“~~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
  - 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

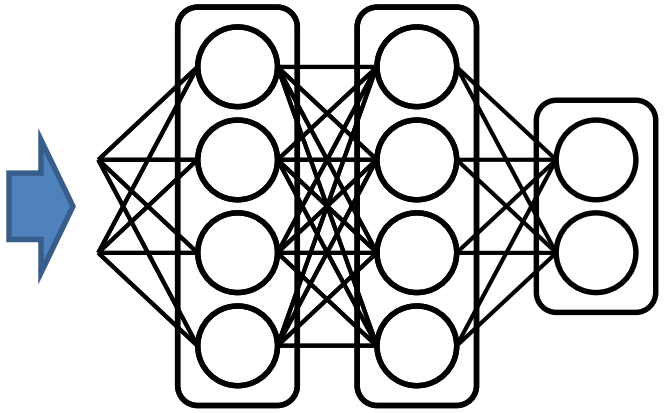
- Three methods for "unsupervised" deep learning
  - Context Prediction. Doersch et al. ICCV 2015
  - Colorful Image Colorization. Zhang et al. ECCV 2016
  - SimCLR. Chen et al. ICML 2020
- Big picture: do we need big, labeled datasets like ImageNet to make deep learning worthwhile? Can we learn from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

Unsupervised Visual Representation Learning by Context Prediction

Carl Doersch, Alexei A. Efros, and Abhinav Gupta

ICCV 2015

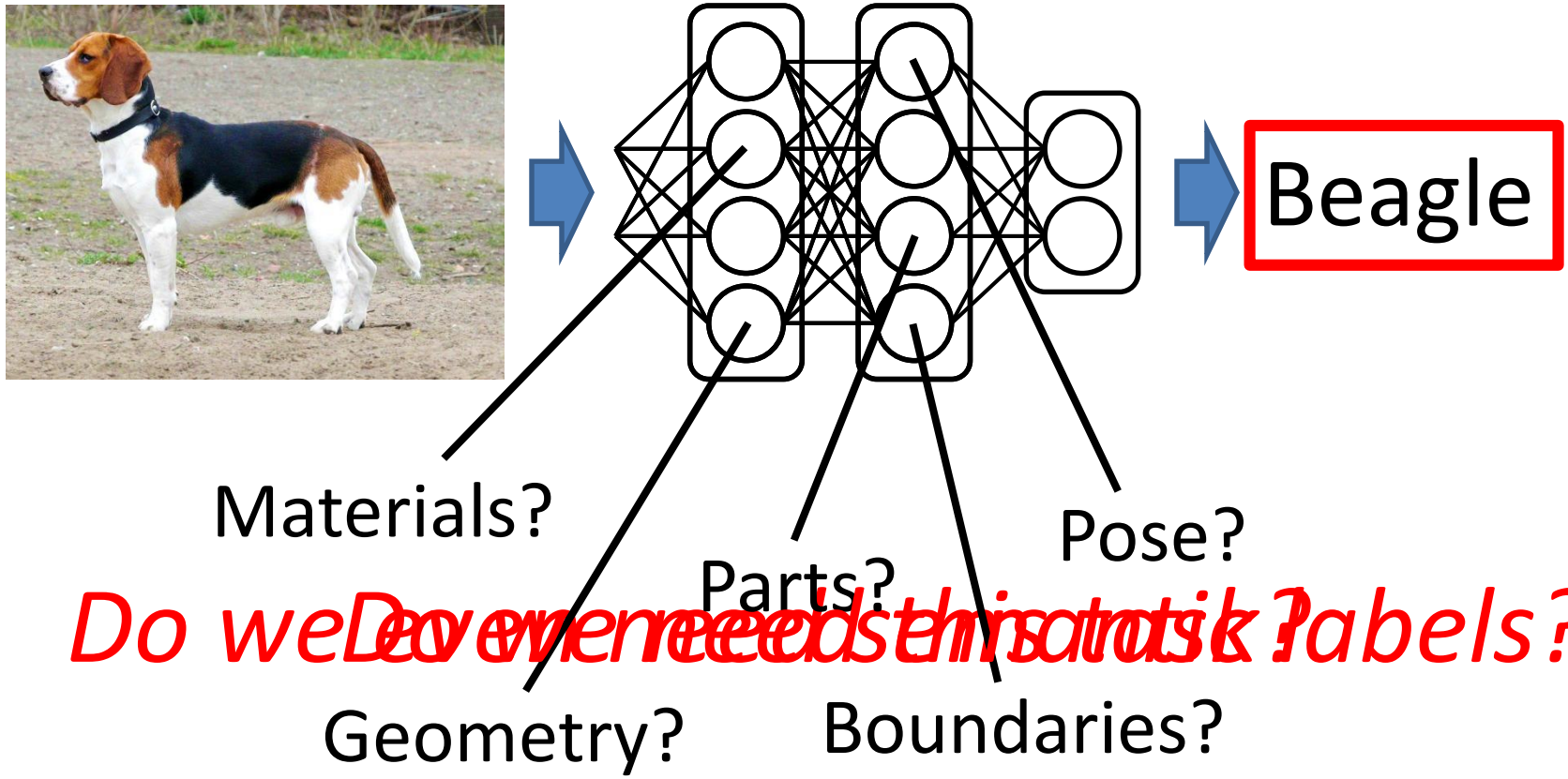
ImageNet + Deep Learning



Beagle

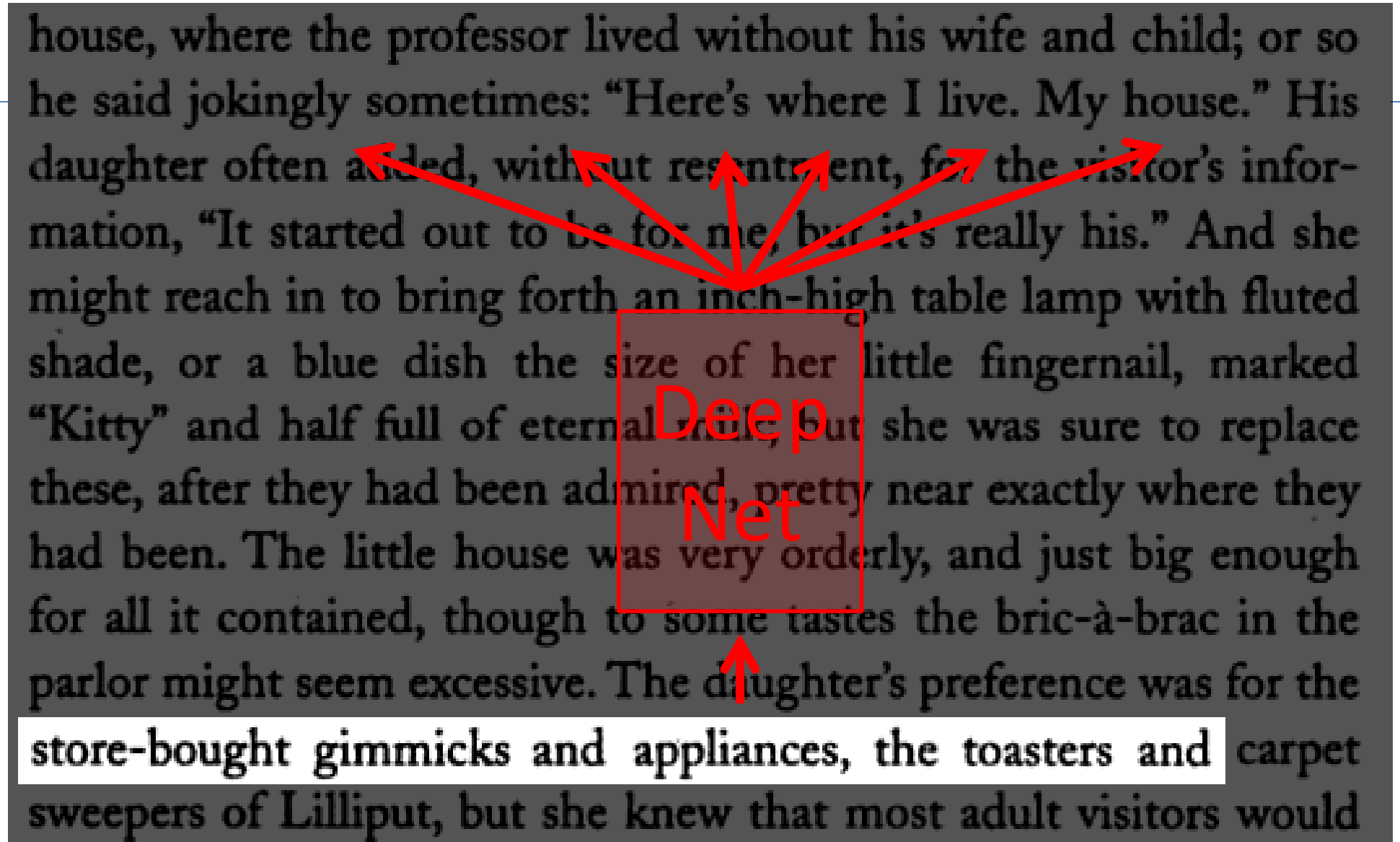
- Image Retrieval
- Detection (RCNN)
- Segmentation (FCN)
- Depth Estimation
- …

ImageNet + Deep Learning

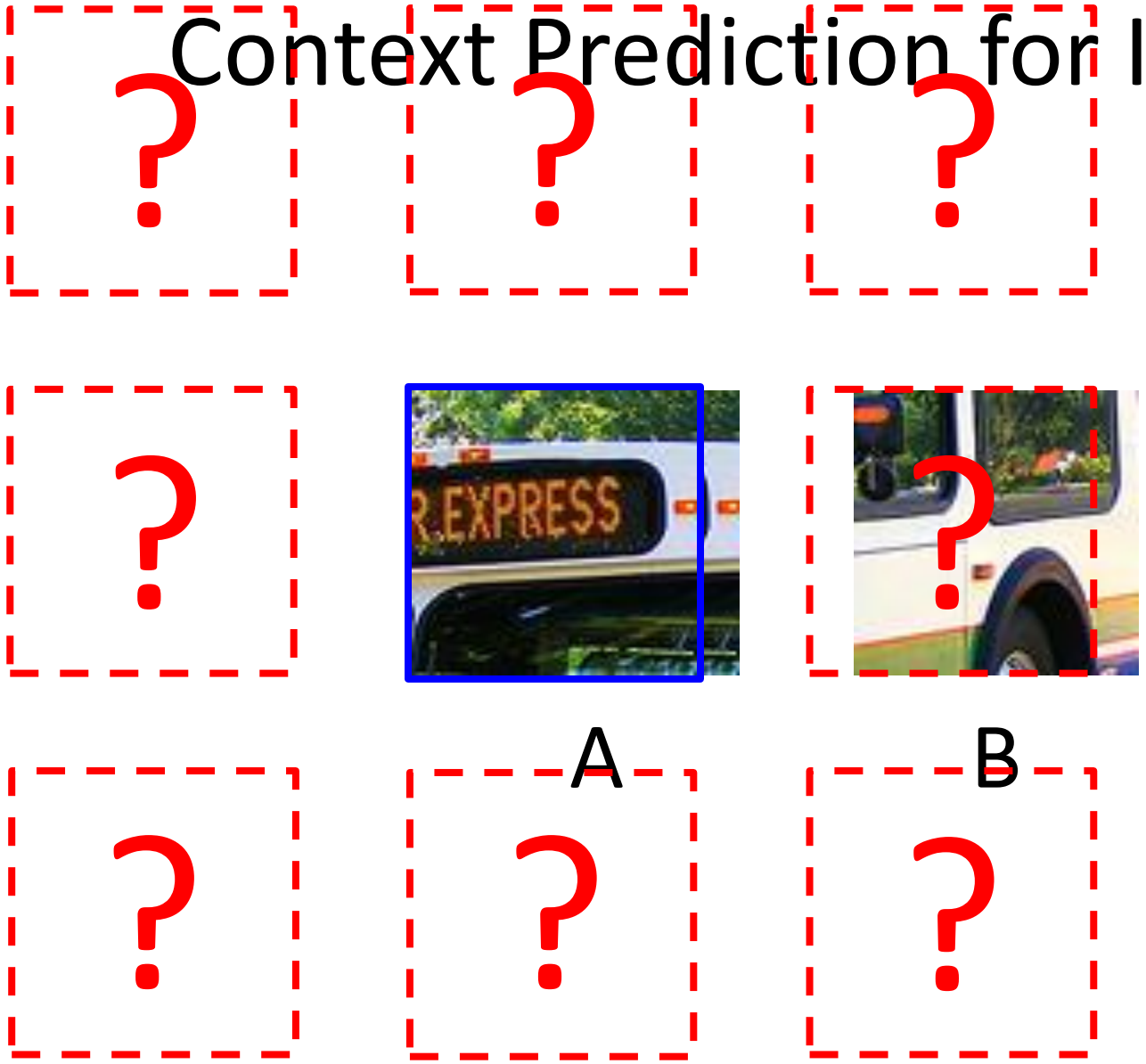


Context as Supervision

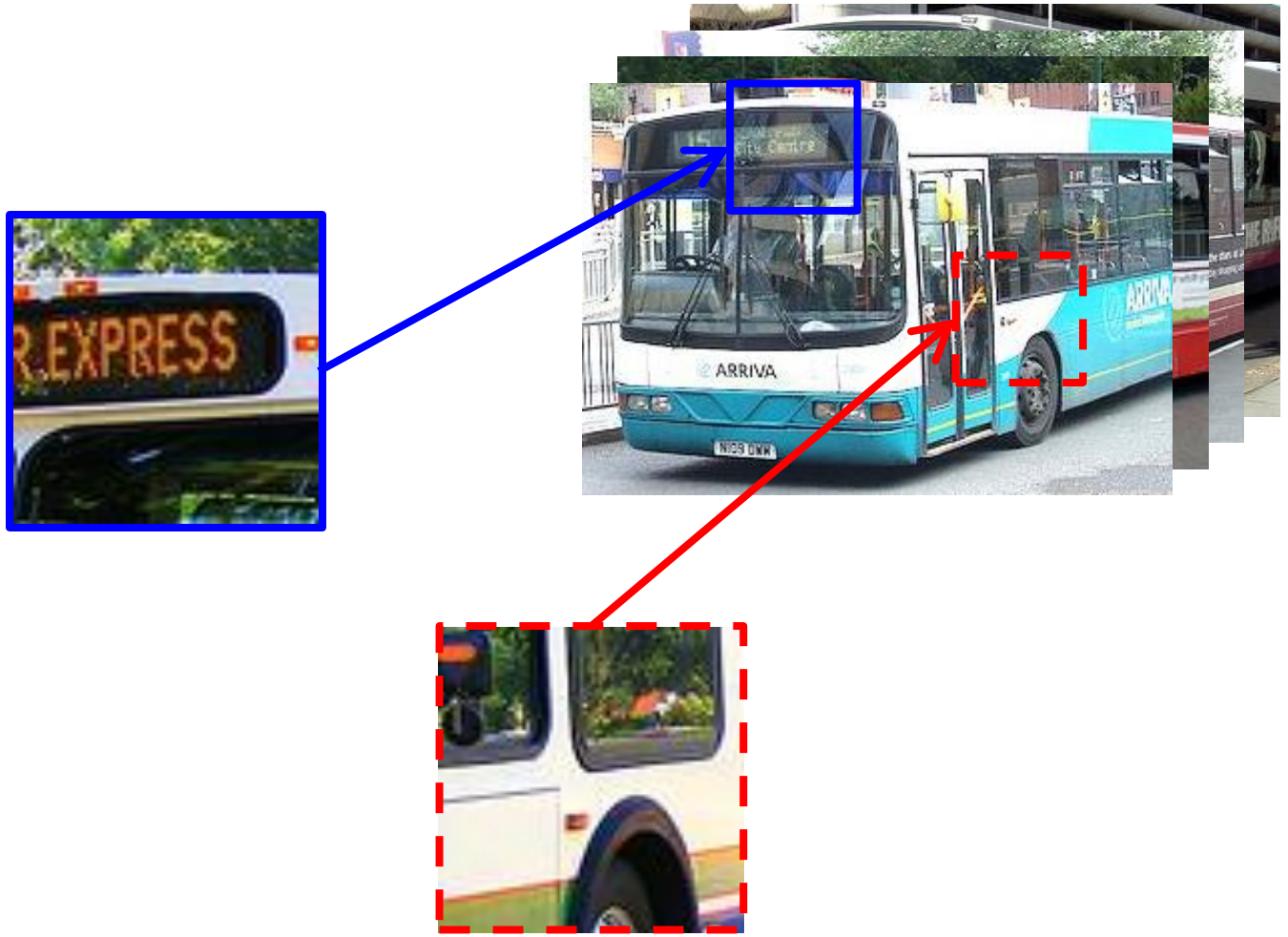
[Collobert & Weston 2008; Mikolov et al. 2013]



