

Deep learning for drone data

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What we will cover today

- Demystifying *deep learning* for drone data
- Choosing the right model for your questions
- Turning drone images into training data
- Training a simple deep learning model
- Using a model to extract knowledge from images

Session N

Deep learning for drone data

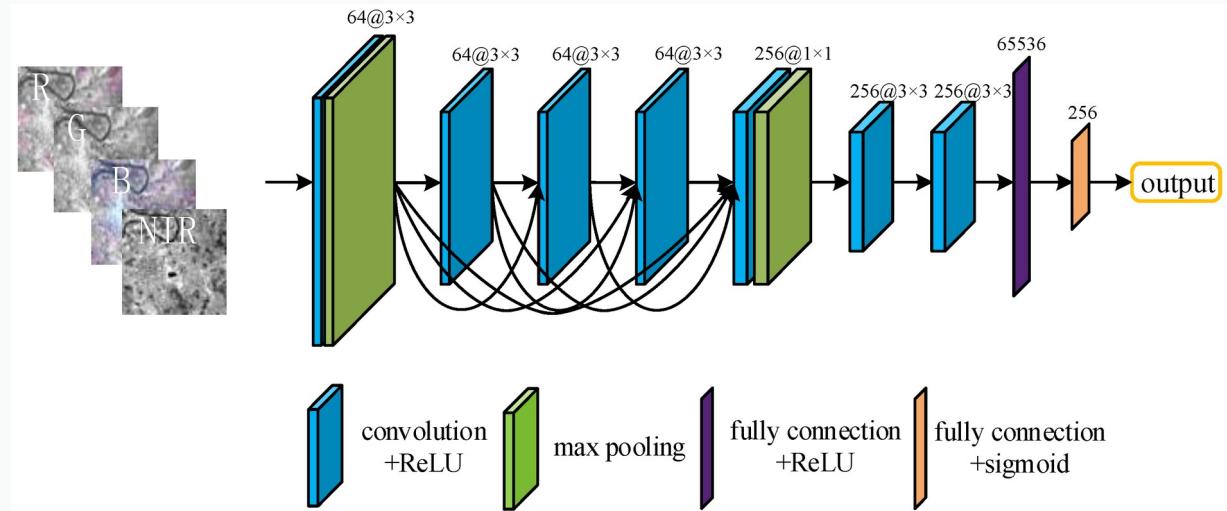


Deep learning with drone data

- Use 2D imagery to train a neural network to recognise shapes in a landscape
- Turn drone imagery into **training data**
- Get an overview of **different deep learning techniques** for remote sensing
- More detail on the Attention U-Net model we're using today
- Monitoring, measuring and testing the process of training
- Steps to trying this on your own data

Demystifying deep learning

- Set of **images** showing what we want to learn about
- Set of **labels** for each image, describing what it shows
- Neural network which takes RGB+ pixels and labels as **input**
- When the network is shown a new image it outputs **predictions**
- What the predictions look like depends on the problem we're trying to solve

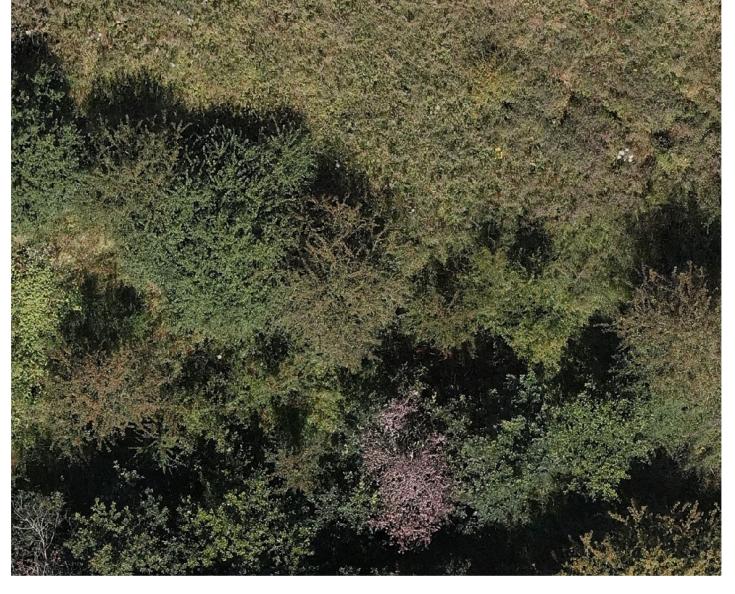


Step 1: prepare your data!

