Deep Learning

Convolutional Neural Networks - Part II

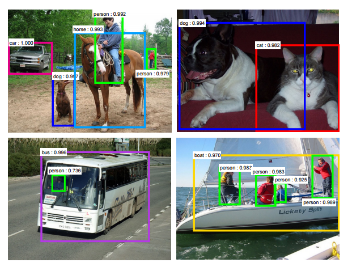
Alex Olson

Adapted from material by Charles Ollion & Olivier Grisel

CNNs for computer Vision

[Krizhevsky 2012]

[Ciresan et al. 2013]



[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Beyond Image Classification

CNNs

- Previous lecture: image classification

Beyond Image Classification

CNNs

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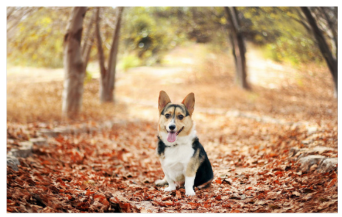
Limitations

- Mostly on centered images
- Only a single object per image
- Not enough for many real world vision tasks

Beyond Image Classification

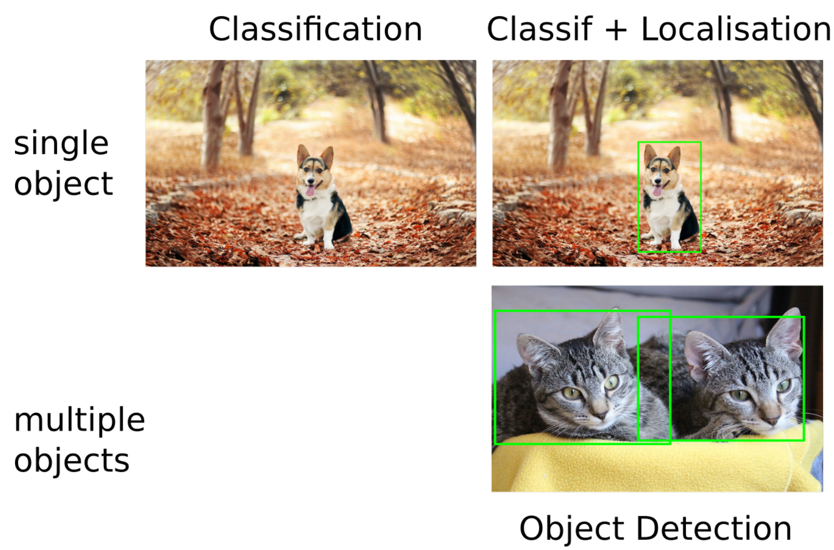
Classification

single
object



Beyond Image Classification

Beyond Image Classification



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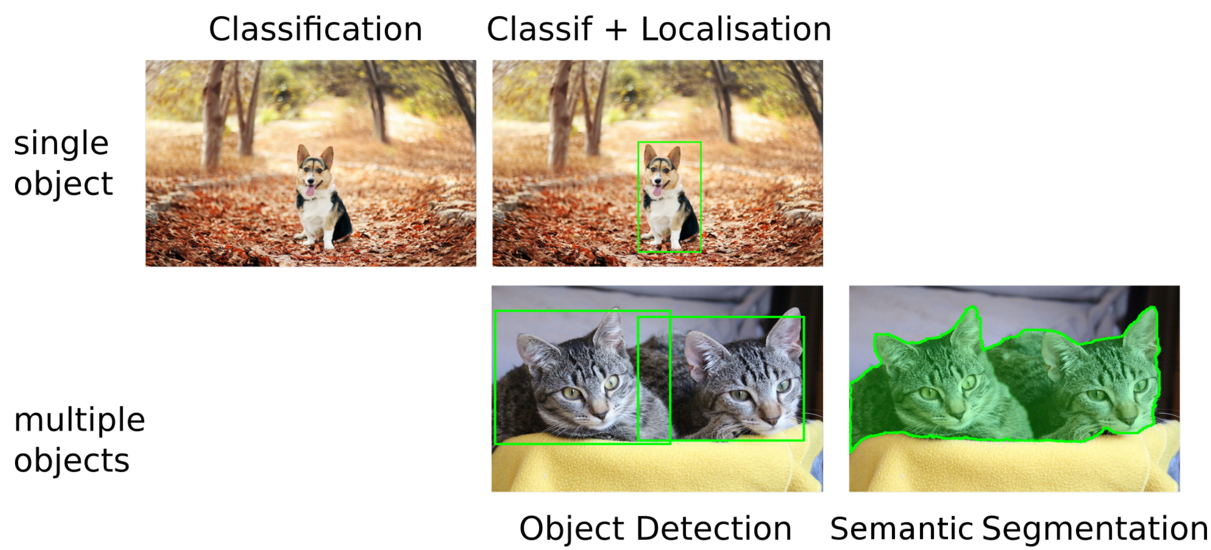

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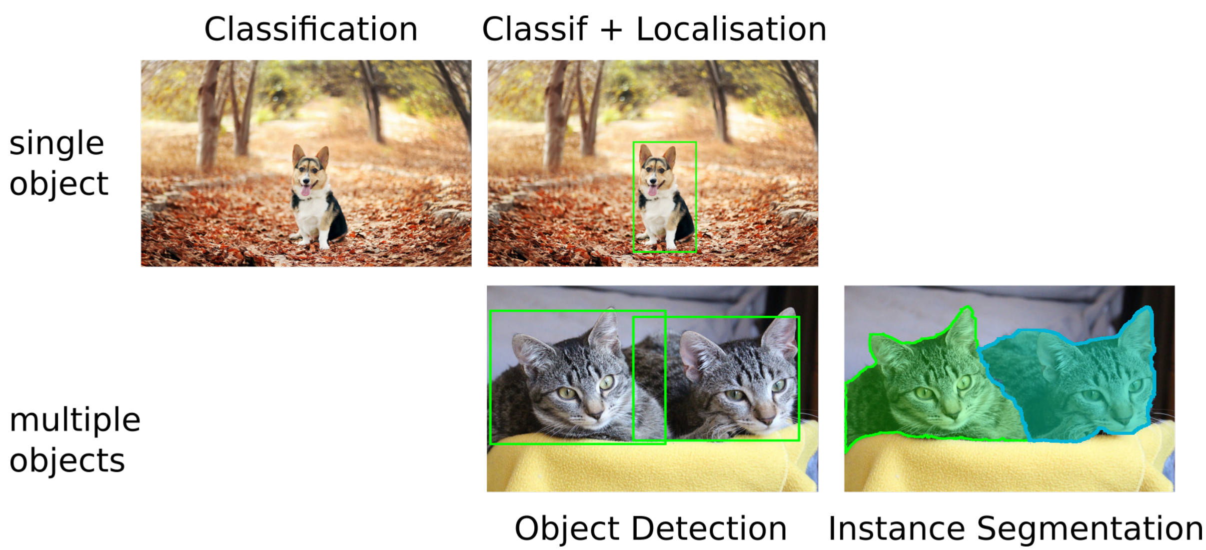

Outline

Simple Localisation as regression

Outline

Simple Localisation as regression

Detection Algorithms

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Detection Algorithms

Fully convolutional Networks

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Simple Localisation as regression

