Semantic Segmentation, PSPNet, and MSeg

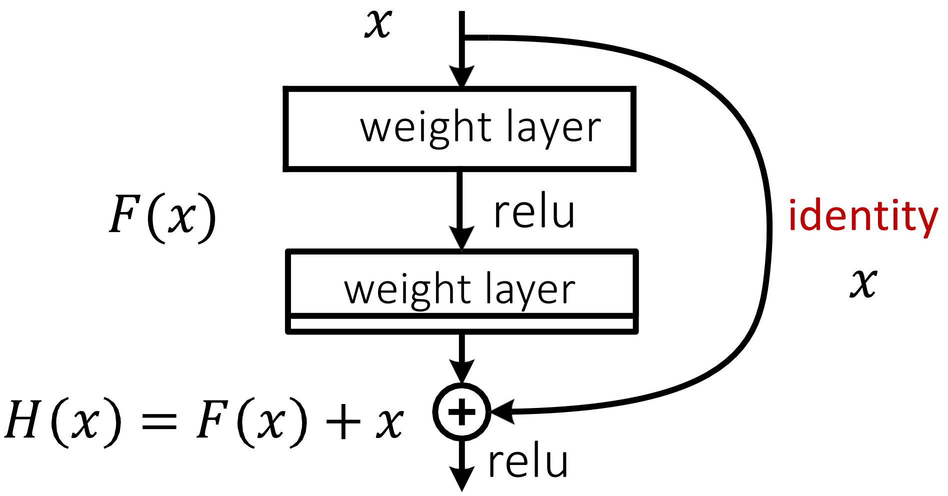
Many slides by John Lambert

Recap

- Big Data
  - The Unreasonable Effectiveness of Data
  - Scene Completion
  - Im2gps
  - Recognition via Tiny Images
- Crowdsourcing
  - “Wisdom of the Crowds” / consensus
  - Find good annotators through grading
  - Pricing affects throughput but not quality
  - User interface and instructions matter a lot

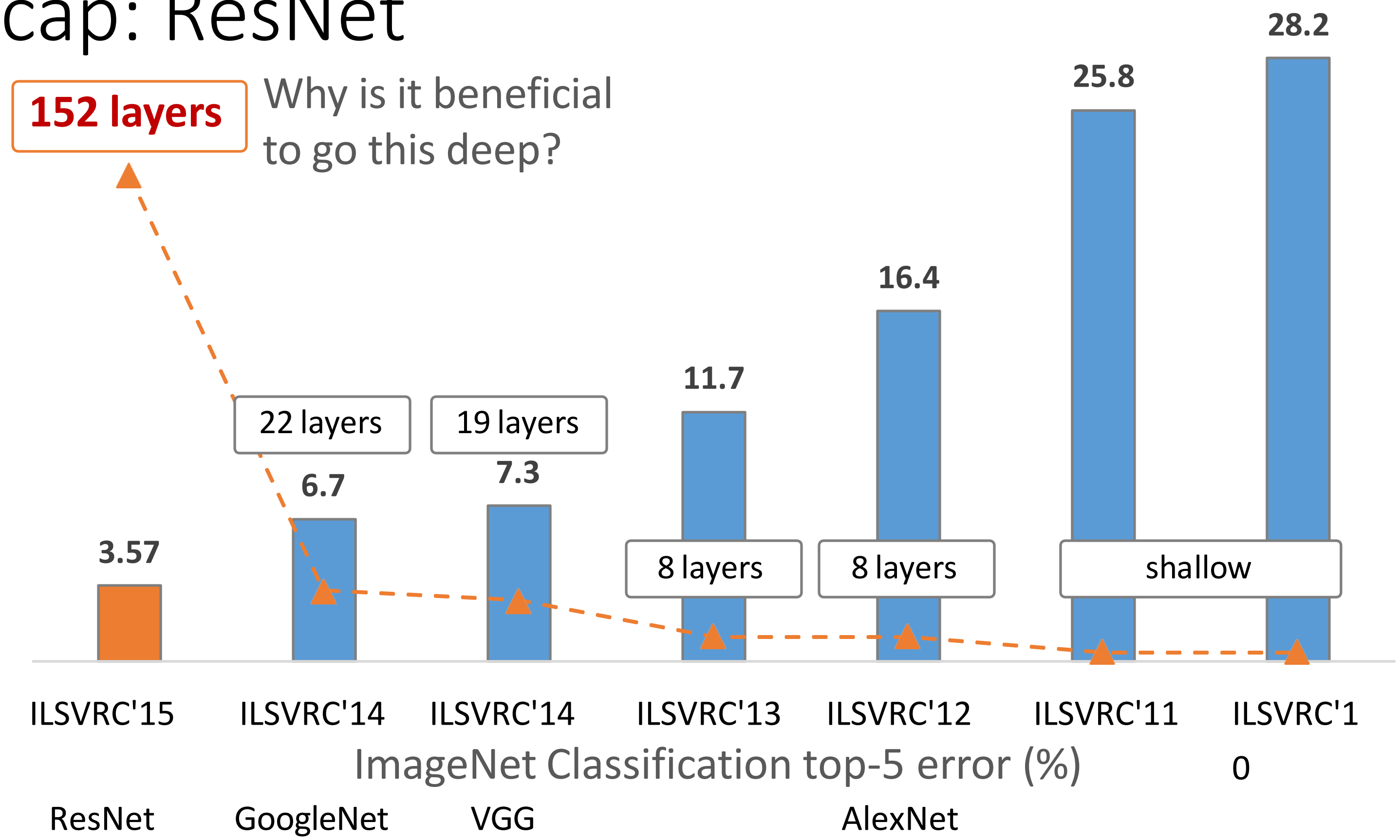
Recap: ResNet

- $F(x)$ is a residual mapping w.r.t. identity



- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identity, easier to find small fluctuations

Recap: ResNet



Semantic Segmentation

Project 4

Dataset

The dataset to be used in this assignment is the Camvid dataset, a small dataset of 701 images for self-driving perception. It was first introduced in 2008 by researchers at the University of Cambridge [1]. You can read more about it at the original dataset page or in the paper describing it. The images have a typical size of around 720 by 960 pixels. We'll downsample them for training though since even at 240 x 320 px, most of the scene detail is still recognizable.

Today there are much larger semantic segmentation datasets for self-driving, like Cityscapes, WildDashV2, Audi A2D2, but they are too large to work with for a homework assignment.

The original Camvid dataset has 32 ground truth semantic categories, but most evaluate on just an 11-class subset, so we'll do the same. These 11 classes are 'Building', 'Tree', 'Sky', 'Car', 'SignSymbol', 'Road', 'Pedestrian', 'Fence', 'Column_Pole', Sidewalk', 'Bicyclist'. A sample collection of the Camvid images can be found below:

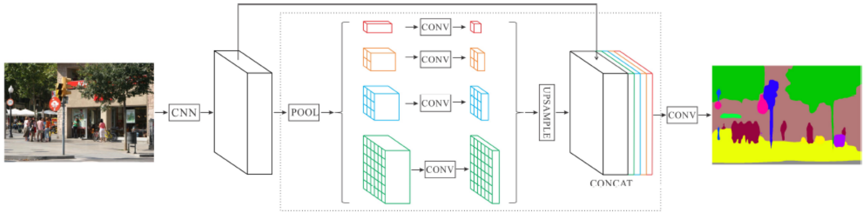
(a) Image A, RGB (b) Image A, Ground Truth (c) Image B, RGB (d) Image B, Ground Truth

Figure 2: Example scenes from the Camvid dataset. The RGB image is shown on the left, and the corresponding ground truth "label map" is shown on the right.

1 Implementation

For this project, the majority of the details will be provided into two separate Jupyter notebooks. The first, `proj4_local.ipynb` includes unit tests to help guide you with local implementation. After finishing that, upload `proj4_colab.ipynb` to Colab. Next, zip up the files for Colab with our script `zip_for_colab.py`, and upload these to your Colab environment.

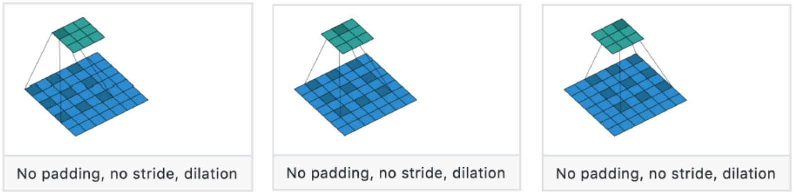
We will be implementing the PSPNet [3] architecture. You can read the original paper here. This network uses a ResNet [2] backbone, but uses *dilation* to increase the receptive field, and aggregates context over different portions of the image with a "Pyramid Pooling Module" (PPM).