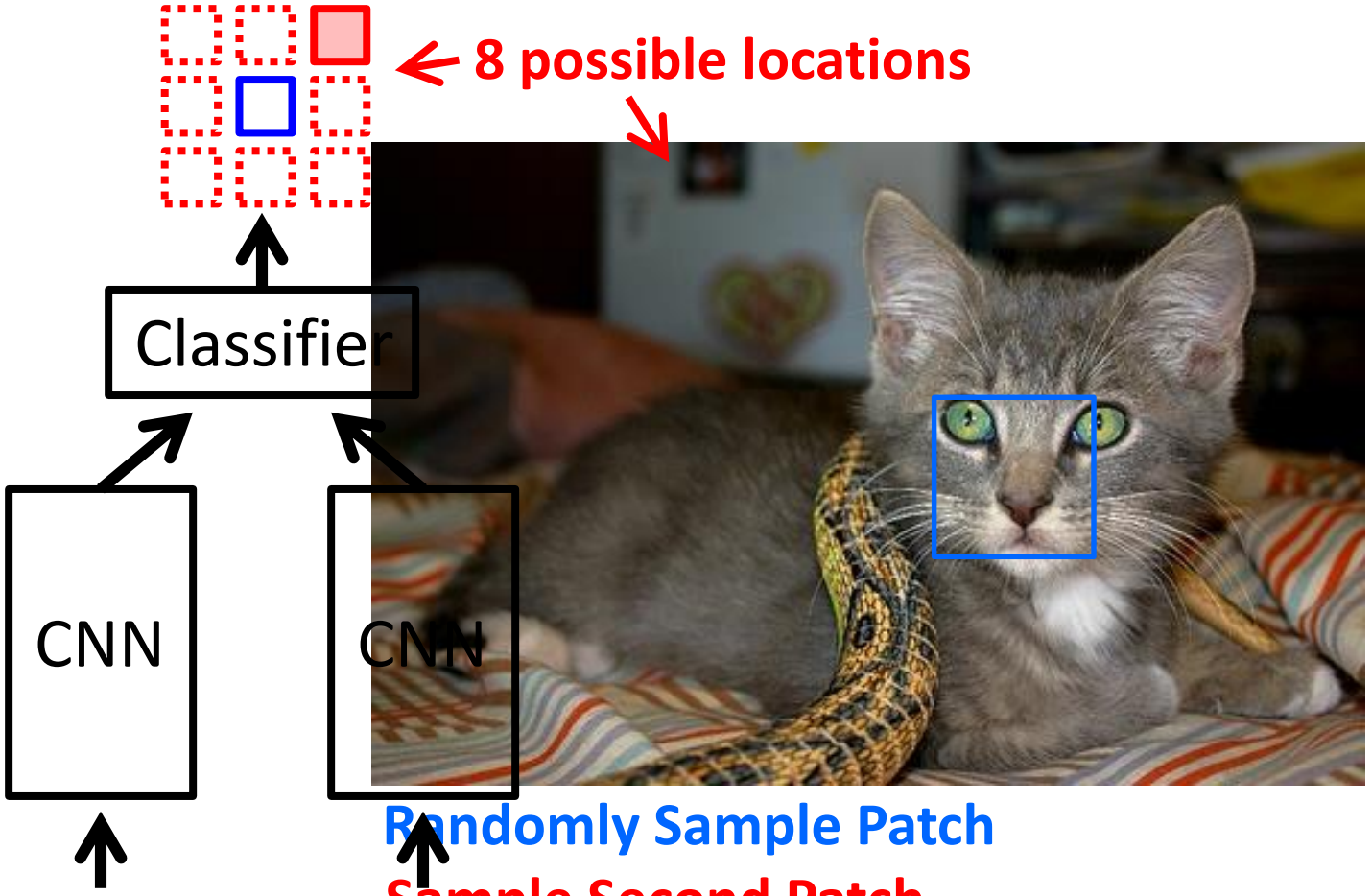
Context Prediction for Images

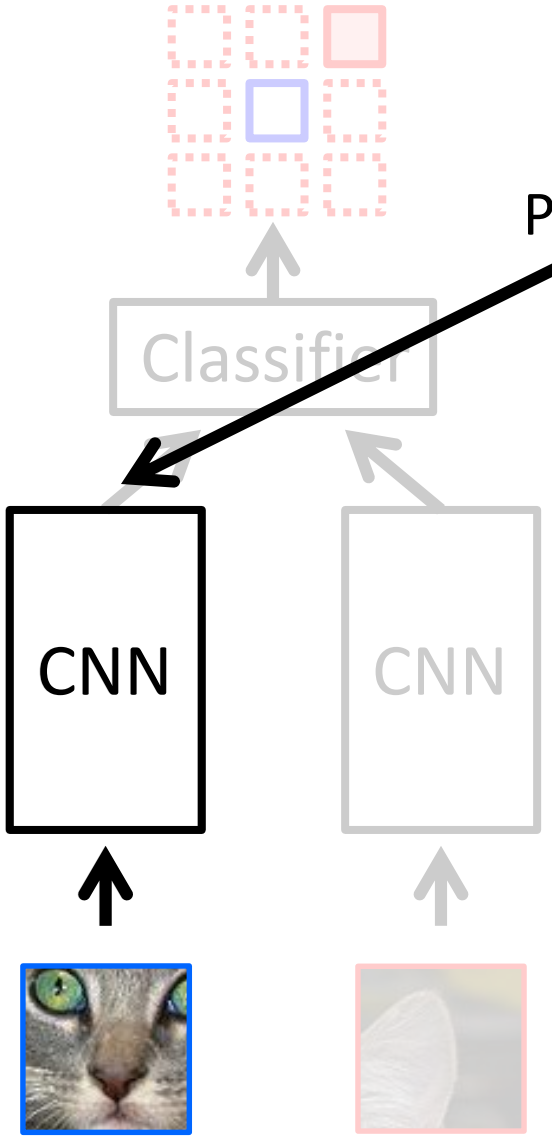


Semantics from a non-semantic task



Relative Position Task



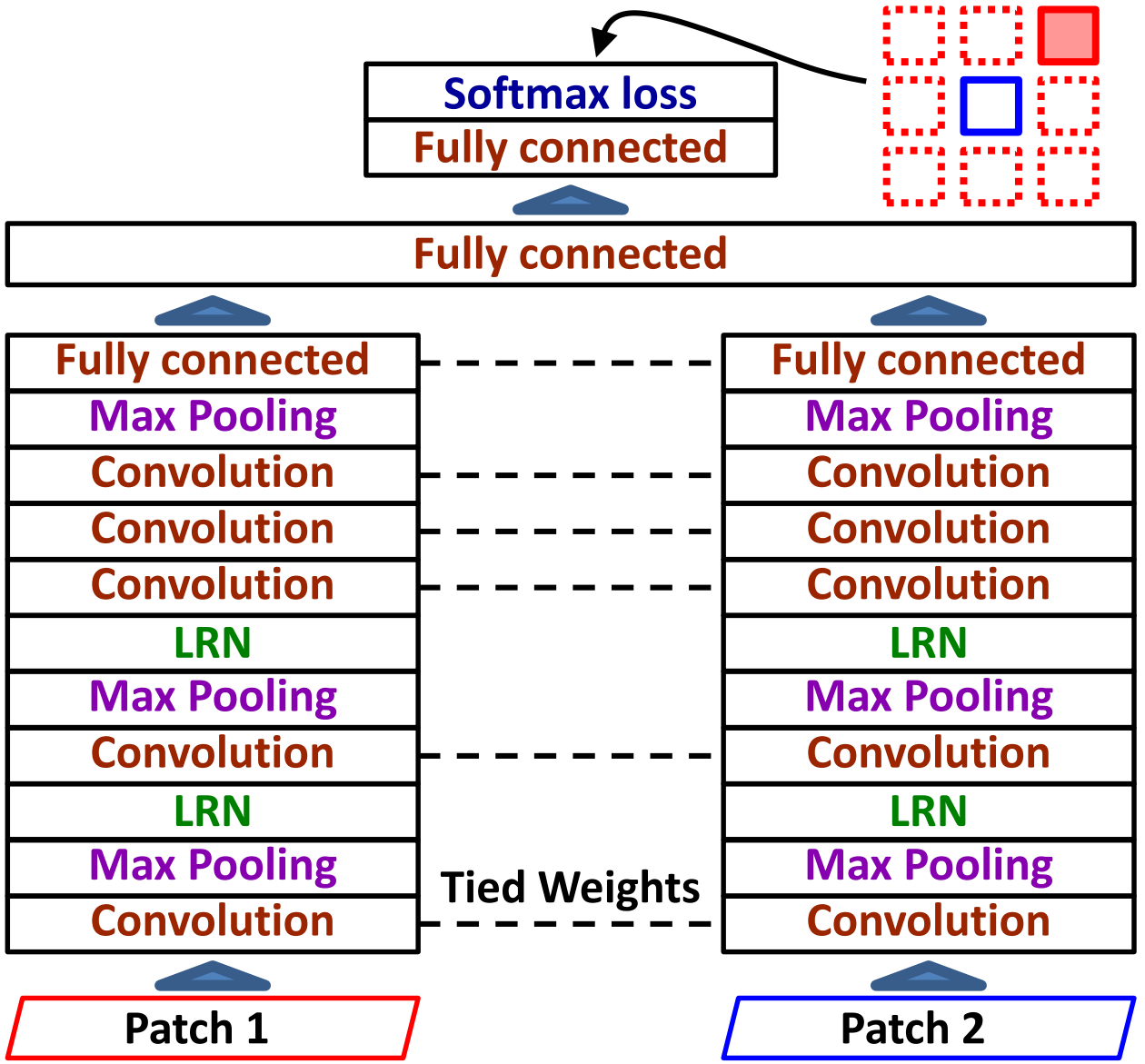


Input

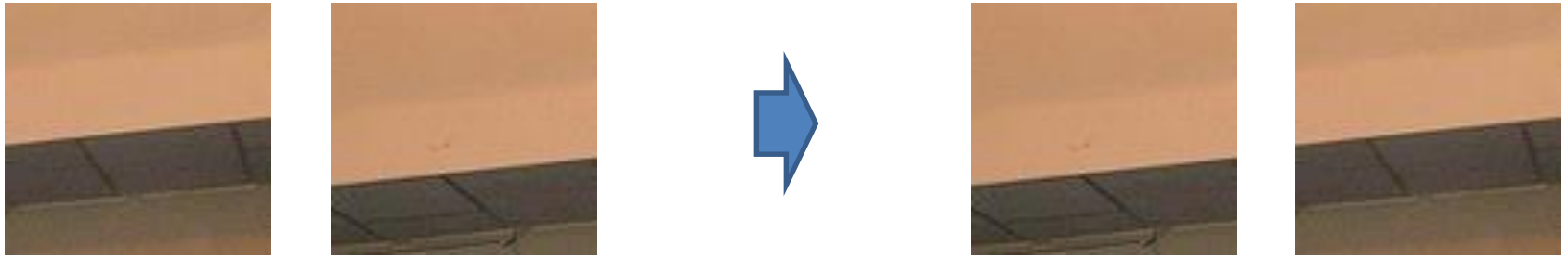
Nearest Neighbors

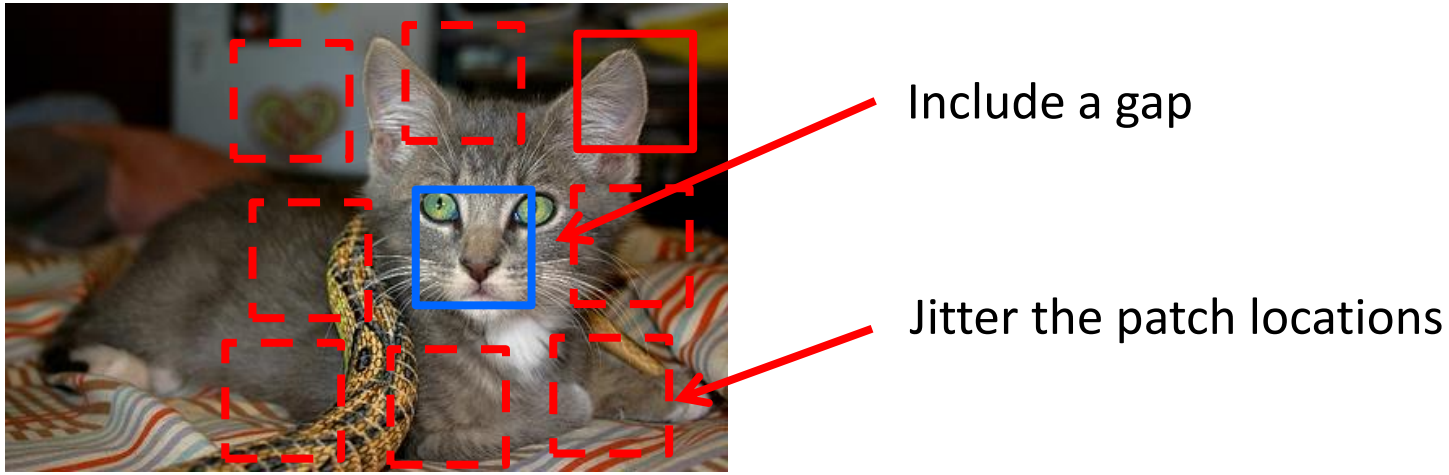
Note: connects ***across*** instances!

