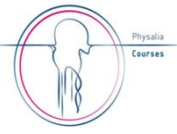


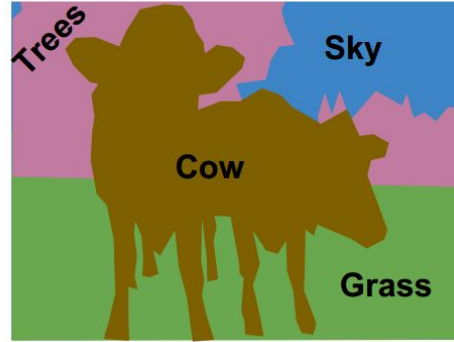
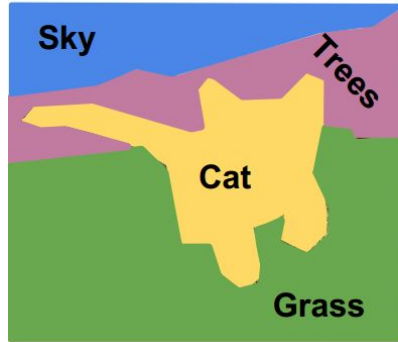
Image Segmentation



What is semantic segmentation?



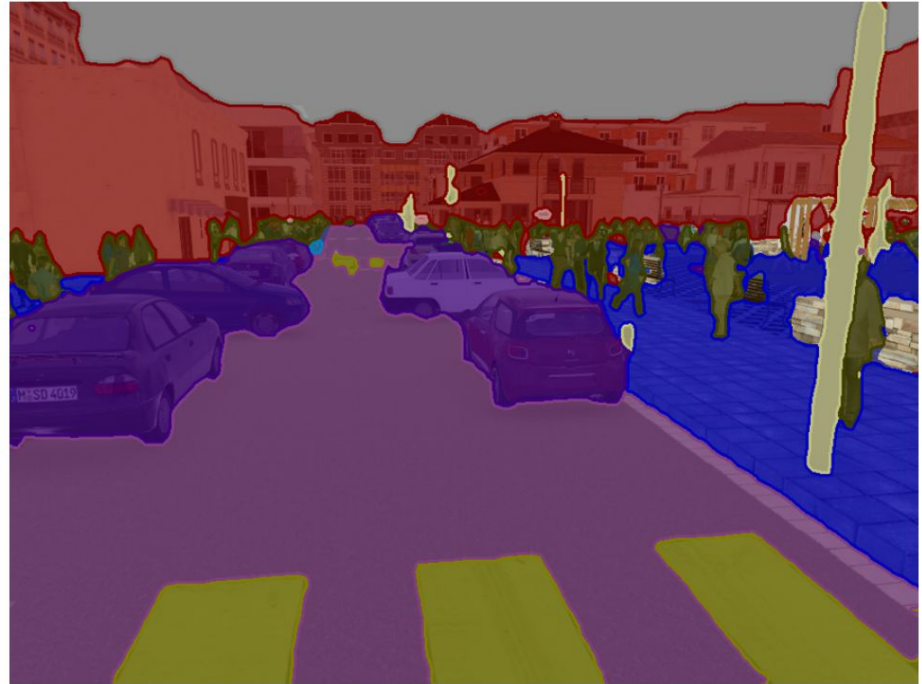
[This image is CC0 public domain](#)



Source: <https://tariq-hasan.github.io/concepts/computer-vision-semantic-segmentation/>