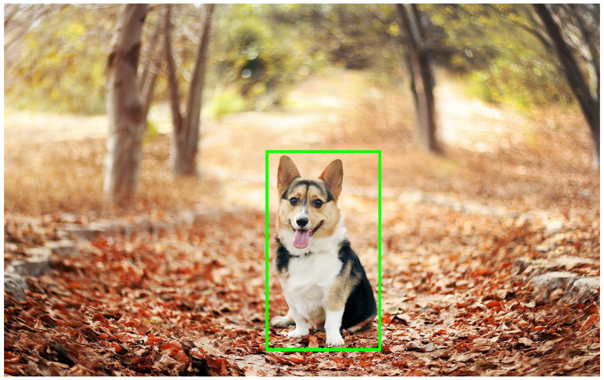
Detection Algorithms

Fully convolutional Networks

Semantic & Instance Segmentation

Localisation

Localisation



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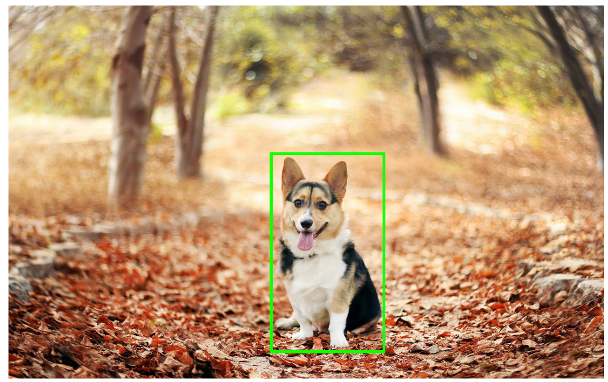
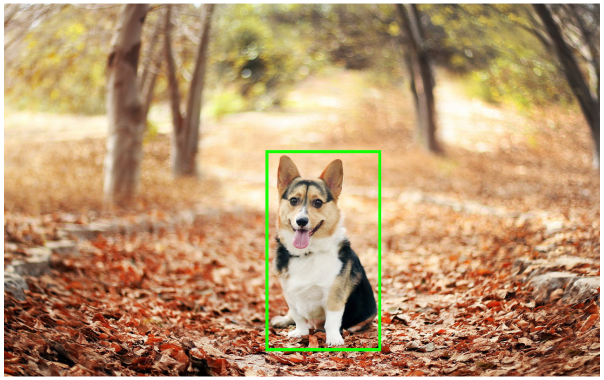


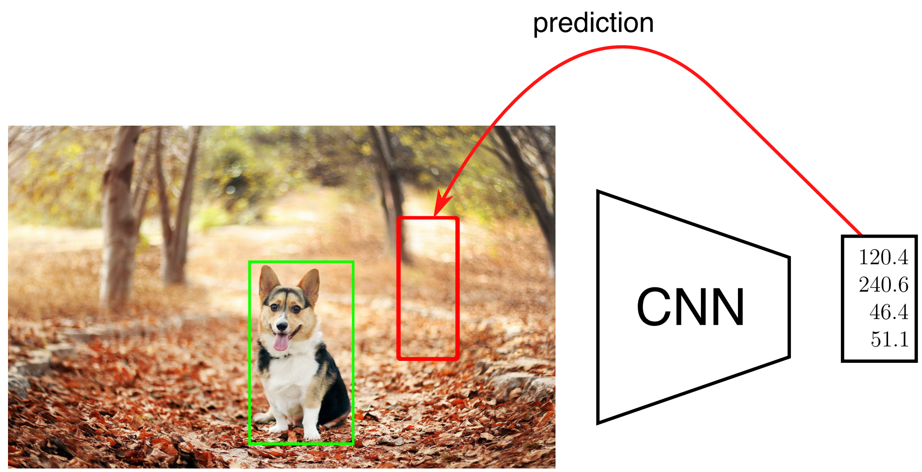
- Single object per image
- Predict coordinates of a bounding box (x, y, w, h)

Localisation



- Single object per image
- Predict coordinates of a bounding box (x, y, w, h)
- Evaluate via Interection over Union (IoU)

Localisation as regression



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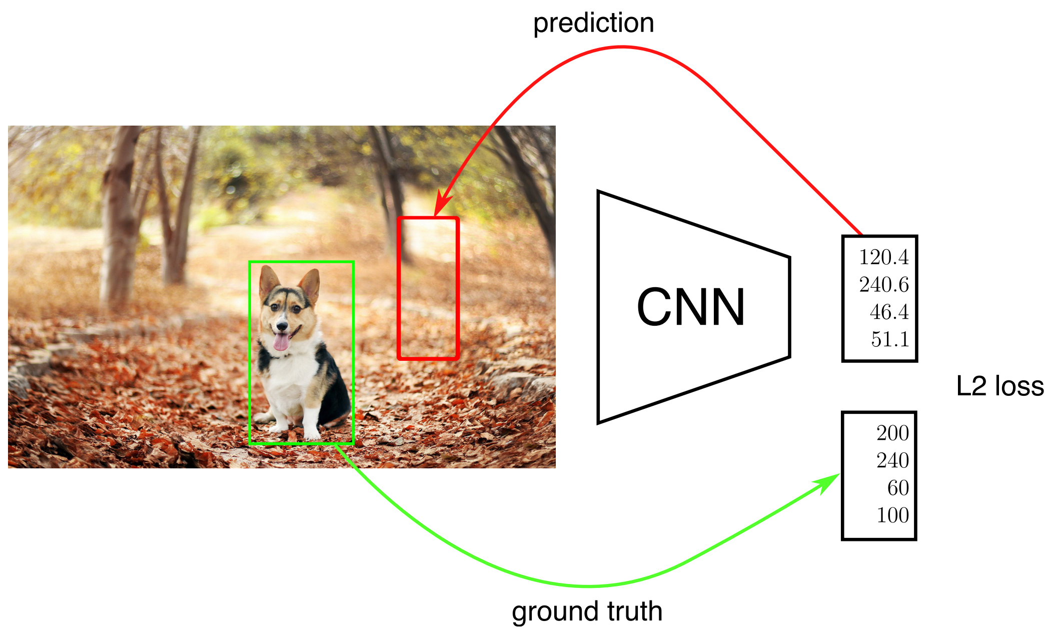
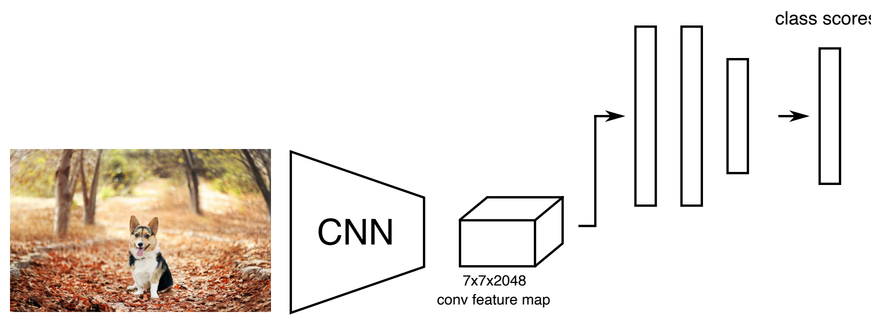


