Image Analysis

Deep learning-based object detection

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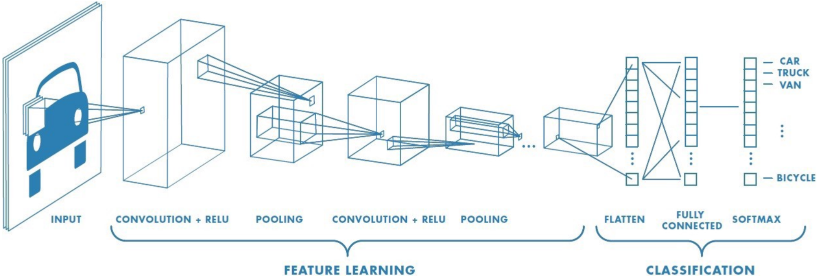
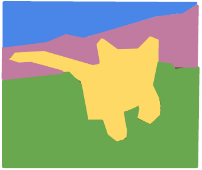
Introduction So far: image classification using CNN



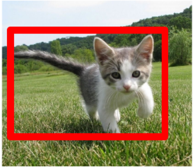
Maybe some remarks? questions?

Other computer vision tasks:

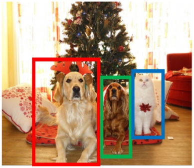
Semantic Segmentation



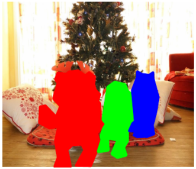
Classification + Localization



Object Detection



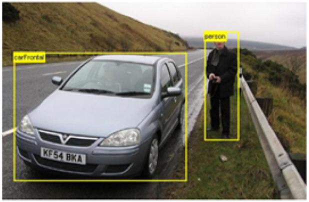
Instance Segmentation

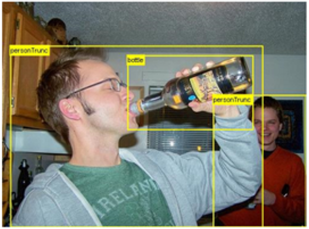


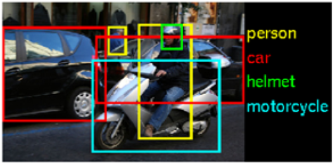
Applications of object detection:

- Computer vision:
  - facial detection and recognition
  - industrial quality check
  - autonomous cars
  - people counting and tracking, etc.
- Remote sensing:
  - wildlife animal detection
  - vehicle detection and counting from space
  - ship detection, etc.
- And many others in medical imaging, robotics, astronomy, etc.

In general: bounding box + class for each object within the image[1]







[1] Zhengxia Zou et al. Object Detection in 20 Years: A Survey

In computer vision[2]

Dataset	train		validation		trainval		test	
	images	objects	images	objects	images	objects	images	objects
VOC-2007	2,501	6,301	2,510	6,307	5,011	12,608	4,952	14,976
VOC-2012	5,717	13,609	5,823	13,841	11,540	27,450	10,991	-
ILSVRC-2014	456,567	478,807	20,121	55,502	476,688	534,309	40,152	-
ILSVRC-2017	456,567	478,807	20,121	55,502	476,688	534,309	65,500	-
MS-COCO-2015	82,783	604,907	40,504	291,875	123,287	896,782	81,434	-
MS-COCO-2018	118,287	860,001	5,000	36,781	123,287	896,782	40,670	-
OID-2018	1,743,042	14,610,229	41,620	204,621	1,784,662	14,814,850	125,436	625,282

[2] Zhengxia Zou et al. Object Detection in 20 Years: A Survey

In remote sensing[2]

Dataset	Year	Description	#Cites
TAS [85]	2008	Consists of 30 images of 729x636 pixels from Google Earth and ~1,300 vehicles. url: http://ai.stanford.edu/~gaheitz/Research/TAS/	419
OIRDS [86]	2009	Consists for 900 images (0.08-0.3m/pixel) captured by aircraft-mounted camera and 1,800 annotated vehicle targets. url: https://sourceforge.net/projects/oirds/	32
DLR3K [87]	2013	The most frequently used datasets for small vehicle detection. Consists of 9,300 cars and 160 trucks. url: https://www.dlr.de/eoc/en/desktopdefault.aspx/tabid-5431/9230_read-42467/	68
UCAS-AOD [88]	2015	Consists of ~900 Google Earth images, ~2,800 vehicles and ~3,200 airplanes. url: http://www.ucassdl.cn/resource.asp	19
VeDAI [89]	2016	Consists of ~1,200 images (0.1-0.25m/pixel), ~3,600 targets of 9 classes. Designed for detecting small target in remote sensing images. url: https://downloads.greyc.fr/vedai/	65
NWPU-VHR10 [90]	2016	The most frequently used remote sensing detection dataset in recent years. Consists of ~800 images (0.08-2.0m/pixel) and ~3,800 remote sensing targets of ten classes (e.g., airplanes, ships, baseball diamonds, tennis courts, etc). url: http://jiong.tea.ac.cn/people/JunweiHan/NWPUVHR10dataset.html	204
LEVIR [91]	2018	Consists of ~22,000 Google Earth images and ~10,000 independently labeled targets (airplane, ship, oil-pot). url: https://pan.baidu.com/s/1geTwAVD	15
DOTA [92]	2018	The first remote sensing detection dataset to incorporate rotated bounding boxes. Consists of ~2,800 Google Earth images and ~200,000 instances of 15 classes. url: https://captain-whu.github.io/DOTA/dataset.html	32
xView [93]	2018	The largest remote sensing detection dataset so far. Consists of ~1,000,000 remote sensing targets of 60 classes (0.3m/pixel), covering1,415km^2 of land area. url: http://xviewdataset.org	10

