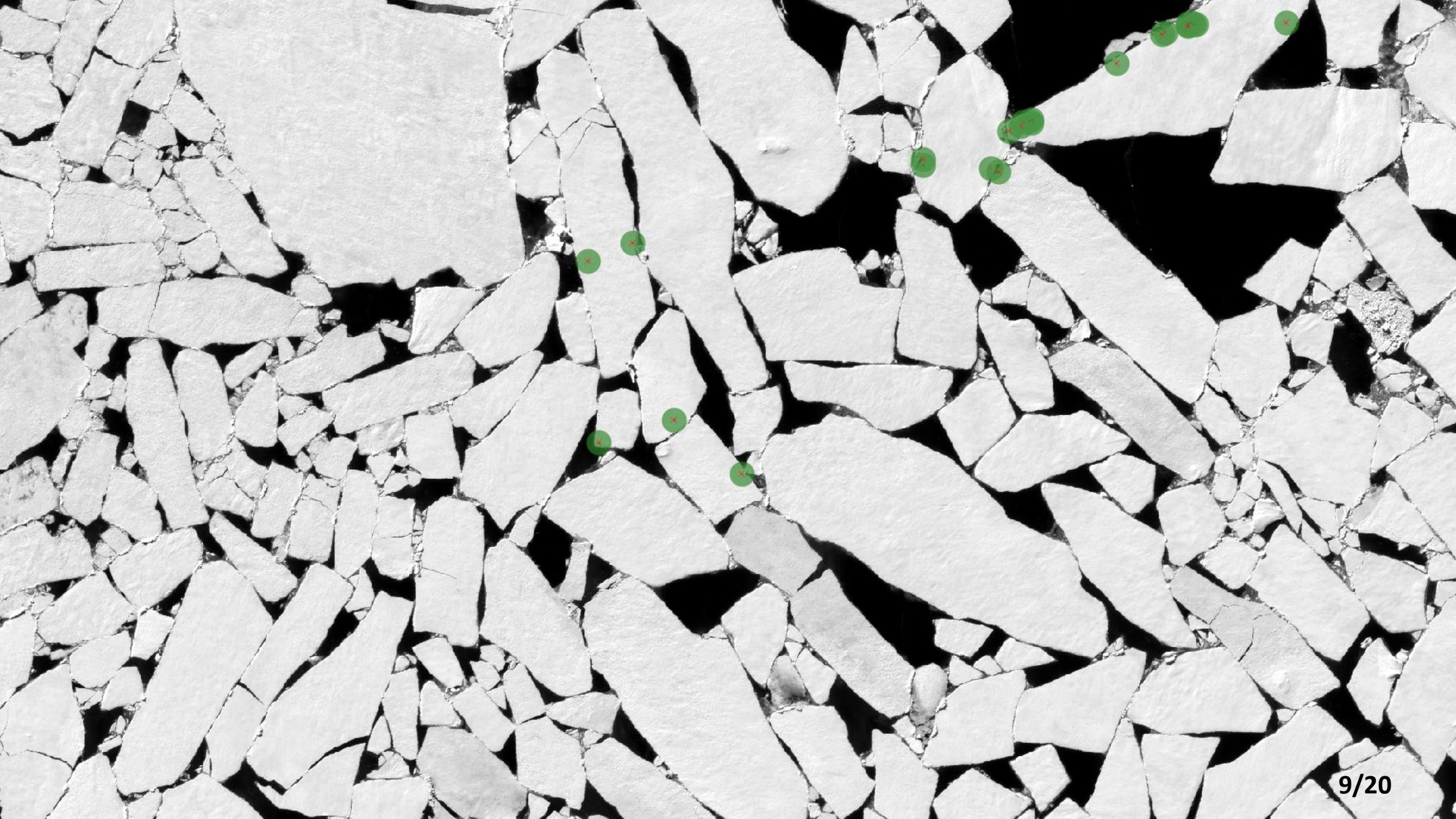
BONUS: emperor penguins

Present work

Training set creation

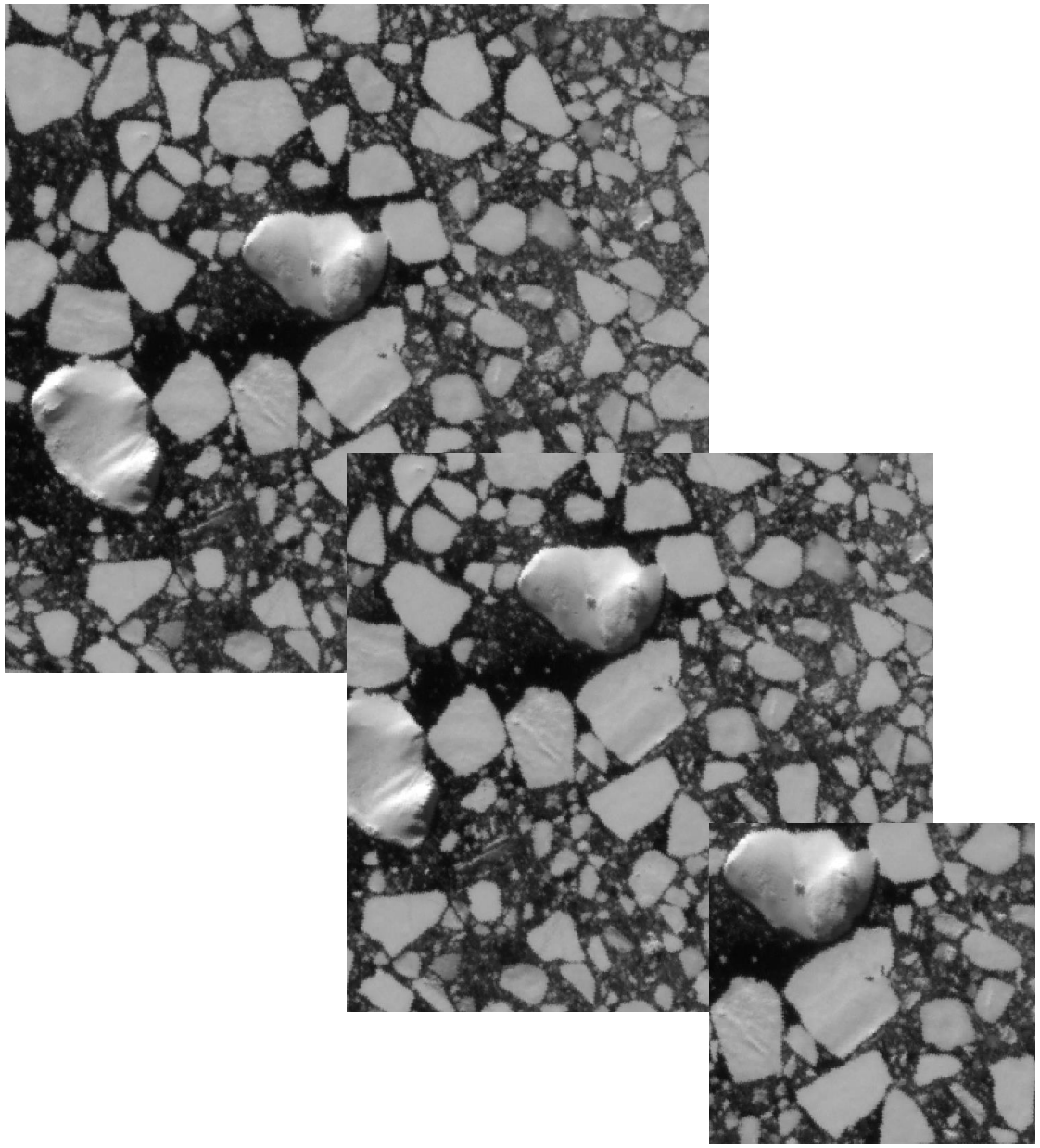
- Patch extraction
  - ~78000 labeled patches across >30 scenes
  - 11 training classes
- Context information:
  - Broad spatial context
  - Environmental covariates





Multiscale training set

- Spatial pyramid
- Provide broad spatial context
- Broad context bands down-sampled to patch size



