Semantic Segmentation
and
Image Processing

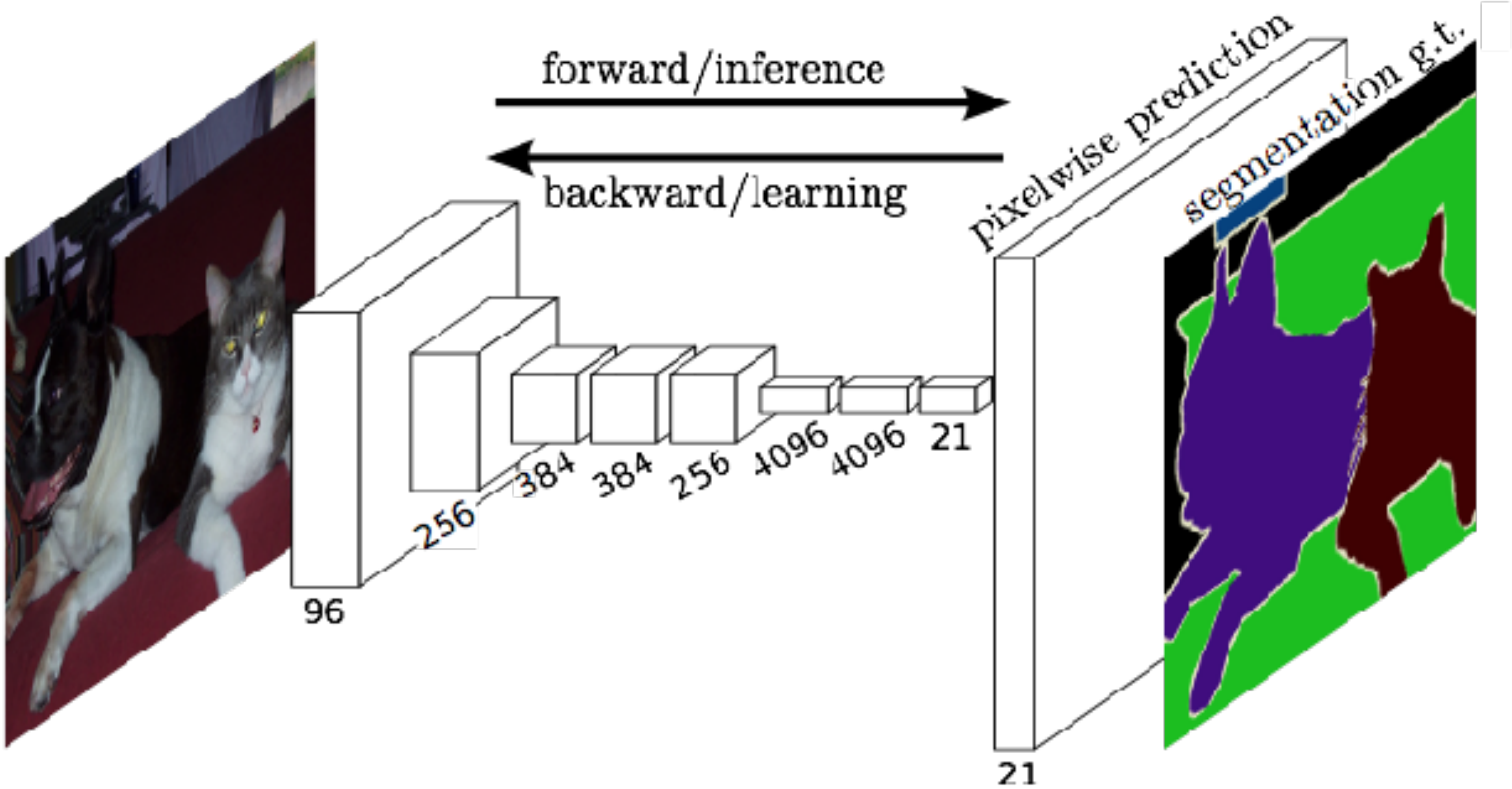
with Convnets

Overview

- Methods where output is also an image
  - Fully Convolutional Nets [Long et al., CVPR 2015]
  - Depth, normals and semantic labels from a single image [Eigen ICCV 2015]

- Image processing with Convnets
  - Image colorization [Zhang et al. ECCV 2016]

A Fuller Understanding of Fully Convolutional Networks

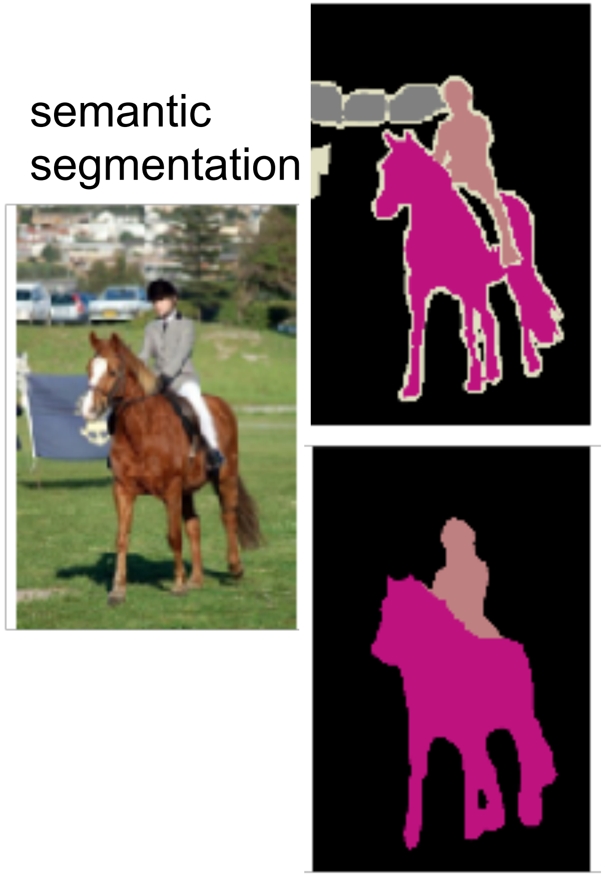


Evan Shelhamer* Jonathan Long* Trevor Darrell

UC Berkeley in CVPR'15, PAMI'16

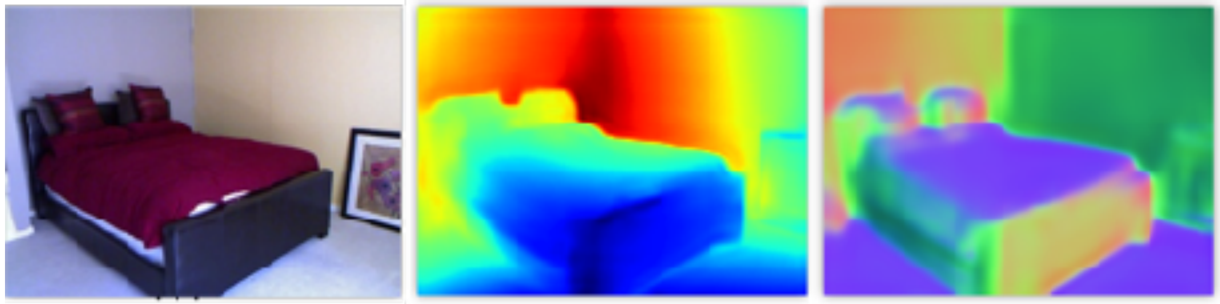
pixels in, pixels out

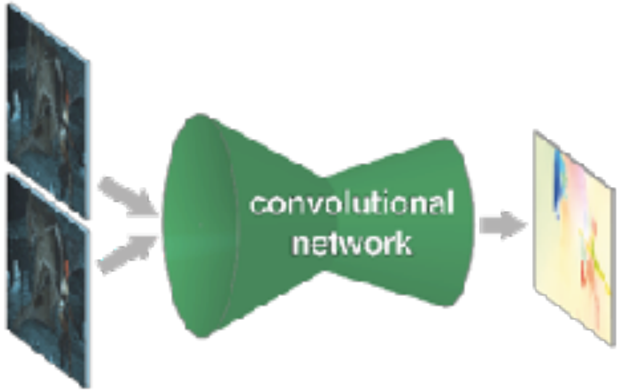
semantic segmentation



colorization
Zhang et al.2016

monocular depth + normals Eigen & Fergus 2015

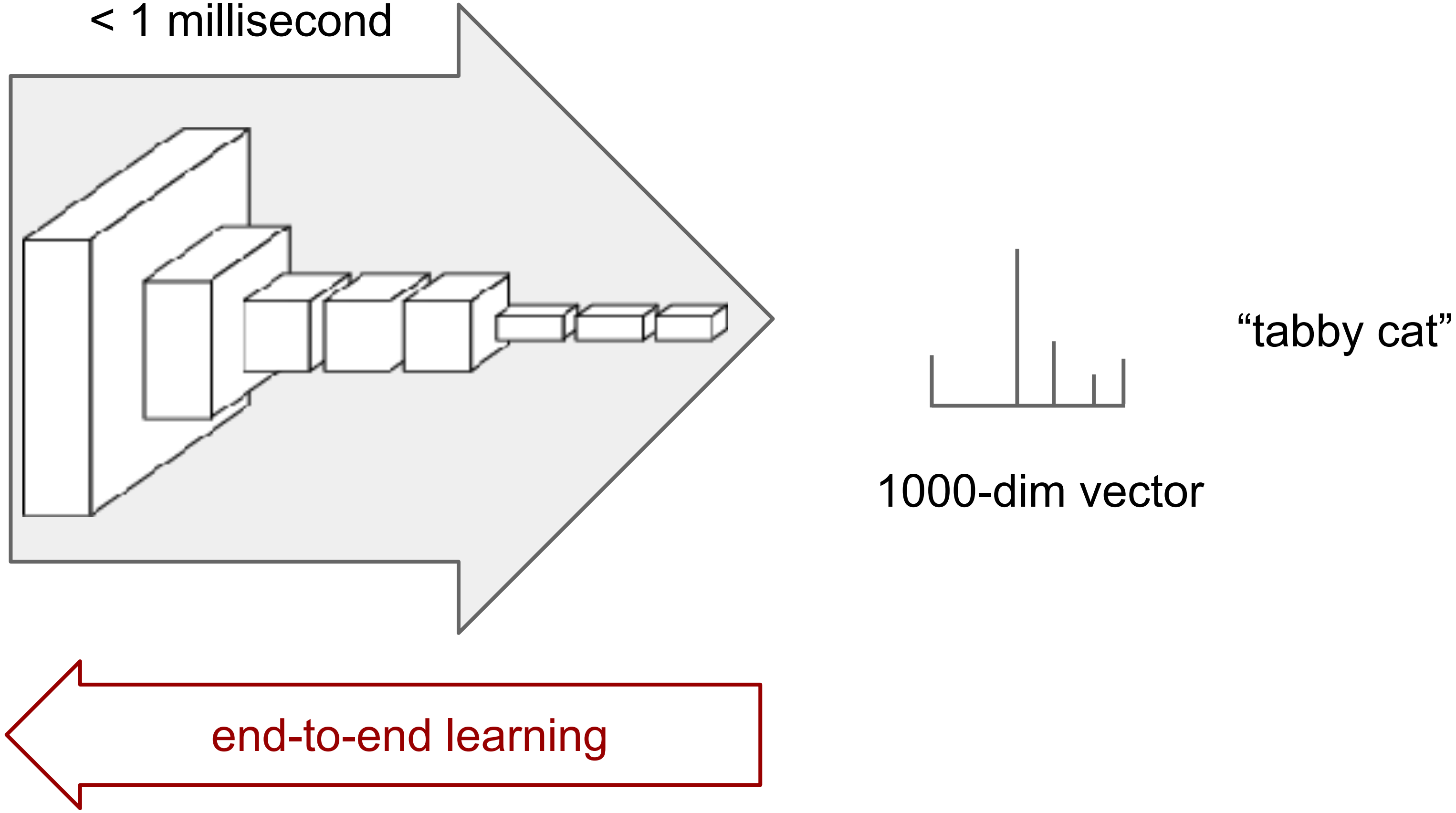




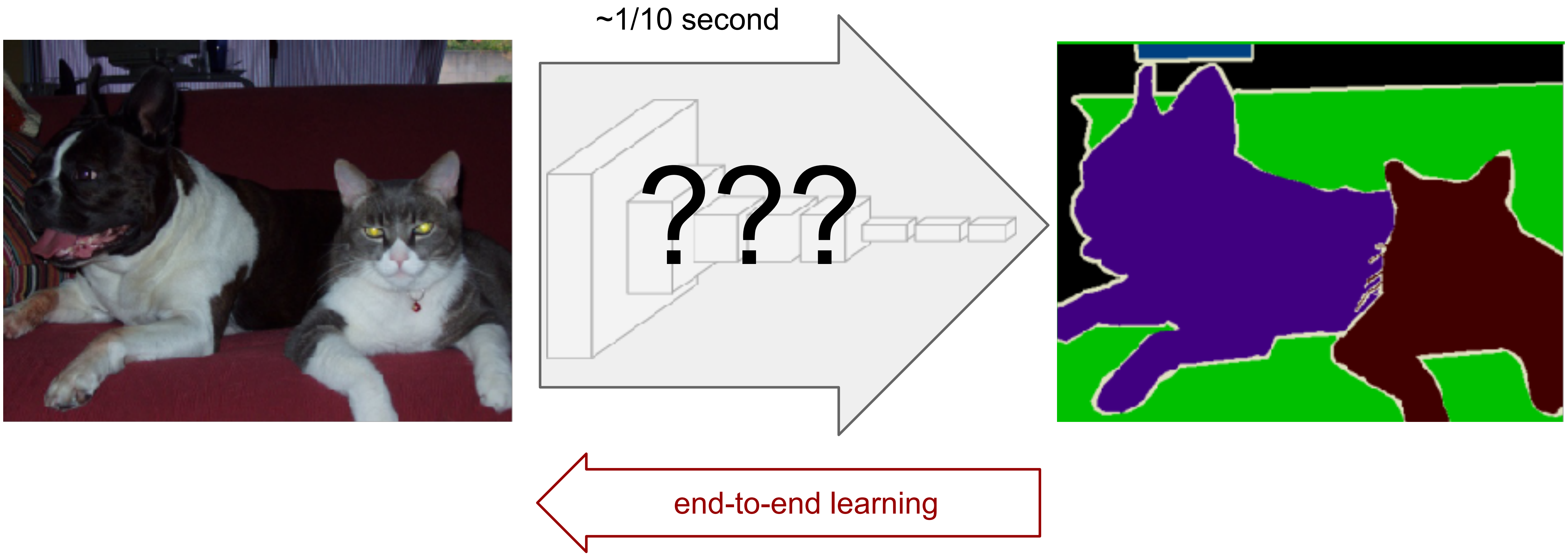
optical flow Fischer et al. 2015

boundary prediction Xie & Tu 2015

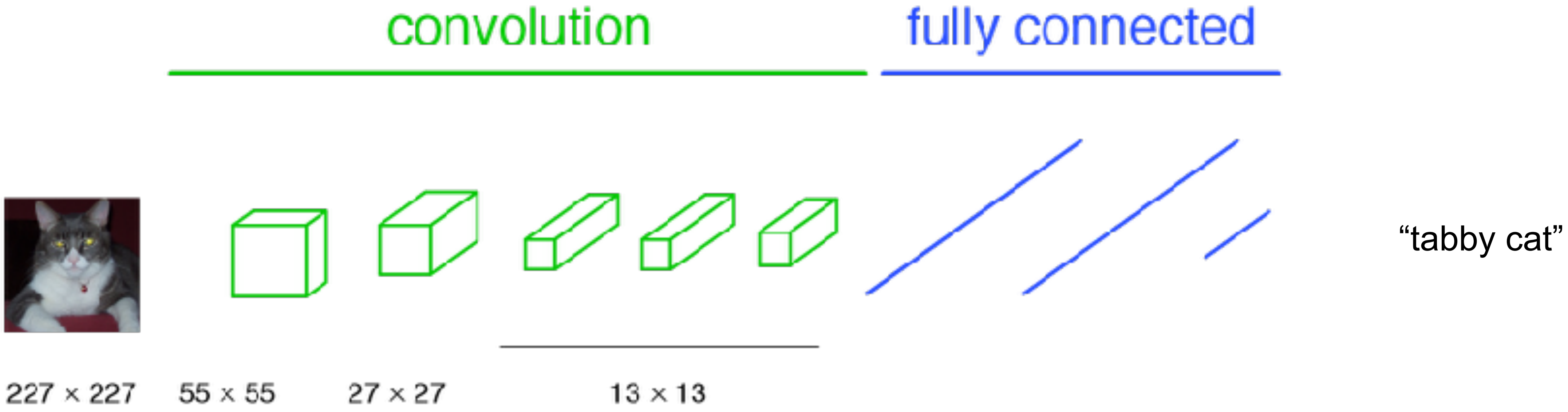
convnets perform classification



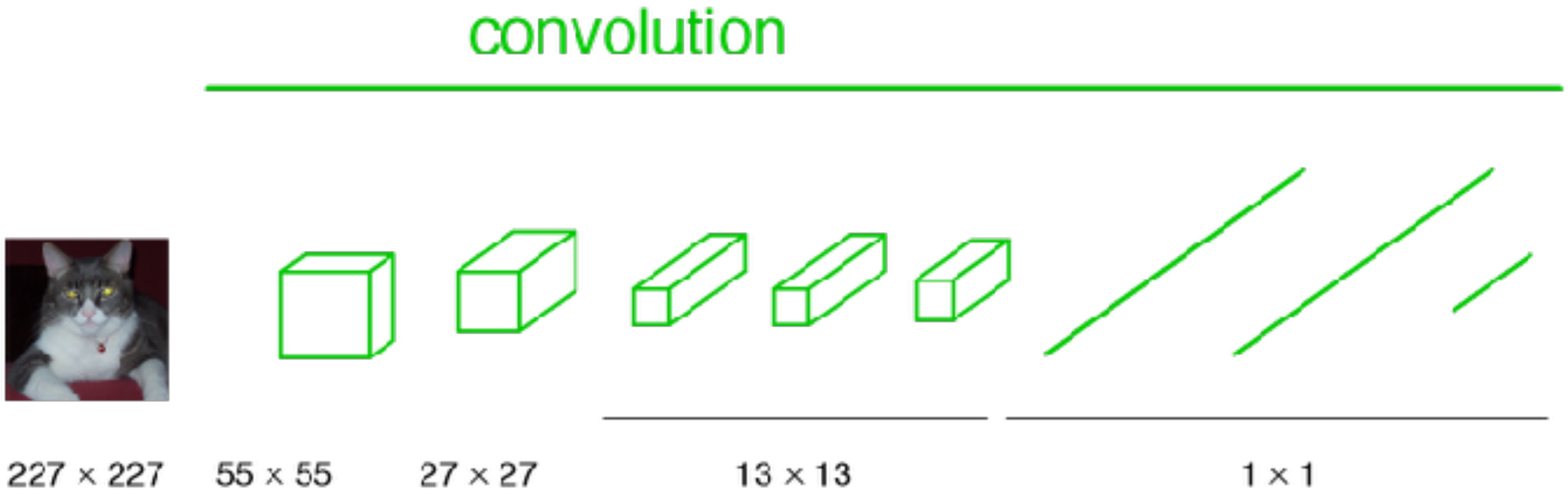
lots of pixels, little time?



