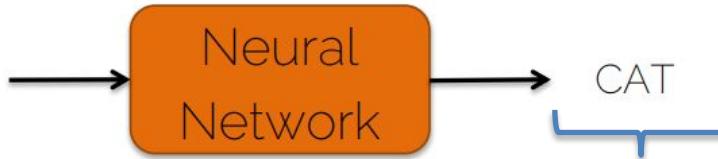
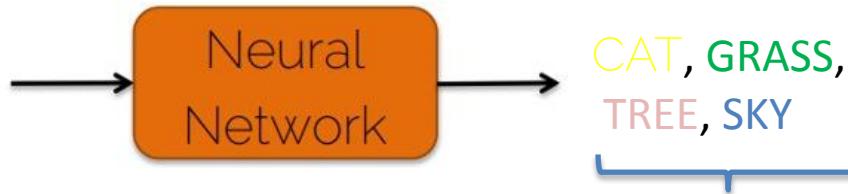
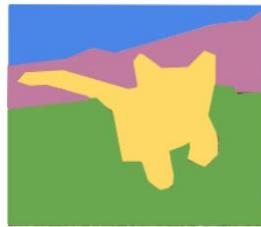


Semantic segmentation

Task definition: semantic segmentation

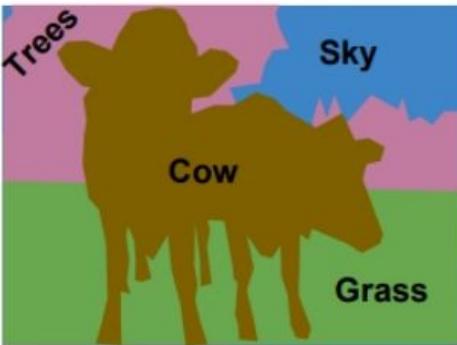
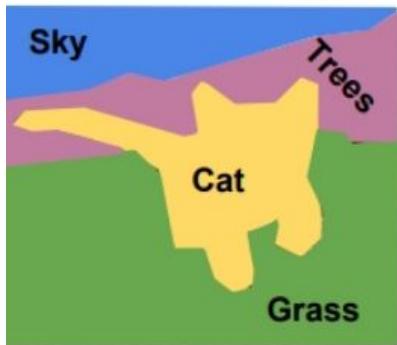


Classify the main object
in the image.



No objects, just classify
each pixel.

Semantic Segmentation

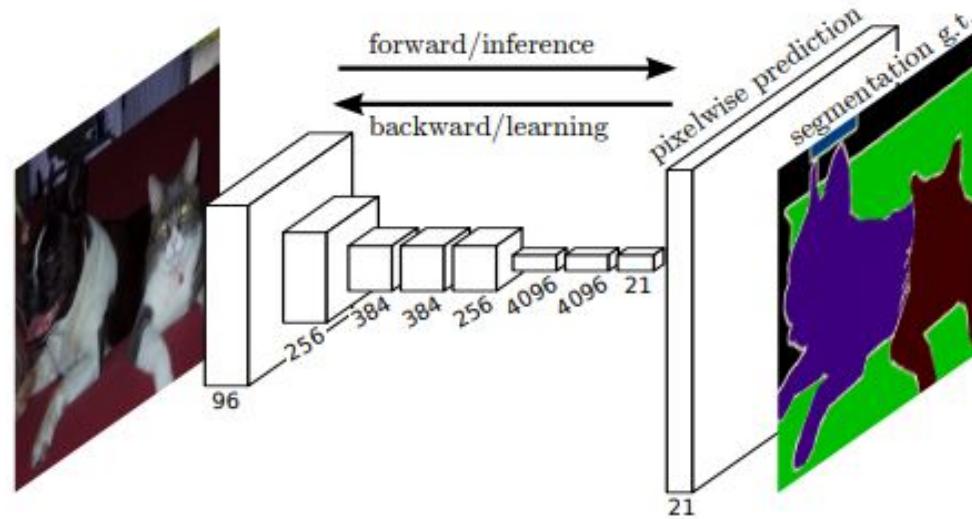


- Every pixel in the image needs to be labelled with a category label.
- Do not differentiate between the instances (see how we do not differentiate between pixels coming from different cows).

Fully Convolutional Networks

Fully convolutional neural networks

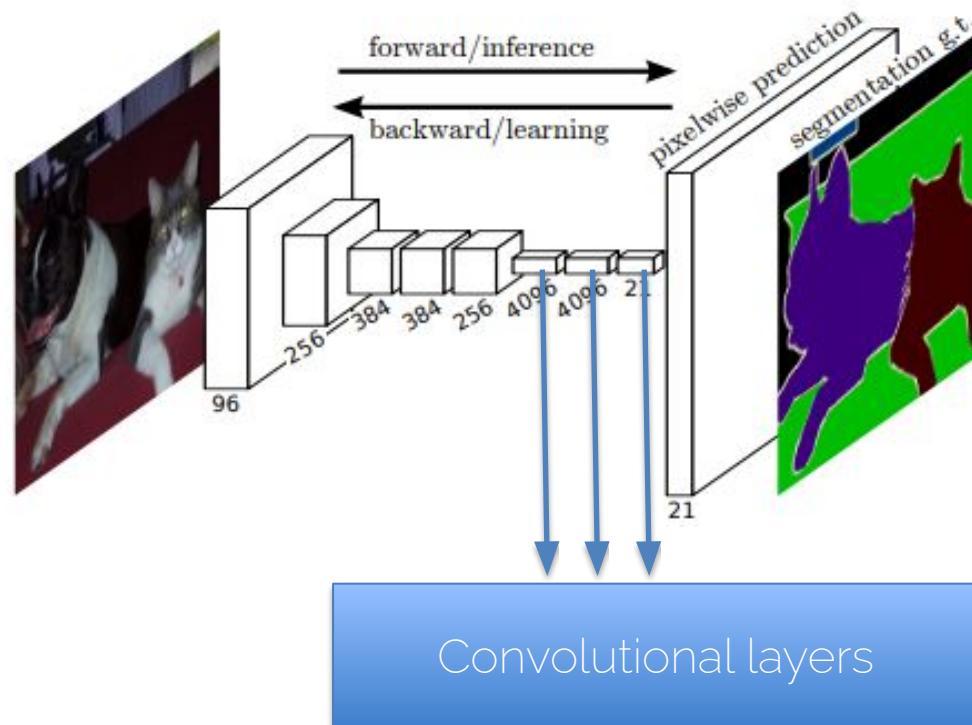
- A FCN is able to deal with any input/output size



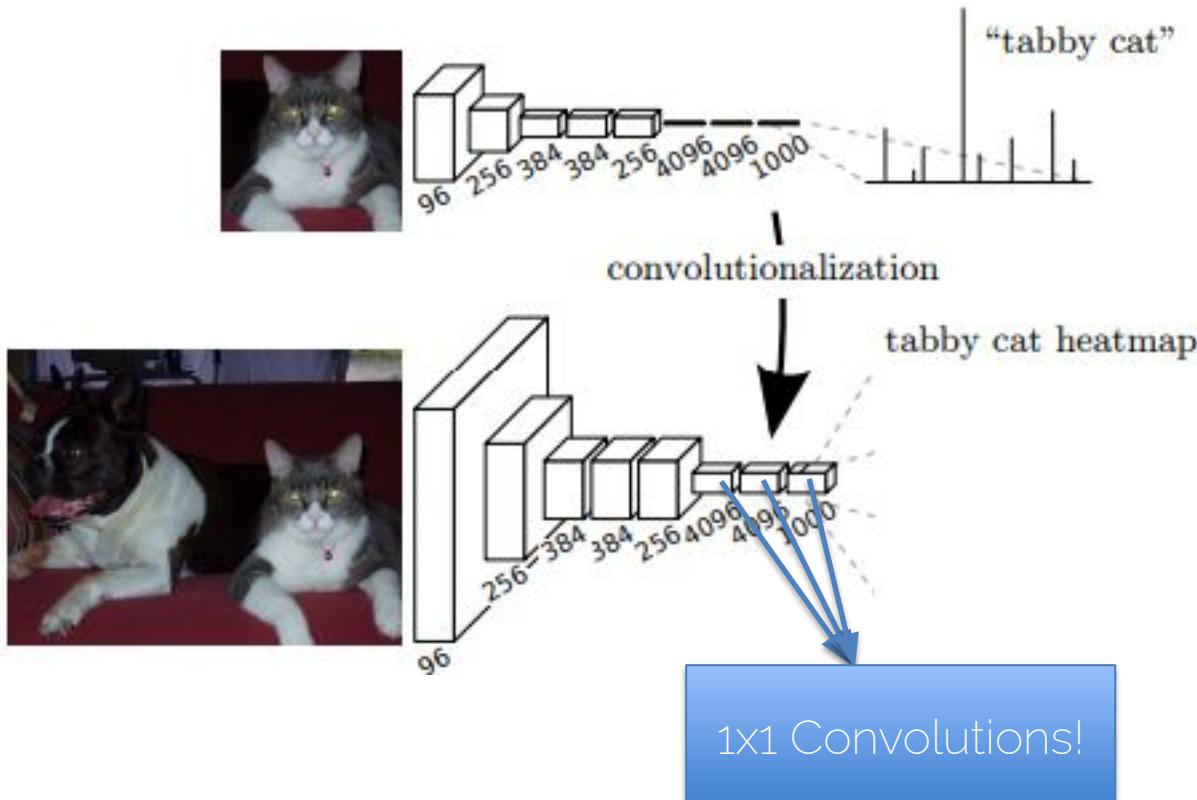
Long, Shelhamer, Darrell - Fully Convolutional Networks for Semantic Segmentation, CVPR 2015, PAMI 2016

Fully convolutional neural networks

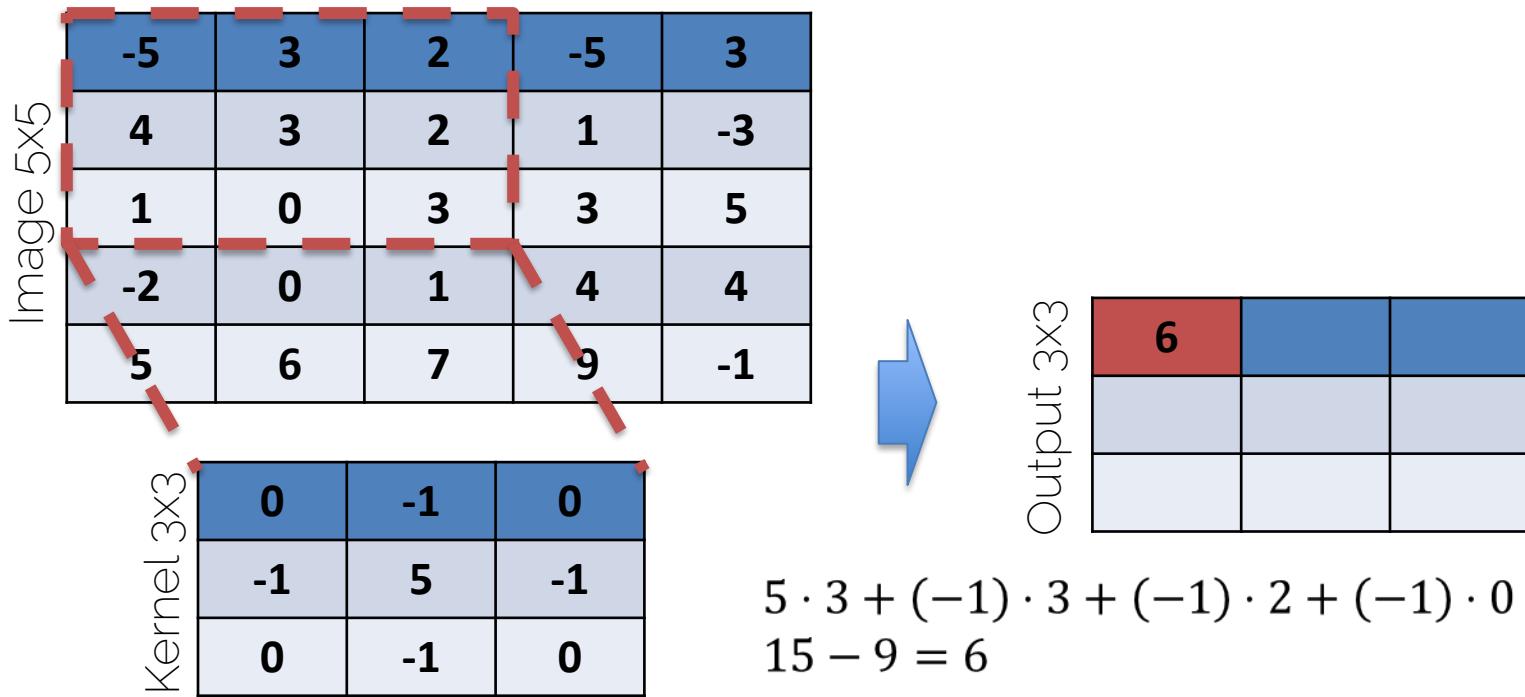
1. Replace FC layers with convolutional layers.
2. Convert the last layer output to the original resolution.
3. Do softmax-cross entropy between the pixelwise predictions and segmentation ground truth.
4. Backprop and SGD



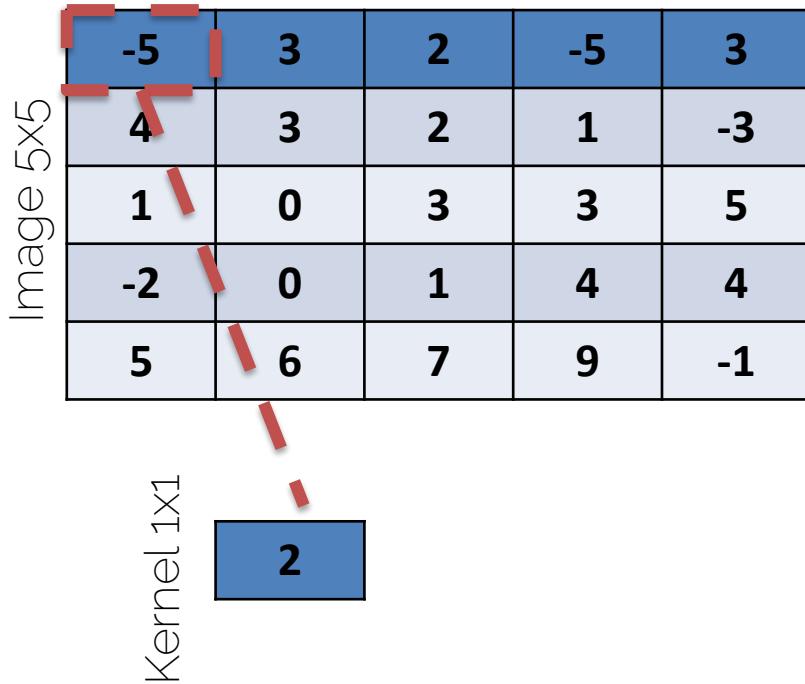
“Convolutionalization”



Recall: Convolutions on Images



1x1 Convolution



What is the output size?

1x1 Convolution

Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Kernel 1x1

2

-10				

$$-5 * 2 = -10$$

1x1 Convolution

Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Kernel 1x1

2

-10	6	4	-10	6
8	6	4	2	-6
2	0	6	6	10
-4	0	2	8	8
10	12	14	18	-2

$$-1 * 2 = -2$$

1x1 Convolution

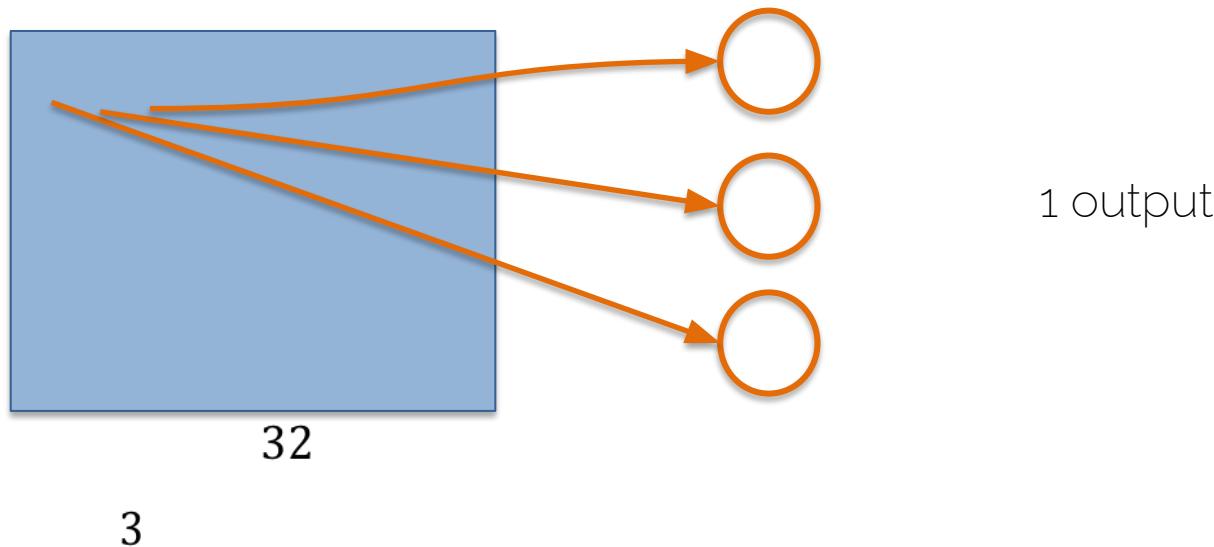
Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

-10	6	4	-10	6
8	6	4	2	-6
2	0	6	6	10
-4	0	2	8	8
10	12	14	18	-2

- 1x1 kernel: keeps the dimensions and scales input

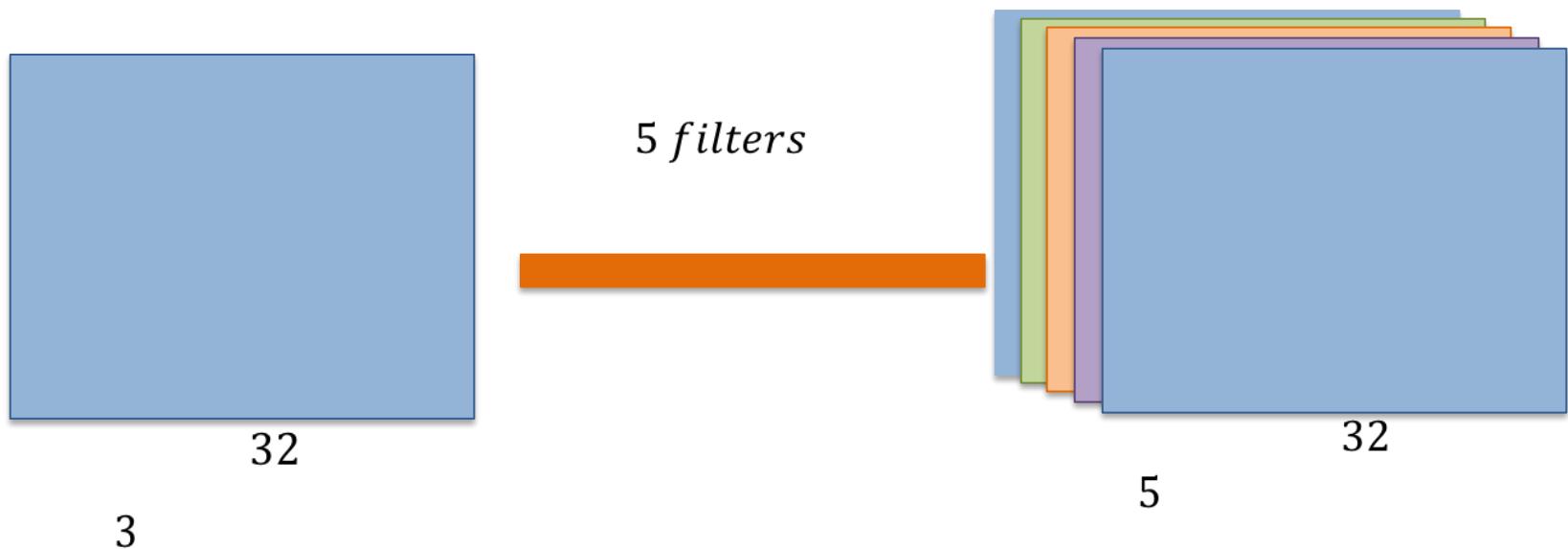
1x1 Convolution



- Same as having a 3 neuron fully connected layer

1x1 Convolution

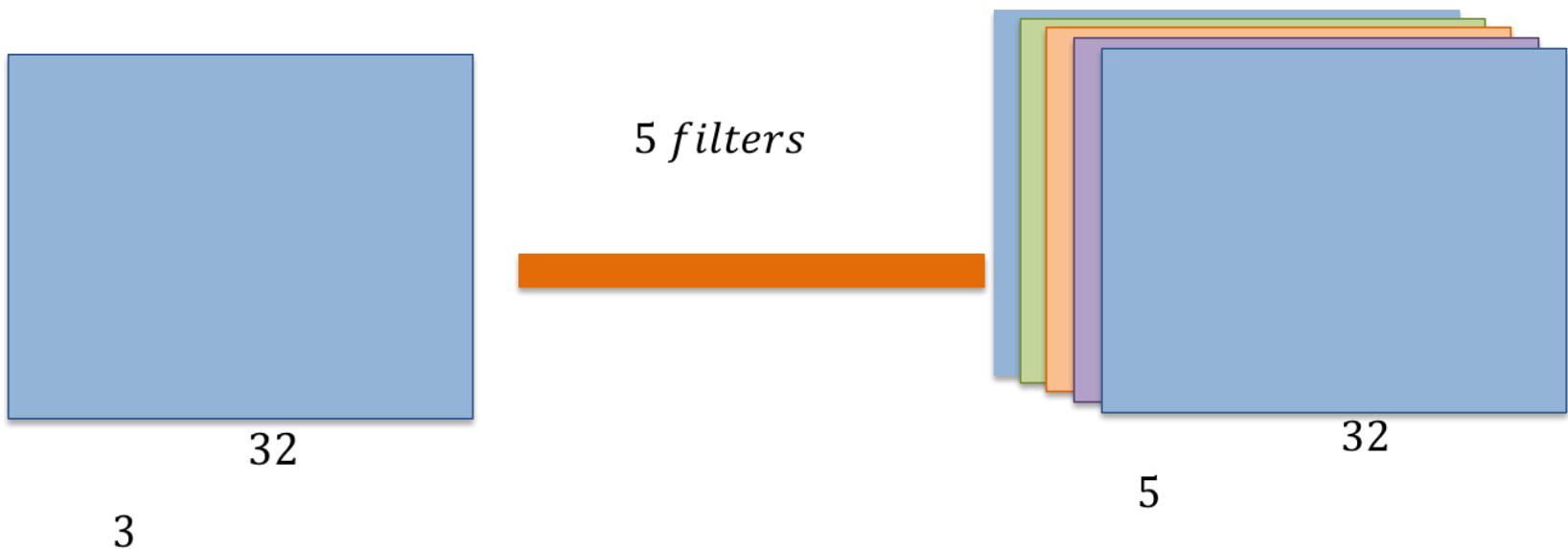
[Li et al. 2013]



