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

Computer Vision

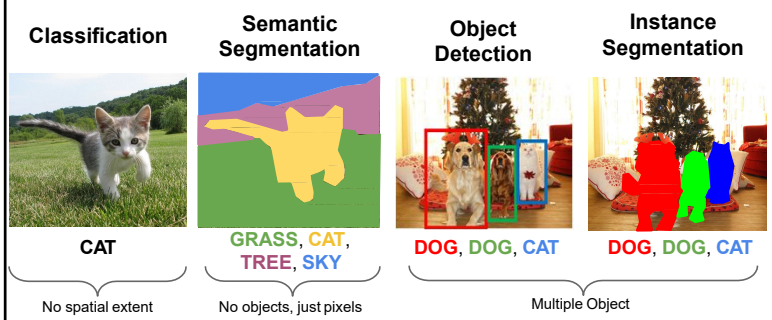
Ch (part 3): Deep Learning for CV

Nguyễn Thị Oanh
oanhnt@soict.hust.edu.vn

Deep learning for CV

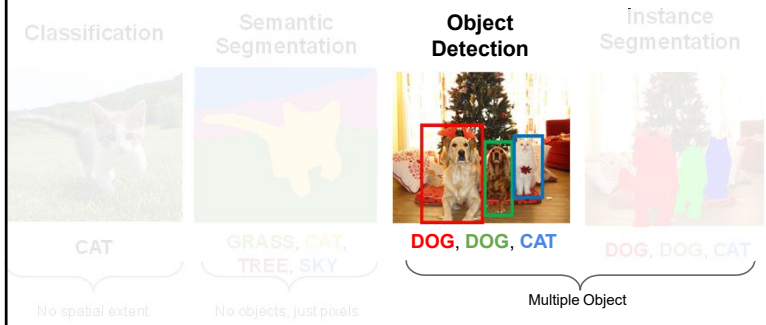
Contents

Computer Vision Tasks

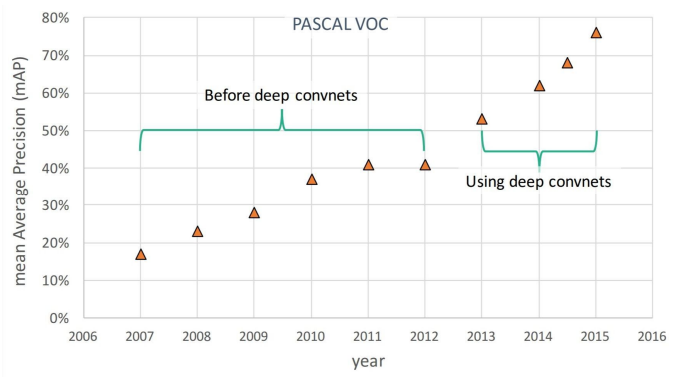


Object detection: sliding windows

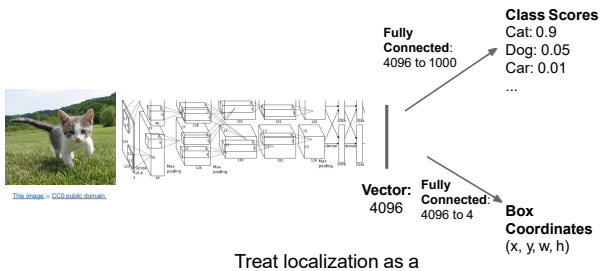
Object Detection



Object Detection: Impact of Deep Learning

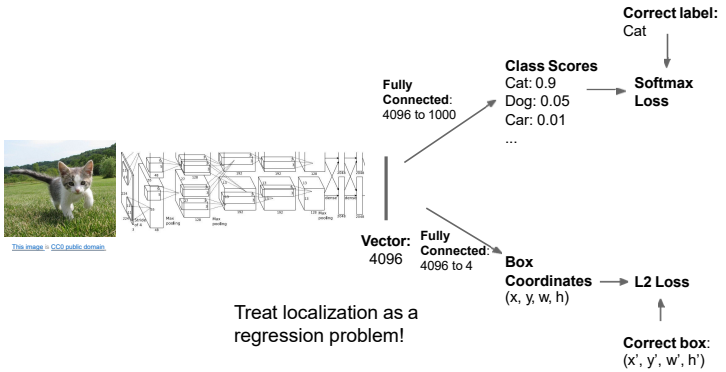


Object Detection: Single Object (Classification + Localization)

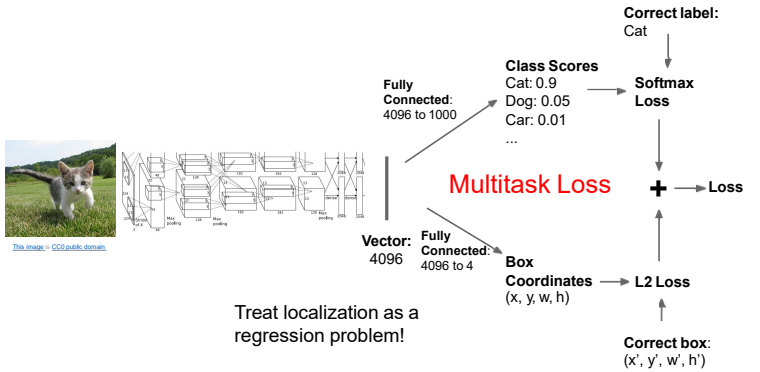


Treat localization as a regression problem!

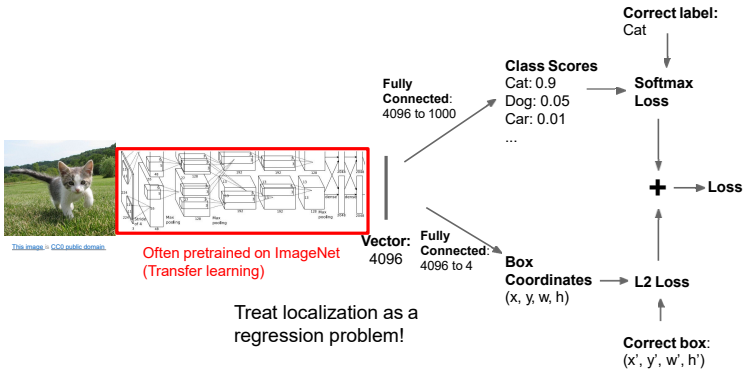
Object Detection: Single Object (Classification + Localization)



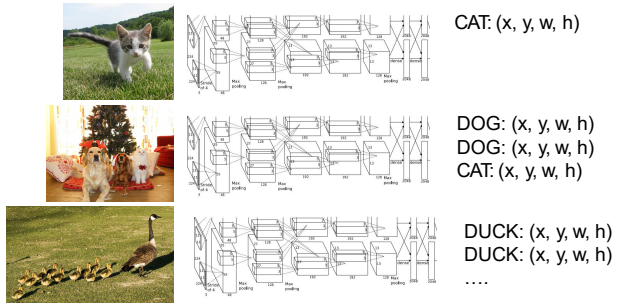
Object Detection: Single Object (Classification + Localization)



Object Detection: Single Object (Classification + Localization)

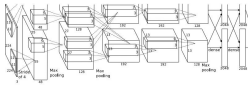


Object Detection: Multiple Objects

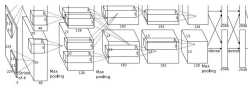


Object Detection: Multiple Objects

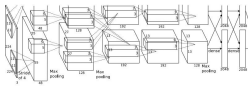
Each image needs a different number of outputs!



CAT: (x, y, w, h) — 4 numbers



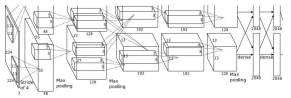
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h) — 16 numbers



DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
…. — Many numbers!

Object Detection: Multiple Objects

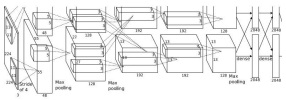
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection: Multiple Objects

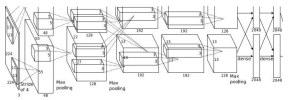
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

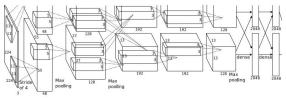
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection: Multiple Objects

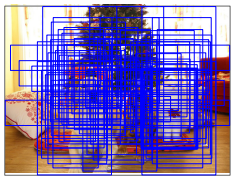
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

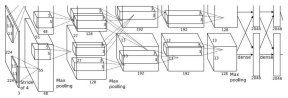


Dog? NO
Cat? YES
Background? NO

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!

Two-stage Object detection

Object Detection

Two Stages

- Propose “objects”
- Classify each candidate

One-Stage

- Sliding window to classify all candidates

Object Detection

Two Stages

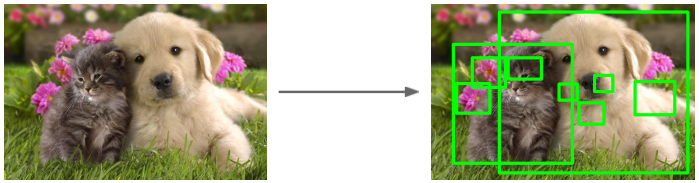
- Propose “objects”
- Classify each candidate

One-Stage

- Sliding window to classify all candidates

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

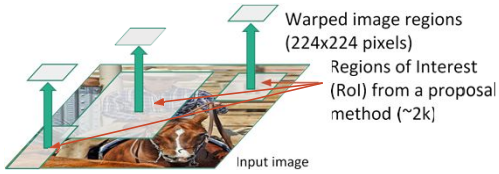
R-CNN

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



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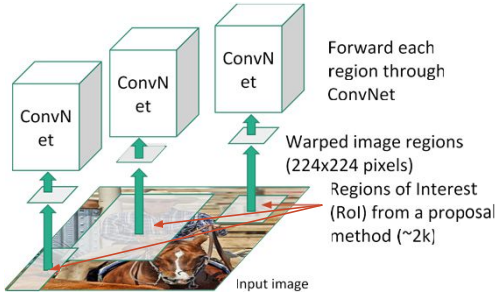
R-CNN



