TECHNISCHE UNIVERSITÄT
CHEMNITZ

Neurocomputing

Object detection

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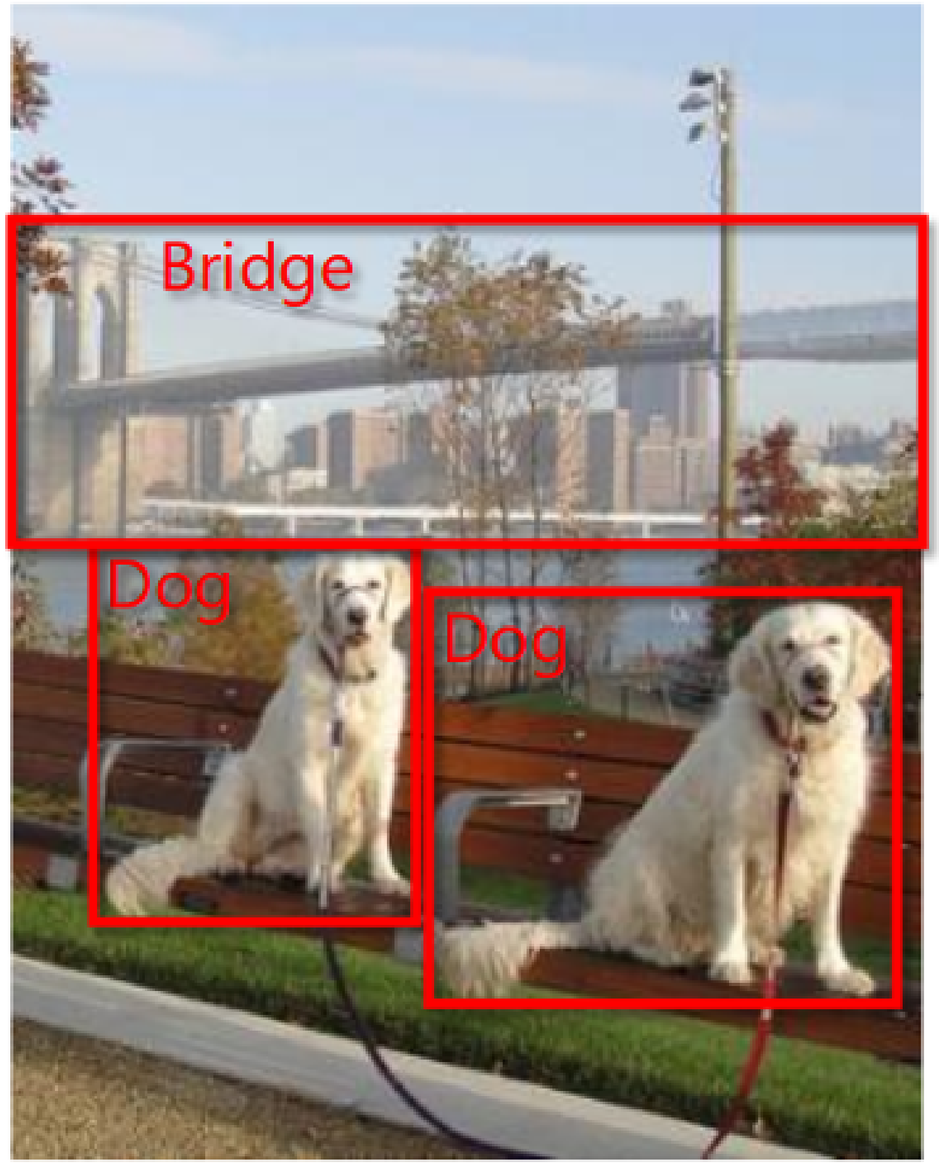
https://tu-chemnitz.de/informatik/KI/edu/neurocomputing

