High Level Computer Vision

Deep Learning for Computer Vision
Part 3

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https://www.mpi-inf.mpg.de/hlcv

Overview Today

- Deep residual learning for image recognition
  - [He,Zhang,Ren,Sun@cvpr16] - https://arxiv.org/abs/1512.03385
- From detection to segmentation
  - Main Reading: Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs, Chen, Papandreou, Kokkins, Murphy, Yuille, ICLR'15 - https://arxiv.org/abs/1412.7062
  - Also
    - Hypercolumns for object segmentation and fine-grained localization
      Bharath Hariharan, Pablo Arbeláez, Ross Girshick, Jitendra Malik, CVPR'15
      https://arxiv.org/abs/1411.5752
    - Fully Convolutional Networks for Semantic Segmentation
      John Long, Evan Shelhamer, Trevor Darelle, CVPR'15
      https://arxiv.org/abs/1411.4038
- Cityscapes - https://www.cityscapes-dataset.com

1. Deep Residual Learning for Image Recognition

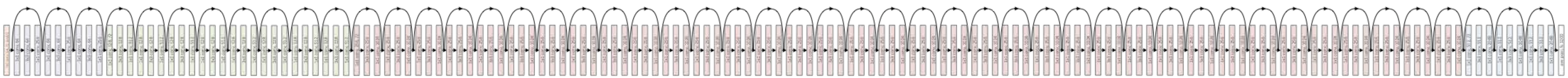
- Deep residual learning for image recognition
  He,Zhang,Ren,Sun@cvpr16
  https://arxiv.org/abs/1512.03385

- Following slides from first authors of the paper: **Kaiming He**

Deep Residual Learning for Image Recognition

Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun

work done at
Microsoft Research Asia



ResNet @ ILSVRC & COCO 2015 Competitions

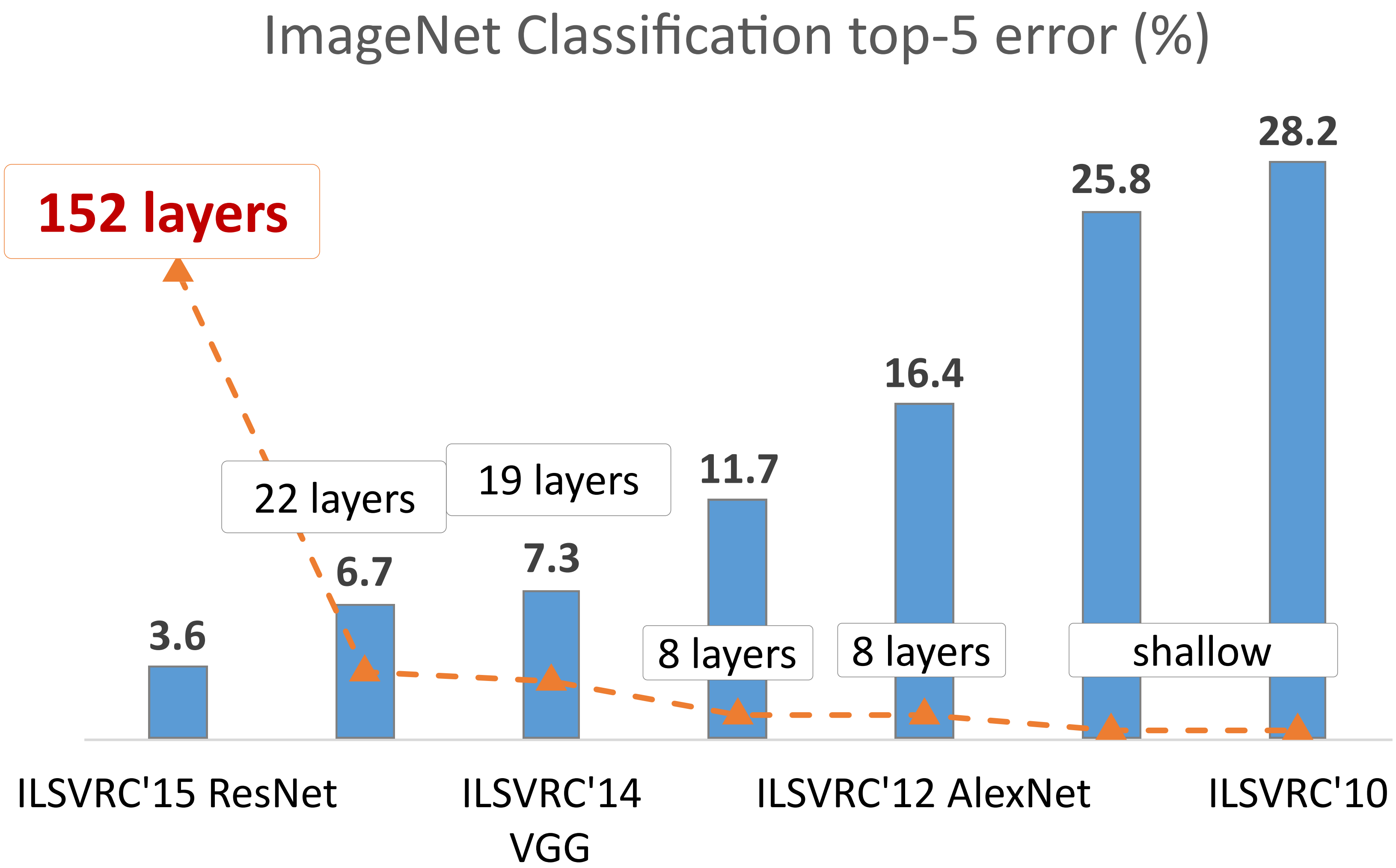
1st places in all five main tracks

- ImageNet Classification: "*Ultra-deep*" 152-layer nets
- ImageNet Detection: 16% better than 2nd
- ImageNet Localization: 27% better than 2nd
- COCO Detection: 11% better than 2nd
- COCO Segmentation: 12% better than 2nd

*improvements are relative numbers

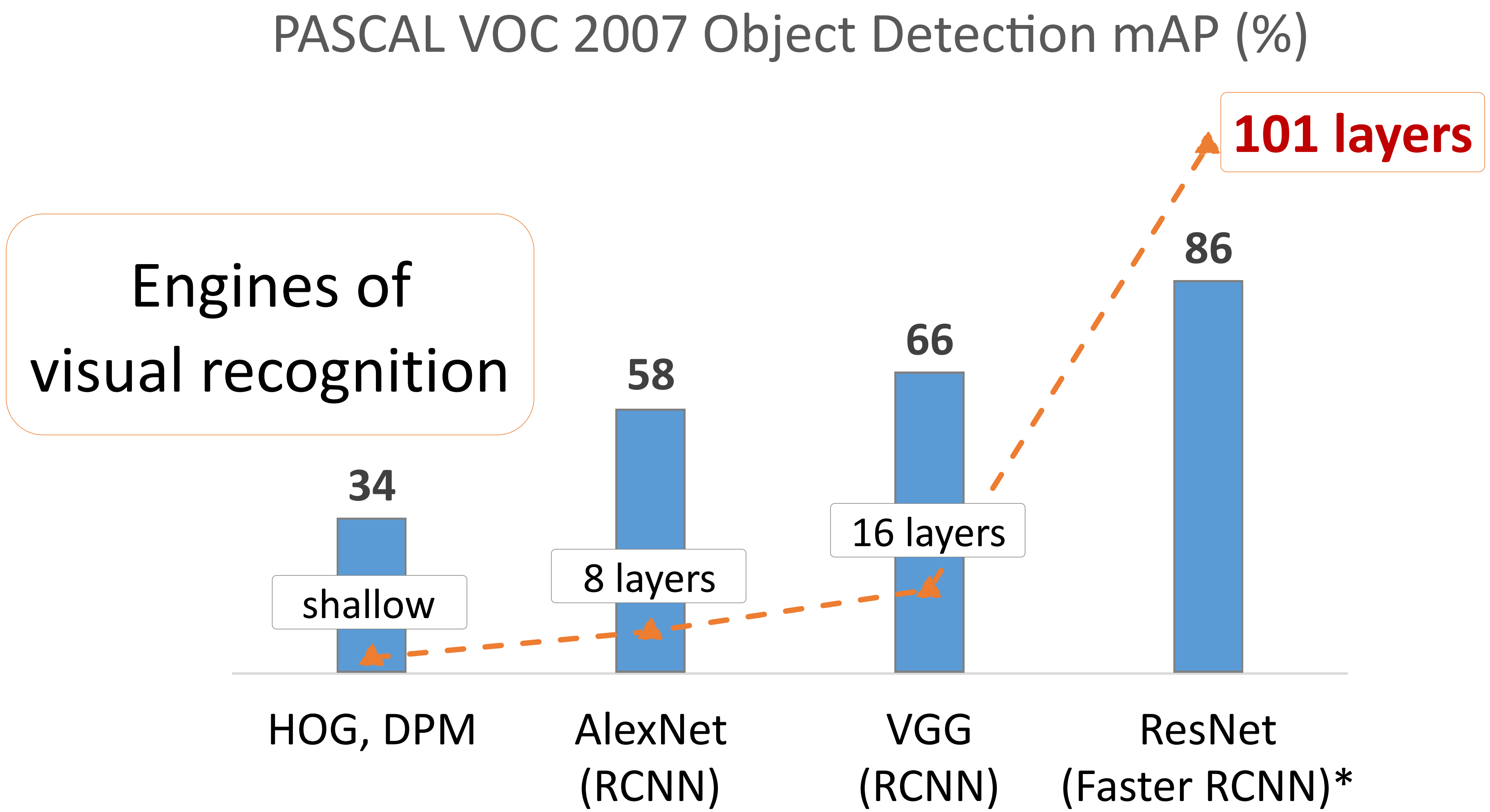
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

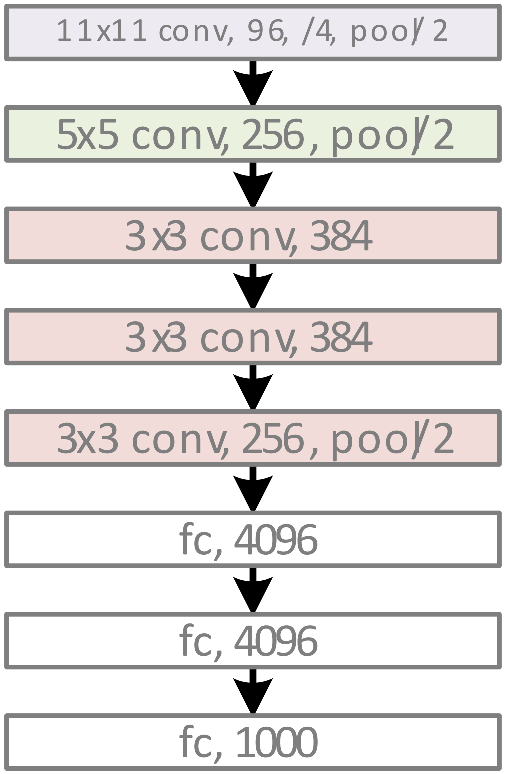


*w/ other improvements & more data

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

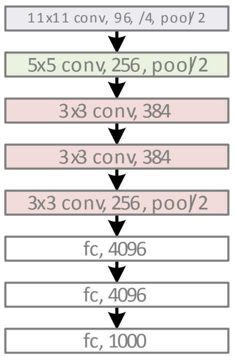
AlexNet, 8 layers (ILSVRC 2012)



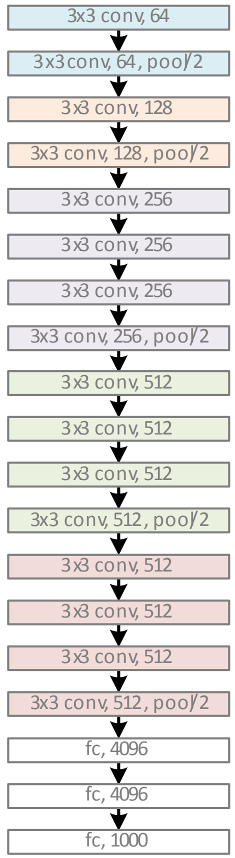
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

AlexNet, 8 layers (ILSVRC 2012)



VGG, 19 layers (ILSVRC 2014)

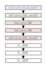


GoogleNet, 22 layers (ILSVRC 2014)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Revolution of Depth

AlexNet, 8 layers (ILSVRC 2012)



VGG, 19 layers (ILSVRC 2014)

ResNet, 152 layers (ILSVRC 2015)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth

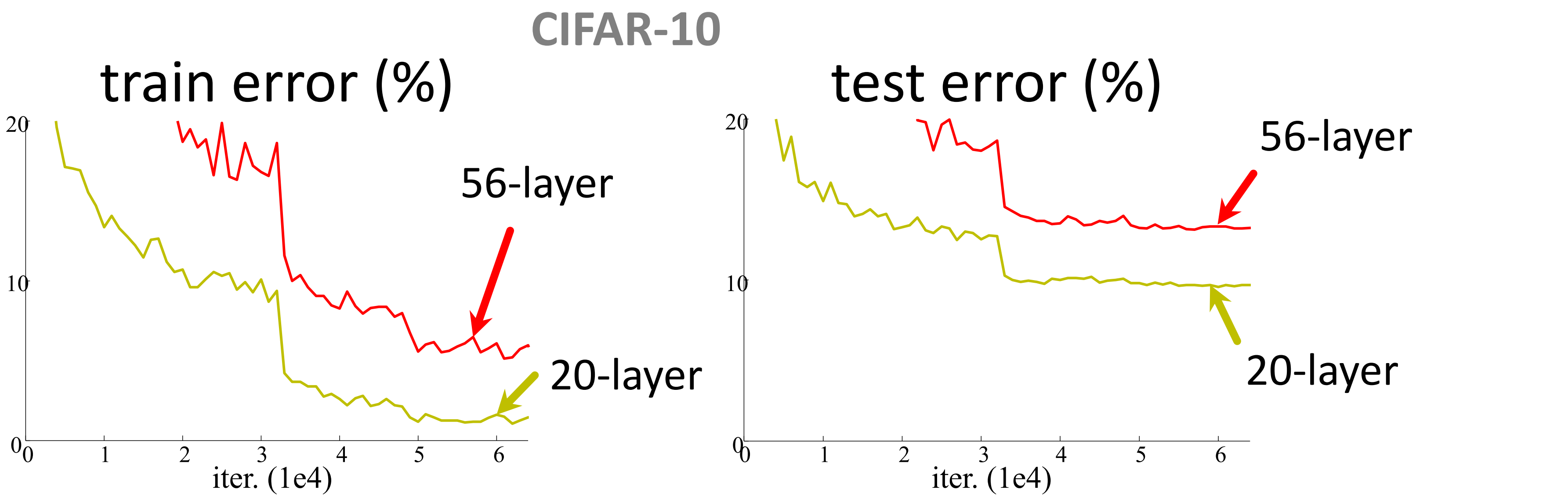
ResNet, 152 layers

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Is learning better networks as simple as stacking more layers?

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

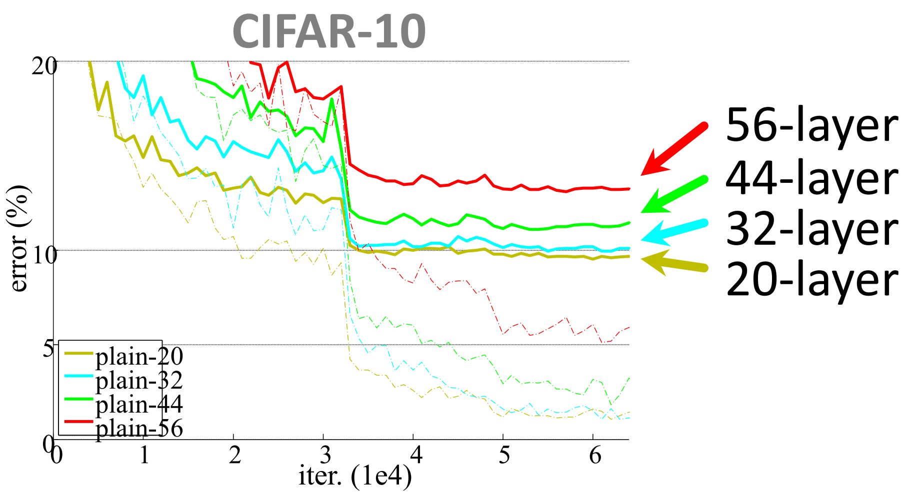
Simply stacking layers?

