Indian Institute of Information Technology, Allahabad

CVBL IIIT Allahabad

CNN Architectures for Dense Recognition: Image segmentation

By

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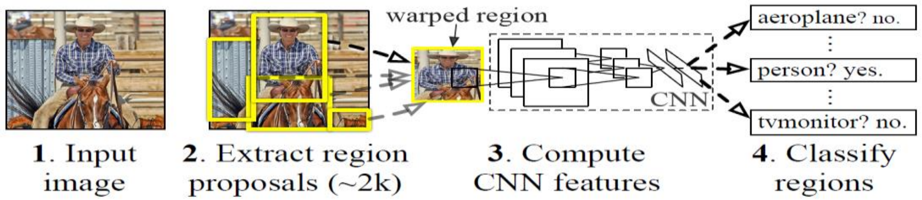
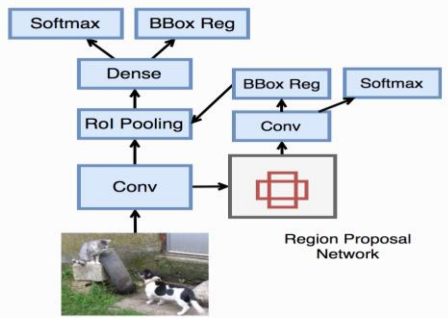
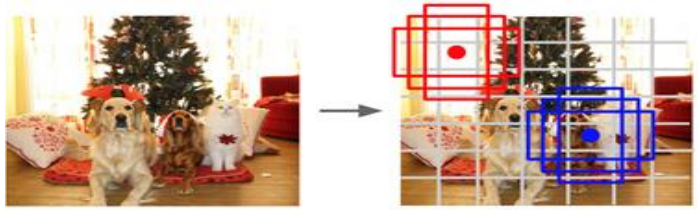
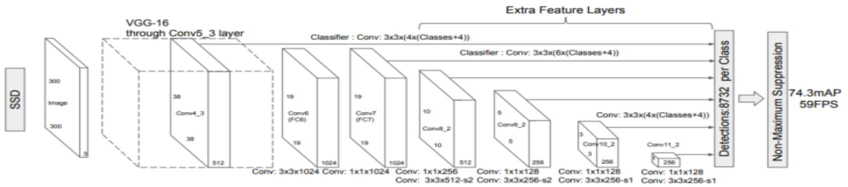
PREVIOUS CLASS: OBJECT BOUNDING BOX DETECTIONS

- Deep learning based detectors
  - Two-stage detectors
    - R-CNN
    - Fast R-CNN
    - Faster R-CNN
  - One-stage detectors
    - YOLO
    - SSD
    - RetinaNet





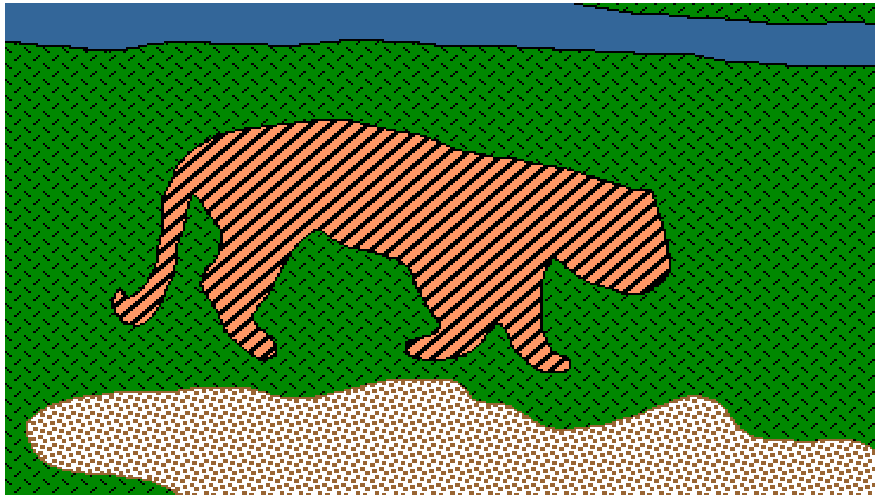




TODAY'S CLASS

Image Segmentation

Group pixels into meaningful or perceptually similar regions



OUTLINE

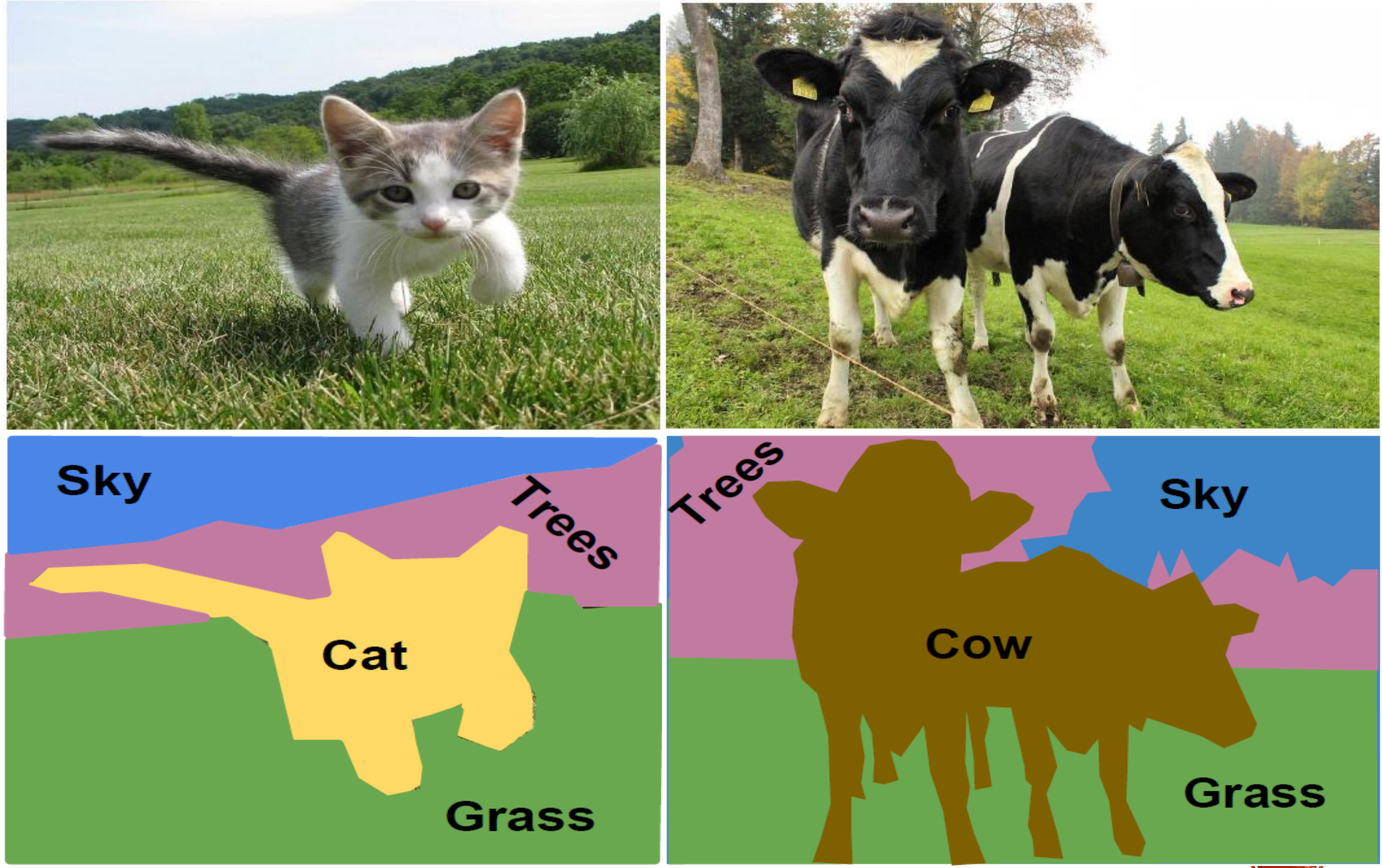
- Early “hacks”
  - Sliding window
  - Fully convolutional networks
- Deep network operations for dense prediction
  - Transposed convolutions
  - Unpooling
  - Dilated convolutions
- Instance segmentation
  - Mask R-CNN
- Other dense prediction problems

SEMANTIC SEGMENTATION

Label each pixel in the image with a category label

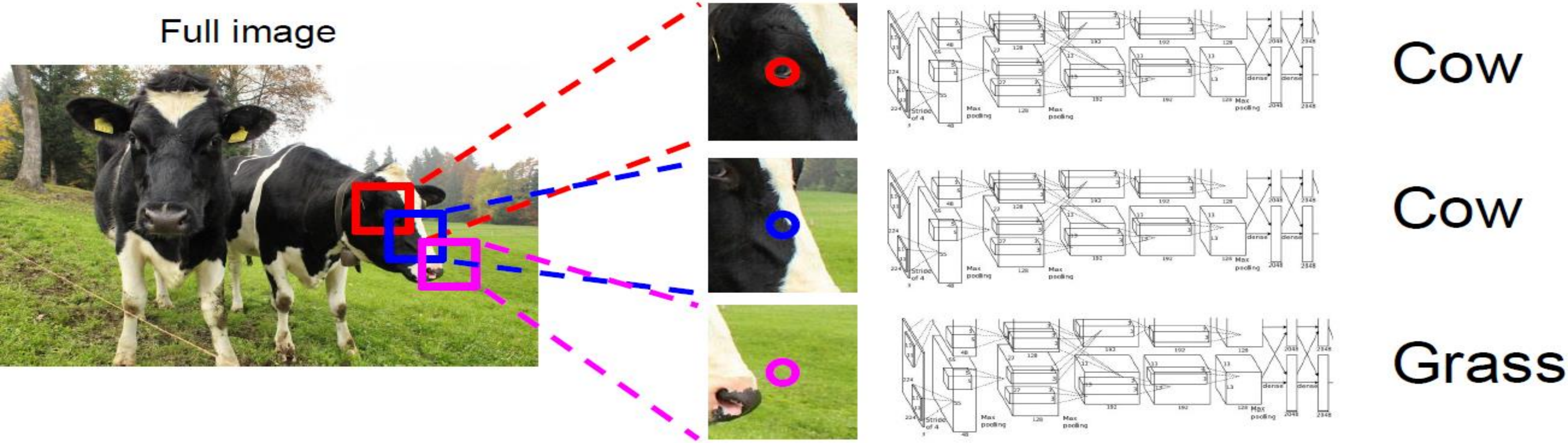
Don't differentiate instances, only care about pixels

These images are CC0 public domain source1 source2



Slide credit: cs231n

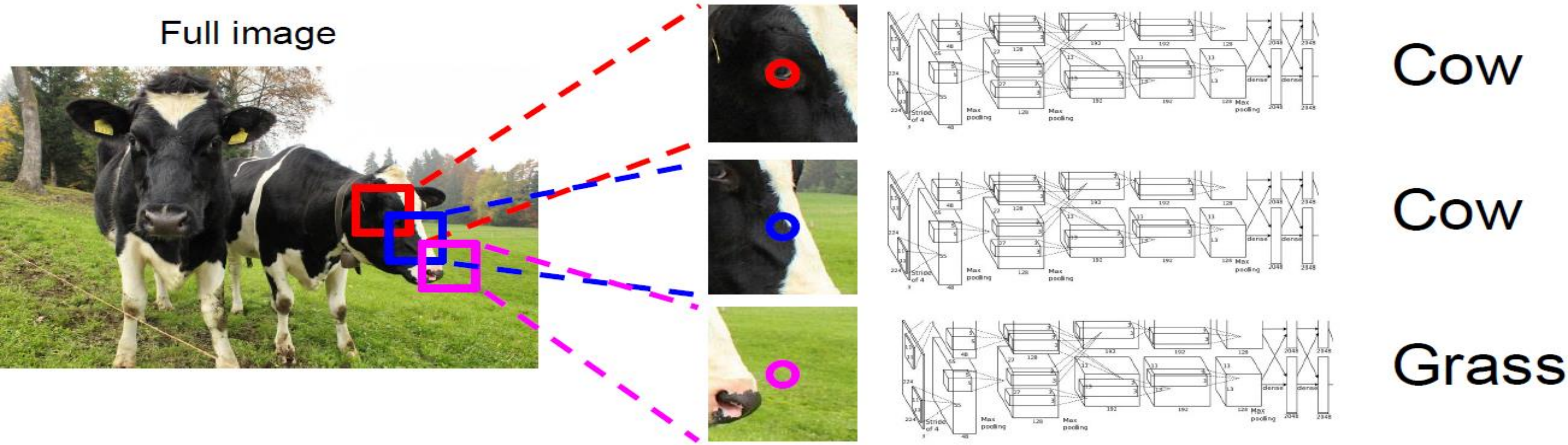
SEMANTIC SEGMENTATION: SLIDING WINDOW



Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Slide credit: cs231n

SEMANTIC SEGMENTATION: SLIDING WINDOW



Problem:

Very inefficient!

Not reusing shared features between overlapping patches

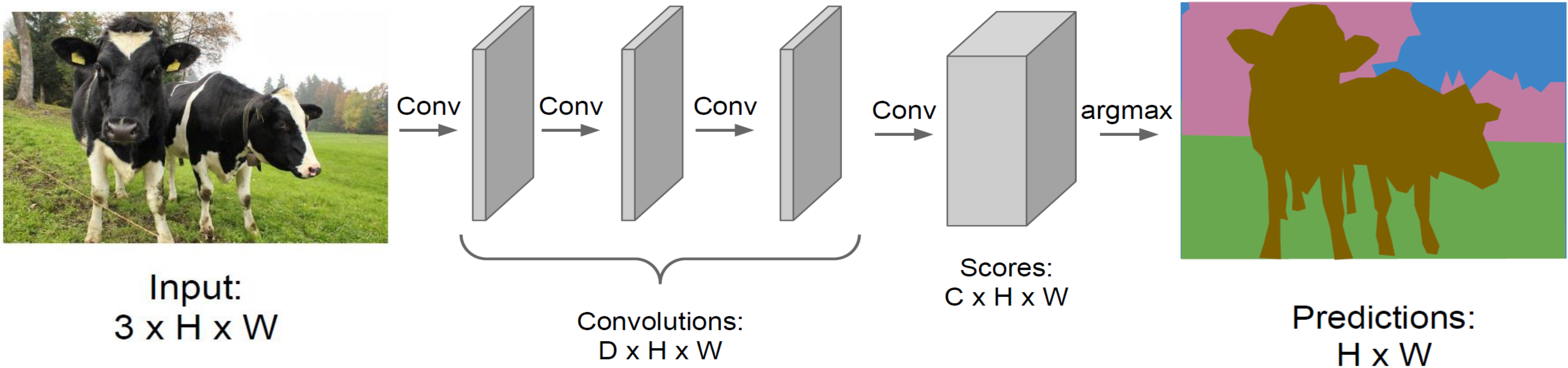
Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013

Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Slide credit: cs231n

SEMANTIC SEGMENTATION: FULLY CONVOLUTIONAL

Design a network as a bunch of convolutional layers
to make predictions for pixels all at once!



