Fully Convolutional Networks for Semantic Segmentation

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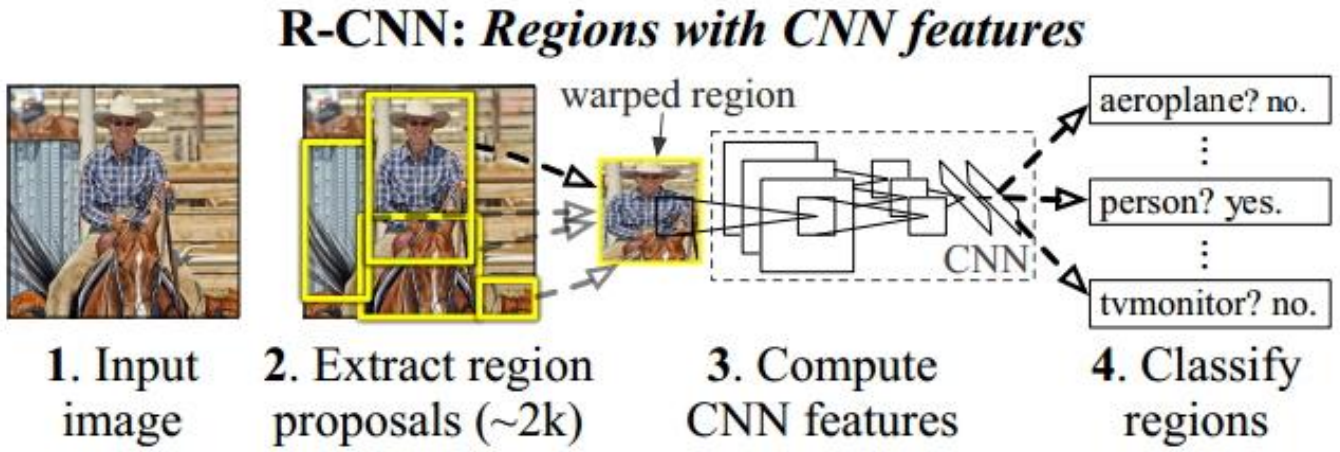
Background

