Semantic segmentation

Task definition: semantic segmentation

Neural Network

CAT

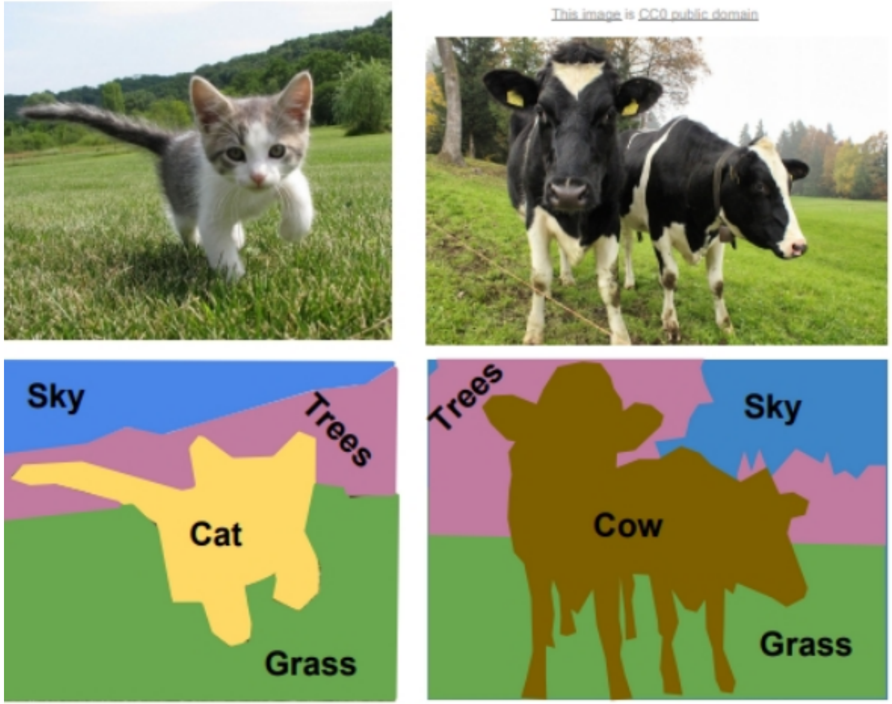
Classify the main object in the image.

Neural Network

CAT, GRASS, TREE, SKY

No objects, just classify each pixel.

Semantic Segmentation



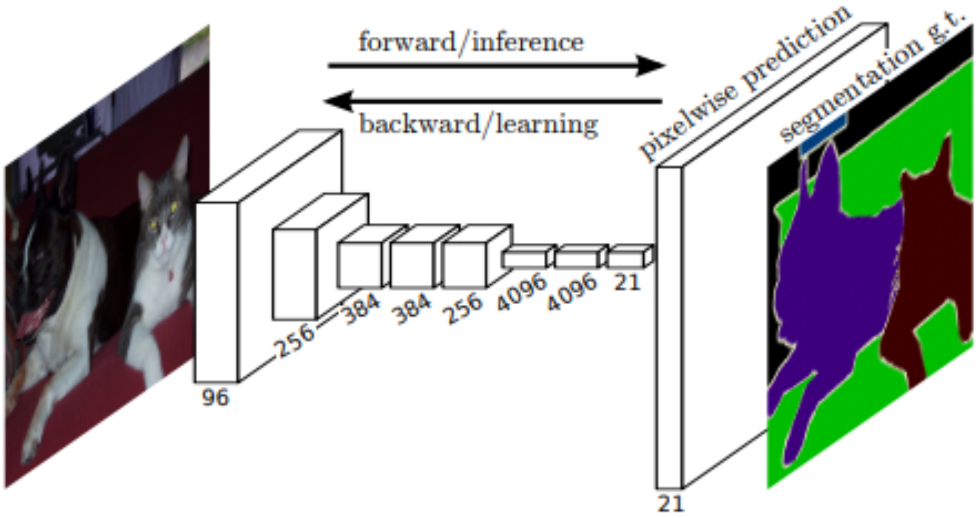
- Every label in the image needs to be labelled with a category label.

- 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

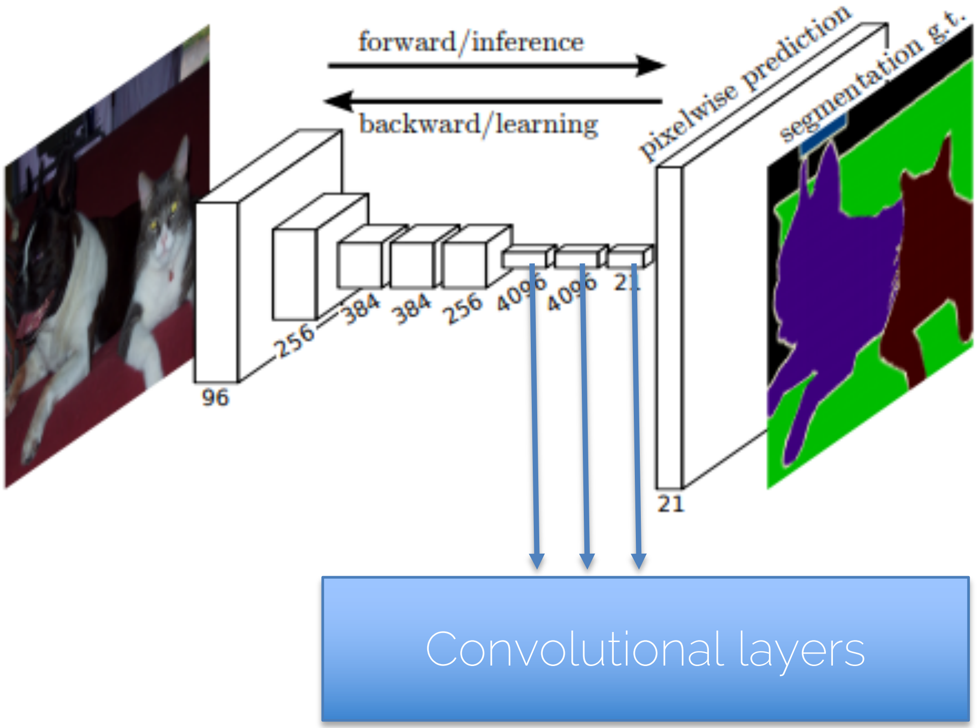
- A FCN is able to deal with any input/output size



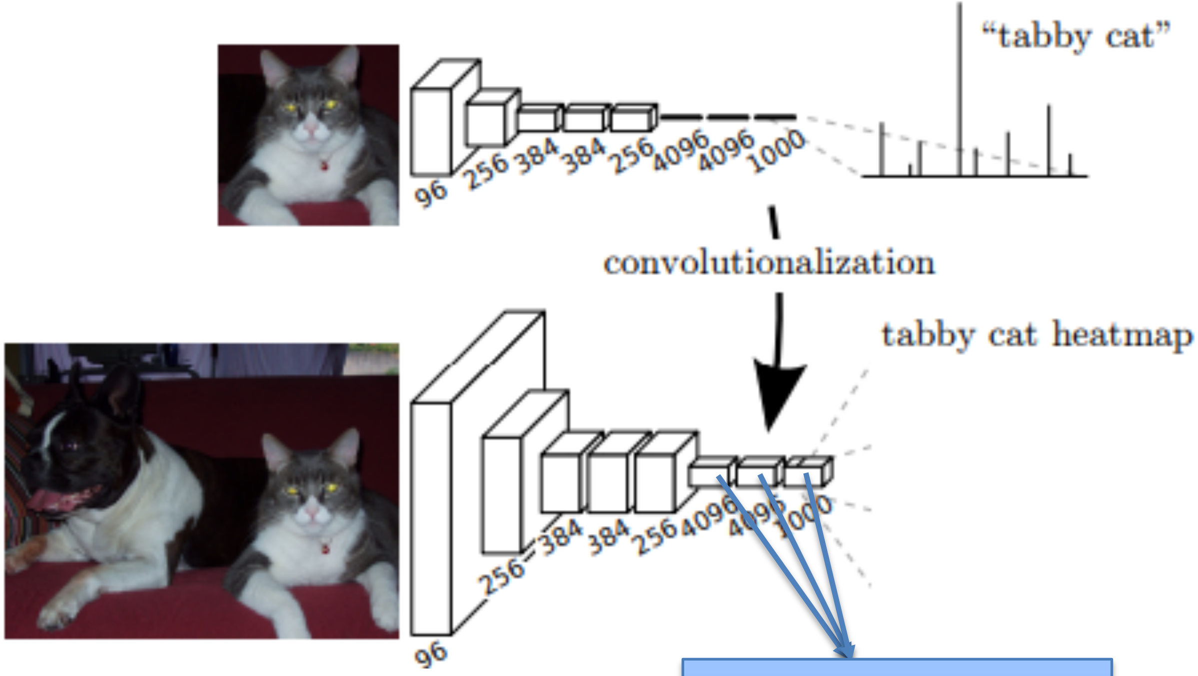
Long, Shelhamer, Darrell - Fully Convolutional Networks for Semantic Segmentation, CVPR 2015, PAMI 2016

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



"Convolutionalization"



1x1 Convolutions!

"Convolutionalization"

Yann LeCun
April 6, 2015 ·

See a more detailed explanation in this quora answer.

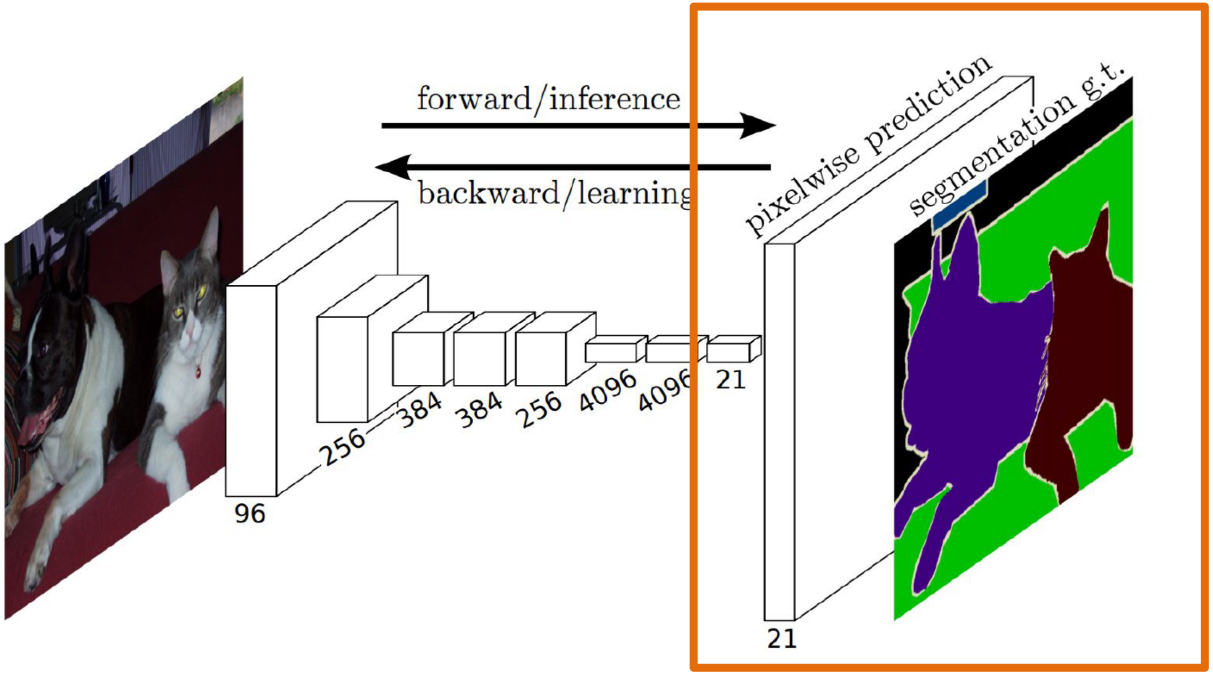
In Convolutional Nets, there is no such thing as "fully-connected layers". There are only convolution layers with 1x1 convolution kernels and a full connection table.

It's a too-rarely-understood fact that ConvNets don't need to have a fixed-size input. You can train them on inputs that happen to produce a single output vector (with no spatial extent), and then apply them to larger images. Instead of a single output vector, you then get a spatial map of output vectors. Each vector sees input windows at different locations on the input.

In that scenario, the "fully connected layers" really act as 1x1 convolutions.

Semantic Segmentation (FCN)

- Fully Convolutional Networks for Semantic Segmentation

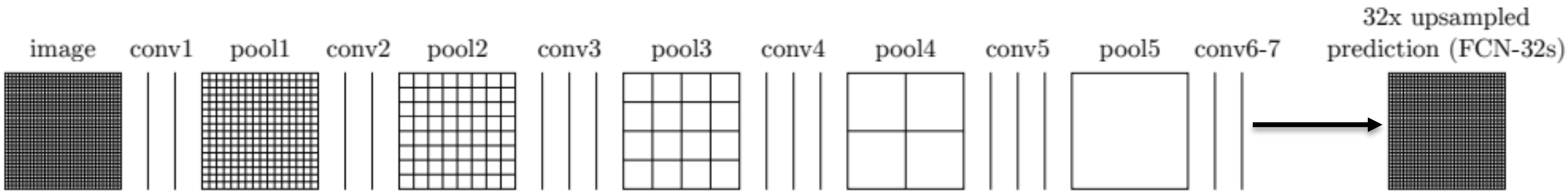


How do we upsample?

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

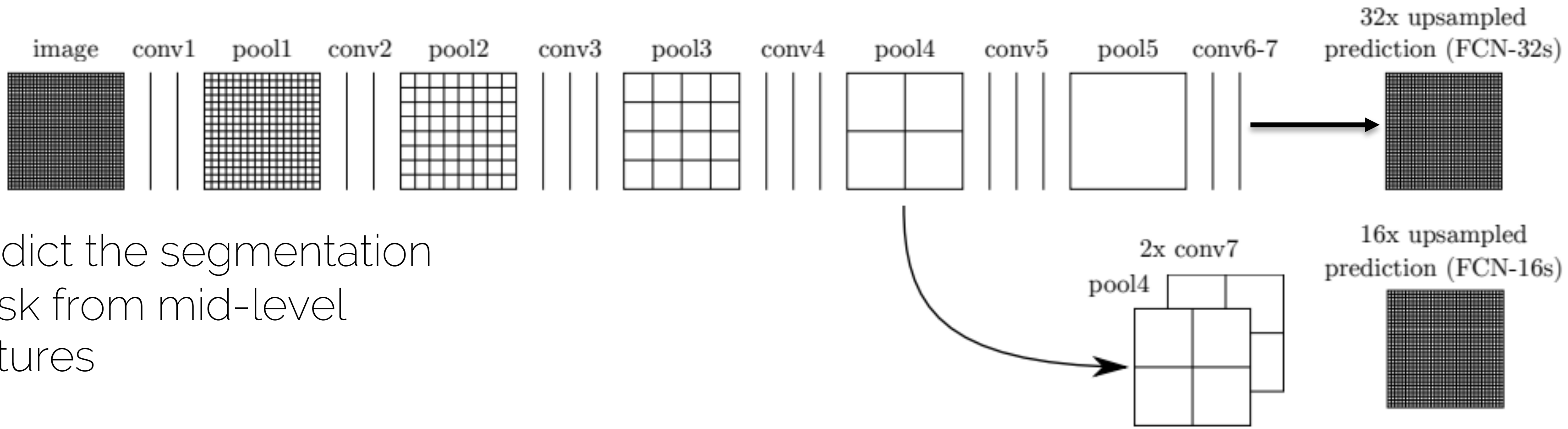
Network's architecture

Predict the segmentation mask from high level features



Network's architecture

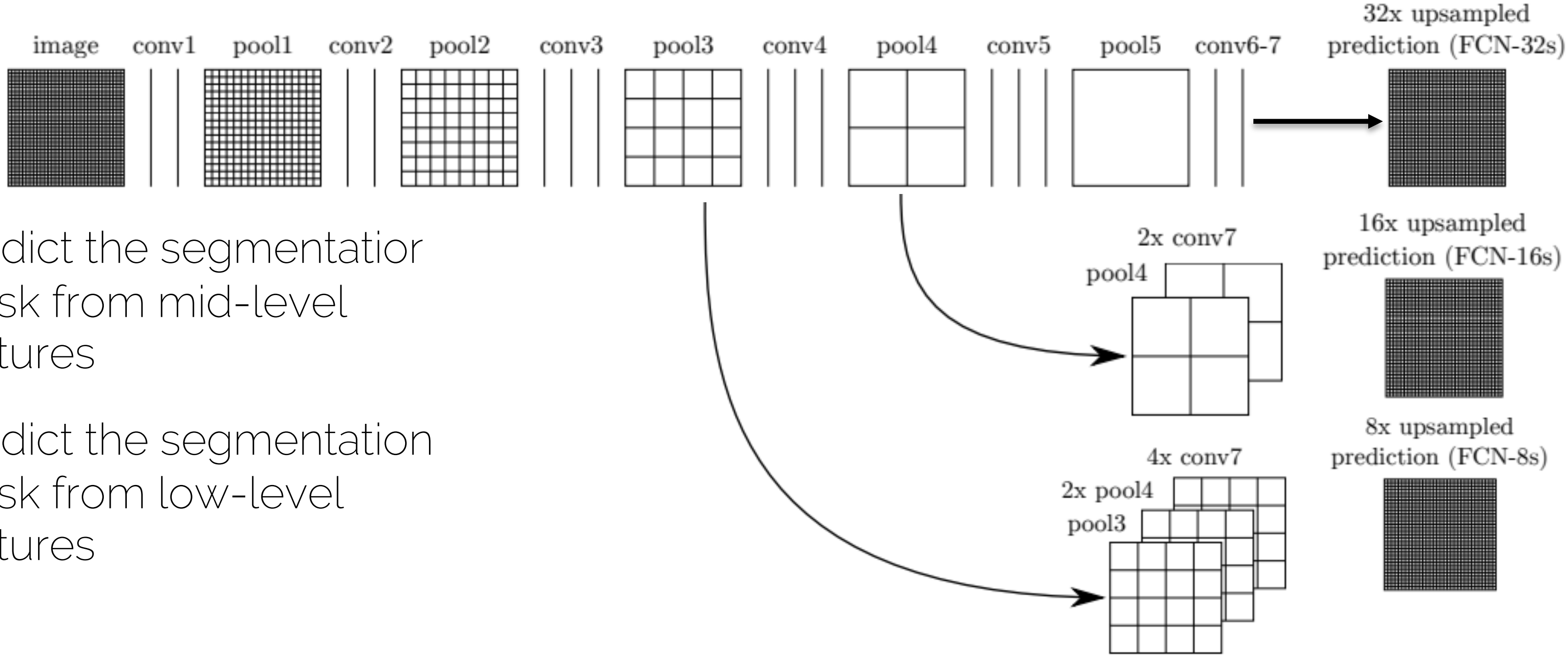
Predict the segmentation mask from high level features



