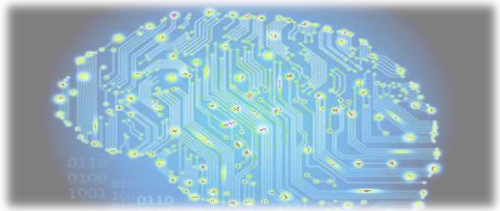
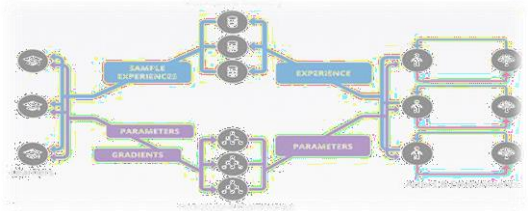
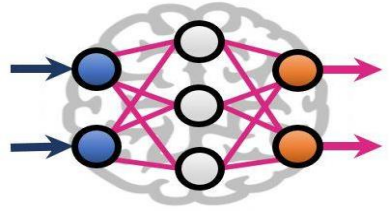
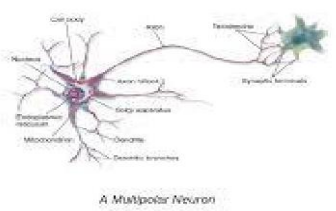
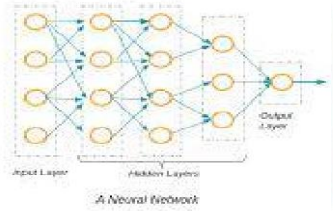





A Multipolar Neuron


A Neural Network

U-Net: Convolutional Networks for Biomedical Image Segmentation

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2021. 11. 30.