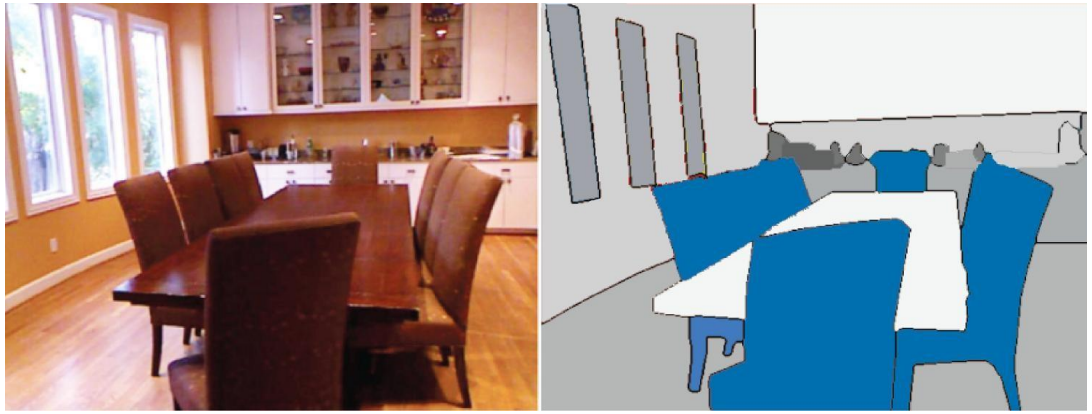
(a) Siberian husky (b) Eskimo dog

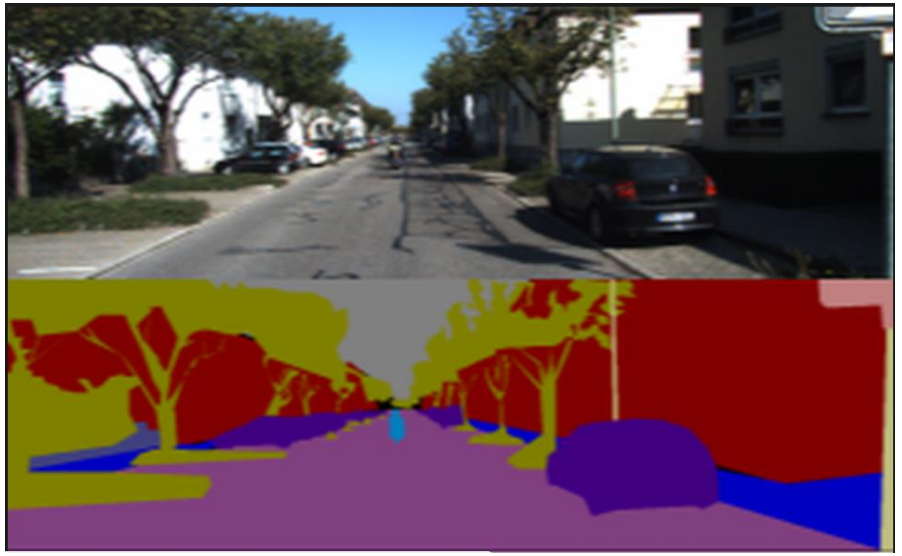
Classification

Bounding box object detection

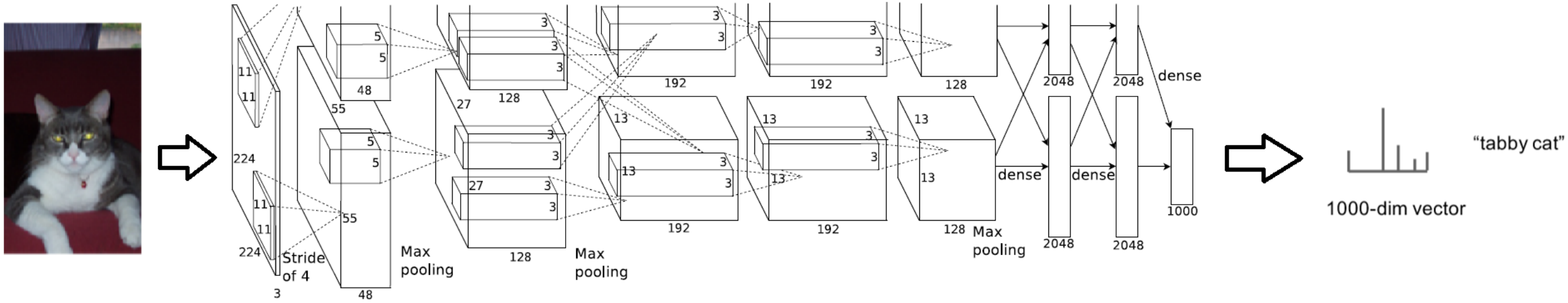