Architecture

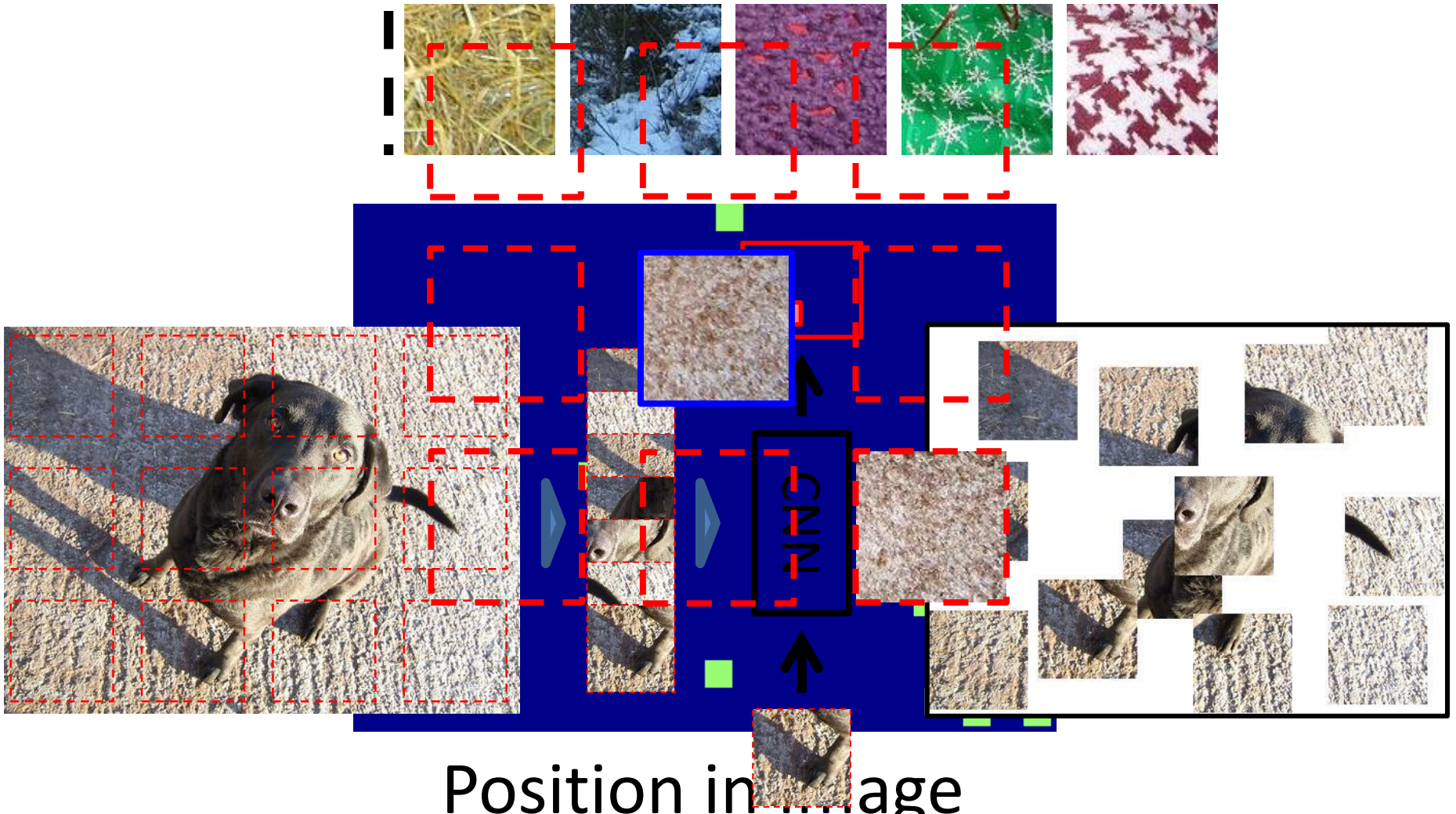


Avoiding Trivial Shortcuts

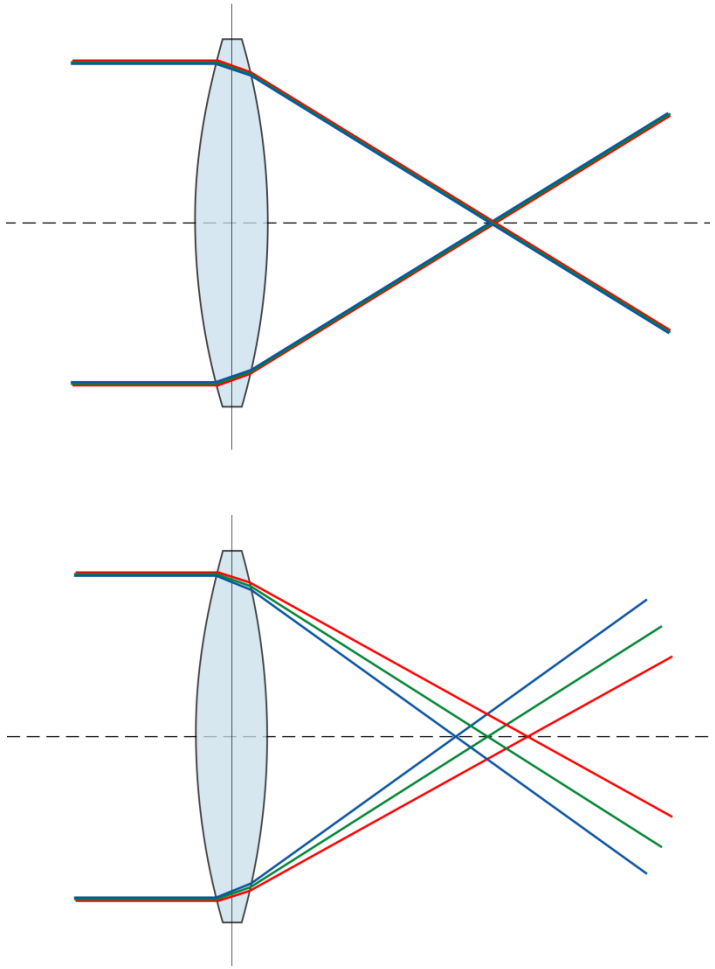


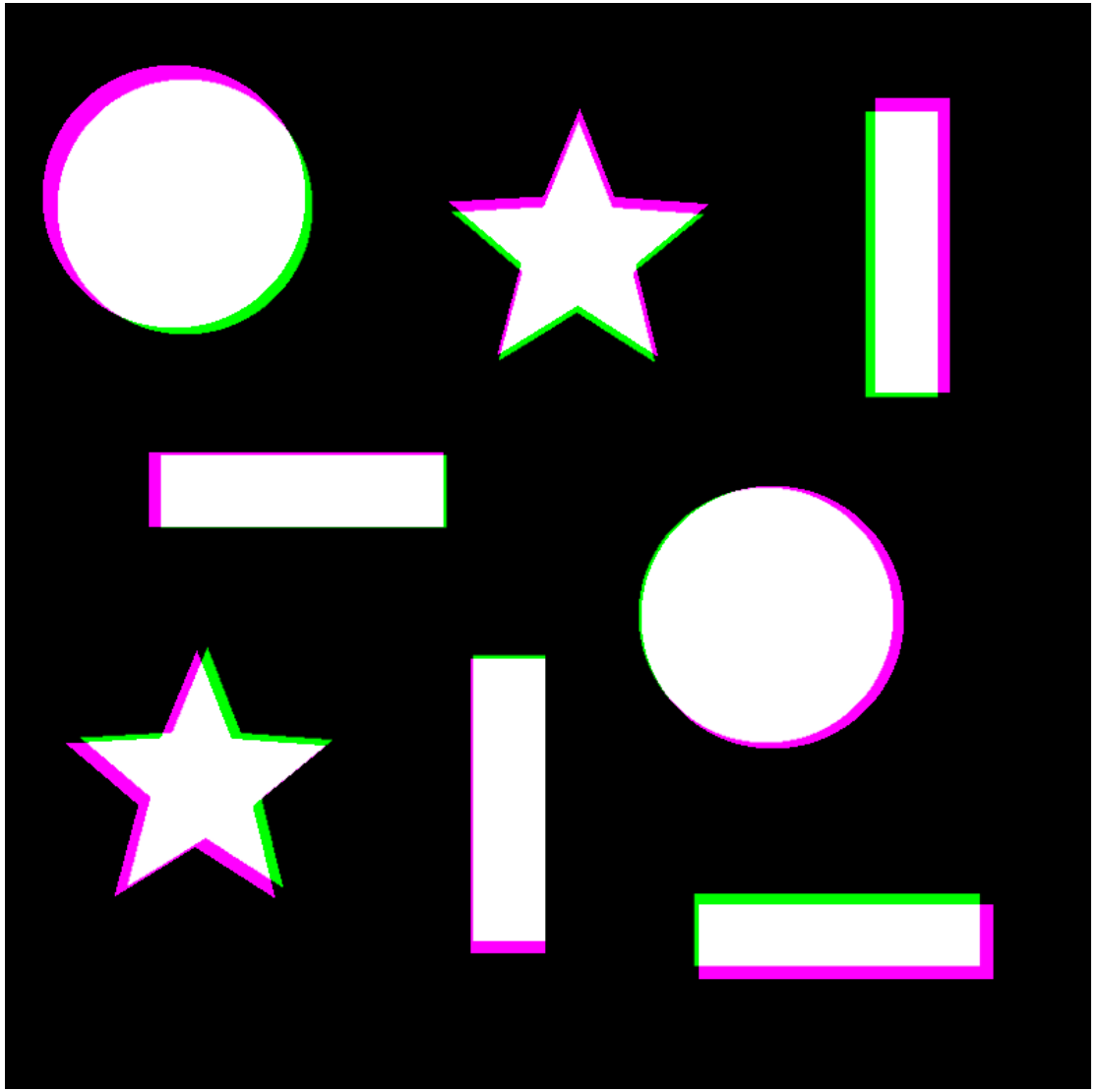


A Not-So “Trivial” Shortcut

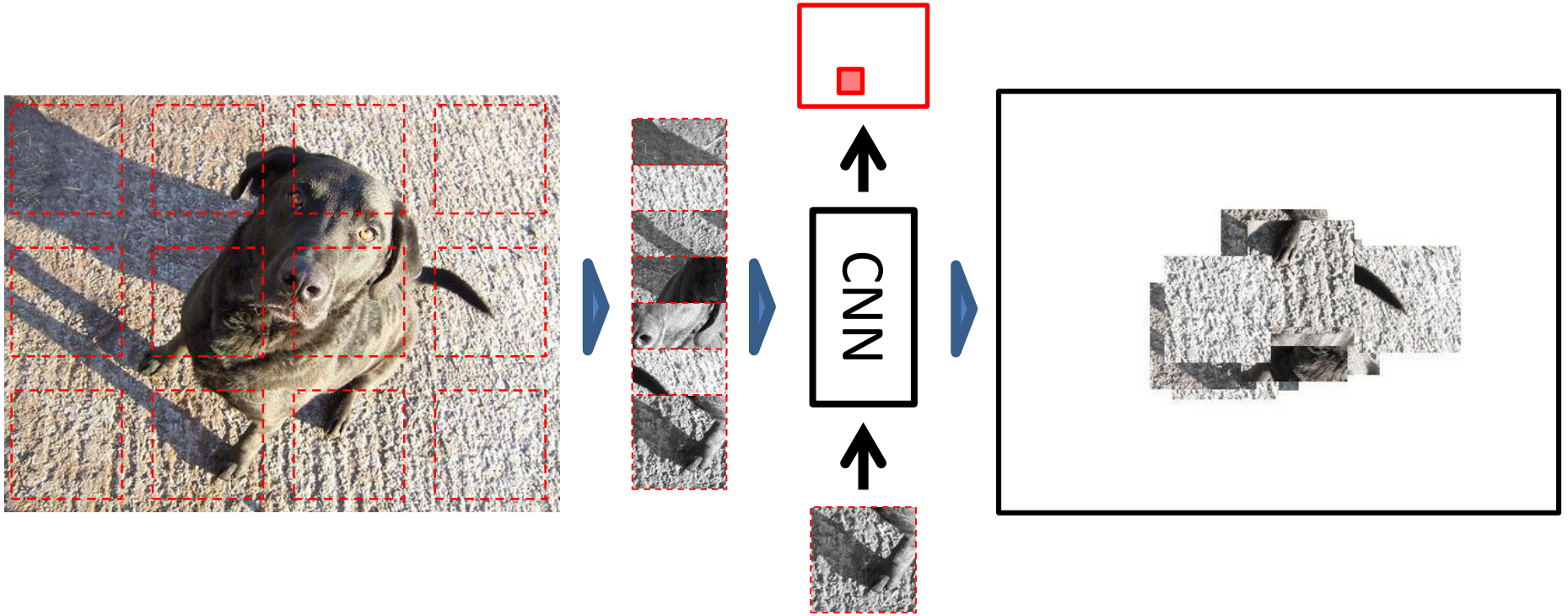


Chromatic Aberration

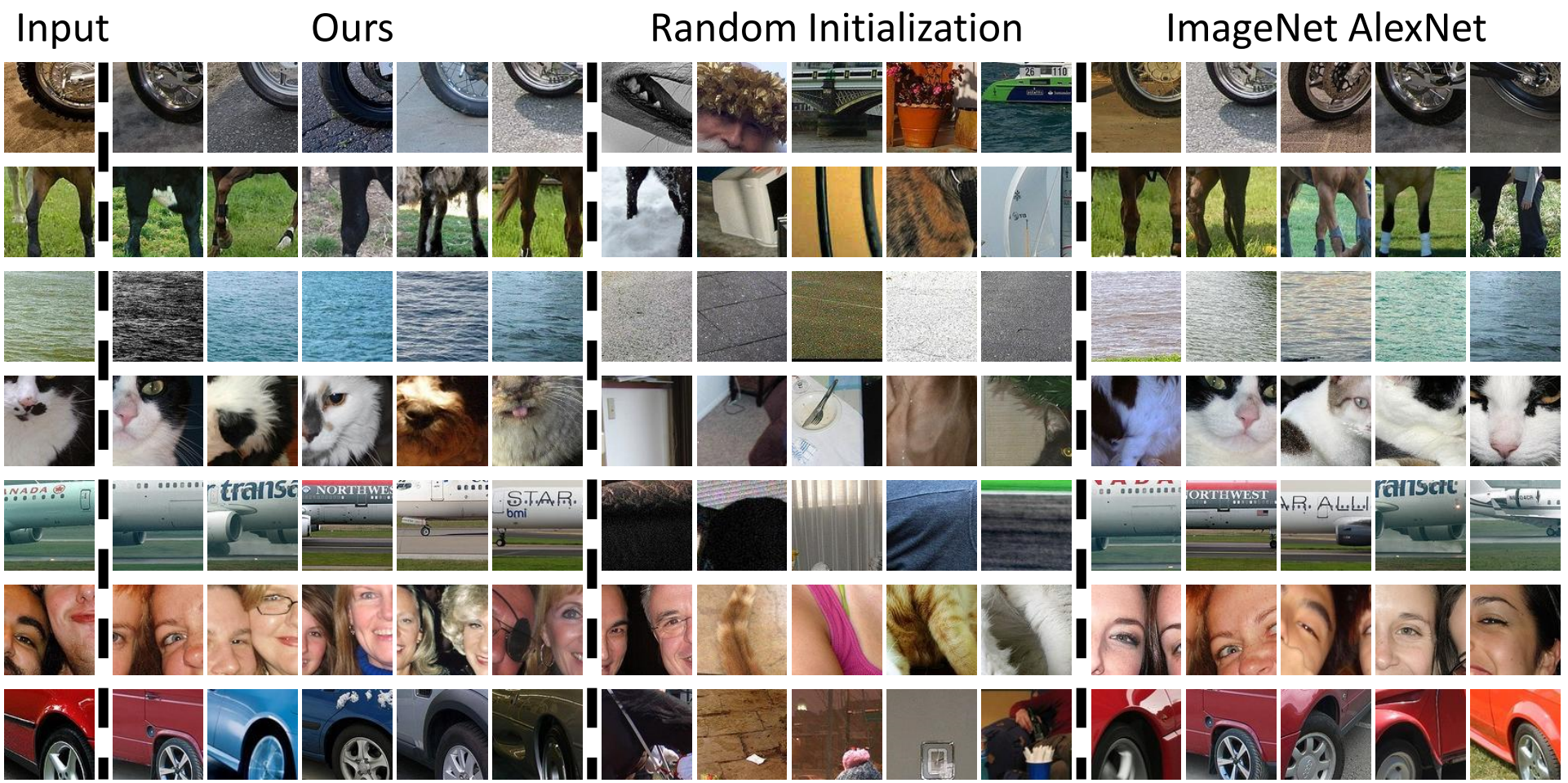




Chromatic Aberration



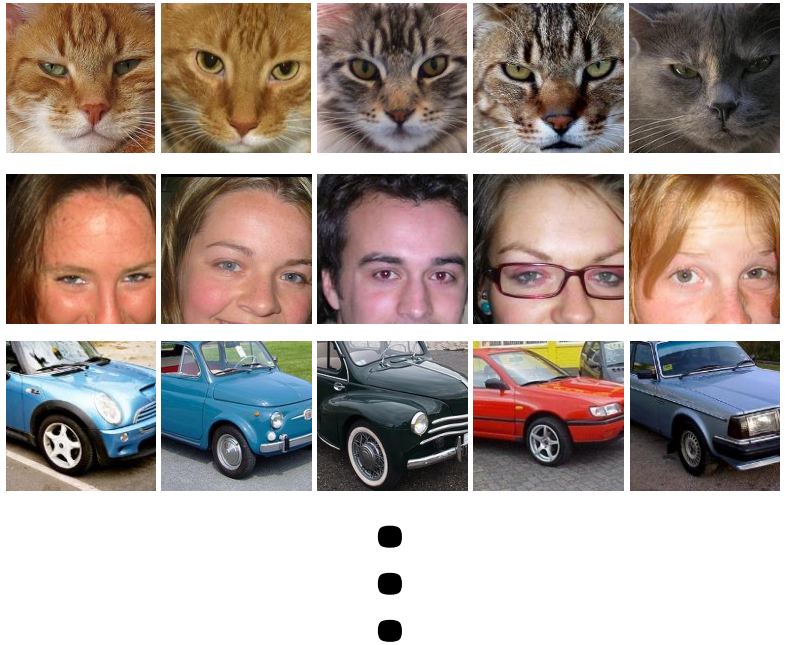
What is learned?



Still don’t capture everything

You don’t always need to learn!

Visual Data Mining

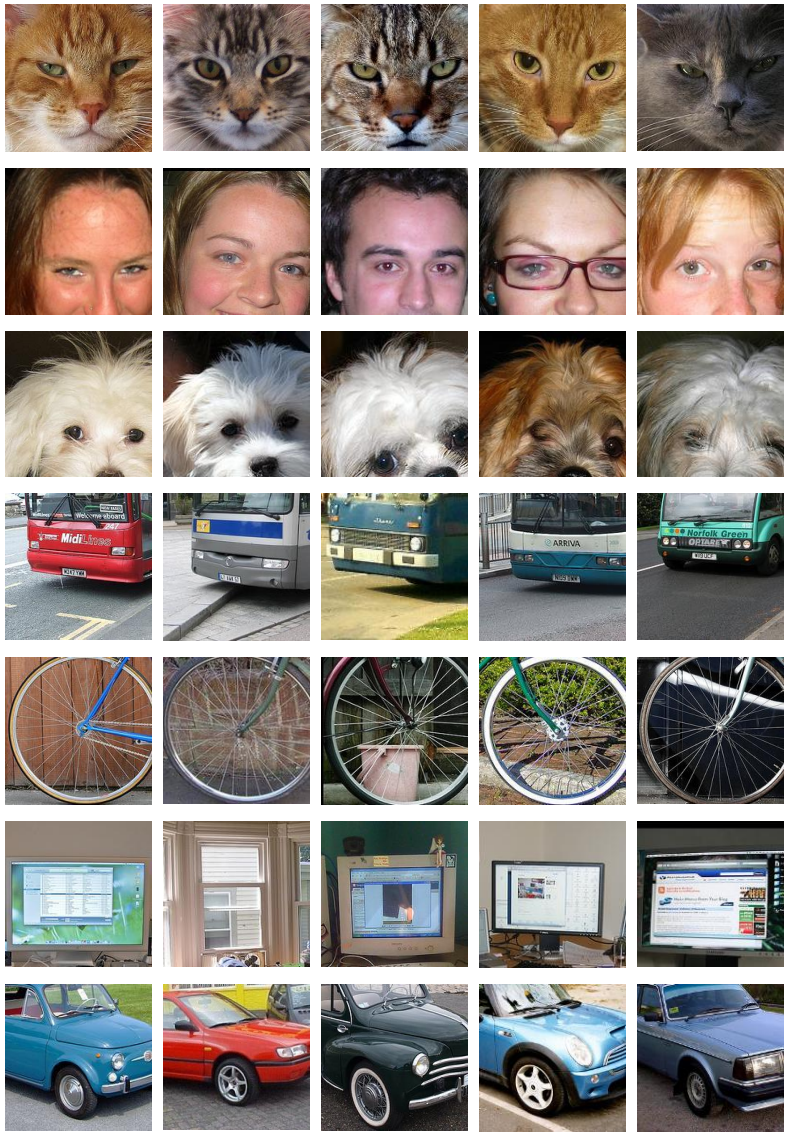


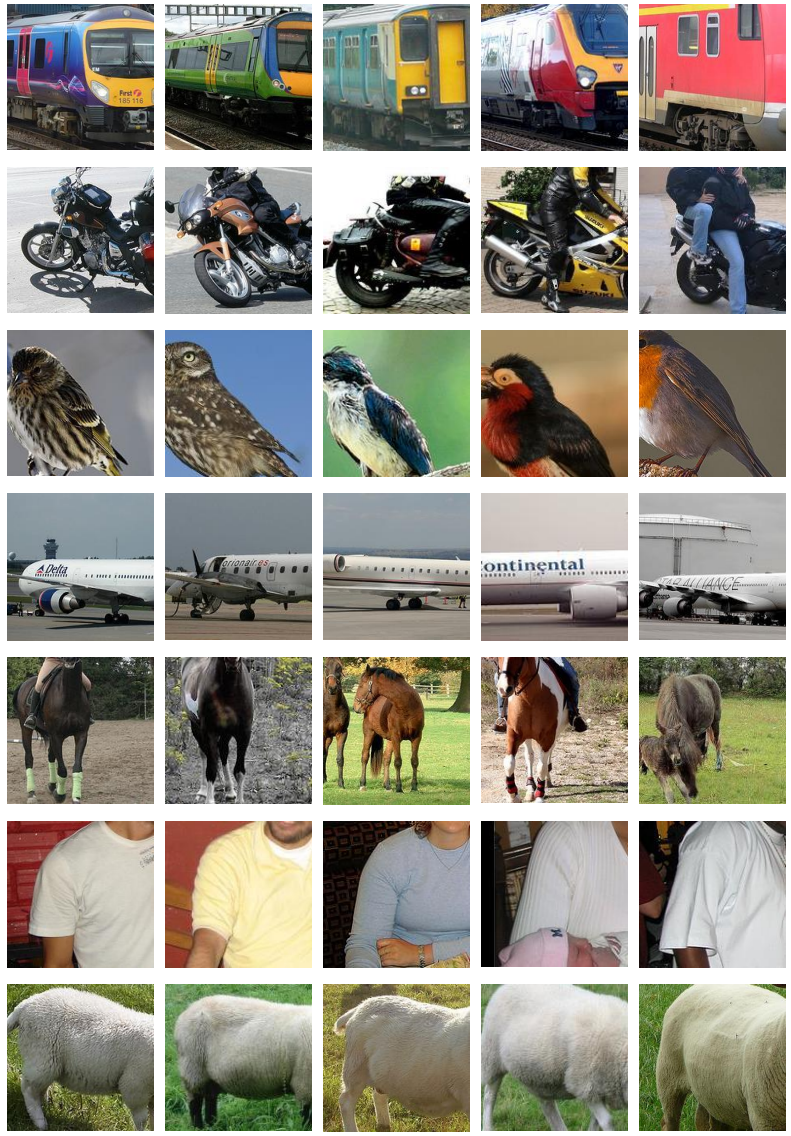
Via Geometric Verification

Simplified from [Chum et al 2007]

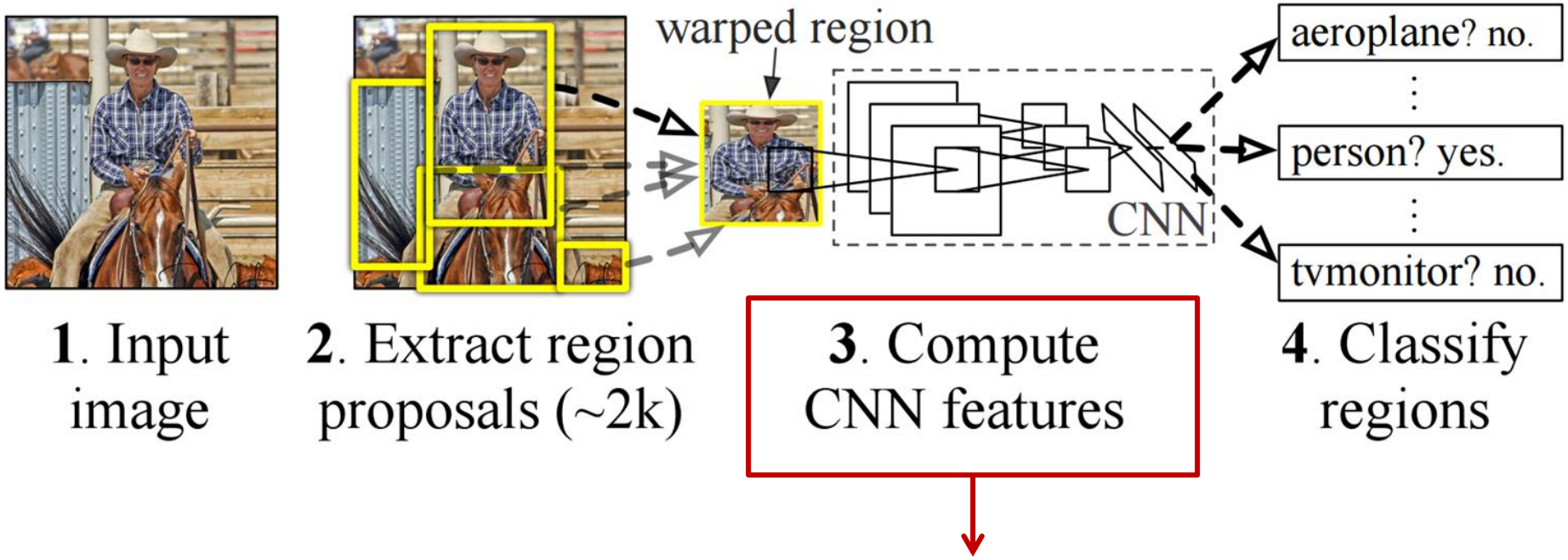
Sample patches in a square formation, and check if their nearest neighbors are also in a square formation

Mined from Pascal VOC2011





Pre-Training for R-CNN

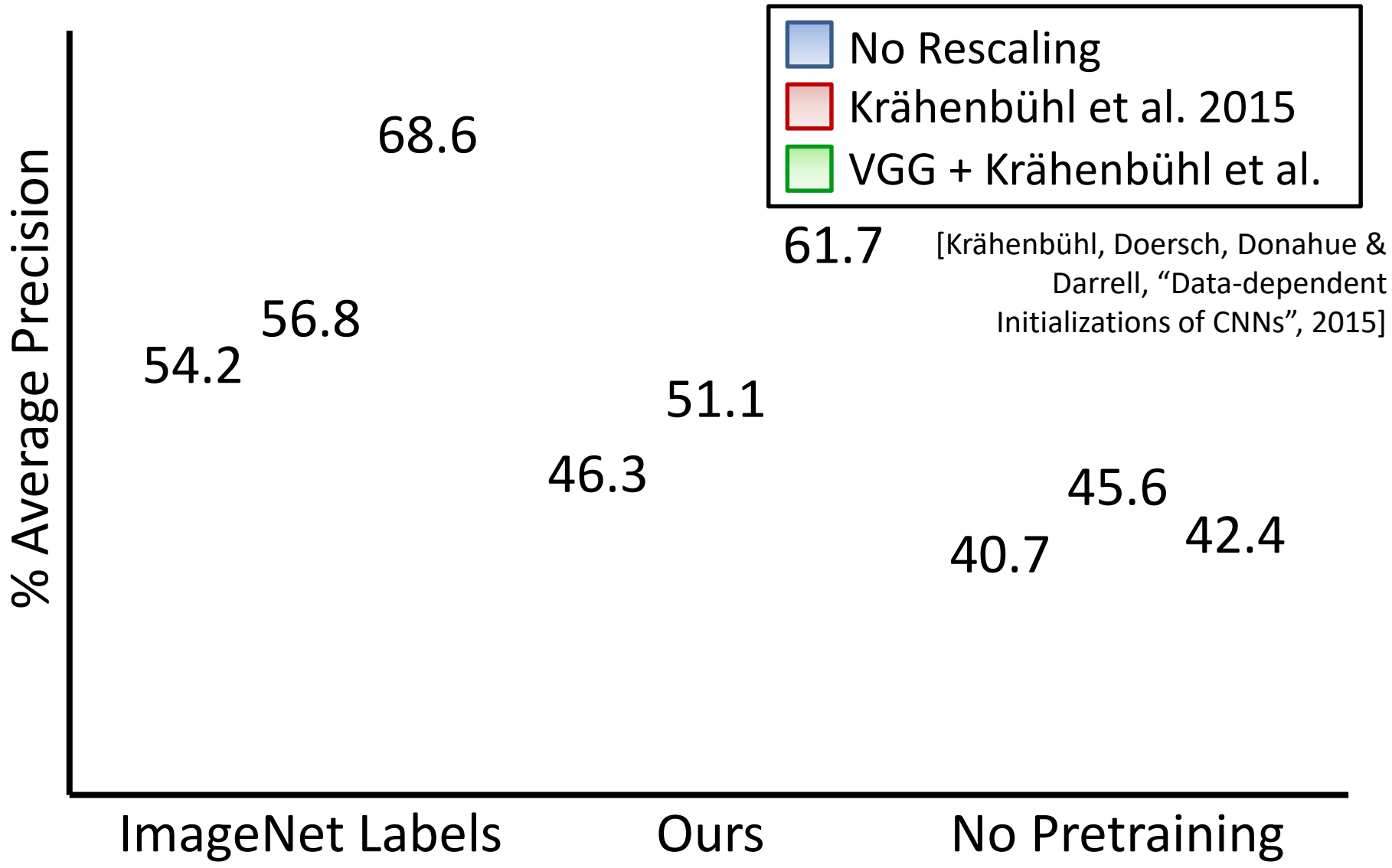


Pre-train on relative-position task, w/o labels

[Girshick et al. 2014]

VOC 2007 Performance

(pretraining for R-CNN)

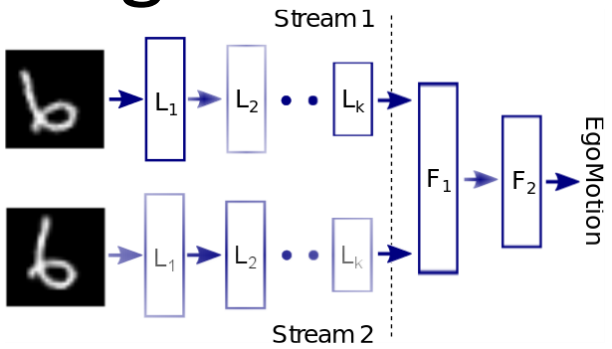


[Krähenbühl, Doersch, Donahue & Darrell, "Data-dependent Initializations of CNNs", 2015]

So, do we need semantic labels?

