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

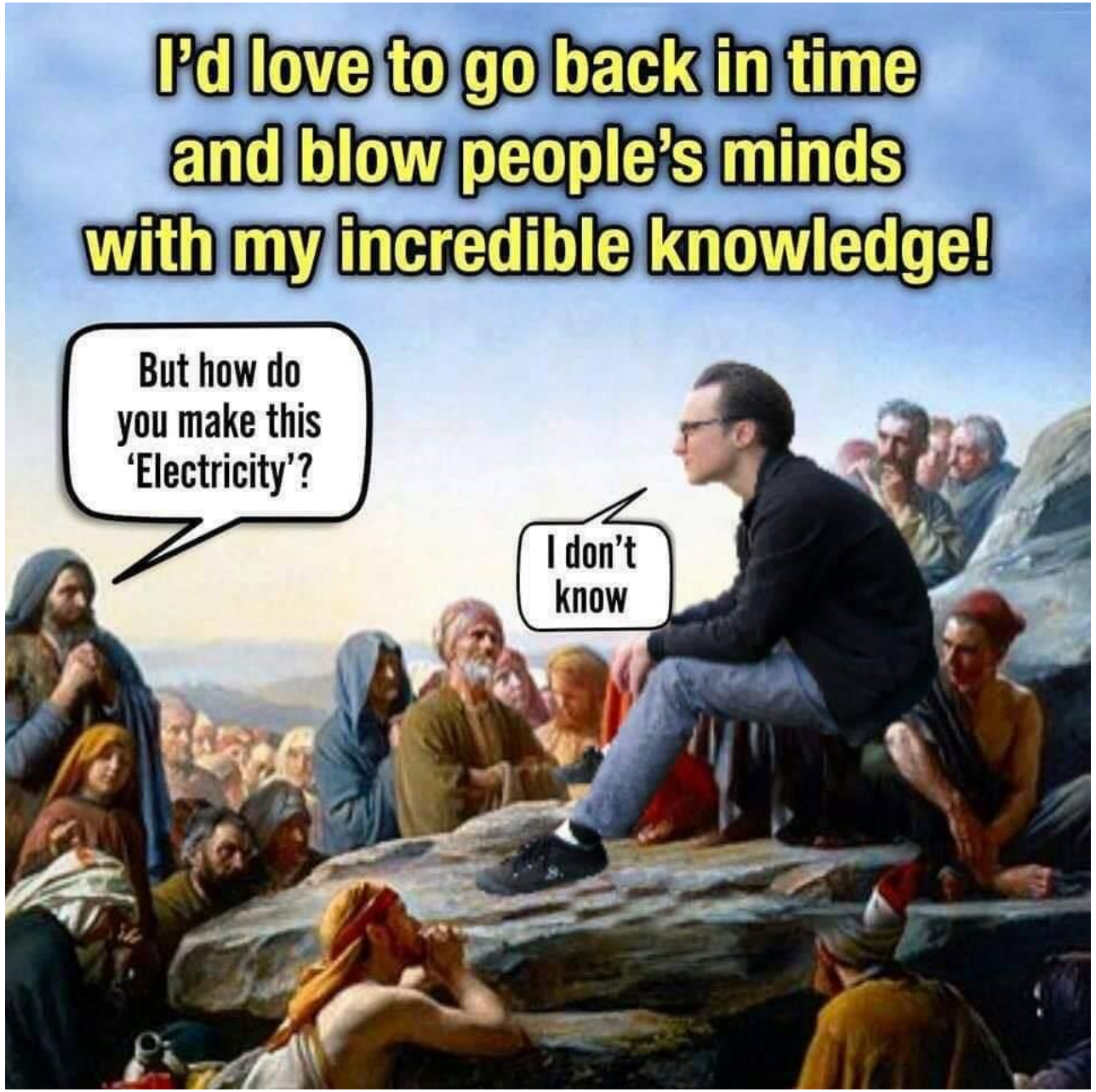
James Hays
slides from Carl Doersch and Richard Zhang

Recap

- Big Data
  - The Unreasonable Effectiveness of Data
  - Scene Completion
  - Im2gps
- 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

Large Pretrained Model?

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”

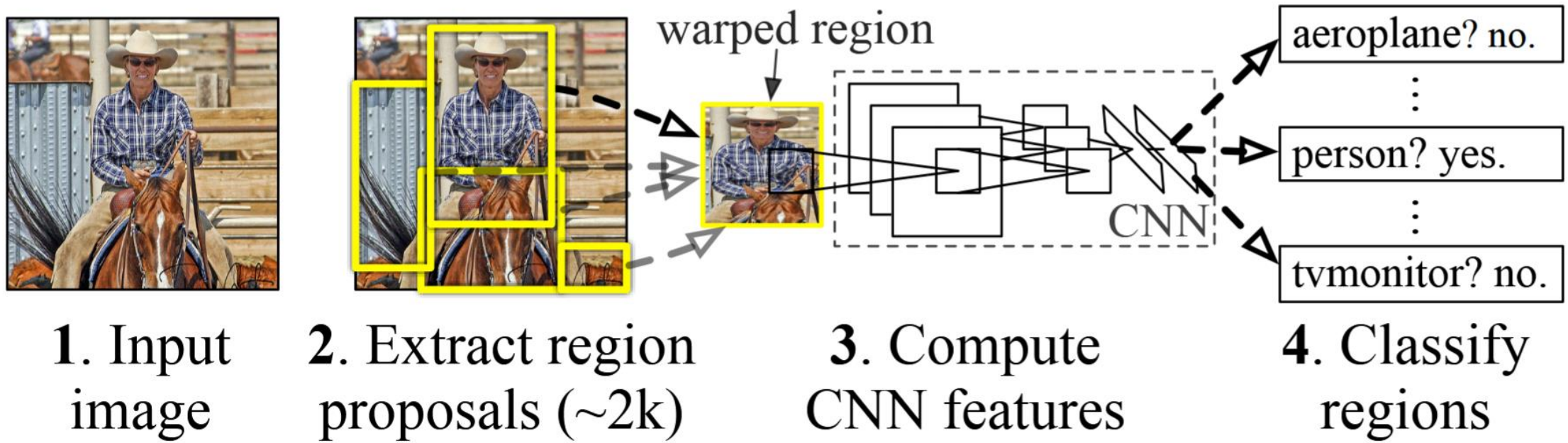


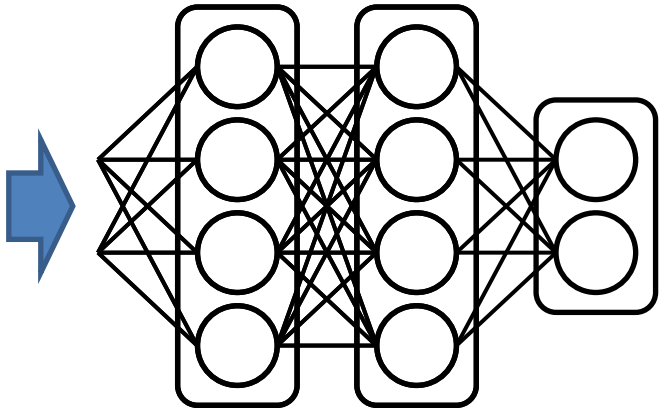
Figure 1: Object detection system overview. Our system (1) takes an input image, (2) extracts around 2000 bottom-up region proposals, (3) computes features for each proposal using a large convolutional neural network (CNN), and then (4) classifies each region using class-specific linear SVMs. R-CNN achieves a mean average precision (mAP) of **53.7% on PASCAL VOC 2010**. For

Unsupervised Visual Representation Learning by Context Prediction

Carl Doersch, Alexei A. Efros, and Abhinav Gupta

ICCV 2015

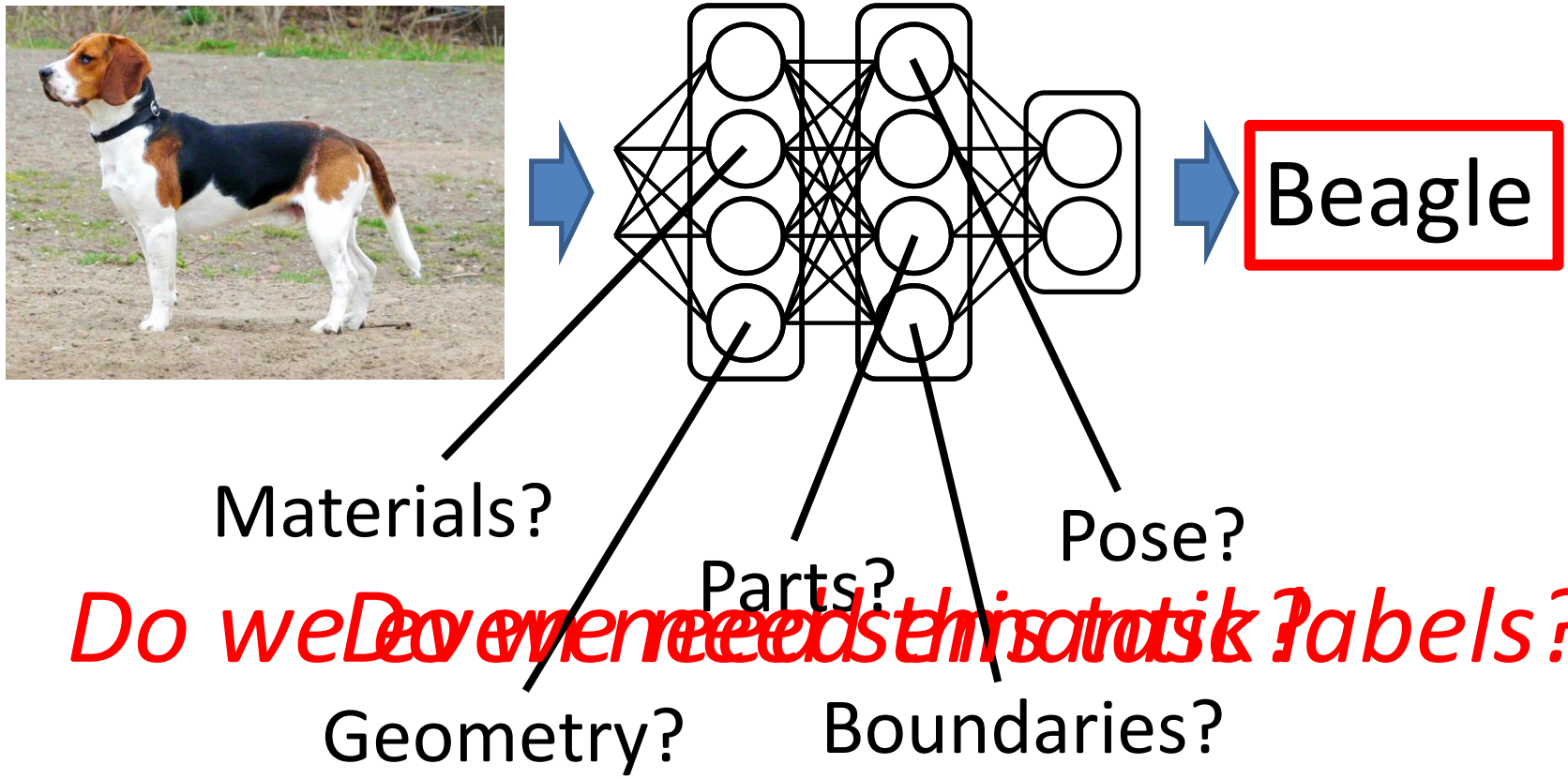
ImageNet + Deep Learning



Beagle

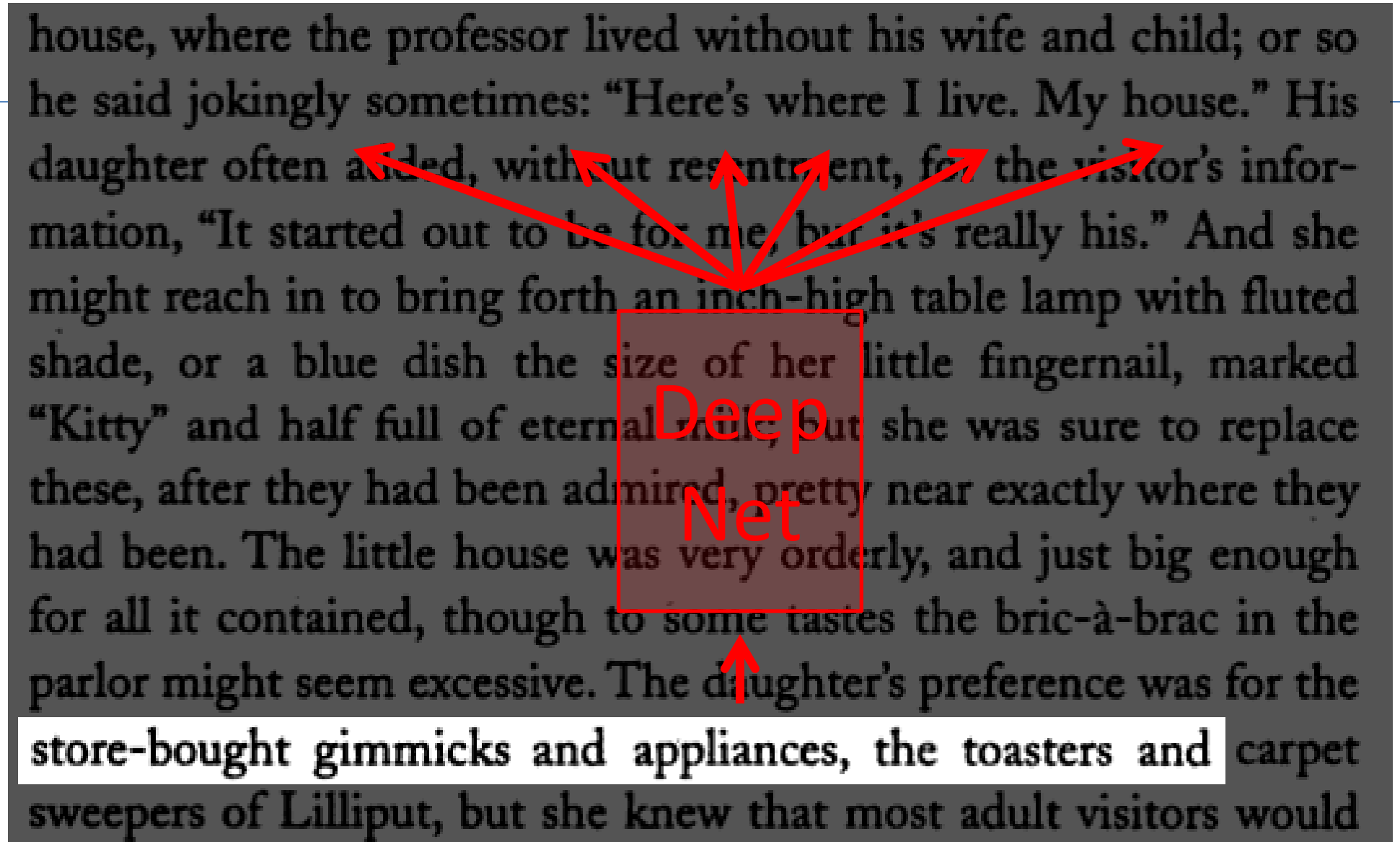
- Image Retrieval
- Detection (RCNN)
- Segmentation (FCN)
- Depth Estimation
- …

ImageNet + Deep Learning

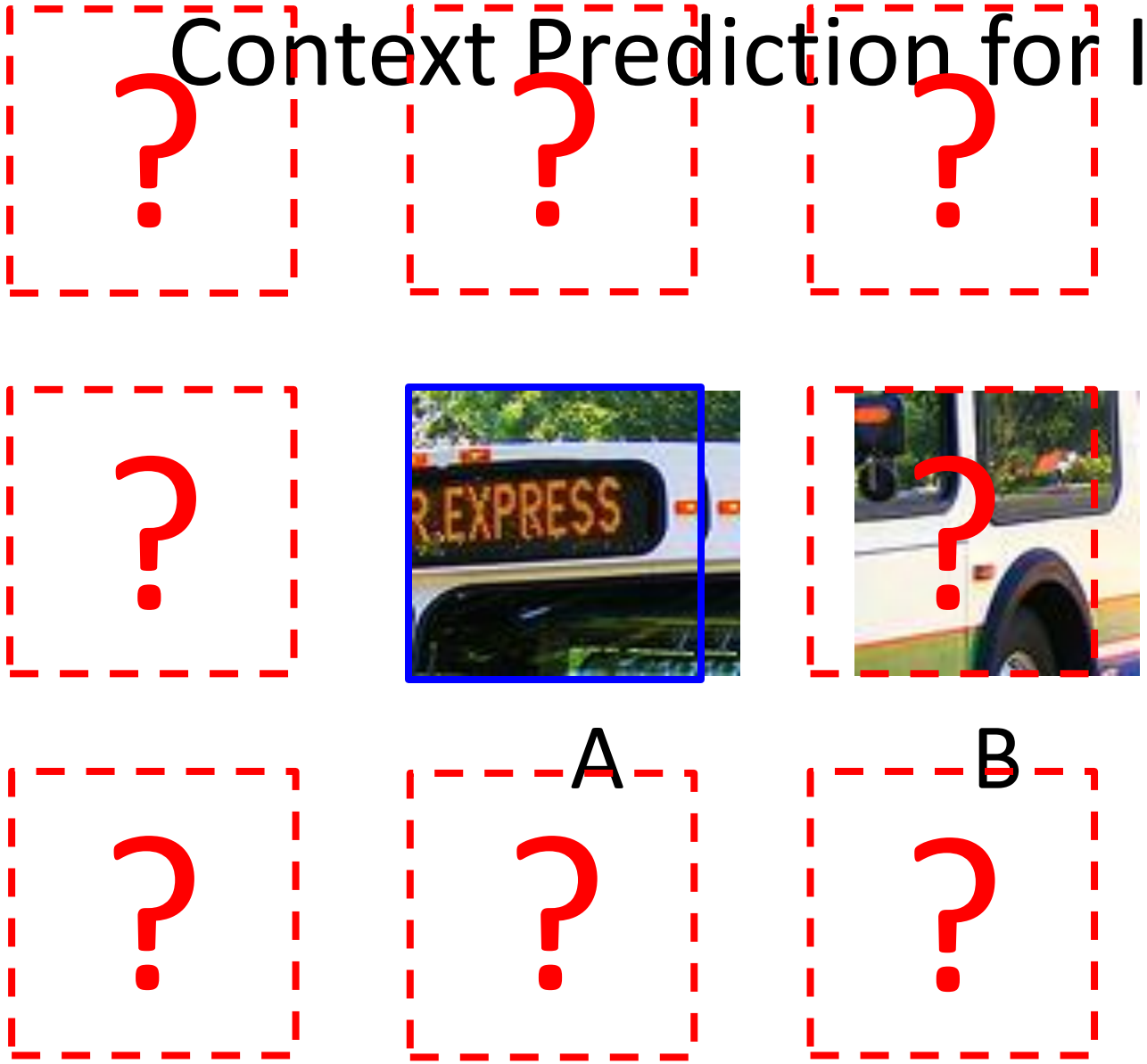


Context as Supervision

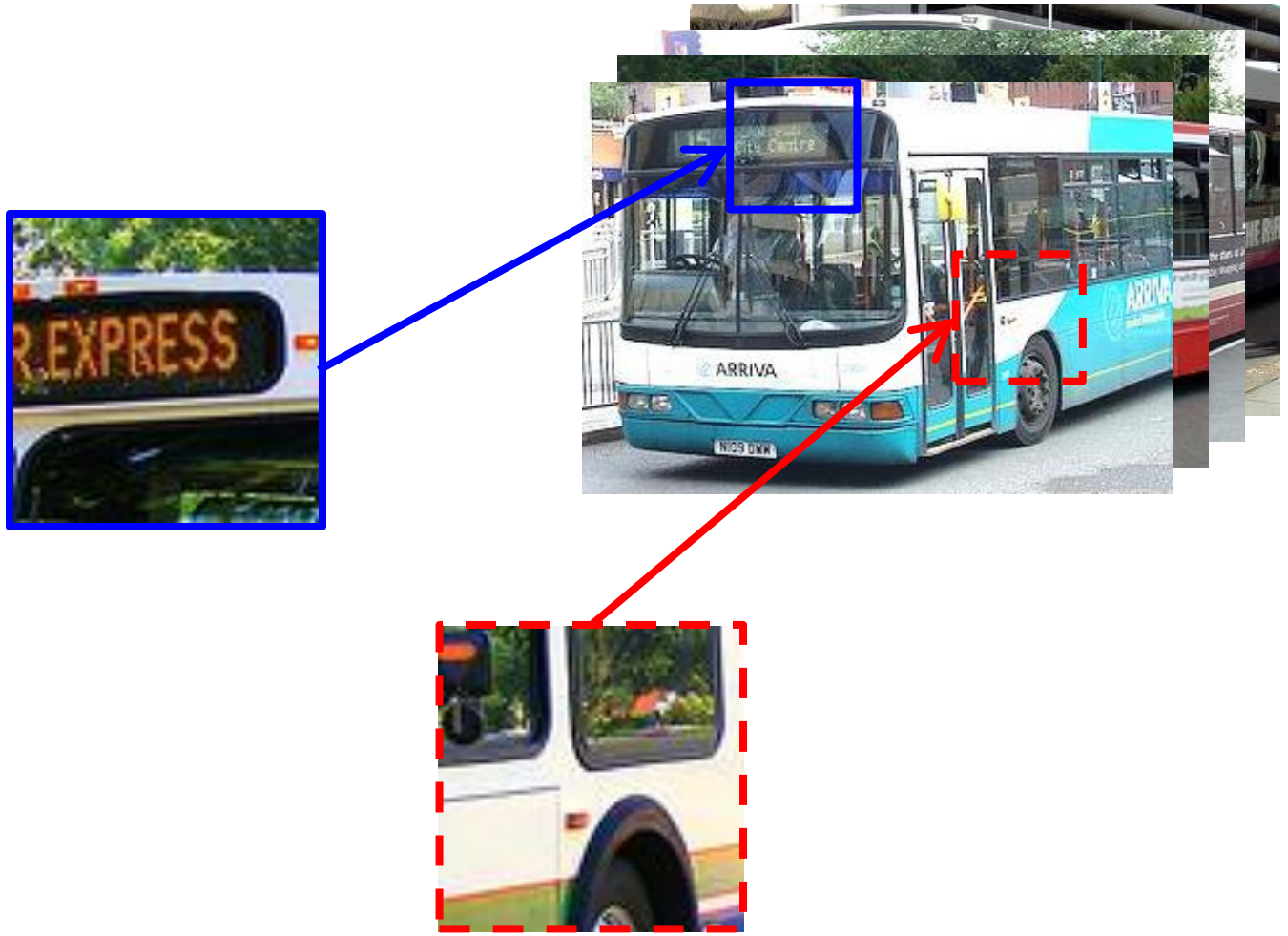
[Collobert & Weston 2008; Mikolov et al. 2013 (Word2Vec)]