Semantic Segmentation

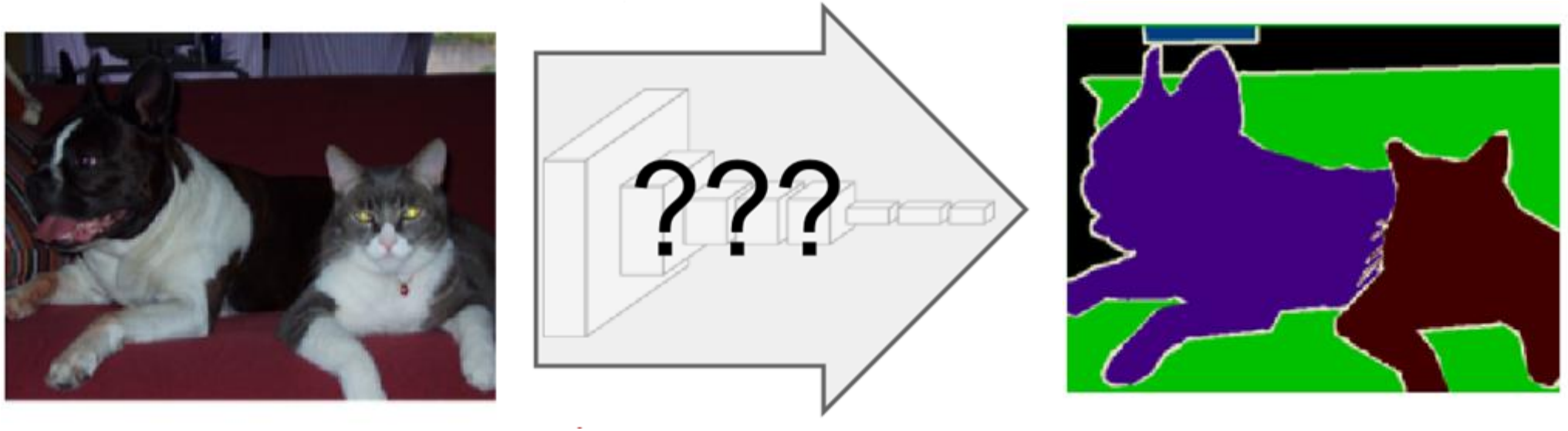




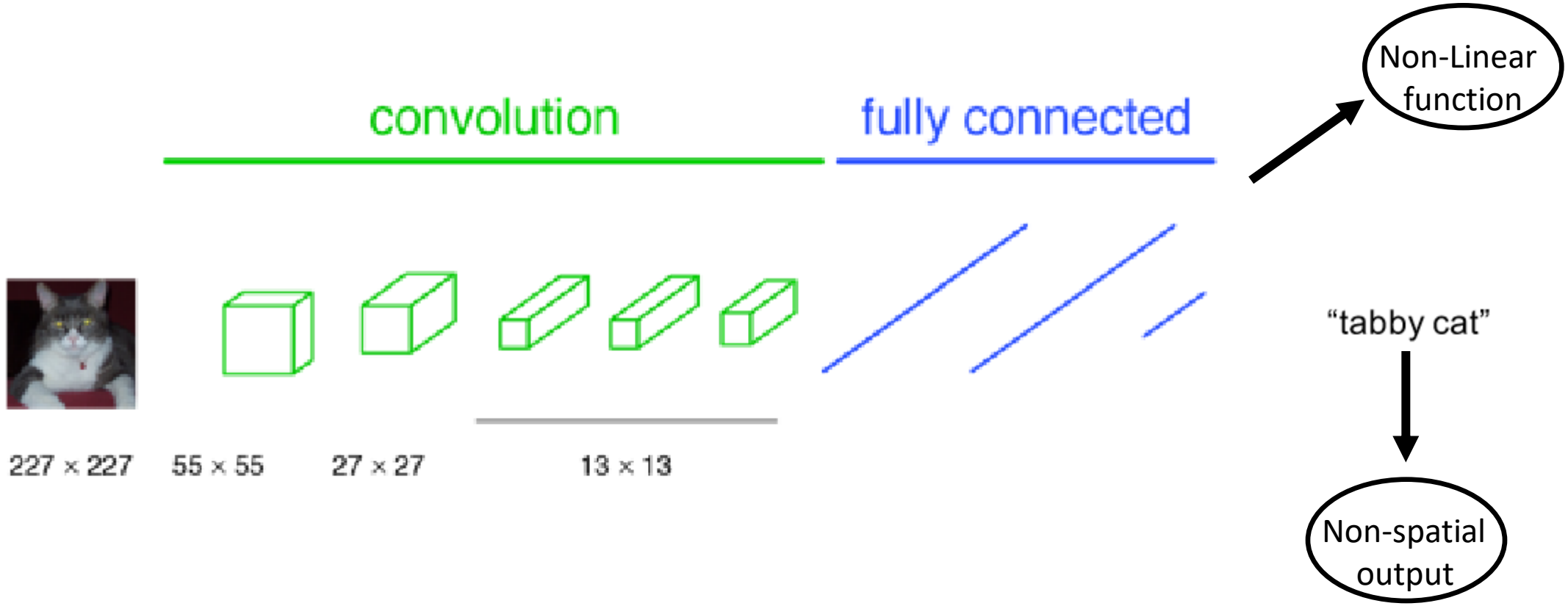
Classification networks



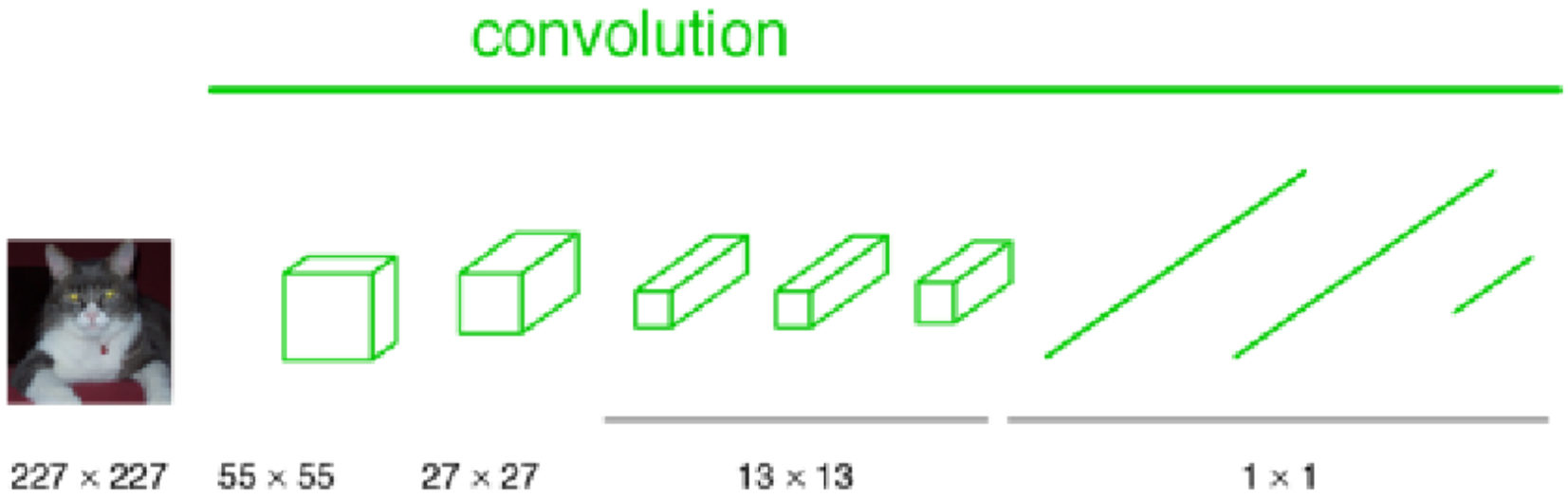
Network for Semantic Segmentation?



