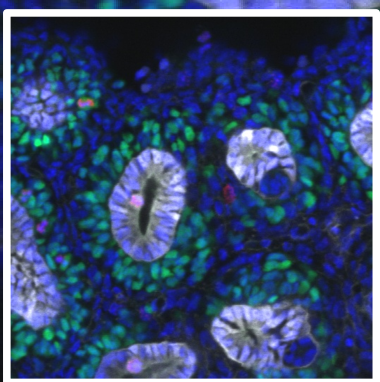
Datasets and slides:
https://github.com/doktor-nick/adv-ML-image-segmentation-with-UNET

Advanced Machine Learning Image Segmentation with UNET



Dr Nick Hamilton
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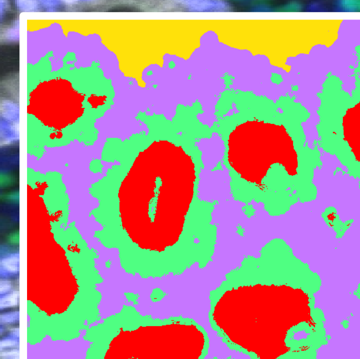


Power corrupts.

PowerPoint corrupts absolutely.

- Edward Tufte

Images: Melissa Little Lab

Outline

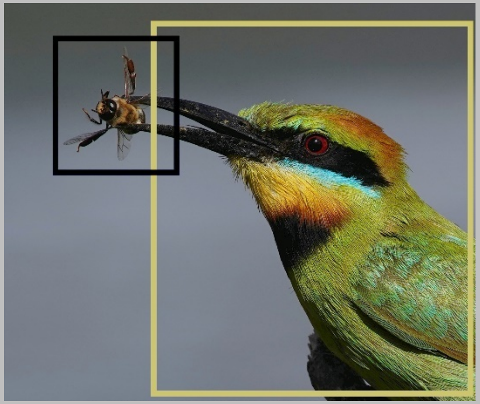
- Brief machine vision applications overview
- Semantic image segmentation
- The UNET architecture for image segmentation
- Setting up Google Colab
- Exercises
  - Introduction for UNET
  - More advanced UNET use

Applications of Computer Vision

- Classification

Rainbow bee-eater

- Object Detection



Bee-eater, bee

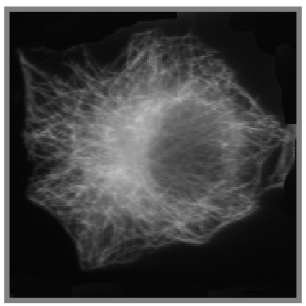
- Semantic Segmentation

Bee-eater, bee, stick, background

- Instance Segmentation

Bee-eater, bee

Image Classification



=

```
(  0.000772532, 0.00154506, 0.00343348, 0.0139056, 0.0308155,
   0.0440343, 0.0337339, 0.0433476, 0.828412, 0.000235031,
   0.000352547, 0.00205653, 0.00593454, 0.0223867, 0.0351372,
   0.022093, 0.0312004, 0.880604, 0.000420663, 0.00117786,
   0.00496382, 0.0165741, 0.058388, 0.107017, 0.0904425,
   0.110803, 0.61024)
```

Cell
Cytoskeleton

Convolutional networks are typically good at extracting features for classification.

See “Introduction for Deep Learning and Tensorflow” Workshop.

Image Segmentation

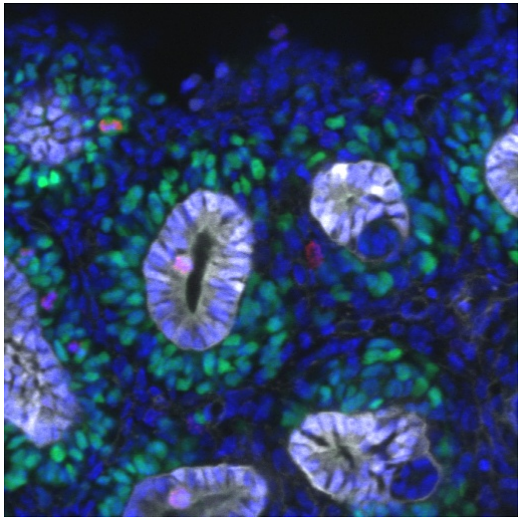
Semantic Image Segmentation

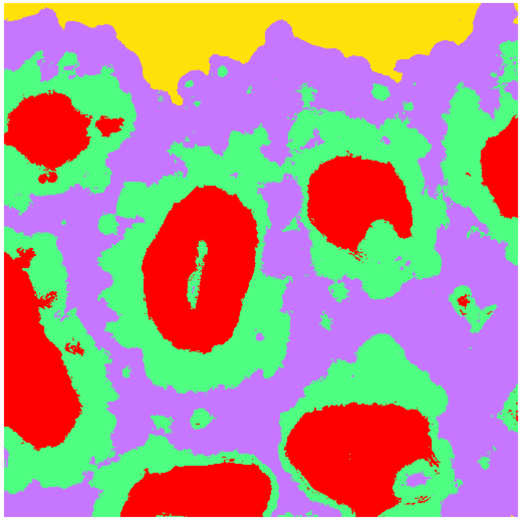
Definition

A segmentation is a partition of an image into regions that label the class of each region. e.g. foreground/background