Classification + Localisation



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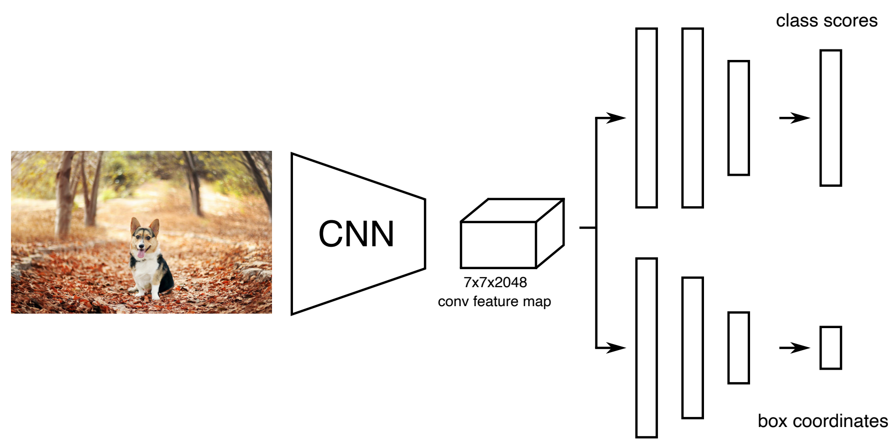

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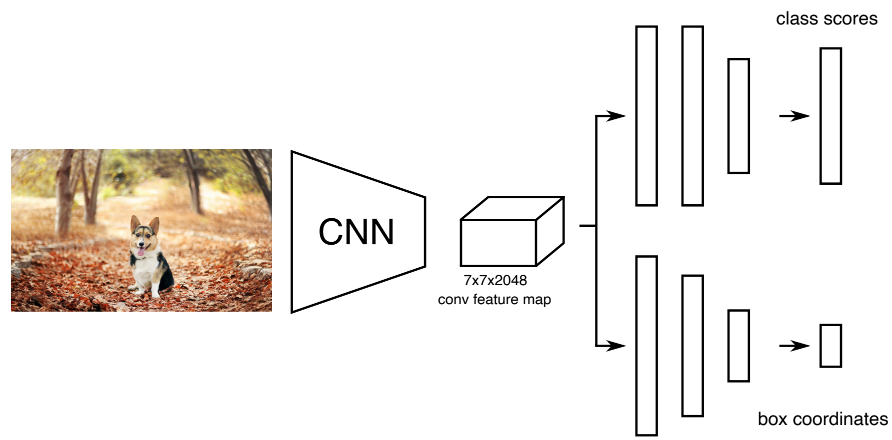
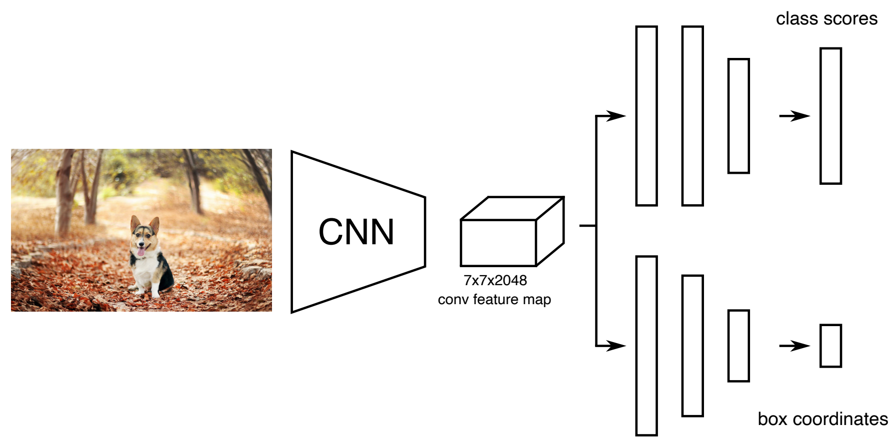


- Use a pre-trained CNN on ImageNet (ex. ResNet)
- The "localisation head" is trained seperately with regression

Classification + Localisation



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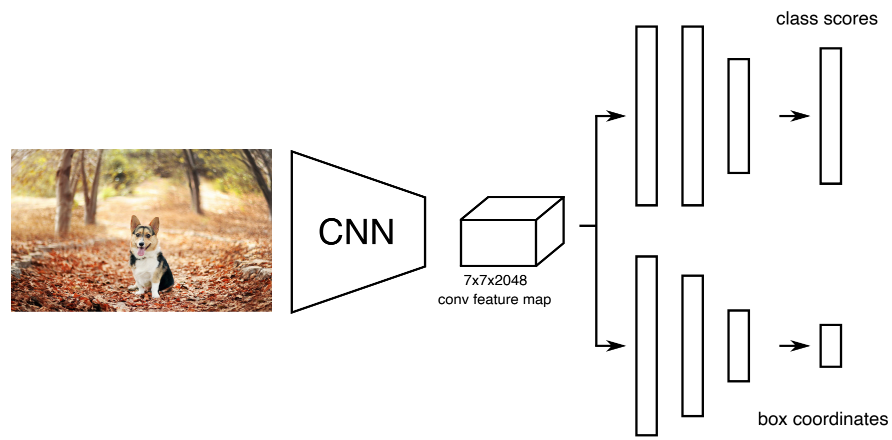
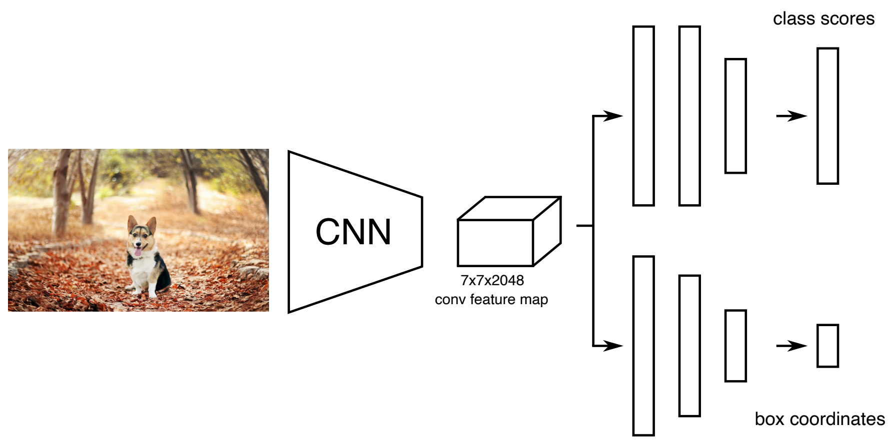