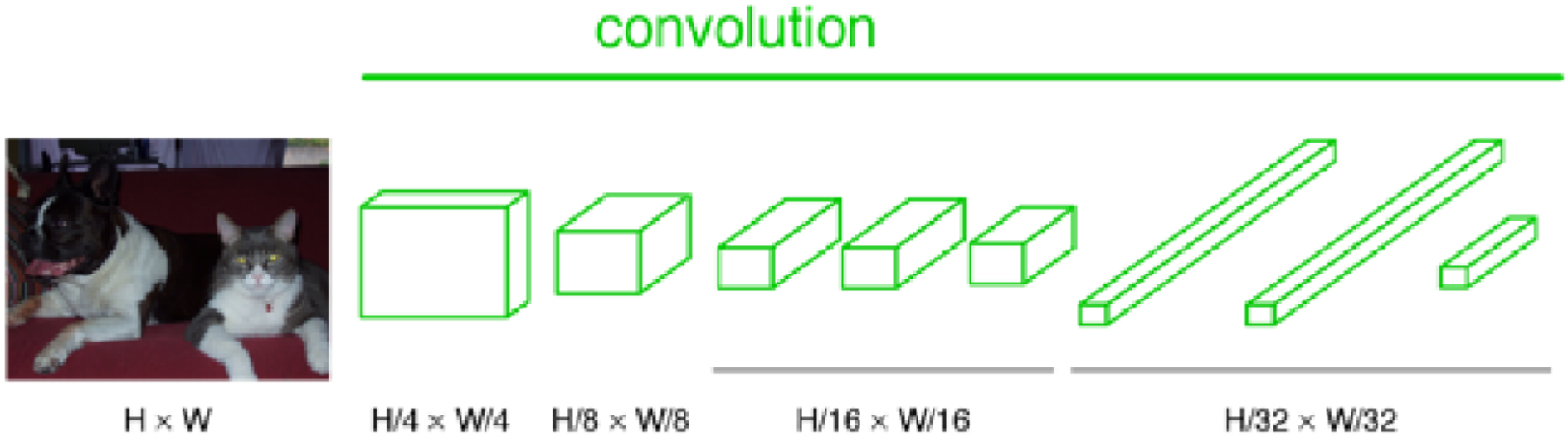
Classification Networks



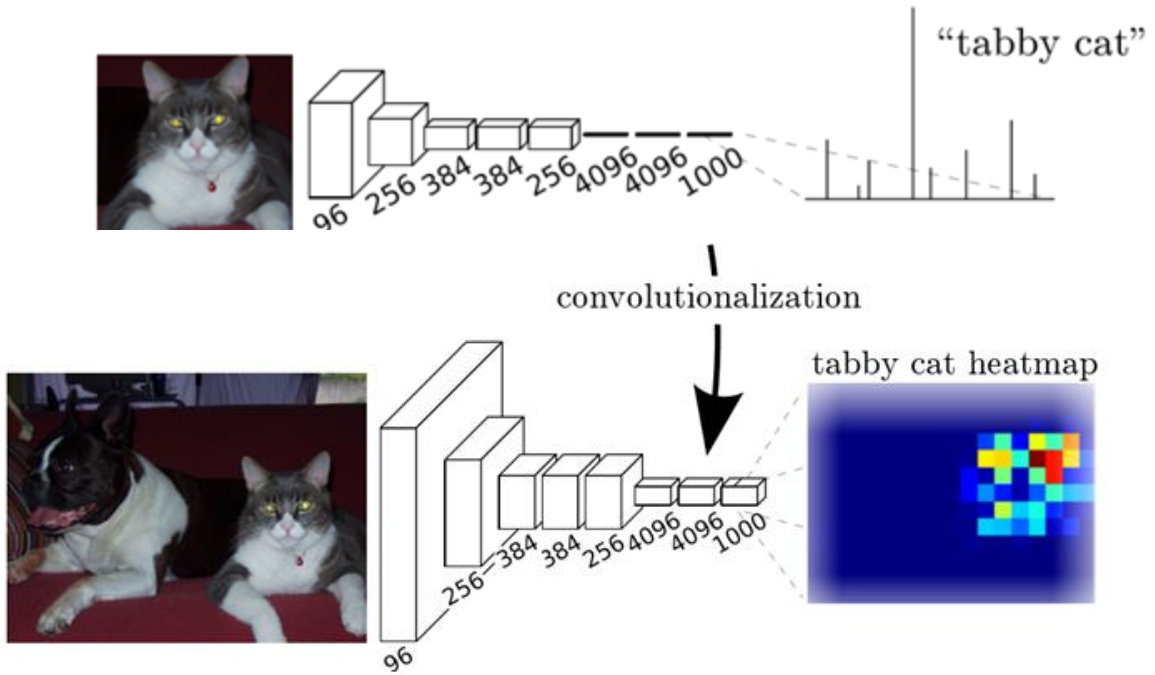
Classification -> Full Convolution



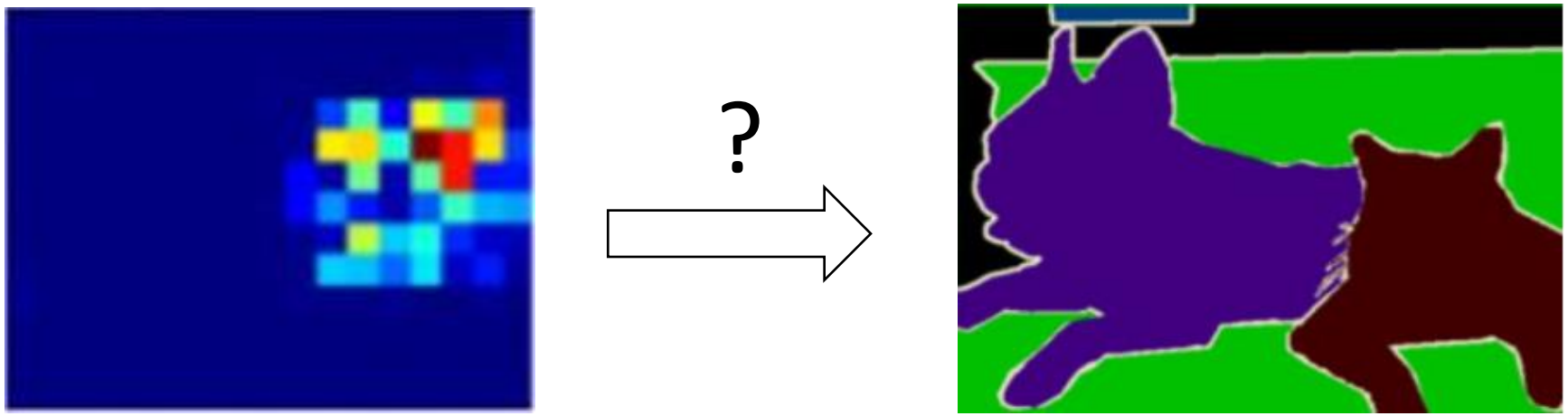
Fully Convolution Networks



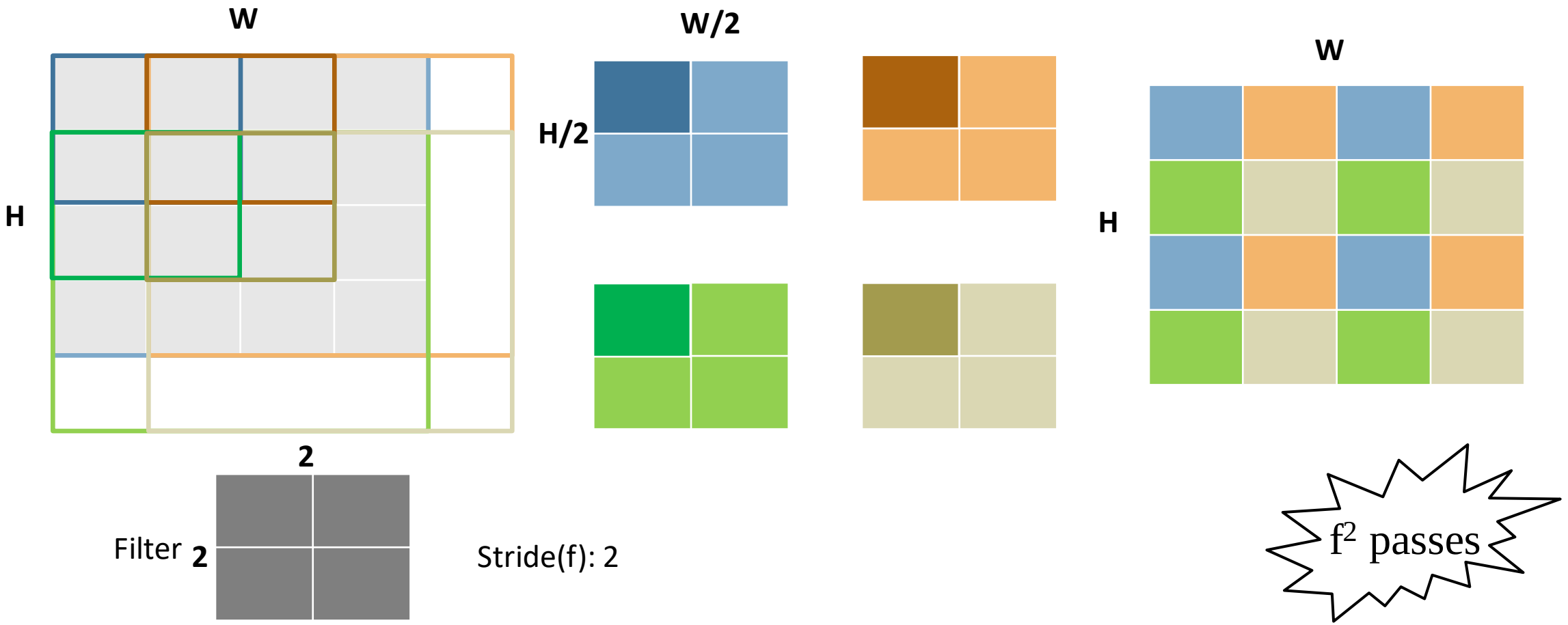
Fully Convolution Networks



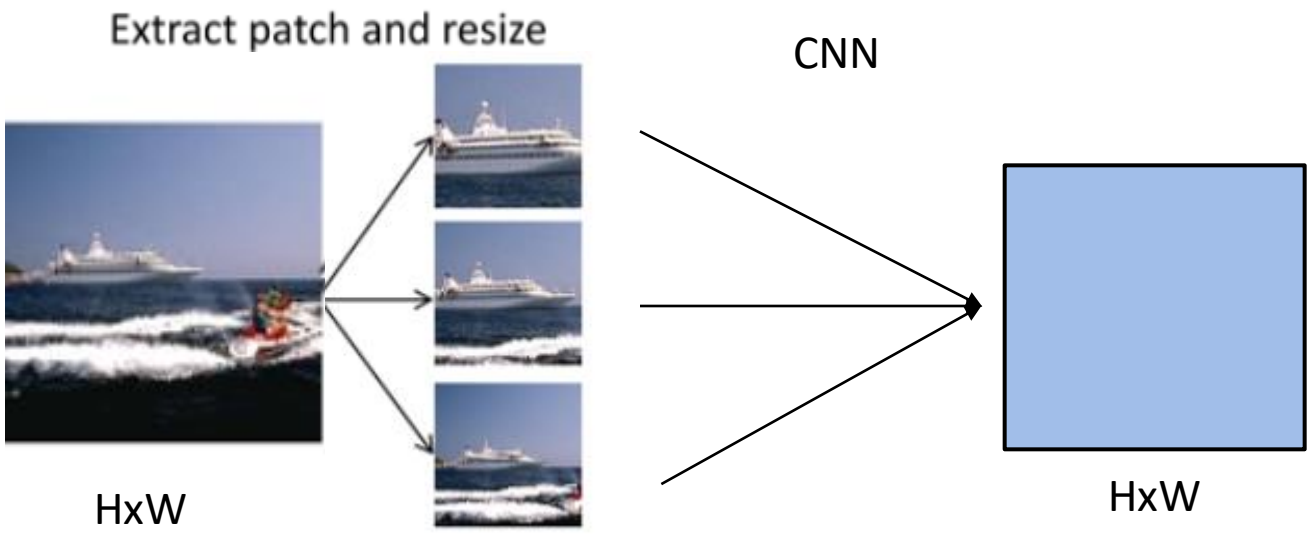
End-to-end Dense predictions



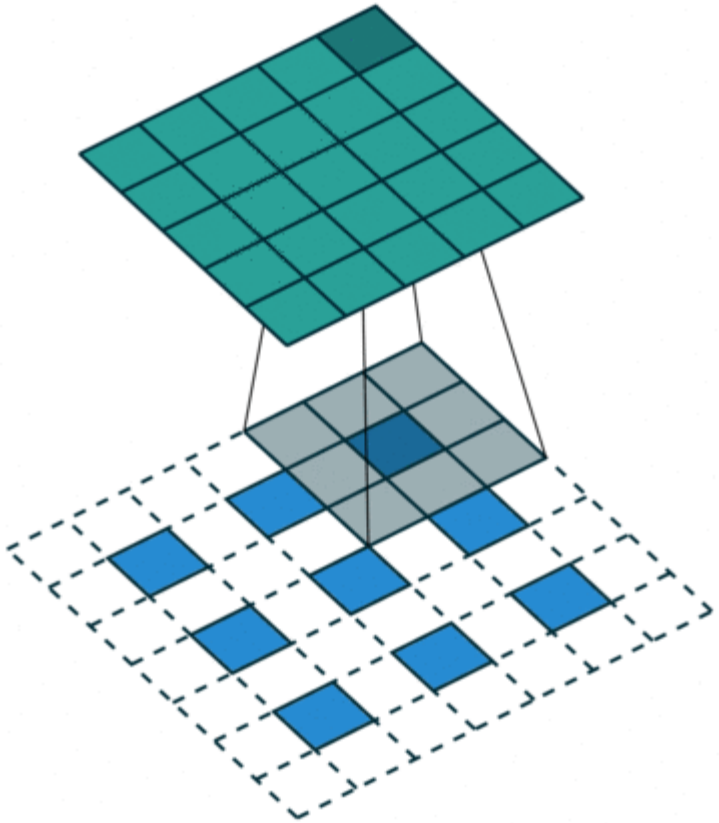
Shift and Stitch



Patch wise Training

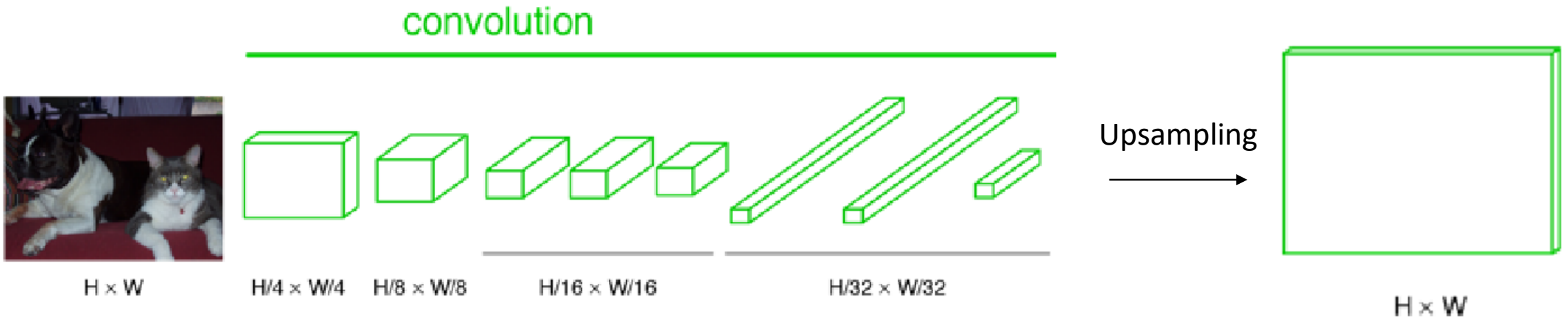


Upsampling

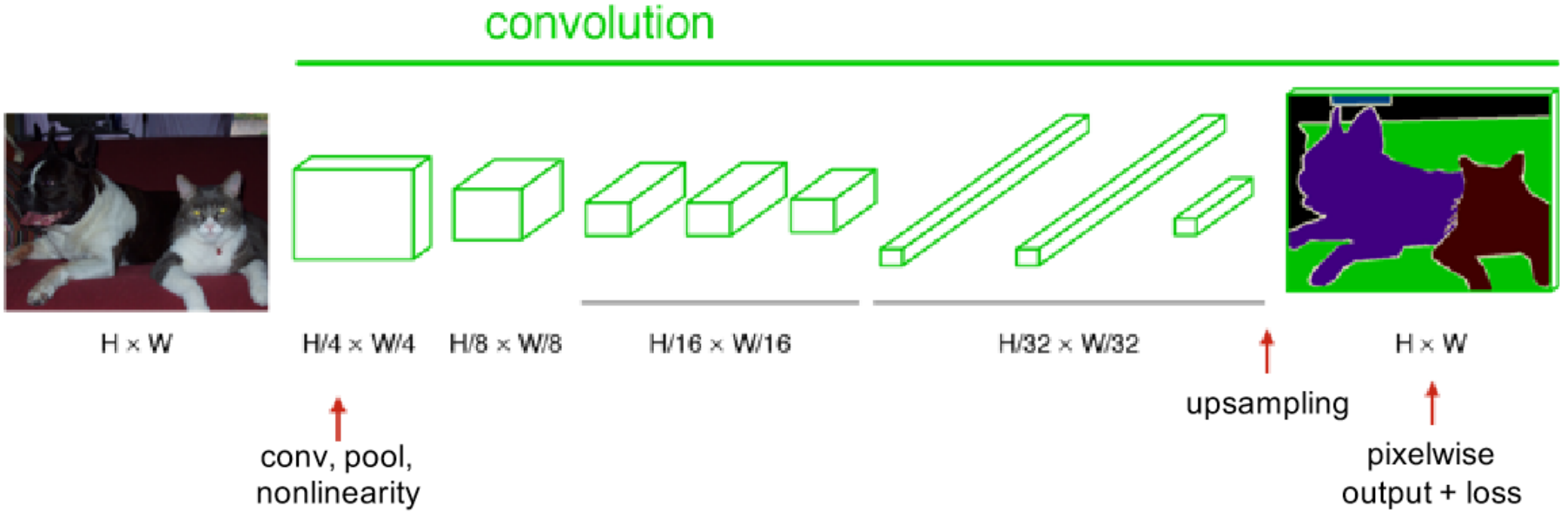