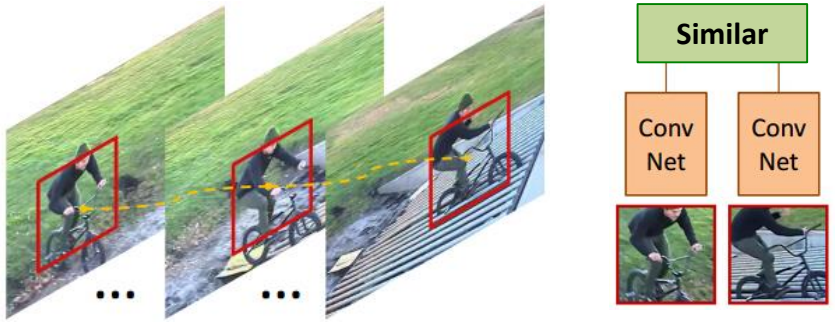
“Self-Supervision” and the Future

Ego-Motion



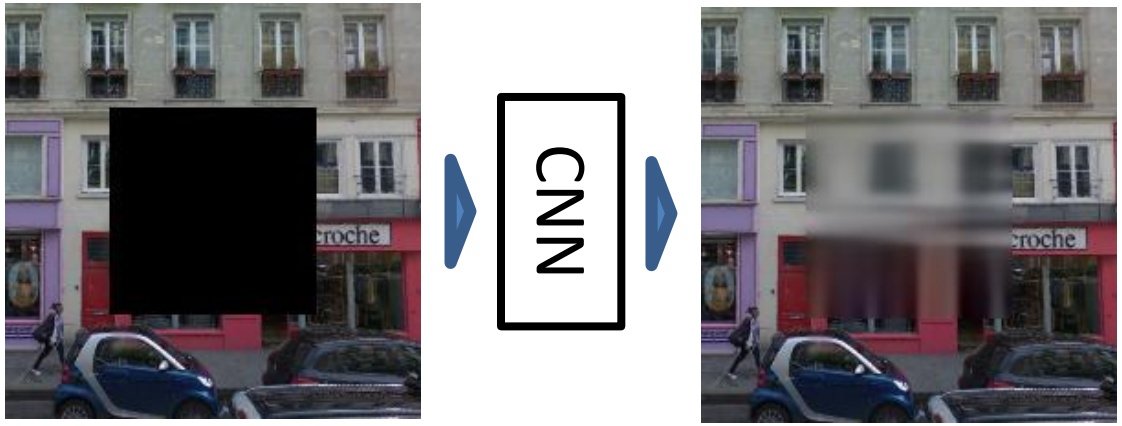
[Agrawal et al. 2015; Jayaraman et al. 2015]

Video

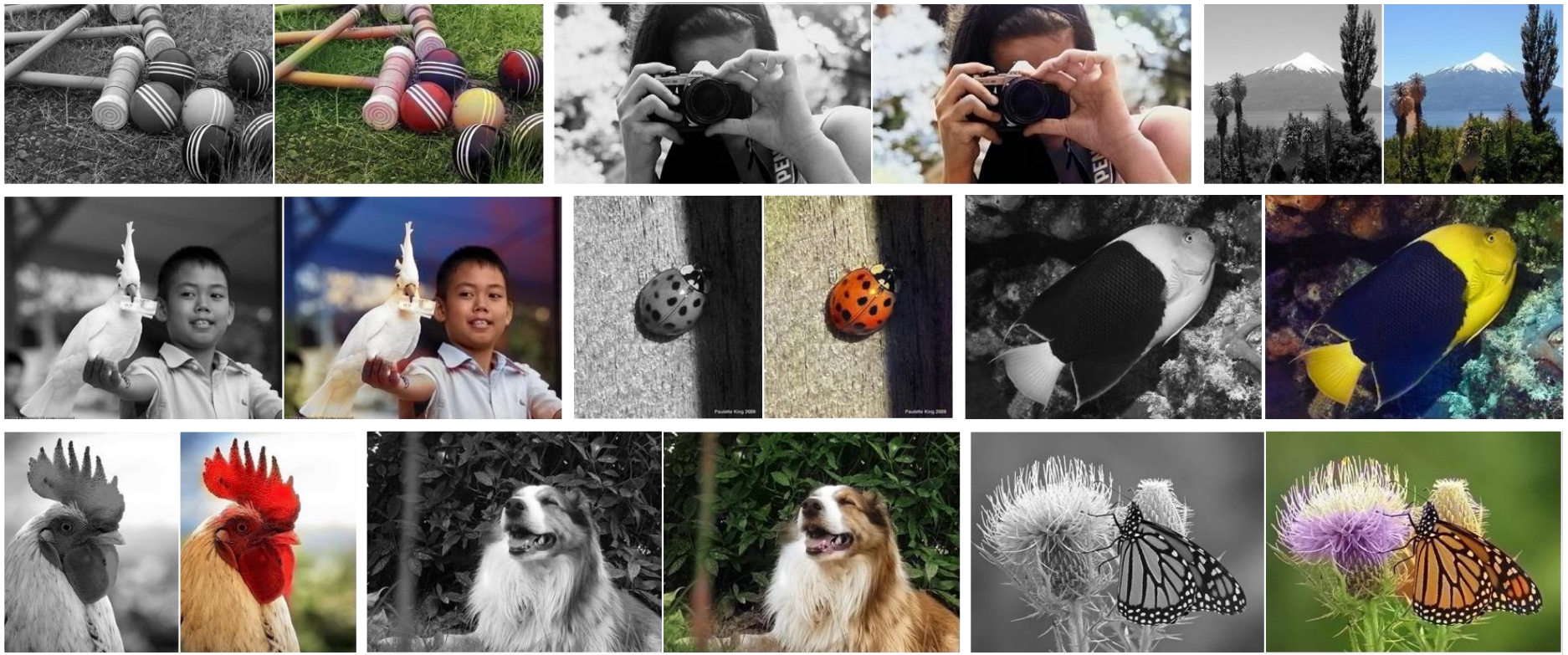


[Wang et al. 2015; Srivastava et al 2015; …]

Context



[Doersch et al. 2014; Pathak et al. 2015; Isola et al. 2015]

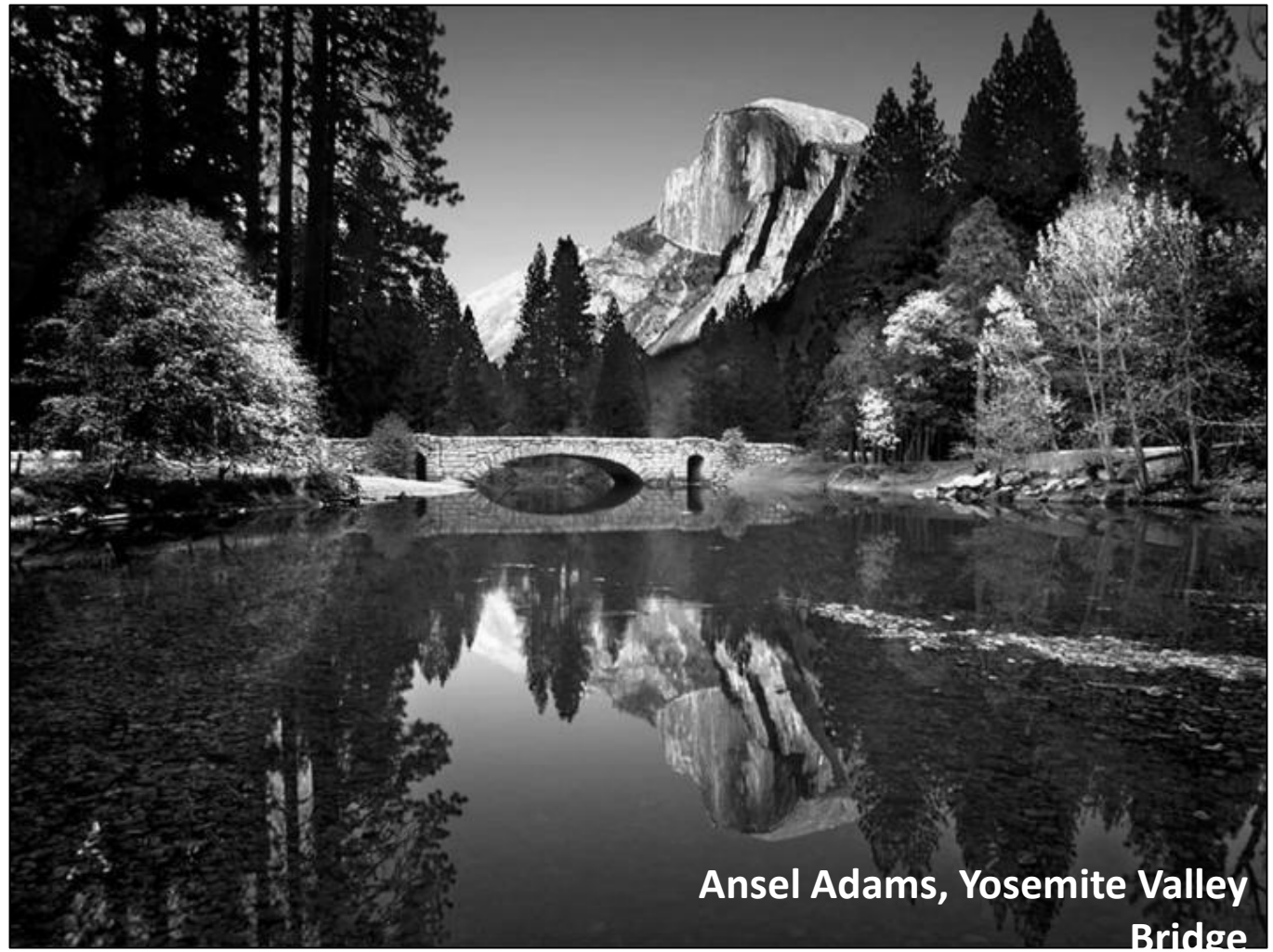


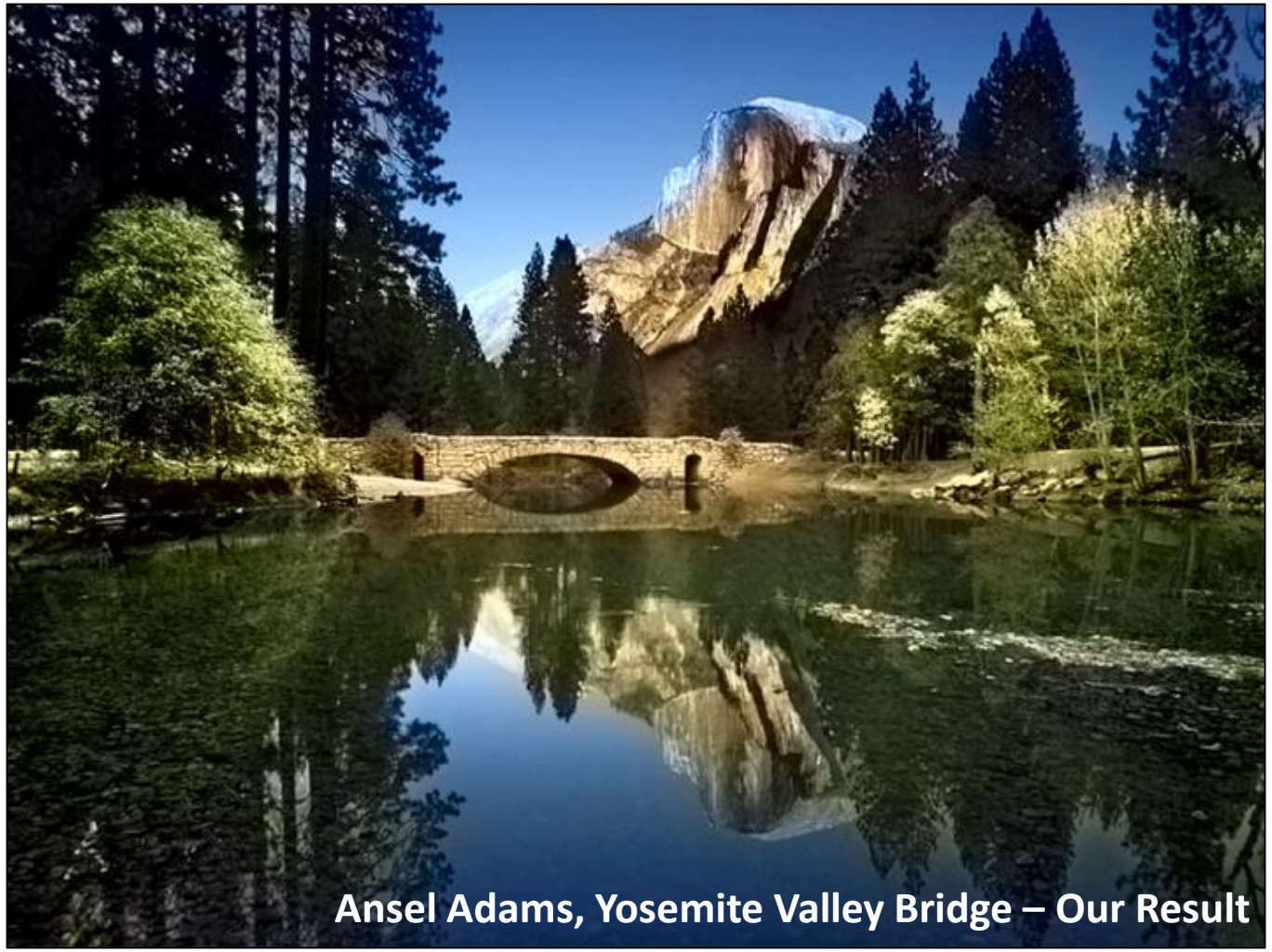
Colorful Image Colorization

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

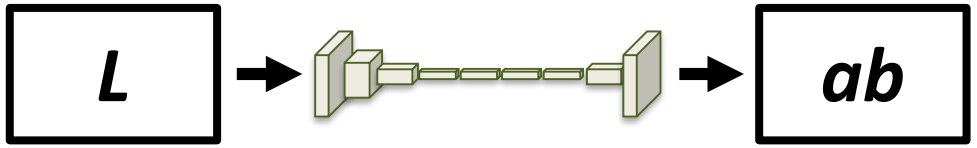
$\mathcal{F}$

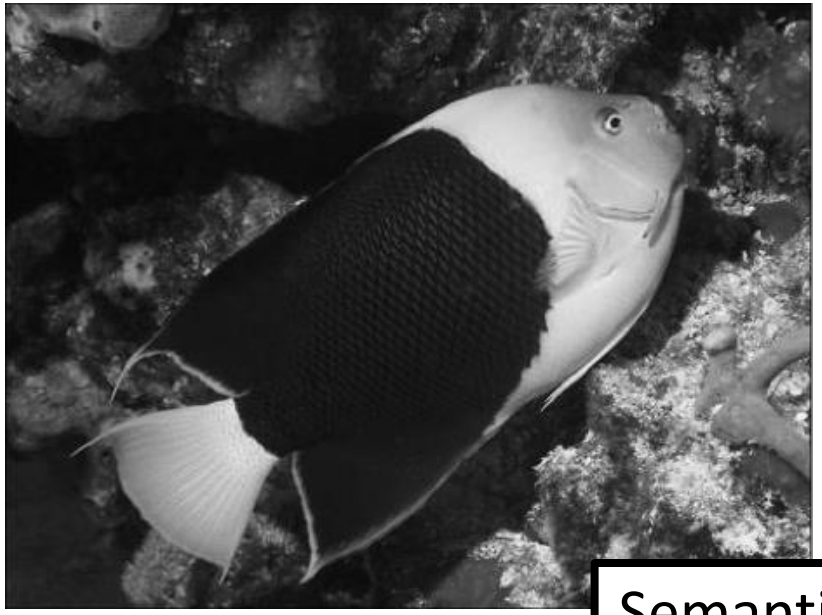
Grayscale image: *L* channel

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

Color information: *ab* channels

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



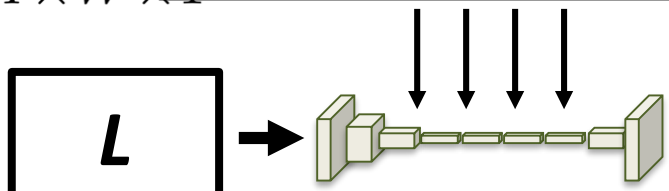


$\mathcal{F}$

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?



L → ***ab*** ← "Free" supervisory signal

Inherent Ambiguity

Grayscale

Inherent Ambiguity

Our Output

Ground Truth

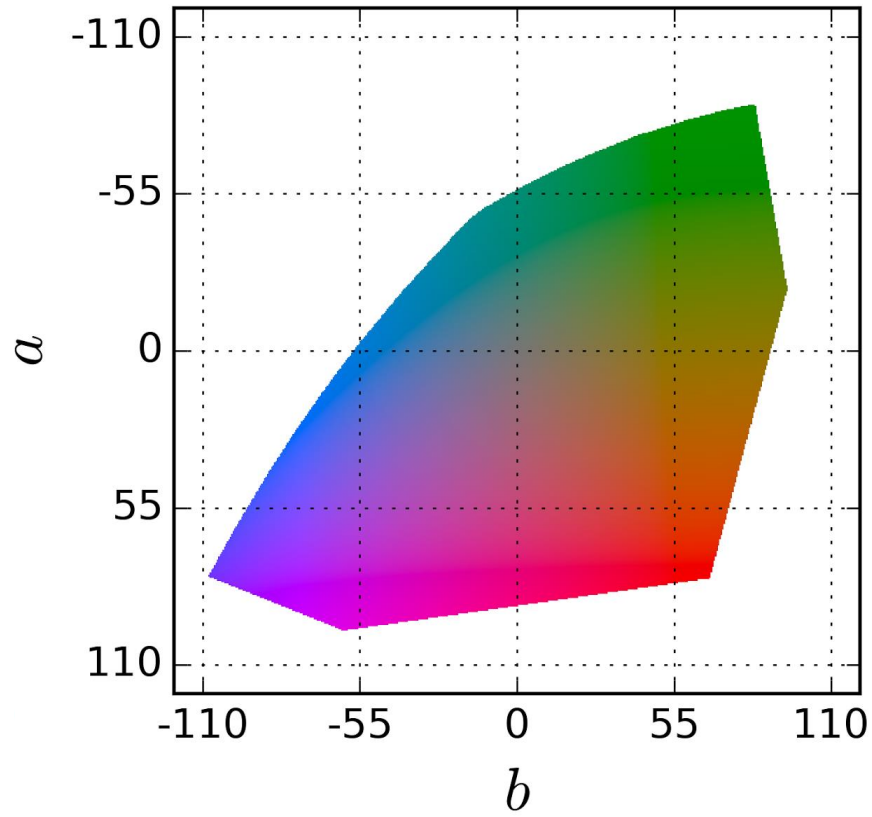
Better Loss Function

- 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)



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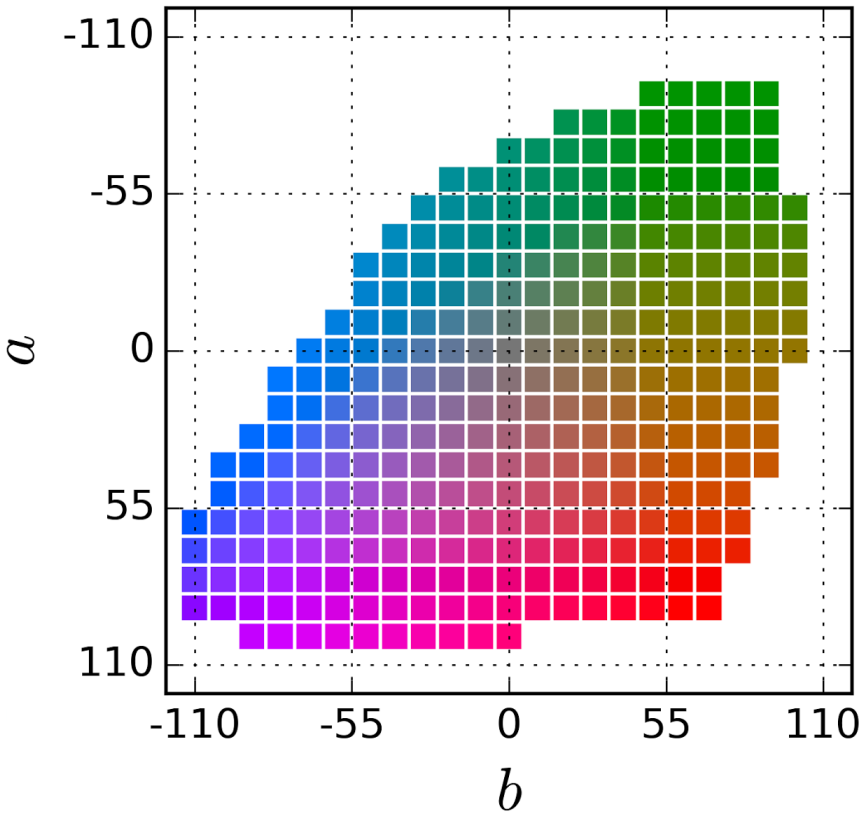
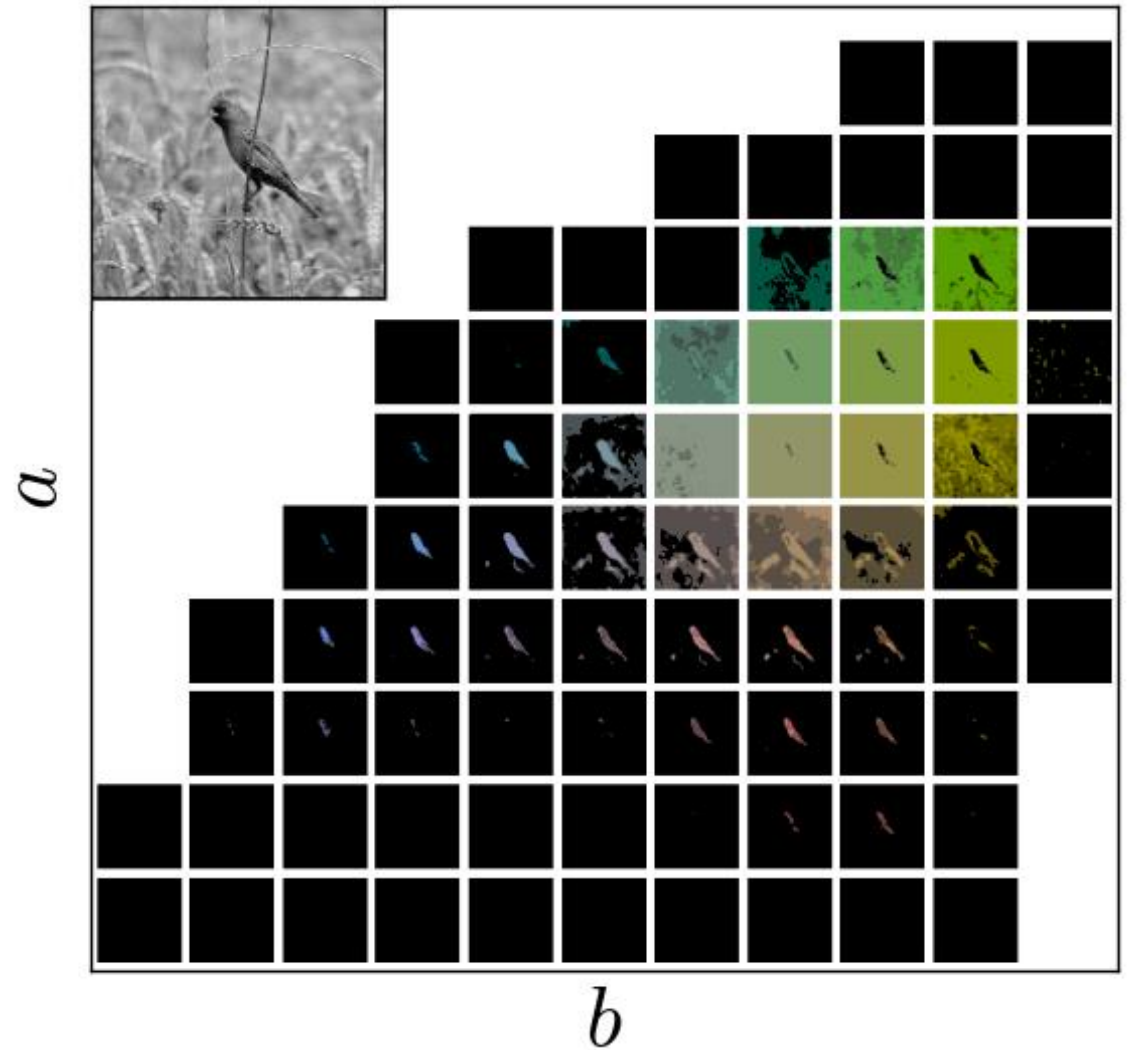
- Use **multinomial classification**

