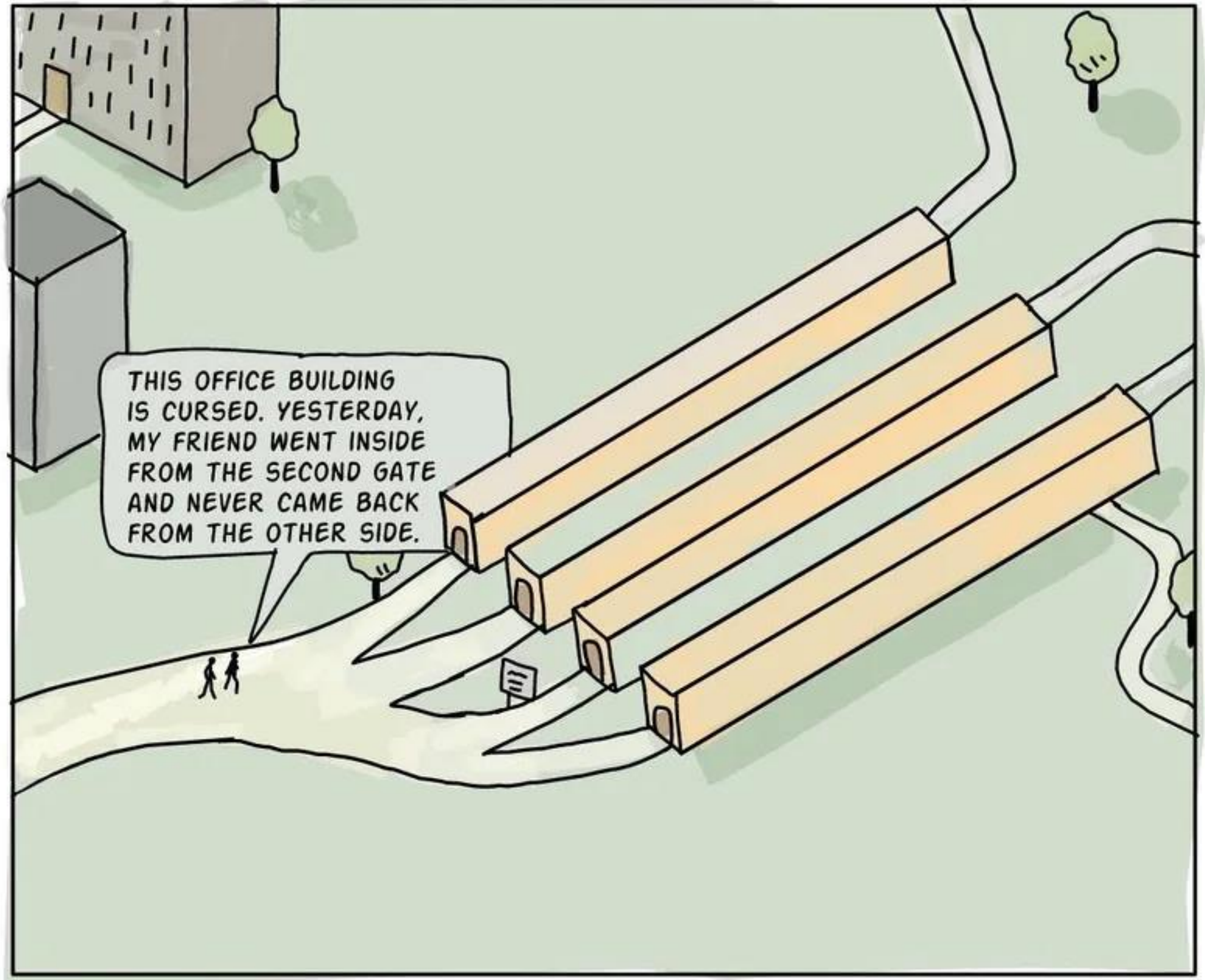


https://en.wikipedia.org/wiki/Impossible_trident

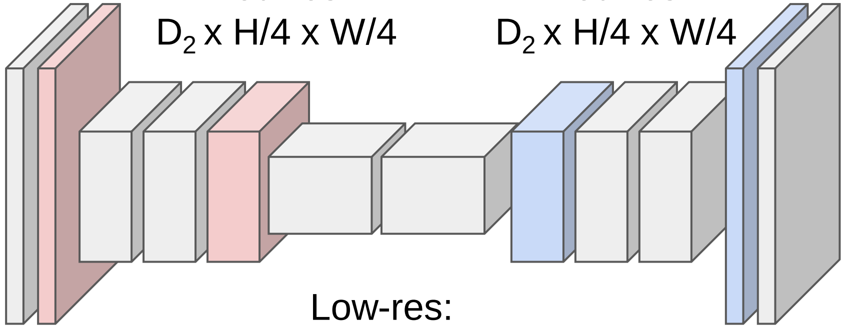
“~~Unsupervised~~” *Self Supervised* Deep Learning

James Hays
slides from Carl Doersch and Richard Zhang

Recap: Fully Convolutional Network

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

Med-res:
D_2 x H/4 x W/4

Low-res:
D_3 x H/4 x W/4

Med-res:
D_2 x H/4 x W/4

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

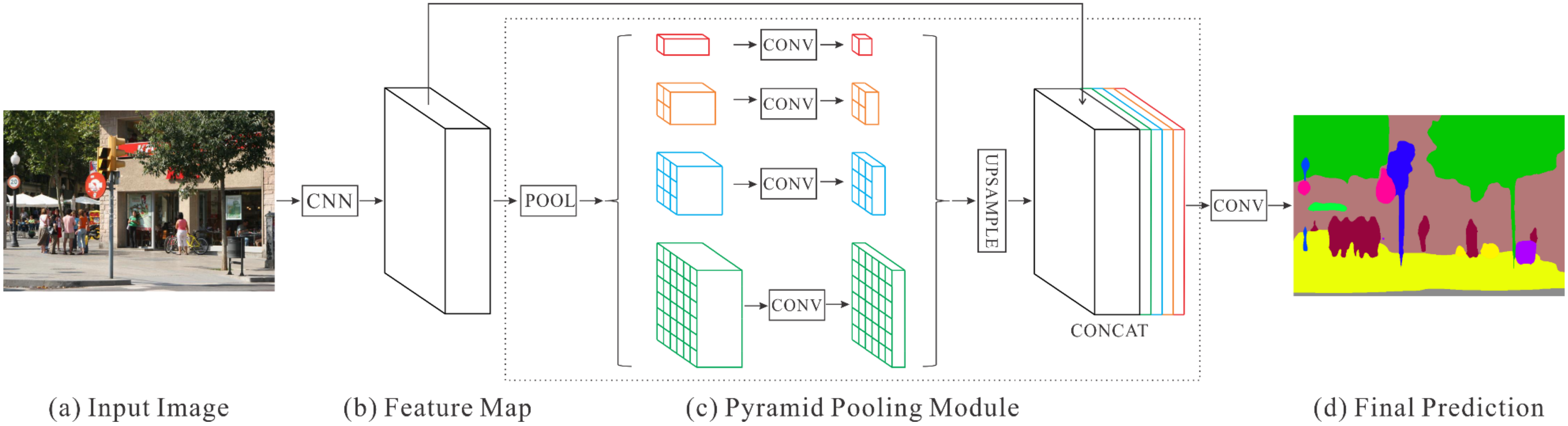
Downsampling:
Pooling, strided convolution

Upsampling:
???

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Slide Credit: Justin Johnson and David Fouhey

Recap: Pyramid Scene Parsing Network



Framework overview of PSPNet

"Pyramid Scene Parsing Network", Zhao et al. CVPR 2017 [15,000+ citation]

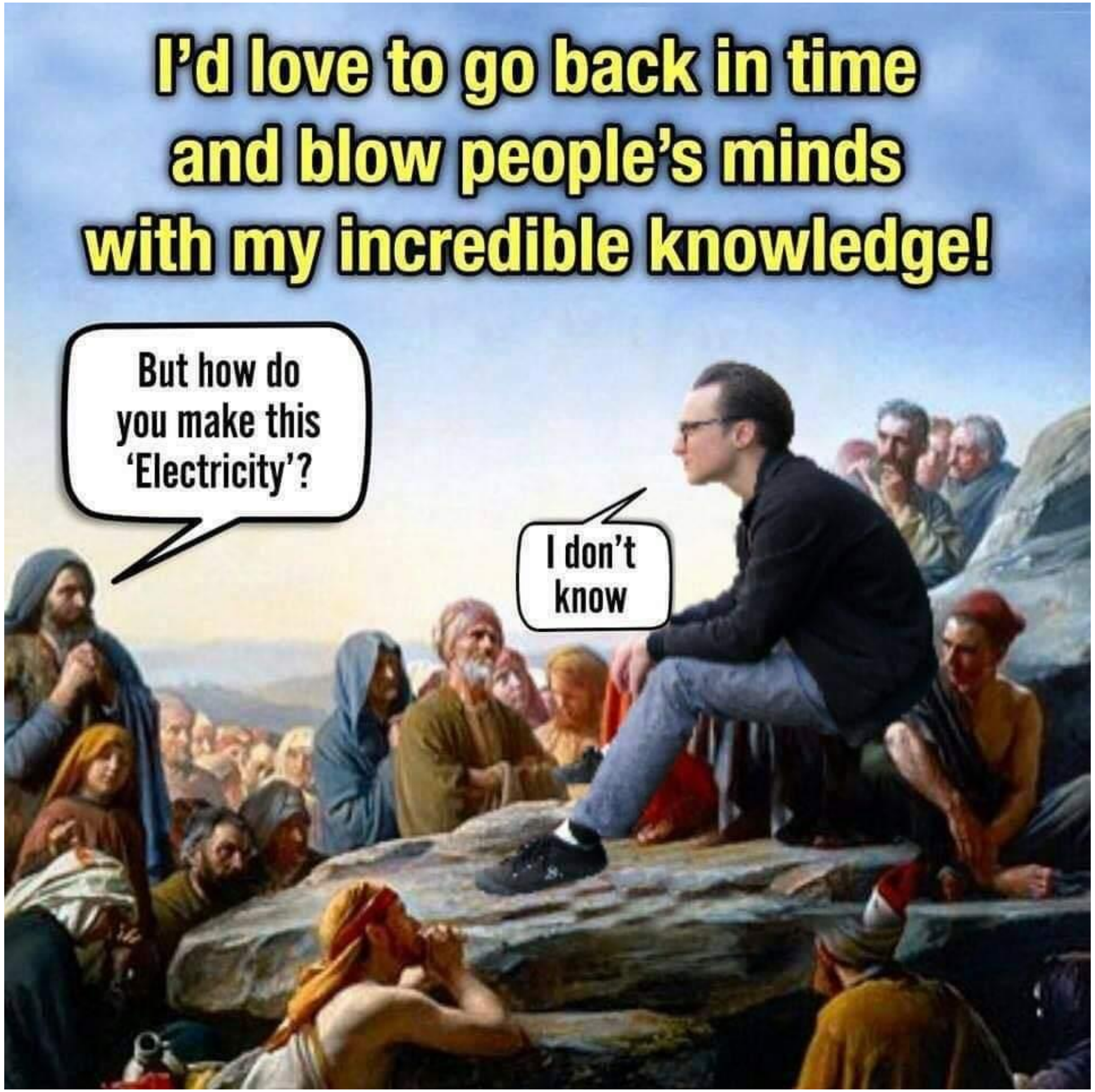
Slide Credit: Hengshuang Zhao and Jiaya Jia

Recap

- Big Data
  - The Unreasonable Effectiveness of Data
  - Scene Completion
  - Im2gps
  - Recognition via Tiny Images
- Crowdsourcing
  - “Wisdom of the Crowds” / consensus
  - Find good annotators through grading
  - Pricing affects throughput but not quality
  - User interface and instructions matter a lot

Today’s Lecture

- Four methods for “unsupervised” deep learning
  - Context Prediction. Doersch et al. ICCV 2015
  - Colorful Image Colorization. Zhang et al. ECCV 2016
  - SimCLR. Chen et al. ICML 2020
  - Masked Autoencoders. He et al. CVPR 2022
- Big picture: do we need big, labeled datasets like ImageNet to make deep learning worthwhile? Can we learn from something else?


I'd love to go back in time and blow people's minds with my incredible knowledge!
But how do you make this 'Electricity'?
I don't know


I'd love to go back in time and blow people's minds with my incredible knowledge!
But how do you make this
Large Pretrained Model?
I don't know

The Gelato Bet

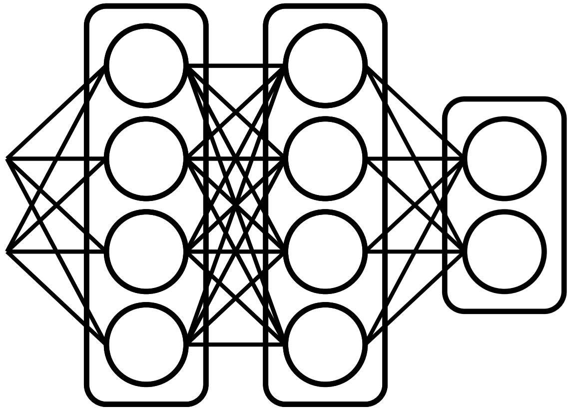
"If, by the first day of autumn (Sept 23) of 2015, a method will exist that can match or beat the performance of R-CNN on Pascal VOC detection, without the use of any extra, human annotations (e.g. ImageNet) as pre-training, Mr. Malik promises to buy Mr. Efros one (1) gelato”

Unsupervised Visual Representation Learning by Context Prediction

Carl Doersch, Alexei A. Efros, and Abhinav Gupta

ICCV 2015

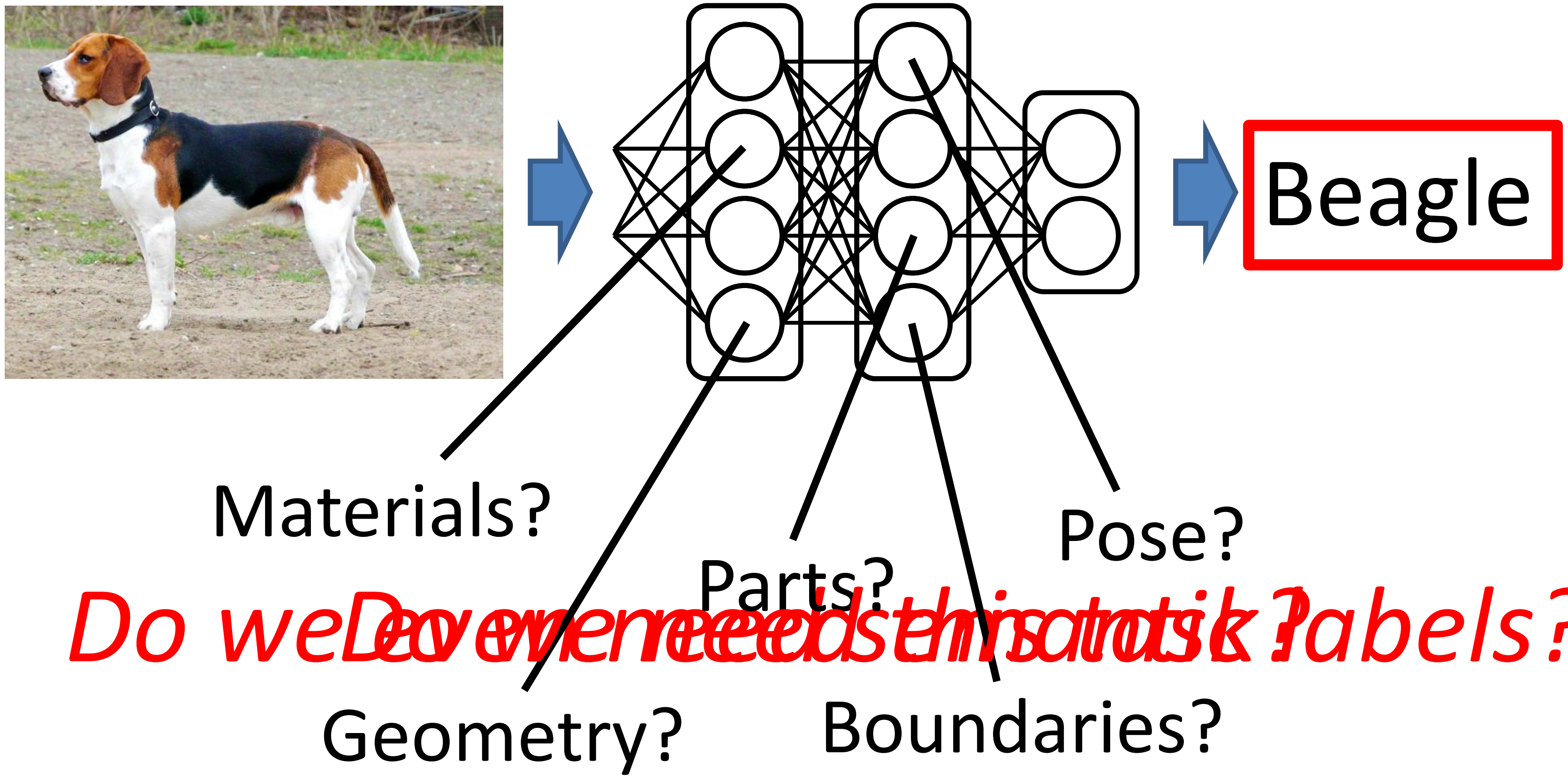
ImageNet + Deep Learning



Beagle

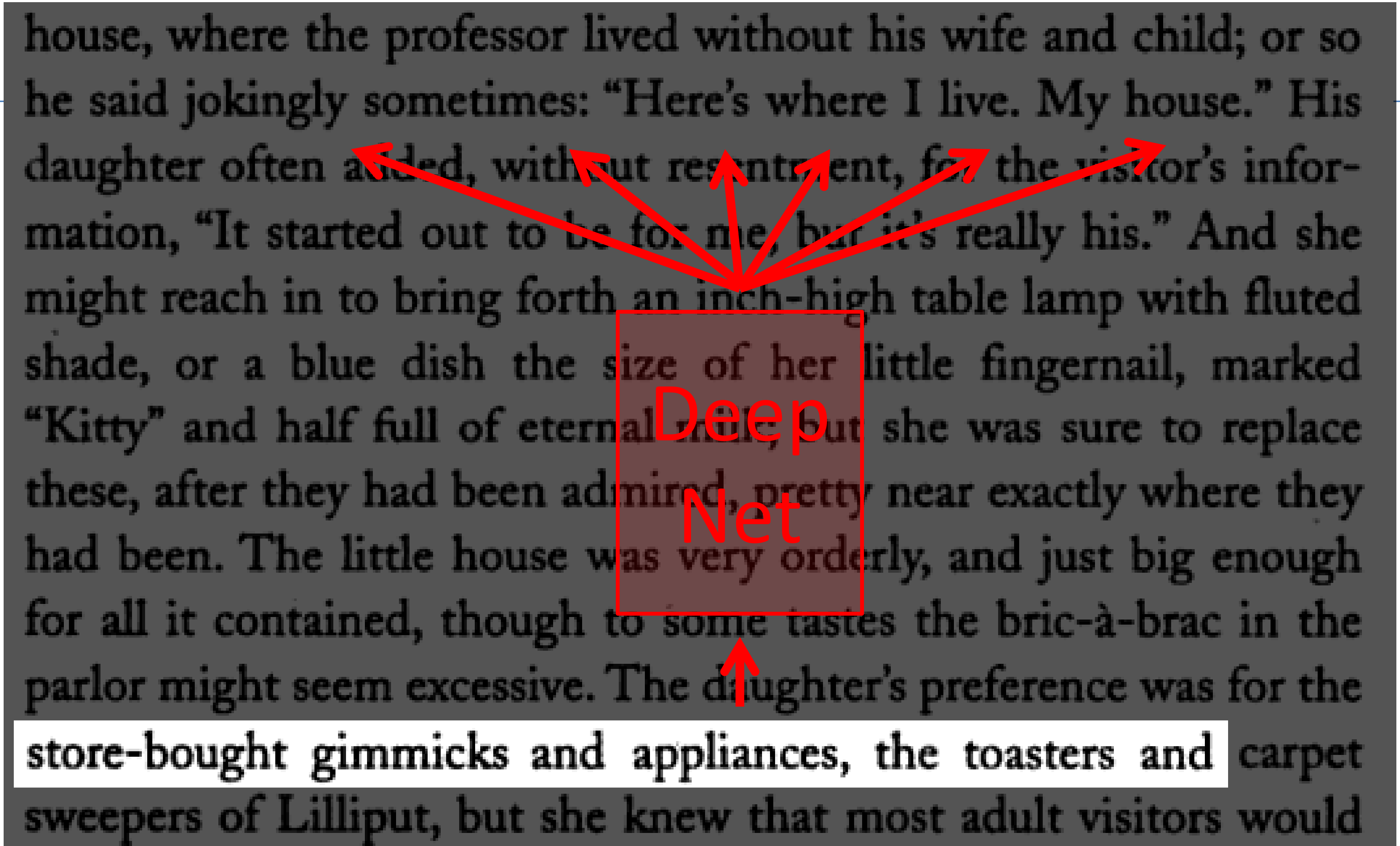
- Image Retrieval
- Detection (RCNN)
- Segmentation (FCN)
- Depth Estimation
- ...