SOURCE: HTTPS://GITHUB.COM/VDUMOULIN/CONV_ARITHMETIC

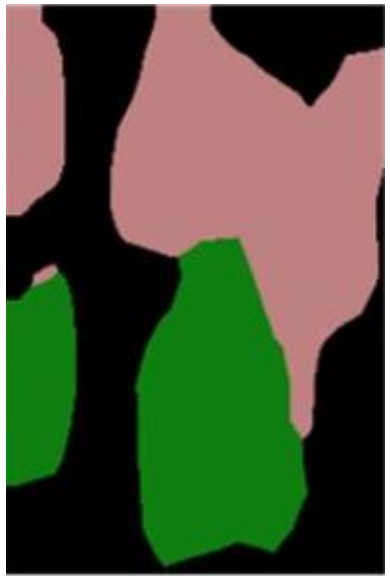
Upsampling



Fully Convolution Networks



Spatial Precision of the O/P

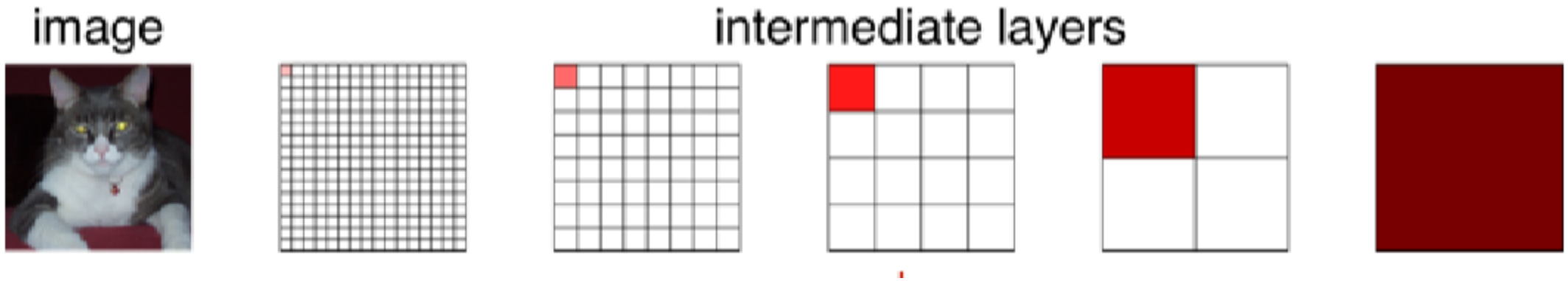


FCN – 32s

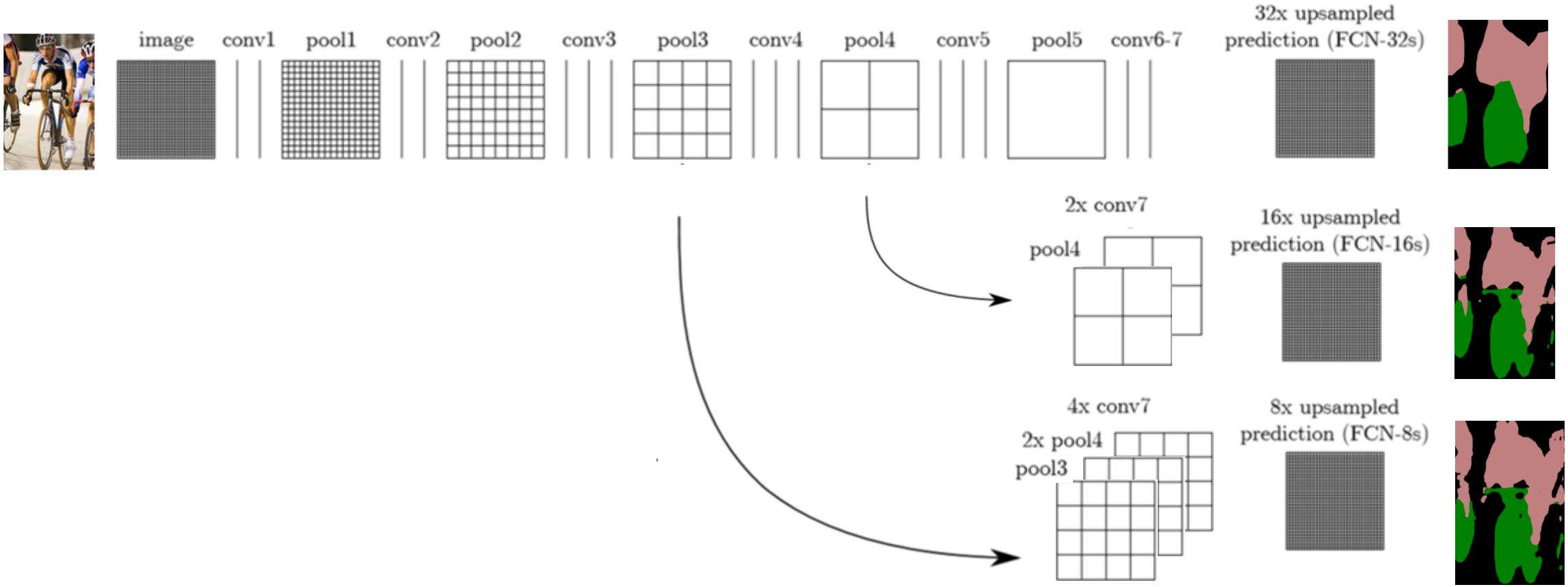
Image

Ground Truth

Combining What and Where



Skip Architecture



Pros

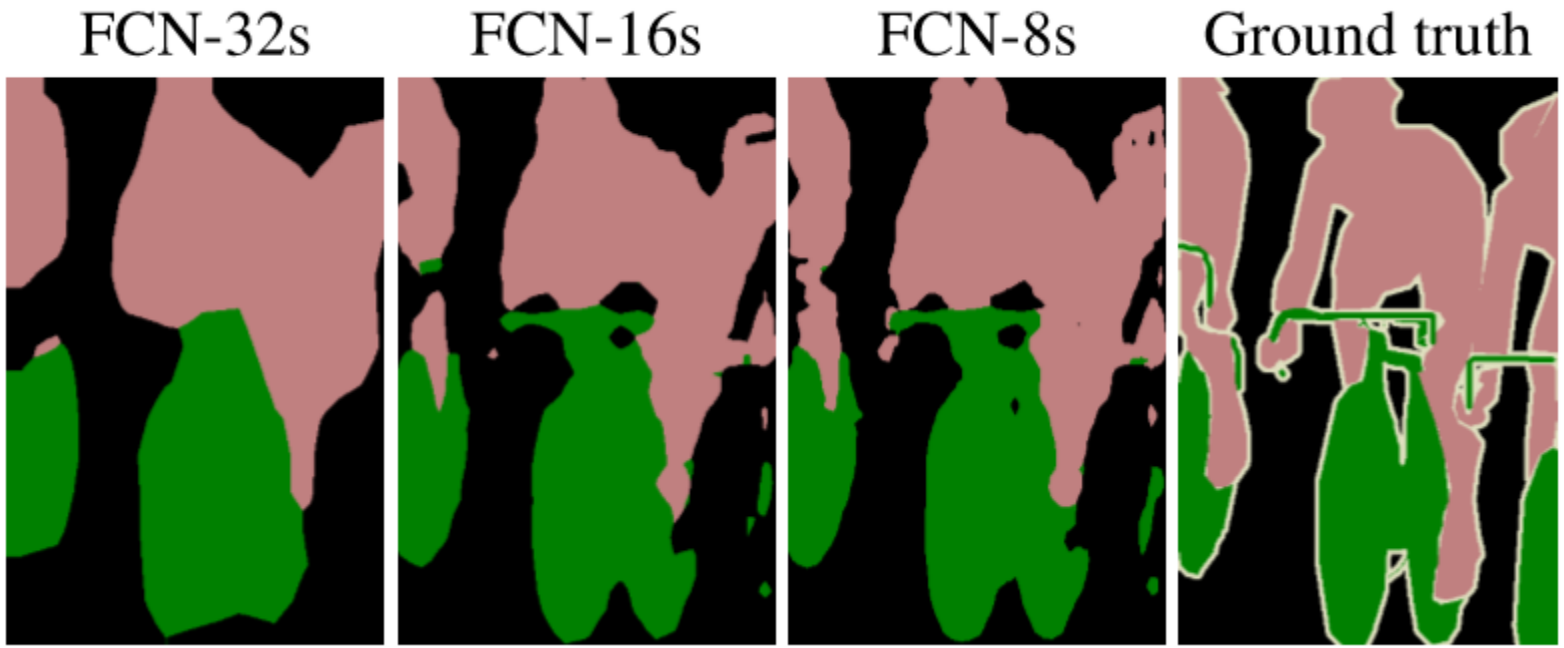
Well structured paper

Supervised pre-training

Intuitive idea

Combining what & where

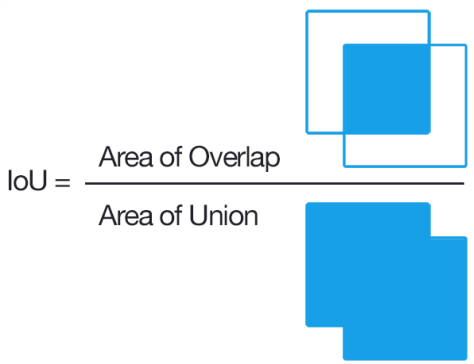
