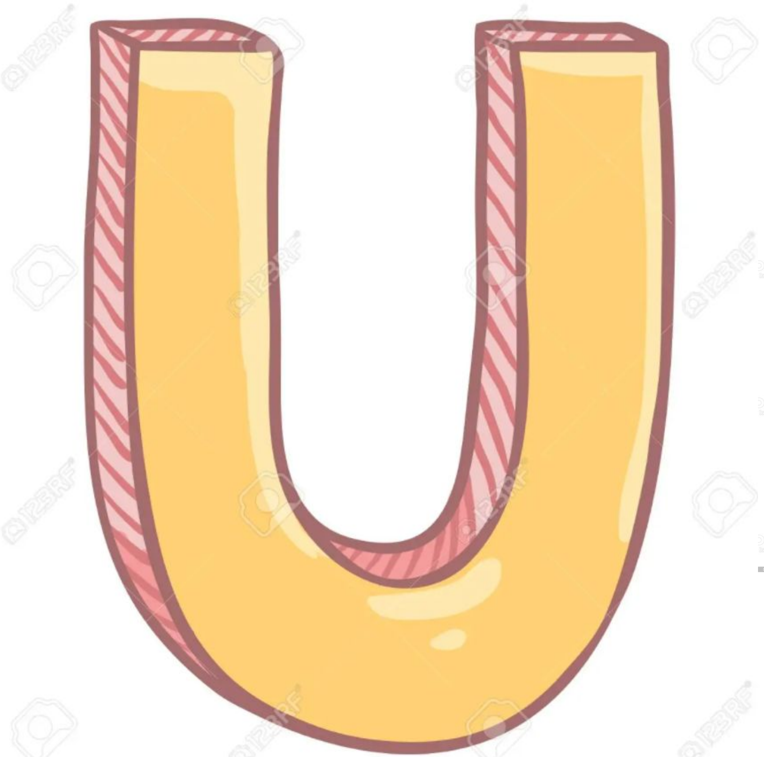


MAY THE FORCE BE WITH U

Why U?

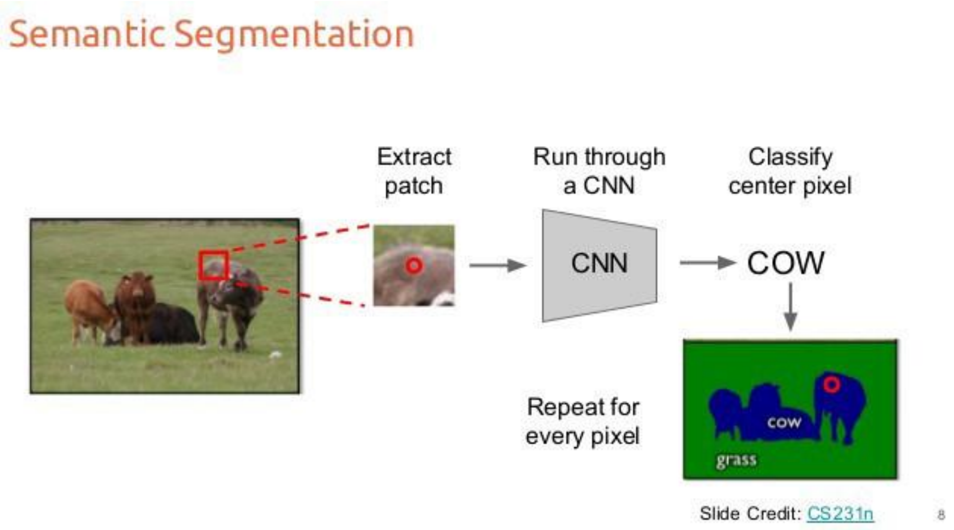
Deep network with thousands of training samples

Strong use of augmentation with a U architecture.

- Best results in segmentation task
- Works even with very less training data
- Very fast (less than a second)
- Precise localization.

Sliding Window Approach

INPUT – Local Region or patch around the pixel whose class is predicted.



