

Dealing with image analysis? Let the computer do the heavy lifting



IMAS and AAPP Machine Learning Workshop

Presentation #5, Charley Gros

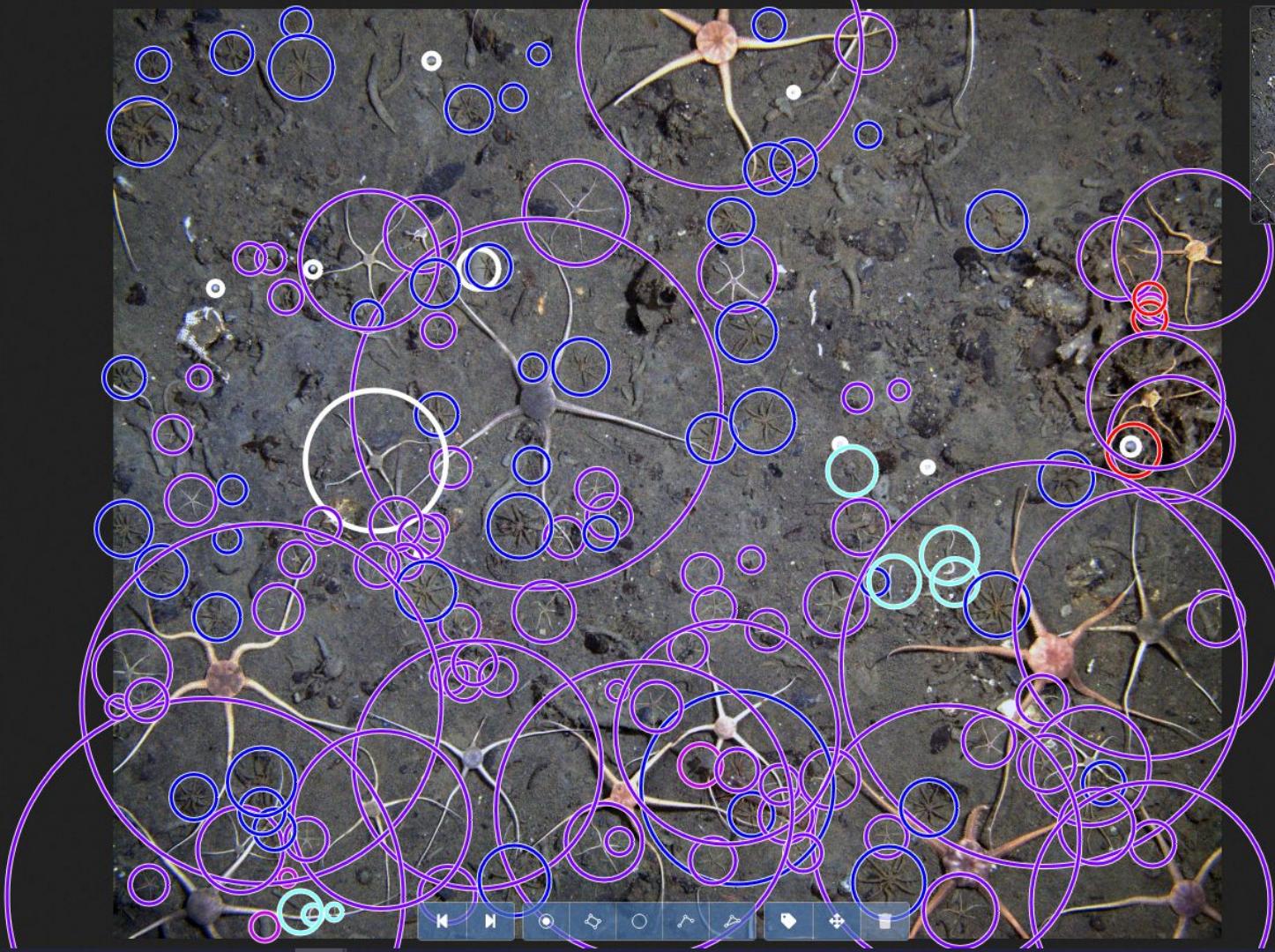
UNIVERSITY of TASMANIA

IMAS 

Institute for Marine and Antarctic Studies



*I acknowledge the palawa people as the Traditional Owners and ongoing custodians of lutruwita (Tasmania)
and pay my respects to their Elders past, present and future.*

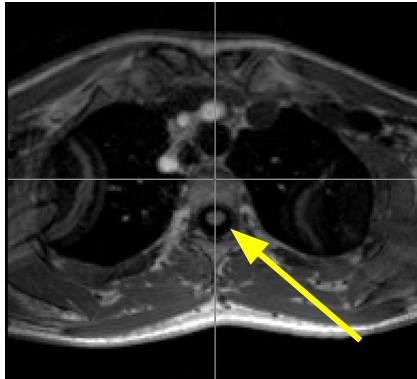




When I first met CNNs...

Project with Dominique:

- 80 MRI scans of patients with Multiple Sclerosis, ~ 500 axial slices per patient
- Question: Is there a correlation between the spatial distribution of lesions in the spinal cord with patients' clinical score?



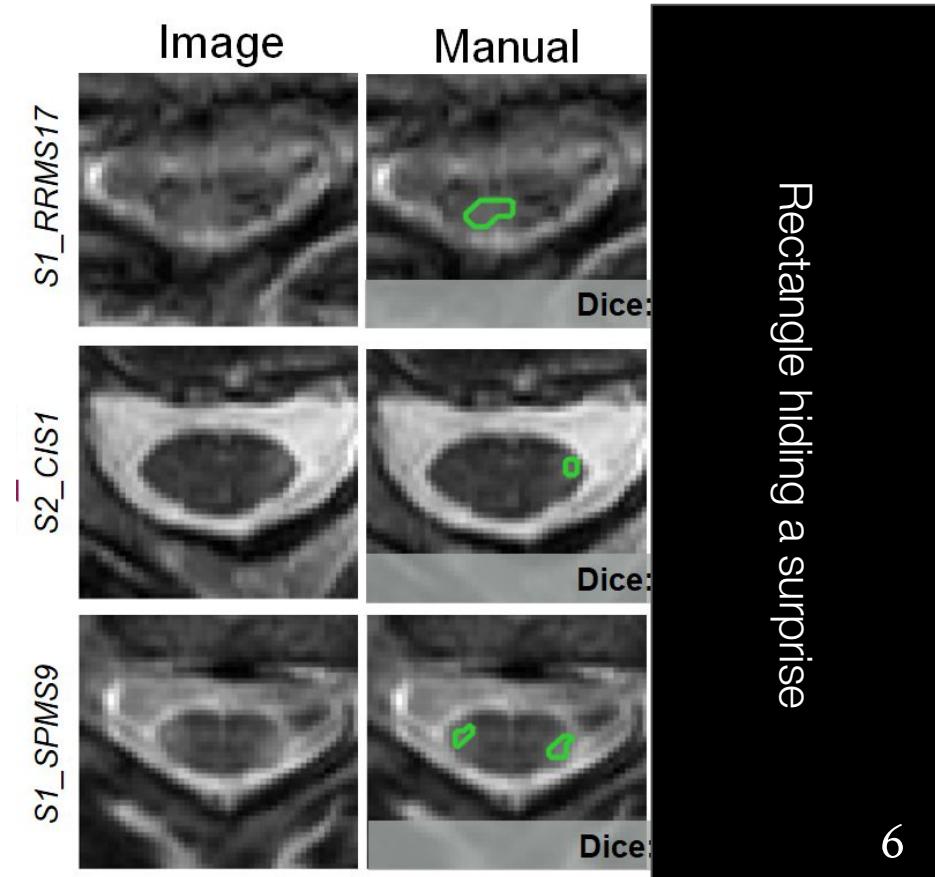
When I first met CNNs...

Manual delineation of lesions on 20 patients...

