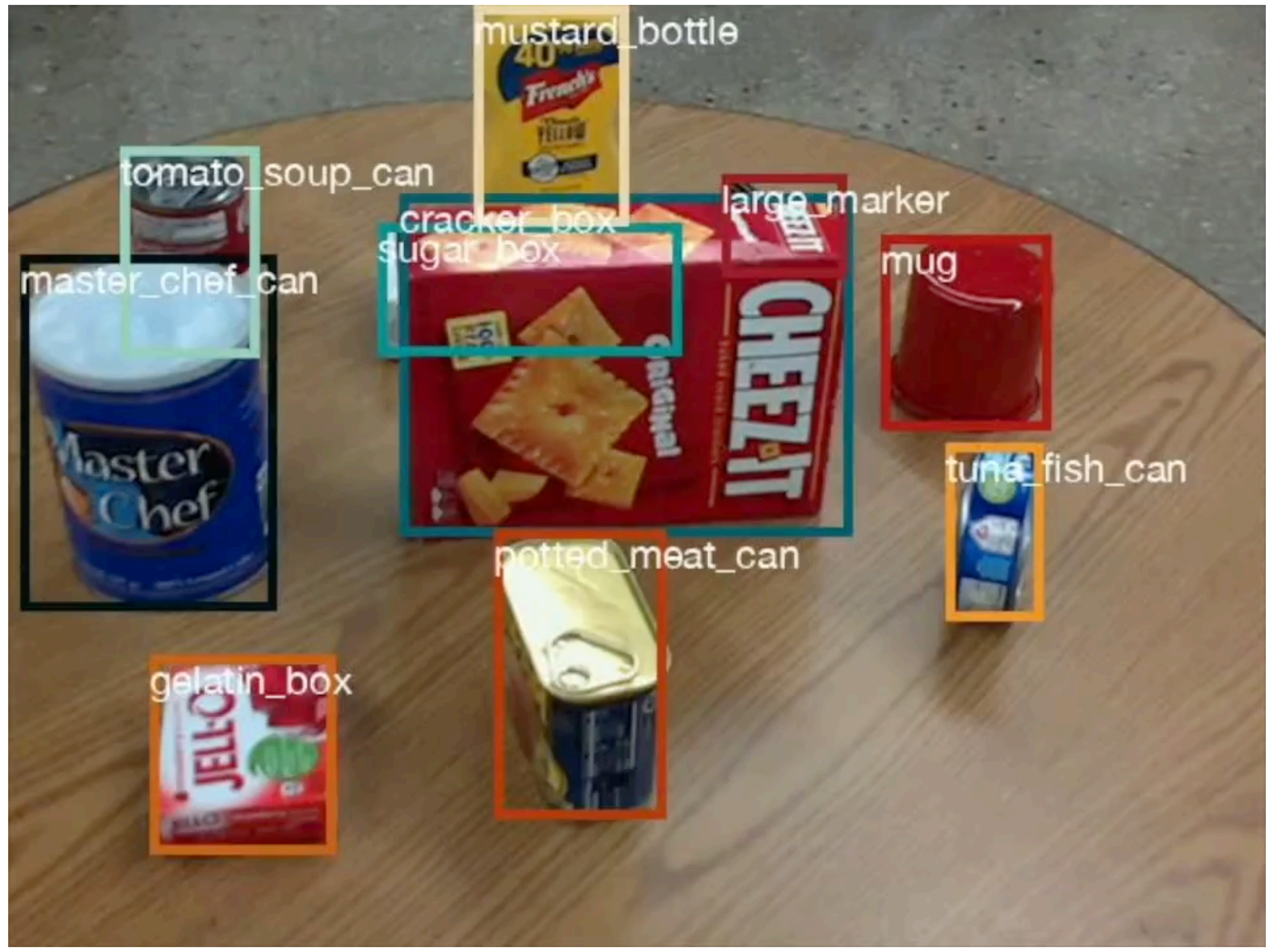
DeepRob

Lecture 12
Object Detection
University of Michigan and University of Minnesota

Slides adapted from Justin Johnson's Deep Learning for Computer Vision course

Project 3 Released

- Instructions available on the website
  - Here: deeprob.org/projects/project3/
  - New [PROPS Detection dataset]()



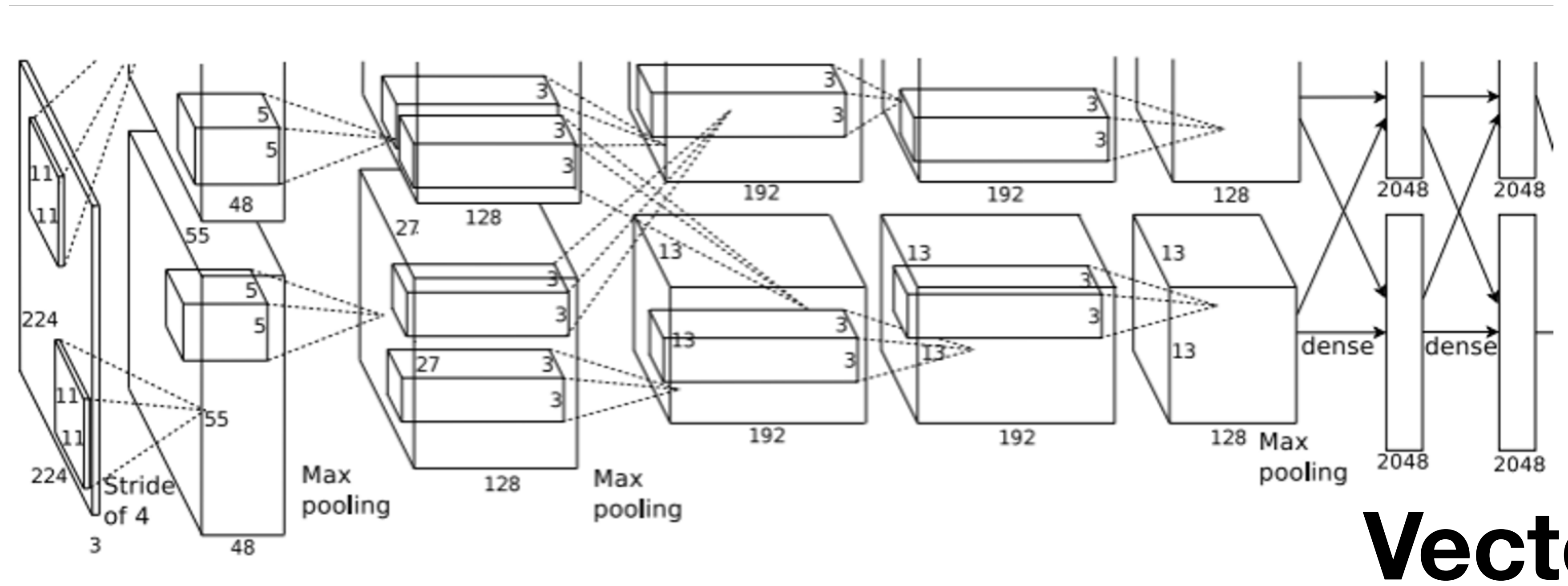
- Implement CNN for classification and Faster R-CNN for detection
- **Due Tuesday, February 28th 11:59 PM EST**

Recap: Deep Learning Software

Static Graphs vs **Dynamic Graphs**

PyTorch vs **TensorFlow**

So far: Image Classification



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Vector:
4096

Fully connected:
4096 to 10

Chocolate Pretzels

Granola Bar

Potato Chips

Water Bottle

Popcorn

Computer Vision Tasks

Classification

"Chocolate Pretzels"

No spatial extent

Semantic Segmentation

Chocolate Pretzels,
Shelf

No objects, just pixels

Object Detection

Instance Segmentation

Flipz, Hershey's, Keese's

Multiple objects

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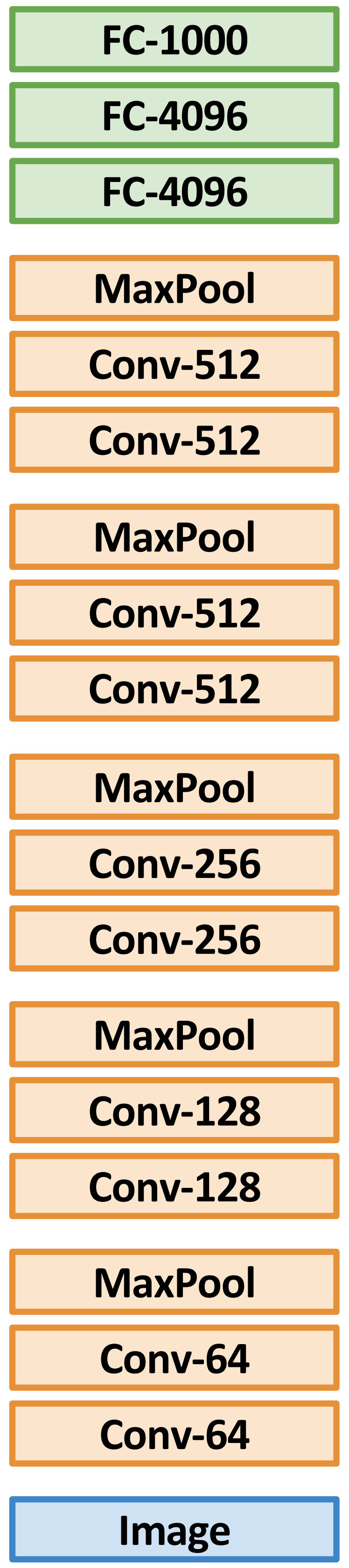
Transfer Learning: Generalizing to New Tasks

Transfer Learning with CNNs

1. Train on ImageNet



Donahue et al, “DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition”, ICML 2014

Transfer Learning with CNNs

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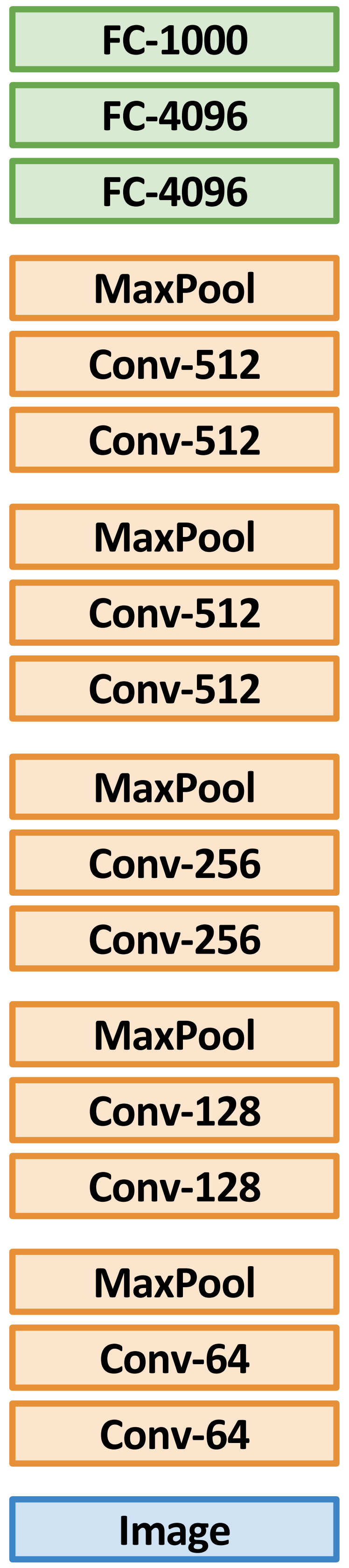
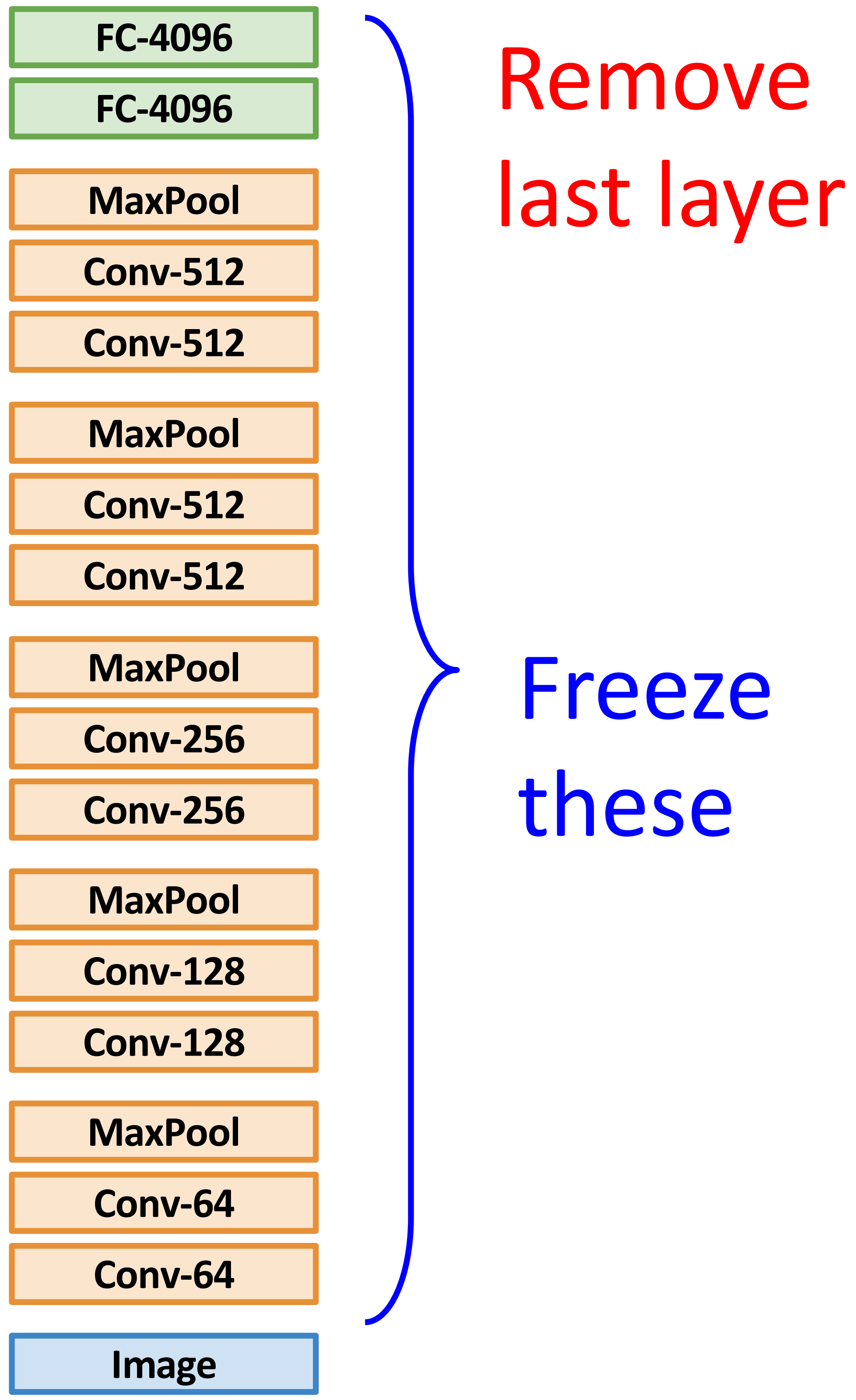


2. Use CNN as a feature extractor



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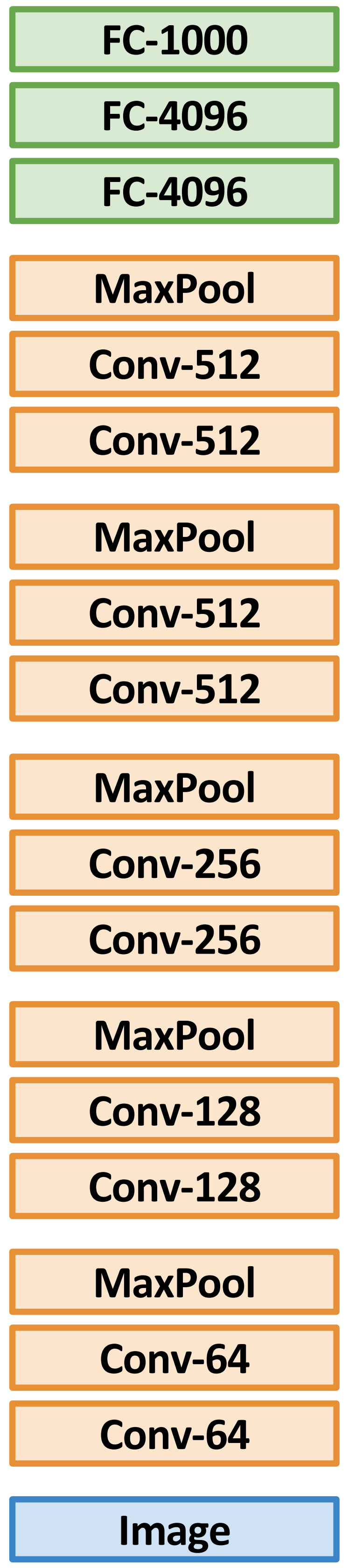
Transfer Learning: Feature Extraction

1. Train on ImageNet



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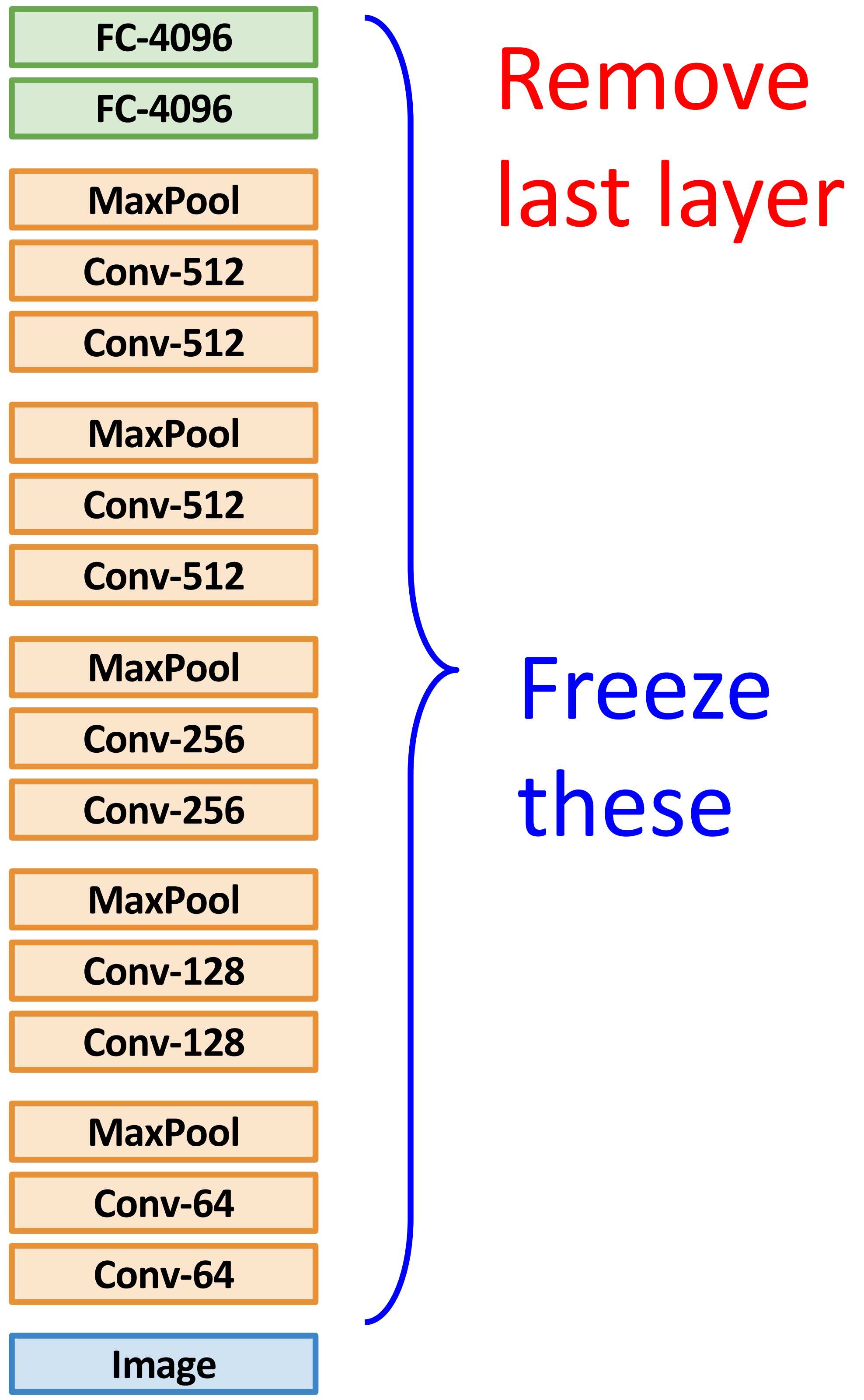
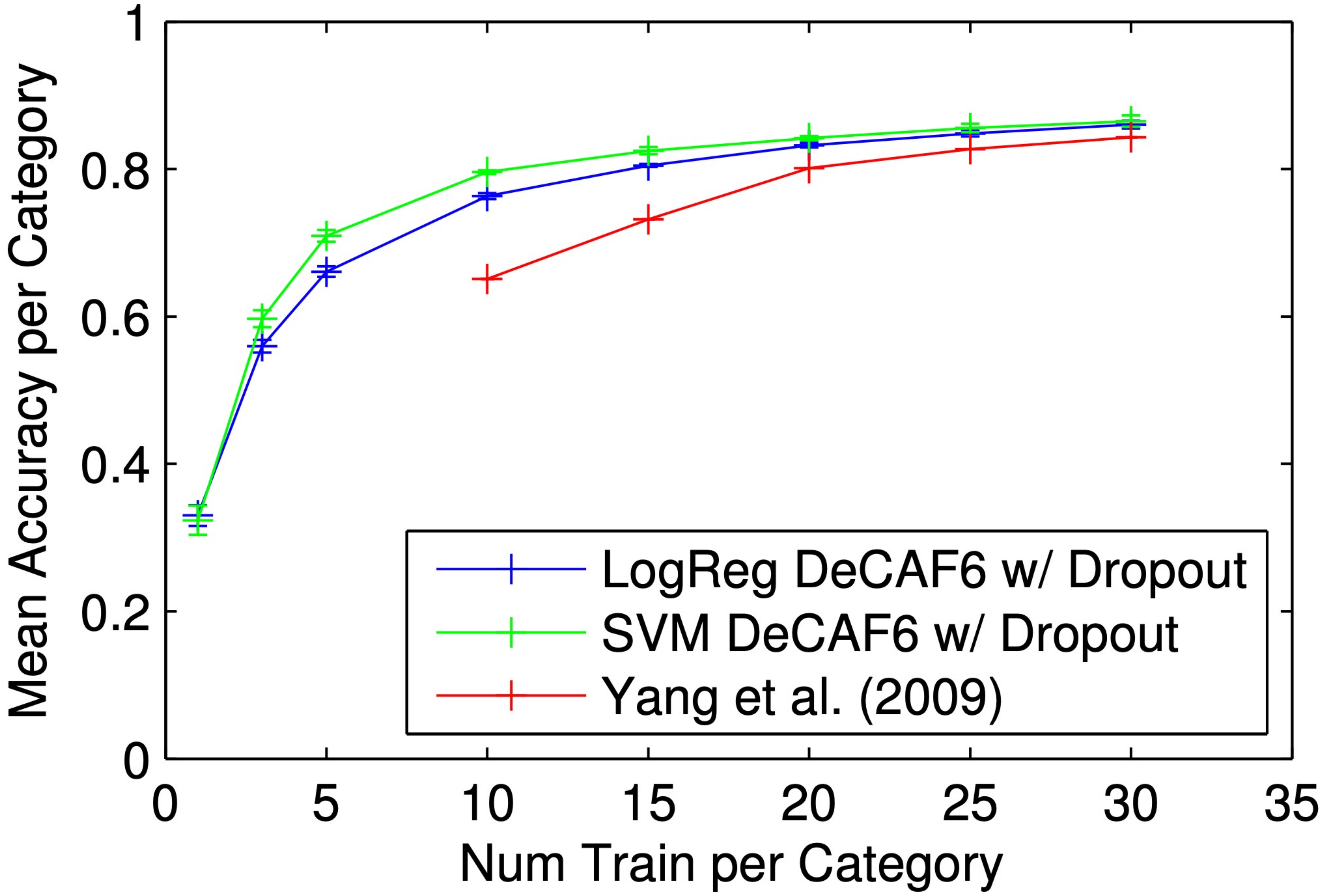


Classification on Caltech-101



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Transfer Learning: Feature Extraction

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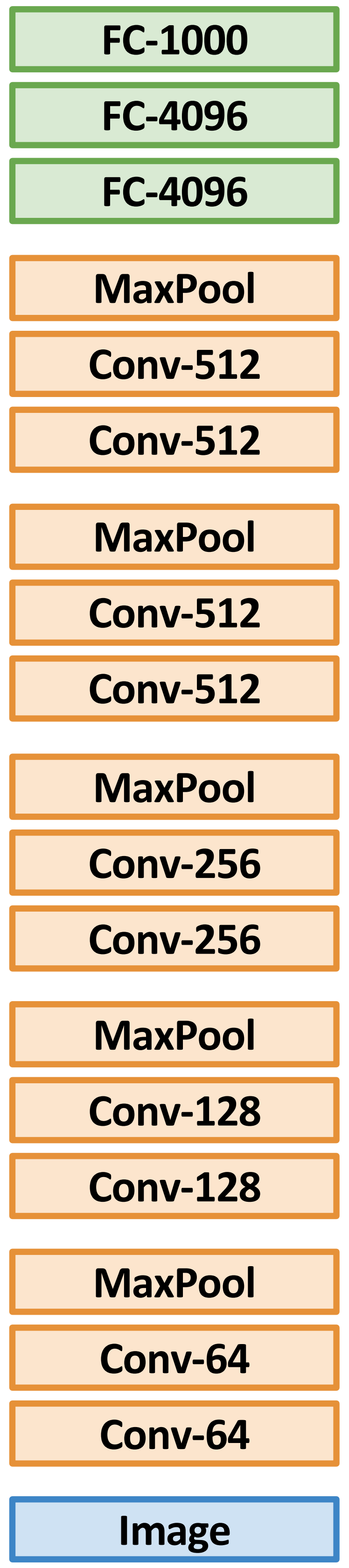

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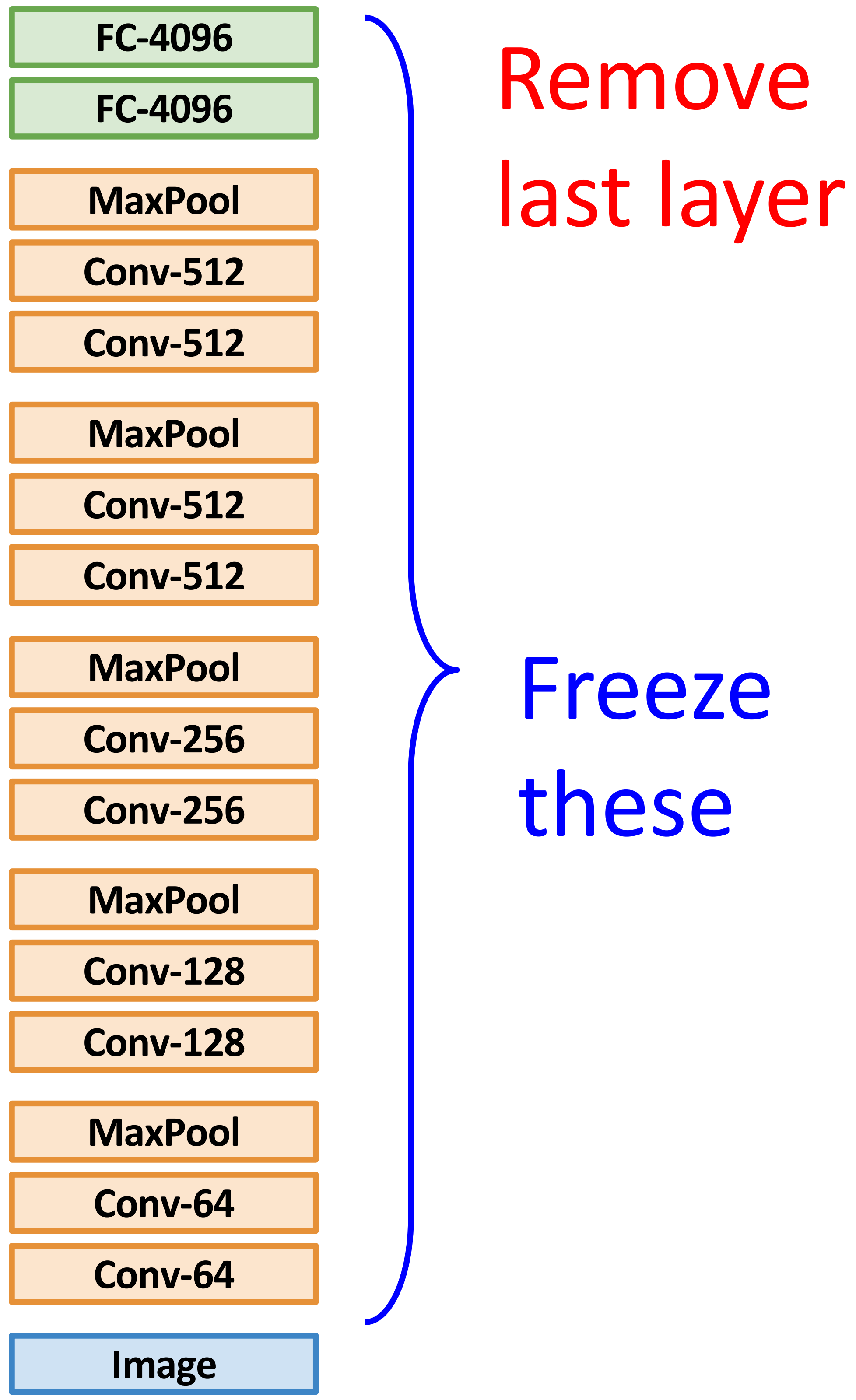
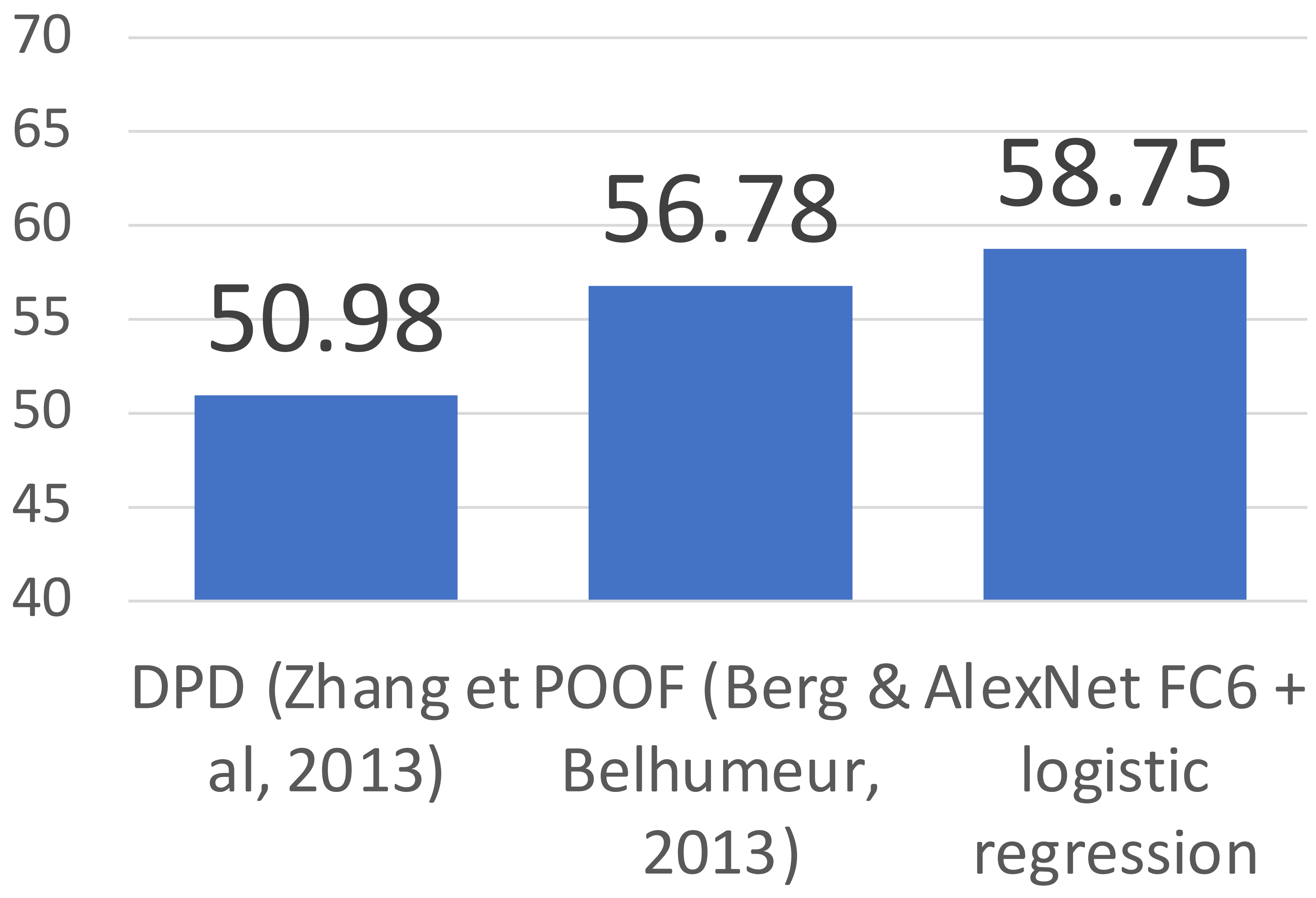