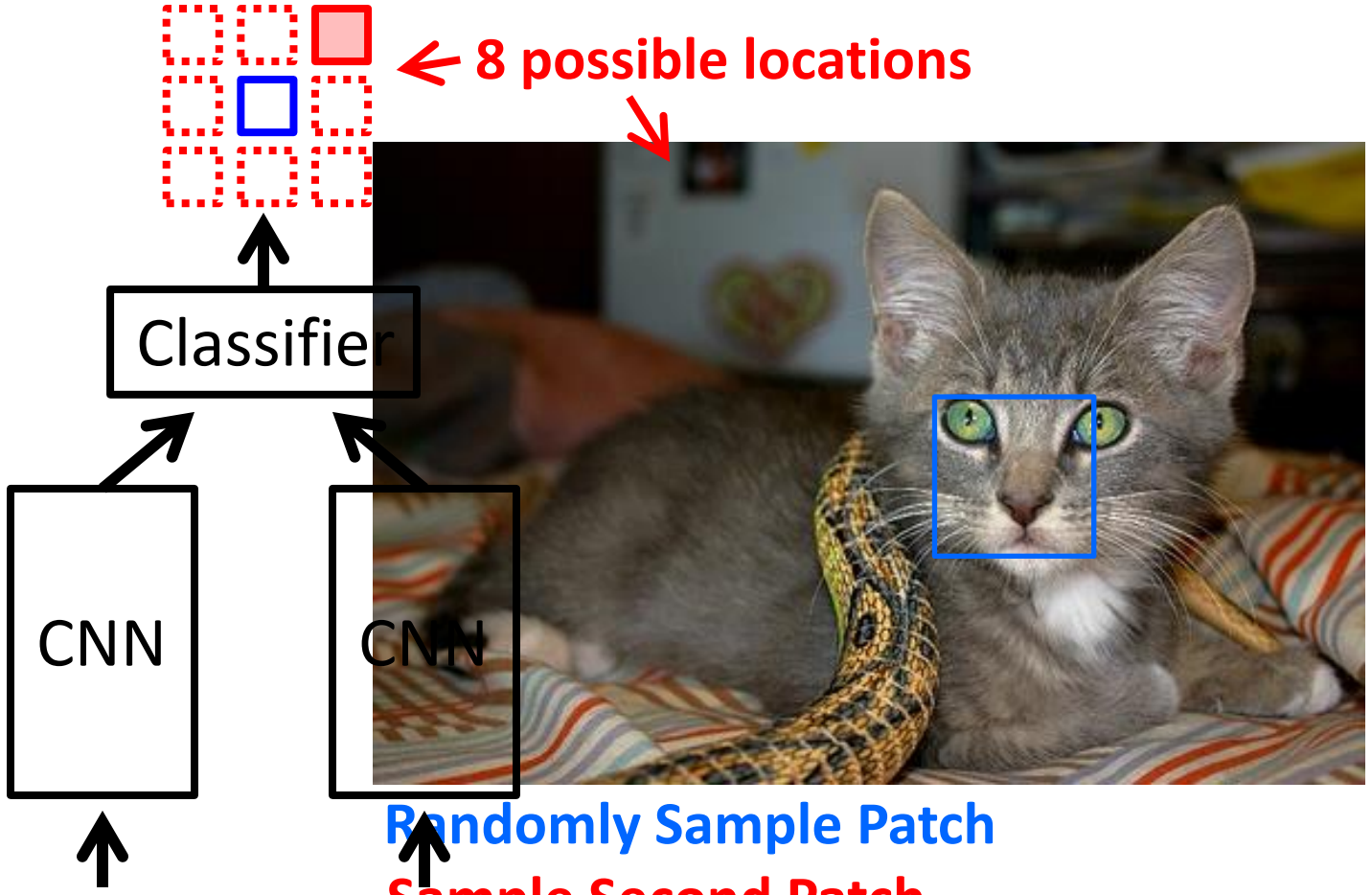
Context Prediction for Images

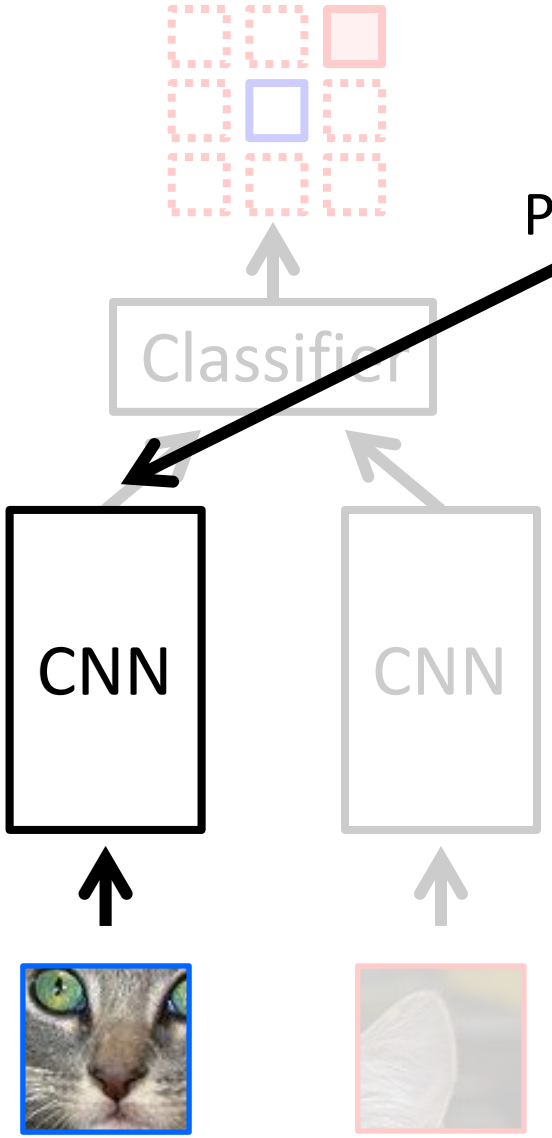


Semantics from a non-semantic task



Relative Position Task



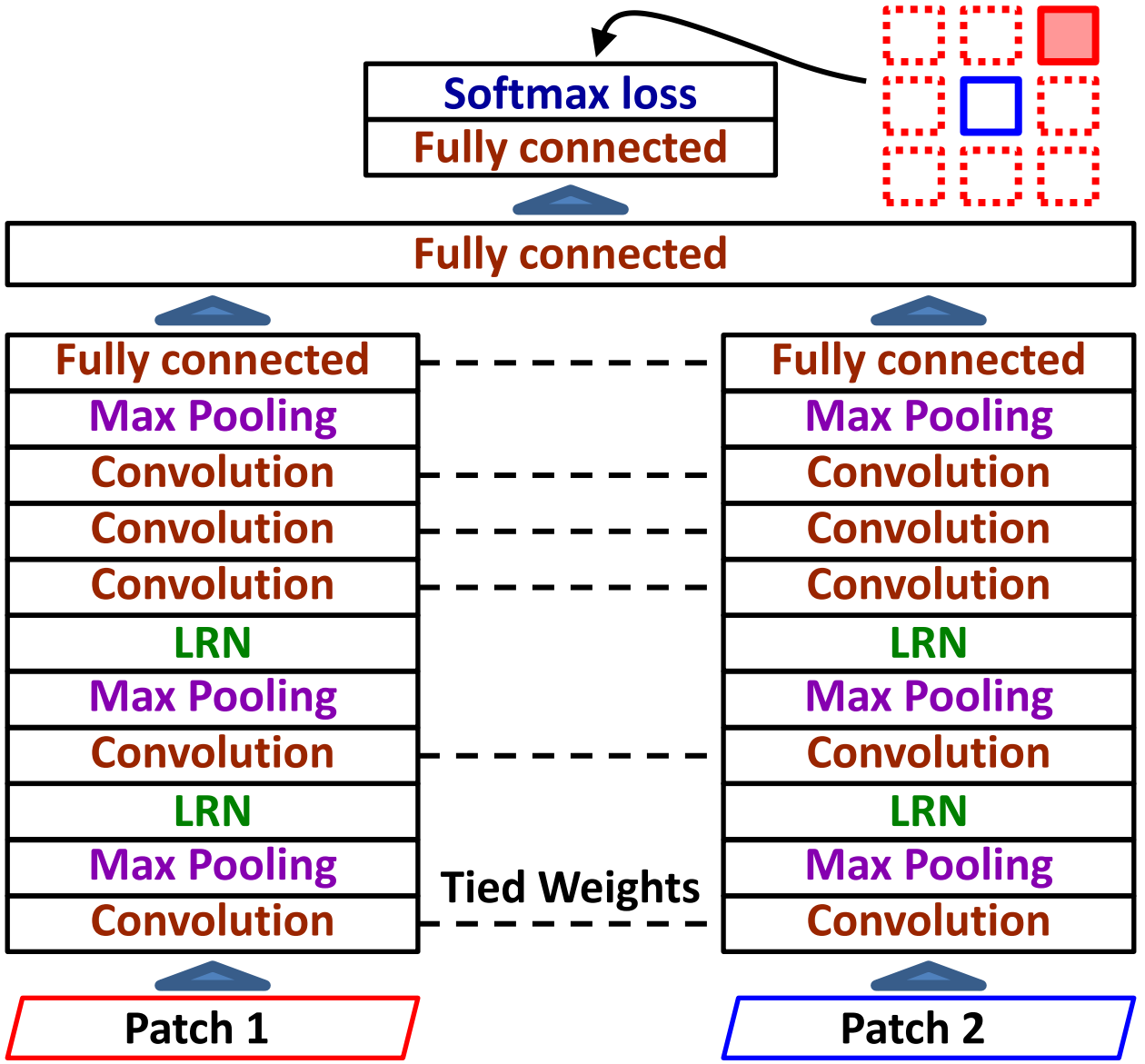


Input

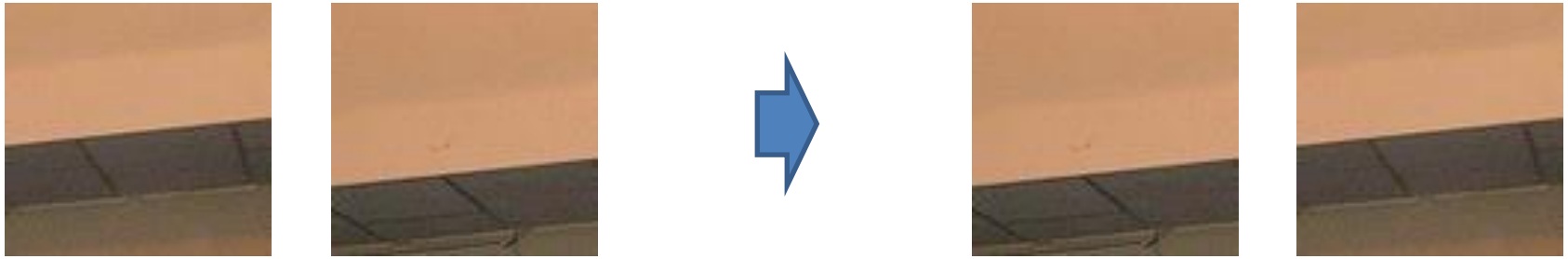
Nearest Neighbors

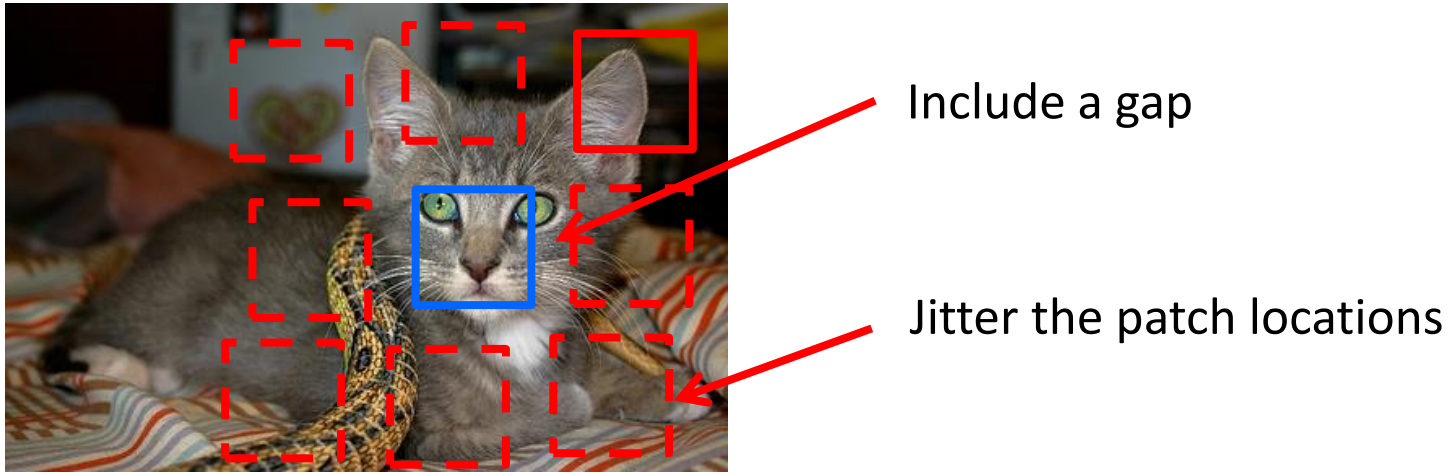
Note: connects ***across*** instances!

