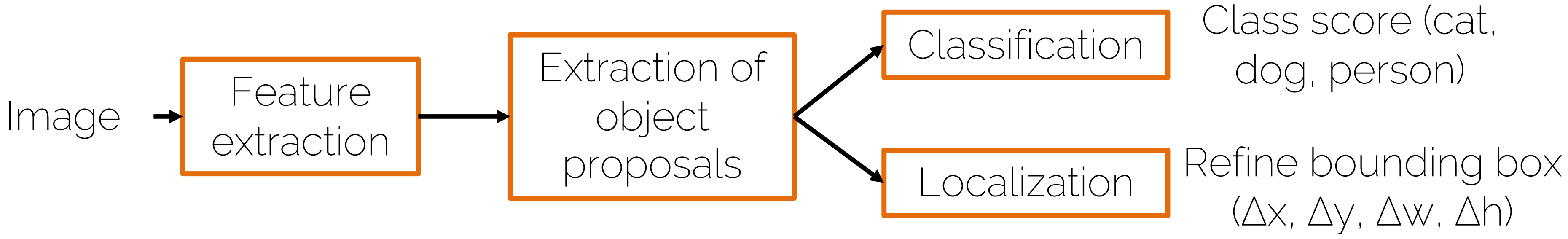
Two-stage detectors: short recap

Types of object detectors

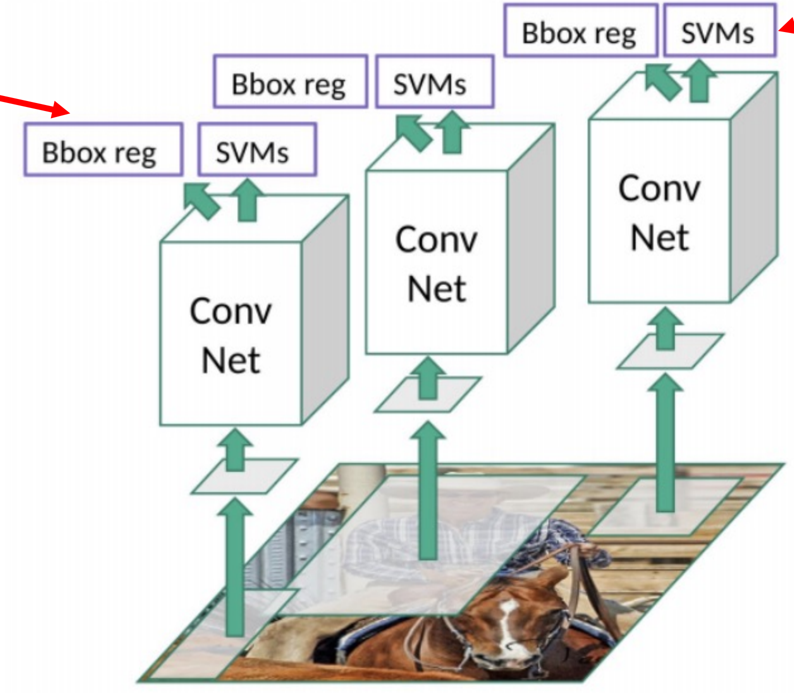
- One-stage detectors

- Two-stage detectors



R-CNN

Regression head to refine the bounding box location



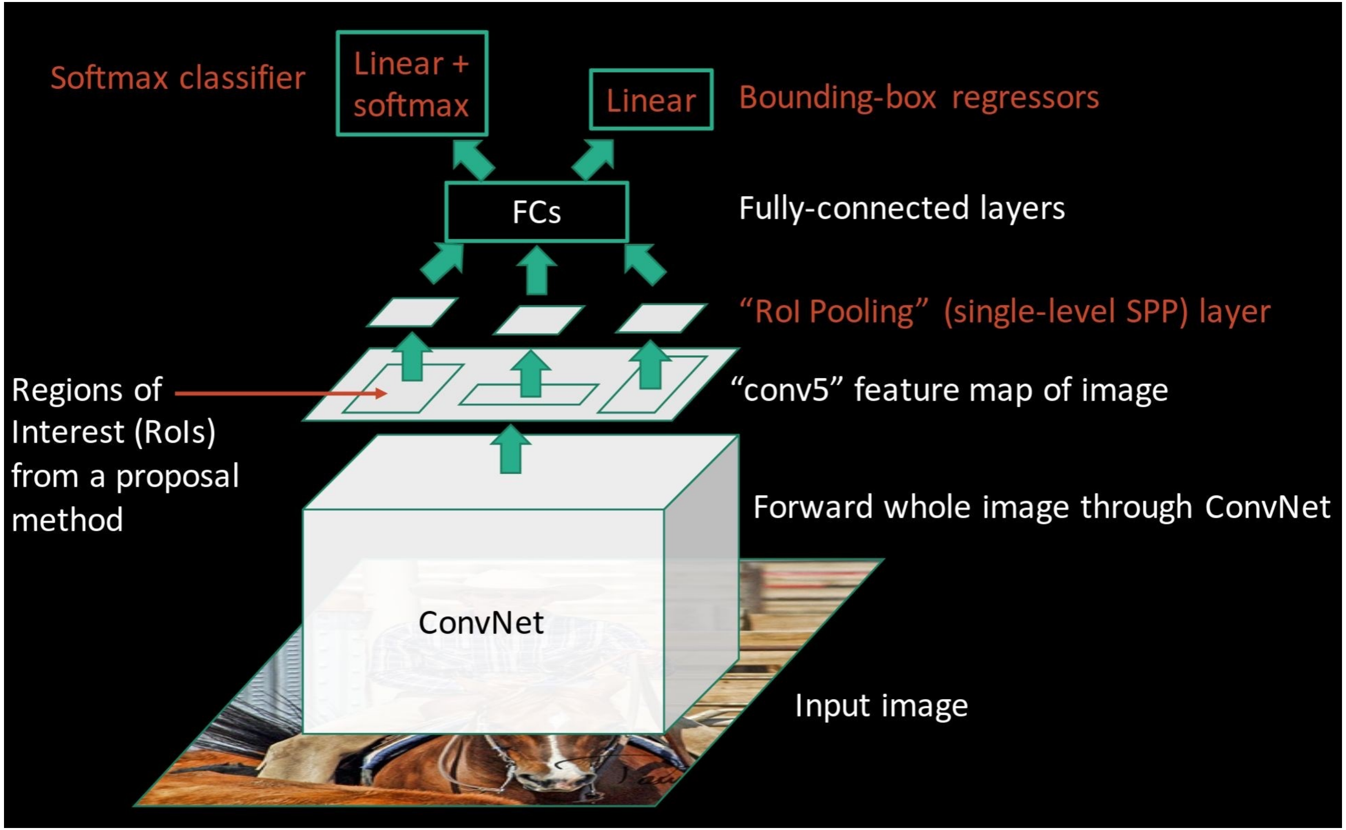
Classification head

Extract features

Warping to a fix size 227 x 227

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

Fast R-CNN

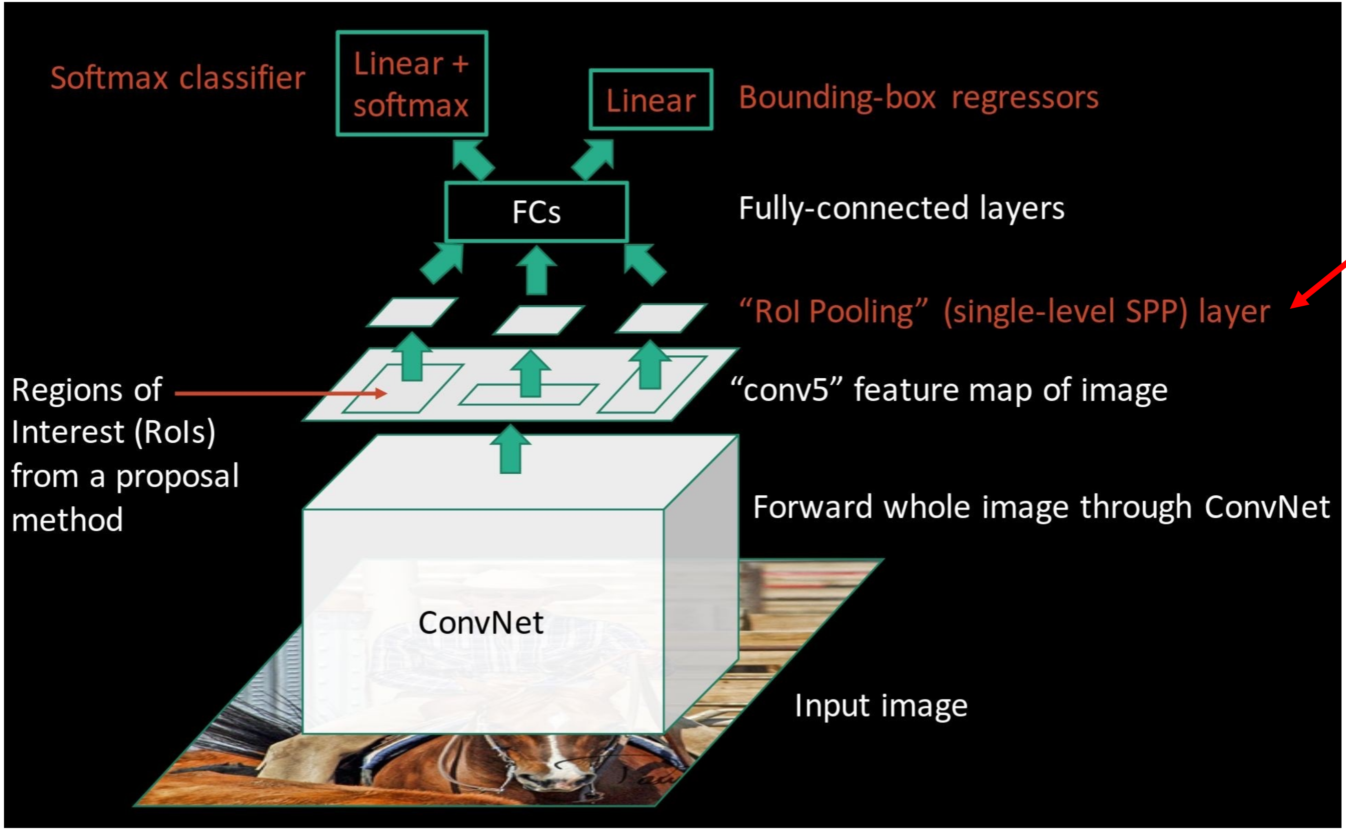


Shared computation at test time (like SPP)

Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

Fast R-CNN

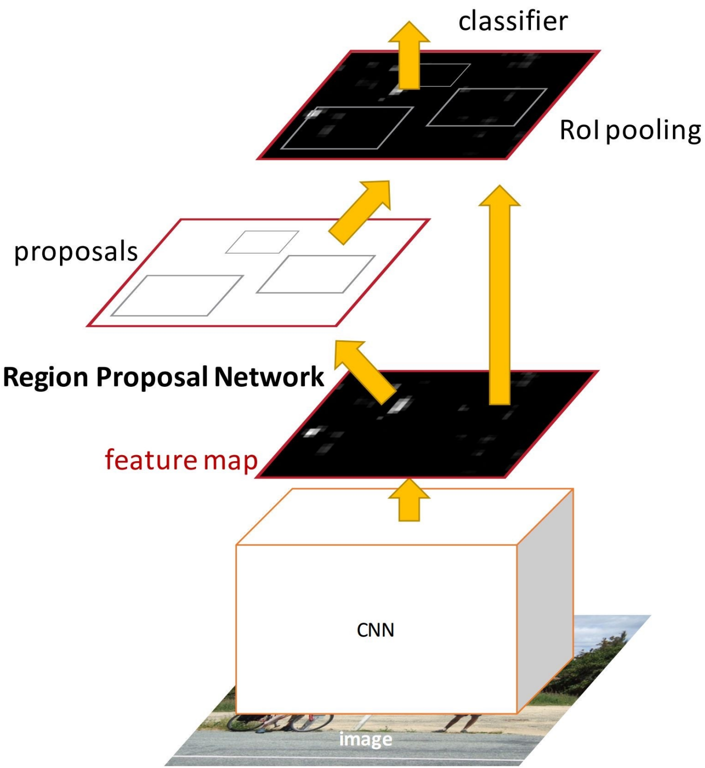


Region of Interest Pooling

Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

Faster R-CNN:



- Solution: Have the proposal generation integrated with the rest of the pipeline
- Region Proposal Network (RPN) trained to produce region proposals directly.
- After RPN, everything is like Fast R-CNN

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

Slide credit: Ross Girschick

Region proposal network

- How to extract proposals

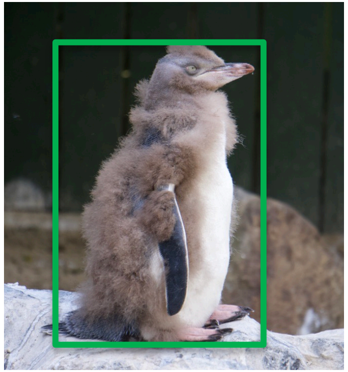
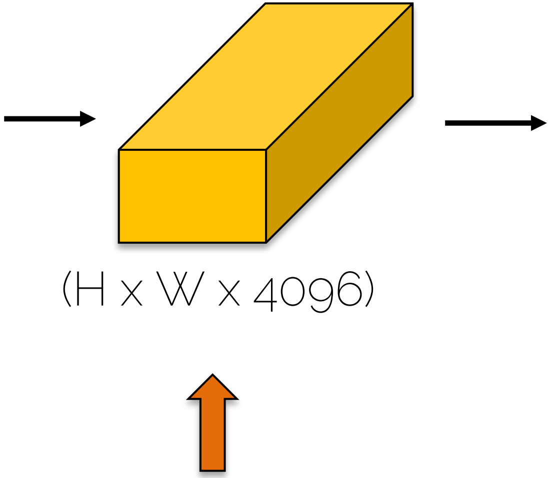


Image
(N x M x 3)



(H x W x 4096)

Zoom in

Extract proposals

- How many proposals?

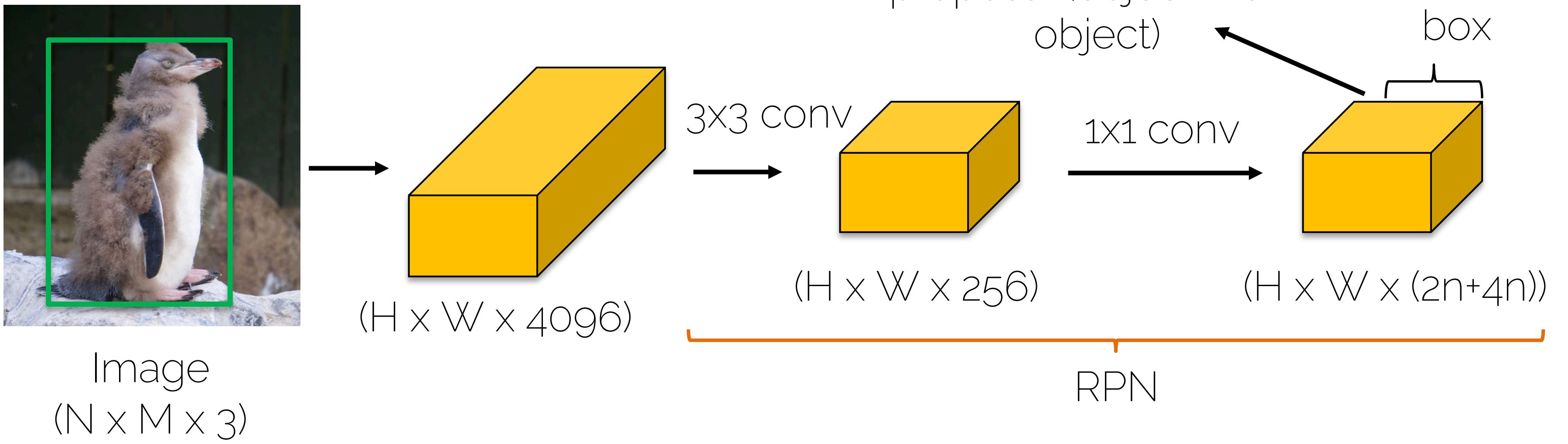
✓ We need to decide a fixed number

- Where are they placed?

✓ Densely

Region proposal network

- How to extract proposals

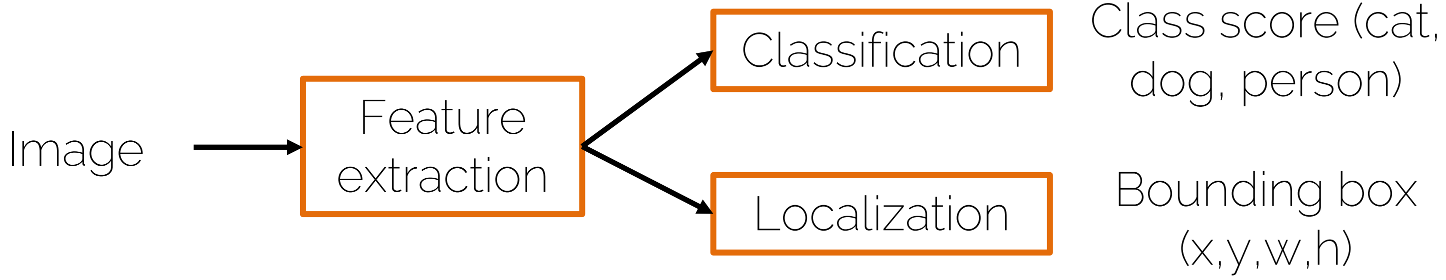


Per feature map location, I get a set of anchor correction and classification into object/non-object

One-stage detectors

Types of object detectors

- One-stage detectors



- Two-stage detectors

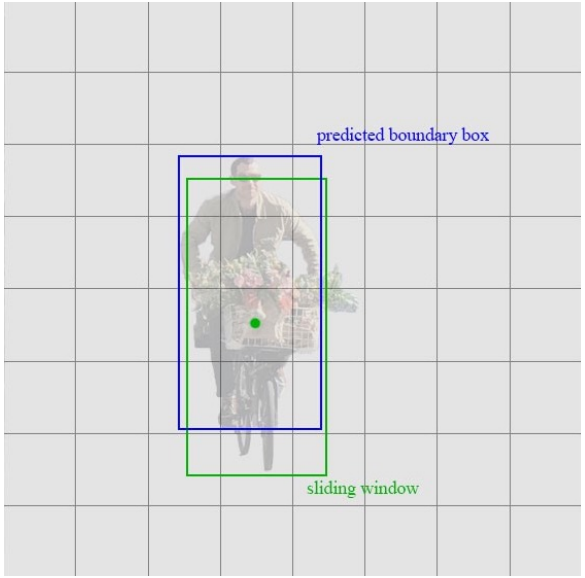
YOLO: You Only Look Once

- Recall sliding window object detection
- To make it efficient, we will "slide our window" only on certain locations of the image
- We divide our image in a grid.

