Southwest Jiaotong University

图像分割经典网络 之Unet

Computer Technology

The School of Information Science and Technology

汇报人-胡毕杰



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图像分类

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(一张图片)

(单个标签)

為意文章/李 (1896)

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CNN 卷积神经网络

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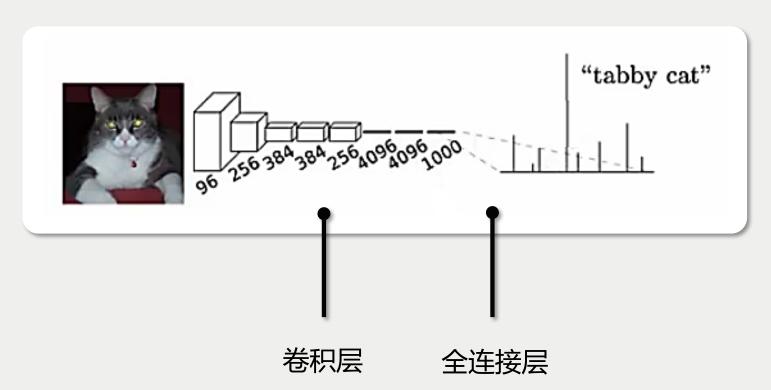
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CNN 卷积神经网络





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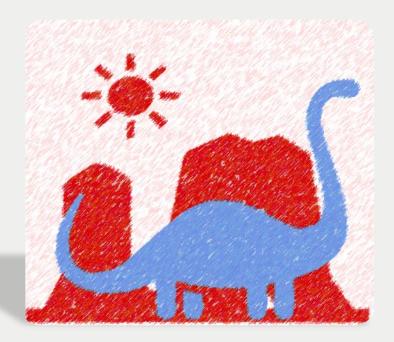
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图像分割



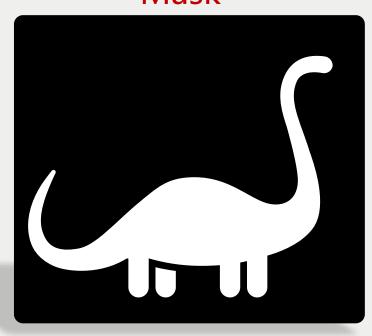
海点交换等 (1836)

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给每一个 像素进行分类

输出 Mask

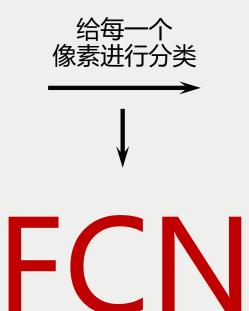


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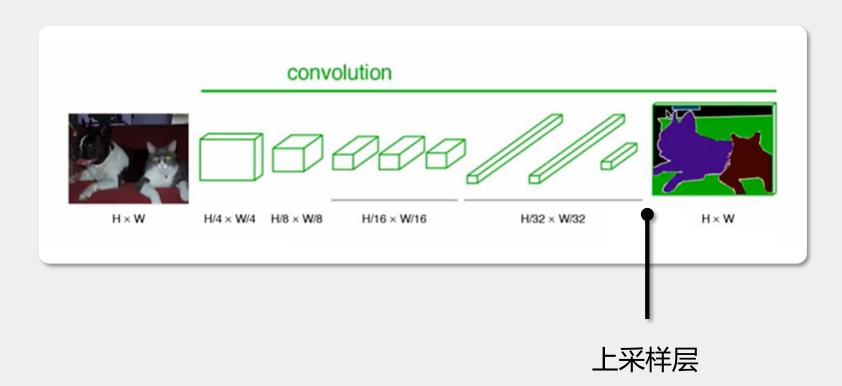
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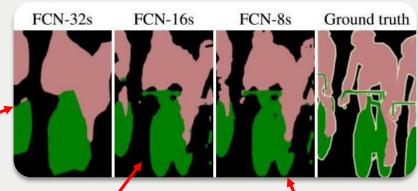


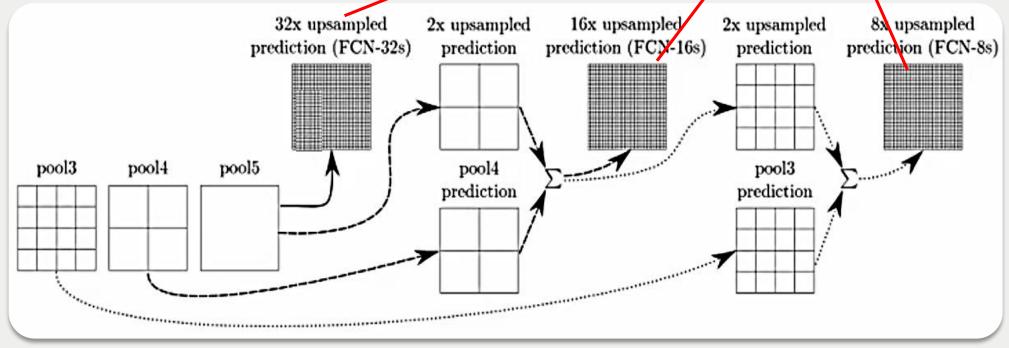
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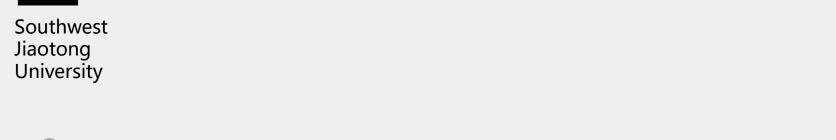
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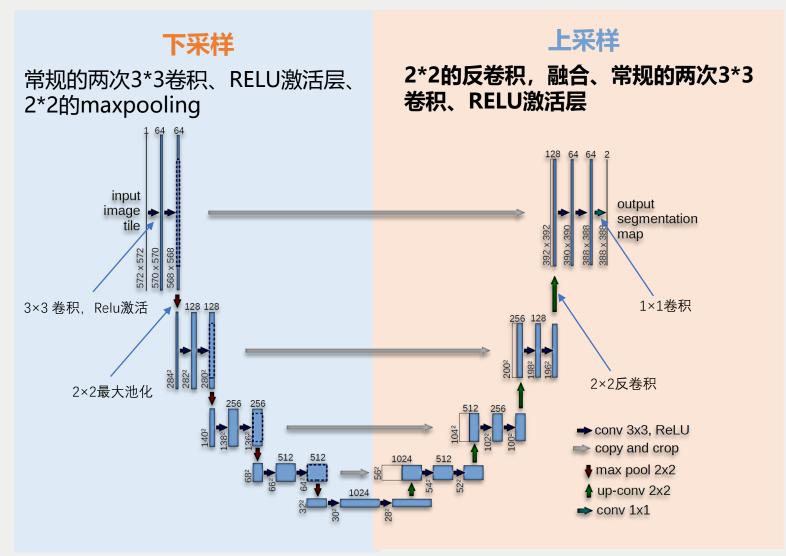
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U-Net: Convolutional Networks for Biomedical Image Segmentation(cs.CV 2015.03.18)



