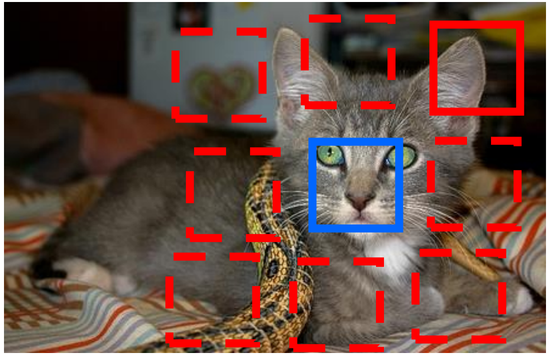
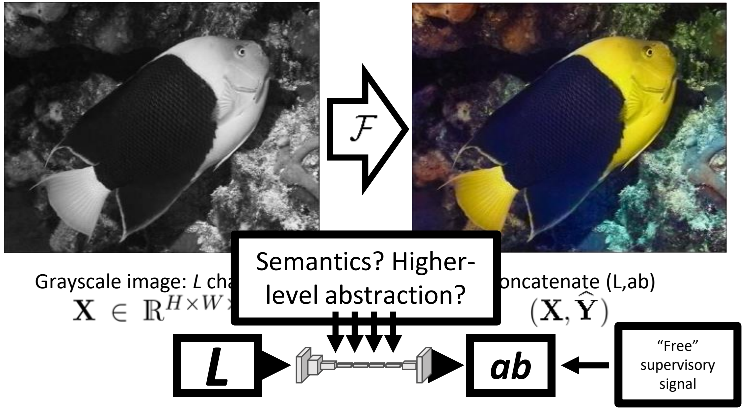
# Semantic Segmentation, PSPNet, and MSeg

Many slides by John Lambert

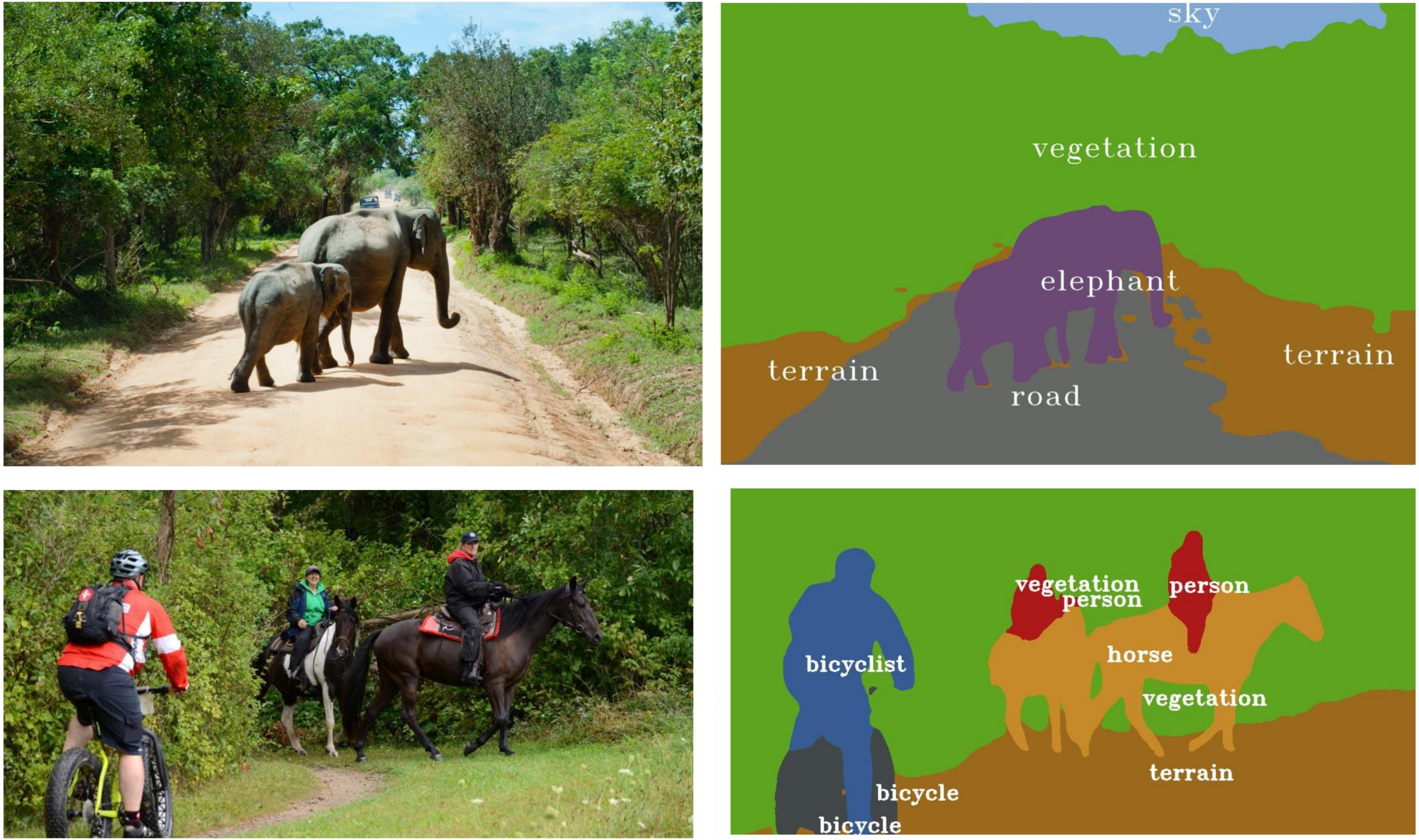
# Recap – Self-supervised learning






We looked at two of many ways to “self supervised” deep networks. These networks, trained on “pretext” tasks, generalize to other learning problems.

# Semantic Segmentation


sky
vegetation
elephant
terrain
road
terrain
vegetation
person
person
bicyclist
horse
vegetation
terrain
bicycle
bicycle


sky
vegetation
truck
truck
building
road
sky
vegetation
vegetation
terrain
truck
terrain
terrain
car
road


wall
counter_other
refrigerator
cabinet
wall
oven
floor
cabinet
cabinet
paper
wall
paper
vegetation
sink
counter_other
wall
cabinet

# Measuring Performance: Intersection over Union


$$IoU = \frac{\text{area of overlap}}{\text{area of union}}$$


Applies to segmentations, as well

Figure source: http://cs230.stanford.edu/section/8/

Figure source: https://www.pinterest.com/pin/457959855830667185/


Figure source: https://www.gettyimages.com/photos/moss-rock?phrase=moss%20rock&sort=mostpopular

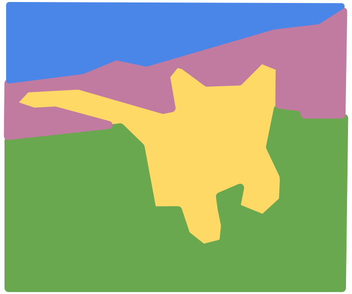
# Tasks: Semantic Segmentation

**Classification**

CAT

No spatial extent

**Semantic Segmentation**



GRASS, CAT, TREE, SKY

No objects, just pixels

**Object Detection**

DOG, DOG, CAT

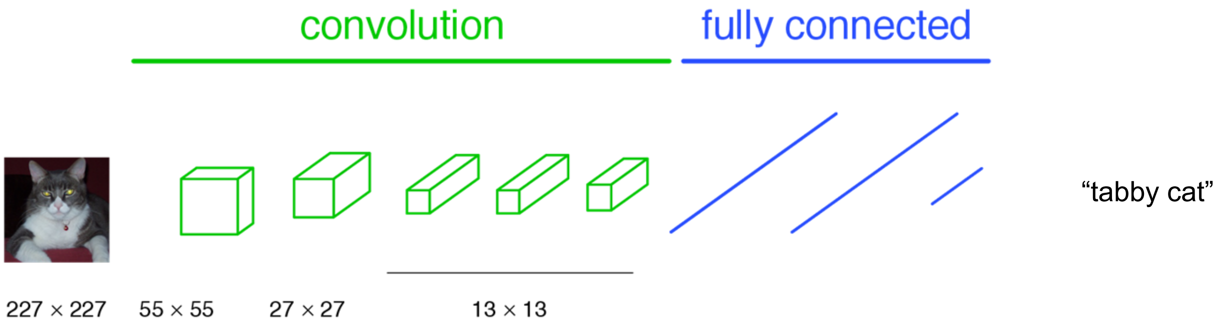
**Instance Segmentation**

DOG, DOG, CAT

Multiple Objects

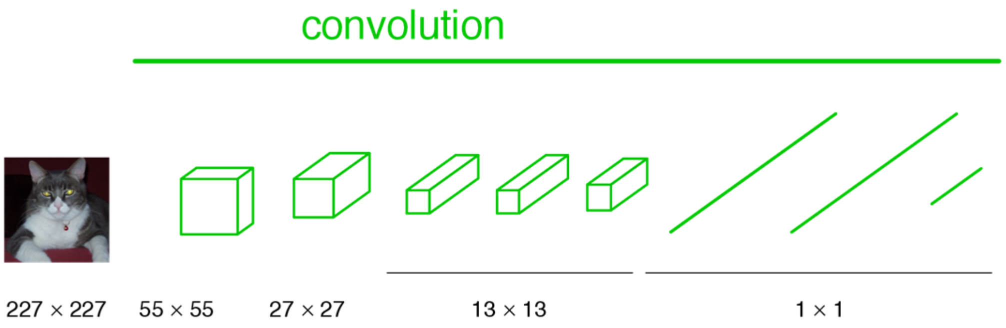
Slide Credit: Justin Johnson and David Fouhey

# a classification network



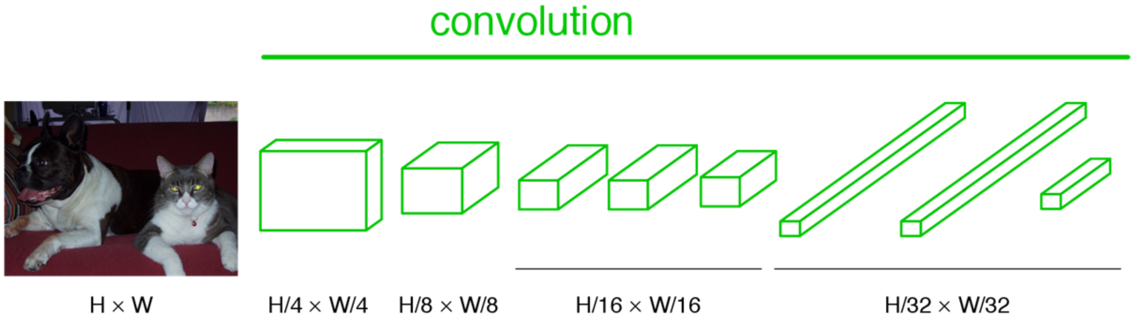

Fully Convolutional Networks for Semantic Segmentation.
Jon Long, Evan Shelhamer, Trevor Darrell. CVPR 2015