Slide credit: cs231n

SEMANTIC SEGMENTATION: FULLY CONVOLUTIONAL

Design a network as a bunch of convolutional layers
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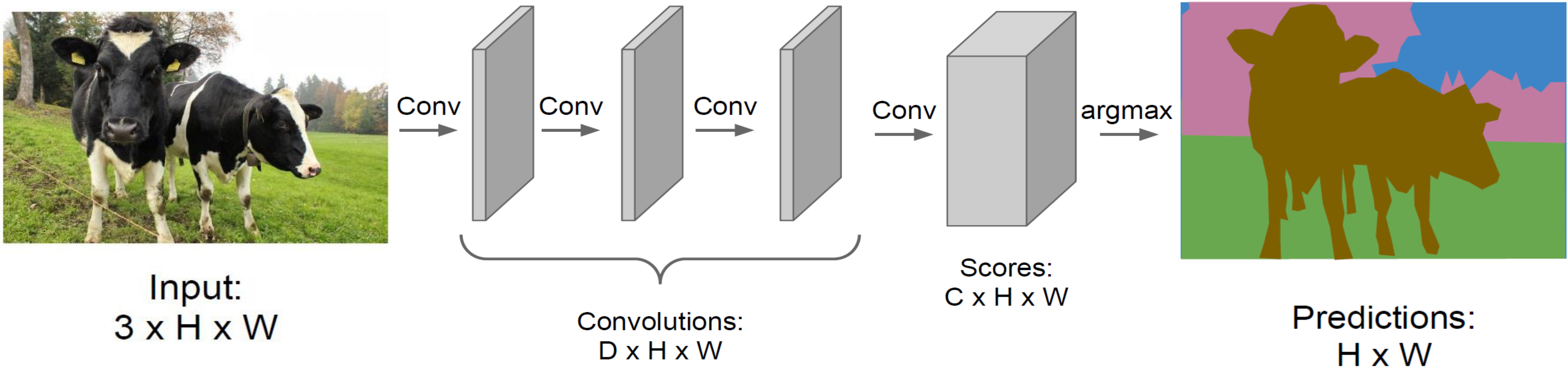

Problem:

Convolutions at original image resolution will be
very expensive ...

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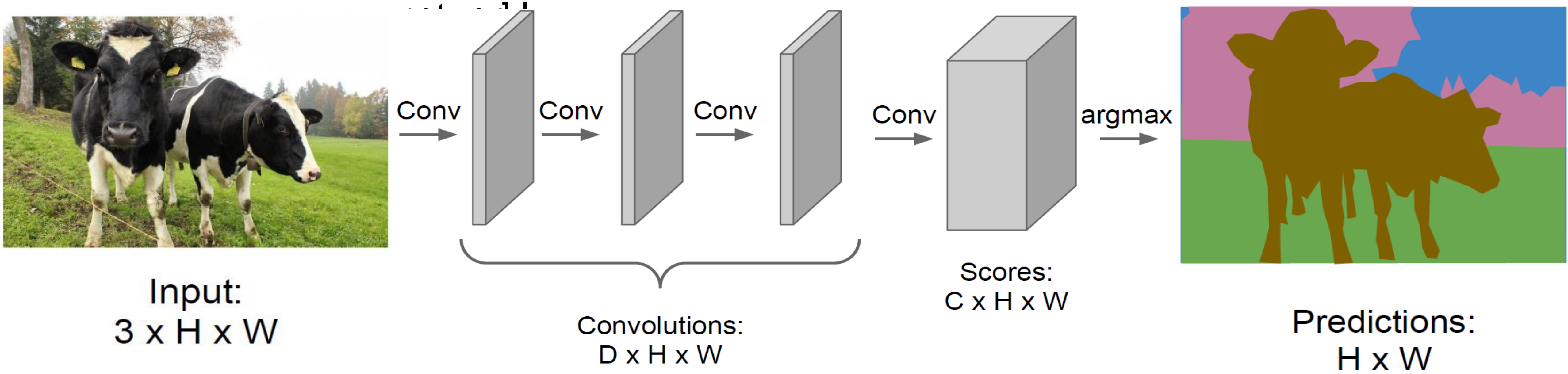
SEMANTIC SEGMENTATION: FULLY CONVOLUTIONAL

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the



Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Slide credit: cs231n

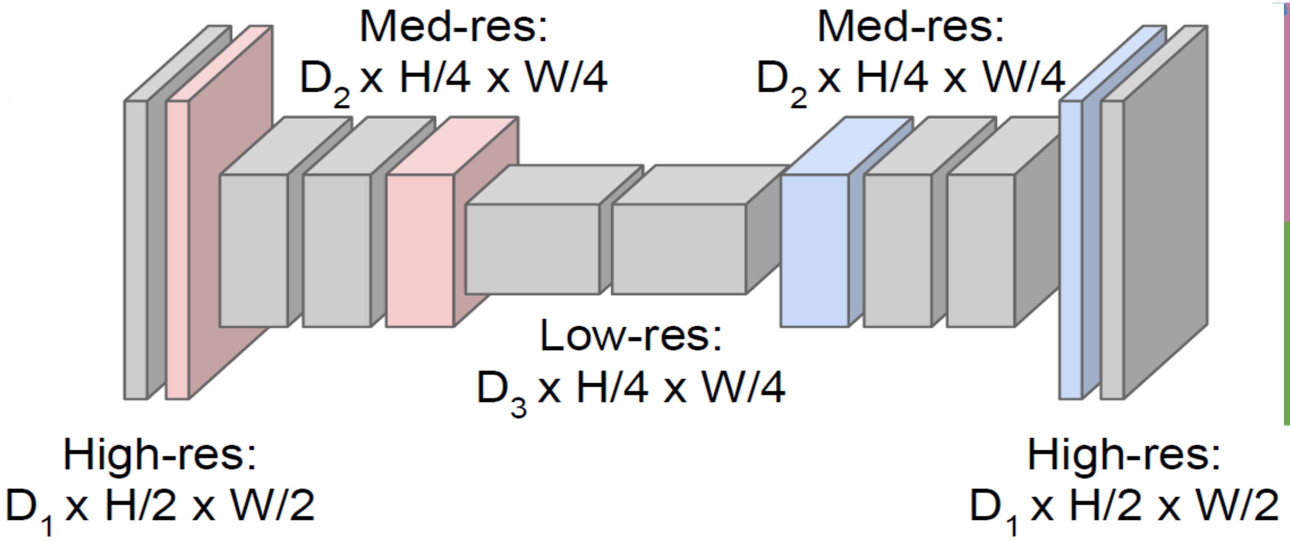
SEMANTIC SEGMENTATION: FULLY CONVOLUTIONAL

Downsampling:
Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
??

Input:
3 x H x W



Predictions:
H x W

Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

Slide credit: cs231n

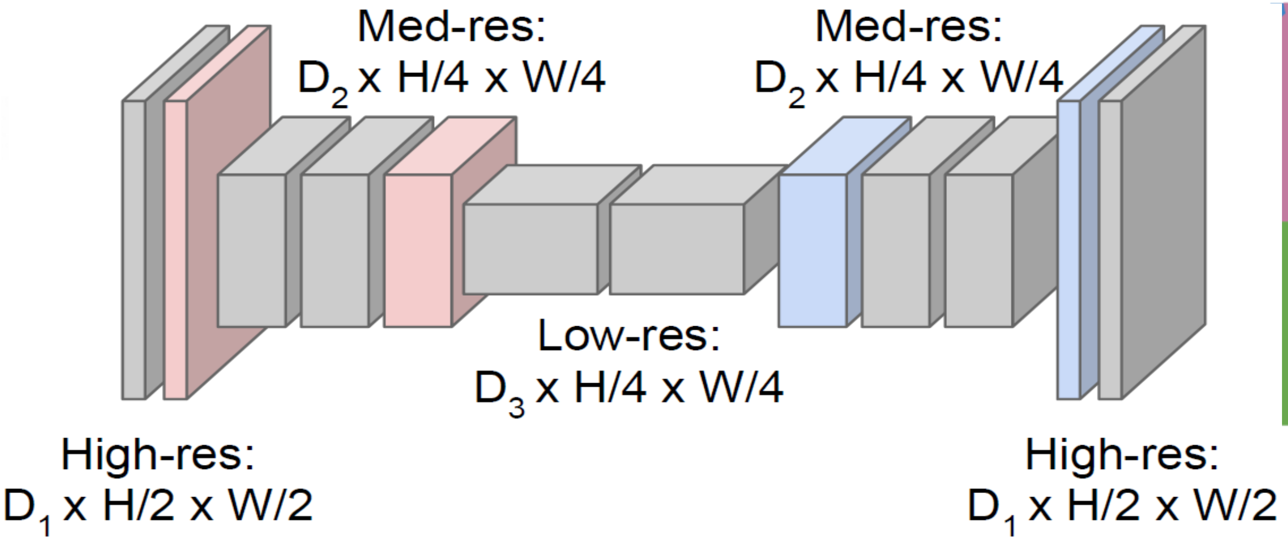
SEMANTIC SEGMENTATION: FULLY CONVOLUTIONAL

Downsampling:
Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
Unpooling or strided transpose convolution

Input:
3 x H x W



Predictions:
H x W

Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015
Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

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UPSAMPLING: UNPOOLING

Nearest Neighbor

1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

Slide credit: cs231n

UPSAMPLING: UNPOOLING

Nearest Neighbor

1	2
3	4

Input: 2 x 2

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

Output: 4 x 4

"Bed of Nails"

1	2
3	4

Input: 2 x 2

1	0	2	0
0	0	0	0
3	0	4	0
0	0	0	0

Output: 4 x 4

Slide credit: cs231n

UPSAMPLING: MAX UNPOOLING

Max Pooling

Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

→

5	6
7	8

Output: 2 x 2

Slide credit: cs231n

UPSAMPLING: MAX UNPOOLING

Max Pooling

Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

→

5	6
7	8

Output: 2 x 2

Max Unpooling

Use positions from pooling layer

1	2
3	4

Input: 2 x 2

→

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

UPSAMPLING: MAX UNPOOLING

Max Pooling

Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

Max Unpooling

Use positions from pooling layer

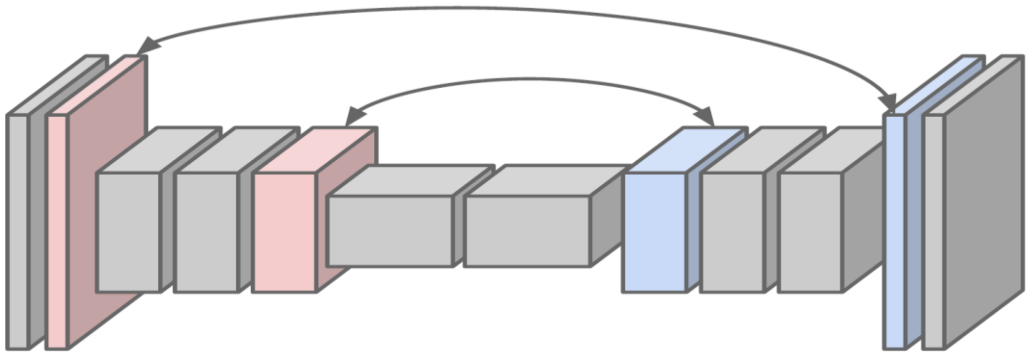
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

