Introduction to Computer Vision

Lecture 13

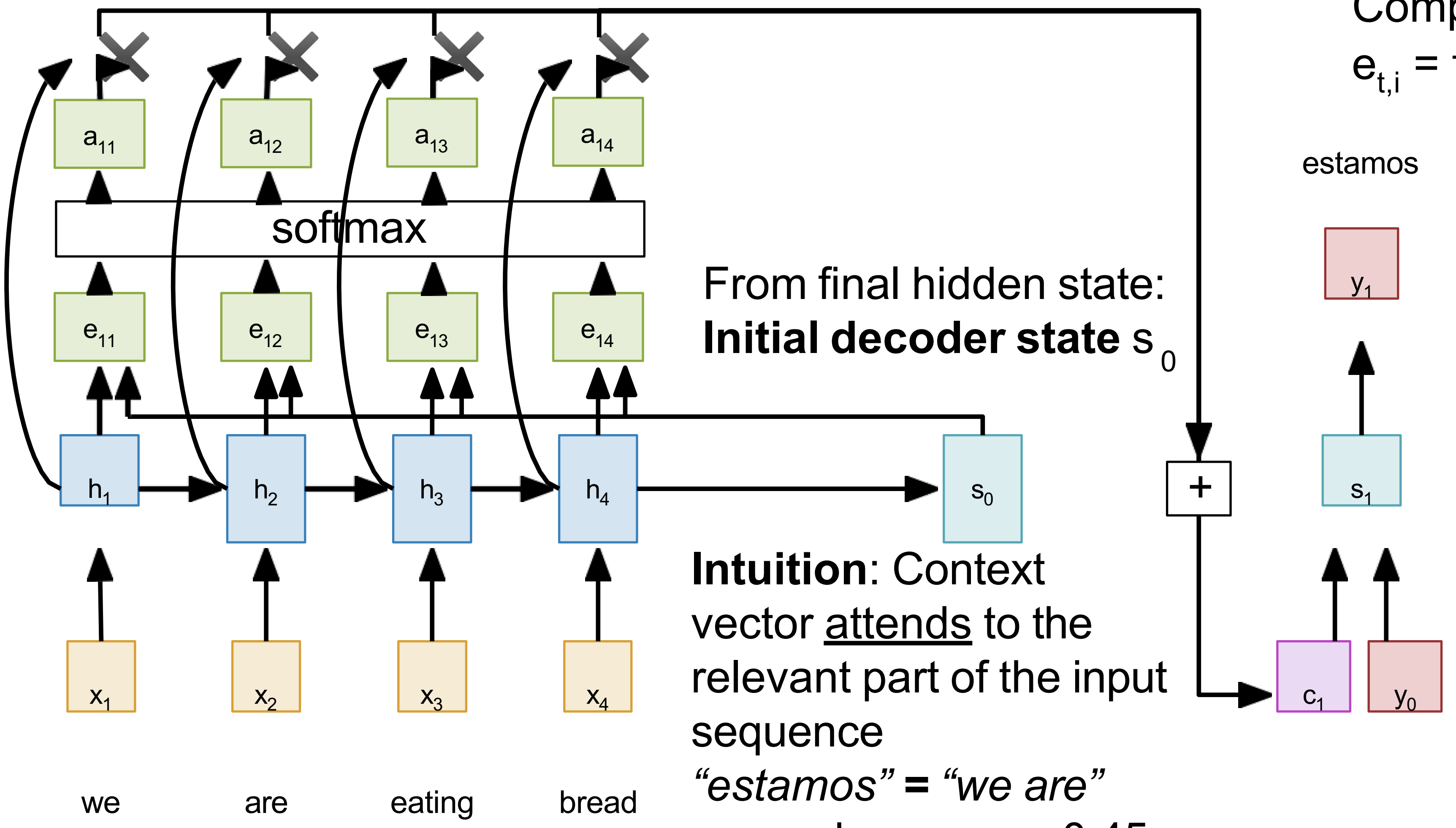
Detection and Instance Segmentation

Prof. He Wang

Logistics

- Assignment 4 (Point Cloud Learning, Detection & RNN)
  - To be released on 5/23
  - Due on 6/7 11:59PM

Sequence to Sequence with RNNs and Attention



From final hidden state: **Initial decoder state s_0**

Intuition: Context vector <u>attends</u> to the relevant part of the input sequence
"estamos" **=** *"we are"*
so maybe $a_{11}=a_{12}=0.45$, $a_{13}=a_{14}=0.05$

Compute (scalar) **alignment scores**
$e_{t,i} = f_{att}(s_{t-1}, h_i)$ (f_{att} is an MLP)

Normalize alignment scores to get **attention weights**
$0 < a_{t,i} < 1$ $\sum_i a_{t,i} = 1$

Compute context vector as linear combination of hidden states
$c_t = \sum_i a_{t,i} h_i$

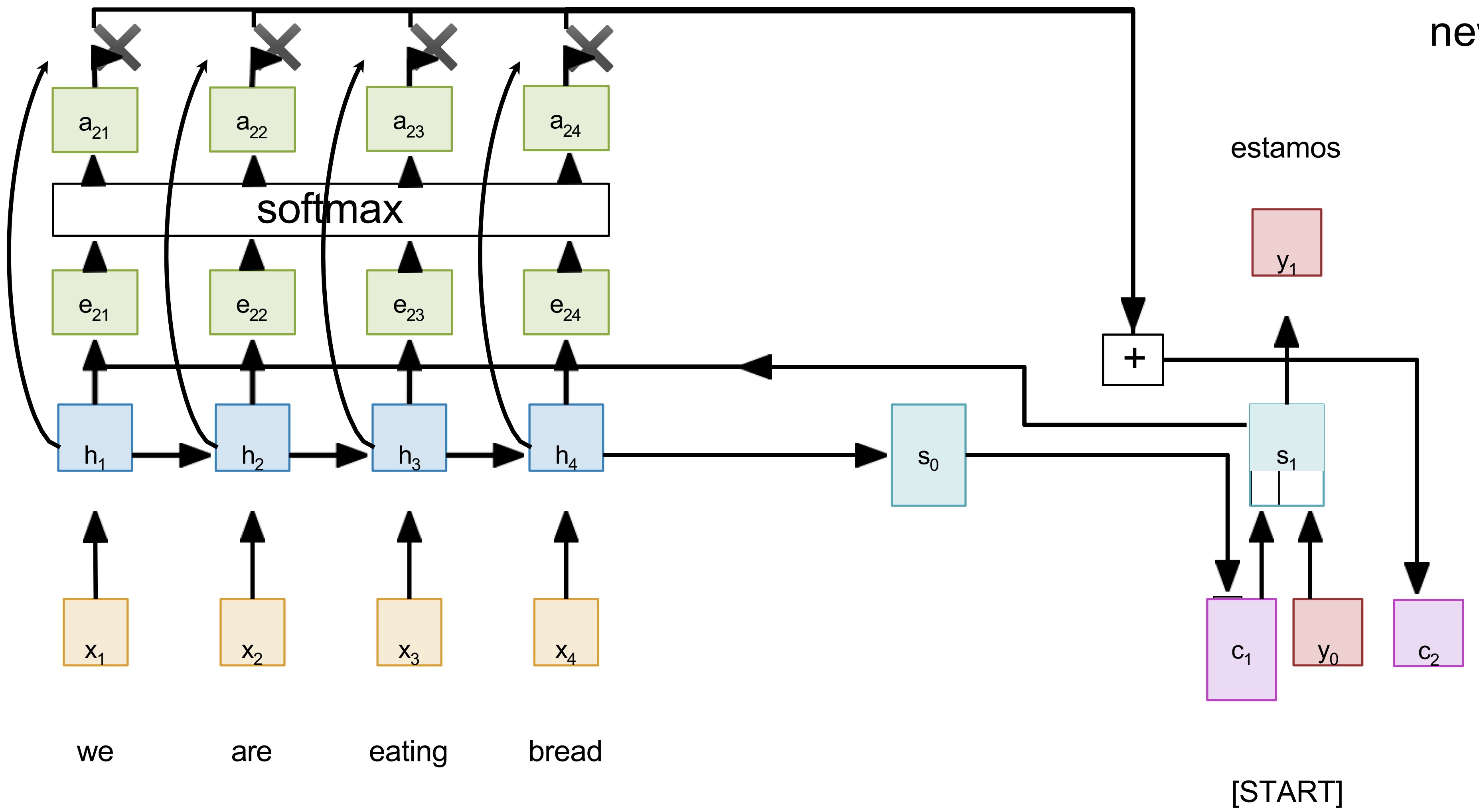
Use context vector in decoder: $s_t = g_U(y_{t-1}, s_{t-1}, c_t)$

This is all differentiable! No supervision on attention weights – backprop through everything

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Sequence to Sequence with RNNs and Attention

Repeat: Use s_1 to compute new context vector c_2



To be continued in next lecture!

Bahdanau et al, "Neural machine translation by jointly learning to align and translate", ICLR 2015

Object Detection

Some slides are borrowed from Stanford CS231N.

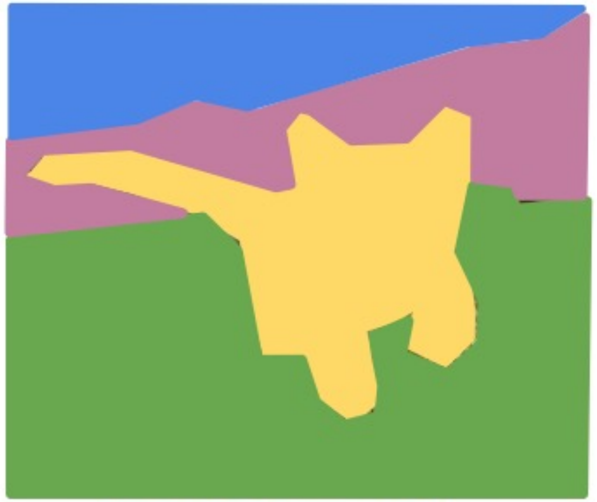
Computer Vision Tasks

Classification

CAT

No spatial extent

Semantic Segmentation



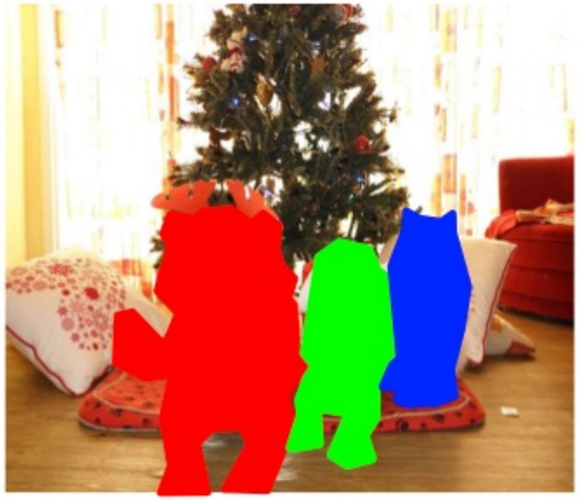
GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

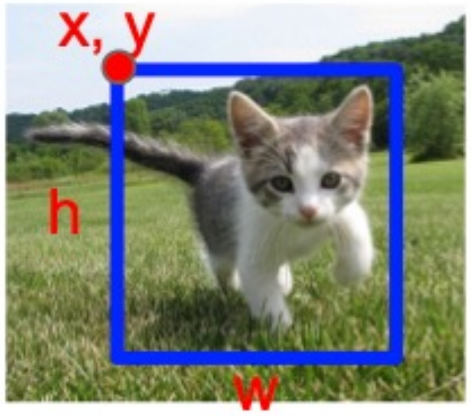


DOG, DOG, CAT

Multiple Object

This image is CC0 public domain

Object Detection: Single Object

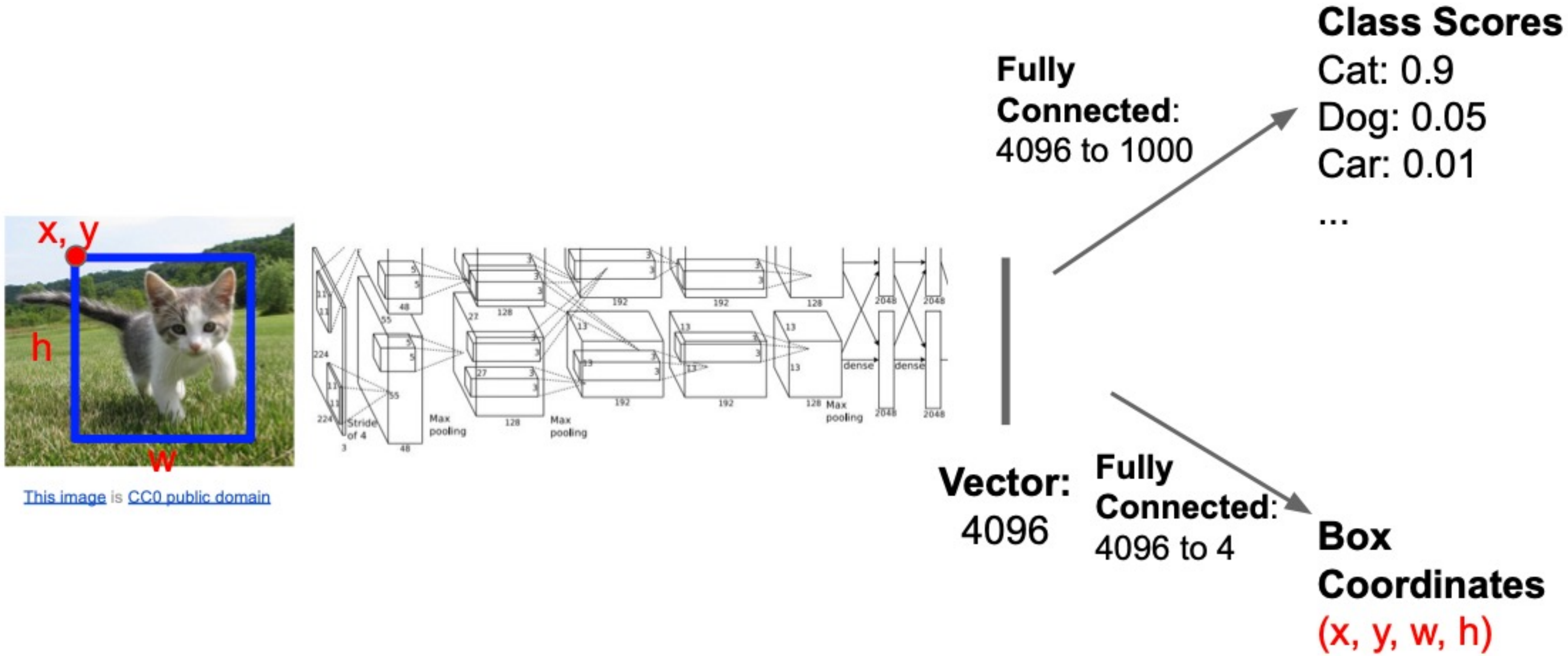


This image is CC0 public domain

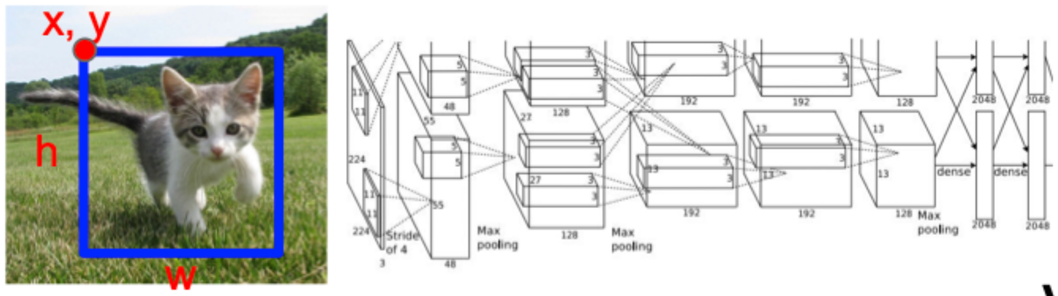
- Task: localization + classification
- Output: 2D (axis aligned) bounding box
  - How many degree-of-freedom?
    - 4 DoF
  - How to parameterize such a bounding box?
    - x,y,h,w

Object Detection: Single Object

- Localization + Classification



Object Detection: Single Object



Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Correct label:
Cat

Fully Connected: 4096 to 4

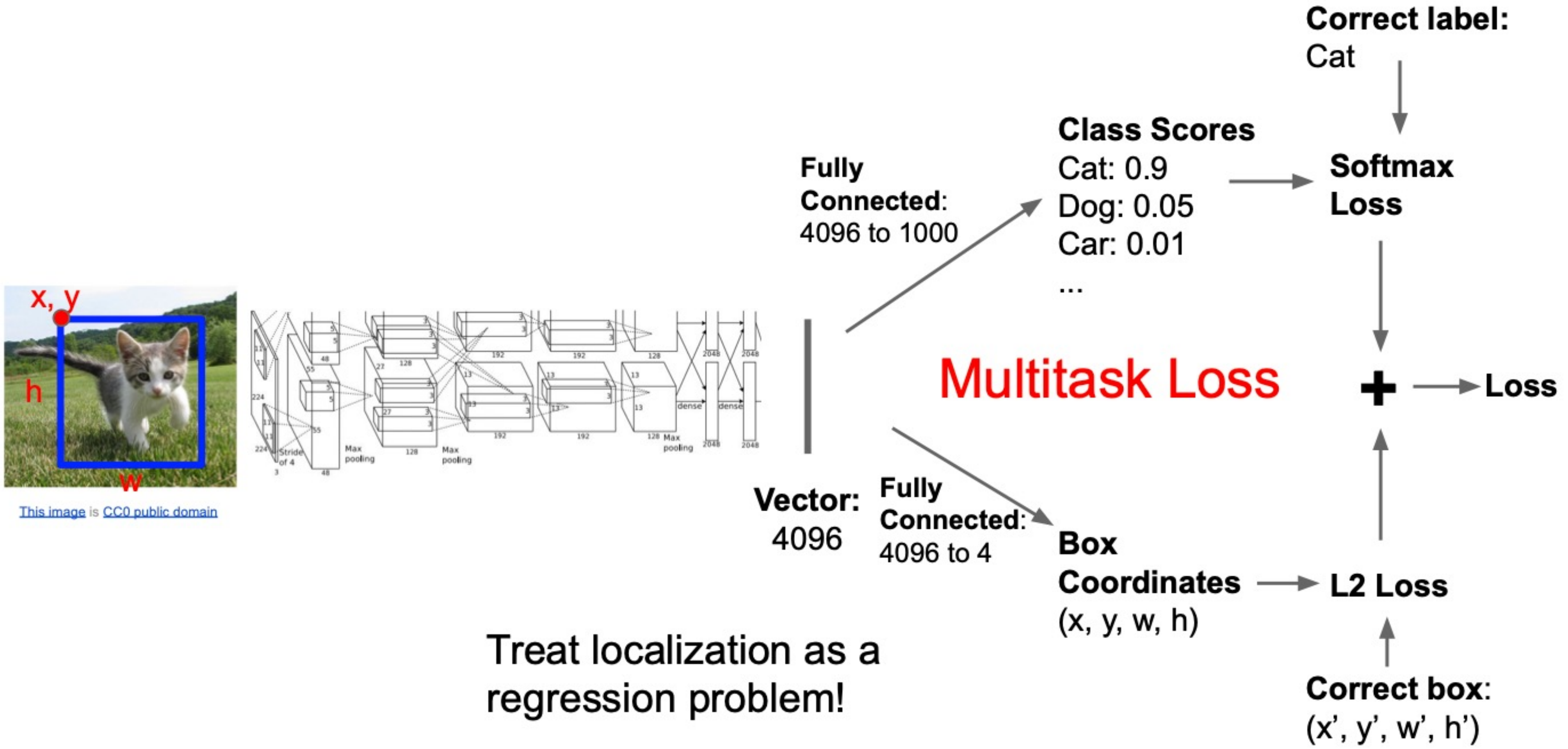
Box Coordinates
(x, y, w, h)

L2 Loss

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

Treat localization as a regression problem!

Object Detection: Single Object



Treat localization as a regression problem!

Regression Loss

- Error: $(\Delta x, \Delta y, \Delta w, \Delta h)$
- L1 loss: $\Sigma|\Delta_i|$ — robust, however not good at convergence
- L2 loss: $\Sigma\Delta_i^2$ (not the same to L2 norm) — not robust to a larger error, however good at convergence
- Rooted mean squared loss (RMSE): $\sqrt{\frac{1}{N}\Sigma\Delta_i^2}$ — the gradient of sqrt function is bad at 0

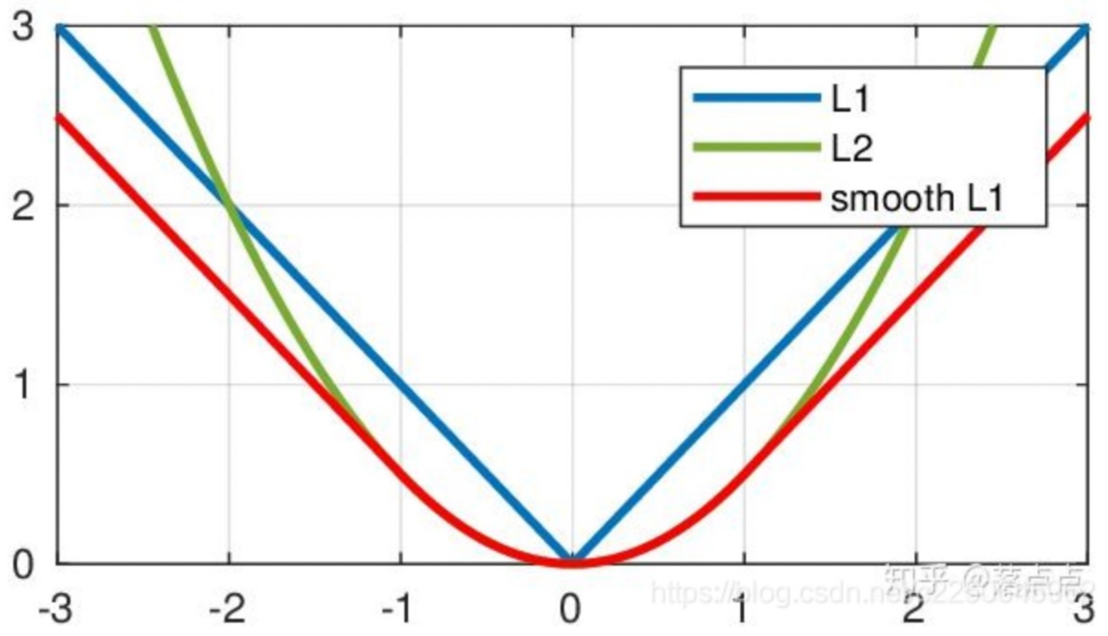
Regression Loss

- Smooth L1 loss (proposed by Fast RCNN, very similar to Huber loss widely used in robust optimization)

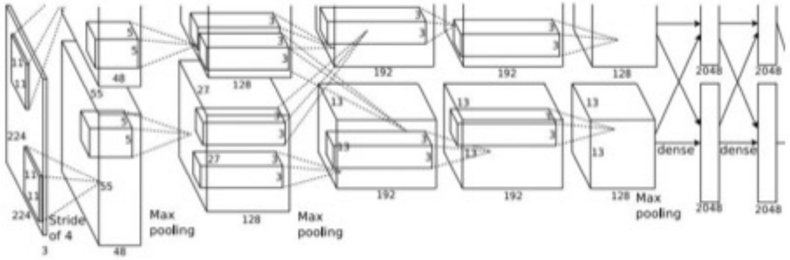
$$L_2(x) = x^2 \tag{1}$$

$$L_1(x) = |x| \tag{2}$$

$$\mathrm{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases} \tag{3}$$

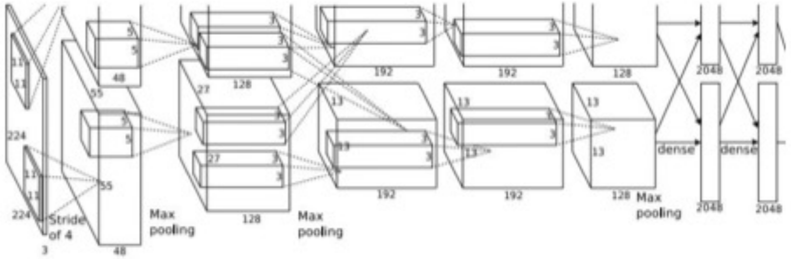


Object Detection: Multiple Objects



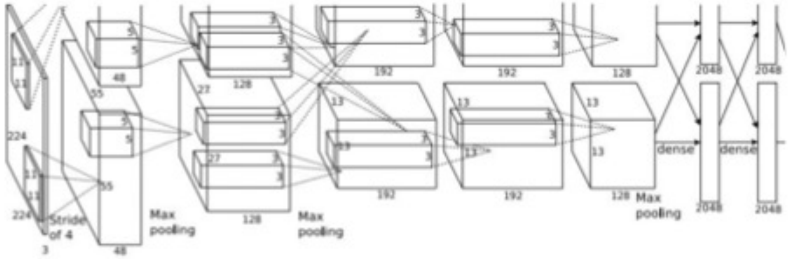
CAT: (x, y, w, h)

1 bounding box



DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)

3 bounding boxes



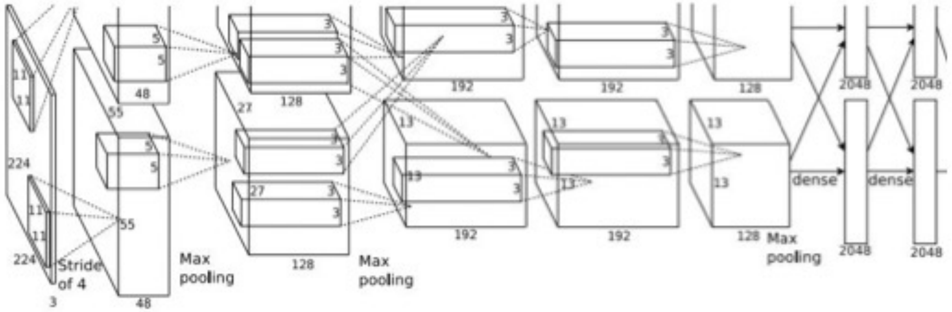
DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Many bounding boxes!

Different images need different numbers of outputs!

Sliding-Window based Multi-Object Detection

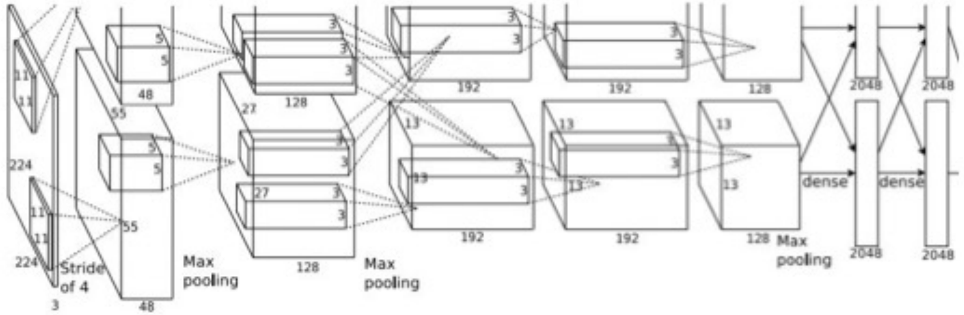
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Sliding-Window based Multi-Object Detection

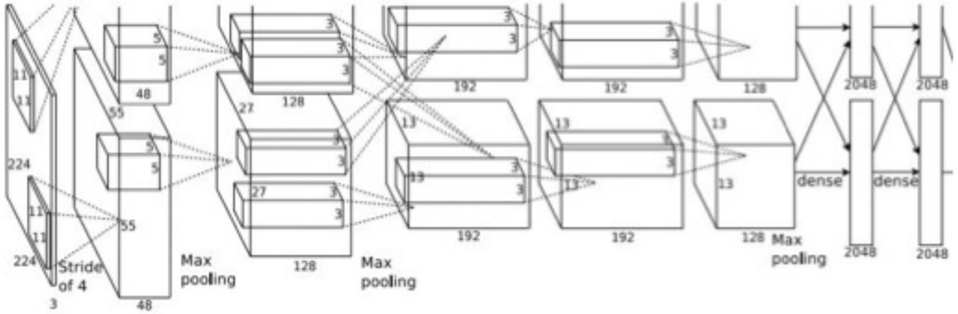
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Sliding-Window based Multi-Object Detection

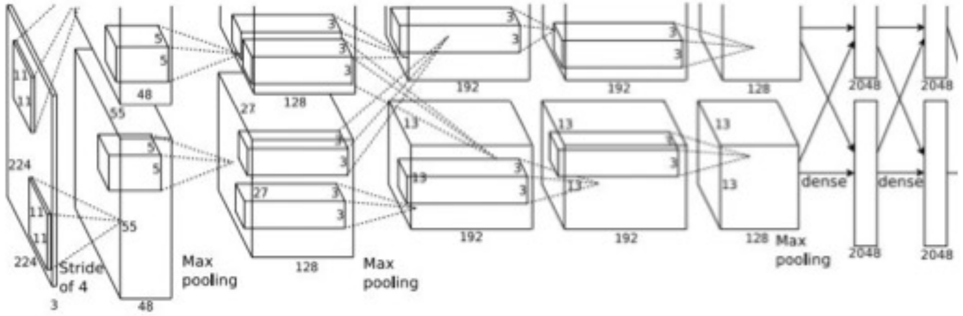
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Sliding-Window based Multi-Object Detection

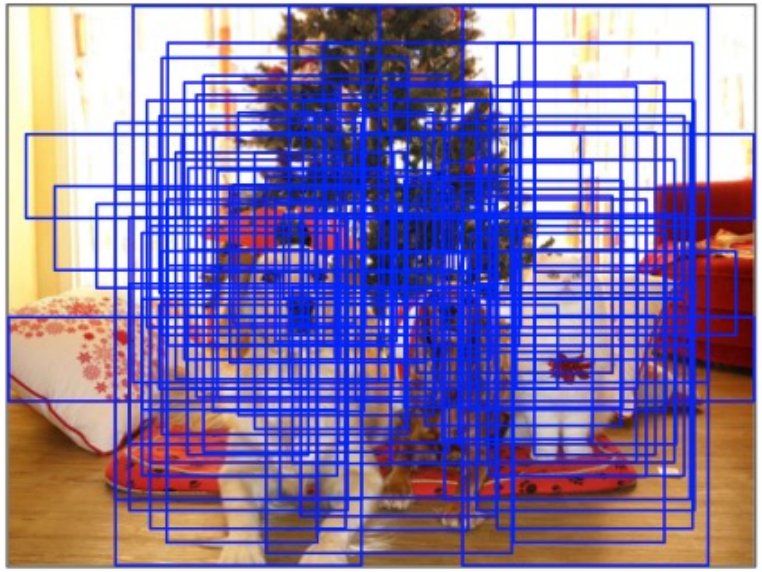
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



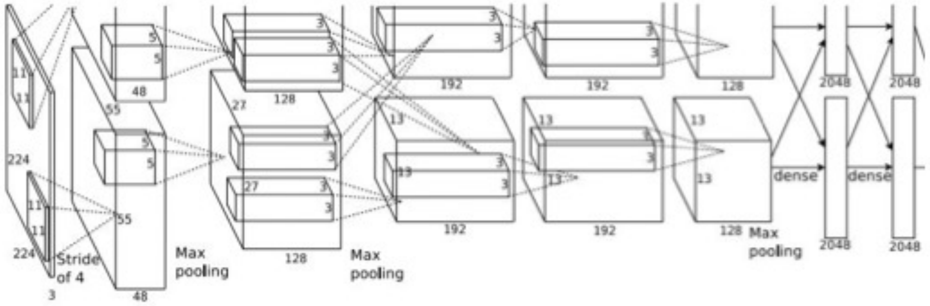
Dog? NO
Cat? YES
Background? NO

Q: What's the problem with this approach?

Sliding-Window based Multi-Object Detection



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

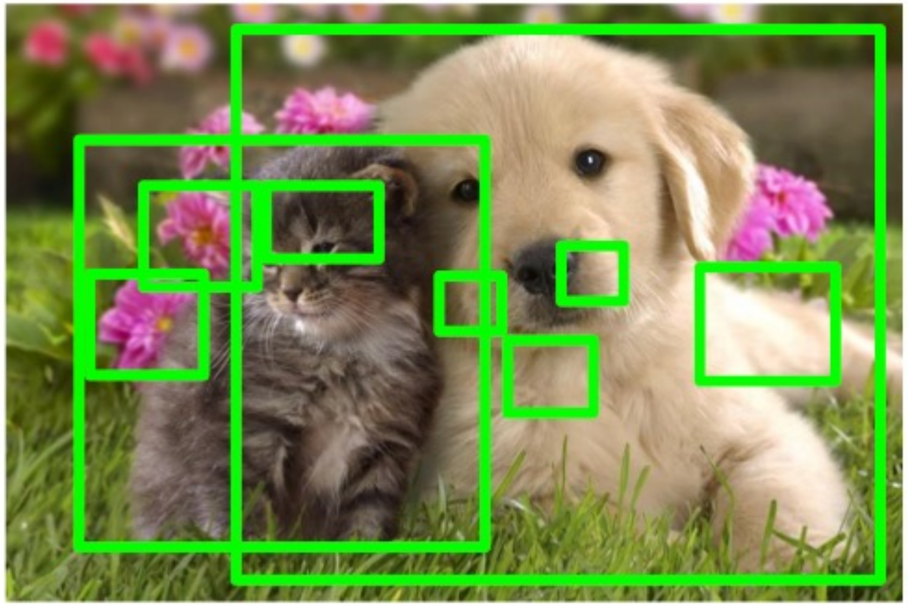


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations, scales, and aspect ratios, very computationally expensive!