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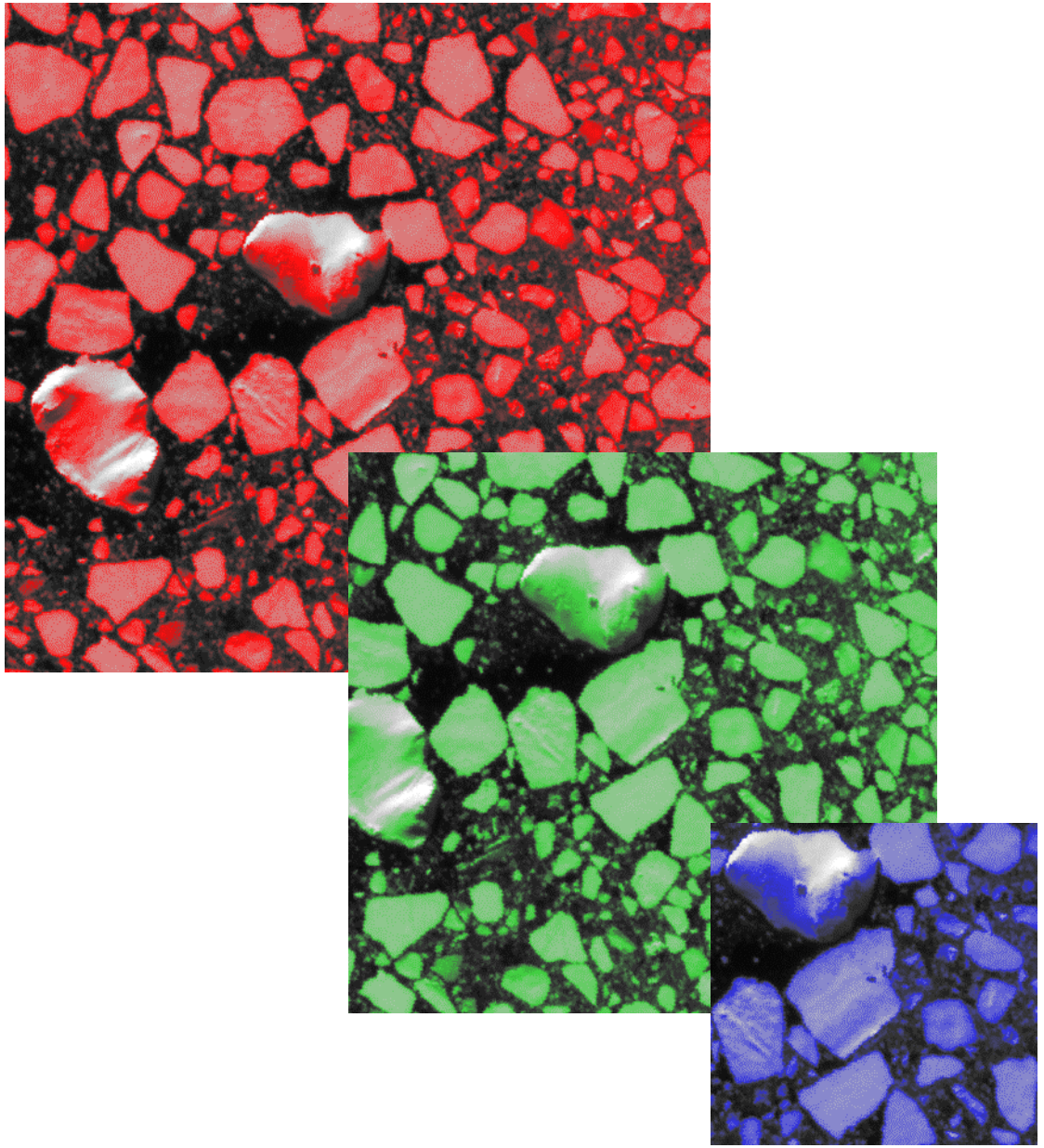

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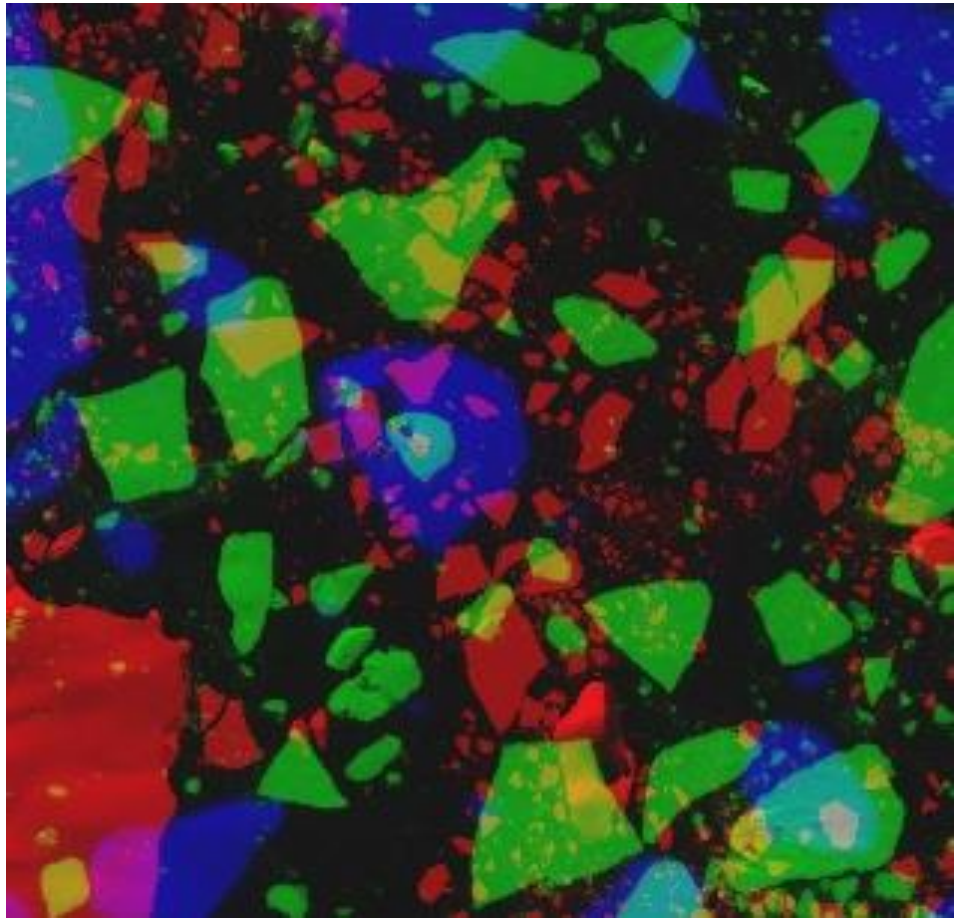
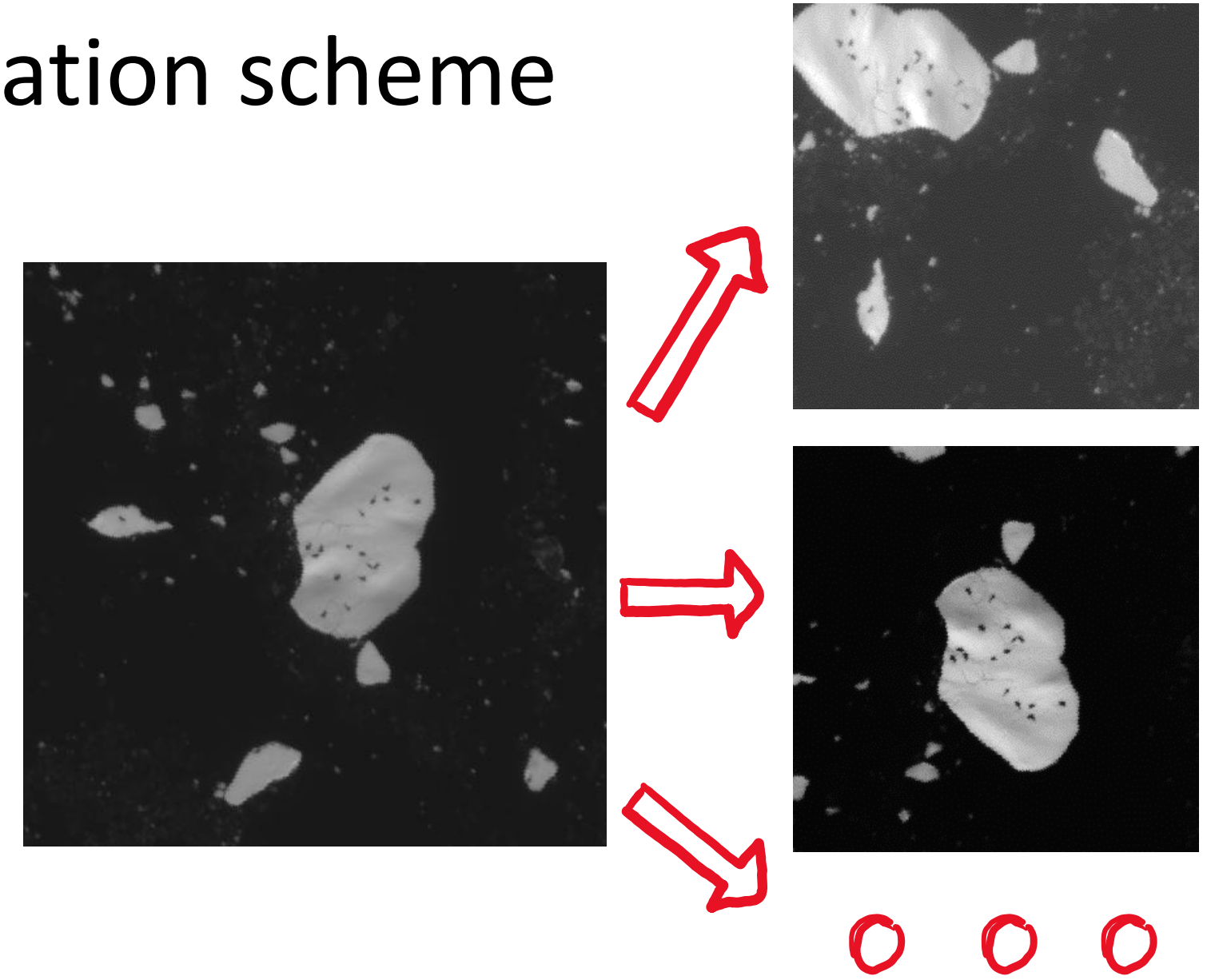
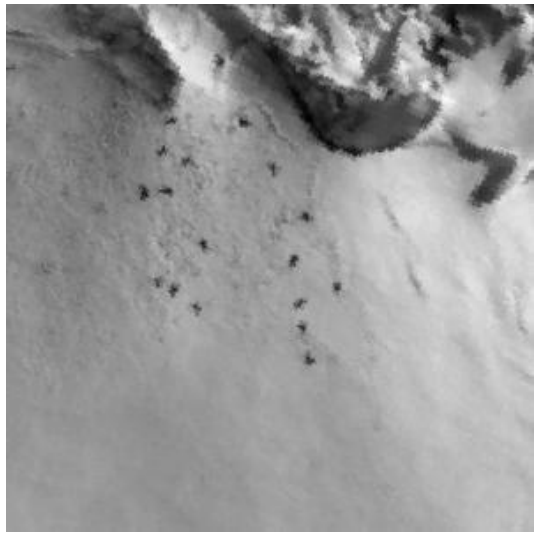


