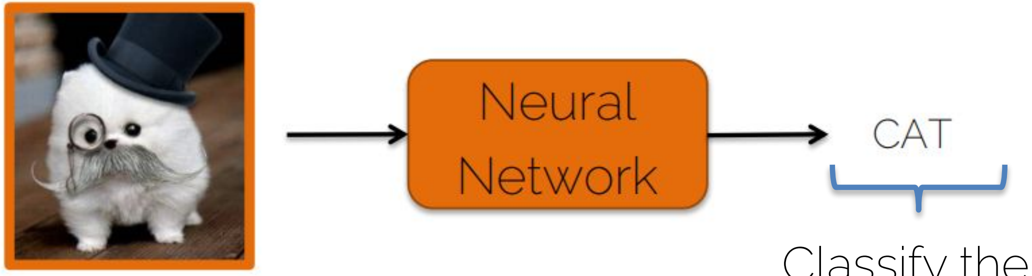
Semantic segmentation

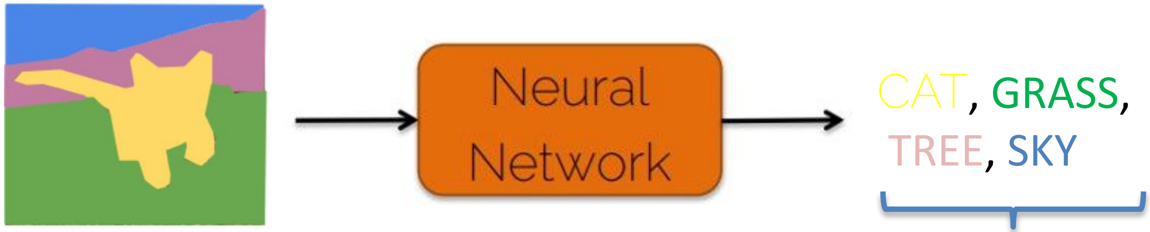
Task definition: semantic segmentation



Neural Network

CAT

Classify the main object in the image.

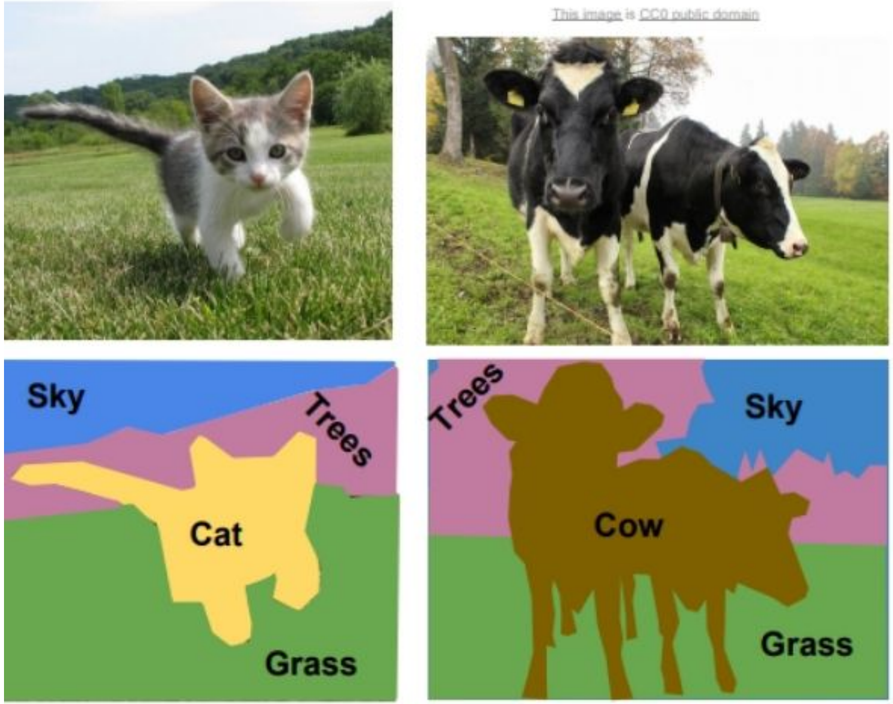


Neural Network

CAT, GRASS, TREE, SKY

No objects, just classify each pixel.

Semantic Segmentation


This image is CC0 public domain

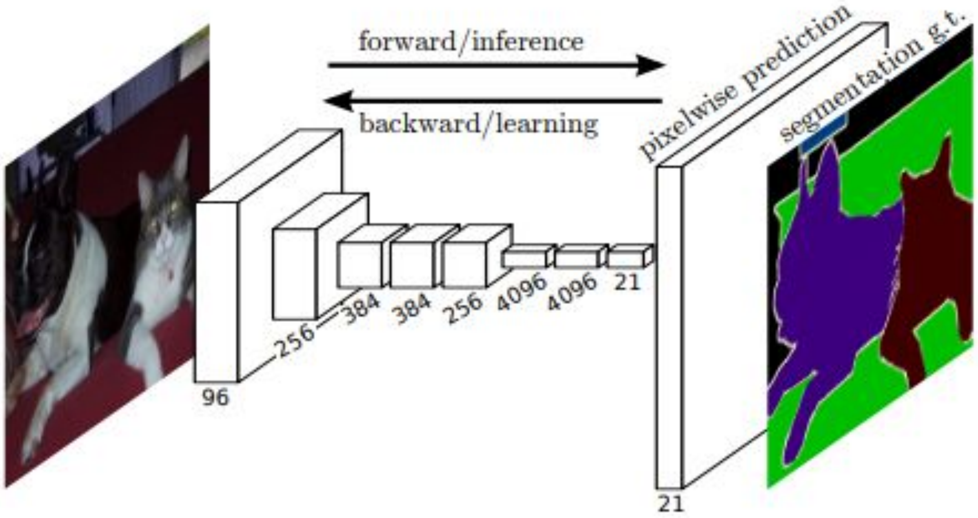
- Every pixel in the image needs to be labelled with a category label.

- 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

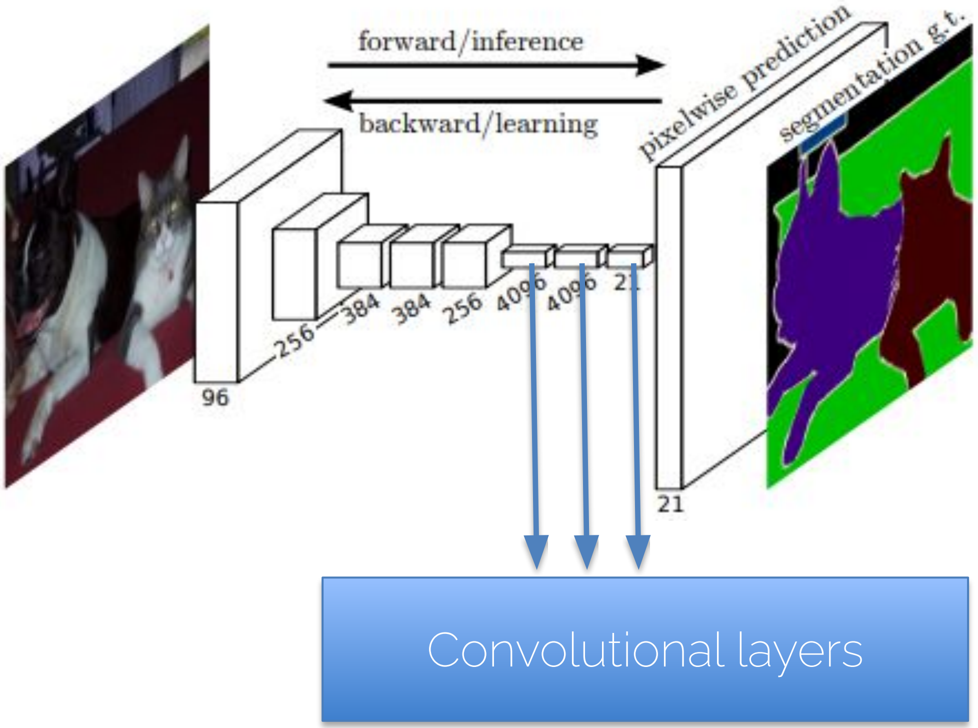
- A FCN is able to deal with any input/output size



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

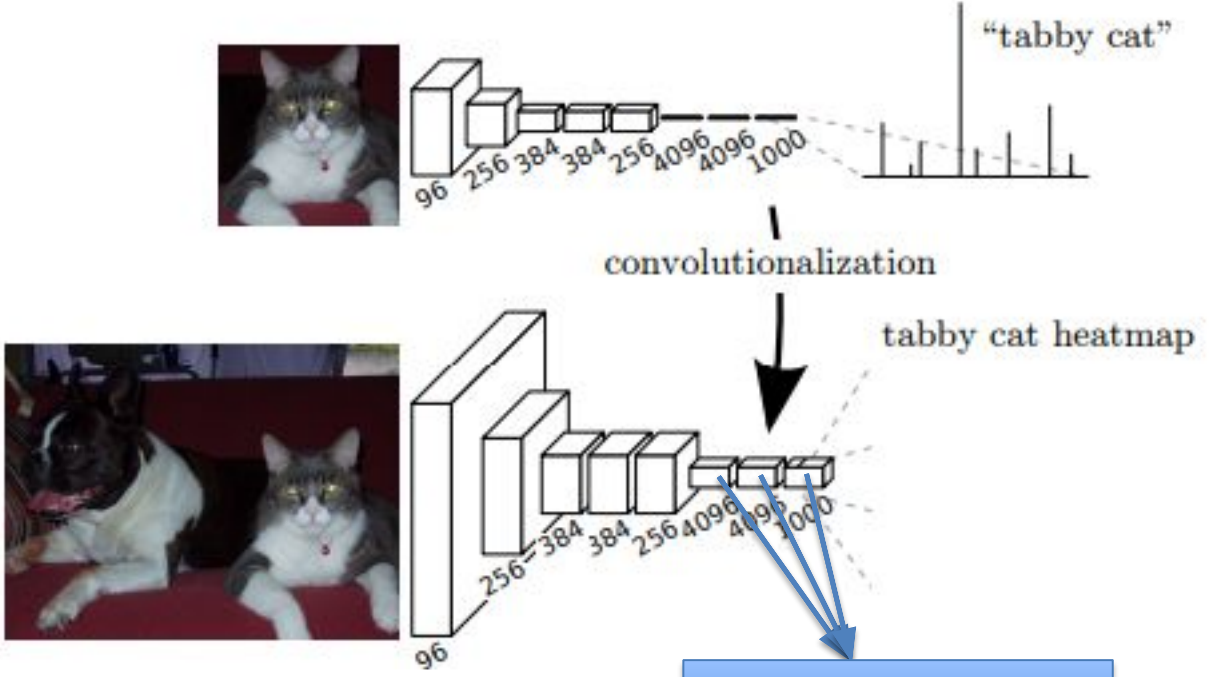
Fully convolutional neural networks

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 segmentaion ground truth.
4. Backprop and SGD



Convolutional layers

"Convolutionalization"



1x1 Convolutions!

Recall: Convolutions on Images

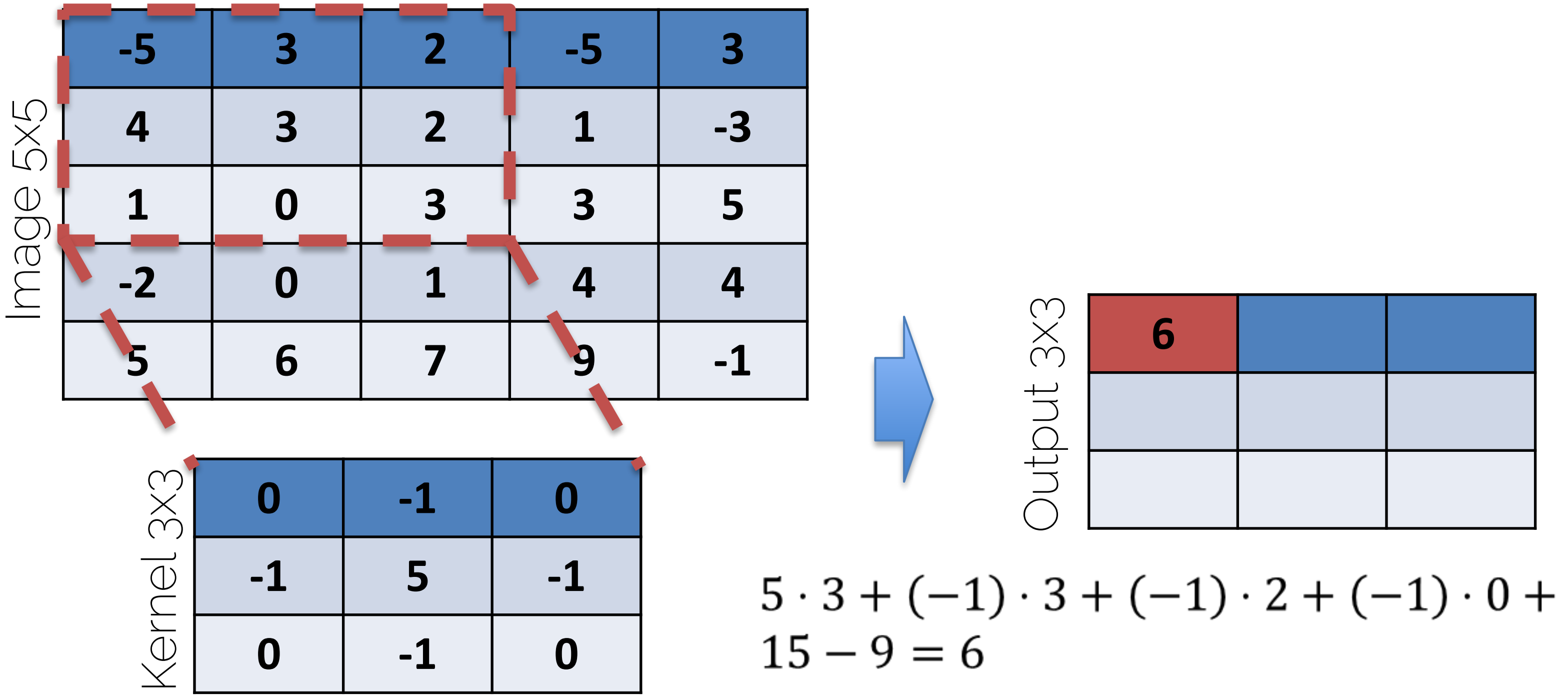


Image 5x5

-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 3x3

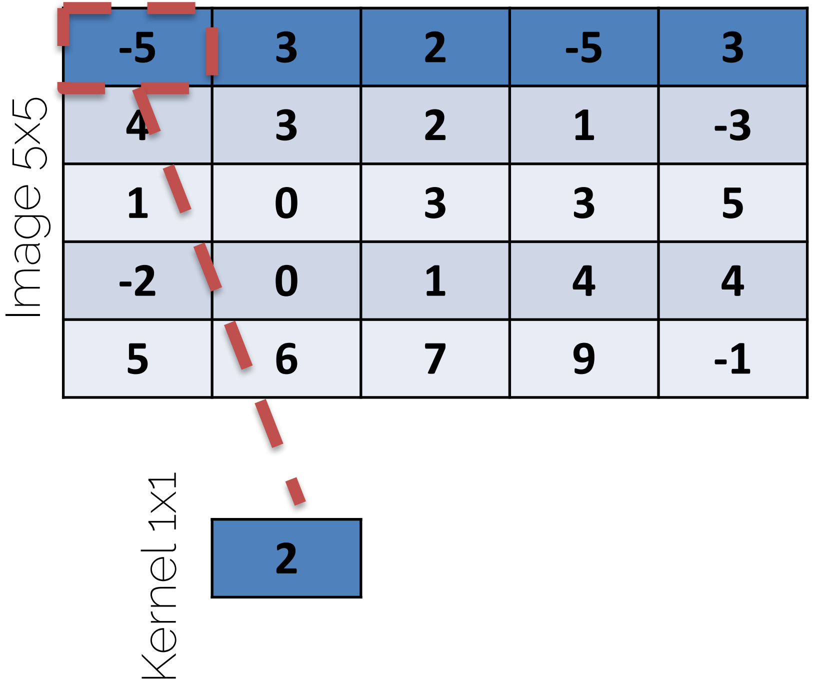
0	-1	0
-1	5	-1
0	-1	0

Output 3x3

6		

$$5 \cdot 3 + (-1) \cdot 3 + (-1) \cdot 2 + (-1) \cdot 0 + (-1) \cdot 4 =$$
$$15 - 9 = 6$$

1x1 Convolution

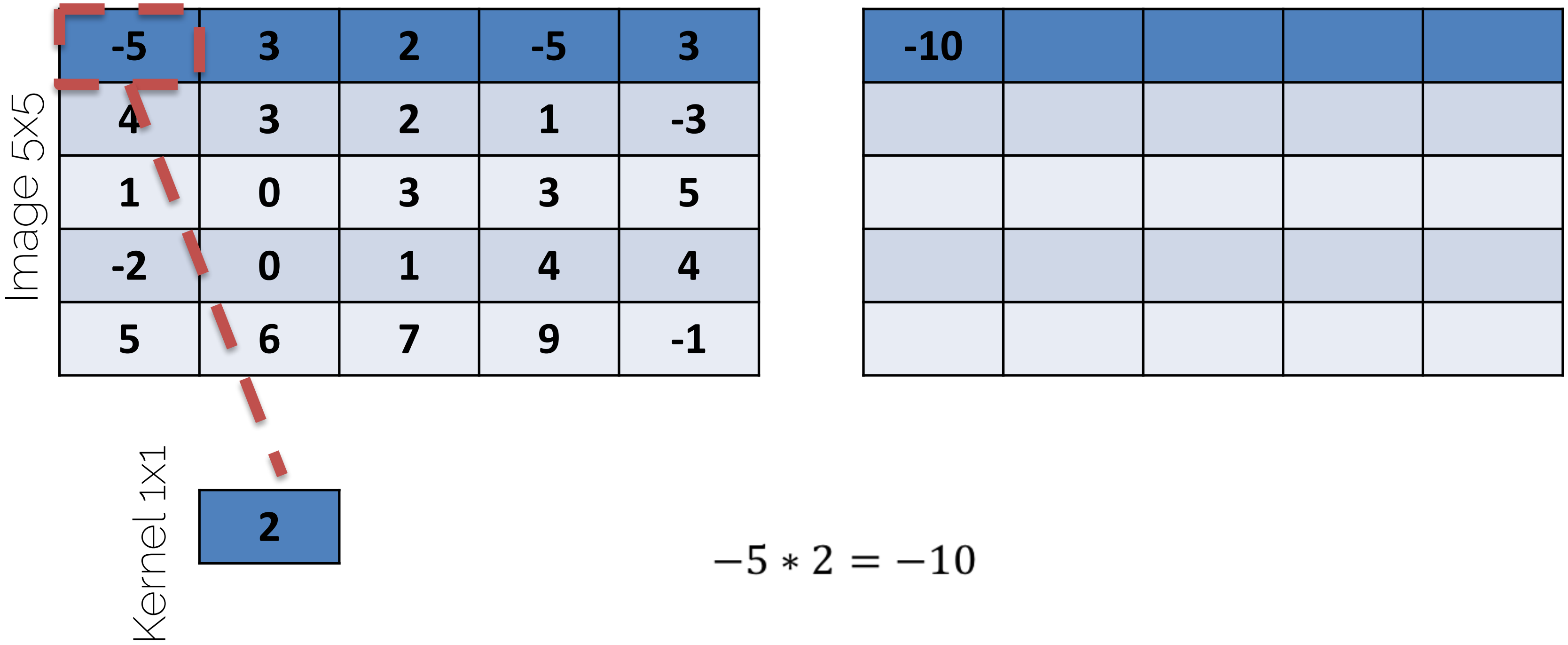


-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

2

What is the output size?

1x1 Convolution



-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

2

-10				

$$-5 * 2 = -10$$

1x1 Convolution

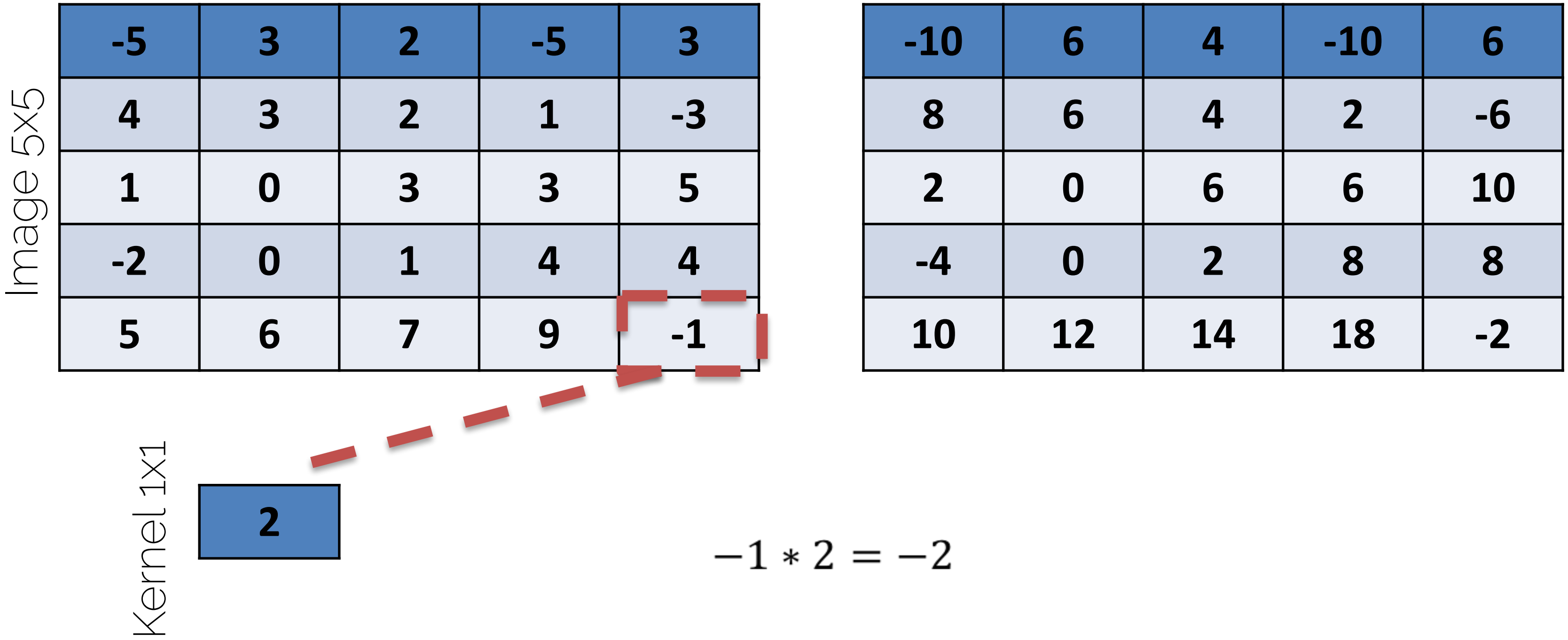


Image 5x5

-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

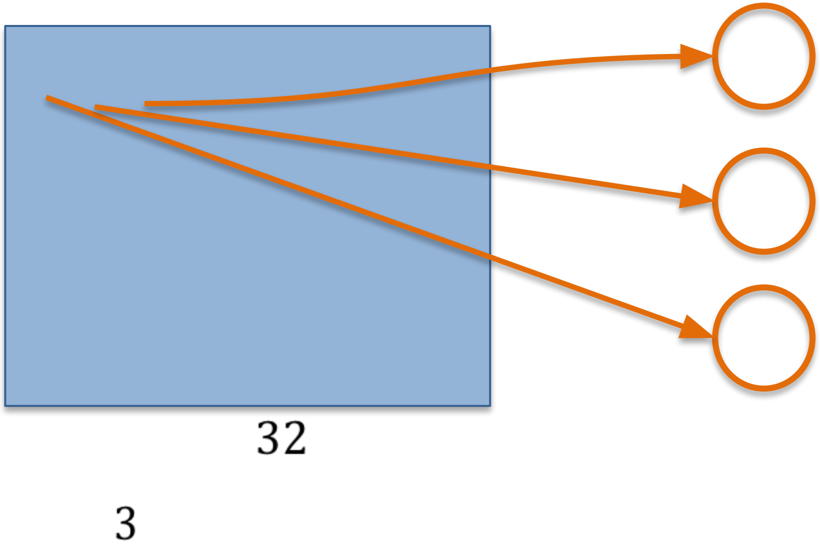
Image 5x5

-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

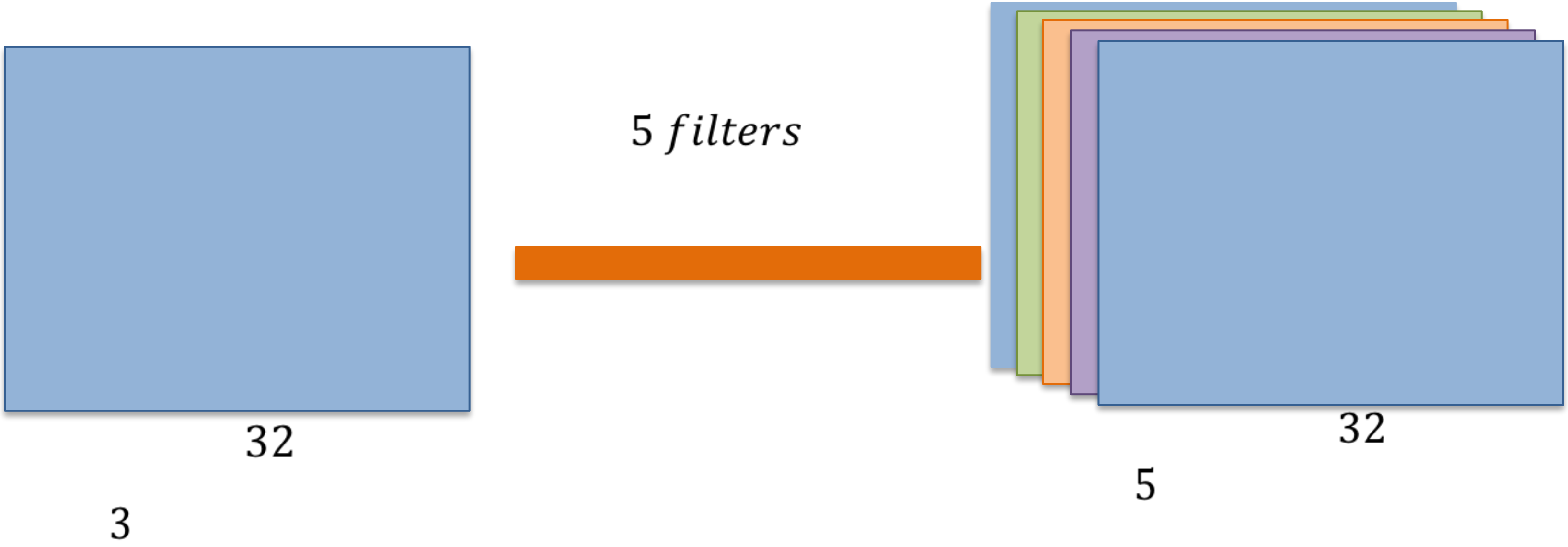


1 output

- Same as having a 3 neuron fully connected layer

1x1 Convolution

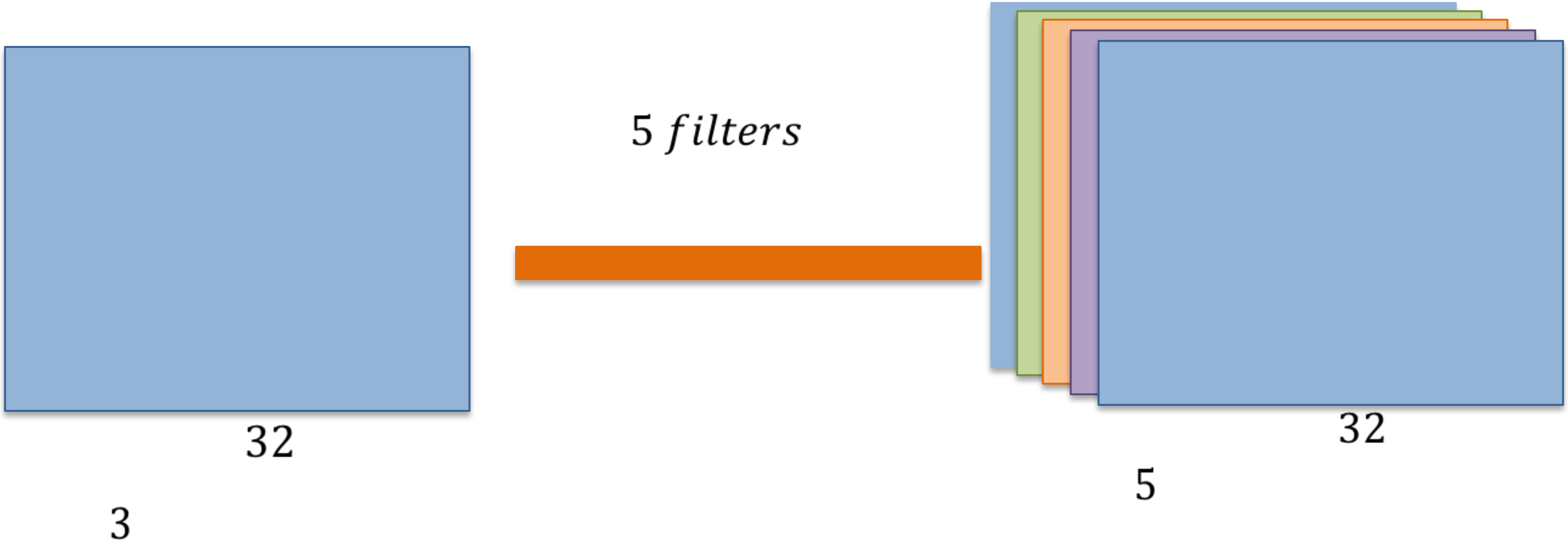
[Li et al. 2013]



