HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Computer Vision

Chapter 7 : Deep Learning for CV

1

Chapter 7: Deep Learning for CV (Part 3) Content

- Object detection: sliding-windows
- Two-stage object detection
- One-stage object detection: Anchor-based
- One-stage object detection: Anchor-free
- Semantic segmentation
- Instance segmentation

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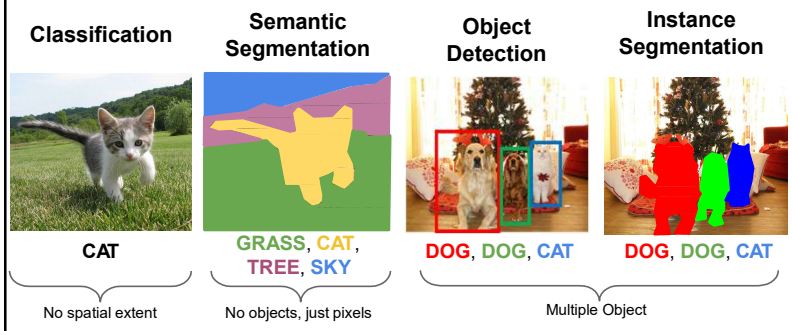
Computer Vision Tasks

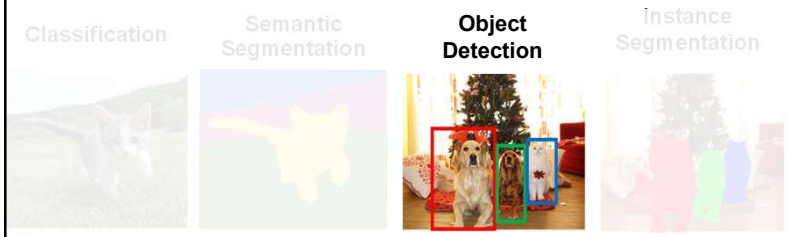


3

Object detection: Sliding windows

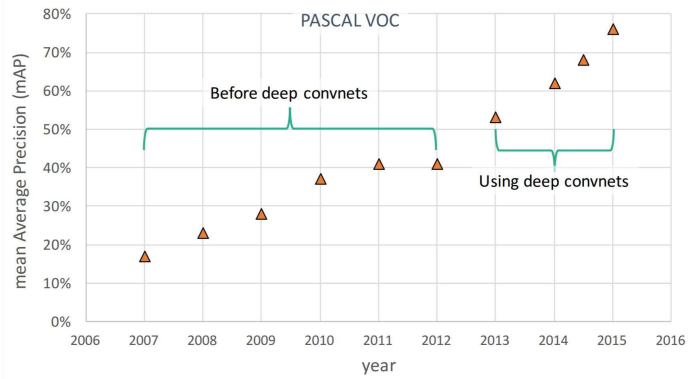
4

Object Detection



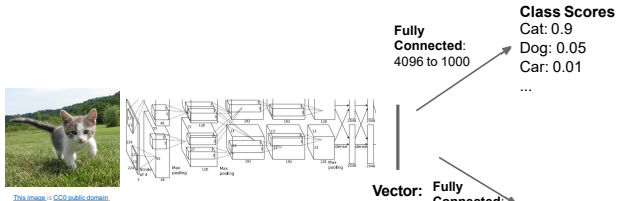
5

Object Detection: Impact of Deep Learning



6

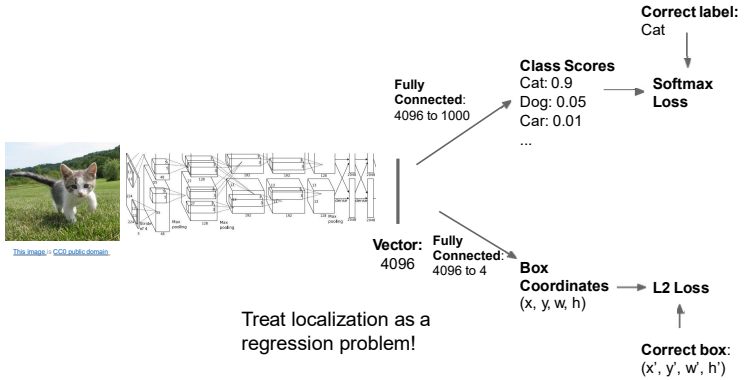
Object Detection: Single Object (Classification + Localization)



Treat localization as a regression problem!

7

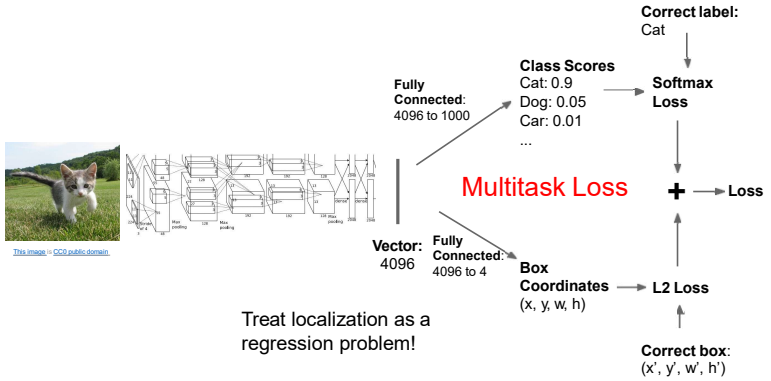
Object Detection: Single Object (Classification + Localization)



Treat localization as a regression problem!

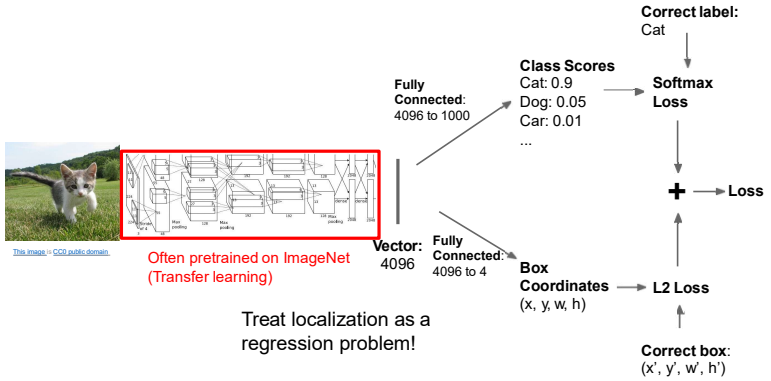
8

Object Detection: Single Object (Classification + Localization)



9

Object Detection: Single Object (Classification + Localization)



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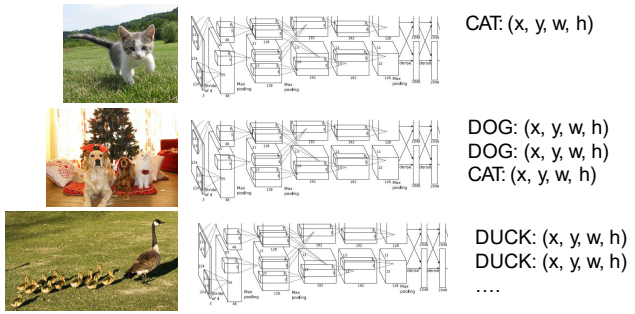
Object Detection: Multiple Objects



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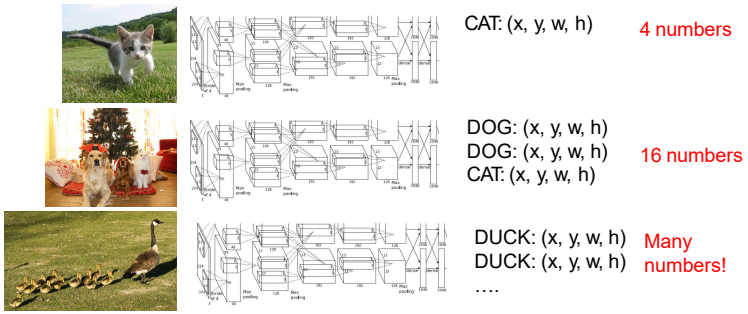
Object Detection: Multiple Objects

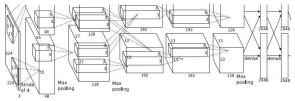
Each image needs a different number of outputs!



12

Object Detection: Multiple Objects

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

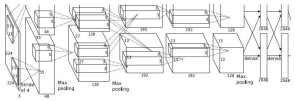


Dog? NO
Cat? NO
Background? YES

13

Object Detection: Multiple Objects

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

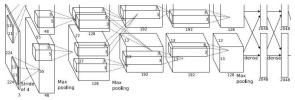


Dog? YES
Cat? NO
Background? NO

14

Object Detection: Multiple Objects

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



Dog? YES
Cat? NO
Background? NO

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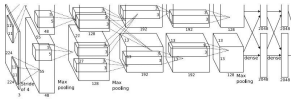
Object Detection: Multiple Objects

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



Dog? NO
Cat? YES
Background? NO

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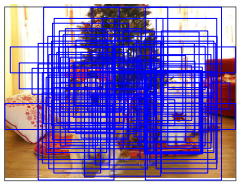
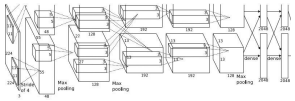
Object Detection: Multiple Objects

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!

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Two-stage Object detection

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Object Detection

Two Stages

- Propose “objects”
- Classify each candidate

One-Stage

- Sliding window to classify all candidates

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Object Detection

Two Stages

- Propose “objects”
- Classify each candidate

One-Stage

- Sliding window to classify all candidates

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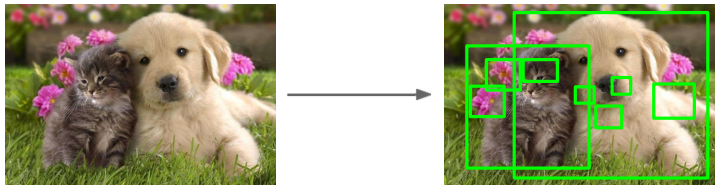
Region Proposals: Selective Search

- 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

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R-CNN

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

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R-CNN

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

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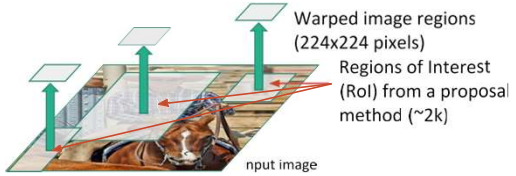
R-CNN



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

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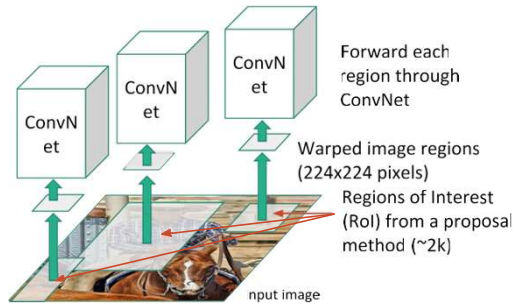
R-CNN



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

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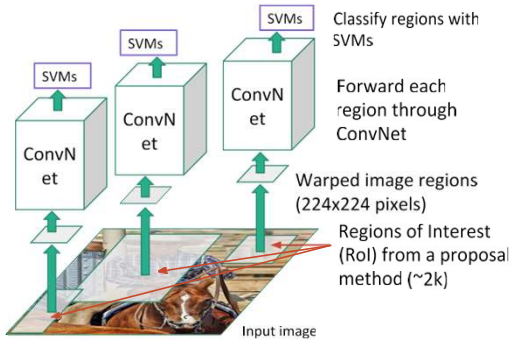
R-CNN



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

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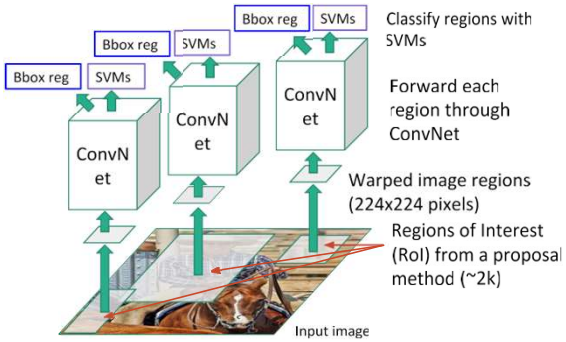
R-CNN

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



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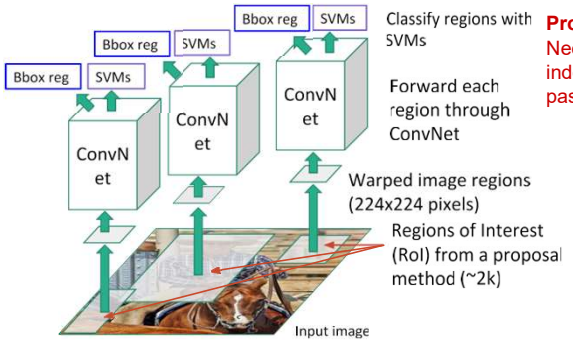
R-CNN

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



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

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

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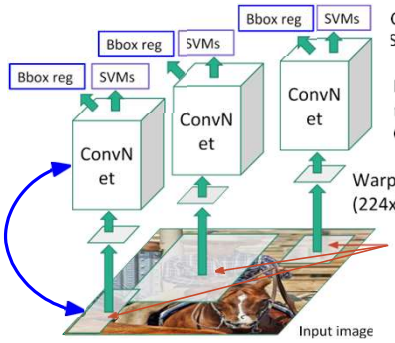
"Slow" R-CNN

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



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

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

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

Idea: Process image before cropping! Swap convolution and cropping!