Data augmentation scheme

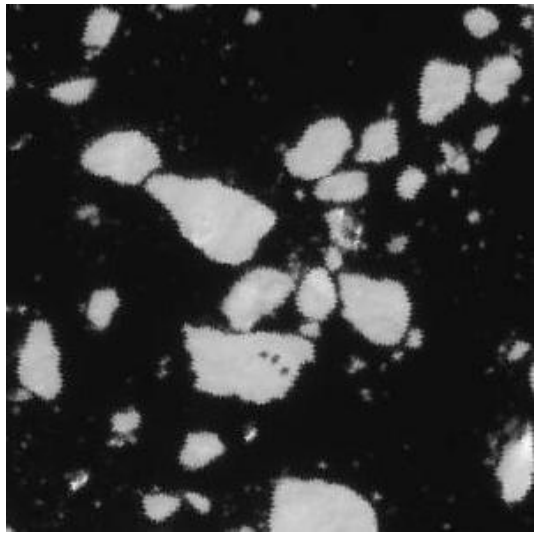
- Random crops
- Random rotations
- Mirroring
- Contrast
- Brightness



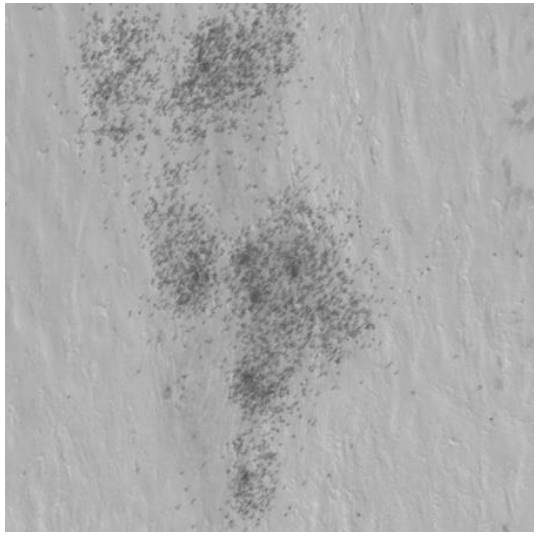
Positive classes



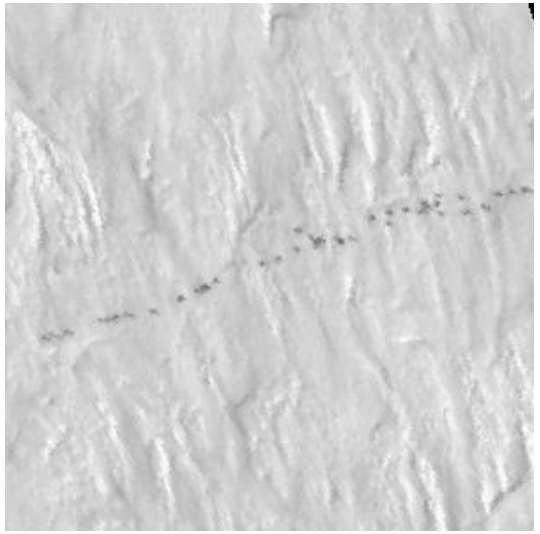
Weddell seal – 981 patches



Crabeater seal – 4174 patches



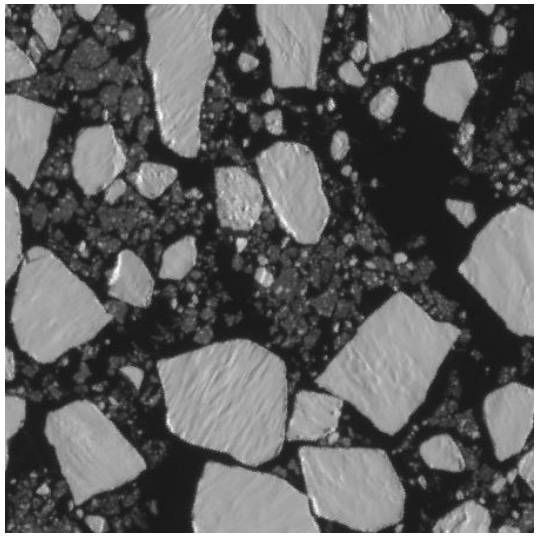
Emperor penguin – 7105 patches

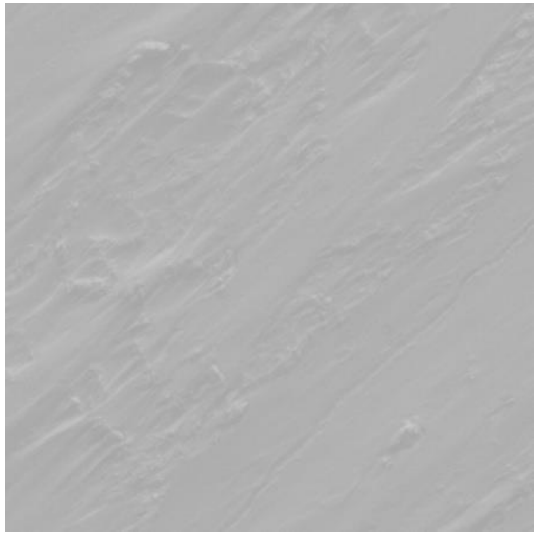


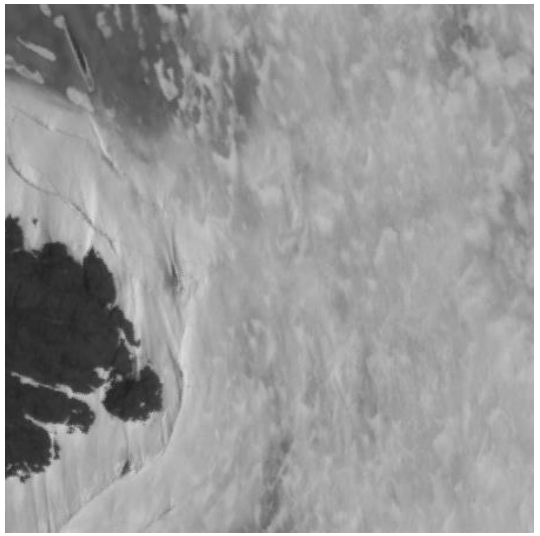
Marching-emperor – 1060 patches

Hard negatives

- 7 classes, including open water, pack ice (without seals), etc.