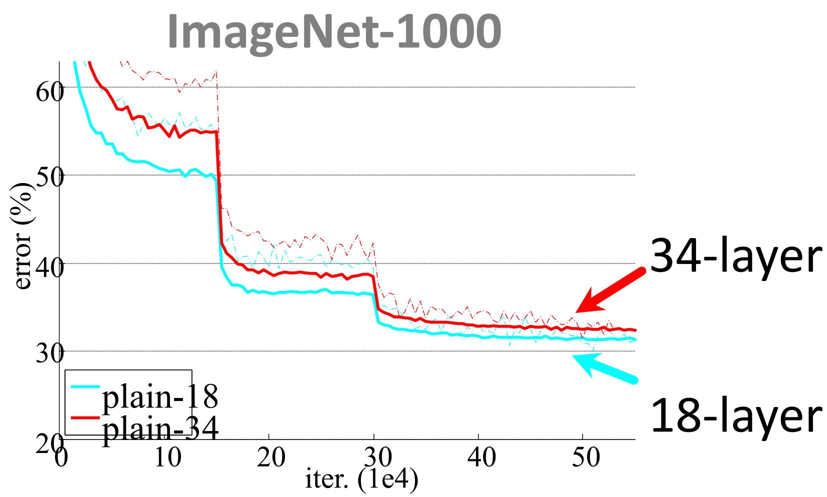


- *Plain* nets: stacking 3x3 conv layers…
- 56-layer net has **higher training error** and test error than 20-layer net

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Simply stacking layers?



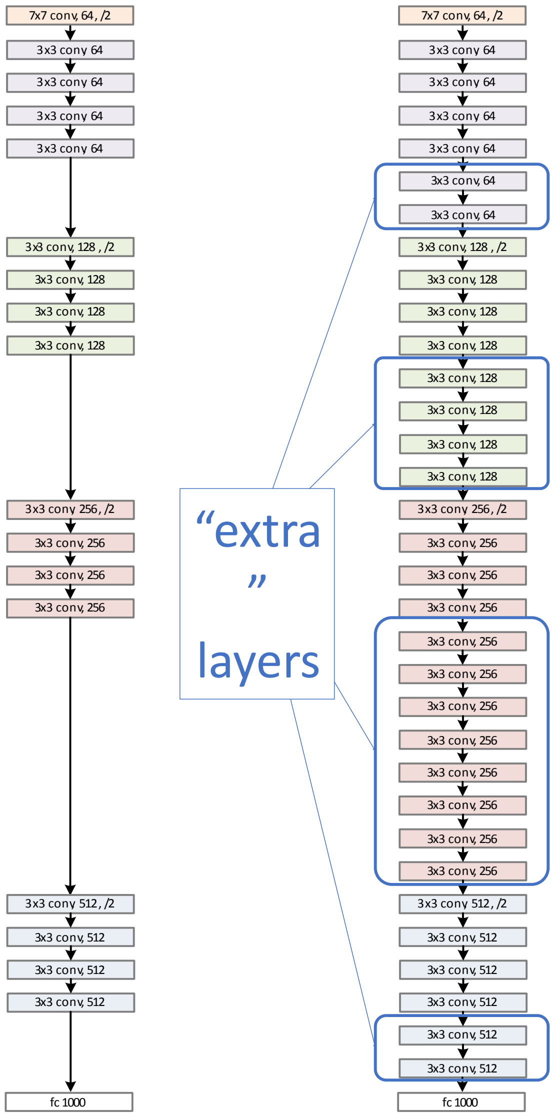


solid: test/val
dashed: train

- “Overly deep” plain nets have **higher training error**
- A general phenomenon, observed in many datasets

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

a shallower model (18 layers)



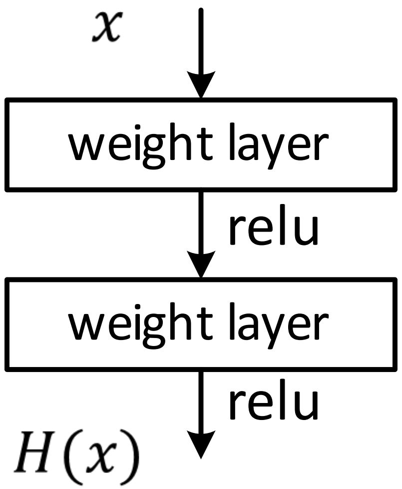
a deeper counterpart (34 layers)

- Richer solution space
- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution when going deeper…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Deep Residual Learning

- Plaint net



any two stacked layers

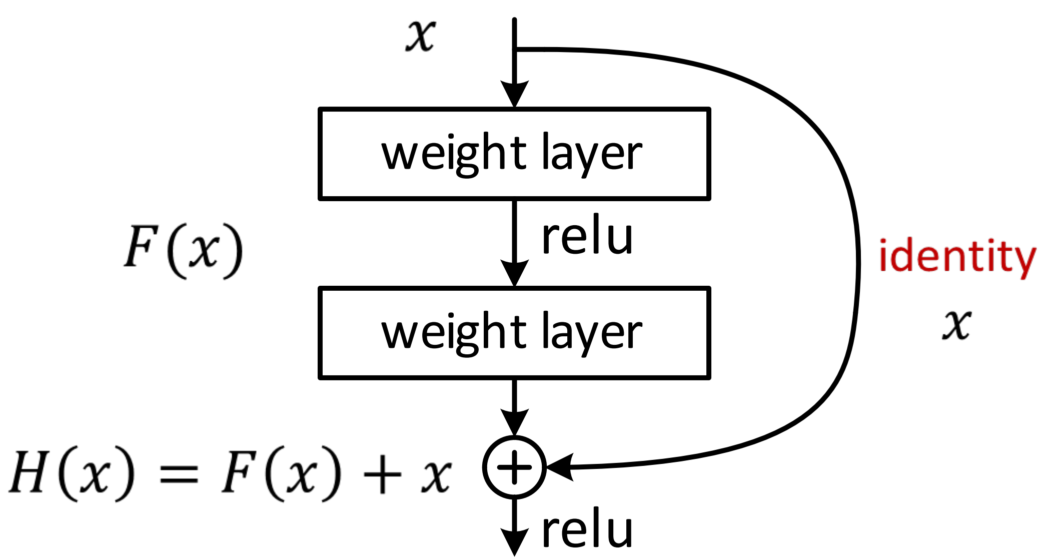
$H(x)$ is any desired mapping,

hope the 2 weight layers fit $H(x)$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Deep Residual Learning

- Residual net



$H(x)$ is any desired mapping,

~~hope the 2 weight layers fit $H(x)$~~

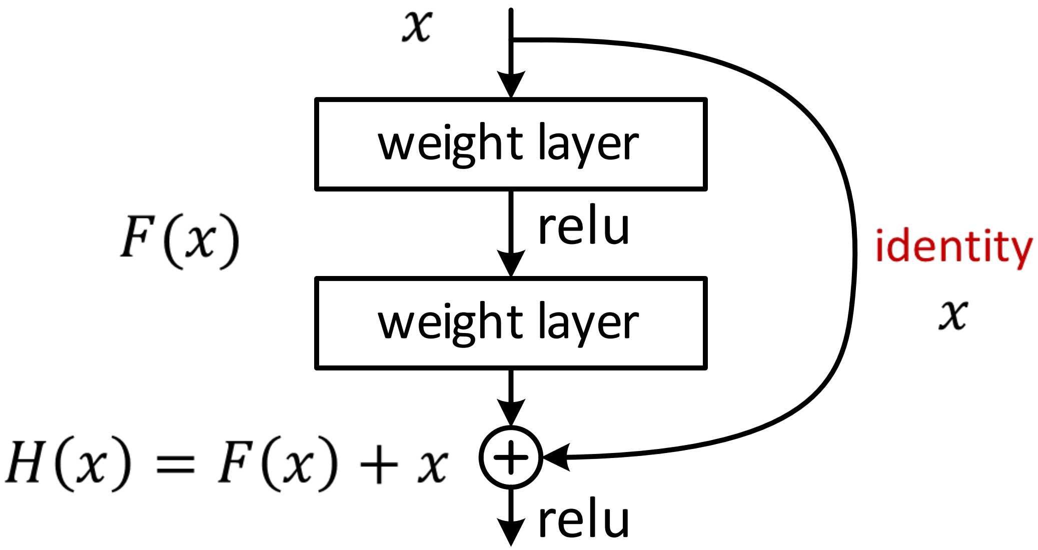
hope the 2 weight layers fit $F(x)$

let $H(x) = F(x) + x$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Deep Residual Learning

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



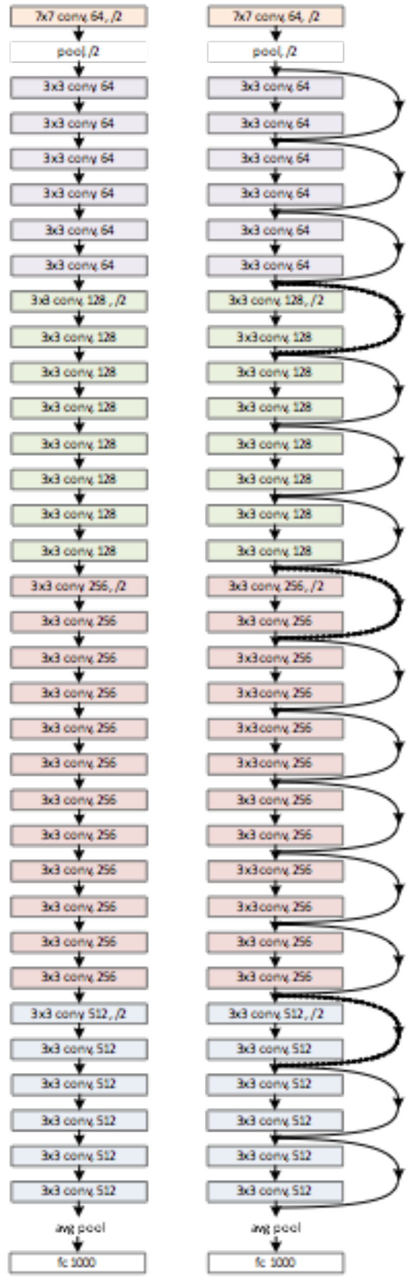
- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identity, easier to find small fluctuations

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Network “Design”

- Keep it simple
- Our basic design (VGG-style)
  - all 3x3 conv (almost)
  - spatial size /2 => # filters x2
  - Simple design; just deep!

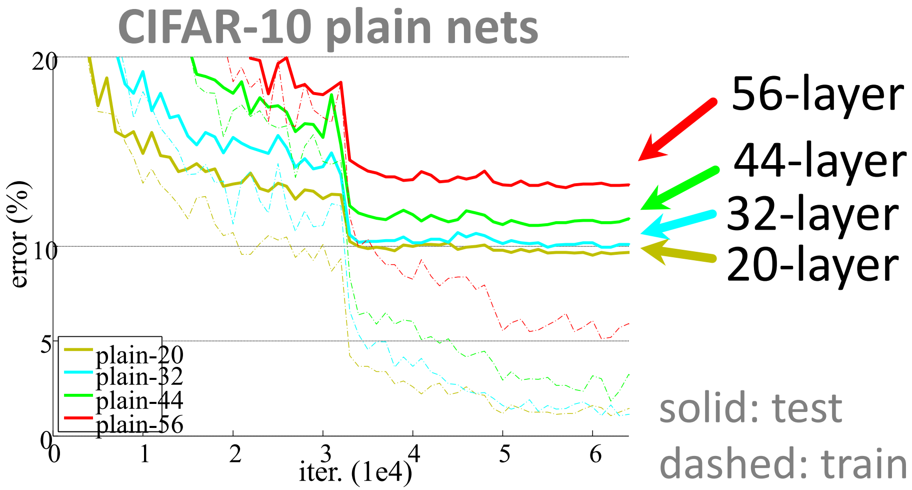
plain net

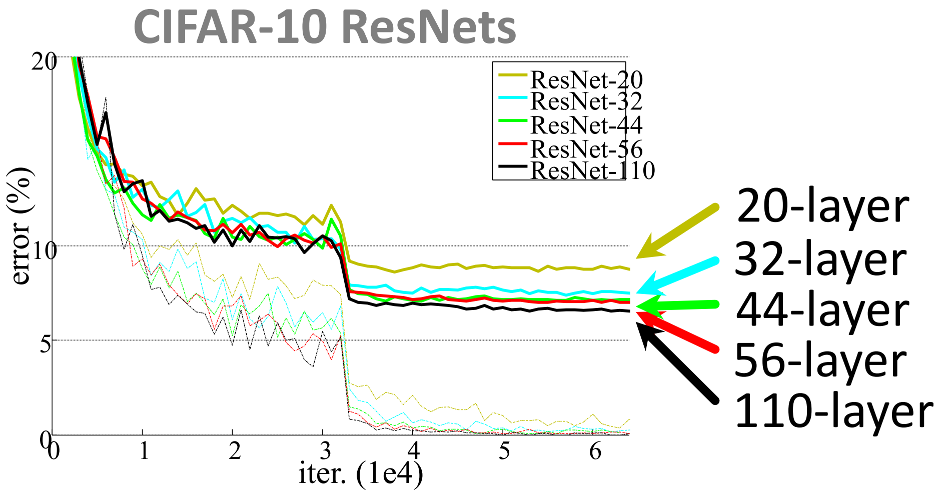


ResNet

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

CIFAR-10 experiments



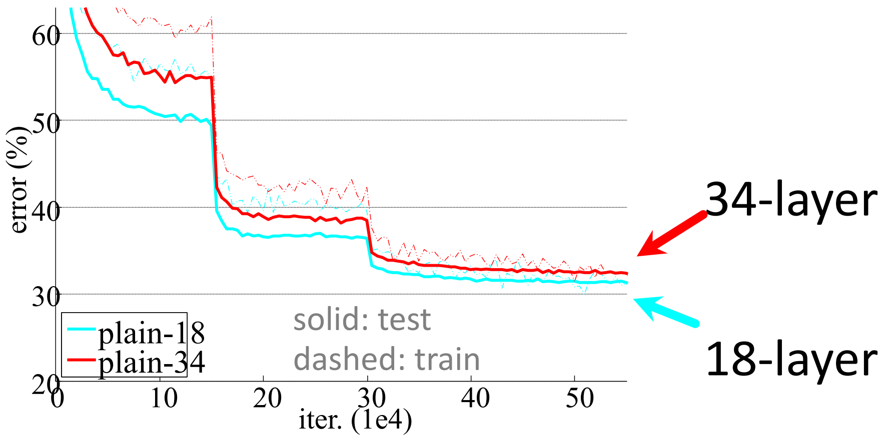


- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

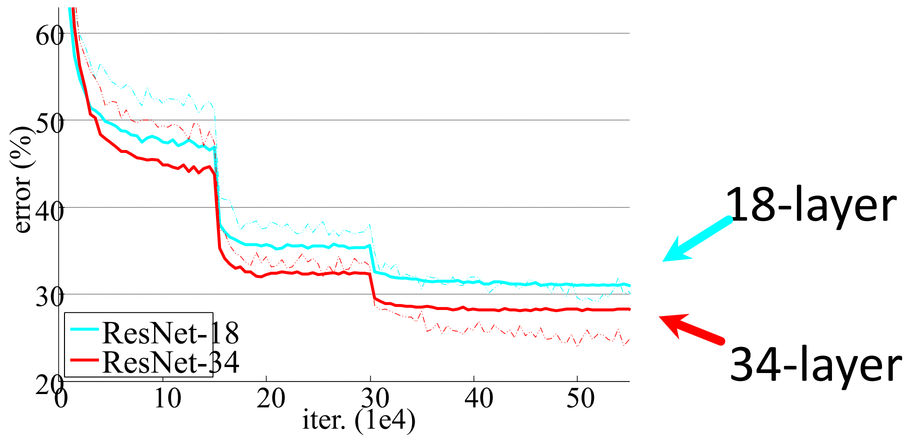
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