Object recognition vs. object detection

Classification, easy these days

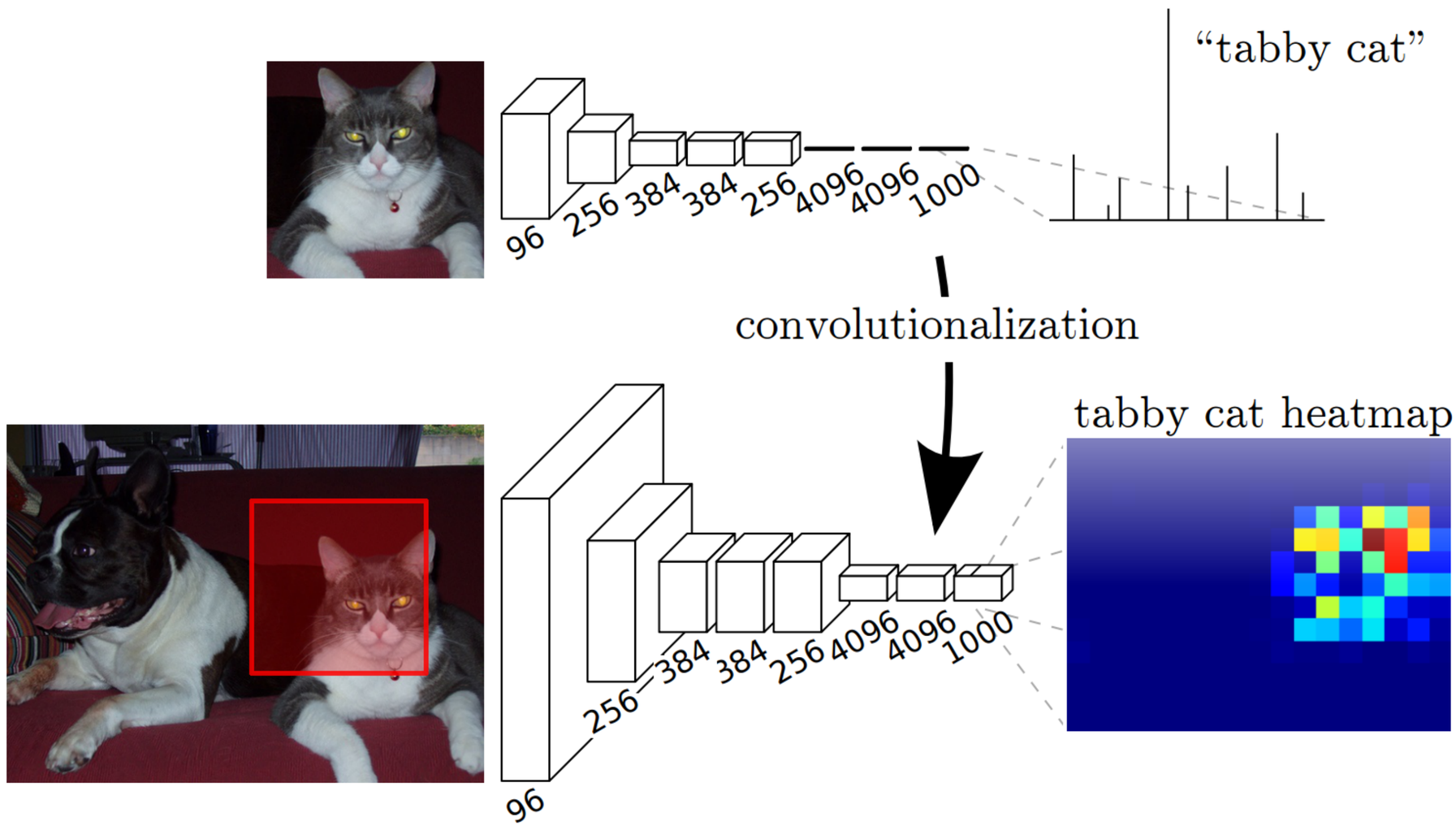


Object detection, still a lot harder

Source: https://blog.athelas.com/a-brief-history-of-cnns-in-image-segmentation-from-r-cnn-to-mask-r-cnn-34ea83205de4

Object detection with heatmaps

- A naive and very expensive method is to use a trained CNN as a high-level filter.
- The CNN is trained on small images and convolved on bigger images.
- The output is a heatmap of the probability that a particular object is present.

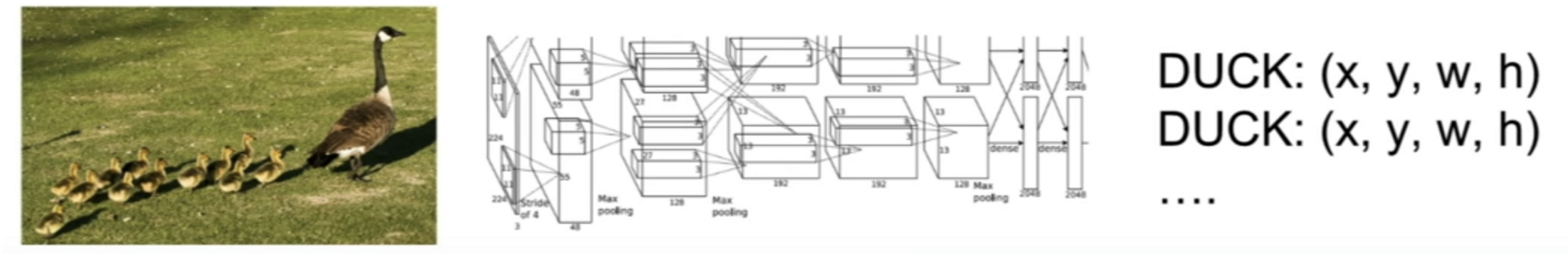


Source: https://blog.athelas.com/a-brief-history-of-cnns-in-image-segmentation-from-r-cnn-to-mask-r-cnn-34ea83205de4

