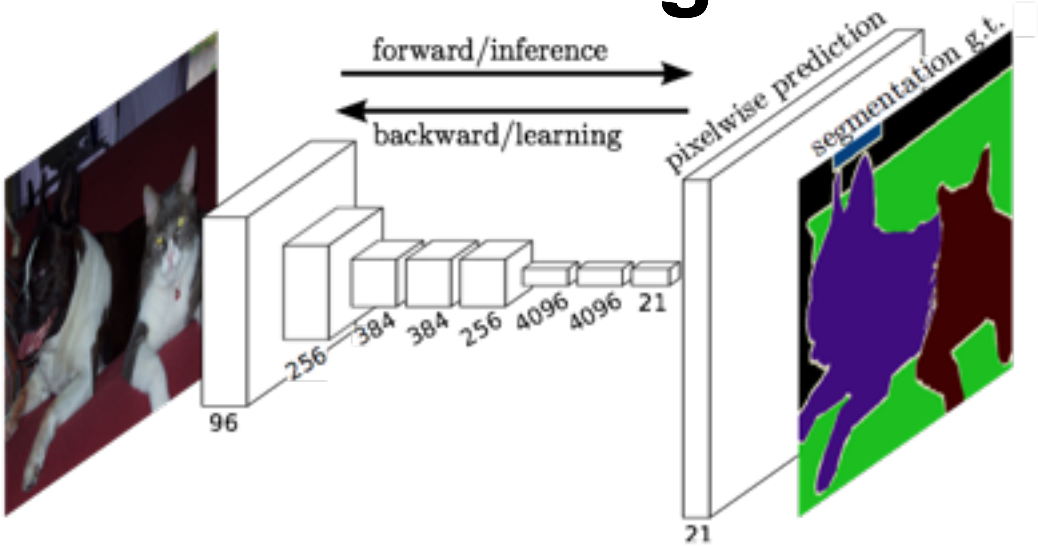
Fully Convolutional Networks for Semantic Segmentation



Jonathan Long*   Evan Shelhamer*   Trevor Darrell

UC Berkeley

Presented by: Gordon Christie

Slide credit: Jonathan Long

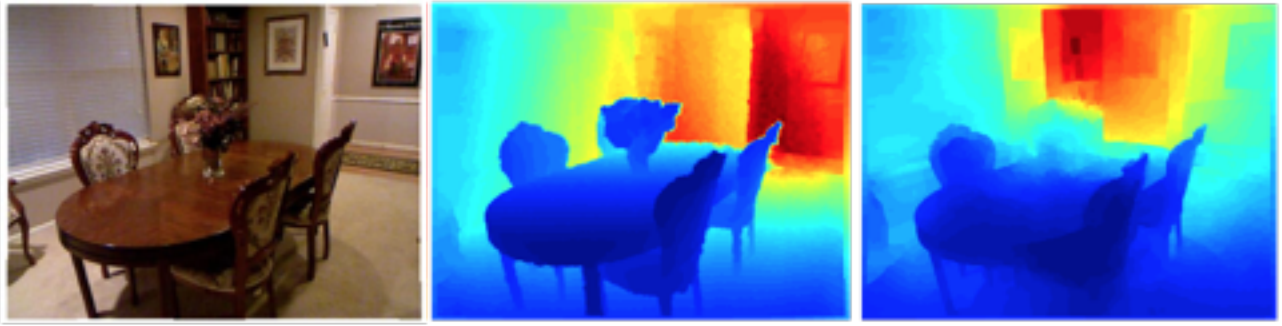
Overview

- Reinterpret standard classification convnets as “Fully convolutional” networks (FCN) for semantic segmentation
- Use AlexNet, VGG, and GoogleNet in experiments
- Novel architecture: combine information from different layers for segmentation
- State-of-the-art segmentation for PASCAL VOC 2011/2012, NYUDv2, and SIFT Flow at the time
- Inference less than one fifth of a second for a typical image

Slide credit: Jonathan Long

pixels in, pixels out

monocular depth estimation (Liu et al. 2015)



semantic segmentation

boundary prediction (Xie & Tu 2015)

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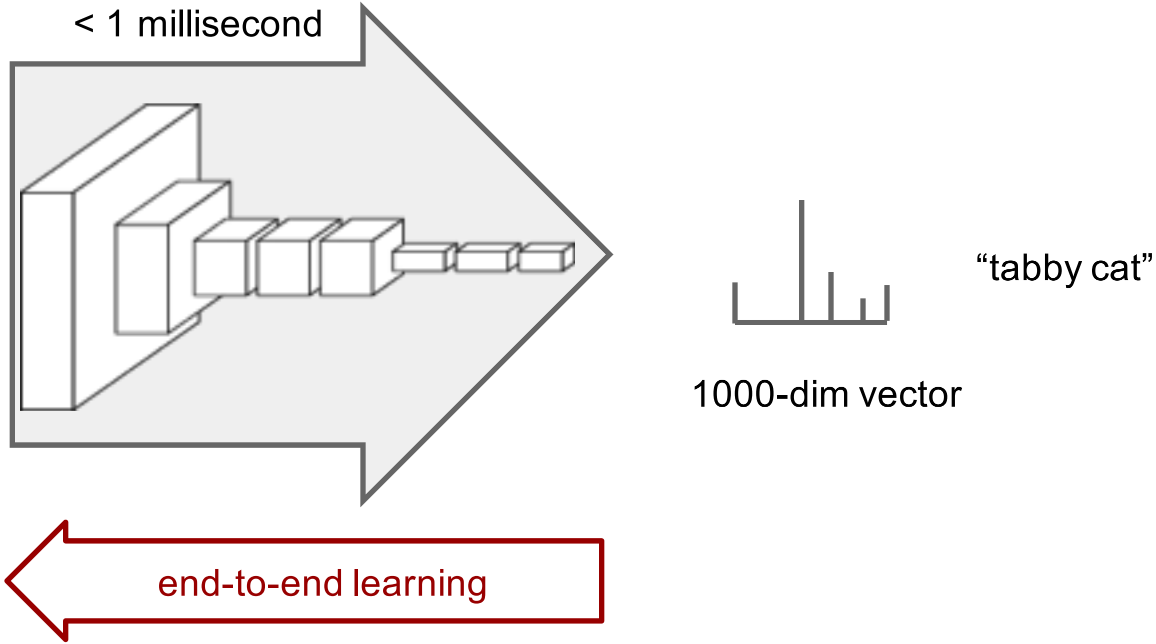
convnets perform classification