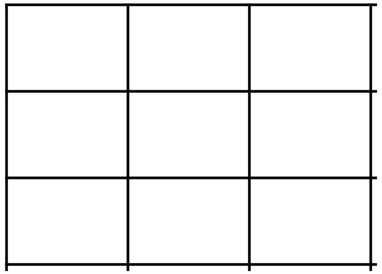


Slide credit: cs231n

UPSAMPLING: TRANSPOSE CONVOLUTION

3 x 3 **transpose** convolution, stride 2 pad 1

Input: 2 x 2

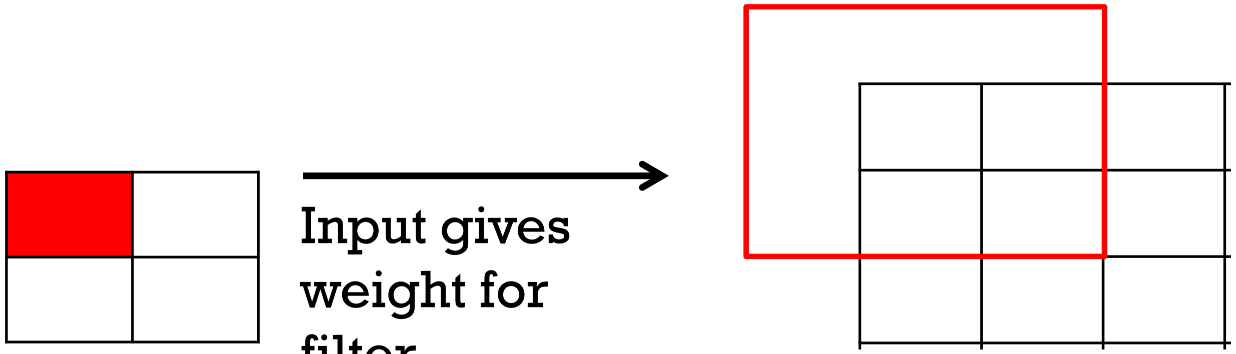


Output: 3 x 3

Slide credit: cs231n

UPSAMPLING: TRANSPOSE CONVOLUTION

3 x 3 **transpose** convolution, stride 2 pad 1

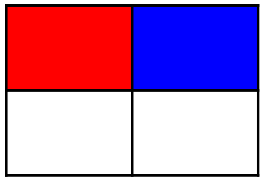


Input: 2 x 2

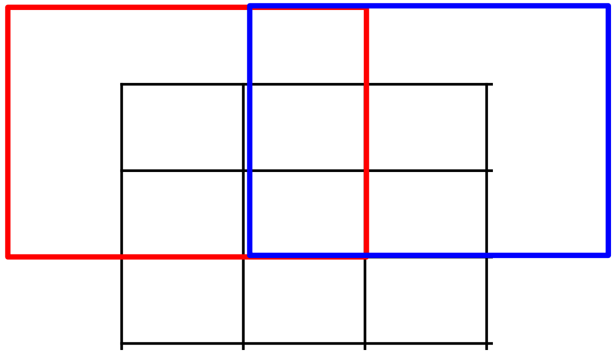
Output: 3 x 3

UPSAMPLING: TRANSPOSE CONVOLUTION

3 x 3 **transpose** convolution, stride 2 pad 1



Input gives weight for filter



Input: 2 x 2

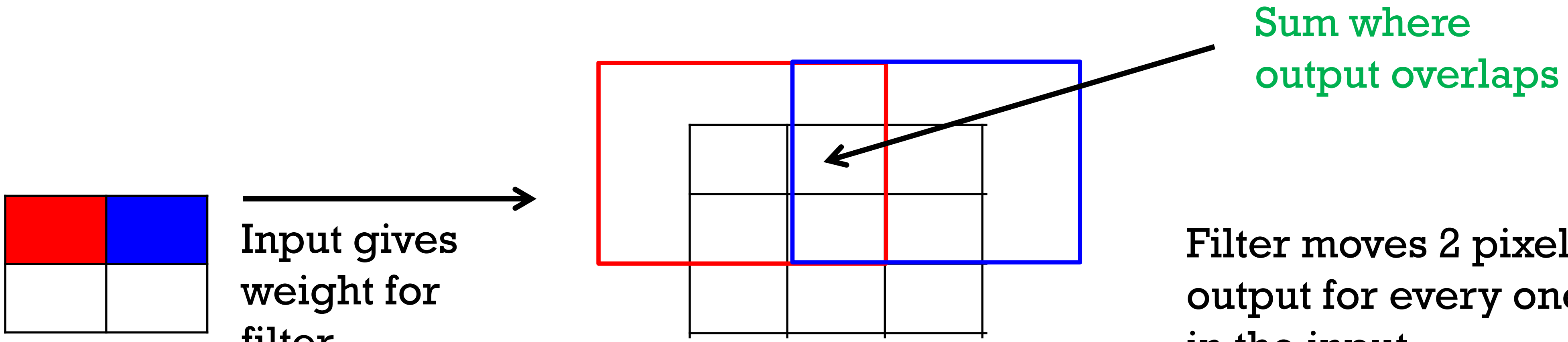
Output: 3 x 3

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

UPSAMPLING: TRANSPOSE CONVOLUTION

3 x 3 **transpose** convolution, stride 2 pad 1



Input: 2 x 2

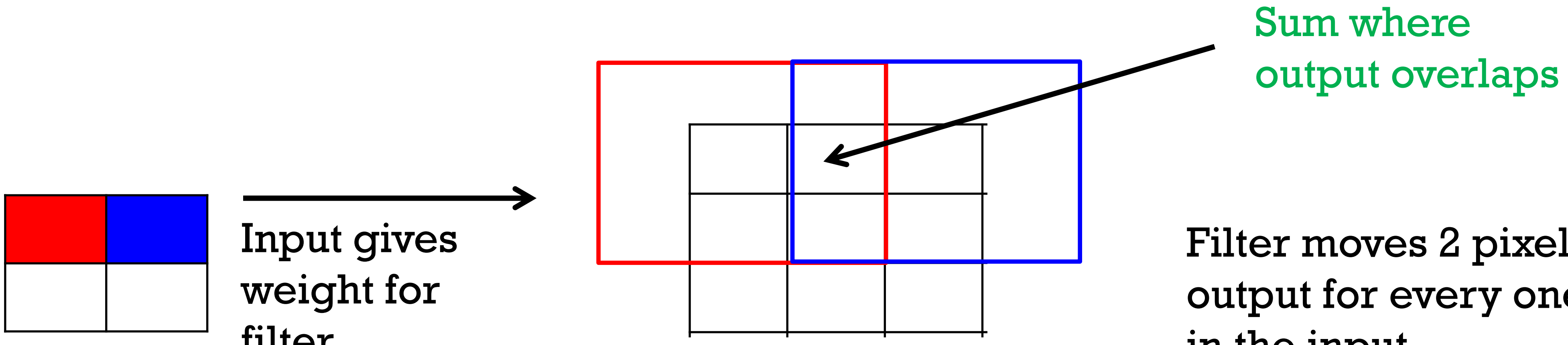
Output: 3 x 3

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

UPSAMPLING: TRANSPOSE CONVOLUTION

3 x 3 **transpose** convolution, stride 2 pad 1



Input: 2 x 2

Output: 3 x 3

Filter moves 2 pixels in the output for every one pixel in the input

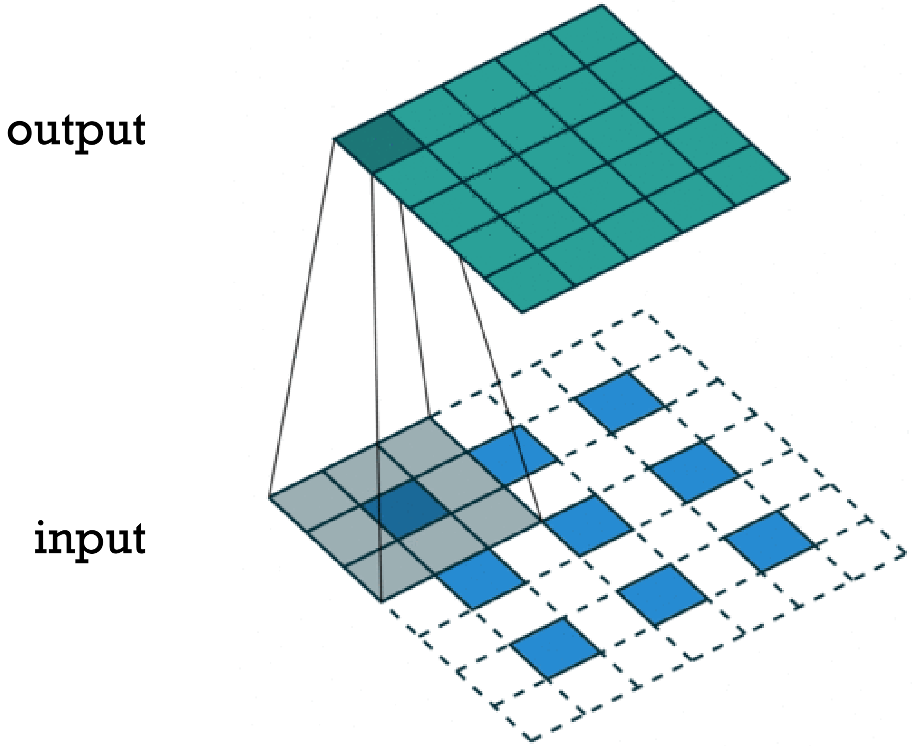
Stride gives ratio between movement in output and input

Actual output: 5*5

Need to crop 3*3 centrally

UPSAMPLING IN A DEEP NETWORK

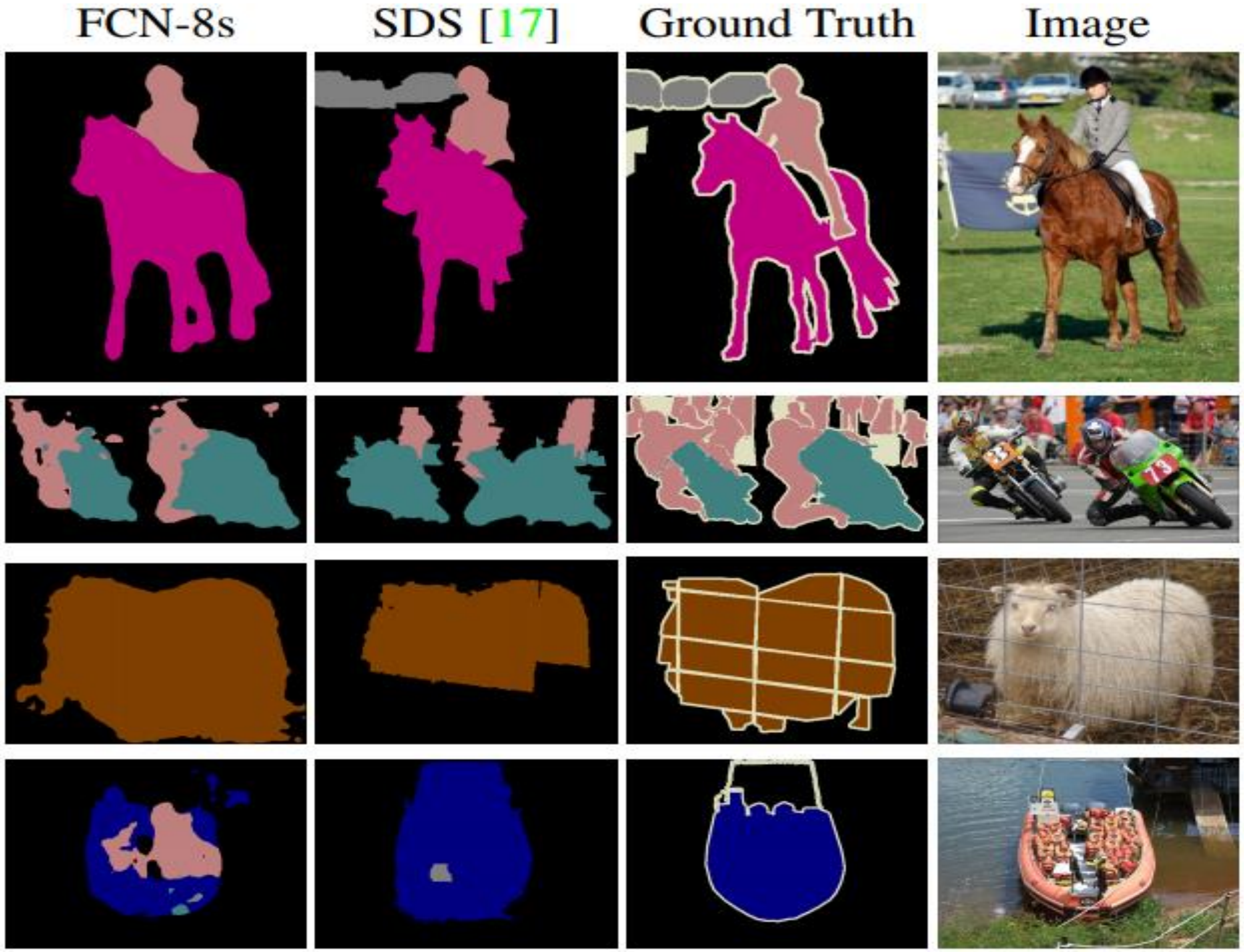
- *Backwards-strided Convolution (Dilted Convolution)*: to increase resolution, use *output stride* > 1
  - For stride 2, dilate the input by inserting rows and columns of zeros between adjacent entries
  - Sometimes called convolution with *fractional input stride* 1/2



V. Dumoulin and F. Visin, A guide to convolution arithmetic for deep learning, arXiv 2018

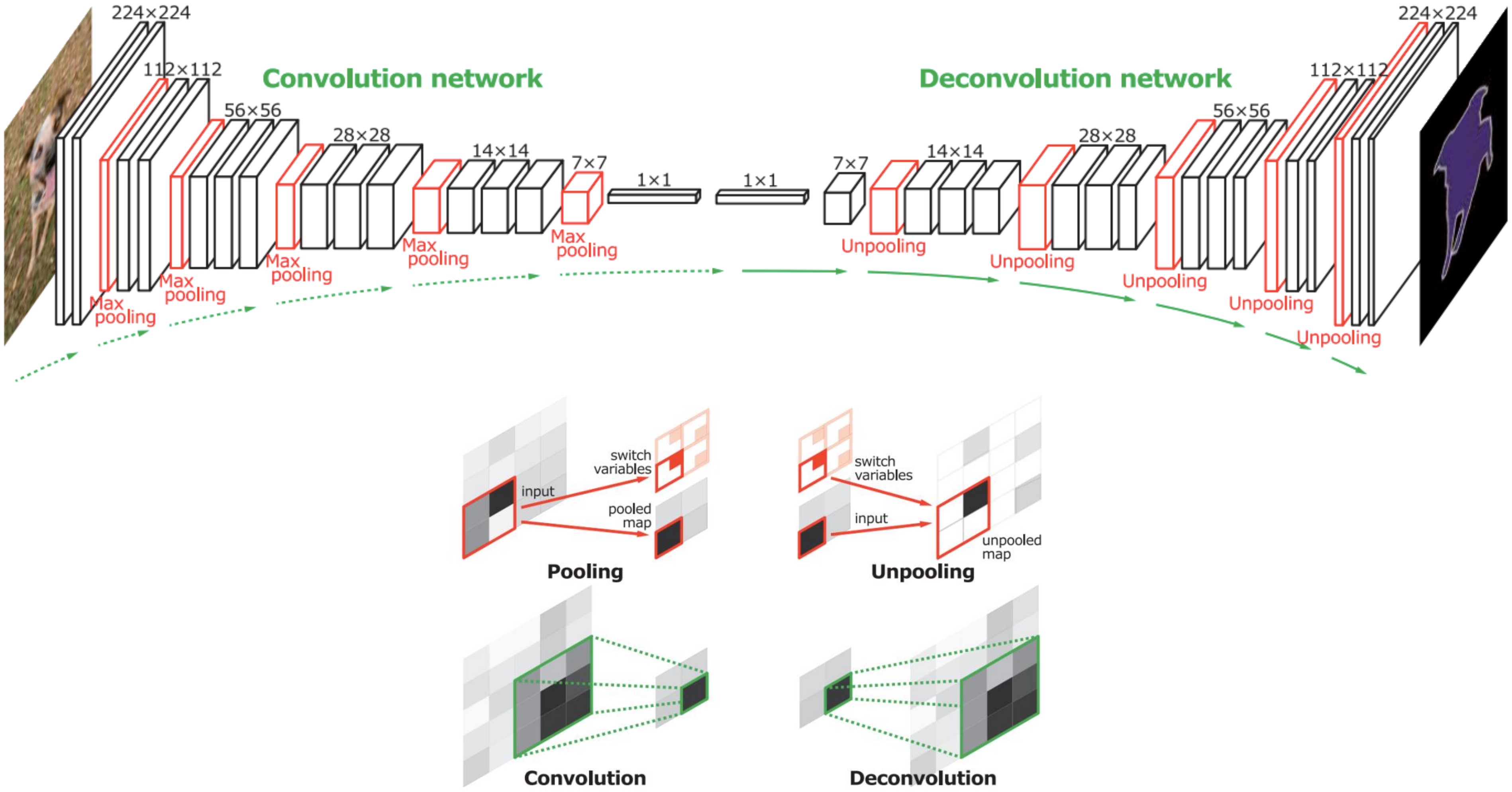
"FULLY CONVOLUTIONAL (FCN)" RESULTS

- Takes advantage of pre-training from classification
- Applied to objects and scenes (NYUd v2)
- But feature pooling reduces spatial sensitivity and resolution