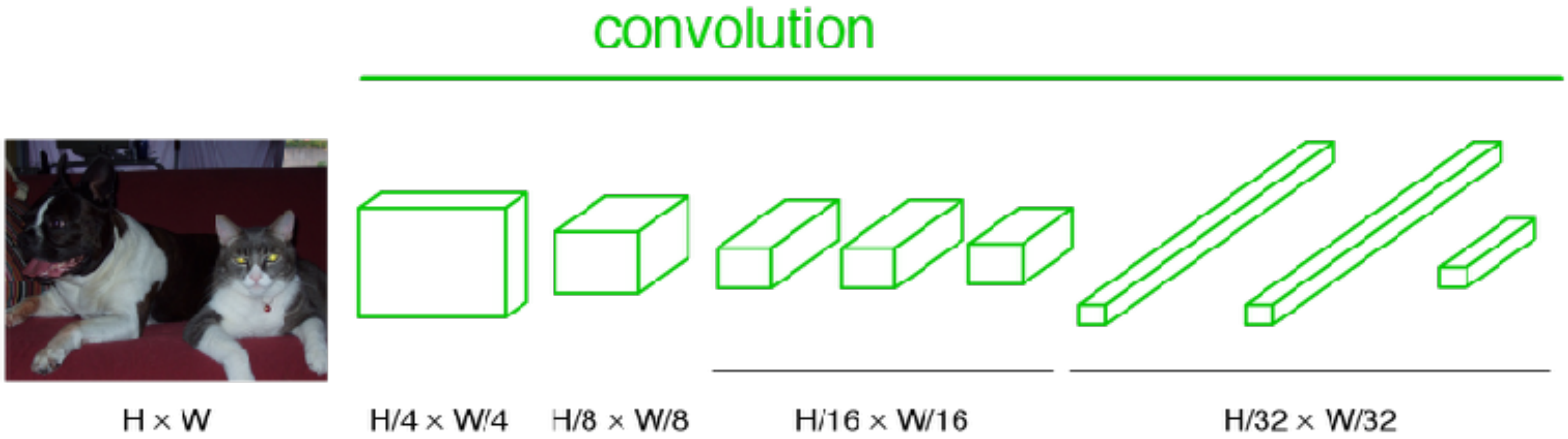
a classification network



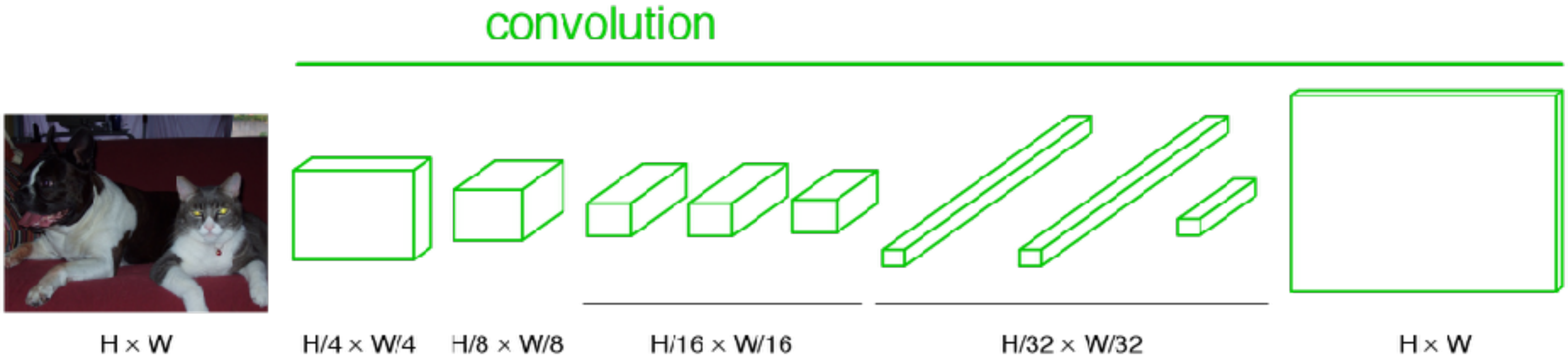
becoming fully convolutional



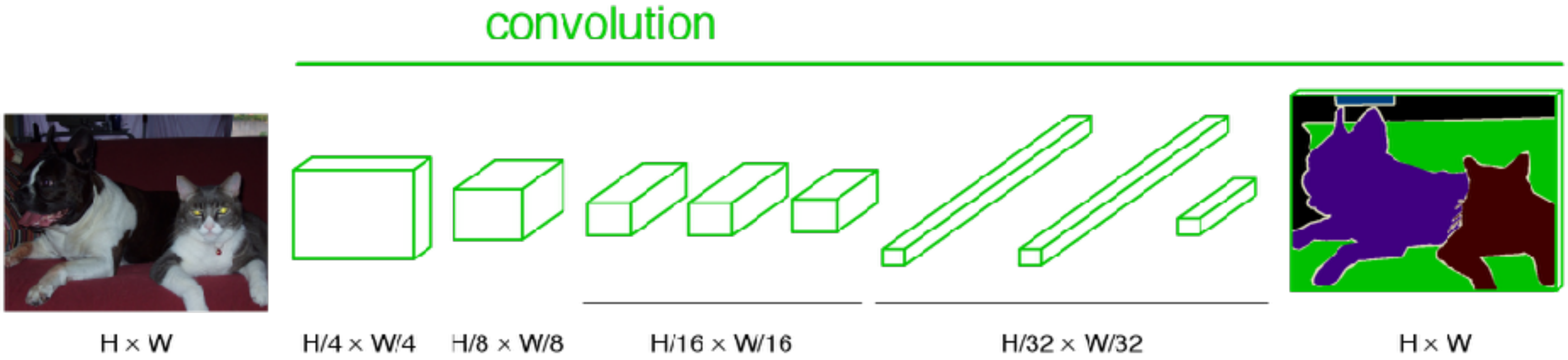
becoming fully convolutional



upsampling output



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



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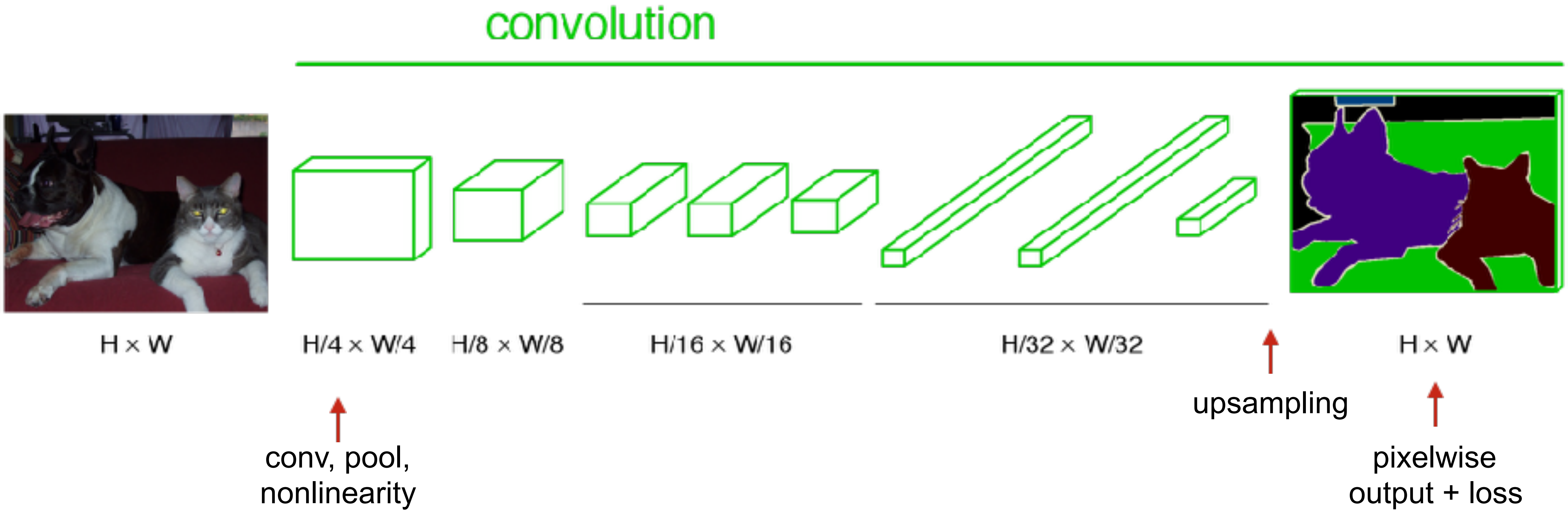
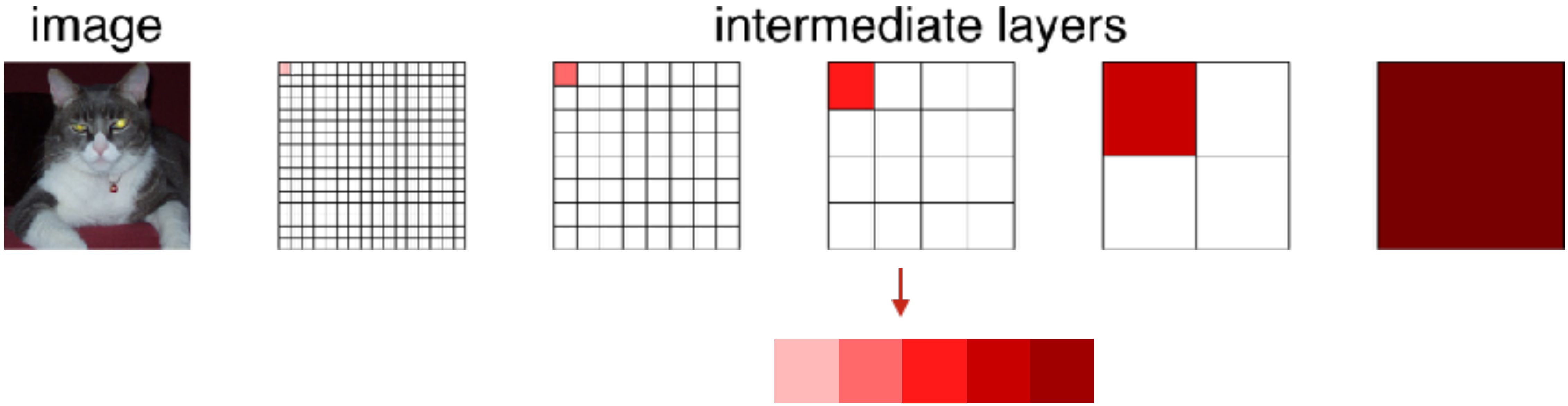


spectrum of deep features

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



fuse features into deep jet

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

skip layers

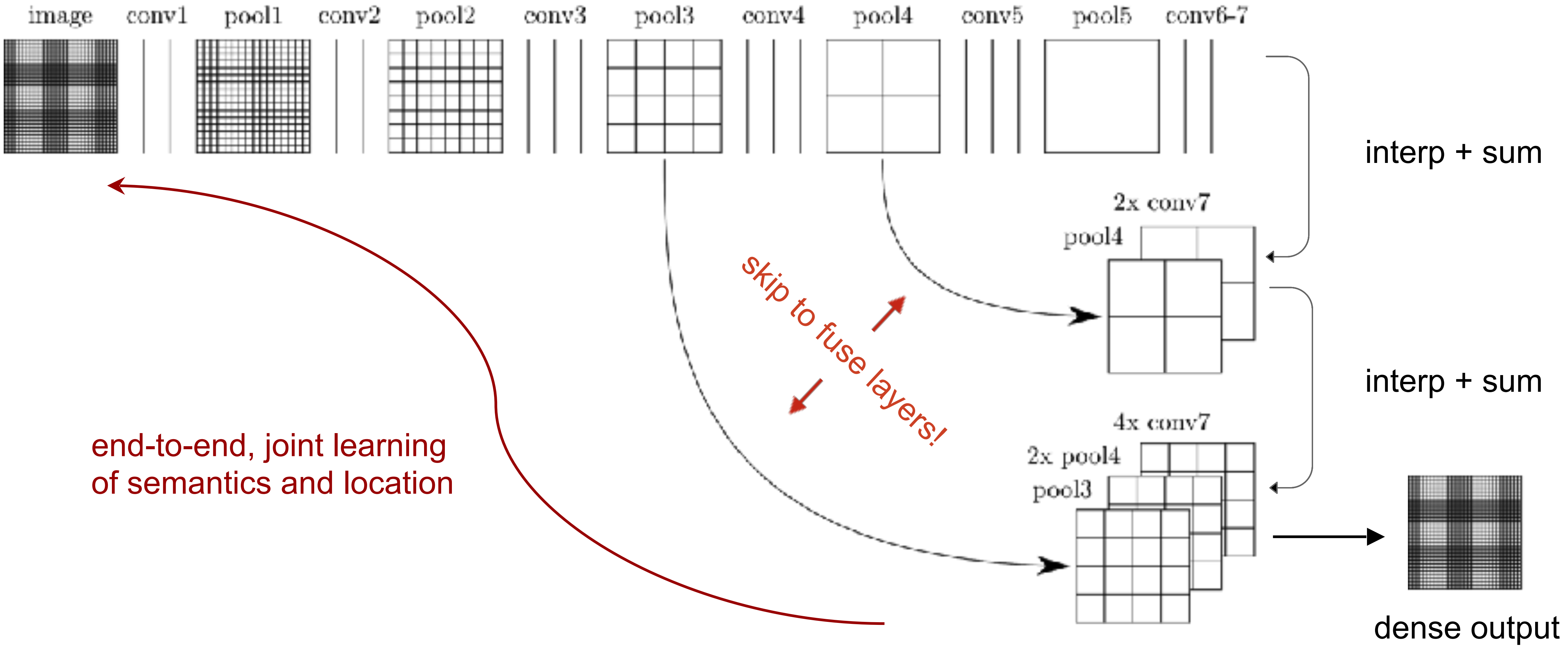
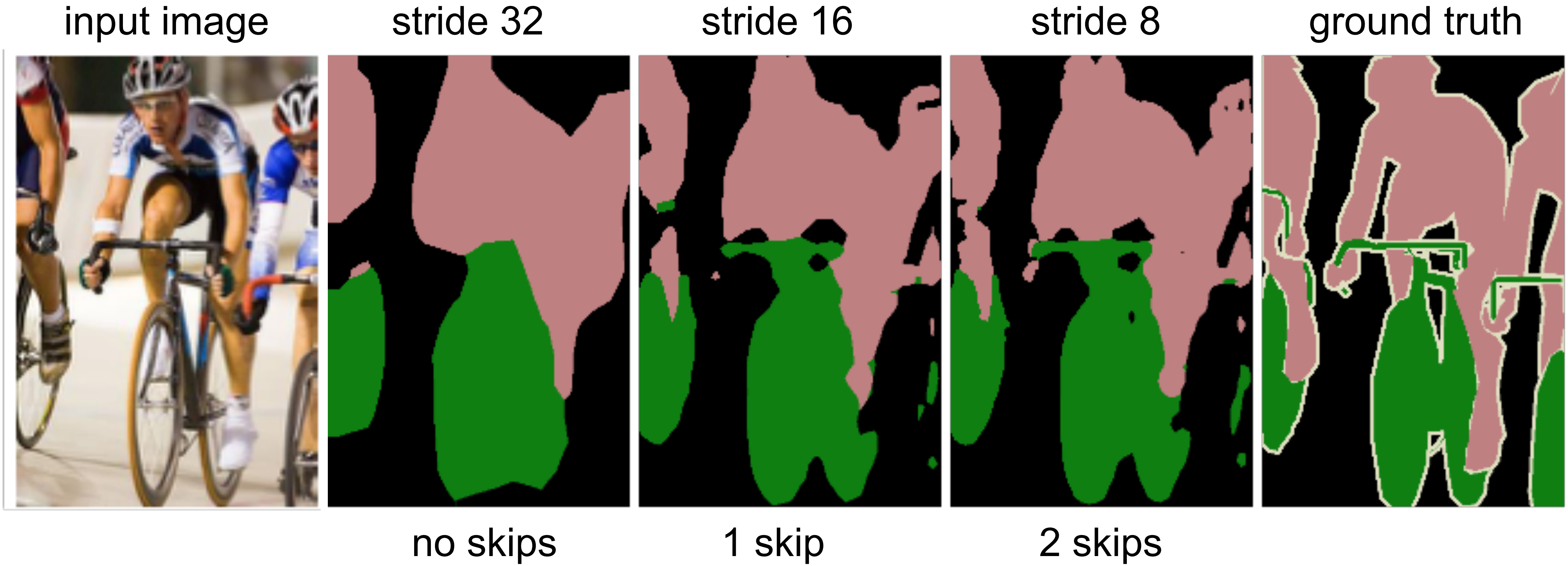
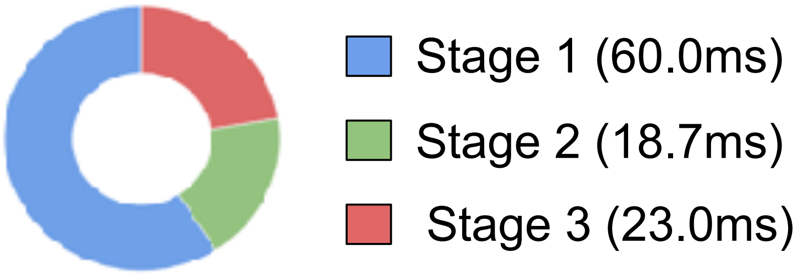


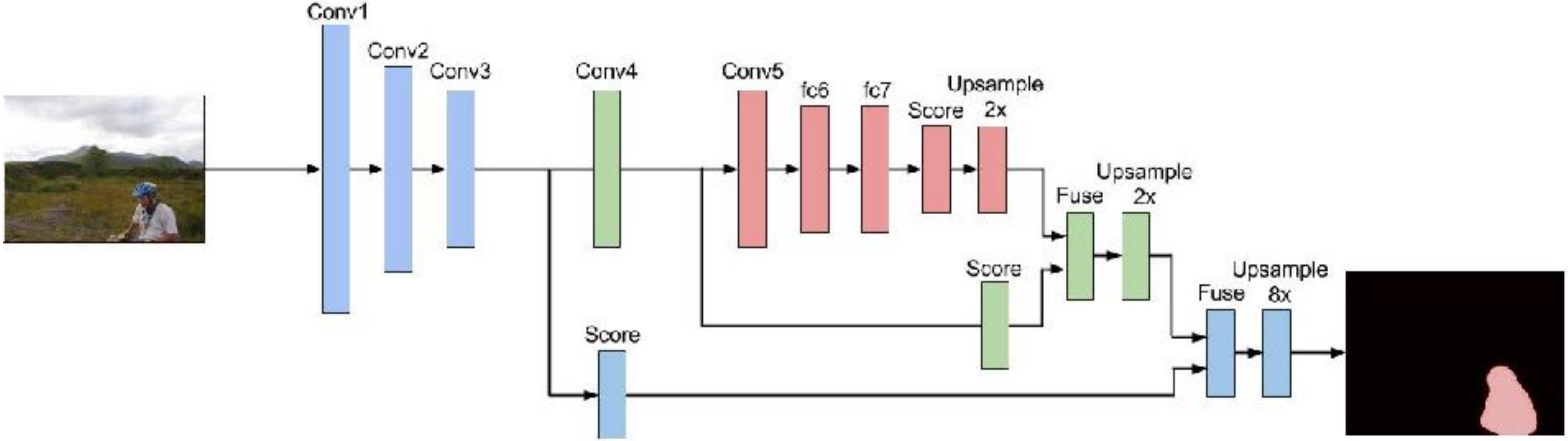
image
conv1
pool1
conv2
pool2
conv3
pool3
conv4
pool4
conv5
pool5
conv6-7
interp + sum
2x conv7
pool4
skip to fuse layers!
interp + sum
4x conv7
2x pool4
pool3
end-to-end, joint learning
of semantics and location
dense output

skip layer refinement

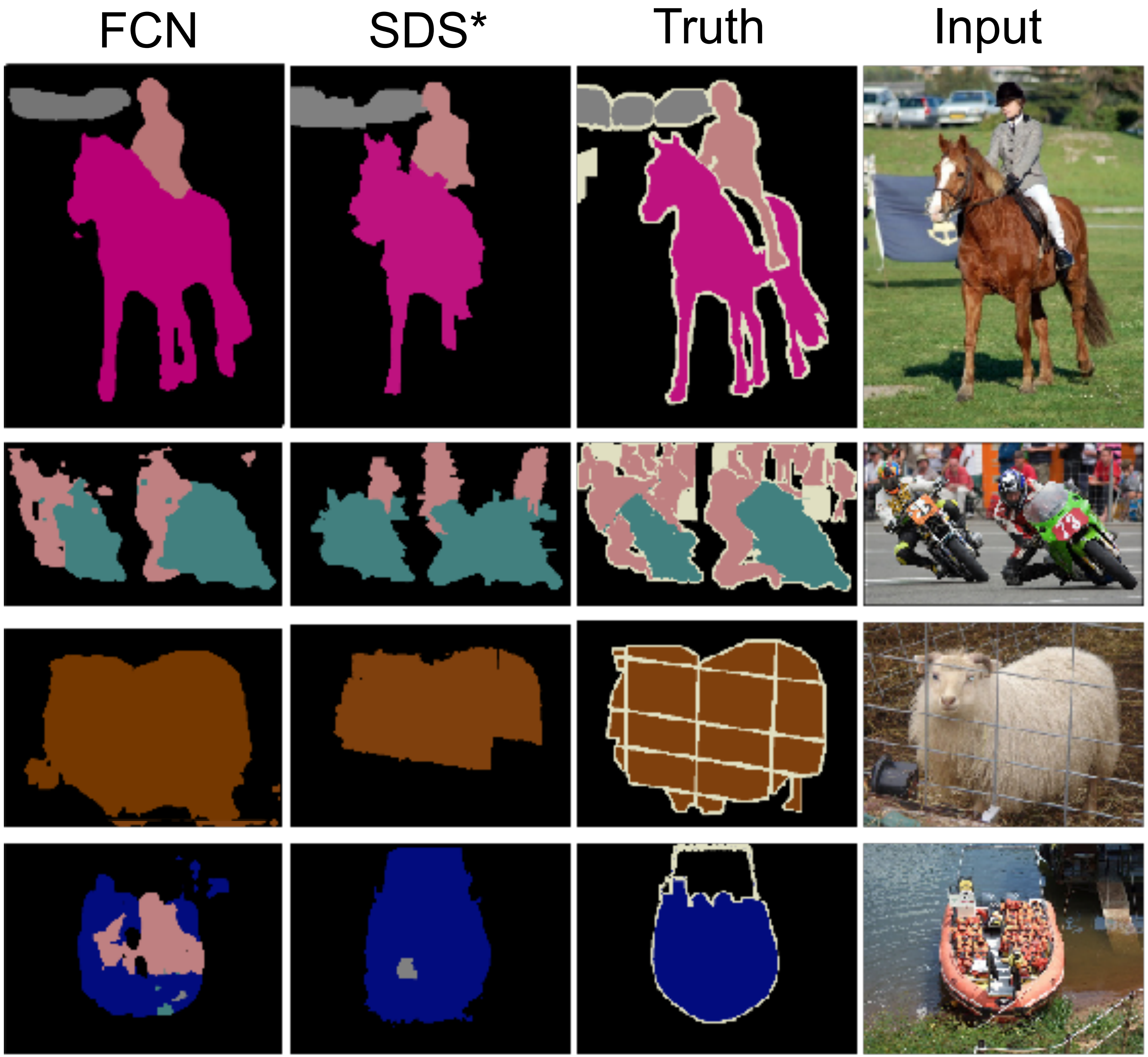


skip FCN computation





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



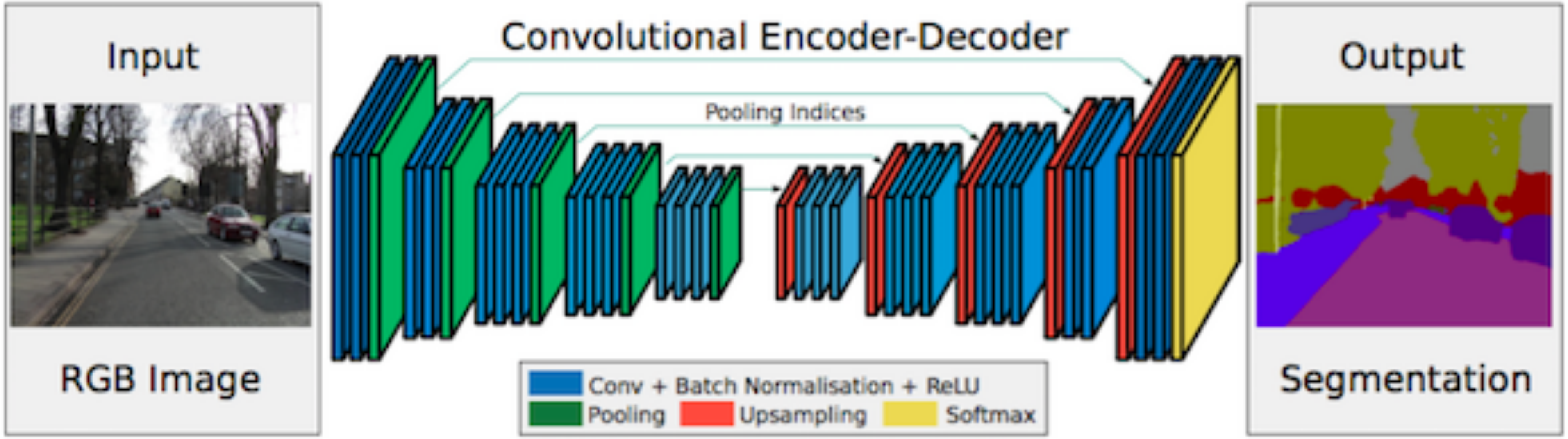
Relative to prior state-of-the-art SDS:

30% relative improvement for mean IoU

286× faster

*Simultaneous Detection and Segmentation
Hariharan et al. ECCV14

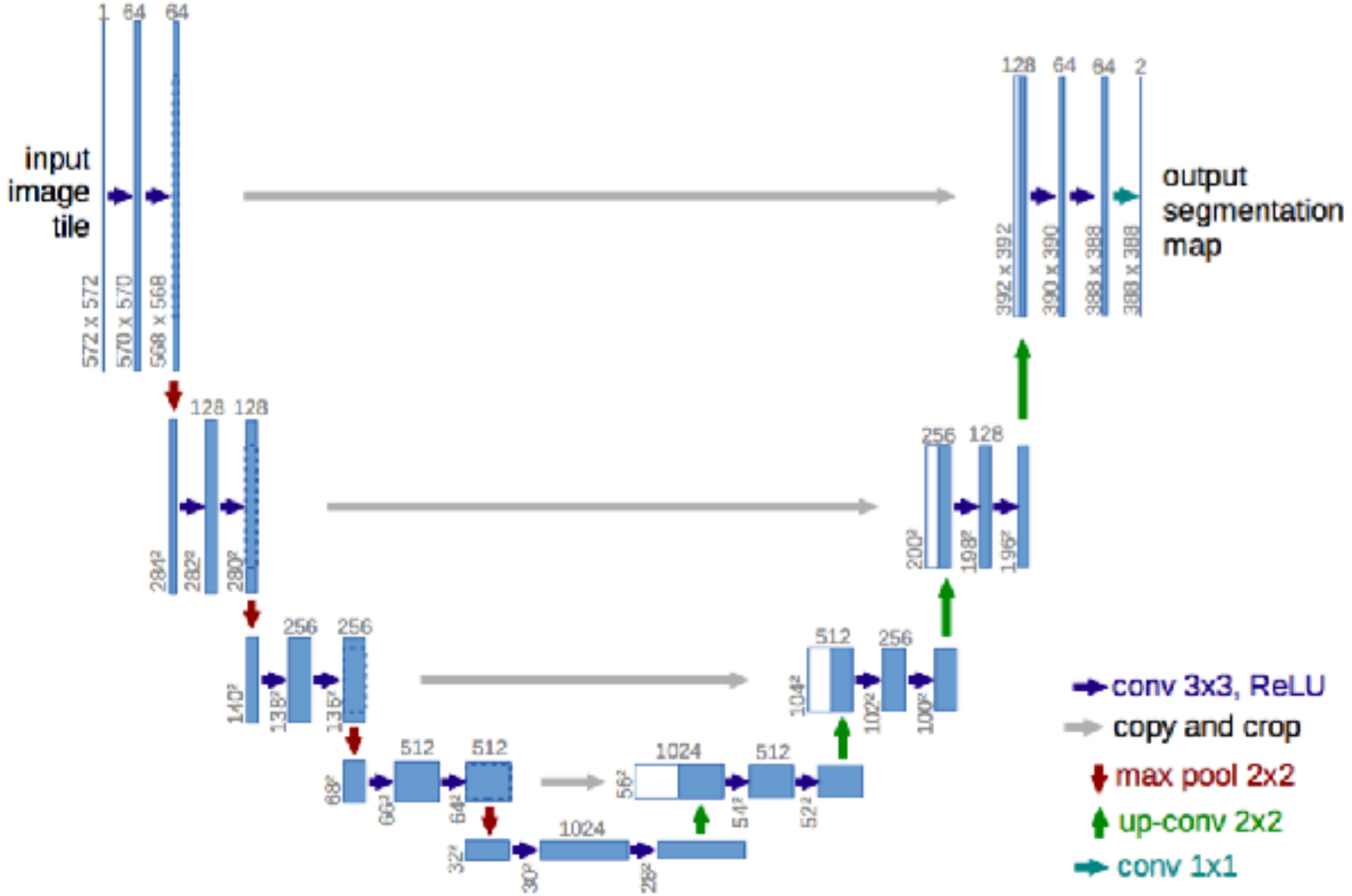
SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation



Max pooling indices transferred to decoder to improve output resolution

https://arxiv.org/abs/1511.00561

UNet: Convolutional Networks for Biomedical Image Segmentation



Segmentation of a 512x512 image takes less than a second on a recent GPU

https://arxiv.org/abs/1505.04597

Further Resources

http://blog.qure.ai/notes/semantic-segmentation-deep-learning-review

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    - Depth, normals and semantic labels from a single image [Eigen ICCV 2015]

