CSE 252D: Advanced Computer Vision

Manmohan Chandraker

Lecture 14: Semantic Segmentation 2

Virtual classrooms

- Virtual lectures on Zoom
  - Only host shares the screen
  - Keep video off and microphone muted
  - But please do speak up (remember to unmute!)
  - Slides uploaded on webpage just before class
- Virtual interactions on Zoom
  - Ask and answer plenty of questions
  - “Raise hand” feature on Zoom when you wish to speak
  - Post questions on chat window
  - Happy to try other suggestions!
- Lectures recorded and upload on Canvas
  - Available under “My Media” on Canvas

Overall goals for the course

- Introduce the state-of-the-art in computer vision
- Study principles that make them possible
- Get understanding of tools that drive computer vision
- Enable one or all of several such outcomes
  - Pursue higher studies in computer vision
  - Join industry to do cutting-edge work in computer vision
  - Gain appreciation of modern computer vision technologies
- This is a great time to study computer vision!

Papers for Wed, May 19

- Context Encoding for Semantic Segmentation
  - https://arxiv.org/abs/1803.08904
- Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation
  - https://arxiv.org/abs/1802.02611
- High-Resolution Representations for Labeling Pixels and Regions
  - https://arxiv.org/abs/1904.04514
- MSeg: A Composite Dataset for Multi-Domain Semantic Segmentation
  - https://ieeexplore.ieee.org/document/9157628

Papers for Fri, May 21

- R-FCN: Object Detection via Region-based Fully Convolutional Networks
  - https://arxiv.org/abs/1605.06409
- Deformable Convolutional Networks
  - https://arxiv.org/abs/1703.06211
- Feature Pyramid Networks for Object Detection
  - https://arxiv.org/abs/1612.03144
- Training Region-Based Object Detectors with Online Hard Example Mining
  - https://arxiv.org/abs/1604.03540

Papers for Wed, May 26

- You Only Look Once: Unified, Real-Time Object Detection
  - https://arxiv.org/abs/1506.02640
- Focal Loss for Dense Object Detection
  - https://arxiv.org/abs/1708.02002
- Single-Shot Refinement Neural Network for Object Detection
  - https://arxiv.org/abs/1711.06897
- CornerNet: Detecting Objects as Paired Keypoints
  - https://arxiv.org/abs/1808.01244

Recap

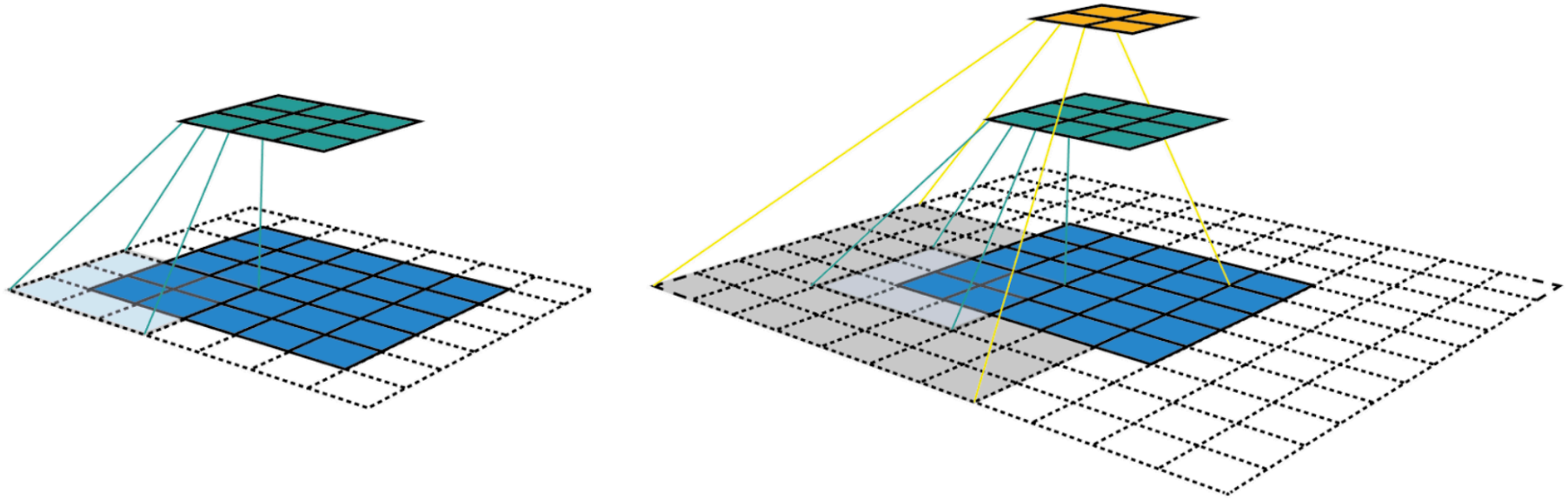
Semantic Segmentation

Global Reasoning ⟷ Locally accurate Boundaries

Figure from CityScapes Dataset

Receptive fields in CNNs

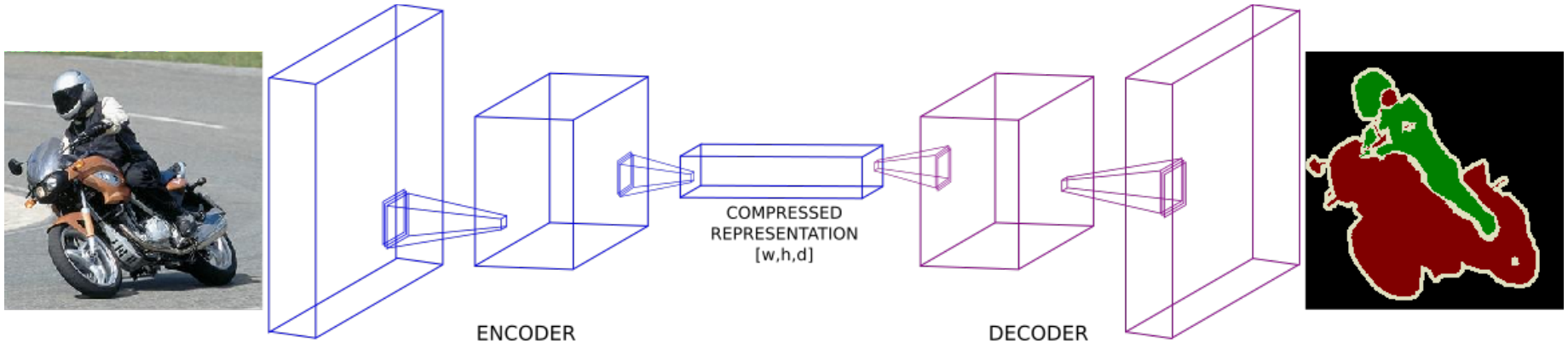
- The area in the input image "seen" by a unit in a CNN
- Units in deeper layers will have wider receptive fields



Output Going to Image Resolution

- Encoder aggressively pools and subsamples image
- Necessary to capture context information which is necessary for segmentation
- But spatial detail is also necessary

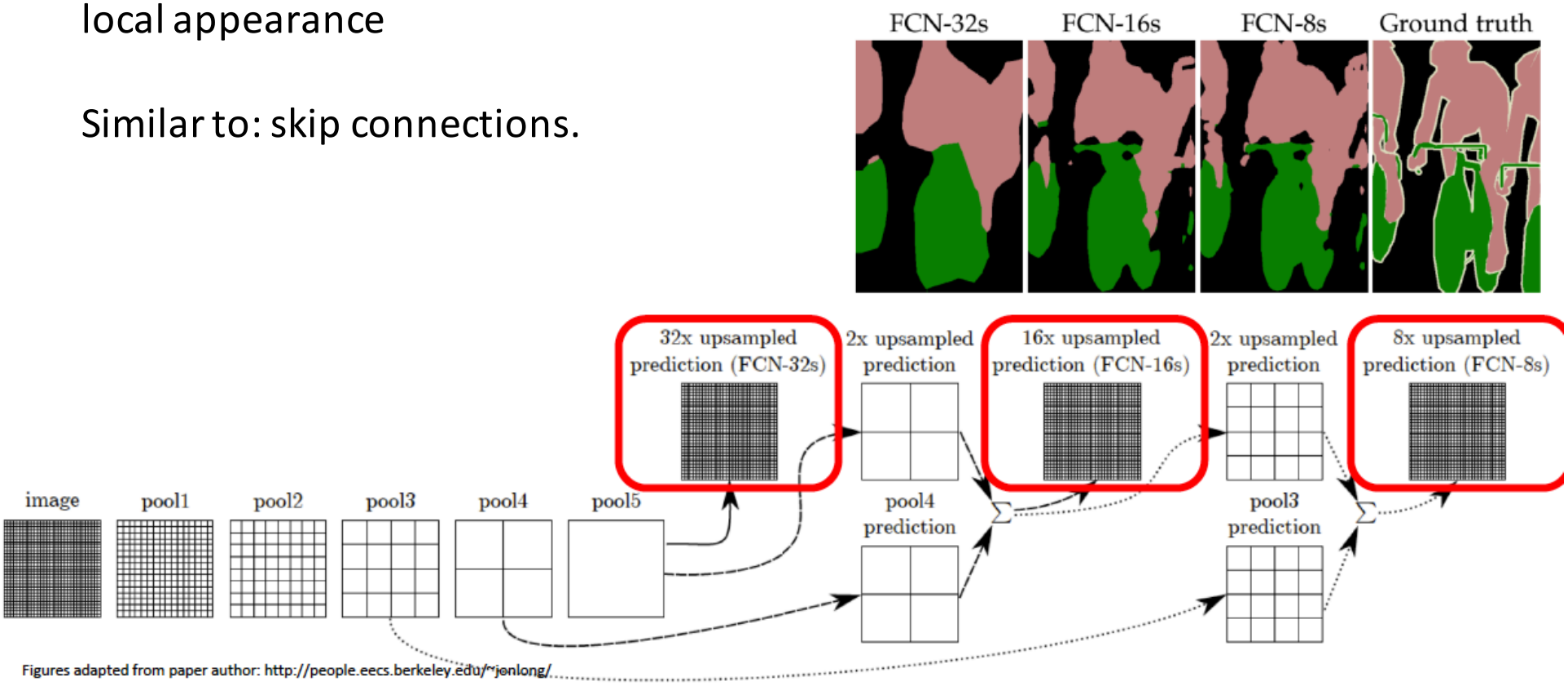
- Goal for decoder: obtain output at image *resolution*
- Goal for decoder: recover *detail* in encoder feature maps before subsampling