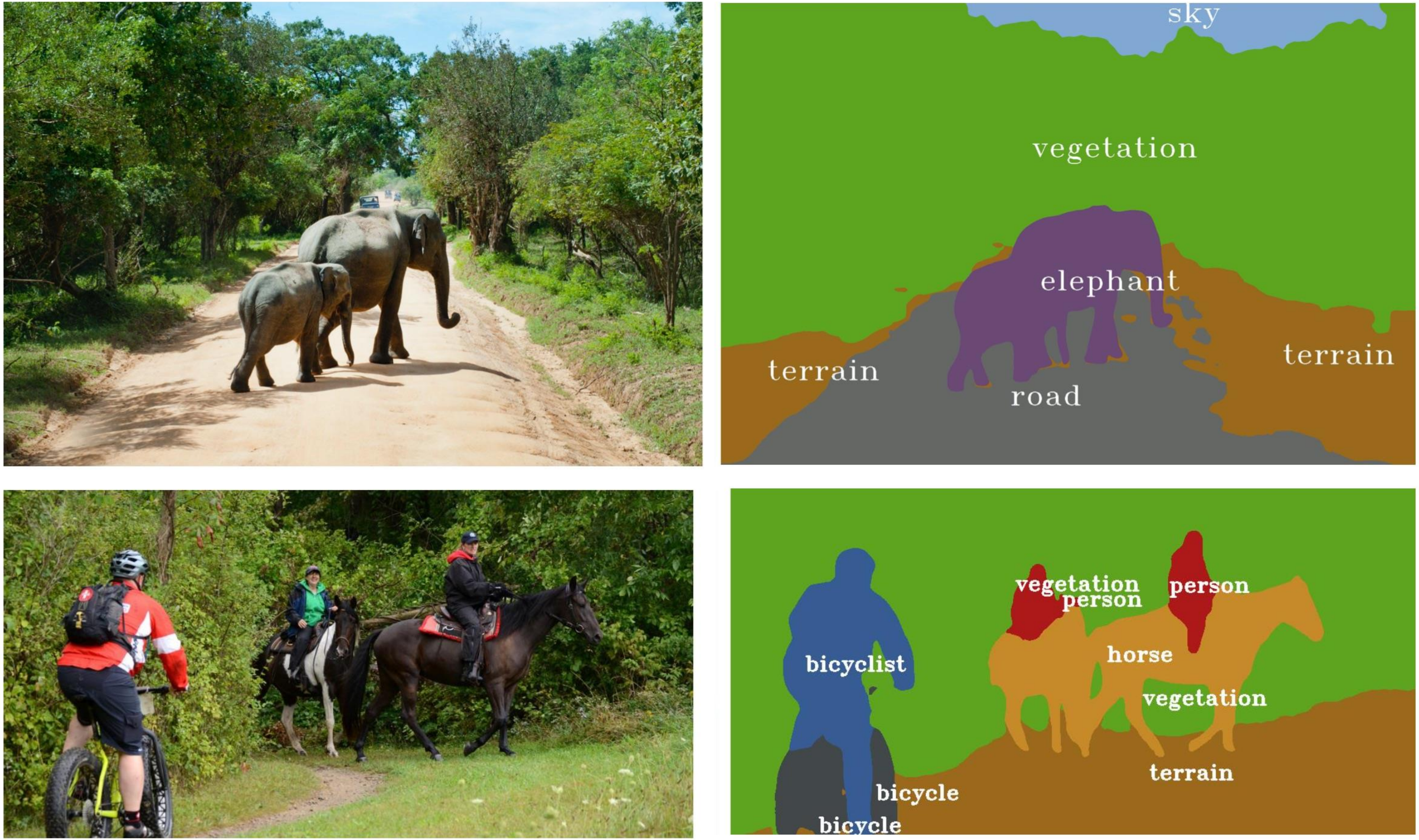


(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

Figure 3: PSPNet architecture. The Pyramid Pooling Module (PPM) splits the $H \times W$ feature map into KxK grids. Here, 1×1, 2×2, 3×3, and 6×6 grids are formed, and features are average-pooled within each grid cell. Afterwards, the 1×1, 2×2, 3×3, and 6×6 grids are upsampled back to the original $H \times W$ feature map resolution, and are stacked together along the channel dimension.

You can read more about dilated convolution in the Dilated Residual Network here, which PSPNet takes some ideas from. Also, you can watch a helpful animation about dilated convolution here.




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

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

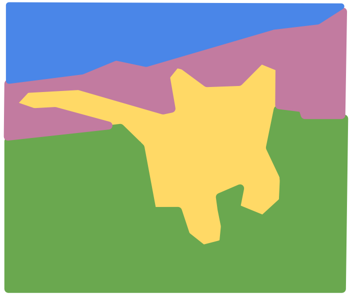
Tasks: Semantic Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

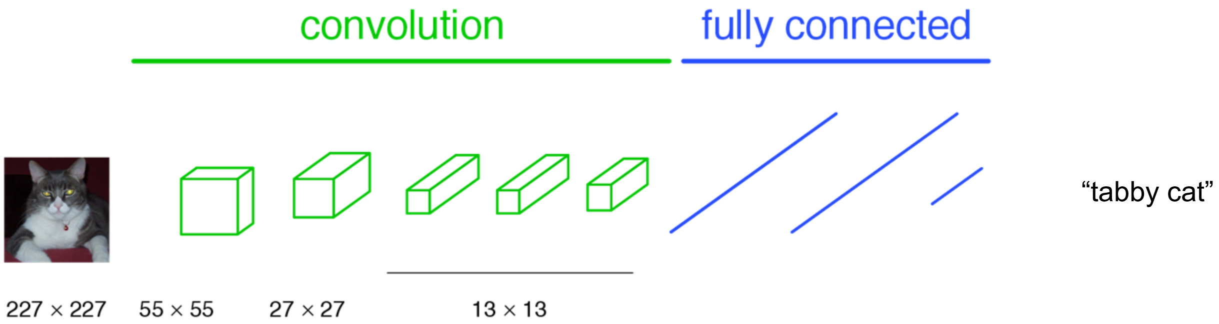
Instance Segmentation

DOG, DOG, CAT

Multiple Objects

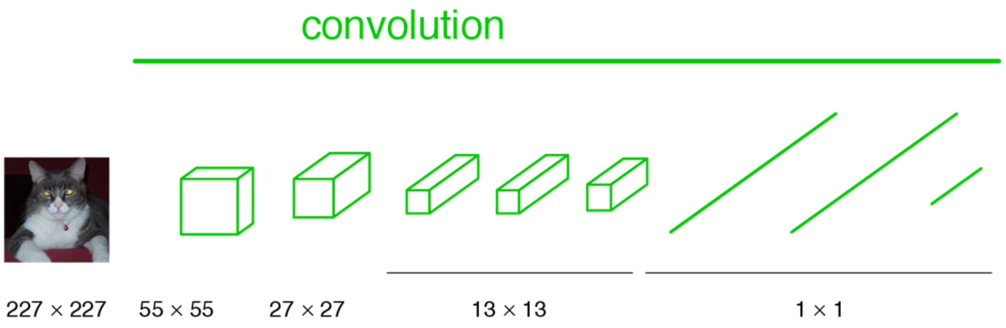
Slide Credit: Justin Johnson and David Fouhey

a classification network



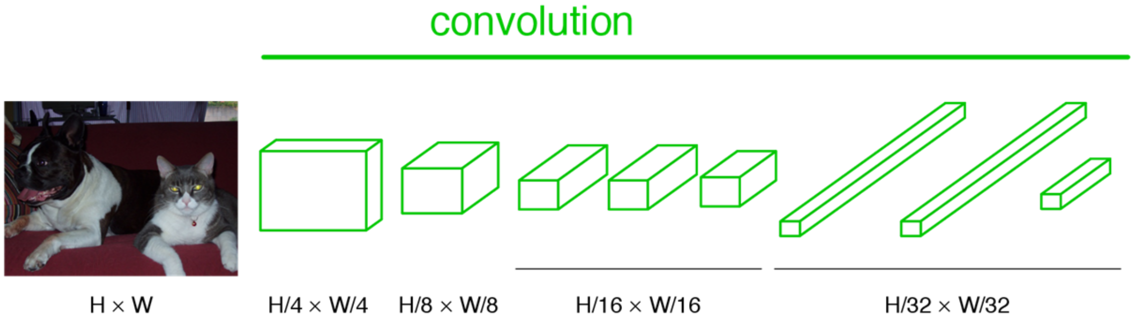
Fully Convolutional Networks for Semantic Segmentation.
Jon Long, Evan Shelhamer, Trevor Darrell. CVPR 2015

becoming fully convolutional

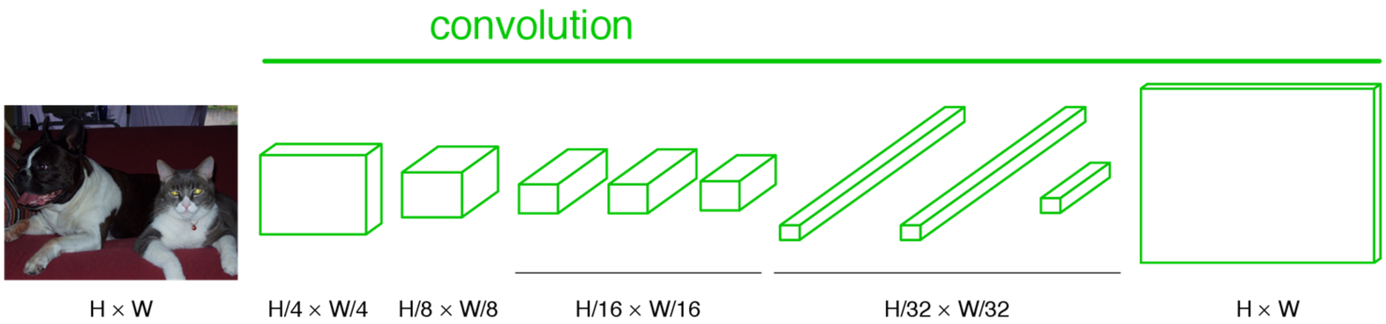


Note: “Fully Convolutional” and “Fully Connected” aren’t the same thing.
They’re almost opposites, in fact.

