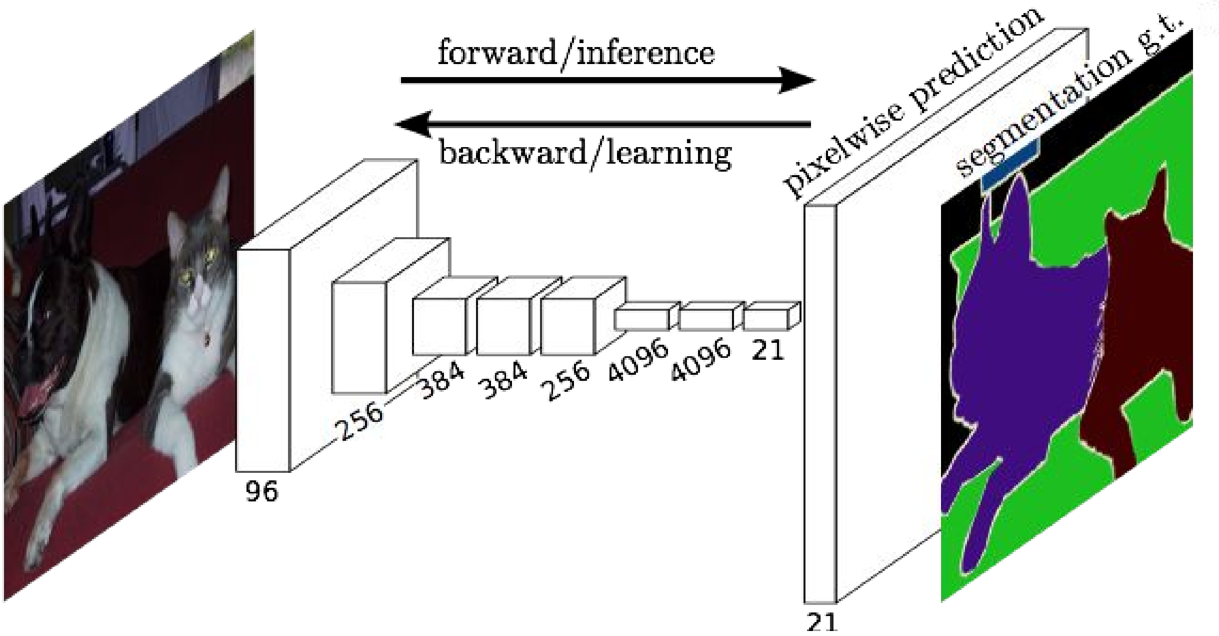
A Fuller Understanding of Fully Convolutional Networks



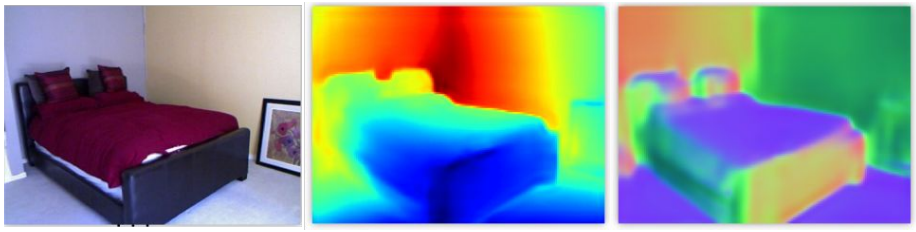
Evan Shelhamer*   Jonathan Long*   Trevor Darrell