Combine Global and Local Information

Fuse coarse semantic information with local appearance

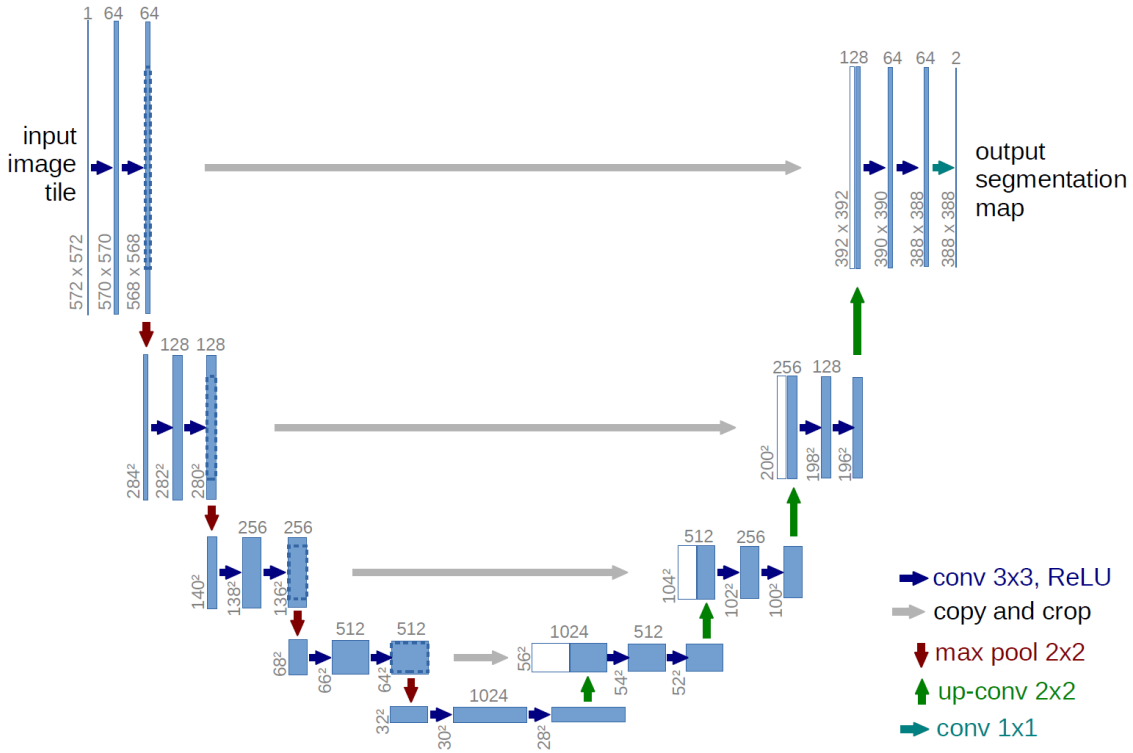
Similar to: skip connections.



[Long et al., FCNs for Semantic Segmentation]

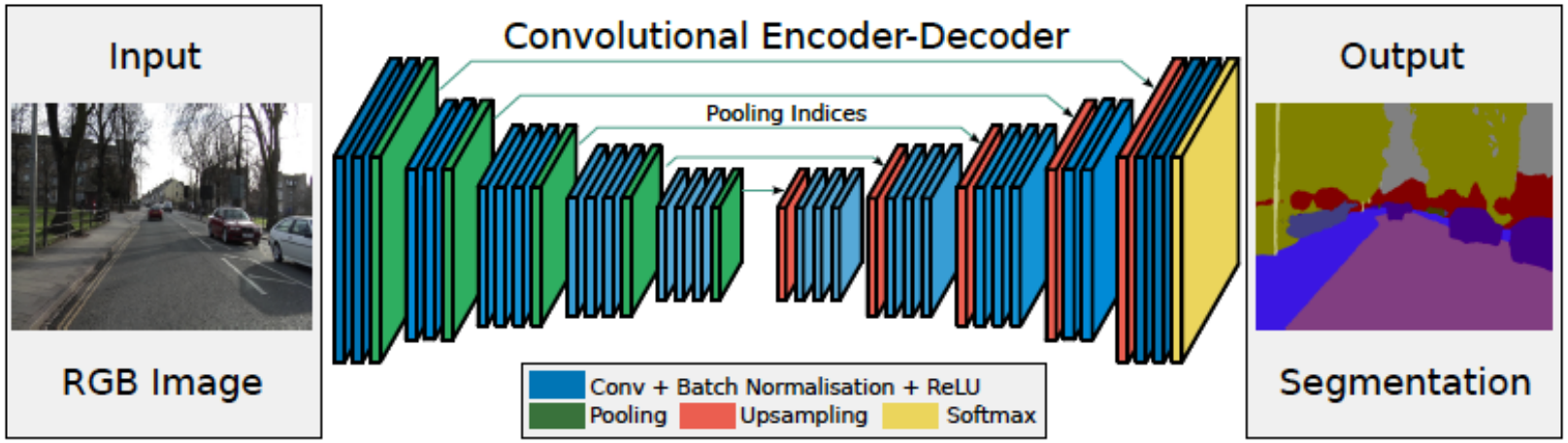
U-Net

- Encoder: Modules of two 3x3 convolution, followed by 2x2 pooling
- Decoder:
  - Upsample with 2x2 transposed convolution
  - Concatenate feature map from corresponding encoder level
  - Two 3x3 convolutions

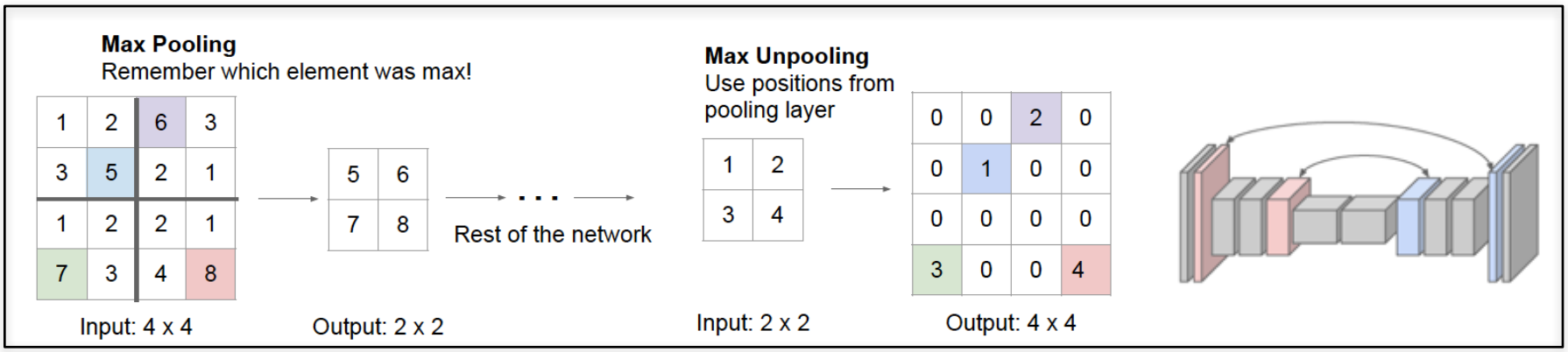


[Ronneberger et al., U-Net]

Output Going to Image Resolution



- In U-Net, encoder feature maps need to be stored in memory for concatenation
- In SegNet, only store the indices where max-pool is active
- Store 2x2 pooling index with 2 bits, as opposed to floating point feature map
- Significant memory reduction at inference time



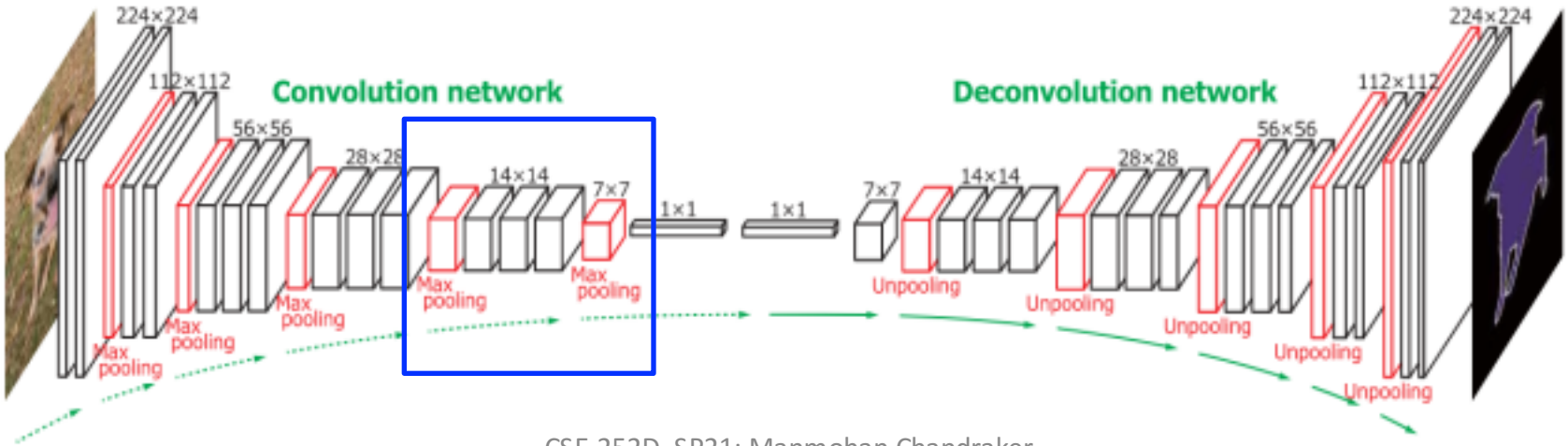
 [Badrinarayanan et al., SegNet]

Wide Receptive Fields

- Most networks have similar encoders (inspired by classification networks)
- Downsample to save memory and obtain large receptive fields

- Consider not downsampling features, but still achieve large receptive fields
  - Once downsampled, signal might be lost for small objects
  - Hard to recover by subsequent layers during training

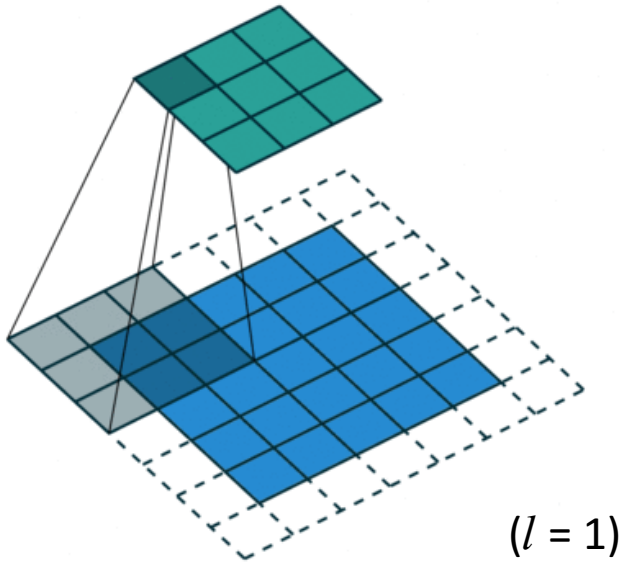
- Challenge: maintain spatial resolution along with a large receptive field
  - Solution: use dilated convolutions



