ECE371
Neural Network and Deep Learning

Lecture 5
Computer Vision Basic - Part II

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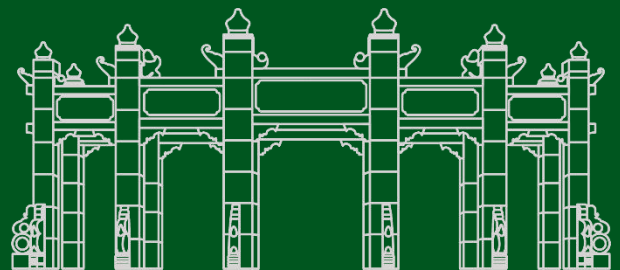


Slides partially credited to Prof. Hongsheng Li at CUHK.

What is segmentation?

Task: Segment the image into regions according to the class of the object

Equivalent to: Classify each pixel

Semantic v.s. Instance v.s. Panoramic Segmentation

Semantic Segmentation

- Only consider the class of pixels
- Do not segment different entities of the same class

Instance Segmentation

- Segment different entities
- Only consider the foreground objects

Panoramic Segmentation

- Background (stuff) only considers categories
- The foreground (thing) needs to distinguish entities

Application: Portrait Segmentation

- Replace the background of the video in real time

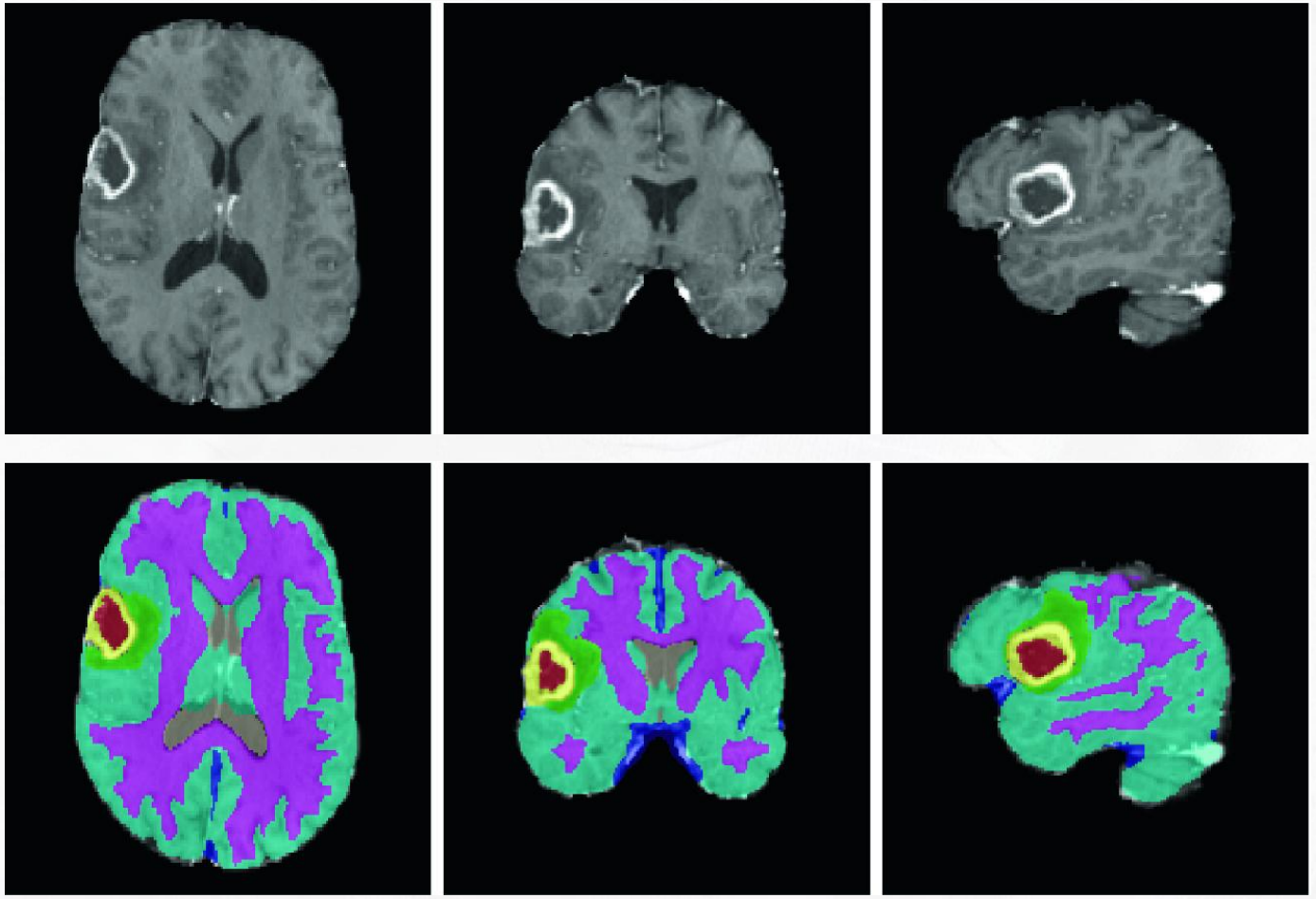
- In smart entertainment and smart conference scenarios, this method can increase the diversity of interactions

Application: Self-driving Car

The self-driving algorithms will segment pedestrians, other vehicles, lanes, sidewalks, traffic signs, houses, grass, trees, etc. in the image according to their categories, so as to assist the vehicle to perceive the road situation

Application: Medical Imaging Analysis

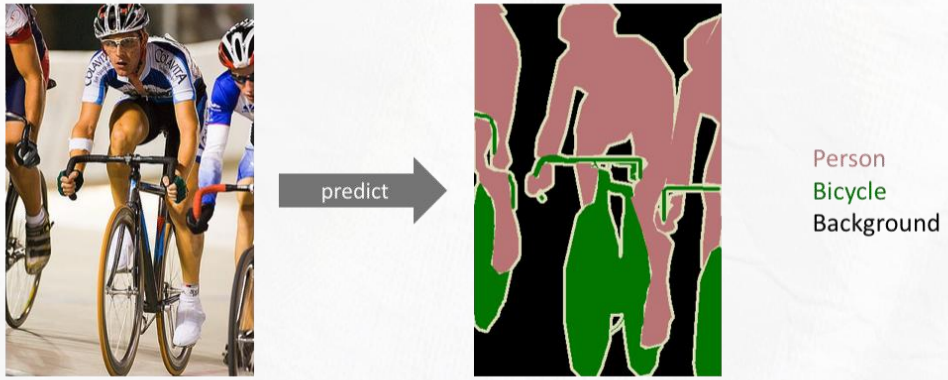
- Assist in medical diagnosis through image segmentation technology. As shown on the right, the position of the tumor in the brain is identified.



Outline

The Problem of Semantic Segmentation

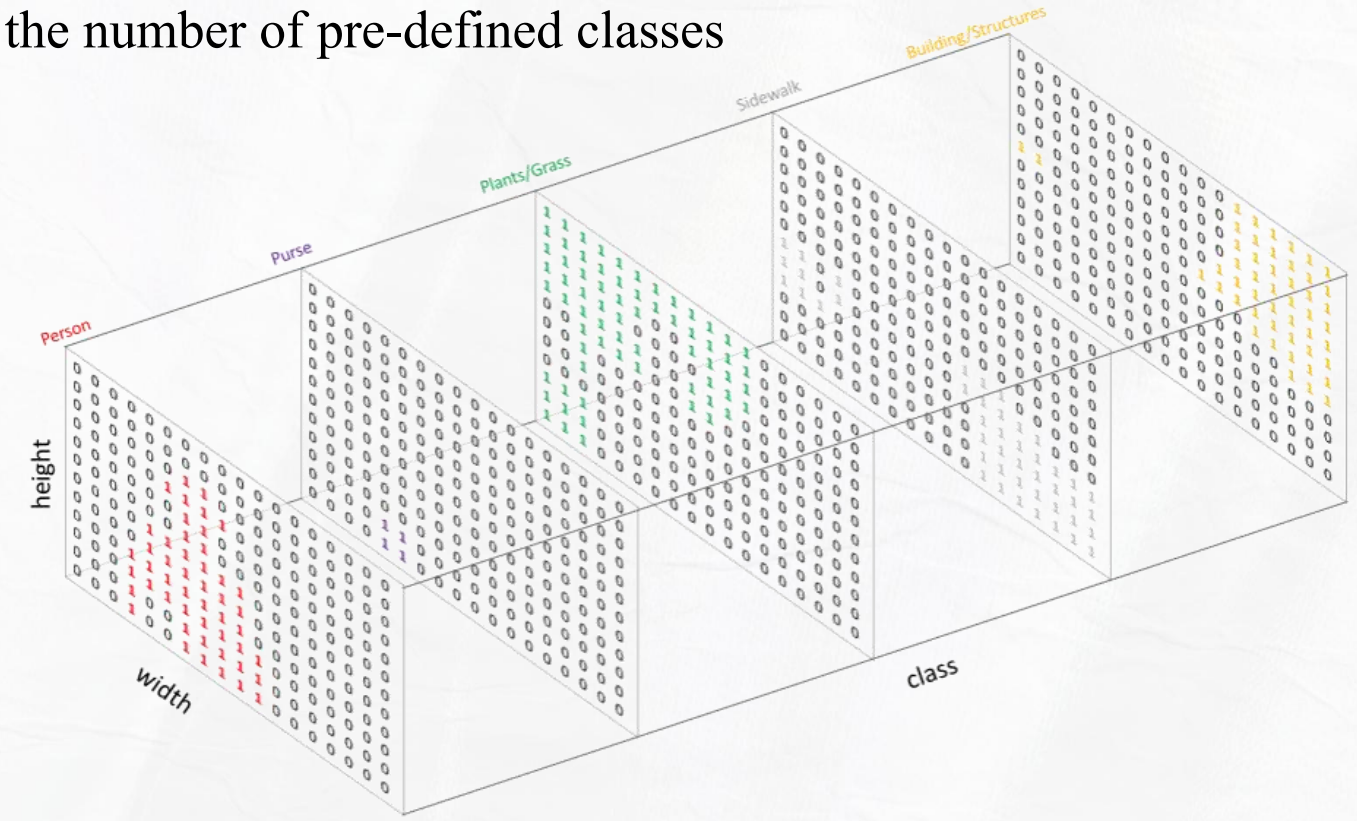
- Given an input image, semantic segmentation aims at assigning each pixel a pre-defined class labels



- Ground-truth representation: each pixel stores a ground-truth class label

Interpretation of 2D Class Maps and Pixel-wise Cross-entropy Loss

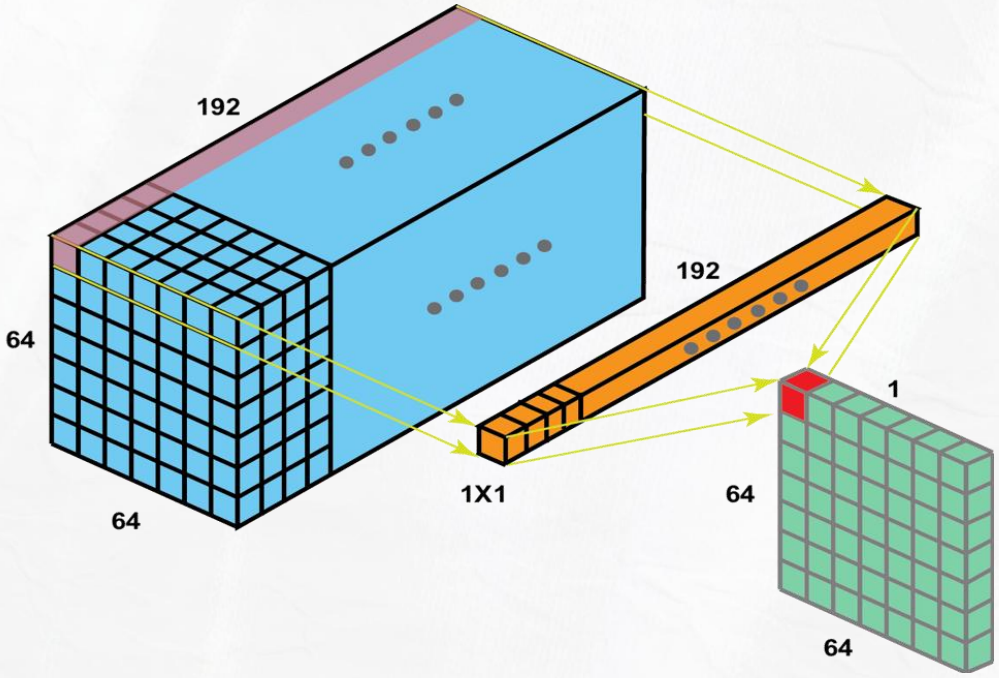
- The target class maps should be of size $H \times W \times N$, where H, W are height and width of the input image, and N is the number of pre-defined classes



- For each pixel, it requires to conduct a multi-class classification
- The multi-class cross entropy loss is therefore used for each pixel. In other words, the number of samples in a mini-batch would be (number of pixels × number of images)

Interpretation of 1 × 1 Convolution

- The 2D feature maps of size $H \times W \times C$ can be viewed as a series of C-dimensional feature vector at each spatial location (x, y) to describe the image contents centered at (x, y)
- 1 × 1 convolutions can be considered as a fully-connected layer applied to each of the C-dimensional feature vector for local feature transformation