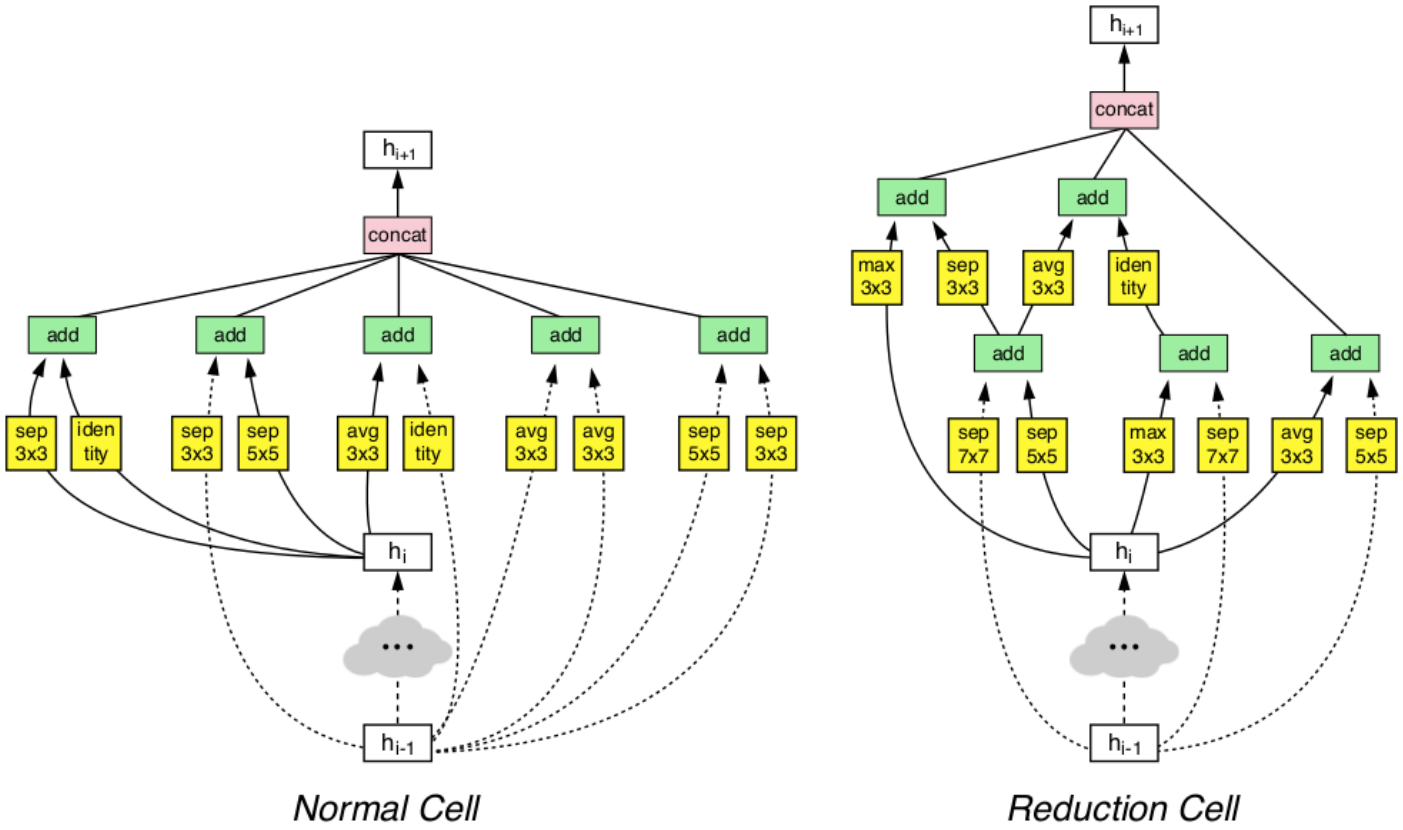
Haul out detection CNNs

Model architectures:

- Resnet18, Densenet169, etc.. (already implemented with PyTorch)
- NASNet (Zoph et al 2017)

Training setup

- Adam optimizer with learning rate 0.001 and 0.95 learning rate decay per epoch
- Trained from scratch with cross-entropy loss



Normal Cell *Reduction Cell*

Validation

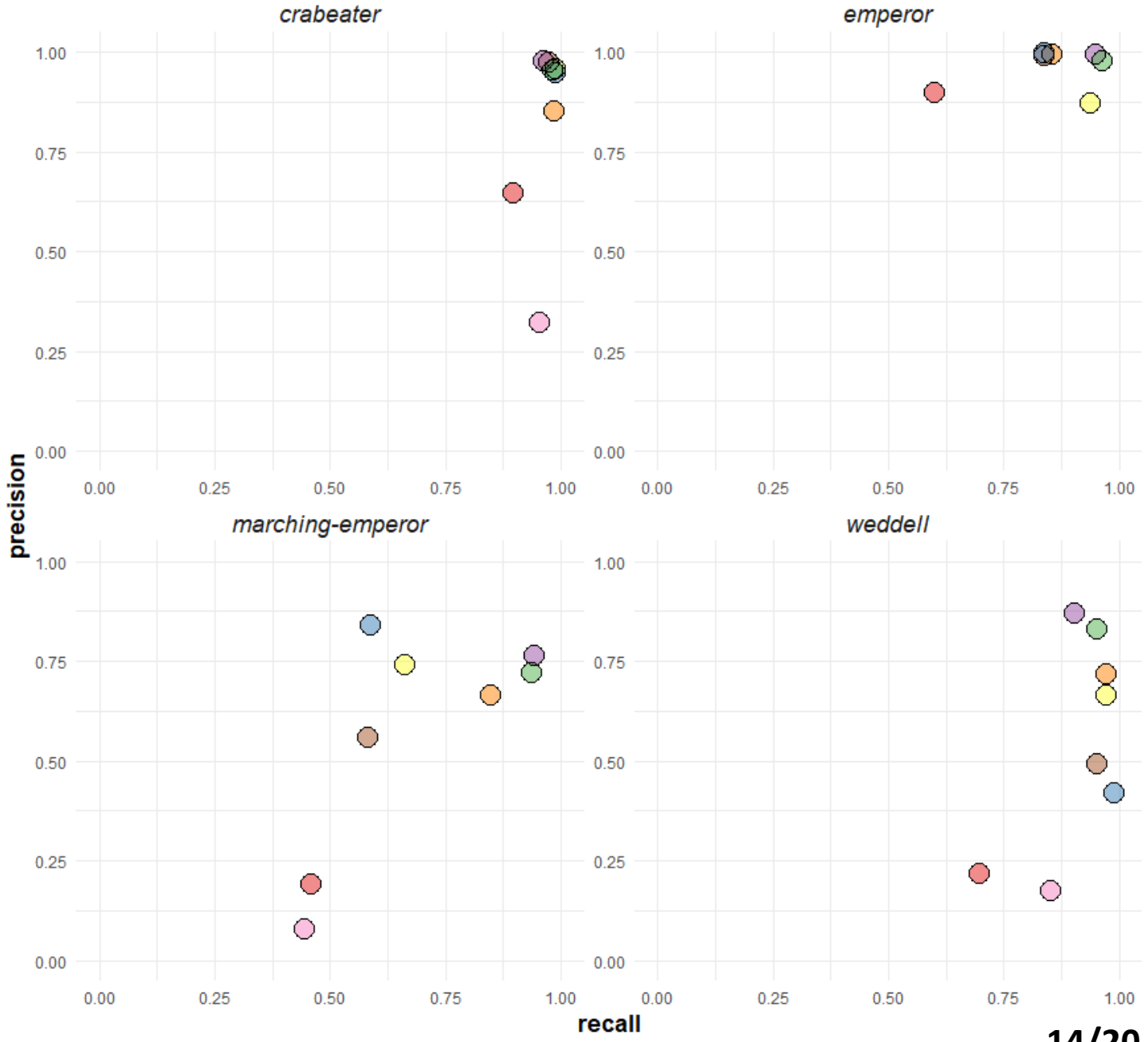
- Best performing architecture is task dependent
- Precision:

  TP / (TP + FP)
- Recall:

  TP / (TP + FN)

model architecture

- Alexnet
- Densenet121
- Densenet169
- NasnetA
- Resnet18
- Resnet34
- Resnet50
- Squeezenet11
- VGG16



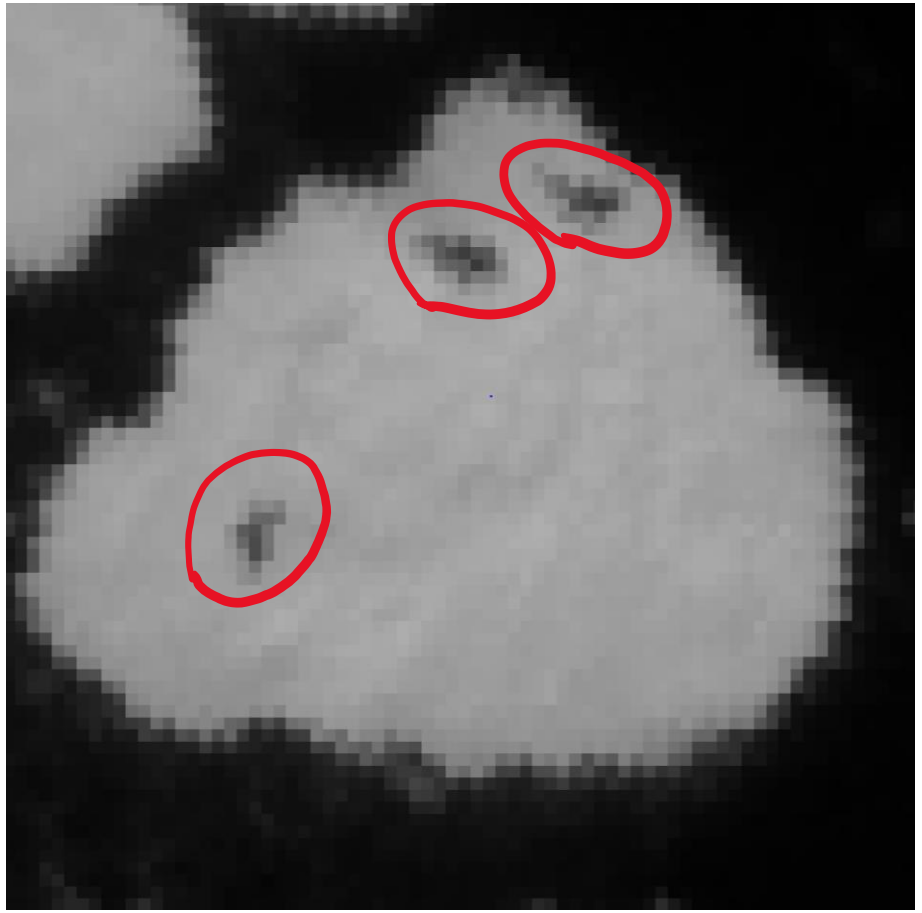
Solutions for counting small objects

Regression CNN

- Maps image to a real number
- Training objective: match ground-truth count (minimize mean-squared error)

Object detection CNN

- Detects individual seals in an image
- Training objective: match the position of predicted seals and ground-truth location (minimize Euclidean distance)