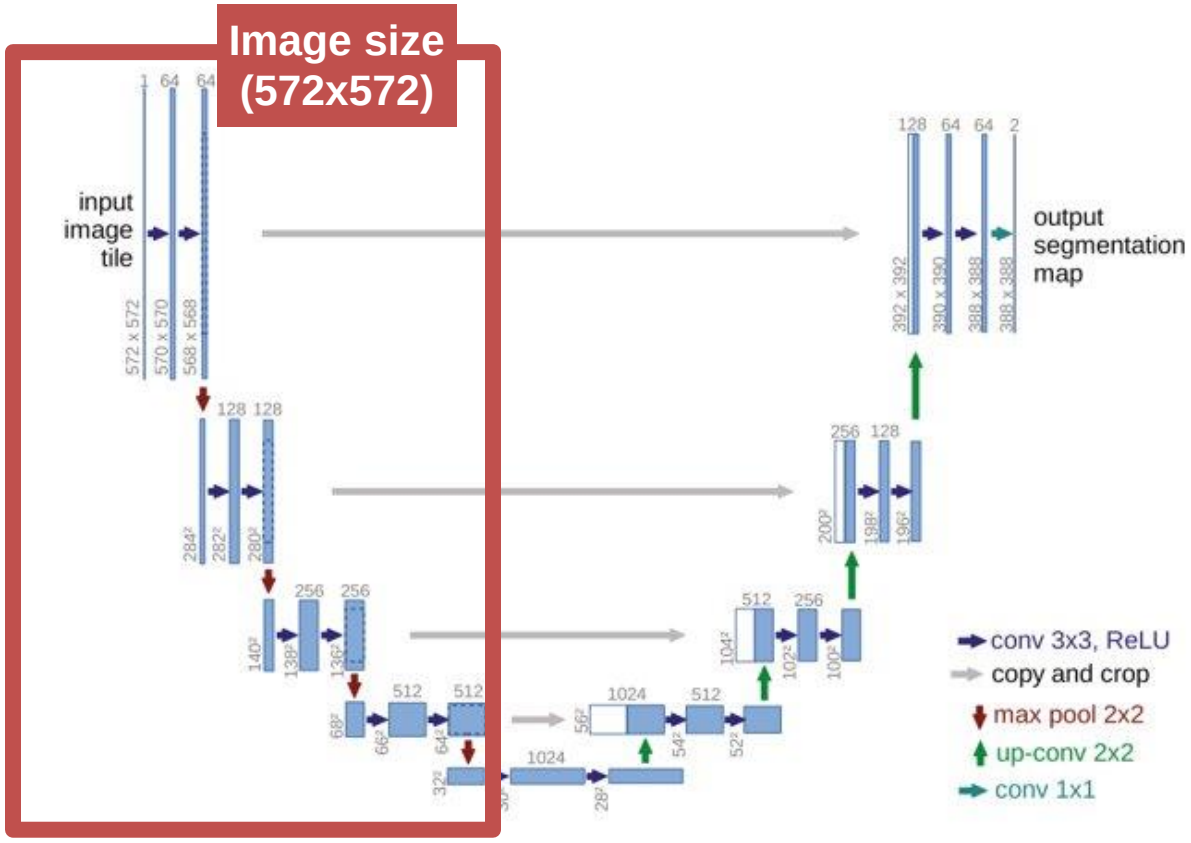
Overview

- **Network Architecture**
  - Contracting Path
  - Bottle Neck
  - Expanding Path
- **Learning method**
  - Overlap-tite strategy
- **Experiments and Result**
  - EM Segmentation challenge Dataset
  - ISBI cell tracking challenge
- **Conclusion**

Network Architecture

- **U-Net (Contracting Path)**

  - Contracting Path that extracts context information by looking at a wide range of image pixels gradually



Contracting Path

Repeat the downsampling process to create a feature map

Extracting contextual information from the image by expanding the reference range of surrounding pixels

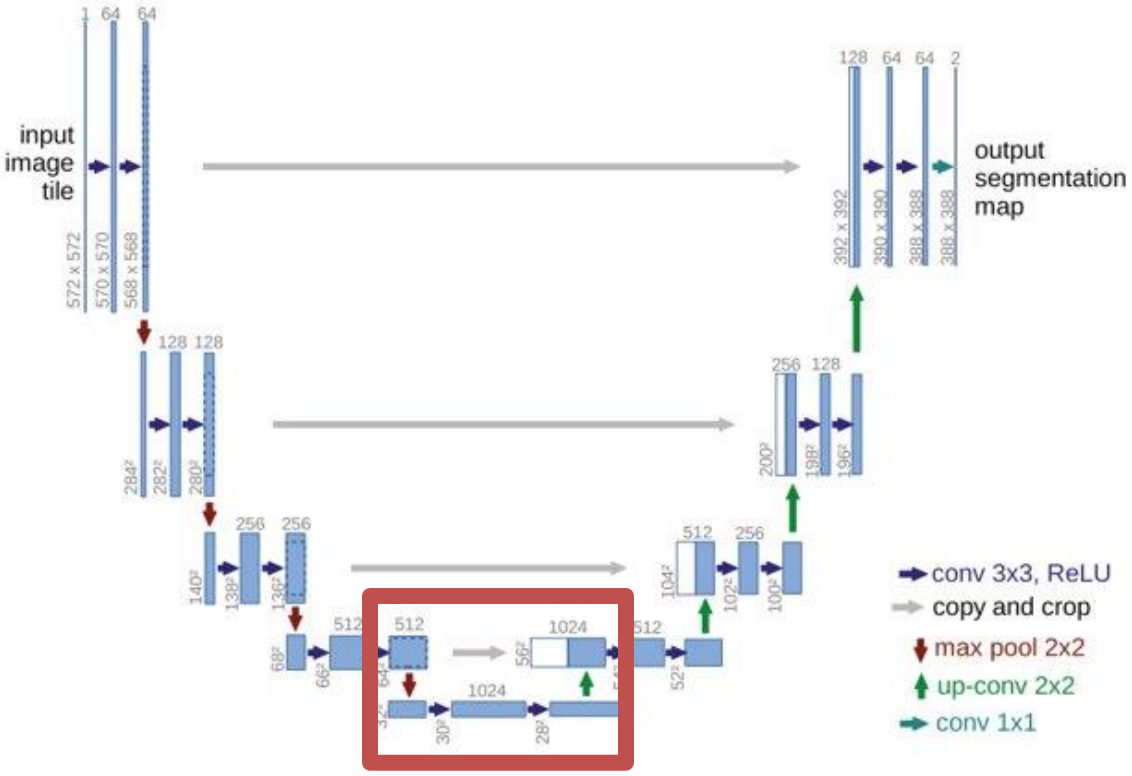
When performing 3×3 convolution, **there is no padding**, so the size of **the feature map is reduced**

Each time downsampling, the number of channels is doubled
1 -> 64 -> 128 -> 256 -> 512 -> 1024

