Object Detection
(Plus some bonuses)

EECS 442 – David Fouhey

Winter 2023, University of Michigan

http://web.eecs.umich.edu/~fouhey/teaching/EECS442_W23/

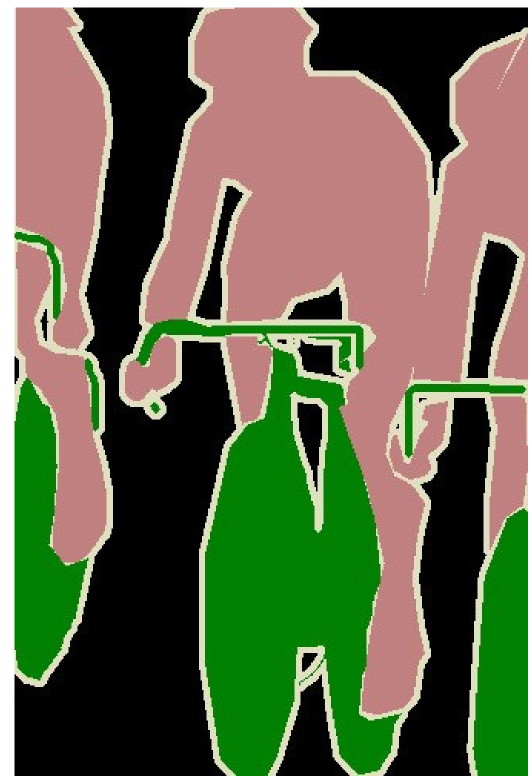
Last Time

"Semantic Segmentation": Label each pixel with the object category it belongs to.

Input

CNN

Target

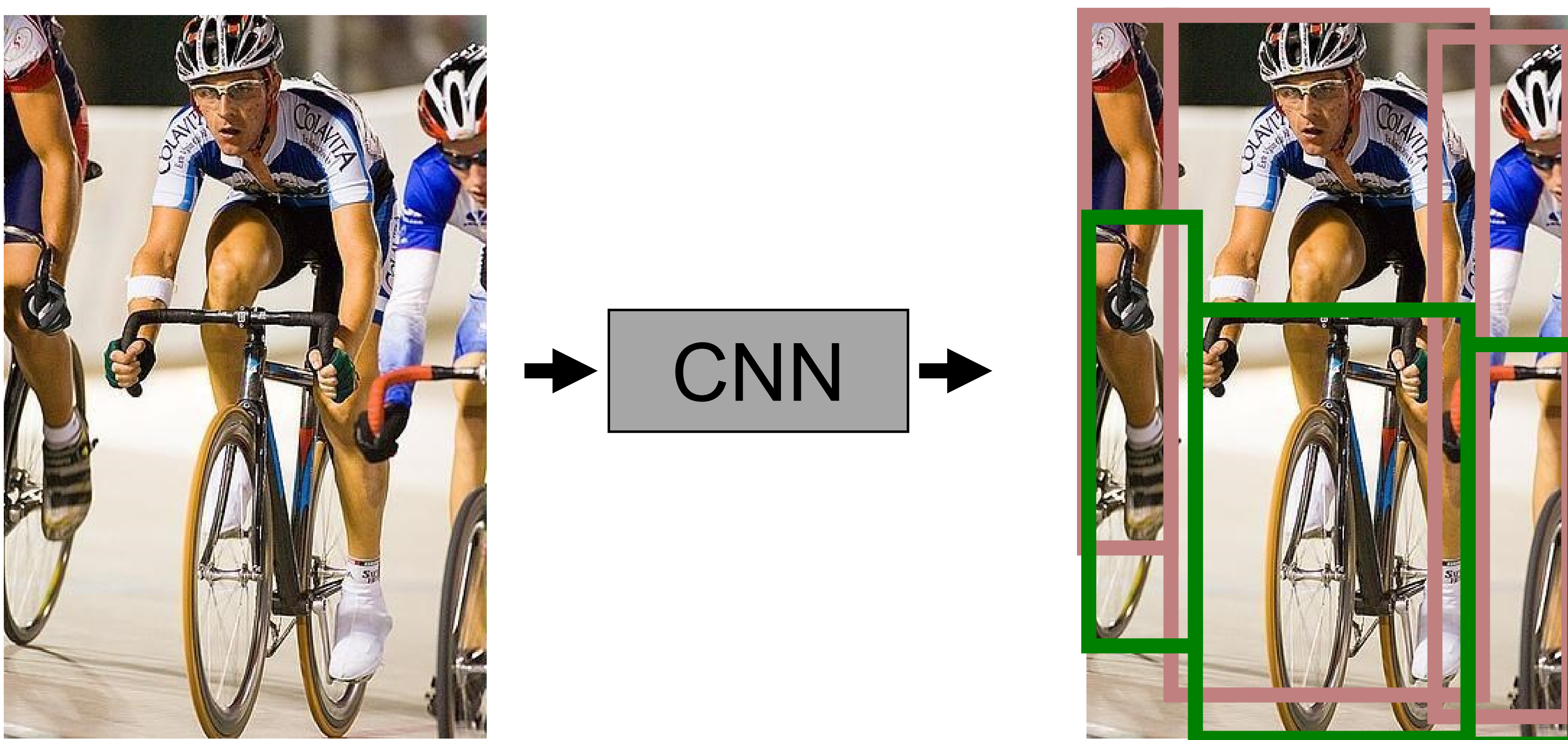


Today – Object Detection

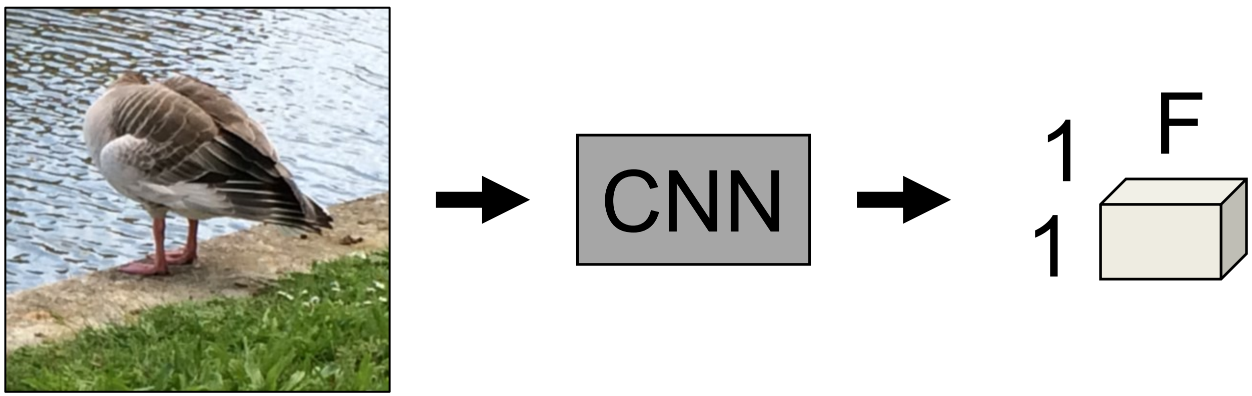
"Object Detection": Draw a box around each instance of a list of categories

Input

Target



The Wrong Way To Do It

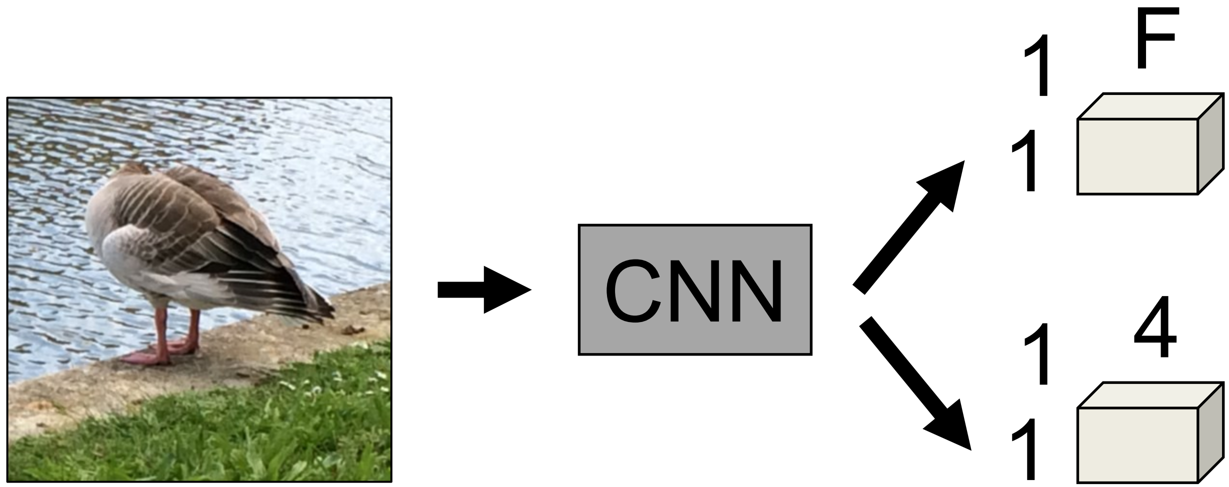


Starting point:

Can predict the probability of F classes

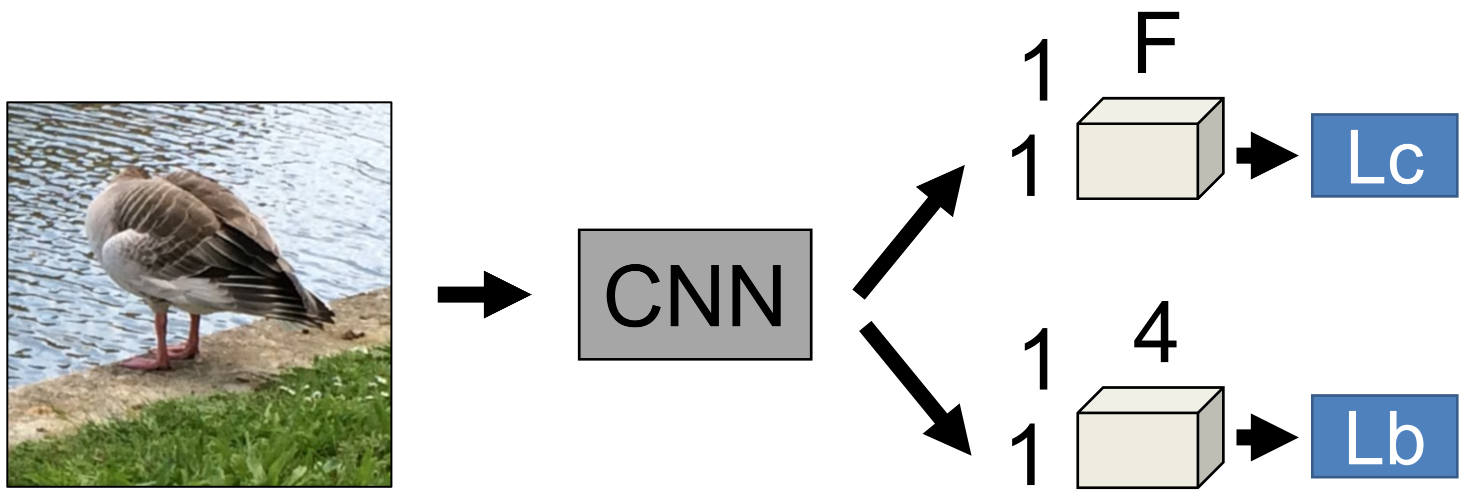
P(cat), P(goose), … P(tractor)

The Wrong Way To Do It



Add another output (why not):
Predict the *bounding box* of the object
[x,y,width,height] or [minX,minY,maxX,maxY]

The Wrong Way To Do It



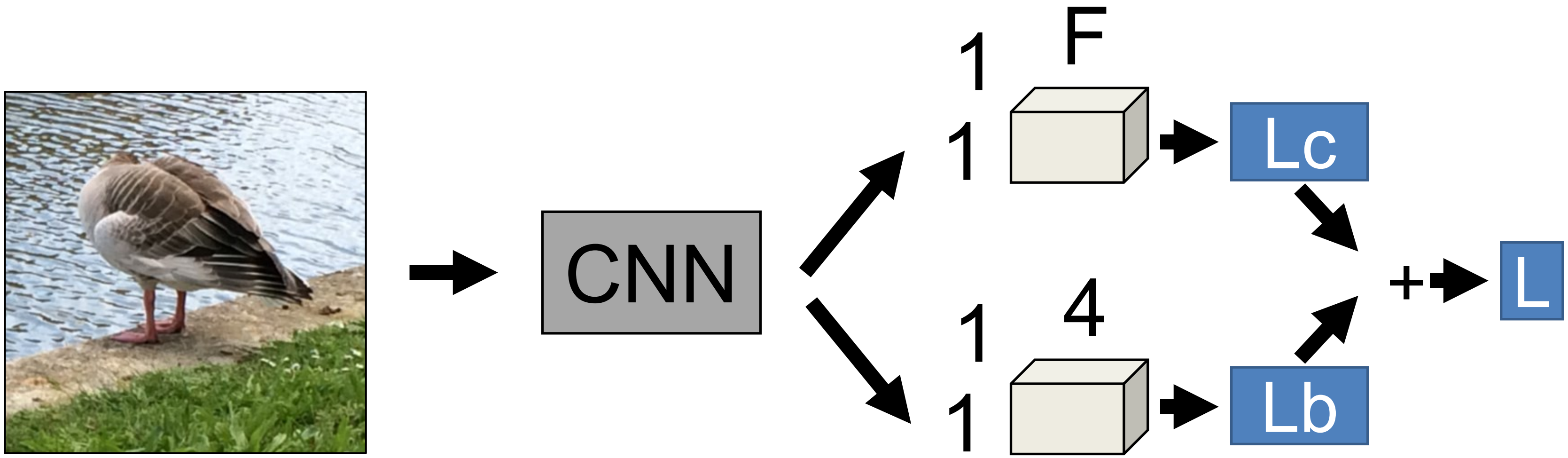
Put a loss on it:

Penalize mistakes on the classes with

Lc = negative log-likelihood

Lb = L2 loss

The Wrong Way To Do It

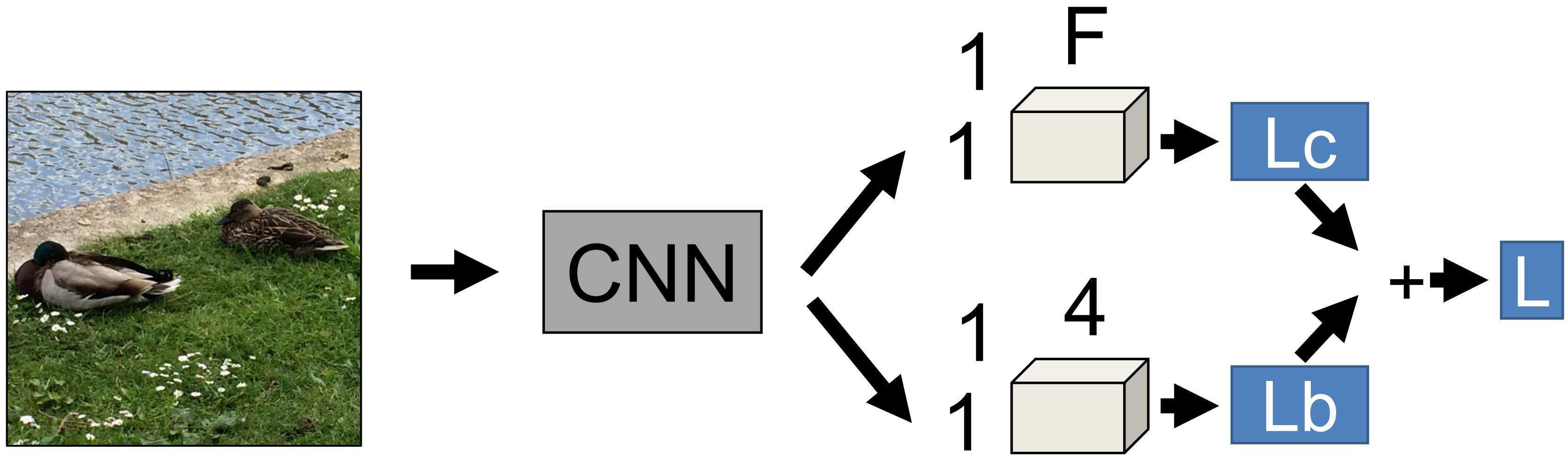


Add losses, backpropagate

Final loss: L = Lc + λLb

Why do we need the λ?

The Wrong Way To Do It

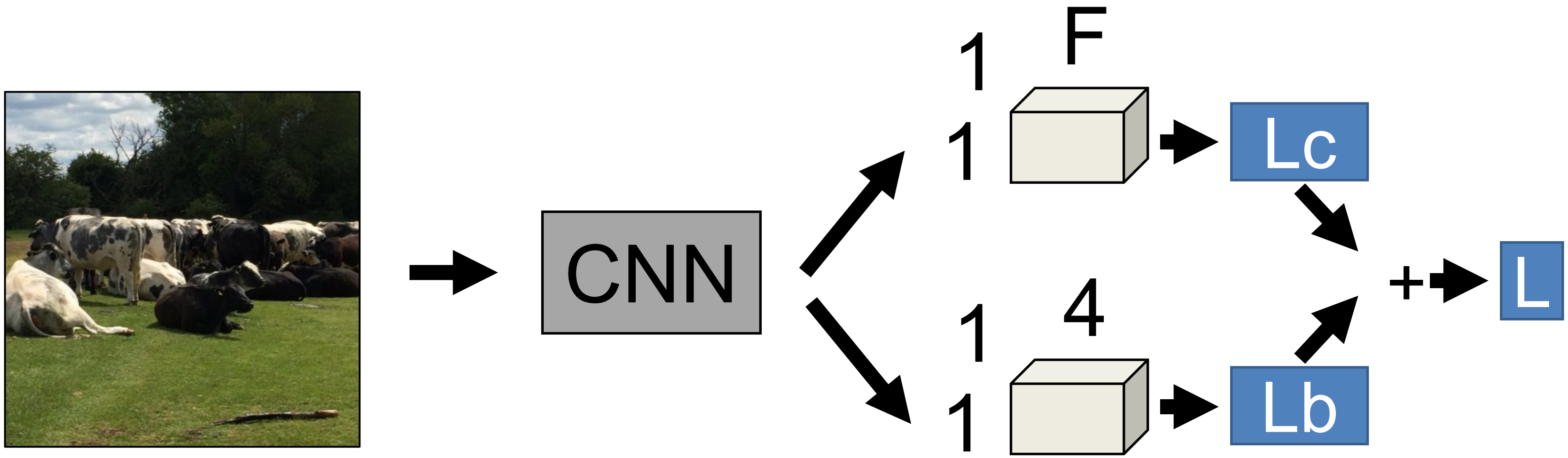


Now there are two ducks.

How many outputs do we need?

F, 4, F, 4 = 2*(F+4)

The Wrong Way To Do It

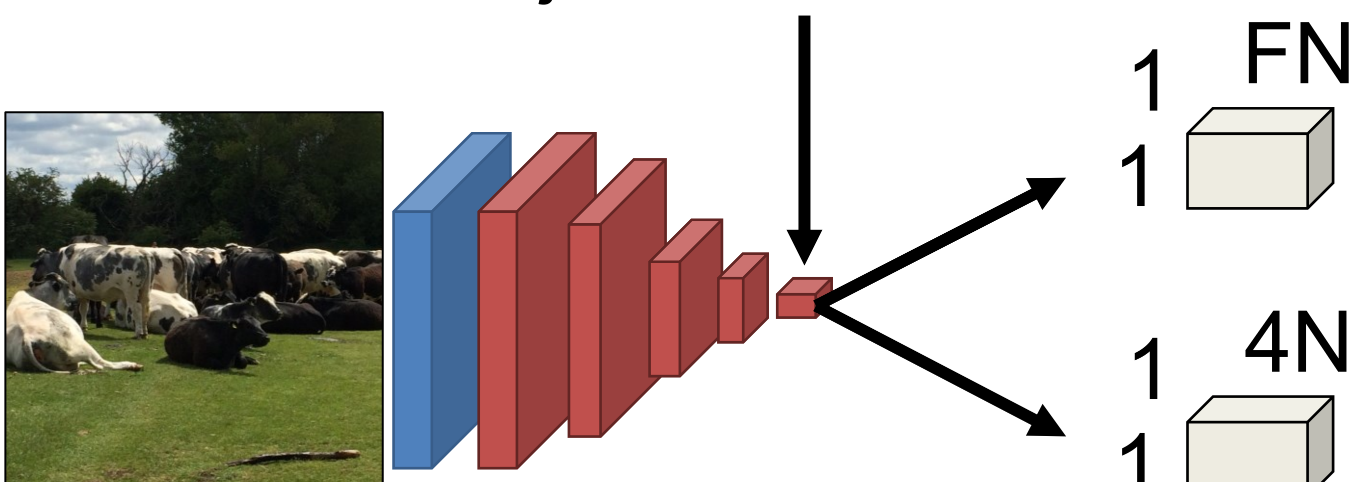


Now it's a herd of cows.
We need *lots* of outputs
(in fact the precise number of objects that are in the image, which is circular reasoning).

In General

- Usually can't do varying-size outputs.
- Even if we could, think about how *you* would solve it if you were a network.

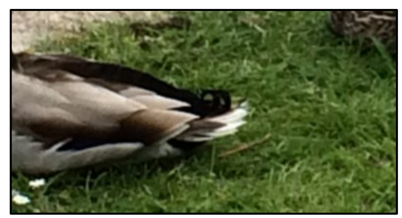
Bottleneck has to *encode* where the objects are for all objects and all N



An Alternate Approach

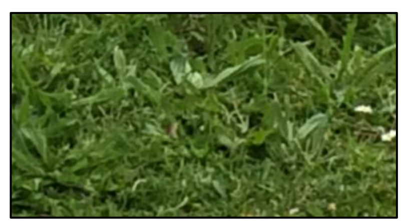
Examine every sub-window and determine if it is a tight box around an object

Yes



No?

Hold this thought



No

Sliding Window Classification

Let’s assume we’re looking for pedestrians in a box with a fixed aspect ratio.

Slide credit: J. Hays

Sliding Window

Key idea – just try all the subwindows in the image at all positions.

Slide credit: J. Hays

Generating hypotheses

Key idea – just try all the subwindows in the image at all positions **and scales.**

Note – Template did not change size

Slide credit: J. Hays

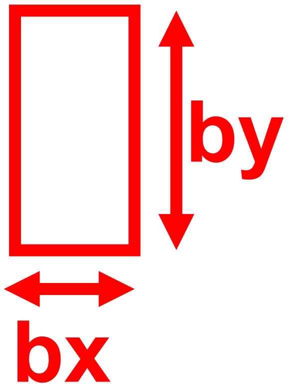
Each window classified separately

How Many Boxes Are There?

Given a HxW image and a “template” of size by, bx.

Q. How many sub-boxes are there of size (by,bx)?

A. (H-by)*(W-bx)

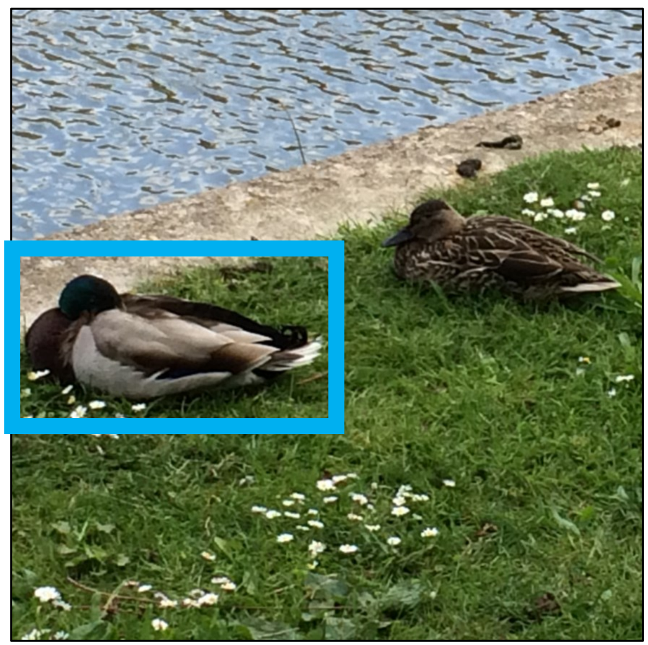


This is before considering adding:

- *scales* (by*s,bx*s)
- *aspect ratios* (by*sy,bx*sx)

Challenges of Object Detection

- Have to evaluate *tons* of boxes
- Positive instances of objects are *extremely* rare



How many ways can we get the box wrong?