# becoming fully convolutional

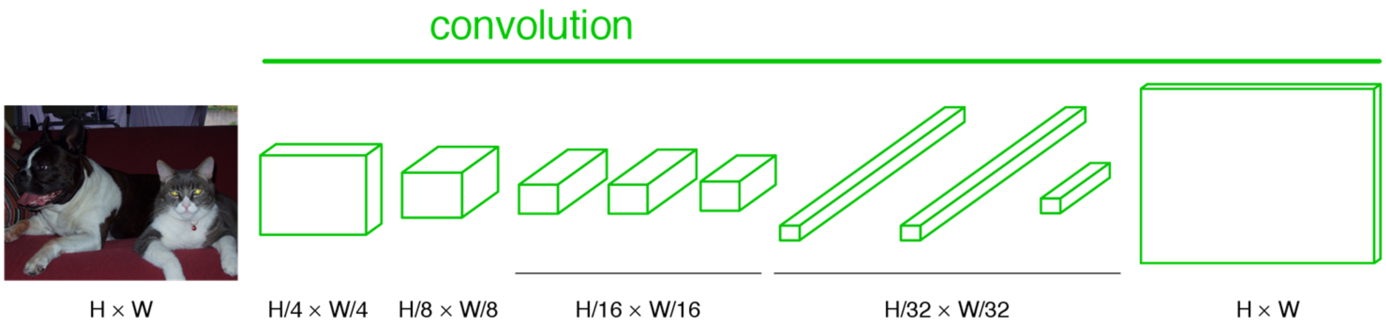



Note: “Fully Convolutional” and “Fully Connected” aren’t the same thing.
They’re almost opposites, in fact.

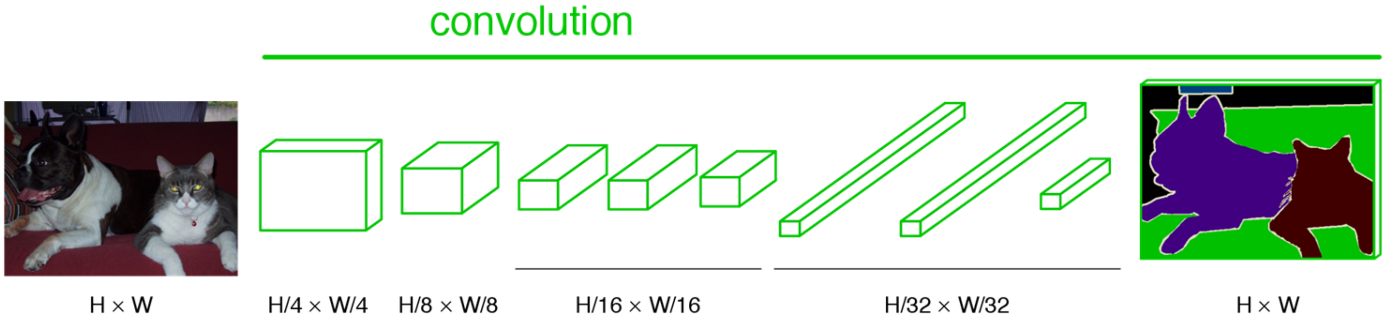
# becoming fully convolutional



# upsampling output

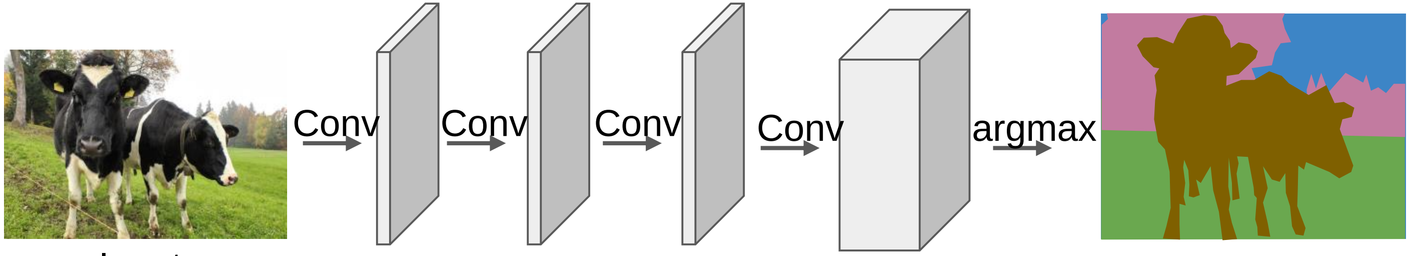


# end-to-end, pixels-to-pixels network



# Fully Convolutional Network

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




Input:
3 x H x W

Convolutions:
D x H x W

Scores:
C x H x W

Predictions:
H x W

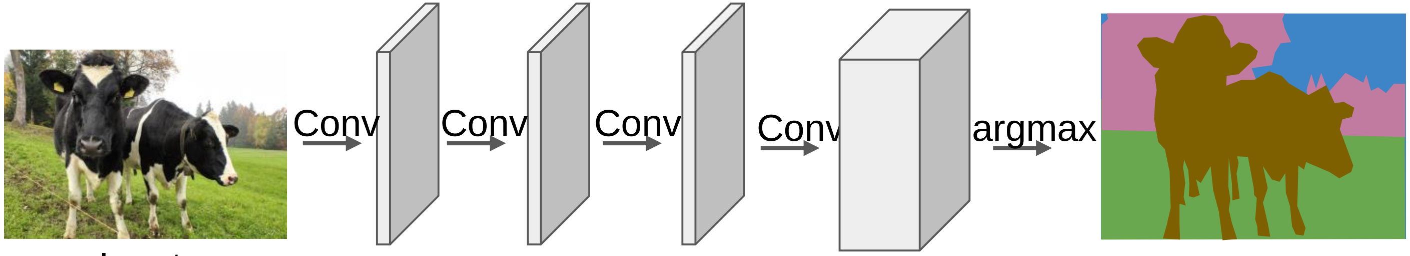
Loss function: Per-Pixel cross-entropy

Long et al, “Fully convolutional networks for semantic segmentation”, CVPR 2015

Slide Credit: Justin Johnson and David Fouhey

# Fully Convolutional Network

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

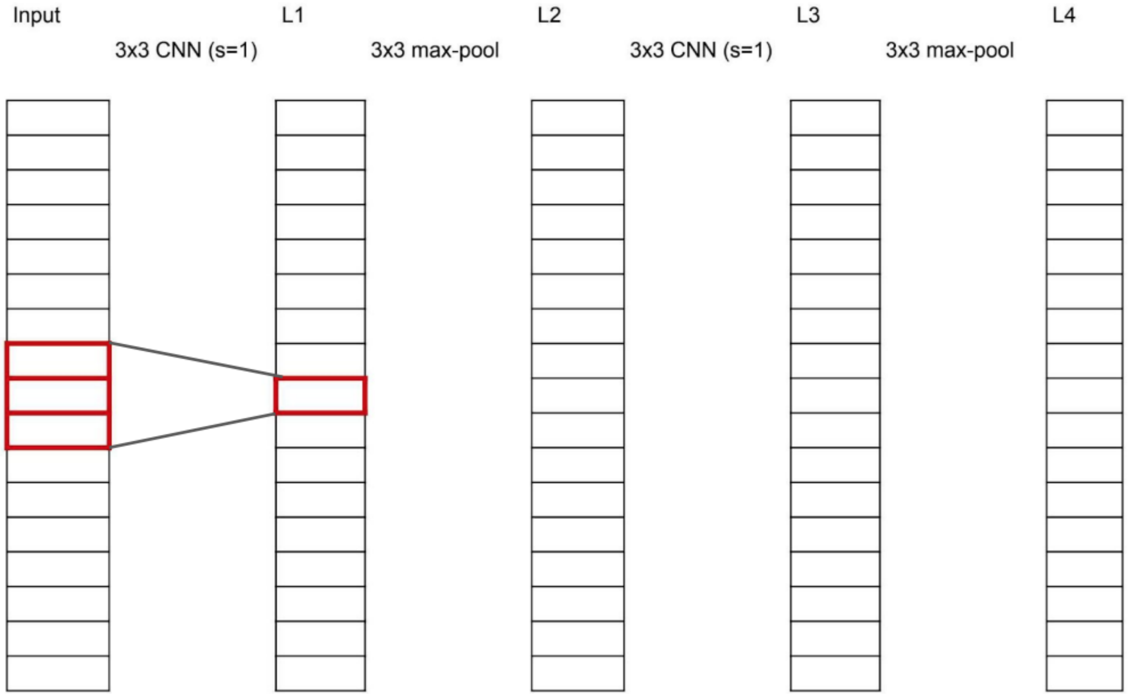



Input:
3 x H x W

**Problem #1**: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

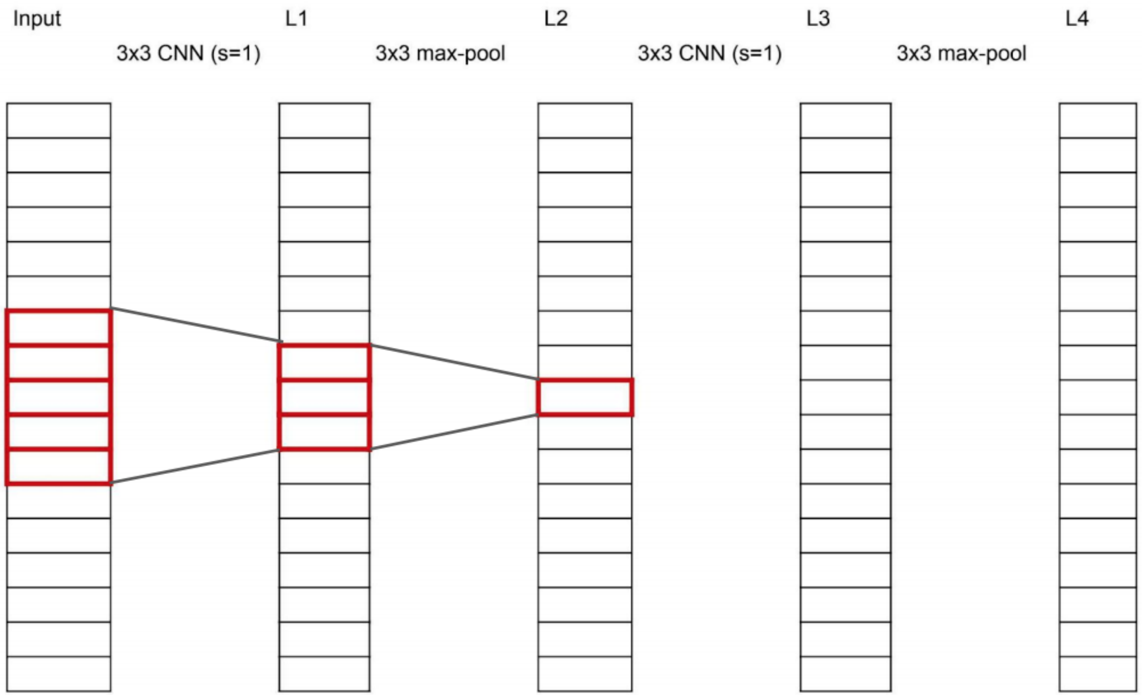
Long et al, "Fully convolutional networks for semantic segmentation", CVPR 2015