Application: car vision

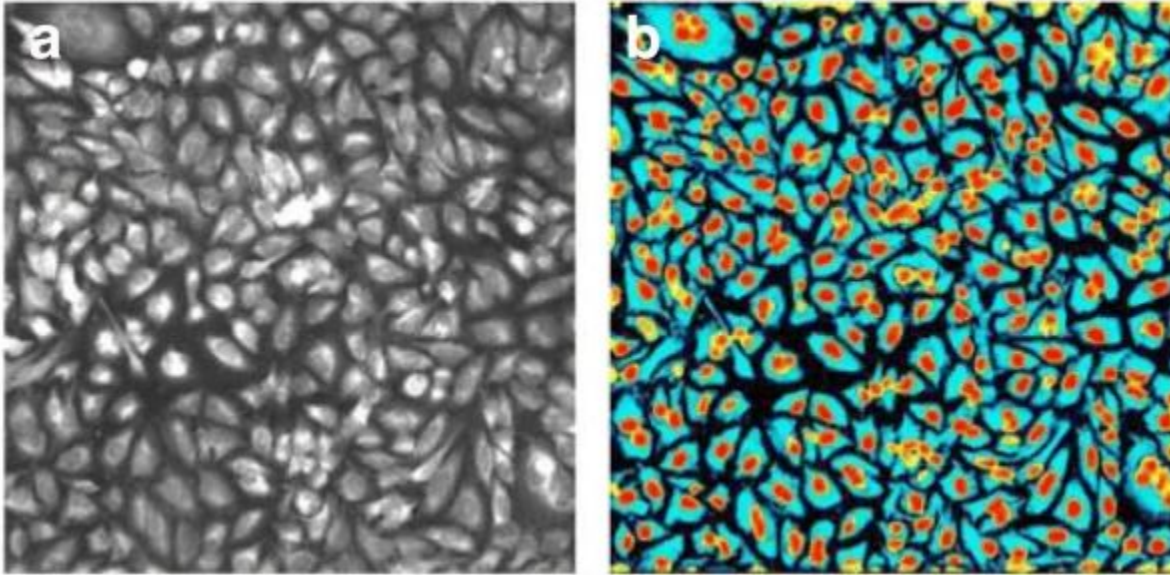


■ Sky ■ Building ■ Road ■ Sidewalk ■ Fence ■ Vegetation ■ Pole ■ Car ■ Sign ■ Pedestrian ■ Cyclist

Source: <https://developer.nvidia.com/blog/image-segmentation-using-digits-5/>



Application: cell images

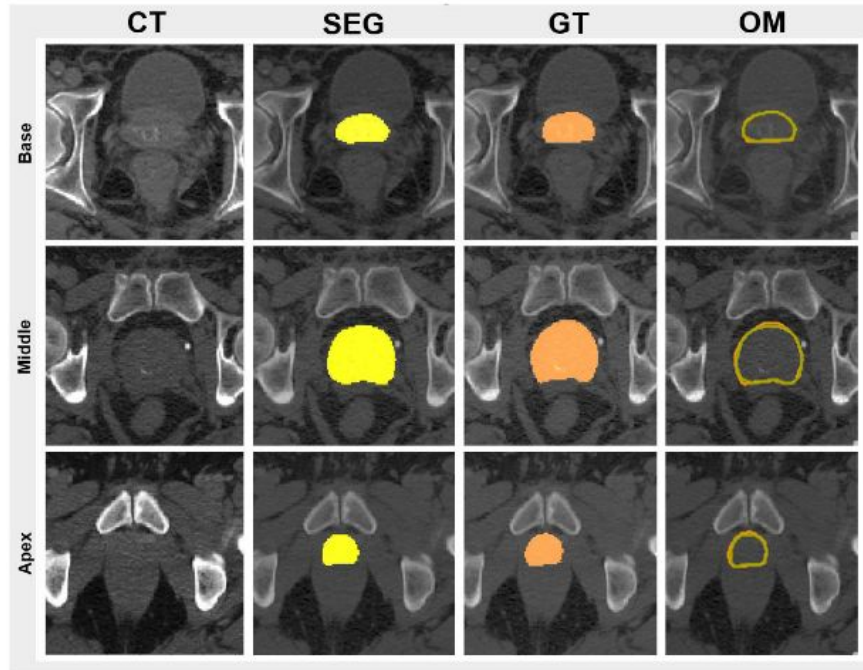


a) Input image
b) Nuclei (Yellow-Red) and
Cells (Blue-Cyan) prediction
map.