Region Proposals: Selective Search

- Find "blobby" image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 2000 region proposals in a few seconds on CPU



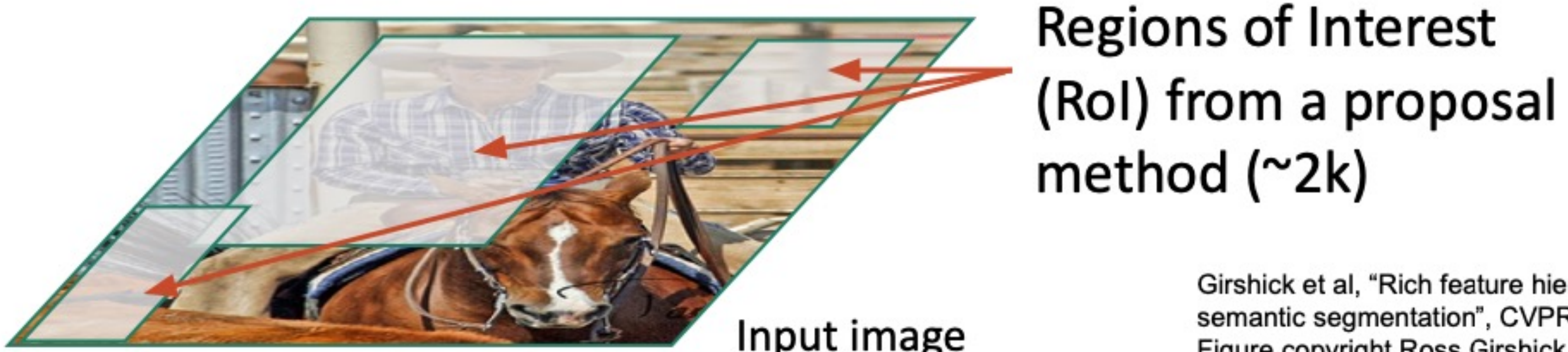
Alexe et al, "Measuring the objectness of image windows", TPAMI 2012
Uijlings et al, "Selective Search for Object Recognition", IJCV 2013
Cheng et al, "BING: Binarized normed gradients for objectness estimation at 300fps", CVPR 2014
Zitnick and Dollar, "Edge boxes: Locating object proposals from edges",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

R-CNN


Input image

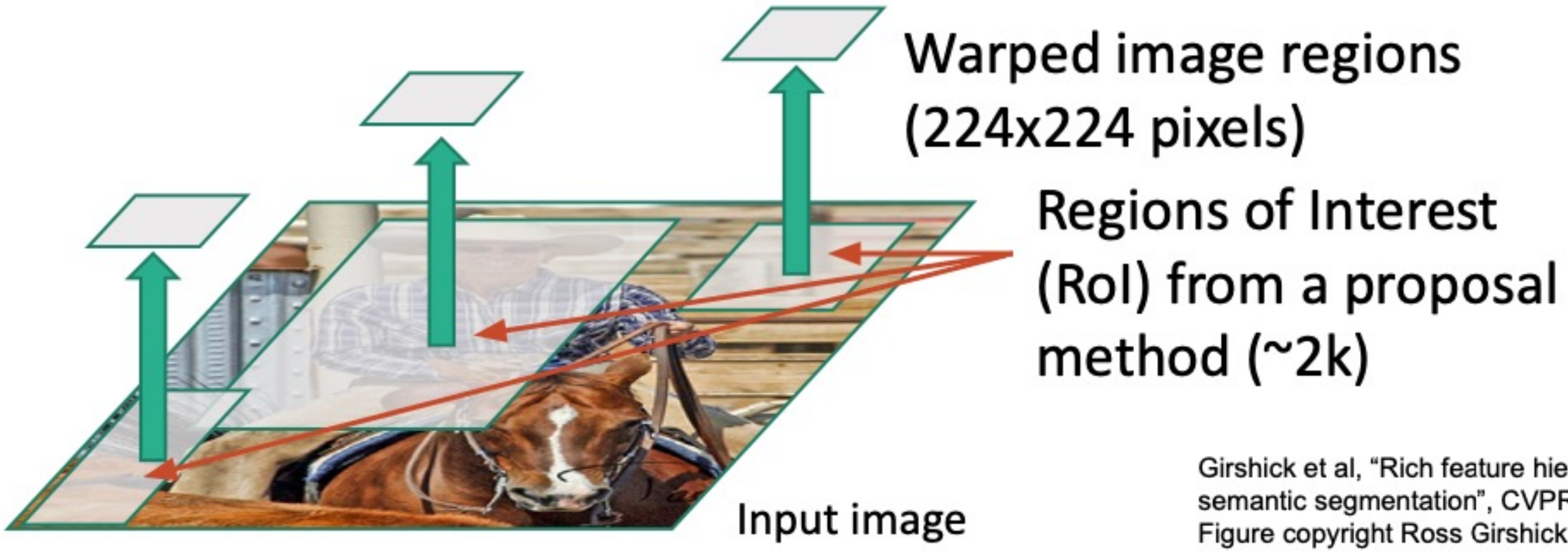
Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

R-CNN



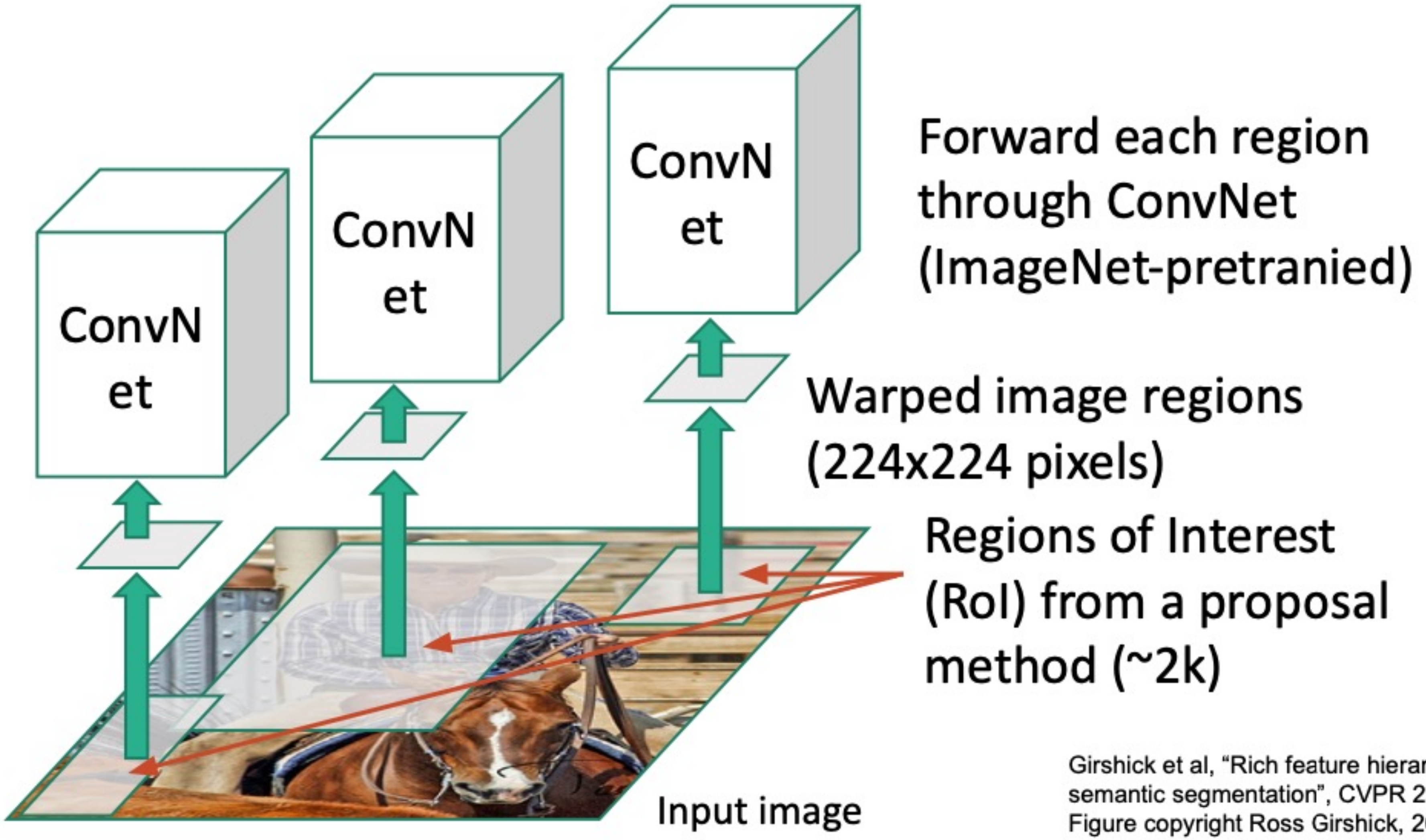
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN



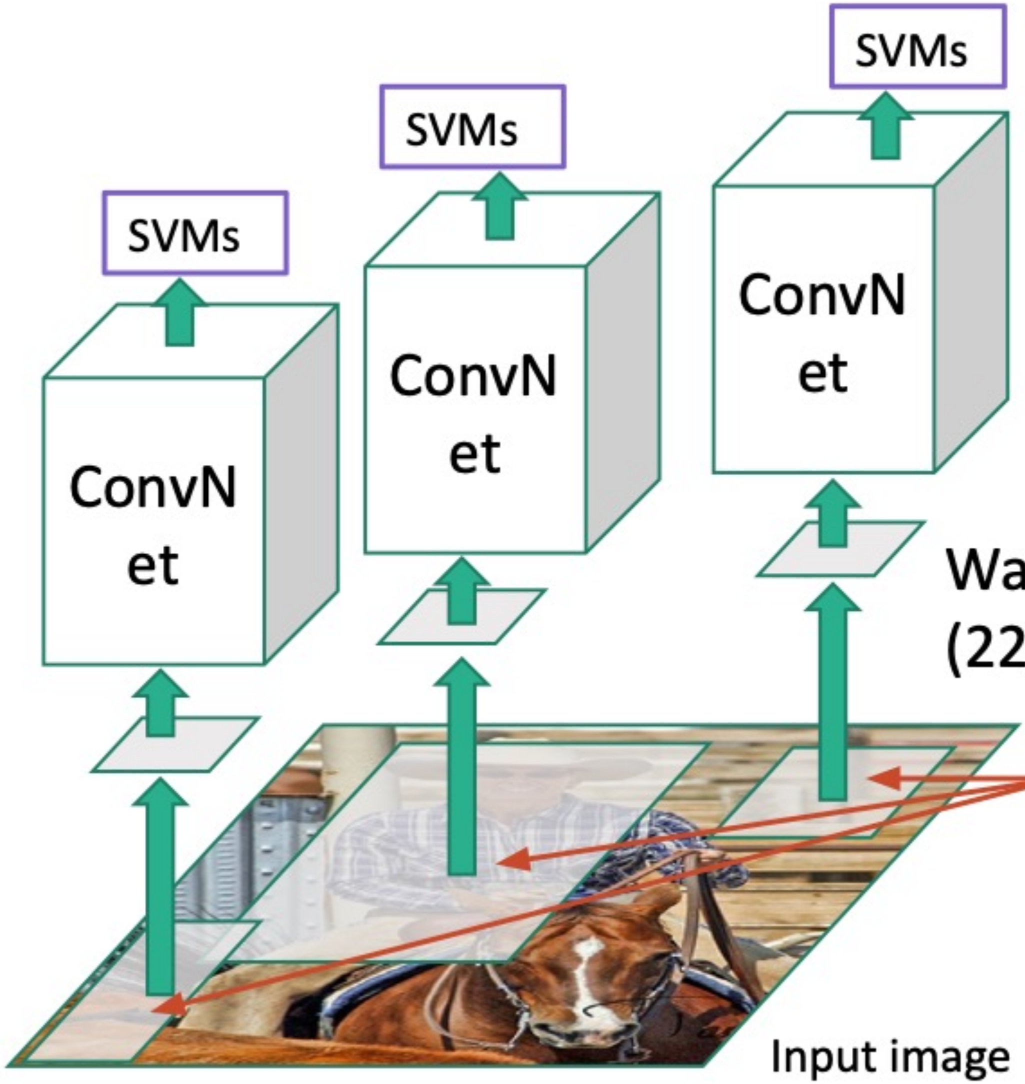
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN



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

R-CNN



Classify regions with SVMs

Forward each region through ConvNet (ImageNet-pretranied)

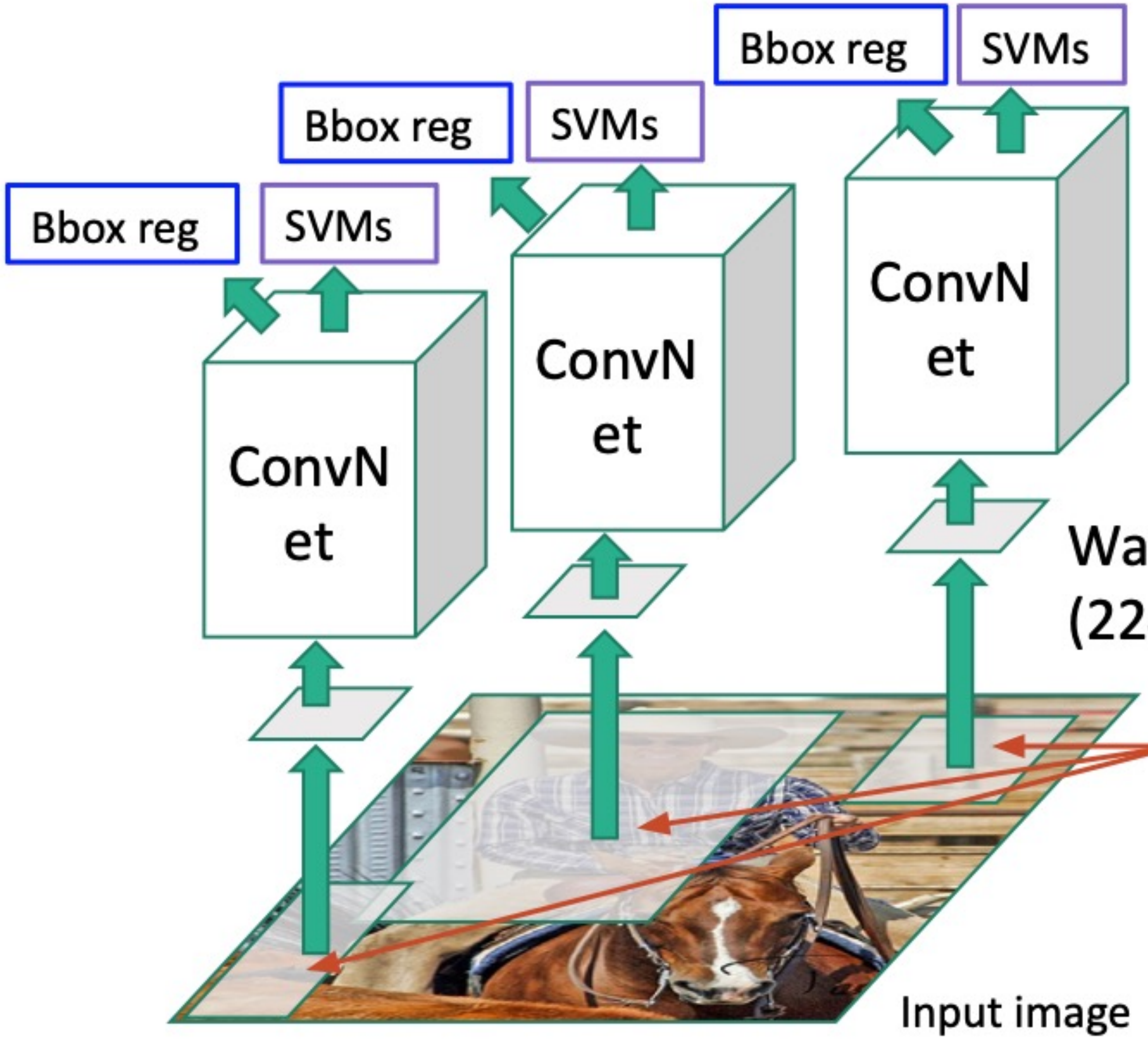
Warped image regions (224x224 pixels)

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

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN

Predict "corrections" to the RoI: 4 numbers: (dx, dy, dw, dh)



Classify regions with SVMs

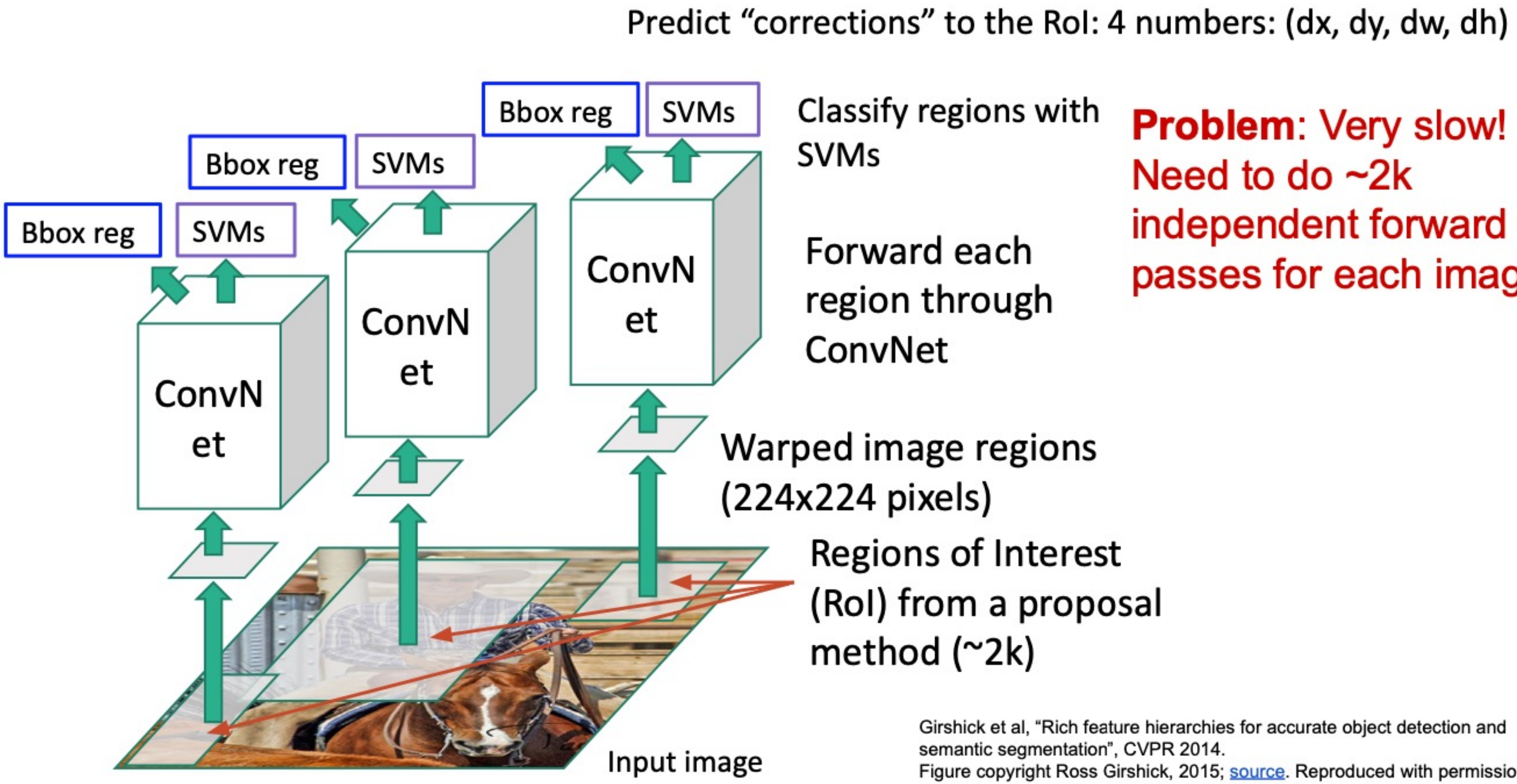
Forward each region through ConvNet (ImageNet-pretranied)

Warped image regions (224x224 pixels)

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

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

R-CNN

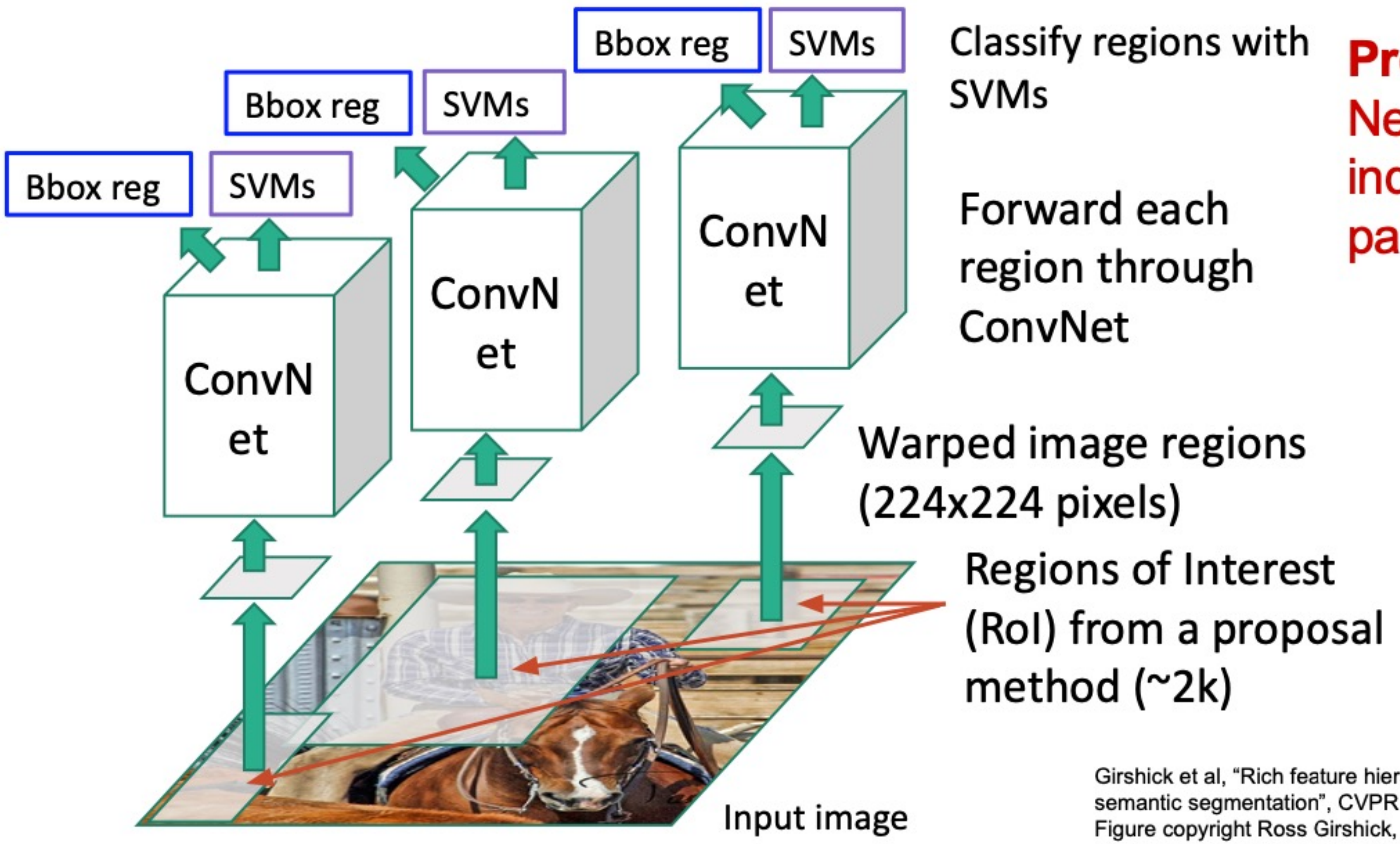


Problem: Very slow! Need to do ~2k independent forward passes for each image!

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

R-CNN

Predict "corrections" to the RoI: 4 numbers: (dx, dy, dw, dh)

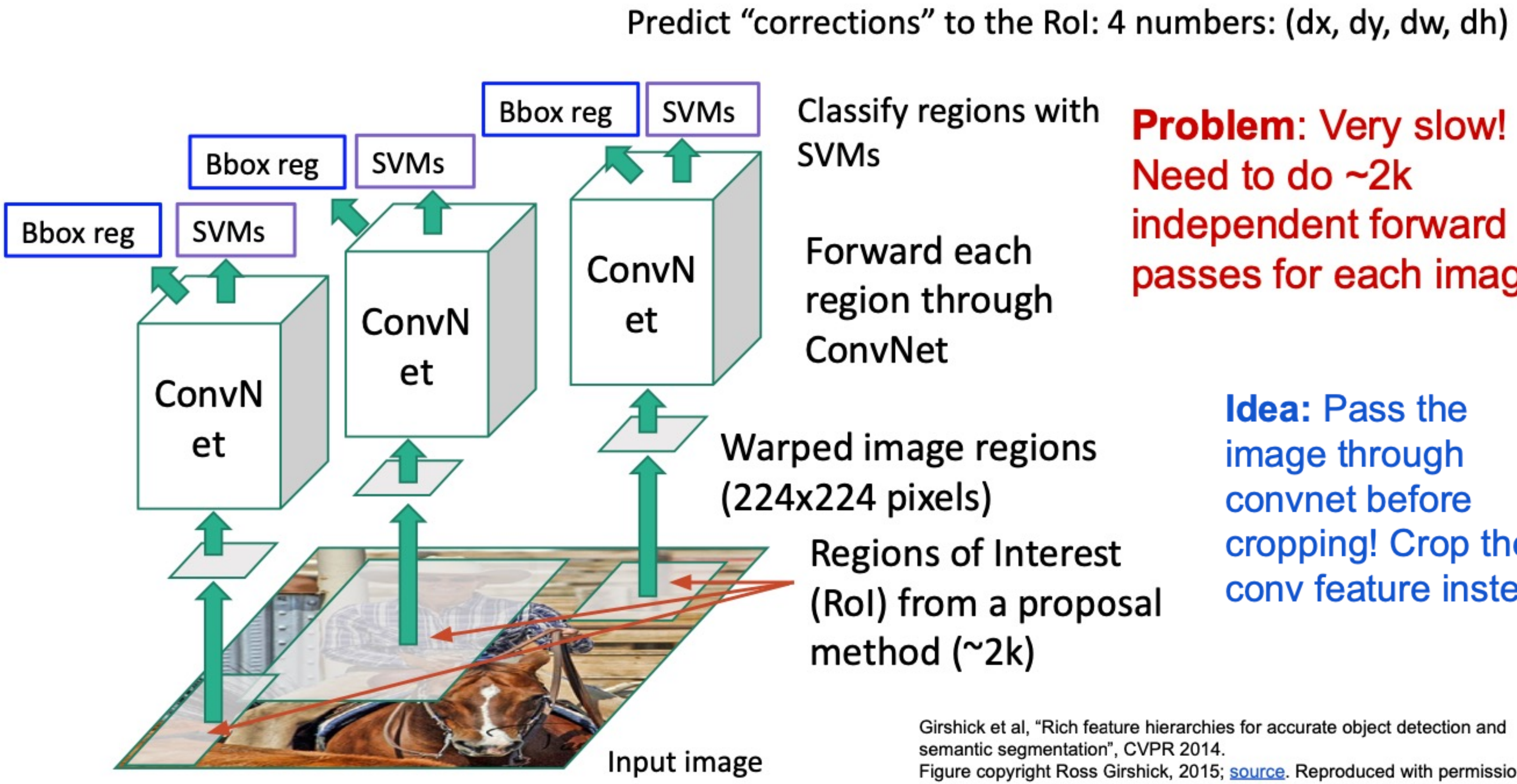


Problem: Very slow! Need to do ~2k independent forward passes for each image!

Problem 2: The cropped region doesn't contain sufficient information to regress bounding box refinements.

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN



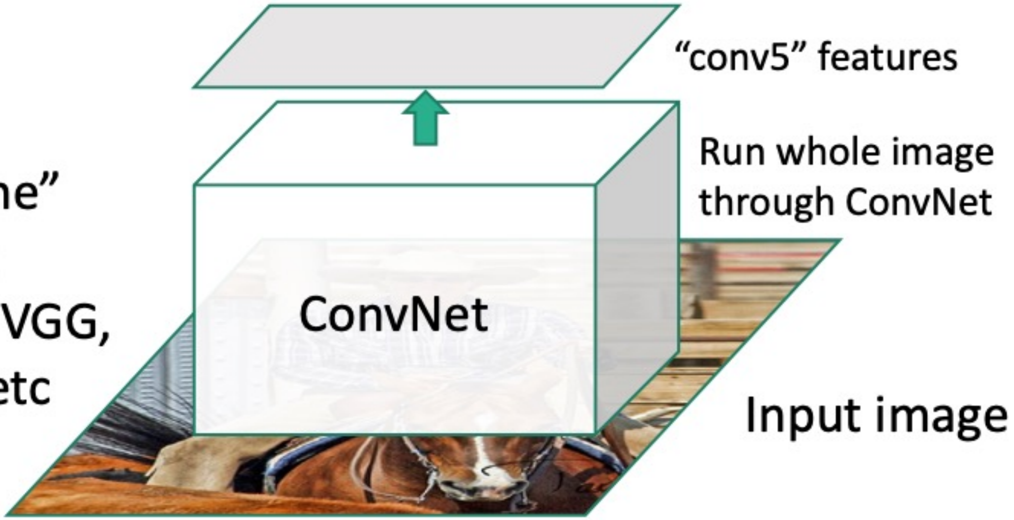
Problem: Very slow! Need to do ~2k independent forward passes for each image!

Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

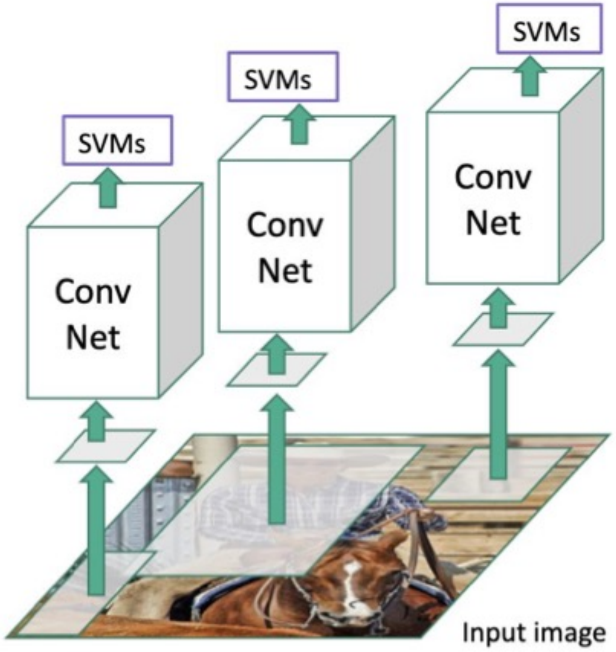
Fast R-CNN

"Backbone" network: AlexNet, VGG, ResNet, etc



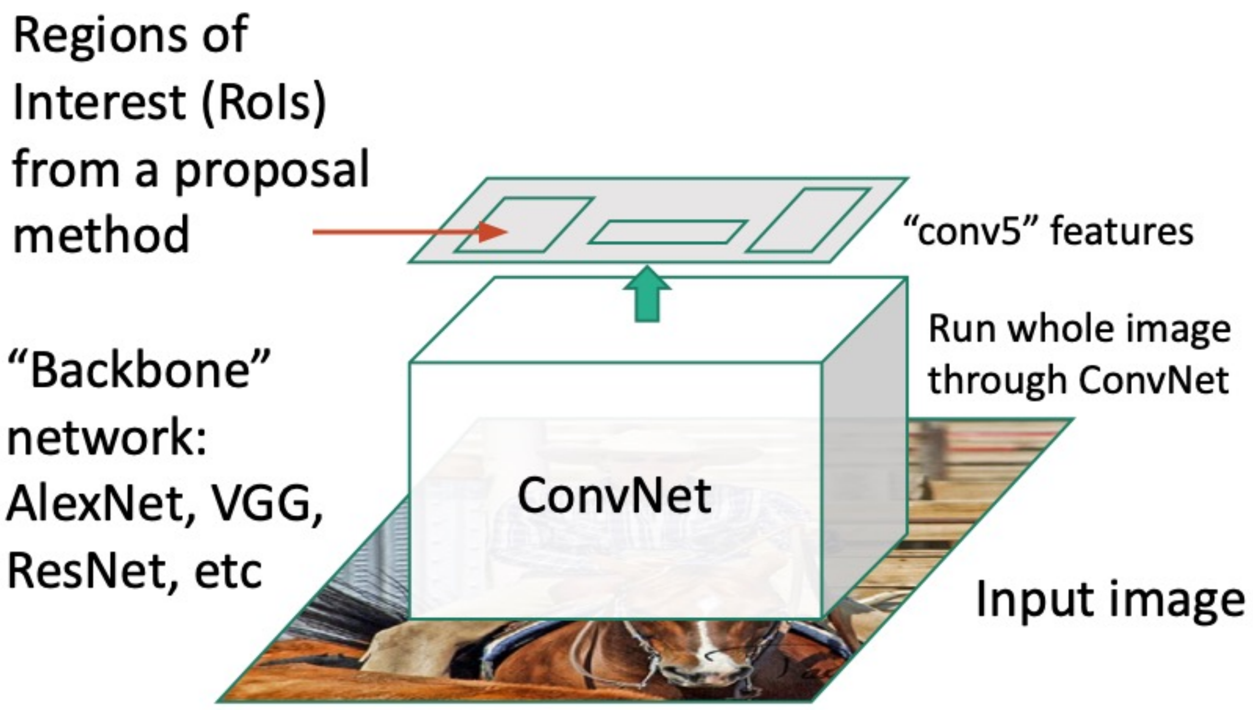
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast RCNN

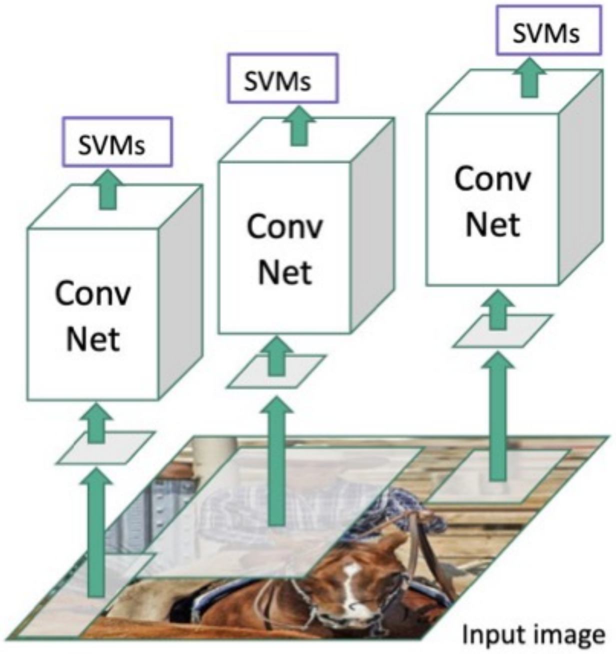


R-CNN

Fast R-CNN



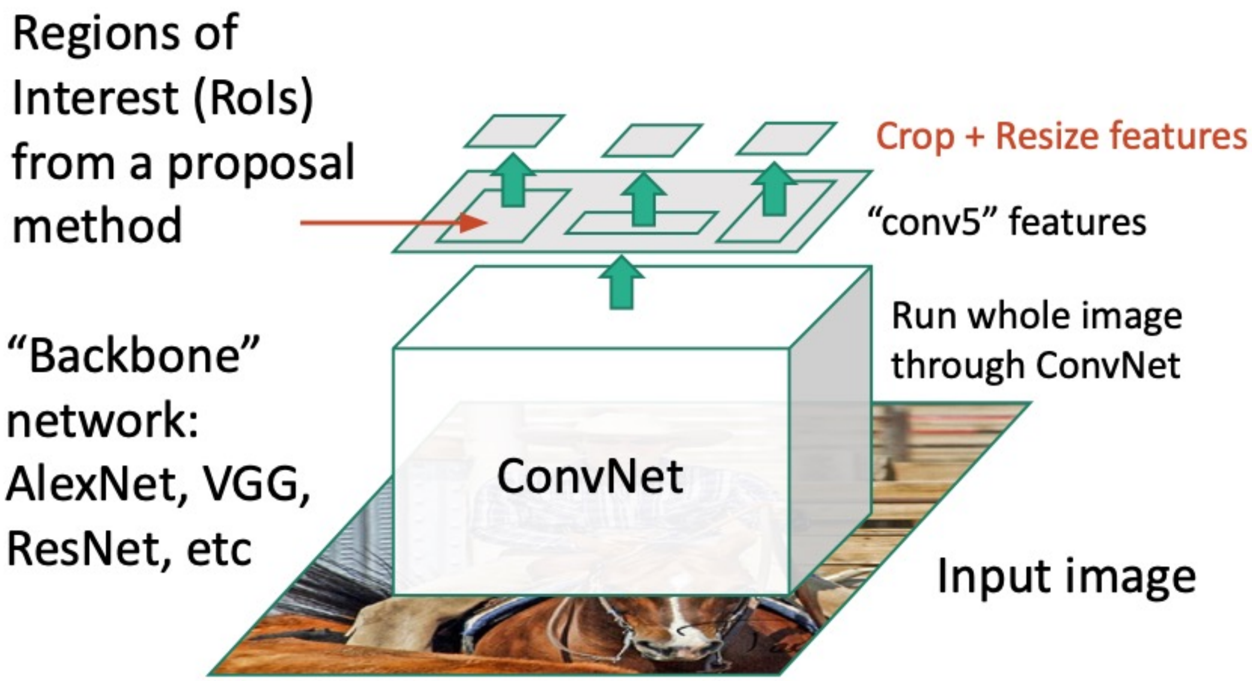
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.



