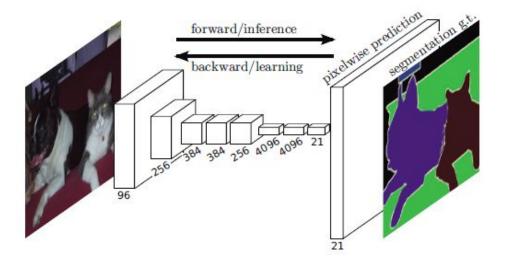
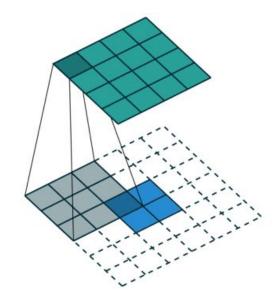
# Основные архитектуры для задачи сегментации

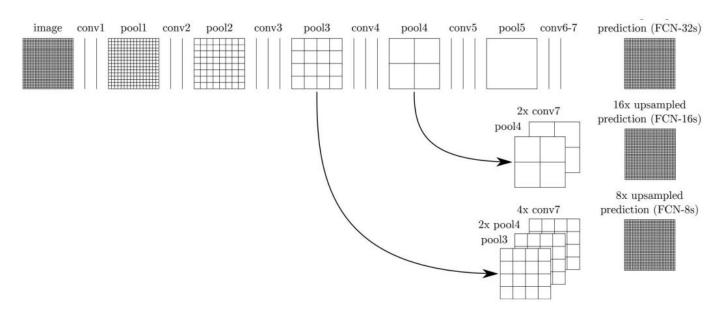
## Fully convolutional network



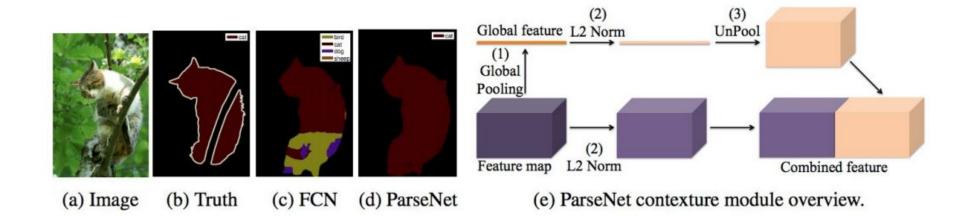
## **Deconvolution**



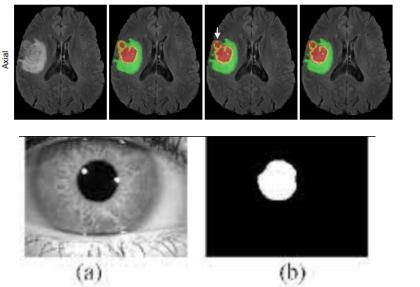
# Fully convolutional network

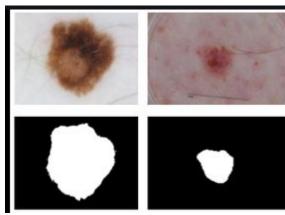


#### **ParseNet**

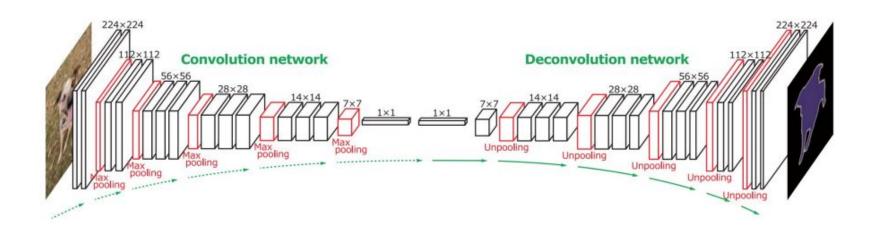


# Fully convolutional network

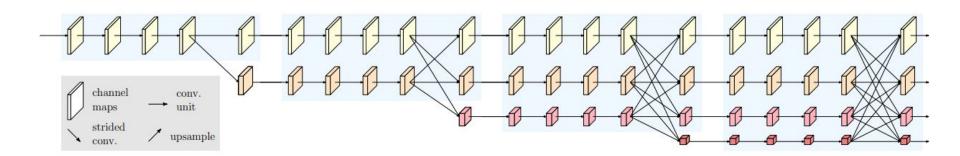




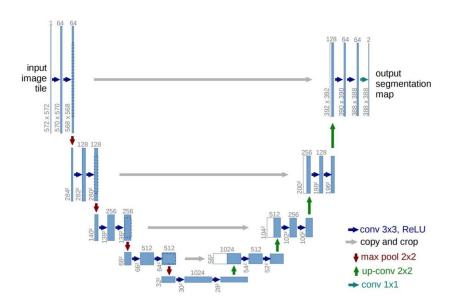
#### **Encoder-Decoder**



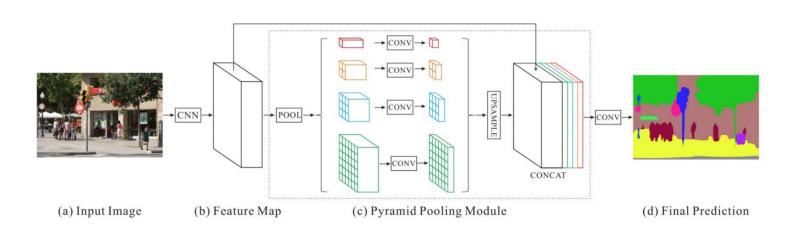
## **HRNet**



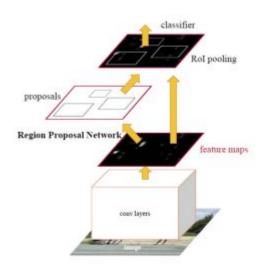