Dilated Convolutions

- Regular convolution:

$$(F * k)(\mathbf{p}) = \sum_{\mathbf{s}+\mathbf{t}=\mathbf{p}} F(\mathbf{s})\, k(\mathbf{t}).$$

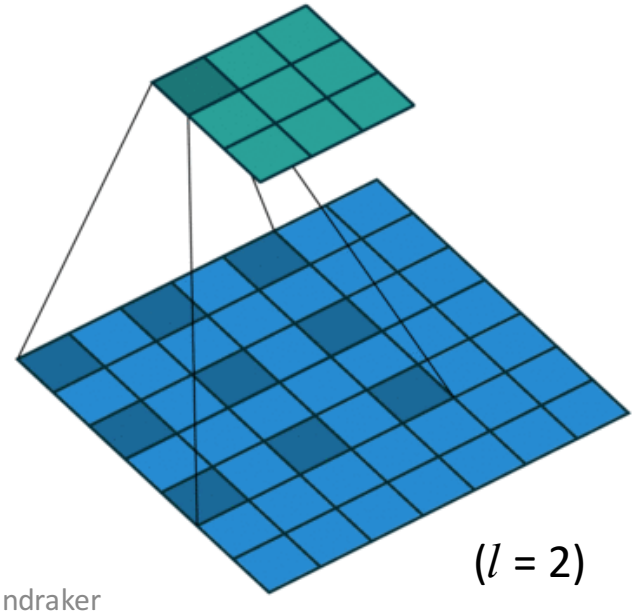


(l = 1)

- Dilated convolution:

$$(F *_l k)(\mathbf{p}) = \sum_{\mathbf{s}+l\mathbf{t}=\mathbf{p}} F(\mathbf{s})\, k(\mathbf{t}).$$

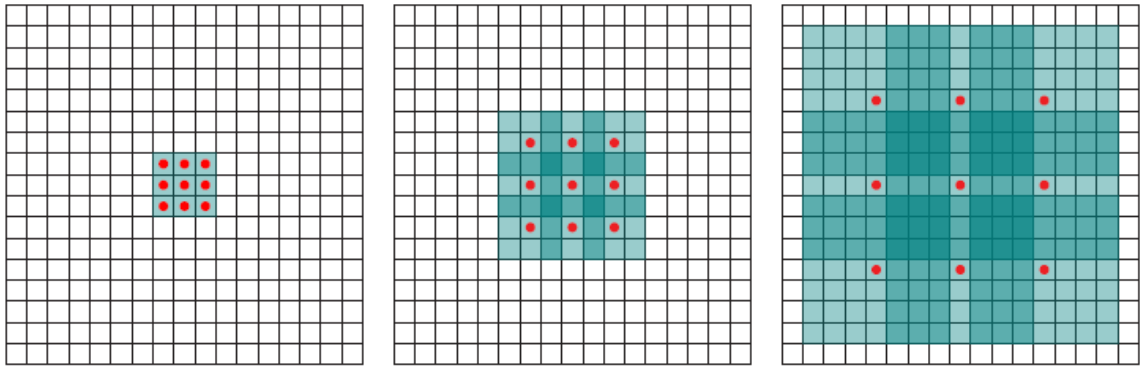
- Sometimes called dilated filter
- Filter is the same, convolution type changes



(l = 2)

Dilated Convolutions

- Receptive field increases with greater dilation factor



(i = 0) (i = 1) (i = 2)

$(l = 2^i)$

- Number of parameters remains the same

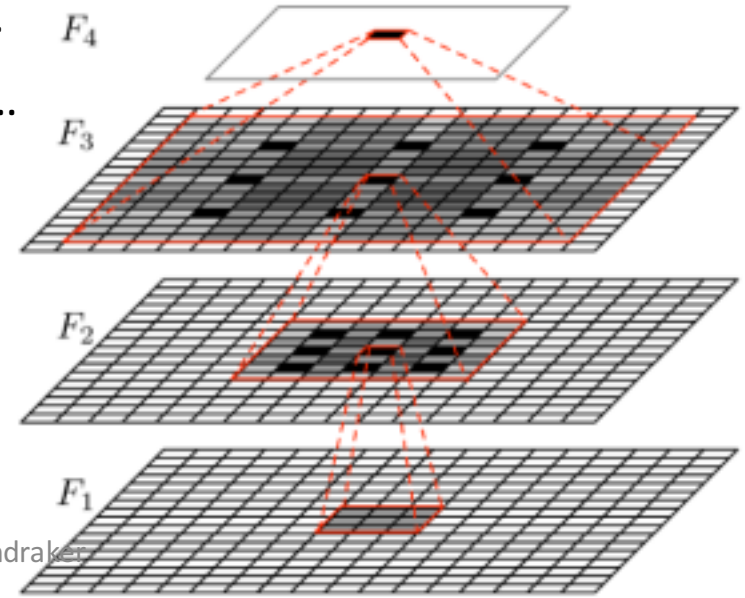
- F1: dilation = 1, F2: dilation = 2, F3: dilation = 4, ...
- **Exponential RF** on stacking with dilations 1, 2, 4, ...

$$F_{i+1} = F_i *_{2^i} k_i \quad \text{for } i = 0, 1, \ldots, n-2.$$

- (i+1) layer receptive field:

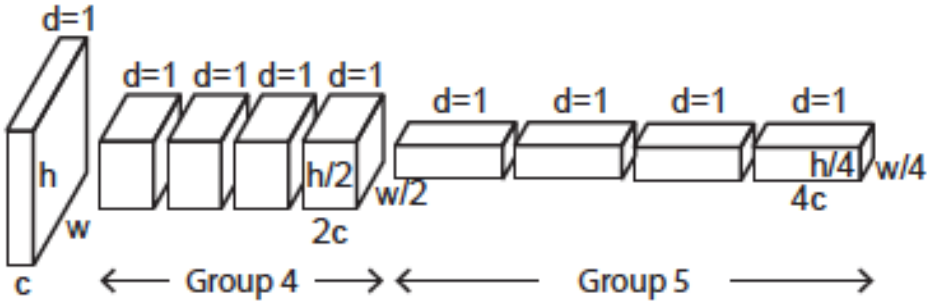
$$(2^{i+2} - 1) \times (2^{i+2} - 1)$$

- **Multiscale** and **full resolution!**

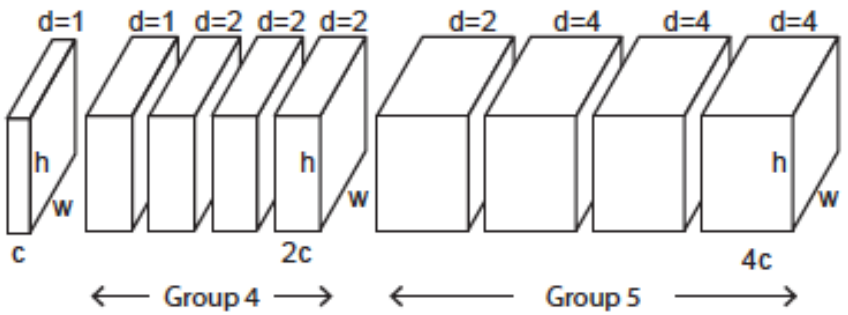


Dilated Residual Network

- Goals: Exploit the power of residual networks with advantages of dilation
  - Once training signal lost by downsampling, hard to recover it
  - Preserve spatial resolution of feature maps
  - Provide training signals that densely cover the input field
  - Backpropagation can now learn to preserve small but salient details
  - Also beneficial when classification network is transferred to other tasks



ResNet



Dilated ResNet

[Yu et al., Dilated Residual Networks]

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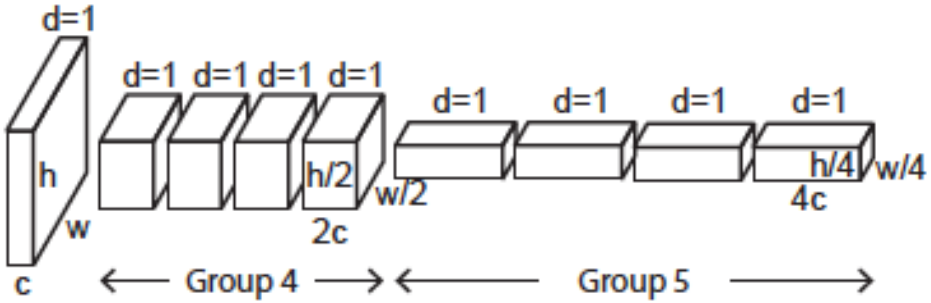
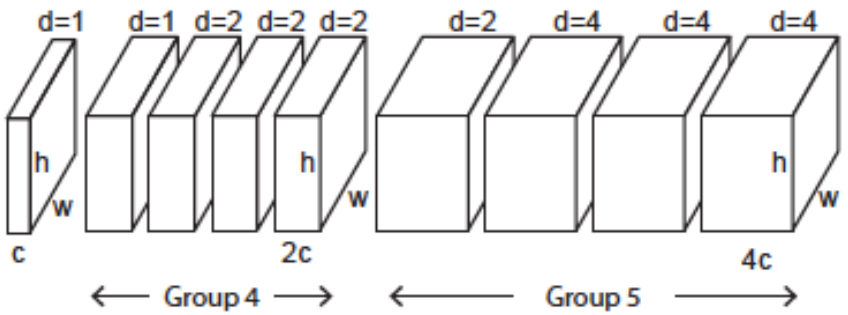
- ResNet uses stride 2 to downsample from block G_k to G_{k+1}
- Do not use stride to downsample, maintain resolution
- Dilate subsequent layers by another factor of 2 to maintain receptive field



ResNet

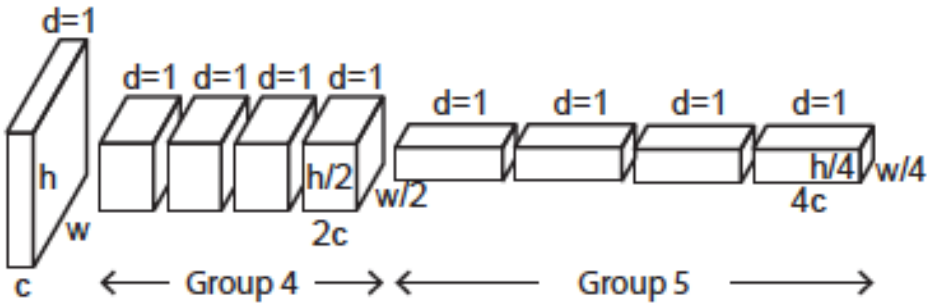


Dilated ResNet

[Yu et al., Dilated Residual Networks]