[2] Zhengxia Zou et al. Object Detection in 20 Years: A Survey

How to evaluate the predicted bounding boxes ?

(a) Intersection over Union (IoU)

(b) IoU > 0.5 (accept)

(c) IoU < 0.5 (reject)

What could be other criteria to evaluate the predicted bounding boxes?

Non Maximum Suppression: If predicted bounding boxes overlap, only consider the most confident.

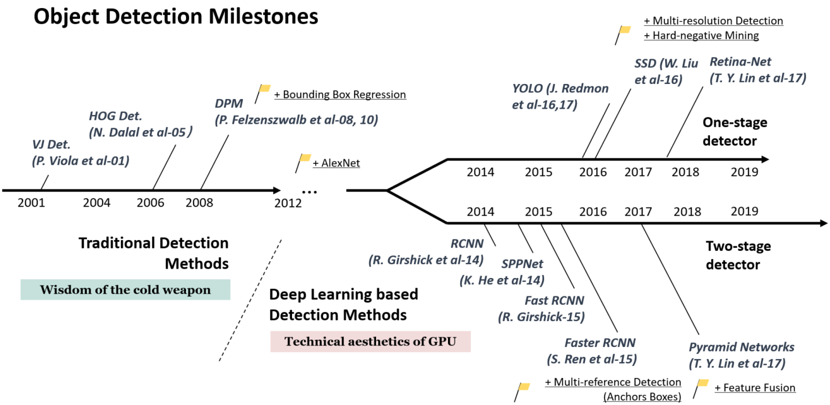
Bounding Box Regression: Regression used to find bounding box parameters (usually the box's center, width and height)

Example Loss Function

$$\sum_{i\ in\ I} [(\boxed{x_i} - \boxed{\hat{x}_i})^2 + (\boxed{y_i} - \boxed{\hat{y}_i})^2 + (\boxed{\sqrt{w_i}} - \boxed{\sqrt{\hat{w}_i}})^2 + (\boxed{\sqrt{h_i}} - \boxed{\sqrt{\hat{h}_i}})^2]$$

I is the set of all matching bounding boxes (Highest IoU with ground truth)

A road map of object detection in computer vision[3]



[3] Zhengxia Zou et al. Object Detection in 20 Years: A Survey

Before deep learning: traditional detection methods

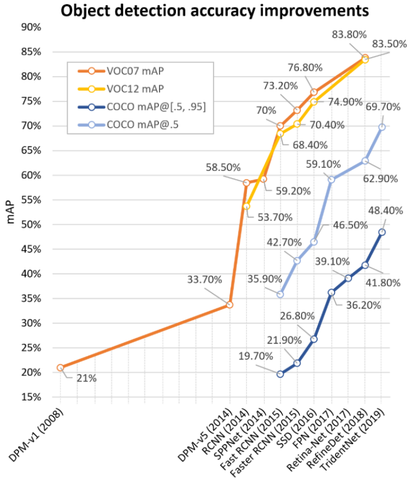
- Hand-crafted feature + classifier
- Features: HOG (Histogram of Gradients), LBP (Local Binary Pattern), textural features, etc.
- Classifier: SVM, Random Forest, etc.