1. Wrong left x
2. Wrong right x
3. Wrong top y
4. Wrong bottom y

Prime-time TV

Are You Smarter Than A 5th Grader?

Adults compete with 5th graders on elementary school facts.

Adults often not smarter.

Computer Vision TV

Are You Smarter Than A Random Number Generator?

Models trained on data compete with making random guesses.

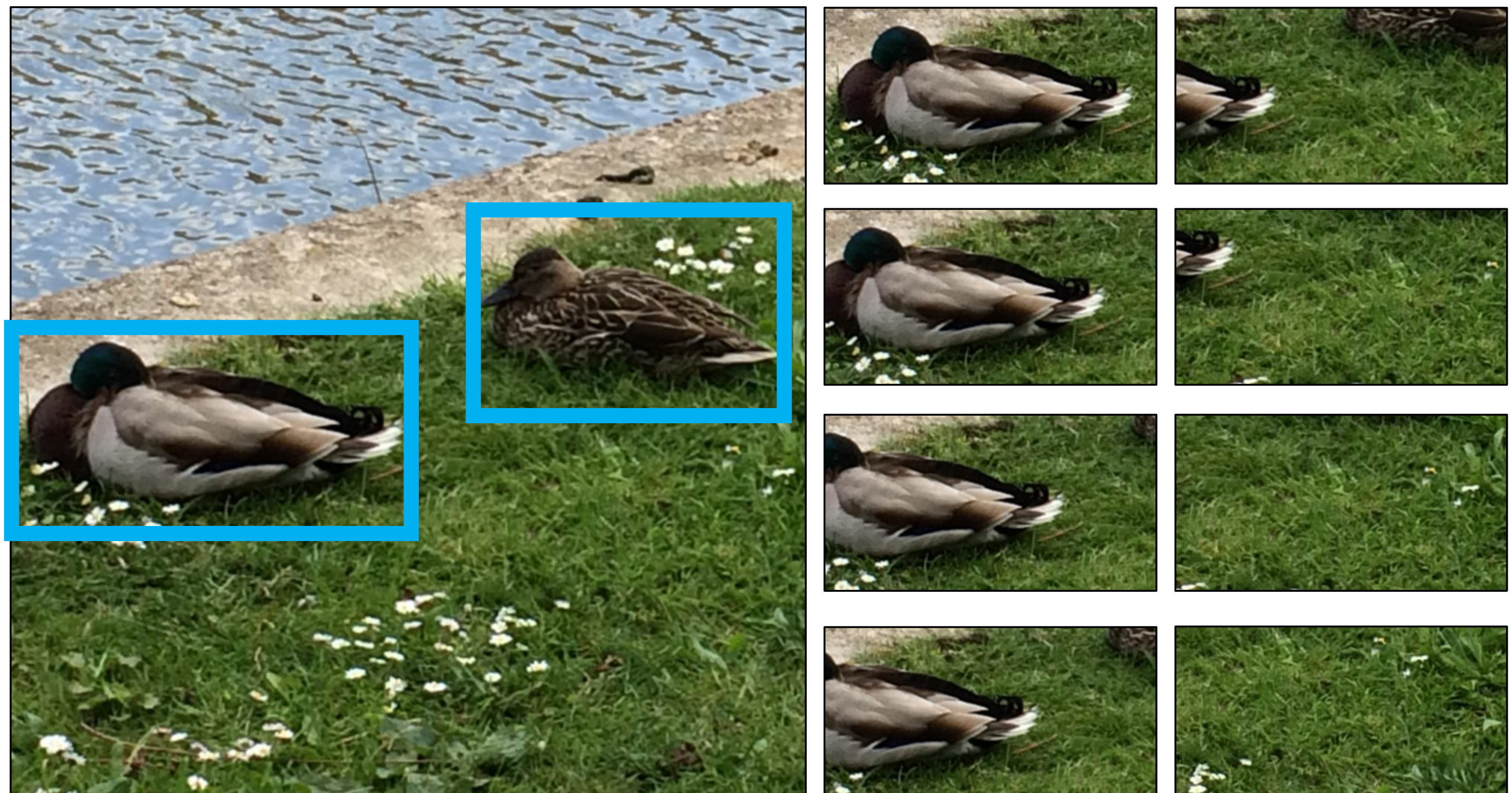
Models often not better.

Are You Smarter than a Random Number Generator?

- **Prob. of guessing 1k-way classification?**
  - 1/1,000
- **Prob. of guessing all 4 bounding box corners within 10% of image size**?
  - (1/10)*(1/10)*(1/10)*(1/10)=1/10,000
- Probability of guessing both: 1/10,000,000
- Detection is **hard** (via guessing and in general)
- Should *always compare* against guessing or picking most likely output label

Evaluating – Bounding Boxes

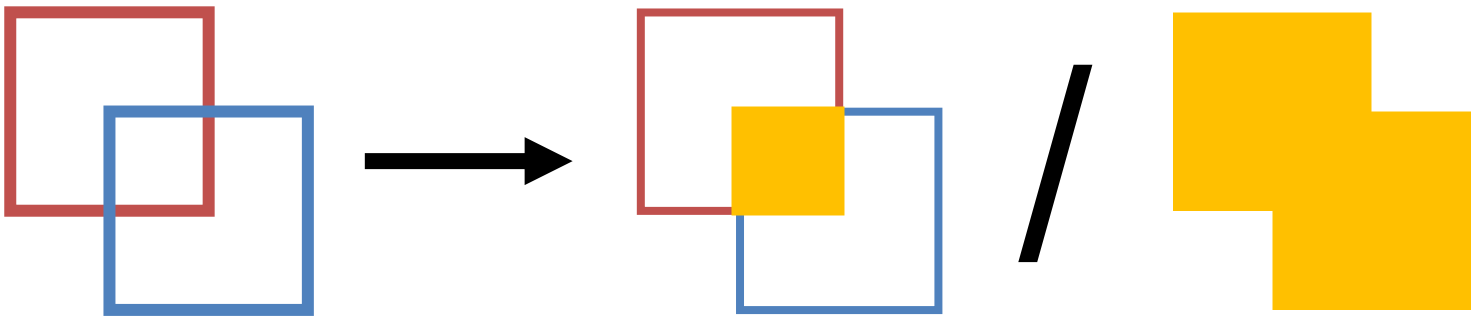
Raise your hand when you think the detection stops being correct.

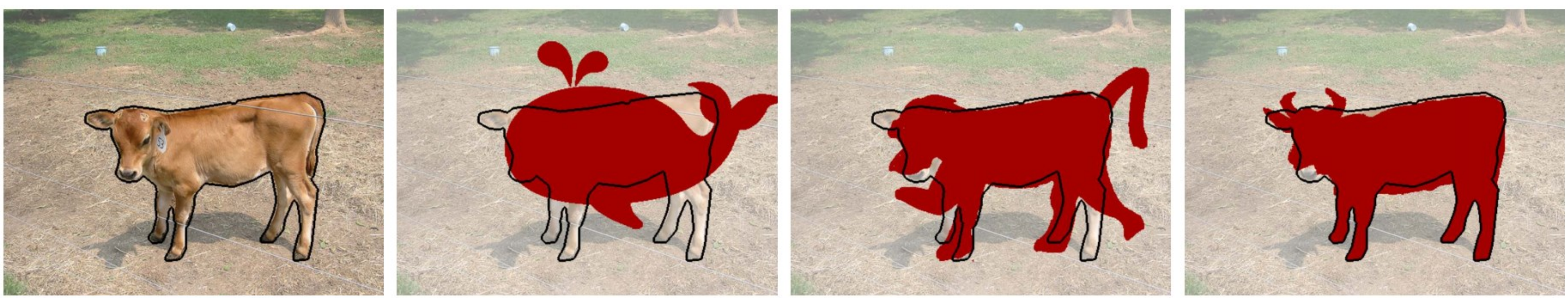


Evaluating – Bounding Boxes

Standard metric for two boxes:

Intersection over union/IoU/Jaccard coefficient





(a) Ground truth (b) $\mathcal{J} = 0.554$ (c) $\mathcal{J} = 0.703$ (d) $\mathcal{J} = 0.910$

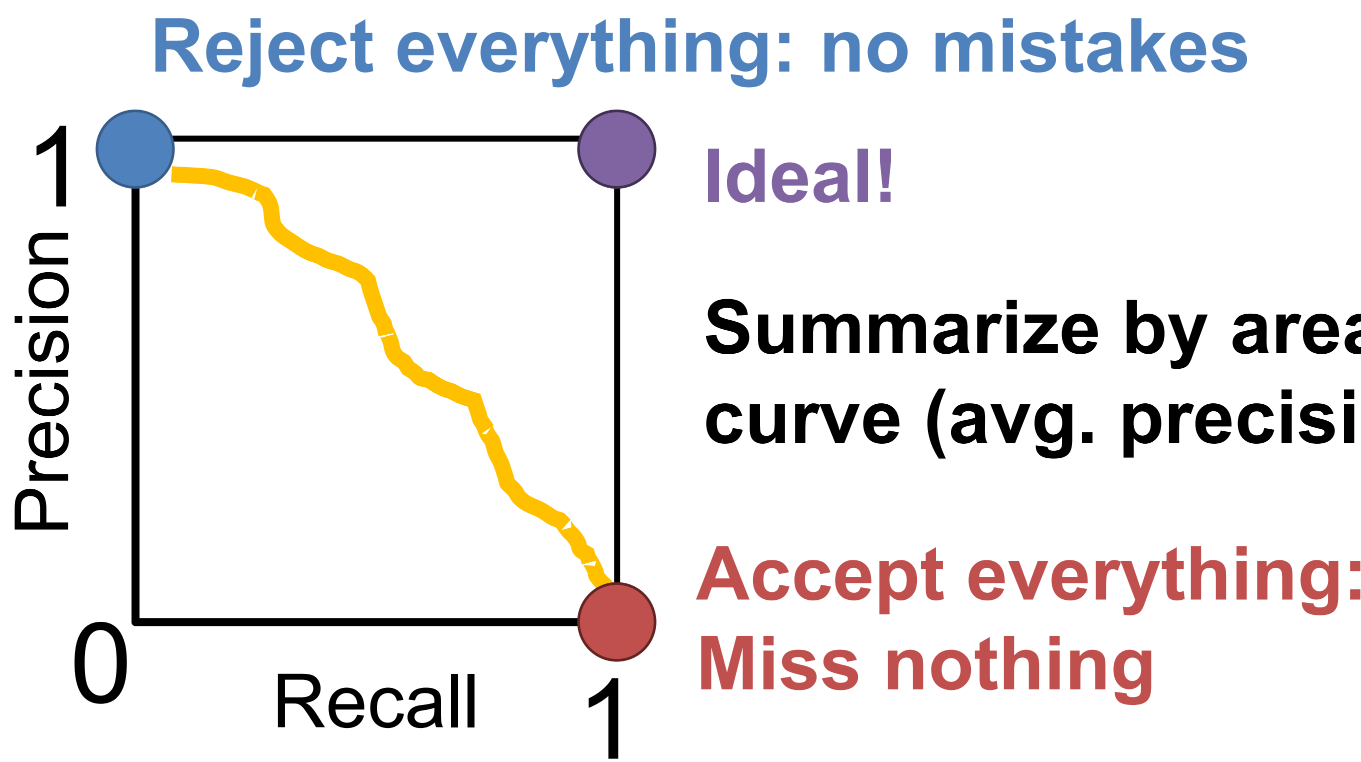
Jaccard example credit: P. Kraehenbuehl et al. ECCV 2014

Evaluating Performance

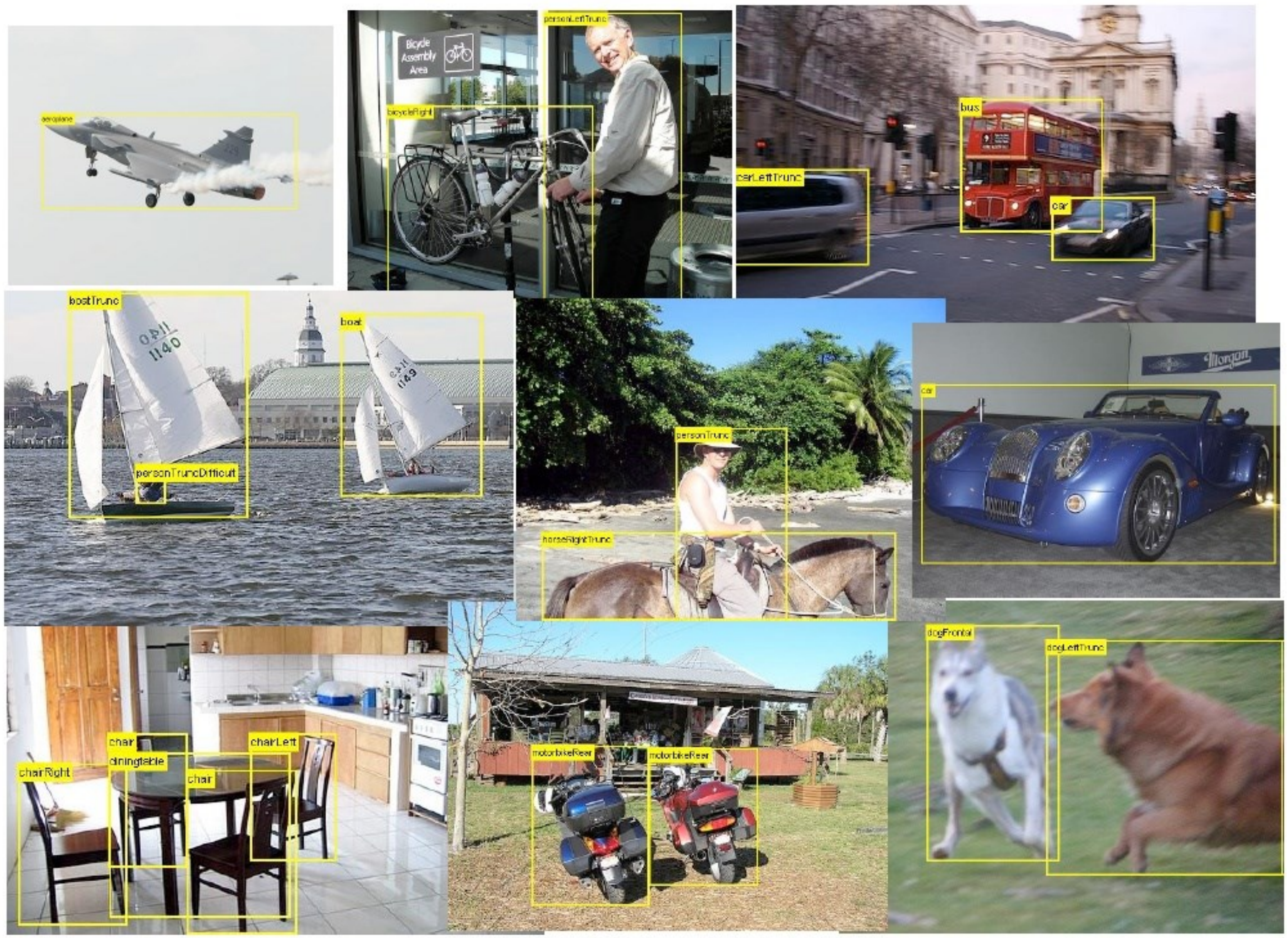
- Remember: accuracy = average of whether prediction is correct
- Suppose I have a system that gets 99% accuracy in person detection.
- **What's wrong?**
- I can get that by just saying no object everywhere!

Evaluating Performance

- True detection aka true positive: high IoU
- Precision: #true detections / #detections by detector
- Recall: #true detections / #ground truth positives



Generic object detection



Slide Credit: S. Lazebnik

Histograms of oriented gradients (HOG)

Partition image into blocks and compute histogram of gradient orientations in each block

HxWx3 Image

H’xW’xC’ Image

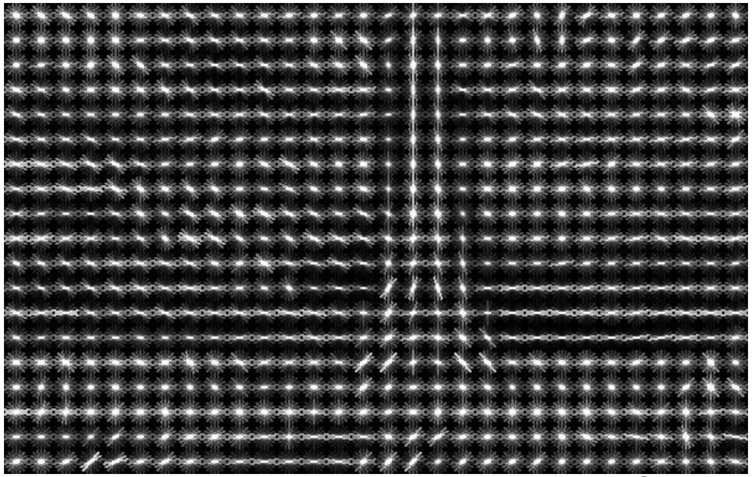


Image credit: N. Snavely

N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

Slide Credit: S. Lazebnik

Pedestrian detection with HOG

- Train a pedestrian template using a linear support vector machine

positive training examples

negative training examples

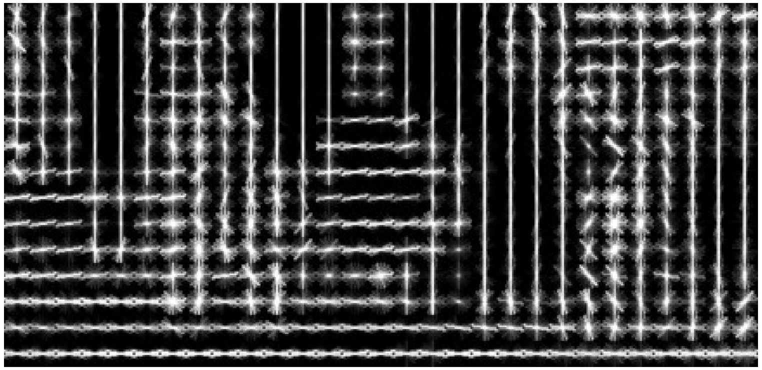
N. Dalal and B. Triggs, [Histograms of Oriented Gradients for Human Detection](), CVPR 2005

Slide Credit: S. Lazebnik

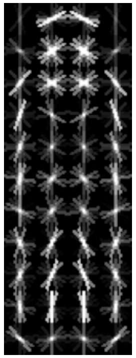
Pedestrian detection with HOG

- Train pedestrian “template” using a linear svm
- At test time, convolve feature map with template
- Find local maxima of response
- For multi-scale detection, repeat over multiple levels of a HOG *pyramid*

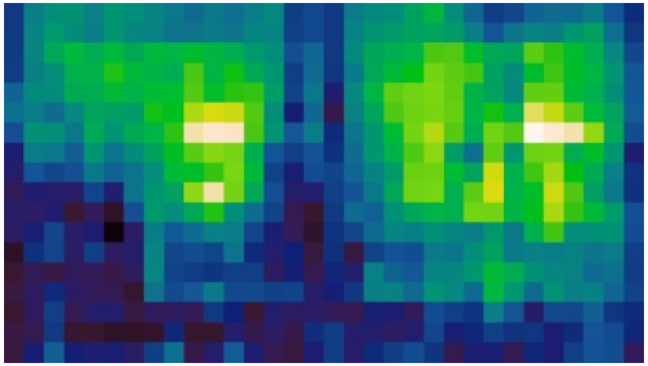
HOG feature map



Template



Detector response map



N. Dalal and B. Triggs, Histograms of Oriented Gradients for Human Detection, CVPR 2005

Slide Credit: S. Lazebnik

Example detections

[Dalal and Triggs, CVPR 2005]

Slide Credit: S. Lazebnik

PASCAL VOC Challenge (2005-2012)

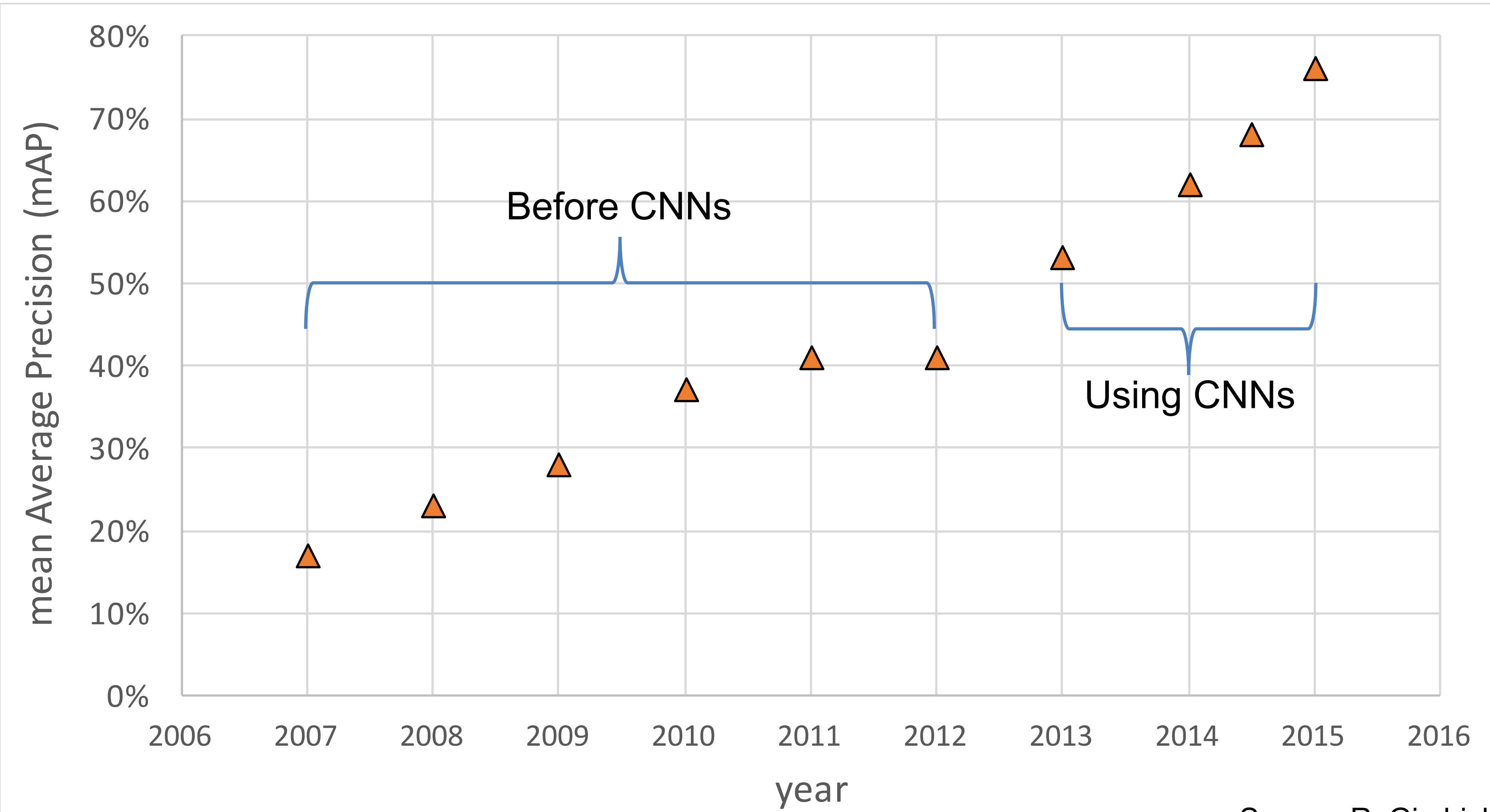
- 20 challenge classes:
- *Person*
- *Animals:* bird, cat, cow, dog, horse, sheep
- *Vehicles:* aeroplane, bicycle, boat, bus, car, motorbike, train
- *Indoor:* bottle, chair, dining table, potted plant, sofa, tv/monitor
- Dataset size (by 2012): 11.5K training/validation images, 27K bounding boxes, 7K segmentations