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

Colors in *ab* space

(discrete)




a
b

Better Loss Function

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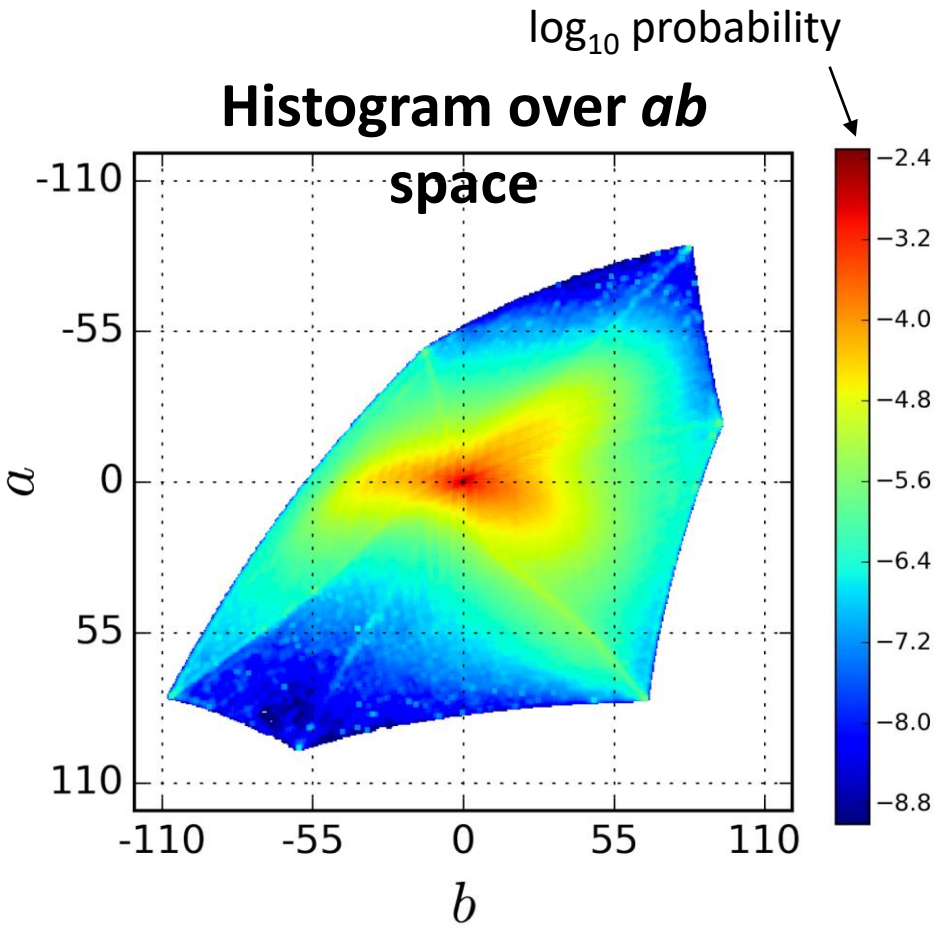

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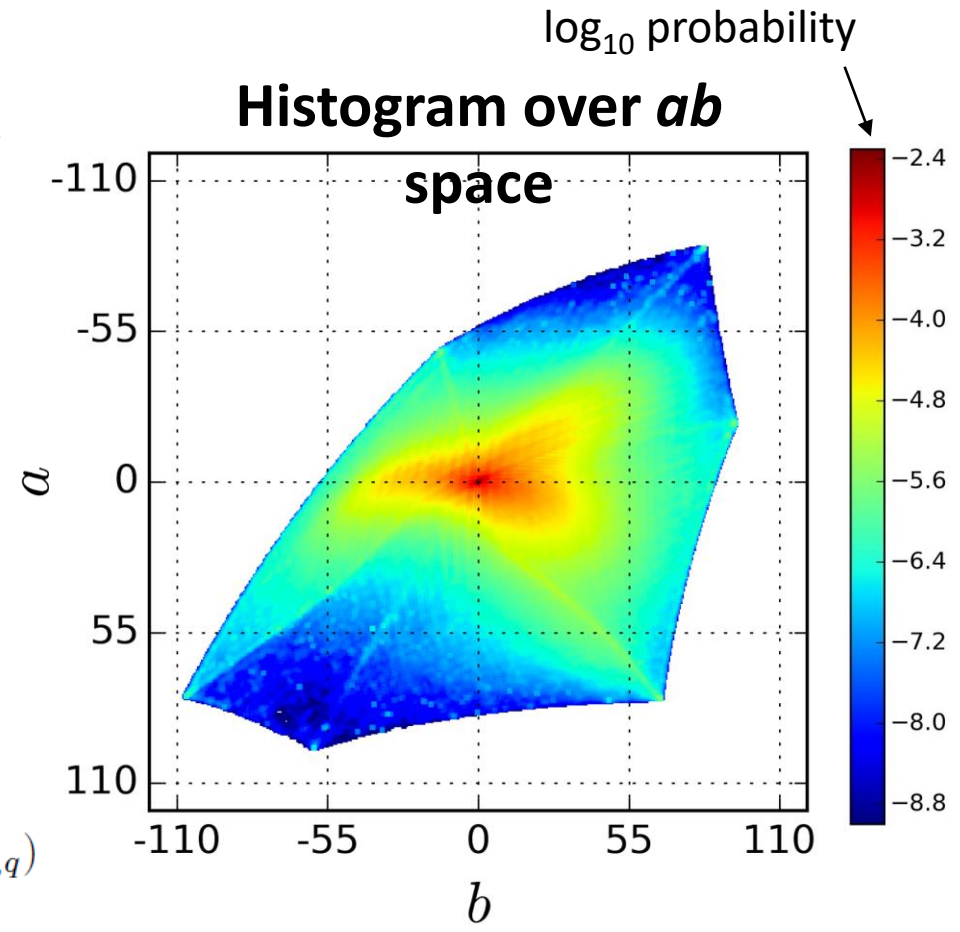
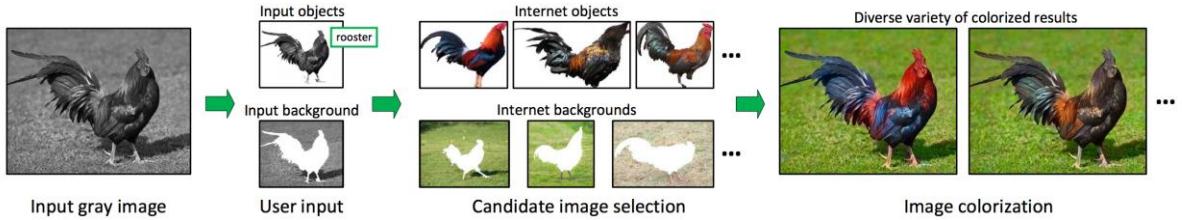
- **Class rebalancing** to encourage learning of *rare* colors

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



Non-parametric

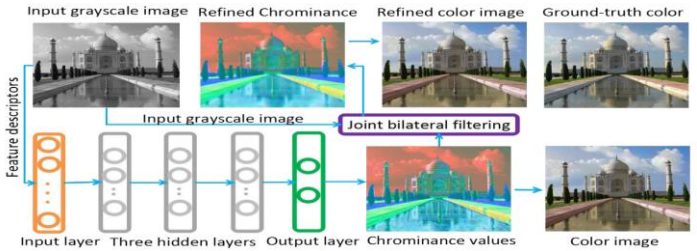
Hertzmann et al. In SIGGRAPH, 2001.
Welsh et al. In TOG, 2002.
Irony et al. In Eurographics, 2005.
Liu et al. In TOG, 2008.
Chia et al. In ACM 2011.
Gupta et al. In ACM, 2012.



Parametric

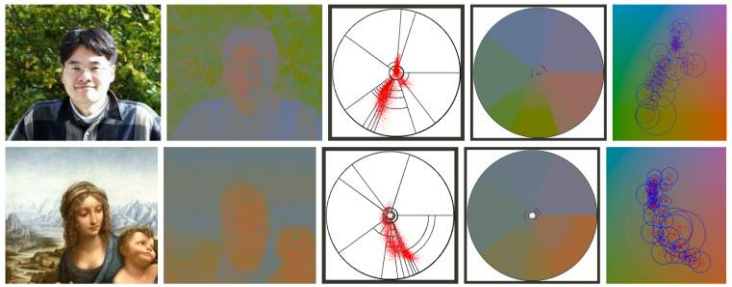
Hand-engineered Features

L2 Regression



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

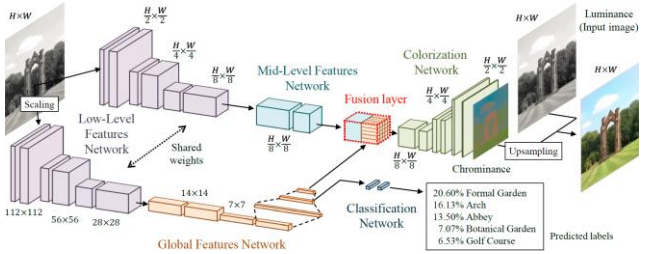
Classification



Charpiat et al. In ECCV 2008.

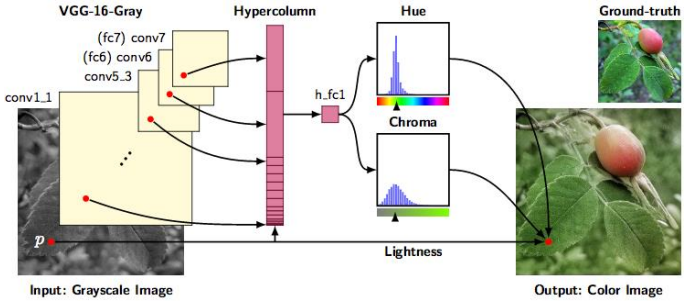
Deep Networks

L2 Regression



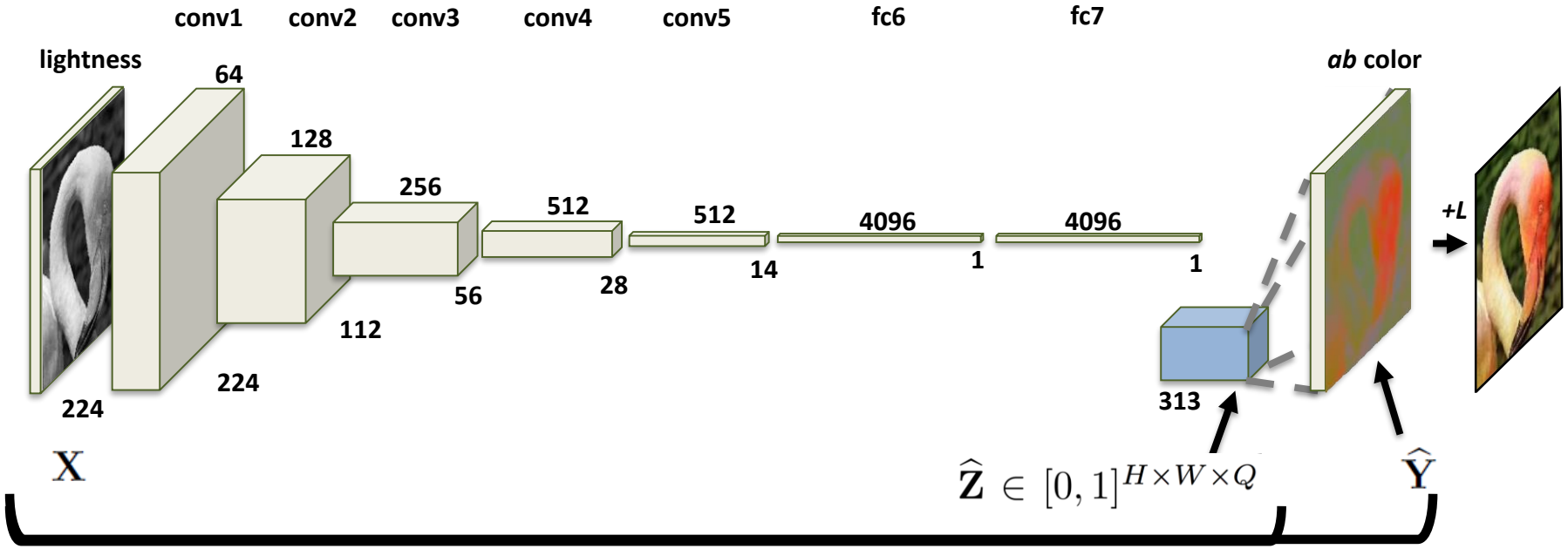
Dahl. Jan 2016. Iizuka et al. In SIGGRAPH, 2016.

Classification



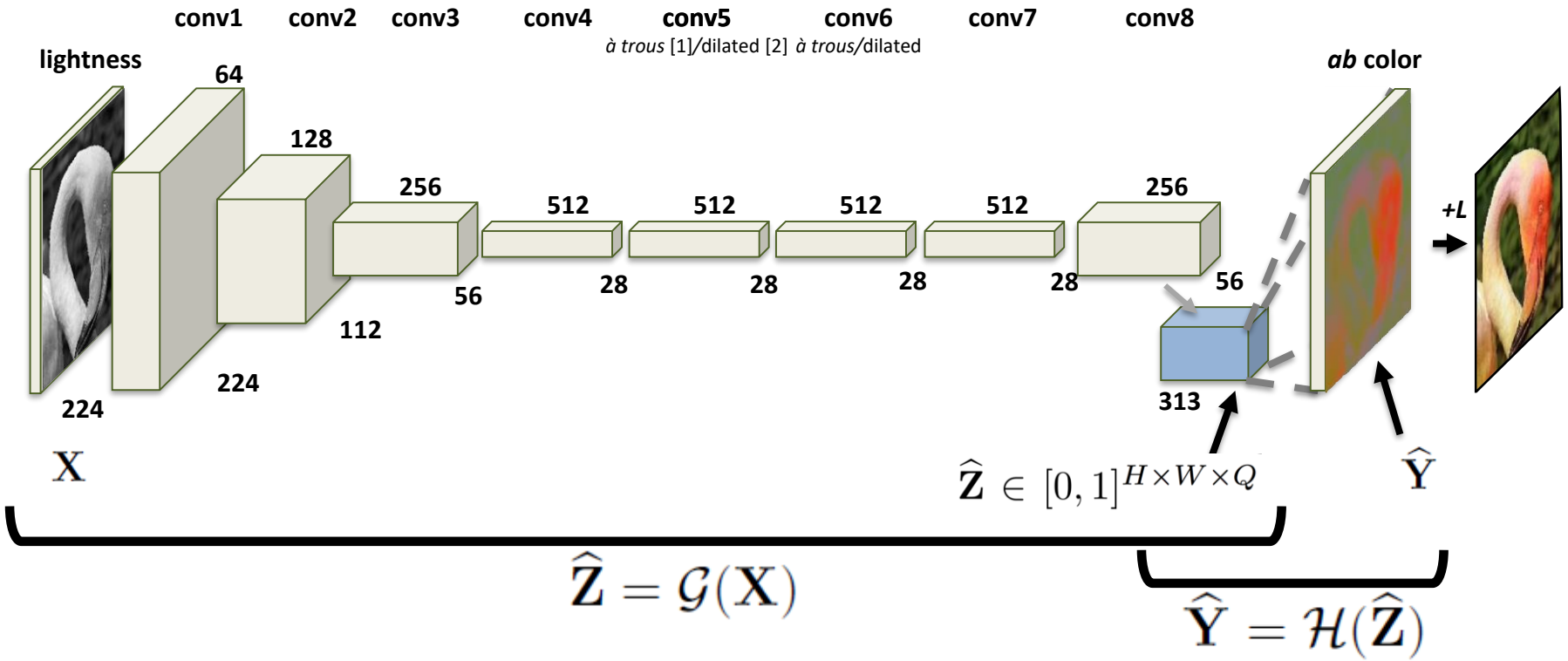
Larsson et al. In ECCV 2016. [Concurrent]

Network Architecture



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

Network Architecture



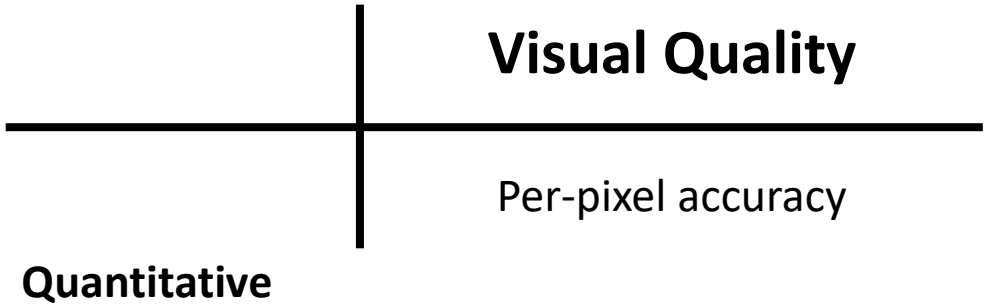
[1] Chen *et al.* In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016