PASCAL Visual Object Classes Challenge

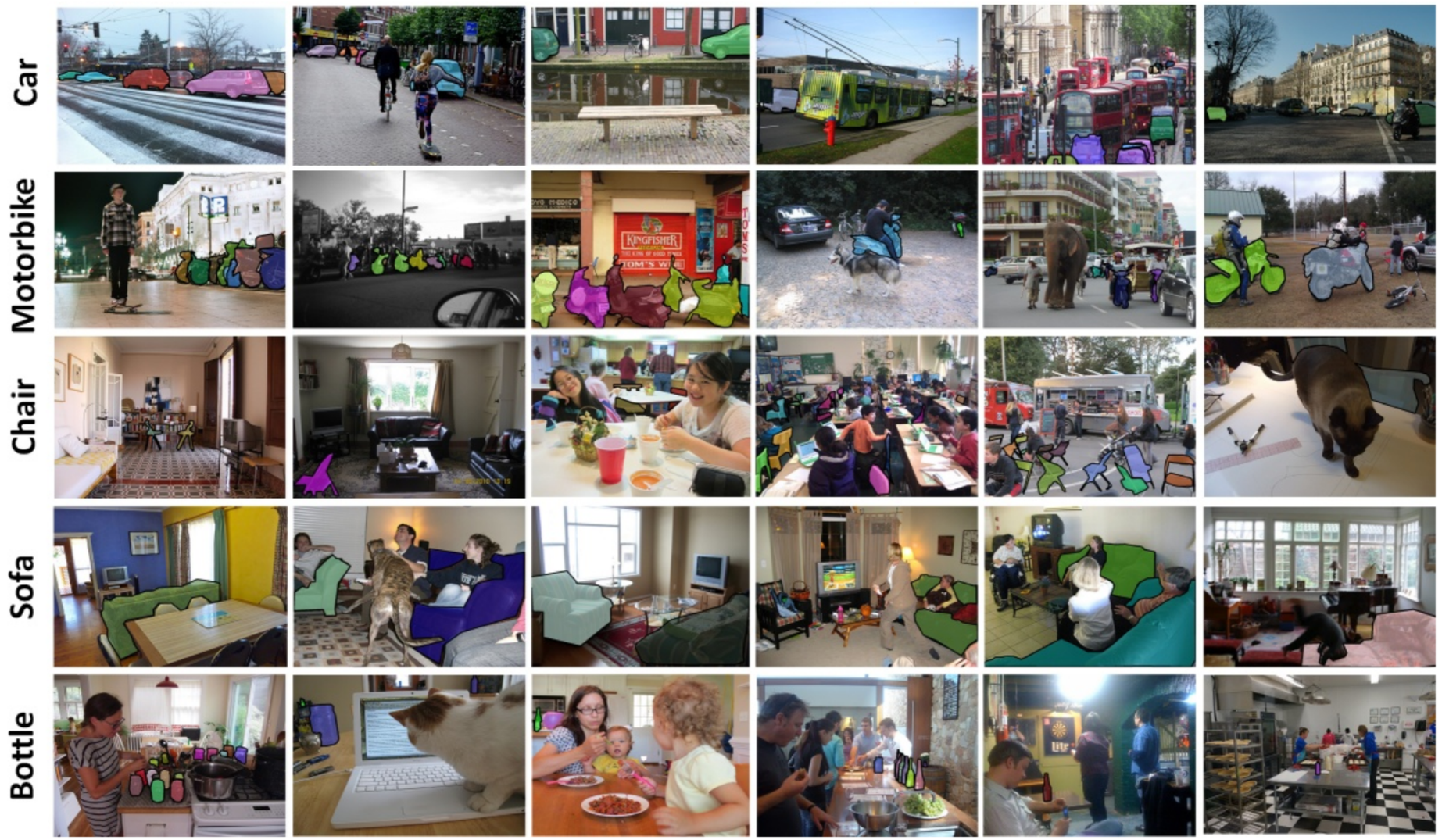
- The main dataset for object detection is the **PASCAL** Visual Object Classes Challenge:
  - 20 classes
  - ~10K images
  - ~25K annotated objects
- It is both a:
  - **Classification** problem, as one has to recognize an object.
  - **Regression** problem, as one has to predict the coordinates (x, y, w, h) of the bounding box.