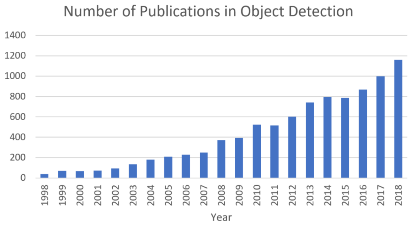
Modern deep-learning object detection[3]

- Two-stage detectors
- One-stage detectors

[3] http://zoey4ai.com/2018/05/12/deep-learning-object-detection/

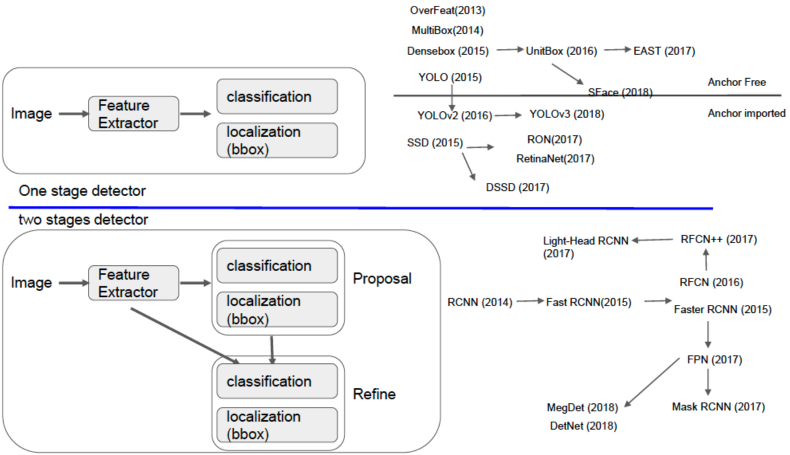
The evolution of deep-learning based object detection[3]





[3] Zhengxia Zou et al. Object Detection in 20 Years: A Survey

One-stage vs Two-stage detectors [3]



[3] Image source: Gang Yu, An Introduction to Modern Object Detection

Reading exercise:

- One-stage vs two-stage object detectors:
  `http://zoey4ai.com/2018/05/12/deep-learning-object-detection/`
- Zhengxia Zou et al. Object Detection in 20 Years: A Survey
  `https://arxiv.org/pdf/1905.05055.pdf`
  $\Rightarrow$ Reading the first 4 pages: Section 1 + Section 2.1

Answer the following questions:

1) What are the differences between one-stage and two-stage object detectors ?

2) Which one is better in which case?

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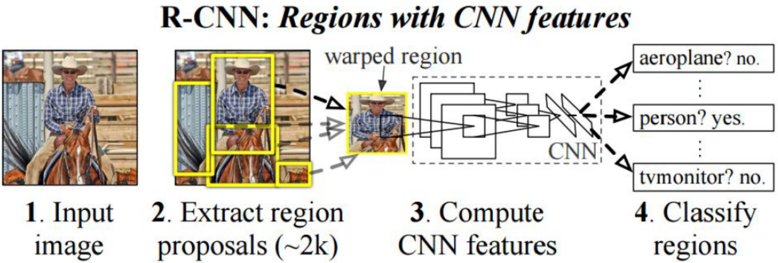
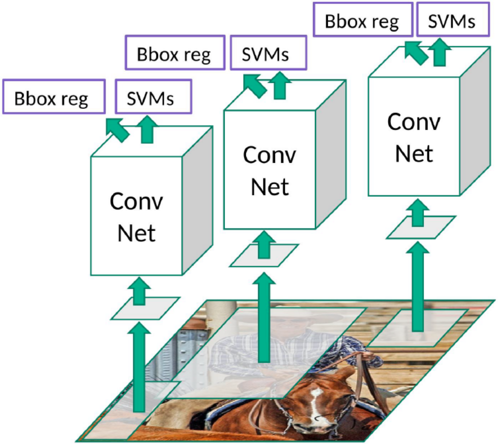
R-CNN: Region proposal + CNN [4]

- Use **Selective Search** to come up with regional proposal
- Then classification + bounding box regression for each proposal
- First object detection method using CNN



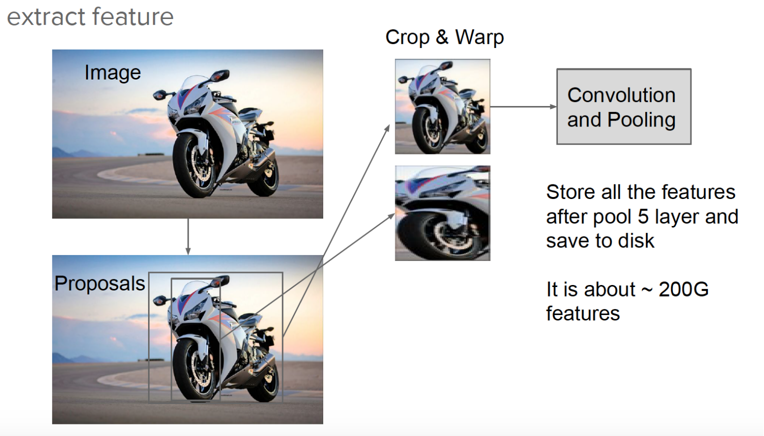
[4] Ross Girshick et al., Rich feature hierarchies for accurate object detection and semantic segmentation, CVPR 2014.