Bird Classification on Caltech-UCSD



Transfer Learning: Feature Extraction

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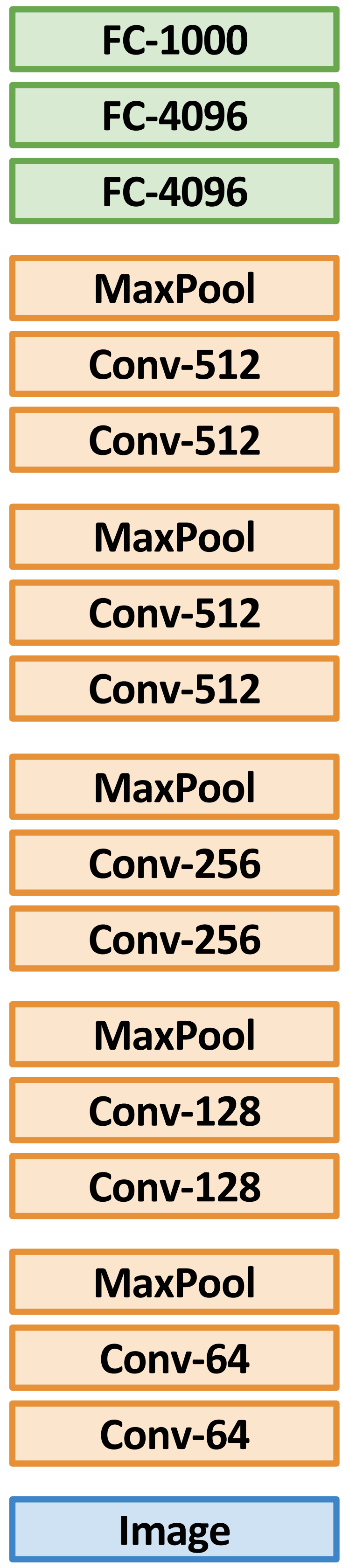

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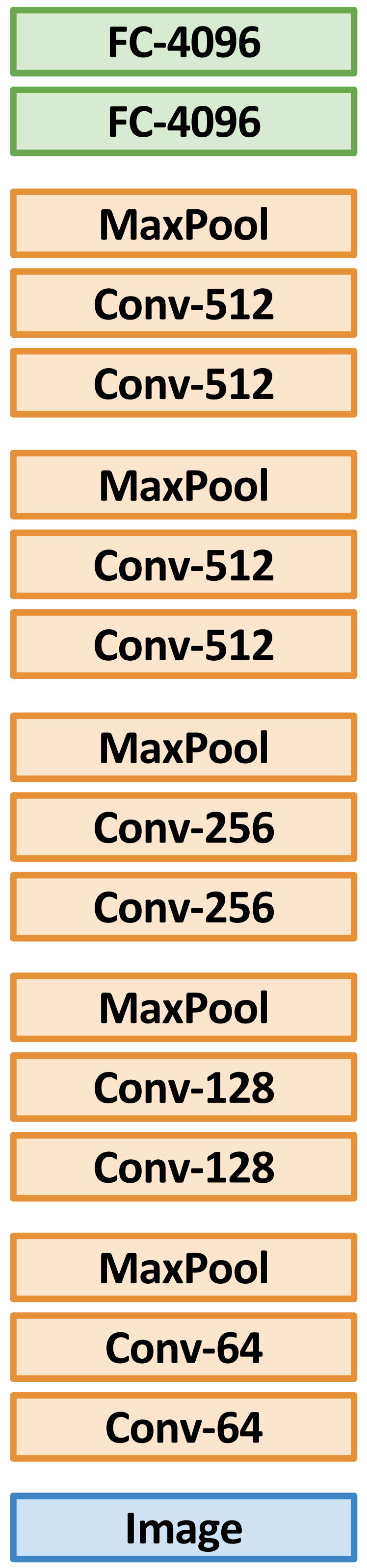
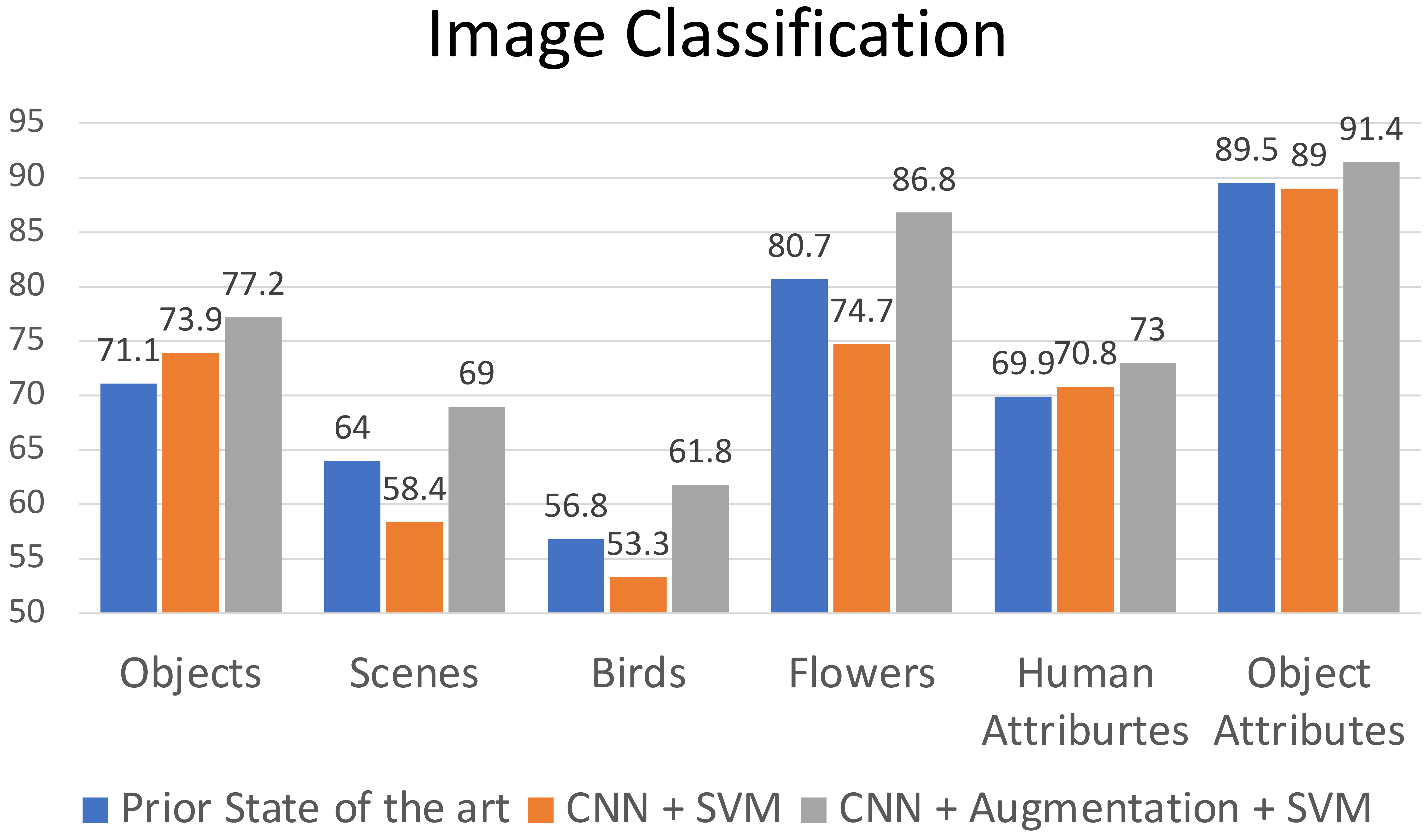
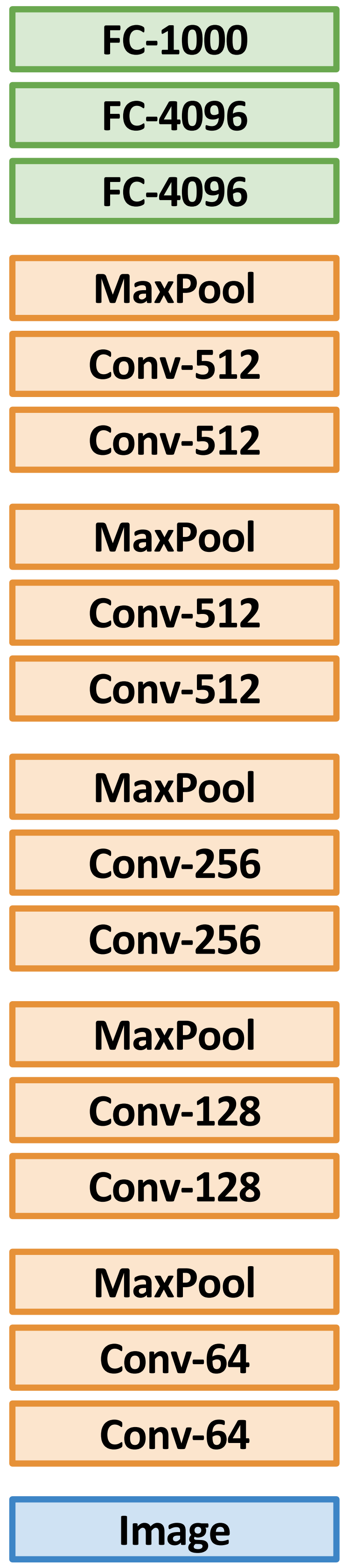




Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Transfer Learning: Fine Tuning

1. Train on ImageNet



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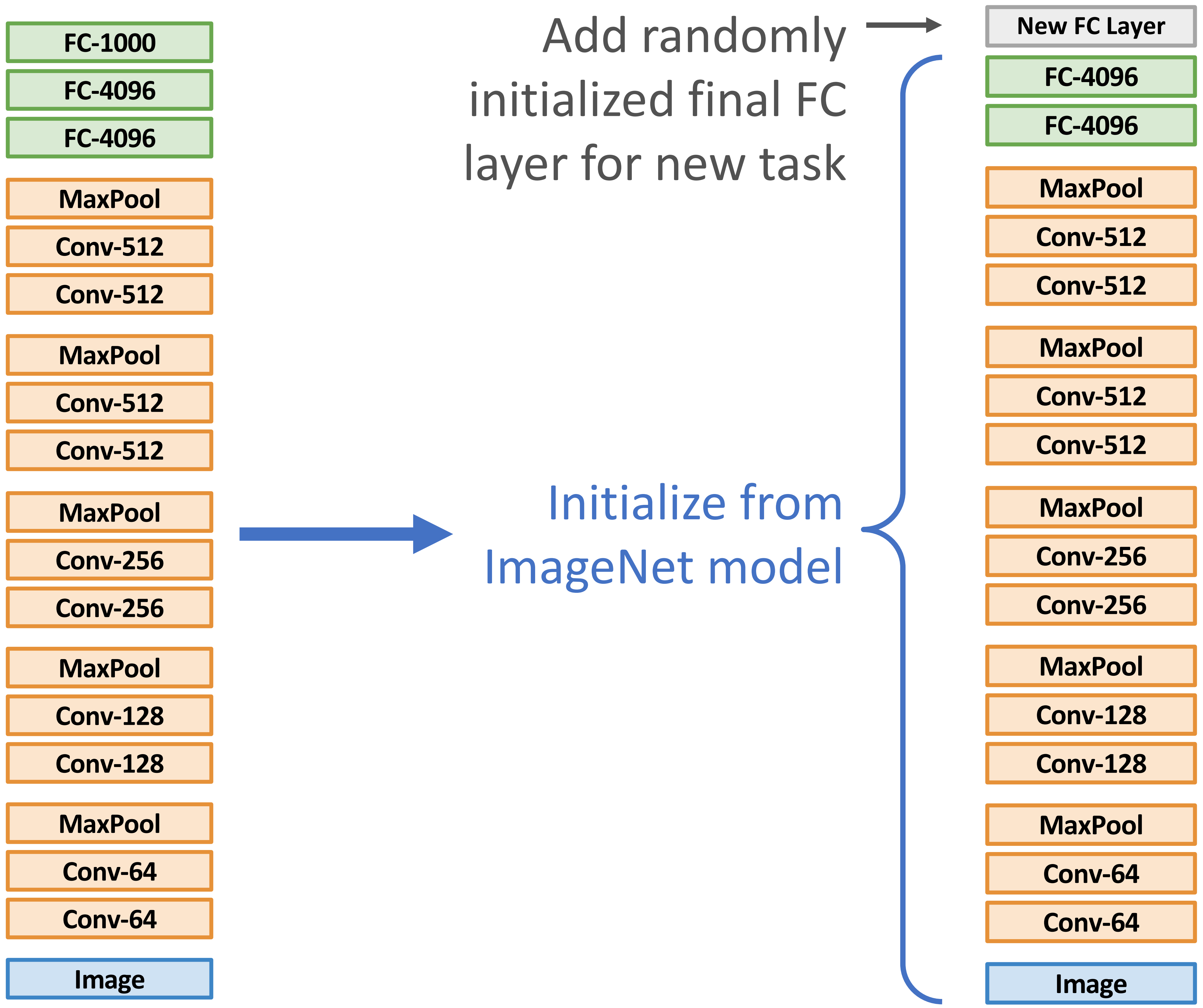
1. Train on ImageNet



Transfer Learning: Fine Tuning

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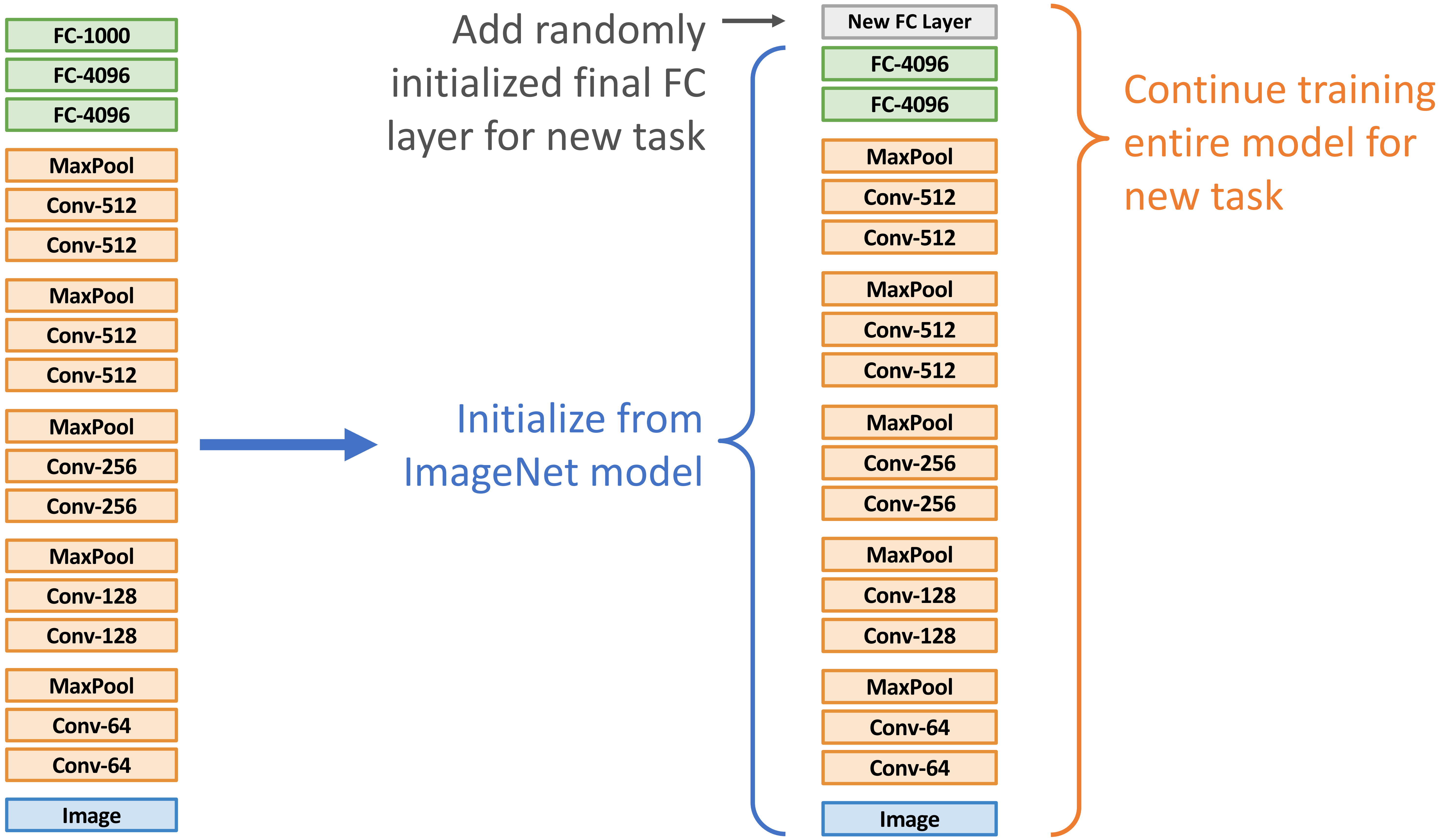

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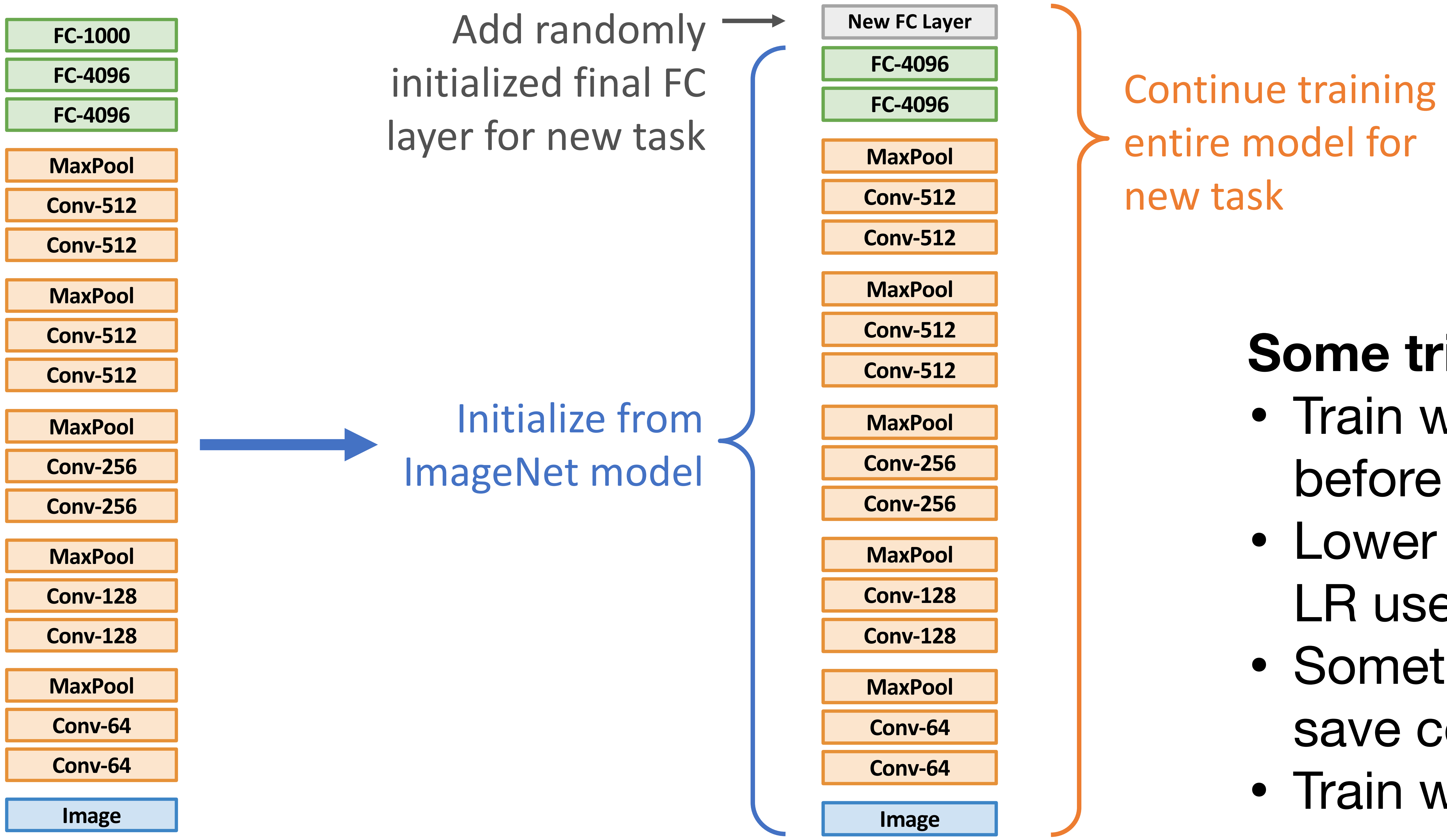
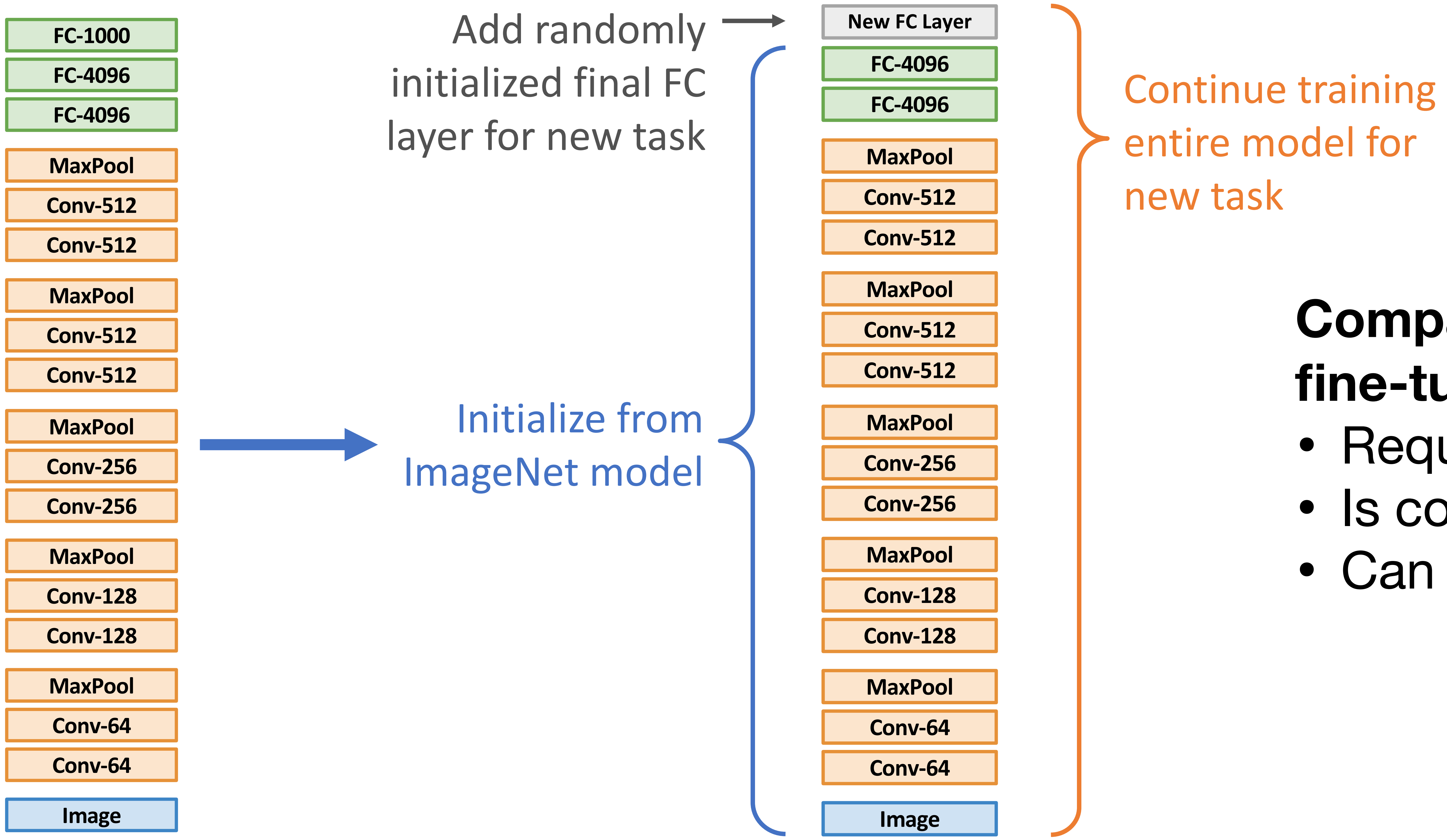


Some tricks:

- Train with feature extraction first before finetuning
- Lower the learning rate: use ~1/10 of LR used in original training
- Sometimes freeze lower layers to save computation
- Train with BatchNorm in “test” mode

Transfer Learning: Fine Tuning

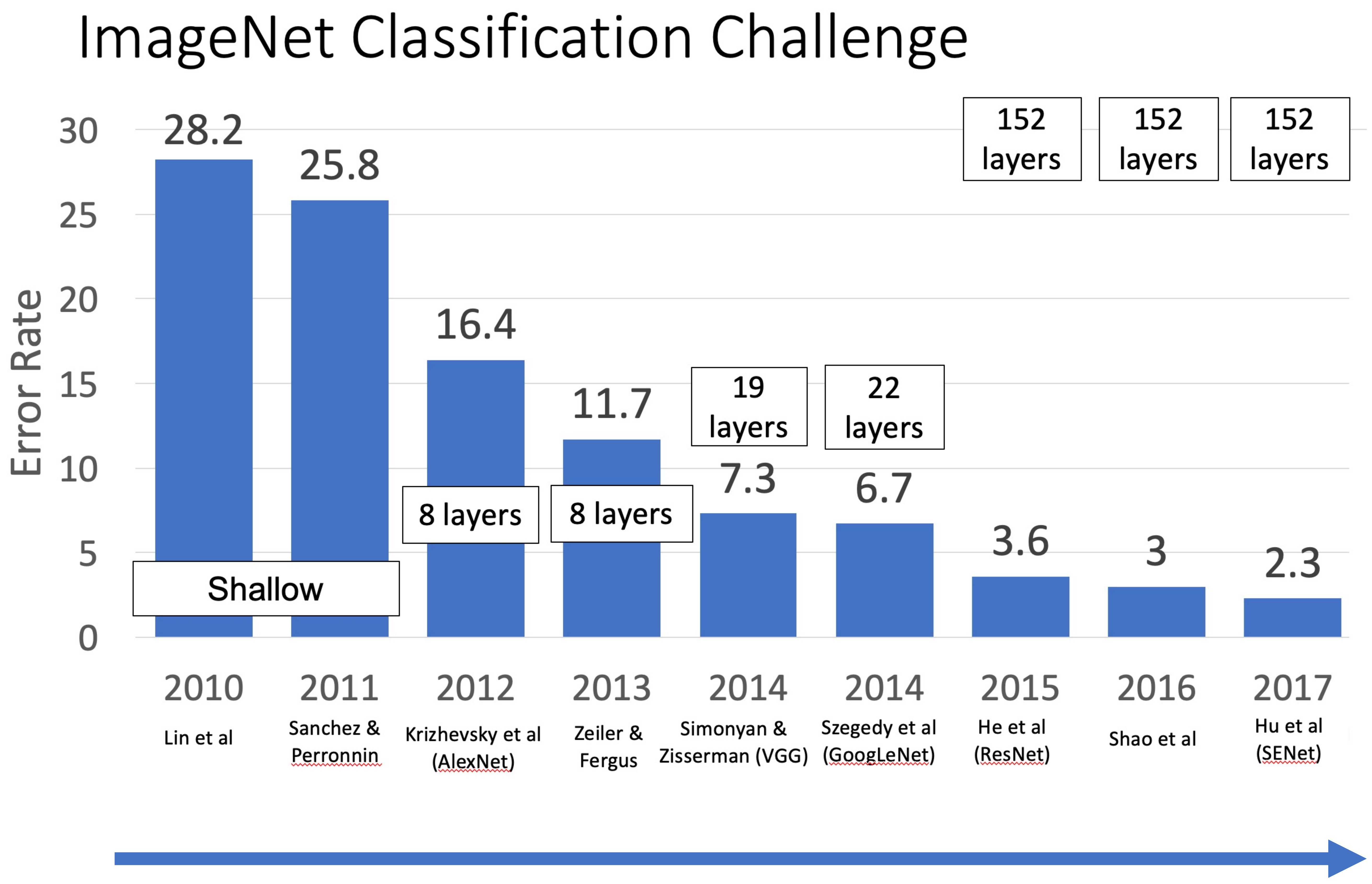
1. Train on ImageNet



Compared with feature extraction, fine-tuning:

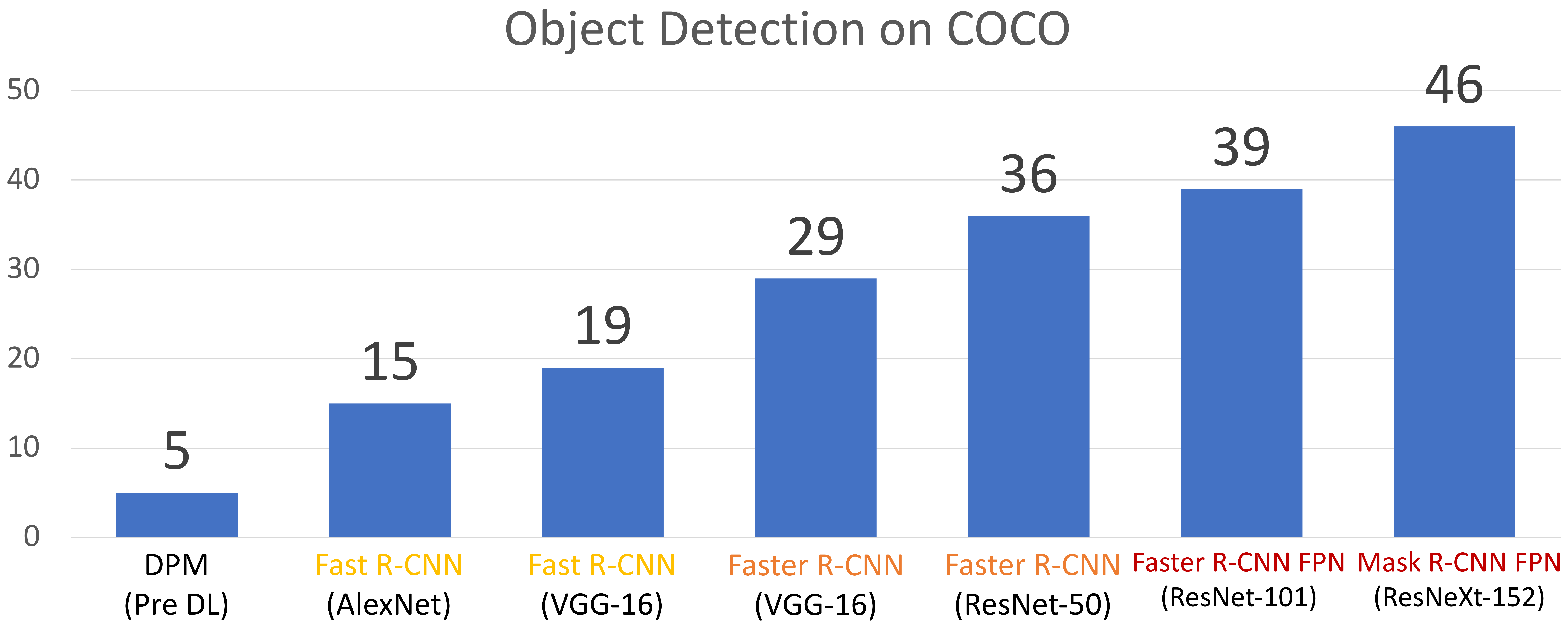
- Requires more data
- Is computationally expensive
- Can give higher accuracies

Transfer Learning: Architecture Matters!