Source: http://host.robots.ox.ac.uk/pascal/VOC/voc2008/



Source: https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e

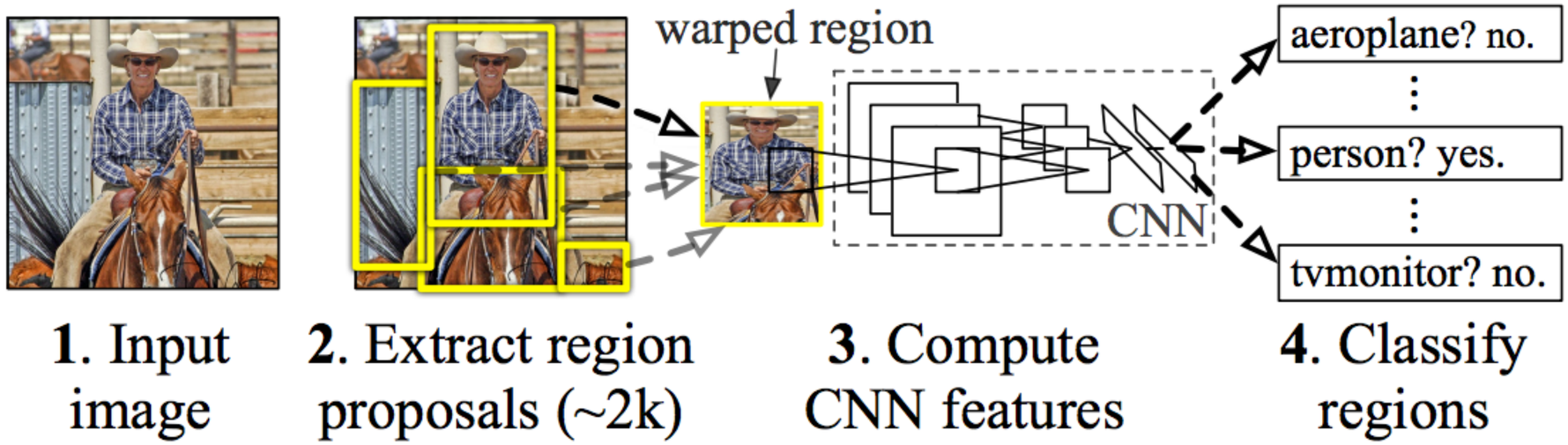
MS COCO dataset (Common Objects in COntext)



Source: http://cocodataset.org

- 330K images, 80 labels.
- Also contains data for semantic segmentation, caption generation, etc.

R-CNN : Regions with CNN features



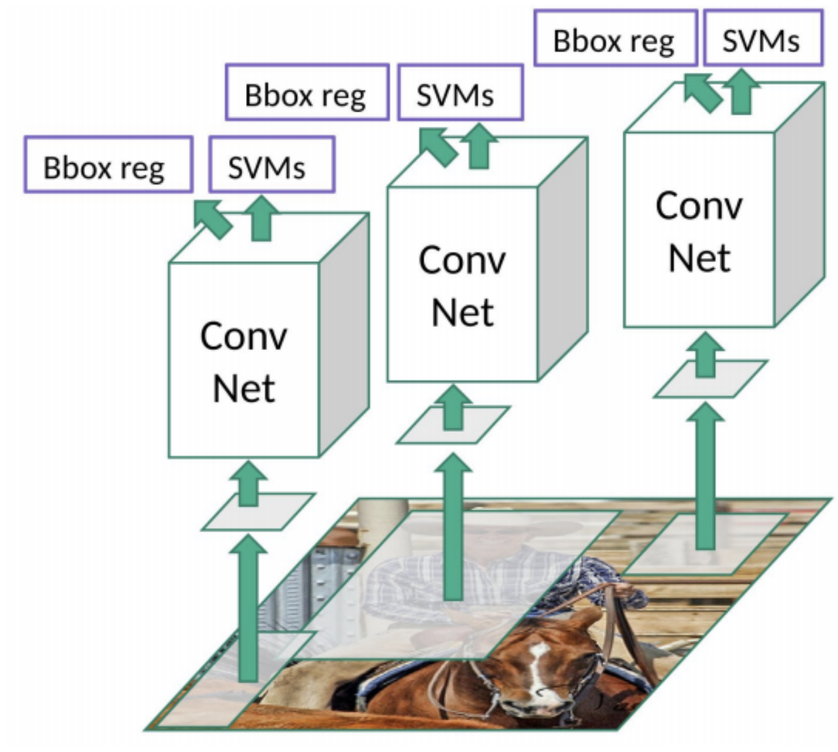
1. Bottom-up region proposals (selective search) by searching bounding boxes based on pixel info.
2. Feature extraction using a pre-trained CNN (AlexNet).
3. Classification using a SVM (object or not; if yes, which one?)
4. If an object is found, linear regression on the region proposal to generate tighter bounding box coordinates.