UC Berkeley in CVPR'15, PAMI'16

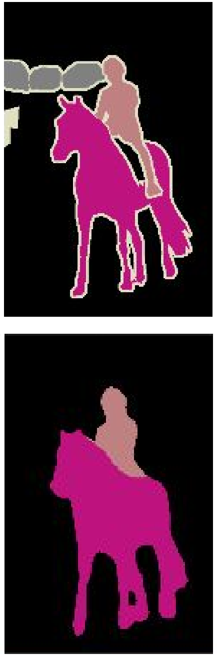
pixels in, pixels out

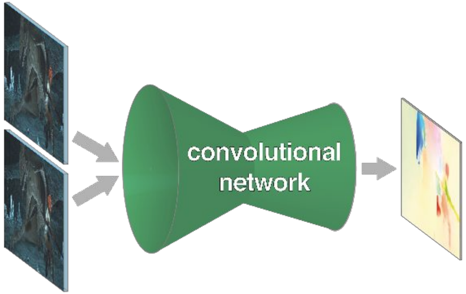
colorization
Zhang et al.2016

monocular depth + normals Eigen & Fergus 2015

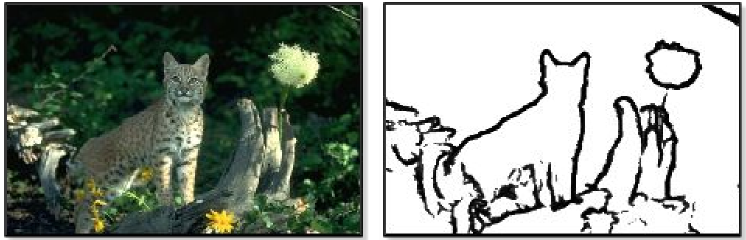


semantic
segmentation



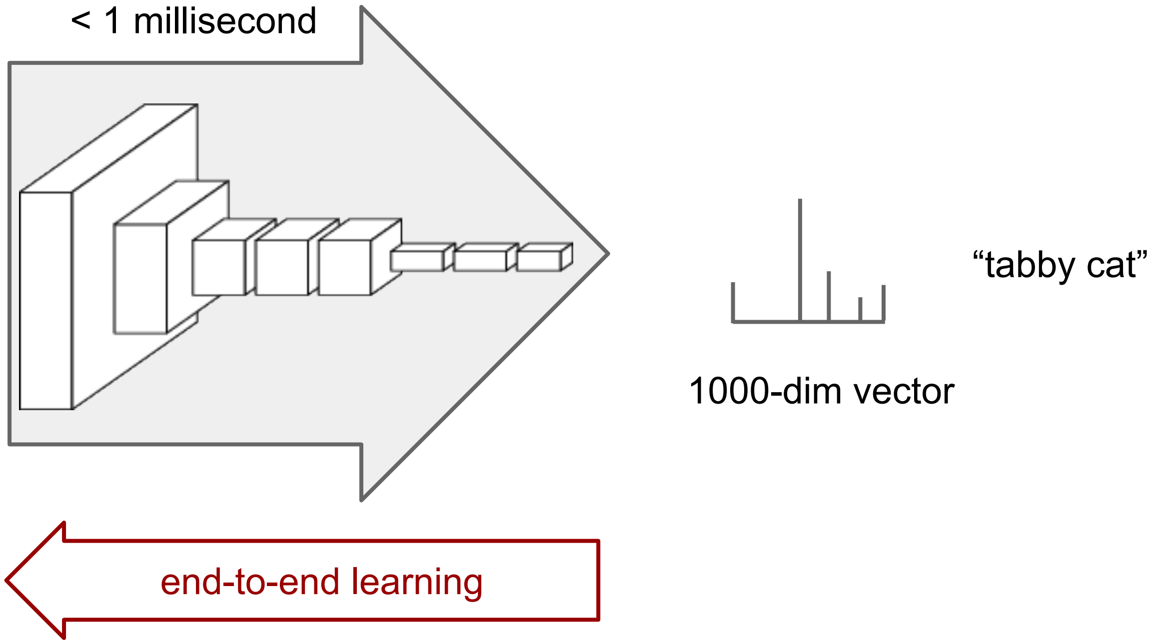


optical flow Fischer et al. 2015

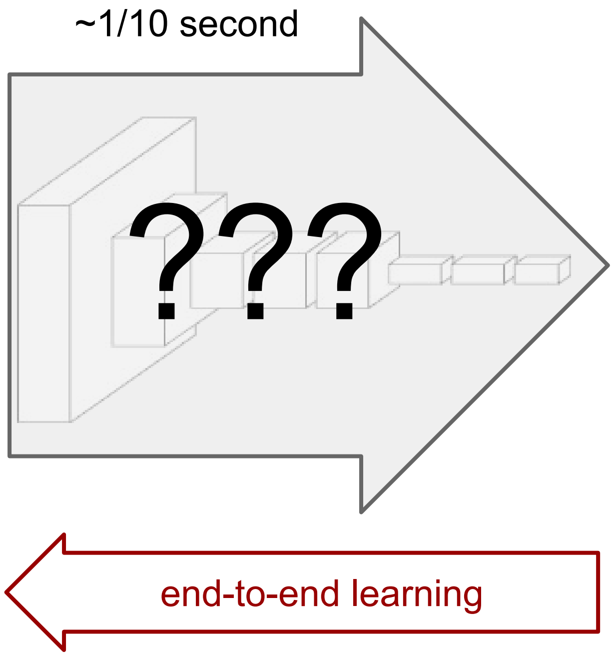


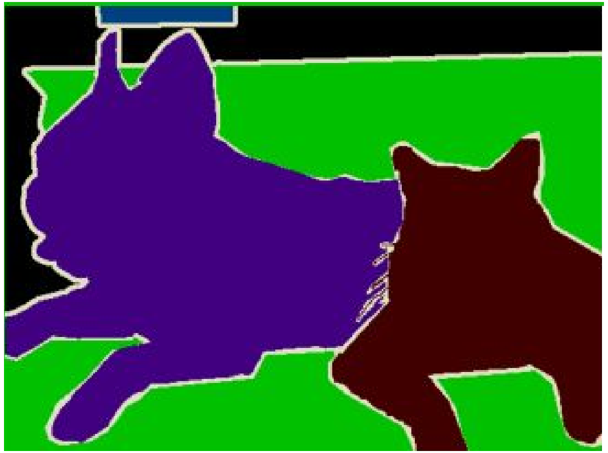
boundary prediction Xie & Tu 2015

convnets perform classification

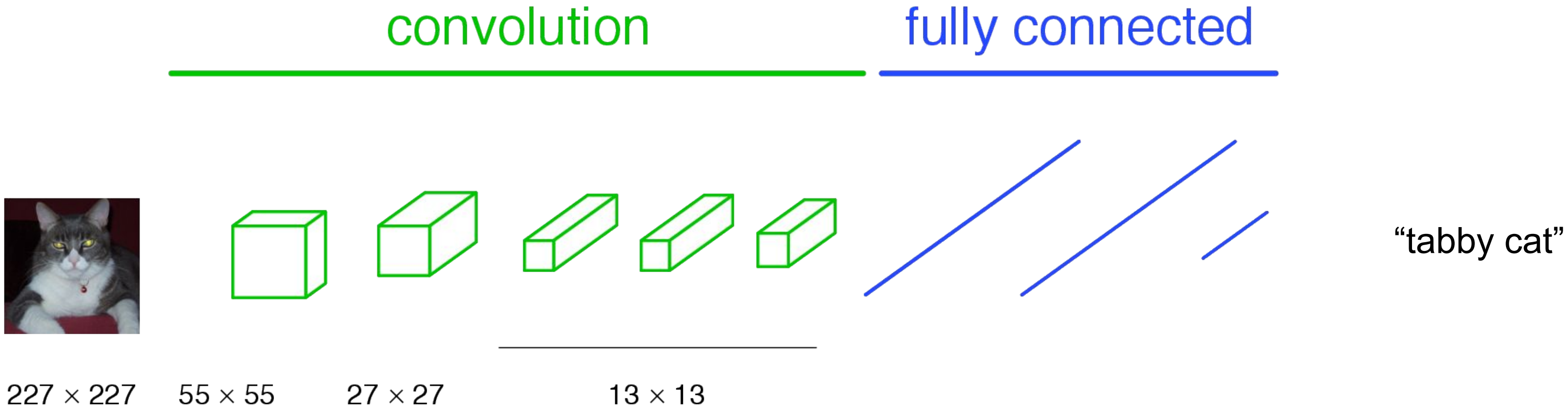


lots of pixels, little time?