Architecture

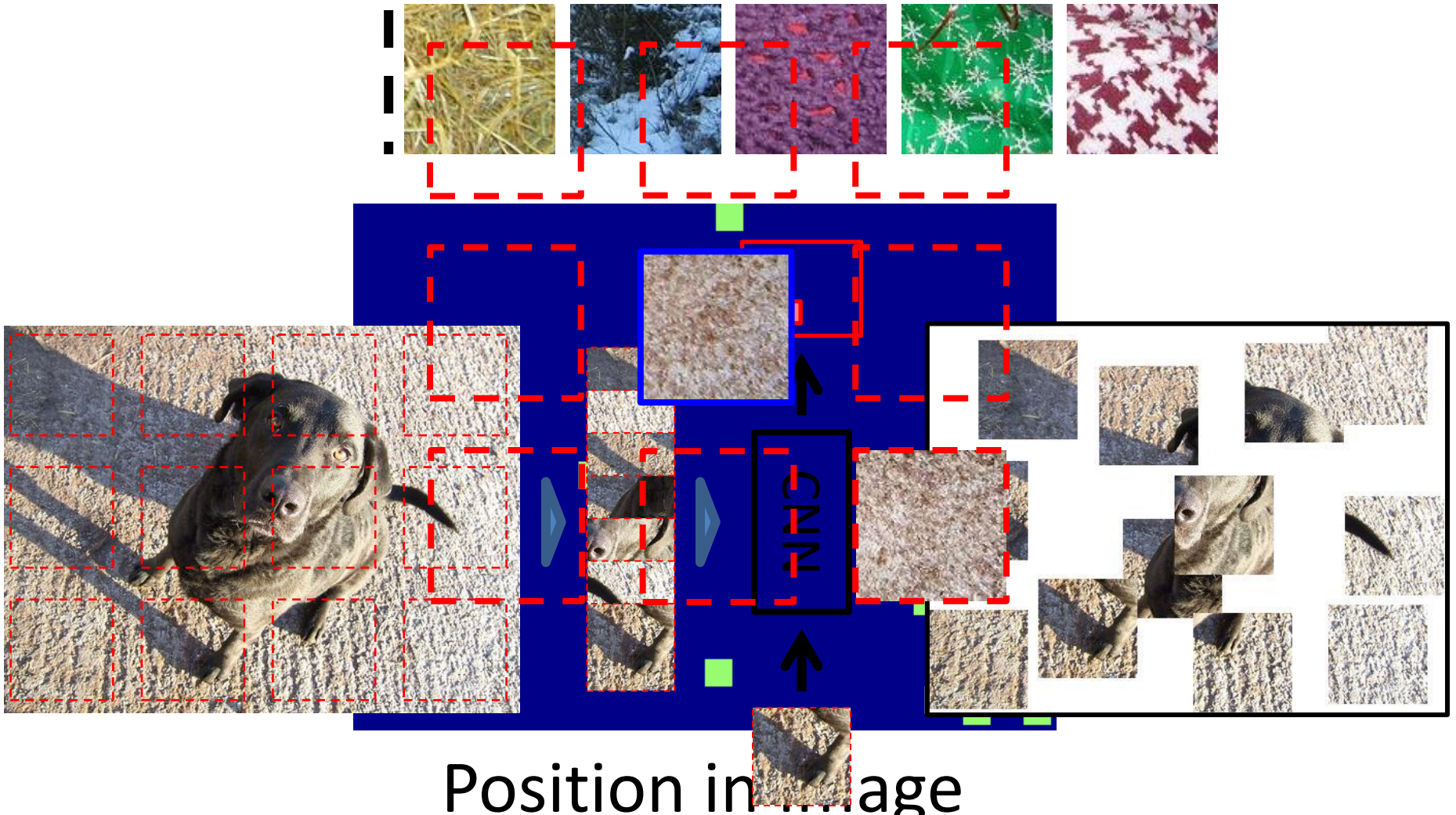


Avoiding Trivial Shortcuts

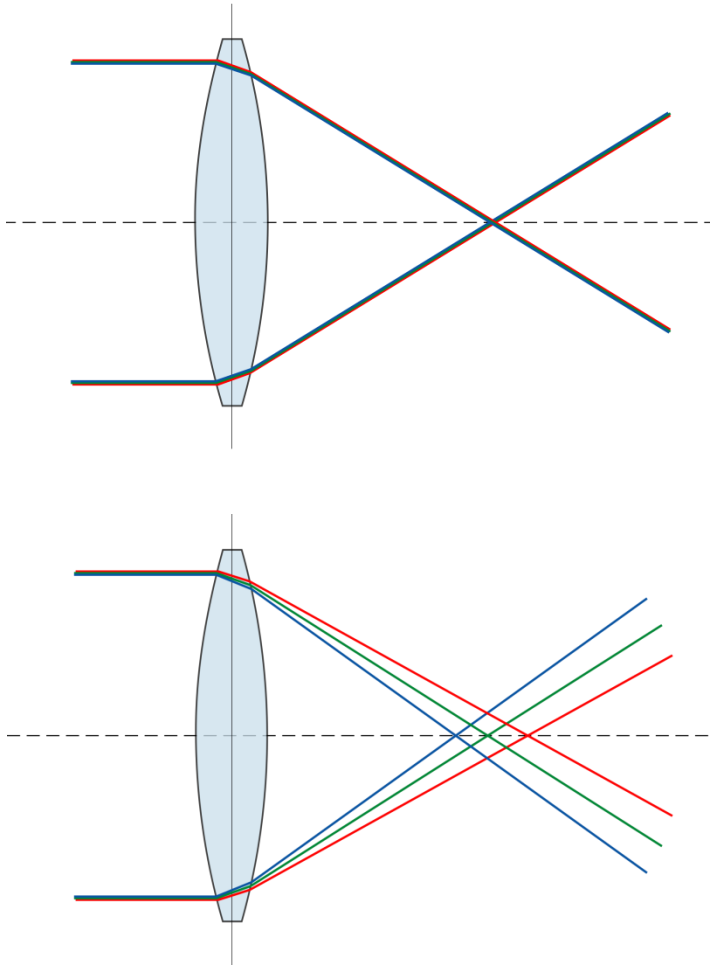


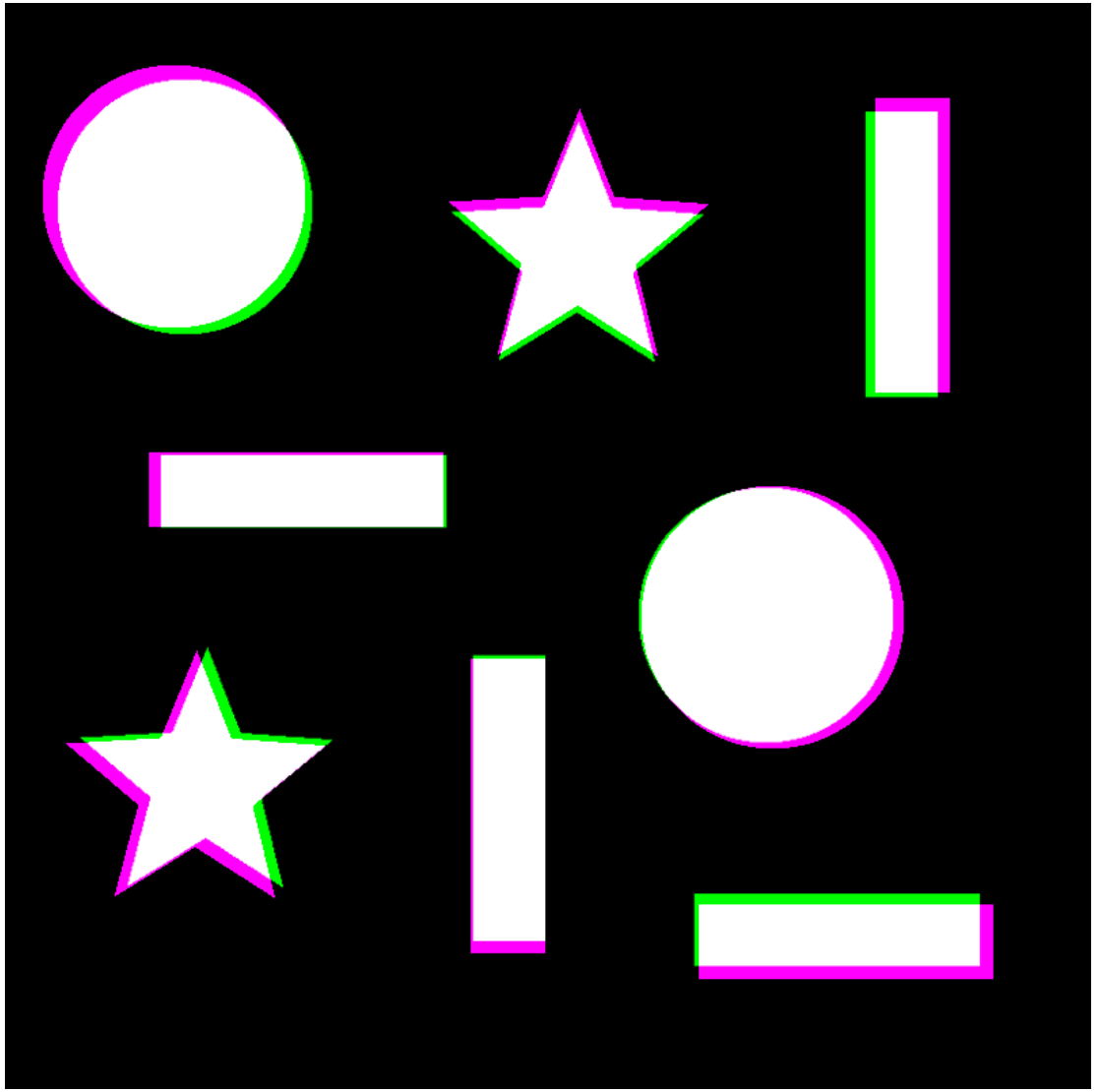


A Not-So “Trivial” Shortcut

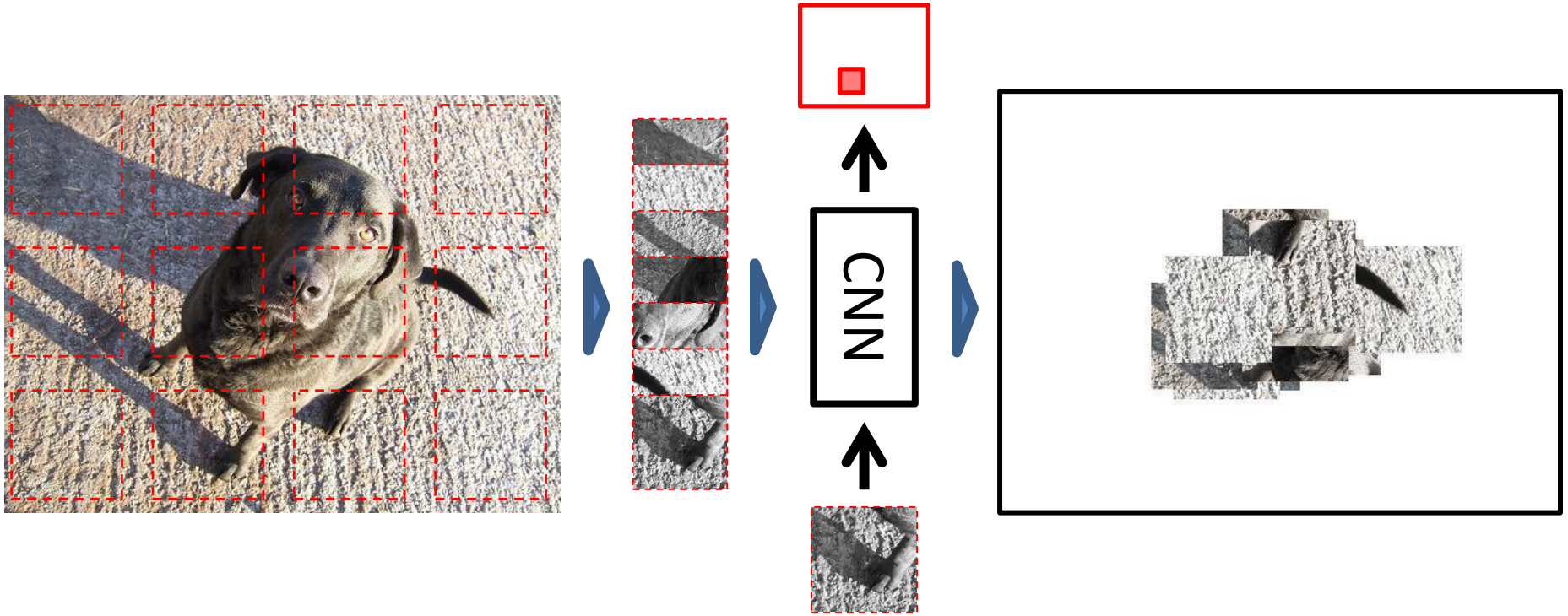


Chromatic Aberration

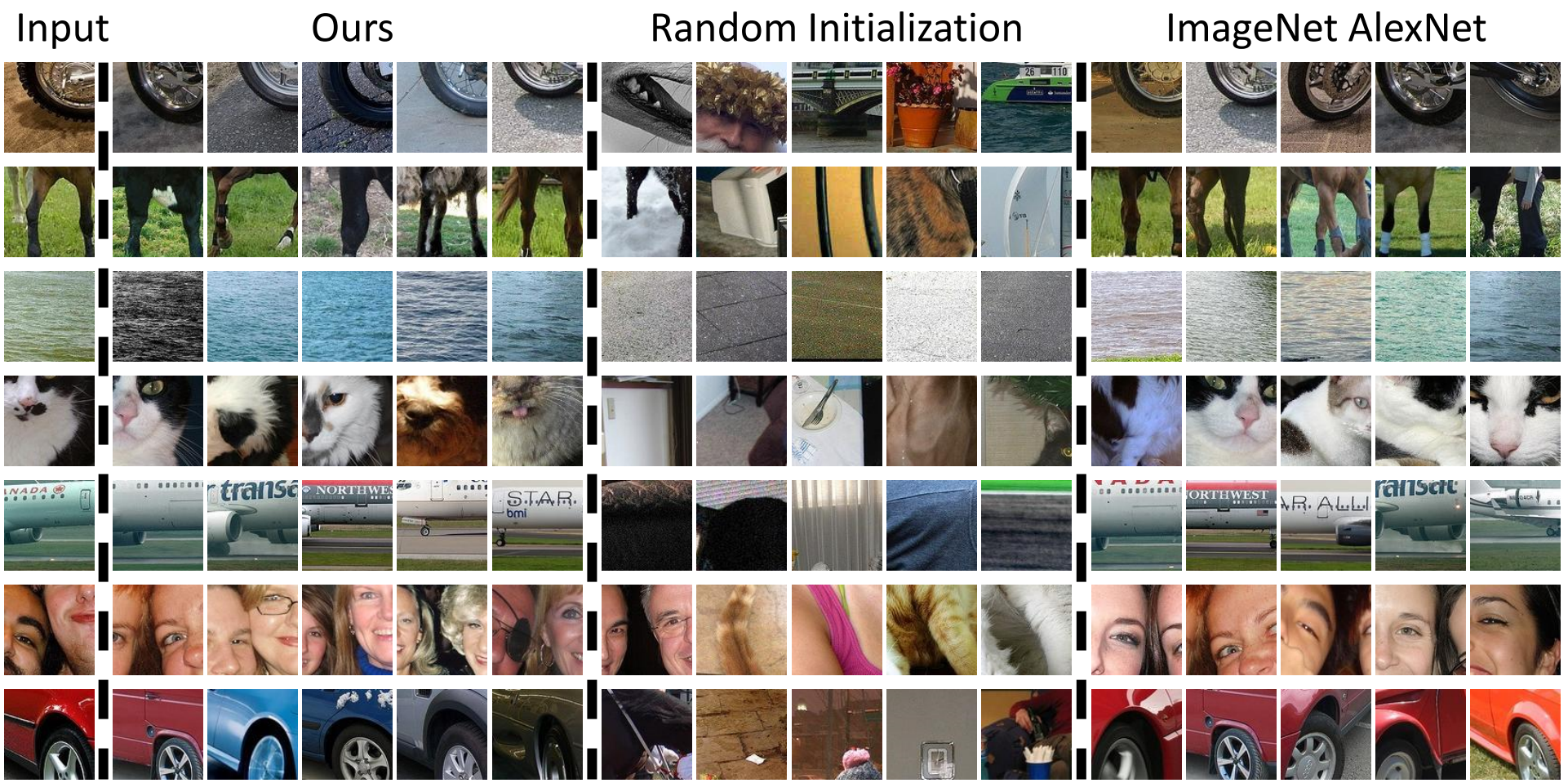




Chromatic Aberration



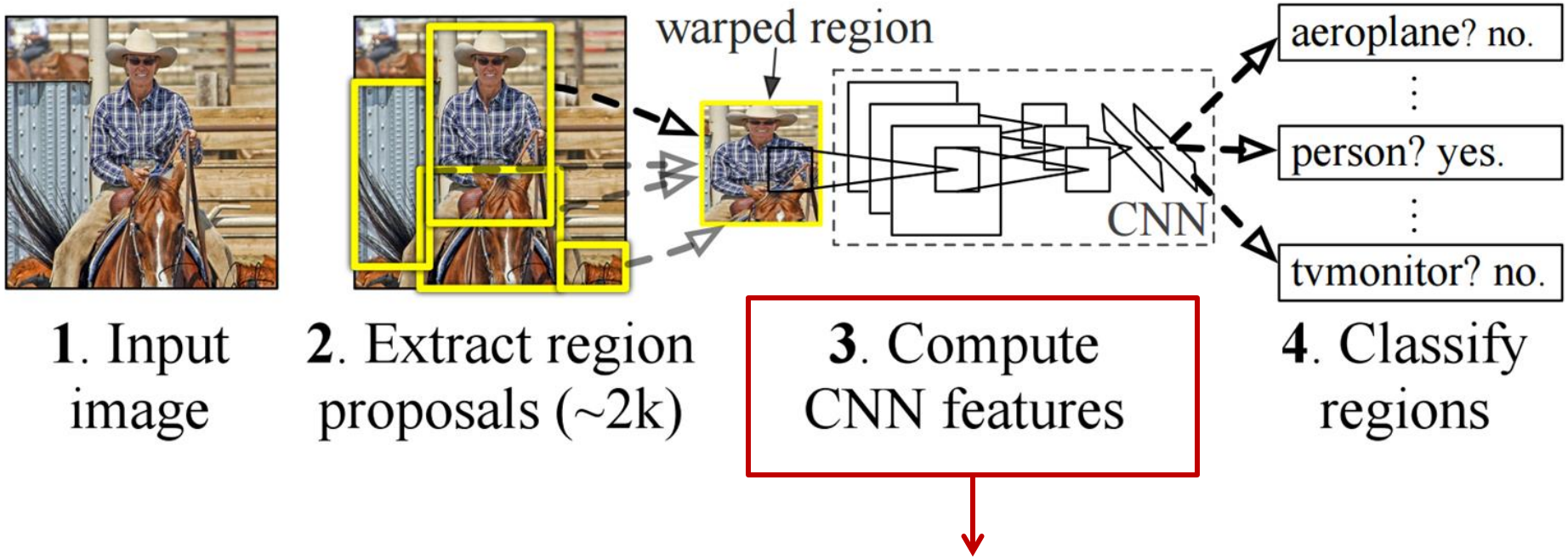
What is learned?



Still don’t capture everything

You don’t always need to learn!

Pre-Training for R-CNN

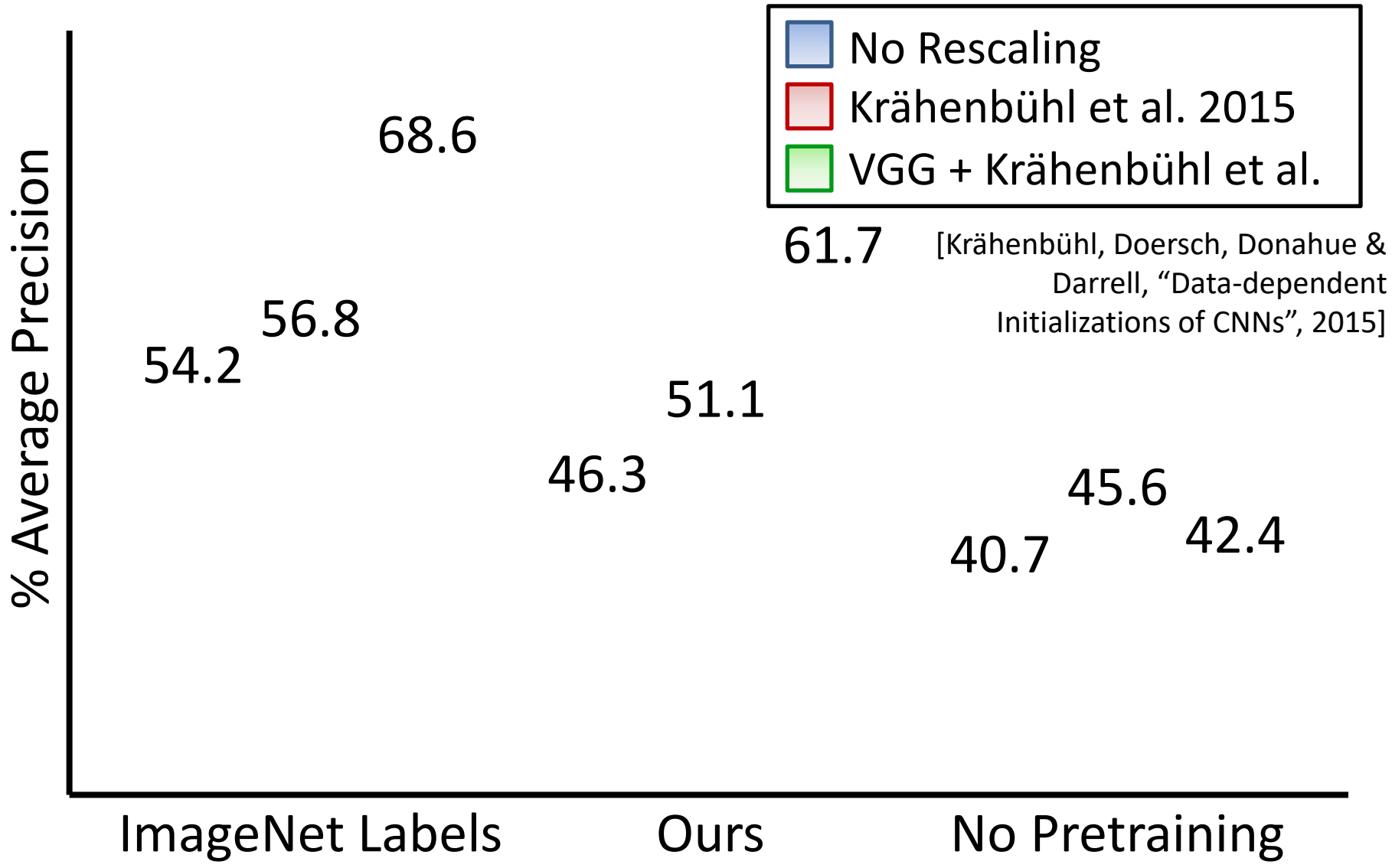


Pre-train on relative-position task, w/o labels

[Girshick et al. 2014]

VOC 2007 Performance

(pretraining for R-CNN)

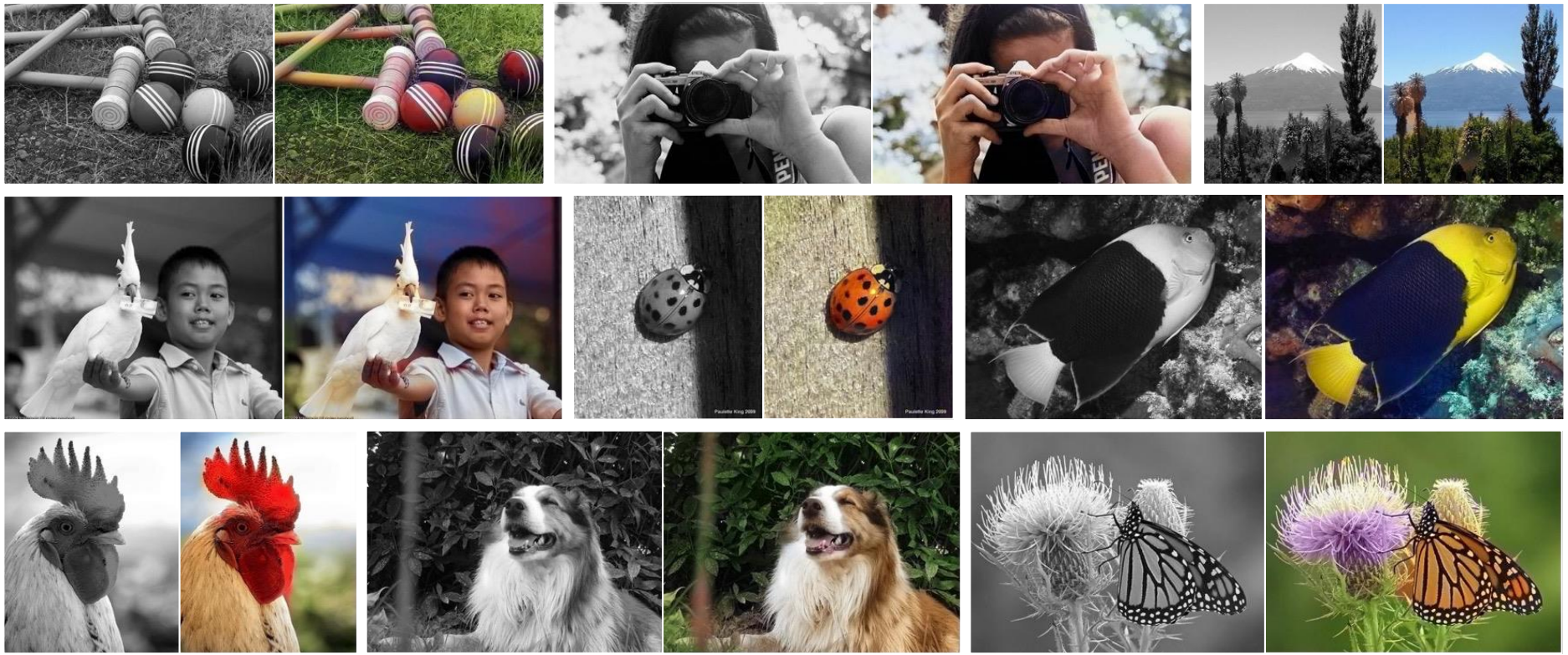


[Krähenbühl, Doersch, Donahue & Darrell, "Data-dependent Initializations of CNNs", 2015]

Clever ideas to keep in mind

- “Pretext” tasks to train networks
- Avoiding shortcuts in learning by
  - Dropping out modalities
  - Randomizing patch offsets
  - Including gaps in patch offsets

So, do we need semantic labels?