- As always we use more convolutional filters

Network in Network

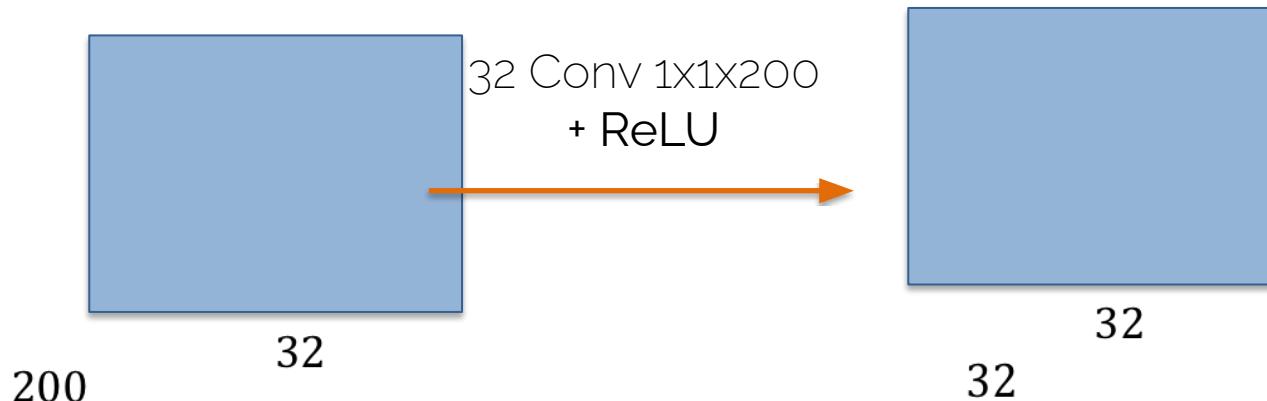
[Li et al. 2013]



- As always, we use more convolutional filters

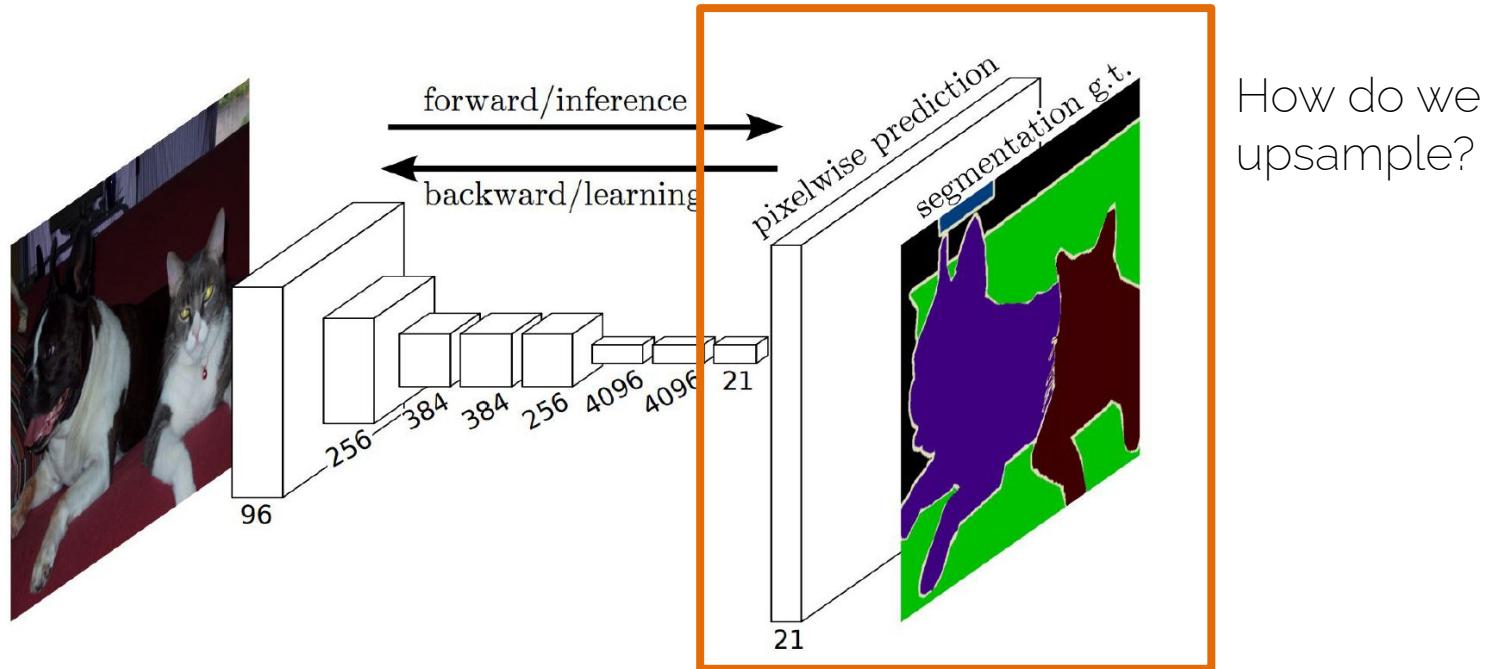
Using 1x1 Convolutions

- Use it to shrink the number of channels
- Further adds a non-linearity □ one can learn more complex functions



Semantic Segmentation (FCN)

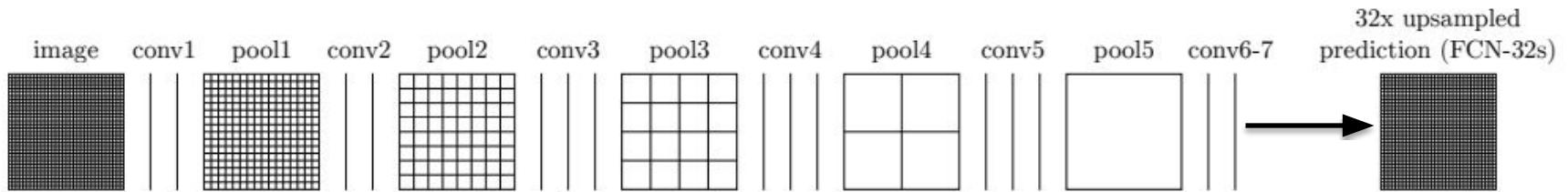
- Fully Convolutional Networks for Semantic Segmentation



Long, Shelhamer, Darrell - Fully Convolutional Networks for Semantic Segmentation, CVPR 2015, PAMI 2016

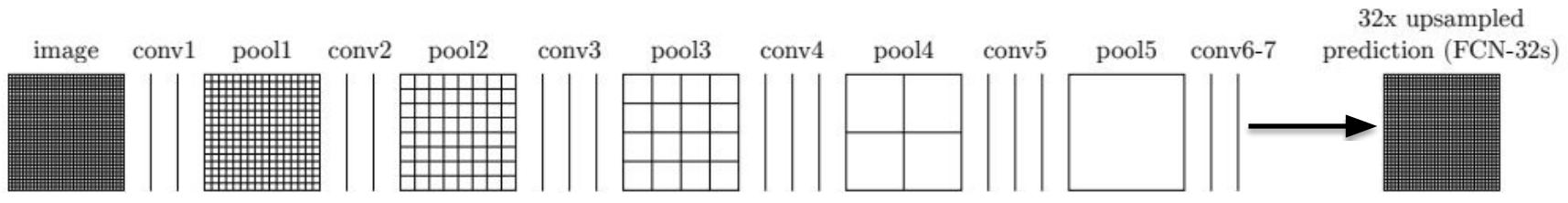
Network's architecture

Predict the
segmentation mask
from high level features



Network's architecture

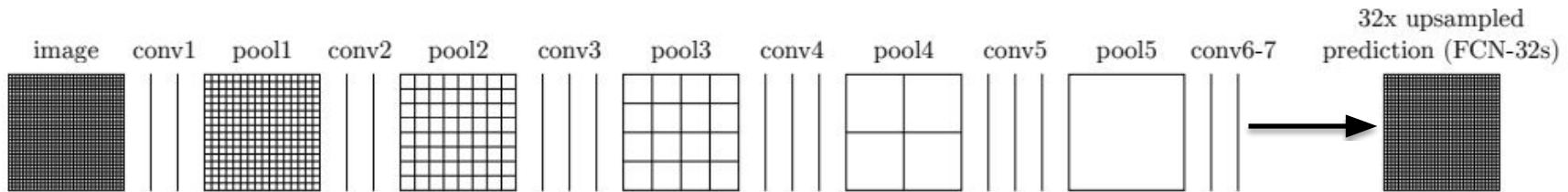
Predict the segmentation mask from high level features



Predict the segmentation mask from mid-level features

Network's architecture

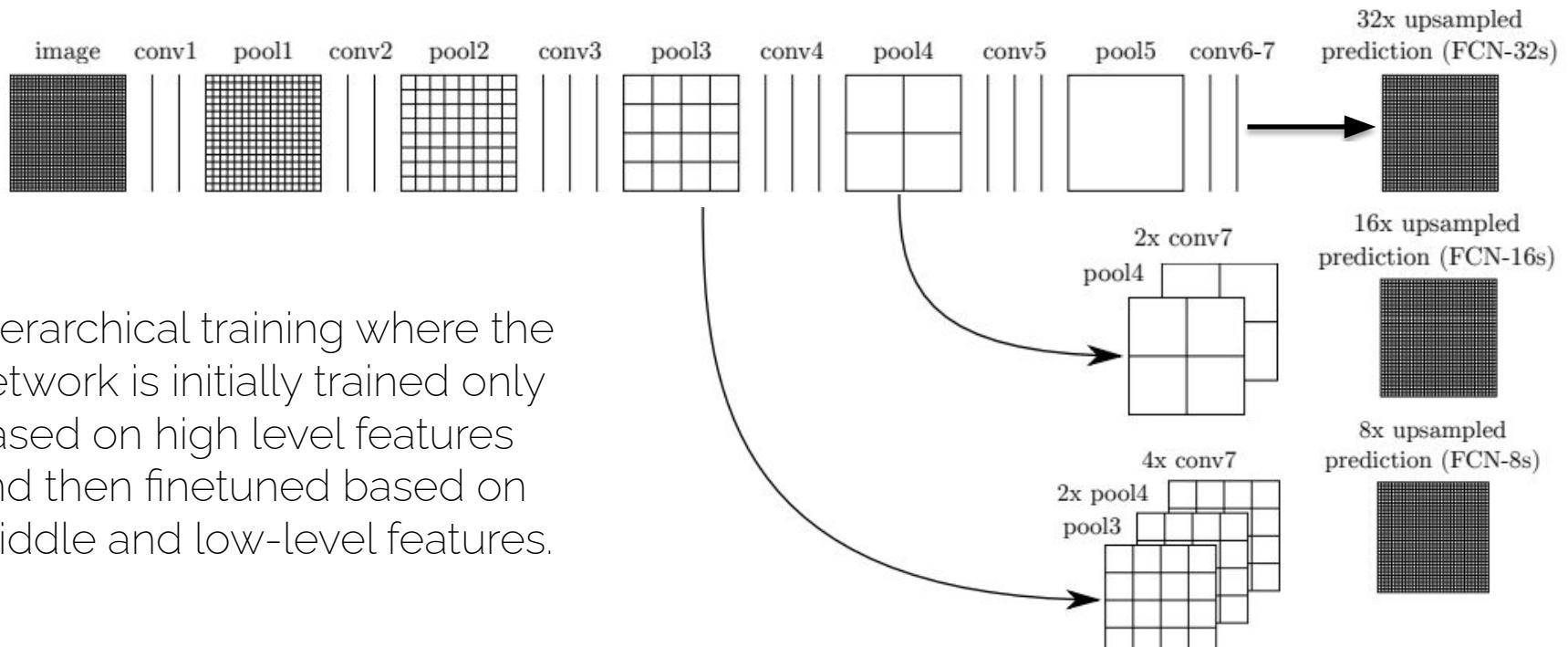
Predict the segmentation mask from high level features



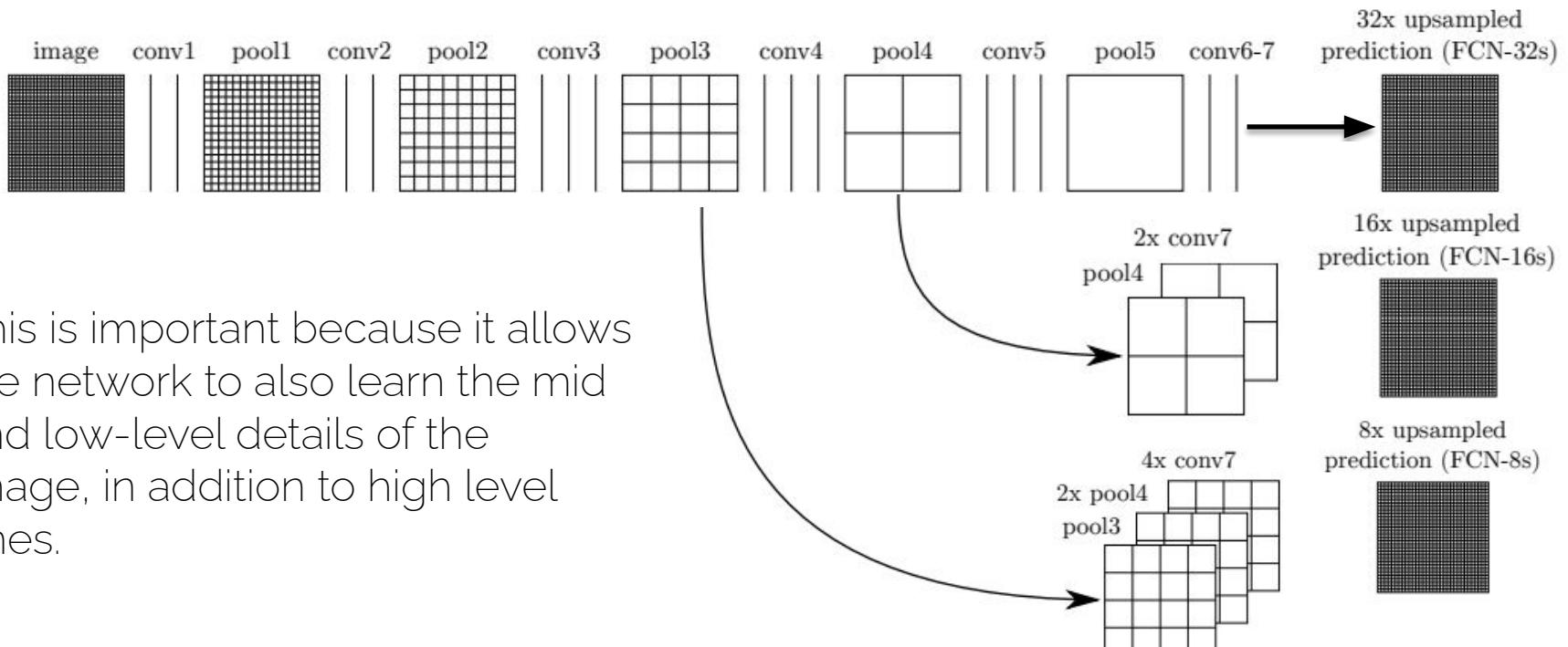
Predict the segmentation mask from mid-level features

Predict the segmentation mask from low-level features

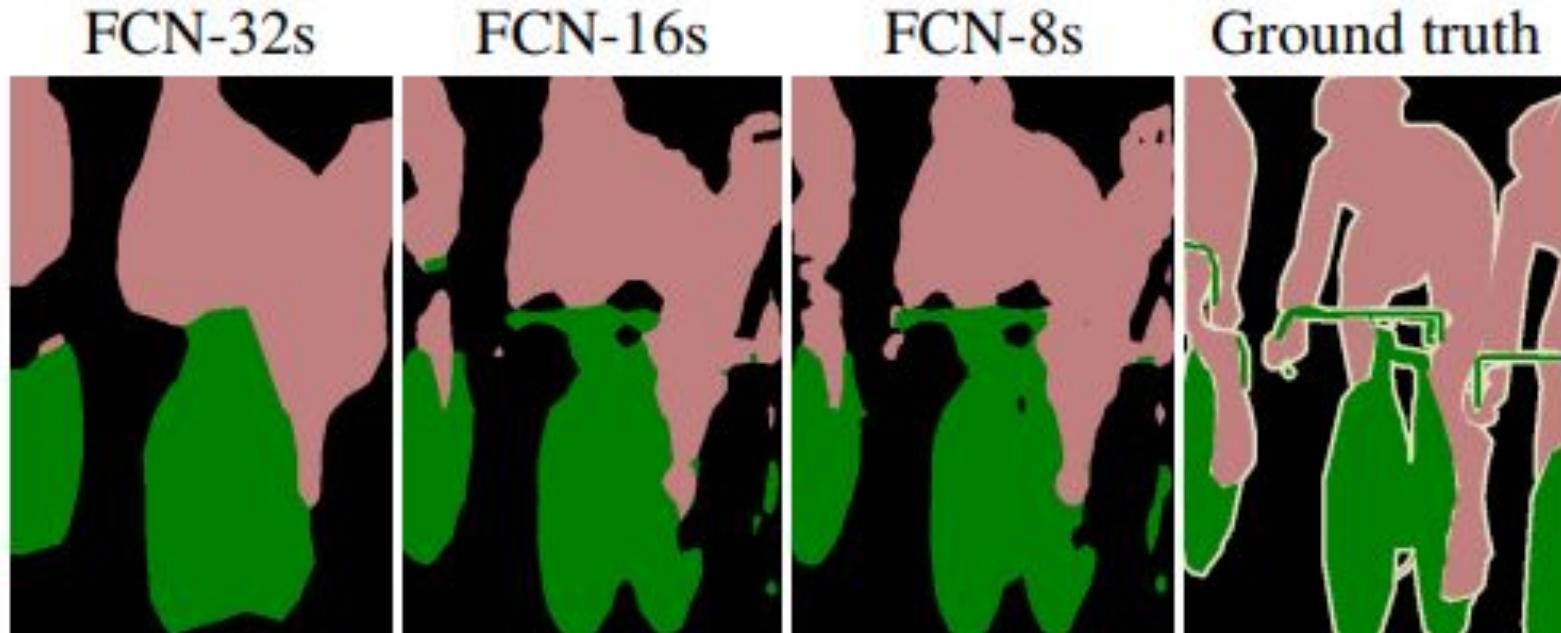
Network's architecture



Network's architecture



Qualitative results

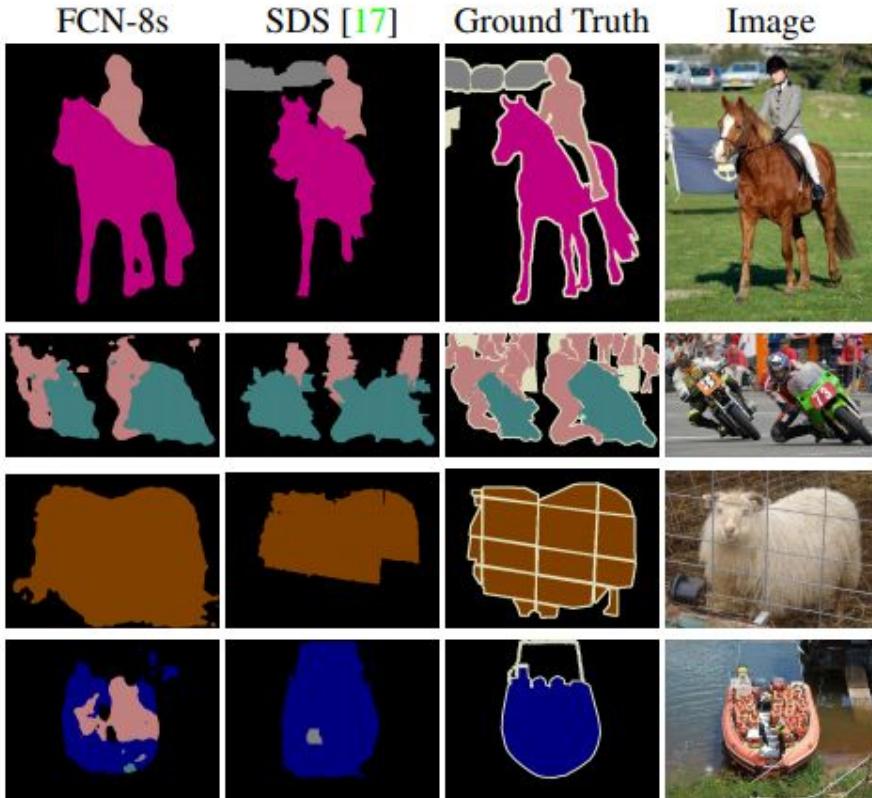


Good

Better

Best

Qualitative results



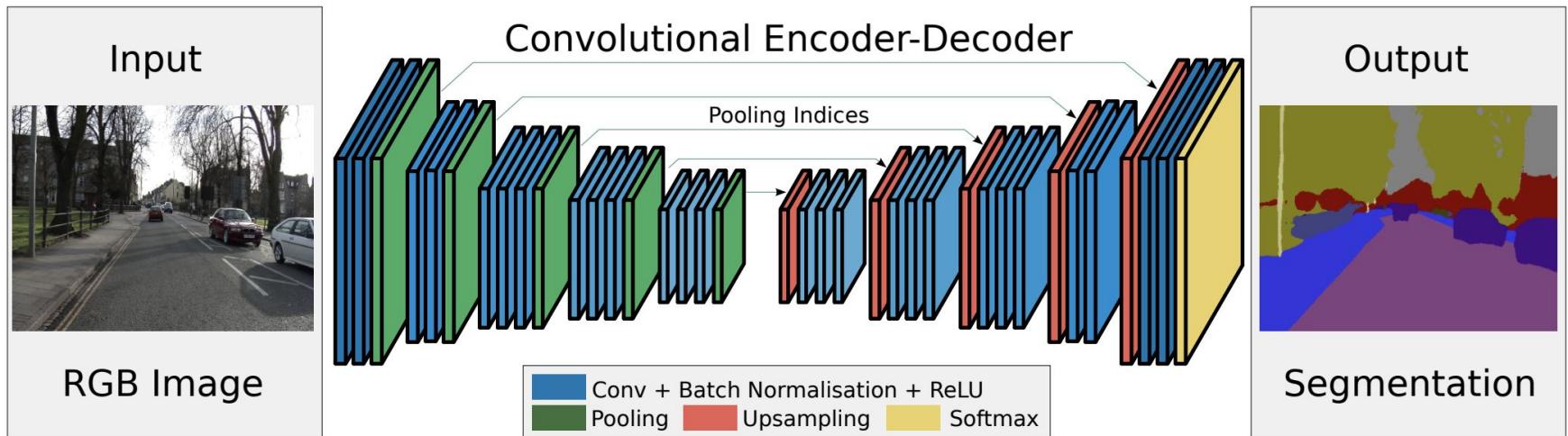
SDS is an R-CNN-based method, i.e., it uses object proposals.

In general, FCN outperforms significantly (both qualitatively and quantitatively) pre-deep learning and quasi-deep learning methods and is recognized as the AlexNet of semantic segmentation.