- Image processing with Convnets
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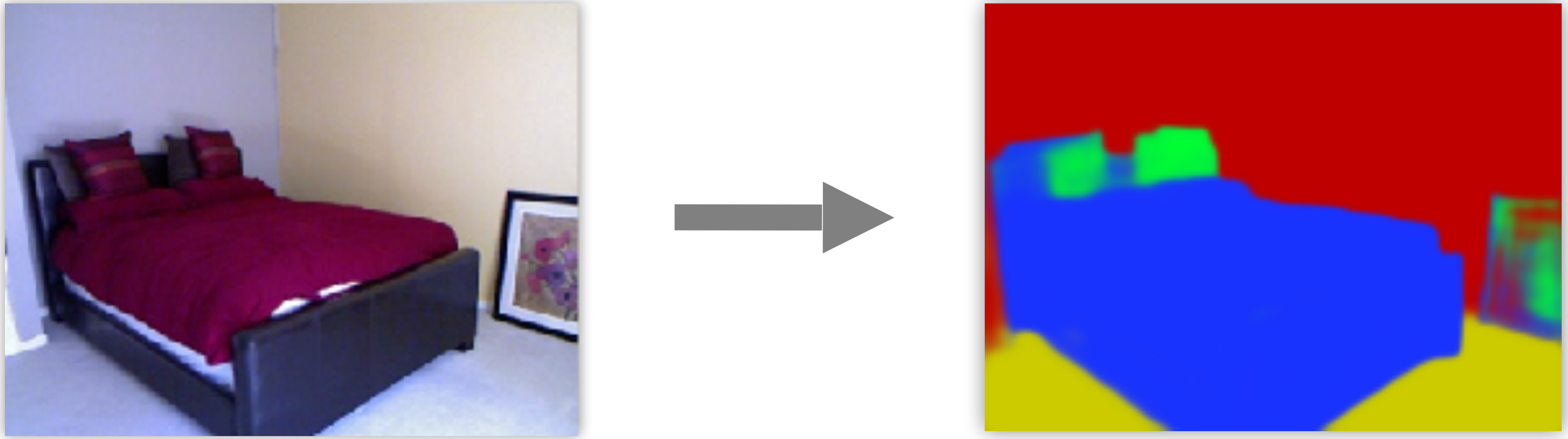
Beyond Object Classification with Convolutional Networks

David Eigen (NYU -> Clarifai)
Rob Fergus (Facebook / NYU)

Motivation

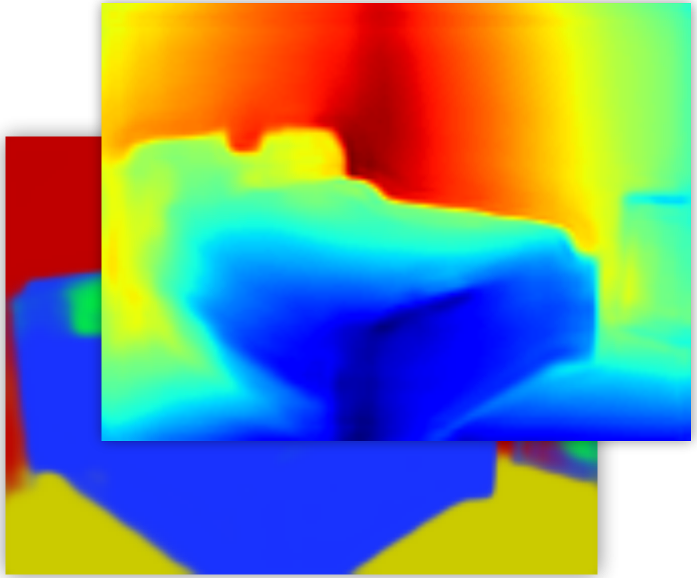


Input Image　　　　　　　　Semantic Map

- Understand input scene
  - Semantic
  - Geometric

Motivation

Input Image

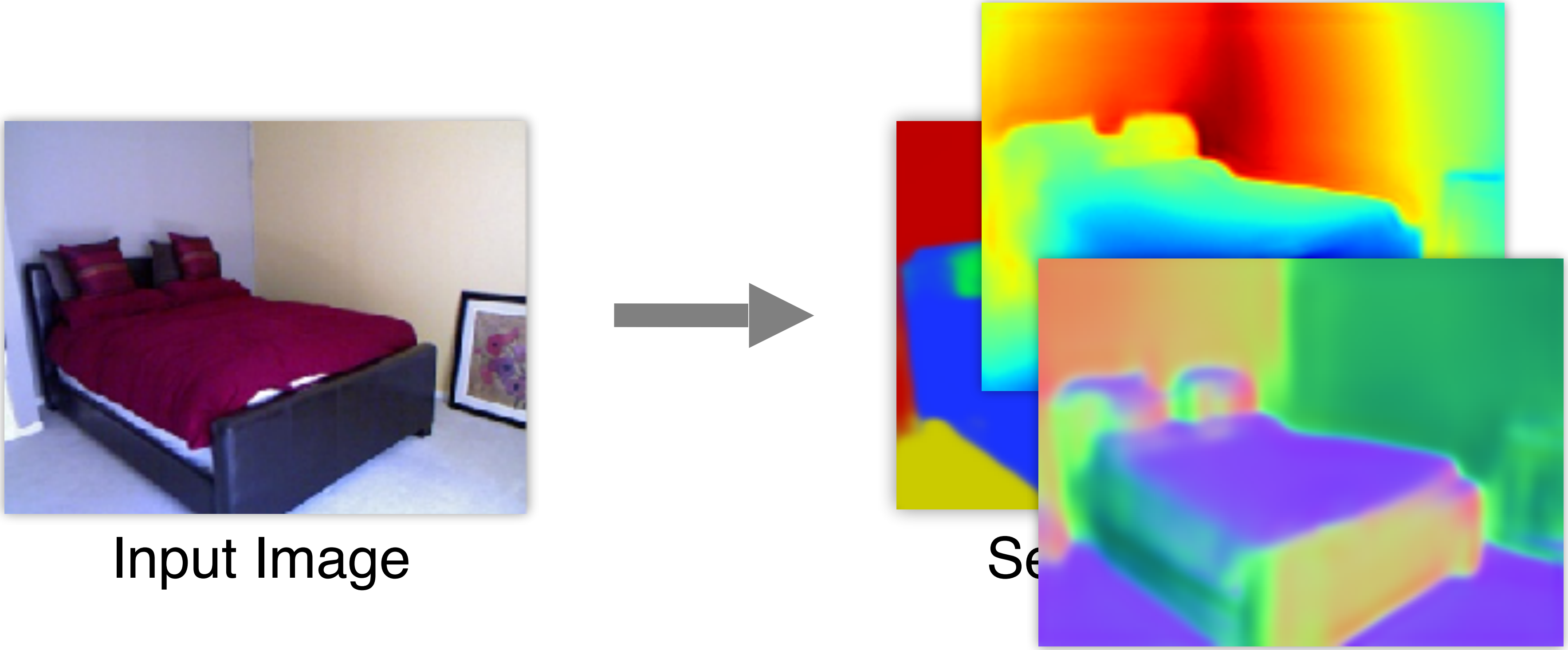


Semantic Map

- Understand input scene
  - Semantic
  - Geometric

Motivation

Depth

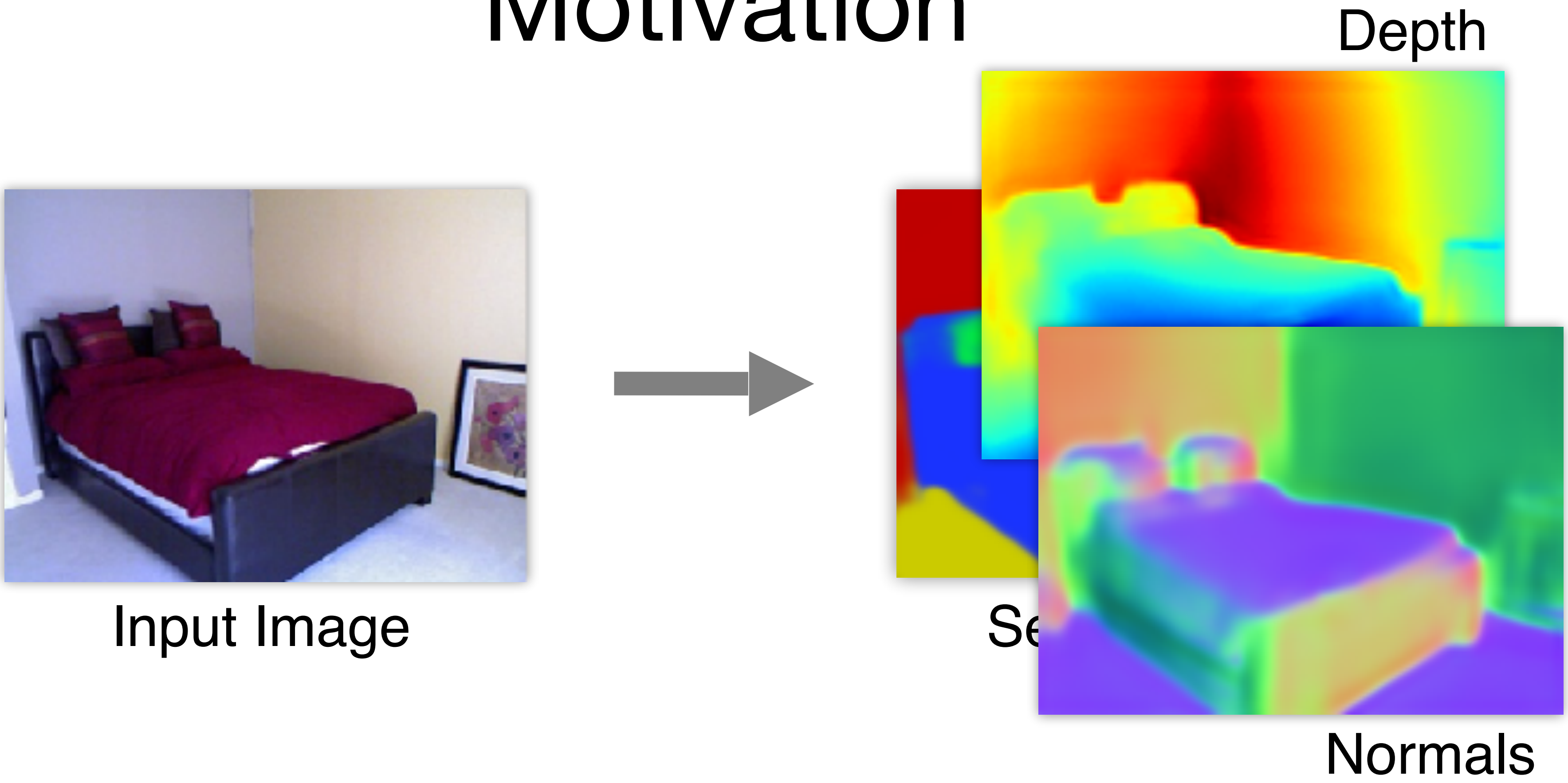


Input Image

Normals

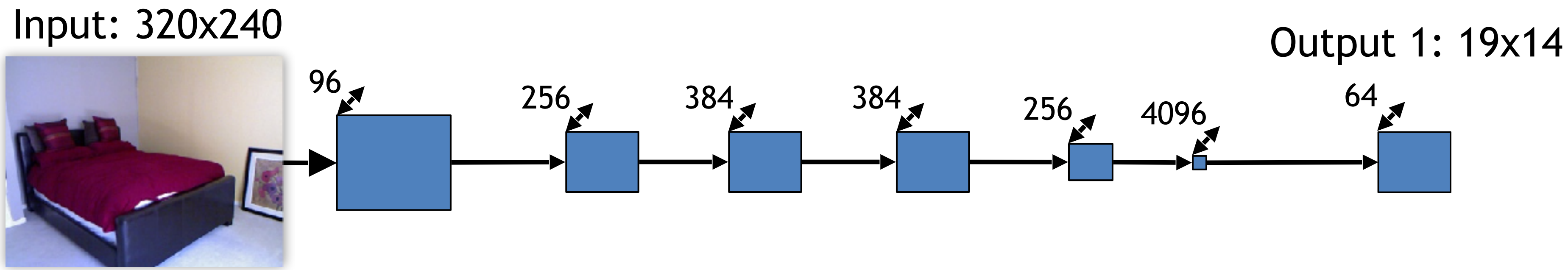
- Understand input scene
  - Semantic
  - Geometric

Motivation

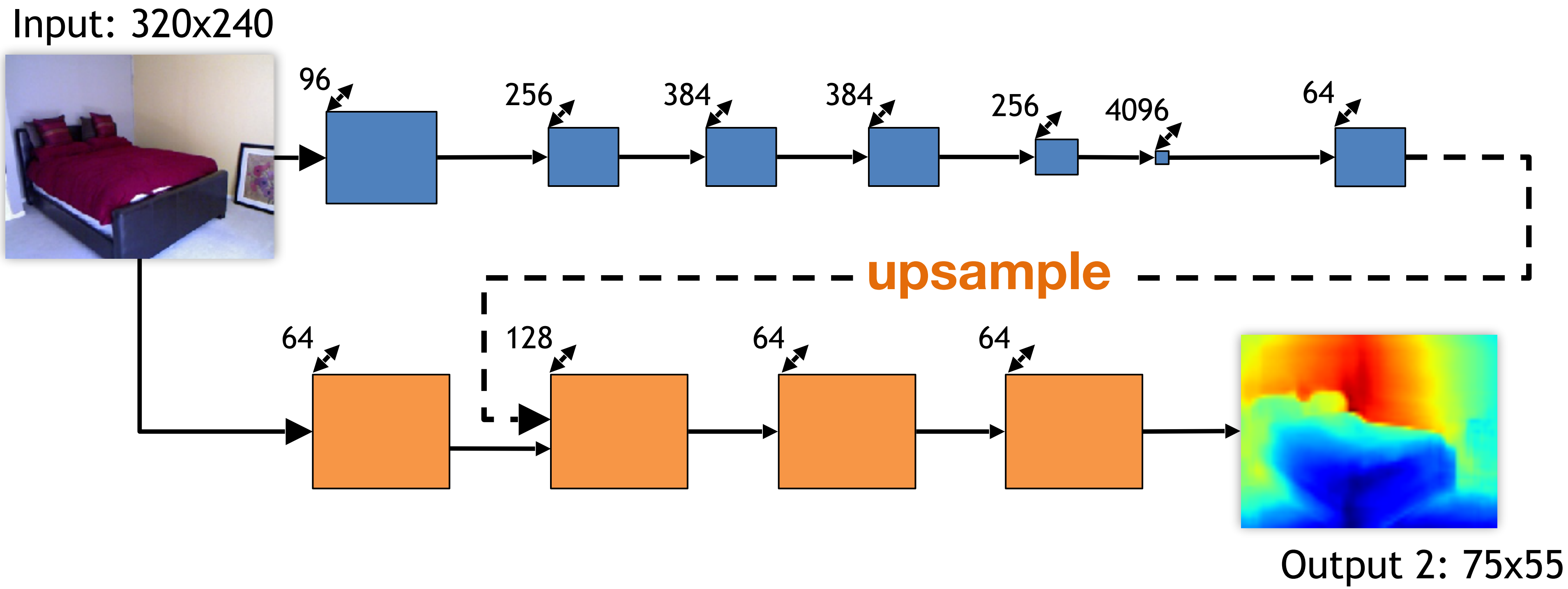


- **<u>Predict Pixel Maps from a Single Image</u>**

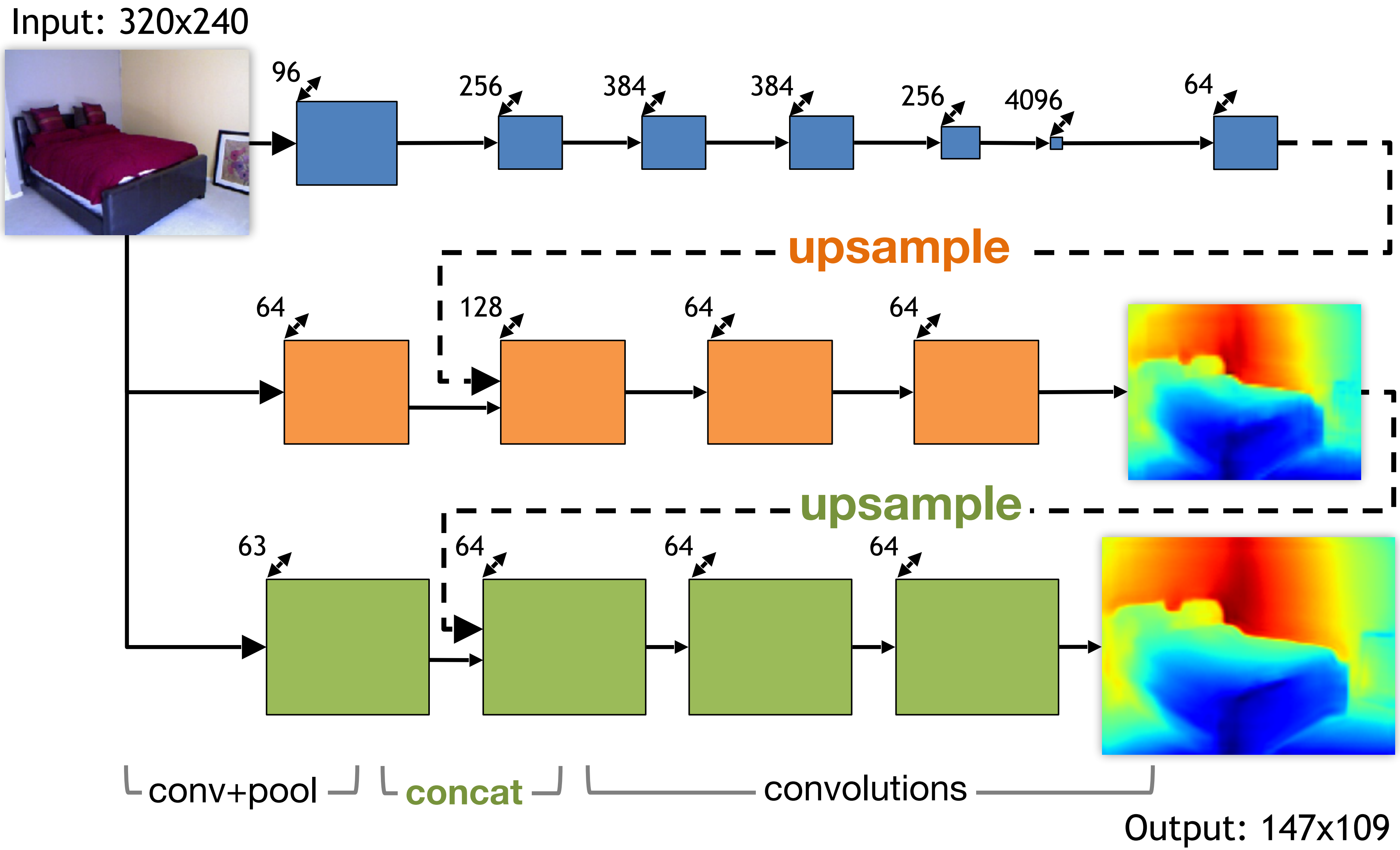
Architecture



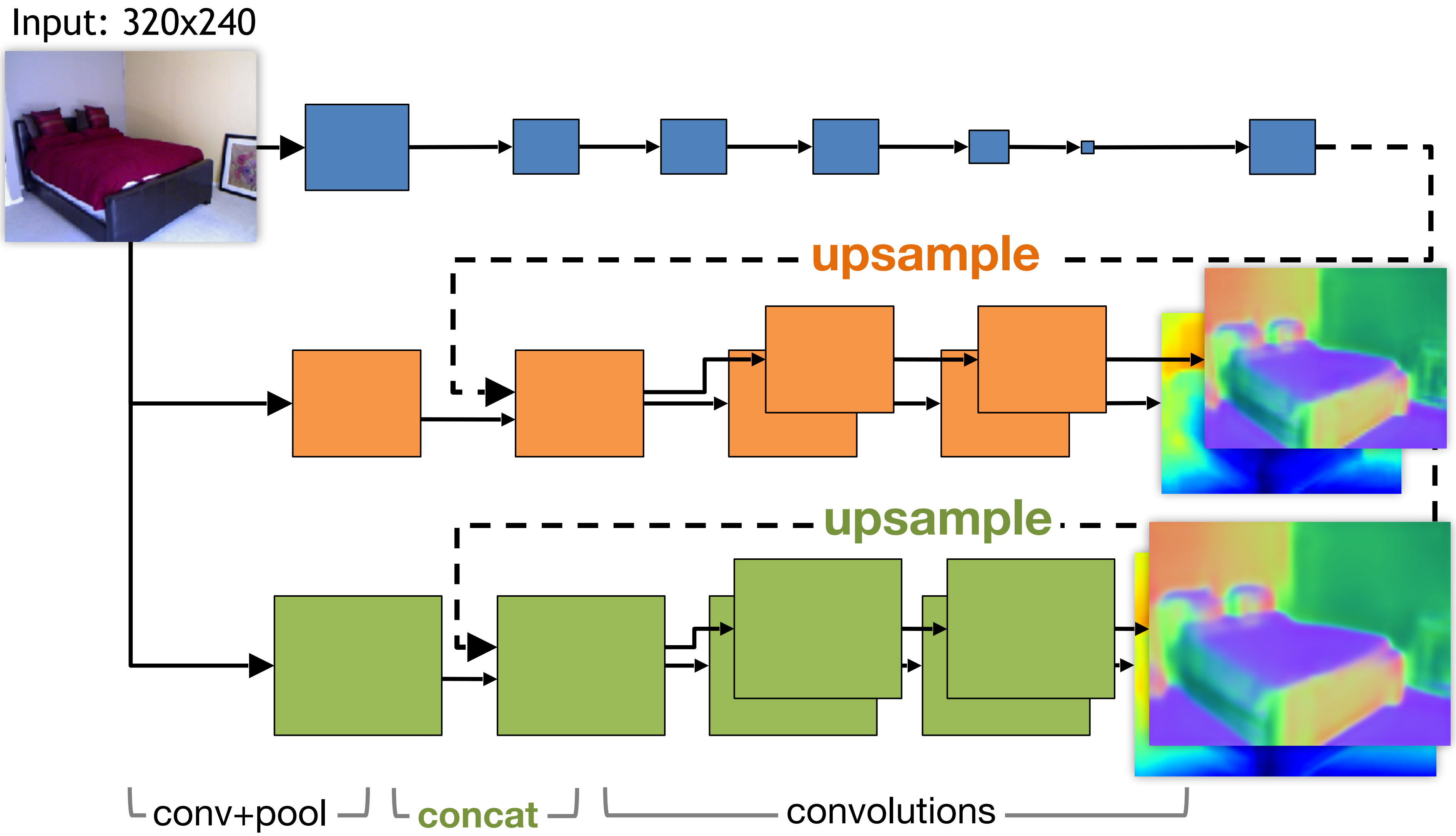
Architecture



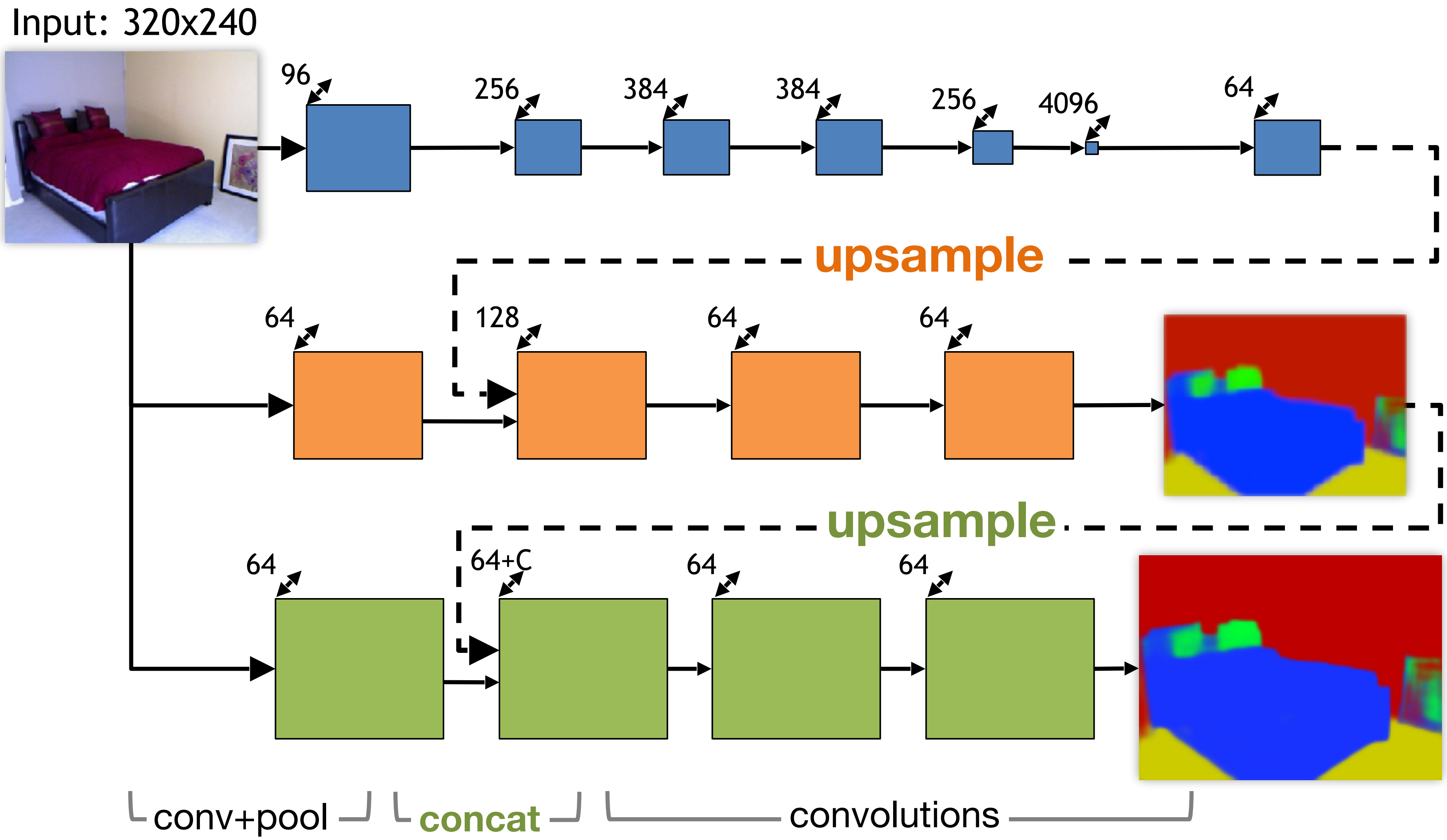
Architecture



Architecture



Architecture



Losses

Depth: $d = D - D^*$ D = log predicted depth, D* = log true depth

$$L_{depth}(D, D^*) = \frac{1}{n}\sum_i d_i^2 - \frac{1}{2n^2}\left(\sum_i d_i\right)^2 + \frac{1}{n}\sum_i[(\nabla_x d_i)^2 + (\nabla_y d_i)^2]$$