Improvements in CNN architecture leads to improvements in many down stream tasks thanks to transfer learning!

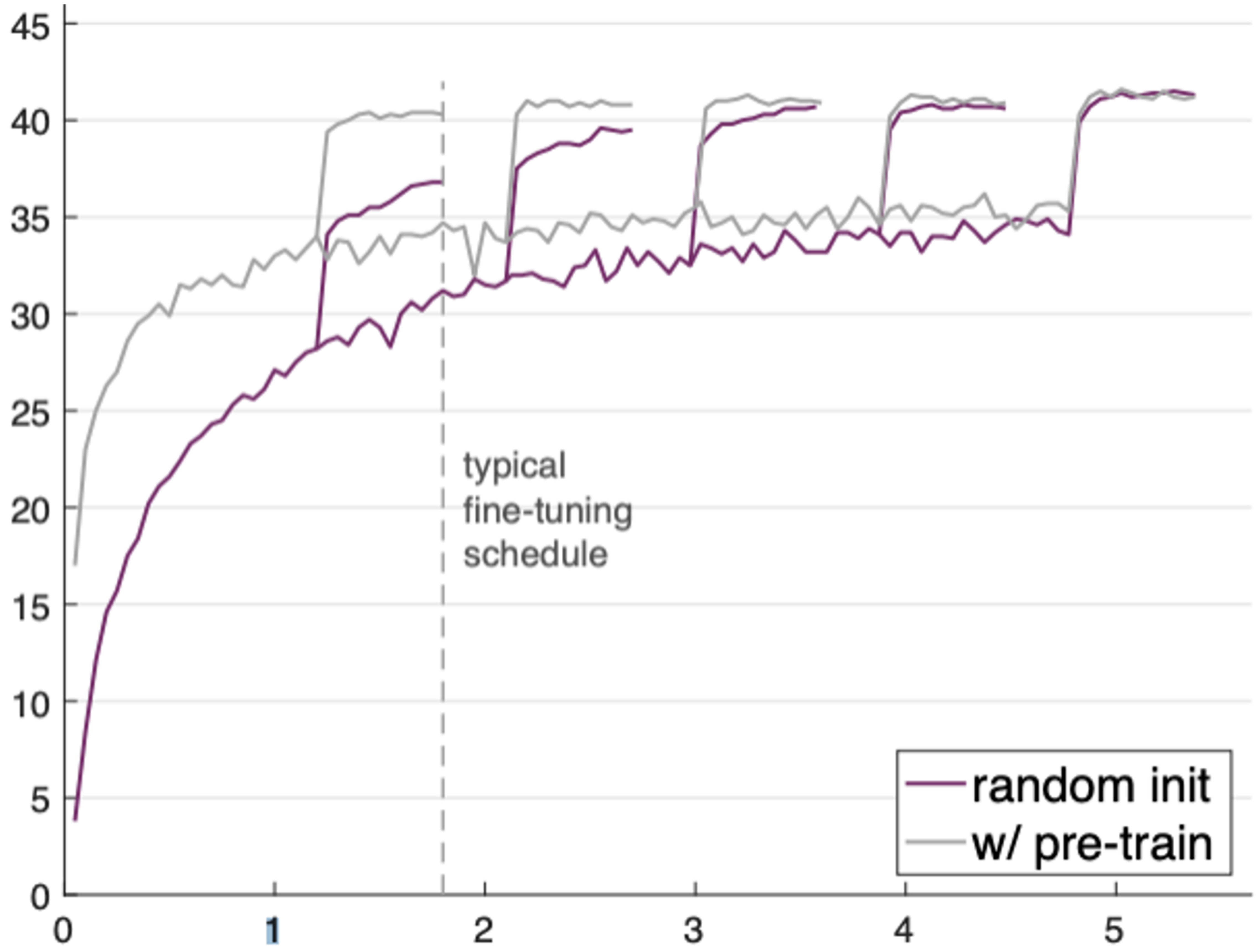
Transfer Learning: Architecture Matters!



Ross Girshick, "The Generalized R-CNN Framework for Object Detection", ICCV 2017 Tutorial on Instance-Level Visual Recognition

Transfer Learning can help you converge faster

COCO object detection



If you have enough data and train for much longer, random initialization can sometimes do as well as transfer learning

He et al, "Rethinking ImageNet Pre-Training", ICCV 2019

Transfer Learning is persvasive!
It’s the norm, not the exception

Very active area of research!

Call for papers

Important dates (all times AoE)

- Submissions open: Feb 15th 2023
- Submission deadline: Apr 14th 2023
- Decision notification: Apr 30th 2023
- Camera ready deadline: May 14th 2023
- Workshop: May 29th 2023

Classification: Transferring to New Tasks

Classification

"Chocolate Pretzels"

No spatial extent

Semantic Segmentation

Chocolate Pretzels, Shelf

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Instance Segmentation

Flipz, Hershey's, Keese's

Multiple objects

Today: Object Detection

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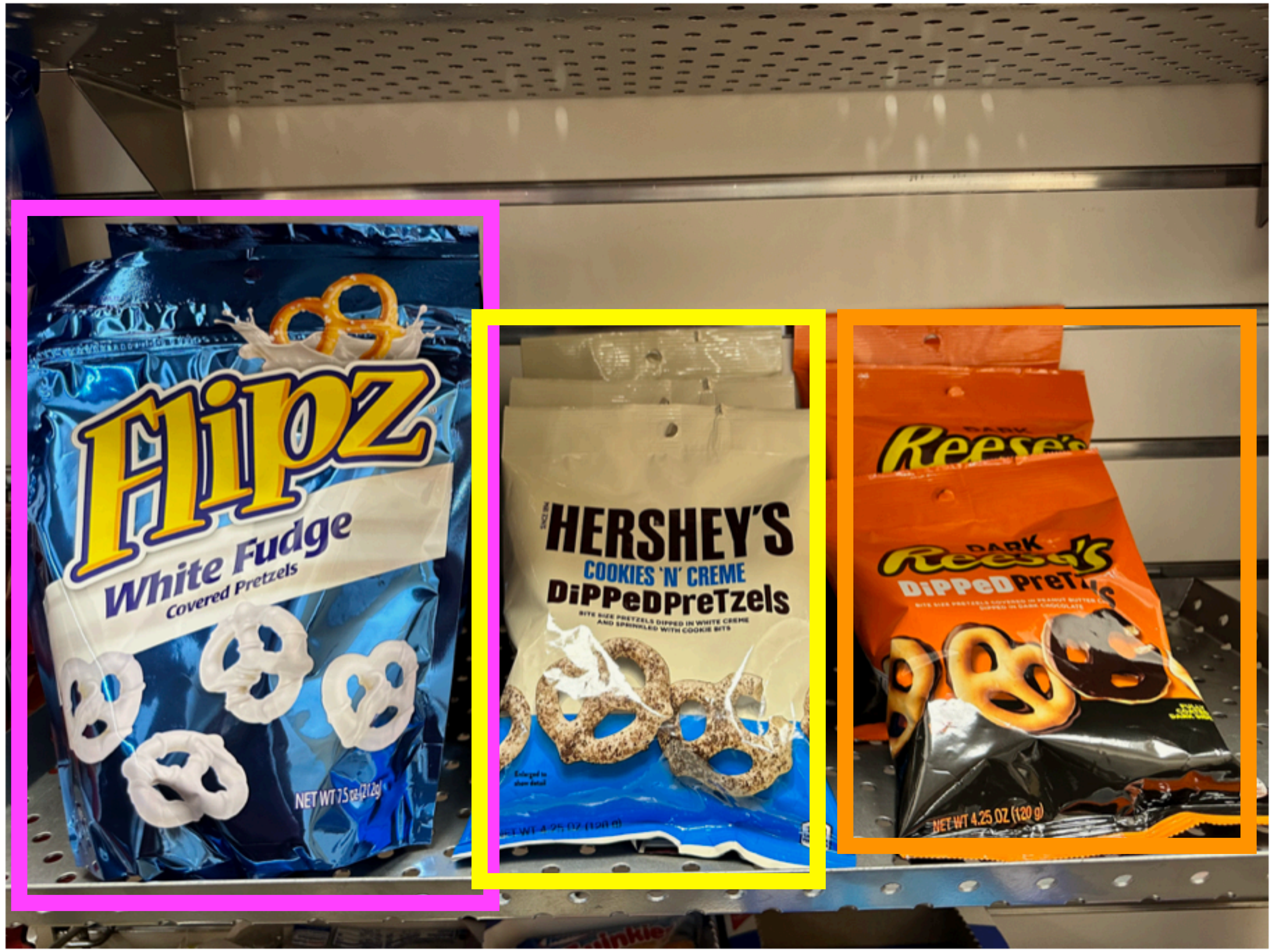
Object Detection: Task definition

Input: Single RGB image

Output: A set of detected objects;
For each object predict:

1. Category label (from a fixed set of labels)
2. Bounding box (four numbers: x, y, width, height)



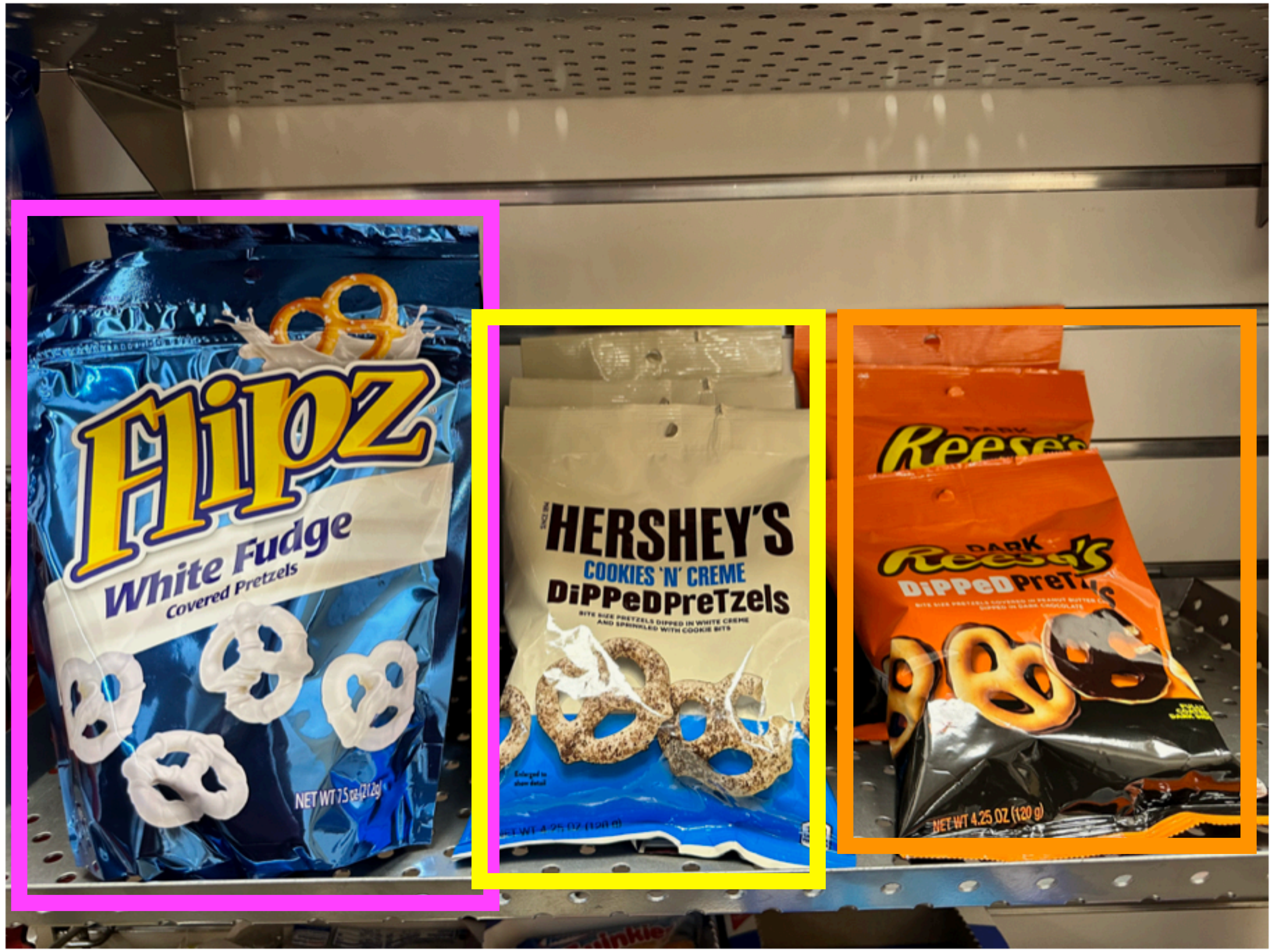
Object Detection: Challenges

Multiple outputs: Need to output variable numbers of objects per image

Multiple types of output: Need to predict ”what” (category label) as well as “where” (bounding box)

Large images: Classification works at 224x224; need higher resolution for detection, often ~800x600

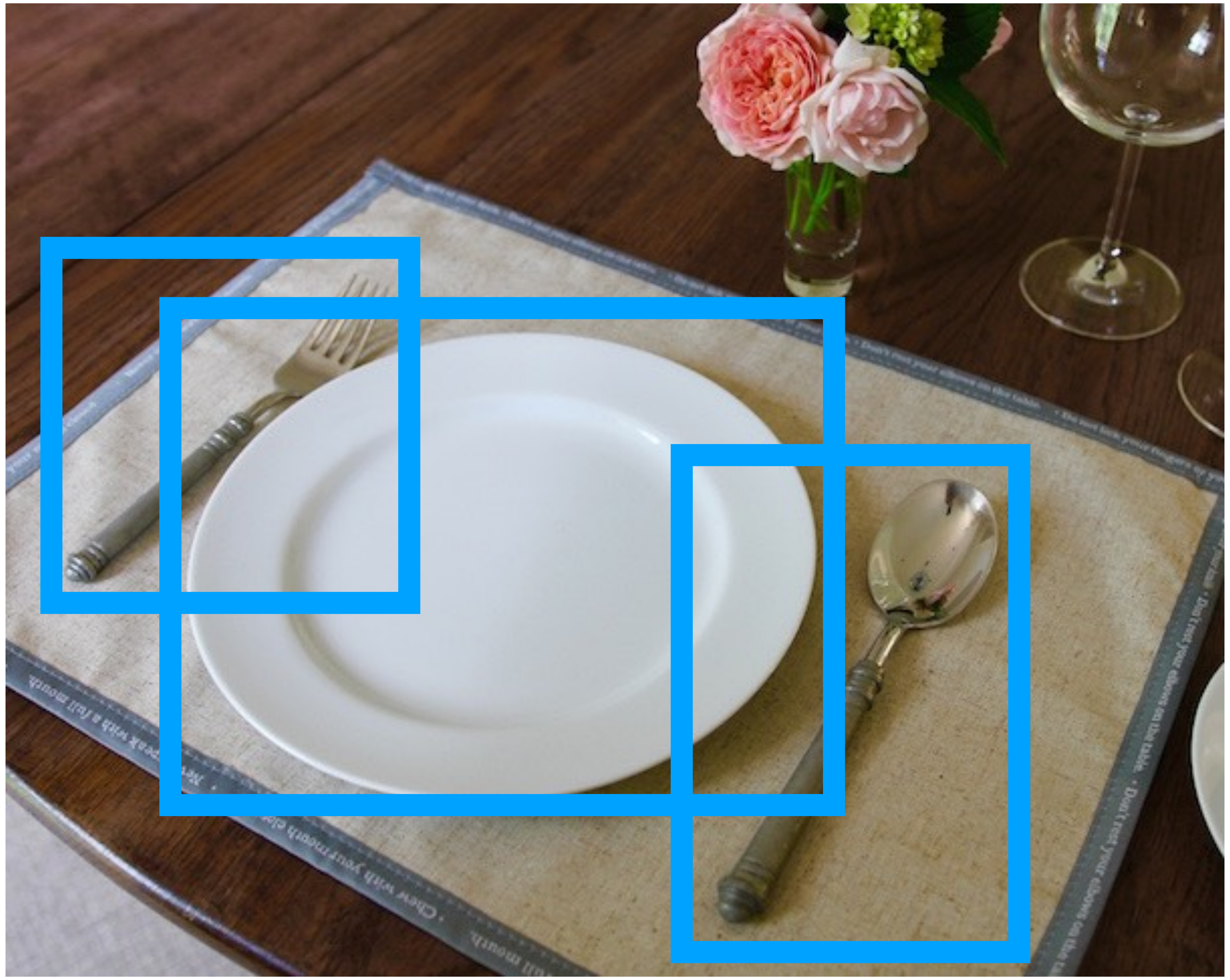
1.



Bounding Boxes

Bounding boxes are typically *axis-aligned*

1.



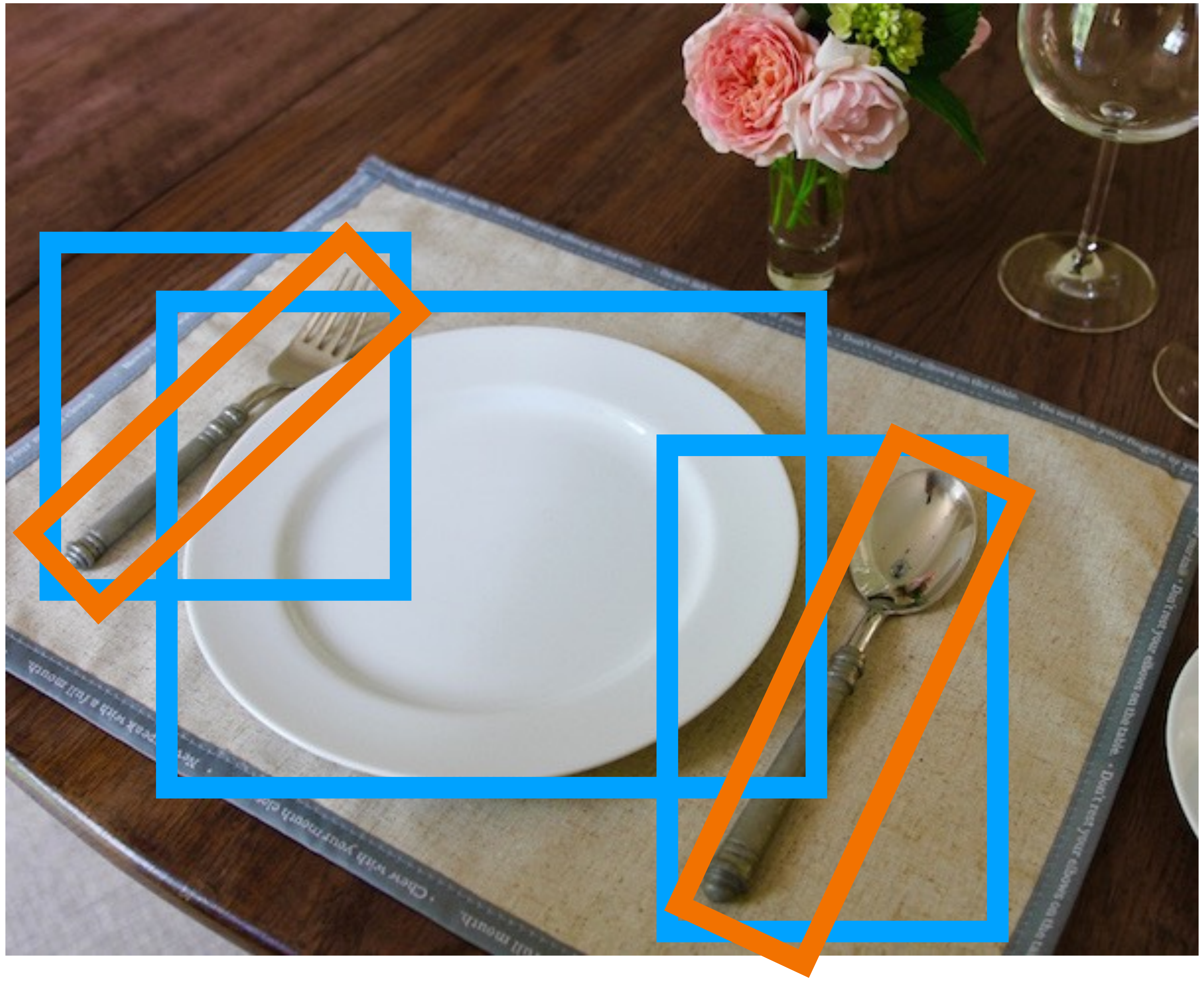
Bounding Boxes

Bounding boxes are typically *axis-aligned*

1.

Oriented boxes are much less common

1.



Object Detection: Modal vs Amodal Boxes

Bounding boxes cover only the visible portion of the object

1.

Zhu et al, "Semantic Amodal Segmentation", CVPR 2017

Object Detection: Modal vs Amodal Boxes

Bounding boxes cover only the visible portion of the object

1.

<u>Amodal detection:</u> box covers the entire extent of the object, even occluded parts

1.

Zhu et al, "Semantic Amodal Segmentation", CVPR 2017

Object Detection: Modal vs Amodal Boxes

"Modal" detection: Bounding boxes (usually) cover only the visible portion of the object

1.

Amodal detection: box covers the entire extent of the object, even occluded parts

1.

Zhu et al, "Semantic Amodal Segmentation", CVPR 2017

Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?

Comparing Boxes: Intersection over Union (IoU)

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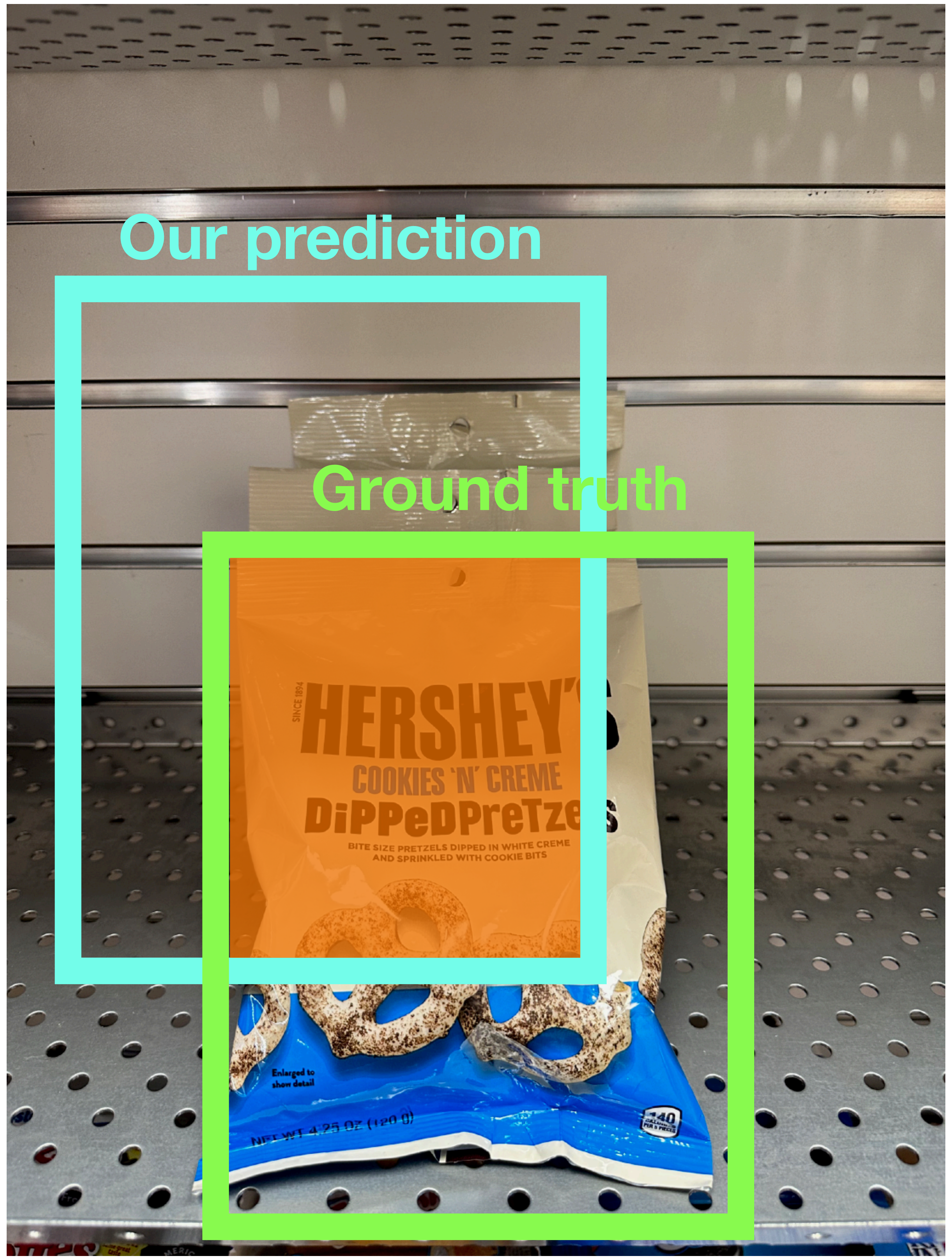
Intersection over Union (IoU) (Also called “Jaccard similarity” or “Jaccard index”):

$$\frac{\textit{Area of Intersection}}{\textit{Area of Union}}$$



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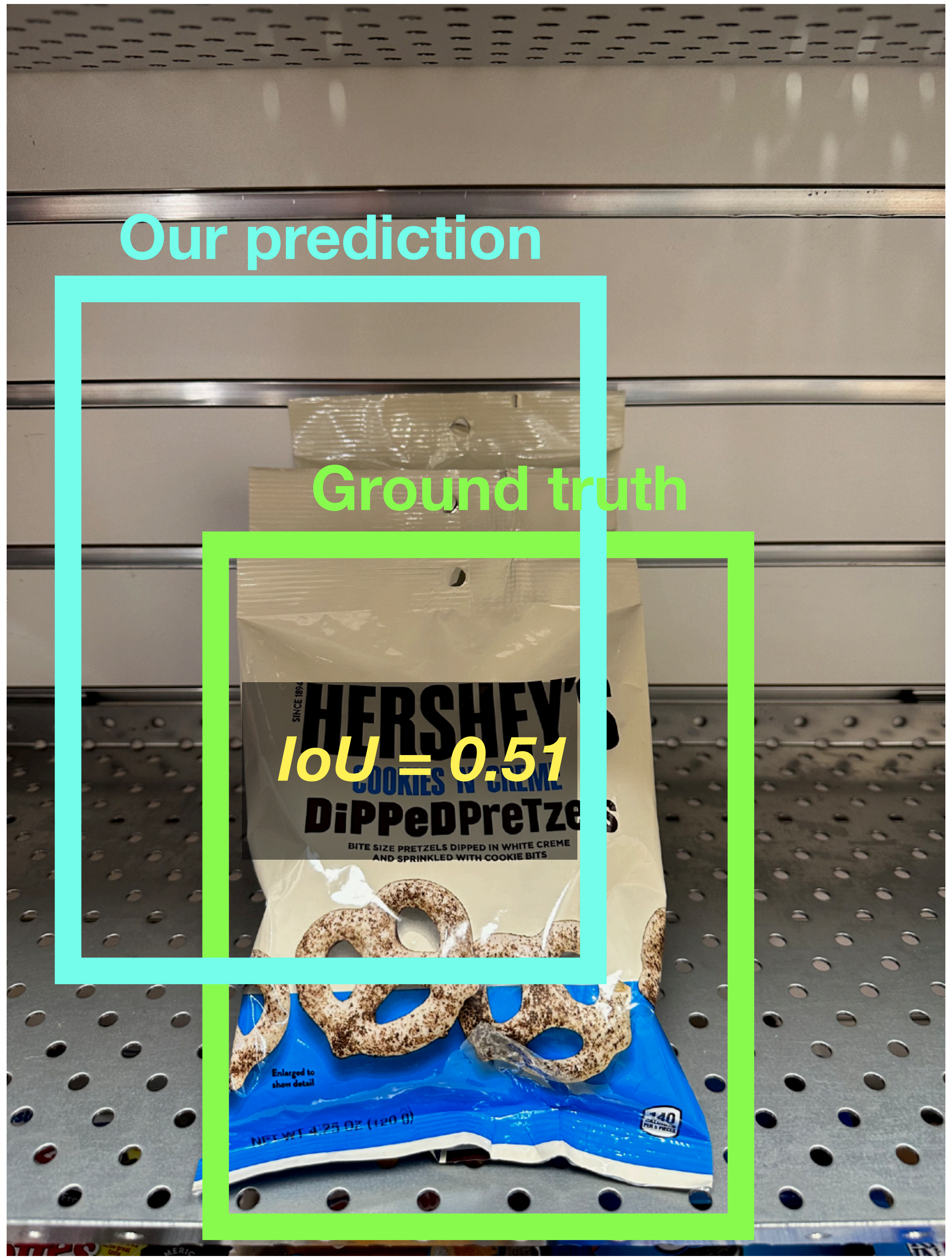
IoU > 0.5 is "decent",



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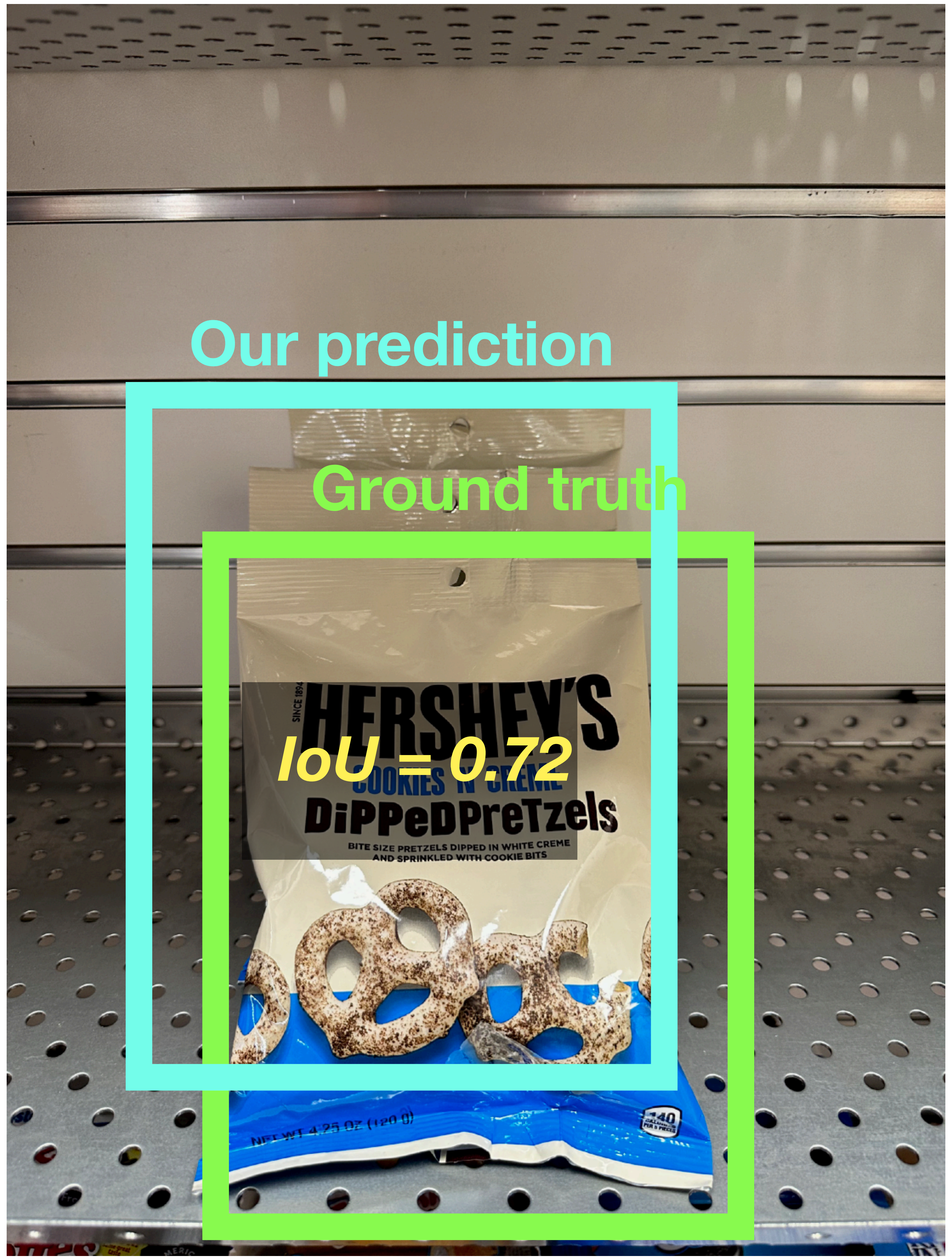
IoU > 0.5 is “decent”,
IoU > 0.7 is “pretty good”,



Comparing Boxes: Intersection over Union (IoU)

How can we compare our prediction to the ground-truth box?