Source: Yousef Al-Kofahi et al., A deep learning-based algorithm for 2-D cell segmentation in microscopy images. BMC Bioinformatics, 2018



Application: organs contouring

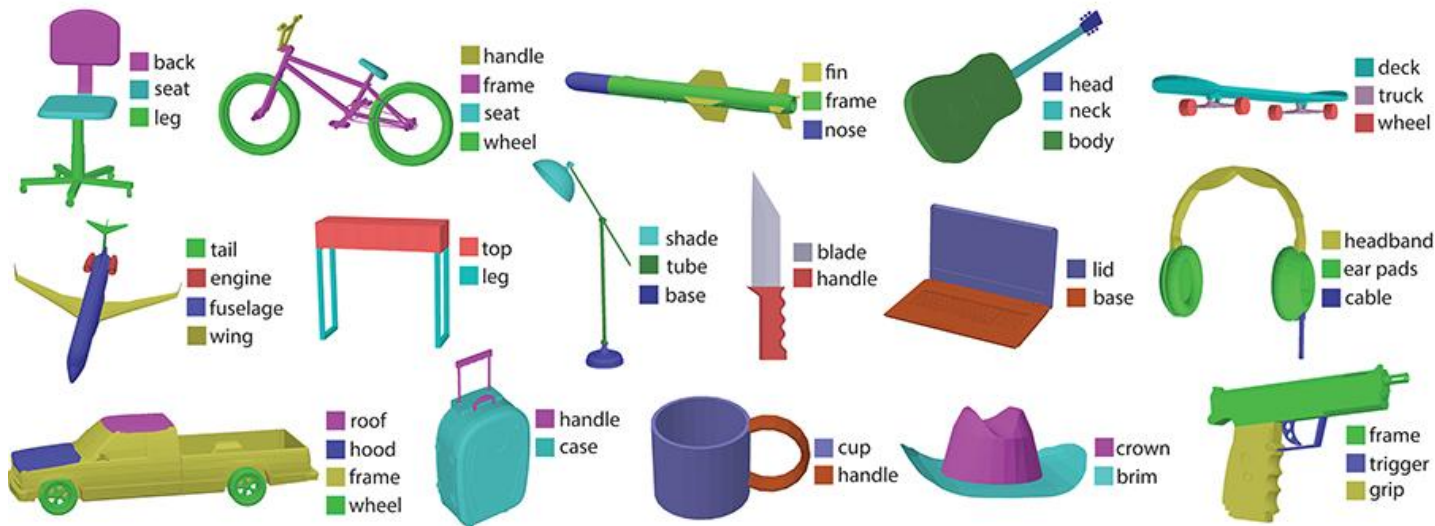


CT: original CT scan image
SEG: U-Net segmentation
GT: ground truth
OM: overlay map of ground truth and segmented images.

Source: Kazemifar et al., Segmentation of the prostate and organs at risk in male pelvic CT images using deep learning. Biomedical Physics & Engineering Express, 2018



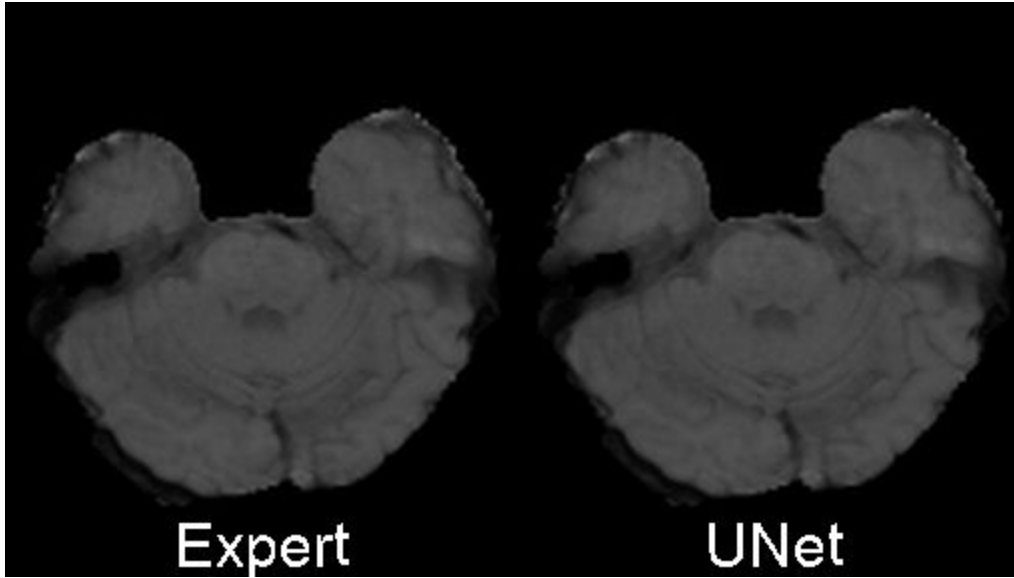
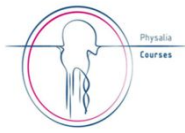
Beyond bidimensional images: 3D