ImageNet + Deep Learning



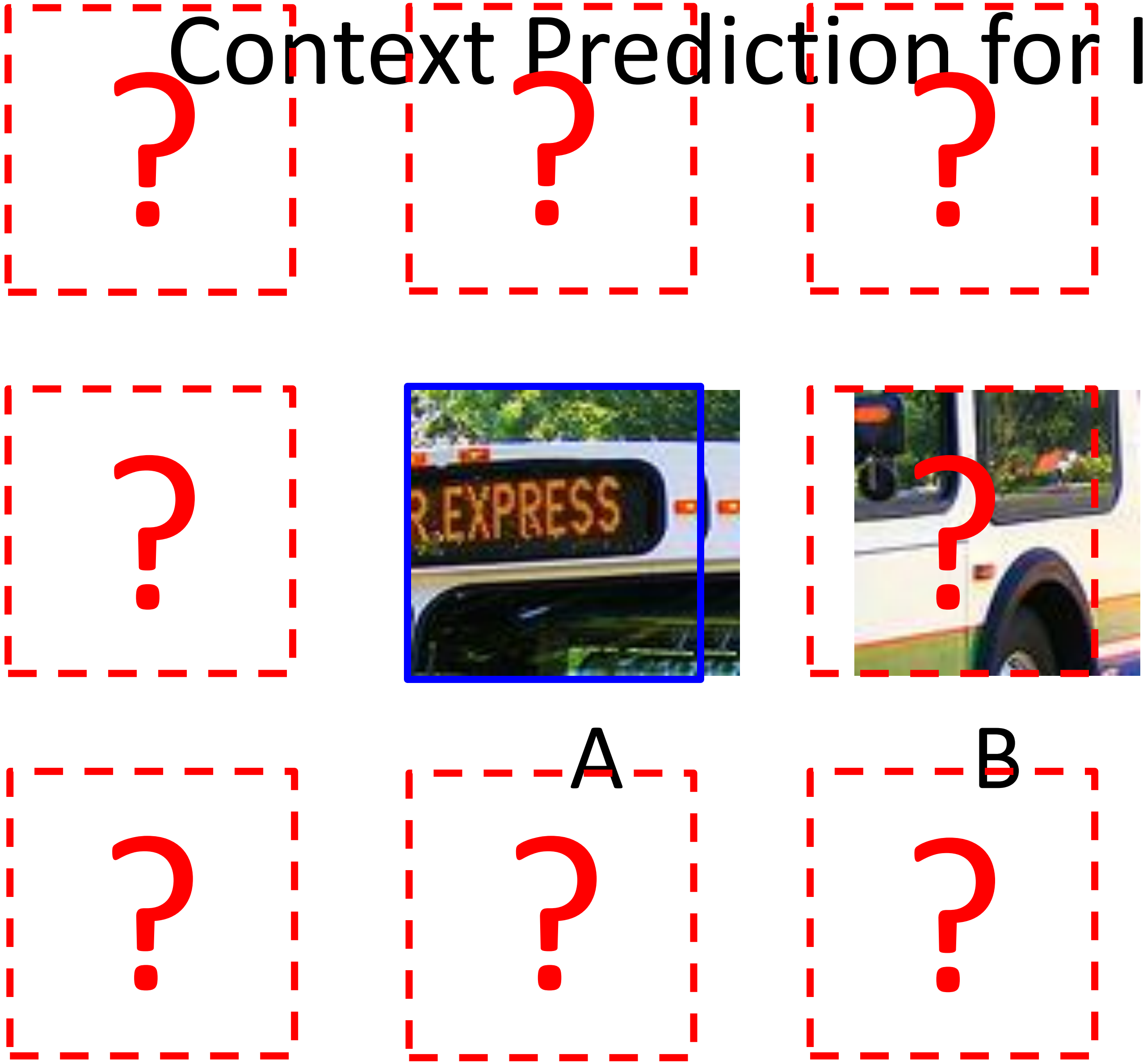
Context as Supervision

[Collobert & Weston 2008; Mikolov et al. 2013 (Word2Vec)]

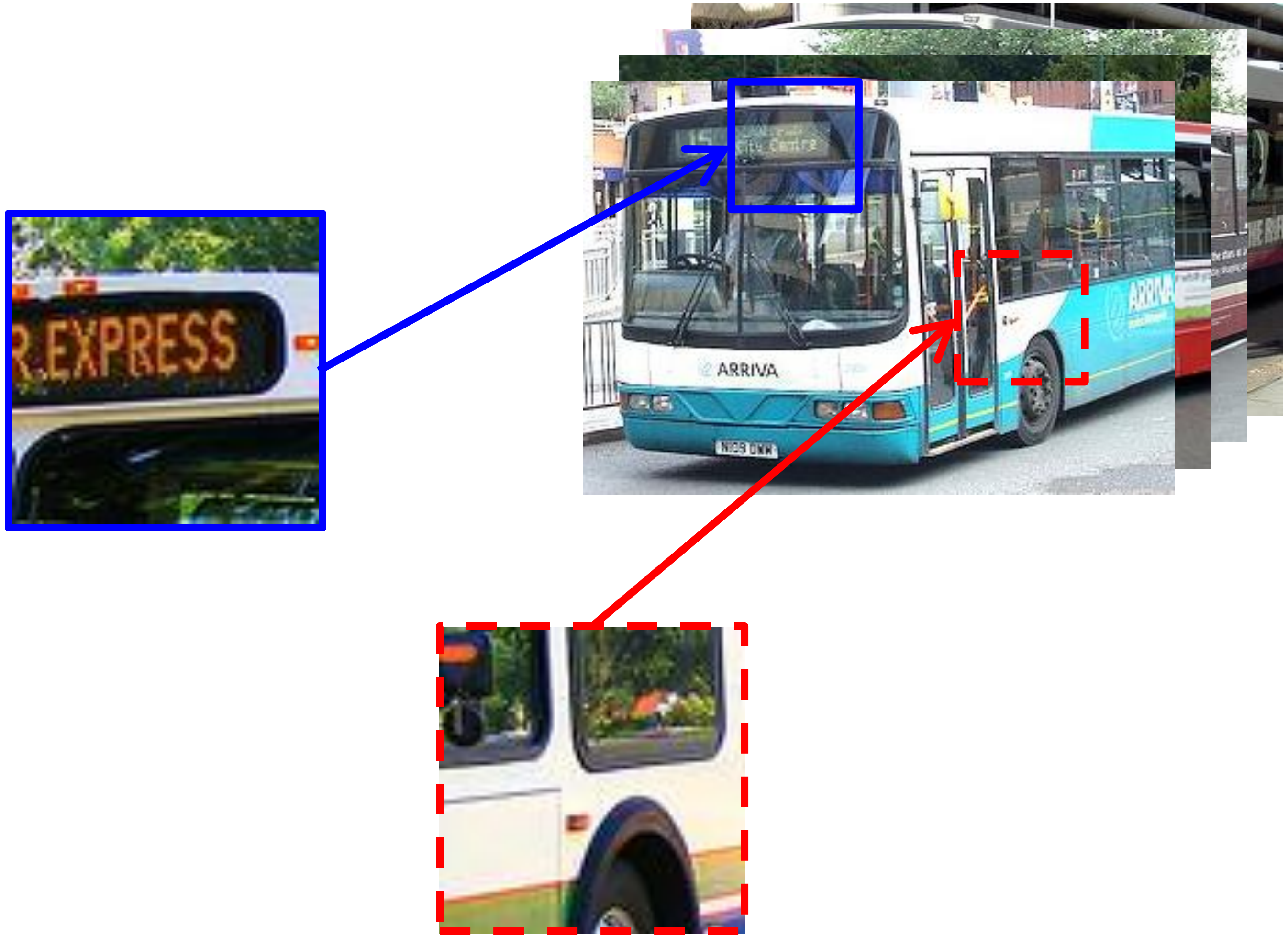


house, where the professor lived without his wife and child; or so he said jokingly sometimes: “Here’s where I live. My house.” His daughter often added, without resentment, for the visitor’s information, “It started out to be for me, but it’s really his.” And she might reach in to bring forth an inch-high table lamp with fluted shade, or a blue dish the size of her little fingernail, marked “Kitty” and half full of eternal milk, but she was sure to replace these, after they had been admired, pretty near exactly where they had been. The little house was very orderly, and just big enough for all it contained, though to some tastes the bric-à-brac in the parlor might seem excessive. The daughter’s preference was for the store-bought gimmicks and appliances, the toasters and carpet sweepers of Lilliput, but she knew that most adult visitors would

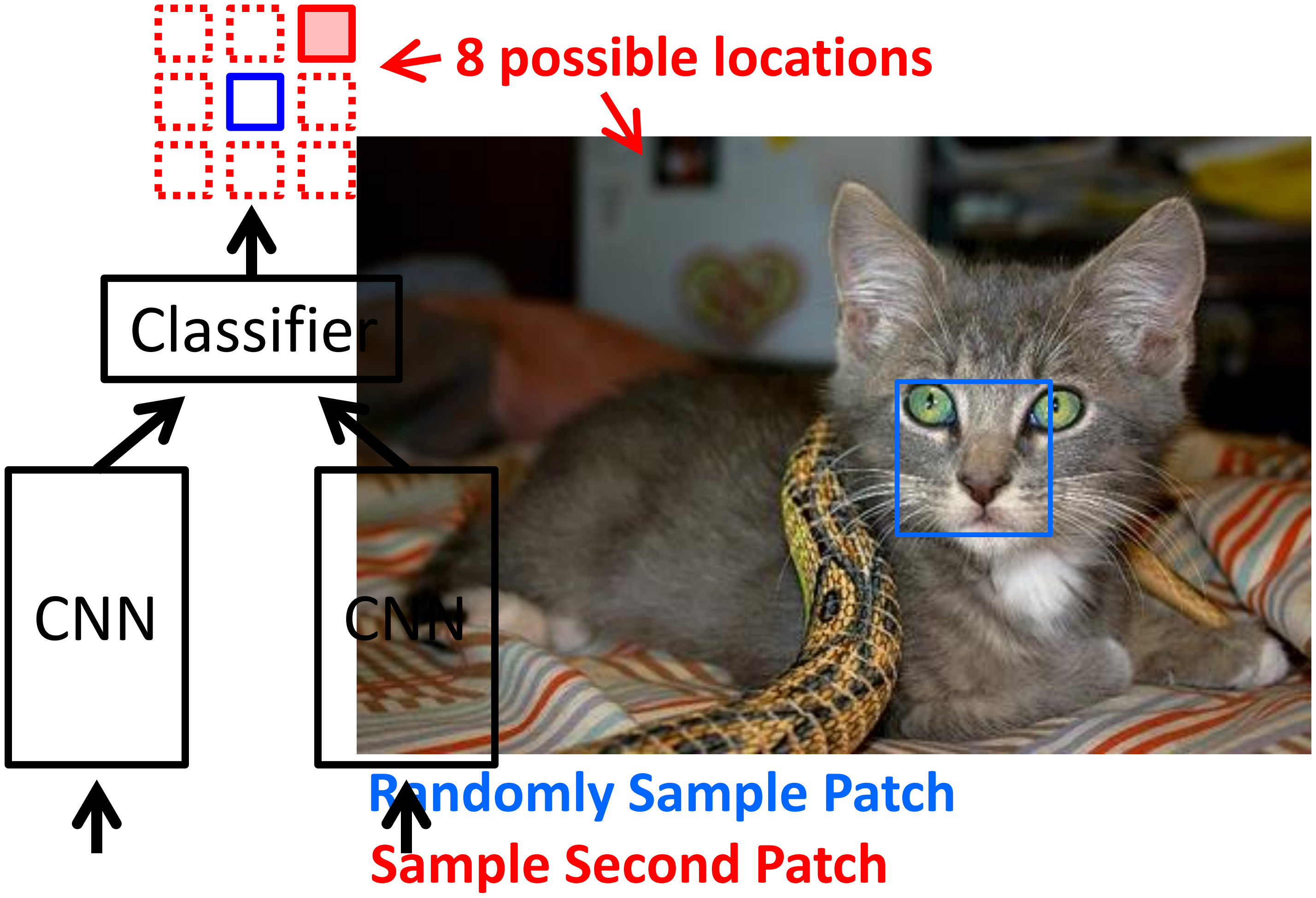
Context Prediction for Images

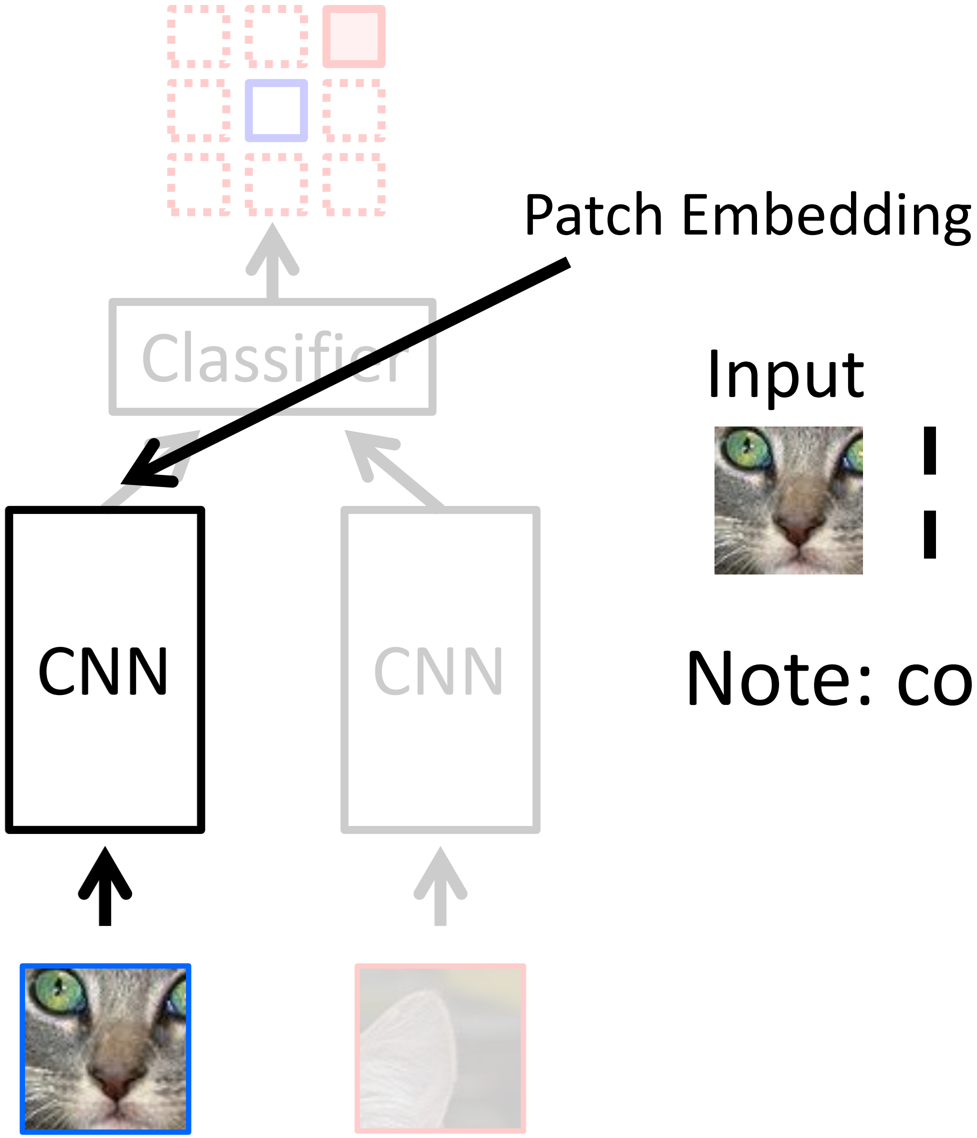


Semantics from a non-semantic task



Relative Position Task

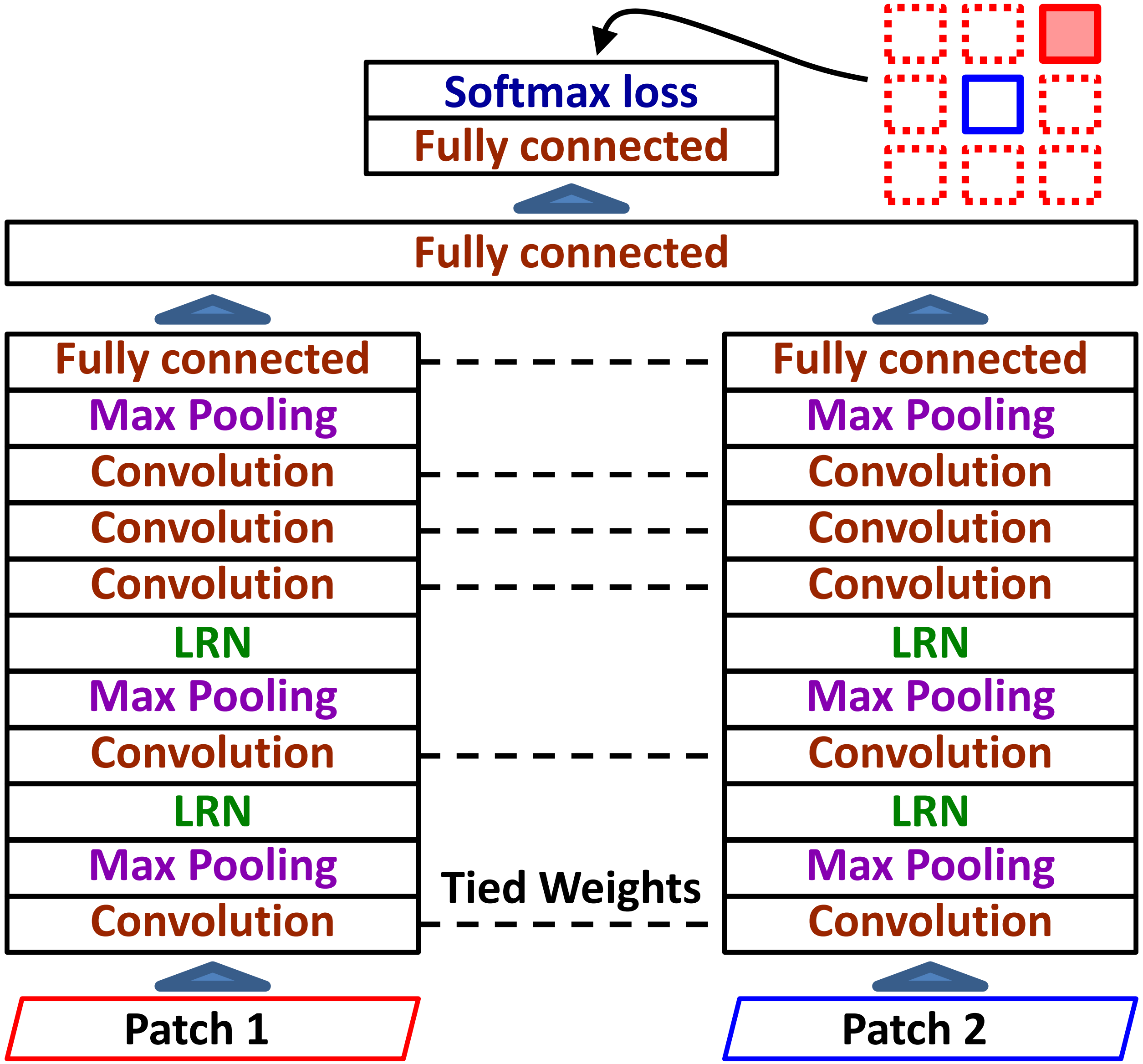




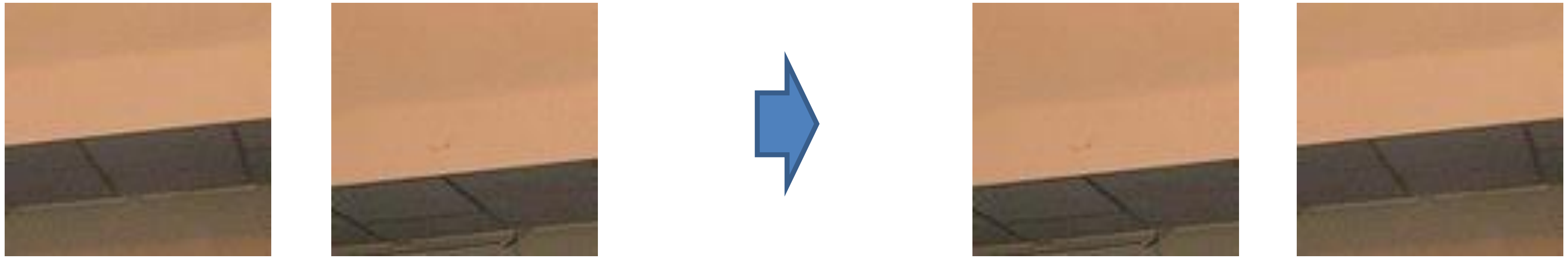
Input | Nearest Neighbors

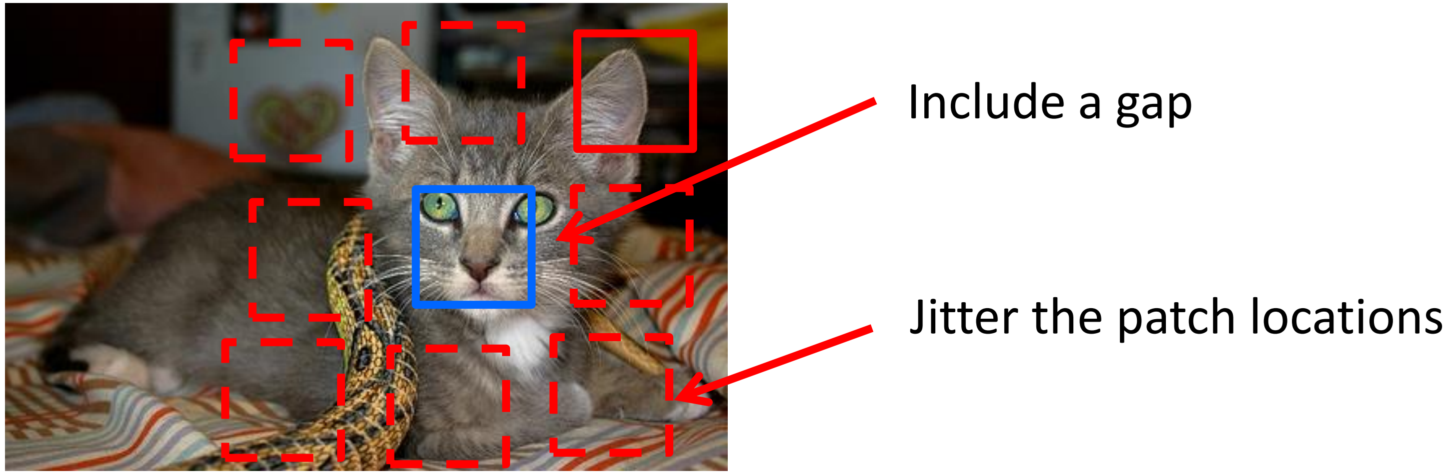
Note: connects ***across*** instances!