- **Drone imagery** flown over Strawberry Hill
- **Labels** describing the shape of each shrub, made by tracing in a GIS
- Extract small, square images - "**patches**" - centered around each shrub
- Create a **greyscale image** showing either 0 (background) or 255 (shrub)
- Extract about twice as many images that don't have shrubs in them
- Create all-zero, blank labels for these **negative examples**

Strawberry Hill

- High-resolution imagery flown by Charles
- Well-known "rewilding" site in the UK



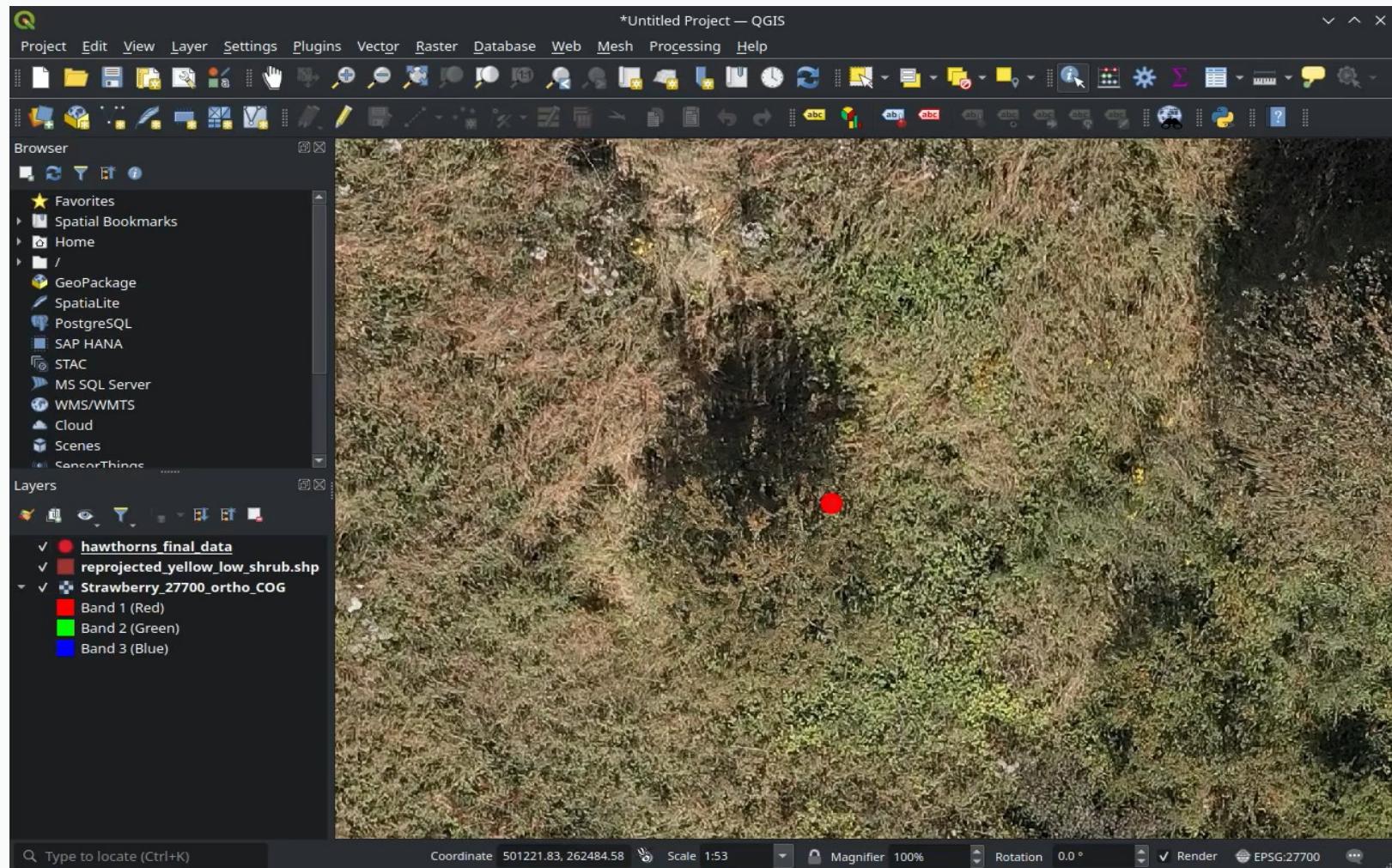
MAMBO

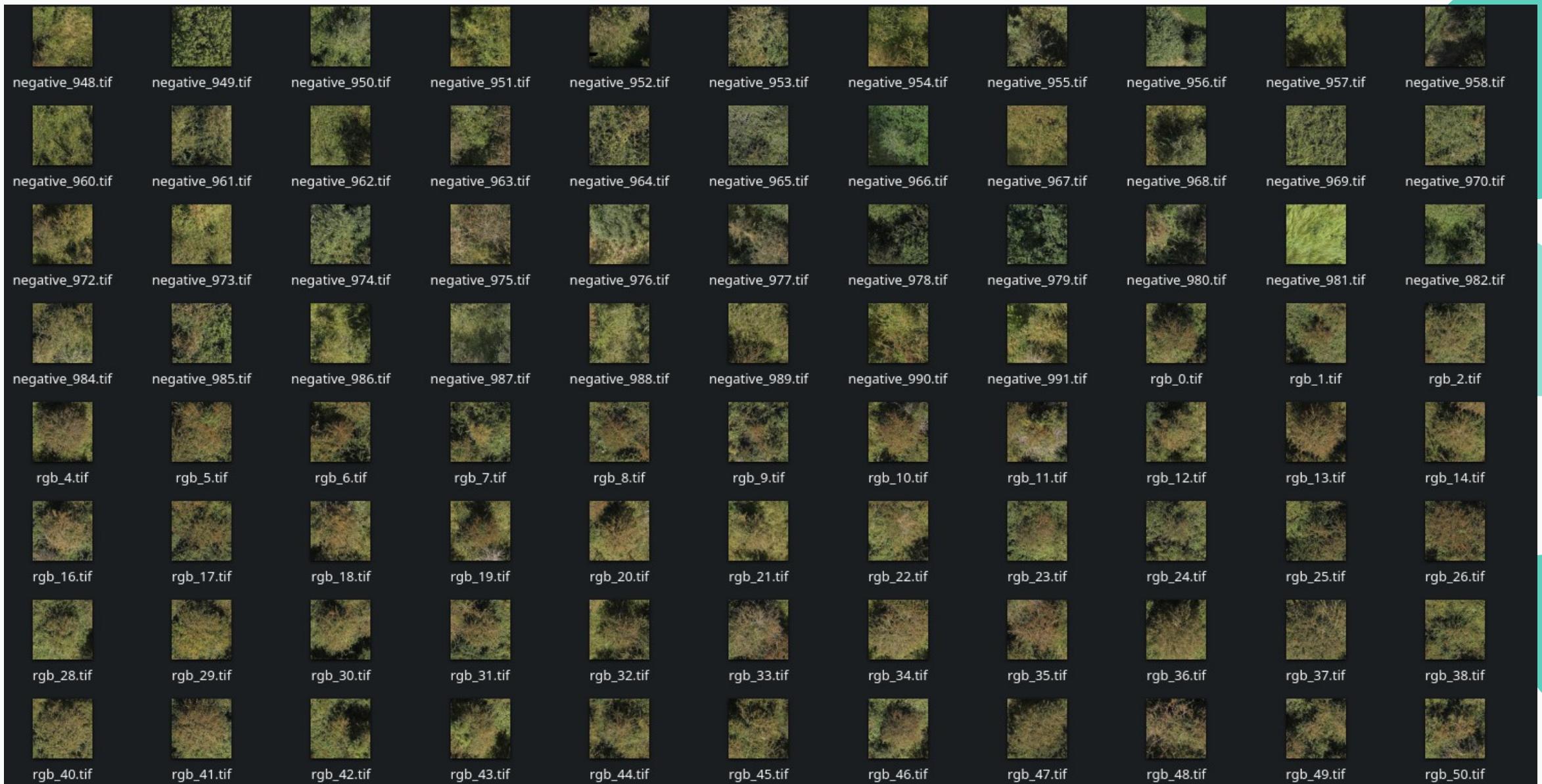


UK Centre for
Ecology & Hydrology

Labelling shrubs

- For part of this large image we have a detailed vector layer