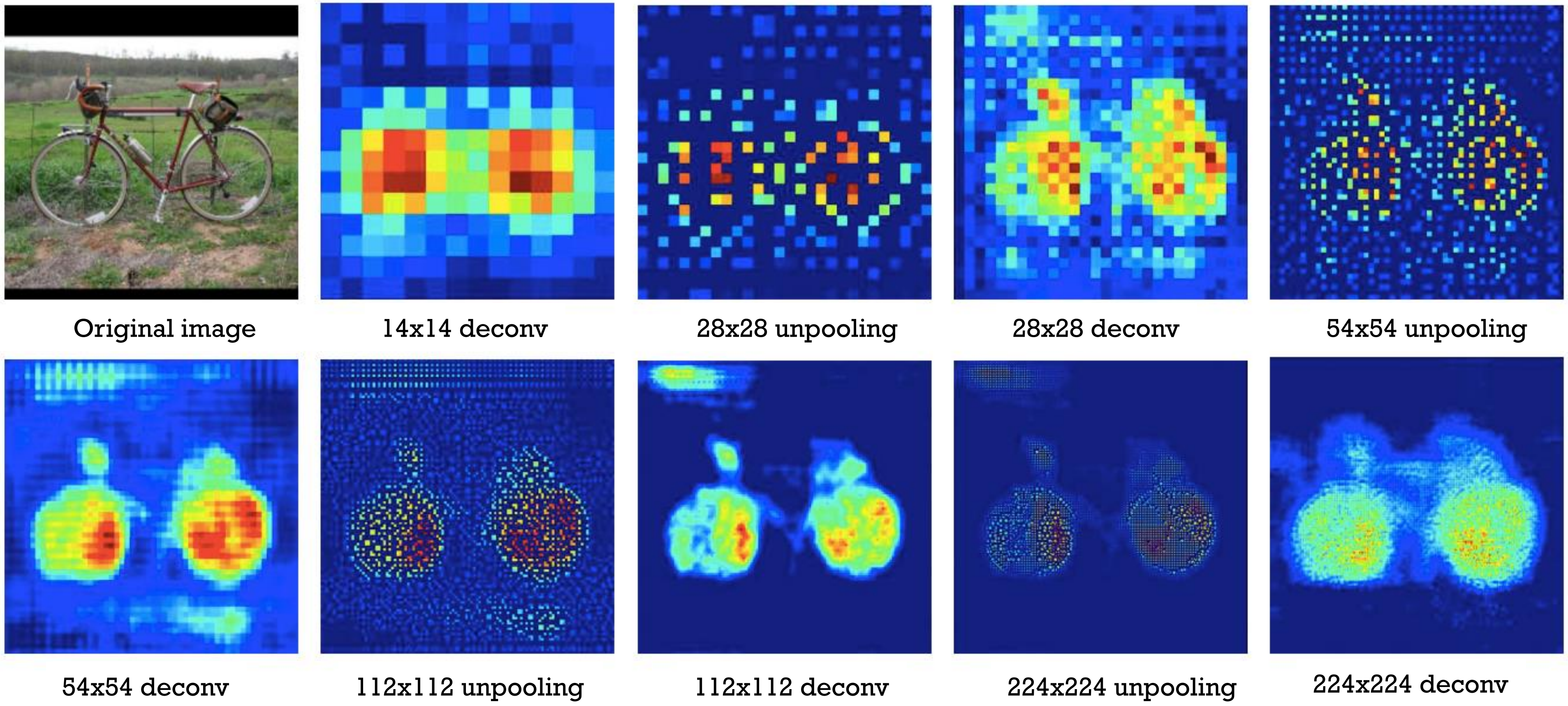
Long et al. Fully Convolutional Networks for Semantic Segmentation, CVPR 2015

DECONVNET



H. Noh, S. Hong, and B. Han, [Learning Deconvolution Network for Semantic Segmentation](), ICCV 2015

DECONVNET

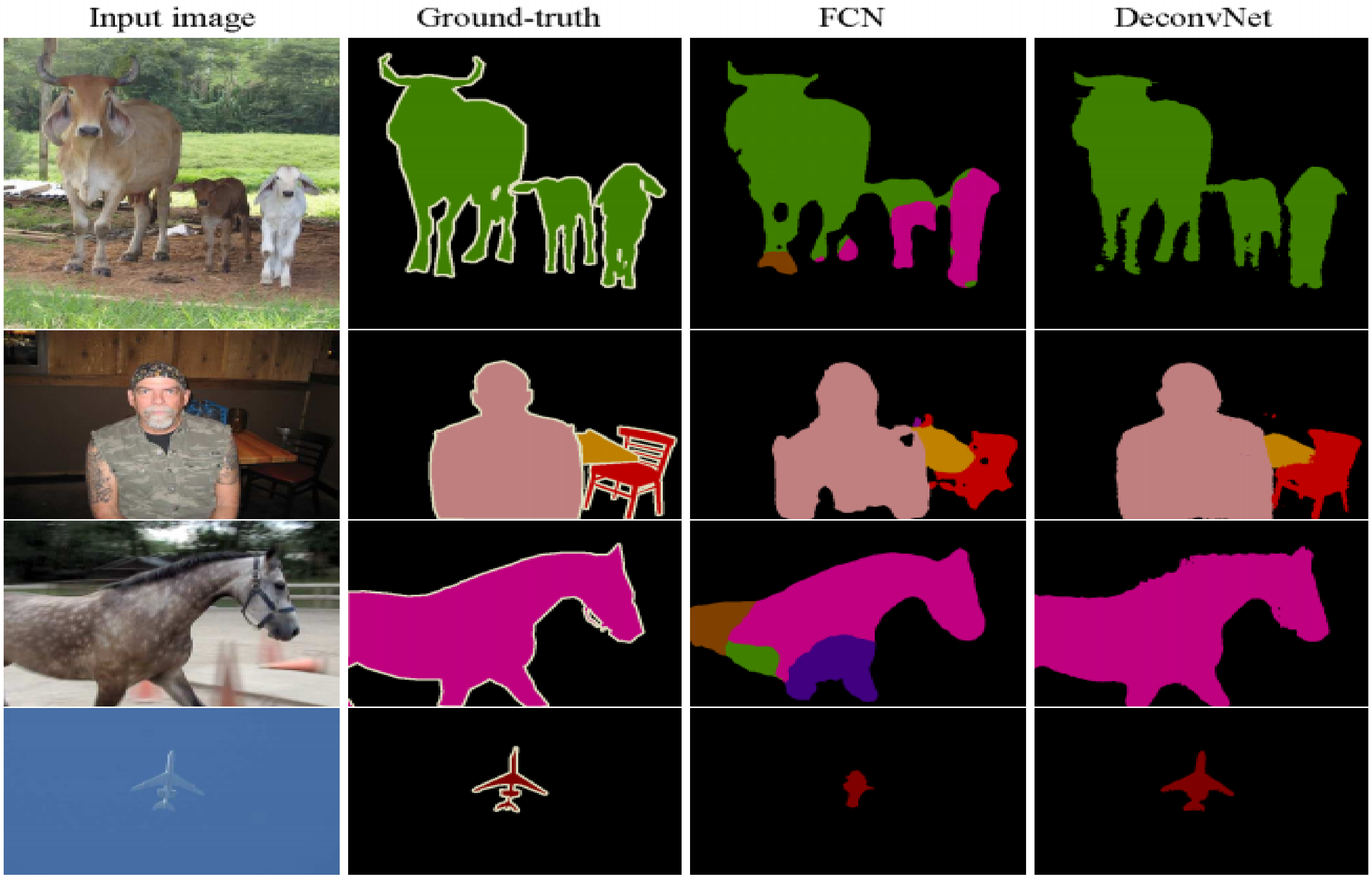


H. Noh, S. Hong, and B. Han, Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

DECONVNET RESULTS

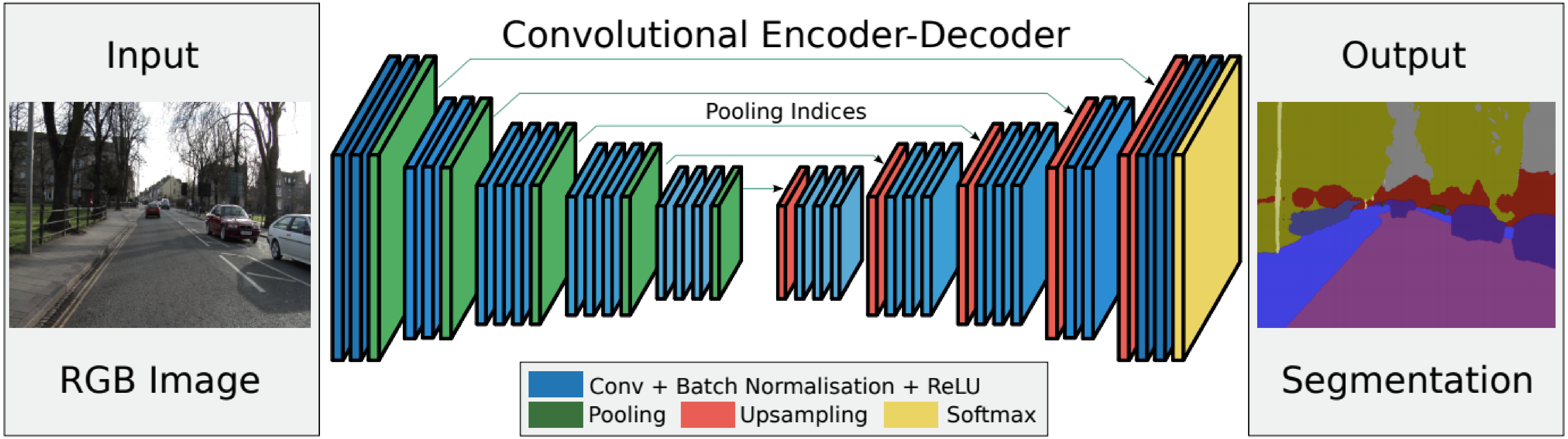
PASCAL VOC 2012	mIoU
FCN-8	62.2
DeconvNet	69.6
Ensemble of DeconvNet and FCN	71.7

DECONVNET RESULTS



Noh et al. Learning Deconvolution Network for Semantic Segmentation, ICCV 2015

SIMILAR ARCHITECTURE: SEGNET

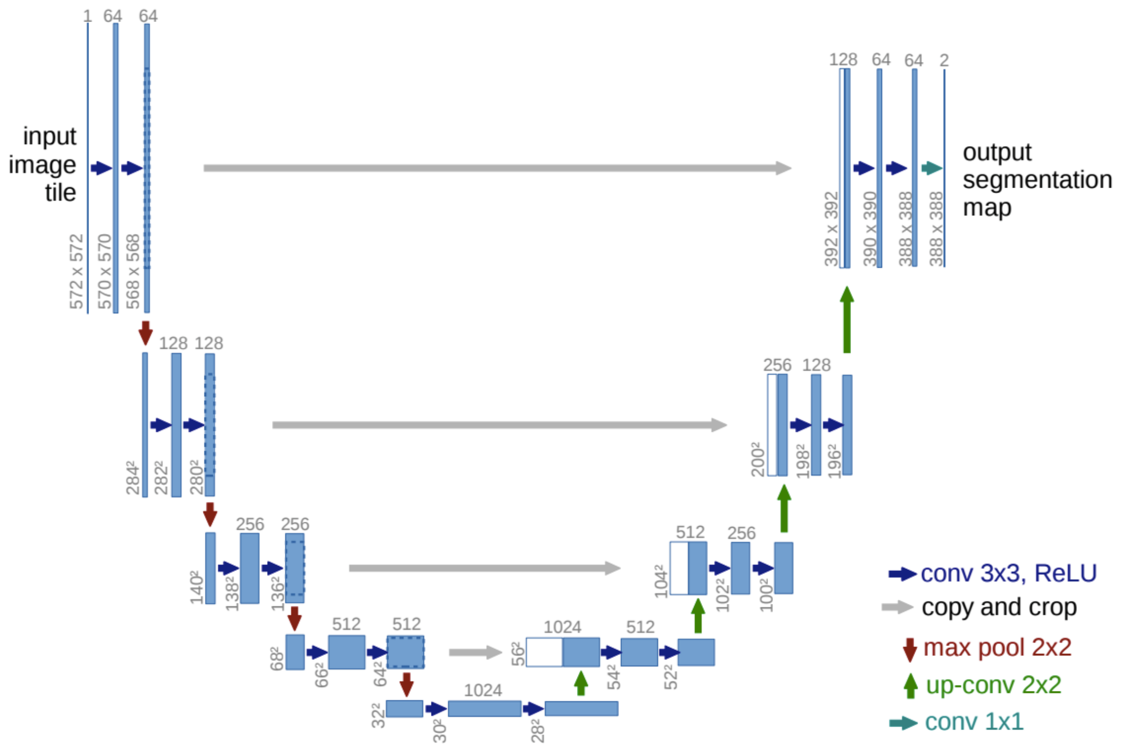


Drop the FC layers,
get better results

V. Badrinarayanan, A. Kendall and R. Cipolla, [SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation](), PAMI 2017

U-NET

- Like FCN, fuse upsampled higher-level feature maps with higher-resolution, lower-level feature maps
- Unlike FCN, fuse by concatenation, predict at the end