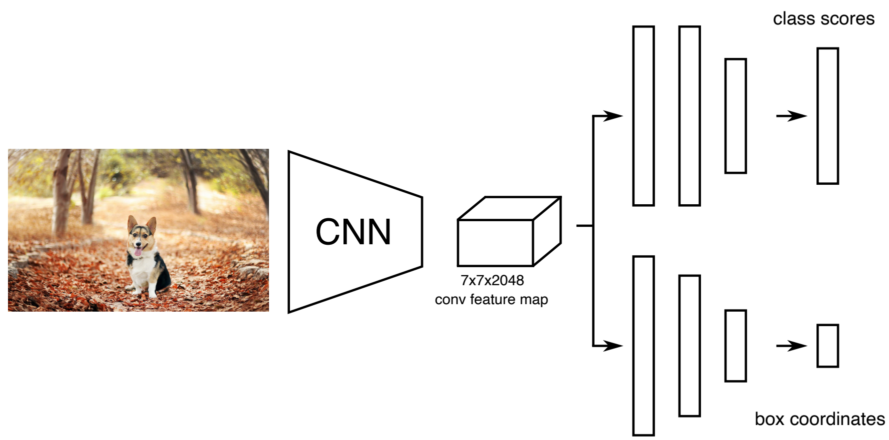
- Use a pre-trained CNN on ImageNet (ex. ResNet)
- The "localisation head" is trained seperately with regression
- Possible end-to-end finetuning of both tasks
- At test time, use both heads

Classification + Localisation



C classes, 4 output dimensions (1 box)

Classification + Localisation



C classes, 4 output dimensions (1 box)

Predict exactly N objects: predict $(N \times 4)$ coordinates and $(N \times K)$ class scores

Object detection

We don't know in advance the number of objects in the image. Object detection relies on *object proposal* and *object classification*

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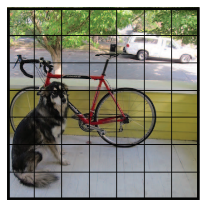
Two main families:

- Single-Stage: A grid in the image where each cell is a proposal (SSD, YOLO, RetinaNet)
- Two-Stage: Region proposal then classification (Faster-RCNN)

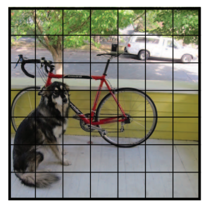
YOLO



S × S grid on input

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

YOLO



S × S grid on input

For each cell of the $S \times S$ predict:

- B **boxes** and **confidence scores** C ($5 \times B$ values) + **classes** c

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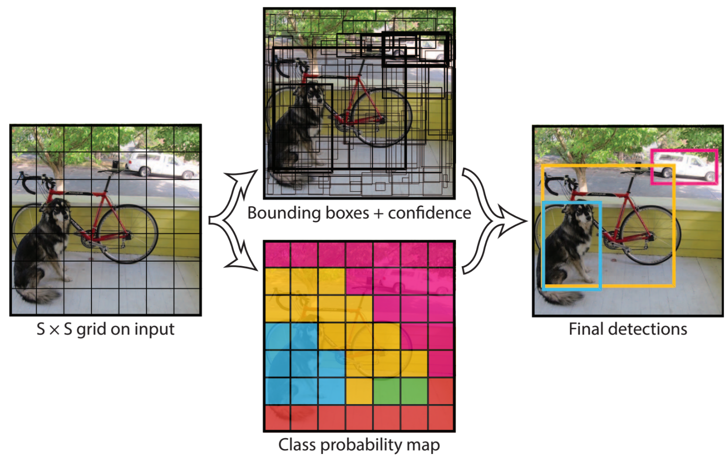
YOLO



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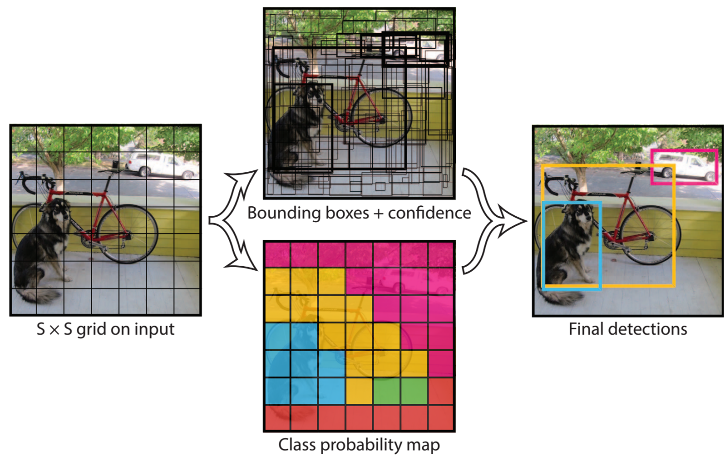

Final detections: $C_j * prob(c) >$ threshold

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YOLO

- After ImageNet pretraining, the whole network is trained end-to-end

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

YOLO

- After ImageNet pretraining, the whole network is trained end-to-end
- The loss is a weighted sum of different regressions

$$
\begin{aligned}
&\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
&+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)
\end{aligned}
$$

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Box Proposals

Instead of having a predefined set of box proposals, find them on the image:

- **Selective Search** - from pixels (not learnt, no longer used)
- **Faster - RCNN** - Region Proposal Network (RPN)

Girshick, Ross, et al. "Fast r-cnn." ICCV 2015

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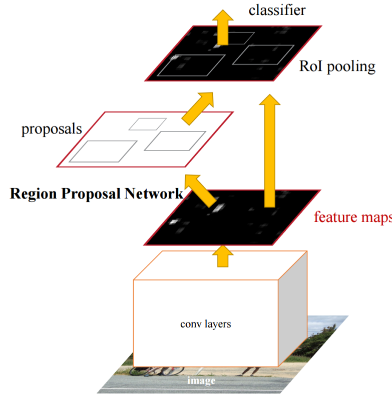
Crop-and-resize operator (**RoI-Pooling**):

- Input: convolutional map + N regions of interest
- Output: tensor of $N \times 7 \times 7 \times$ depth boxes
- Allows to propagate gradient only on interesting regions, and efficient computation

Girshick, Ross, et al. "Fast r-cnn." ICCV 2015

Faster-RCNN



Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." NIPS 2015

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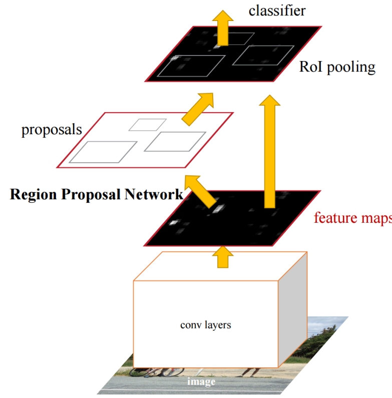

- Train jointly RPN and other head

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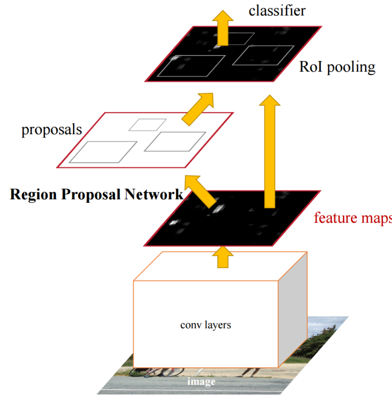

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- 200 box proposals, gradient propagated only in positive boxes