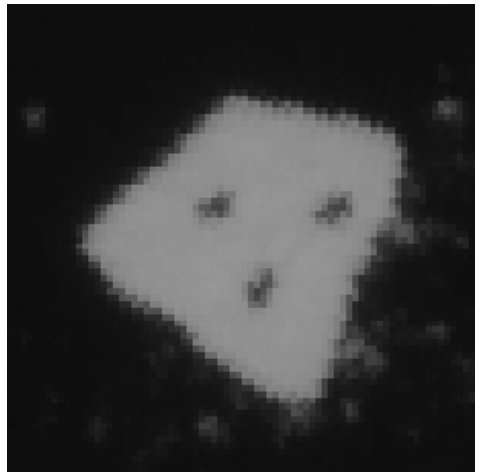


Regression CNNs

Model architectures

- CountCeption (Cohen et al 2017)
- WideResnet
- Modified classification CNNs

Subitizing



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Regression CNNs

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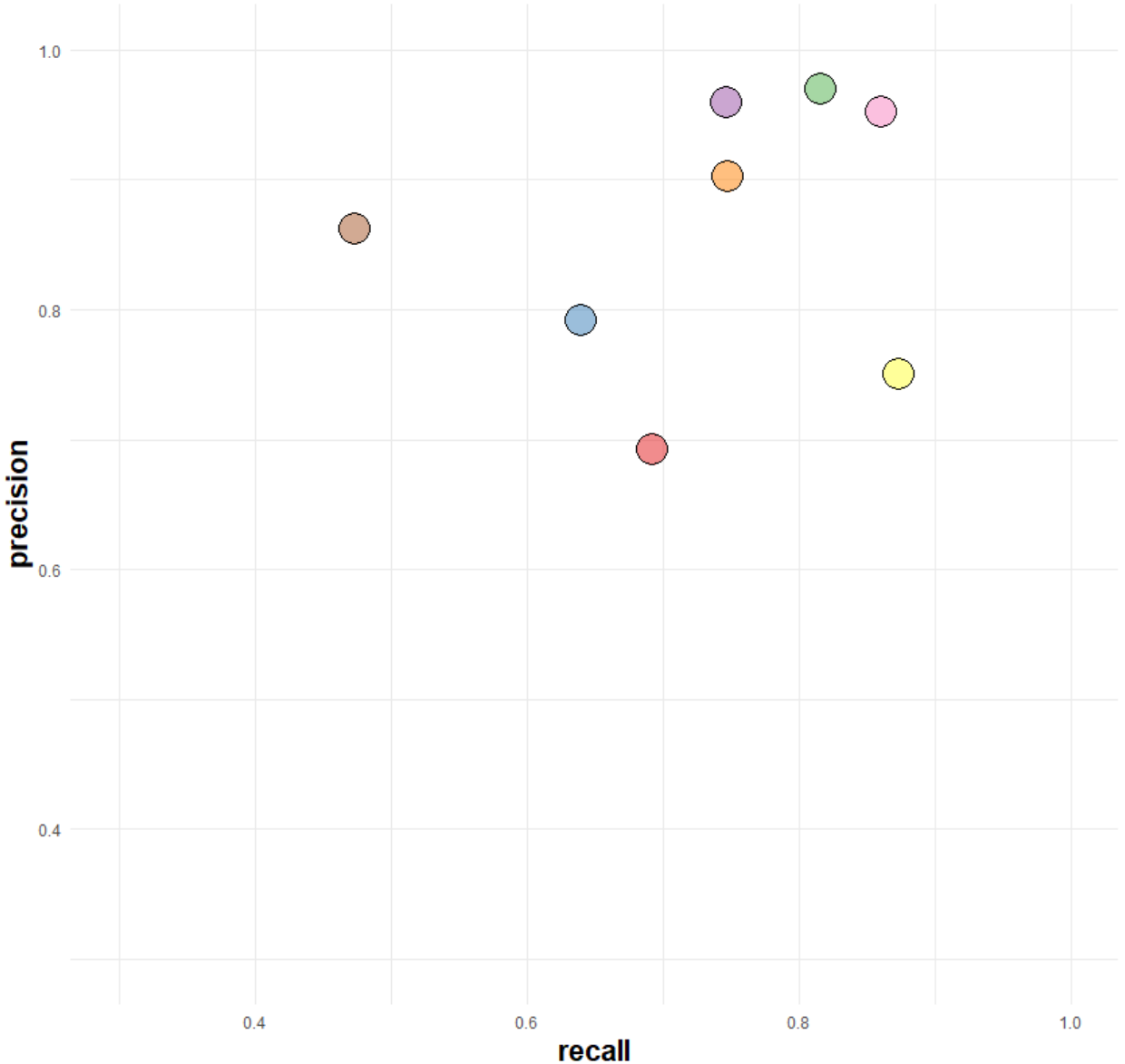
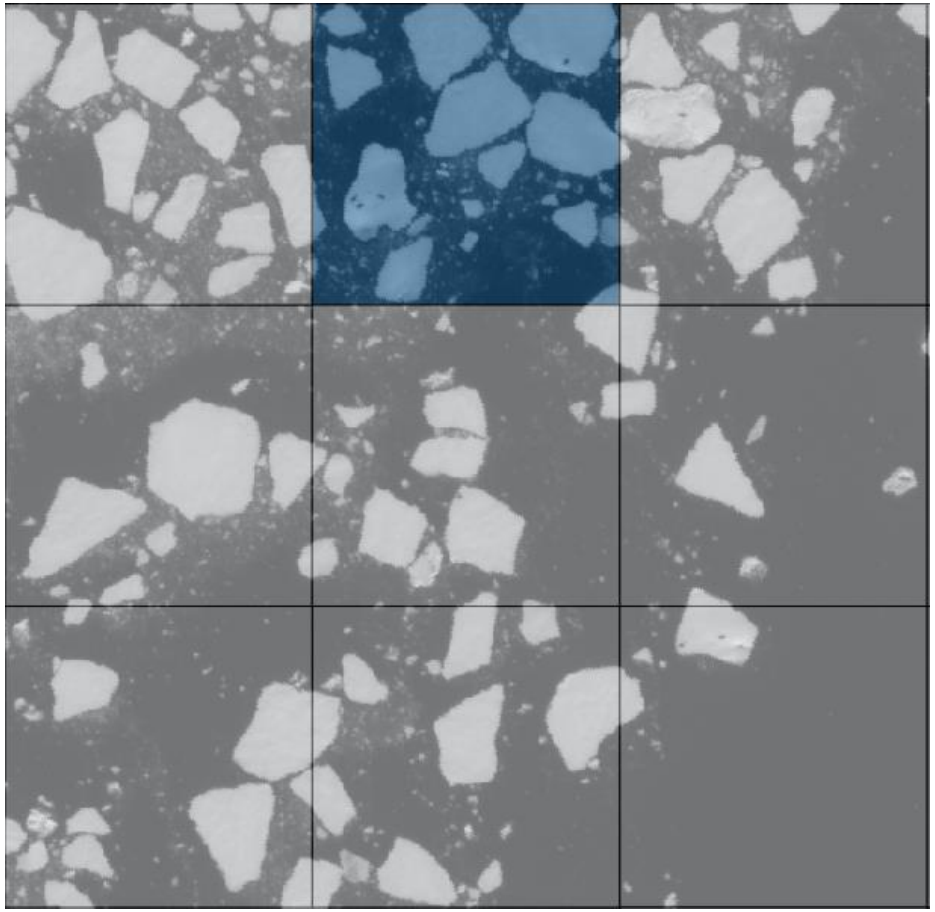
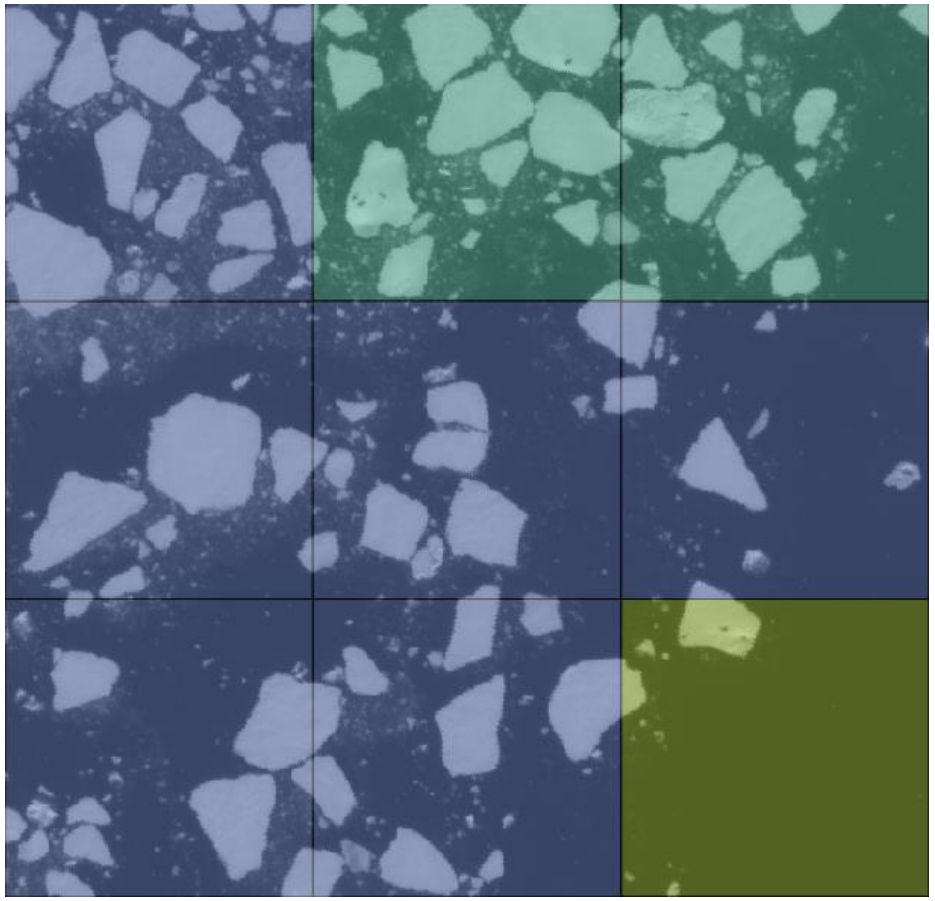
Subitizing