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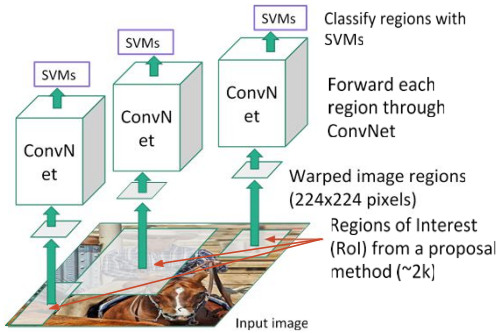
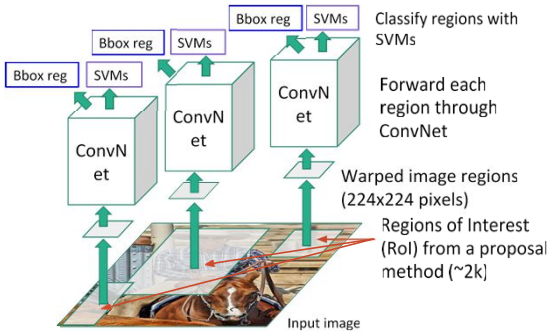


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN

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



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R-CNN

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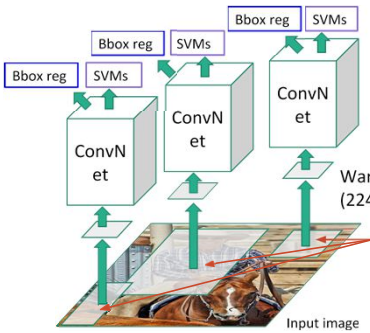


Classify regions with SVMs

Forward each region through ConvNet

Warped image regions (224x224 pixels)

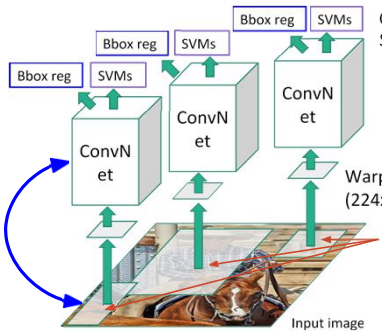
Regions of Interest (RoI) from a proposal method (~2k)

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

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

"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!

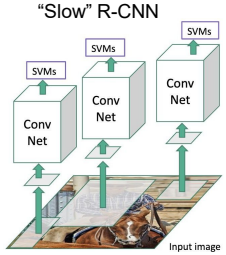
Idea: Process image before cropping! Swap convolution and cropping!

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

Fast R-CNN

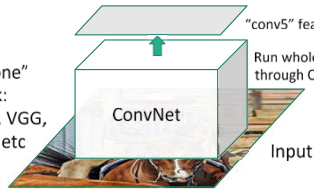
Input image

"Slow" R-CNN



Fast R-CNN

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

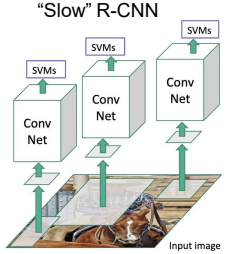


"conv5" features

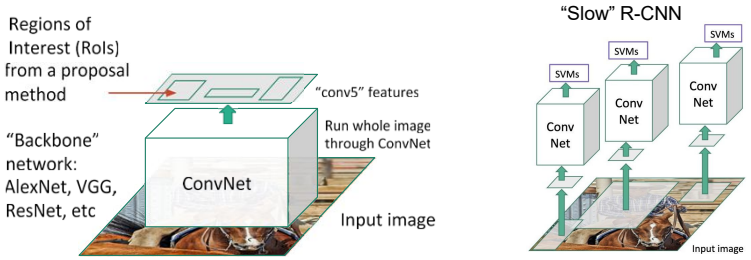
Run whole image through ConvNet

Input image

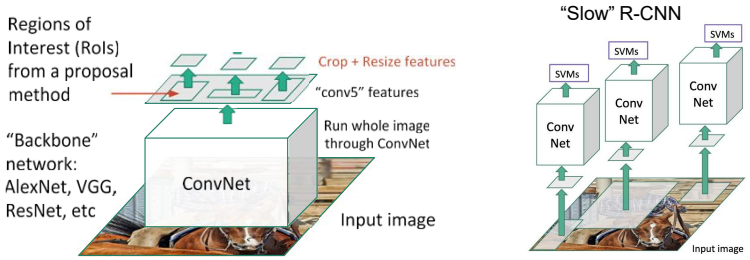
"Slow" R-CNN



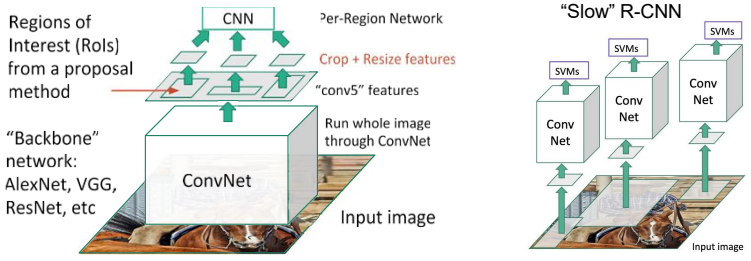
Fast R-CNN



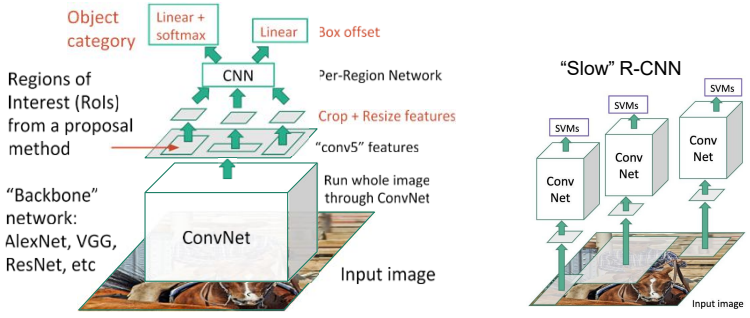
Fast R-CNN



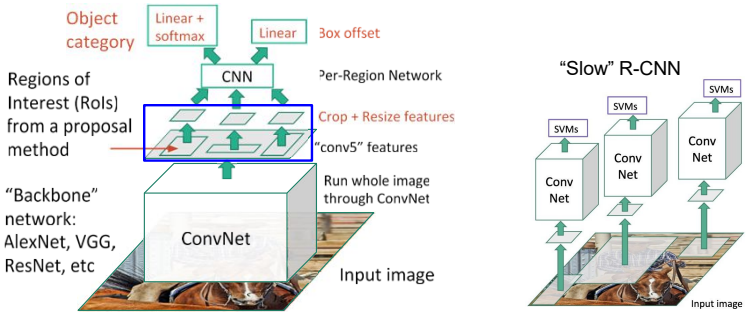
Fast R-CNN



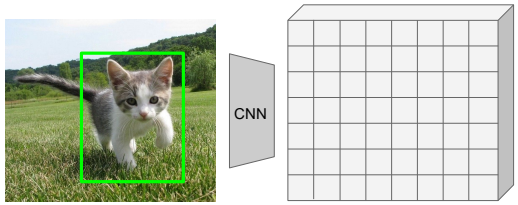
Fast R-CNN



Fast R-CNN

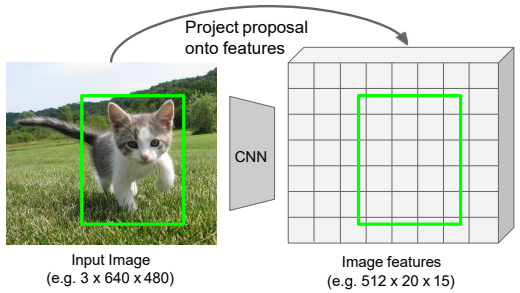


Cropping Features: RoI Pool



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

Cropping Features: RoI Pool



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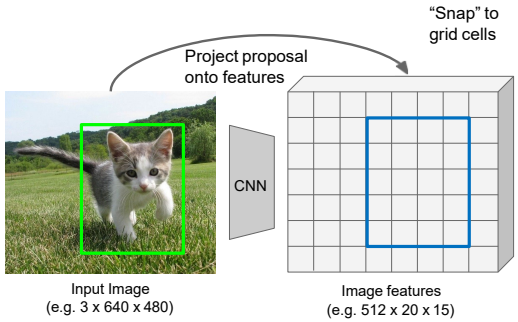

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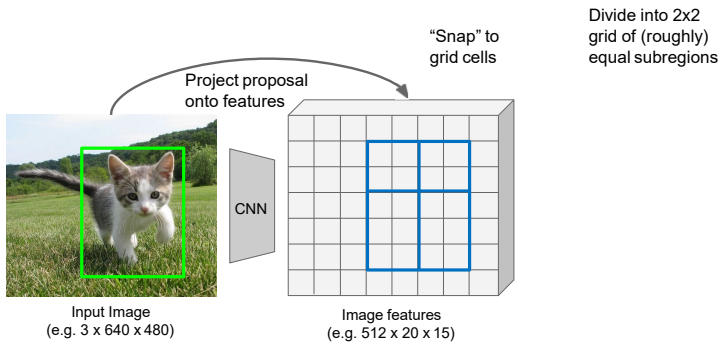

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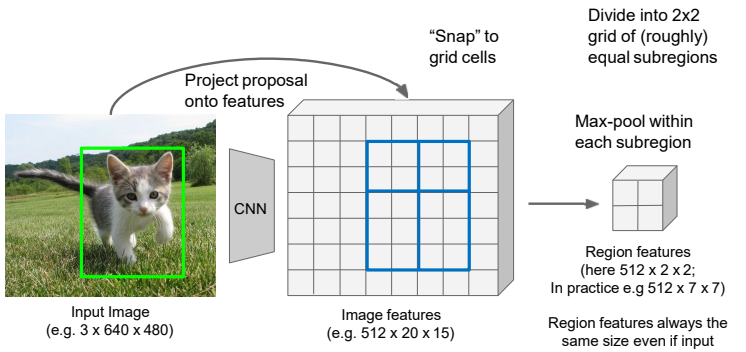
Cropping Features: RoI Pool