Combining what & where



Discussion of approaches for dense predictions

Good Results

Results



mean IU: $(1/n_{\text{cl}}) \sum_i n_{ii} / \left(t_i + \sum_j n_{ji} - n_{ii}\right)$

	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

Results

	mean IU VOC2011 test	mean IU VOC2012 test	inference time
R-CNN [12]	47.9	-	-
SDS [17]	52.6	51.6	~ 50 s
FCN-8s	**62.7**	**62.2**	~ **175 ms**

PASCAL VOC

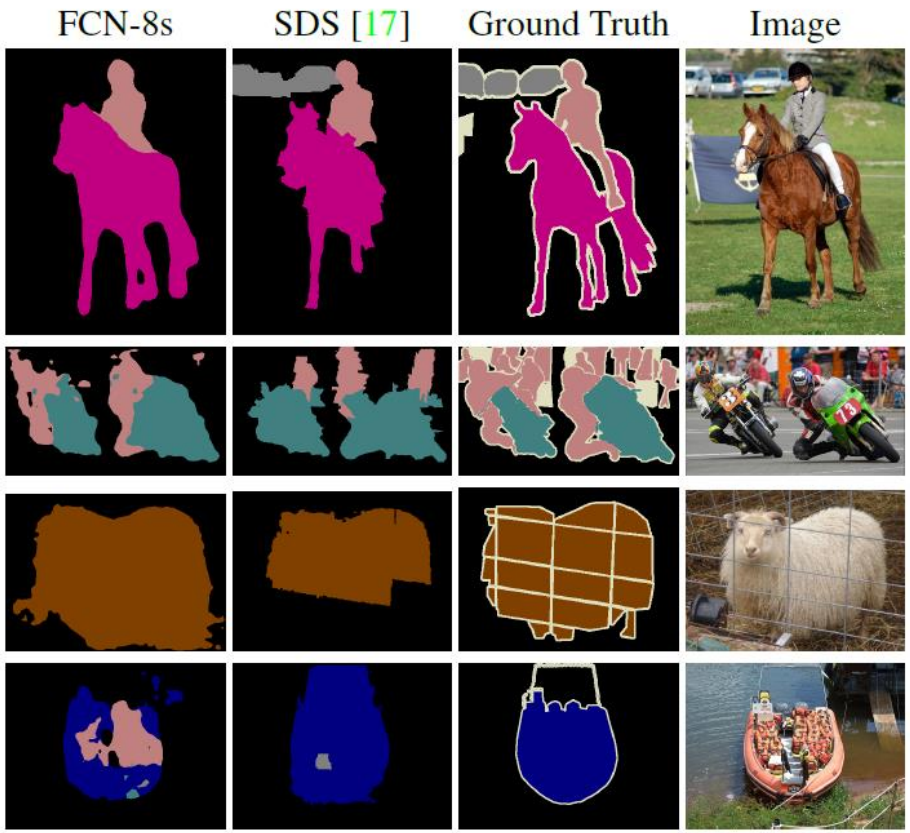
	pixel acc.	mean acc.	mean IU	f.w. IU
Gupta *et al.* [15]	60.3	-	28.6	47.0
FCN-32s RGB	60.0	42.2	29.2	43.9
FCN-32s RGBD	61.5	42.4	30.5	45.5
FCN-32s HHA	57.1	35.2	24.2	40.4
FCN-32s RGB-HHA	64.3	44.9	32.8	48.0
FCN-16s RGB-HHA	**65.4**	**46.1**	**34.0**	**49.5**

NYUDv2

	pixel acc.	mean acc.	mean IU	f.w. IU	geom. acc.
Liu *et al.* [25]	76.7	-	-	-	-
Tighe *et al.* [36]	-	-	-	-	90.8
Tighe *et al.* [37] 1	75.6	41.1	-	-	-
Tighe *et al.* [37] 2	78.6	39.2	-	-	-
Farabet *et al.* [9] 1	72.3	50.8	-	-	-
Farabet *et al.* [9] 2	78.5	29.6	-	-	-
Pinheiro *et al.* [31]	77.7	29.8	-	-	-
FCN-16s	**85.2**	**51.7**	39.5	76.1	**94.3**