Intersection over Union (IoU) (Also called “Jaccard similarity” or “Jaccard index”):

$$\frac{\textit{Area of Intersection}}{\textit{Area of Union}}$$

IoU > 0.5 is “decent”,
IoU > 0.7 is “pretty good”,
IoU > 0.9 is “almost perfect”

Detecting a single object

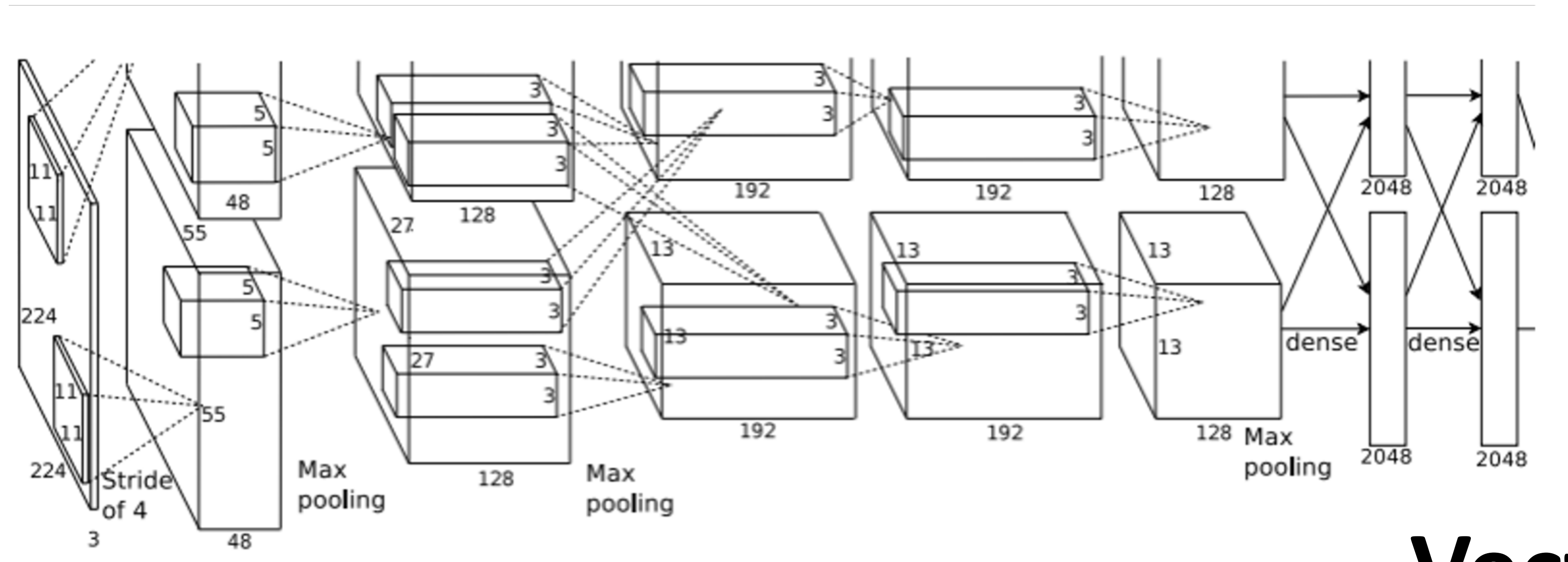


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Vector:
4096

Loss

Treat localization as a regression problem!

Detecting a single object

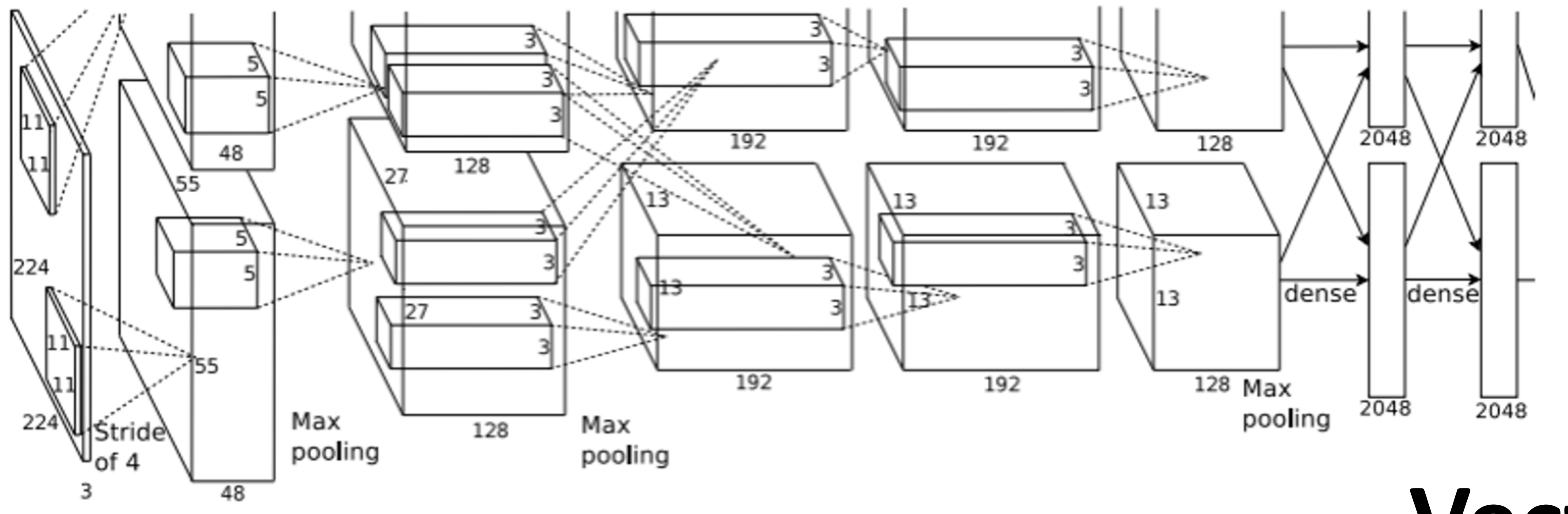


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Vector:
4096

Fully connected:
4096 to 10

What??

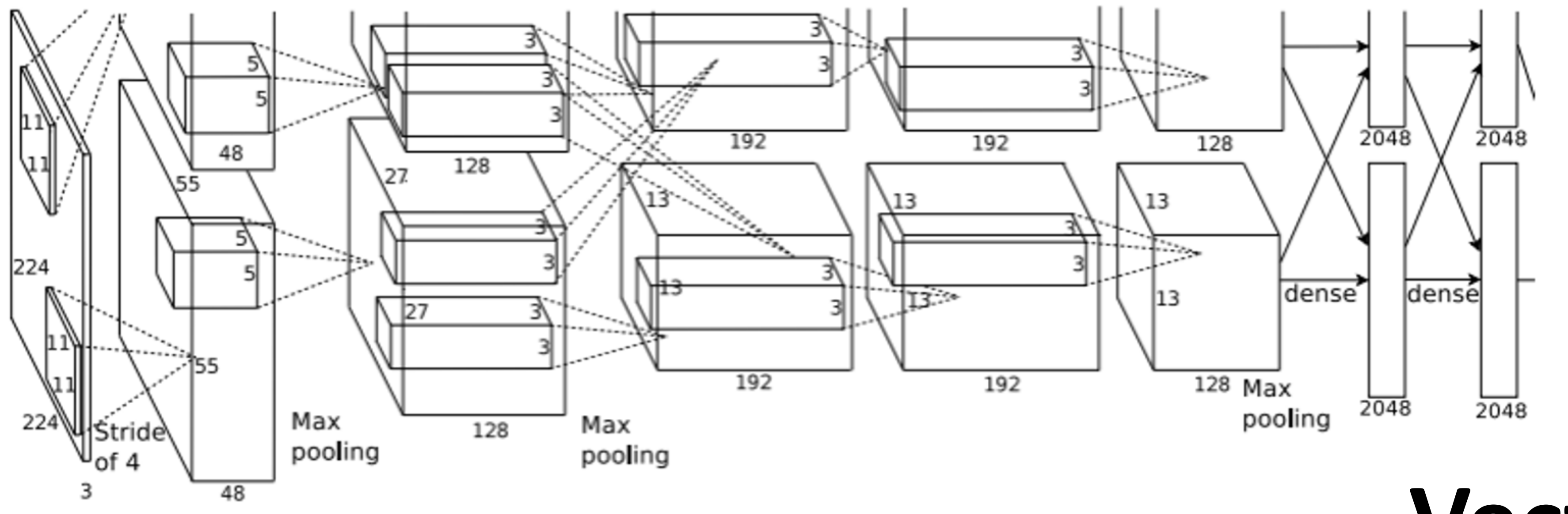
<u>Class scores:</u>
Chocolate Pretzels: 0.9
Granola Bar: 0.02
Potato Chips: 0.02
Water Bottle: 0.02
Popcorn: 0.01
….

<u>Correct Label:</u>
Chocolate Pretzels

Softmax Loss

Treat localization as a regression problem!

Detecting a single object



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Vector:
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What??

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Softmax Loss

Treat localization as a regression problem!

Fully connected:
4096 to 10

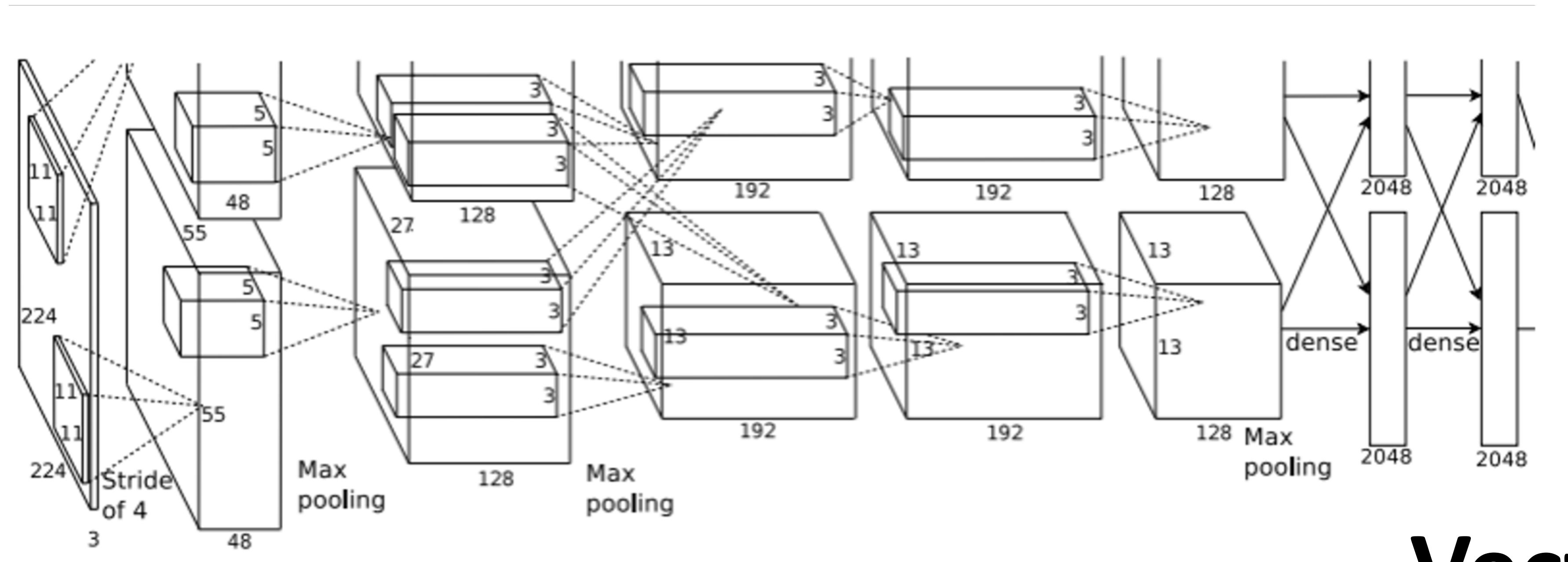
<u>Box coordinates:</u>
(x, y, w, h)

L2 Loss

<u>Correct coordinates:</u>
(x', y', w', h')

Where??

Detecting a single object



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Softmax Loss

Multitask Loss

Weighted Sum → Loss

$$L = L_{cls} + \lambda L_{reg}$$

Fully connected:
4096 to 10

Box coordinates:
(x, y, w, h)

L2 Loss

Where??

Correct coordinates:
(x’, y', w’, h’)

Treat localization as a regression problem!

Detecting a single object

Often pretrained on ImageNet: Transfer learning

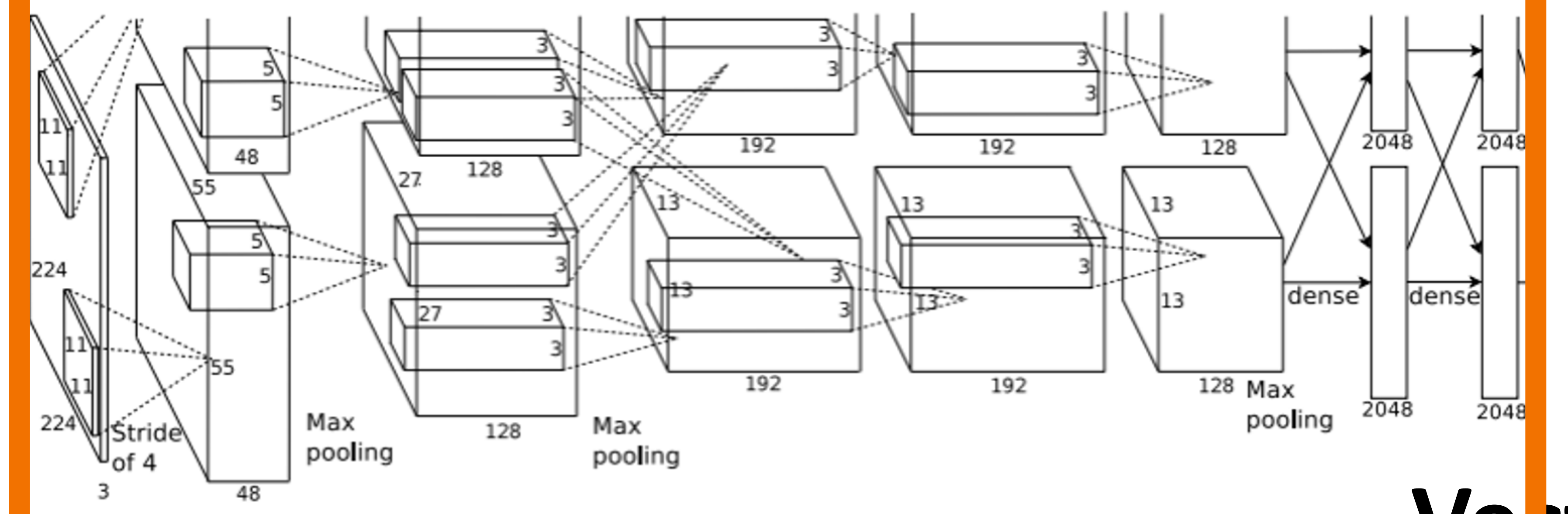

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Vector: 4096

Fully connected: 4096 to 10

What??

Class scores:
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Fully connected: 4096 to 10

Box coordinates:
(x, y, w, h)

L2 Loss

Where??

Correct coordinates:
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Treat localization as a regression problem!

Detecting a single object

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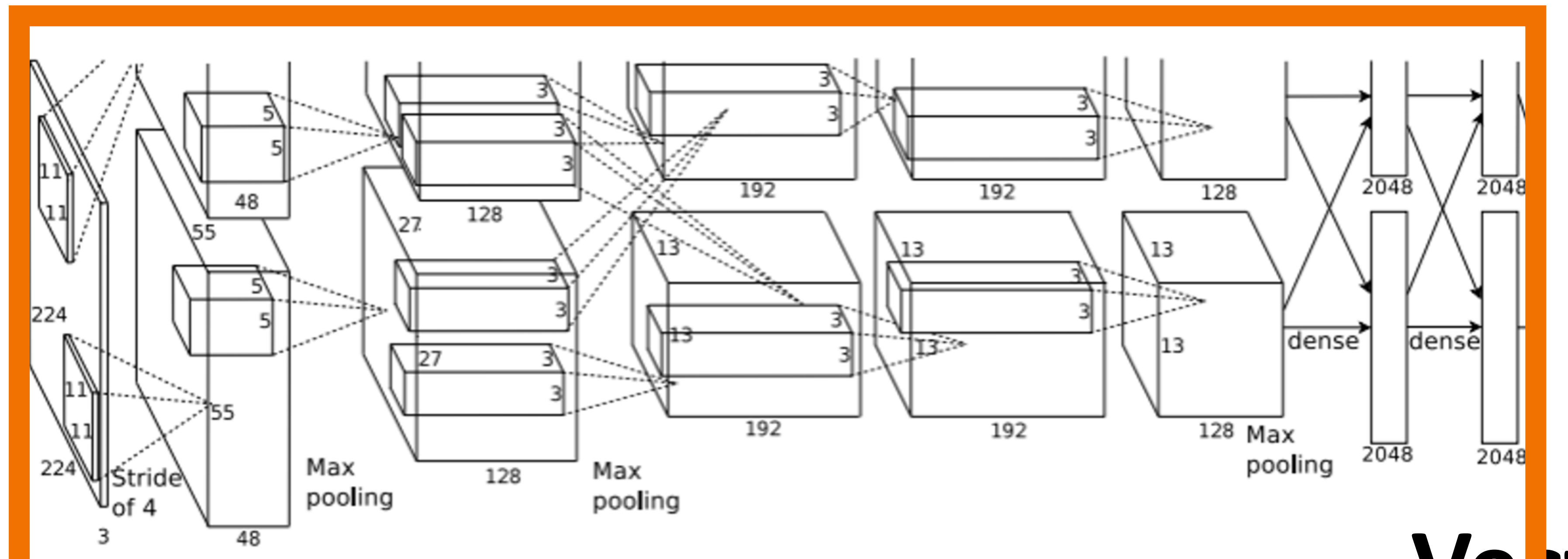

Vector: 4096

Fully connected: 4096 to 10

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$$L = L_{cls} + \lambda L_{reg}$$

Fully connected: 4096 to 10

Box coordinates:
(x, y, w, h)

L2 Loss

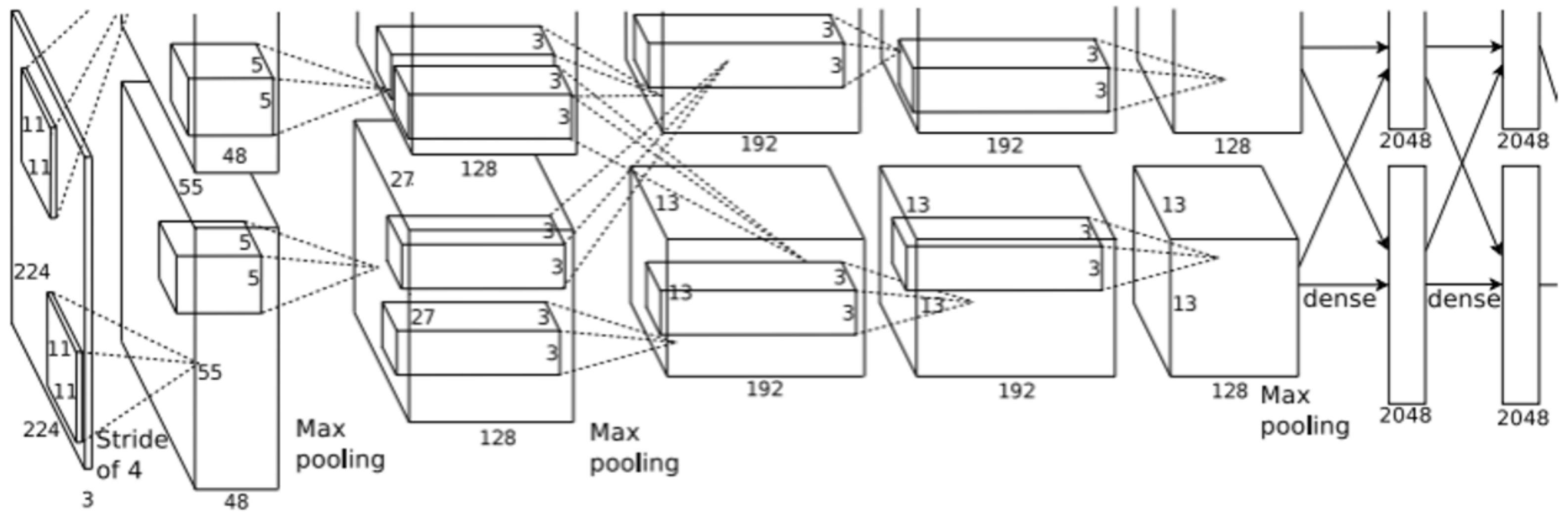
Correct coordinates:
(x', y', w', h')

Where??

Treat localization as a regression problem!

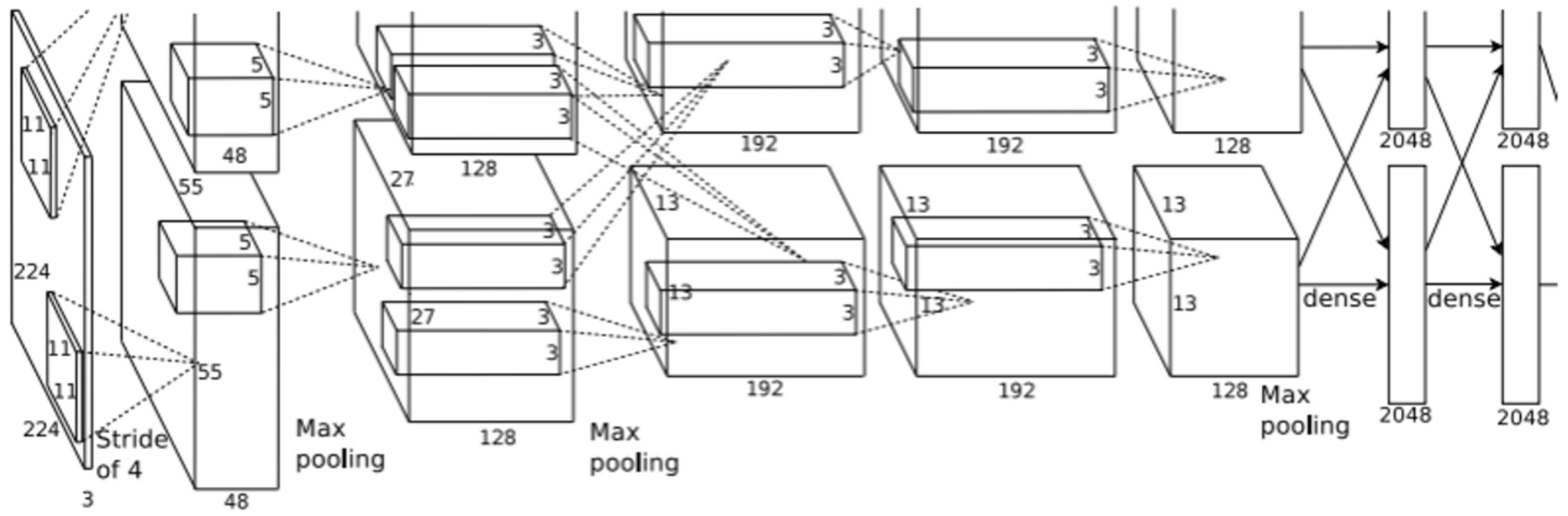
Problem: Images can have more than one object!

Detecting Multiple Objects



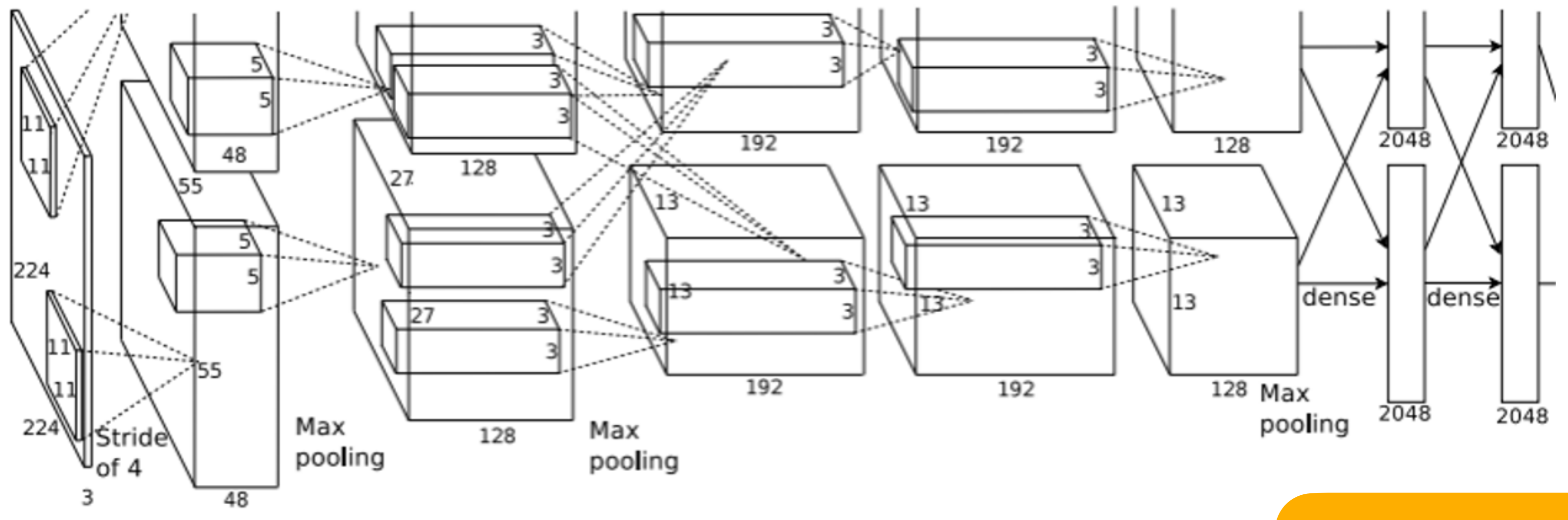
Hershey's: (x, y, w, h)

4 numbers



Hershey's: (x, y, w, h)
Flipz: (x, y, w, h)
Reese's (x, y, w, h)

12 numbers



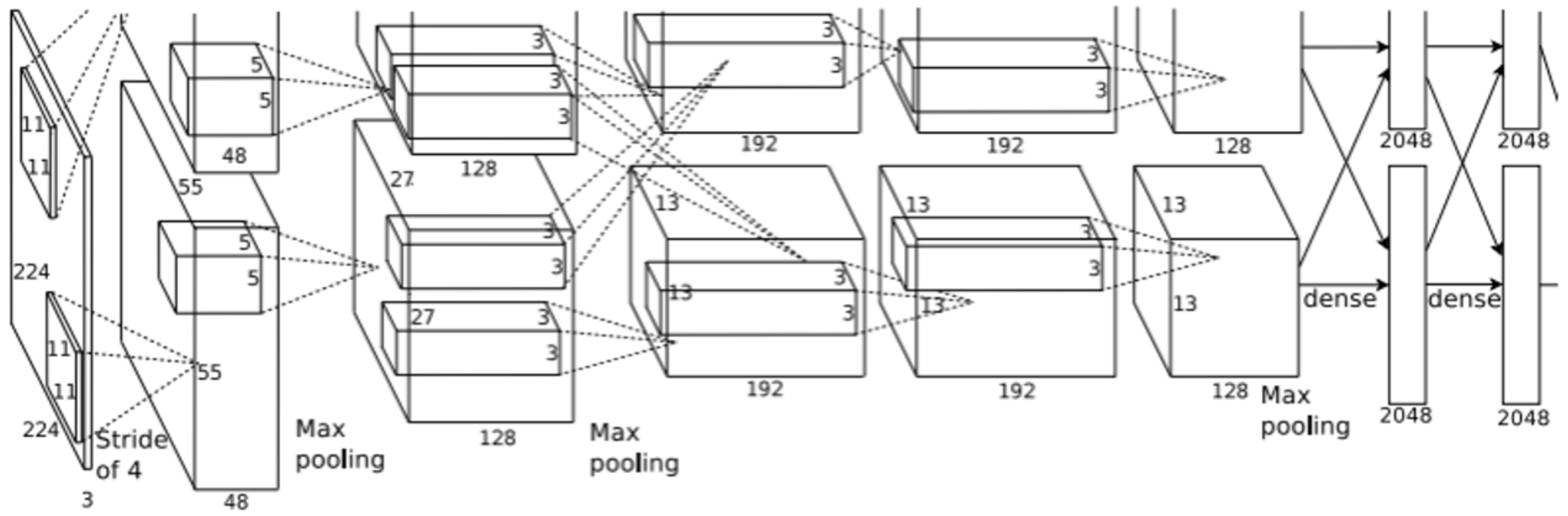
Chips: (x, y, w, h)
Chips: (x, y, w, h)
.....

Many numbers!