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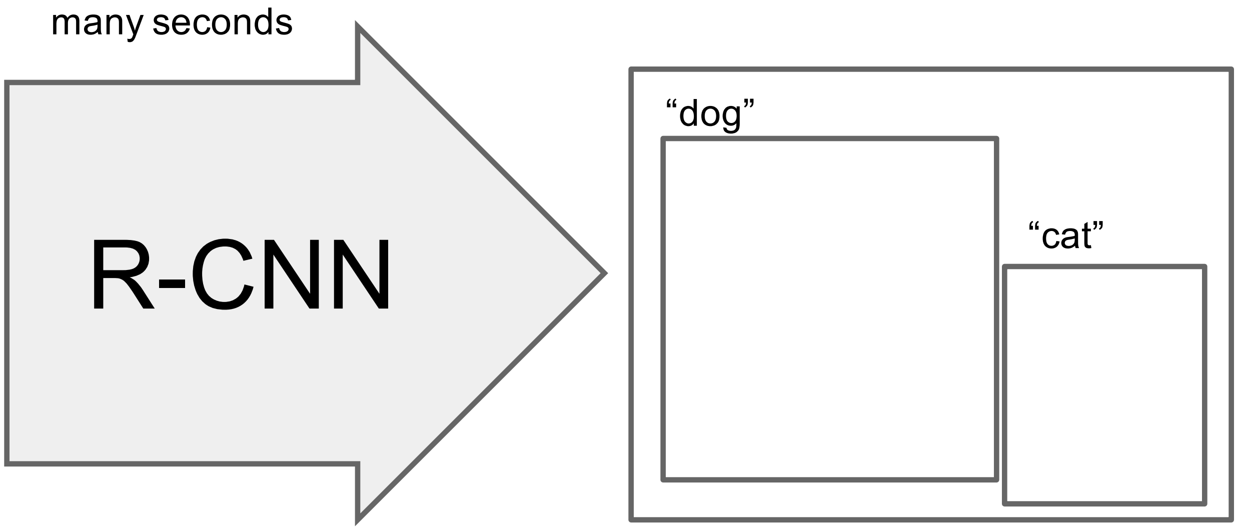
R-CNN does detection