- These show where the canopies of hawthorn shrubs are
- We will use the image and labels to create **training data**
- And train a **deep learning model** to identify shrub outlines







Turning drone data into training data

- We're going to use [Google Colab](#) for these exercises
- This provides free interactive notebooks for running code in python
- Please [open this notebook in Colab](#) and save your own copy

- Use open source GIS libraries to work with data in cloud storage
- Read small windows of the large drone image – our "patches"
- Turn our vector data into labels that match each small image
- Save hundreds of examples, which we'll then use for training!

The hard work is data curation

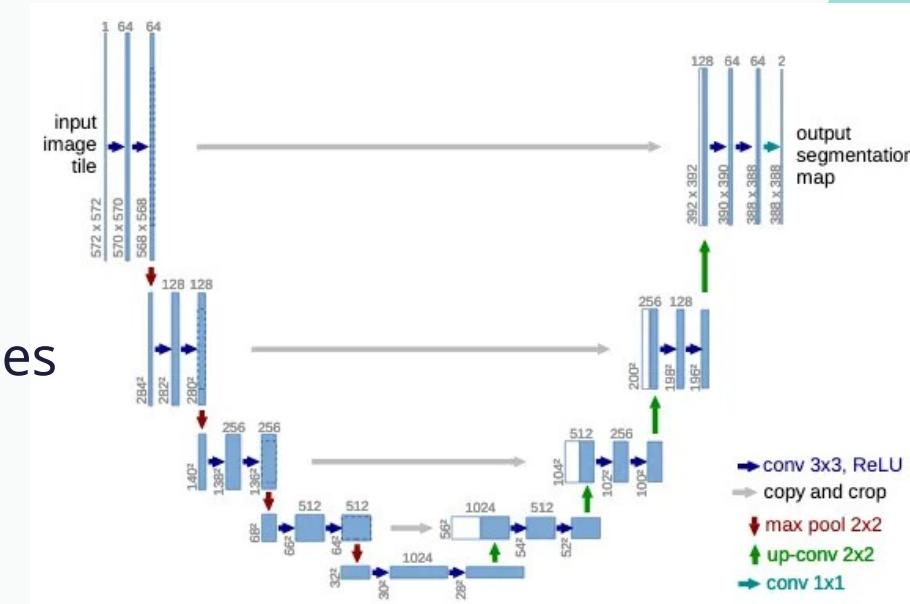
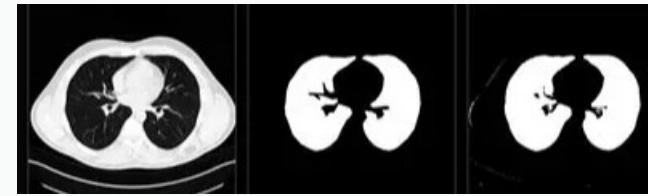
- Time and effort spent labelling
- Careful selection to show the model a good variety ("class balance")
- Realistic test data - good metrics don't guarantee good results
- Keeping track of data versions
- Reproducibility - linking training data to model versions

Approaches to image machine learning for remote sensing applications

- Different “model architectures”
- What each layer of the neural network does, how they are connected
- Different sets of labels:
 - A classification for an image, or bounding boxes, or a label per pixel...