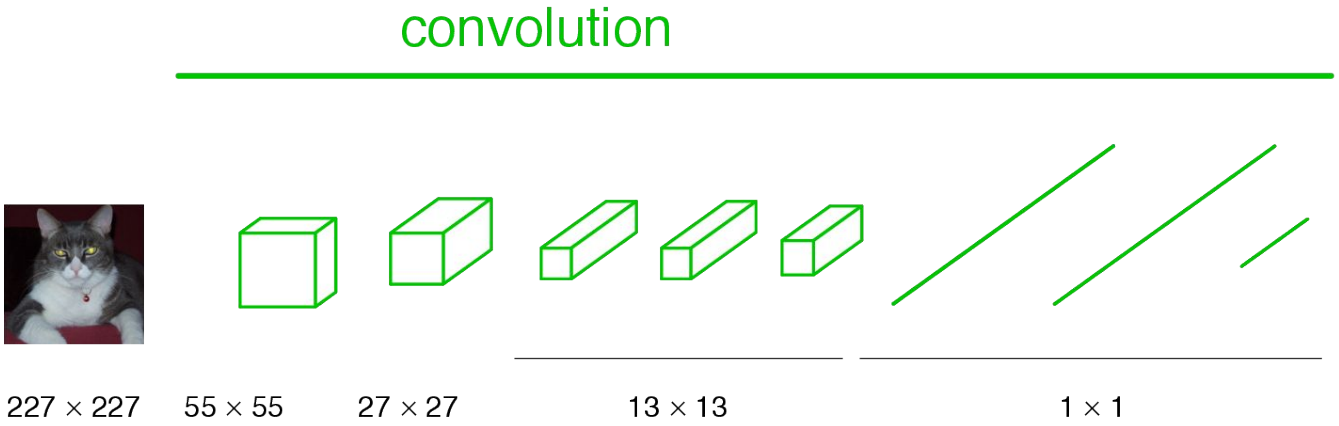




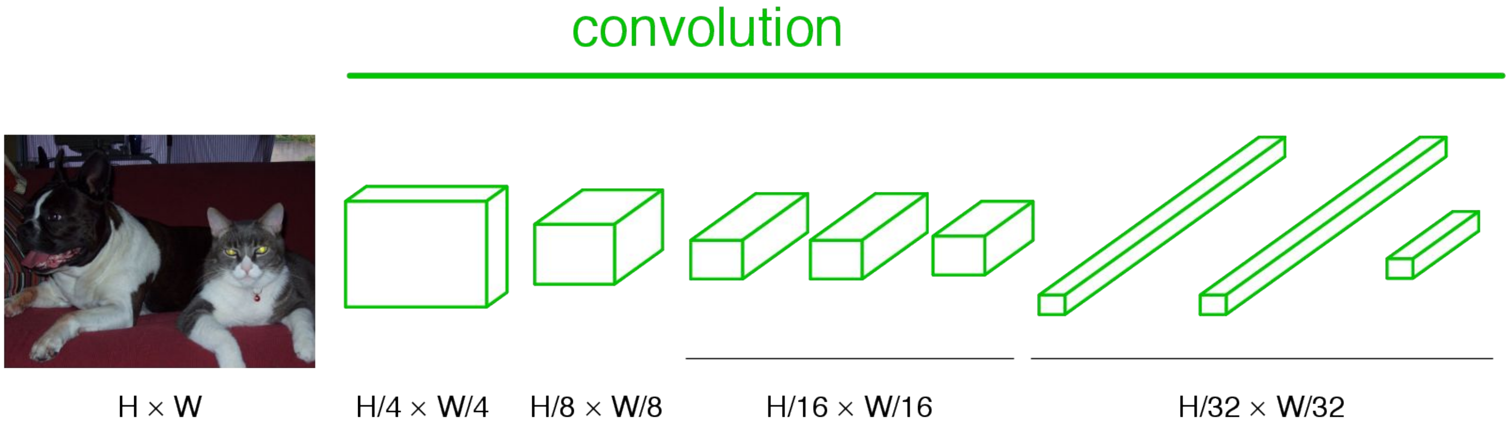
a classification network



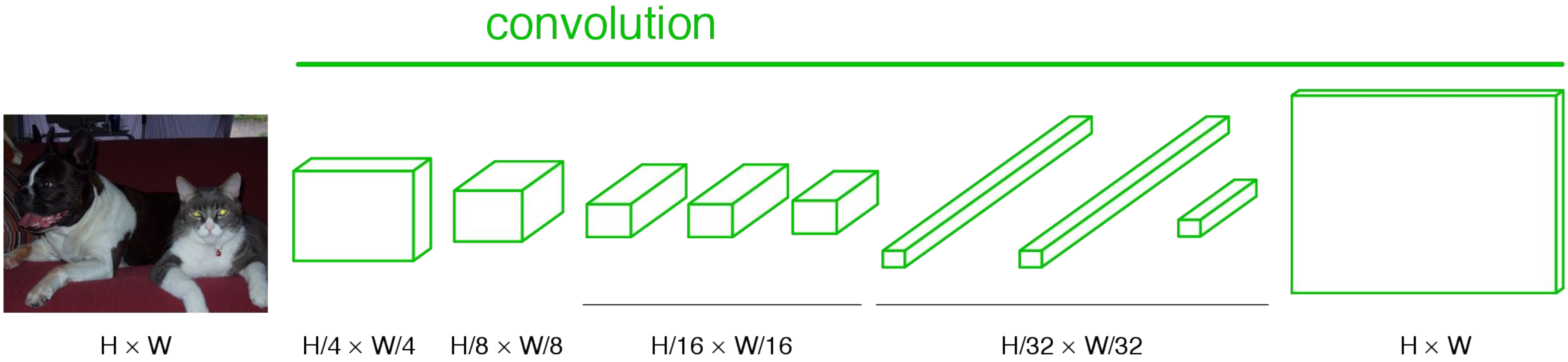
becoming fully convolutional



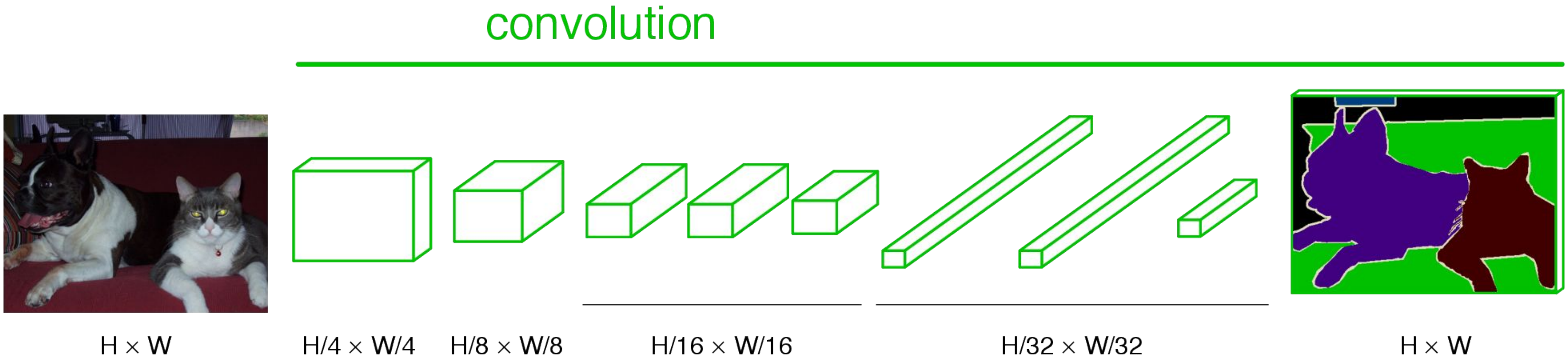
becoming fully convolutional



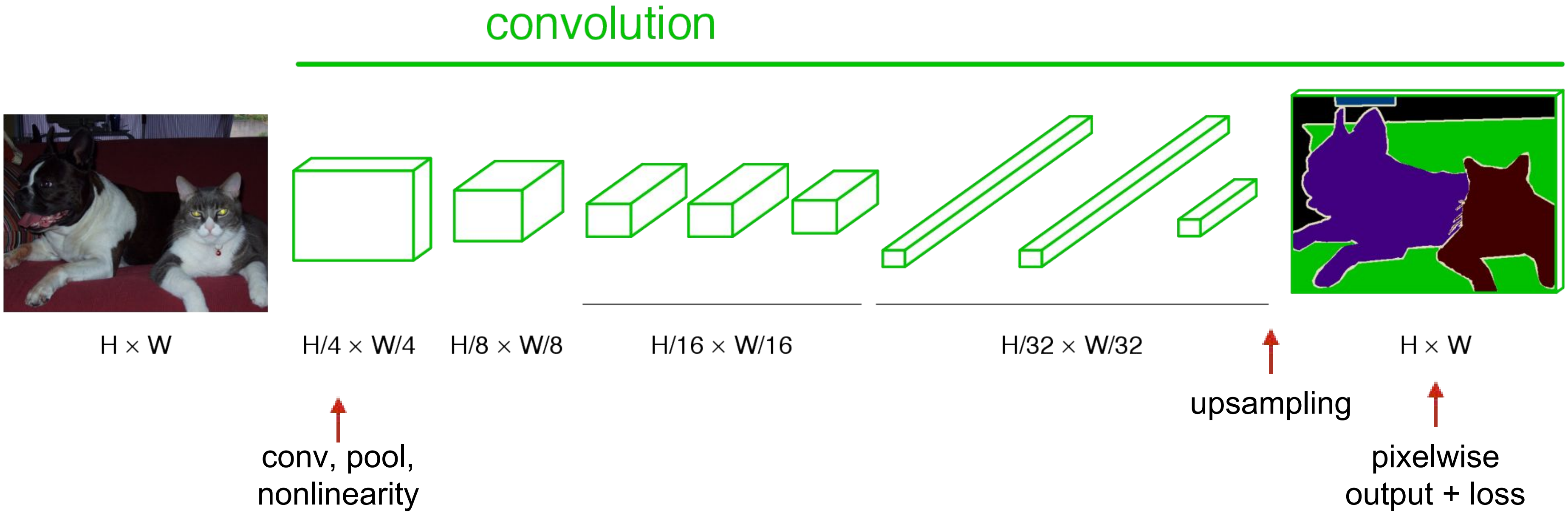
upsampling output



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



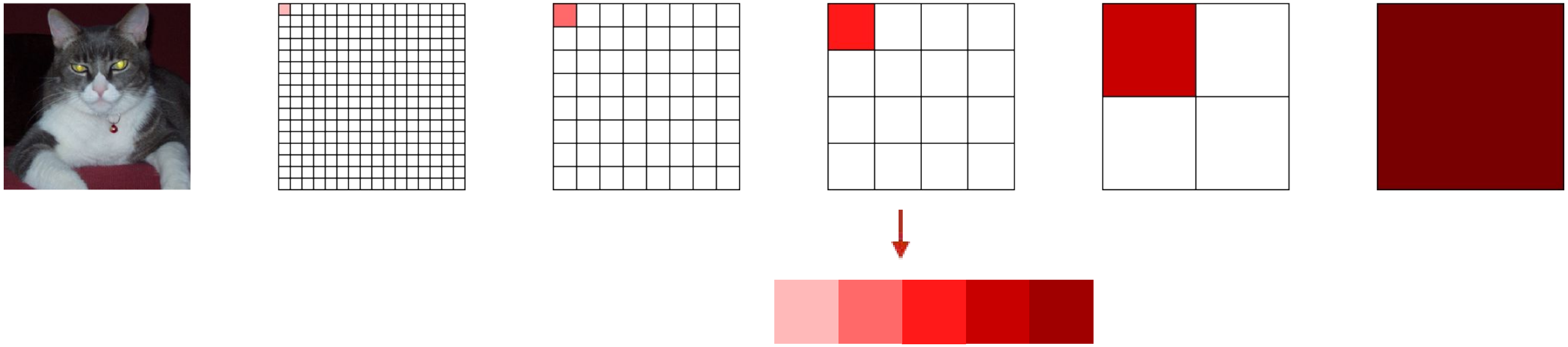
end-to-end, pixels-to-pixels network



spectrum of deep features

combine *where* (local, shallow) with *what* (global, deep)

image intermediate layers



fuse features into **deep jet**

(cf. Hariharan et al. CVPR15 “hypercolumn”)

skip layers

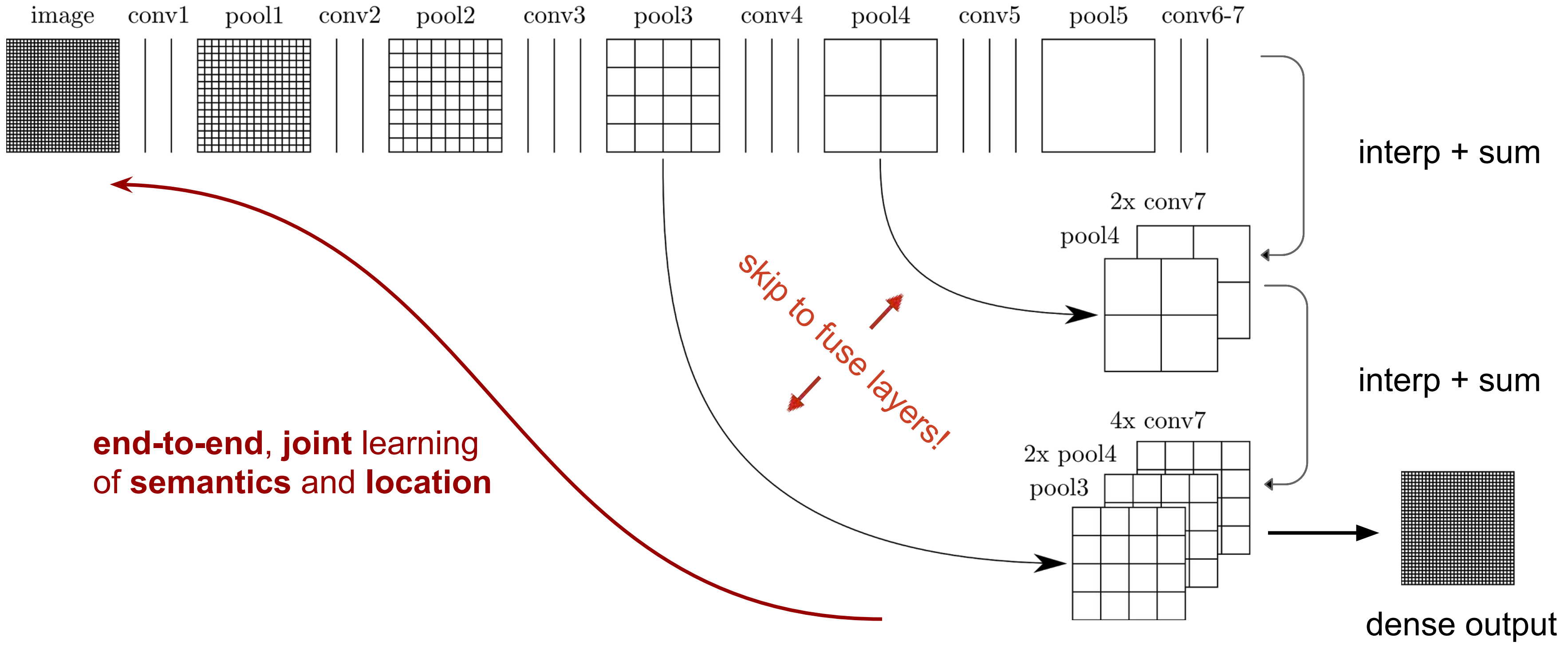
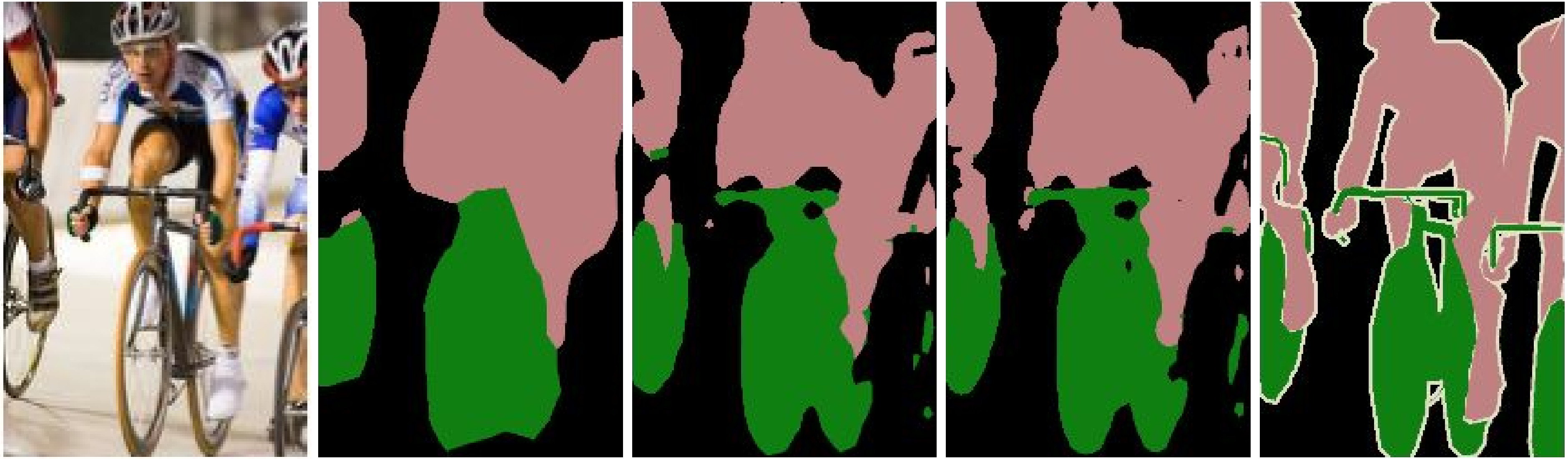


image
conv1
pool1
conv2
pool2
conv3
pool3
conv4
pool4
conv5
pool5
conv6-7
interp + sum
2x conv7
pool4
skip to fuse layers!
interp + sum
4x conv7
2x pool4
pool3
end-to-end, joint learning
of semantics and location
dense output