Fast RCNN

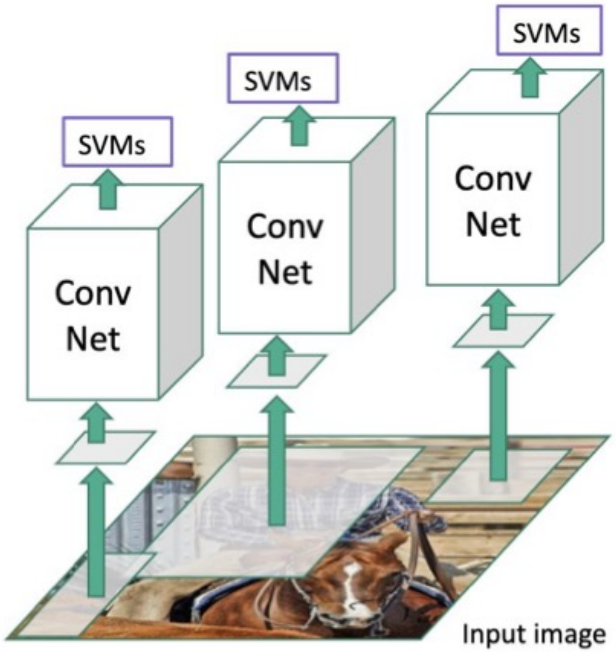
R-CNN

Fast R-CNN



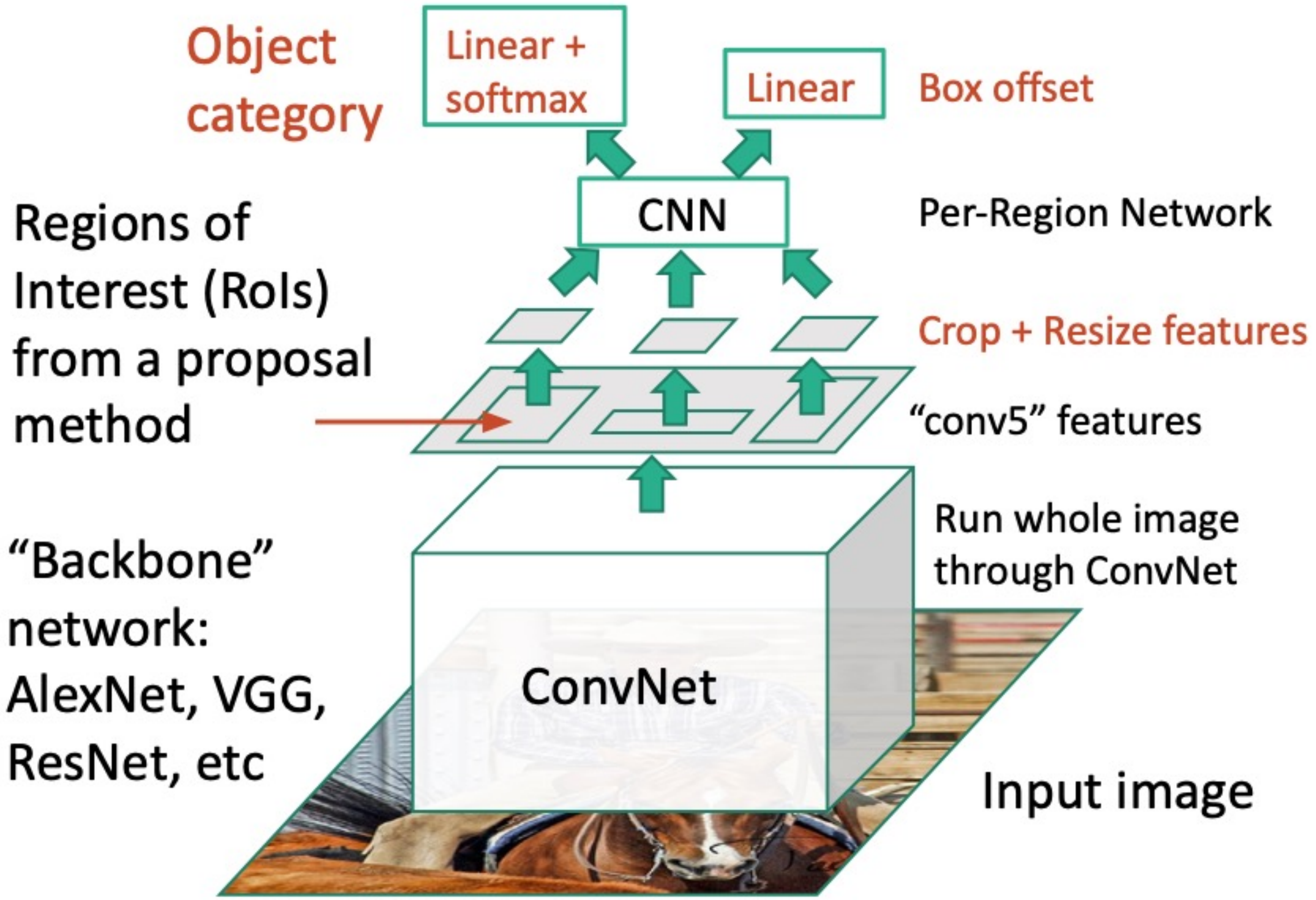
Girshick, "Fast R-CNN", ICCV 2015. Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast RCNN

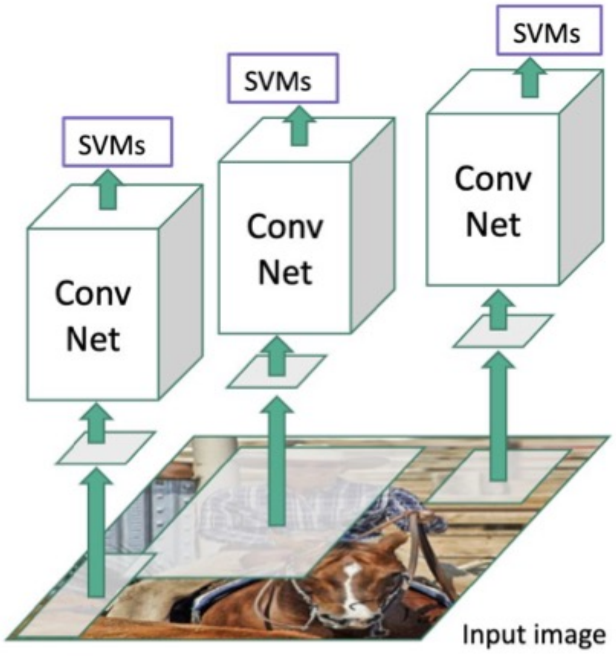


R-CNN

Fast R-CNN

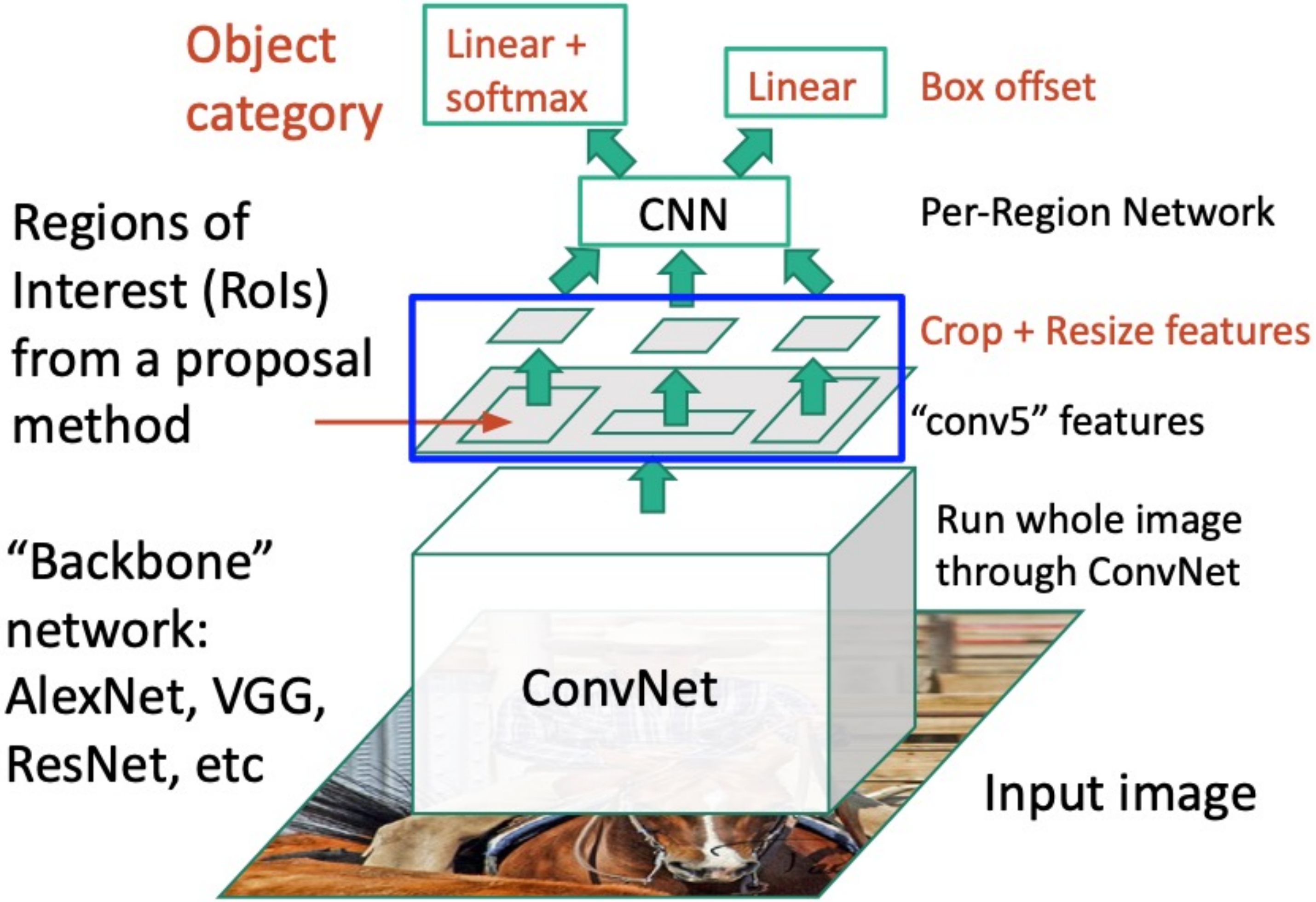


Fast RCNN

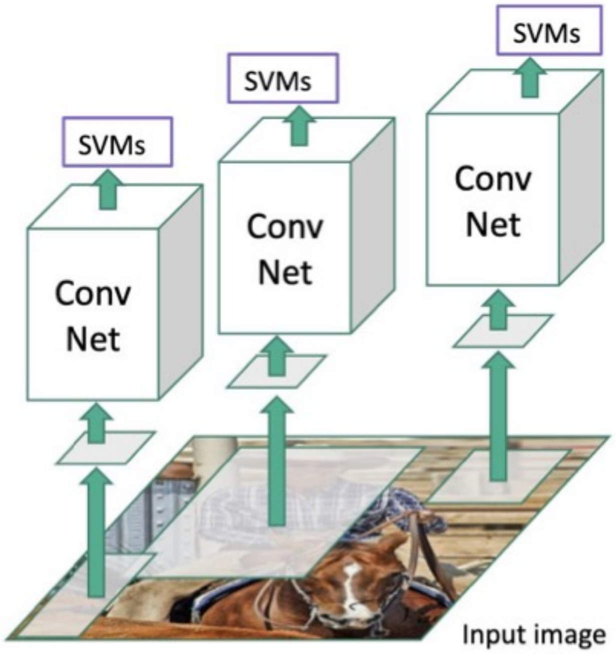


R-CNN

Fast R-CNN

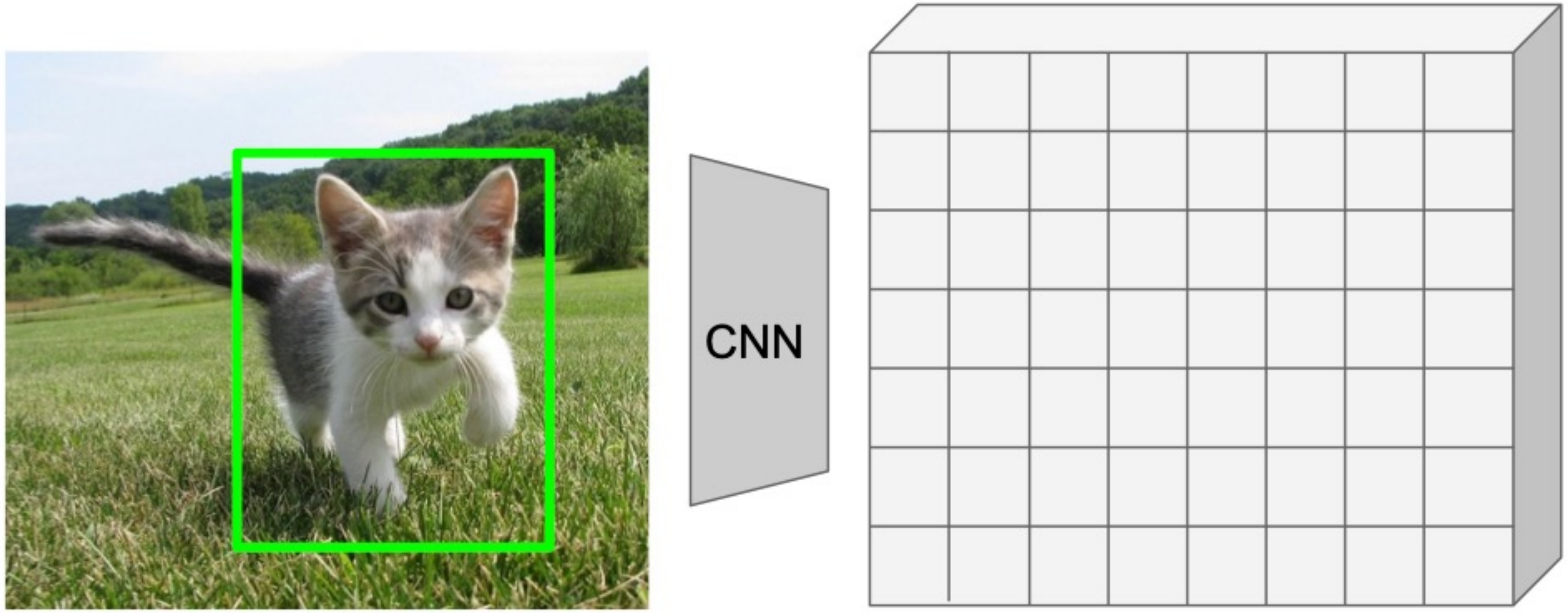


Fast RCNN



R-CNN

Cropping Features: RoI Pool

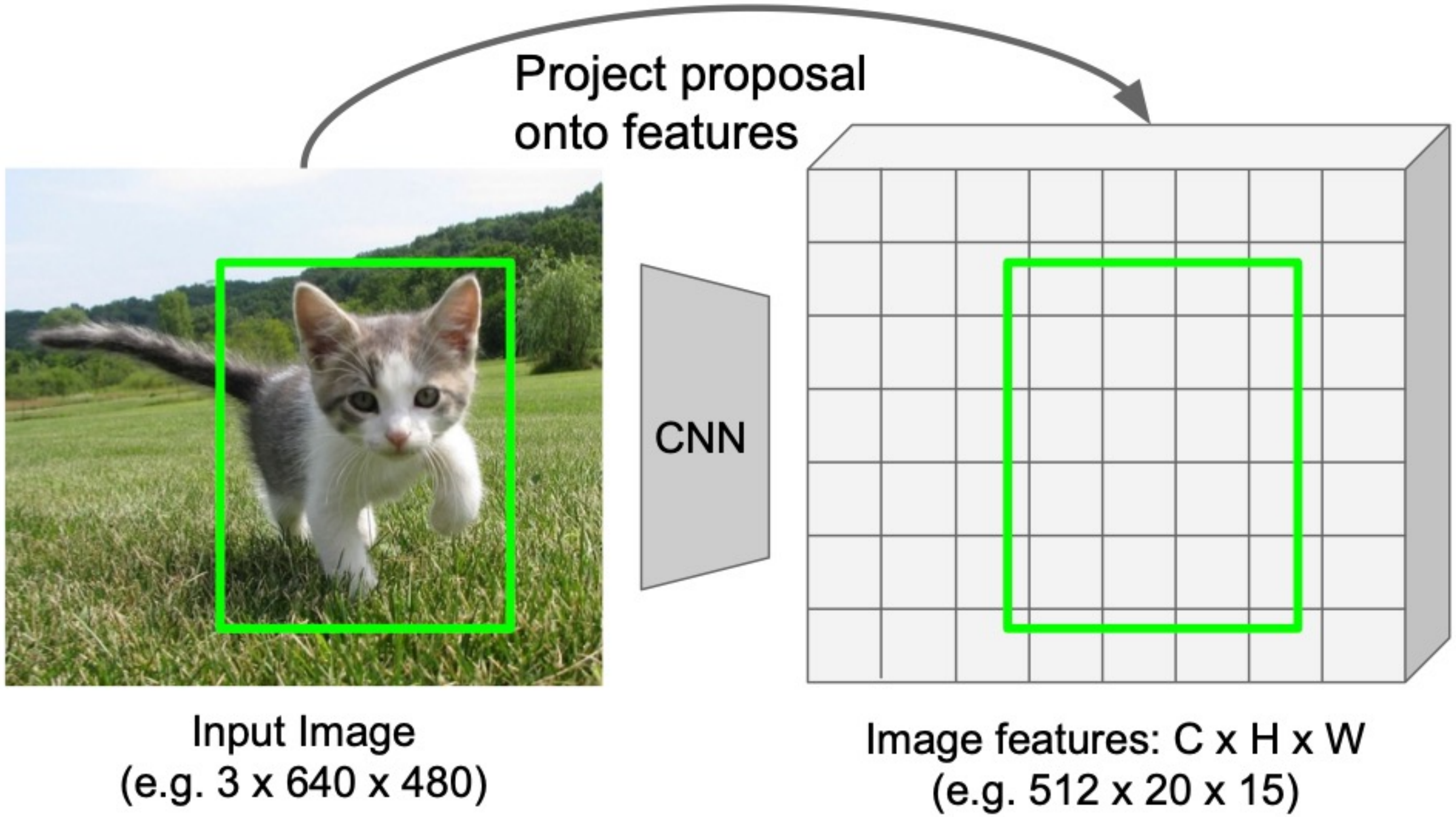


Input Image
(e.g. 3 x 640 x 480)

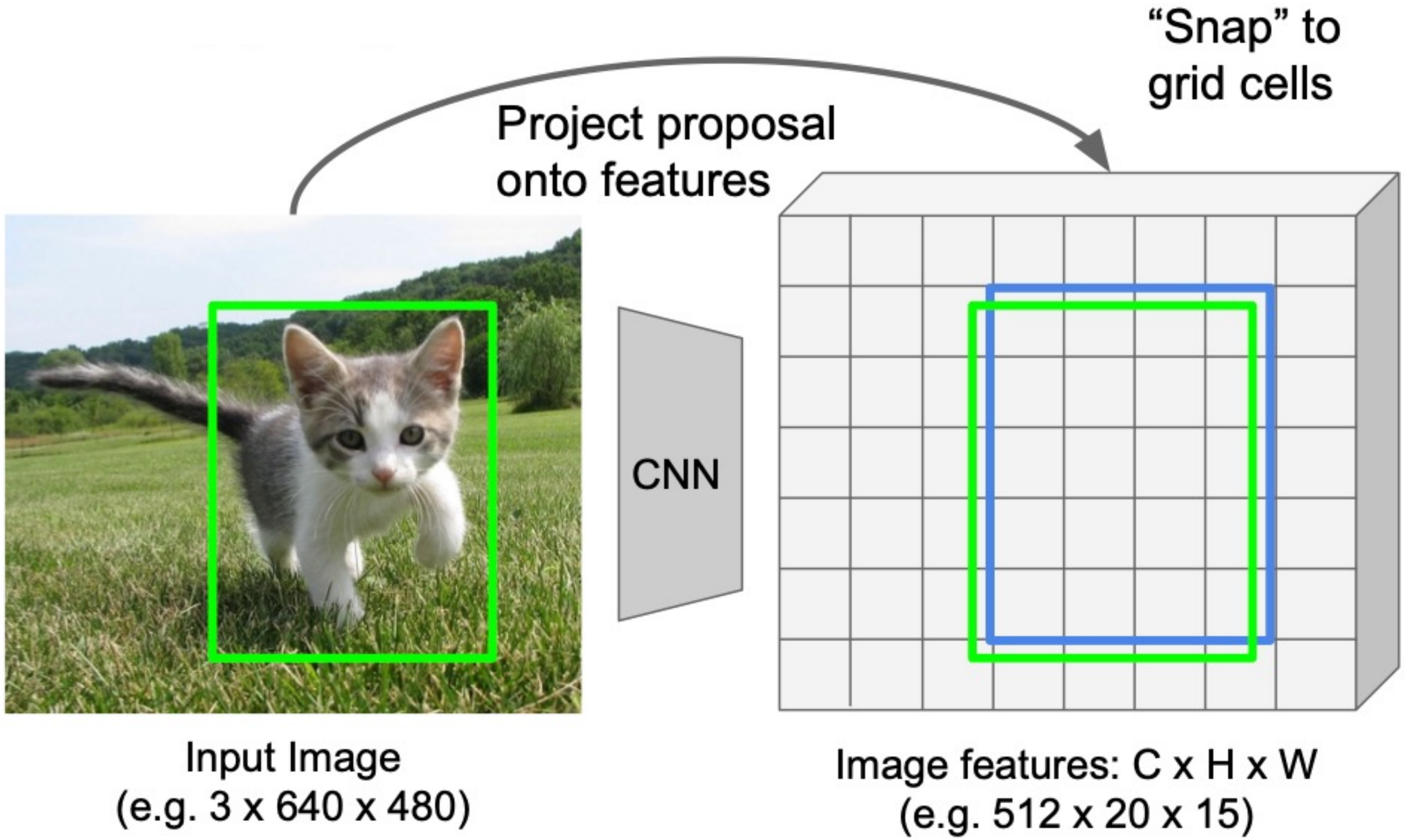
Image features: C x H x W
(e.g. 512 x 20 x 15)

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

Cropping Features: RoI Pool

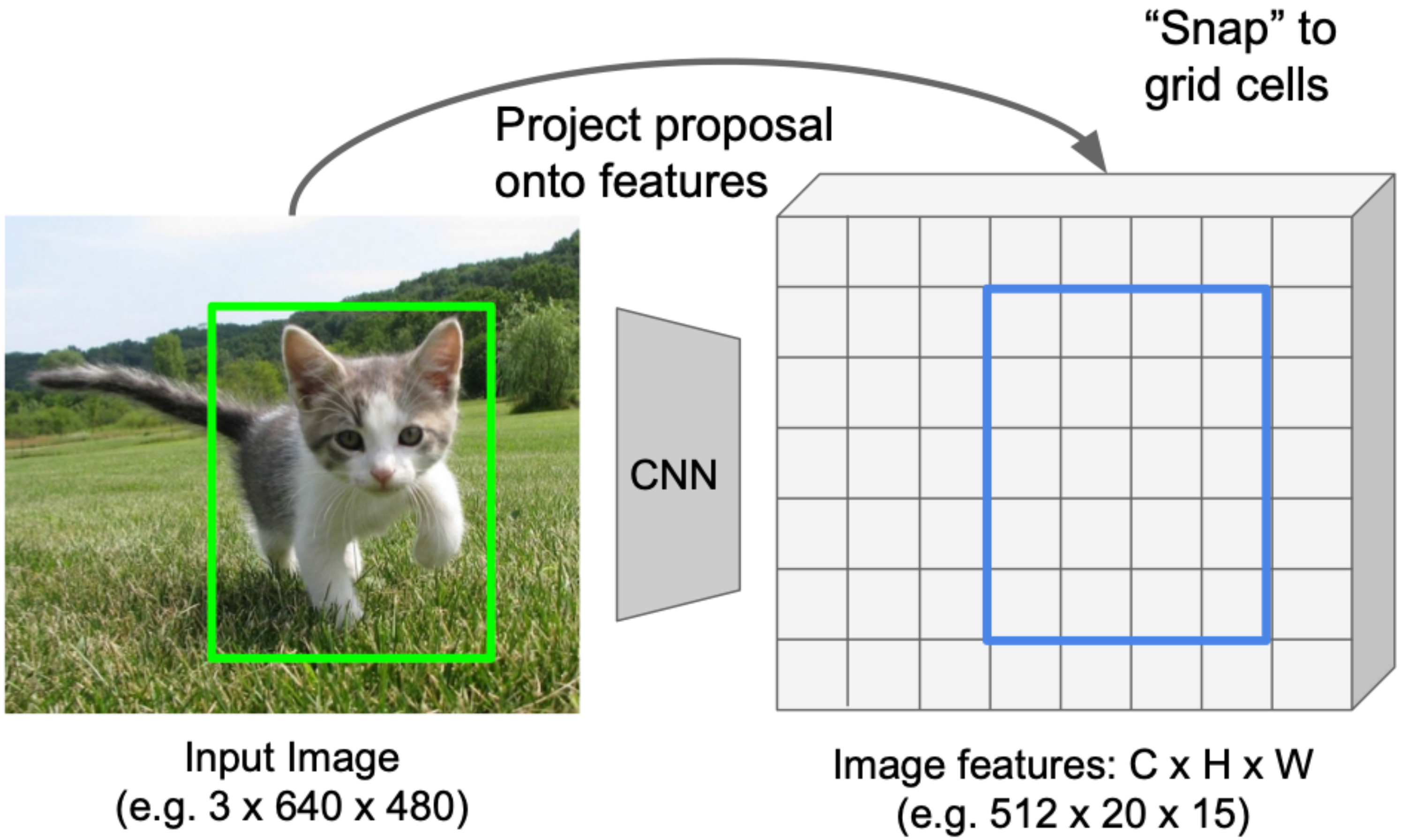


Cropping Features: RoI Pool



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

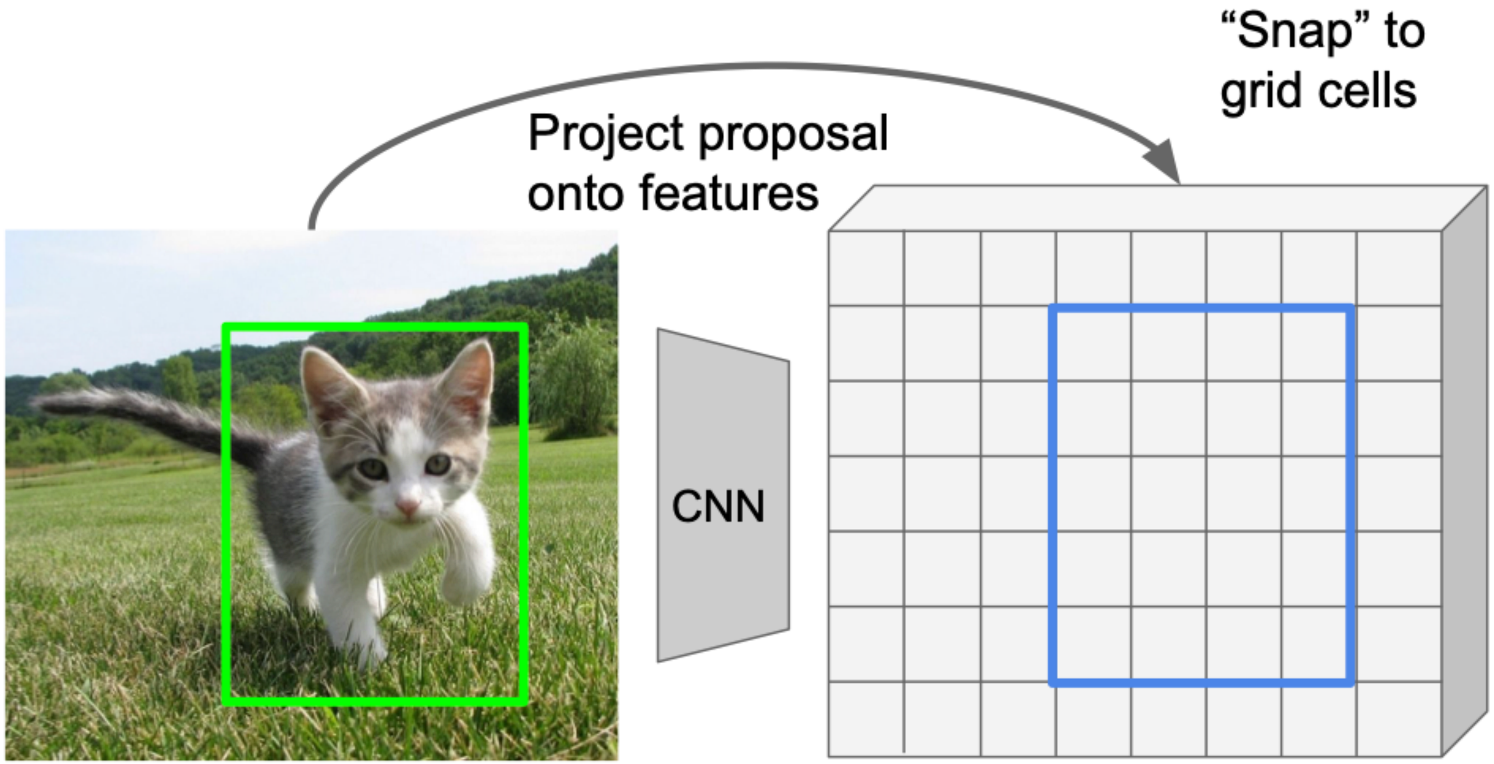
Cropping Features: RoI Pool



Q: how do we resize the 512 x 20 x 15 region to, e.g., a 512 x 2 x 2 tensor?.