Redmon et al, "You only look once: Unified real-time object detection", CVPR 2016.

YOLO: You Only Look Once

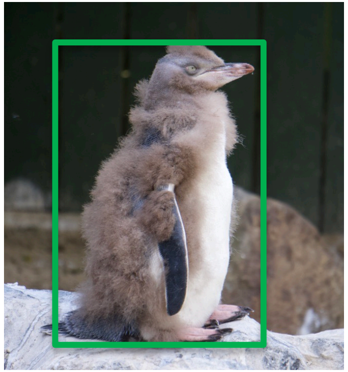
- We will place a box at the center of each cell in the grid, and this will be our initial box guess for that object



Redmon et al, "You only look once: Unified real-time object detection", CVPR 2016.

YOLO: You Only Look Once

- Direct regression from image to box coordinates



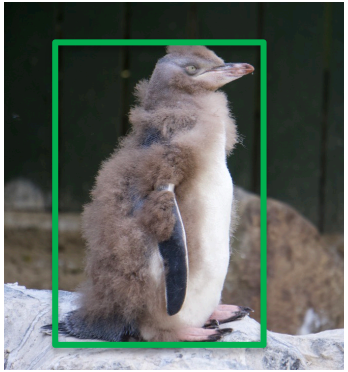
→ Convolutional neural network → Detections

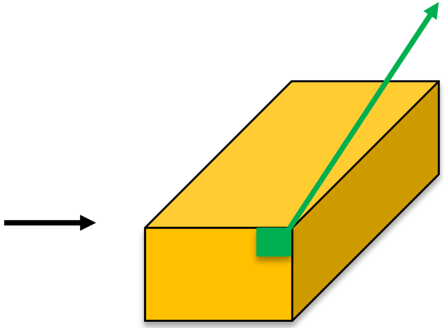
Redmon et al, "You only look once: Unified real-time object detection", CVPR 2016.

YOLO: You Only Look Once

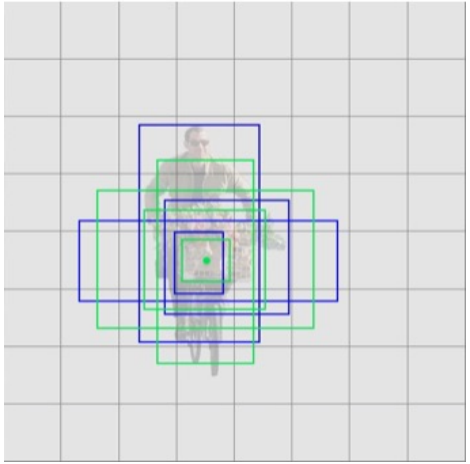
- In YOLOv2 we use anchor boxes

For each grid location we predict *n* boxes





(7 x 7 x C)

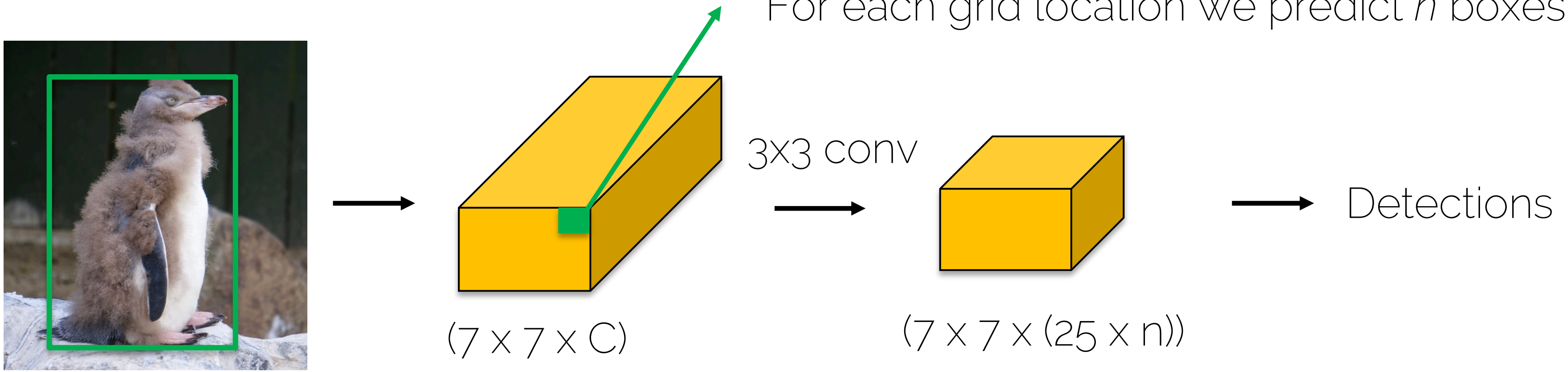


Green = anchors
Blue = predictions

Redmon and Farhadi, "YOLO9000: Better, faster, stronger", CVPR 2017.

YOLO: You Only Look Once

- In YOLOv2 we use anchor boxes

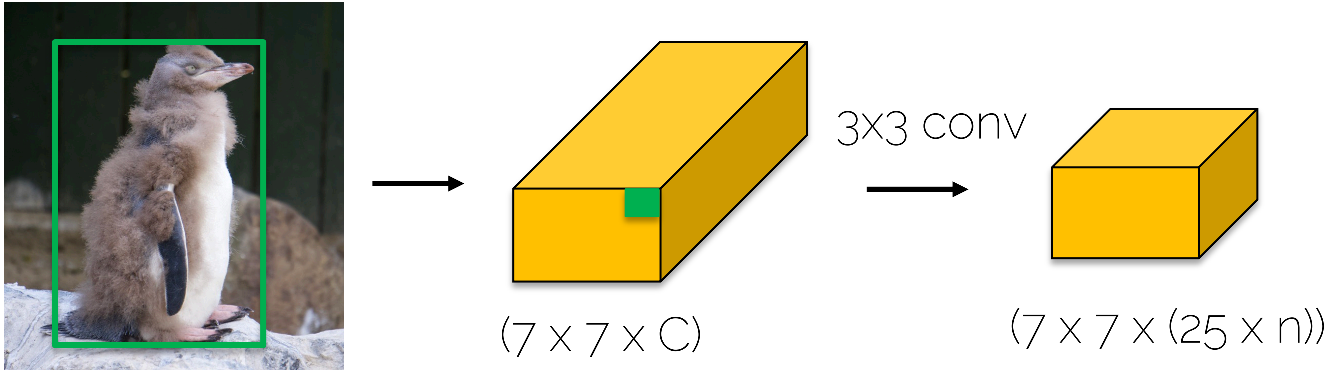


Similar to Faster R-CNN region proposal network

Redmon and Farhadi, "YOLO9000: Better, faster, stronger", CVPR 2017.

YOLO: You Only Look Once

- In YOLOv2 we use anchor boxes



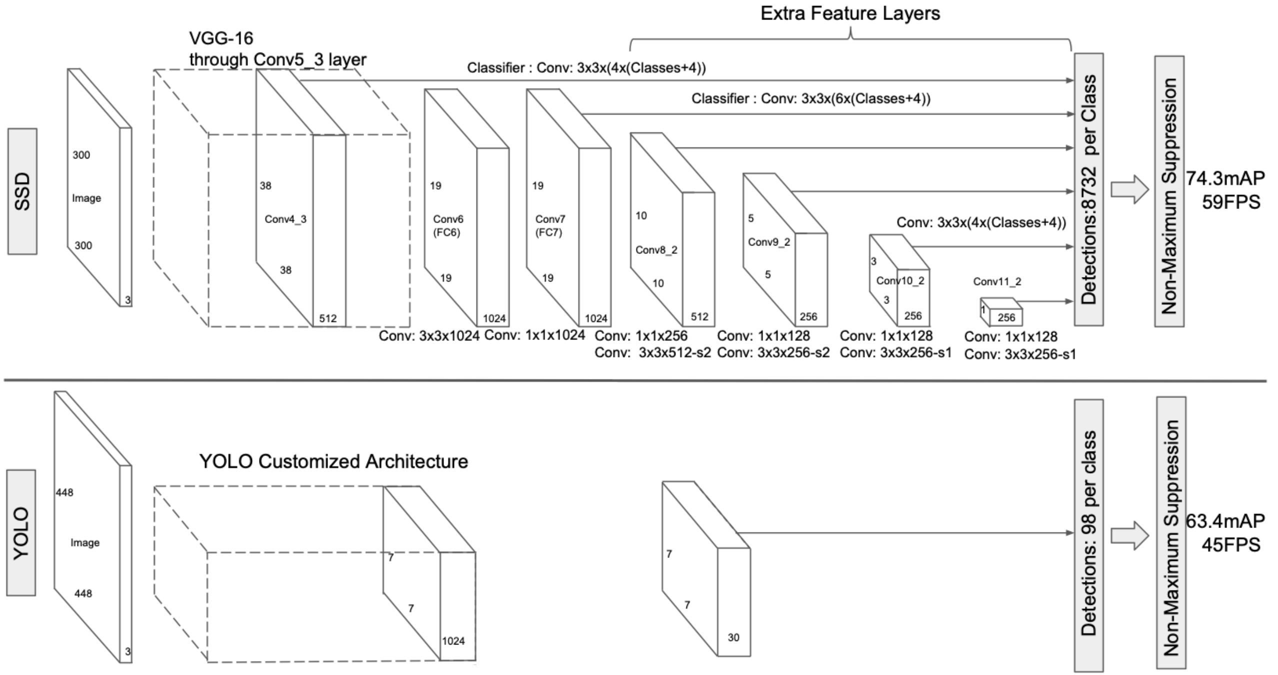
- 1 class prediction (20)
- Anchor relative box regression (4)
- Object/non-object (1)

Redmon and Farhadi, "YOLO9000: Better, faster, stronger", CVPR 2017.

SSD: Single Shot multibox Detector

- SSD predicts at different scales

Only few extra layers!



Liu et al. "SSD: Single shot multibox detector". ECCV 2016

YOLO and SSD

- PROS:
  - Very fast
  - End-to-end trainable and fully convolutional
  - SSD detects more objects than YOLO

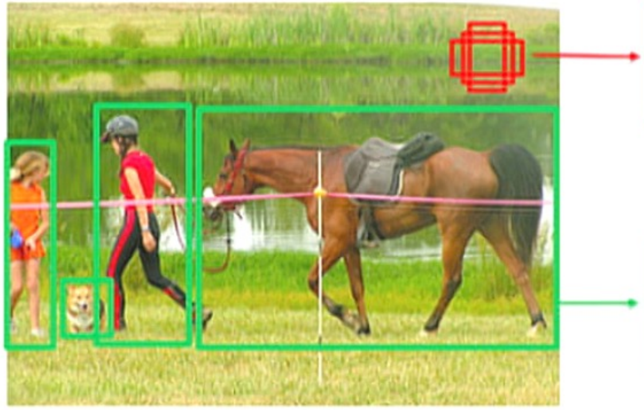
- CONS:
  - Performance is not as good as two-stage detectors
  - Difficulty with small objects

Problem with one-stage detectors?

- Two-stage detectors:
  - Classification only work on "interesting" foreground regions (proposals, ~1-2k). Most background examples are already filtered out.
  - Class balance between foreground and background objects is manageable.
  - Classifier can concentrate on analyzing proposals with rich information content

Problem with one-stage detectors?

- **One-stage** detectors:
  - Many locations need to be analyzed (100k) densely covering the image → foreground-background imbalance
  - Hard negative mining is useful, but not sufficient

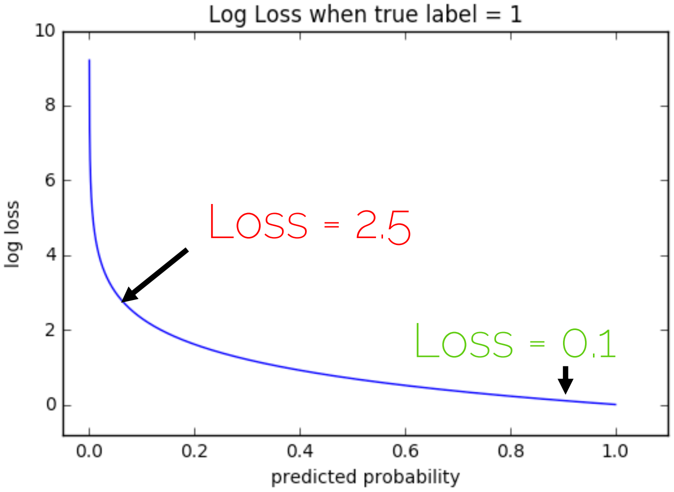


Many negative examples, no useful signal

Few positive examples, rich information for learning

RetinaNet

- Solution: change the loss function!
- Recall cross-entropy loss



Very hard example, we get loss 2.5

Well classified (easy) examples, we get loss 0.1

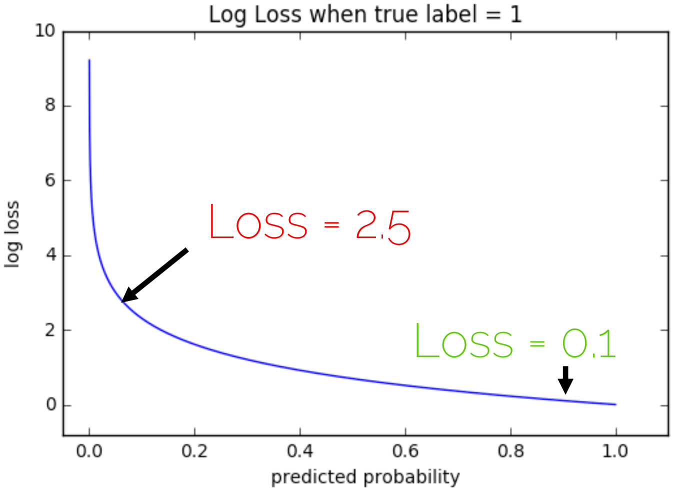
TY Lin et al. "Focal Loss for Dense Object Detection ". ICCV 2017

RetinaNet

- Solution: change the loss function!
- Recall cross-entropy loss

100 hard examples * 2.5 = 250

100000 easy examples * 0.1 = 10000



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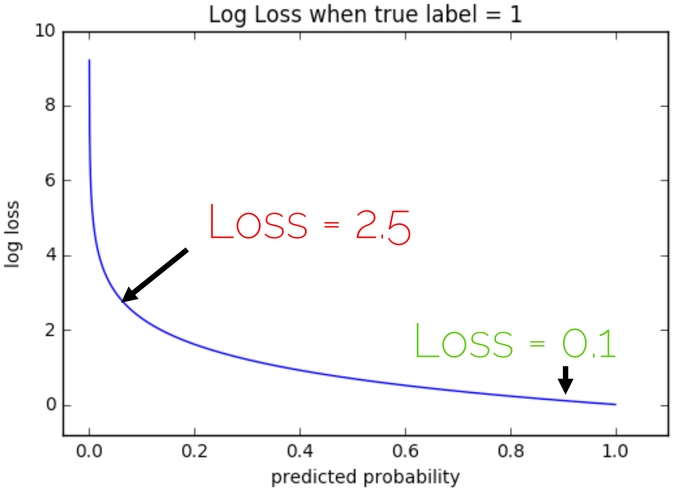

Very hard example, we get loss 2.5

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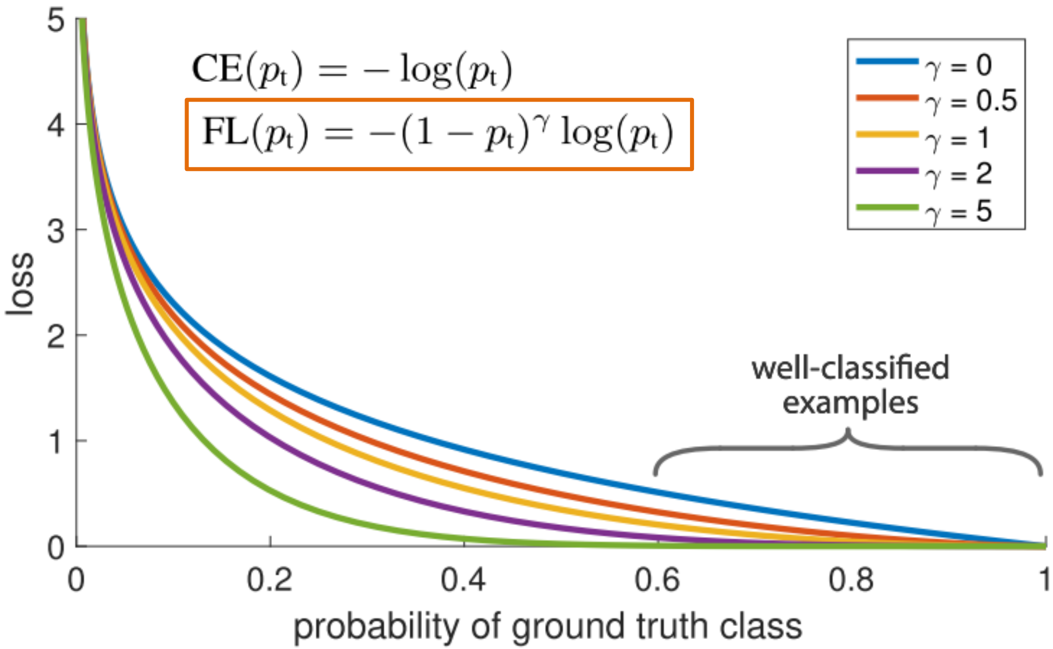
TY Lin et al. "Focal Loss for Dense Object Detection ". ICCV 2017

RetinaNet

- Proposed: Focal loss



- When $\gamma = 0$ it is equivalent to the cross-entropy loss
- As γ goes towards 1, the easy examples are down-weighted.
- Example: $\gamma = 2$, if $p_t = 0.9$, FL is 100 lower than CE.