Dilated Residual Network

- State-of-the-art performance on classification, segmentation
- High resolution features, classification network easily used for segmentation
- But two problems with DRN:
  - Gridding artifacts
  - Memory consumption



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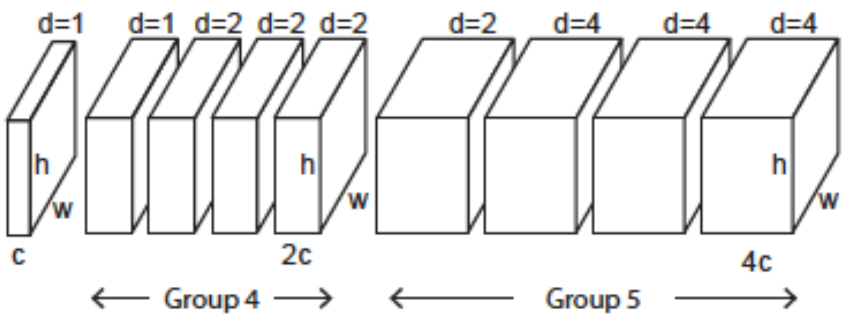
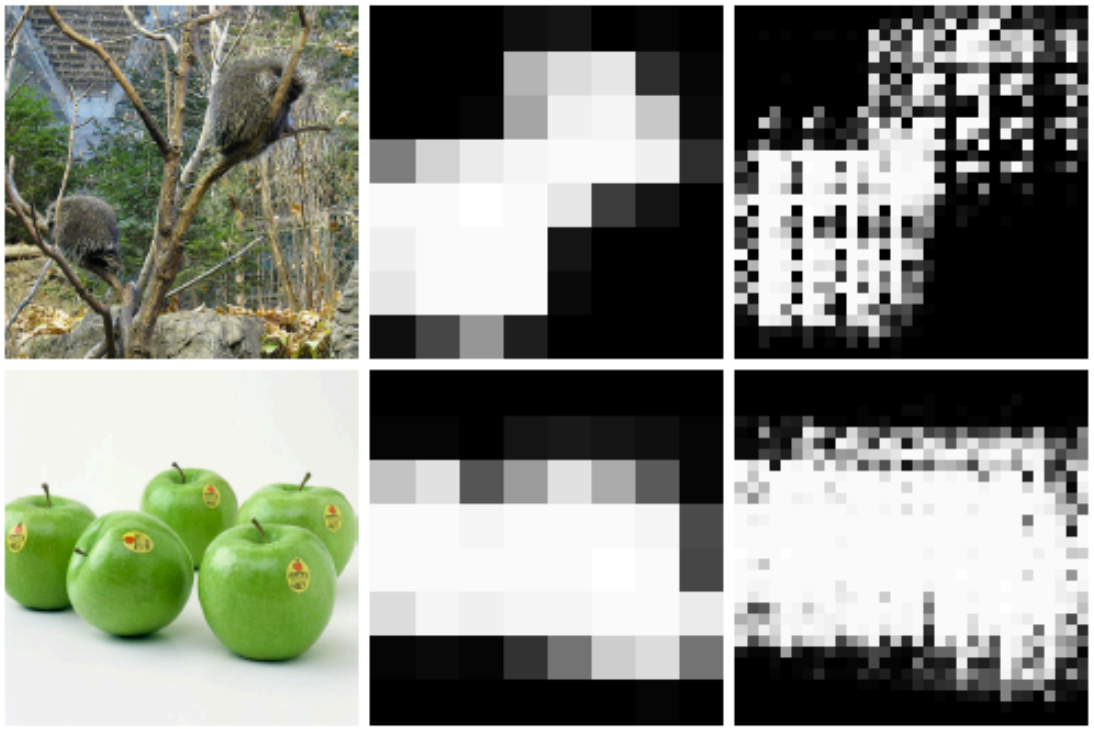


Dilated ResNet

Dilated Residual Network: Degridding

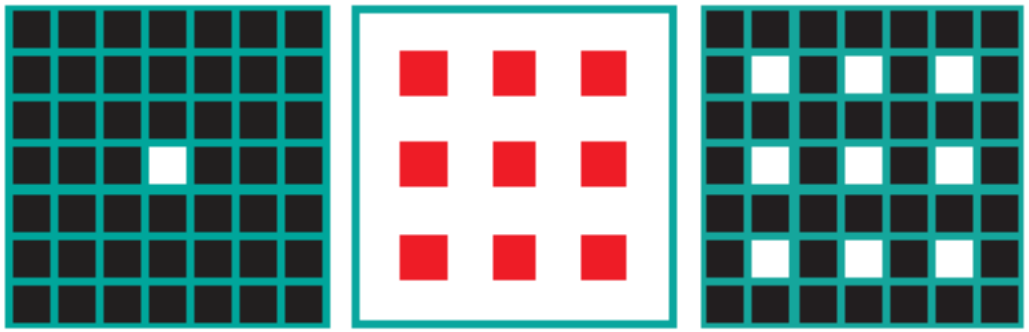
- Gridding artifacts sometimes observed with DRN



(a) Input (b) ResNet-18 (c) DRN-A-18

Dilated Residual Network: Degridding

- Gridding artifacts sometimes observed with DRN
  - Frequency in features maps exceeds sampling rate of filter
  - Filters with higher dilation are at “lower frequency”

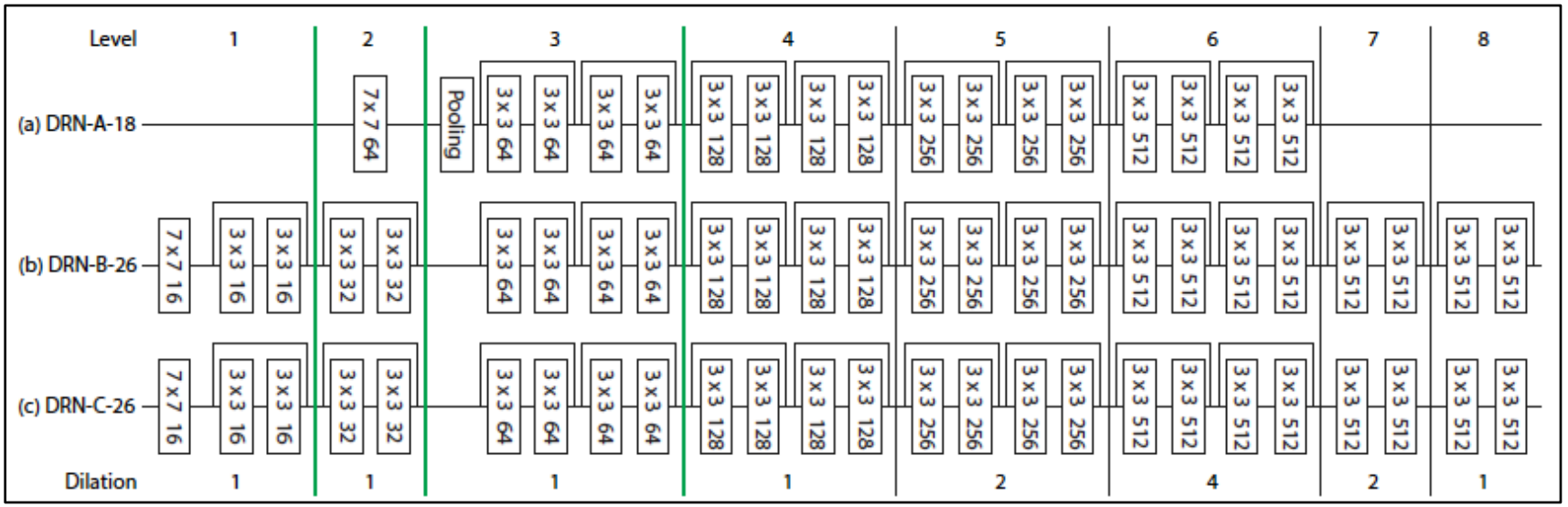


(a) Input (b) Dilation 2 (c) Output

Dilated Residual Network: Degridding

- Degridding solutions
  - Replace max-pooling in preceding layer with convolutional layers

(a) Input (b) DRN-A-18 (c) DRN-B-26



[Yu et al., Dilated Residual Networks]

Dilated Residual Network: Degridding

- Degridding solutions
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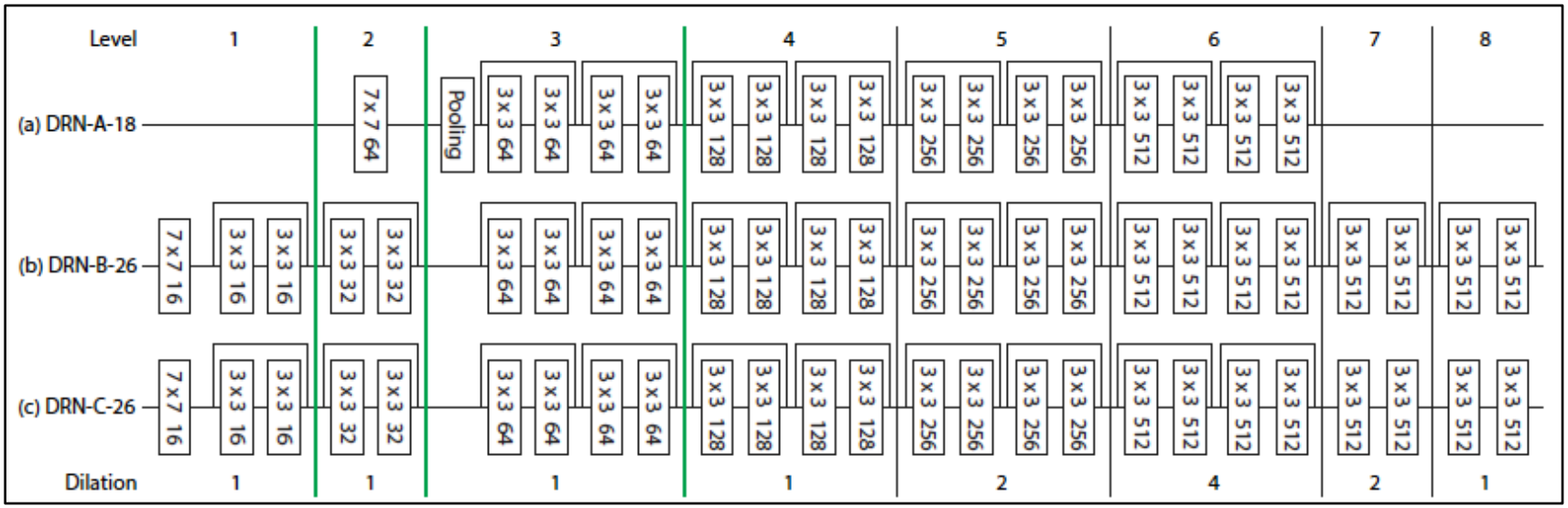