Note

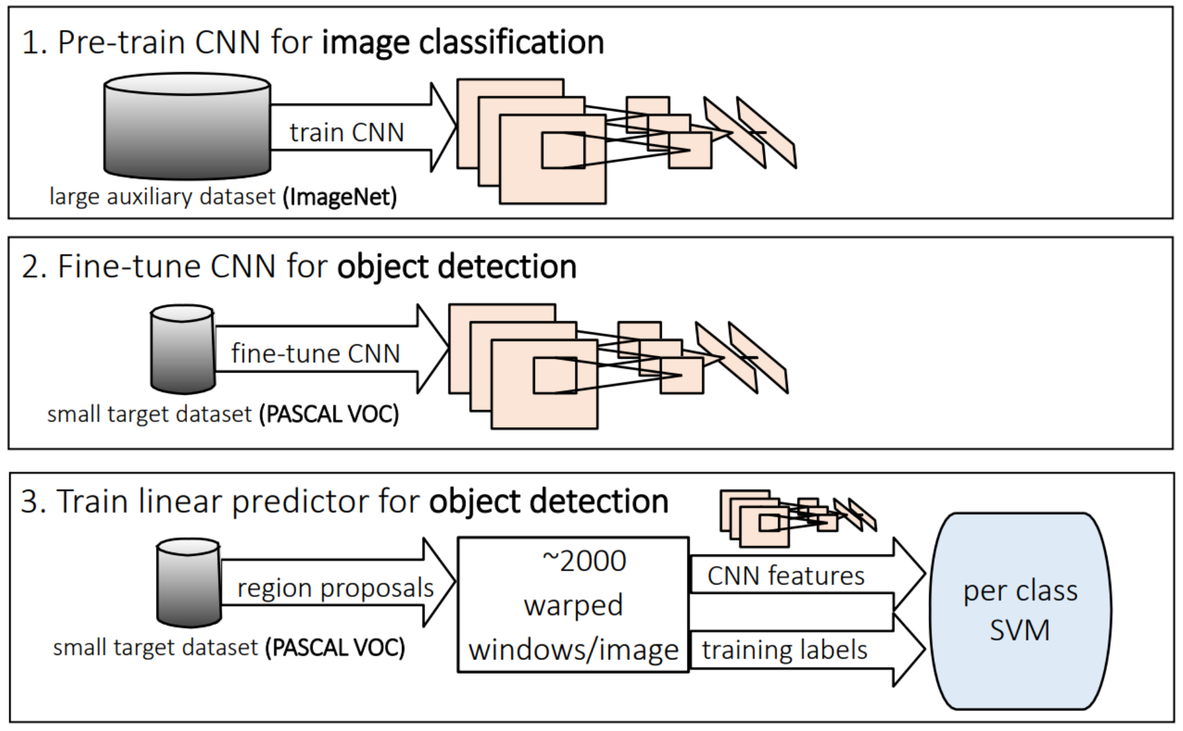
Selective search: https://ivi.fnwi.uva.nl/isis/publications/2013/UijlingsIJCV2013/UijlingsIJCV2013.pdf

R-CNN : Regions with CNN features

- Each region proposal is processed by the CNN, followed by a SVM and a bounding box regressor.



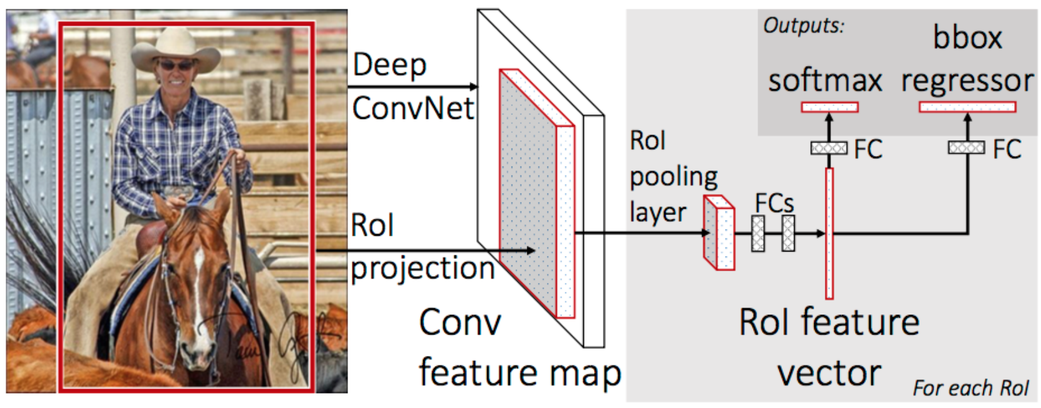
- The CNN is pre-trained on ImageNet and fine-tuned on Pascal VOC.



Source: https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e

Source: https://courses.cs.washington.edu/courses/cse590v/14au/cse590v_wk1_rcnn.pdf