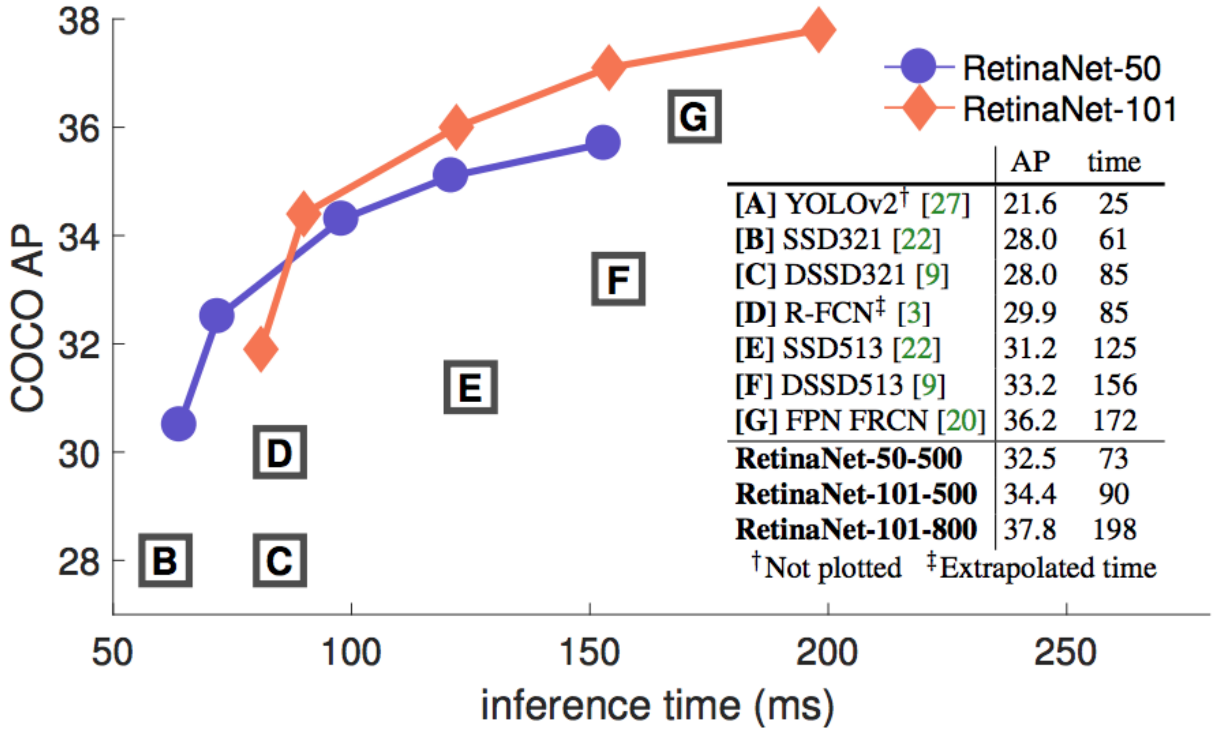
TY Lin et al. "Focal Loss for Dense Object Detection ". ICCV 2017

RetinaNet

- Proposed: Focal loss
- Powerful feature extraction: ResNet
- Multi-scale prediction
- 9 anchors per level, each one with a classification and regression target

TY Lin et al. "Focal Loss for Dense Object Detection ". ICCV 2017

RetinaNet

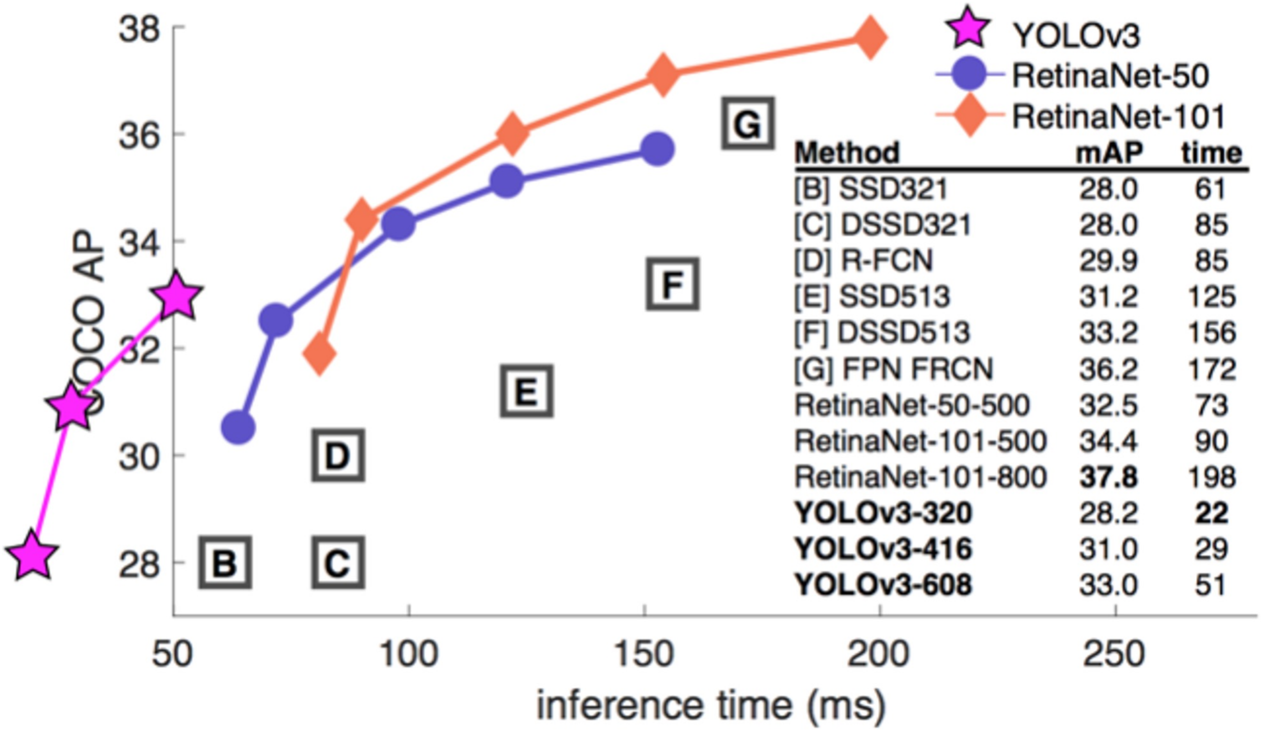


	AP	time
[A] YOLOv2† [27]	21.6	25
[B] SSD321 [22]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [22]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [20]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

TY Lin et al. "Focal Loss for Dense Object Detection ". ICCV 2017

RetinaNet

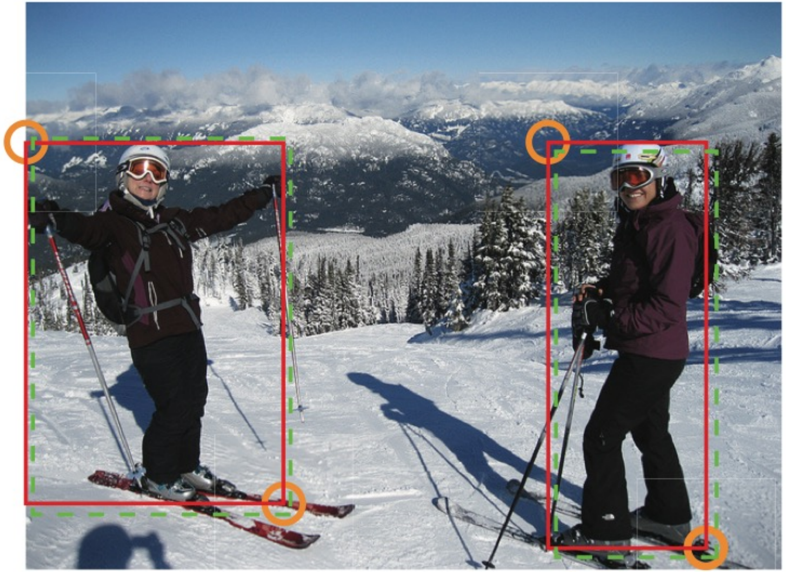


YOLOv3
RetinaNet-50
RetinaNet-101
Method mAP time
[B] SSD321 28.0 61
[C] DSSD321 28.0 85
[D] R-FCN 29.9 85
[E] SSD513 31.2 125
[F] DSSD513 33.2 156
[G] FPN FRCN 36.2 172
RetinaNet-50-500 32.5 73
RetinaNet-101-500 34.4 90
RetinaNet-101-800 37.8 198
YOLOv3-320 28.2 22
YOLOv3-416 31.0 29
YOLOv3-608 33.0 51
COCO AP
38
36
34
32
30
28
B
C
D
E
F
G
50
100
150
200
250
inference time (ms)

One-stage (point-based) detectors

Getting rid of anchors?

- CornerNet: express bounding boxes with 2 points, the top-left and bottom-right corners.

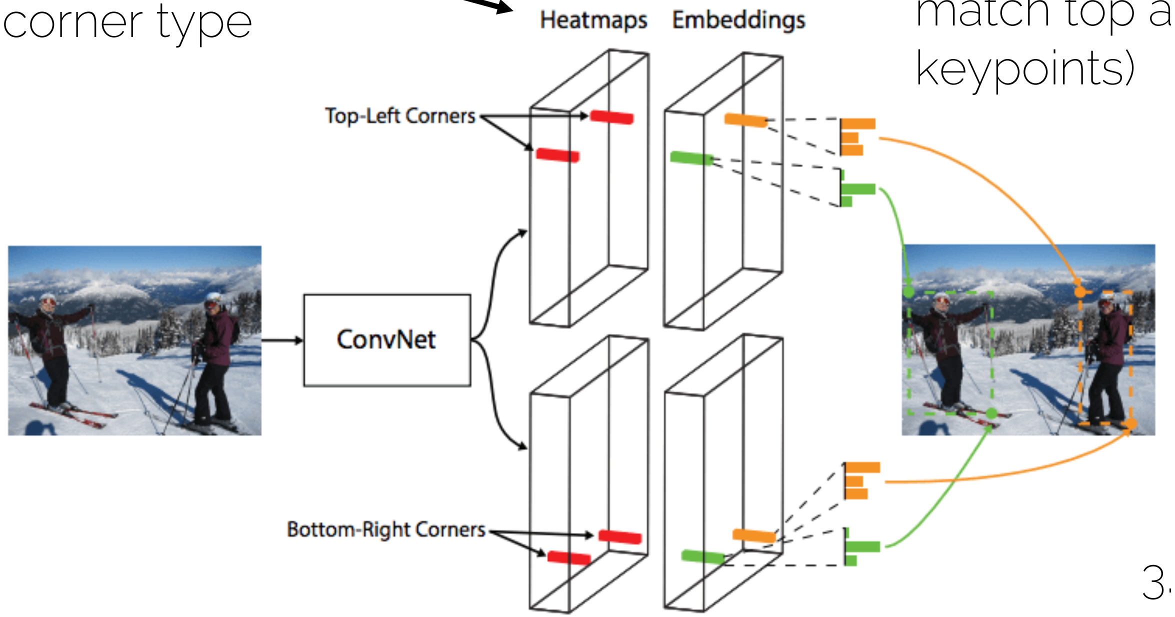


H. Law and J. Deng. „CornerNet: Detecting Objects as Paired Keypoints". ECCV 2018

CornerNet

1. Probability map for each corner type

2. Box identification with an embedding (needed to match top and bottom keypoints)

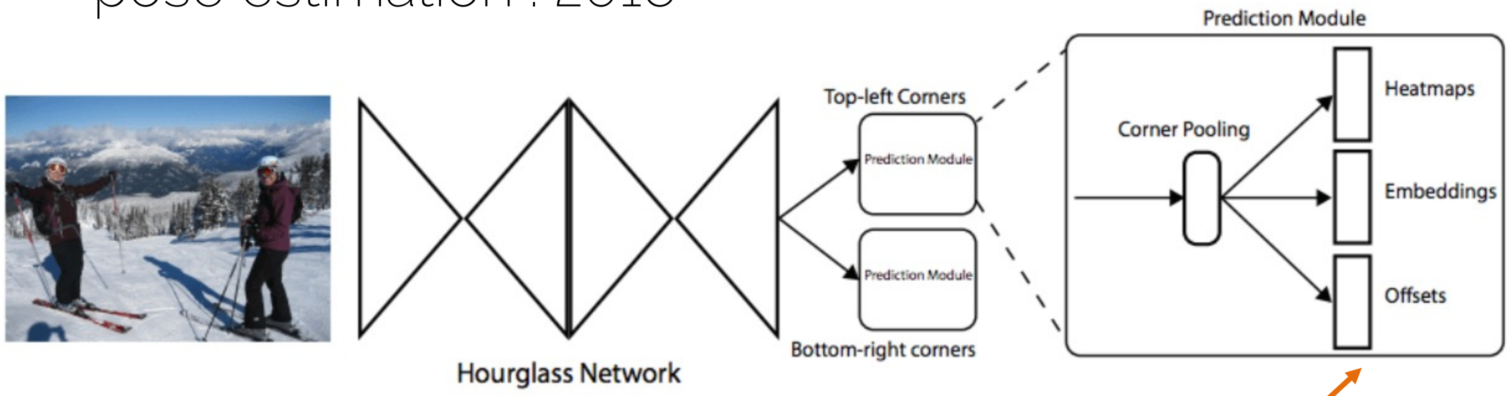


3. Class

H. Law and J. Deng. „CornerNet: Detecting Objects as Paired Keypoints". ECCV 2018

CornerNet

- Hourglass network, originally published in:
  - A. Newell et al. "Stacked hourglass networks for human pose estimation". 2016

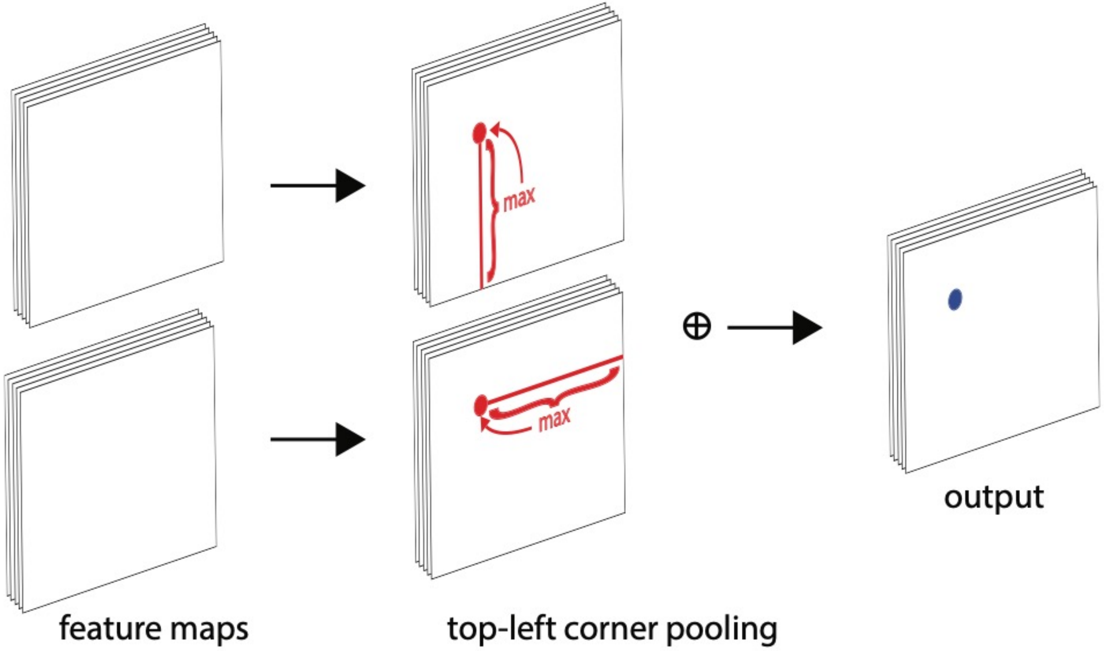


We predict corners at a lower resolution and then regress an offset (bounding box correction as we have seen for all methods)

H. Law and J. Deng. „CornerNet: Detecting Objects as Paired Keypoints". ECCV 2018

CornerNet

- Corner pooling



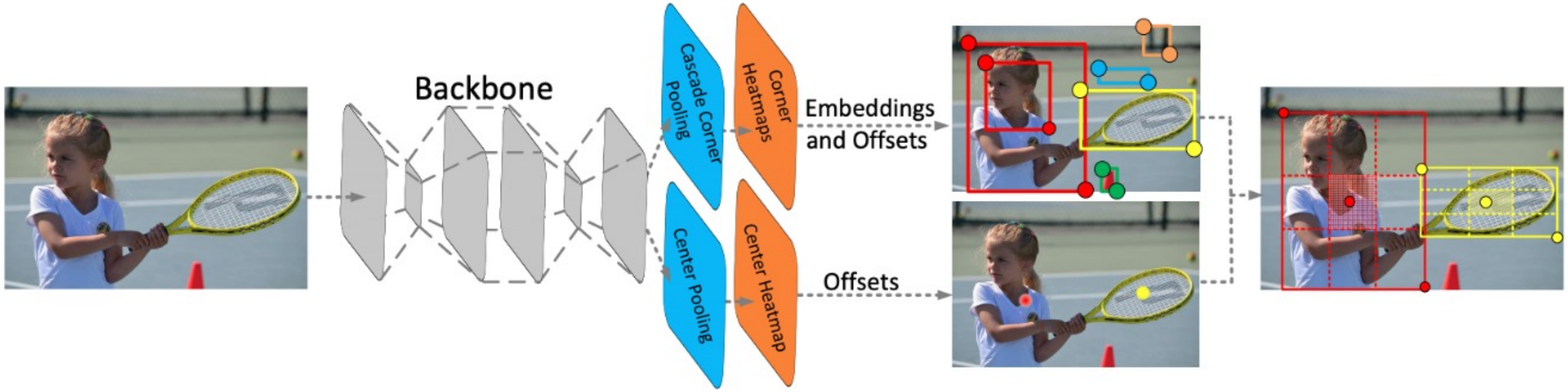
H. Law and J. Deng. „CornerNet: Detecting Objects as Paired Keypoints". ECCV 2018

CornetNet

- What is the problem with CornetNet?
- Many incorrect bounding boxes (especially small) → too many False Positives
- Hypothesis: It is hard to infer the class of the box if the network is focused on the boundaries

CenterNet

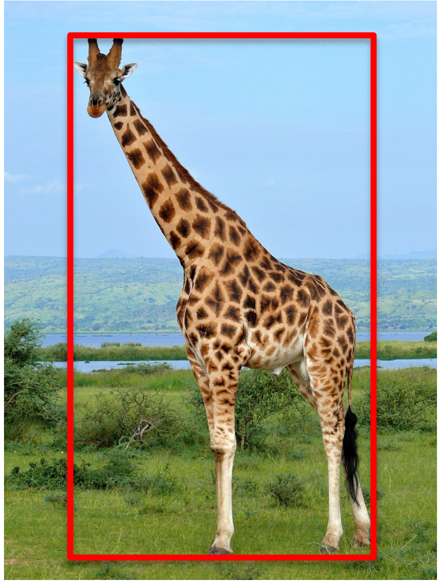
- Idea: focus on the *center* of the object to infer its class
- Use the corners as proposals, and the center to verify the class of the object and filter out outliers



K. Duan et al. „CenterNet: Keypoint Triplets for Object Detection“. ICCV 2019

ExtremeNet

- Bounding box corner representation is not ideal, why?