Slide Credit: S. Lazebnik

http://host.robots.ox.ac.uk/pascal/VOC/

Object detection progress

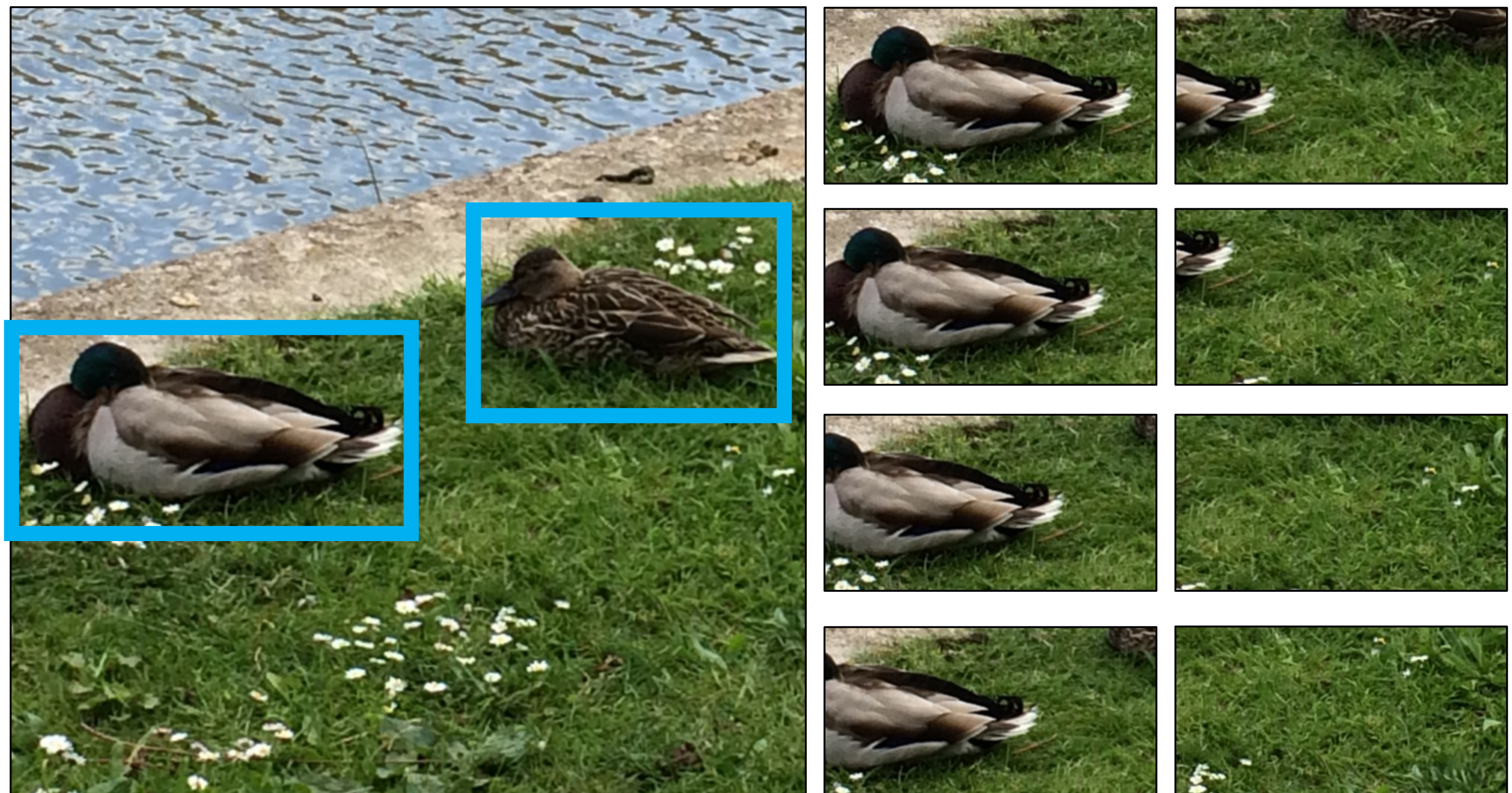
PASCAL VOC



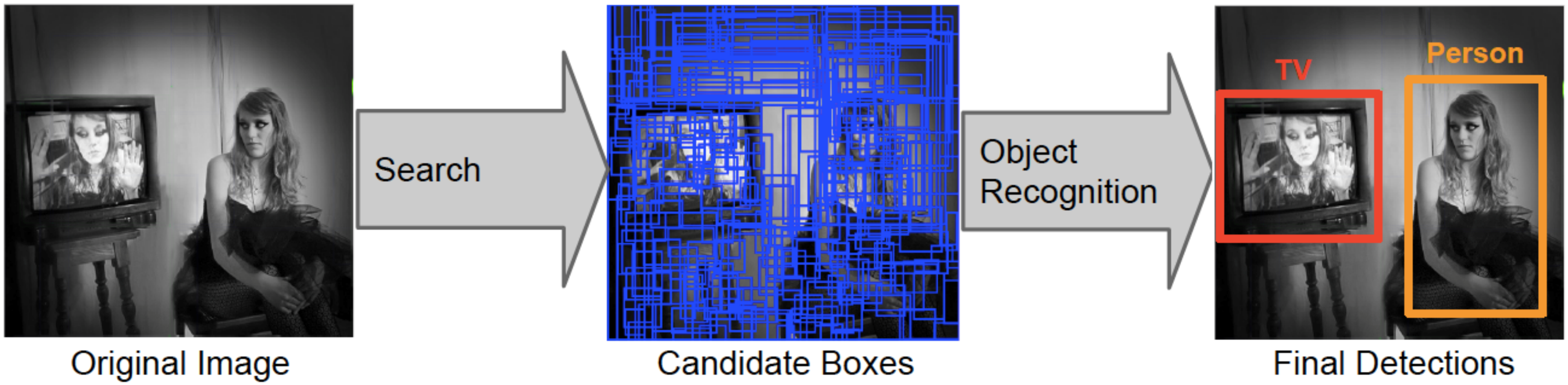
Source: R. Girshick

Region Proposals

Do I need to spend a lot of time filtering all the boxes covering grass?



Region Proposals

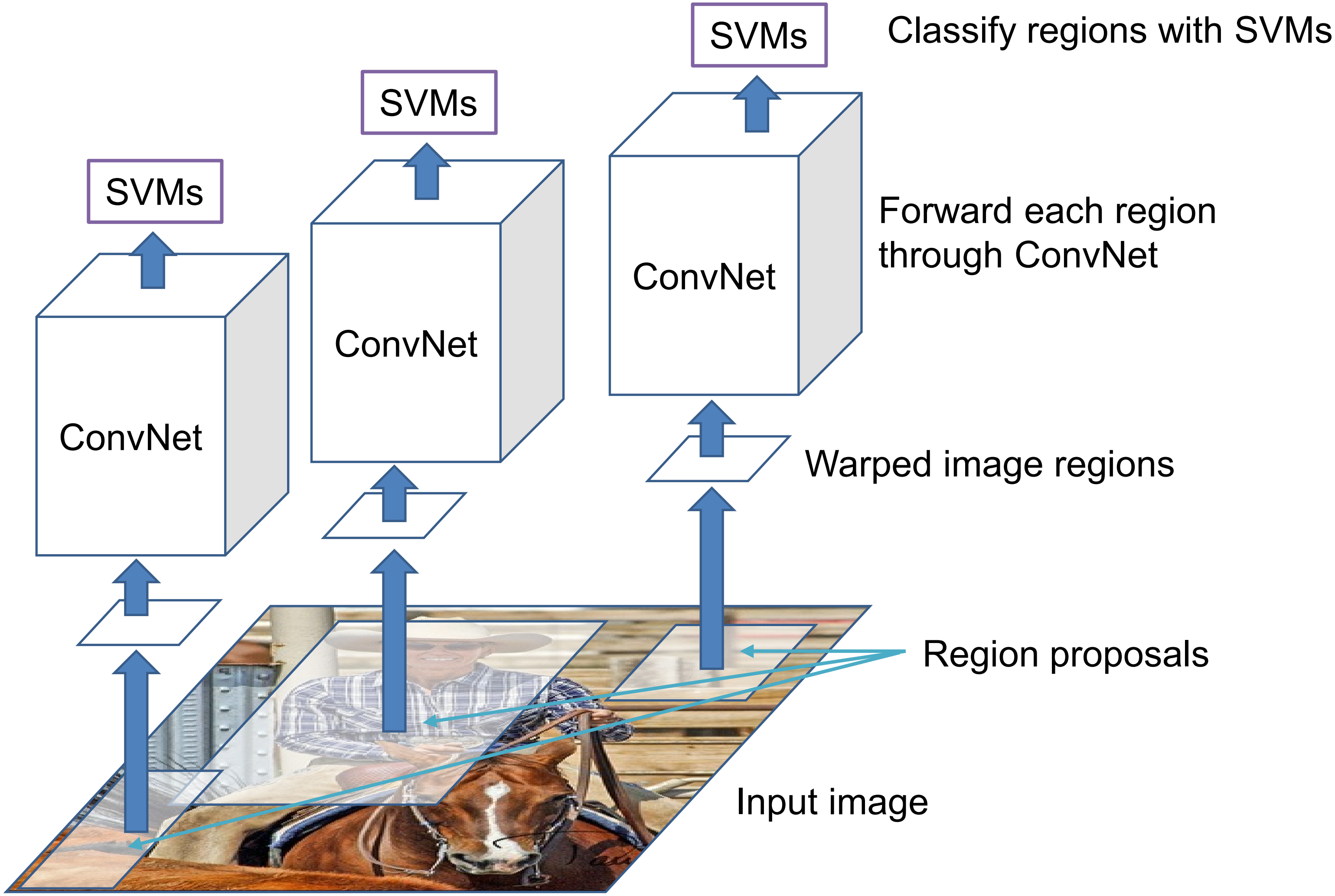


- As an alternative to sliding window search, evaluate a few hundred *region proposals*
  - Can use slower but more powerful features and classifiers
  - Proposal mechanism can be category-independent
  - Proposal mechanism can be trained

Slide Credit: S. Lazebnik

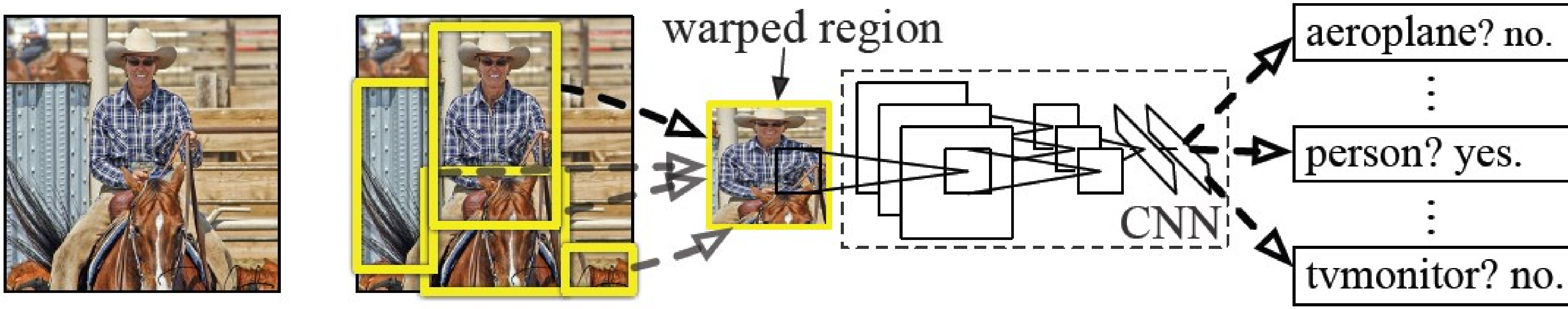
R-CNN: Region proposals + CNN features

Source: R. Girshick



R. Girshick, J. Donahue, T. Darrell, and J. Malik, [Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation](), CVPR 2014.

R-CNN details



- **Regions**: ~2000 Selective Search proposals
- **Network**: AlexNet *pre-trained* on ImageNet (1000 classes), *fine-tuned* on PASCAL (21 classes)
- **Final detector**: warp proposal regions, extract fc7 network activations (4096 dimensions), classify with linear SVM
- **Bounding box regression** to refine box locations
- **Performance:** mAP of 53.7% on PASCAL 2010 (vs. 35.1% for Selective Search and 33.4% for DPM).

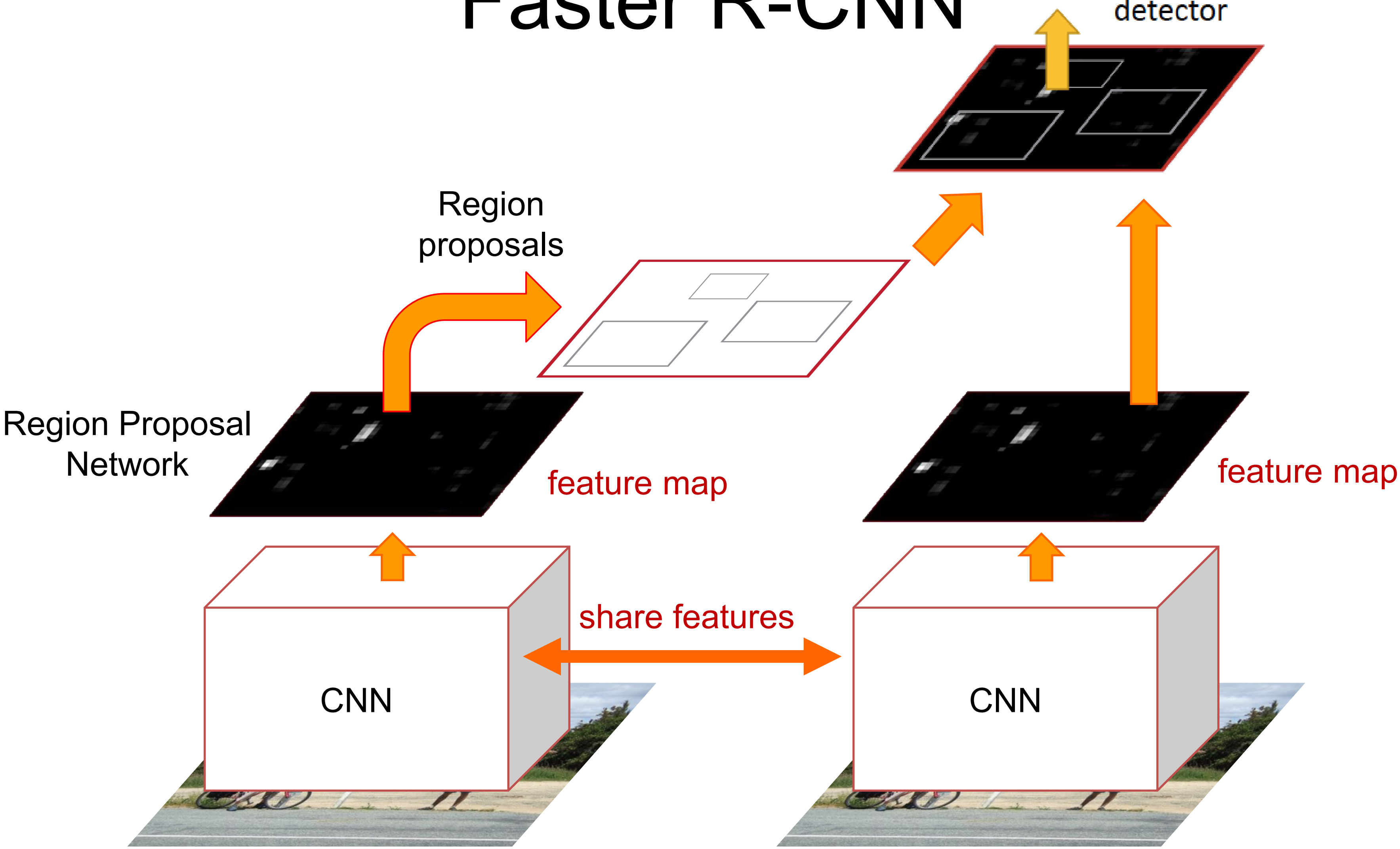
R. Girshick, J. Donahue, T. Darrell, and J. Malik, [Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation](), CVPR 2014.

R-CNN pros and cons

- Pros
  - Accurate!
  - Any deep architecture can immediately be “plugged in”
- Cons
  - Ad hoc training objectives
    - Fine-tune network with softmax classifier (log loss)
    - Train post-hoc linear SVMs (hinge loss)
    - Train post-hoc bounding-box regressions (least squares)
  - Training is slow (84h), takes a lot of disk space
    - 2000 CNN passes per image
  - Inference (detection) is slow (47s / image with VGG16)

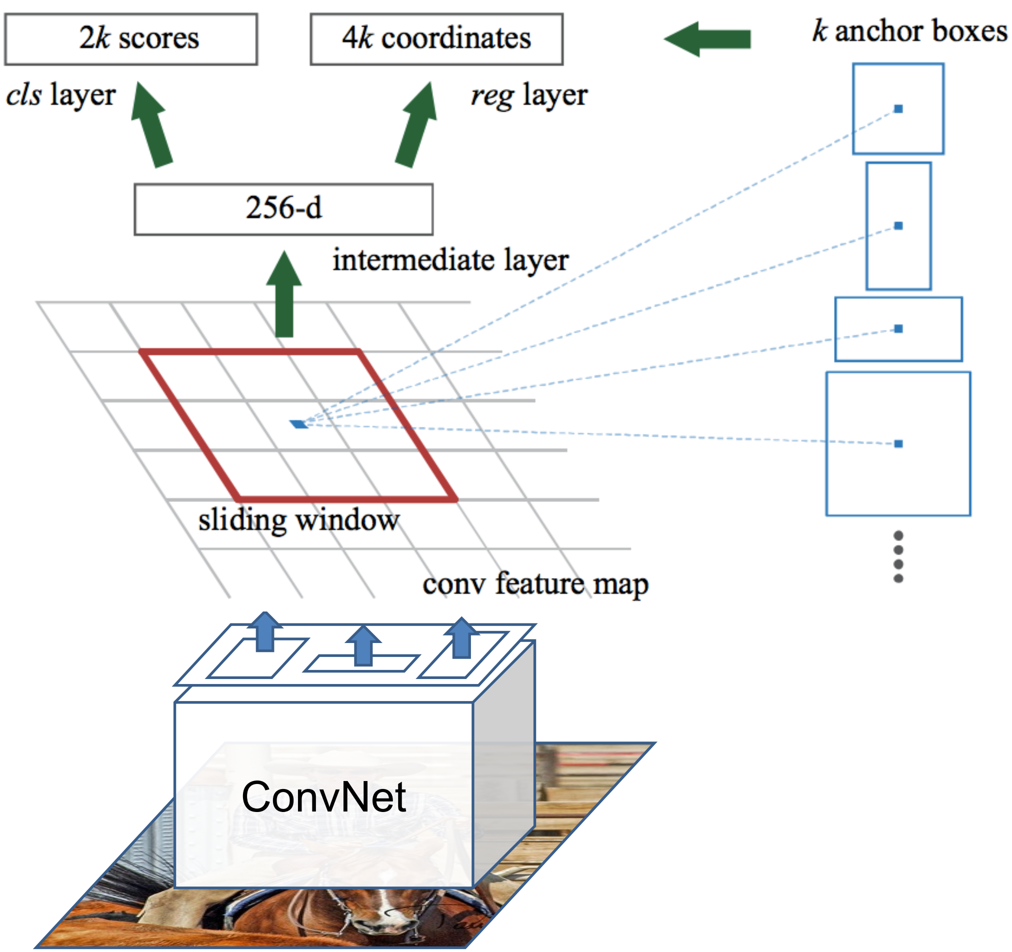
Slide Credit: S. Lazebnik

Faster R-CNN



S. Ren, K. He, R. Girshick, and J. Sun, Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NIPS 2015

Region Proposal Network (RPN)



Small network applied to conv5 feature map.

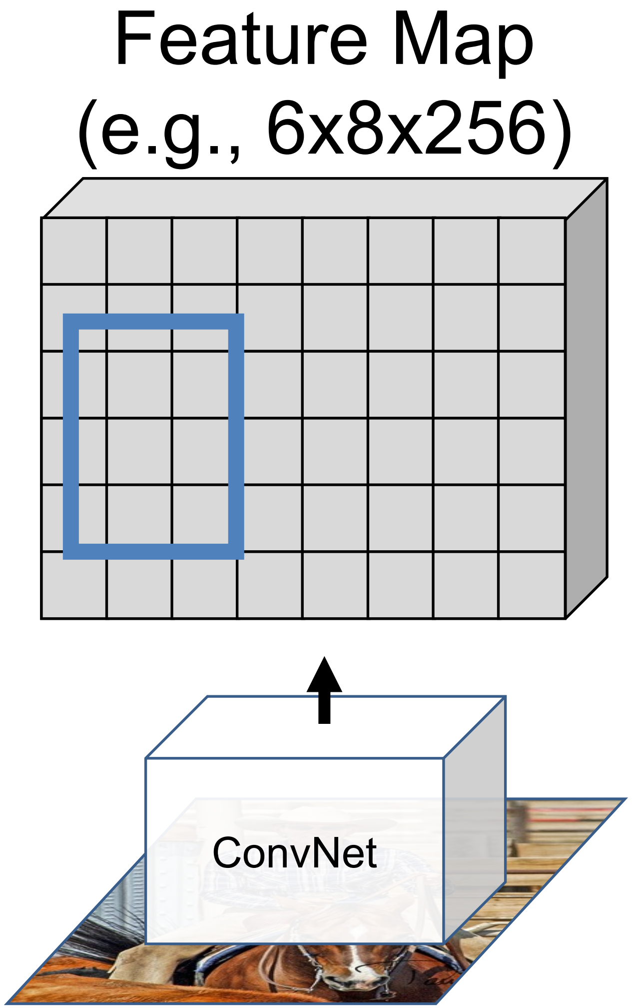
Predicts:

- good box or not (classification),
- how to modify box (regression)

for k “anchors” or boxes relative to the position in feature map.

Source: R. Girshick

ROI Pooling/Align

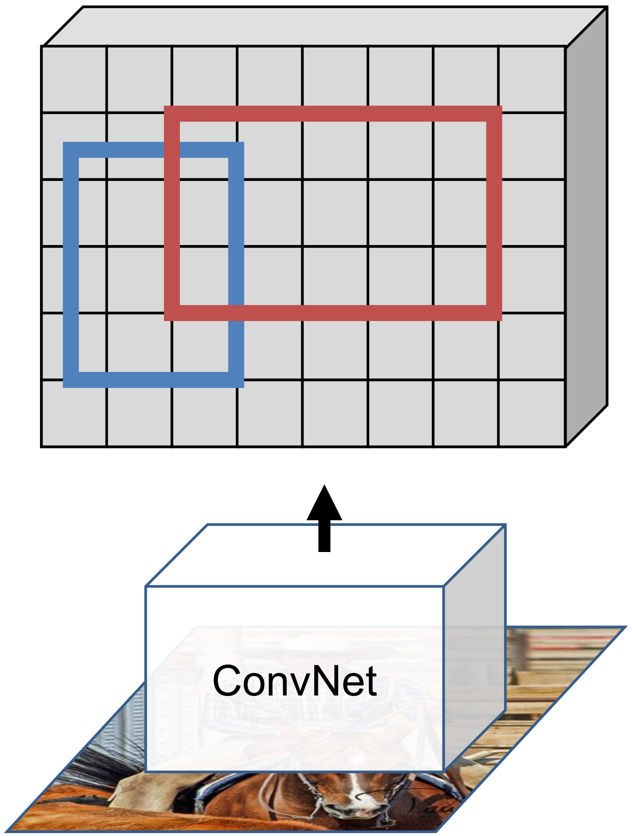


Given box in original image, calculate where the box goes.