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Dilated Residual Network: Degridding

- Degridding solutions
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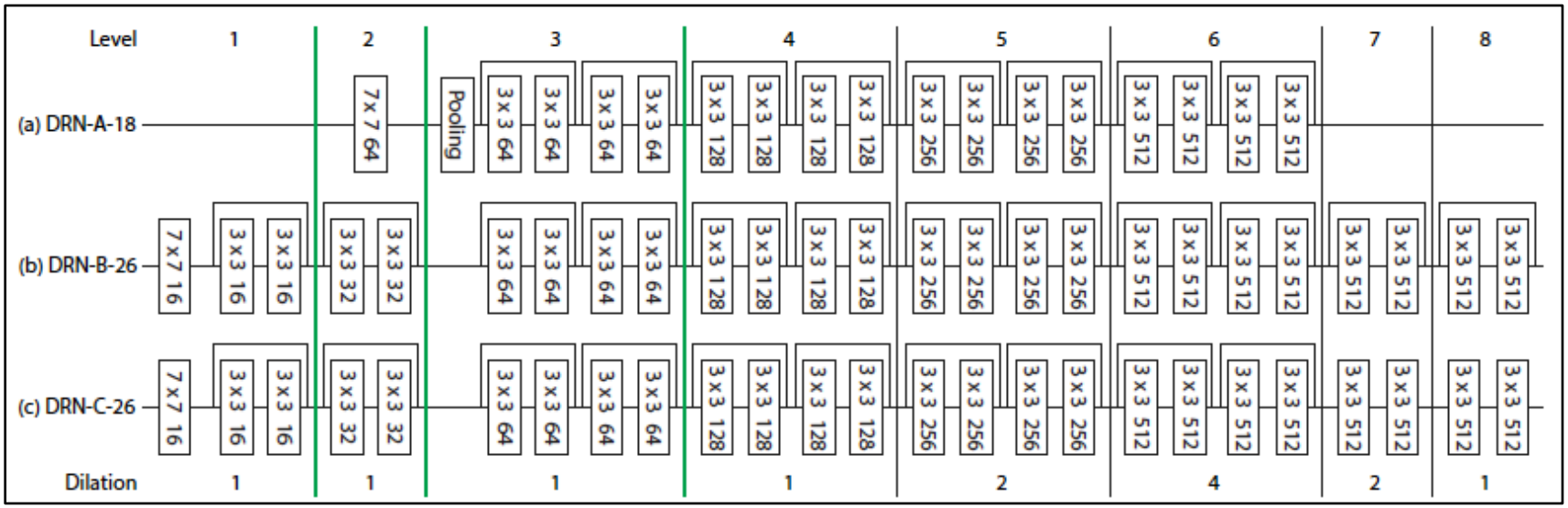
  - Remove skip connections in newly added layers
    - Skip connections can propagate gridding artifacts from previous layers



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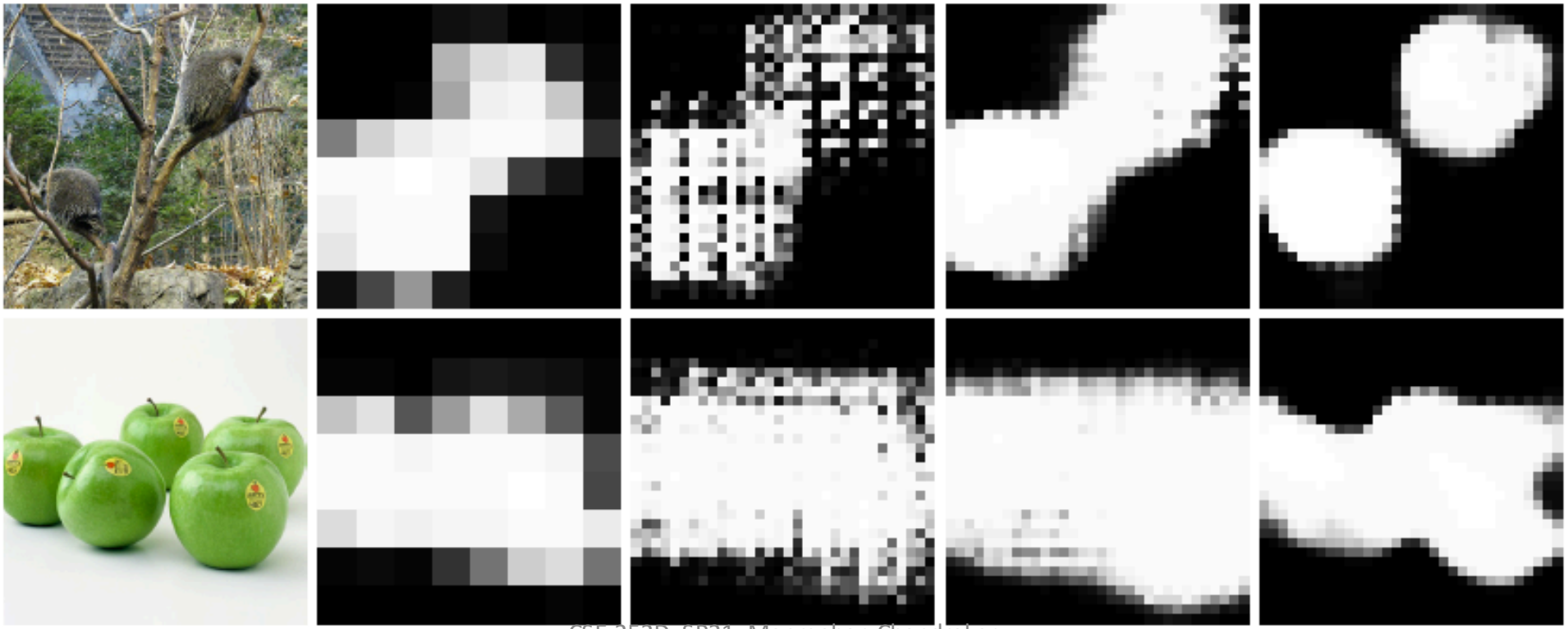


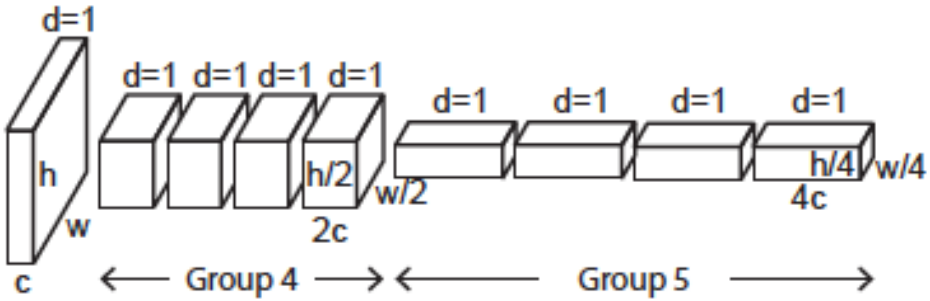
(a) Input (b) ResNet-18 (c) DRN-A-18 (d) DRN-B-26 (e) DRN-C-26

Dilated Residual Network : Memory

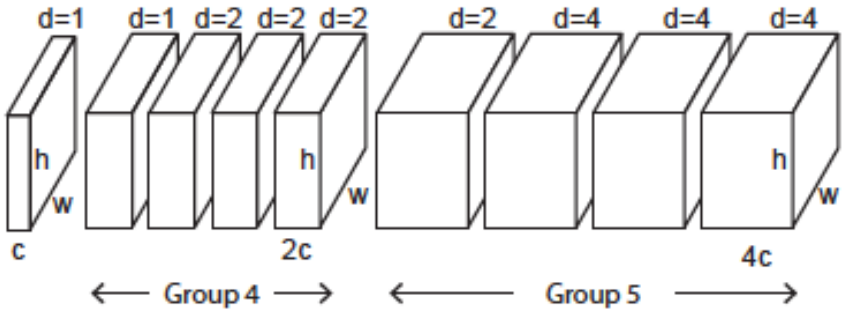
- State-of-the-art performance on classification, segmentation
- High resolution features, classification network easily used for segmentation

- But two problems with DRN:
  - Gridding artifacts
  - Memory consumption

- Dilation preserves number of parameters, but feature maps are bigger
- In practice, only G_4 and G_5 use dilation
- Output produced at 8-times smaller resolution



ResNet

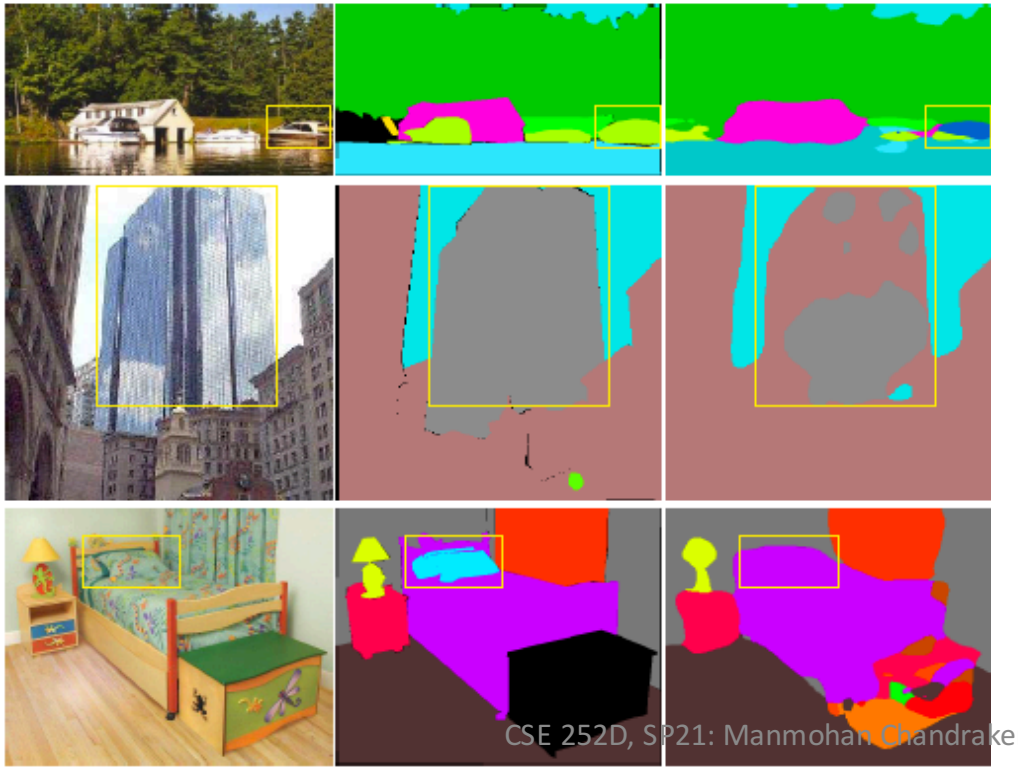


Dilated ResNet

Importance of Context: Issue with FCN

- Use of co-occurring visual statistics is crucial for semantic segmentation
  - Mismatched classes: predict car on water
  - Confusion classes: predict same object as skyscraper and building
  - Inconspicuous classes: miss the pillow since cannot correlate with bed