X. Zhou et al. „Bottom-up object detection by grouping extreme and center points". CVPR 2019

ExtremeNet

- Bounding box corner representation is not ideal, why?

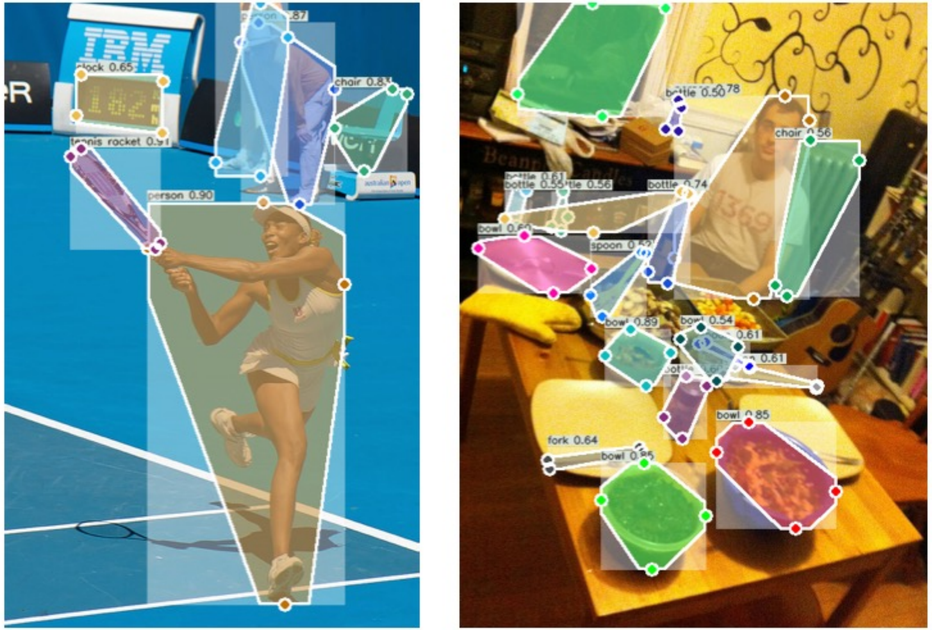
- Corner lies on the object
- Corner does not lie on the object

Hard for a CNN to predict ● as a corner

X. Zhou et al. „Bottom-up object detection by grouping extreme and center points". CVPR 2019

ExtremeNet

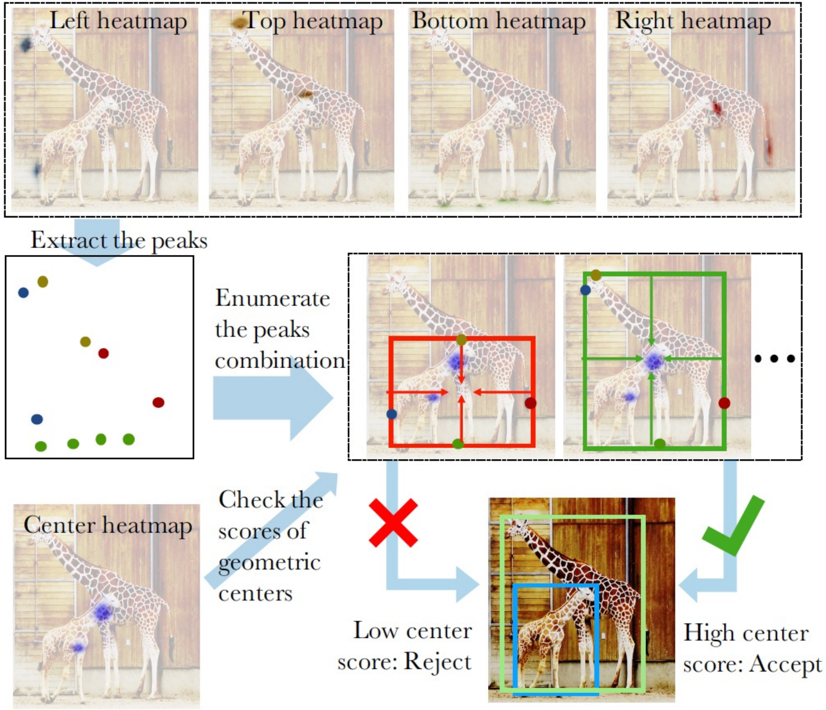
- Represent objects by their extreme points



X. Zhou et al. „Bottom-up object detection by grouping extreme and center points". CVPR 2019

ExtremeNet

- No need to predict embeddings for the box computation



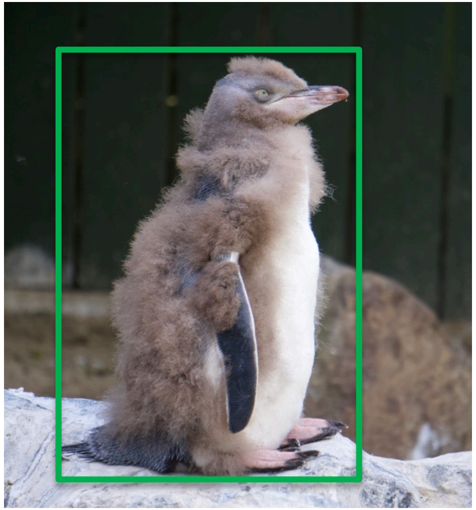
X. Zhou et al. „Bottom-up object detection by grouping extreme and center points". CVPR 2019

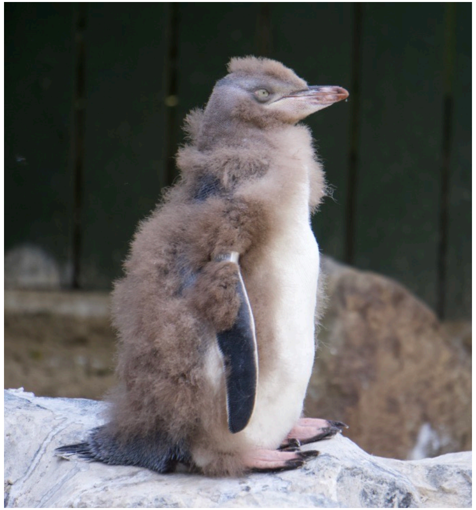
Extreme points

- Extreme points are used commonly for annotation
  - D. P. Papadopoulos et al. „Extreme clicking for efficient object annotation". ICCV 2017
  - K. Maninis et al. „Deep extreme cut: From extreme points to object segmentation". CVPR 2018

Detection evaluation

Detection evaluation





TP = True positives. FP = False positives. FN = False negatives

Detection evaluation

- Precision: how accurate your predictions are.

$$Precision = \frac{TP}{TP + FP}$$

Good boxes detected

All boxes that you detected

- Recall: how good you are at finding all positives

$$Recall = \frac{TP}{TP + FN}$$

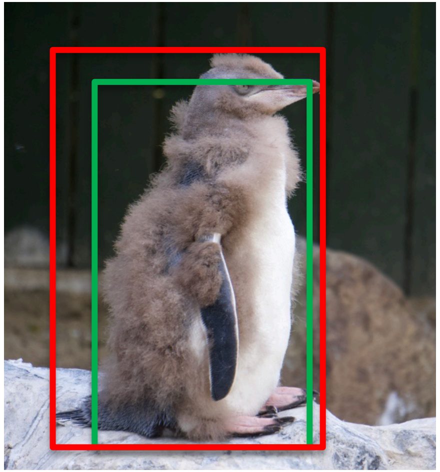
Good boxes detected

All ground truth boxes

TP = True positives.   FP = False positives. FN = False negatives

Detection evaluation

- What is a positive?
- We use the Intersection over Union (IoU) or Jaccard Index
- If IoU>0.5 → positive match
- Depending on the dataset it is 0.5 or 0.7



TP = True positives.   FP = False positives. FN = False negatives

Detection evaluation: AP

- Mean Average Precision (mAP)
  - For each image and class independently, rank the predicted boxes by confidence score. Assign the boxes to the corresponding ground truth if IoU>0.5.
  - Each ground truth box can only be matched to one predicted box.
  - For each class independently, compute Average Precision
  - Mean over all classes to obtain mAP

Henderson and Ferrari. „End-to-End Training of Object Class Detectors for Mean Average Precision". ACCV 2016

Average Precision

- Rank predictions by confidence

Rank	True/false	Precision	Recall
1	T		
2	T		
3	F		
4	T		
5	F		
6	F		
7	T		
8	F		
9	T		
10	T		
11	F		
12	F		

My method predicts 12 boxes, 6 of them are true boxes present in the image

Average Precision

- Rank predictions by confidence

Rank	True/false	Precision	Recall
1	T	1.0	0.17
2	T		
3	F		
4	T		
5	F		
6	F		
7	T		
8	F		
9	T		
10	T		
11	F		
12	F		

Average Precision

- Rank predictions by confidence

Rank	True/false	Precision	Recall
1	T	1.0	0.17
2	T	1.0	0.33
3	F		
4	T		
5	F		
6	F		
7	T		
8	F		
9	T		
10	T		
11	F		
12	F		

Average Precision

- Rank predictions by confidence

Rank	True/false	Precision	Recall
1	T	1.0	0.17
2	T	1.0	0.33
3	F	0.67	0.33
4	T		
5	F		
6	F		
7	T		
8	F		
9	T		
10	T		
11	F		
12	F		

Average Precision

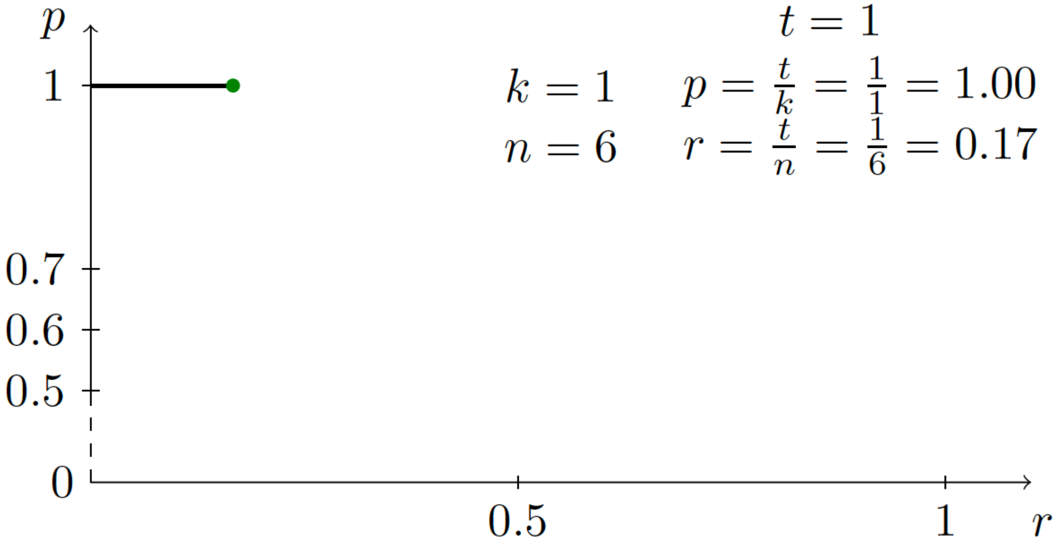
- Rank predictions by confidence

Rank	True/false	Precision	Recall
1	T	1.0	0.17
2	T	1.0	0.33
3	F	0.67	0.33
4	T	0.75	0.5
5	F	0.6	0.5
6	F	0.5	0.5
7	T	0.57	0.67
8	F	0.5	0.67
9	T	0.56	0.83
10	T	0.6	1.0
11	F	0.55	1.0
12	F	0.5	1.0

Average Precision

- Plot Precision vs Recall

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 1$$

$$k = 1 \qquad p = \frac{t}{k} = \frac{1}{1} = 1.00$$

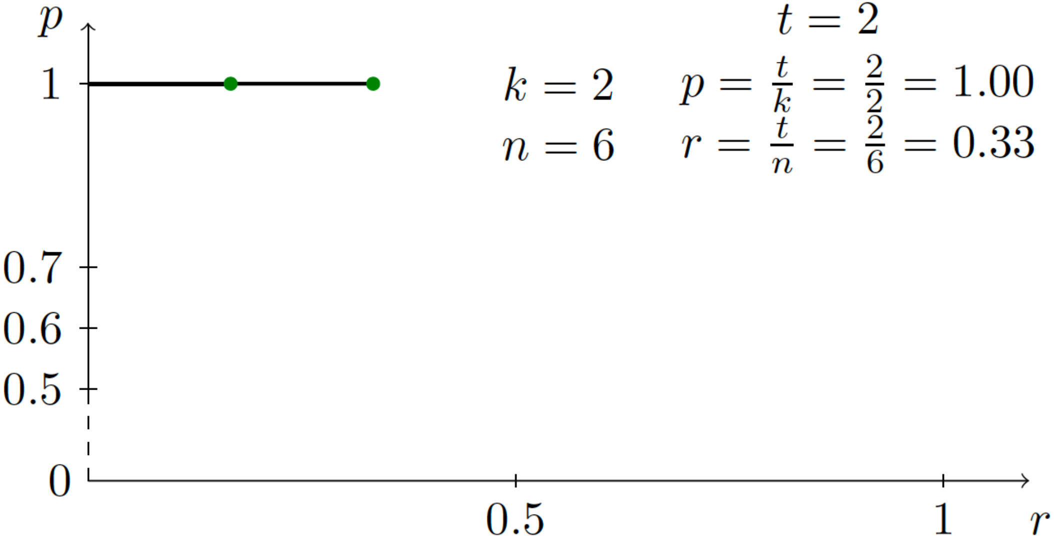
$$n = 6 \qquad r = \frac{t}{n} = \frac{1}{6} = 0.17$$

Images from: Y. Avrithis, Object detection lecture. INRIA.

Average Precision

- Plot Precision vs Recall

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 2$$

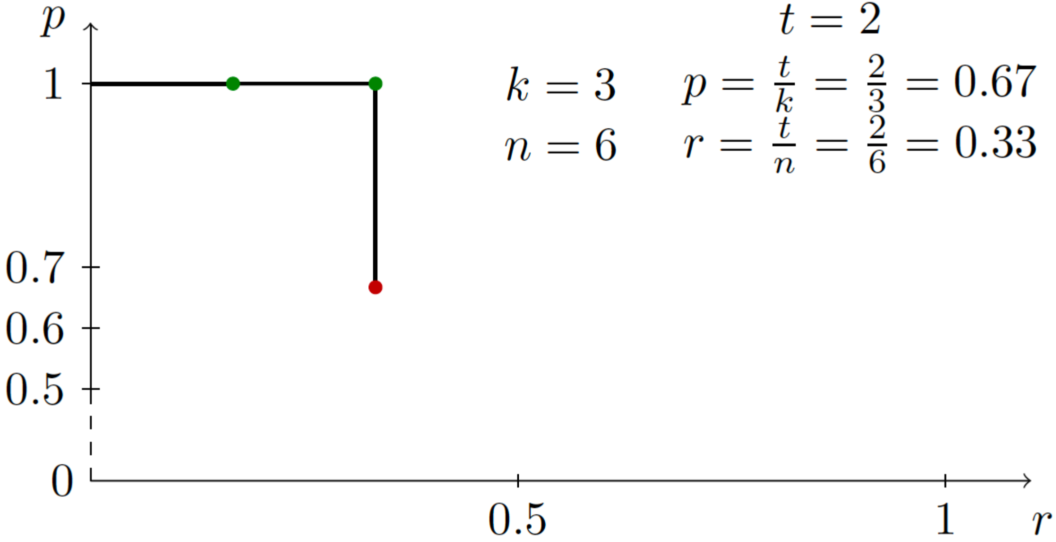
$$k = 2 \qquad p = \frac{t}{k} = \frac{2}{2} = 1.00$$