Approach

Instead of a whole image we want to label/classify individual pixels

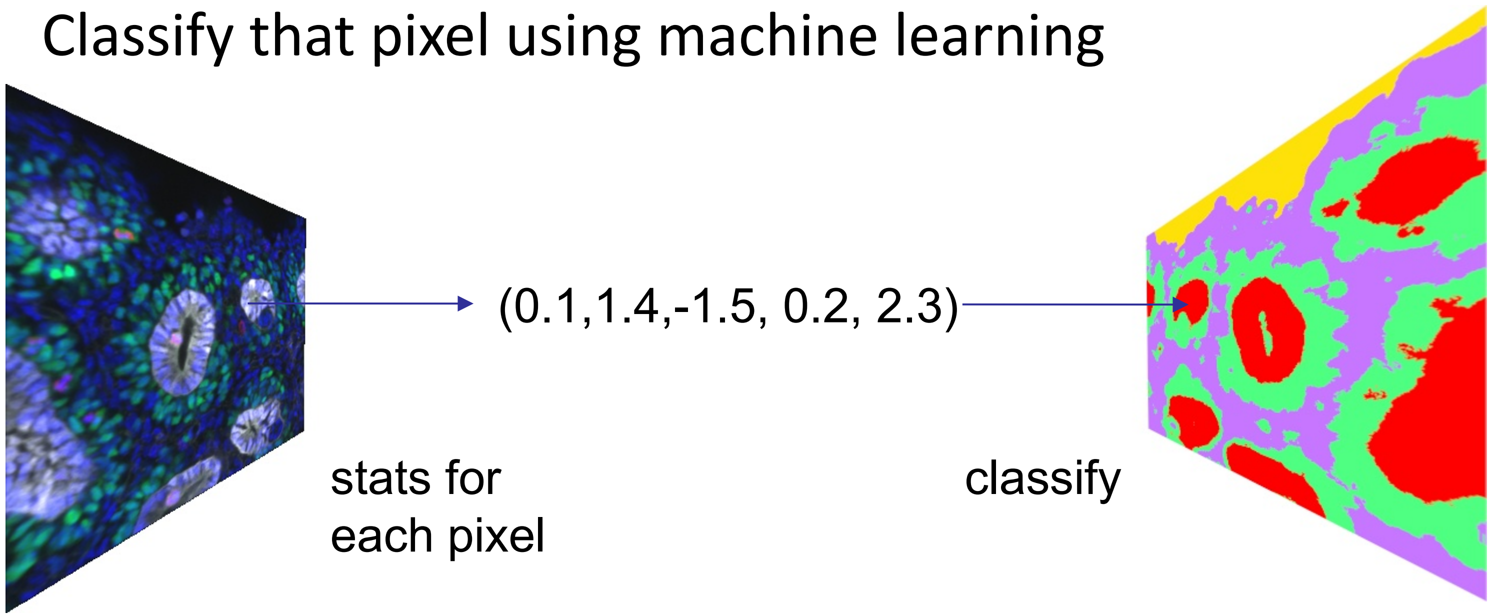




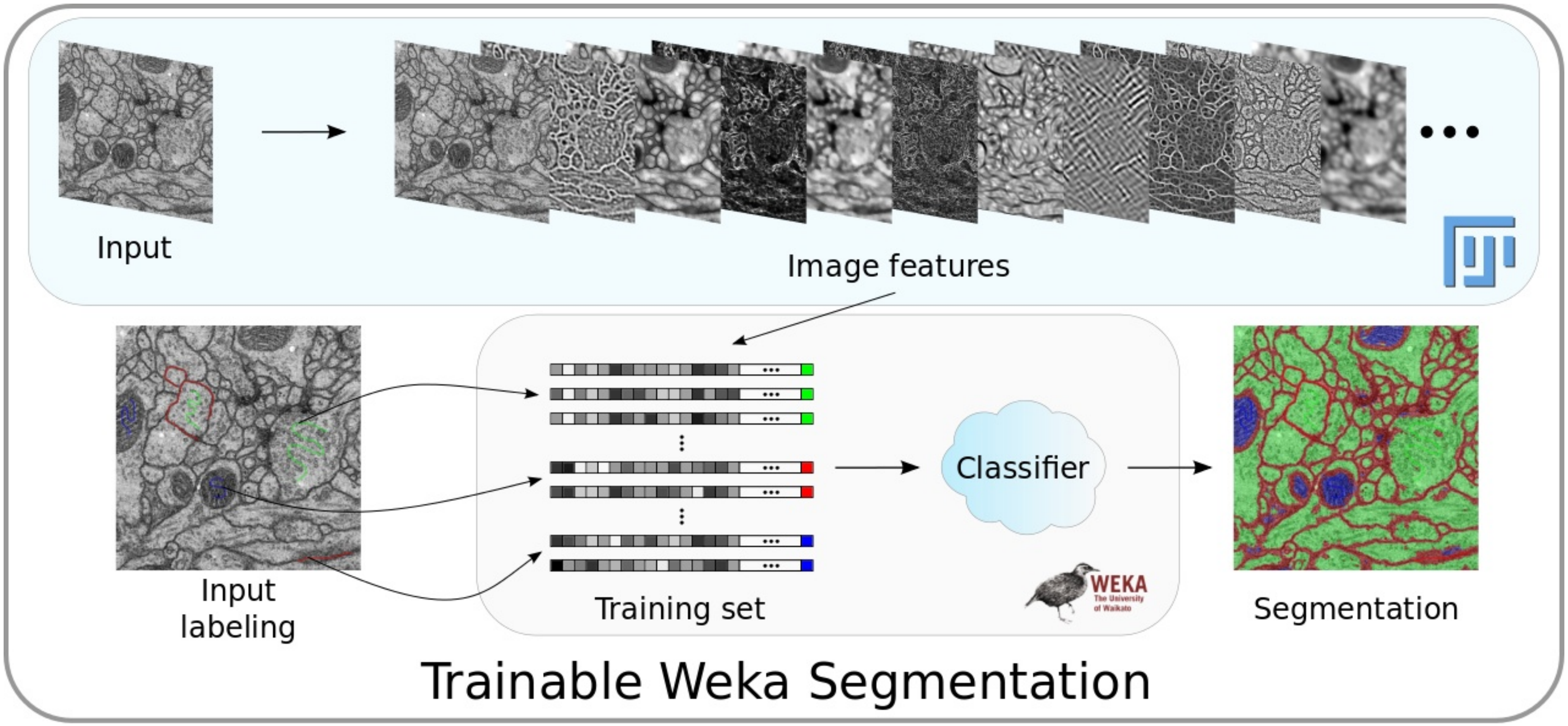
Microscopy image of a kidney by Alex Combes, Melissa Little Lab