Network Architecture

- **U-Net (Bottle Neck)**

  - Transition from contraction path to expansion path



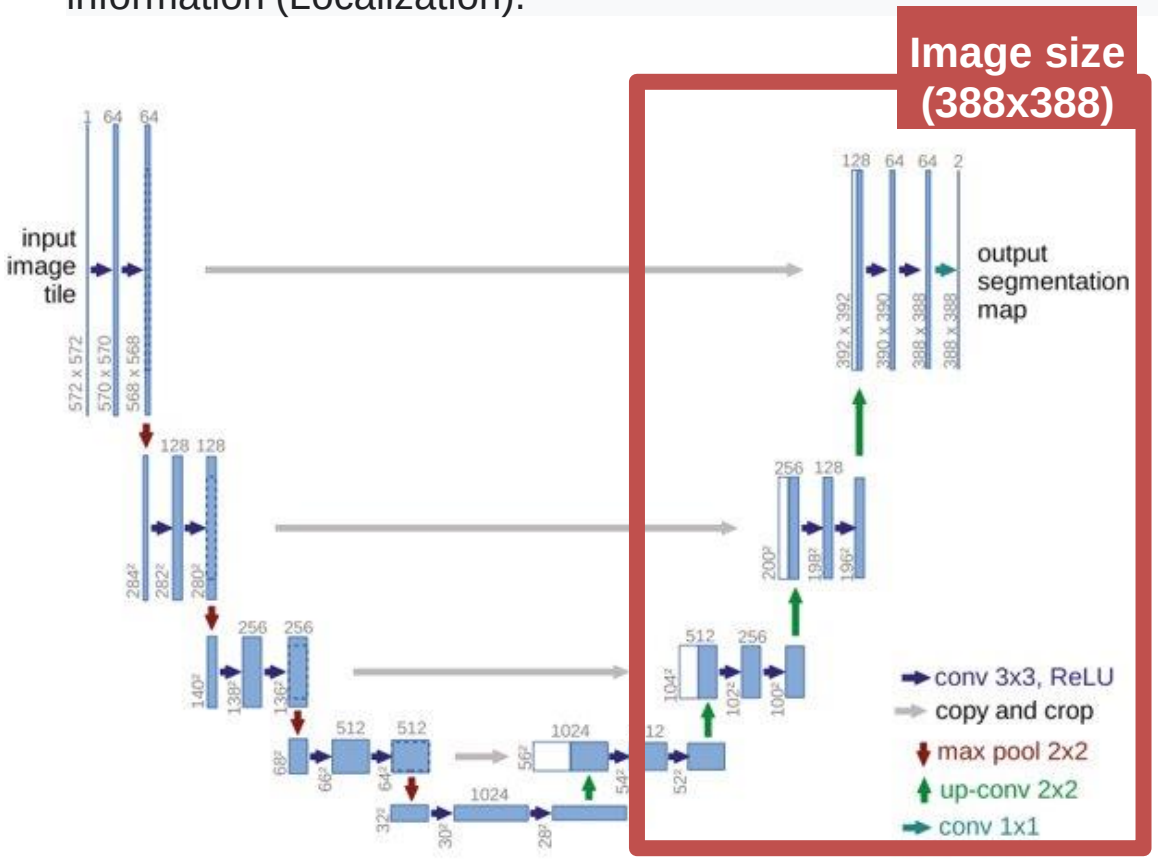
Bottle Neck

The Dropout Layer applied at the end is a device that **generalizes** the model and makes it robust to noise.

Network Architecture

- **U-Net (Expanding Path)**

  - An extension path that identifies which object each pixel belongs to by combining semantic information with pixel location information (Localization).