Fast R-CNN

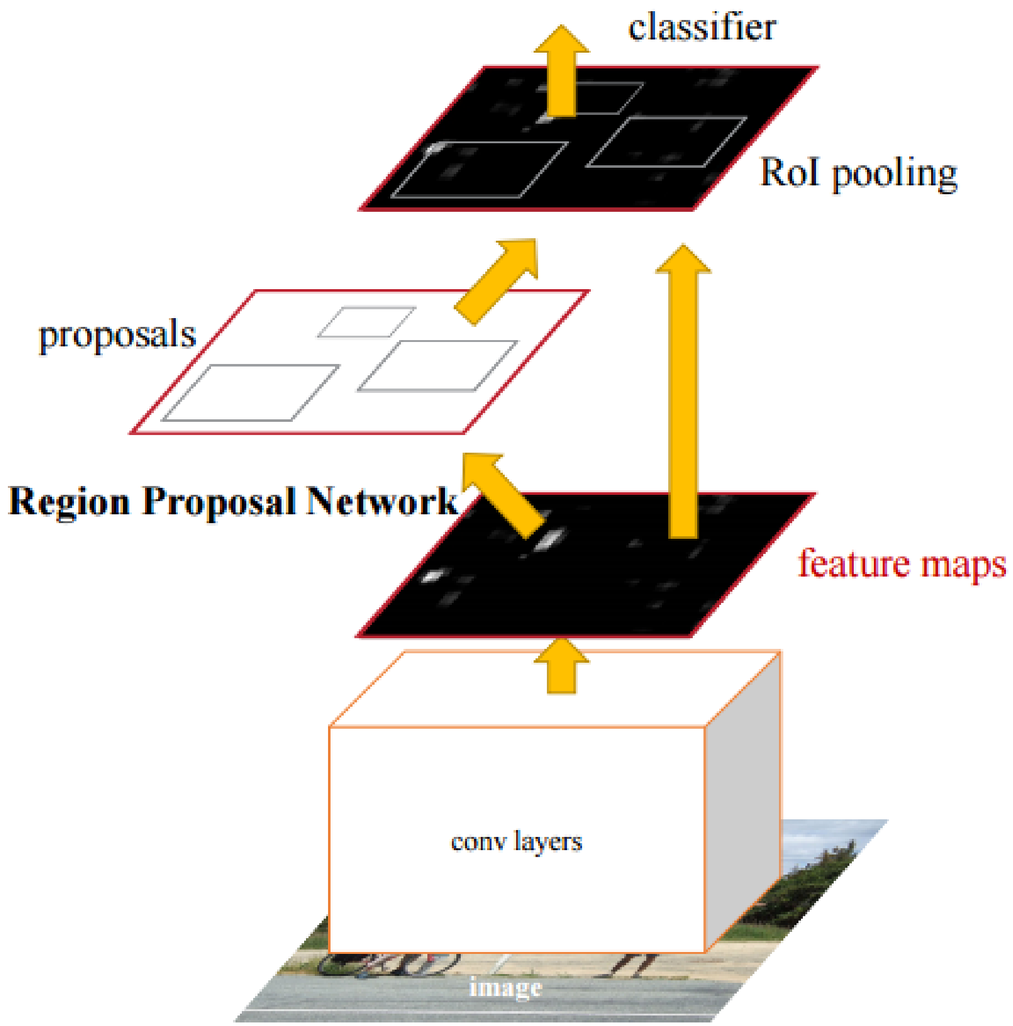


- The main drawback of R-CNN is that each of the 2000 region proposals have to go through the CNN: extremely slow.
- The idea behind **Fast R-CNN** is to extract region proposals in higher feature maps and to use transfer learning.

- The network first processes the whole image with several convolutional and max pooling layers to produce a feature map.
- Each object proposal is projected to the feature map, where a region of interest (RoI) pooling layer extracts a fixed-length feature vector.
- Each feature vector is fed into a sequence of FC layers that finally branch into two sibling output layers:
  - a softmax probability estimate over the K classes plus a catch-all “background” class.
  - a regression layer that outputs four real-valued numbers for each class.
- The loss function to minimize is a composition of different losses and penalty terms:

$$\mathcal{L}(\theta) = \lambda_1 \, \mathcal{L}_{\text{classification}}(\theta) + \lambda_2 \, \mathcal{L}_{\text{regression}}(\theta) + \lambda_3 \, \mathcal{L}_{\text{regularization}}(\theta)$$