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

Cropping Features: RoI Pool



Input Image
(e.g. 3 x 640 x 480)

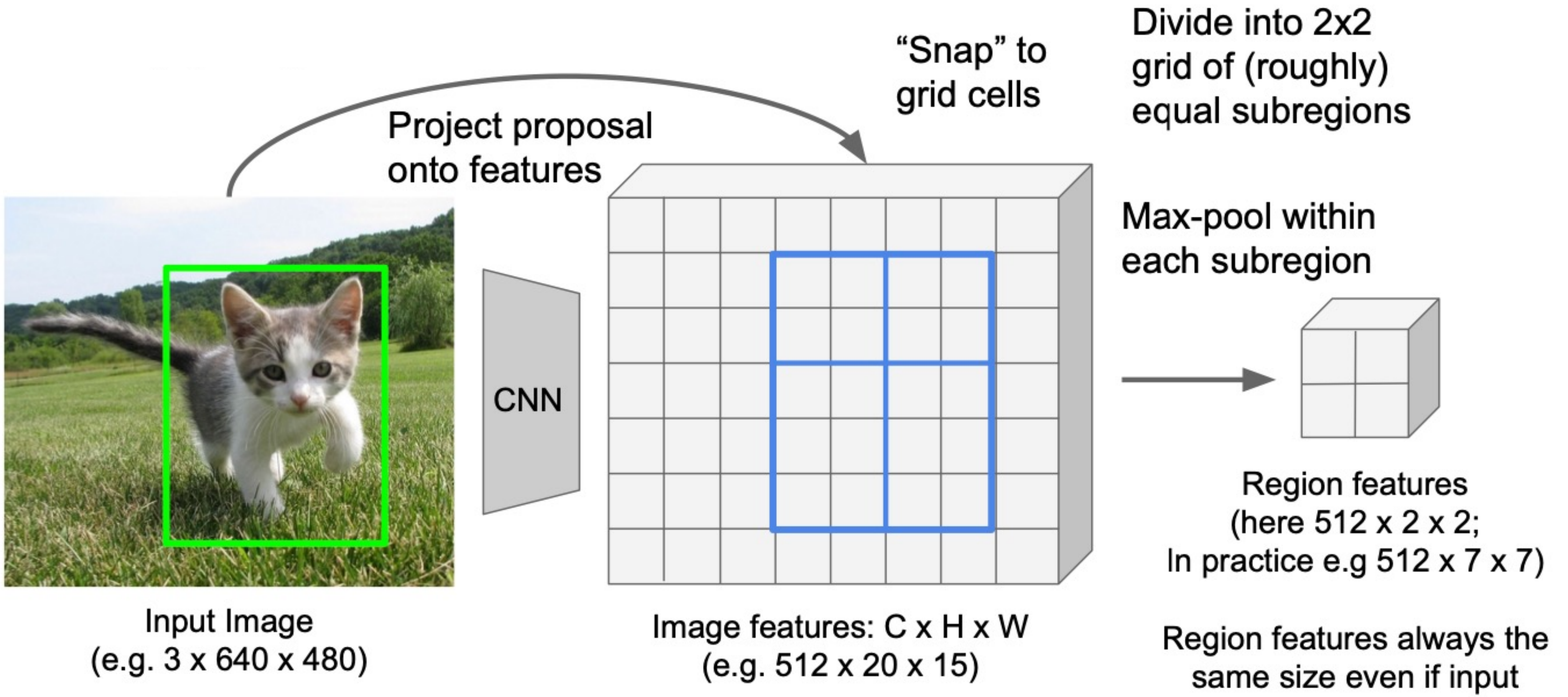
Image features: C x H x W
(e.g. 512 x 20 x 15)

Divide into 2x2 grid of (roughly) equal subregions

Q: how do we resize the 512 x 20 x 15 region to, e.g., a 512 x 2 x 2 tensor?.

Girshick, “Fast R-CNN”, ICCV 2015.

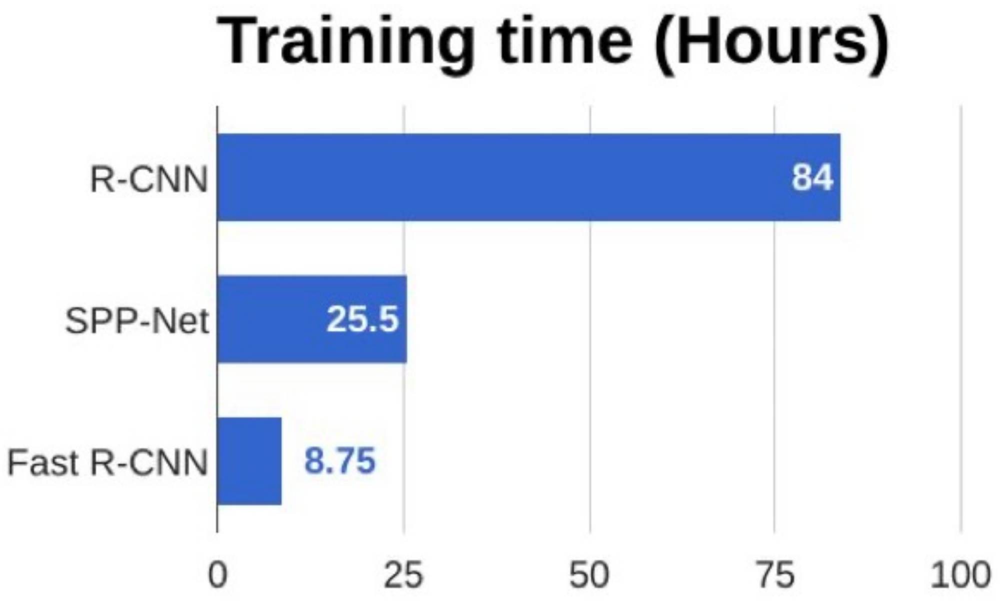
Cropping Features: RoI Pool

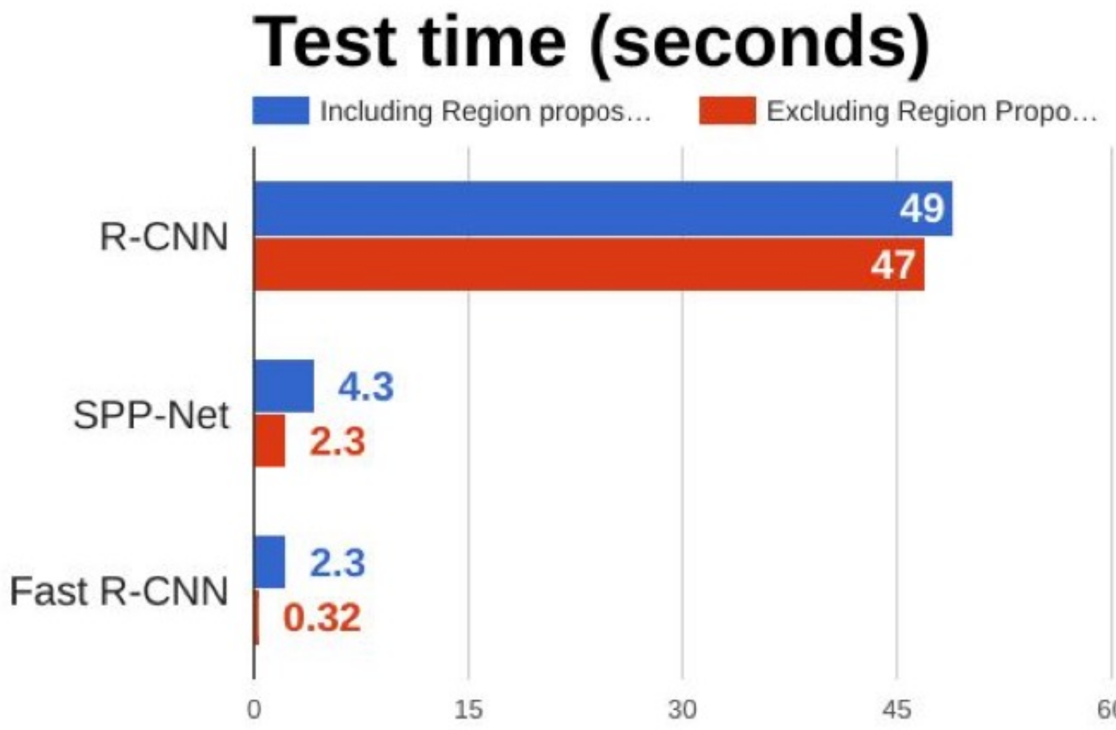


Region features always the same size even if input regions have different sizes!

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

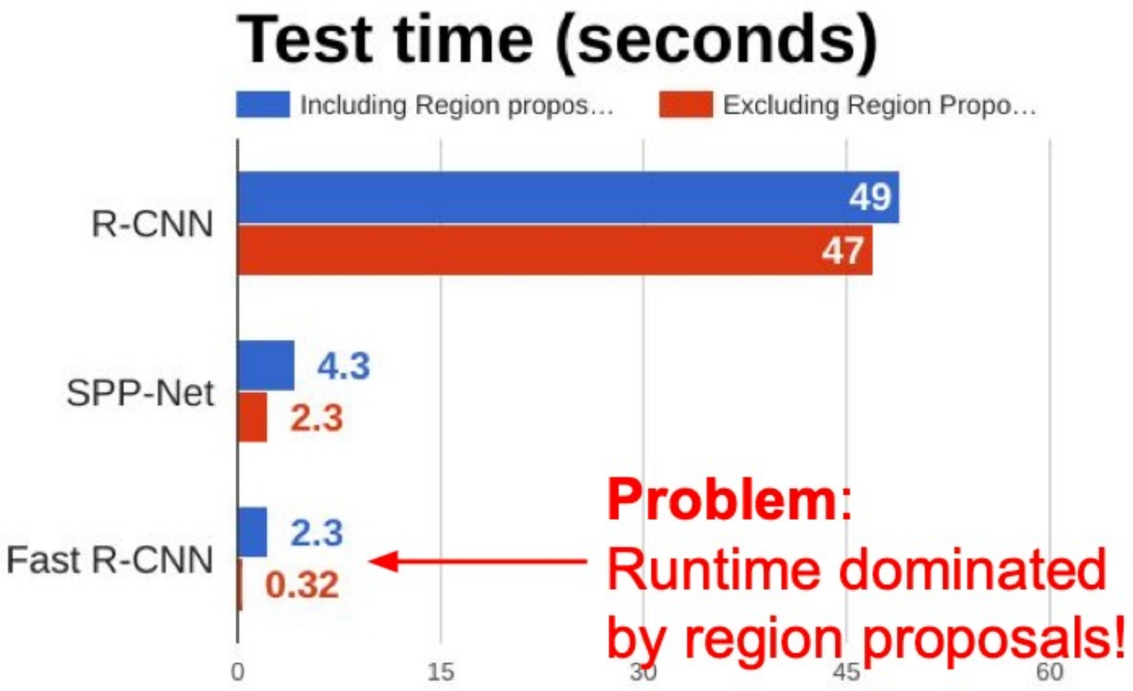
R-CNN vs. Fast R-CNN





Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs. Fast R-CNN



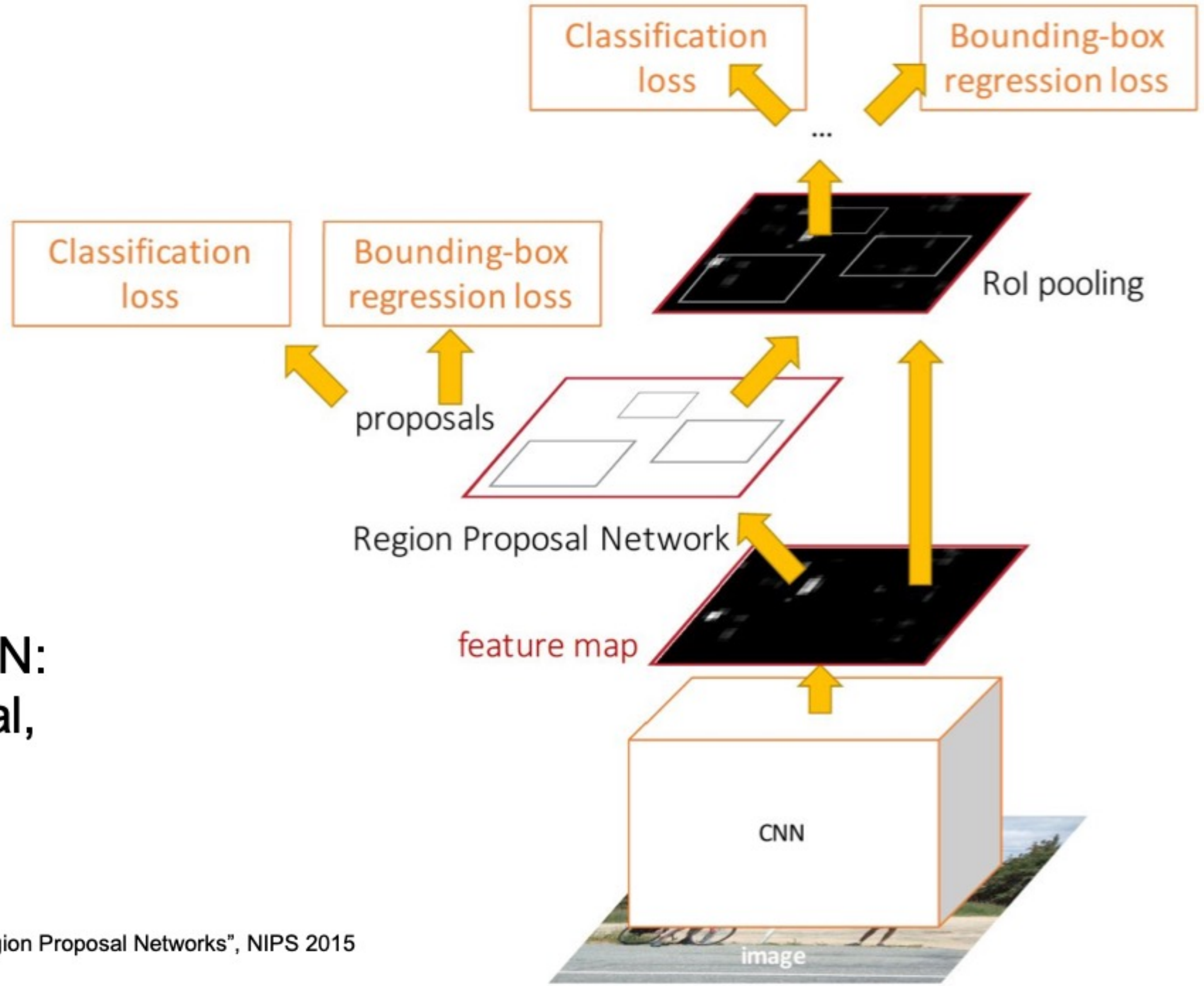
Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

Faster R-CNN

Make CNN do proposals!

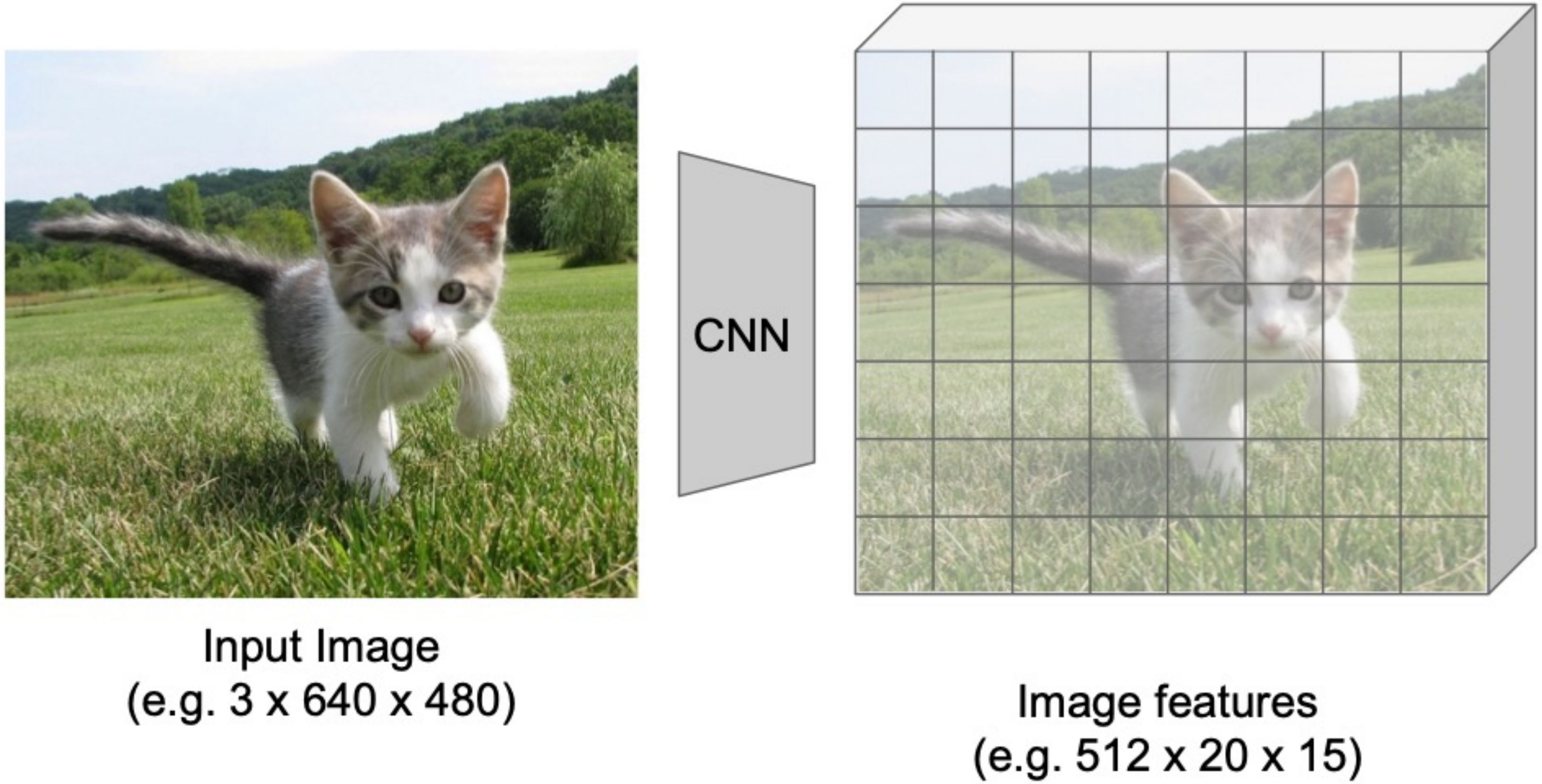
Insert **Region Proposal Network (RPN)** to predict proposals from features

Otherwise same as Fast R-CNN: Crop features for each proposal, classify each one

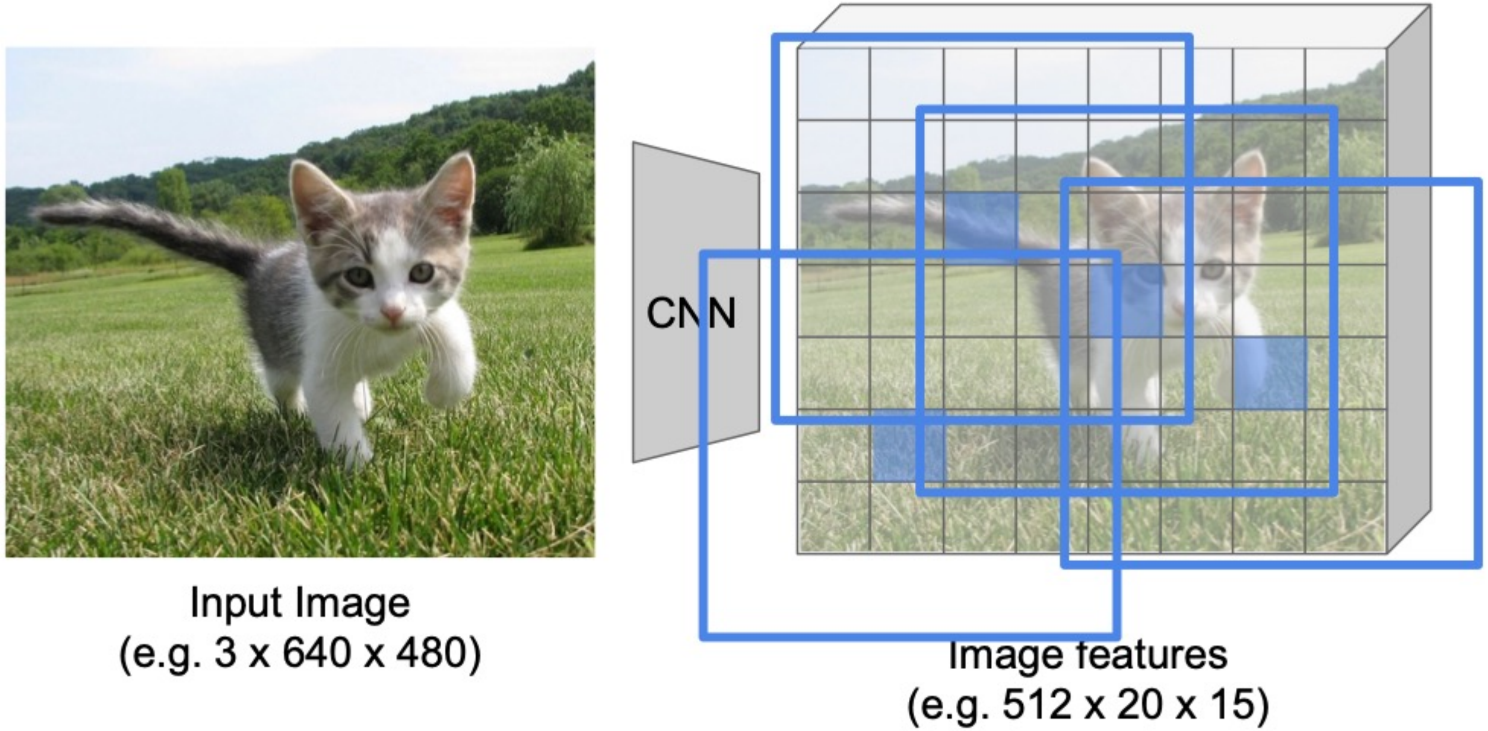


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Region Proposal Network

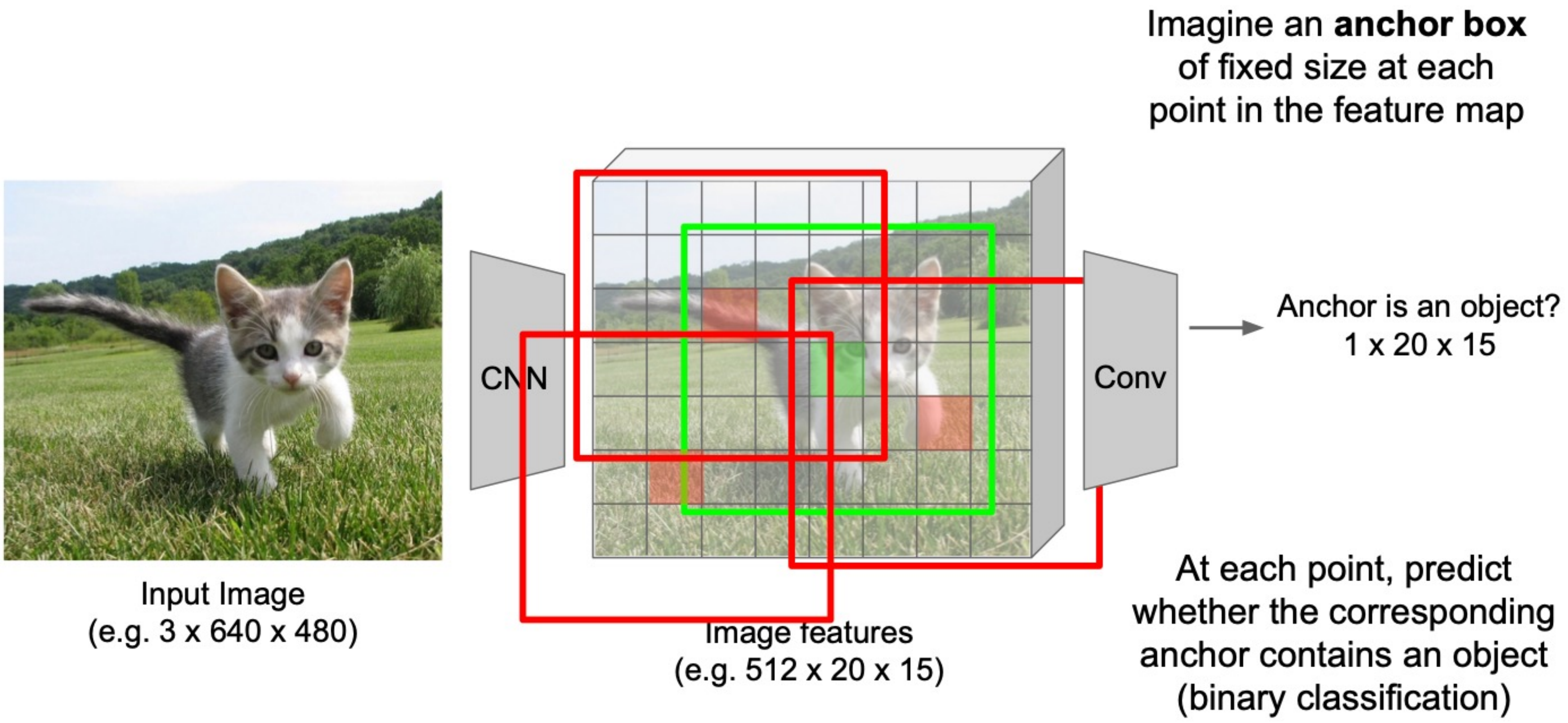


Region Proposal Network



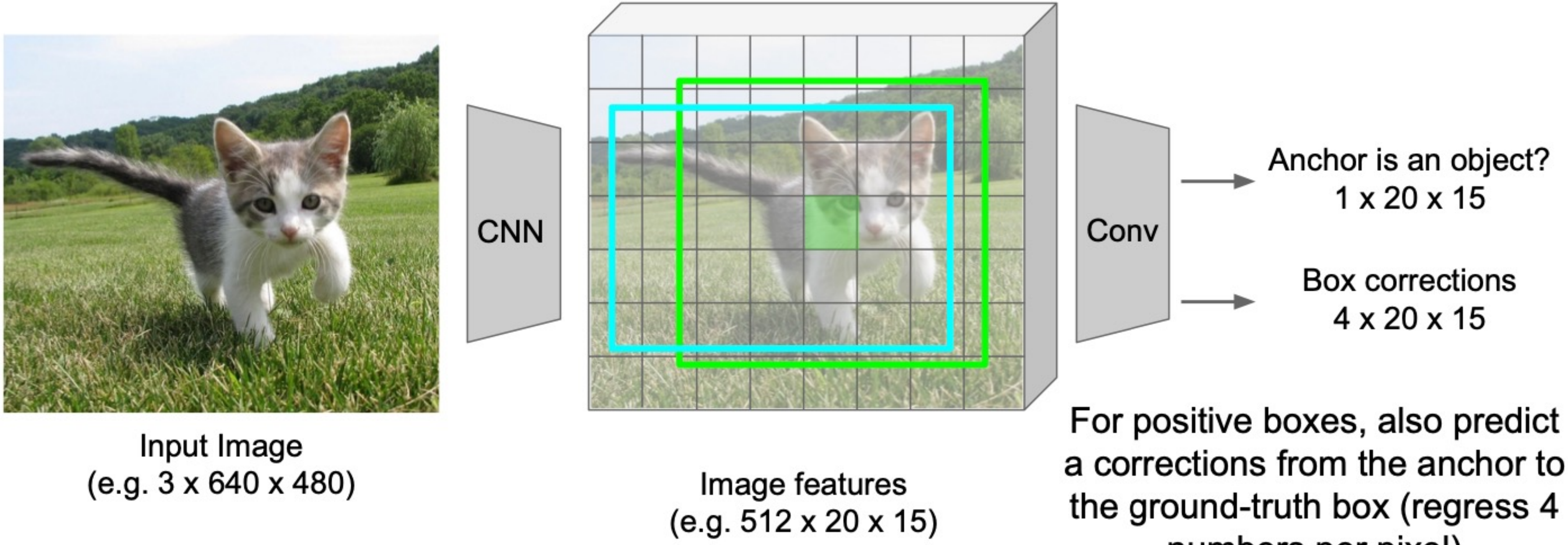
Imagine an **anchor box** of fixed size at each point in the feature map

Region Proposal Network



Region Proposal Network

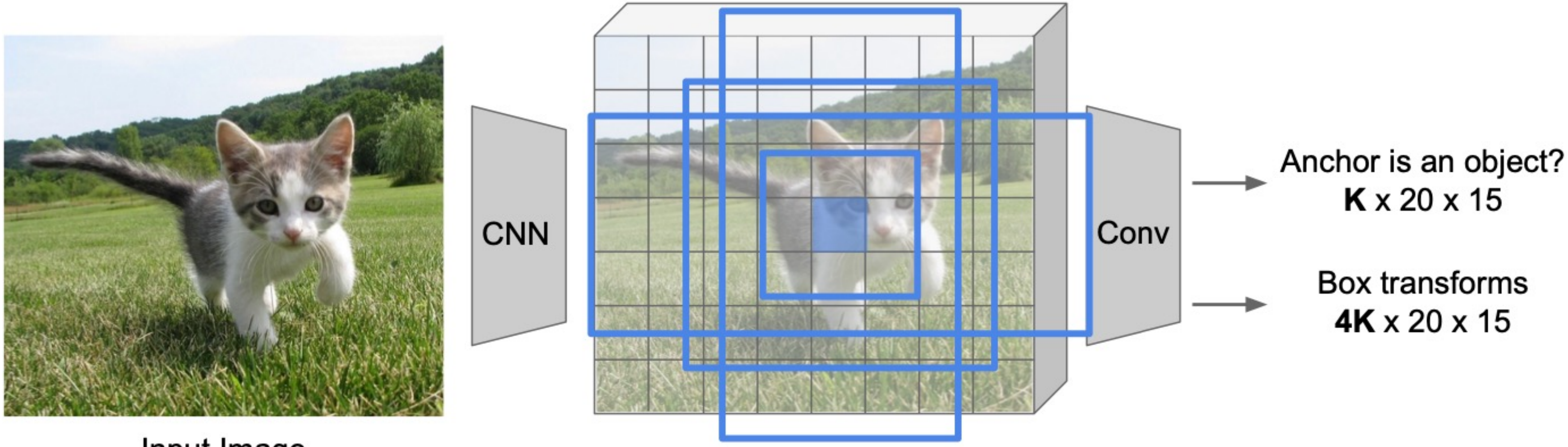
Imagine an **anchor box** of fixed size at each point in the feature map



For positive boxes, also predict a corrections from the anchor to the ground-truth box (regress 4 numbers per pixel)

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point

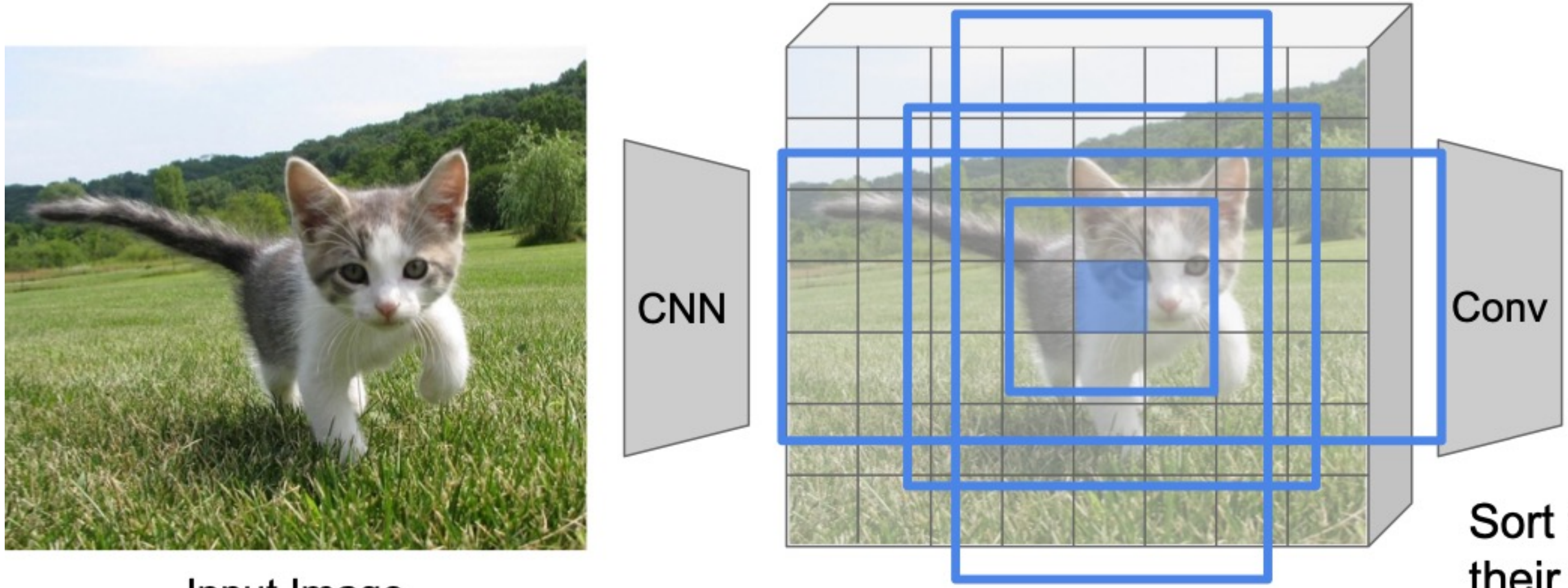


Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512 x 20 x 15)