- It seems not enough context information is being learned



More Context Information

- But a deep ResNet should encode sufficient context
  - Theoretically, ResNet has receptive field that covers entire image
  - Empirical size of receptive field can be much smaller

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- But a deep ResNet should encode sufficient context
  - Theoretically, ResNet has receptive field that covers entire image
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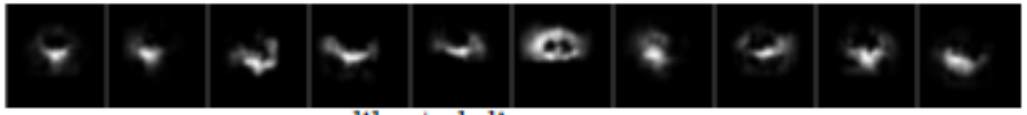
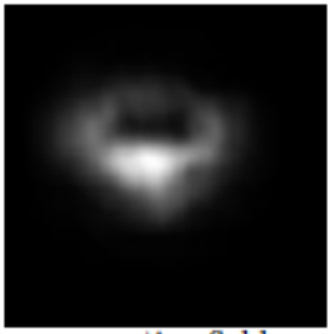
- A data-driven way to determine empirical receptive field for a unit
  - Consider top K images that cause maximum activation for a unit
  - Slide a small occluder on each of the K images
  - A region is important if there is significant change in the activation
  - Empirical receptive field: average of discrepancy maps for the K images

sliding-window stimuli

discrepancy maps for top 10 images



calibrated discrepancy maps



receptive field

[Zhou et al., ICLR 2015]

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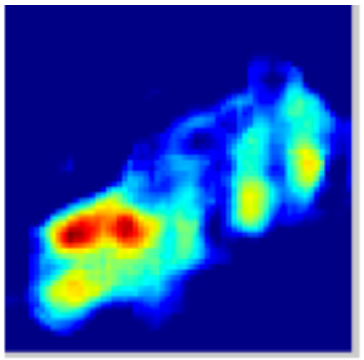
(a) Original Image



(b) Activation map

(c) Theoretical RF

(d) Empirical RF

[Zhou et al., ICLR 2015]

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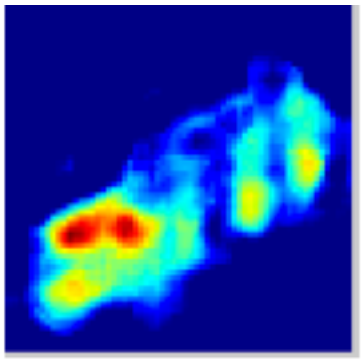
	pool1	pool2	conv3	conv4	pool5
Theoretic size	19	67	99	131	195
ImageNet-CNN actual size	17.9± 1.6	36.7± 5.4	51.1±9.9	60.4± 16.0	70.3± 21.6

(a) Original Image



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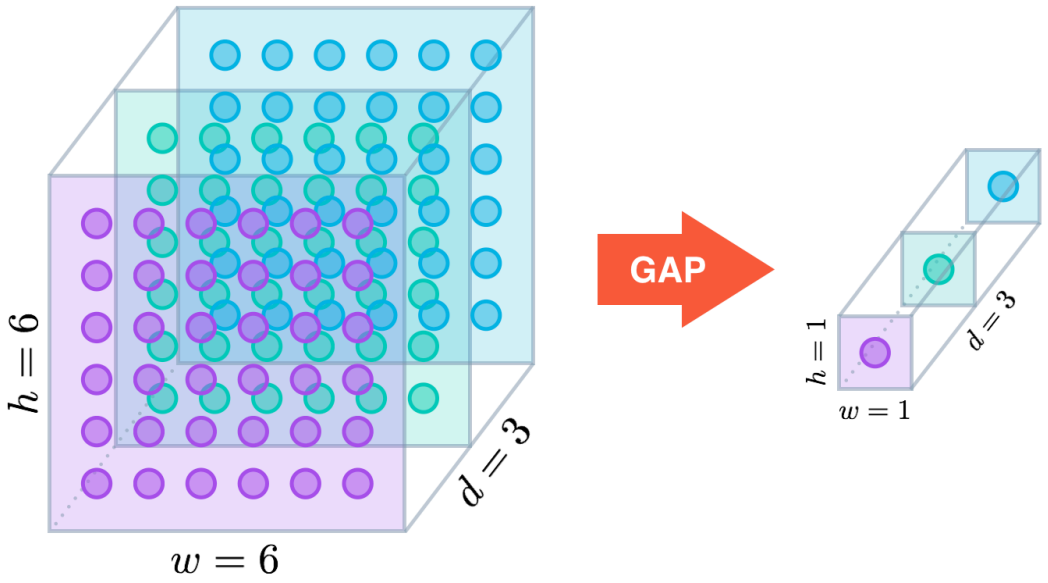
[Zhou et al., ICLR 2015]

More Context Information: Global Pooling

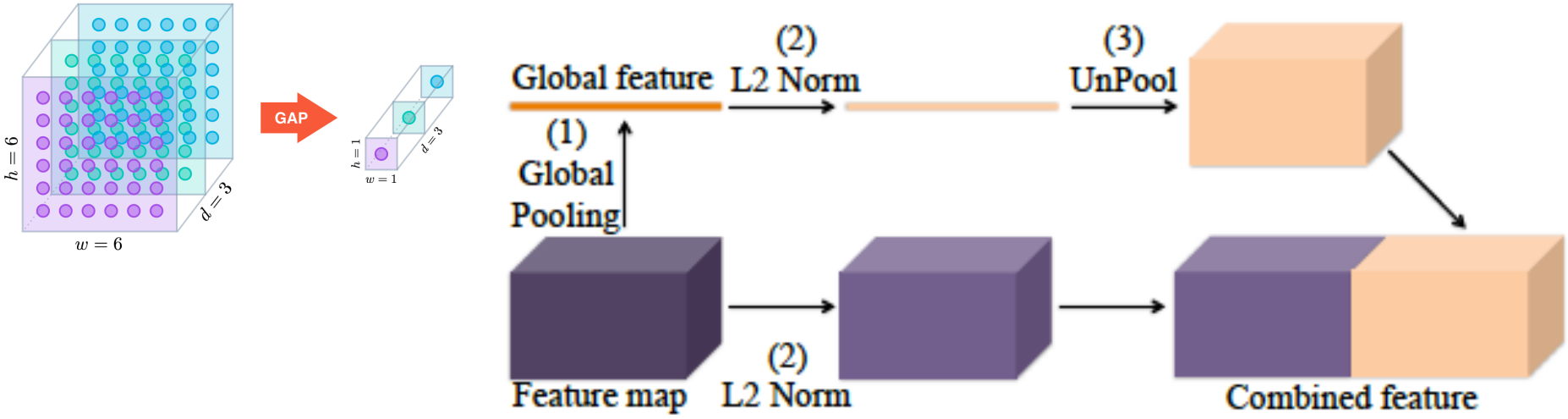
- Need a mechanism to explicitly encode context information
- Option 1: Global average pooling



More Context Information: Global Pooling

- Need a mechanism to explicitly encode context information

- Option 1: Global average pooling
  - Obtain context vector from feature maps in a layer
  - Unpool (replicate) to feature dimensions and concatenate
  - L2-normalization before concatenation for stable training

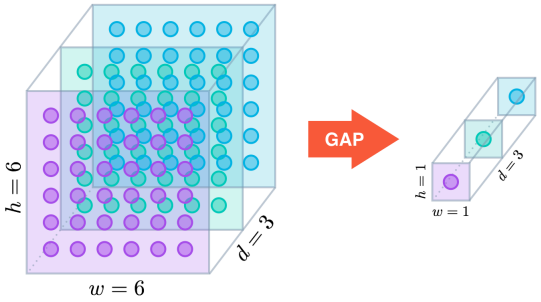


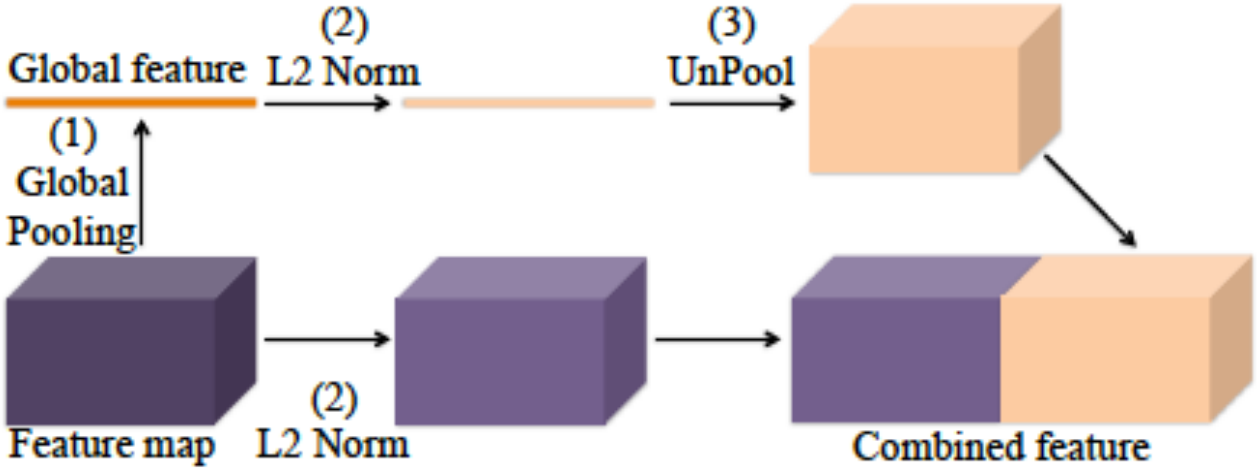
[Liu et al., ParseNet]

More Context Information: Global Pooling

- Need a mechanism to explicitly encode context information

- Option 1: Global average pooling
  - Obtain context vector from feature maps in a layer
  - Unpool (replicate) to feature dimensions and concatenate
  - L2-normalization before concatenation for stable training
  - Issue: spatial relationships may be lost in global pooling