- Example: H=600,W=800
- Feature map is H'=6, W'=8
- Box: left x=50, top y=150, width=250, height=350
- Feature map box: left x=0.5, y =1.5, width=2.5, height=3.5

ROI Pooling/Align

Feature Map
(e.g., 6x8x256)



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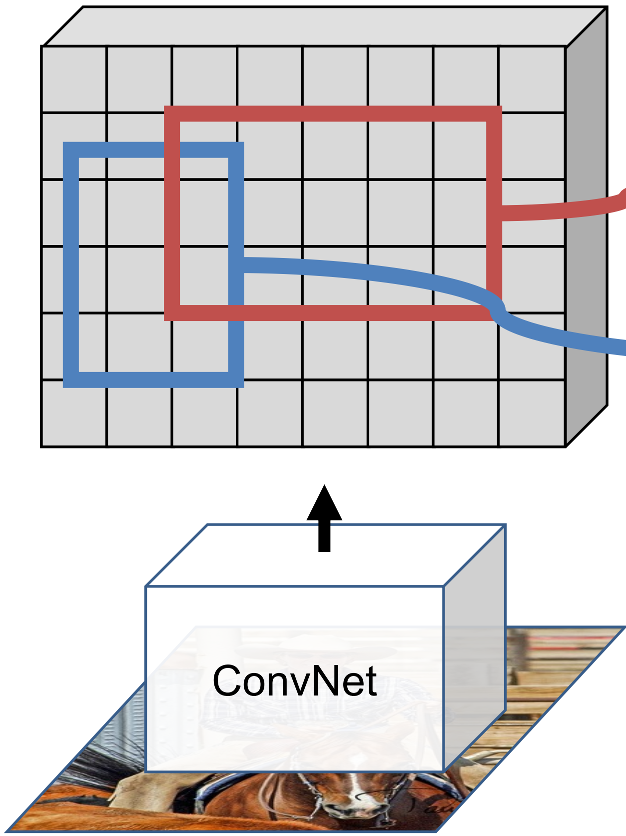
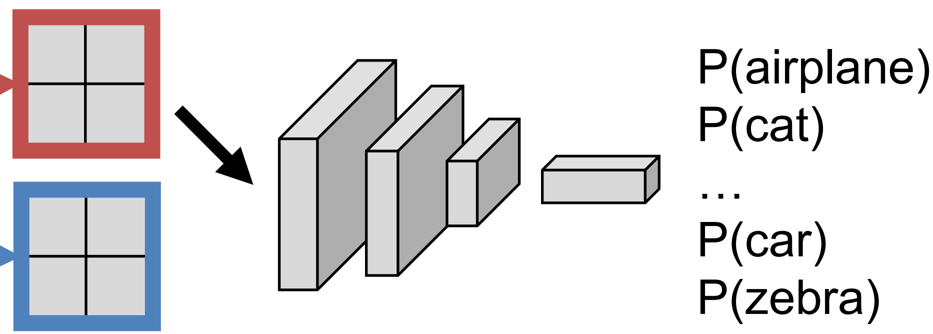
- Box: left x=50, top y=150, width=250, height=350
- Feature map box: left x=0.5, y =1.5, width=2.5, height=3.5
- Other feature map box: left x=2, top y = 1, width=5, height=3

ROI Pooling/Align

Feature Map
(e.g., 6x8x256)



Resize to fixed size (e.g., 7x7)
Details **critical**, but beyond scope of class.

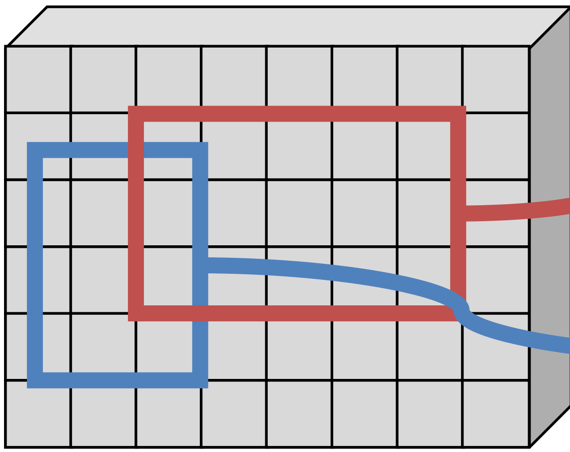


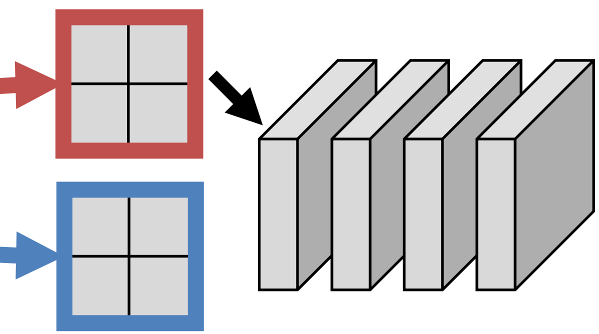
Afterwards, can add a small neural network that classifies the box and is applied to each window.

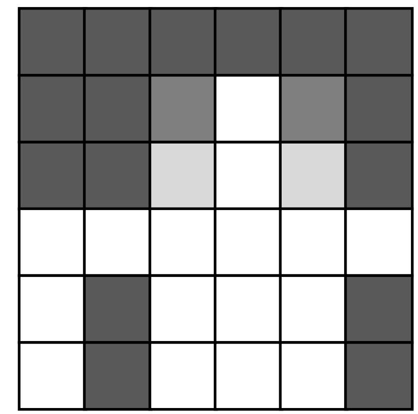
Mask RCNN

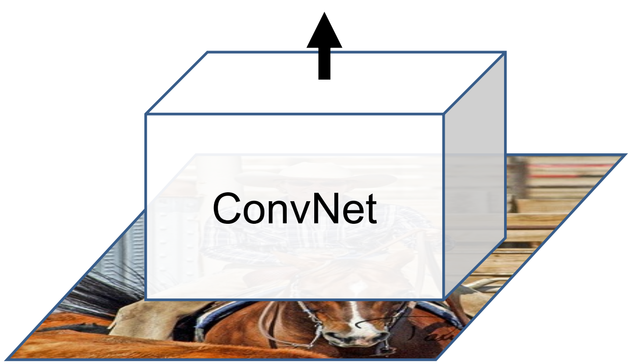
Feature Map
(e.g., 6x8x256)

Resize to fixed size (e.g., 7x7)
Details **critical**, but beyond scope of class.







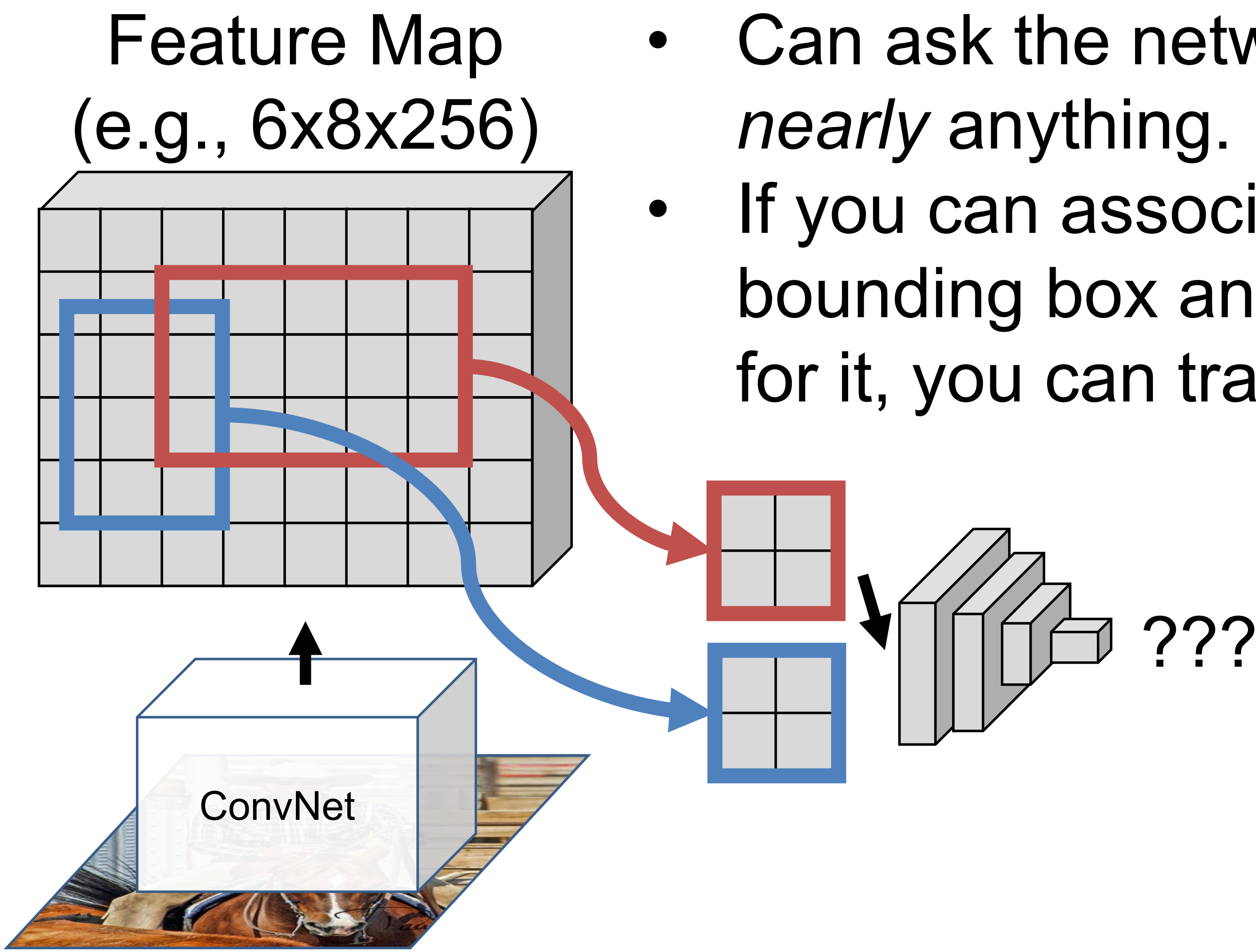


Can also predict a mask!
Everything is learned together
Simple and effective; details critical

Mask RCNN: He, Gkioxari, Dollar, Girshick . ICCV 2017.

MaskRCNN – Results

Extending Object Detection



- Can ask the network to predict *nearly* anything.
- If you can associate it with a bounding box and can get data for it, you can train the model

Liu et al. *PlaneRCNN: 3D Plane Detection and Reconstruction from a Single Image.* CVPR 2019.

Extending Object Detection

Example: RGB image input, detect planar surfaces

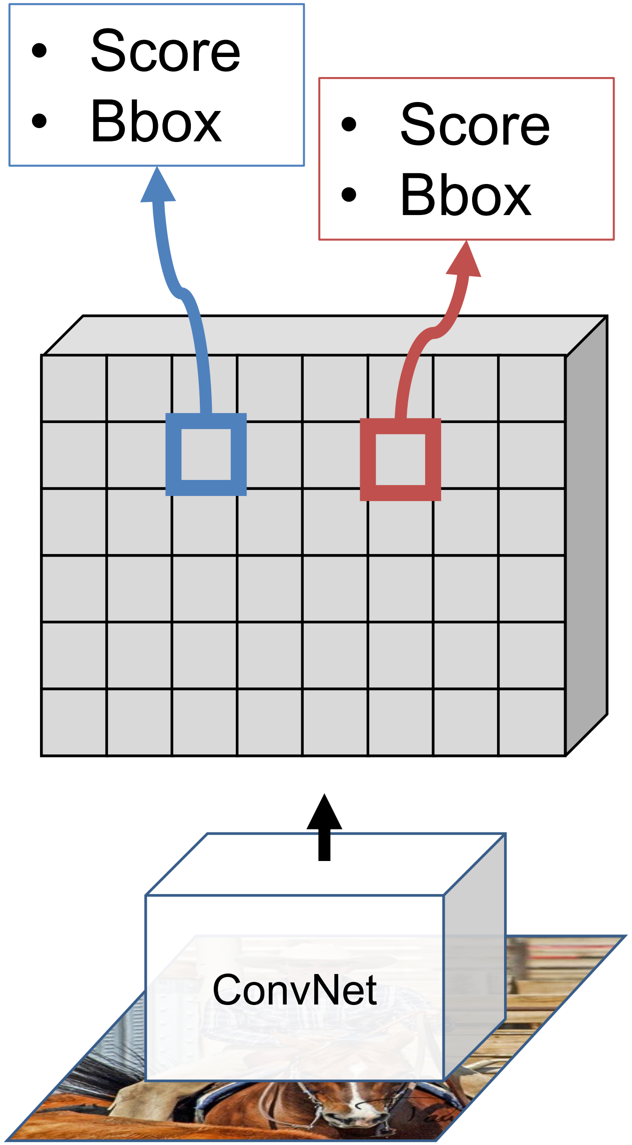
Liu et al. *PlaneRCNN: 3D Plane Detection and Reconstruction from a Single Image.* CVPR 2019.

Extending Object Detection

Core building block is detecting plane in image.

S. Agarwala, L. Jin, C. Rockwell, D.F. Fouhey. PlaneFormers: From Sparse View Planes to 3D Reconstruction.???, 2022

YOLO



- No proposals
- Predict at each location in 7x7 feature map, score for each class + 2 bboxes
- 7x faster than Faster-RCNN, but worse accuracy, precision
- Immensely popular in robotics
- Loads of similar methods (YOLOv2, YOLOv3)

J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, [You Only Look Once: Unified, Real-Time Object Detection](), CVPR 2016

YOLO

• Score

7

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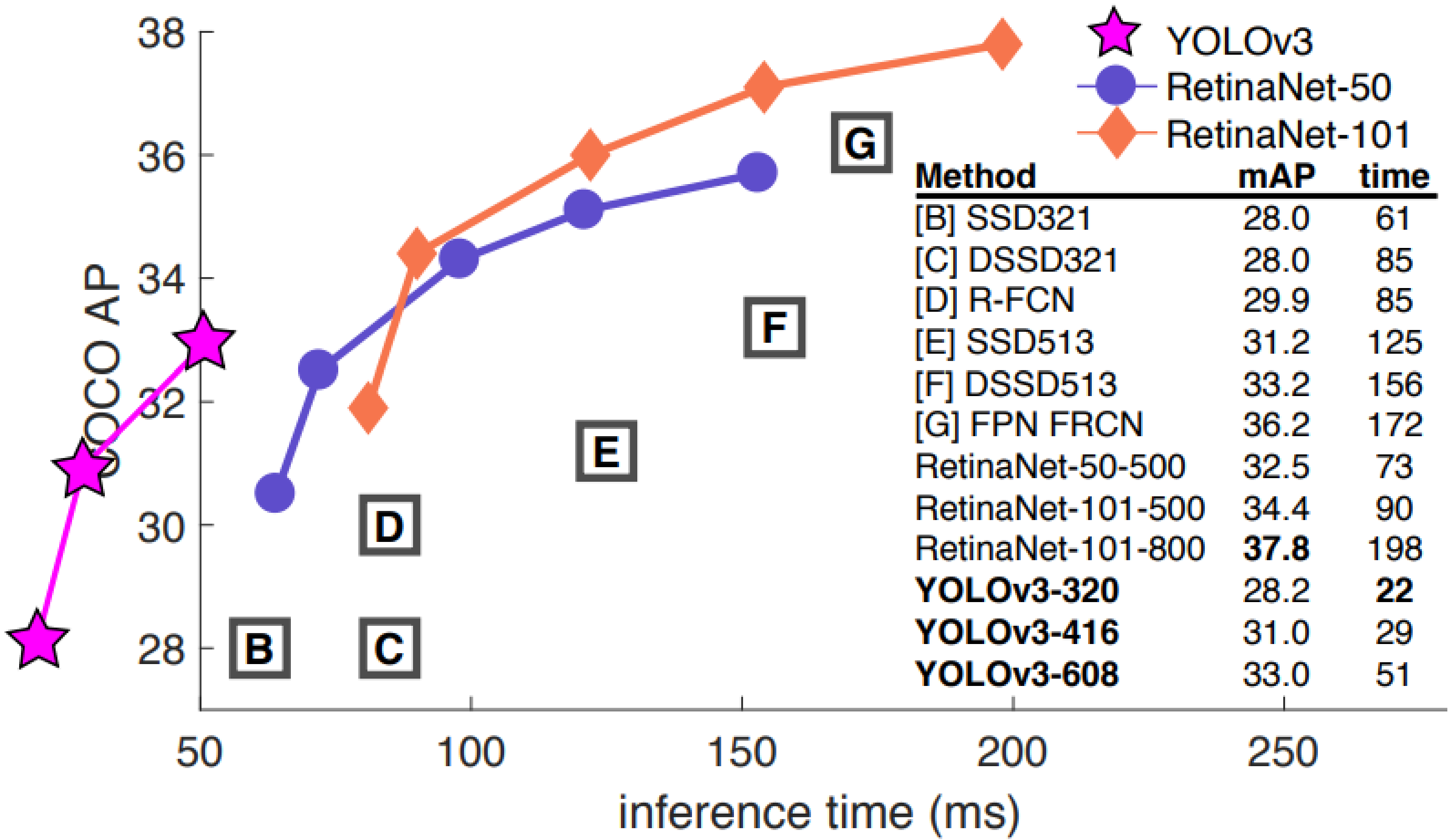


J. Redmon, A. Farhadi, *YOLOv3: An Incremental Improvement* .

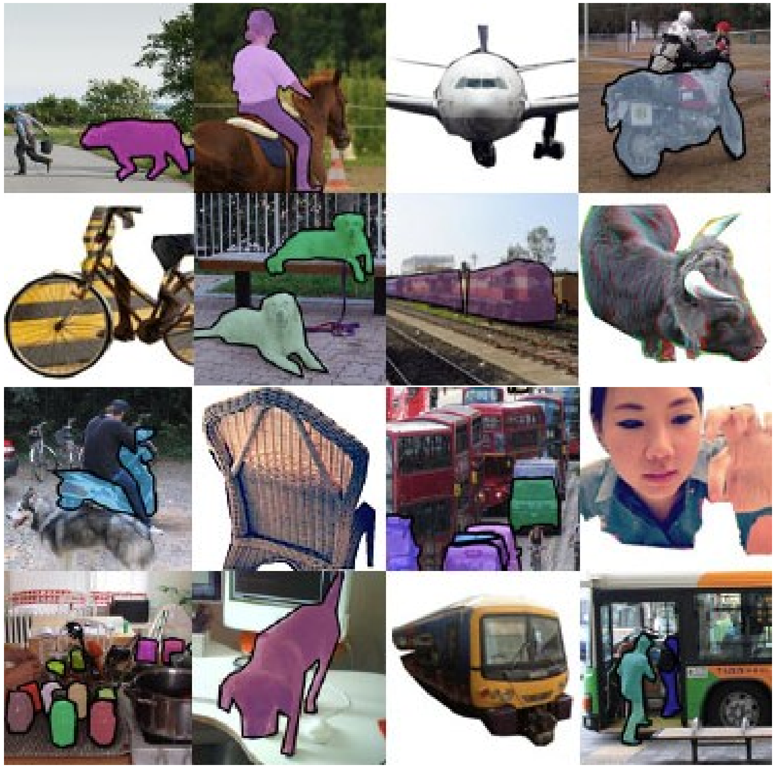
New detection benchmark: COCO (2014)

- 80 categories instead of PASCAL's 20
- Current best mAP: 52%

COCO
Common Objects in Context

COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

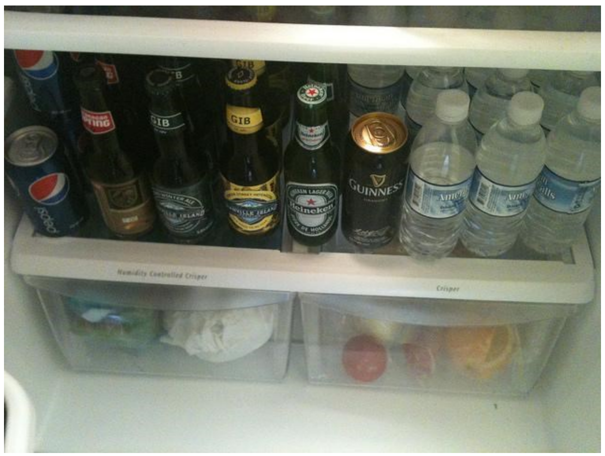
- ✔ Object segmentation
- ✔ Recognition in context
- ✔ Superpixel stuff segmentation
- ✔ 330K images (>200K labeled)
- ✔ 1.5 million object instances
- ✔ 80 object categories
- ✔ 91 stuff categories
- ✔ 5 captions per image
- ✔ 250,000 people with keypoints



http://cocodataset.org/#home

A Few Caveats

- Flickr images come from a really weird process
- Step 1: user takes a picture
- Step 2: user decides to upload it
- Step 3: user decides to write something like “refrigerator” somewhere in the description
- Step 4: a vision person stumbles on it while searching Flickr for refrigerators for a dataset



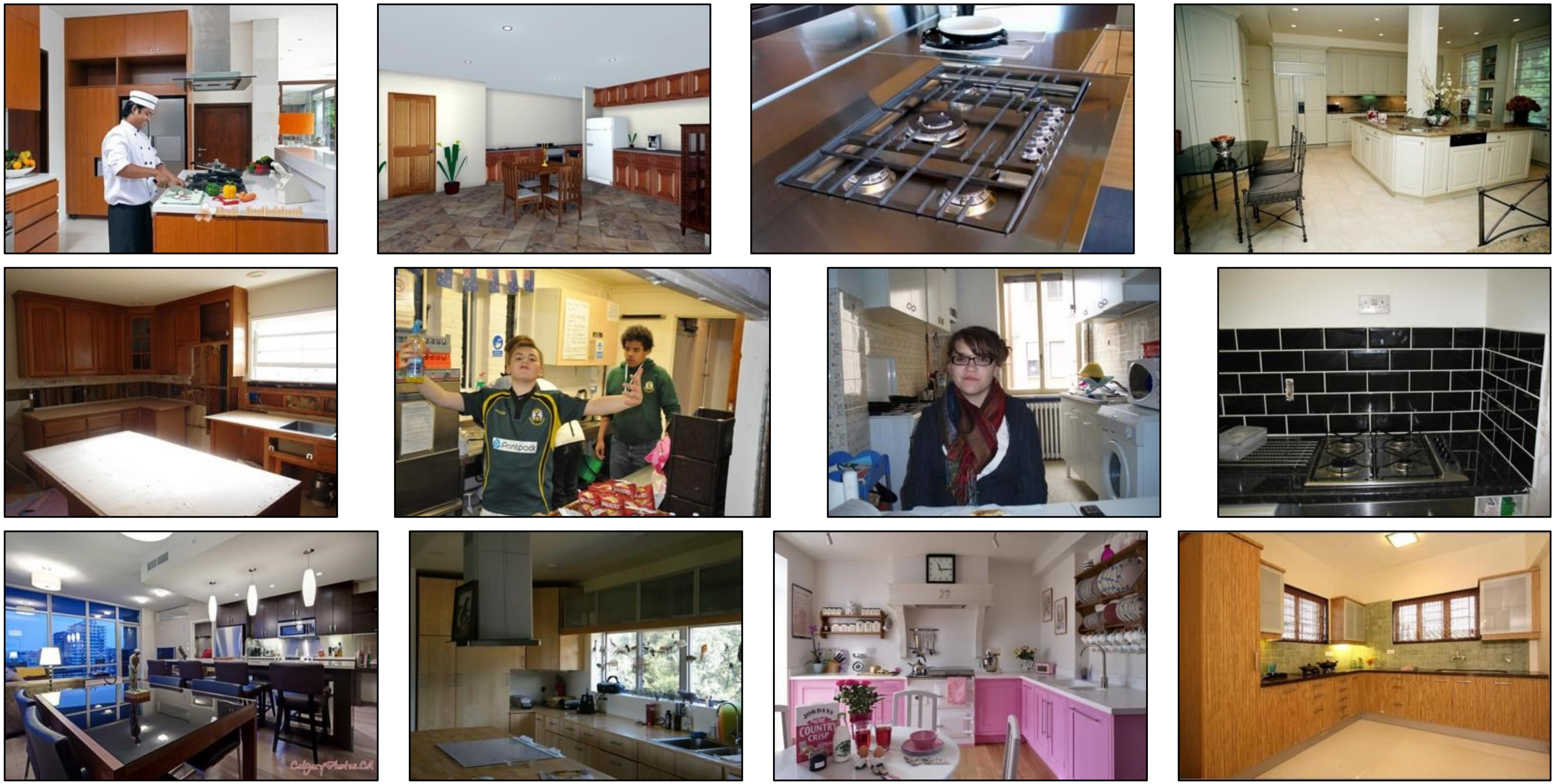
Who takes photos of open refrigerators ?????