Basic Image Segmentation

- Generate **statistics** for **each pixel** in the image
- E.g. intensity, local median intensity, gradient, …
- Classify that pixel using machine learning



The ImageJ/Fiji Trainable Weka Pipeline



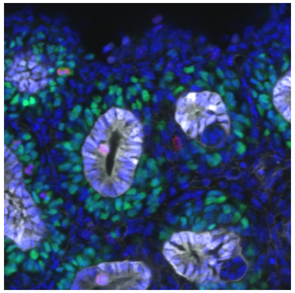
See “Introduction to Machine Learning for Imaging” workshop

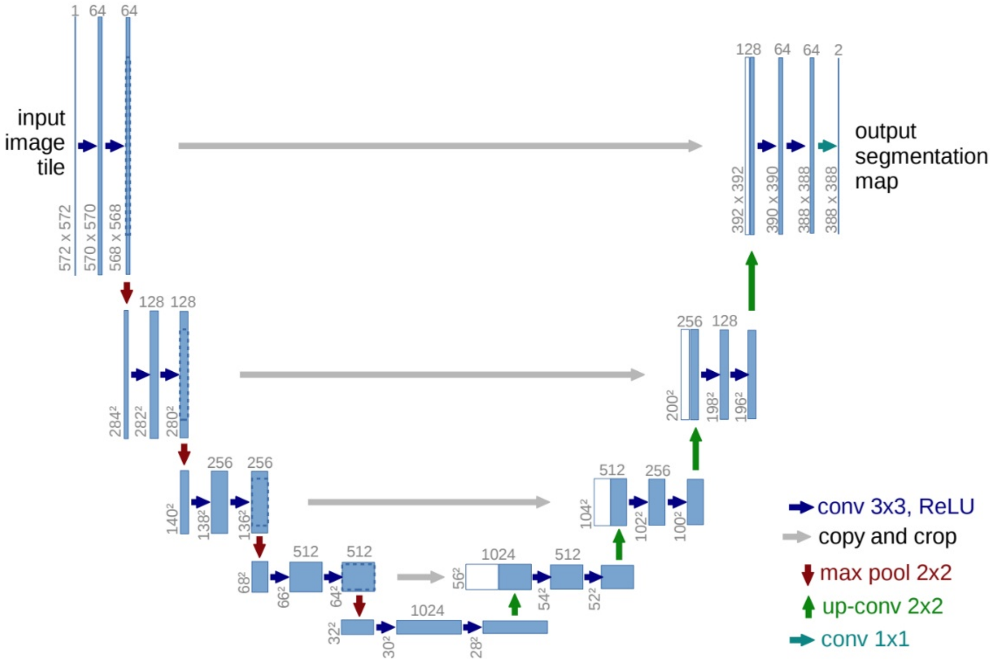
Image: https://imagej.net/Trainable_Weka_Segmentation

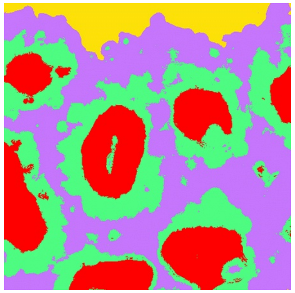
The UNET Architecture for Image Segmentation

Convolutional Deep Learning with U-net

- **U-net** was a new type of neural network architecture introduced in 2015
- It down-scales then up-scales an image to create a segmentation





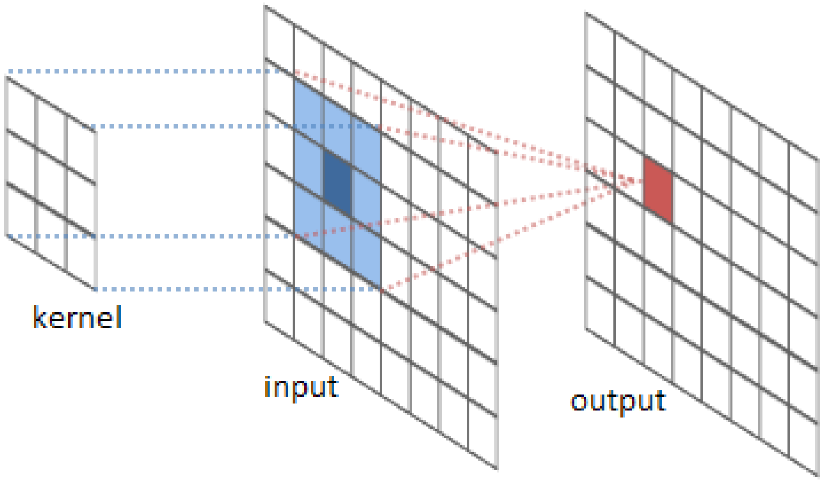


- U-Net and its variants are the state of the art in segmentation
- U-net paper: https://arxiv.org/pdf/1505.04597.pdf