$$n = 6 \qquad r = \frac{t}{n} = \frac{2}{6} = 0.33$$

Average Precision

- Plot Precision vs Recall

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 2$$

$$k = 3 \qquad p = \frac{t}{k} = \frac{2}{3} = 0.67$$

$$n = 6 \qquad r = \frac{t}{n} = \frac{2}{6} = 0.33$$

Average Precision

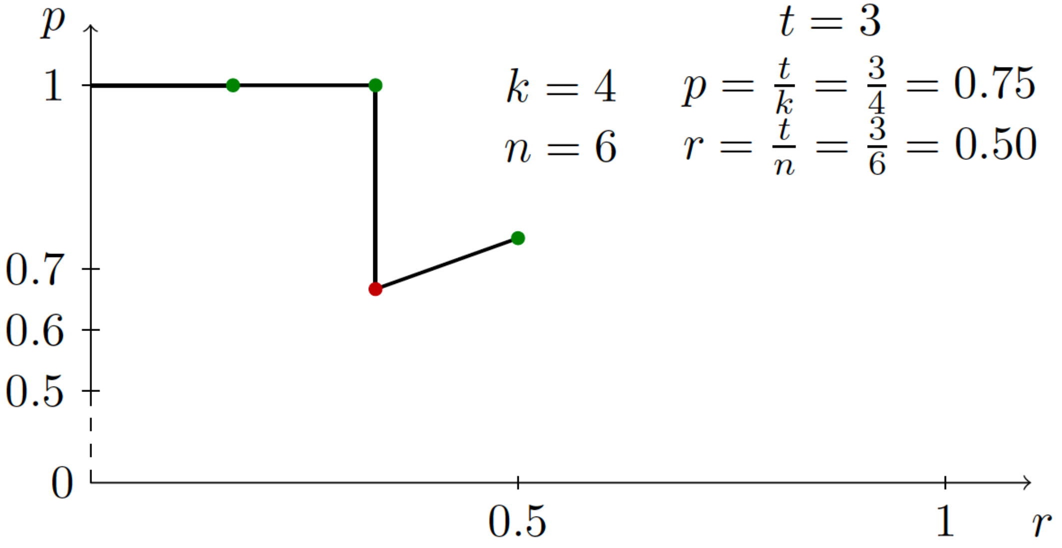
- Plot Precision vs Recall

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

$$t = 3$$

$$k = 4 \qquad p = \frac{t}{k} = \frac{3}{4} = 0.75$$

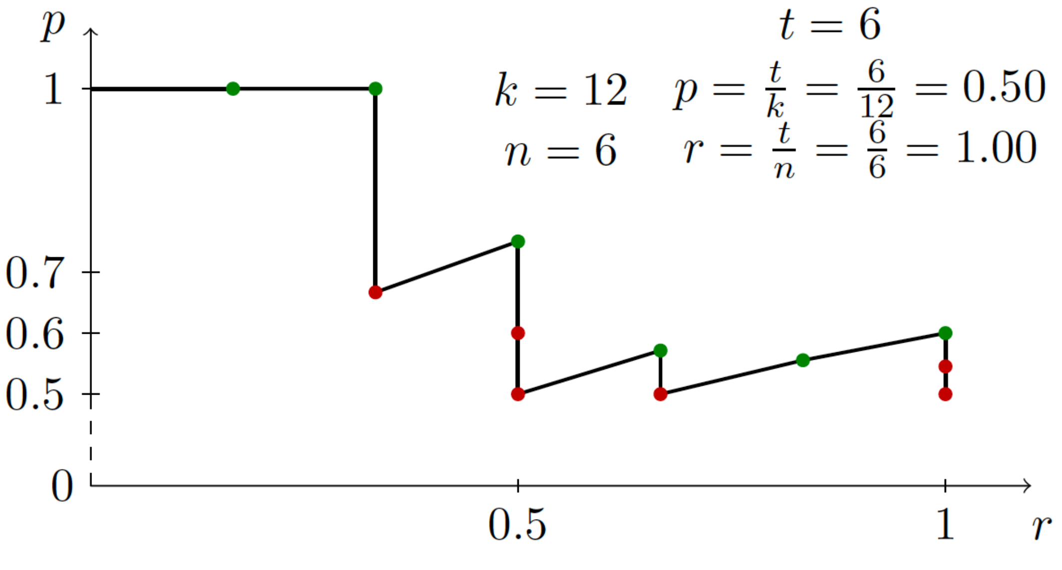
$$n = 6 \qquad r = \frac{t}{n} = \frac{3}{6} = 0.50$$



Average Precision

- Plot Precision vs Recall

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$t = 6$

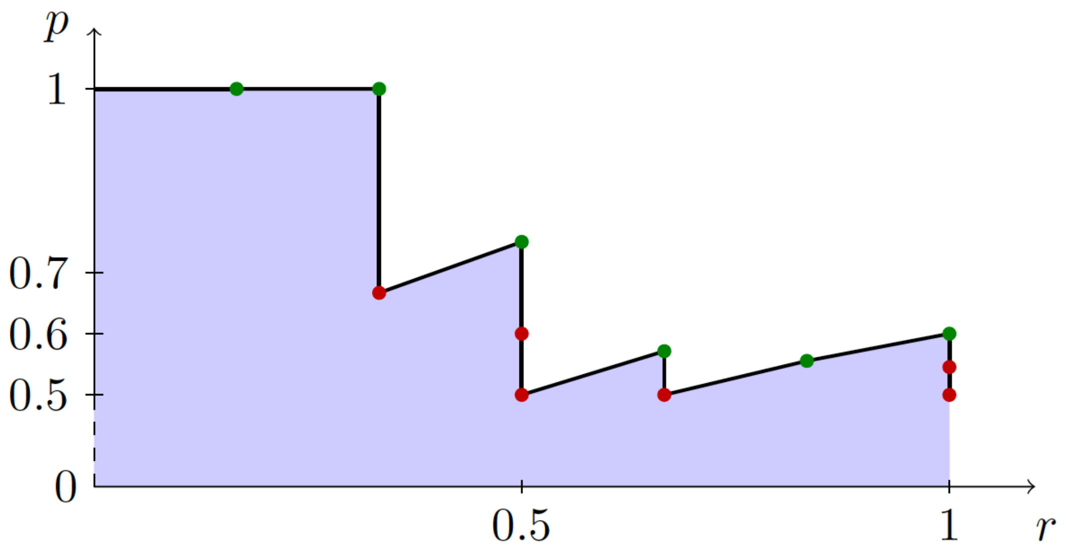
$k = 12 \quad p = \frac{t}{k} = \frac{6}{12} = 0.50$

$n = 6 \quad r = \frac{t}{n} = \frac{6}{6} = 1.00$

Average Precision

- Average precision = area under curve

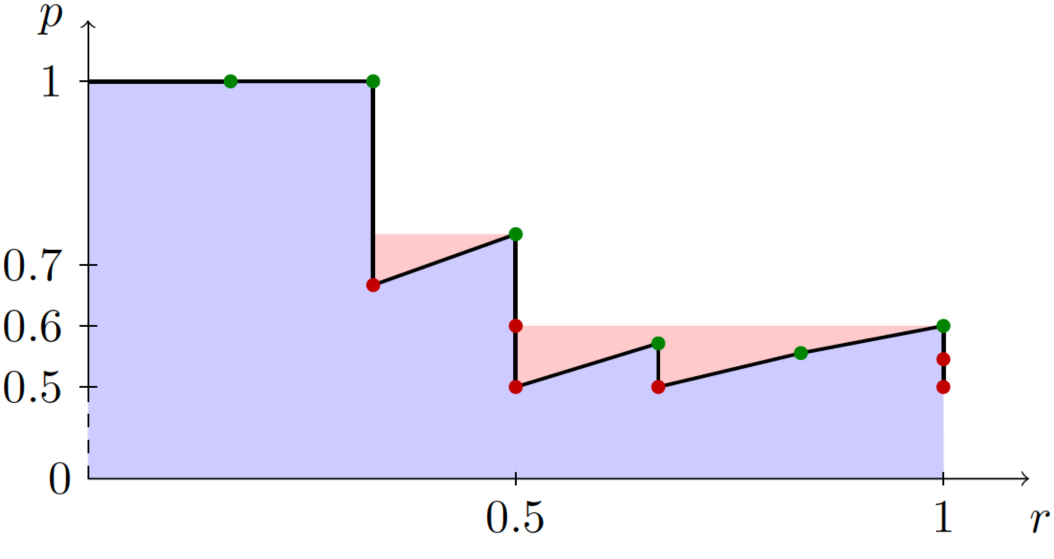
1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



Average Precision

- Average precision = area under curve (filled)

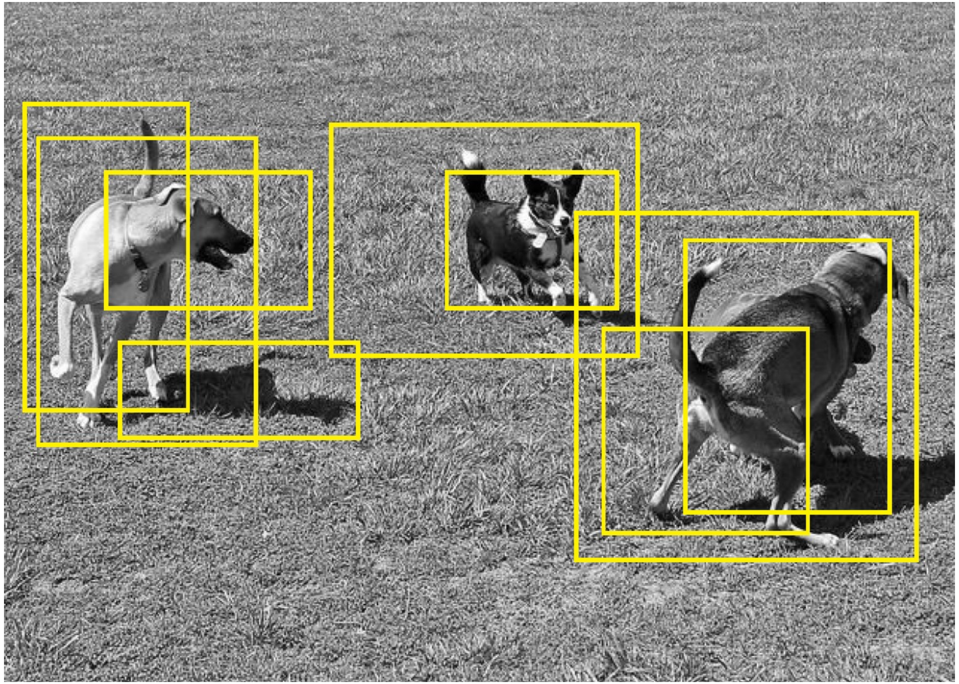
1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



Recall non-maximum suppression

NMS

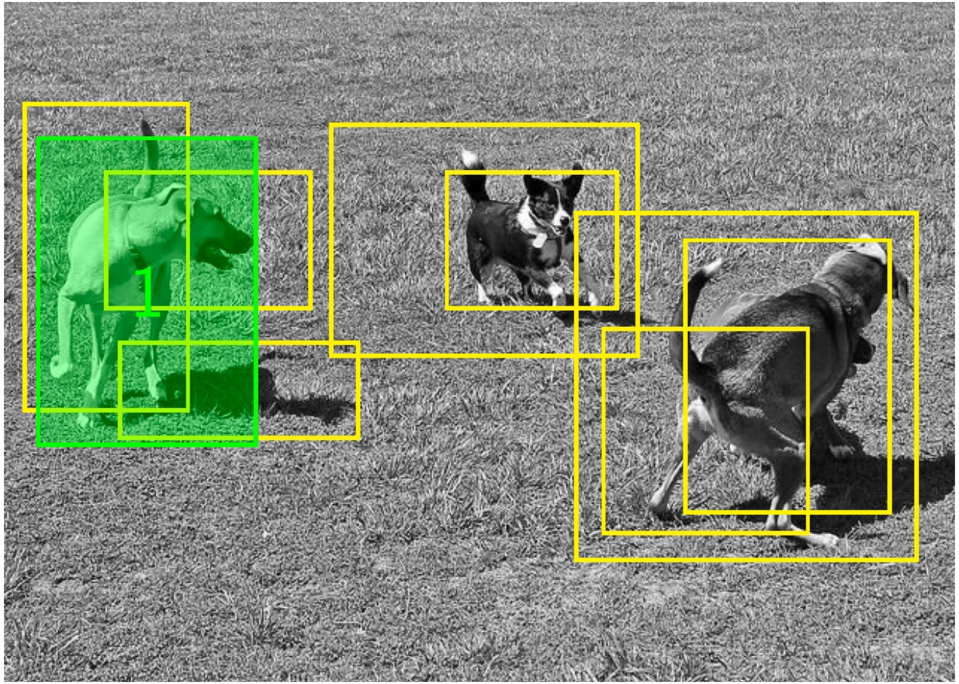
- Many bounding boxes are predicted by the CNN



Images from: Y. Avrithis, Object detection lecture. INRIA.

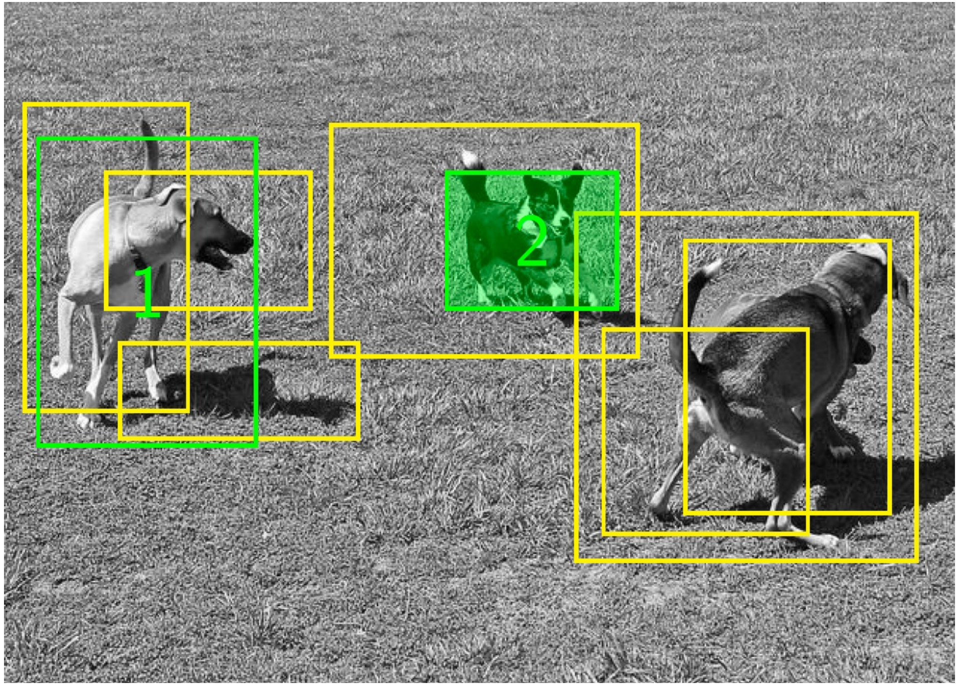
NMS

- Most confident region remains



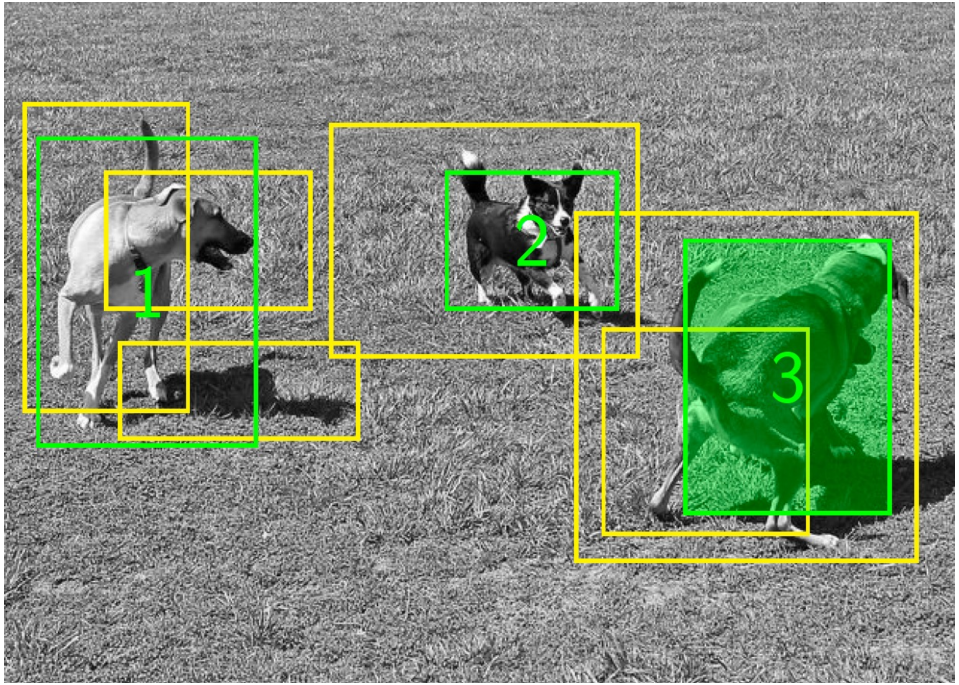
NMS

- Second most confident region remains



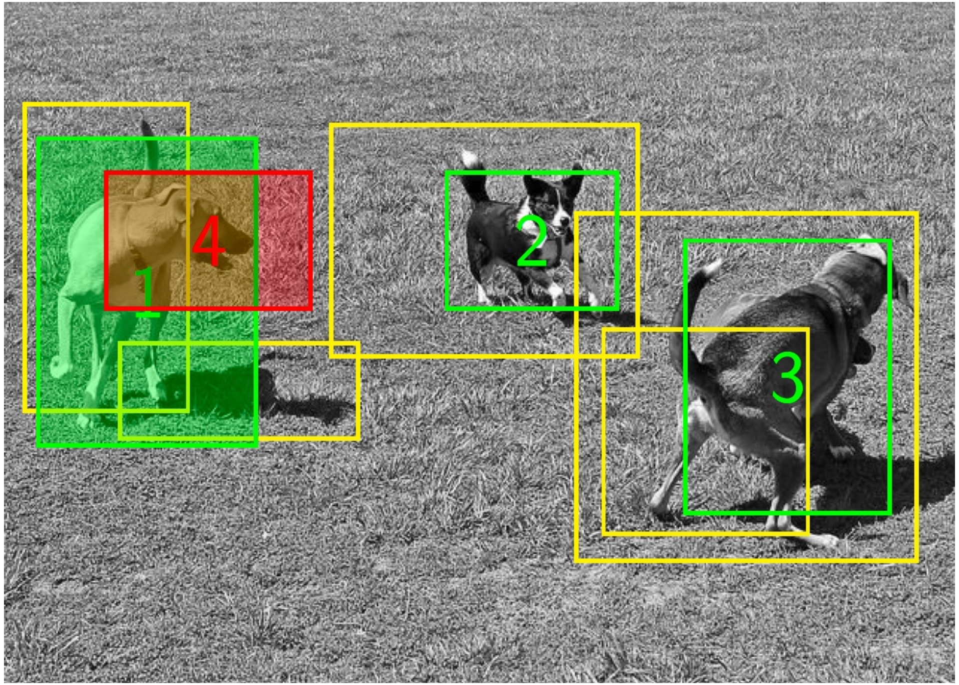
NMS

- Third most confident region remains



NMS

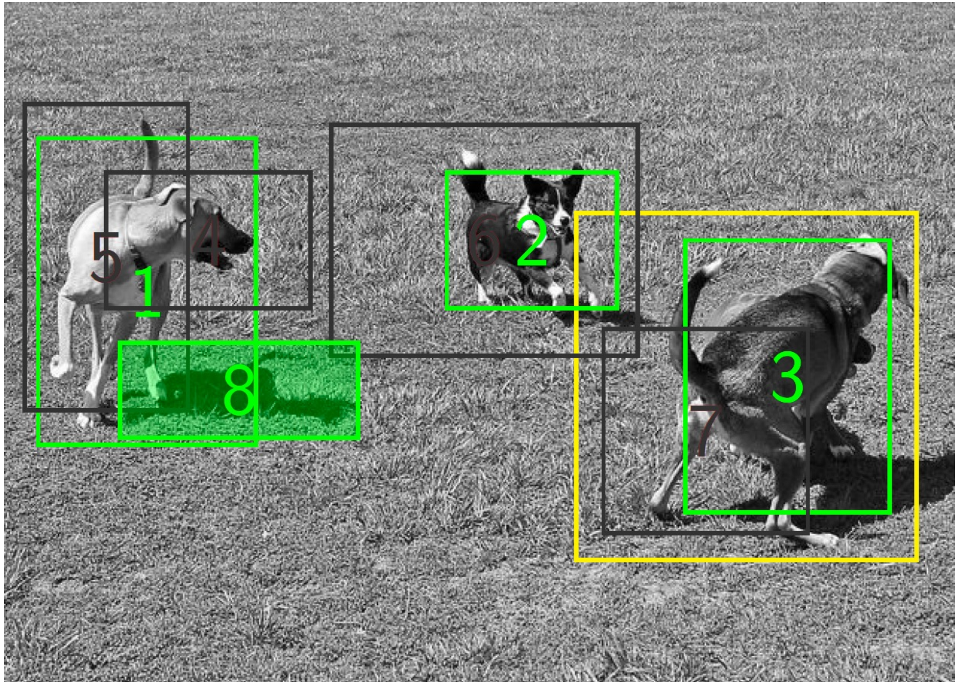
- Region 4 overlap with 1 more than threshold → remove