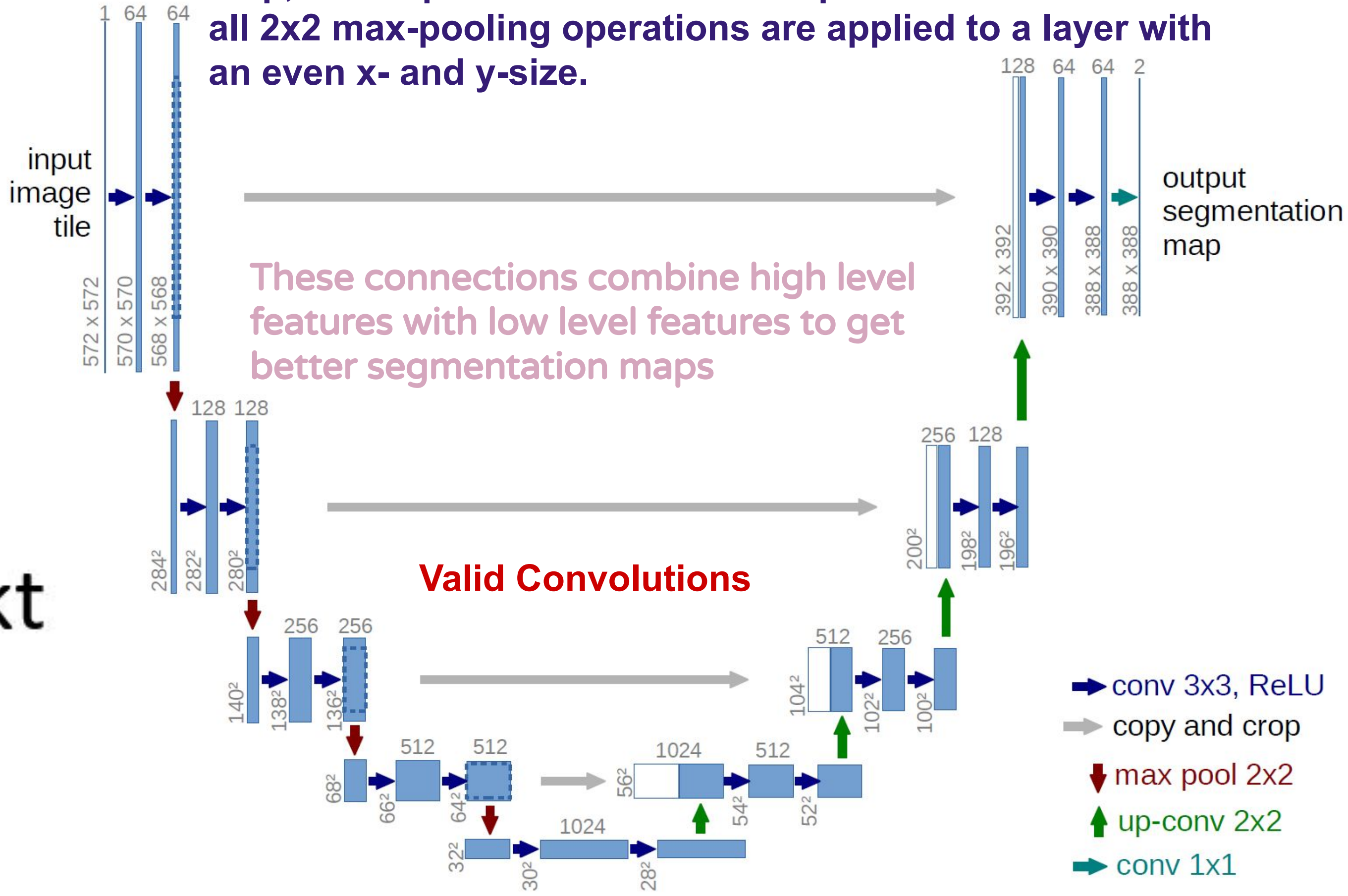
Drawbacks-

1. Quite slow, network runs separately for each patch.
2. Tradeoff between context and localization accuracy.

To allow a seamless tiling of the output segmentation map, it is important to select the input tile size such that all 2x2 max-pooling operations are applied to a layer with an even x- and y-size.

These connections combine high level features with low level features to get better segmentation maps