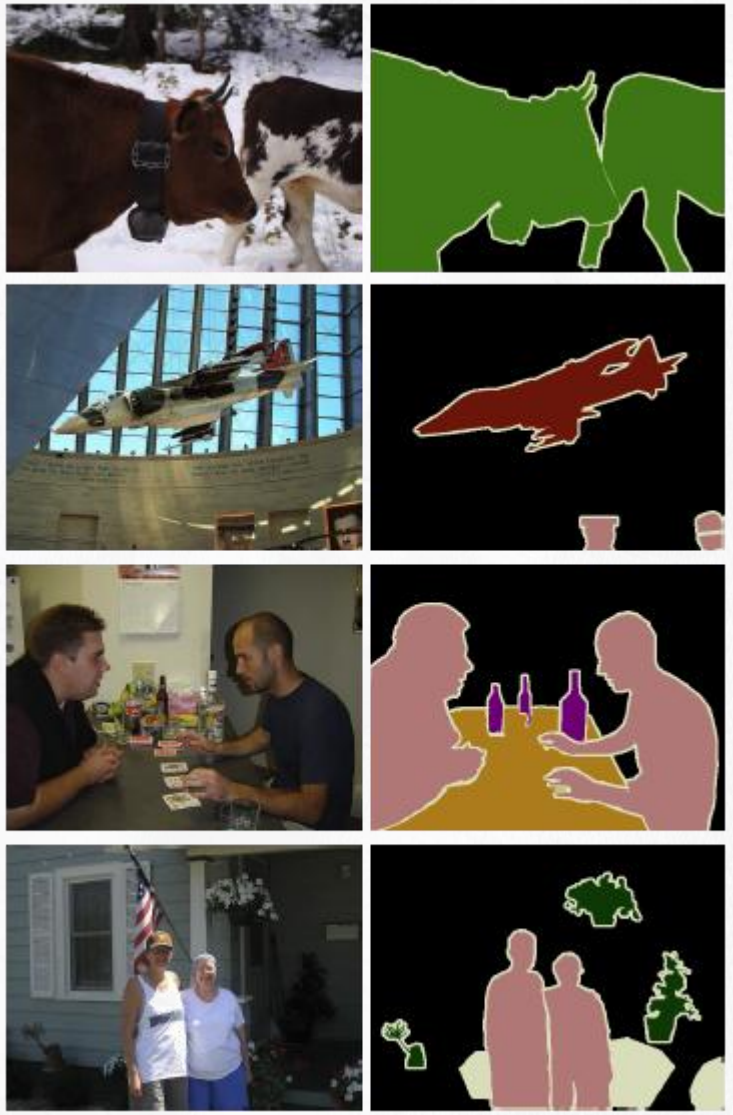


- Figure: $H = 64$, $W = 64$ and $C = 192$. 1 × 1 convolution can be considered as applying a fully-connected layer to each 192-dimensional feature vector for feature transformation.

PASCAL VOC 2012 Dataset

- 1,464 images for training, 1,449 for validation, and 1,456 for testing

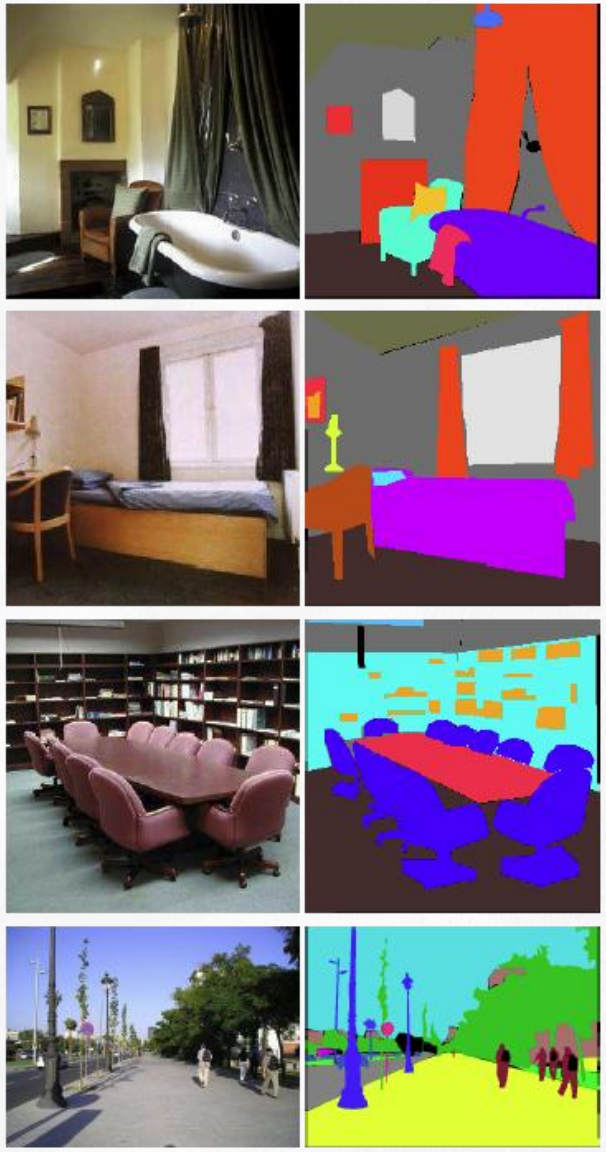
- 20 foreground objects classed and one background class



(a) Image (b) Ground Truth

ADE20k Dataset

- 20K images for training, 2K images for validation, and 3K images for testing
- Used for ImageNet Scene Parsing Challenge 2016
- This dataset is more complex and challenging with 150 labeled classes and more diverse scenes



(a) Image (b) Ground Truth

Cityscapes Dataset

- Images of driving scenes from 50 cities
- 5,000 high quality pixel-level finely annotated scene images, which is divided into 2,975/500/1,525 images for training, validation and testing
- 30 classes, and 19 classes among them are used for evaluation.

(a) Image (b) Ground Truth

Evaluation metrics

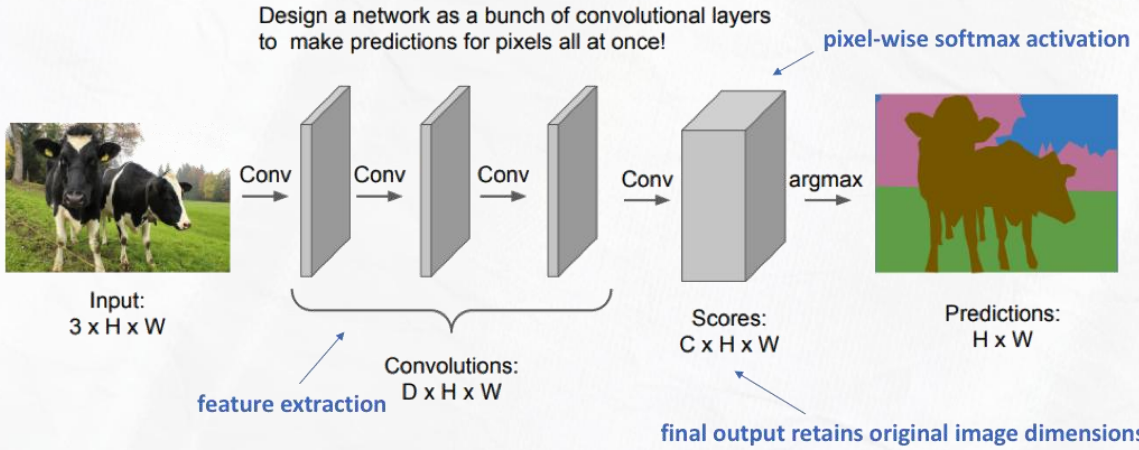
- Naively, one can use pixel accuracy as the evaluation metric. However, as there generally exist a large number of background pixels, accuracy is rarely used nowadays
- Currently, the most popular metric is mean of class-wise intersection over union (mIoU). The following equation is used for each class separately and their IoUs are averaged to obtain mIoU

$$\text{IoU} = \frac{\text{TP}}{\text{TP} + \text{FP} + \text{FN}}$$

- There are also other metrics, such as F1 score (mainly for binary segmentation), iIoU (used for Cityscapes), etc.

Constructing Semantic Segmentation Networks

- A naive approach for constructing a network for segmentation would be to simply stacking a number of convolutional layer without any downsampling operations



- On the one hand, such a design makes each pixel in the final feature map have very small receptive field, which cannot result in satisfactory performance
- On the other hand, general CNN for whole-image classification gradually decreases the spatial size but increases the feature channels to use longer feature vectors for encoding image contents
- However, such a mechanism cannot be achieved in the above design because if the spatial size is maintained throughout the whole network, increasing the feature channels would occupy the limited GPU memory

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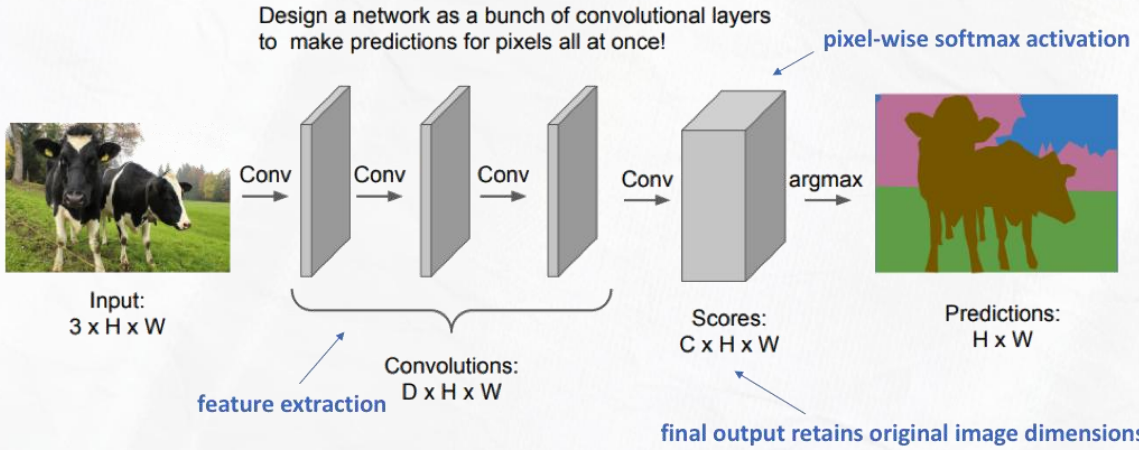

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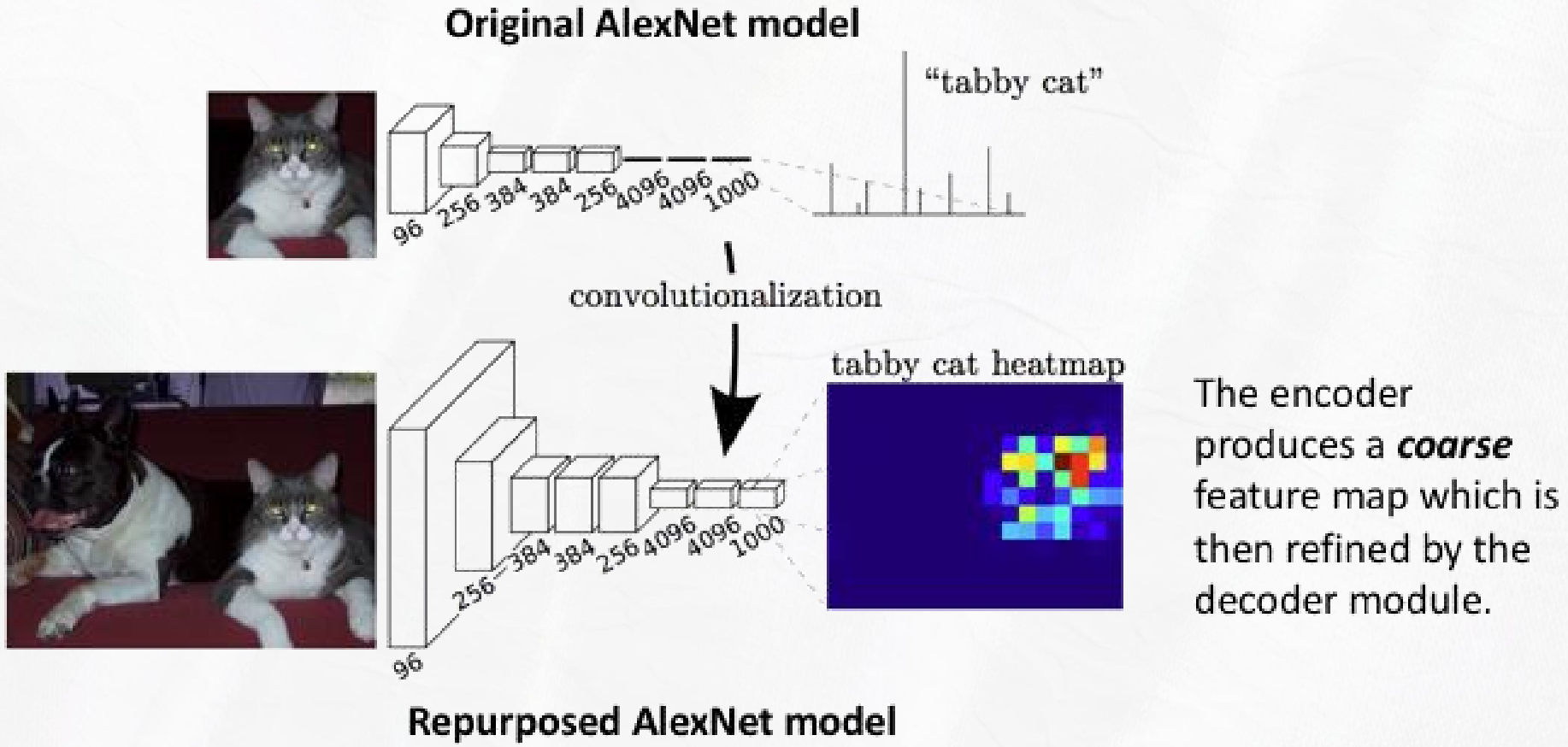
Fully Convolutional Network (FCN)