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

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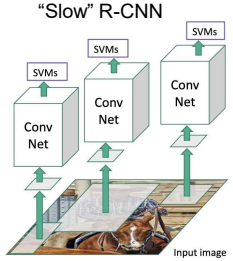
Fast R-CNN

Input image

"Slow" R-CNN



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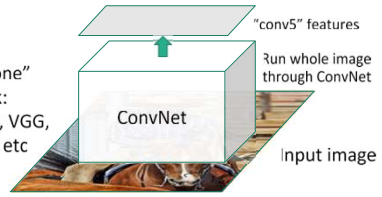
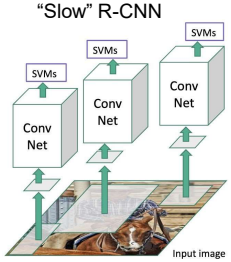
Fast R-CNN

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



"Slow" R-CNN



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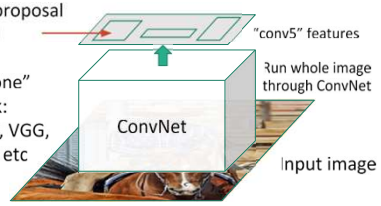
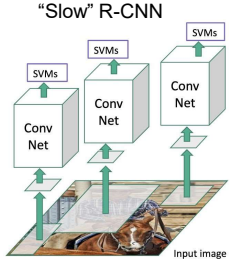
Fast R-CNN

Regions of Interest (RoIs) from a proposal method

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



"Slow" R-CNN



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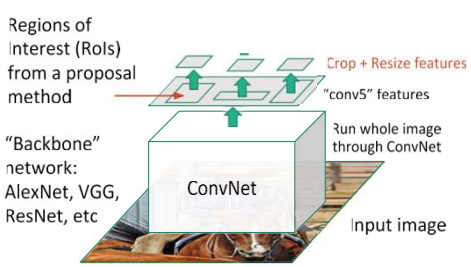
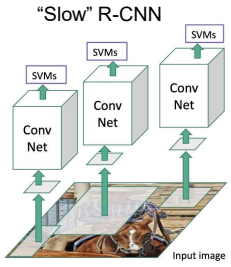
Fast R-CNN





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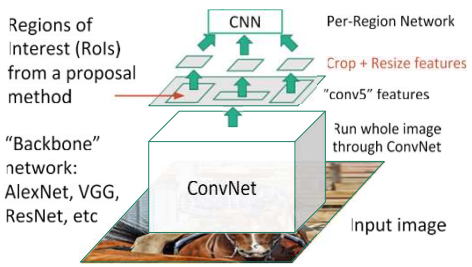
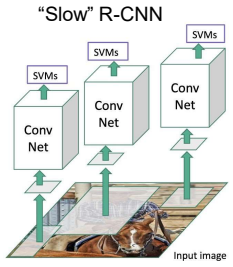
Fast R-CNN





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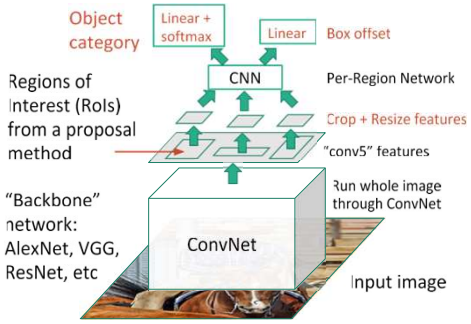
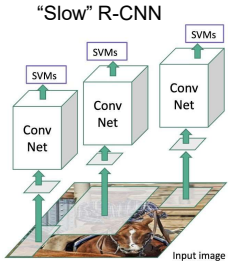
Fast R-CNN





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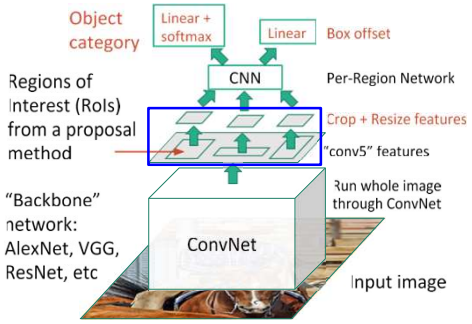
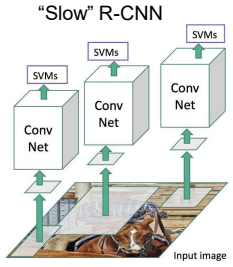
Fast R-CNN





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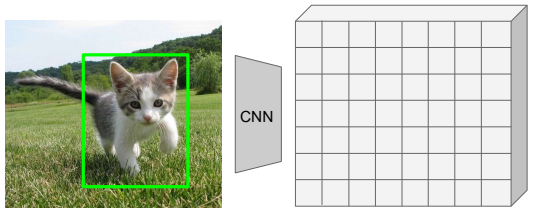
Cropping Features: RoI Pool



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

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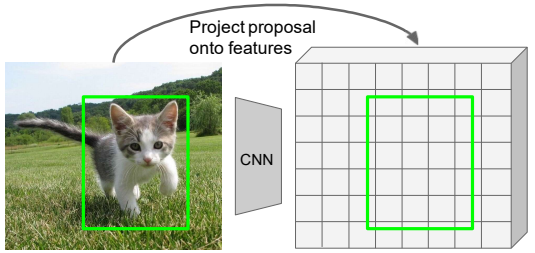
Cropping Features: RoI Pool



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

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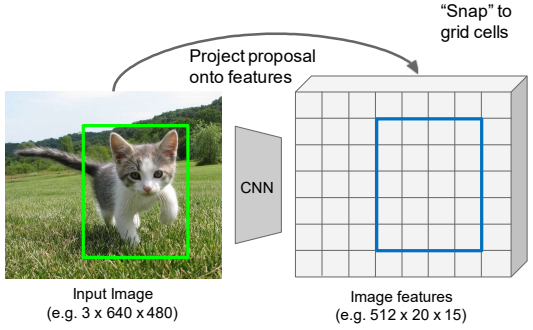
Cropping Features: RoI Pool



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

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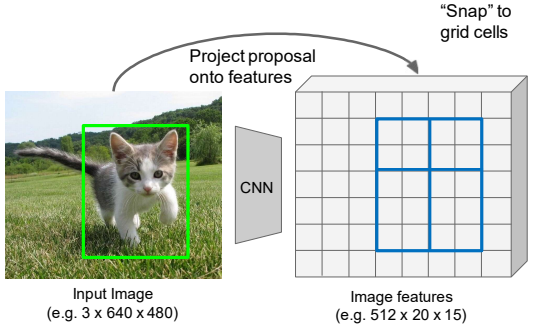
Cropping Features: RoI Pool

Divide into 2x2
grid of (roughly)
equal subregions



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

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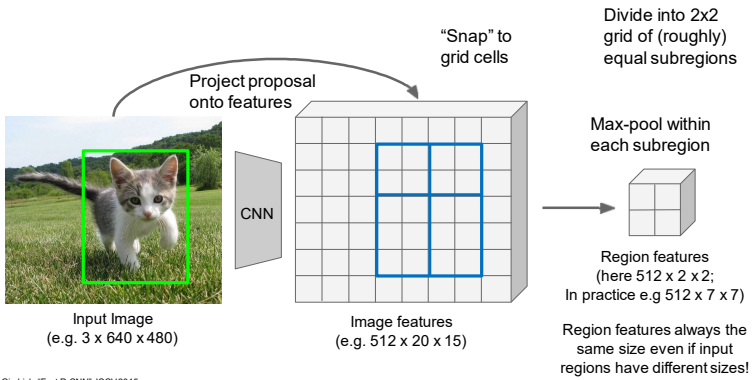
Cropping Features: RoI Pool



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

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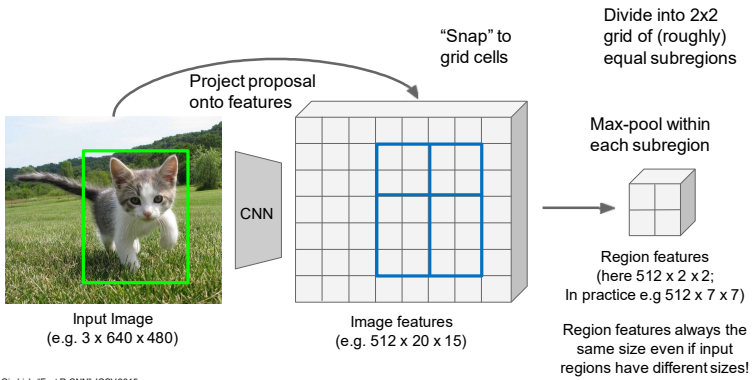
Cropping Features: RoI Pool



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

Problem: Region features slightly misaligned

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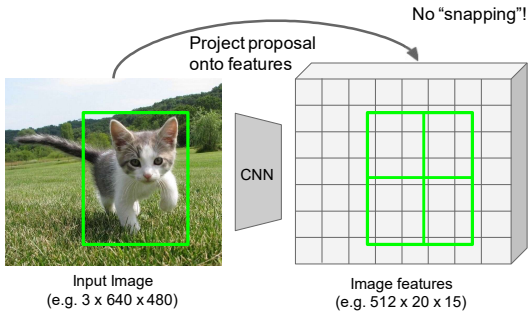
Cropping Features: RoI Align



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

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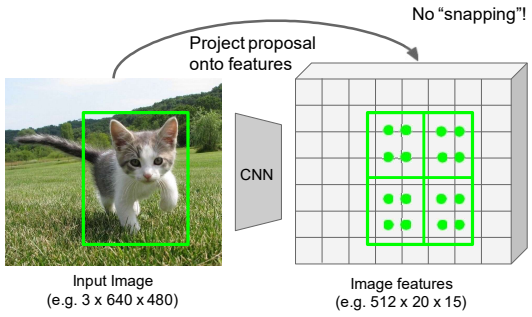
Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



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

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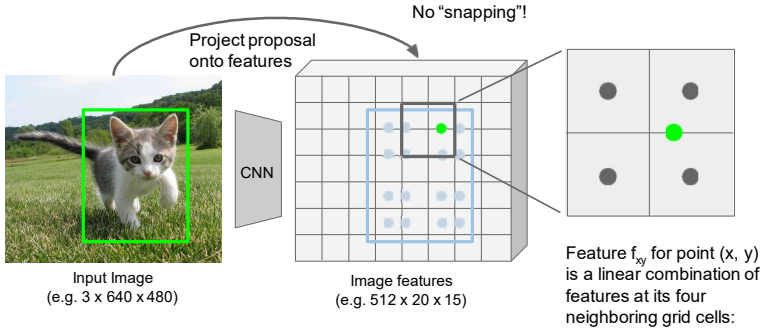
Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation

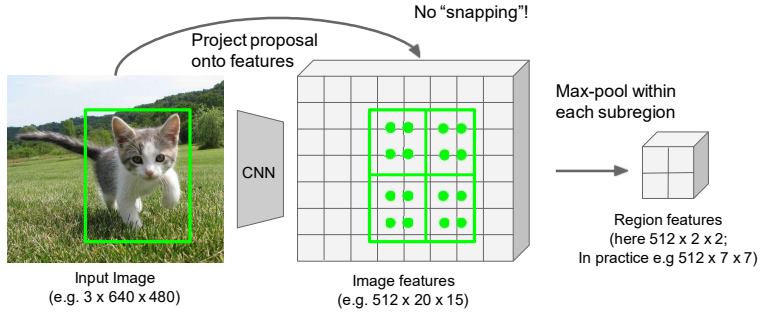


Girshick, "Fast R-CNN", ICCV 2015.