Guess the category!

These were detected with >90% confidence, corresponding to 99% precision on original dataset

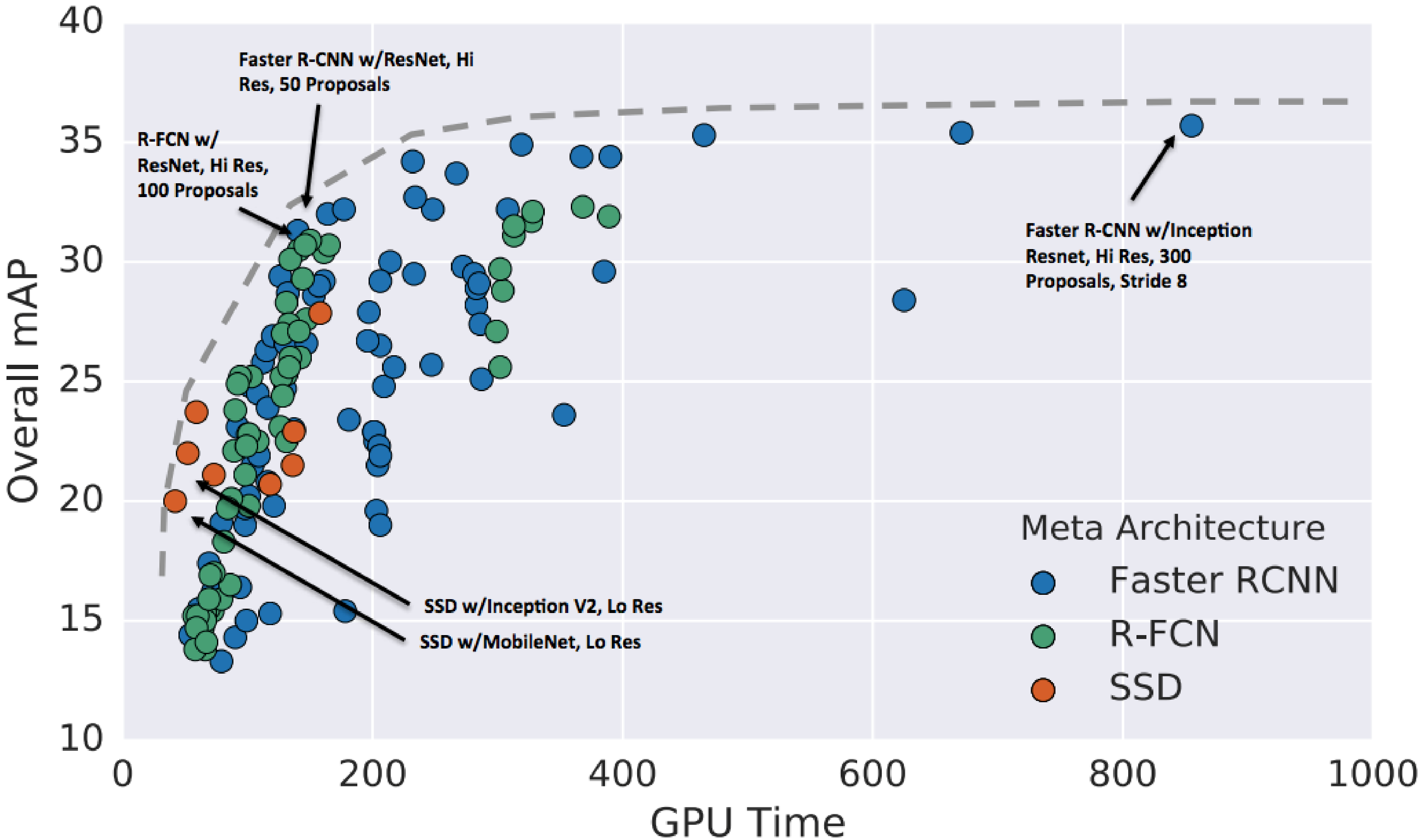
(1) Person (2) Giraffe (3) Bicycle

Kitchens from Googling



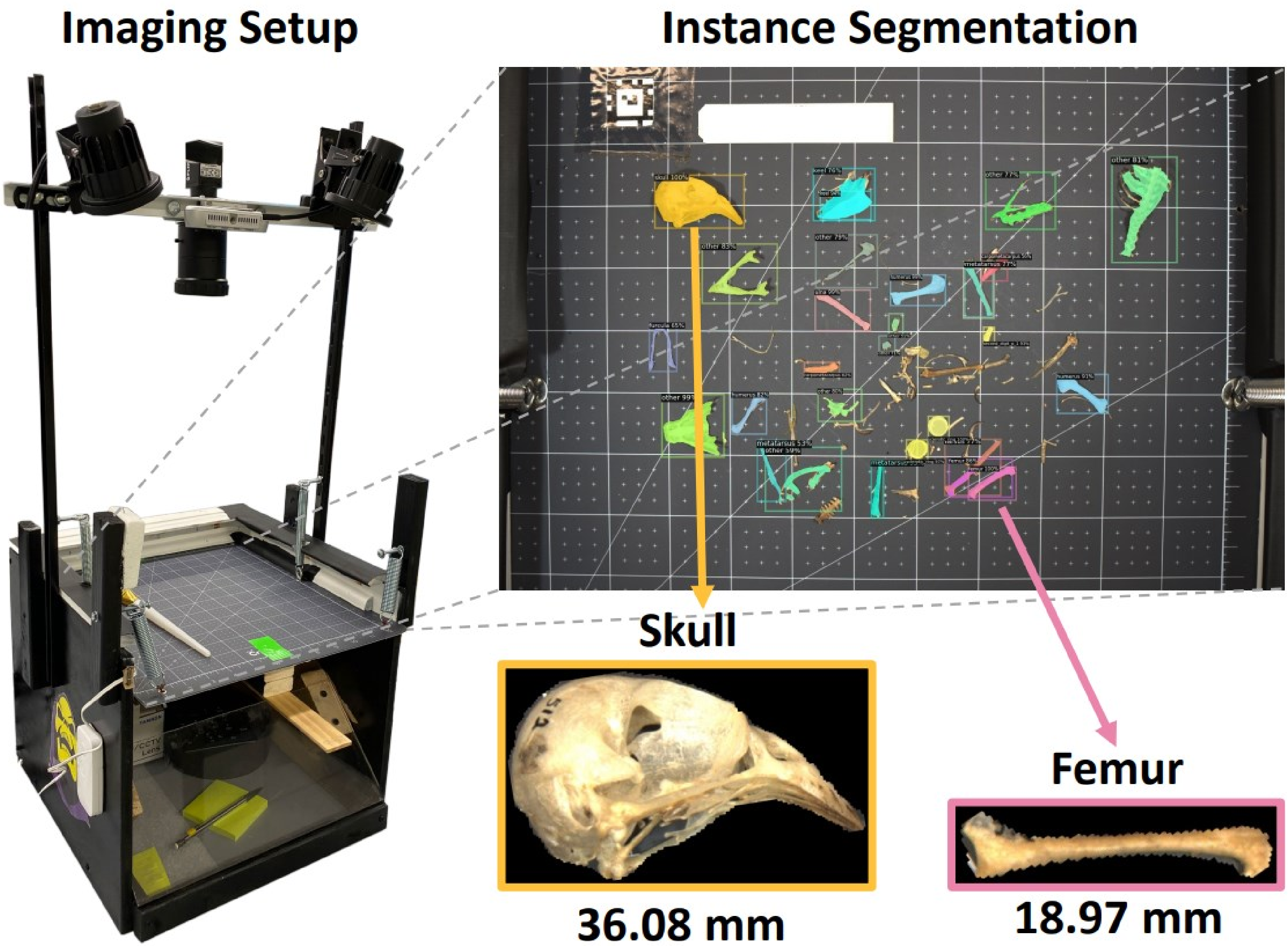
Places 365 Dataset, Zhou et al. ‘17

New detection benchmark: COCO (2014)



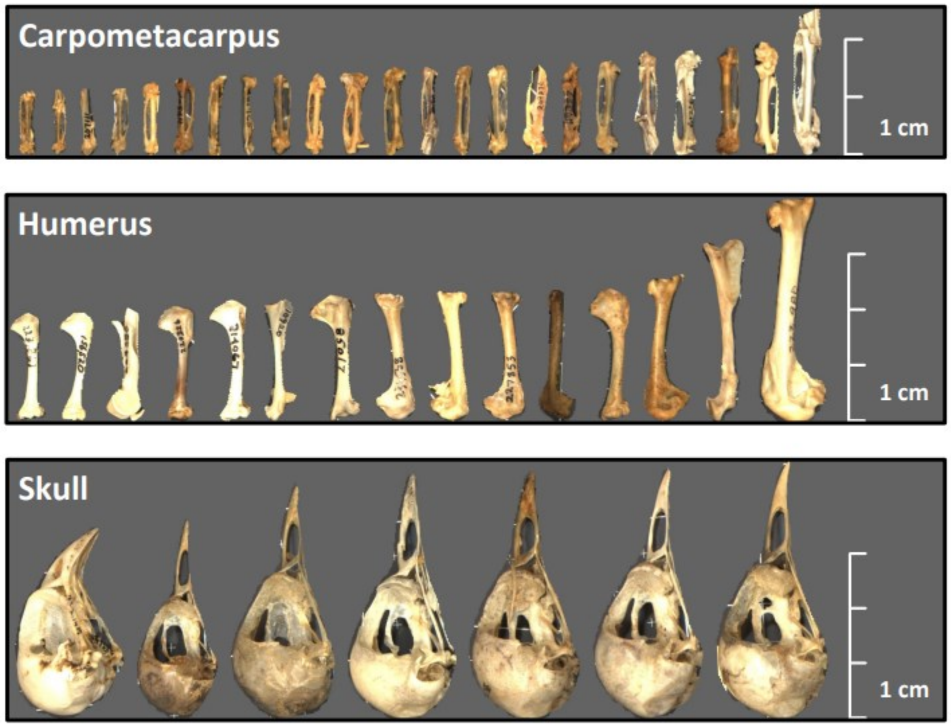
J. Huang et al., [Speed/accuracy trade-offs for modern convolutional object detectors](), CVPR 2017

What’s It Good For?



Z. Zhou, G. Hassena, B.C. Weeks, D.F. Fouhey. *Quantifying Bird Skeletons.* CVPR Workshops, 2021.
B.C. Weeks, Z. Zhou, B.K. O'Brien, R. Darling, M. Dean, T. Dias, G. Hassena, M. Zhang, D.F. Fouhey. *A deep neural network for high throughput measurement of functional traits on museum skeletal specimens.* Methods in Ecology and Evolution, 2022.

What’s It Good For?



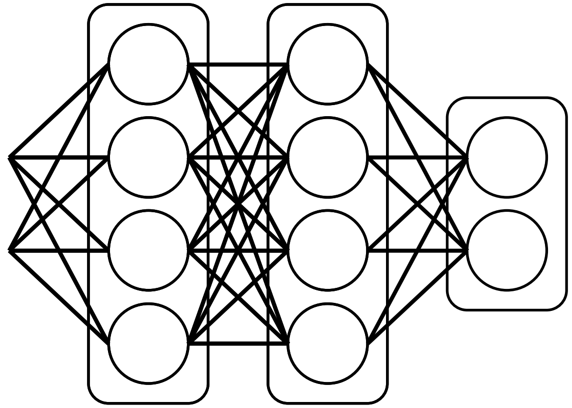
- UM has 25K bird skeletons but measuring bird bones by hand is hard and tedious.
- New solution: dump the bones, take a picture, use a deep network.
- Now enabling testing hypotheses about birds at huge scale

Z. Zhou, G. Hassena, B.C. Weeks, D.F. Fouhey. *Quantifying Bird Skeletons.* CVPR Workshops, 2021.
B.C. Weeks, Z. Zhou, B.K. O'Brien, R. Darling, M. Dean, T. Dias, G. Hassena, M. Zhang, D.F. Fouhey. *A deep neural network for high throughput measurement of functional traits on museum skeletal specimens*. Methods in Ecology and Evolution, 2022.

And Now For Something Completely Different

- I planned to cover this, but I’ll cover it in the next class.

ImageNet + Deep Learning

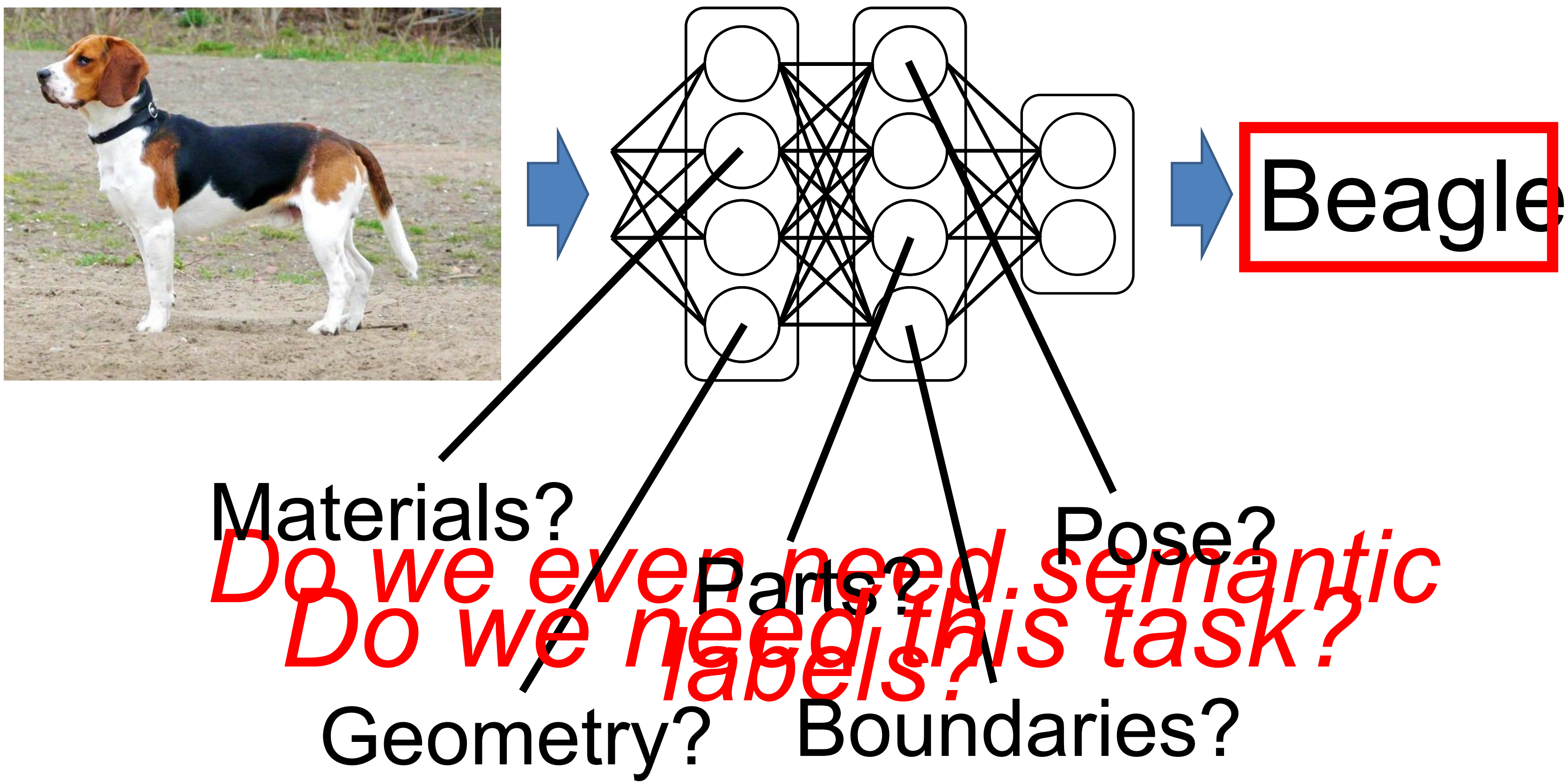


Beagle

- Image Retrieval
- Detection
- Segmentation
- Depth Estimation
- …

Slide Credit: C. Doersch

ImageNet + Deep Learning



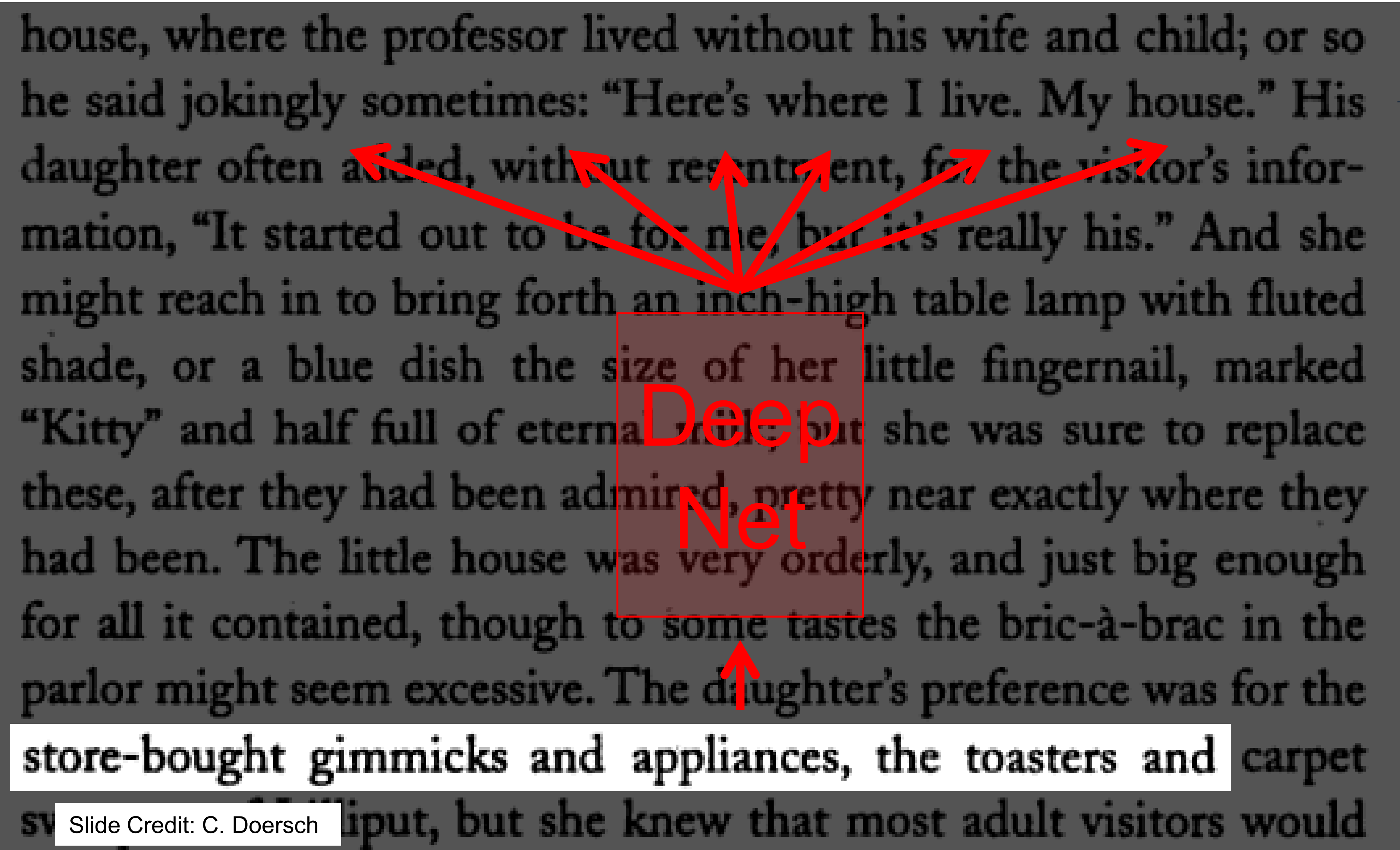
Slide Credit: C. Doersch

To Make It Super Clear

- w = **weights_from_somewhere_else**
- for batch in batches:
  - inputs, labels = batch
  - calculate gradient of loss function with respect to w applied to samples in inputs
  - w += gradient