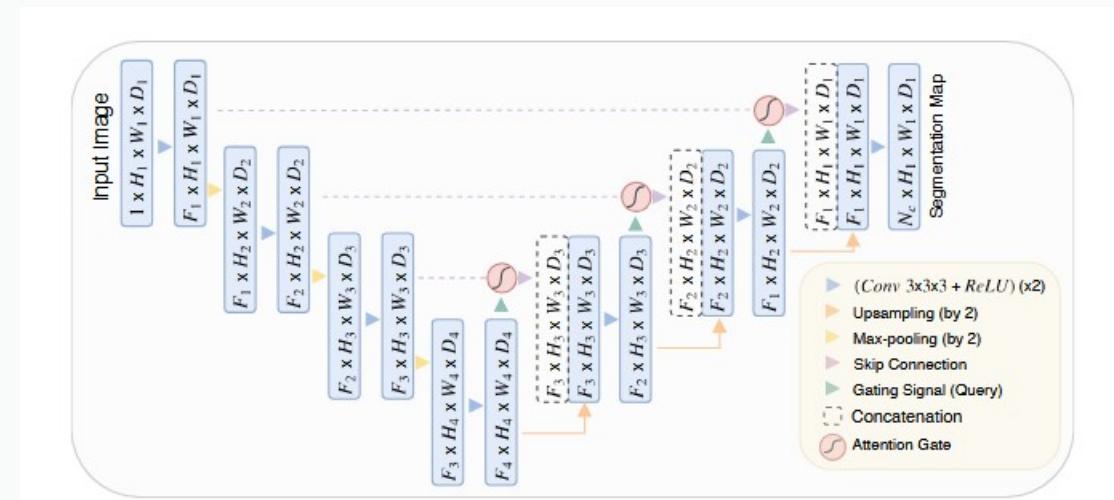
U-Net

- Called that because of its U-shape!
- The left half compresses the image into a flat list of features
- The right half decompresses it back into its original form
- Shown an image without labels, it outputs a version with them
- These are a prediction, per pixel, of what it's showing.
- From the biomedical domain where data is scarce
- Works with hundreds rather than many thousands of images
- <https://arxiv.org/pdf/1505.04597>



Attention U-Net

- Later than the original U-Net
- Helps to pick out most “salient” parts of image
- Also from the biomedical imaging field
- <https://arxiv.org/pdf/1804.03999>



Training our model (an Attention U-Net)

- Training a useful model can take many hours, or even days!
- Using a GPU speeds this up considerably
- Please [open this notebook in Colab](#) and save your own copy.
- Re-use the training data that we've just prepared
- Train a small Attention U-Net model to recognise shrubs