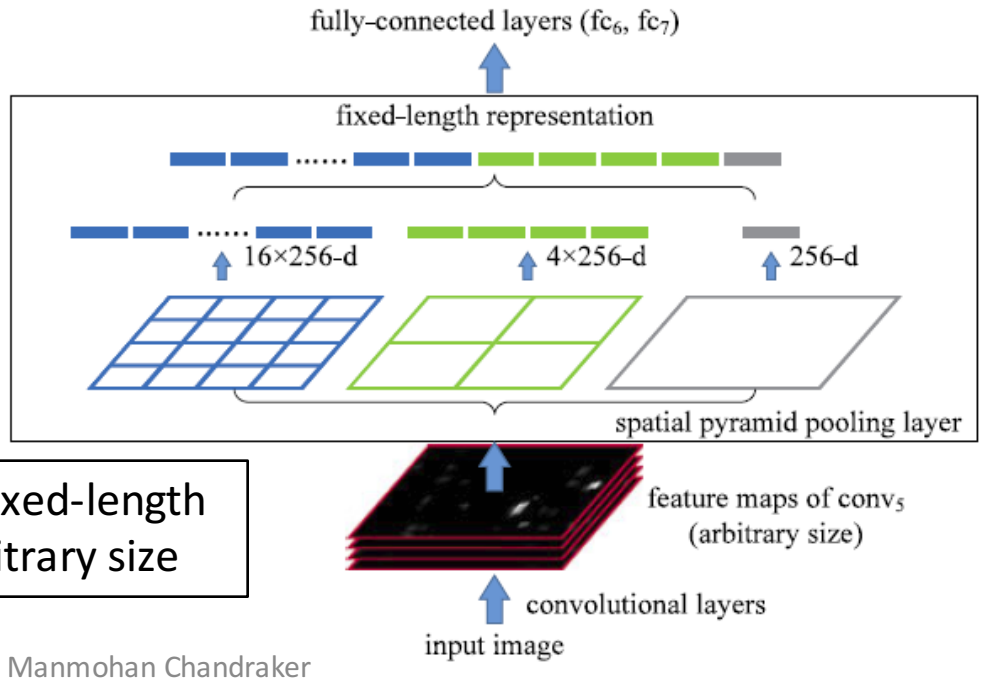
[Liu et al., ParseNet]

More Context Information: Pyramid Pooling

- Need a mechanism to explicitly encode context information

- Option 1: Global average pooling
  - Obtain context vector from feature maps in a layer
  - Unpool (replicate) to feature dimensions and concatenate
  - L2-normalization before concatenation for stable training
  - Issue: spatial relationships may be lost in global pooling

- Option 2: Pyramid pooling

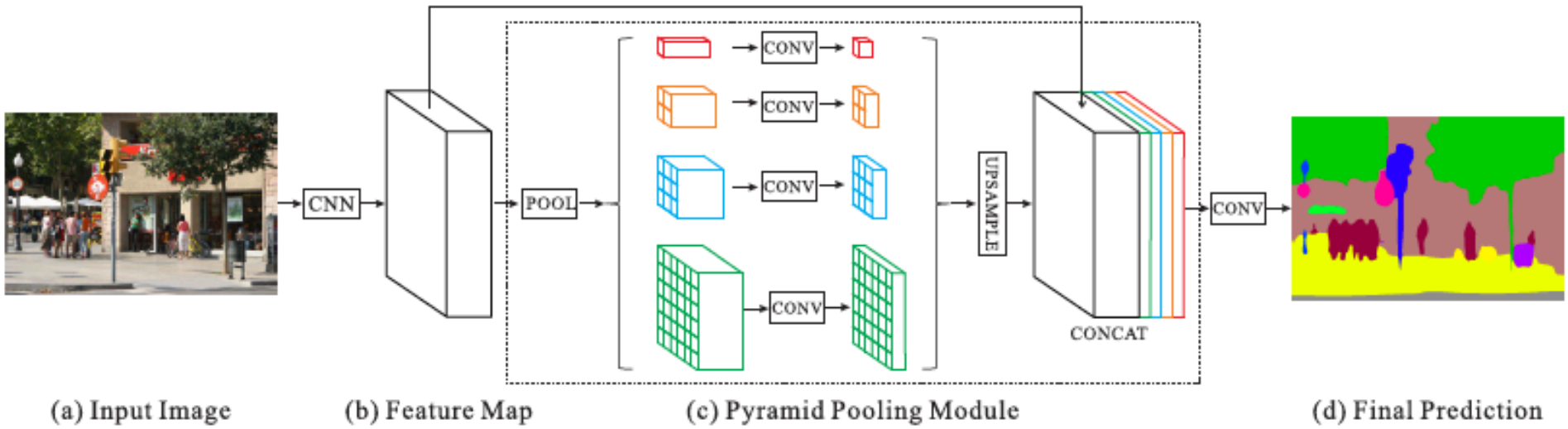


Originally proposed for obtaining fixed-length representation from images of arbitrary size

More Context Information: Pyramid Pooling

- Role in segmentation: Extract both global and regional context
  - A hierarchical global prior, with information across scales and regions

- Fuse features in several different pyramid scales
  - Pool input feature map into hierarchy of context features
  - Do 1x1 convolution to ensure each pyramid level gets equal weight
  - Upsample to original resolution and concatenate



[Zhao et al., PSPNet]

Dense Multiclass Prediction

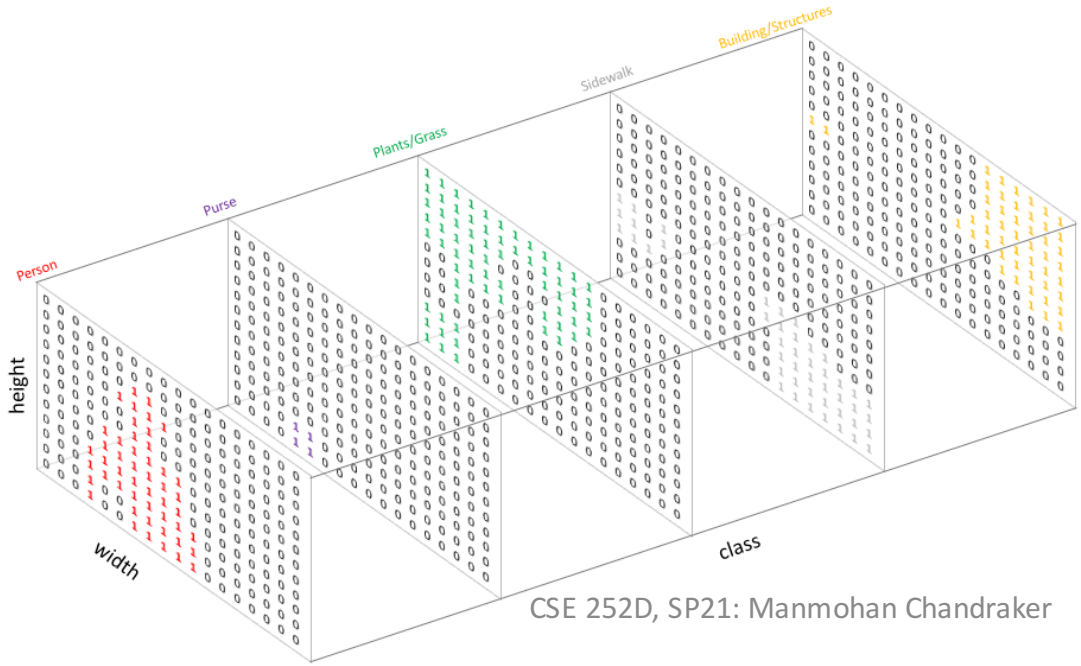
segmented

1: Person
2: Purse
3: Plants/Grass
4: Sidewalk
5: Building/Structures

3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	3	3	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	3	5	5	5	5	5	5
3	3	3	3	3	1	1	1	1	3	3	3	5	5	5	5	5	5
3	3	3	3	3	3	1	1	3	3	3	5	5	5	5	5	5	5
5	5	3	3	3	3	1	1	3	3	5	5	5	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	5	5	5	5	5
4	4	3	4	1	1	1	1	1	1	4	4	4	4	4	5	5	5
4	4	4	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	1	1	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4
3	3	3	1	2	2	1	1	1	1	1	4	4	4	4	4	4	4

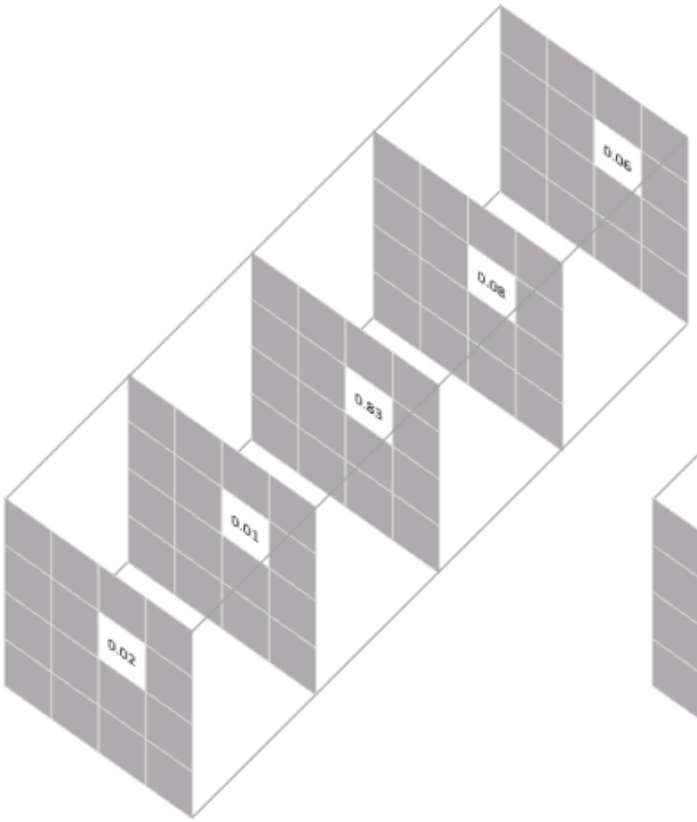
Input

Semantic Labels

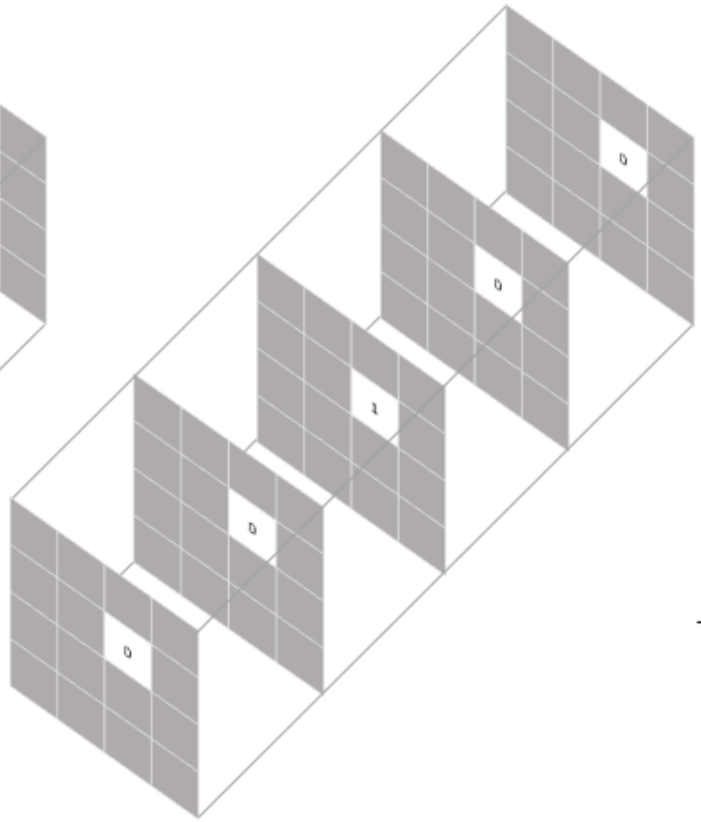


[Images from: Jeremy Jordan]