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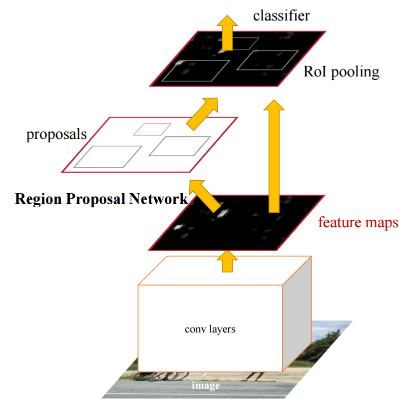

- Train jointly RPN and other head
- 200 box proposals, gradient propagated only in positive boxes
- Region proposal is translation invariant, compared to YOLO

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Measuring performance

method	test size shorter edge/max size	feature pyramid	align	mAP@[0.5:0.95]	AP_s	AP_m	AP_l
R-FCN [17]	600/1000			32.1	12.8	34.9	46.1
Faster R-CNN (2fc)	600/1000			30.3	9.9	32.2	47.4
Deformable [3]	600/1000		√	34.5	14.0	37.7	50.3
G-RMI [13]	600/1000			35.6	-	-	-
FPN [19]	800/1200	√		36.2	18.2	39.0	48.2
Mask R-CNN [7]	800/1200	√	√	38.2	20.1	41.1	50.2
RetinaNet [20]	800/1200	√		37.8	20.2	41.1	49.2
RetinaNet ms-train [20]	800/1200	√		39.1	21.8	42.7	50.2
Light head R-CNN	800/1200		√	**39.5**	21.8	43.0	50.7
Light head R-CNN ms-train	800/1200		√	**40.8**	22.7	44.3	52.8
Light head R-CNN	800/1200	√	√	**41.5**	25.2	45.3	53.1

Measures: mean Average Precision **mAP** at given **IoU** thresholds

Zeming Li et al. Light-Head R-CNN: In Defense of Two-Stage Object Detector 2017

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- AP @0.5 for class "cat": average precision for the class, where $IoU(box^{pred}, box^{true}) > 0.5$

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State-of-the-art

Model	FLOPs	# Params	AP_{val}	$AP_{test\text{-}dev}$
SpineNet-190 (1536) [11]	2076B	176.2M	52.2	52.5
DetectoRS ResNeXt-101-64x4d [43]	—	—	—	55.7†
SpineNet-190 (1280) [11]	1885B	164M	52.6	52.8
SpineNet-190 (1280) w/ self-training [71]	1885B	164M	54.2	54.3
EfficientDet-D7x (1536) [56]	410B	77M	54.4	55.1
YOLOv4-P7 (1536) [60]	—	—	—	55.8†
Cascade Eff-B7 NAS-FPN (1280)	1440B	185M	54.5	54.8
w/ Copy-Paste	1440B	185M	(+1.4) **55.9**	(+1.2) **56.0**
w/ self-training Copy-Paste	1440B	185M	(+2.5) **57.0**	(+2.5) **57.3**

Ghiasi G. et al. Simple Copy-Paste is a Strong Data Augmentation Method for Instance Segmentation, 2020

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- Larger image sizes, larger and better models, better augmented data
- https://paperswithcode.com/sota/object-detection-on-coco

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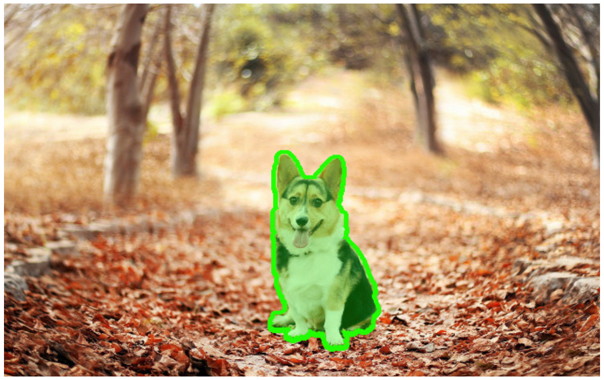
Segmentation

Segmentation

Output a class map for each pixel (here: dog vs background)



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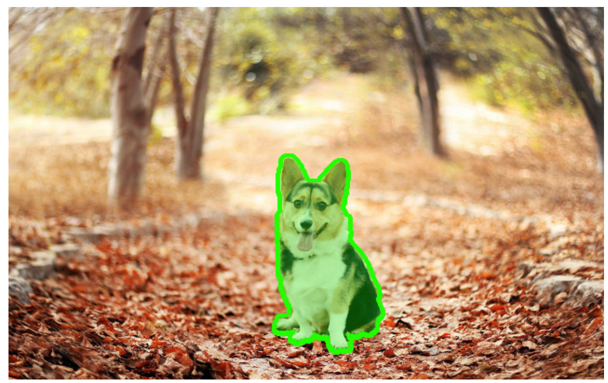

- **Instance segmentation**: specify each object instance as well (two dogs have different instances)

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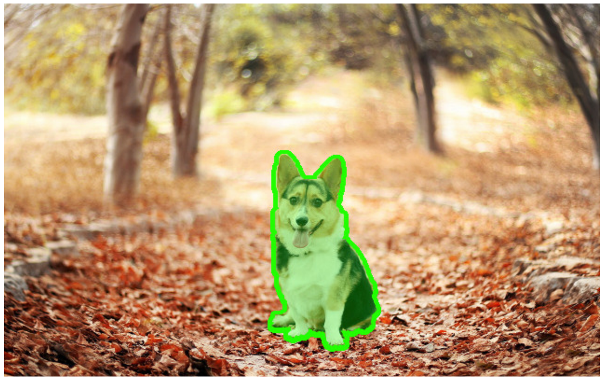
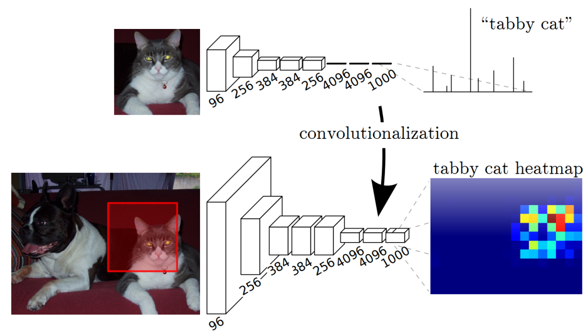


- **Instance segmentation**: specify each object instance as well (two dogs have different instances)
- This can be done through **object detection + segmentation**

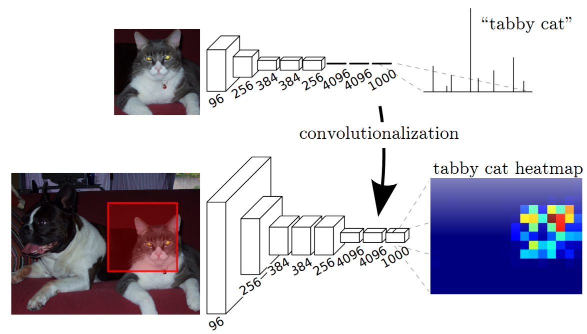
Convolutionize



- Slide the network with an input of $(224, 224)$ over a larger image. Output of varying spatial size

Long, Jonathan, et al. "Fully convolutional networks for semantic segmentation." CVPR 2015