Principle UNET Components

- 3x3 Convolution followed by ReLU (rectified linear activation function)
- 2 x 2 Maxpooling with stride 2 (halves image size)
- Double number of feature channels (convolutions) 64, 128, 256, 512, at each down sampling to compensate
- Dropout layers
- Skip layers
- Transpose convolutions / up convolutions

Convolutions



$$Output = \sum Kernel_{i,j} * Input_{i,j}$$

- The kernel represents the pattern to be detected

- The more the input matches the kernel, the more positive the output response would be

- Convolutions are pattern detectors

- The kernel weights are learned during training
  i.e. it learns what patterns to detect and respond to

Slide courtesy Titus Tang, Monash

Max Pooling with step size 2

10	6	6	0
5	-3	14	-2
0	2	-7	-3
0	0	-5	-5

Input 4x4 image

10	14
2	-3

Output 2x2 image

- Slide a window across the input and pick a value at every window position.
- Max pooling – take the max value.
- Average pooling – take the average value.
- Pooling layers are information filters.
- Images are reduced in scale, typically by ½ x ½

Slide courtesy Titus Tang, Monash

Spatial Dropout Layers

- Dropout regularisation is a simple computational method to prevent over-fitting to data
- SpatialDropout2D in Keras drops (sets to 0) entire feature maps with a given probability during training
- Helps promote independence between feature maps

Up Convolutions (scaling up)

10	14
2	-3

10	6	6	0
5	-3	14	-2
0	2	-7	-3
0	0	-5	-5

- Also known as **transpose convolutions**
- Max pooling scales an image down (½ x ½ smaller)
- Up Convolutions scale an image up (e.g. 2 x 2 bigger)
- Want 4 pixels to become 16
- Roughly (??)

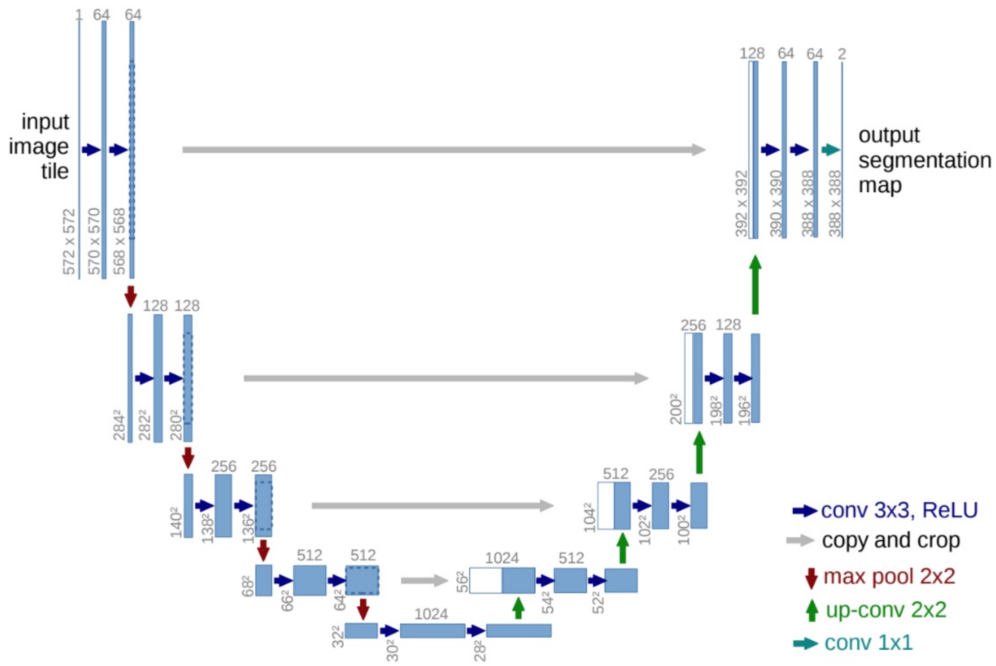
  Rearrange 2x2 input to be 4x1

  Rearrange a 3x3 kernel into a 16x4 by repeating entries

  The 16x4 then maps a 4x1 to a 1x16

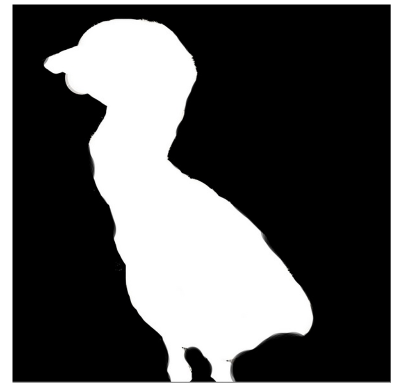
  Rearrange 1x16 to a 4x4 output

Skip Connections



- Copy some of the outputs from the scaling down to the scaling up side
- Crop middle and copy, add/combine with up side of the network

UNET Output Segmentation

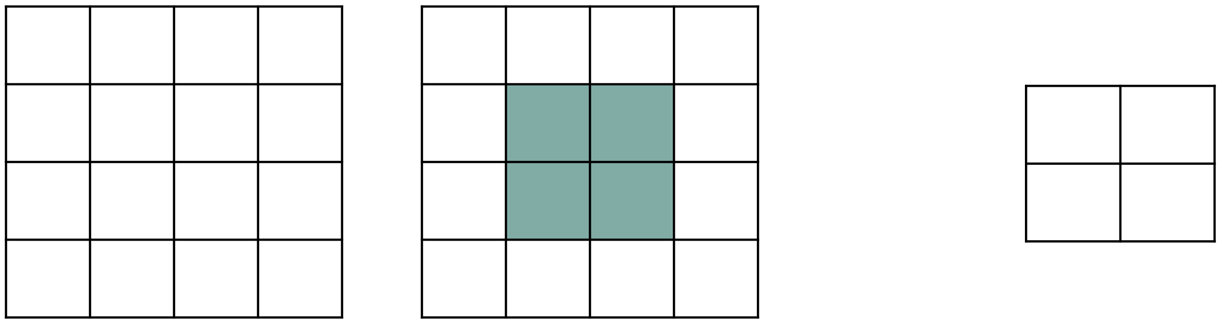


- Output is a binary image that selects the object region
- May be multiple binary images, one for each object class