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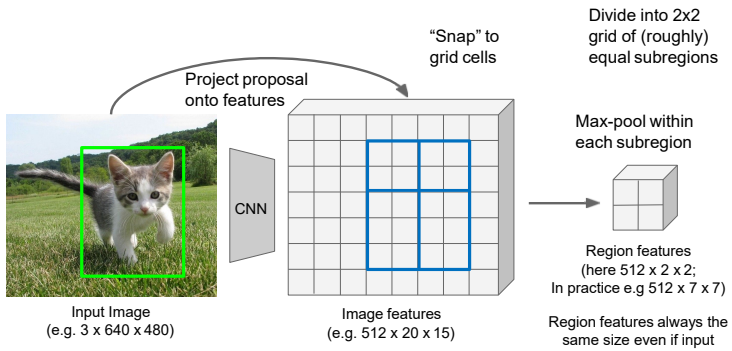
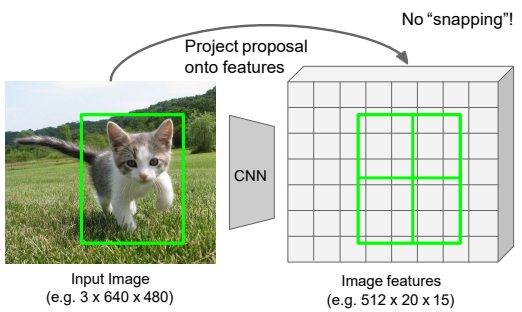
Cropping Features: RoI Pool



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

Problem: Region features slightly misaligned

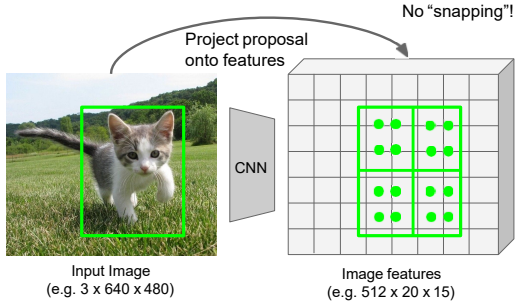
Cropping Features: RoI Align



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

Cropping Features: RoI Align

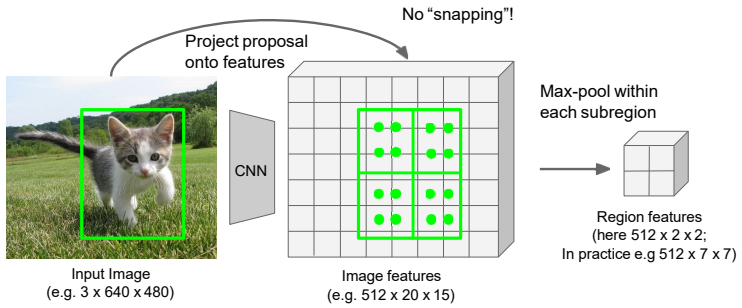
Sample at regular points in each subregion using bilinear interpolation



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

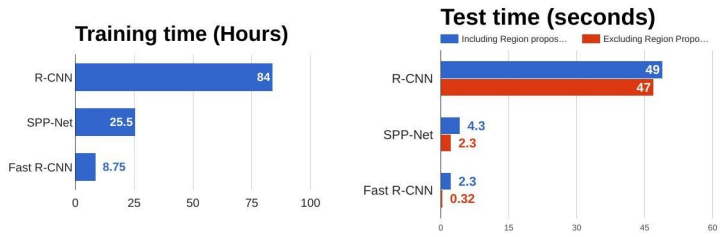
Cropping Features: RoI Align

Sample at regular points in each subregion using bilinear interpolation



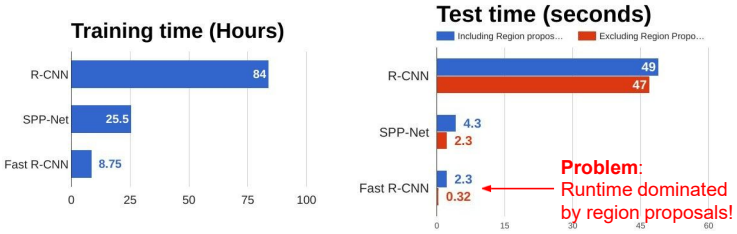
Girshick, "Fast R-CNN", ICCV 2015.

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", ECCV2014
Girshick, "Fast R-CNN", ICCV 2015

R-CNN vs Fast R-CNN



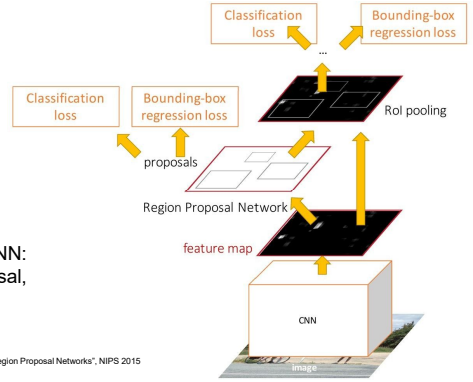
Problem: Runtime dominated by region proposals!

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!

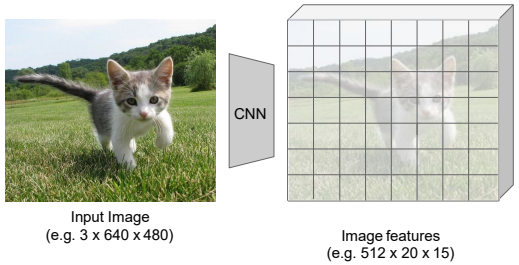
Insert **Region Proposal Network (RPN)** to predict proposals from features

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
Figure copyright 2015, Ross Girshick; reproduced with permission

Region Proposal Network

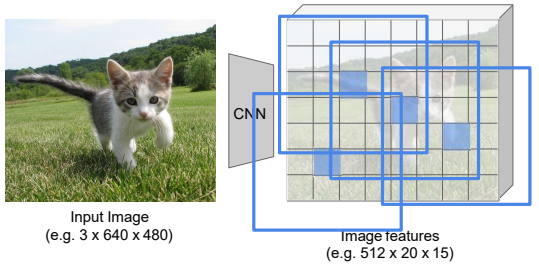


Input Image
(e.g. 3 x 640 x 480)

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

Region Proposal Network

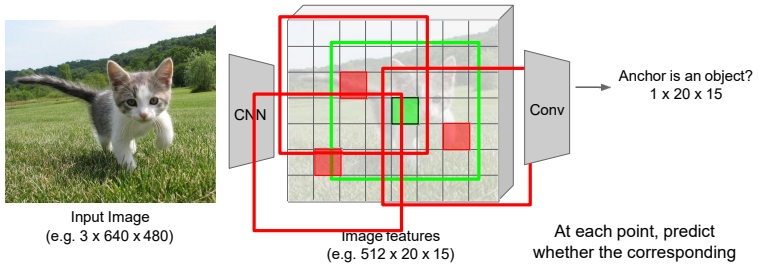
Imagine an **anchor box** of fixed size at each point in the feature map



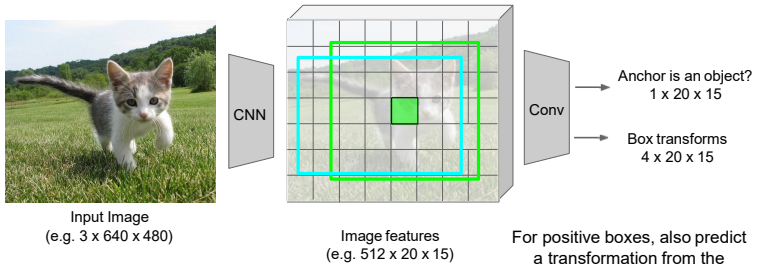
Input Image
(e.g. 3 x 640 x 480)

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

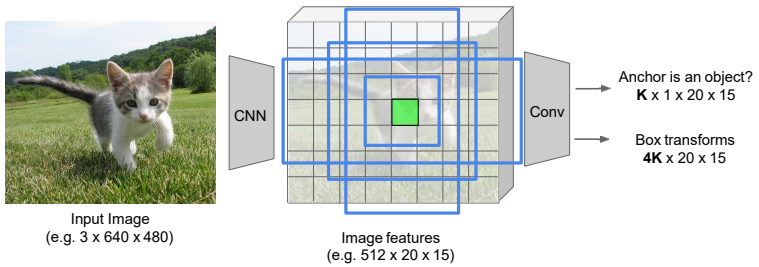
Region Proposal Network



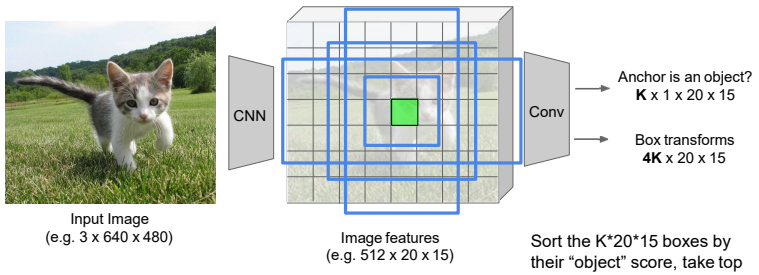
Region Proposal Network



Region Proposal Network

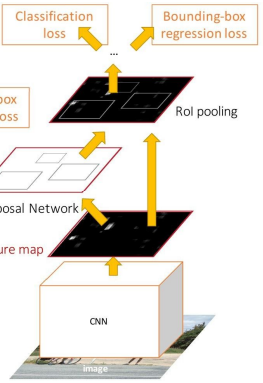


Region Proposal Network



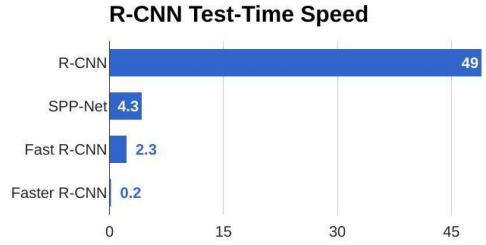
Faster R-CNN: Make CNN do proposals!