Need different numbers of output per image

Detecting Multiple Objects: Sliding Window

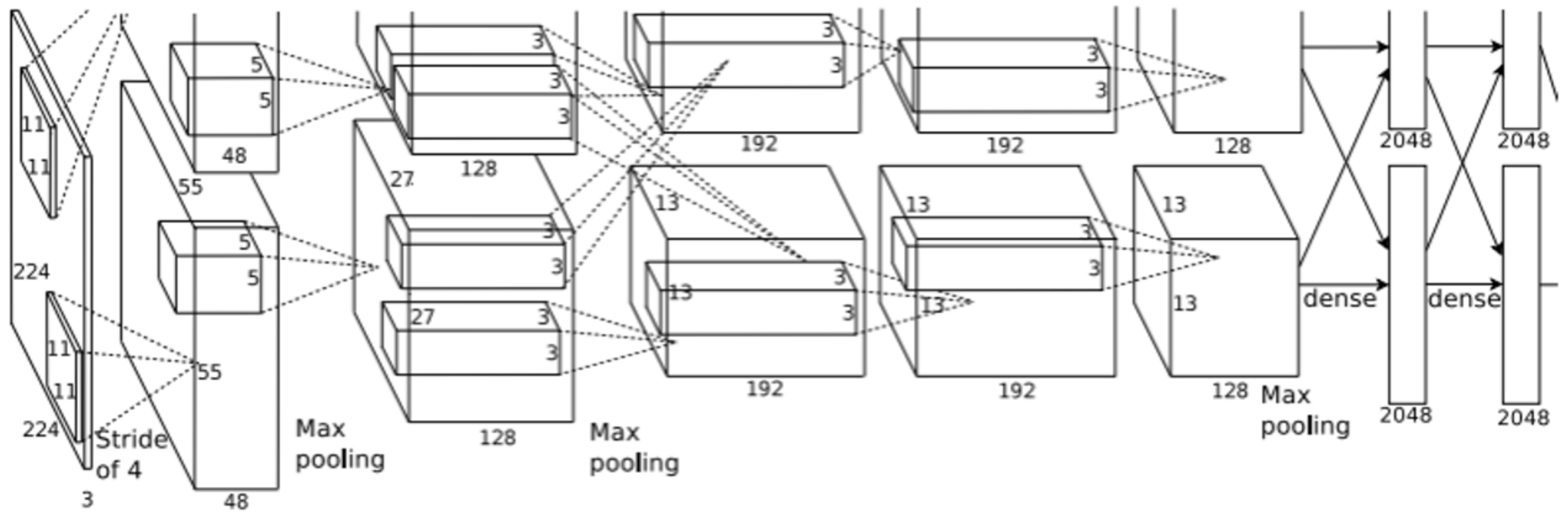
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Hershey's: No
Flipz: No
Reese's: No
Background: Yes

Detecting Multiple Objects: Sliding Window

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



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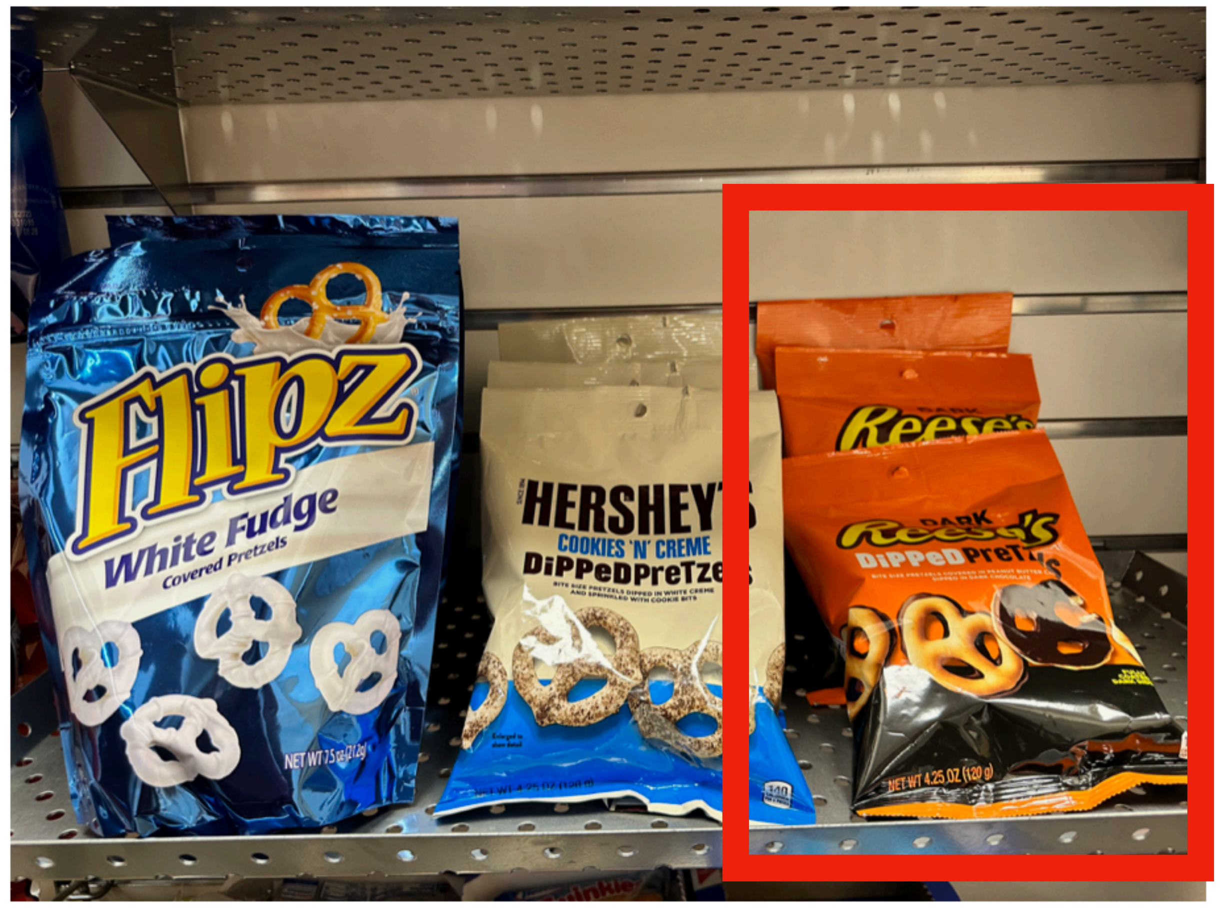

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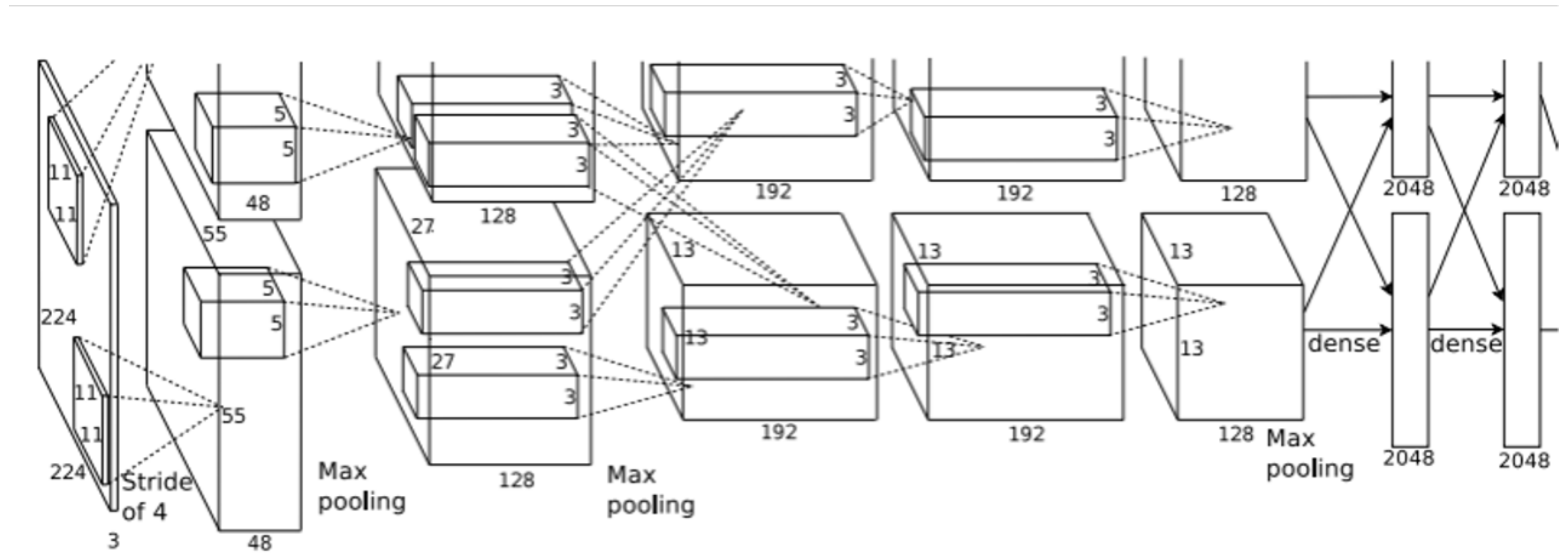

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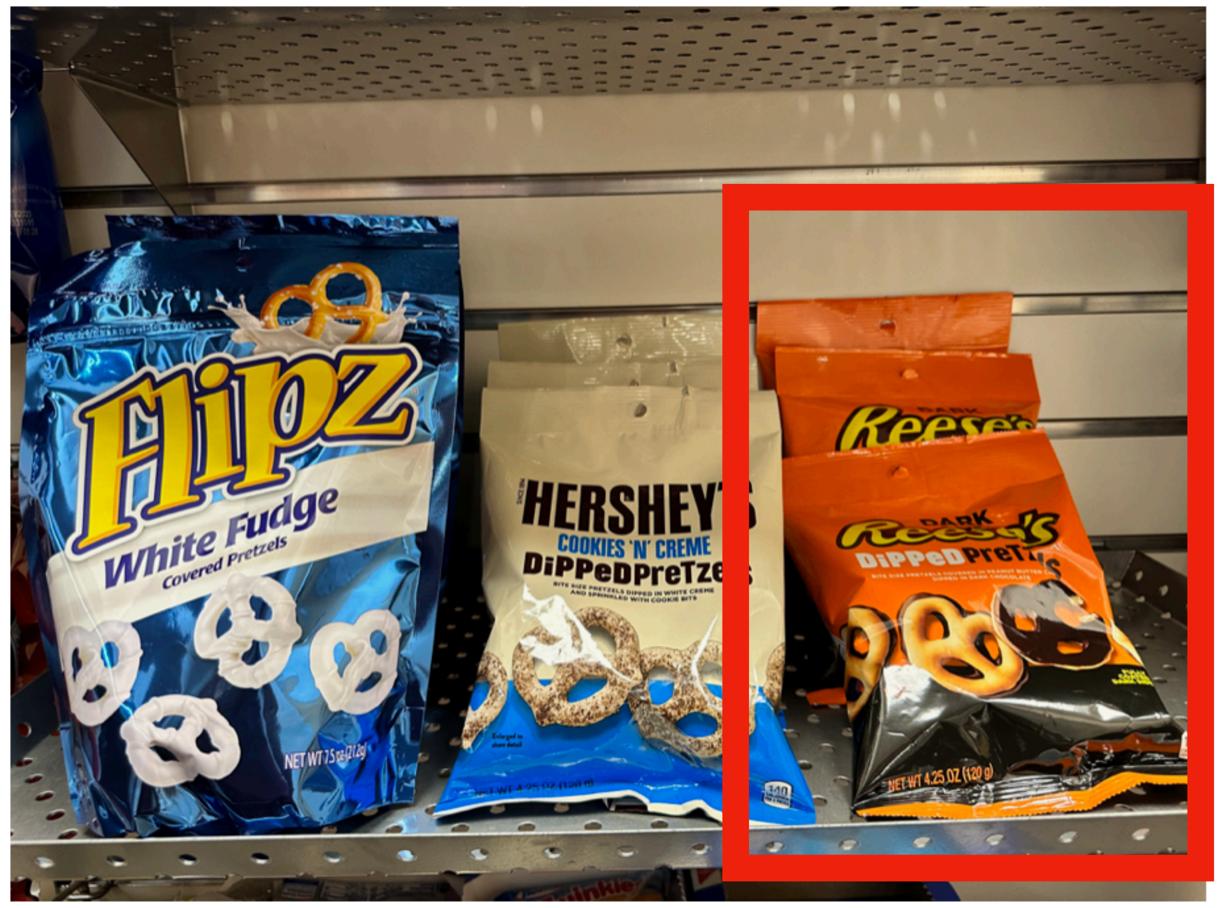


Question: How many possible boxes are there in an image of size H x W?

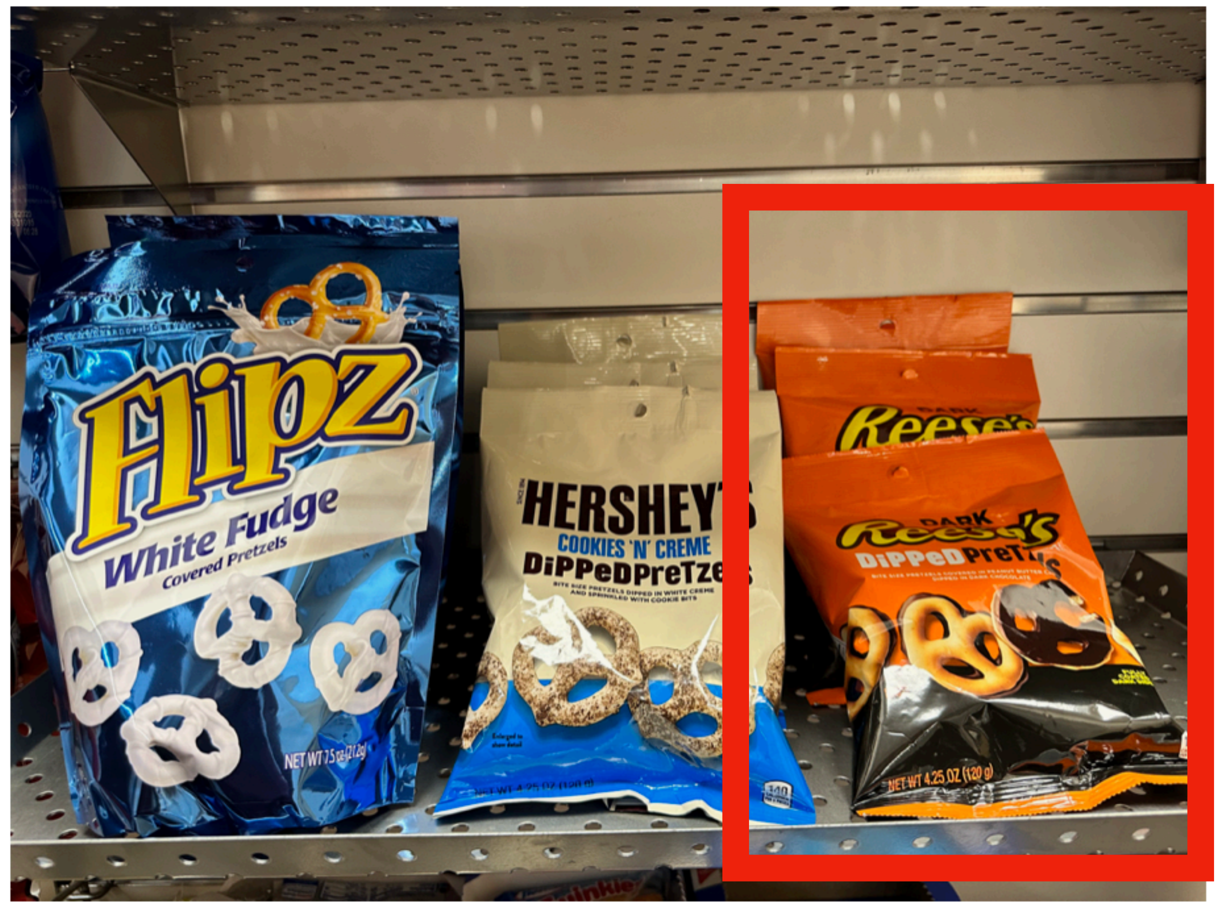
Consider box of size h x w:
Possible x positions: W - w + 1
Possible y positions: H - h + 1
Possible positions:
(W-w+1) x (H-h+1)

Total possible boxes:

$$\sum_{h=1}^{H} \sum_{w=1}^{W} (W - w + 1)(H - h + 1)$$

$$= \frac{H(H+1)}{2} \frac{W(W+1)}{2}$$

Detecting Multiple Objects: Sliding Window



Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

800 x 600 image has ~58M boxes. No way we can evaluate them all

Question: How many possible boxes are there in an image of size H x W?

Consider box of size h x w:
Possible x positions: W - w + 1
Possible y positions: H - h + 1
Possible positions:
(W-w+1) x (H-h+1)

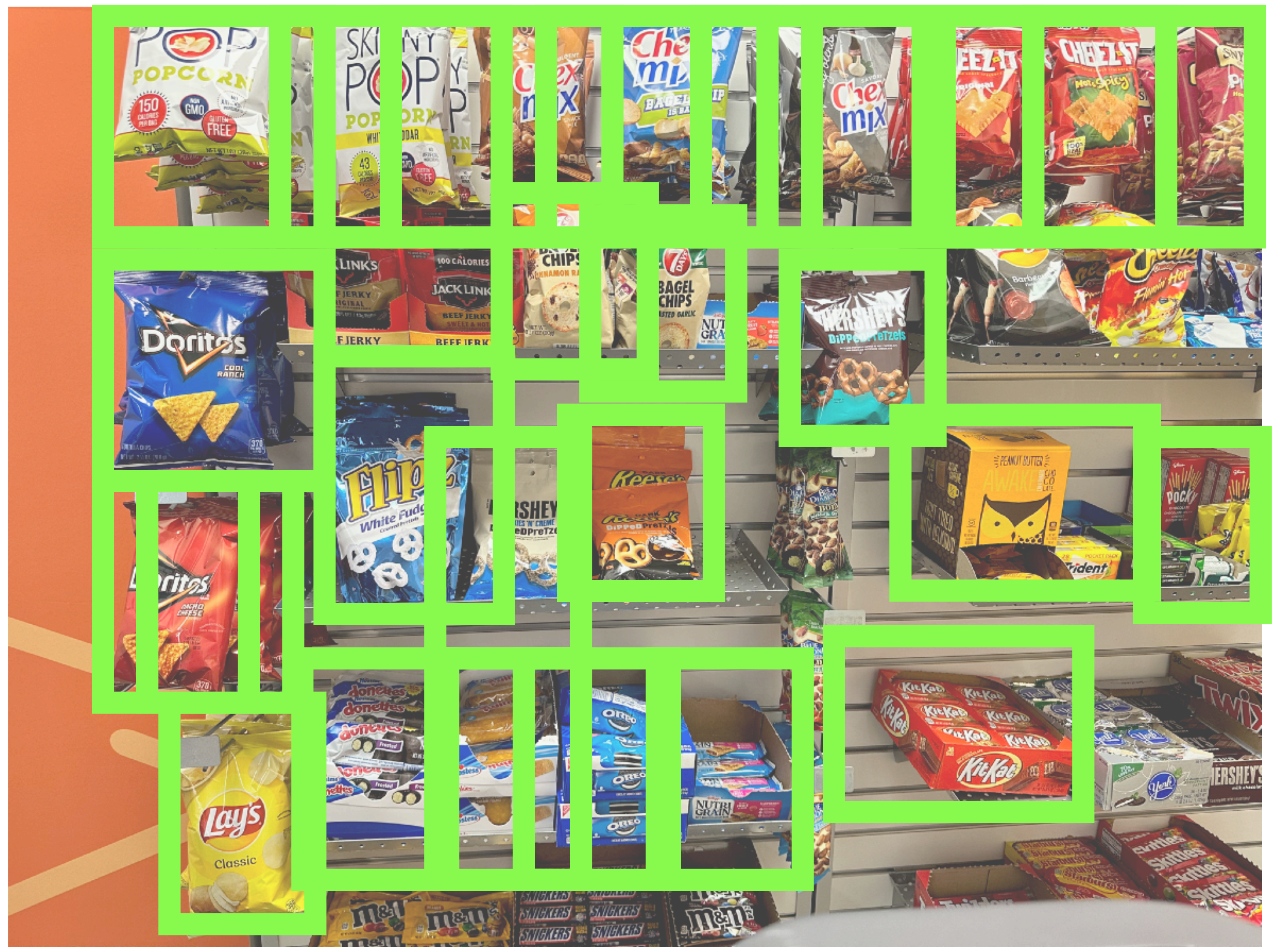
Total possible boxes:

$$\sum_{h=1}^{H} \sum_{w=1}^{W} (W - w + 1)(H - h + 1)$$

$$= \frac{H(H+1)}{2} \frac{W(W+1)}{2}$$

Region Proposals

- Find a small set of boxes that are likely to cover all objects
- Often based on heuristics: e.g. look for “blob-like” image regions
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”, ECCV 2014

R-CNN: Region-Based CNN

R-CNN: Region-Based CNN

Input image

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN: Region-Based CNN

R-CNN: Region-Based CNN

Input image

Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
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R-CNN: Region-Based CNN

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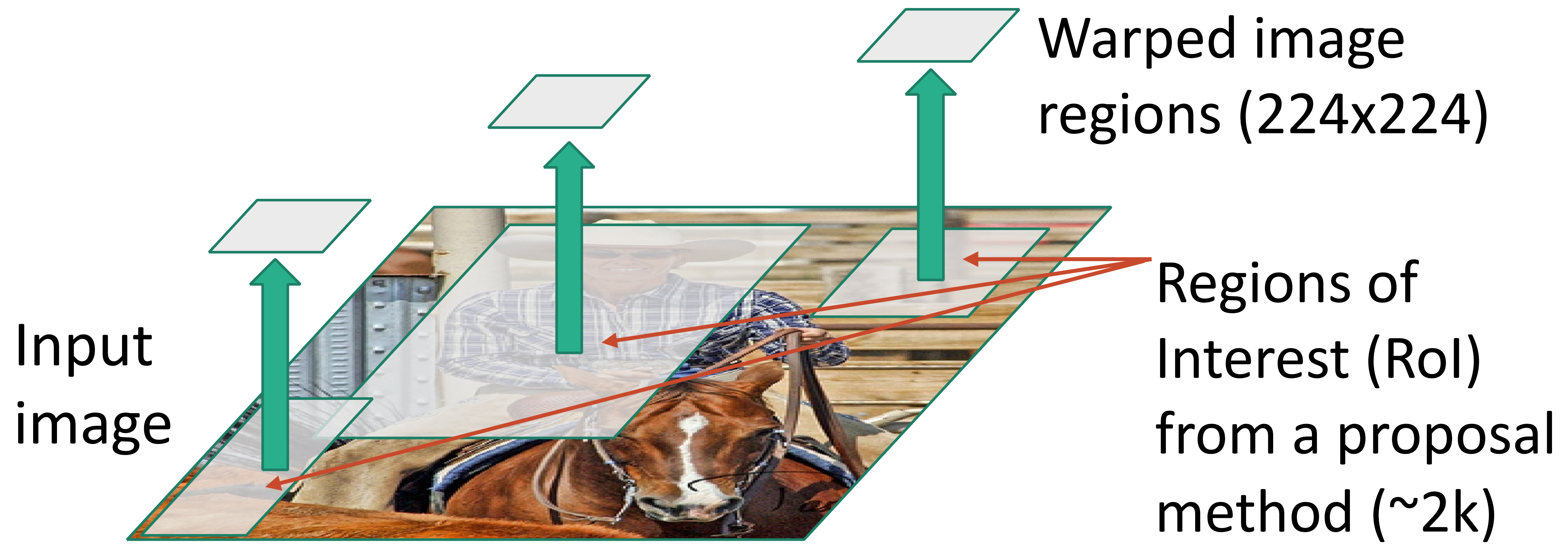

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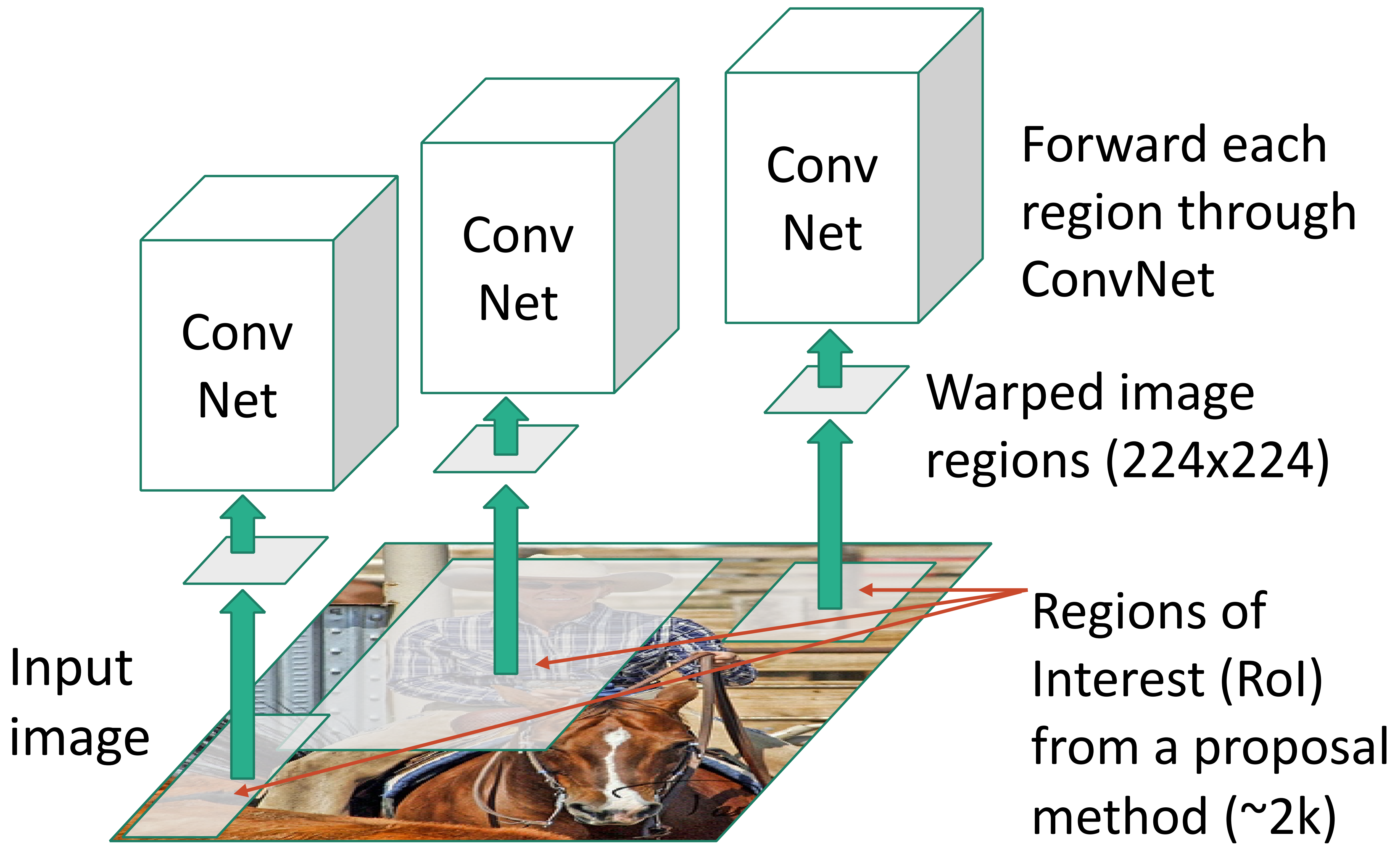

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R-CNN: Region-Based CNN

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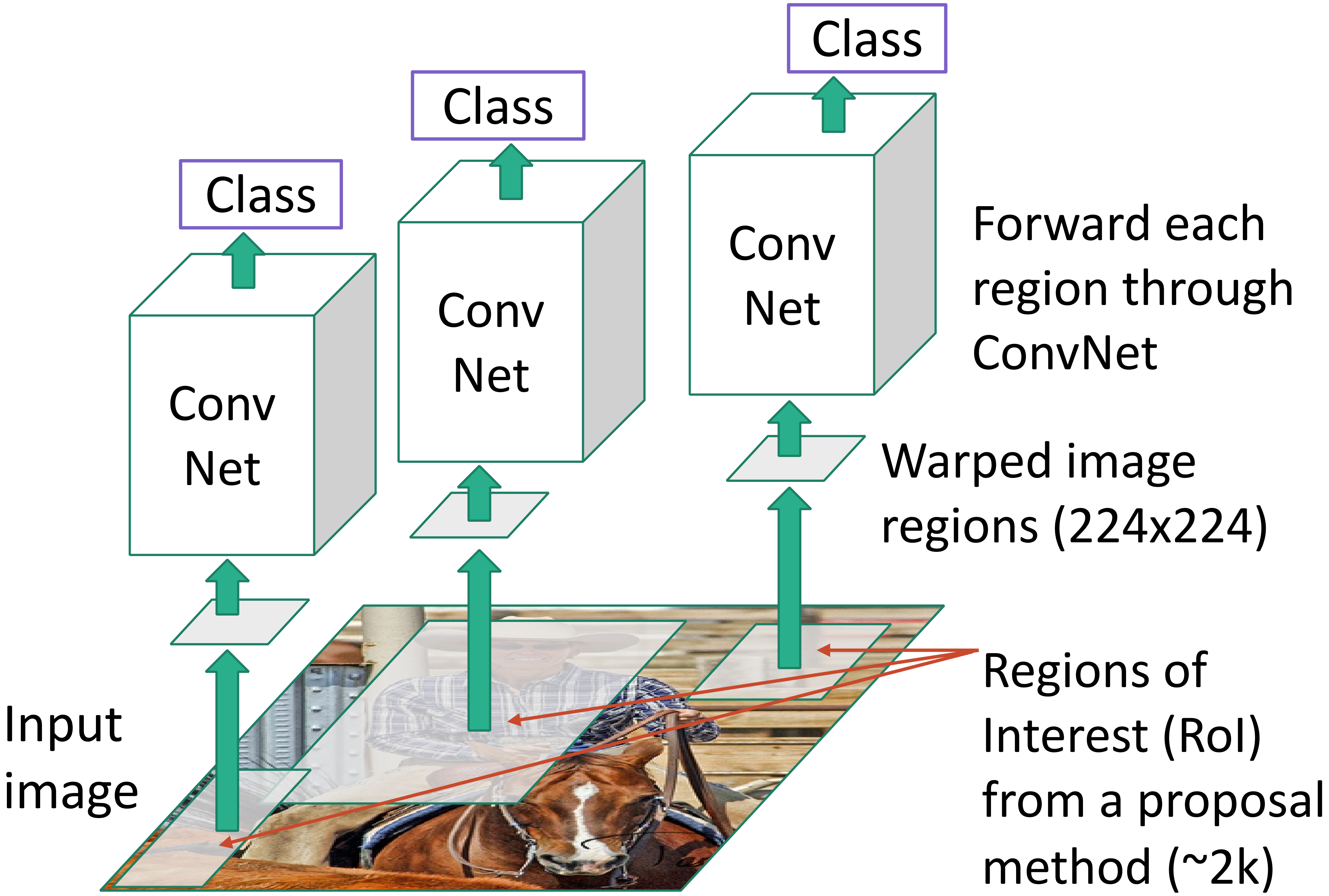