- Note that while the input is 572x572 output is 388x388
- Lose some of the edges due to convolutions
- Later versions of U-Net use **padding** for convolutions to maintain original image size

Padding Convolutions

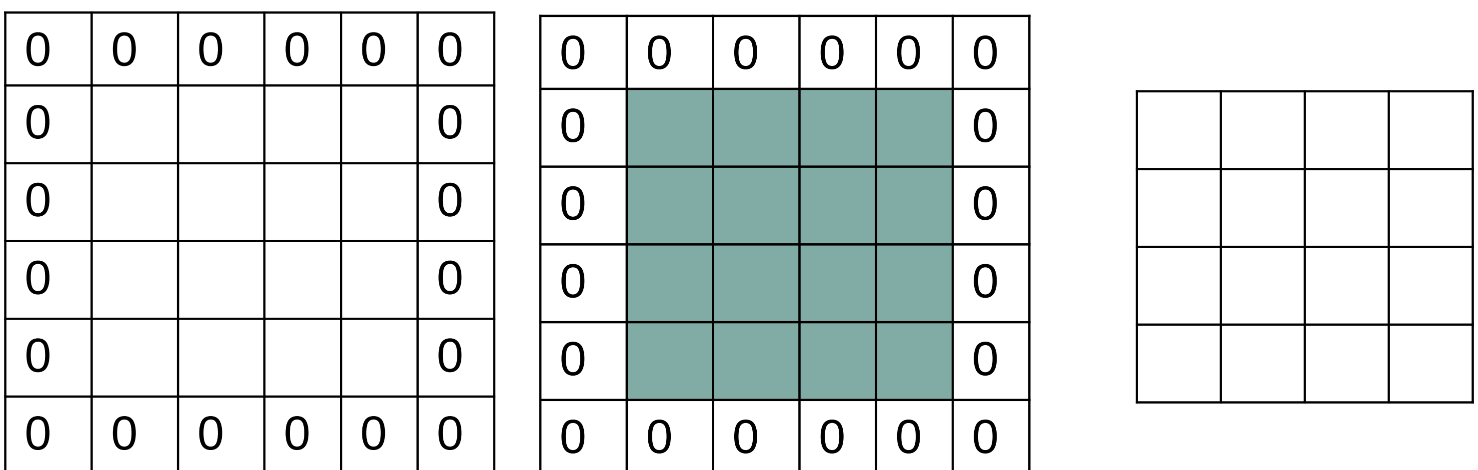
Suppose we had a 4 x 4 image & we applied a 3x3 convolution