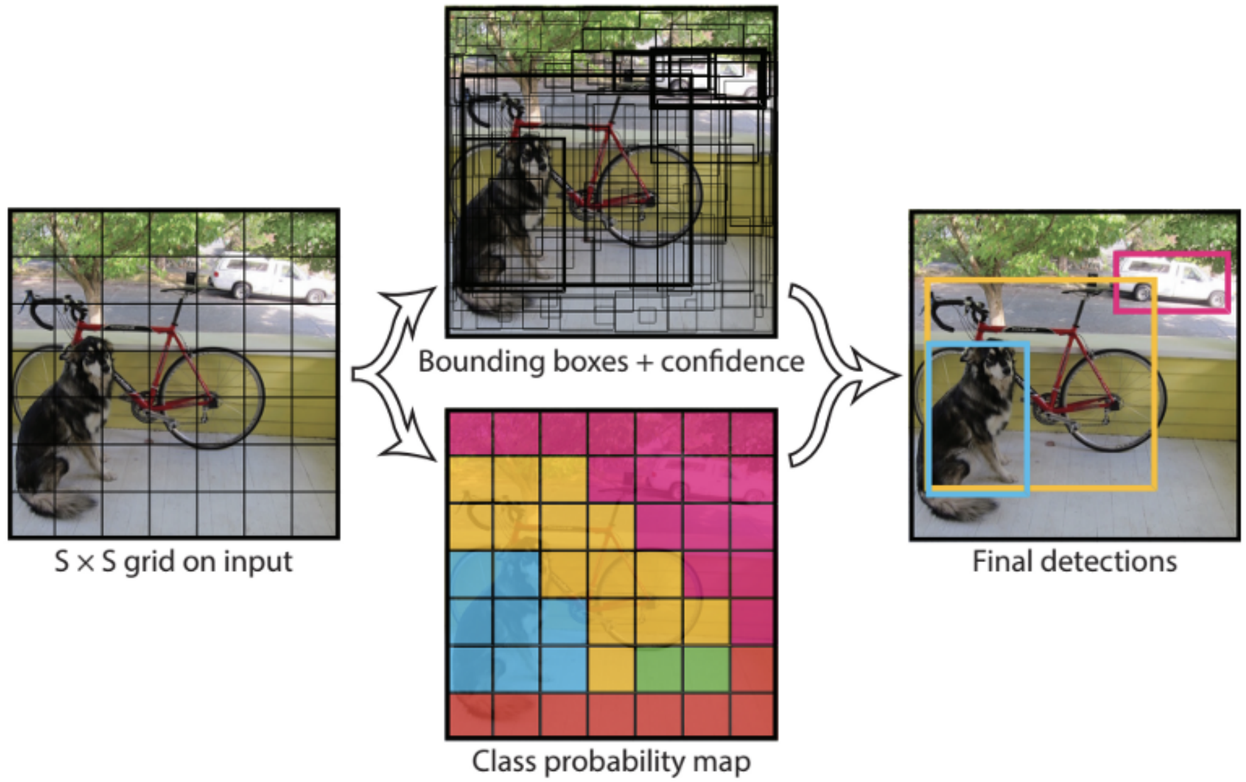
Faster R-CNN



- Both R-CNN and Fast R-CNN use selective search to find out the region proposals: slow and time-consuming.
- Faster R-CNN introduces an object detection algorithm that lets the network learn the region proposals.
- The image is passed through a pretrained CNN to obtain a convolutional feature map.
- A separate network is used to predict the region proposals.
- The predicted region proposals are then reshaped using a RoI pooling layer which is then used to classify the object and predict the bounding box.

Ren et al. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. arXiv:1506.01497

YOLO (You Only Look Once)

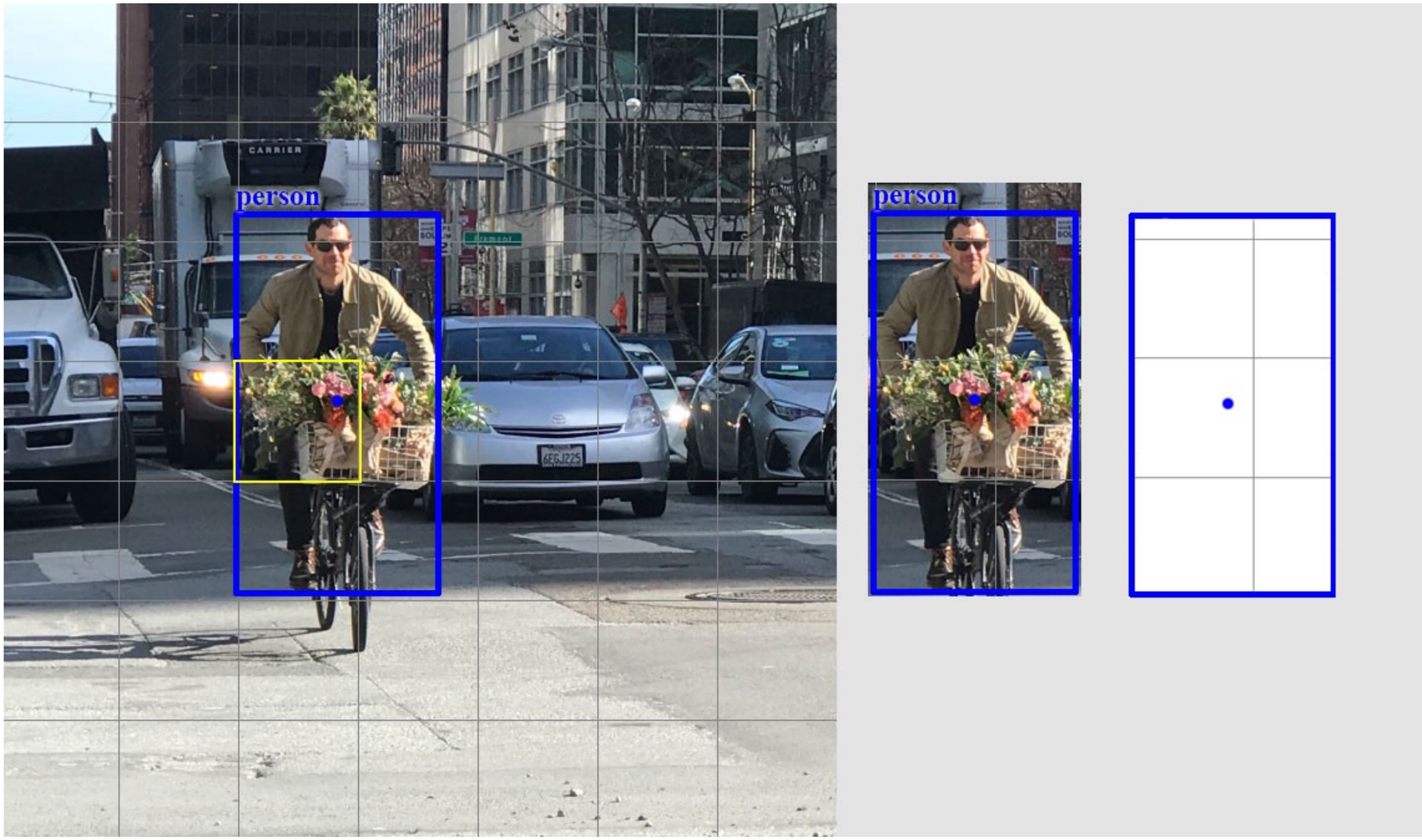


- (Fast(er)) R-CNN perform classification for each region proposal sequentially: slow.
- YOLO applies a single neural network to the full image to predict all possible boxes and the corresponding classes.
- YOLO divides the image into a SxS grid of cells.