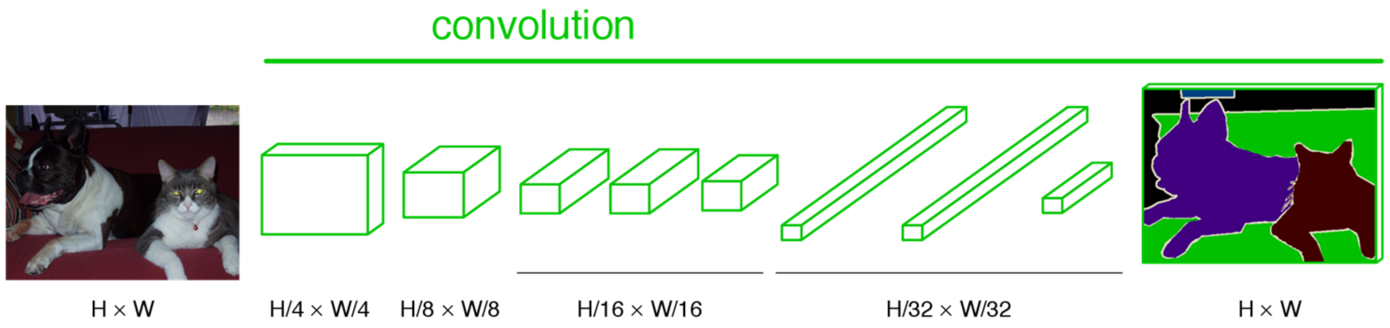
becoming fully convolutional



upsampling output

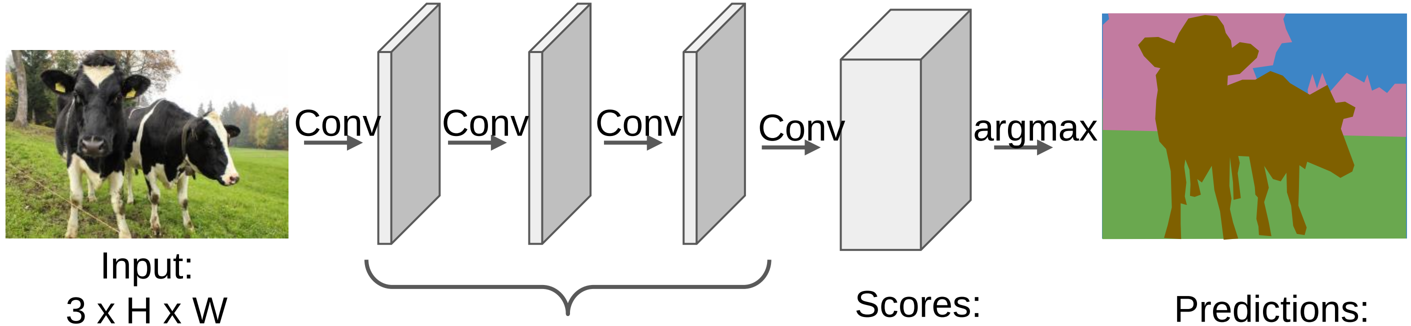


end-to-end, pixels-to-pixels network



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

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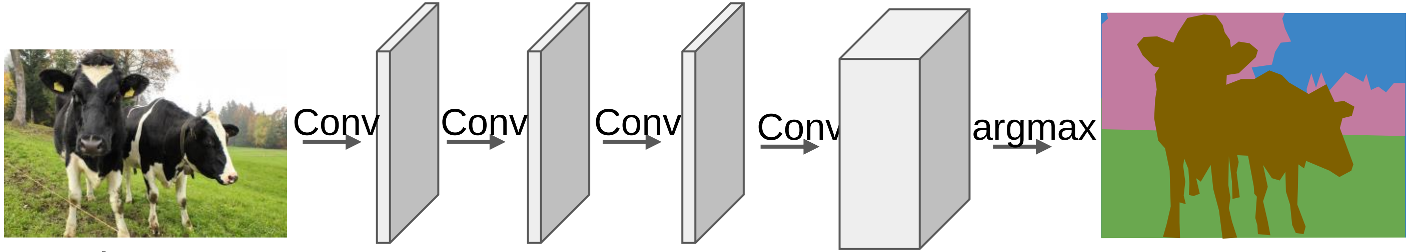
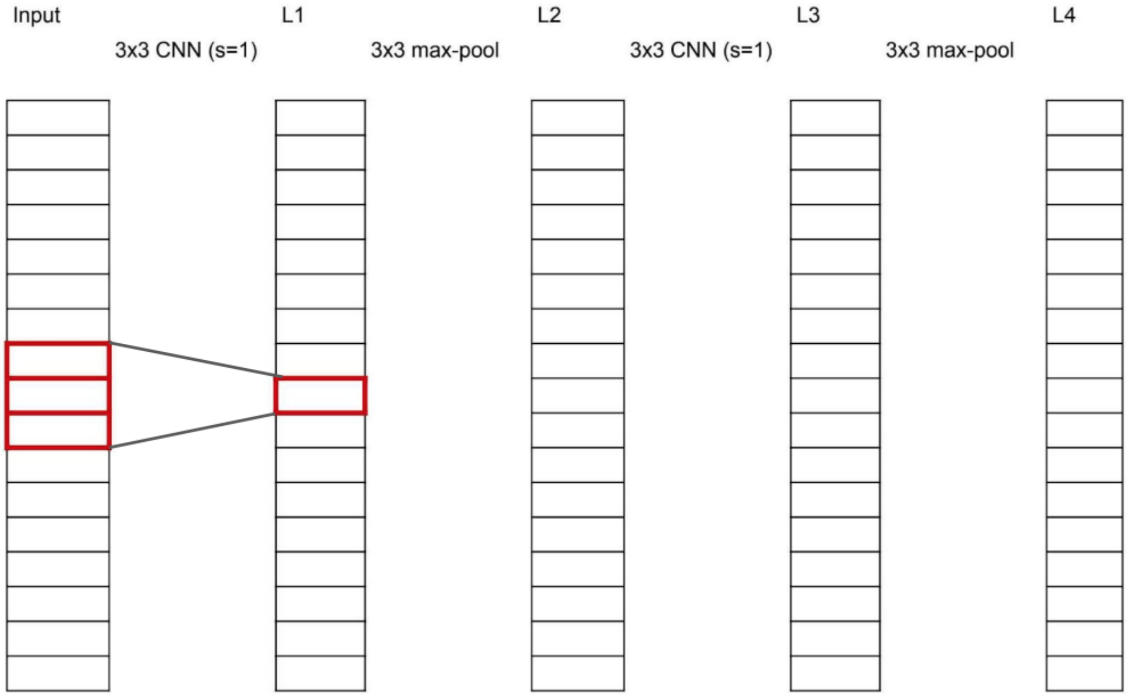


Input:
3 x H x W

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

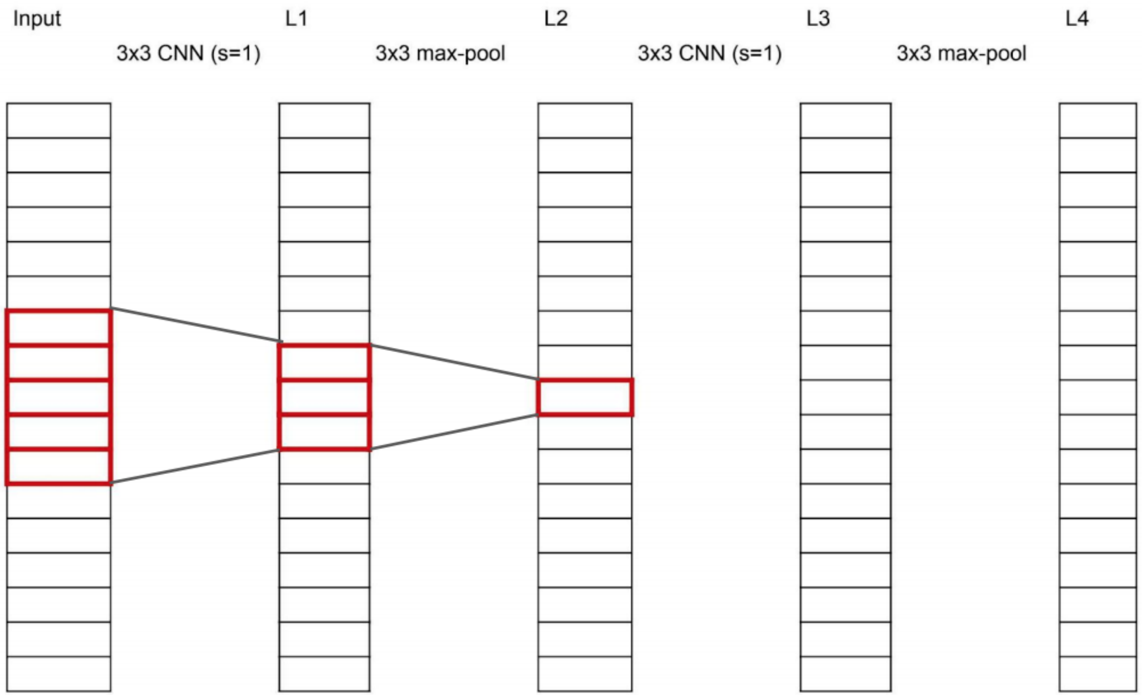
Long et al, “Fully convolutional networks for semantic segmentation”, CVPR 2015

Receptive field



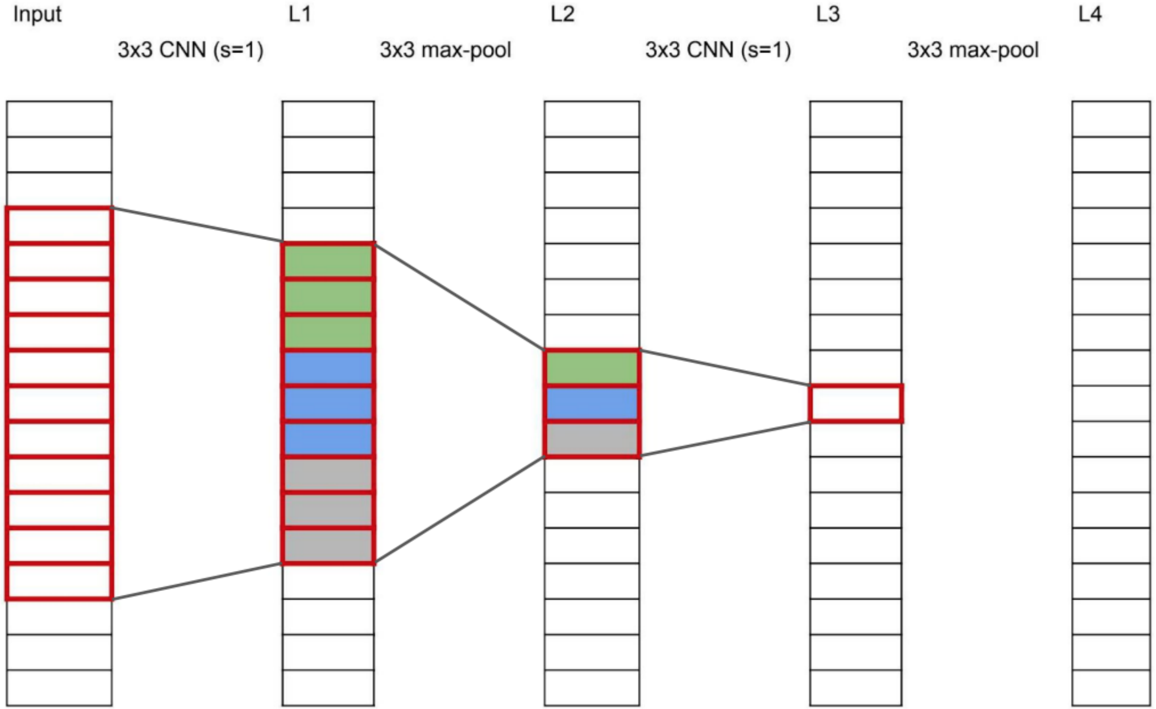
Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

Receptive field



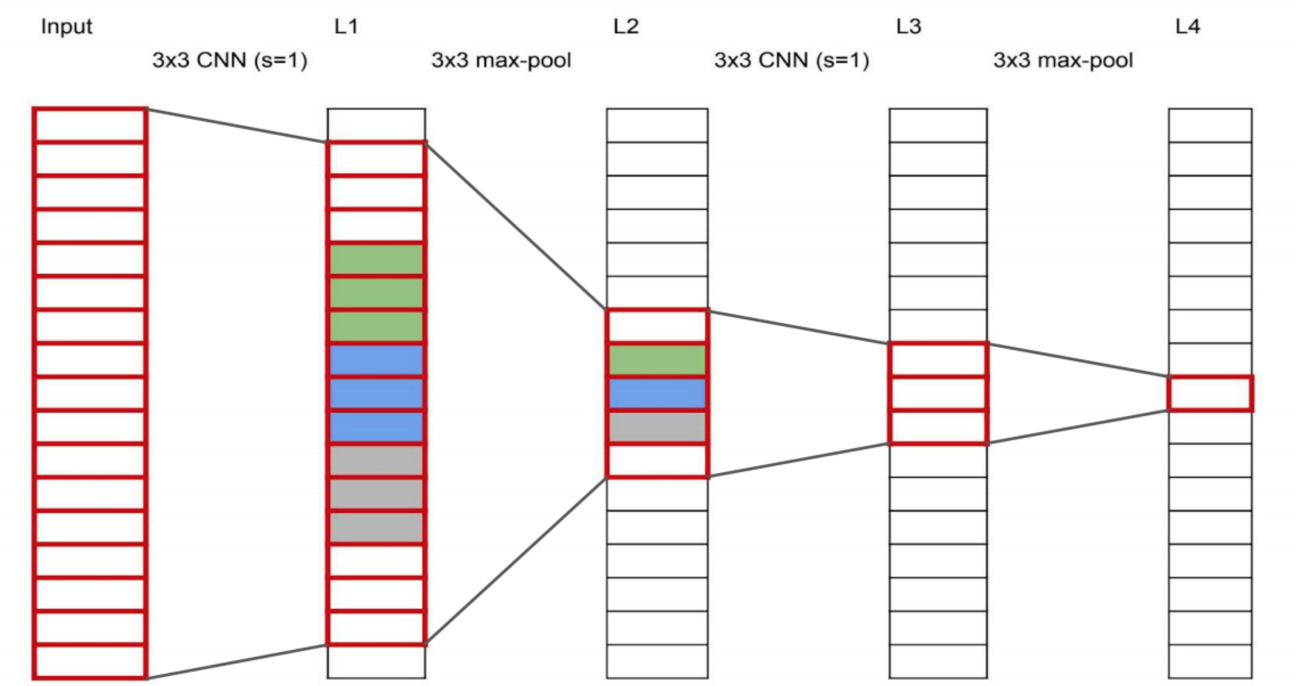
Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