R-CNN

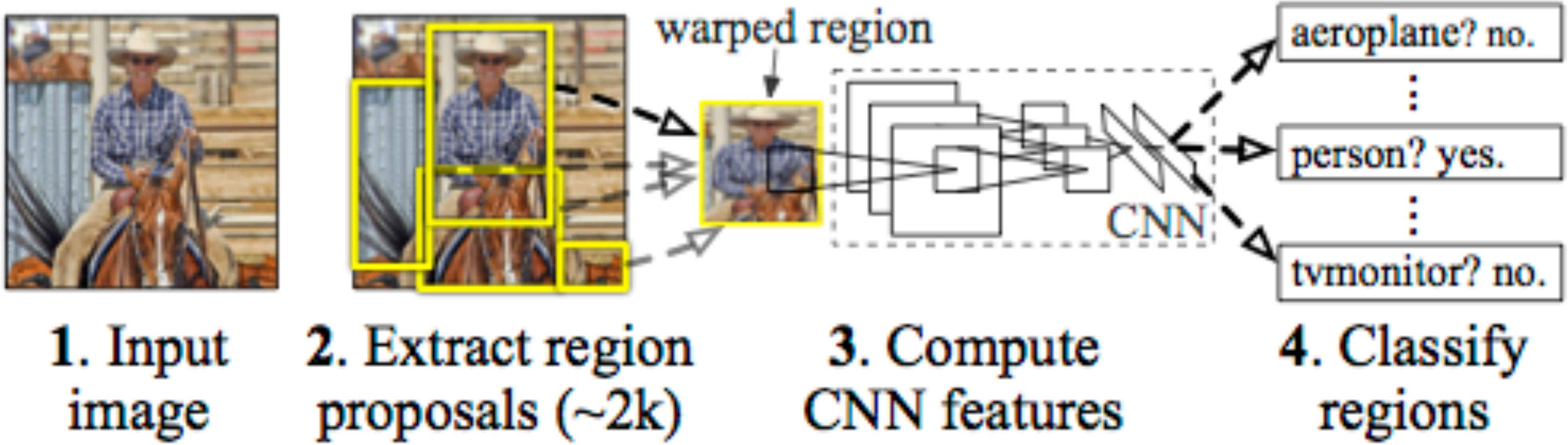
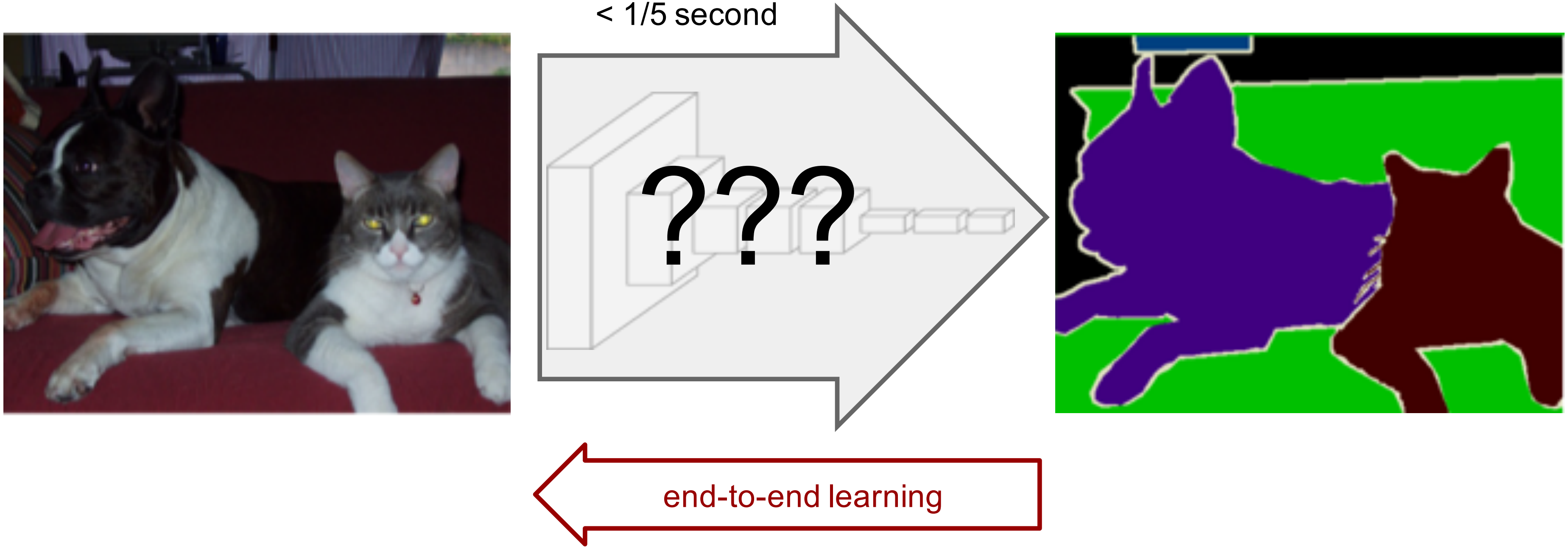
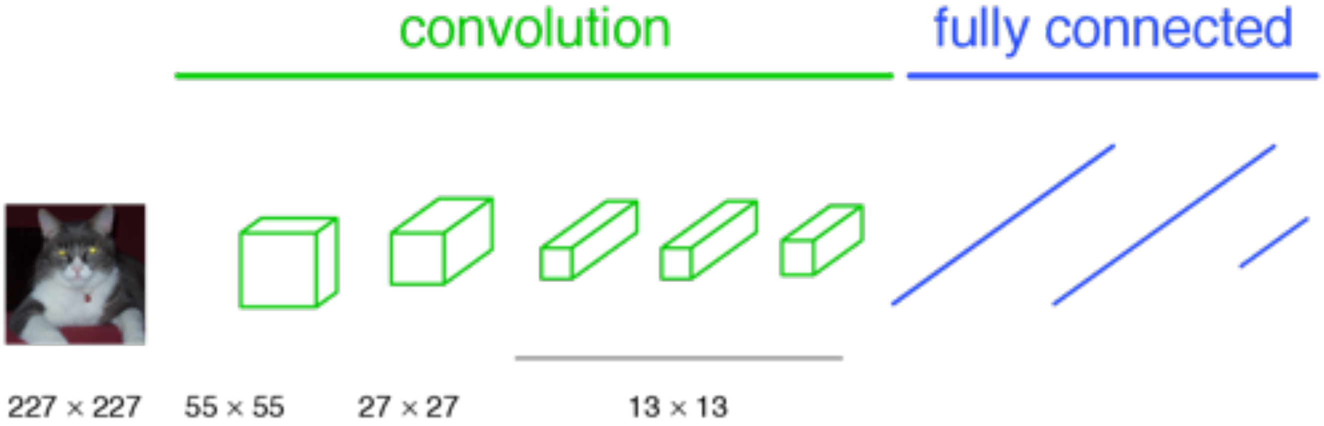


figure: Girshick et al.


< 1/5 second
???
end-to-end learning

a classification network



“tabby cat”