O. Ronneberger, P. Fischer, T. Brox [U-Net: Convolutional Networks for Biomedical Image Segmentation], MICCAI 2015

SUMMARY OF UPSAMPLING ARCHITECTURES

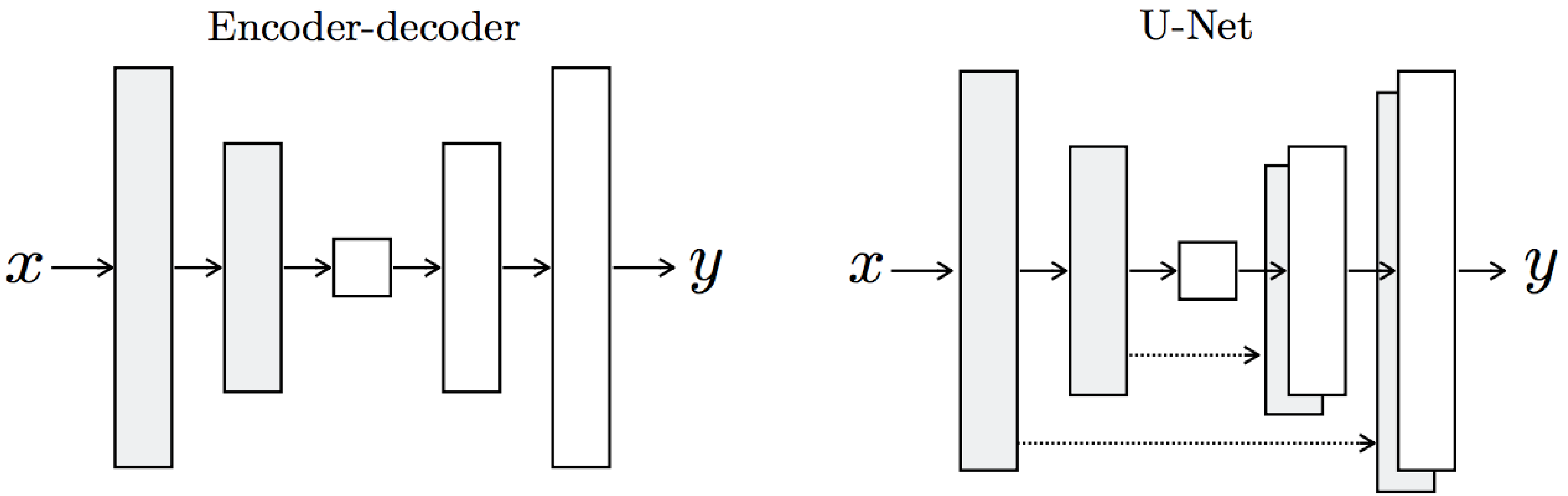


Figure source

DILATED CONVOLUTIONS

- Idea: instead of reducing spatial resolution of feature maps, use a large sparse filter
  - Also known as *à trous* convolution

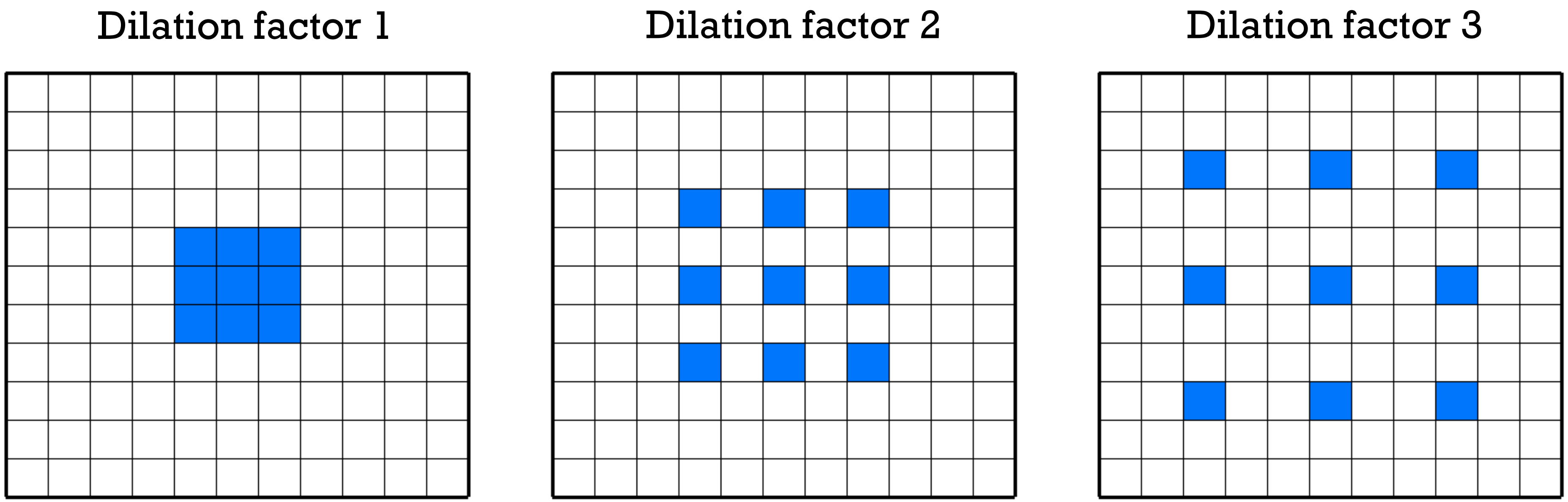
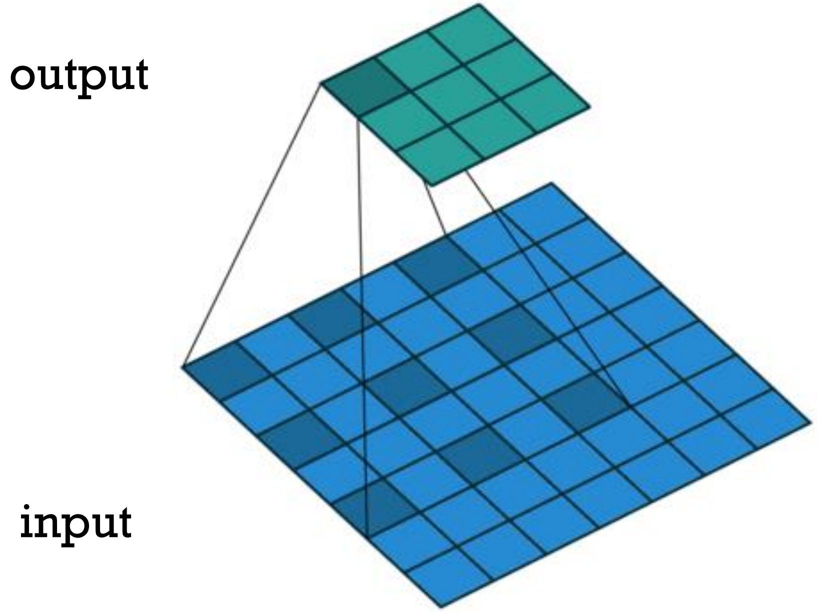


Image source

DILATED CONVOLUTIONS

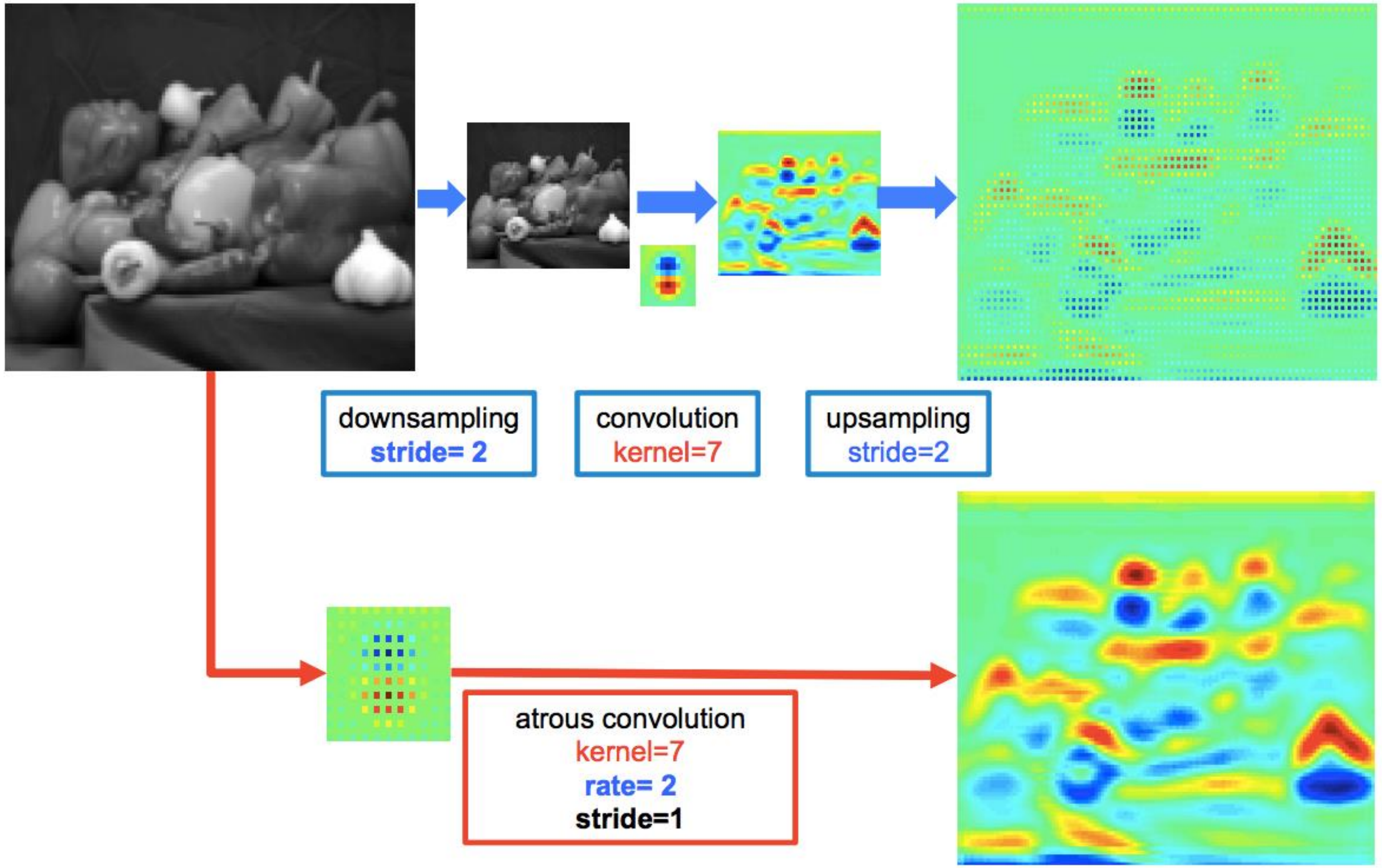
- Idea: instead of reducing spatial resolution of feature maps, use a large sparse filter



Like 2x downsampling followed by 3x3 convolution followed by 2x upsampling

V. Dumoulin and F. Visin, [A guide to convolution arithmetic for deep learning](), arXiv 2018

DILATED CONVOLUTIONS



L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. Yuille, DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs, PAMI 2017

DILATED CONVOLUTIONS

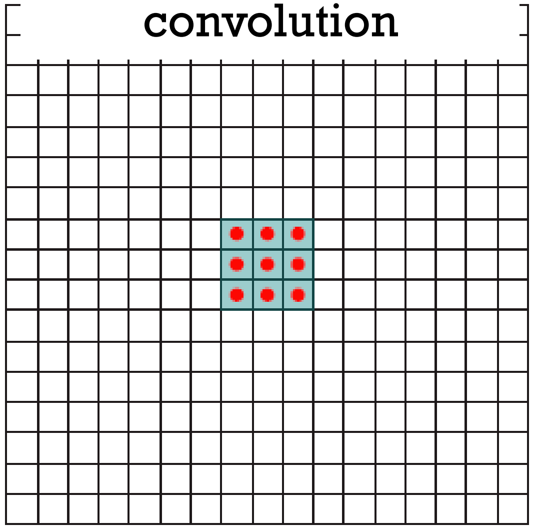
- Can be used in FCN to remove downsampling:
  change stride of max pooling layer from 2 to 1, dilate subsequent convolutions by factor of 2.

L. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. Yuille, DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs, PAMI 2017

DILATED CONVOLUTIONS

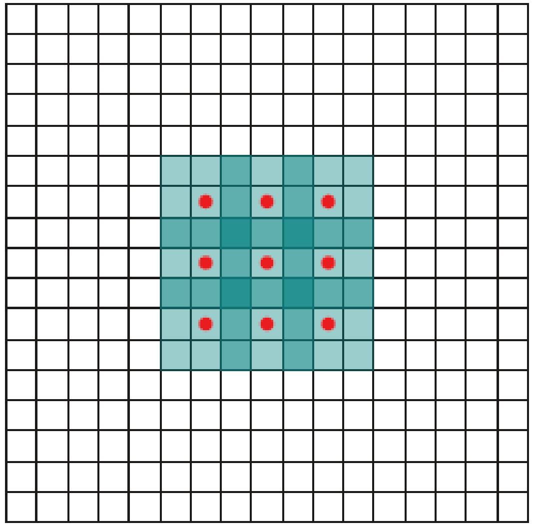
- Can increase receptive field size exponentially with a linear growth in the number of parameters