... used to train a Deep Learning algorithm to automatically segment lesions on the 60 remaining patients

... key challenges include:

- Class imbalance
- Intensity / shape / size heterogeneity
- Intra- and inter-expert disagreement



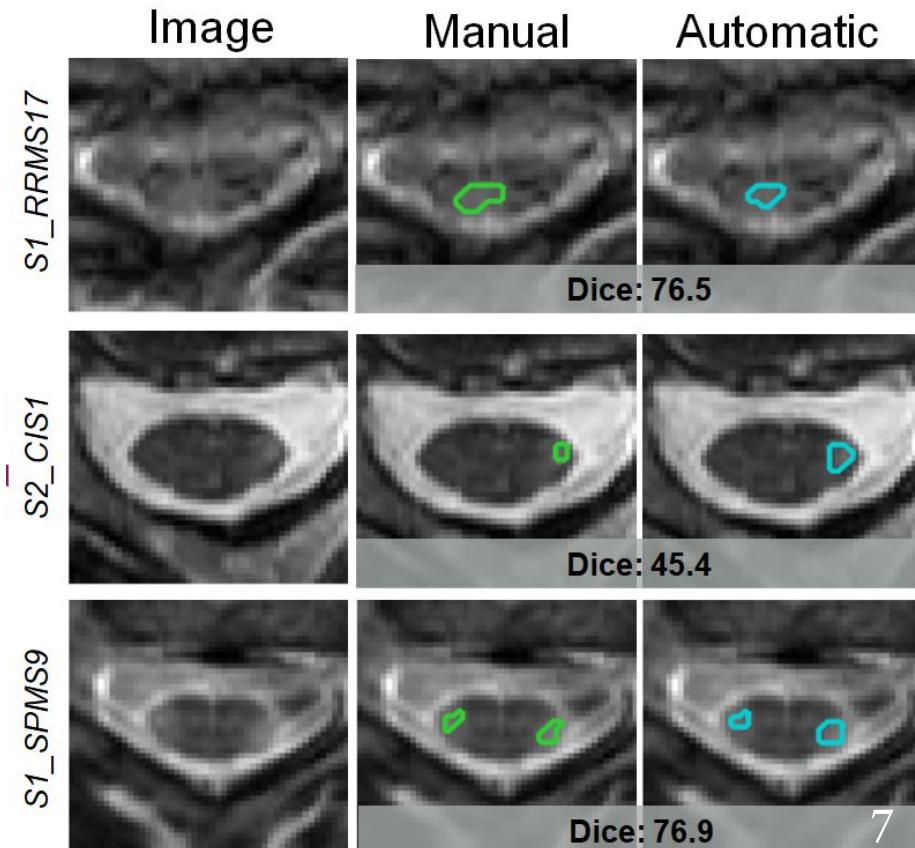
When I first met CNNs...

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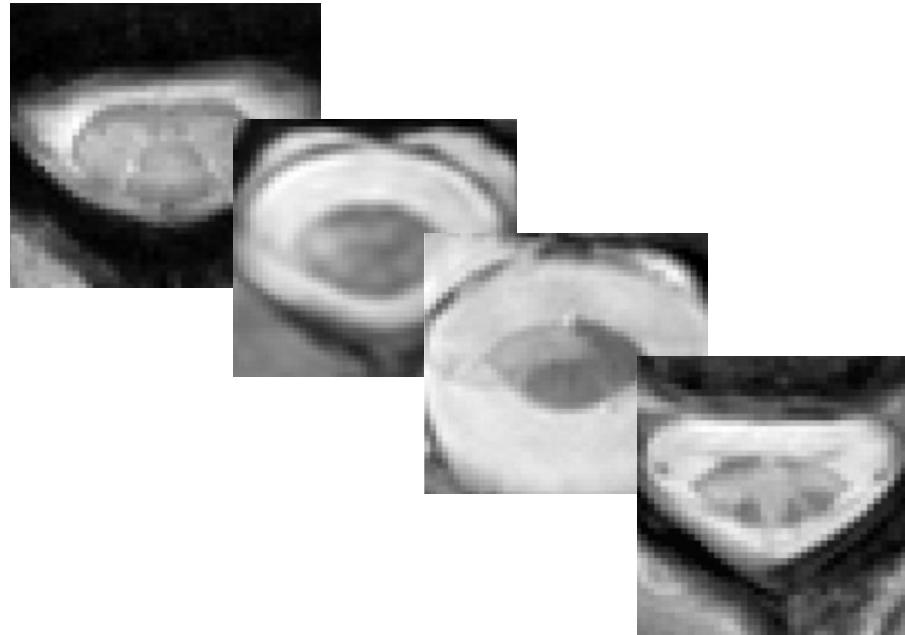
... key challenges include:

- Class imbalance
- Intensity / shape / size heterogeneity
- Intra- and inter-expert disagreement



When I first met CNNs...

- From 80 patients to... 672 patients, from 13 different clinical around the world.
- Re-train a segmentation model to account for the dataset heterogeneity

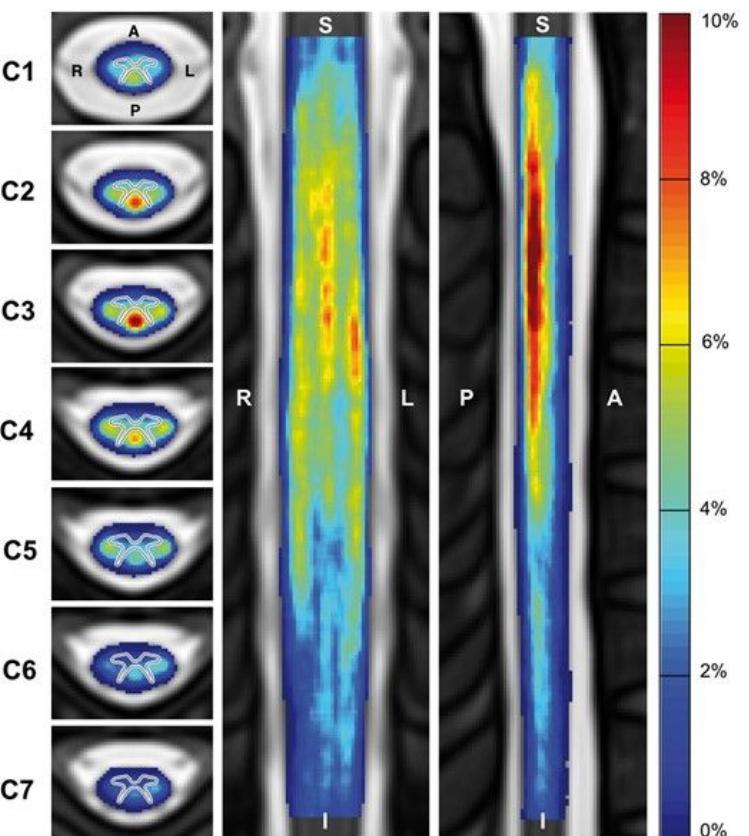


ZUCKERBERG
SAN FRANCISCO GENERAL
Hospital and Trauma Center

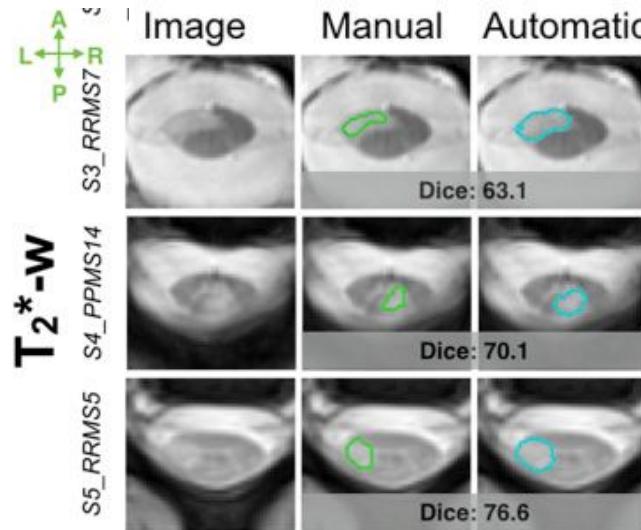


When I first met CNNs...

Frequency of multiple sclerosis lesions in the cervical spinal cord for all patients (n = 642)



Eden and Gros et al. 2019
doi: 10.1093/brain/awy352



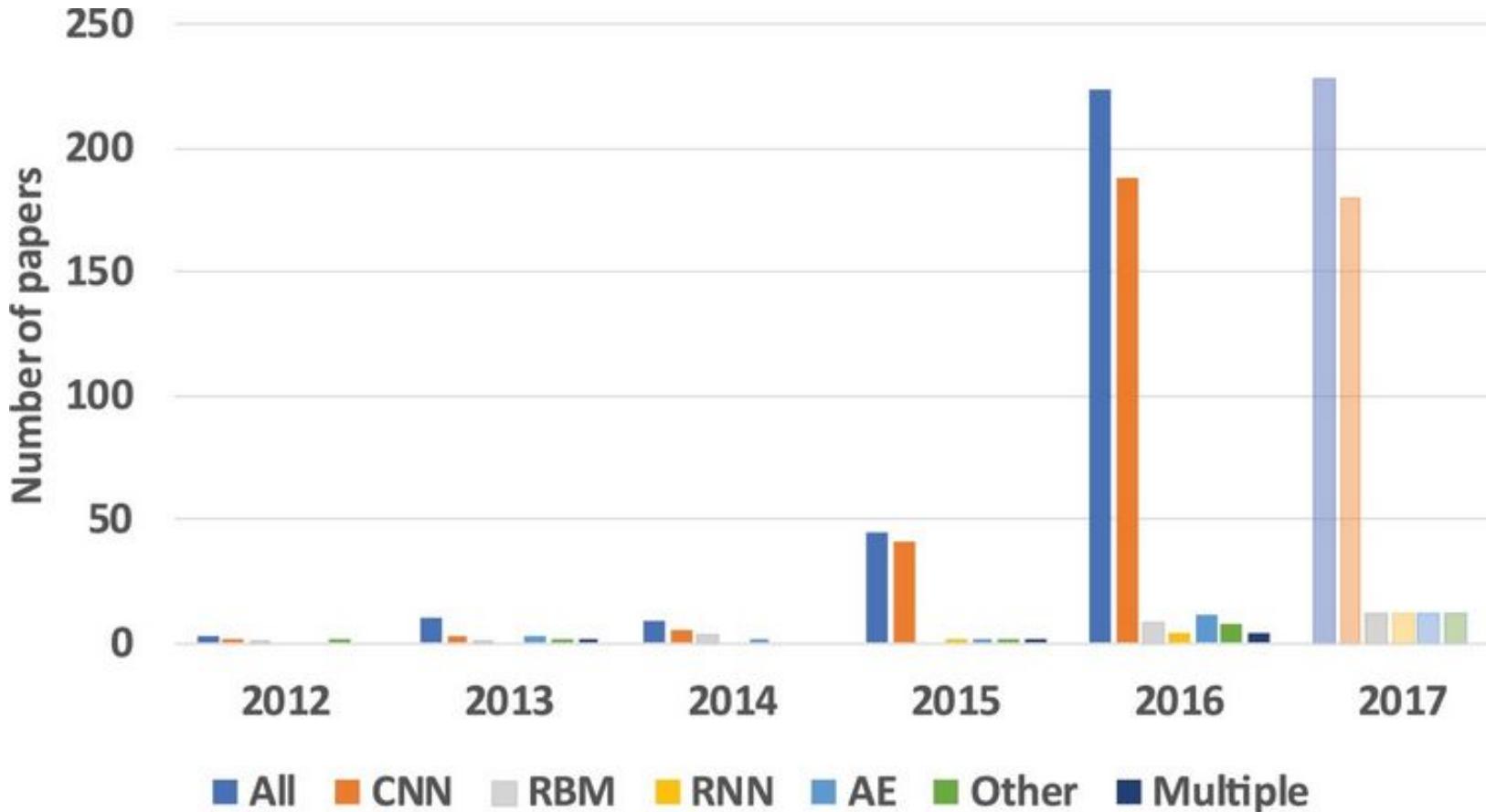
The automatic tool is now integrated into an open-source software, SCT (250+ citations).