ImageNet experiments

ImageNet plain nets



ImageNet ResNets



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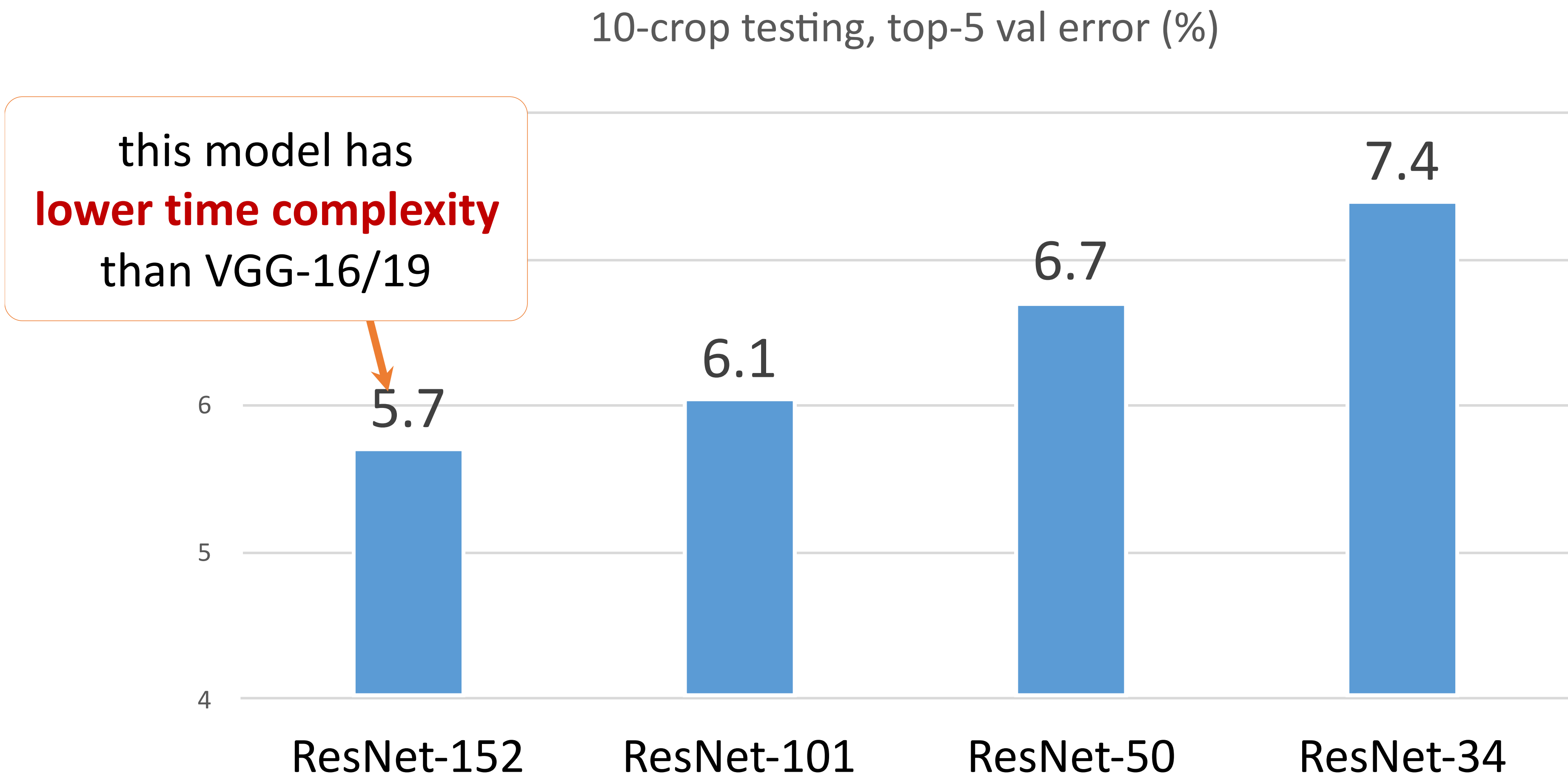
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

ImageNet experiments

- Deeper ResNets have lower error



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

“Features matter.”

(quote [Girshick et al. 2014], the R-CNN paper)

task	2nd-place winner	ResNets	margin (relative)
ImageNet Localization (top-5 error)	12.0	9.0	**27%**
ImageNet Detection (mAP@.5)	53.6	62.1	**16%**
COCO Detection (mAP@.5:.95)	33.5	37.3	**11%**
COCO Segmentation (mAP@.5:.95)	25.1	28.2	**12%**

absolute 8.5% better!

- Our results are all based on ResNet-101
- Our features are well transferrable

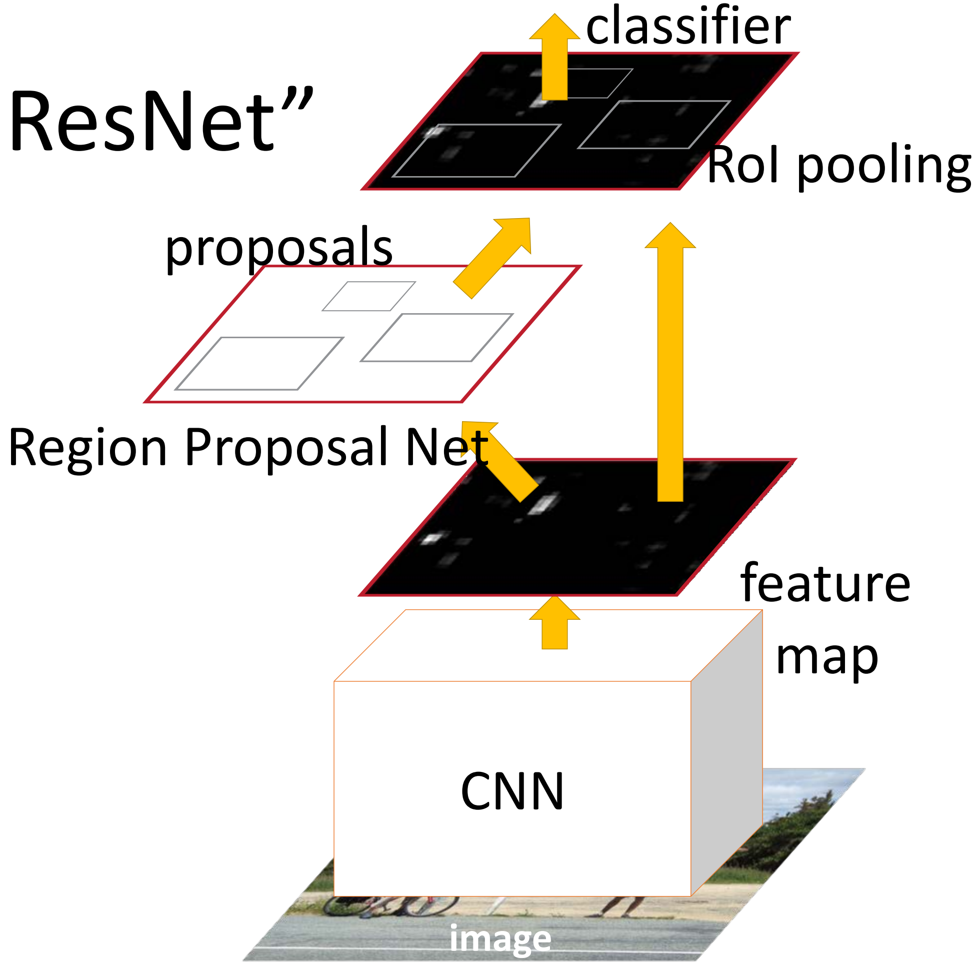
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Object Detection (brief)

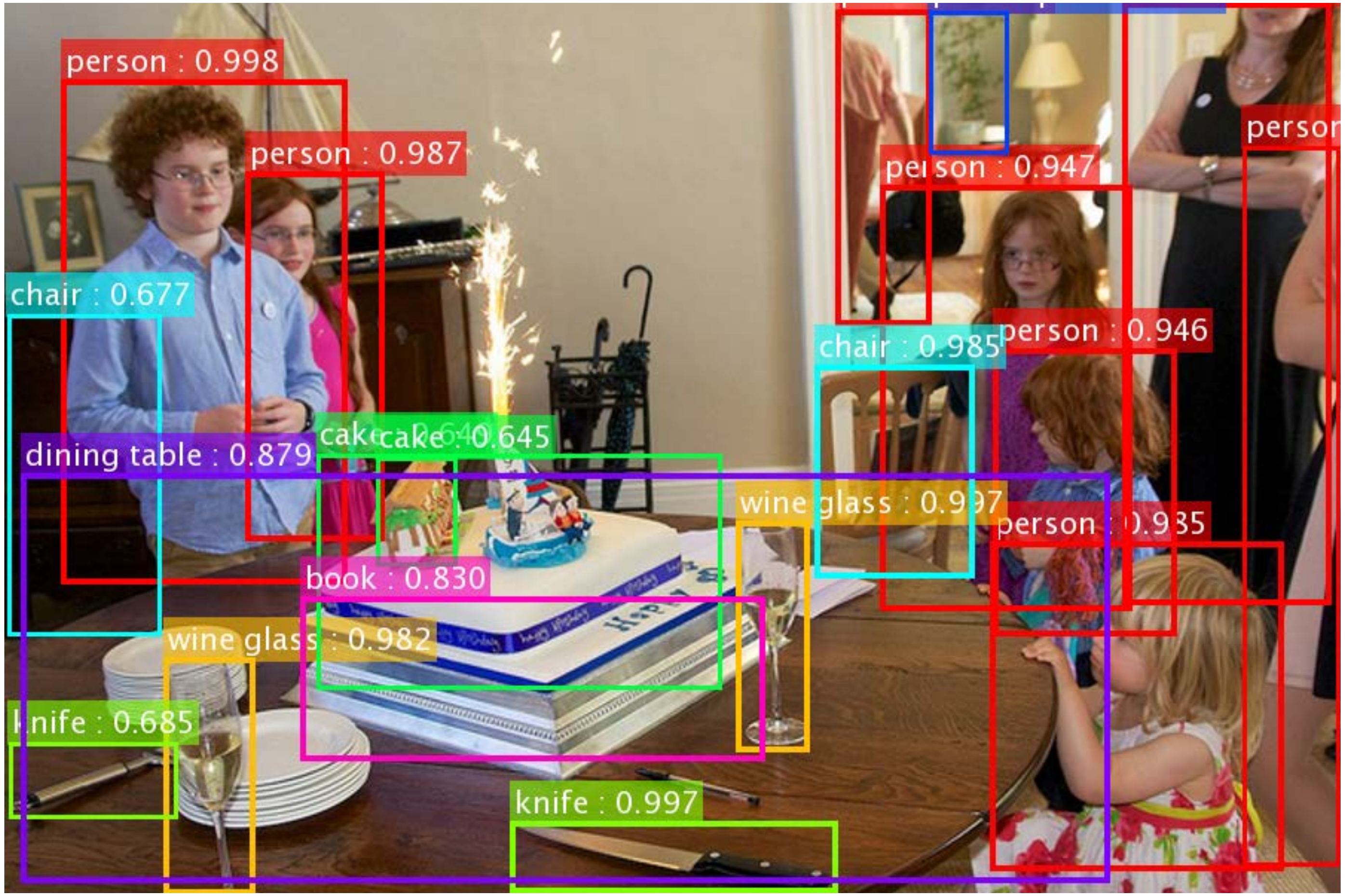
- Simply “Faster R-CNN + ResNet”

Faster R-CNN baseline	mAP@.5	mAP@.5:.95
VGG-16	41.5	21.5
ResNet-101	**48.4**	**27.2**

COCO detection results
(ResNet has 28% relative gain)



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.



Our results on MS COCO

*the original image is from the COCO dataset

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

this video is available online: https://youtu.be/WZmSMkK9VuA

Results on real video. Model trained on MS COCO w/ 80 categories.
(frame-by-frame; no temporal processing)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015.

More Visual Recognition Tasks

ResNets lead on these benchmarks (incomplete list):

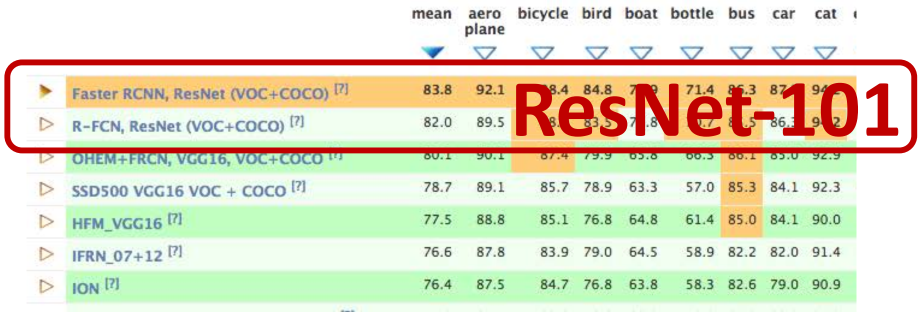
- **ImageNet** classification, detection, localization
- **MS COCO** detection, segmentation

- **PASCAL VOC** detection, segmentation
- **VQA** challenge 2016

- Human pose estimation [Newell et al 2016]
- Depth estimation [Laina et al 2016]
- Segment proposal [Pinheiro et al 2016]
- …

	mean	aero plane	bicycle	bird	boat	bottle	bus	car	ca
DeepLabv2-CRF [?]	79.7	92.6	60.4	91.6	63.4	76.3	95.0	88.4	92.
CASIA_SegResNet_CRF_COCO [?]	79.3	[illegible]	[illegible]	[illegible]	[illegible]	75.3	[illegible]	[illegible]	[illegible]
Adelaide_VeryDeep_FCN_VOC [?]	79.1	91.9	[illegible]	93.4	[illegible]	75.5	94.2	[illegible]	92.
LRR_4x_COCO [?]	78.7	93.2	44.2	89.4	65.4	74.9	93.9	87.0	92.
CASIA_IVA_OASeg [?]	78.3	93.8	41.9	89.4	67.5	71.5	94.6	85.3	89.
Oxford_TVG_HO_CRF [?]	77.9	92.5	59.1	90.3	70.6	74.4	92.4	84.1	88.
Adelaide_Context_CNN_CRF_COCO [?]	77.8	92.9	39.6	84.0	67.9	75.3	92.7	83.8	90.

PASCAL **segmentation** leaderboard



	mean	aero plane	bicycle	bird	boat	bottle	bus	car	cat
Faster RCNN, ResNet (VOC+COCO) [?]	83.8	92.1	[illegible]	84.8	[illegible]	71.4	[illegible]	[illegible]	[illegible]
R-FCN, ResNet (VOC+COCO) [?]	82.0	89.5	[illegible]	83.5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
OHEM+FRCN, VGG16, VOC+COCO [?]	80.1	90.1	87.4	79.9	65.8	66.3	86.1	85.0	92.9
SSD500 VGG16 VOC + COCO [?]	78.7	89.1	85.7	78.9	63.3	57.0	85.3	84.1	92.3
HFM_VGG16 [?]	77.5	88.8	85.1	76.8	64.8	61.4	85.0	84.1	90.0
IFRN_07+12 [?]	76.6	87.8	83.9	79.0	64.5	58.9	82.2	82.0	91.4
ION [?]	76.4	87.5	84.7	76.8	63.8	58.3	82.6	79.0	90.9

PASCAL **detection** leaderboard

Potential Applications

ResNets have shown outstanding or promising results on:

- Visual Recognition
- Image Generation (Pixel RNN, Neural Art, etc.)
- Natural Language Processing (Very deep CNN)
- Speech Recognition (preliminary results)
- Advertising, user prediction (preliminary results)

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Conclusions

- Deep Residual Learning:
  - Ultra deep networks can be easy to train
  - Ultra deep networks can simply gain accuracy from depth
  - Ultra deep representations are well transferrable
- Follow-up [He et al. arXiv 2016]
  - 200 layers on ImageNet, 1000 layers on CIFAR

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Identity Mappings in Deep Residual Networks”. arXiv 2016.
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

Resources

Thank You!