Predict the segmentation mask from mid-level features

Network's architecture

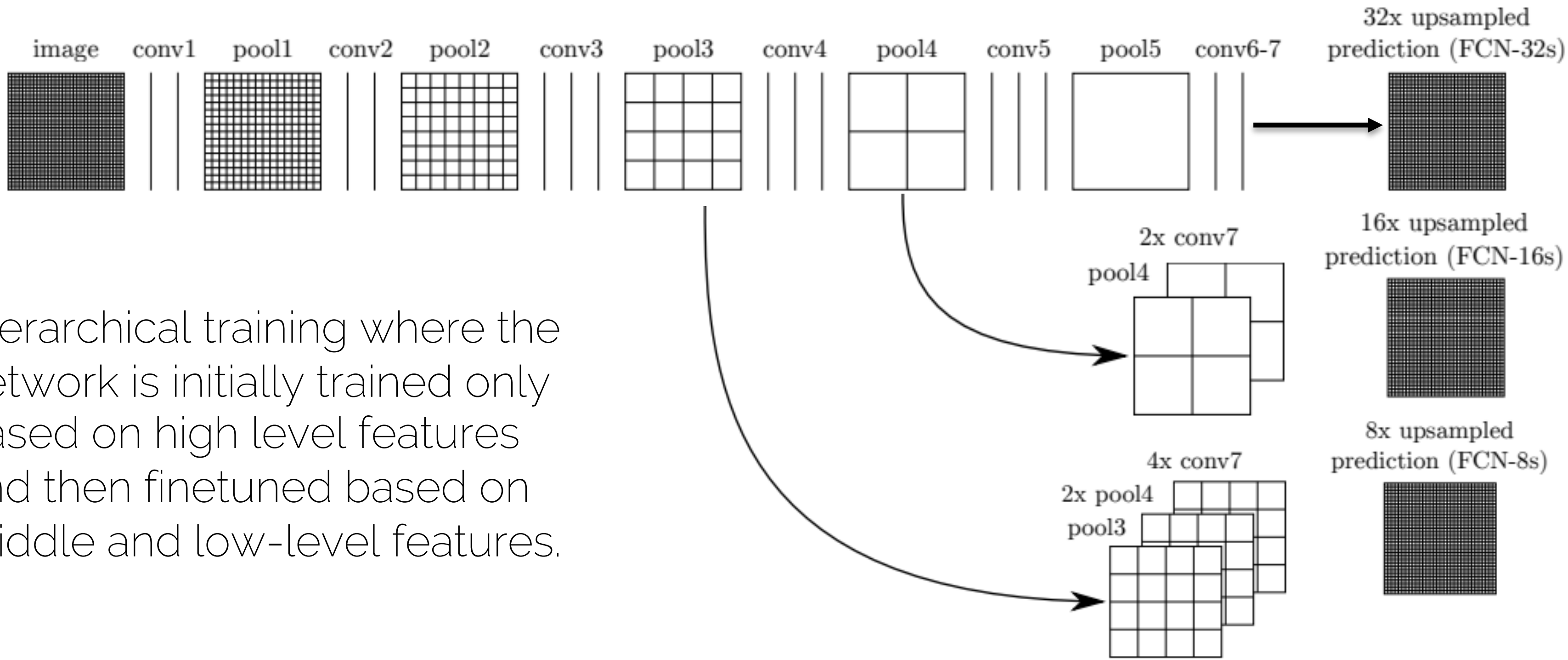
Predict the segmentation mask from high level features



Predict the segmentation mask from mid-level features

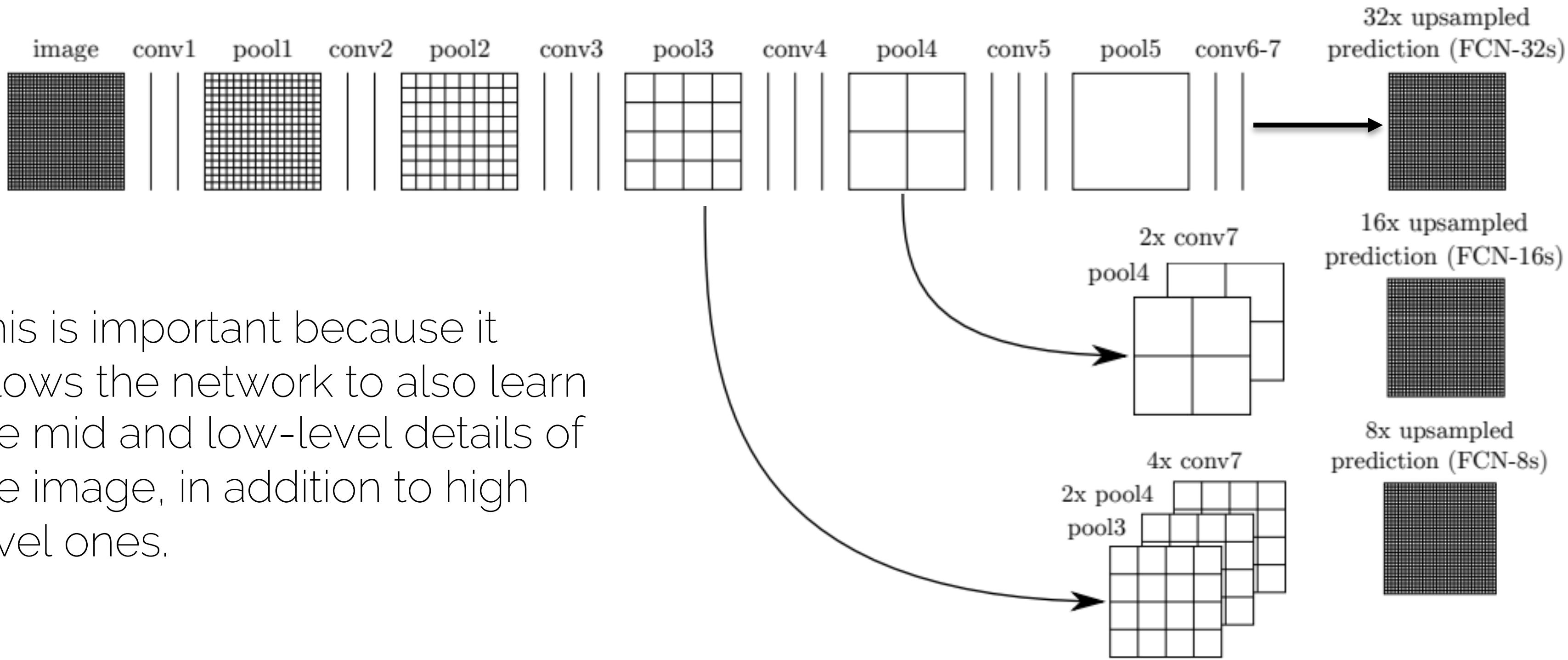
Predict the segmentation mask from low-level features

Network's architecture



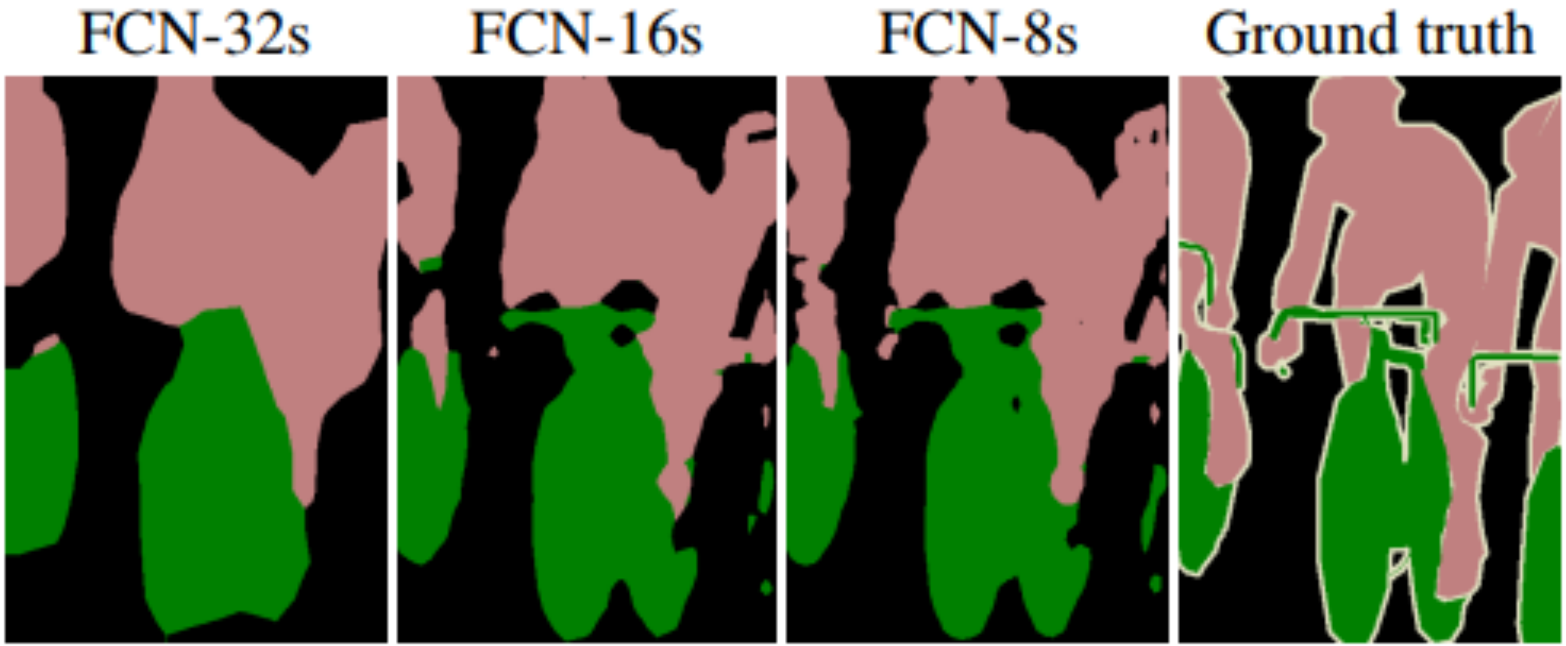
Hierarchical training where the network is initially trained only based on high level features and then finetuned based on middle and low-level features.

Network's architecture



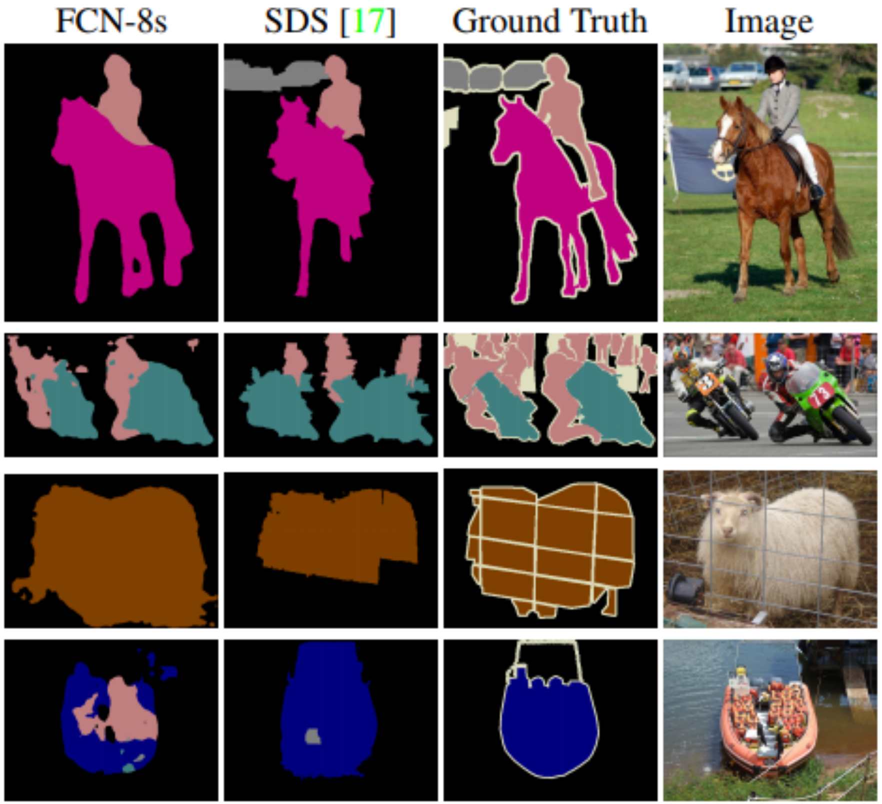
This is important because it allows the network to also learn the mid and low-level details of the image, in addition to high level ones.

Qualitative results



Good | Better | Best

Qualitative results

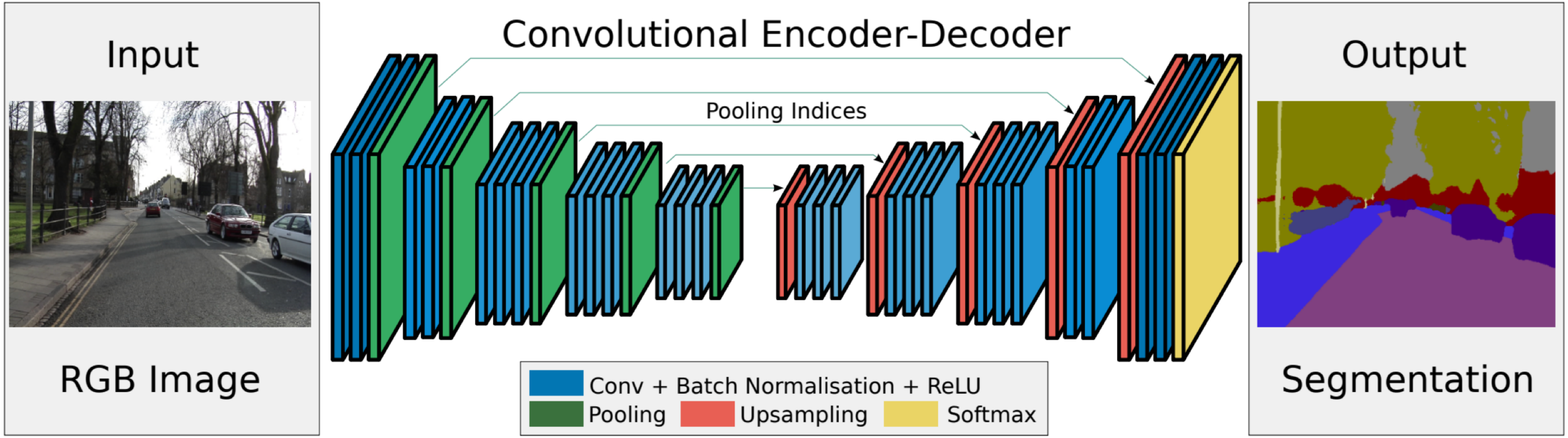


SDS is an R-CNN-based method, i.e., it uses object proposals.
In general, FCN outperforms significantly (both qualitatively and quantitatively) pre-deep learning and quasi-deep learning methods and is recognized as the AlexNet of semantic segmentation.

Autoencoder-style architecture

SegNet

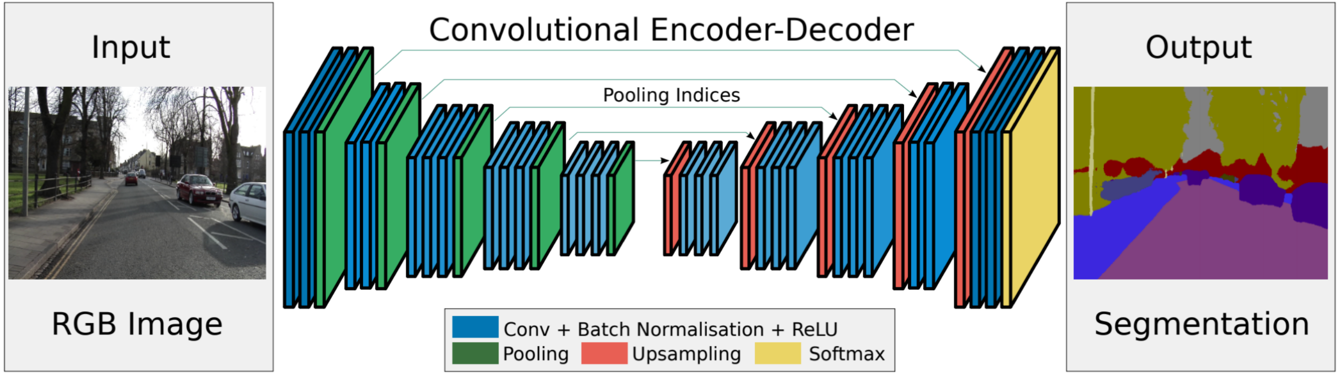
- Step-wise upsampling



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

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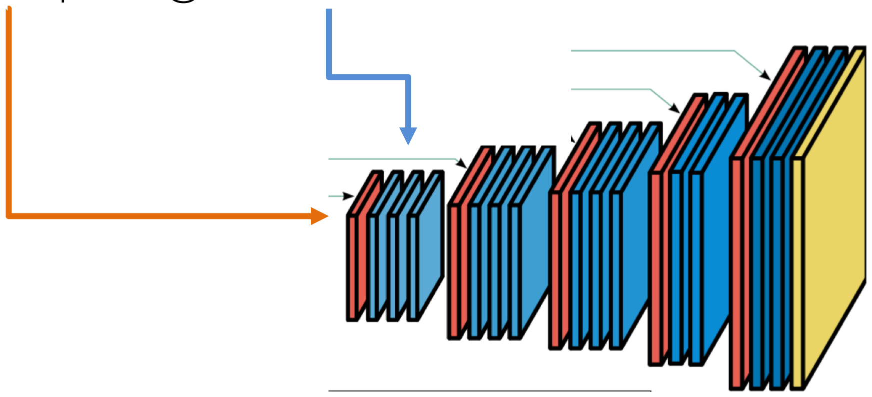