45

Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



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

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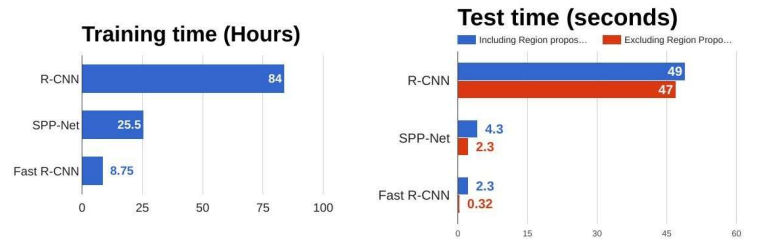
R-CNN vs Fast R-CNN



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

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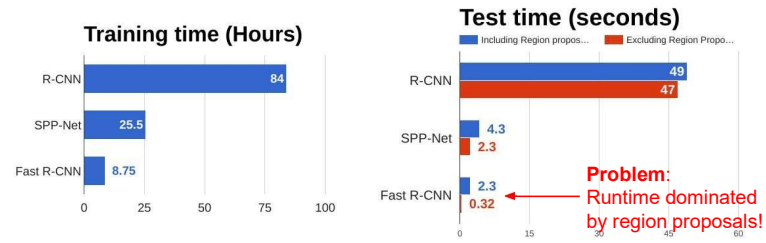
R-CNN vs Fast R-CNN



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

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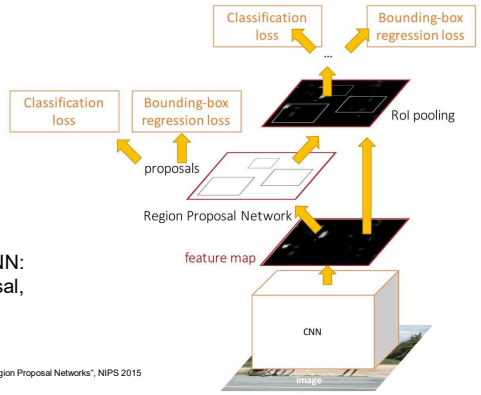
Faster R-CNN: Make CNN do proposals!

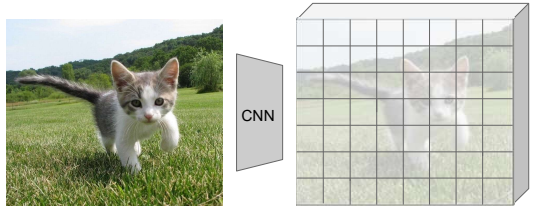
Insert **Region Proposal Network (RPN)** to predict proposals from features

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
Figure copyright 2015, Ross Girshick; reproduced with permission

Region Proposal Network



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

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

Region Proposal Network

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

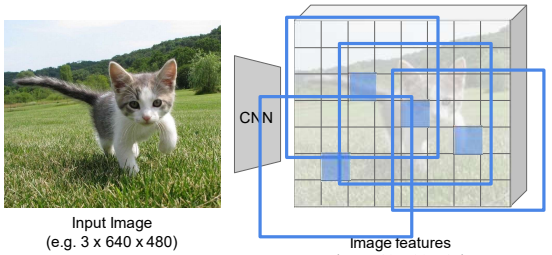


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Image features
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Region Proposal Network

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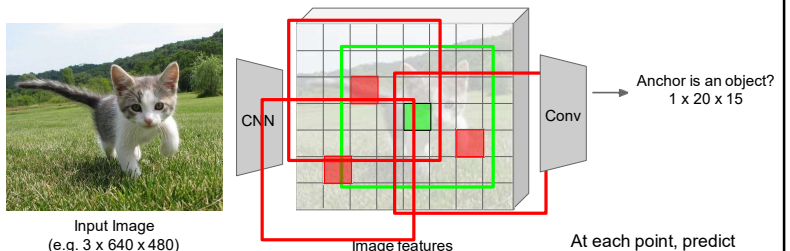
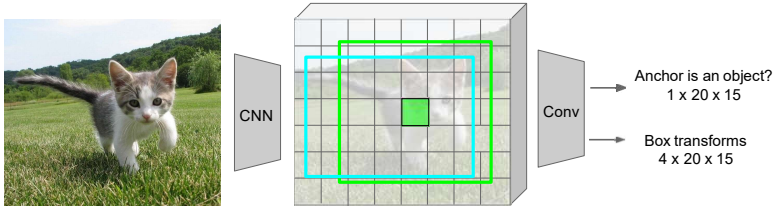


Input Image
(e.g. 3 x 640 x 480)

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

At each point, predict whether the corresponding anchor contains an object (per-pixel logistic regression)

Region Proposal Network



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

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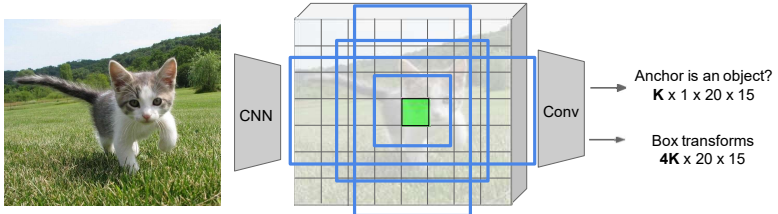
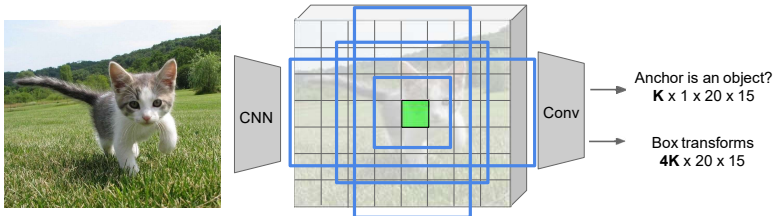
Region Proposal Network



54

Region Proposal Network



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

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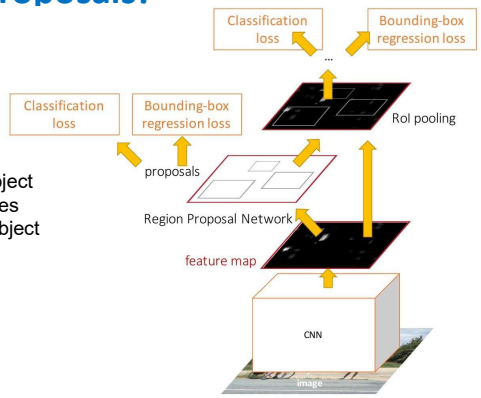
Faster R-CNN: Make CNN do proposals!

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

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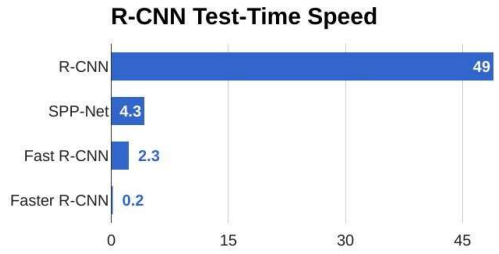
Faster R-CNN: Make CNN do proposals!



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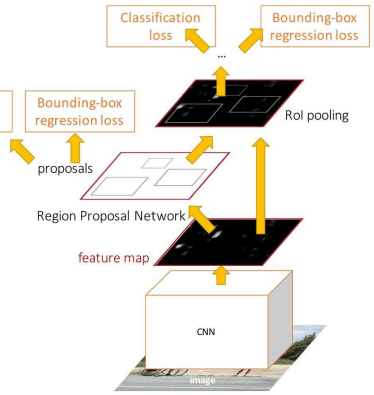
Faster R-CNN: Make CNN do proposals!

Glossing over many details:
- Ignore overlapping proposals with **non-max suppression**
- How to determine whether a proposal is positive or negative?
- How many positives / negatives to send to second stage?
- How to parameterize bounding box regression?



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

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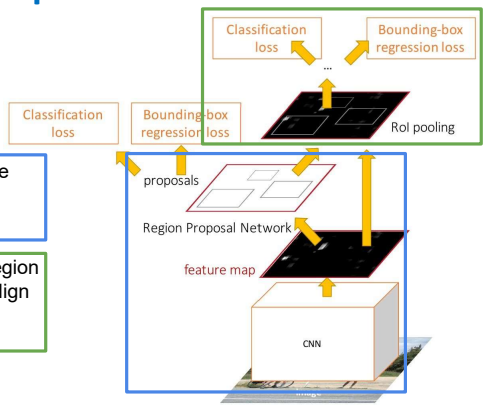
Faster R-CNN: Make CNN do proposals!

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



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

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Faster R-CNN: Make CNN do proposals!

Do we really need the second stage?

Faster R-CNN is a **Two-stage object detector**

First stage: Run once per image
- Backbone network
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Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
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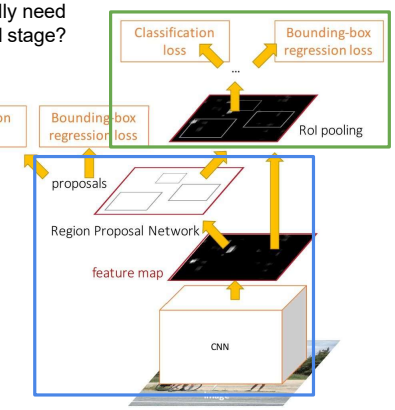

Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

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One-stage Object detection

Anchor-based

Object Detection

Two Stages

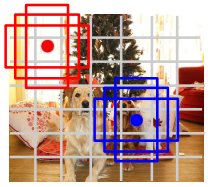
- Propose "objects"
- Classify each candidate

One-Stage

- Sliding window to classify all candidates

Single-Stage Object 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

Imbalance

Number of "negative" anchors ~O(10K)
Number of "positive" anchors ~O(10)

What happens to CE loss in this case?

$$\mathcal{L} = -\frac{1}{N}\sum_i y_i \log(p_i), \qquad \frac{\partial \mathcal{L}}{\partial p_i} = \begin{cases} p_{i,l} & \text{if } y_i \neq l \\ p_{i,l} - 1 & \text{if } y_i = l \end{cases}$$

On Board

Loss and gradient are dominated by correctly classified negative examples

Training outcome → constant "negative" prediction.

Imbalance – Focal Loss

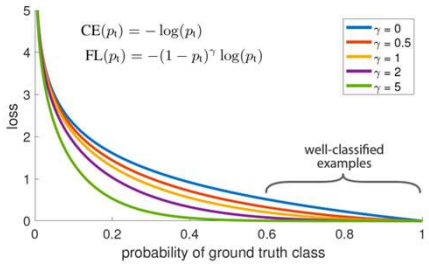
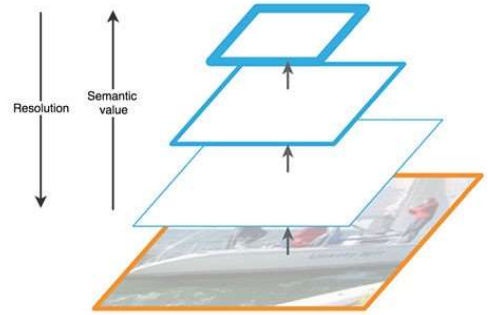


Figure 1: We propose a novel loss we term the *Focal Loss* that adds a factor $(1 - p_t)^{\gamma}$ to the standard cross entropy criterion. Setting $\gamma > 0$ reduces the relative loss for well-classified examples ($p_t > .5$), putting more focus on hard, misclassified examples. As our experiments will demonstrate, the proposed focal loss enables training highly accurate dense object detectors in the presence of vast numbers of easy background examples.