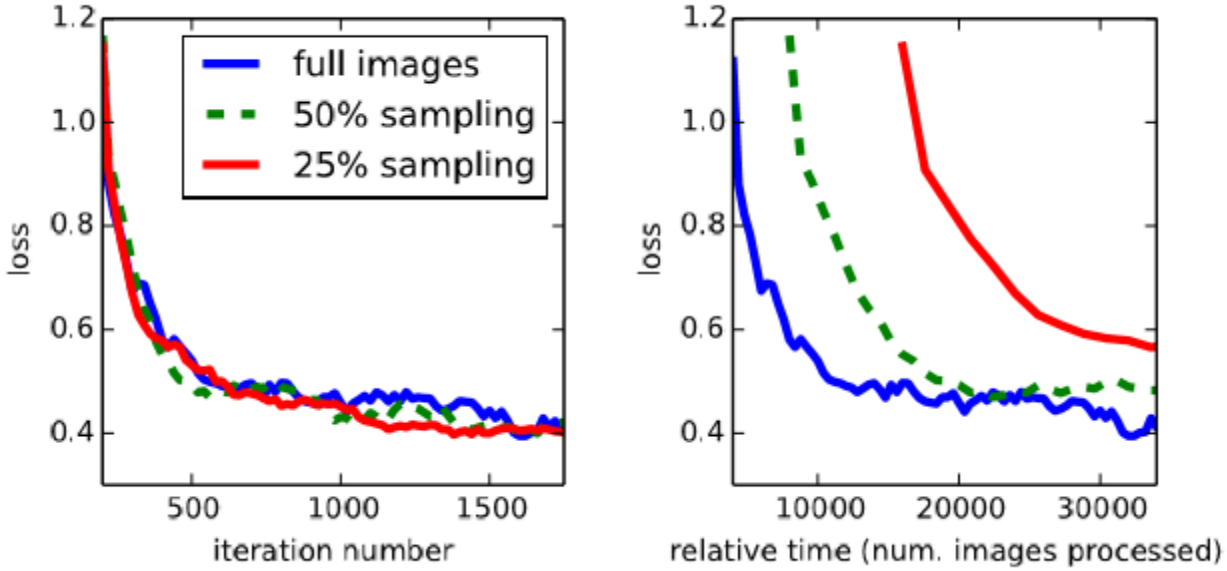
SIFT Flow

Results – PASCAL VOC



Speed improvement

Whole image Vs Patchwise training



Heavily used in practice

Google fully convolutional networks for semantic segmentation

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Articles

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Any time

Since 2017

Fully convolutional networks for semantic segmentation

J Long, E Shelhamer, T Darrell - Proceedings of the IEEE …, 2015 - cv-foundation.org

Abstract Convolutional networks are powerful visual models that yield hierarchies of features. We show that convolutional networks by themselves, trained end-to-end, pixels-to-pixels, exceed the state-of-the-art in semantic segmentation. Our key insight is to build" fully convolutional" networks that take input of arbitrary size and produce correspondingly-sized output with efficient inference and learning. We define and detail the space of fully ...

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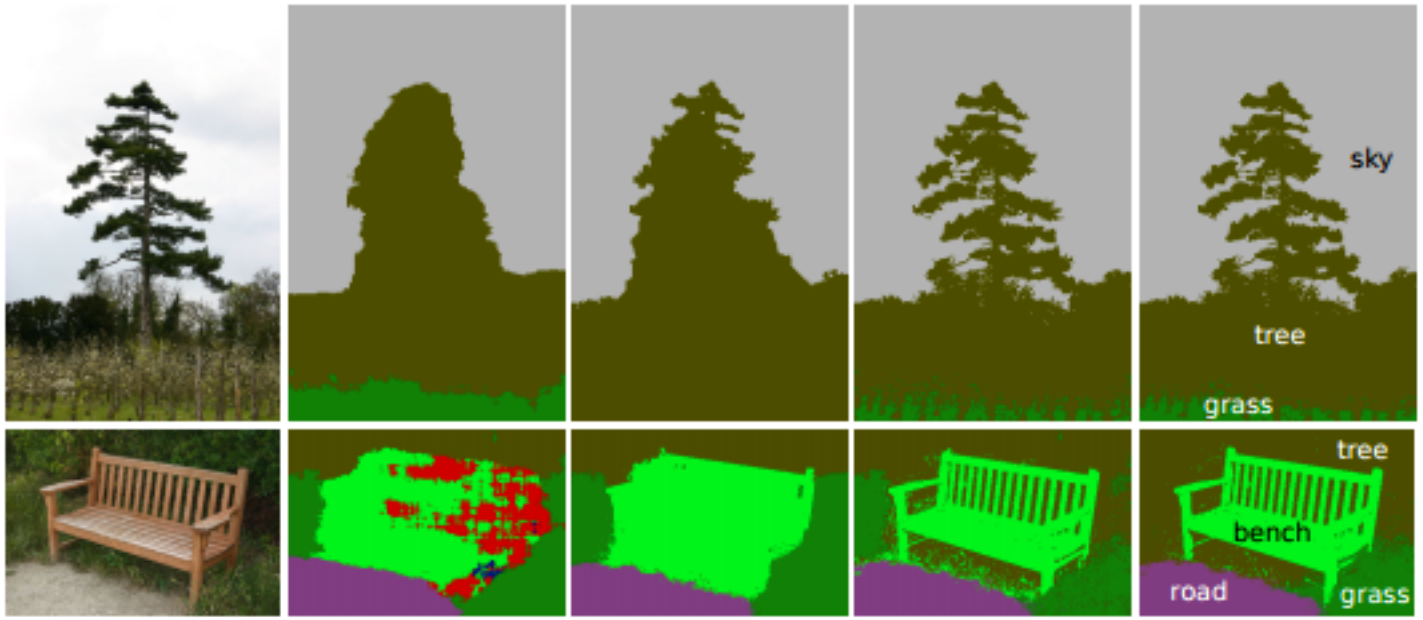
Cons

Cons1: What about Fully connected CRF?

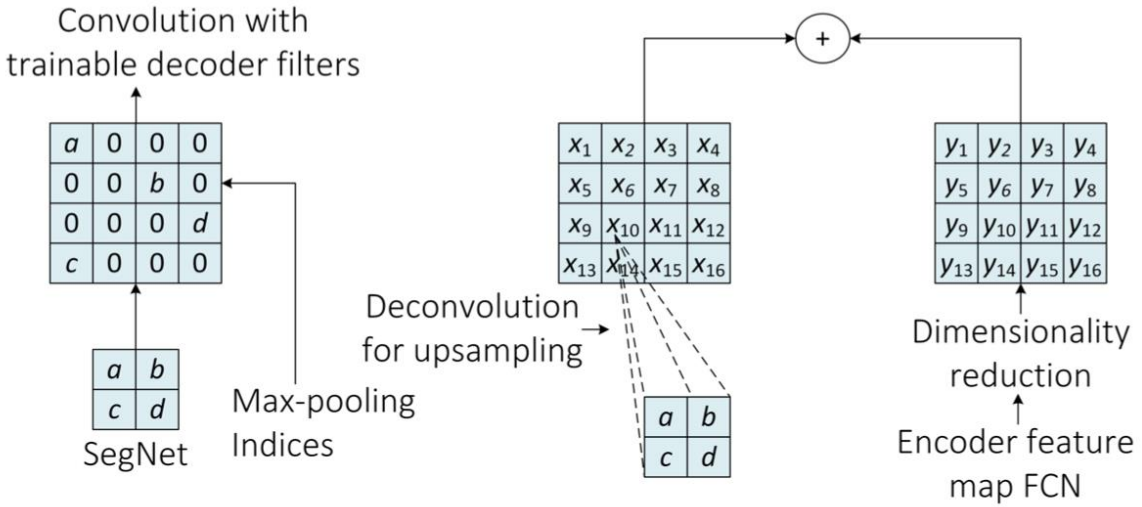
(Efficient Inference in Fully Connected CRFs with Gaussian Edge Potentials, Krähenbühl and Koltun)



(a) Image (b) Unary classifiers (c) Robust P^n CRF (d) Fully connected CRF, MCMC inference, 36 hrs (e) Fully connected CRF, our approach, 0.2 seconds

Cons2: Qualitative Claims -> possible explanations?

Cons3: Execution time vs Memory footprint vs. Accuracy trade-off



SegNet vs. FCN

Cons4: Future directions?

Questions?