Region Proposal Network

In practice use K different anchor boxes of different size / scale at each point



Anchor is an object?
K x 20 x 15

Box transforms
4K x 20 x 15

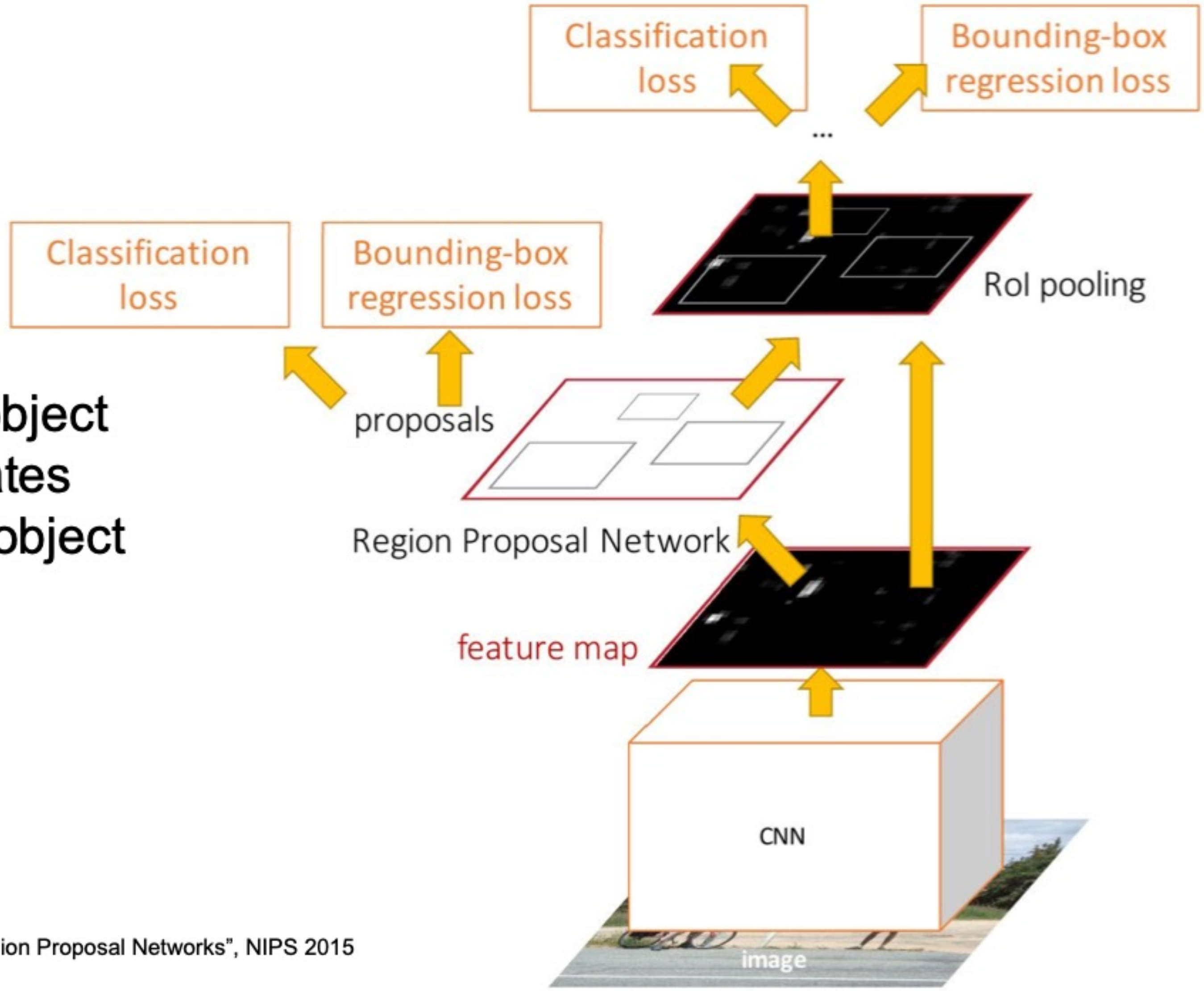
Input Image
(e.g. 3 x 640 x 480)

Image features
(e.g. 512 x 20 x 15)

Sort the K*20*15 boxes by their "objectness" score, take top ~300 as our proposals

Training Faster RCNN

Jointly train with 4 losses:
1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



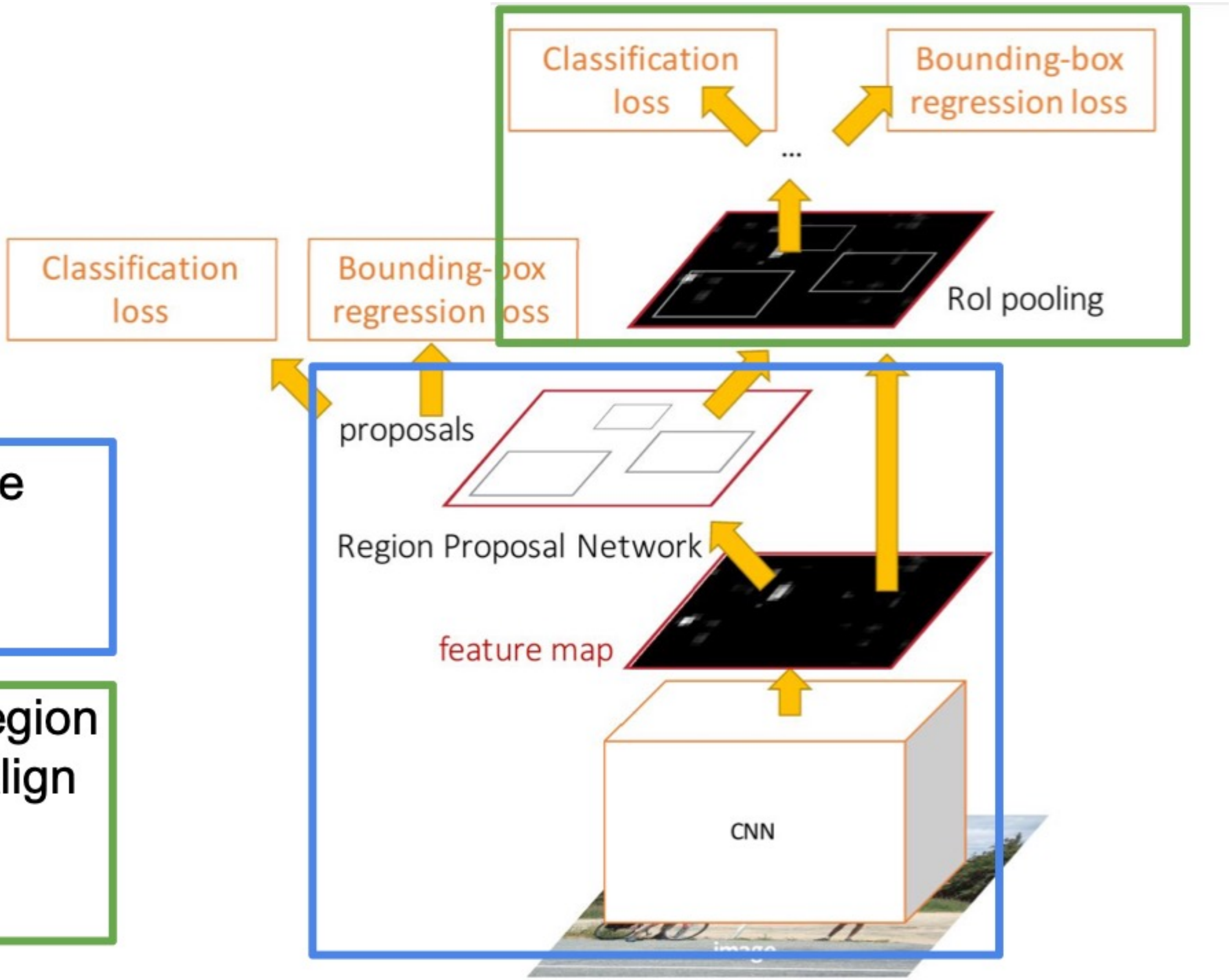
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Inference Time: Two-Stage Detector

Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Inference Time

- First stage:
  - Use backbone to extract features
  - Use RPN to generate ~ 300 proposals
- Second stage:
  - For each proposal, predict class label and bbox refinement
  - Perform confidence thresholding to remove low-confidence bbox predictions
  - Perform non-maximal suppression (NMS) for deduplication

Non-Maximal Suppression (NMS)

Input: A list of Proposal boxes B, corresponding confidence scores S (in Faster RCNN, simply the classification score) and IoU threshold τ.
Output: A list of detected bounding boxes D.

https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

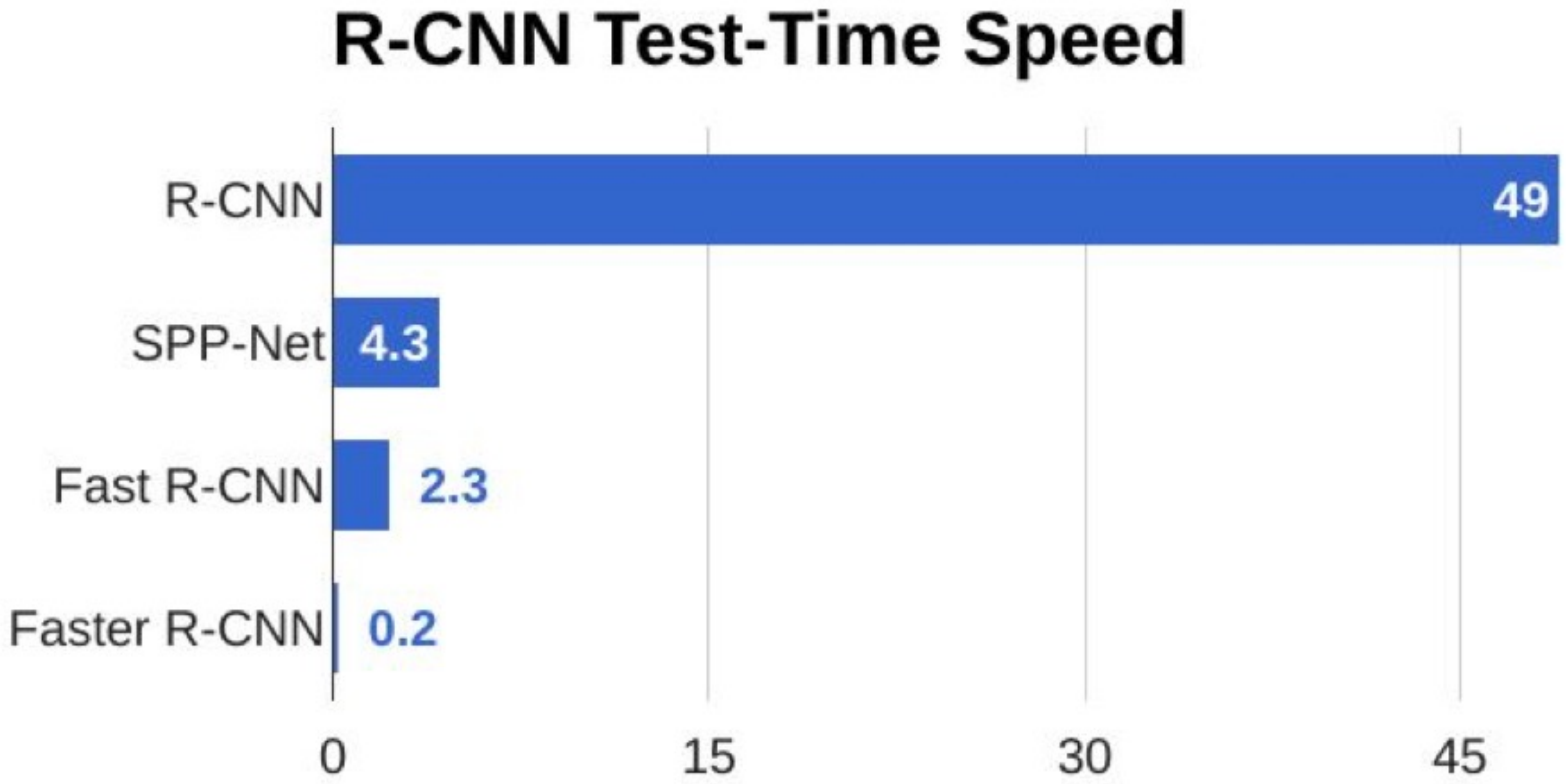
NMS

Algorithm:

- Initially D is empty
- Select the proposal with highest confidence score, remove it from B and add it to the final detection list D.
- Now compare this proposal with all the proposals — calculate the IoU of this proposal with every other proposal. If the IOU is greater than the threshold τ, remove that proposal from B.
- Again take the proposal with the highest confidence from the remaining proposals in B and remove it from B and add it to D.
- Once again calculate the IOU of this proposal with all the proposals in B and eliminate the boxes which have a IoU higher than τ.
- This process is repeated until there are no more proposals left in B.

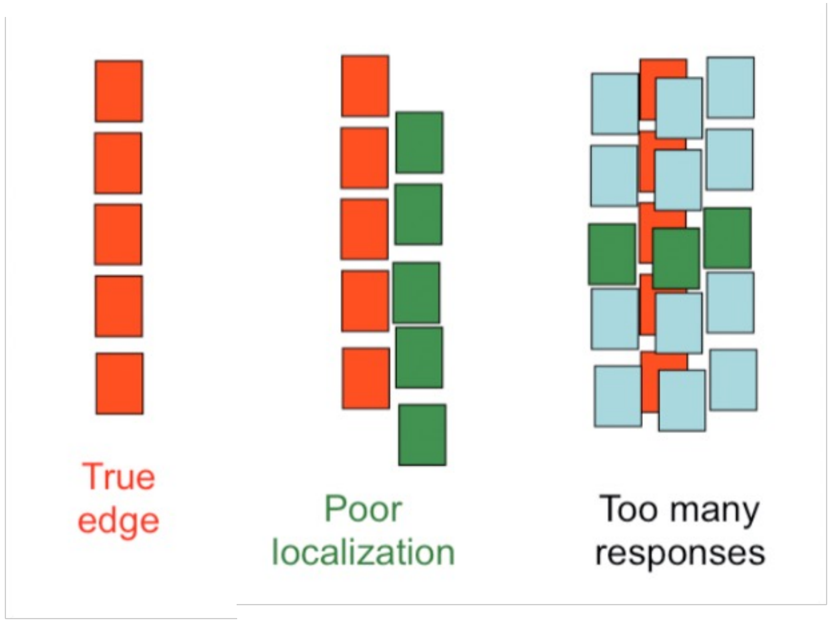
https://towardsdatascience.com/non-maximum-suppression-nms-93ce178e177c

Speed Comparison



How to Evaluate Detection?

Recall from optimal edge detection, Lecture 02

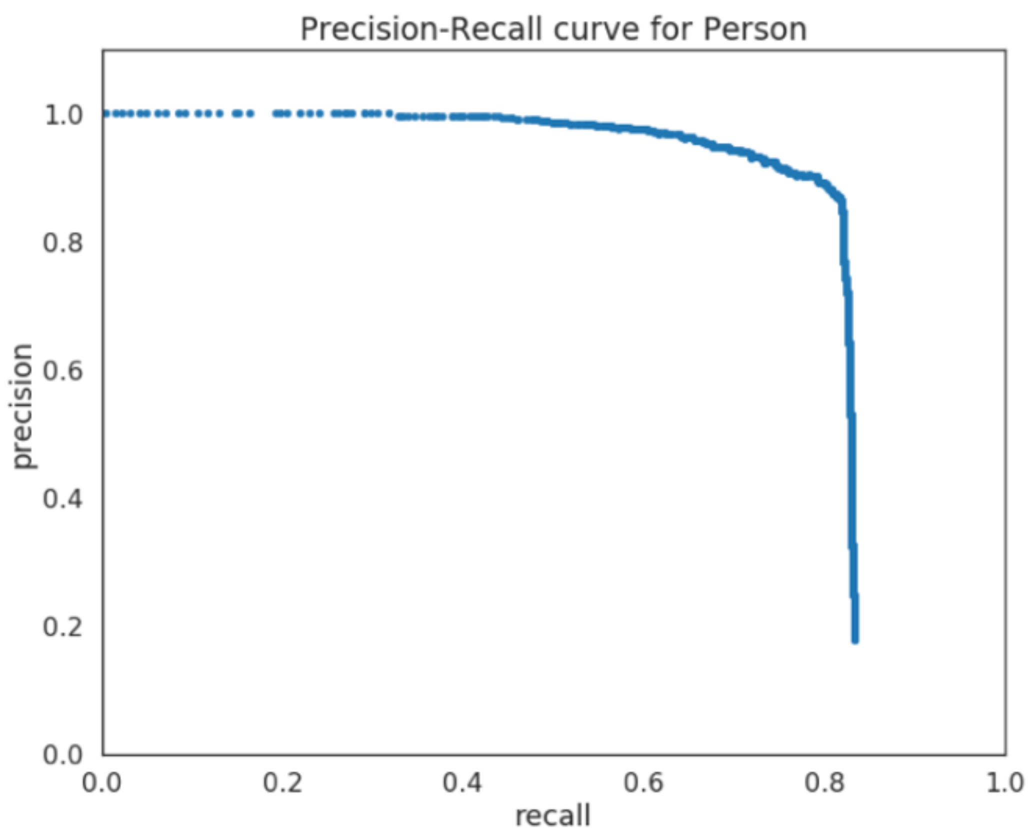


- Good accuracy (precision): minimize false positive
- Good localization (precision): maximize IoU
- Single response constraint (precision): minimize redundant responses
- Good coverage (recall): make sure all edges are detected.

Evaluation Metric: AP (Average Precision)

- Per category rank the output bounding boxes according to the confidence (classification score) in a descending order.
- Select top n outputs and compute recall.
- Precision: the ratio of bboxes that satisfy IoU > x% threshold
- Compute the area under precision-recall curve (approximate by 11 points).

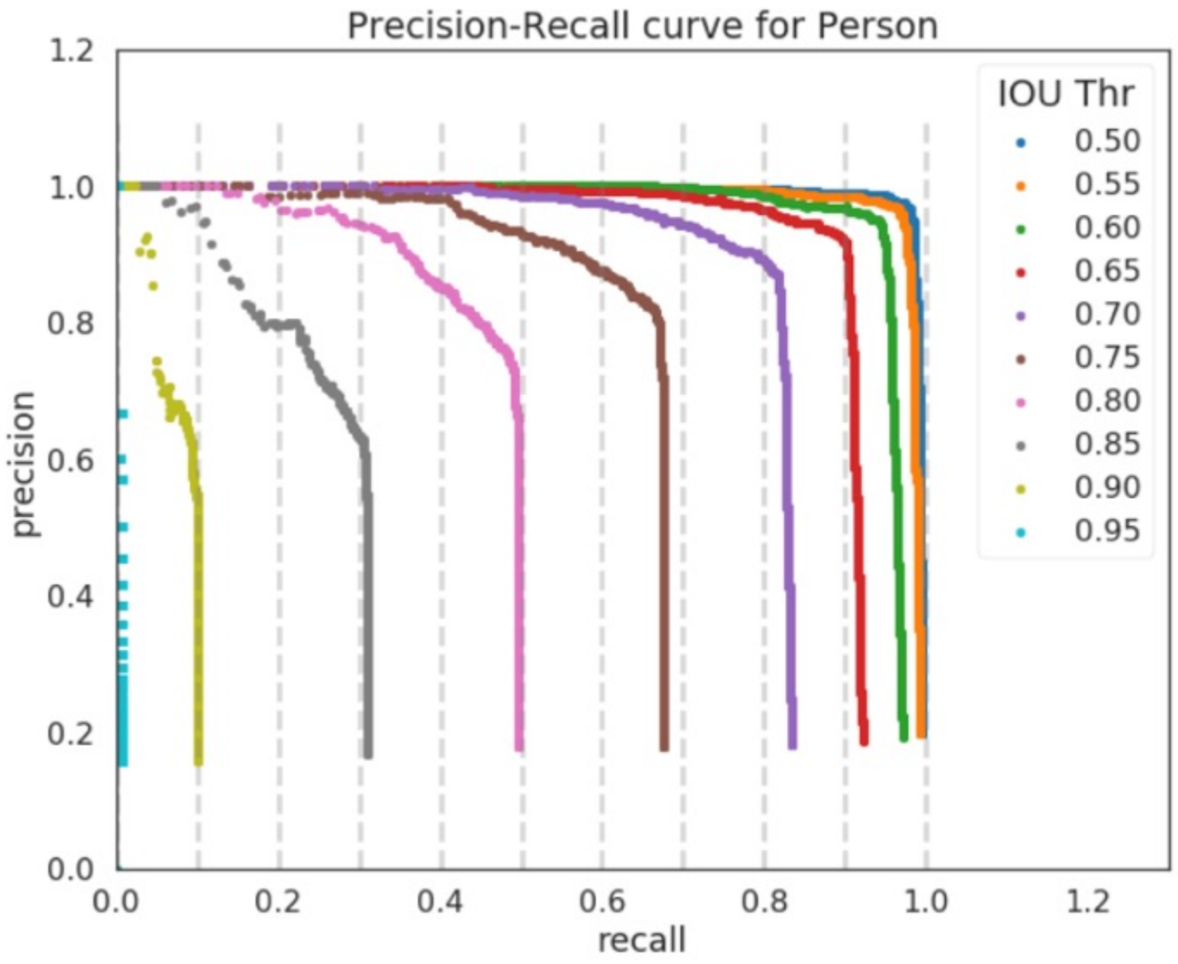
$$AP = \frac{1}{11} \sum_{\mathrm{Recall}_i} \mathrm{Precision}(\mathrm{Recall}_i)$$



Recall_i = [0, 0.1, 0.2, …, 1.0].

https://medium.com/@timothycarlen/understanding-the-map-evaluation-metric-for-object-detection-a07fe6962cf3

Evaluation Metric: AP at Different IoU Thres.



Precision-Recall curves calculated at various IoU thresholds, according to the COCO challenge. Dashed lines correspond to equally spaced recall values where the AP is calculated.

https://medium.com/@timothycarlen/understanding-the-map-evaluation-metric-for-object-detection-a07fe6962cf3

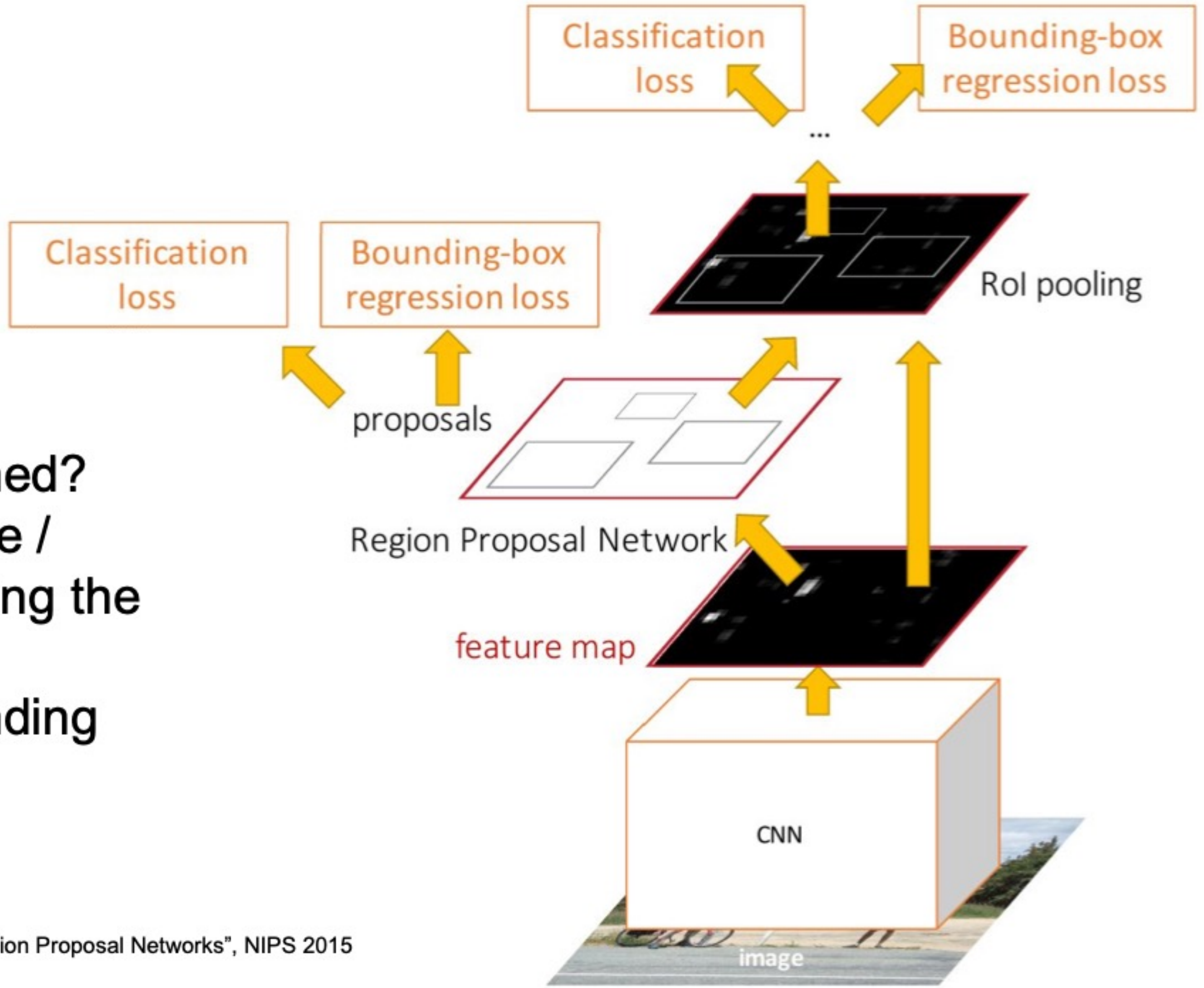
Evaluation Metric: mAP

- mAP is the mean of AP across different categories and/or IoU thresholds. Sometimes m is ignored.
- Examples when evaluating on MS COCO:
  - AP
  - AP_{50}

Faster RCNN

Glossing over many details:

- How are anchors determined?
- How do we sample positive / negative samples for training the RPN?
- How to parameterize bounding box regression?



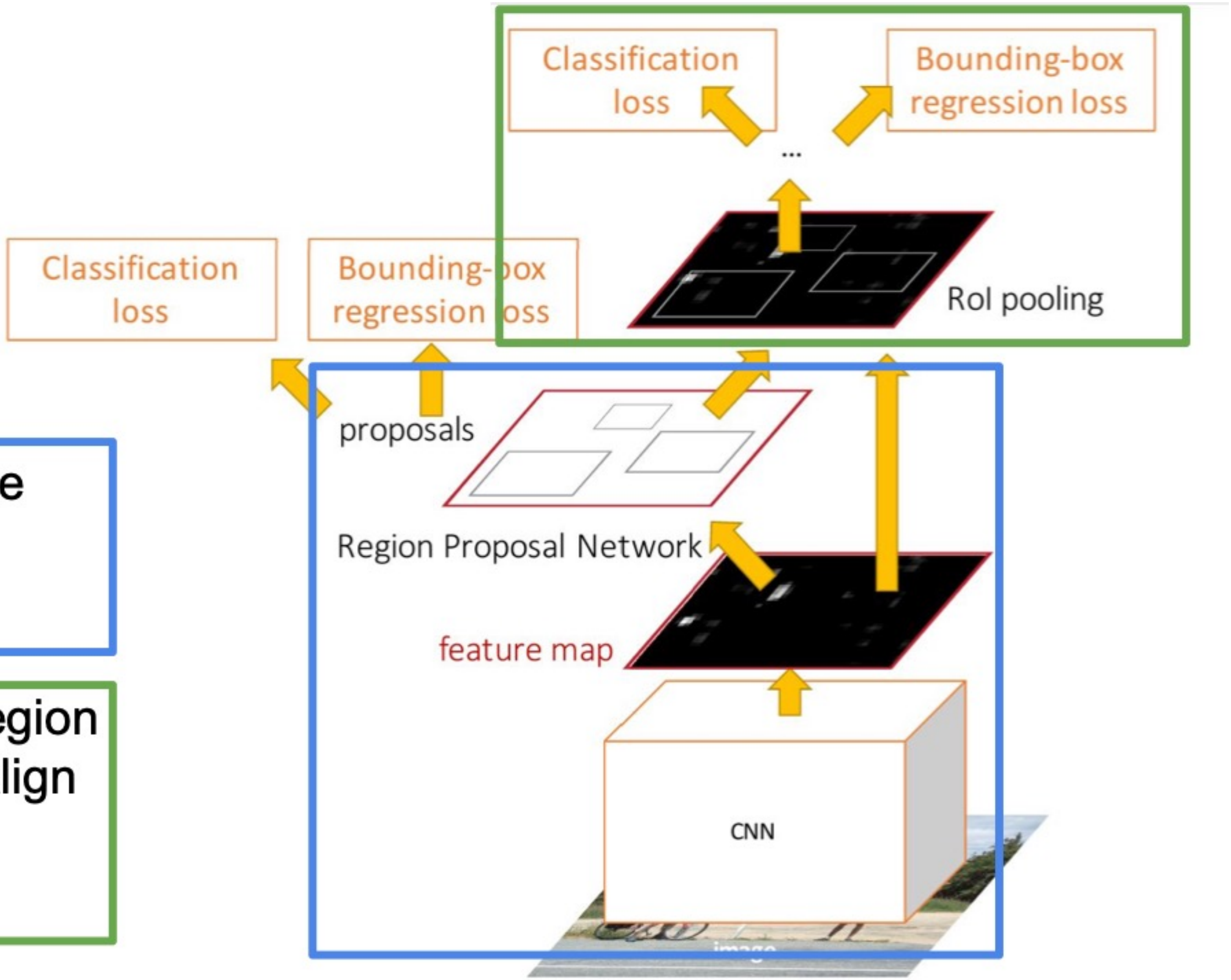
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Two-Stage Detector

Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



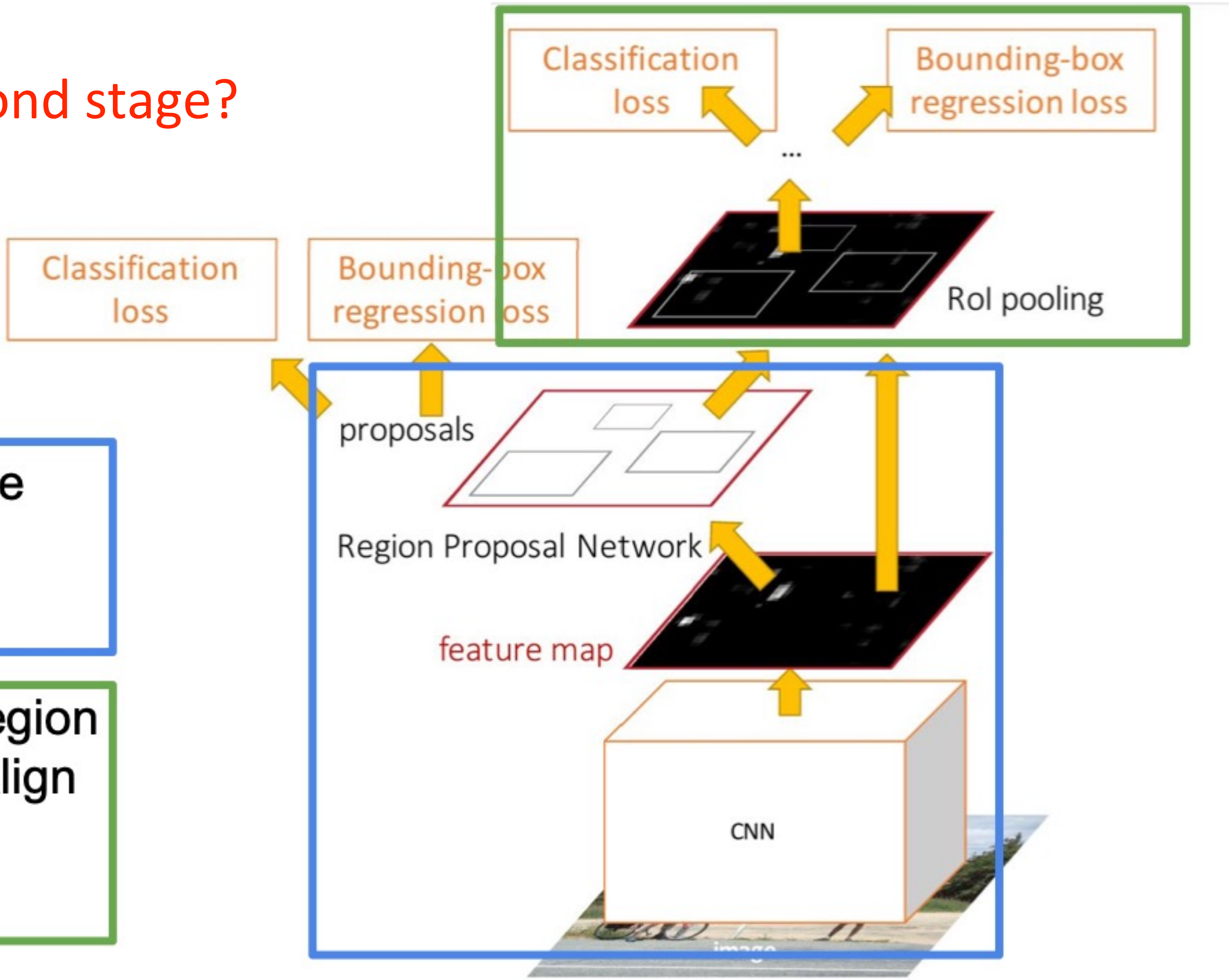
Two-Stage Detector

Do we really need the second stage?