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation“. TPAMI 2016

SegNet

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

- **Decoder**: Upsampling + convolutional filters

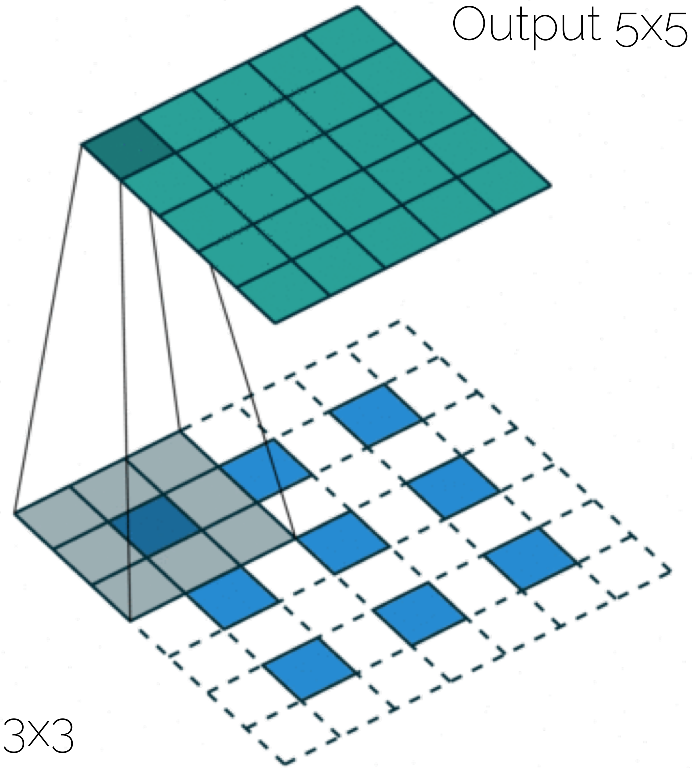
- The convolutional filters in the decoder are learned using backprop and their goal is to refine the upsampling

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)



SegNet

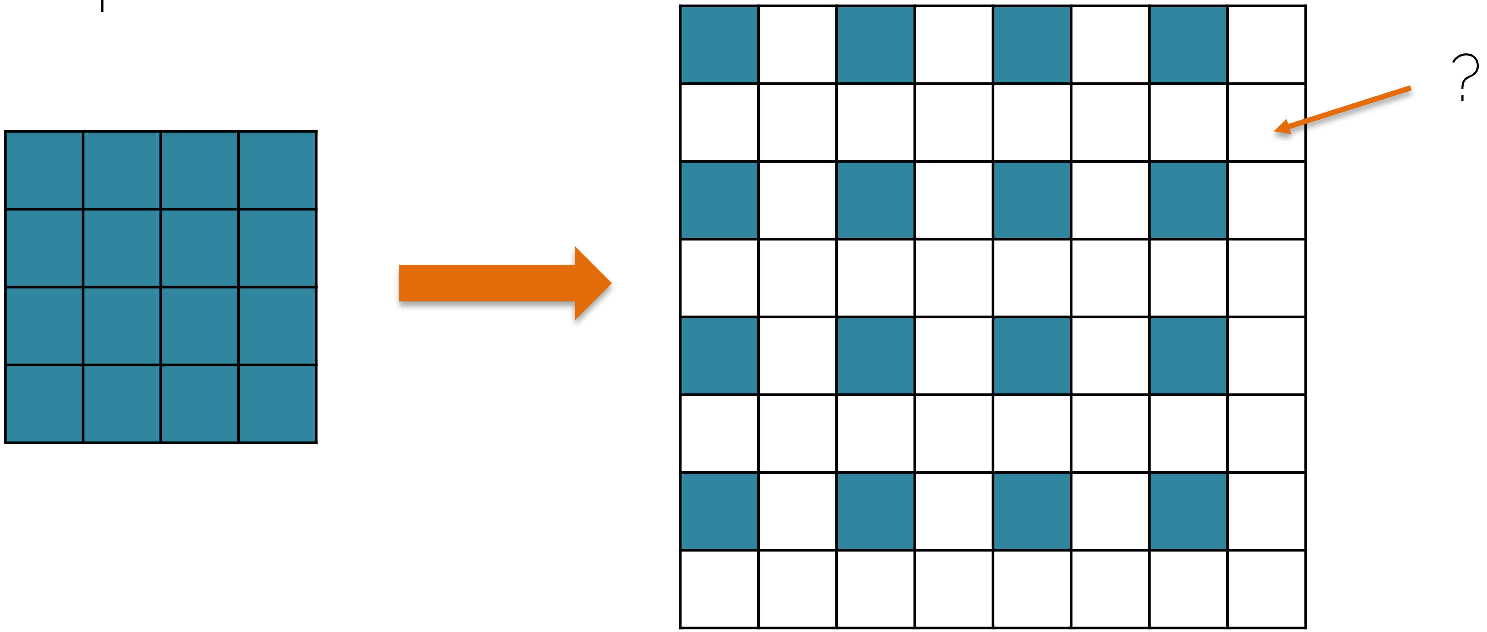
- **Encoder**: normal convolutional filters + pooling
- **Decoder**: Upsampling + convolutional filters
- **Softmax** layer: The output of the soft-max classifier is a K channel image of probabilities where K is the number of classes.

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

Upsampling

Types of upsamplings

- 1. Interpolation



Types of upsamplings

- 1. Interpolation

Original image  x 10

Nearest neighbor interpolation

Bilinear interpolation

Bicubic interpolation

Image: Michael Guerzhoy

Types of upsamplings

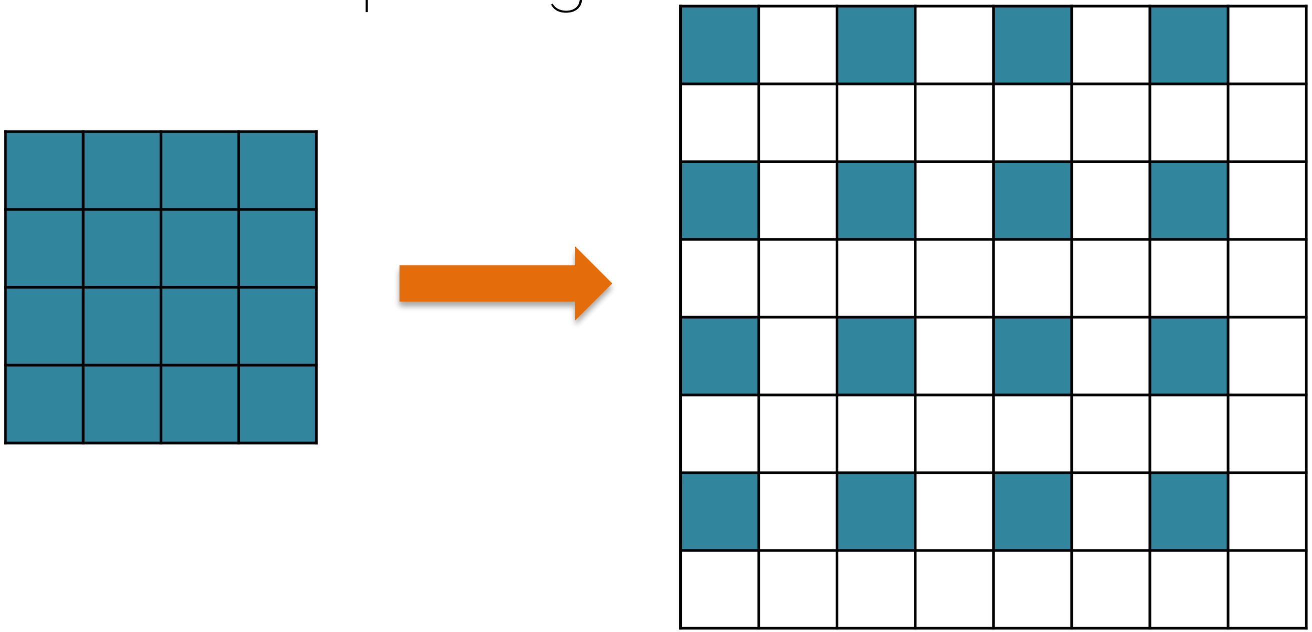
- 1. Interpolation

Few artifacts

Types of upsamplings

- 2. Fixed unpooling

efficient



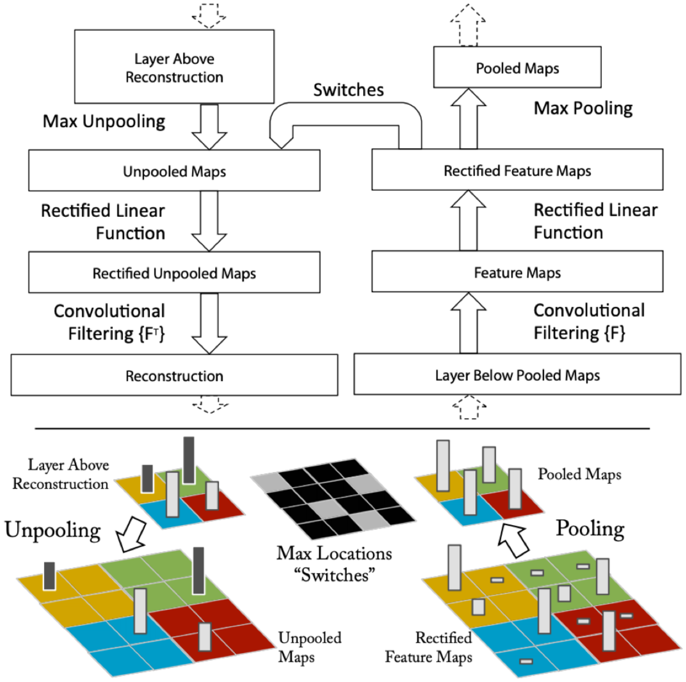
+ CONVS

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



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)