- As always we use more convolutional filters

Network in Network

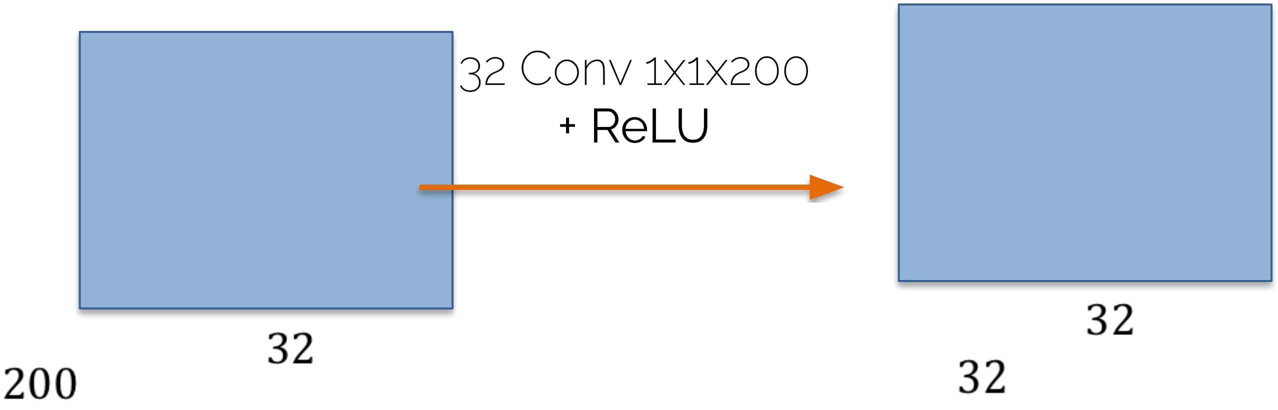
[Li et al. 2013]



- As always, we use more convolutional filters

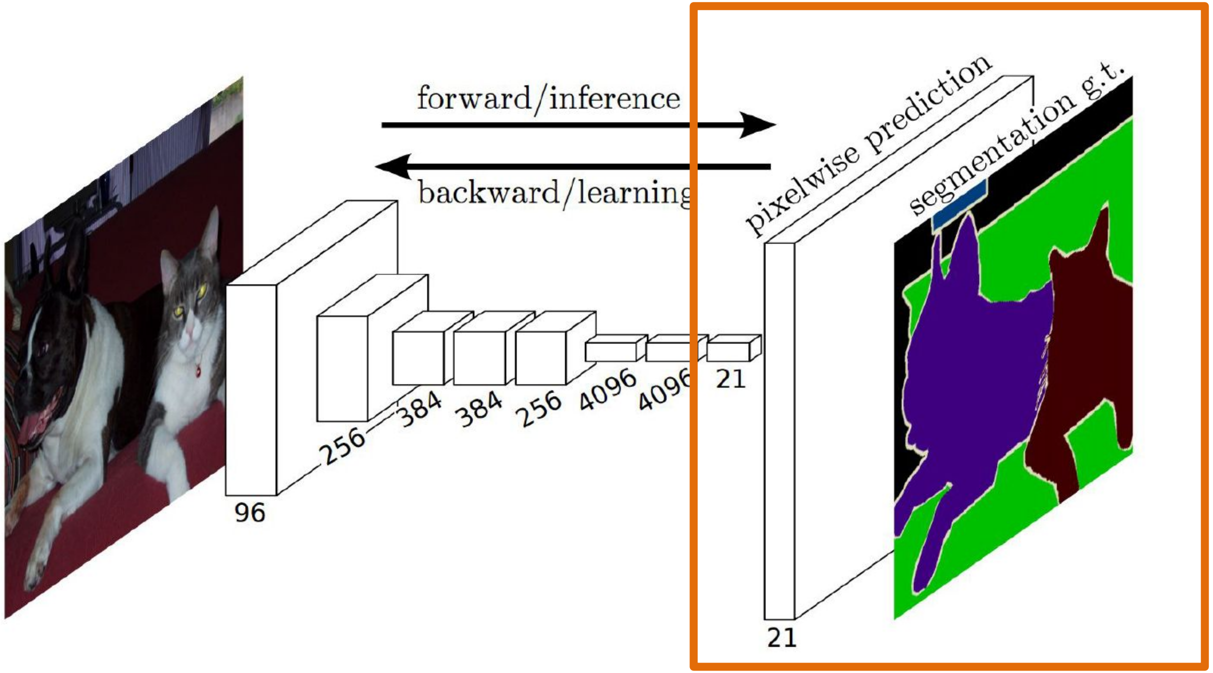
Using 1x1 Convolutions

- 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

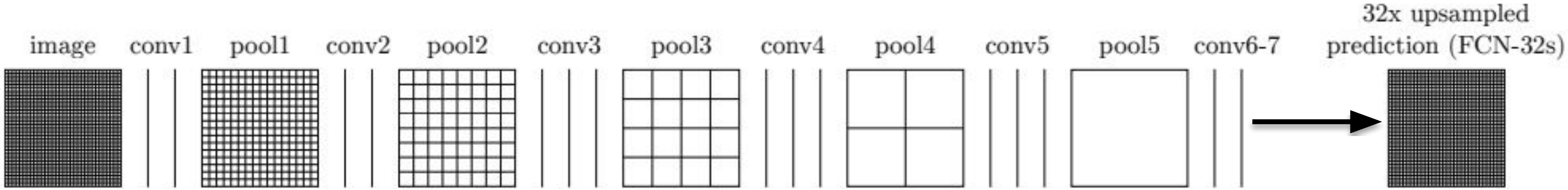


How do we upsample?

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

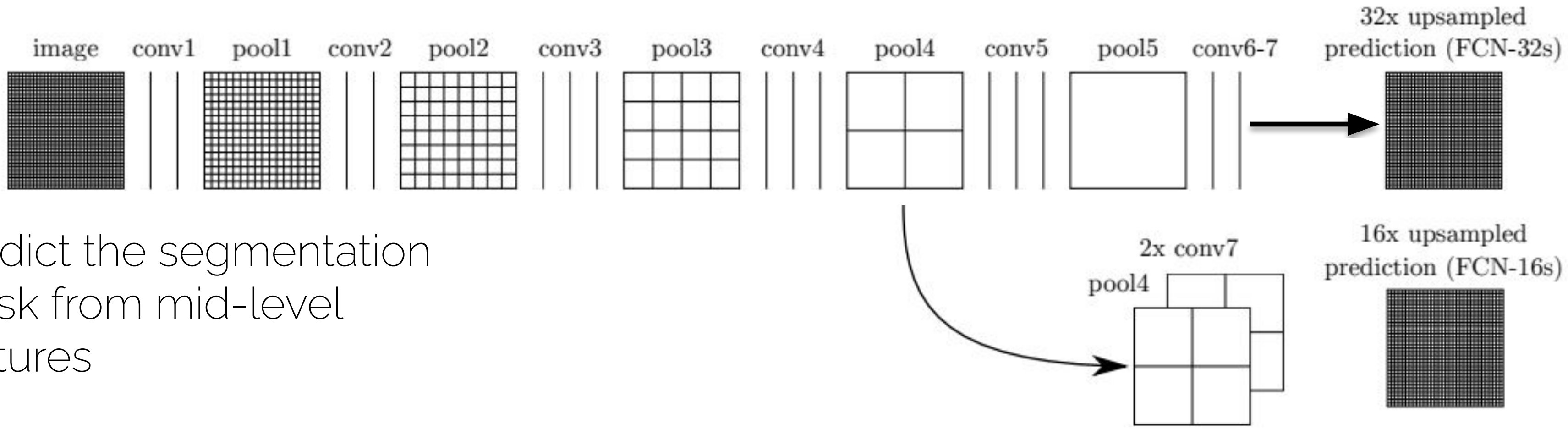
Network's architecture

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

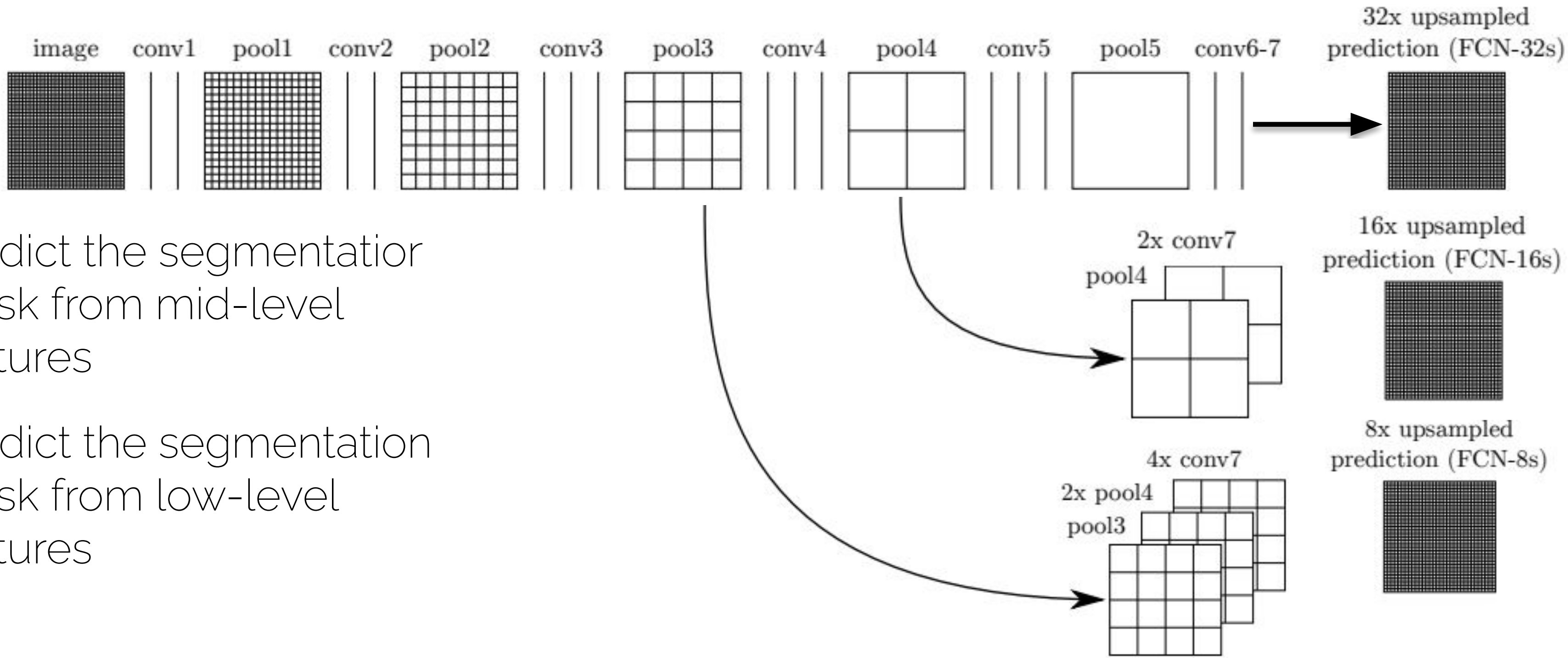
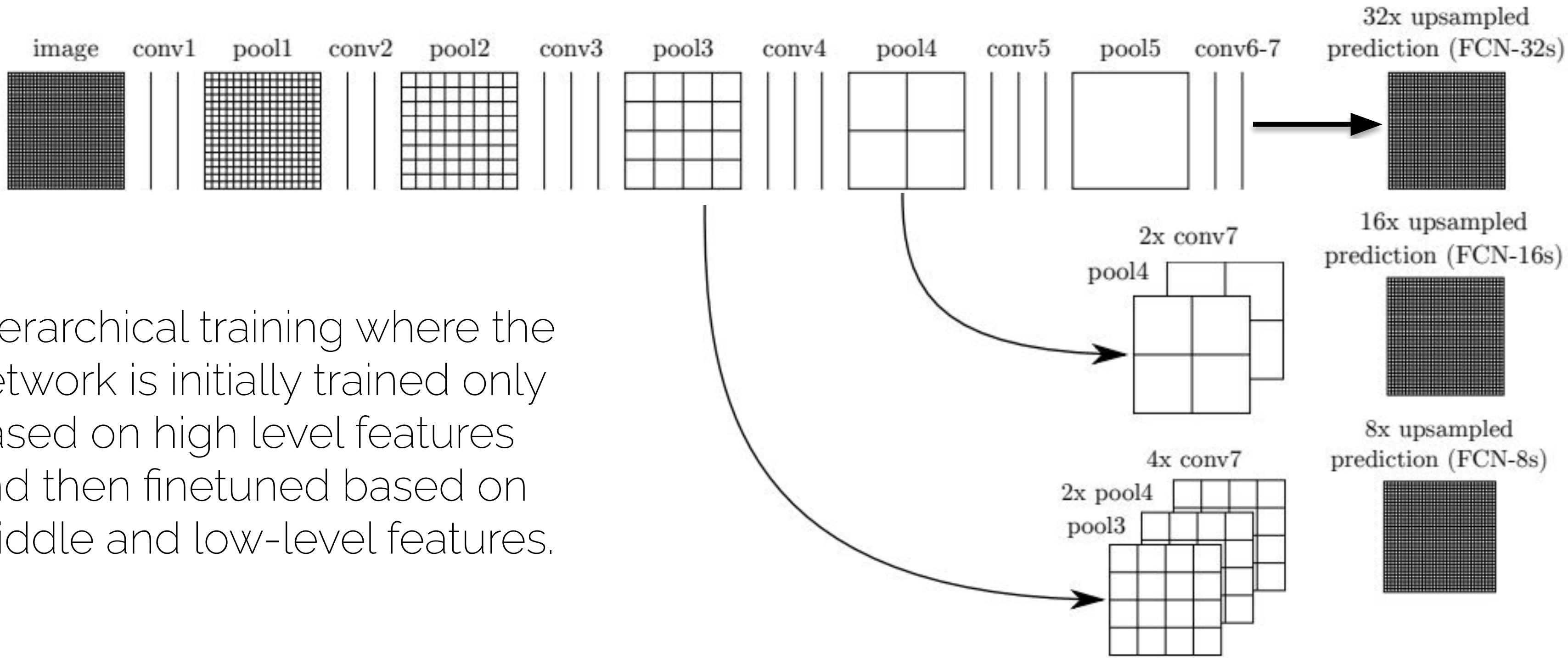


image
conv1
pool1
conv2
pool2
conv3
pool3
conv4
pool4
conv5
pool5
conv6-7
32x upsampled prediction (FCN-32s)
2x conv7
pool4
16x upsampled prediction (FCN-16s)
4x conv7
2x pool4
pool3
8x upsampled prediction (FCN-8s)

Predict the segmentatior mask from mid-level features

Predict the segmentation mask from low-level features

Network's architecture



Hierarchical training where the network is initially trained only based on high level features and then finetuned based on middle and low-level features.

Network's architecture

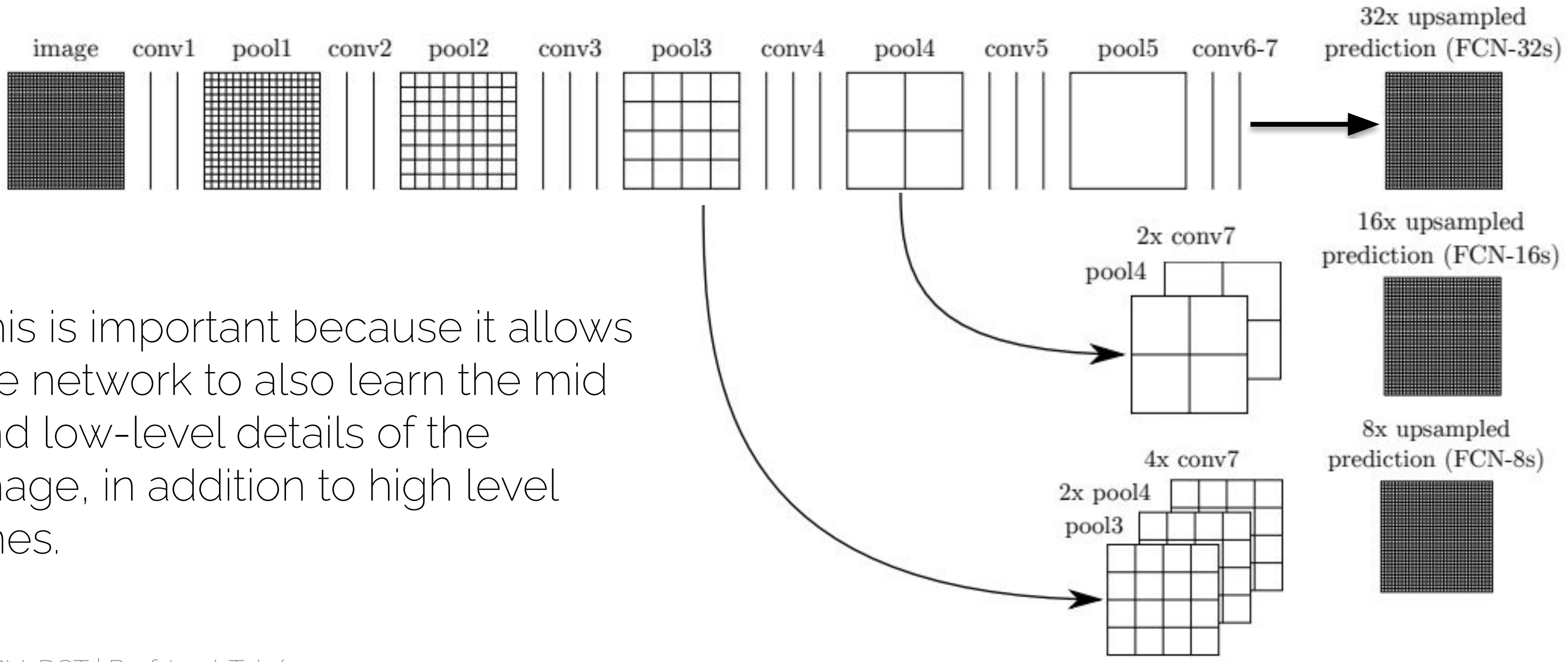
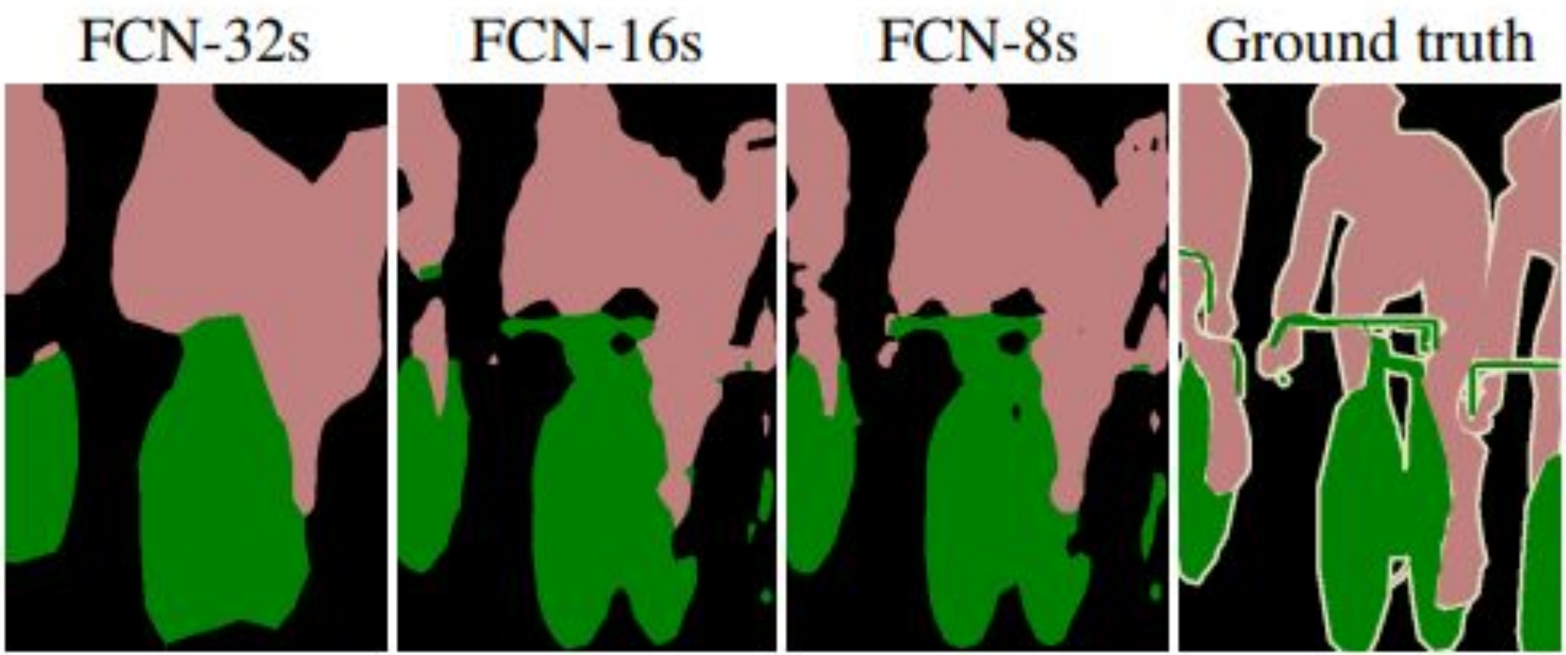


image
conv1
pool1
conv2
pool2
conv3
pool3
conv4
pool4
conv5
pool5
conv6-7
32x upsampled prediction (FCN-32s)
2x conv7
pool4
16x upsampled prediction (FCN-16s)
4x conv7
2x pool4
pool3
8x upsampled prediction (FCN-8s)

This is important because it allows the network to also learn the mid and low-level details of the image, in addition to high level ones.