Expanding Path

Repeat the Upsampling process to create a feature map

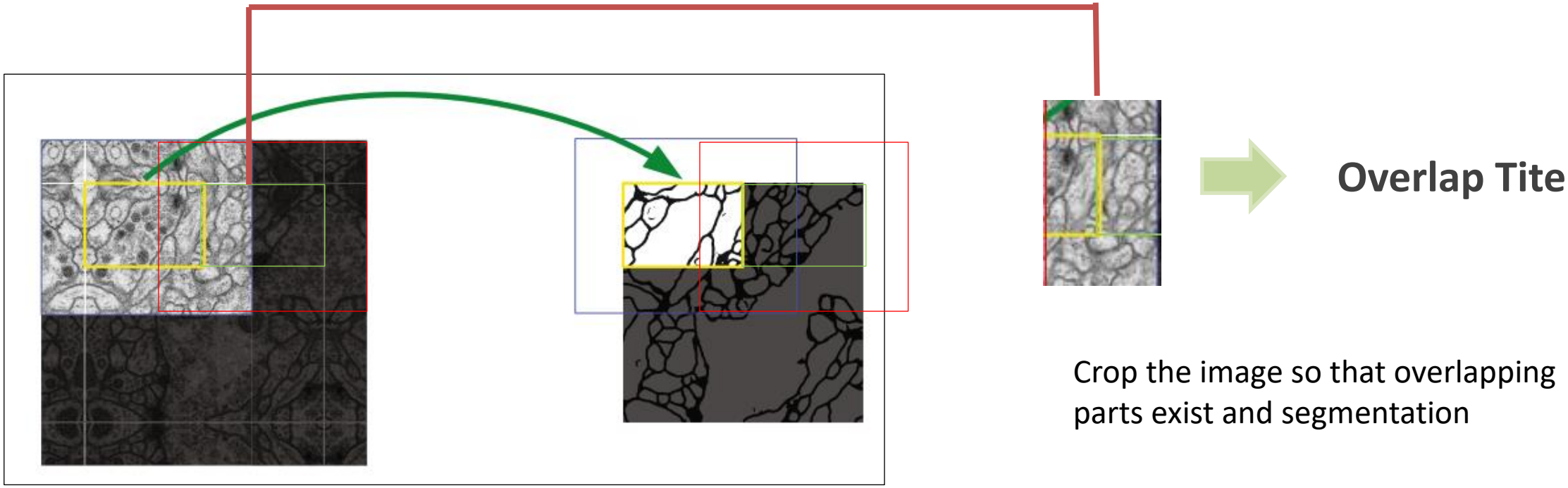
Extract the feature map of the same level from the shrinkage path and **cut it to fit the size (Cropping)** and connect it with the feature map created in the previous layer **(Concatenation)**

The role of combining **contextual information and positional information** generated in the contraction path through Skip Connection

After passing through the **1×1 convolution layer**, **a three-dimensional (Width × Height × Class) vector** representing information about which **class each pixel corresponds** to is generated

Learning method

- **Overlap-tite strategy**



Overlap Tite

Crop the image so that overlapping parts exist and segmentation

he second closest boundary and distance from the position of pixel x

Learning method

- **Touching cells separation**

- Main challenges in cell segmentation is to separate contact objects of the same class.

Softmax

$$p_k(\mathbf{x}) = \exp(a_k(\mathbf{x})) / \left(\sum_{k'=1}^{K} \exp(a_{k'}(\mathbf{x}))\right)$$

Cross-Entropy

$$E = \sum_{\mathbf{x}\in\Omega} w(\mathbf{x}) \log(p_{\ell(\mathbf{x})}(\mathbf{x}))$$

$$\ell : \Omega \to \{1, \ldots, K\}$$
$$w : \Omega \to \mathbb{R}$$

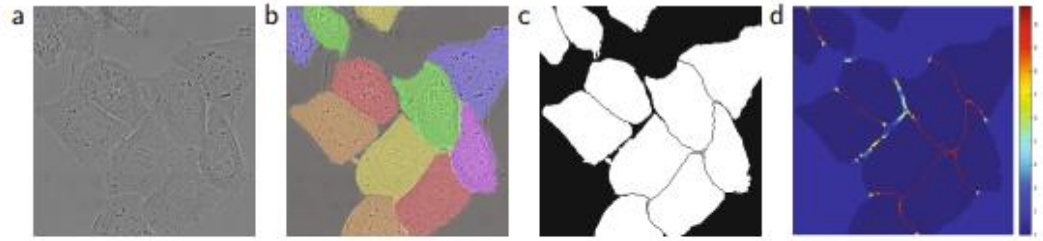


Fig. 3. HeLa cells on glass recorded with DIC (differential interference contrast) microscopy. (**a**) raw image. (**b**) overlay with ground truth segmentation. Different colors indicate different instances of the HeLa cells. (**c**) generated segmentation mask (white: foreground, black: background). (**d**) map with a pixel-wise loss weight to force the network to learn the border pixels.

Use a pre-trained weight map to separate the boundaries between contacting cells.