Lin,Goyal, Girshick, He, and Dollár
Focal loss for dense object detection (PAMI 2018)

Feature Pyramid Network (FPN)

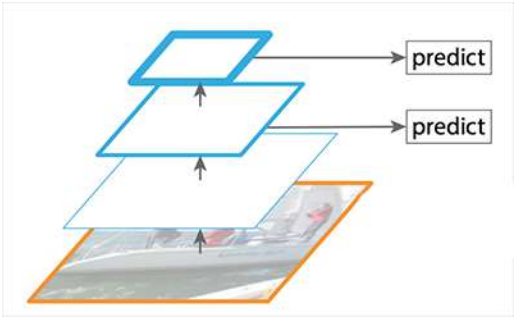
- How to handle multiscale predictions?



Tsung-Yi, Dollár, Girshick, He, Hariharan and Belongie. Feature Pyramid Networks for Object Detection (CVPR 2017)

Feature Pyramid Network (FPN)

- How to handle multiscale predictions?



Tsung-Yi, Dollár, Girshick, He, Hariharan and Belongie. Feature Pyramid Networks for Object Detection (CVPR 2017)

Feature Pyramid Network (FPN)

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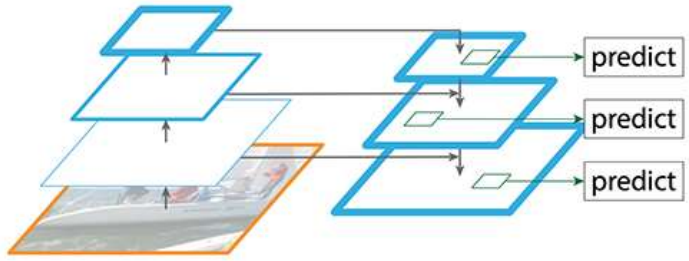
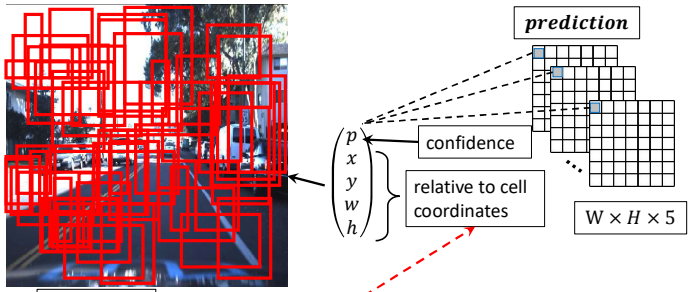


Tsung-Yi, Dollár, Girshick, He, Hariharan and Belongie. Feature Pyramid Networks for Object Detection (CVPR 2017)

Postprocessing: NMS



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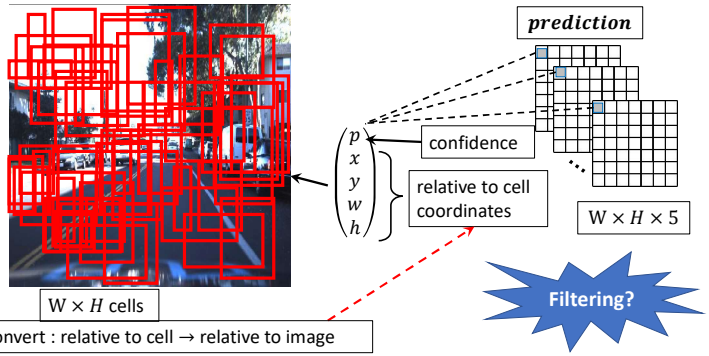
69

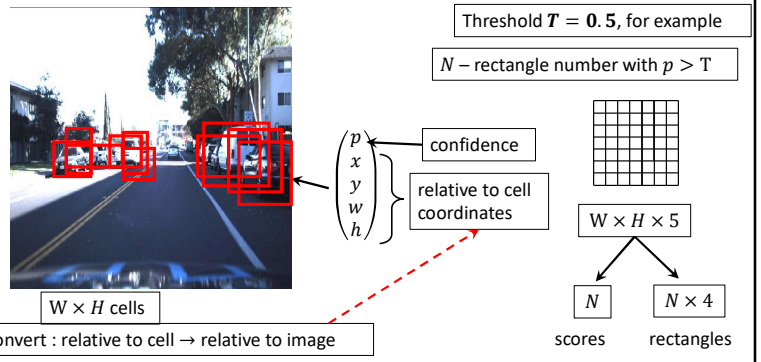
Postprocessing: NMS



70

70

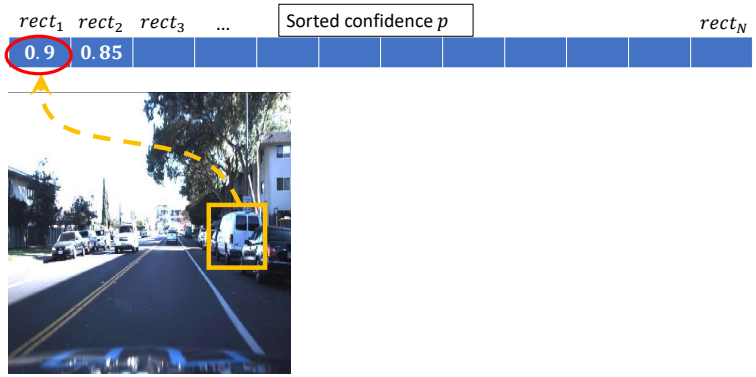
Postprocessing: NMS



71

71

Postprocessing: NMS



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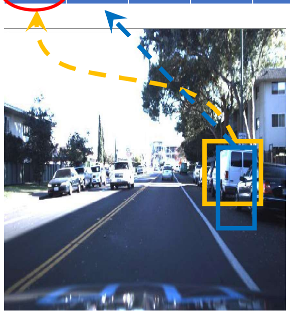
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

0.9 | 0.85



Compare IOU of the **1st** rectangle with others

SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

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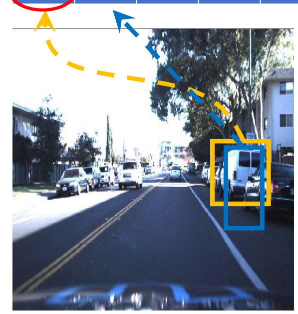
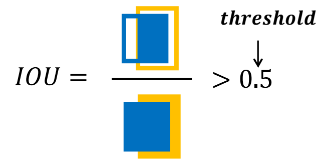


Compare IOU of the **1st** rectangle with others

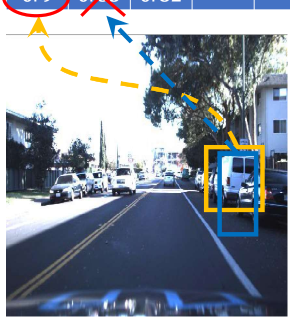


SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

0.9 | ~~0.85~~ | 0.82



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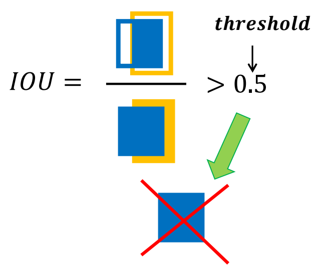
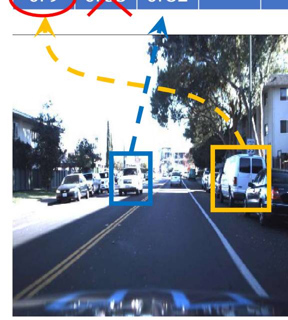


SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

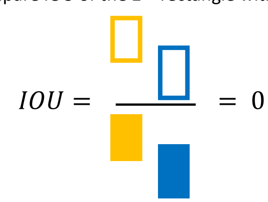
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

0.9 | ~~0.85~~ | 0.82



Compare IOU of the **1st** rectangle with others

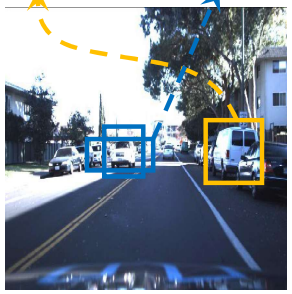


SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

0.9 | 0.85 | 0.82 | 0.77



Compare IOU of the 1st rectangle with others

$$IOU = \frac{\square}{\square} = 0$$

IOU = 0 with the chosen rectangle ⟹ ***do nothing***!

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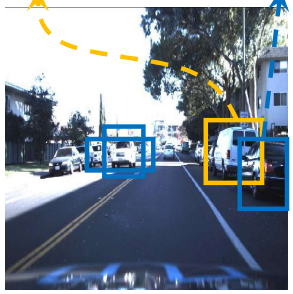
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_N$

0.9 | 0.85 | 0.82 | 0.77 | 0.75



Compare IOU of the 1st rectangle with others

$$IOU = \frac{\square}{\square} < 0.5$$

do nothing

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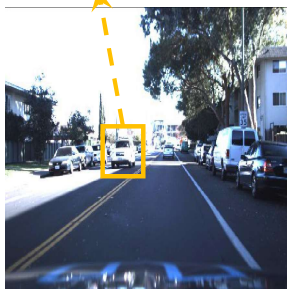
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_{N_1}$

0.9 | 0.82 | 0.77 | 0.75



Compare IOU of the **2nd** rectangle with others

$N_1 \leq N$ because we have thrown out rectangles

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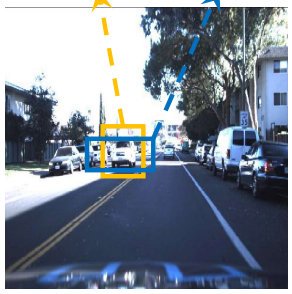
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... Sorted confidence p $rect_{N_1}$

0.9 | 0.82 | 0.77 | 0.75



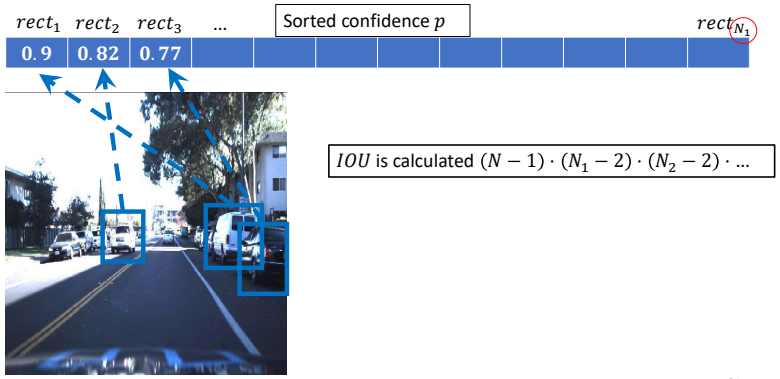
Compare IOU of the **2nd** rectangle with others

$$IOU = \frac{\square}{\square} > 0.5$$

threshold

80

Postprocessing: NMS



One-stage Object detection

Anchor-free

Drawbacks of Anchor Boxes

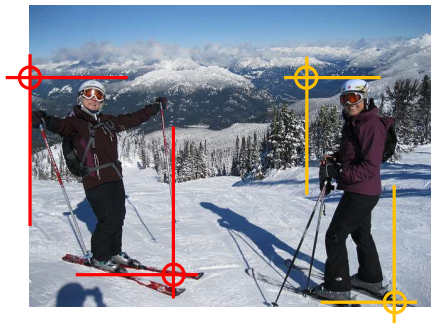
1. Need a large number of anchors

→ A tiny fraction of anchors are positive examples

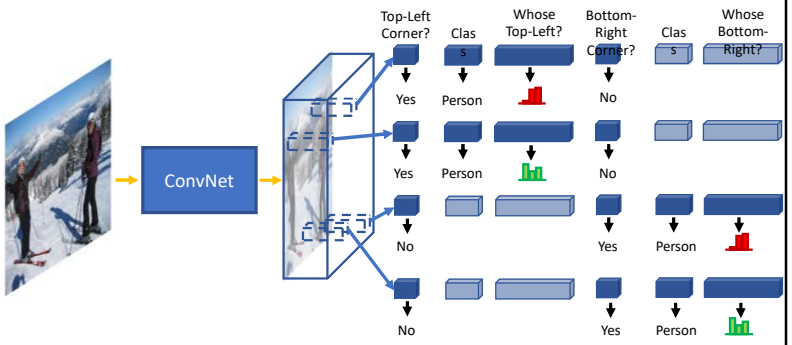
→ Slow down training [Lin et al. ICCV'17]