NMS

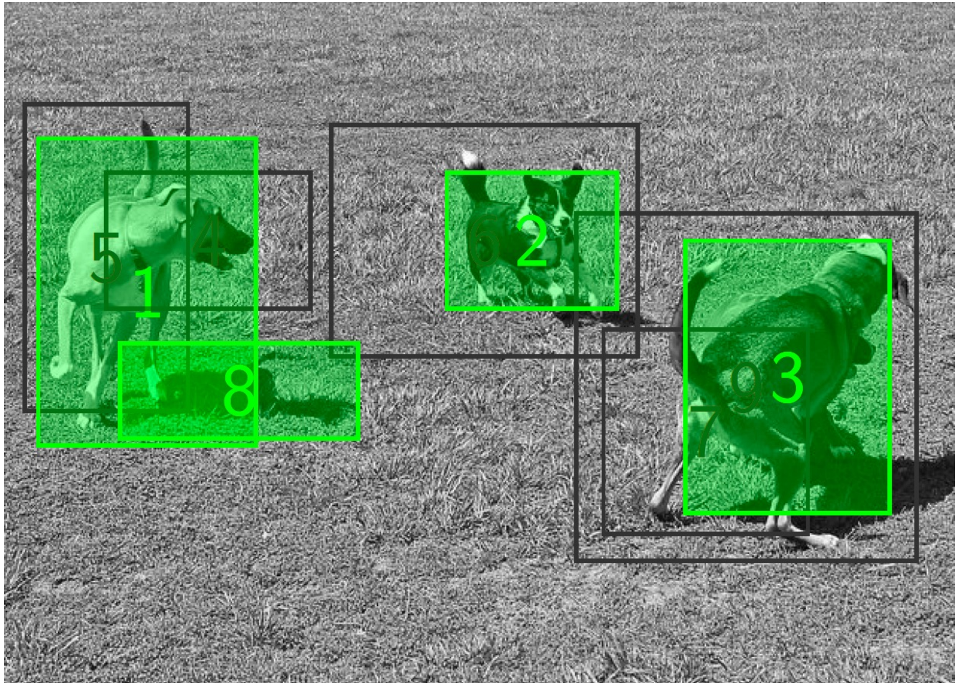
- The same will happen to all the regions in black

Region 8 does not overlap with green boxes (confirmed detections), hence we keep it.



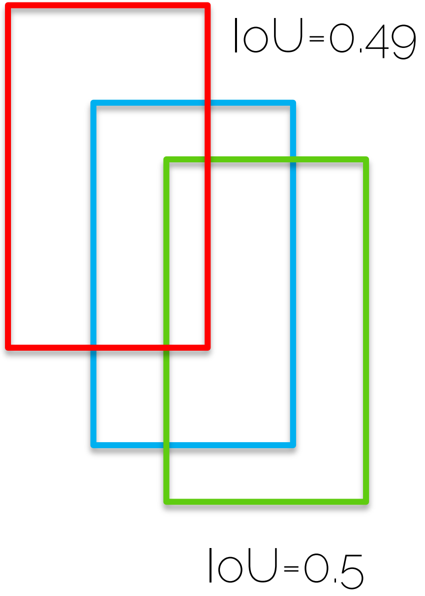
NMS

- In the end, we have 4 confirmed predicted boxes.



NMS

- Problem with highly overlapping objects

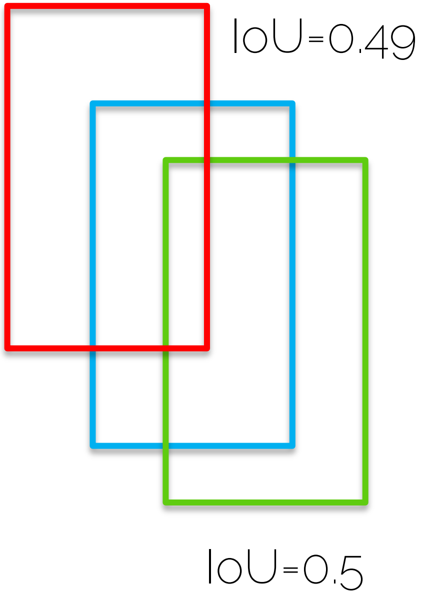


With an NMS threshold of 0.4, we remove both boxes, hence we have a False Negative.

NMS

- Problem with highly overlapping objects

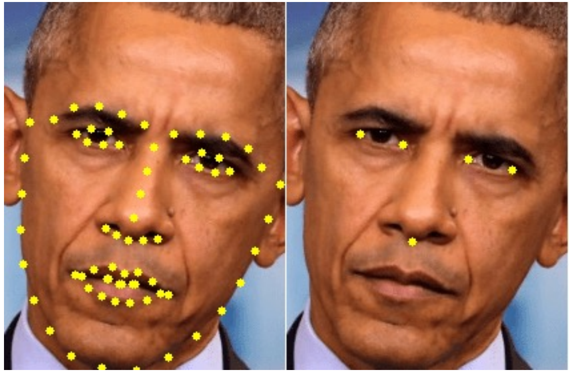
With an NMS threshold of 0.6, we keep both boxes, hence we have a False Positive.



Detection beyond 2D boxes

Prediction “as points”

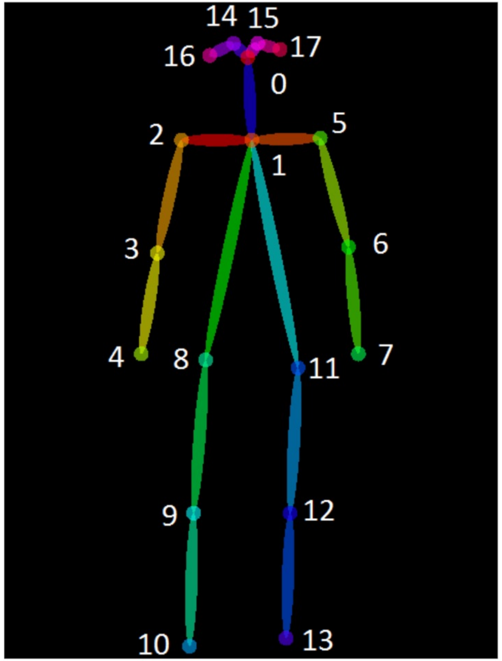
- 3D bounding boxes: prediction of the center + orientation + width + height + depth
- Facial landmarks



- Human pose estimation: body joints

Human pose estimation

- Estimate a 2D pose (x,y) coordinates for each joint from a RGB image.
- Parameterization:
  - 17 joints*
  - Left/right ankle
  - Left/right knee
  - etc

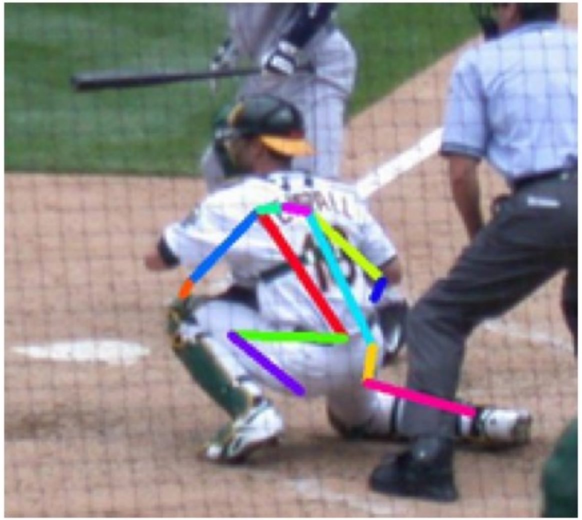


* As defined in http://cocodataset.org/#keypoints-2019

Image: https://nanonets.com/blog/human-pose-estimation-2d-guide/

Human pose estimation

- It might seem an easy problem, but it is challenging: occlusions, clothing, extreme poses, viewpoint changes



Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

Human pose estimation

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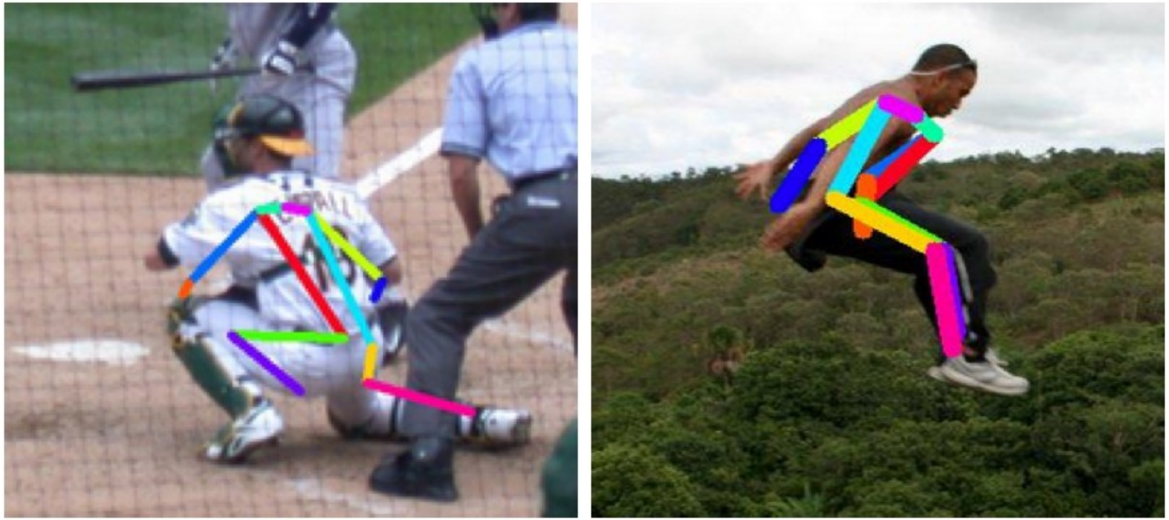
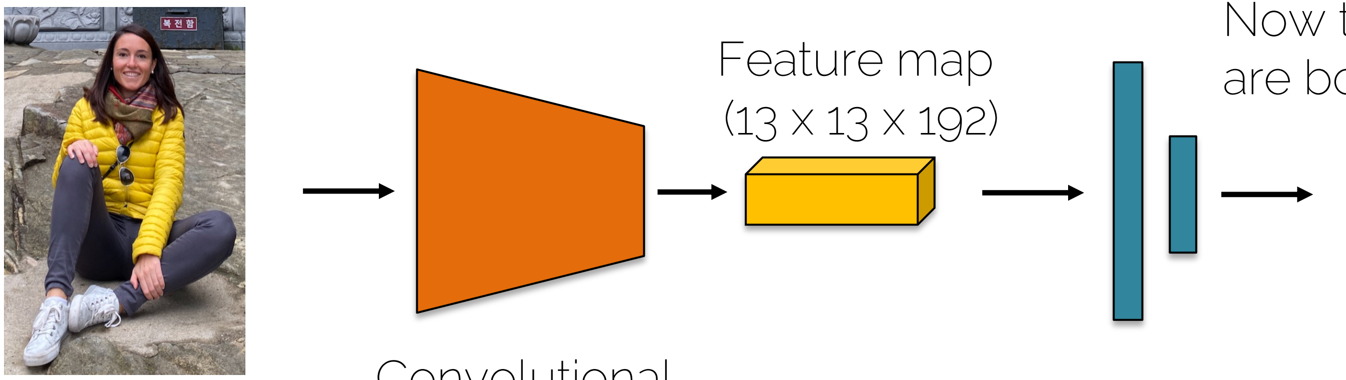


Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

Human pose estimation

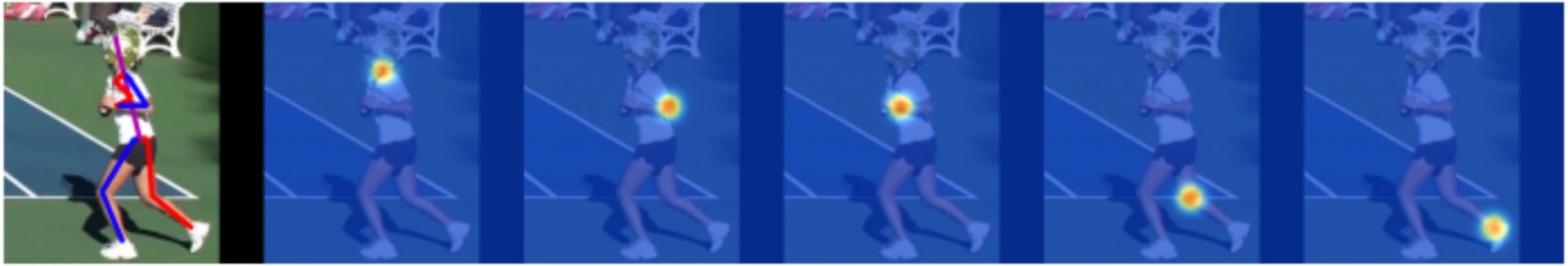
- Approach 1: direct regression



Toshev and Szegedy, “DeepPose: Human Pose Estimation via Deep Neural Networks”, CVPR 2014

Human pose estimation

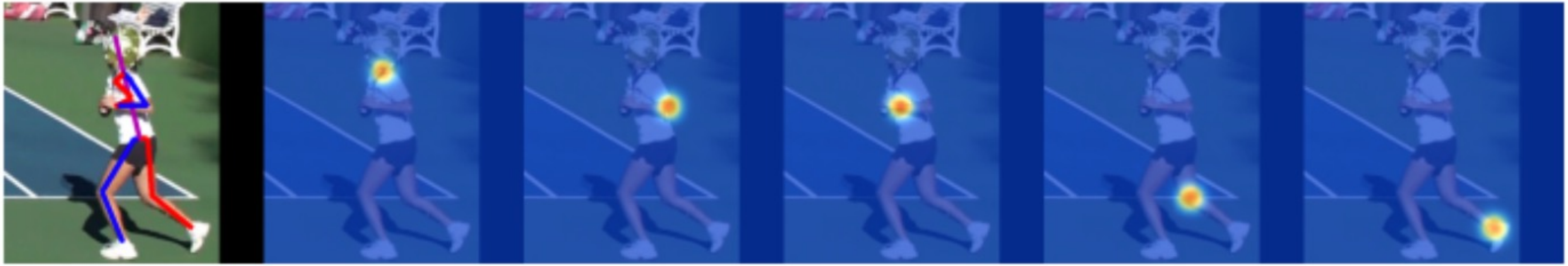
- Approach 2: heatmap prediction
  - Instead of prediction by regression, for each joint one predicts a full image with a heatmap of the joint location



J. Tompson et al, "Join training of a convolutional network and a graphical model for human pose estimation". NeurIPS, 2014.

Human pose estimation

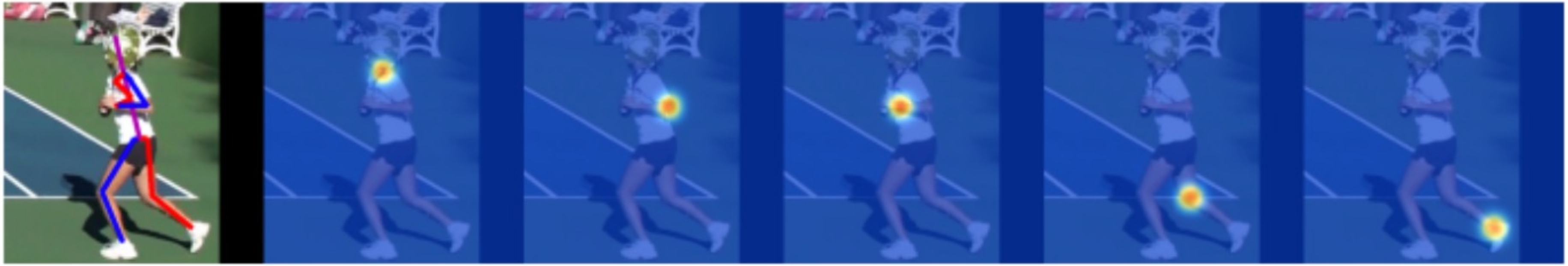
- Approach 2: heatmap prediction
  - Instead of prediction by regression, for each joint one predicts a full image with a heatmap of the joint location
  - Powerful representation, easier to predict a confidence per location, rather than regress a value for the position



J. Tompson et al, "Join training of a convolutional network and a graphical model for human pose estimation". NeurIPS, 2014.