Convolutionize



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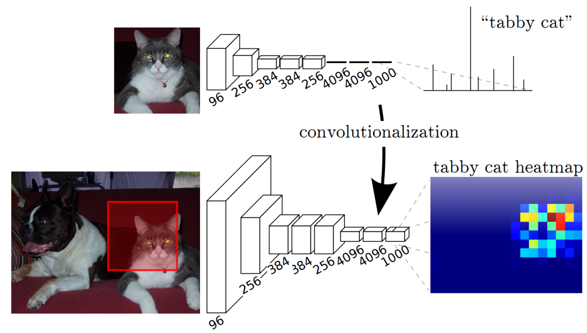

- Slide the network with an input of $(224, 224)$ over a larger image. Output of varying spatial size
- **Convolutionize**: change Dense $(4096, 1000)$ to 1×1 Convolution, with $4096, 1000$ input and output channels
- Gives a coarse **segmentation** (no extra supervision)

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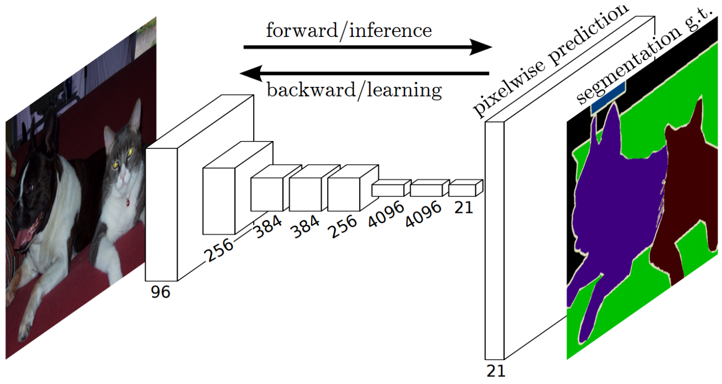
Fully Convolutional Network



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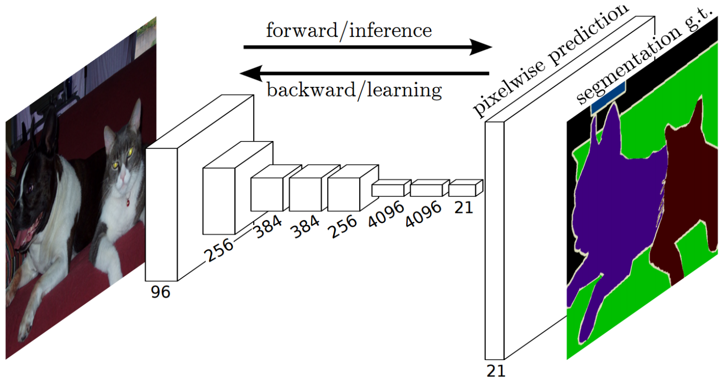

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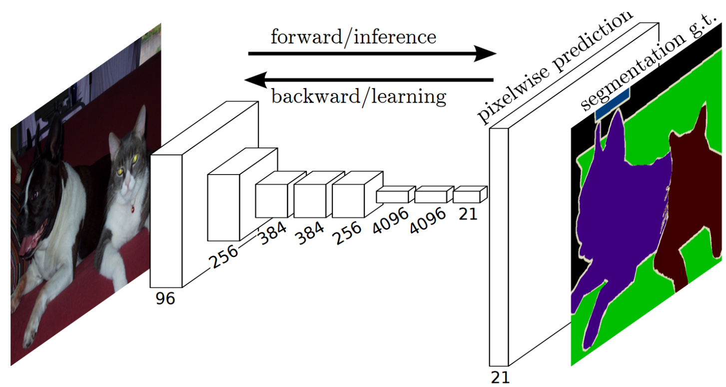

- Predict / backpropagate for every output pixel
- Aggregate maps from several convolutions at different scales for more robust results

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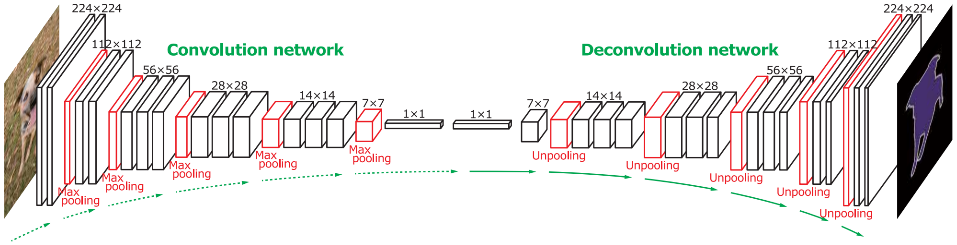
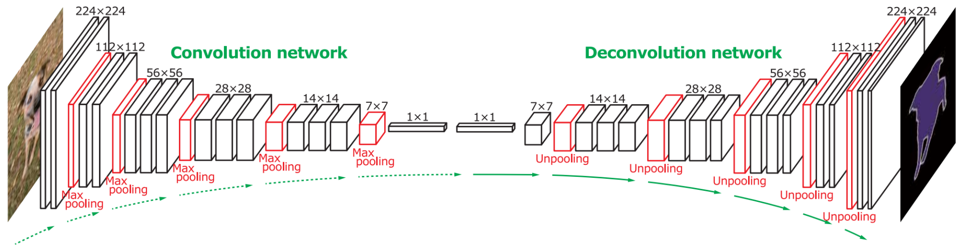
Deconvolution

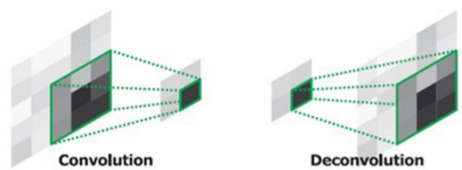


Noh, Hyeonwoo, et al. "Learning deconvolution network for semantic segmentation." ICCV 2015

Deconvolution

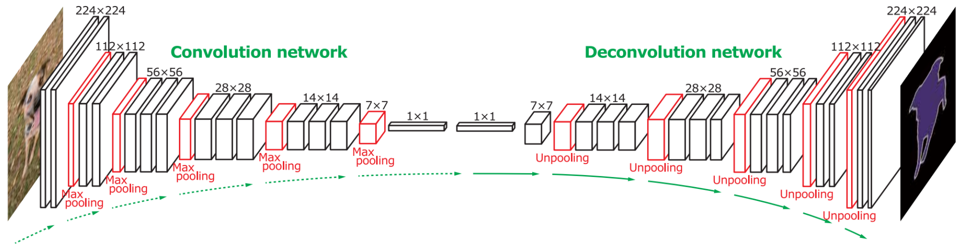


- "Deconvolution": transposed convolutions



Noh, Hyeonwoo, et al. "Learning deconvolution network for semantic segmentation." ICCV 2015

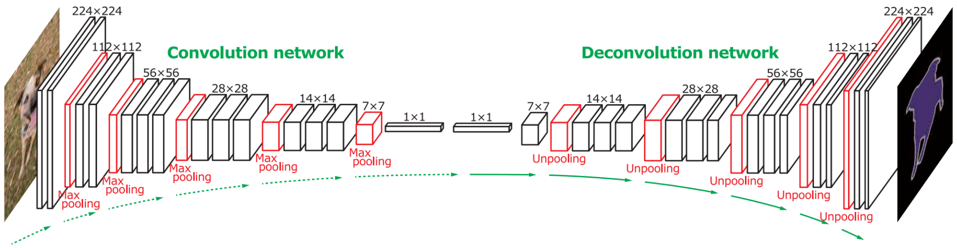
Deconvolution



- **skip connections** between corresponding convolution and deconvolution layers