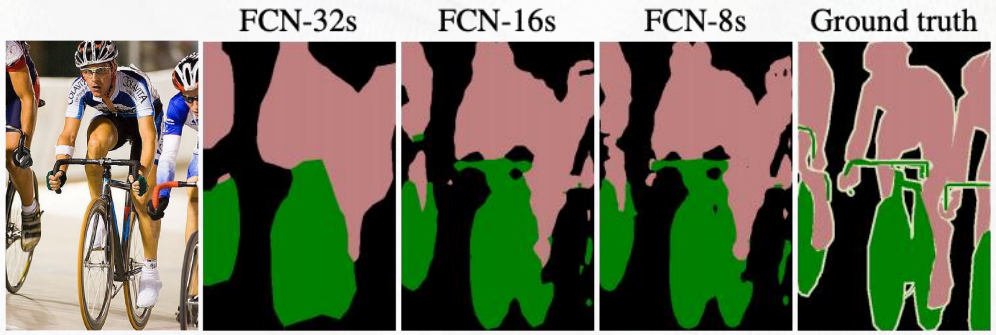
- Fully Convolutional Network (FCN) converts the image classification network to tackle the task of image segmentation. However, the last 2D feature maps has 1/32 spatial size as the original input image

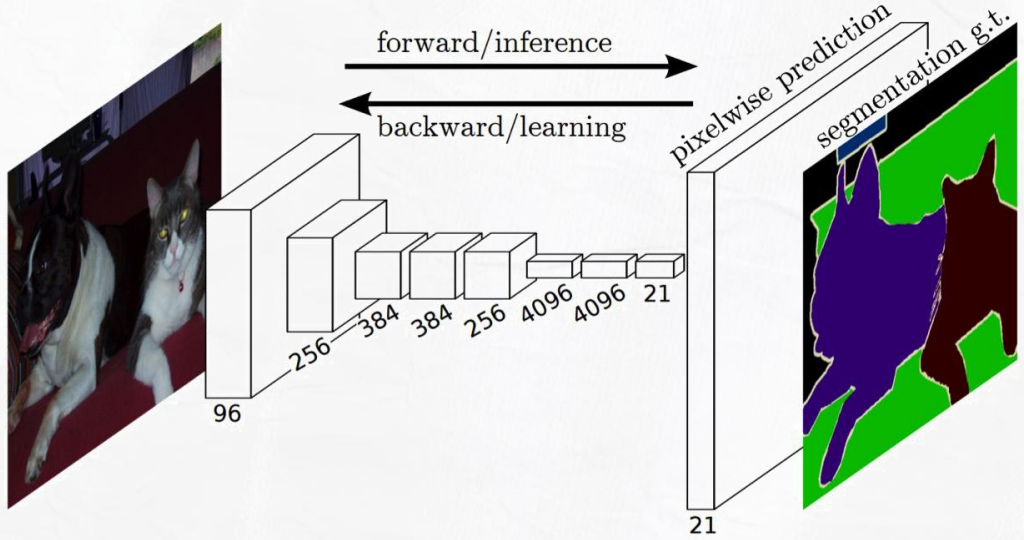


The encoder produces a ***coarse*** feature map which is then refined by the decoder module.

Fully Convolutional Network (FCN)

- **Problem:** Direct upsampling the 1/32 segmentation results show over-smoothed segmentation boudaries
- **Analysis:** The high-level features are down-sampled multiple times, and the details are seriously lost.
- **Solution:** Combining low-level and high-level feature maps.



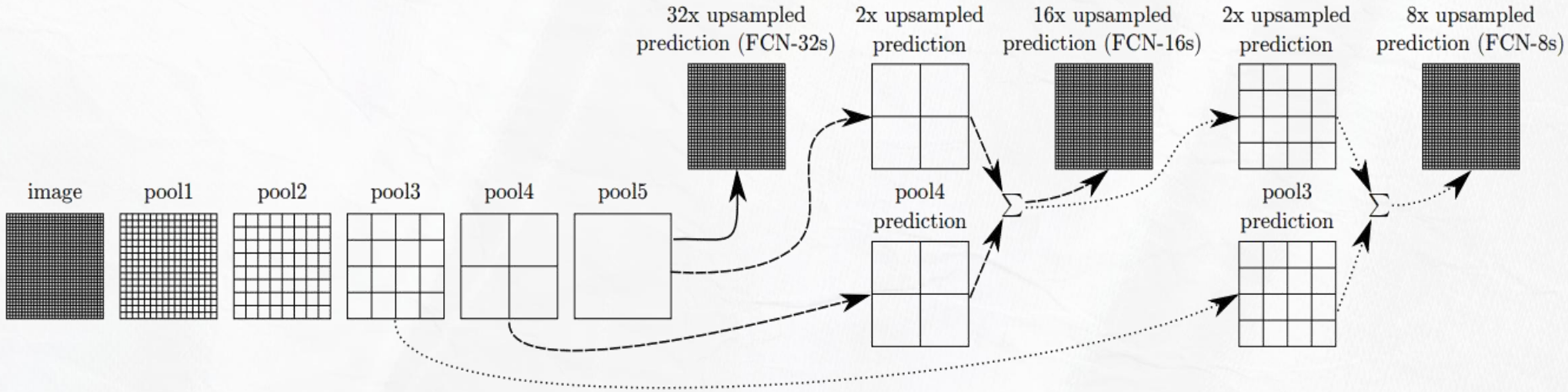


rich in details but lack of semantic information ⟷ rich in semantic information but with poor details

Long, Jonathan, Evan Shelhamer, and Trevor Darrell. "Fully convolutional networks for semantic segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2015.

Context information and receptive field

- The last pool5 (1/32) predictions are upsampled to 1/16 and summed with pool4 (1/16) predictions. The summed 1/16 predictions are upsampled to 1/8 and summed with pool3 (1/8). The network outputs 1/8 segmentation maps and upsample the results to the original resolution



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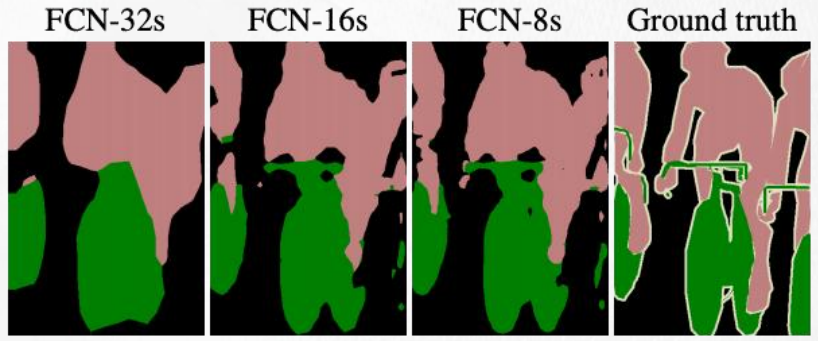
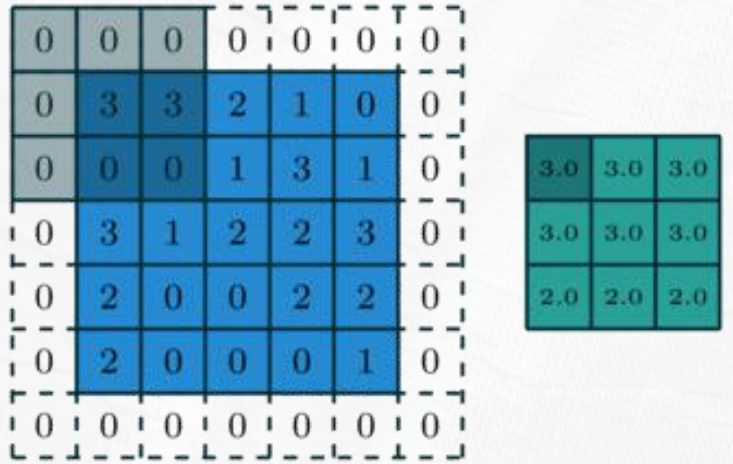


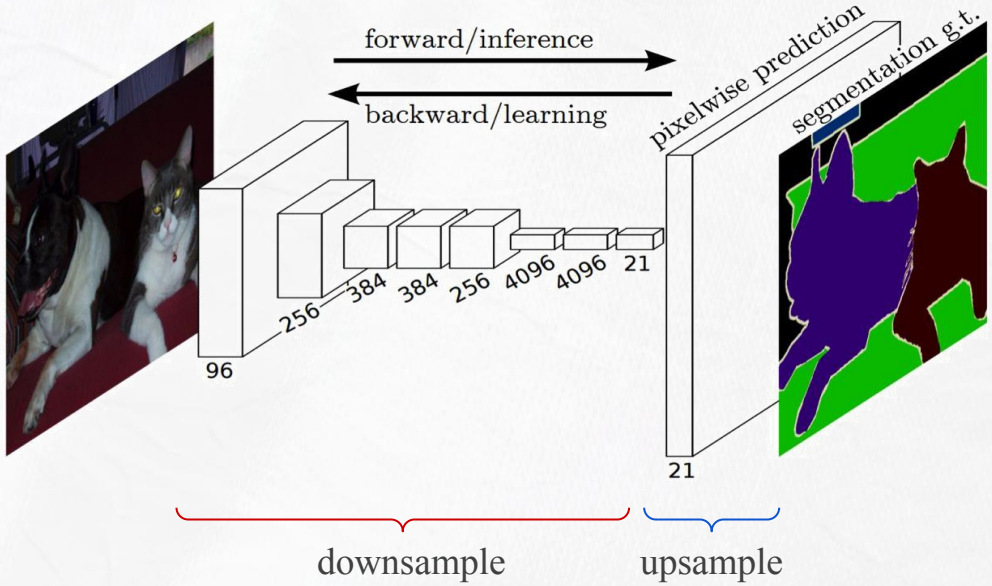
Maintain the resolution of the feature maps

Problem: The image classification model uses the downsampling layer (step size convolution or pooling) to obtain high-level features, resulting in the output size of the full convolutional network being smaller than the original image, while segmentation requires the same size output



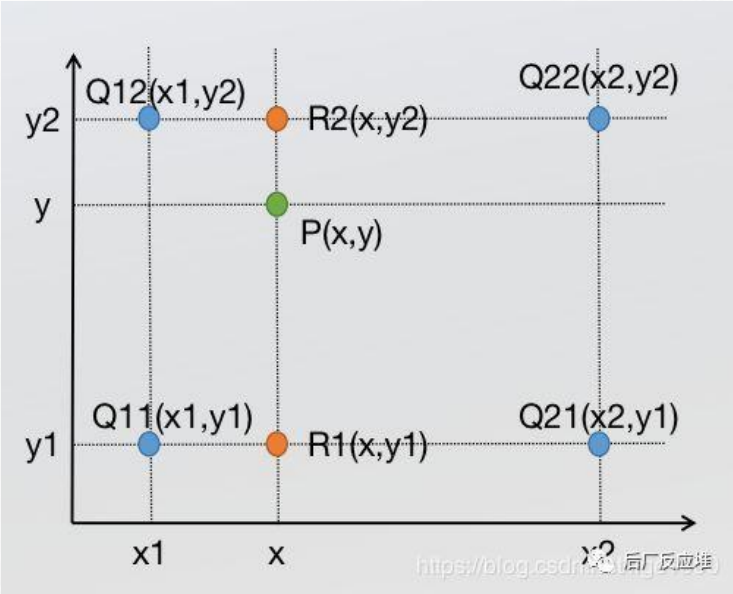
Solution: Upsampling the predicted segmentation image, restoring the resolution of the original image, and the upsampling scheme:

- **Bilinear interpolation**
- Transposed Convolutions: Learnable Upsampling



https://d2l.ai/chapter_computer-vision/transposed-conv.html

Maintain the resolution of the feature maps



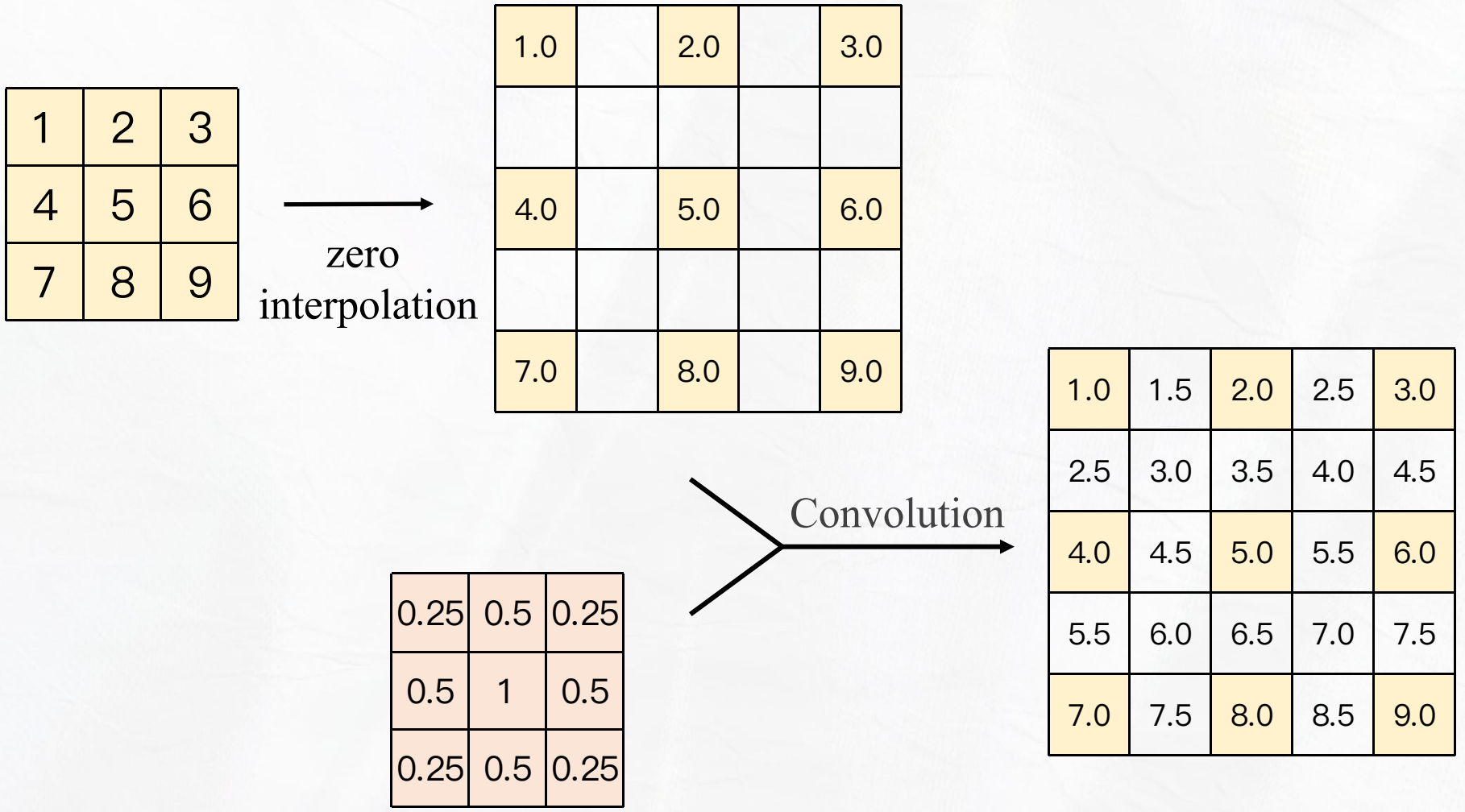
$$f(x,y) = \frac{1}{(x_2-x_1)(y_2-y_1)} \begin{bmatrix} x_2-x & x-x_1 \end{bmatrix} \begin{bmatrix} f(Q_{11}) & f(Q_{12}) \\ f(Q_{21}) & f(Q_{22}) \end{bmatrix} \begin{bmatrix} y_2-y \\ y-y_1 \end{bmatrix}.$$

1	2	3
4	5	6
7	8	9

→

1.0	1.5	2.0	2.5	3.0
2.5	3.0	3.5	4.0	4.5
4.0	4.5	5.0	5.5	6.0
5.5	6.0	6.5	7.0	7.5
7.0	7.5	8.0	8.5	9.0

Convolution implements bilinear interpolation



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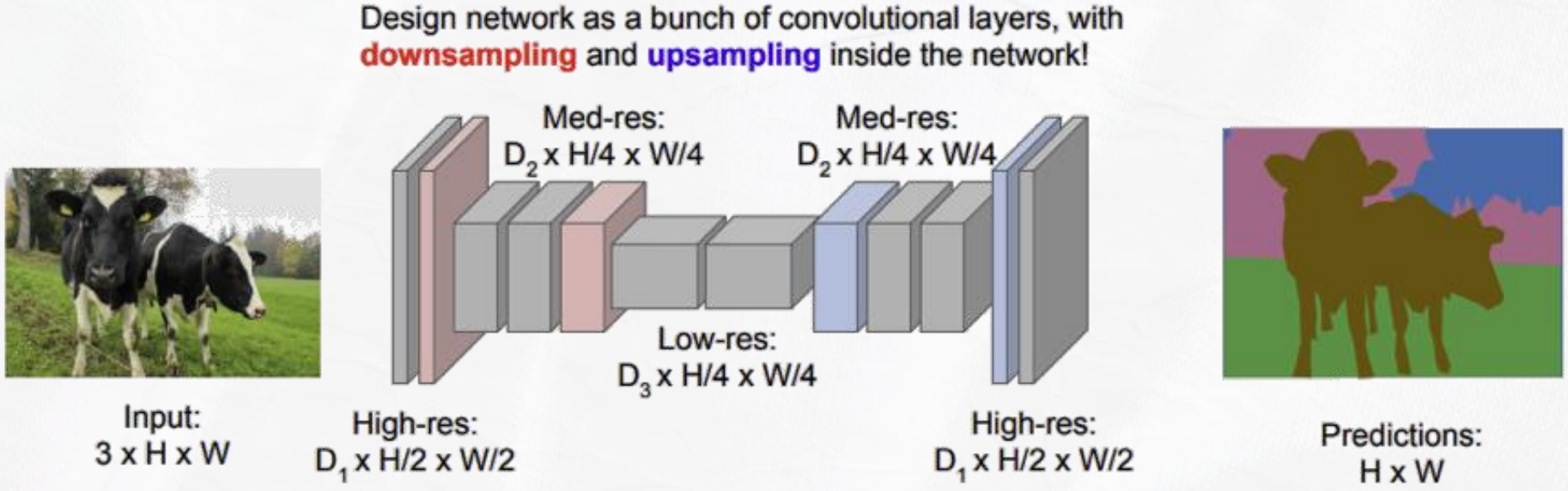
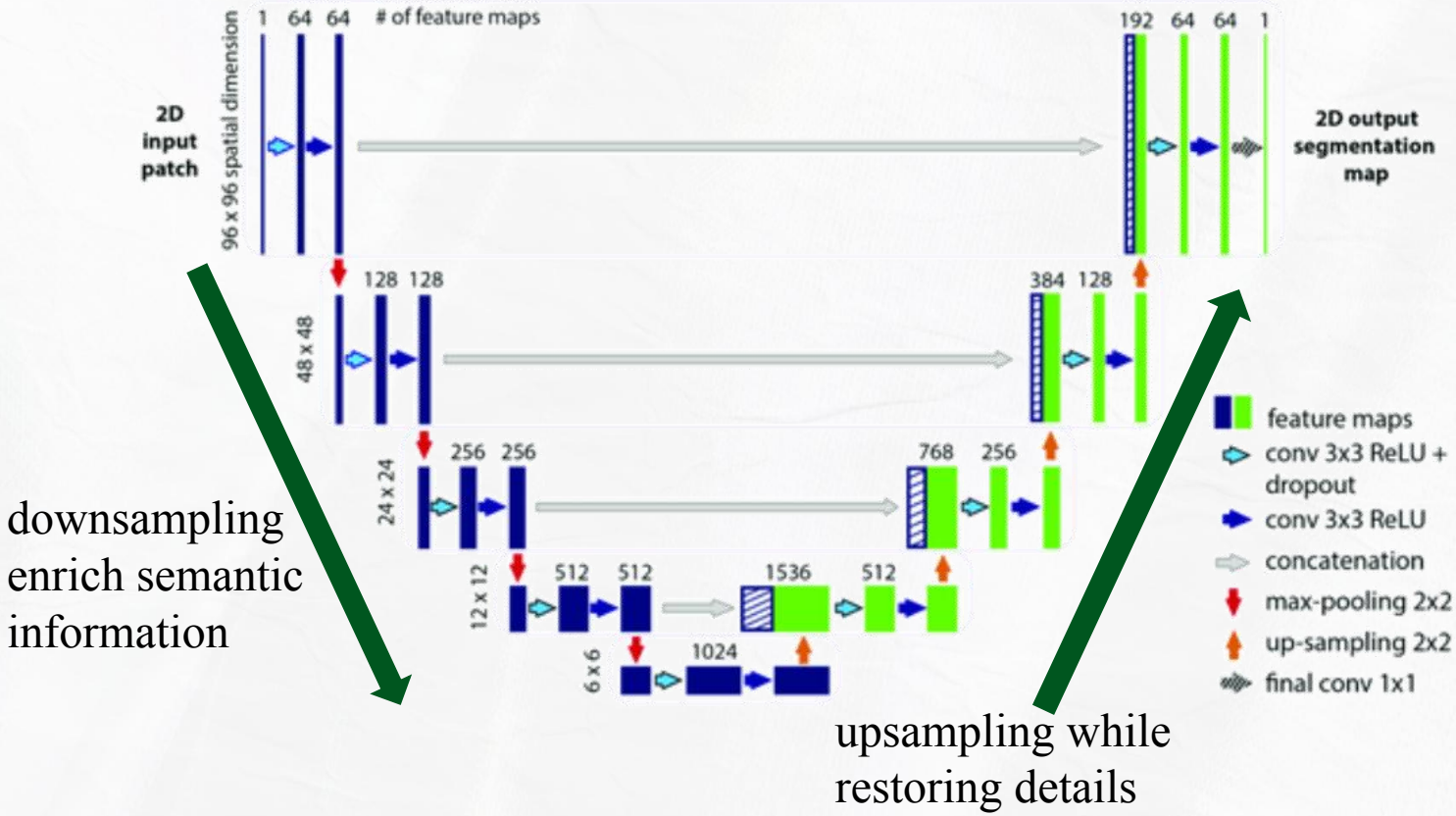
Encoder-decoder Architecture

- However, the FCN obtains the segmentation result by upsampling feature maps of each size once, and the summed feature maps only go through a single layer of linear classifier (fully-connected layer)
- FCN therefore can only achieve mediocre performance
- One popular category of approaches is the encoder-decoder architecture, whose encoder gradually downsamples the spatial size but increases the feature channel number, and the decoder gradually upsamples the spatial size but decrease the feature channel number
- Two choices for upsampling the feature maps into higher spatial resolution: bilinear interpolation (more frequently adopted nowadays) and deconvolution (transposed convolution)



U-Net Architecture (2015)

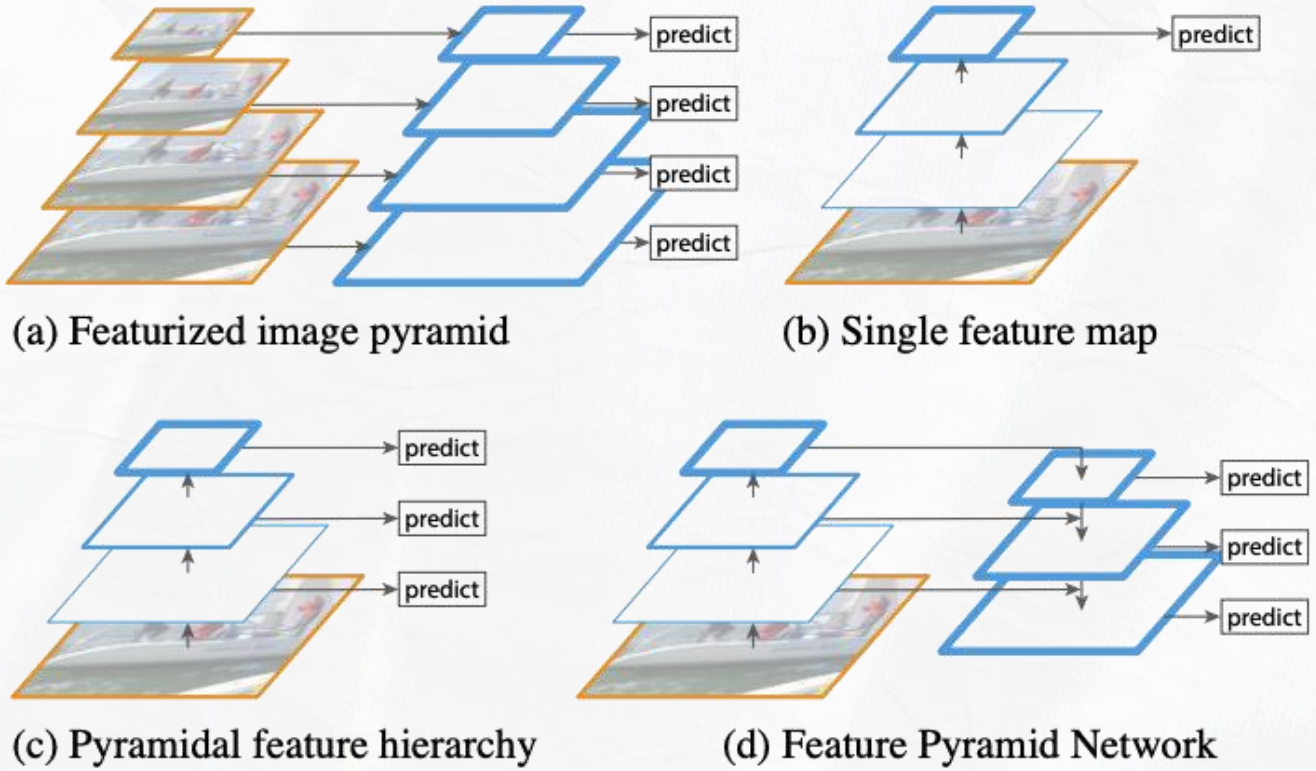
- U-Net establishes shortcuts between feature maps of the same size of encoder and decoder
- In this way, the high-resolution information in the feature maps of the encoder would be fused with those of the decoder via channel-wise concatenation