SCT
Spinal Cord Toolbox

github.com/spinalcordtoolbox/spinalcordtoolbox

The 2015 sparkle



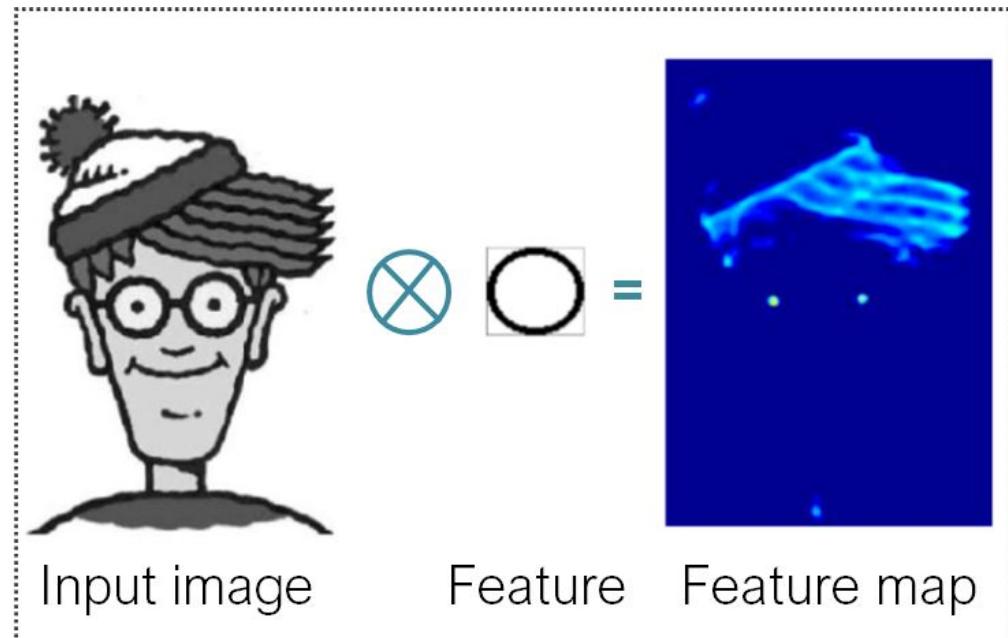
Why do they work bloody so well?

-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

“Ideal”
image

-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1

“Real life”
image



From “Feature engineering” to “Automatic feature selection” ...

Why do they work bloody so well?

1

Convolution

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	-1	1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1



1	-1	-1
-1	1	-1
-1	-1	1

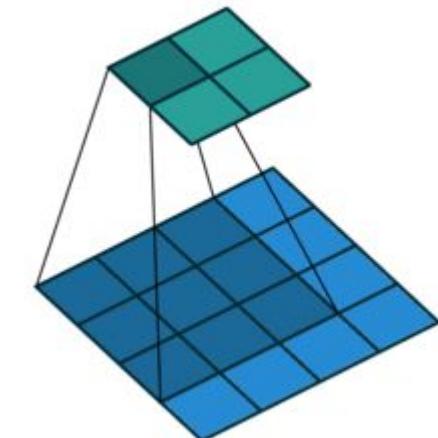
=

0.77	0.11	0.11	0.33	0.55	-0.11	0.33
0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.11	0.11	-0.33	0.55	-0.33	0.11	0.11
0.55	0.11	0.11	-0.33	1.00	-0.11	0.11
0.11	0.11	-0.33	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Input image

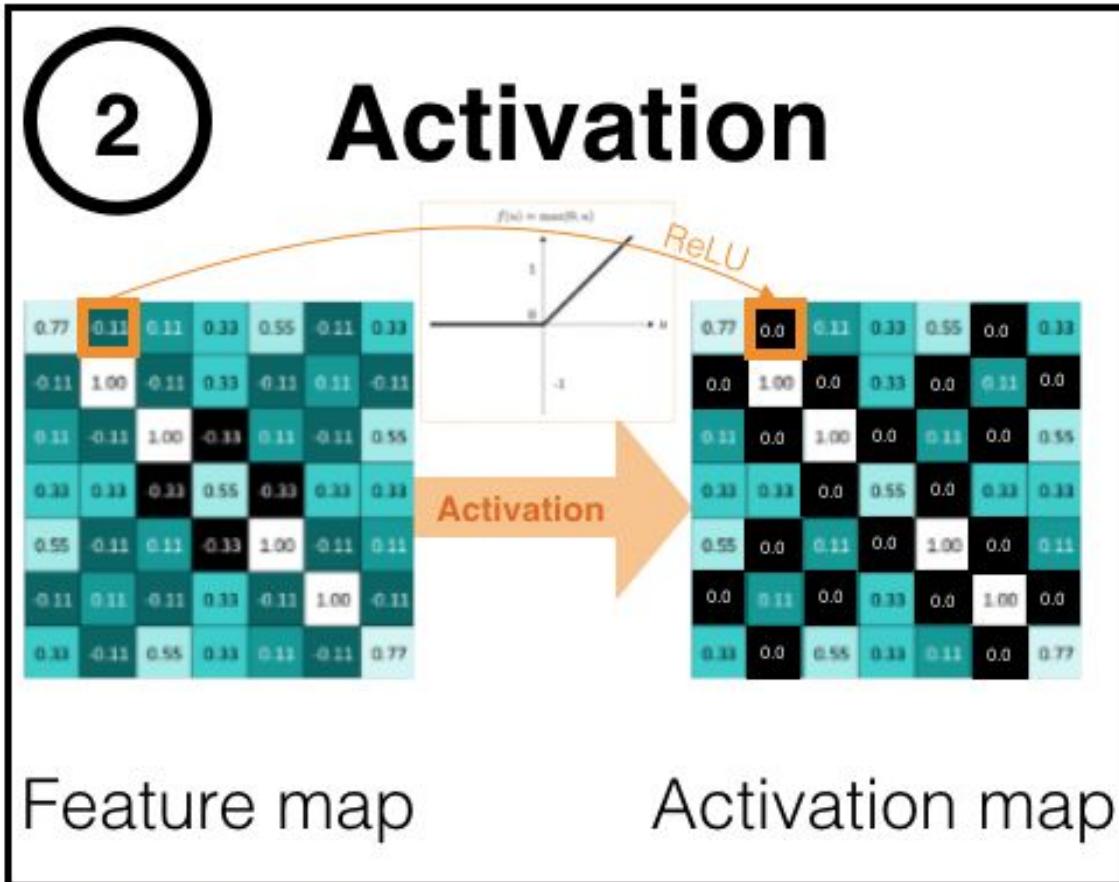
Feature

Feature map



GIF from
github.com/vdumoulin/conv_arithmetic

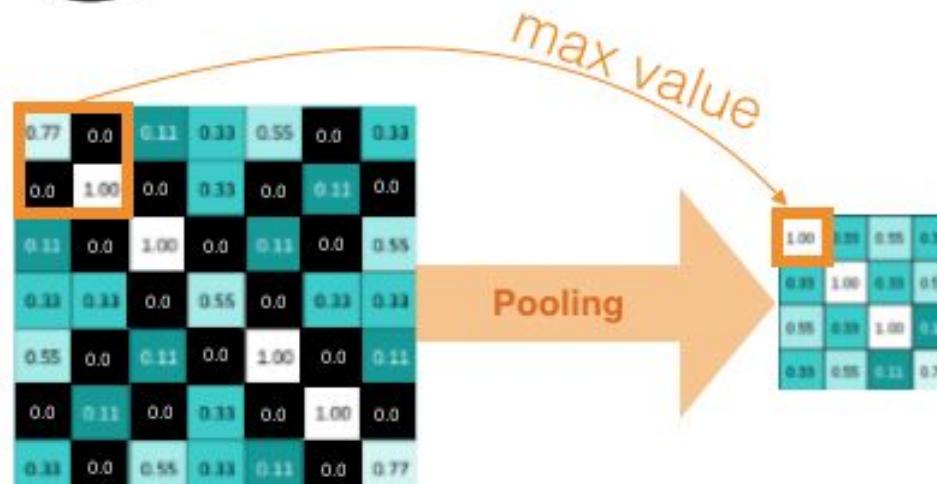
Why do they work bloody so well?