- Weight map for Ground-Truth

$$w(\mathbf{x}) = w_c(\mathbf{x}) + w_0 \cdot \exp\left(-\frac{(d_1(\mathbf{x}) + d_2(\mathbf{x}))^2}{2\sigma^2}\right)$$

$$w_0 = 10$$
$$\sigma \approx 5 \text{ pixels}$$

- $a_k(x)$ - Value where pixel x is class k (output of model per pixel)
- $p_k(x)$ - Probability that pixel x is class k (0~1)
- $l(x)$: - Actual Label of pixel x
- w_0 - Weight hyper-parameter of the paper, set to 10 in the paper
- σ : - Weight hyper-parameter of the paper, set to 5 in the paper
- $d_1(x)$ - The nearest boundary and distance from the position of pixel x
- $d_2(x)$ - The second closet boundary and distance from the posirion of pixel x

- Use the image as large as possible
- Adjust the optimizer to learn consistently by giving Momentum (0.99)

Experiments and Result

- **EM Segmentation challenge Dataset**

  - EM Segmentation challenge Dataset provides 30 training data
  - Each data includes a Ground Truth Segmentation Map with separate objects and backgrounds (0 or 1) with images.

- Data augmentation methods : Rotation, Shift, Elastic distortion

Table 1. Ranking on the EM segmentation challenge [14] (march 6th, 2015), sorted by warping error.

Rank	Group name	Warping Error	Rand Error	Pixel Error
	** human values **	0.000005	0.0021	0.0010
1.	u-net	**0.000353**	0.0382	0.0611
2.	DIVE-SCI	0.000355	0.0305	0.0584
3.	IDSIA [2]	0.000420	0.0504	0.0613
4.	DIVE	0.000430	0.0545	**0.0582**
⋮				
10.	IDSIA-SCI	0.000653	**0.0189**	0.1027

Experiments and Result

- **ISBI cell tracking challenge**

  - "PhC-U373" data provided as training data from 35 images recorded with a phase-contrast microscope
  - "DIC-HeLa" data were recorded from HeLa cells under a microscope and 20 images were provided as training data.

Table 2. Segmentation results (IOU) on the ISBI cell tracking challenge 2015.

Name	PhC-U373	DIC-HeLa
IMCB-SG (2014)	0.2669	0.2935
KTH-SE (2014)	0.7953	0.4607
HOUS-US (2014)	0.5323	-
second-best 2015	0.83	0.46
u-net (2015)	**0.9203**	**0.7756**

Conclusion

- **Conclusion**
  - "U-Net is a model that applies Up-sampling and Skip Architecture of an expanded concept than FCNs.
  - As a result, the structure of U-Net exhibits excellent performance in various biomedical image segmentation problems by utilizing Data Augmentation with only a very small amount of training data.
  - Skip Architecture makes it possible to stack layers deeply, so that complex tasks can be performed well.
  - Reducing the loss of information from the bottle neck

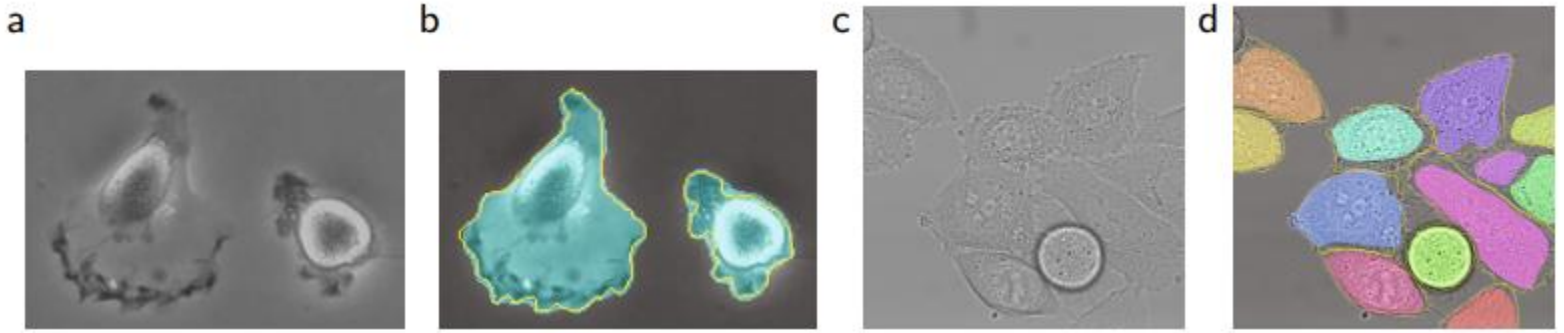


Fig. 4. Result on the ISBI cell tracking challenge. (**a**) part of an input image of the "PhC-U373" data set. (**b**) Segmentation result (cyan mask) with manual ground truth (yellow border) (**c**) input image of the "DIC-HeLa" data set. (**d**) Segmentation result (random colored masks) with manual ground truth (yellow border).

Thank you