- Models and Code
  - Our ImageNet models in Caffe: https://github.com/KaimingHe/deep-residual-networks

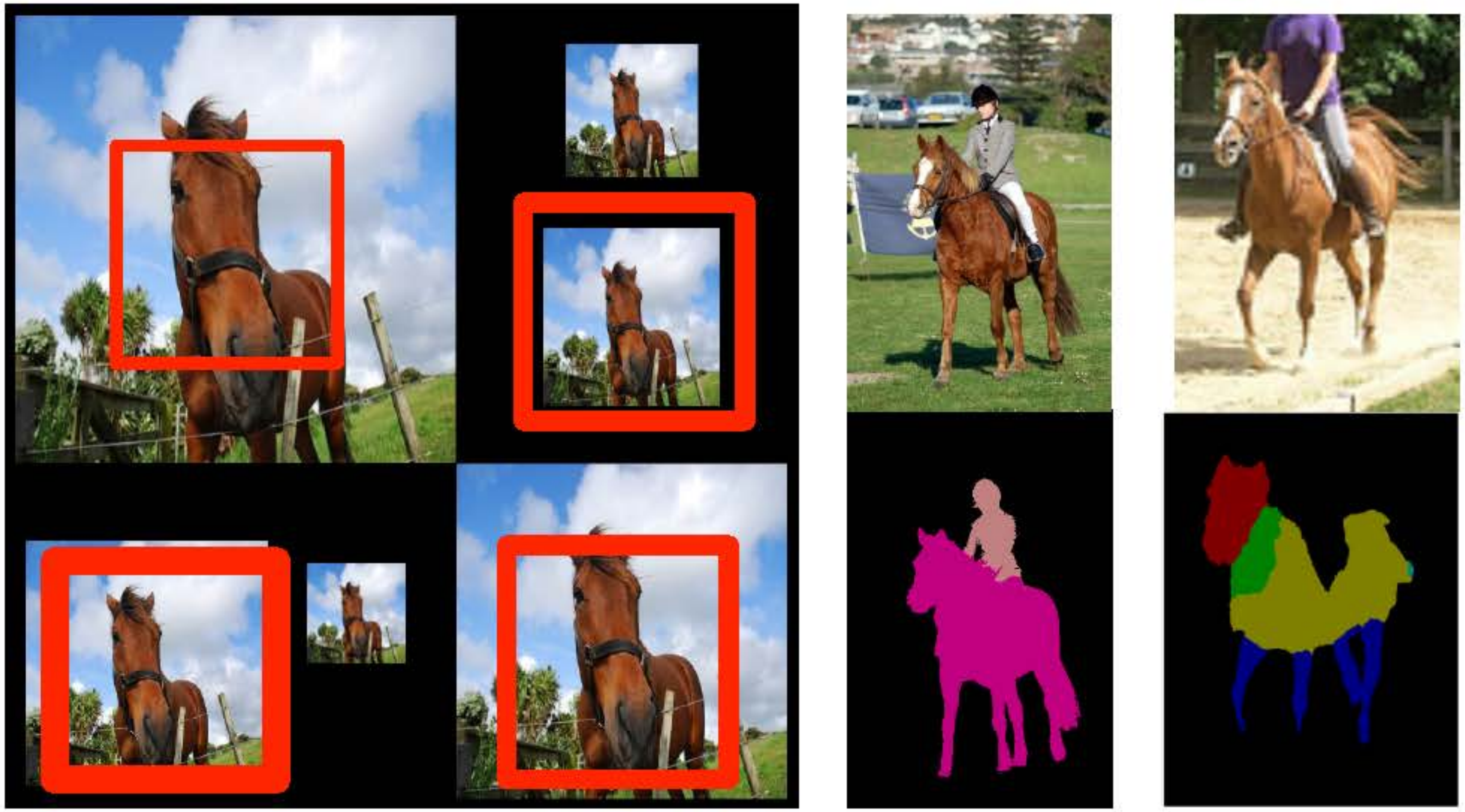
- Many available implementations:
  (list in https://github.com/KaimingHe/deep-residual-networks)
  - Facebook AI Research's Torch ResNet: https://github.com/facebook/fb.resnet.torch
  - Torch, CIFAR-10, with ResNet-20 to ResNet-110, training code, and curves: code
  - Lasagne, CIFAR-10, with ResNet-32 and ResNet-56 and training code: code
  - Neon, CIFAR-10, with pre-trained ResNet-32 to ResNet-110 models, training code, and curves: code
  - Torch, MNIST, 100 layers: blog, code
  - A winning entry in Kaggle's right whale recognition challenge: blog, code
  - Neon, Place2 (mini), 40 layers: blog, code
  - …….

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

2. From detection to segmentation

- Main Reading:
  - Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs, Chen, Papandreou, Kokkins, Murphy, Yuille, ICLR'15 - https://arxiv.org/abs/1412.7062
- Also
  - Hypercolumns for object segmentation and fine-grained localization
    Bharath Hariharan, Pablo Arbeláez, Ross Girshick, Jitendra Malik, CVPR'15 - https://arxiv.org/abs/1411.5752
  - Fully Convolutional Networks for Semantic Segmentation
    John Long, Evan Shelhamer, Trevor Darelle, CVPR'15
    https://arxiv.org/abs/1411.4038

Fully Convolutional Neural Networks for Classification, Detection & Segmentation

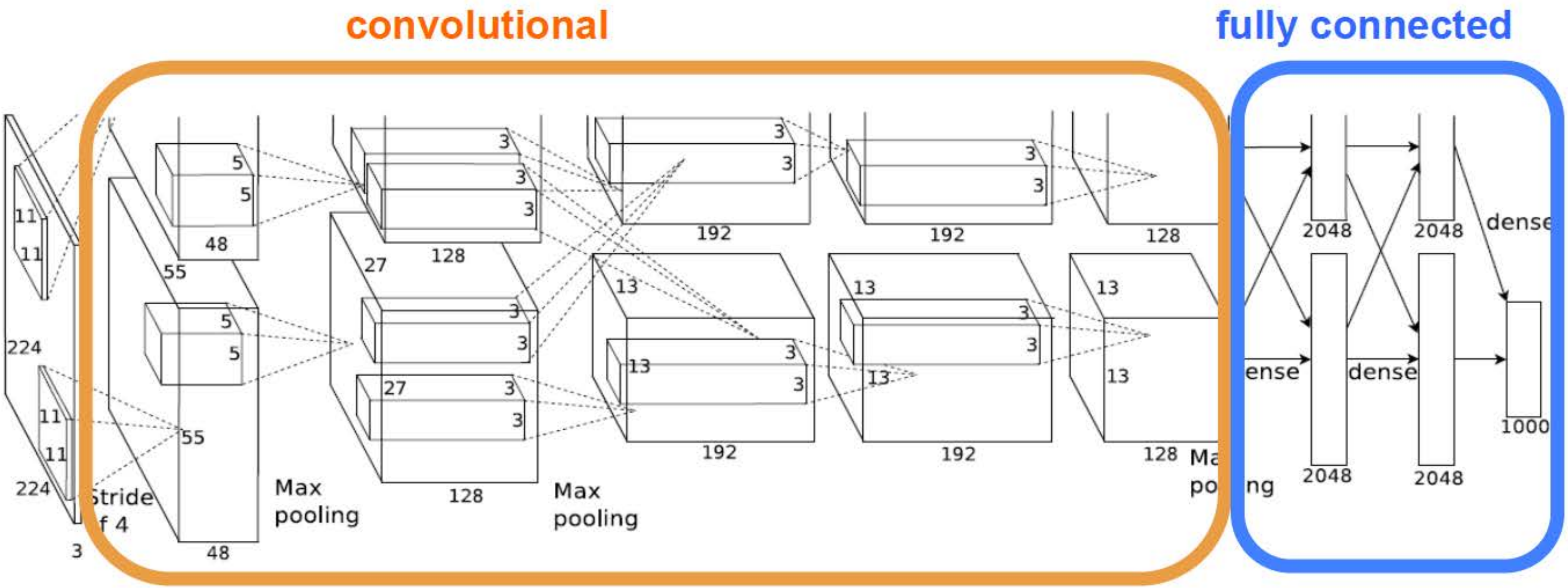


or, all your computer wanted to know about horses

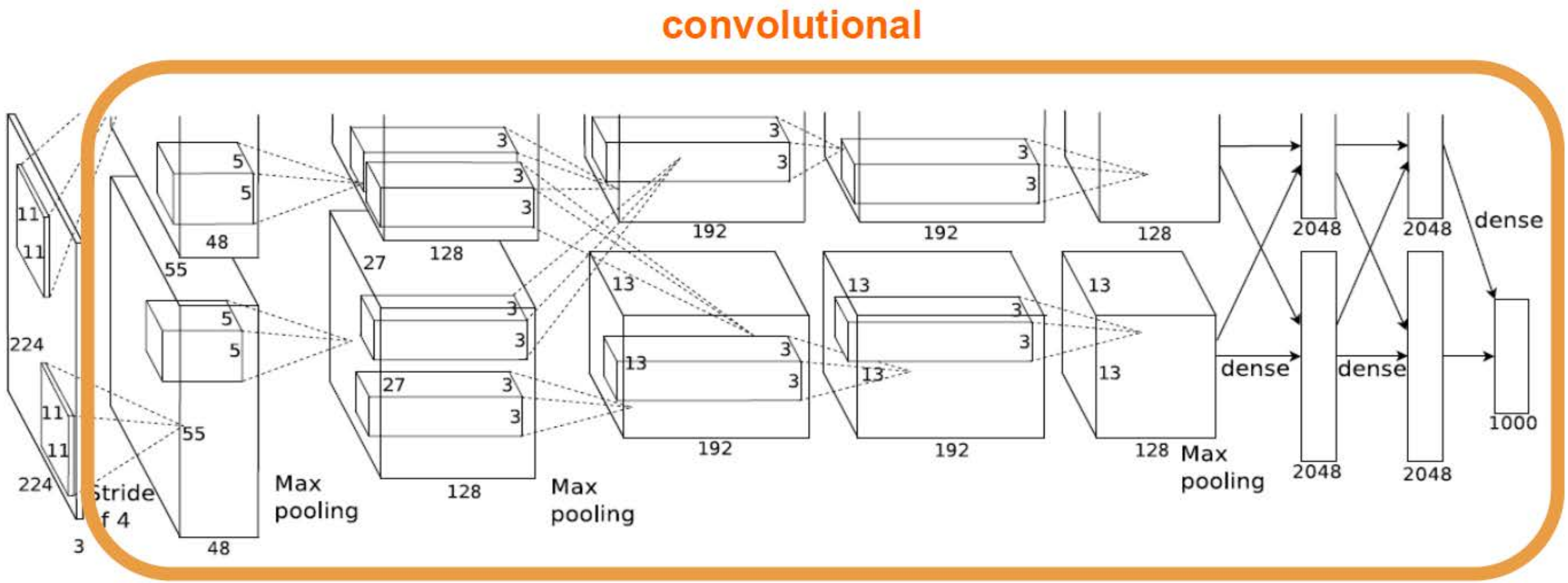
Iasonas Kokkinos
Ecole Centrale Paris / INRIA Saclay

& G. Papandreou, P.-A. Savalle, S. Tsogkas,
L-C Chen, K. Murphy, A. Yuille, A. Vedaldi

Fully convolutional neural networks



Fully convolutional neural networks

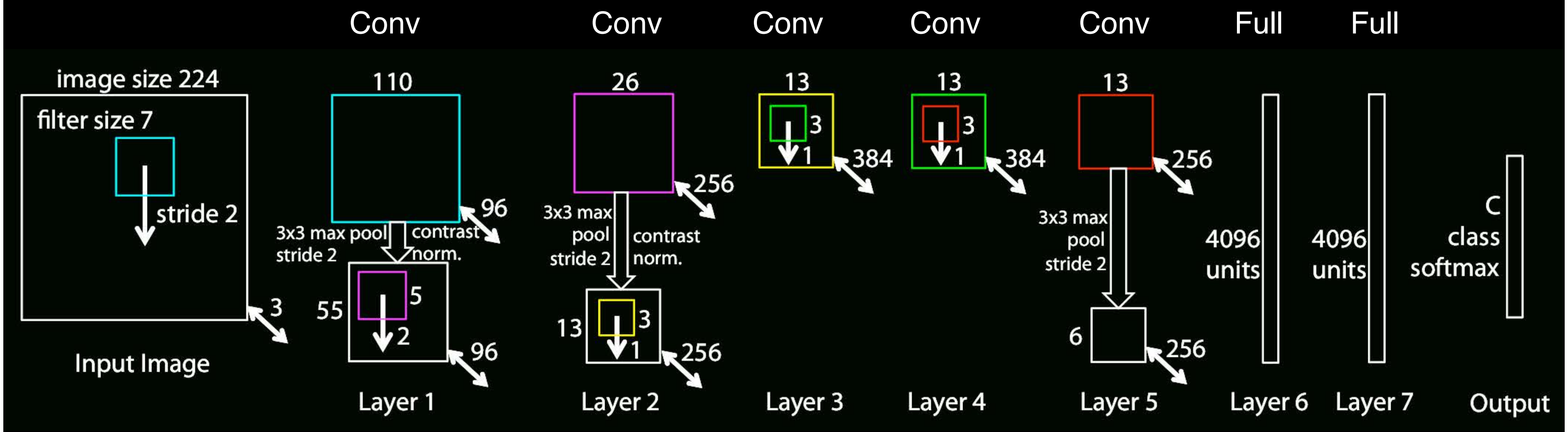


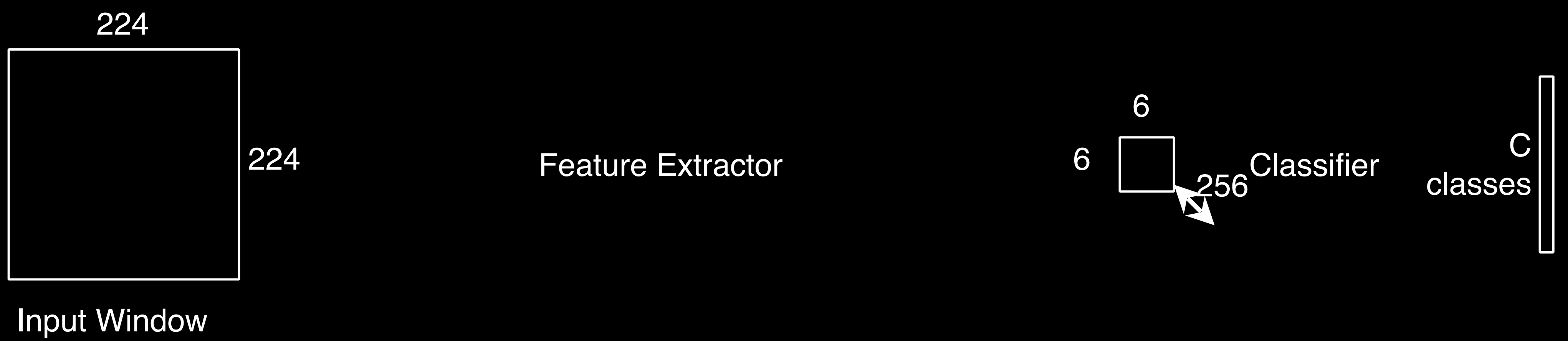
Fully connected layers: 1x1 spatial convolution kernels