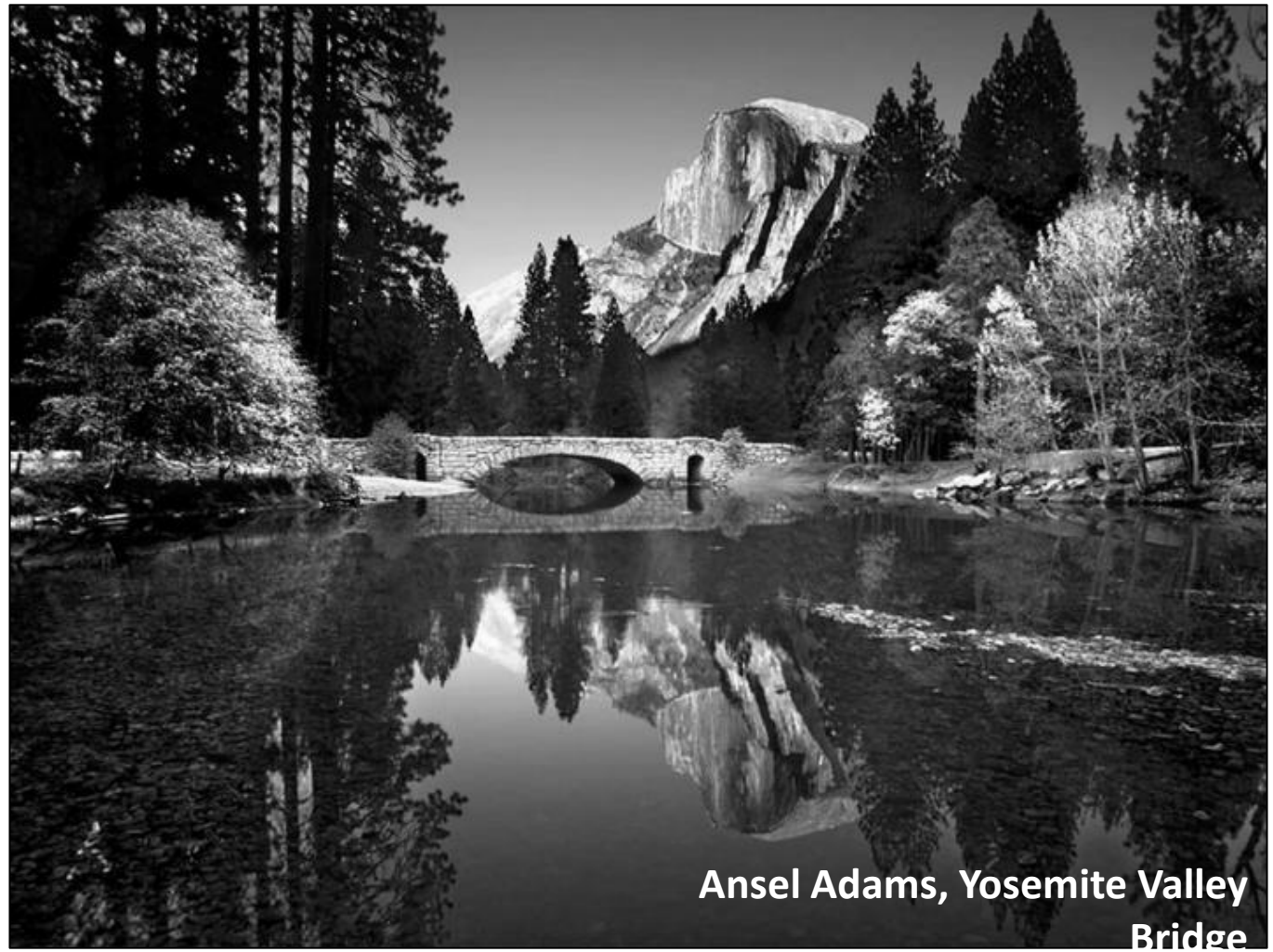


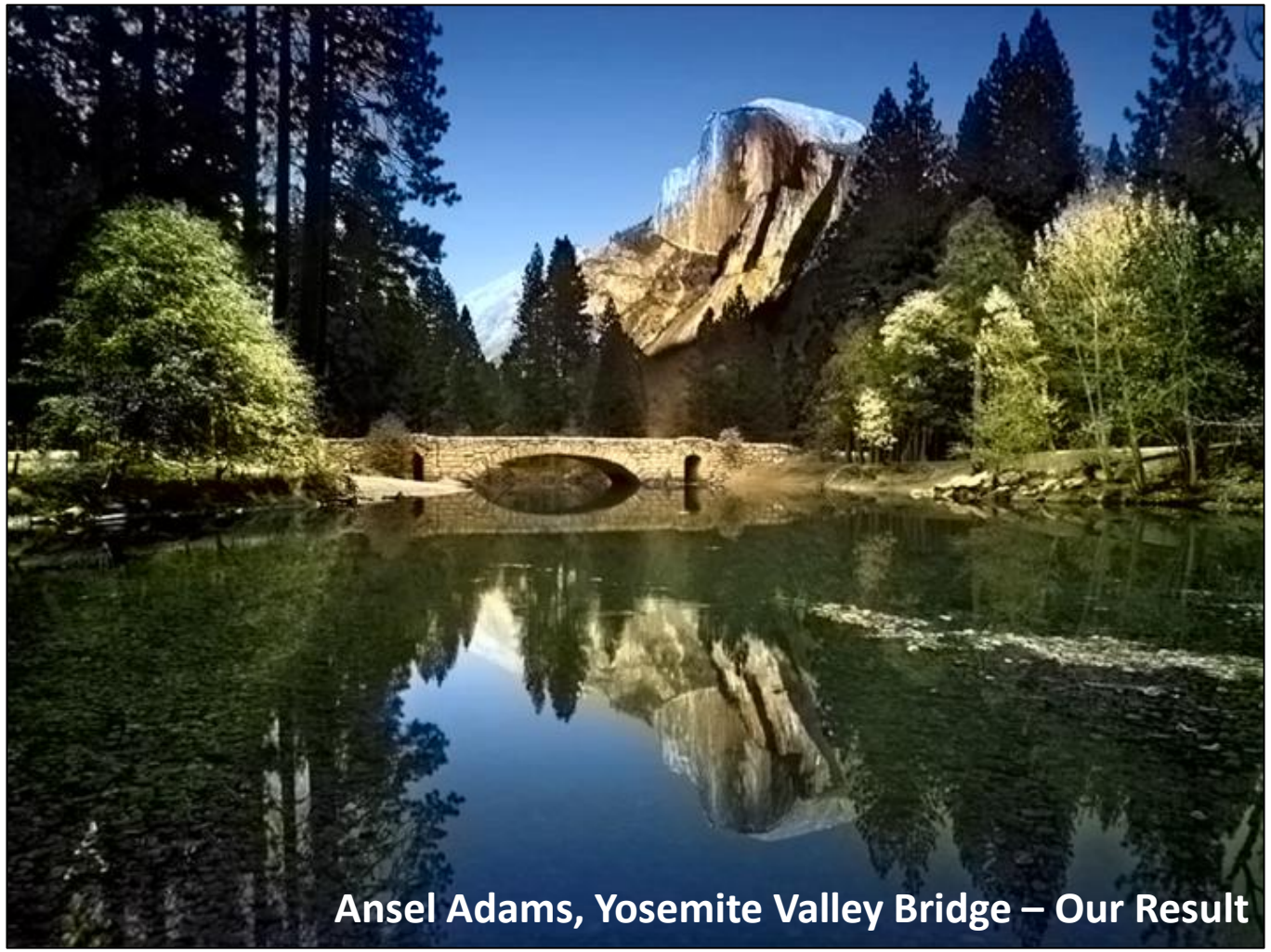
Colorful Image Colorization

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

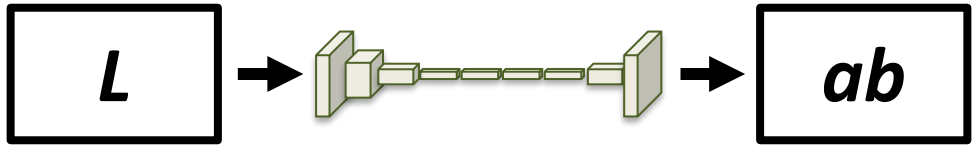
$\mathcal{F}$

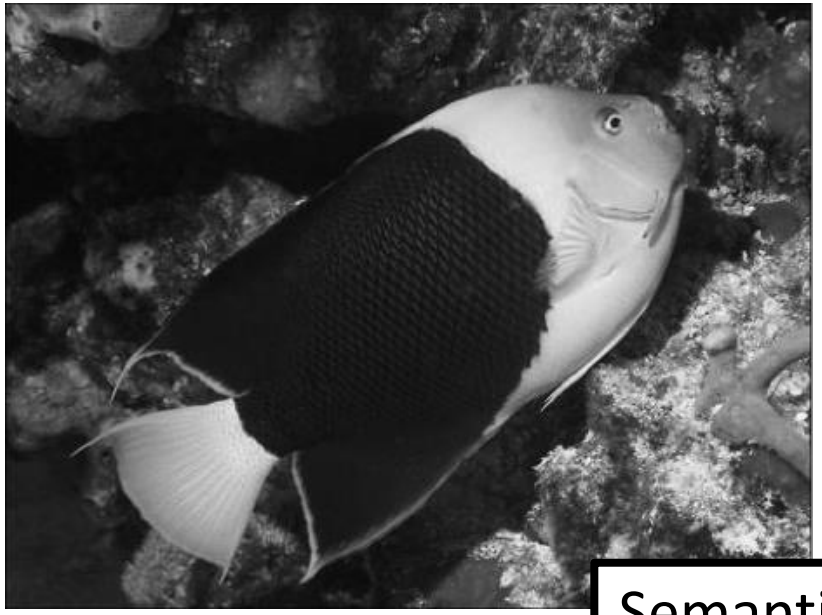
Grayscale image: *L* channel

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

Color information: *ab* channels

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



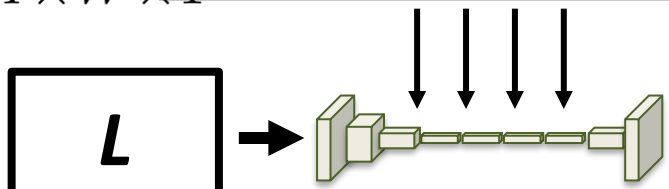


$\mathcal{F}$

Grayscale image: *L* ch… ncatenate (L,ab)

$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$ $(\mathbf{X}, \widehat{\mathbf{Y}})$

Semantics? Higher-level abstraction?



"Free" supervisory signal

Inherent Ambiguity

Grayscale

Inherent Ambiguity

Our Output

Ground Truth

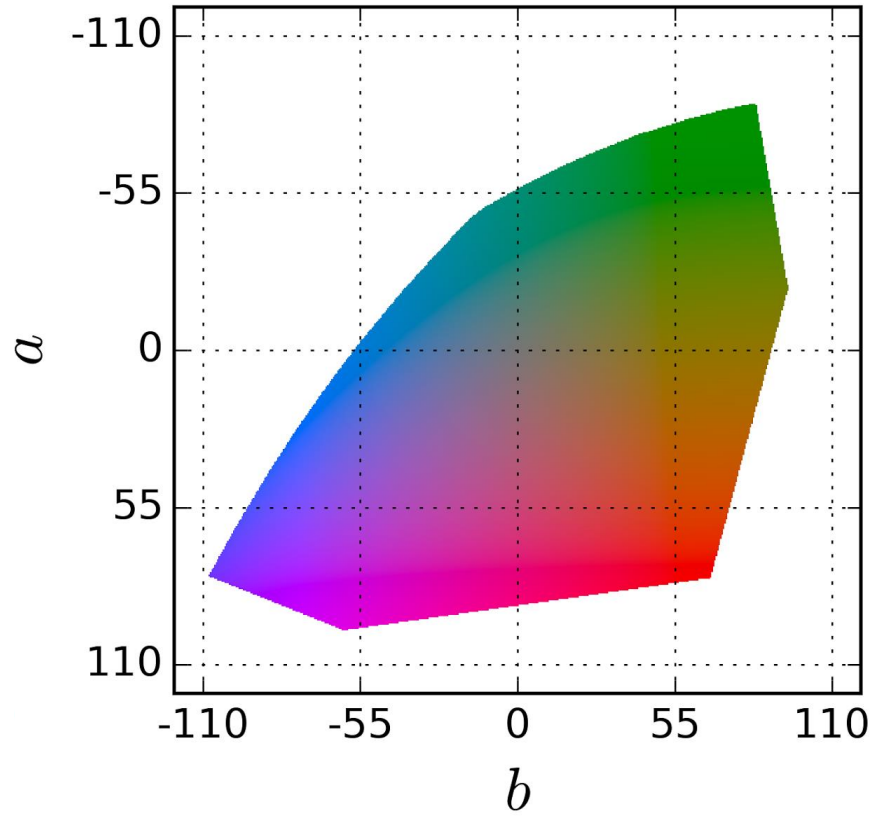
Better Loss Function

- 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

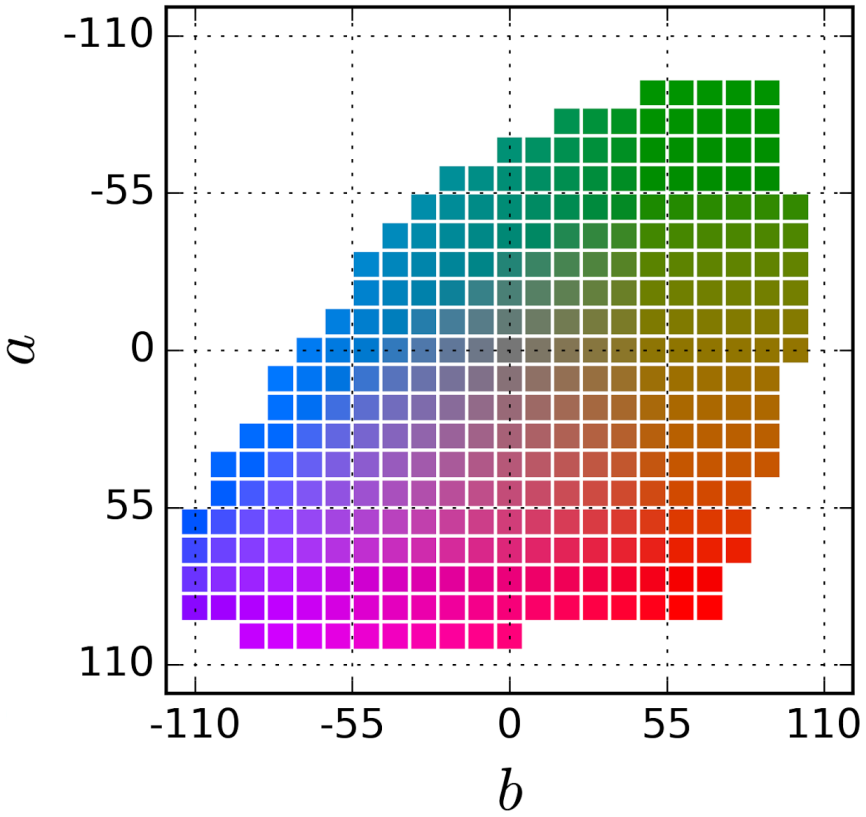
$$\mathrm{L}_2(\widehat{\mathbf{Y}}, \mathbf{Y}) = \frac{1}{2}\sum_{h,w} \|\mathbf{Y}_{h,w} - \widehat{\mathbf{Y}}_{h,w}\|_2^2$$

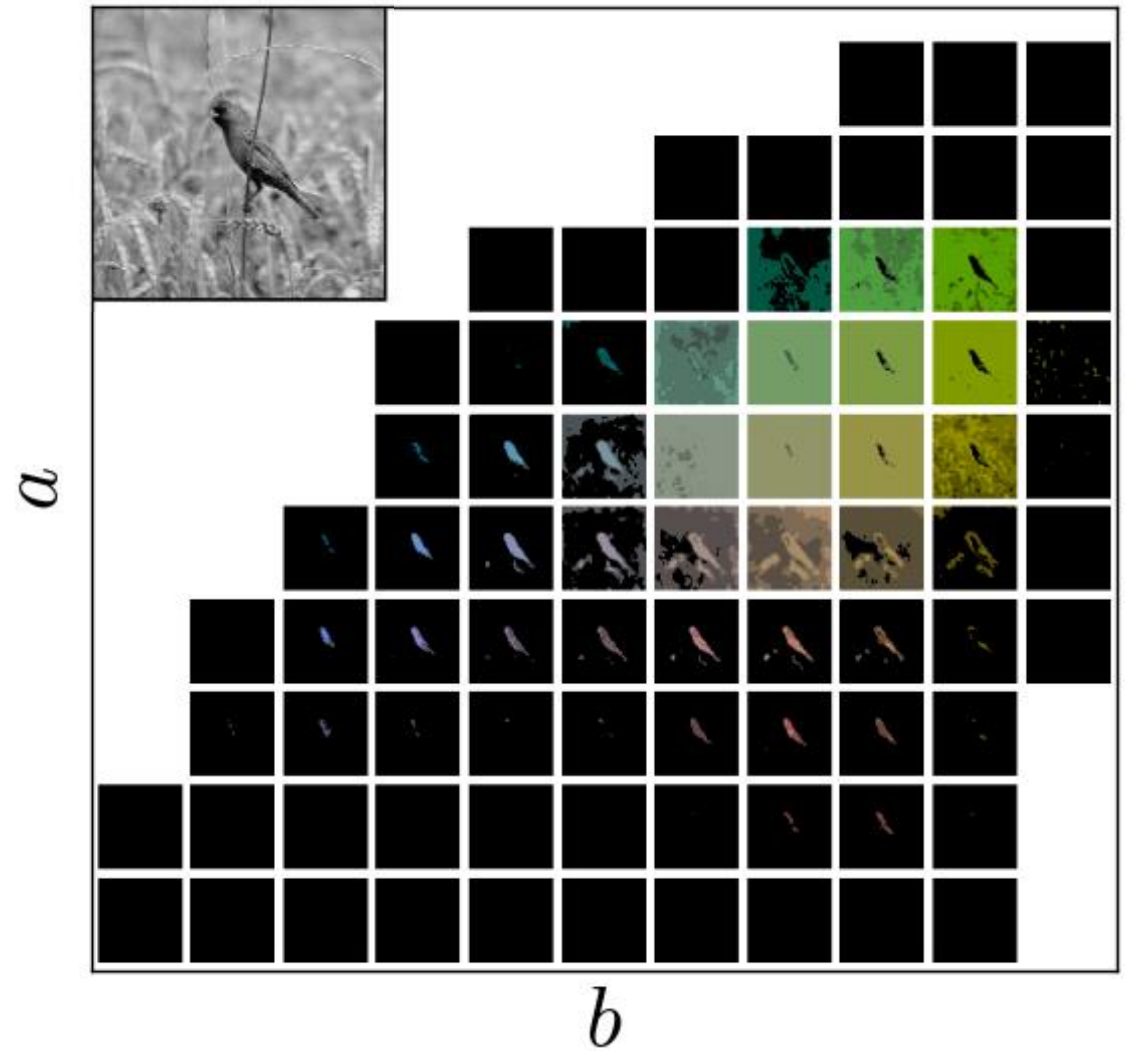
- Use **multinomial classification**

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

Colors in *ab* space

(discrete)