Source: Kalogerakis et al., 3D Shape Segmentation with Projective Convolutional Networks. Proceedings of the IEEE Computer Vision and Pattern Recognition (CVPR) 2017



Application: tumor recognition



A CT scan is a set of (usually equally spaced) slices

Source:

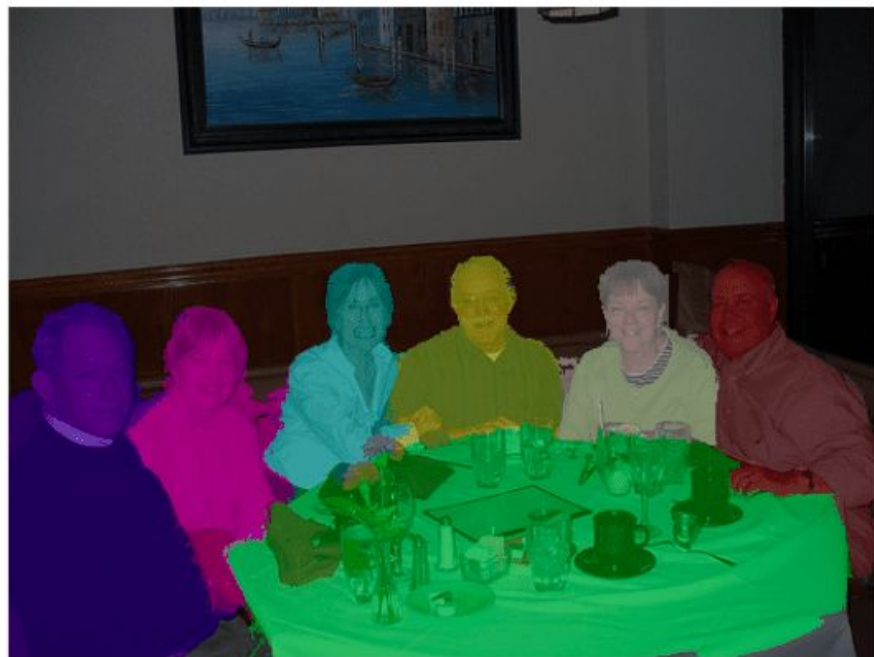
<https://pythonawesome.com/keras-3d-u-net-convolution-neural-network-designed-for-medical-image-segmentation/>



Semantic vs. Instance



Semantic Segmentation



Instance Segmentation

Source: Anurag Arnab, Shuai Zheng et. al 2018 “Conditional Random Fields Meet Deep Neural Networks for Semantic Segmentation”



Classification vs. Segmentation

INPUT	
Image (2d, 3d...)	Image (2d, 3d...)
Ground Truth: CLASS	Ground Truth: MASK
OUTPUT	
Predicted class	Predicted mask
LOSS	
Accuracy, Binary cross entropy, ...	???