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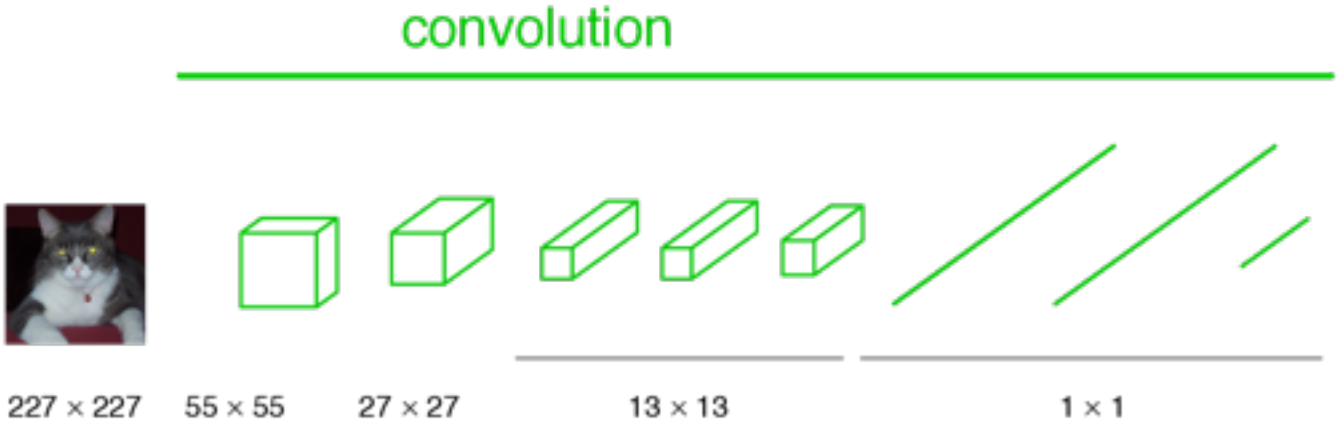
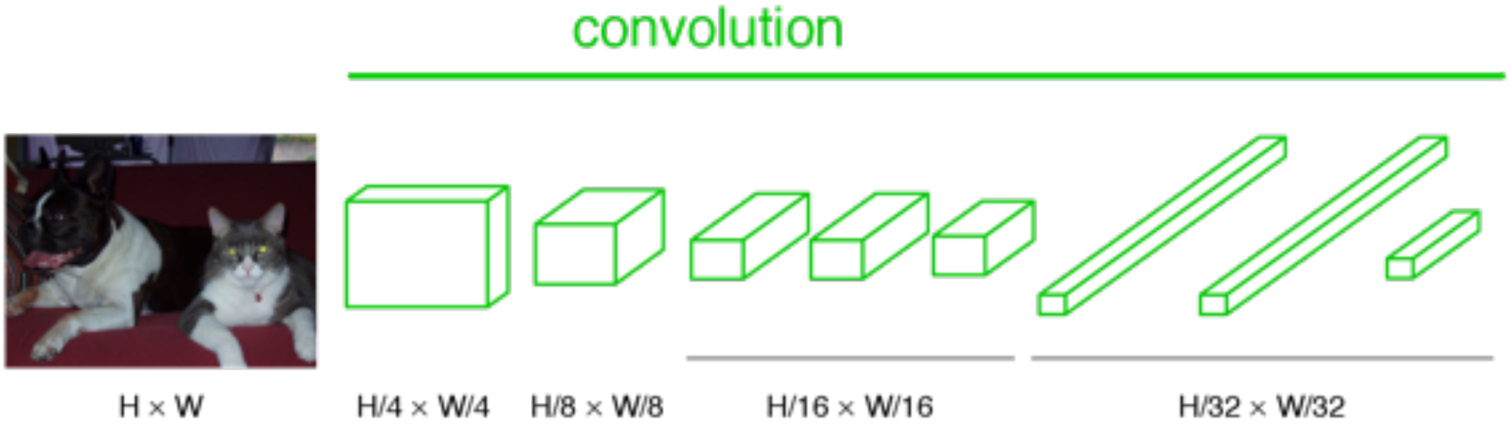
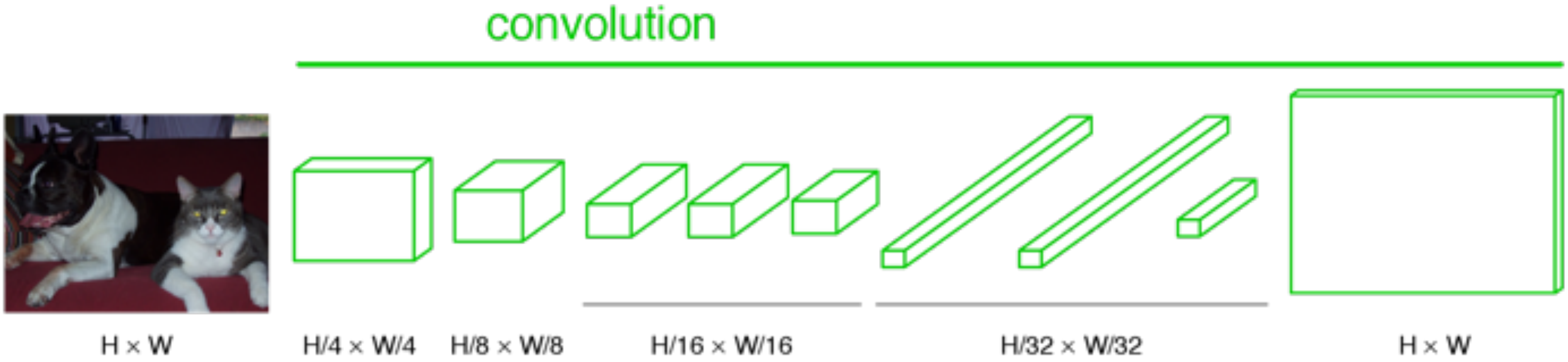
becoming fully convolutional