Receptive field



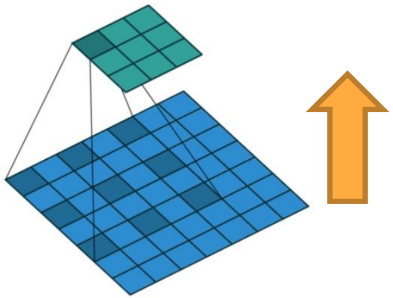
Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

Receptive field

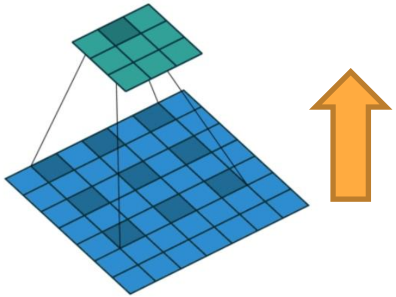


Slide Credit: Frank Dellaert https://dellaert.github.io/19F-4476/resources/receptiveField.pdf

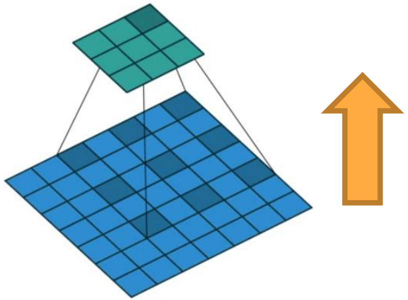
Dilated Convolution



No padding, no stride, dilation



No padding, no stride, dilation

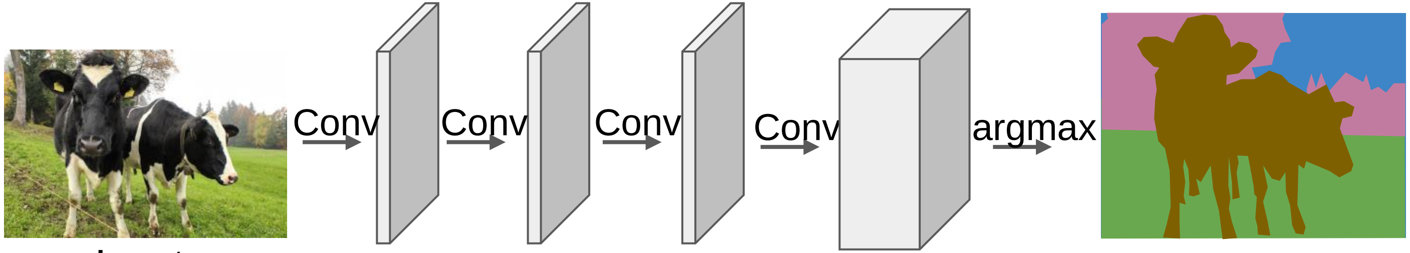


No padding, no stride, dilation

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!

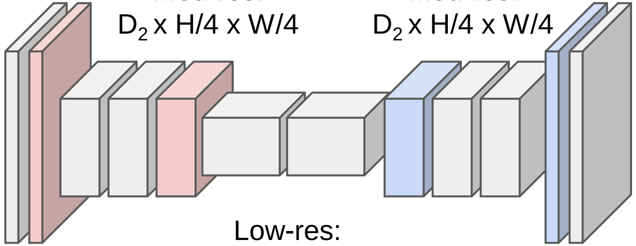
Long et al, “Fully convolutional networks for semantic segmentation”, CVPR 2015

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



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

$$\begin{bmatrix}1 & 2\\ 3 & 4\end{bmatrix} \rightarrow \begin{bmatrix}1 & 0 & 2 & 0\\ 0 & 0 & 0 & 0\\ 3 & 0 & 4 & 0\\ 0 & 0 & 0 & 0\end{bmatrix}$$

Input
C x 2 x 2

Output
C x 4 x 4

Nearest Neighbor

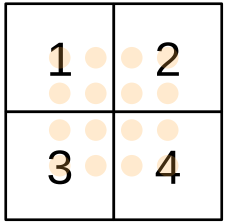
$$\begin{bmatrix}1 & 2\\ 3 & 4\end{bmatrix} \rightarrow \begin{bmatrix}1 & 1 & 2 & 2\\ 1 & 1 & 2 & 2\\ 3 & 3 & 4 & 4\\ 3 & 3 & 4 & 4\end{bmatrix}$$

Input
C x 2 x 2

Output
C x 4 x 4

Slide Credit: Justin Johnson and David Fouhey

Upsampling: Bilinear Interpolation



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

Input: C x 2 x 2

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

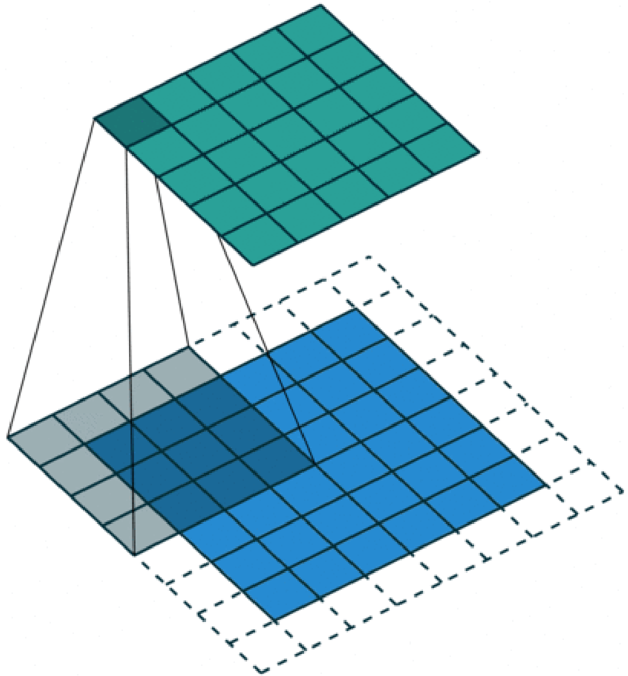
Slide Credit: Justin Johnson and David Fouhey

Upsampling: Transpose Convolution

Sometimes called "Deconvolution" but that is a problematic name

I like the term "broadcast" convolution

In this case, the filter is 4x4 and the outer boundary of the output is unused



A guide to convolution arithmetic for deep learning
Vincent Dumoulin, Francesco Visin

Upsampling: Transpose Convolution

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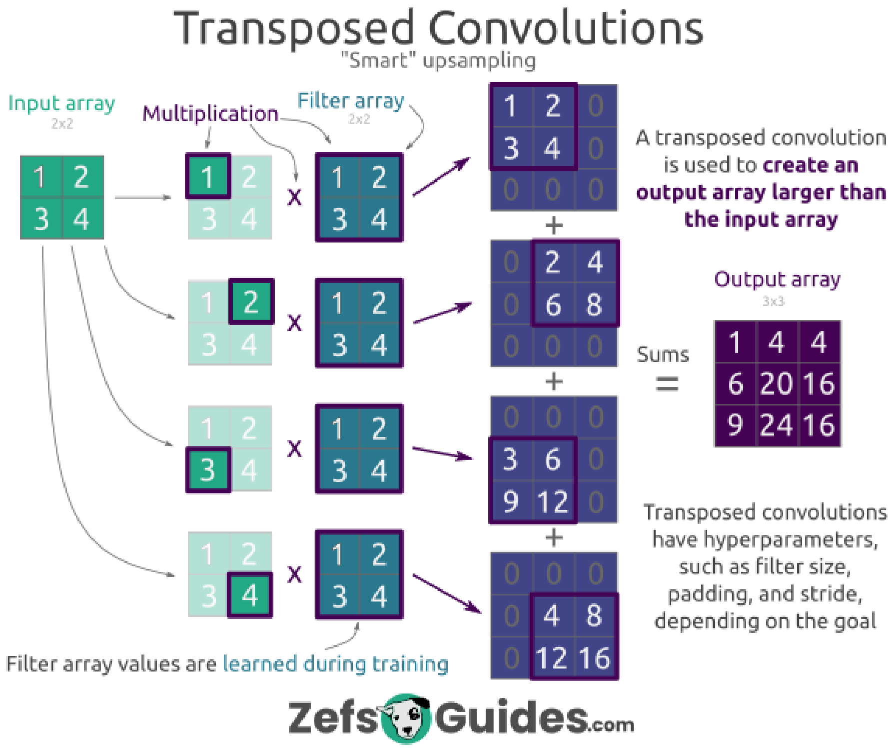
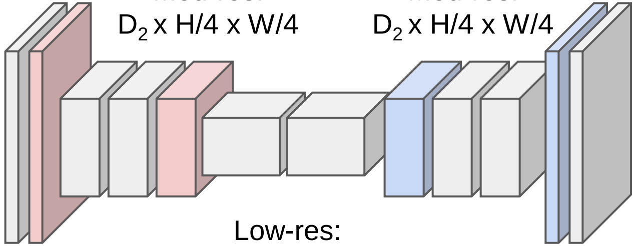


Fully Convolutional Network

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

Input:
$3 \times H \times W$



Predictions:
$H \times W$

Downsampling:
Pooling, strided convolution

Upsampling:
???