Input 4x4 image

Output 2x2 image

The centre of 3x3 conv can only fit in the green squares above

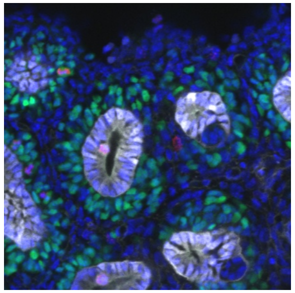


Padded 6x6 input image

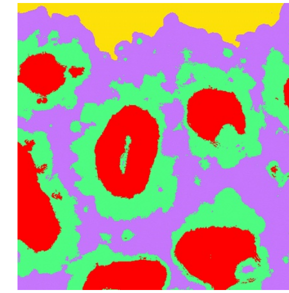
Output 4x4 image

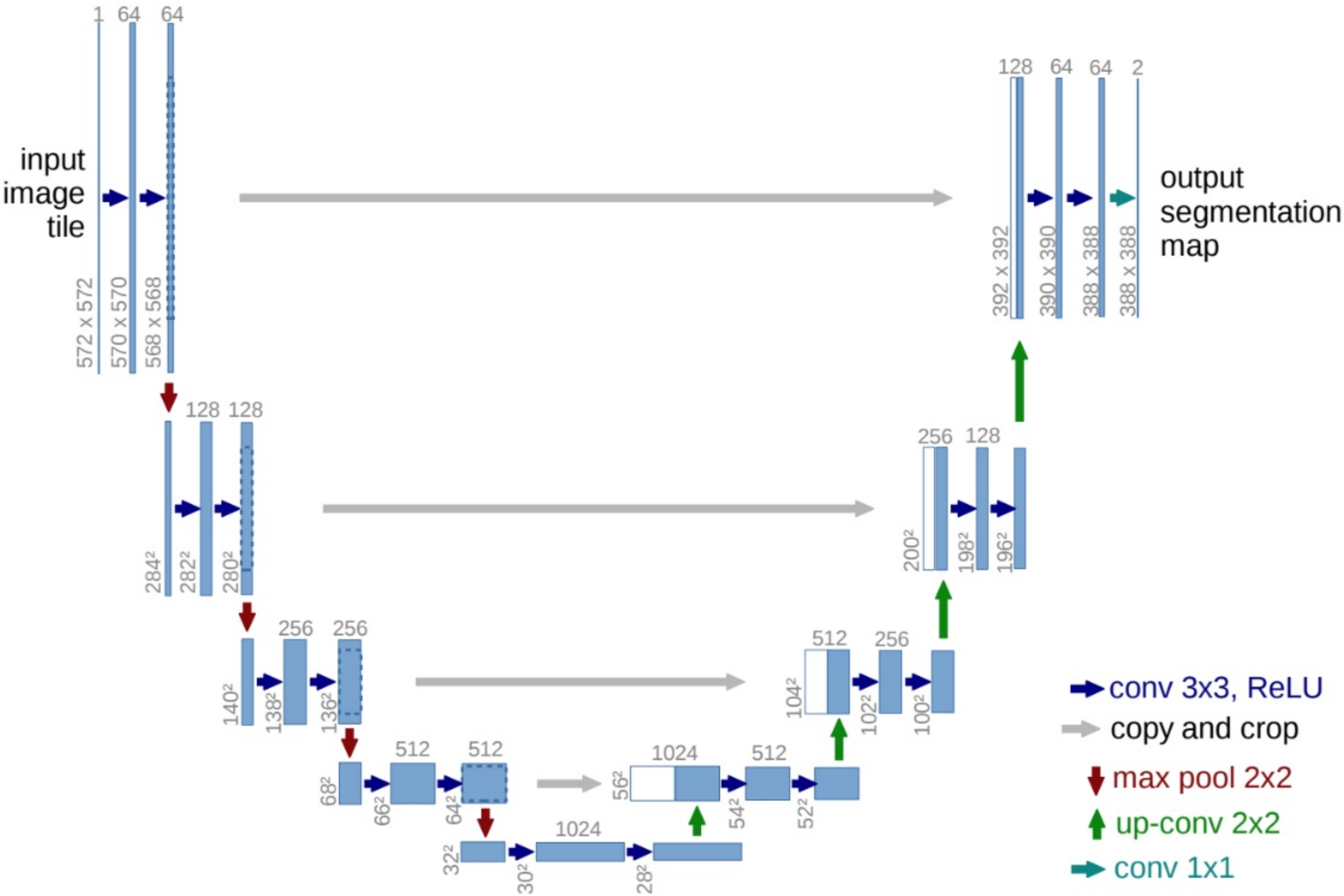
UNET Advantages and Disadvantages

- Fast to segment
- Field-leading accuracy for segmentation
- Do not need large numbers (1000s) of examples
- Does not separate objects of same type
- Labor intensive to create manual segmentations for training
  - Every training image needs to be completely segmented
  - Conversely, a basic pixel classifier approach does not this
- Now implemented in Keras / tensorflow for easy use



U-net





input
image
tile
1
64
64
572 x 572
570 x 570
568 x 568
128
128
284^2
282^2
280^2
256
256
140^2
138^2
136^2
512
512
68^2
66^2
64^2
1024
32^2
30^2
28^2
1024
512
56^2
54^2
52^2
512
256
104^2
102^2
100^2
256
128
200^2
198^2
196^2
128
64
64
2
392 x 392
390 x 390
388 x 388
388 x 388
output
segmentation
map
conv 3x3, ReLU
copy and crop
max pool 2x2
up-conv 2x2
conv 1x1

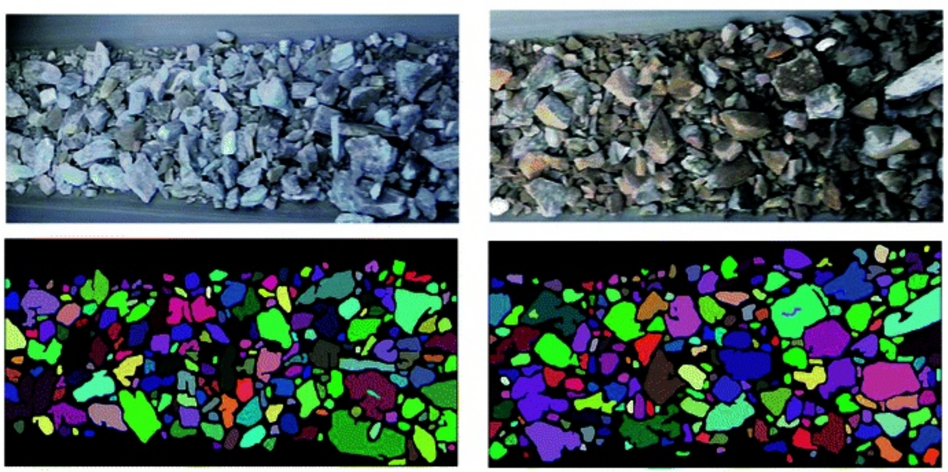
Real-World Applications of U-Net

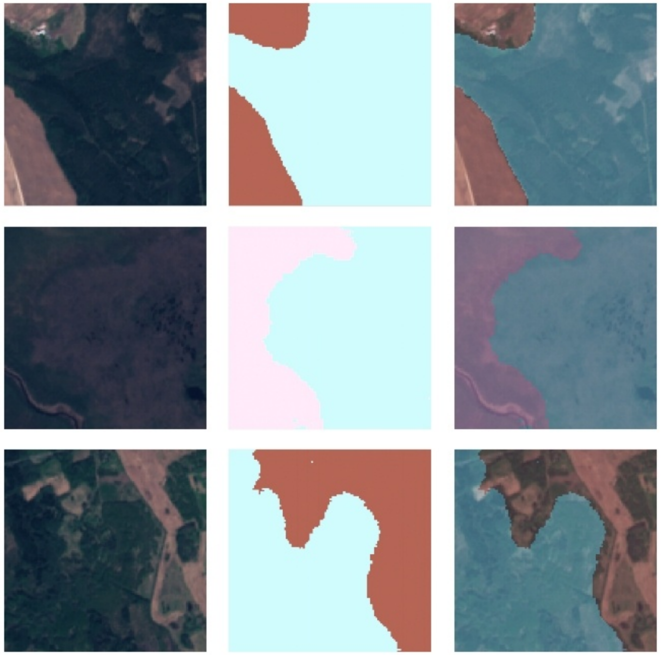
Medical images

https://arxiv.org/pdf/2011.01118.pdf

Ore segmentation

https://pubs.rsc.org/en/content/articlelanding/2020/ra/c9ra05877j





Satellite Images

https://arxiv.org/pdf/2003.02899.pdf

U-Net in Keras

- Three U-net networks are built into Keras
  Vanilla: based in the original implementation of U-Net
  Custom: a customisable U-Net architecture
  Satellite: optimised for satellite imaging