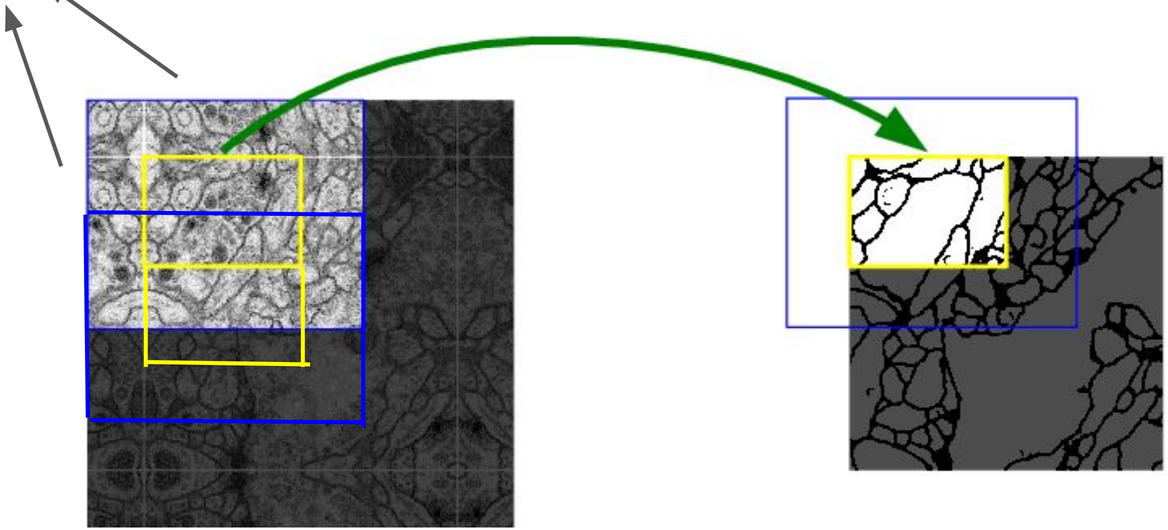
Valid Convolutions



Arkitekt

Overlap Tile Strategy

Extrapolation here
by mirroring



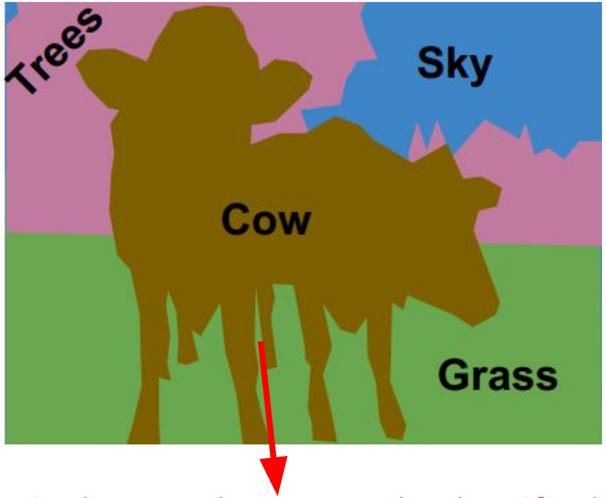
The network does not have any fully connected layers and only uses the valid part of each convolution, i.e., the segmentation map only contains the pixels, for which the full context is available in the input image. This strategy allows the seamless segmentation of arbitrarily large images by an overlap-tile strategy. To predict the pixels in the border region of the image, the missing context is extrapolated by mirroring the input image.

Data Augmentation and Intuition for weighted loss

In various fields where less data is available like the biomedical field, augmentation play a huge role. This allows network to learn invariance without the need to see them in actual training data.

For an instance, since deformation used to be the most common variation in tissue and realistic deformations can be simulated efficiently

In the segmentation tasks, it is very necessary to separate objects from same class that are placed very close to each other.



These pixels must be correctly classified as grass to separate the two cows(objects). Hence in the loss function, these will have higher weight.

U-Net
Part-2

Akash Gupta • 15.12.2021

Introduction

Why U-net?

Sliding Window Approach

Architecture

Overlap Tile Strategy

Data Augmentation and Intuition for weighted loss

-
-

Training

- Use of input images and their corresponding segmentation maps to train with stochastic gradient descent.
- Favour large input tiles over large batch size.(Batch size=1)
- High momentum(0.99)
- Energy function is pixel-wise soft max over final feature map then cross entropy loss.
- Weighted map to give some pixels more importance than the others and force learn the border pixels.

Data Augmentation

- Less data, so extensive use of Augmentation.
- For microscopic images, we need shift, rotation invariance as well as robustness to deformations and gray value variations.(Random Elastic deformations are utilized.)
- Drop-out layers perform further implicit data augmentation.

Experiments

Applications (3 segmentation tasks**)**

1) **Segmentation of Neuronal Structures in electron microscopy reading**

Data set: EM segmentation challenge by ISBI 2012

2) **Segmentation of light microscopic images.**

Part of ISBI cell tracking challenge 2014 and 2015.
Dataset: “PhC-U373”

Conclusion

1. U-net architecture achieves very good performance on very different biomedical segmentation applications.
2. With the use of data-augmentation with elastic deformations, it needs very few annotated images and has a very resonable training tme.