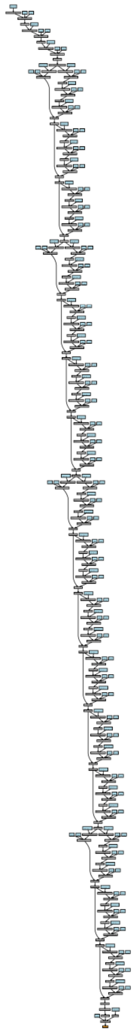
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Slide Credit: Justin Johnson and David Fouhey

PSPNet

PSPNet uses a ResNet backbone

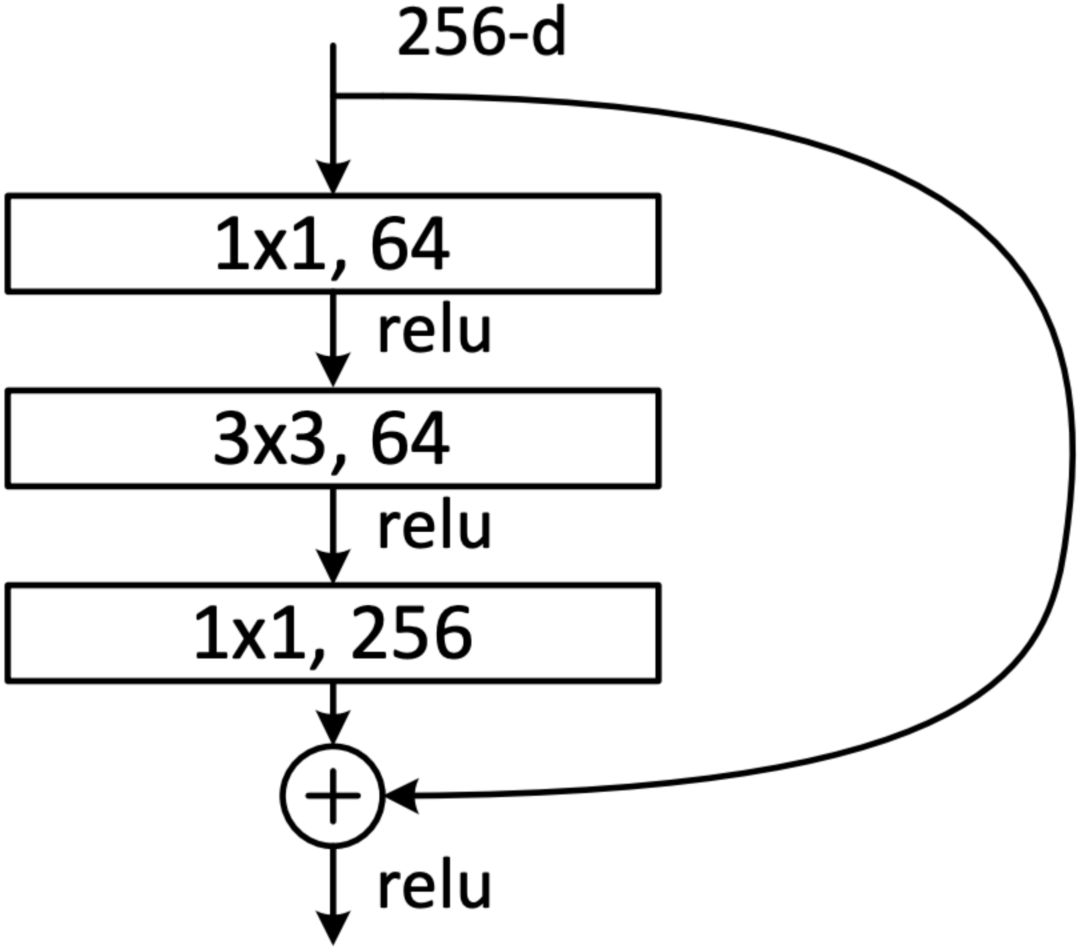
- 50, 101, or 152 Layers
- 50 Layers is already quite deep!



3.2. Pyramid Pooling Module

With above analysis, in what follows, we introduce the pyramid pooling module, which empirically proves to be an effective global contextual prior.

In a deep neural network, the size of receptive field can roughly indicates how much we use context information. Although theoretically the receptive field of ResNet [13] is already larger than the input image, it is shown by Zhou *et al*. [42] that the empirical receptive field of CNN is much smaller than the theoretical one especially on high-level layers. This makes many networks not sufficiently incorporate



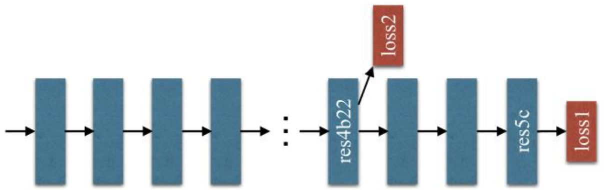
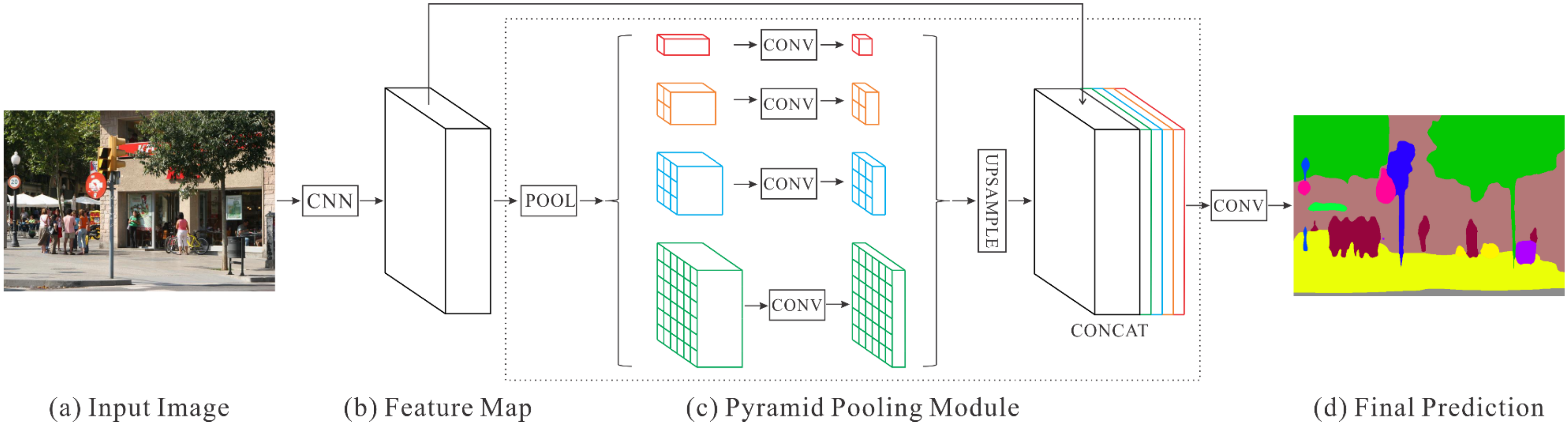


Figure 4. Illustration of auxiliary loss in ResNet101. Each blue box denotes a residue block. The auxiliary loss is added after the res4b22 residue block.

Pyramid Scene Parsing Network

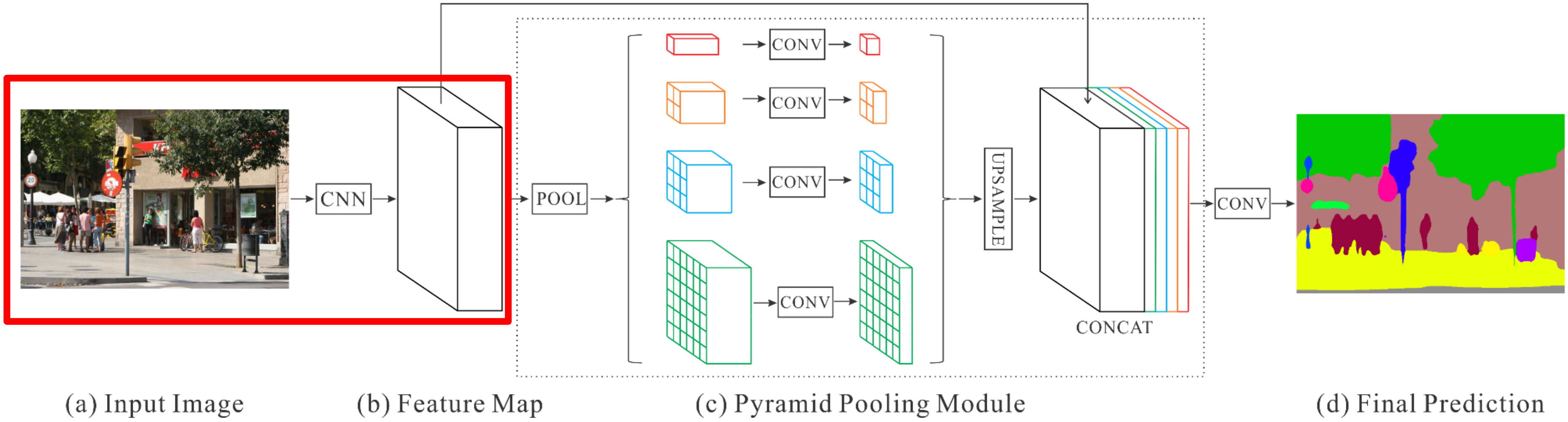


Framework overview of PSPNet

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [15,000+ citation]

Slide Credit: Hengshuang Zhao and Jiaya Jia

Pyramid Scene Parsing Network

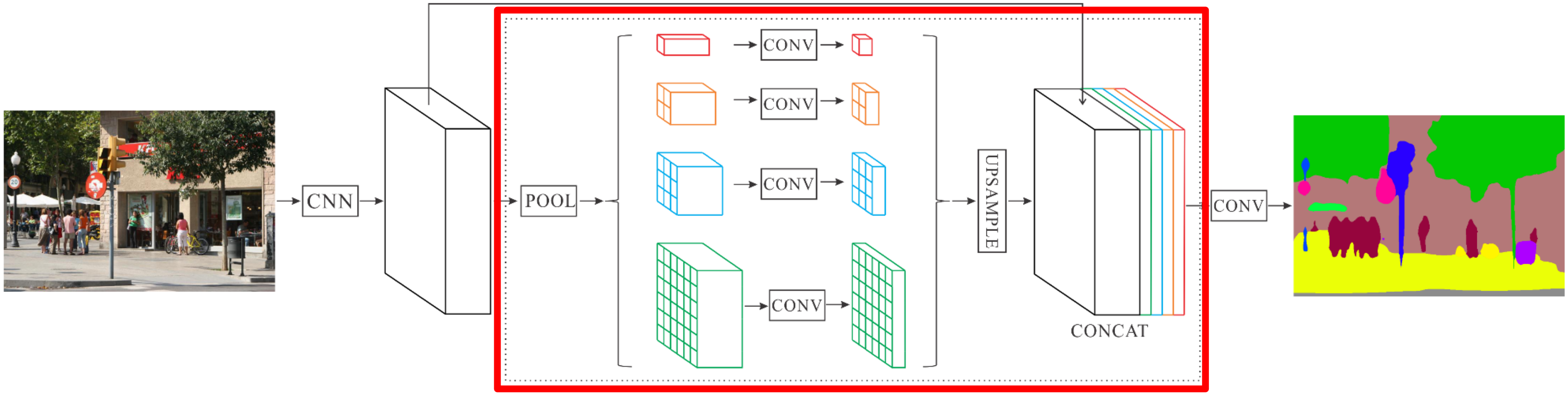


Regular feature extractor

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [15,000+ citation]