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

Faster R-CNN: Make CNN do proposals!

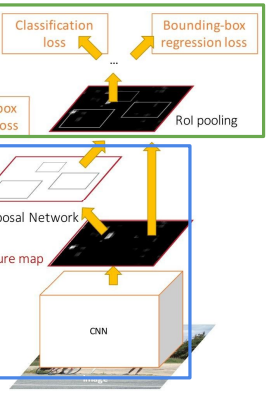


Faster R-CNN: Make CNN do proposals!

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

One-stage Object detection

Anchor-based

Object Detection

Two Stages

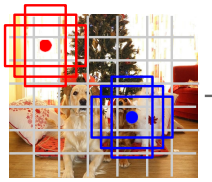
- Propose "objects"
- Classify each candidate

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?

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

(Derivative of CE loss : https://deepnotes.io/softmax-crossentropy#derivative-of-cross-entropy-loss-with-softmax)

Loss and gradient are dominated by correctly classified negative examples

Training outcome → constant "negative" prediction.

Imbalance – Focal Loss

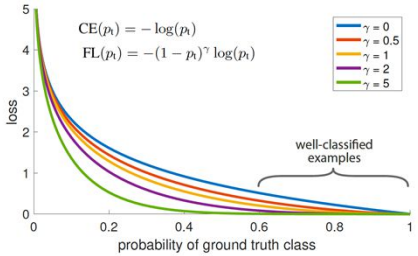
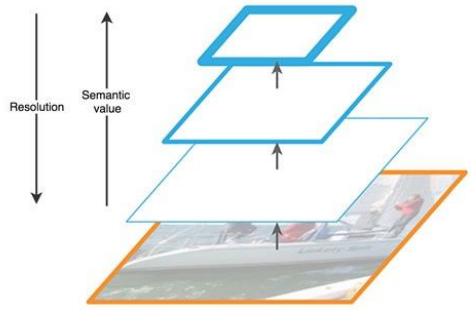


Figure 1: We propose a novel loss we term the *Focal Loss* that adds a factor $(1 - p_t)^\gamma$ to the standard cross entropy criterion. Setting $\gamma > 0$ reduces the relative loss for well-classified examples ($p_t > .5$), putting more focus on hard, misclassified examples. As our experiments will 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)

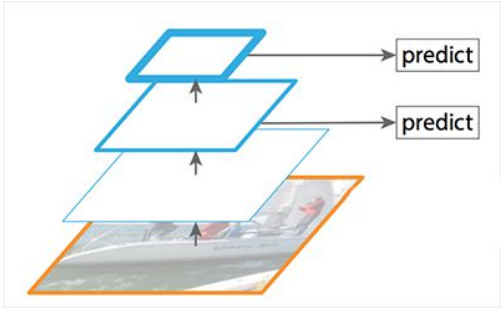
Feature Pyramid Network (FPN)

- How to handle multiscale predictions?



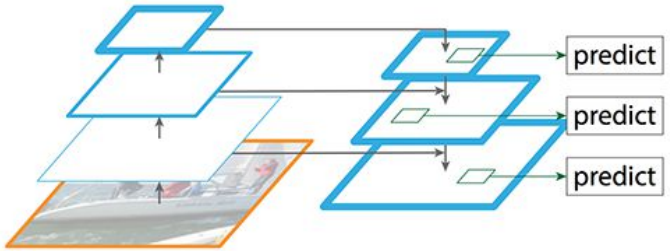
Feature Pyramid Network (FPN)

- How to handle multiscale predictions?

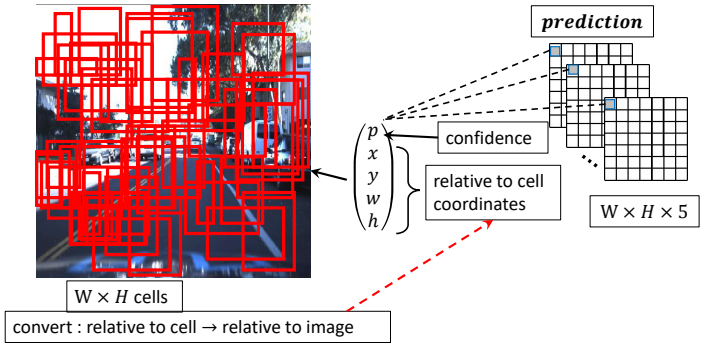


Feature Pyramid Network (FPN)

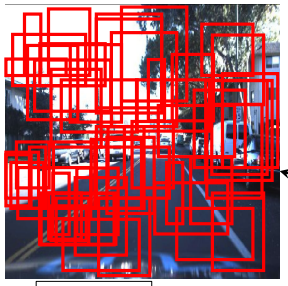
- How to handle multiscale predictions?



Postprocessing: NMS



Postprocessing: NMS



$W \times H$ cells

$prediction$

$\begin{pmatrix} p \\ x \\ y \\ w \\ h \end{pmatrix}$

confidence

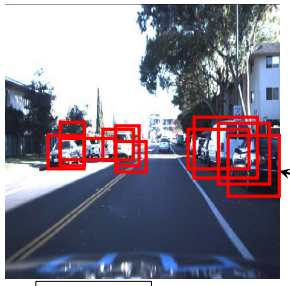
relative to cell coordinates

$W \times H \times 5$

Filtering?

convert : relative to cell → relative to image

Postprocessing: NMS



Threshold $T = 0.5$, for example

N – rectangle number with $p > T$

$W \times H$ cells

$\begin{pmatrix} p \\ x \\ y \\ w \\ h \end{pmatrix}$

confidence

relative to cell coordinates

$W \times H \times 5$

N scores

$N \times 4$ rectangles

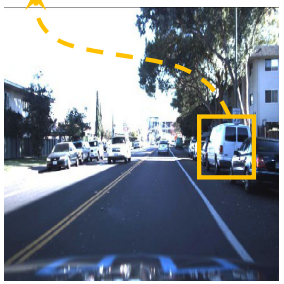
convert : relative to cell → relative to image

Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... $rect_N$

Sorted confidence p

0.9 0.85



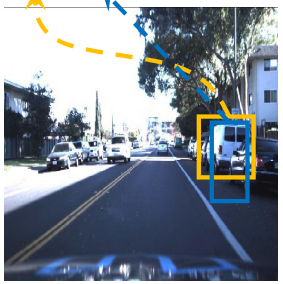
Postprocessing: NMS

$rect_1$ $rect_2$ $rect_3$ ... $rect_N$

Sorted confidence p

0.9 0.85

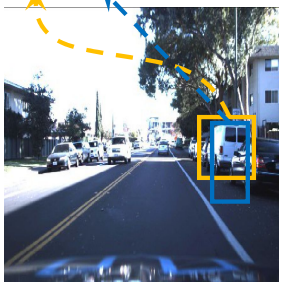
Compare IOU of the 1st rectangle with others



Postprocessing: NMS

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

0.9 | 0.85



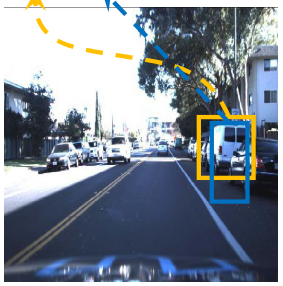
Compare IOU of the **1st** rectangle with others

$$IOU = \frac{\quad}{\quad} > 0.5 \quad (\textit{threshold})$$

Postprocessing: NMS

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

0.9 | ~~0.85~~ | 0.82



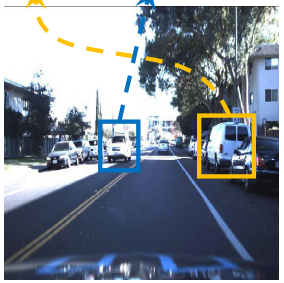
Compare IOU of the **1st** rectangle with others

$$IOU = \frac{\quad}{\quad} > 0.5 \quad (\textit{threshold})$$

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

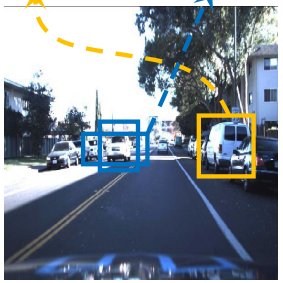
$$IOU = \frac{\quad}{\quad} = 0$$

do nothing

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

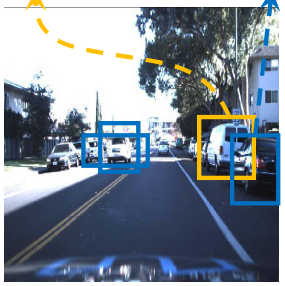
$$IOU = \frac{\quad}{\quad} = 0$$

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

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

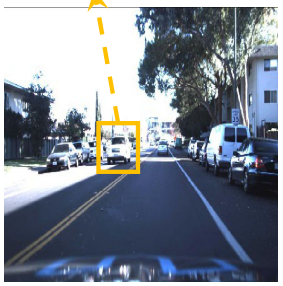
$$IOU = \frac{\square}{\square} < 0.5$$

do nothing

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

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

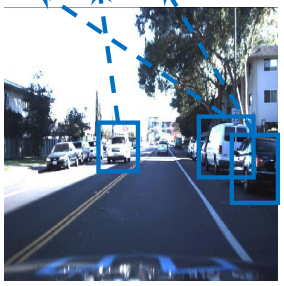
$$IOU = \frac{\square}{\square} > 0.5$$

threshold

Postprocessing: NMS

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

0.9	0.82	0.77									



IOU is calculated $(N-1)\cdot(N_1-2)\cdot(N_2-2)\cdot\ldots$

One-stage Object detection

Anchor-free

Drawbacks of Anchor Boxes

1. Need a large number of anchors

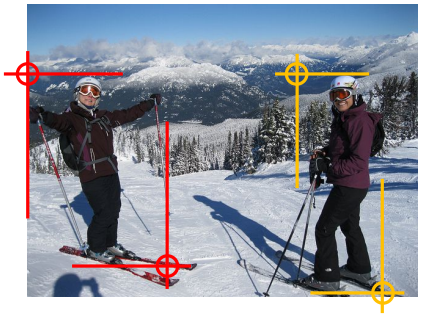
→ A tiny fraction of anchors are positive examples