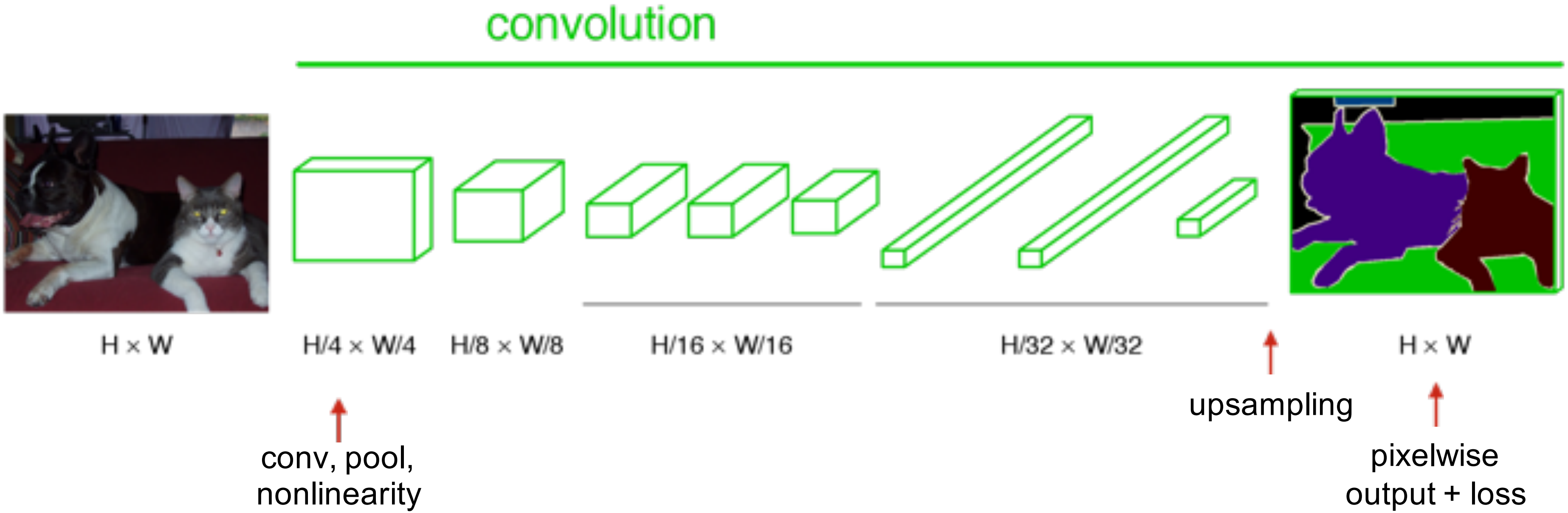
becoming fully convolutional



upsampling output



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



Dense Predictions

- Shift-and-stitch: trick that yields dense predictions without interpolation
- Upsampling via deconvolution
- Shift-and-stitch used in preliminary experiments, but not included in final model
- Upsampling found to be more effective and efficient

Classifier to Dense FCN

- Convolutionalize proven classification architectures: AlexNet, VGG, and GoogLeNet (reimplementation)
- Remove classification layer and convert all fully connected layers to convolutions
- Append 1x1 convolution with channel dimensions and predict scores at each of the coarse output locations (21 categories + background for PASCAL)

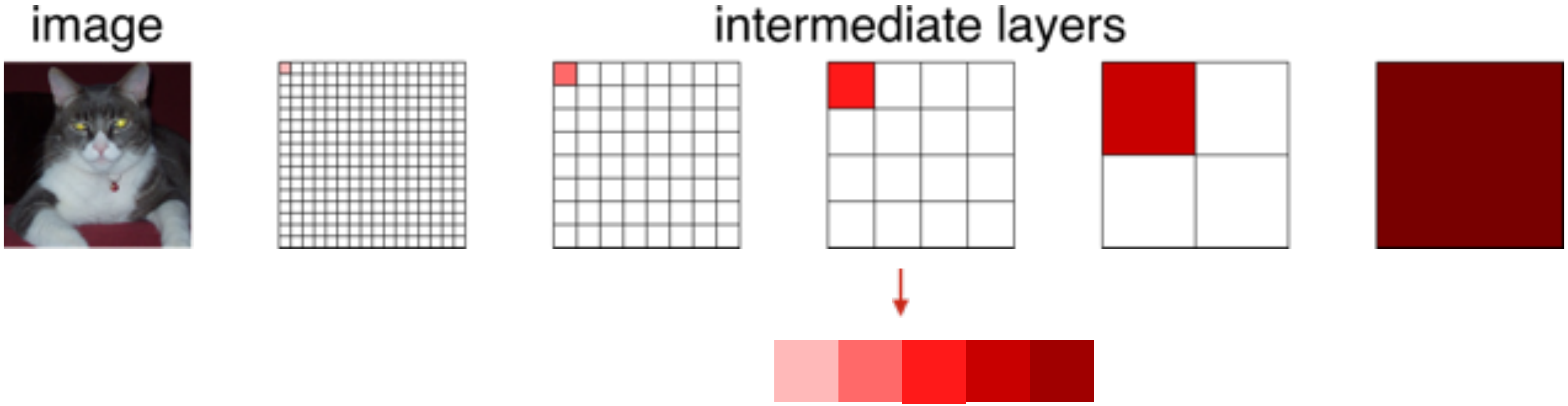
Classifier to Dense FCN

Cast ILSVRC classifiers into FCNs and compare performance on validation set of PASCAL 2011