Autoencoder-style architecture

SegNet

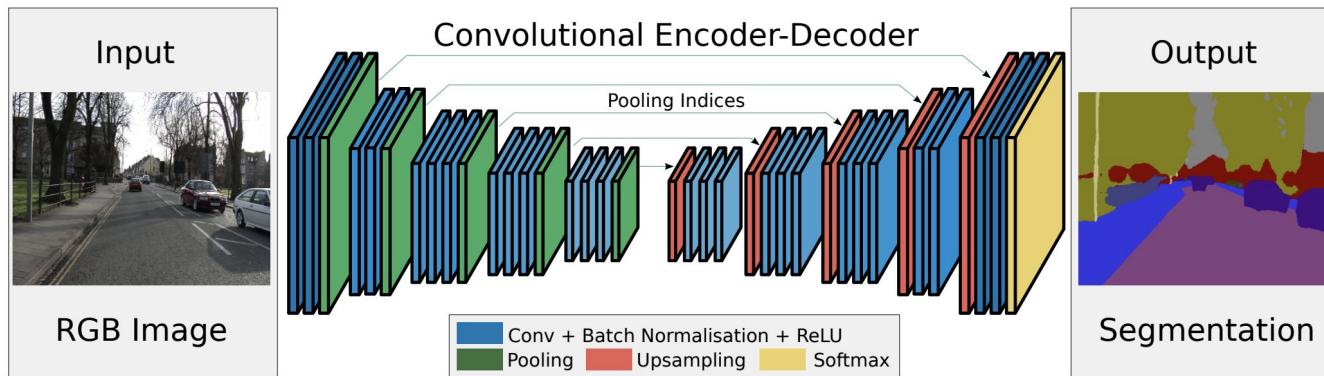
- Step-wise upsampling



Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

SegNet

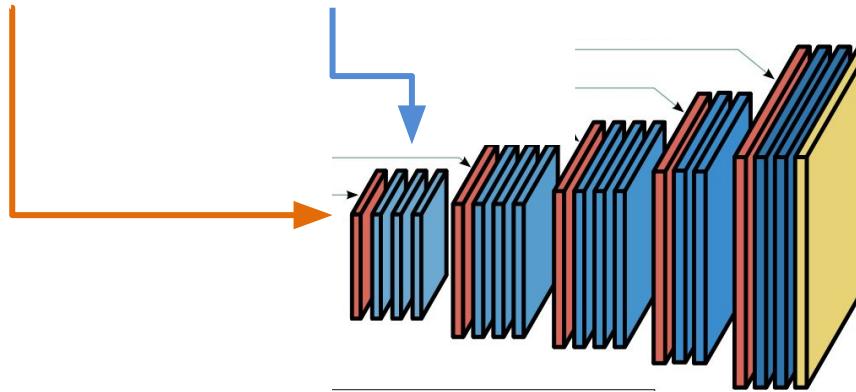
- Encoder: normal convolutional filters + pooling
- Decoder: Upsampling + convolutional filters



Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

SegNet

- Encoder: normal convolutional filters + pooling
- Decoder: Upsampling + convolutional filters



Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

SegNet

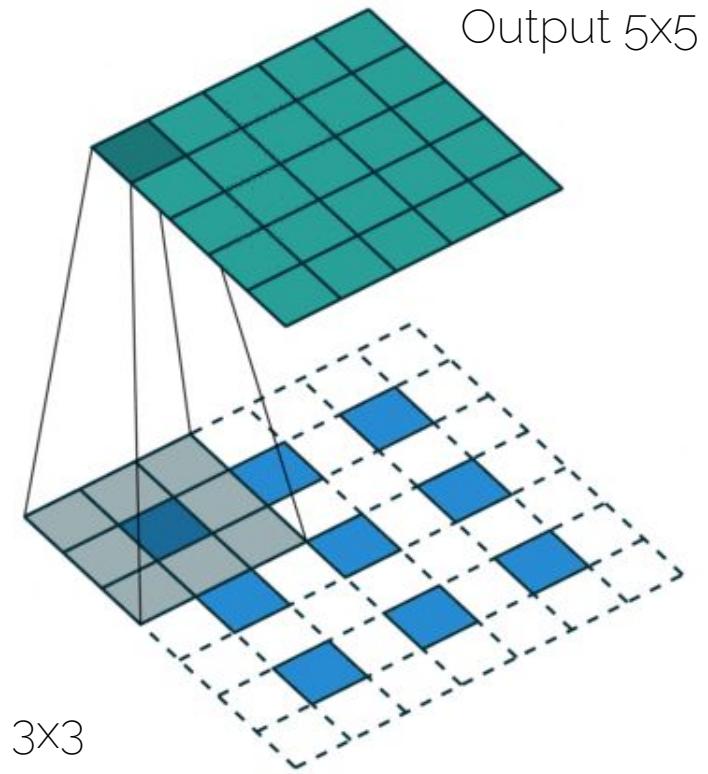
- Encoder: normal convolutional filters + pooling
- Decoder: Upsampling + convolutional filters
- The convolutional filters in the decoder are learned using backprop and their goal is to refine the upsampling

Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

Transposed convolution

- Transposed convolution

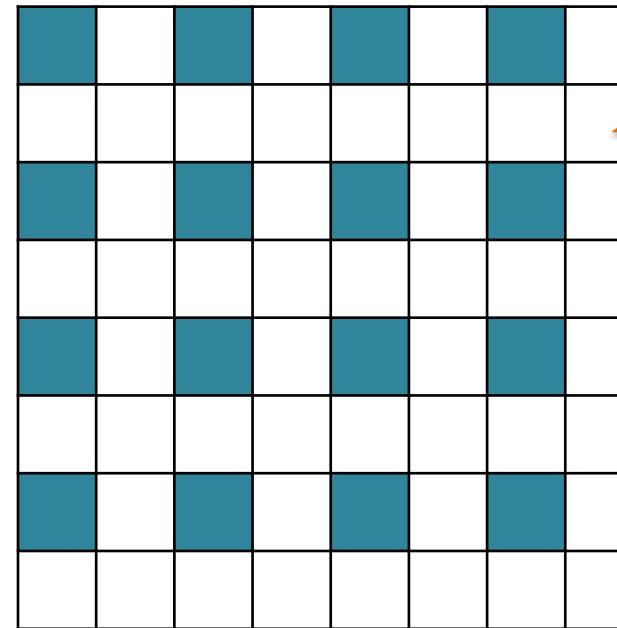
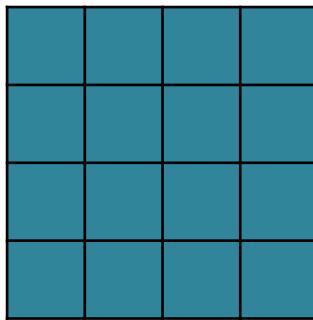
- Unpooling
- Convolution filter (learned)
- Also called up-convolution
(never deconvolution)



Upsampling

Types of upsamplings

- 1. Interpolation



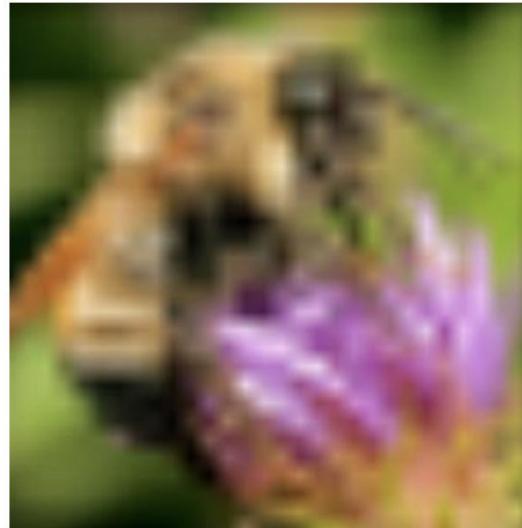
Types of upsamplings

- 1. Interpolation

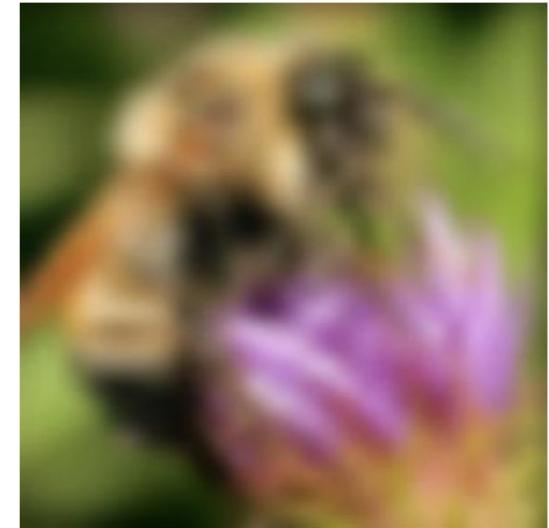
Original image  **x 10**



Nearest neighbor interpolation



Bilinear interpolation



Bicubic interpolation

Types of upsamplings

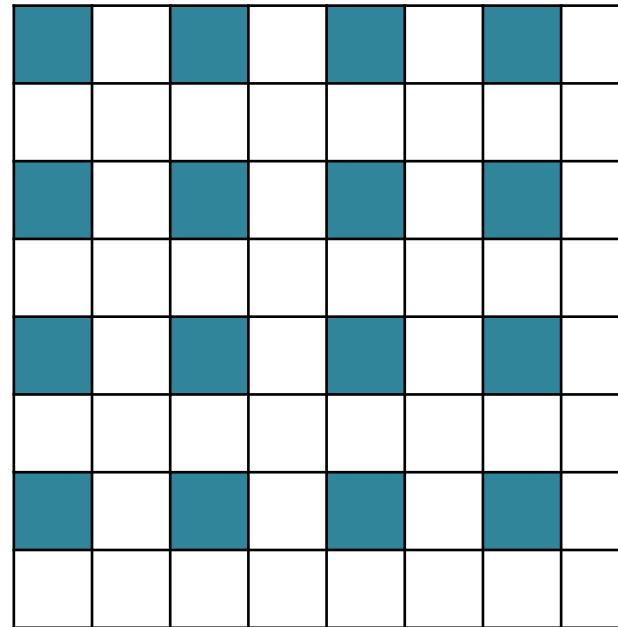
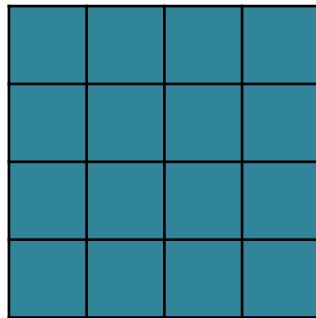
- 1. Interpolation



Few artifacts

Types of upsamplings

- 2. Fixed unpooling



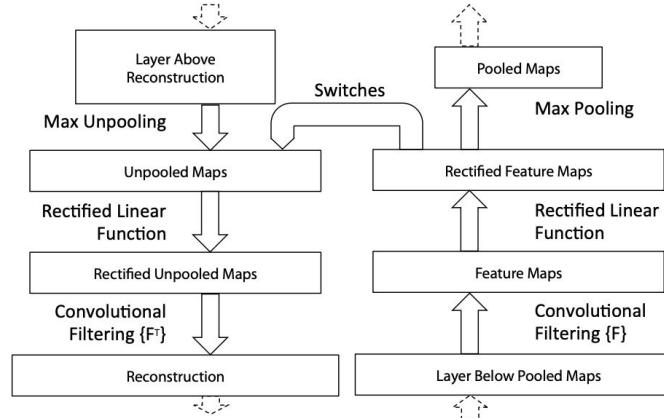
efficient

+ CONVS

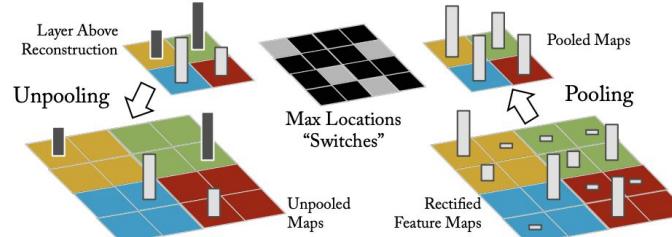
A. Dosovitskiy, "Learning to Generate Chairs, Tables and Cars with Convolutional Networks". TPAMI 2017

Types of upsamplings

- 3. Unpooling: “à la DeconvNet”



Keep the
locations where
the max came
from



Types of upsamplings

- 3. Unpooling: “à la DeconvNet”



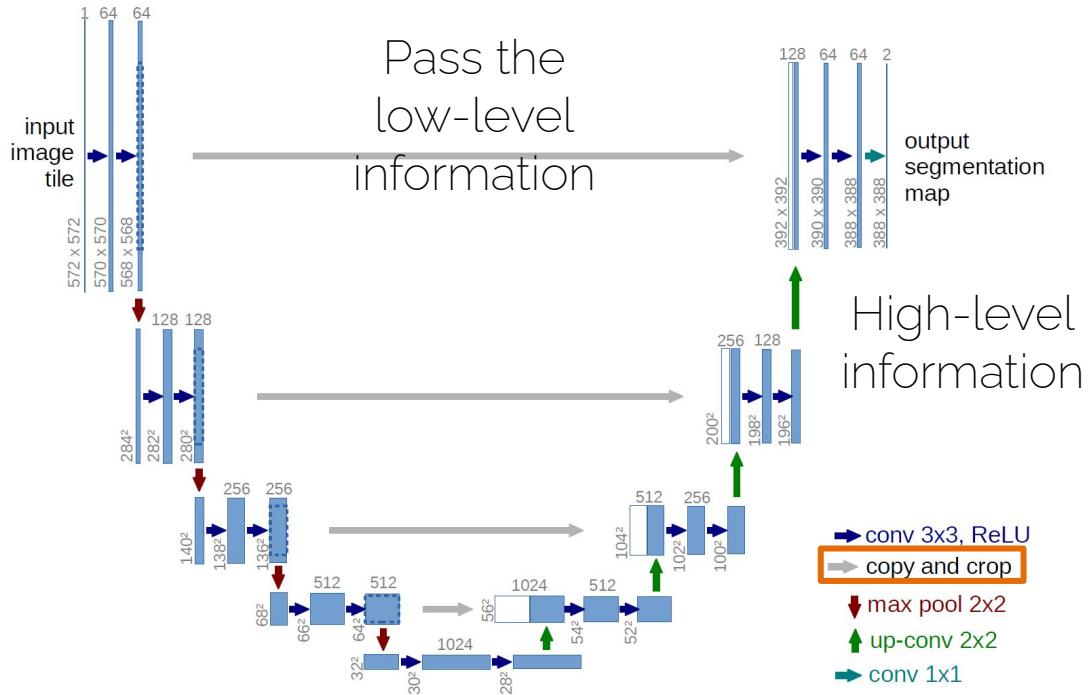
Keep the details of the structures

Skip connections (U-Net)

Skip Connections

- U-Net

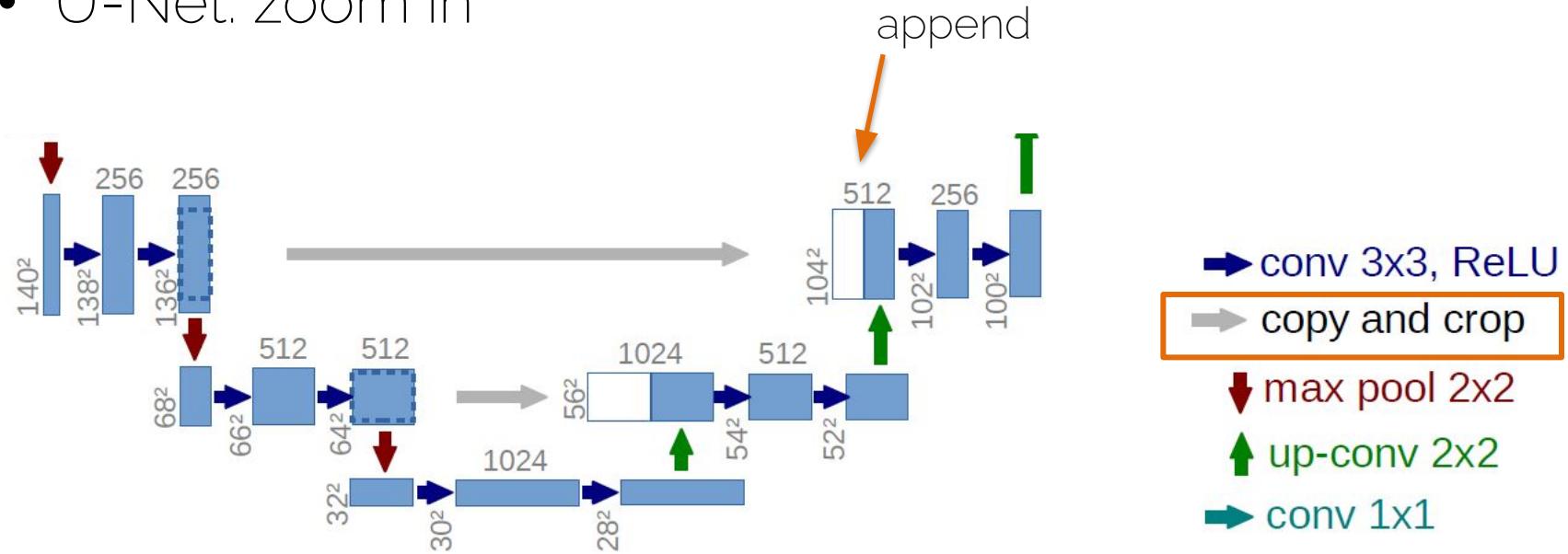
Recall ResNet



O. Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation". MICCAI 2015

Skip Connections

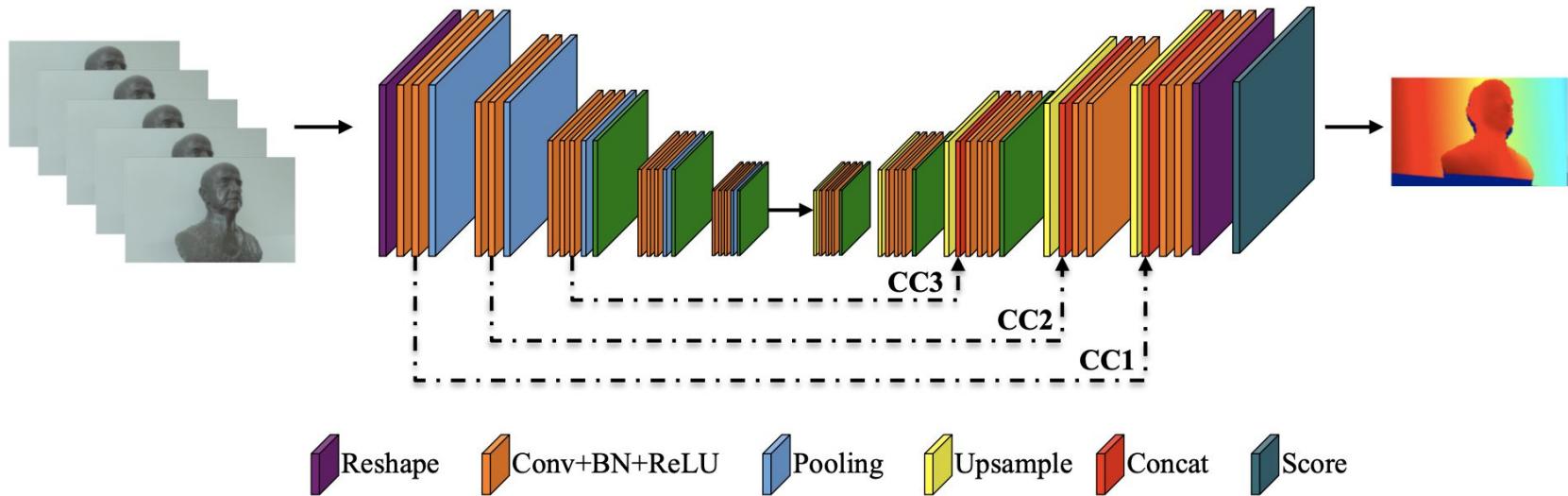
- U-Net: zoom in



O. Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation". MICCAI 2015

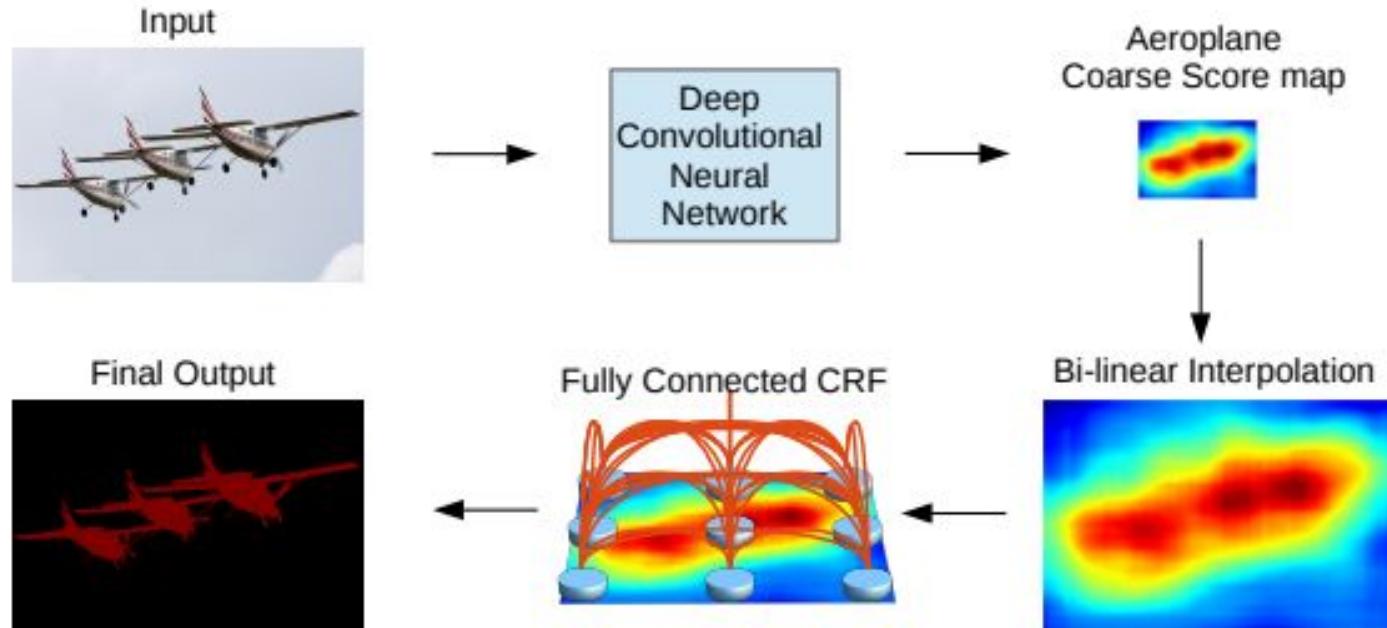
Skip Connections

- Concatenation connections



DeepLab

DeepLab



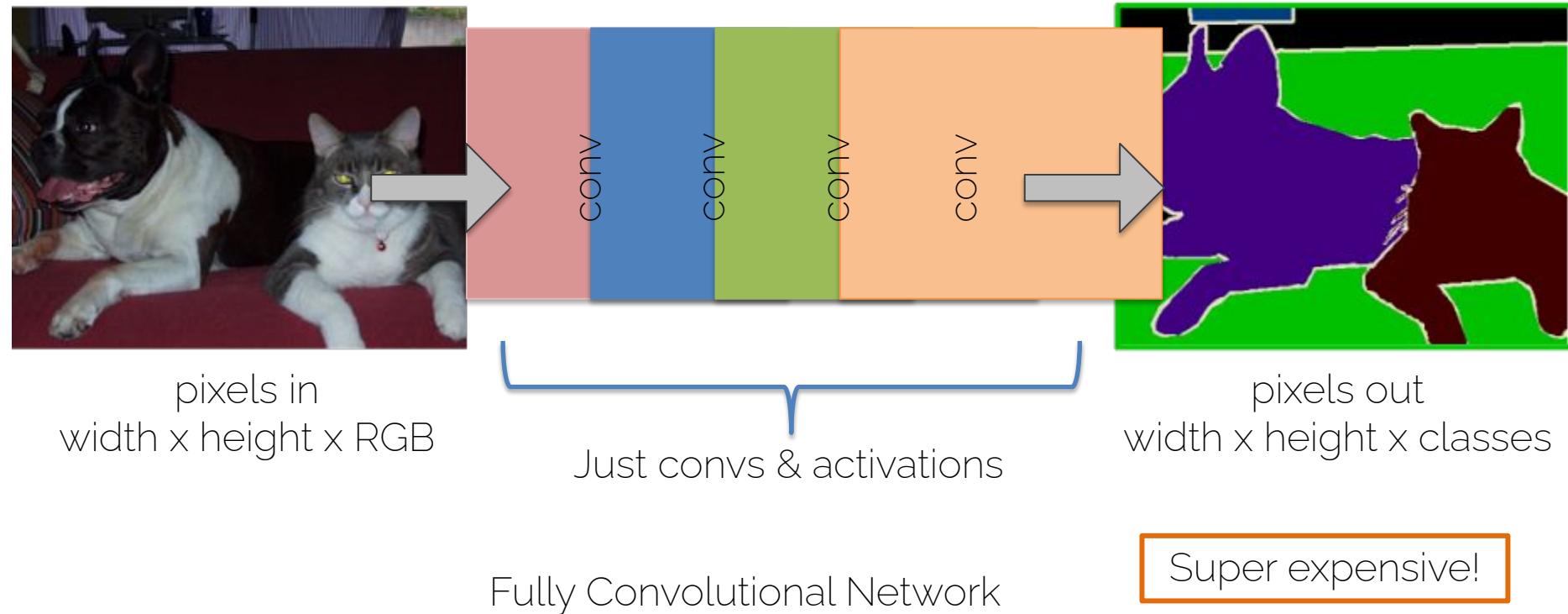
Semantic Segmentation: 3 challenges

- Reduced feature resolution
 - Proposed solution: Atrous convolutions
- Objects exist at multiple scales
 - Proposed solution: Pyramid pooling, as in detection.
- Poor localization of the edges
 - Proposed solution: Refinement with Conditional Random Field (CRF)