Slide Credit: Hengshuang Zhao and Jiaya Jia

Pyramid Scene Parsing Network



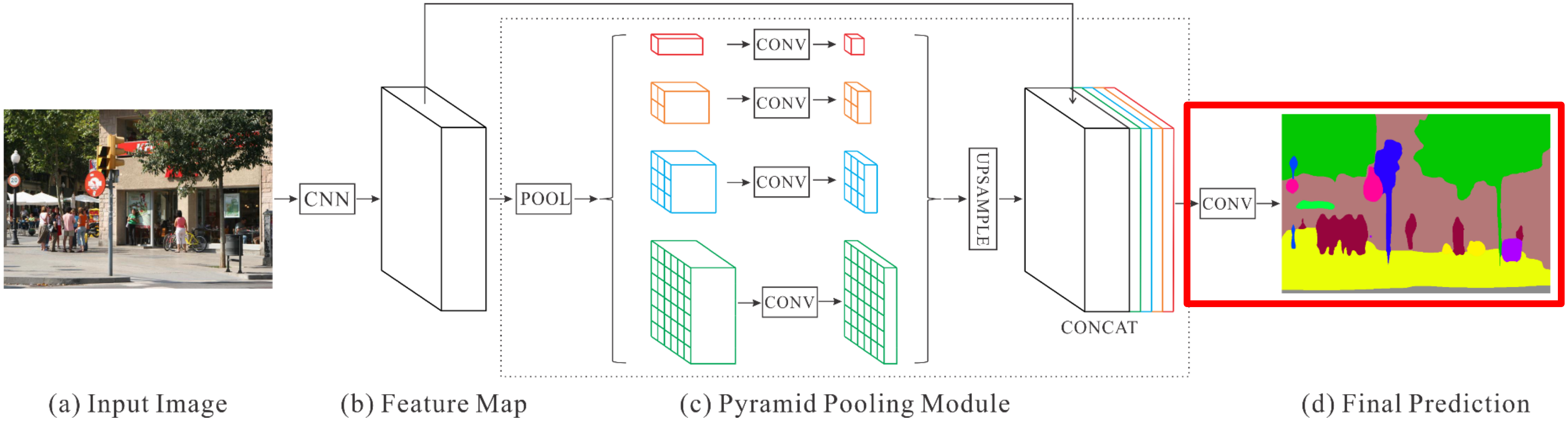
(a) Input Image (b) Feature Map (c) Pyramid Pooling Module (d) Final Prediction

Context modeling: pyramid pooling module

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [15,000+ citation]

Slide Credit: Hengshuang Zhao and Jiaya Jia

Pyramid Scene Parsing Network

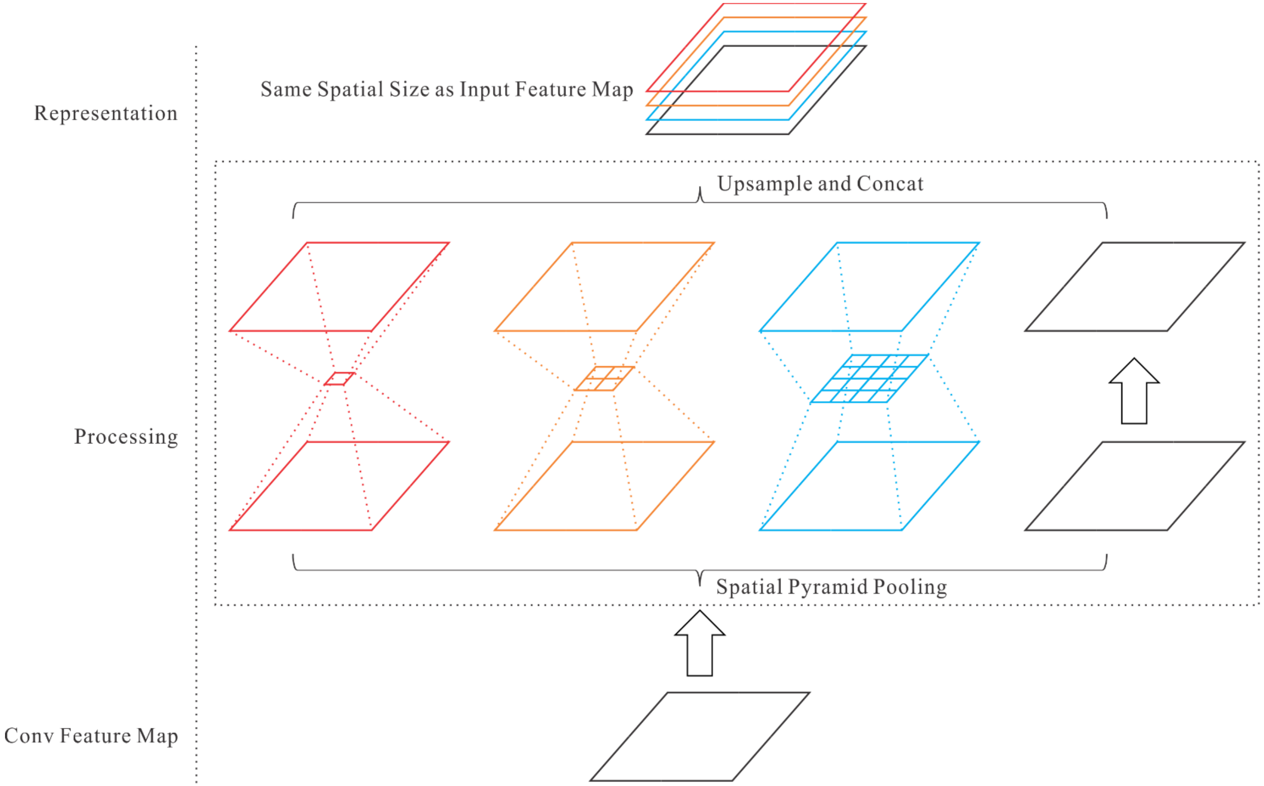


Convolutional classifier for pixel-wise prediction

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [15,000+ citation]

Slide Credit: Hengshuang Zhao and Jiaya Jia

Pyramid Pooling Module



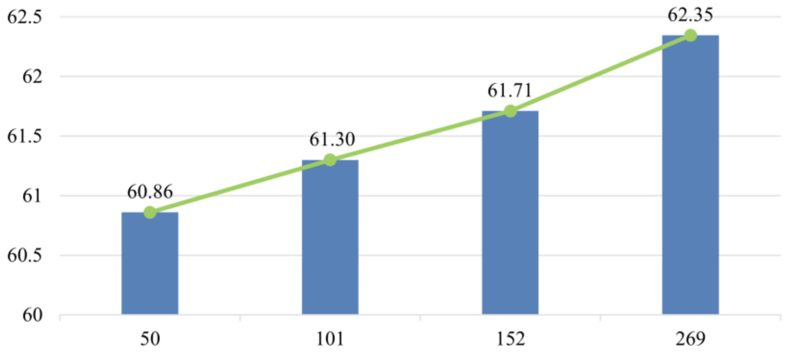
PPM: spatial illustration

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

Hengshuang Zhao[1] Jianping Shi[2] Xiaojuan Qi[1] Xiaogang Wang[1] Jiaya Jia[1]
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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


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, ...

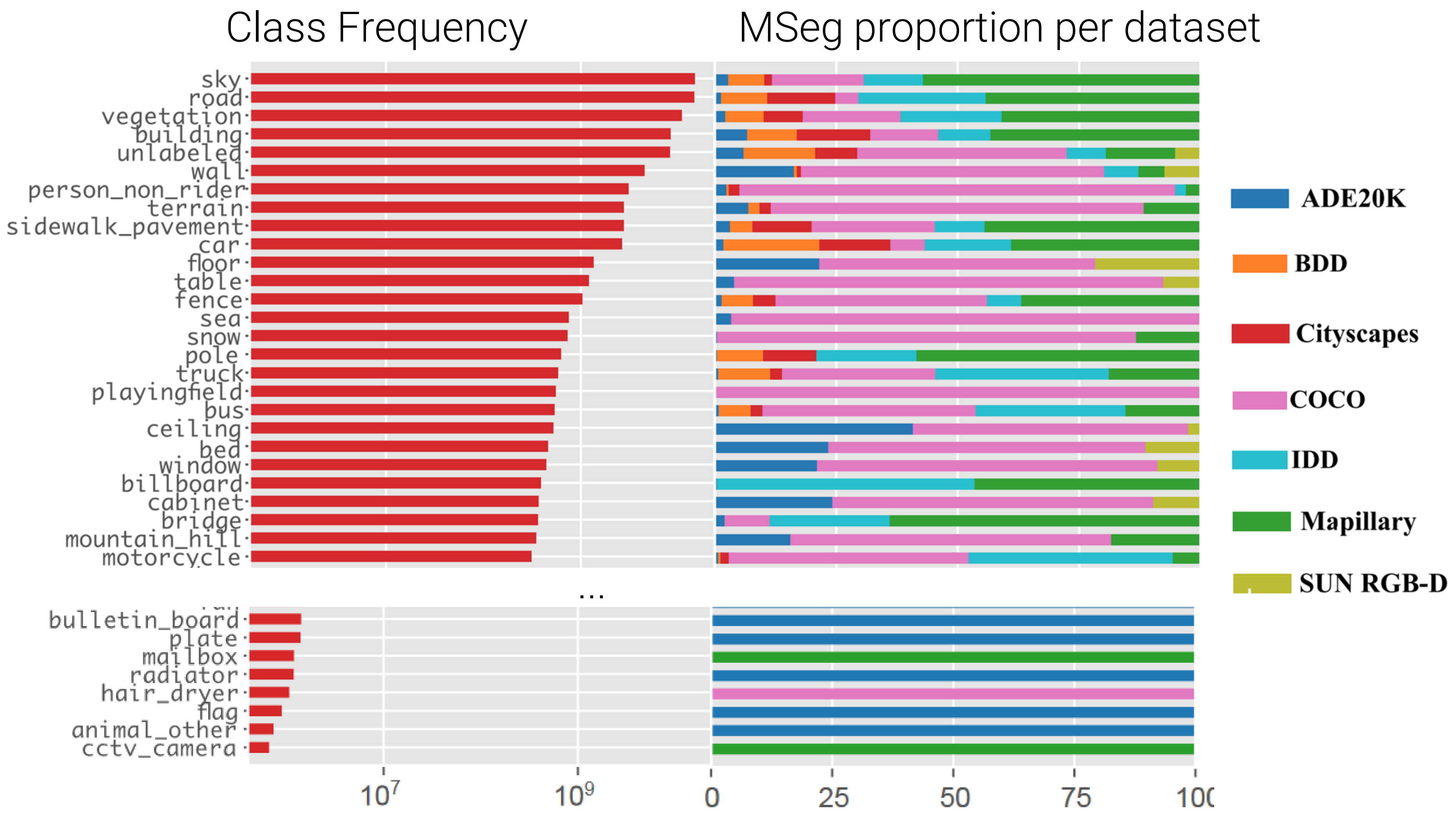
Multi-domain: COCO, ADE20K, PASCAL VOC, ...