Norm

Label

Training

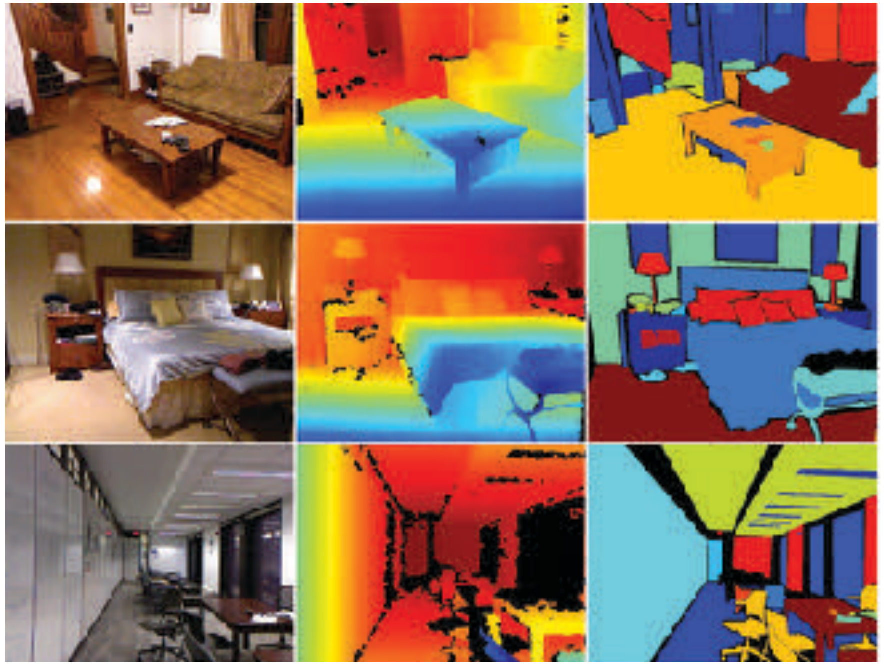
- Pre-train Alexnet/VGGnet scale 1 with Imagenet
- Scale 2 & 3 random initialization
- Joint train layers 1 & 2 for each task
  – Loss on output of layer 2

- Fix layers 1 & 2, train layer 3

- For depth & normals task, share scale 1
  – But separate scale 2 & 3’s
  – 1.6x speedup

Evaluation

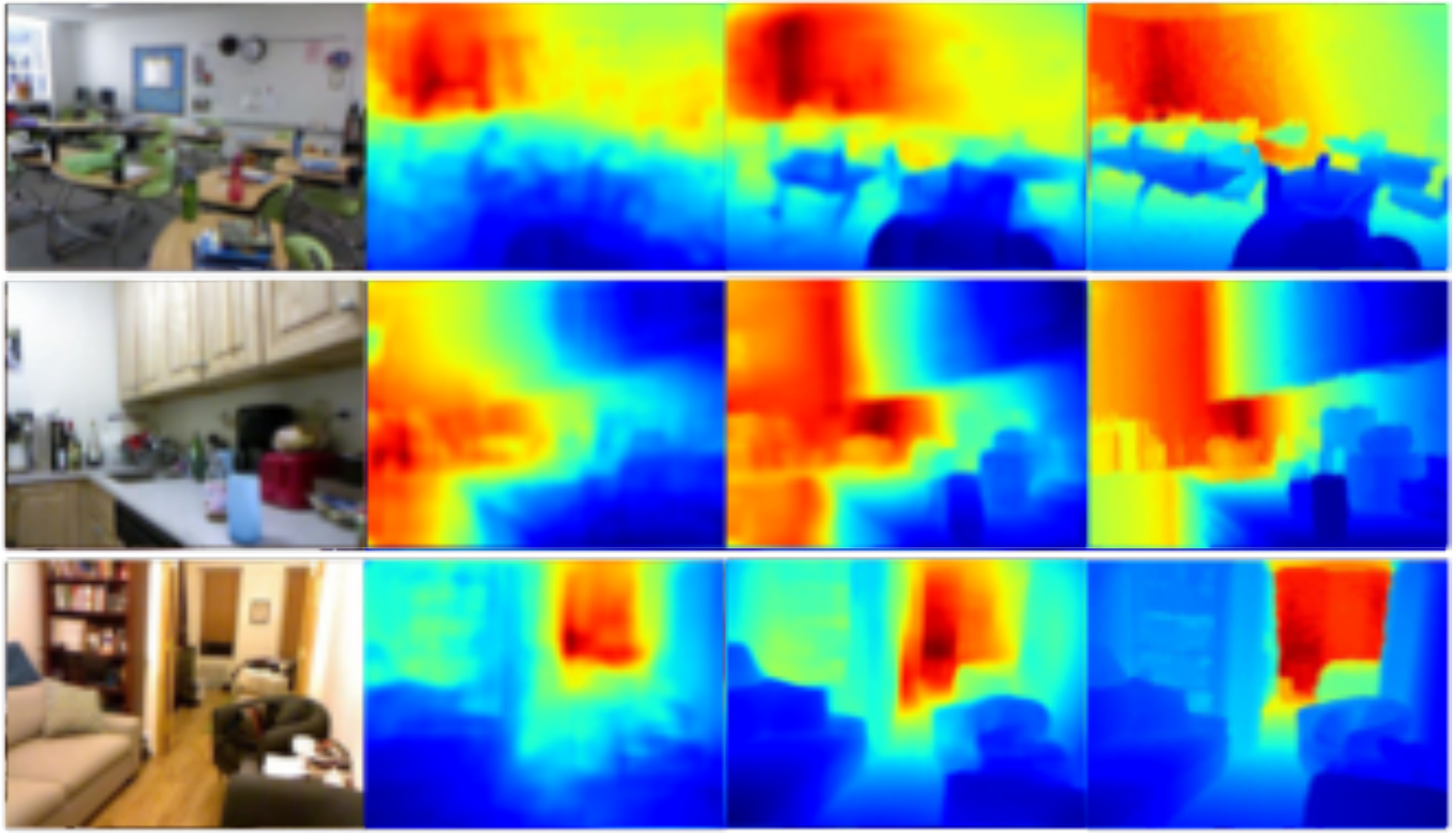
- NYU Depth dataset
  - RGB, Depth
    and per-pixel labels
  - Indoor scenes



- Supervised training of models

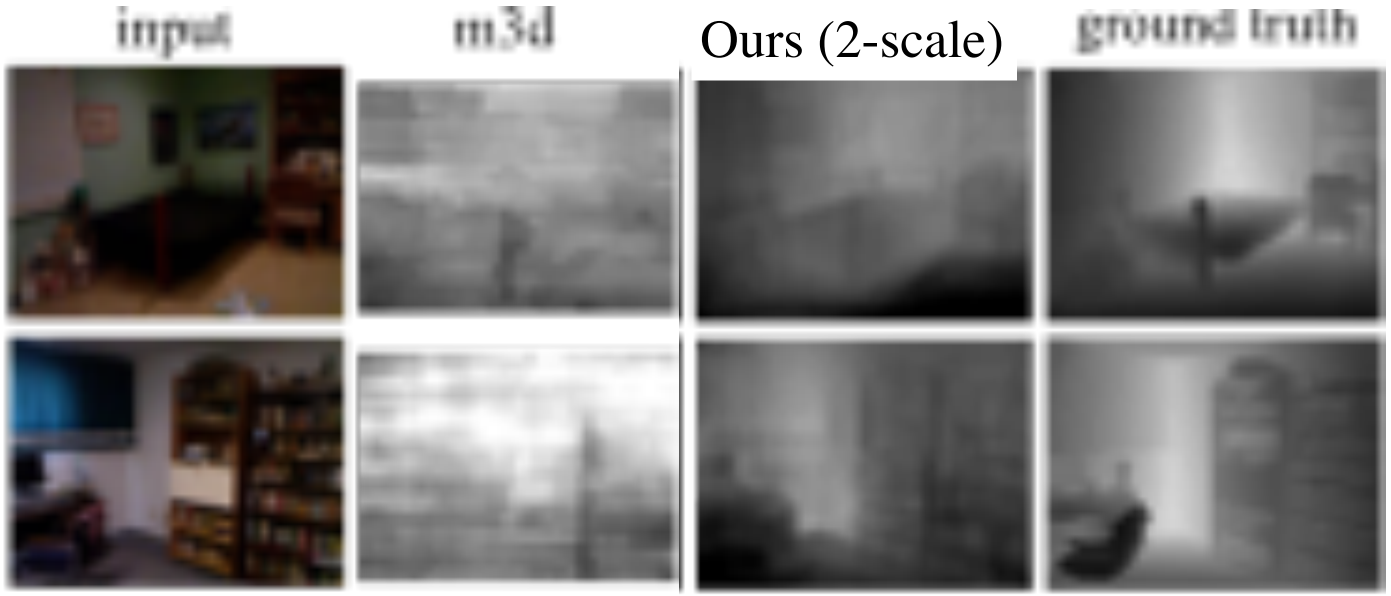
- Compare to range of other methods
  - Also on SIFTFlow and PASCAL VOC’11

Depths Comparison



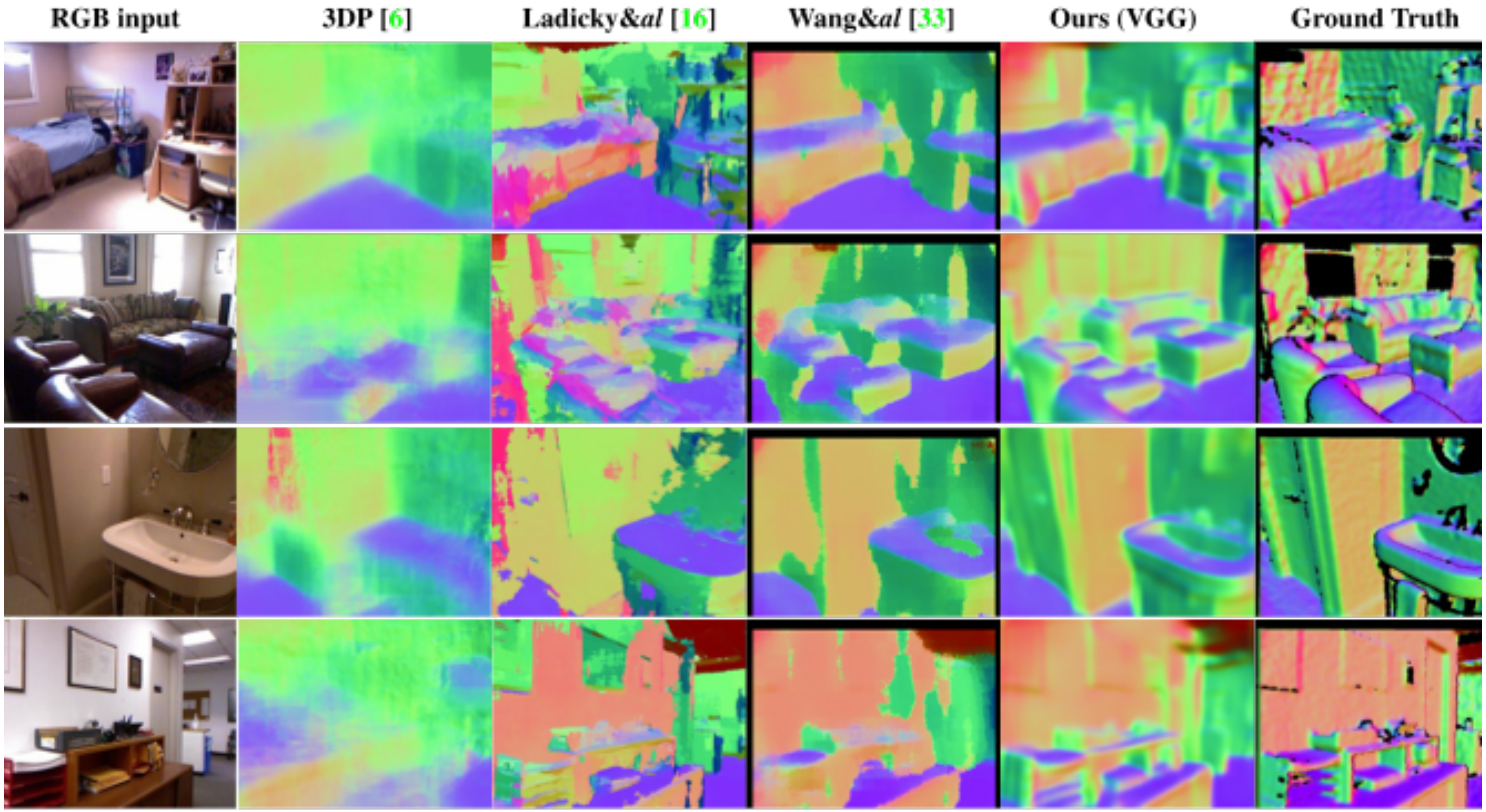
Depth Comparison

- m3d = Make3D [Saxena & Ng 2006]



Depth Prediction							
	Ladicky[20]	Karsch[14]	Baig [1]	Liu [18]	Eigen[4]	Ours(A)	Ours(VGG)
$\delta < 1.25$	0.542	–	0.597	0.614	0.614	0.697	**0.769**
$\delta < 1.25^2$	0.829	–	–	0.883	0.888	0.912	**0.950**
$\delta < 1.25^3$	0.940	–	–	0.971	0.972	0.977	**0.988**
abs rel	–	0.350	0.259	0.230	0.214	0.198	**0.158**
sqr rel	–	–	–	–	0.204	0.180	**0.121**
RMS(lin)	–	1.2	0.839	0.824	0.877	0.753	**0.641**
RMS(log)	–	–	–	–	0.283	0.255	**0.214**
sc-inv.	–	–	0.242	–	0.219	0.202	**0.171**

Surface Normals

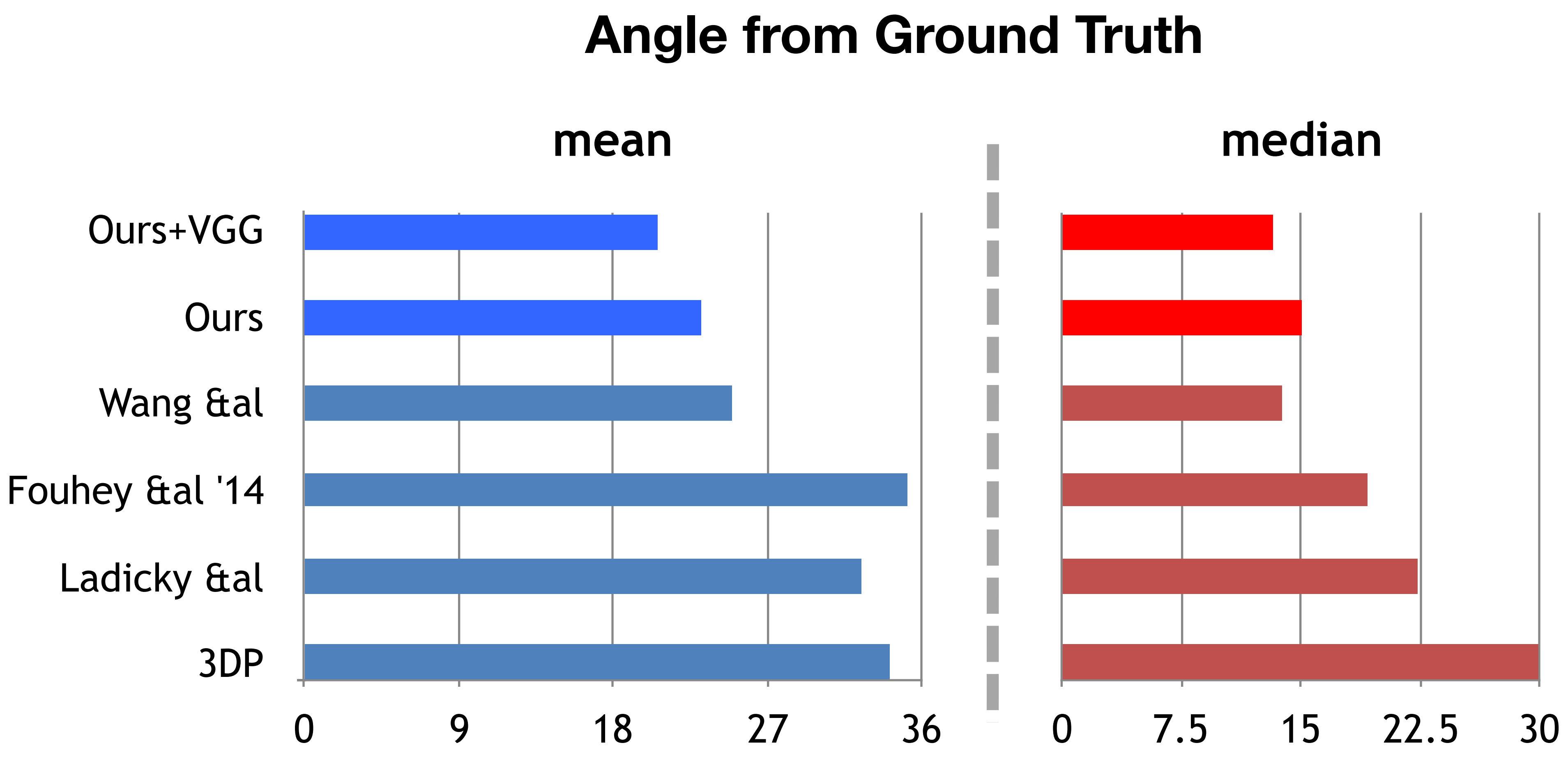


Surface Normals

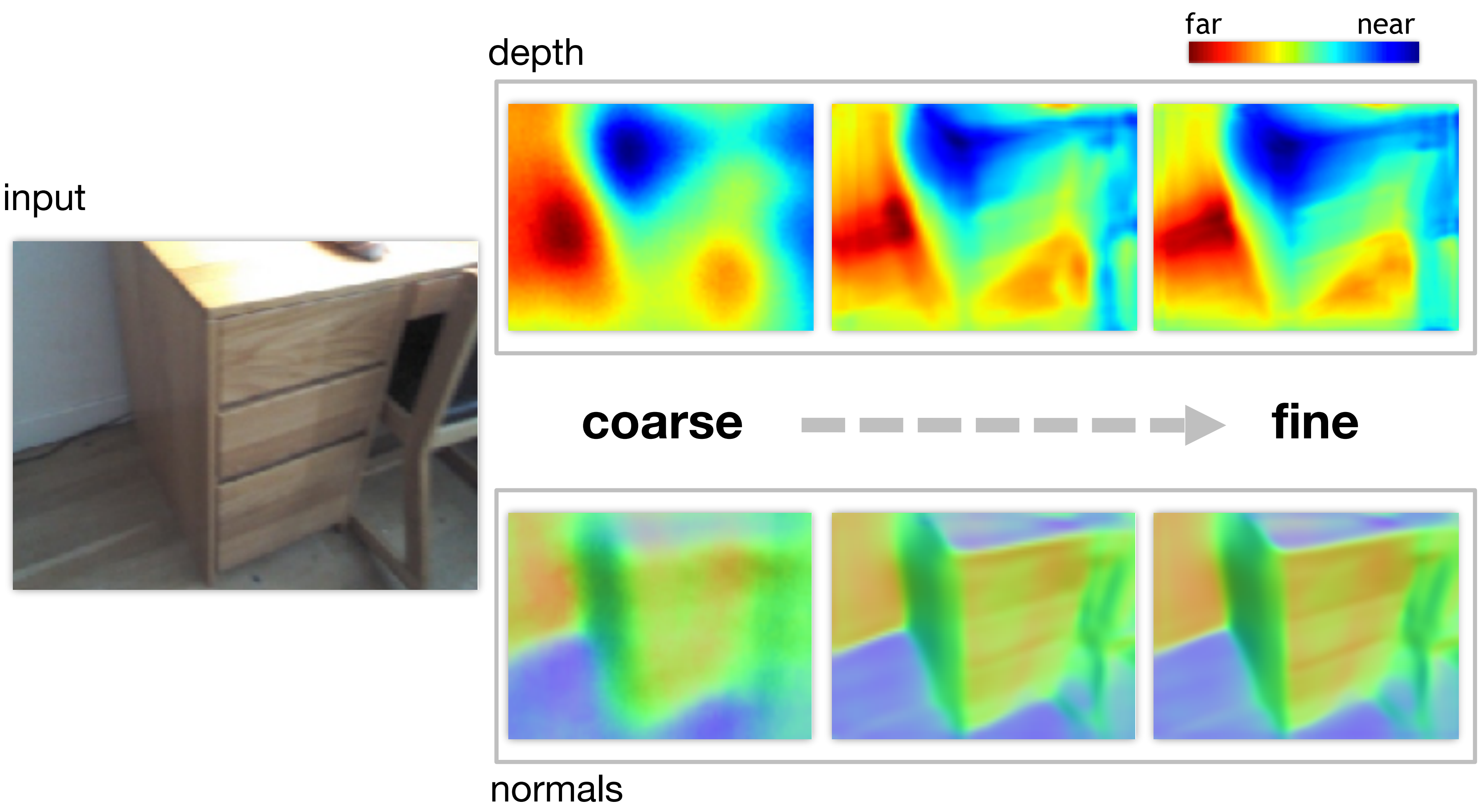
Surface Normal Estimation (GT [6])					
	Angle Distance		Within t° Deg.		
	Mean	Median	11.25°	22.5°	30°
3DP [6]	34.2	30.0	18.5	38.6	50.0
Ladicky *&al* [16]	32.5	22.3	27.4	50.2	60.1
Fouhey *&al* [7]	35.1	19.2	37.6	53.3	58.9
Wang *&al* [33]	26.6	15.3	40.1	61.4	69.0
Ours (AlexNet)	23.1	15.1	39.4	63.6	72.7
Ours (VGG)	**20.5**	**13.2**	**44.0**	**68.5**	**77.2**

Surface Normal Estimation (GT [27])					
	Angle Distance		Within t° Deg.		
	Mean	Median	11.25°	22.5°	30°
3DP [6]	37.7	34.1	14.0	32.7	44.1
Ladicky *&al* [16]	35.5	25.5	24.0	45.6	55.9
Wang *&al* [33]	28.8	17.9	35.2	57.1	65.5
Ours (AlexNet)	25.9	18.2	33.2	57.5	67.7
Ours (VGG)	**22.2**	**15.3**	**38.6**	**64.0**	**73.9**