UNet

Network Architectur e





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反卷积

(Transposed convolution)

$$W = \begin{pmatrix} w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{0,0} & w_{0,1} & w_{0,2} & 0 & w_{1,0} & w_{1,1} & w_{1,2} & 0 & w_{2,0} & w_{2,1} & w_{2,2} \end{pmatrix}$$

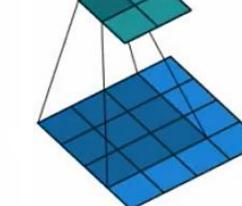
$$X = (x_1, x_2, \dots, x_{16})^T$$

$$Y = (y_1, y_2, y_3, y_4)^T$$

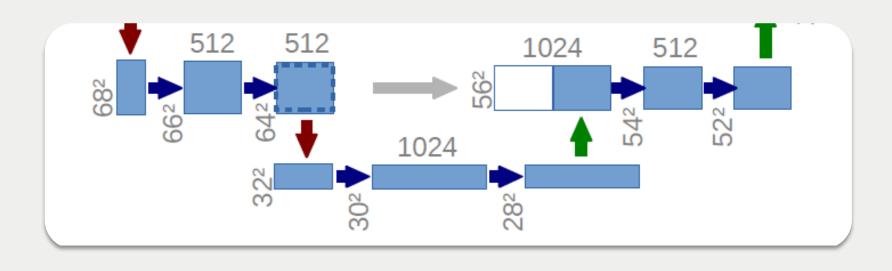
卷积: $W \cdot X$ 反卷积: $W^T \cdot Y$

4x16, 16x1 4x1

16x4, 4x1 16x1



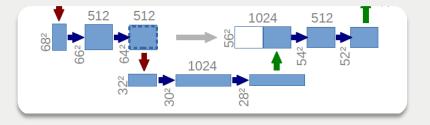
| W | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 1835 | 18



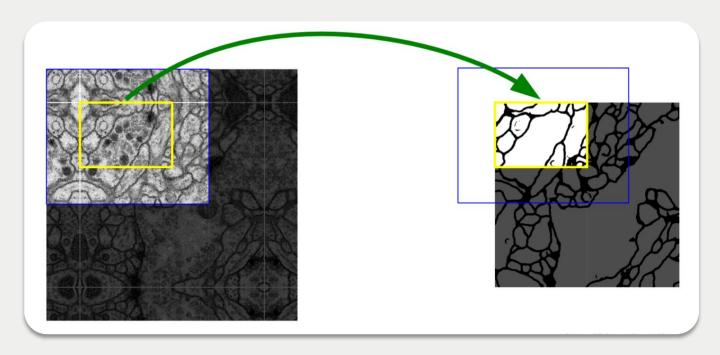




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Overlap-tile 策略









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数据增强



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增强

色彩抖动	尺度变换	翻转变换
平移变换	噪声扰动	随机弹性变形



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数据 增强





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损失函数

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

像素点形式的softmax, a_k(x)表示像素x在特征图中的第k层的激活值, k表示是第几个特征通道, x表示像素点, K表示类别的个数。

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

 $\ell:\Omega\to\{1,\ldots,K\}$ 每个像素的真实标签

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

表示训练构成中像素点的重要性 w。表示平衡类别频率的权重图 d₁表示此像素点到离它最近cell边界的距离, d₂表示此像素点到离他第二近cell边界的距离。

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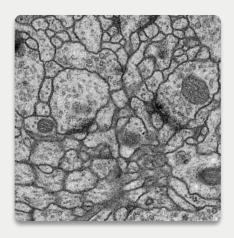
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● 实验

• 框架: keras

• 训练集: 30张细胞图

• 测试集: 30张细胞图



原图



结果

论文连接: https://arxiv.org/pdf/1505.04597.pdf

源码连接: https://github.com/FENGShuanglang/unet



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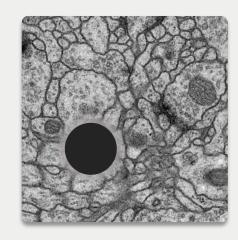
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原图



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THANK FOR YOUR ATTENTION

BY Hu.

2020