a
b

Better Loss Function

- Regression with L2 loss inadequate

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

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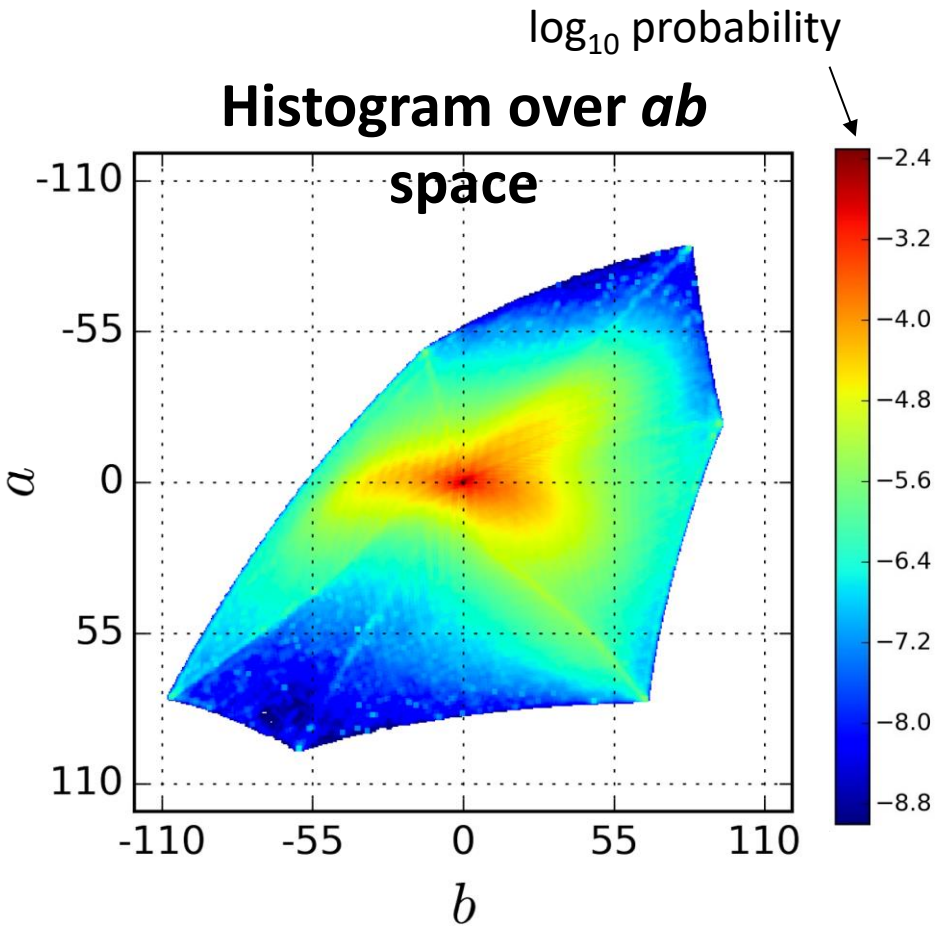

Better Loss Function

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

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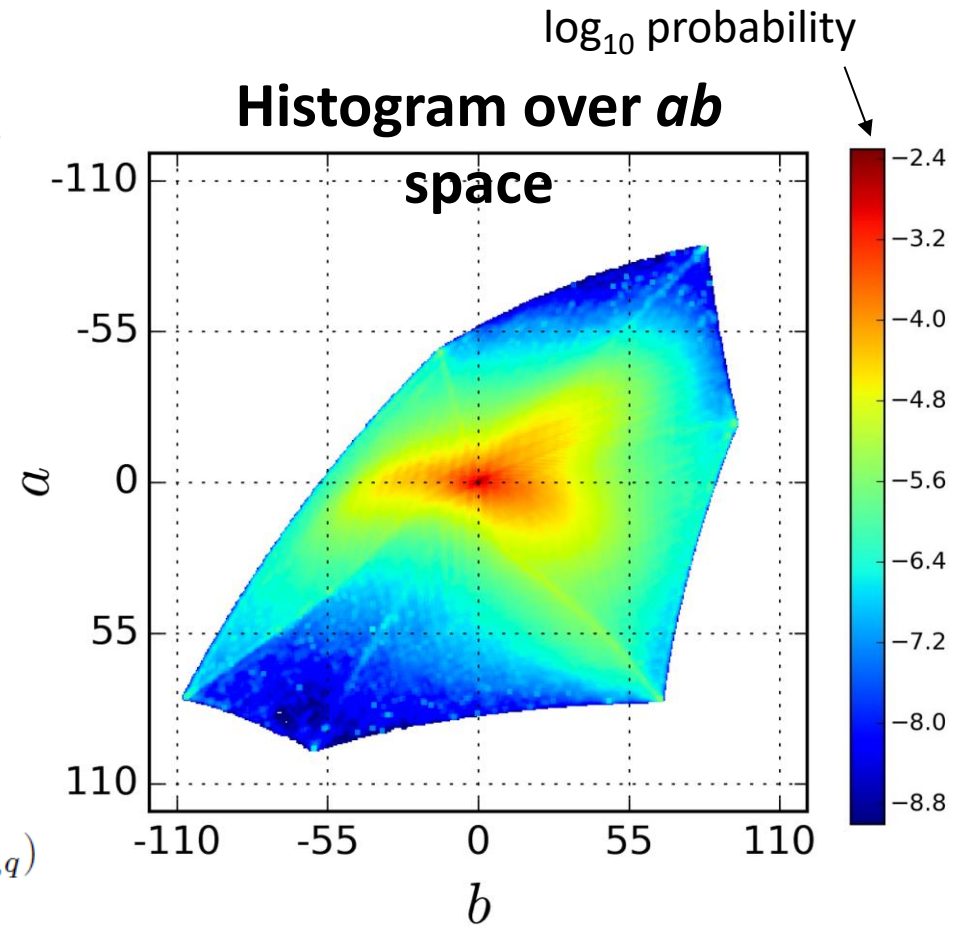
$$\mathrm{L}(\widehat{\mathbf{Z}}, \mathbf{Z}) = -\frac{1}{HW} \sum_{h,w} \sum_{q} \mathbf{Z}_{h,w,q} \log(\widehat{\mathbf{Z}}_{h,w,q})$$

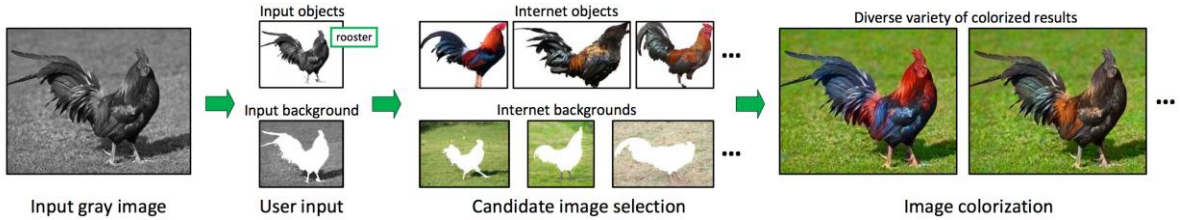
- **Class rebalancing** to encourage learning of *rare* colors

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



Non-parametric

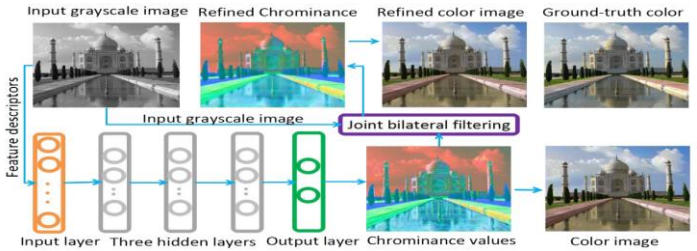
Hertzmann et al. In SIGGRAPH, 2001.
Welsh et al. In TOG, 2002.
Irony et al. In Eurographics, 2005.
Liu et al. In TOG, 2008.
Chia et al. In ACM 2011.
Gupta et al. In ACM, 2012.



Parametric

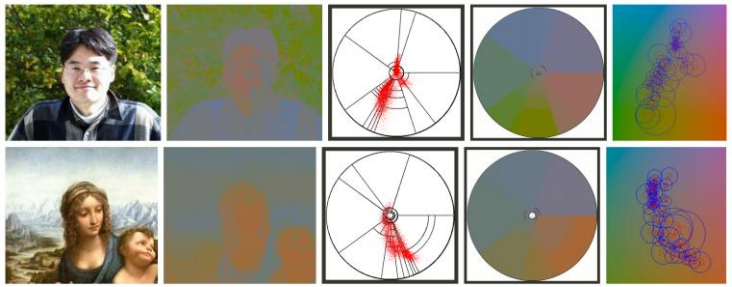
Hand-engineered Features

L2 Regression



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

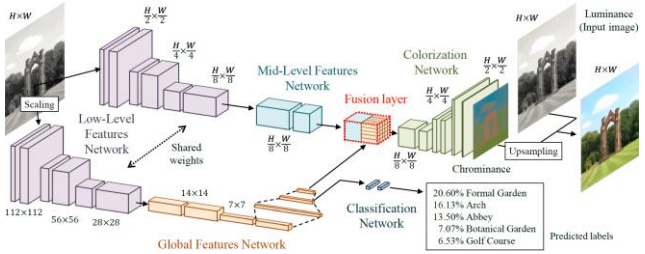
Classification



Charpiat et al. In ECCV 2008.

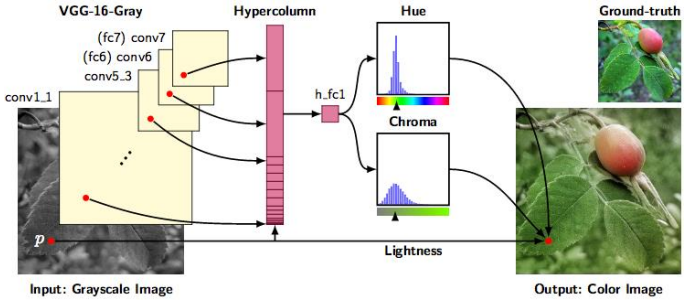
Deep Networks

L2 Regression



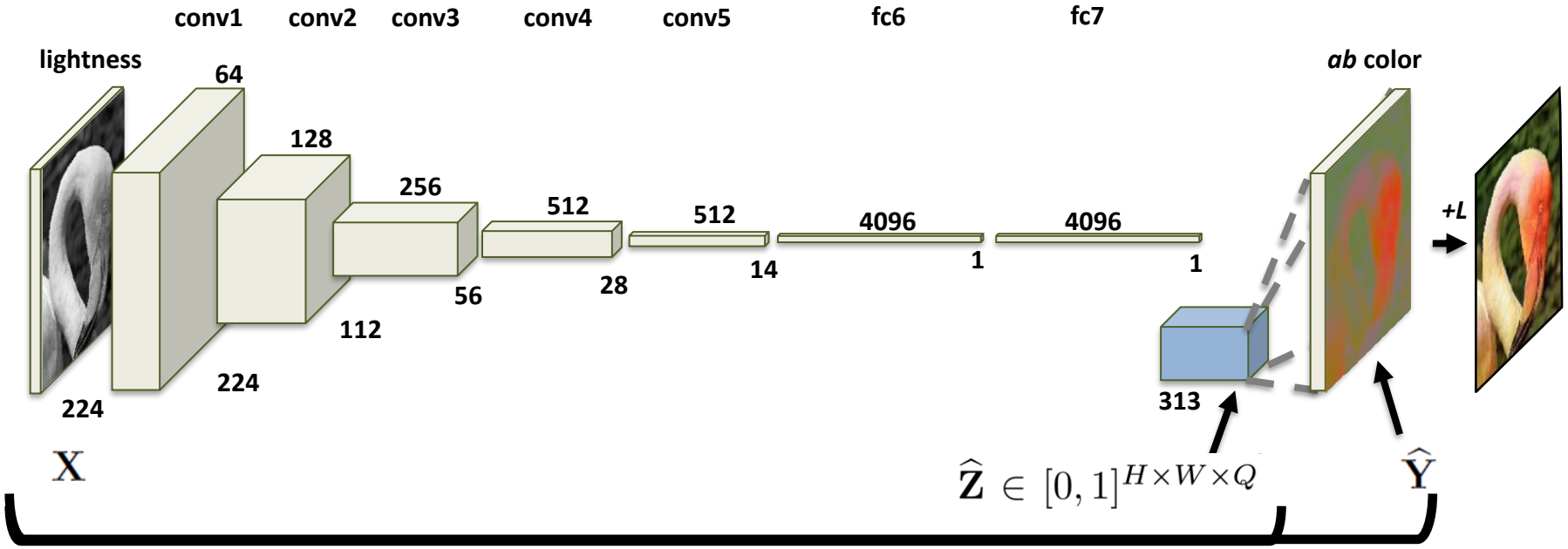
Dahl. Jan 2016. Iizuka et al. In SIGGRAPH, 2016.

Classification



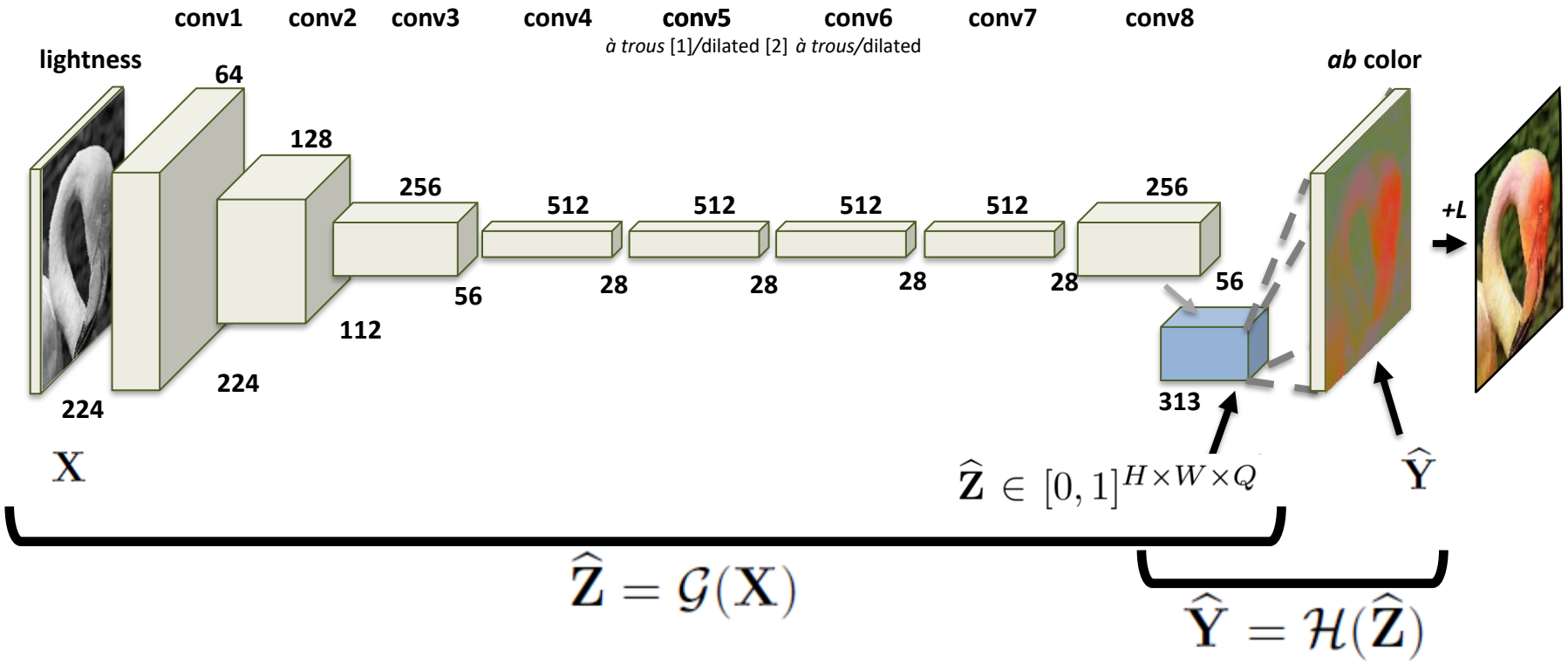
Larsson et al. In ECCV 2016. [Concurrent]