Allows network to process images of arbitrary size

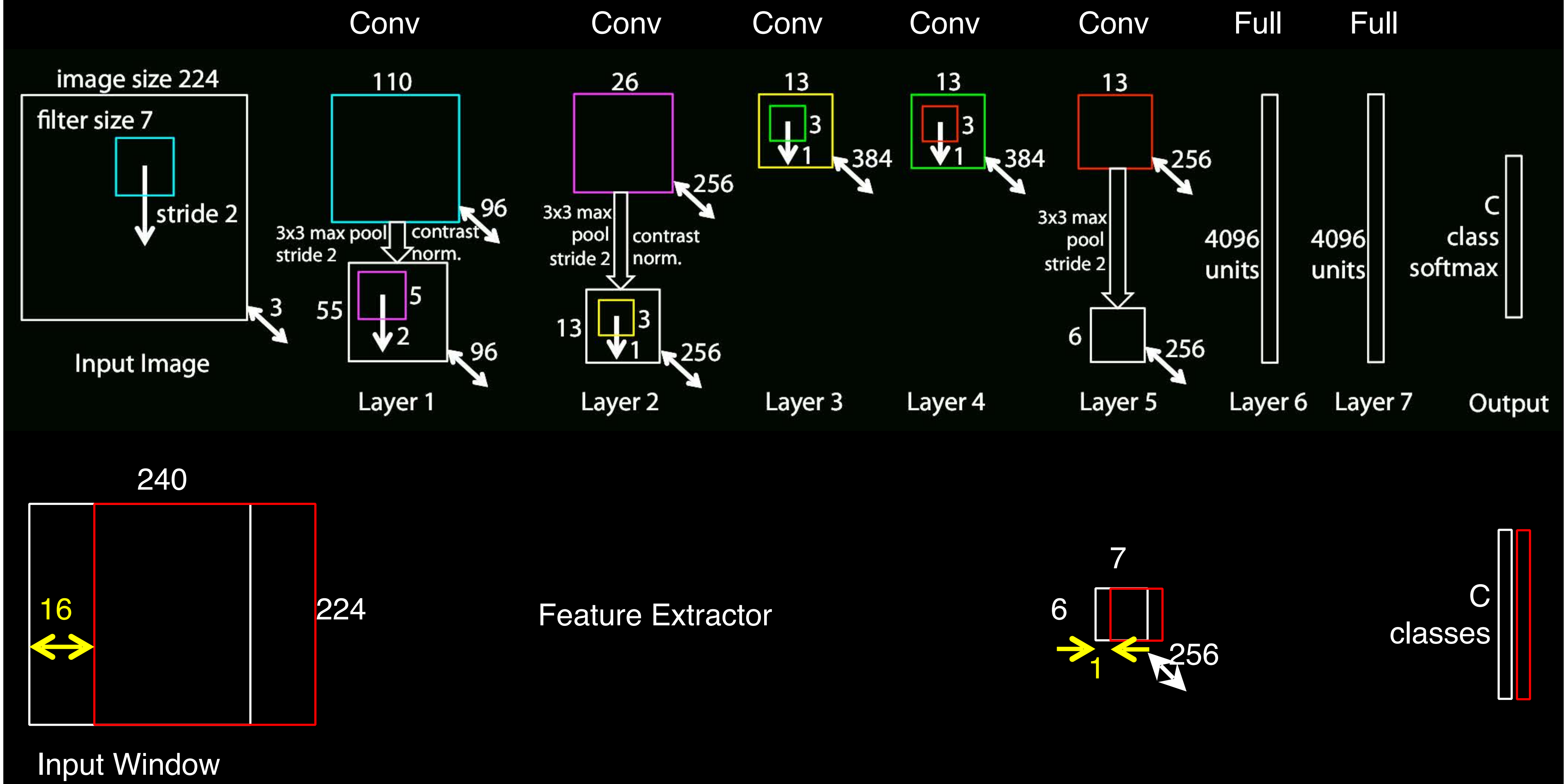
P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus and Y. LeCun, OverFeat, ICLR, 2014
M. Oquab, L. Bottou, I. Laptev, J. Sivic, Weakly Supervised Object Recognition with CNNs, TR2014
J. Long, E. Shelhamer, T. Darrell, Fully Convolutional Networks for Semantic Segmentation, CVPR 15

Sliding Window with ConvNet





Sliding Window with ConvNet



No need to compute two separate windows
Just one big input window, computed in a single pass

Fully convolutional neural networks

Fast (shared convolutions)
Simple (dense)

Part 2: FCNNs for semantic segmentation

G. Papandreou

L-C. Chen, UCLA

K. Murphy, Google

A. Yuille, UCLA

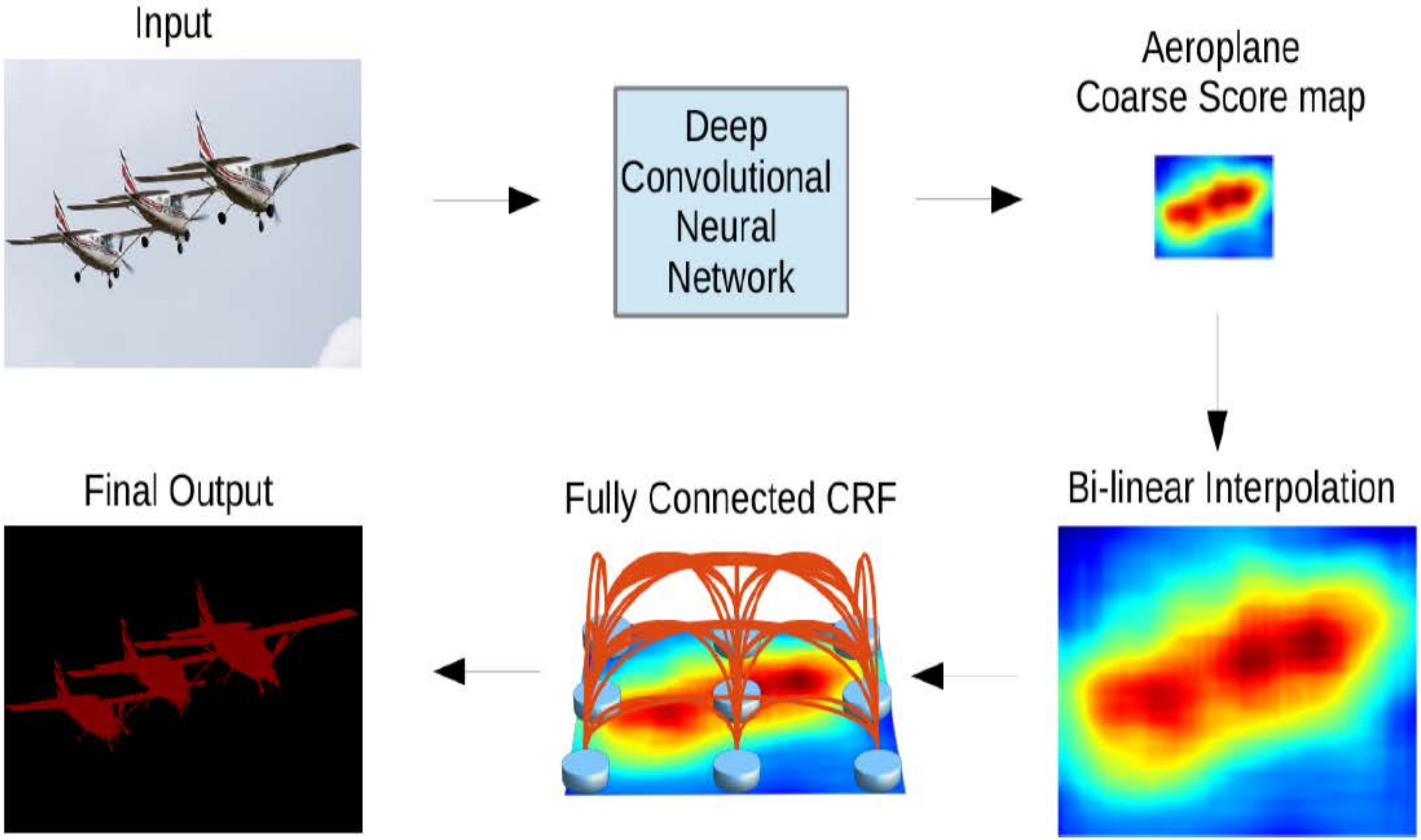
L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy and A. Yuille
Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs, http://arxiv.org/abs/1412.7062

Semantic segmentation task

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

Microsoft COCO
Common Objects in Context

System outline



J. Long, E. Shelhamer, T. Darrell, FCNNs for Semantic Segmentation, CVPR 15

P. Krähenbühl and V. Koltun, Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials, NIPS 2011

Repurposing DCNNs for semantic segmentation

- Accelerate CNN evaluation by 'hard dropout' & finetuning
  - In VGG: Subsample first FC layer 7x7 → 3x3

- Decrease score map stride (32->8) with 'atrous' (w. holes) algorithr

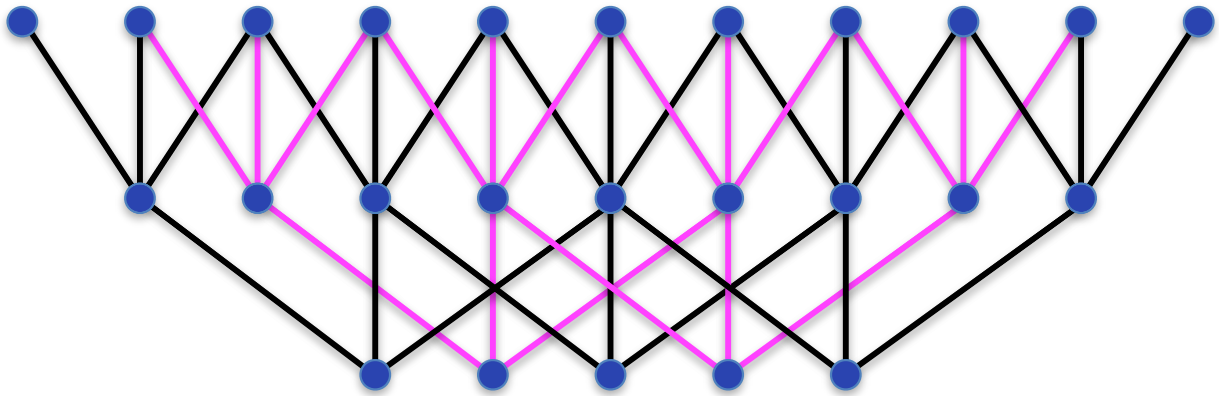
 

8 FPS

M. Holschneider, et al, A real-time algorithm for signal analysis with the help of the wavelet transform, *Wavelets, Time-Frequency Methods and Phase Space,* 1989.

“Hole” algorithm

- “Normal” Resolution
  - Black: Filter width = 3, Stride = 2
- Increase Resolution by Factor of 2:
  - Magenta: same Filter with width 3, Stride = 1



“Hole” algorithm

- skip subsampling
  - in their case for VGG-net: after the last two max-pooling layers)
- for the next layer filter: sparsely sample the feature map with “input stride” 2 (or 4 respectively)

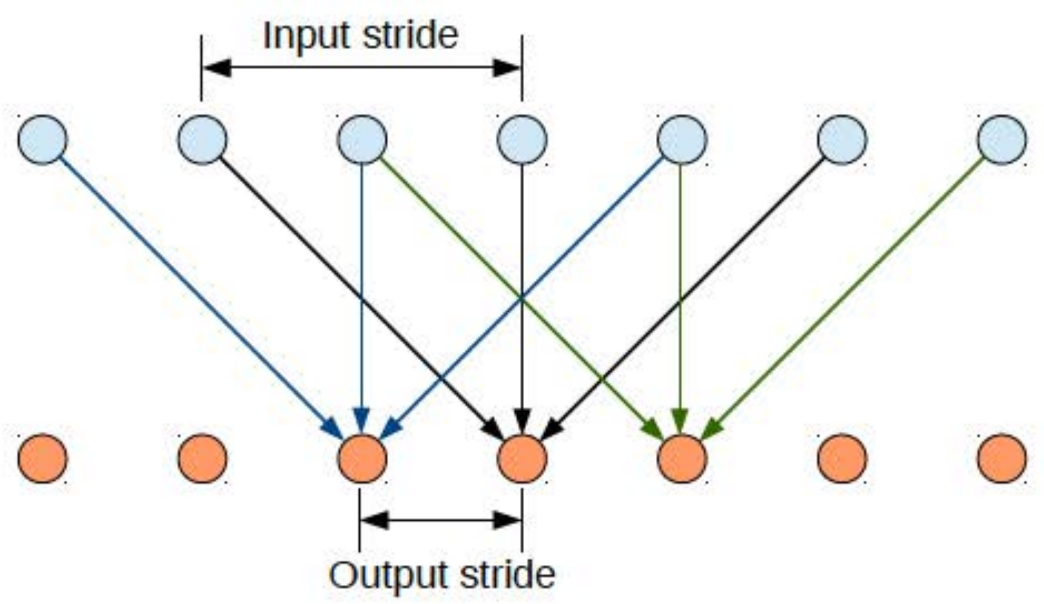
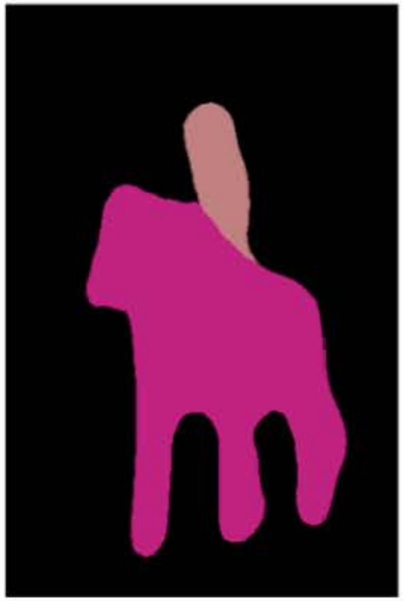


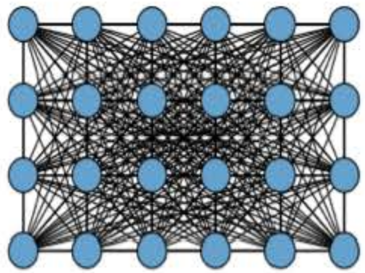
Figure 1: Illustration of the hole algorithm in 1-D, when *kernel_size* = *3*, *input_stride* = *2*, and *output_stride* = *1*.