Architecture

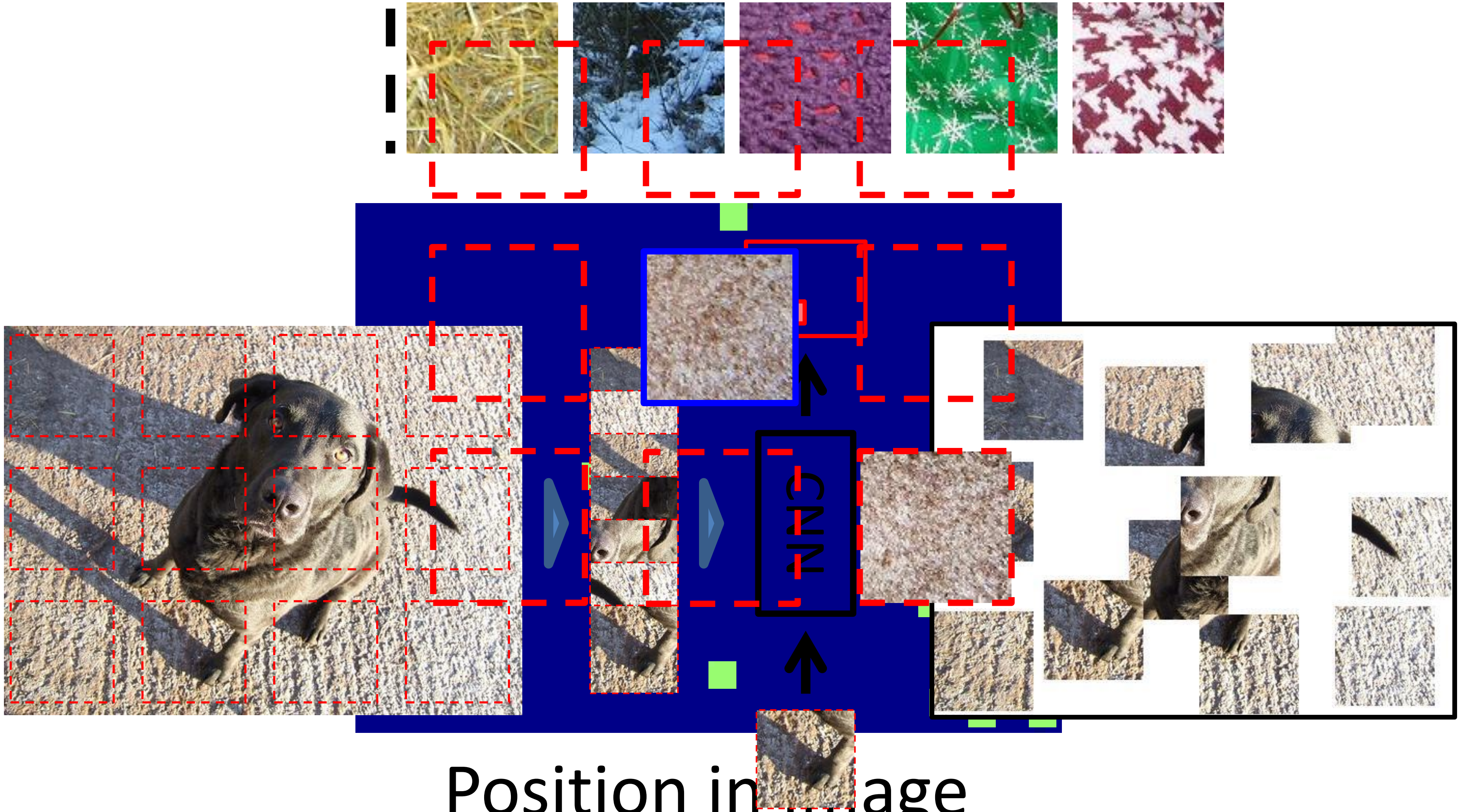


Avoiding Trivial Shortcuts



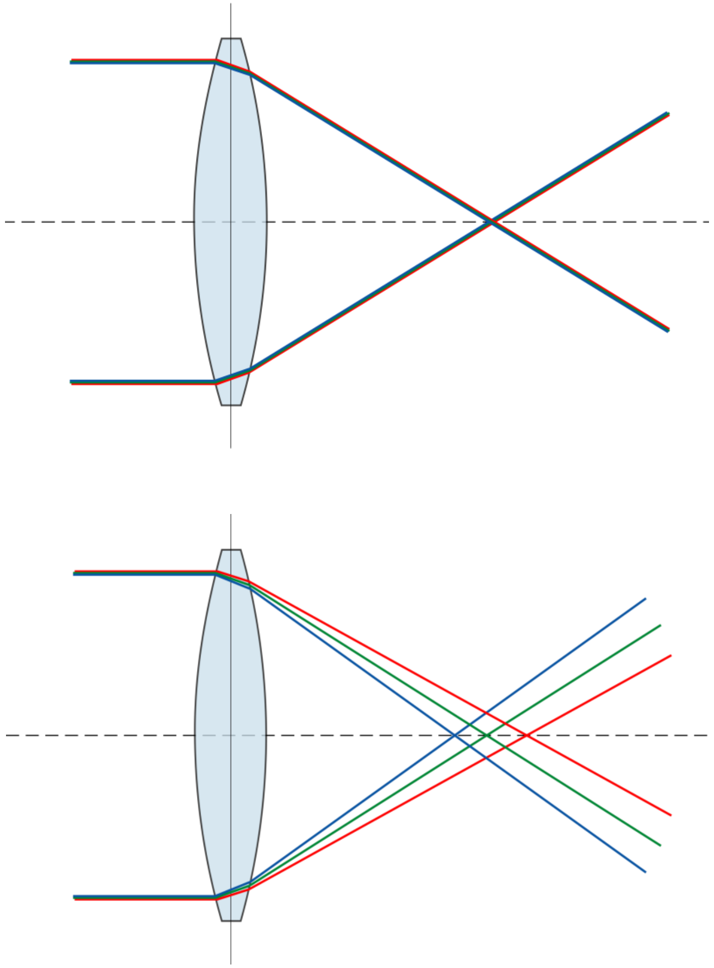


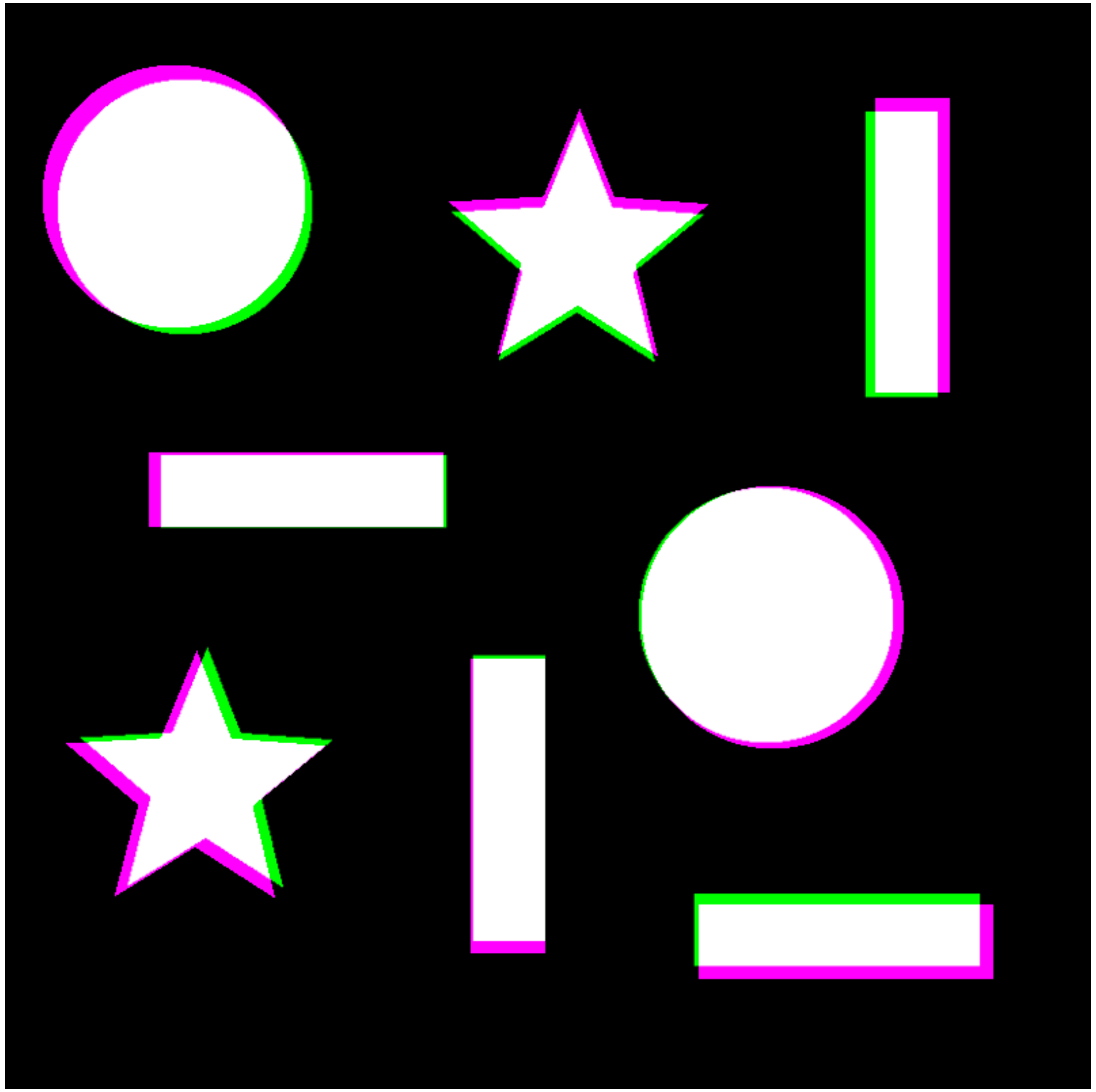
A Not-So "Trivial" Shortcut



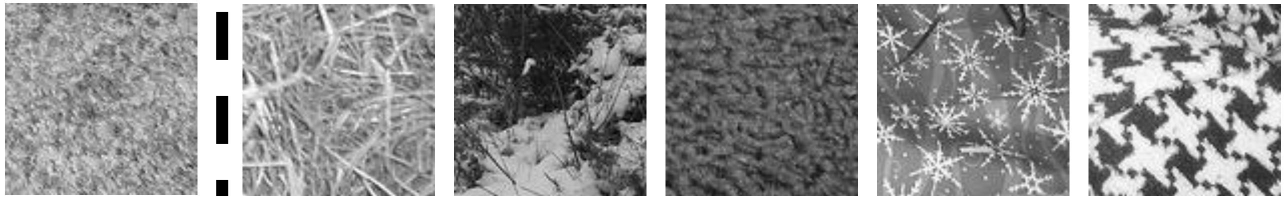
Position in ...age

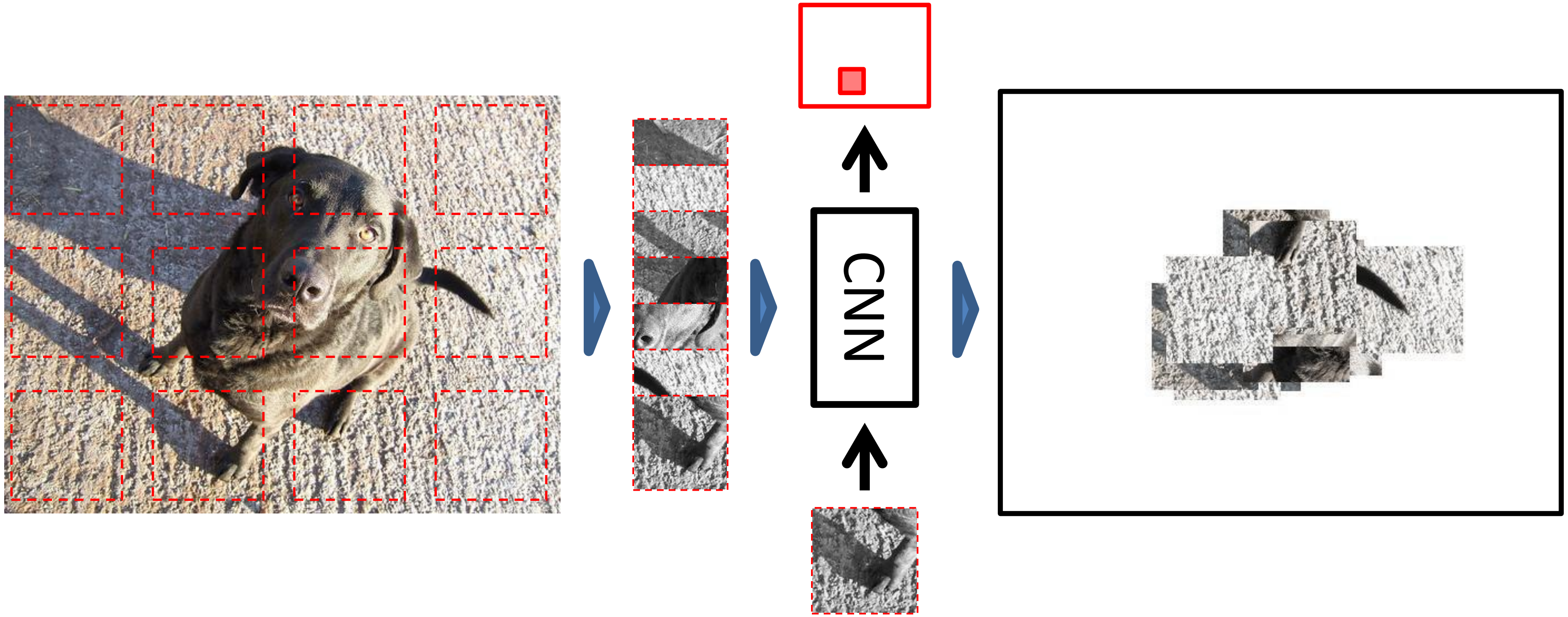
Chromatic Aberration



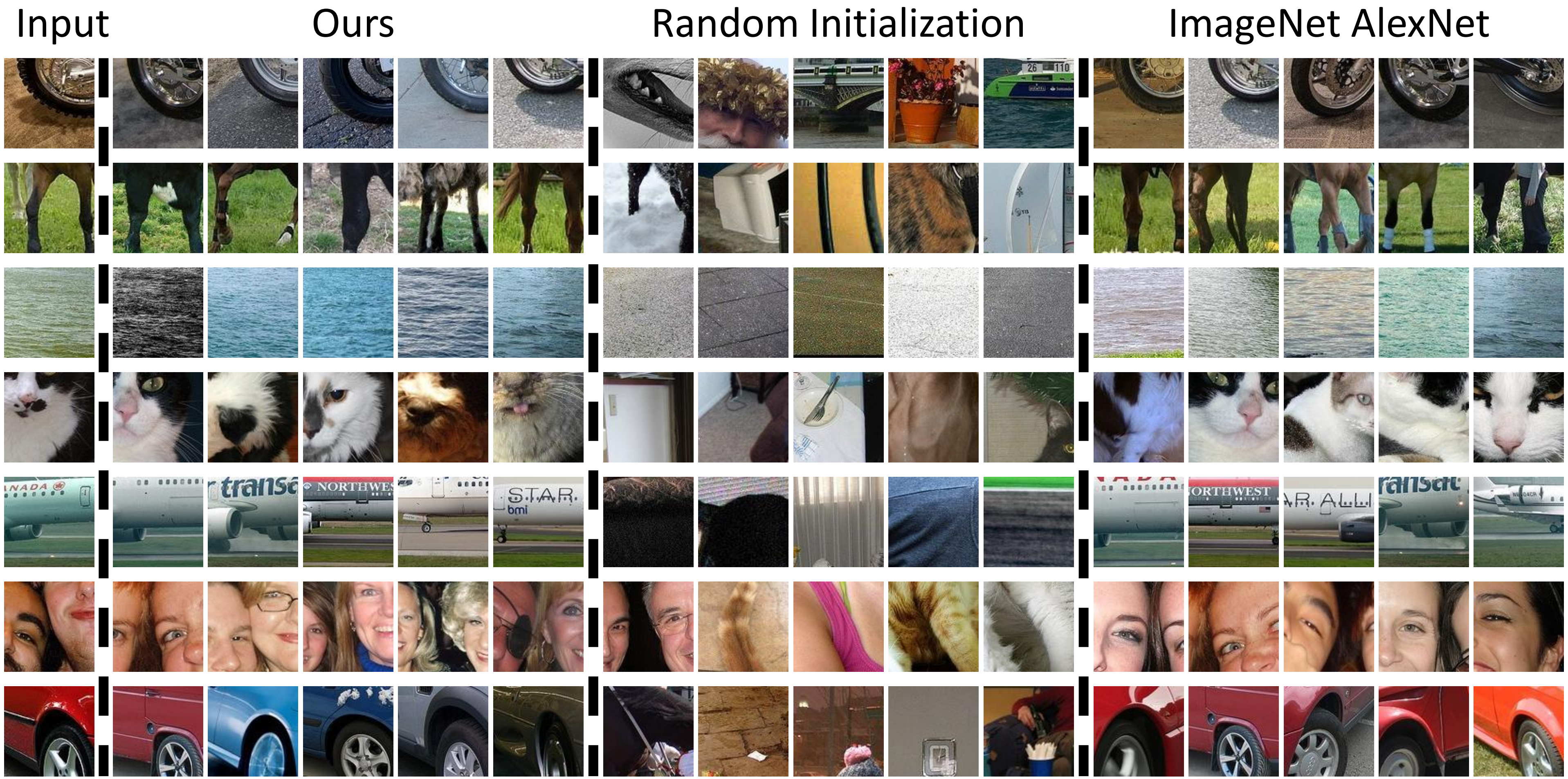


Chromatic Aberration





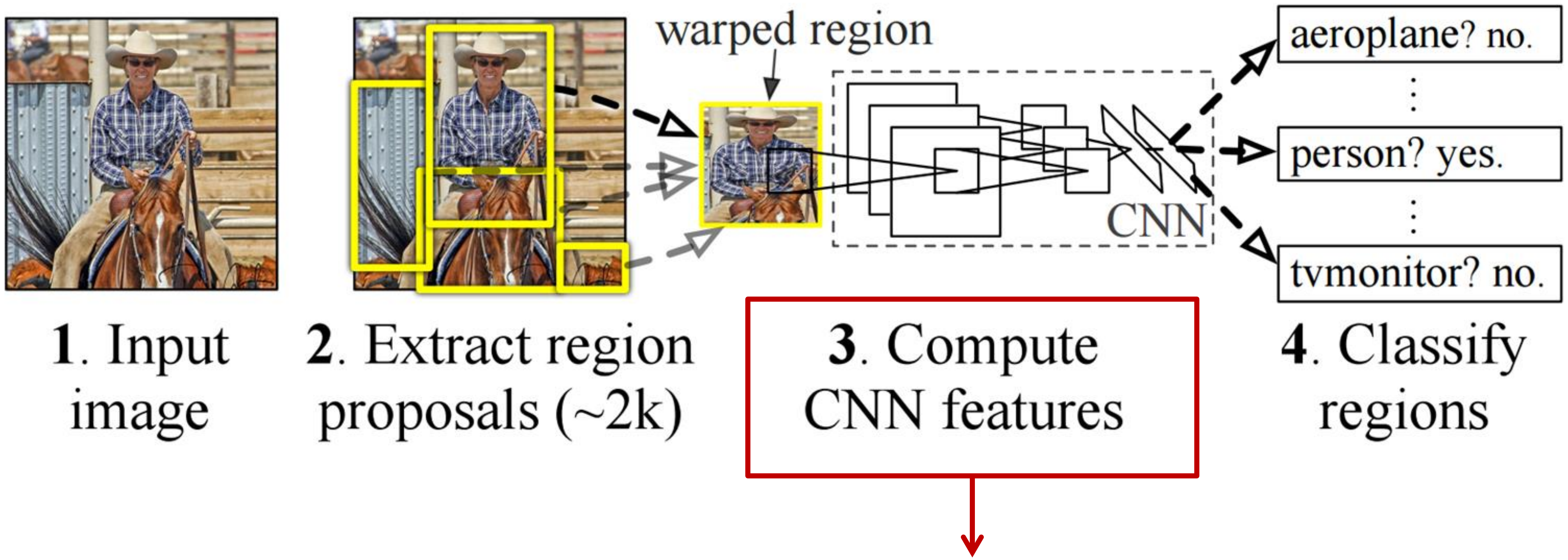
What is learned?



Still don't capture everything

You don't always need to learn!

Pre-Training for R-CNN

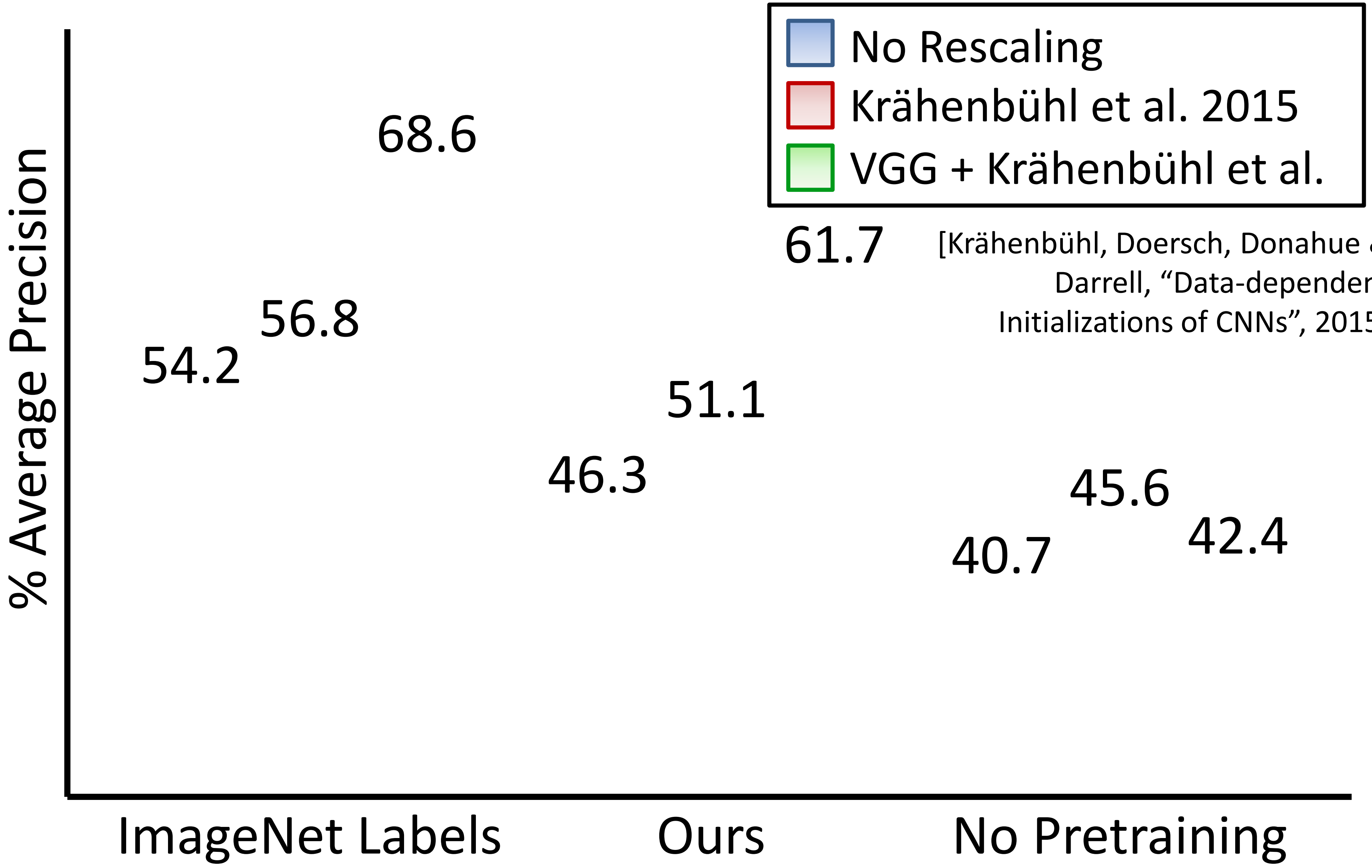


Pre-train on relative-position task, w/o labels

[Girshick et al. 2014]

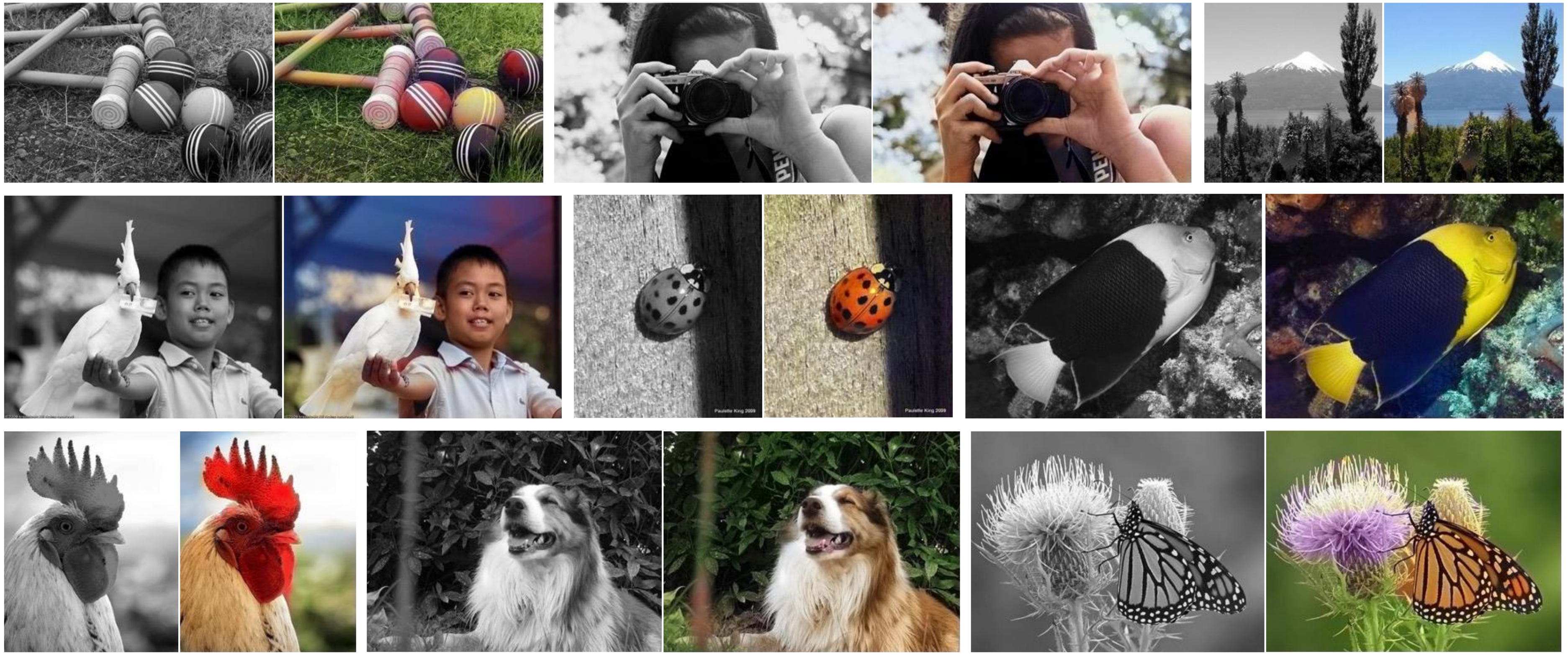
VOC 2007 Performance

(pretraining for R-CNN)



[Krähenbühl, Doersch, Donahue & Darrell, "Data-dependent Initializations of CNNs", 2015]

So, do we need semantic labels?