Context as Supervision

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

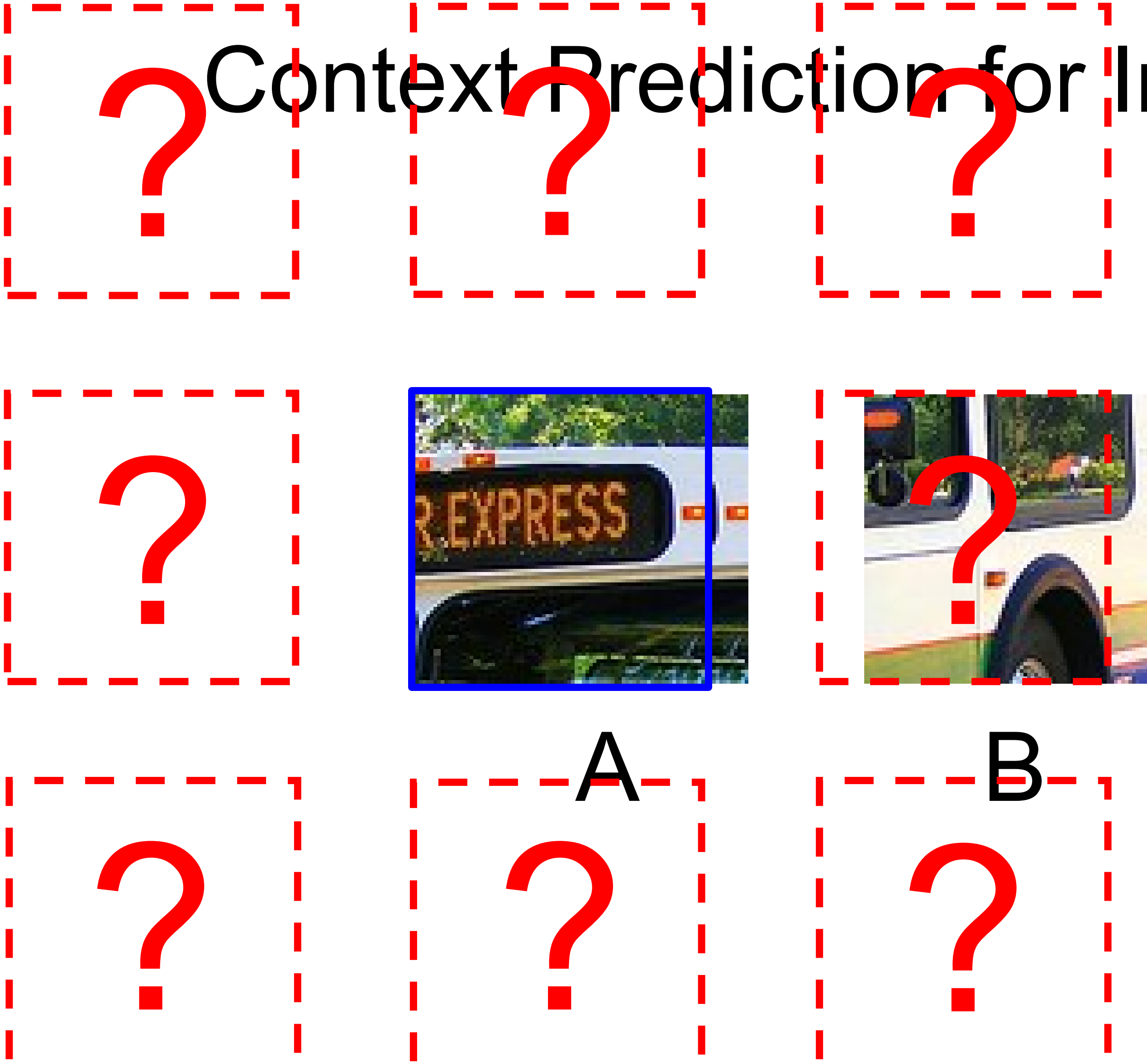


house, where the professor lived without his wife and child; or so he said jokingly sometimes: “Here’s where I live. My house.” His daughter often added, without resentment, for the visitor’s information, “It started out to be for me, but it’s really his.” And she might reach in to bring forth an inch-high 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