Validation results



Pipeline output

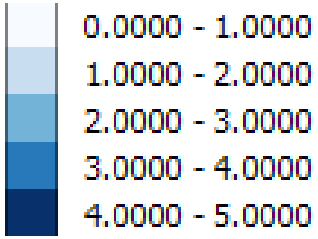


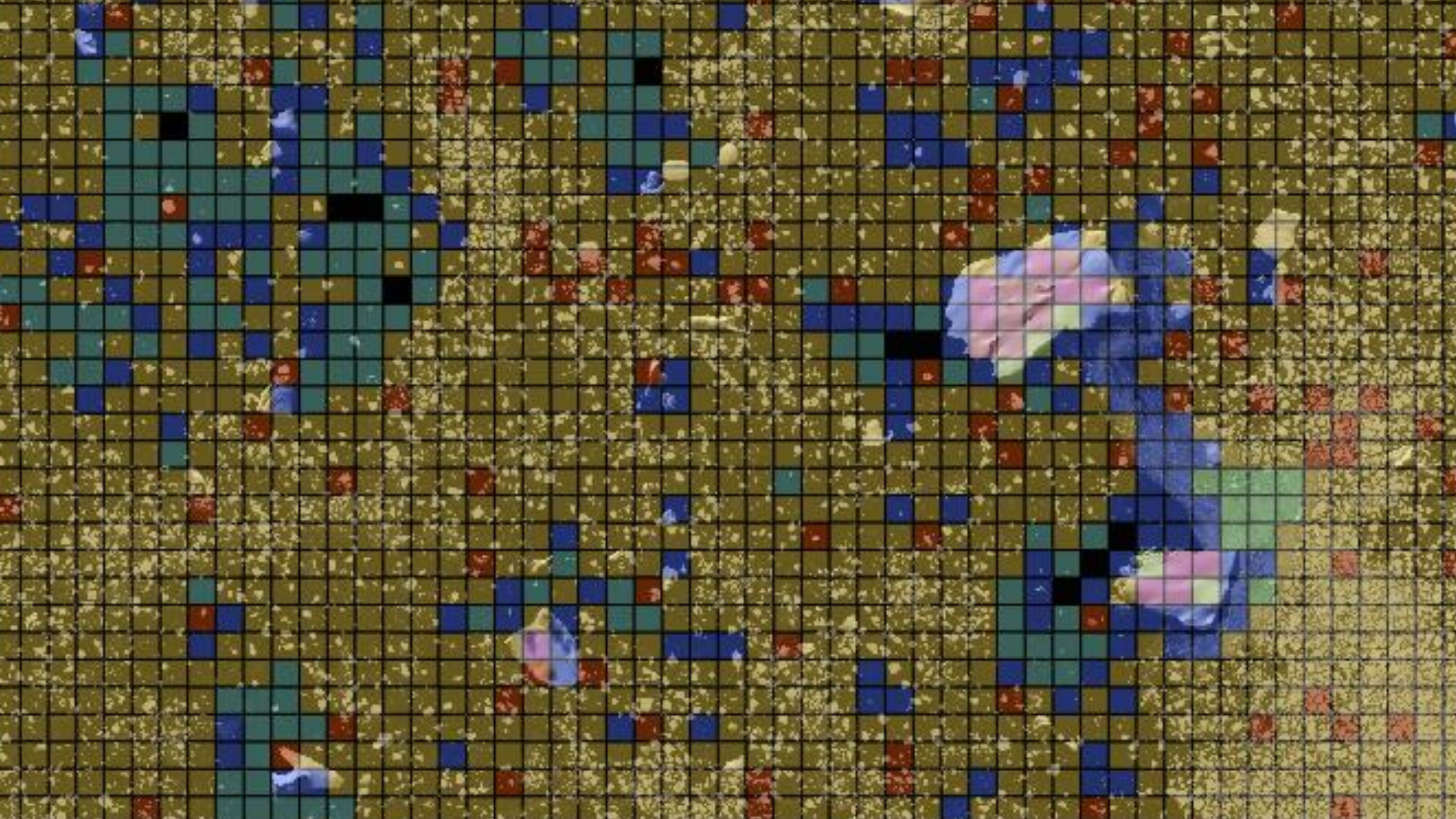


Class

- crabeater
- rock
- Pack-ice

Count

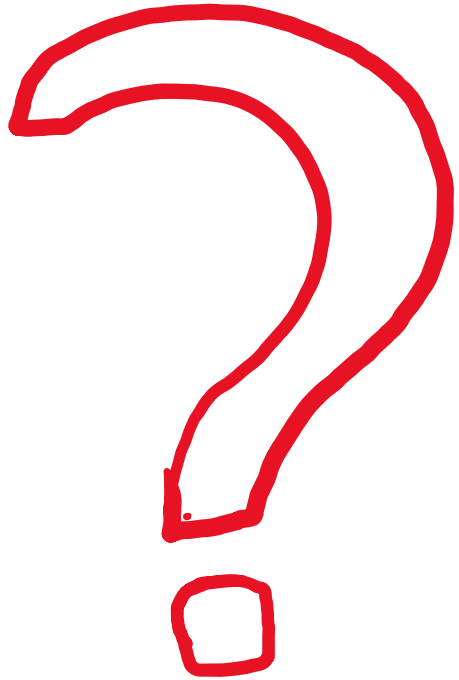




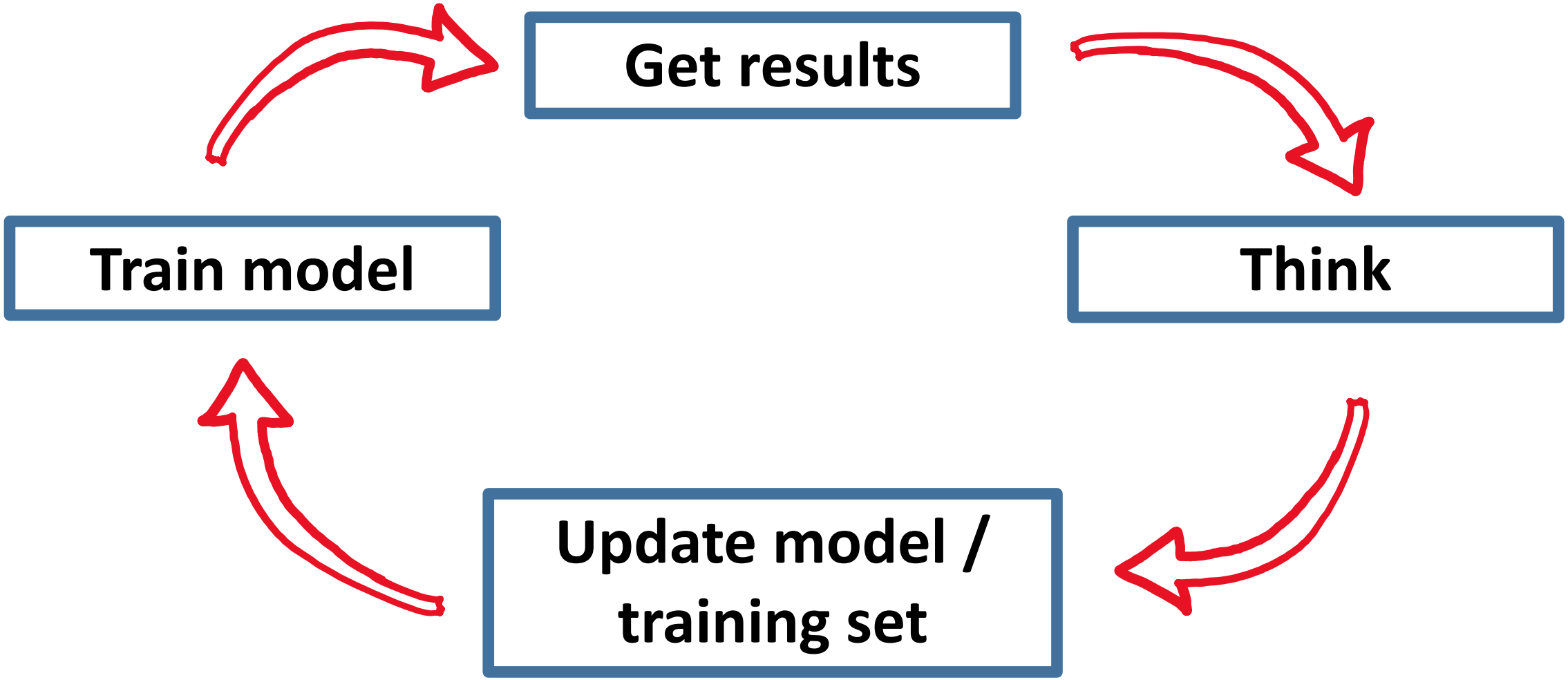
2018 onwards

Hyperparameter search

- The usual… (learning rate, decay, batch size, etc.)
- Input image size (training set and model)
- Augmentation scheme
- Number (and dimensions) of multi-scale bands (multiscale training set)
- Model architectures



Training a CNN: an iterative process



Summary

- Promising approach for pan-Antarctic pack-ice seal survey
- 2018 onwards:
  1. Larger training set (2017-18 imagery not yet incorporated)
  2. Apply pan-sharpening to panchromatic imagery training set
  3. Leverage environmental covariates and a priori knowledge about pack-ice seal biology
  4. Include broad spatial context for input patches
  5. Get better ground-truth for seal counts / locations