- There are also several utility functions to help with training and visualisation of the data and model outputs

- Documentation: https://pypi.org/project/keras-unet/

- Keras U-Net model python code:
  https://github.com/karolzak/keras-unet/tree/master/keras_unet/models

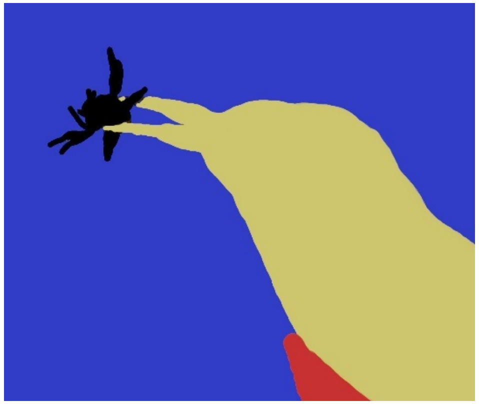
Some UNET Resources

- A line by line explanation/construction of UNET in tensorflow
  https://towardsdatascience.com/unet-line-by-line-explanation-9b191c76baf5
- The original U-net paper
  https://arxiv.org/pdf/1505.04597.pdf
- U-net in Keras
  https://pypi.org/project/keras-unet/
- Keras documentation on layer types
  Convolution: https://keras.io/api/layers/convolution_layers/convolution2d/
  Max Pooling: https://keras.io/api/layers/pooling_layers/max_pooling2d/
  Conv Transpose: https://keras.io/api/layers/convolution_layers/convolution2d_transpose/
  Dropout: https://keras.io/api/layers/regularization_layers/dropout/
- An explanation of Up Sampling
  https://naokishibuya.medium.com/up-sampling-with-transposed-convolution-9ae4f2df52d0

Data Preparation, Training UNET and Evaluating the Results

Creating a Training Set

- In to create a U-net segmenter, you will need to create a set of labeled examples
- This represents the **ground truth** that U-net will learn
- This is typically a laborious and boring process drawing outlines on numerous images



- How many you will need will depend on the problem
- **Data augmentation** during training can reduce the number

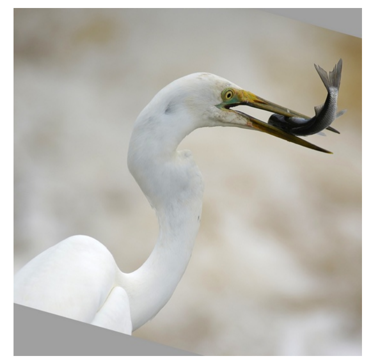
Data Augmentation for Imaging

- Creating image sets is time consuming and there may be limited numbers of examples available
- One approach to extending a set of images is to apply geometric transformations to create new examples

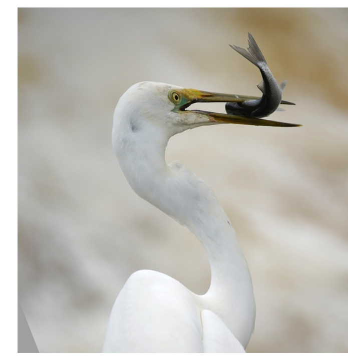
Original

Flip horizontal

Flip vertical



Rotate



Shear

- Keras has **ImageDataGenerator** and **flow_from_directory**
- Keras-Unet has **get_augmented** function

Image Batch Generators for Training

- Usually, image sets are too large to present all at once during training as they will not fit in CPU/GPU memory
- Also calculations to update network weights may get too large
- Hence training usually occurs in **batches**, where subsets of images of a fixed size are selected and trained on
- Subsets are repeatedly drawn from the training set, and the network trained, until all of the training set had been presented
- The process is usually repeated multiple times

- In Keras you can set **batchsize** as a parameter to **model.fit** and pass all of your training data to **model.fit**
- The disadvantage of this is that it makes data **augmentation** tricky ...

Using Google Colab

- Colab is a web-based iPython Notebook service
- You can play/run blocks of python code interactively
- Your code can run on Googles CPU/GPU or TPU in the cloud
- It is free but has usage limitations

- Using Tensorflow with image applications on Colab with GPU can be 10 or 20 times faster than with CPU

  (In Colab set Runtime / Change Runtime Type → GPU)
- TPUs are Tensorflow Processing units – designed for Tensorflow

- Colab Code is interchangeable with Jupyter Notebooks
- Colab basics:

  https://colab.research.google.com/drive/1YKHHLSlG-B9Ez2-zf-YFxXTVgfC_Aqtt

Setting up Google Colab for the Workshop

- Create a folder in your Google Drive called **Colab Notebooks**
- Download code and slides for this workshop:
  https://github.com/doktor-nick/intro-to-ml-for-imaging/archive/master.zip
- Unzip it and copy the folder into **Colab Notebooks**
- Go into the folder **intro-to-ml-for-imaging-master**
- Right-click on Unet_in_Keras_introduction.ipynb
- Select **Open with / + Connect more apps**
- Search for and install Colaboratory
- Double clicking on the Unet_in_Keras_introduction.ipynb should open it in Colab

- When running the code for the workshop you will need to link and authorise your Google Drive to be used by the notebook. The provided notebook has code/instructions for doing this.