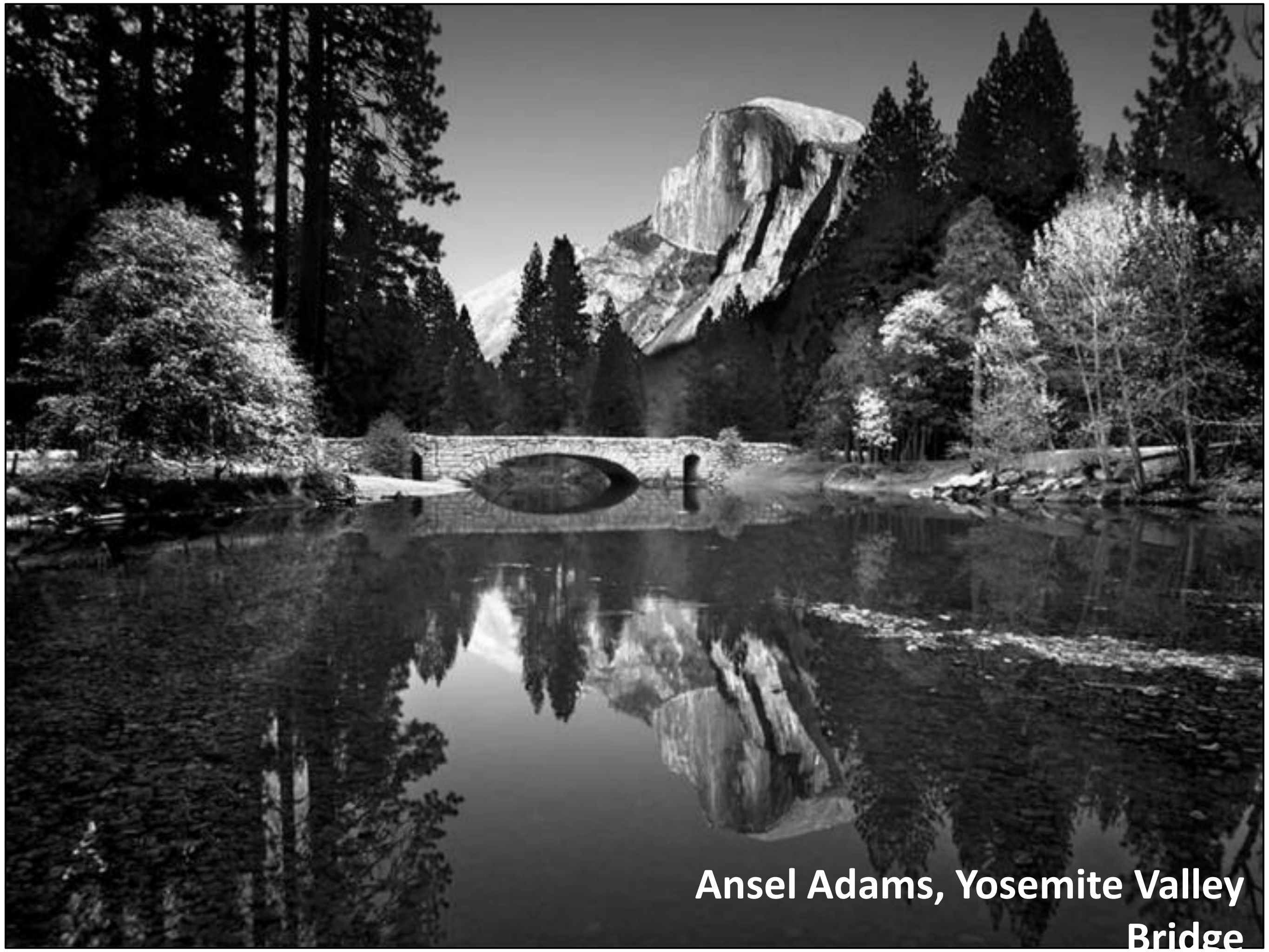


Colorful Image Colorization

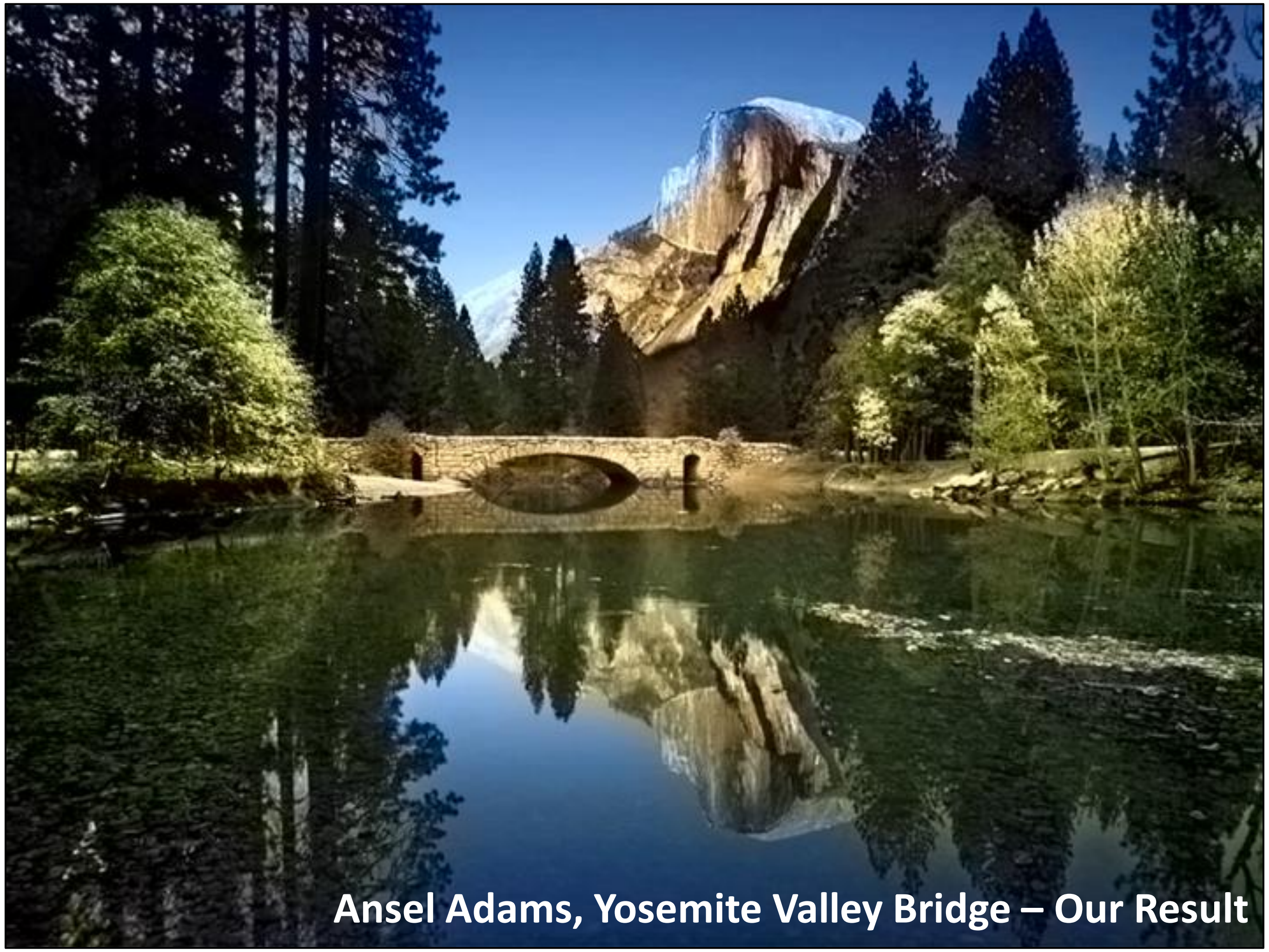
Richard Zhang, Phillip Isola, Alexei (Alyosha) Efros

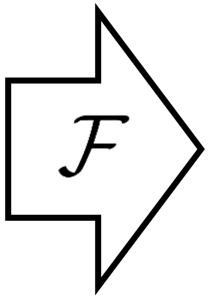
richzhang.github.io/colorization

ECCV 2016



Ansel Adams, Yosemite Valley Bridge


Ansel Adams, Yosemite Valley Bridge – Our Result

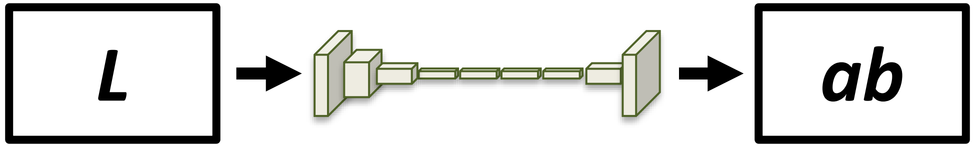


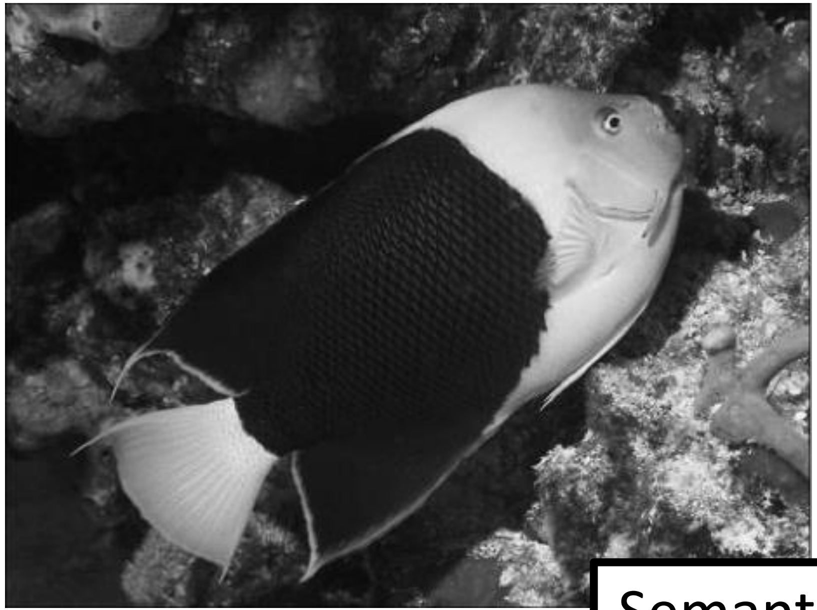
Grayscale image: *L* channel

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

Color information: *ab* channels

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





$\mathcal{F}$

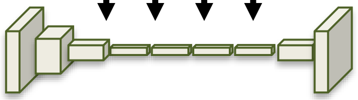
Semantics? Higher-level abstraction?

Grayscale image: *L* ch

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

ncatenate (L,ab)

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

L →  → ***ab*** ← “Free” supervisory signal

Inherent Ambiguity

Grayscale

Inherent Ambiguity

Our Output

Ground Truth

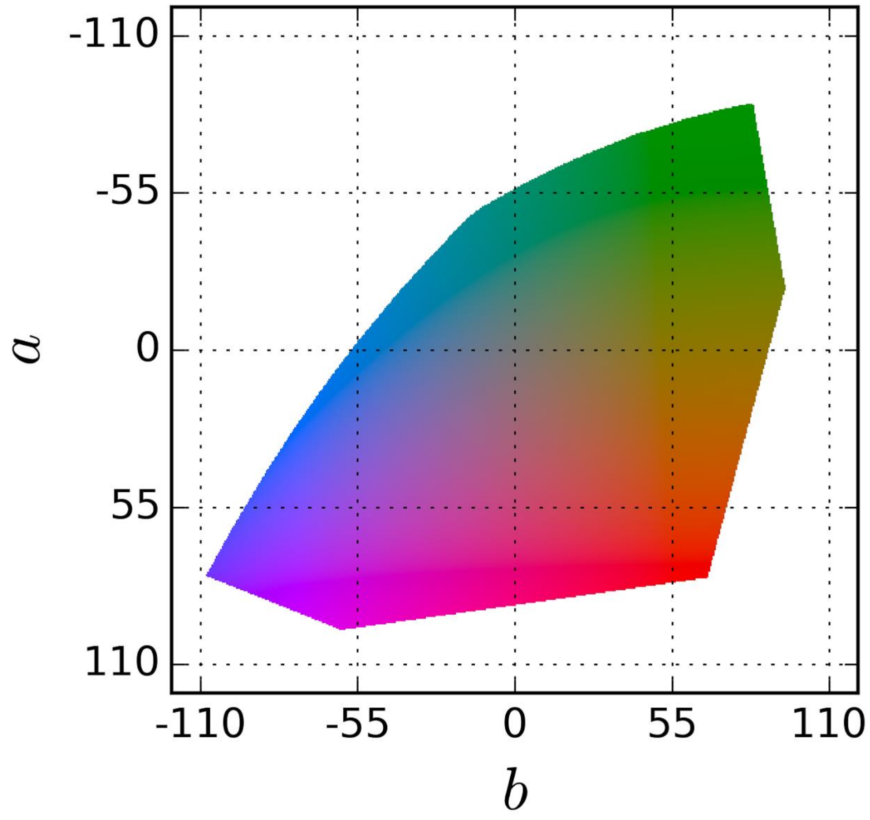
Better Loss Function

- Regression with L2 loss inadequate

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

Colors in *ab* space

(continuous)



Better Loss Function

- Regression with L2 loss inadequate

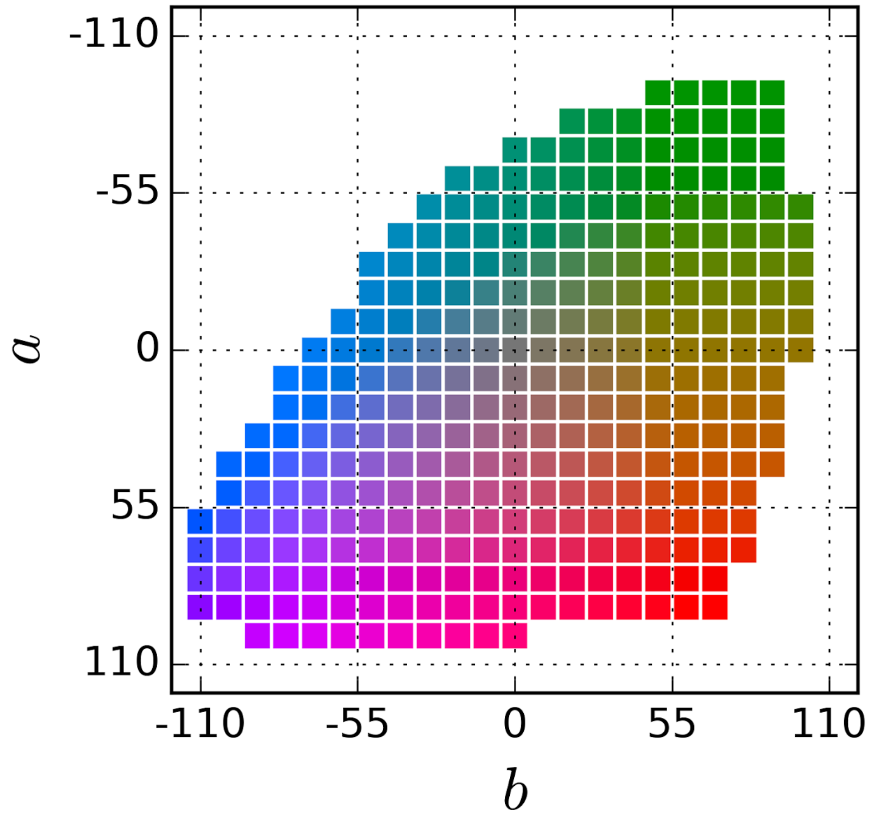
$$\mathrm{L}_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2} \sum_{h,w} \|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$

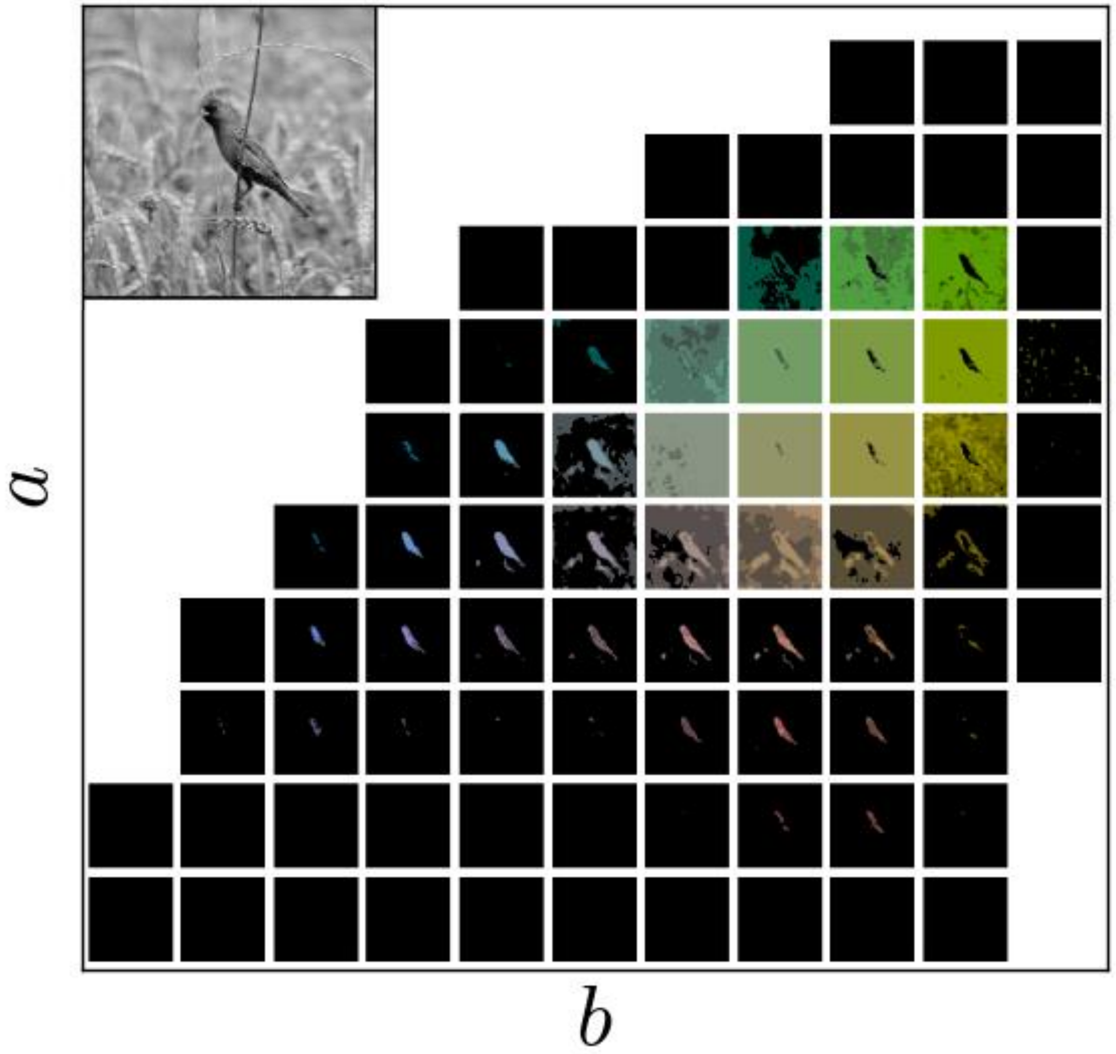
- Use **multinomial classification**

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

Colors in *ab* space

(discrete)




a
b

Better Loss Function

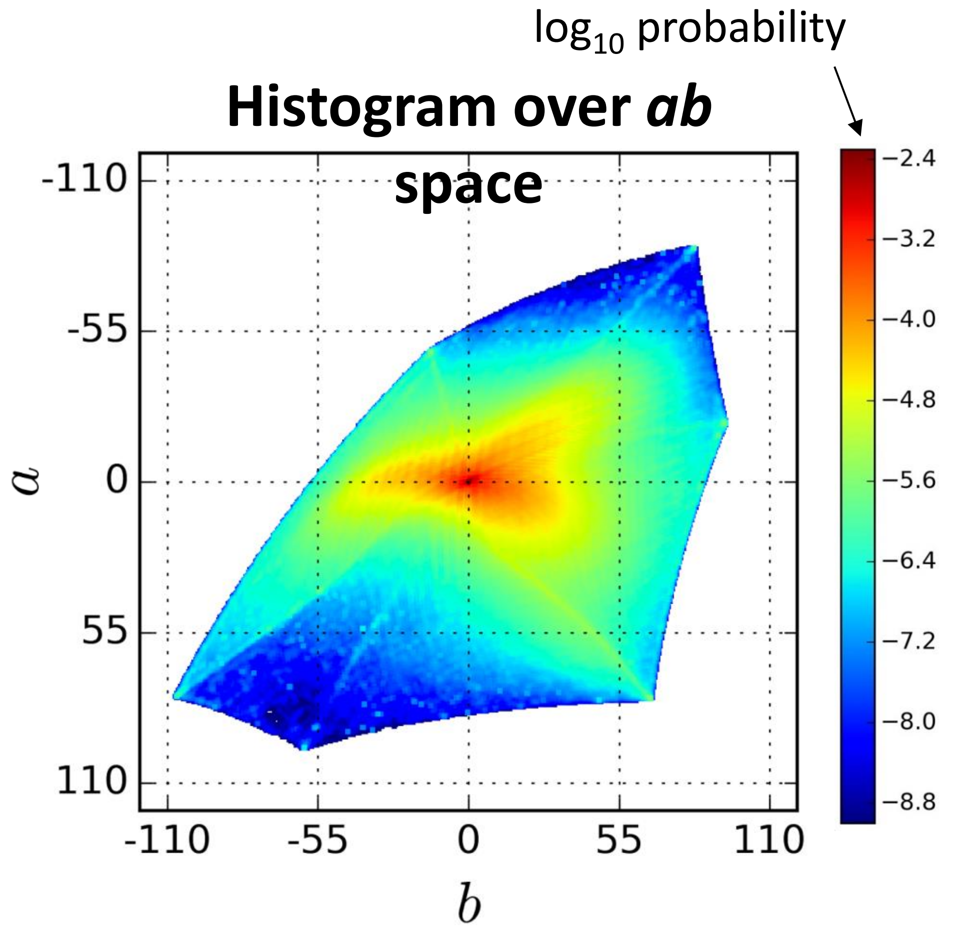
- Regression with L2 loss inadequate

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

- Use **multinomial classification**

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

Histogram over *ab* space



Better Loss Function

- Regression with L2 loss inadequate

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

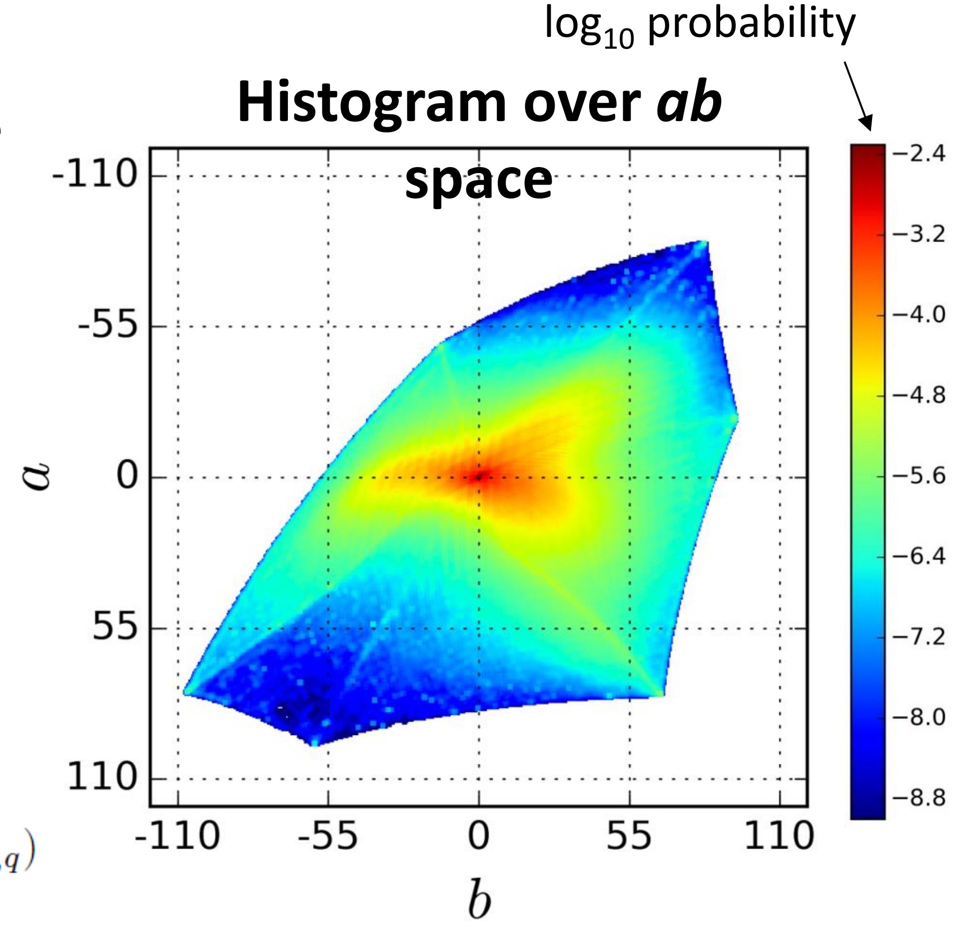
- Use **multinomial classification**

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

- **Class rebalancing** to encourage learning of *rare* colors

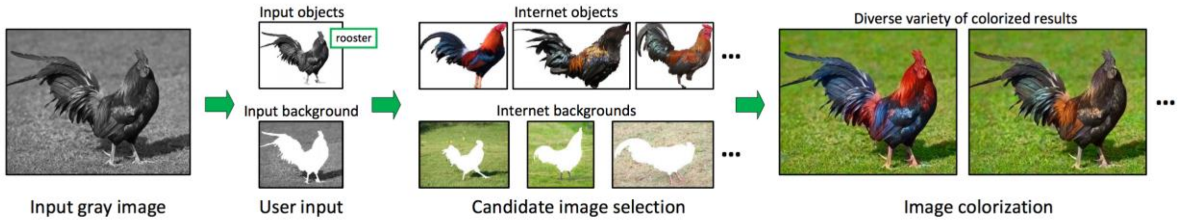
$$\mathrm{L}(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW}\sum_{h,w} v(\mathbf{Z}_{h,w})\sum_{q}\mathbf{Z}_{h,w,q}\log(\widehat{\mathbf{Z}}_{h,w,q})$$

Histogram over *ab* space



Non-parametric

Hertzmann et al. In SIGGRAPH, 2001.
Welsh et al. In TOG, 2002.
Irony et al. In Eurographics, 2005.
Liu et al. In TOG, 2008.
Chia et al. In ACM 2011.
Gupta et al. In ACM, 2012.