Faster R-CNN is a
Two-stage object detector

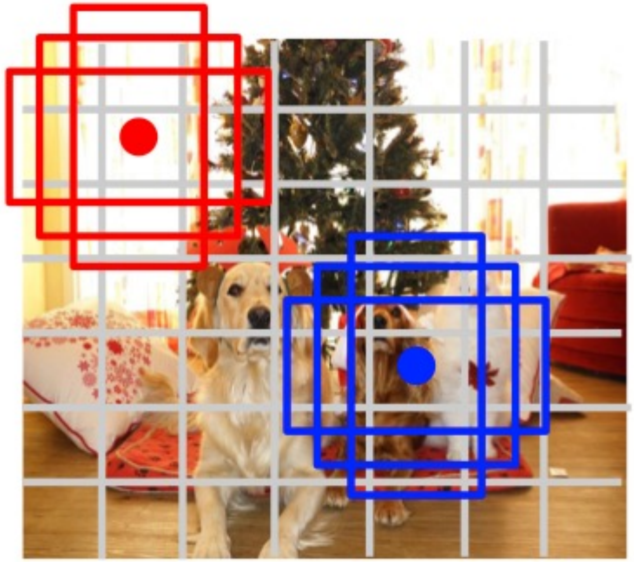
First stage: Run once per image
- Backbone network
- Region proposal network

Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



Single-Stage Detectors: YOLO/SSD/RetinaNet

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers: (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)
- Looks a lot like RPN, but category-specific!

Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016
Lin et al, "Focal Loss for Dense Object Detection", ICCV 2017

Object Detection: Lots of Variables

Backbone Network
VGG16
ResNet-101
Inception V2
Inception V3
Inception
ResNet
MobileNet

"Meta-Architecture"
Two-stage: Faster R-CNN
Single-stage: YOLO / SSD
Hybrid: R-FCN

Image Size
 # Region Proposals
...

Takeaways
Faster R-CNN is slower but more accurate

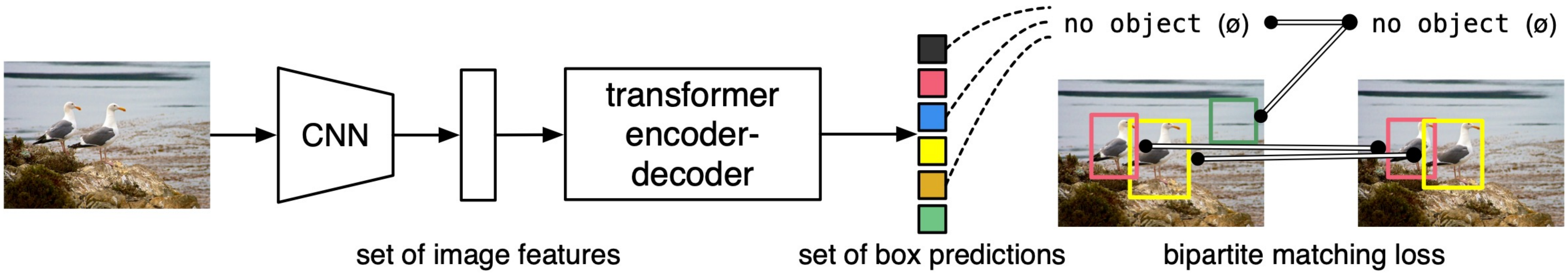
SSD is much faster but not as accurate

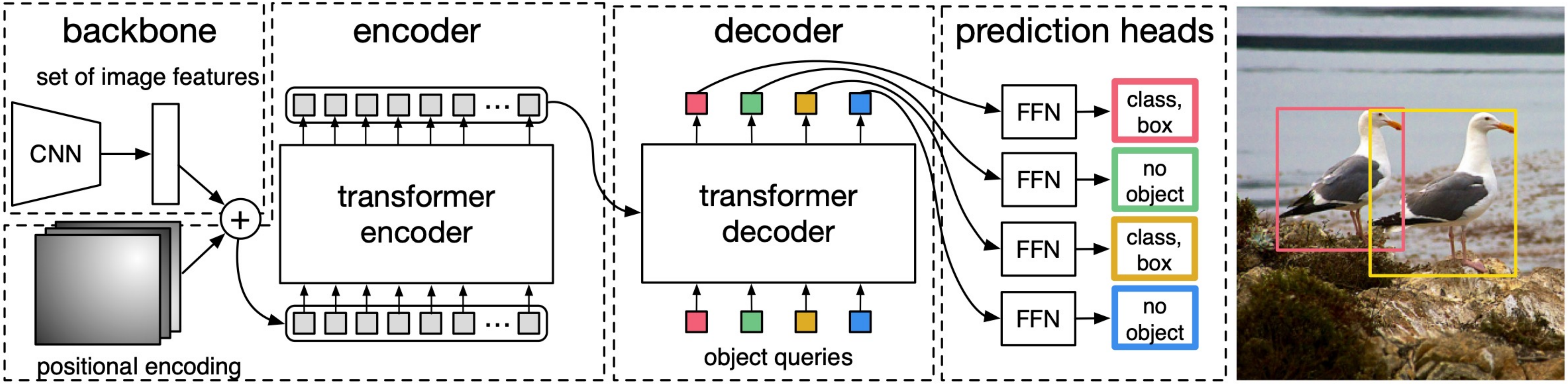
Bigger / Deeper backbones work better

Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017
Zou et al, "Object Detection in 20 Years: A Survey", arXiv 2019

R-FCN: Dai et al, "R-FCN: Object Detection via Region-based Fully Convolutional Networks", NIPS 2016
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015
Inception V3: Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", arXiv 2016
Inception ResNet: Szegedy et al, "Inception-V4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv 2016
MobileNet: Howard et al, "Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv 2017

End-to-End Object Detection with Transformers (DETR)

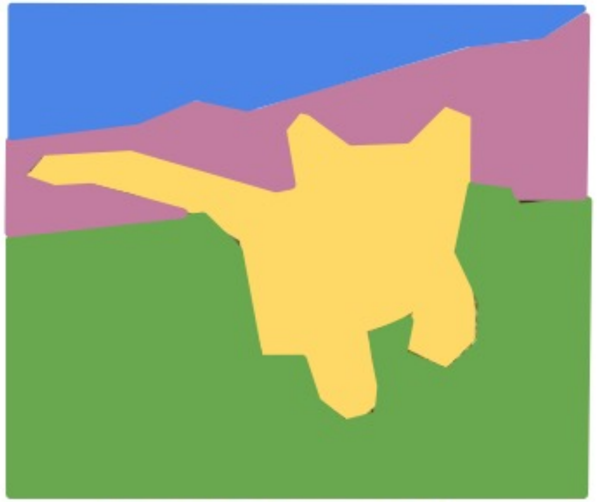
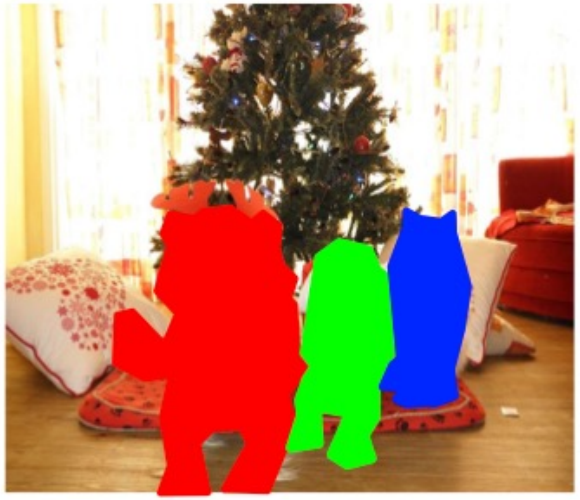




Instance Segmentation

Some slides are borrowed from Stanford CS231N.

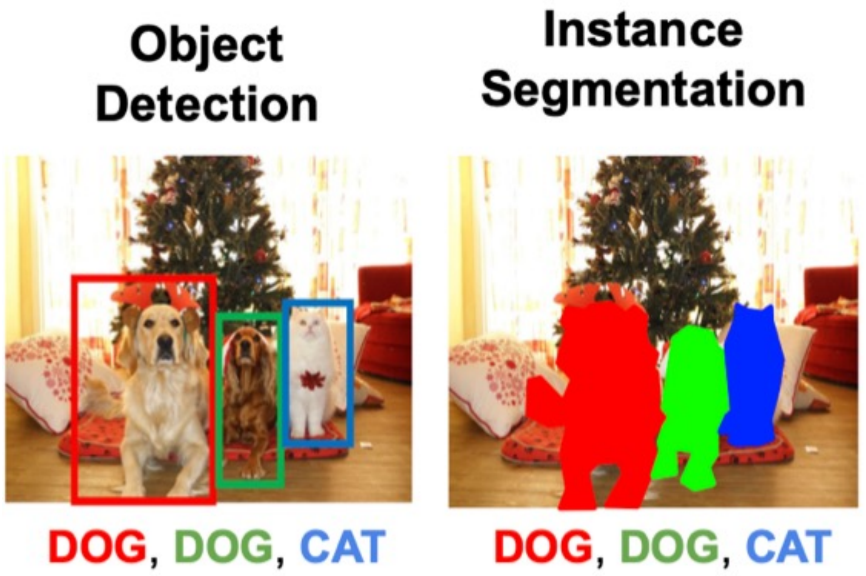
Computer Vision Tasks

Classification	Semantic Segmentation	Object Detection	Instance Segmentation
			
CAT	GRASS, CAT, TREE, SKY	DOG, DOG, CAT	DOG, DOG, CAT
No spatial extent	No objects, just pixels	Multiple Object	

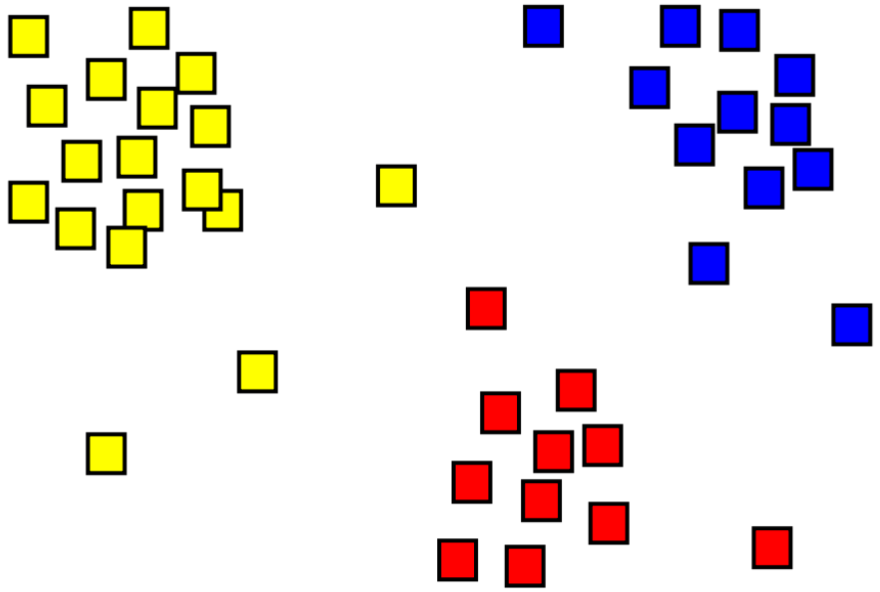
This image is CC0 public domain

Different Approaches for Instance Segmentation

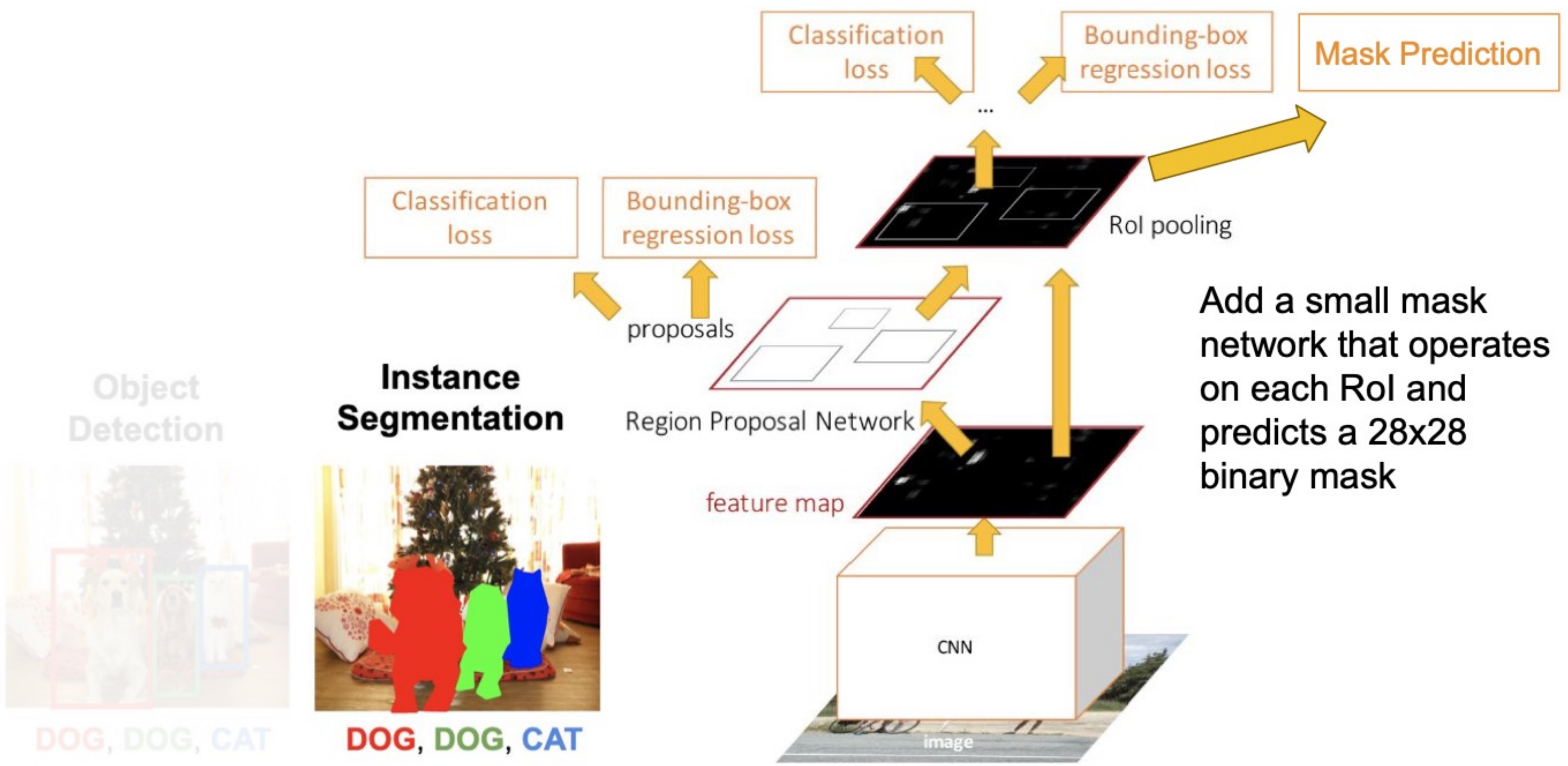
- Top-down approach:object detection and then further find a binary mask inside the bounding box



- Bottom-up approach:grouping and then classification
  - Grouping: group together similar data points and represents them with a single token



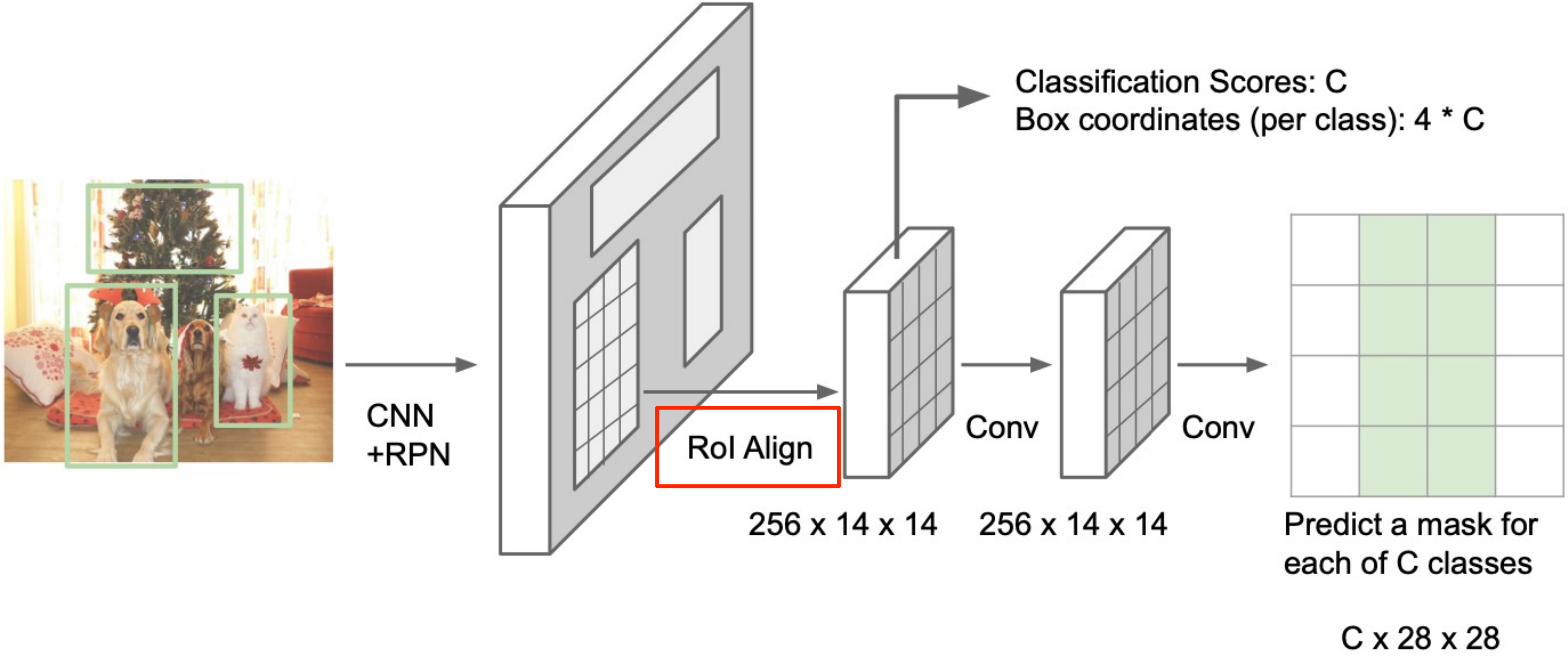
Top-Down Approach: Mask R-CNN



Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

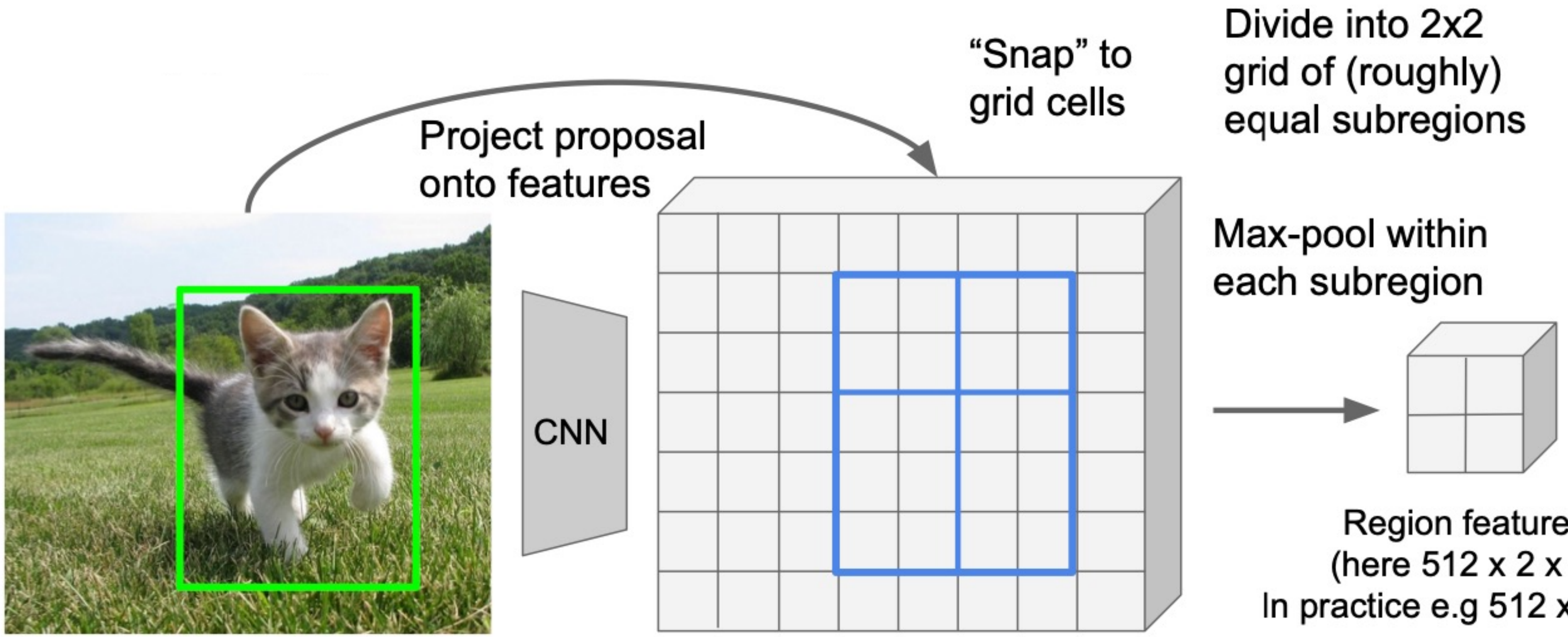
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN



He et al, "Mask R-CNN", arXiv 2017

Problems with RoI Pool



Input Image (e.g. 3 x 640 x 480)

Image features: C x H x W (e.g. 512 x 20 x 15)

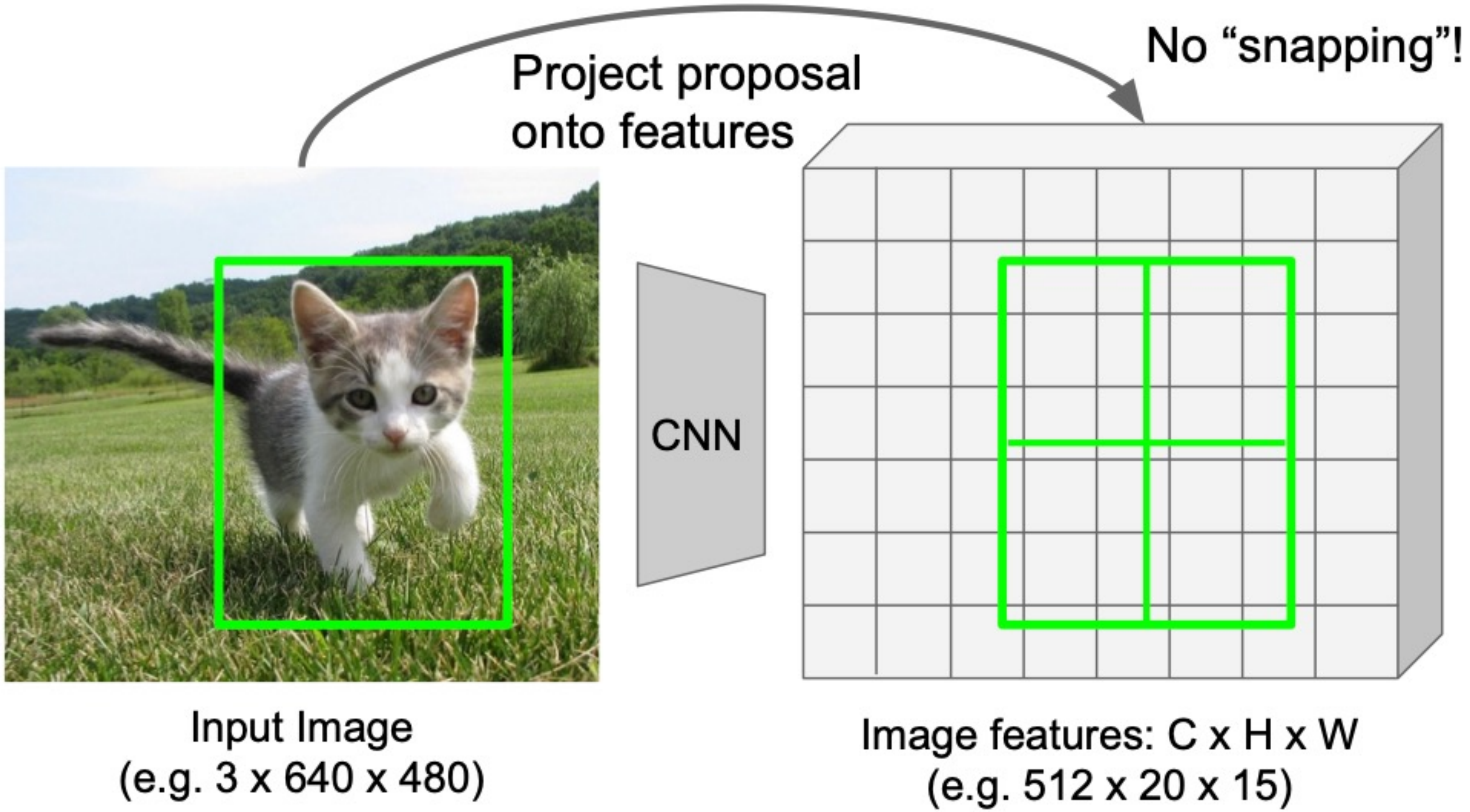
Region features (here 512 x 2 x 2; In practice e.g 512 x 7 x 7)

Region features always the same size even if input regions have different sizes!

Problem: Region features slightly misaligned

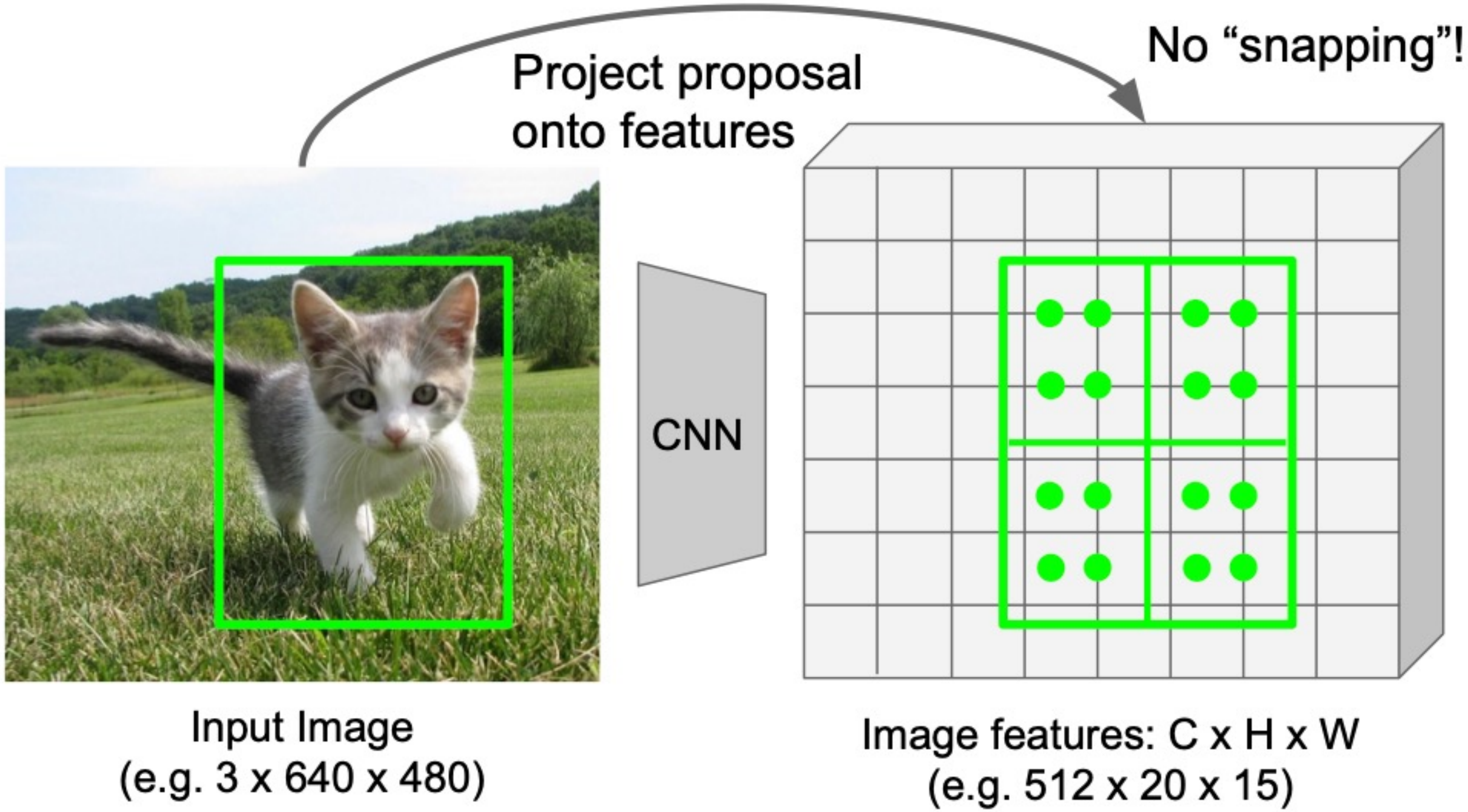
Girshick, "Fast R-CNN", ICCV 2015.