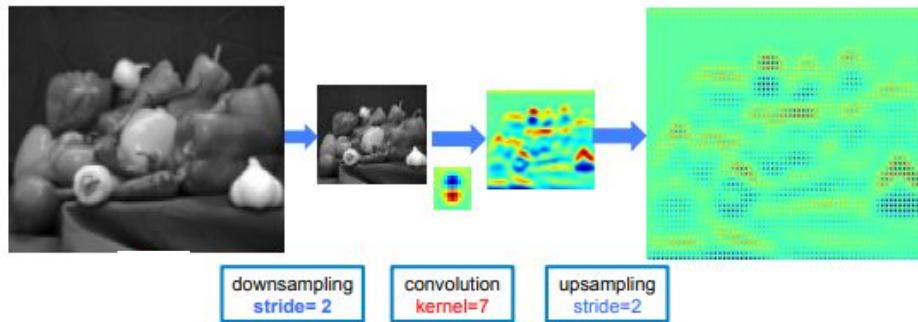
Semantic Segmentation: 3 challenges

- Reduced feature resolution
 - Proposed solution: Atrous convolutions
- Objects exist at multiple scales
 - Proposed solution: Pyramid pooling, as in detection.
- Poor localization of the edges
 - Proposed solution: Refinement with Conditional Random Field (CRF)

Wish: no reduced feature resolution

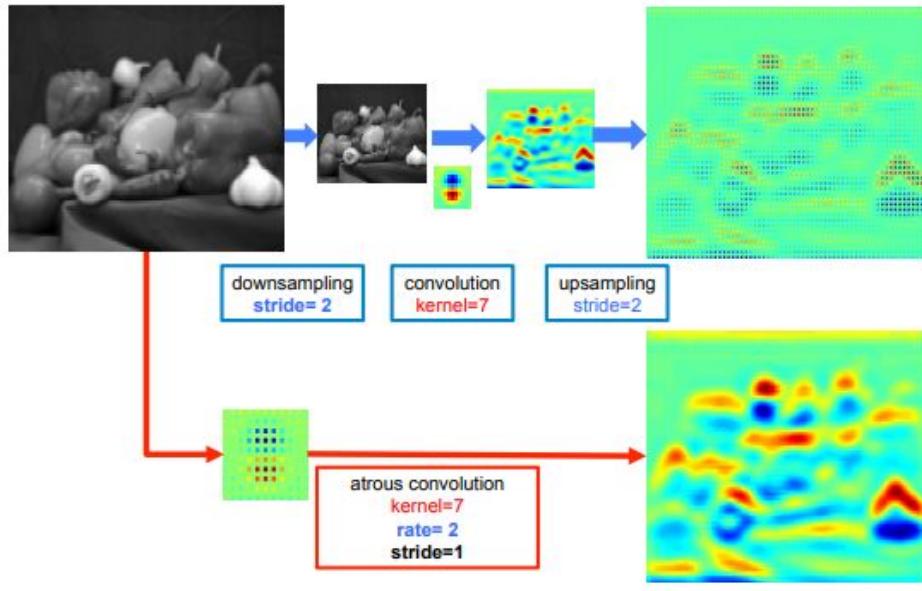


Alternative: Dilated (atrous) convolutions



Sparse feature extraction with standard convolution on a low resolution input feature map.

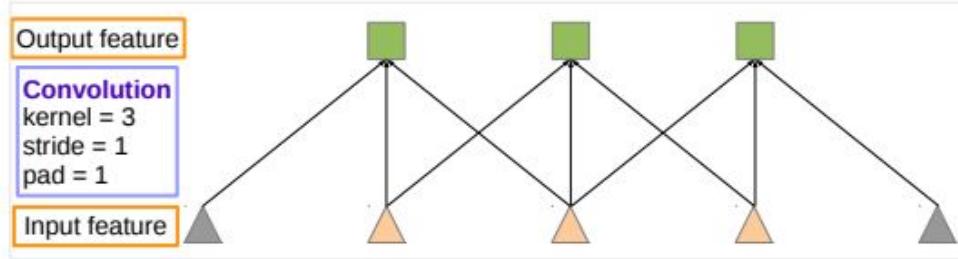
Alternative: Dilated (atrous) convolutions



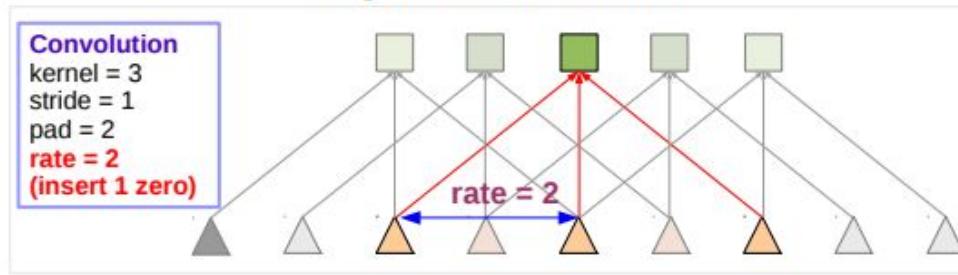
Sparse feature extraction with standard convolution on a low resolution input feature map.

Dense feature extraction with atrous convolution with rate $r=2$, applied on a high resolution input feature map.

Dilated (atrous) convolutions 1D



(a) Sparse feature extraction

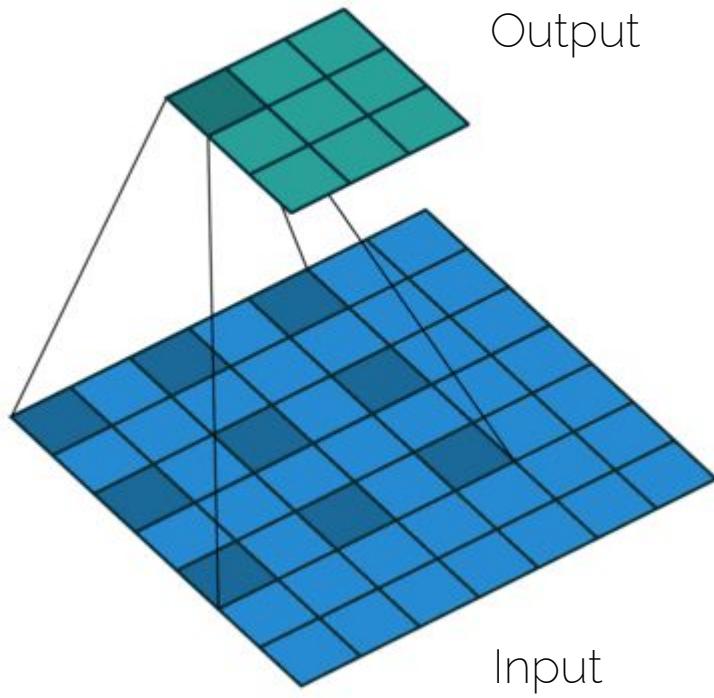


(b) Dense feature extraction

(a) Sparse feature extraction with standard convolution on a low resolution input feature map.

(b) Dense feature extraction with atrous convolution with rate $r = 2$, applied on a high resolution input feature map.

Dilated (atrous) convolutions in 2D



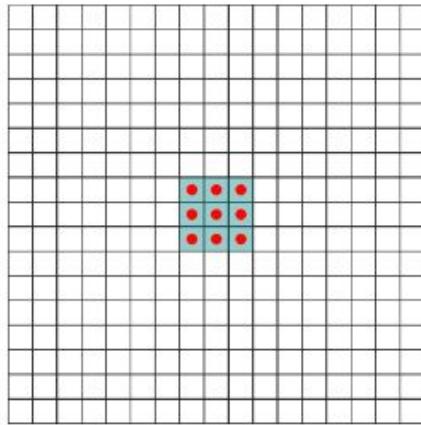
Standard convolution has dilation 1

An analogy for dilated conv is a conv filter with holes

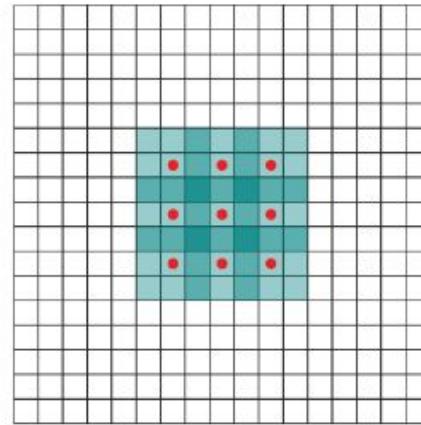
```
class torch.nn.Conv2d (in_channels,  
out_channels, kernel_size, stride=1,  
padding=0, dilation=2)
```

```
class torch.nn.ConvTranspose2d  
(in_channels, out_channels, kernel_size,  
stride=1, padding=0, dilation=2)
```

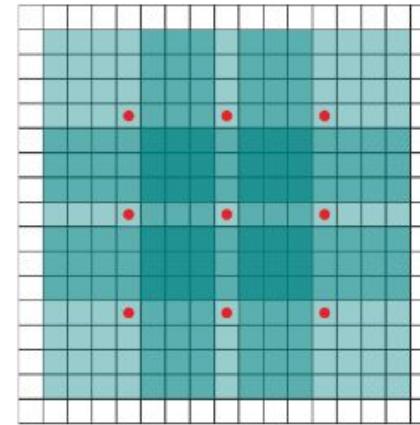
Dilated (atrous) convolutions 2D



(a)



(b)



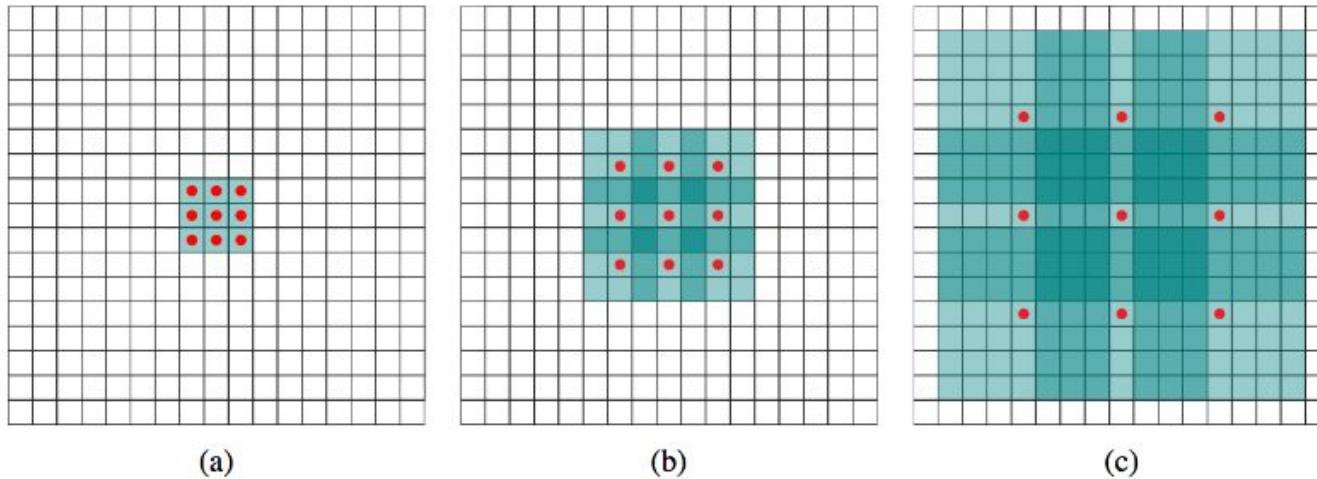
(c)

(a) the dilation parameter is 1, and each element produced by this filter has receptive field of 3×3 .

(b) the dilation parameter is 2, and each element produced by it has receptive field of 7×7 .

(c) the dilation parameter is 4, and each element produced by it has receptive field of 15×15 .

Dilated (atrous) convolutions 2D



Each layer has the same number of parameters, but the receptive field grows exponentially while the number of parameters grows linearly.

Semantic Segmentation: 3 challenges

- Reduced feature resolution
 - Proposed solution: Atrous convolutions
- Objects exist at multiple scales
 - Proposed solution: Pyramid pooling, as in detection.
- Poor localization of the edges
 - Proposed solution: Refinement with Conditional Random Field (CRF)

Conditional Random Fields (CRF)

- Boykov and Jolly (2001)

$$E(x, y) = \sum_i \varphi(x_i, y_i) + \sum_{ij} \psi(x_i, x_j)$$

- Variables

- ▶ x_i : Binary variable
 - ★ foreground/background
- ▶ y_i : Annotation
 - ★ foreground/background/empty

- Unary term

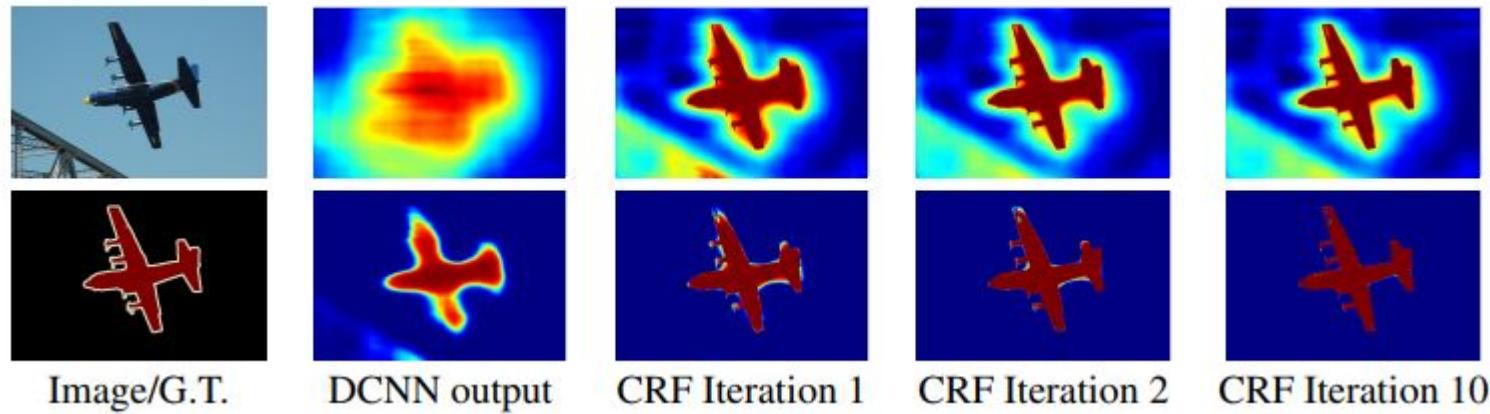
- ▶ $\varphi(x_i, y_i) = K[x_i \neq y_i]$
- ▶ Pay a penalty for disregarding the annotation

- Pairwise term

- ▶ $\psi(x_i, x_j) = [x_i \neq x_j] w_{ij}$
- ▶ Encourage smooth annotations
- ▶ w_{ij} affinity between pixels i and j

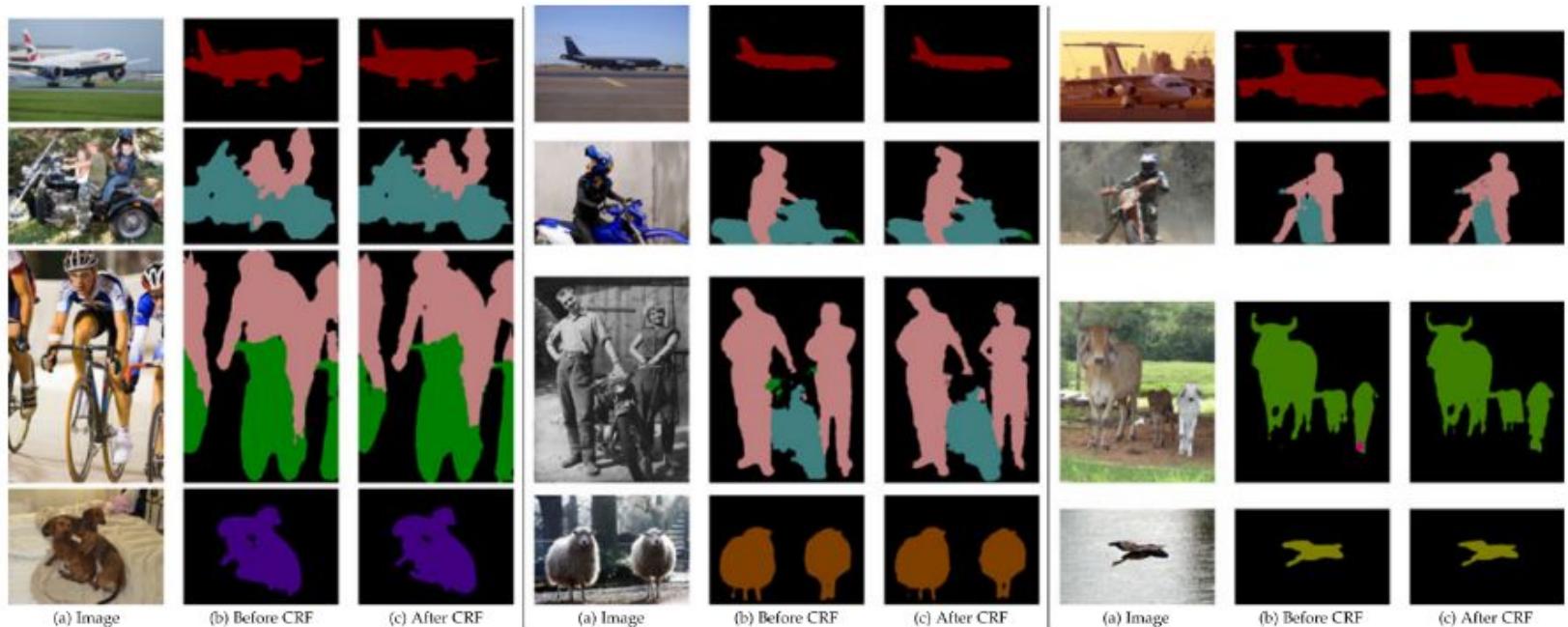


Effect of number of iterations of CRF

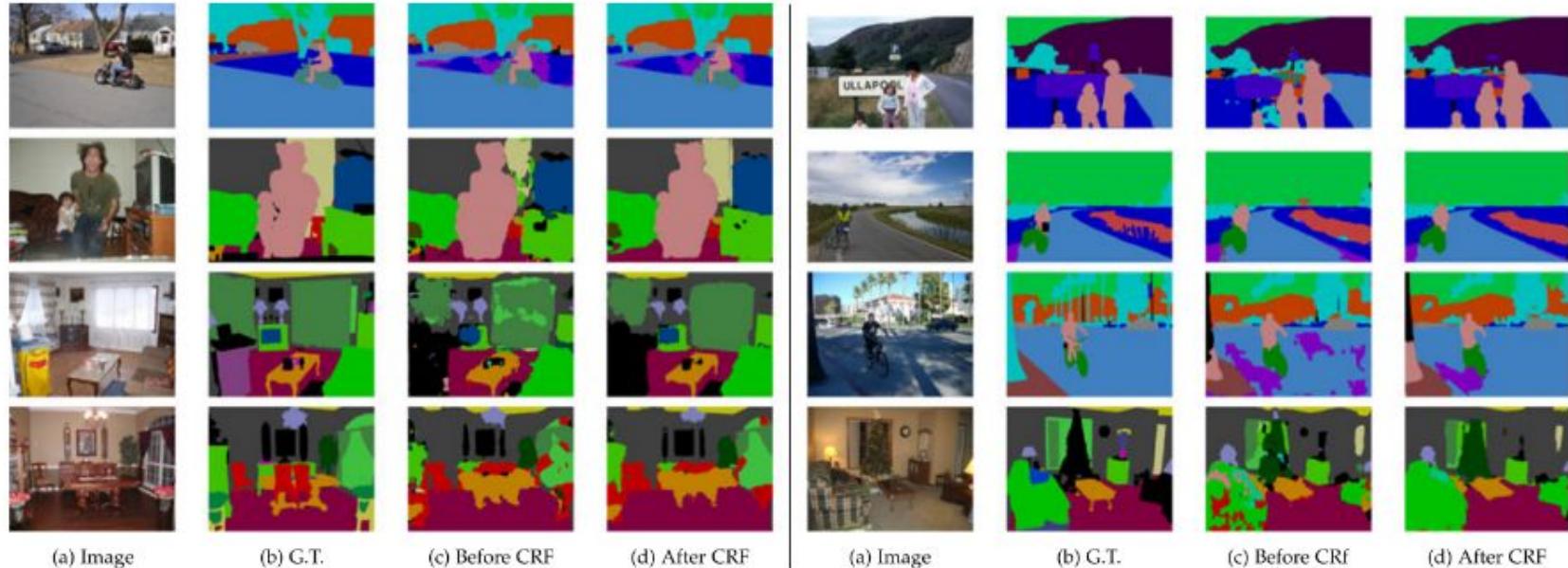


Score map (input before softmax function) and belief map (output of softmax function) for Aeroplane. The image shows the score (1st row) and belief (2nd row) maps after each mean field iteration. The output of last DCNN layer is used as input to the mean field inference.