Ground Truth
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

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

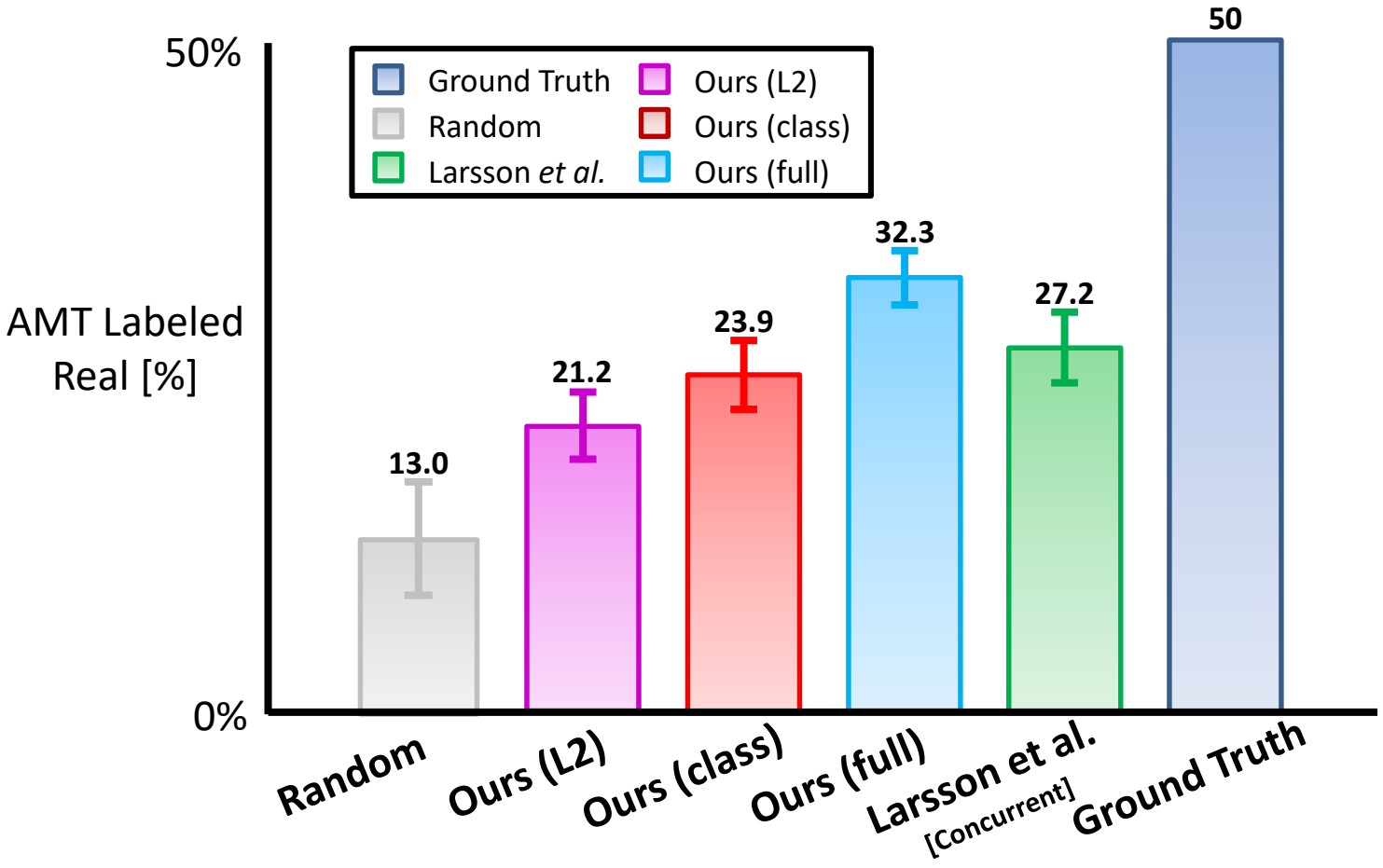
from Reddit /u/SherySantucci

Recolorized by Reddit ColorizeBot

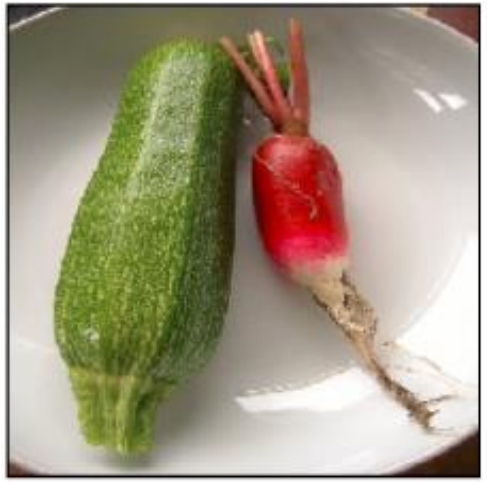
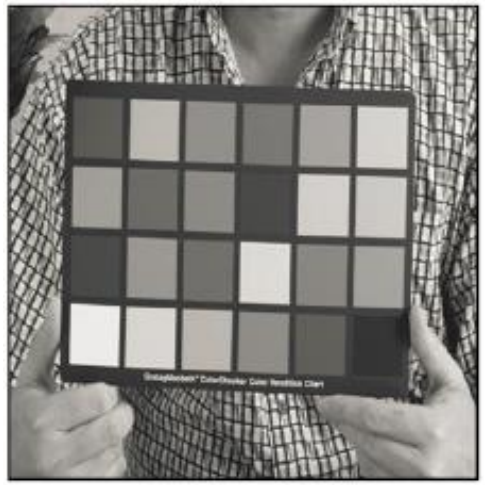
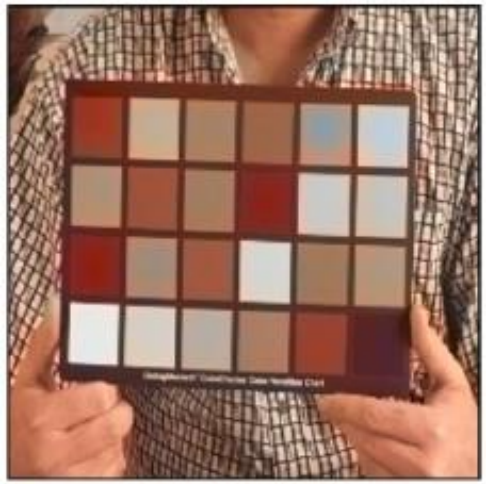
Photo taken by Reddit /u/Timteroo, Mural from street artist Eduardo Kobra

Recolorized by Reddit ColorizeBot

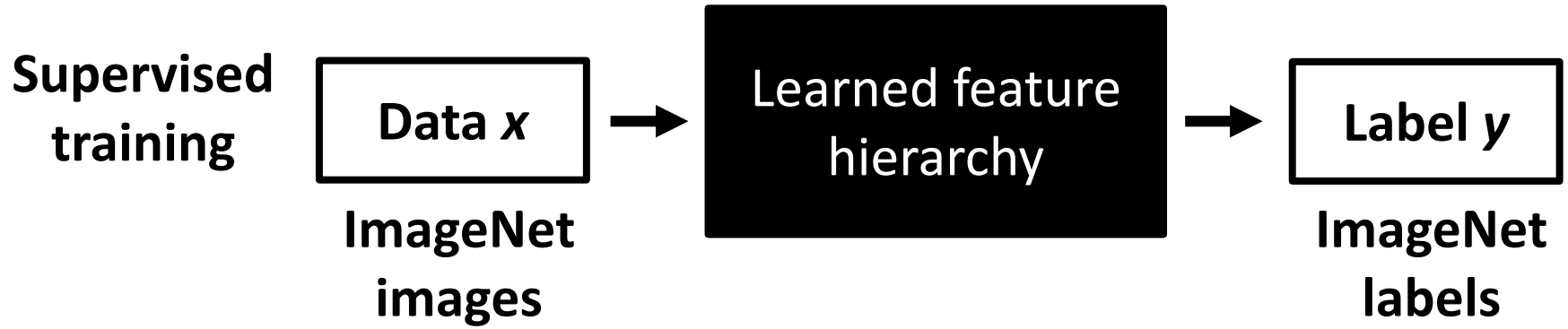
Perceptual Realism Test



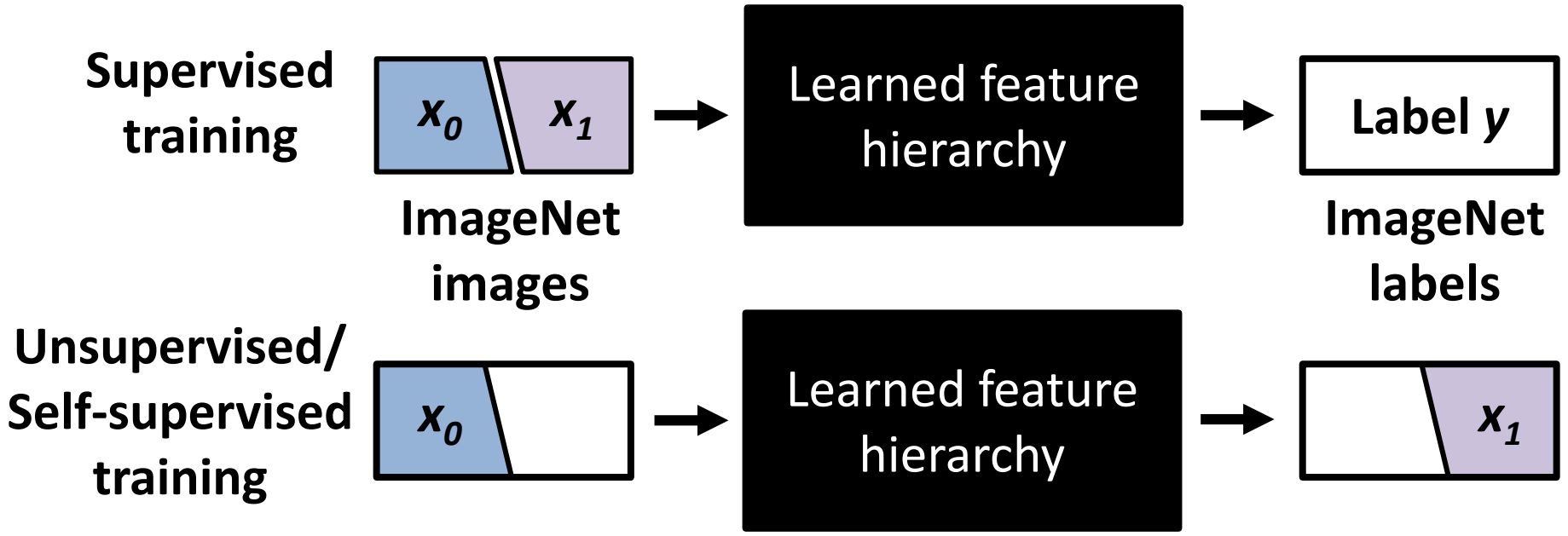
1600 images tested per algorithm

Input	Ground Truth	Output
		
		

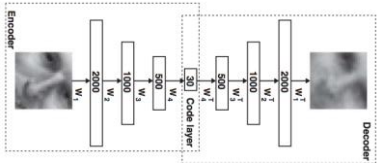
Predicting Labels from Data



Predicting Data from Data

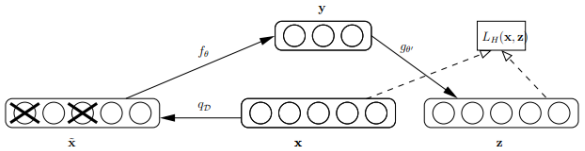


Autoencoders



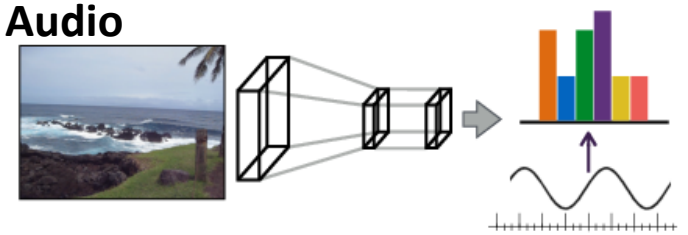
Hinton & Salakhutdinov. Science 2006.

Denoising Autoencoders



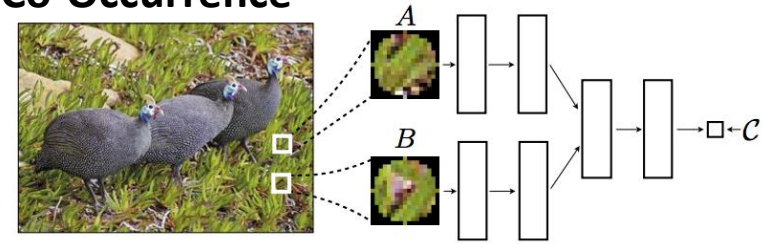
Vincent *et al.* ICML 2008.

Audio



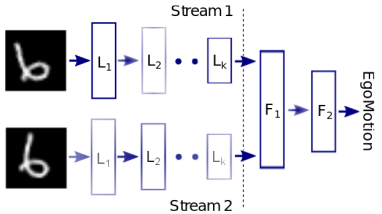
Owens *et al.* CVPR 2016, ECCV 2016

Co-Occurrence

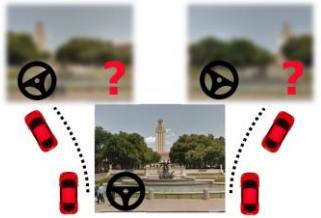


Isola *et al.* ICLR Workshop 2016.

Egomotion

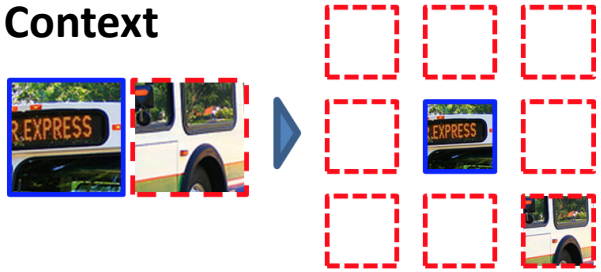


Agrawal *et al.* ICCV 2015



Jayaraman *et al.* ICCV 2015

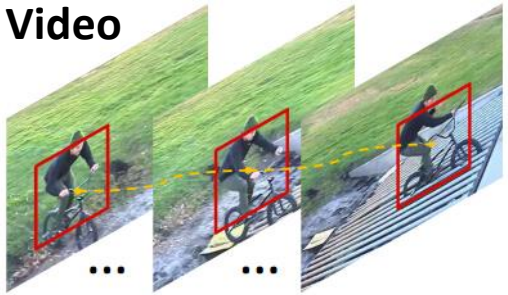
Context



Doersch *et al.* ICCV 2015

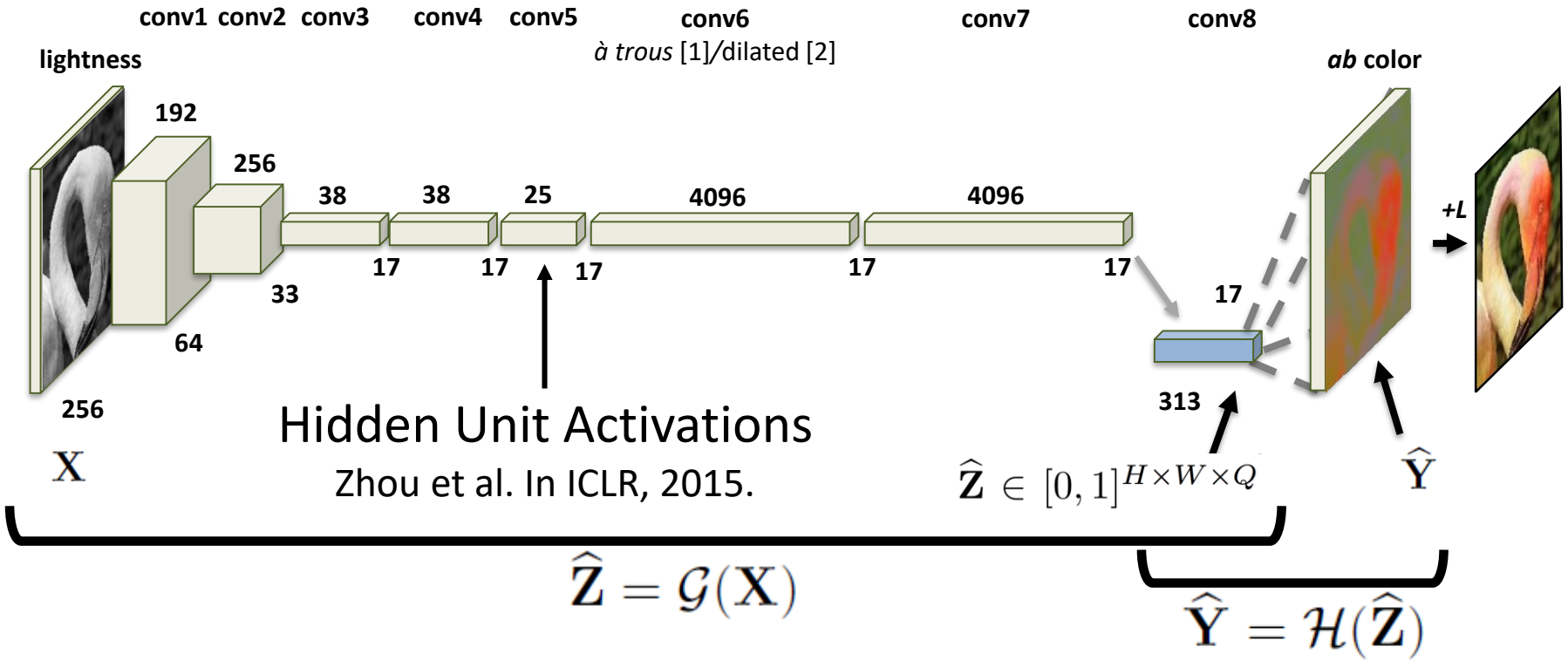
Pathak *et al.* CVPR 2016

Video



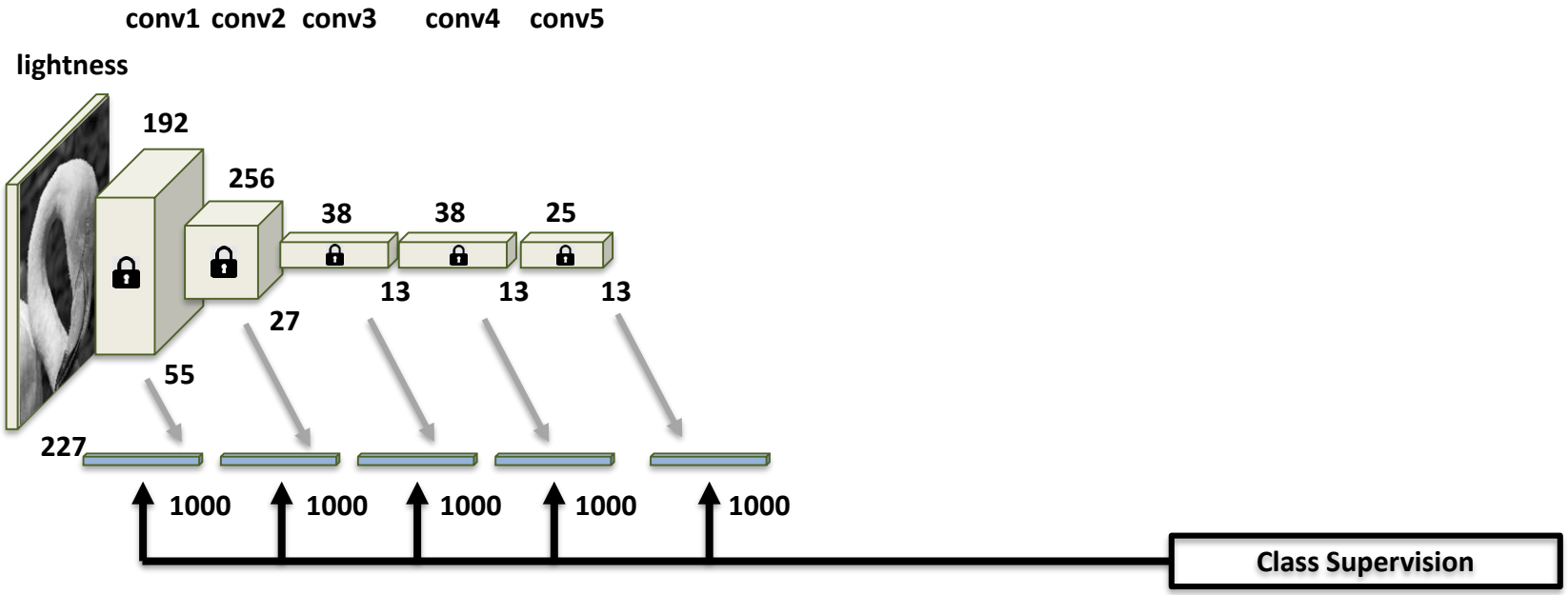
Wang *et al.* ICCV 2015

Cross-Channel Encoder



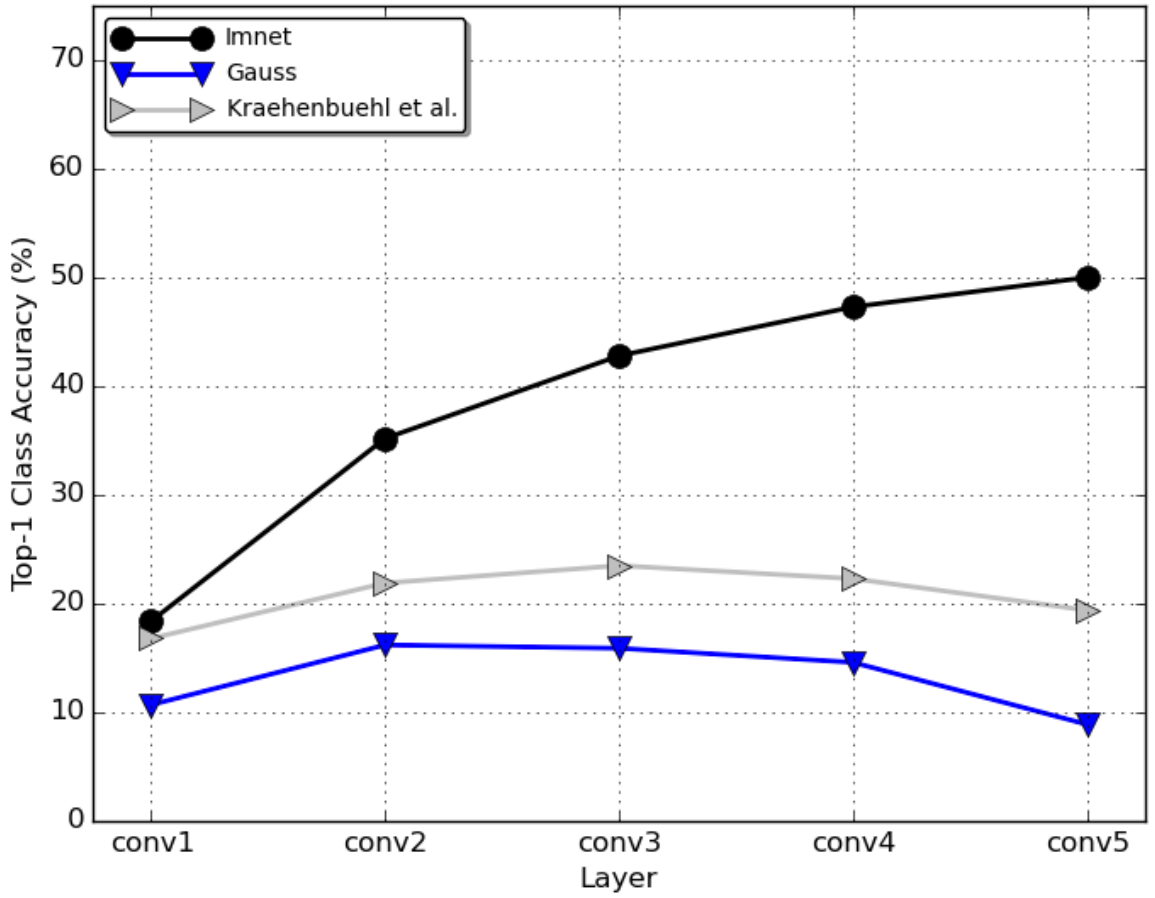
[1] Chen *et al.* In arXiv, 2016.
[2] Yu and Koltun. In ICLR, 2016