2. Extra hyperparameters – sizes and aspect ratios

CornerNet: Detecting Objects as Paired Keypoints

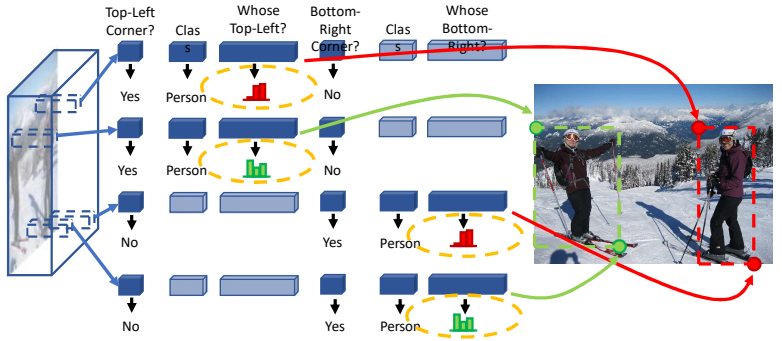


CornerNet: Detecting Objects as Paired Keypoints



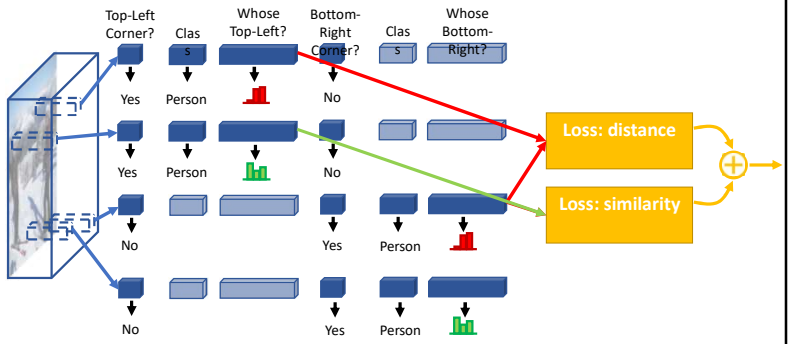
85

CornerNet: Detecting Objects as Paired Keypoints



86

CornerNet: Detecting Objects as Paired Keypoints



87

Associative Embedding [Newell et al. NIPS'17]

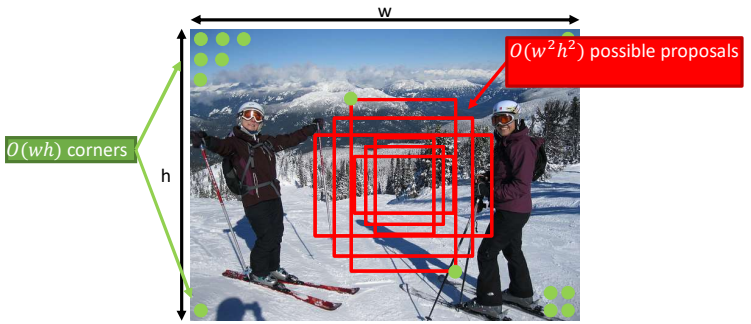
88

Advantages of Detecting Corners

Detecting corner is easier than detecting center

89

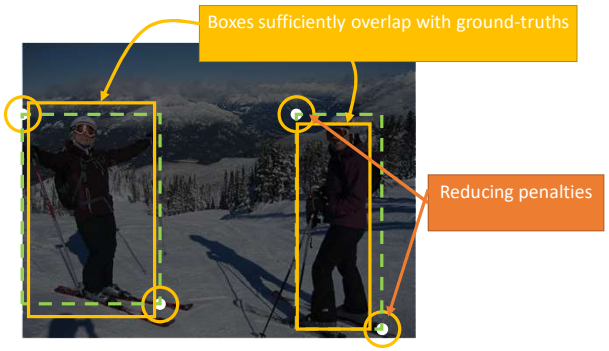
Advantages of Detecting Corner



Represent $O(w^2h^2)$ possible proposals using only $O(wh)$ corners

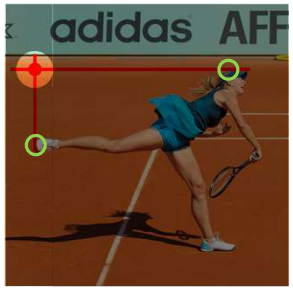
90

Supervising Corner Detection



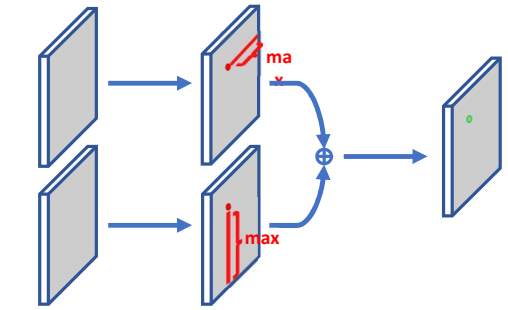
91

Corner Pooling



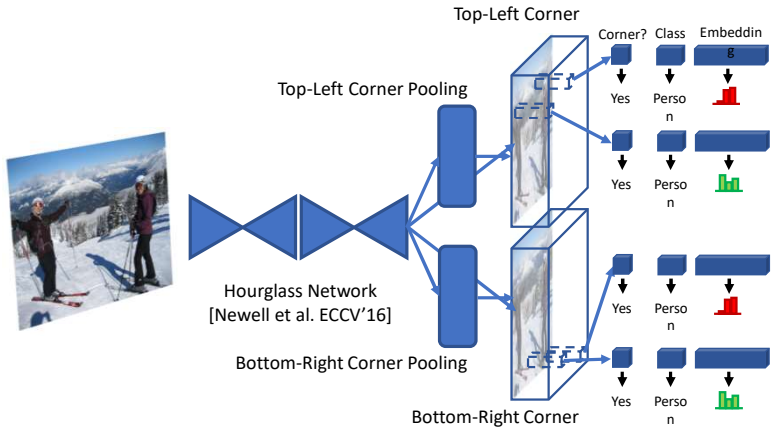
92

Top-Left Corner Pooling



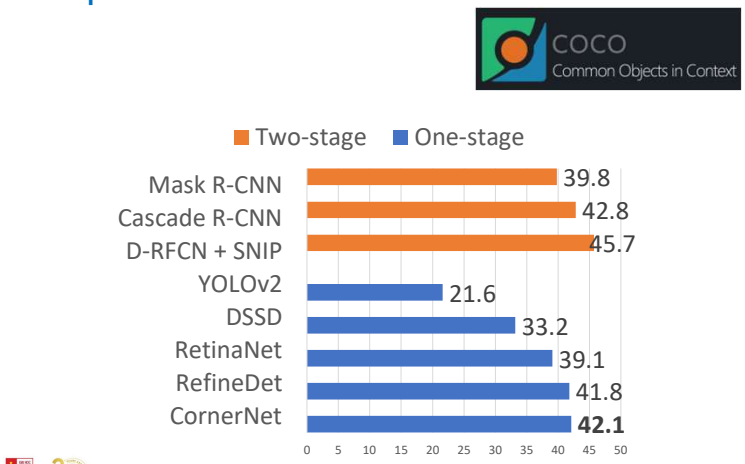
93

CornerNet



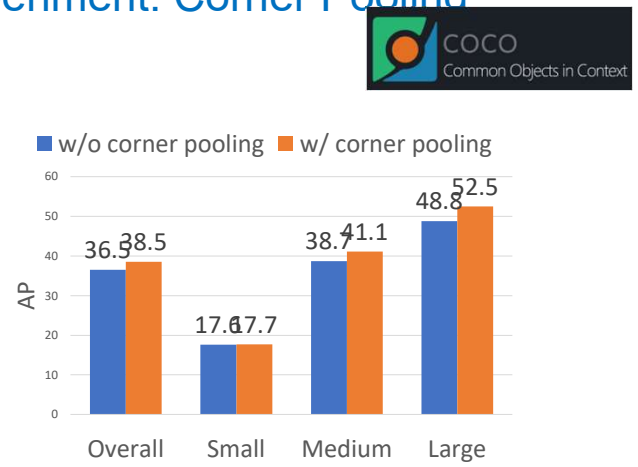
94

Experiment: CornerNet versus Others



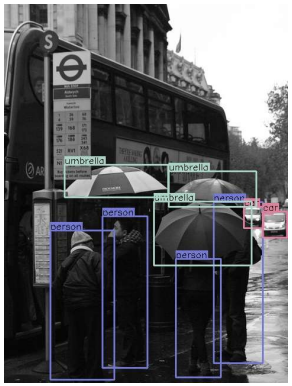
95

Experiment: Corner Pooling



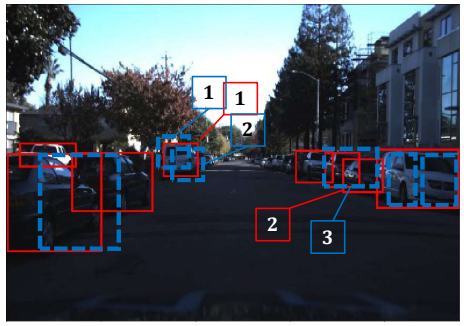
96

97



98

Accuracy evaluation



$\boldsymbol{n}$ predicted

$\boldsymbol{m}$ Ground Truth

$$IoU = \frac{A \cap B}{A \cup B}$$

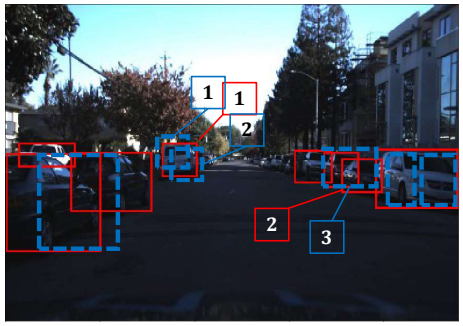
A – ground truth
B – detector result

Correspondence between GT and predicted?