Feature map 1 (F1) produced from F0 by 1-dilated convolution



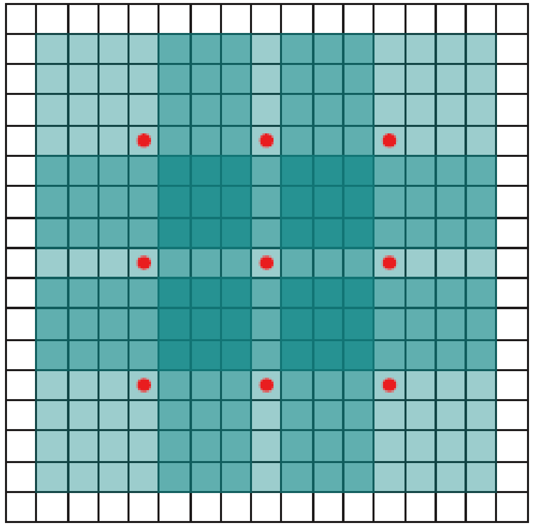
Receptive field: 3x3

F2 produced from F1 by 2-dilated convolution



Receptive field: 7x7

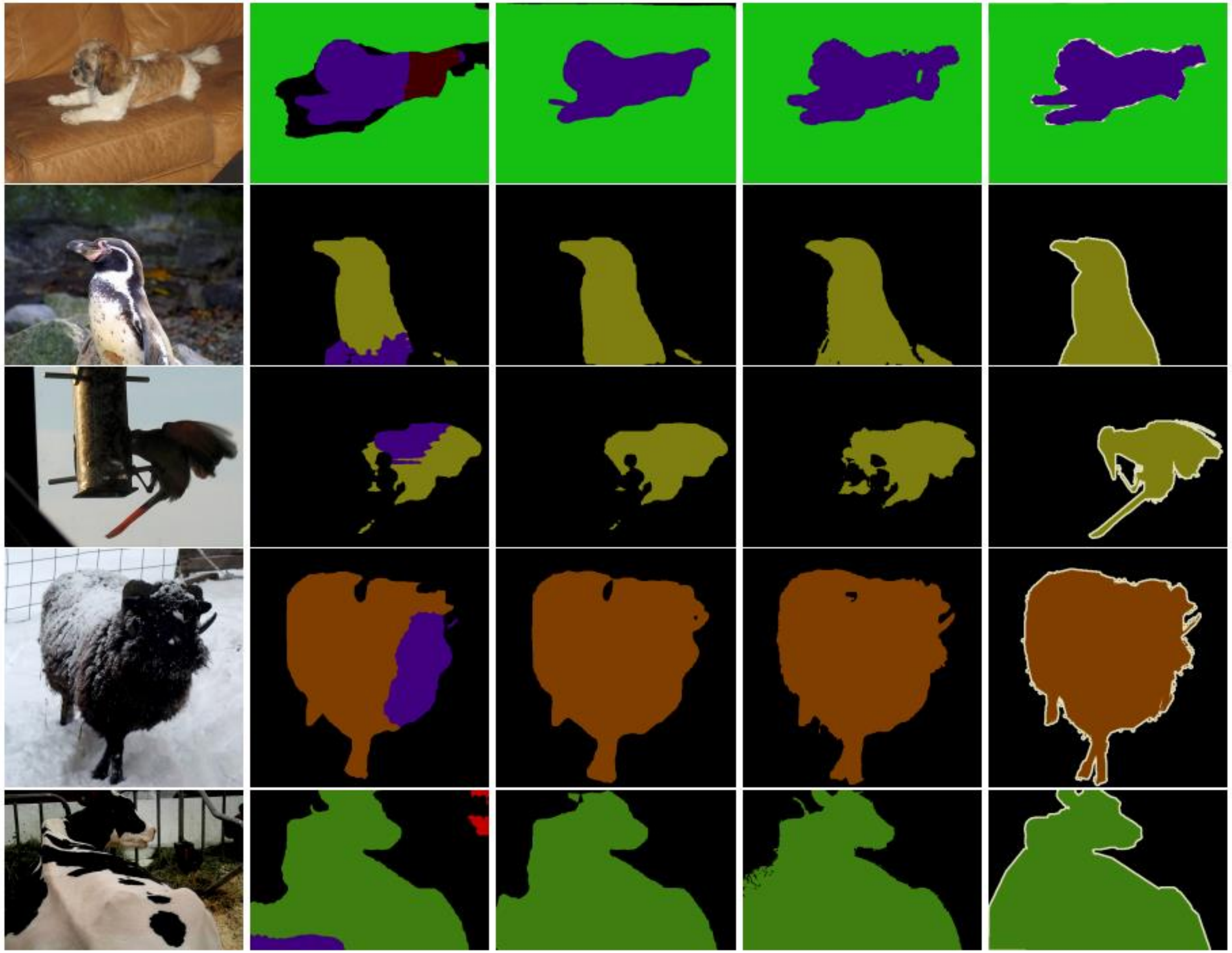
F3 produced from F2 by 4-dilated convolution



Receptive field: 15x15

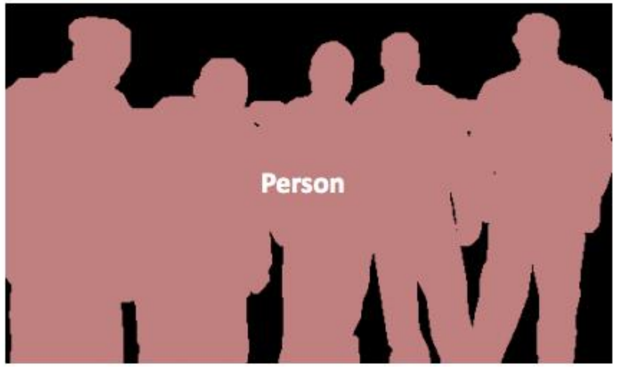
F. Yu and V. Koltun, [Multi-scale context aggregation by dilated convolutions](), ICLR 2016

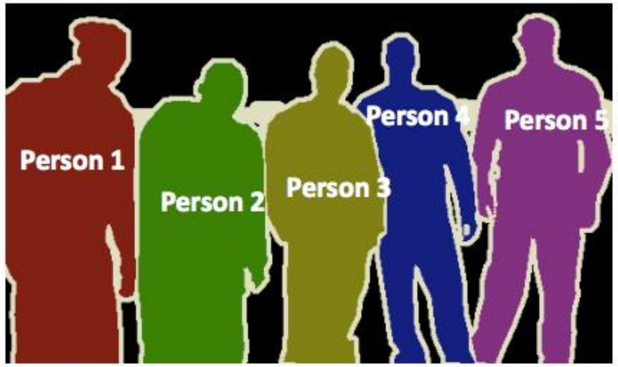
DILATED CONVOLUTIONS: EVALUATION



(a) Image (b) Front end (c) + Context (d) + CRF-RNN (e) Ground truth

INSTANCE SEGMENTATION

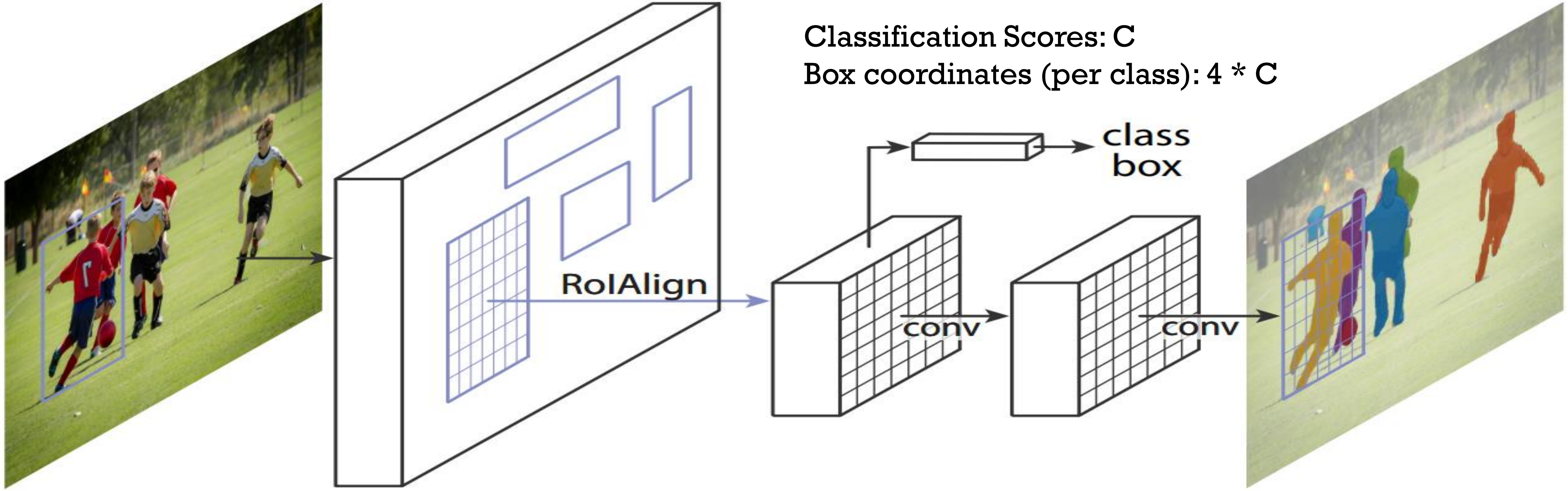




Object Detection	Semantic Segmentation	**Instance Segmentation**
✓	✓	?

Source: Kaiming He

Instance Segmentation: Mask R-CNN (He et al. ICCV 2017)

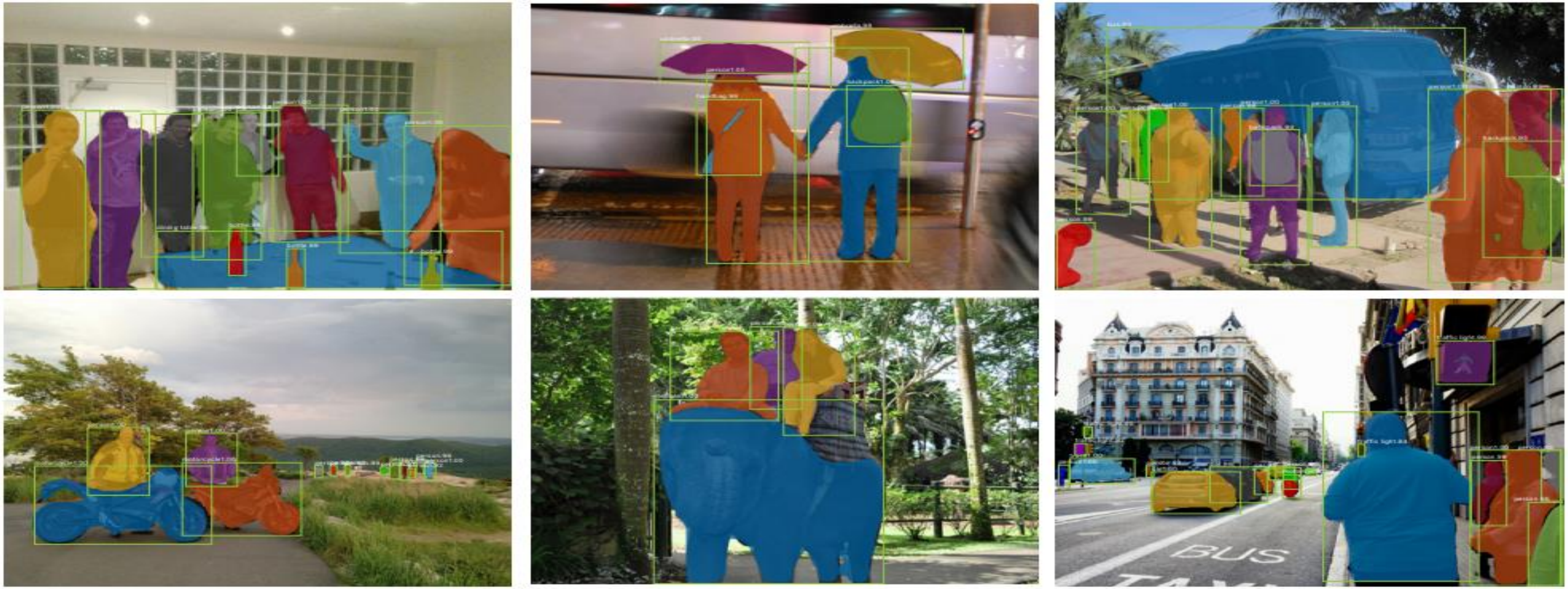


Mask R-CNN - extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition.

Mask R-CNN is simple to train and adds only a small overhead to Faster R-CNN, running at 5 fps.

He et al. Mask R-CNN, ICCV 2017. https://arxiv.org/pdf/1703.06870.pdf

Instance Segmentation: Mask R-CNN (He et al. ICCV 2017)



Mask R-CNN results on the COCO test set. These results are based on ResNet-101, achieving a mask AP of 35.7 and running at 5 fps. Masks are shown in color, and bounding box, category, and confidences are also shown.

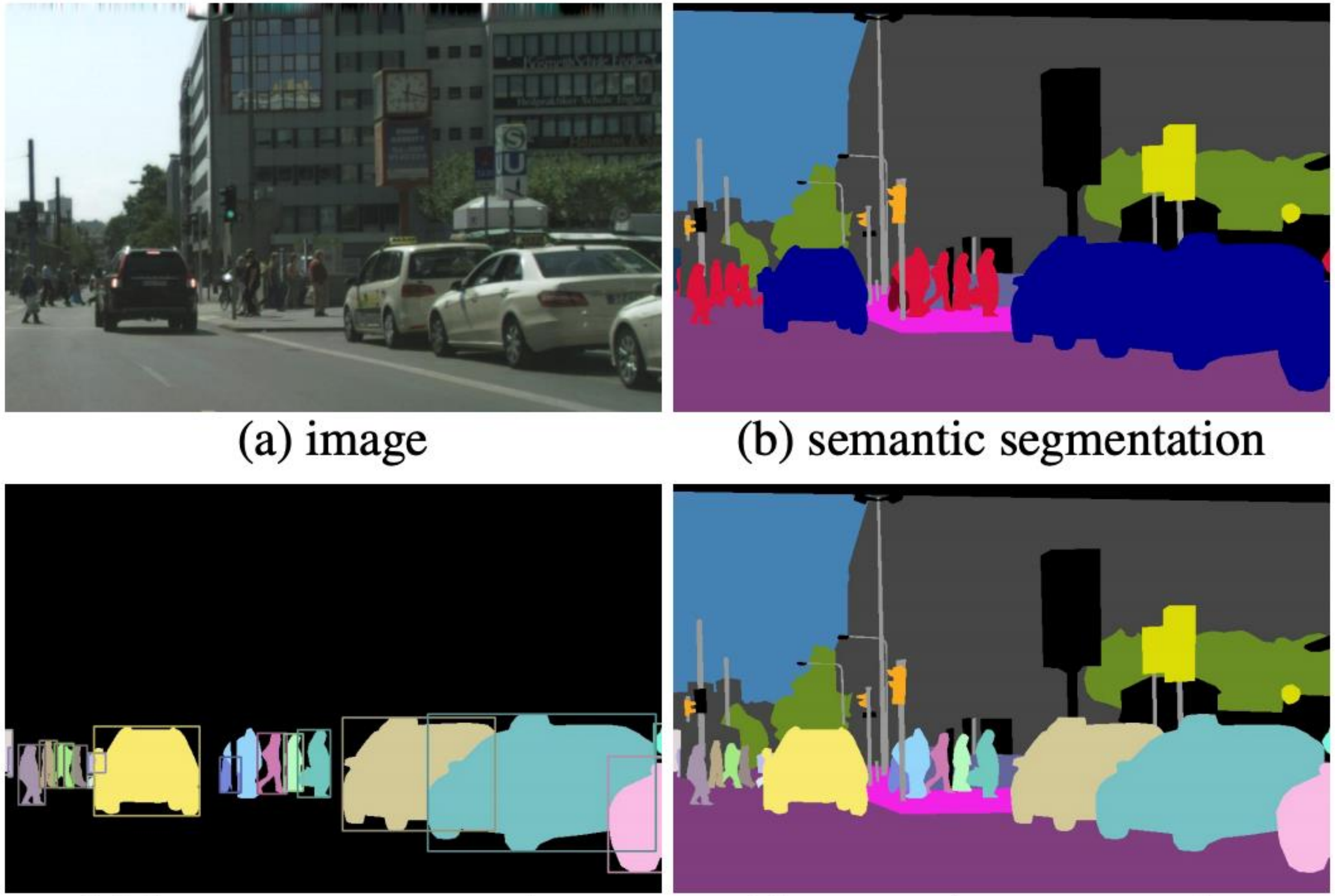
He et al. Mask R-CNN, ICCV 2017. https://arxiv.org/pdf/1703.06870.pdf