Human pose estimation

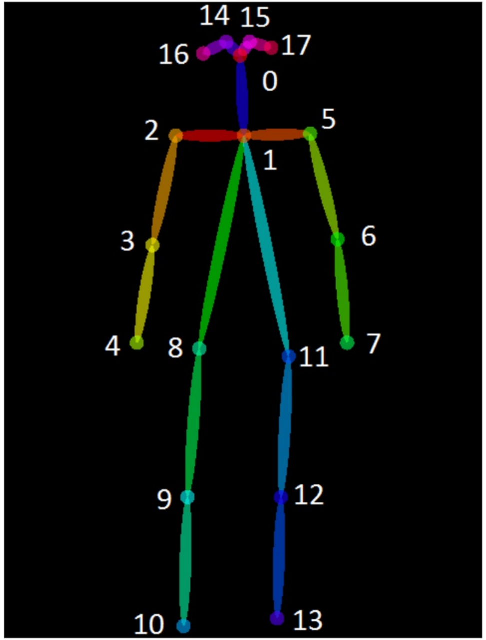
- Approach 2: heatmap prediction
  - Ground truth (GT) heatmap is constructed by placing a 2D Gaussian around the joint position (e.g. variance 1.5 pixels)
  - Loss: MSE between predicted and GT heatmap



J. Tompson et al, "Join training of a convolutional network and a graphical model for human pose estimation". NeurIPS, 2014.

Human pose estimation

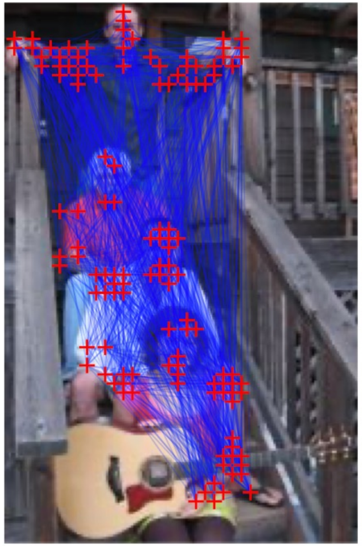
- Bringing the structure of the problem
  - Body parts are linked to each other
  - Body symmetries
  - Joint limits, e.g., elbow cannot bend backwards
  - Physical connectivity: elbow connected to wrist



J. Tompson et al, "Join training of a convolutional network and a graphical model for human pose estimation". NeurIPS, 2014.

Human pose estimation

- Using graphical models also allows us to find the pose of several targets



All joint detections as provided directly by the CNN

L. Pischchulin et al, "DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation" CVPR 2016

Human pose estimation

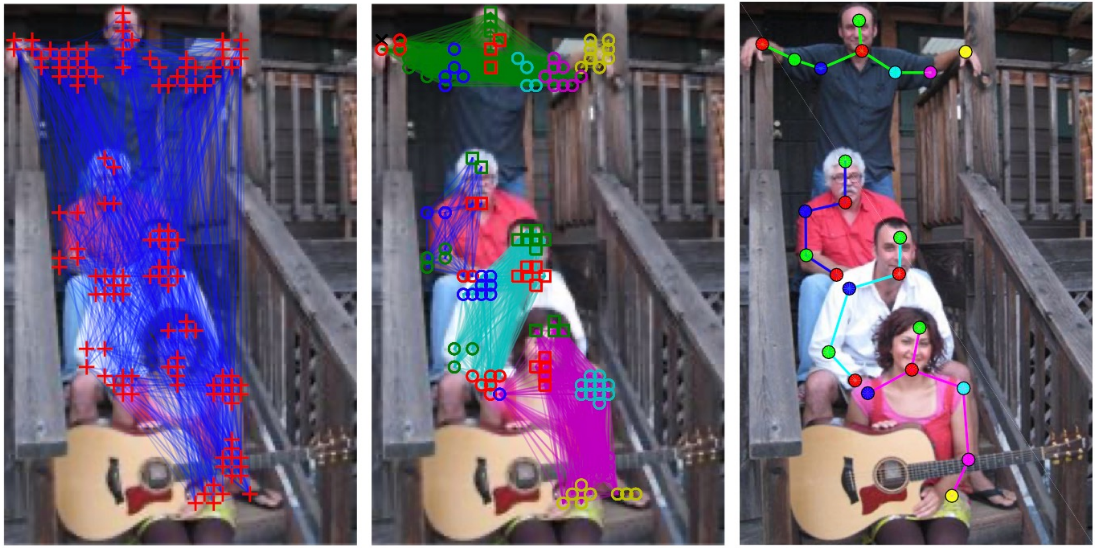
- Using graphical models also allows us to find the pose of several targets

Cluster the joints based on joint type and target ID

L. Pischchulin et al, "DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation" CVPR 2016

Human pose estimation

- Using graphical models also allows us to find the pose of several targets



Final predictions

L. Pischchulin et al, "DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation" CVPR 2016

Human pose estimation

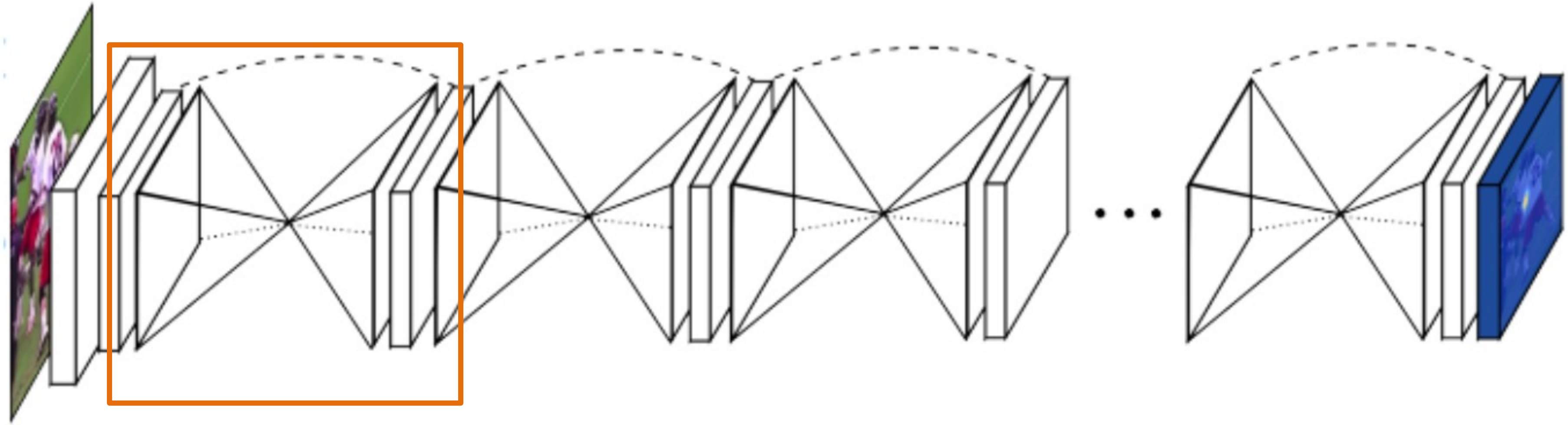
- Using graphical models also allows us to find the pose of several targets

- Alternatively, 1. Object detection + 2. Pose estimation

L. Pischchulin et al, "DeepCut: Joint Subset Partition and Labeling for Multi Person Pose Estimation" CVPR 2016

Human pose estimation

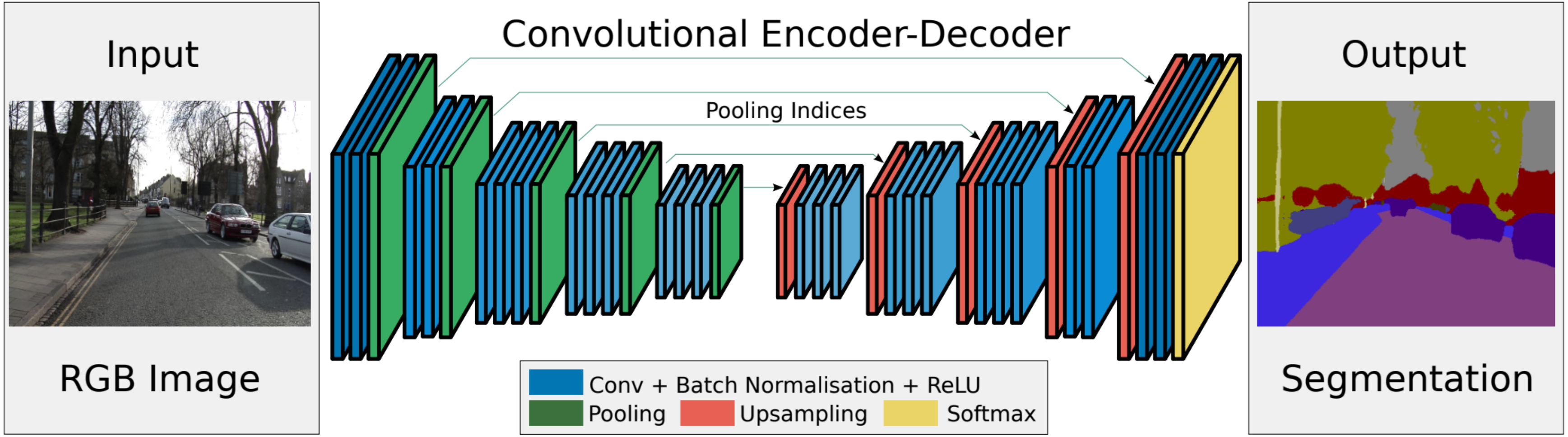
- Improving the architecture: Stacked hourglass
  - Repeated bottom-up (high-to-low-res) and top-down processing (low-to-high-res)



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Hourglass – Unet - Autoencoder

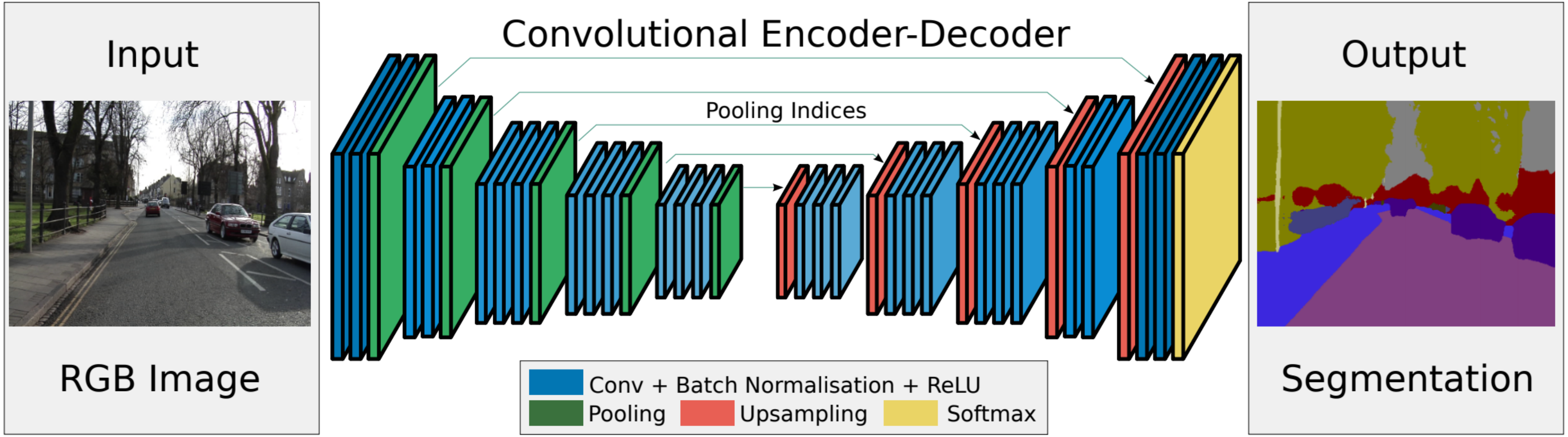
- Architecture that first scales down the resolution and then upsamples it to get to the initial resolution



Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

Hourglass – Unet - Autoencoder

- **Encoder**: normal convolutional filters + pooling
- **Decoder**: Upsampling + convolutional filters



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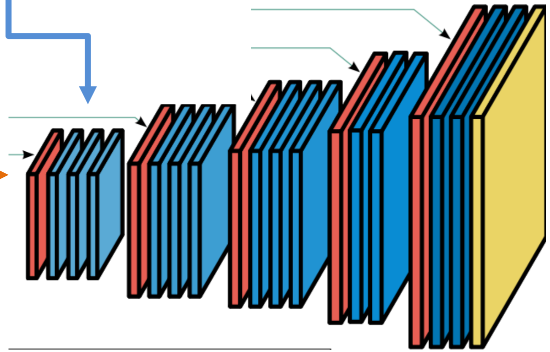


Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

Hourglass – Unet - Autoencoder

- **Encoder**: normal convolutional filters + pooling

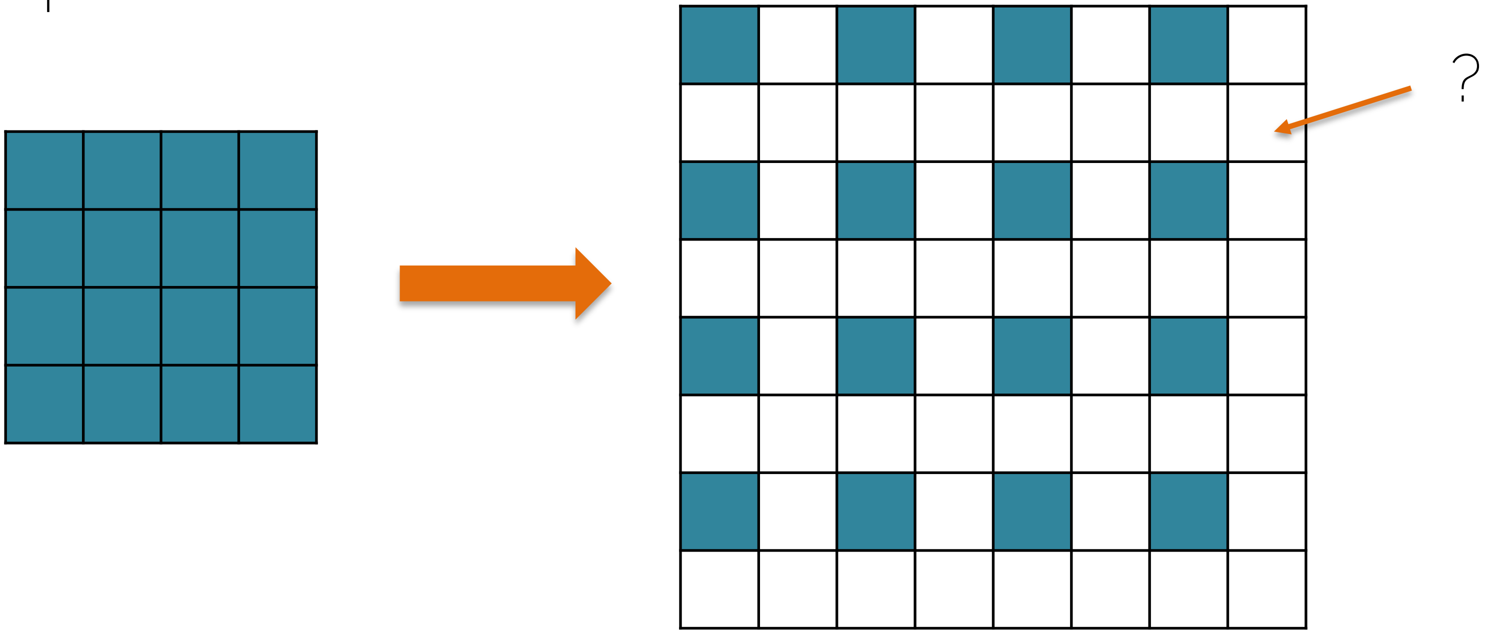
- **Decoder**: Upsampling + convolutional filters

- The convolutional filters in the decoder are learned using backprop and their goal is to refine the upsampling

Badrinarayanan et al. „SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation". TPAMI 2016