	FCN-AlexNet	FCN-VGG16	FCN-GoogLeNet[4]
mean IU	39.8	**56.0**	42.5
forward time	50 ms	210 ms	59 ms
conv. layers	8	16	22
parameters	57M	134M	6M
rf size	355	404	907
max stride	32	32	32

spectrum of deep features

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



fuse features into **deep jet**

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

skip layers

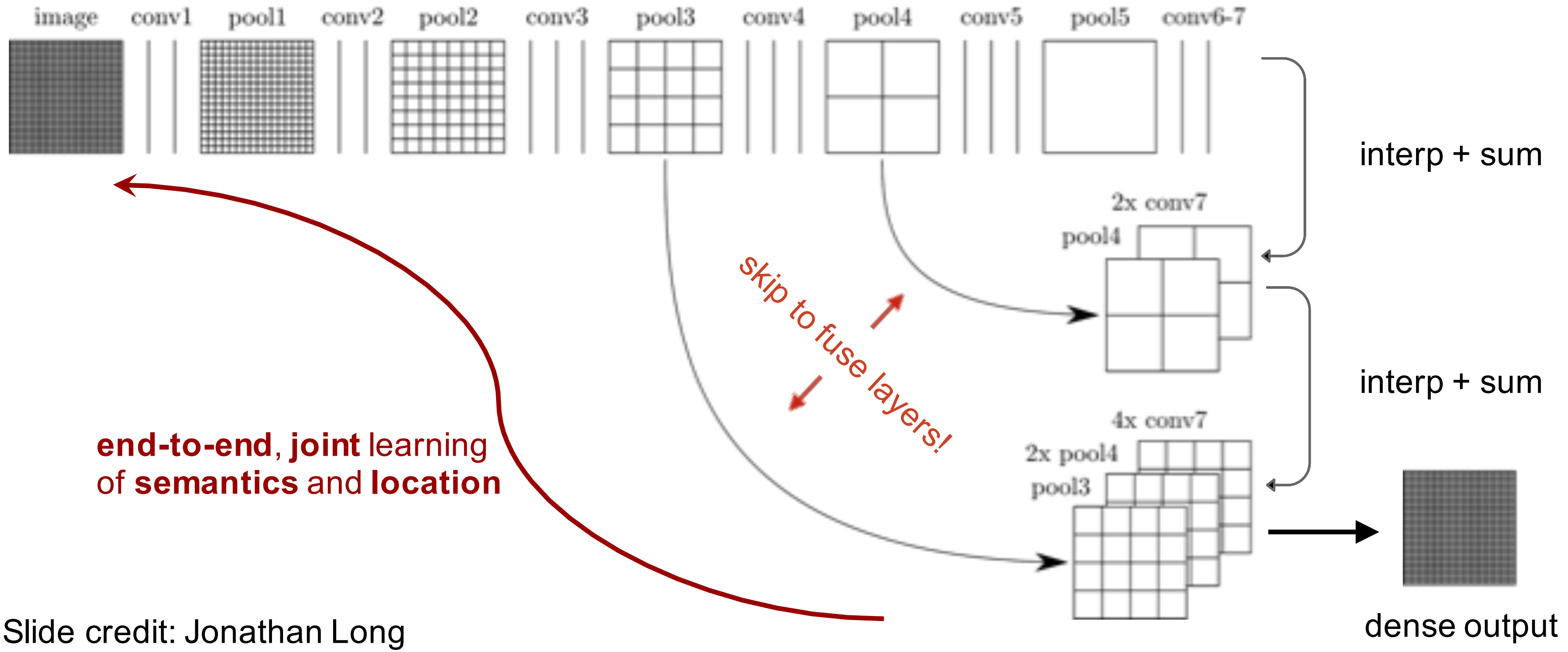
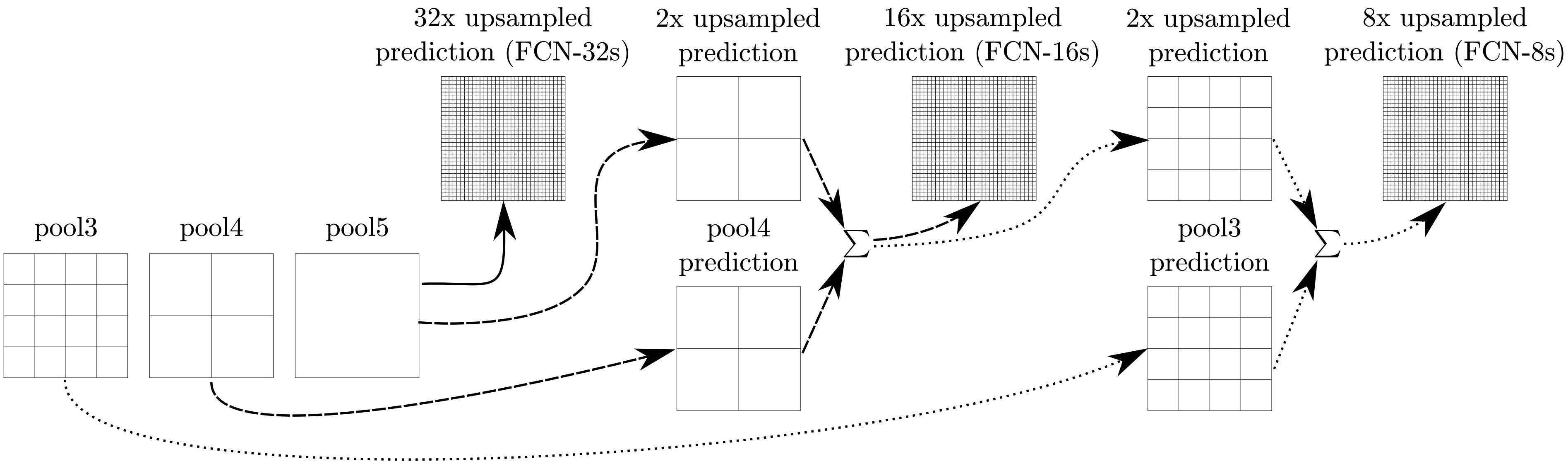


image
conv1
pool1
conv2
pool2
conv3
pool3
conv4
pool4
conv5
pool5
conv6-7
interp + sum
2x conv7
pool4
skip to fuse layers!
interp + sum
4x conv7
2x pool4
pool3
end-to-end, joint learning of semantics and location
dense output

skip layers


32x upsampled prediction (FCN-32s)
2x upsampled prediction
16x upsampled prediction (FCN-16s)
2x upsampled prediction
8x upsampled prediction (FCN-8s)
pool3
pool4
pool5
pool4 prediction
pool3 prediction
$\sum$
$\sum$