Qualitative results

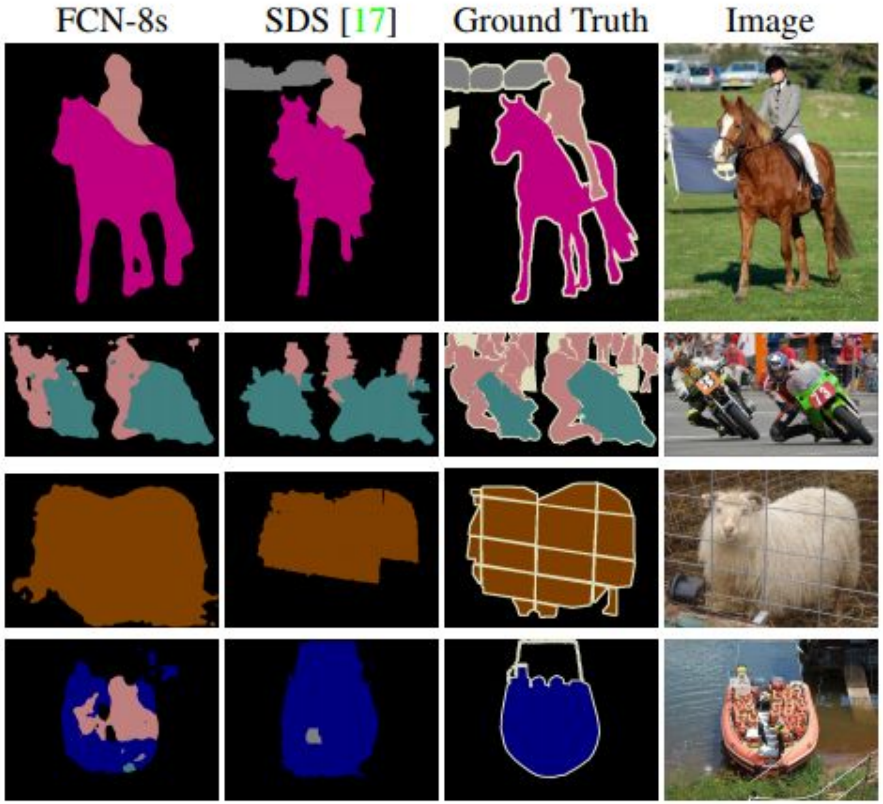


Good

Better

Best

Qualitative results

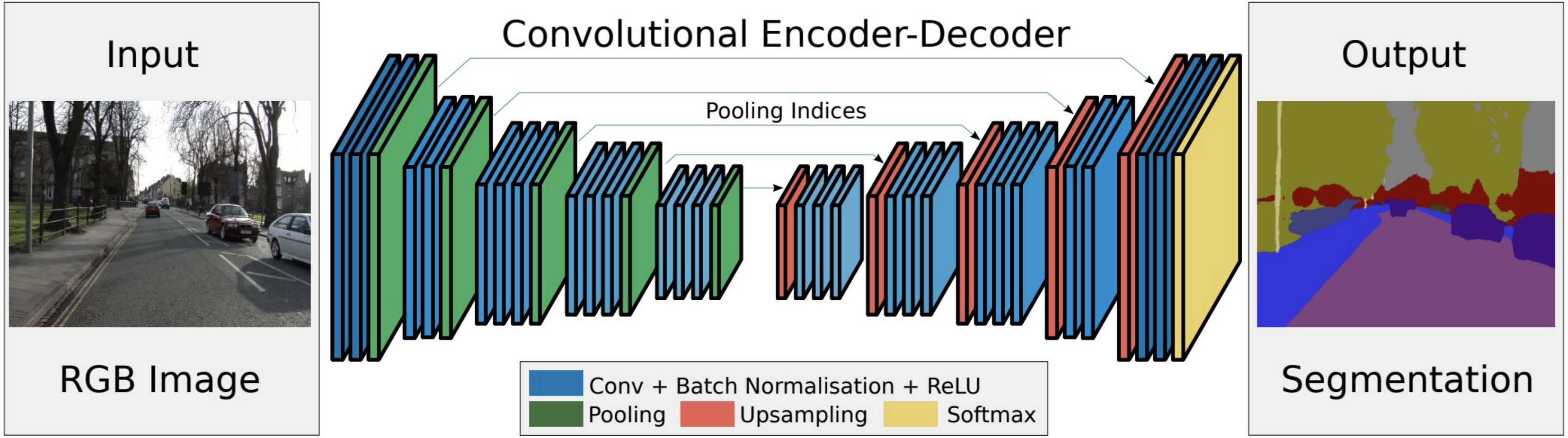


SDS is an R-CNN-based method, i.e., it uses object proposals.
In general, FCN outperforms significantly (both qualitatively and quantitatively) pre-deep learning and quasi-deep learning methods and is recognized as the AlexNet of semantic segmentation.

Encoder-decoder architecture

SegNet

- Step-wise upsampling

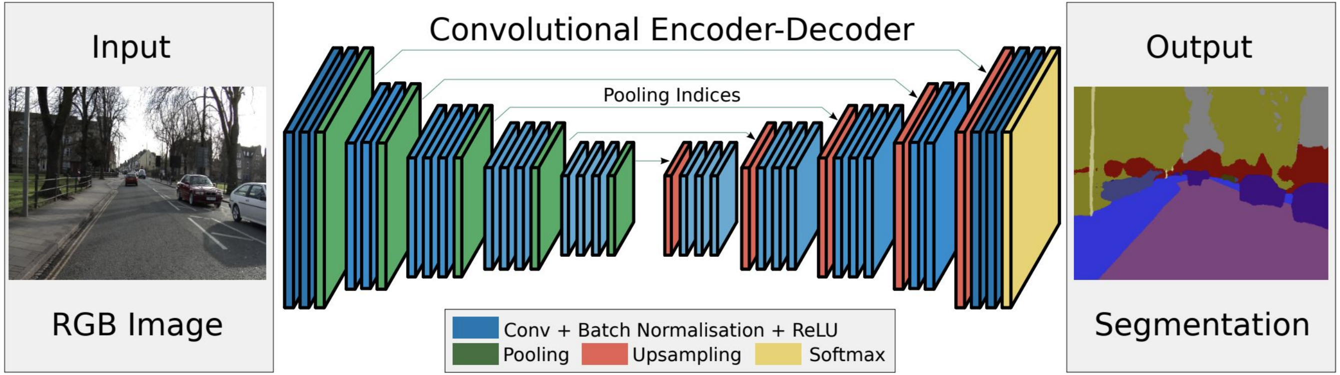


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

SegNet

- **Encoder**: normal convolutional filters + pooling

- **Decoder**: Upsampling + convolutional filters

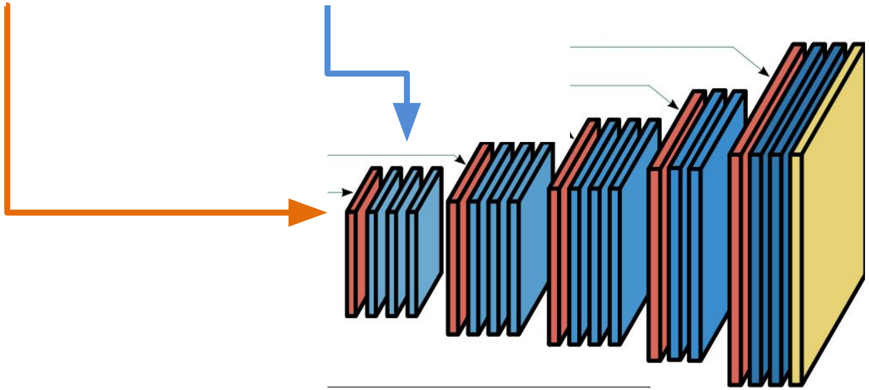


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

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

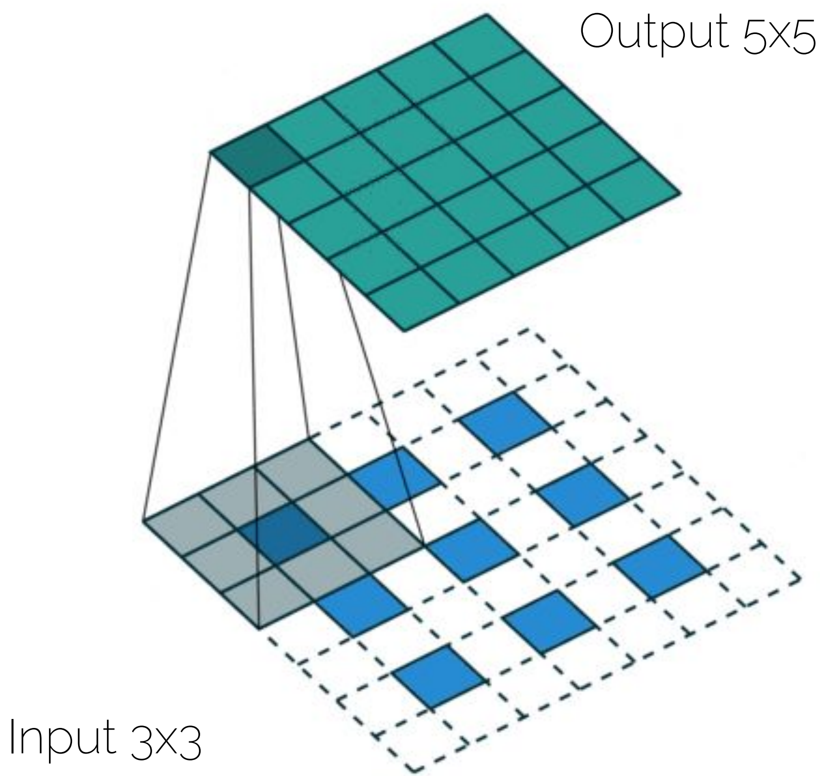
SegNet

- **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

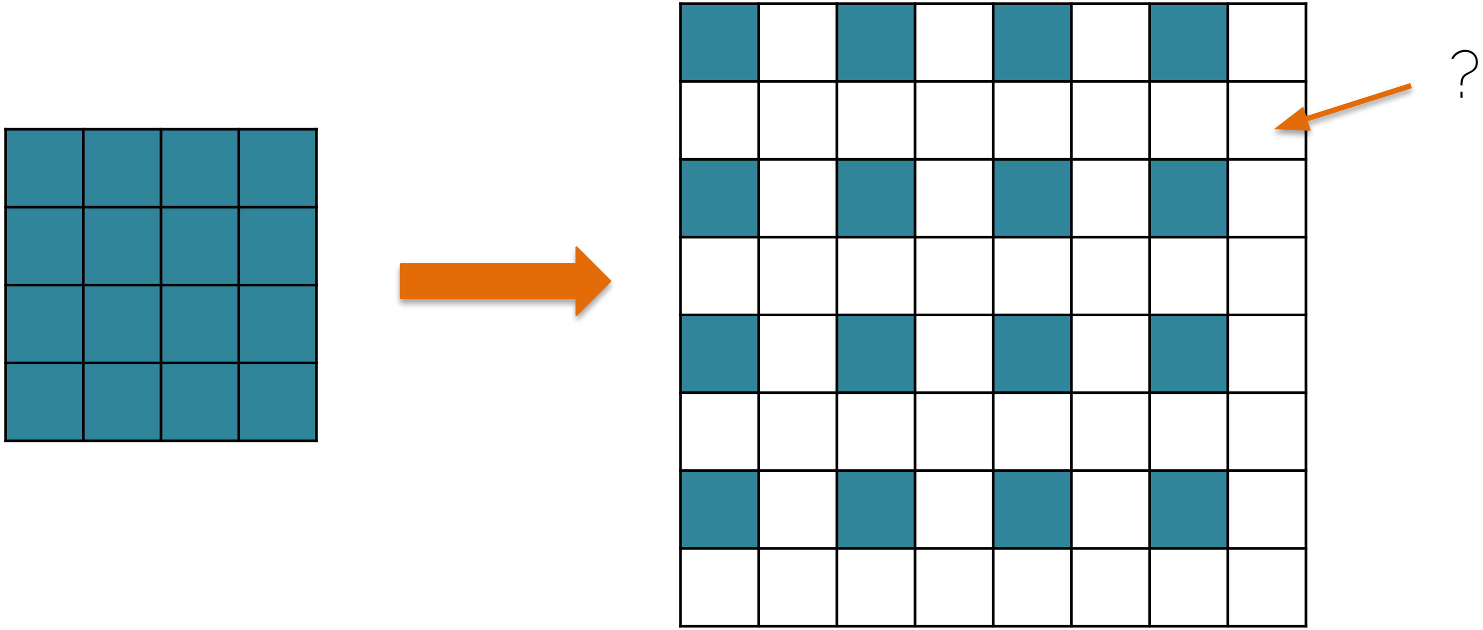
Transposed convolution

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



Upsampling

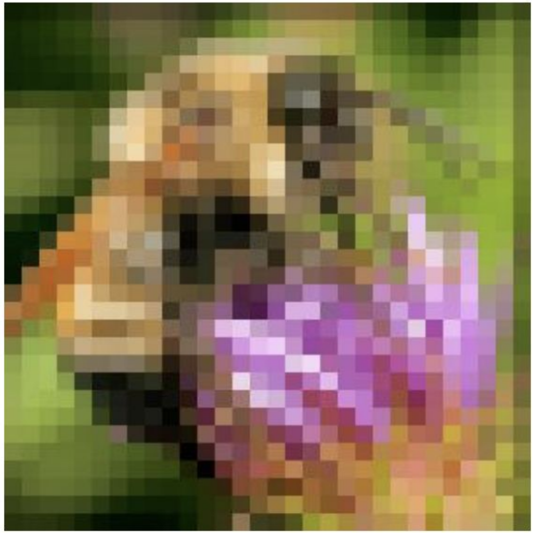
Upsampling: Interpolation



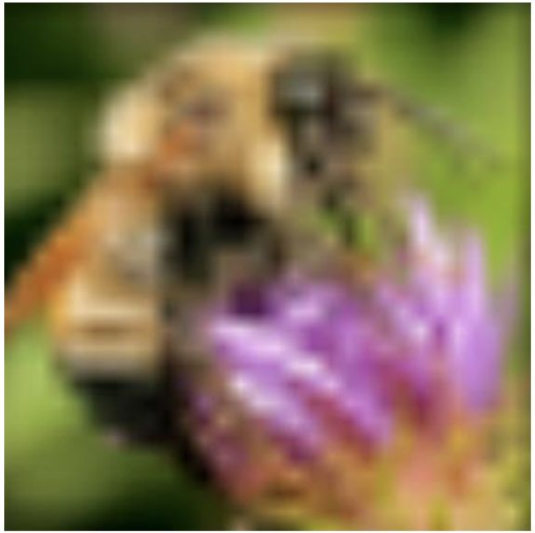
Types of upsamplings

- 1. Interpolation

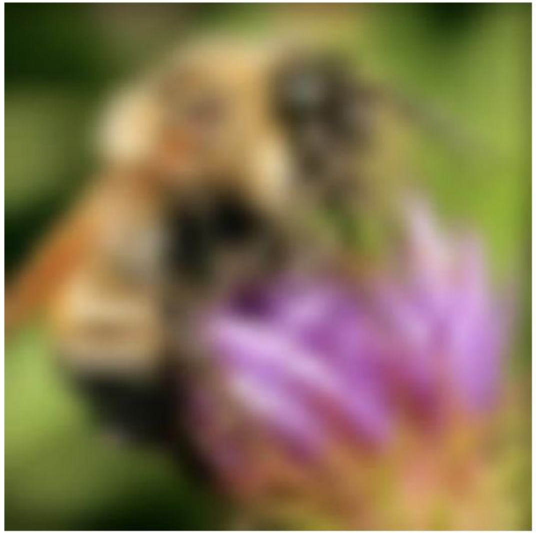
Original image x 10



Nearest neighbor interpolation



Bilinear interpolation



Bicubic interpolation

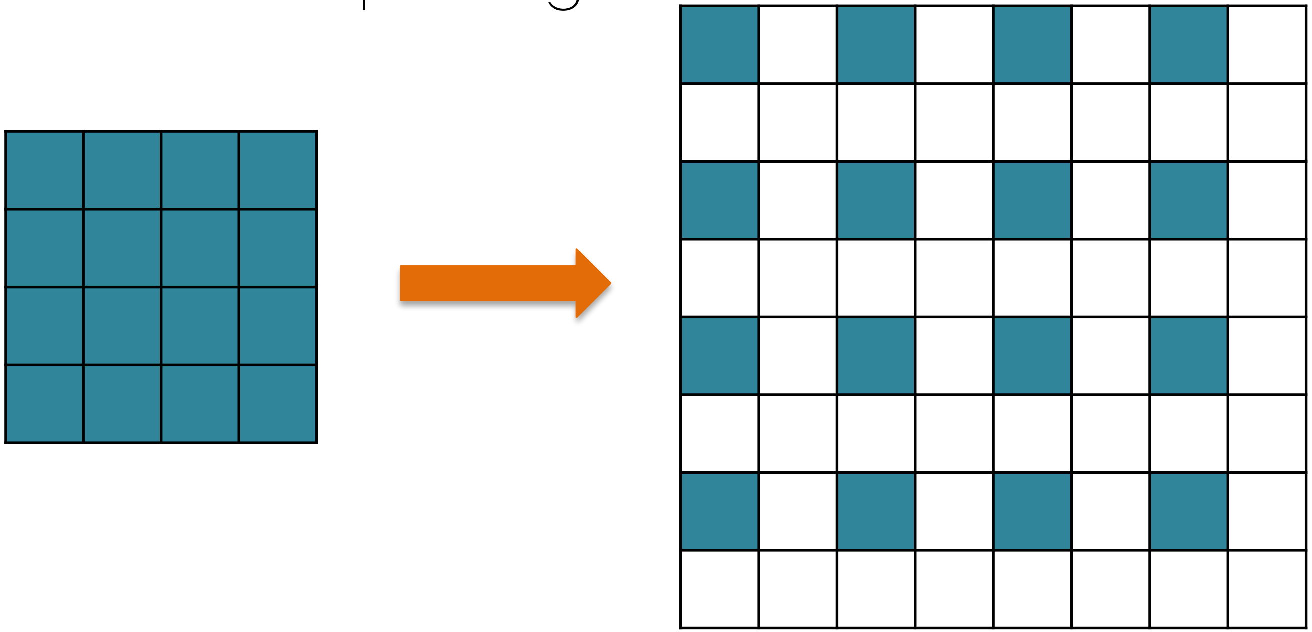
Image: Michael Guerzhoy

Upsampling

Transposed convolution gives similar effect to interpolation + convolution.

Types of upsamplings

- 2. Fixed unpooling



✅ efficient

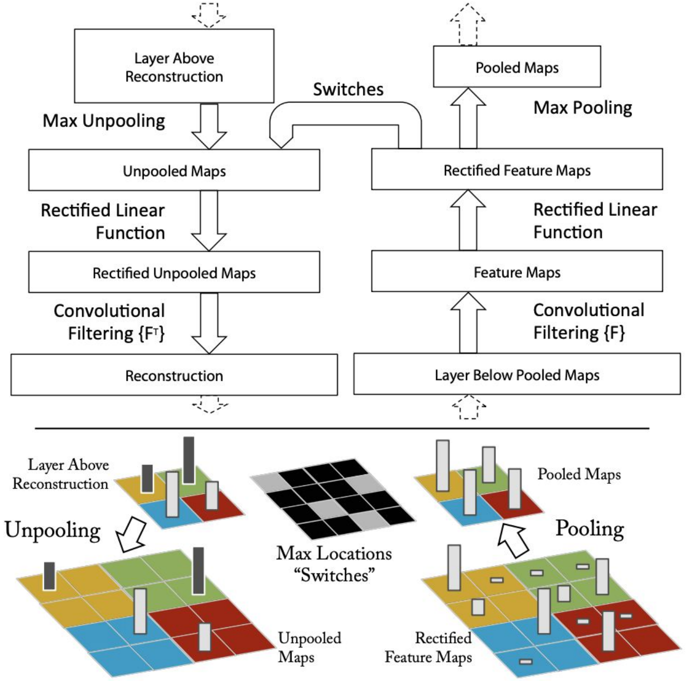
+ CONVS

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



Zeiler and Fergus. „Visualizing and understanding convolutional neural networks". ECCV 2014

Types of upsamplings

- 3. Unpooling: “à la DeconvNet”

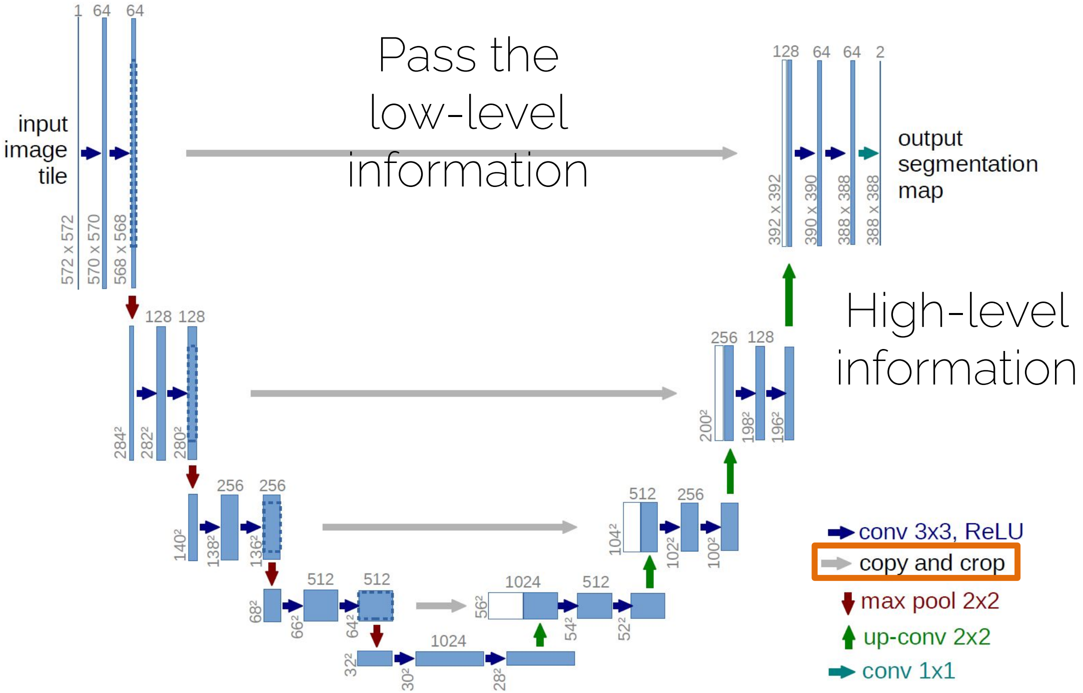
  ✅ Keep the details of the structures

Skip connections (U-Net)

Skip Connections

- U-Net

Recall ResNet



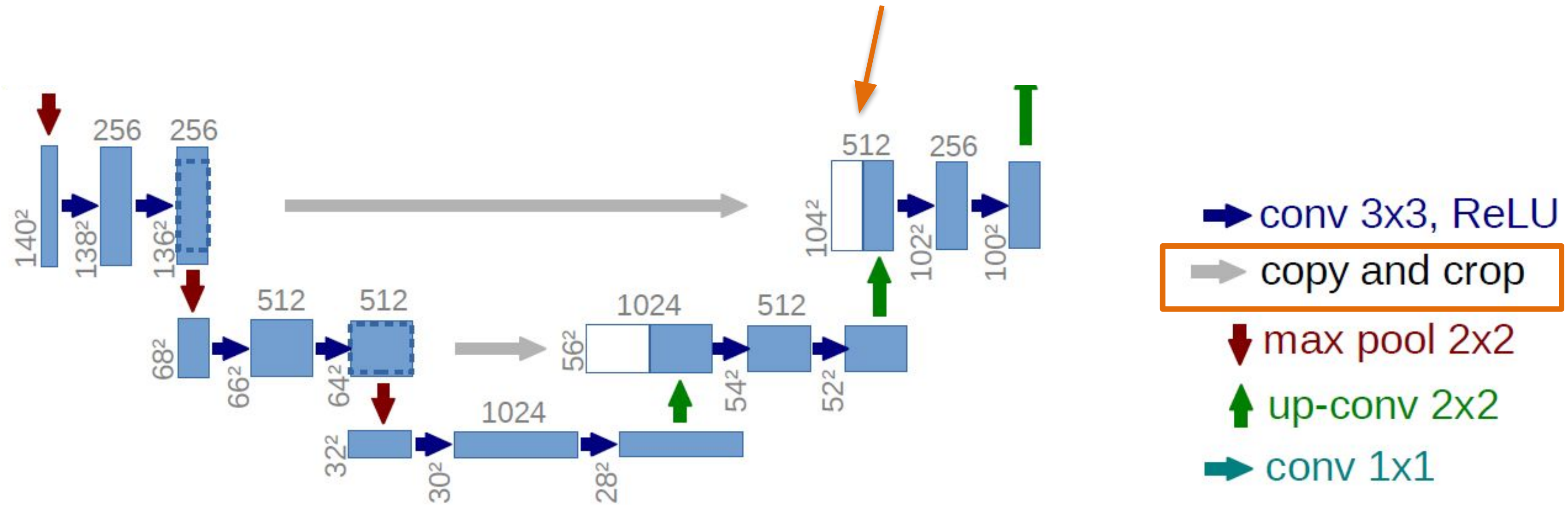
Pass the low-level information

High-level information

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

Skip Connections

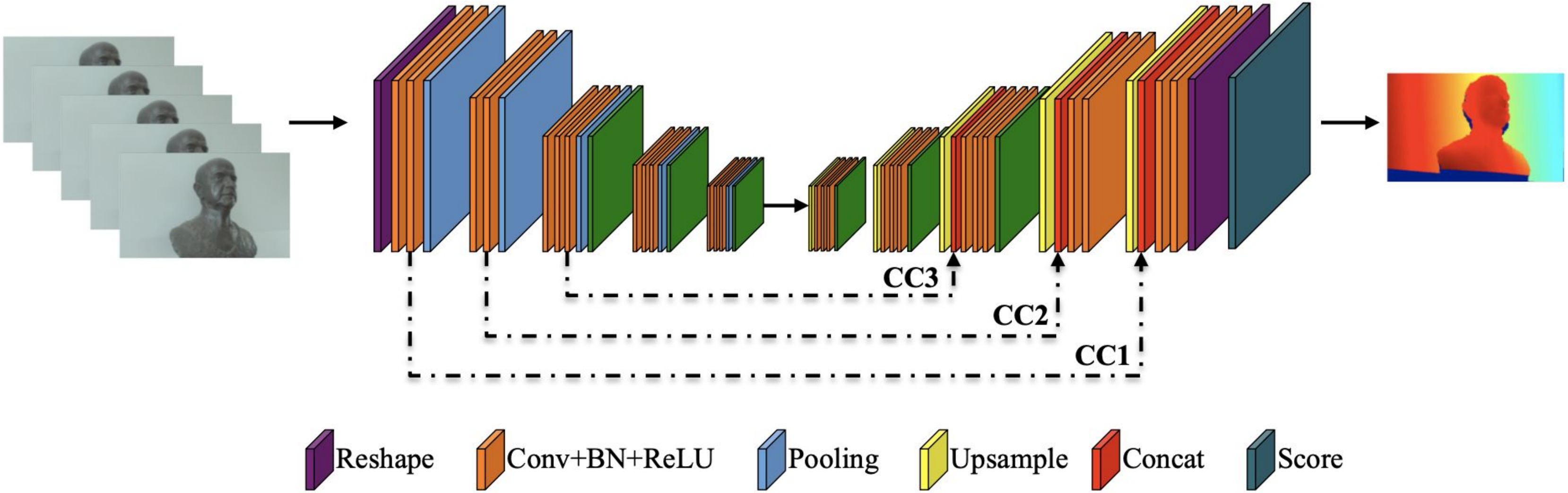
- U-Net: zoom in


append

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

Skip Connections

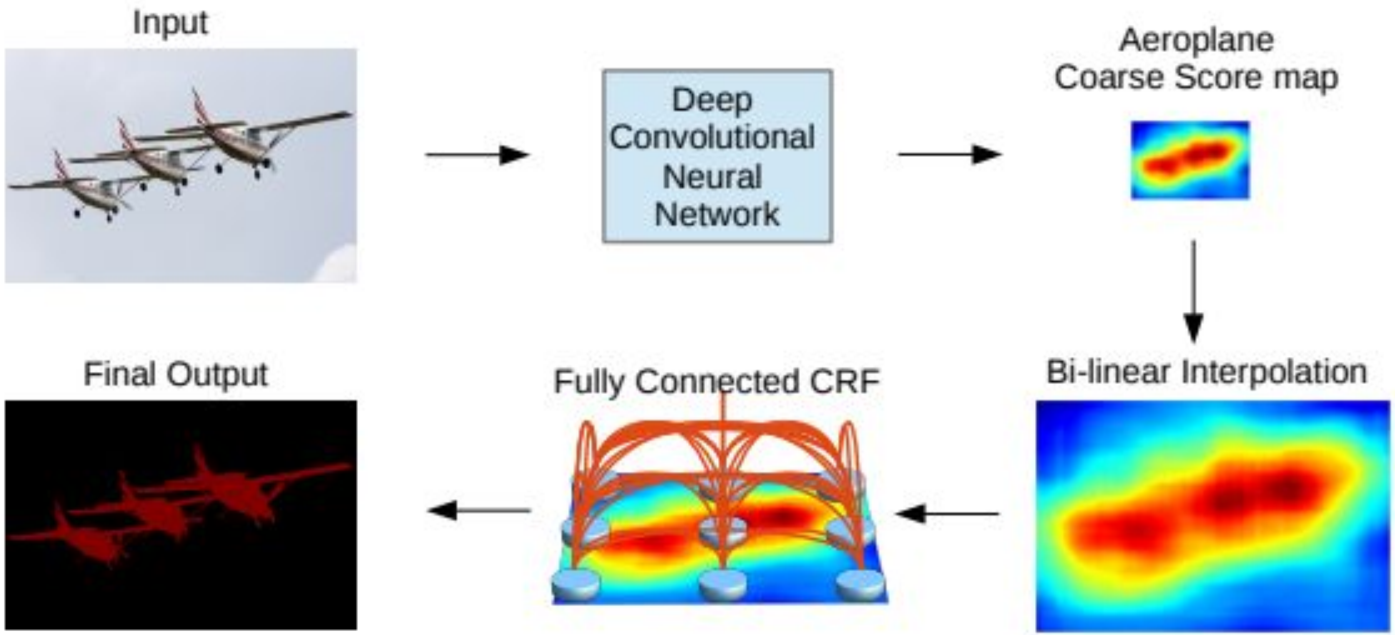
- Concatenation connections



C. Hazirbas et al. "Deep depth from focus". ACCV 2018

DeepLab

DeepLab


Input
Deep Convolutional Neural Network
Aeroplane Coarse Score map
Bi-linear Interpolation
Fully Connected CRF
Final Output