99

99

Accuracy evaluation



Sorted array of $\boldsymbol{IOU} > T$ between GT and predicted (max length = $\boldsymbol{n} \cdot \boldsymbol{m}$)

$\uparrow \quad \downarrow$
$(iou_1, iou_2, iou_3, \ldots)$

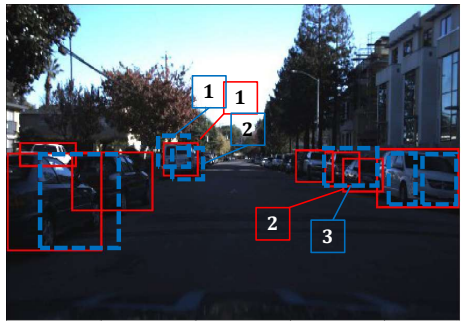
GT	2	1	1
pred	3	1	2

evaluator.py -> sort_ious(gt_boxes, pred_boxes, iou_thr)

100

100

Accuracy evaluation



Sorted array of $IOU > T$ between GT and predicted (max length = $n \cdot m$)

$\uparrow (iou_1, iou_2, iou_3, \dots) \downarrow$

GT	2	1	1
pred	3	1	2

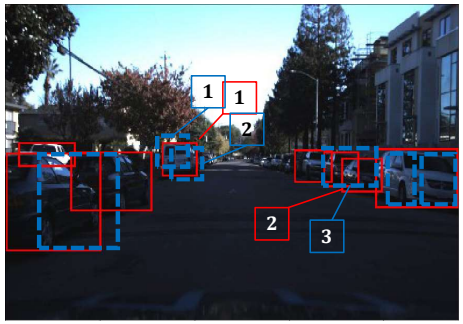
if appear firstly

matched GT	2	1
matched pred	3	1

evaluator.py -> get_single_image_results(gt_boxes, pred_boxes, iou_thr)

101

Accuracy evaluation



Sorted array of $IOU > T$ between GT and predicted (max length = $n \cdot m$)

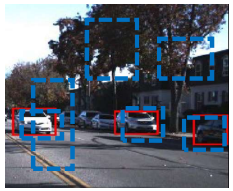
True predicted

matched GT	2	1
matched pred	3	1

evaluator.py -> get_single_image_results(gt_boxes, pred_boxes, iou_thr)

102

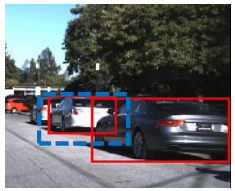
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



$precision$–?
$recall$-?

$$precision = \frac{true\ predicted}{predicted}$$

What part of predicted is true

$\sum$

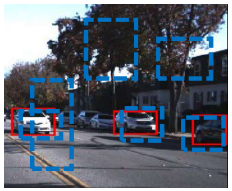
$precision$–?
$recall$-?

$$recall = \frac{true\ predicted}{ground\ truth}$$

What part of true predicted from all GT objects

103

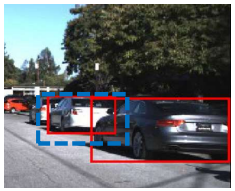
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



- predicted = 4
- ground truth = 3
- **true predicted = 1**

$$precision = \frac{true\ predicted}{predicted}$$

What part of predicted is true

$\sum$

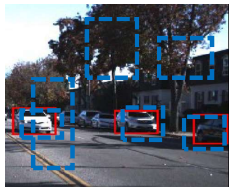
- predicted = 1
- ground truth = 2
- **true predicted = 1**

$$recall = \frac{true\ predicted}{ground\ truth}$$

What part of true predicted from all GT objects

104

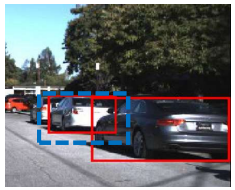
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



- predicted = 4
- ground truth = 3
- **true predicted = 1**

$$precision = \frac{true\ predicted}{predicted}$$

- predicted = 1
- ground truth = 2
- **true predicted = 1**

$$recall = \frac{true\ predicted}{ground\ truth}$$

evaluator.py -> calc_precision_recall(img_results)

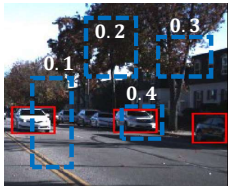
105

Accuracy evaluation: precision, recall

sorted box confidence

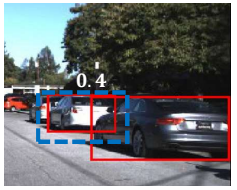
$\downarrow \qquad \uparrow$

$(p_1, p_2, \dots p_i, \dots, p_{N-1}, p_N)$



• • •

Each predicted box has confidence $\boldsymbol{p}$



106

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow \qquad \uparrow$

$(p_1, p_2, \dots p_i, \dots, p_{N-1}, p_N)$

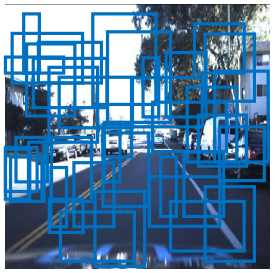
I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

score	prec	recall
p_1	**0. 1**	**0. 9**

high recall

low precision



For all images together!

107

Accuracy evaluation: precision, recall

sorted box confidence

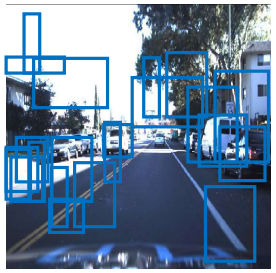
$\downarrow \qquad \uparrow$

$(p_1, p_2, \dots p_i, \dots, p_{N-1}, p_N)$

I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

score	prec	recall
p_1	**0. 1**	**0. 9**
p_2	**0. 2**	**0. 8**
…	…	…



For all images together!

108

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow \quad \uparrow$

$(p_1, p_2, \dots p_i, \dots, p_{N-1}, p_N)$

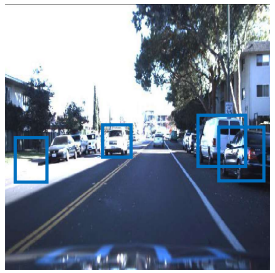
I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

score	prec	recall
p_1	**0.1**	**0.9**
p_2	**0.2**	**0.8**
...	...	...
p_N	**0.9**	**0.1**

High precision

low recall



For all images together!

109

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow \quad \uparrow$

$(p_1, p_2, \dots p_i, \dots, p_{N-1}, p_N)$

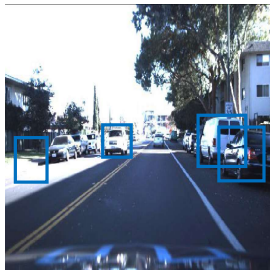
I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

score	prec	recall
p_1	**0.1**	**0.9**
p_2	**0.2**	**0.8**
...	...	...
p_N	**0.9**	**0.1**

High precision

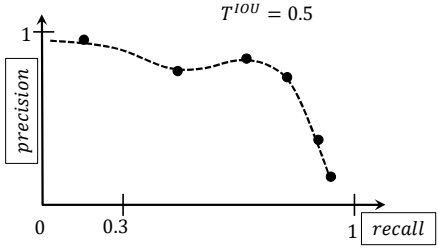
low recall



get_thr_prec_rec(...)

110

Accuracy evaluation: mAP

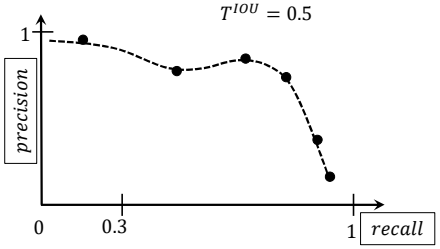


hundreds of values for real data sets

score	prec	recall
p_1	**0.1**	**0.9**
p_2	**0.2**	**0.8**
...	...	...
p_N	**0.9**	**0.1**

111

Accuracy evaluation: mAP



hundreds of values for real data sets

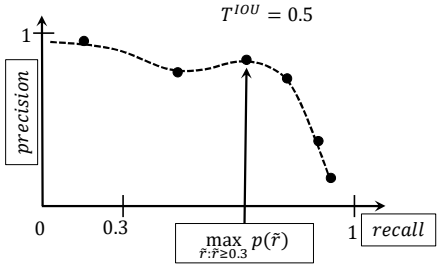
score	prec	recall
p_1	**0.1**	**0.9**
p_2	**0.2**	**0.8**
...	...	...
p_N	**0.9**	**0.1**

11 recall thresholds

$$AP^T = \sum_{r \in \{0, 0.1, \dots, 1\}} \max_{\tilde{r}: \tilde{r} \geq r} p(\tilde{r})$$

112

Accuracy evaluation: mAP



hundreds of values for real data sets

score	prec	recall
p_1	0.1	0.9
p_2	0.2	0.8
...	...	...
p_N	0.9	0.1

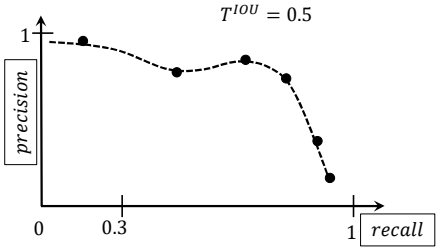
A lot of mAP tutorials has misunderstanding : "area under curve" (AUC) is not the same!

11 recall thresholds

$$AP^T = \sum_{r\in\{0,0.1,\ldots,1\}} \max_{\tilde{r}:\tilde{r}\geq r} p(\tilde{r})$$

113

Accuracy evaluation: mAP



hundreds of values for real data sets

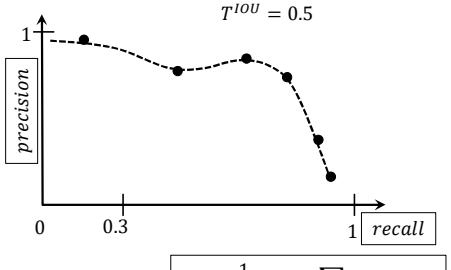
score	prec	recall
p_1	0.1	0.9
p_2	0.2	0.8
...	...	...
p_N	0.9	0.1

$$AP^T = \sum_{r\in\{0,0.1,\ldots,1\}} \max_{\tilde{r}:\tilde{r}\geq r} p(\tilde{r})$$

Pascal VOC metric is $AP^{0.5}$

114

Accuracy evaluation: mAP



hundreds of values for real data sets

score	prec	recall
p_1	0.1	0.9
p_2	0.2	0.8
...	...	...
p_N	0.9	0.1

$$AP = \frac{1}{10} \cdot \sum_{T\in\{0.5,0.55,\ldots,0.95\}} AP^T$$

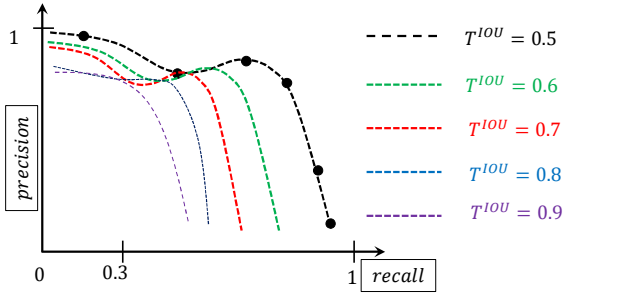
MS COCO has metrics $AP^{0.5}, AP^{0.75}, AP$

115

Accuracy evaluation: mAP

$$AP = \frac{1}{10} \cdot \sum_{T\in\{0.5,0.55,\ldots,0.95\}} AP^T$$

MS COCO uses 10 IOU thresholds 0.5, 0.55, ... 0.95



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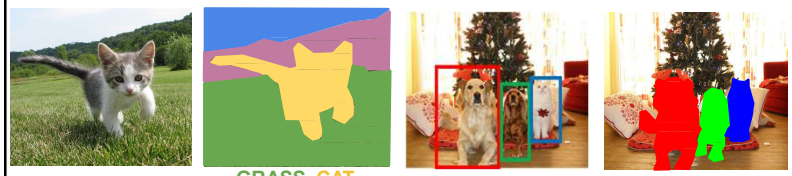
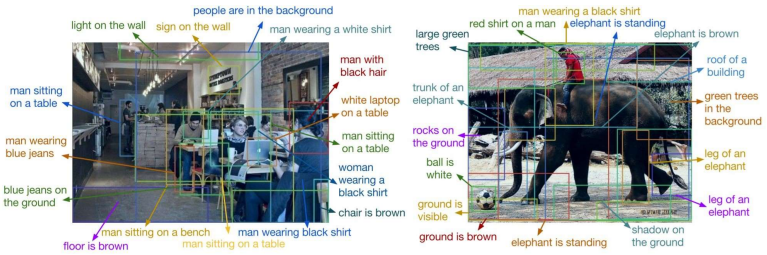
Computer Vision Tasks



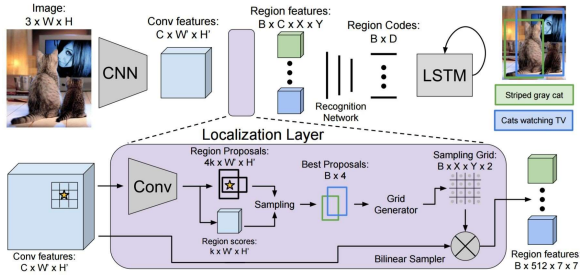
Beyond 2D Object Detection...

Object Detection + Captioning = Dense Captioning



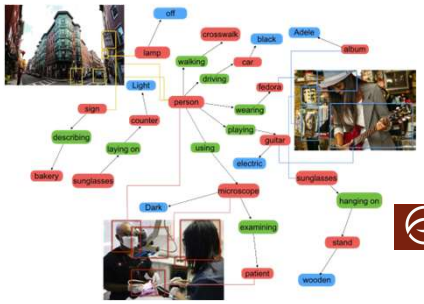
Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016
Figure copyright IEEE, 2016. Reproduced for educational purposes.