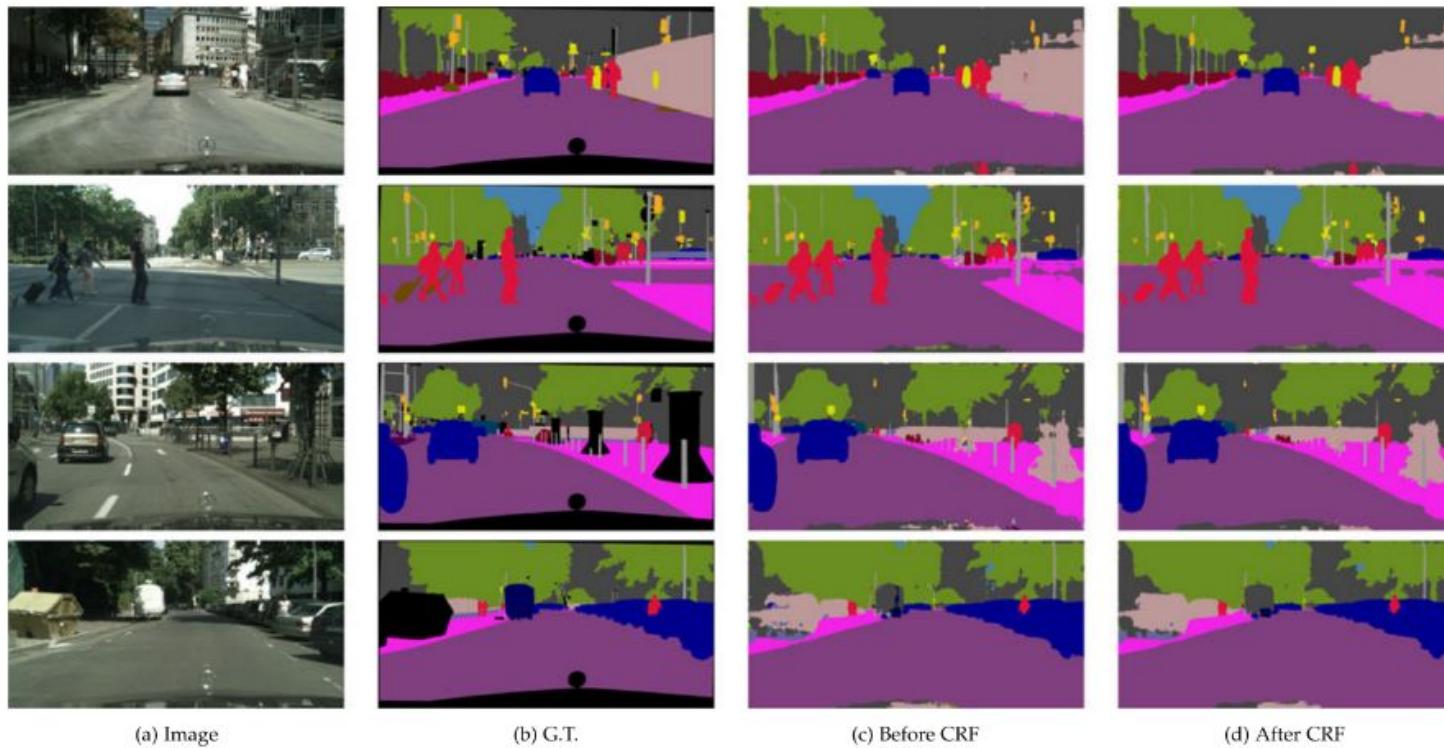
DeepLab: qualitative results



DeepLab: qualitative results



DeepLab: qualitative results



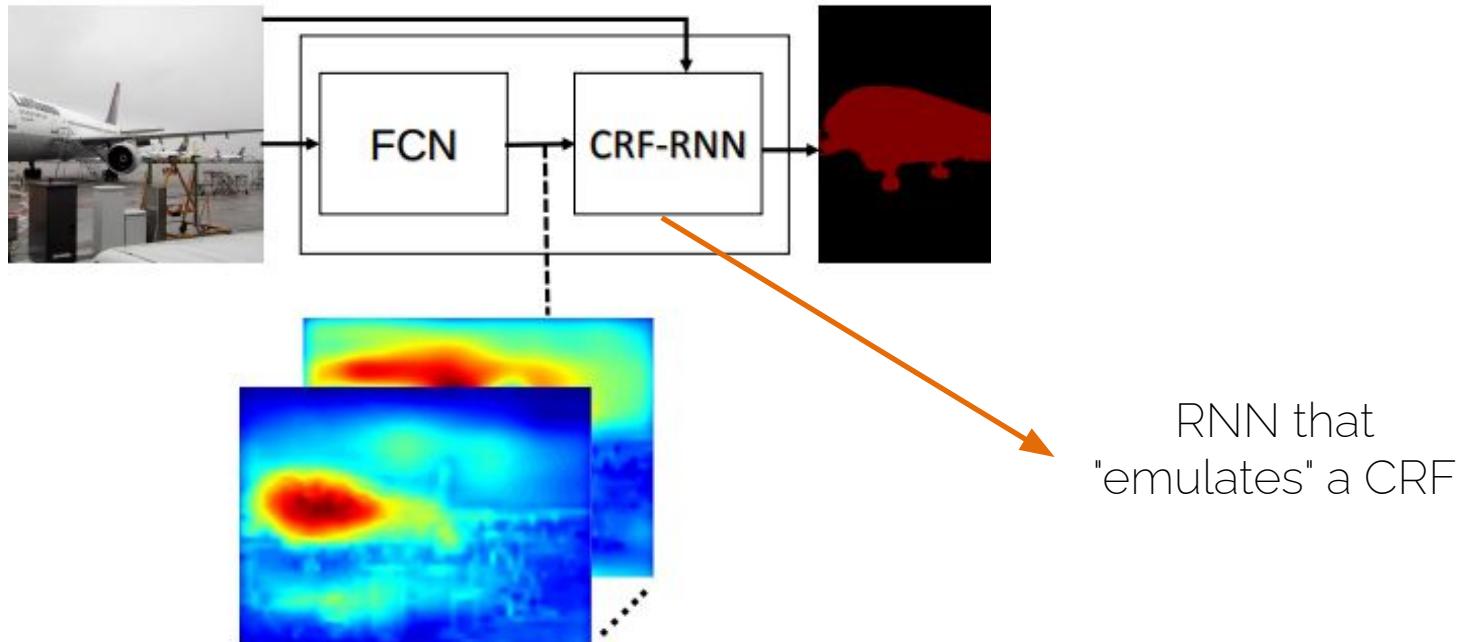
Problems with CRF

- The network is not trained end-to-end. The FCN and the CRF are trained independently from each other.
- This makes the training both slow and arguably suboptimal.

Solution: Formulate CRF as an Recurrent Neural Network

Zheng et al., Conditional Random Fields as Recurrent Neural Networks, ICCV 2015

Replacing CRF with an RNN

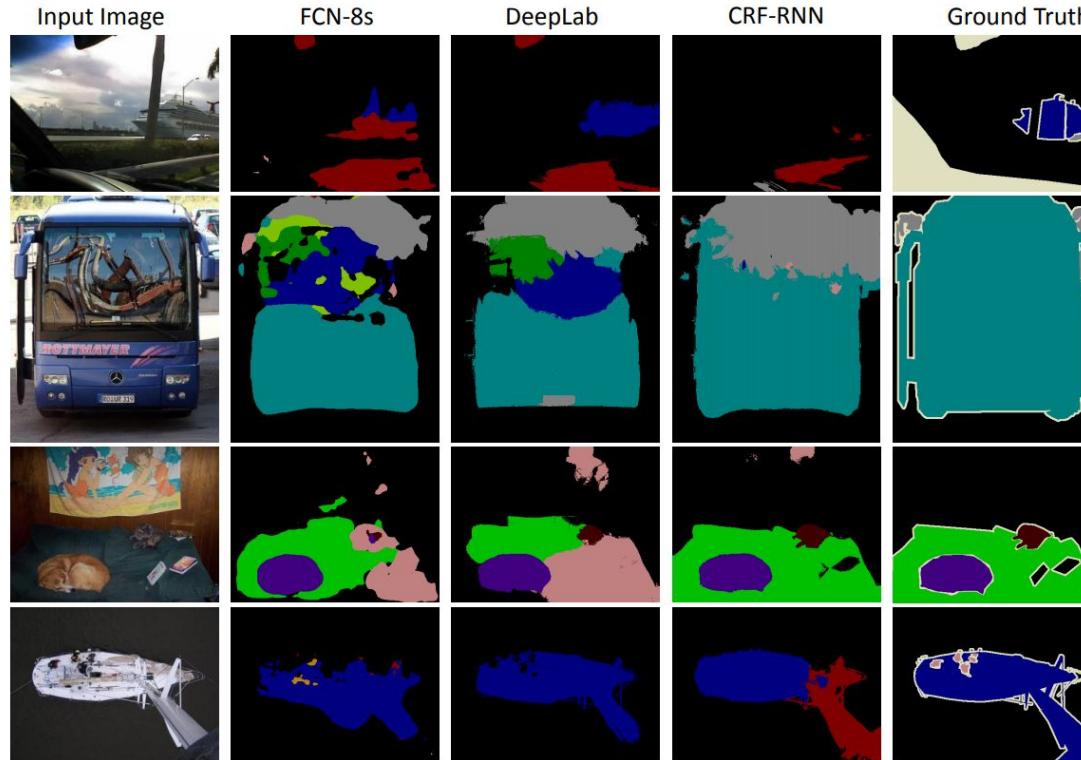


Zheng et al., Conditional Random Fields as Recurrent Neural Networks, ICCV 2015

CRF-RNN: qualitative results



CRF-RNN: qualitative results



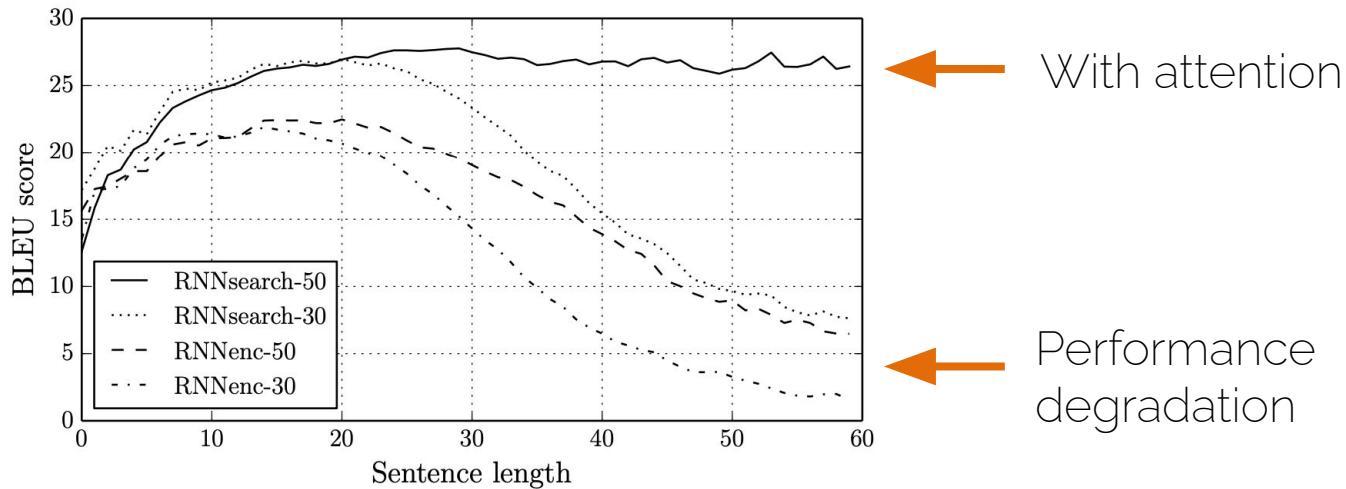
Why do we need the CRF?

- To properly localize the masks, i.e., get the contours correctly
- We need to process information at the original (image) resolution for this. We need to look at the pixels. □ CRF is conditioned on the RGB image.
- What if we use attention?

Attention

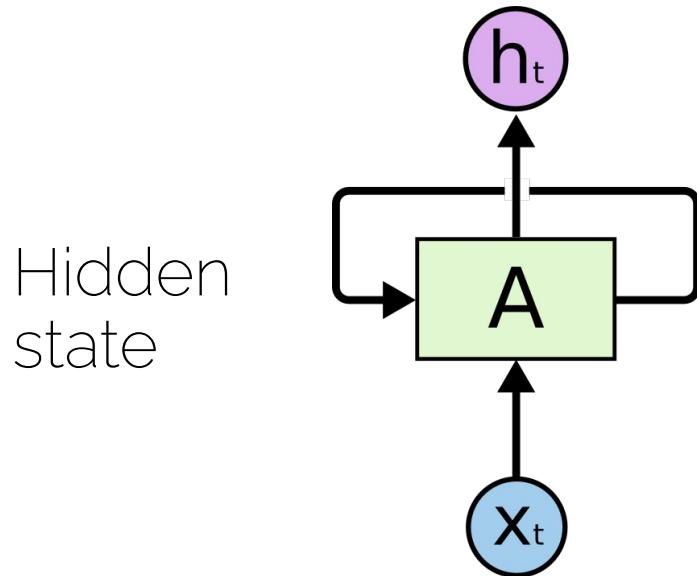
The problem

- For very long sentences, the score for machine translation really goes down after 30-40 words.



Basic structure of a RNN

- We want to have notion of "time" or "sequence"

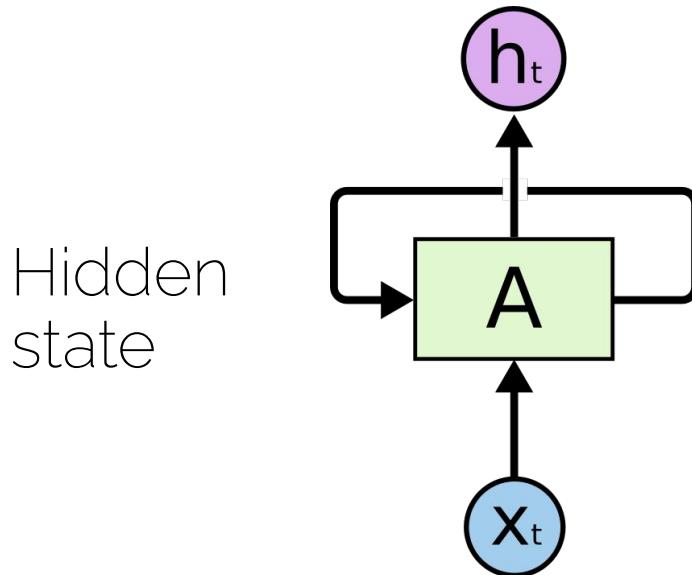


$$\mathbf{A}^t = \theta^c \mathbf{A}^{t-1} + \theta^x \mathbf{x}^t$$


Previous input

Basic structure of a RNN

- We want to have notion of "time" or "sequence"



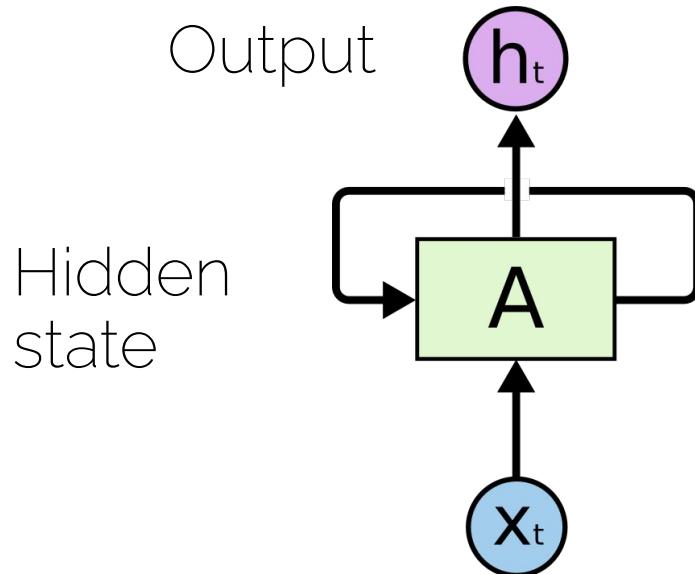
$$A^t = \theta^c A^{t-1} + \theta^x x^t$$

Two orange arrows point upwards from the text "Parameters to be learned" towards the terms $\theta^c A^{t-1}$ and $\theta^x x^t$ in the equation.

Parameters to be learned

Basic structure of a RNN

- We want to have notion of "time" or "sequence"



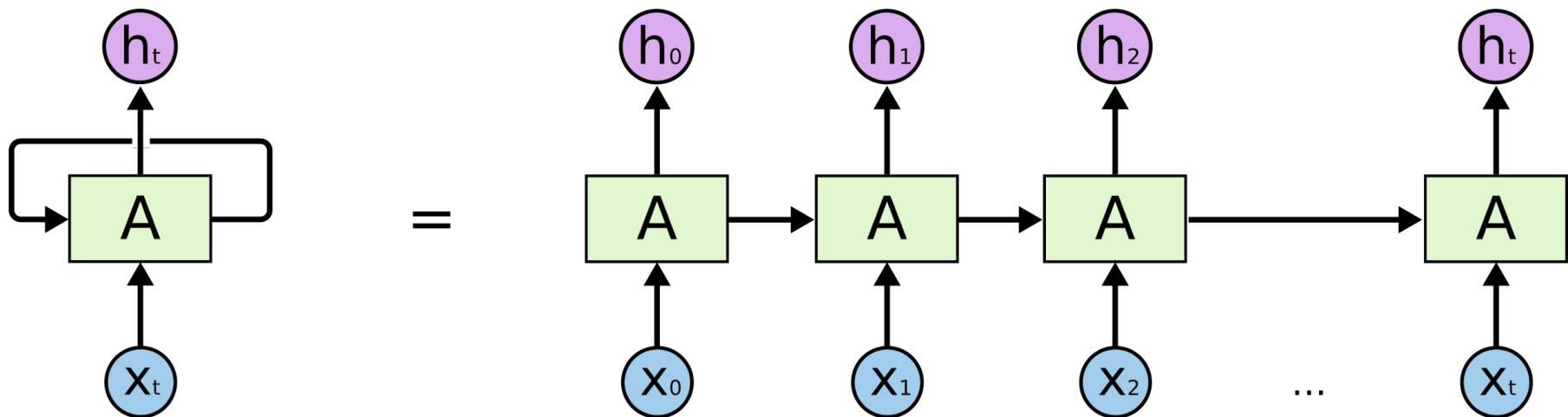
$$\begin{aligned} \mathbf{A}^t &= \theta_v \mathbf{A}^{t-1} + \theta_x \mathbf{x}^t \\ \mathbf{p}^t &= \theta_y \mathbf{A}^t \end{aligned}$$

Same parameters for
each time step =
generalization!

Basic structure of a RNN

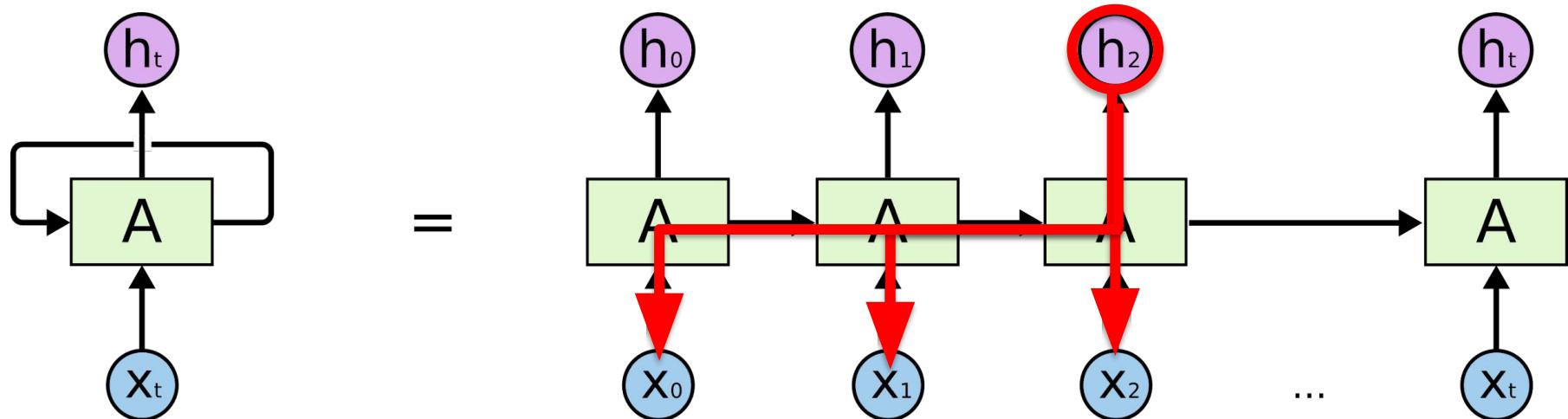
- Unrolling RNNs

Hidden layer is the same

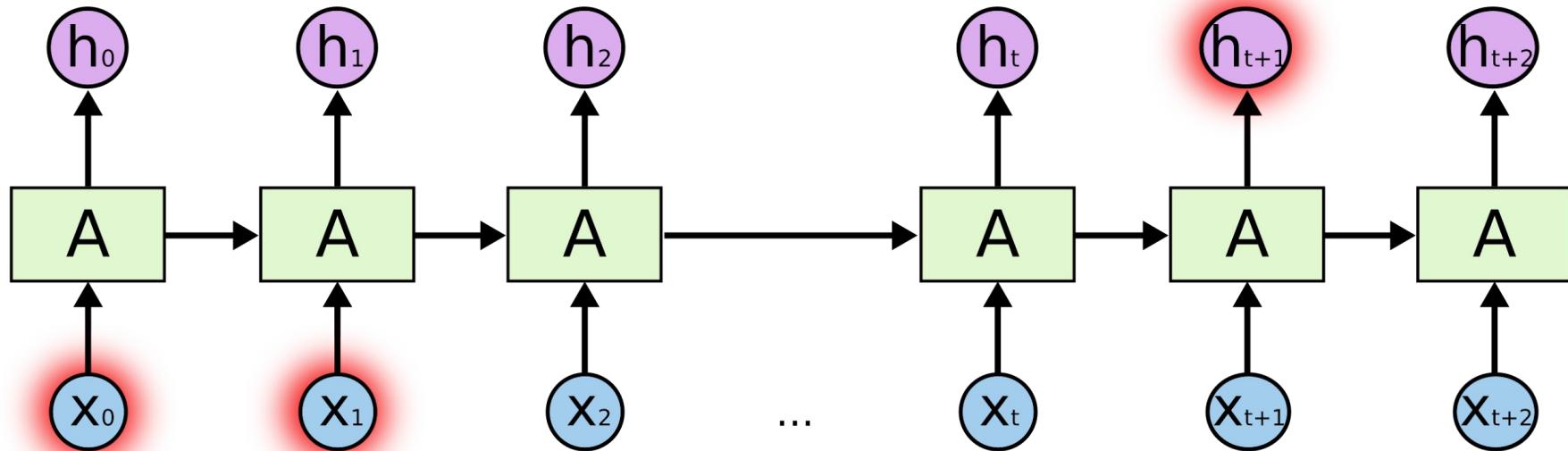


Basic structure of a RNN

- Unrolling RNNs



Long-term dependencies



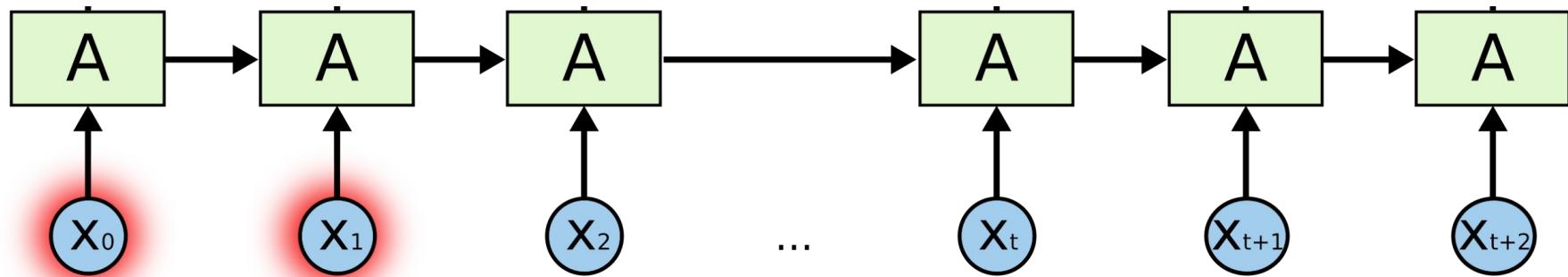
I moved to Germany ...

so I speak German fluently

Attention: intuition



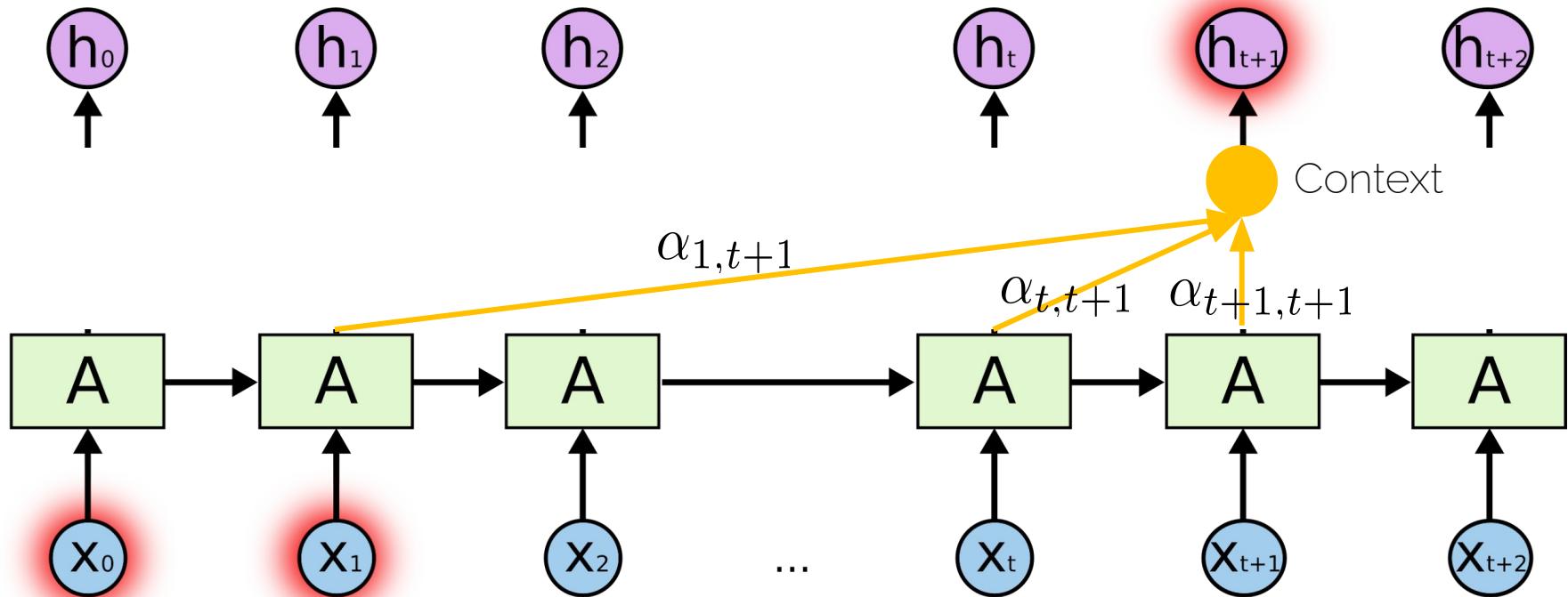
ATTENTION: Which hidden states are more important to predict my output?