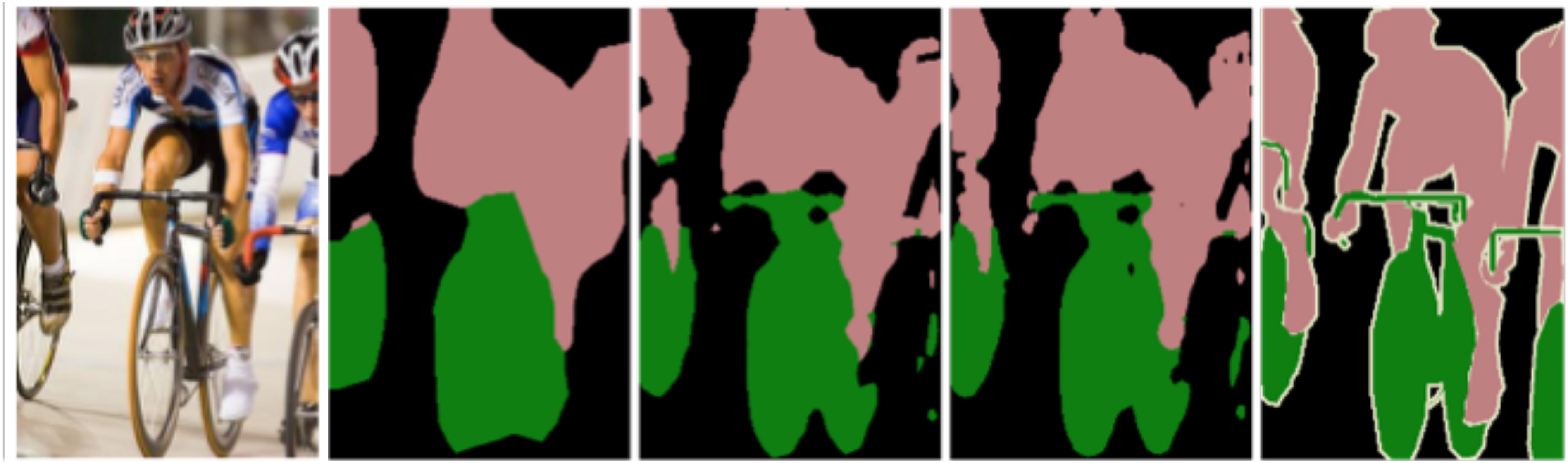
Comparison of skip FCNs

Results on subset of validation set of PASCAL VOC 2011

	pixel acc.	mean acc.	mean IU	f.w. IU
FCN-32s-fixed	83.0	59.7	45.4	72.0
FCN-32s	89.1	73.3	59.4	81.4
FCN-16s	90.0	75.7	62.4	83.0
FCN-8s	**90.3**	**75.9**	**62.7**	**83.2**

skip layer refinement

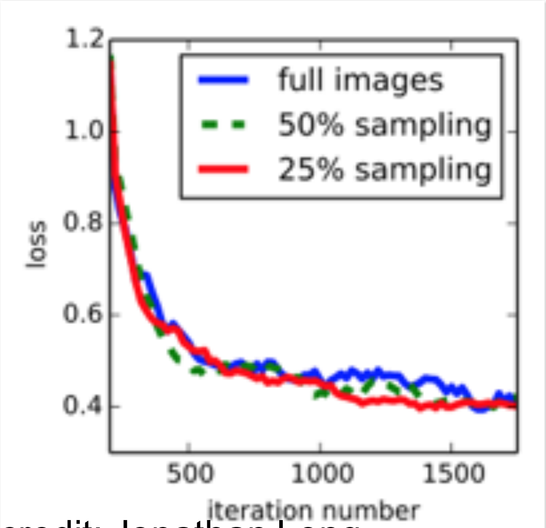
input image | stride 32 | stride 16 | stride 8 | ground truth

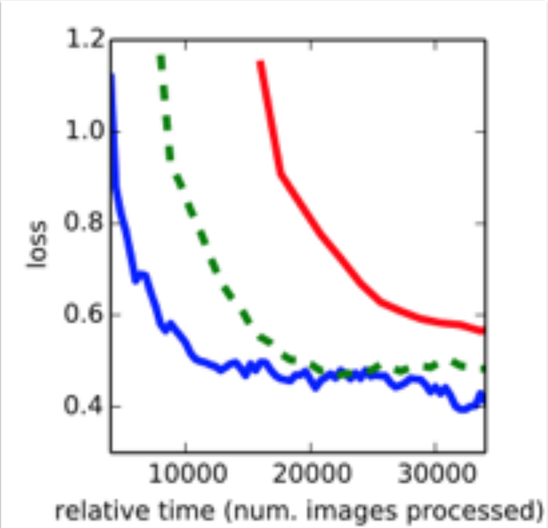


no skips | 1 skip | 2 skips

training + testing

- train full image at a time *without patch sampling*
- reshape network to take input of any size
- forward time is ~150ms for 500 x 500 x 21 output





Results – PASCAL VOC 2011/12

VOC 2011: 8498 training images (from additional labeled data

	mean IU VOC2011 test	mean IU VOC2012 test	inference time
R-CNN [12]	47.9	-	-
SDS [16]	52.6	51.6	$\sim$ 50 s
FCN-8s	**62.7**	**62.2**	$\sim$ **175 ms**