Noh, Hyeonwoo, et al. "Learning deconvolution network for semantic segmentation." ICCV 2015

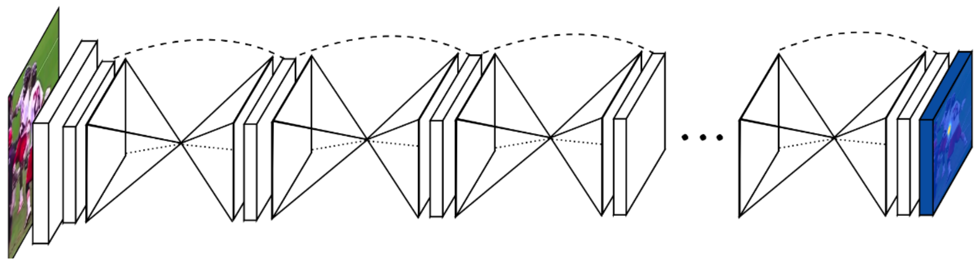
Deconvolution



- **skip connections** between corresponding convolution and deconvolution layers
- **sharper masks** by using precise spatial information (early layers)
- **better object detection** by using semantic information (late layers)

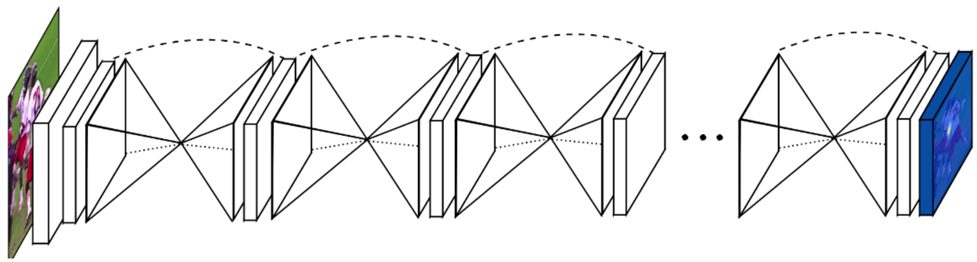
Noh, Hyeonwoo, et al. "Learning deconvolution network for semantic segmentation." ICCV 2015

Hourglass network



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

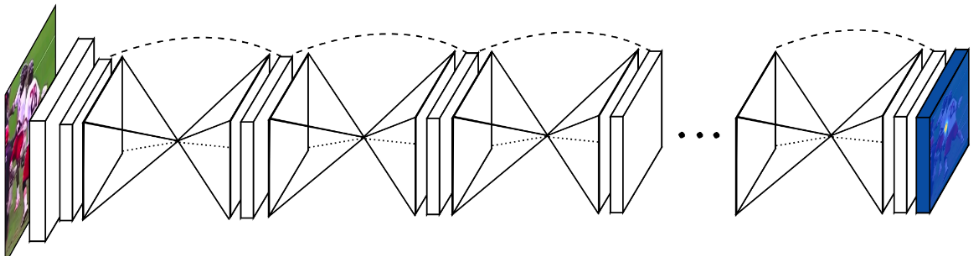
Hourglass network



- U-Net like architectures repeated sequentially

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

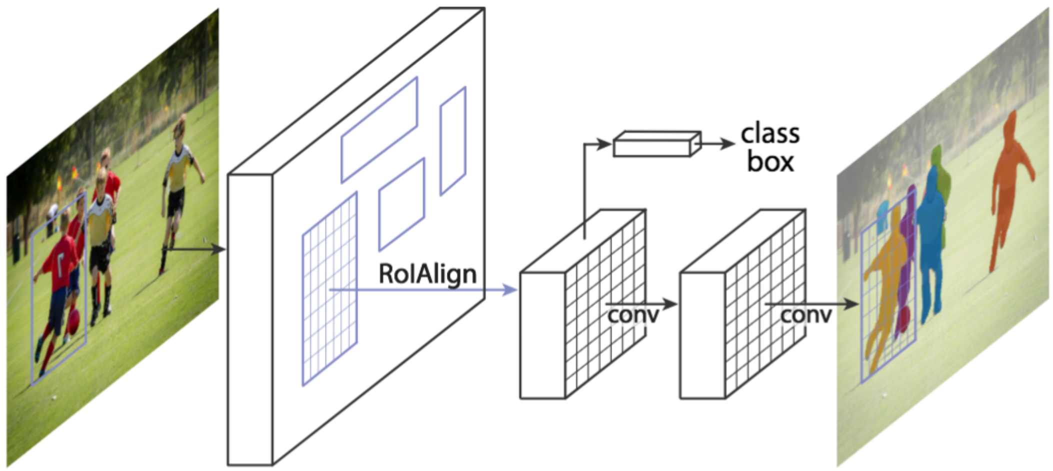
Hourglass network



- U-Net like architectures repeated sequentially
- Each block refines the segmentation for the following
- Each block has a segmentation loss

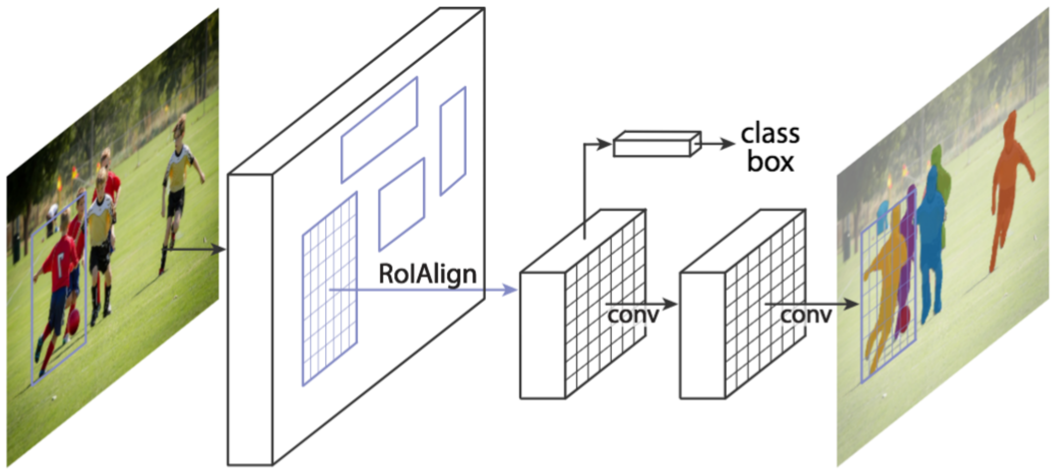
Newell, Alejandro, et al. "Stacked Hourglass Networks for Human Pose Estimation." ECCV 2016