R-CNN: Region proposal + CNN [4]



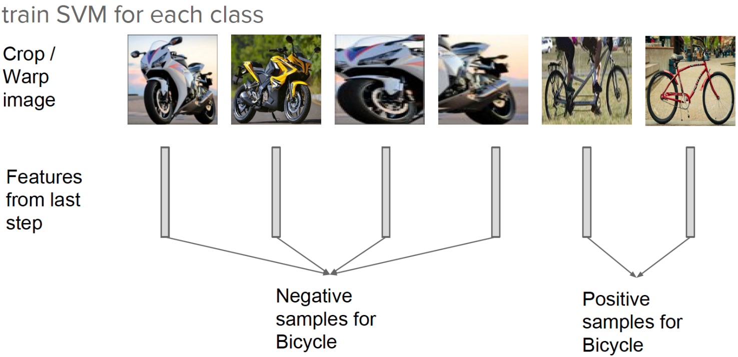
[4] Ross Girshick et al., Rich feature hierarchies for accurate object detection and semantic segmentation, CVPR 2014.

Example: [5]



[5] Sihao Liang, Jiajun Lu and Kevin Perkins, Lecture on Object detection.

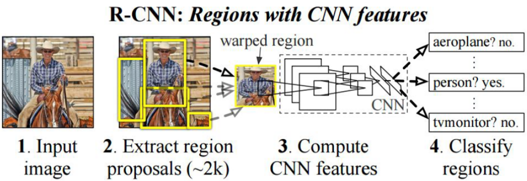
Example: [5]



[5] Sihao Liang, Jiajun Lu and Kevin Perkins, Lecture on Object detection.

R-CNN: Summary [6]

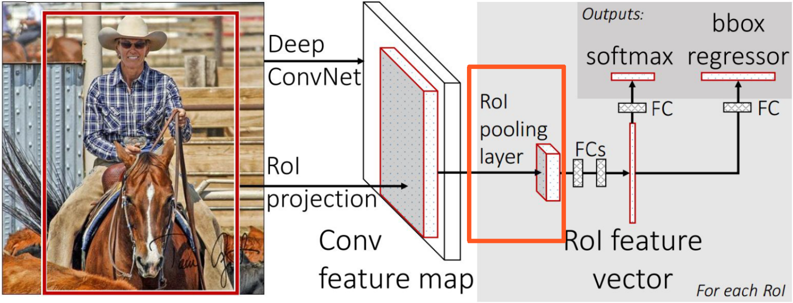
- Simple pipeline!
- Use the CNN as a feature extractor
- Warp cropped regions to make them “square"
- Run an SVM (one per category) on the deep features (stocked on disk ⇒ very heavy!!!)
- Accuracy ☺ but very slow ☹
- Not end-to-end ☹



[6] Ross Girshick et al., Rich feature hierarchies for accurate object detection and semantic segmentation, CVPR 2014.

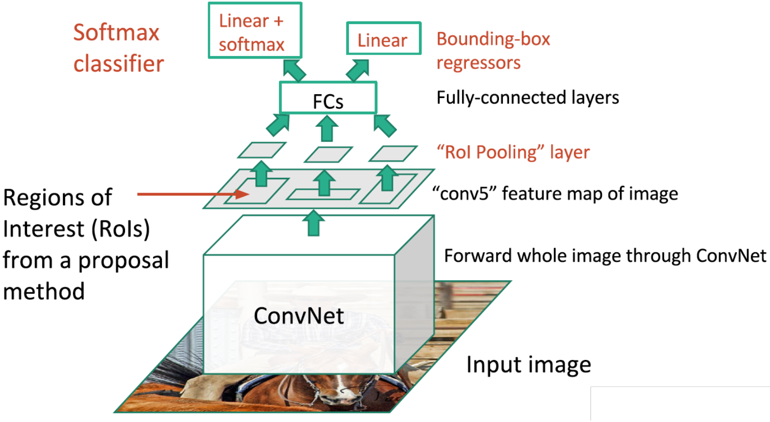
Fast R-CNN: architecture [7]

- **Share convolution layers** for proposals from the same image
- Introduce the **ROI Pooling**
- Faster and more accurate than R-CNN



[7] Ross Girshick et al. Fast RCNN, ICCV 2015.