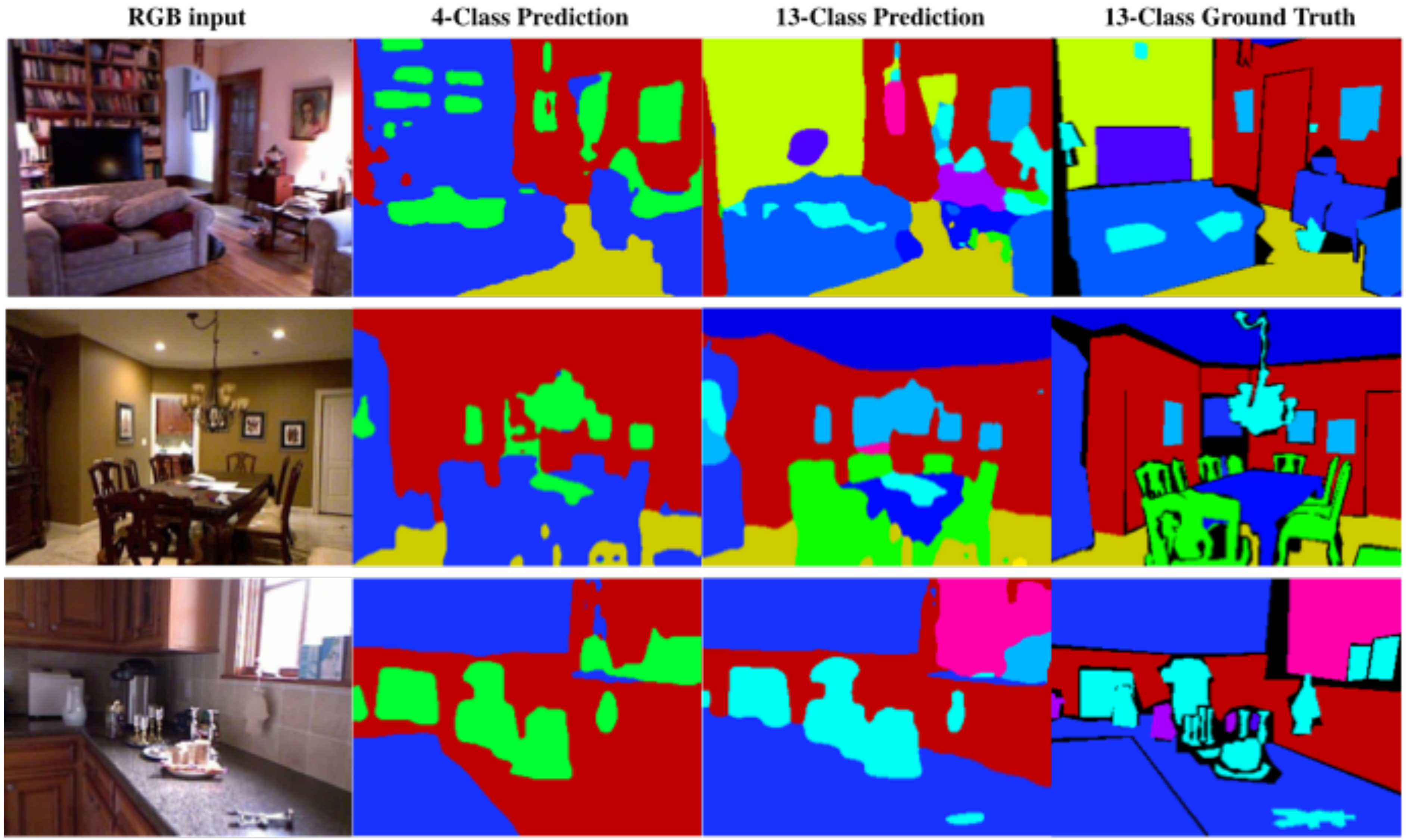
Results: Normals



Output from each scale

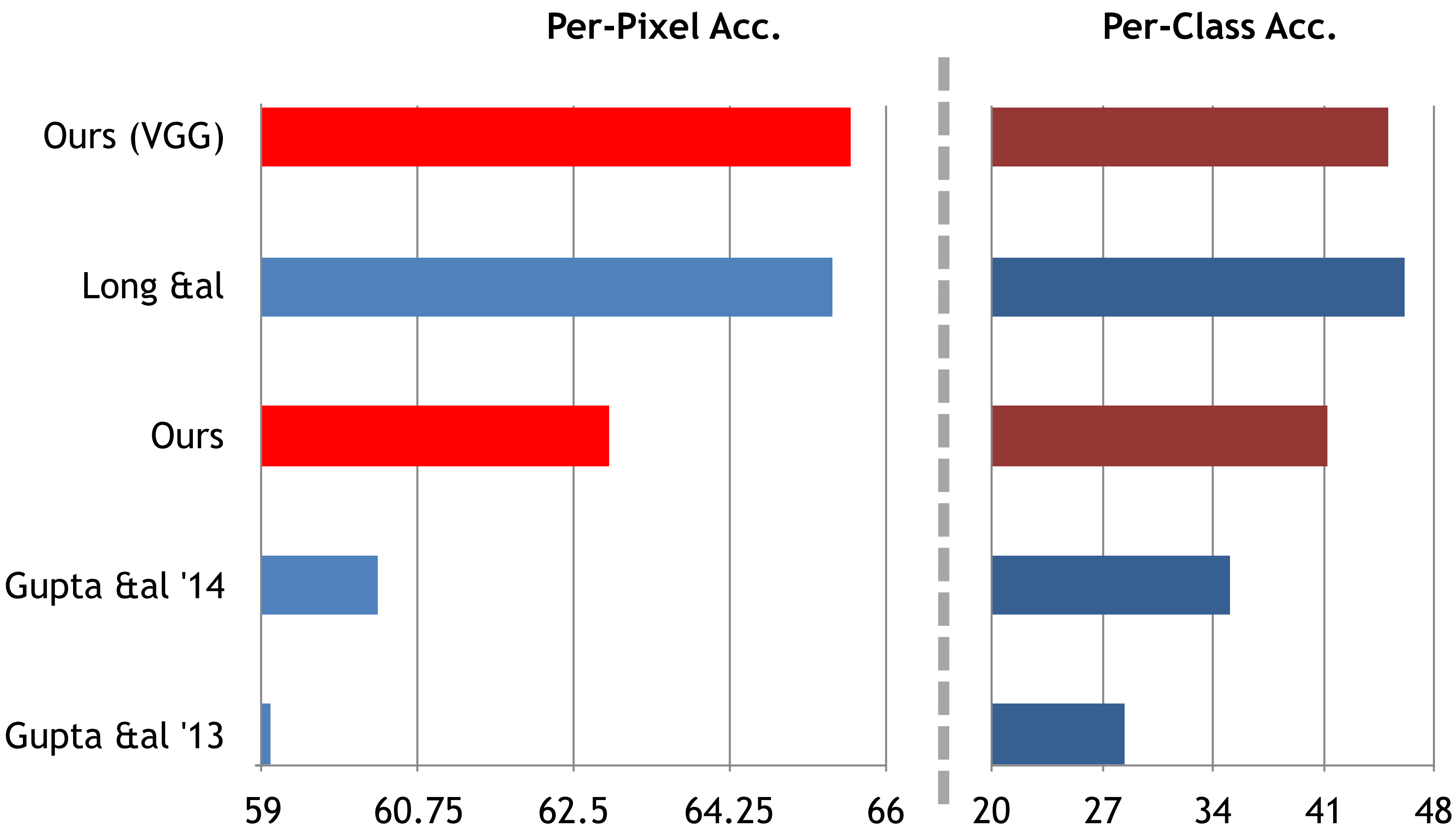


Semantic Labels: NYUD



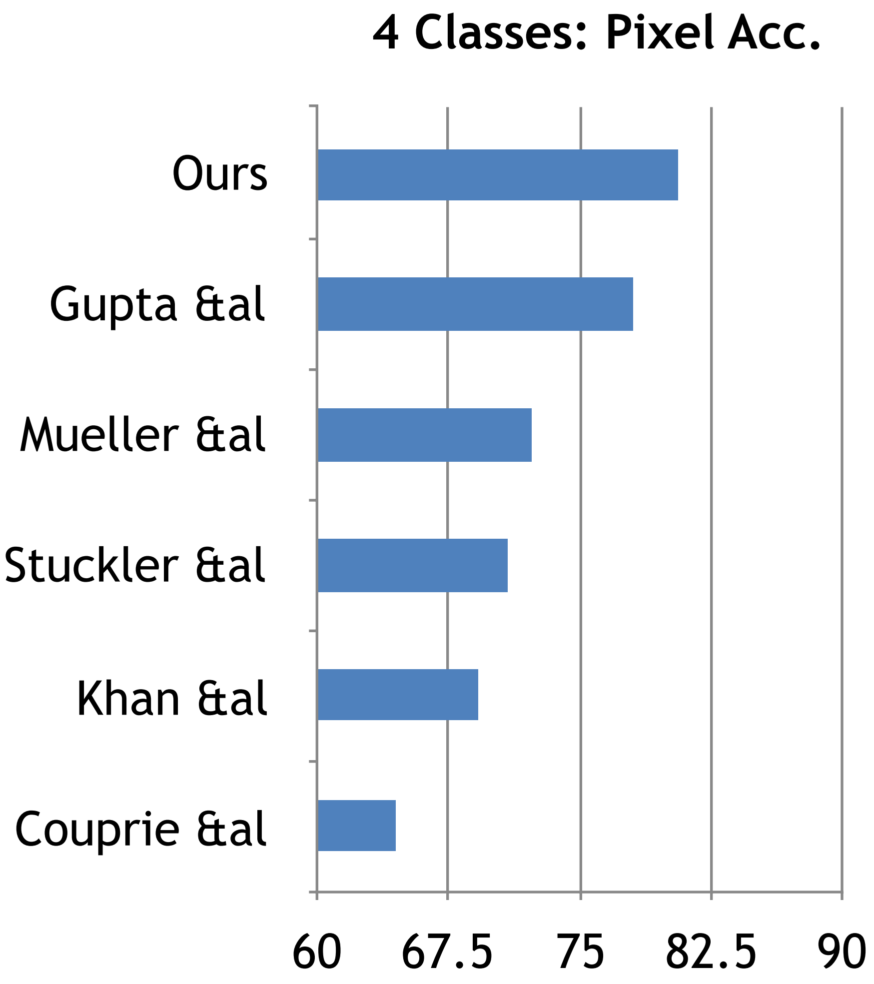
Results: NYUD 40 Classes

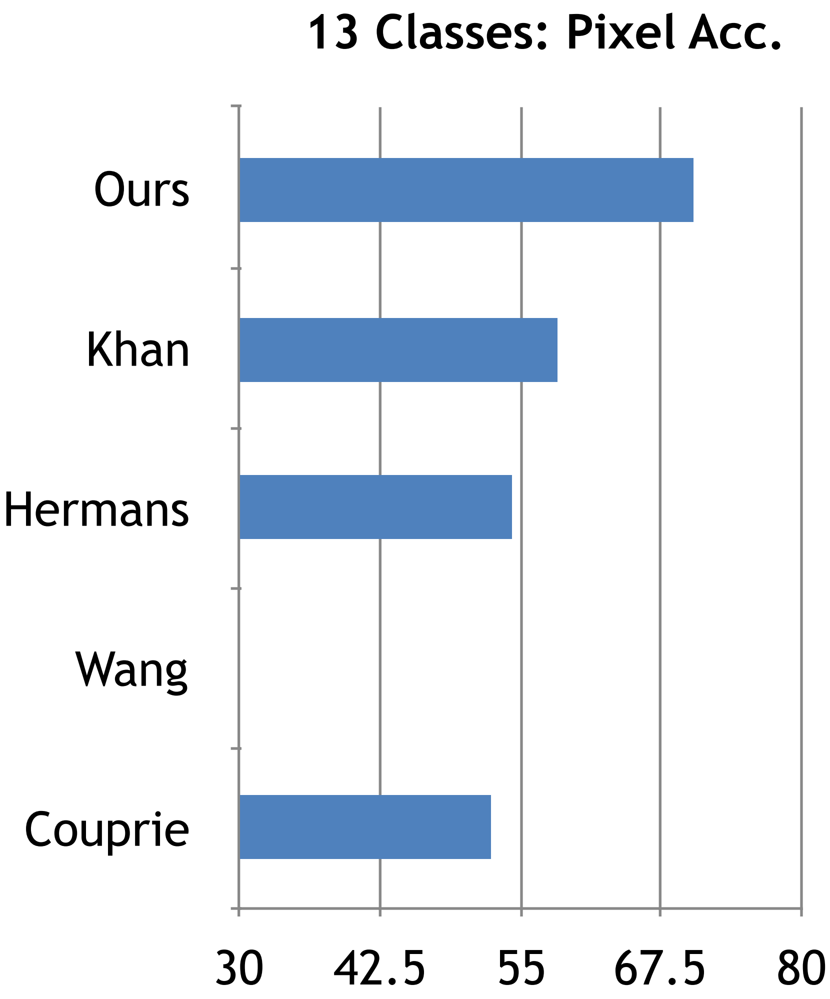
- Use RGB + ground truth depth & normals as inputs



Results: NYUD Labels

- Use RGB + ground truth depth & normals as inputs





Semantic Labels: Pascal VOC'11

Pascal VOC Semantic Segmentation				
	Pix. Acc.	Per-Cls Acc.	Freq. Jaccard	Av. Jaccard
Long&al [19]	**90.3**	**75.9**	**83.2**	**62.7**
Ours (VGG)	**90.3**	72.4	82.9	62.2

Contribution from different scales

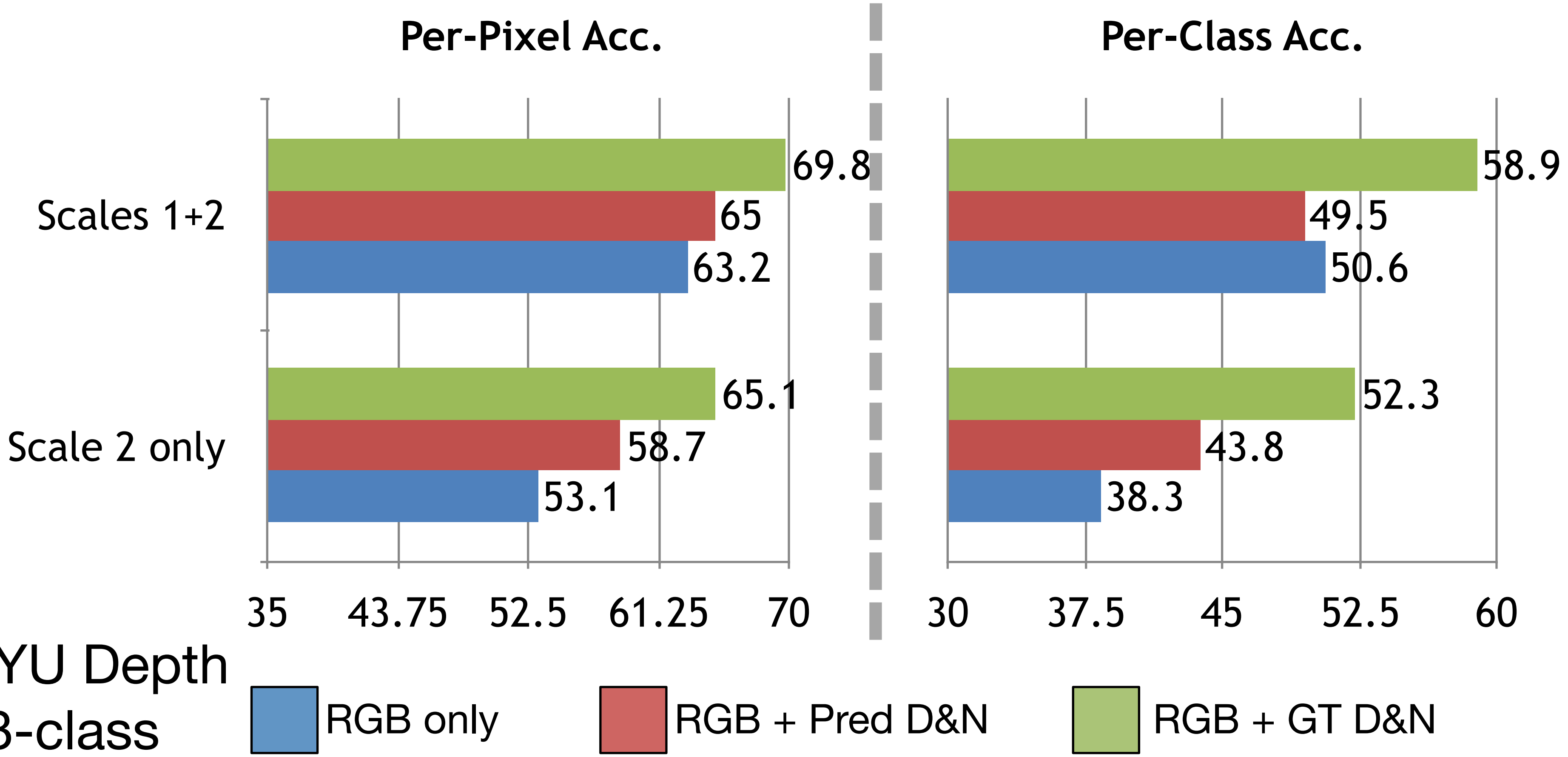
- On NYU Depth

Contributions of Scales						
	Depth	Normals	4-Class RGB+D+N	4-Class RGB	13-Class RGB+D+N	13-Class RGB
	Pixelwise Error lower is better		Pixelwise Accuracy higher is better			
Scale 1 only	0.218	29.7	71.5	71.5	58.1	58.1
Scale 2 only	0.290	31.8	77.4	67.2	65.1	53.1
Scales 1 + 2	0.216	26.1	80.1	74.4	69.8	63.2
Scales 1 + 2 + 3	0.198	25.9	80.6	75.3	70.5	64.0

- Depth & normals: scale 1 most important
- Semantic labels: scale 2 most important (if D & N are available)

Using Predicted Depths

- Use predicted depth/normals as input?



- NYU Depth 13-class

Summary

- Relatively simple multi-scale model gives good results for depth, normals & labels
- Coarse interpretation of scene important for understanding depth/normals
- See ICCV 2015 paper: “Predicting Depth, Surface Normals and Semantic Labels with a Common Multi-Scale Convolutional Architecture”, D. Eigen and R. Fergus, arXiv 1411.4734
- Code available

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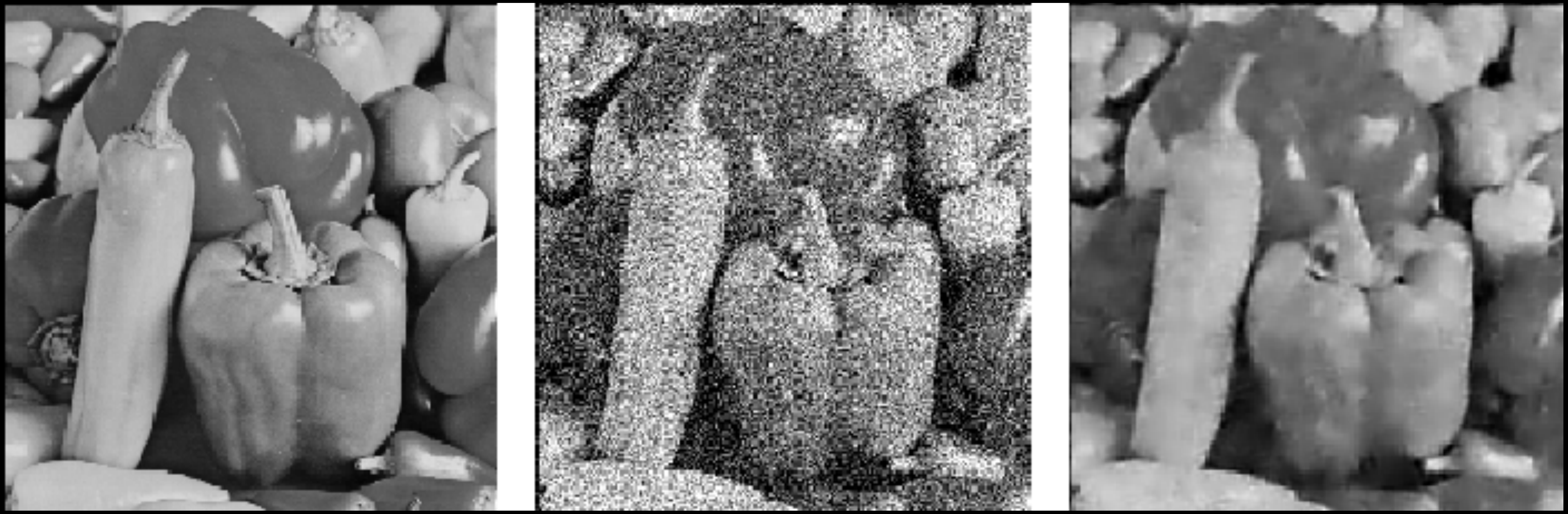
Denoising with ConvNets

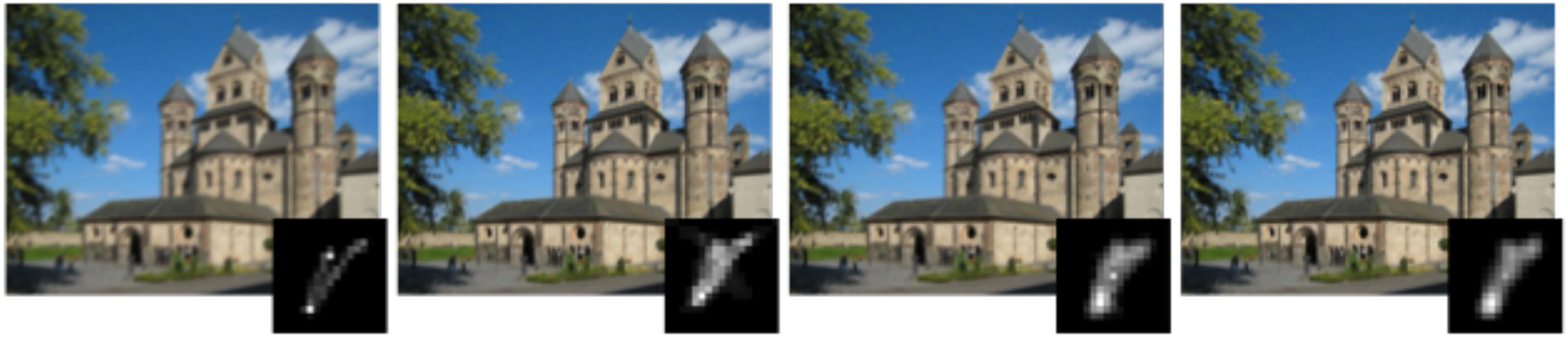
- Burger et al. “Can plain NNs compete with BM3D?” CVPR 2012

Original Noised Denoised



Deblurring with Convnets

- Blind deconvolution
  - Learning to Deblur, Schuler et al., arXiv 1406.7444, 2014



Blurry image with ground truth kernel	Result of [Zho+13] PSNR 23.17	Deblurring result w. noise *agnostic* training PSNR 23.29	Deblurring result w. noise *specific* training **PSNR 23.41**

Inpainting with Convnets

- Image Denoising and Inpainting with Deep Neural Networks, Xie et al. NIPS 2012.
- Mask-specific inpainting with deep neural networks, Köhler et al., Pattern Recognition 2014



Original

Schmid CVPR'10

Köhler et al. '14

Removing Local Corruption

- Restoring An Image Taken Through a Window Covered with Dirt or Rain, Eigen et al., ICCV 2013.