Hands On

Unet_in_Keras_introduction.ipynb

Colab Notebook

Measuring Success: Loss functions for imaging

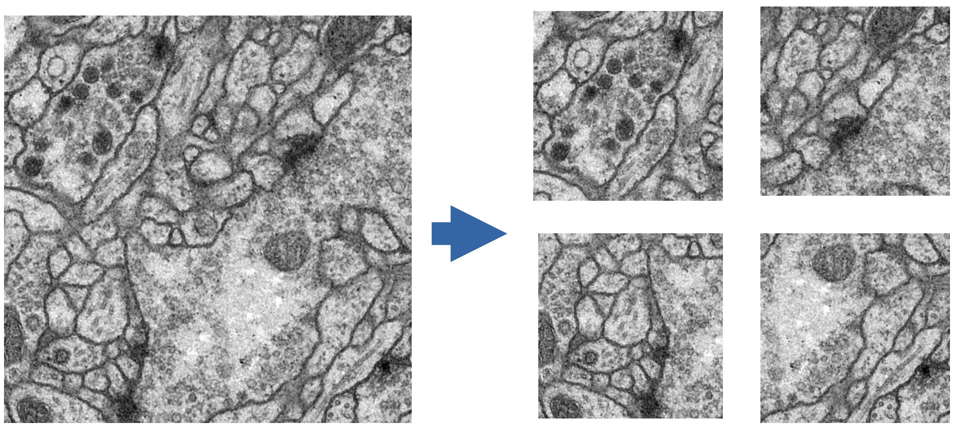
- Binary Cross-entropy
- Jaccard : intersection over union.

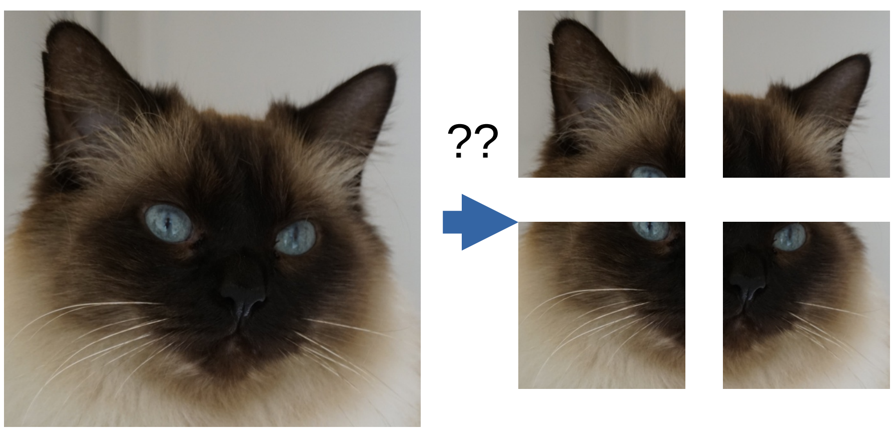
  (|X & Y|)/ (|X|+ |Y| - |X & Y|)

  Good for unbalanced problems.
- Other metrics, cf metrics.py

Image Tiling

- Available memory on a GPU can often be an issue for imaging
- During training, **reducing batch** size may help or **scaling down**
- **Tiling**, that is chopping an image into smaller pieces is another approach
- Care needs to be taken that each tile contains enough information so that it can be accurately segmented





- Usually want to use **overlapping tiles** to avoid edge effects
- The Keras Unet libraries can generate patches easily

Which Optimiser for Semantic Image Segmentation?

- In Keras there are a range of optimisers available including SGD, RMSprop, Adam, Adadelta, Adagrad, Adamax, Nadam Ftrl
- Performance may vary according to the application
- Generally Adam and SGD are reasonable choices
- For a discussion of different optimiser types see https://ruder.io/optimizing-gradient-descent/
- For optimisers available in Keras see https://keras.io/api/optimizers/

Overview of choices in network/evaluations

-
- Optimiser: Adam
- Loss function: Jaccard distance
- Batchsize if size is a problem
-
- Sometimes the optimiser will get stuck. It is worth running the fitting functions more than once to ensure better results
-

Hands on

Unet_in_Keras_further_topics.ipynb

Colab Notebook

Random notes 1

- Colab getting started
  https://towardsdatascience.com/getting-started-with-google-colab-f2fff97f594c
- Colab overview
- https://colab.research.google.com/drive/1CRYG_y2ACXy0Q3NJcsbNHhF4658jvVox
- How to make a colab notebook available to others
- https://research.google.com/colaboratory/faq.html#:~:text=Colab%20notebooks%20are%20stored%20in,Google%20Drive%20file%20sharing%20instructions
  .
- Colab test share:
  https://colab.research.google.com/drive/1G9gtgfhrfkSX95mJfUC5fFil3z7jslsR?usp=sharing
  - then 'save a copy in drive'
- Do Monash do viz of convolutions?
- The architectures are given in keras_unet_master
- Vanilla scales down, custom does not. Padding? padding='valid', padding="same"

Random notes 2

- Multi-class def custom_unet(input_shape, num_classes=1, …
-
- Code will run on colab without GPU , but it is very slow (5 mins per epoch)
-
- TPU vs GPU? Google claims TPU 15-30x faster