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

2. Extra hyperparameters – sizes and aspect ratios

Source: https://pvl.cs.princeton.edu/assets/CornerNet.pptx

CornerNet: Detecting Objects as Paired Keypoints



Hei Law, Jia Deng. CornerNet: Detecting Objects as Paired Keypoints – ECCV2018

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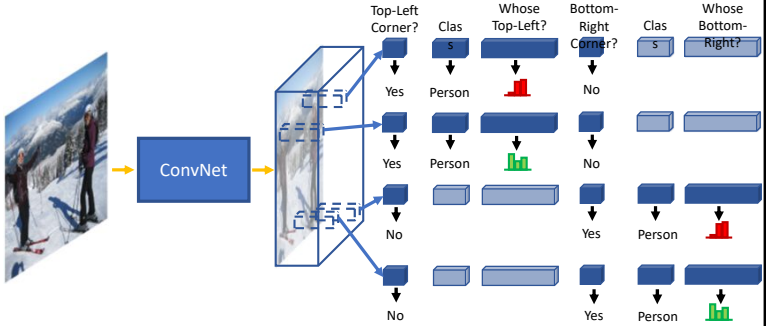
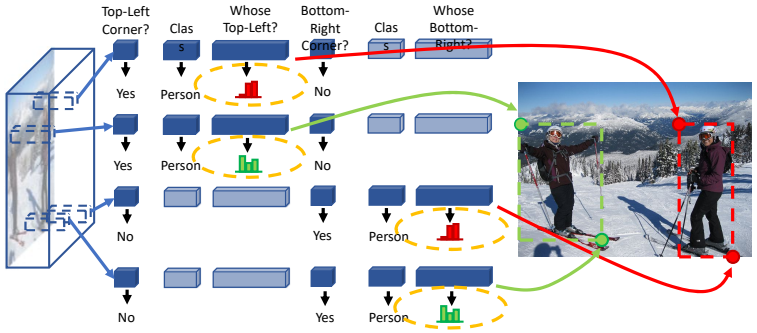
CornerNet: Detecting Objects as Paired Keypoints



Source: https://pvl.cs.princeton.edu/assets/CornerNet.pptx

CornerNet: Detecting Objects as Paired Keypoints



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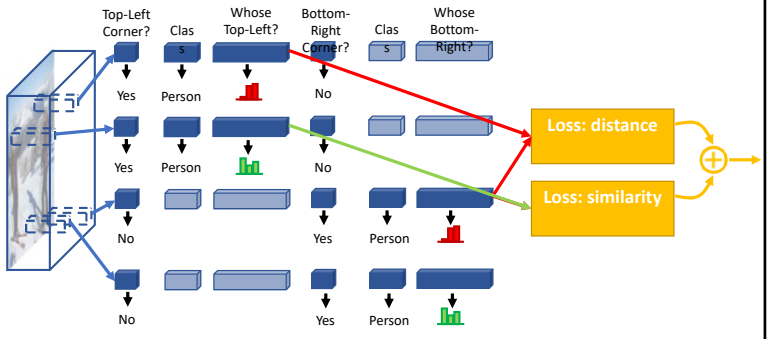
CornerNet: Detecting Objects as Paired Keypoints



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Associative Embedding [Newell et al. NIPS'17]

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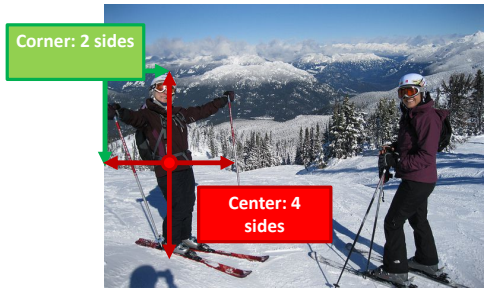
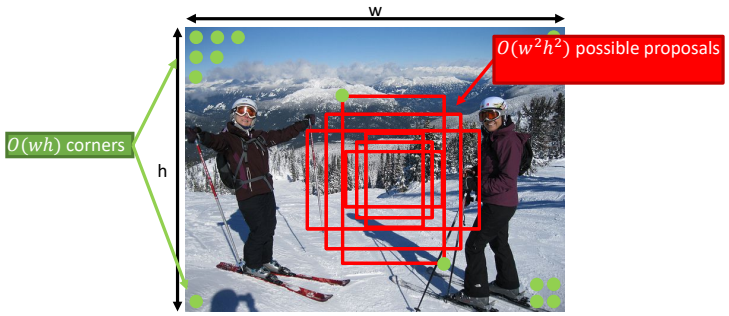
Advantages of Detecting Corners



Detecting corner is easier than detecting center

Source: https://pvl.cs.princeton.edu/assets/CornerNet.pptx

Advantages of Detecting Corner



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

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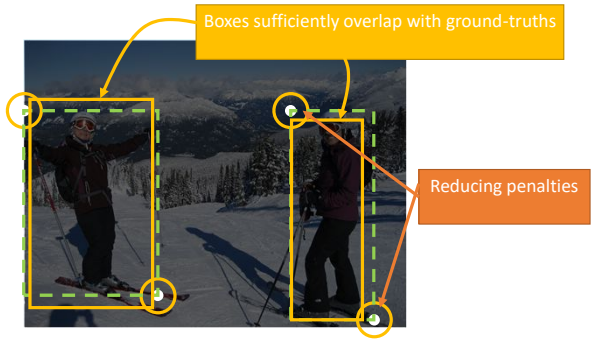
Supervising Corner Detection



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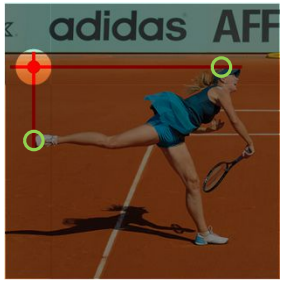
Corner Pooling



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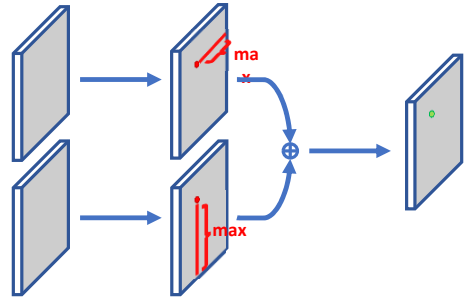
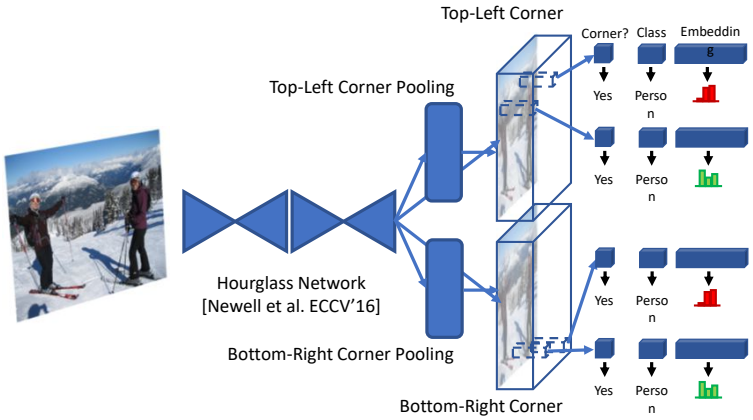
Top-Left Corner Pooling