FCNN-DCRF: Full & densely connected



FCNN-based labelling

from densely-connected CRF



- Large CNN receptive field:
  + good accuracy
  - worse performance near boundaries
- Dense CRF: sharpen boundaries using image-based info

P. Krähenbühl and V. Koltun, Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials, NIPS 2011

CRF - Conditional Random Field

- Energy function to be minimized

$$E(\boldsymbol{x}) = \sum_i \theta_i(x_i) + \sum_{ij} \theta_{ij}(x_i, x_j)$$

  - with unary terms obtained from the CNN:

$$\theta_i(x_i) = -\log P(x_i)$$

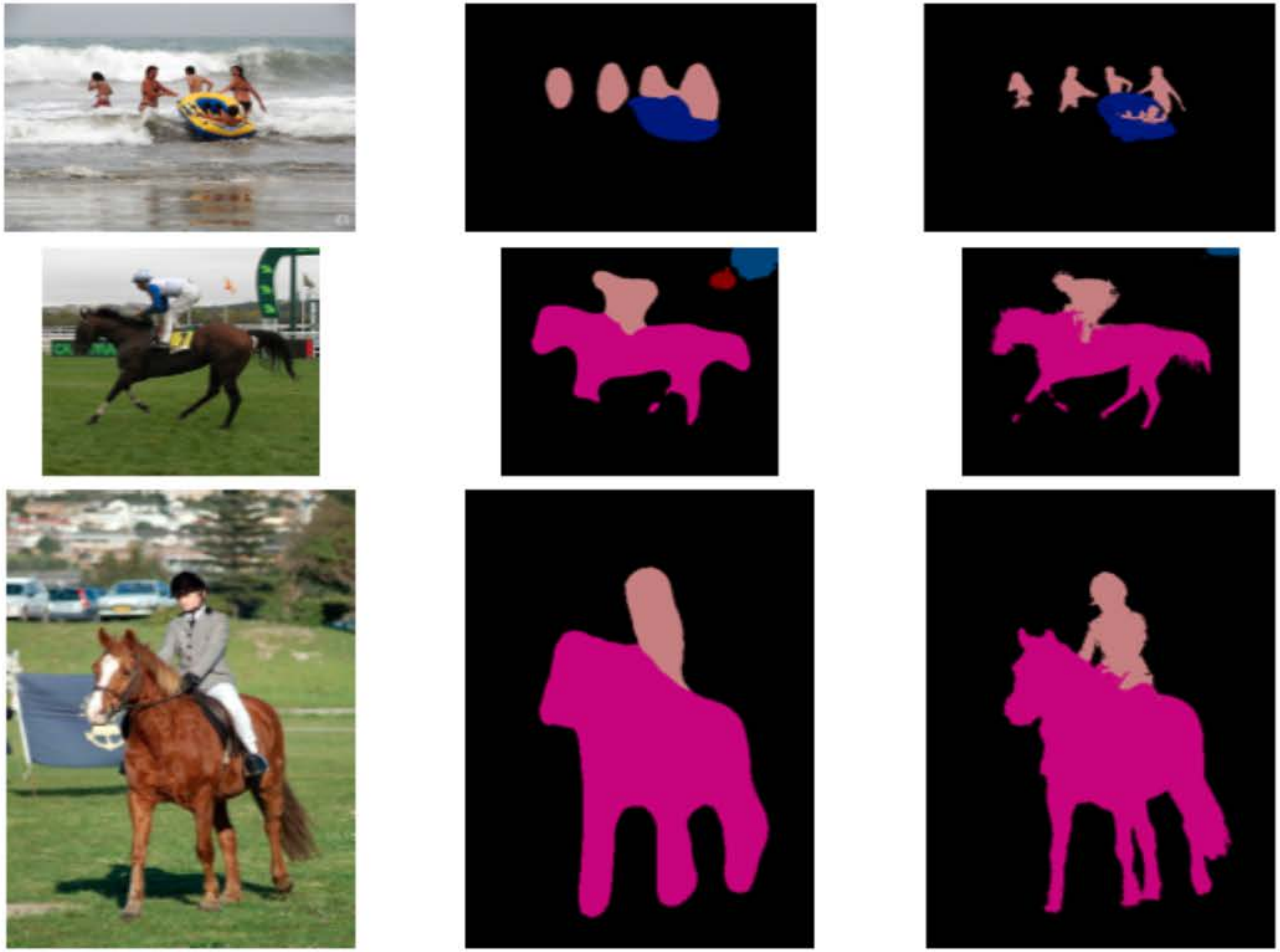
  - and pairwise terms (Potts model)

$$\theta_{ij}(x_i, x_j) = \mu(x_i, x_j) \sum_{m=1}^{K} w_m \cdot k^m(\boldsymbol{f}_i, \boldsymbol{f}_j)$$

    - with $\mu(x_i, x_j) = 1 \text{ if } x_i \neq x_j$

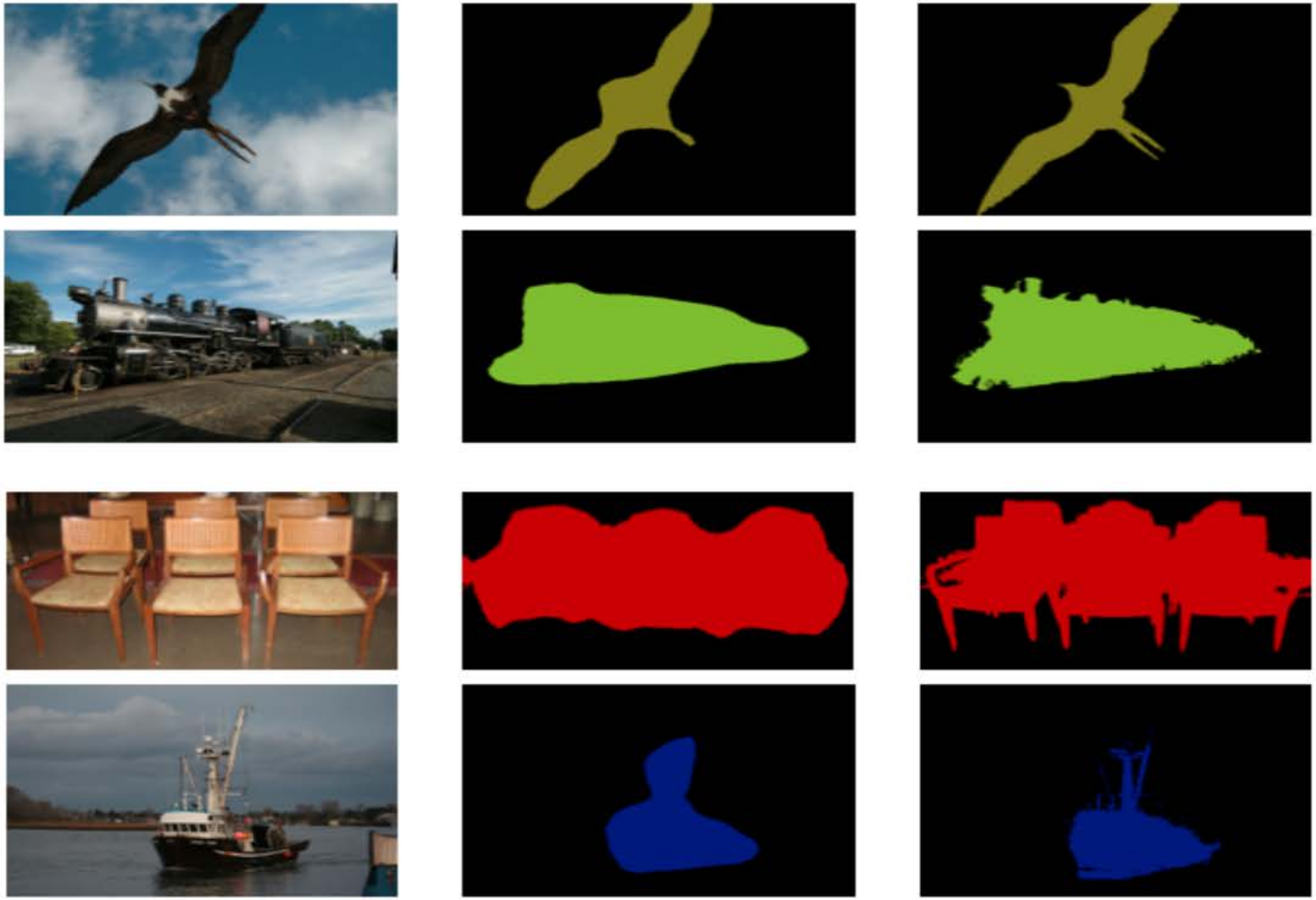
$$\sum_{m=1}^{K} w_m \cdot k^m(\boldsymbol{f}_i, \boldsymbol{f}_j) = w_1 \exp\left(-\frac{||p_i - p_j||^2}{2\sigma_\alpha^2} - \frac{||I_i - I_j||^2}{2\sigma_\beta^2}\right) + w_2 \exp\left(-\frac{||p_i - p_j||^2}{2\sigma_\gamma^2}\right)$$

Indicative Results



Raw score maps After dense CRF

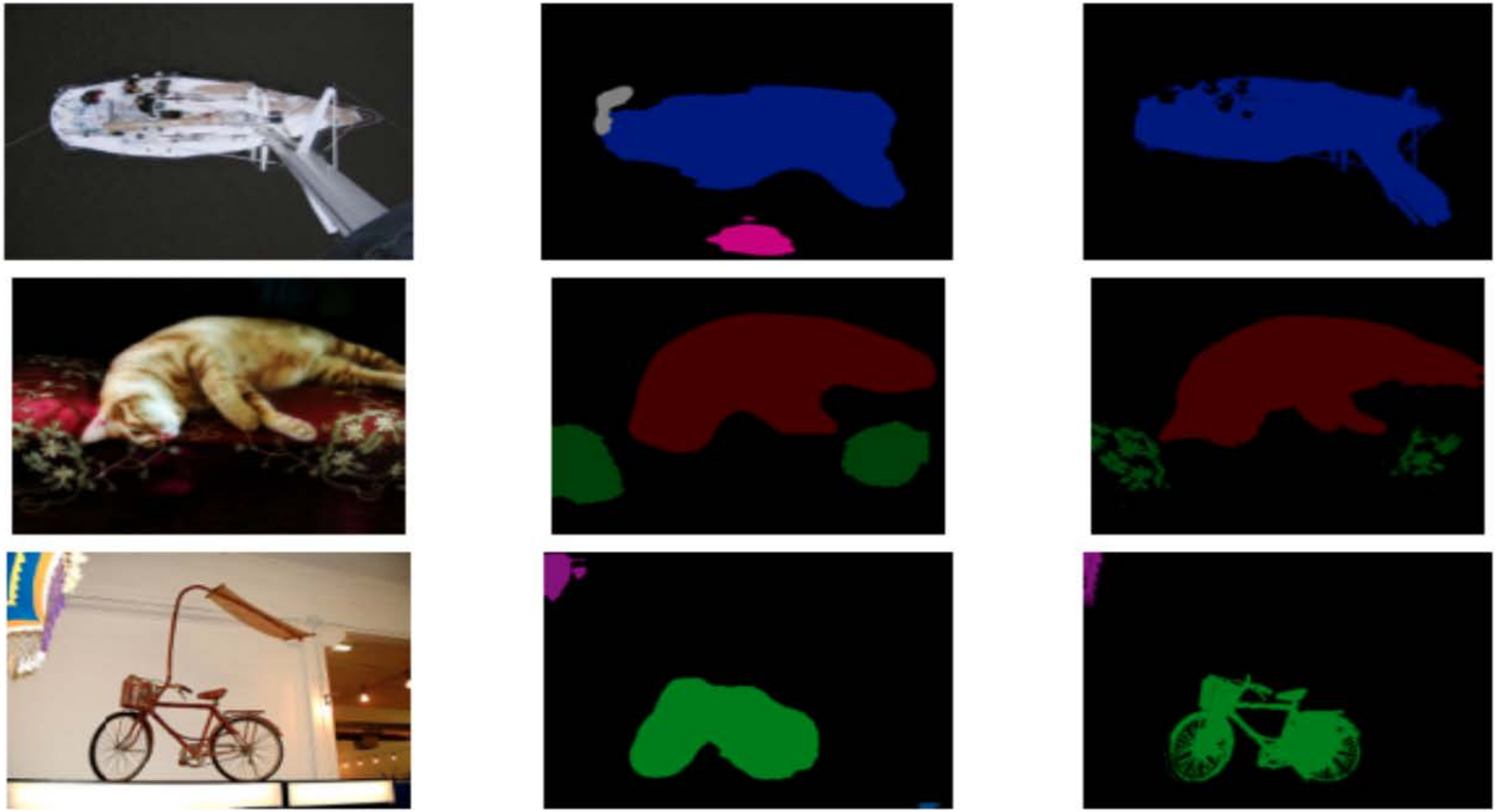
Indicative Results



Raw score maps

After dense CRF

Indicative Results



Raw score maps

After dense CRF

Indicative Results

Raw score maps

After dense CRF

Improvements due to fully-connected CRF

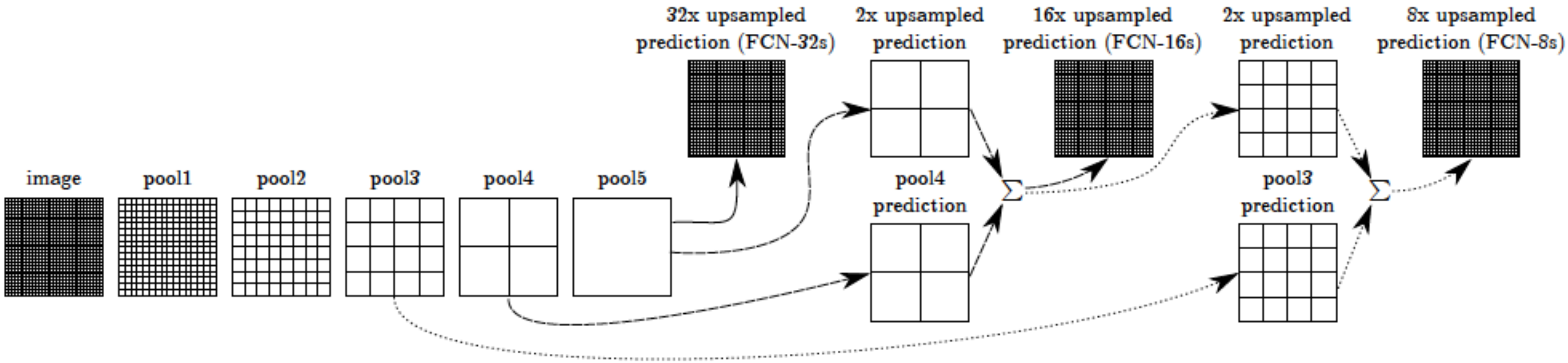
Method	mean IOU (%)
DeepLab	59.80
DeepLab-CRF	63.74
DeepLab-MSc	61.30
DeepLab-MSc-CRF	65.21

Improvements due to Dense CRF

Krahenbuhl et. al. (TextonBoost unaries)
27.6 -> 29.1 (+1.5)

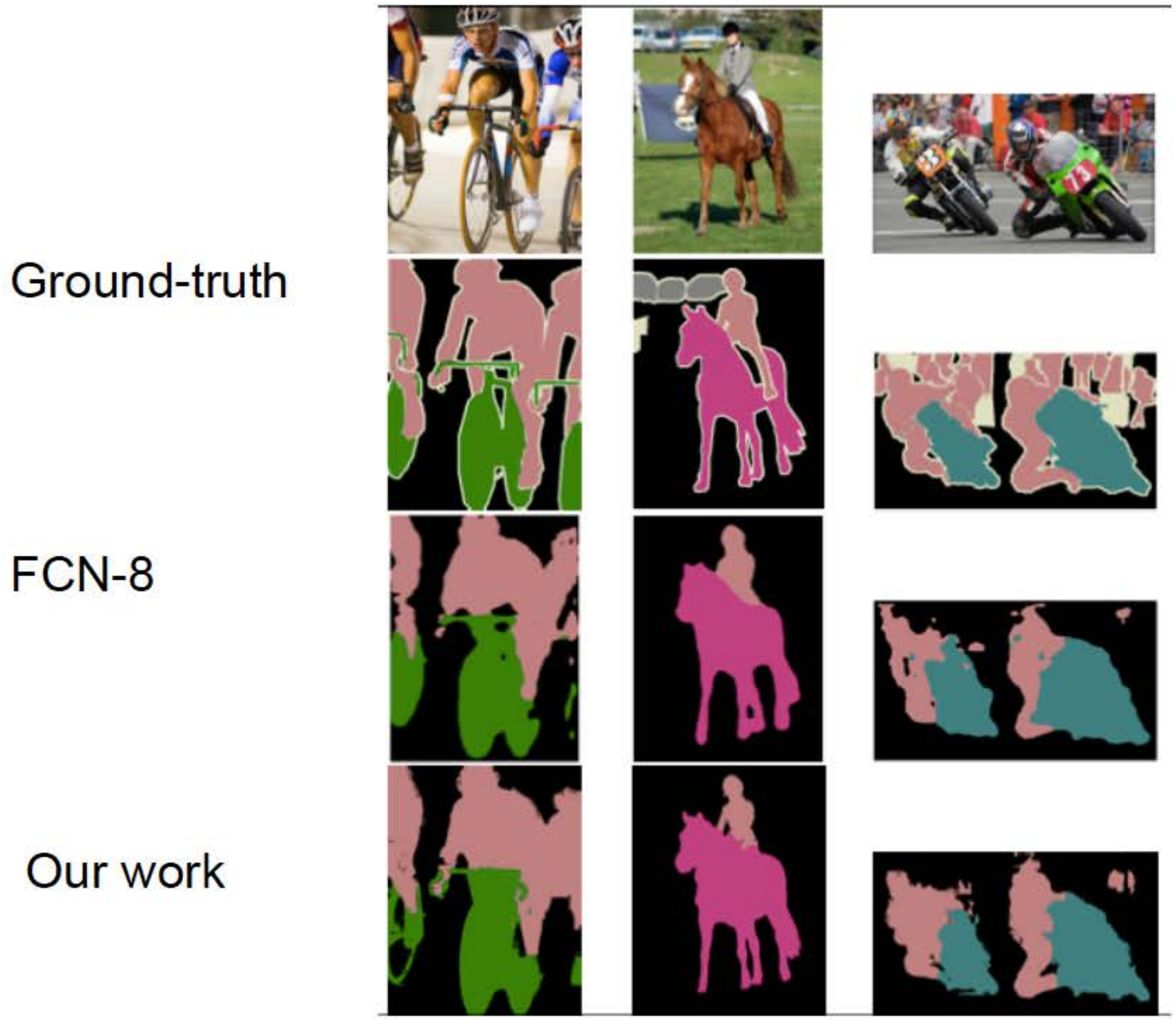
Our work (FCNN unaries)
61.3 -> 65.21 (+3.9)

Another fully convolutional network for semantic segmentation (without CRF)



J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *arXiv:1411.4038*, 2014.