Classify each region

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN: Region-Based CNN

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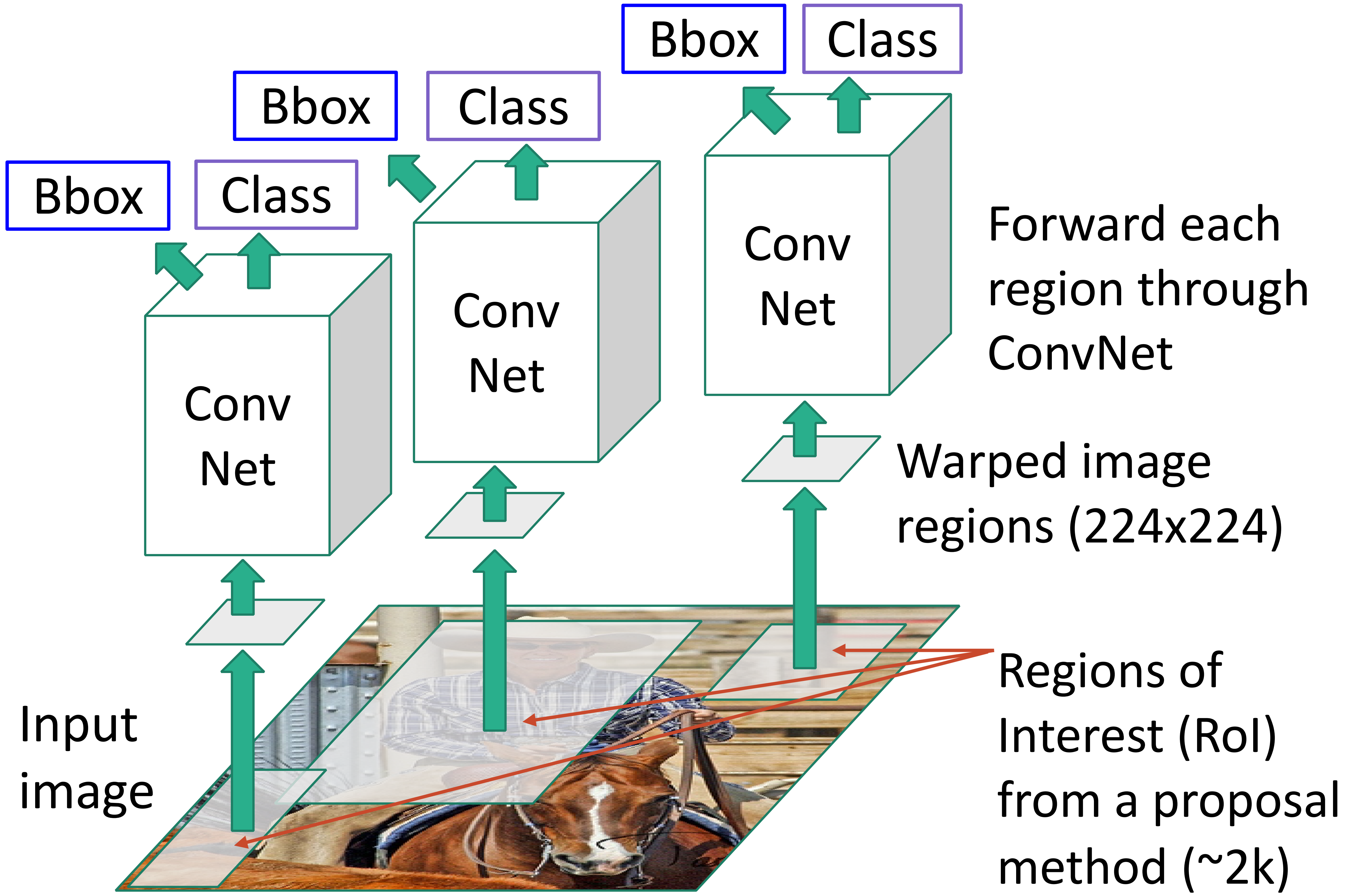
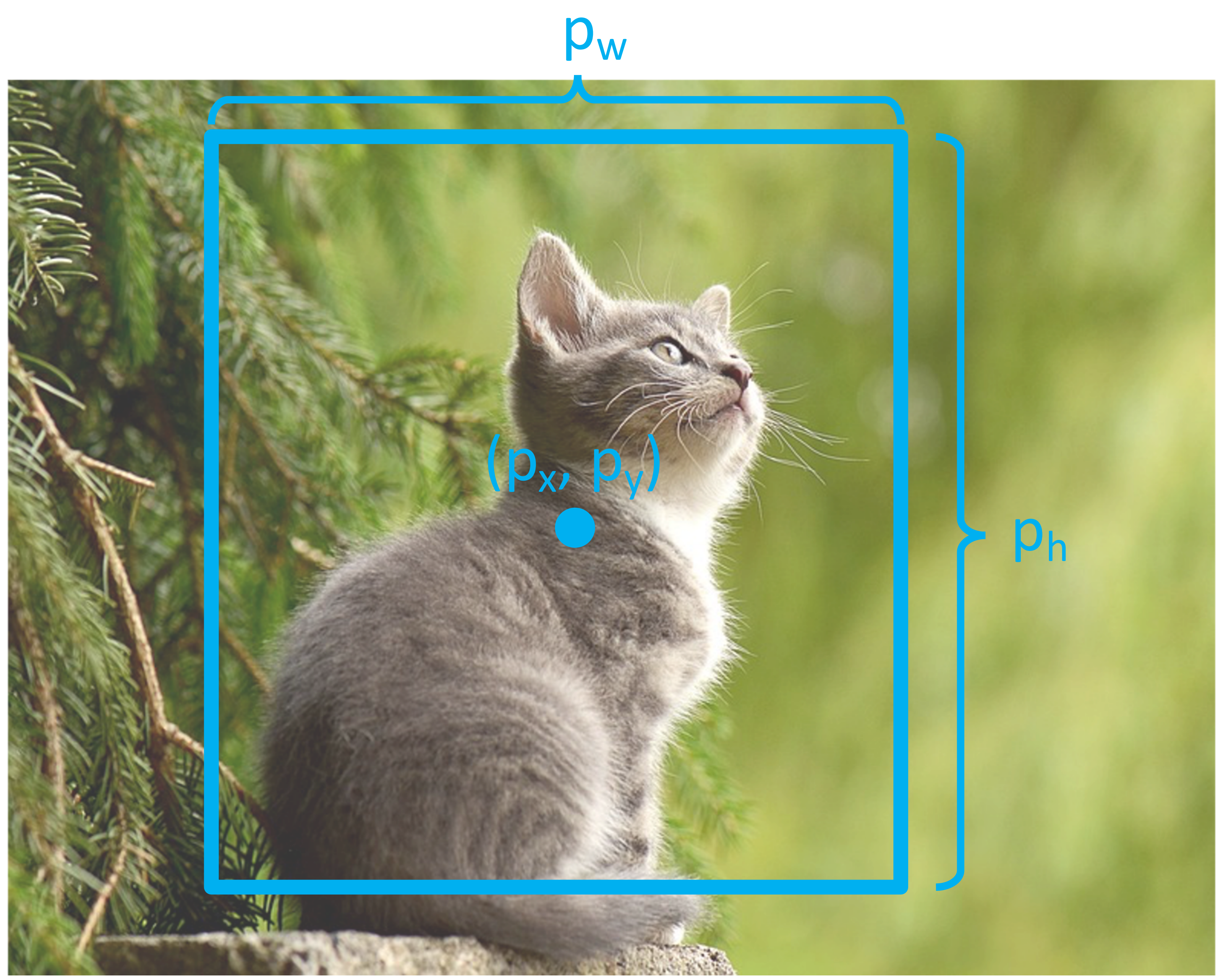


Classify each region

Bounding box regression:
Predict "transform" to correct the RoI: 4 numbers (t_x, t_y, t_h, t_w)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

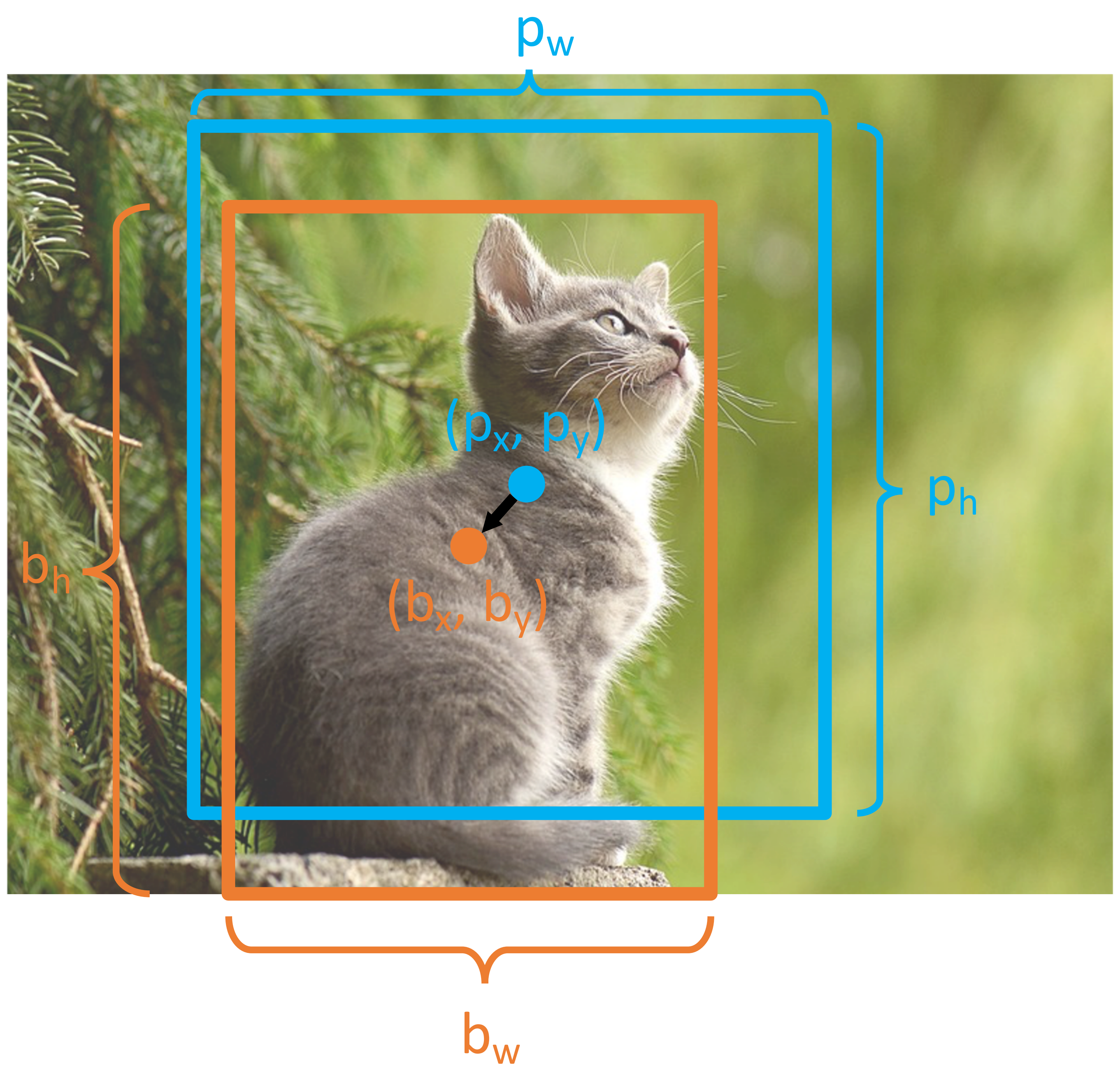
R-CNN: Box Regression



Consider a region proposal with center (p_x, p_y), width p_w, height p_h

Model predicts a transform (t_x, t_y, t_w, t_h) to correct the region proposal

R-CNN: Box Regression



Consider a region proposal with center (p_x, p_y), width p_w, height p_h

Model predicts a transform (t_x, t_y, t_w, t_h) to correct the region proposal

The output box is defined by:

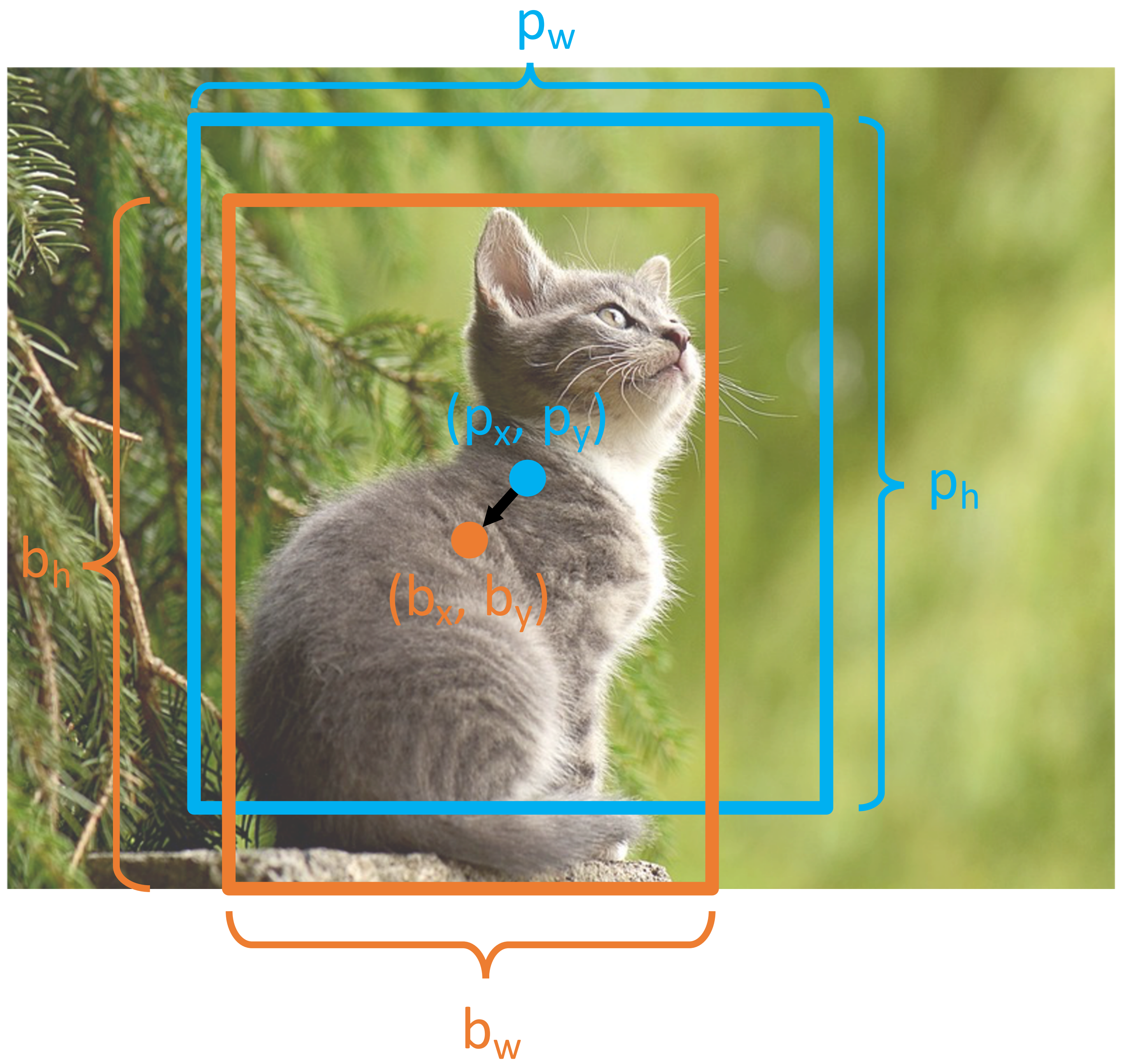
$$b_x = p_x + p_w t_x$$
$$b_y = p_y + p_h t_y$$

Shift center by amount relative to proposal size

$$b_w = p_w \exp(t_w)$$
$$b_h = p_h \exp(t_h)$$

Scale proposal; exp ensures that scaling factor is > 0

R-CNN: Box Regression



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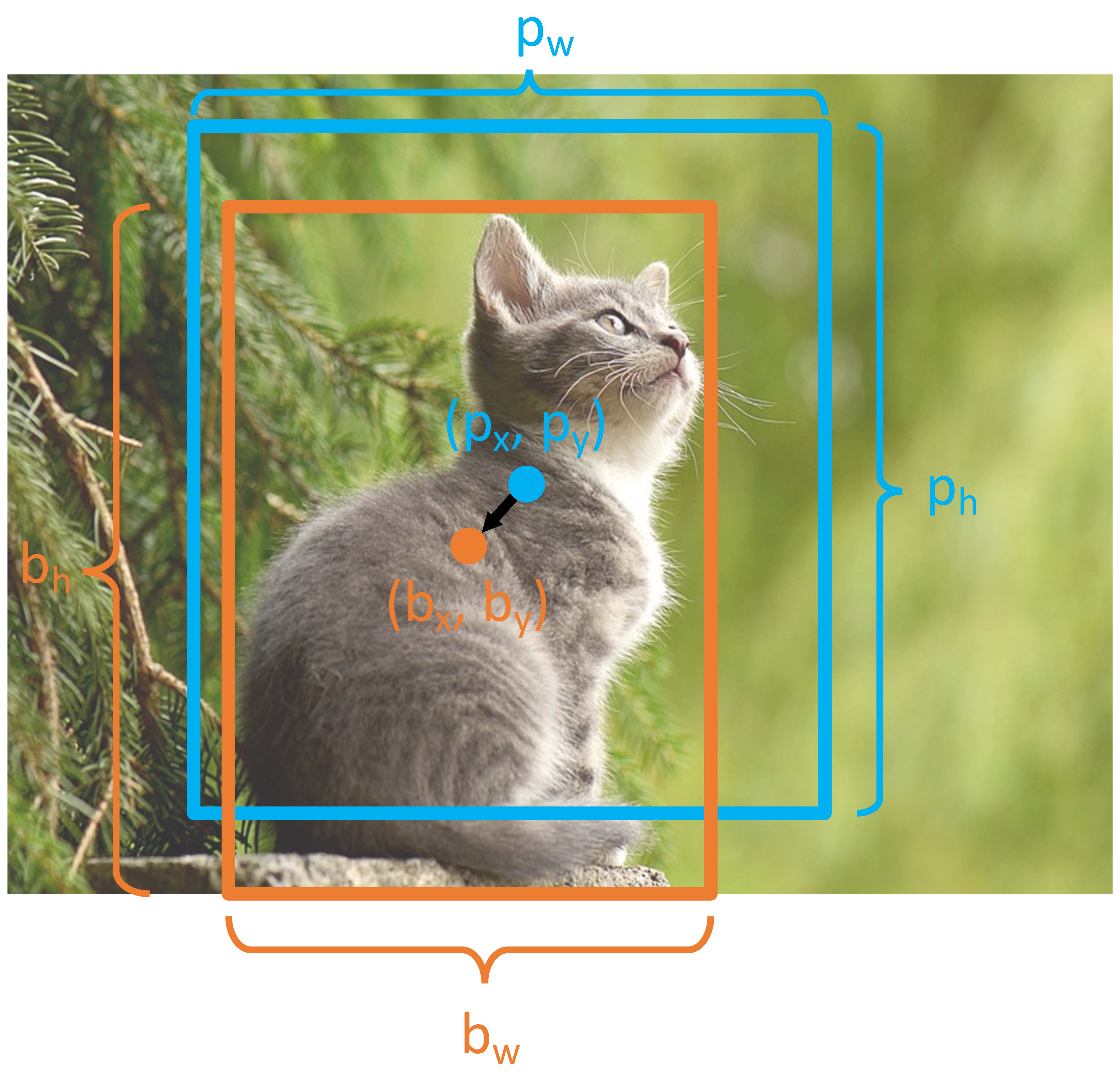
$$b_y = p_y + p_h t_y$$
$$b_w = p_w \exp(t_w)$$
$$b_h = p_h \exp(t_h)$$

When transform is 0, output = proposal

L2 regularization encourages leaving proposal unchanged

R-CNN: Box Regression



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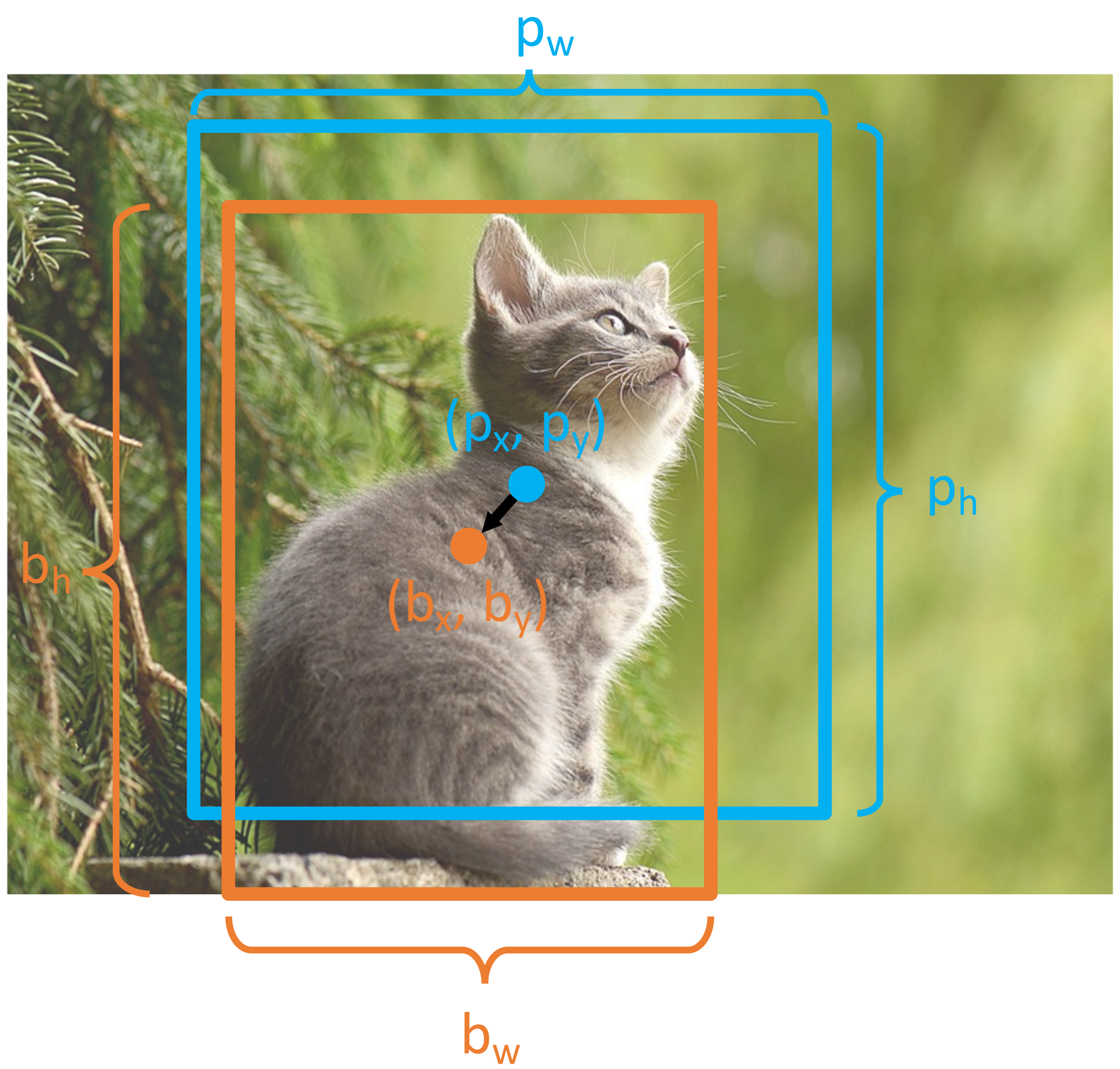
Scale / Translation invariance: Transform encodes *relative* difference between proposal and output; important since CNN doesn't see absolute size or position after cropping

R-CNN: Box Regression



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$$b_w = p_w \exp(t_w)$$
$$b_h = p_h \exp(t_h)$$

Given proposal and target output, we can solve for the transform the network should output:

$$t_x = (b_x - p_x)/p_w$$
$$t_y = (b_y - p_y)/p_h$$
$$t_w = \log(b_w/p_w)$$
$$t_h = \log(b_h/p_h)$$

R-CNN: Training

Input Image

Ground Truth

R-CNN: Training

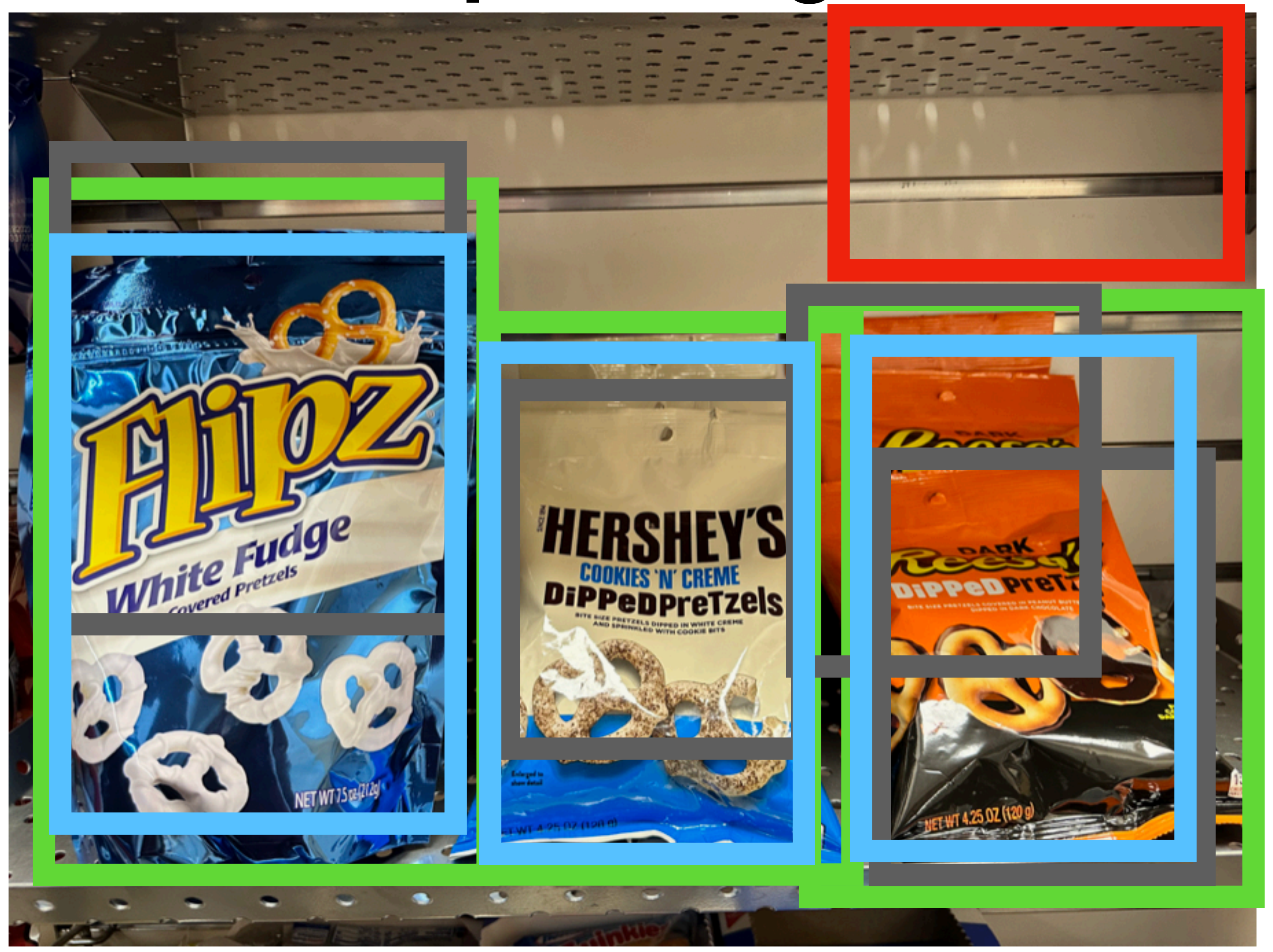
Input Image

Ground Truth

Region Proposals

R-CNN: Training

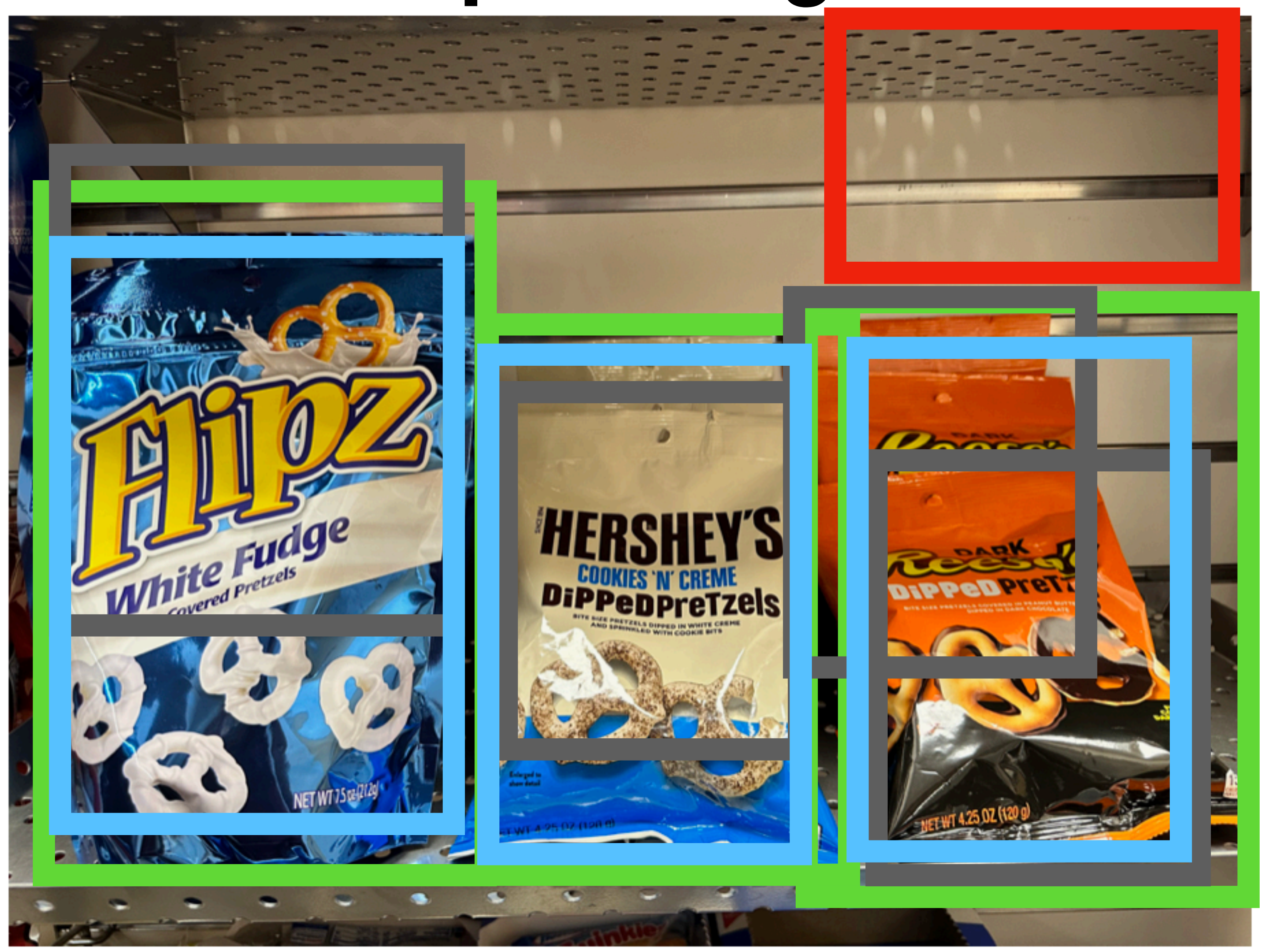
Input Image



Ground Truth	Positive
Neutral	Negative

R-CNN: Training

Input Image



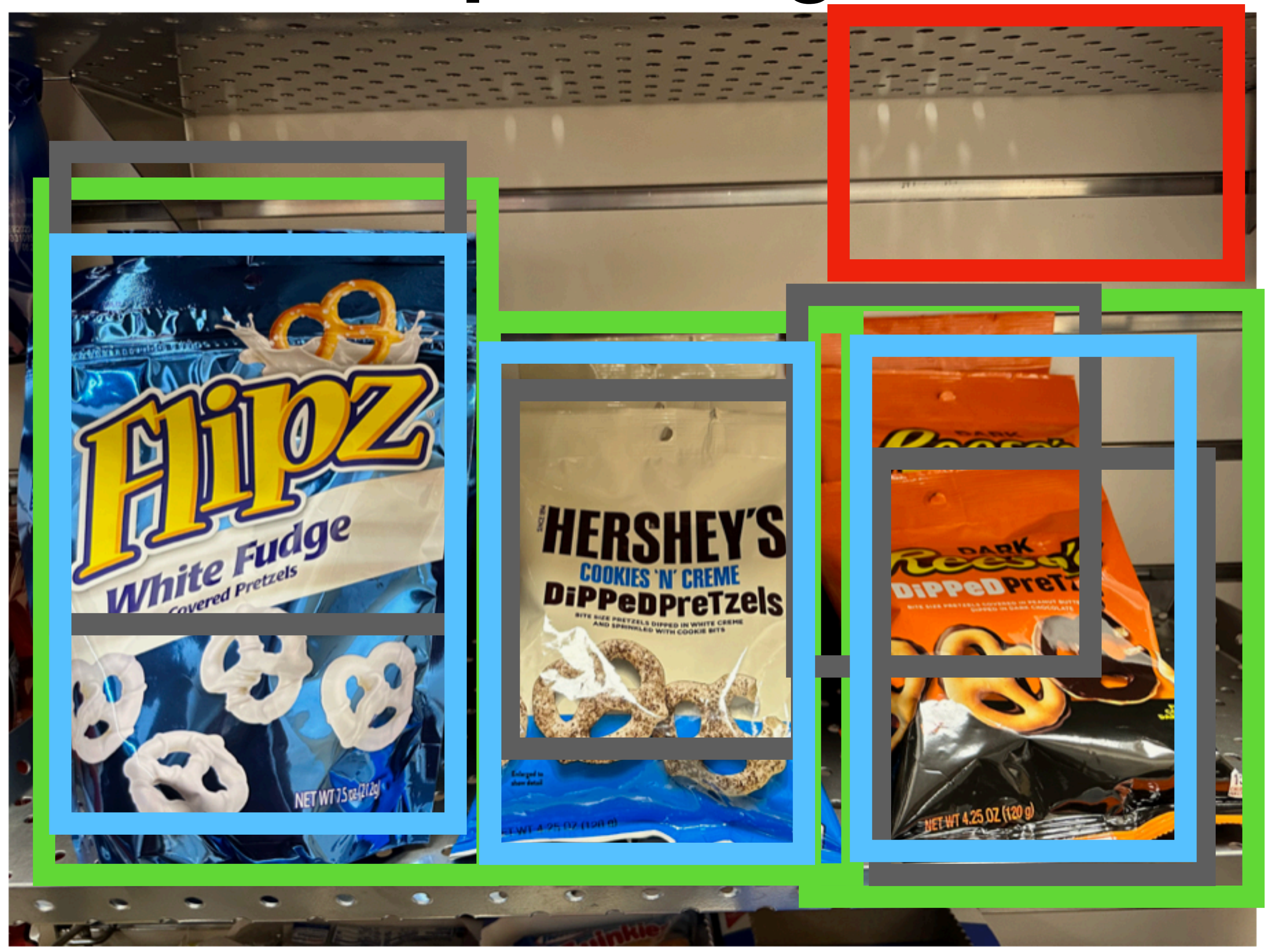
Ground Truth	Positive
Neutral	Negative

Categorize each region proposal as positive, negative or neutral based on overlap with the Ground truth boxes:

Positive: > 0.5 IoU with a GT box
Negative: < 0.3 IoU with all GT boxes
Neutral: between 0.3 and 0.5 IoU with GT boxes

R-CNN: Training

Input Image



Ground Truth | Positive

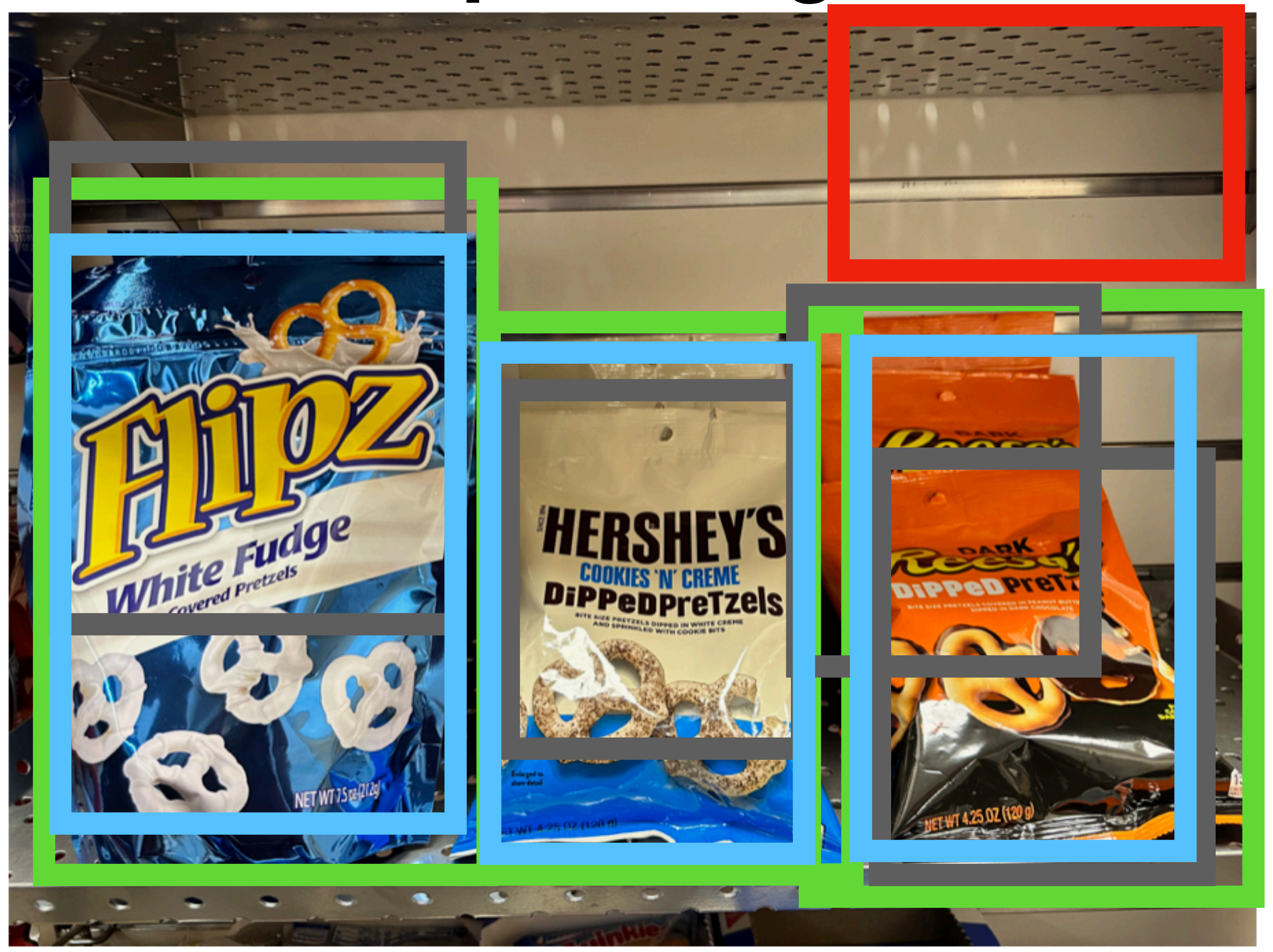
Neutral | Negative

Crop pixels from each positive and negative proposal, resize to 224 x 224

Run each region through CNN
Positive regions: predict class and transform
Negative regions: just predict class

R-CNN: Training

Input Image



Ground Truth	Positive
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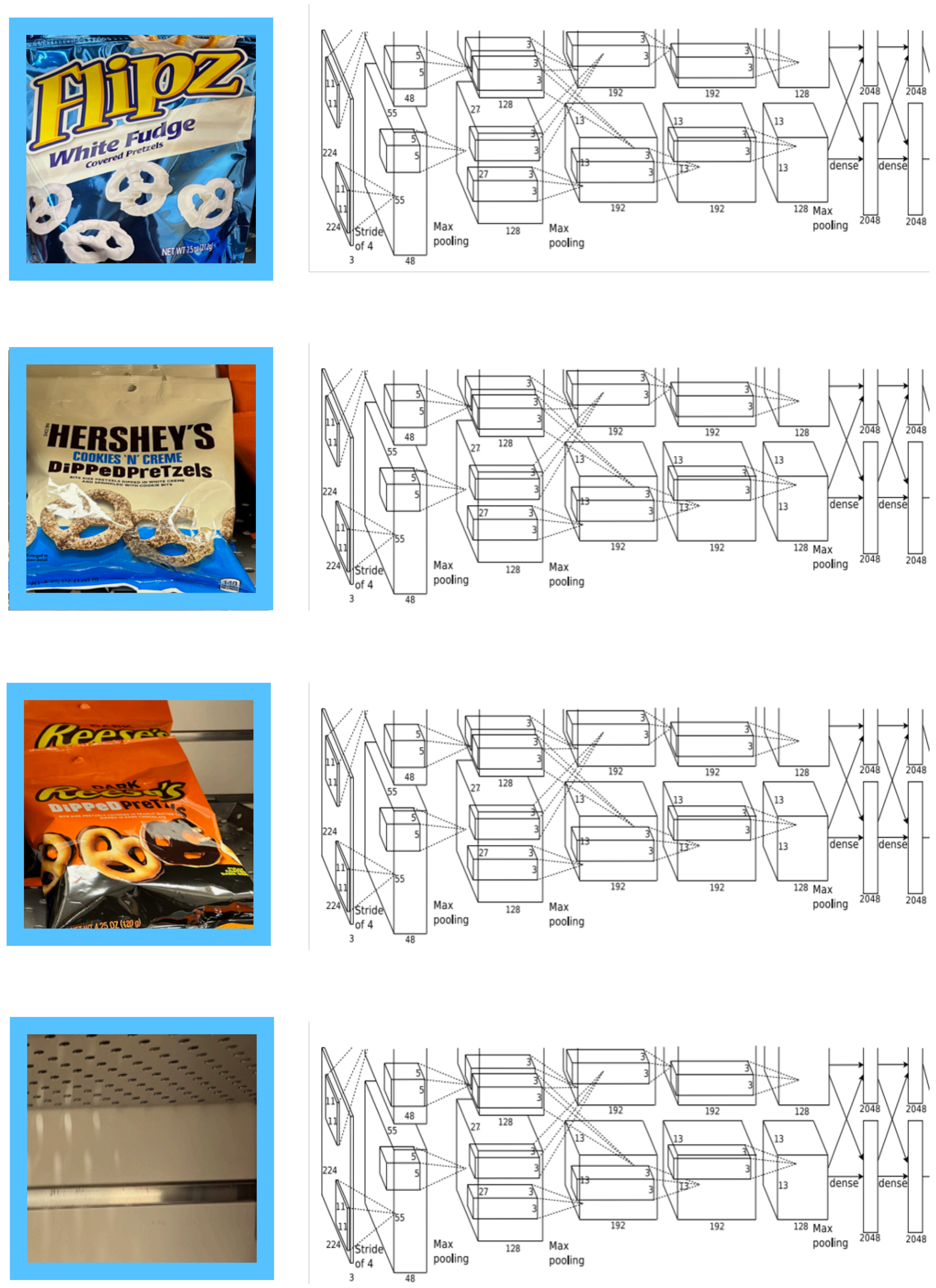

Class target: Flipz
Box target:

Class target: Hershey's
Box target:

Class target: Reese's
Box target:

Class target: Background
Box target: None

Run each region through CNN
Positive regions: predict class and transform
Negative regions: just predict class

R-CNN: Test time

Input Image

Region Proposals

Run proposal method:

1. Run CNN on each proposal to get class scores, transforms
2. Threshold class scores to get a set of detections

2 Problems:

1. CNN often outputs overlapping boxes
2. How to set thresholds?

Overlapping Boxes

Problem: Object detectors often output many overlapping detections

Overlapping Boxes: Non-Max Suppression (NMS)

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Solution: Post-process raw detections using Non-Max Suppression (NMS)

1. Select next highest-scoring box
2. Eliminate lower-scoring boxes with IoU> threshold (e.g. 0.7)
3. If any boxes remain, GOTO 1

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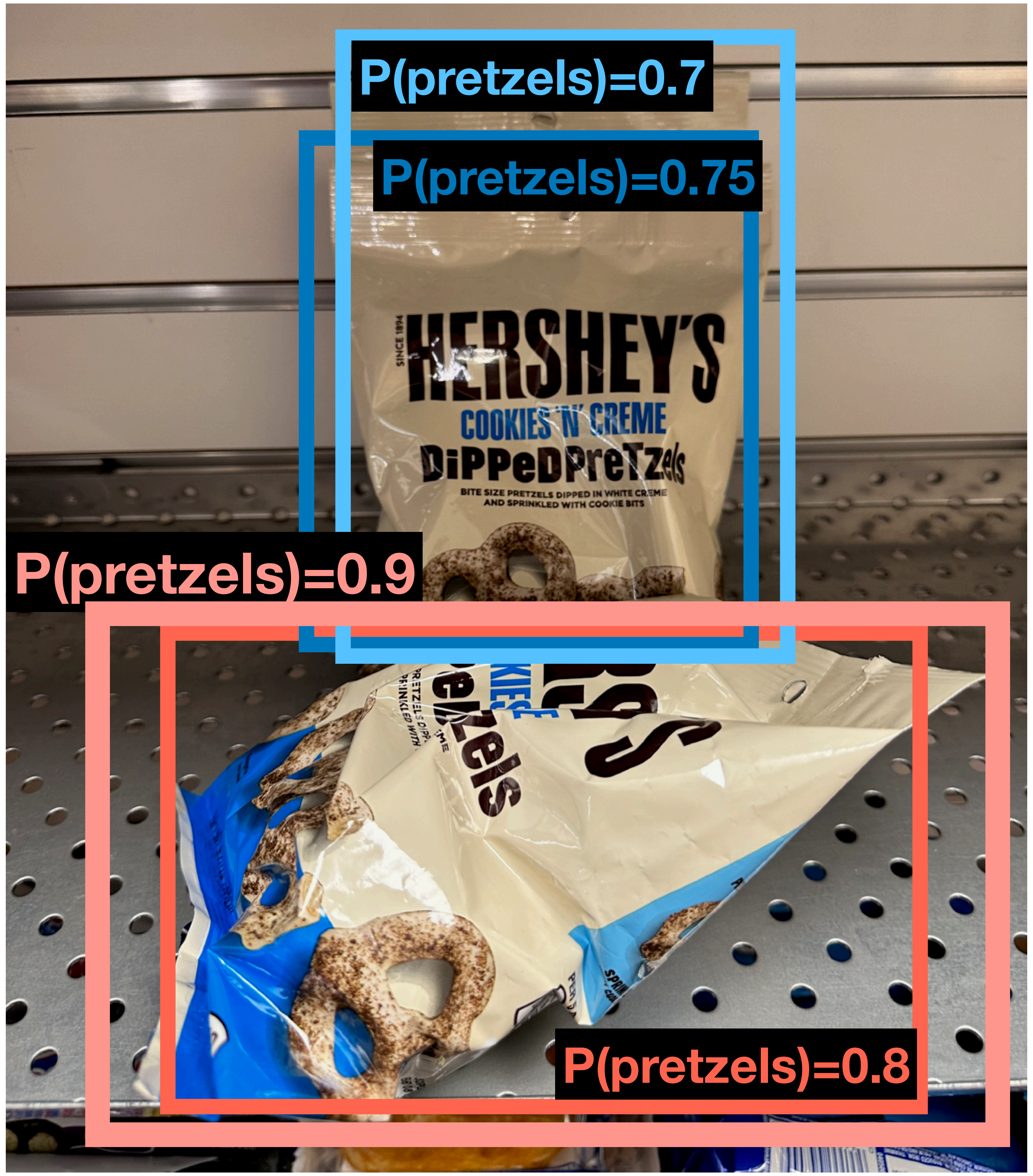
IoU(,) = 0.8
IoU(,) = 0.03
IoU(,) = 0.05



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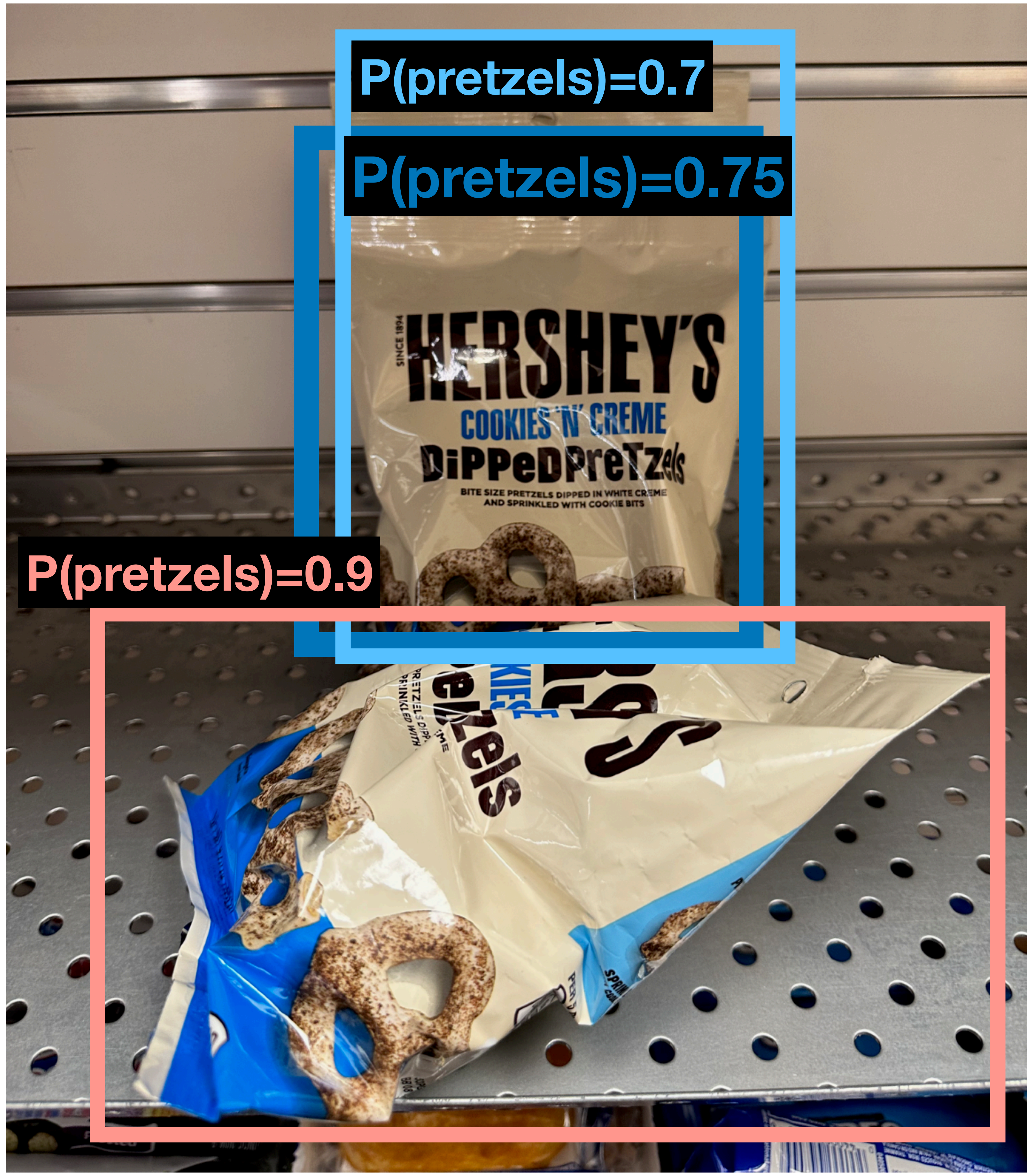
IoU(■, ■) = 0.85



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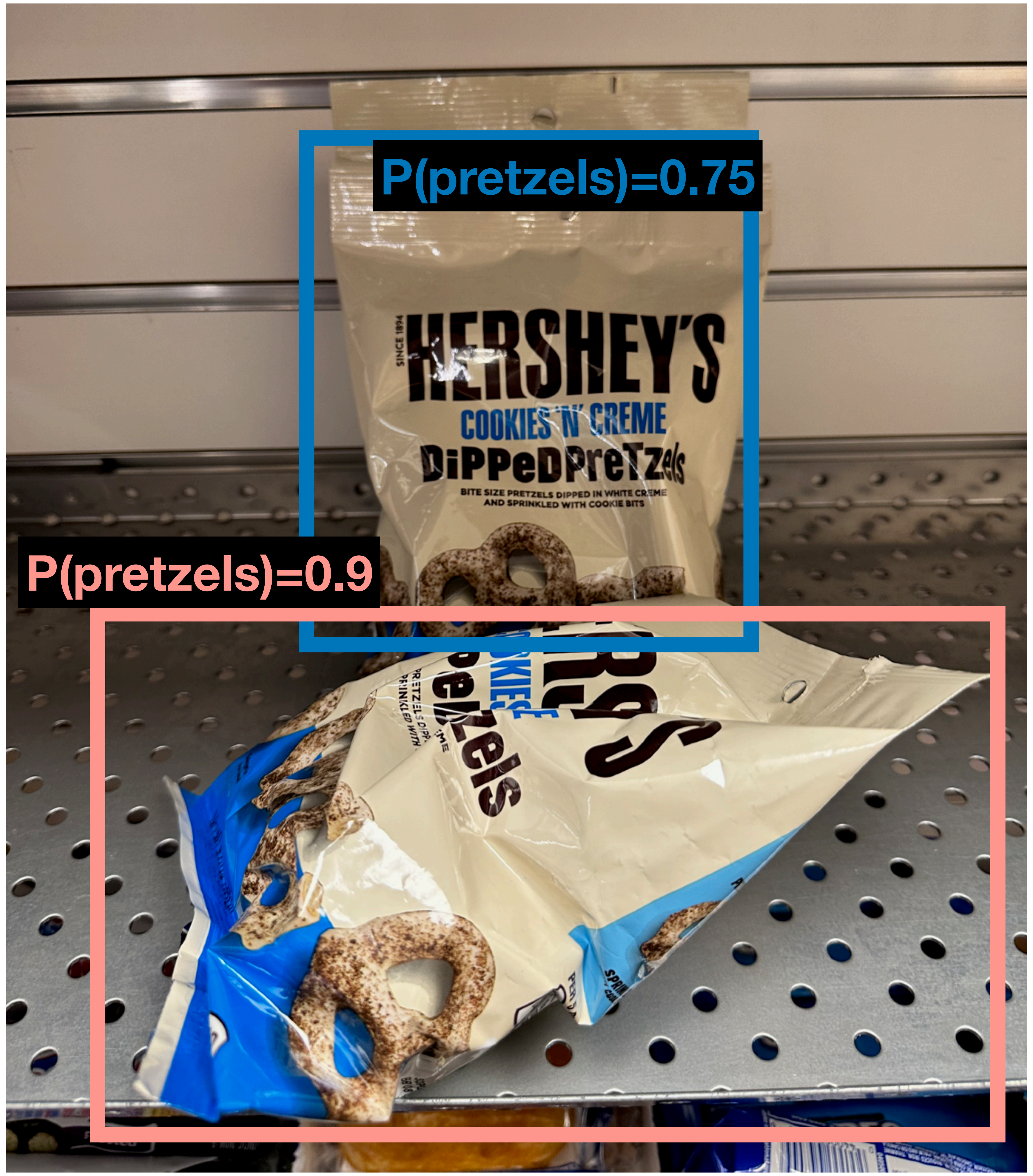

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Problem: NMS may eliminate "good" boxes when objects are highly overlapping… no good solution

Evaluating Object Detectors: Mean Average Precision (mAP)

1. Run object detector on all test images (with NMS)
2. For each category, compute Average Precision (AP) = area under Precision vs Recall Curve

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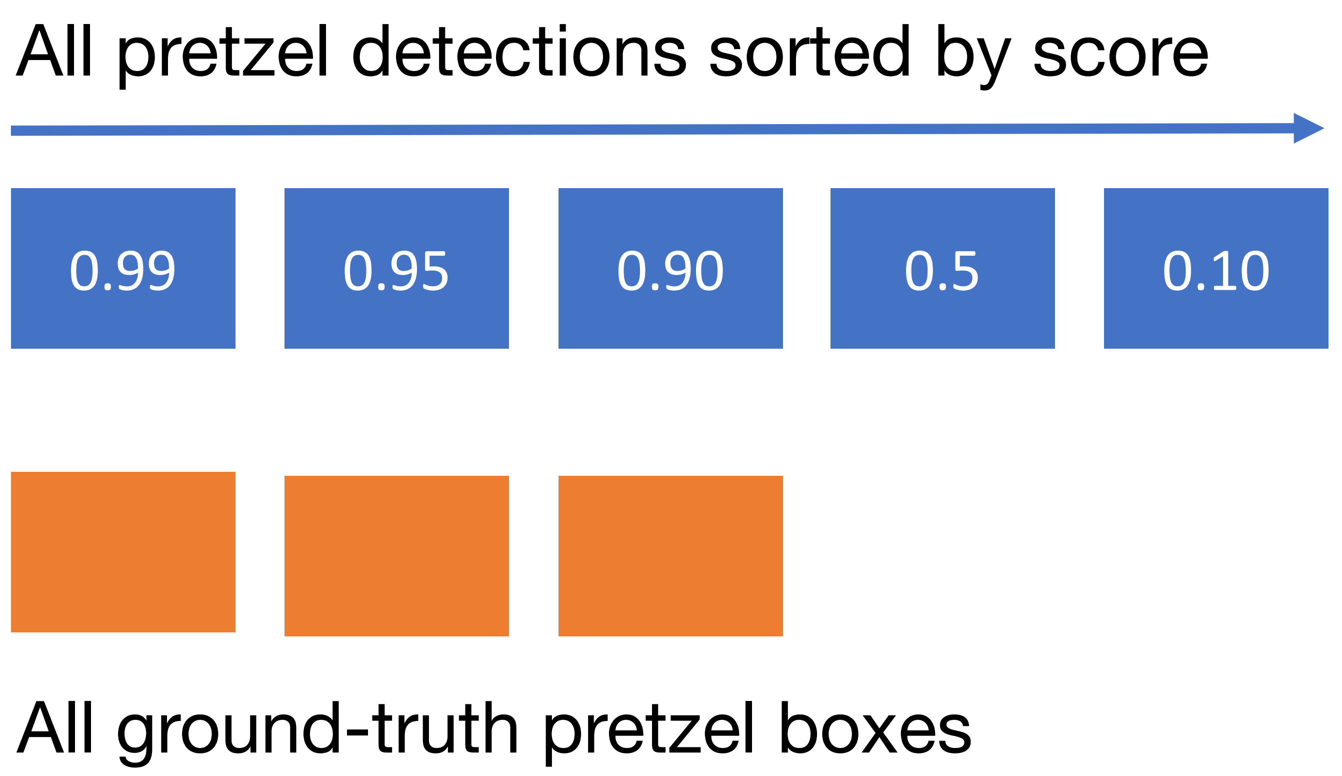

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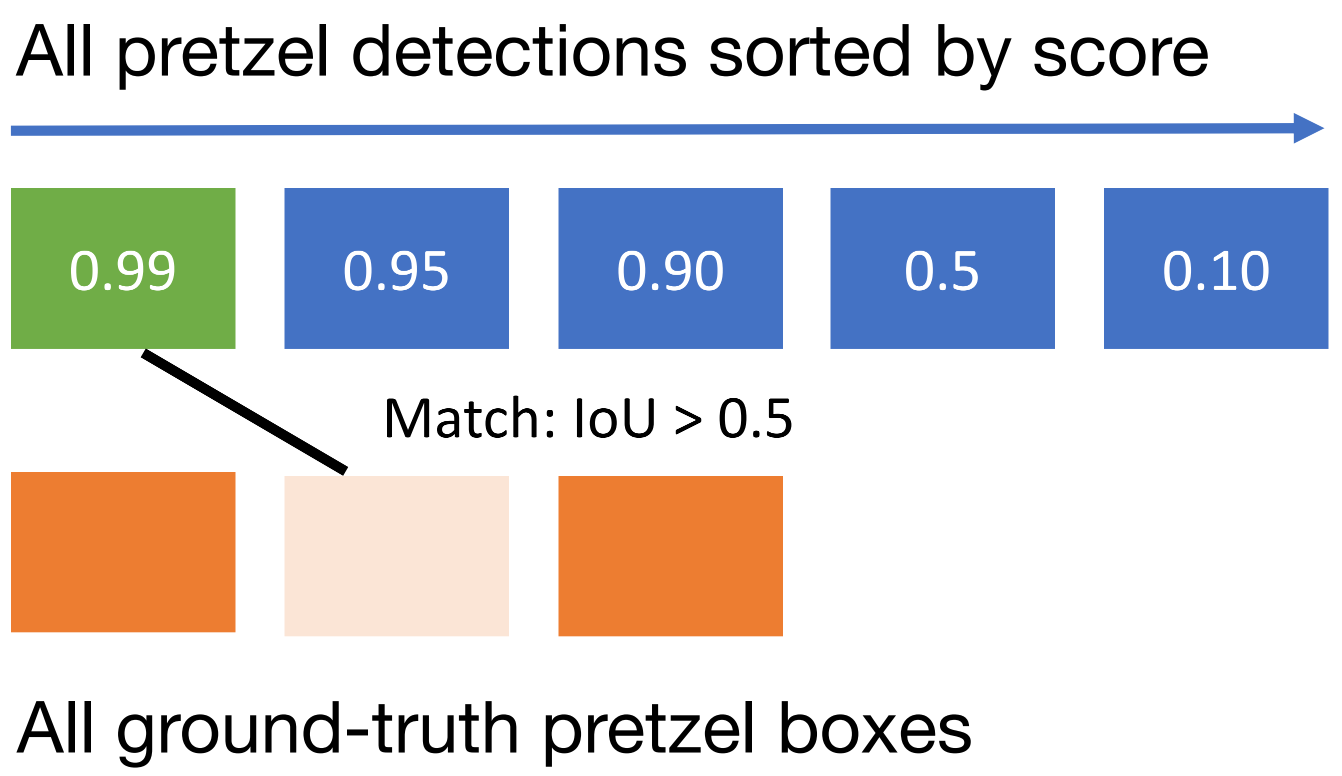

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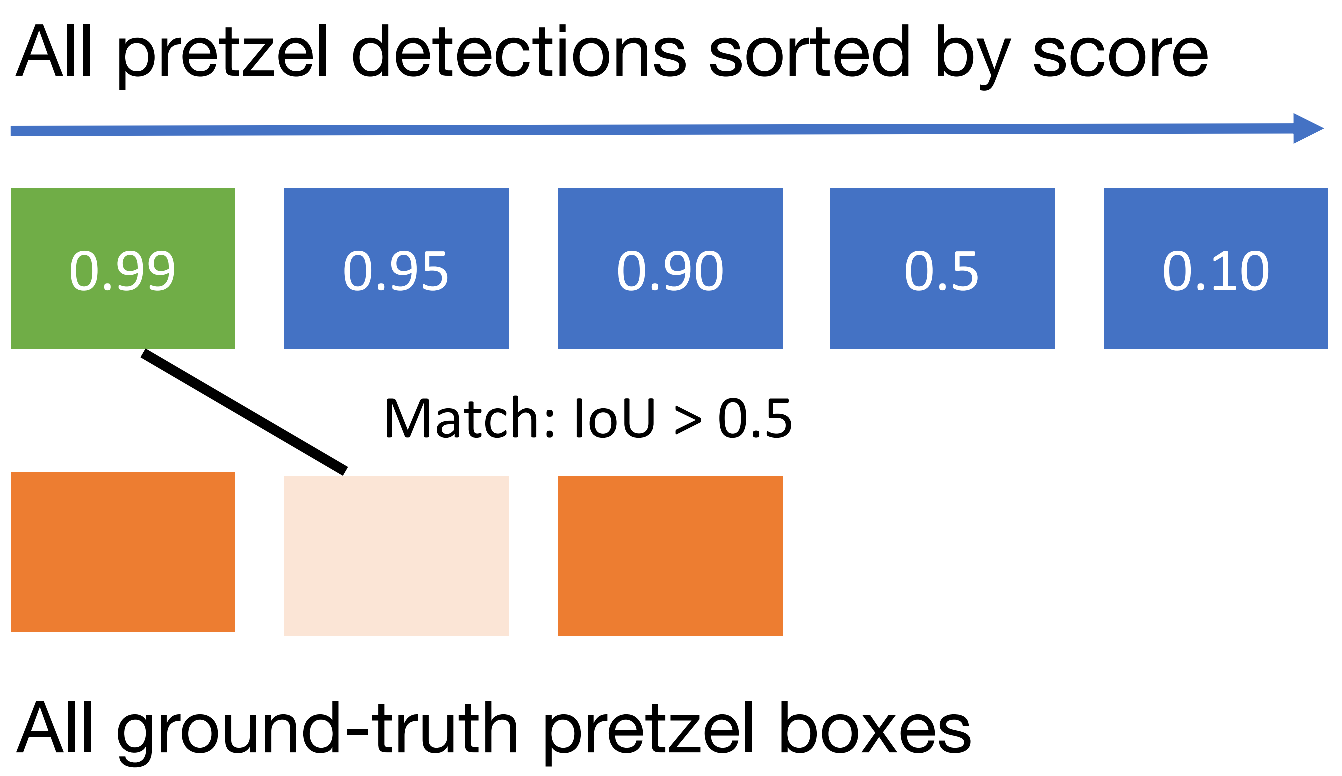
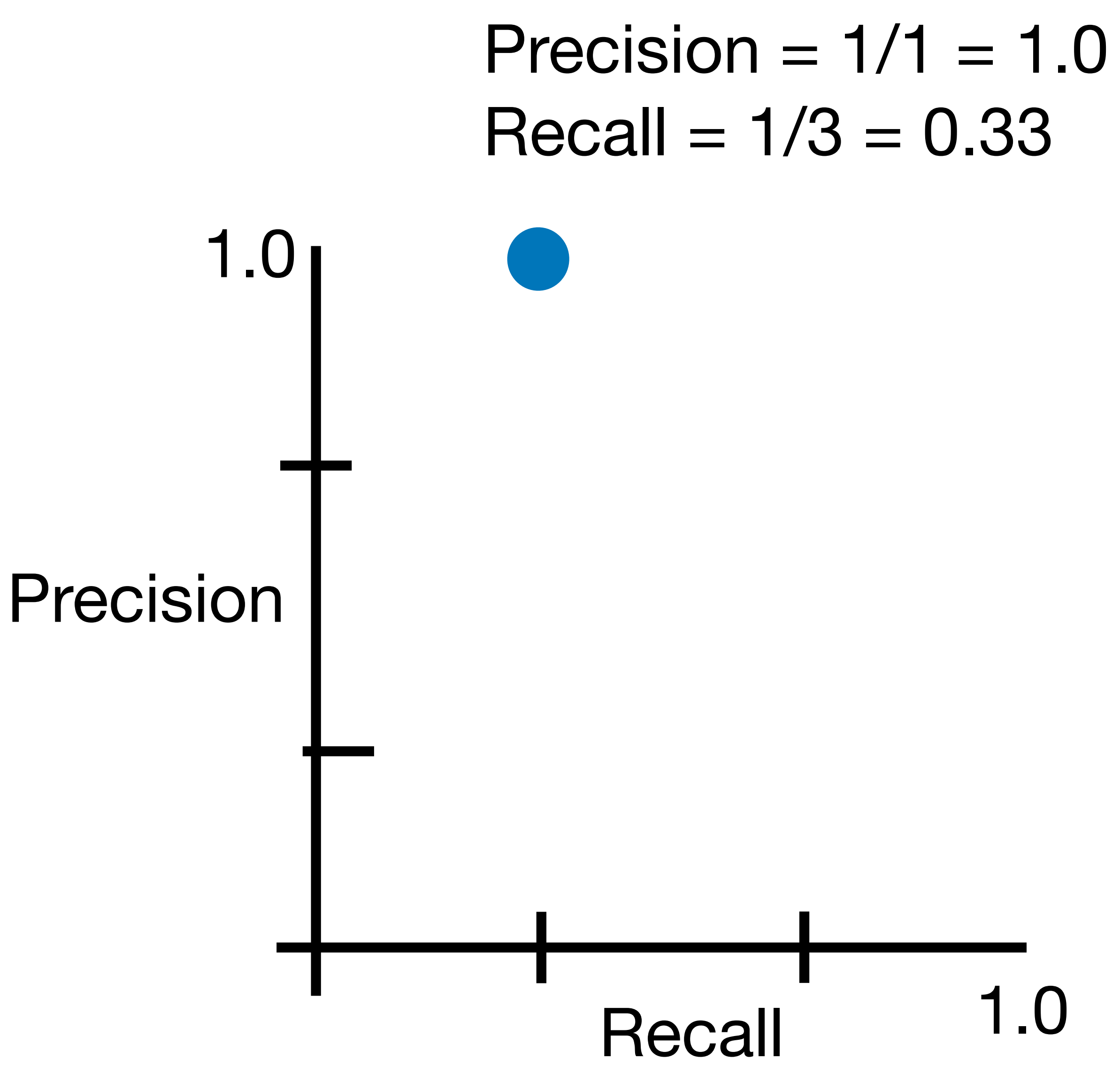
      3. Plot a point on PR curve