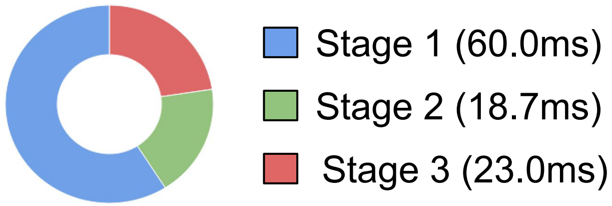
skip layer refinement

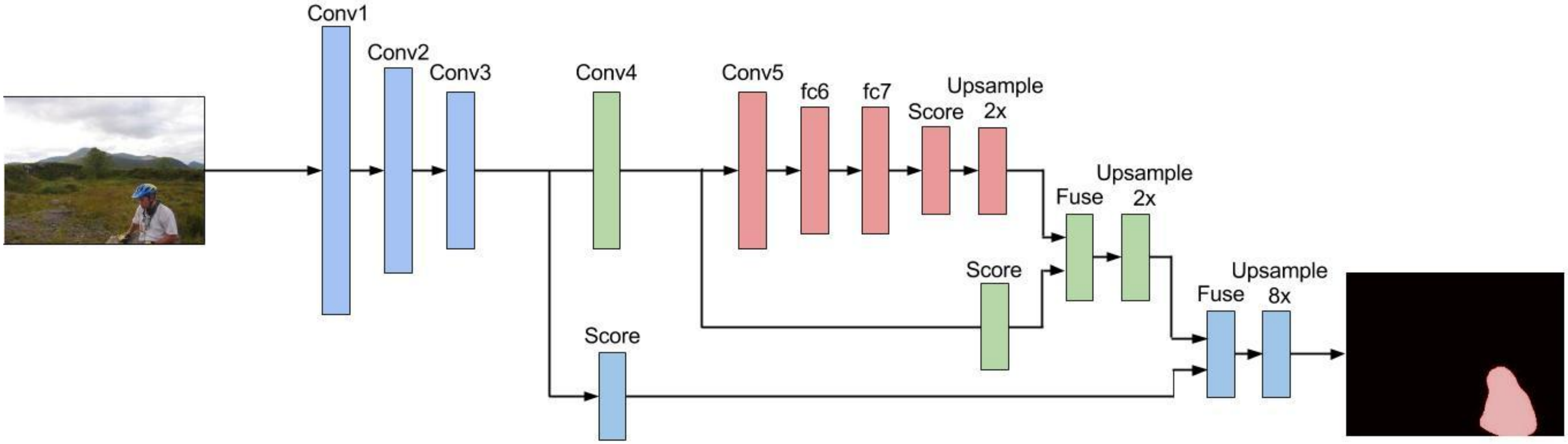
input image | stride 32 | stride 16 | stride 8 | ground truth



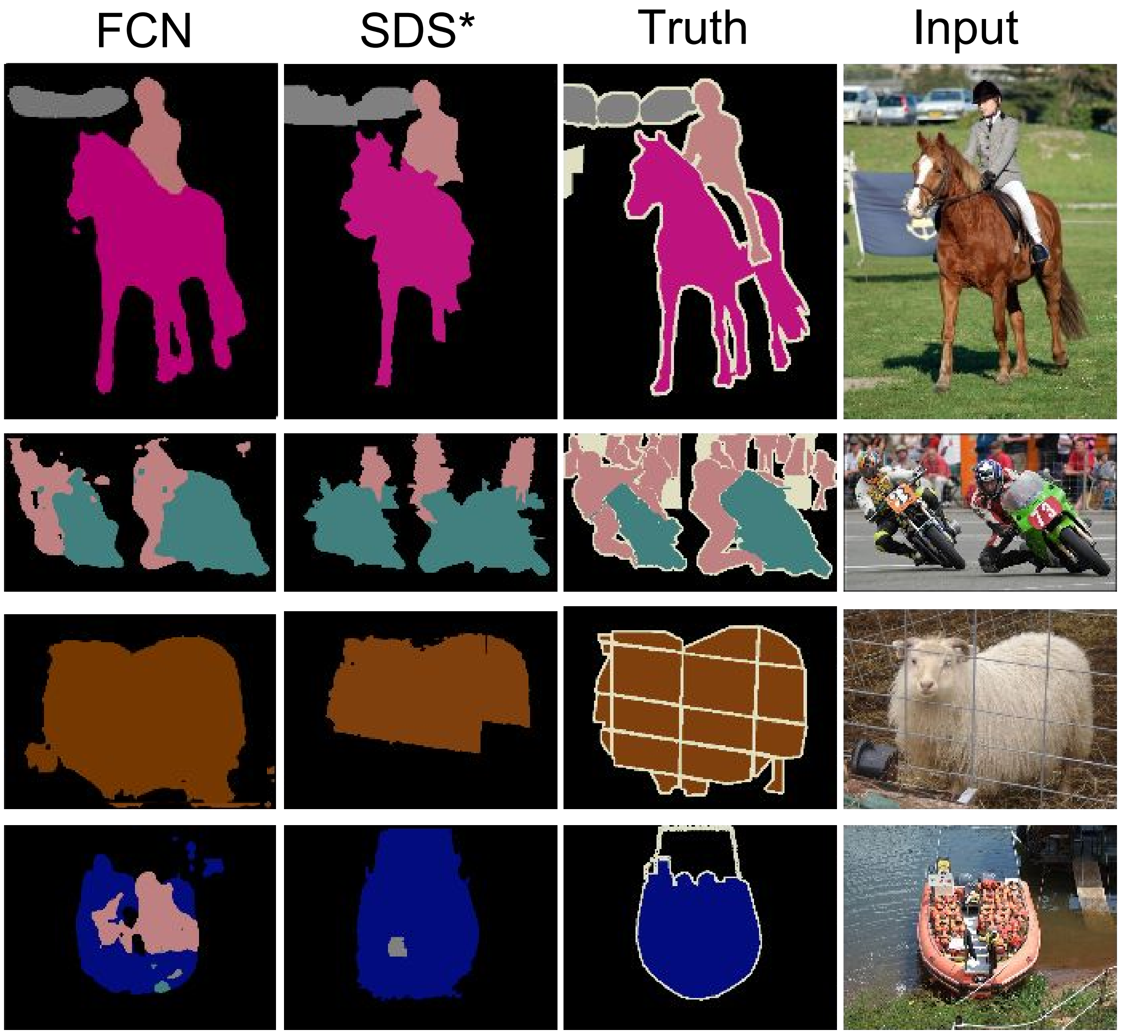
no skips | 1 skip | 2 skips

skip FCN computation





A multi-stream network that fuses features/predictions across layers



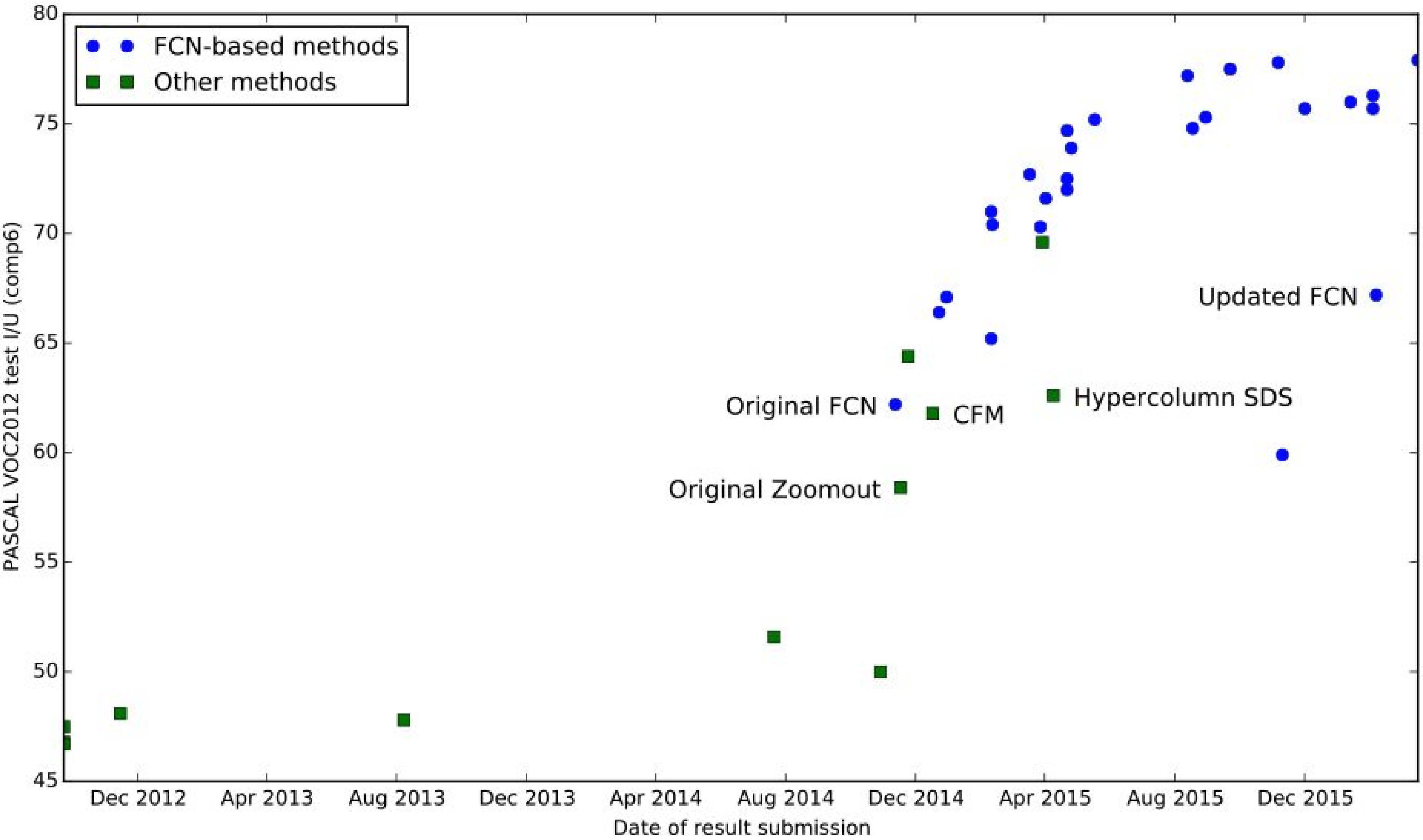
Relative to prior state-of-the-art SDS:

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

*Simultaneous Detection and Segmentation
Hariharan et al. ECCV14

		mean	aero plane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	dining table	dog	horse	motor bike	person	potted plant	sheep	sofa	train	tv/ monitor	submission date
MSRA_BoxSup [?]	FCN	75.2	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	18-May-2015
Oxford_TVG_CRF_RNN_COCO [?]	FCN	74.7	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	22-Apr-2015
DeepLab-MSc-CRF-LargeFOV-COCO-CrossJoint [?]	FCN	73.9	89.2	46.7	88.5	63.5	68.4	87.0	81.2	86.3	32.6	80.7	62.4	81.0	81.3	84.3	82.1	56.2	84.6	58.3	76.2	67.2	26-Apr-2015
Adelaide_Context_CNN_CRF_VOC [?]	FCN	72.9	89.7	37.6	77.4	62.1	72.9	88.1	84.8	81.9	34.4	80.0	55.9	79.3	82.3	84.0	82.9	59.7	82.8	54.1	77.5	70.3	25-May-2015
DeepLab-CRF-COCO-LargeFOV [?]	FCN	72.7	89.1	38.3	88.1	63.3	69.7	87.1	83.1	85.0	29.3	76.5	56.5	79.8	77.9	85.8	82.4	57.4	84.3	54.9	80.5	64.1	18-Mar-2015
POSTECH_EDeconvNet_CRF_VOC [?]	FCN	72.5	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	22-Apr-2015
Oxford_TVG_CRF_RNN_VOC [?]	FCN	72.0	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	22-Apr-2015
DeepLab-MSc-CRF-LargeFOV [?]	FCN	71.6	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	02-Apr-2015
MSRA_BoxSup [?]	FCN	71.0	86.4	35.5	79.7	65.2	65.2	84.3	78.5	83.7	30.5	76.2	62.6	79.3	76.1	82.1	81.3	57.0	78.2	55.0	72.5	68.1	10-Feb-2015
DeepLab-CRF-COCO-Strong [?]	FCN	70.4	85.3	36.2	84.8	61.2	67.5	84.6	81.4	81.0	30.8	73.8	53.8	77.5	76.5	82.3	81.6	56.3	78.9	52.3	76.6	63.3	11-Feb-2015
DeepLab-CRF-LargeFOV [?]	FCN	70.3	83.5	36.6	82.5	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	28-Mar-2015
TTI_zoomout_v2 [?]		69.6	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	30-Mar-2015
DeepLab-CRF-MSc [?]	FCN	67.1	80.4	36.8	77.4	55.2	66.4	81.5	77.5	78.9	27.1	68.2	52.7	74.3	69.6	79.4	79.0	56.9	78.8	45.2	72.7	59.3	30-Dec-2014
DeepLab-CRF [?]	FCN	66.4	78.4	33.1	78.2	55.6	65.3	81.3	75.5	78.6	25.3	69.2	52.7	75.2	69.0	79.1	77.6	54.7	78.3	45.1	73.3	56.2	23-Dec-2014
CRF_RNN [?]	FCN	65.2	80.9	34.0	72.9	52.6	62.5	79.8	76.3	79.9	23.6	67.7	51.8	74.8	69.9	76.9	76.9	49.0	74.7	42.7	72.1	59.6	10-Feb-2015
TTI_zoomout_16 [?]		64.4	81.9	35.1	78.2	57.4	56.5	80.5	74.0	79.8	22.4	69.6	53.7	74.0	76.0	76.6	68.8	44.3	70.2	40.2	68.9	55.3	24-Nov-2014
Hypercolumn [?]		62.6	68.7	33.5	69.8	51.3	70.2	81.1	71.9	74.9	23.9	60.6	46.9	72.1	68.3	74.5	72.9	52.6	64.4	45.4	64.9	57.4	09-Apr-2015
FCN-8s [?]	FCN	62.2	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	12-Nov-2014
MSRA_CFM [?]		61.8	75.7	26.7	69.5	48.8	65.6	81.0	69.2	73.3	30.0	68.7	51.5	69.1	68.1	71.7	67.5	50.4	66.5	44.4	58.9	53.5	17-Dec-2014
TTI_zoomout [?]		58.4	70.3	31.9	68.3	46.4	52.1	75.3	68.4	75.3	19.2	58.4	49.9	69.6	63.0	70.1	67.6	41.5	64.0	34.9	64.2	47.3	17-Nov-2014
SDS [?]		51.6	63.3	25.7	63.0	39.8	59.2	70.9	61.4	54.9	16.8	45.0	48.2	50.5	51.0	57.7	63.3	31.8	58.7	31.2	55.7	48.5	21-Jul-2014
NUS_UDS [?]		50.0	67.0	24.5	47.2	45.0	47.9	65.3	60.6	58.5	15.5	50.8	37.4	45.8	59.9	62.0	52.7	40.8	48.2	36.8	53.1	45.6	29-Oct-2014
TTIC-divmbest-rerank [?]		48.1	62.7	25.6	46.9	43.0	54.8	58.4	58.6	55.6	14.6	47.5	31.2	44.7	51.0	60.9	53.5	36.6	50.9	30.1	50.2	46.8	15-Nov-2012
BONN_O2PCPMC_FGT_SEGM [?]		47.8	64.0	27.3	54.1	39.2	48.7	56.6	57.7	52.5	14.2	54.8	29.6	42.2	58.0	54.8	50.2	36.6	58.6	31.6	48.4	38.6	08-Aug-2013
BONN_O2PCPMC_FGT_SEGM [?]		47.5	63.4	27.3	56.1	37.7	47.2	57.9	59.3	55.0	11.5	50.8	30.5	45.0	58.4	57.4	48.6	34.6	53.3	32.4	47.6	39.2	23-Sep-2012
BONNGC_O2P_CPMC_CSI [?]		46.8	63.6	26.8	45.6	41.7	47.1	54.3	58.6	55.1	14.5	49.0	30.9	46.1	52.6	58.2	53.4	32.0	44.5	34.6	45.3	43.1	23-Sep-2012
BONN_CMBR_O2P_CPMC_LIN [?]		46.7	63.9	23.8	44.6	40.3	45.5	59.6	58.7	57.1	11.7	45.9	34.9	43.0	54.9	58.0	51.5	34.6	44.1	29.9	50.5	44.5	23-Sep-2012

== segmentation with Caffe


FCN-based methods
Other methods
PASCAL VOC2012 test I/U (comp6)
80
75
70
65
60
55
50
45
Updated FCN
Original FCN
CFM
Hypercolumn SDS
Original Zoomout
Dec 2012
Apr 2013
Aug 2013
Dec 2013
Apr 2014
Aug 2014
Dec 2014
Apr 2015
Aug 2015
Dec 2015
Date of result submission

care and feeding of fully convolutional networks

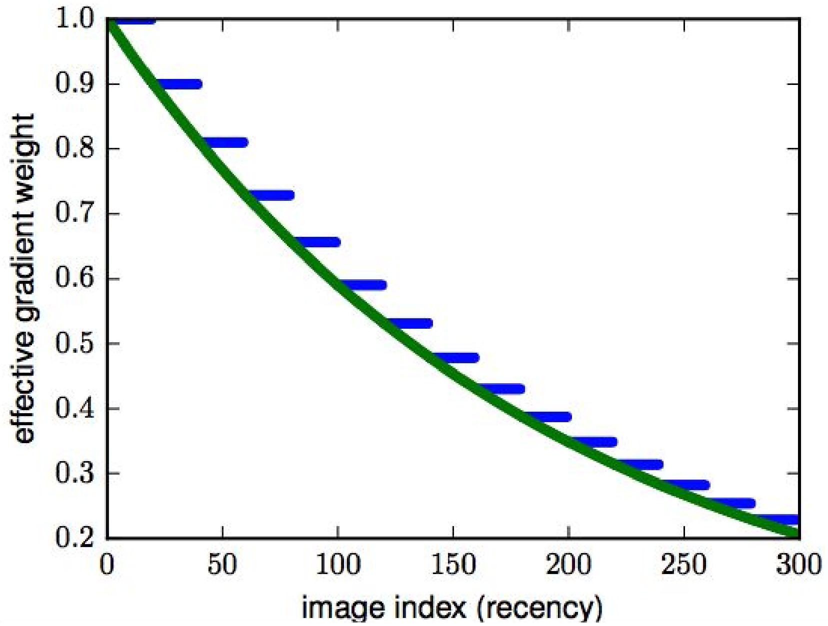
usage

- train full image at a time *without sampling*
- reshape network to take input of any size
- forward time is ~100ms for 500 x 500 x 21 output
  (on M. Titan X)

image-to-image optimization

	batch size	mom.	pixel acc.	mean acc.	mean IU	f.w. IU
FCN-accum	20	0.9	86.0	66.5	51.9	76.5
FCN-online	1	0.9	89.3	76.2	60.7	81.8
FCN-heavy	1	0.99	**90.5**	**76.5**	**63.6**	**83.5**

momentum and batch size



momentum p and batch size k

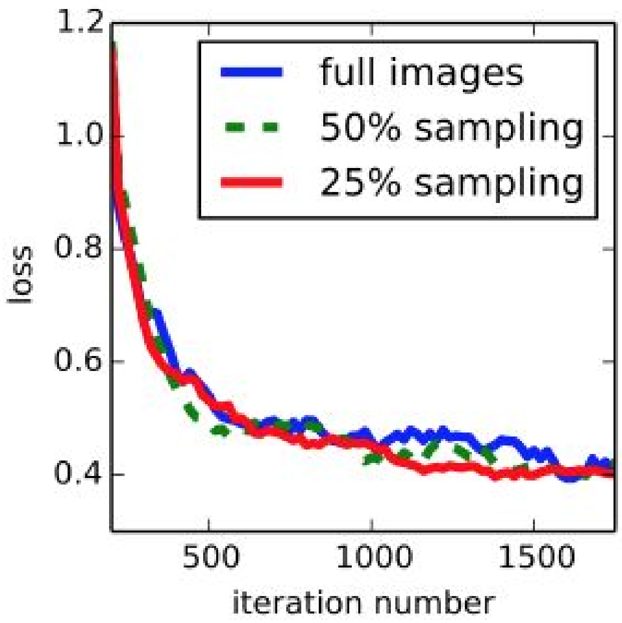
$$p^{(1/k)} = p'^{(1/k')}$$

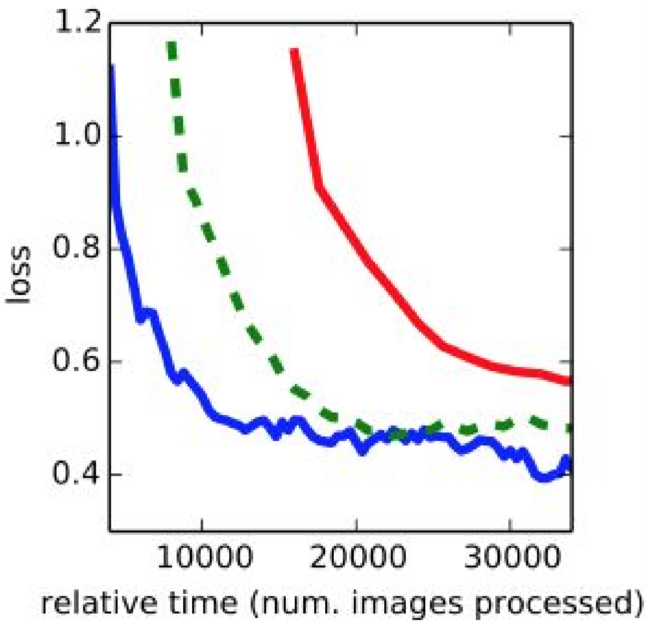
$$g_t = -\eta \sum_{i=0}^{k-1} \nabla_\theta \ell(x_{kt+i}; \theta_{t-1}) + p g_{t-1}$$

$$g_t = -\eta \sum_{s=0}^{\infty} \sum_{i=0}^{k-1} p^s \nabla_\theta \ell(x_{k(t-s)+i}; \theta_{t-s})$$

sampling images?