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

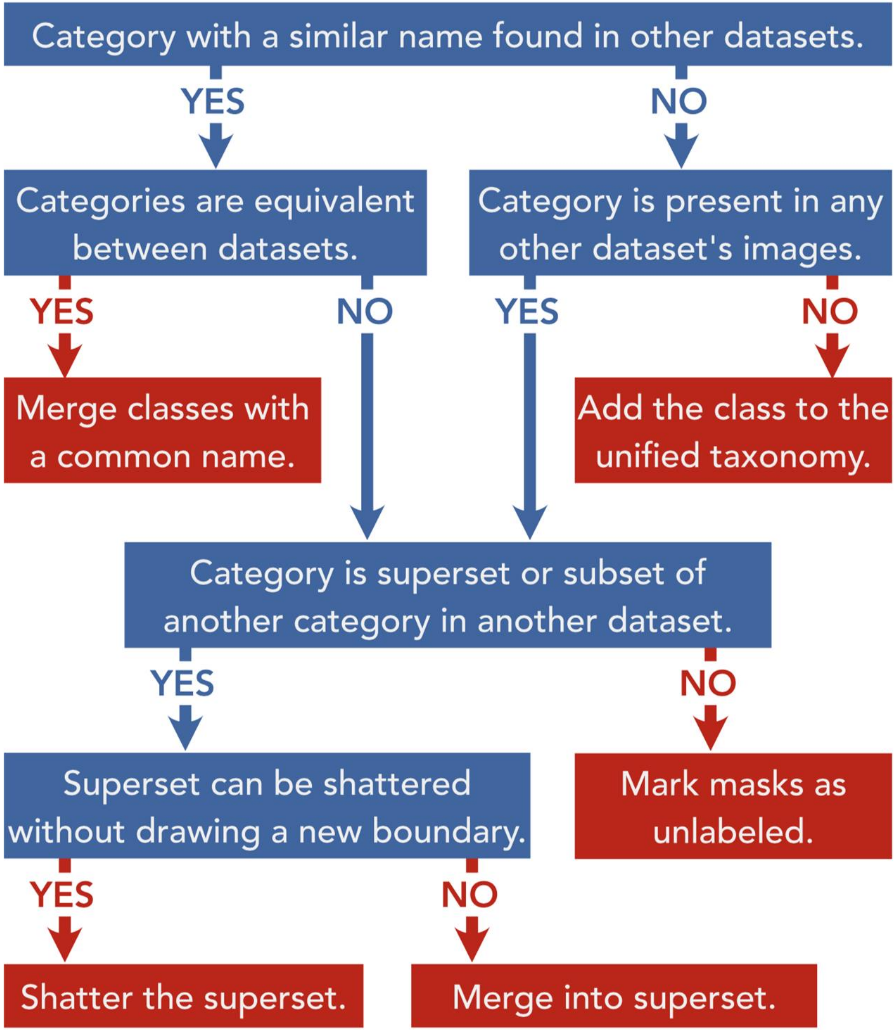
- Perform a training/test split at the level of datasets
- Train on many diverse datasets
- Test on datasets that were never seen during training
- Zero-shot cross-dataset transfer is a proxy for generality and robustness in the real world

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
Building
Television
Floor
Rug
Armchair
Bench
Chair-other
Ottoman
Seat
Stool
Swivelchair
Sofa
Chandelier
Lamp
Light-other
Sconce
Streetlight
A
A
A
B
A
C
B
Building
Phone Booth
Building
A
Sidewalk
Curb
Curb Cut
Pedestrian Area
Pavement
B
Floor - Wood
Floor - Other
Rug
Floor
Rug
A
Chandelier
Lamp
Light
Sconce
Streetlight
Light-other
C
Pavement
Road
Runway
Pavement - Sidewalk
Road
D
Non-rider
Bicyclist
Person
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
Armchair
Basket
Bench
Chair-Other
Ottoman
Chair
Seat
Slow Wheeled Object
Stool
Swivel Chair
B
Bath. Counter
Counter - other
Counter
Kitchen Island
Cabinet
Desk
Table
Nightstand
Dining Table
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

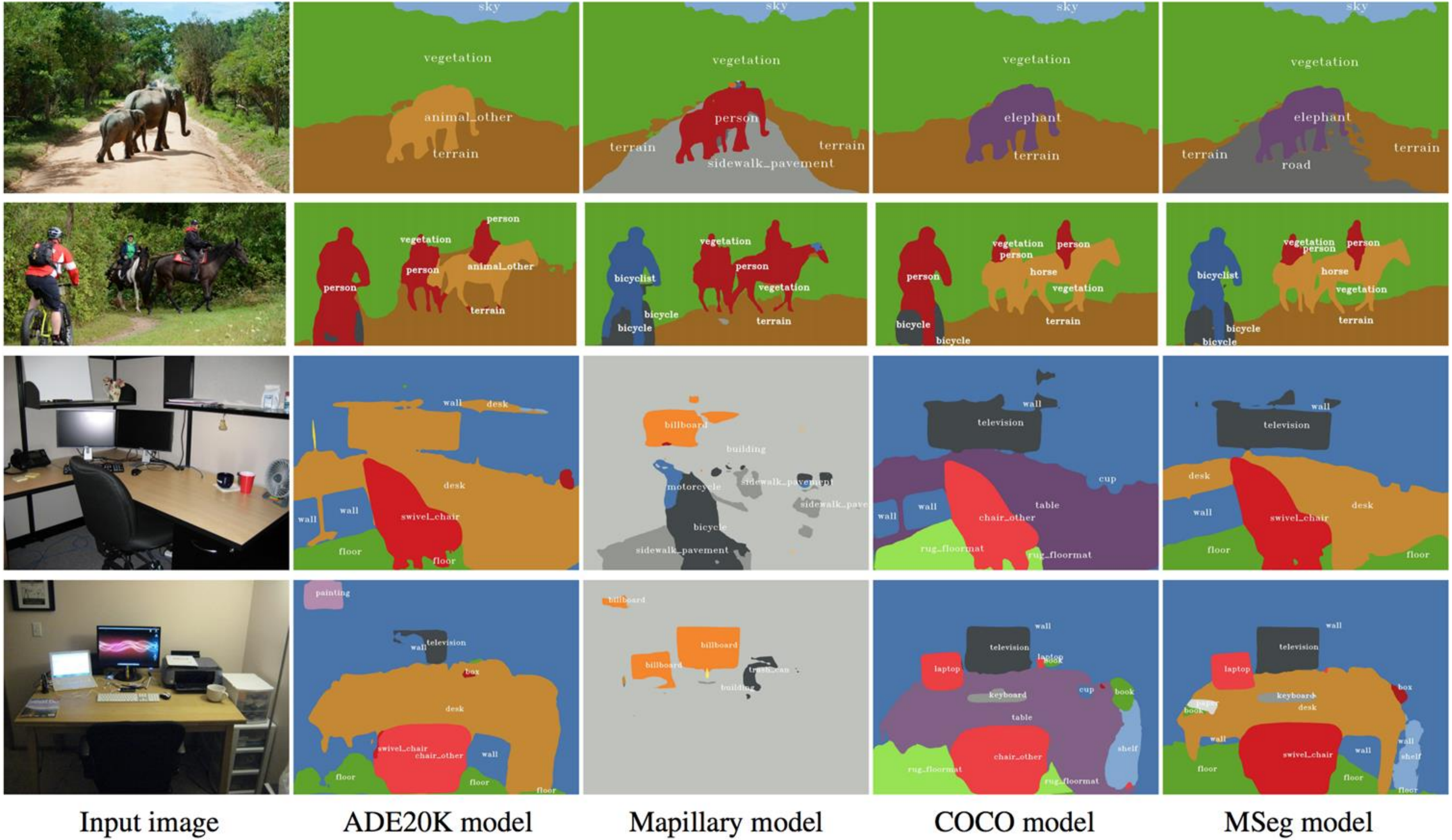
Train/Test	COCO	ADE20K	Mapillary	IDD	BDD	Cityscapes	SUN	*h. mean*
COCO	**52.7**	19.1	28.4	31.1	44.9	46.9	29.6	32.4
ADE20K	14.6	**45.6**	24.2	26.8	40.7	44.3	36.0	28.7
Mapillary	7.0	6.2	**53.0**	50.6	59.3	71.9	0.3	1.7
IDD	3.2	3.0	24.6	**64.9**	42.4	48.0	0.4	2.3
BDD	3.8	4.2	23.2	32.3	63.4	58.1	0.3	1.6
Cityscapes	3.4	3.1	22.1	30.1	44.1	77.5	0.2	1.2
SUN RGBD	3.4	7.0	1.1	1.0	2.2	2.6	43.0	2.1
MSeg-w/o relabeling	50.4	**45.4**	**53.1**	**65.1**	66.5	**79.5**	**49.9**	**56.6**
MSeg	50.7	**45.7**	**53.1**	**65.3**	**68.5**	**80.4**	**50.3**	**57.1**

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**

Accuracy on MSeg *training* datasets

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



sky
vegetation
animal_other
terrain
person
sidewalk_pavement
elephant
road
bicyclist
bicycle
horse
wall
desk
swivel_chair
floor
billboard
building
motorcycle
television
cup
table
chair_other
rug_floormat
painting
box
laptop
keyboard
book
shelf
trash_can
Input image
ADE20K model
Mapillary model
COCO model
MSeg model