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

Feature Pyramid Network

- The Feature Pyramid Network (FPN) was originally proposed for object detection, but it can also create multi-scale feature maps as the U-Net does. The only difference is that FPN use addition as shortcut connections while U-Net uses concatenation as shortcut connections
- Unlike object detection, we only use the topmost feature maps, which is followed by an MLP to generate the resulting label map



(a) Featurized image pyramid (b) Single feature map

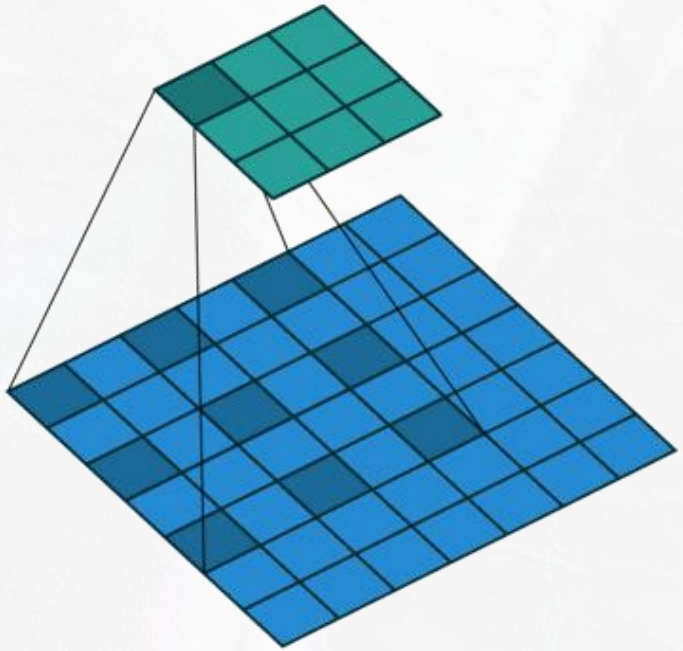
(c) Pyramidal feature hierarchy (d) Feature Pyramid Network

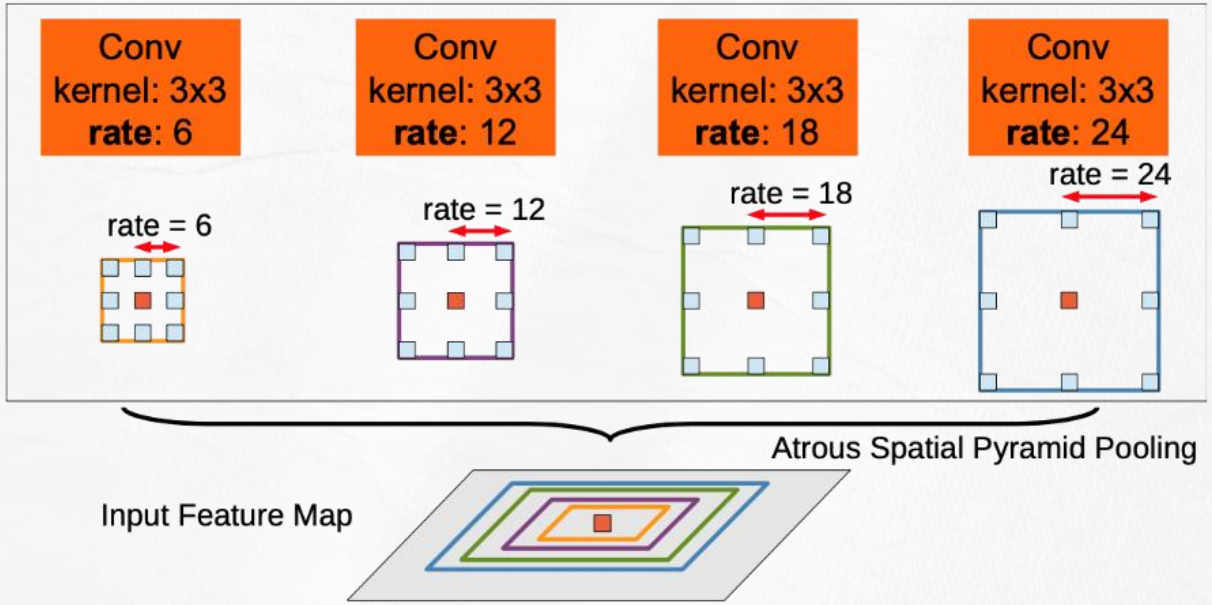
The DeepLab Series

DeepLab is another series of work on semantic segmentation, and its main contributions are as follows:

- Using atrous convolutions (**dilated convolutions**) to solve downsampling in networks
- Capturing contextual information using multi-scale **dilated convolutions** (ASPP module)

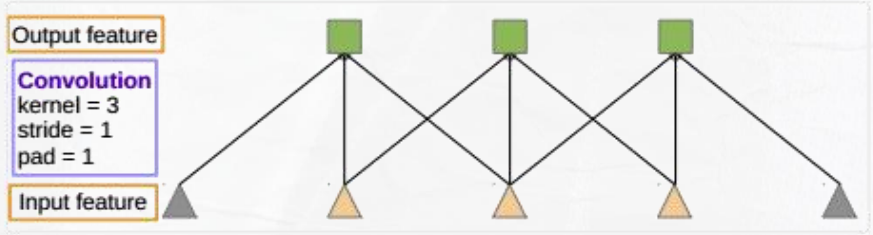
DeepLab v1 was published in 2014, and then v2, v3, and v3+ versions were proposed in 2016, 2017, and 2018 respectively.



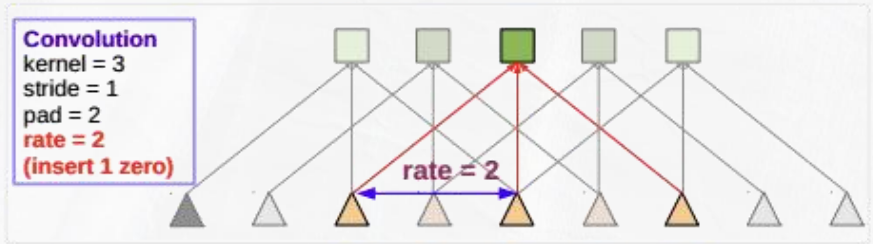


DeepLab v1

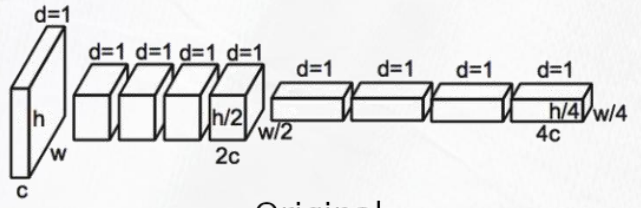
- A VGG-16 backbone pre-trained on ImageNet with fully connected layers being adopted
- Original VGG network downsamples the topmost feature maps to 1/32
- **Plausible Solution:** Remove the last two 2x max-pooling layers so that the topmost feature maps is 1/8 of the input size
- **Problem:** The un-maxpooled feature maps would mis-align with the pre-trained kernels of ImageNet
- **Solution:** Astrous convolution (dilation greater than 1) is introduced. Removing the first 2x max pooling makes the following convolution layers have dilation 2. Removing the second 2x max pooling maks the following convolution layer have dilation 4



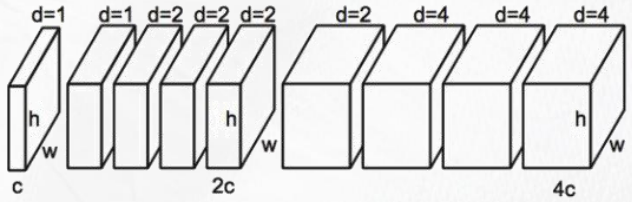
(a) Sparse feature extraction



(b) Dense feature extraction



Original



Max pooling removed

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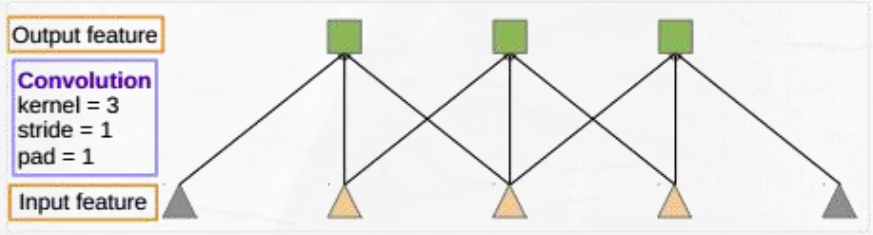

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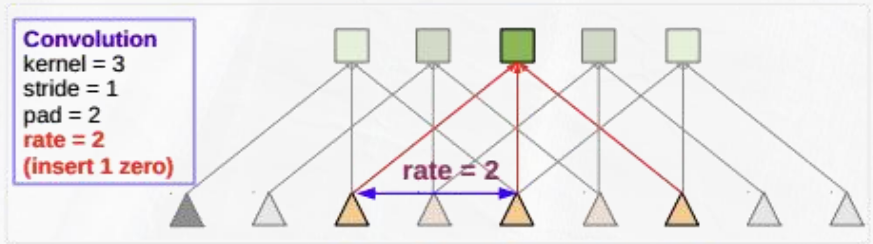

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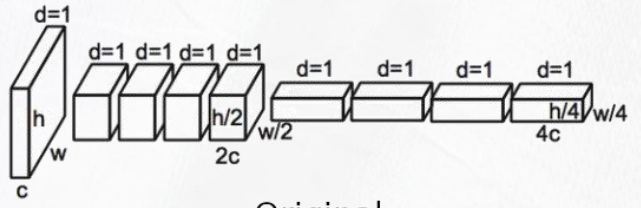

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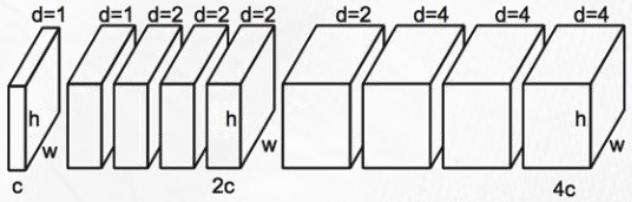
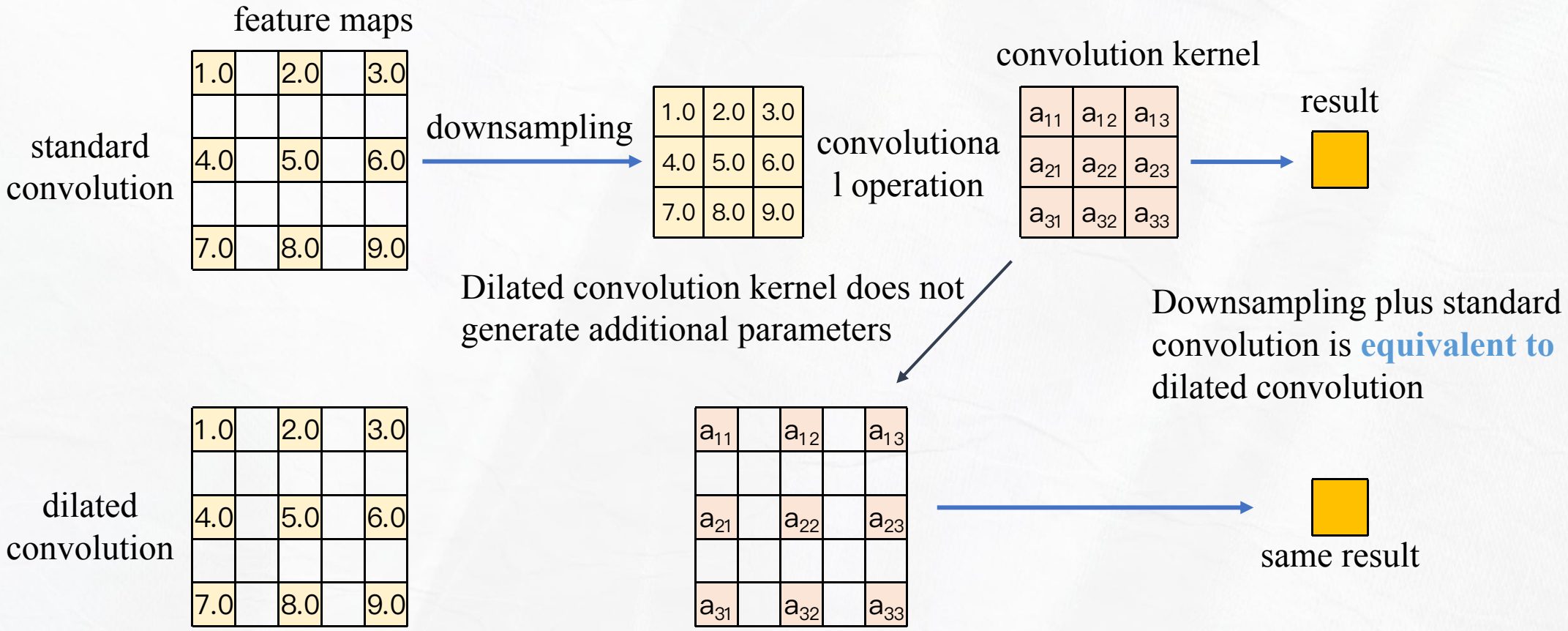