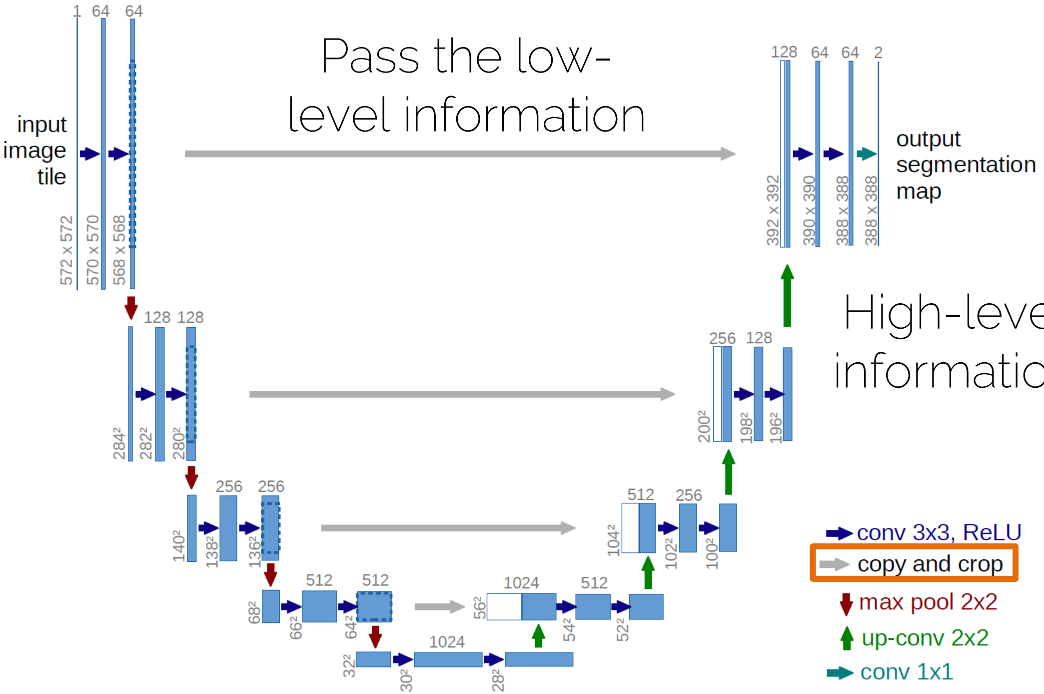
Skip Connections

- U-Net

Recall ResNet

Pass the low-level information

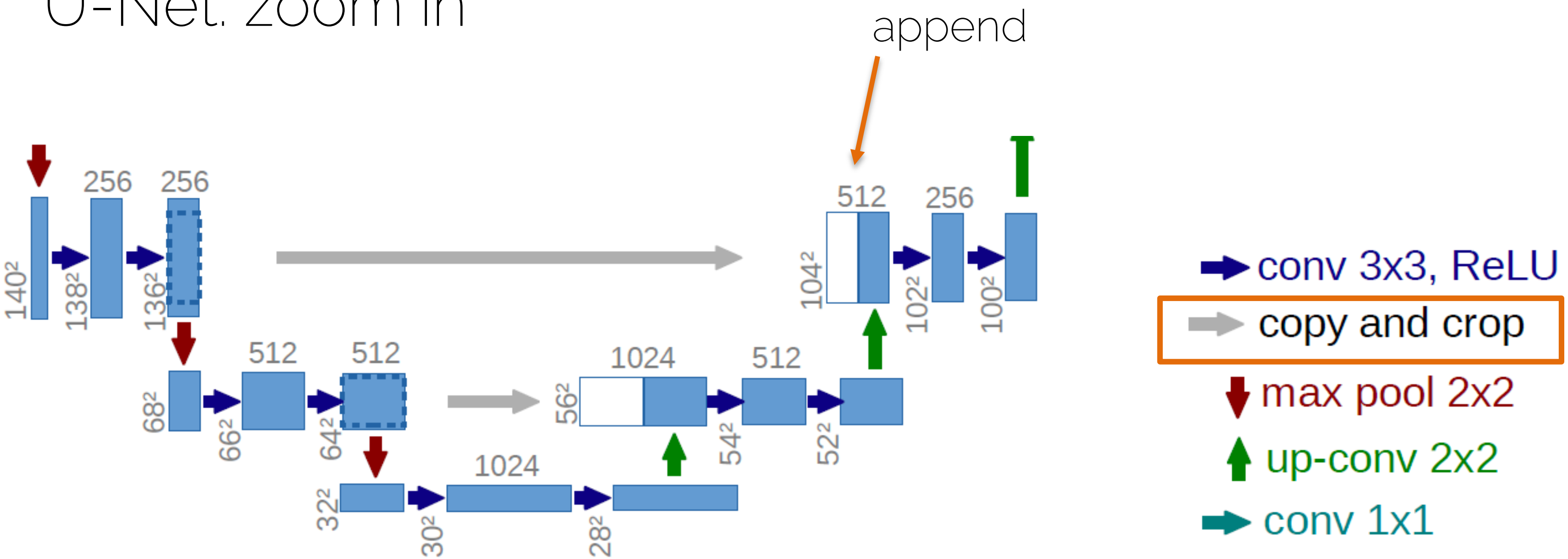
High-level information



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

Skip Connections

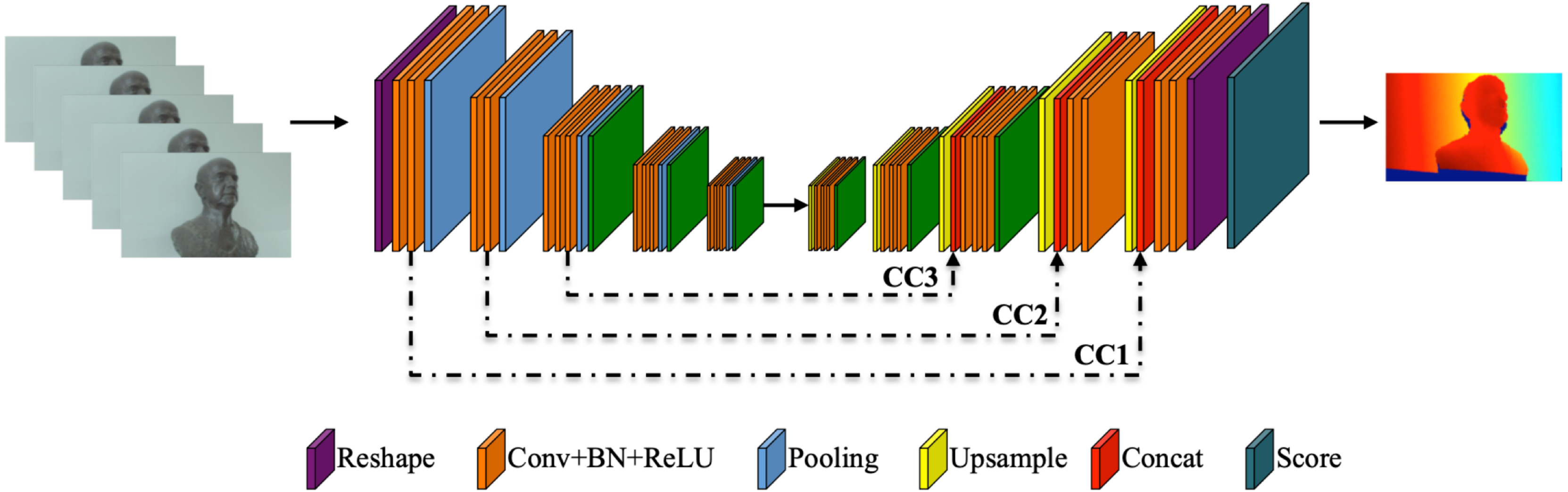
- U-Net: zoom in



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

Skip Connections

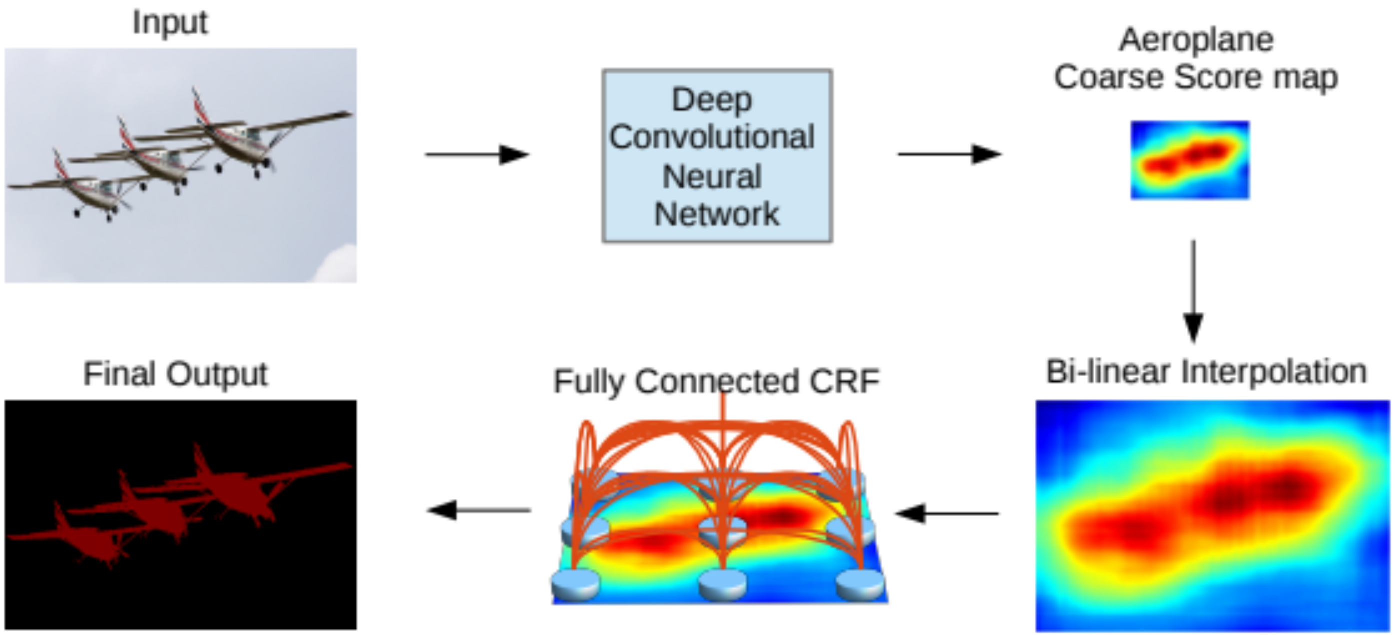
- Concatenation connections



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
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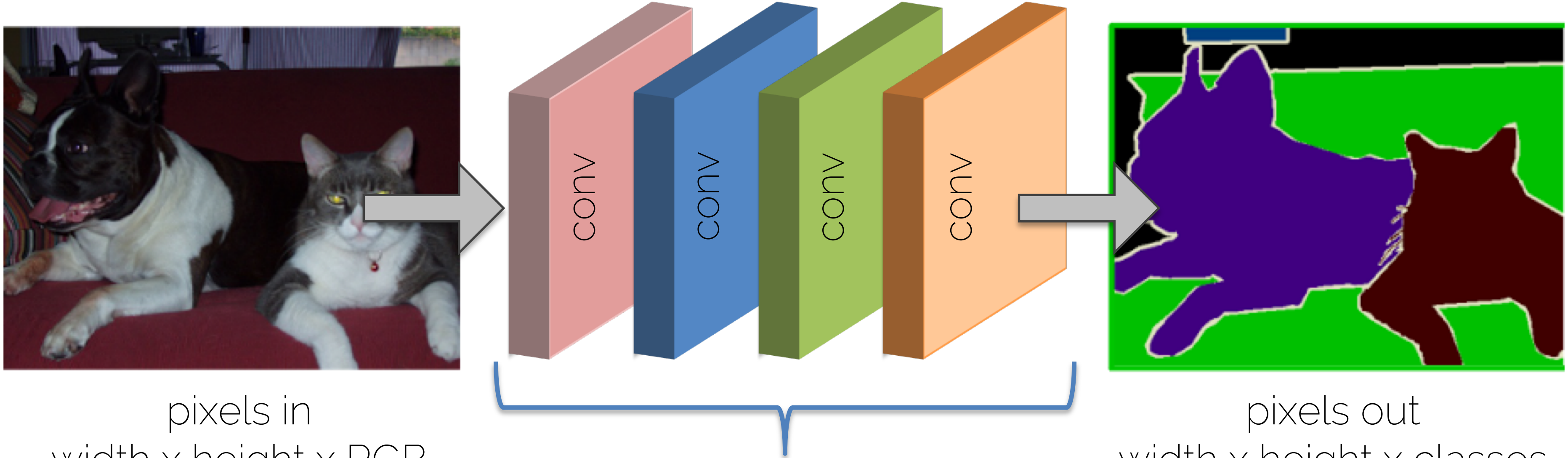
  - Proposed solution: Refinement with Conditional Random Field (CRF)

Wish: no reduced feature resolution



pixels in
width x height x RGB

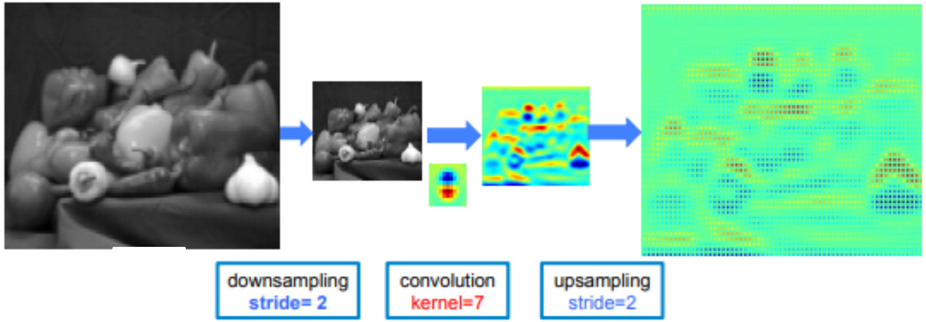
Just convs & activations

pixels out
width x height x classes

Fully Convolutional Network

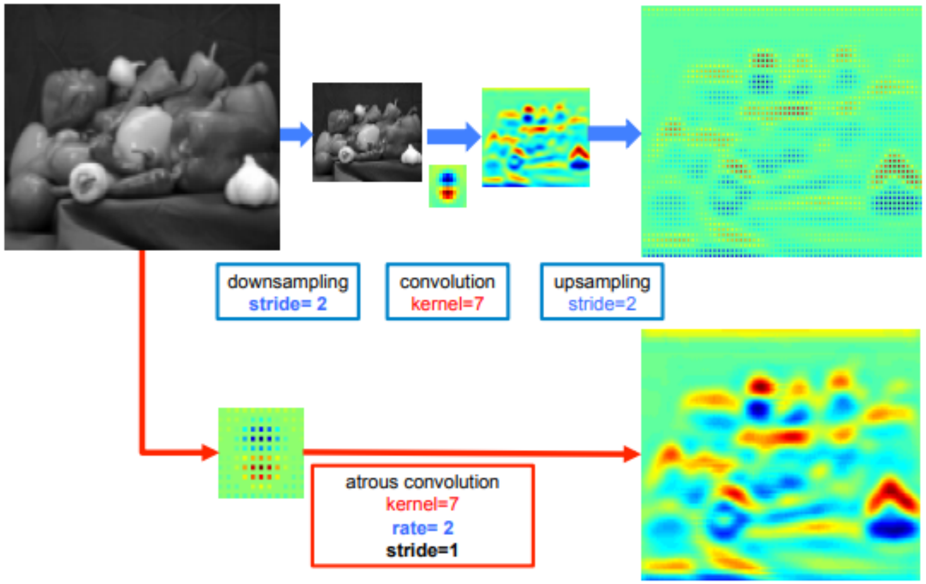
Super expensive!

Alternative: Dilated (atrous) convolutions



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

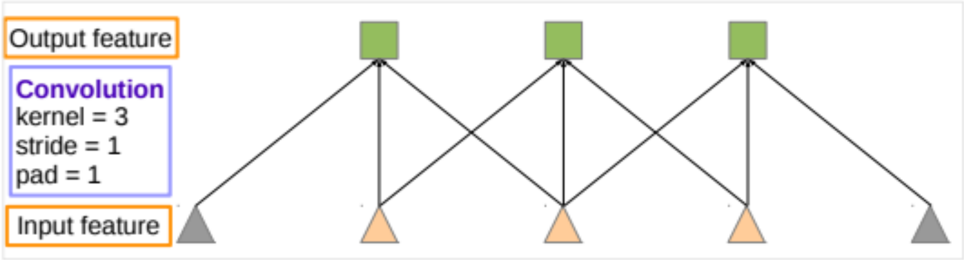
Alternative: Dilated (atrous) convolutions



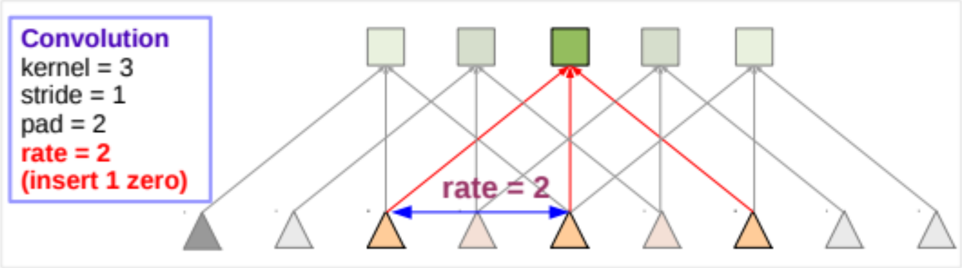
Sparse feature extraction with standard convolution on a low resolution input feature map.

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

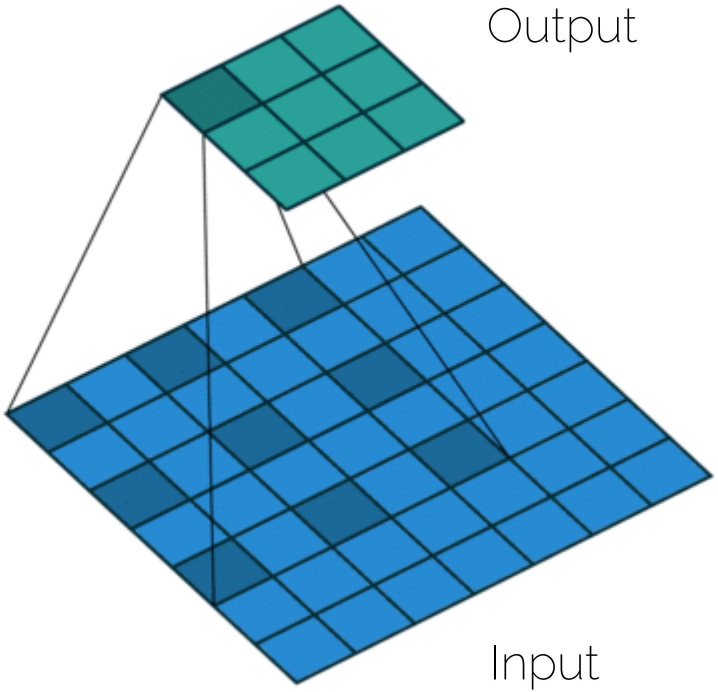


(b) Dense feature extraction

(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



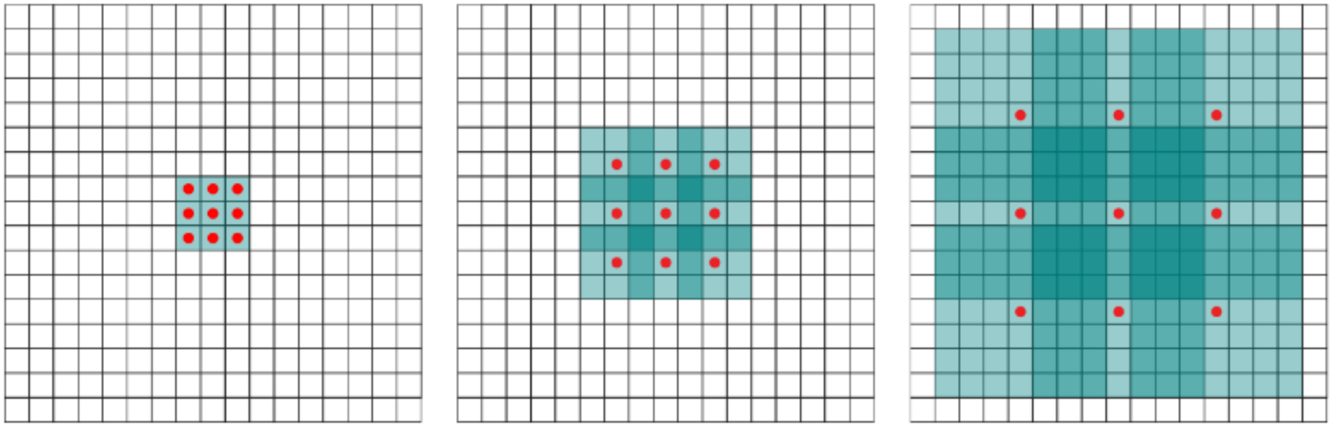
Standard convolution has dilation 1

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



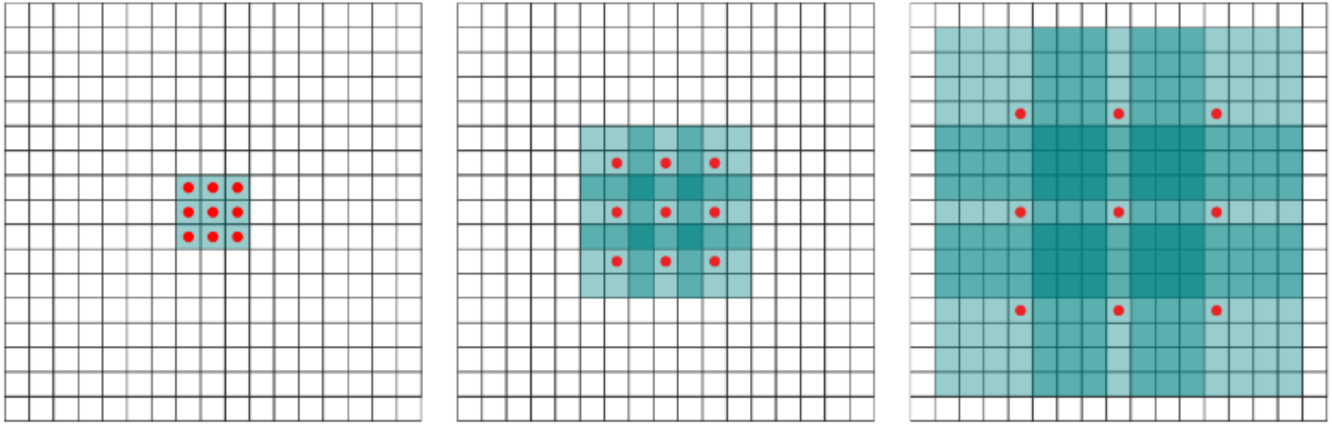
(a) (b) (c)

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

(b) the dilation parameter is 2, and each element produced by it has reception field of 7x7.

(c) the dilation parameter is 4, and each element produced by it has reception field of 15x15.

Dilated (atrous) convolutions 2D



(a) (b) (c)

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

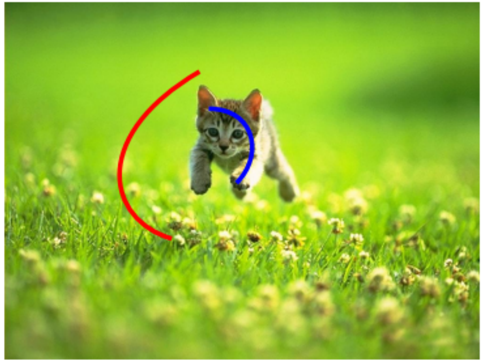
- Reduced feature resolution
  - Proposed solution: Atrous convolutions
- Objects exist at multiple scales
  - Proposed solution: Pyramid pooling, as in detection.
- Poor localization of the edges
  - Proposed solution: Refinement with Conditional Random Field (CRF)

Conditional Random Fields (CRF)

- Boykov and Jolly (2001)

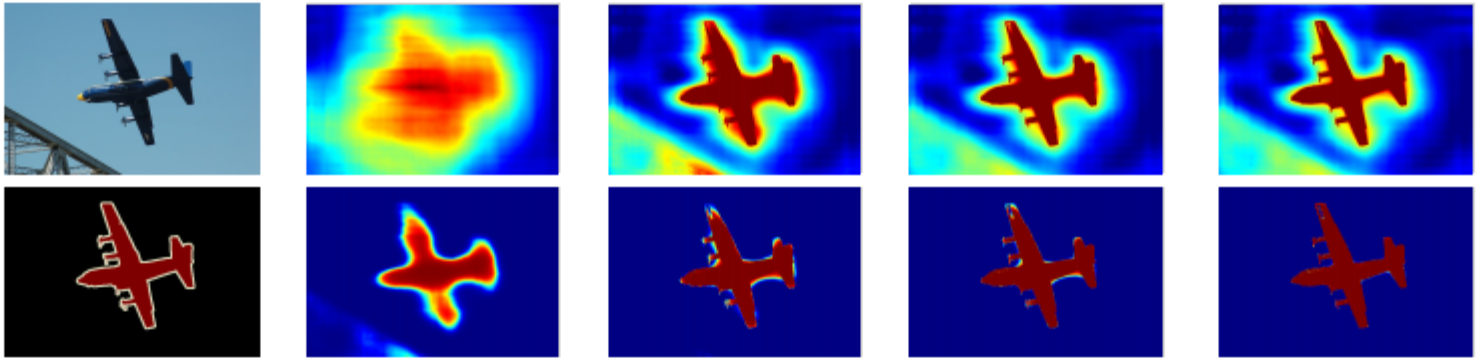
$$E(x, y) = \sum_i \varphi(x_i, y_i) + \sum_{ij} \psi(x_i, x_j)$$