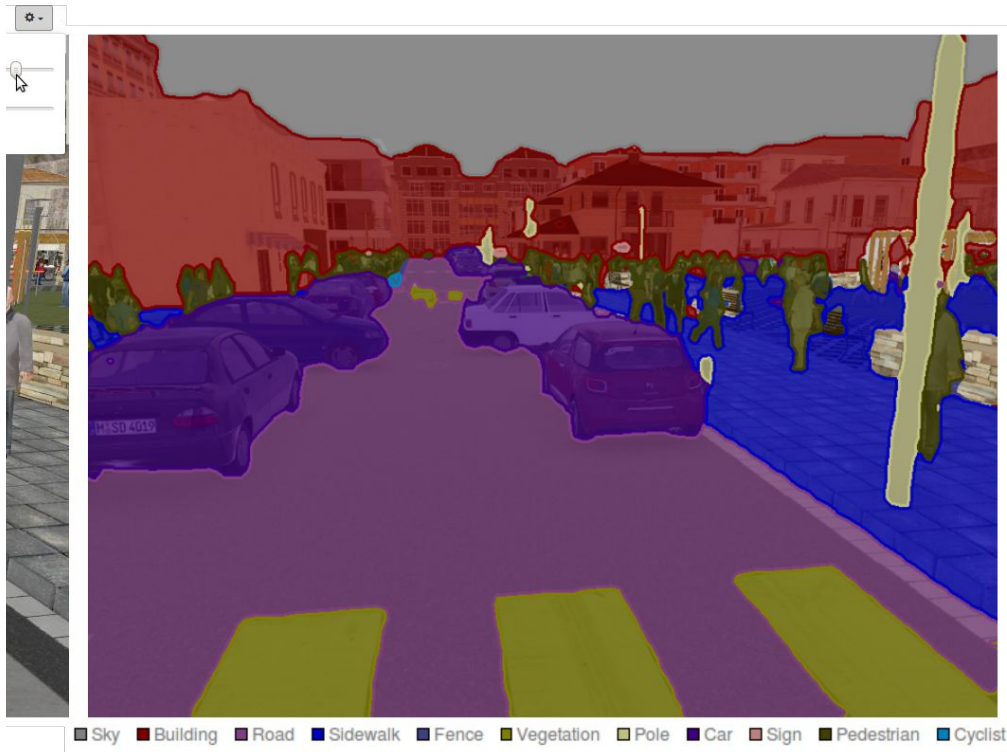
Metric proposal: pixel accuracy



$$\text{Pixel Accuracy} = \frac{\text{Number of pixel correctly classified}}{\text{Total number of pixels in the image}}$$



Metric proposal: pixel accuracy

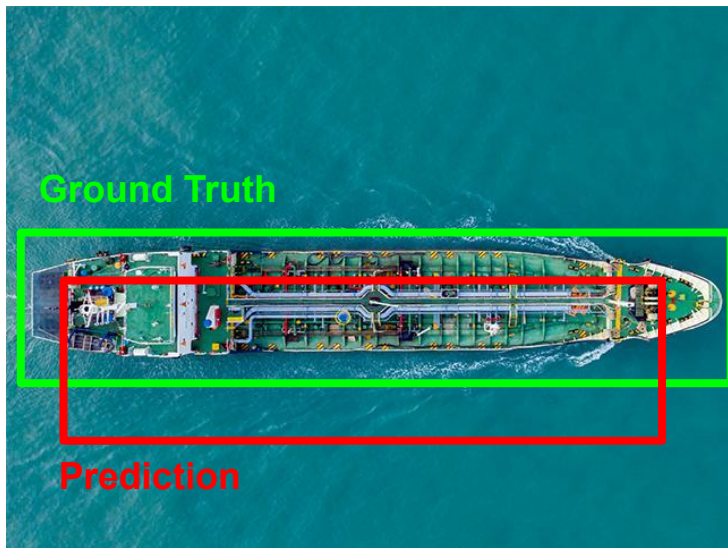


Other metrics

- PA - Pixel accuracy
 - MPA - Mean Pixel Accuracy
- Intersection over Union (IoU) - Jaccard Index
- Dice coefficient
- (Precision/Recall/F1 index)