Max pooling removed

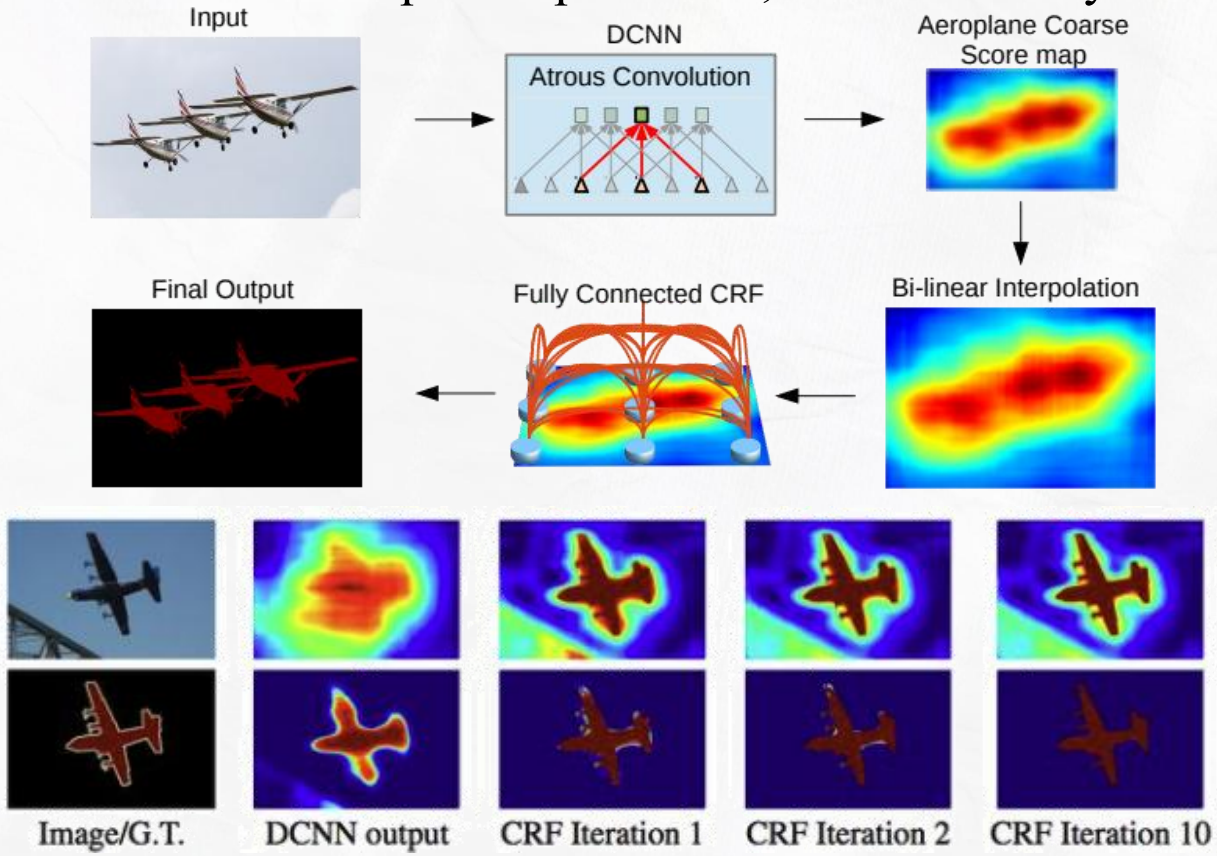
Atrous convolution v.s. Downsampling



- The feature map does not change
- Using dilated convolution kernel to perform the convolution operation

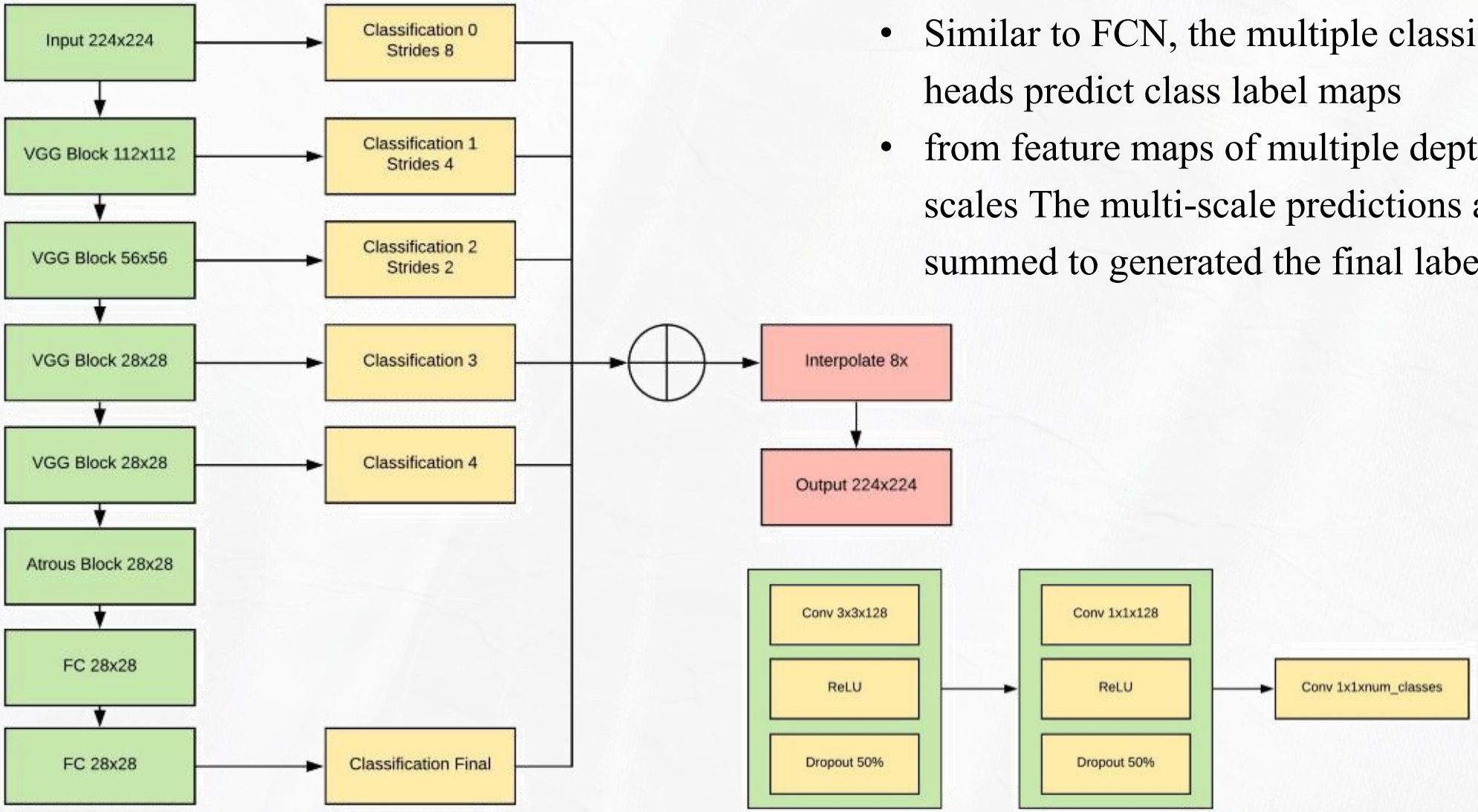
DeepLab v1

- Use bilinear interpolation to upsample the 1/8 feature maps into the original resolution
- Use continuous Conditional Random Field model to encourage the label maps follow the RGB pixel values: the more similar and closer a pair of pixels are, the more likely their labels are



DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs, IEEE Transaction on Pattern Analysis and Machine Intelligence 2016

DeepLab v1



- Similar to FCN, the multiple classification heads predict class label maps
- from feature maps of multiple depths and scales The multi-scale predictions are summed to generated the final label map

Context information and receptive field

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Ambiguous Regions

boat or car?

pillow or quilt?

Context information and receptive field

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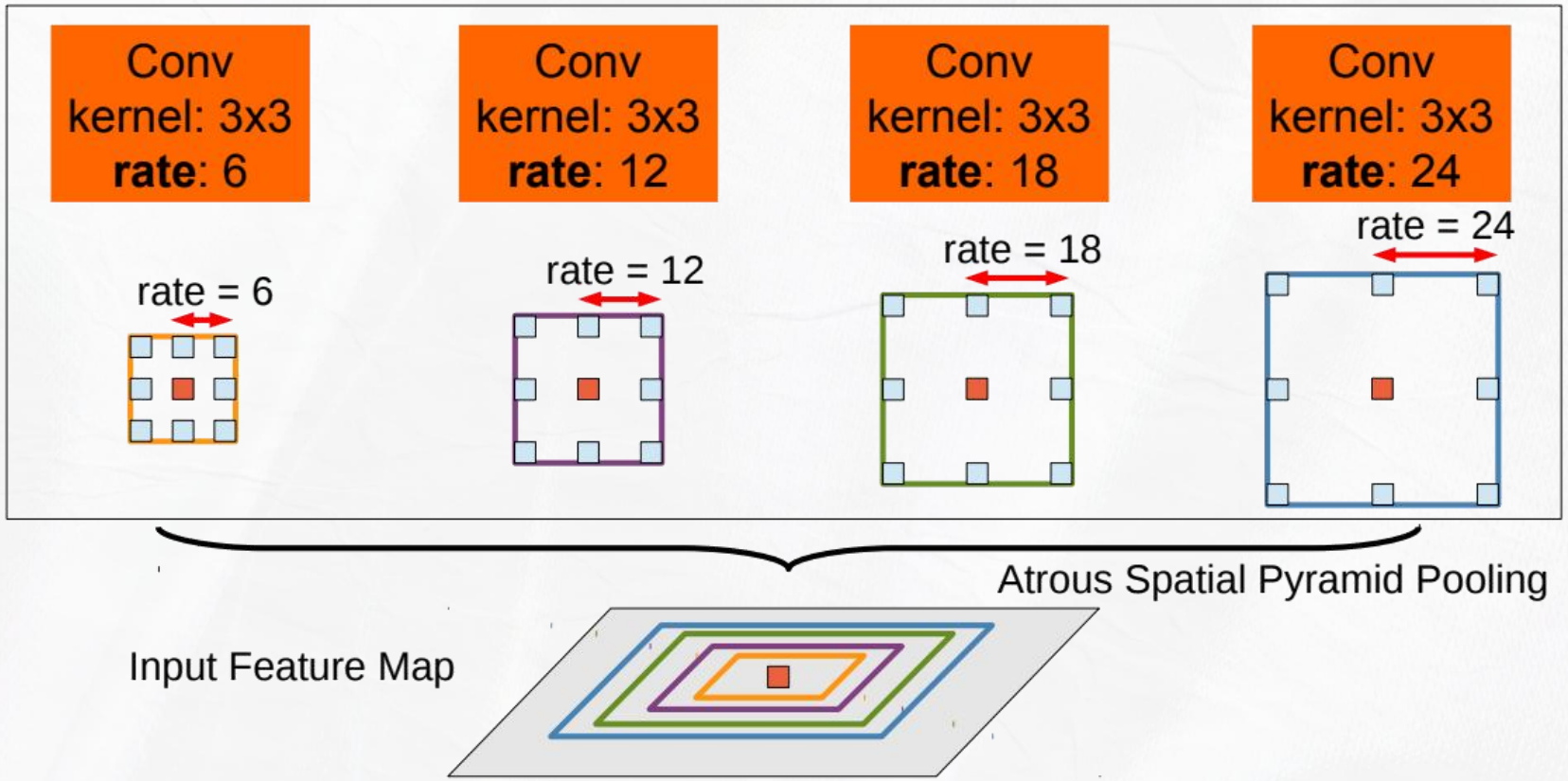
The Importance of Context

The content around the patches (also known as context) can help us make more accurate prediction.