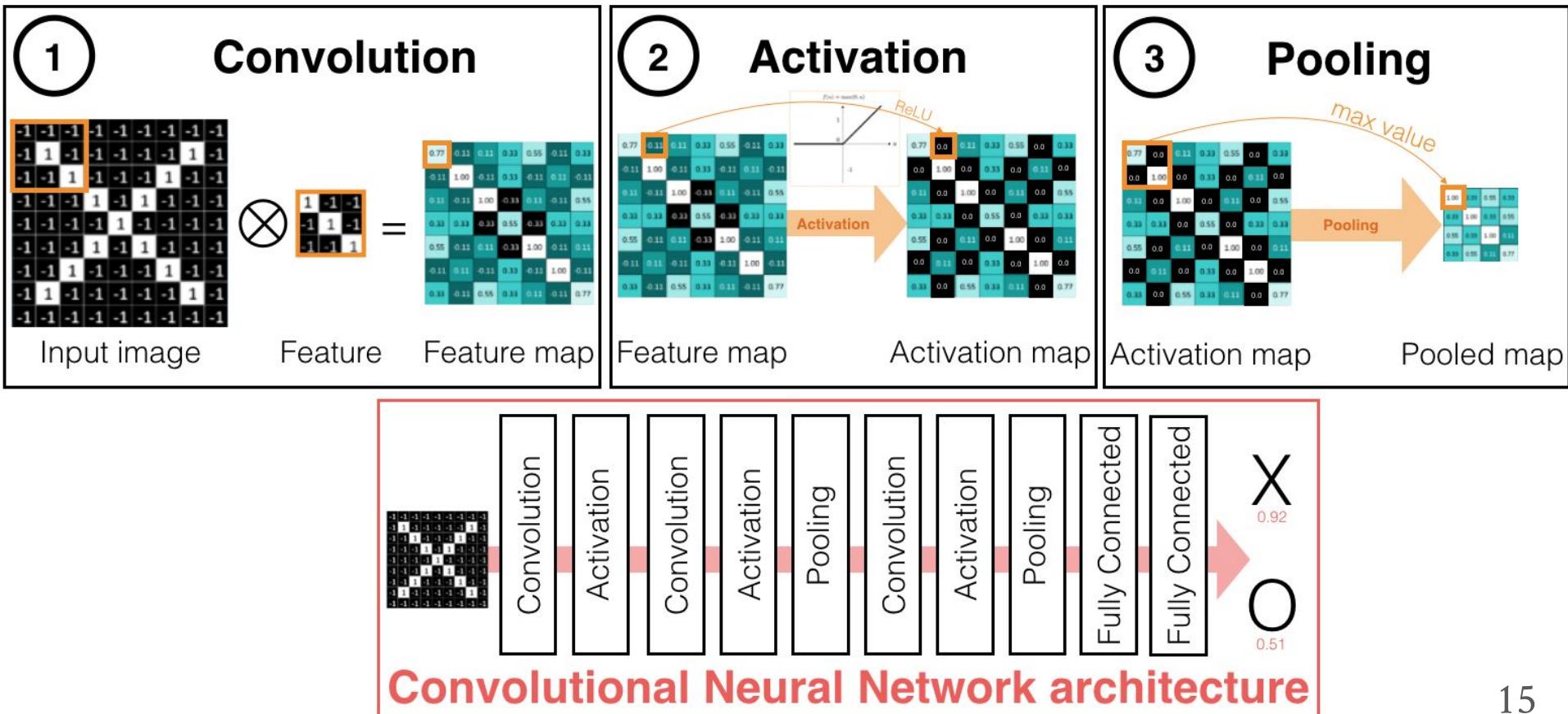
Why do they work bloody so well?

3

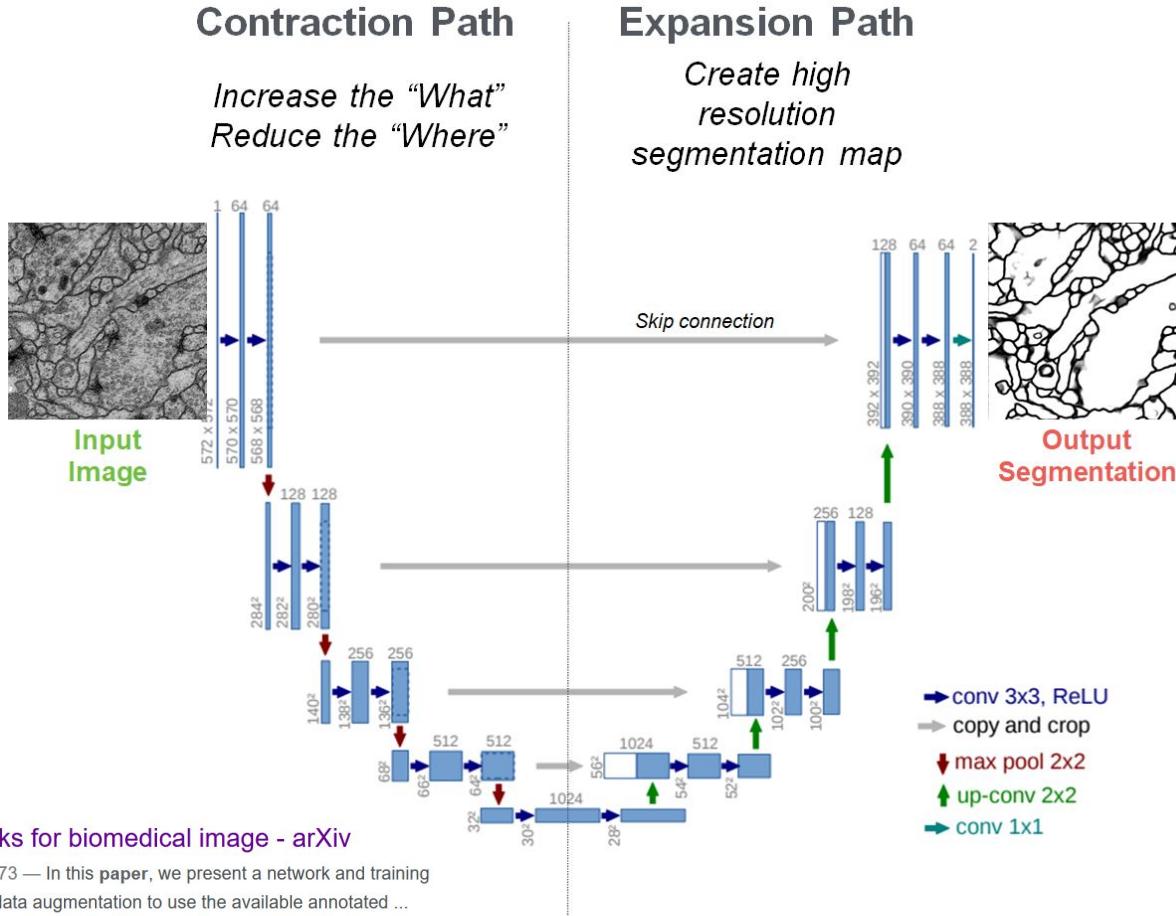
Pooling



Why do they work bloody so well?



One famous critter: the U-Net



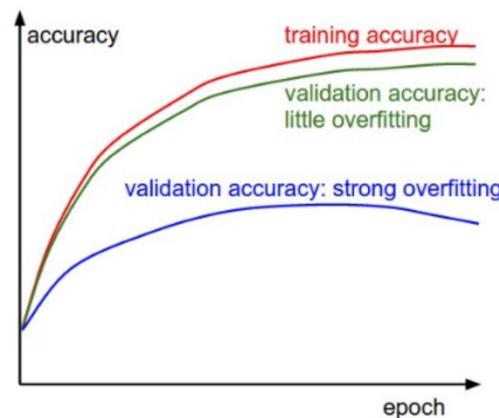
U-Net: Convolutional networks for biomedical image - arXiv

by O Ronneberger · 2015 · Cited by 30073 — In this paper, we present a network and training strategy that relies on the strong use of data augmentation to use the available annotated ...