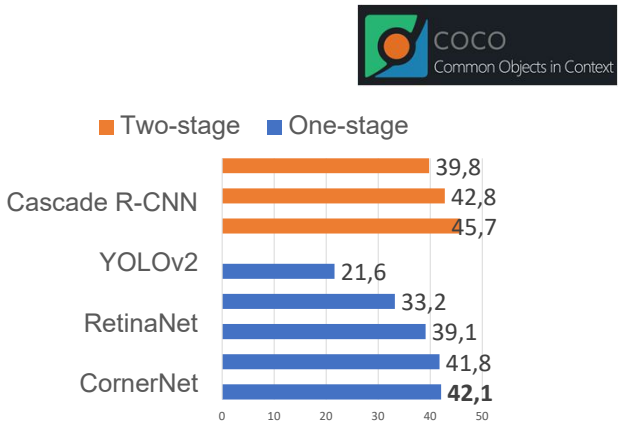
feature maps

Source: https://pvl.cs.princeton.edu/assets/CornerNet.pptx

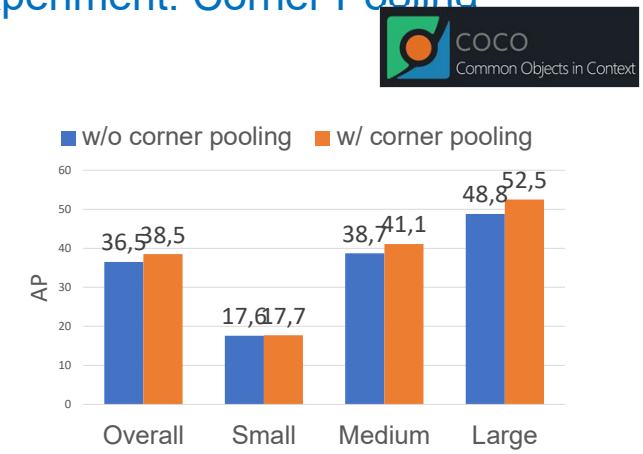
CornerNet

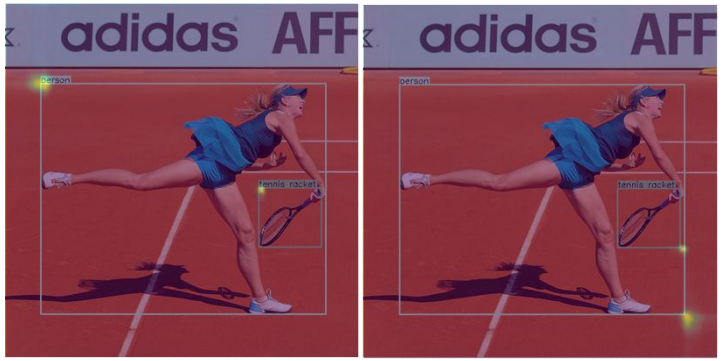


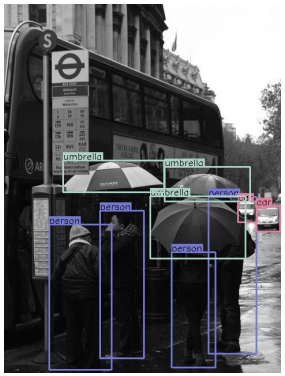
Experiment: CornerNet versus Others



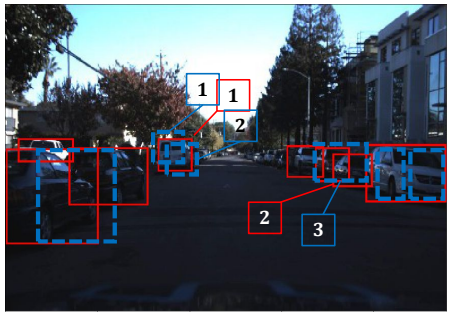
Experiment: Corner Pooling







Accuracy evaluation



$\boldsymbol{n}$ predicted

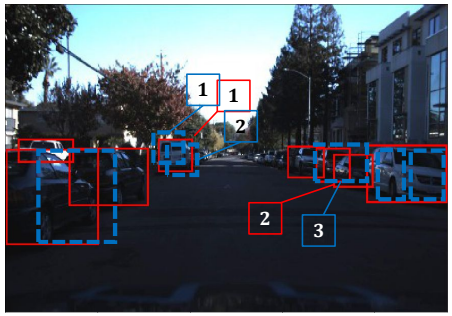
$\boldsymbol{m}$ Ground Truth

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

A – ground truth
B – detector result

Correspondence between GT and predicted?

Accuracy evaluation



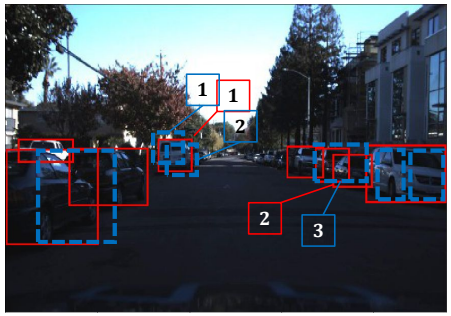
Sorted array of $\boldsymbol{IOU} > T$ between GT and predicted (max length = $\boldsymbol{n} \cdot \boldsymbol{m}$)

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

GT	2	1	1
pred	3	1	2

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

Accuracy evaluation



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

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

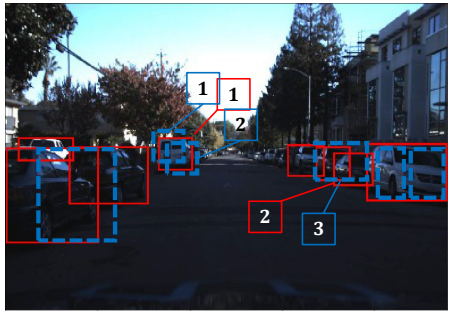
GT	2	1	1
pred	3	1	2

if appear firstly

matched GT	2	1
matched pred	3	1

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

Accuracy evaluation



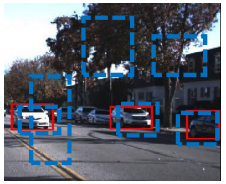
Sorted array of $IOU > T$ between GT and predicted (max length = $n \cdot m$)

True predicted

matched GT	2	1
matched pred	3	1

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

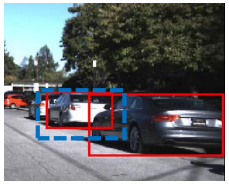
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



$\sum$

$precision$–?
$recall$-?

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

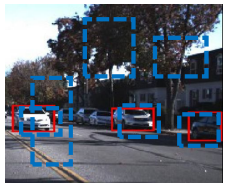
What part of predicted is true

$precision$–?
$recall$-?

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

What part of true predicted from all GT objects

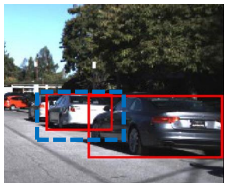
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



$\sum$

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

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

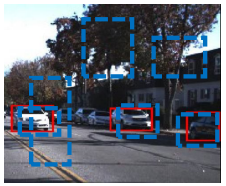
What part of predicted is true

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

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

What part of true predicted from all GT objects

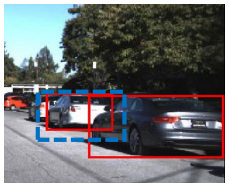
Accuracy evaluation: precision, recall



$T = 0.5$

• • •

getTruePredicted



$\sum$

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

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

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

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

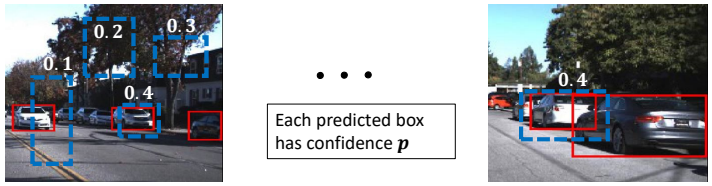
evaluator.py -> calc_precision_recall(img_results)

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow$ $\uparrow$

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



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

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow$ $\uparrow$

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

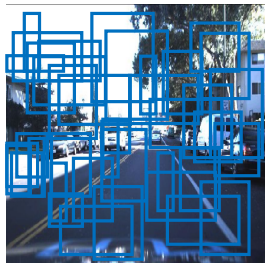
I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

score	prec	recall
p_1	**0.1**	**0.9**

high recall

low precision



For all images together!

Accuracy evaluation: precision, recall

sorted box confidence

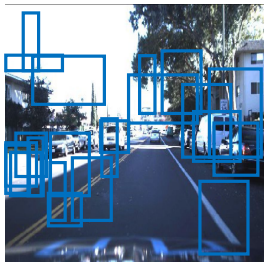
$\downarrow$ $\uparrow$

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

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!

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow$ $\uparrow$

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

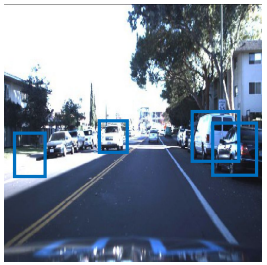
I. Get boxes with $p \geq p_1$, i.e. all boxes

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!

Accuracy evaluation: precision, recall

sorted box confidence

$\downarrow \quad \uparrow$

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

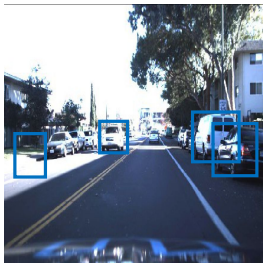
I. Get boxes with $p \geq p_1$, i.e. all boxes

calcPrecisionRecall

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

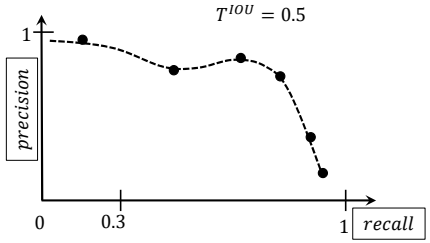
High precision

low recall



get_thr_prec_rec(...)

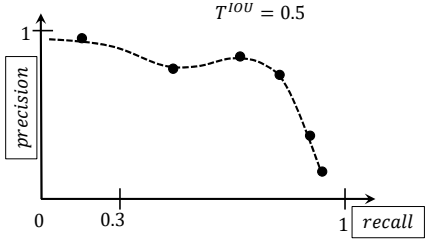
Accuracy evaluation: mAP



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**

Accuracy evaluation: mAP



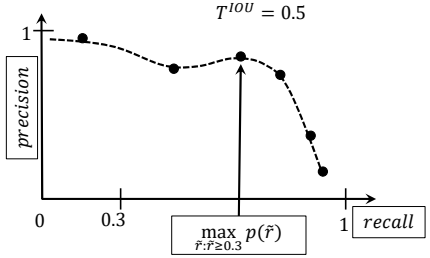
hundreds of values for real data sets

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

11 recall thresholds

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

Accuracy evaluation: mAP



hundreds of values for real data sets

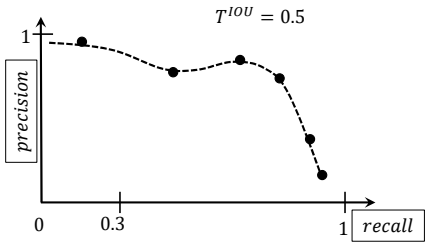
score	prec	recall
p_1	**0.1**	**0.9**
p_2	**0.2**	**0.8**
...	...	...
p_N	**0.9**	**0.1**

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

11 recall thresholds

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

Accuracy evaluation: mAP



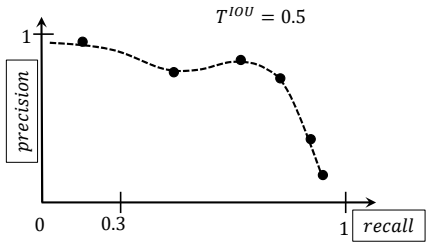
hundreds of values for real data sets

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 $AP^{0.5}$

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

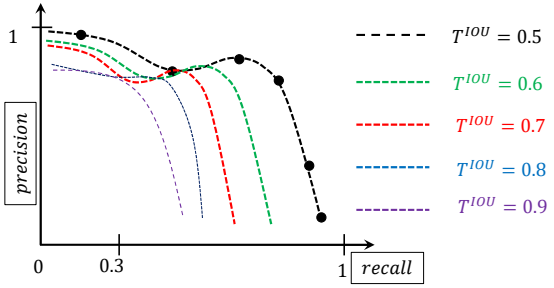
$$AP = \frac{1}{10} \cdot \sum_{T \in \{0.5, 0.55, \ldots, 0.95\}} AP^T$$