I moved to Germany ...

so I speak German fluently

Attention: intuition

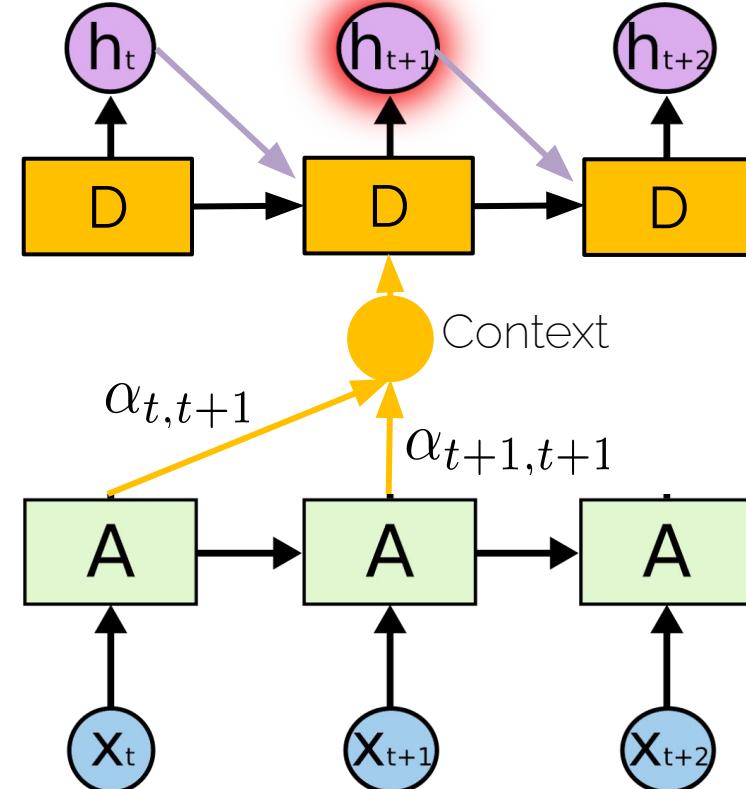


I moved to Germany ...

so I speak German fluently

Attention: architecture

- A decoder processes the information
- Decoders take as input:
 - Previous decoder hidden state
 - Previous output
 - Attention



Attention

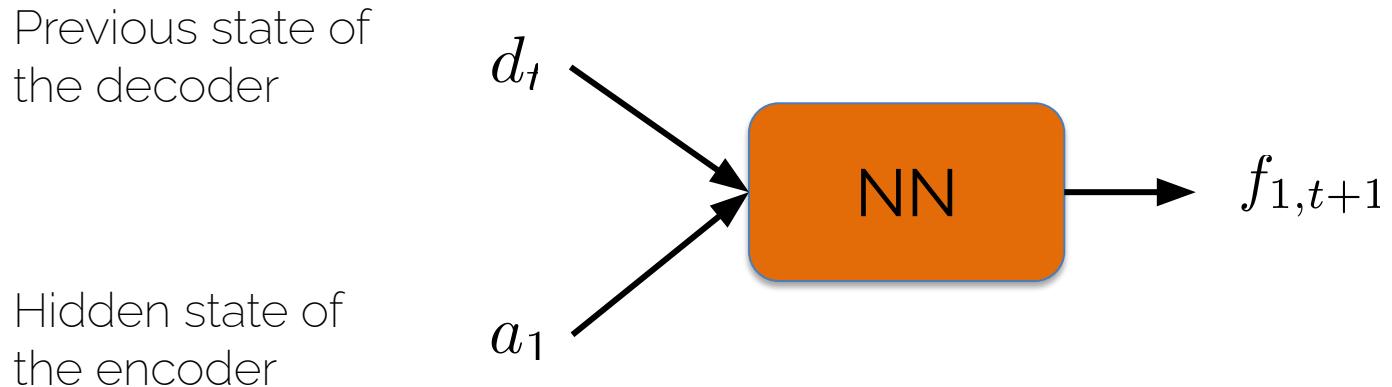
- $\alpha_{1,t+1}$ indicates how much the word in the position 1 is important to translate the word in position $t + 1$
- The context aggregates the attention

$$c_{t+1} = \sum_{k=1}^{t+1} \alpha_{k,t+1} a_k$$

- **Soft** attention: All attention masks alpha sum up to 1

Computing the attention mask

- We can train a small neural network

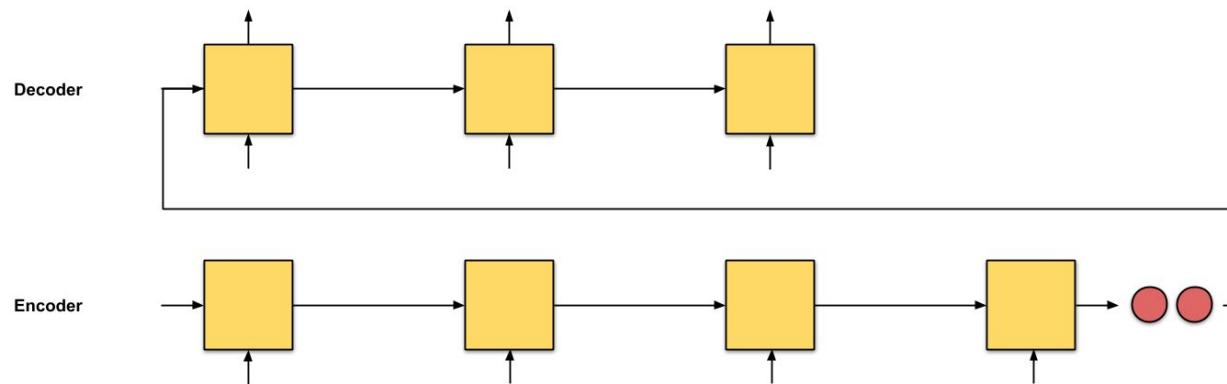


- Normalize

$$\alpha_{1,t+1} = \frac{\exp^{f_{1,t+1}}}{\sum_{k=1}^{t+1} \exp^{f_{k,t+1}}}$$

Seq2Seq

- How do we translate?
- First read *the whole sentence* in language 1.
- Afterwards, translate the whole sentence in language 2.

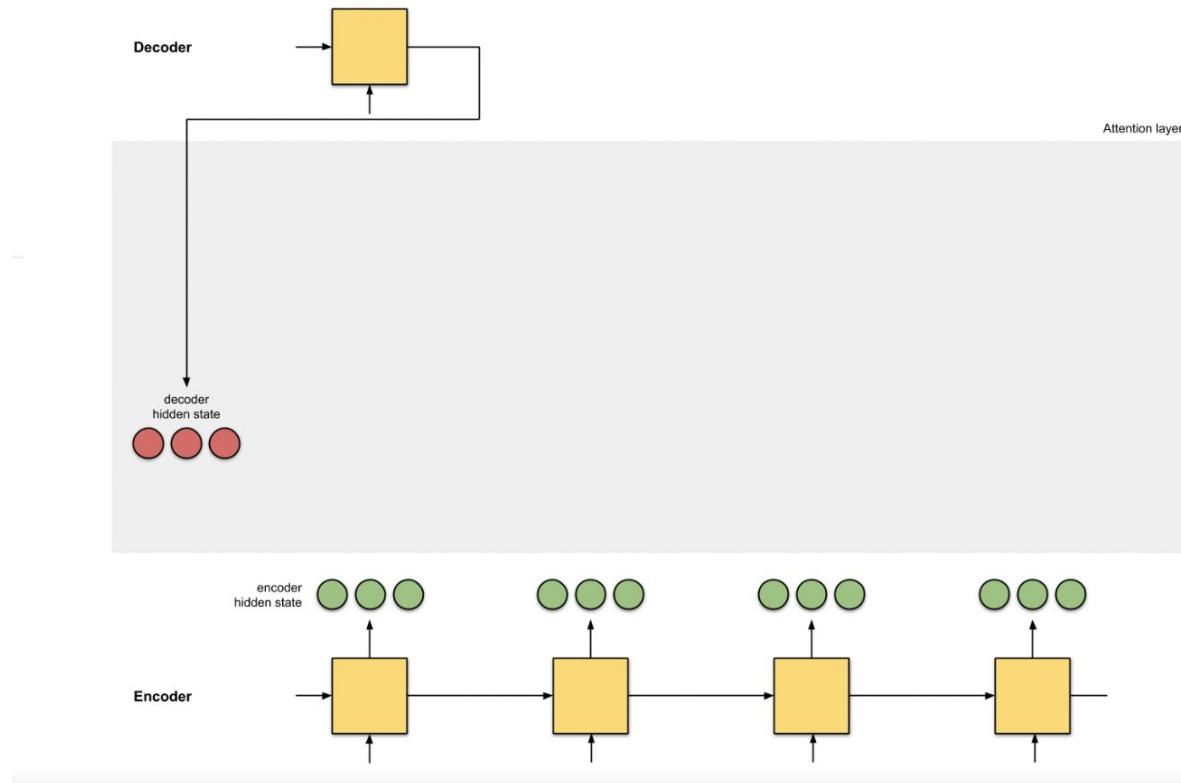


Sutskever et al. „Sequence to Sequence Learning with Neural Networks“. NIPS 2014
Picture from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention?

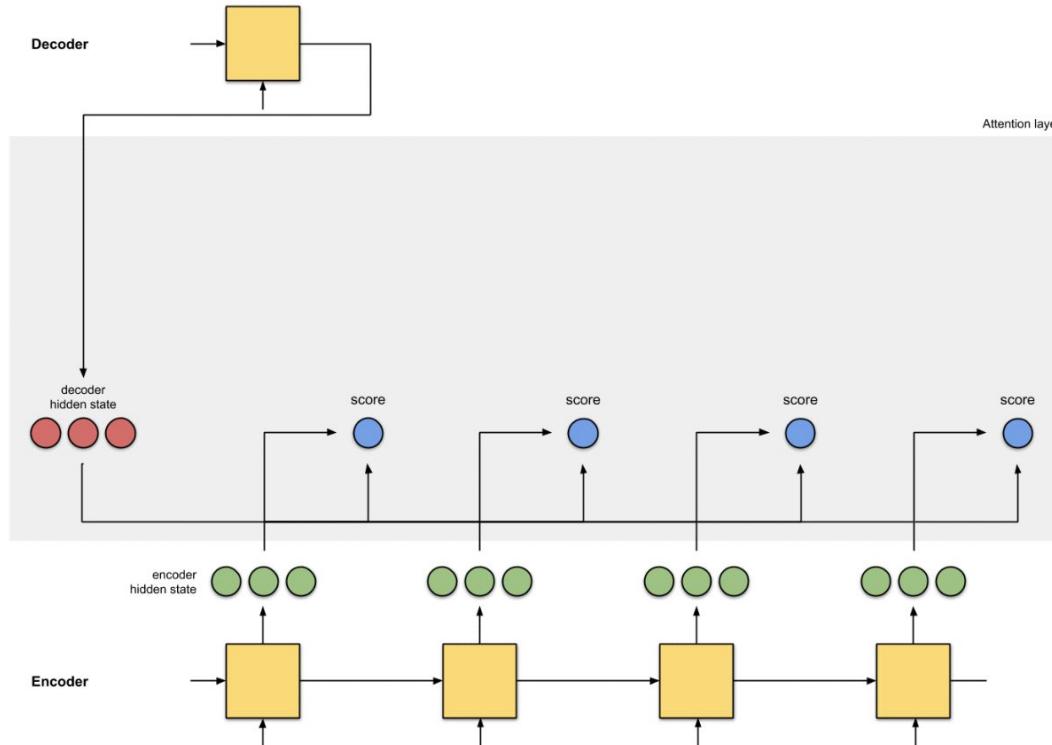
- If the sentence is very long, we might have forgotten what was said at the beginning.
- Solution: take “notes” of keywords as we read the sentence in language 1.
- Use attention!

Seq2Seq + Attention



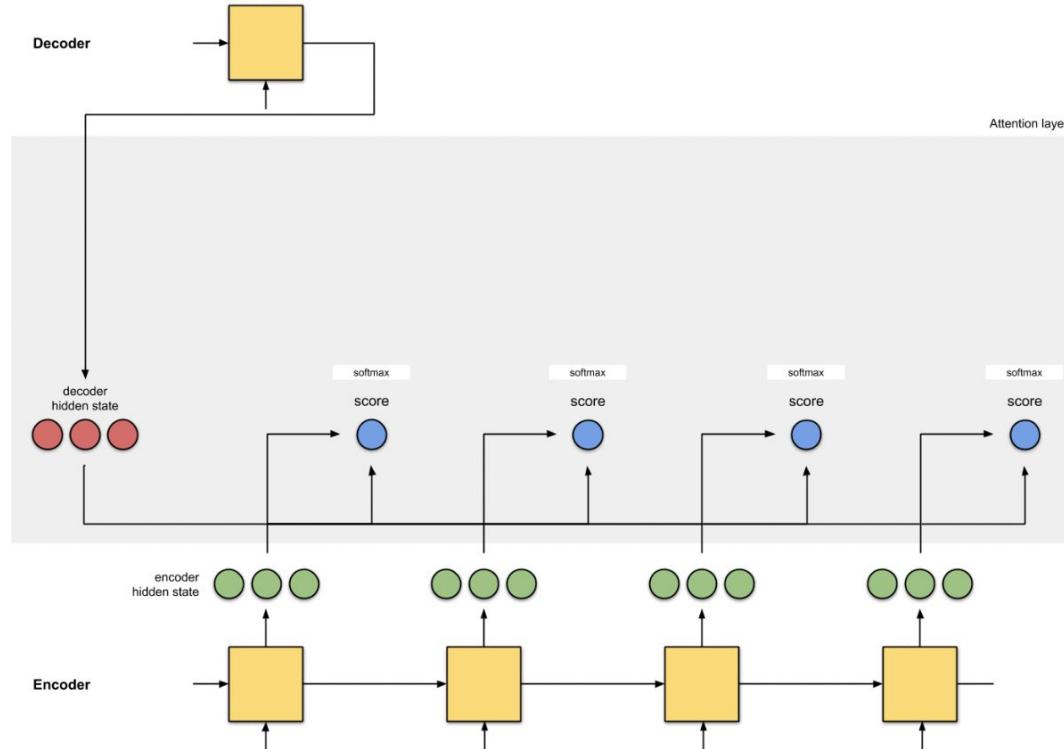
Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention



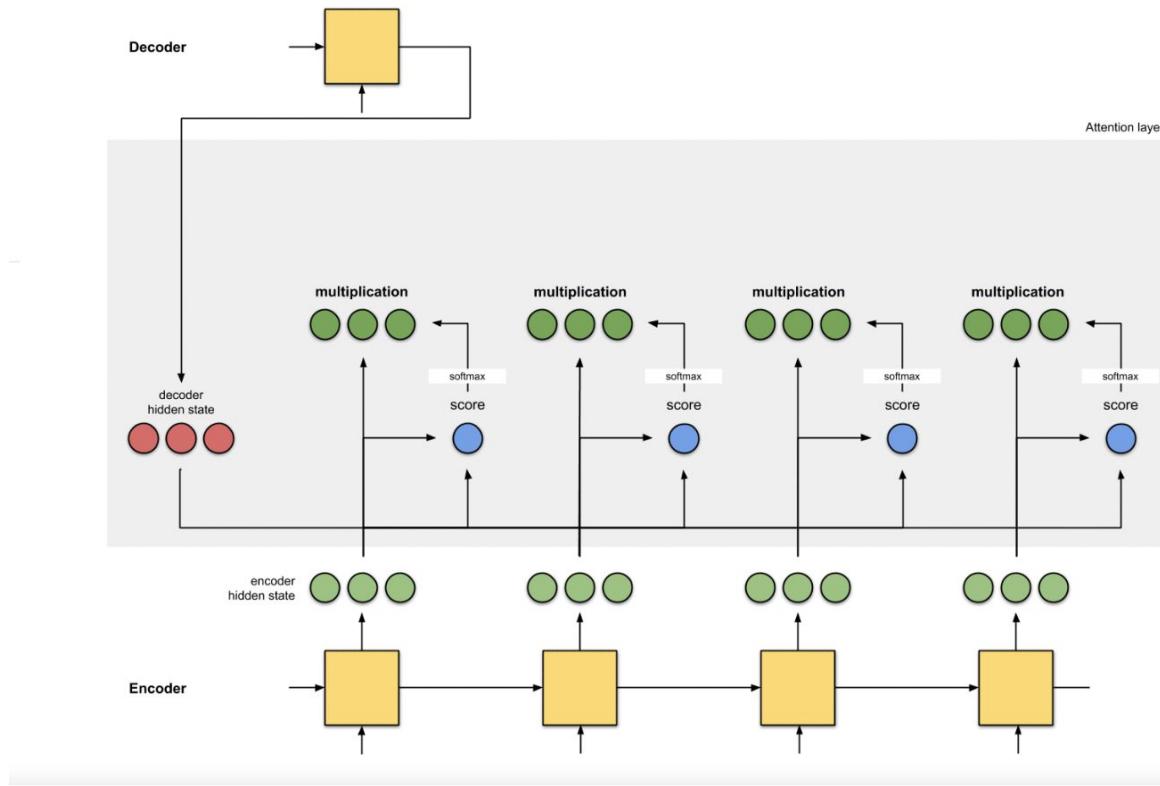
Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention



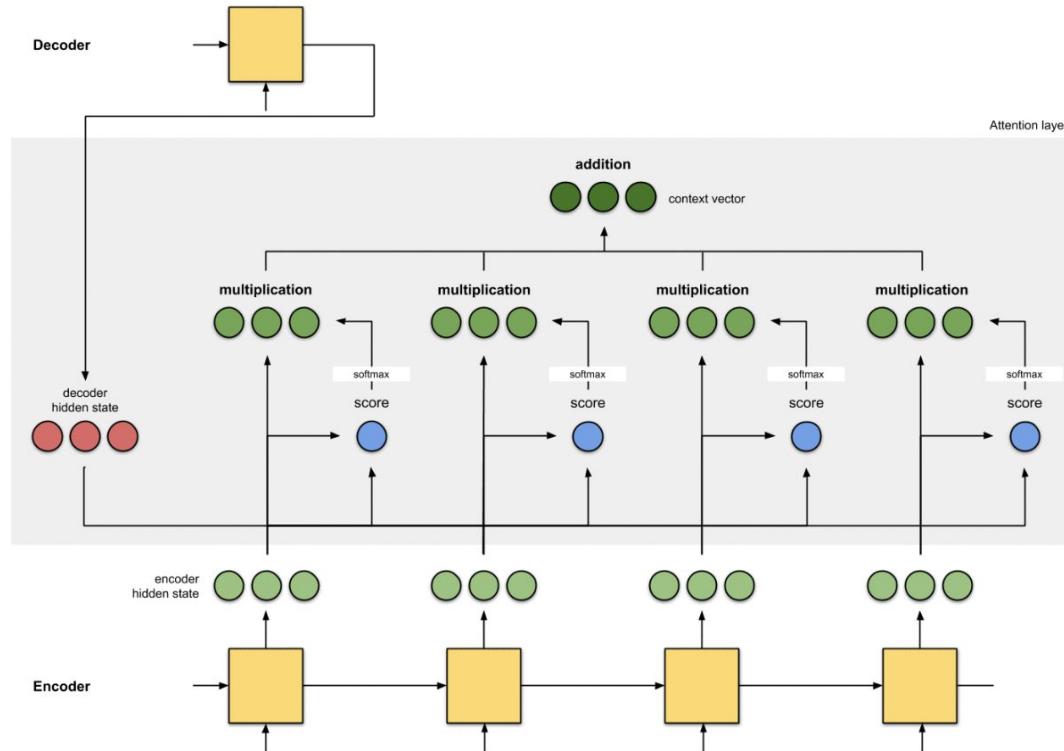
Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention



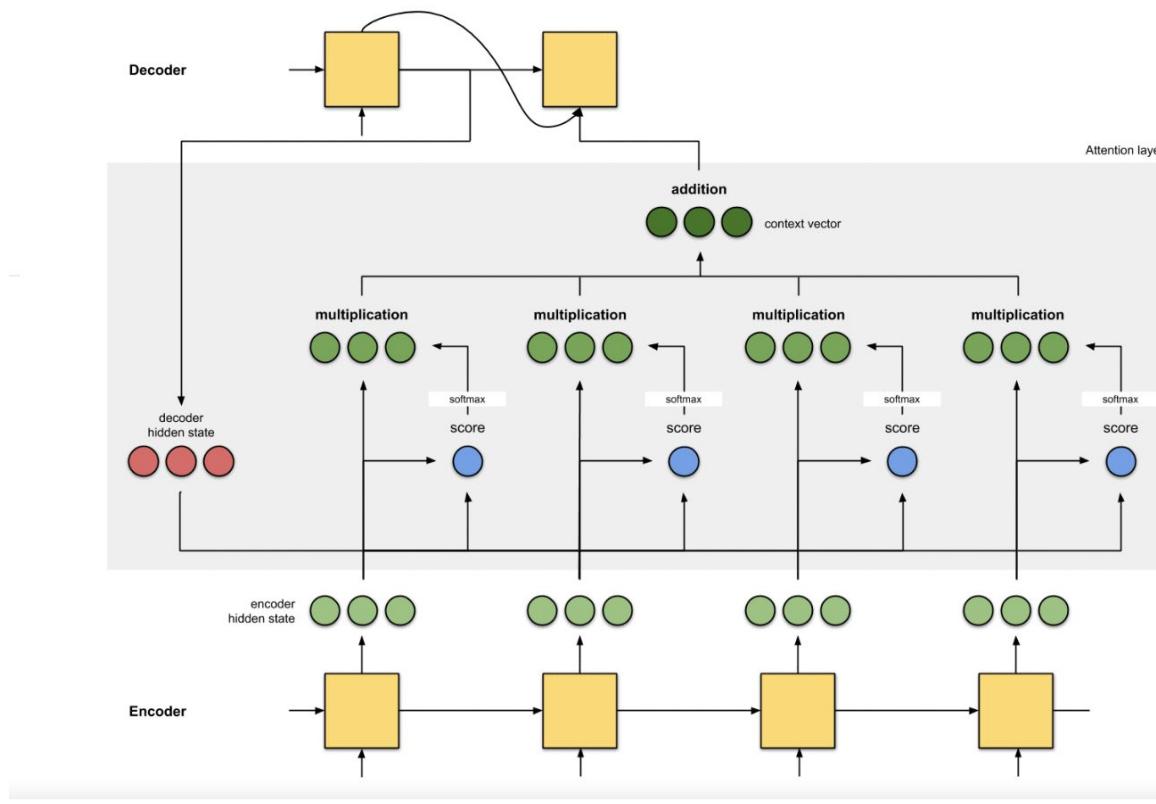
Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention



Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Seq2Seq + Attention

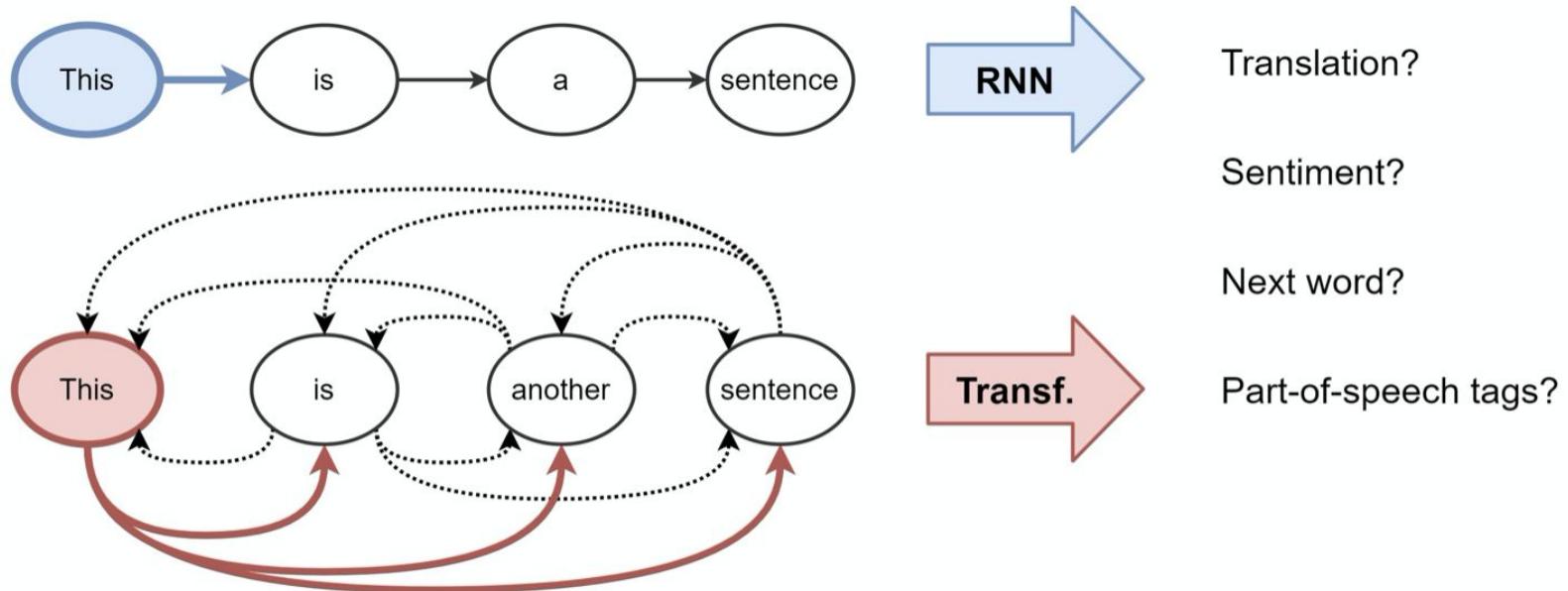


Animation from: <https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3>

Transformers

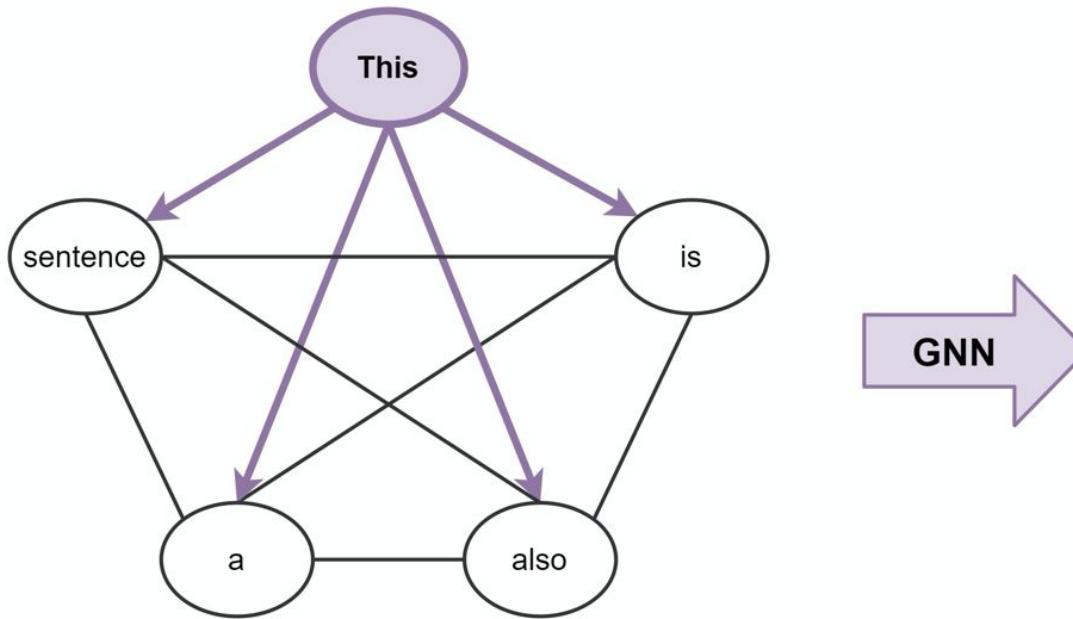
- What if we could get rid of the recurrent architecture and use only attention?
- All the memory problems of RNNs could disappear
- No RNN, no CNN, just attention!
- Current state-of-the-art in NLP!

Transformers



Transformers

- Wait, what does this remind you of?



Translation?

Sentiment?

Next word?

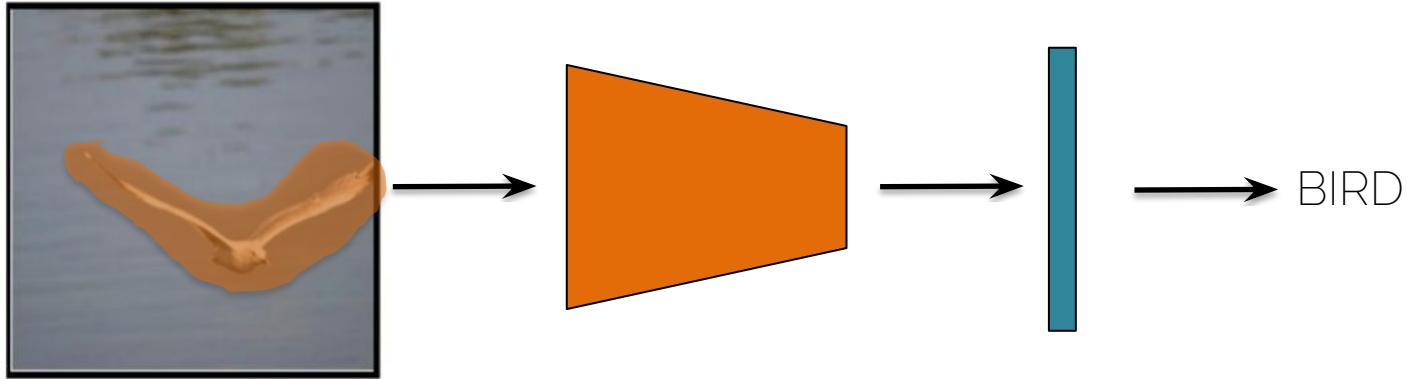
Part-of-speech tags?

Transformers

- Broadly speaking, Transformers are based on Graph Attention Networks (GAT)
- GAT replace the aggregation operation of GNN (usually a summation) by a weighted sum, i.e., an attention mechanism

Why do we need attention?

- We use the whole image to make the classification



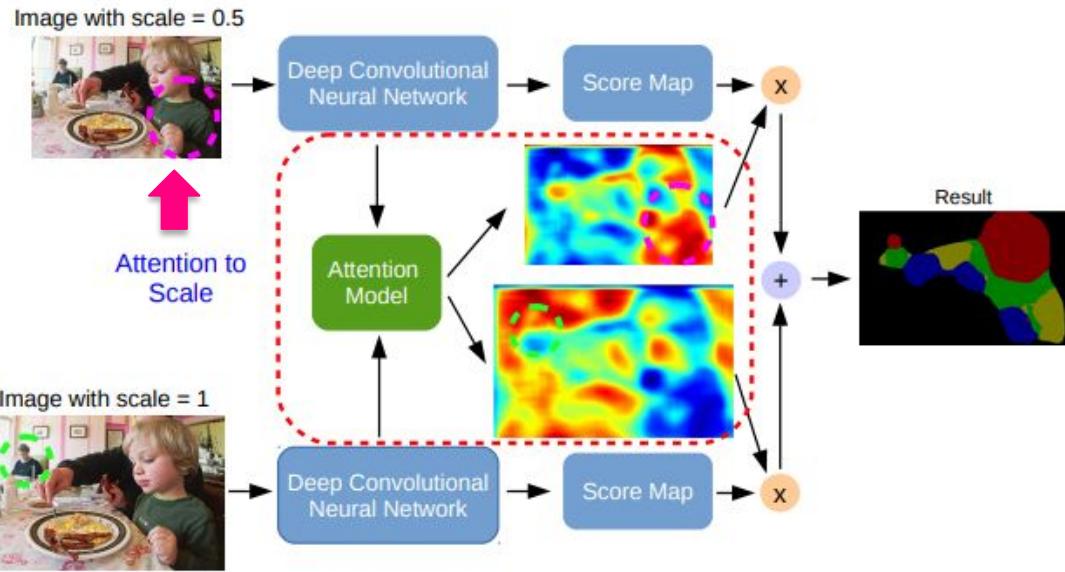
- Are all pixels equally important?

Why do we need attention?

- Wouldn't it be easier and computationally more efficient to just run our classification network on the patch?



Attention for semantic segmentation



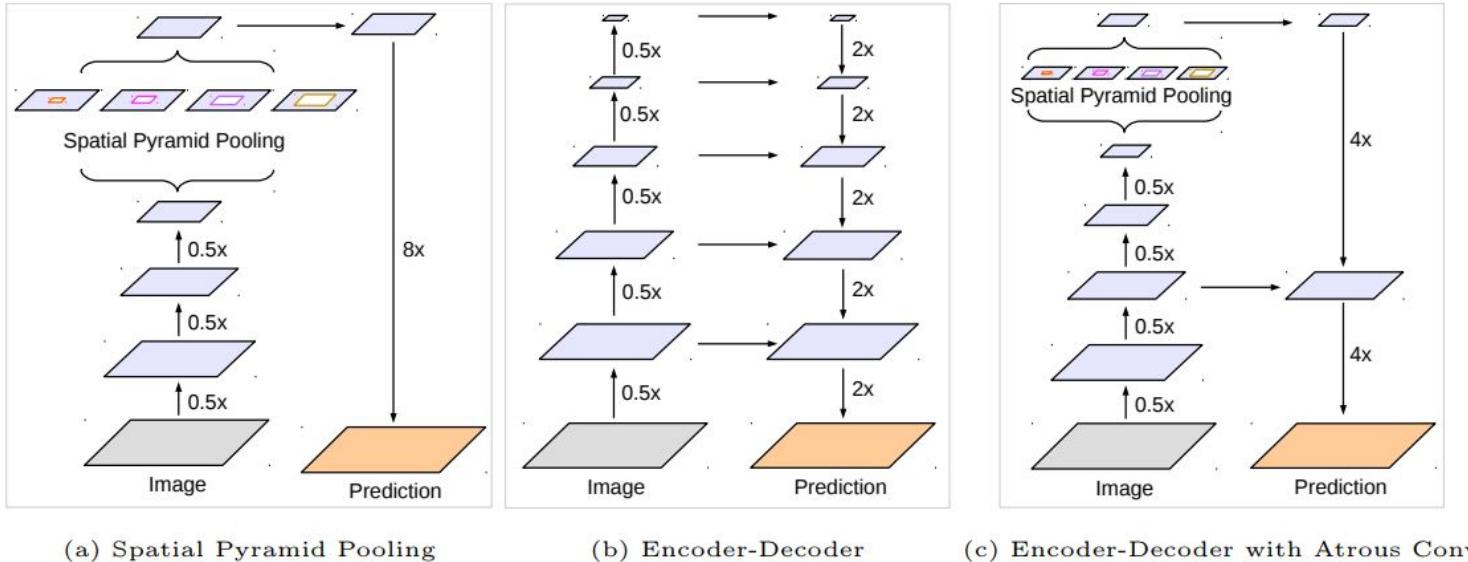
The attention model learns to put different weights on objects of different scales.

For example, the model learns to put large weights on the small-scale person (**green dashed circle**) for features from scale = 1, and large weights on the large-scale child (**magenta dashed circle**) for features from scale = 0.5. We jointly train the network component and the attention model.

- Do we even need these blocks which include the global information (CRF, RNN, attention)?

Spoiler alert: Not necessarily.

DeepLabv3+



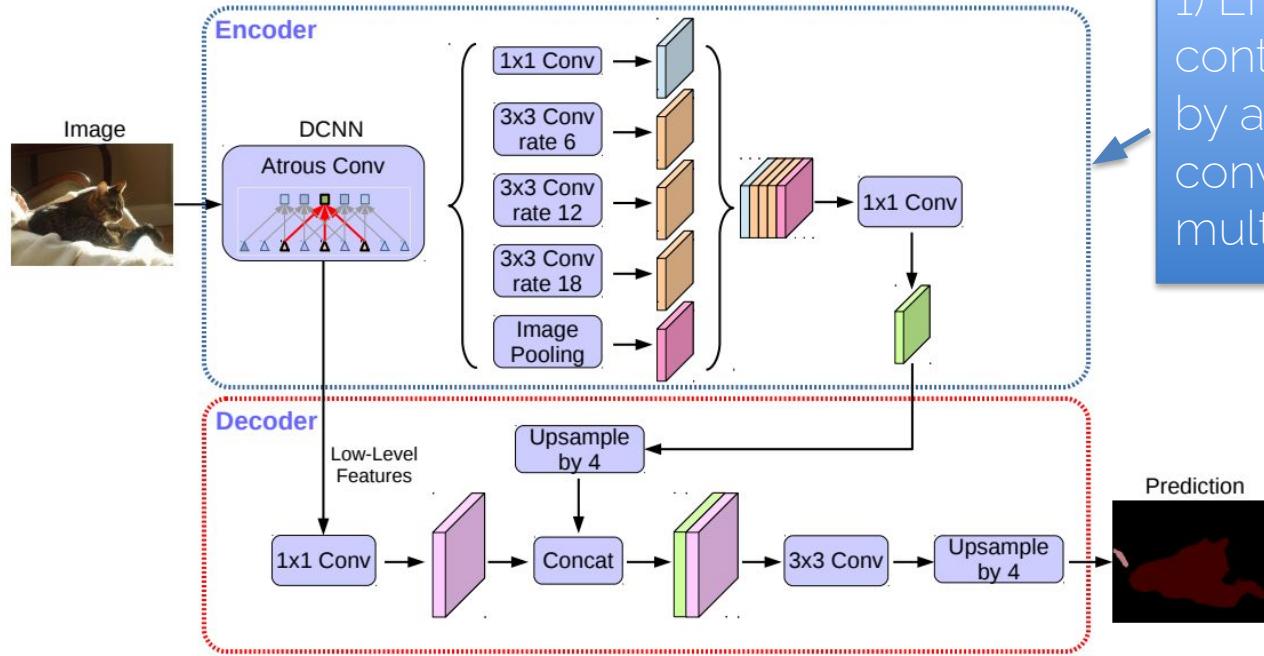
(a) Spatial Pyramid Pooling

(b) Encoder-Decoder

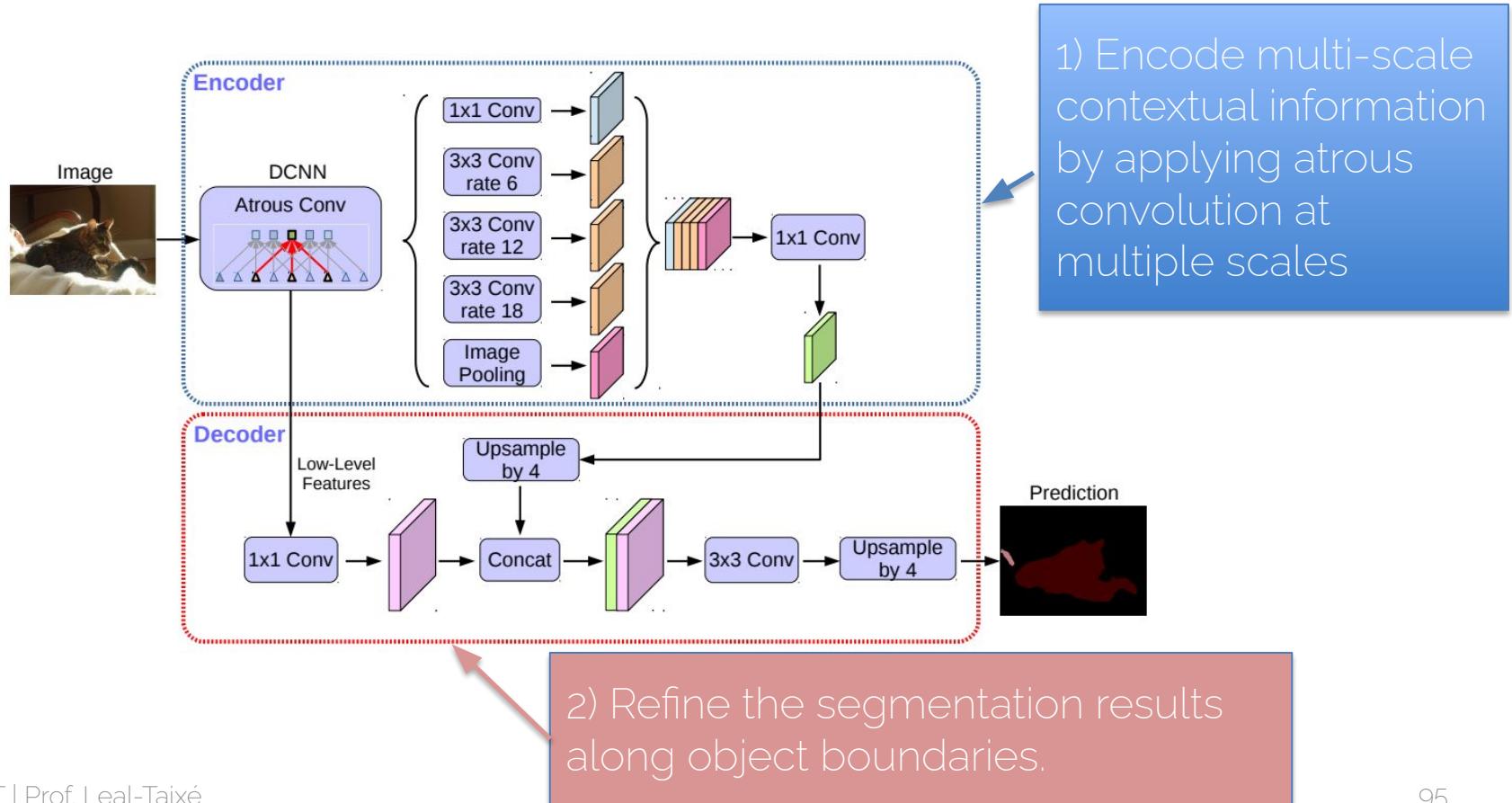
(c) Encoder-Decoder with Atrous Conv

Combine atrous convolutions and spatial pyramid pooling with an encoder-decoder module.