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)

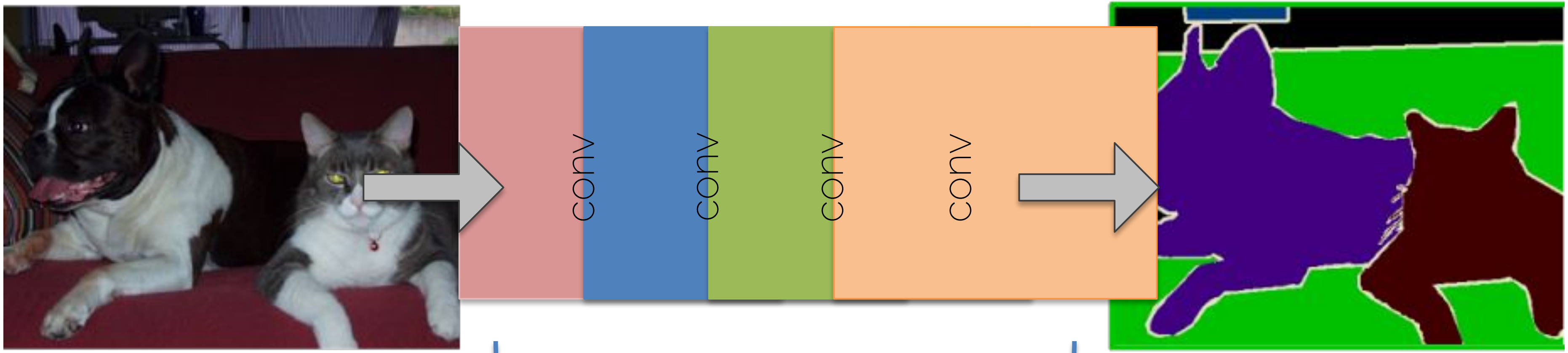
Semantic Segmentation: 3 challenges

- 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



pixels in
width x height x RGB

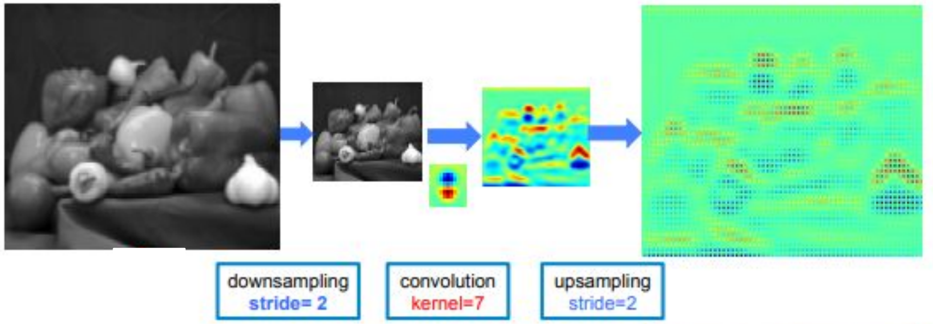
Just convs & activations

pixels out
width x height x classes

Super expensive!

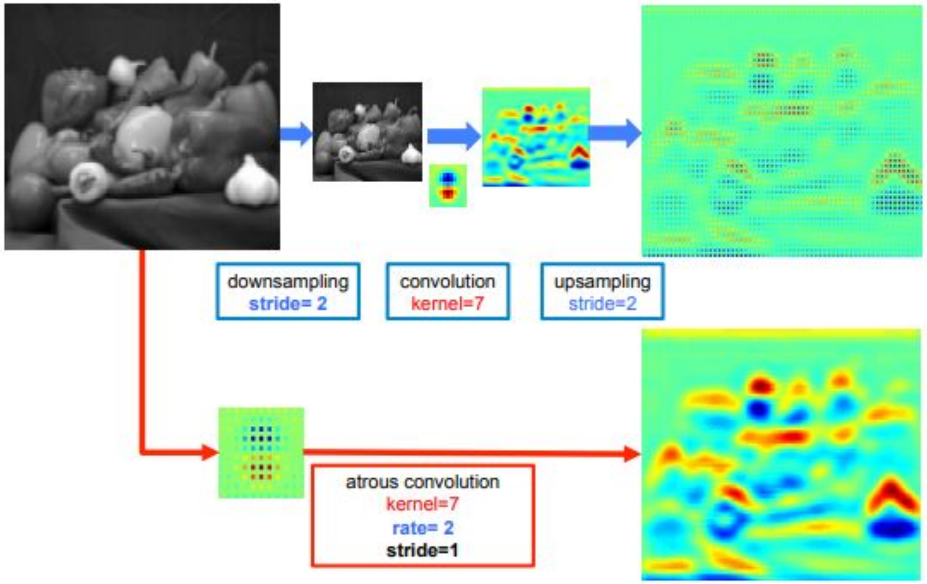
Fully Convolutional Network

Alternative: Dilated (atrous) convolutions



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

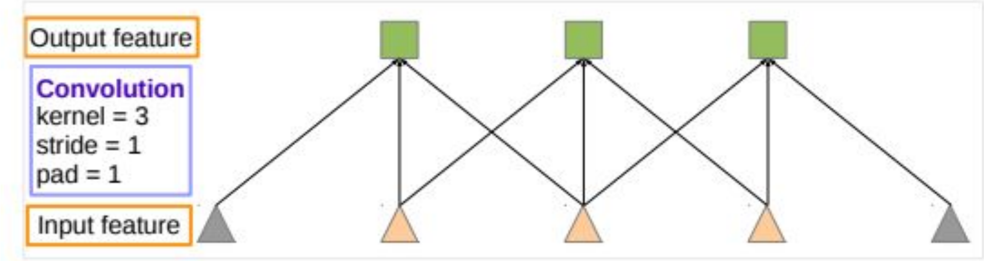
Alternative: Dilated (atrous) convolutions



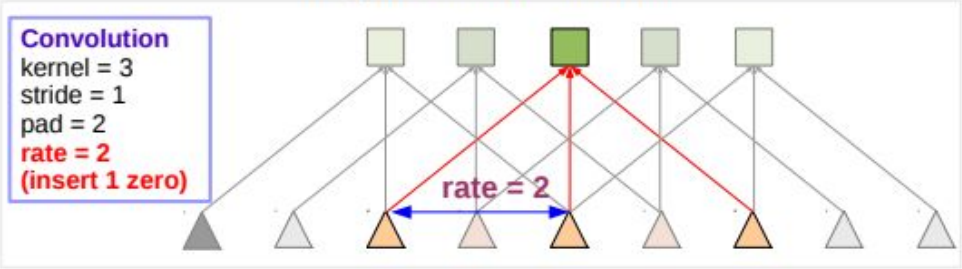
Sparse feature extraction with standard convolution on a low resolution input feature map.

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

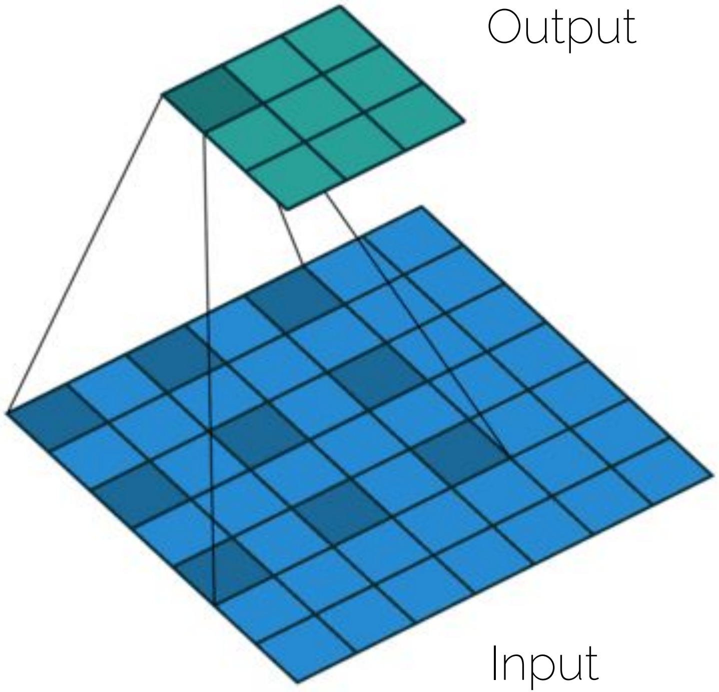


(b) Dense feature extraction

(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



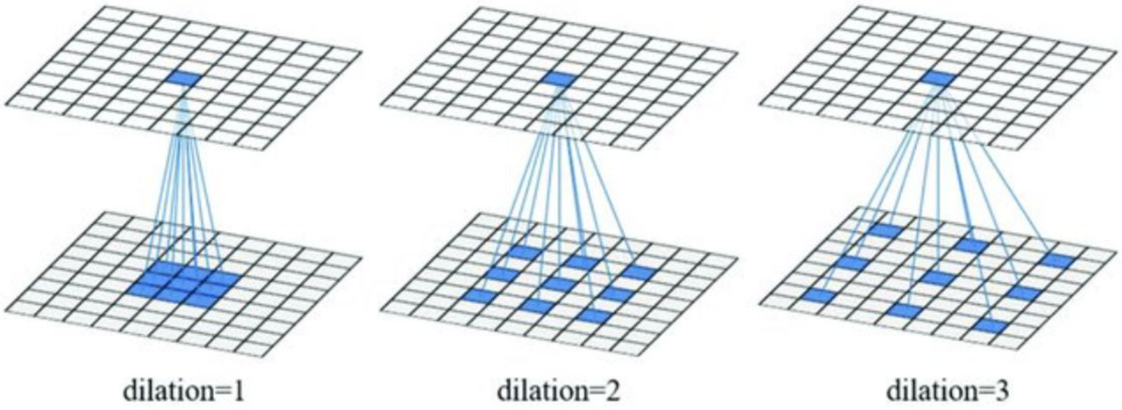
Standard convolution has dilation 1

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

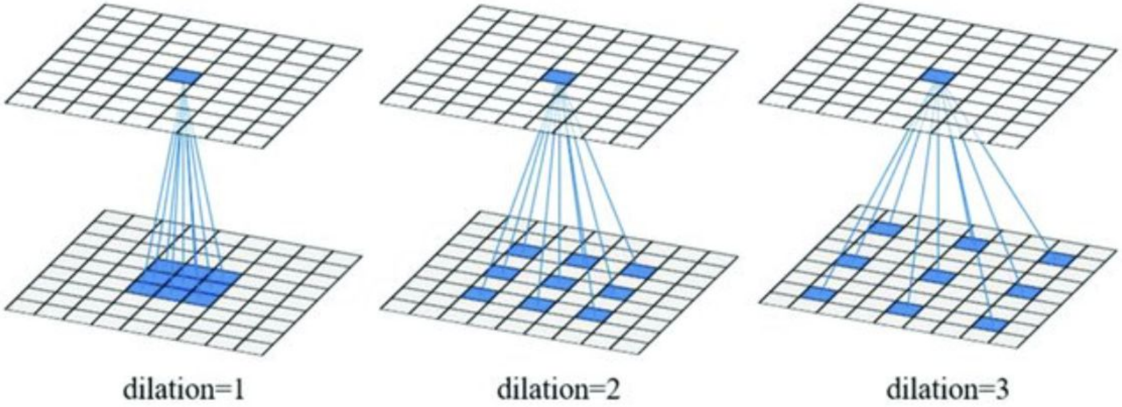


(a) the dilation parameter is 1, and each element produced by this filter has receptive field of 3x3.

(b) the dilation parameter is 2, and each element produced by it has receptive field of 5x5.

(c) the dilation parameter is 3, and each element produced by it has receptive field of 9x9.

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)

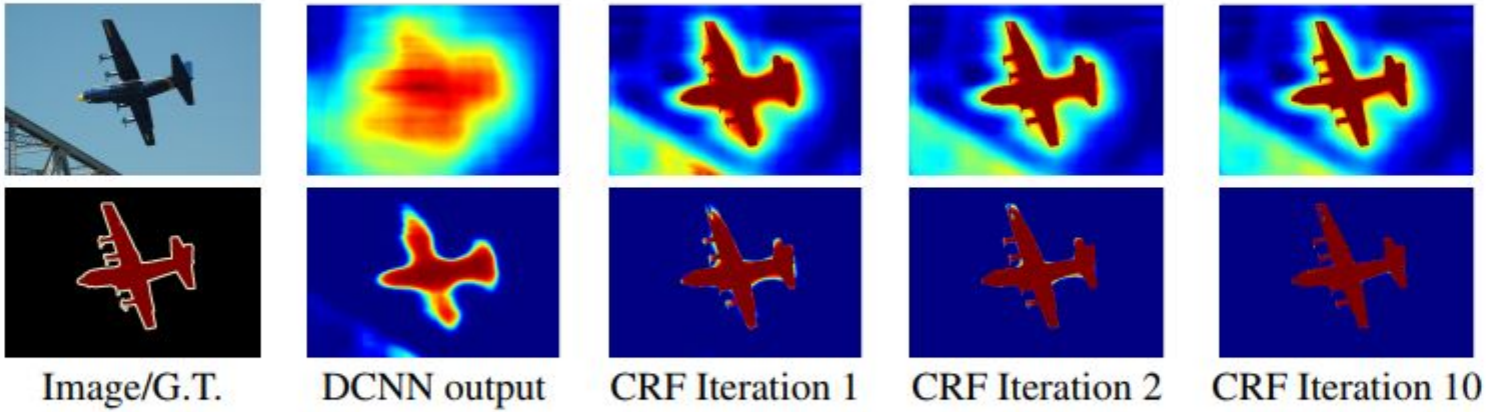
- Boykov and Jolly (2001)

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

- 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

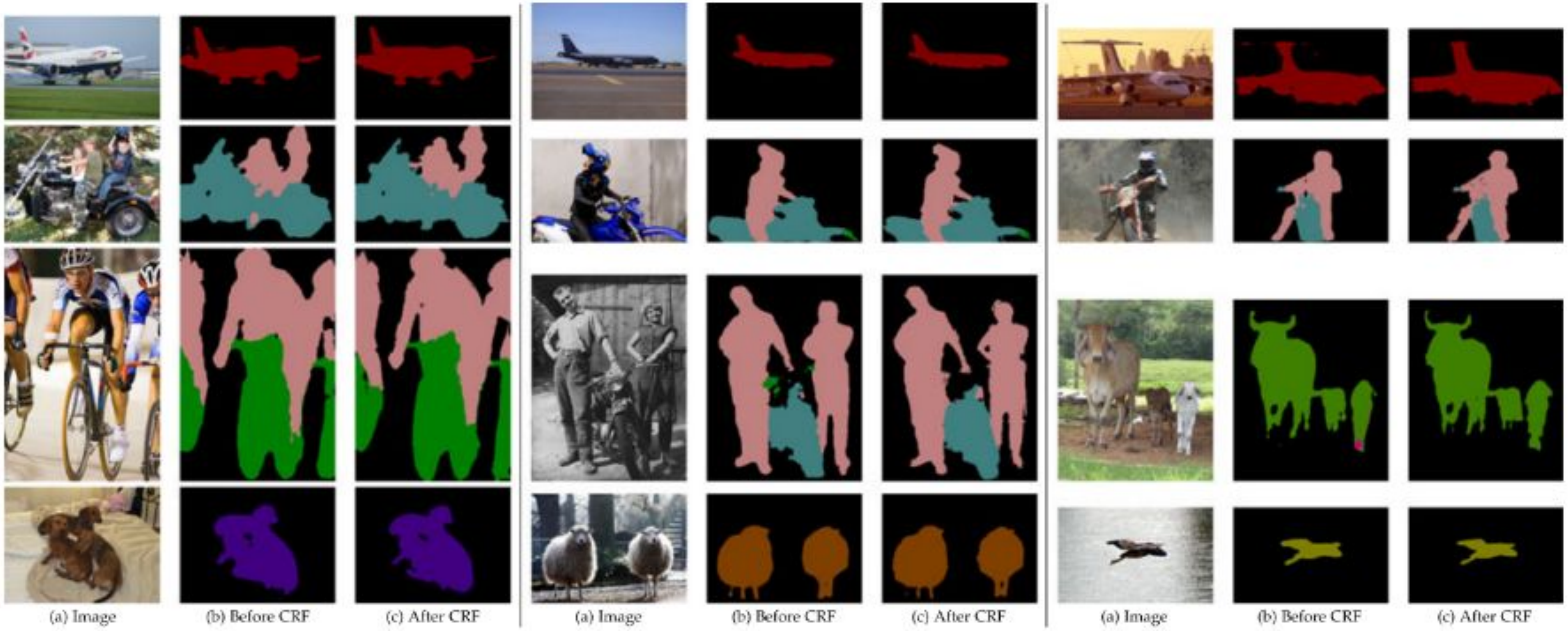
Slide Credit: Philipp Krahenbuhl

Effect of number of iterations of CRF

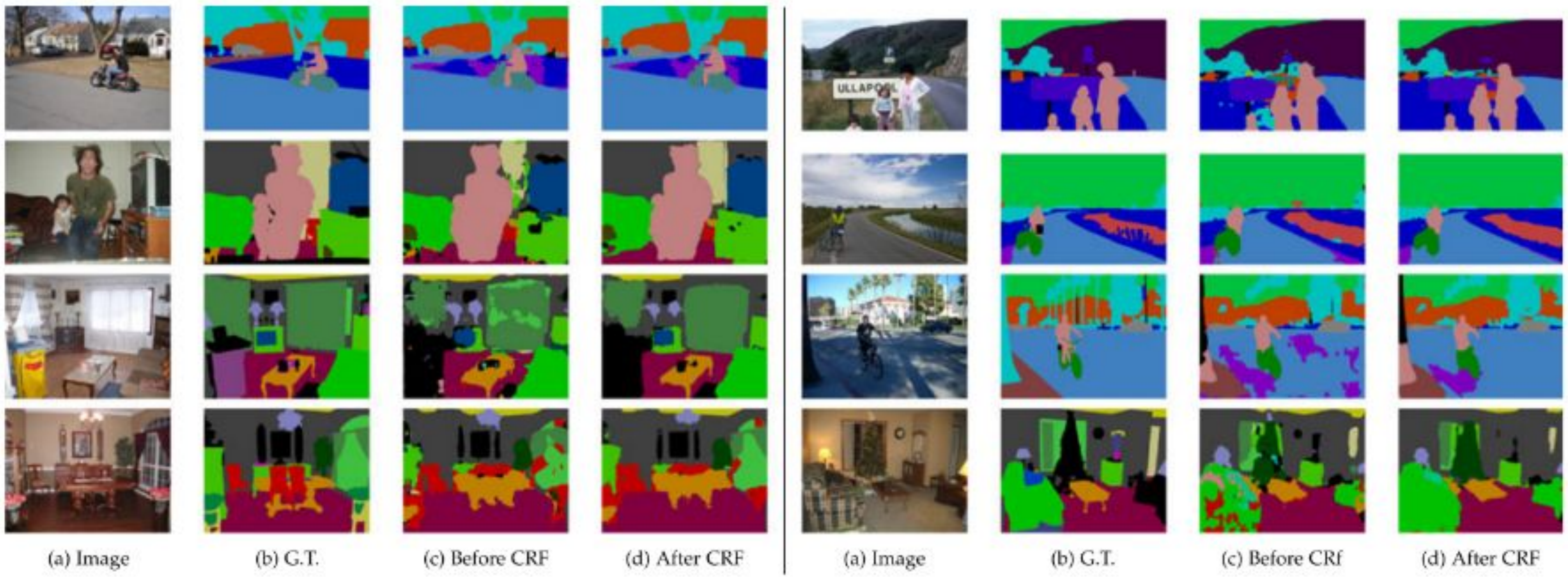


Score map (input before softmax function) and belief map (output of softmax function) for Aeroplane. The image shows the score (1st row) and belief (2nd row) maps after each mean field iteration. The output of last DCNN layer is used as input to the mean field inference.

DeepLab: qualitative results

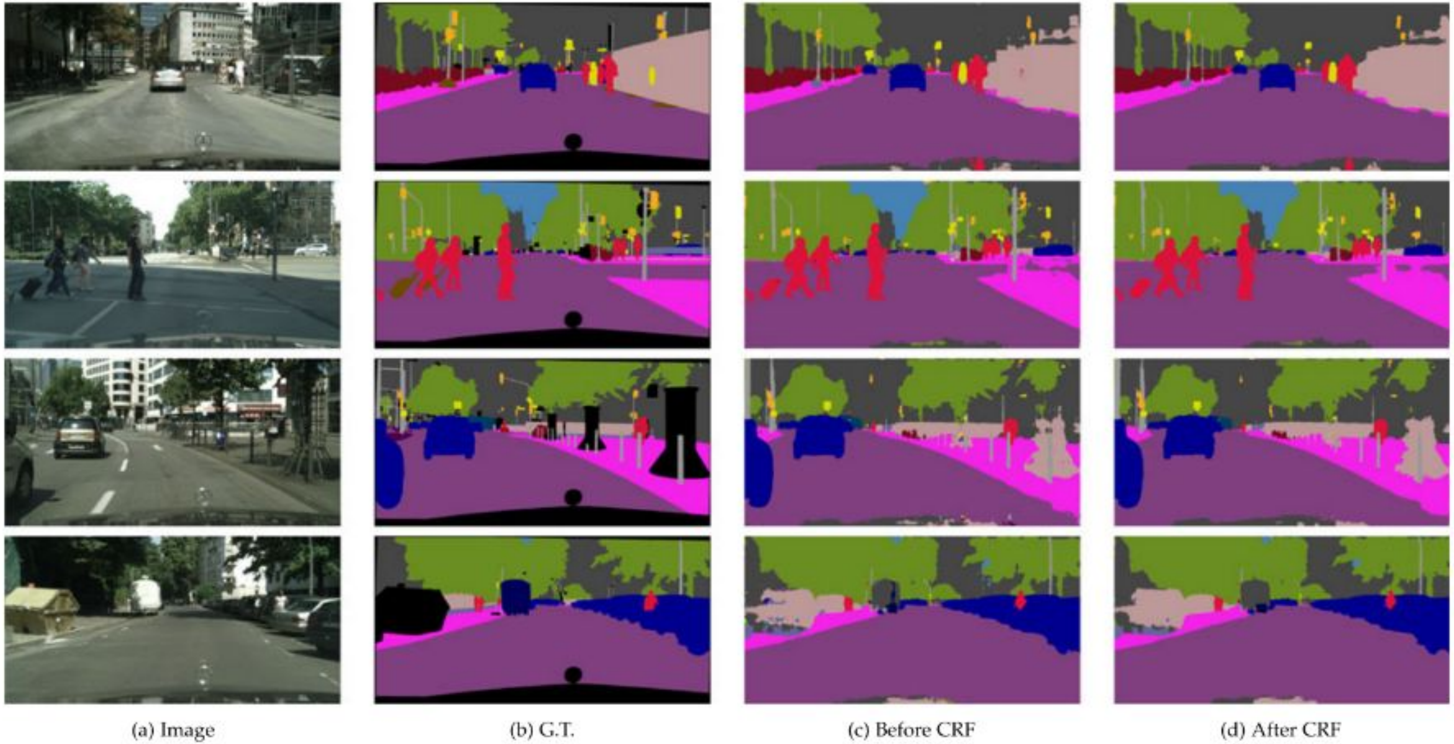


DeepLab: qualitative results



(a) Image (b) G.T. (c) Before CRF (d) After CRF (a) Image (b) G.T. (c) Before CRf (d) After CRF

DeepLab: qualitative results



(a) Image

(b) G.T.