Network Architecture



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

Network Architecture

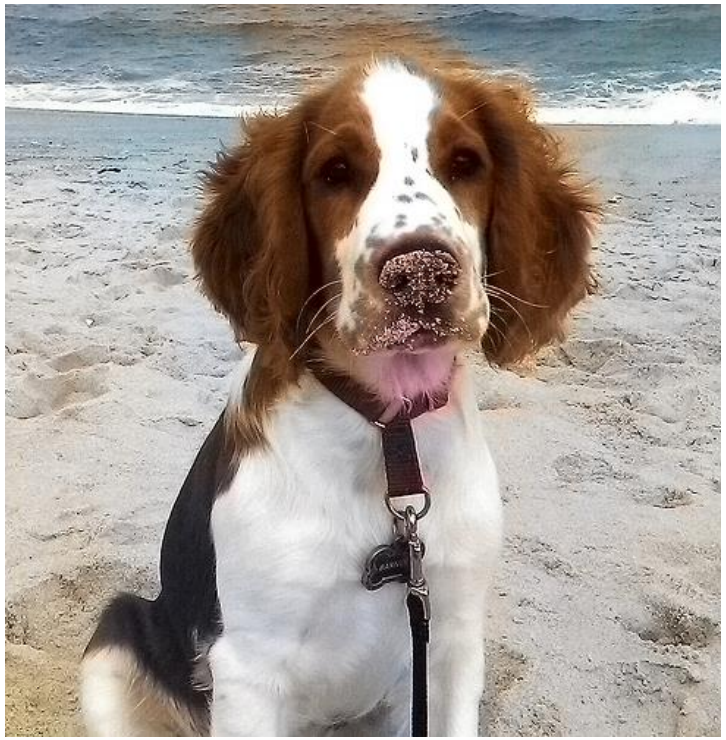


[1] Chen *et al.* In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016

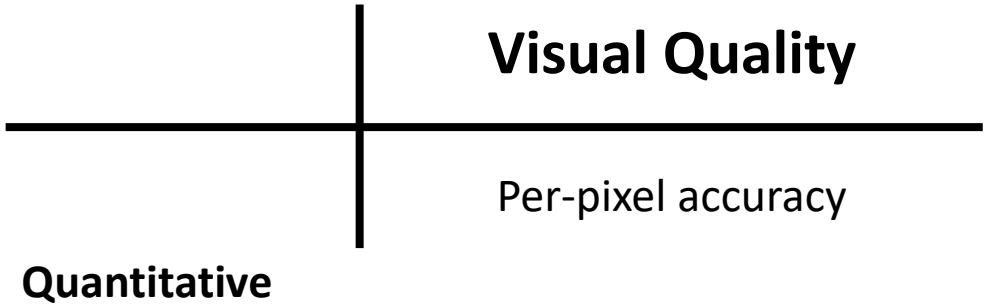

Ground Truth
Input
L2 Regression
Class w/ Rebalancing

Failure Cases

Biases



Evaluation



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

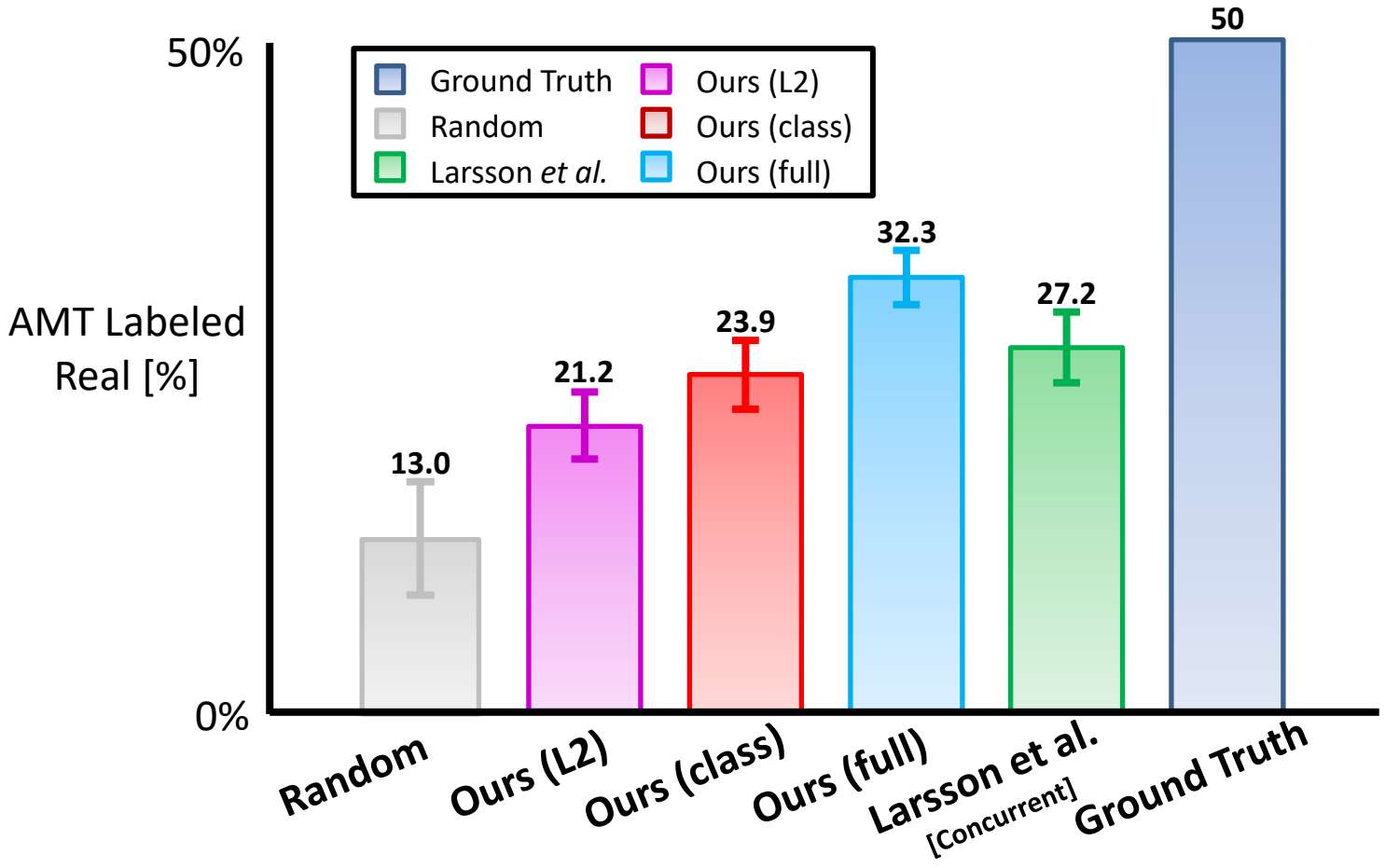
from Reddit /u/SherySantucci

Recolorized by Reddit ColorizeBot

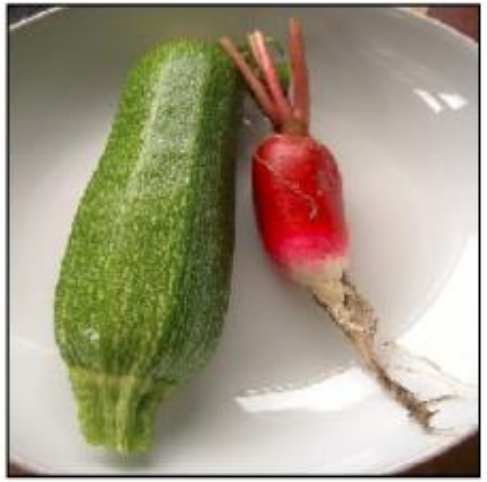
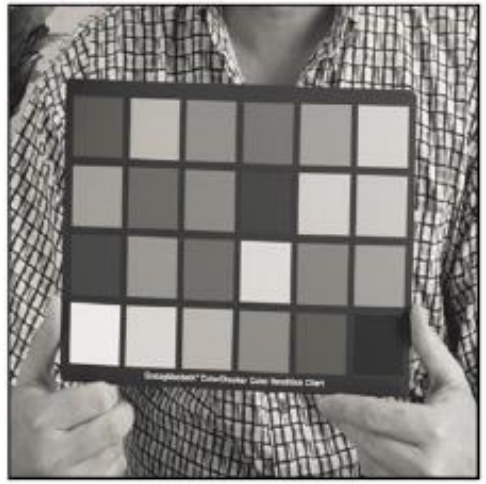
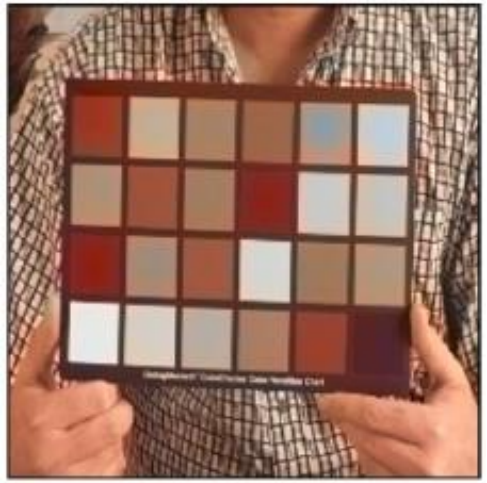
Photo taken by Reddit /u/Timteroo, Mural from street artist Eduardo Kobra

Recolorized by Reddit ColorizeBot

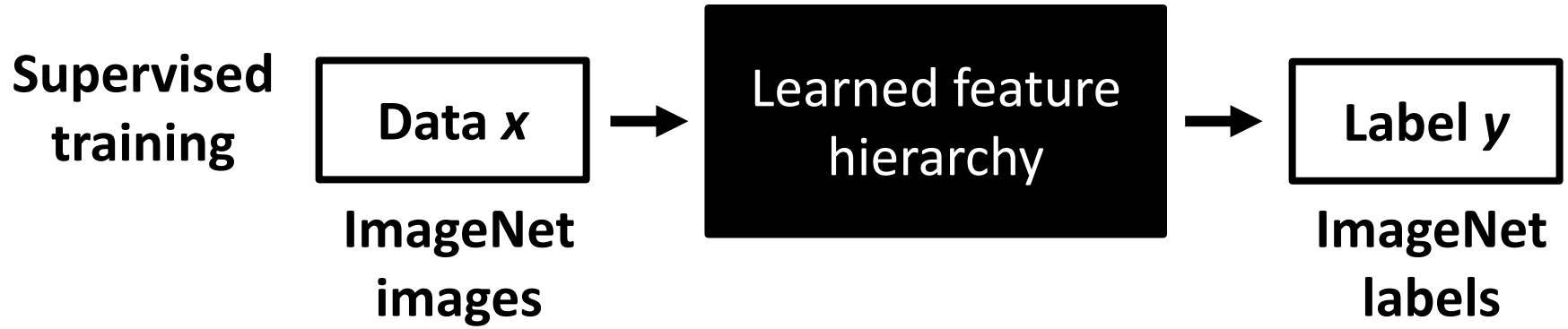
Perceptual Realism Test



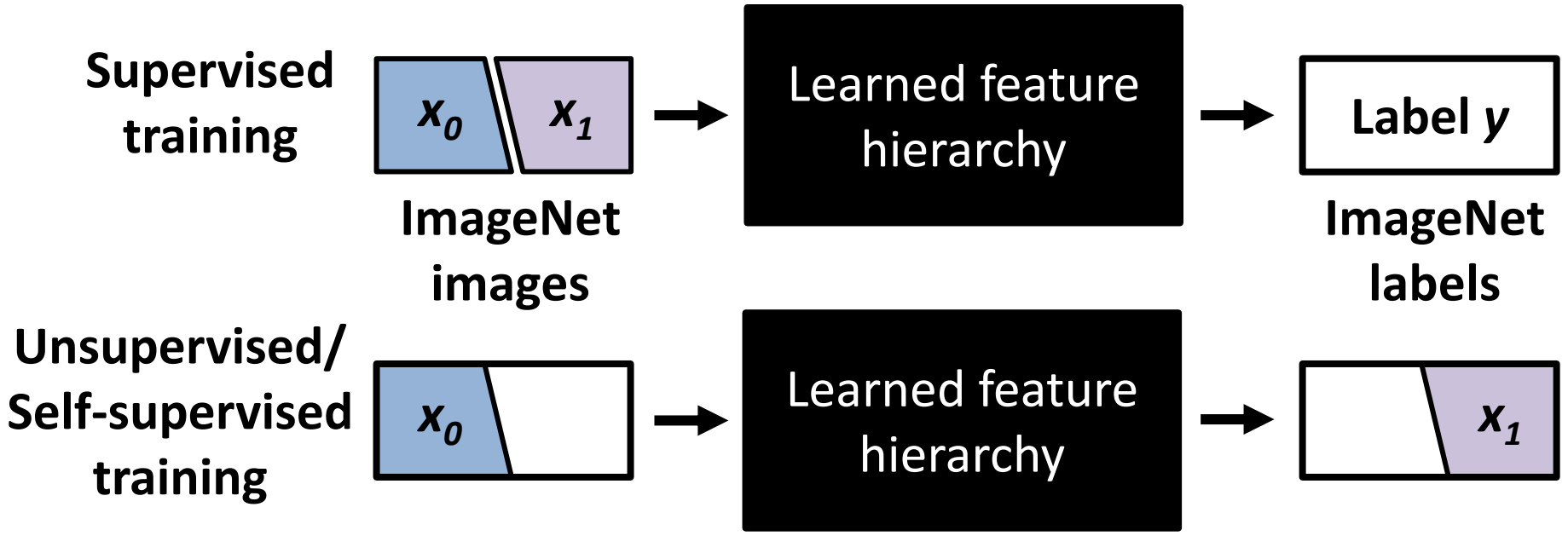
1600 images tested per algorithm

Input	Ground Truth	Output
		
		

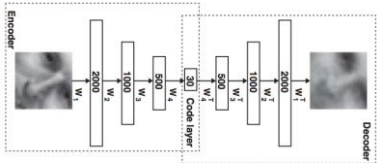
Predicting Labels from Data



Predicting Data from Data

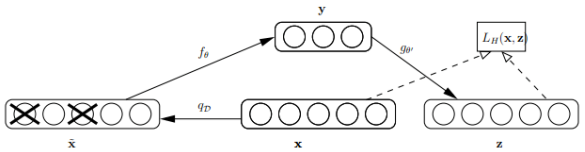


Autoencoders



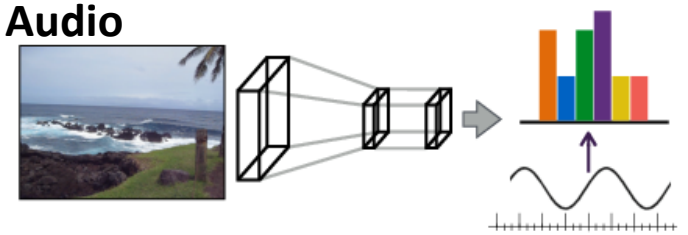
Hinton & Salakhutdinov. Science 2006.

Denoising Autoencoders



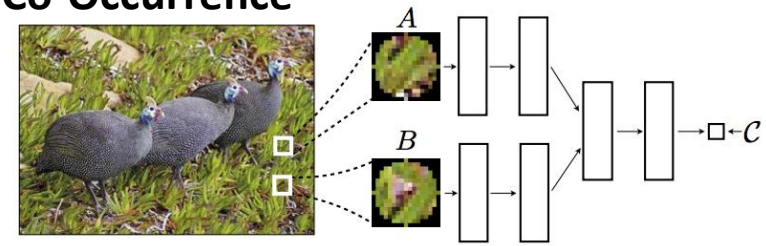
Vincent *et al.* ICML 2008.

Audio



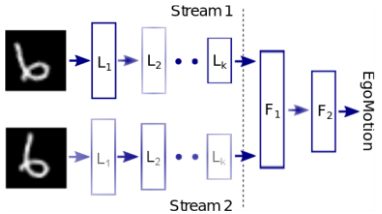
Owens *et al.* CVPR 2016, ECCV 2016

Co-Occurrence

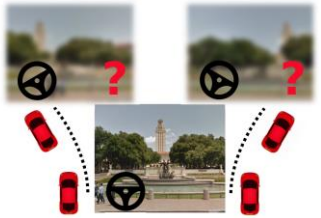


Isola *et al.* ICLR Workshop 2016.

Egomotion

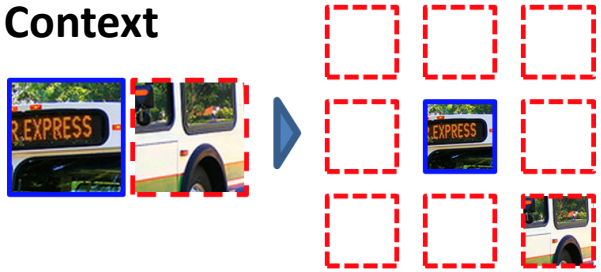


Agrawal *et al.* ICCV 2015



Jayaraman *et al.* ICCV 2015

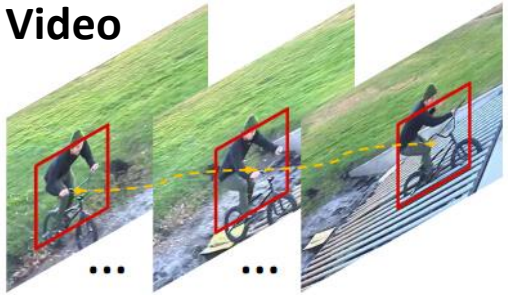
Context



Doersch *et al.* ICCV 2015

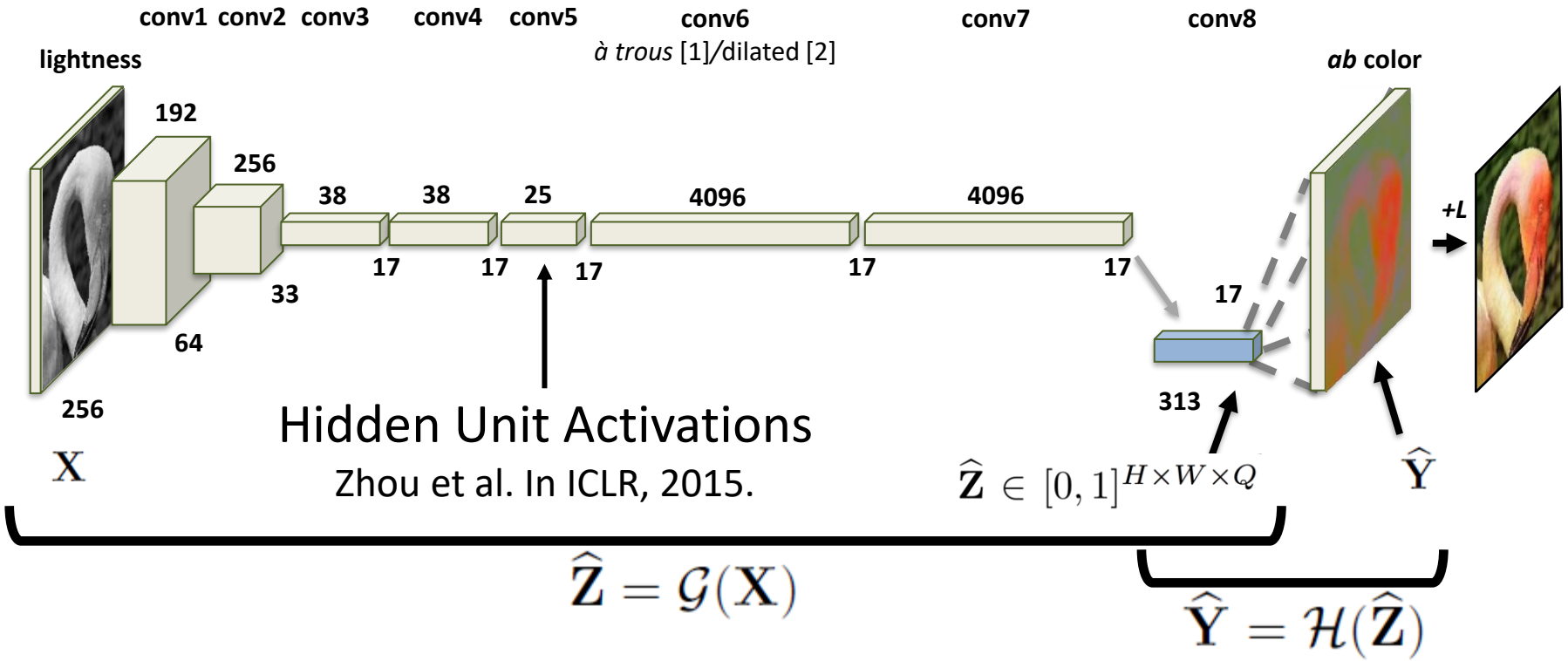
Pathak *et al.* CVPR 2016

Video



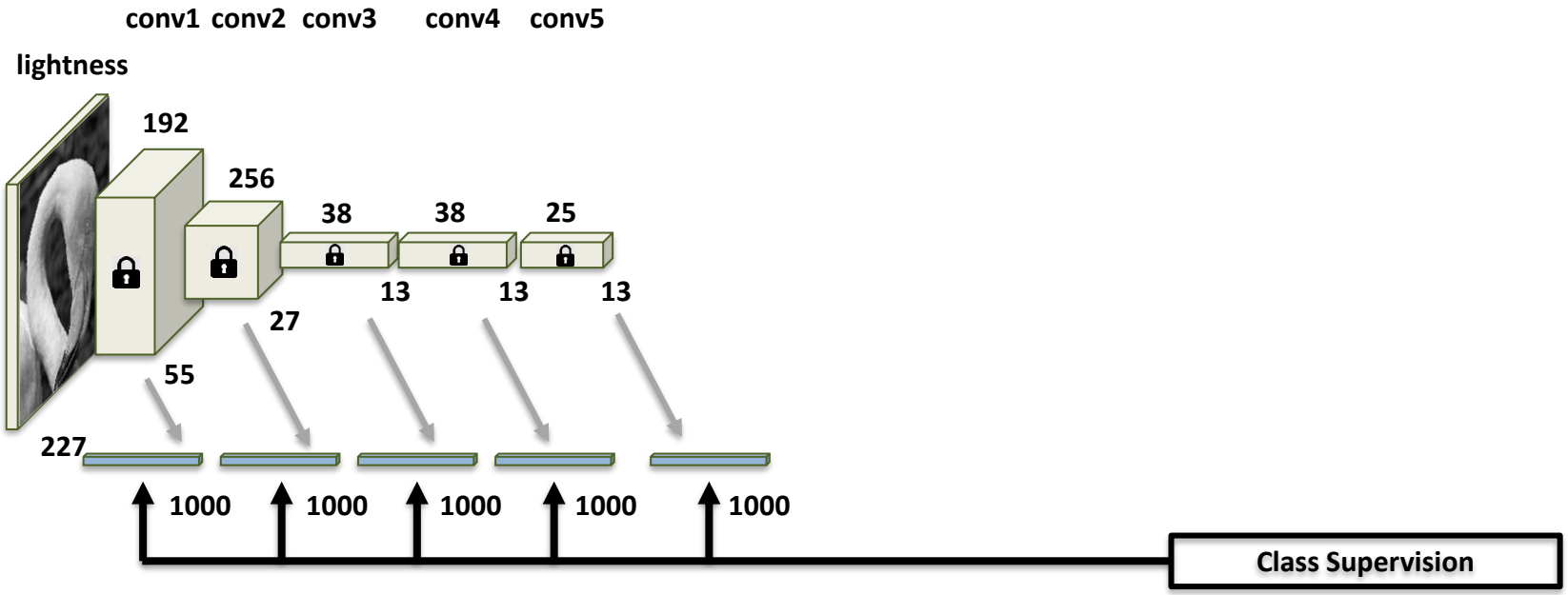
Wang *et al.* ICCV 2015

Cross-Channel Encoder



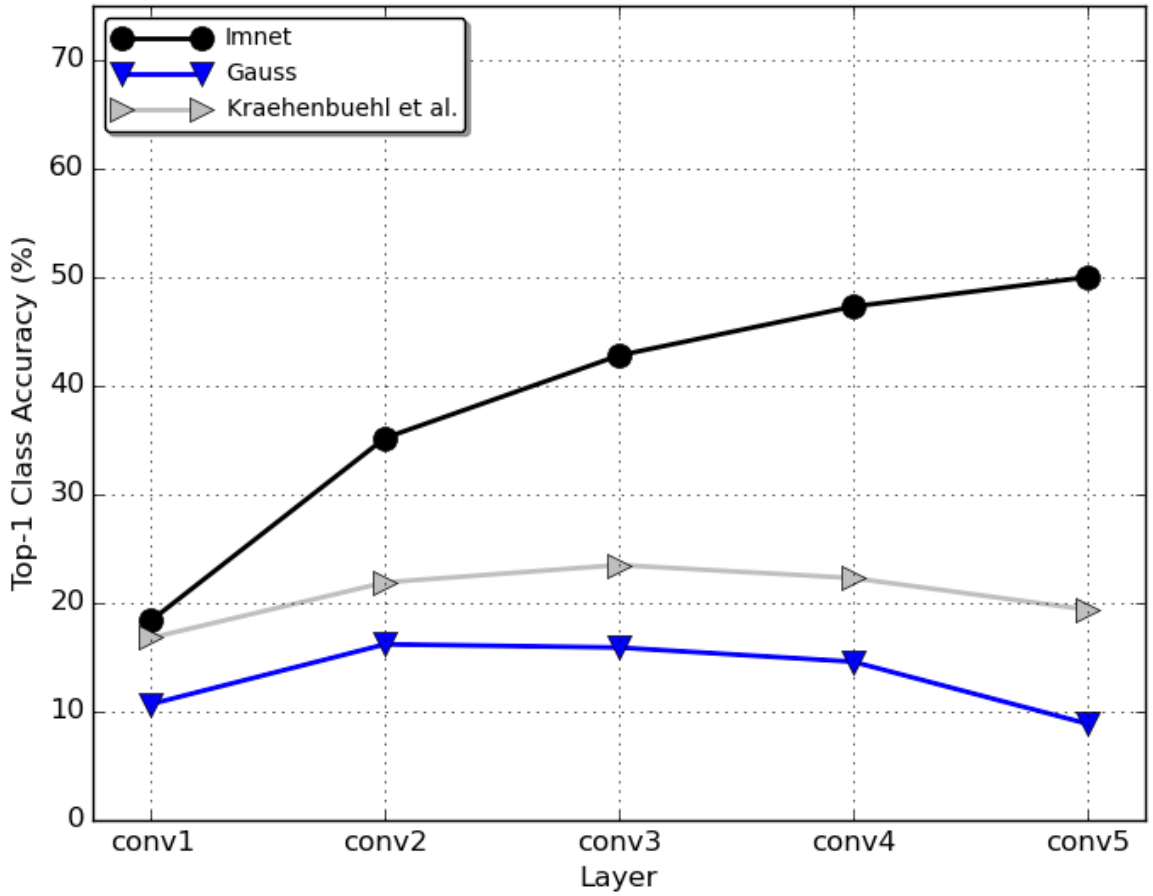
[1] Chen *et al.* In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016