# Receptive field




Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

# Receptive field

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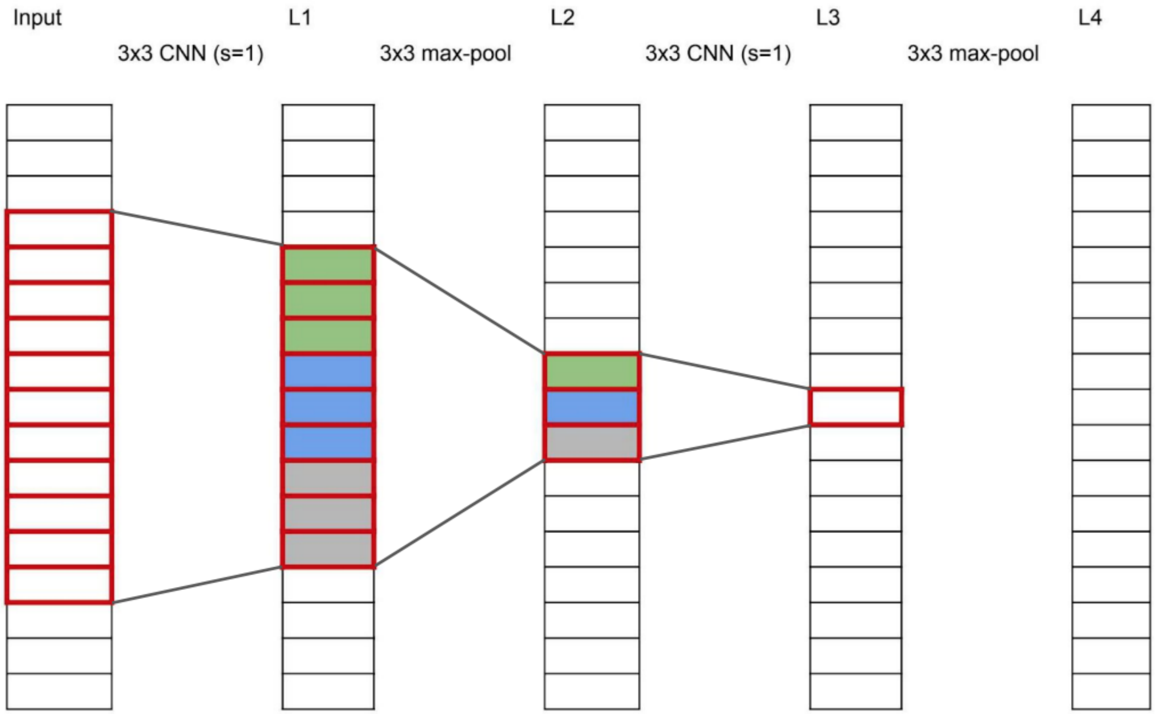
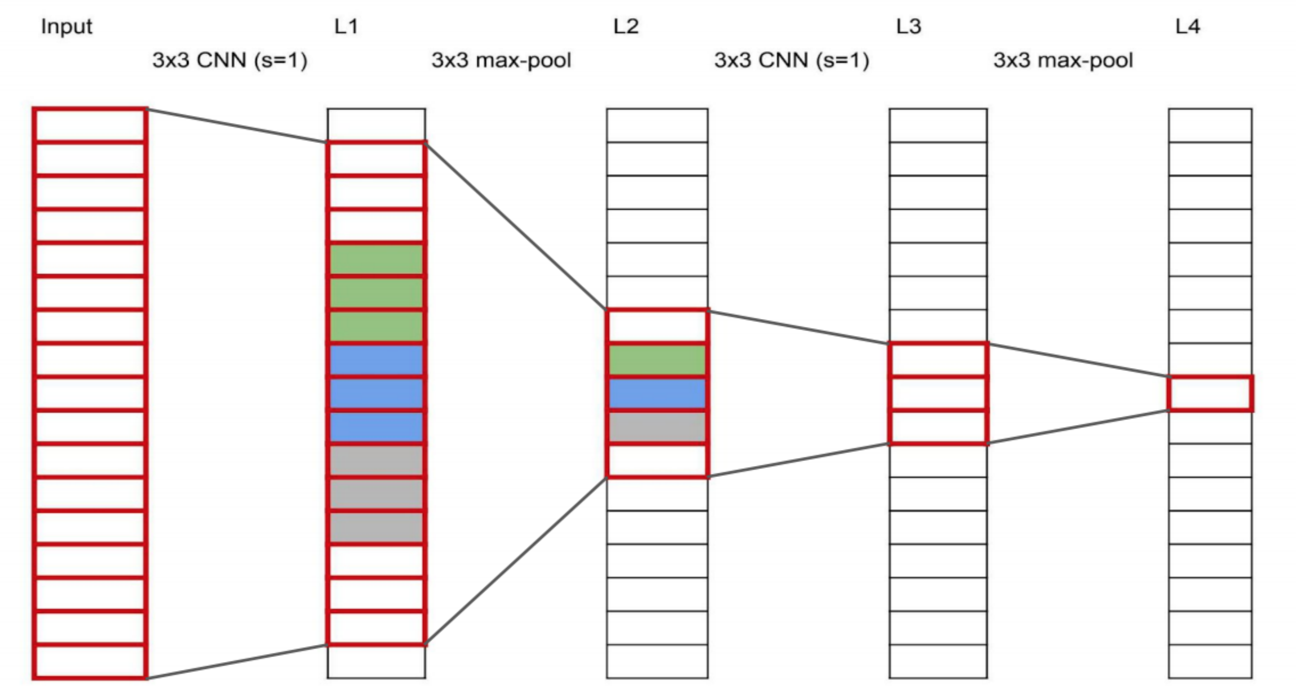
# Receptive field



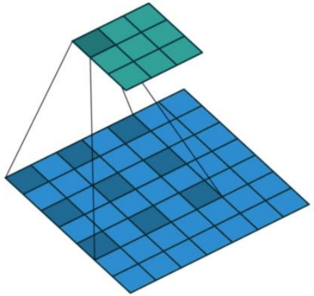

Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

# Receptive field

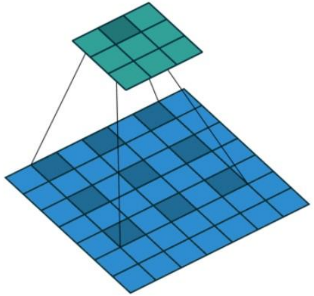



Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

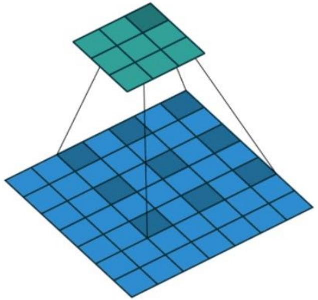
# Dilated Convolution



No padding, no stride, dilation



No padding, no stride, dilation

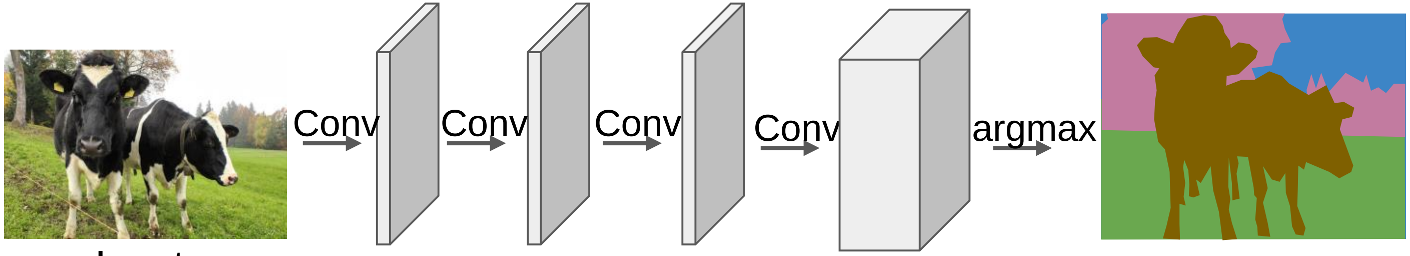


No padding, no stride, dilation

Figure source: https://github.com/vdumoulin/conv_arithmetic

# Fully Convolutional Network

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




Input:
3 x H x W

**Problem #1**: Effective receptive field size is linear in number of conv layers: With L 3x3 conv layers, receptive field is 1+2L

**Problem #2:** Convolution on high res images is expensive!

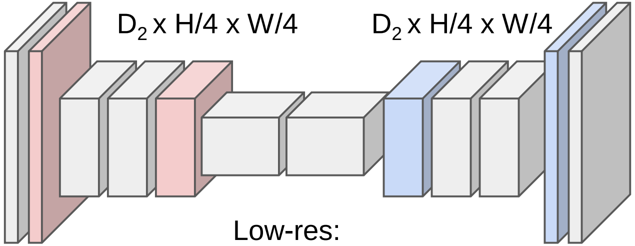
Long et al, “Fully convolutional networks for semantic segmentation”, CVPR 2015

# Fully Convolutional Network

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

Input:
3 x H x W

Med-res:
$D_2$ x H/4 x W/4



Med-res:
$D_2$ x H/4 x W/4

High-res:
$D_1$ x H/2 x W/2

Low-res:
$D_3$ x H/4 x W/4

High-res:
$D_1$ x H/2 x W/2

Predictions:
H x W

**Downsampling**:
Pooling, strided convolution

**Upsampling**:
???

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Slide Credit: Justin Johnson and David Fouhey