(c) Before CRF

(d) After CRF

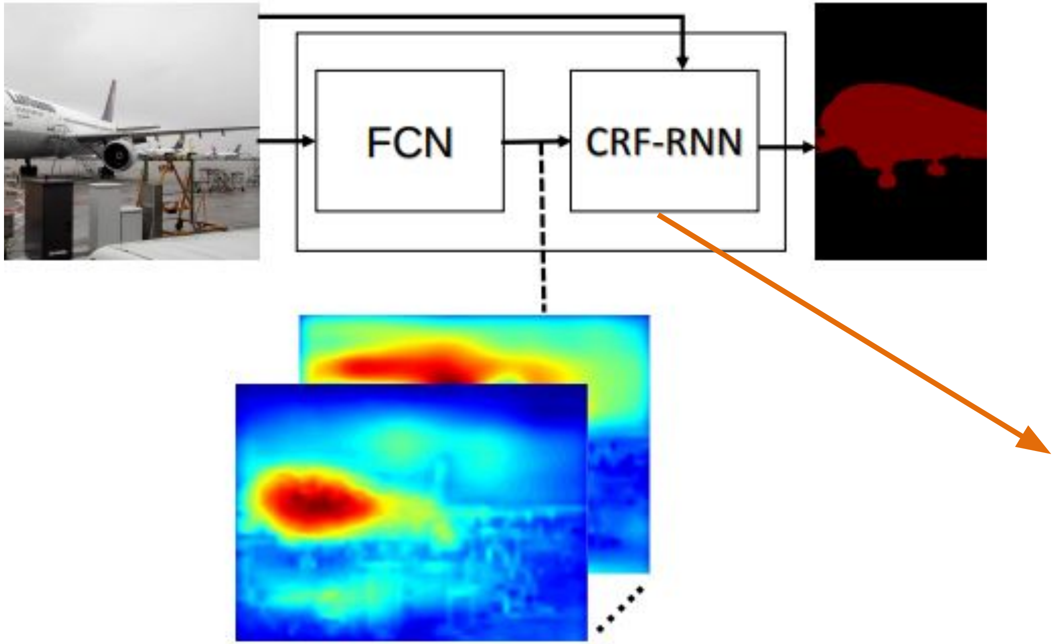
Problems with CRF

- 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 suboptiomal.

Solution: Formulate CRF as an Recurrent Neural Network

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

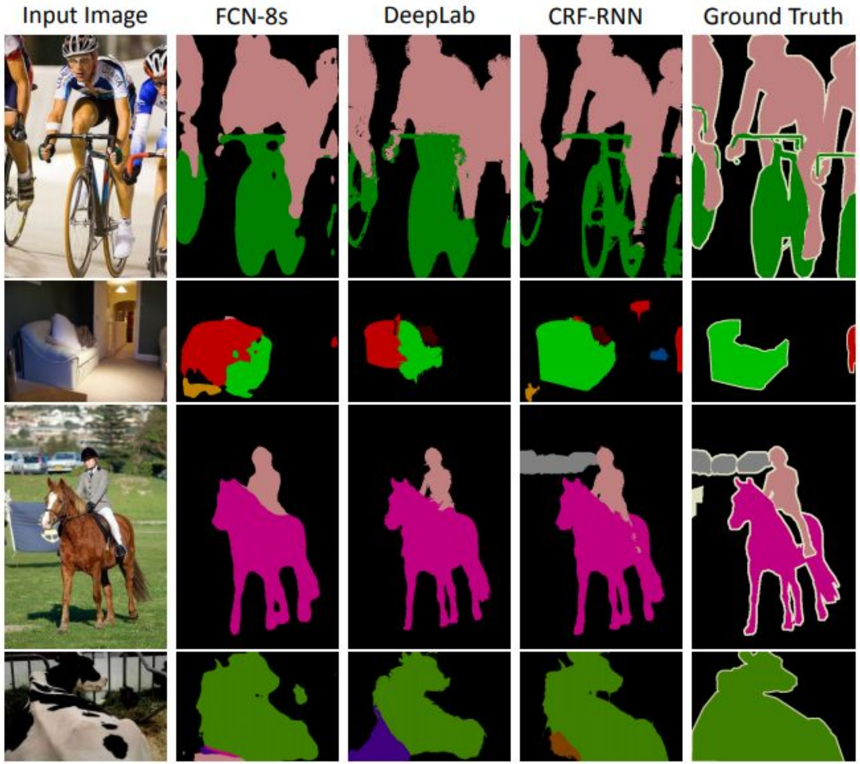
Replacing CRF with an RNN



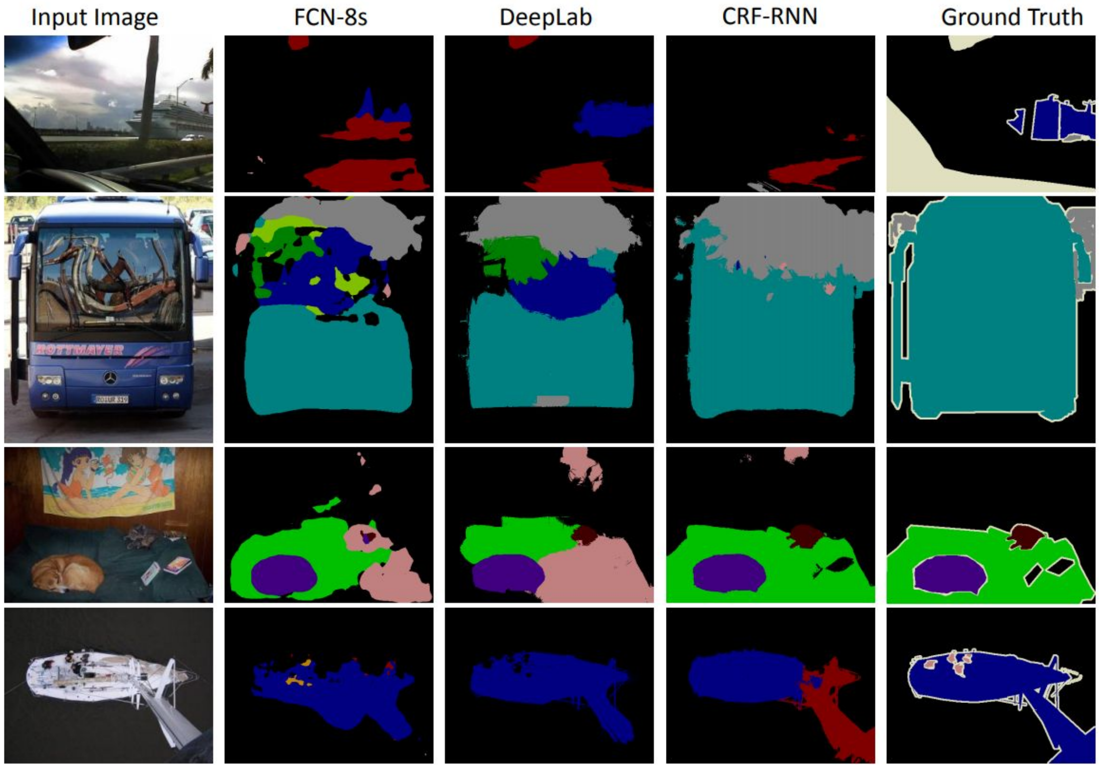
RNN that "emulates" a CRF

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

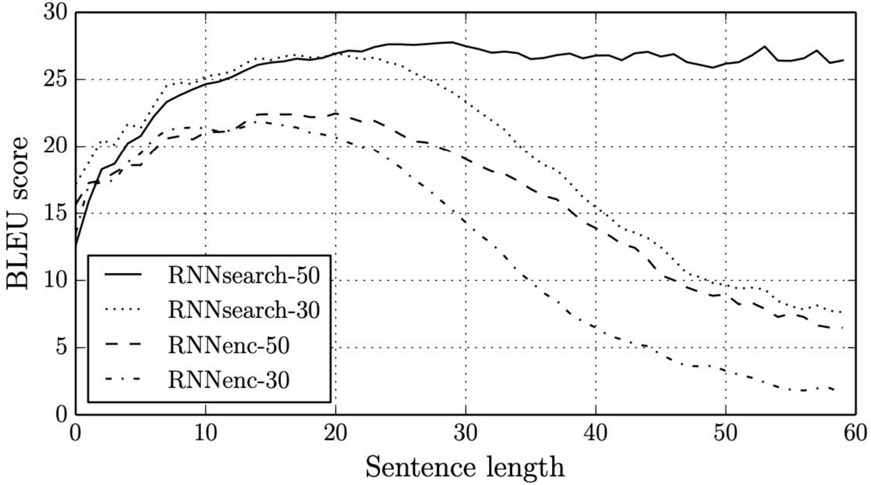
- We need to process information at the original (image) resolution for this. We need to look at the pixels. CRF is conditioned on the RGB image.

- What if we use attention?

Attention

The problem

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



With attention

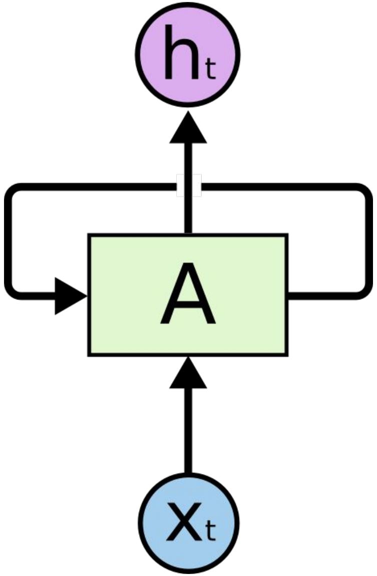
Performance degradation

Bahdanau et al 2014. Neural machine translation by jointly learning to align and translate.

Basic structure of a RNN

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

Hidden state



$$\mathbf{A}_t = \boldsymbol{\theta}_c \mathbf{A}_{t-1} + \boldsymbol{\theta}_x \mathbf{x}_t$$

Previous hidden state

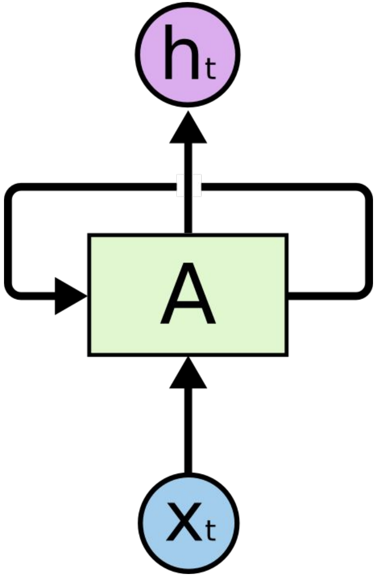
input

Image: Christopher Olah - Understanding LSTMs

Basic structure of a RNN

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

Hidden state

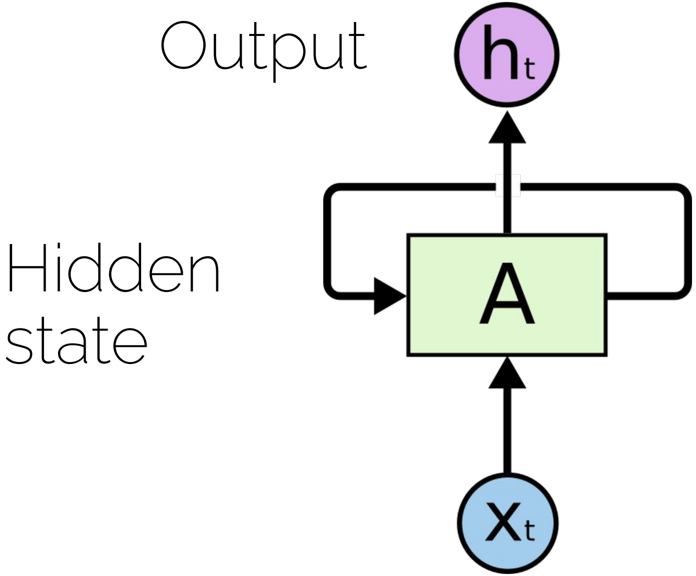


$$\mathbf{A}_t = \theta_c \mathbf{A}_{t-1} + \theta_x \mathbf{x}_t$$

Parameters to be learned

Basic structure of a RNN

- We want to have notion of “time” or “sequence”



$$A_t = \theta_c A_{t-1} + \theta_x x_t$$

$$h_t = \theta_h A_t$$

Same parameters for each time step = generalization!

Basic structure of a RNN

- Unrolling RNNs

Hidden layer is the same

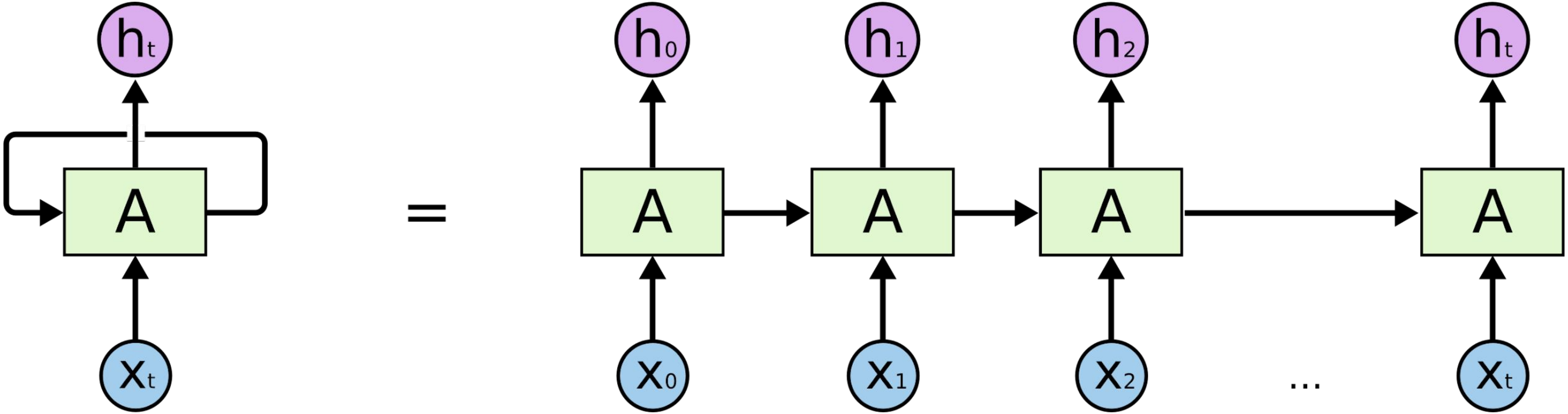
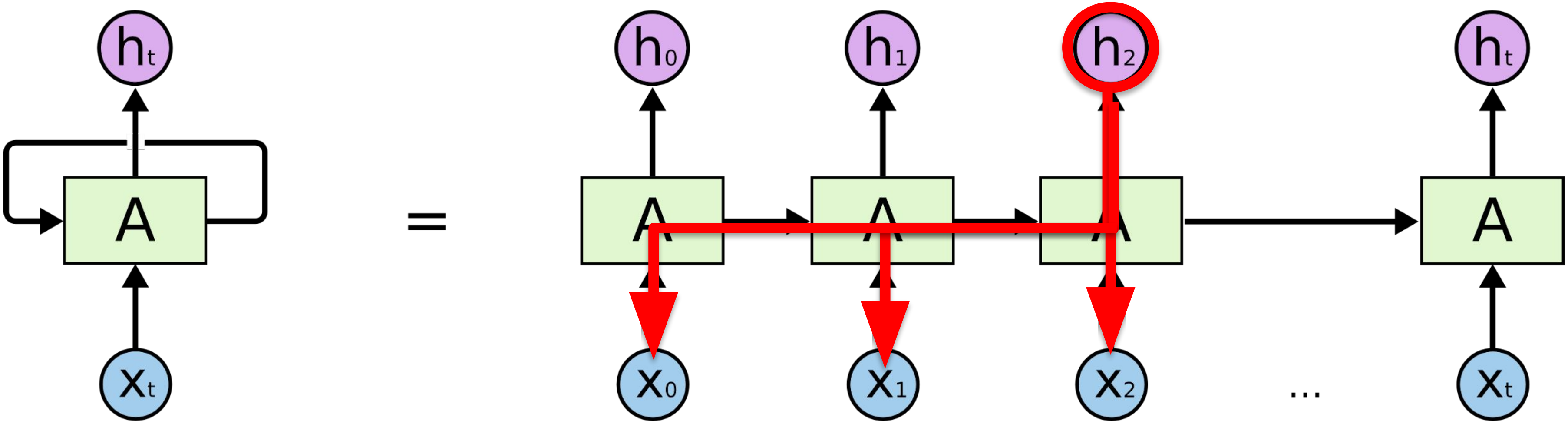


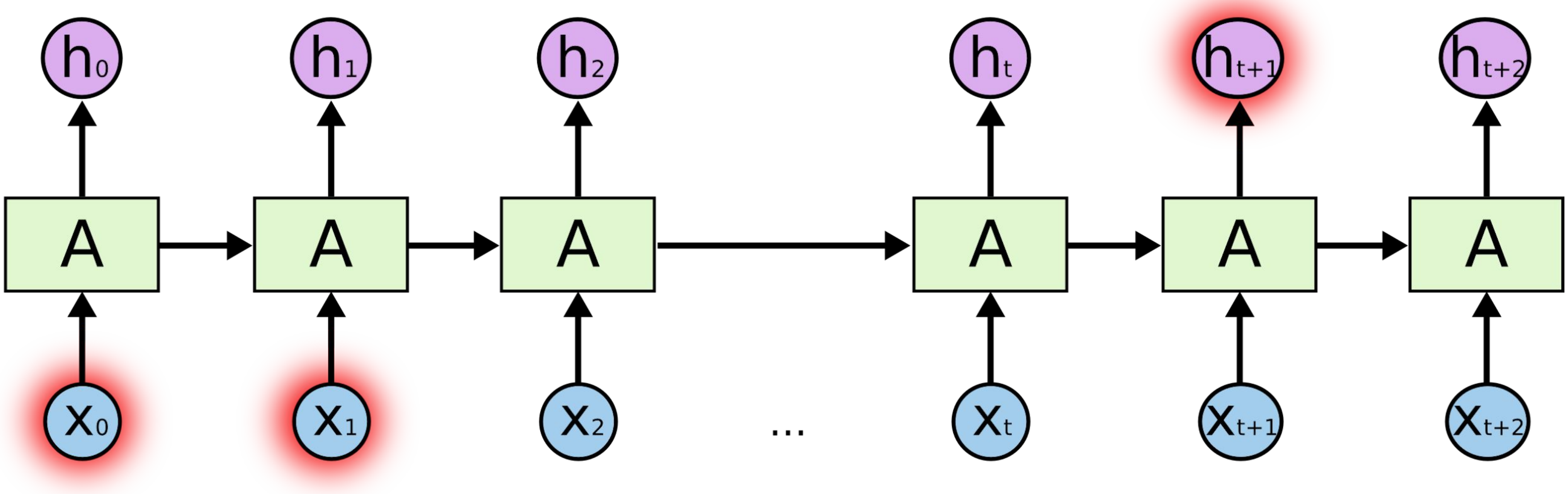
Image: Christopher Olah - Understanding LSTMs

Basic structure of a RNN

- Unrolling RNNs

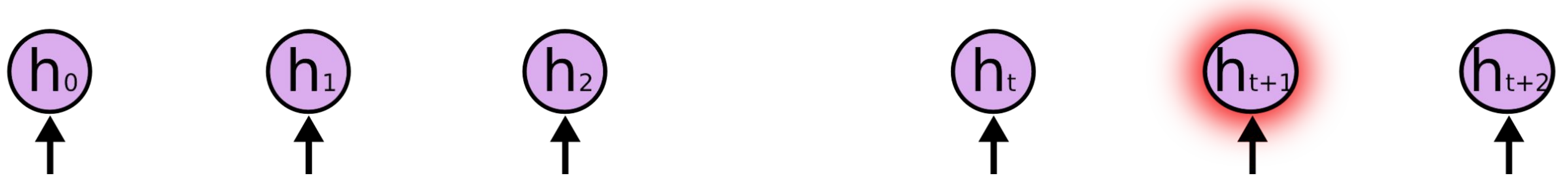


Long-term dependencies

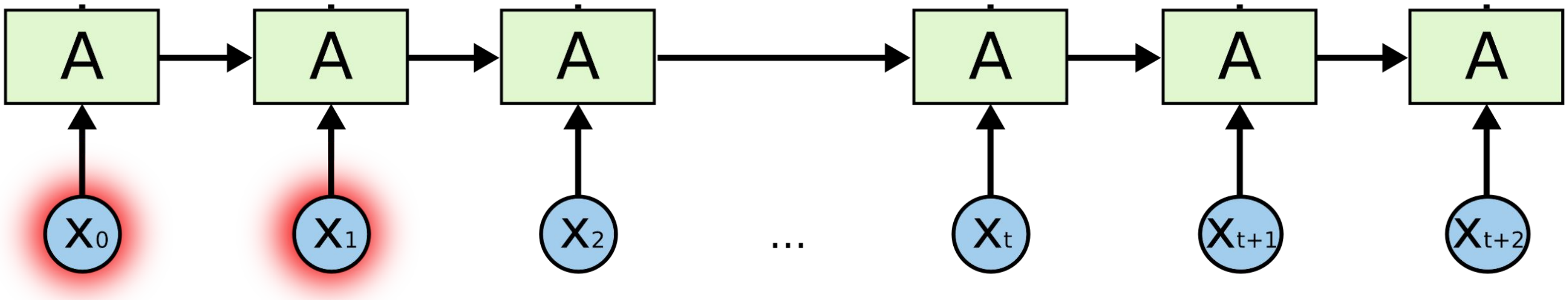


I moved to Germany … so I speak German fluently

Attention: intuition

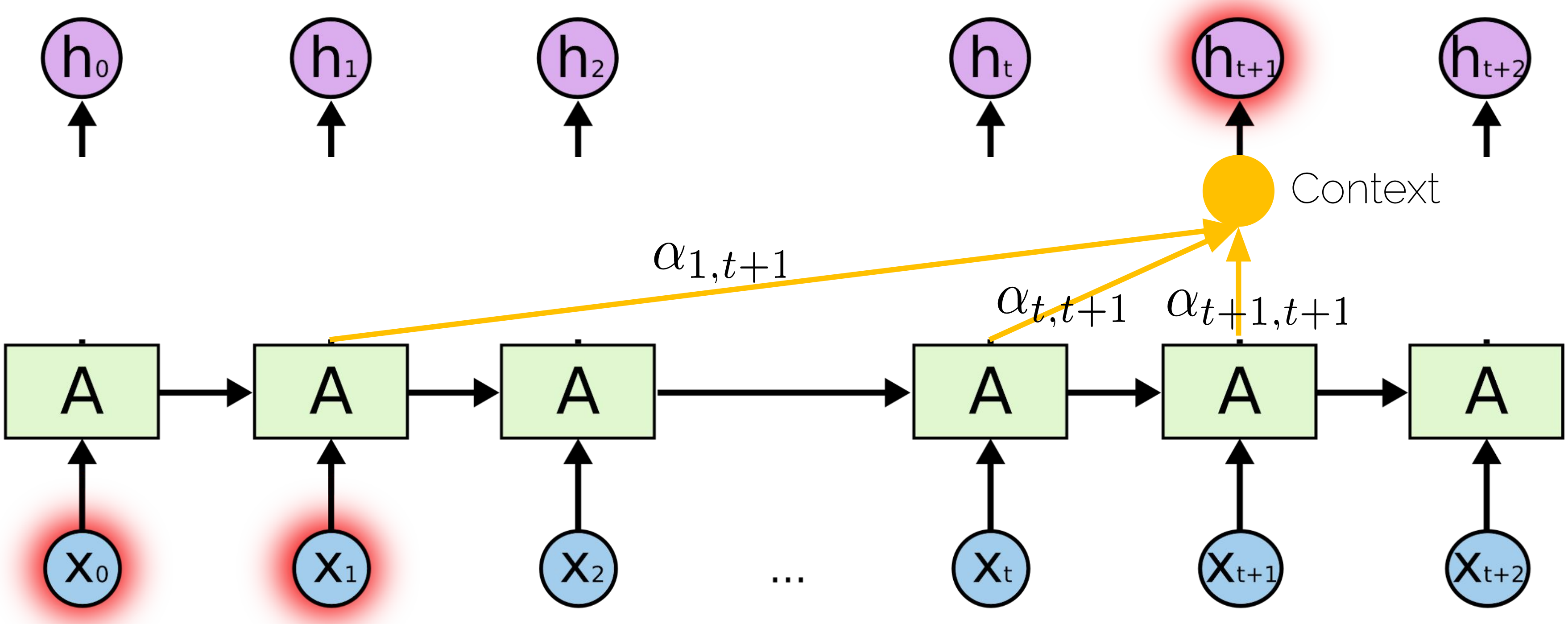


ATTENTION: Which hidden states are more important to predict my output?