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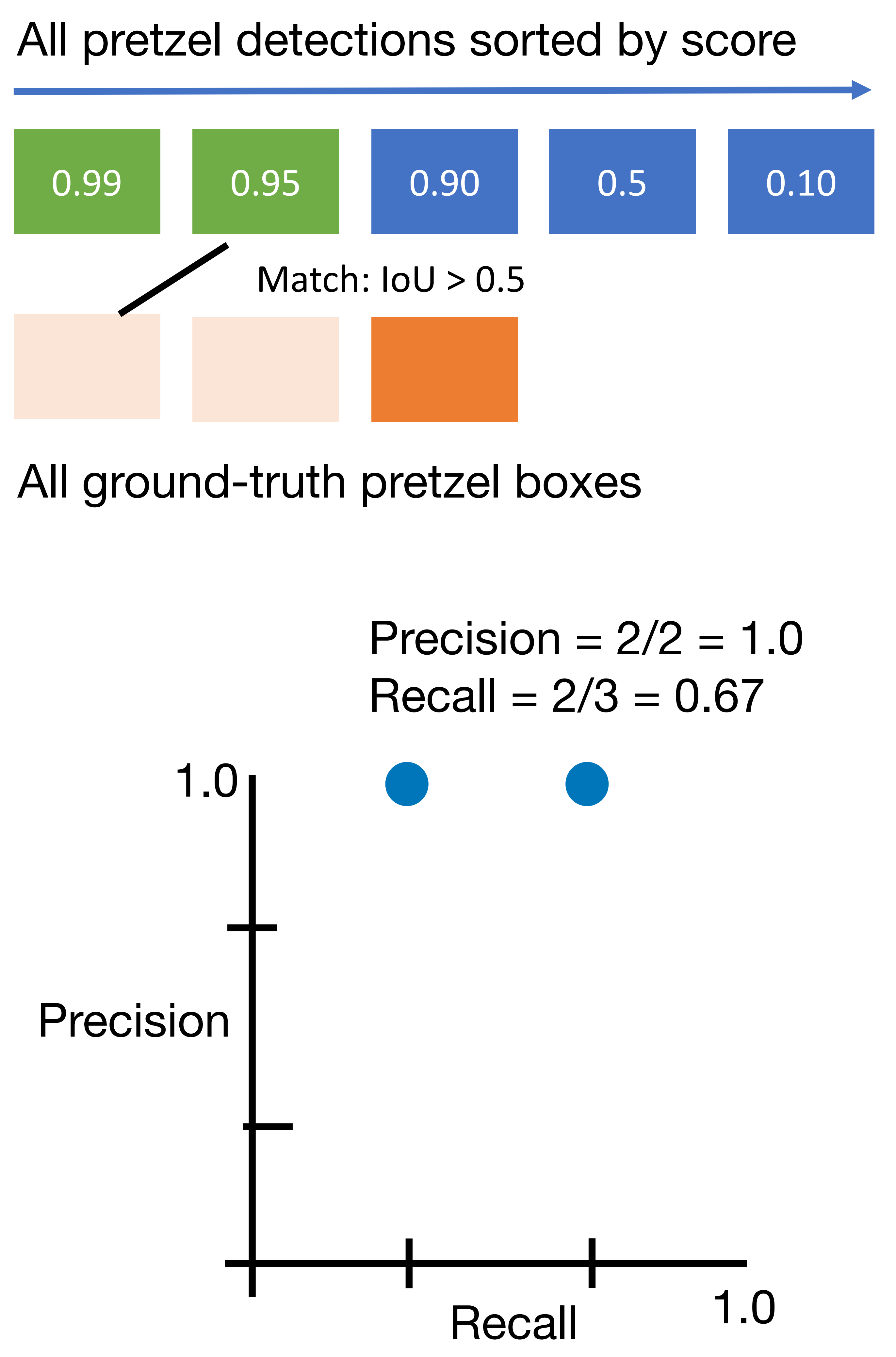

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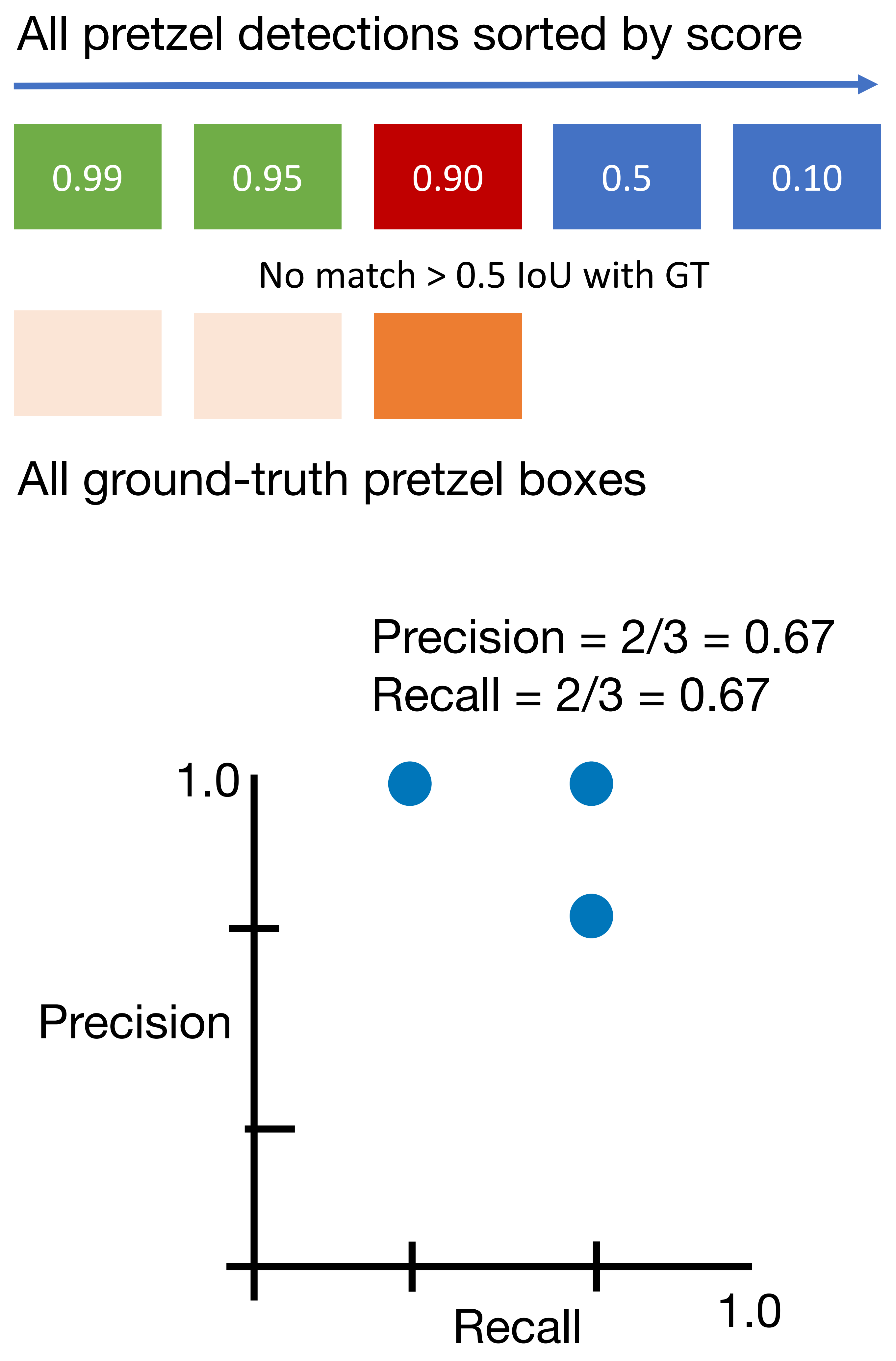

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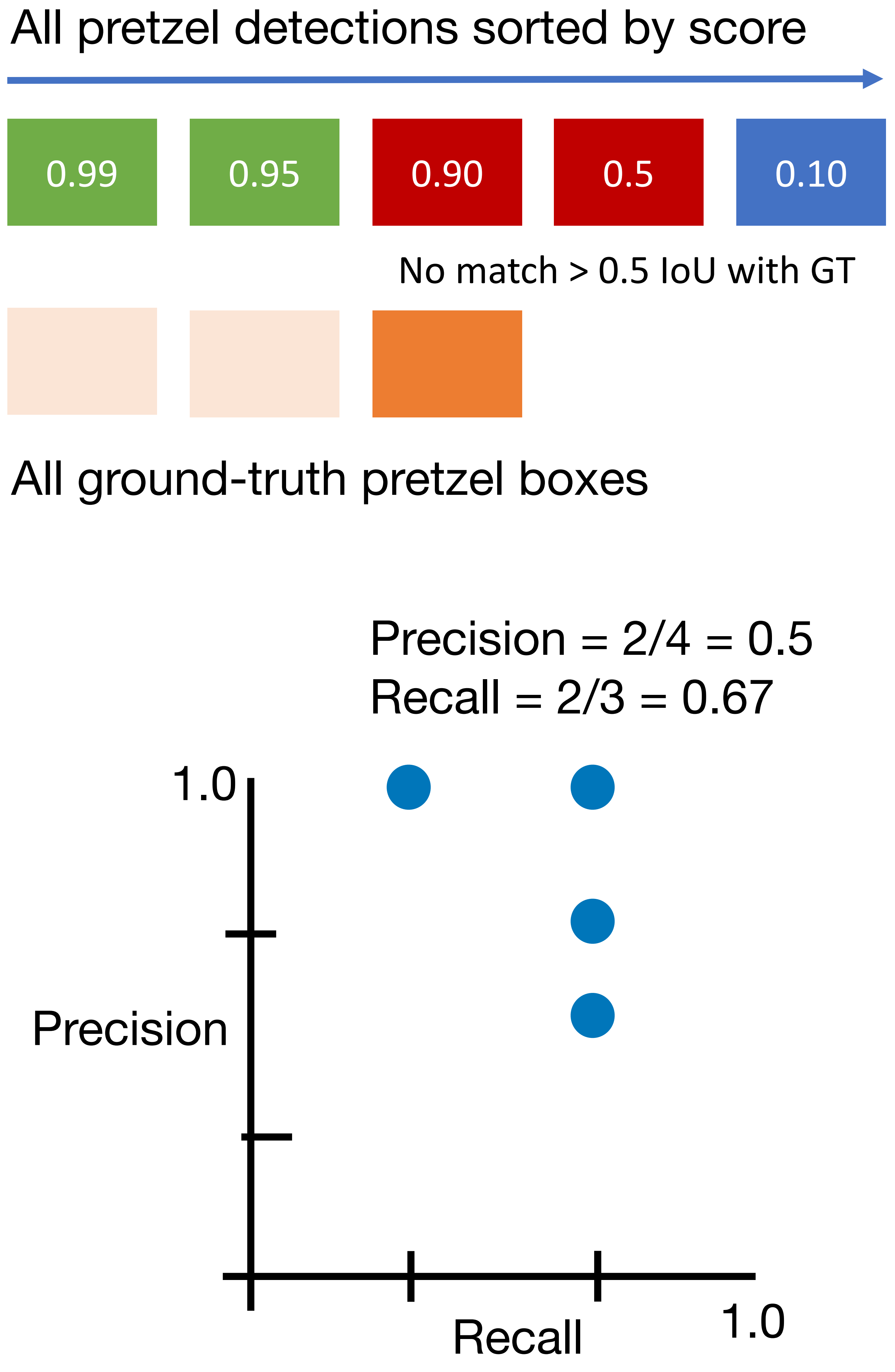

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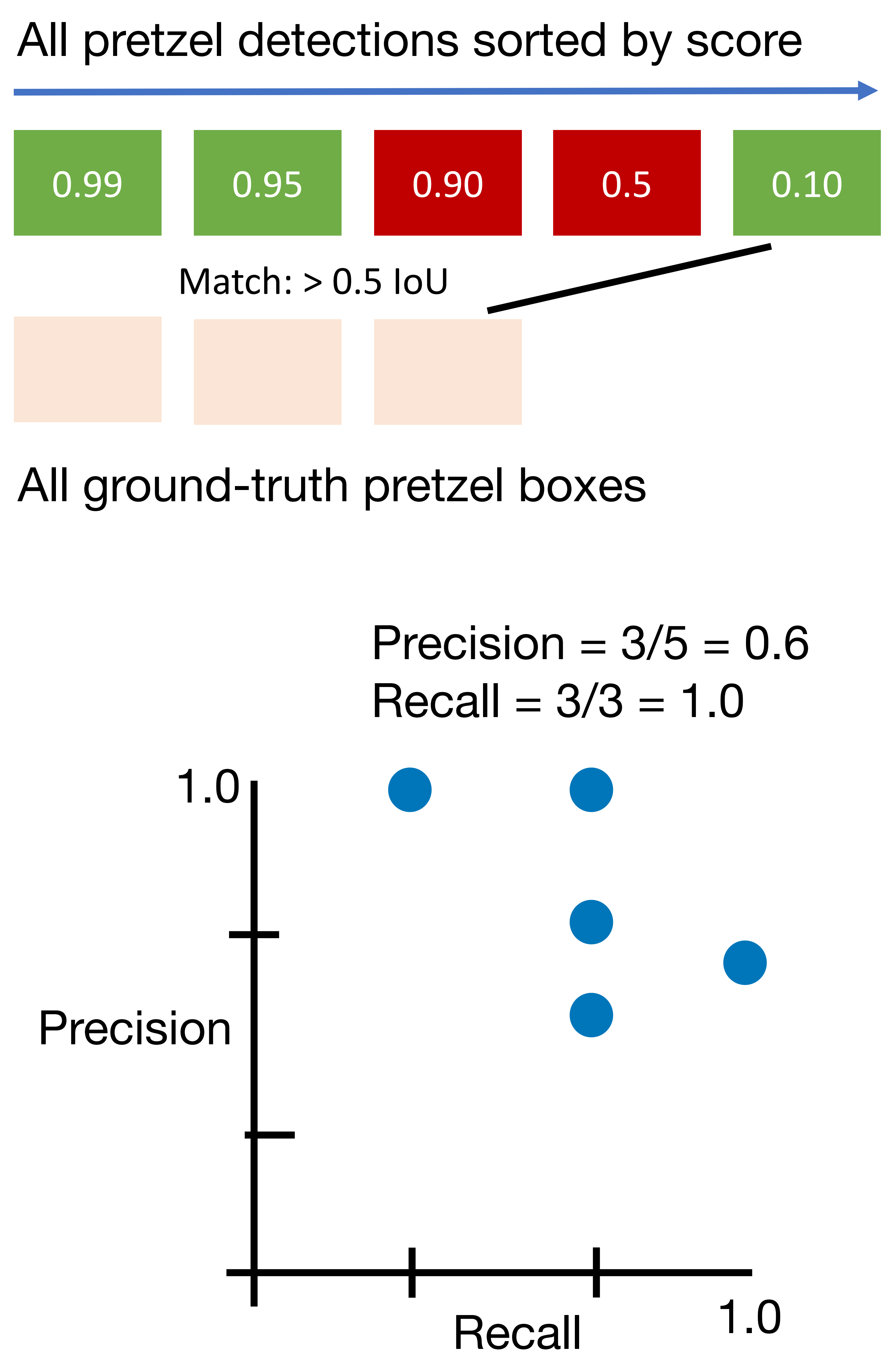

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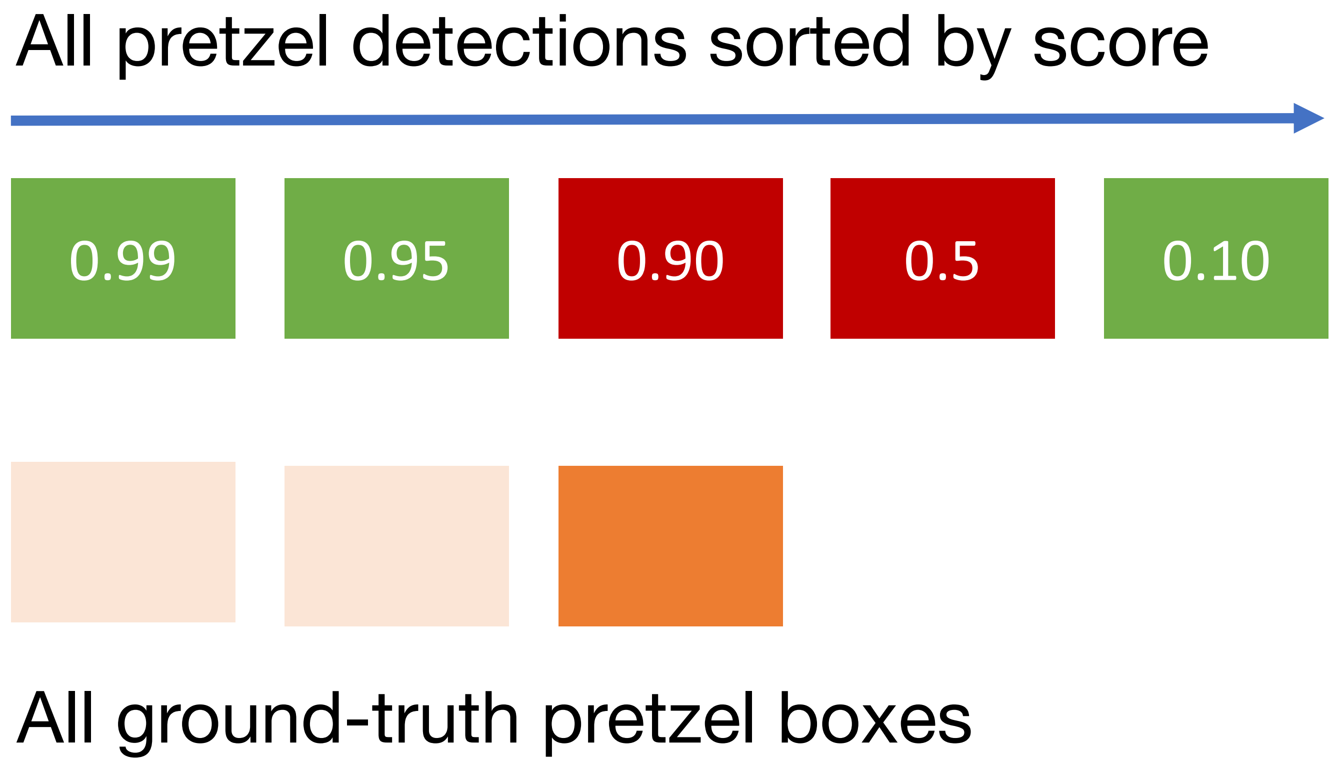
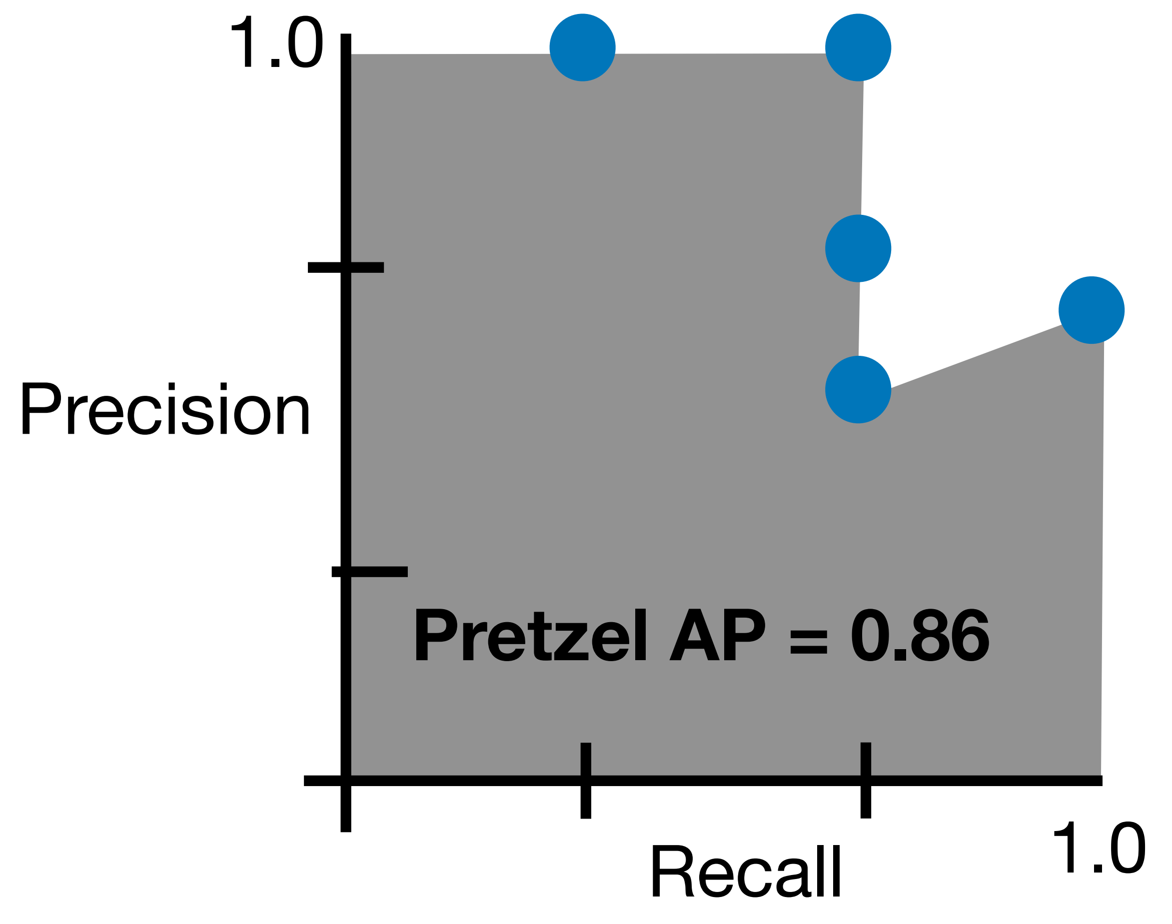
    2. Average Precision (AP) = area under PR curve





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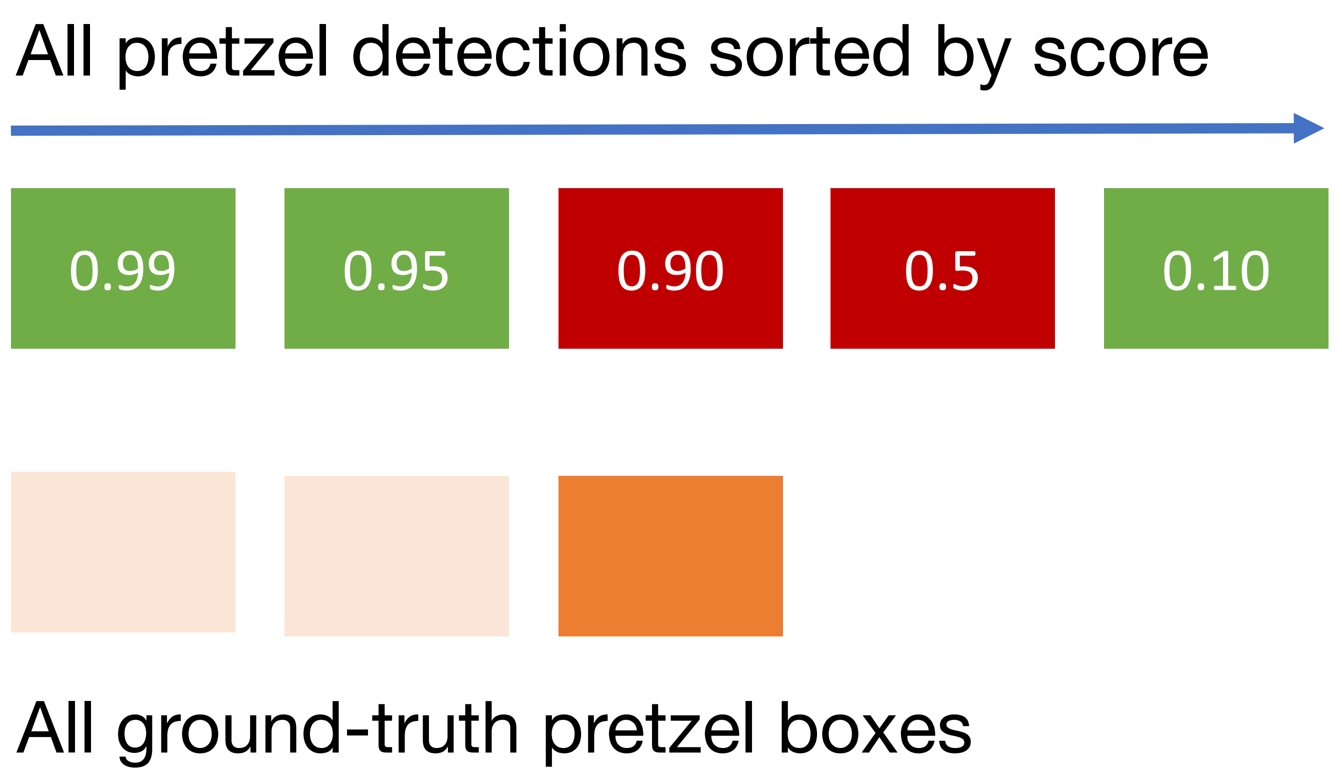
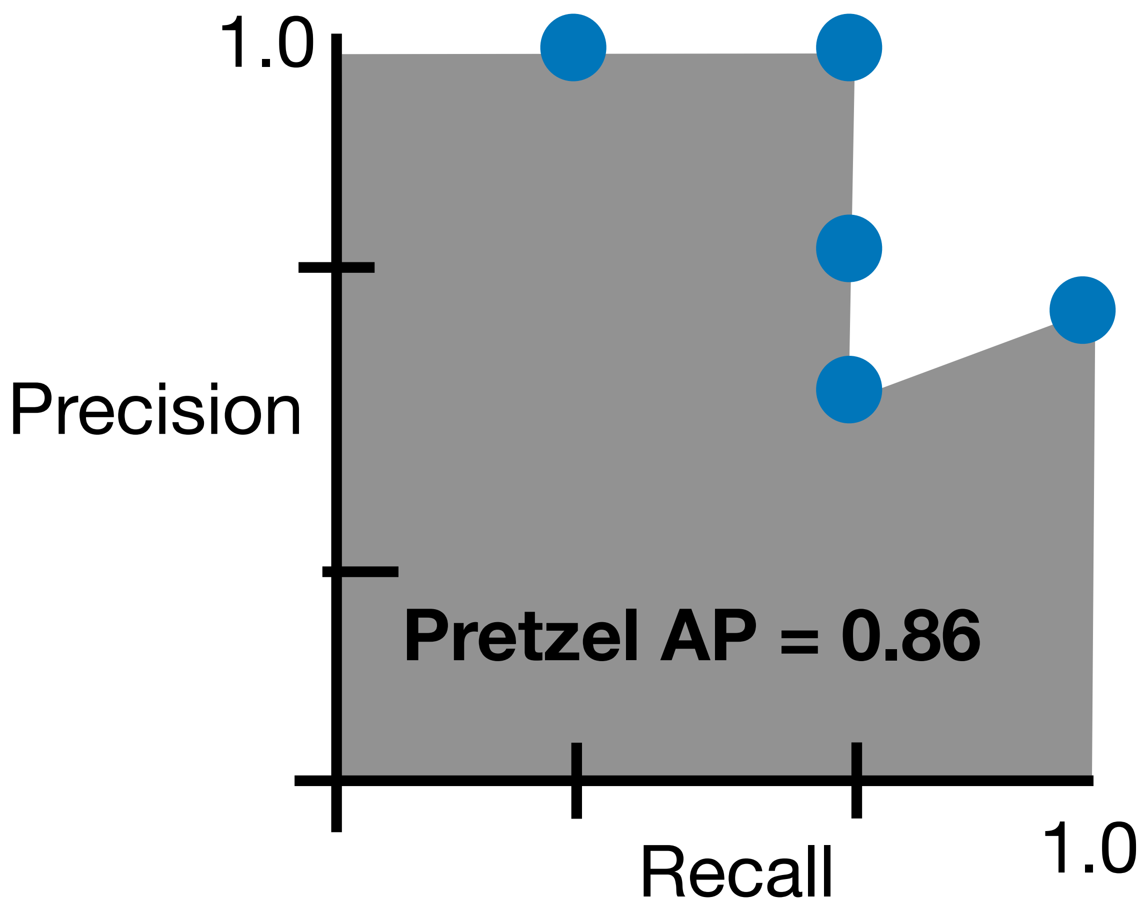
        3. Plot a point on PR curve
    2. Average Precision (AP) = area under PR curve

How to get AP = 1.0: Hit all GT boxes with IoU > 0.5, and have no "false positive" detections ranked above any "true positives"





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      2. Otherwise mark it as negative
      3. Plot a point on PR curve
   2. Average Precision (AP) = area under PR curve
3. Mean Average Precision (mAP) = average of AP for each category

Flipz AP = 0.60
Hershey's AP = 0.85
Reese's AP = 0.81
mAP@0.5 = 0.75

Next Time: Object Detectors and Segmentation

DeepRob

Lecture 12
Object Detection
University of Michigan and University of Minnesota

DeepRob

Lecture 12
Object Detection
University of Michigan and University of Minnesota