- 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

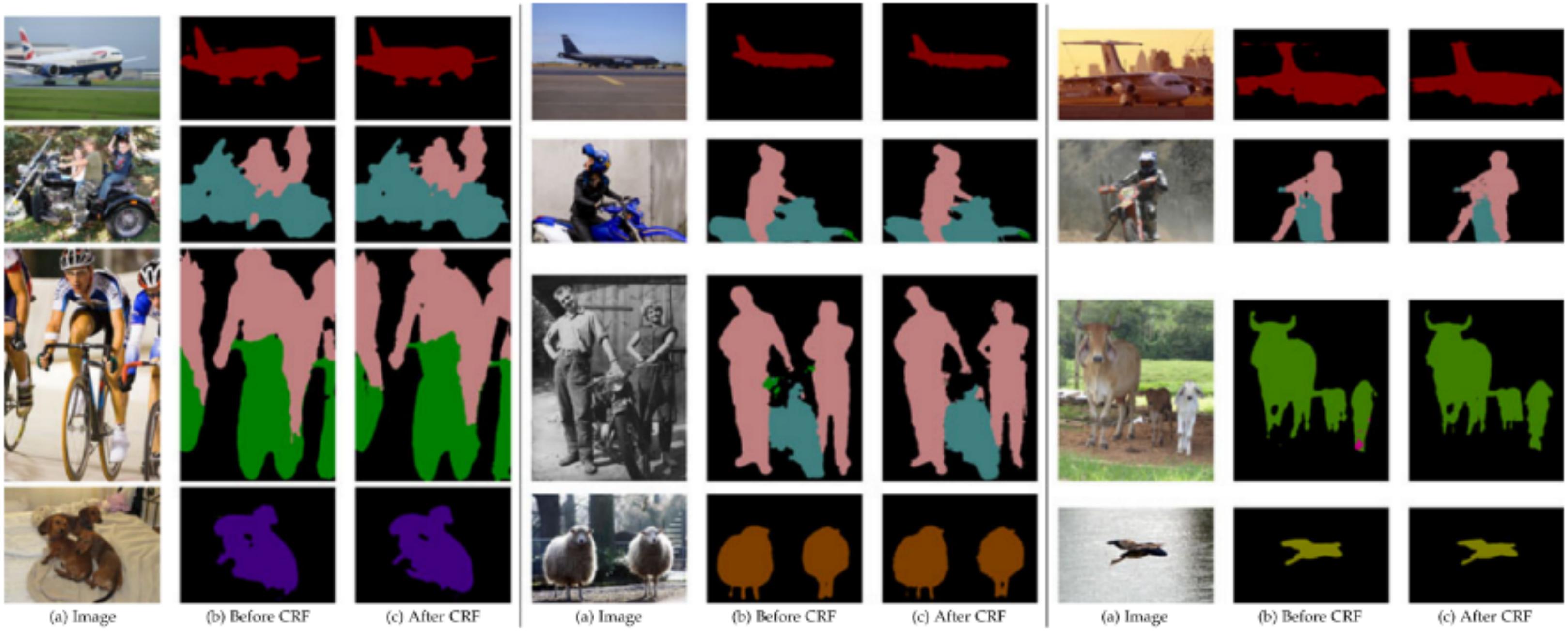
Effect of number of iterations of CRF



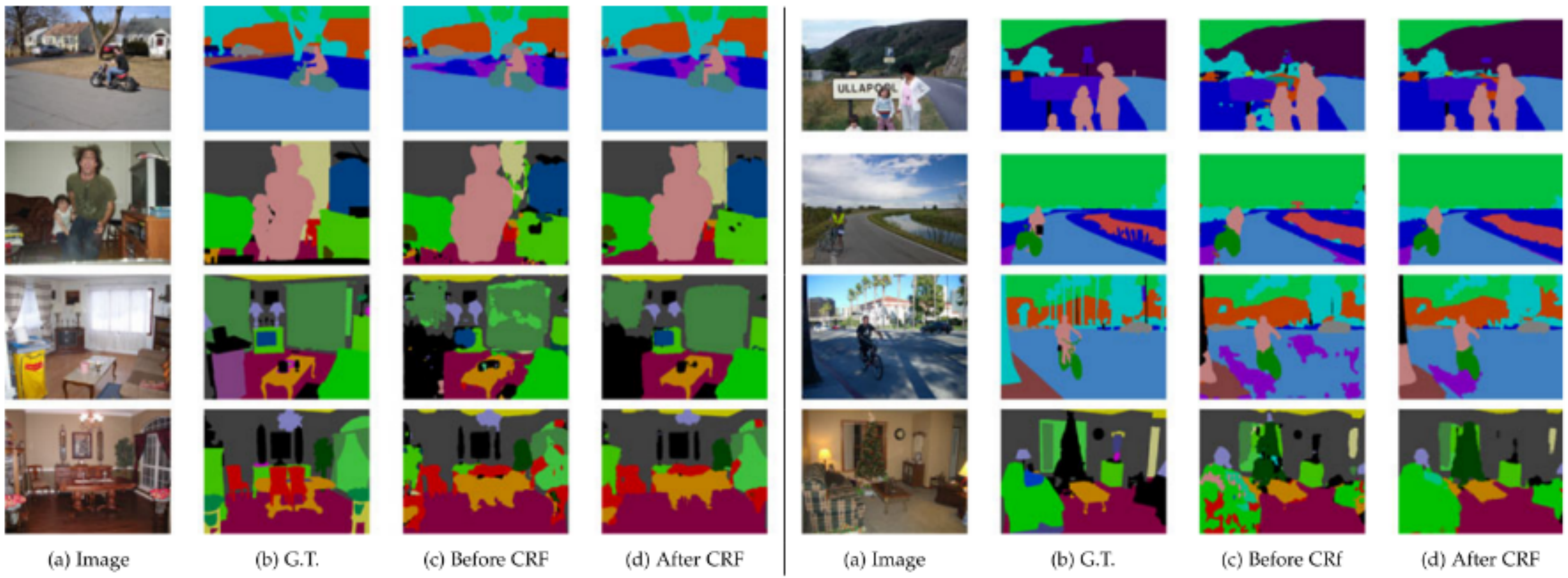
Image/G.T. DCNN output CRF Iteration 1 CRF Iteration 2 CRF Iteration 10

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.

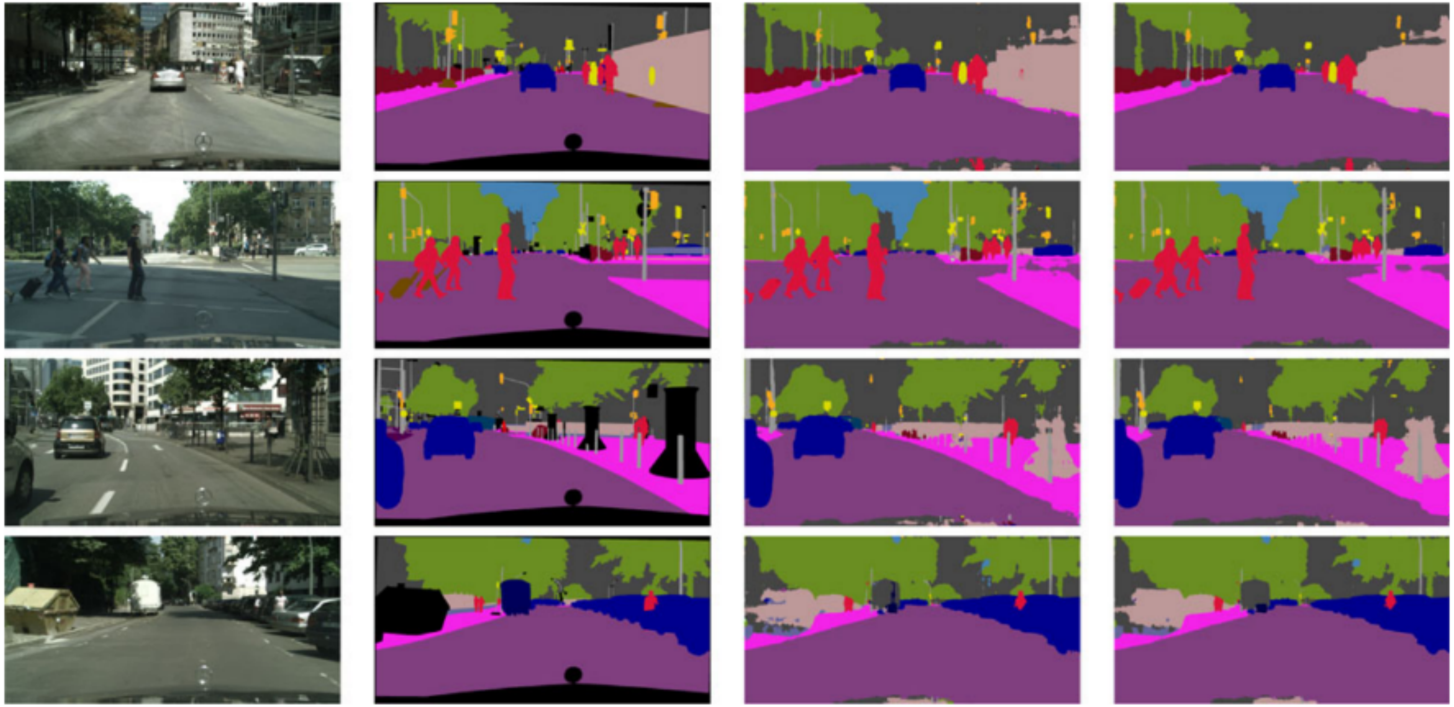
DeepLab: qualitative results



DeepLab: qualitative results



DeepLab: qualitative results



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

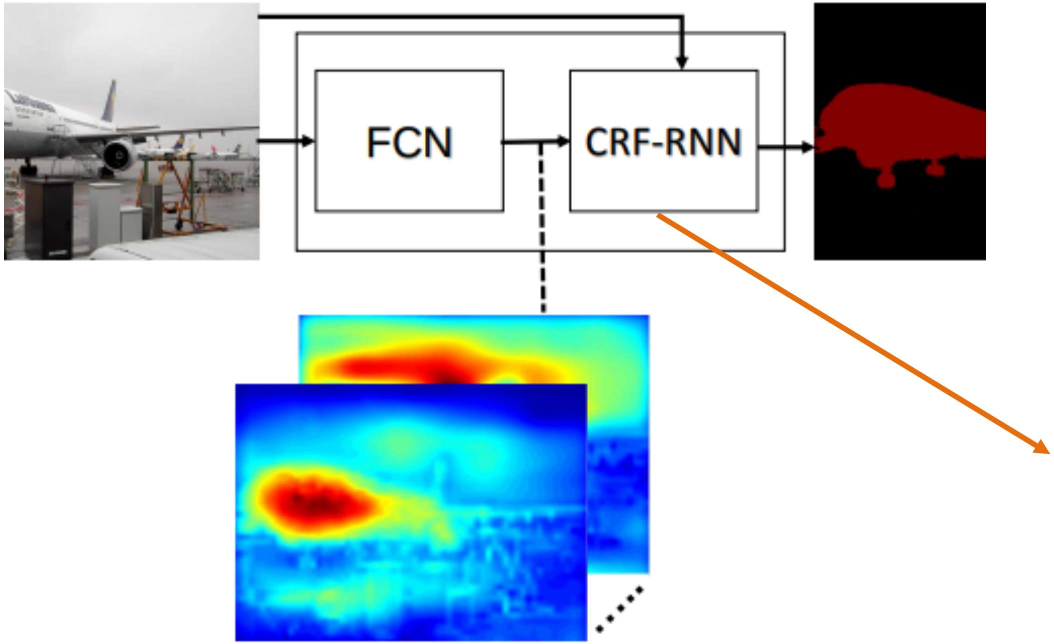
Problems with CRF

- 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

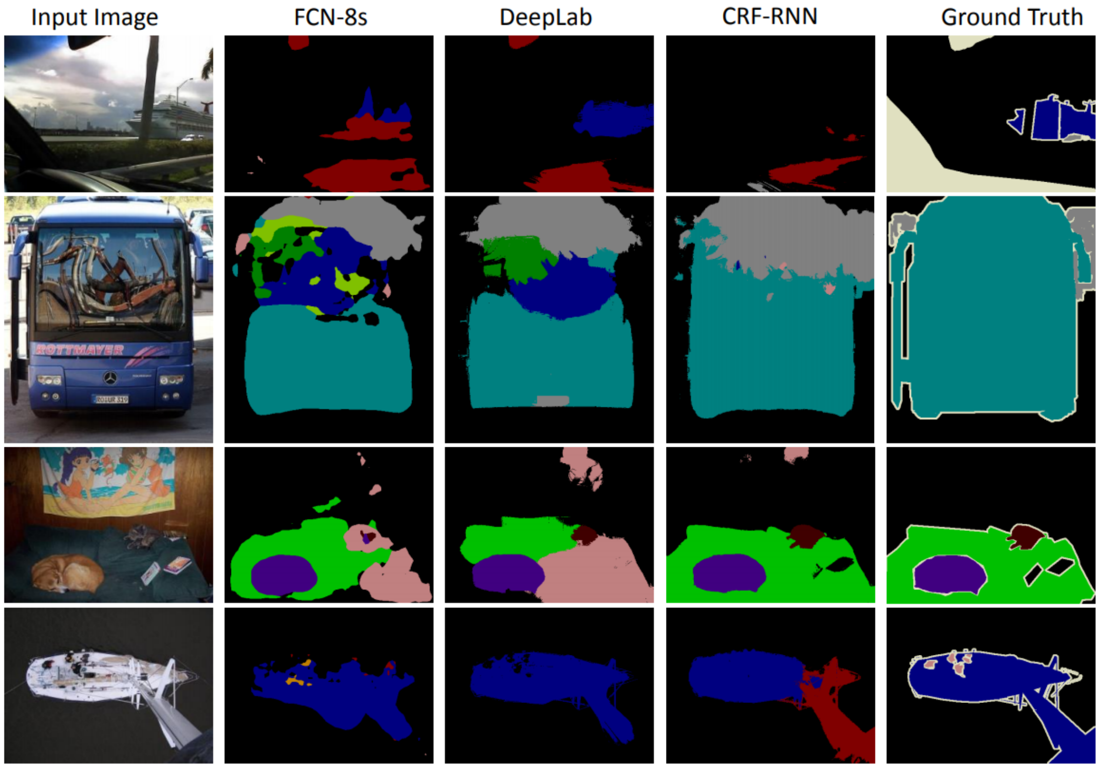


RNN that "emulates" a CRF

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

CRF-RNN: qualitative results

CRF-RNN: qualitative results



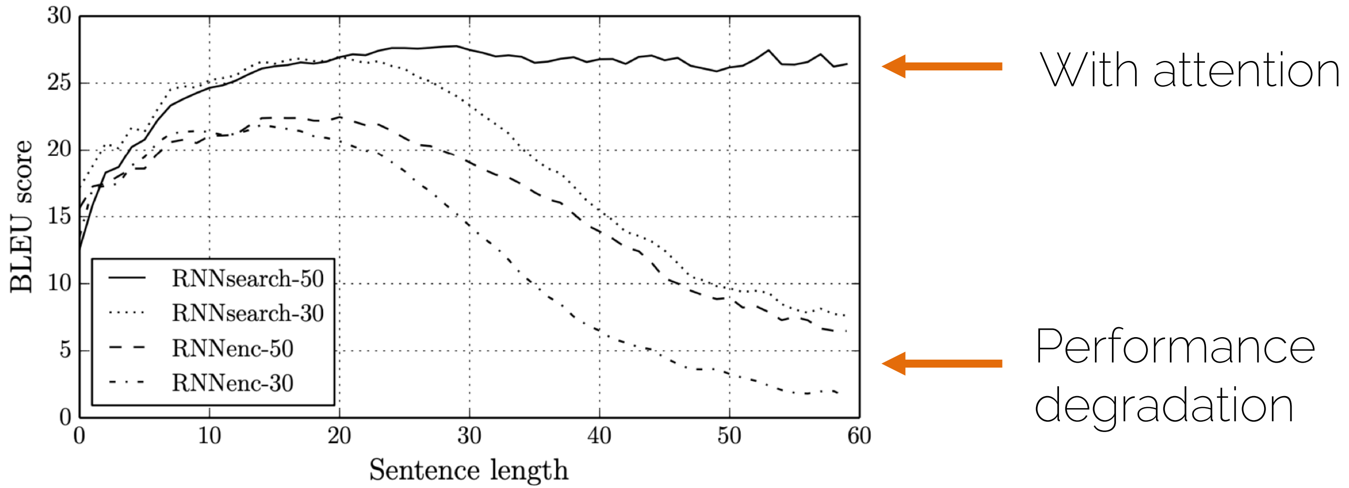
Why do we need the CRF?

- 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

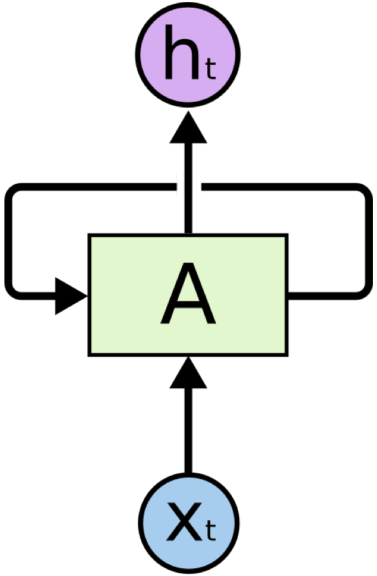
- For very long sentences, the score for machine translation really goes down after 30-40 words.



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

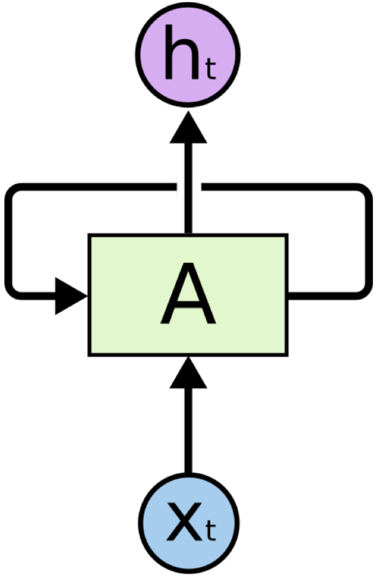
input

[Christopher Olah] Understanding LSTMs

Basic structure of a RNN

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

Hidden state

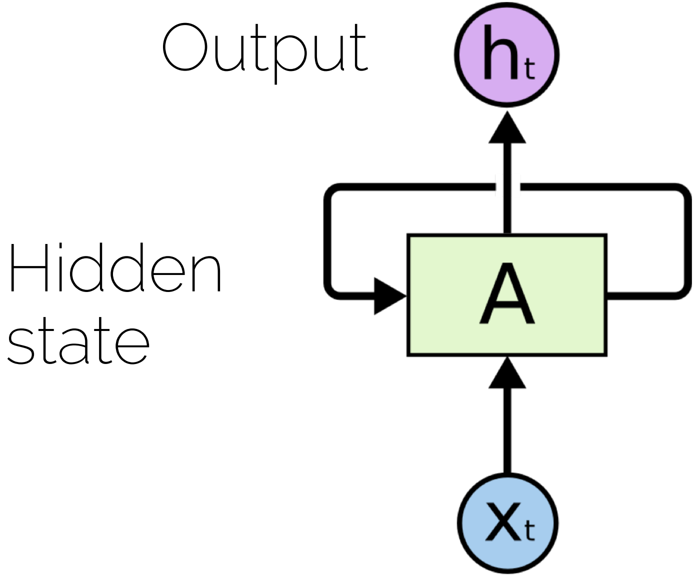


$$\mathbf{A}_t = \boldsymbol{\theta}_c \mathbf{A}_{t-1} + \boldsymbol{\theta}_x \mathbf{x}_t$$

Parameters to be learned

Basic structure of a RNN

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



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

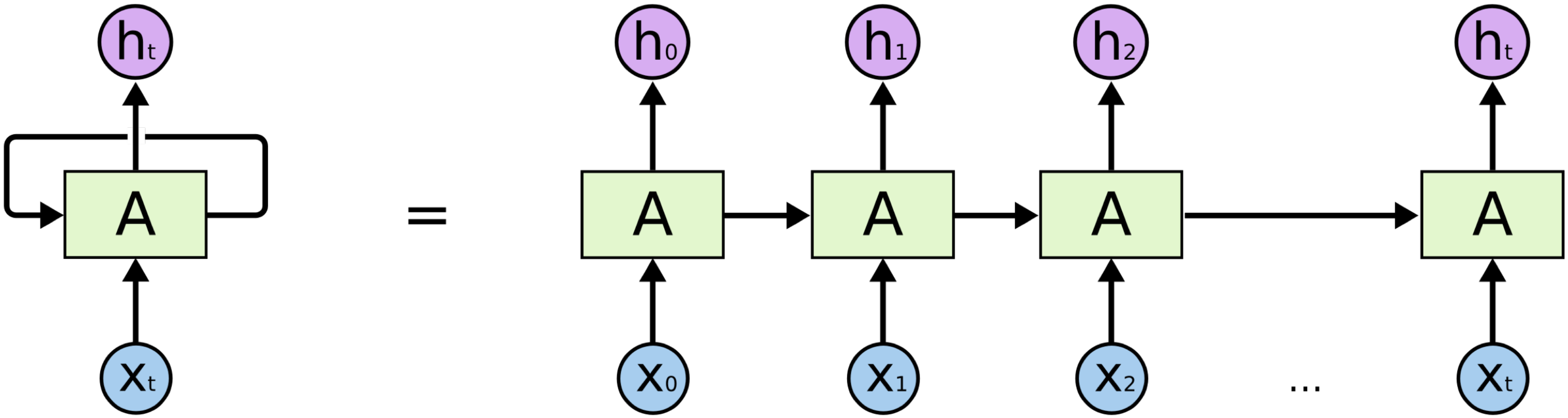
$$\mathbf{h}_t = \boldsymbol{\theta}_h \mathbf{A}_t$$

Same parameters for each time step = generalization!