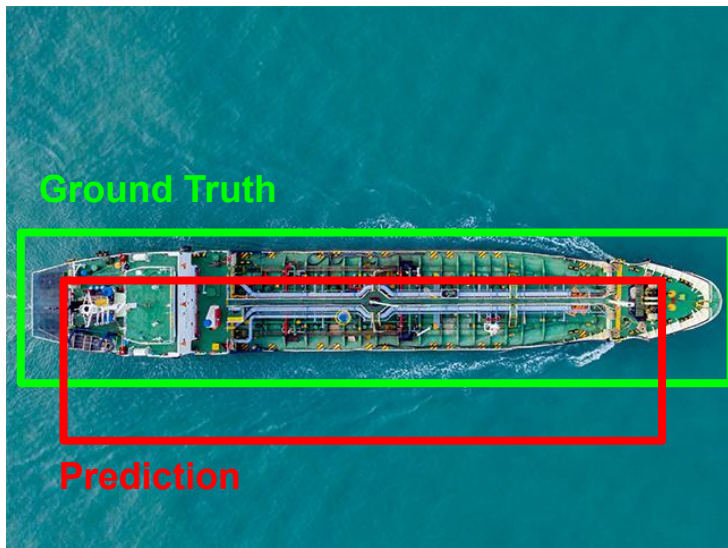
Intersection Over Union



$$\text{IoU} = \frac{\text{Number of pixel correctly classified}}{\text{Union(Ground Truth, Prediction)}}$$



Dice coefficient



$$DC = \frac{2 \times \text{Number of pixel correctly classified}}{\text{Ground Truth} + \text{Prediction}}$$



Metrics summary

$$\text{Pixel Accuracy} = \frac{\text{Number of pixel correctly classified}}{\text{Total number of pixels in the image}}$$

$$\text{IoU} = \frac{\text{Number of pixel correctly classified}}{\text{Union(Ground Truth, Prediction)}}$$

$$\text{Dice Coefficient} = \frac{2 \times \text{Number of pixel correctly classified}}{\text{Ground Truth} + \text{Prediction}}$$