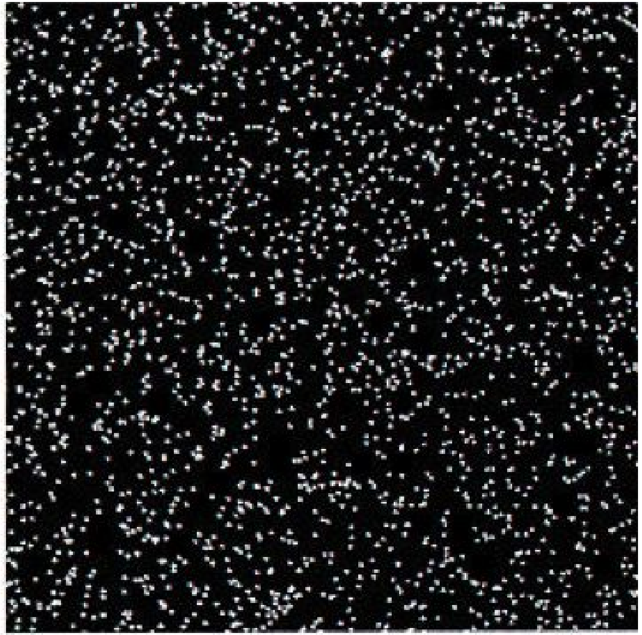
no need! no improvement from sampling across images



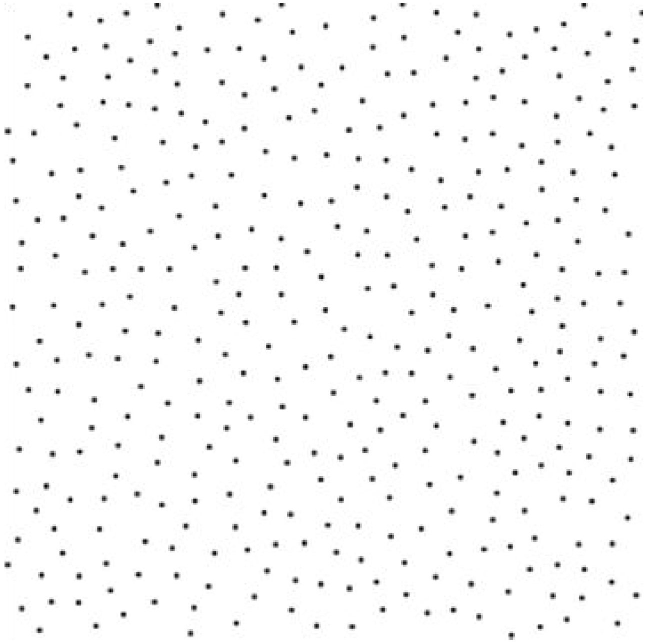


sampling pixels?

no need! no improvement from (partially) decorrelating pixels



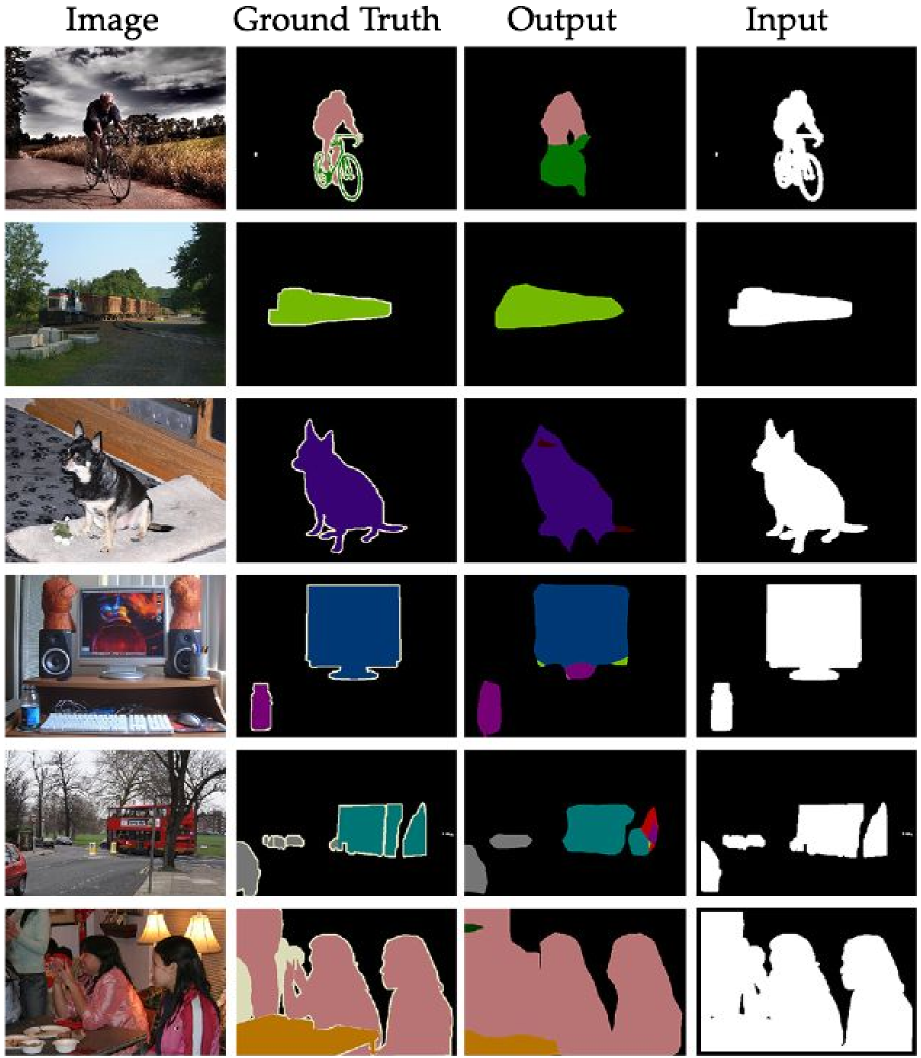
uniform



poisson

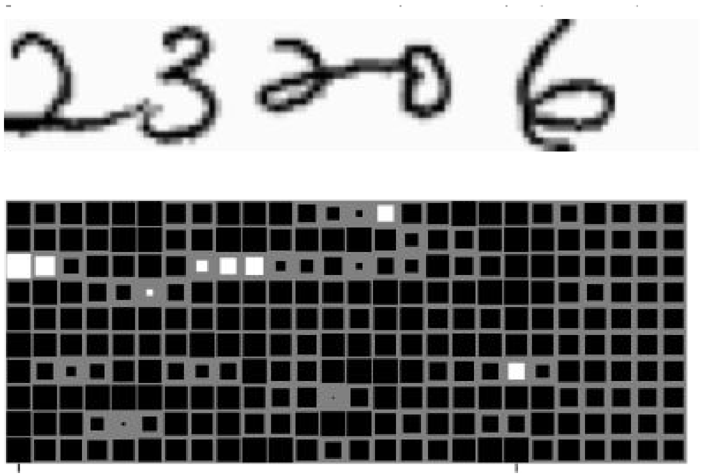
context?

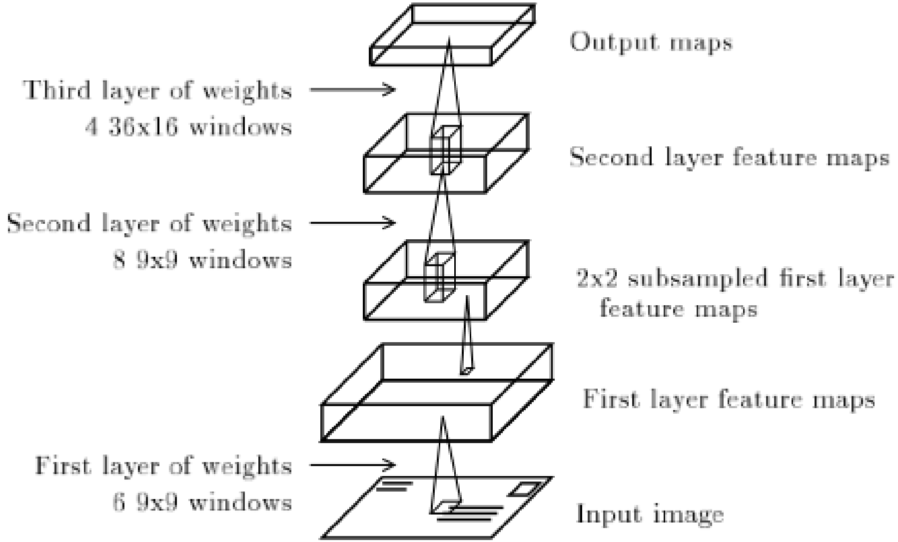
- do FCNs incorporate contextual cues?
- loses 3-4 % points when the background is masked
- can learn from BG/shape alone if forced to!
  - Standard 85 IU
  - BG alone 38 IU
  - Shape 29 IU