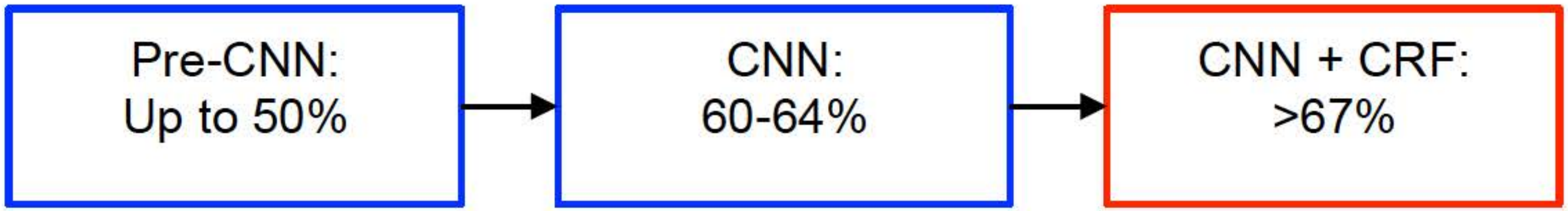
Comparisons to Fully Convolutional Net



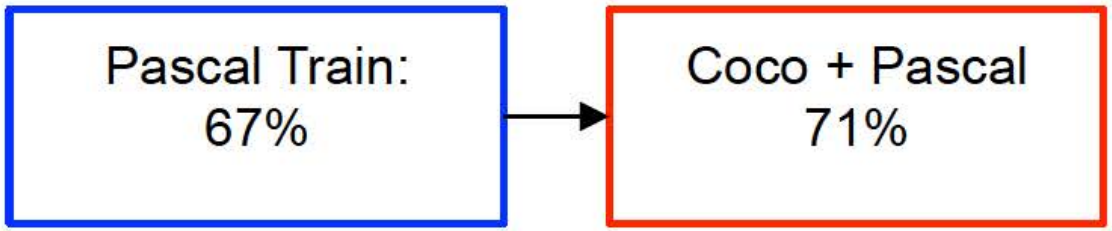
J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. *arXiv:1411.4038*, 2014.

Comparison to state-of-the-art (Pascal VOC test)

Method	mean IOU (%)
MSRA-CFM	61.8
FCN-8s	62.2
TTI-Zoomout-16	64.4
DeepLab-CRF (our)	66.4
DeepLab-MSc-CRF (our)	67.1



G. Papandreou, et al, Weakly- and Semi-Supervised Learning of a DCNN for Semantic Image Segmentation, arxiv 2015



3. Cityscapes Dataset

- Dataset for semantic labeling and "understanding"
  - Cordts, Omaran, Ramos, Rehfeld, Enzweiler, Benenson, Franke, Roth, Schiele @ cvpr16
  - https://www.cityscapes-dataset.net
  - http://arxiv.org/abs/1604.01685

The Cityscapes Dataset

for Semantic Scene Labeling and Understanding

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

Marius Cordts[1,3] Mohamed Omran[2] Sebastian Ramos[1]
Timo Rehfeld[1,3] Markus Enzweiler[1] Rodrigo Benenson[2]
Uwe Franke[1] Stefan Roth[3] Bernt Schiele[2]

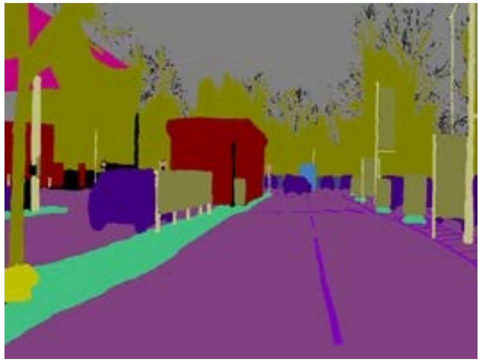
1 DAIMLER

2 max planck institut informatik

3 TECHNISCHE UNIVERSITÄT DARMSTADT

Previous Work

CITYSCAPES DATASET



CamVid [Brostow et al., to appear]

- monocular video

KITTI [Geiger et al. '12]

- stereo video
- no official semantic labeling or instance labeling challen

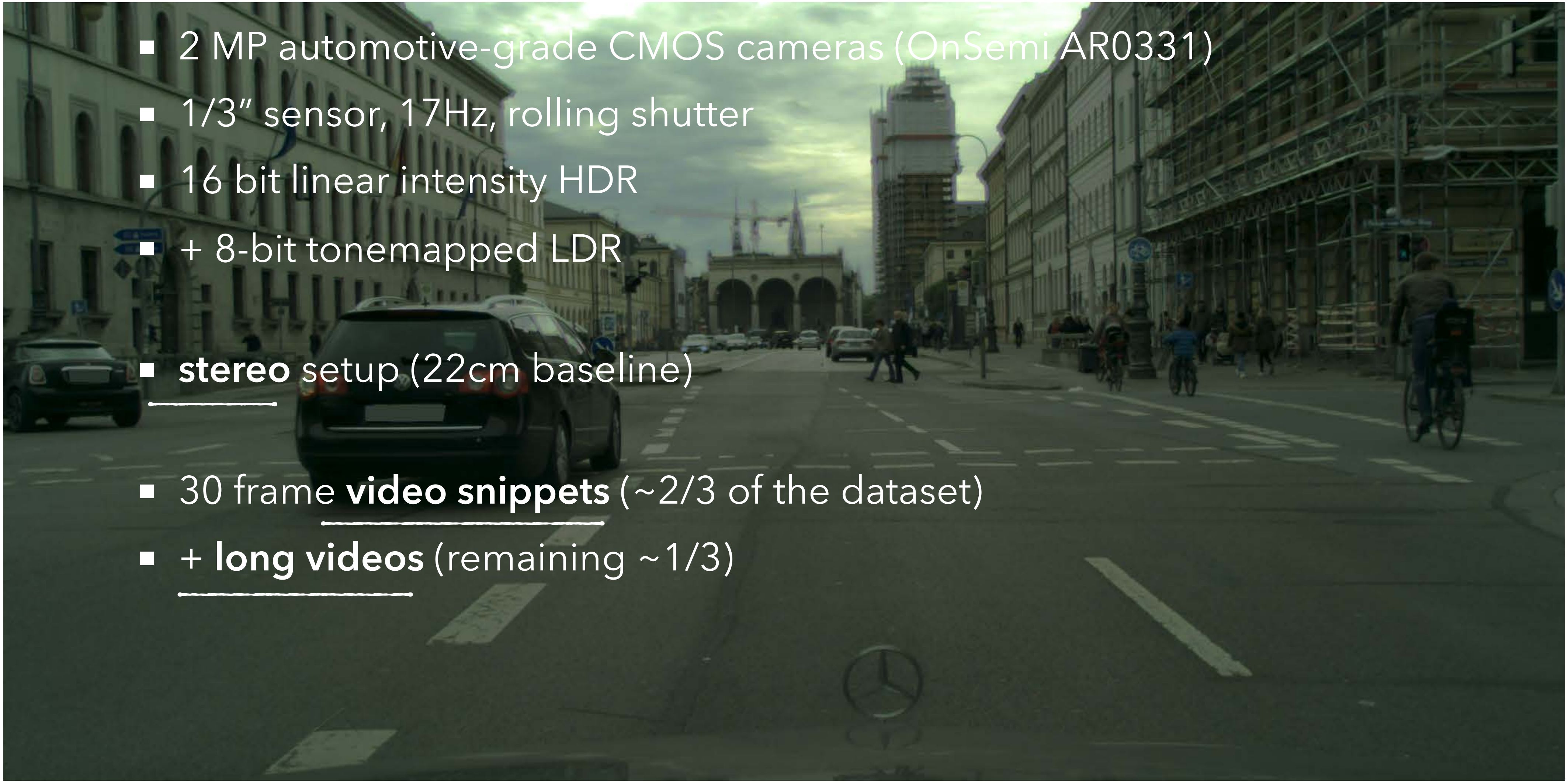
Daimler Urban Scenes [Scharwächter et al. '14]

- stereo video
- limited number of classes / annotation density

Overview

CITYSCAPES DATASET

https://www.cityscapes-dataset.net



- 2 MP automotive-grade CMOS cameras (OnSemi AR0331)
- 1/3″ sensor, 17Hz, rolling shutter
- 16 bit linear intensity HDR
- + 8-bit tonemapped LDR
- **stereo** setup (22cm baseline)
- 30 frame **video snippets** (~2/3 of the dataset)
- + **long videos** (remaining ~1/3)