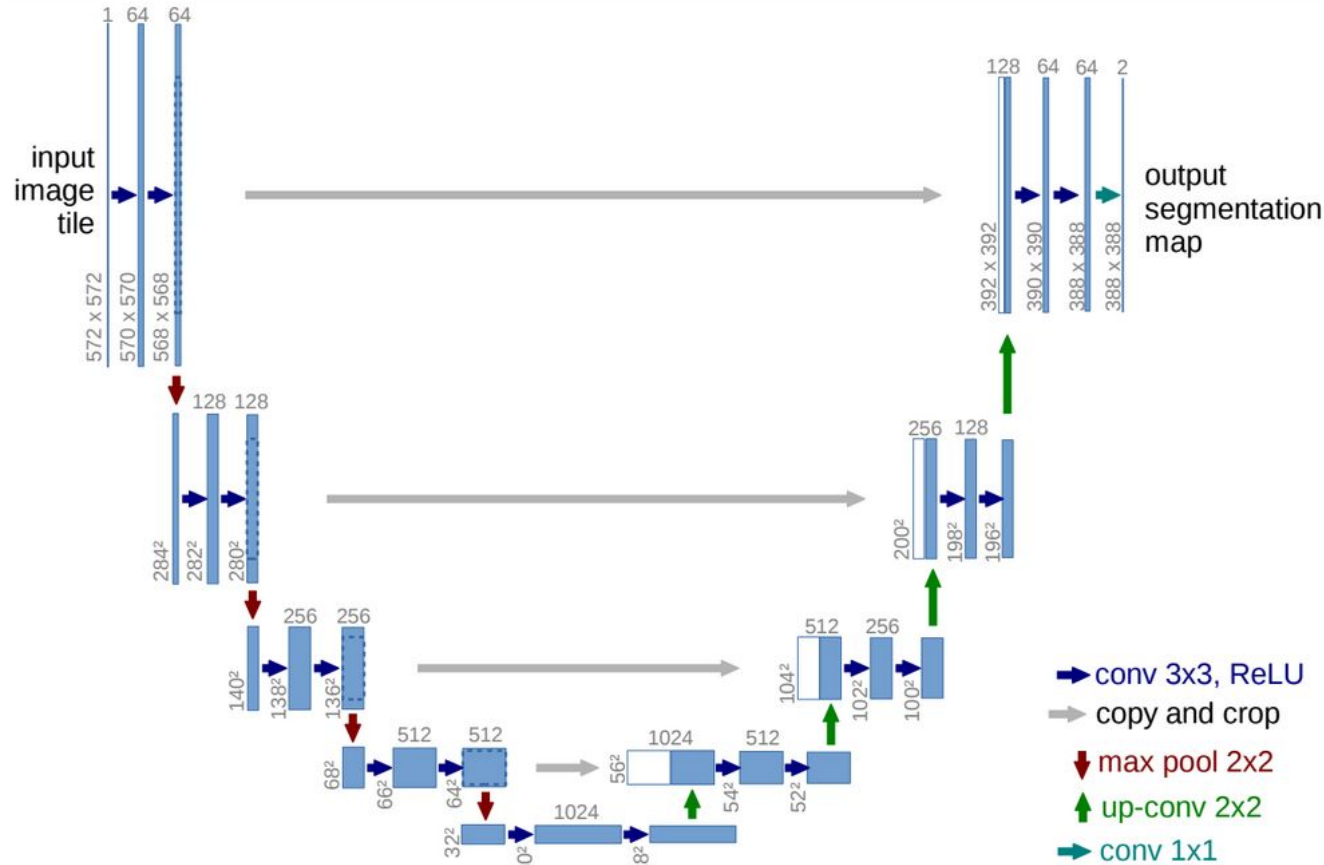


Let's do that





U-Net



Source: Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." *International Conference on Medical image computing and computer-assisted intervention*. Springer, Cham, 2015.

Let's also do that



Tips

- Expensive to generate training set
- Less standard than classification
- Actively developed...
- ...but you need to follow the architecture authors
- Transfer learning is your friend



[REF] Architectures

- **U-Net**
 - Olaf Ronneberger et. al 2015 “U-net architecture image segmentation”
 - <https://arxiv.org/abs/1505.04597>
- **FastFCN**
 - Huikai Wu et.al 2019 “FastFCN: Rethinking Dilated Convolution in the Backbone for Semantic Segmentation”
 - <https://arxiv.org/abs/1903.11816>
- **Gated-SCNN**
 - Towaki Takikawa et. al 2019 “Gated-SCNN: Gated Shape CNNs for Semantic Segmentation”
 - <https://arxiv.org/abs/1907.05740>
- **DeepLab**
 - Liang-Chieh Chen et. al 2016 “DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs”
 - <https://arxiv.org/abs/1606.00915>
- **Mask R-CNN**
 - Kaiming He et. al 2017 “Mask R-CNN”
 - <https://arxiv.org/abs/1703.06870>



[REF] Databases

- **[2D] Pascal Visual Object Classes (VOC)**
 - <http://host.robots.ox.ac.uk/pascal/VOC/index.html>
 - 21 object classes (vehicle, household, animal, airplane...)
- **[2D] Microsoft COCO: Common Objects in Context**
 - <https://paperswithcode.com/dataset/coco>
 - “91 objects types that would be easily recognizable by a 4 year old”
- **[2D] Cityscapes**
 - <https://www.cityscapes-dataset.com/>
 - 5 000 images with high quality annotations · 20 000 images with coarse annotations · 50 different cities
- **[2.5D] Sun RGB-D**
 - <https://rgb-d.cs.princeton.edu/>
 - four different sensors and contains 10,000 RGB-D images
- **[3D] Stanford 2D-3D-Semantics Dataset**
 - <http://buildingparser.stanford.edu/dataset.html>
 - It covers over 6,000 m2 and contains over 70,000 RGB images, along with the corresponding depths, surface normals, semantic annotations, global XYZ images



[REF] Useful stuff



- **Image Segmentation Using Deep Learning: A Survey**
 - Minaee, Shervin, et al. "Image segmentation using deep learning: A survey." IEEE Transactions on Pattern Analysis and Machine Intelligence (2021).
- **Data preprocessing and augmentation using Torch.IO**
 - (take away the message, even if using pyTorch)
 - https://colab.research.google.com/github/fepegar/torchio-notebooks/blob/main/notebooks/Data_preprocessing_and_augmentation_using_TorchIO_a_tutorial.ipynb