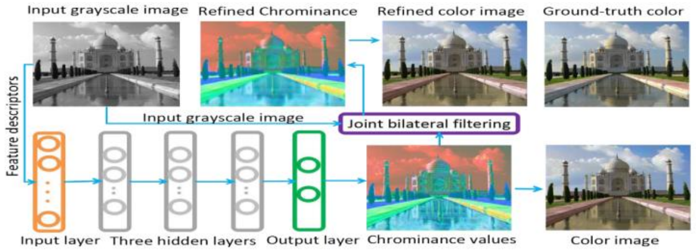


Parametric

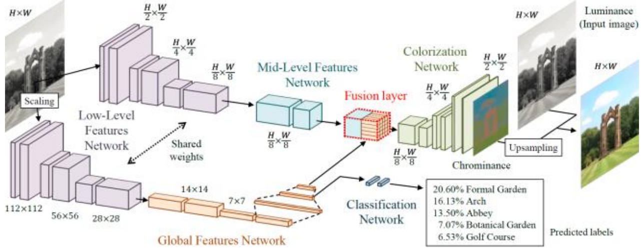
Hand-engineered Features

Deep Networks

L2 Regression

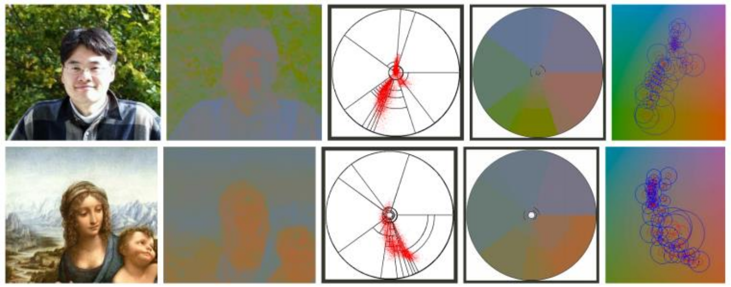


Deshpande et al. Cheng et al. In ICCV 2015.

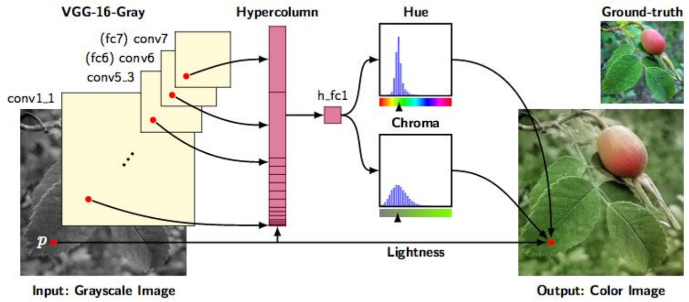


Dahl. Jan 2016. Iizuka et al. In SIGGRAPH, 2016.

Classification

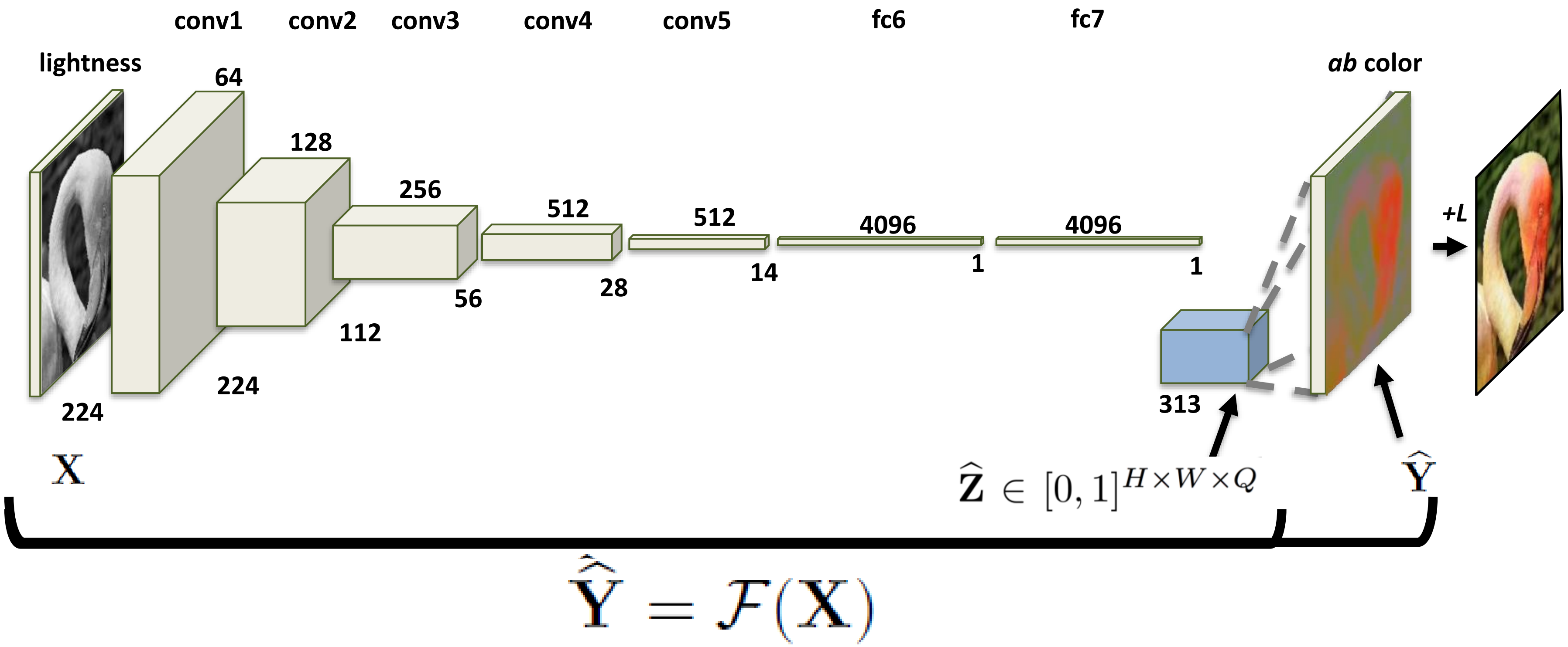


Charpiat et al. In ECCV 2008.

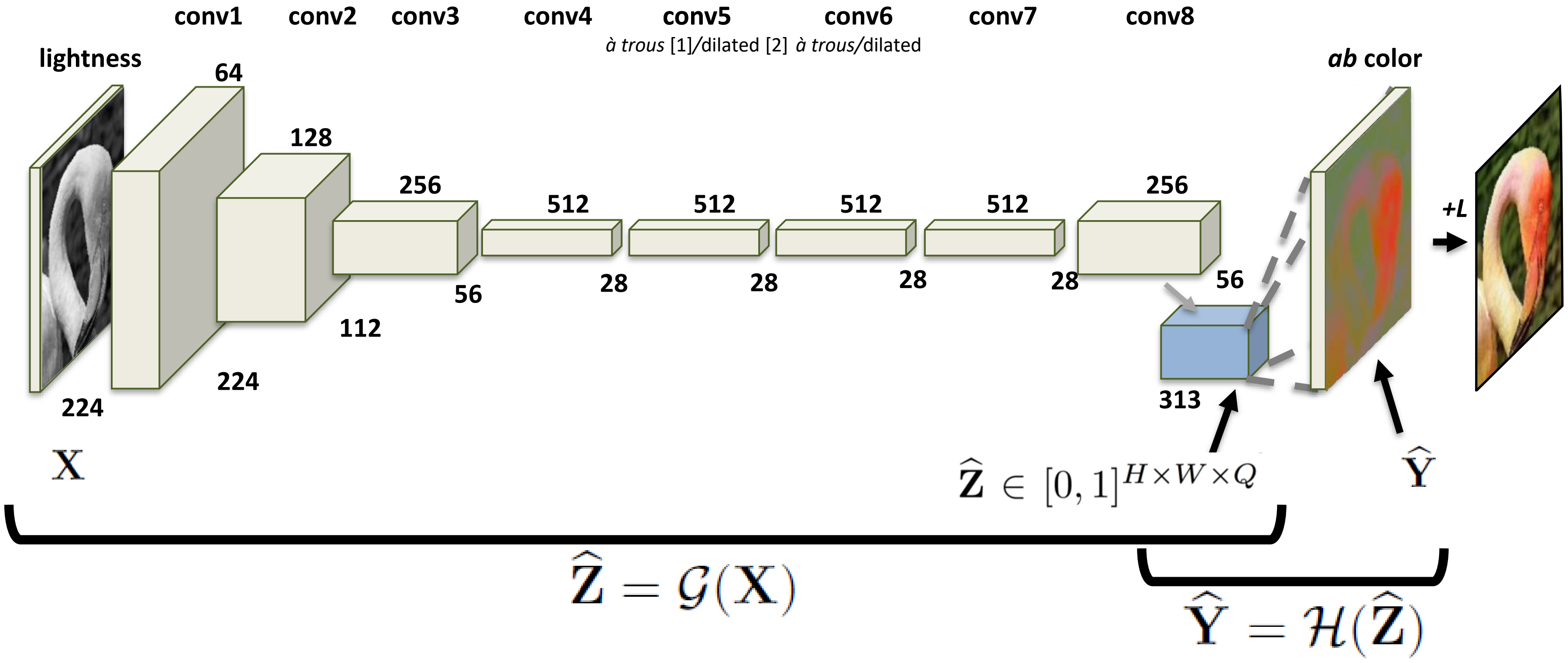


Larsson et al. In ECCV 2016. [Concurrent]