MSeg: A Composite Dataset for Multi-domain Semantic Segmentation

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

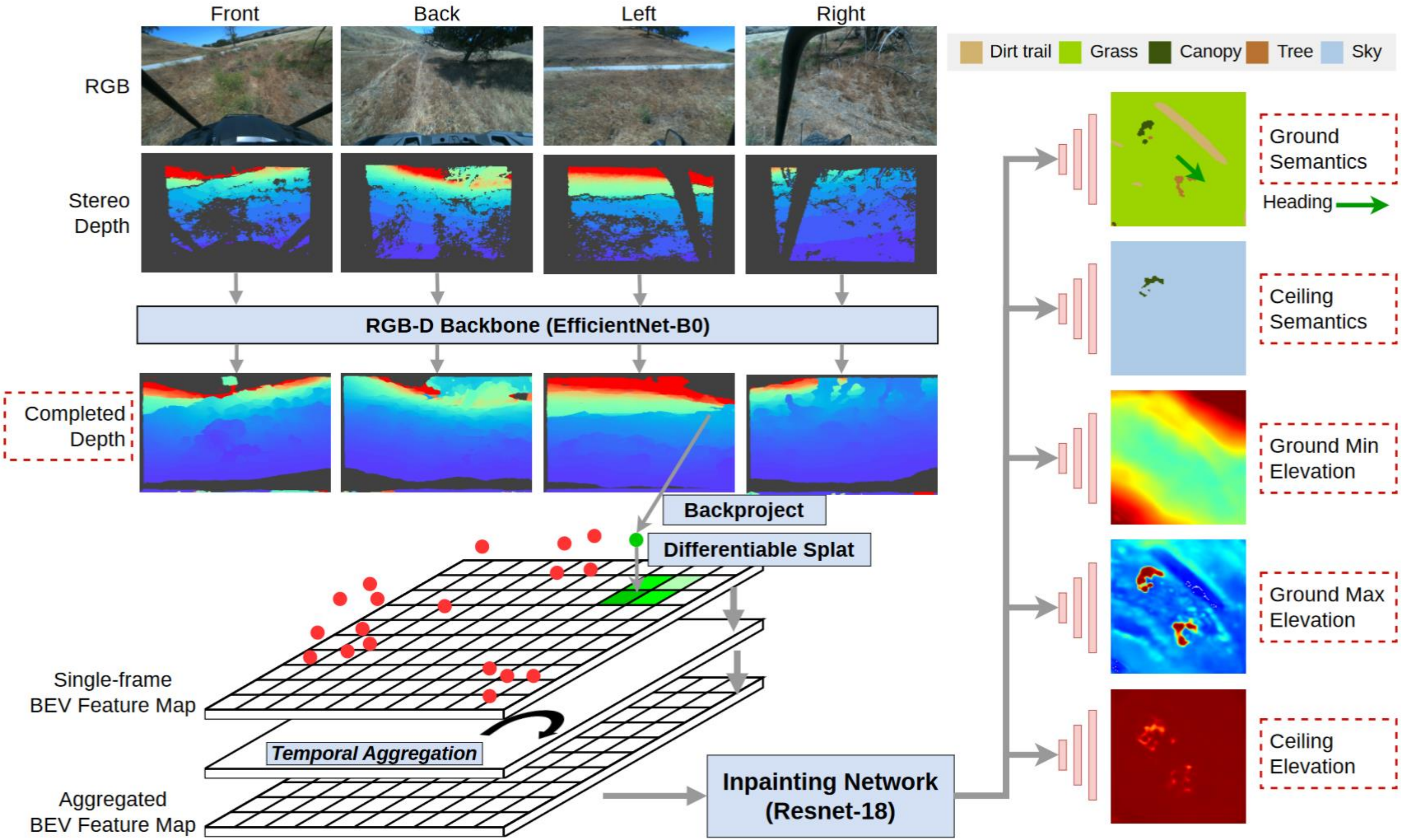
intel

Berkeley
UNIVERSITY OF CALIFORNIA

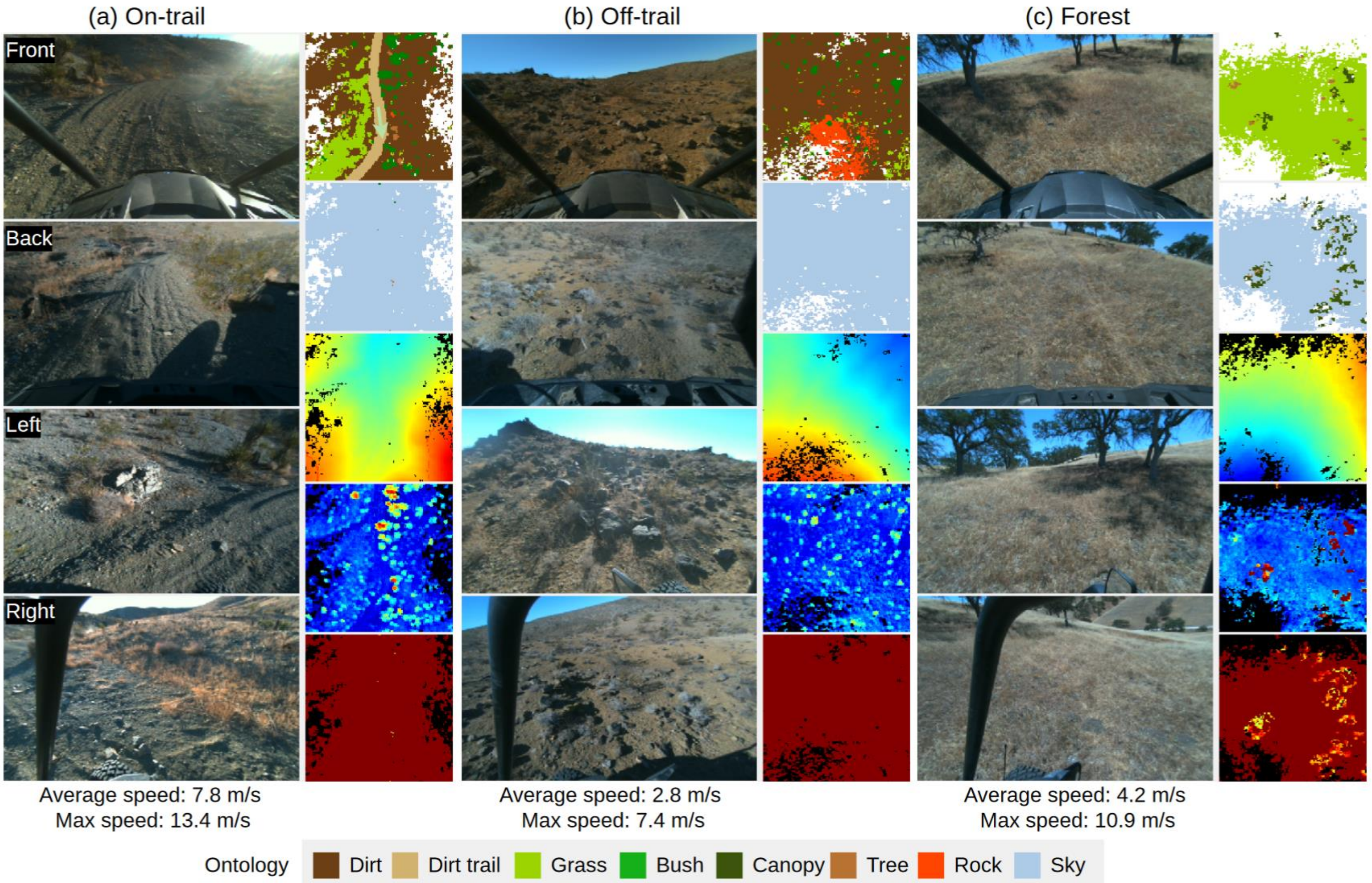
Georgia
Tech

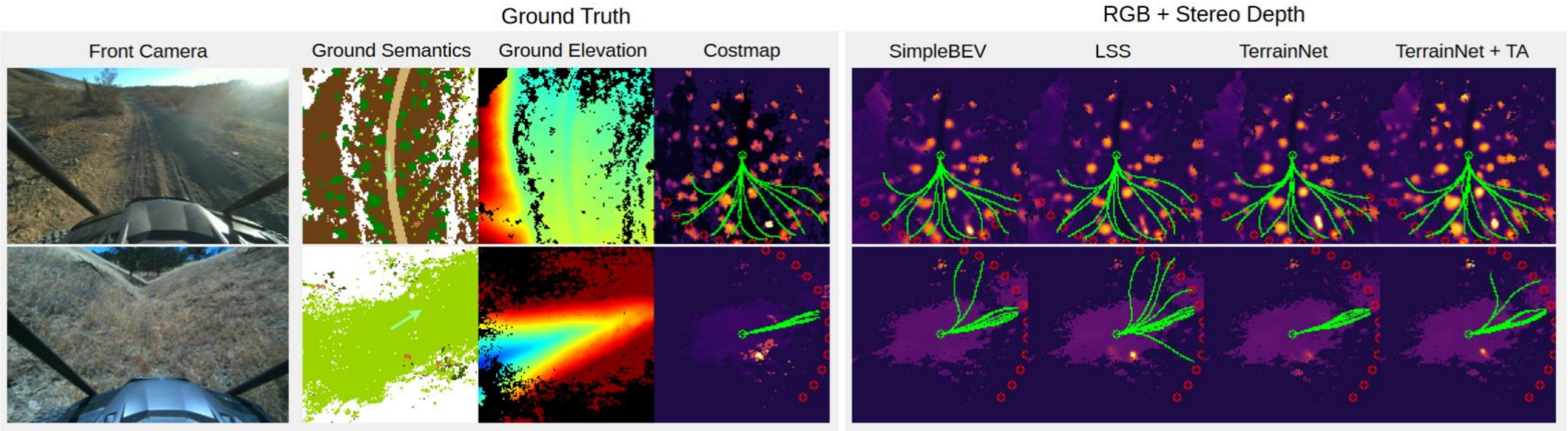
“Bird’s eye” Semantic Segmentation for Robots

TerrainNet: Visual Modeling of Complex Terrain for High-speed, Off-road Navigation
Xiangyun Meng, Nathan Hatch, Alexander Lambert, Anqi Li, Nolan Wagener, Matthew Schmittle, JoonHo Lee, Wentao Yuan, Zoey Chen, Samuel Deng, Greg Okopal, Dieter Fox, Byron Boots, Amirreza Shaban



Front
Back
Left
Right
RGB
Stereo Depth
Dirt trail
Grass
Canopy
Tree
Sky
RGB-D Backbone (EfficientNet-B0)
Completed Depth
Backproject
Differentiable Splat
Single-frame BEV Feature Map
Temporal Aggregation
Aggregated BEV Feature Map
Inpainting Network (Resnet-18)
Ground Semantics
Heading
Ceiling Semantics
Ground Min Elevation
Ground Max Elevation
Ceiling Elevation


(a) On-trail
(b) Off-trail
(c) Forest
Front
Back
Left
Right
Average speed: 7.8 m/s
Max speed: 13.4 m/s
Average speed: 2.8 m/s
Max speed: 7.4 m/s
Average speed: 4.2 m/s
Max speed: 10.9 m/s
Ontology
Dirt
Dirt trail
Grass
Bush
Canopy
Tree
Rock
Sky



Ground Truth
RGB + Stereo Depth
Front Camera
Ground Semantics
Ground Elevation
Costmap
SimpleBEV
LSS
TerrainNet
TerrainNet + TA

Project 4