# In-Network Upsampling: "Unpooling"

**Bed of Nails**

| | |
|---|---|
| 1 | 2 |
| 3 | 4 |

→

| | | | |
|---|---|---|---|
| 1 | 0 | 2 | 0 |
| 0 | 0 | 0 | 0 |
| 3 | 0 | 4 | 0 |
| 0 | 0 | 0 | 0 |

Input
C x 2 x 2

Output
C x 4 x 4

**Nearest Neighbor**

| | |
|---|---|
| 1 | 2 |
| 3 | 4 |

→

| | | | |
|---|---|---|---|
| 1 | 1 | 2 | 2 |
| 1 | 1 | 2 | 2 |
| 3 | 3 | 4 | 4 |
| 3 | 3 | 4 | 4 |

Input
C x 2 x 2

Output
C x 4 x 4

Slide Credit: Justin Johnson and David Fouhey

# Upsampling: Bilinear Interpolation

| | |
|---|---|
| 1 | 2 |
| 3 | 4 |

Input: C x 2 x 2

| | | | |
|---|---|---|---|
| 1.00 | 1.25 | 1.75 | 2.00 |
| 1.50 | 1.75 | 2.25 | 2.50 |
| 2.50 | 2.75 | 3.25 | 3.50 |
| 3.00 | 3.25 | 3.75 | 4.00 |

Output: C x 4 x 4

$$f_{x,y} = \sum_{i,j} f_{i,j} \max(0, 1 - |x - i|) \max(0, 1 - |y - j|) \quad \begin{array}{l} i \in \{\lfloor x \rfloor - 1, \dots, \lceil x \rceil + 1\} \\ j \in \{\lfloor y \rfloor - 1, \dots, \lceil y \rceil + 1\} \end{array}$$

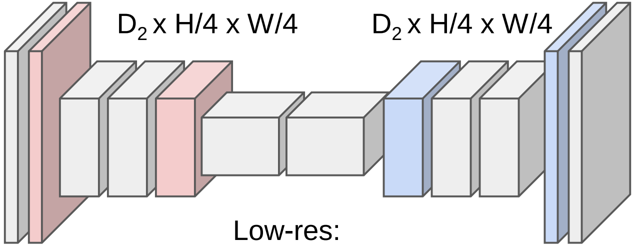
Use two closest neighbors in x and y to construct linear approximations

Slide Credit: Justin Johnson and David Fouhey

# Fully Convolutional Network

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

Input:
3 x H x W




Predictions:
H x W

**Downsampling**:
Pooling, strided convolution

**Upsampling**:
???

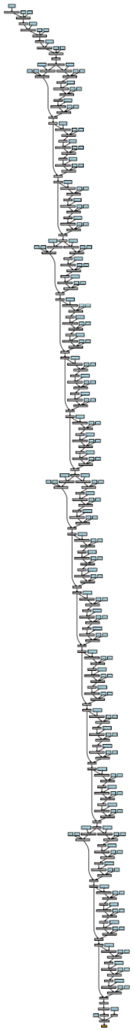
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

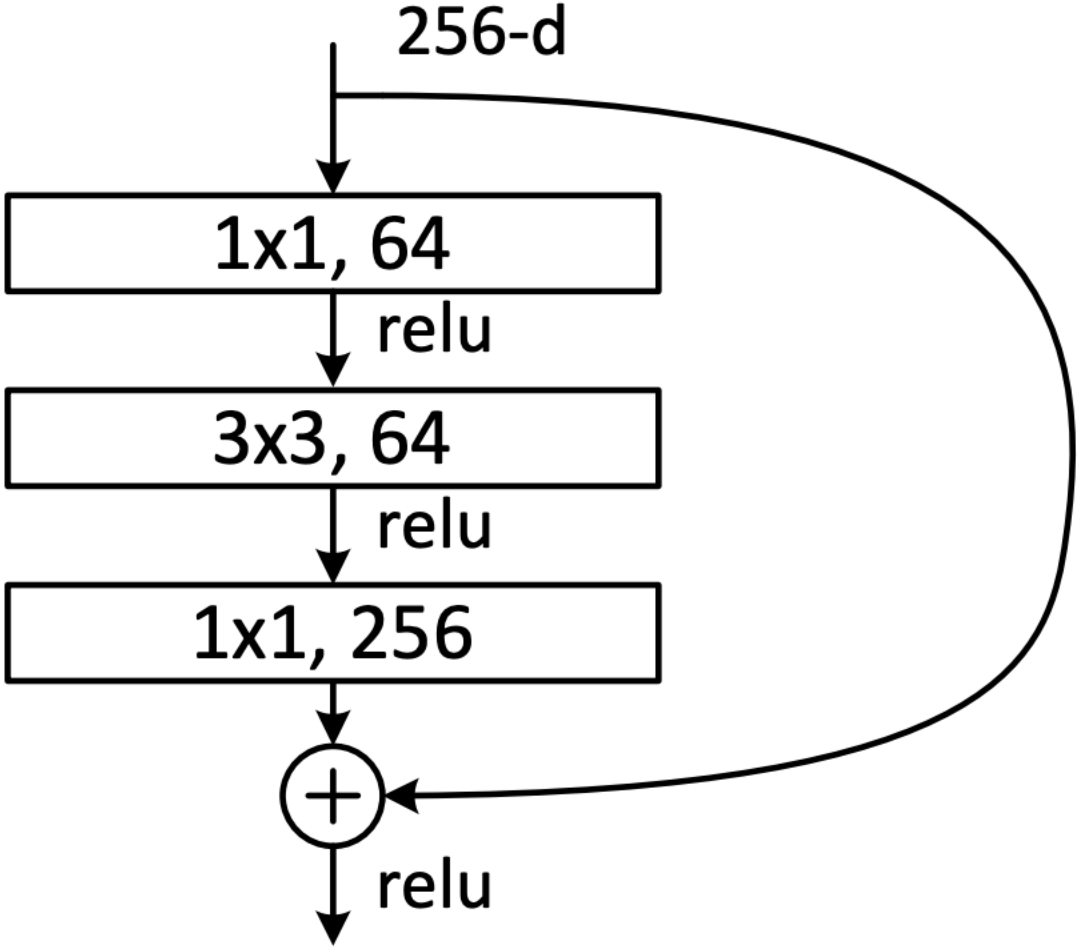
Slide Credit: Justin Johnson and David Fouhey

# PSPNet

# PSPNet uses a ResNet backbone

- 50, 101, or 152 Layers
- 50 Layers is already quite deep!





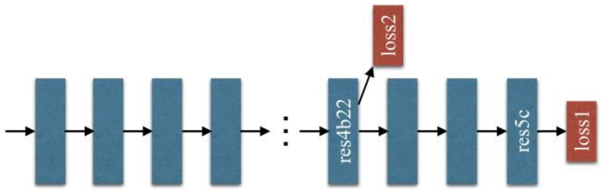
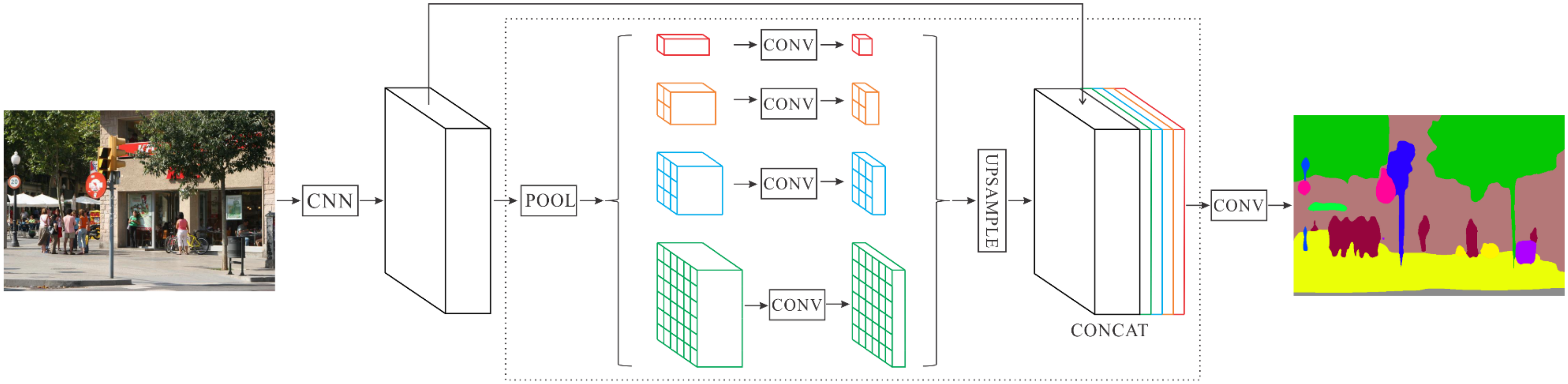




Figure 4. Illustration of auxiliary loss in ResNet101. Each blue box denotes a residue block. The auxiliary loss is added after the res4b22 residue block.