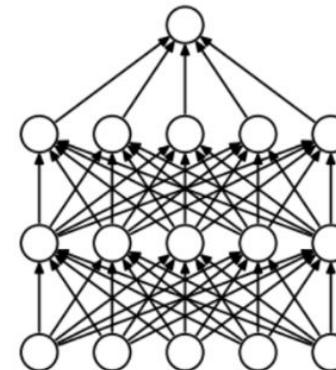
How to improve model's generalisation?

How to avoid overfitting:

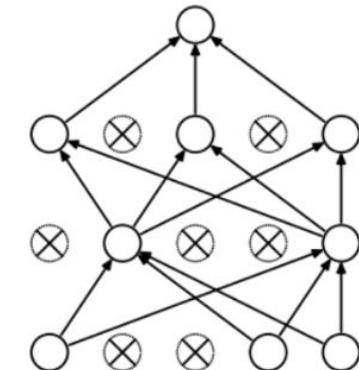
- Reduce model complexity
- Data augmentation
- Dropout
- Early stopping
- Transfer learning



From cs231n.github.io/neural-networks-3/



(a) Standard Neural Net



(b) After applying dropout.

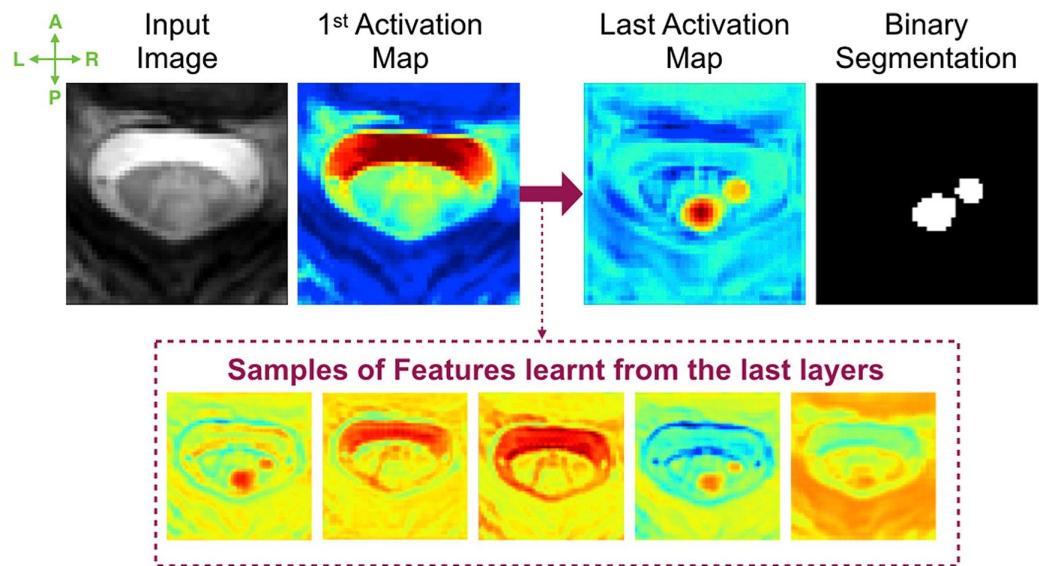
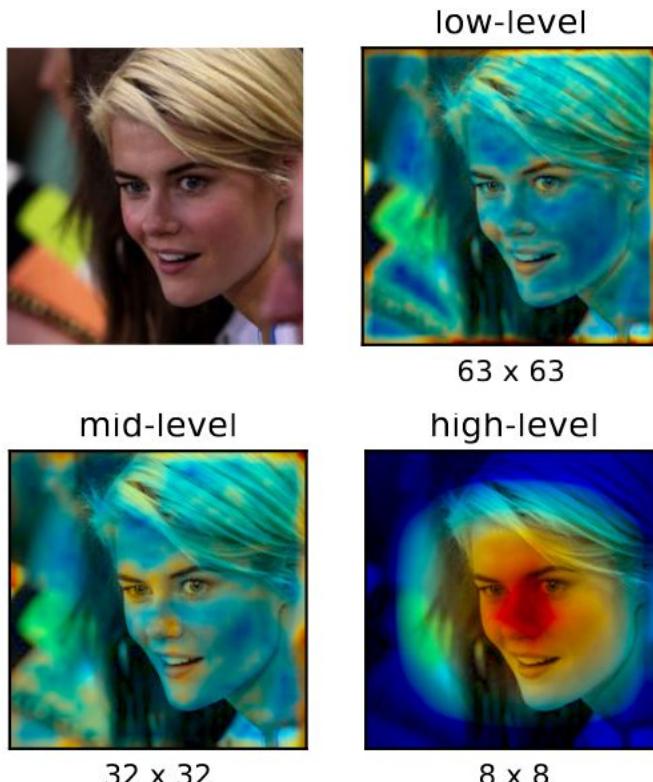
Srivastava et al. 2014

doi: [10.5555/2627435.2670313](https://doi.org/10.5555/2627435.2670313)