Network Architecture



Network Architecture



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

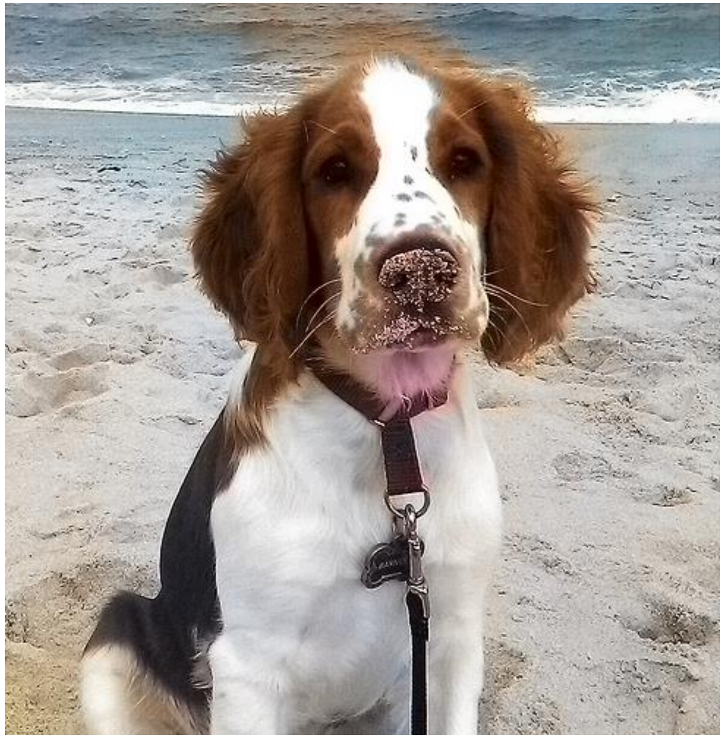
Ground Truth
Input

L2 Regression

Class w/ Rebalancing

Failure Cases

Biases



Evaluation

	Visual Quality
Quantitative	Per-pixel accuracy

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

Fake, 0% fooled


Fake, 55% fooled

Fake, 58% fooled

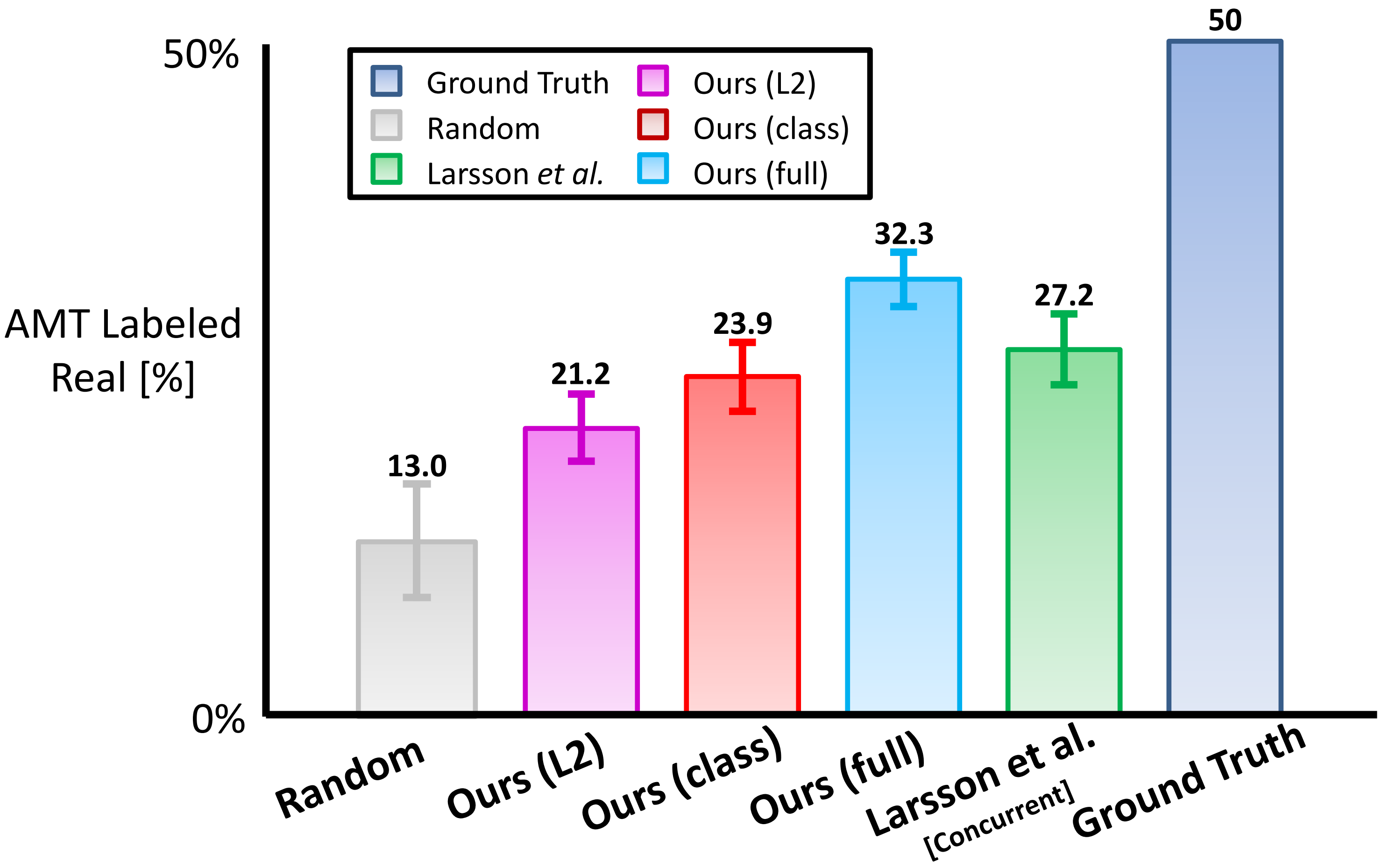
from Reddit /u/SherySantucci

Recolorized by Reddit ColorizeBot

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

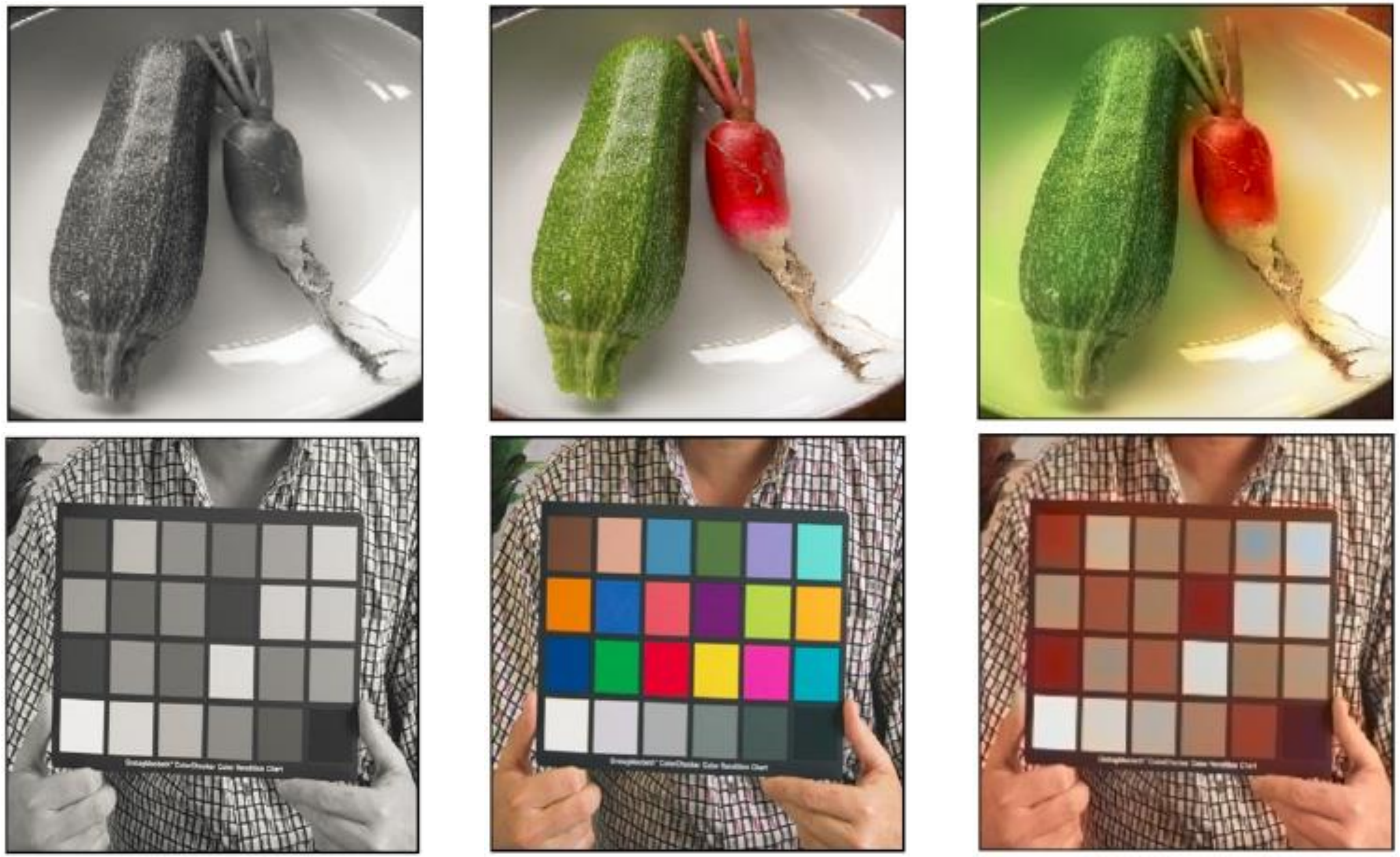
Recolorized by Reddit ColorizeBot

Perceptual Realism Test

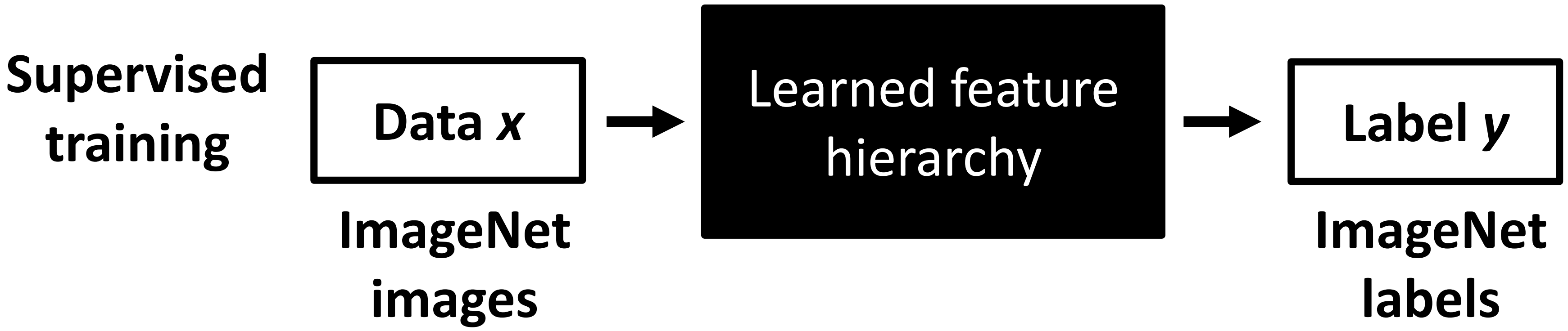


1600 images tested per algorithm

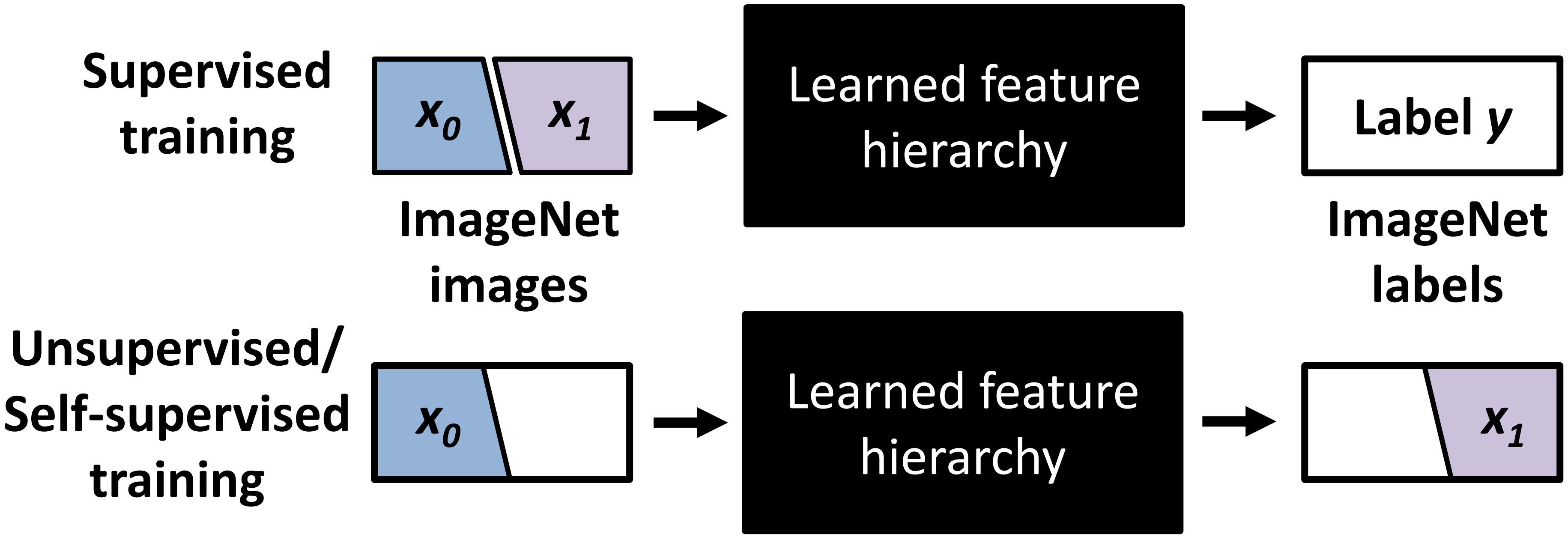
Input **Ground Truth** **Output**

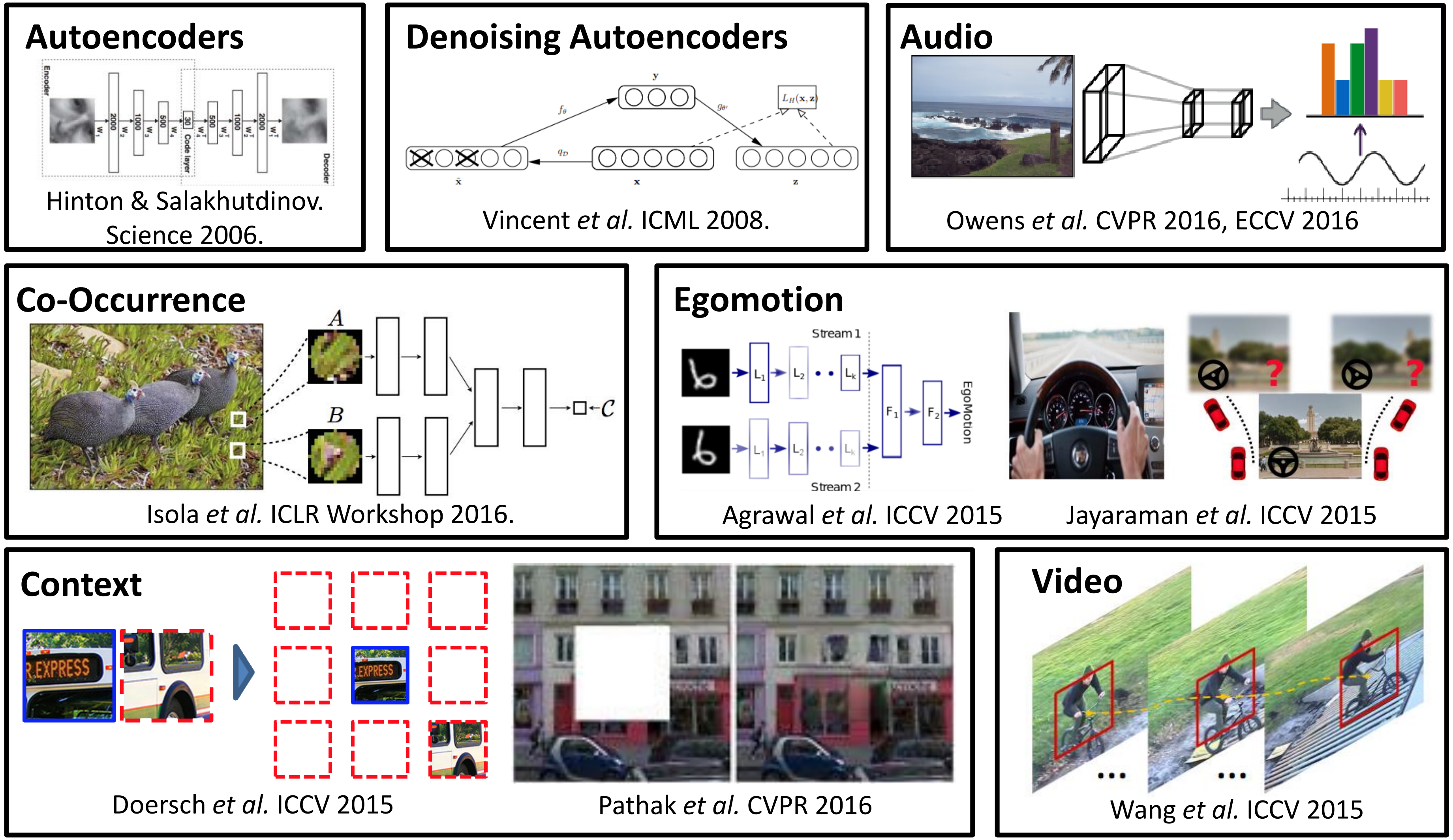


Predicting Labels from Data

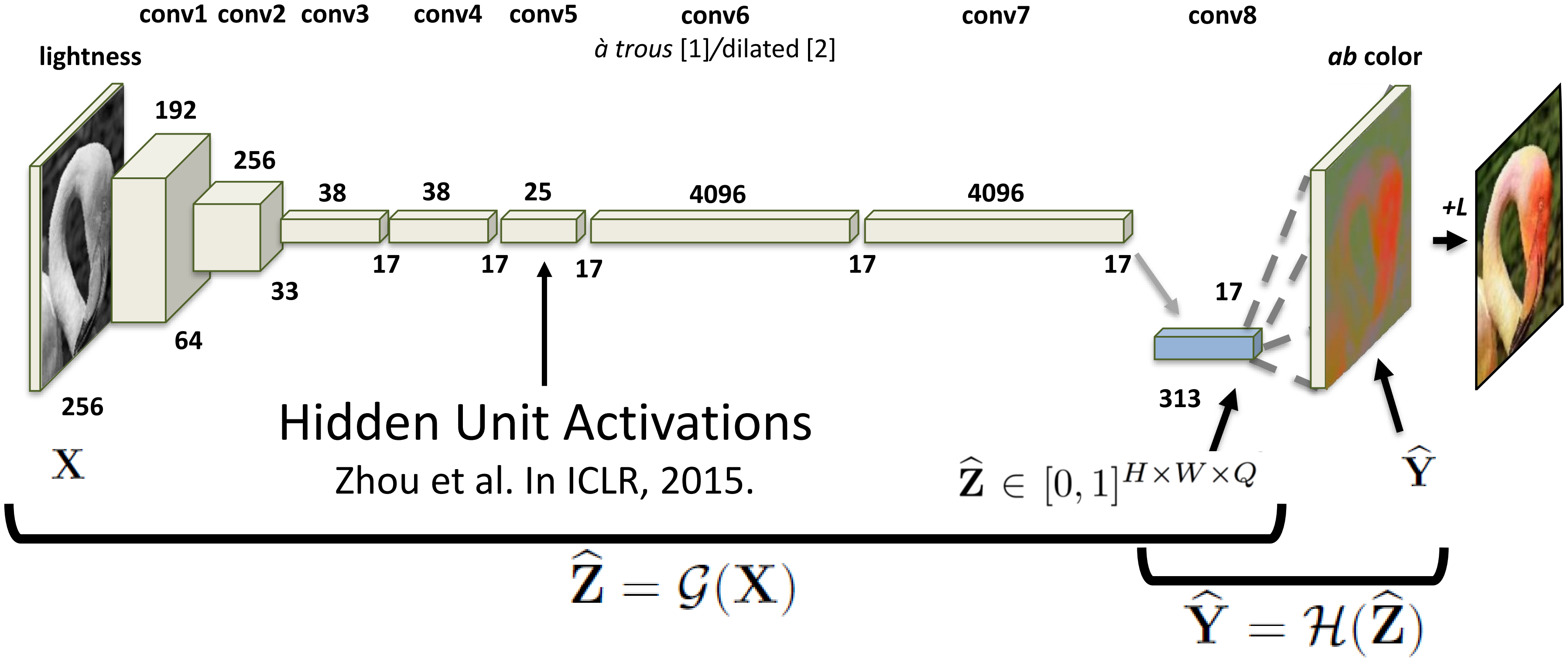


Predicting Data from Data



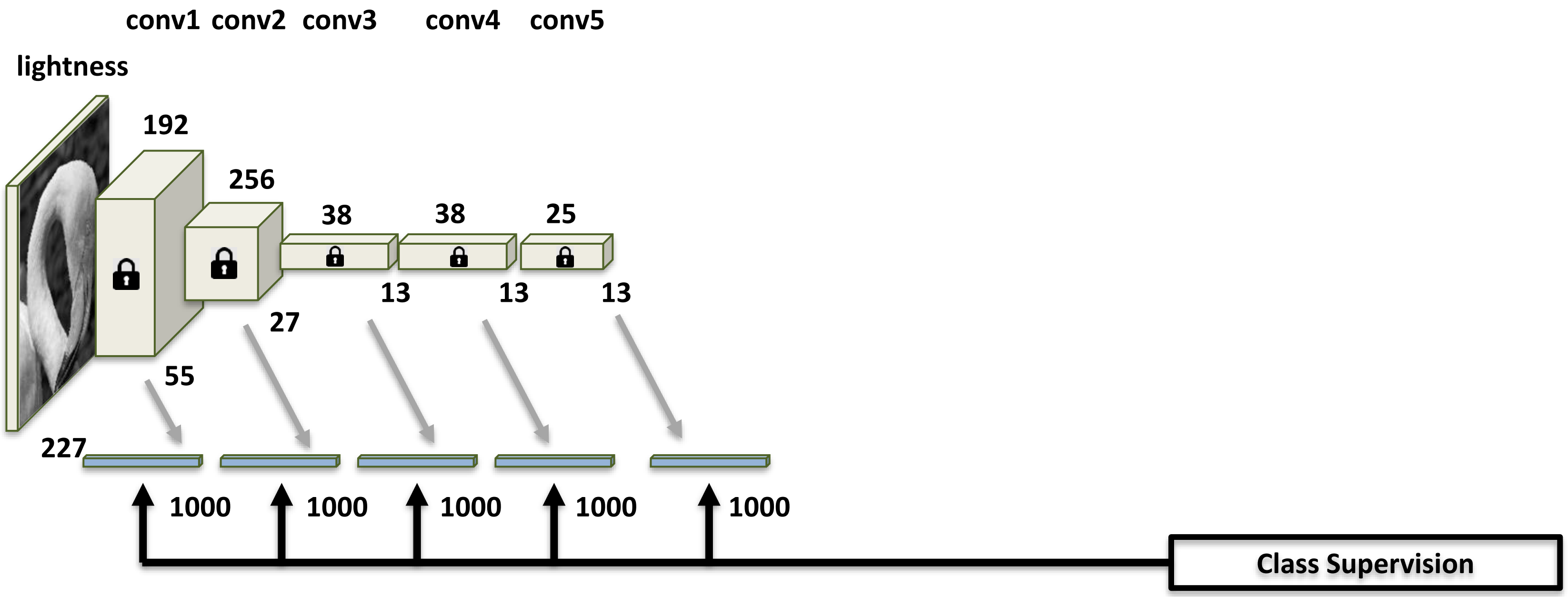

Autoencoders
Hinton & Salakhutdinov. Science 2006.
Denoising Autoencoders
Vincent et al. ICML 2008.
Audio
Owens et al. CVPR 2016, ECCV 2016
Co-Occurrence
A
B
Isola et al. ICLR Workshop 2016.
Egomotion
Stream 1
Stream 2
EgoMotion
Agrawal et al. ICCV 2015
Jayaraman et al. ICCV 2015
Context
Doersch et al. ICCV 2015
Pathak et al. CVPR 2016
Video
Wang et al. ICCV 2015

Cross-Channel Encoder



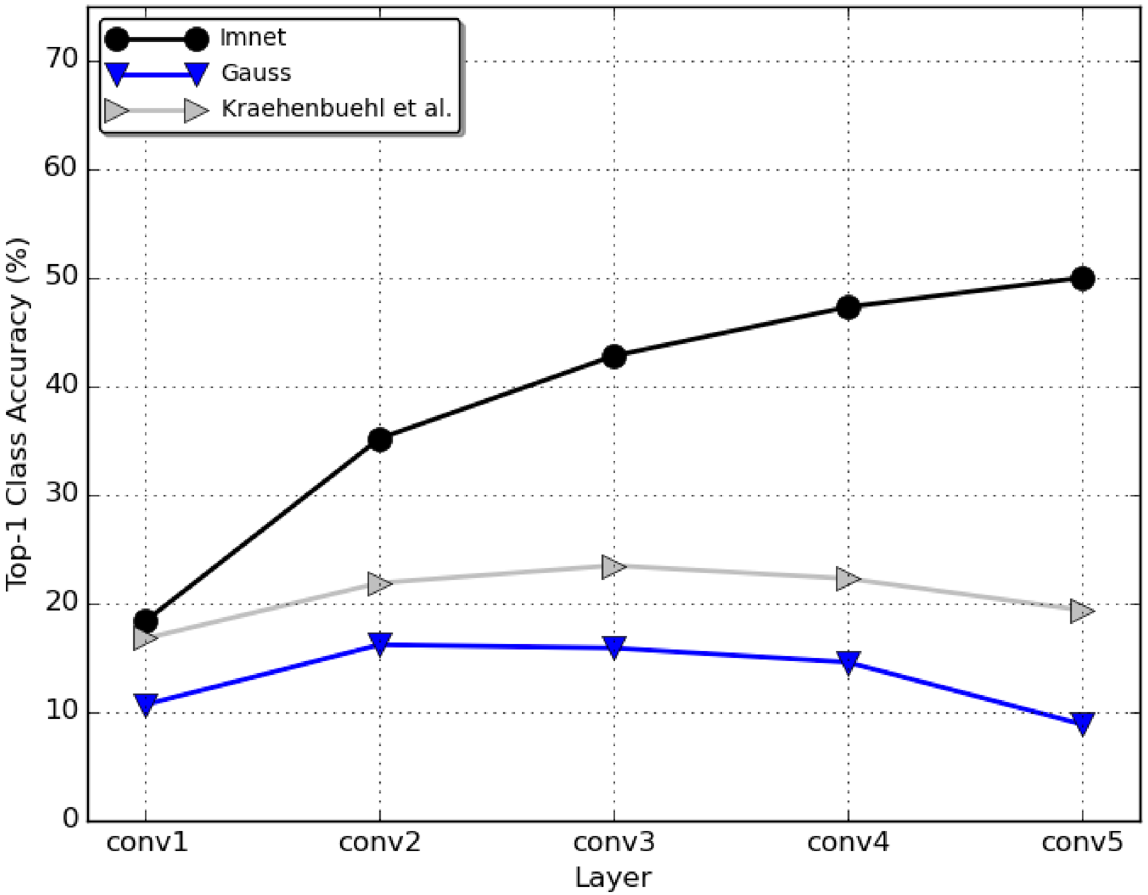
[1] Chen *et al.* In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016

Task Generalization: ILSVRC linear classification

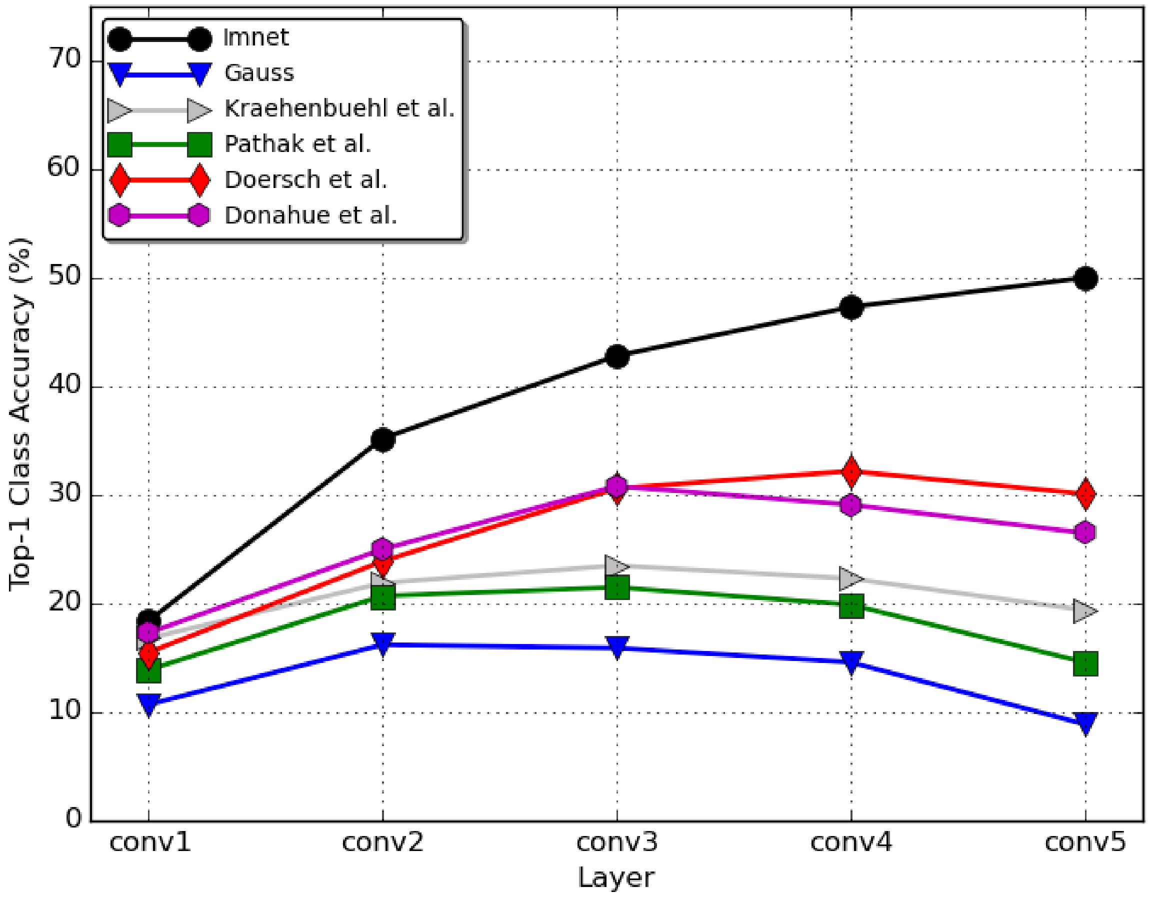


Are semantic classes ***linearly separable***
in the learned feature space?

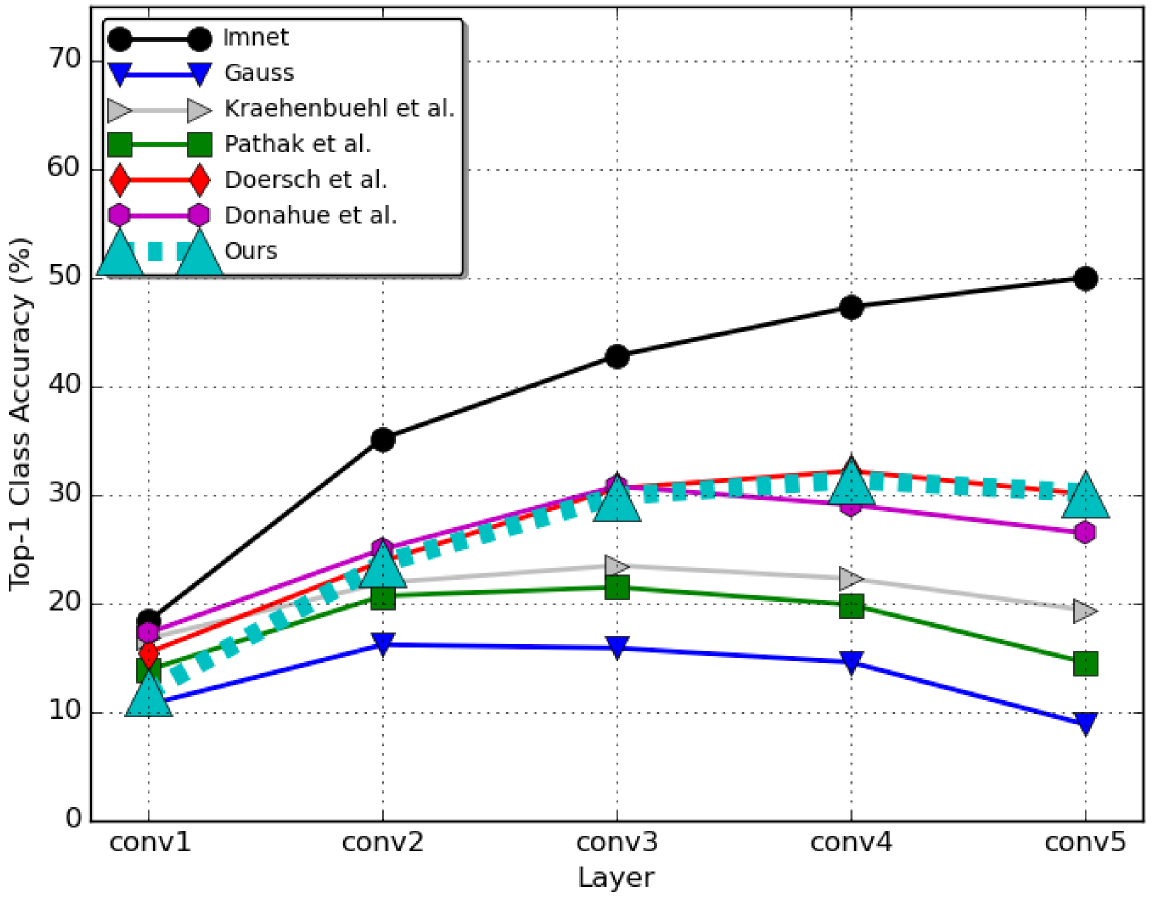
Task Generalization: ILSVRC linear classification