Aside: Object Detection + Captioning = Dense Captioning



Johnson, Karpathy, and Fei-Fei, "DenseCap: Fully Convolutional Localization Networks for Dense Captioning", CVPR 2016
Figure copyright IEEE, 2016. Reproduced for educational purposes.

Objects + Relationships = Scene Graphs

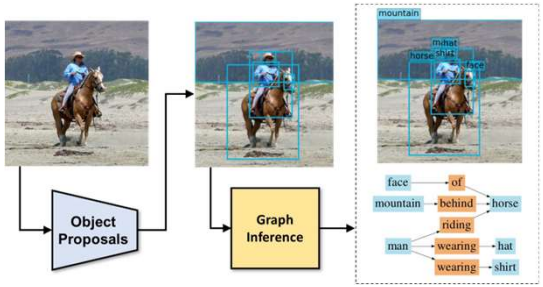


108,077 Images
5.4 Million Region Descriptions
1.7 Million Visual Question Answers
3.8 Million Object Instances
2.8 Million Attributes
2.3 Million Relationships
Everything Mapped to Wordnet Synsets

VISUALGENOME

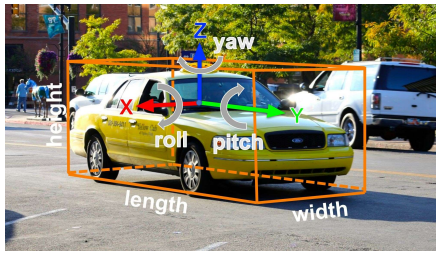
Krishna, Ranjay, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

Scene Graph Prediction



Xu, Zhu, Choy, and Fei-Fei, "Scene Graph Generation by Iterative Message Passing", CVPR 2017
Figure copyright IEEE, 2018. Reproduced for educational purposes.

3D Object Detection



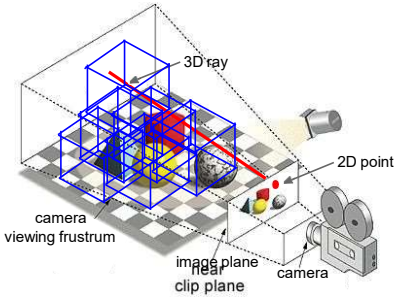
2D Object Detection:
2D bounding box
(x, y, w, h)

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!

3D Object Detection: Simple Camera Model

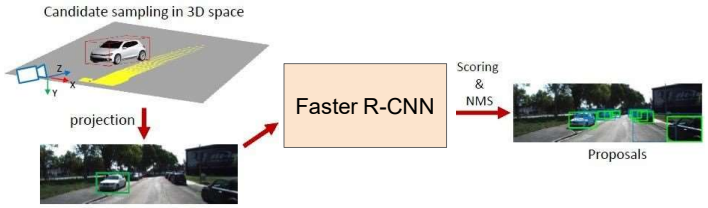


A point on the image plane corresponds to a ray in the 3D space

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**!

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.

3D Shape Prediction

Voxel: D x D x D binary

Pointcloud: V x 3 float

Mesh: V x 3 float, F x 3 int

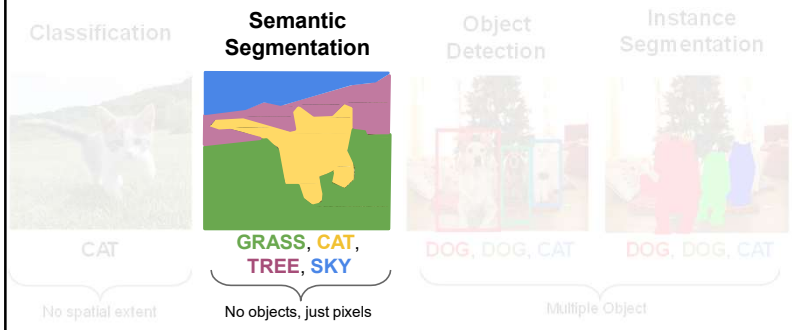
Choy et al, "3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction", ECCV 2016

Fan et al, "A Point Set Generation Network for 3D Object Reconstruction from a Single Image", CVPR 2017

Wang et al, "Pixel2Mesh: Generating 3D Mesh Models from Single RGB Images", ECCV 2018

Semantic segmentation

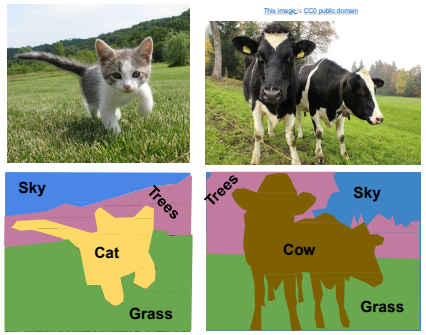
Semantic Segmentation



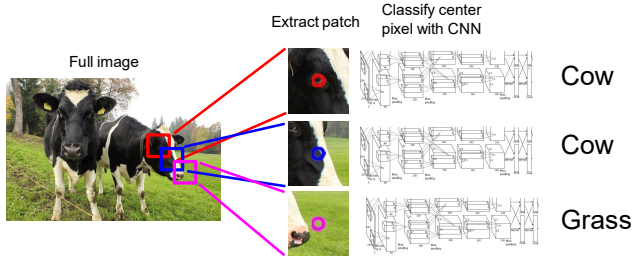
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

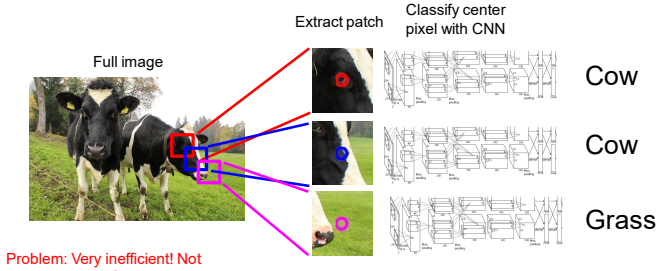


Semantic Segmentation Idea: Sliding Window



Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Semantic Segmentation Idea: Sliding Window

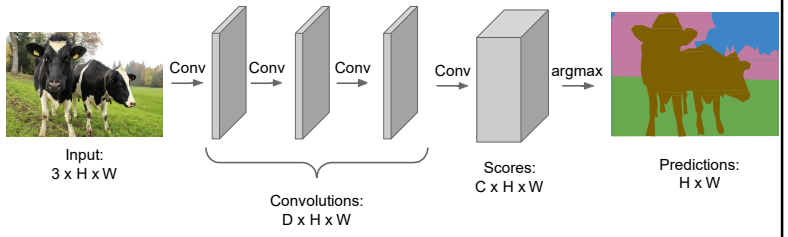


Problem: Very inefficient! Not reusing shared features between overlapping patches

Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

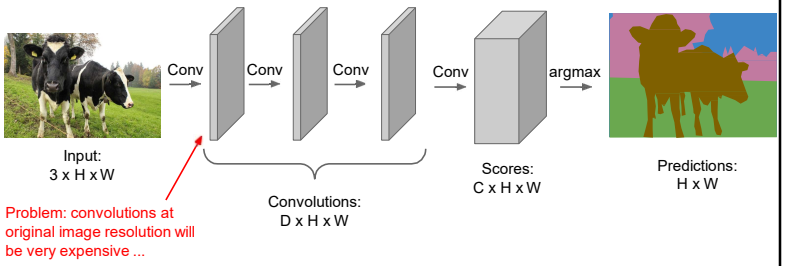
Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!



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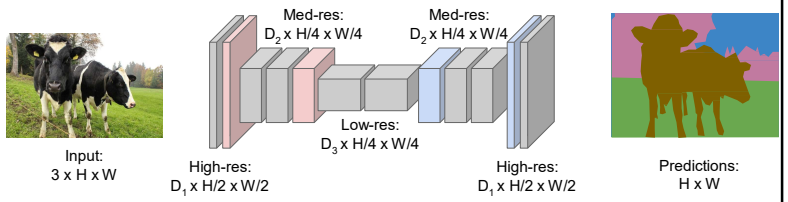
Semantic Segmentation Idea: Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

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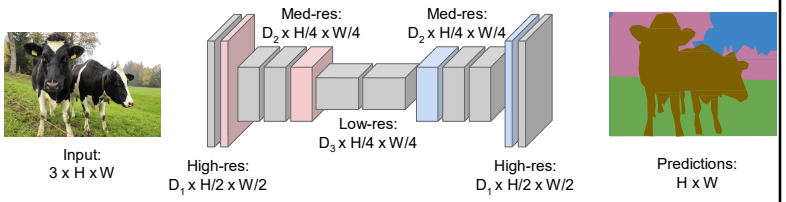
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

Upsampling:
???

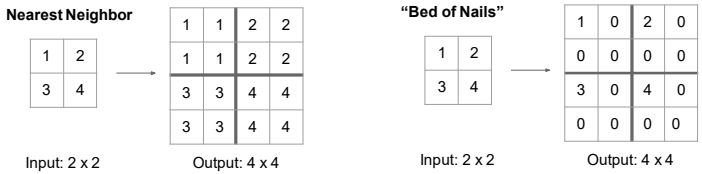
Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

135

In-Network upsampling: "Unpooling"



136

In-Network upsampling: "Max Unpooling"

Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

. . .

Rest of the network

Max Unpooling
Use positions from pooling layer

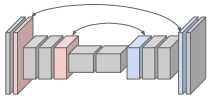
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

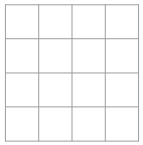
Corresponding pairs of downsampling and upsampling layers



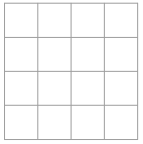
137

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



Input: 4 x 4

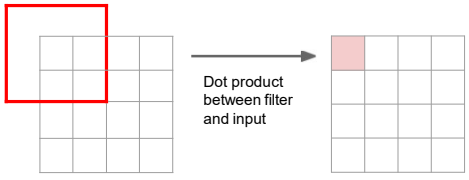


Output: 4 x 4

138

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



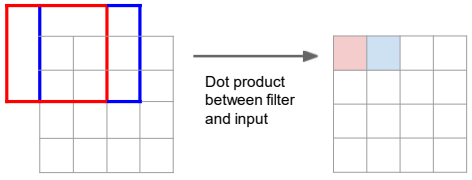
Input: 4 x 4

Output: 4 x 4

139

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



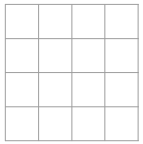
Input: 4 x 4

Output: 4 x 4

140

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



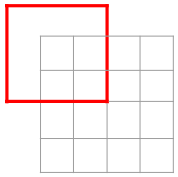
Input: 4 x 4

Output: 2 x 2

141

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

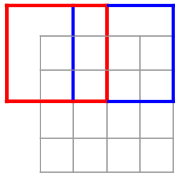
Dot product between filter and input

Output: 2 x 2

142

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Input: 4 x 4

Dot product between filter and input

Output: 2 x 2

Filter moves 2 pixels in the input for every one pixel in the output

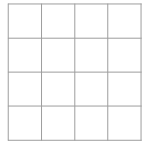
Stride gives ratio between movement in input and output

143

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

Input: 2 x 2

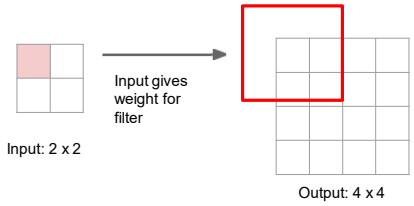


Output: 4 x 4

144

Learnable Upsampling: Transpose Convolution

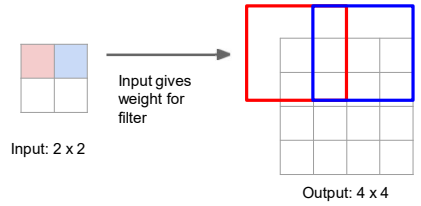
3 x 3 **transpose** convolution, stride 2 pad 1