Basic structure of a RNN

- Unrolling RNNs

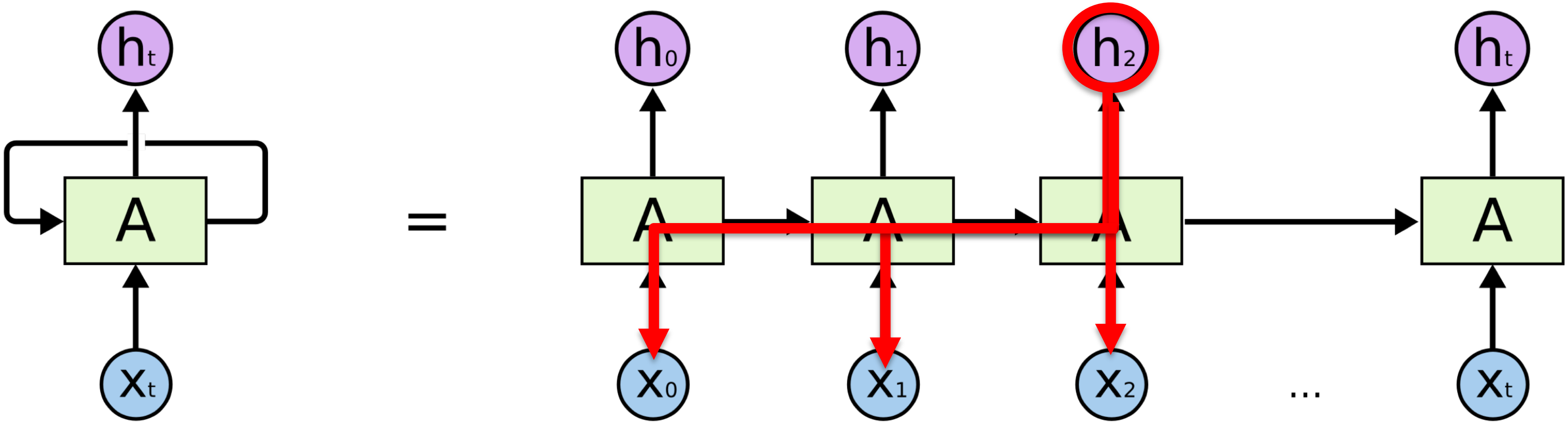
Hidden state is the same



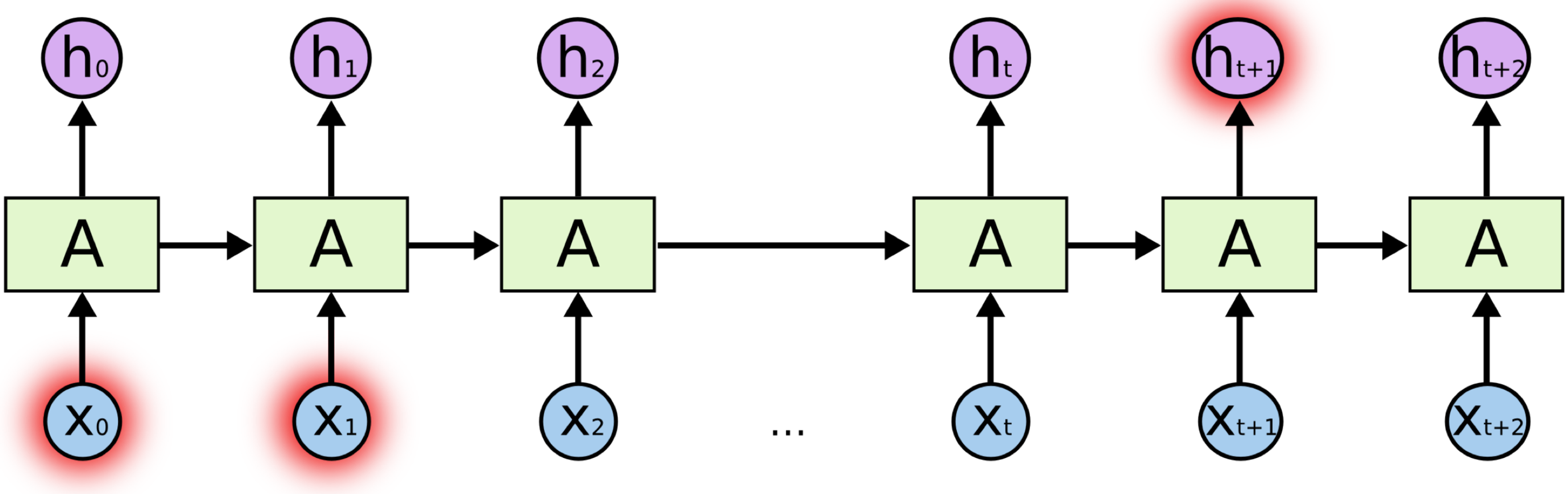
[Christopher Olah] Understanding LSTMs

Basic structure of a RNN

- Unrolling RNNs



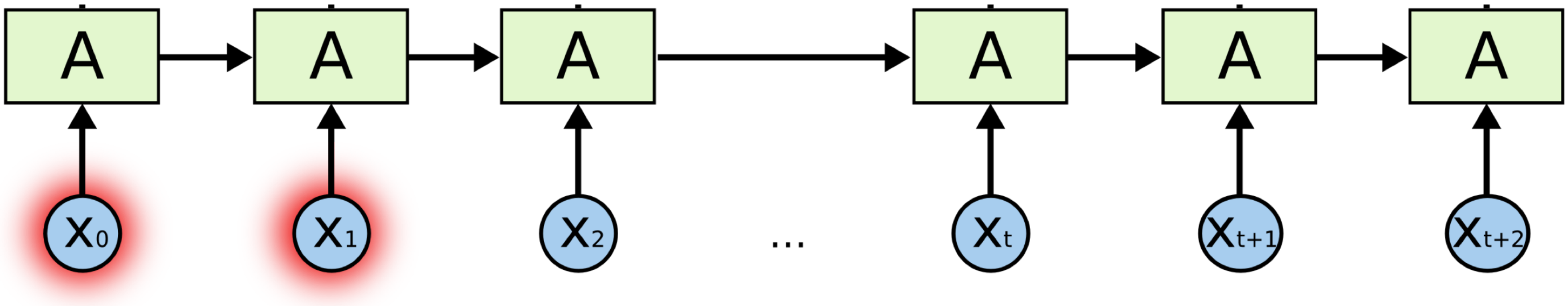
Long-term dependencies



I moved to Germany … so I speak German fluently

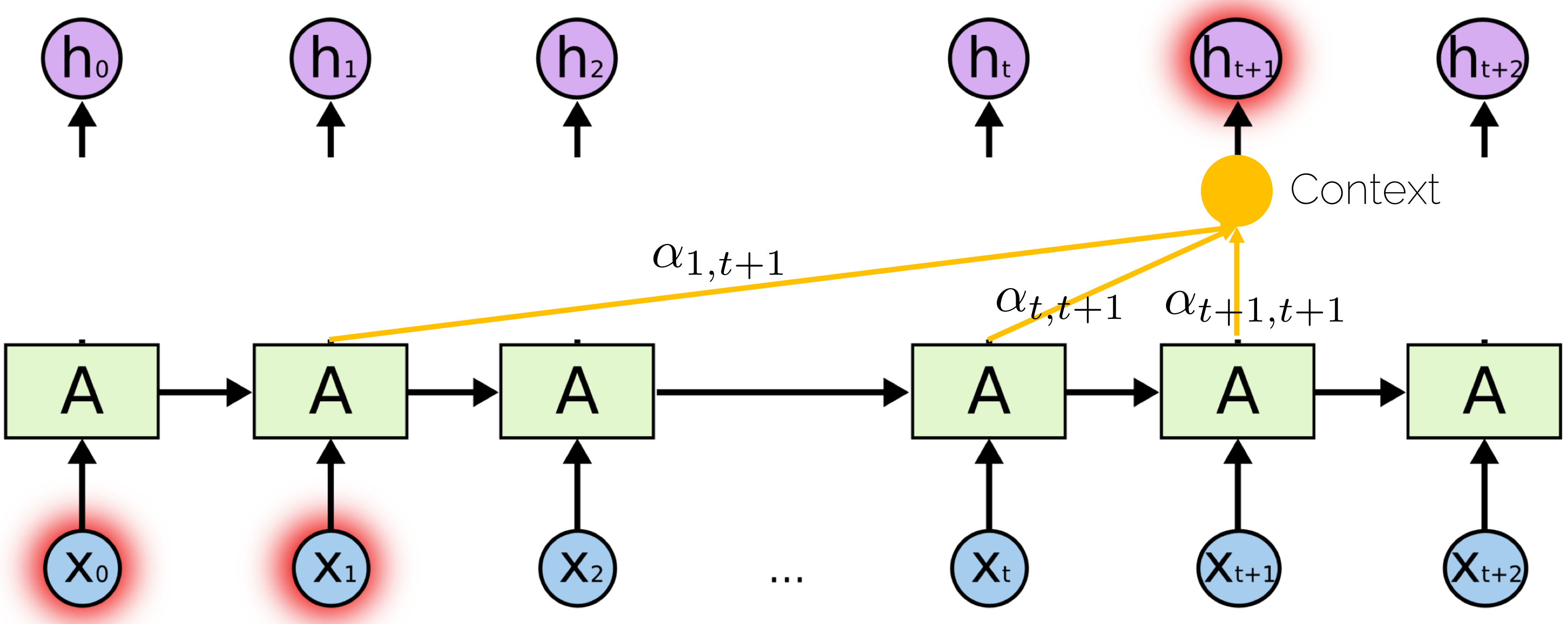
Attention: intuition

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



I moved to Germany … so I speak German fluently

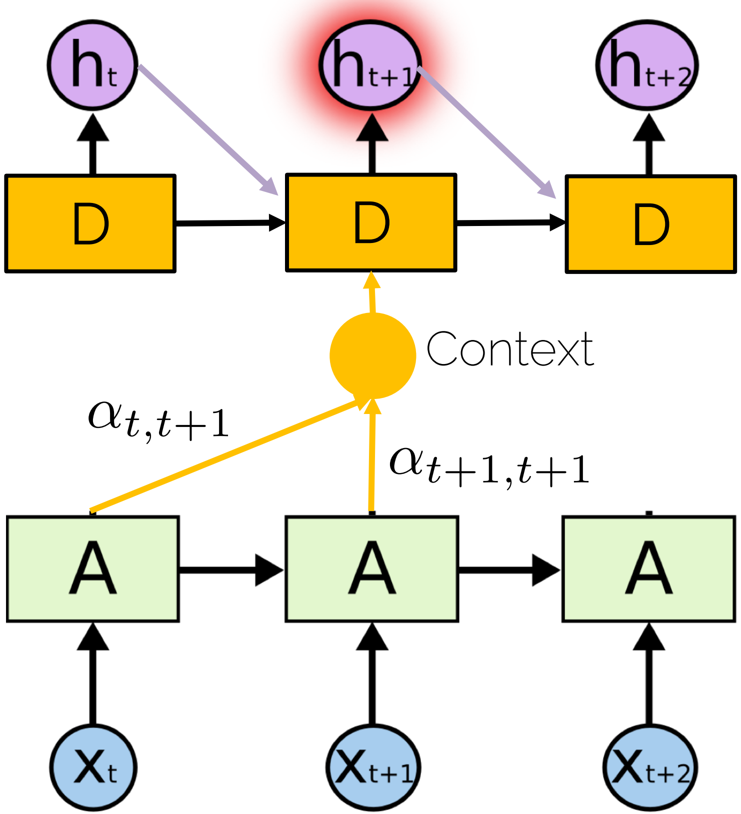
Attention: intuition



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 work in position $t+1$

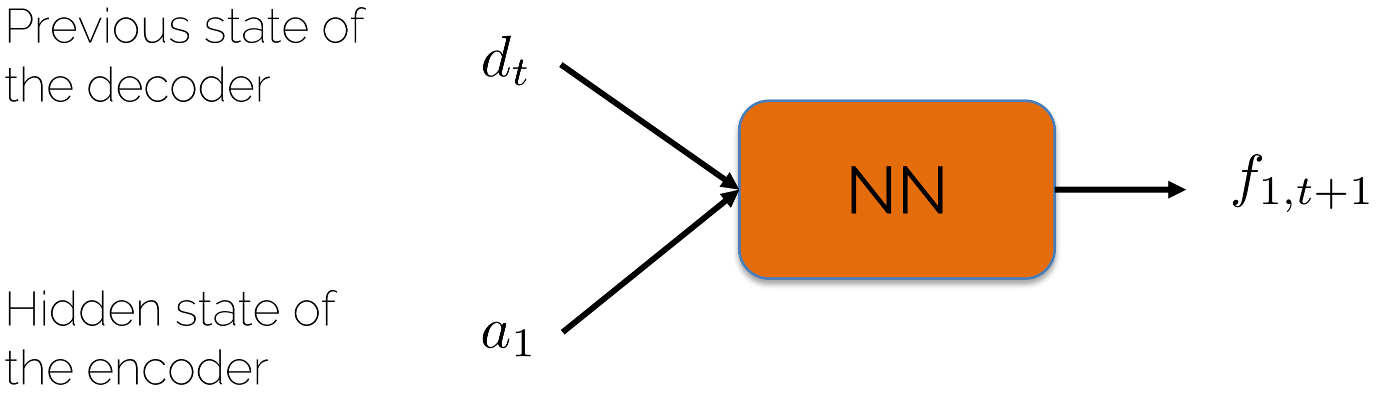
- The context aggregates the attention

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

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

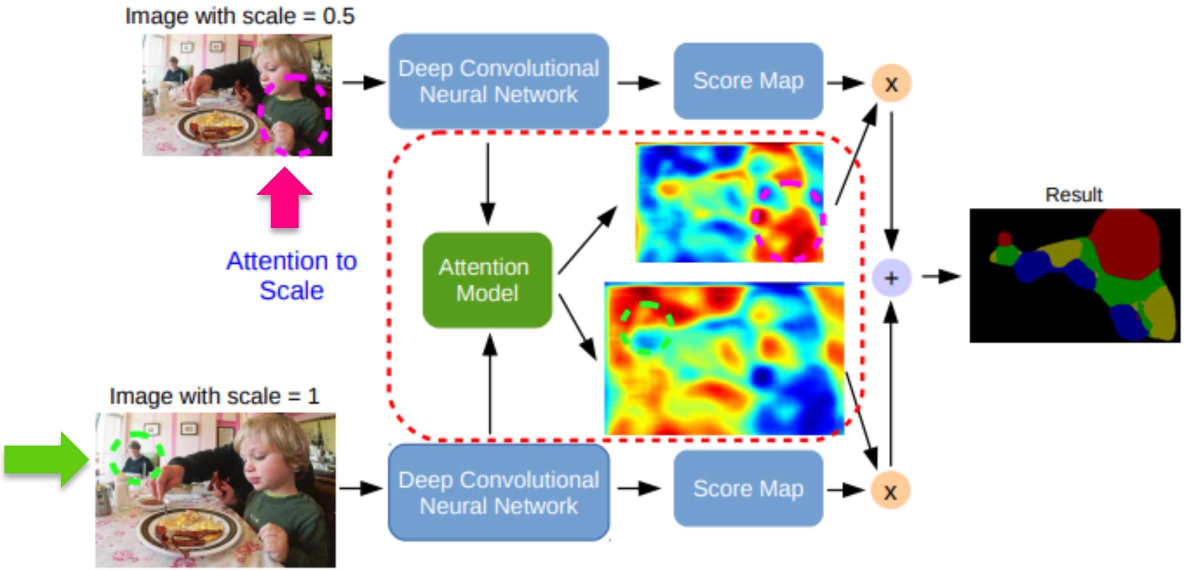
Computing the attention mask

- We can train a small neural network



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

Attention for semantic segmentation



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

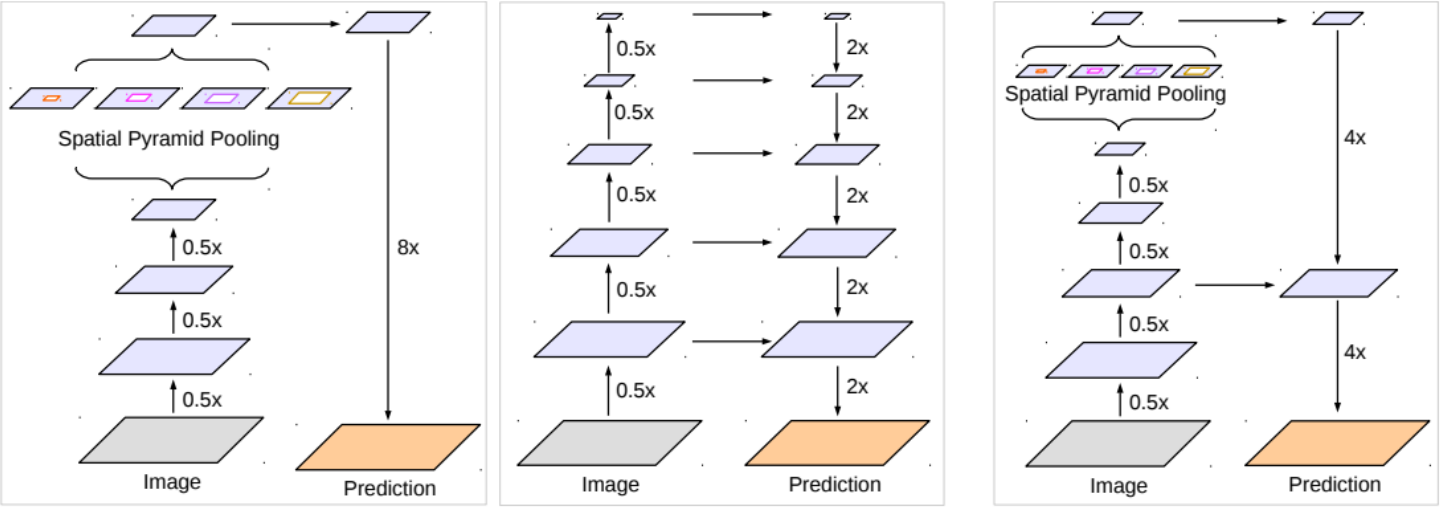
For example, the model learns to put large weights on the small-scale person (green dashed circle) for features from scale = 1, and large weights on the large-scale child (magenta dashed circle) for features from scale = 0.5. We jointly train the network component and the attention model.