Fast R-CNN: architecture [7]



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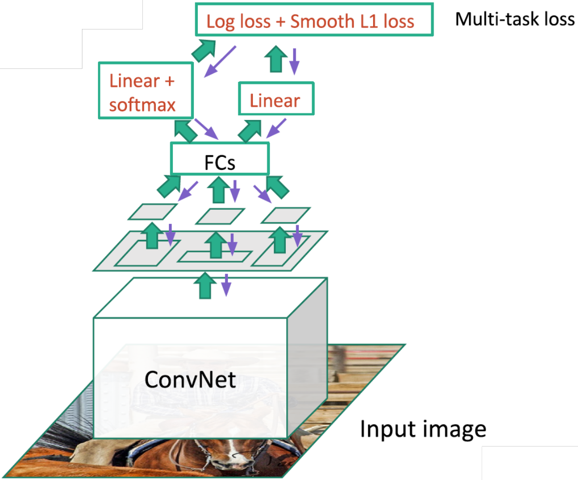
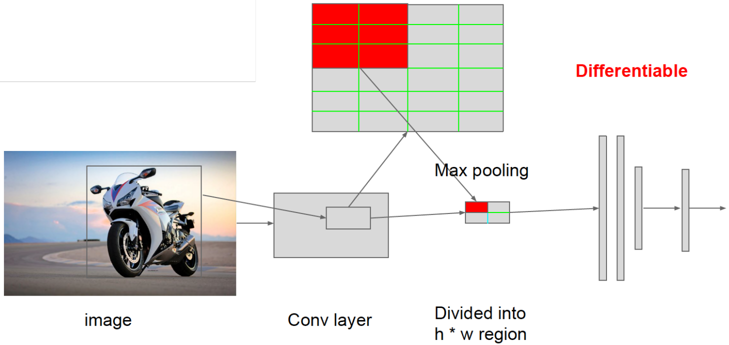


[7] Ross Girshick et al. Fast RCNN, ICCV 2015.

Explanation: [8]

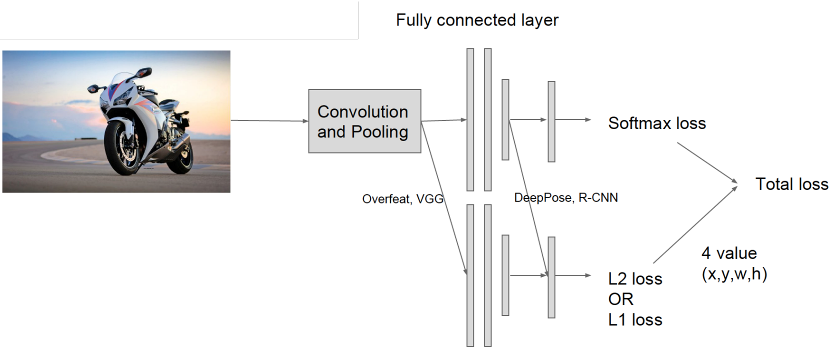
ROI Pooling



[8] Sihao Liang, Jiajun Lu and Kevin Perkins, Lecture on Object detection.

Explanation: [8]

Bbox regressor

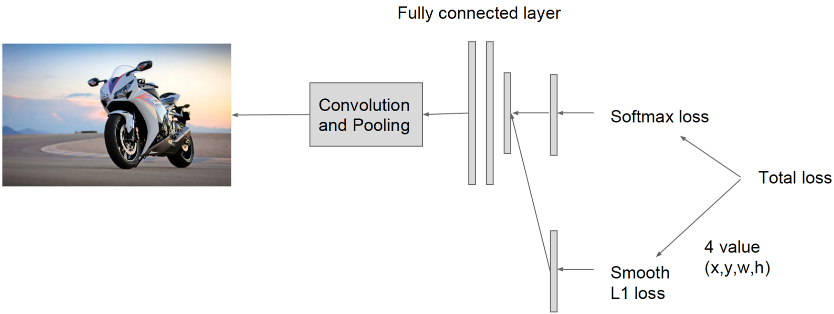


[8] Sihao Liang, Jiajun Lu and Kevin Perkins, Lecture on Object detection.

Two-stage detectors Fast R-CNN

Explanation: [8]

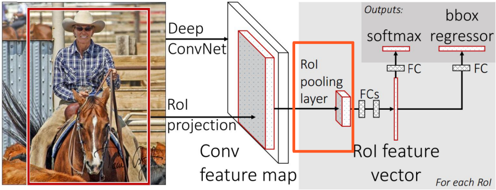
Bbox regressor



[8] Sihao Liang, Jiajun Lu and Kevin Perkins, Lecture on Object detection.