145

Learnable Upsampling: Transpose Convolution

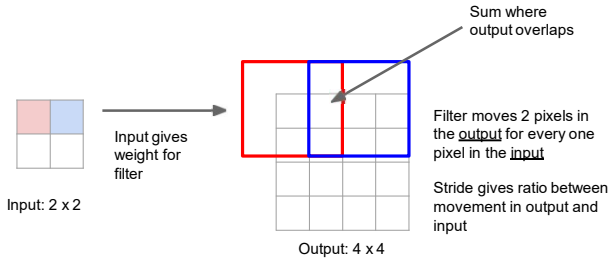
3 x 3 **transpose** convolution, stride 2 pad 1



146

Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1



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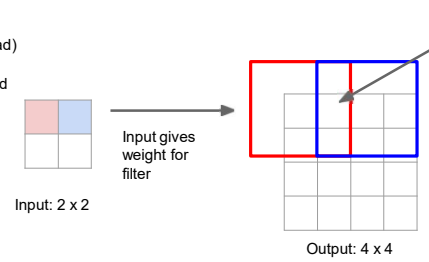
Learnable Upsampling: Transpose Convolution

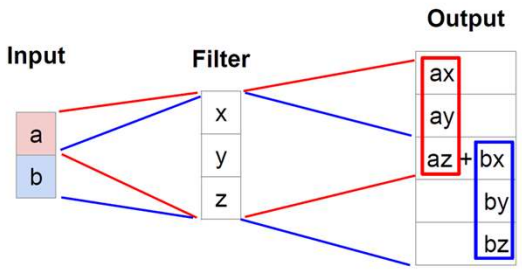
3 x 3 **transpose** convolution, stride 2 pad 1

Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution



148

Learnable Upsampling: Transpose Convolution



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

Need to crop one pixel from output to make output exactly 2x input

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Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & x & y & z & 0 & 0 \\ 0 & 0 & x & y & z & 0 \\ 0 & 0 & 0 & x & y & z \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ ax + by + cz \\ bx + cy + dz \\ cx + dy \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=1, padding=1

150

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & x & y & z & 0 & 0 \\ 0 & 0 & x & y & z & 0 \\ 0 & 0 & 0 & x & y & z \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ ax + by + cz \\ bx + cy + dz \\ cx + dy \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=1, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T \vec{a}$$

$$\begin{bmatrix} x & 0 & 0 & 0 \\ y & x & 0 & 0 \\ z & y & x & 0 \\ 0 & z & y & x \\ 0 & 0 & z & y \\ 0 & 0 & 0 & z \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} ax \\ ay + bx \\ az + by + cx \\ bz + cy + dx \\ cz + dy \\ dz \end{bmatrix}$$

When stride=1, convolution transpose is just a regular convolution (with different padding rules)

151

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=2, padding=1

152

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=2, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T\vec{a}$$

$$\begin{bmatrix} x & 0 \\ y & 0 \\ z & x \\ 0 & y \\ 0 & z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} ax \\ ay \\ az + bx \\ by \\ bz \\ 0 \end{bmatrix}$$

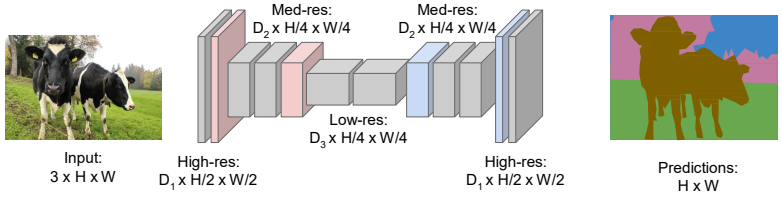
When stride>1, convolution transpose is no longer a normal convolution!

Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling: Unpooling or strided transpose convolution



Metrics for Segmentation Models

- **Pixel Accuracy (PA):**

$$\text{PA} = \frac{\sum_{i=0}^{K} p_{ii}}{\sum_{i=0}^{K} \sum_{j=0}^{K} p_{ij}}$$

  - The ratio of pixels properly classified, divided by the total number of pixels.

- **Mean Pixel Accuracy (MPA):**

$$\text{MPA} = \frac{1}{K+1} \sum_{i=0}^{K} \frac{p_{ii}}{\sum_{j=0}^{K} p_{ij}}$$

  - The ratio of correct pixels is computed in a per-class manner and then averaged over the total number of classes.

Metrics for Segmentation Models

- Intersection over Union (**IoU**):

$$\text{IoU} = J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

$$\text{IOU} = \frac{\text{Area of overlap}}{\text{Area of union}}$$

  - Also called **Jaccard Index**
  - The most commonly used metrics in semantic segmentation. (mean-IoU/mIoU)
  - *A* denotes the ground truth and B denotes the predicted segmentation maps.

Metrics for Segmentation Models

- **Precision / Recall / F1 score:**

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad \text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1-score} = \frac{2\ \text{Prec}\ \text{Rec}}{\text{Prec} + \text{Rec}}$$

F1: harmonic mean of precision and recall

Predicted Value (predicted by the test)	Actual Value (as confirmed by experiment): positives	Actual Value: negatives
positives	**TP** True Positive	**FP** False Positive
negatives	**FN** False Negative	**TN** True Negative

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Metrics for Segmentation Models

- **Dice coefficient:**

$$\text{Dice} = \frac{2|A \cap B|}{|A| + |B|}$$

$$\text{Dice} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} = \text{F1}$$

- Essentially identical to the F1 score.
- The Dice coefficient and IoU are positively correlated.

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Instance segmentation

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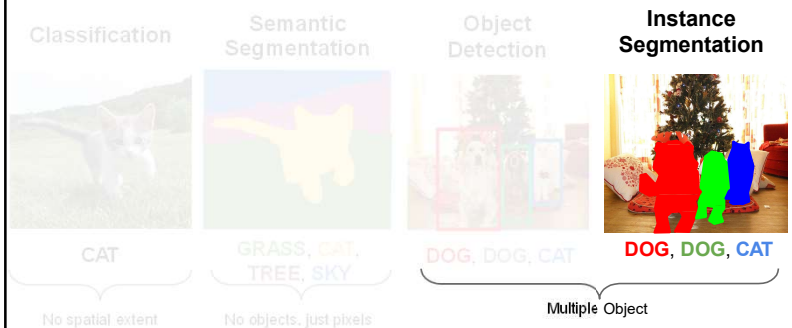
Instance Segmentation



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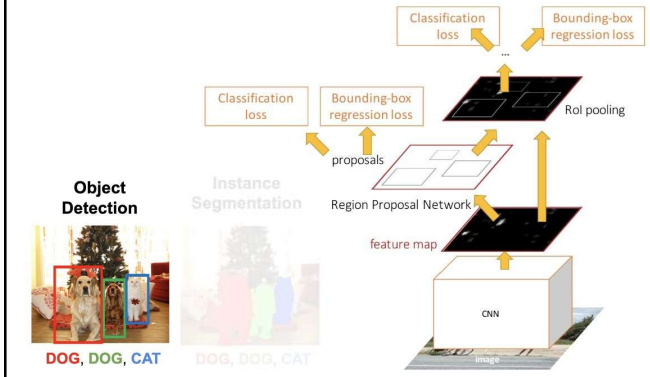
Object Detection: Faster R-CNN



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

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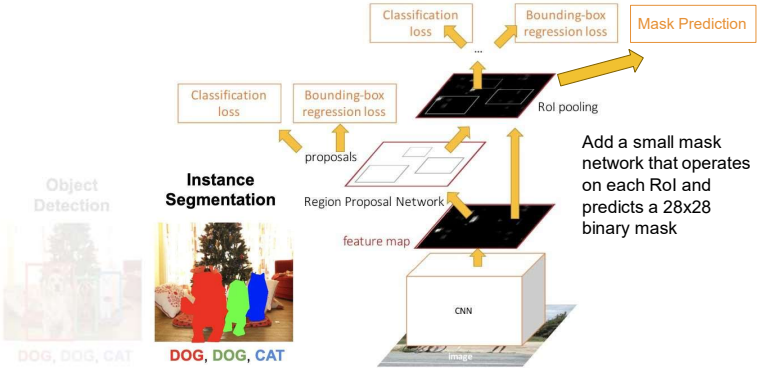
Instance Segmentation: Mask R-CNN



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

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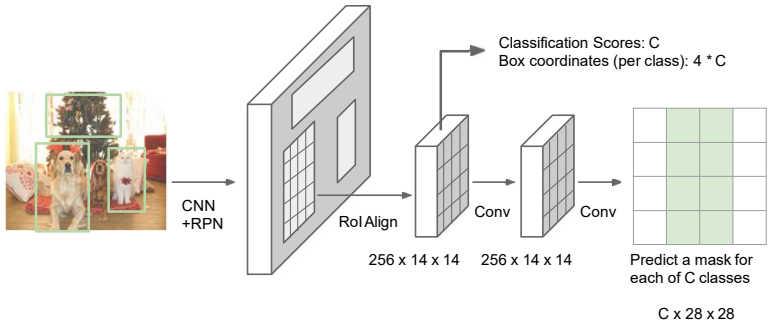
Mask R-CNN



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

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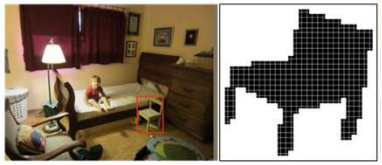
Mask R-CNN: Example Mask Training Targets



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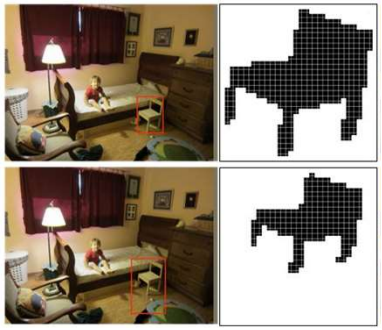
Mask R-CNN: Example Mask Training Targets



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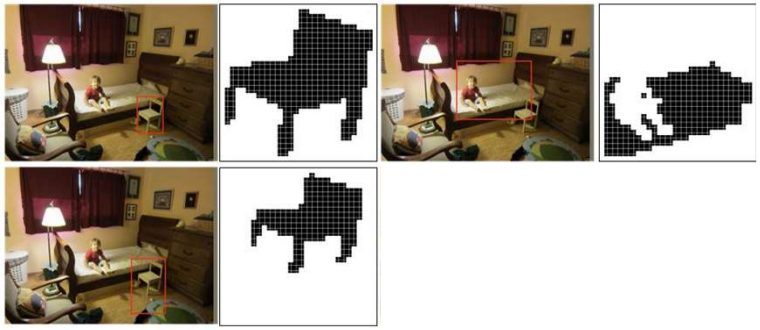
Mask R-CNN: Example Mask Training Targets



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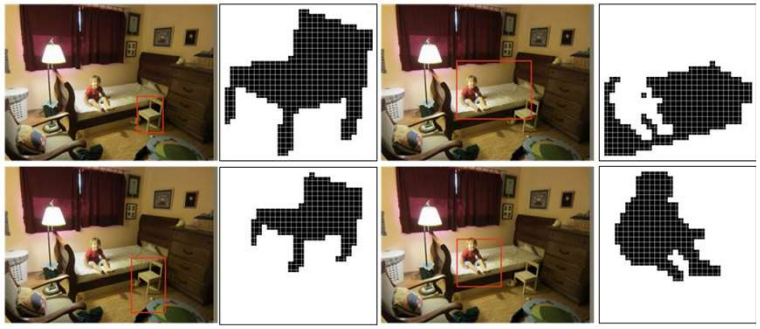
Mask R-CNN: Example Mask Training Targets



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Mask R-CNN: Very Good Results!

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

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Mask R-CNN Also does pose

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

Open Source Frameworks

- 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
- Caffe2 Detectron:
- https://github.com/facebookresearch/Detectron
- Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN
- Finetune on your own dataset with pre-trained models

References

1. CS231n: Convolutional Neural Networks for Visual Recognition
   - http://cs231n.stanford.edu/
2. Object Detection Creation from Scratch. Samsung R&D Institute Ukraine. Vitaliy Bulygin https://aiukraine.com/wp-content/uploads/2018/08/Vitalij-Buly-gin-.pptx
3. CornerNet: Detecting Objects as. Paired Keypoints https://pvl.cs.princeton.edu/assets/CornerNet.pptx

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Thank you!

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