# Pyramid Scene Parsing Network



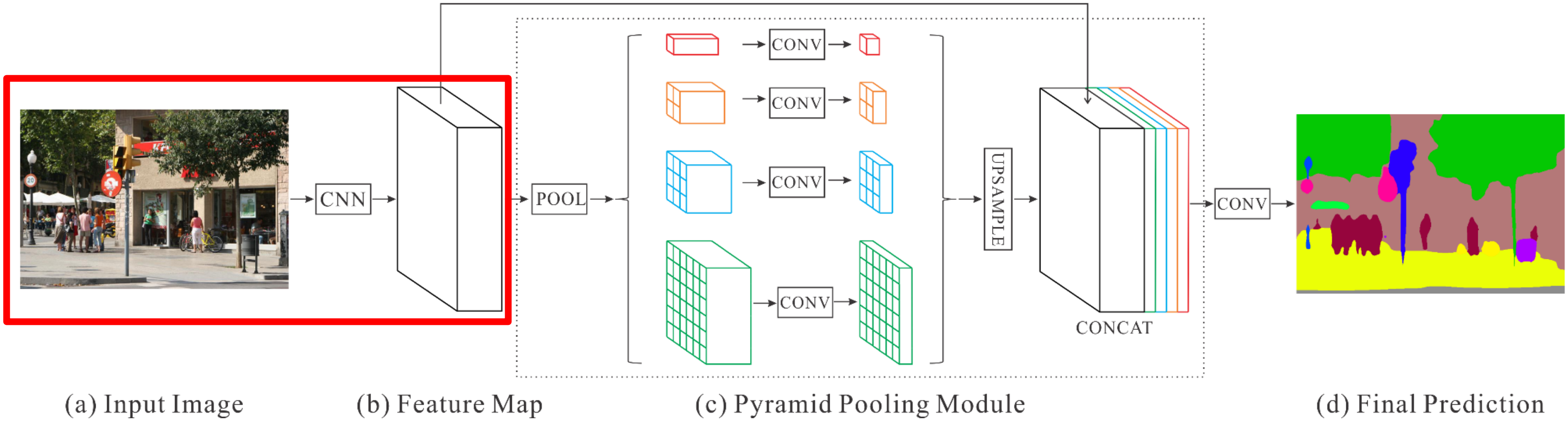

(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

Framework overview of PSPNet

*"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [12,000+ citation]*

Slide Credit: Hengshuang Zhao and Jiaya Jia

# Pyramid Scene Parsing Network

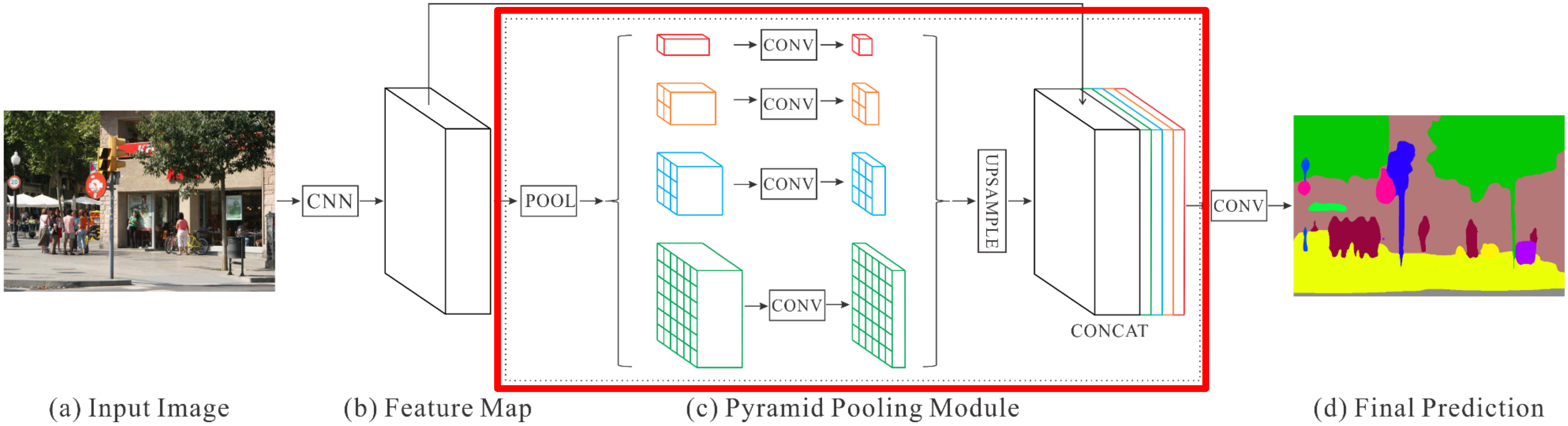



Regular feature extractor

*"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [4,000+ citation]*

Slide Credit: Hengshuang Zhao and Jiaya Jia

# Pyramid Scene Parsing Network

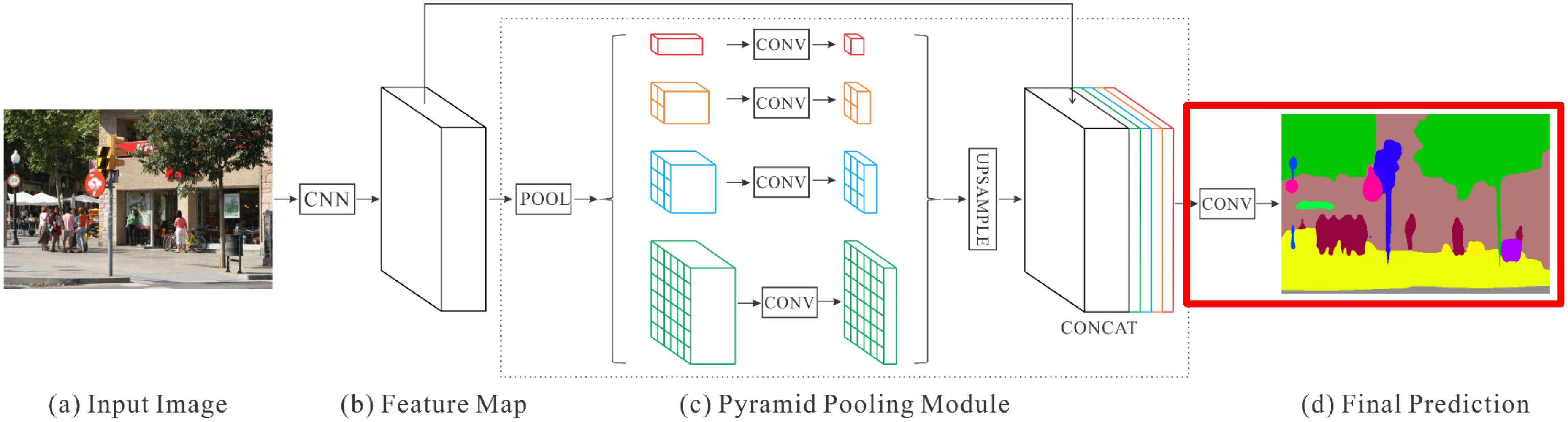



Context modeling: pyramid pooling module

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [4,000+ citation]

Slide Credit: Hengshuang Zhao and Jiaya Jia

# Pyramid Scene Parsing Network

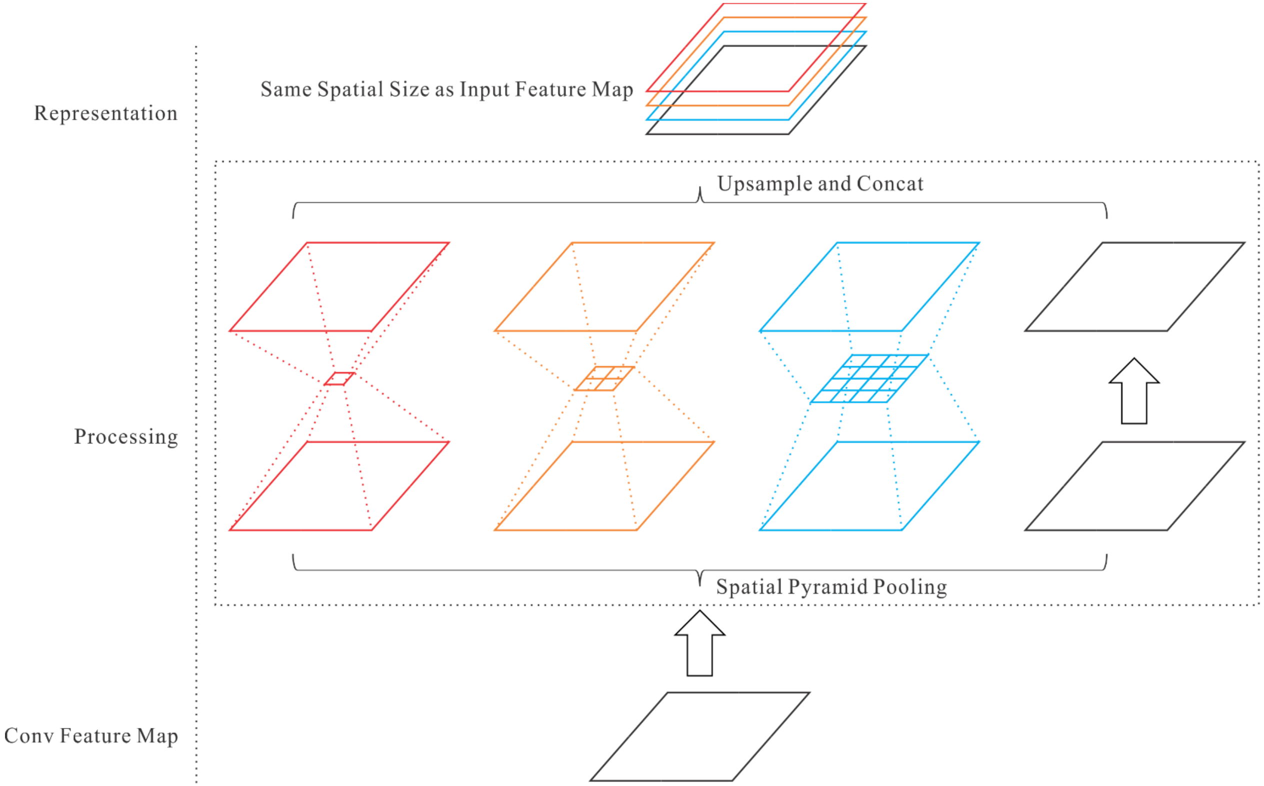



Convolutional classifier for pixel-wise prediction

*"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [4,000+ citation]*

Slide Credit: Hengshuang Zhao and Jiaya Jia

# Pyramid Pooling Module




PPM: spatial illustration

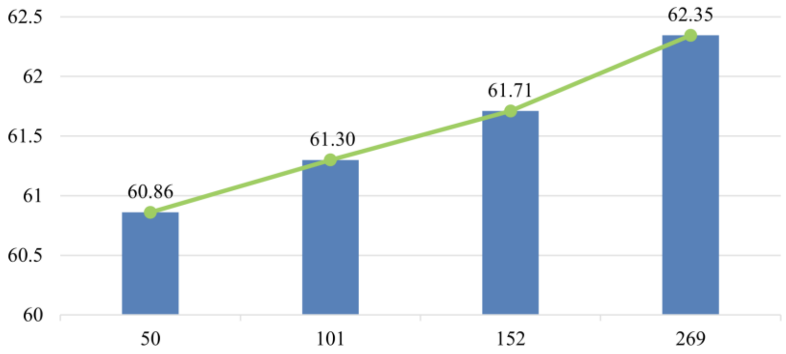


Slide Credit: Hengshuang Zhao and Jiaya Jia

# ImageNet Scene Parsing Challenge

| Method | Mean IoU(%) | Pixel Acc.(%) |
|---|---|---|
| FCN [26] | 29.39 | 71.32 |
| SegNet [2] | 21.64 | 71.00 |
| DilatedNet [40] | 32.31 | 73.55 |
| CascadeNet [43] | 34.90 | 74.52 |
| ResNet50-Baseline | 34.28 | 76.35 |
| ResNet50+DA | 35.82 | 77.07 |
| ResNet50+DA+AL | 37.23 | 78.01 |
| ResNet50+DA+AL+PSP | **41.68** | **80.04** |
| ResNet269+DA+AL+PSP | 43.81 | 80.88 |
| ResNet269+DA+AL+PSP+MS | **44.94** | **81.69** |

detailed performance analysis



consistent improvement over network depth

PSPNet: 1st place among totally 75 submissions worldwide.