liput, but she knew that most adult visitors would

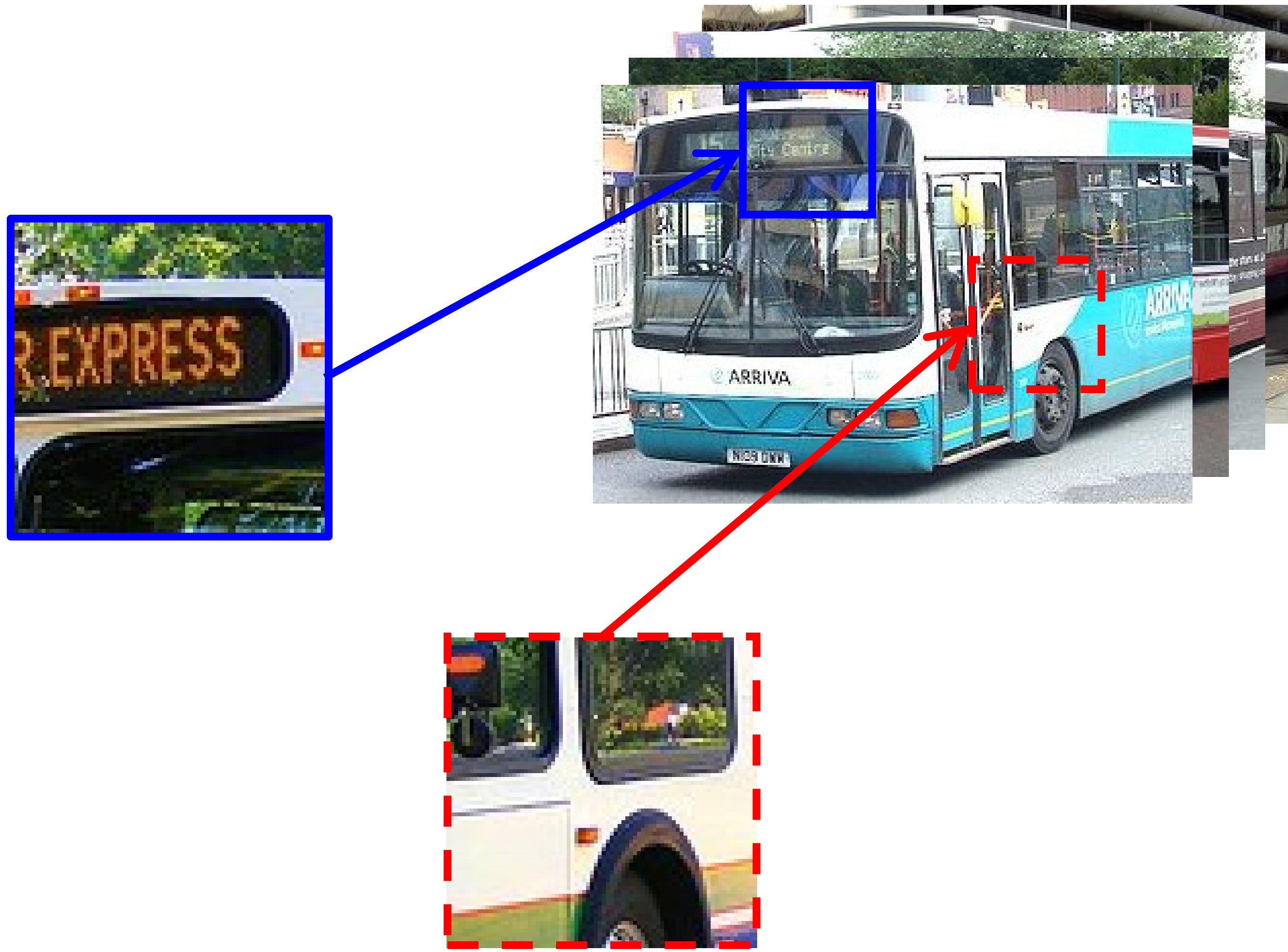
Slide Credit: C. Doersch

Context Prediction for Images



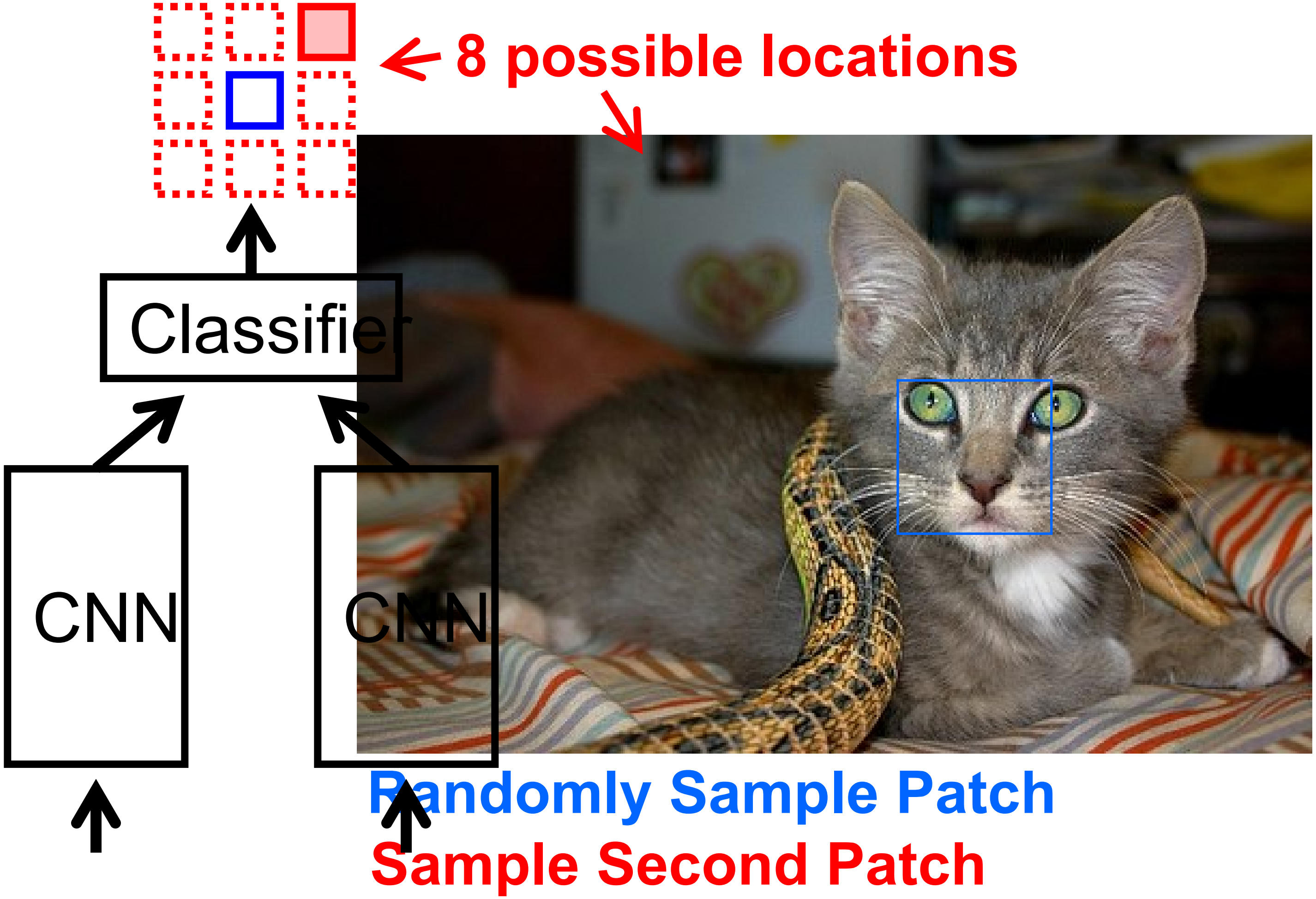
Slide Credit: C. Doersch

Semantics from a non-semantic task

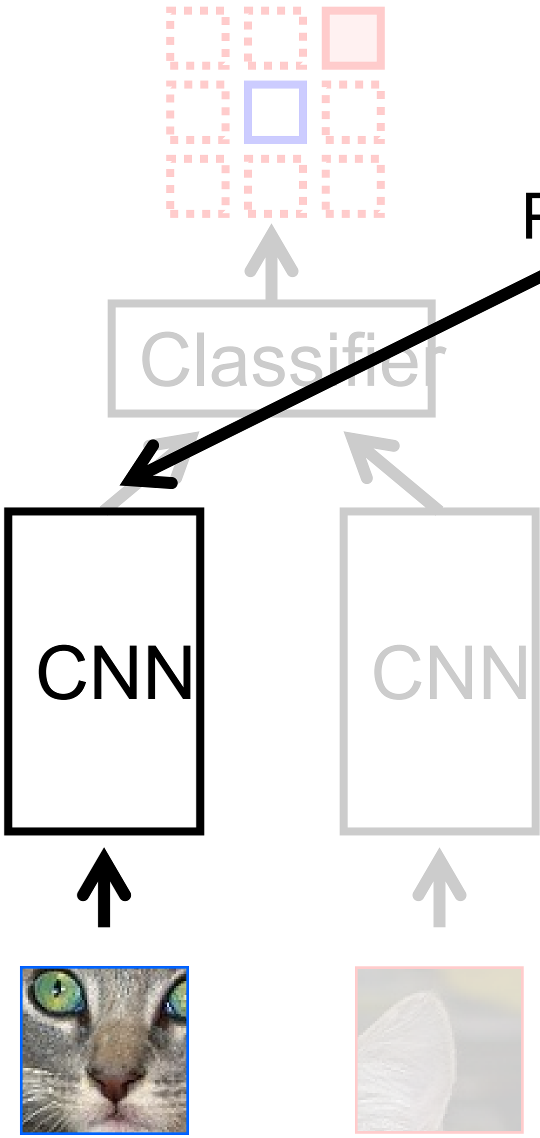


Slide Credit: C. Doersch

Relative Position Task



Slide Credit: C. Doersch



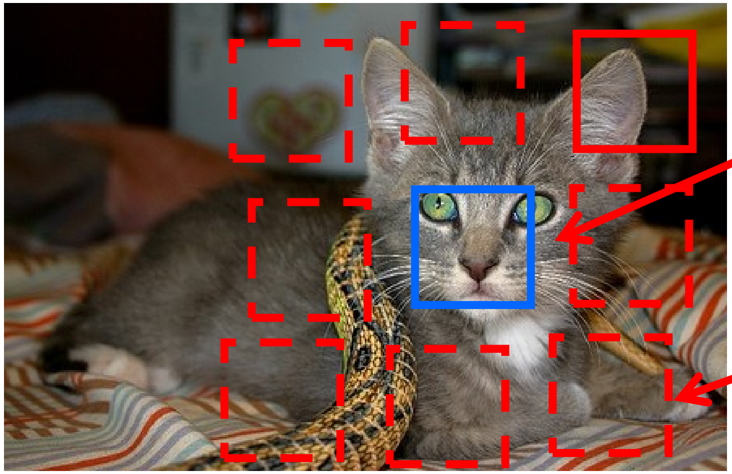
Patch Embedding

Input | Nearest Neighbors

Note: connects ***across*** instances

Slide Credit: C. Doersch

Avoiding Trivial Shortcuts

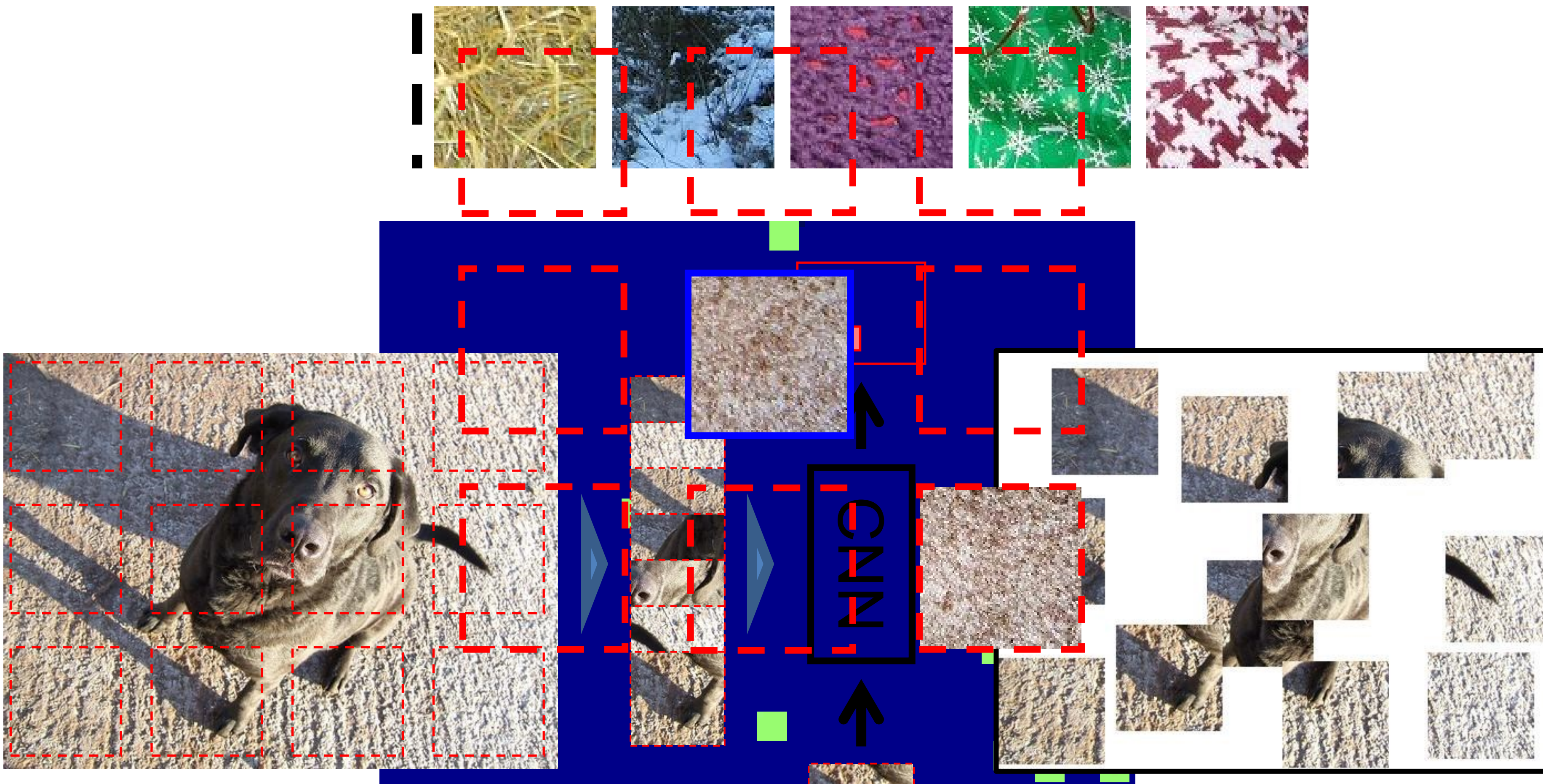


Include a gap

Jitter the patch locations

Slide Credit: C. Doersch

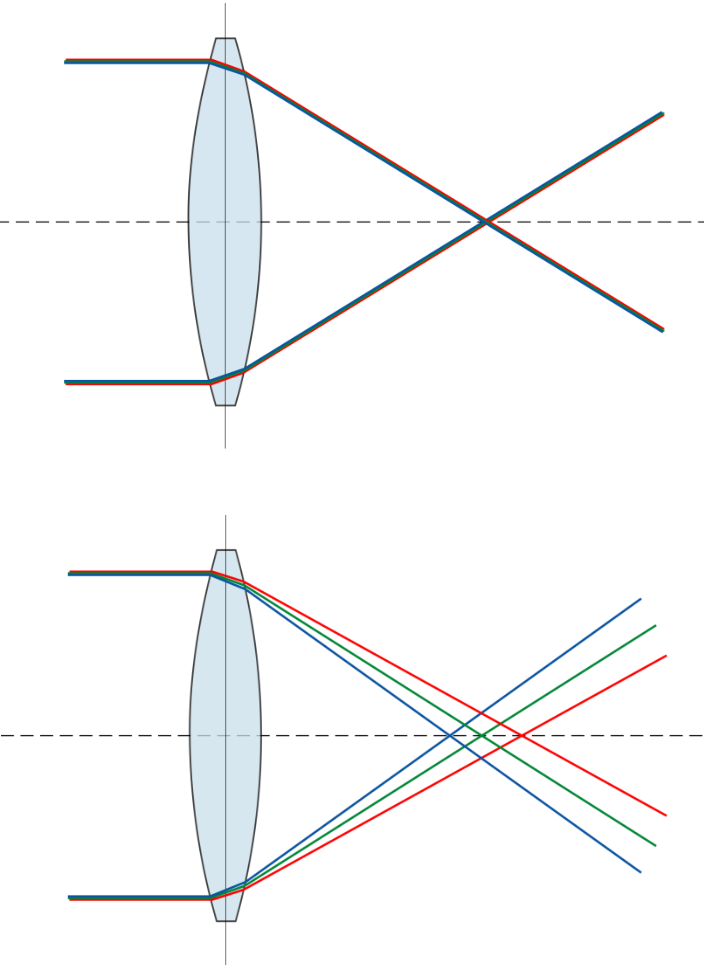
A Not-So “Trivial” Shortcut

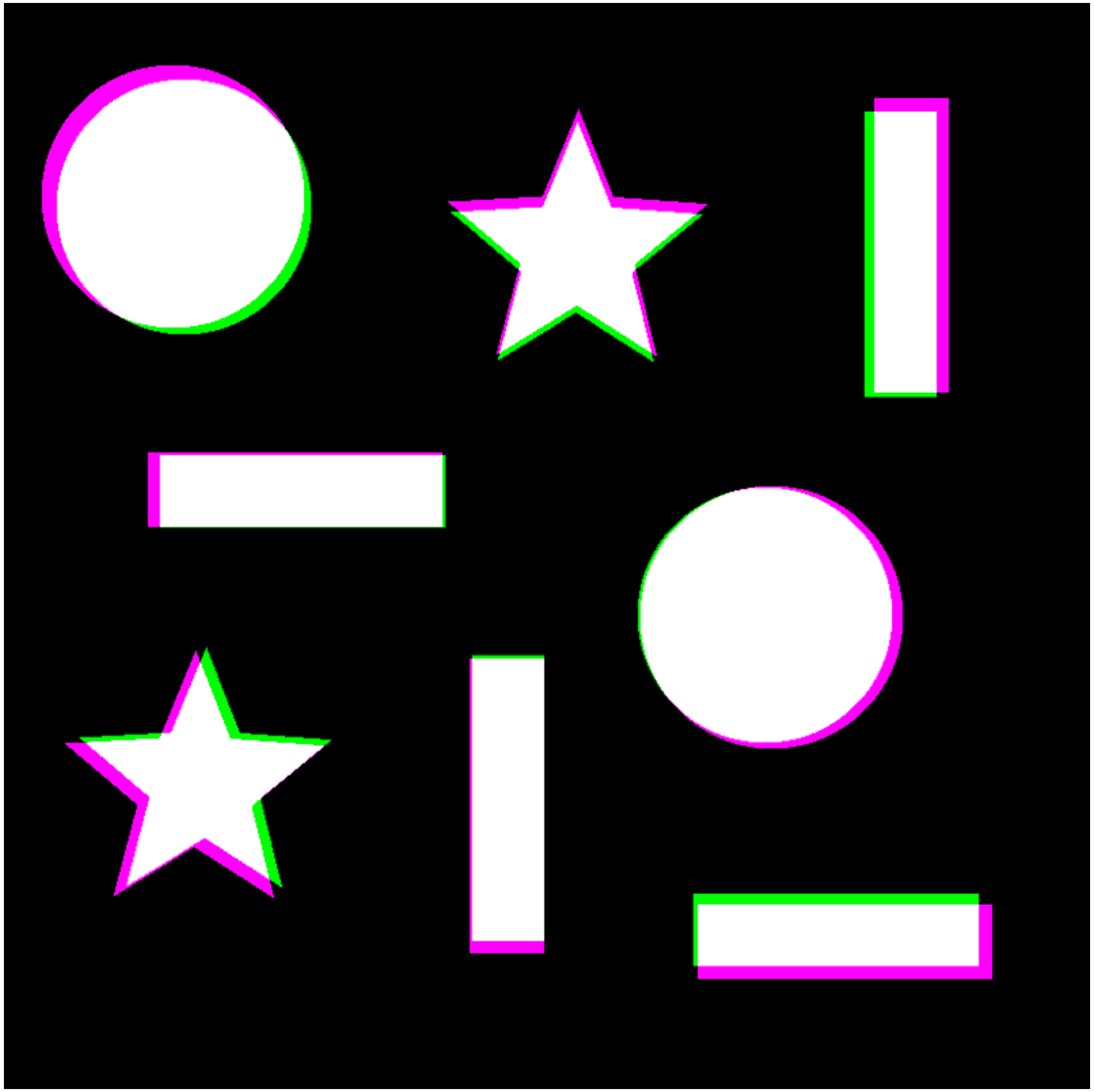


Position i mage

Slide Credit: C. Doersch

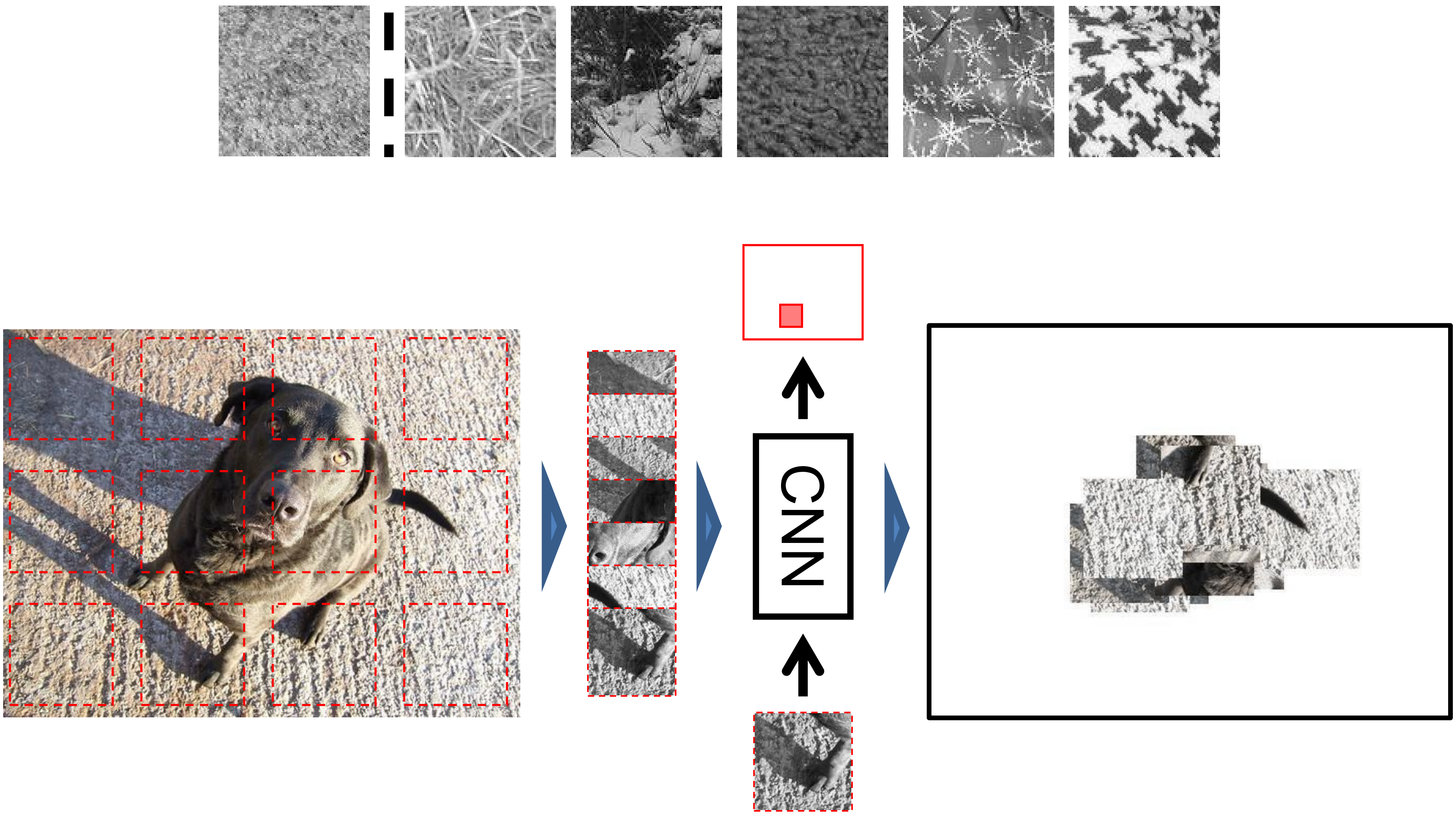
Chromatic Aberration





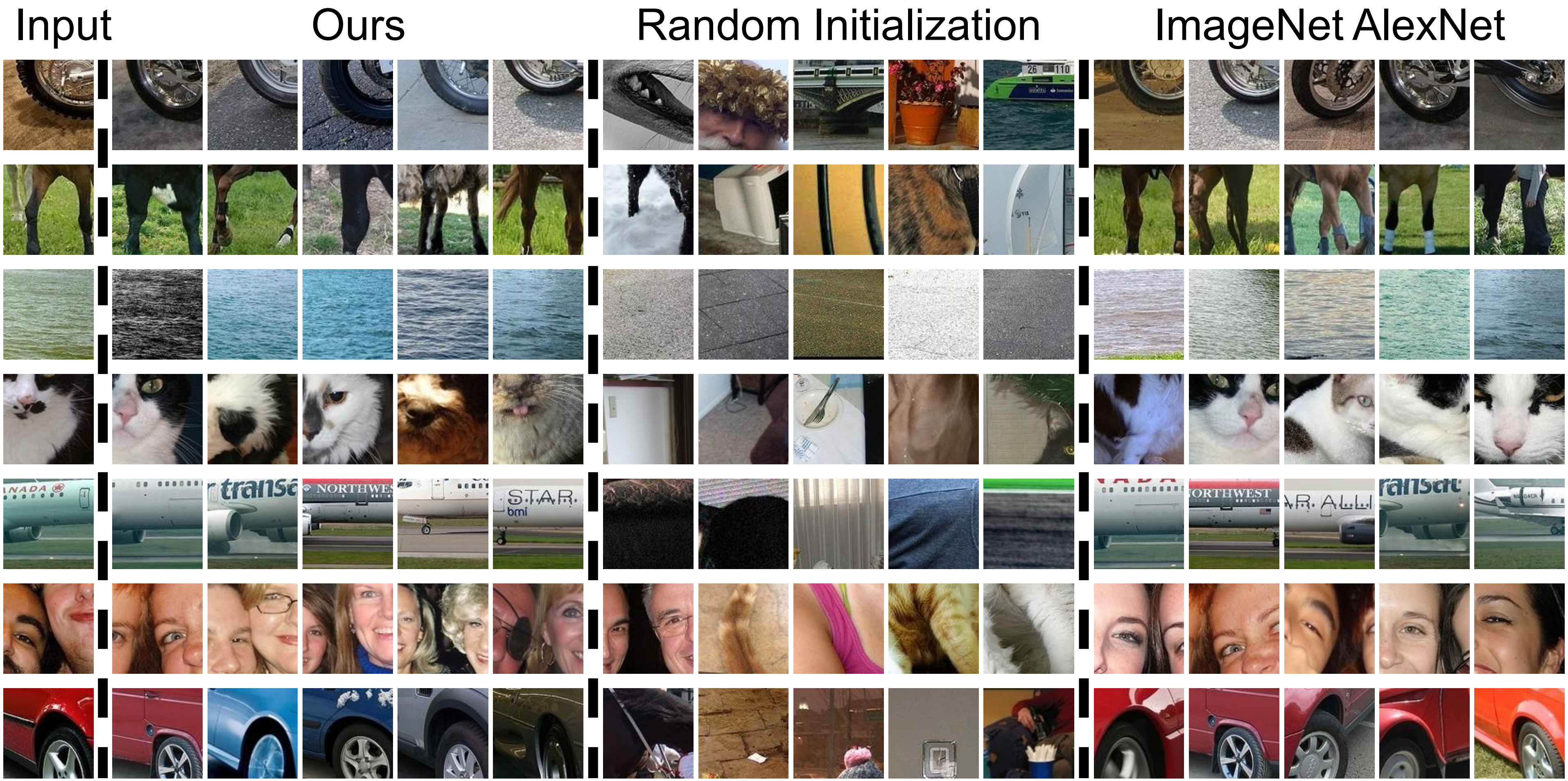
Slide Credit: C. Doersch

Chromatic Aberration



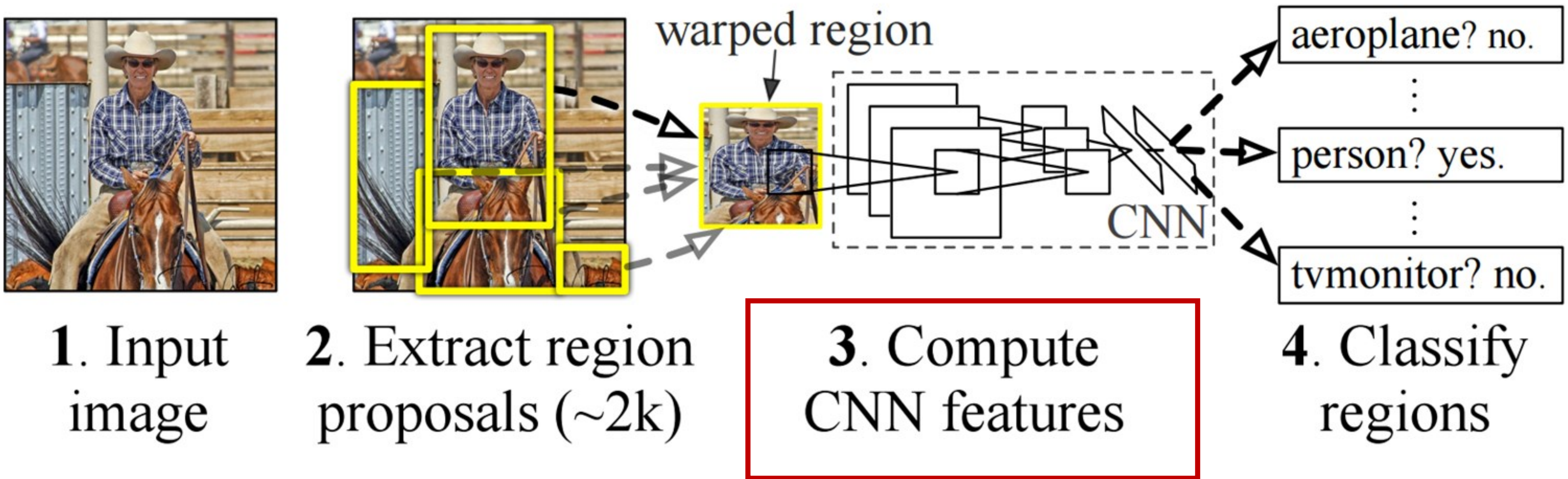
Slide Credit: C. Doersch

What is learned?



Slide Credit: C. Doersch

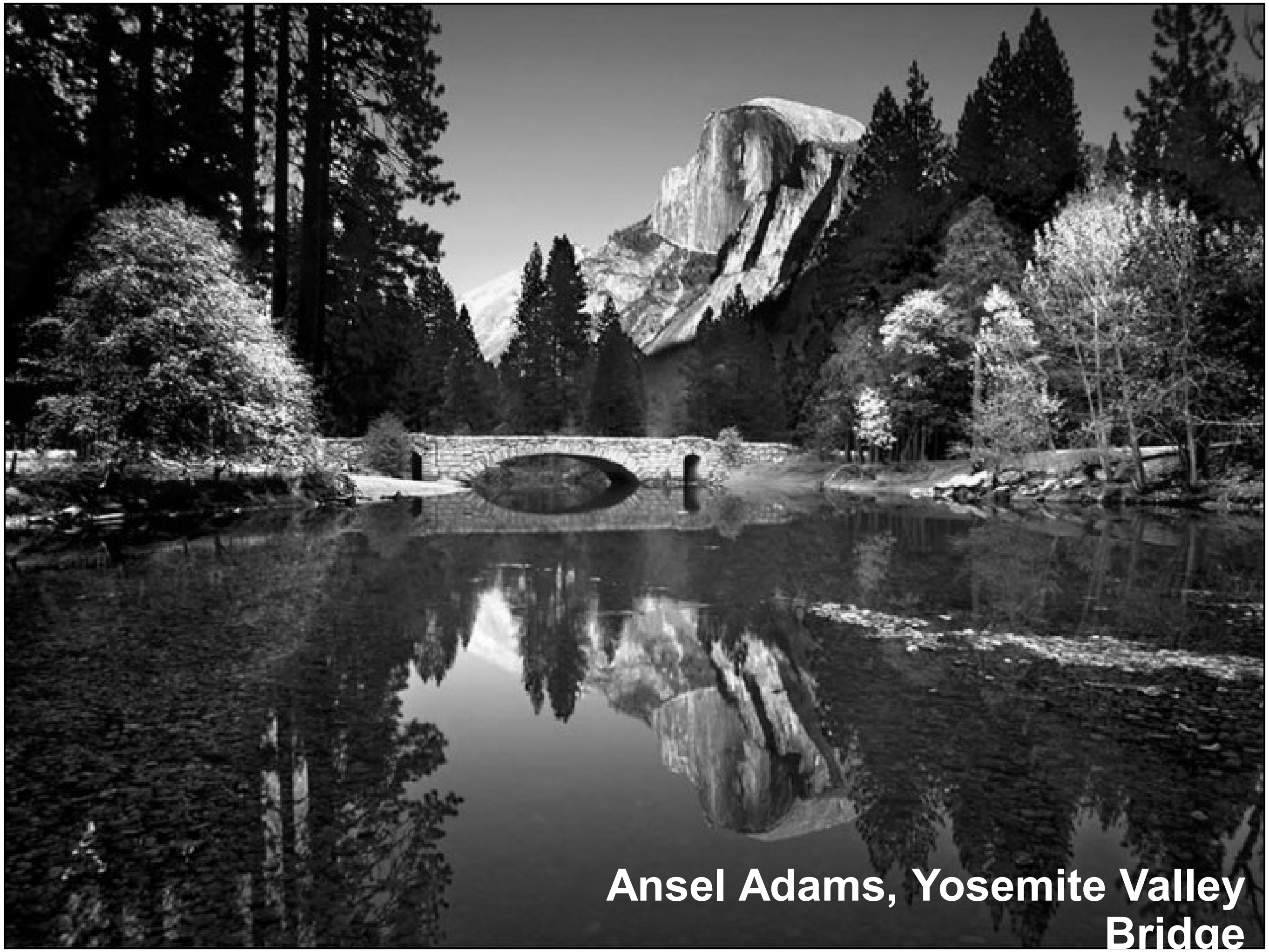
Pre-Training for R-CNN



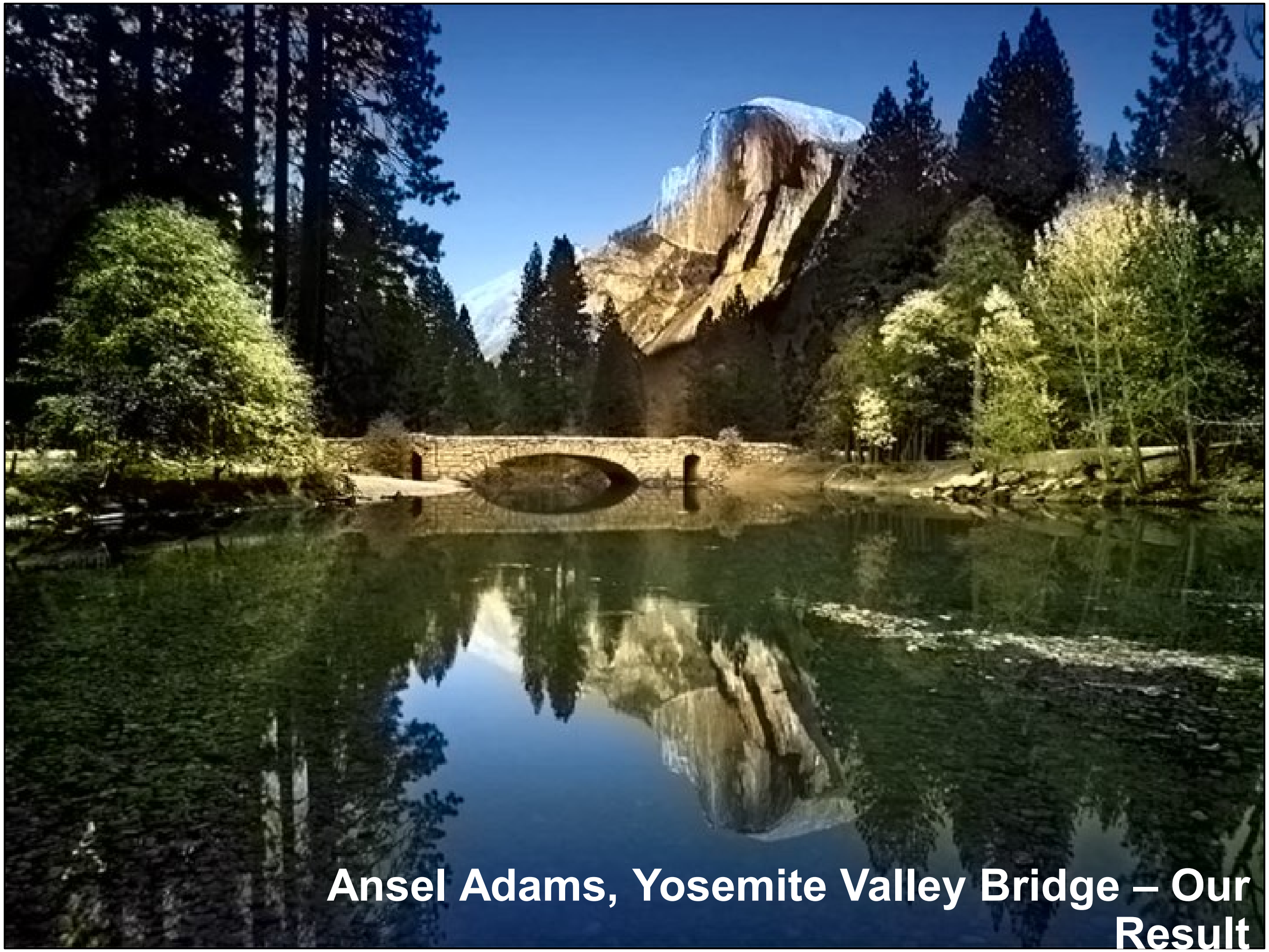
Pre-train on relative-position task, w/o labels

[Girshick et al. 2014]

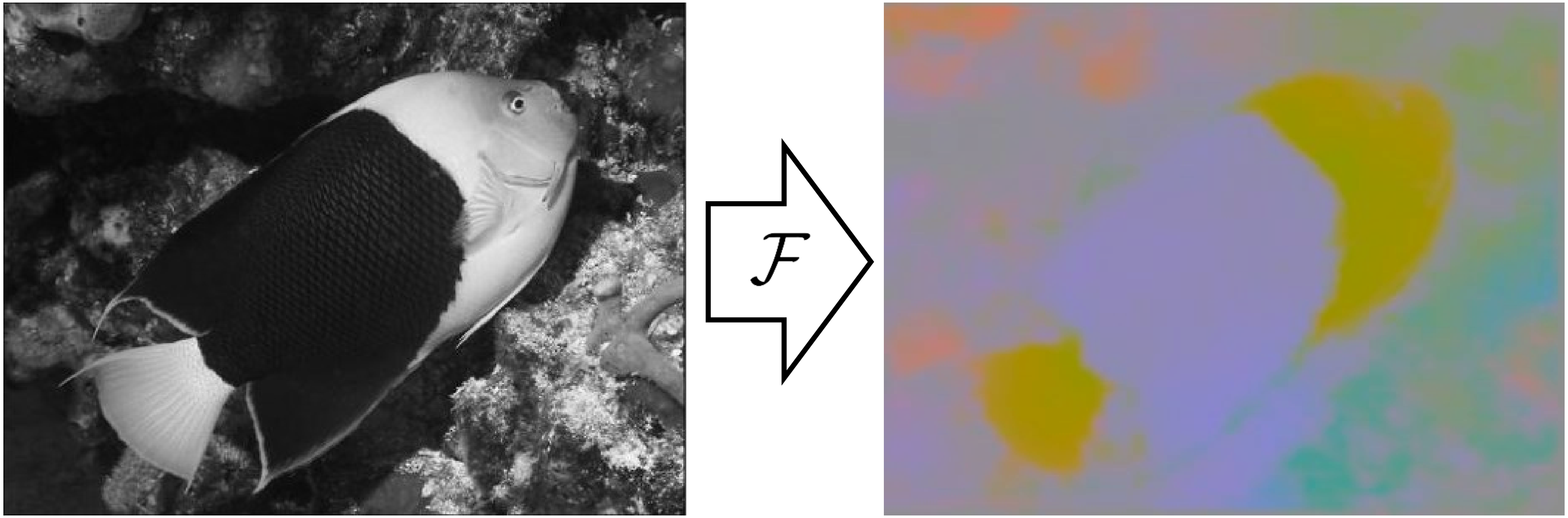
Other Sources Of Signal



Slide Credit: R. Zhang



Slide Credit: R. Zhang

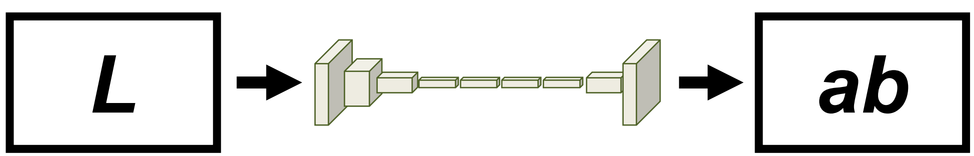


Grayscale image: *L* channel

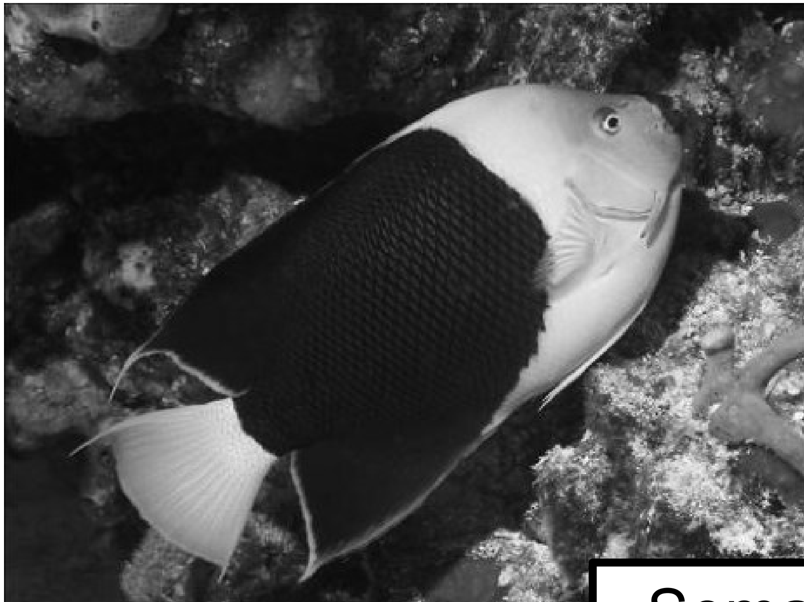
$\mathbf{X} \in \mathbb{R}^{H \times W \times 1}$

Color information: *ab* channels

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



Slide Credit: R. Zhang



$\mathcal{F}$

Semantics? Higher-level abstraction?