Removing Local Corruption

Restoring An Image Taken
Through a Window Covered with
Dirt or Rain

Rain Sequence

Each frame processed independently

David Eigen, Dilip Krishnan and Rob Fergus

ICCV 2013

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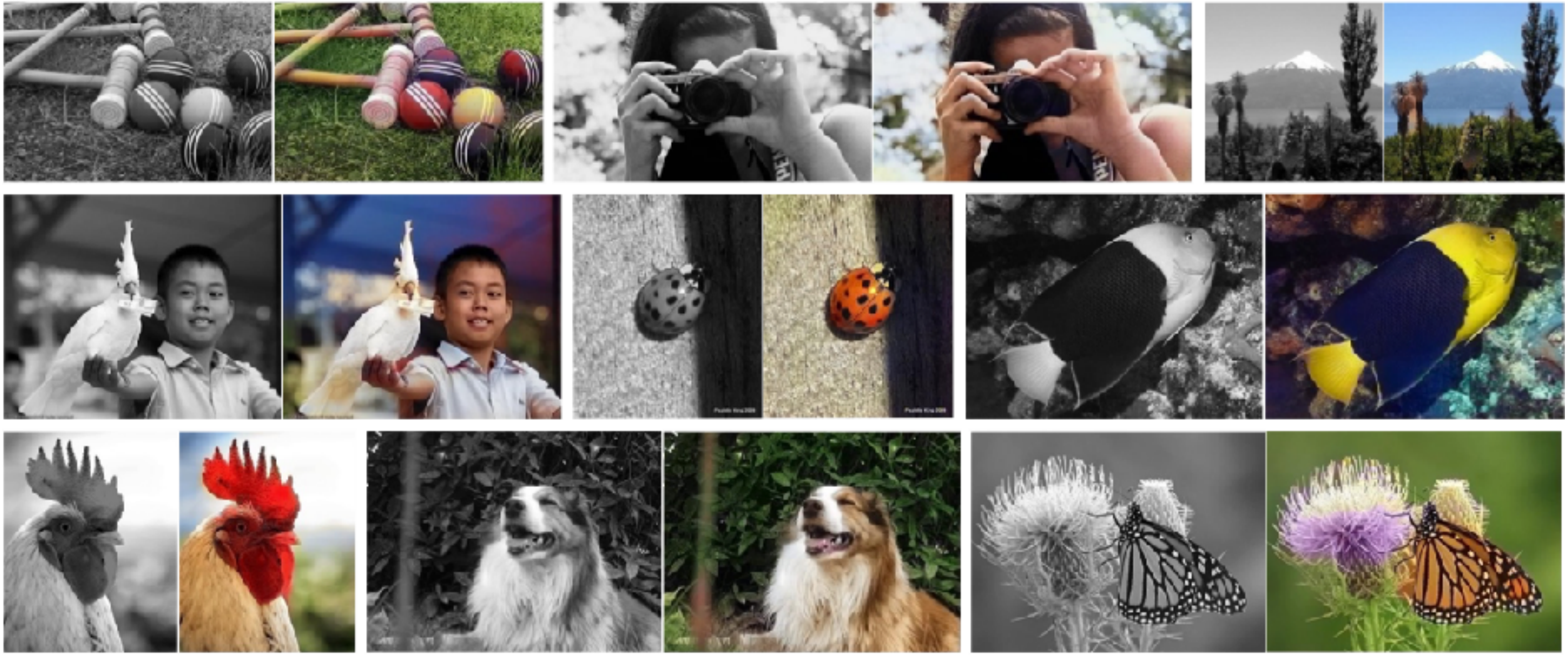
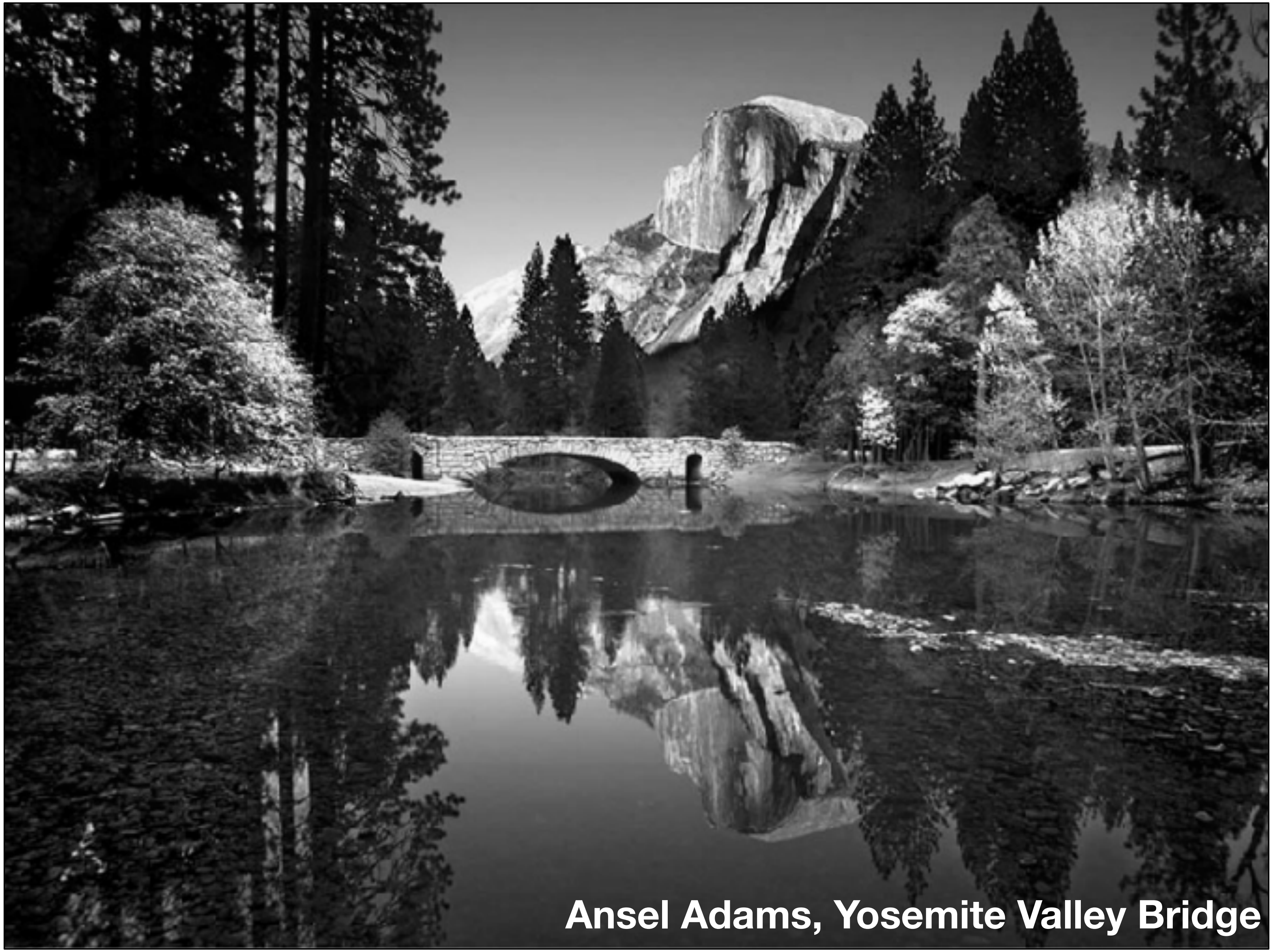
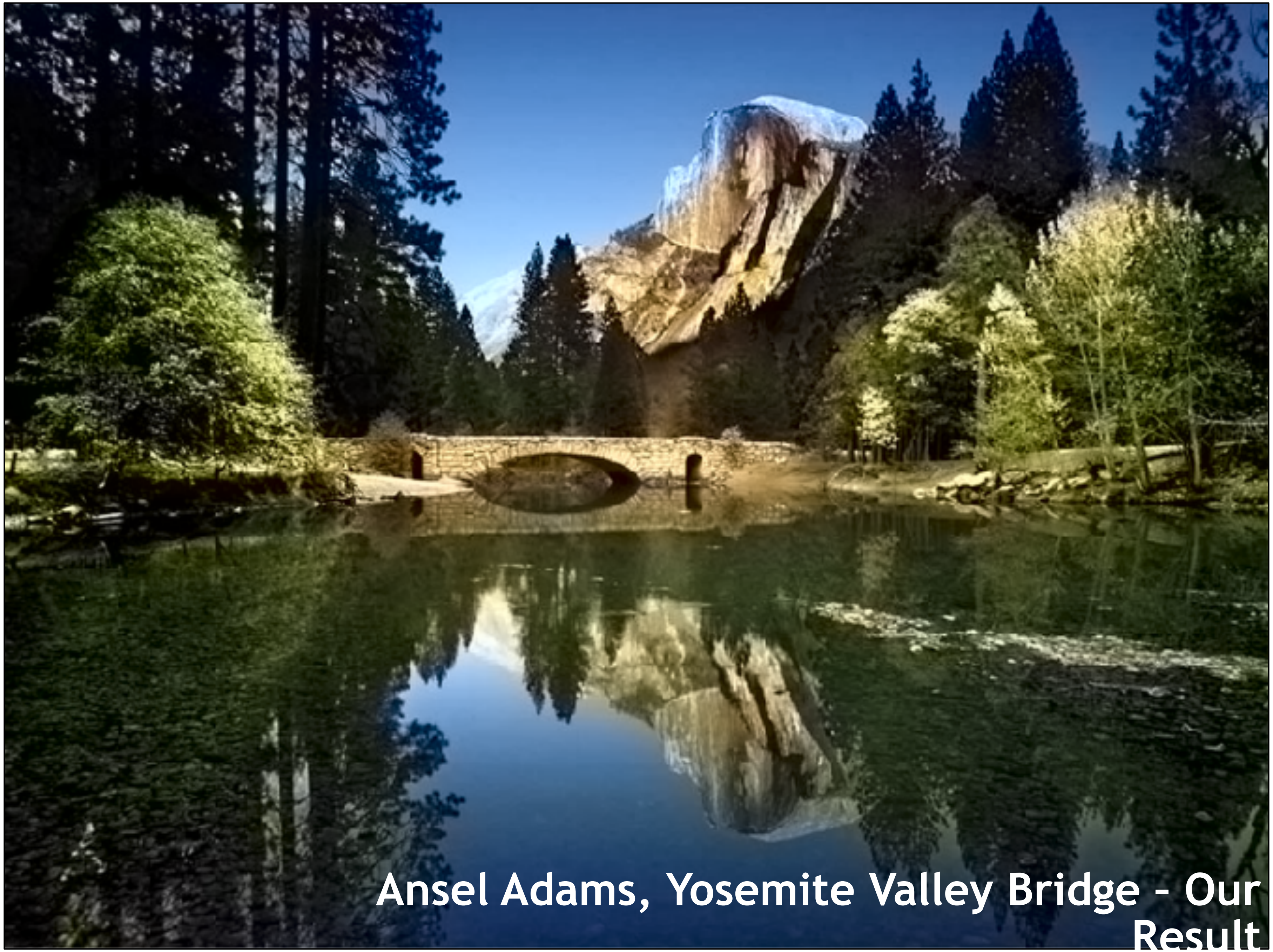


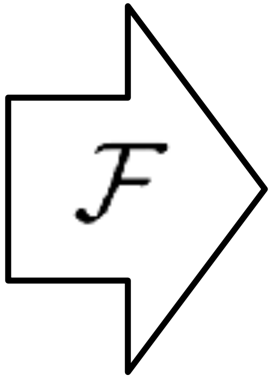
Colorful Image Colorization

Richard Zhang, Phillip Isola, Alexei (Alyosha) Efros

richzhang.github.io/colorization


Ansel Adams, Yosemite Valley Bridge


Ansel Adams, Yosemite Valley Bridge - Our Result

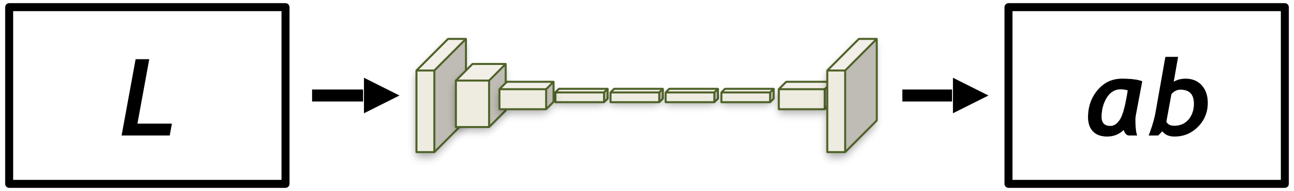


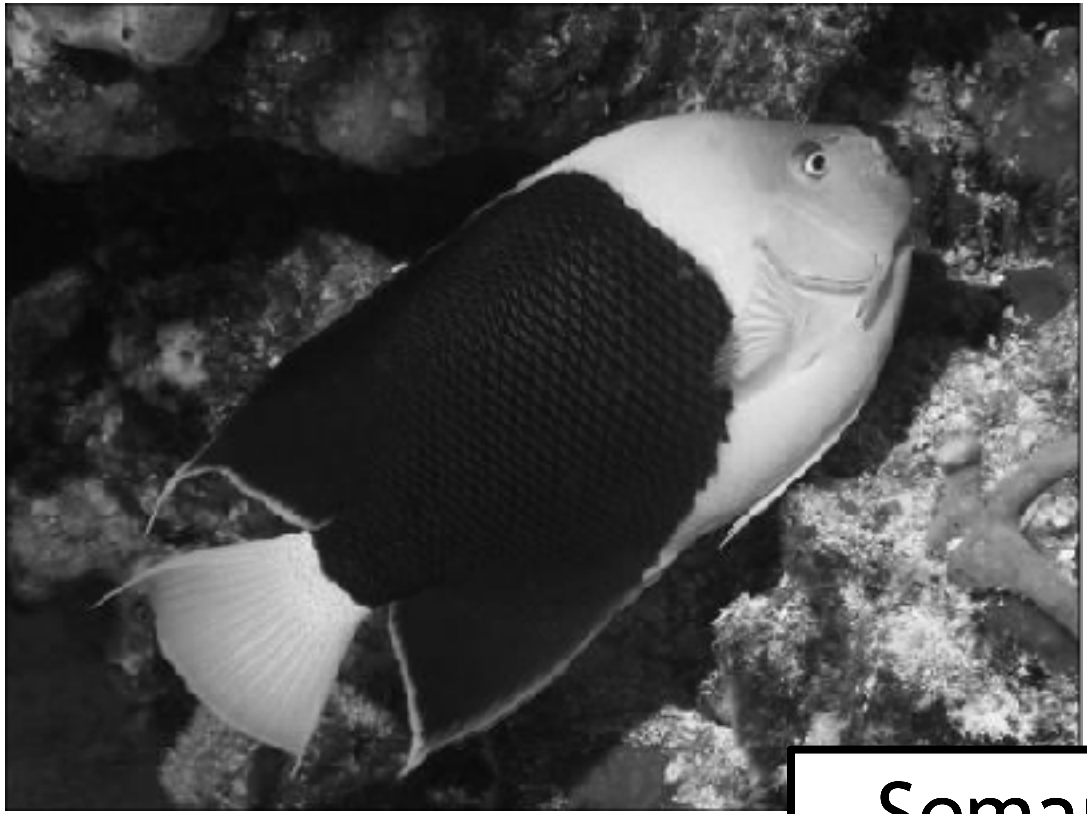
Grayscale image: *L* channel

$$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$$

Color information: *ab* channel

$$\widehat{\mathbf{Y}} \in \mathbb{R}^{H \times W \times 2}$$





$\mathcal{F}$

Semantics? Higher-level abstraction?

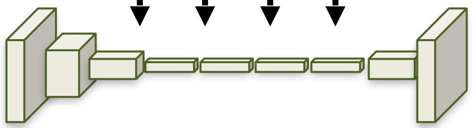
Grayscale image: *L*

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

ncatenate (L,ab)

$(\mathbf{X}, \widehat{\mathbf{Y}})$

L



ab

"Free" supervisory signal

Inherent Ambiguity

Grayscale

Inherent Ambiguity

Our Output

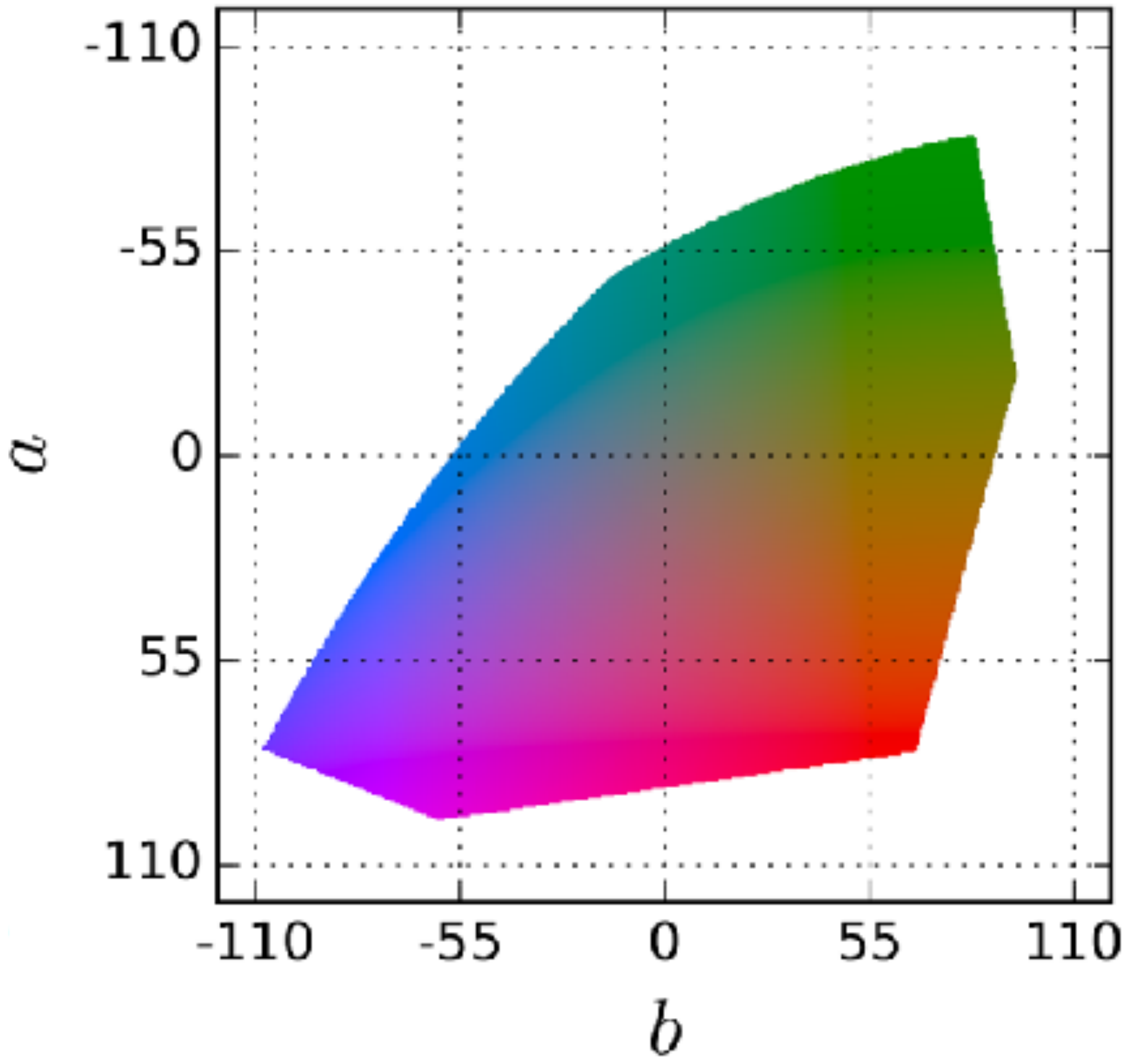
Ground Truth

Better Loss Function

- Regression with L2 loss inac

$$L_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2}\sum_{h,w}\|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$

Colors in *ab* space
(continuous)



Better Loss Function

Colors in *ab* space
(discrete)

- Regression with L2 loss inadequate

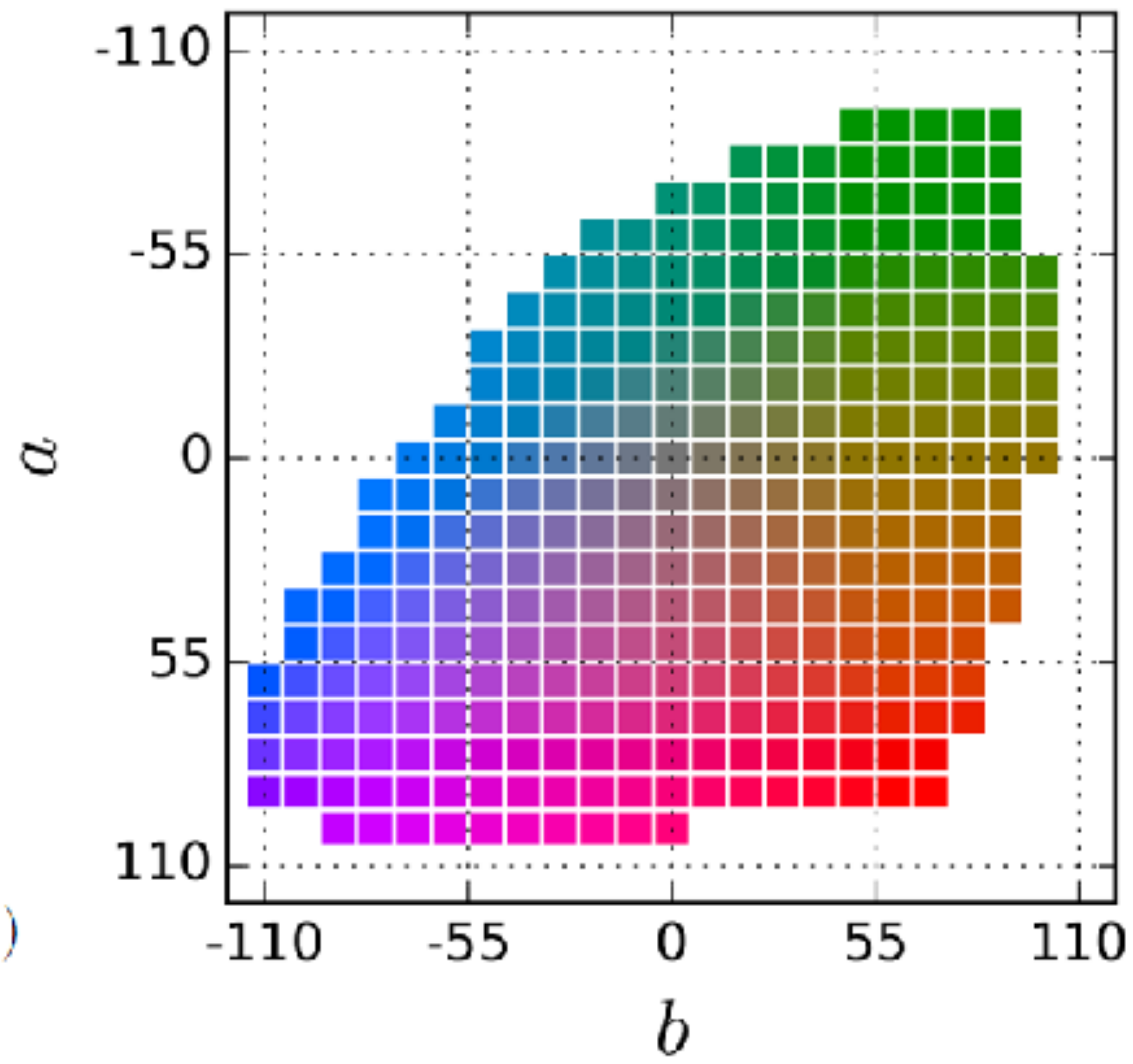
$$\mathrm{L}_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2}\sum_{h,w}\|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$

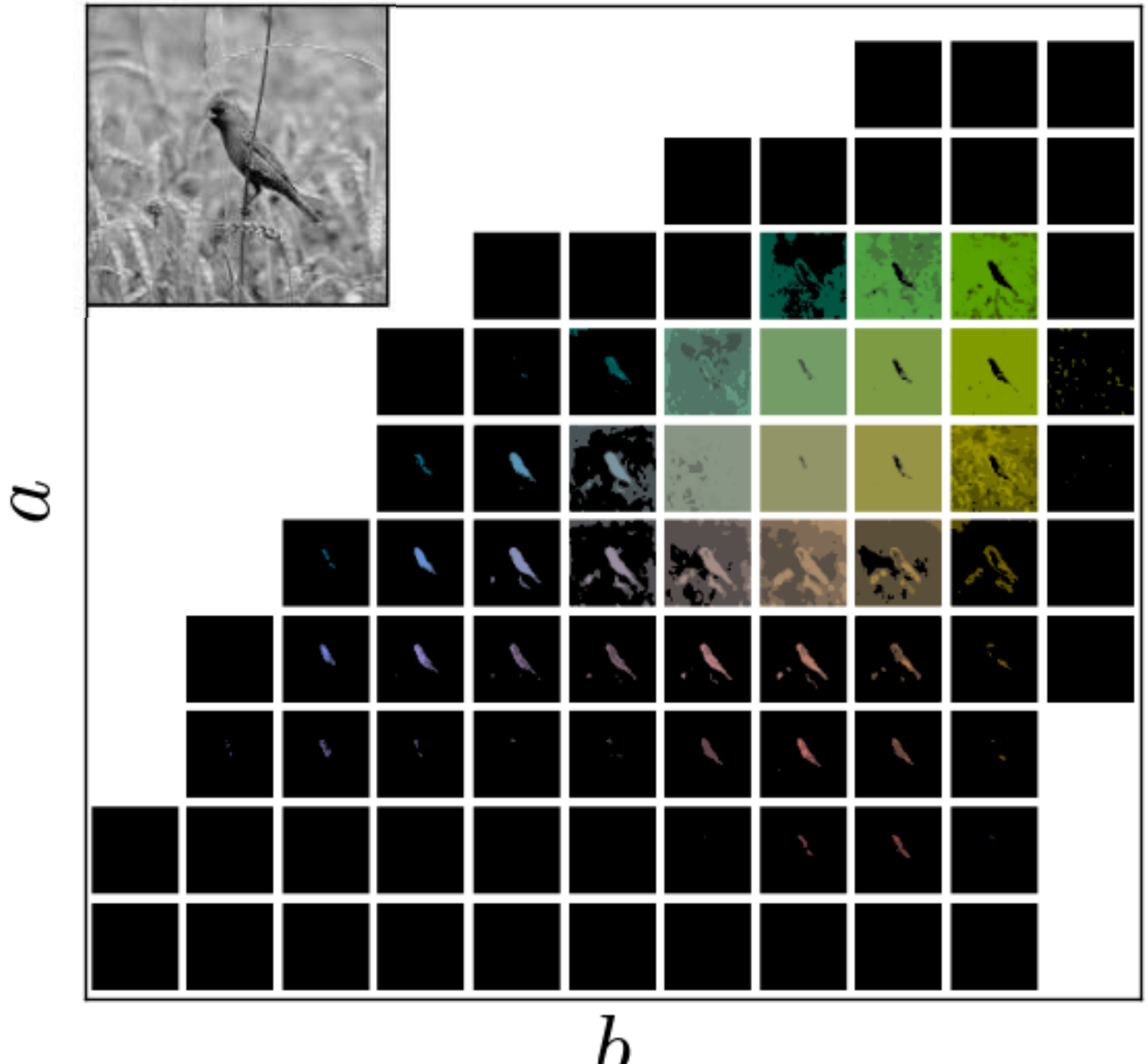
- Use **multinomial classification**

$$\mathrm{L}(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW}\sum_{h,w}\sum_{q}\mathbf{Z}_{h,w,q}\log(\widehat{\mathbf{Z}}_{h,w,q})$$