Slide Credit: Hengshuang Zhao and Jiaya Jia

# Result on PASCAL VOC 2012

| Method | aero | bike | bird | boat | bottle | bus | car | cat | chair | cow | table | dog | horse | mbike | person | plant | sheep | sofa | train | tv | mIoU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| FCN [26] | 76.8 | 34.2 | 68.9 | 49.4 | 60.3 | 75.3 | 74.7 | 77.6 | 21.4 | 62.5 | 46.8 | 71.8 | 63.9 | 76.5 | 73.9 | 45.2 | 72.4 | 37.4 | 70.9 | 55.1 | 62.2 |
| Zoom-out [28] | 85.6 | 37.3 | 83.2 | 62.5 | 66.0 | 85.1 | 80.7 | 84.9 | 27.2 | 73.2 | 57.5 | 78.1 | 79.2 | 81.1 | 77.1 | 53.6 | 74.0 | 49.2 | 71.7 | 63.3 | 69.6 |
| DeepLab [3] | 84.4 | 54.5 | 81.5 | 63.6 | 65.9 | 85.1 | 79.1 | 83.4 | 30.7 | 74.1 | 59.8 | 79.0 | 76.1 | 83.2 | 80.8 | 59.7 | 82.2 | 50.4 | 73.1 | 63.7 | 71.6 |
| CRF-RNN [41] | 87.5 | 39.0 | 79.7 | 64.2 | 68.3 | 87.6 | 80.8 | 84.4 | 30.4 | 78.2 | 60.4 | 80.5 | 77.8 | 83.1 | 80.6 | 59.5 | 82.8 | 47.8 | 78.3 | 67.1 | 72.0 |
| DeconvNet [30] | 89.9 | 39.3 | 79.7 | 63.9 | 68.2 | 87.4 | 81.2 | 86.1 | 28.5 | 77.0 | 62.0 | 79.0 | 80.3 | 83.6 | 80.2 | 58.8 | 83.4 | 54.3 | 80.7 | 65.0 | 72.5 |
| GCRF [36] | 85.2 | 43.9 | 83.3 | 65.2 | 68.3 | 89.0 | 82.7 | 85.3 | 31.1 | 79.5 | 63.3 | 80.5 | 79.3 | 85.5 | 81.0 | 60.5 | 85.5 | 52.0 | 77.3 | 65.1 | 73.2 |
| DPN [25] | 87.7 | 59.4 | 78.4 | 64.9 | 70.3 | 89.3 | 83.5 | 86.1 | 31.7 | 79.9 | 62.6 | 81.9 | 80.0 | 83.5 | 82.3 | 60.5 | 83.2 | 53.4 | 77.9 | 65.0 | 74.1 |
| Piecewise [20] | 90.6 | 37.6 | 80.0 | 67.8 | 74.4 | 92.0 | 85.2 | 86.2 | 39.1 | 81.2 | 58.9 | 83.8 | 83.9 | 84.3 | 84.8 | 62.1 | 83.2 | 58.2 | 80.8 | 72.3 | 75.3 |
| PSPNet | **91.8** | **71.9** | **94.7** | **71.2** | **75.8** | **95.2** | **89.9** | **95.9** | **39.3** | **90.7** | **71.7** | **90.5** | **94.5** | **88.8** | **89.6** | **72.8** | **89.6** | **64.0** | **85.1** | **76.3** | **82.6** |
| CRF-RNN† [41] | 90.4 | 55.3 | 88.7 | 68.4 | 69.8 | 88.3 | 82.4 | 85.1 | 32.6 | 78.5 | 64.4 | 79.6 | 81.9 | 86.4 | 81.8 | 58.6 | 82.4 | 53.5 | 77.4 | 70.1 | 74.7 |
| BoxSup† [7] | 89.8 | 38.0 | 89.2 | 68.9 | 68.0 | 89.6 | 83.0 | 87.7 | 34.4 | 83.6 | 67.1 | 81.5 | 83.7 | 85.2 | 83.5 | 58.6 | 84.9 | 55.8 | 81.2 | 70.7 | 75.2 |
| Dilation8† [40] | 91.7 | 39.6 | 87.8 | 63.1 | 71.8 | 89.7 | 82.9 | 89.8 | 37.2 | 84.0 | 63.0 | 83.3 | 89.0 | 83.8 | 85.1 | 56.8 | 87.6 | 56.0 | 80.2 | 64.7 | 75.3 |
| DPN† [25] | 89.0 | 61.6 | 87.7 | 66.8 | 74.7 | 91.2 | 84.3 | 87.6 | 36.5 | 86.3 | 66.1 | 84.4 | 87.8 | 85.6 | 85.4 | 63.6 | 87.3 | 61.3 | 79.4 | 66.4 | 77.5 |
| Piecewise† [20] | 94.1 | 40.7 | 84.1 | 67.8 | 75.9 | 93.4 | 84.3 | 88.4 | 42.5 | 86.4 | 64.7 | 85.4 | 89.0 | 85.8 | 86.0 | 67.5 | 90.2 | 63.8 | 80.9 | 73.0 | 78.0 |
| FCRNs† [38] | 91.9 | 48.1 | 93.4 | 69.3 | 75.5 | 94.2 | 87.5 | 92.8 | 36.7 | 86.9 | 65.2 | 89.1 | 90.2 | 86.5 | 87.2 | 64.6 | 90.1 | 59.7 | 85.5 | 72.7 | 79.1 |
| LRR† [9] | 92.4 | 45.1 | 94.6 | 65.2 | 75.8 | **95.1** | 89.1 | 92.3 | 39.0 | 85.7 | 70.4 | 88.6 | 89.4 | 88.6 | 86.6 | 65.8 | 86.2 | 57.4 | 85.7 | 77.3 | 79.3 |
| DeepLab† [4] | 92.6 | 60.4 | 91.6 | 63.4 | 76.3 | 95.0 | 88.4 | 92.6 | 32.7 | 88.5 | 67.6 | 89.6 | 92.1 | 87.0 | 87.4 | 63.3 | 88.3 | 60.0 | 86.8 | 74.5 | 79.7 |
| PSPNet† | **95.8** | **72.7** | **95.0** | **78.9** | **84.4** | 94.7 | **92.0** | **95.7** | **43.1** | **91.0** | **80.3** | **91.3** | **96.3** | **92.3** | **90.1** | **71.5** | **94.4** | **66.9** | **88.8** | **82.0** | **85.4** |



Slide Credit: Hengshuang Zhao and Jiaya Jia

# Result on Cityscapes

| Method | road | swalk | build. | wall | fence | pole | tlight | sign | veg. | terrain | sky | person | rider | car | truck | bus | train | mbike | bike | mIoU |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CRF-RNN [41] | 96.3 | 73.9 | 88.2 | 47.6 | 41.3 | 35.2 | 49.5 | 59.7 | 90.6 | 66.1 | 93.5 | 70.4 | 34.7 | 90.1 | 39.2 | 57.5 | 55.4 | 43.9 | 54.6 | 62.5 |
| FCN [26] | 97.4 | 78.4 | 89.2 | 34.9 | 44.2 | 47.4 | 60.1 | 65.0 | 91.4 | 69.3 | 93.9 | 77.1 | 51.4 | 92.6 | 35.3 | 48.6 | 46.5 | 51.6 | 66.8 | 65.3 |
| SiCNN+CRF [16] | 96.3 | 76.8 | 88.8 | 40.0 | 45.4 | 50.1 | 63.3 | 69.6 | 90.6 | 67.1 | 92.2 | 77.6 | 55.9 | 90.1 | 39.2 | 51.3 | 44.4 | 54.4 | 66.1 | 66.3 |
| DPN [25] | 97.5 | 78.5 | 89.5 | 40.4 | 45.9 | 51.1 | 56.8 | 65.3 | 91.5 | 69.4 | 94.5 | 77.5 | 54.2 | 92.5 | 44.5 | 53.4 | 49.9 | 52.1 | 64.8 | 66.8 |
| Dilation10 [40] | 97.6 | 79.2 | 89.9 | 37.3 | 47.6 | 53.2 | 58.6 | 65.2 | 91.8 | 69.4 | 93.7 | 78.9 | 55.0 | 93.3 | 45.5 | 53.4 | 47.7 | 52.2 | 66.0 | 67.1 |
| LRR [9] | 97.7 | 79.9 | 90.7 | 44.4 | 48.6 | 58.6 | 68.2 | 72.0 | 92.5 | 69.3 | 94.7 | 81.6 | 60.0 | 94.0 | 43.6 | 56.8 | 47.2 | 54.8 | 69.7 | 69.7 |
| DeepLab [4] | 97.9 | 81.3 | 90.3 | 48.8 | 47.4 | 49.6 | 57.9 | 67.3 | 91.9 | 69.4 | 94.2 | 79.8 | 59.8 | 93.7 | 56.5 | 67.5 | 57.5 | 57.7 | 68.8 | 70.4 |
| Piecewise [20] | 98.0 | 82.6 | 90.6 | 44.0 | 50.7 | 51.1 | 65.0 | 71.7 | 92.0 | 72.0 | 94.1 | 81.5 | 61.1 | 94.3 | 61.1 | 65.1 | 53.8 | 61.6 | 70.6 | 71.6 |
| PSPNet | **98.6** | **86.2** | **92.9** | **50.8** | **58.8** | **64.0** | **75.6** | **79.0** | **93.4** | **72.3** | **95.4** | **86.5** | **71.3** | **95.9** | **68.2** | **79.5** | **73.8** | **69.5** | **77.2** | **78.4** |
| LRR‡ [9] | 97.9 | 81.5 | 91.4 | 50.5 | 52.7 | 59.4 | 66.8 | 72.7 | 92.5 | 70.1 | 95.0 | 81.3 | 60.1 | 94.3 | 51.2 | 67.7 | 54.6 | 55.6 | 69.6 | 71.8 |
| PSPNet‡ | **98.6** | **86.6** | **93.2** | **58.1** | **63.0** | **64.5** | **75.2** | **79.2** | **93.4** | **72.1** | **95.1** | **86.3** | **71.4** | **96.0** | **73.5** | **90.4** | **80.3** | **69.9** | **76.9** | **80.2** |



Slide Credit: Hengshuang Zhao and Jiaya Jia


road
sidewalk
building
wall
fence
pole
traffic light
traffic sign
vegetation
terrain
sky
person
rider
car
truck
bus
train
motorcycle
bicycle

# PSPNet paper

## Pyramid Scene Parsing Network

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### Abstract

*Scene parsing is challenging for unrestricted open vocabulary and diverse scenes. In this paper, we exploit the capability of global context information by different-region-based context aggregation through our pyramid pooling module together with the proposed pyramid scene parsing network (PSPNet). Our global prior representation is effective to produce good quality results on the scene parsing task, while PSPNet provides a superior framework for pixel-level prediction. The proposed approach achieves state-of-the-art performance on various datasets. It came first in ImageNet scene parsing challenge 2016, PASCAL VOC 2012 benchmark and Cityscapes benchmark. A single PSPNet yields the new record of mIoU accuracy 85.4% on PASCAL VOC 2012 and accuracy 80.2% on Cityscapes.*

(a) Image (b) Ground Truth

Figure 1. Illustration of complex scenes in ADE20K dataset.