# Unet

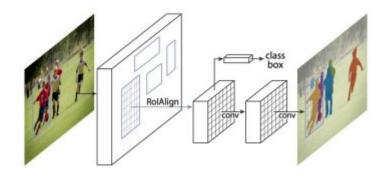


#### **PSPN** architecture



### **R-CNN Based Models**



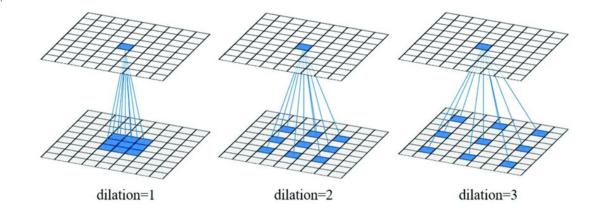


# Современные архитектуры сегментации

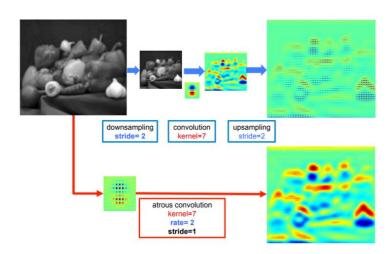
#### **Dilated Convolutional**

$$y_i = \sum_{k=1}^K x[i+rk]w[k].$$

- 1. Multiscale context aggregation
- 2. Dense upsampling convolution, Hybrid dilated convolution
- Densely connected Atrous Spatial Pyramid Pooling (DenseASPP)
- Efficient neural network (Enet)



### **Dilated Convolutional**



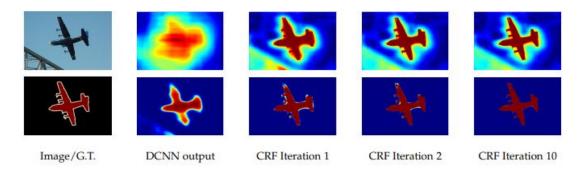
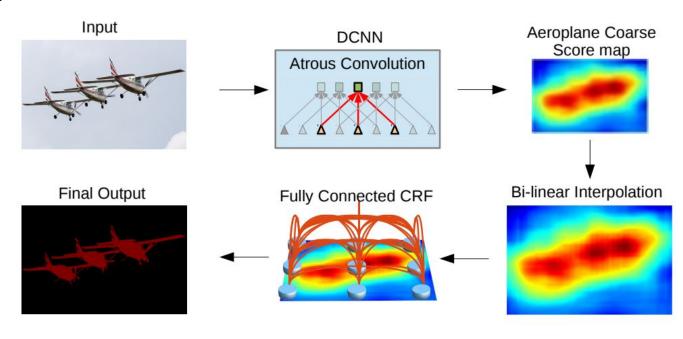
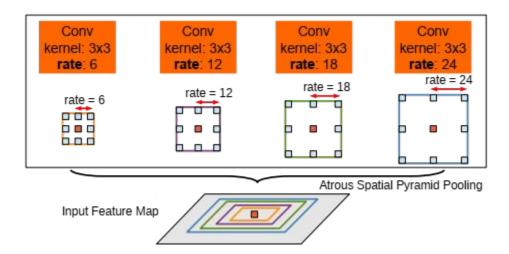
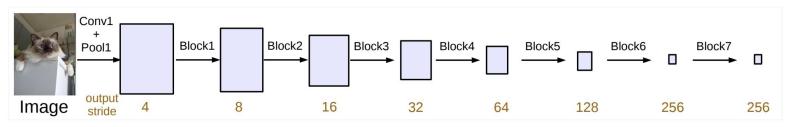