Task Generalization: ILSVRC linear classification



Task Generalization: ILSVRC linear classification

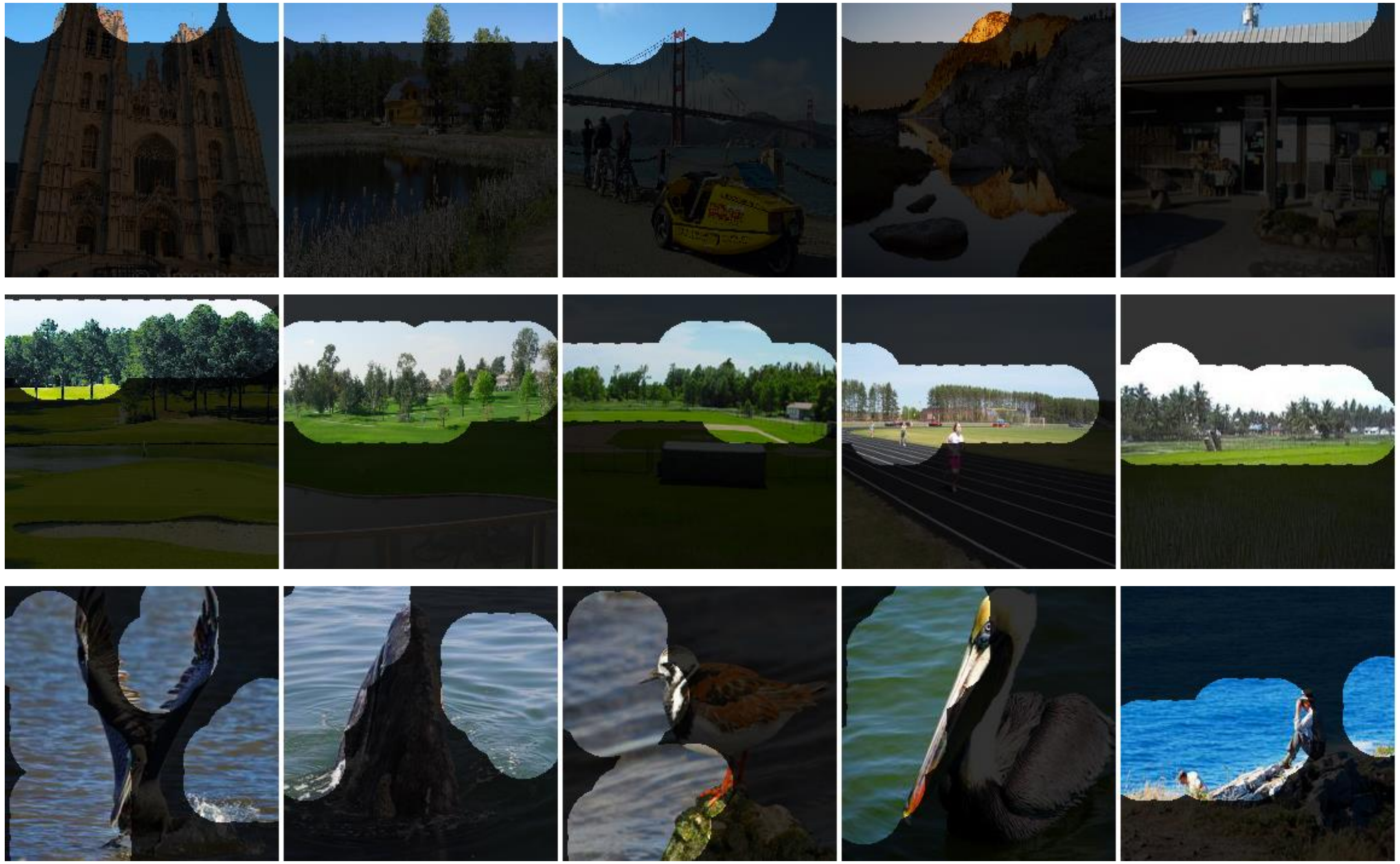


Hidden Unit (conv5) Activations

sky

trees

water

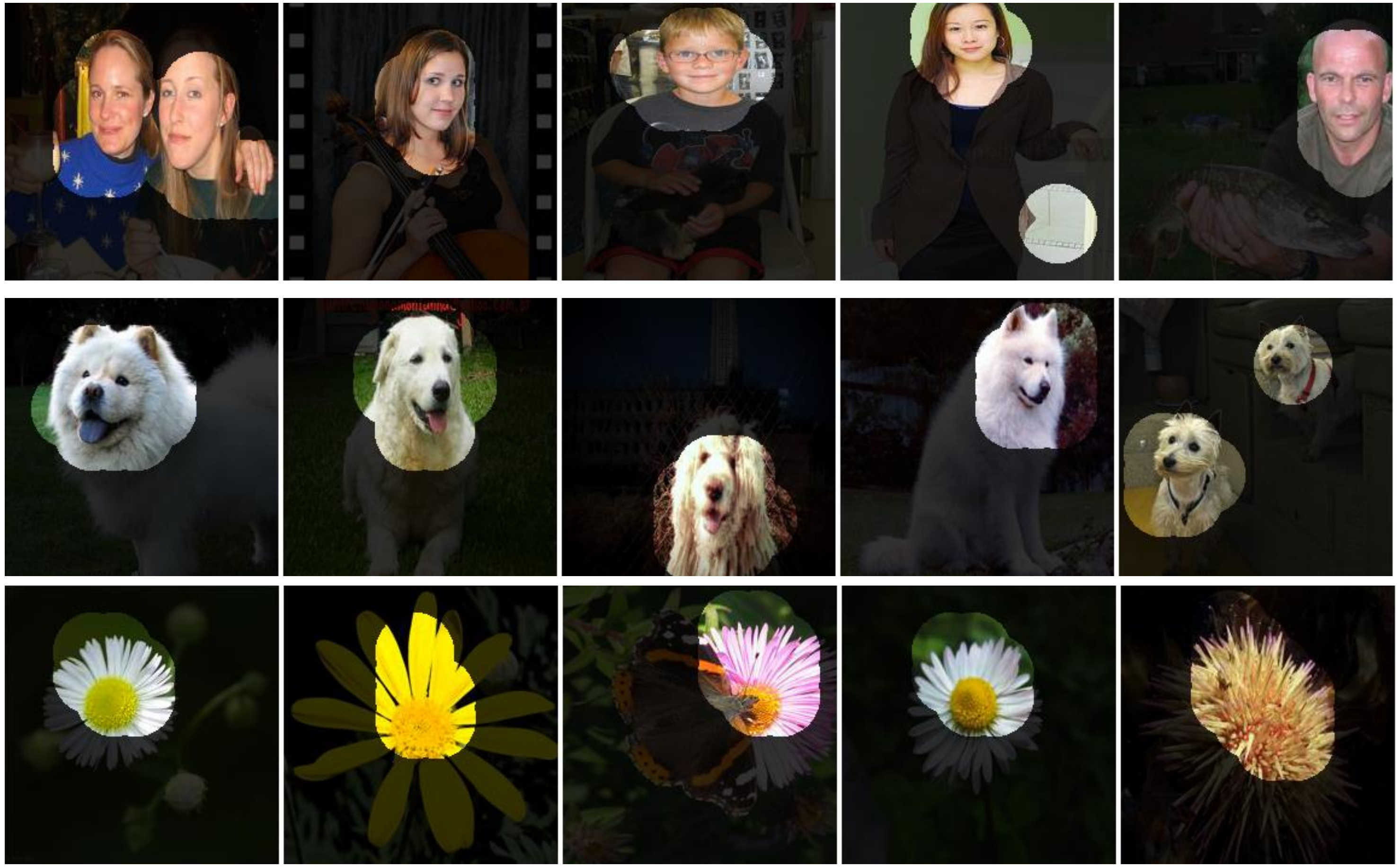


Hidden Unit (conv5) Activations

faces

dog faces

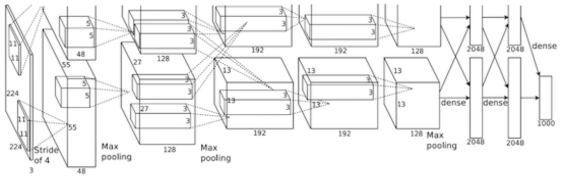
flowers



Dataset & Task Generalization on PASCAL VOC

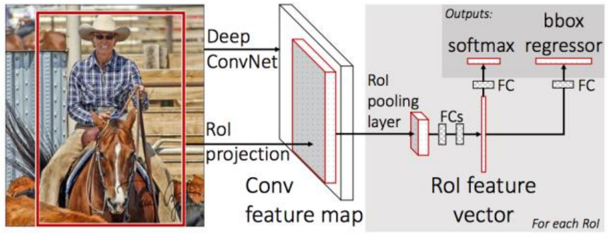
Does the feature representation

transfer to other datasets and tasks?



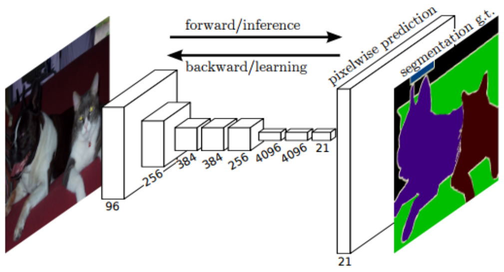
Classification

Krähenbühl et al. In ICLR, 2016.



Detection

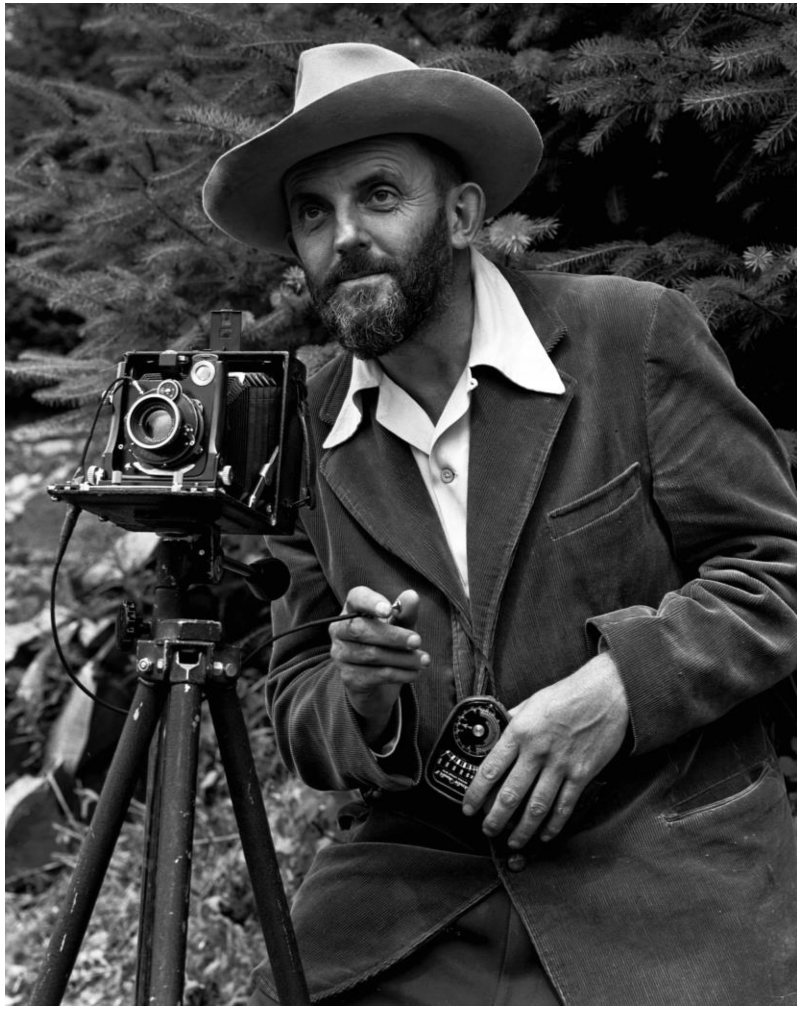
Fast R-CNN. Girshick. In ICCV, 2015.

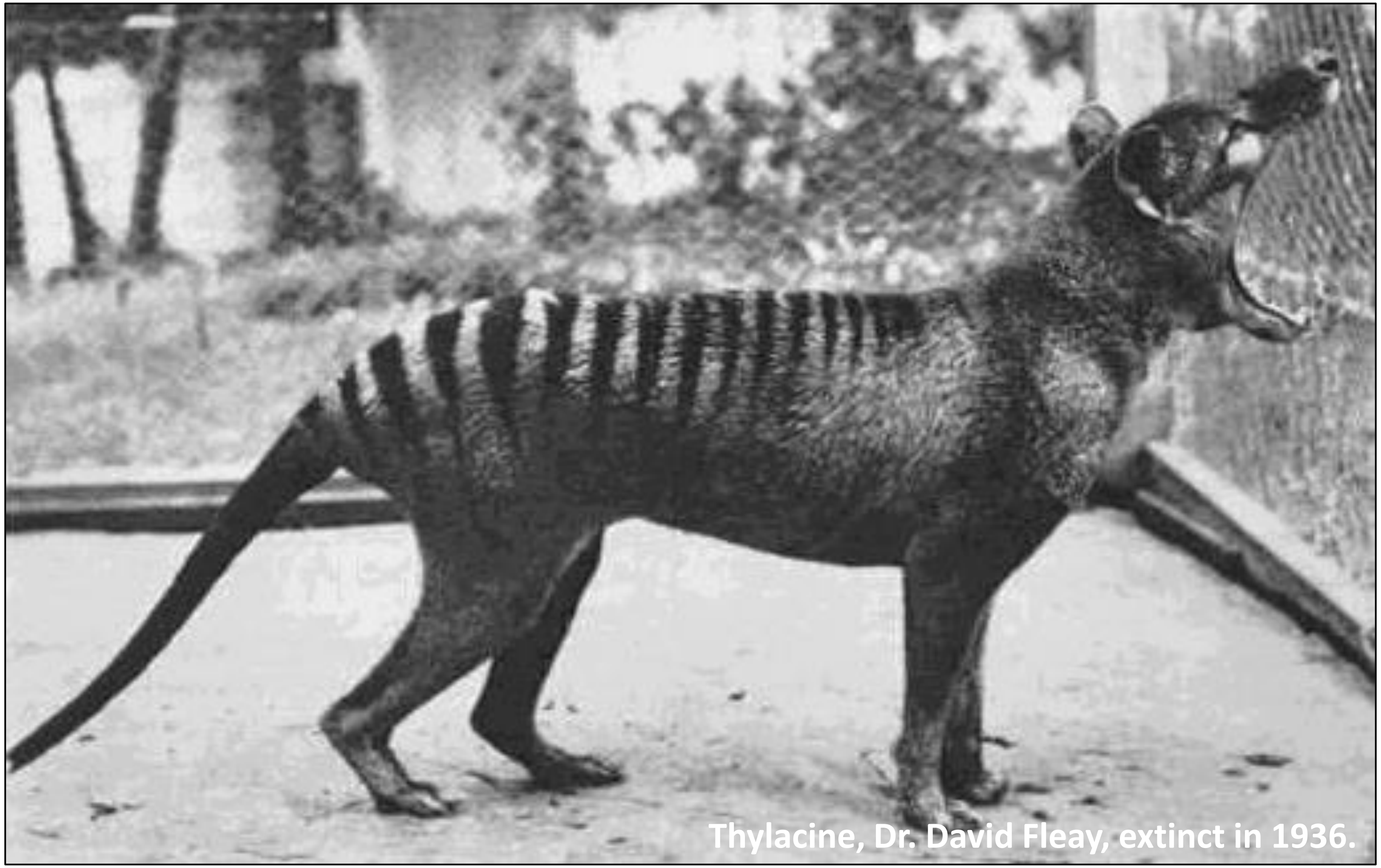


Segmentation

FCNs. Long et al. In CVPR, 2015.

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



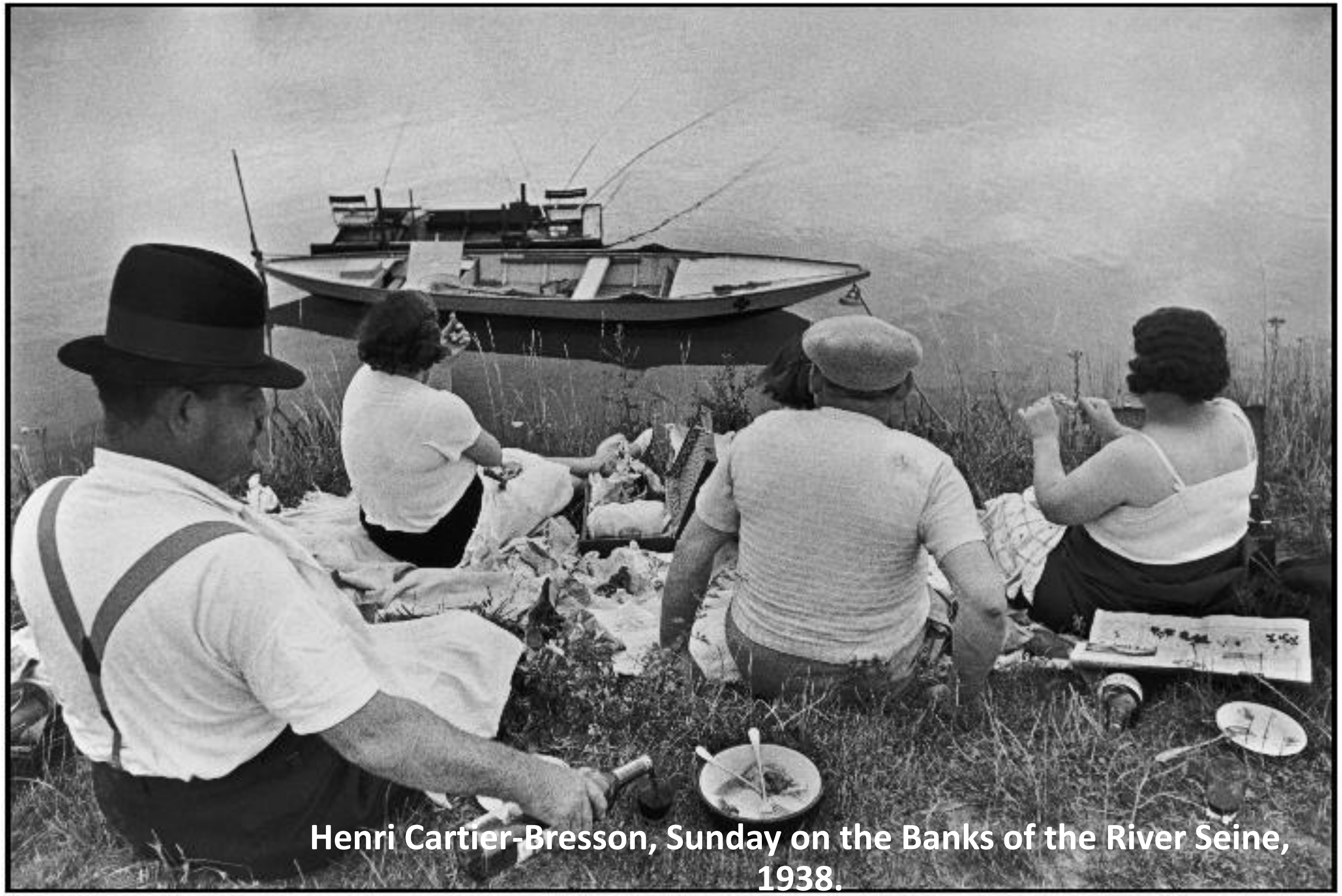


Thylacine, Dr. David Fleay, extinct in 1936.

Thylacine, Dr. David Fleay, extinct in 1936.

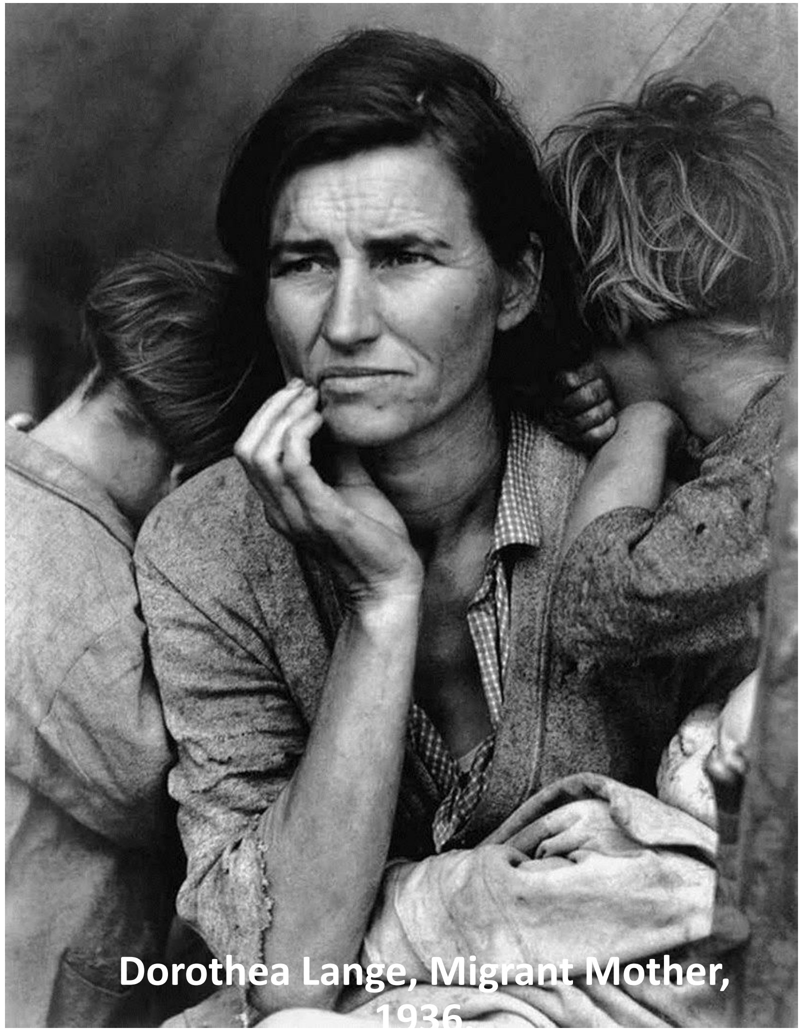
Amateur Family Photo, 1956

Amateur Family Photo, 1956

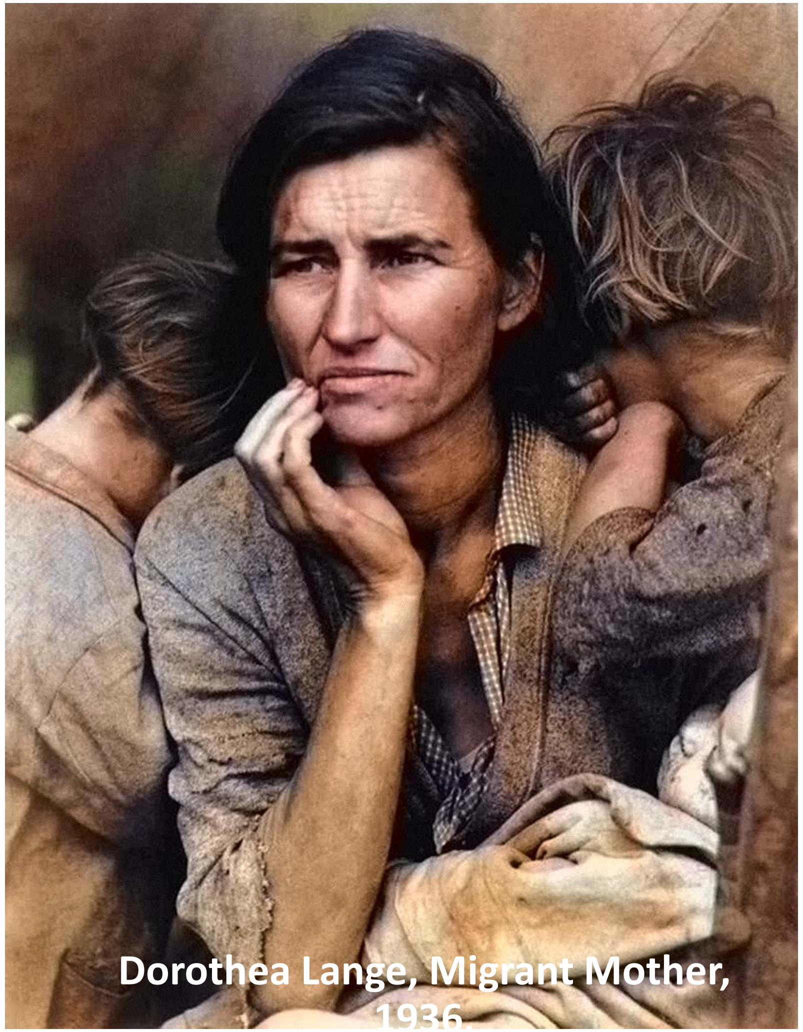


Henri Cartier-Bresson, Sunday on the Banks of the River Seine, 1938.

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



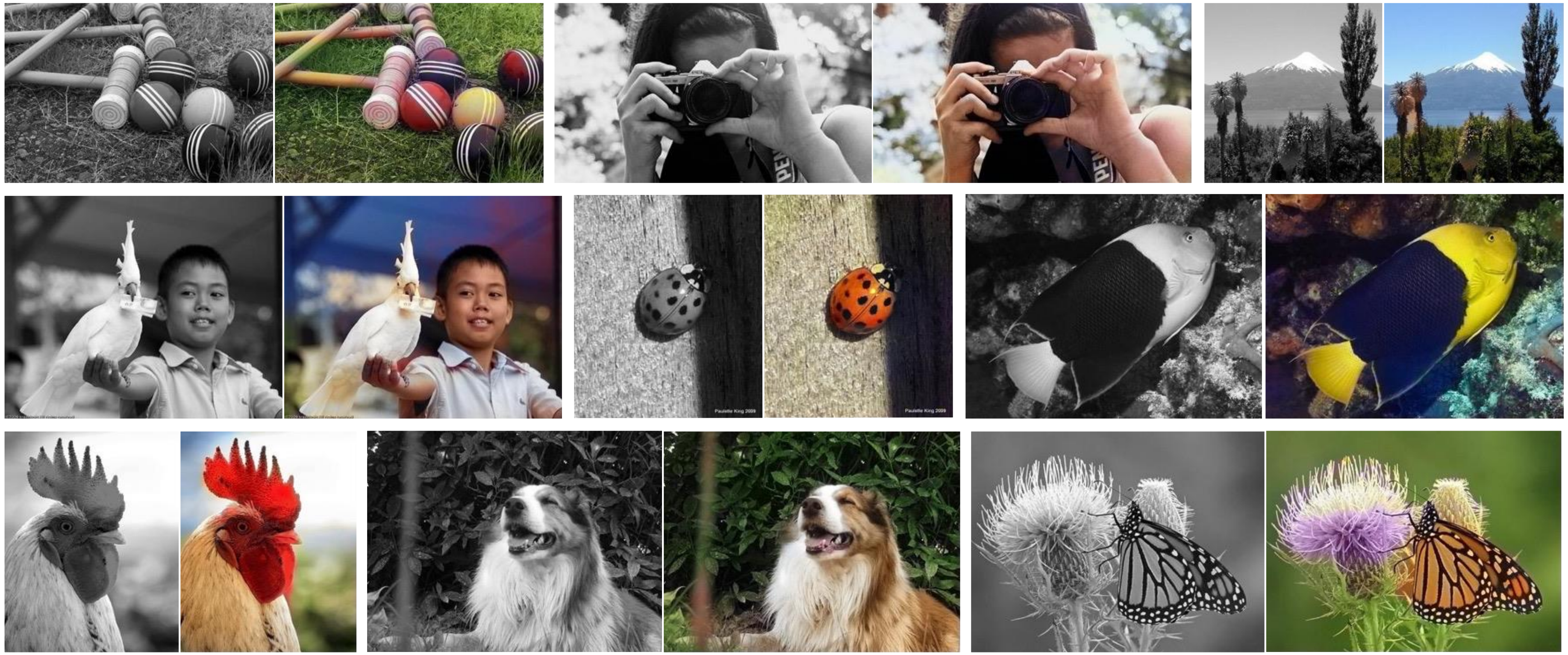
Dorothea Lange, Migrant Mother, 1936



Dorothea Lange, Migrant Mother, 1936.