- **Class rebalancing** to encourage

$$\mathrm{L}(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW}\sum_{h,w}v(\mathbf{Z}_{h,w})\sum_{q}\mathbf{Z}_{h,w,q}\log(\widehat{\mathbf{Z}}_{h,w,q})$$





a
b

Better Loss Function

- Regression with L2 loss inadequate

$$L_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2} \sum_{h,w} \|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$

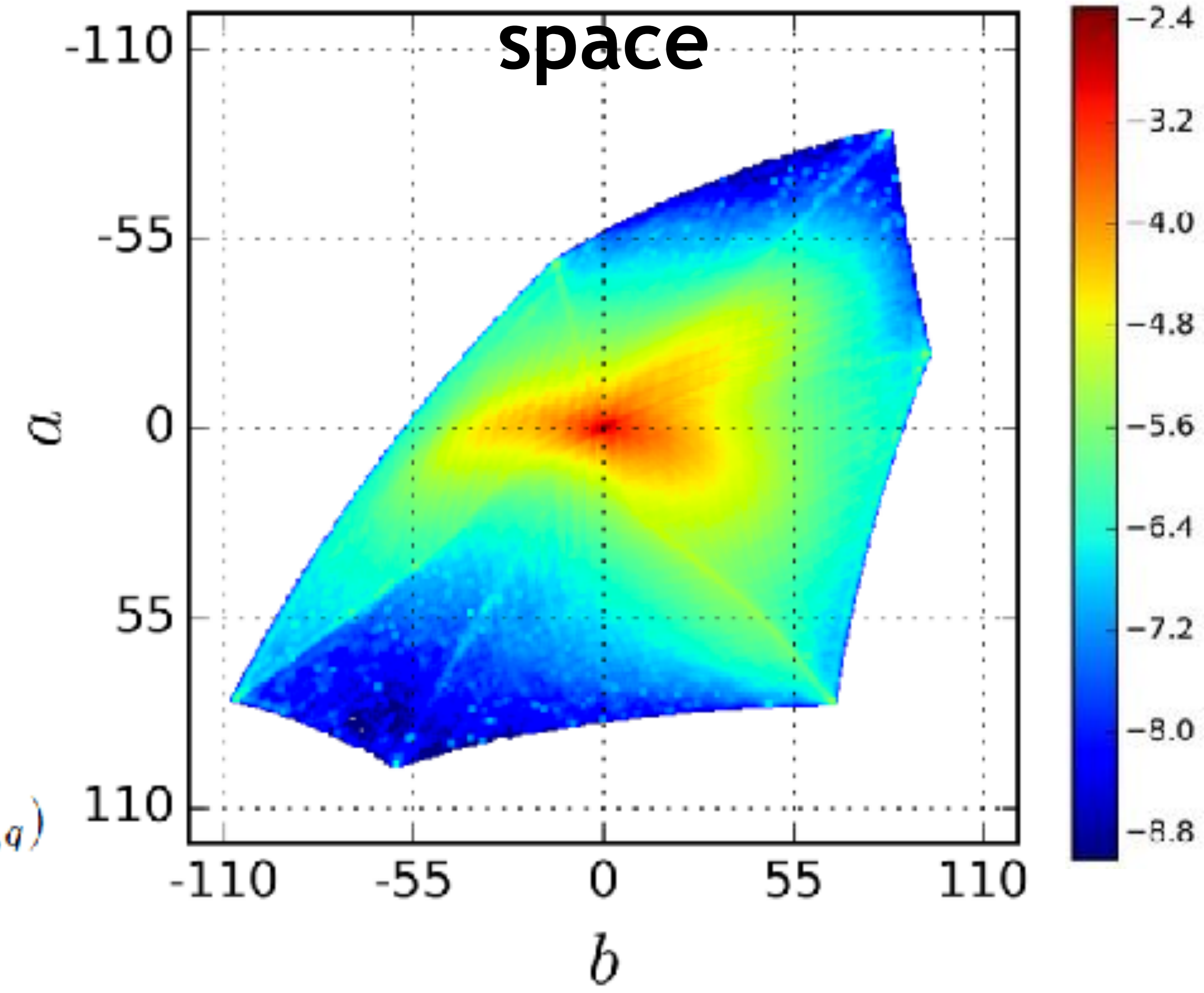
- Use **multinomial classification**

$$L(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW} \sum_{h,w} \sum_{q} \mathbf{Z}_{h,w,q} \log(\widehat{\mathbf{Z}}_{h,w,q})$$

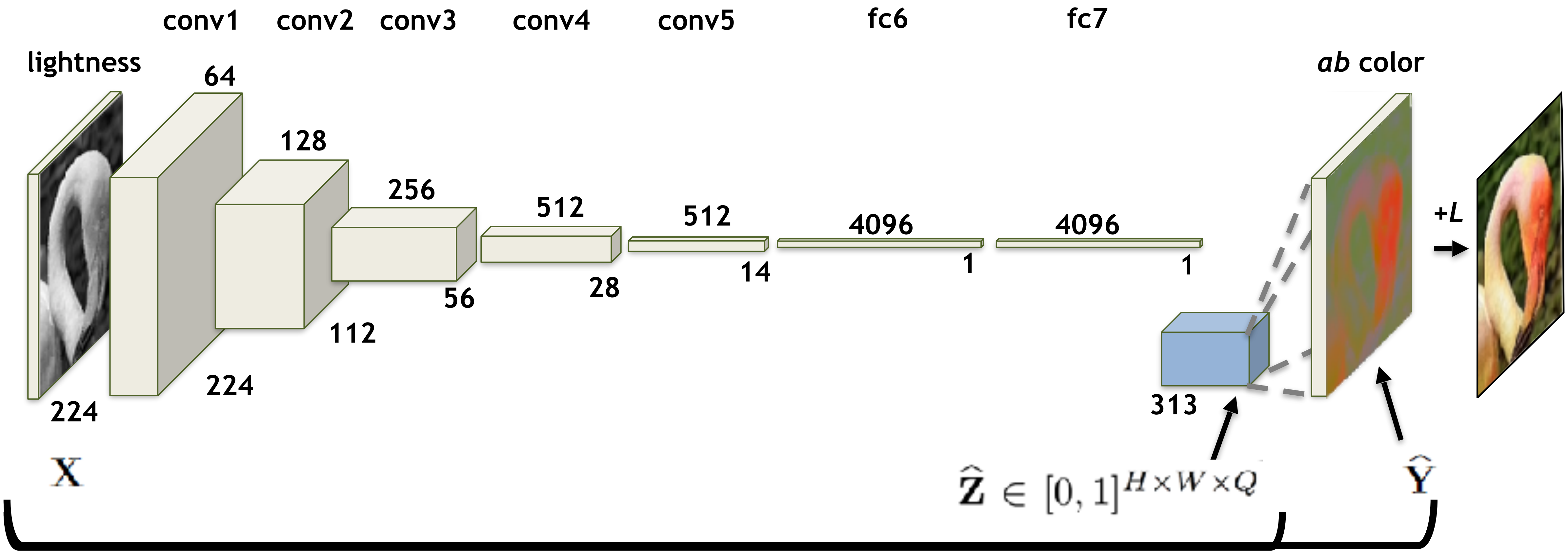
- **Class rebalancing** to encourage

$$L(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW} \sum_{h,w} v(\mathbf{Z}_{h,w}) \sum_{q} \mathbf{Z}_{h,w,q} \log(\widehat{\mathbf{Z}}_{h,w,q})$$

Histogram over *ab* space

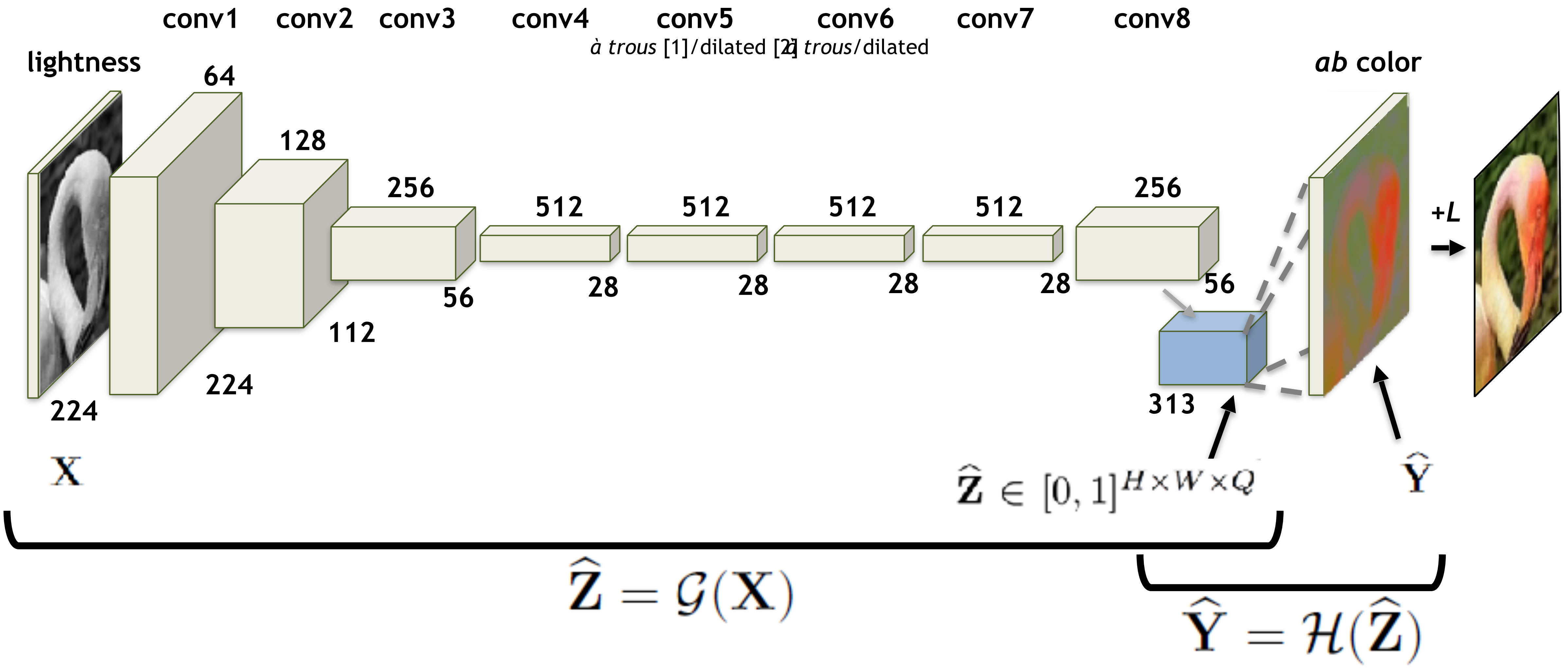


Network Architecture



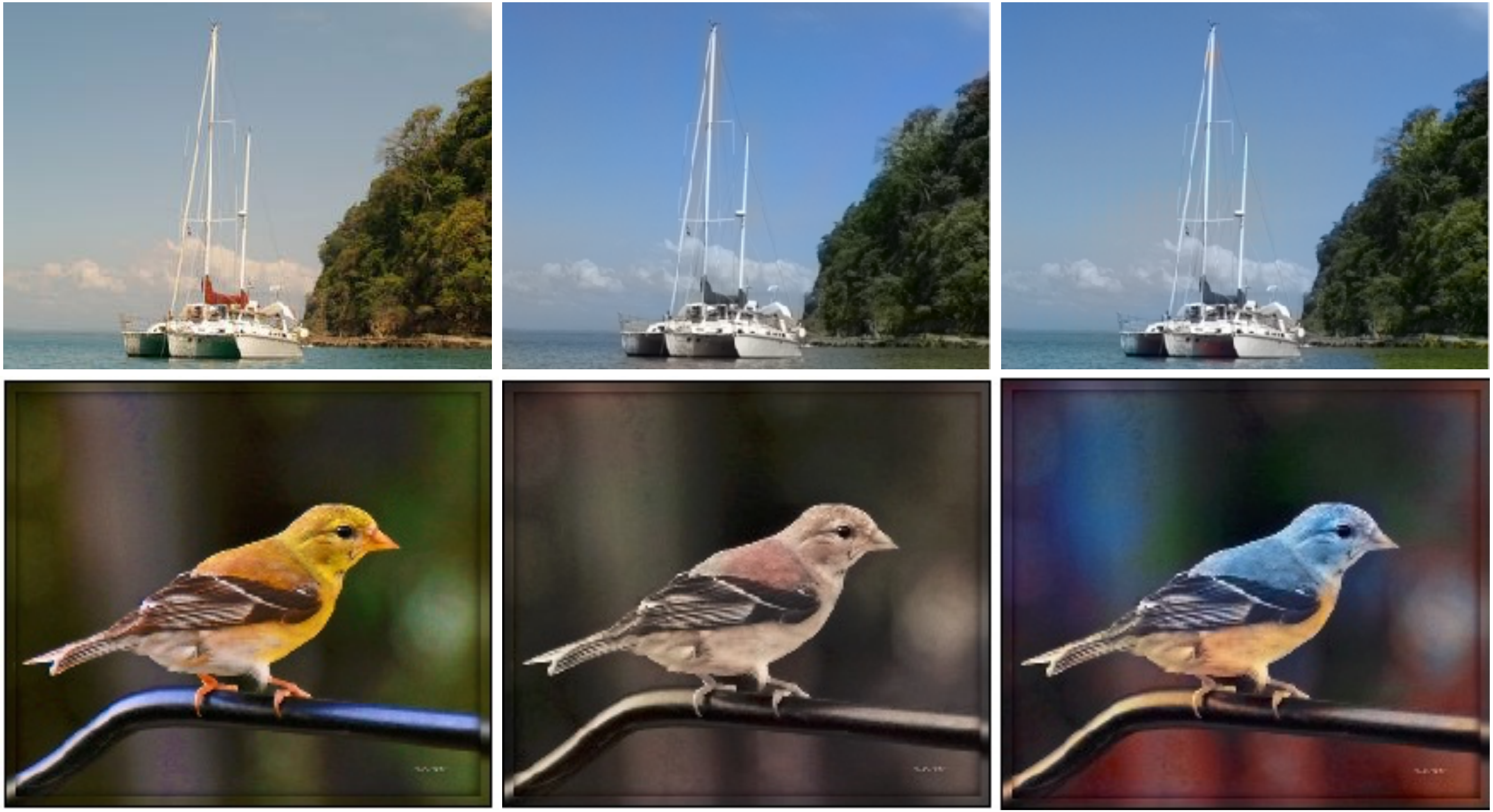
$$\hat{\mathbf{Y}} = \mathcal{F}(\mathbf{X})$$

Network Architecture



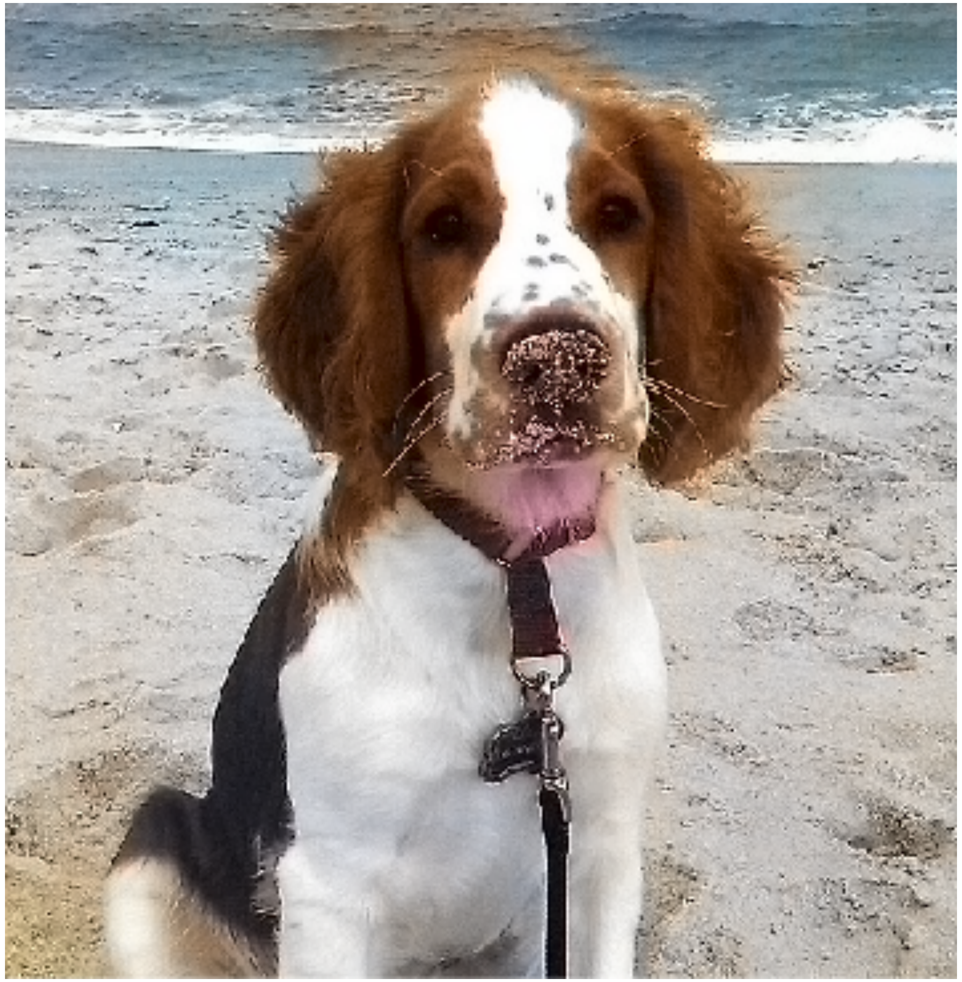
[1] Chen *et al*. In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016.

Ground Truth / Input | L2 Regression | Class w/ Rebalancing



Failure Cases

Biases



Evaluation

	Visual Quality

Quantitative

Evaluation

	Visual Quality	Representation Learning
Quantitative	Per-pixel accuracy Perceptual realism Semantic interpretability	Task generalization ImageNet classification Task & dataset generalization PASCAL classification, detection, segmentation
Qualitative	Low-level stimuli Legacy grayscale photos	Hidden unit activations

Evaluation

	Visual Quality	Representation Learning
Quantitative	Per-pixel accuracy **Perceptual realism** Semantic interpretability	Task generalization ImageNet classification Task & dataset generalization PASCAL classification, detection, segmentation
Qualitative	Low-level stimuli Legacy grayscale photos	Hidden unit activations

Perceptual Realism / Amazon Mechanical Turk Test


clap if “fake”

clap if “fake”

Fake, 0% fooled


clap if “fake”

clap if “fake”

Fake, 55% fooled

clap if “fake”

clap if “fake”