Fast R-CNN: Summary [9]

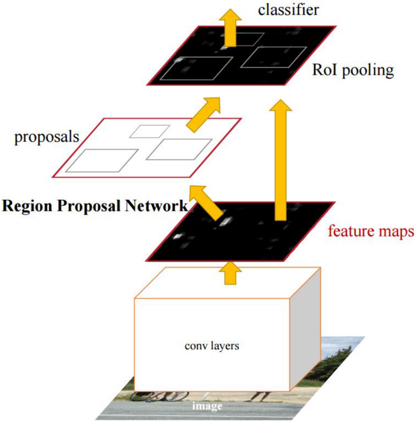
- Do not compute forward propagate from scratch for each box
- Compute feature maps once and reuse the convolutions for different boxes
- New: ROI pooling
- End-to-end training ☺
- More accuracy and must faster (25x) than R-CNN ☺
- External box proposals needed ☹



[9] Ross Girshick et al. Fast RCNN, ICCV 2015.

Faster R-CNN: architecture [10]

- Don't need to have external regional proposals (which is the bottleneck)
- RPN - Regional Proposal Network



[10] Shaoqing Ren et al., Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NeurIPS'15.

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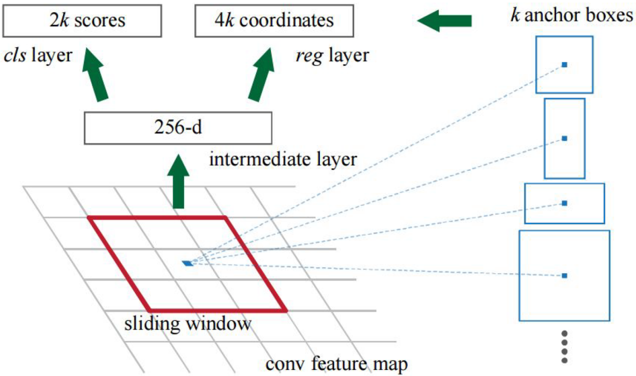

[10] Shaoqing Ren et al., Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NeurIPS’15.

Faster R-CNN: architecture [10]

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	Faster R-CNN	Fast R-CNN	R-CNN
Test time/image With proposal	0.2S	2s	50s
-test speedup	250x	25x	1x
mAP	66.9	66.9	66

(Training on PASCAL VOC 2007 dataset)

[10] Shaoqing Ren et al., Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks, NeurIPS’15.

Other SOTA two-stage detectors

- R-FCN: Object Detection via Region-based fully convolutional networks (NeurIPS 2016)
- FPN: Feature pyramid networks for object detection (CVPR 2017)
  $\Rightarrow$ great performance for detecting objects with a wide variety of scales

Remarks

- Faster R-CNN $\Rightarrow$ most exploited in the literature
- FPN $\Rightarrow$ a basic building block of many latest detectors
- **Faster R-CNN + FPN** $\Rightarrow$ an excellent choice to work on two-stage object detector for your applications !

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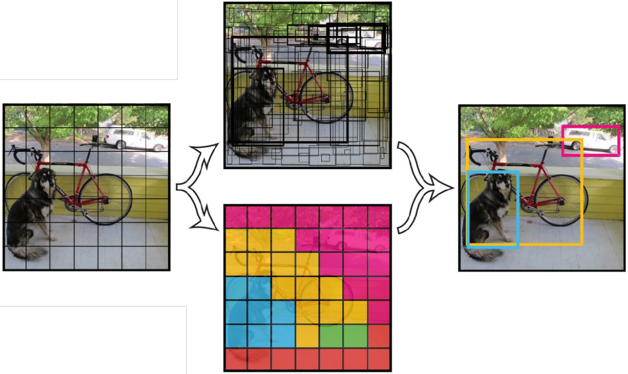
One-stage detectors

Problems with two-stage detectors

- Complex Pipeline
- Hard to optimize each component
- Main: **Slow** (Cannot run in real time)

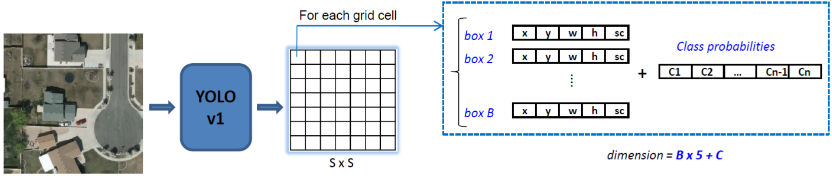
YOLO: You Only Look Once [11]

- Consider detection a regression problem
- Use a single CNN
- Runs once on entire image ⇒ Very Fast!



[11] Joseph Redmon et al., You only look once: Unified, real-time object detection, CVPR 2016.