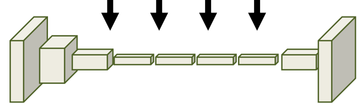
Grayscale image: L

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

Concatenate (L,ab)

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

L

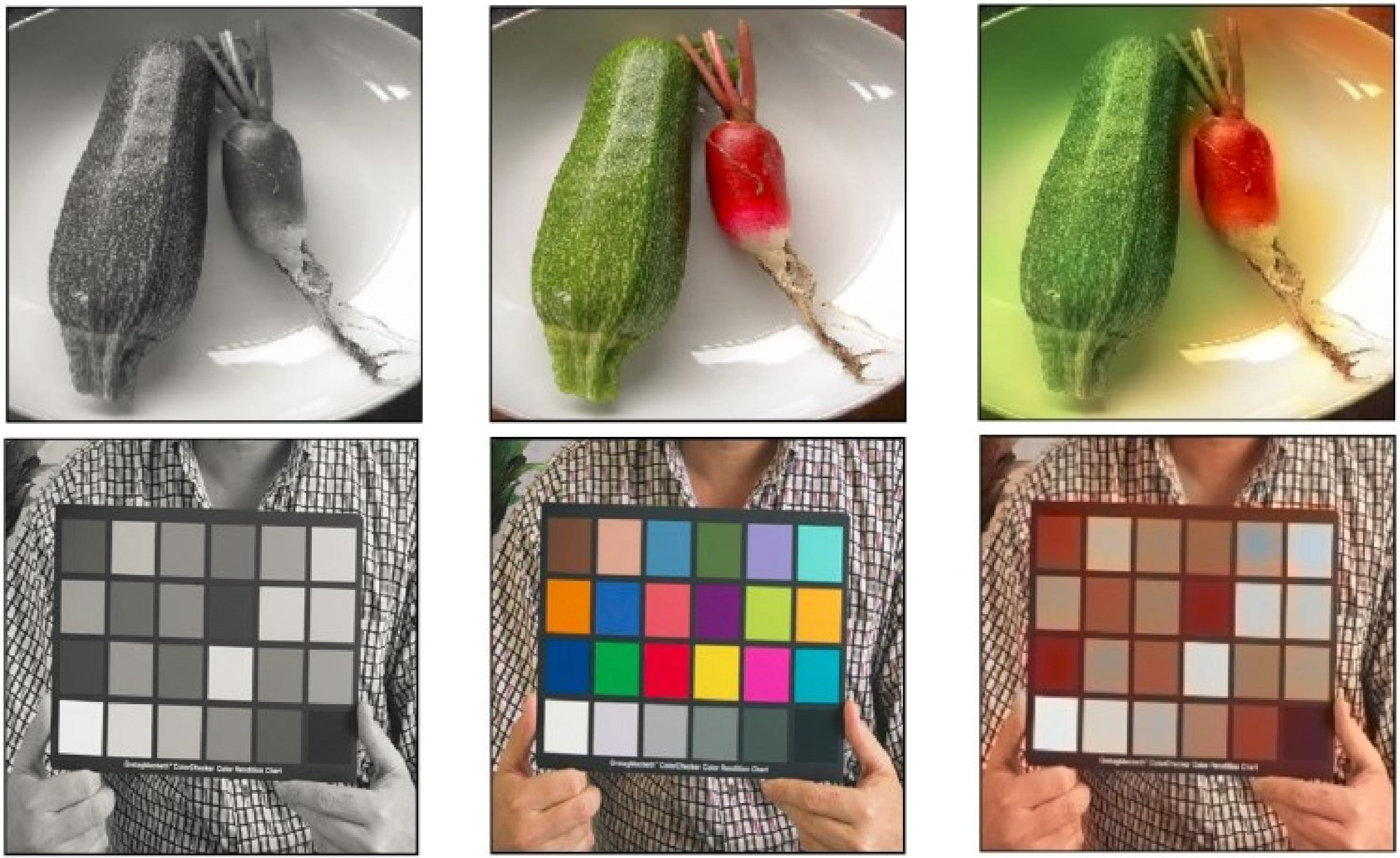


ab

"Free" supervisory signal

Slide Credit: R. Zhang

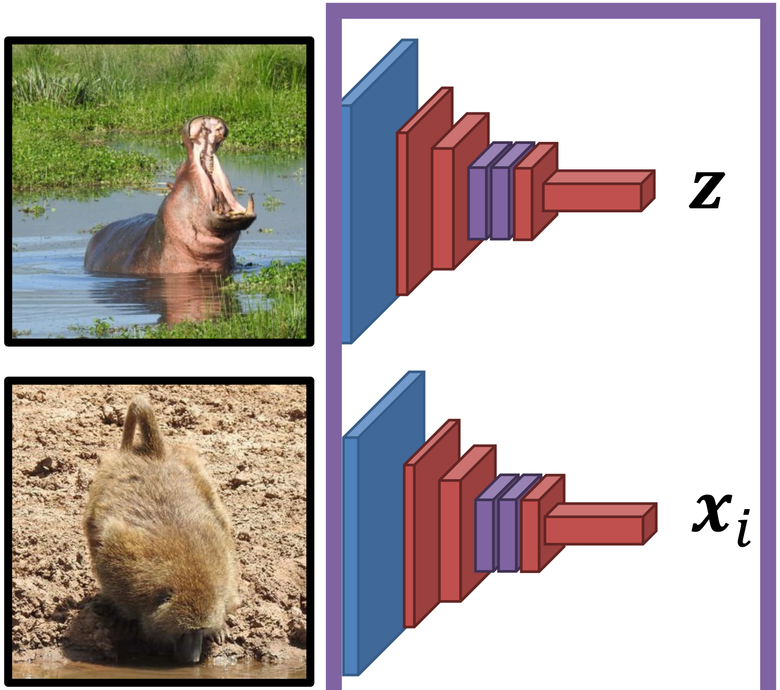
Input | **Ground Truth** | **Output**



Slide Credit: R. Zhang


Visually Indicated Sounds
Andrew Owens
Phillip Isola
Josh McDermott
Antonio Torralba
Edward Adelson
William Freeman

Contrastive Learning



Weights shared between networks, but details important

Given sample, construct feature z; take a bunch of other images, minimize:

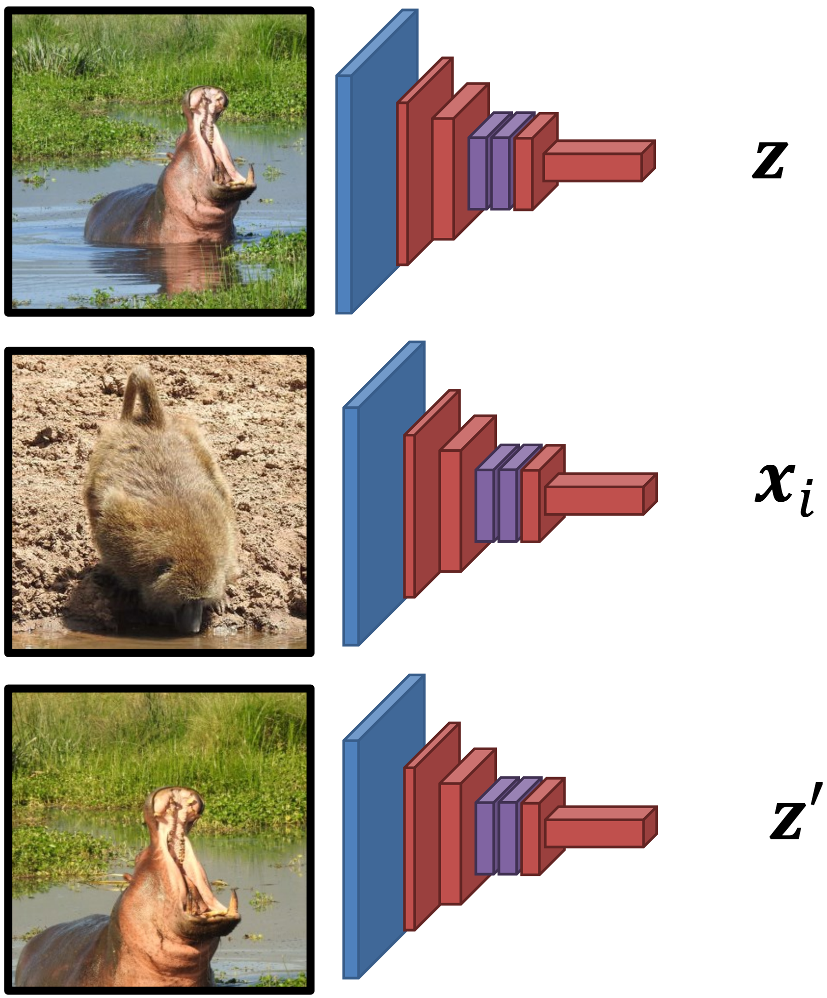
$$\frac{\exp(\boldsymbol{z}^T\boldsymbol{z})}{\exp(\boldsymbol{z}^T\boldsymbol{z} + \sum_i \boldsymbol{z}^T\boldsymbol{x})}$$

Basically, a scoring function with w = z:

$$\frac{\exp(\boldsymbol{w}^T\boldsymbol{z})}{\exp(\boldsymbol{w}^T\boldsymbol{z} + \sum_i \boldsymbol{w}^T\boldsymbol{x})}$$

He et al. Momentum Contrastive Learning, 2019. Wu et al. Instance discrimination 2018

Contrastive Learning



Best performing methods measure distance to augmented sample $\boldsymbol{z}'$:

$$\frac{\exp(\boldsymbol{z}^T \boldsymbol{z}')}{\exp(\boldsymbol{z}^T \boldsymbol{z}' + \sum_i \boldsymbol{z}^T \boldsymbol{x})}$$

Goal: score augmented sample higher than everything else.

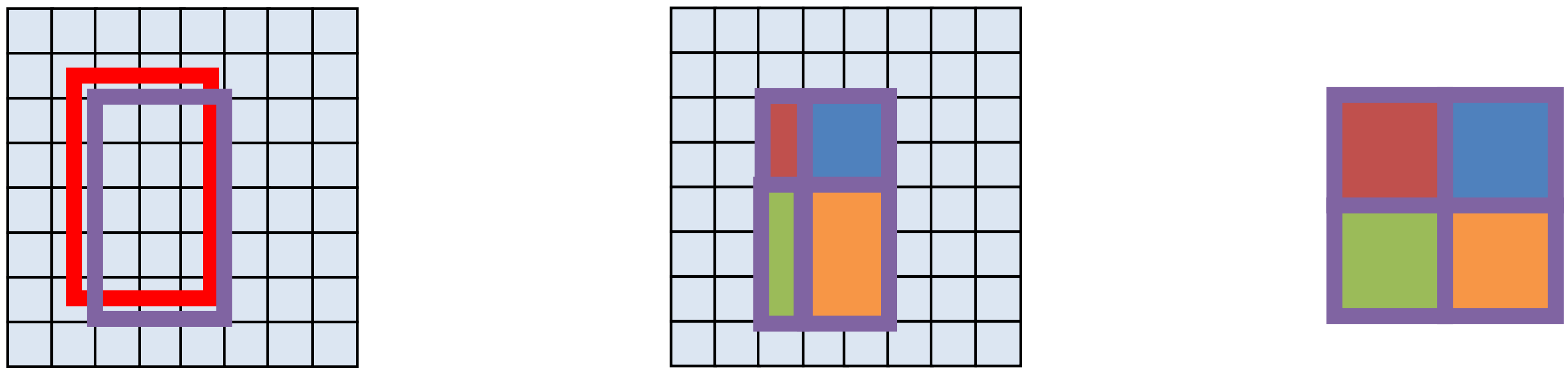
He et al. Momentum Contrastive Learning, 2019. Wu et al. Instance discrimination 2018

Next Time

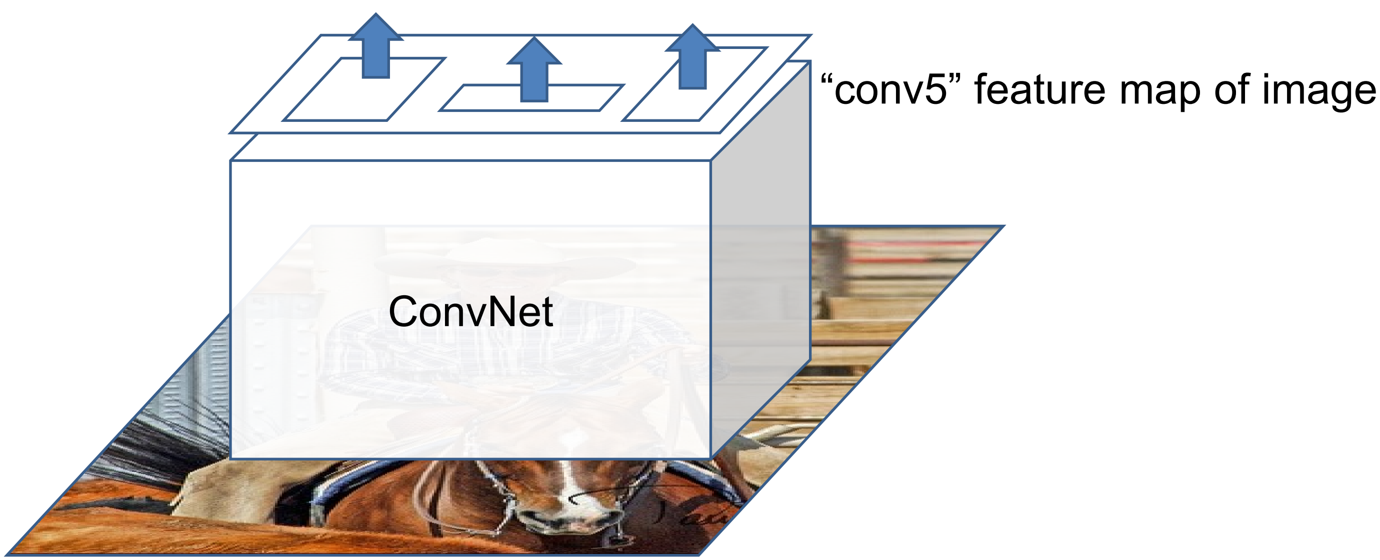
- Synthesizing Images

Extra Stuff

Fast R-CNN – ROI-Pool



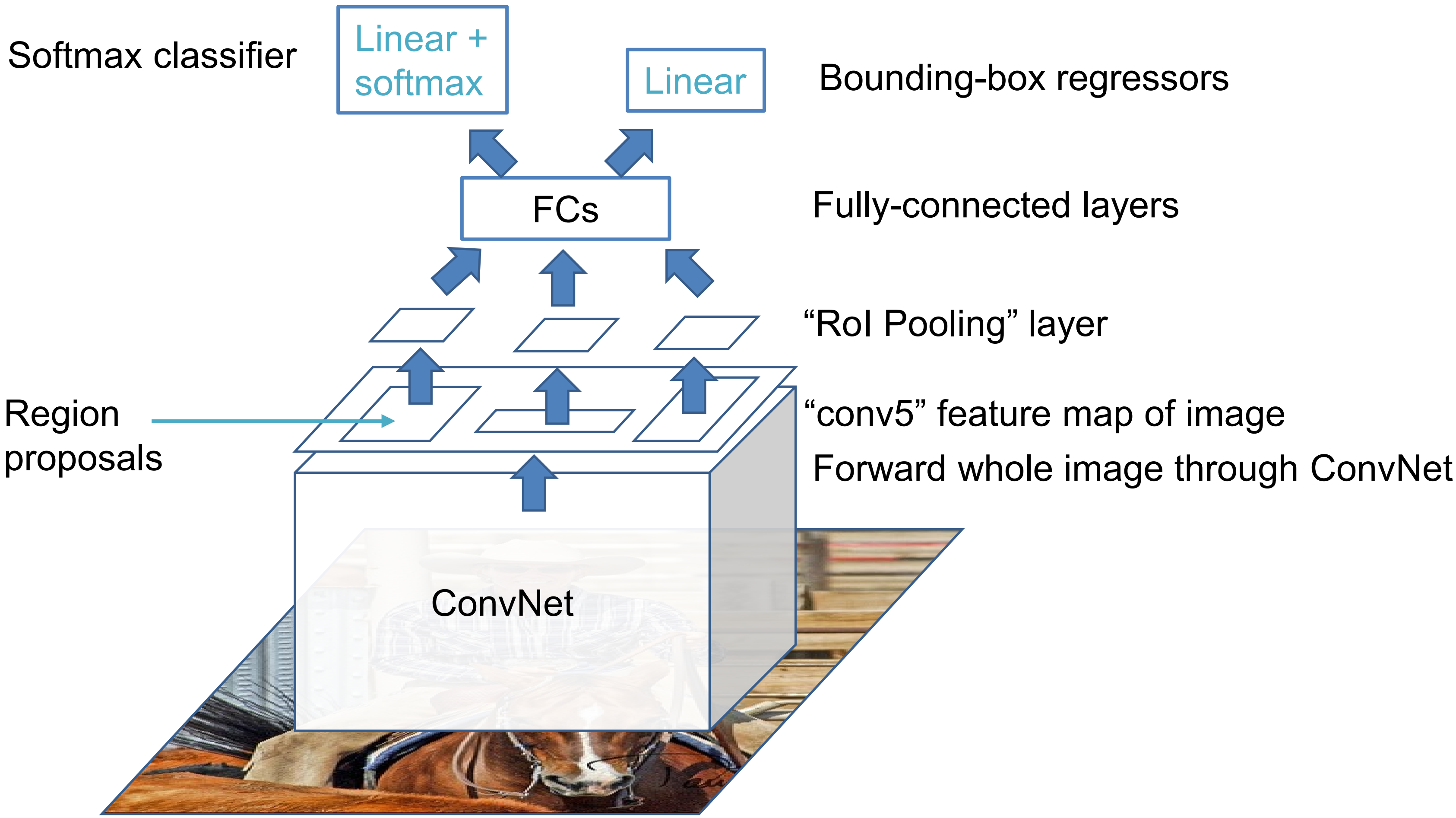
Line up Divide Pool



Source: R. Girshick

R. Girshick, [Fast R-CNN](), ICCV 2015

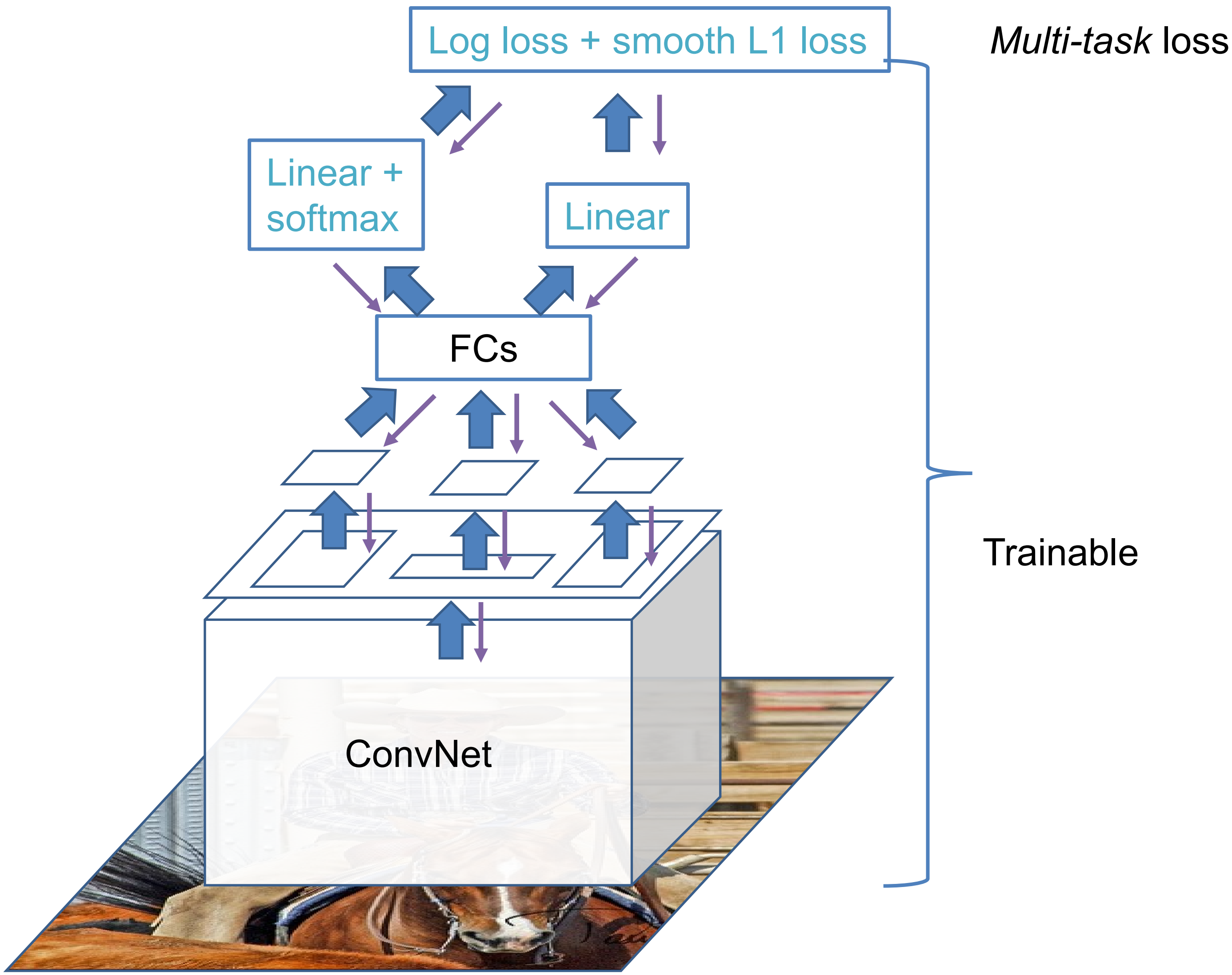
Fast R-CNN



Source: R. Girshick

R. Girshick, [Fast R-CNN](), ICCV 2015

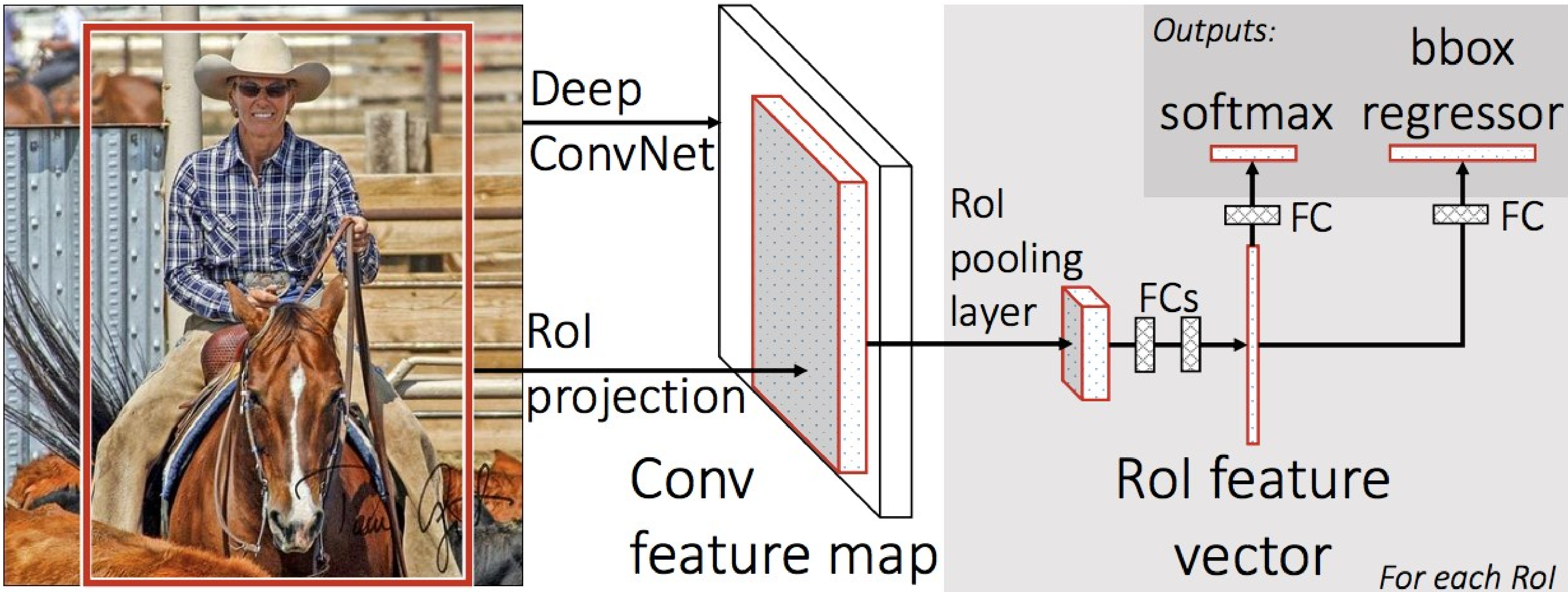
Fast R-CNN training



Source: R. Girshick

R. Girshick, [Fast R-CNN](), ICCV 2015

Fast R-CNN: Another view



Source: R. Girschick

R. Girshick, [Fast R-CNN](), ICCV 2015

Fast R-CNN results

	Fast R-CNN	R-CNN
Train time (h)	**9.5**	84
- Speedup	**8.8x**	1x
Test time / image	**0.32s**	47.0s
Test speedup	**146x**	1x
mAP	**66.9%**	66.0%

Timings exclude object proposal time, which is equal for all methods.
All methods use VGG16 from Simonyan and Zisserman.

Source: R. Girshick