Fake, 58% fooled

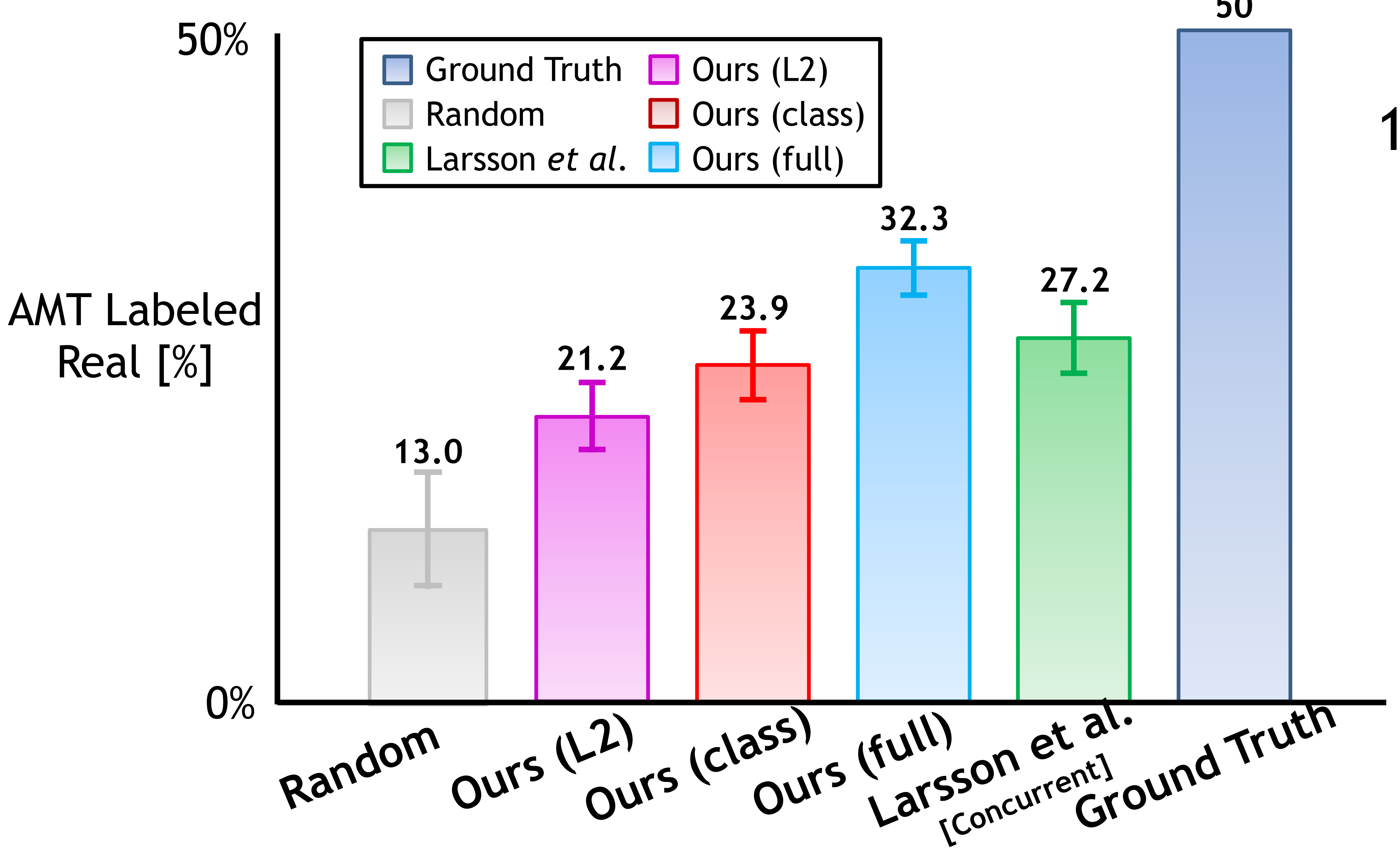
from Reddit /u/SherySantucci

Recolorized by Reddit ColorizeBot

Photo taken by Reddit /u/ Timteroo,
Mural from street artist Eduardo Kobra

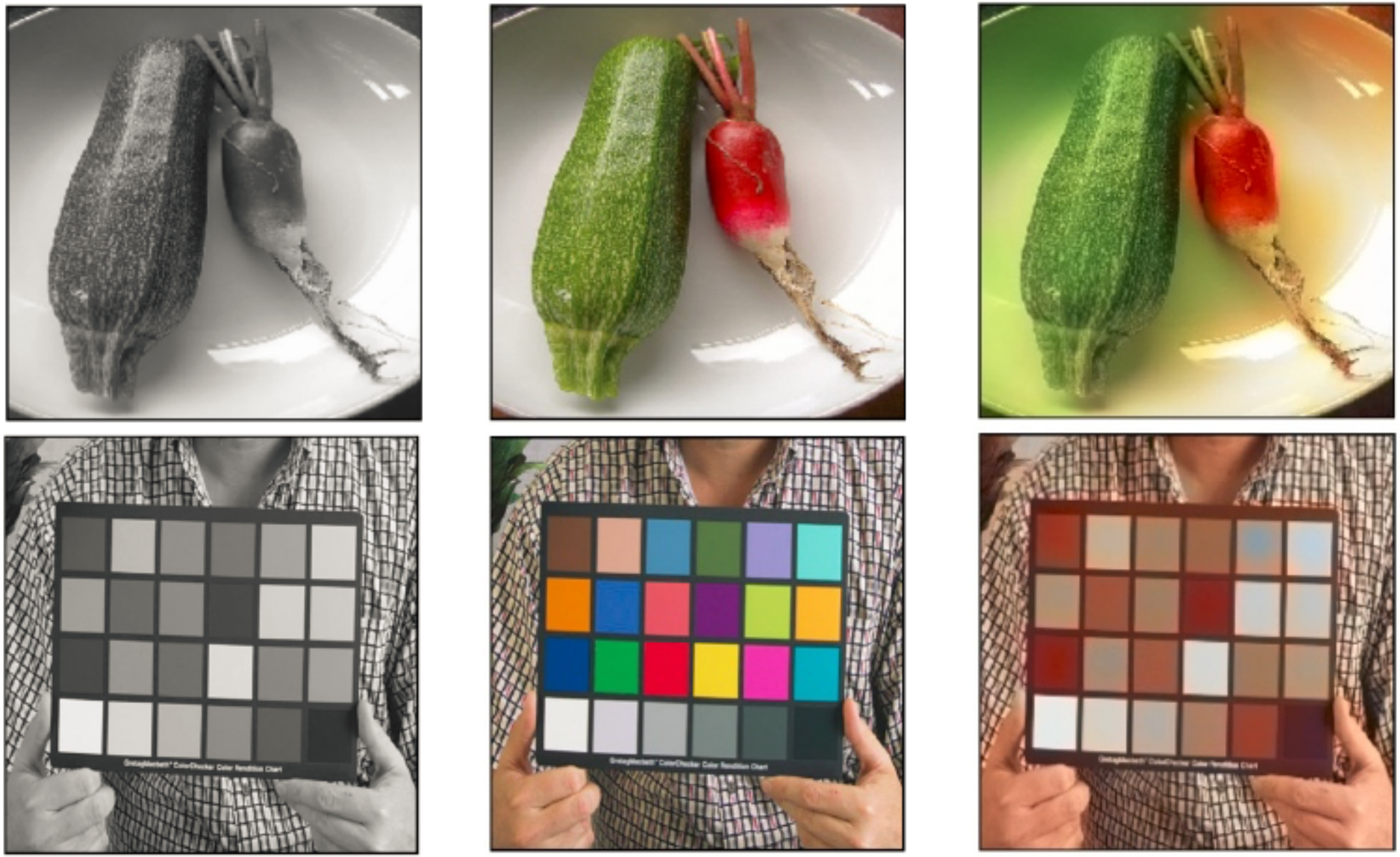
Recolorized by Reddit ColorizeBot

Perceptual Realism Test

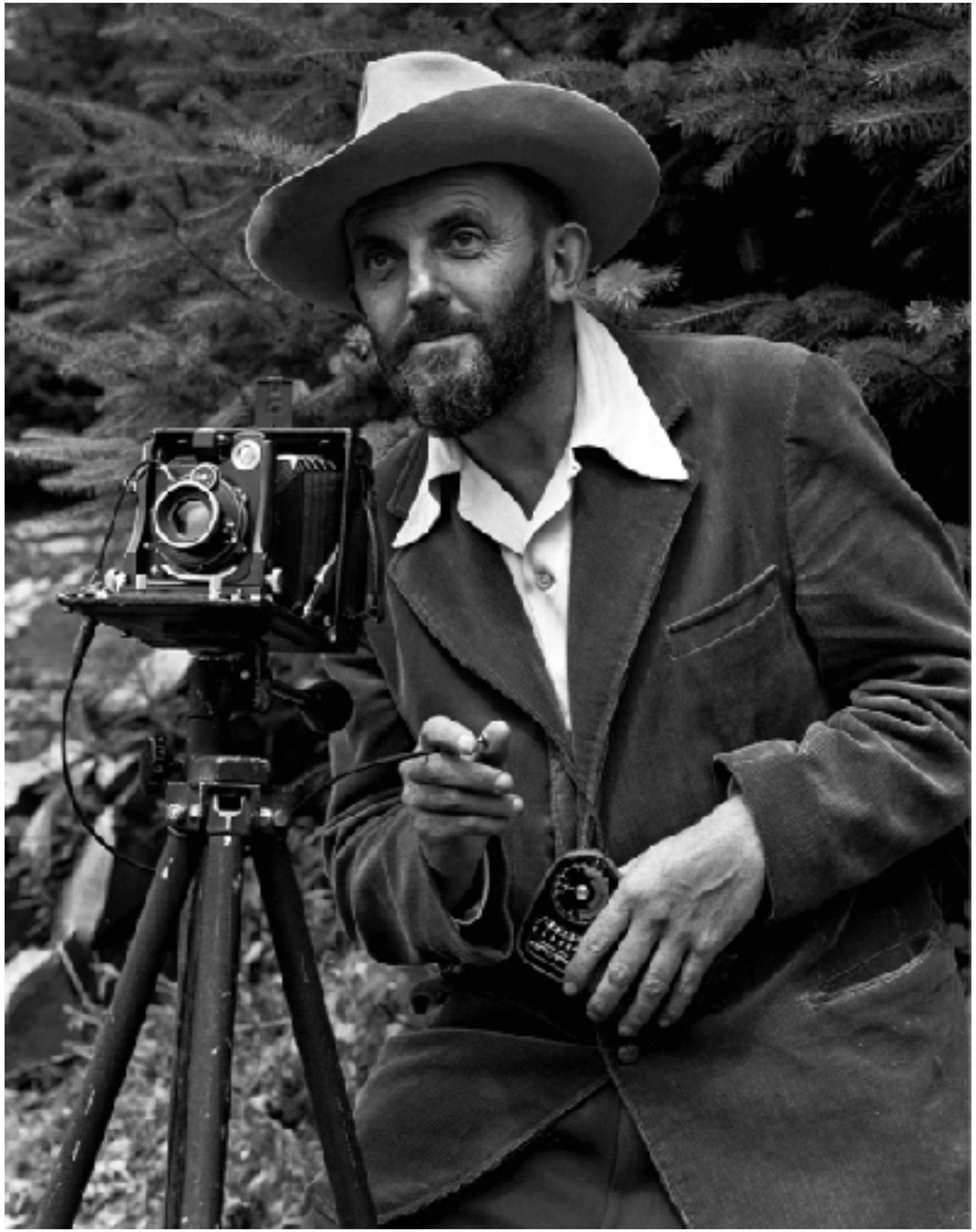


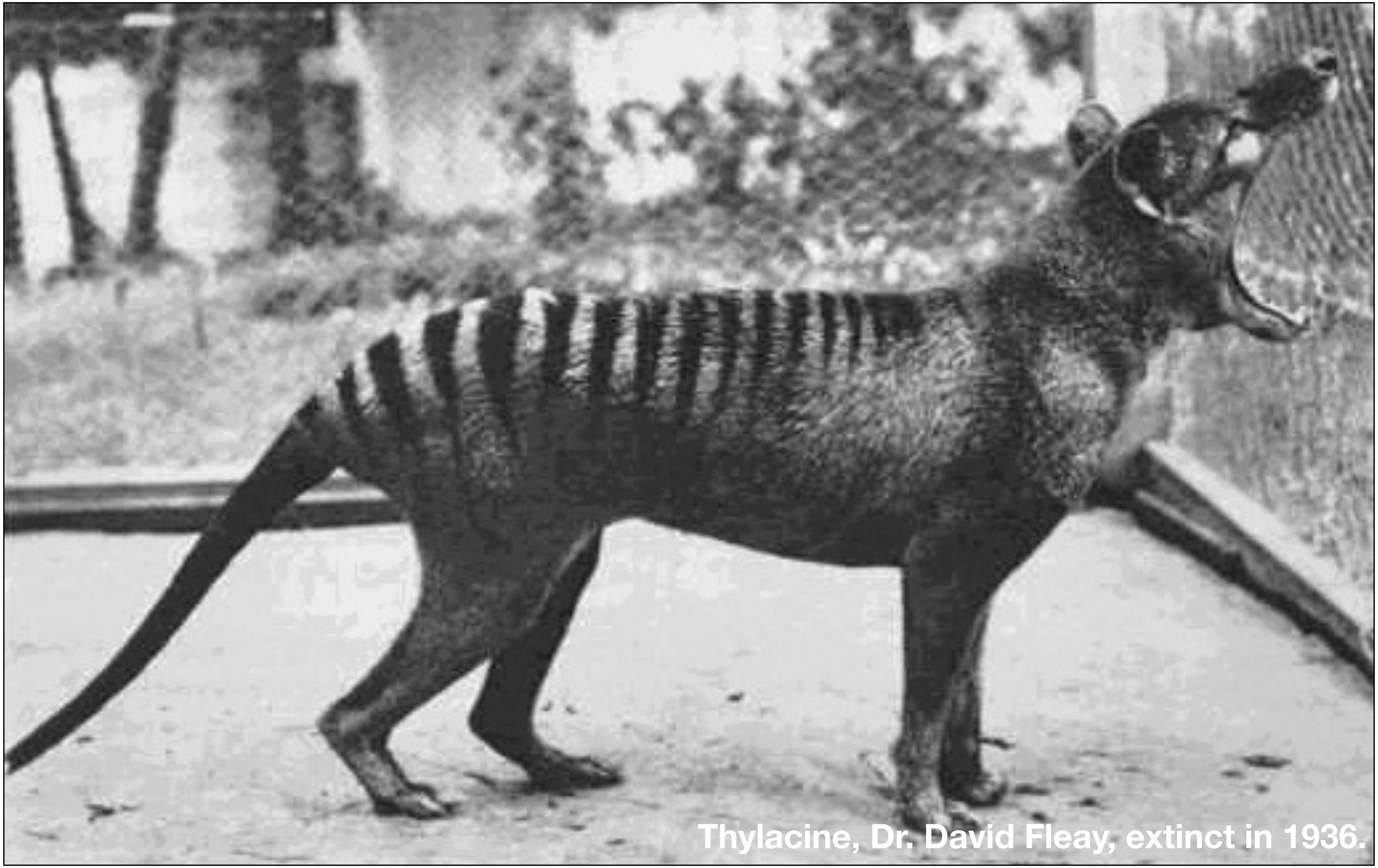
1600 images tested per algorithm

Input **Ground Truth** **Output**



Does the method work on *legacy* black and white photos?



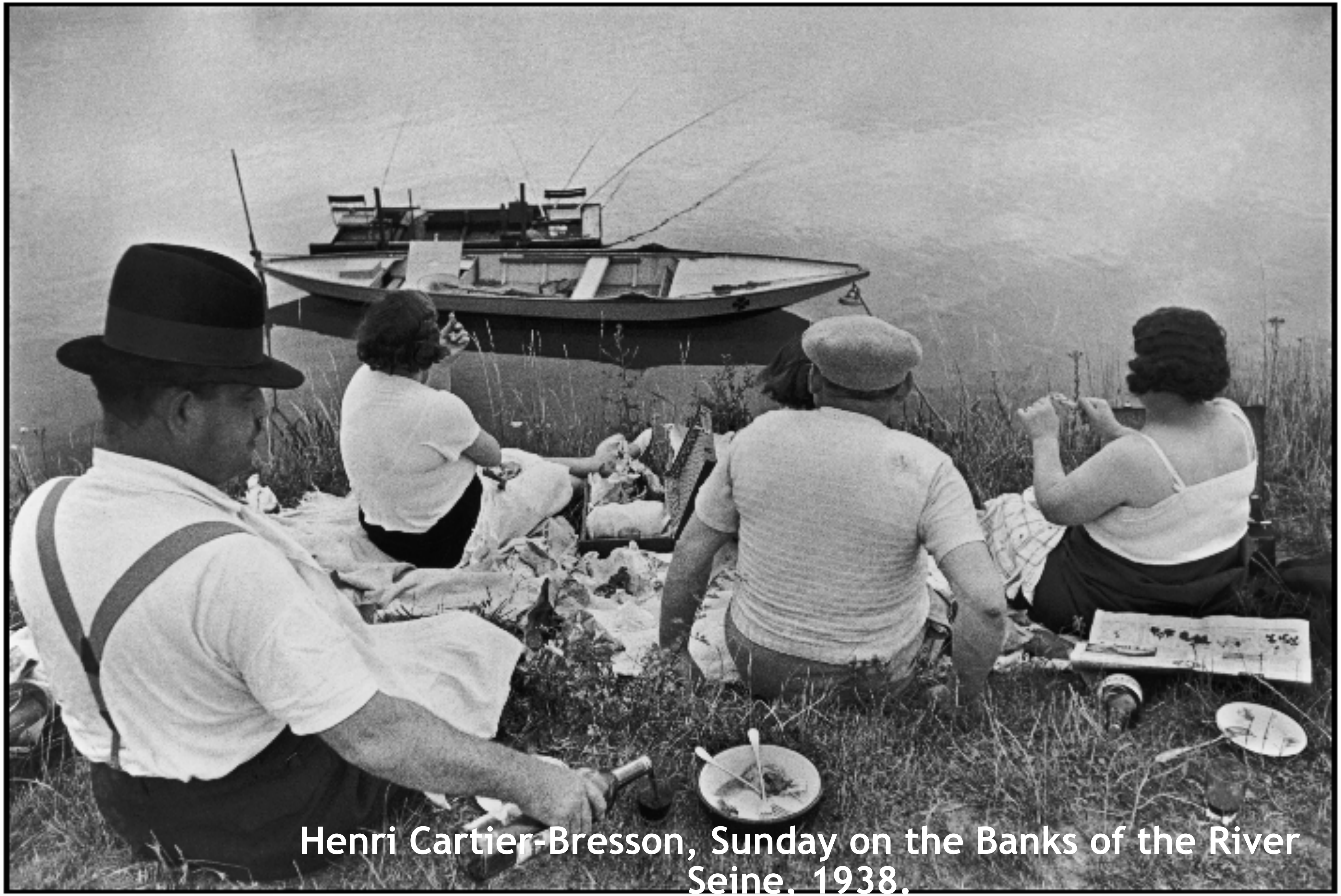


Thylacine, Dr. David Fleay, extinct in 1936.

Thylacine, Dr. David Fleay, extinct in 1936.

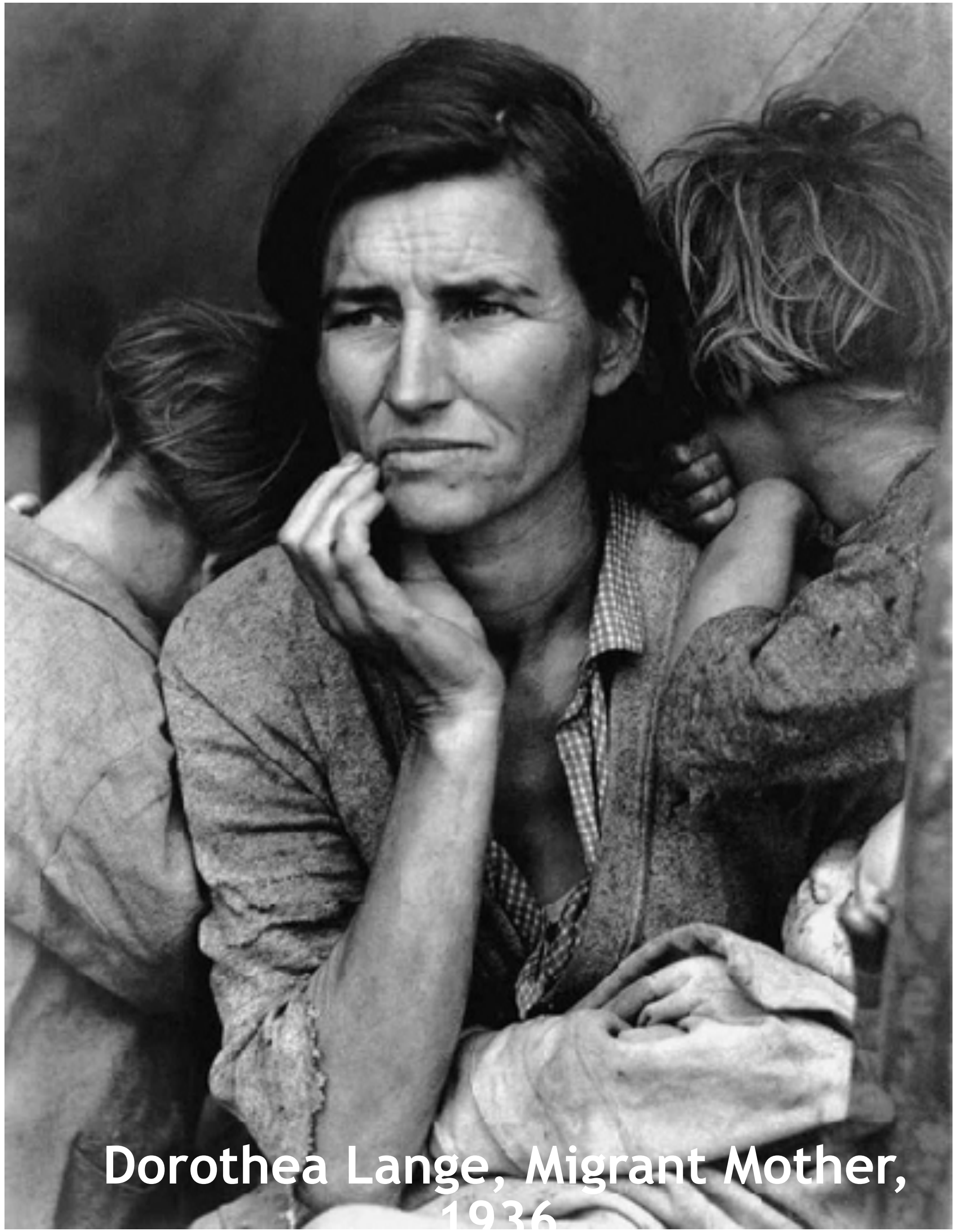
Amateur Family Photo, 1956.

Amateur Family Photo, 1956.

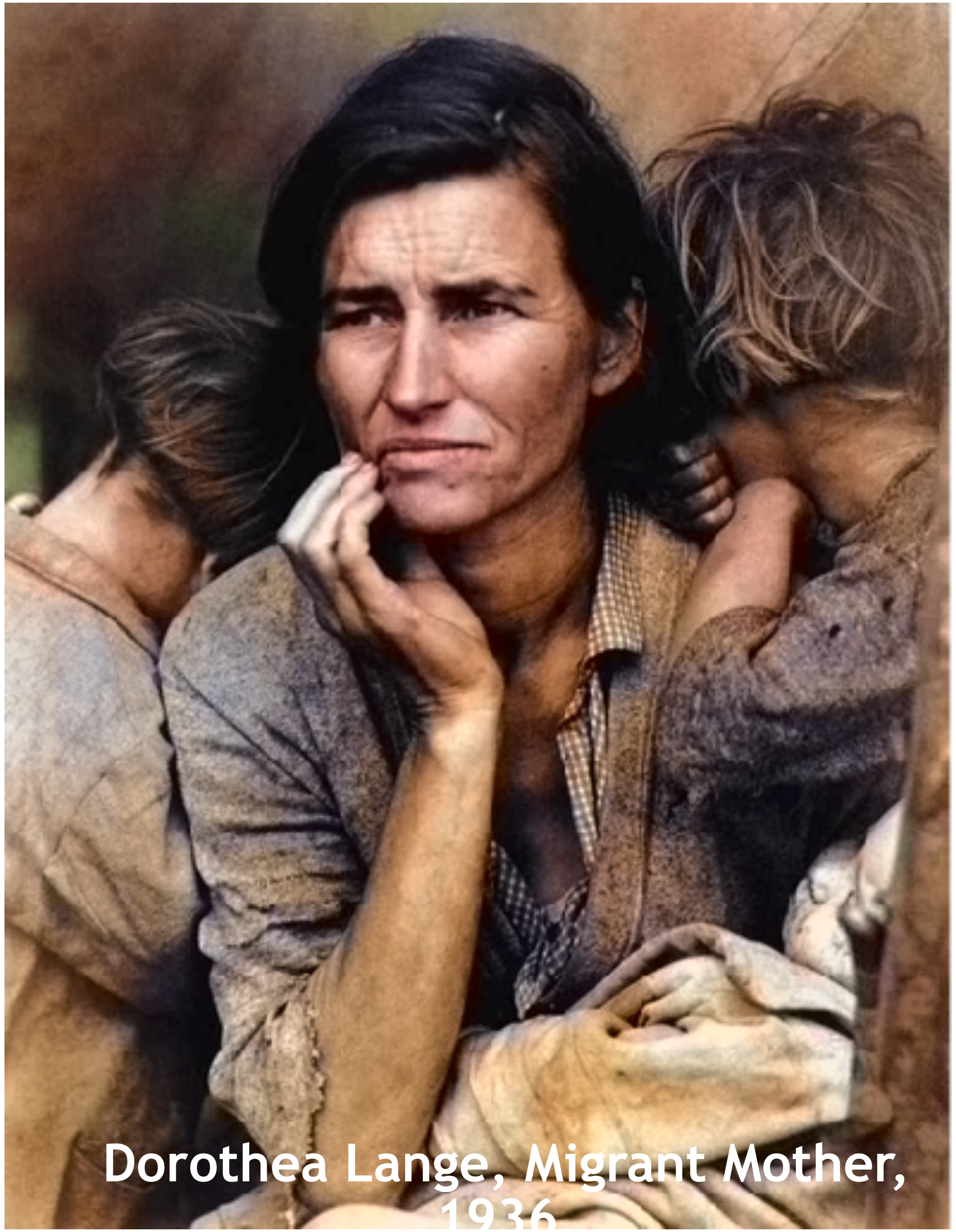


Henri Cartier-Bresson, Sunday on the Banks of the River Seine, 1938.

Henri Cartier-Bresson, Sunday on the Banks of the River Seine, 1938.



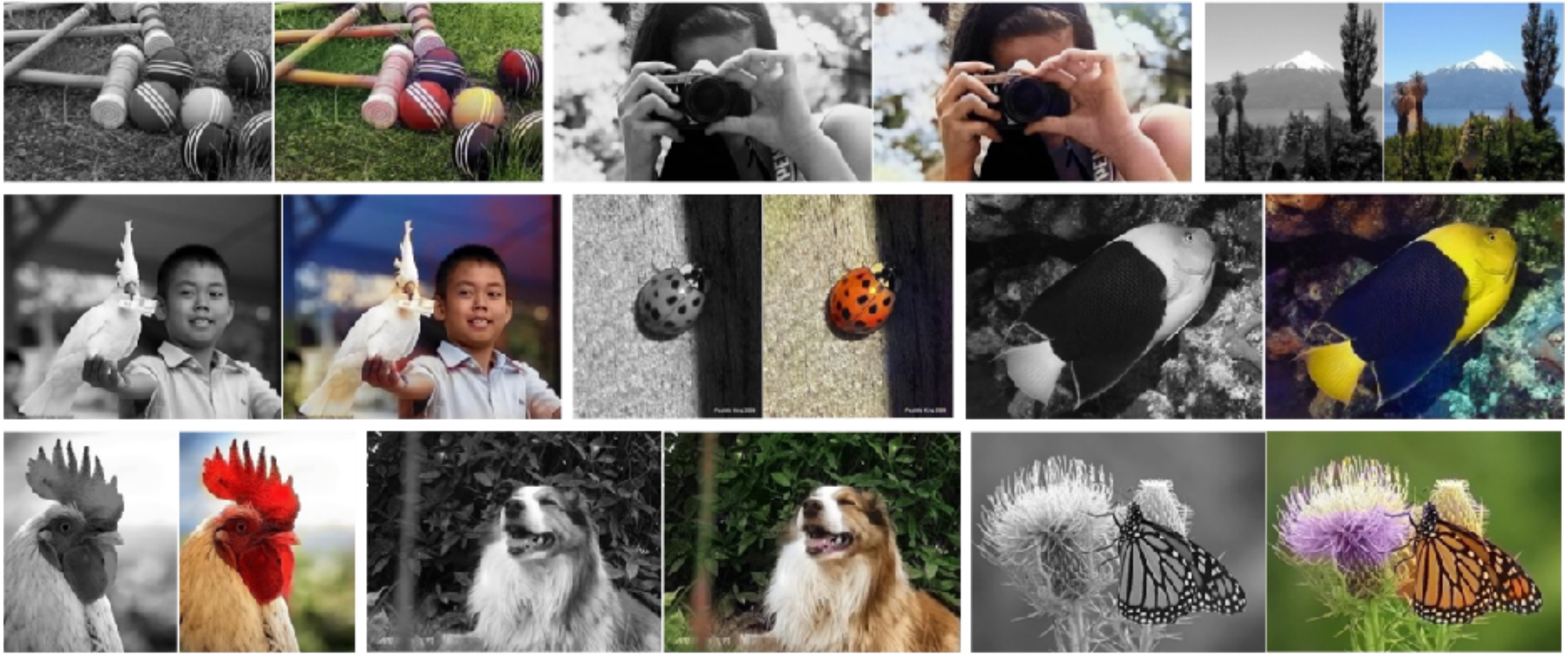
Dorothea Lange, Migrant Mother, 1936



Dorothea Lange, Migrant Mother, 1936

Additional Information

- Demo
  - http://demos.algorithmia.com/colorize-photos/
- Reddit ColorizeBot
  - Type “colorizebot” under any image post
- Code
  - https://github.com/richzhang/colorization
- Website – full paper, user examples, visualizations
  - http://richzhang.github.io/colorization



For the full paper, additional examples and our model:

richzhang.github.io/colorization