past and future history of fully convolutional networks

history





Shape Displacement Network
Matan & LeCun 1992

Convolutional Locator Network
Wolf & Platt 1994

pyramids

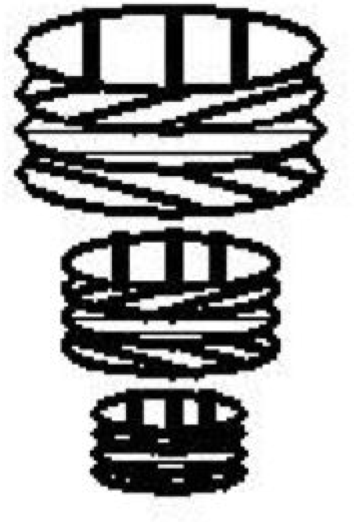
0 1 2

Scale Pyramid, *Burt & Adelson ‘83*

The scale pyramid is a classic multi-resolution representation

Fusing multi-resolution network layers is a learned, nonlinear counterpart

jets



Jet, *Koenderink & Van Doorn '87*

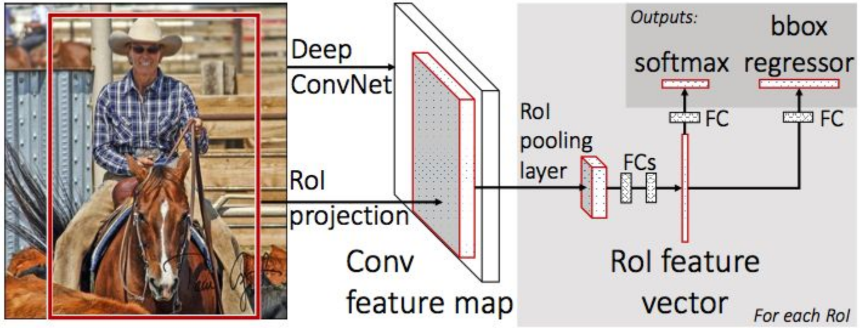
The local jet collects the partial derivatives at a point for a rich local description

The deep jet collects layer compositions for a rich, learned description

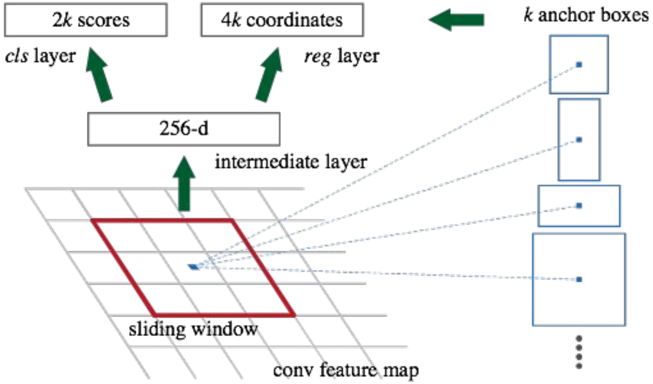
extensions

- detection + instances
- structured output
- weak supervision

detection: fully conv. proposals



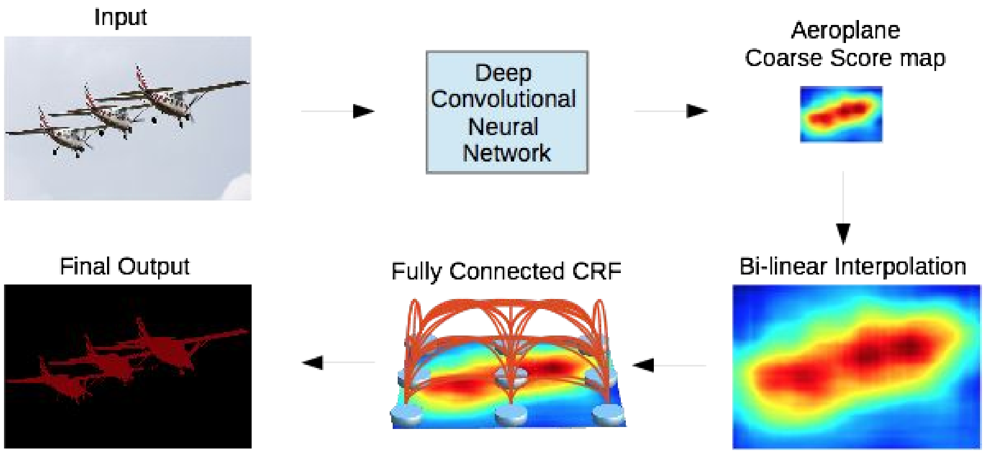
Fast R-CNN, *Girshick* ICCV'15

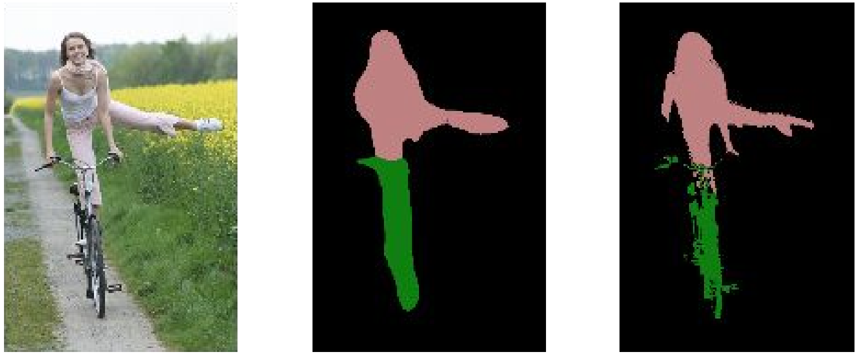


Faster R-CNN, *Ren et al.* NIPS'15

end-to-end detection by proposal FCN RoI classification

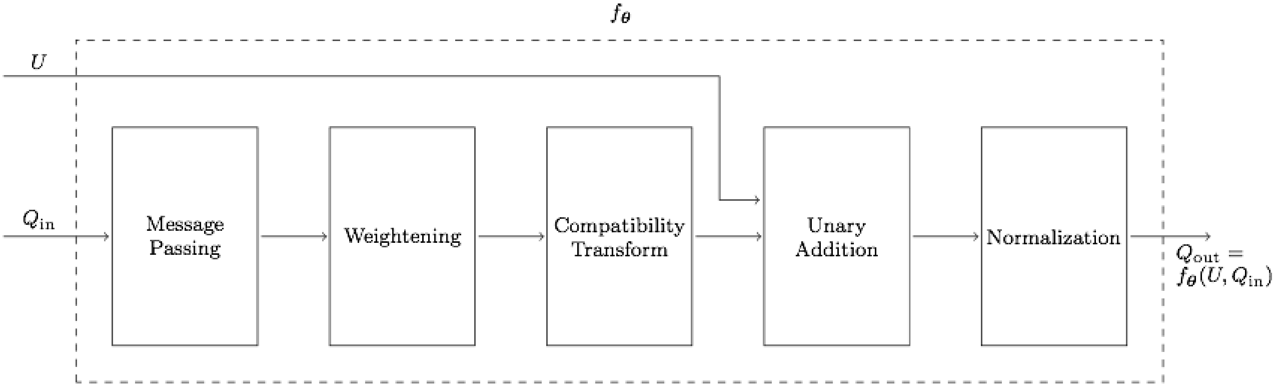
fully conv. nets + structured output





Semantic Image Segmentation with Deep Convolutional Nets and Fully Connected CRFs.
Chen* & Papandreou* et al. ICLR 2015.

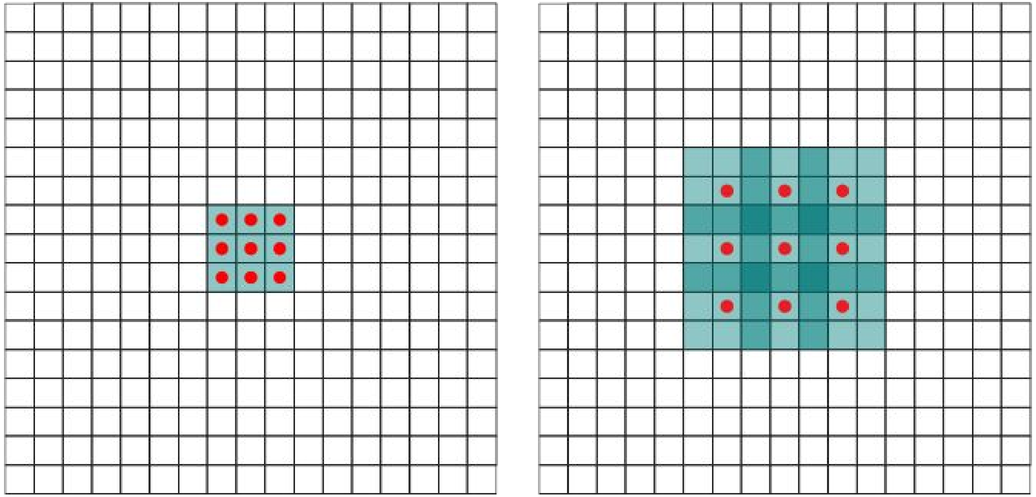
fully conv. nets + structured output



Method	Without COCO	With COCO
Plain FCN-8s	61.3	68.3
FCN-8s and CRF disconnected	63.7	69.5
End-to-end training of CRF-RNN	69.6	72.9