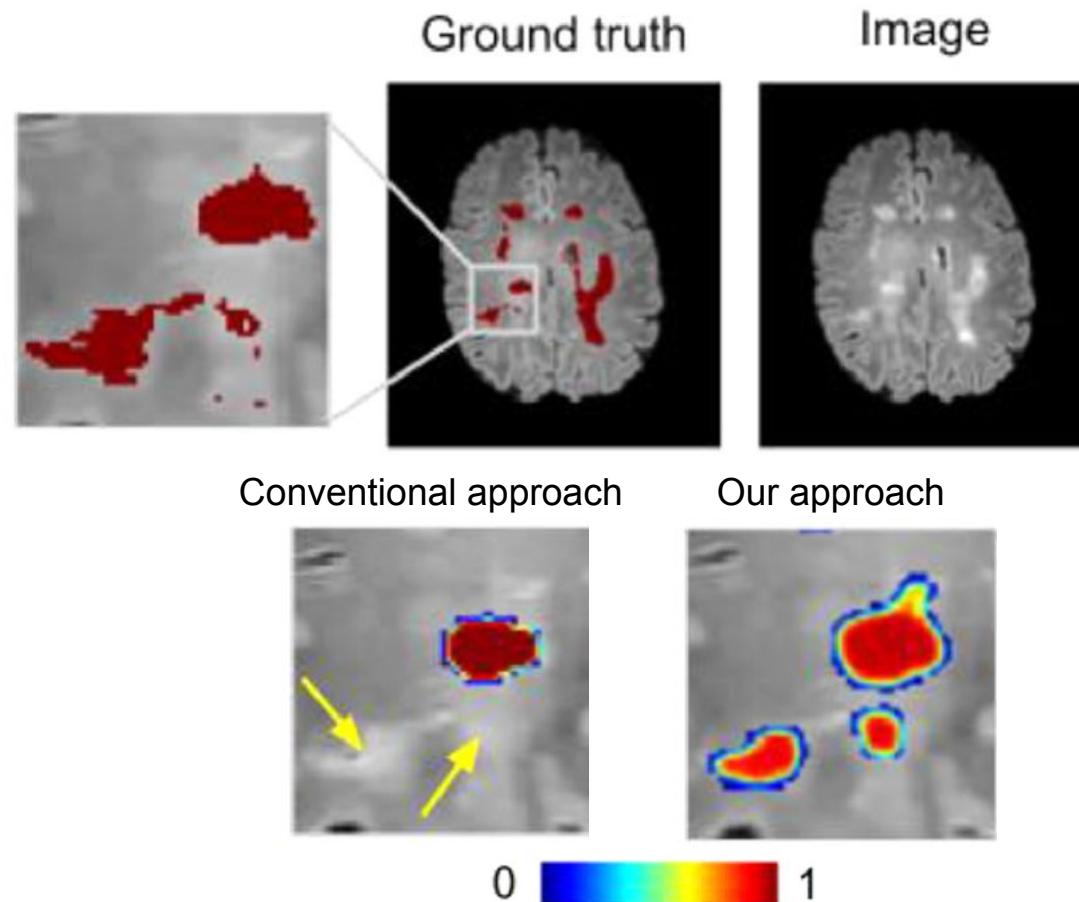
github.com/aleju/imgaug

Under the hood



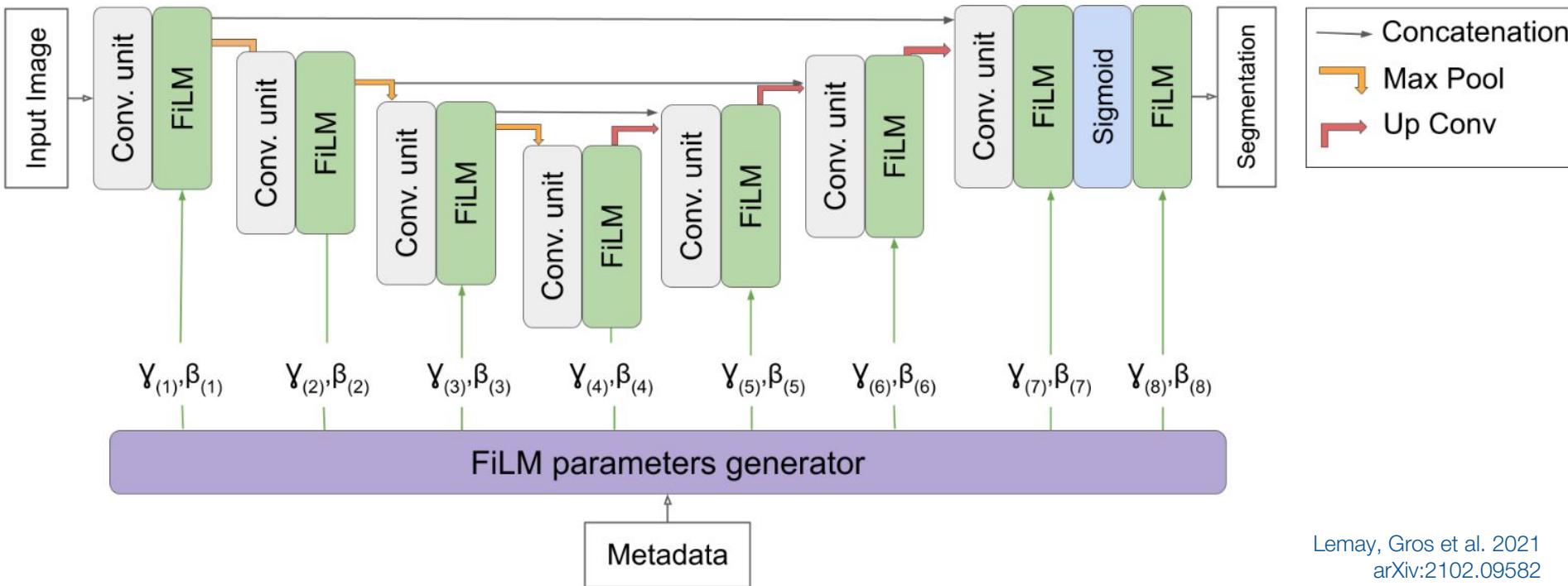
Zagoruyko and Komodakis 2016 ; arXiv: 1612.03928

Uncertainty matters



Gros and Lemay et al. 2021
doi: 10.1016/j.media.2021.102038

Conditioning layers



Lemay, Gros et al. 2021
arXiv:2102.09582

Why now is the time to jump in?

1

Quantity of data collected and shared



2

Computer resources available



3

Large and dynamic community, open-source culture



From your local code to an open-source library

ivadomed / ivadomed

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The diagram shows a sequential process: **DATASET** (represented by a database icon) feeds into the **LOADER** (represented by a circular arrow icon). The **LOADER** then processes the data into **INPUTS** (represented by a brain scan and a red mask icon). These **INPUTS** are fed into the **NETWORK** (represented by a series of vertical layers), which produces the final **OUTPUTS** (represented by a red heatmap and a 3D volume icon).

Dataset: Standardized neuroimaging input format (<https://bids.neuroimaging.io>)
Memory: on RAM or "on the fly" (HDF5)
Sample: 2D/3D ; patch, slice, or whole volume.
Preprocessing: Resampling, Cropping
Options: Adaptive loading (curriculum learning, balance classes), Robust to missing modalities.

Input / Output: Single or Multi input-channel / class.
Options: Metadata, prior predictions (cascade training scheme).

Data augmentation: state-of-the-art operations + inverse transformations for reconstruction.
Weight initialisation: from scratch or transfer learning.
Model: 2D/3D Unet, ResNet, DenseNet, CoUnet, HeMiUNet, FILMedUNet.
Options: FILM, MixUp, AttentionBlock, automate search for optimal binarization threshold and model hyperparameters.

Tasks: Segmentation, classification, detection
Training time: Metrics, training curves, GIFs.
Testing time: 2D/3D predictions, measures of uncertainty, CSV report.
Postprocessing: morphology, search for optimal threshold.

JOSS 10.21105/joss.02868 coverage 71% Run tests passing Publish Package failing docs passing License MIT

Follow 39

Documentation: ivadomed.org/en/latest/

Gros, Lemay et al. 2021
doi: 10.21105/joss.02868

Used by 3

@nidebroux / lumbosacral_segm...
@sct-pipeline / exvivo-template
@spinalcordtoolbox / spinalcordto...

Contributors 25

+ 14 contributors

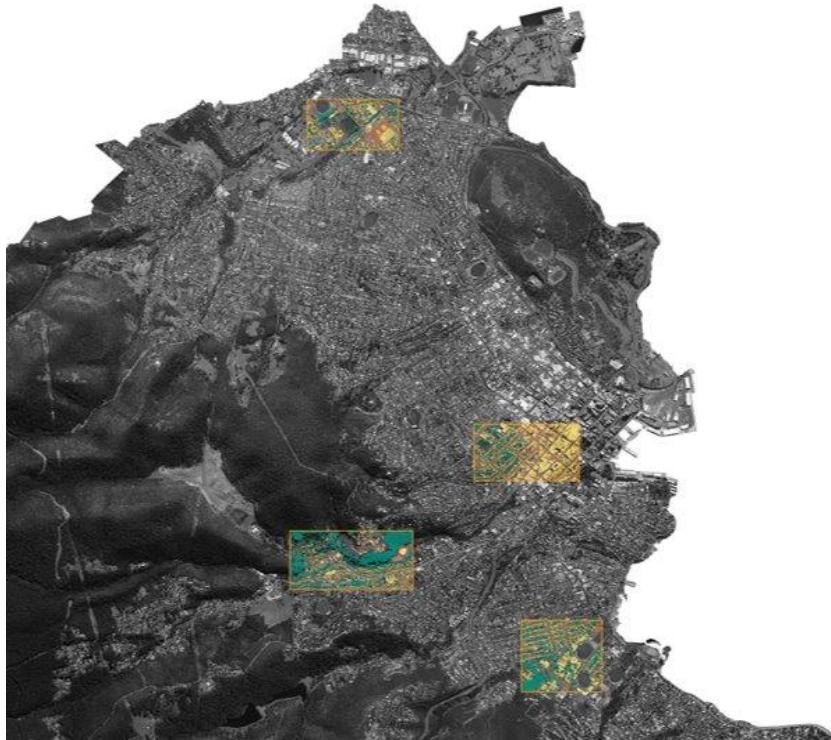
Languages

Python 95.4% TeX 3.0%
Shell 1.6%

Project with Bradley

Geoneon

Research question: *Differences in spatial distribution of human infrastructures vs trees, across Hobart's suburbs.*



Objective: fine-scale segmentation of Hobart area,
~80 km².

Target: trees vs. buildings vs. roads.