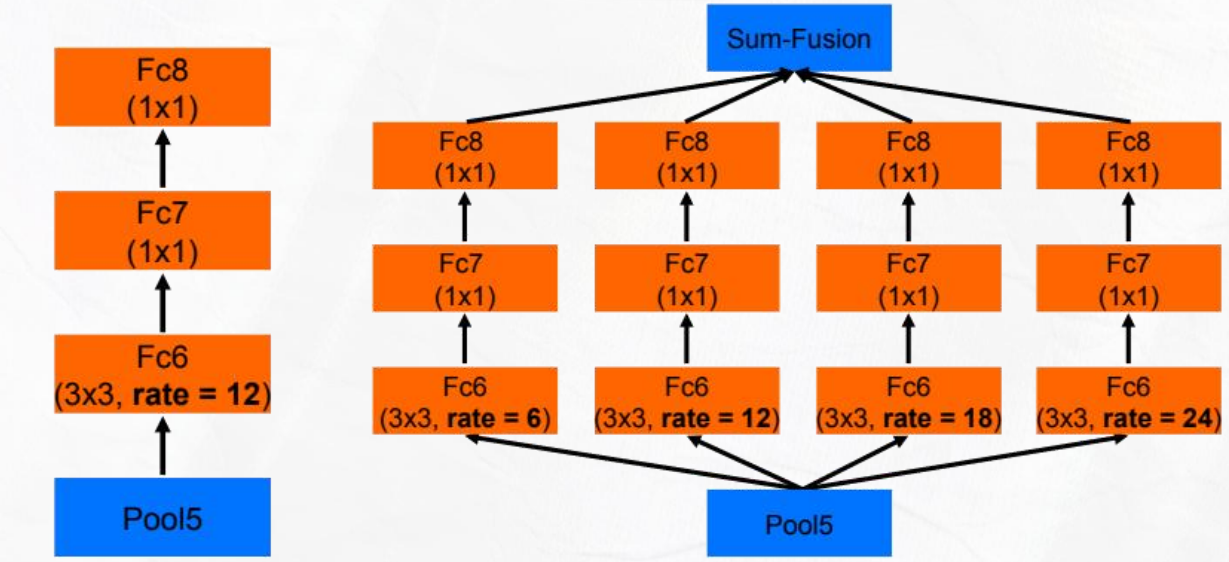
DeepLab v2

- DeepLabv2 introduces Atrous Spacial Pyramid Pooling (ASPP) before the classification head to include convolutions of different dilations to integrate context of different scales
- **Reason**: it is discovered as the sampling rate becomes larger; the number of valid filter weights become smaller

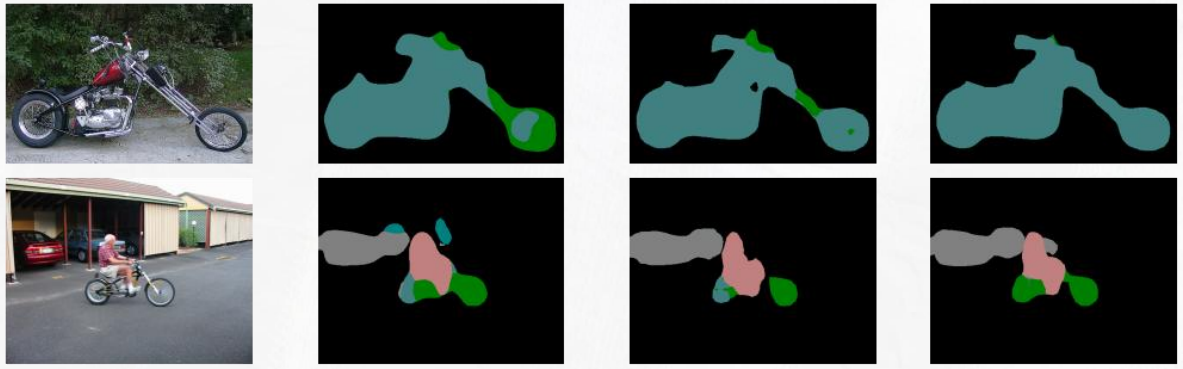


DeepLab v2

- DeepLab-ASPP employs multiple filters with different rates to capture objects and context at multiple scales.



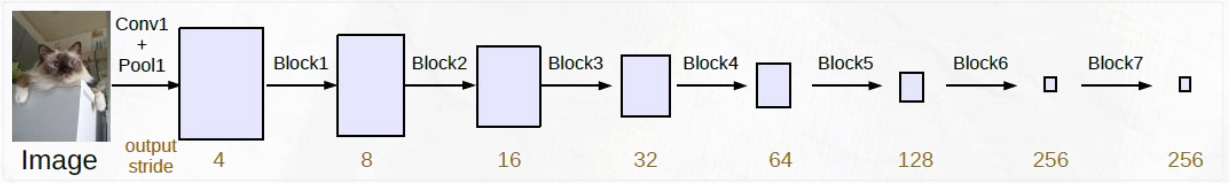
(a) DeepLab-LargeFOV (b) DeepLab-ASPP



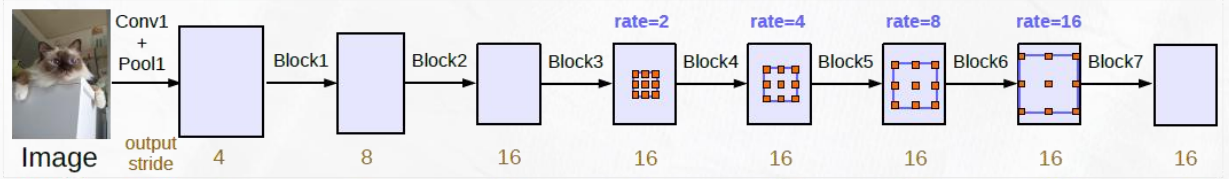
(a) Image (b) LargeFOV (c) ASPP-S (d) ASPP-L

DeepLab v3

- **Multi-grid strategy:** Going deeper with atrous convolution after block3. Keep the stride constant but with large receptive field

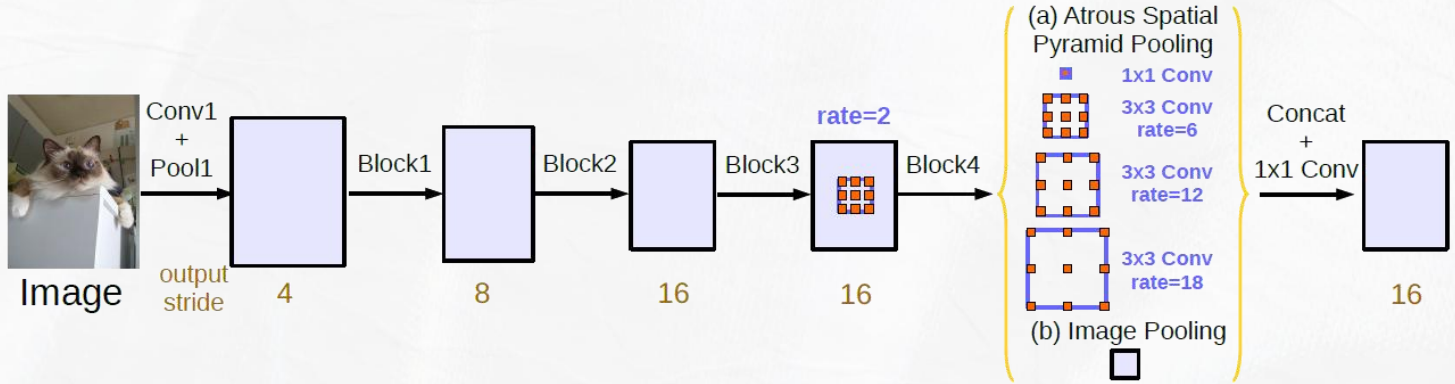


(a) Going deeper without atrous convolution.



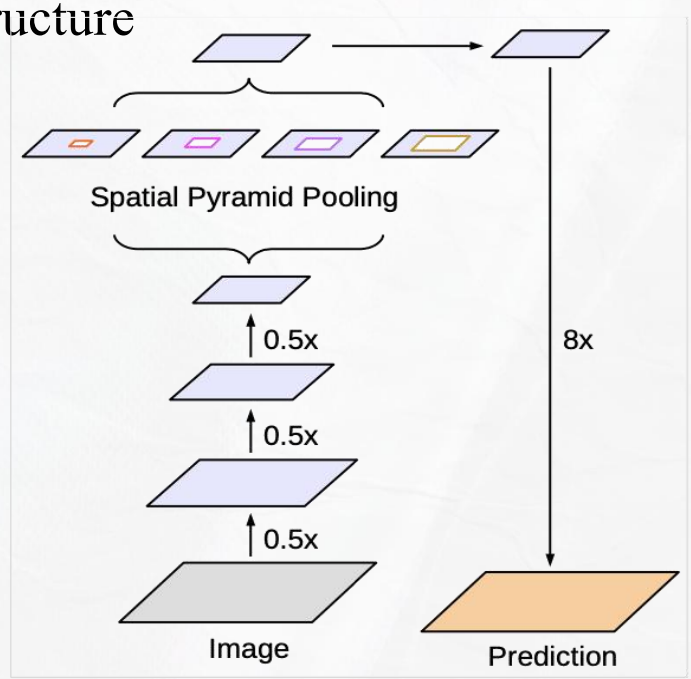
(b) Going deeper with atrous convolution. Atrous convolution with $rate > 1$ is applied after block3 when $output\_stride = 16$.

- Use Batch Normalization into ASPP module
- Introduce a global average pooling to integrate the global contextual information

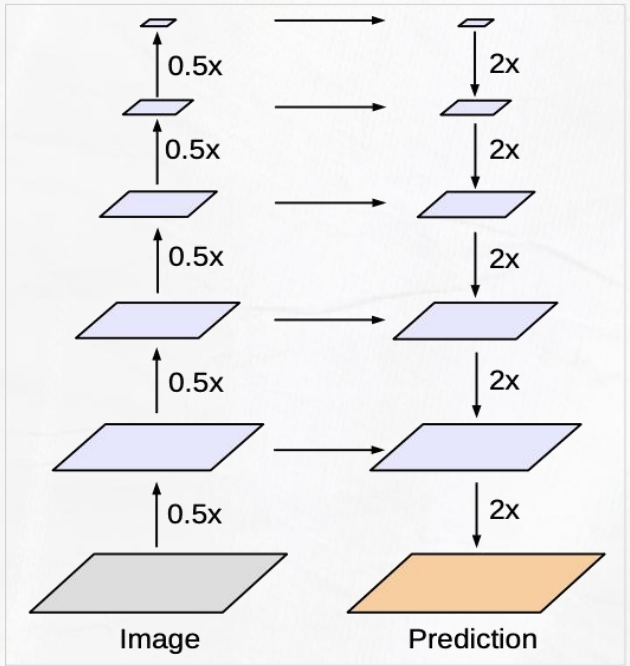


Deeplab v3+: Encoder-decoder Structure

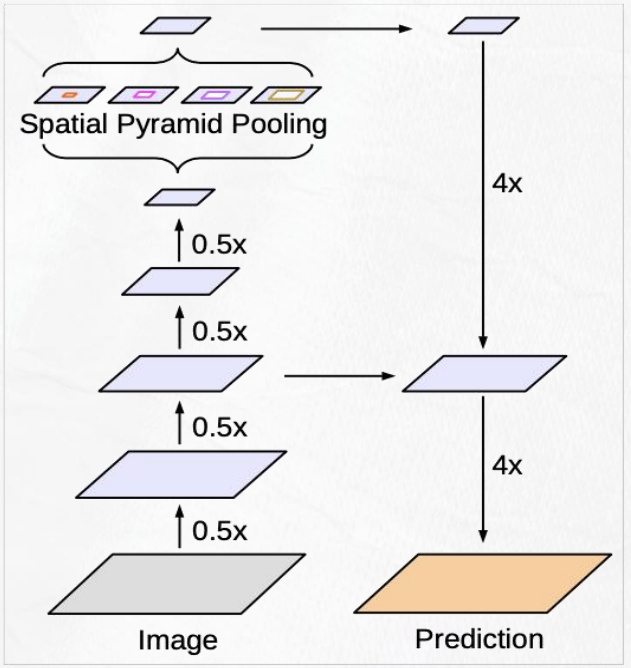
- DeepLab v2/v3 models use ASPP to capture contextual features
- Encoder/Decoder structures (such as UNet) incorporate low-level feature maps during upsampling to obtain finer segmentation maps
- DeepLab v3+ combines the two ideas and adds a simple decoder structure to the original model structure