RoI Align



He et al, "Mask R-CNN", ICCV 2017

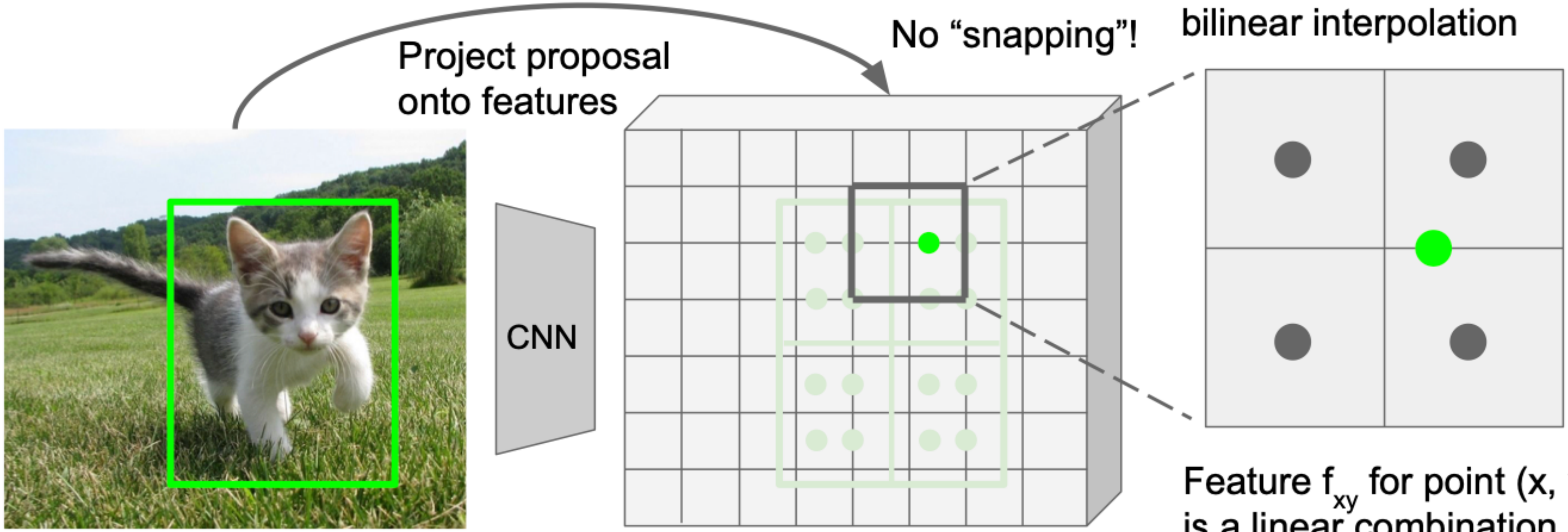
RoI Align



Sample at regular points in each subregion using bilinear interpolation

He et al, “Mask R-CNN”, ICCV 2017

RoI Align



Sample at regular points in each subregion using bilinear interpolation

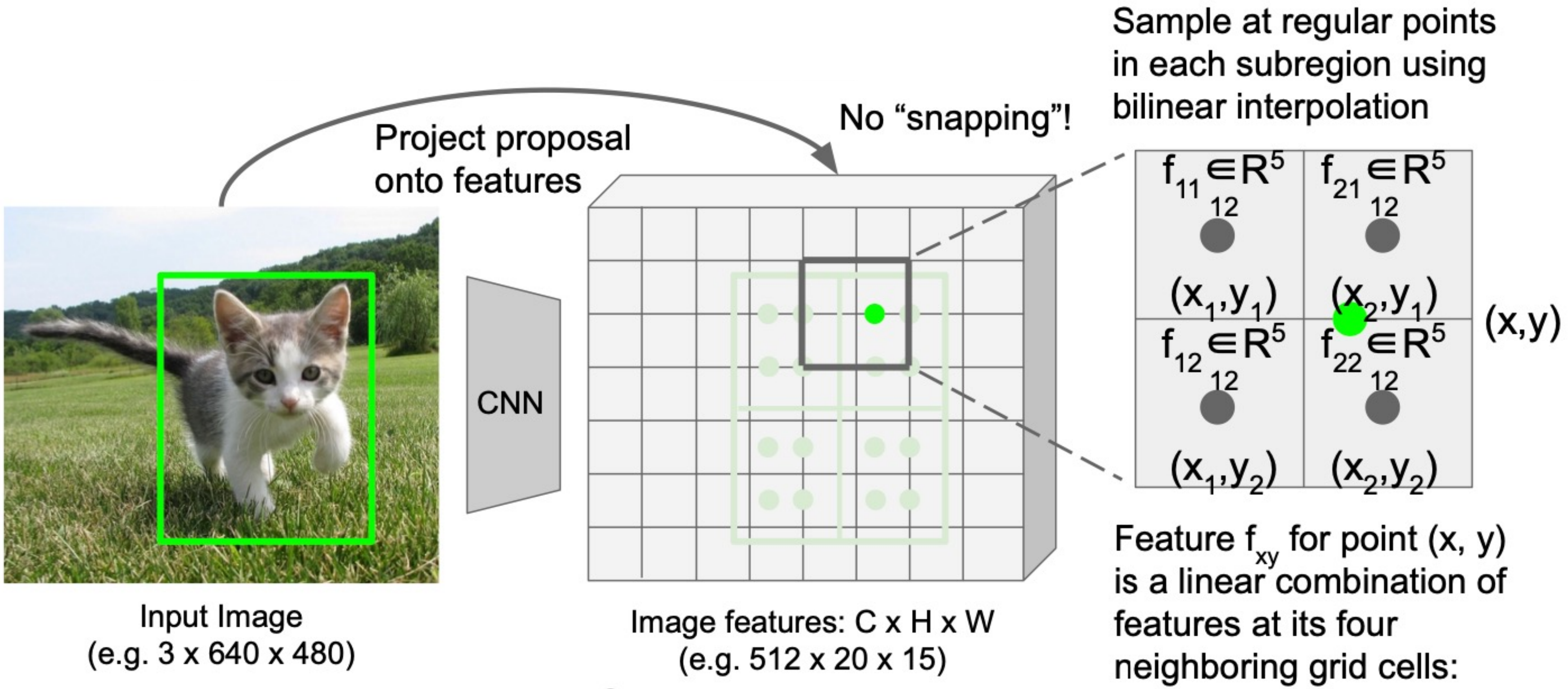
Input Image
(e.g. 3 x 640 x 480)

Image features: C x H x W
(e.g. 512 x 20 x 15)

Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

He et al, “Mask R-CNN”, ICCV 2017

RoI Align

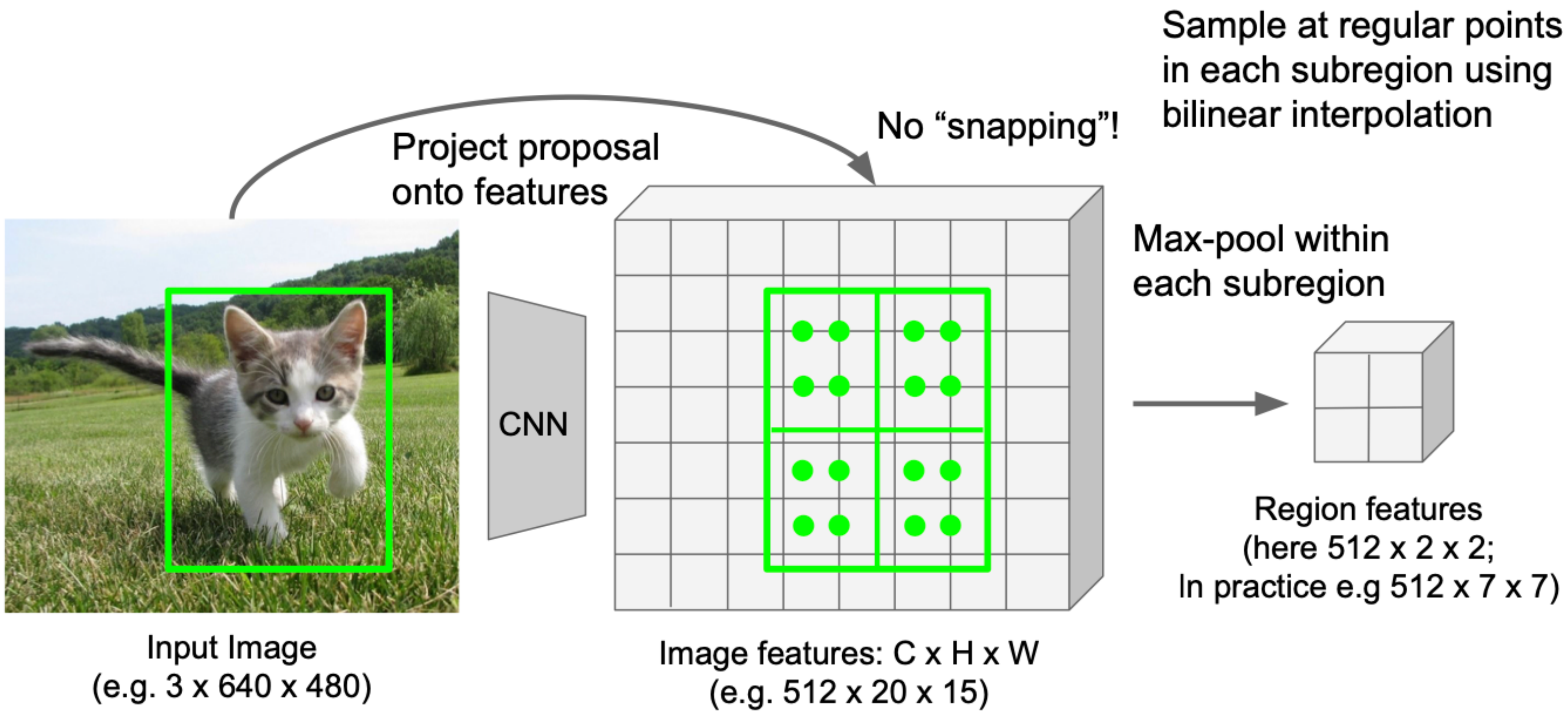


Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

He et al, "Mask R-CNN", ICCV 2017

RoI Align



He et al, “Mask R-CNN”, ICCV 2017

Ablation Study on RoI Align

	AP	AP_{50}	AP_{75}	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}
RoIPool	23.6	46.5	21.6	28.2	52.7	26.9
RoIAlign	**30.9**	**51.8**	**32.1**	**34.0**	**55.3**	**36.4**
	+7.3	*+ 5.3*	*+10.5*	*+5.8*	*+2.6*	*+9.5*

(d) **RoIAlign** (ResNet-50-**C5**, *stride 32*): Mask-level and box-level AP using *large-stride* features. Misalignments are more severe than with stride-16 features (Table 2c), resulting in big accuracy gaps.

He et al, "Mask R-CNN", ICCV 2017

Class-Specific vs. Class-Agnostic Masks

- Our default instantiation predicts class-specific masks, *i.e.*, one m×m mask per class.
- Mask R-CNN with class-agnostic masks (*i.e.*, predicting a single m×m output regardless of class) is nearly as effective.

He et al, "Mask R-CNN", ICCV 2017

Multinomial vs. Independent Masks

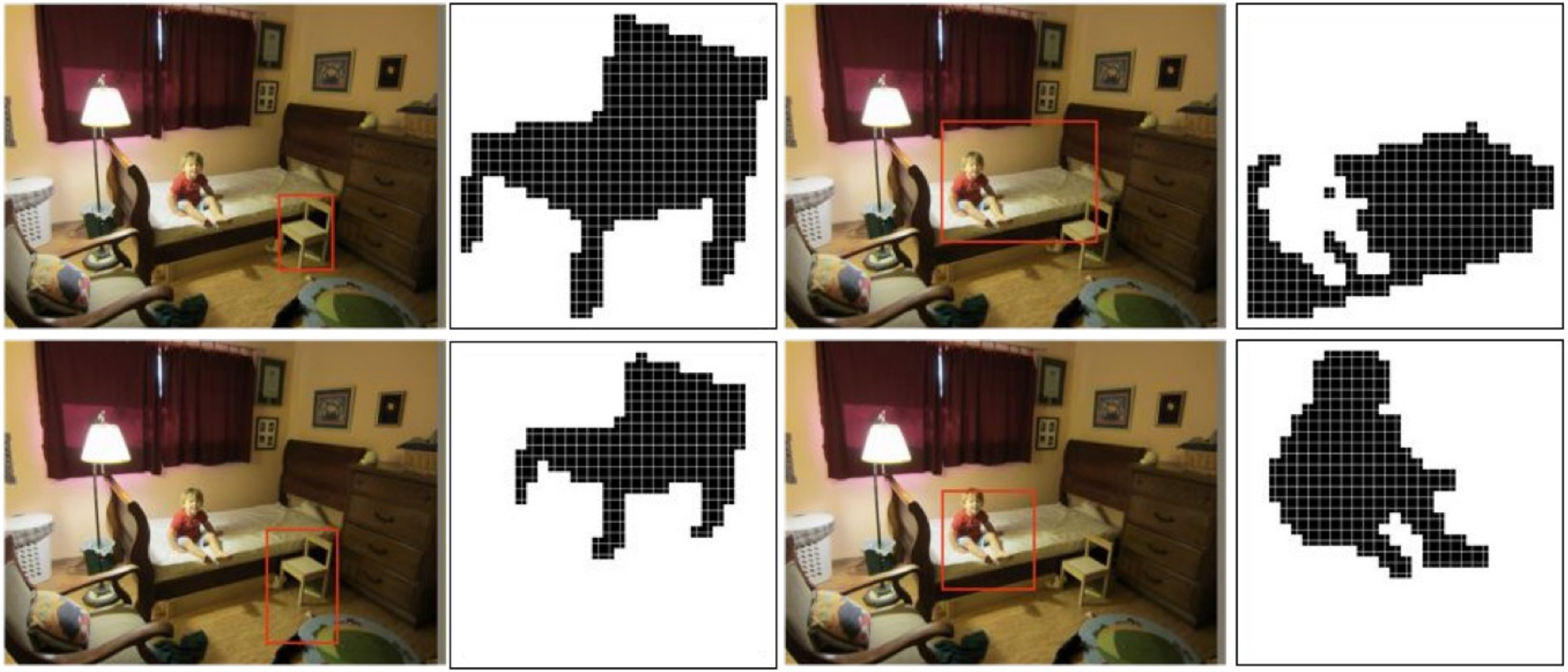
- Decouples mask and class prediction
- Generate a mask for each class without competition among classes (by a per-pixel *sigmoid* and a *binary* loss).

	AP	AP_{50}	AP_{75}
softmax	24.8	44.1	25.1
sigmoid	**30.3**	**51.2**	**31.5**
	+5.5	*+7.1*	*+6.4*

(b) **Multinomial *vs.* Independent Masks** (ResNet-50-C4): *Decoupling* via per-class binary masks (sigmoid) gives large gains over multinomial masks (softmax).

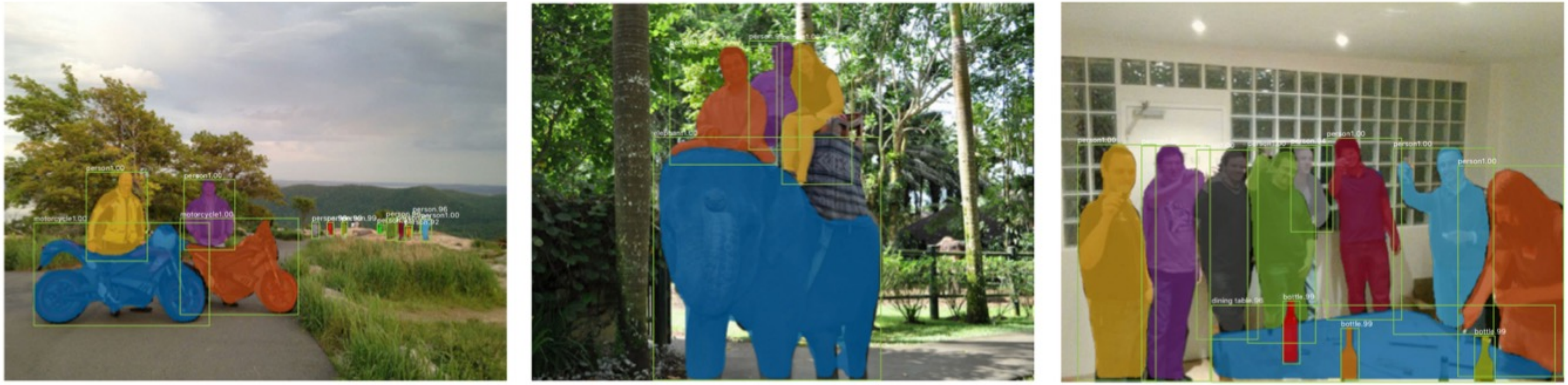
He et al, "Mask R-CNN", ICCV 2017

Mask RCNN: Example Mask Training Target



He et al, "Mask R-CNN", ICCV 2017

Result Visualization



He et al, “Mask R-CNN”, ICCV 2017

Human Pose Visualization

He et al, "Mask R-CNN", ICCV 2017

Open Source Framework

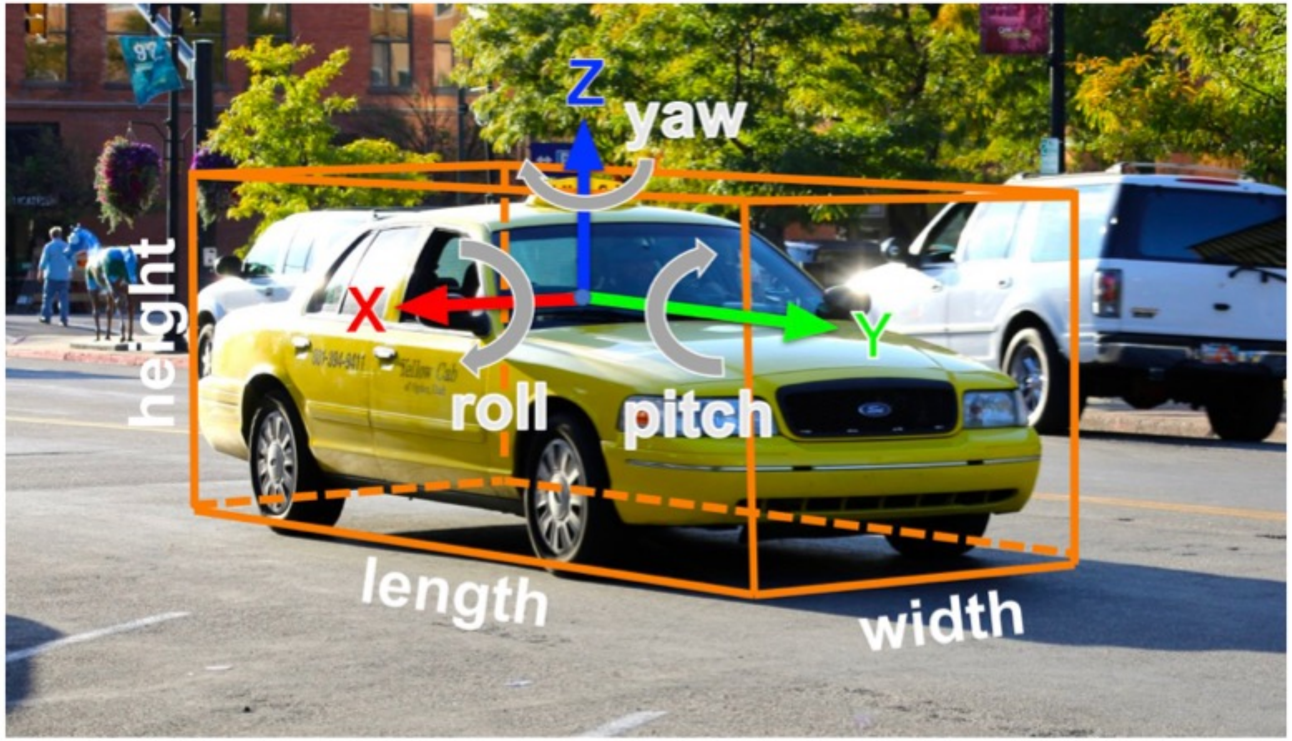
- Lots of good implementations on GitHub!

- TensorFlow Detection API:
  - https://github.com/tensorflow/models/tree/master/research/object_detection
  - Faster RCNN, SSD, RFCN, Mask R-CNN, ...

- Detectron2 (PyTorch) :
  - https://github.com/facebookresearch/detectron2
  - Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN, ... Finetune on your own dataset with pre-trained models

3D Object Detection and Instance Segmentation

3D Object Detection



2D Object Detection:
2D bounding box
(x, y, w, h)

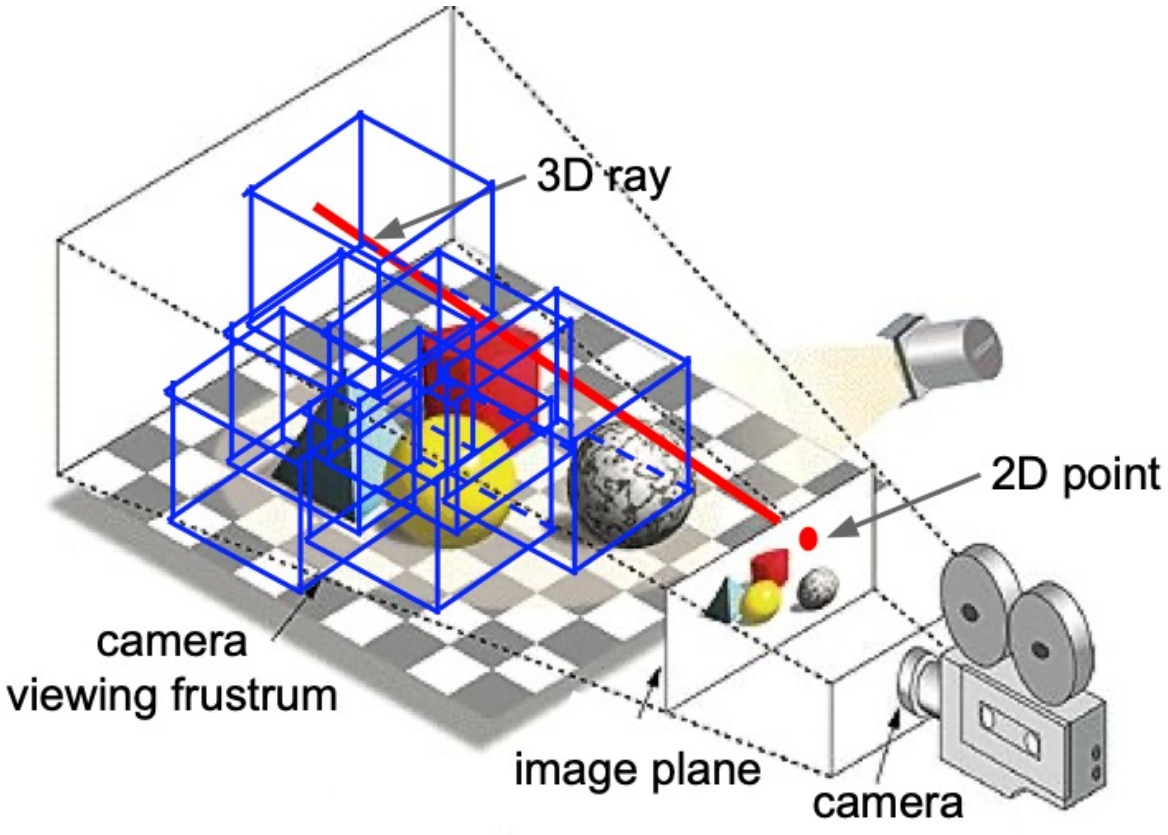
3D Object Detection:
3D oriented bounding box
(x, y, z, w, h, l, r, p, y)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

Slides credit: Stanford CS231N

3D Object Detection



A point on the image plane corresponds to a **ray** in the 3D space

A 2D bounding box on an image is a **frustrum** in the 3D space

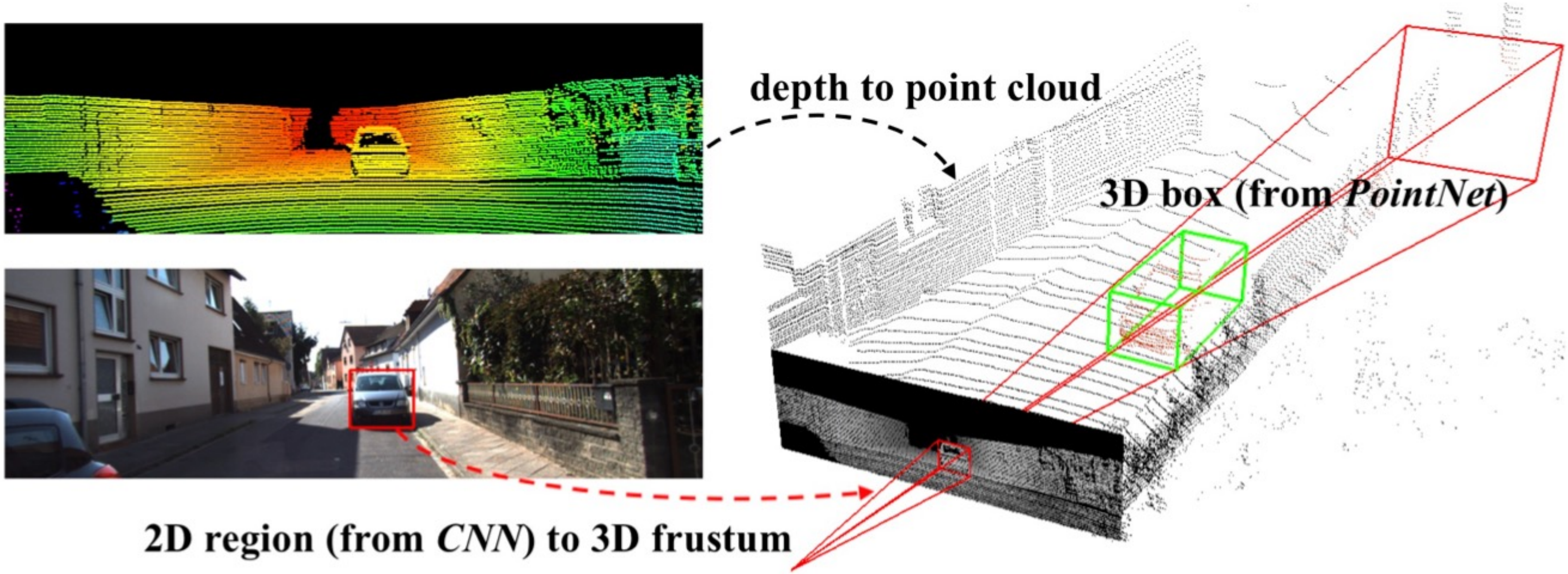
Localize an object in 3D:
The object can be anywhere in the **camera viewing frustrum**!

Image source: https://www.pcmag.com/encyclopedia_images/_FRUSTUM.GIF

Slides credit: Stanford CS231N

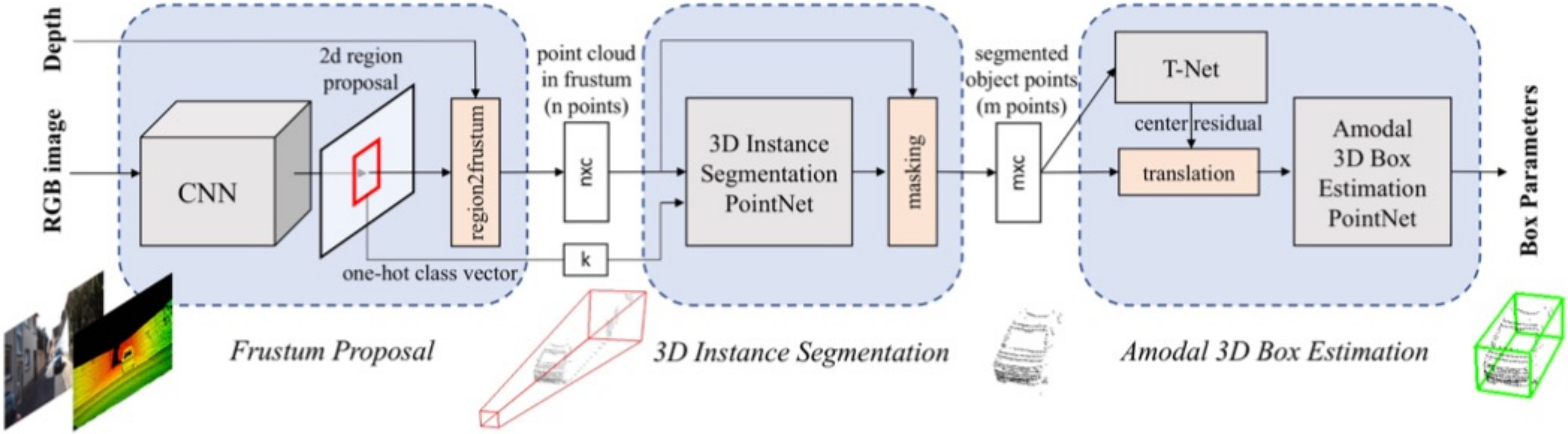
3D Object Detection from RGB-D

Frustum PointNet



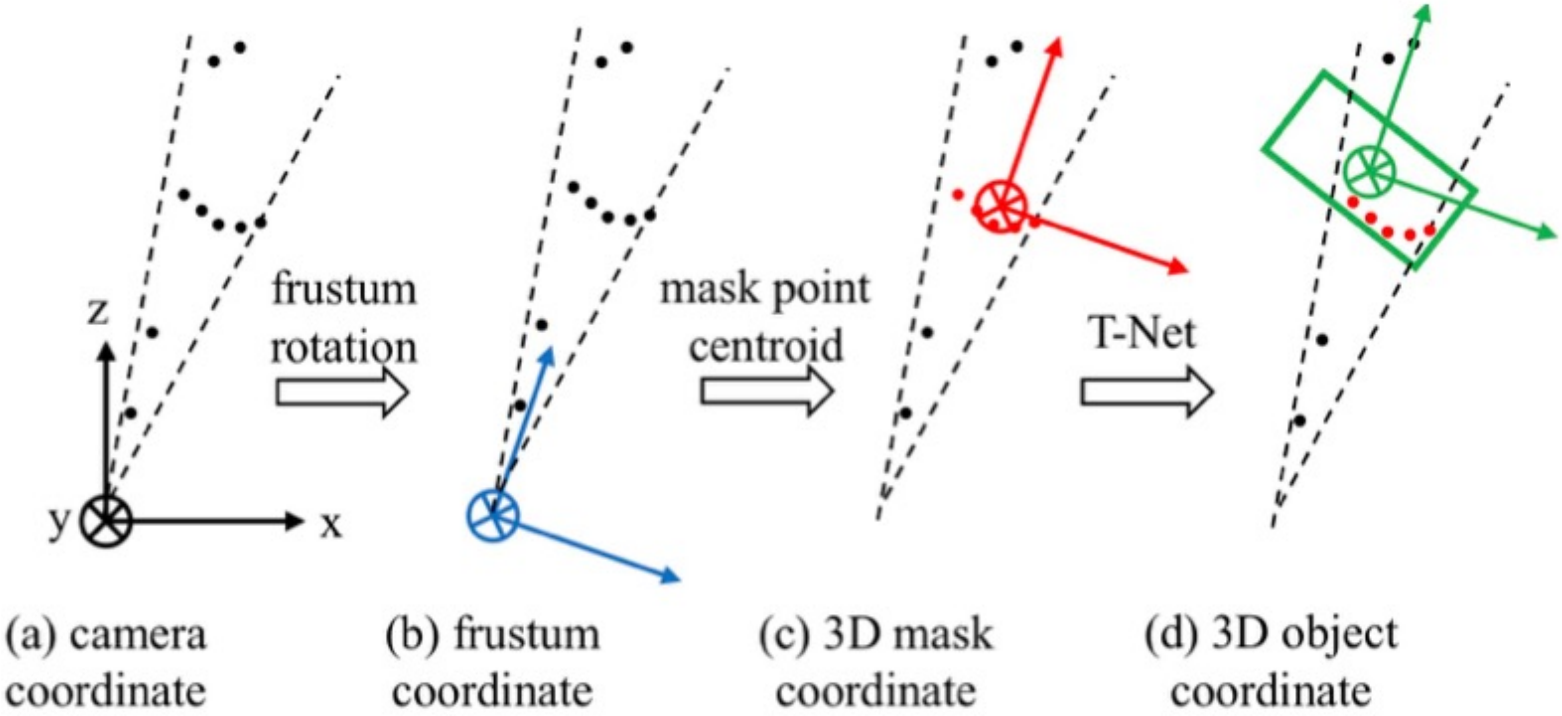
Qi, Charles R., et al. "Frustum pointnets for 3d object detection from rgb-d data." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Pipeline of Frustum PointNet



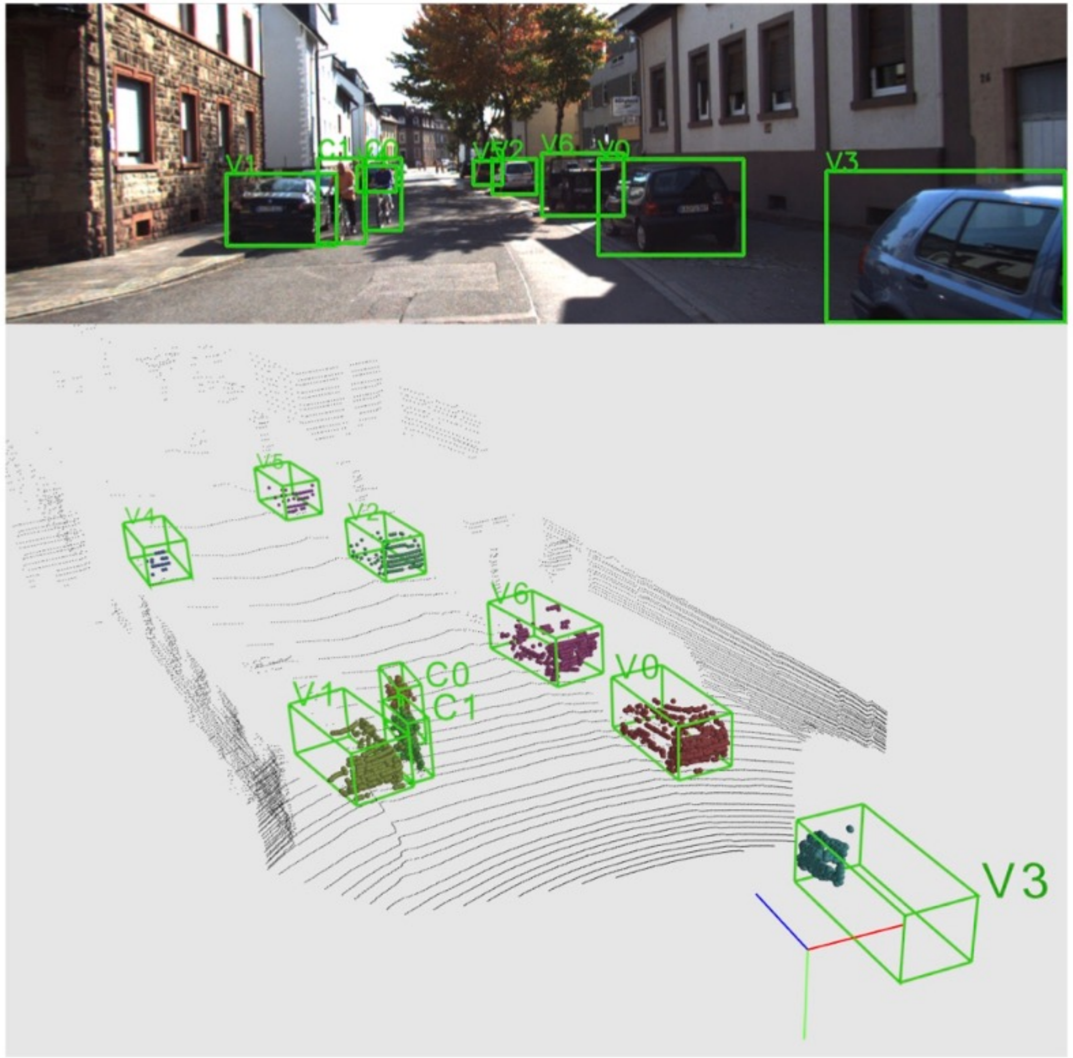
Qi, Charles R., et al. "Frustum pointnets for 3d object detection from rgb-d data." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Coordinate Systems for Point Cloud

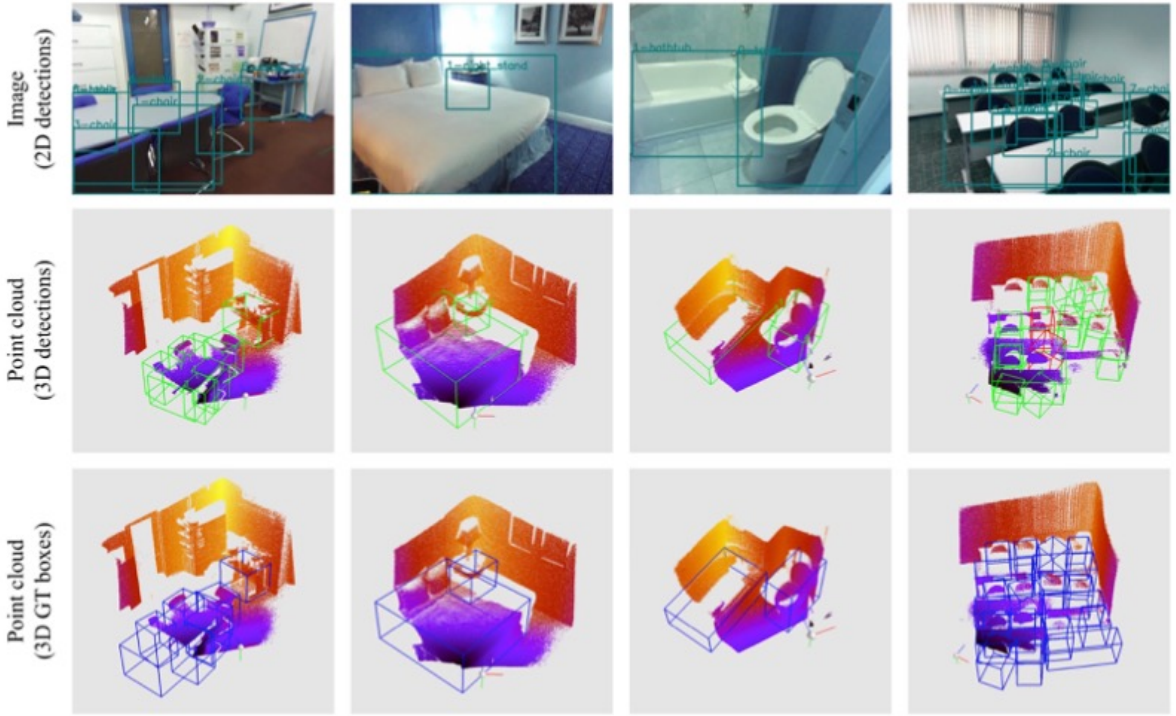


Qi, Charles R., et al. "Frustum pointnets for 3d object detection from rgb-d data." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Result Visualization