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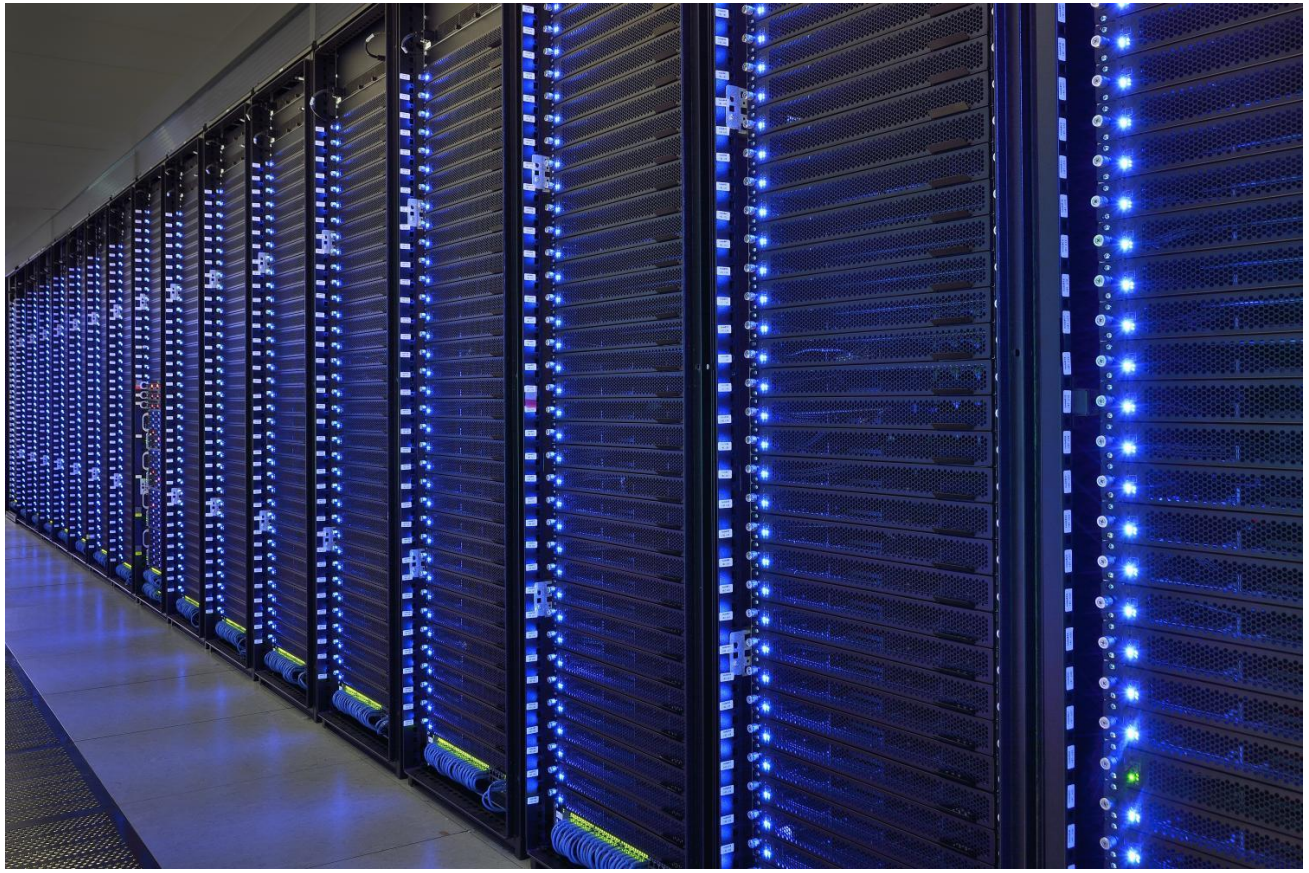
Computational resources significant – requires substantial investment in HPC cyberinfrastructure for imagery

Acknowledgements

ICEBERG - Imagery Cyberinfrastructure and Extensible Building-Blocks to Enhance Research in the Geosciences

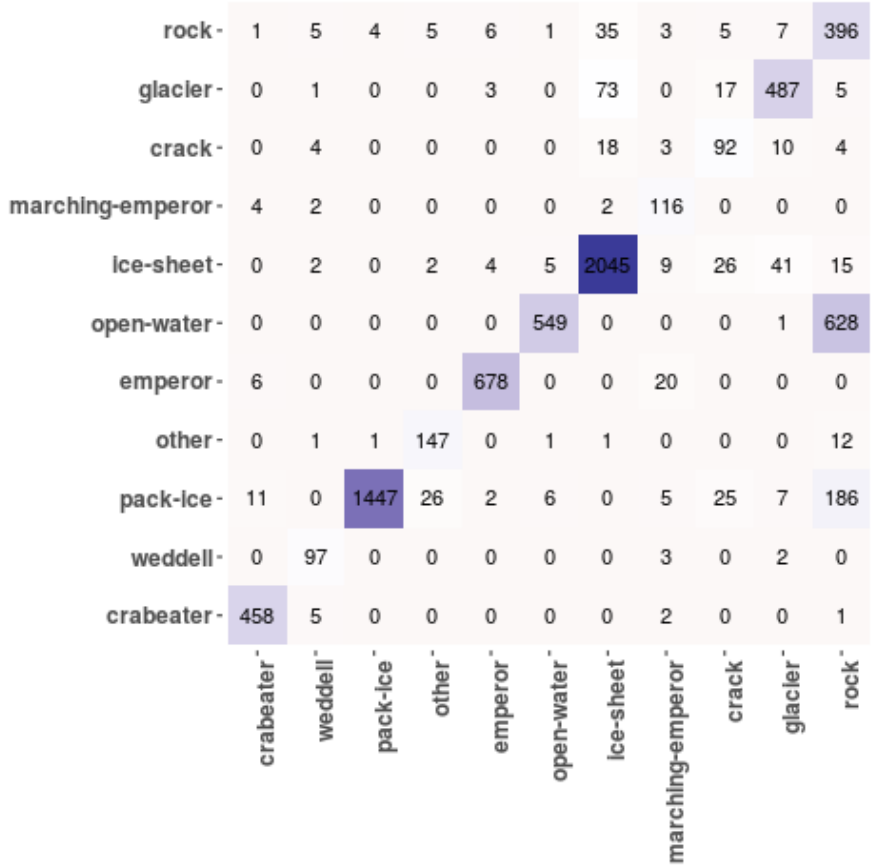
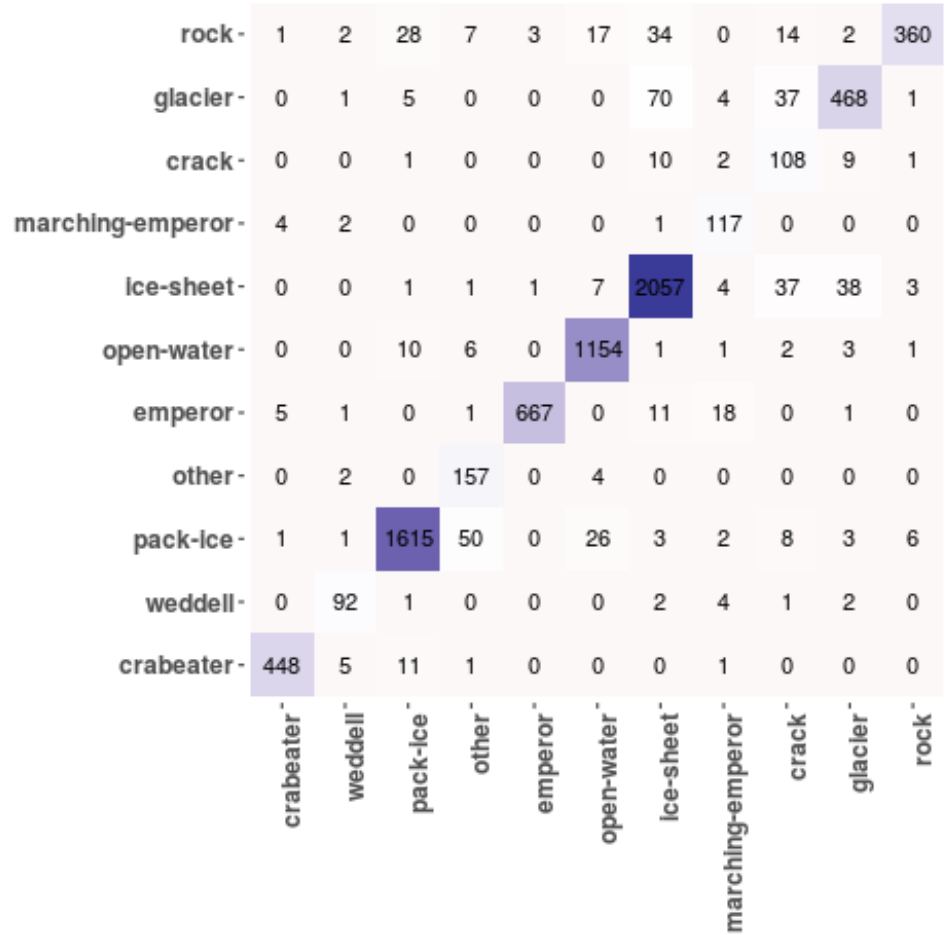
EARTHCUBE
TRANSFORMING GEOSCIENCES RESEARCH

- One piece in the bigger picture
- Empowering polar sciences with HPC
- Bridges supercomputer



Confusion matrices (Haulout CNNs)

Densenet 169



NASnet