Task Generalization: ILSVRC linear classification

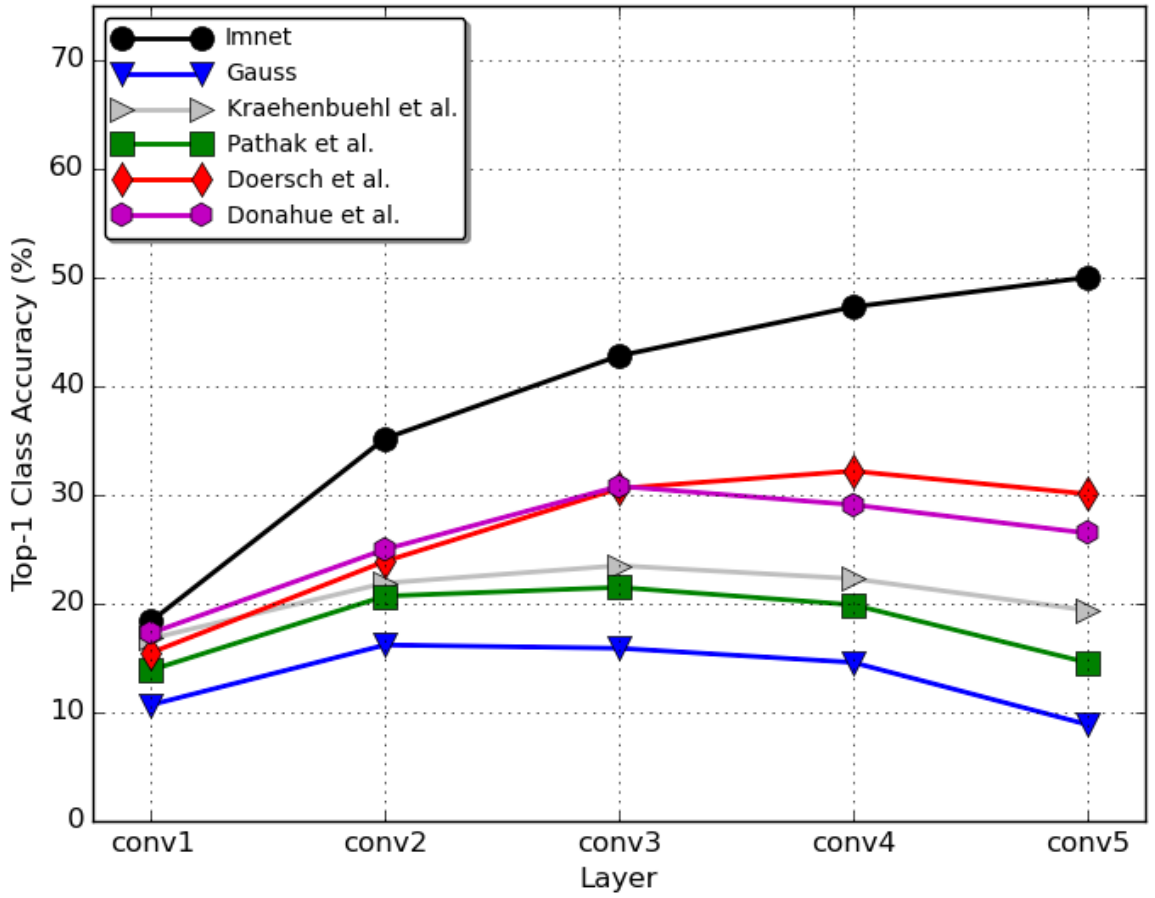


Are semantic classes ***linearly separable***
in the learned feature space?

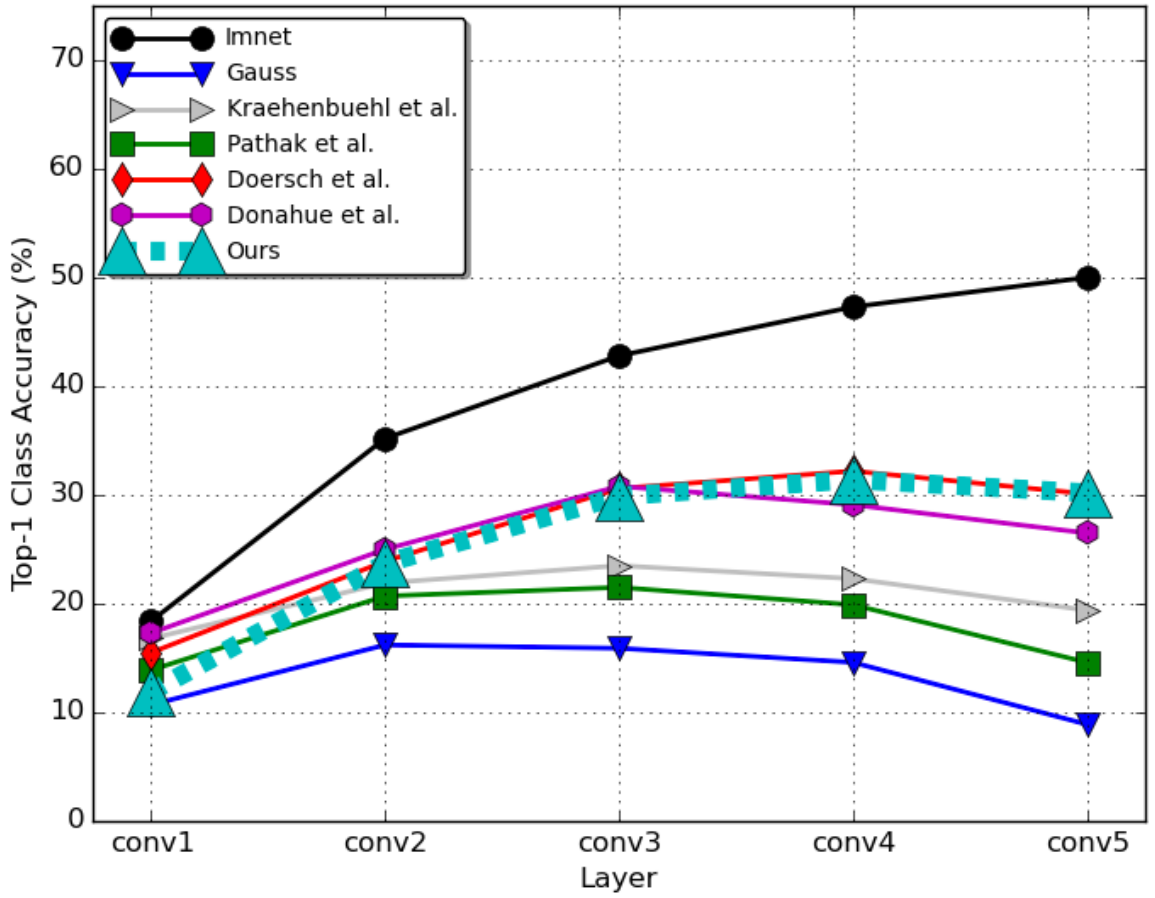
Task Generalization: ILSVRC linear classification



Task Generalization: ILSVRC linear classification



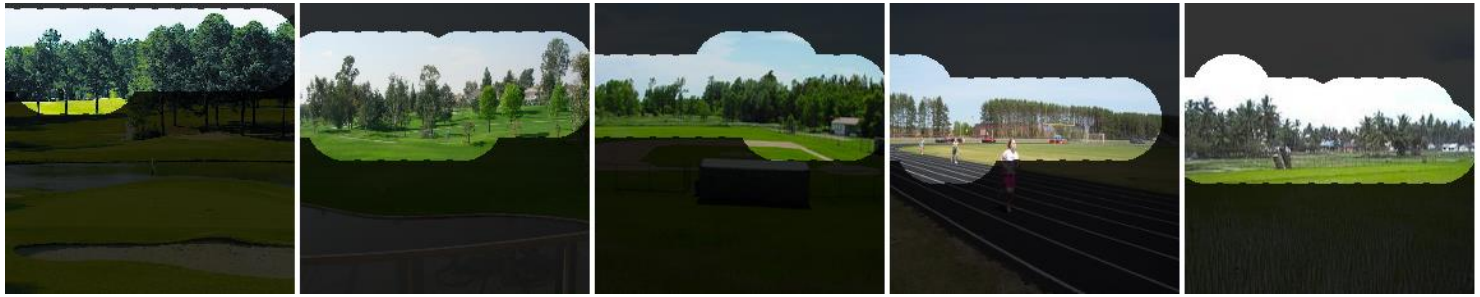
Task Generalization: ILSVRC linear classification



Hidden Unit (conv5) Activations

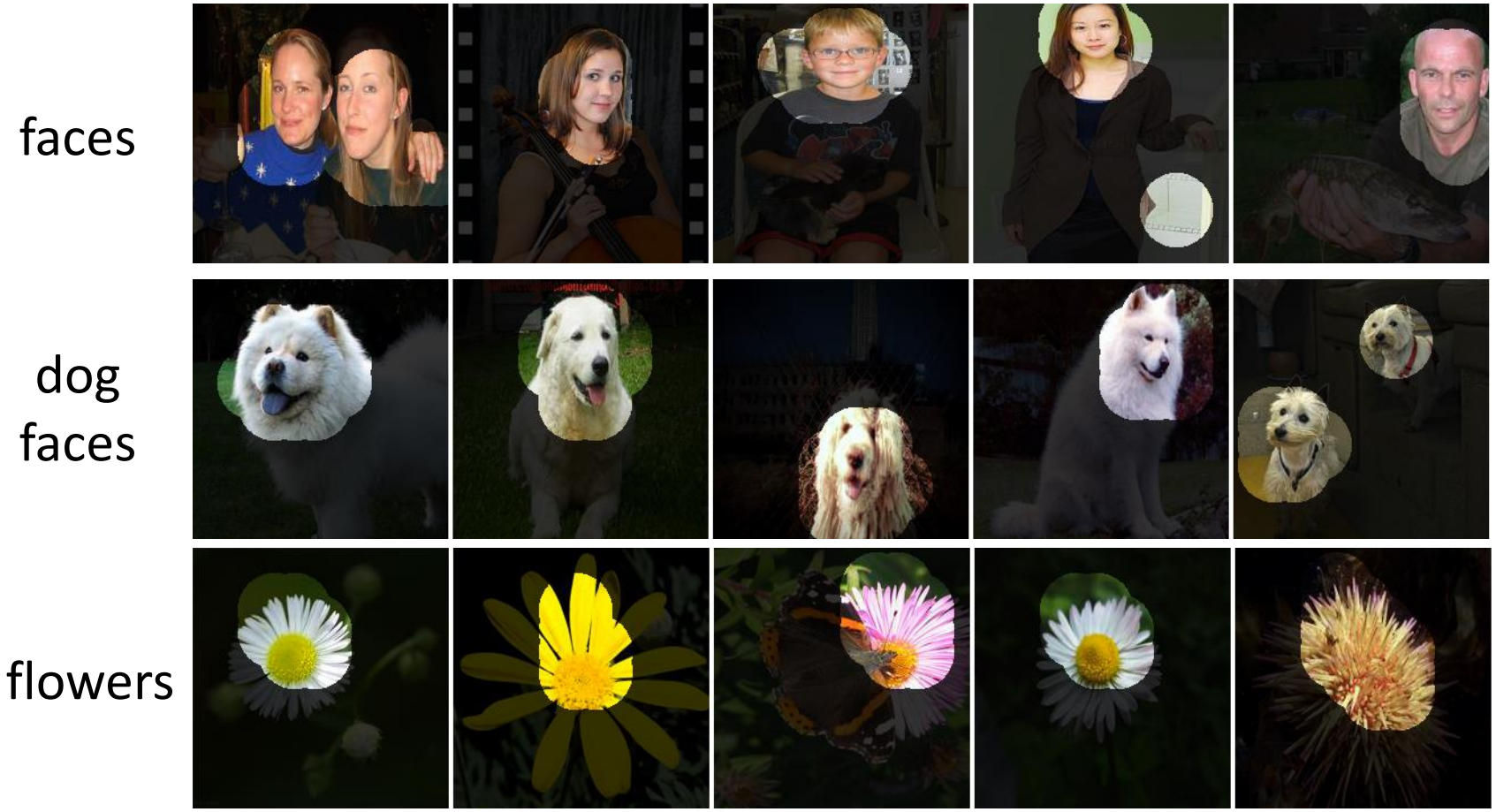
sky

trees



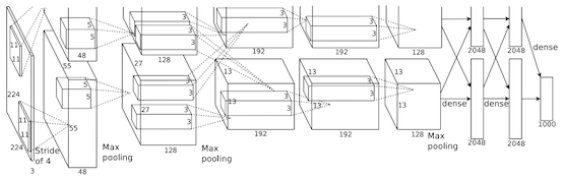
water

Hidden Unit (conv5) Activations



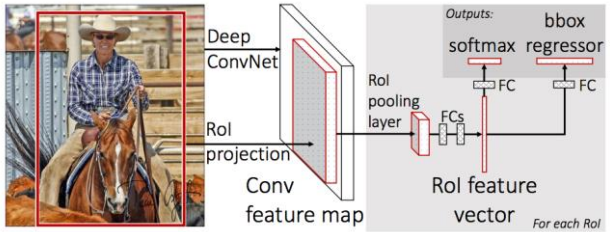
Dataset & Task Generalization on PASCAL VOC

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



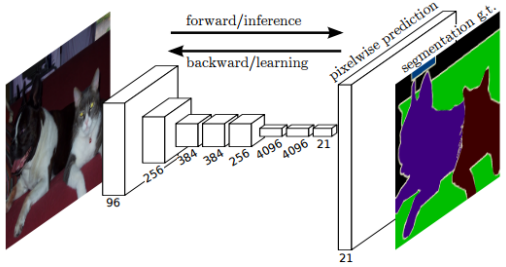
Classification

Krähenbühl et al. In ICLR, 2016.



Detection

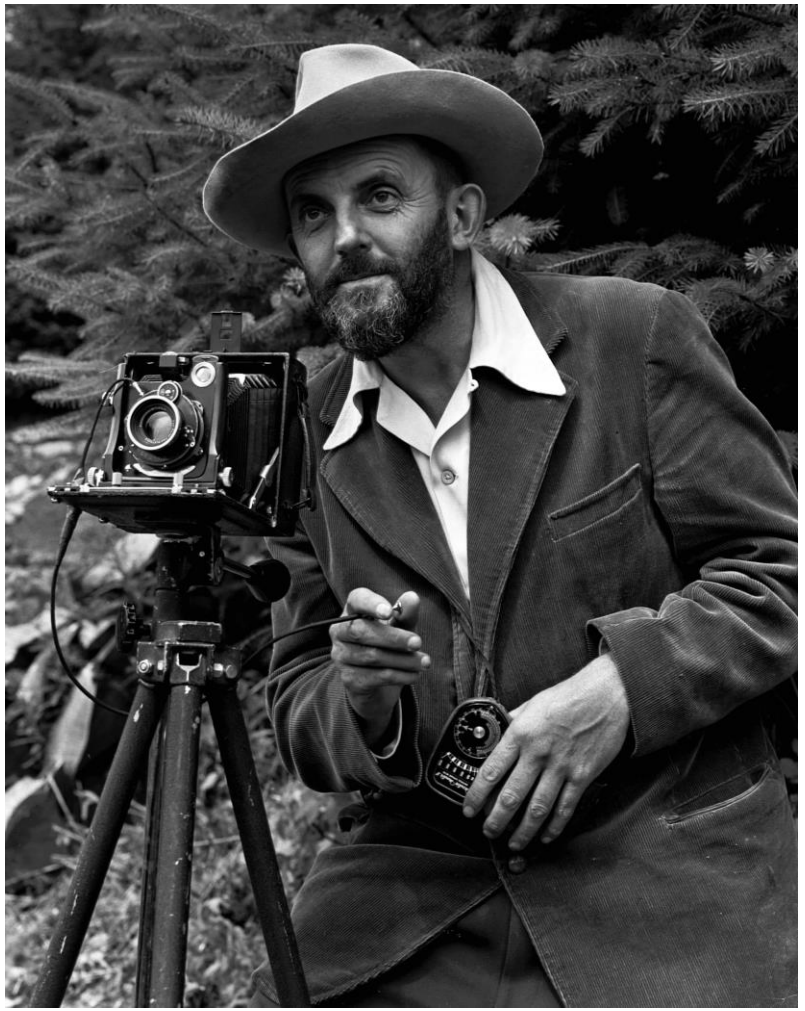
Fast R-CNN. Girshick. In ICCV, 2015.

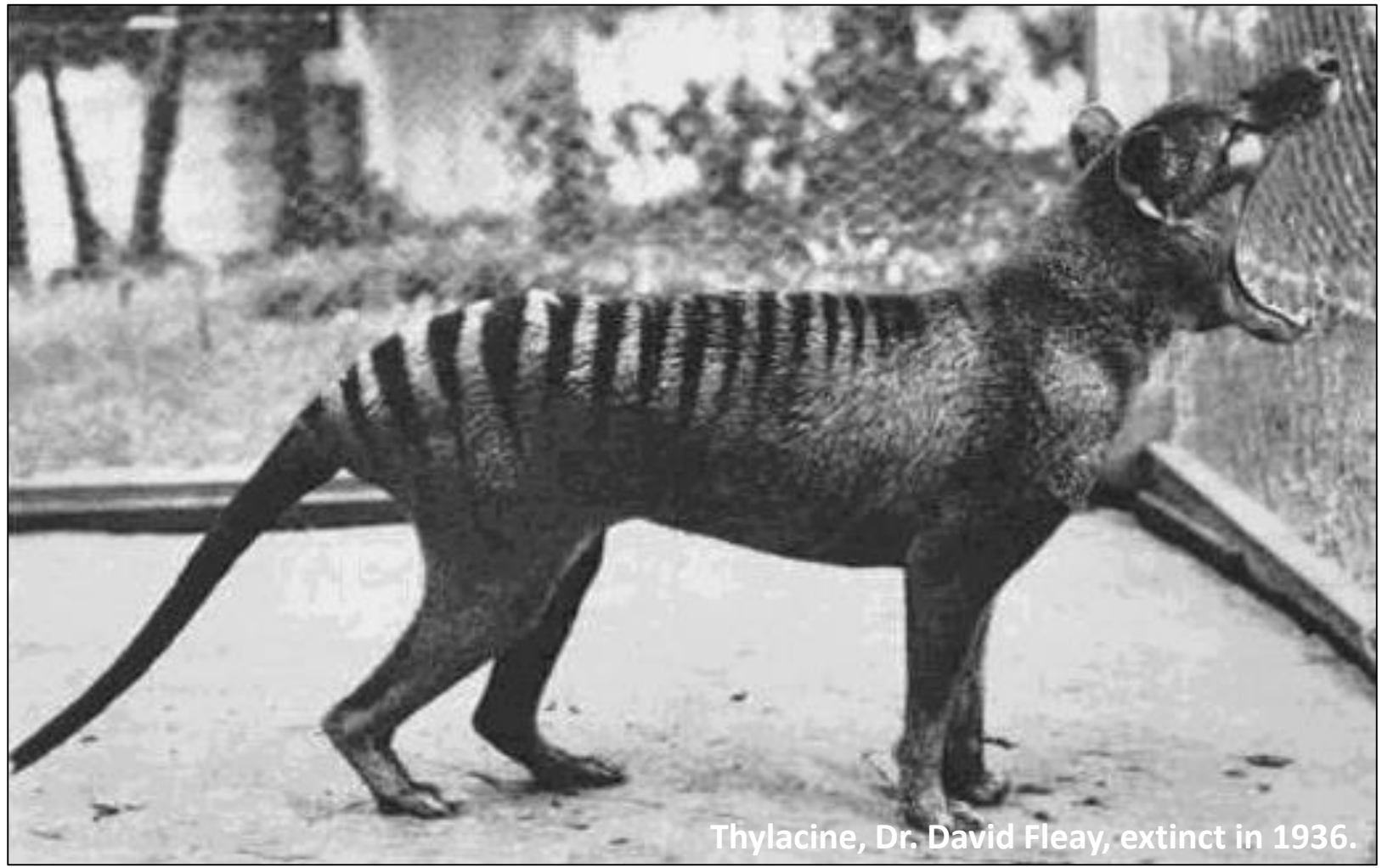


Segmentation

FCNs. Long et al. In CVPR, 2015.