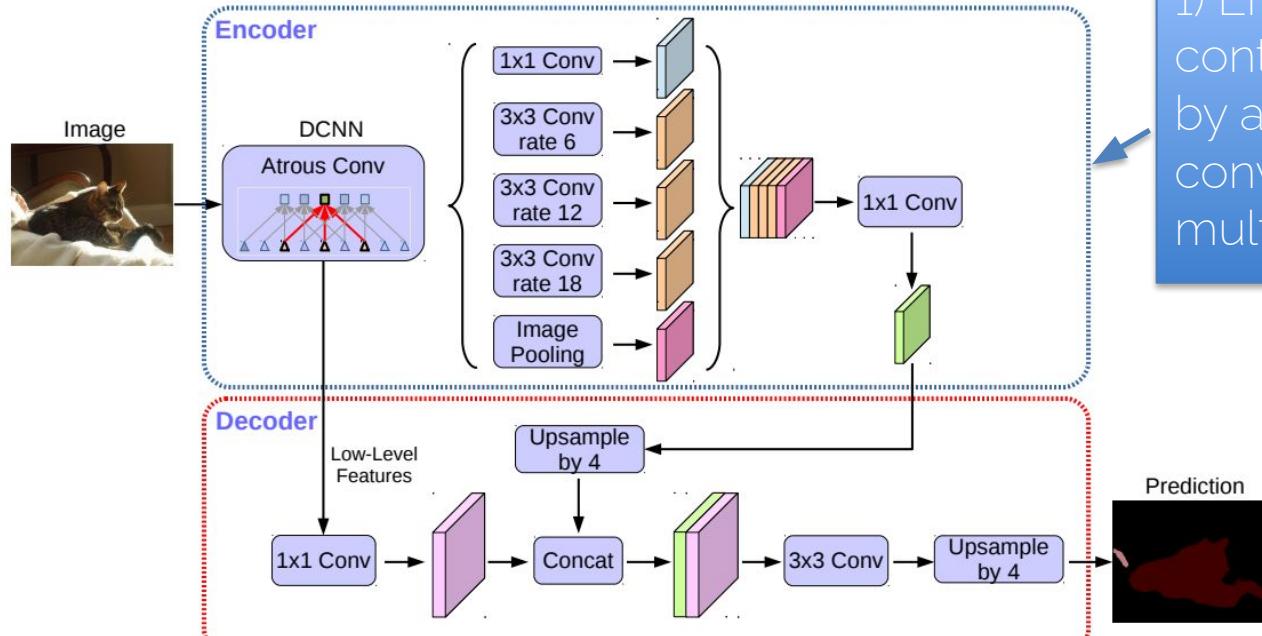
Delving deeper into DeepLabv3+



Delving deeper into DeepLabv3+



Delving deeper into DeepLabv3+

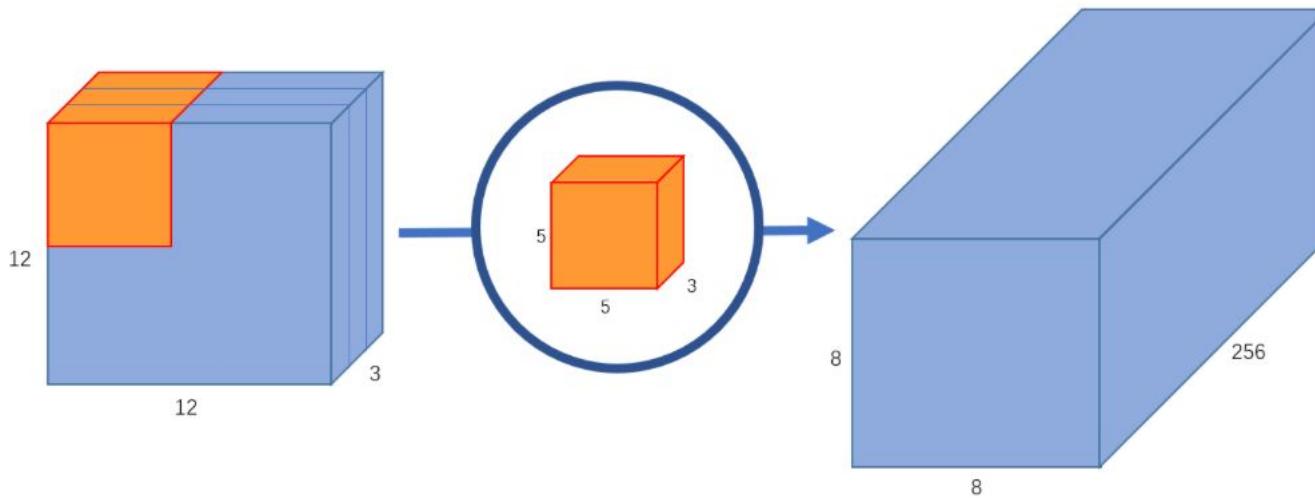


1) Encode multi-scale contextual information by applying atrous convolution at multiple scales

3) Use depthwise separable convolutions.

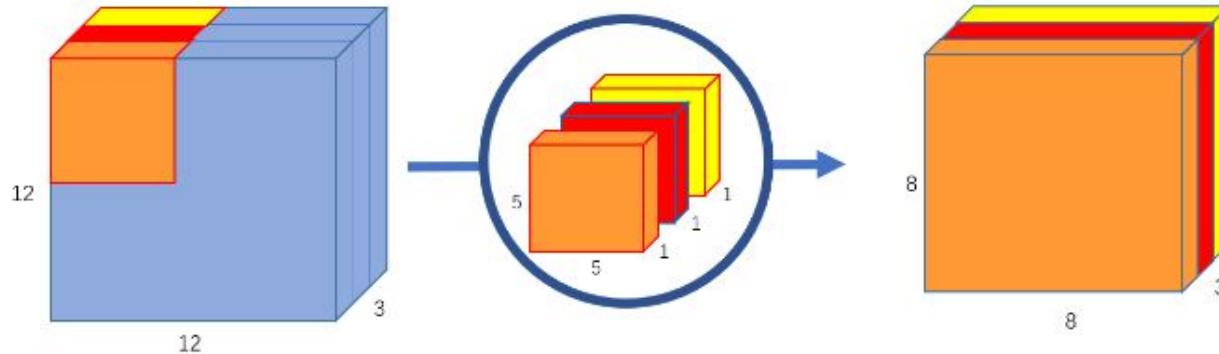
2) Refine the segmentation results along object boundaries.

Depth-wise separable convolutions



Normal convolutions act on all channels.

Depth-wise separable convolutions

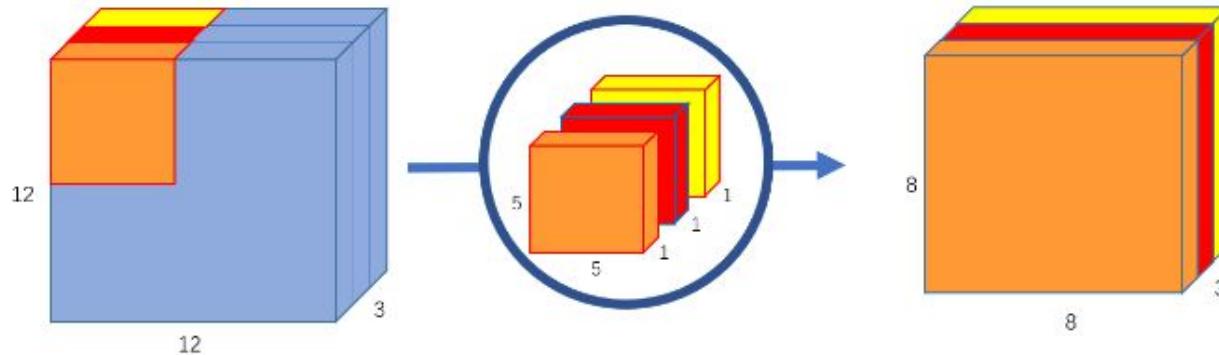


Filters are applied only at certain depths of the features.
Normal convolutions have groups set to 1, the convolutions used in this image have groups set to 3.

```
class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3)
```

```
class torch.nn.ConvTranspose2d(in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3)
```

Depth-wise separable convolutions

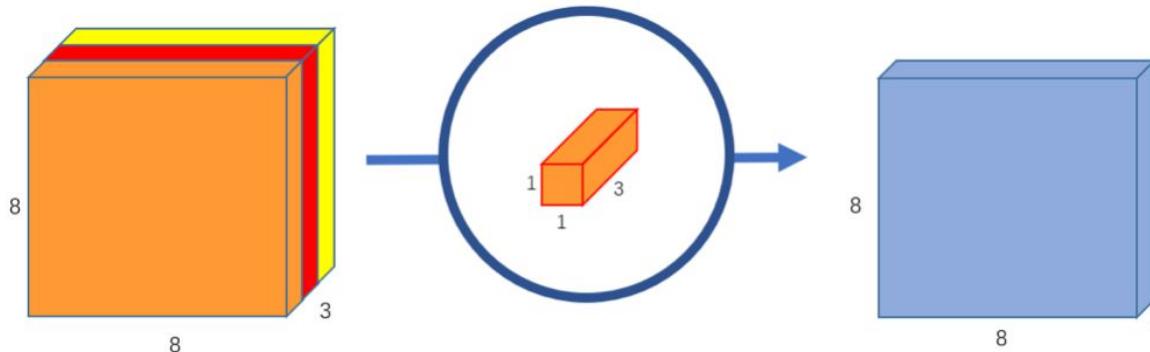
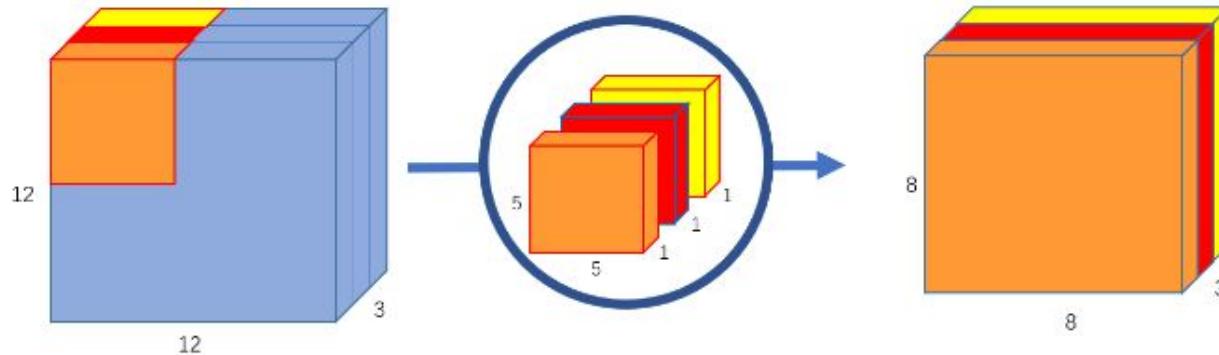


But the depth size is always the same!

```
class torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3)
```

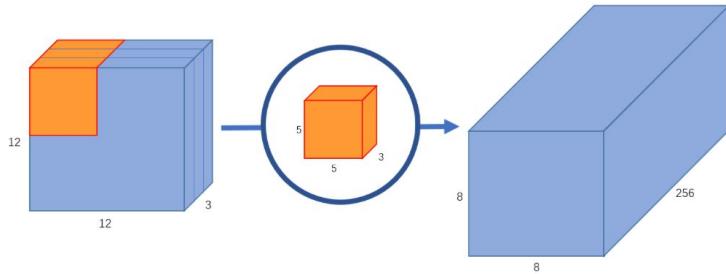
```
class torch.nn.ConvTranspose2d(in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3)
```

Depth-wise separable convolutions



Solution:
1x1 convs!

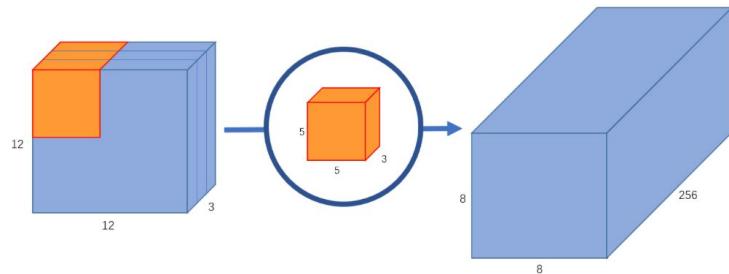
But why?



Original convolution
256 kernels of size 5x5x3

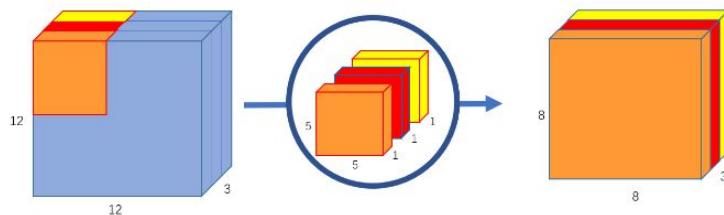
Multiplications:
 $256 \times 5 \times 5 \times 3 \times (8 \times 8 \text{ locations}) = 1.228.800$

But why?



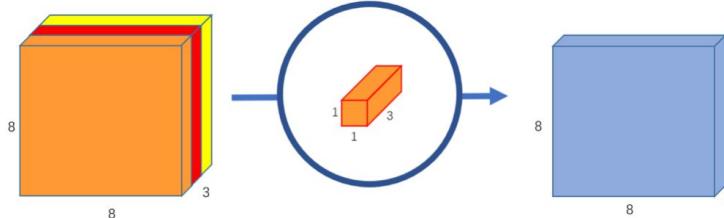
Original convolution
256 kernels of size $5 \times 5 \times 3$

Multiplications:
 $256 \times 5 \times 5 \times 3 \times (8 \times 8 \text{ locations}) = 1.228.800$



Depth-wise convolution
3 kernels of size $5 \times 5 \times 1$

Multiplications:
 $5 \times 5 \times 3 \times (8 \times 8 \text{ locations}) = 4800$

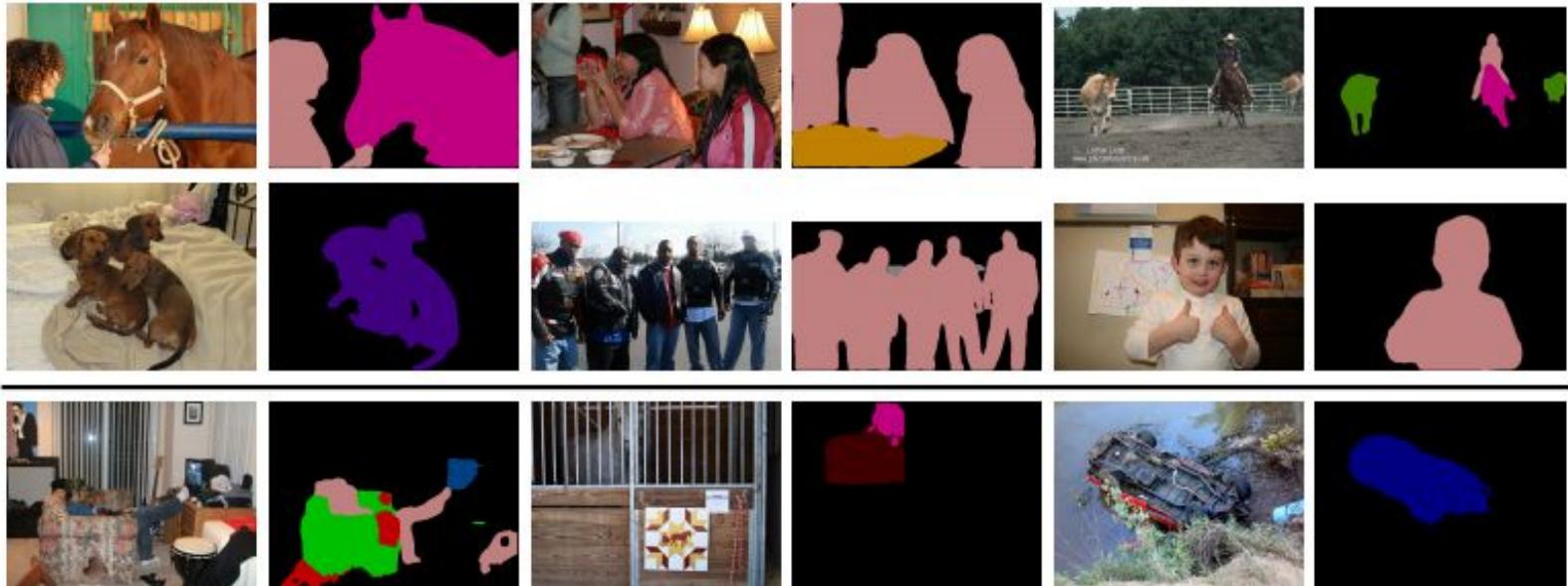


1x1 convolution
256 kernels of size $1 \times 1 \times 3$

Multiplications:
 $256 \times 1 \times 1 \times 3 \times (8 \times 8 \text{ locations}) = 49152$

Less computations!

DeepLabv3+: qualitative results



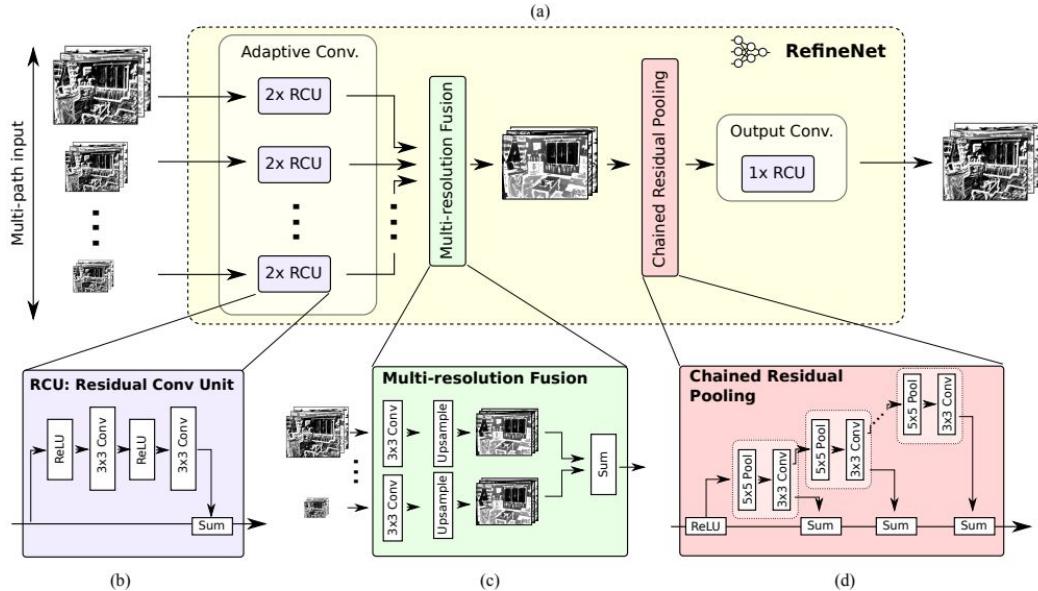
Still considered as SOTA!

Chen et al., Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation, ECCV 2018

DeepLab is great...

- ...but there are other important architectures
- Recommended to read
 - RefineNet
 - PSPNet

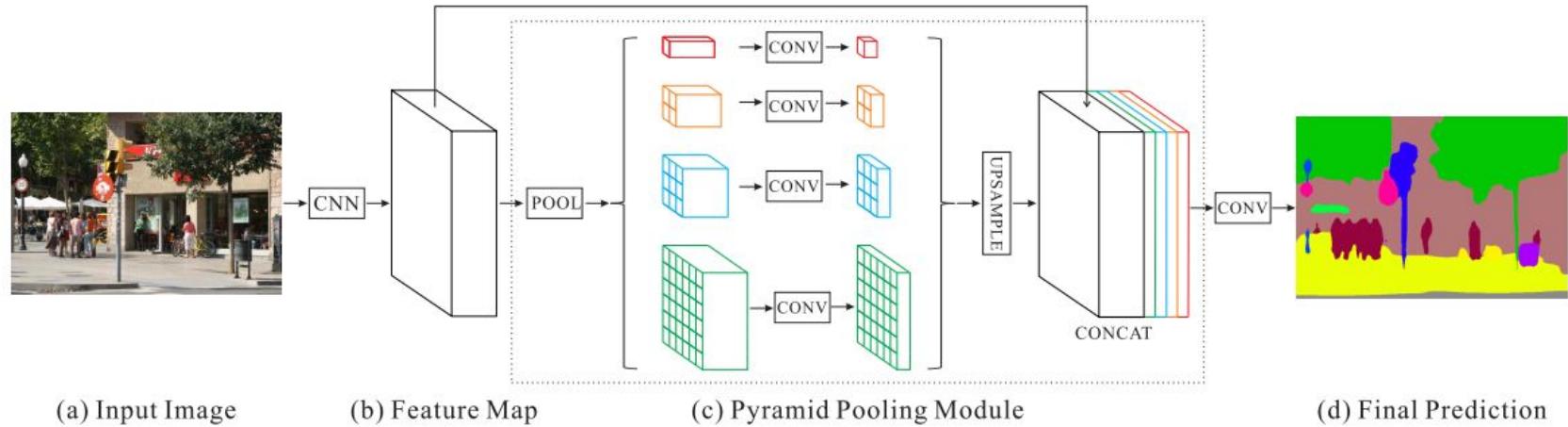
RefineNet



Many building blocks but the goal is the same: use convolutional layers to refine the information coming from different scales.

Lin et al., RefineNet: Multi-Path Refinement Networks for High-Resolution Semantic Segmentation, CVPR 2017

PSPNet



Similar idea to RefineNet (fuse information from multiple scales), but the features here are shared (and the multi-scaling comes from pooling). The method is simpler than RefineNet and performs slightly better.

Datasets and metrics

Datasets

Pascal VOC
2012:

9993 natural
images
divided into
20 classes.

Cityscapes:
25K
urban-street
images
divided into
30 classes.

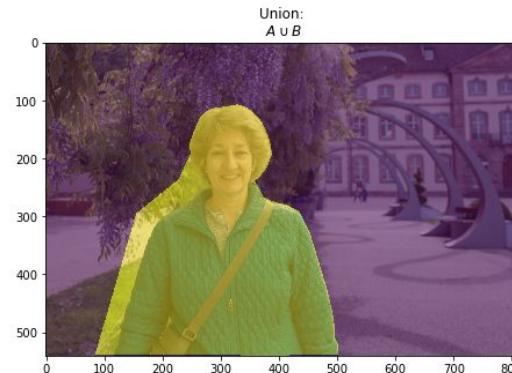
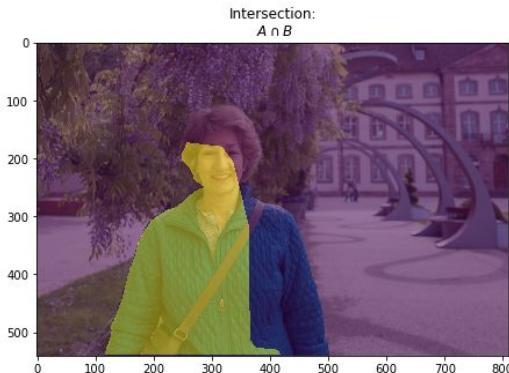
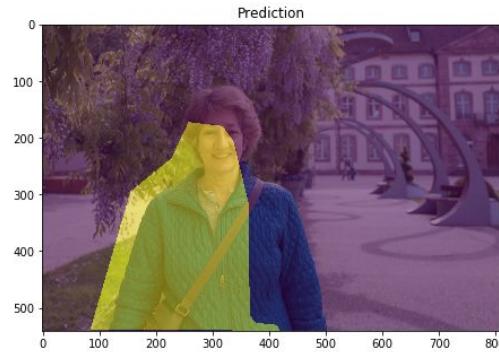
ADE20K:
25K (20 stands
for 20K training)
scene-parsing
images divided
into
150 classes.

Mapillary
Vistas:

25K street
level images,
divided into
152 classes.

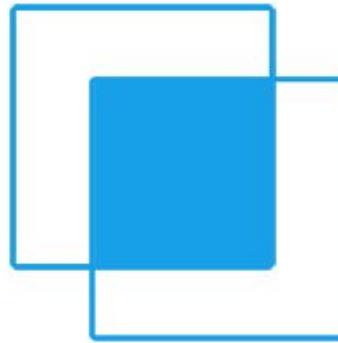
Models are often pre-trained in the large MS-COCO dataset,
before finetuned to the specific dataset.

Metrics: intersection over union (IoU)



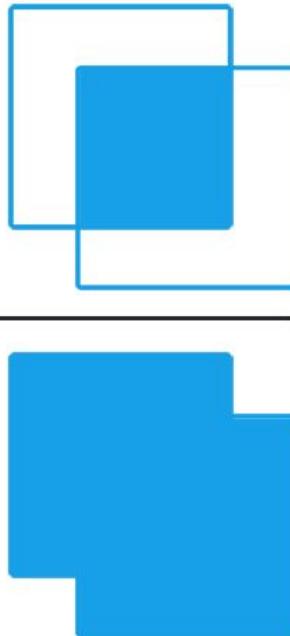
Metrics: intersection over union (IoU)

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Metrics: mean intersection over union (mIoU)

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



MIoU simply computes the IoU for each class and then computes the mean of those values.

Another widely used metric is the pixel accuracy (ratio of pixels classified correctly).

Semantic segmentation