Task Generalization: ILSVRC linear classification

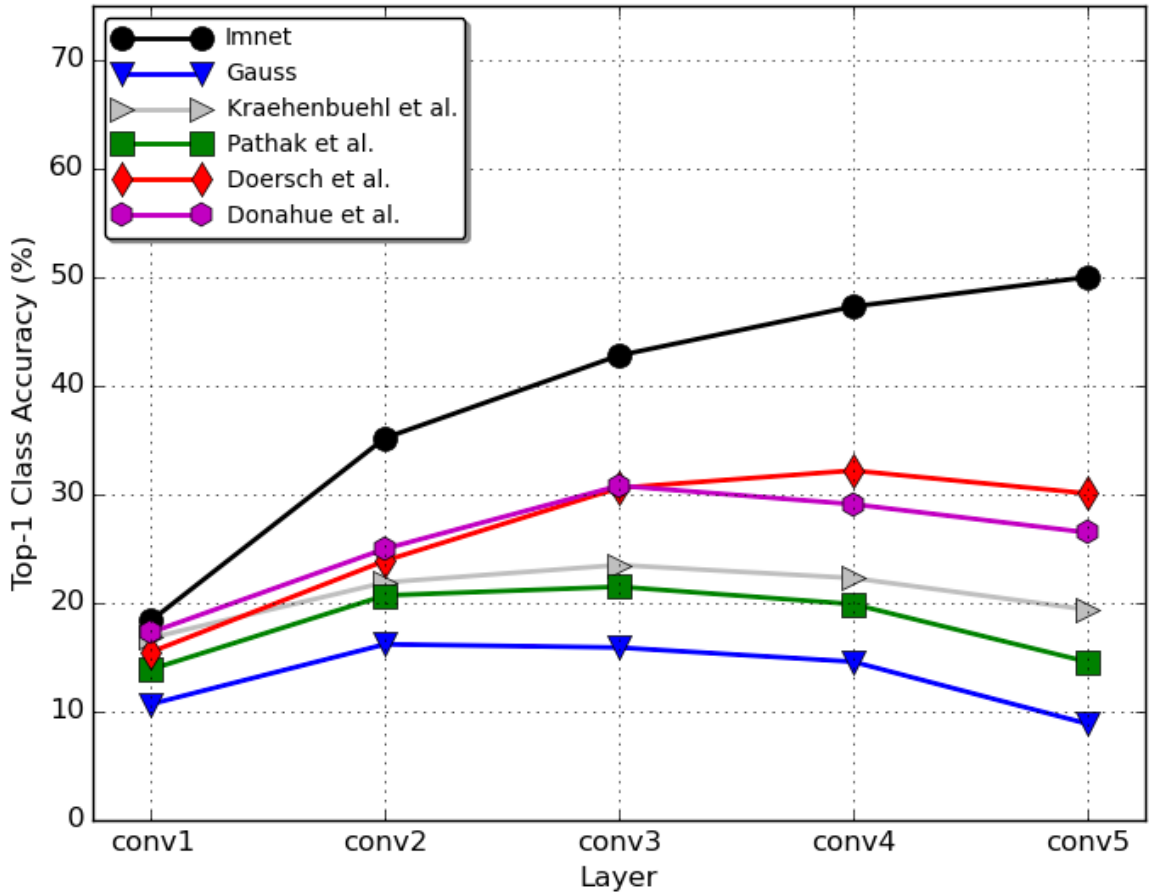


Are semantic classes ***linearly separable***
in the learned feature space?

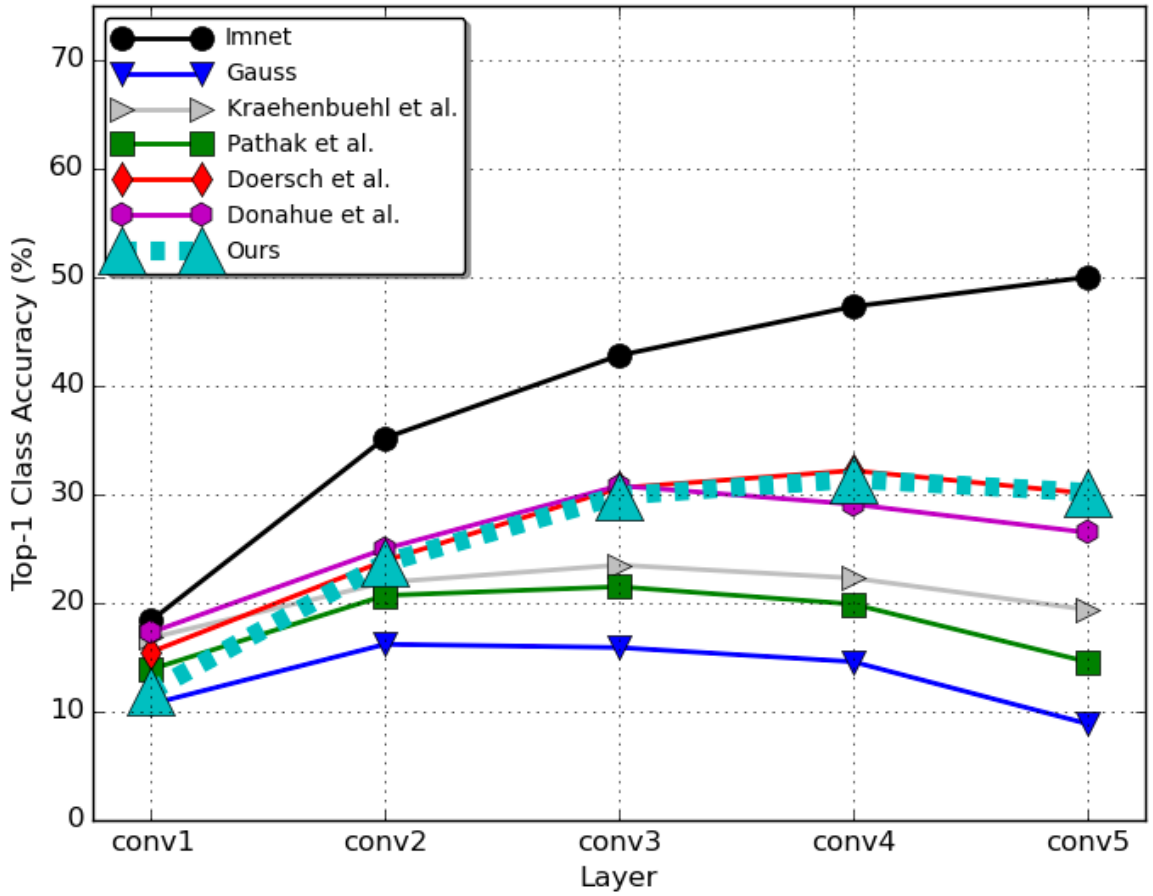
Task Generalization: ILSVRC linear classification



Task Generalization: ILSVRC linear classification

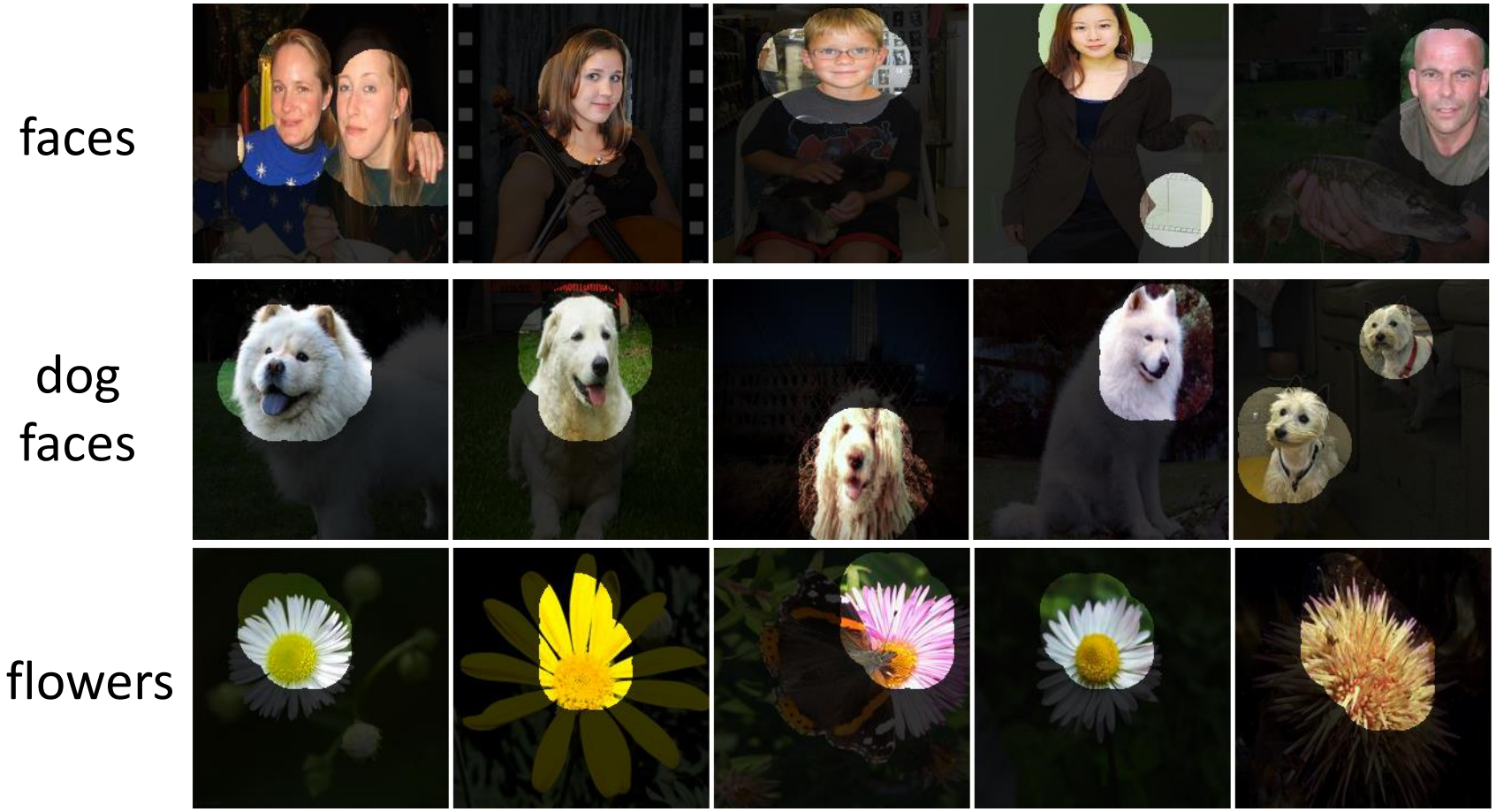


Task Generalization: ILSVRC linear classification



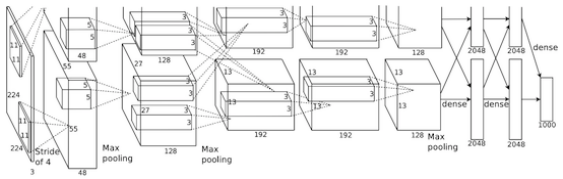
Hidden Unit (conv5) Activations

Hidden Unit (conv5) Activations



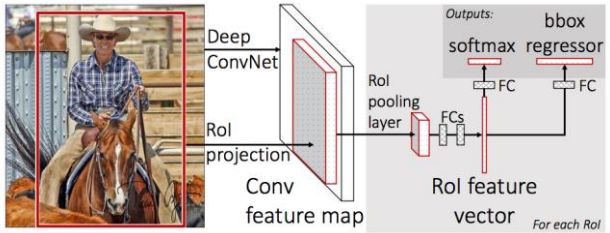
Dataset & Task Generalization on PASCAL VOC

Does the feature representation ***transfer*** to other datasets and tasks?



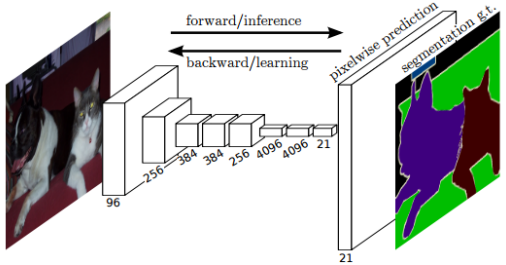
Classification

Krähenbühl et al. In ICLR, 2016.



Detection

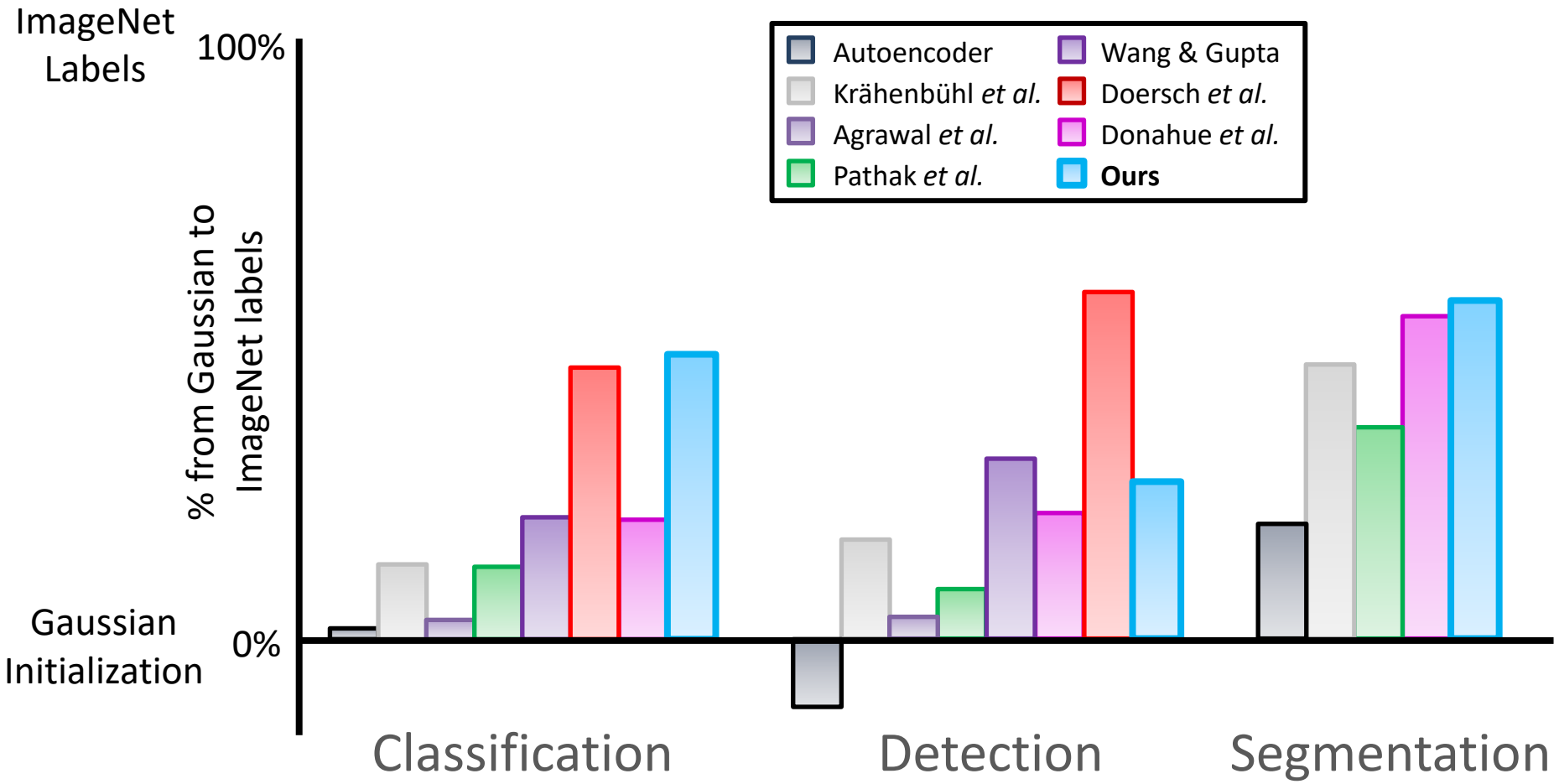
Fast R-CNN. Girshick. In ICCV, 2015.