Pixel-wise Cross-Entropy Loss



Prediction for a selected pixel



Target for the corresponding pixel

Pixel-wise loss is calculated as the log loss, summed over all possible classes

$$-\sum_{classes} y_{true} \log\left(y_{pred}\right)$$

This scoring is repeated over all **pixels** and averaged

- Can weight each output channel for class imbalance in training set (FCN)
- Can assign higher weight to pixels near the boundary (U-Net)

[Images from: Jeremy Jordan]

Semantic Segmentation Metrics

Confusion matrix: $\mathbf{C}_{ij} = \sum_{I \in \mathcal{D}} |\{z \in I \text{ such that } S^I_{gt}(z) = i \text{ and } S^I_{ps}(z) = j\}|$

Number of pixels with ground truth label *i*: $\mathbf{G}_i = \sum_{j=1}^{L} \mathbf{C}_{ij}$

Number of pixels with prediction *j*: $\mathbf{P}_j = \sum_i \mathbf{C}_{ij}$

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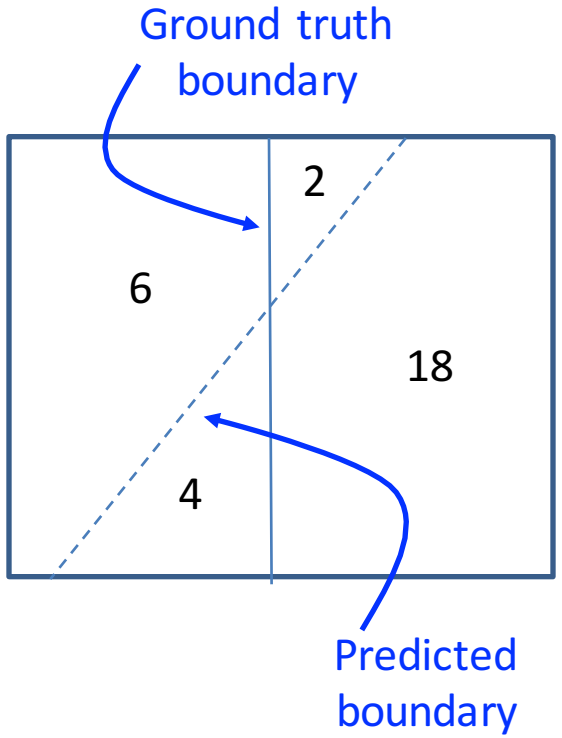
$$\begin{bmatrix} 6 & 4 \\ 2 & 18 \end{bmatrix}$$

Number of pixels with ground truth label *i*: $\mathbf{G}_i = \sum_{j=1}^{L} \mathbf{C}_{ij}$

[10, 20]

Number of pixels with prediction *j*: $\mathbf{P}_j = \sum_i \mathbf{C}_{ij}$

[8, 22]



Semantic Segmentation Metrics

Confusion matrix: $\mathbf{C}_{ij} = \sum_{I \in \mathcal{D}} |\{z \in I \text{ such that } S^I_{gt}(z) = i \text{ and } S^I_{ps}(z) = j\}|$ $\begin{bmatrix} 6 & 4 \\ 2 & 18 \end{bmatrix}$

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[10, 20]

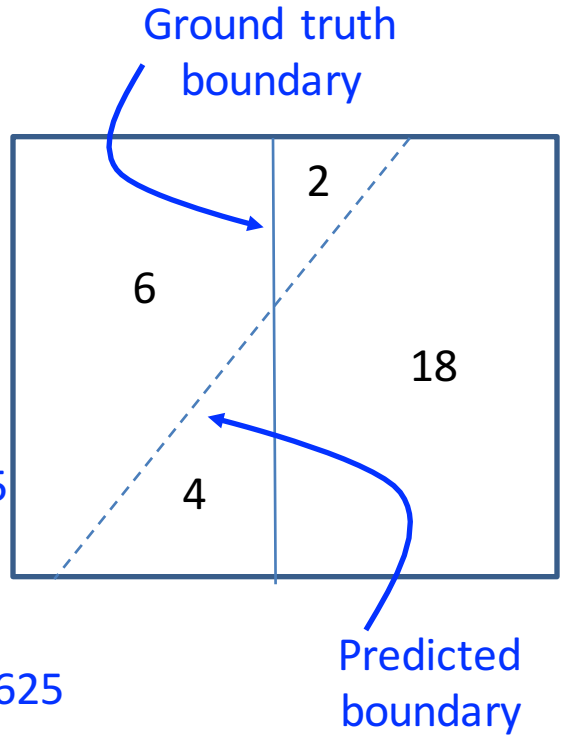
Number of pixels with prediction *j*: $\mathbf{P}_j = \sum_i \mathbf{C}_{ij}$

[8, 22]

Overall pixel accuracy: $OP = \frac{\sum_{i=1}^{L} \mathbf{C}_{ii}}{\sum_{i=1}^{L} \mathbf{G}_i}$ $\frac{6 + 18}{10 + 20}$ = 0.8

Per-class accuracy: $PC = \frac{1}{L} \sum_{i=1}^{L} \frac{\mathbf{C}_{ii}}{\mathbf{G}_i}$ $\frac{1}{2}\left(\frac{6}{10} + \frac{18}{20}\right)$ = 0.75

Intersection-over-union: $JI = \frac{1}{L} \sum_{i=1}^{L} \frac{\mathbf{C}_{ii}}{\mathbf{G}_i + \mathbf{P}_i - \mathbf{C}_{ii}}$ = 0.625



Semantic Segmentation Metrics

Confusion matrix: $\mathbf{C}_{ij} = \sum_{I \in \mathcal{D}} |\{z \in I \text{ such that } S^I_{gt}(z) = i \text{ and } S^I_{ps}(z) = j\}|$

Number of pixels with ground truth label *i*: $\mathbf{G}_i = \sum_{j=1}^{L} \mathbf{C}_{ij}$

Number of pixels with prediction *j*: $\mathbf{P}_j = \sum_i \mathbf{C}_{ij}$

Overall pixel accuracy: $OP = \frac{\sum_{i=1}^{L} \mathbf{C}_{ii}}{\sum_{i=1}^{L} \mathbf{G}_i}$

Biased in favor of large classes

Per-class accuracy: $PC = \frac{1}{L} \sum_{i=1}^{L} \frac{\mathbf{C}_{ii}}{\mathbf{G}_i}$

Biased against background classes, boost all foreground classes

Intersection-over-union: $JI = \frac{1}{L} \sum_{i=1}^{L} \frac{\mathbf{C}_{ii}}{\mathbf{G}_i + \mathbf{P}_i - \mathbf{C}_{ii}}$

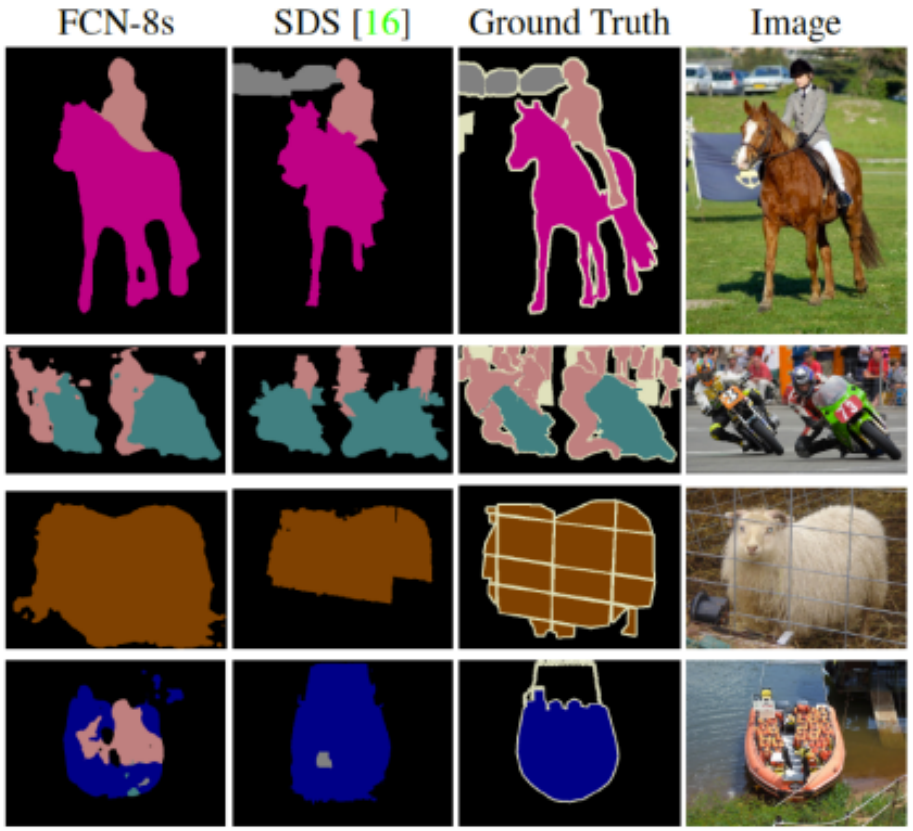
Balances false positives and false negatives

FCN Semantic Segmentation Results

	mean IU VOC2011 test	mean IU VOC2012 test	inference time
R-CNN [12]	47.9	-	-
SDS [16]	52.6	51.6	~ 50 s
FCN-8s	**62.7**	**62.2**	~ **175 ms**

Relative to prior state-of-the-art SDS:

- 30% relative improvement for mean IoU
- 286 times faster



[Long et al., FCNs for Semantic Segmentation]