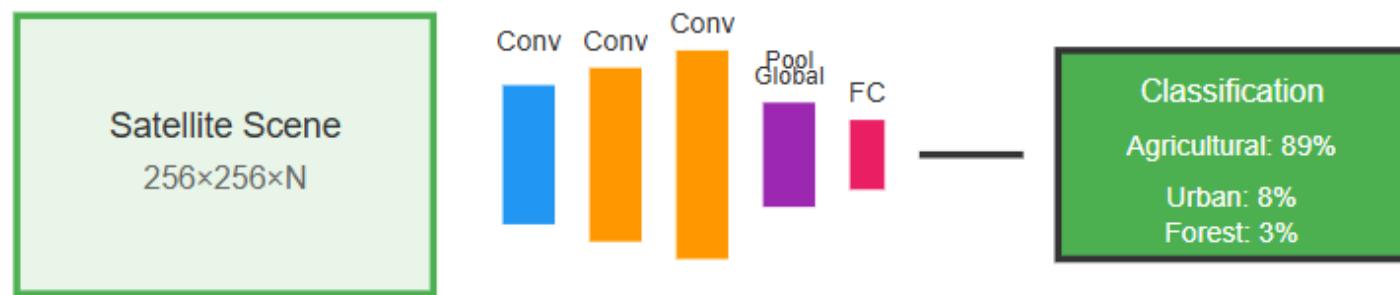
Time for a break



Classification

Scene Classification

Architecture: CNN (ResNet, EfficientNet)



Applications:

- Land use mapping
- Disaster assessment
- Agricultural monitoring

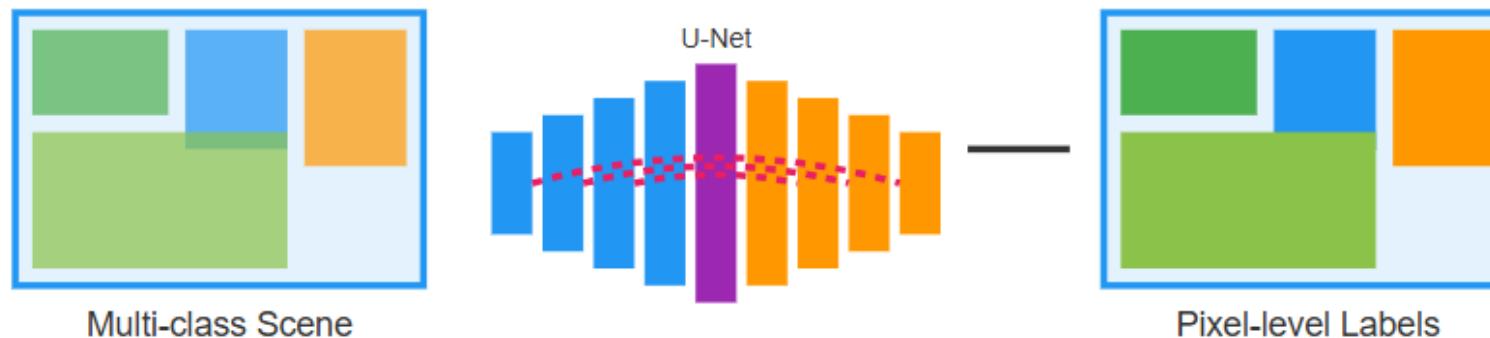
Other uses for classification models

- As a basis to “fine-tune” by changing the final number of output classes to match a new dataset
- As a “backbone” for other models that learn from classification outputs (this is how some Siamese models work)
- As a “feature extractor” (effectively a vector of numbers, extracted from one layer towards the middle or end of the network) that can be used for search
- As a source of features that can be used to train a smaller model, like an SVM

(Semantic) Segmentation

Semantic Segmentation

Architecture: U-Net, DeepLabV3+



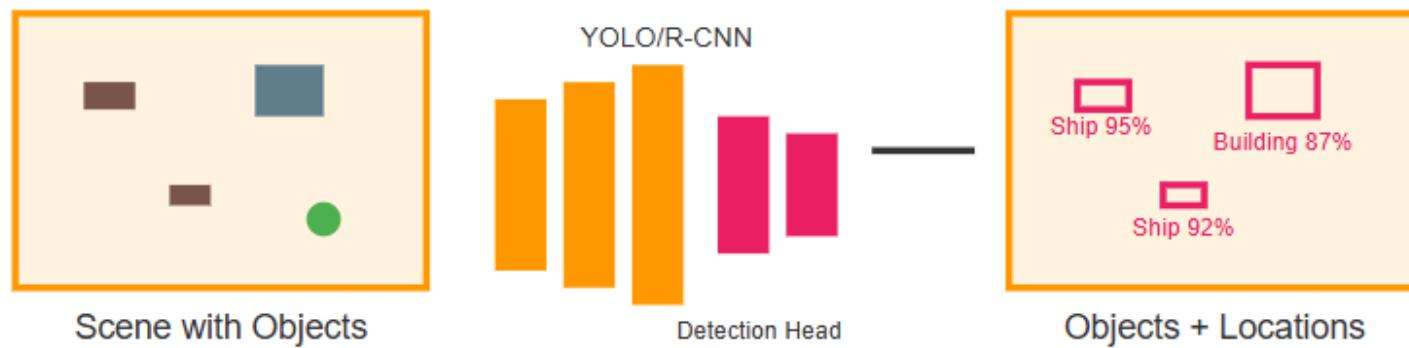
Applications:

- Land cover mapping
- Crop field delineation
- Flood extent mapping

Object Detection

Object Detection

Architecture: YOLO, Faster R-CNN



Applications:

- Ship detection in SAR
- Aircraft monitoring
- Vehicle counting

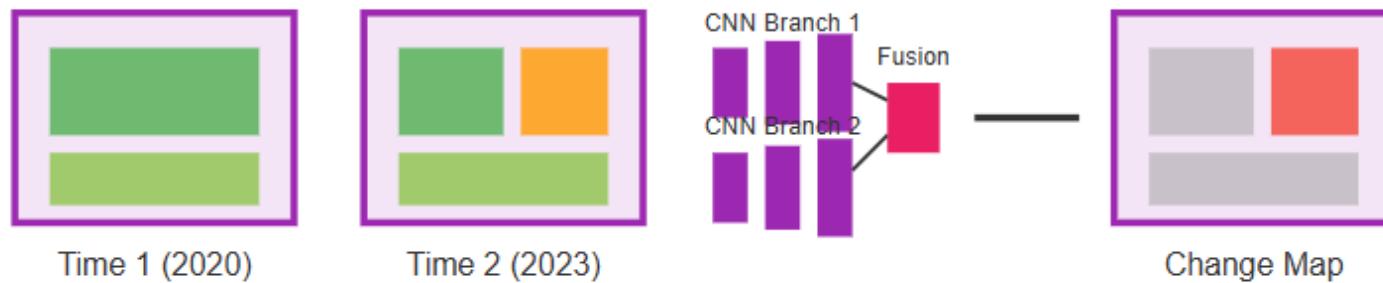
Other uses for object detection models

- Used to identify areas of interest in an image, then run a second model on those
- For example, biodiversity projects using camera traps: a first pass gives you bounding boxes with regions of interest, a second could either be species classification, or terrain segmentation

Change Detection

Change Detection

Architecture: Siamese Networks, 3D CNNs



Applications:

- Deforestation monitoring
- Urban growth tracking
- Disaster impact assessment

How's our model training?

- We hope to see at least a dozen “epochs” completed
- After the break, we’ll visualise how the training has gone
- (It’s quite likely the Colab notebook will switch off!)

Time for a break



Any Questions?

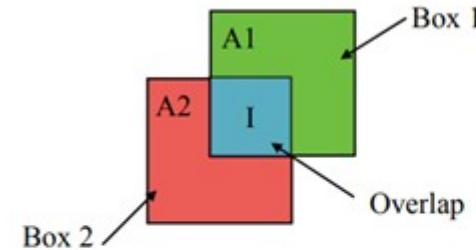
Metrics and test data

- Keeping a set of data in reserve that a model has never seen

Accuracy Assessment

- Per-class F1-scores, confusion matrices
- Segmentation
- Intersection over Union (IoU) / Jaccard Score

Intersection over union (IoU)