Upsampling in hourglass

- Interpolation



Upsampling in hourglass

- Interpolation

Original image  x 10

Nearest neighbor interpolation

Bilinear interpolation

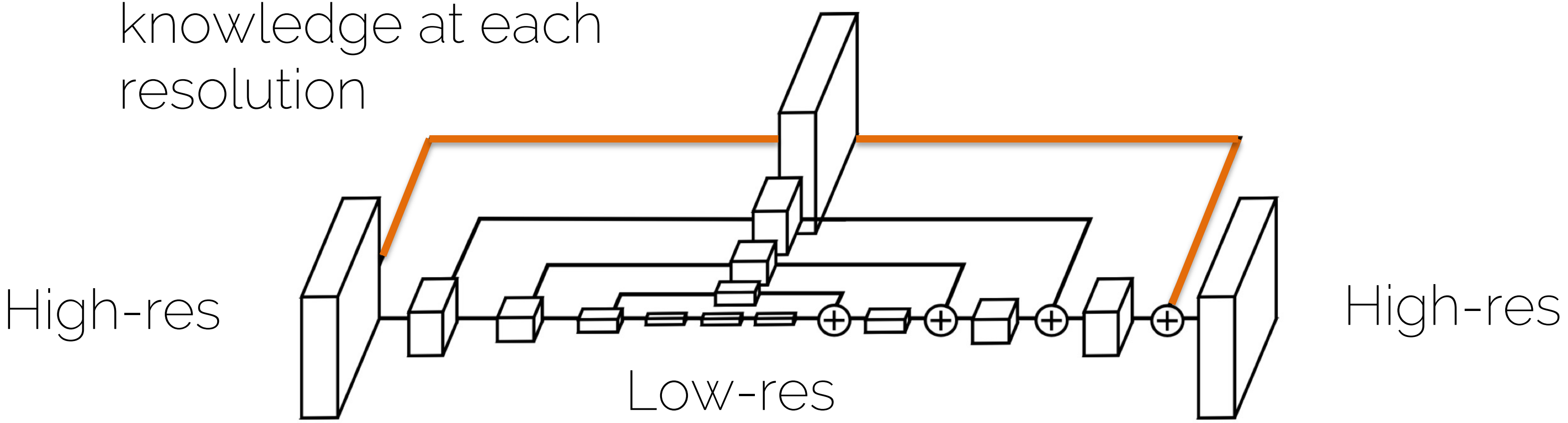
Bicubic interpolation

Image: Michael Guerzhoy

Residual connections

- Improving the architecture: Stacked hourglass

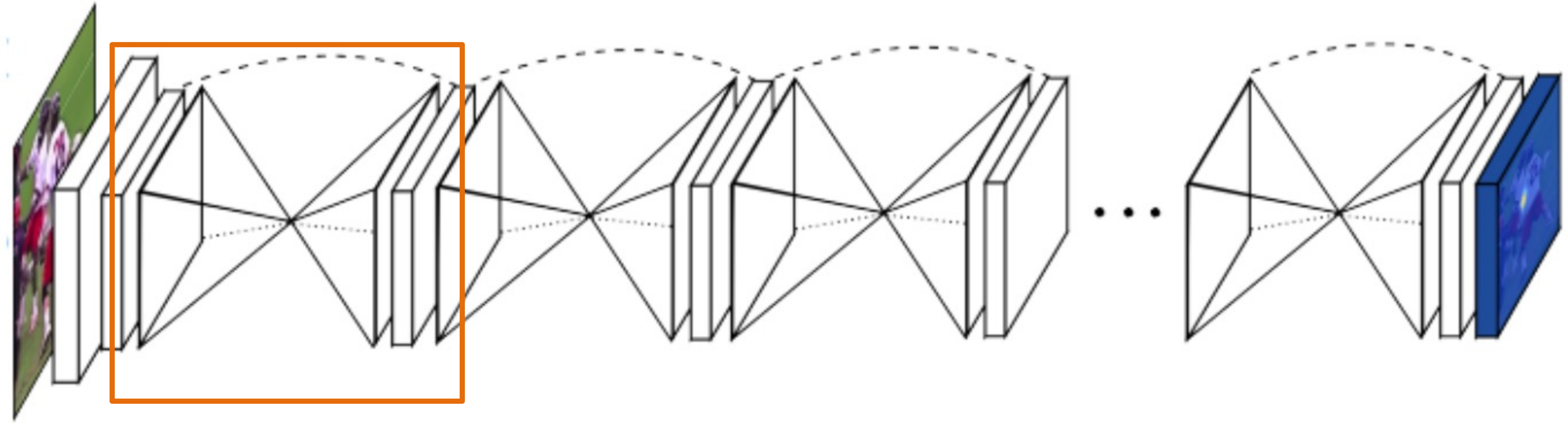
Preserve spatial knowledge at each resolution



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

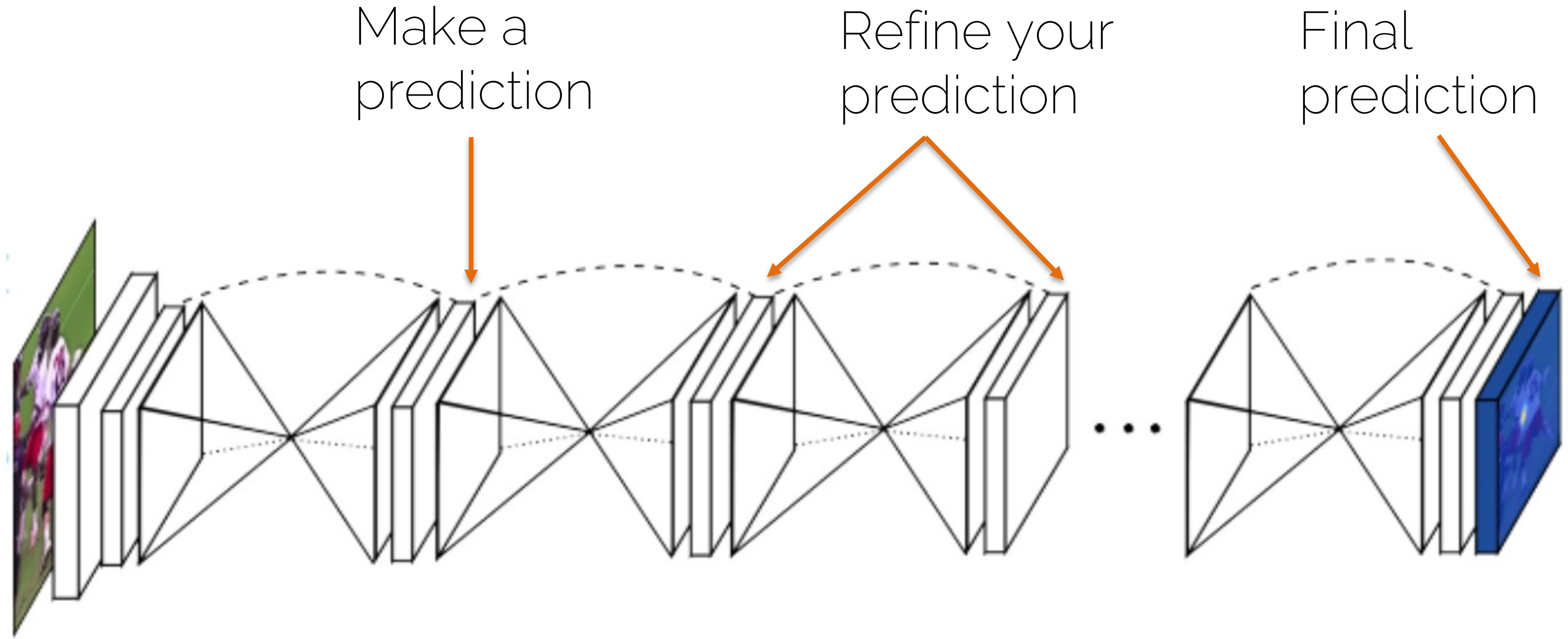
Human pose estimation

- Improving the architecture: Stacked hourglass
  - Repeated bottom-up (high-to-low-res) and top-down processing (low-to-high-res)



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

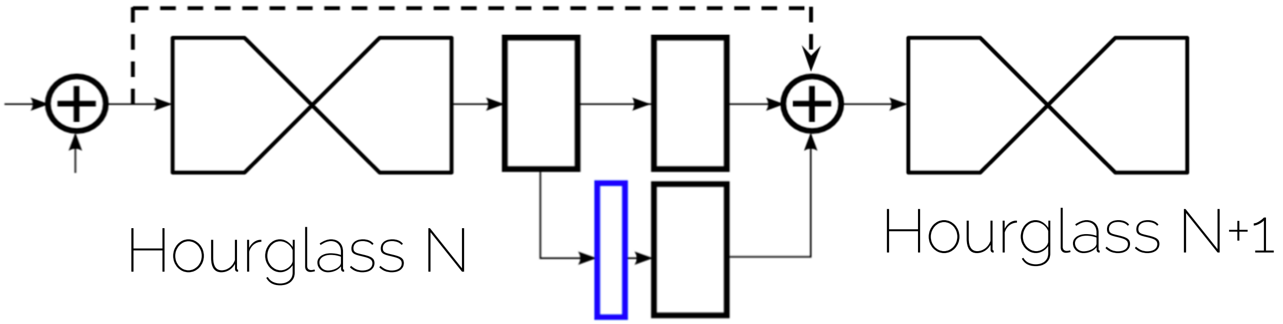
Human pose estimation



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Human pose estimation

- Intermediate supervision

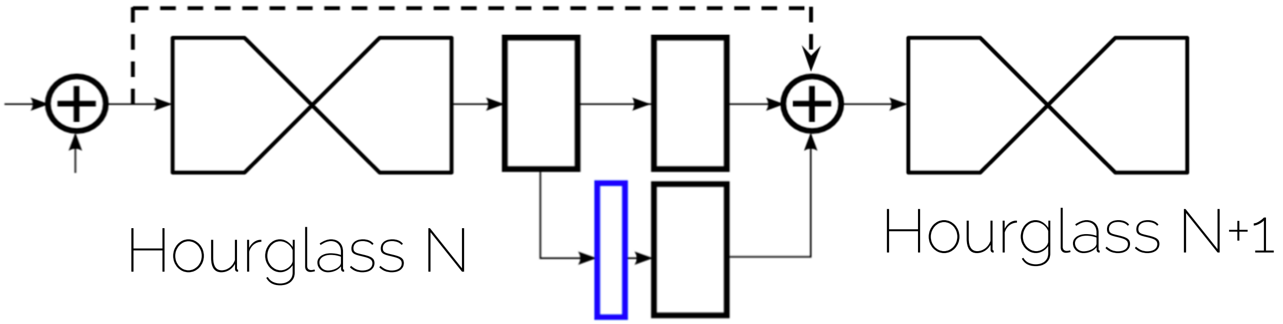


Prediction → loss function is computed

A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Human pose estimation

- Intermediate supervision

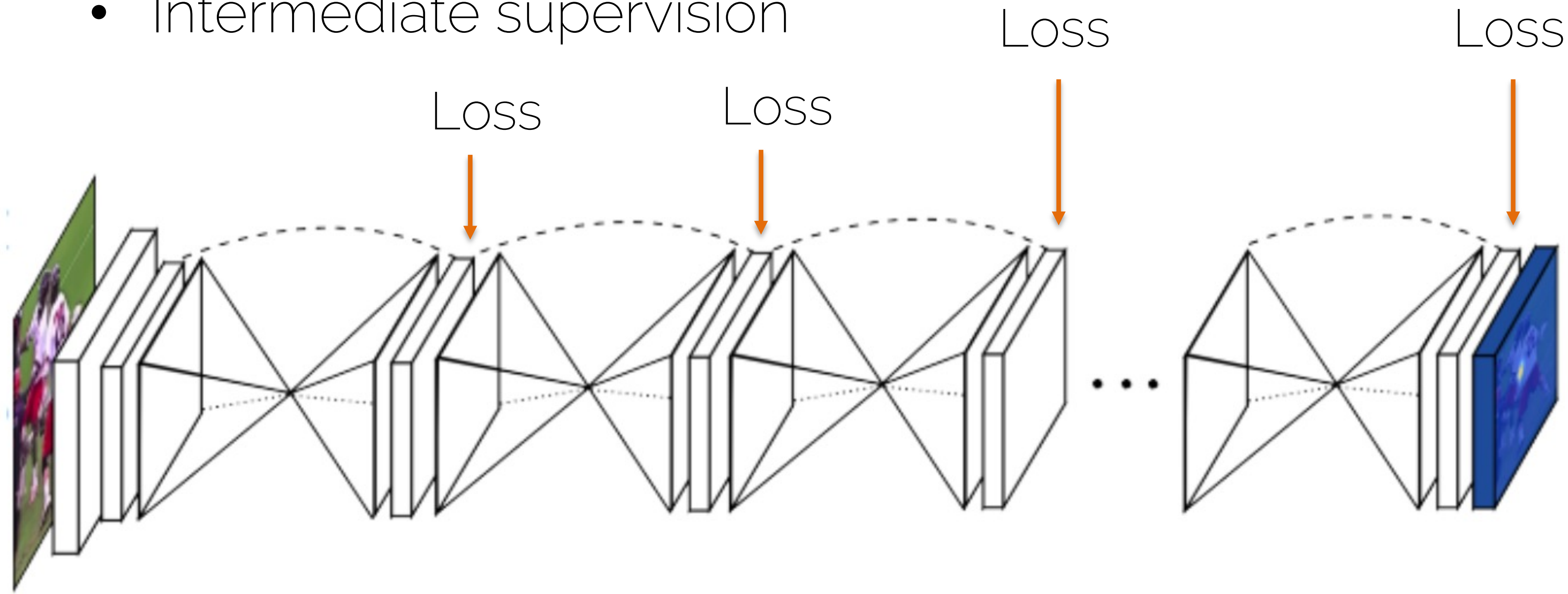


The prediction is reintegrated into the network with 1x1 convs

A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Human pose estimation

- Intermediate supervision



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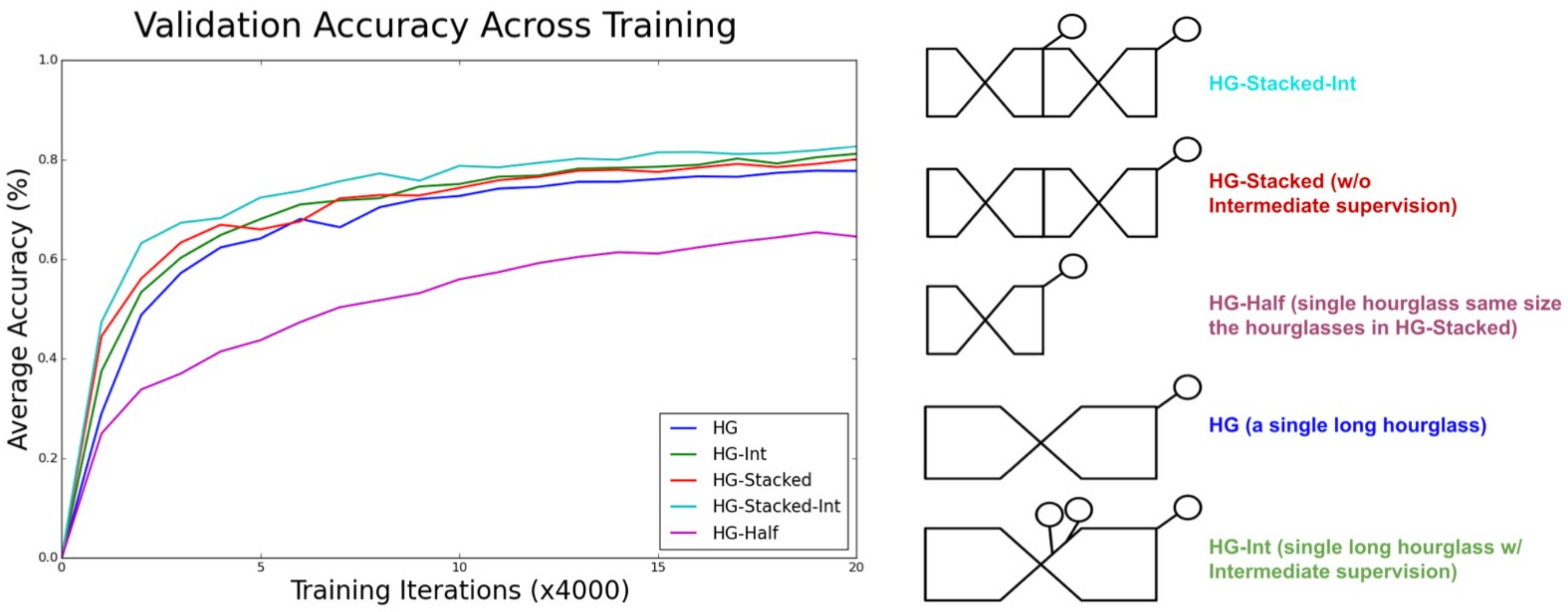
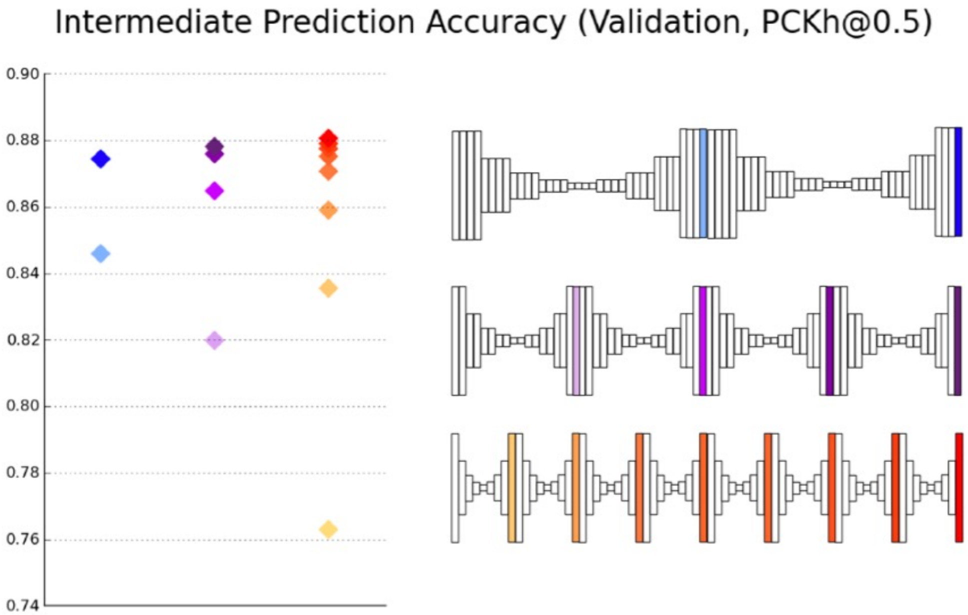
Human pose estimation



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Human pose estimation



A. Newell et al. „Stacked Hourglass Networks for Human Pose Estimation" ECCV, 2016.

Human pose estimation

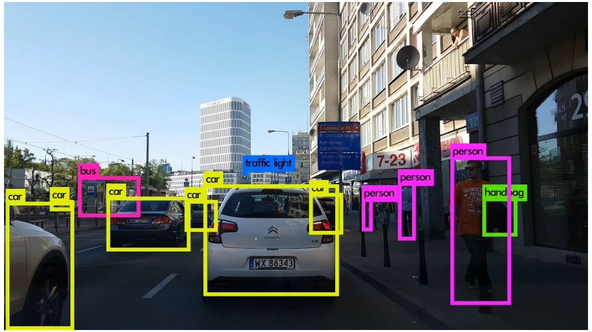
- Open pose – the code to use

Z. Cao et al. „OpenPose: Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields" TPAMI 2019.

https://github.com/CMU-Perceptual-Computing-Lab/openpose

Next lectures

Lectures 2-3



Object Detection

Object Tracking

Lectures 4-5

Lectures 7-8

Object Segmentation

Video Object Segmentation

Lecture 9

One-stage detectors

Interesting read

- Overview paper that analyzes backbone architecture selection, number of proposals used, etc. to see which has an effect on object detection accuracy.

- Huang et al. "Speed/accuracy trade-offs for modern convolutional object detectors". CVPR 2017