# MSeg: A Composite Dataset for Multi-Domain Semantic Segmentation

John Lambert*, Zhuang Liu*, Ozan Sener,
James Hays, Vladlen Koltun

Berkeley
UNIVERSITY OF CALIFORNIA
Georgia Tech


https://www.youtube.com/watch?v=8wqNX7_4vAE

# Which dataset to train on?

**Driving:** Cityscapes, Mapillary Vistas, CamVid, KITTI, VIPER, Indian Driving Dataset, Berkeley Driving Dataset, WildDash, …

**Indoors:** NYU, SUN RGBD, ScanNet, InteriorNet, ...

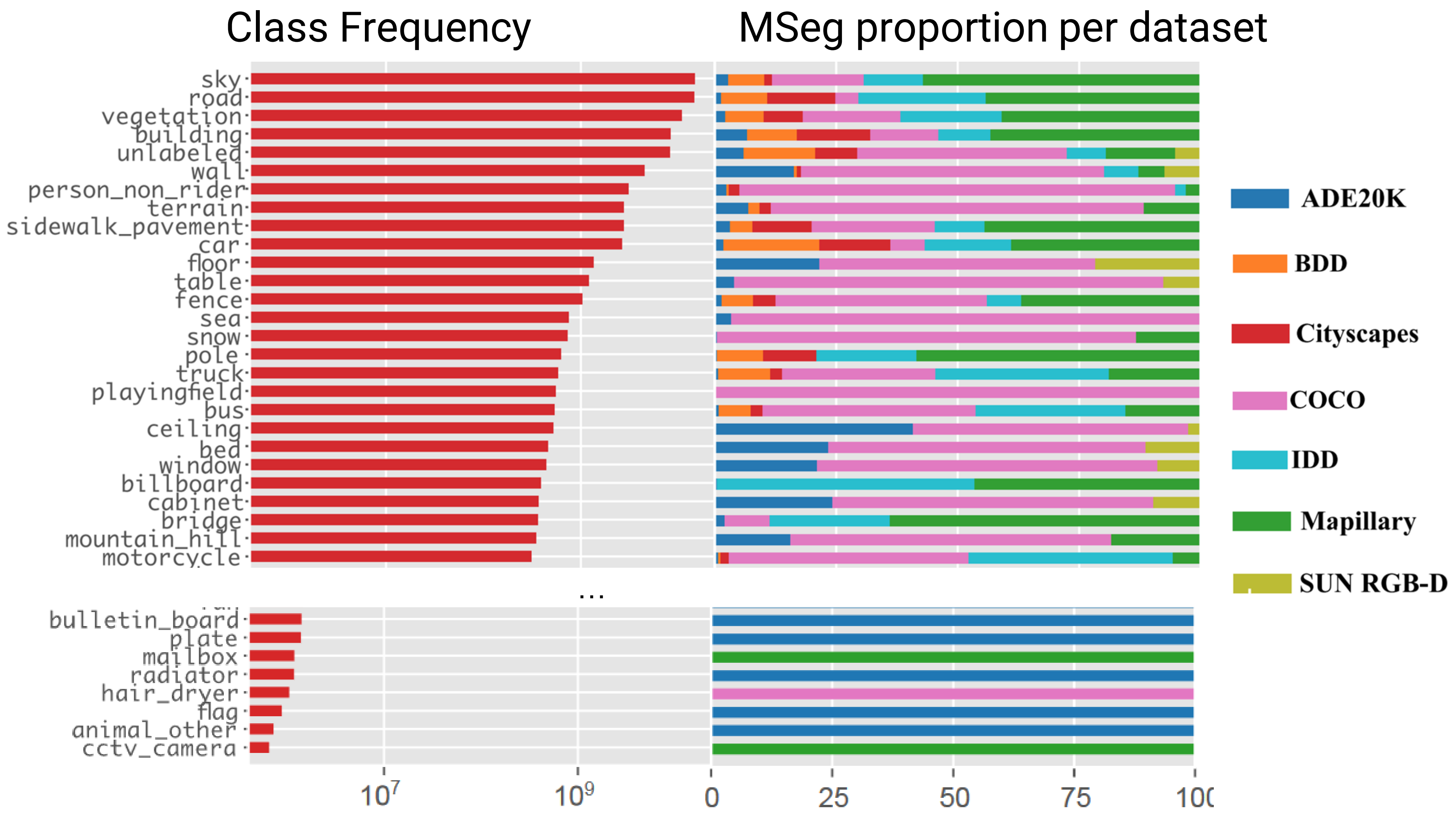
**Multi-domain:** COCO, ADE20K, PASCAL VOC, ...

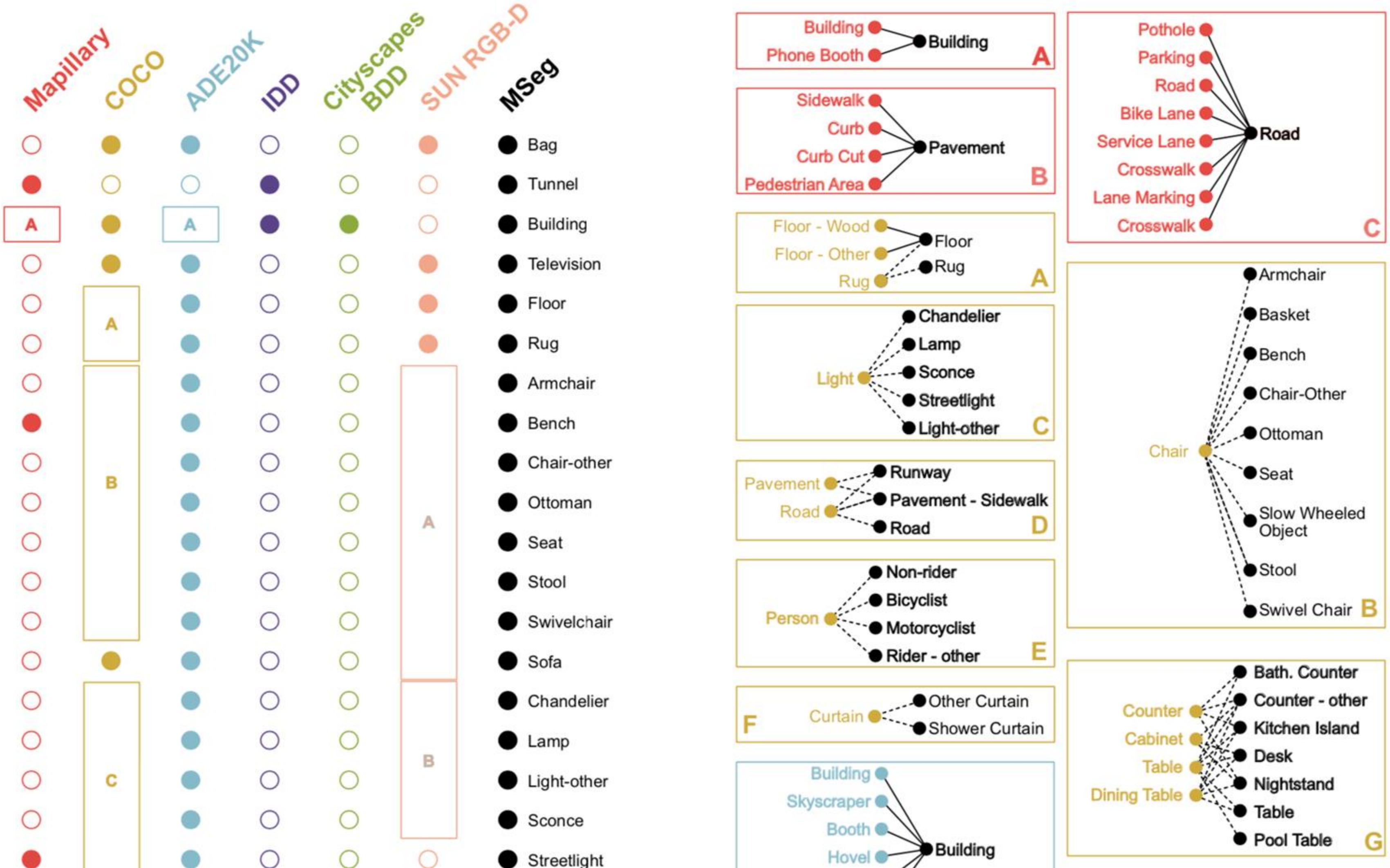
John Lambert*, Zhuang Liu*, Ozan Sener, James Hays, Vladlen Koltun: *MSeg: A Composite Dataset for Multi-domain Semantic Segmentation.* CVPR 2020