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)?

Spoiler alert: Not neccesarly.

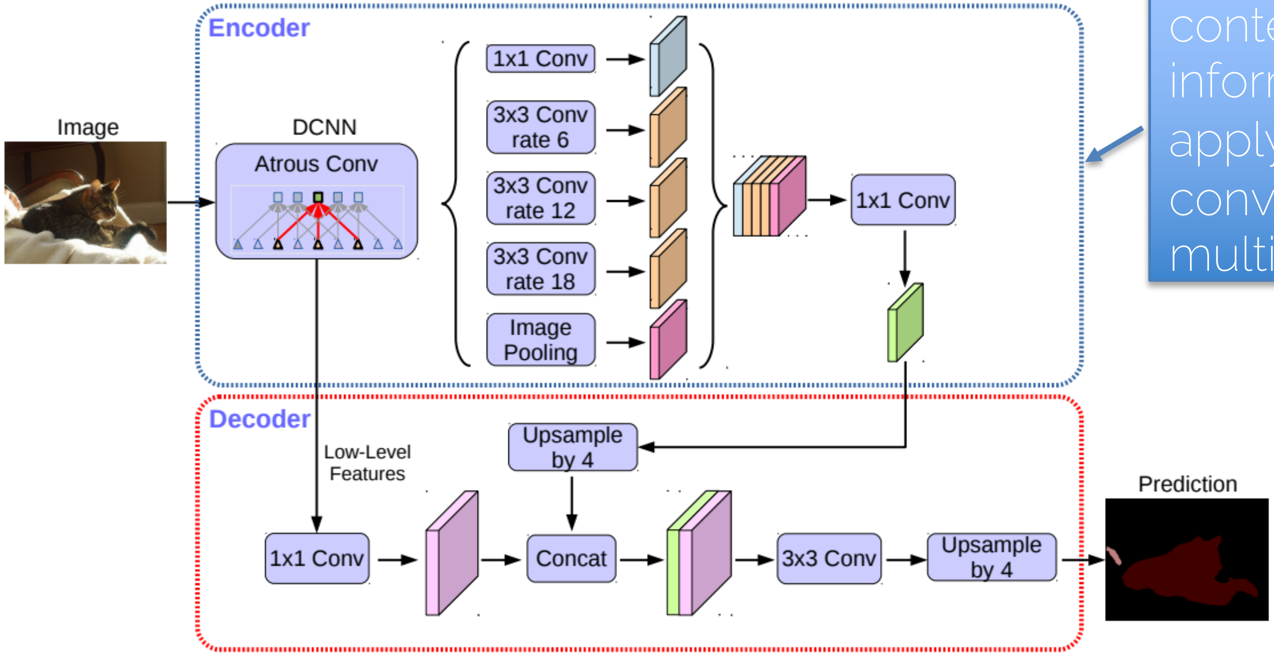
DeepLabv3+



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

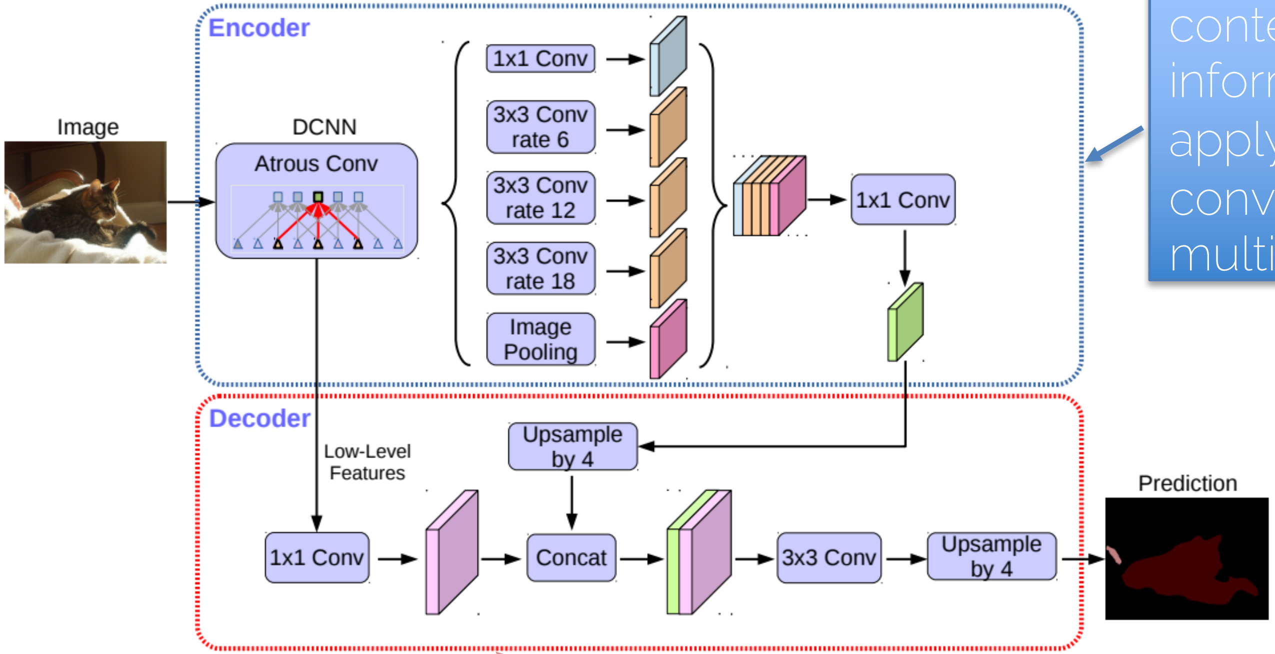
Combine atrous convolutions and spatial pyramid pooling with an encoder-decoder module.

Delving deeper into DeepLabv3+



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

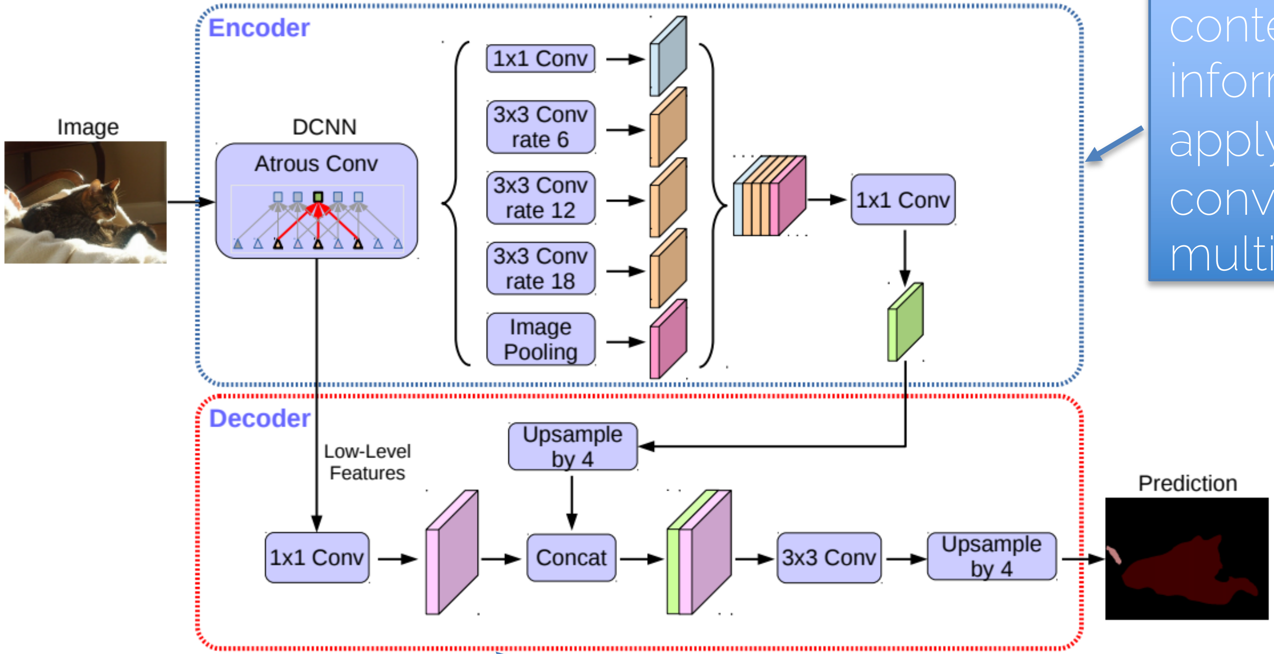
Delving deeper into DeepLabv3+



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+

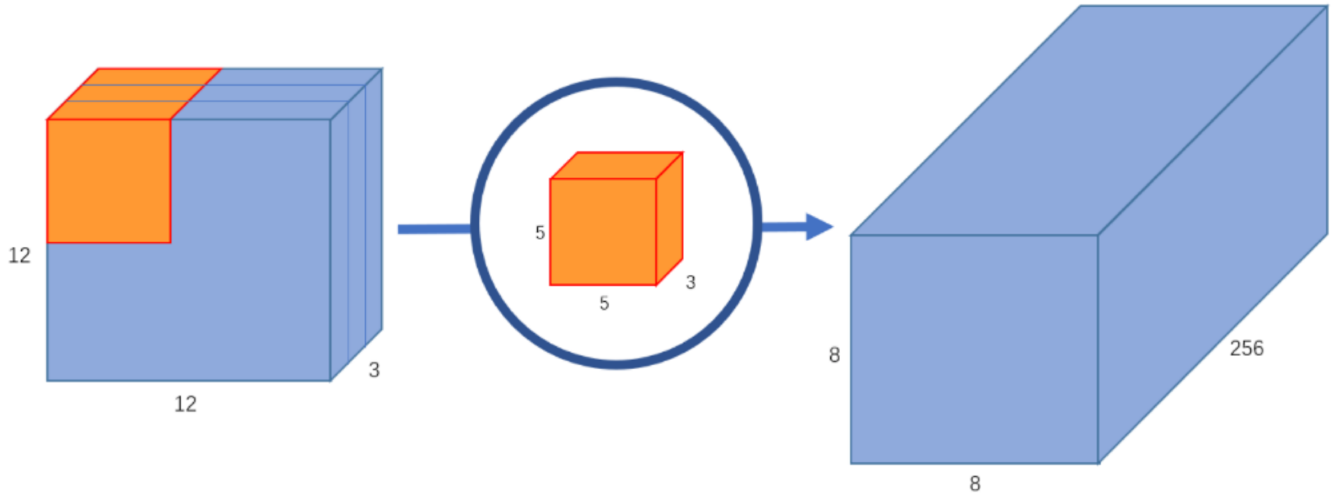


1) Encode multi-scale contextual information by applying atrous convolution at multiple scales

3) Use depthwise separable convolutions.

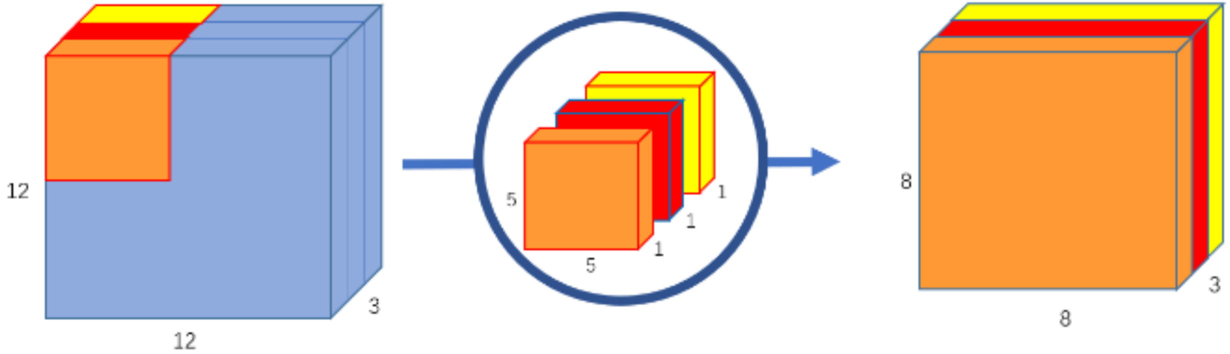
2) Refine the segmentation results along object boundaries.

Depth-wise separable convolutions



Normal convolutions act on all channels.

Depth-wise separable convolutions

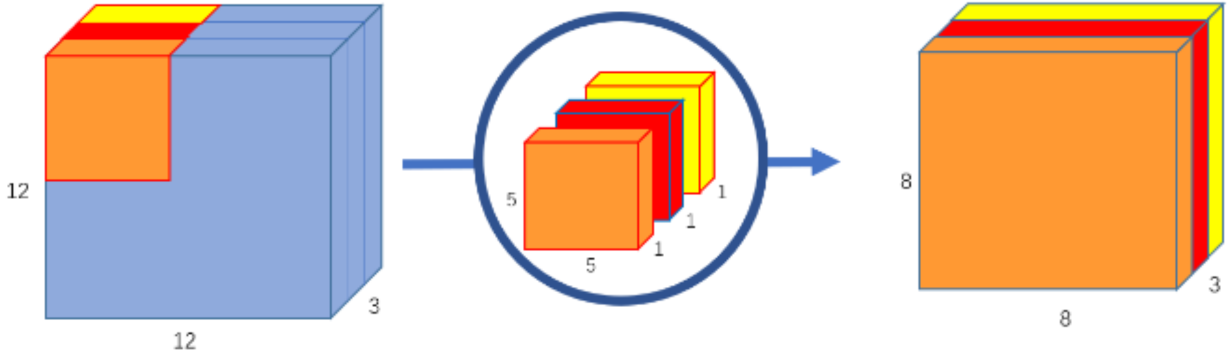


Filters are applied only at certain depths of the features. Normal convolutions have groups set to 1, the convolutions used in this image have groups set to 3.

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

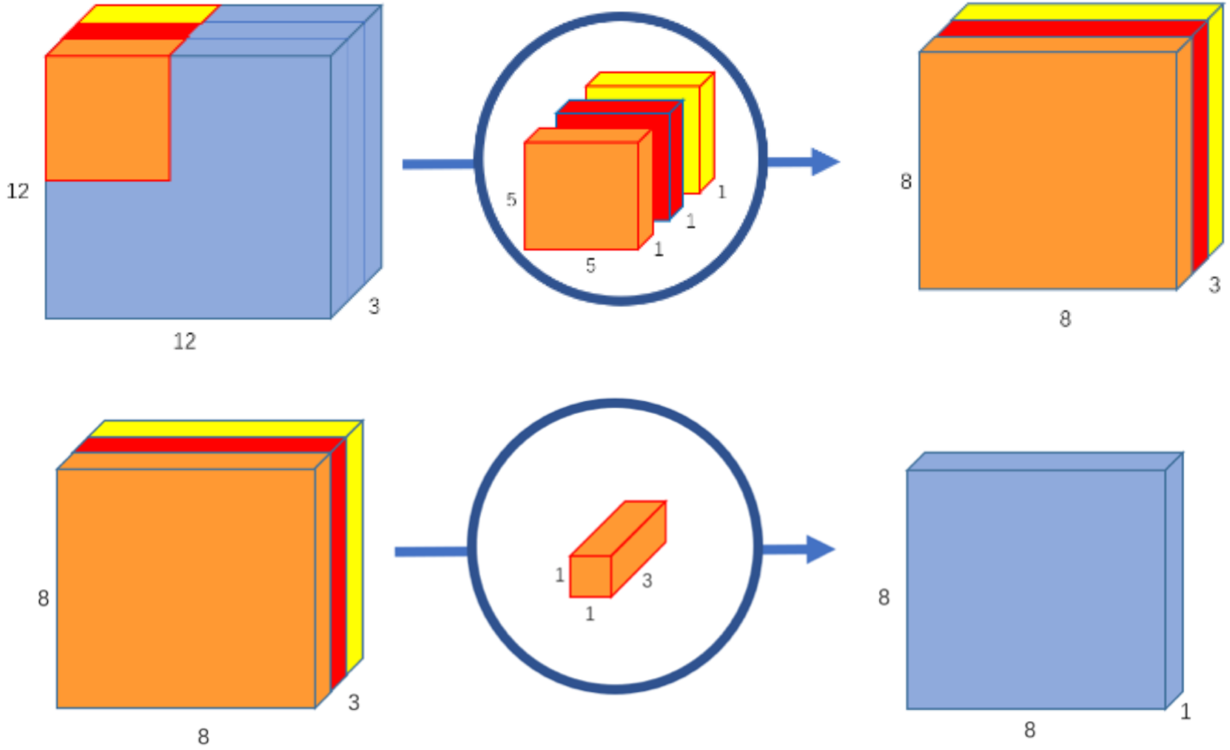


But the depth size is always the same!