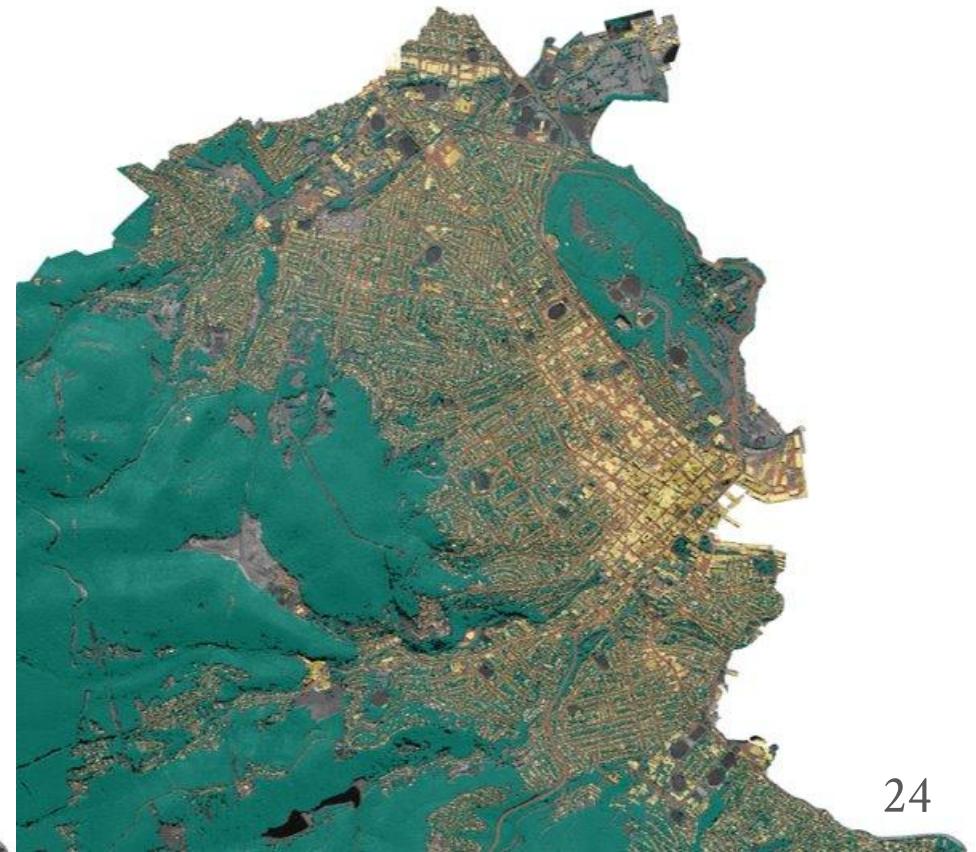
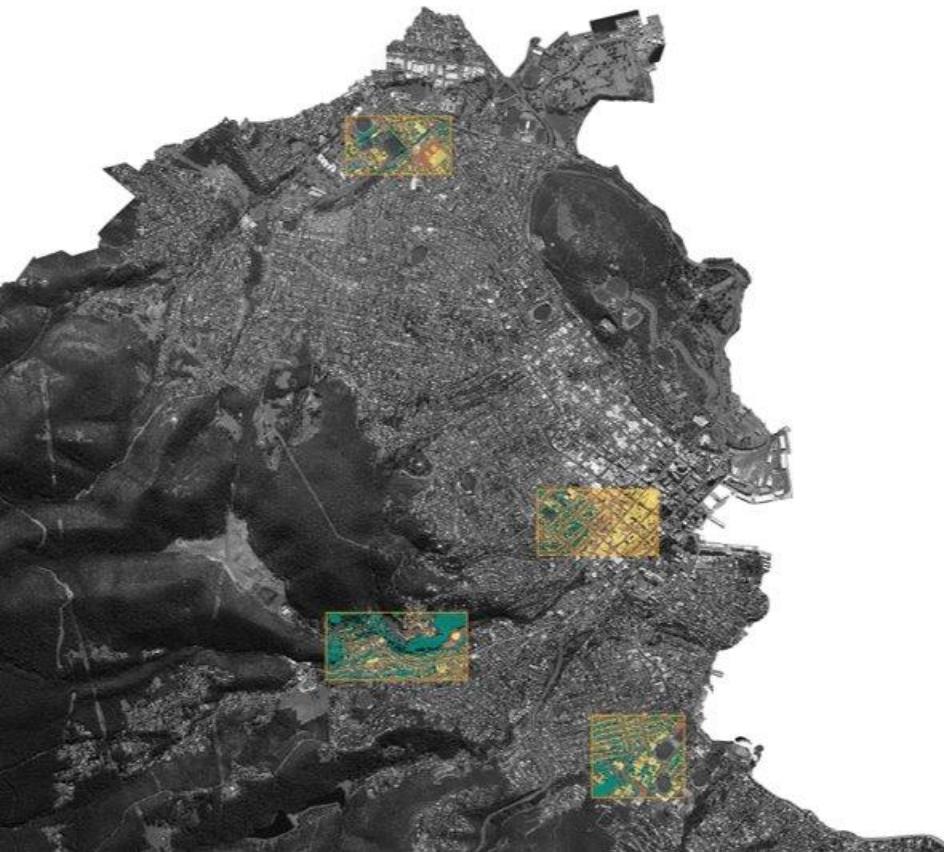
Input data: satellite imagery, 50 cm resolution.

Manual labelling: ~8% of the total area.

Method: U-Net, Dilated convolutions, DropOut,
Batch normalisation, Dice Loss.

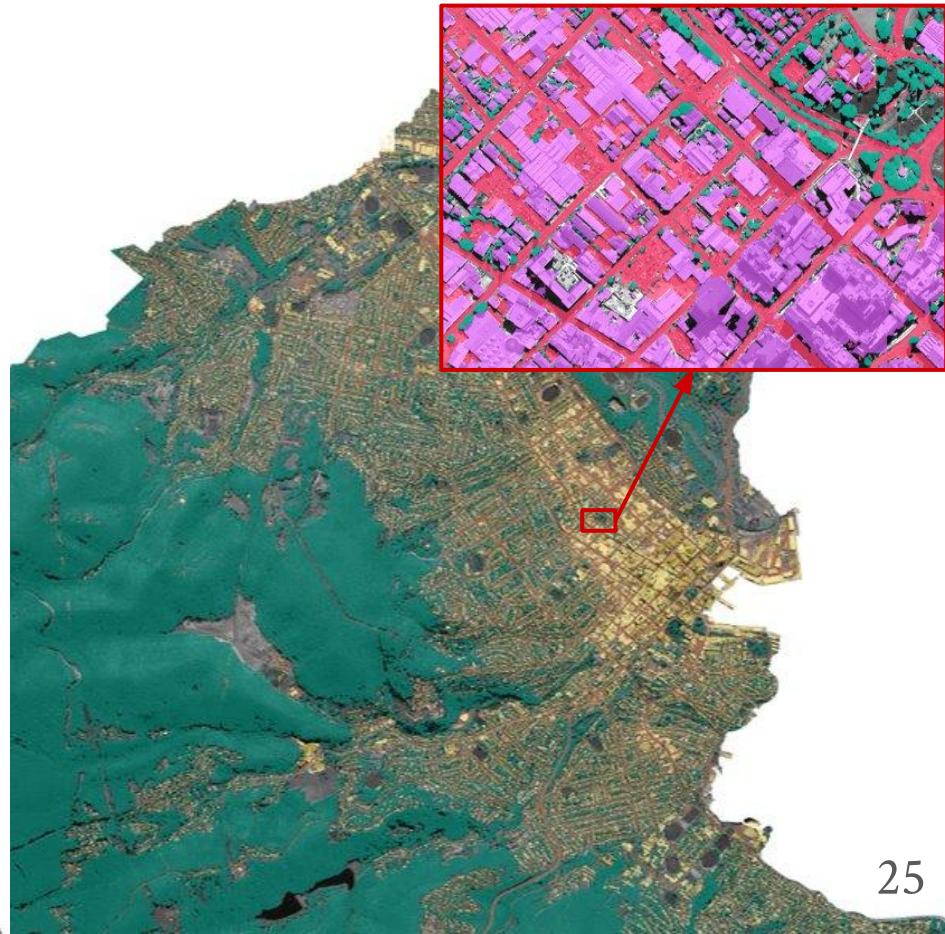
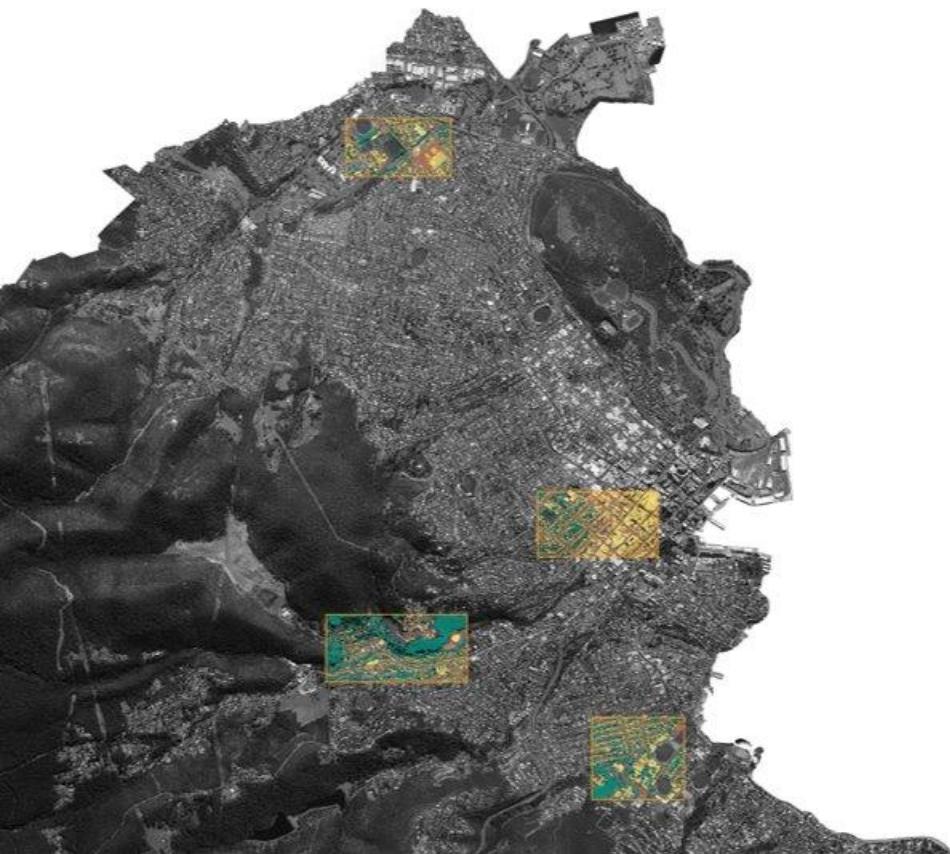
Project with Bradley

Geoneon



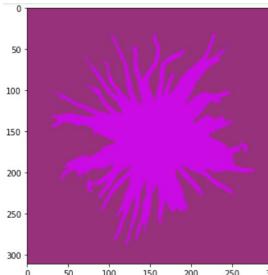
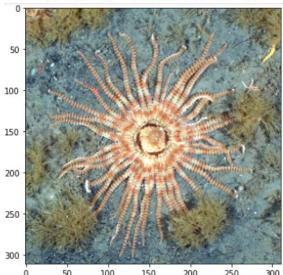
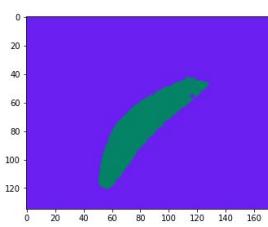
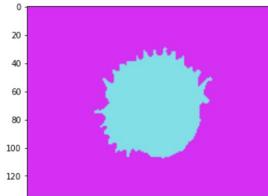
Project with Bradley

Geoneon



Project with Victor

Research question: *understand variability in organism size due to environmental factor or food availability.*



Objective: size estimation of organisms, from 90k+ annotated organisms.