Results – NYUDv2

1449 RGB-D images with pixelwise labels → 40 categories

	pixel acc.	mean acc.	mean IU	f.w. IU
Gupta *et al.* [14]	60.3	-	28.6	47.0
FCN-32s RGB	60.0	42.2	29.2	43.9
FCN-32s RGBD	61.5	42.4	30.5	45.5
FCN-32s HHA	57.1	35.2	24.2	40.4
FCN-32s RGB-HHA	64.3	44.9	32.8	48.0
FCN-16s RGB-HHA	**65.4**	**46.1**	**34.0**	**49.5**

Results – SIFT Flow

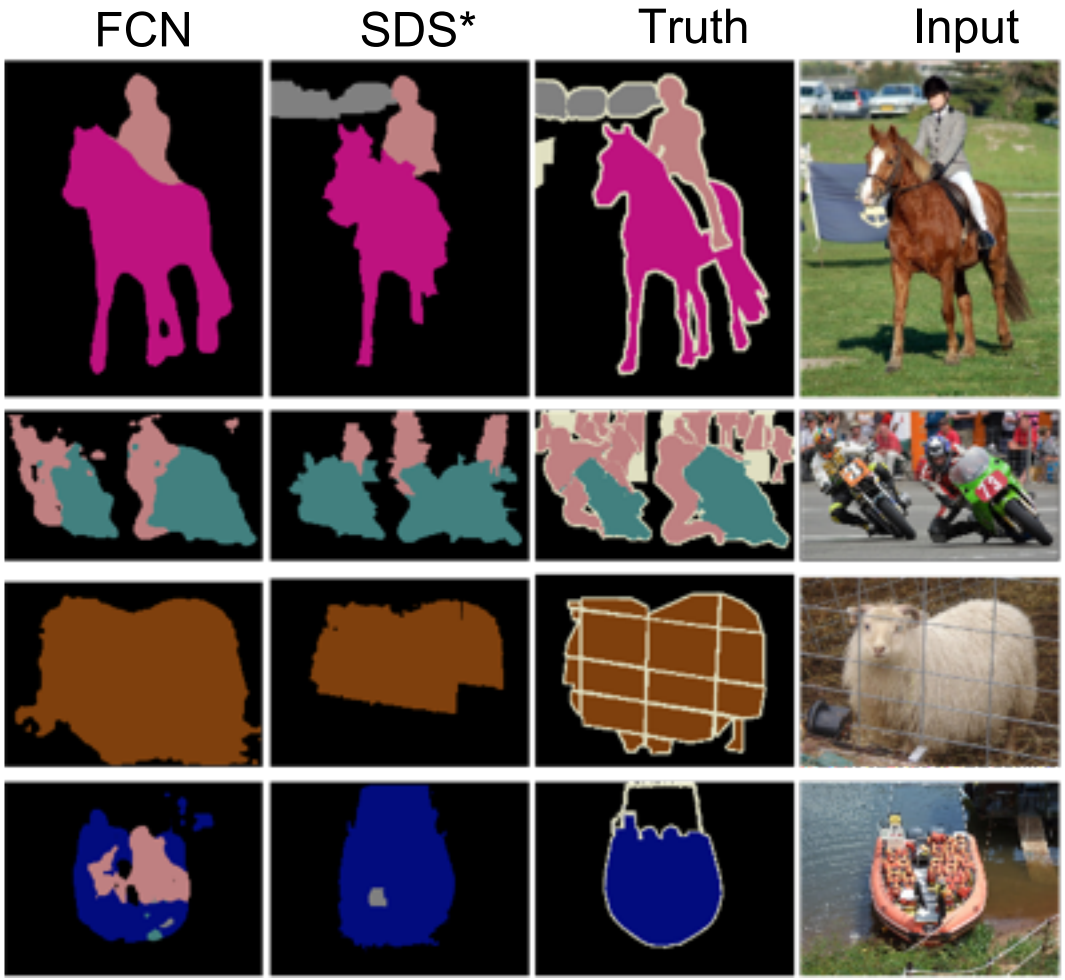
2688 images with pixel labels

→33 semantic categories, 3 geometric categories

Learn both label spaces jointly

→ learning and inference have similar performance and computation as independent models

	pixel acc.	mean acc.	mean IU	f.w. IU	geom. acc.
Liu *et al*. [23]	76.7	-	-	-	-
Tighe *et al*. [33]	-	-	-	-	90.8
Tighe *et al*. [34] 1	75.6	41.1	-	-	-
Tighe *et al*. [34] 2	78.6	39.2	-	-	-
Farabet *et al*. [8] 1	72.3	50.8	-	-	-
Farabet *et al*. [8] 2	78.5	29.6	-	-	-
Pinheiro *et al*. [28]	77.7	29.8	-	-	-
FCN-16s	**85.2**	**51.7**	39.5	76.1	**94.3**



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

- 20% relative improvement for mean IoU
- 286× faster

Slide credit: Jonathan Long

*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-CrossJo[illegible]	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	[illegible]	[illegible]	[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	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	81.1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	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
[illegible]		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	[illegible]-2012

== segmentation with Caffe

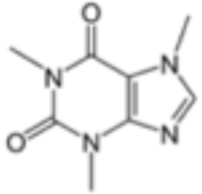
Slide credit: Jonathan Long

conclusion

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

- **code** in Caffe branch (merged soon)
- **models** for PASCAL VOC, NYUDv2, SIFT Flow, PASCAL-Context

fcn.berkeleyvision.org



caffe.berkeleyvision.org

github.com/BVLC/caffe