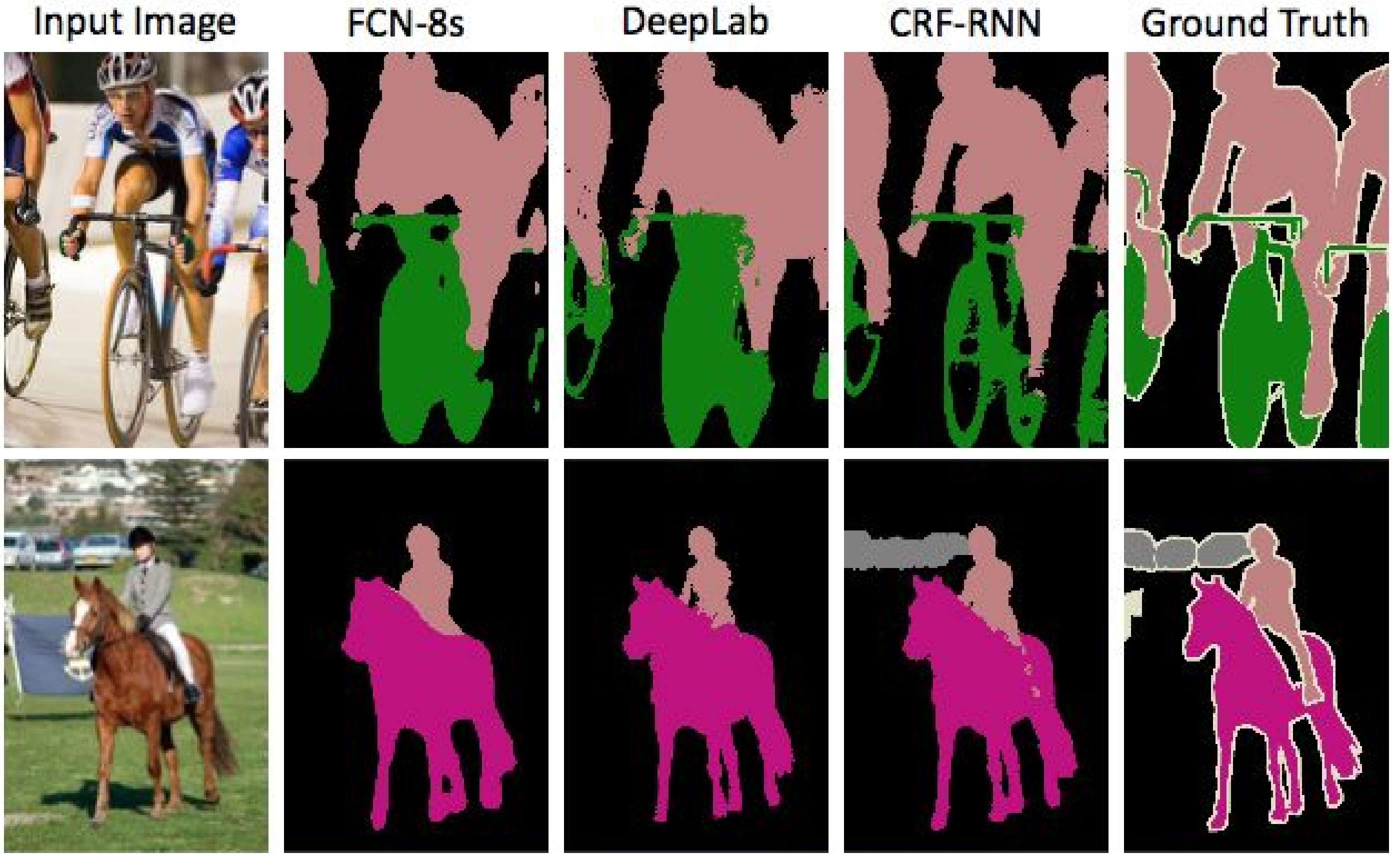
Conditional Random Fields as Recurrent Neural Networks. *Zheng* & Jayasumana* et al.* ICCV 2015.

dilation for structured output



- enlarge effective receptive field for same no. params
- raise resolution
- convolutional context model: similar accuracy to CRF but non-probabilistic

Multi-Scale Context Aggregation by Dilated Convolutions. *Yu & Koltun.* ICLR 2016



[comparison credit: CRF as RNN, Zheng* & Jayasumana* et al. ICCV 2015]

DeepLab: Chen* & Papandreou* et al. ICLR 2015. **CRF-RNN**: Zheng* & Jayasumana* et al. ICCV 2015

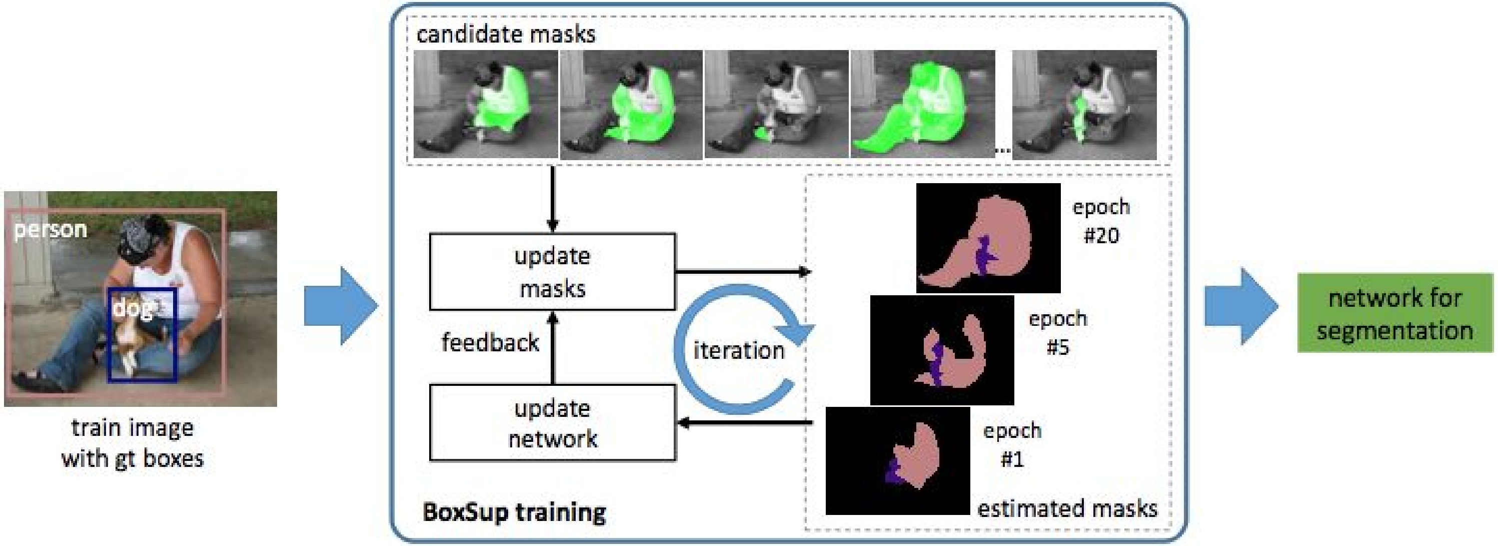
fully conv. nets + weak supervision

FCNs expose a spatial loss map to guide learning:
segment from tags by MIL or pixelwise constraints

Constrained Convolutional Neural Networks for Weakly Supervised Segmentation.
Pathak et al. arXiv 2015.

fully conv. nets + weak supervision

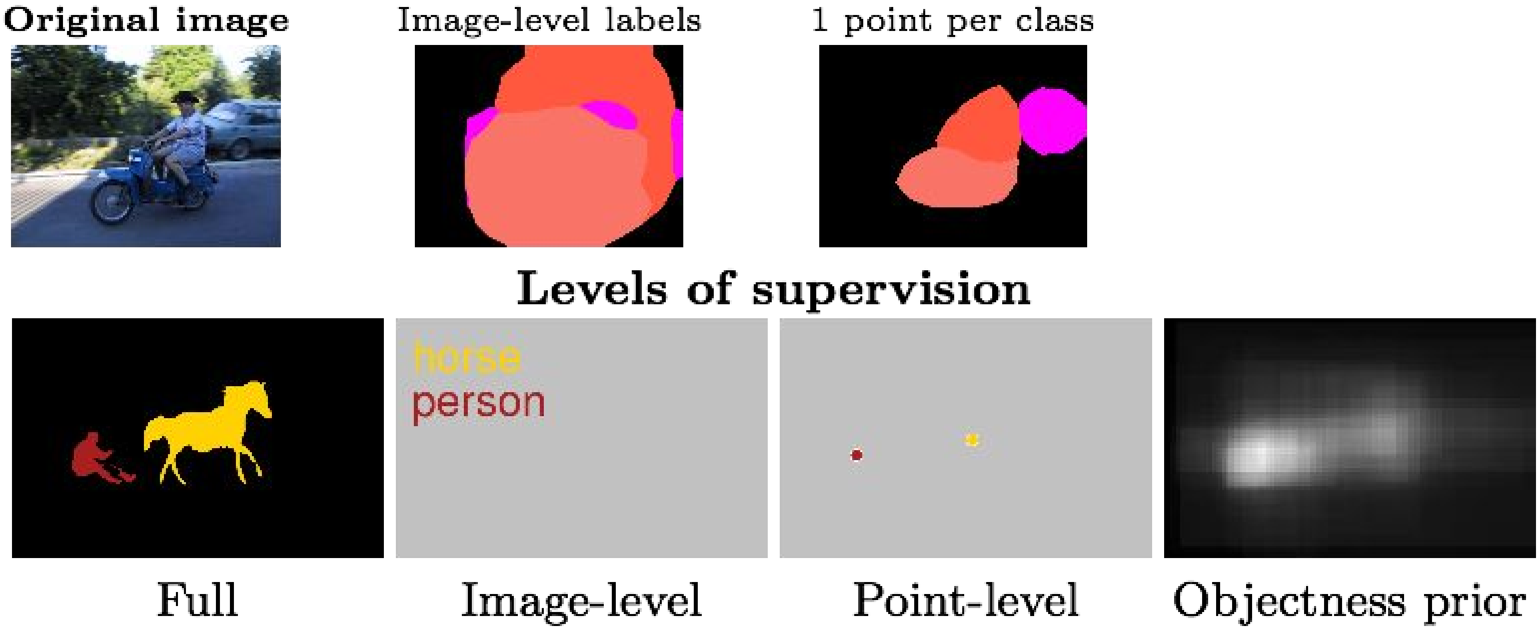
FCNs expose a spatial loss map to guide learning:
mine boxes + feedback to refine masks



BoxSup: Exploiting Bounding Boxes to Supervise Convolutional Networks for Semantic Segmentation.
Dai et al. 2015.

fully conv. nets + weak supervision

FCNs can learn from sparse annotations == sampling the loss

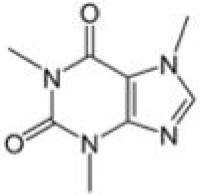


What's the Point? Semantic Segmentation with Point Supervision. *Bearman et al.* ECCV 2016.

conclusion

fully convolutional networks are fast,
end-to-end models for pixelwise problems

- **code** in Caffe
- **models** for PASCAL VOC, NYUDv2, SIFT Flow, PASCAL-Context



caffe.berkeleyvision.org

github.com/BVLC/caffe

fcn.berkeleyvision.org

model example
inference example
solving example