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



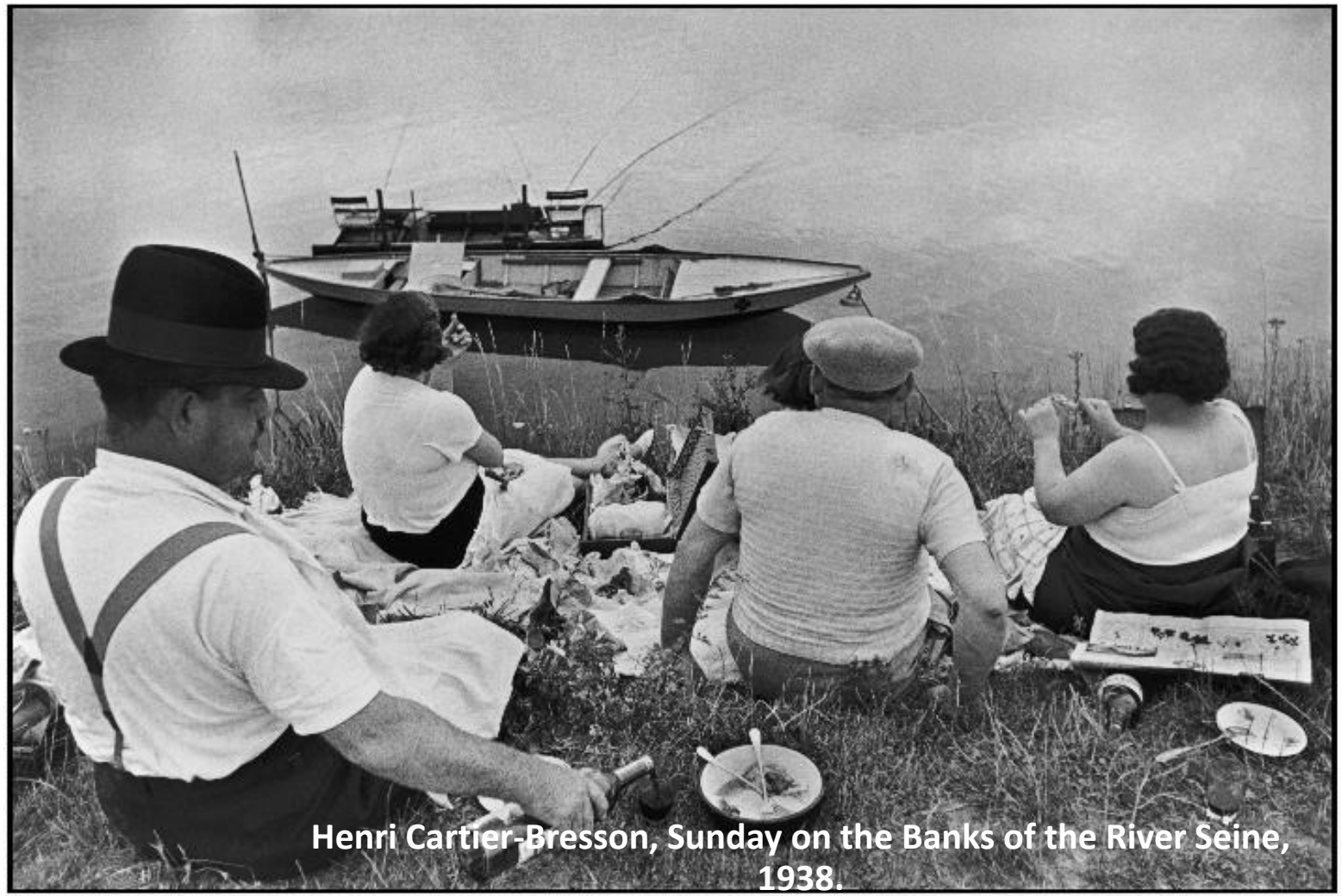


Thylacine, Dr. David Fleay, extinct in 1936.

Thylacine, Dr. David Fleay, extinct in 1936.

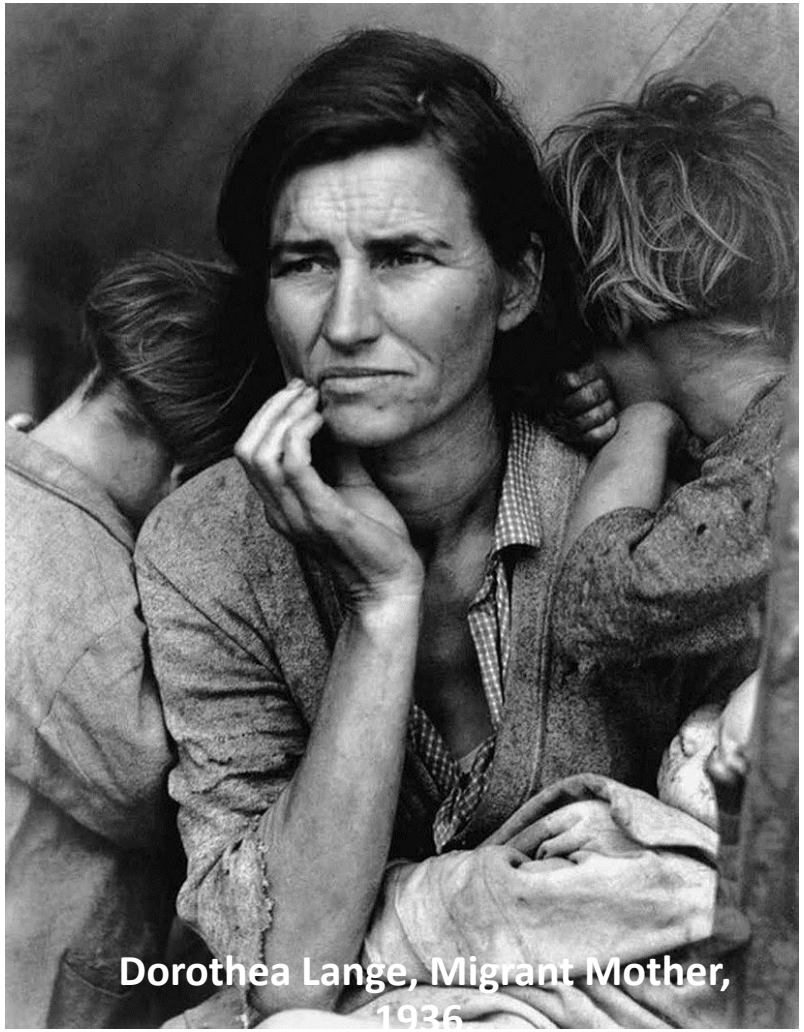
Amateur Family Photo, 1956

Amateur Family Photo, 1956

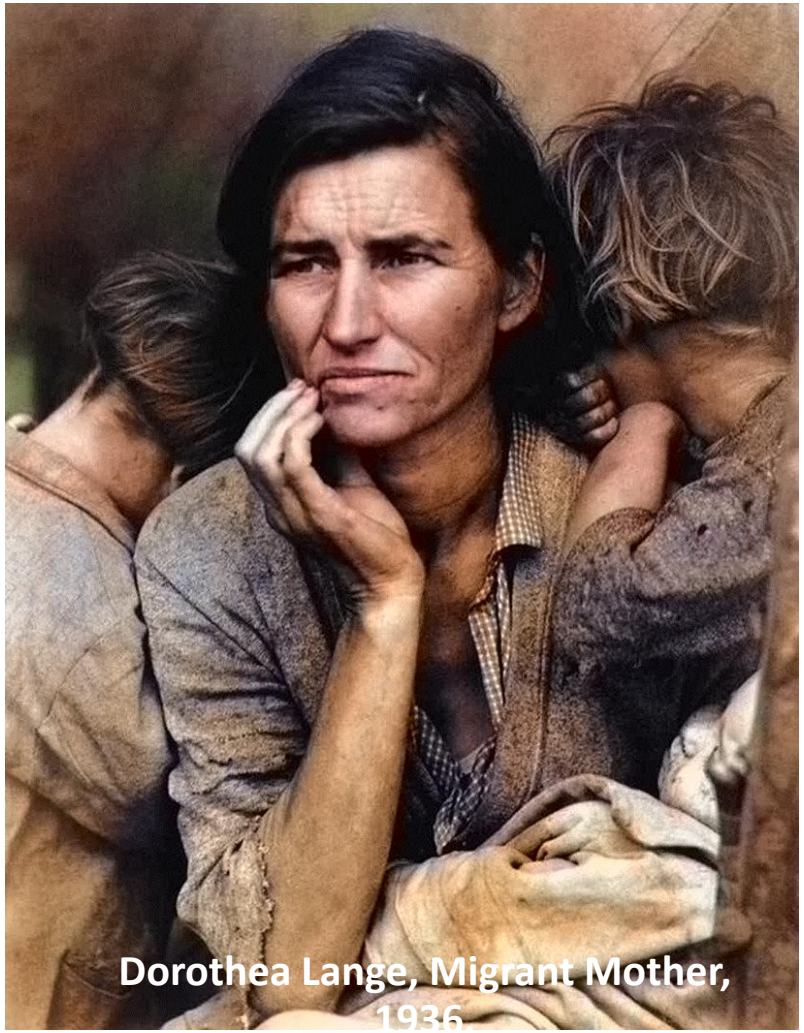


Henri Cartier-Bresson, Sunday on the Banks of the River Seine, 1938.

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



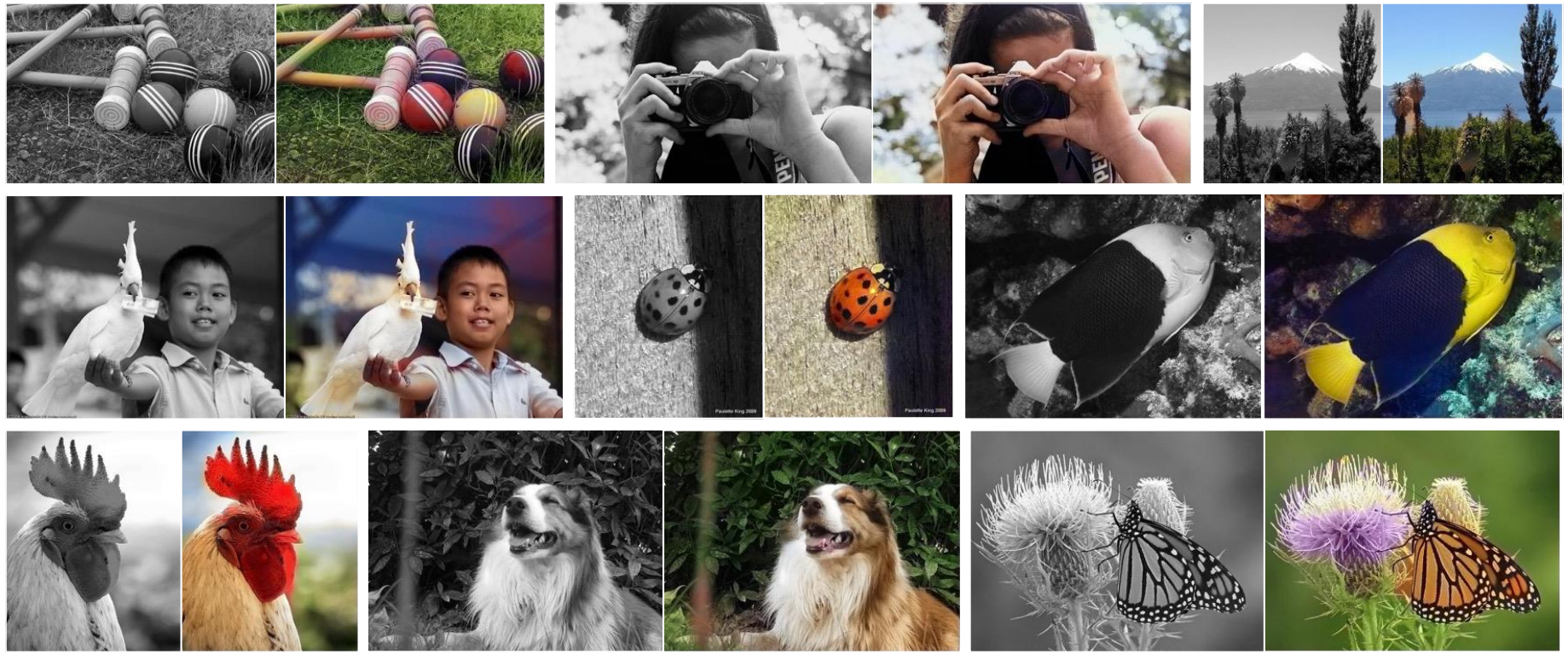
Dorothea Lange, Migrant Mother, 1936



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

A Simple Framework for Contrastive Learning of Visual Representations

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

SimCLR, IMCL 2020

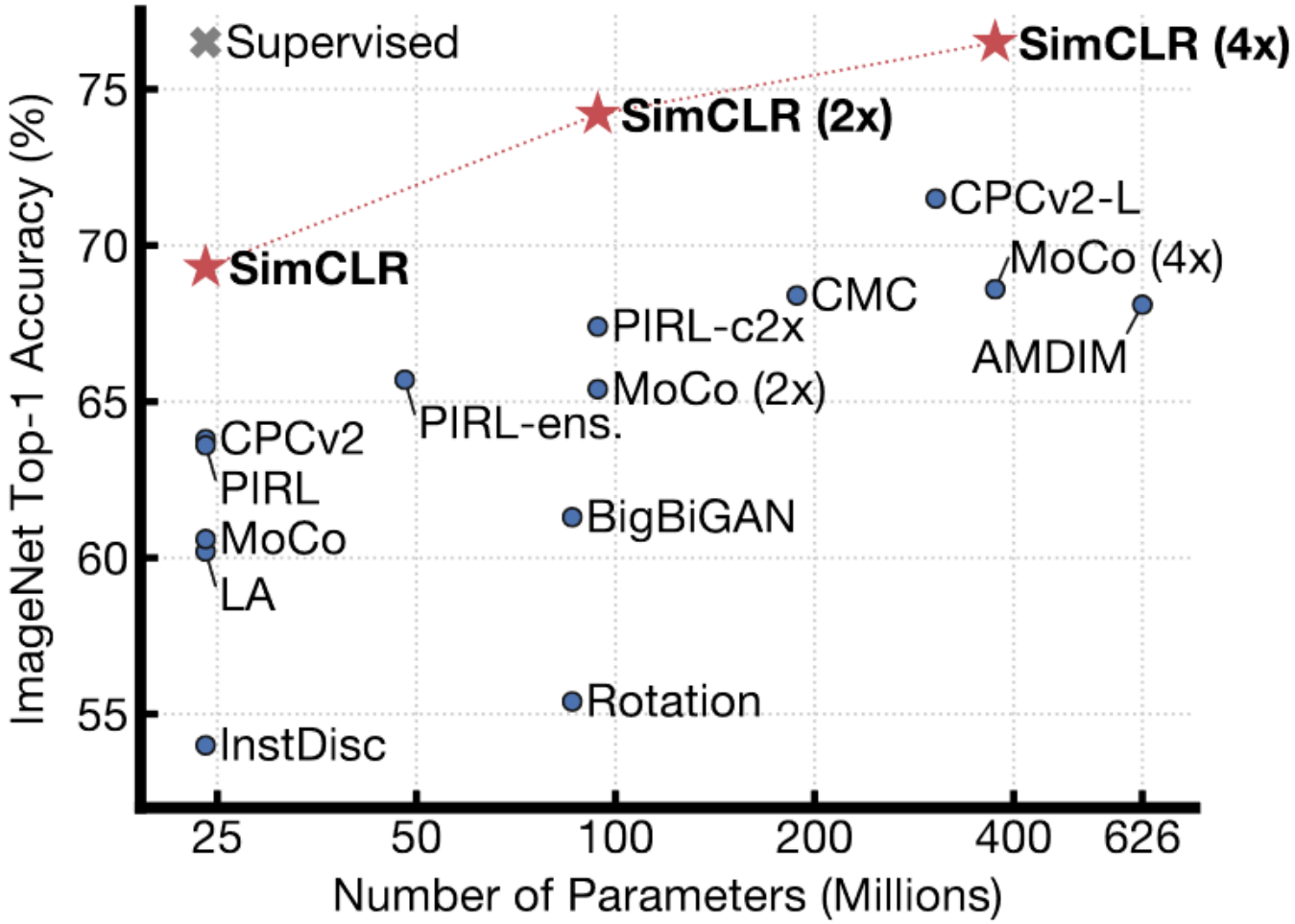
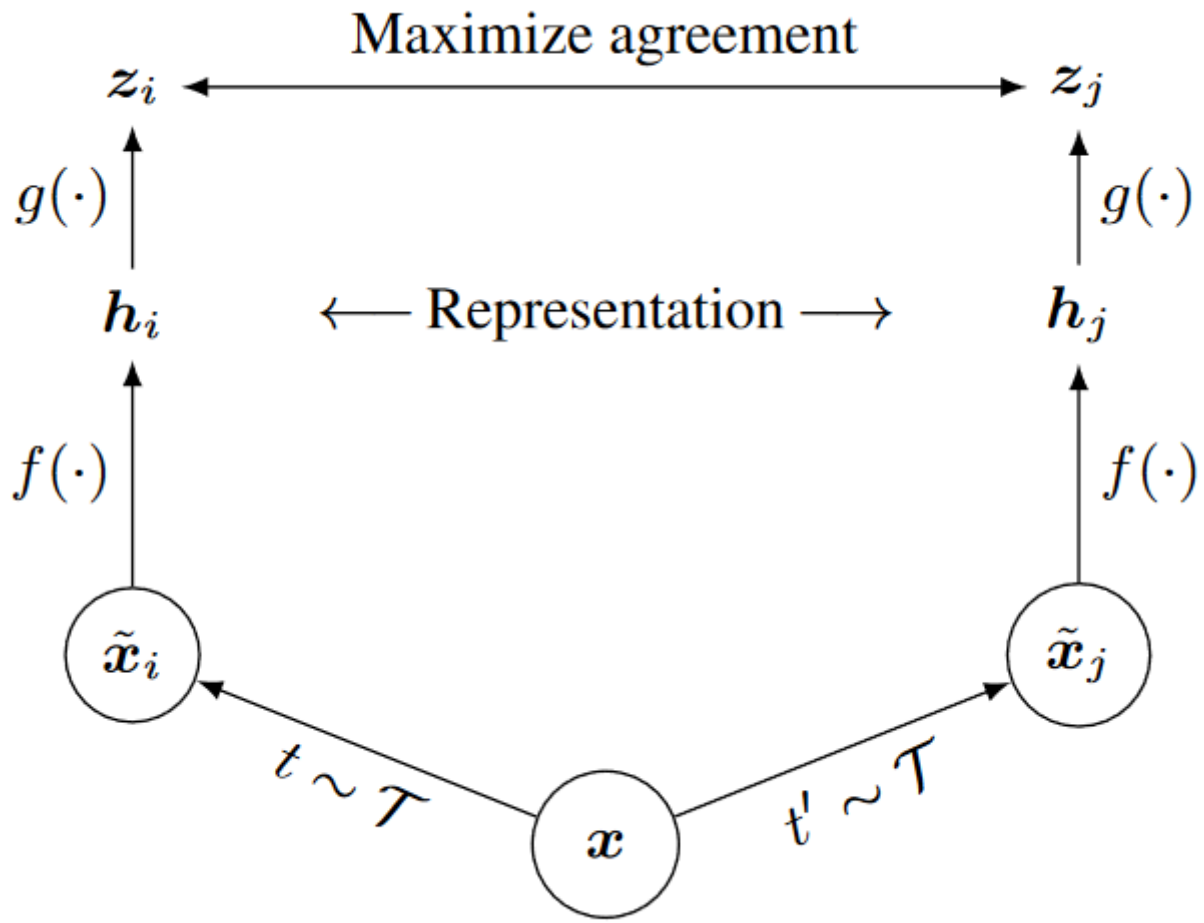


Figure 1. ImageNet Top-1 accuracy of linear classifiers trained on representations learned with different self-supervised methods (pretrained on ImageNet). Gray cross indicates supervised ResNet-50. Our method, SimCLR, is shown in bold.


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

How Useful is Self-Supervised Pretraining for Visual Tasks?

Alejandro Newell Jia Deng
Princeton University
{anewell,jiadeng}@cs.princeton.edu

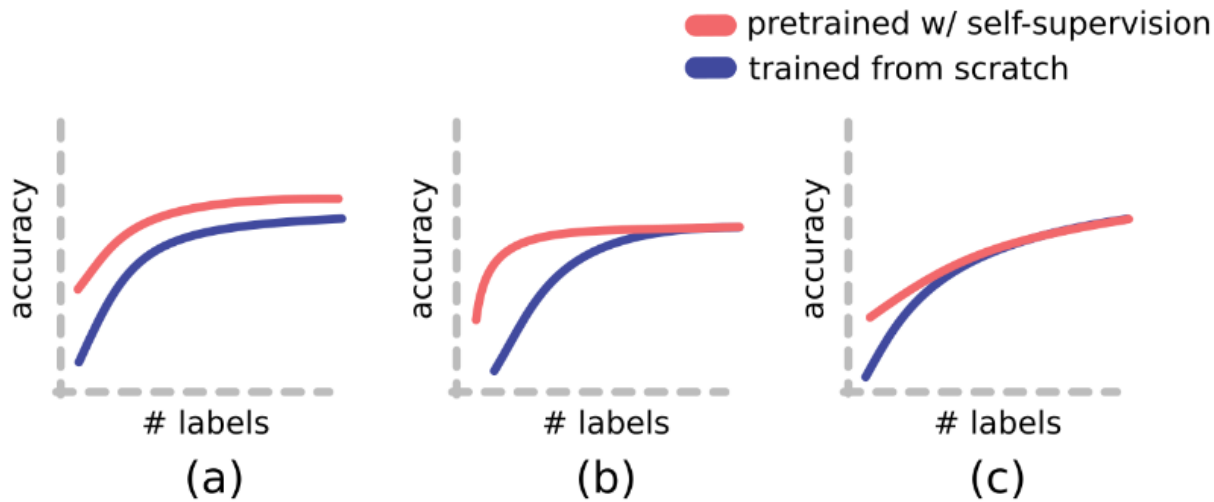


Figure 1. We highlight three possible outcomes when using self-supervised pretraining, the pretrained model either: a) always provides an improvement over the the model trained from scratch even as the amount of labeled data increases, b) reaches higher accuracy with fewer labels but plateaus to the same accuracy as the baseline, c) converges to baseline performance before accuracy plateaus. In our experiments we find option (c) to be the most common outcome.