A1 : Area of Box 1
A2 : Area of Box 2
I : Intersection area

Tells you how well predicted box overlaps ground truth box

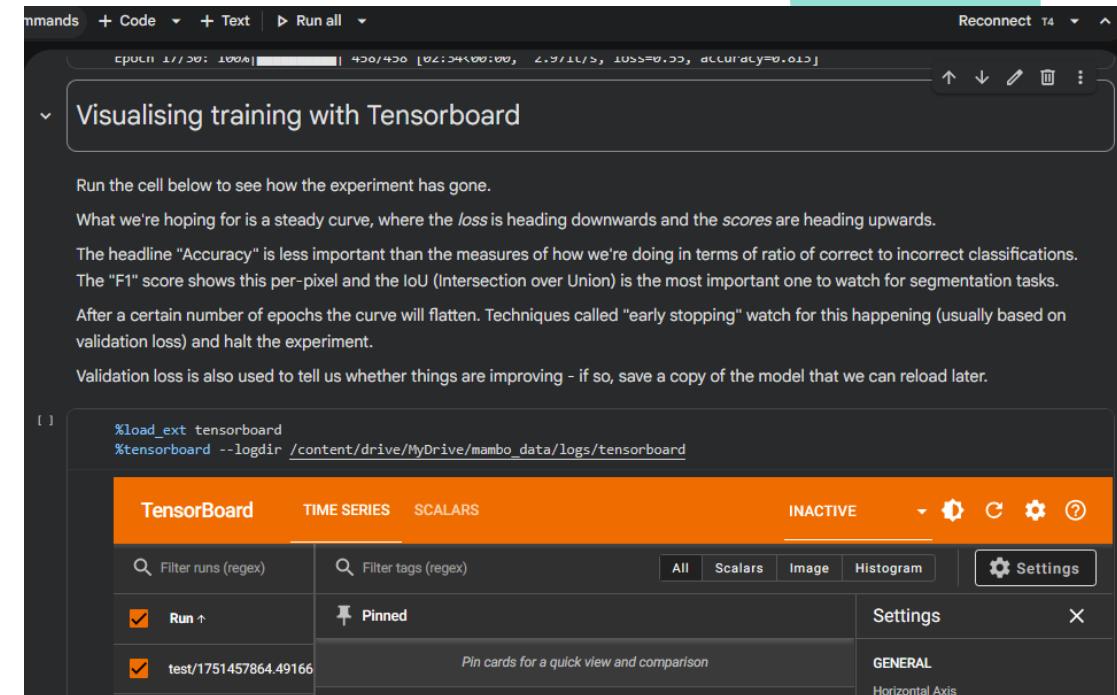
$$\text{IoU} = \frac{I}{A1 + A2 - I}$$

$$\text{IoU} = \frac{\text{blue square}}{\text{red square} + \text{green square} - \text{blue square}}$$

<https://blog.csdn.net/chengyq16>

Testing and measuring our model

- Our training notebook includes a Tensorboard dashboard
- It shows how the model's performance has changed as it learned
- Please [open the training notebook again](#)
- Scroll to “Visualising training with Tensorboard”
- You may have to “Reconnect” (top right)



Using our model for inference

- Now we can use the model for *inference* - new knowledge about unseen data
- For a new image the model has never seen, predict (per pixel) what is a shrub
- Save the output as a GIS vector format, and use it for other calculations
- Please [make a copy of this notebook in Colab](#)
- Try it with the model we've just trained, or “one we prepared earlier”

Reusing others' work

- Segment Geospatial provides geospatial data handling and output around the Segment Anything Model
- Lightning demo of Segment-geospatial on our data during the lunch break
- Huggingface provides a huge repository of reusable models, many with “model cards” documenting how they were produced
- TIMM (pytorch image models) implements many cutting-edge image models
- ThingsVision provides many models for use as feature extractors
- Postgres has a pgvector extension – combine image search with geo query

Recap

- We've used drone imagery to create training data
- We've used free GPU on Colab to train a U-Net model
- We've used it to make inferences about new data

- We've explored the different kinds of deep learning models available for remote sensing problems
- Hopefully you are left empowered to try this with your own data!

Any Questions?