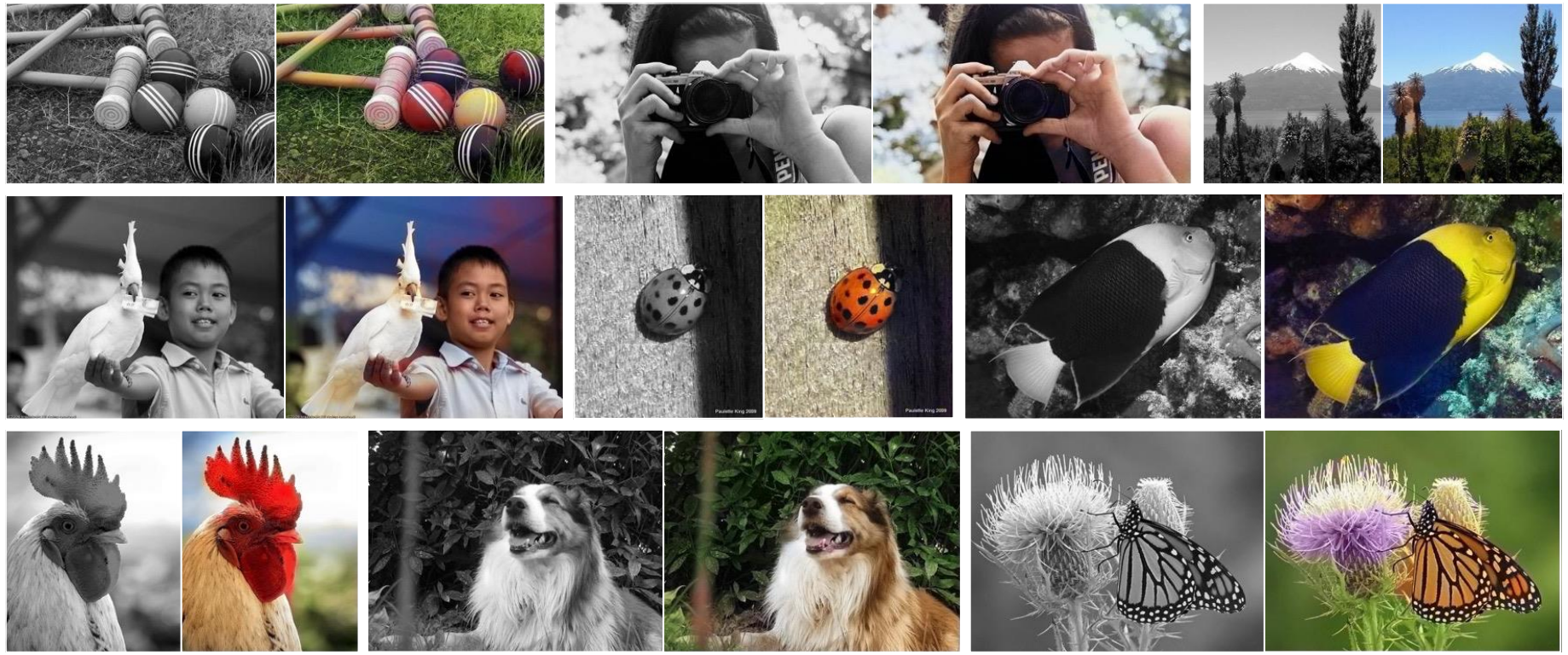


Segmentation

FCNs. Long et al. In CVPR, 2015.

Dataset & Task Generalization on PASCAL VOC





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”

Clever ideas to keep in mind

- Turn a regression task into a classification task
- Fight back against class imbalance
  - Loss functions that emphasize rare classes
  - Replay rare classes more during training

A Simple Framework for Contrastive Learning of Visual Representations

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

SimCLR, IMCL 2020

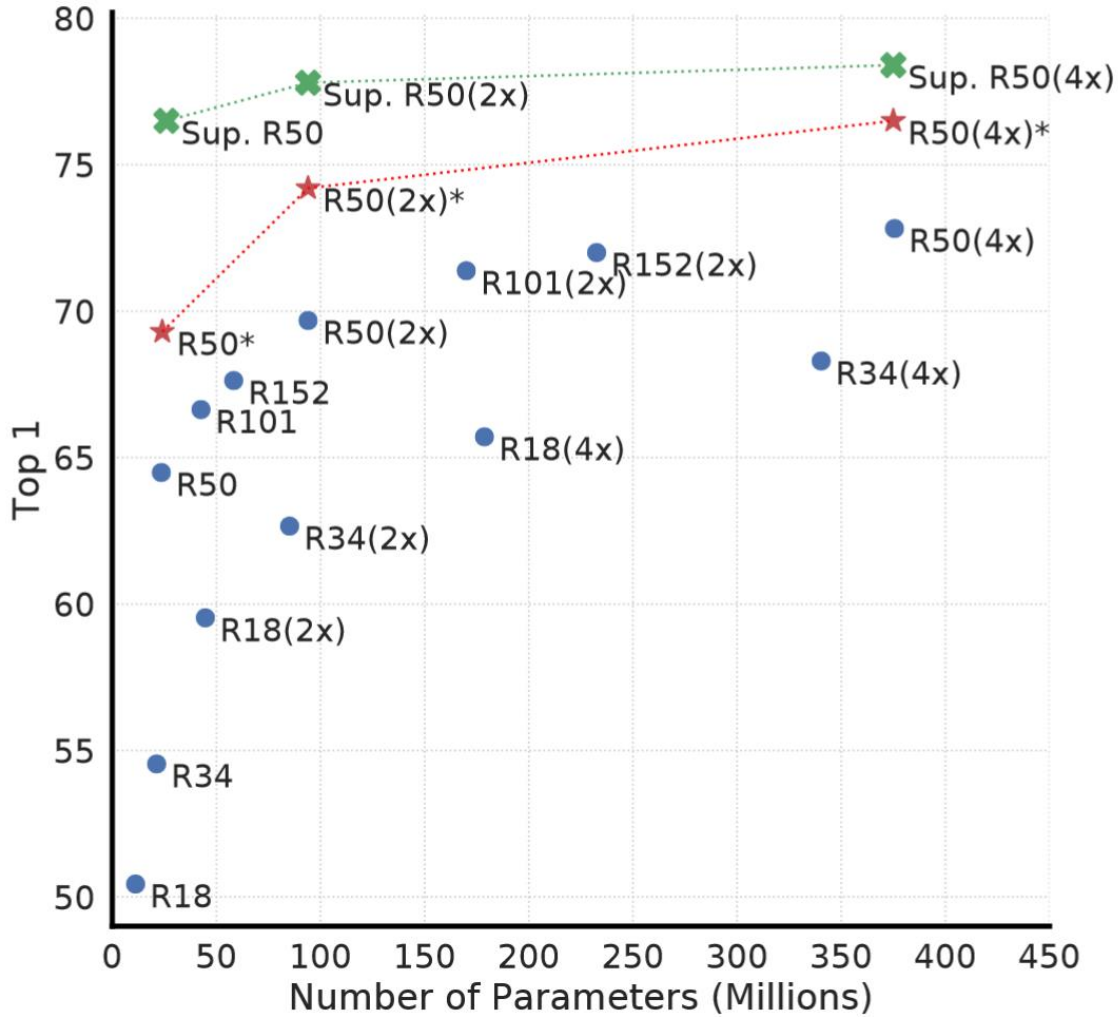
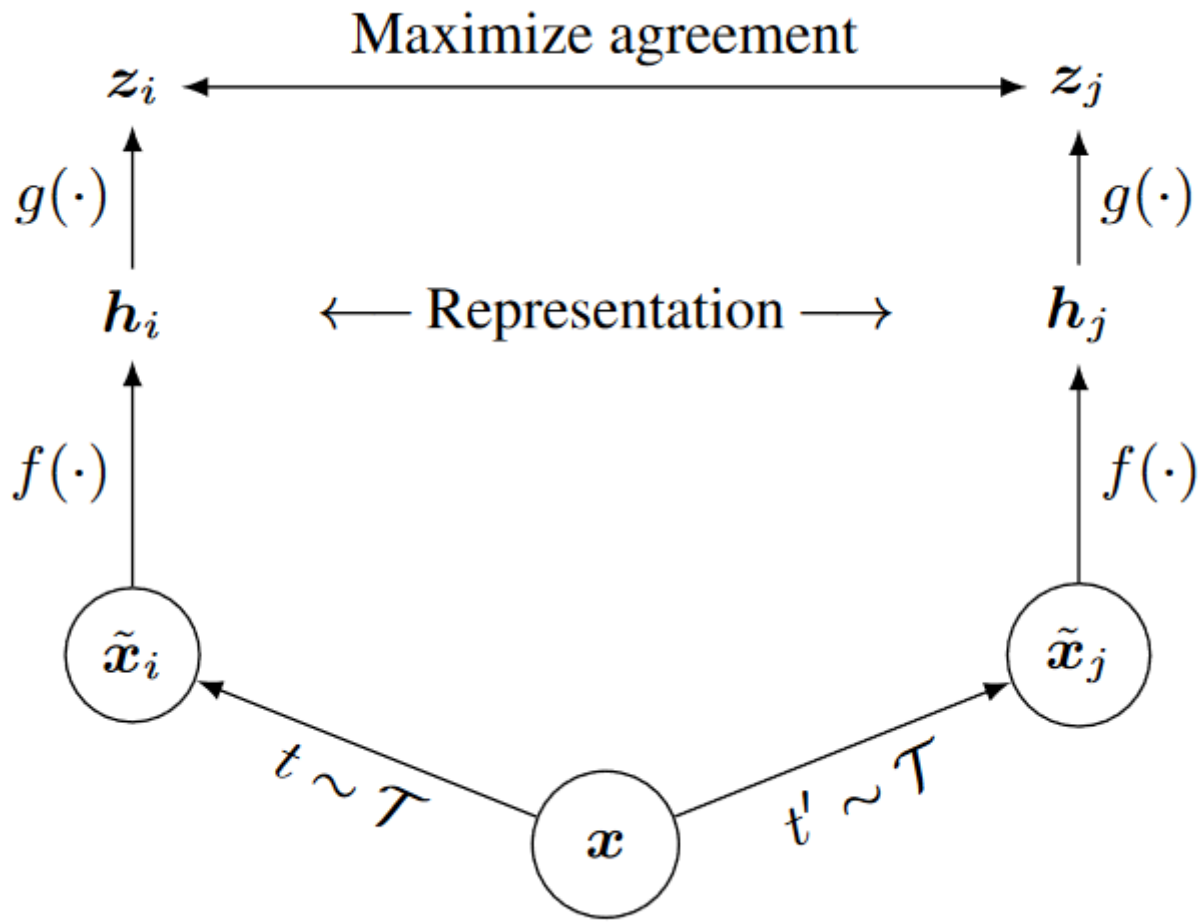


Figure 7. Linear evaluation of models with varied depth and width. Models in blue dots are ours trained for 100 epochs, models in red stars are ours trained for 1000 epochs, and models in green crosses are supervised ResNets trained for 90 epochs[7] (He et al., 2016).


Maximize agreement
z_i
z_j
$g(\cdot)$
$g(\cdot)$
h_i
Representation
h_j
$f(\cdot)$
$f(\cdot)$
$\tilde{x}_i$
$\tilde{x}_j$
$t \sim \mathcal{T}$
x
$t' \sim \mathcal{T}$

(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

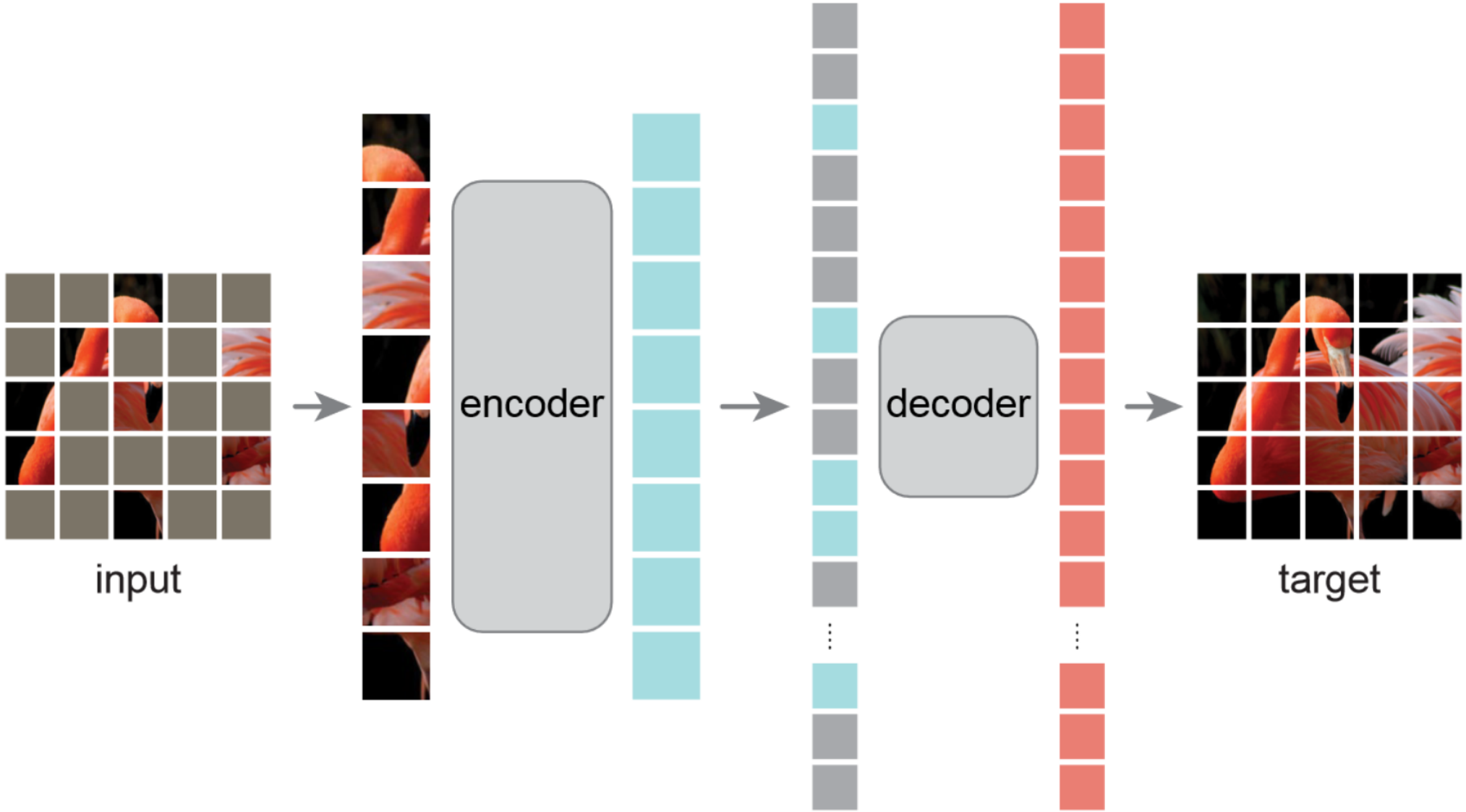
Masked Autoencoders Are Scalable Vision Learners

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

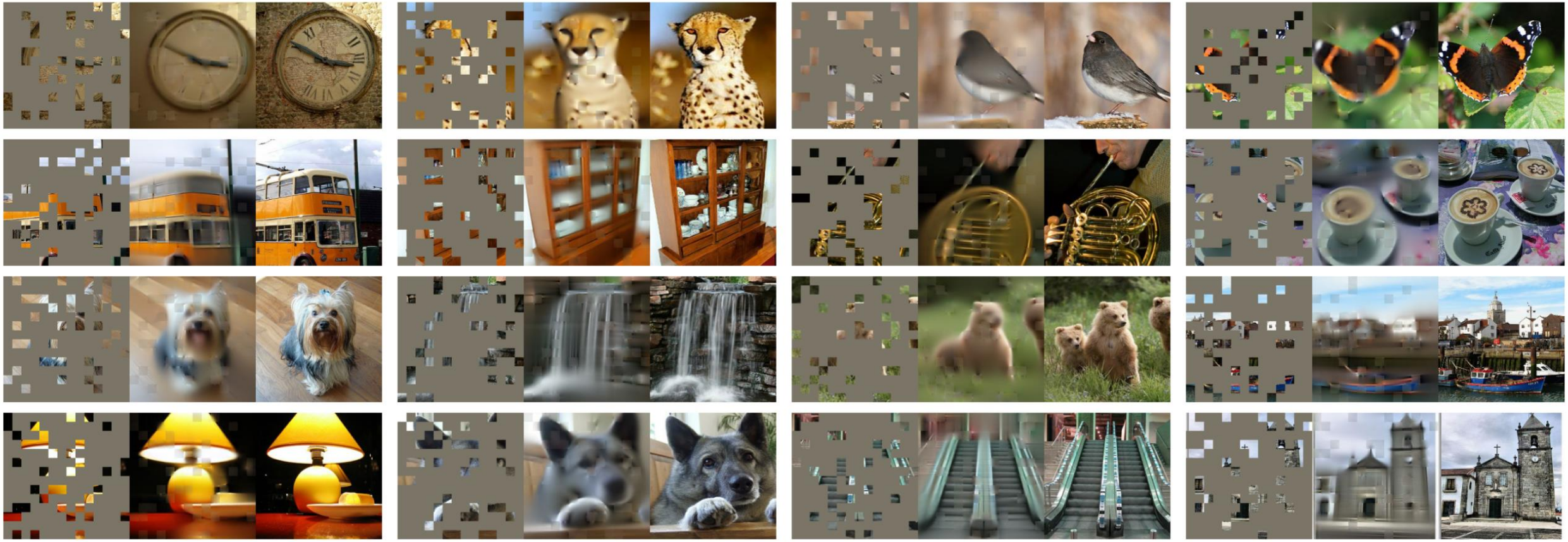
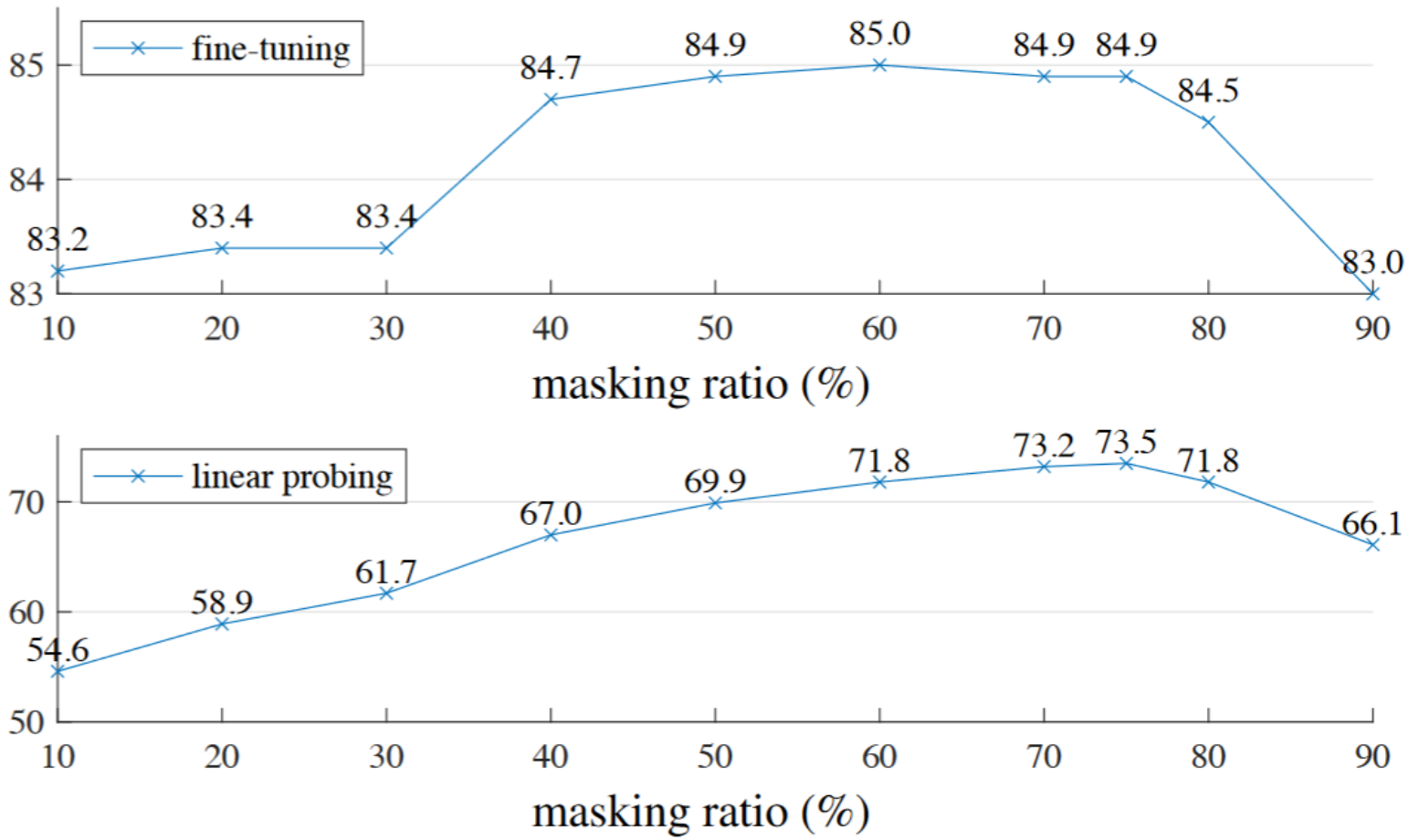


Figure 2. Example results on ImageNet *validation* images. For each triplet, we show the masked image (left), our MAE reconstruction[†] (middle), and the ground-truth (right). The masking ratio is 80%, leaving only 39 out of 196 patches. More examples are in the appendix.

[†]*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 (%)

		AP^{box}		AP^{mask}	
method	pre-train data	ViT-B	ViT-L	ViT-B	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