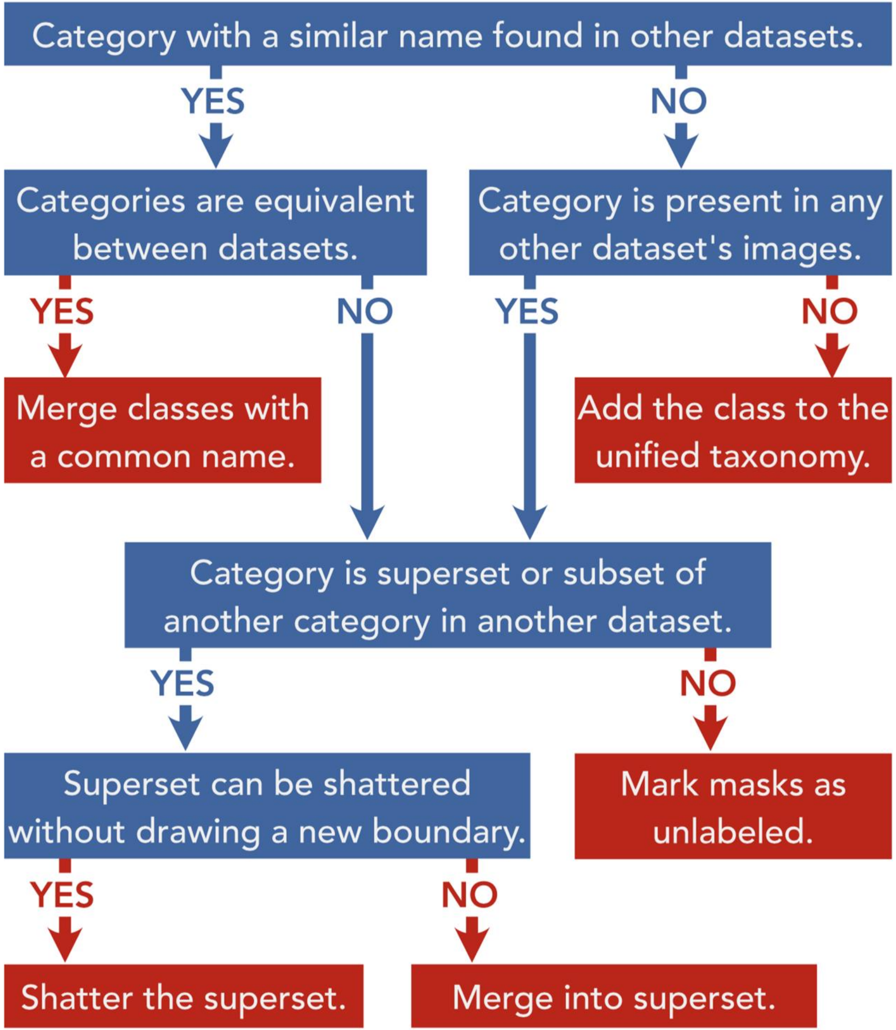
# Methodology:
# Dataset mixing and zero-shot transfer

- Perform a training/test split at the level of datasets
- Train on many diverse datasets
- Test on datasets that were never seen during training
- Zero-shot cross-dataset transfer is a proxy for generality and robustness in the real world

| Dataset name | Origin domain | # Images |
|---|---|---|
| **Training & Validation** | | |
| COCO [19] + COCO STUFF [4] | Everyday objects | 123,287 |
| ADE20K [46] | Everyday objects | 22,210 |
| MAPILLARY [25] | Driving (Worldwide) | 20,000 |
| IDD [40] | Driving (India) | 7,974 |
| BDD [43] | Driving (United States) | 8,000 |
| CITYSCAPES [7] | Driving (Germany) | 3,475 |
| SUN RGBD [36] | Indoor | 5,285 |
| **Test** | | |
| PASCAL VOC [10] | Everyday objects | 1,449 |
| PASCAL CONTEXT [24] | Everyday objects | 5,105 |
| CAMVID [3] | Driving (U.K.) | 101 |
| WILDDASH [44] | Driving (Worldwide) | 70 |
| KITTI [11] | Driving (Germany) | 200 |
| SCANNET-20 [8] | Indoor | 5,436 |


Class Frequency
MSeg proportion per dataset
sky
road
vegetation
building
unlabeled
wall
person_non_rider
terrain
sidewalk_pavement
car
floor
table
fence
sea
snow
pole
truck
playingfield
bus
ceiling
bed
window
billboard
cabinet
bridge
mountain_hill
motorcycle
...
bulletin_board
plate
mailbox
radiator
hair_dryer
flag
animal_other
cctv_camera
$10^7$
$10^9$
0
25
50
75
100
ADE20K
BDD
Cityscapes
COCO
IDD
Mapillary
SUN RGB-D

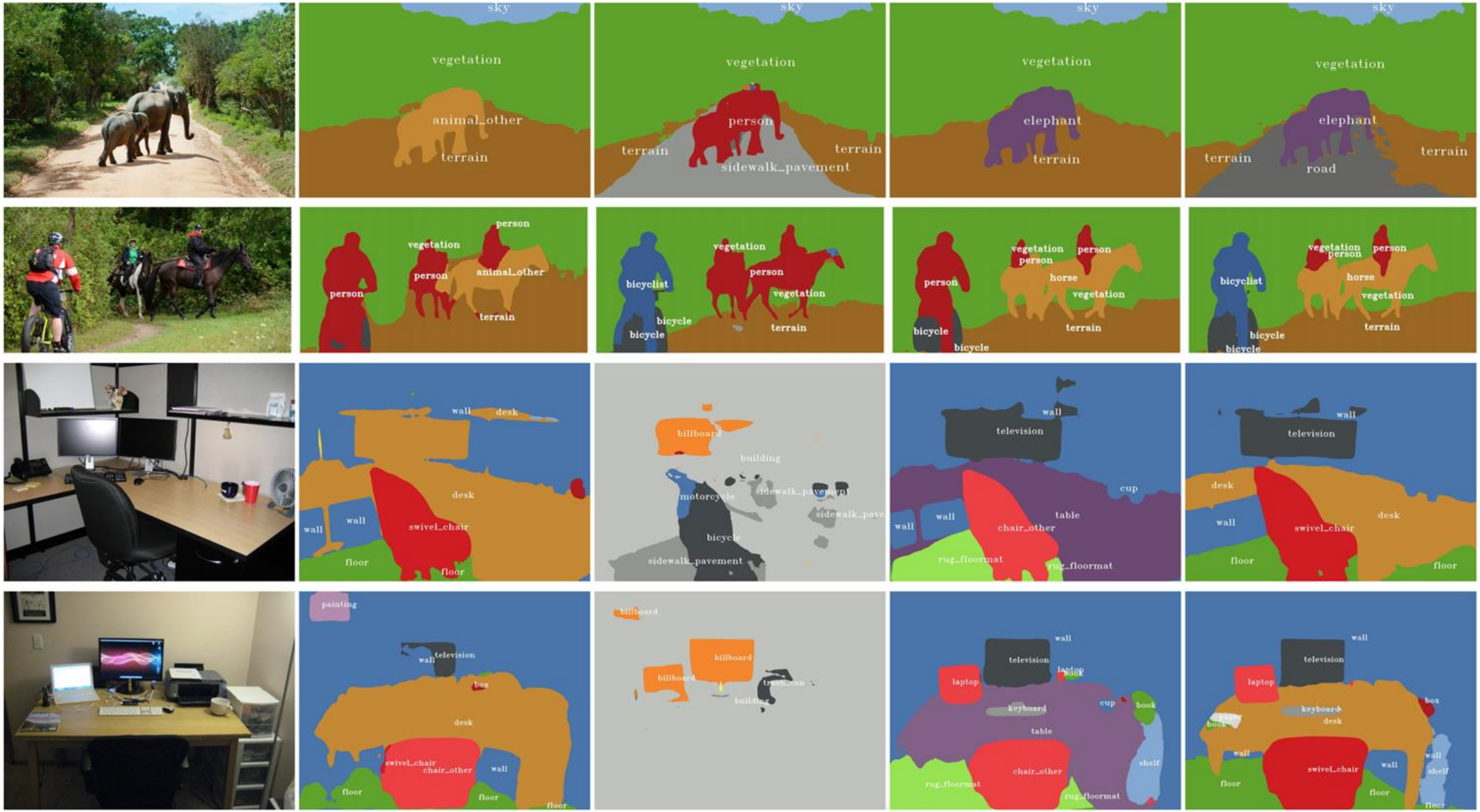

Mapillary
COCO
ADE20K
IDD
Cityscapes
BDD
SUN RGB-D
MSeg
Bag
Tunnel
A
A
Building
Television
A
Floor
Rug
B
A
Armchair
Bench
Chair-other
Ottoman
Seat
Stool
Swivelchair
Sofa
C
B
Chandelier
Lamp
Light-other
Sconce
Streetlight
Building
Phone Booth
Building
A
Sidewalk
Curb
Curb Cut
Pedestrian Area
Pavement
B
Floor - Wood
Floor - Other
Rug
Floor
Rug
A
Light
Chandelier
Lamp
Sconce
Streetlight
Light-other
C
Pavement
Road
Runway
Pavement - Sidewalk
Road
D
Person
Non-rider
Bicyclist
Motorcyclist
Rider - other
E
F
Curtain
Other Curtain
Shower Curtain
Building
Skyscraper
Booth
Hovel
Building
Pothole
Parking
Road
Bike Lane
Service Lane
Crosswalk
Lane Marking
Crosswalk
Road
C
Chair
Armchair
Basket
Bench
Chair-Other
Ottoman
Seat
Slow Wheeled Object
Stool
Swivel Chair
B
Counter
Cabinet
Table
Dining Table
Bath. Counter
Counter - other
Kitchen Island
Desk
Nightstand
Table
Pool Table
G


Category with a similar name found in other datasets.
YES
NO
Categories are equivalent between datasets.
Category is present in any other dataset's images.
YES
NO
YES
NO
Merge classes with a common name.
Add the class to the unified taxonomy.
Category is superset or subset of another category in another dataset.
YES
NO
Superset can be shattered without drawing a new boundary.
Mark masks as unlabeled.
YES
NO
Shatter the superset.
Merge into superset.

# Generality and Robustness

| Train/Test | VOC | Context | CamVid | WildDash | KITTI | ScanNet | *h. mean* |
|---|---|---|---|---|---|---|---|
| COCO | **73.4** | **43.3** | 58.7 | 38.2 | 47.6 | 33.4 | 45.8 |
| ADE20K | 35.4 | 23.9 | 52.6 | 38.6 | 41.6 | 42.9 | 36.9 |
| Mapillary | 22.5 | 13.6 | 82.1 | 55.4 | **67.7** | 2.1 | 9.3 |
| IDD | 14.6 | 6.5 | 72.1 | 41.2 | 51.0 | 1.6 | 6.5 |
| BDD | 14.4 | 7.1 | 70.7 | 52.2 | 54.5 | 1.4 | 6.1 |
| Cityscapes | 13.3 | 6.8 | 76.1 | 30.1 | 57.6 | 1.7 | 6.8 |
| SUN RGBD | 10.0 | 4.3 | 0.1 | 1.9 | 1.1 | 42.6 | 0.3 |
| MSeg-1m | 70.7 | **42.7** | **83.3** | **62.0** | **67.0** | **48.2** | **59.2** |
| MSeg-1m-w/o relabeling | 70.2 | 42.7 | 82.0 | 62.7 | 65.5 | 43.2 | 57.6 |
| Oracle | 77.8 | 45.8 | 78.8 | – | 58.4 | 62.3 | – |

Accuracy on MSeg test datasets




Input image | ADE20K model | Mapillary model | COCO model | MSeg model

# MSeg: A Composite Dataset for Multi-domain Semantic Segmentation

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# Project 6