Additional Information

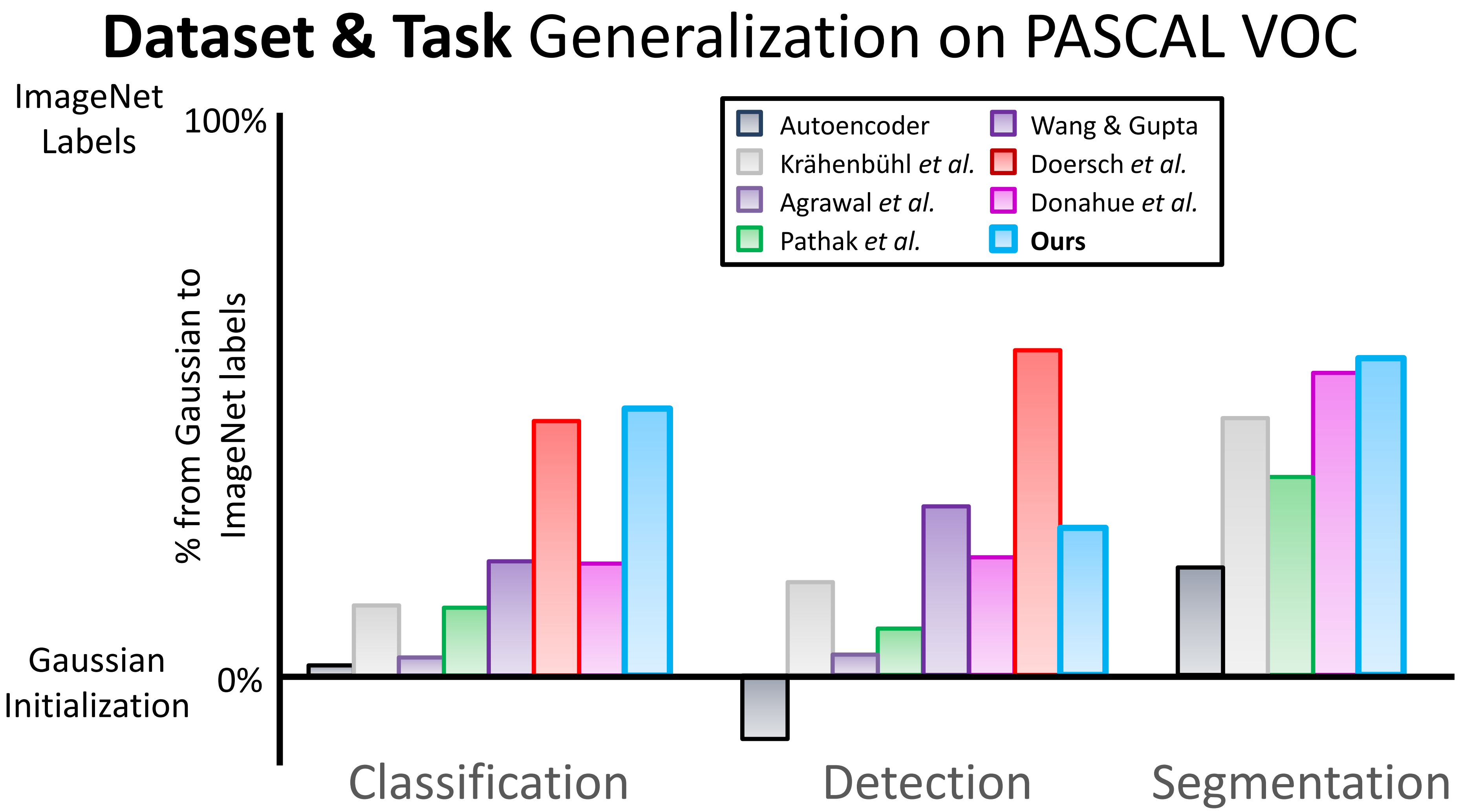
- Demo
  - http://demos.algorithmia.com/colorize-photos/
- Reddit ColorizeBot
  - Type “colorizebot” under any image post
- Code
  - https://github.com/richzhang/colorization
- Website – full paper, user examples, visualizations
  - http://richzhang.github.io/colorization



For the full paper, additional examples and our model:
richzhang.github.io/colorization

The Gelato Bet, Resolved

"If, by the first day of autumn (Sept 23) of 2015, a method will exist that can match or beat the performance of R-CNN on Pascal VOC detection, without the use of any extra, human annotations (e.g. ImageNet) as pre-training, Mr. Malik promises to buy Mr. Efros one (1) gelato"



Dataset & Task Generalization on PASCAL VOC
ImageNet Labels
100%
% from Gaussian to ImageNet labels
Gaussian Initialization
0%
Autoencoder
Krähenbühl *et al.*
Agrawal *et al.*
Pathak *et al.*
Wang & Gupta
Doersch *et al.*
Donahue *et al.*
Ours
Classification
Detection
Segmentation

A Simple Framework for Contrastive Learning of Visual Representations

Ting Chen [1] Simon Kornblith [1] Mohammad Norouzi [1] Geoffrey Hinton [1]

SimCLR, IMCL 2020

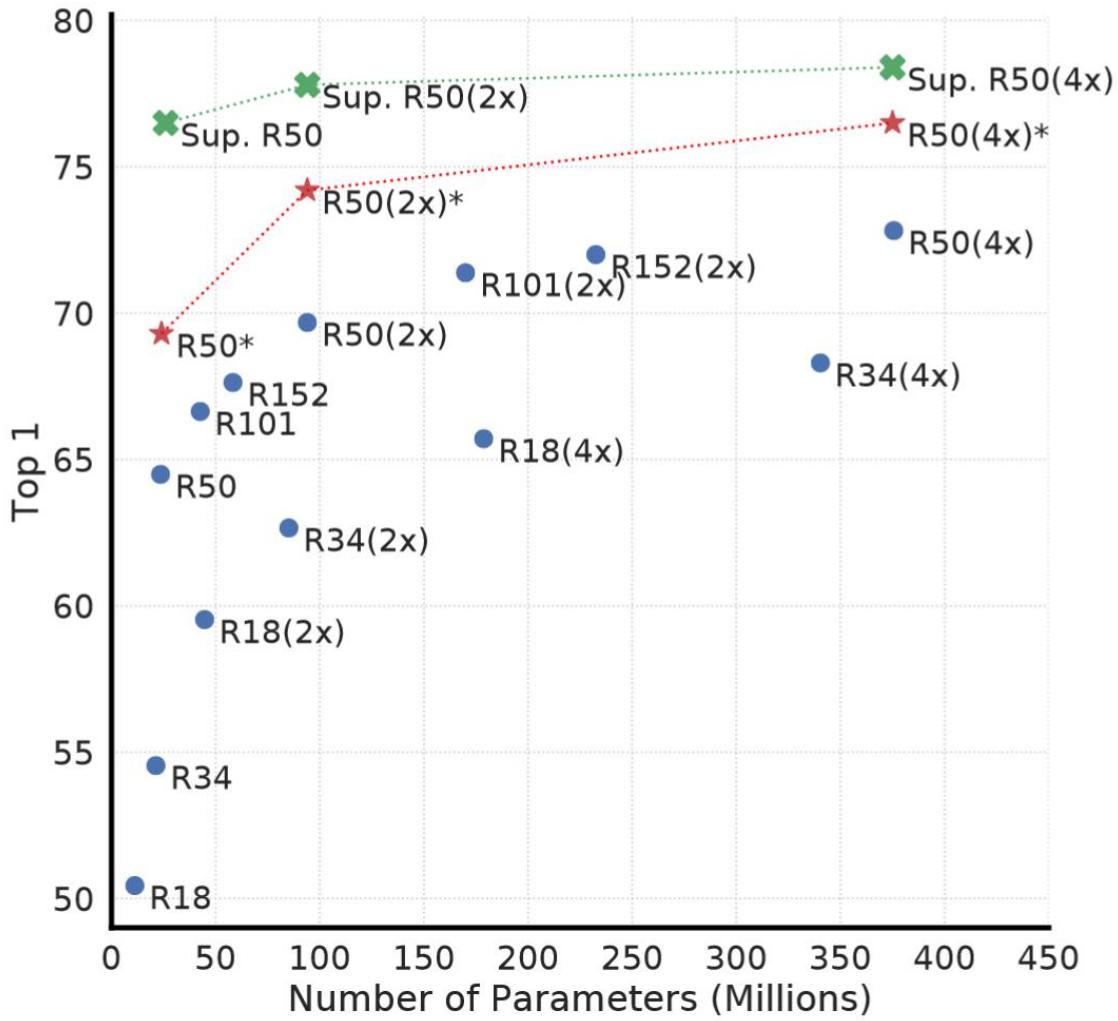
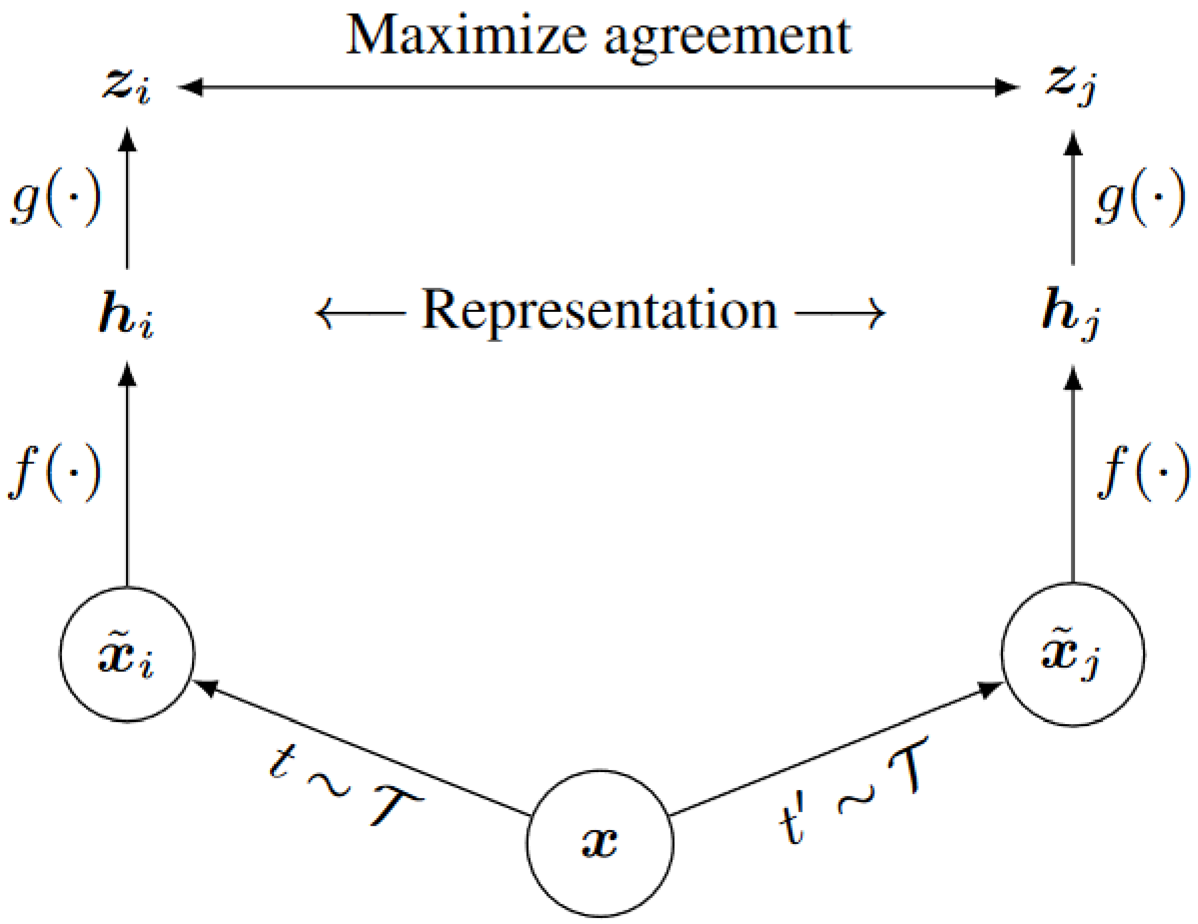


Figure 7. Linear evaluation of models with varied depth and width. Models in blue dots are ours trained for 100 epochs, models in red stars are ours trained for 1000 epochs, and models in green crosses are supervised ResNets trained for 90 epochs[7] (He et al., 2016).


Maximize agreement
$\boldsymbol{z}_i$
$\boldsymbol{z}_j$
$g(\cdot)$
$g(\cdot)$
$\boldsymbol{h}_i$
$\longleftarrow$ Representation $\longrightarrow$
$\boldsymbol{h}_j$
$f(\cdot)$
$f(\cdot)$
$\tilde{\boldsymbol{x}}_i$
$\tilde{\boldsymbol{x}}_j$
$t \sim \mathcal{T}$
$t' \sim \mathcal{T}$
$\boldsymbol{x}$

(a) Original

(b) Crop and resize

(c) Crop, resize (and flip)

(d) Color distort. (drop)

(e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$

(g) Cutout

(h) Gaussian noise

(i) Gaussian blur

(j) Sobel filtering

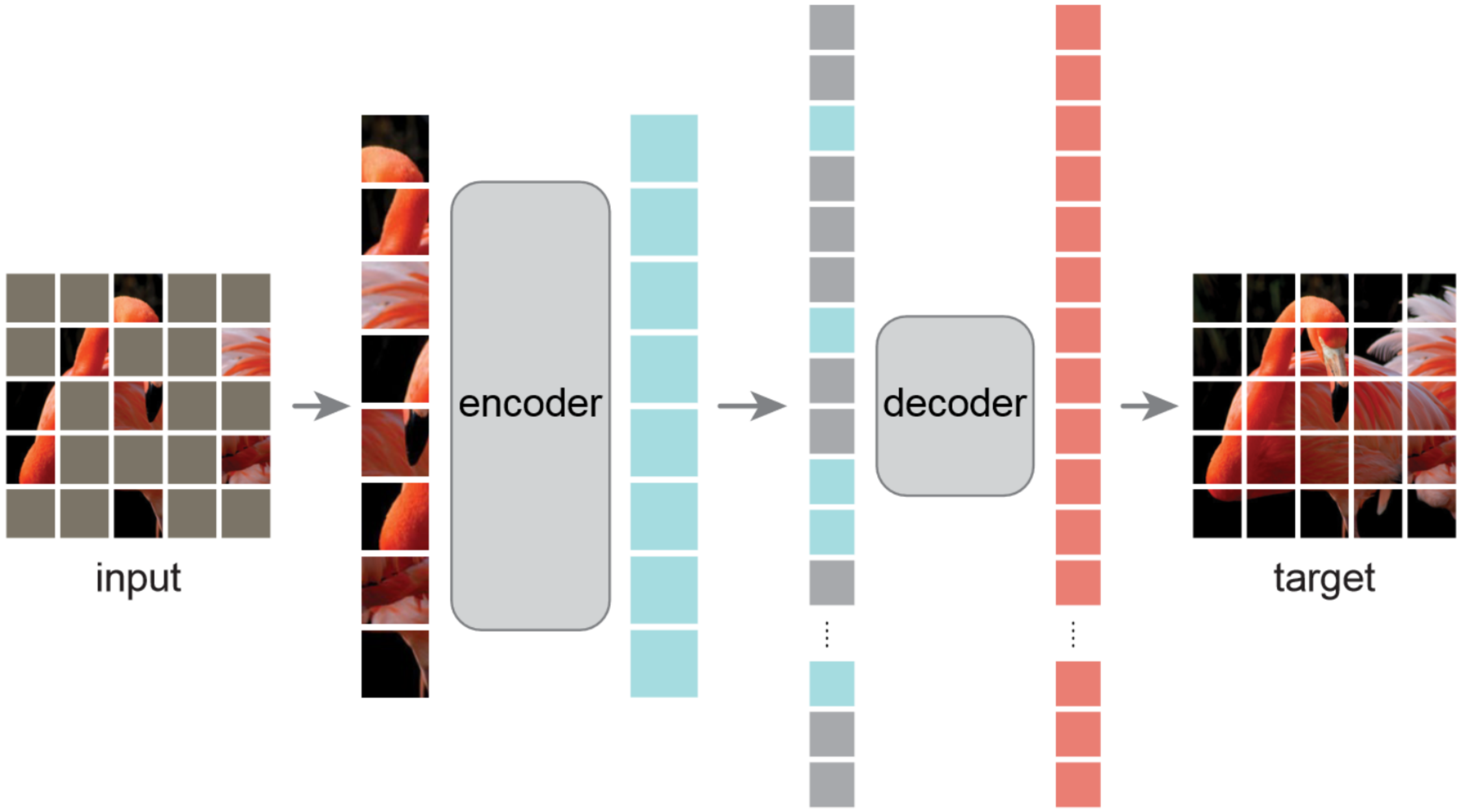
Masked Autoencoders Are Scalable Vision Learners

Kaiming He*,† Xinlei Chen* Saining Xie Yanghao Li Piotr Dollár Ross Girshick

*equal technical contribution †project lead

Facebook AI Research (FAIR)

CVPR 2022



input
encoder
decoder
target

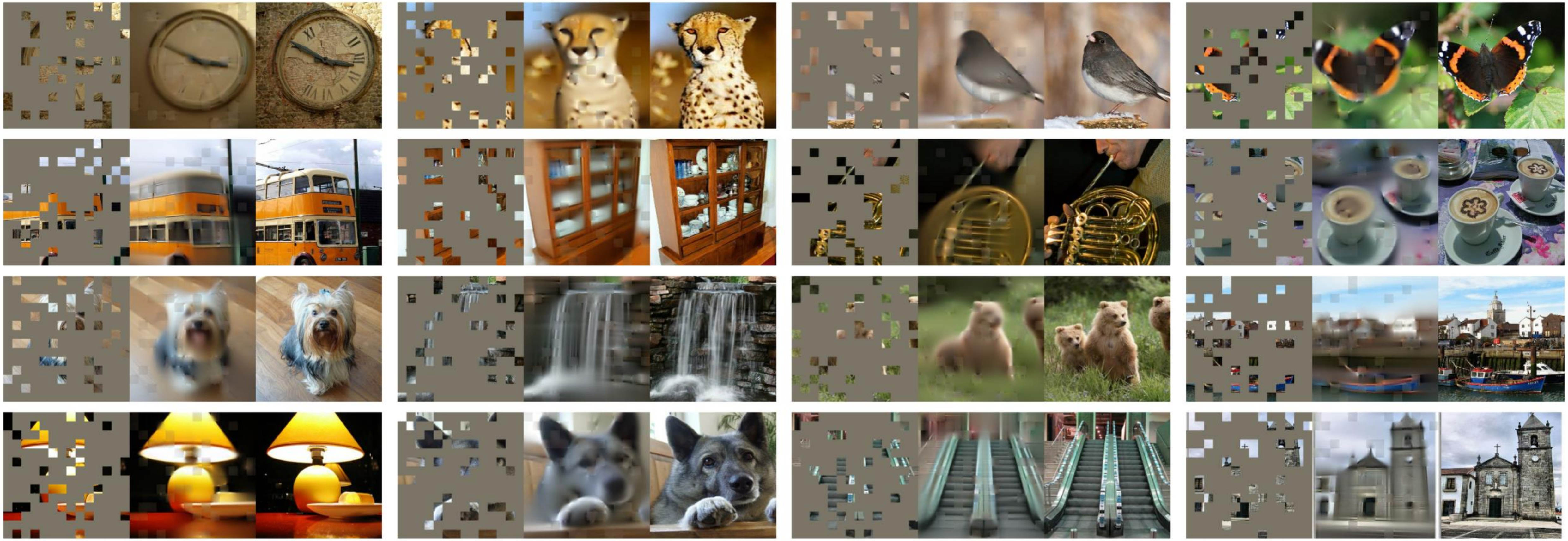
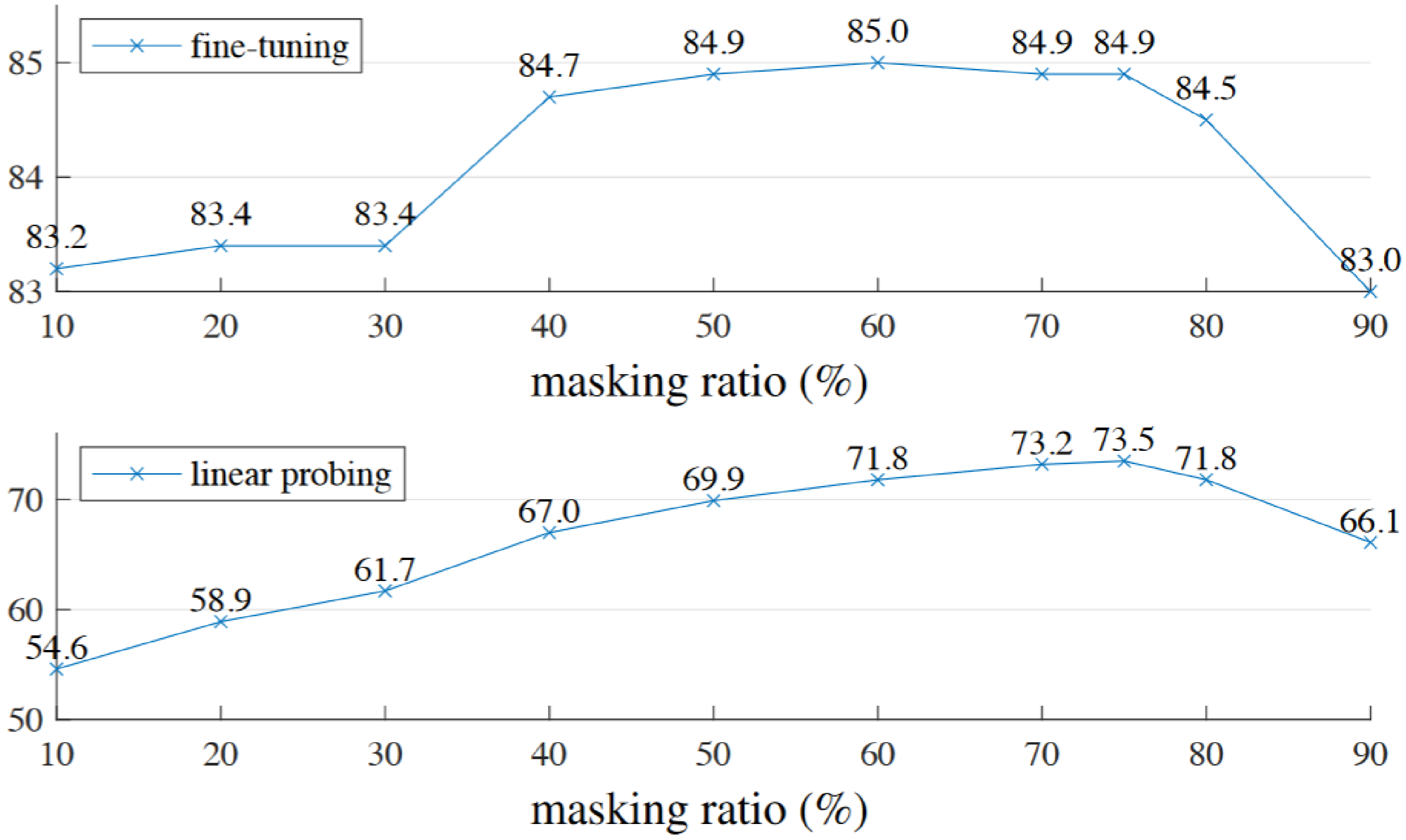


Figure 2. Example results on ImageNet *validation* images. For each triplet, we show the masked image (left), our MAE reconstruction† (middle), and the ground-truth (right). The masking ratio is 80%, leaving only 39 out of 196 patches. More examples are in the appendix.
†*As no loss is computed on visible patches, the model output on visible patches is qualitatively worse. One can simply overlay the output with the visible patches to improve visual quality. We intentionally opt not to do this, so we can more comprehensively demonstrate the method's behavior.*

Figure 3. Example results on COCO validation images, using an MAE trained on ImageNet (the same model weights as in Figure 2). Observe the reconstructions on the two right-most examples, which, although different from the ground truth, are semantically plausible.

Figure 4. Reconstructions of ImageNet *validation* images using an MAE pre-trained with a masking ratio of 75% but applied on inputs with higher masking ratios. The predictions differ plausibly from the original images, showing that the method can generalize.


fine-tuning
85
84
83
83.2
83.4
83.4
84.7
84.9
85.0
84.9
84.9
84.5
83.0
10
20
30
40
50
60
70
80
90
masking ratio (%)
linear probing
70
60
50
54.6
58.9
61.7
67.0
69.9
71.8
73.2
73.5
71.8
66.1
10
20
30
40
50
60
70
80
90
masking ratio (%)

method	pre-train data	AP^{box} ViT-B	AP^{box} ViT-L	AP^{mask} ViT-B	AP^{mask} ViT-L
supervised	IN1K w/ labels	47.9	49.3	42.9	43.9
MoCo v3	IN1K	47.9	49.3	42.7	44.0
BEiT	IN1K+DALLE	49.8	**53.3**	44.4	47.1
MAE	IN1K	**50.3**	**53.3**	**44.9**	**47.2**

Table 4. **COCO object detection and segmentation** using a ViT Mask R-CNN baseline. All entries are based on our implementation. Self-supervised entries use IN1K data *without* labels. Mask AP follows a similar trend as box AP.

Conclusion

- With the right “pretext” tasks and architectures, we are pretty close to matching supervised performance with self-supervised approaches. But it takes some work (longer training, bigger models, precise hyperparameter tuning)
- SimCLR and Masked AutoEncoder only train on ImageNet images. But couldn’t you use a lot more data if you don’t need human labels?
- The gelato bet was just a bit premature