Other dense prediction problems

KEYPOINT PREDICTION

- Given K keypoints, train model to predict K $m \times m$ *one-hot* maps with cross-entropy losses over m^2 outputs

PANOPTIC SEGMENTATION



(a) image (b) semantic segmentation

(c) instance segmentation (d) panoptic segmentation

A. Kirillov et al. [Panoptic segmentation](). CVPR 2019

PANOPTIC SEGMENTATION

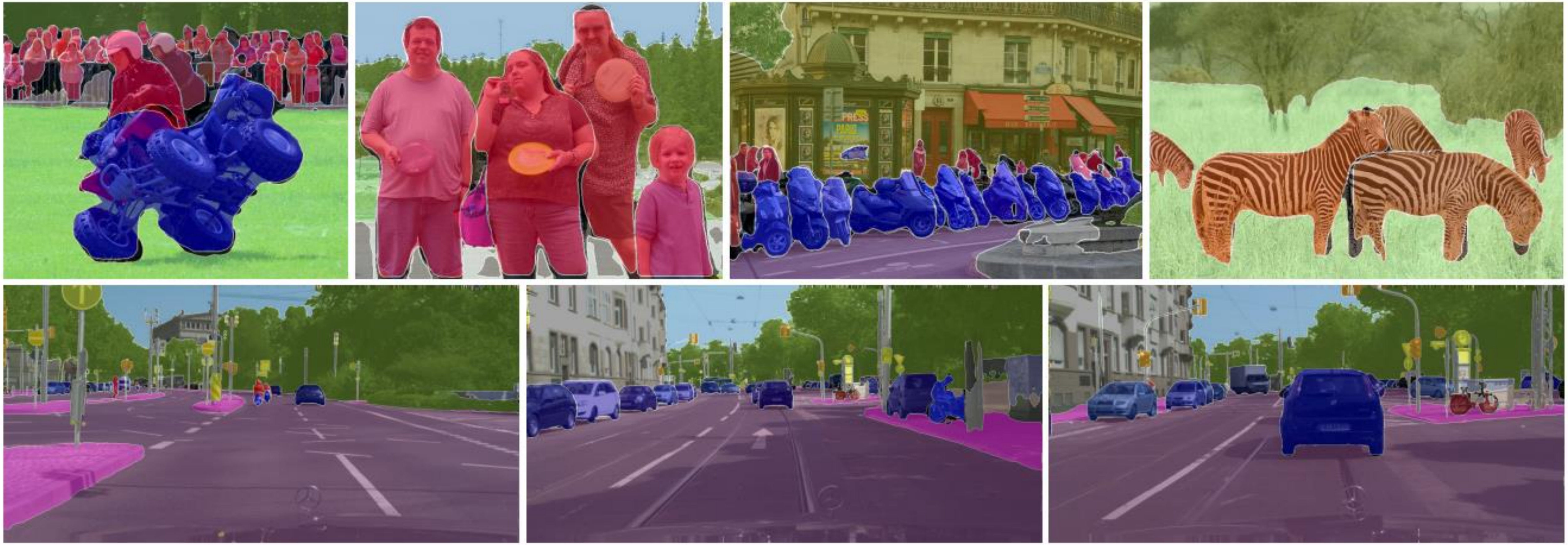


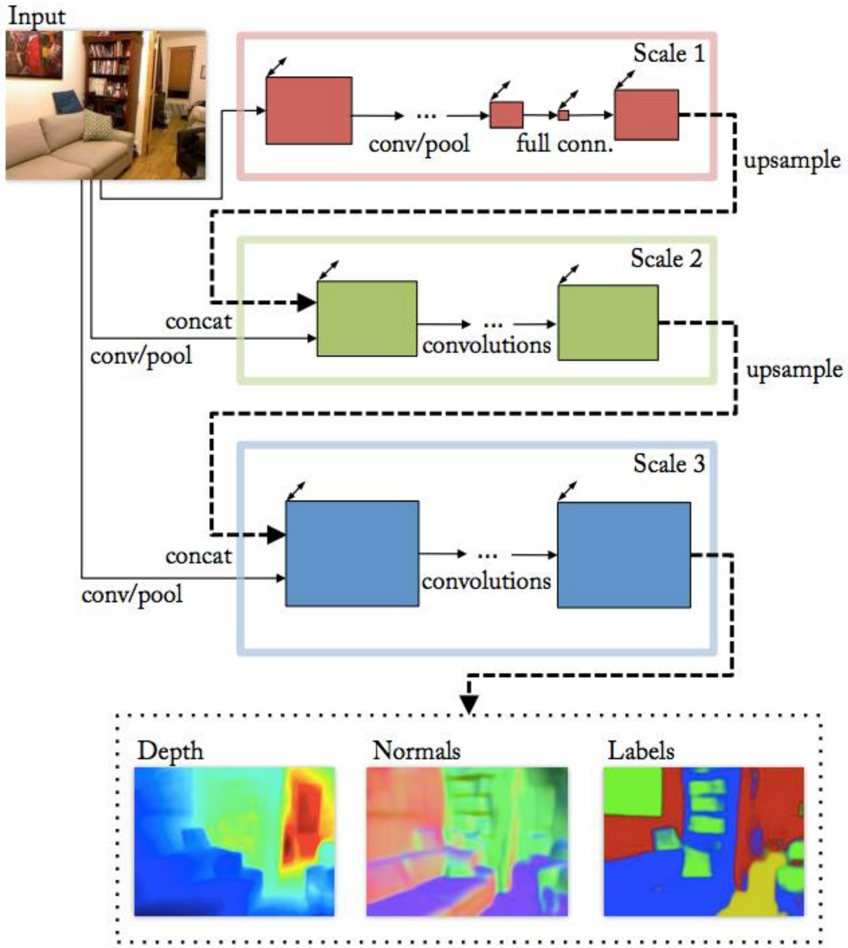
Figure 2: Panoptic FPN results on COCO (top) and Cityscapes (bottom) using a single ResNet-101-FPN network.

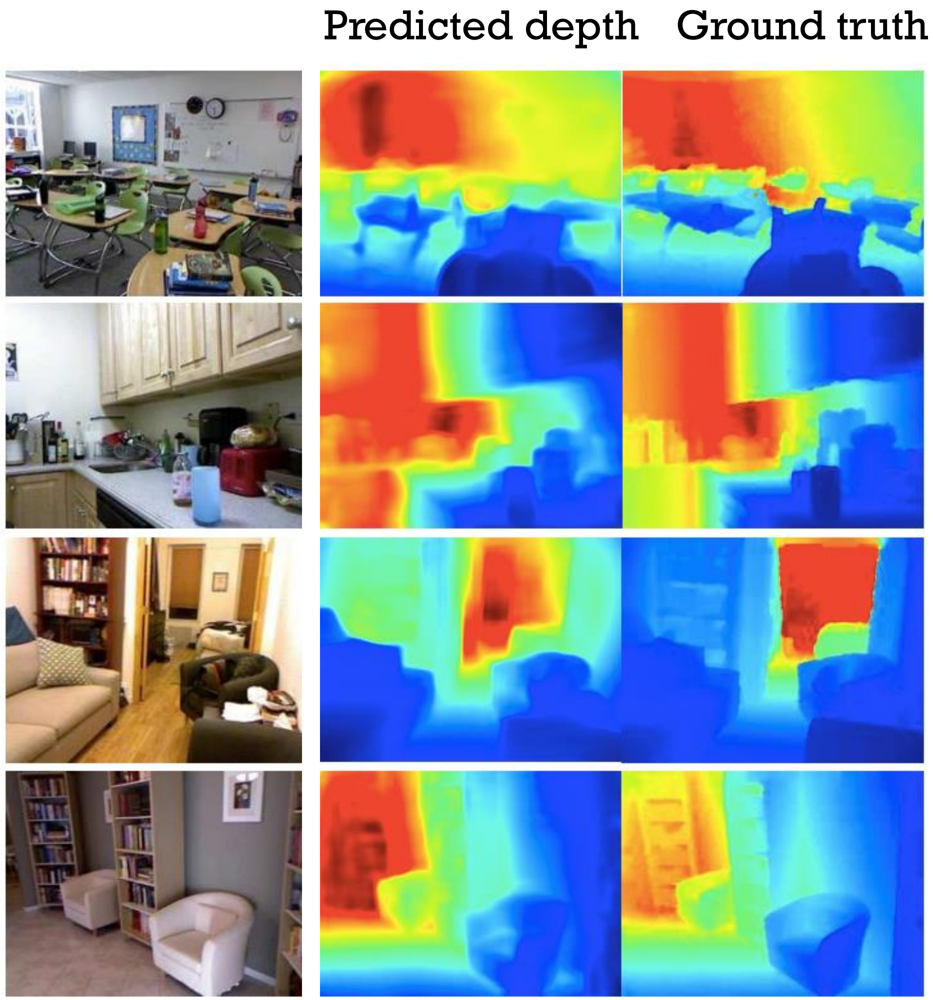
A. Kirillov et al. Panoptic feature pyramid networks. CVPR 2019

EVEN MORE DENSE PREDICTION PROBLEMS

- Depth estimation
- Surface normal estimation
- Colorization
- ….