Example video snippet

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

Example video snippet

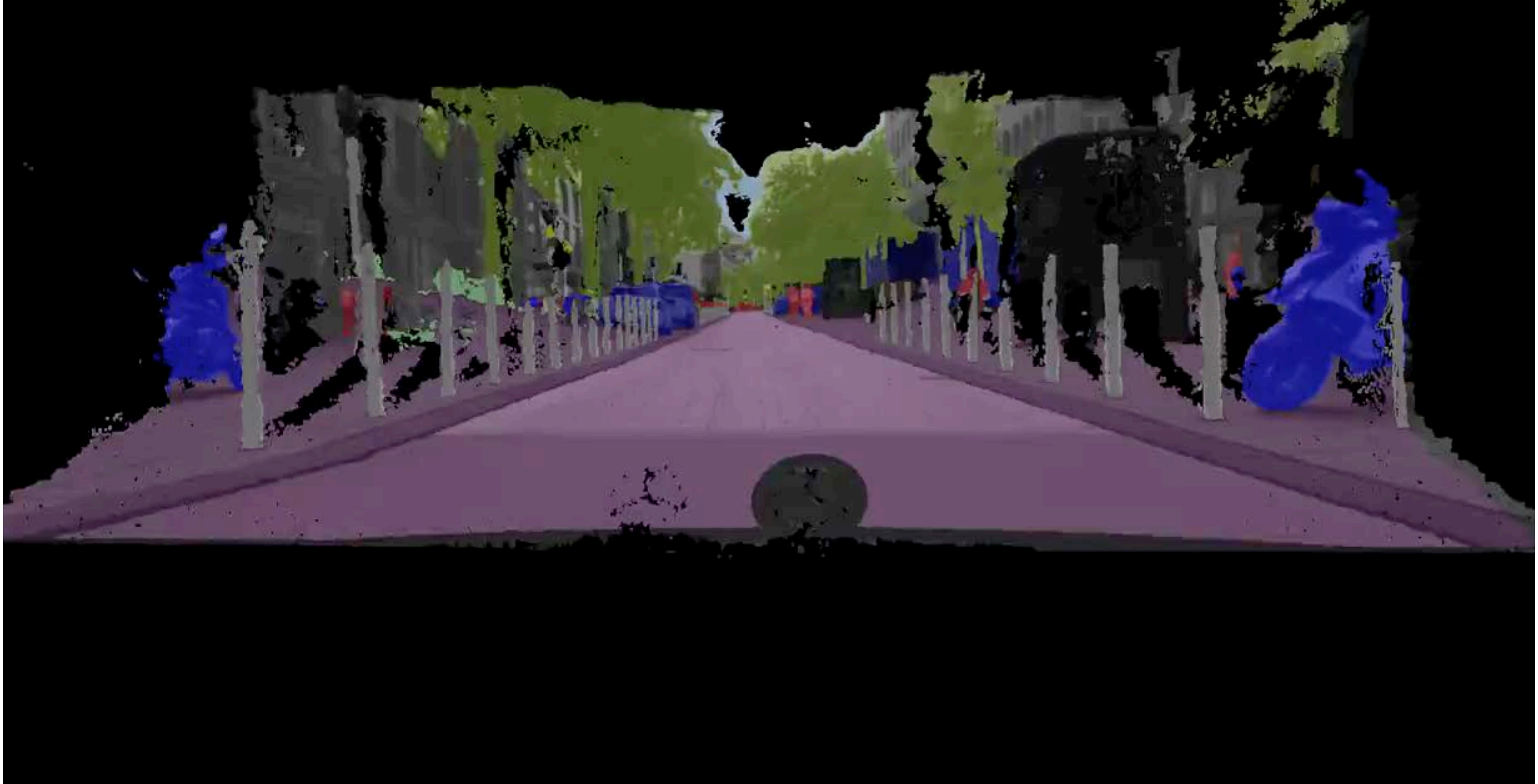
CITYSCAPES DATASET

https://www.cityscapes-dataset.net

Overview

https://www.cityscapes-dataset.net

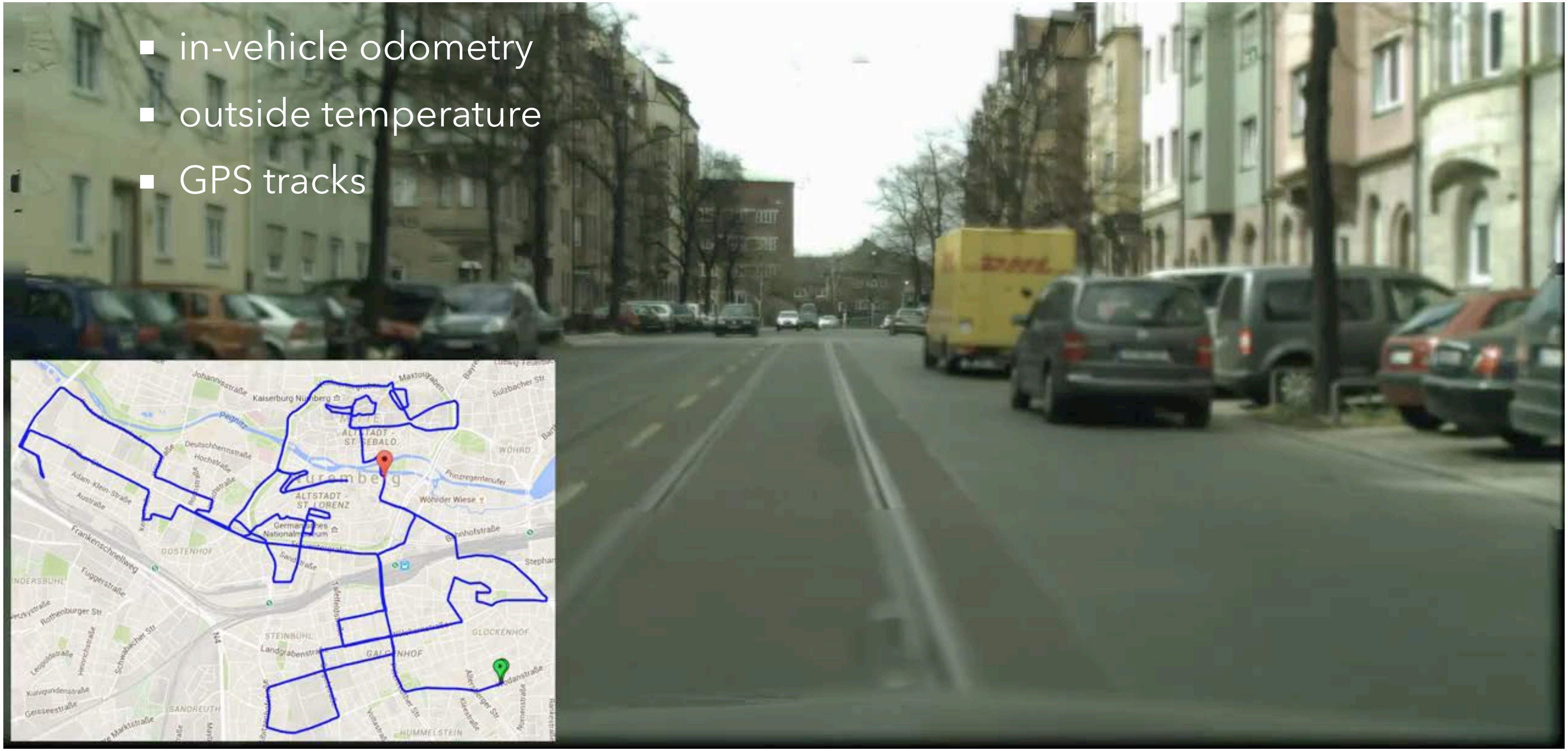
- precomputed disparity



Overview

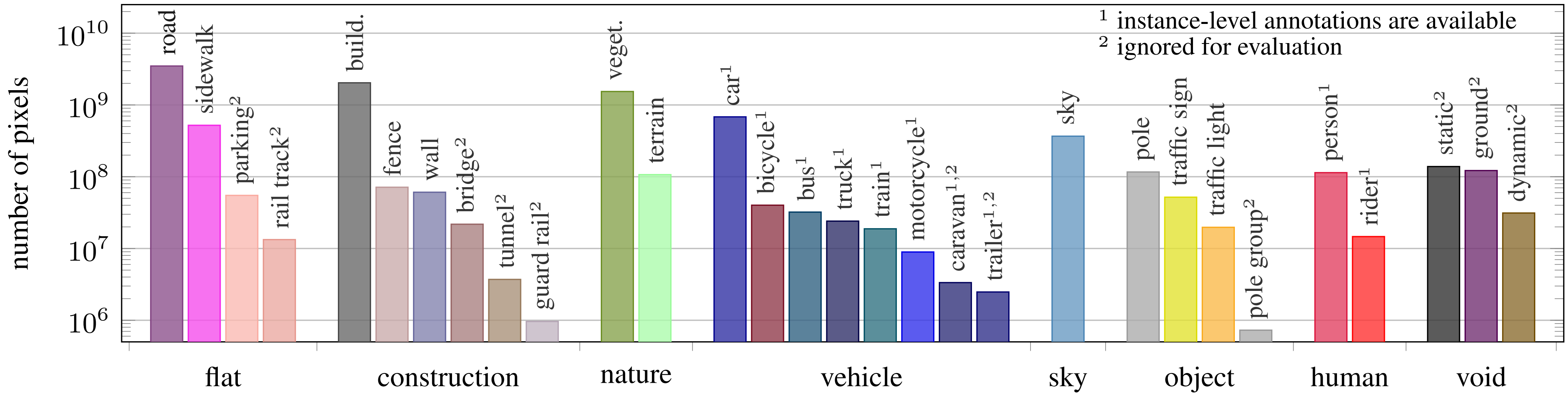
https://www.cityscapes-dataset.net

- in-vehicle odometry
- outside temperature
- GPS tracks



Labels

https://www.cityscapes-dataset.net



- 8 categories – 30 classes
  - instance-level annotations for all vehicles & humans
- 19 classes evaluated
  - rare cases excluded

Dense Labeling: 5,000 images

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

- 2975 training images
- 500 validation images
- 1525 test images (for benchmark)
- annotated 20th frame from every video snippet
- **instance labels** for dynamic classes

Coarse Labeling: 20,000 images

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

- all for weakly-supervised training
- annotated every 20th frame from long video

Objective: Complexity

https://www.cityscapes-dataset.net

- **Complex, real-world scenes**

Objective: Diversity

CITYSCAPES DATASET

- **50 cities**
  - across all of Germany
  - + Zürich + Strasbourg
  - KITTI, CamVid & DUS: 1 city only
- **3 seasons**
  - spring, summer, fall
  - winter purposely excluded
- **fair weather**
  - rain & snow are excluded
  - daytime only

Comparison to Previous Datasets

CITYSCAPES DATASET

	#pixels $[10^9]$	annot. density [%]
Ours (fine)	9.41	**97.0**
Ours (coarse)	**26.0**	67.5
CamVid	0.62	96.2
DUS	0.14	63.0
KITTI	0.23	88.9

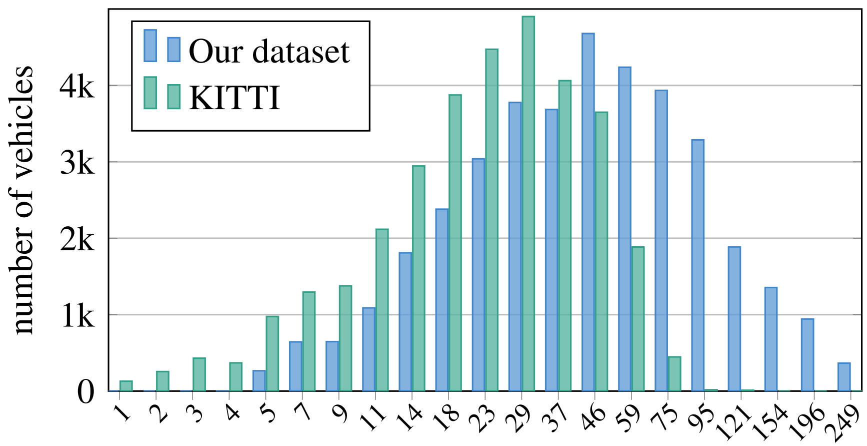
dataset size & density

	#humans $[10^3]$	#vehicles $[10^3]$	#h/image	#v/image
Ours (fine)	24.2	**49.1**	**7.0**	**14.1**
KITTI	6.1	30.3	0.8	4.1
Caltech	**192**[1]	-	1.5	-

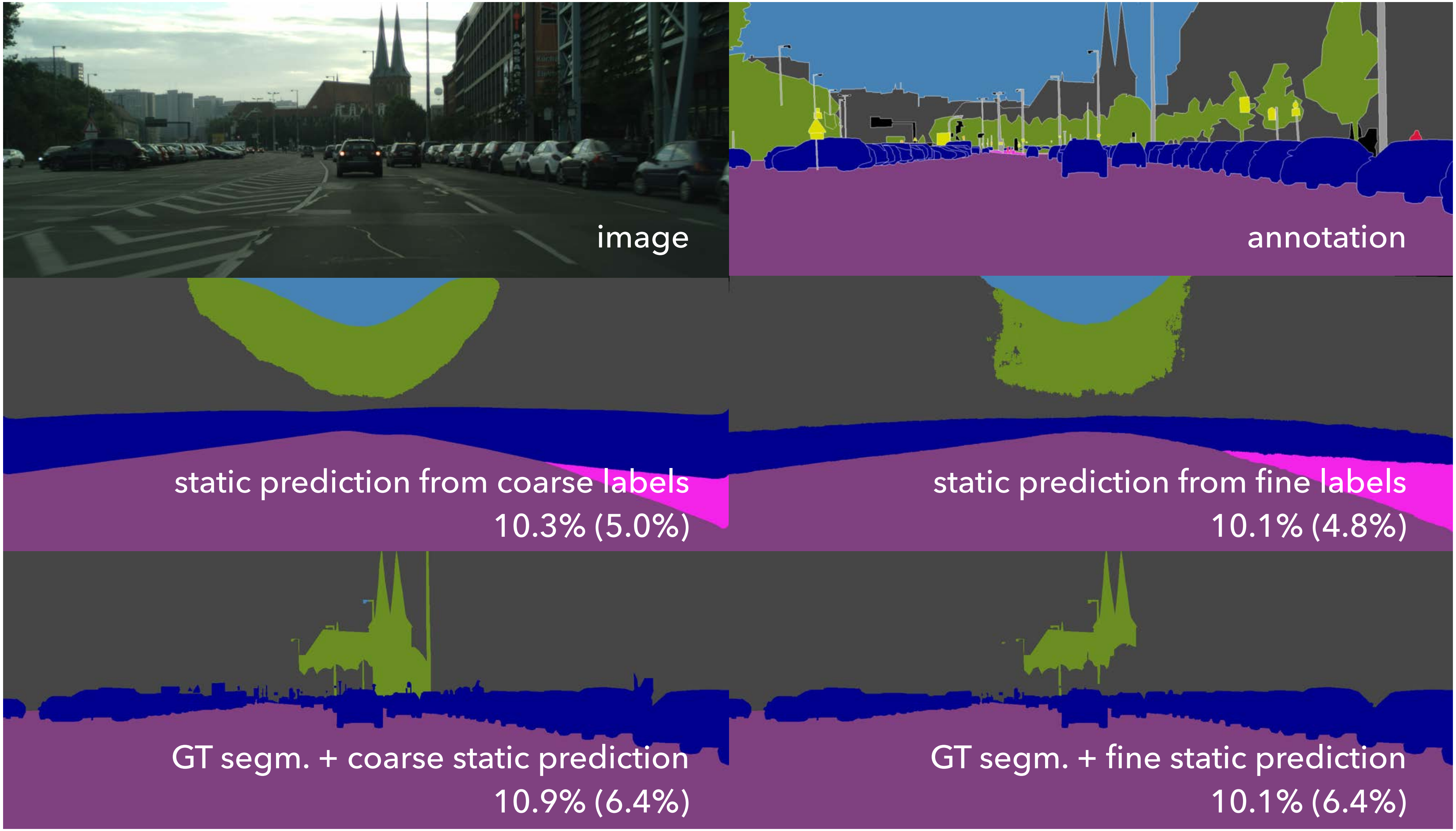
instance statistics

- CamVid & DUS: no instance annotations
- KITTI: only bboxes

histogram of vehicle distances



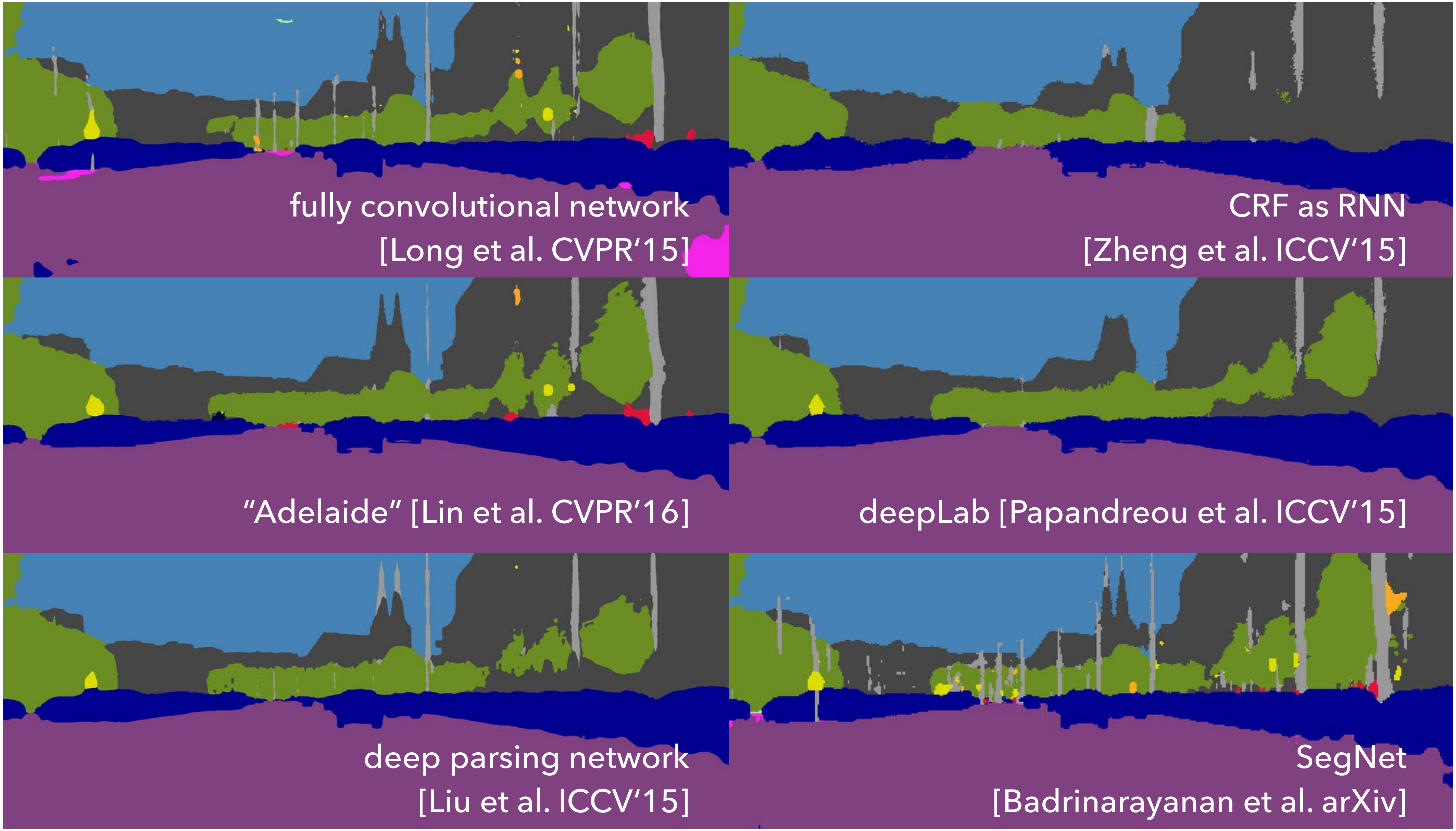
Control experiments



IoU (iIoU)

Baselines

CITYSCAPES DATASET



FCN Results

FCN Results

CITYSCAPES DATASET

Baselines - Quantitative Results

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

	train	val	coarse	sub	Classes IoU	Classes iIoU	Categories IoU	Categories iIoU	
FCN-8s	✓	✓			65.3	41.7	85.7	70.1	~3,500 **finely** annotated images
FCN-8s	✓	✓		2	61.9	33.6	81.6	60.9	
FCN-8s		✓			58.3	37.4	83.4	67.2	500 **finely** annotated images
FCN-8s			✓		58.0	31.8	78.2	58.4	20,000 **coarsely** annotated images
[4] extended	✓			4	56.1	34.2	79.8	66.4	Badrinarayanan et al. @ arXiv'15
[4] basic	✓			4	57.0	32.0	79.1	61.9	Badrinarayanan et al. @ arXiv'15
[40]	✓	✓	✓	3	59.1	28.1	79.5	57.9	Liu et al @ ICCV'15
[81]	✓			2	62.5	34.4	82.7	66.0	Zheng et al @ ICCV'15
[9]	✓	✓		2	63.1	34.5	81.2	58.7	Chen et al. @ ICLR'15
[48]	✓	✓	✓	2	64.8	34.9	81.3	58.7	Papandreou et al @ ICCV'15
[37]	✓				66.4	**46.7**	82.8	67.4	Lin et al. @ CVPR'16
[79]	✓				**67.1**	42.0	**86.5**	**71.1**	Yu & Koltun @ ICLR'16

Cross-Dataset Generalization

CITYSCAPES DATASET

https://www.cityscapes-dataset.net

Dataset	Best reported result	Our result
Camvid [6]	62.9 [3]	72.6
KITTI [53]	61.6 [3]	70.9
KITTI [59]	82.2 [65]	81.2

FCN [Long et al. CVPR'15] trained on Cityscapes

Cityscapes: Conclusions

https://www.cityscapes-dataset.net

- Cityscapes is the largest and most diverse datasets for semantic segmentation of urban street scenes
  - aim is to become the standard dataset for
    - scene labeling (urban scenarios)
    - instance segmentation (people, cars, etc)
  - planned as dynamic entity which will be expanded & adapted

- Recent CNNs approaches:
  - already achieve very good results
  - impressive cross-dataset generalization
  - using coarse annotations only leads to reduced performance