Mask-RCNN



K. He and al. Mask Region-based Convolutional Network (Mask R-CNN) NIPS 2017

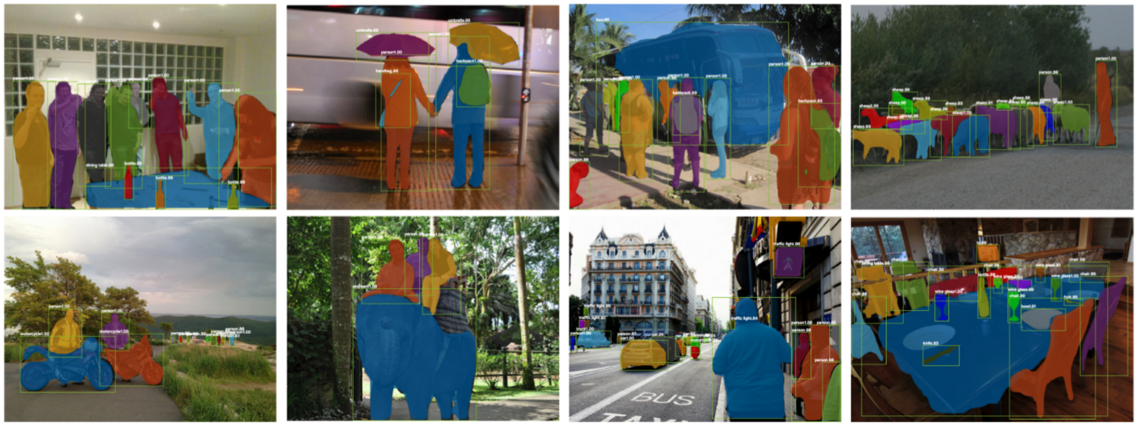
Mask-RCNN



Faster-RCNN architecture with a third, binary mask head

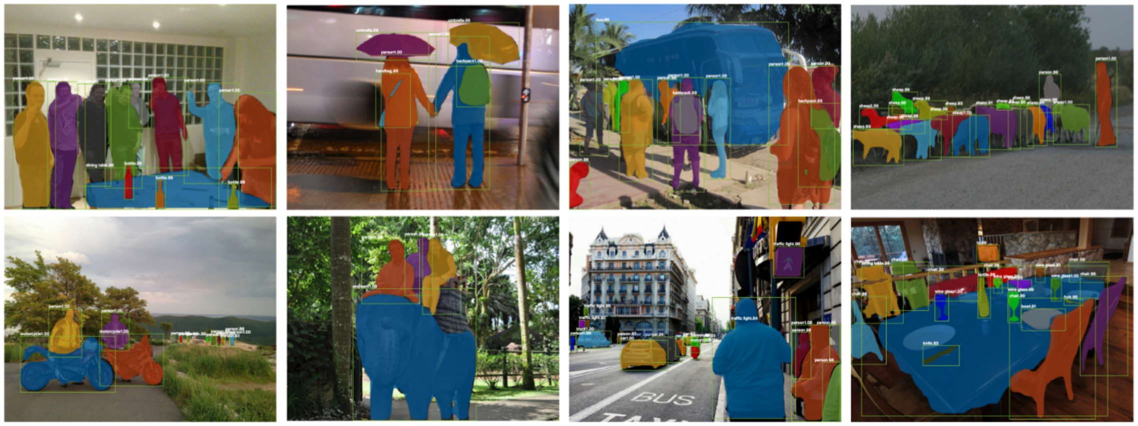
K. He and al. Mask Region-based Convolutional Network (Mask R-CNN) NIPS 2017

Results



K. He and al. Mask Region-based Convolutional Network (Mask R-CNN) NIPS 2017

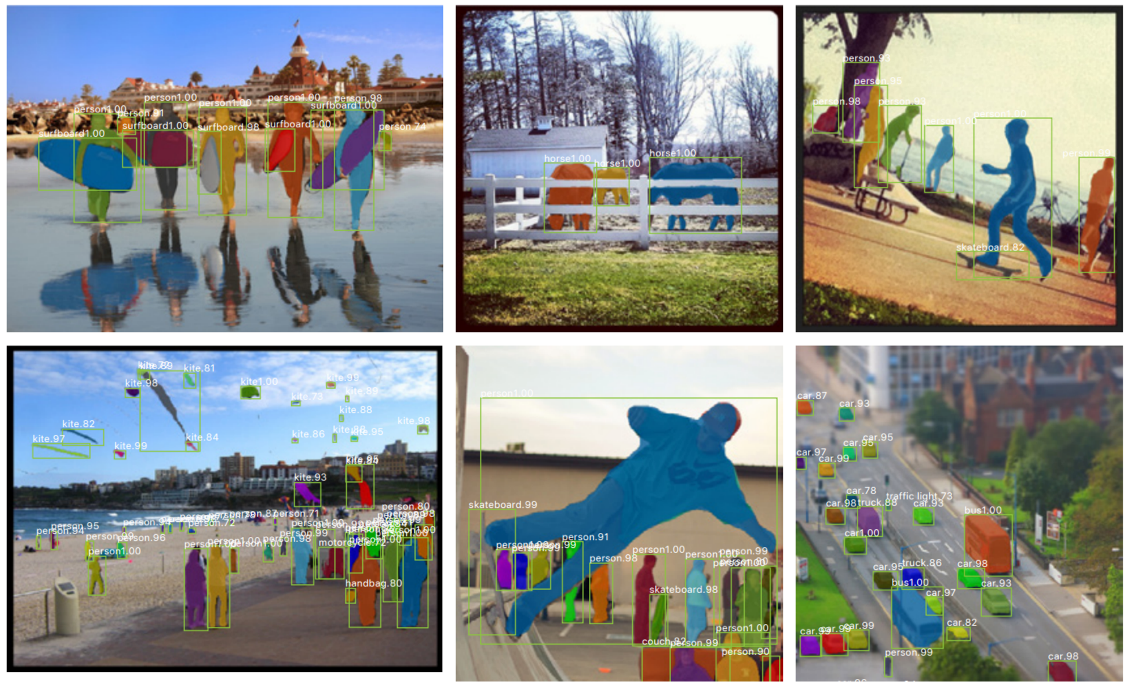
Results



- Mask results are still coarse (low mask resolution)
- Excellent instance generalization

K. He and al. Mask Region-based Convolutional Network (Mask R-CNN) NIPS 2017

Results



He, Kaiming, et al. "Mask r-cnn." Internal Conference on Computer Vision (ICCV), 2017.

State-of-the-art & links

Most benchmarks and recent architectures are reported here:

https://paperswithcode.com/area/computer-vision

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Tensorflow

object detection API

State-of-the-art & links

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Tensorflow

object detection API

Pytorch

Detectron https://github.com/facebookresearch/Detectron

- Mask-RCNN, Retina Net and other architectures
- Focal loss, Feature Pyramid Networks, etc.

Take away NN for Vision

Pre-trained features as a basis

- ImageNet: centered objects, very broad image domain
- 1M+ labels and many different classes resulting in very **general** and **disentangling** representations
- Better Networks (i.e. ResNet vs VGG) have **a huge impact**

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Fine tuning

- Add new layers on top of convolutional or dense layer of CNNs
- **Fine tune** the whole architecture end-to-end
- Make use of a smaller dataset but with richer labels (bounding boxes, masks...)

Next: Lab 5!