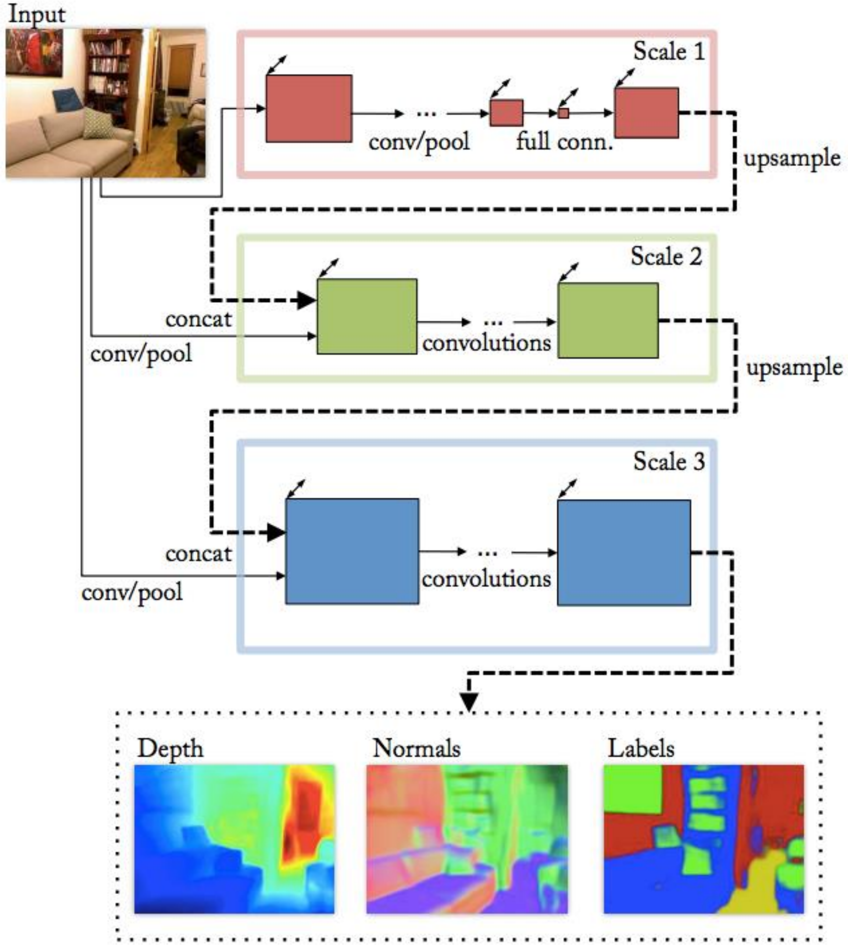
DEPTH AND NORMAL ESTIMATION

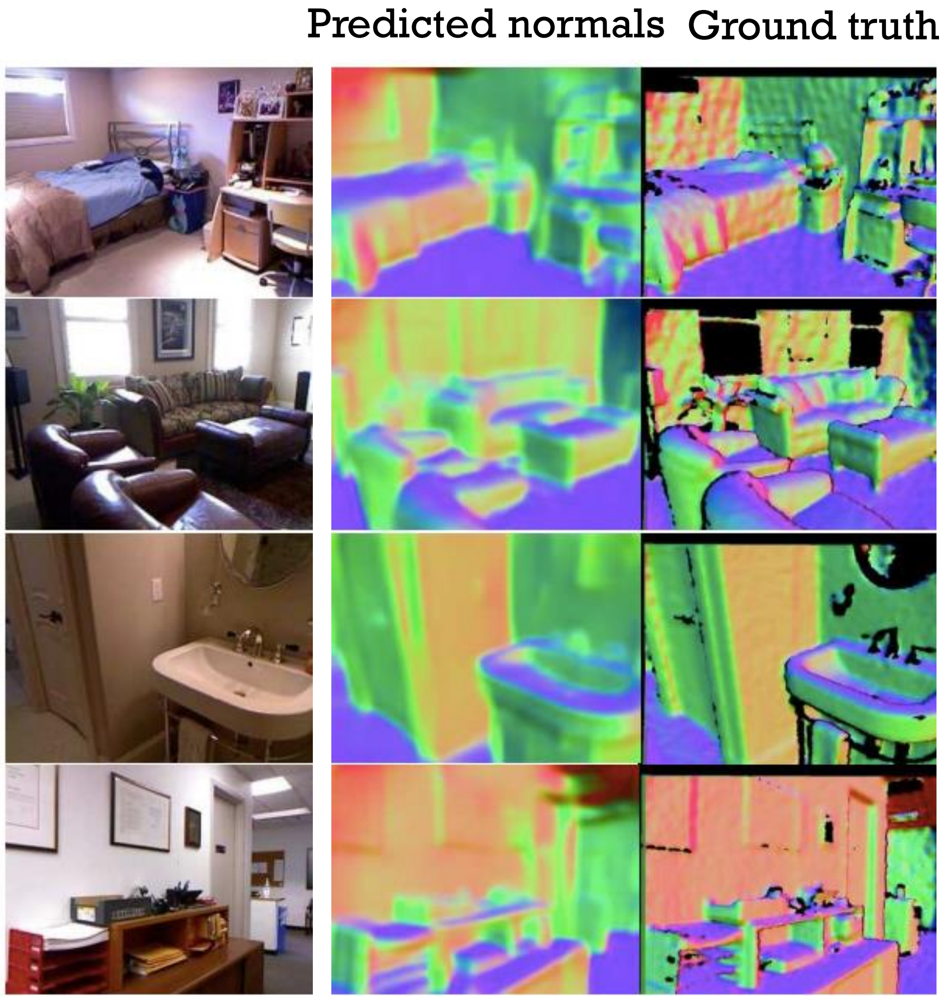




D. Eigen and R. Fergus, [Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture](), ICCV 2015

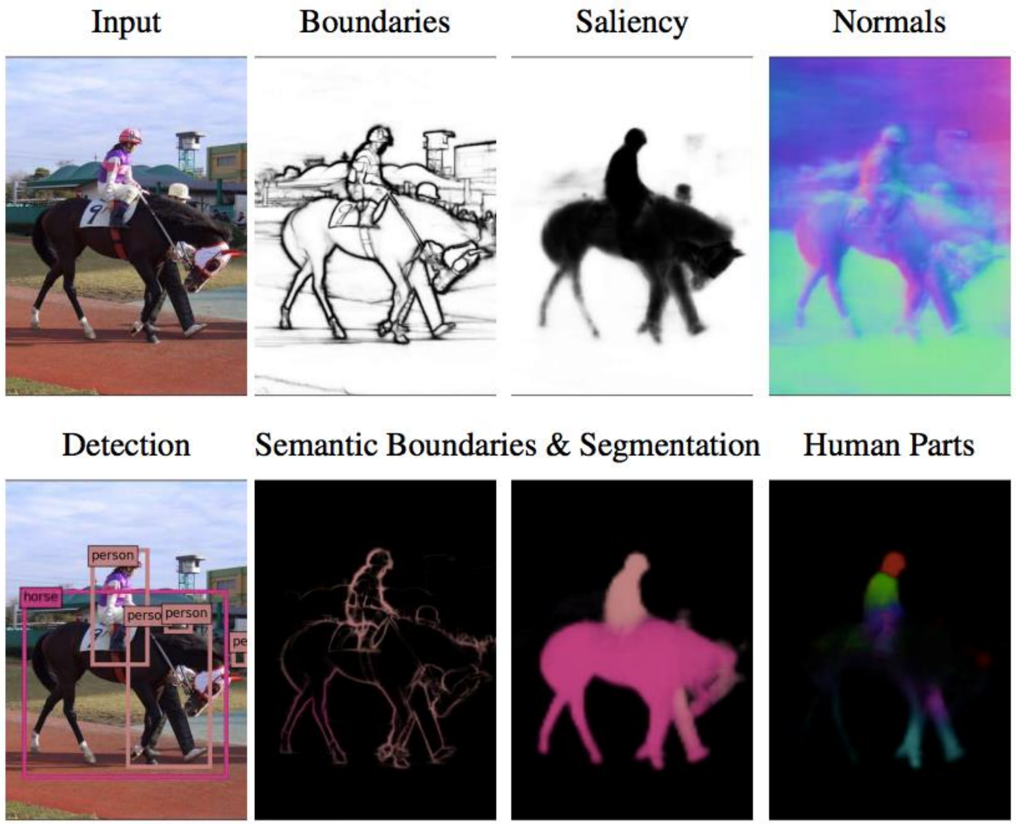
DEPTH AND NORMAL ESTIMATION





D. Eigen and R. Fergus, Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture, ICCV 2015

ESTIMATION OF EVERYTHING AT THE SAME TIME



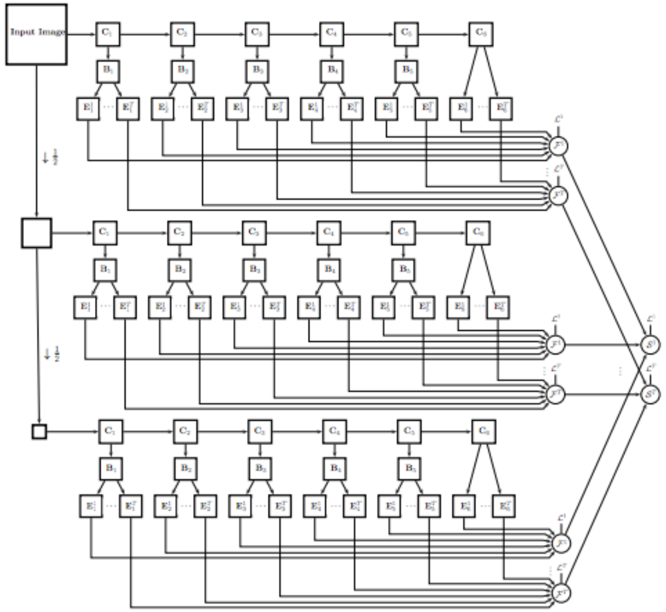
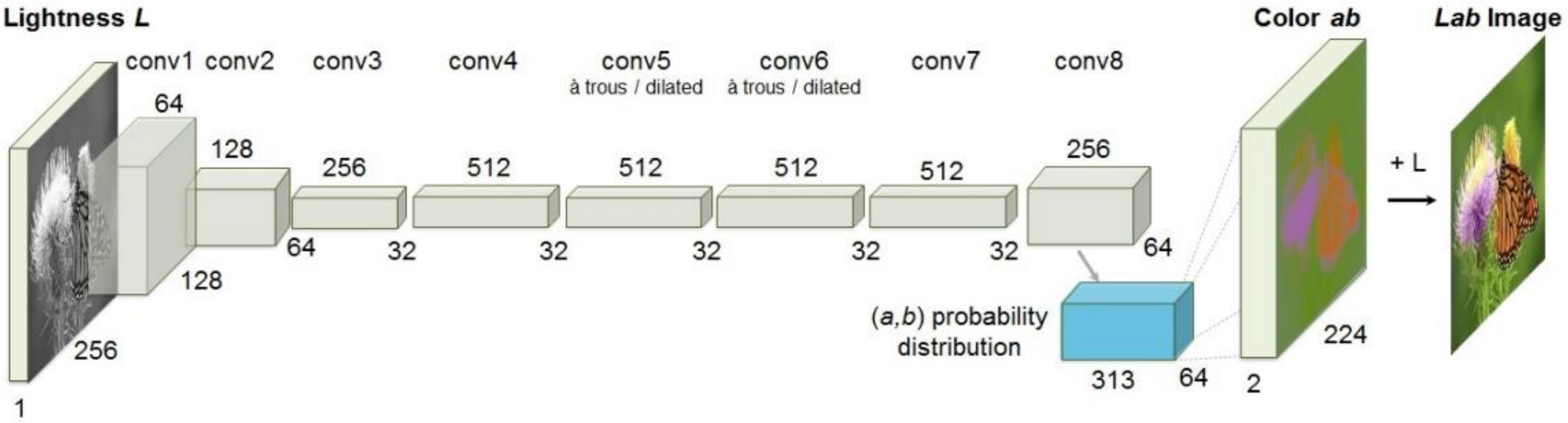
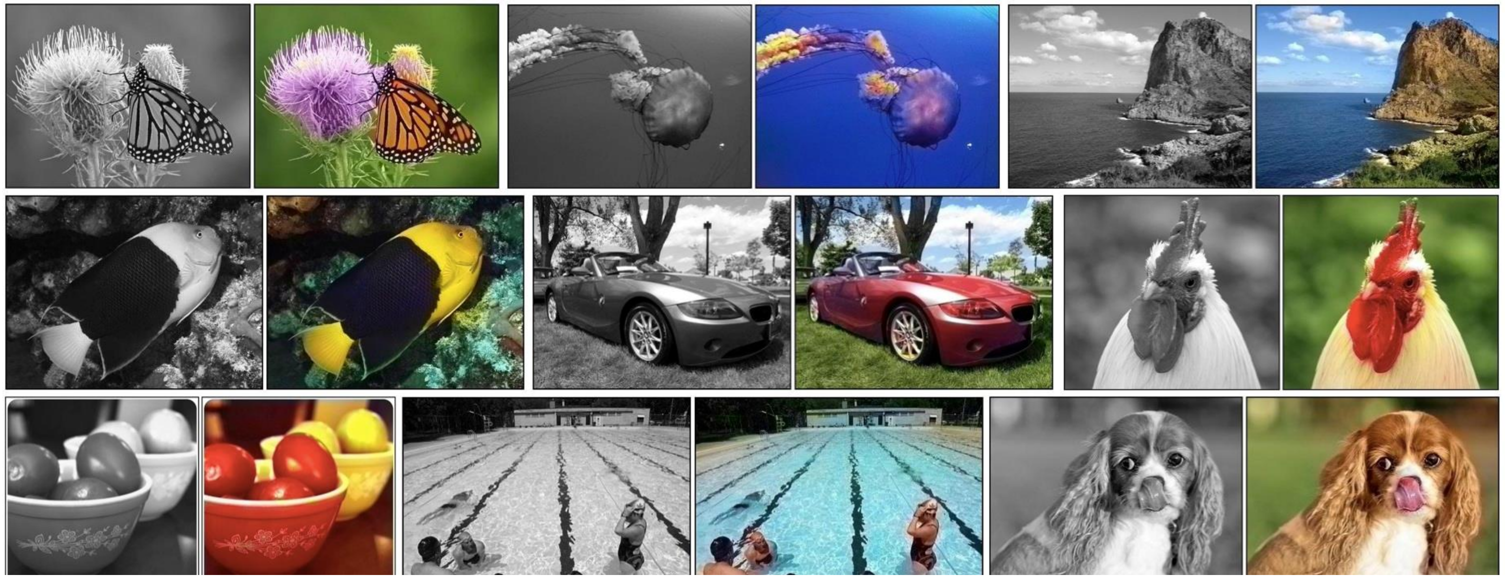


Figure 2: UberNet architecture: an image pyramid is formed by successive down-sampling operations, and each image is processed by a CNN with tied weights; the responses of the network at consecutive layers ($\mathbf{C}_i$) are processed with Batch Normalization ($\mathbf{B}_i$) and then fed to task-specific skip layers ($\mathbf{E}_i^t$); these are combined across network layers ($\mathcal{F}^t$) and resolutions ($\mathcal{S}^t$) and trained using task-specific loss functions ($\mathcal{L}^t$), while the whole architecture is jointly trained end-to-end. For simplicity we omit the interpolation and detection layers mentioned in the text.

I. Kokkinos, [UberNet: Training a Universal Convolutional Neural Network for Low-, Mid-, and High-Level Vision using Diverse Datasets and Limited Memory](), ICCV 2017

COLORIZATION

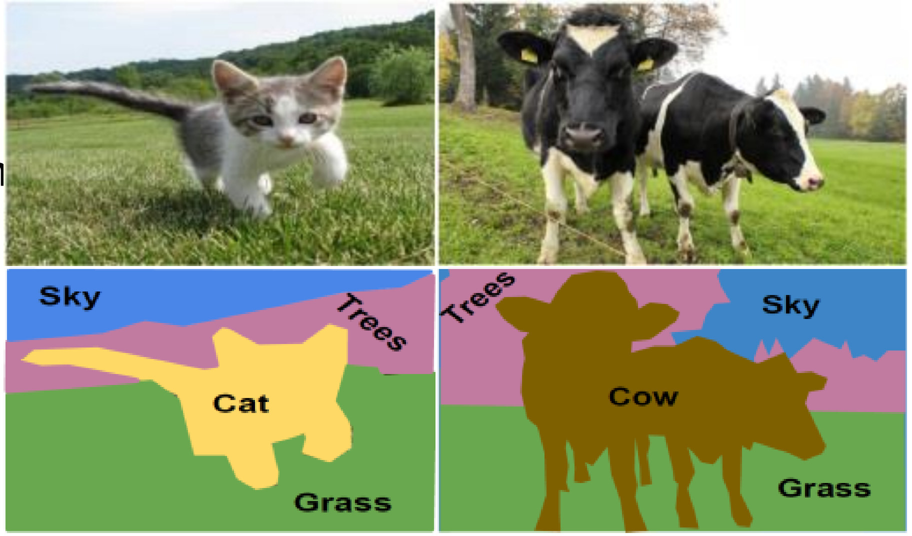




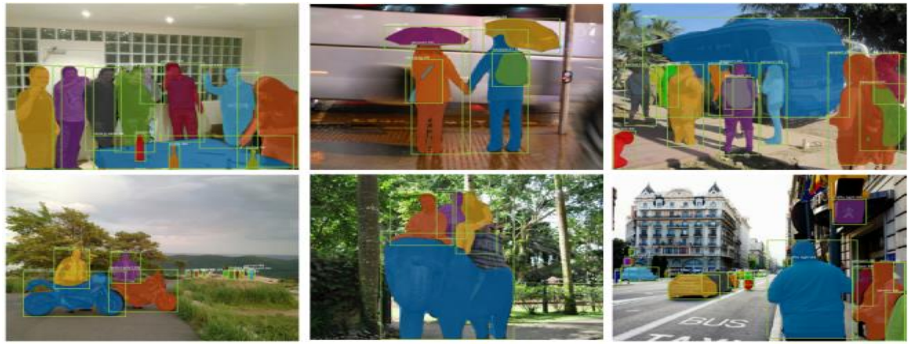
R. Zhang, P. Isola, and A. Efros, Colorful Image Colorization, ECCV 2016

THINGS TO REMEMBER

- Semantic Segmentation
  - Sliding window inefficient
  - Fully Convolutional: Convolutions at original image resolution is very expensive
  - Fully Convolutional: Down sampling and Up sampling
  - Unsampling usning Unpooling and Transpose Convolution
  - DeconvNet: deeper network



- Instance Segmentation
  - Mak-RCNN: Extension of faster RCNN



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- Deep Learning, Stanford University
- Introduction to Deep Learning, University of Illinois at Urbana-Champaign
- Introduction to Deep Learning, Carnegie Mellon University
- Convolutional Neural Networks for Visual Recognition, Stanford University
- Natural Language Processing with Deep Learning, Stanford University
- NVDIEA Deep Learning Teaching Kit
- And many more…