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

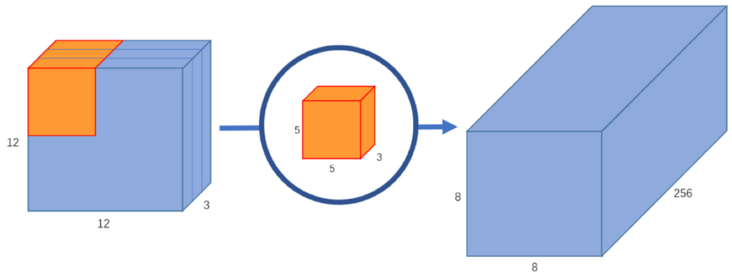
class **torch.nn.ConvTranspose2d**(*in_channels, out_channels, kernel_size, stride=1, padding=0, groups=3*)

Depth-wise separable convolutions



Solution:
1x1 convs!

But why?



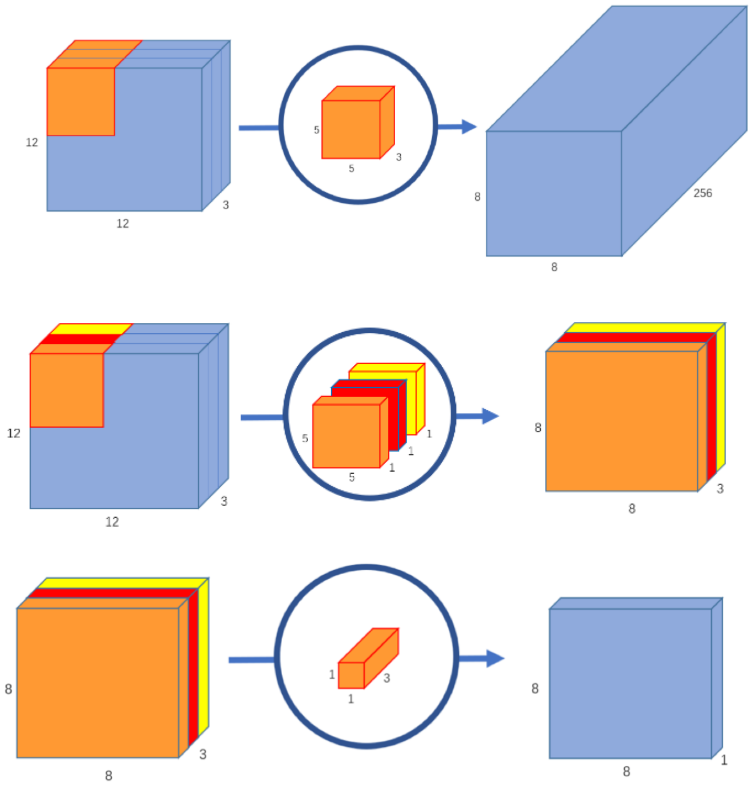
Original convolution

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

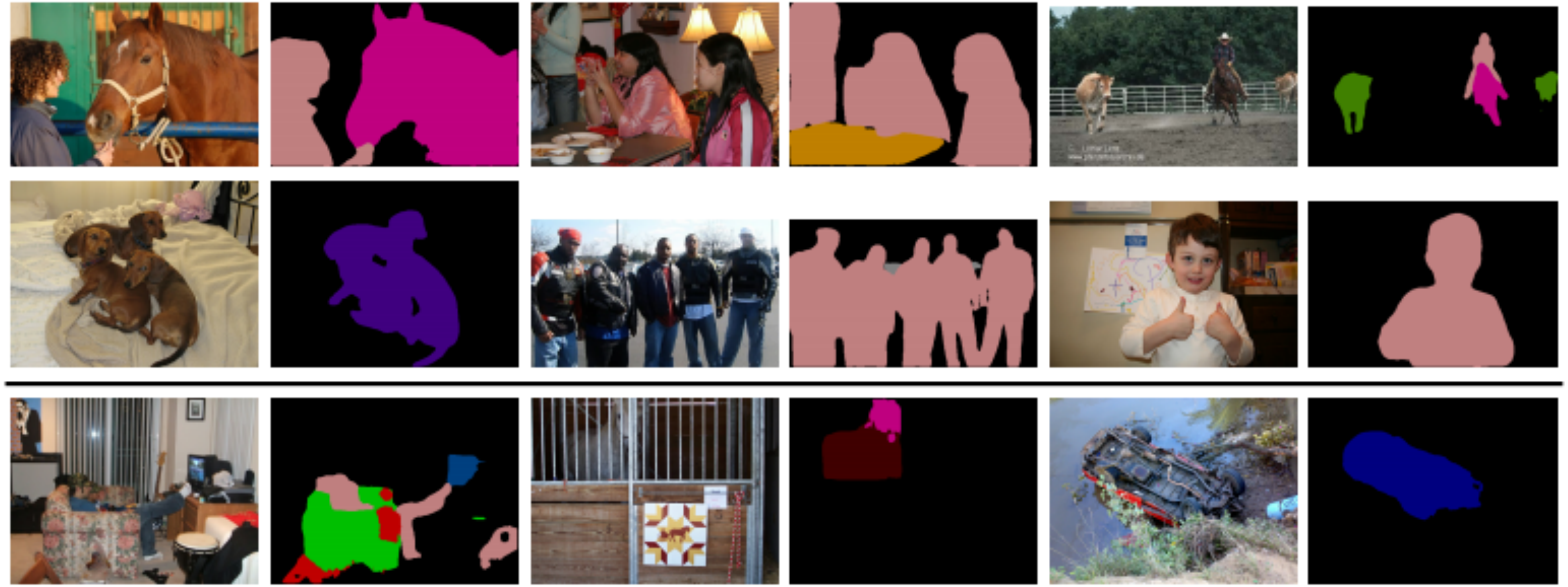
Multiplications:
5x5x3 x (8x8 locations) = 4800

1x1 convolution
256 kernels of size 1x1x3

Multiplications:
256x1x1x3x (8x8 locations) = 49152

Less computations!

DeepLabv3+: qualitative results



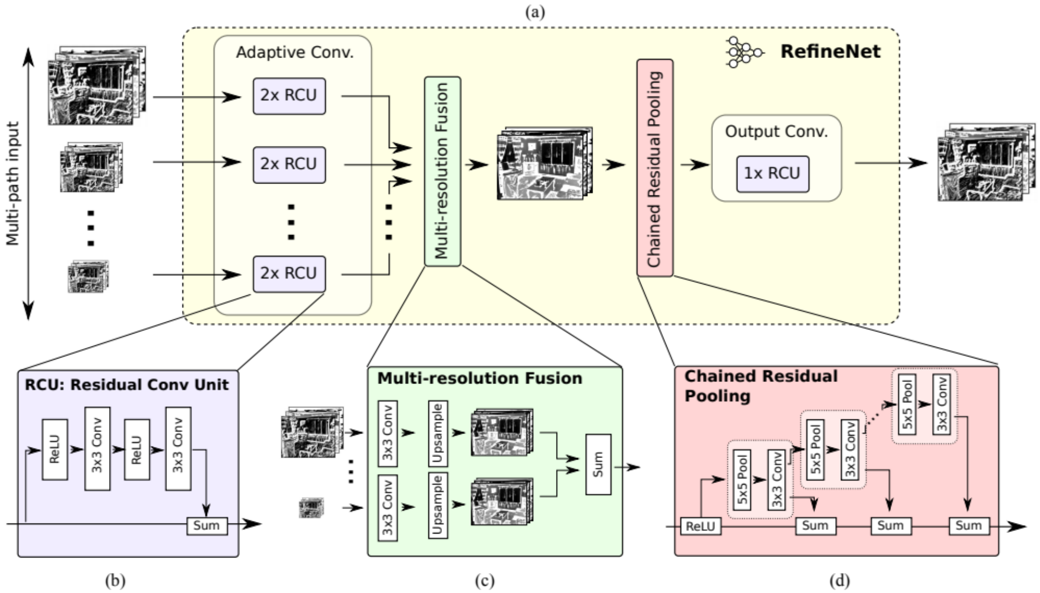
Still considered as SOTA!

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

DeepLab is amazing, but there are other important architectures to know.

Recommended reads

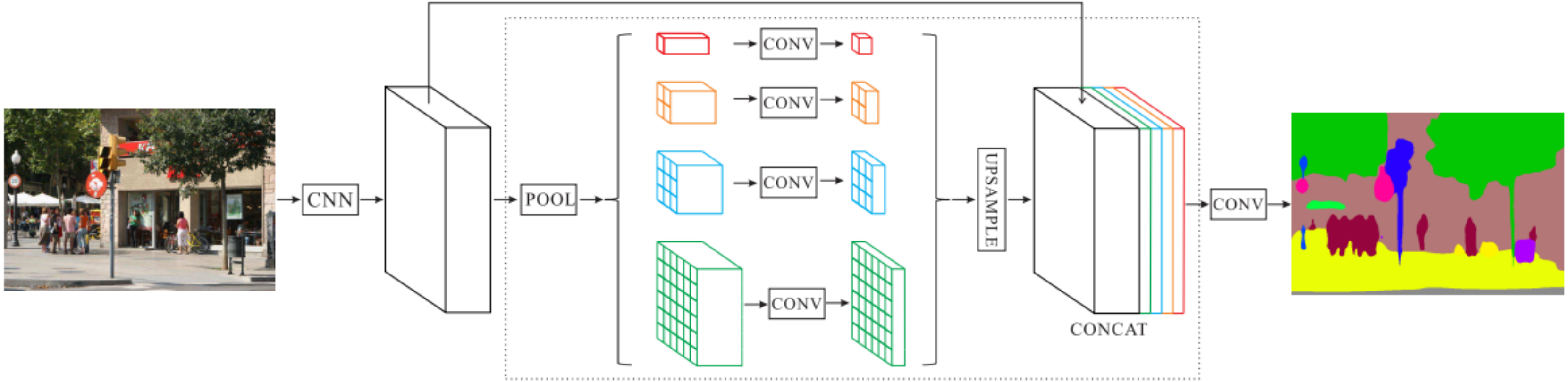
RefineNet



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



(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

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

Datasets and metrics

Datasets

Pascal VOC 2012:

9993 natural images divided into 20 classes.

Cityscapes:

25K urban-street images divided into 30 classes.

ADE20K:

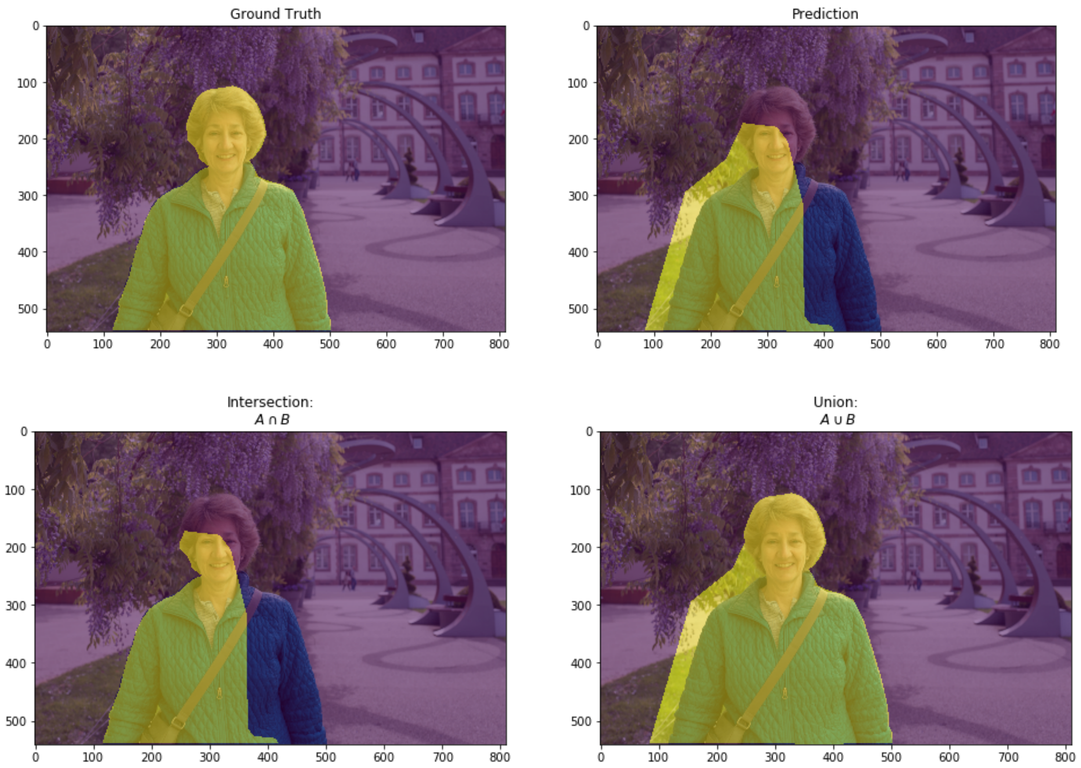
25K (20 stands for 20K training) scene-parsing images divided into 150 classes.

Mapillary Vistas:

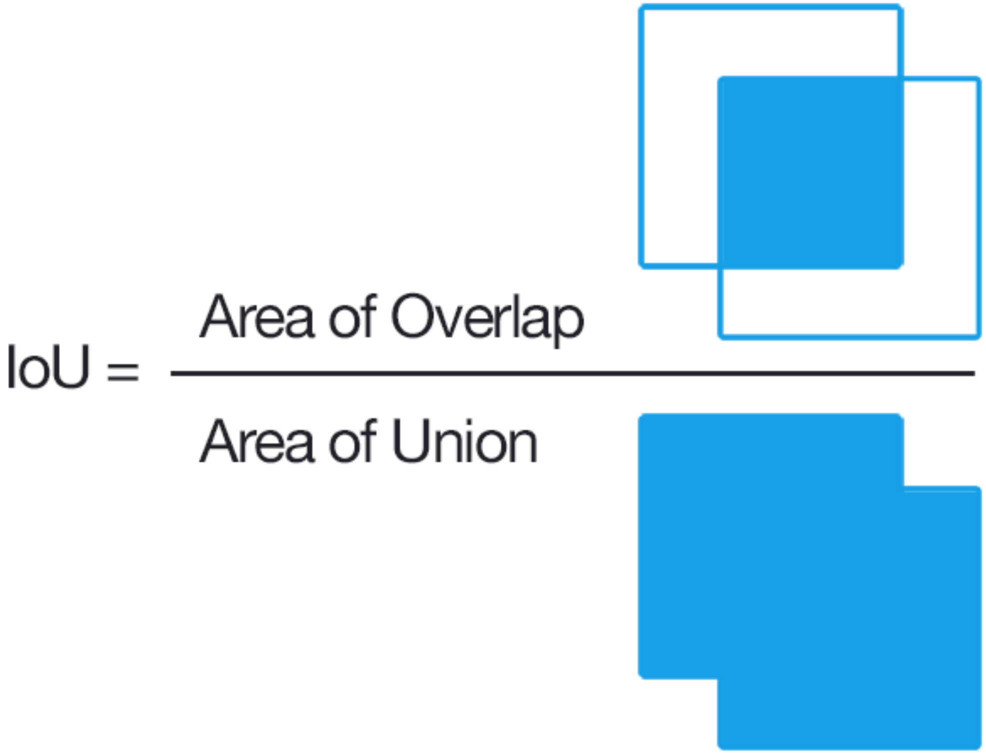
25K street level images, divided into 152 classes.

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

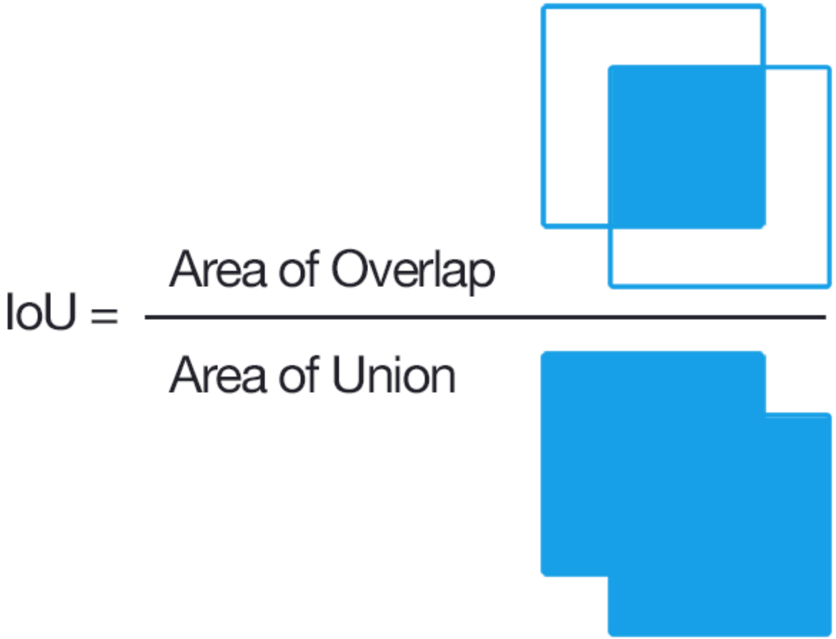
Metrics: intersection over union (IoU)



Metrics: intersection over union (IoU)



Metrics: mean intersection over union (mIoU)



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).

So, what model to use?

- Typically DeepLab models are considered to be good baselines. Nevetheless, different problems might require different models (no free lunch in deep learning).
- Don't be a hero! Before making up your own model, use some of the SOTA models, for example the best performing model in PASCAL VOC.

CV3DST Competition

- The tracking challenge is evaluated on a subset of the MOT16 test data. (Sequences 01, 03, 08, 12)
- The training data can be downloaded from the MOT challenge website: https://motchallenge.net/data/MOT16/
- The submission website is https://admg.in.tum.de/embed.php/prakt/cv3dst
- You will have to sign with your matriculation number to get your account. If you do not have a TUM matriculation number, please send a mail to dst@dvl.in.tum.de

- Every student only has 1 ACCOUNT.
- You are allowed to submitt 4 TIMES to the challenge. Always the most recent submission is considered for the bonus (BE CAREFUL, YOU CAN WORSEN YOUR RESULTS)

CV3DST Competition

- In order to be eligible for the bonus you will need to achieve a MOTA > Threshold (tbd)

- Every student has to submit their own results (we will check code and results!).

CV3DST Competition

- Dates:
  - 15.01.20: Test set is open for submission!
  - 02.02.20 (midnight): Competition closes
  - 03.02.20 (midnight): Abstract and code submission deadline
  - 04.02.20: Presenters are announced
  - 07.02.20: Presentation of selected methods

Next lectures

- Instance segmentation and panoptic segmentation
- Next lecture on January 17th.