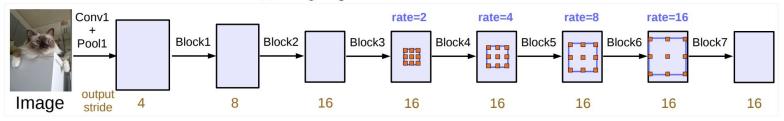
Fig. 5: Score map (input before softmax function) and belief map (output of softmax function) for Aeroplane. We show the score (1st row) and belief (2nd row) maps after each mean field iteration. The output of last DCNN layer is used as input to the mean field inference.



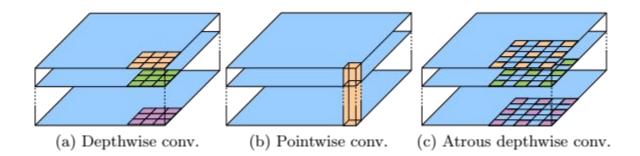




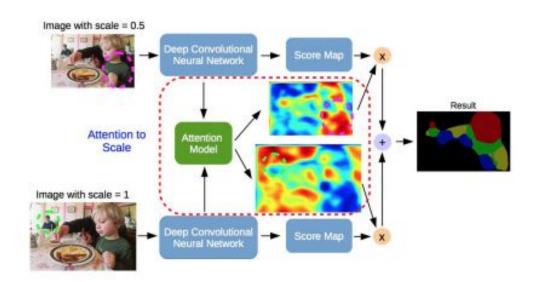
(a) Going deeper without atrous convolution.



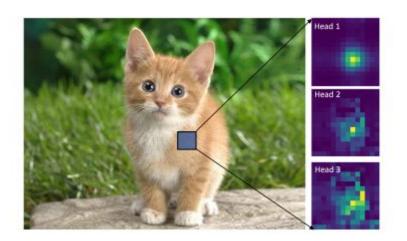
(b) Going deeper with atrous convolution. Atrous convolution with rate > 1 is applied after block3 when  $output\_stride = 16$ . Figure 3. Cascaded modules without and with atrous convolution.

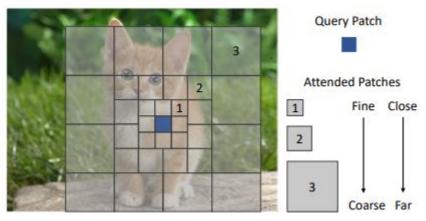


## Attention модели



#### Self-attention и Патчи





https://arxiv.org/abs/2107.00641

#### **Focal Transformer**

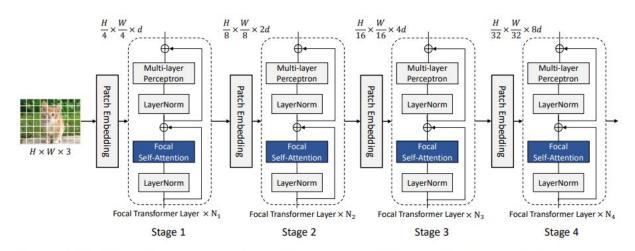
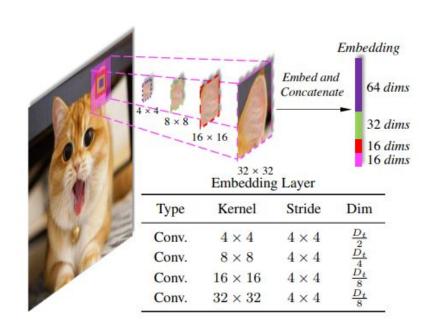


Figure 2: Model architecture for our Focal Transformers. As highlighted in light blue boxes, our main innovation is the proposed focal self-attention mechanism in each Transformer layer.

## Пример



### **Self-attention**