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

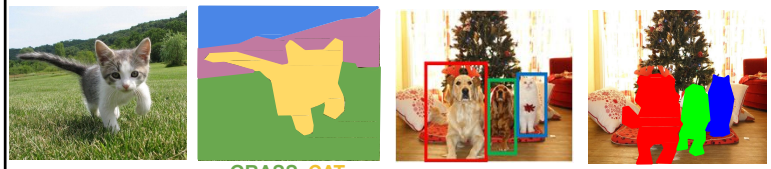
Accuracy evaluation: mAP

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

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

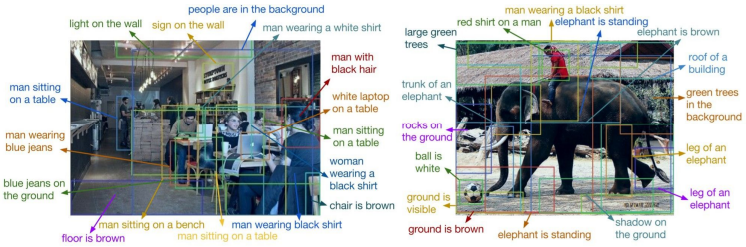


Computer Vision Tasks



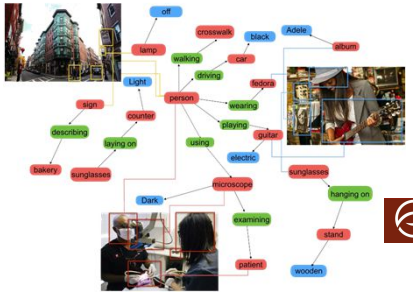
Beyond 2D Object Detection...

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.

Objects + Relationships = Scene Graphs

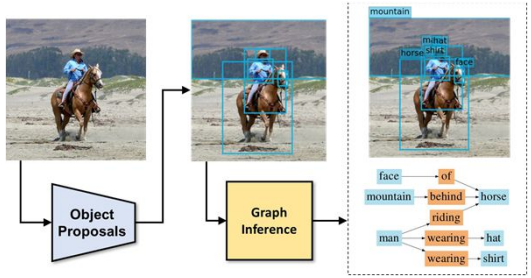


108,077 Images
5.4 Million Region Descriptions
1.7 Million Visual Question Answers
3.8 Million Object Instances
2.8 Million Attributes
2.3 Million Relationships
Everything Mapped to Wordnet Synsets

VISUALGENOME

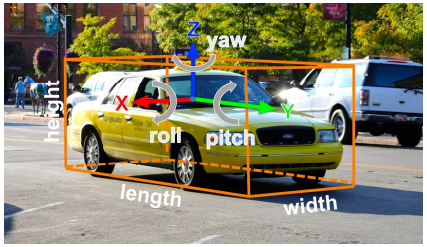
Krishna, Ranjay, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen et al. "Visual genome: Connecting language and vision using crowdsourced dense image annotations." International Journal of Computer Vision 123, no. 1 (2017): 32-73.

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)

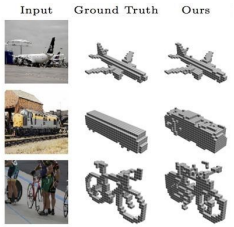
3D Object Detection:
3D oriented bounding box
(x, y, z, w, h, l, r, p, y)

Simplified bbox: no roll & pitch

Much harder problem than 2D object detection!

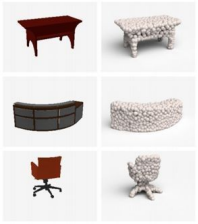
3D Shape Prediction

Voxel:
D x D x D binary



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

Pointcloud:
V x 3 float



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

Mesh:
V x 3 float, F x 3 int

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

Semantic segmentation

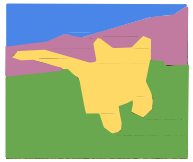
Semantic Segmentation

Classification

CAT

No spatial extent

Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Object Detection

DOG, DOG, CAT

Instance Segmentation

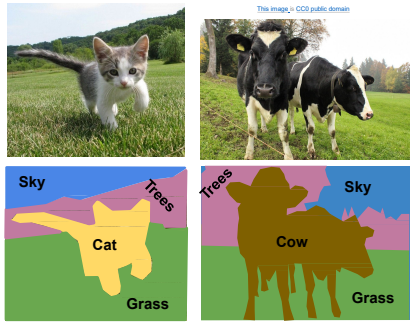
DOG, DOG, CAT

Multiple Object

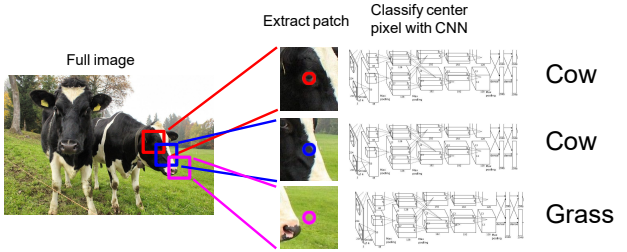
Semantic Segmentation

Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

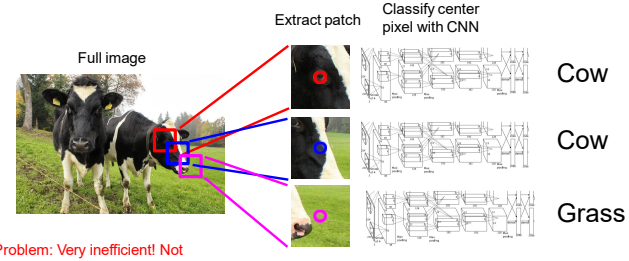


Semantic Segmentation Idea: Sliding Window



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

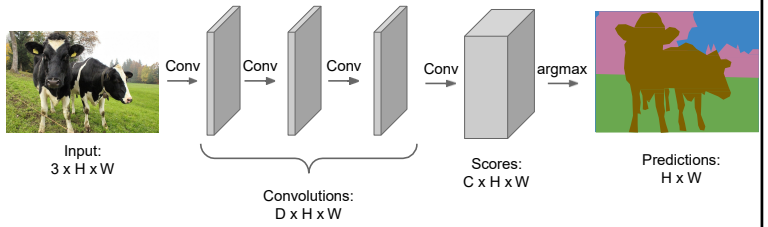


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

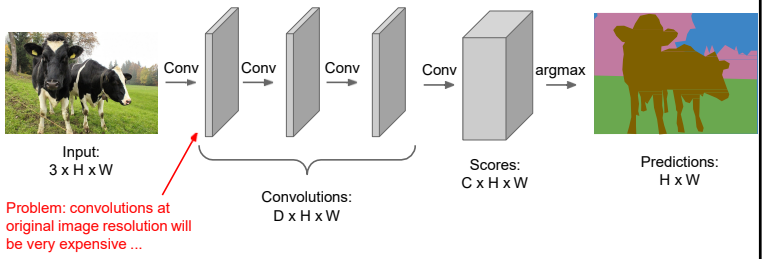
Semantic Segmentation Idea: Fully Convolutional

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



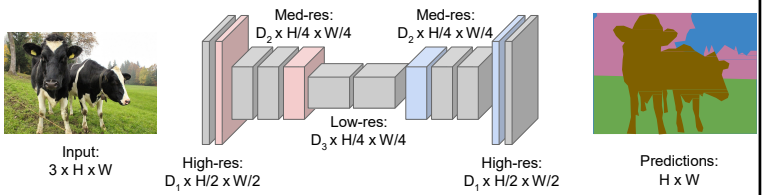
Semantic Segmentation Idea: Fully Convolutional

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



Semantic Segmentation Idea: Fully Convolutional

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



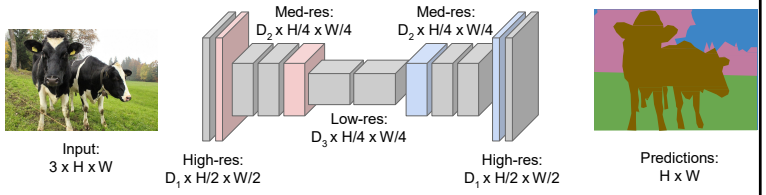
Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

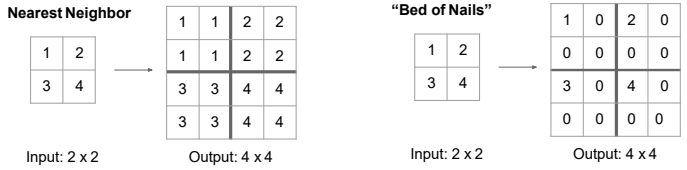
Upsampling: ???