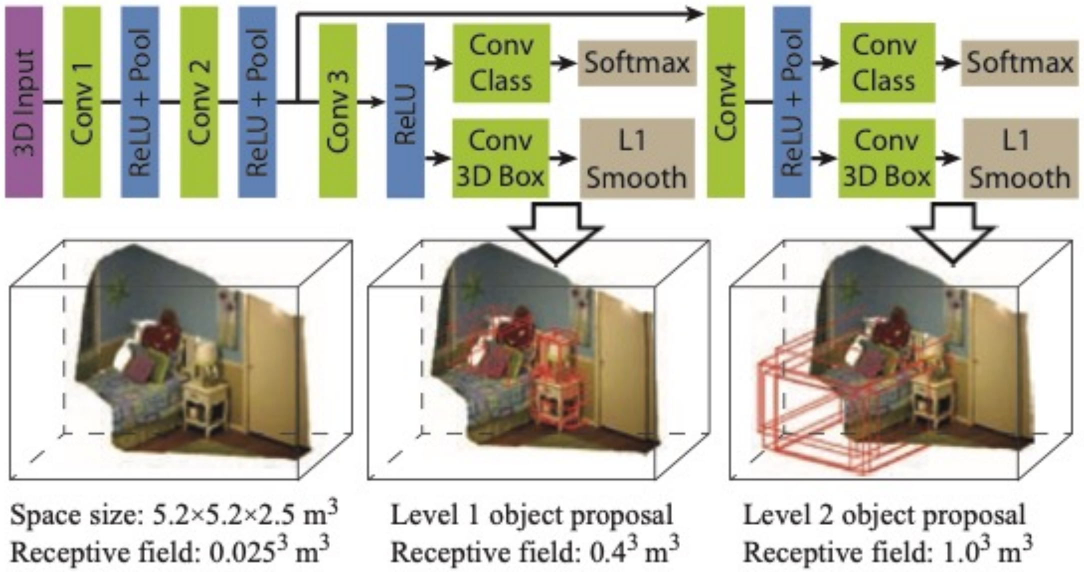


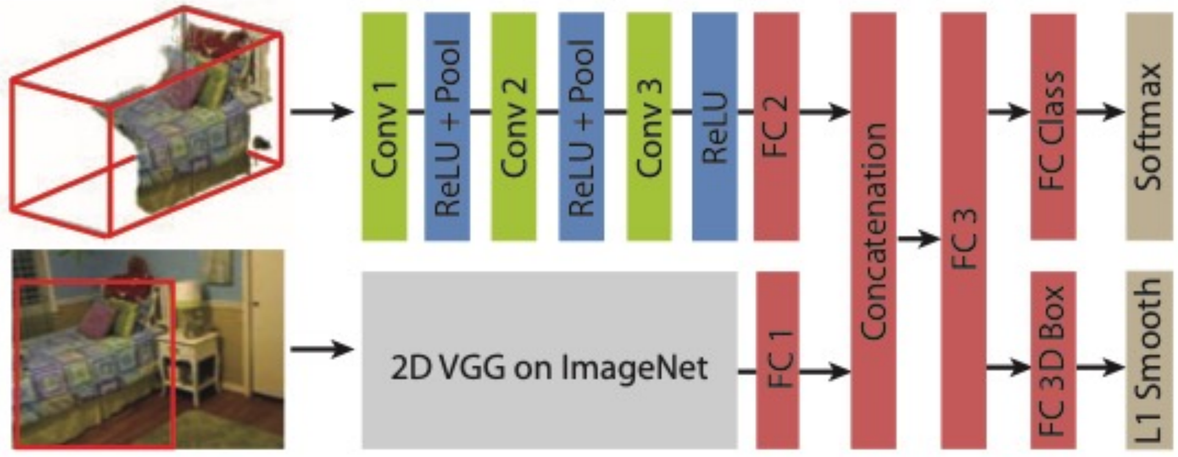
KITTI



SUN-RGBD

Deep Sliding Shape

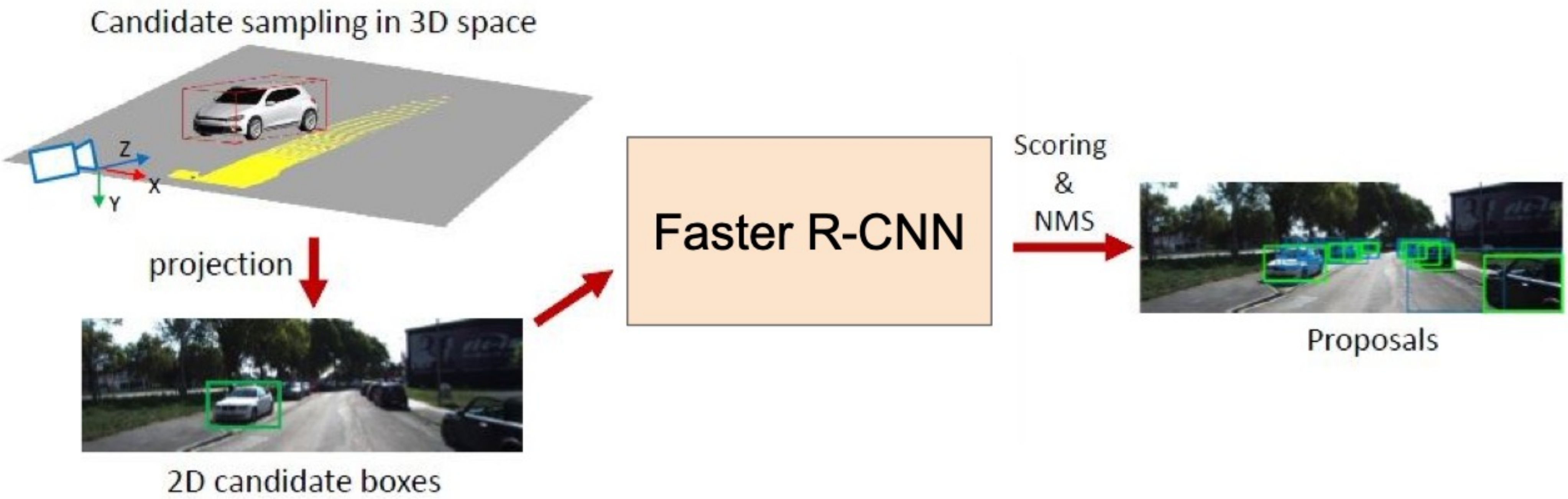




Very expensive to perform sliding windows in 3D!

Song, Shuran, and Jianxiong Xiao. "Deep sliding shapes for amodal 3d object detection in rgb-d images." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016.

3D Object Detection: Monocular Camera

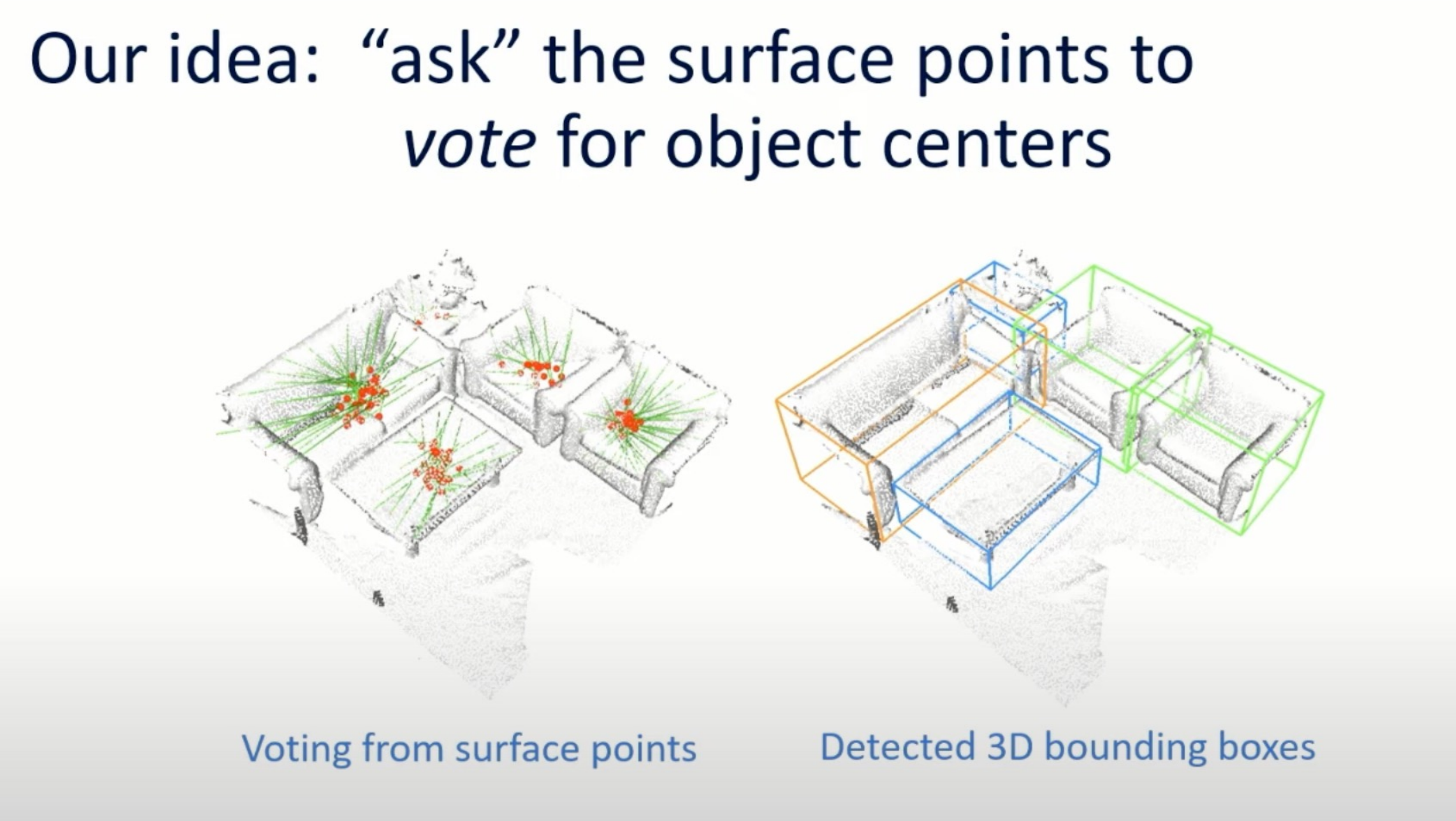


- Same idea as Faster RCNN, but proposals are in 3D
- 3D bounding box proposal, regress 3D box parameters + class score

Chen, Xiaozhi, Kaustav Kundu, Ziyu Zhang, Huimin Ma, Sanja Fidler, and Raquel Urtasun. "Monocular 3d object detection for autonomous driving." CVPR 2016.

Slides credit: Stanford CS231N

VoteNet

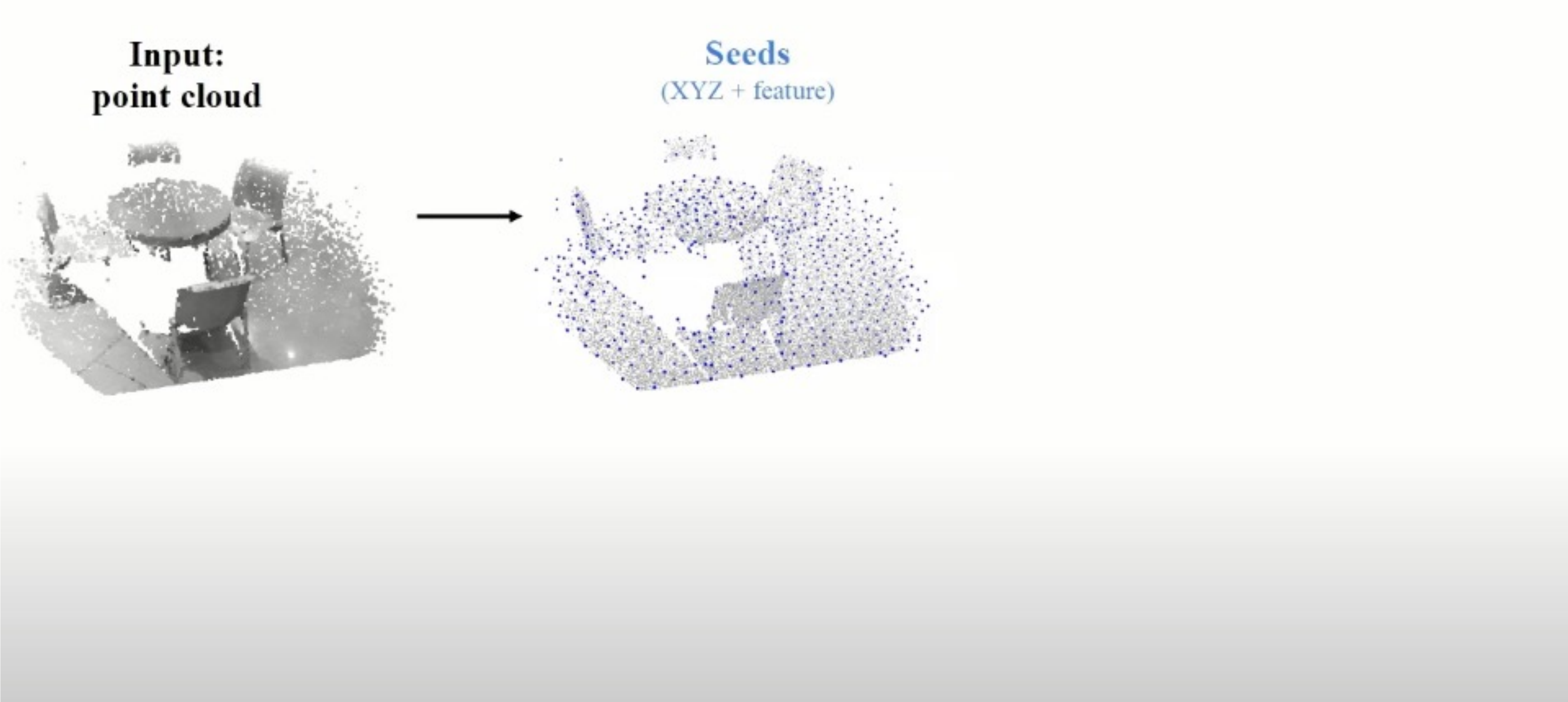


Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Deep Hough Voting: Detection Pipeline

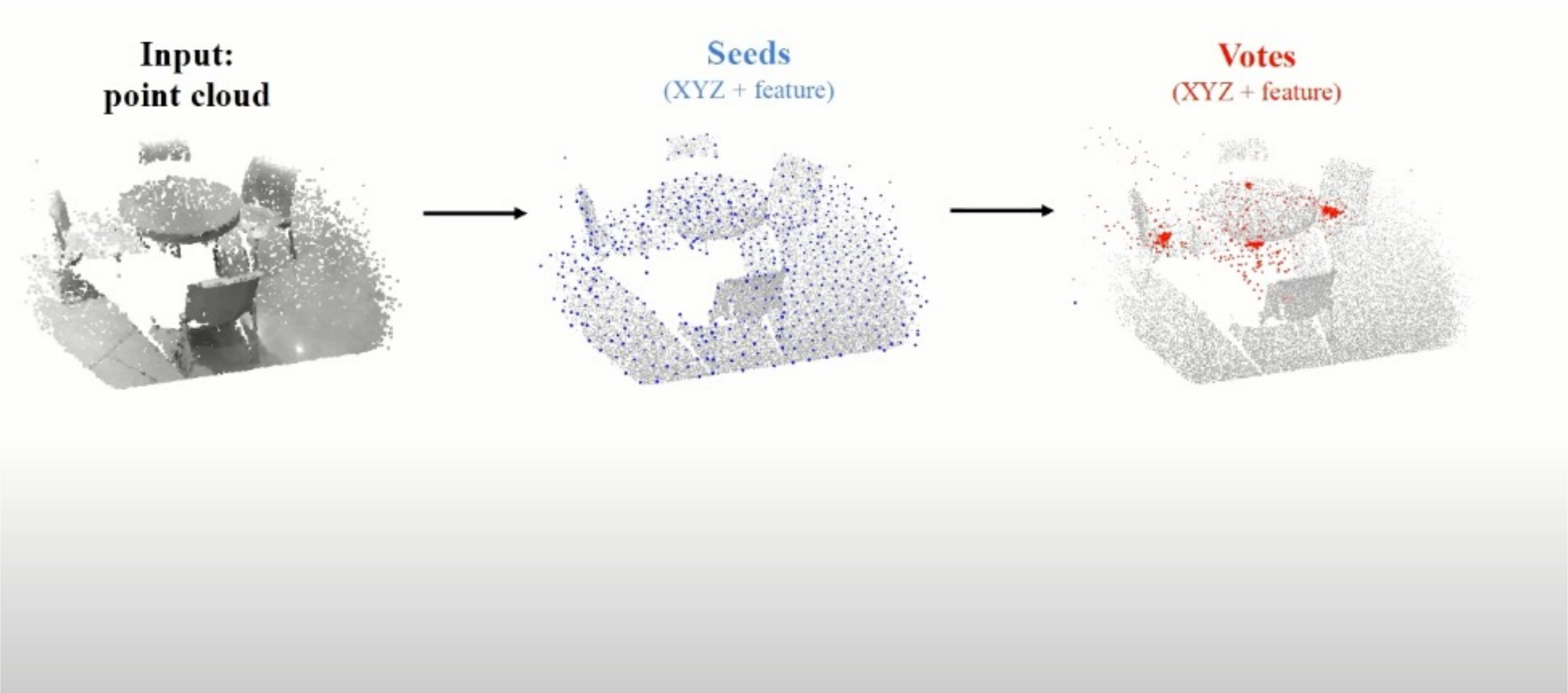
Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Deep Hough Voting: Detection Pipeline



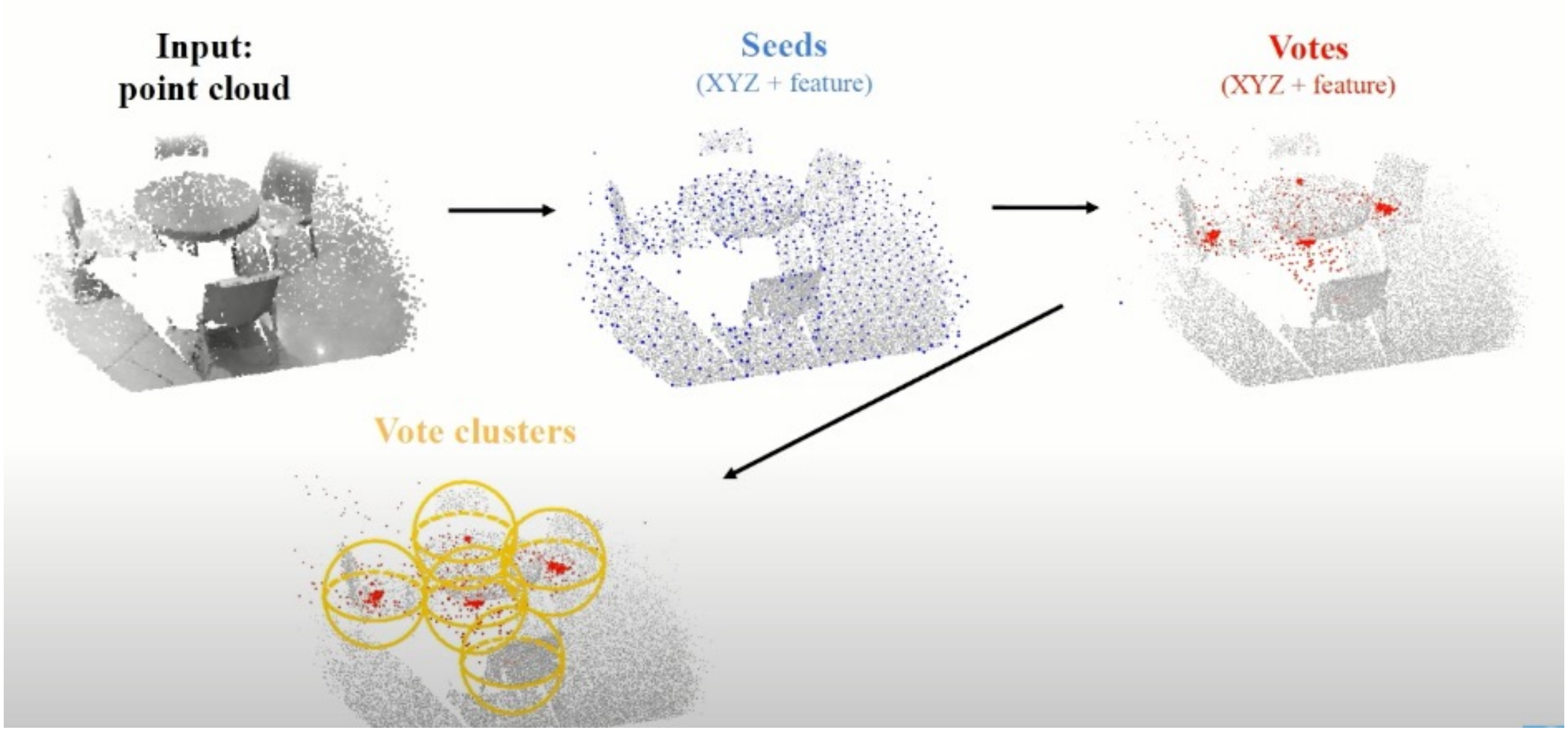
Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Deep Hough Voting: Detection Pipeline



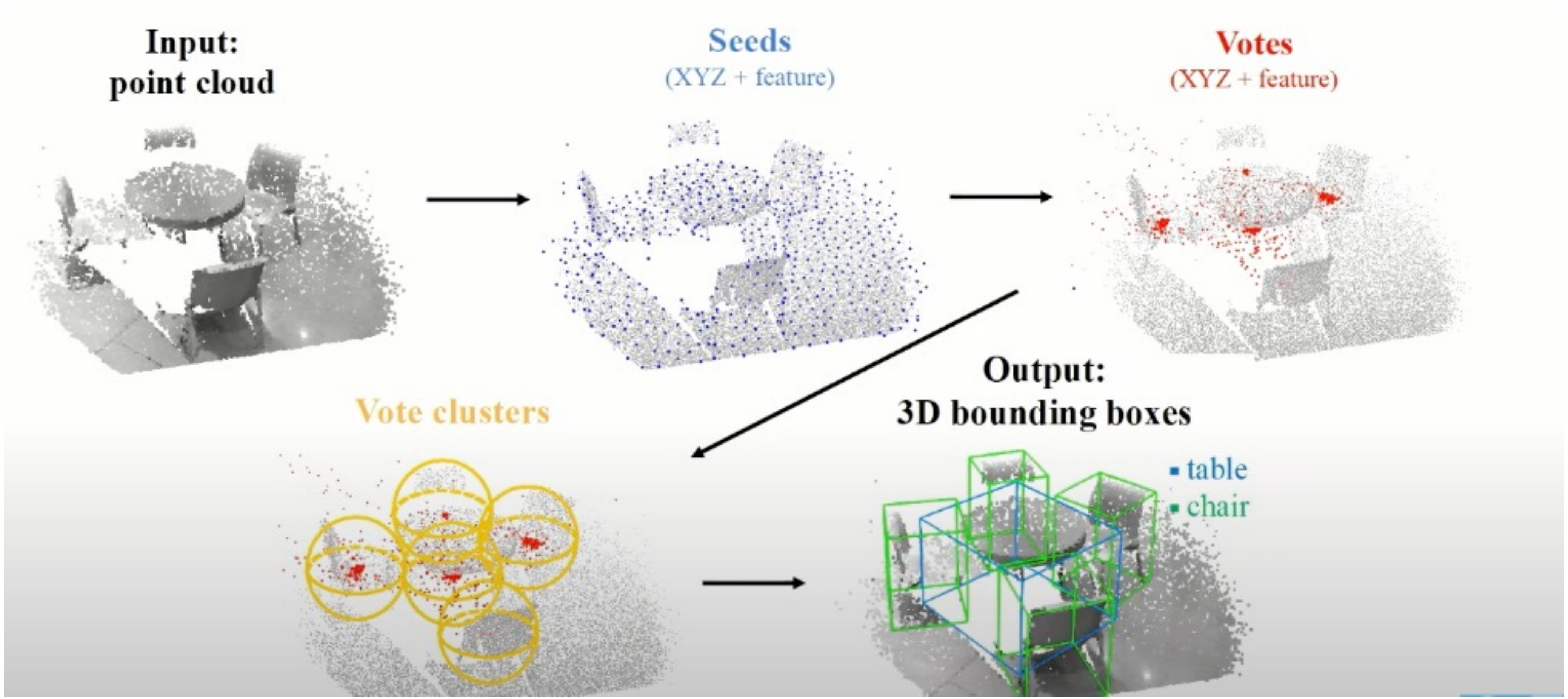
Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Deep Hough Voting: Detection Pipeline



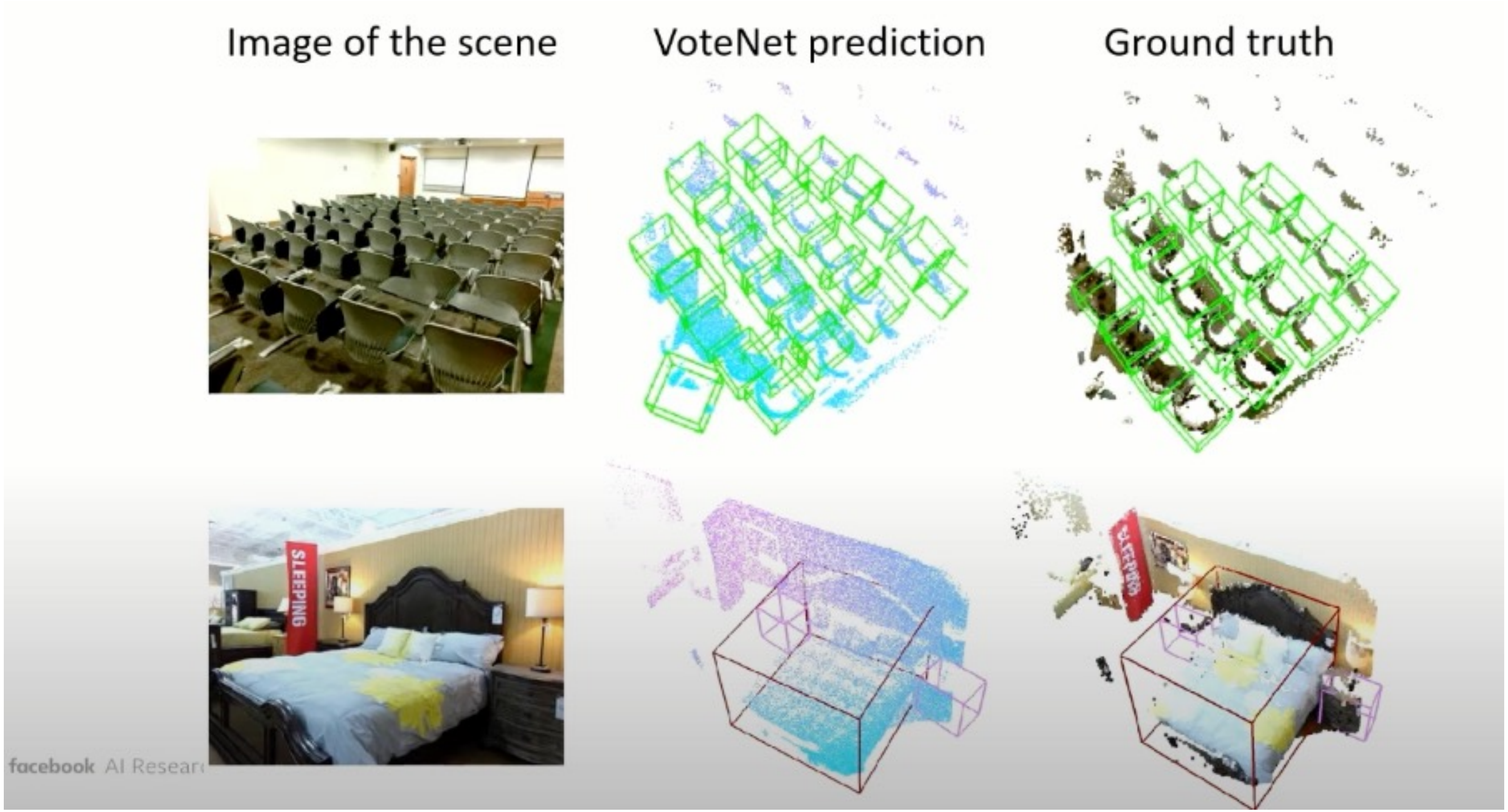
Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Deep Hough Voting: Detection Pipeline



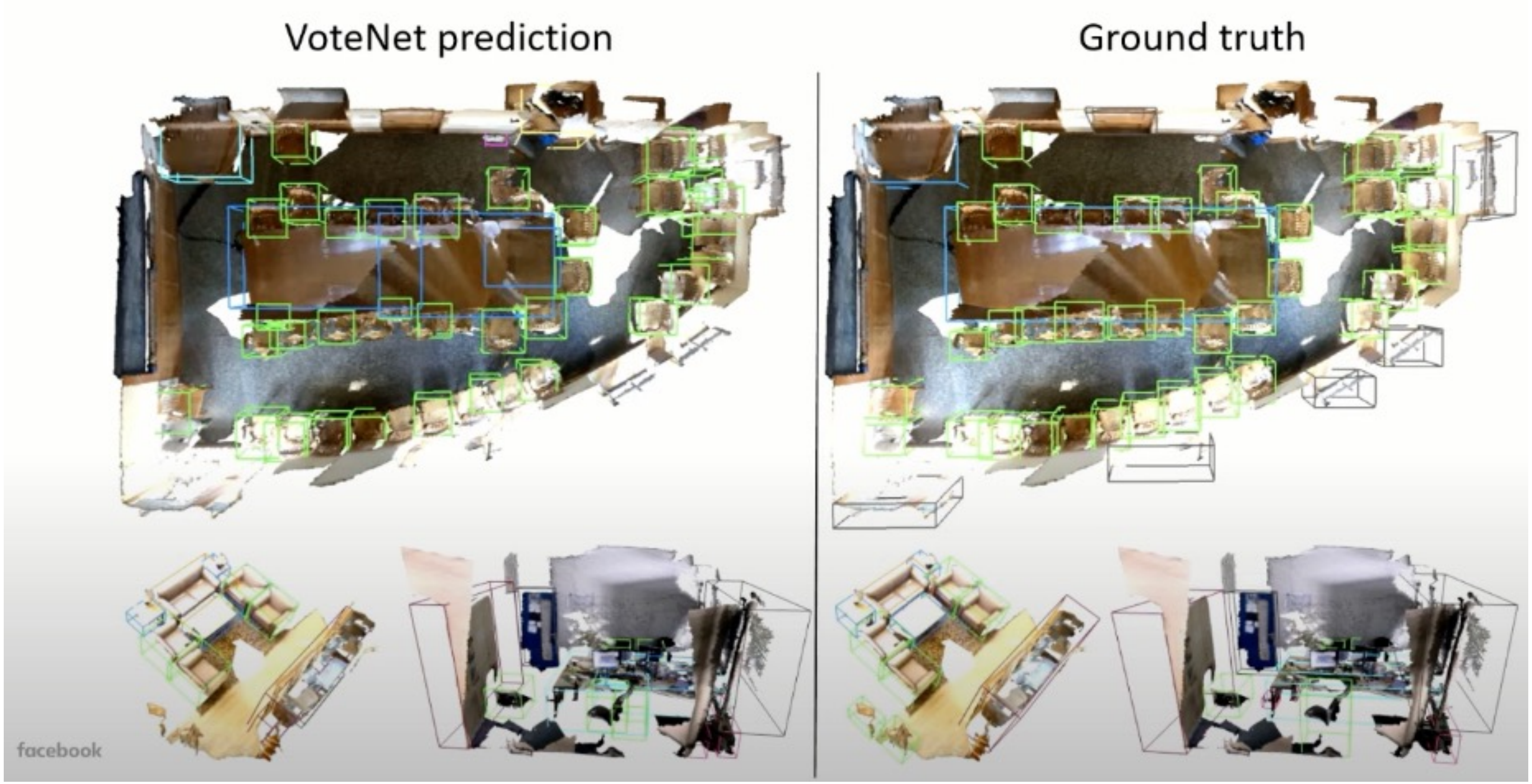
Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Results: SUN RGB-D (single depths)



Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

Results: ScanNet (3D Reconstruction)



Qi, Charles R., et al. "Deep hough voting for 3d object detection in point clouds." *proceedings of the IEEE/CVF International Conference on Computer Vision*. 2019.

3D Instance Segmentation

- Top-Down
    - GSPN
- Bottom-Up
    - SGPN
    - PointGroup

Next week: Lecture 14,
Self-Attention & Transformer