I moved to Germany … so I speak German fluently

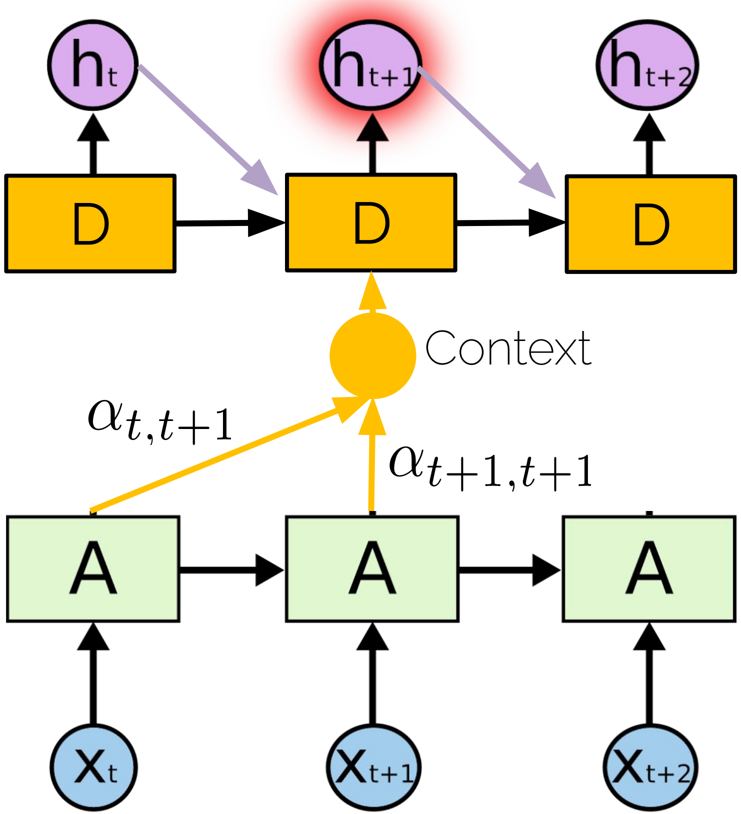
Attention: intuition



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 $t+1$

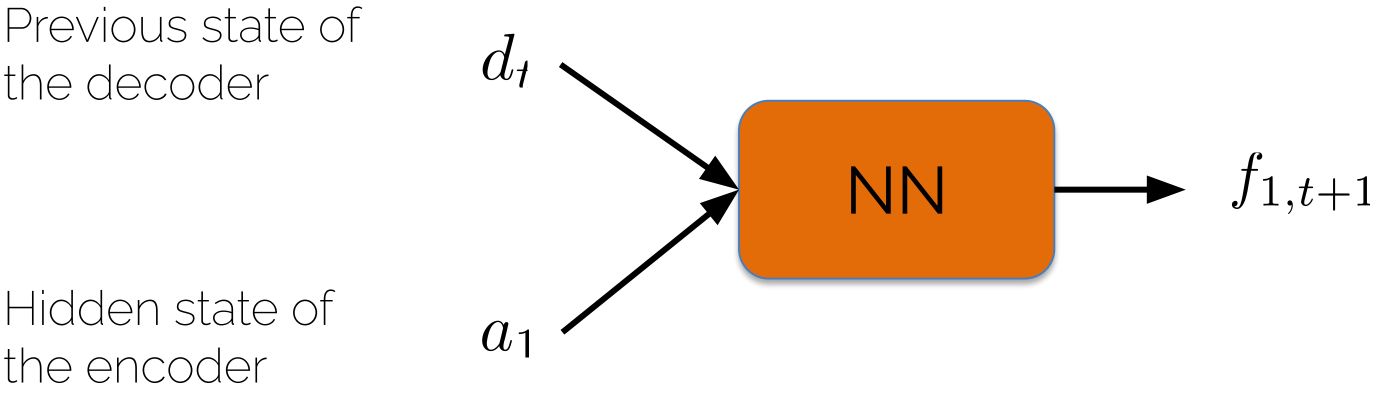
- The context aggregates the attention

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

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

Computing the attention mask

- We can train a small neural network

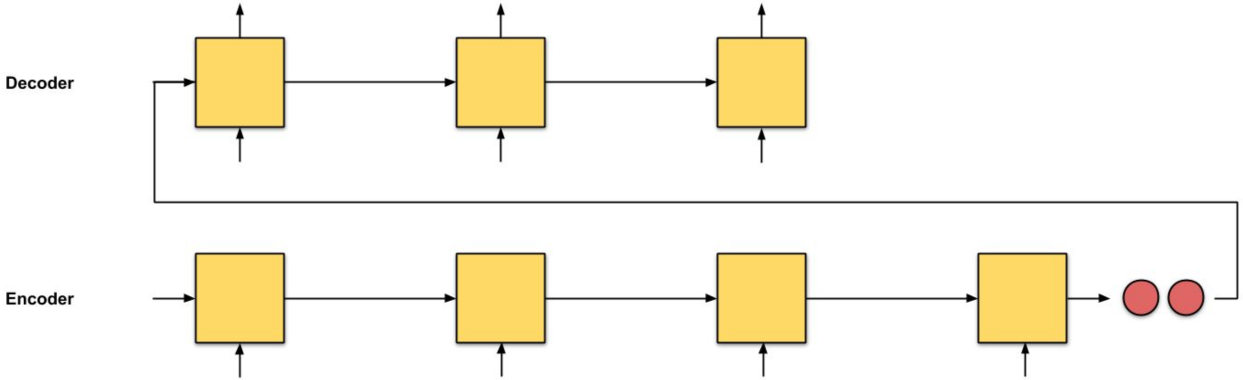


- Normalize

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

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

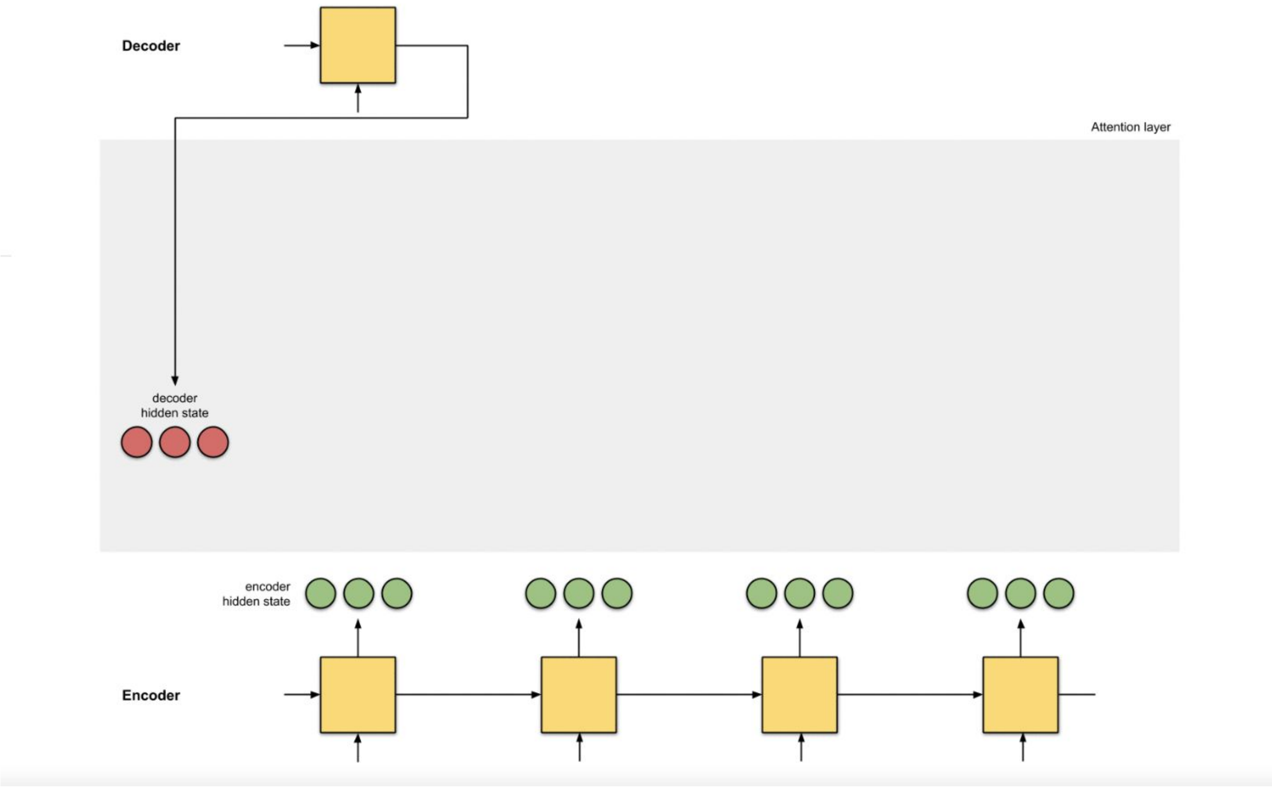
Seq2Seq + Attention?

- 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.

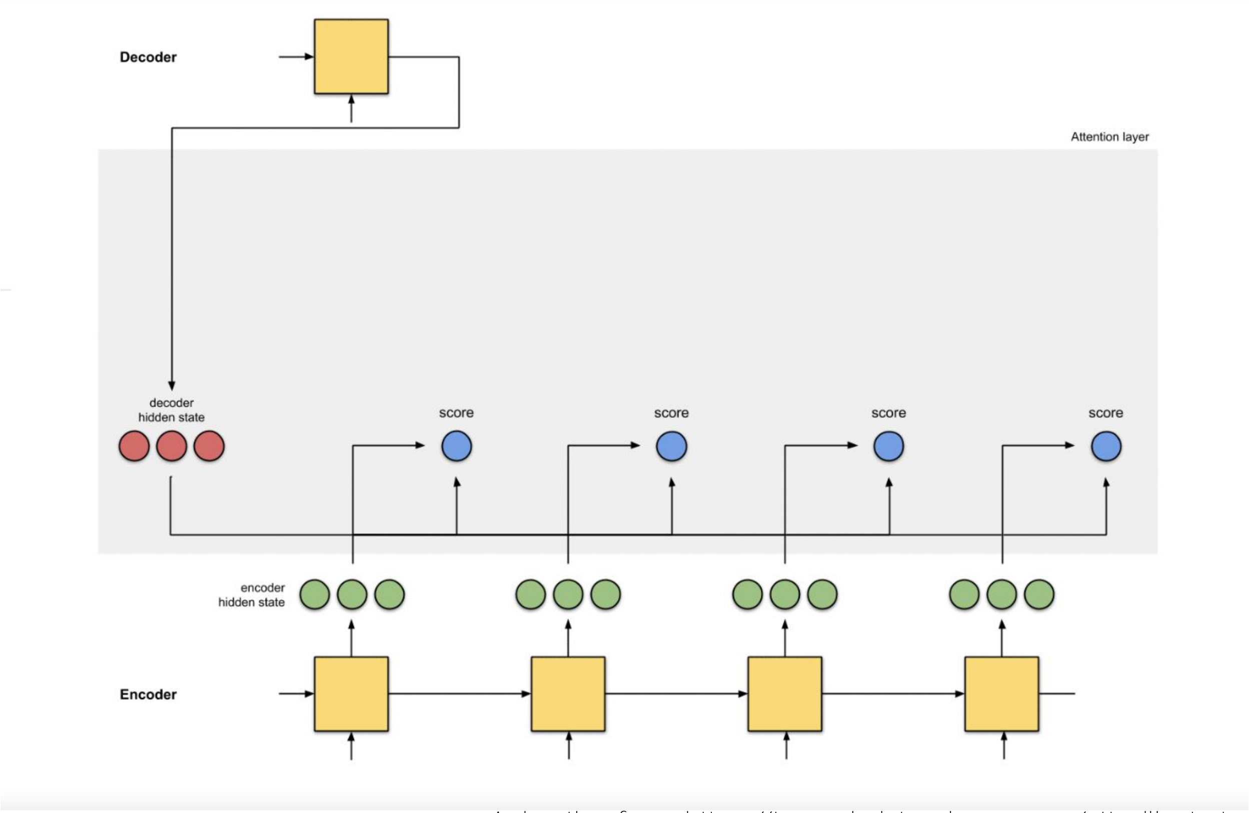
- Use attention!

Seq2Seq + Attention



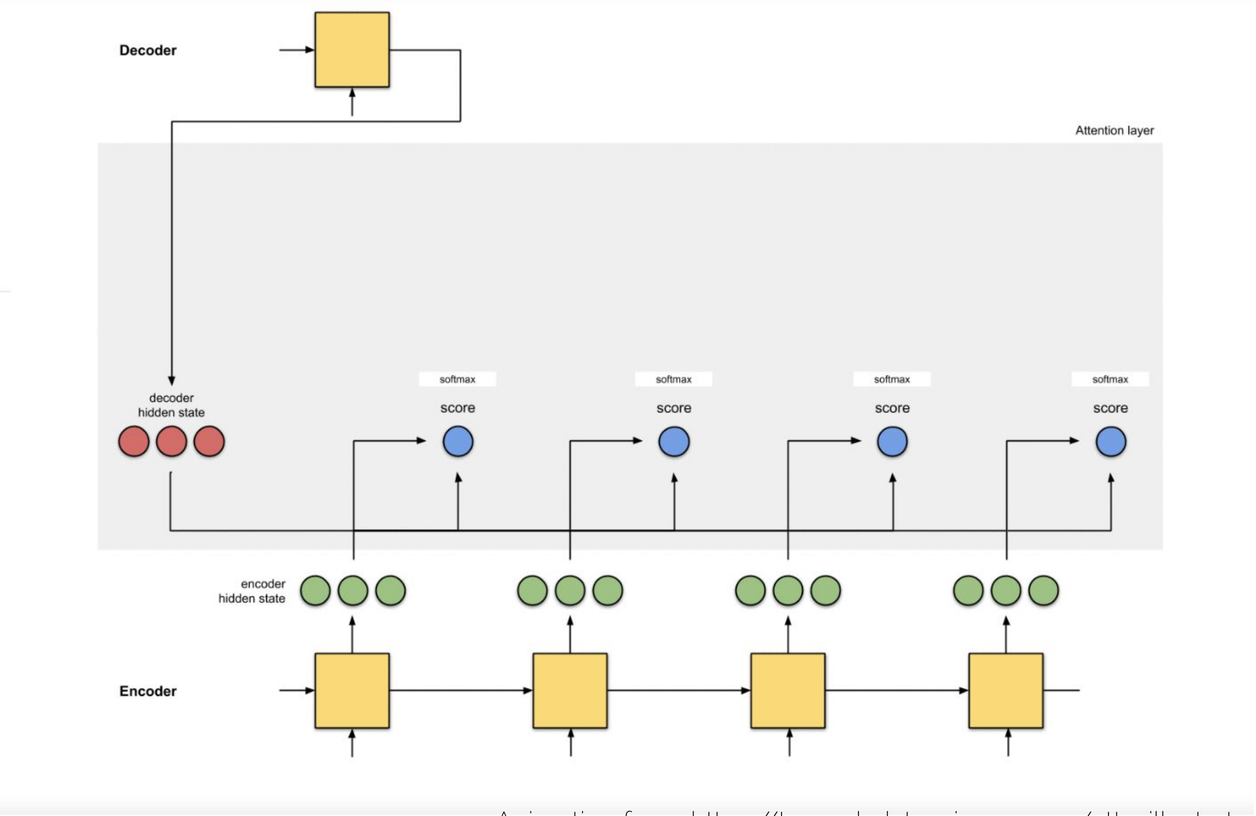
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



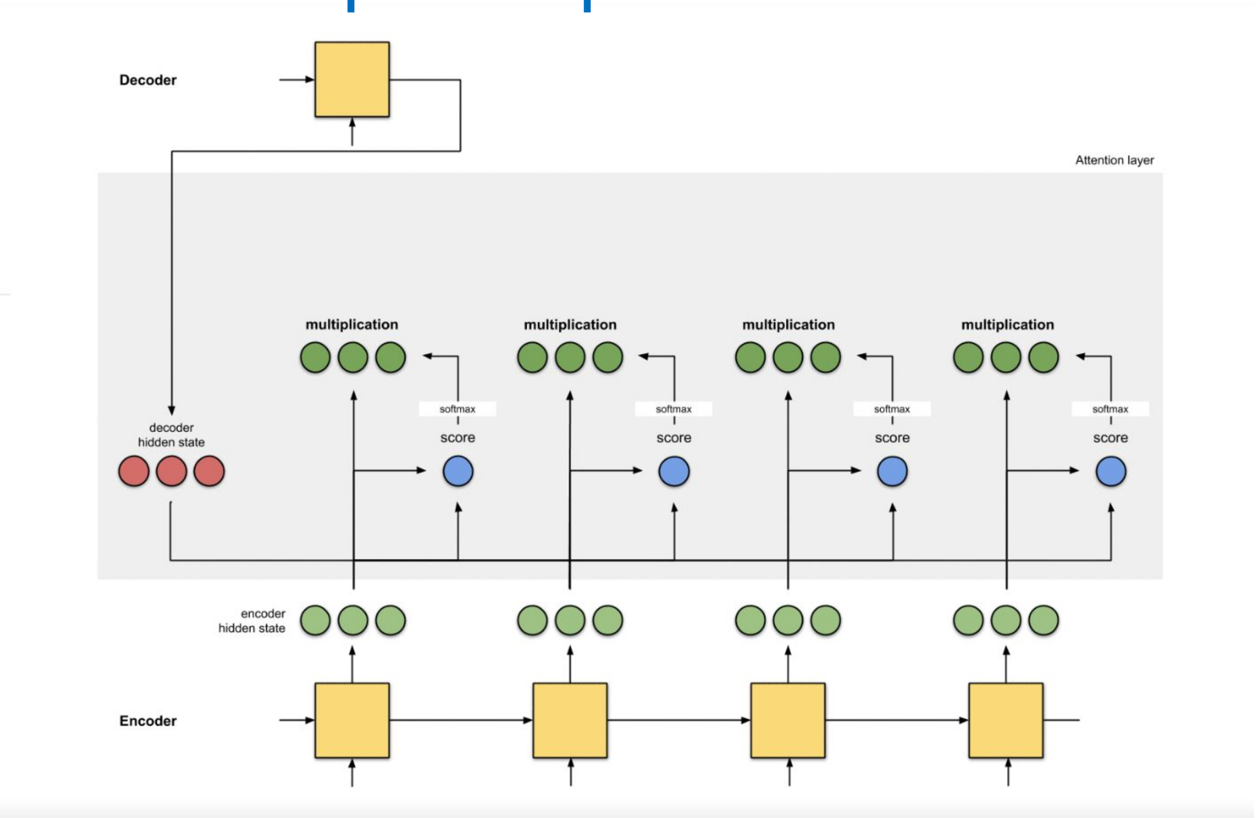
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



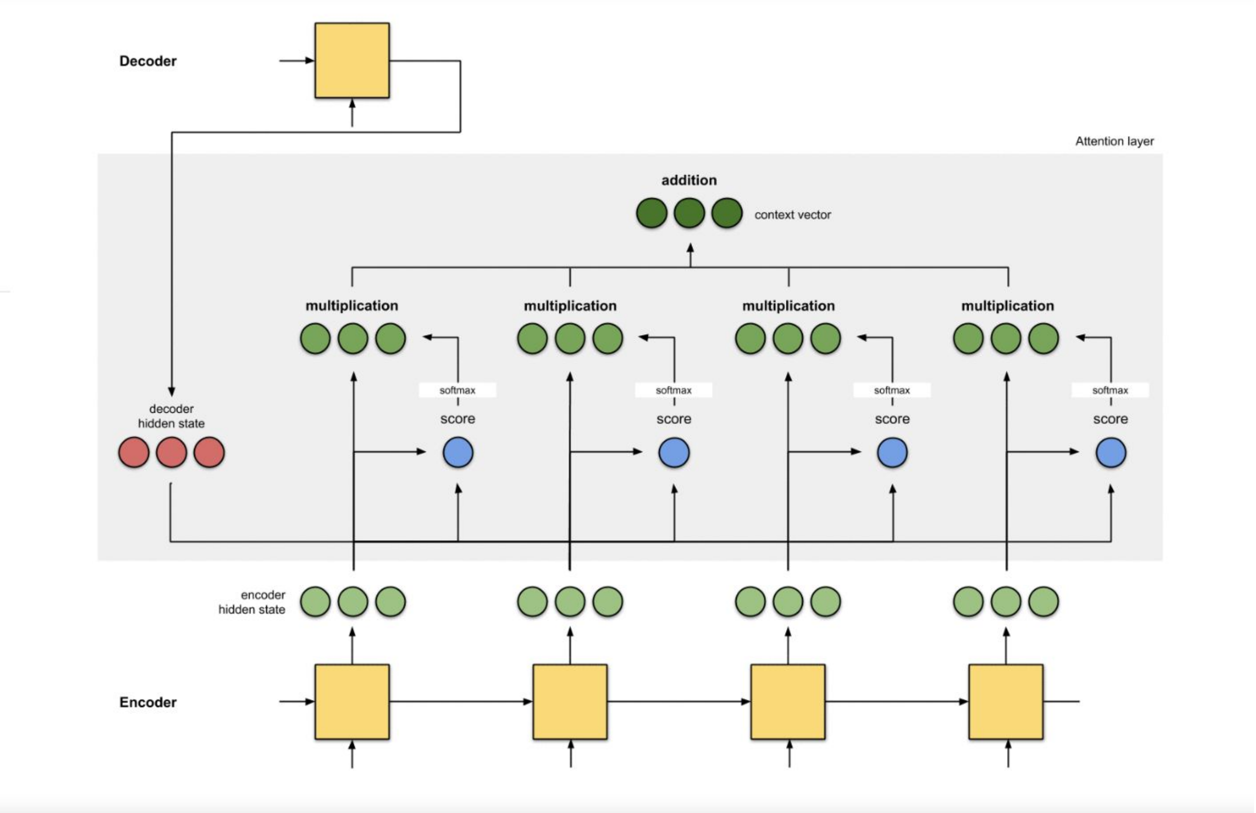
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

Seq2Seq + Attention



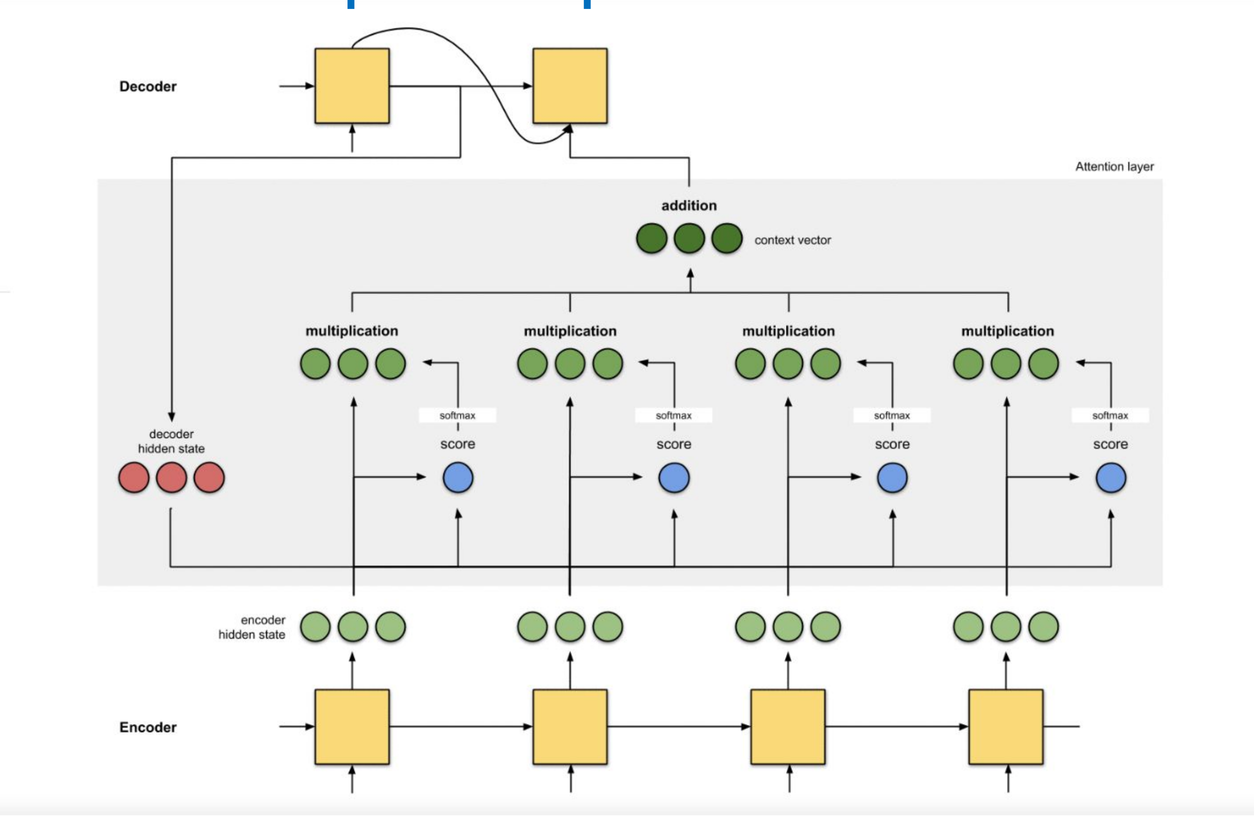
Animation from: https://towardsdatascience.com/attn-illustrated-attention-5ec4ad276ee3

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 everywhere!