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

In-Network upsampling: "Unpooling"



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

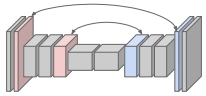
1	2
3	4

Input: 2 x 2

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

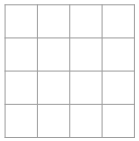
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

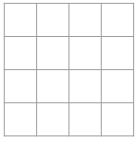


Learnable Upsampling: Transpose Convolution

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



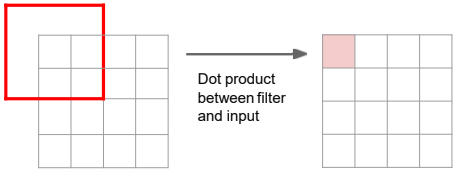
Input: 4 x 4



Output: 4 x 4

Learnable Upsampling: Transpose Convolution

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

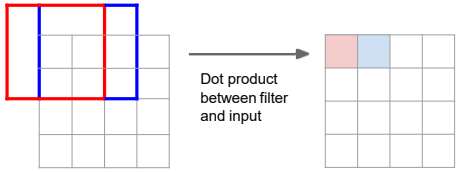


Input: 4 x 4

Output: 4 x 4

Learnable Upsampling: Transpose Convolution

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

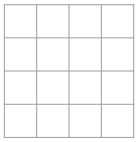


Input: 4 x 4

Output: 4 x 4

Learnable Upsampling: Transpose Convolution

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

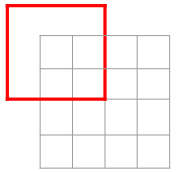


Input: 4 x 4

Output: 2 x 2

Learnable Upsampling: Transpose Convolution

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



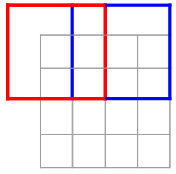
Dot product between filter and input

Input: 4 x 4

Output: 2 x 2

Learnable Upsampling: Transpose Convolution

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



Dot product between filter and input

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

Stride gives ratio between movement in input and output

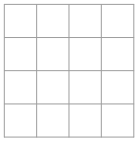
Input: 4 x 4

Output: 2 x 2

Learnable Upsampling: Transpose Convolution

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

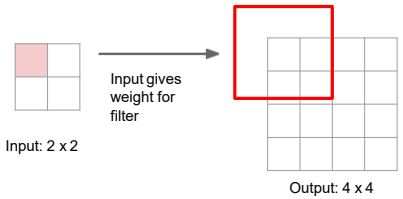
Input: 2 x 2



Output: 4 x 4

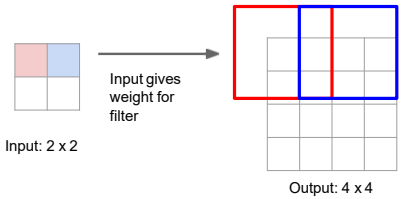
Learnable Upsampling: Transpose Convolution

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



Learnable Upsampling: Transpose Convolution

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

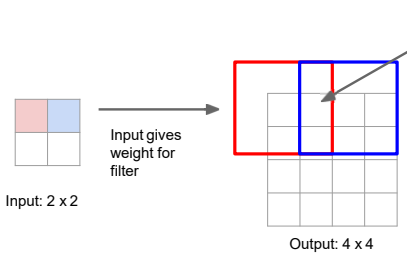


Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transpose Convolution

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



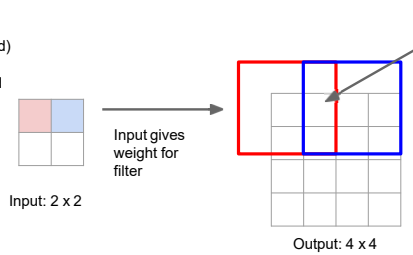
Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transpose Convolution

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

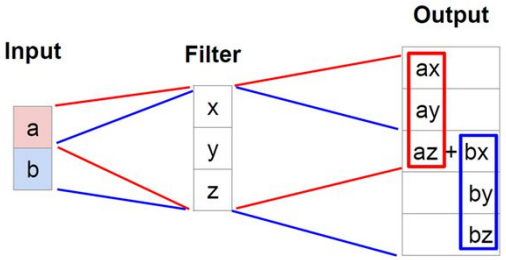
Other names:
-Deconvolution (bad)
-Upconvolution
-Fractionally strided convolution
-Backward strided convolution



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

Stride gives ratio between movement in output and input

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

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 as Matrix Multiplication (1D Example)

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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)

Convolution as Matrix Multiplication (1D Example)

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

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

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

Convolution 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

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

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

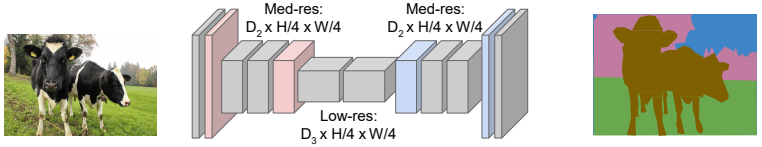
When stride>1, convolution transpose is no longer a normal convolution!

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

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

Metrics for Segmentation Models

- **Dice coefficient:**

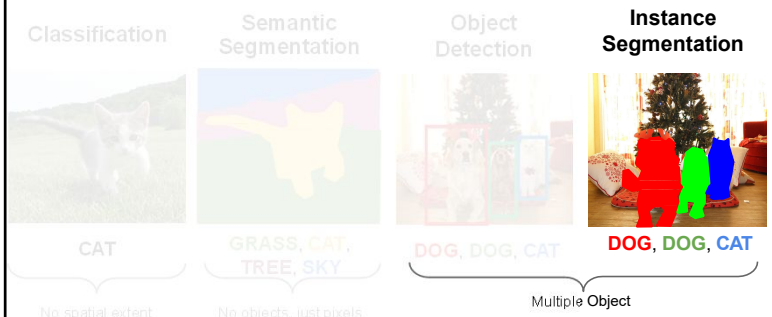
$$\text{Dice} = \frac{2|A \cap B|}{|A| + |B|}$$

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

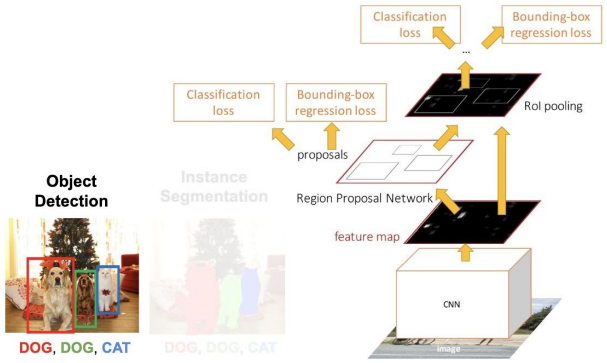
- Essentially identical to the F1 score.
- The Dice coefficient and IoU are positively correlated.

Instance segmentation

Instance Segmentation

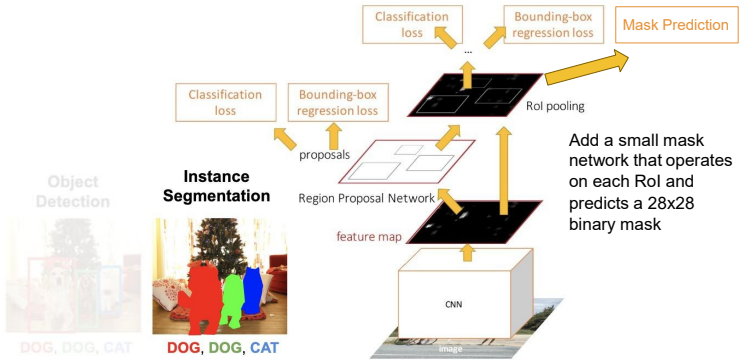


Object Detection: Faster R-CNN



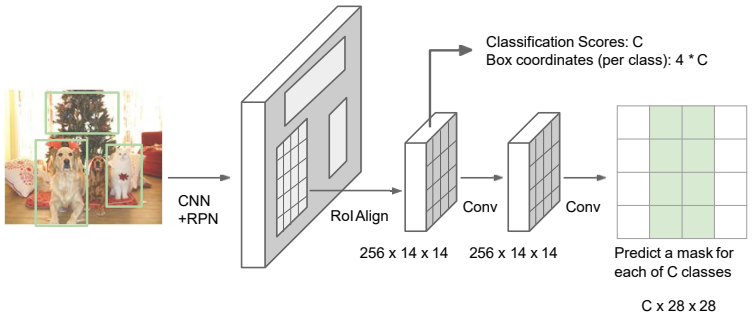
He et al, "Mask R-CNN", ICCV 2017

Instance Segmentation: Mask R-CNN



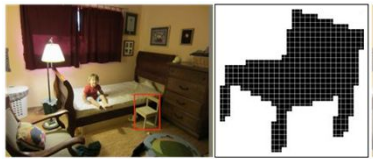
He et al, "Mask R-CNN", ICCV 2017

Mask R-CNN

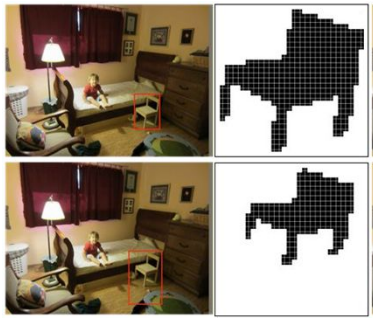


He et al, "Mask R-CNN", arXiv 2017

Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Example Mask Training Targets



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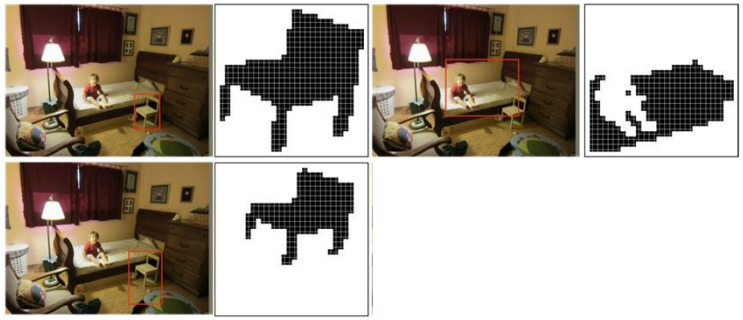
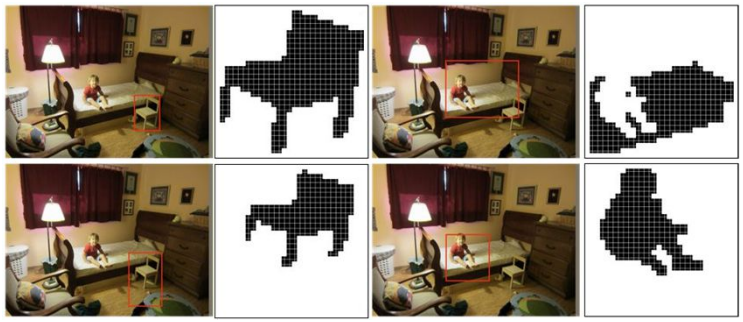


Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Very Good Results!

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

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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SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

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