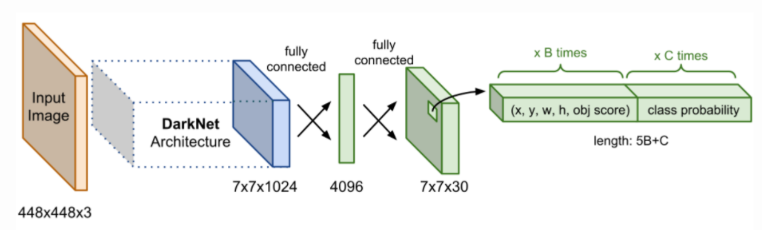
YOLO: You Only Look Once [11]

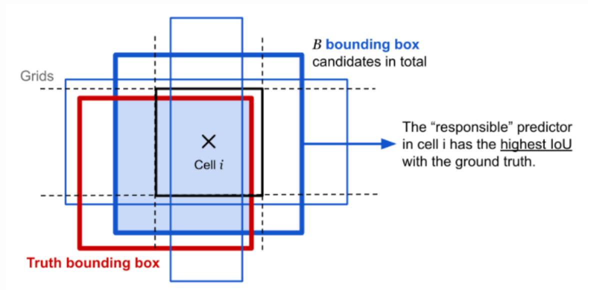


In YOLOv1, the output is a tensor of dimension $(S, S, B \times 5 + C)$ with (S, S) the size of the grid, B the number of predicted boxes for each cell and C the number of classes. By default, $S = 7, B = 2$ and $C = 20$ for the PASCAL VOC dataset. For an input image of size 448×448 pixels, the output is a tensor of size $7 \times 7 \times 30$.

[11] Joseph Redmon et al., You only look once: Unified, real-time object detection, CVPR 2016.

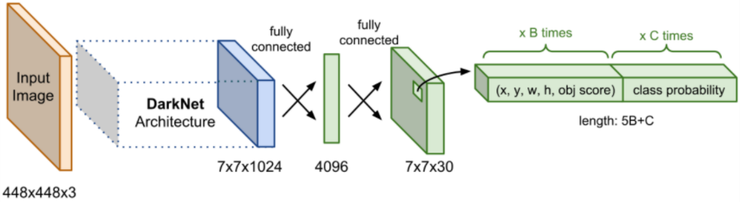
YOLO: You Only Look Once [11] Let's take a closer look!





[11] Joseph Redmon et al., You only look once: Unified, real-time object detection, CVPR 2016.

YOLO: You Only Look Once [11] And the loss function!



$$\mathcal{L}_{\text{loc}} = \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2]$$

$$\mathcal{L}_{\text{cls}} = \sum_{i=0}^{S^2} \sum_{j=0}^{B} \big(\mathbb{1}_{ij}^{\text{obj}} + \lambda_{\text{noobj}}(1 - \mathbb{1}_{ij}^{\text{obj}})\big)(C_{ij} - \hat{C}_{ij})^2 + \sum_{i=0}^{S^2} \sum_{c \in \mathcal{C}} \mathbb{1}_i^{\text{obj}} (p_i(c) - \hat{p}_i(c))^2$$

$$\boxed{\mathcal{L} = \mathcal{L}_{\text{loc}} + \mathcal{L}_{\text{cls}}}$$

[11] Joseph Redmon et al., You only look once: Unified, real-time object detection, CVPR 2016.

YOLO: Very fast but many limitations

- Struggles with small objects
- Struggles with unusual aspect ratios
- Poor localization

	Yolo	Faster R-CNN (VGG-16)
mAP	63.4	73.2
FPS	45	7

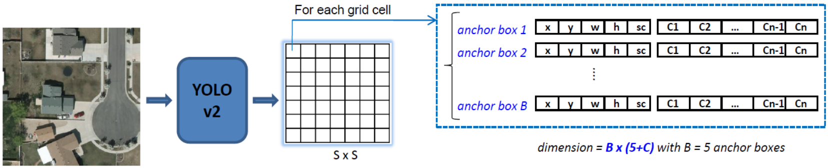
Trained on Pascal VOC 2007 + 2012 dataset

YOLO9000: better, faster, stronger [12]

	YOLO								YOLOv2
batch norm?		✓	✓	✓	✓	✓	✓	✓	✓
hi-res classifier?			✓	✓	✓	✓	✓	✓	✓
convolutional?				✓	✓	✓	✓	✓	✓
anchor boxes?				✓	✓				
new network?					✓	✓	✓	✓	✓
dimension priors?						✓	✓	✓	✓
location prediction?						✓	✓	✓	✓
passthrough?							✓	✓	✓
multi-scale?								✓	✓
hi-res detector?									✓
VOC2007 mAP	63.4	65.8	69.5	69.2	69.6	74.4	75.4	76.8	**78.6**

[12] Joseph Redmon et al., YOLO9000: better, faster, stronger, CVPR 2017.