A. Vaswani et al. „Attention is all you need". NeurIPS 2017

Transformers

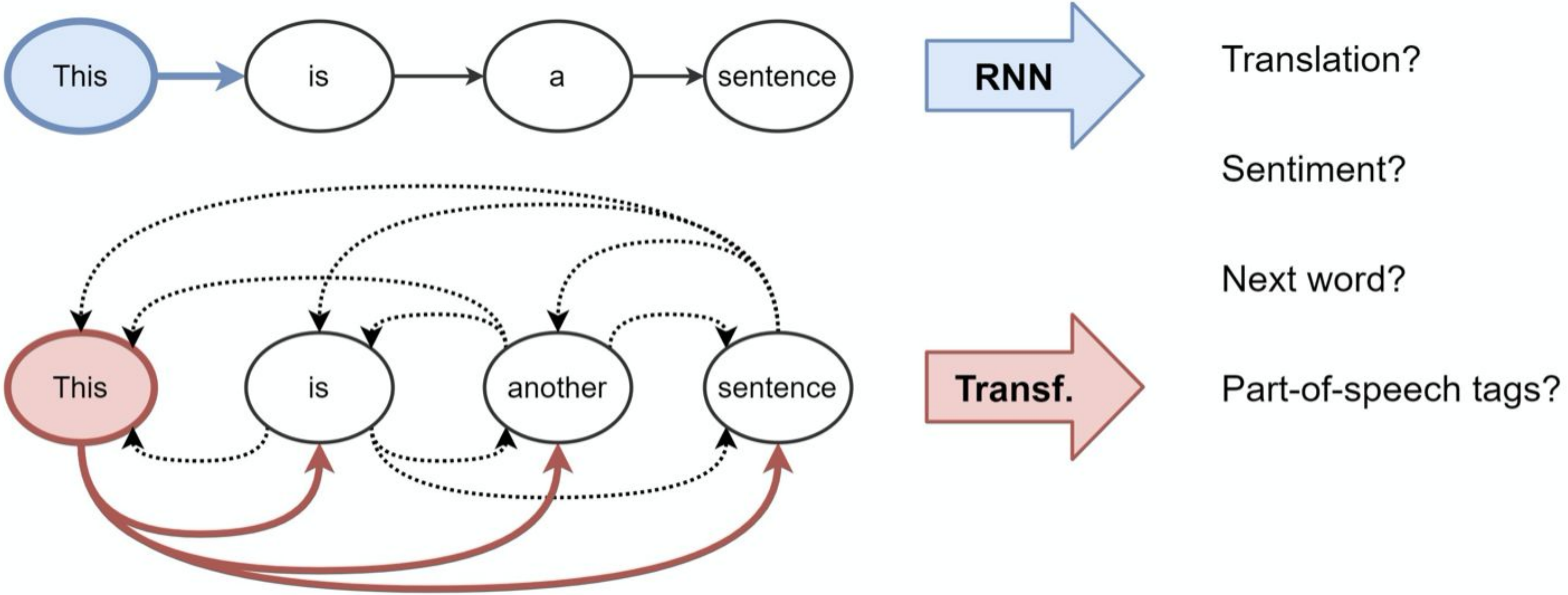
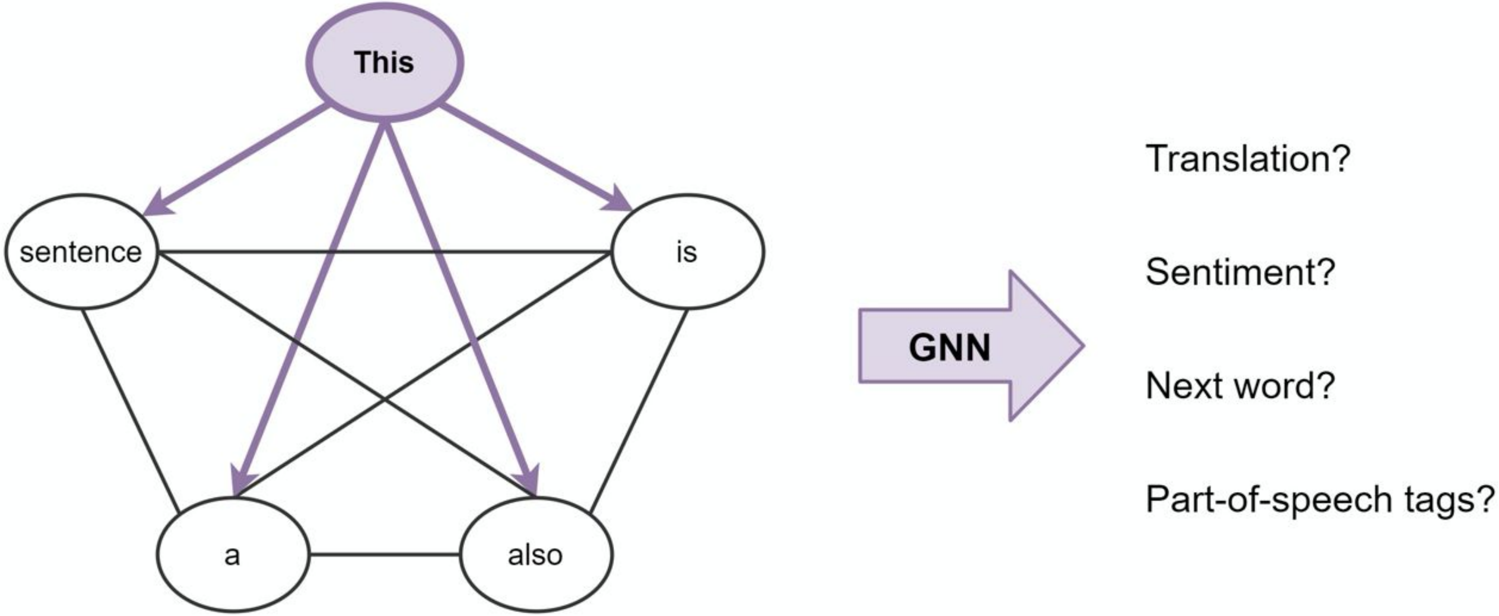


Image: https://graphdeeplearning.github.io/post/transformers-are-gnns/

Transformers

- Wait, what does this remind you of?



Translation?

Sentiment?

Next word?

Part-of-speech tags?

Image: https://graphdeeplearning.github.io/post/transformers-are-gnns/

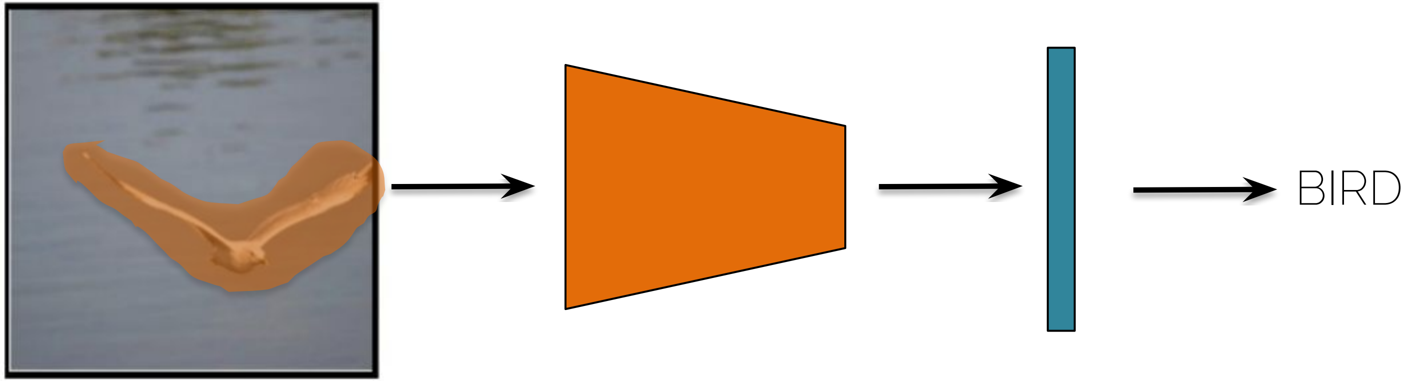
Transformers

- 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

Image: https://graphdeeplearning.github.io/post/transformers-are-gnns/

Why do we need attention?

- We use the whole image to make the classification

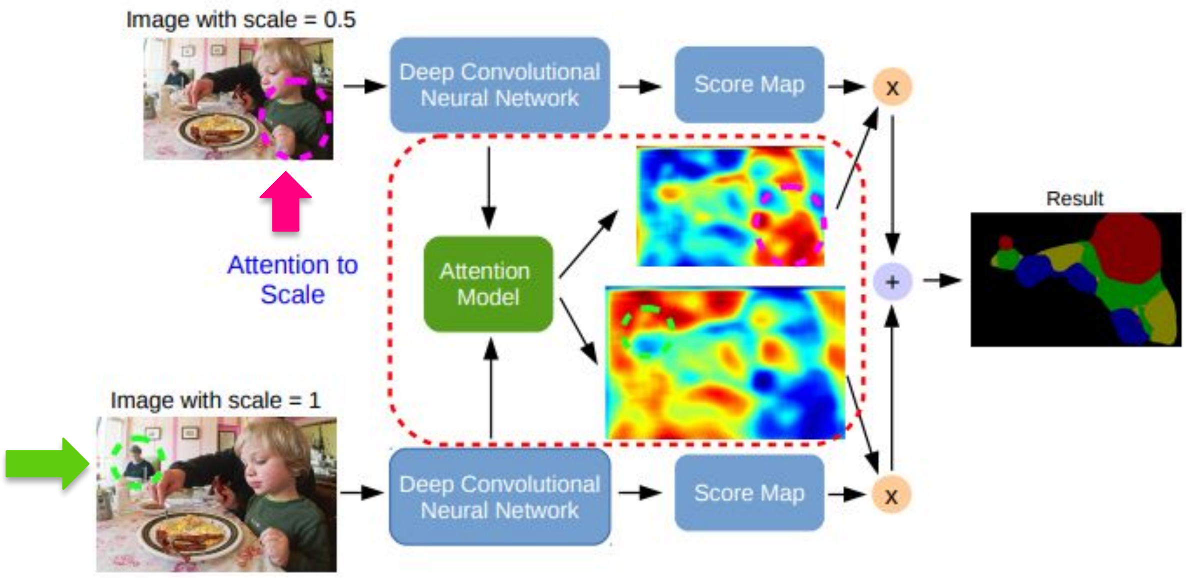


- Are all pixels equally important?

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.

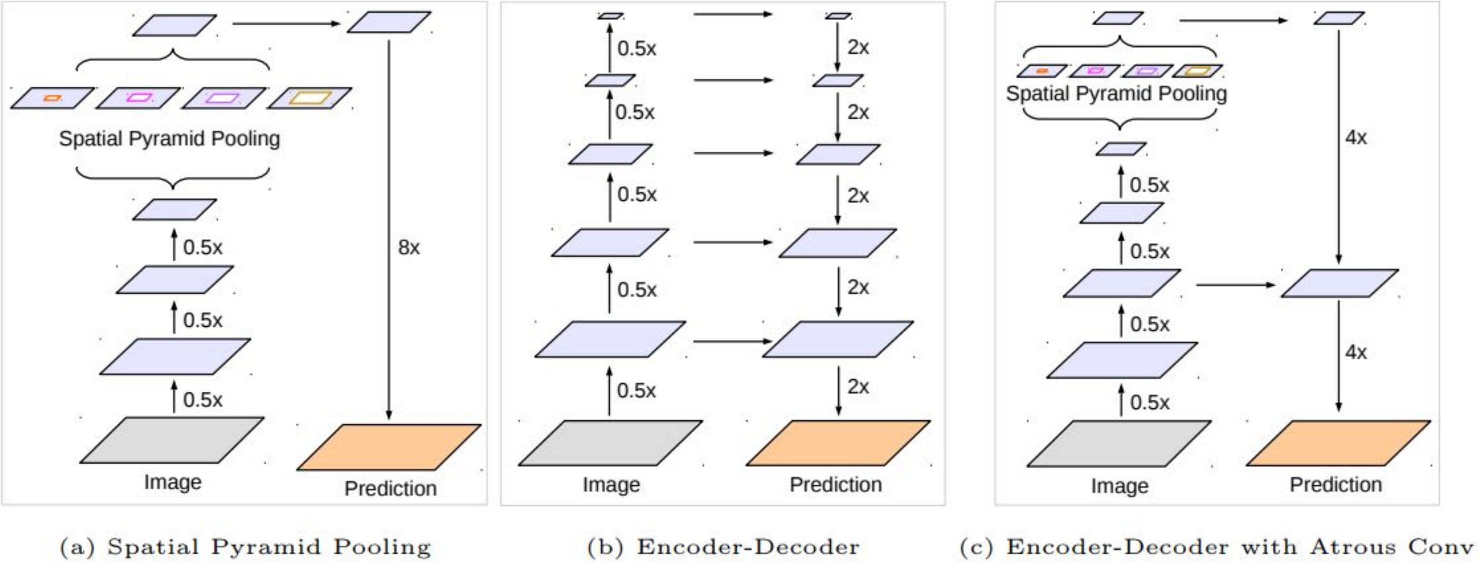
Chen et al., Attention to Scale: Scale-aware Semantic Image Segmentation, CVPR 2016

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

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

Spoiler alert: Not necessarily.

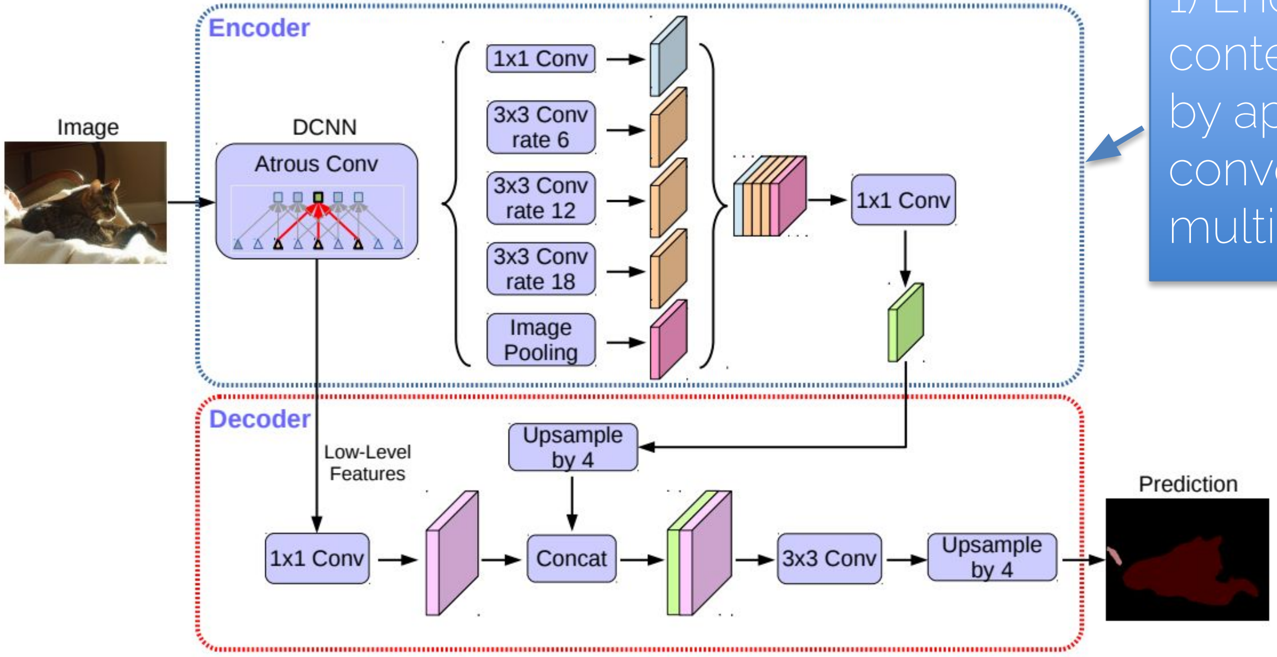
DeepLabv3+



(a) Spatial Pyramid Pooling (b) Encoder-Decoder (c) Encoder-Decoder with Atrous Conv

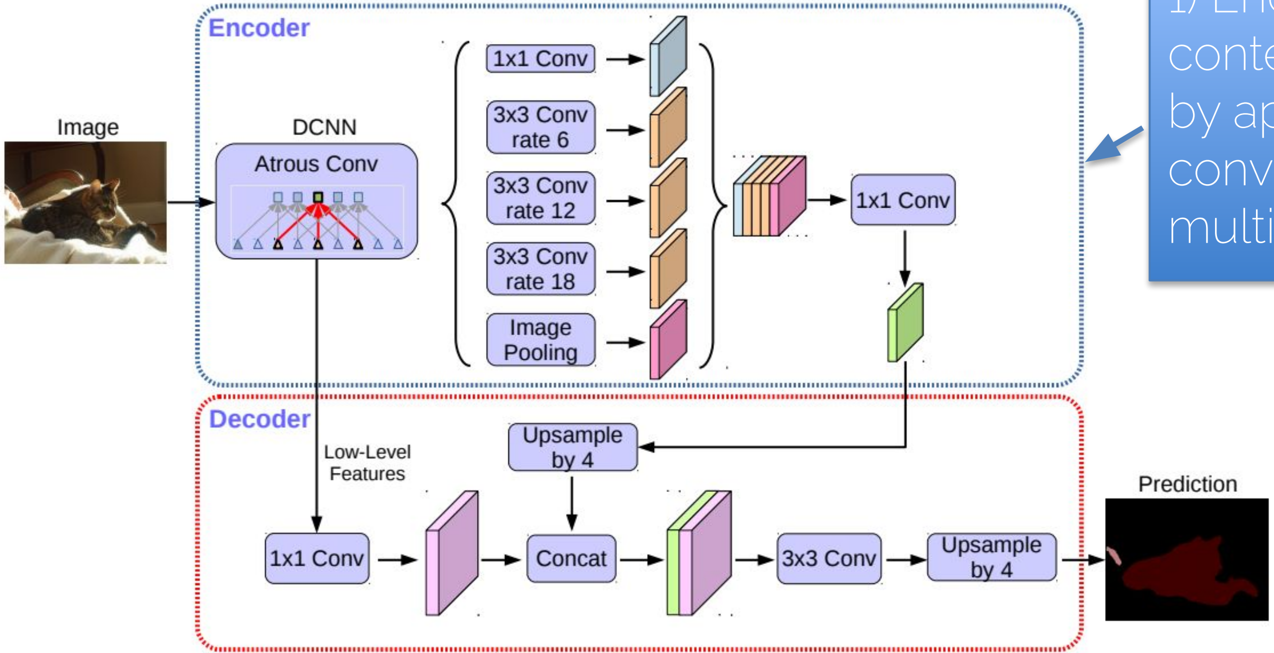
Combine atrous convolutions and spatial pyramid pooling with an encoder-decoder module.

Delving deeper into DeepLabv3+



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

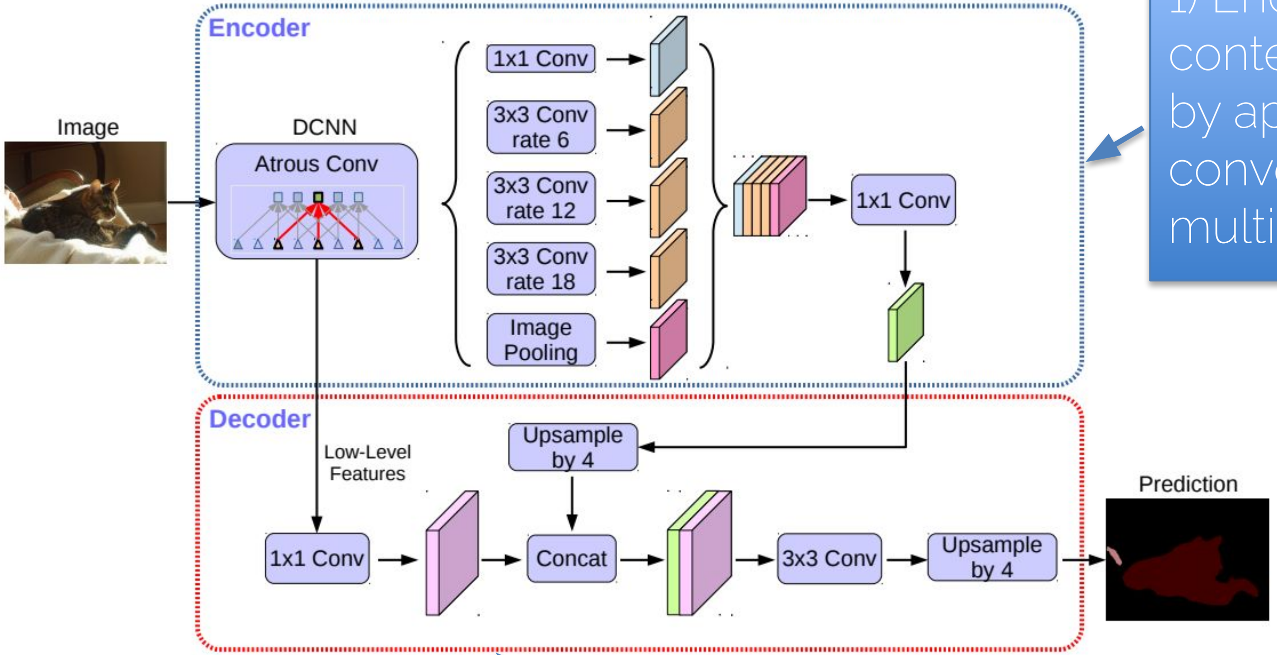
Delving deeper into DeepLabv3+



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

2) Refine the segmentation results along object boundaries.

Delving deeper into DeepLabv3+

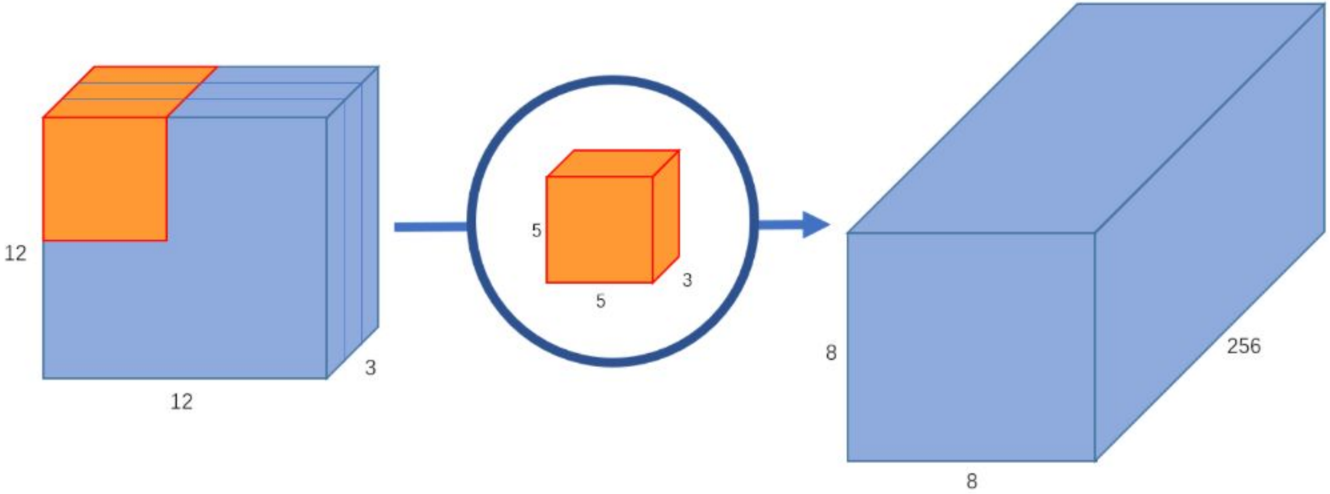


1) Encode multi-scale contextual information by applying atrous convolution at multiple scales

3) Use depthwise separable convolutions.

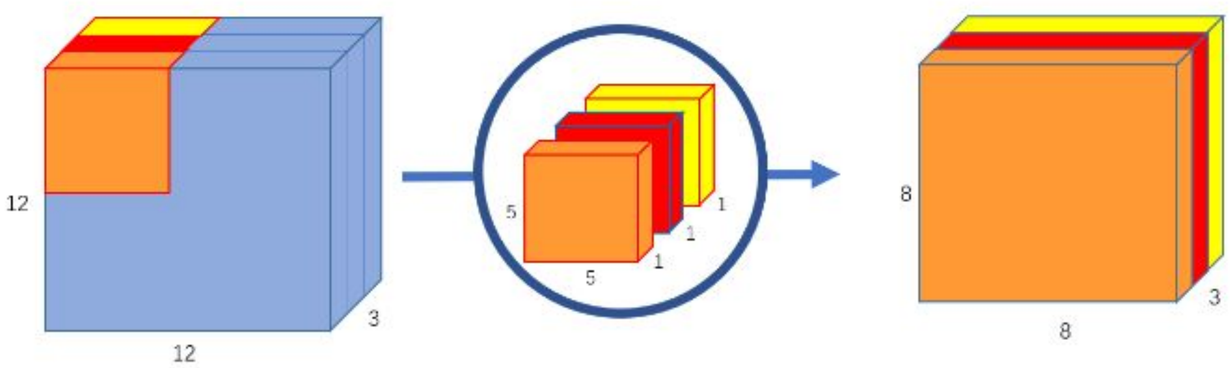
2) Refine the segmentation results along object boundaries.

Depth-wise separable convolutions



Normal convolutions act on all channels.

Depth-wise separable convolutions

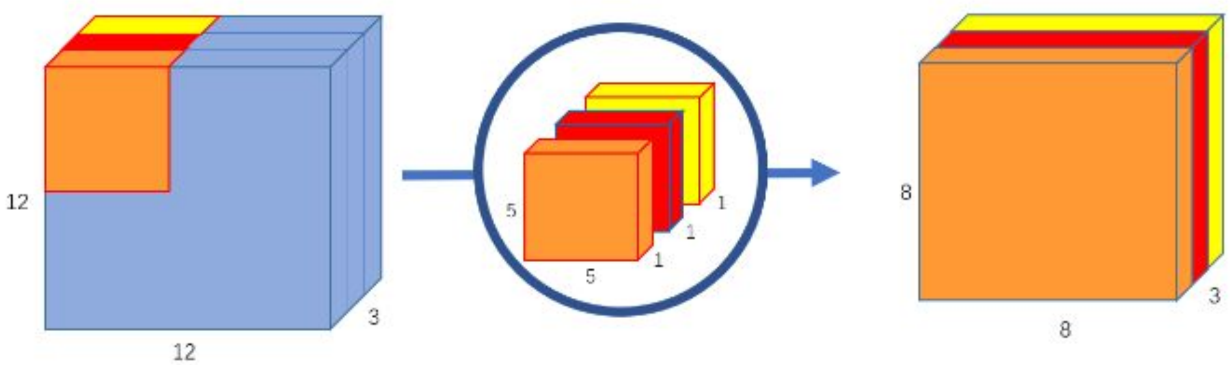


Filters are applied only at certain depths of the features. Normal convolutions have groups set to 1, the convolutions used in this image have groups set to 3.

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

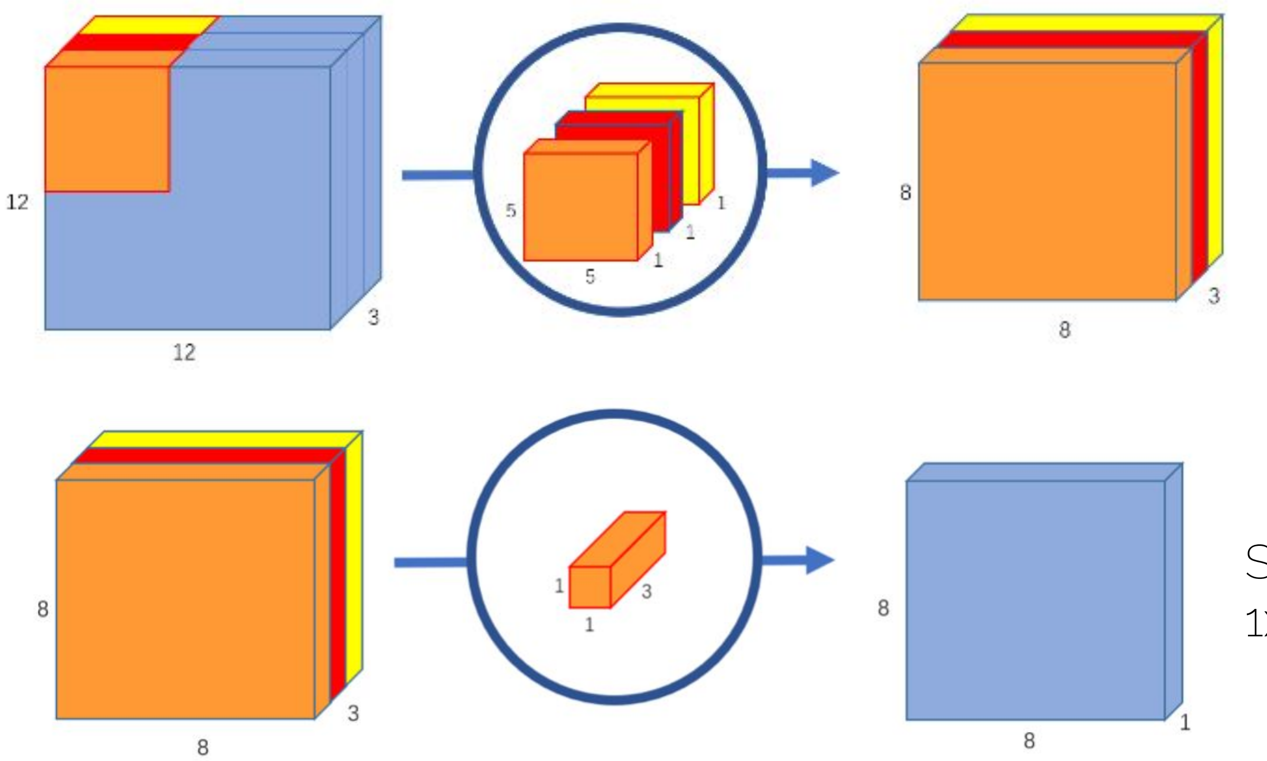


But the depth size is always the same!