(a) ASPP
DeepLab v2 / v3



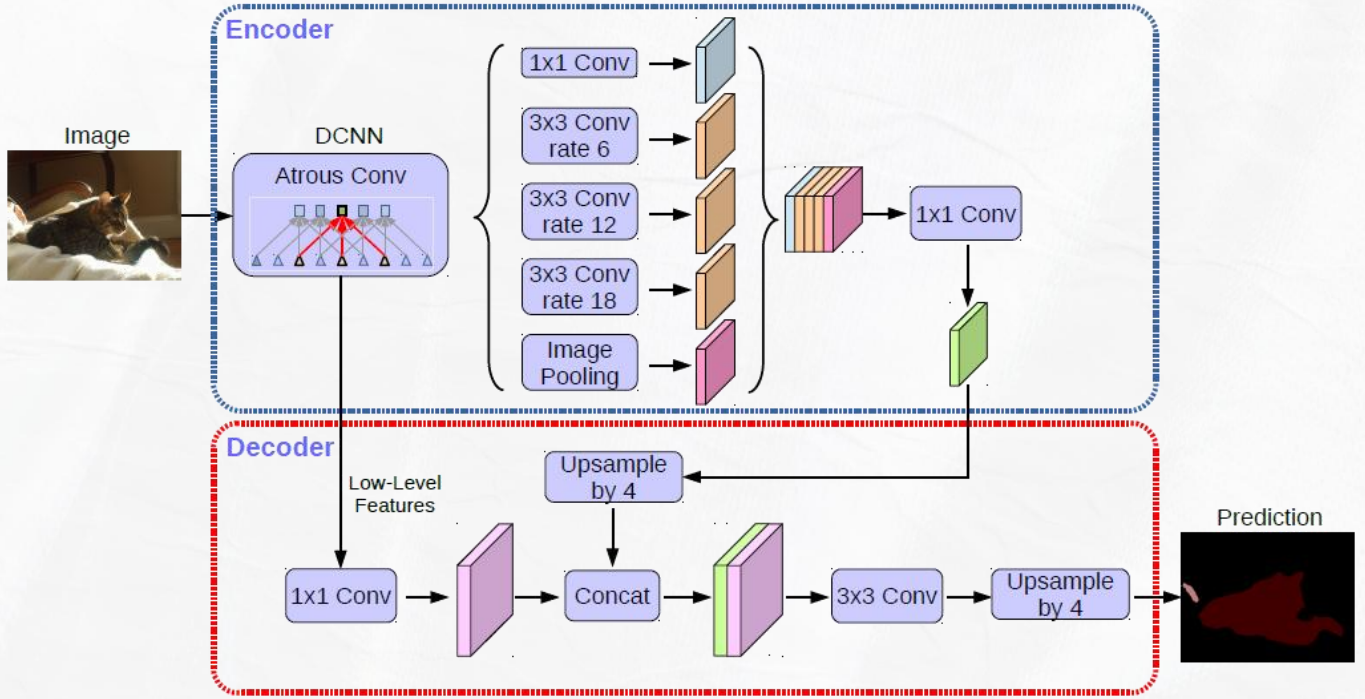
(b) Encoder / Decoder
UNet



(c) DeepLab v3+

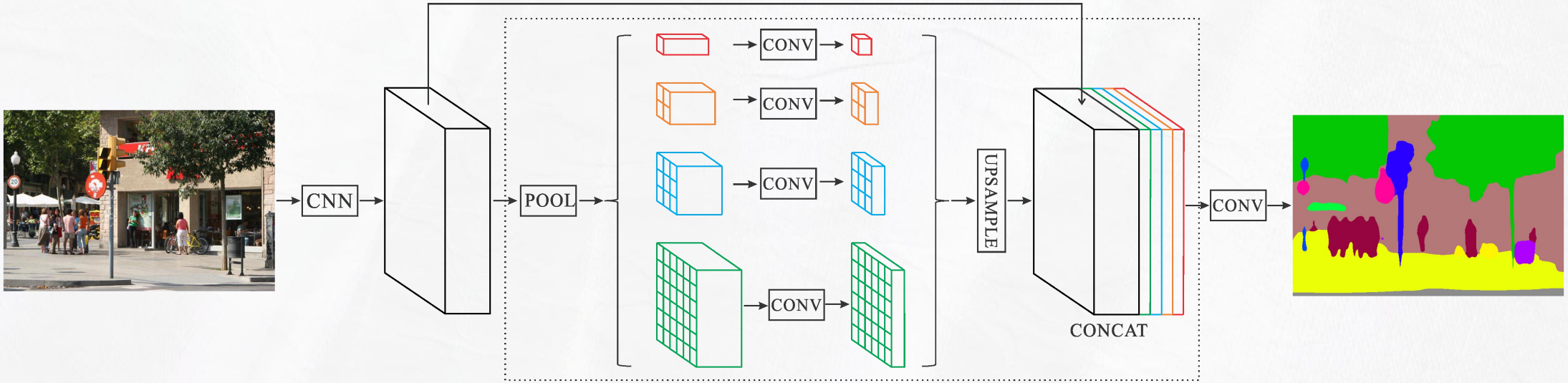
Deeplab v3+: Encoder-decoder Structure

- **Encoder.** Use DeepLabv3 as the encoder. **Decoder.** The encoder features are first bilinearly upsampled by a factor of 4 and then concatenated with the corresponding low-level features
- There is 1 × 1 convolution on the low-level features before concatenation to reduce the number of channels. After the concatenation, we apply a few 3 × 3 convolutions to refine the features followed by another simple bilinear upsampling by a factor of 4
- Much better comparing bilinearly upsampling 16x directly



PSPNet: Pyramid Scene Parsing Network

- First use CNN to get the feature map of the last convolutional layer
- A pyramid parsing module is applied to harvest different sub-region representations, followed by upsampling and concatenation layers to form the final feature representation
- Our pyramid pooling module is a four-level one with kernel sizes and stride of 2×2, 3×3 and 6×6 and GLOBAL average pooling
- The final representation carries both local and global context information
- The representation is fed into a convolution layer to get the final per-pixel prediction



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

Summary

Basic Idea
Pixel-wise Prediction

→ **Fully Convolutional Network (FCN)**

Maintain the resolution of the feature map

Bilinear interpolation or Deconvolution

- **FCN**
- **UNet**

→ Dilated convolution with large receptive field

- **DeepLab series**

Restore the details of the predicted results

Merge predictions from high and low layers

- **FCN**

Merge multi-scales' feature and then predict

- **UNet**
- **DeepLab v3+**

CRF post-processing

- **DeepLab v1/v2**

Context information and receptive field

Pyramid pooling module

- **PSPNet**

Multi-scale atrous convolution ASPP

- **DeepLab v3/v3+**

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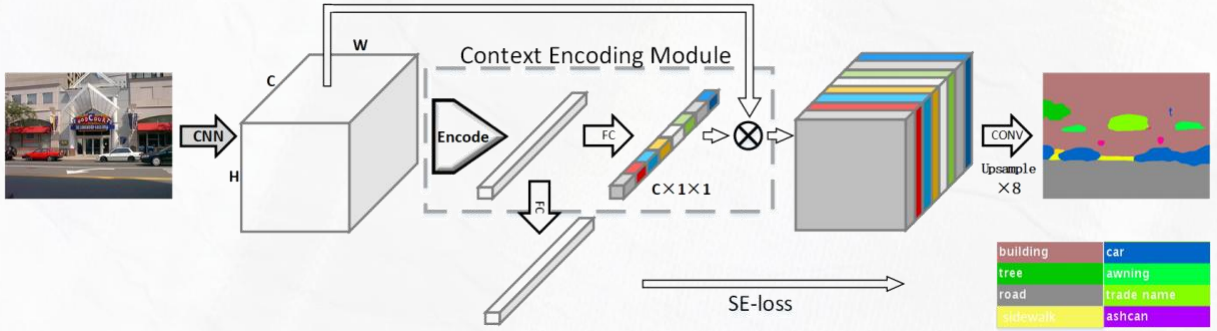
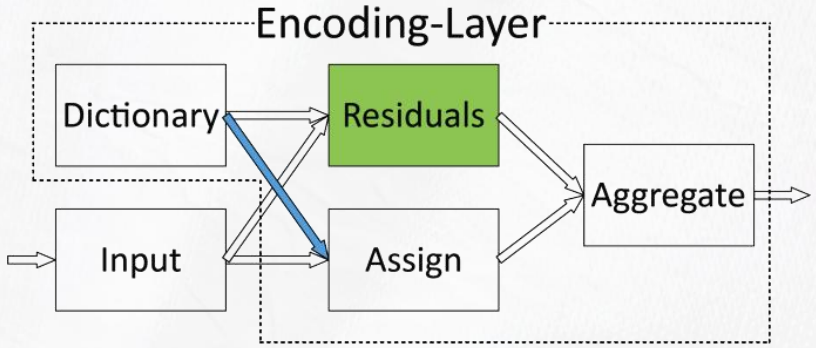
EncNet: Context Encoding for Semantic Segmentation

- Segmentation is always about capture contextual information for predicting pixel-wise labels
- EncNet proposed to encode global context for improving the classification performance

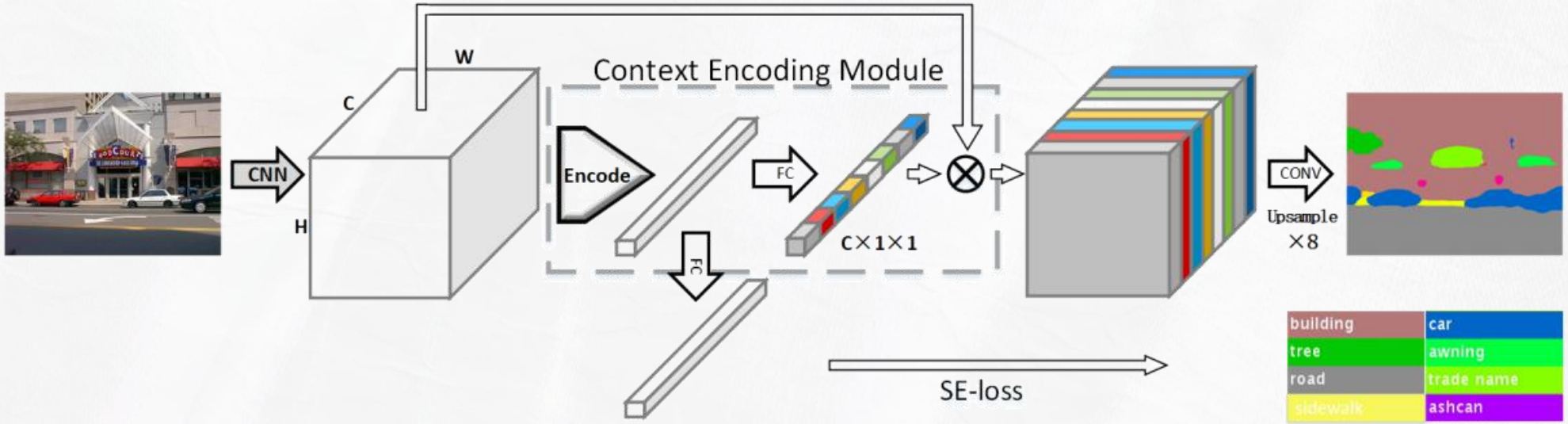


- Encoder layer aims at capturing the global context. It learns an inherent dictionary. Residuals are pairwise differences between visual features of the input and the dictionary codewords. Weights are assigned based on pairwise distance between descriptors and codewords. Finally, the residual vectors are aggregated with the assigned weights



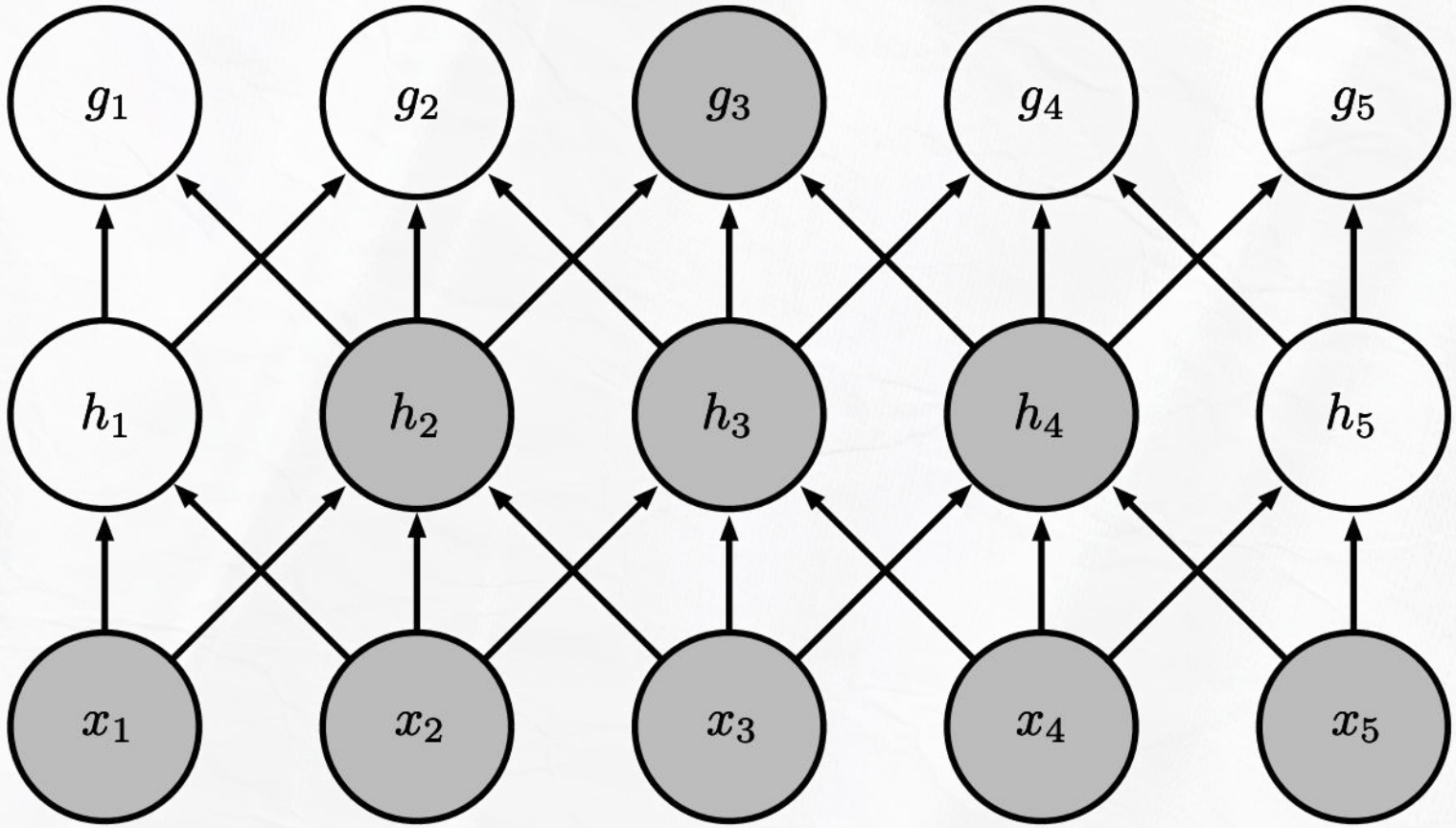
EncNet: Context Encoding for Semantic Segmentation

- **Channel attention (re-weighting).** The encoded global context features is processed by a fully connected layer and a softmax function along the channel dimension to obtain a C-dimensional weighting vector, which sums up to 1
- It is element-wisely and spatially multiplied with each spatial pixel of the feature maps
- **Semantic Encoding Loss.** The encoded semantics is processed by a fully connected layer and a sigmoid function to make individual predictions for the presences of object categories in the scene. It is trained with binary cross entropy loss



Growing receptive field

- **Receptive field** will increase along the layer goes deeper.



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Thanks for Listening

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