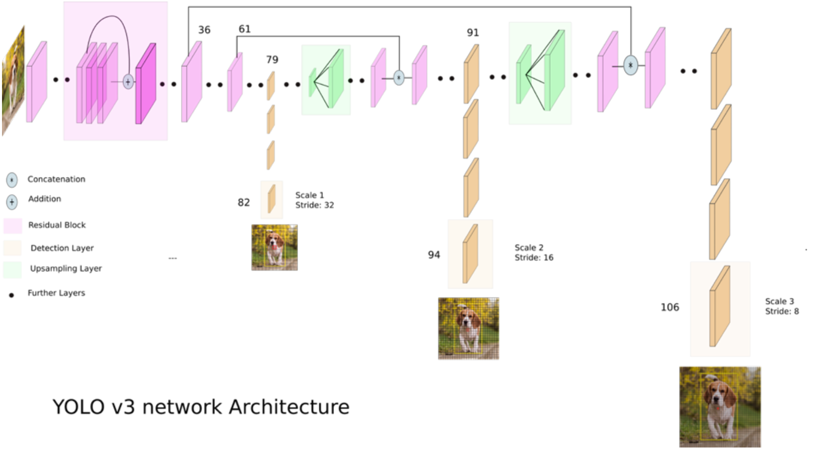
YOLO9000: better, faster, stronger [12]



In YOLOv2, the output is a tensor of dimension $(S, S, B \times (5 + C))$. The difference is that the class probabilities are calculated for each anchor box. By default, $S = 13, B = 5$ anchor boxes and $C = 20$ for the PASCAL VOC dataset. For an input image of size 416×416 pixels, the output is a tensor of size $13 \times 13 \times 125$.

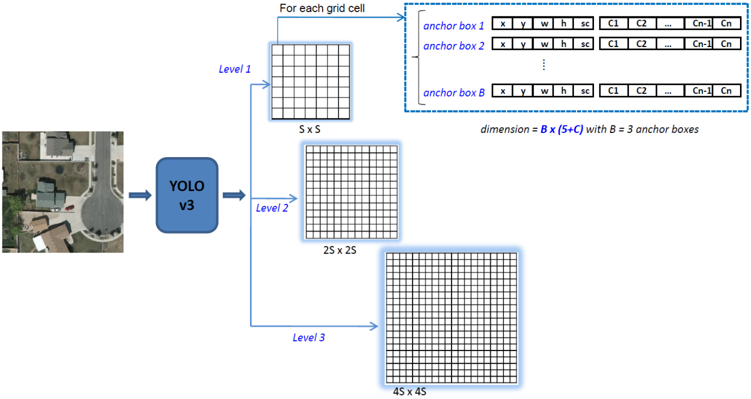
[12] Joseph Redmon et al., YOLO9000: better, faster, stronger, CVPR 2017.

YOLOv3: multi-level detection [13]



[13] Joseph Redmon et al., Yolov3: An incremental improvement, Arxiv 2018.

YOLOv3: multi-level detection [13]



In YOLOv3, the output consists of 3 tensors of dimension $(S, S, B \times (5 + C))$, $(2S, 2S, B \times (5 + C))$ and $(4S, 4S, B \times (5 + C))$ which correspond to the 3 detection levels (scales). By default, $S = 13, B = 3$ anchor boxes and $C = 80$ for the COCO dataset. For an input image of size 416×416 pixels, the outputs are three tensors of size $13 \times 13 \times 255$, $26 \times 26 \times 255$ and $52 \times 52 \times 255$.

[13] Joseph Redmon et al., Yolov3: An incremental improvement, Arxiv 2018.

Other SOTA one-stage detectors

- SSD: Single shot multibox detector (ECCV 2016) and its variants!
- RetinaNet (ICCV 2017): focal loss
- EfficientDet (CVPR 2020)
- YOLOv4: Optimal Speed and Accuracy of Object Detection, Arxiv 2020.

Your remarks ???

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Object detection in remote sensing

Reading exercise:

- Object detection in optical remote sensing images: A survey and a new benchmark
  `https://doi.org/10.1016/j.isprsjprs.2019.11.023`

Answer the following questions:

1) What are the main challenges in detecting objects within remote sensing images ?

2) If we want to detect objects with known size in fixed spatial resolution satellite image (i.e. car detection and counting), is one-stage or two-stage detection approach more relevant?

References I

Books & articles:

1. Zhengxia Zou et al. **Object Detection in 20 Years: A Survey.** Arxiv, 2020.
2. Liu, Li, et al. **Deep learning for generic object detection: A survey.** International journal of computer vision 128.2 (2020): 261-318.
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Courses:

1. Lecture 11: Detection and Segmentation, Fei-Fei Li, Justin Johnson & Serena Yeung
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2. Lecture 07: Object Detection, Sihao Liang, Jiajun Lu & Kevin Perkins
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3. Lecture 6: Convnets for object detection and segmentation, Deep Learning at UvA
`https://uvadlc.github.io/lectures/feb2016/`