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

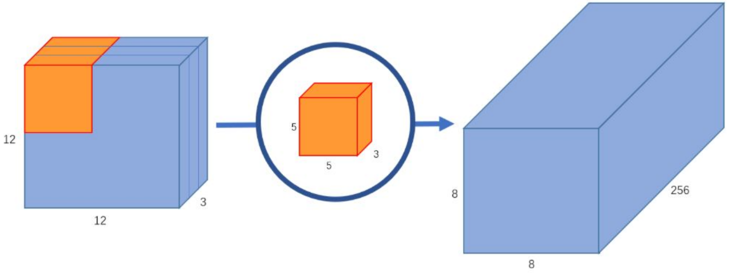
class **torch.nn.ConvTranspose2d**(*in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3*)

Depth-wise separable convolutions



Solution:
1x1 convs!

But why?



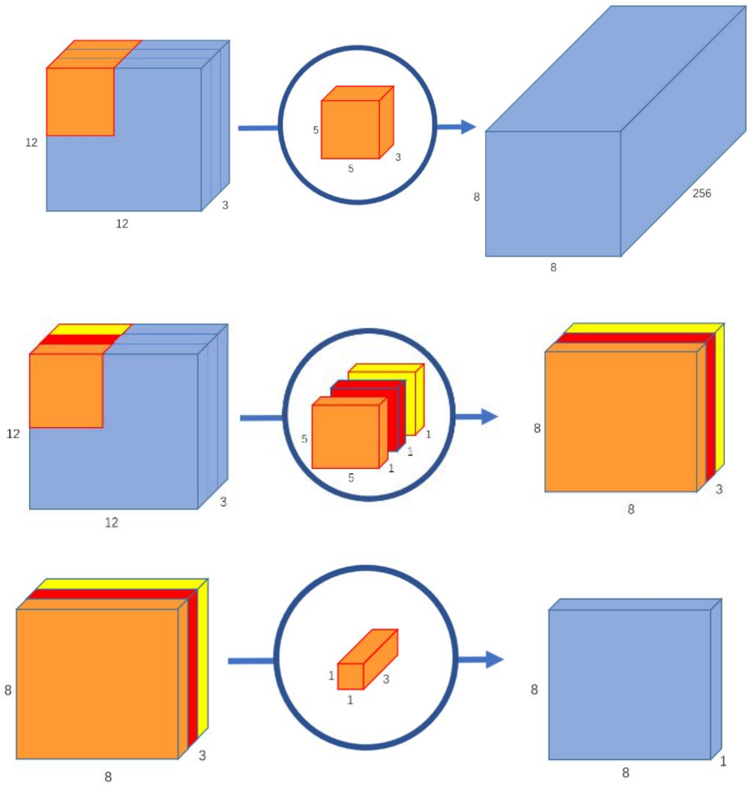
Original convolution

256 kernels of size 5x5x3

Multiplications:

256x5x5x3 x (8x8 locations) = 1.228.800

But why?



Original convolution
256 kernels of size 5x5x3

Multiplications:
256x5x5x3 x (8x8 locations) = 1.228.800

Depth-wise convolution
3 kernels of size 5x5x1

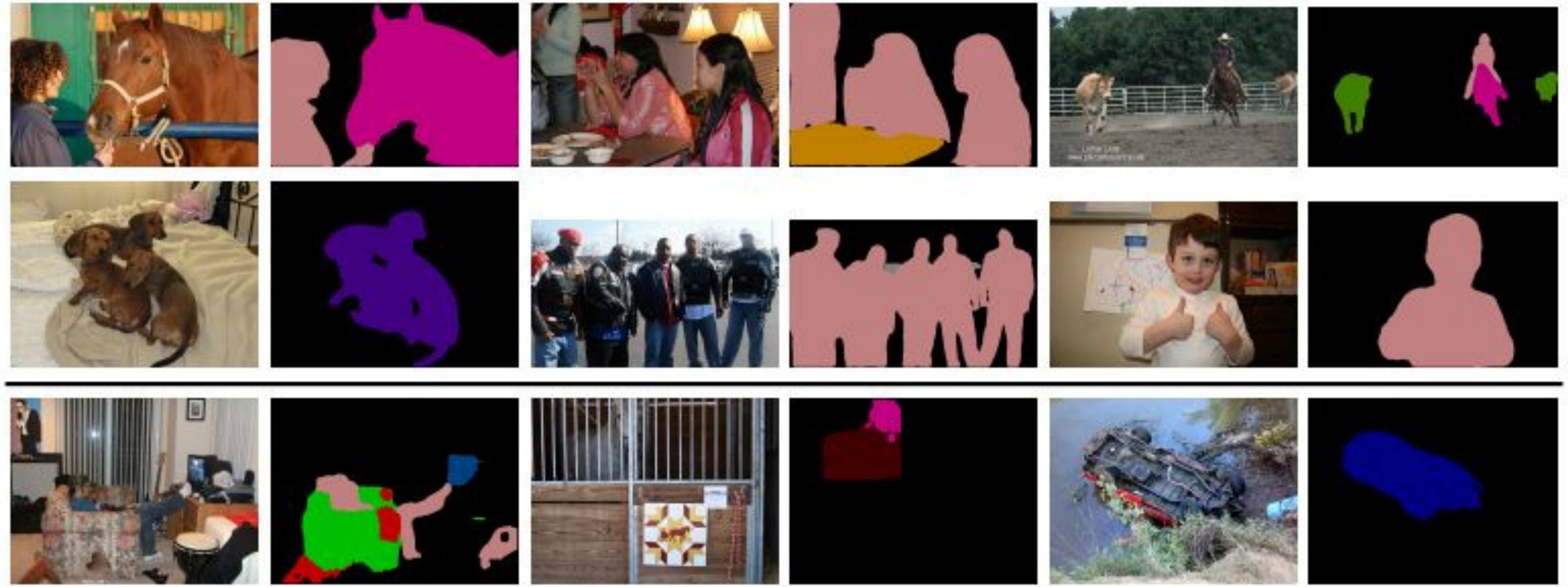
Multiplications:
5x5x3 x (8x8 locations) = 4800

1x1 convolution
256 kernels of size 1x1x3

Multiplications:
256x1x1x3x (8x8 locations) = 49152

Less computations!

DeepLabv3+: qualitative results



Still considered as SOTA!

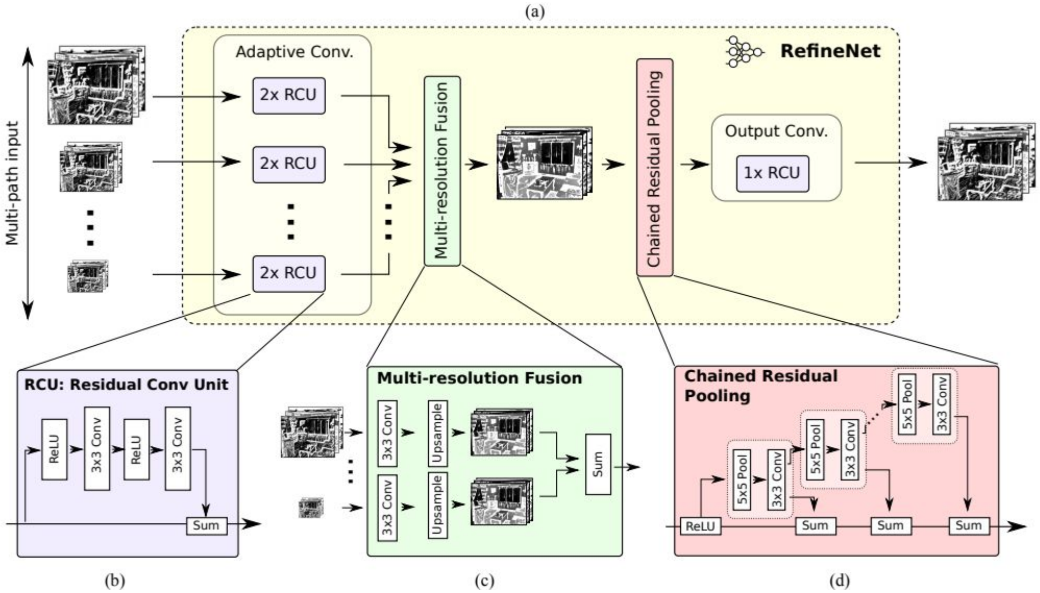
Chen et al., Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation, ECCV 2018

DeepLab is great…

- …but there are other important architectures

- Recommended to read
  - RefineNet
  - PSPNet

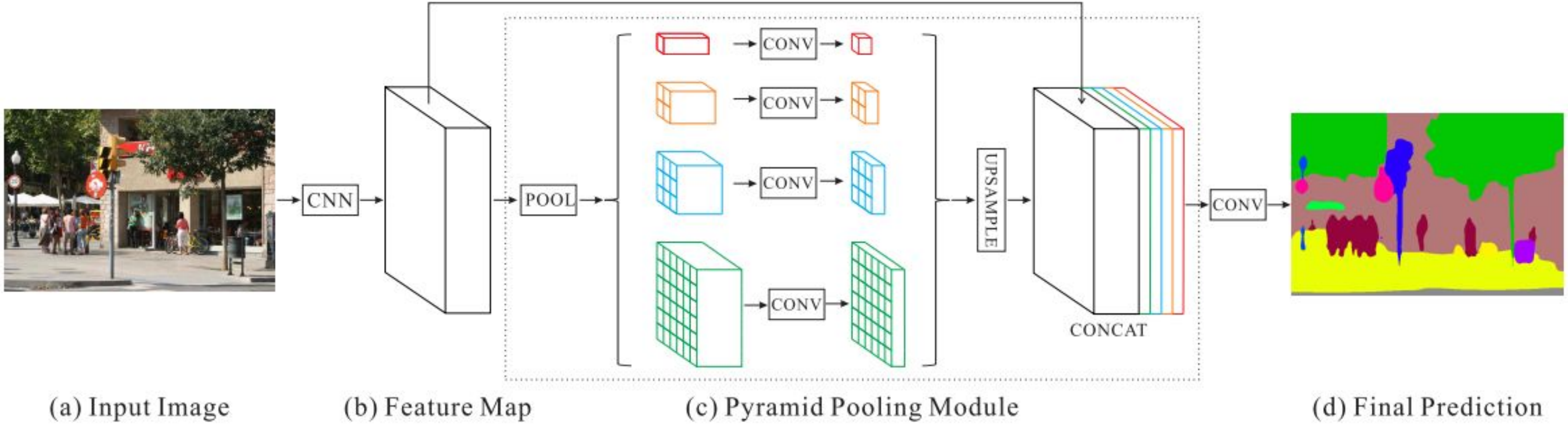
RefineNet



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

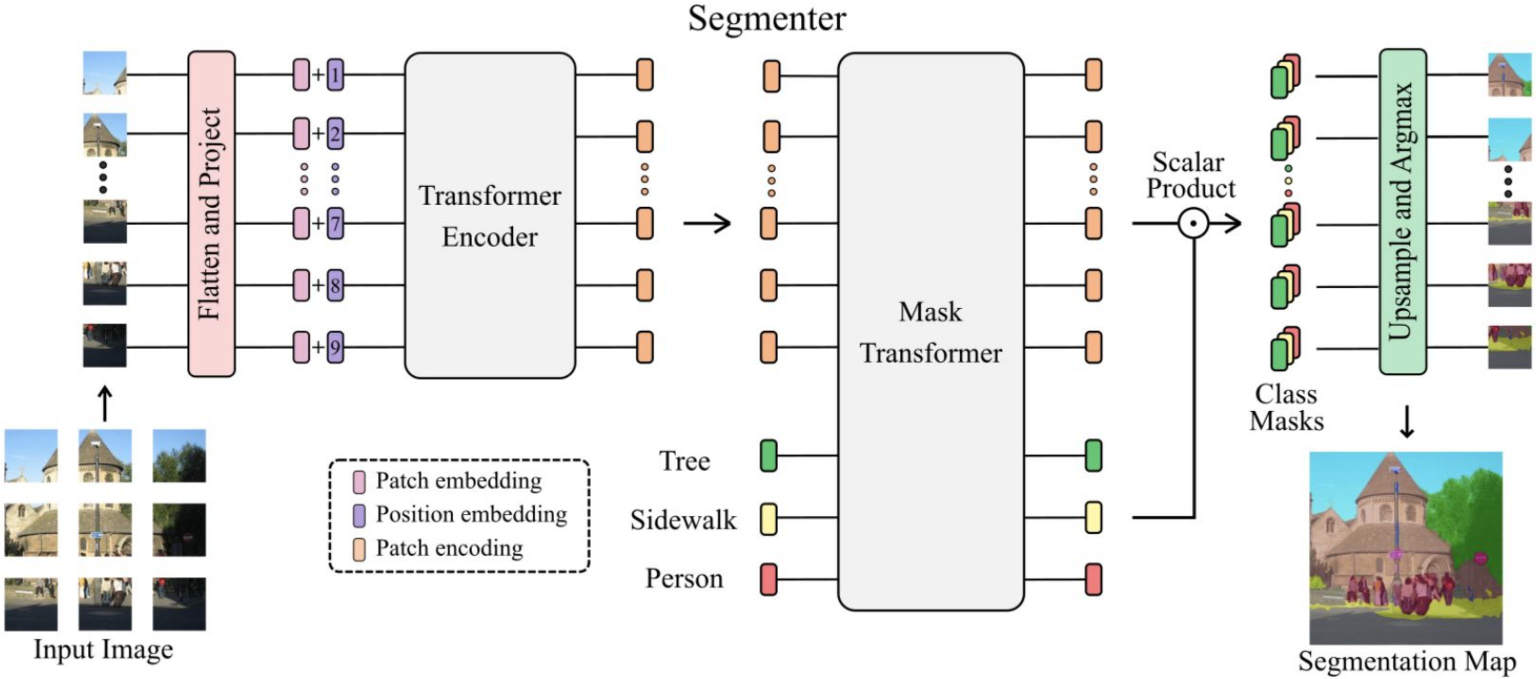
PSPNet



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.

Zhao et al., Pyramid Scene Parsing Network, CVPR 2017

And of course, Transformers



Strudel et al., Transformer for Semantic Segmentation, ICCV 2021

Datasets and metrics

Datasets

Pascal VOC 2007/12:

Circa 16k training natural images divided into 20 classes.

Cityscapes:

25K urban-street images divided into 30 classes.

ADE20K:

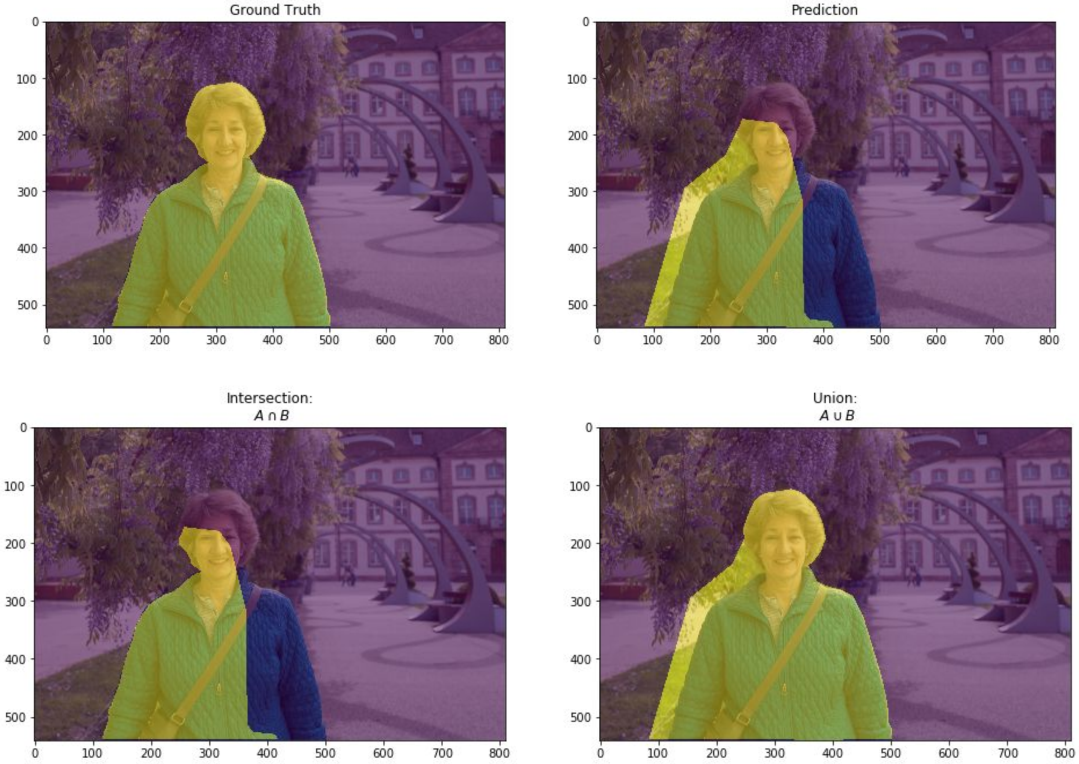
25K (20 stands for 20K training) scene-parsing images divided into 150 classes.

Mapillary Vistas:

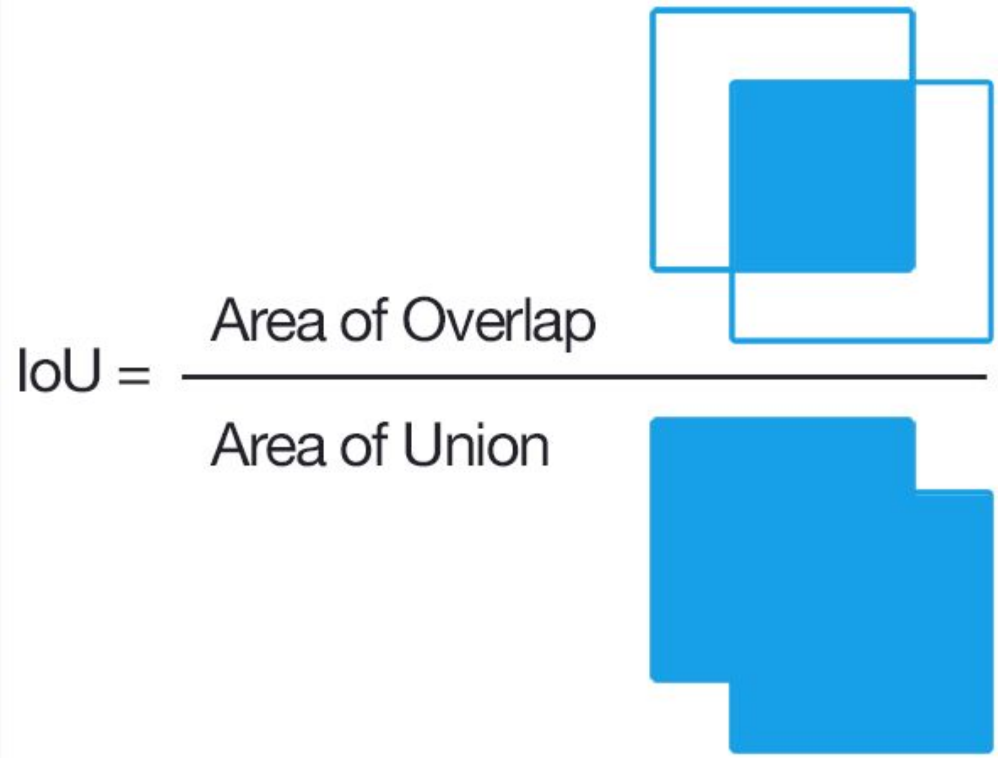
25K street level images, divided into 152 classes.

Models are often pre-trained in the large MS-COCO dataset (83-115K), before finetuned to the specific dataset.

Metrics: intersection over union (IoU)

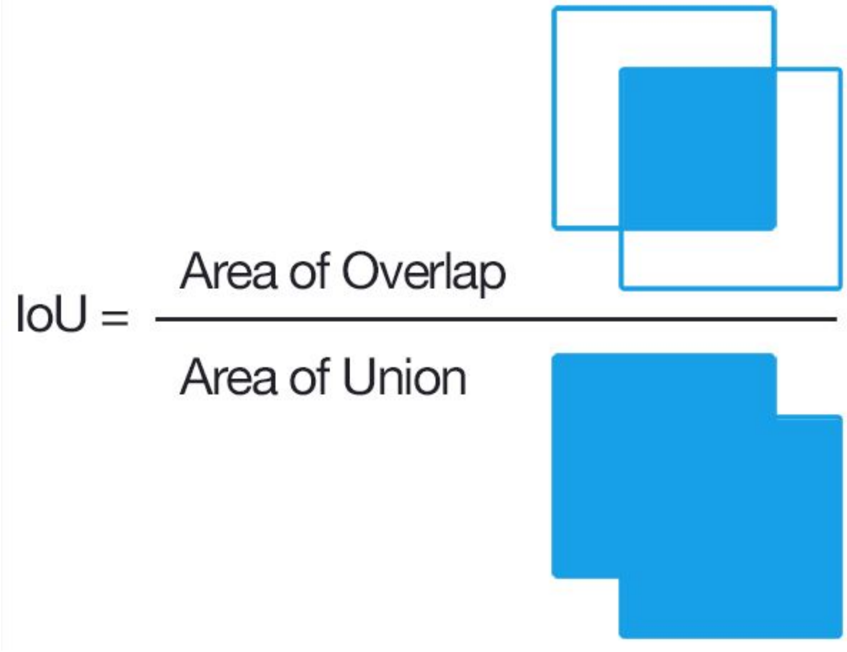


Metrics: intersection over union (IoU)



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

Metrics: mean intersection over union (mIoU)

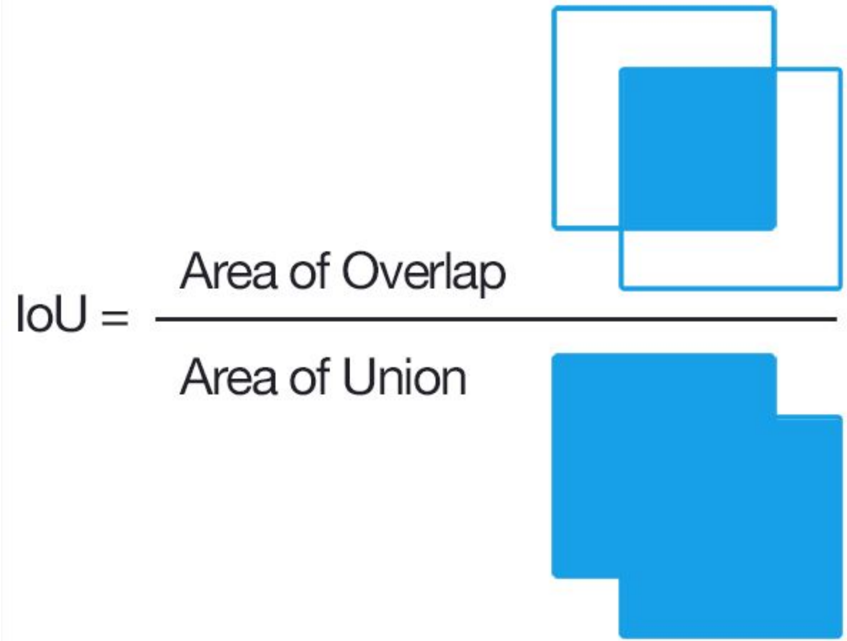


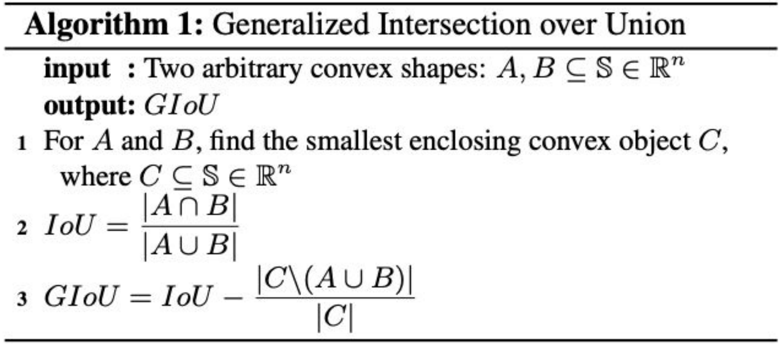
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

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). Recently, generalized mIoU is also used (.Rezatofighi et al., Generalized intersection over union: a metric and a loss for bounding box regression, CVPR 2019).

Metrics: mean intersection over union (mIoU)





```
Algorithm 1: Generalized Intersection over Union
  input  : Two arbitrary convex shapes: $A, B \subseteq \mathbb{S} \in \mathbb{R}^n$
  output: $GIoU$
  For $A$ and $B$, find the smallest enclosing convex object $C$,
    where $C \subseteq \mathbb{S} \in \mathbb{R}^n$
  $IoU = \frac{|A \cap B|}{|A \cup B|}$
  $GIoU = IoU - \frac{|C \backslash (A \cup B)|}{|C|}$
```

Another widely used metric is the pixel accuracy (ratio of pixels classified correctly). Recently, generalized mIoU is also used (.Rezatofighi et al., Generalized intersection over union: a metric and a loss for bounding box regression, CVPR 2019).

Next lecture: Instance and panoptic segmentation