Target: organism vs. background.

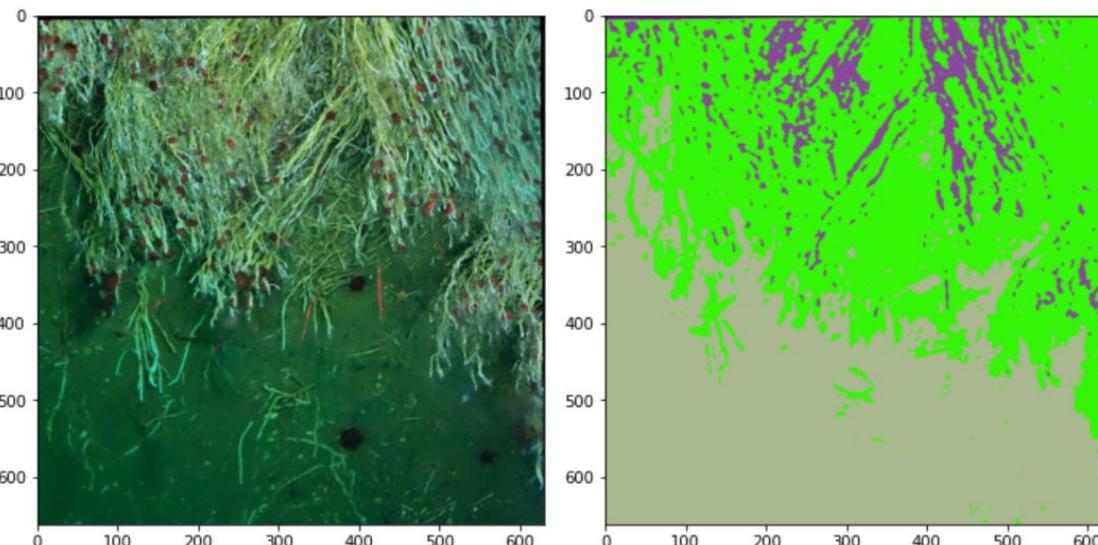
Input data: underwater imagery, heterogeneous acquisition method.

Method:

1. Unsupervised segmentation with spatial constraint
2. Review and cherry picking
3. Supervised training
4. Review and cherry picking + manual segmentation of some hard samples
5. Back to step 3 until satisfied

Project with Juan Carlos

Research question: *correlation between seafloor habitat and environmental variables.*



Objective: clustering of the seafloor habitats without assumption on the number or type of habitat.

Target: spatial clustering of different habitats.

Input data: orthomosaics from photogrammetry.

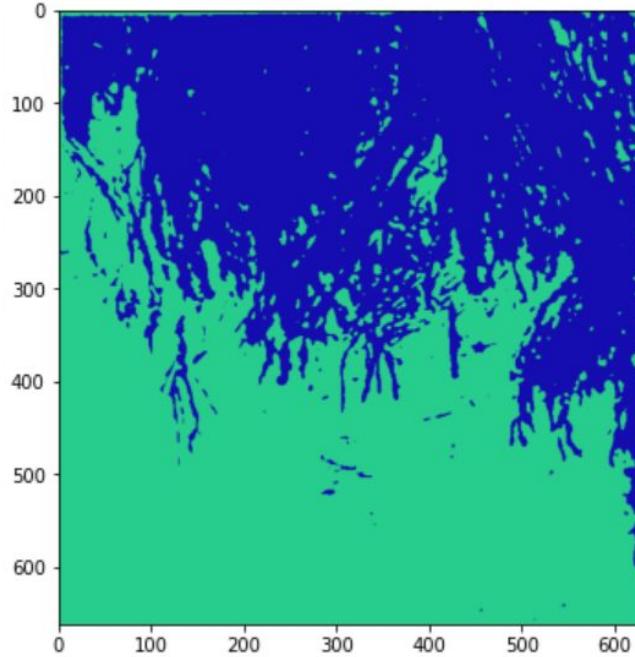
Method: Unsupervised image segmentation.

Project with Juan Carlos

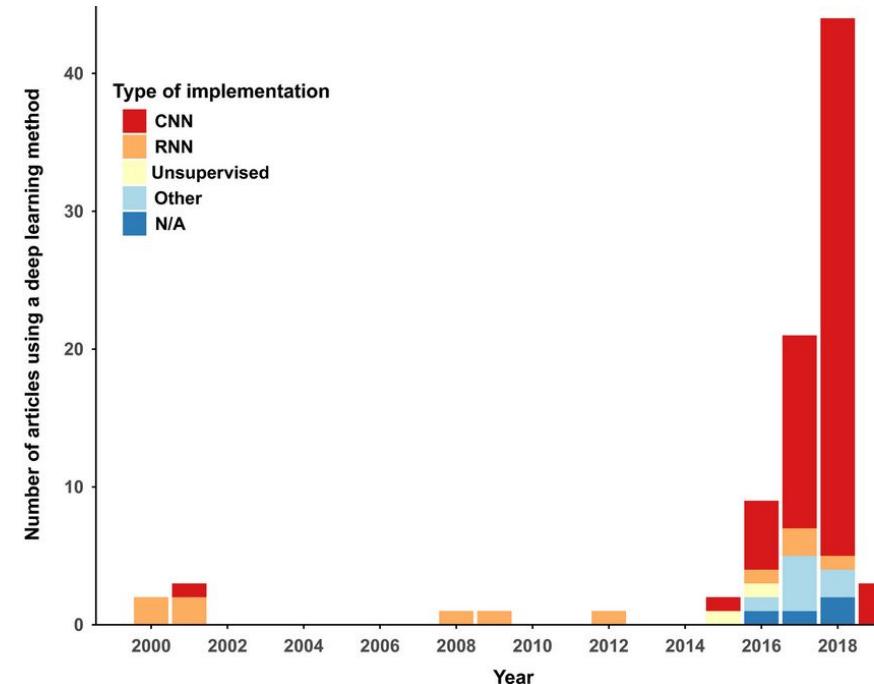
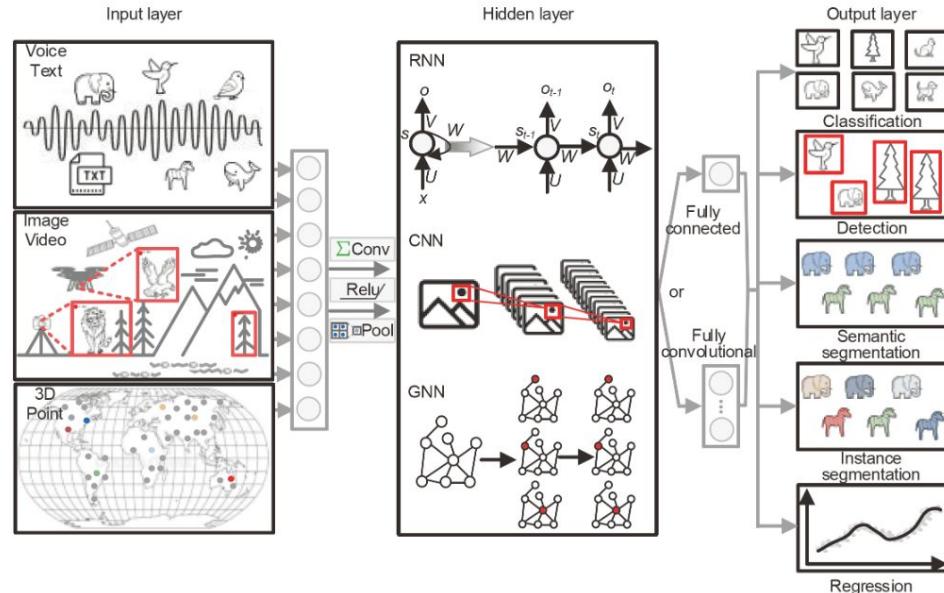
Alternative method: Weakly-supervised
image segmentation.



- Mouse click to start a scribble
- Change label with digits or <up>/<down> arrows
- <r> to reset current label, <t> to change random colors



What's up in Ecology?



Guo et al. 2020 ; doi: 10.1007/s11430-019-9584-9

Christin et al. 2019 ; doi: 10.1111/2041-210X.13256

Practice



Research question: *Where is bloody Wally?*

1. Dataset preparation and exploration
2. Data loading
3. Dataset splitting
4. Data augmentation
5. Model configuration
6. Model training and optimisation
7. Model evaluation on independent dataset

[github.com/charleygros/IMAS
_workshop_Where_is_Wally](https://github.com/charleygros/IMAS_workshop_Where_is_Wally)

PyTorch

colab