- Each grid cell predicts a single object, with the corresponding C **class probabilities** (softmax).
- It also predicts the coordinates of B possible **bounding boxes** (x, y, w, h) as well as a box **confidence score**.
- The SxSxB predicted boxes are then pooled together to form the final prediction.

YOLO (You Only Look Once)

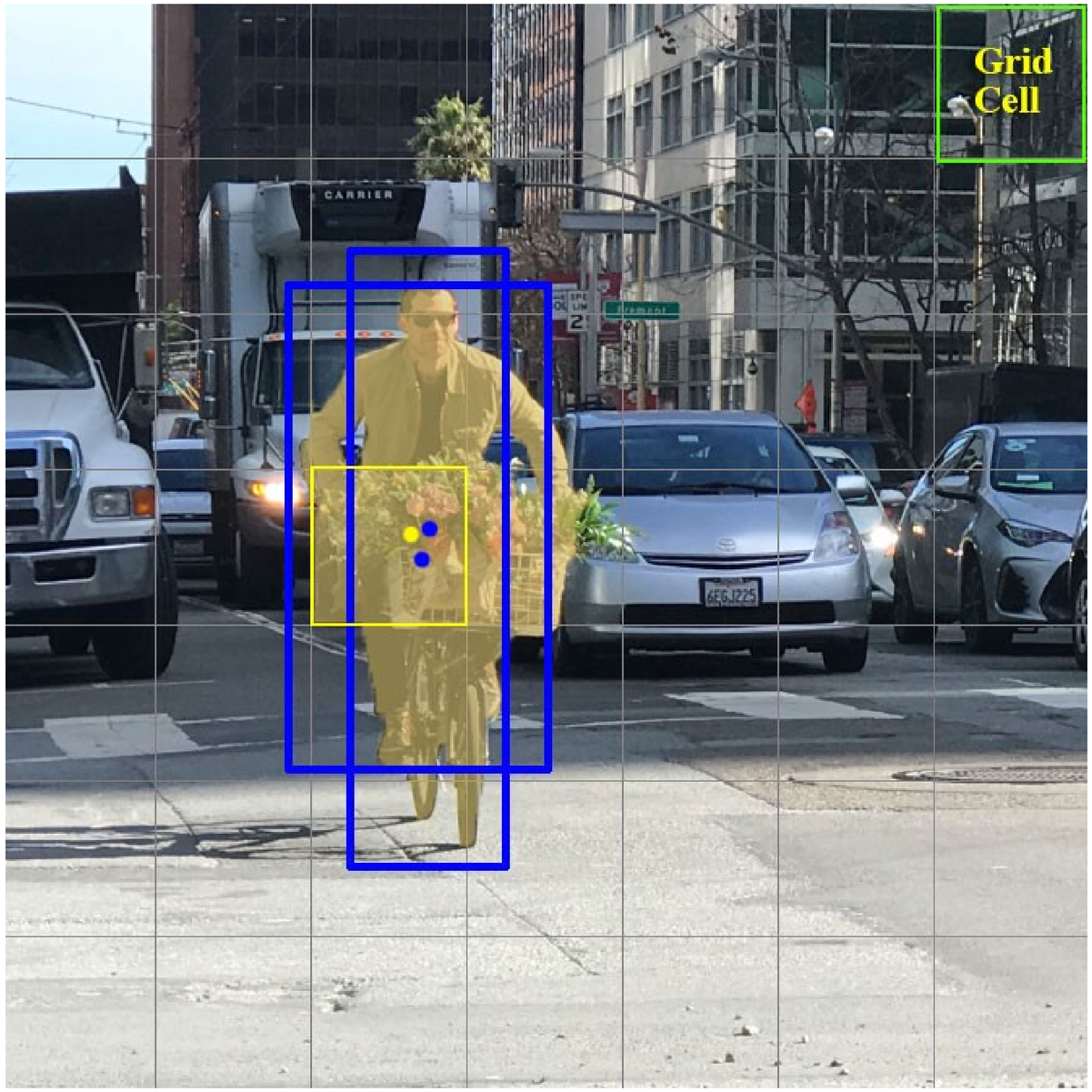
- The yellow box predicts the presence of a **person** (the class) as well as a candidate **bounding box** (it may be bigger than the grid cell itself).



Source: https://medium.com/@jonathan_hui/real-time-object-detection-with-yolo-yolov2-28b1b93e2088

YOLO (You Only Look Once)

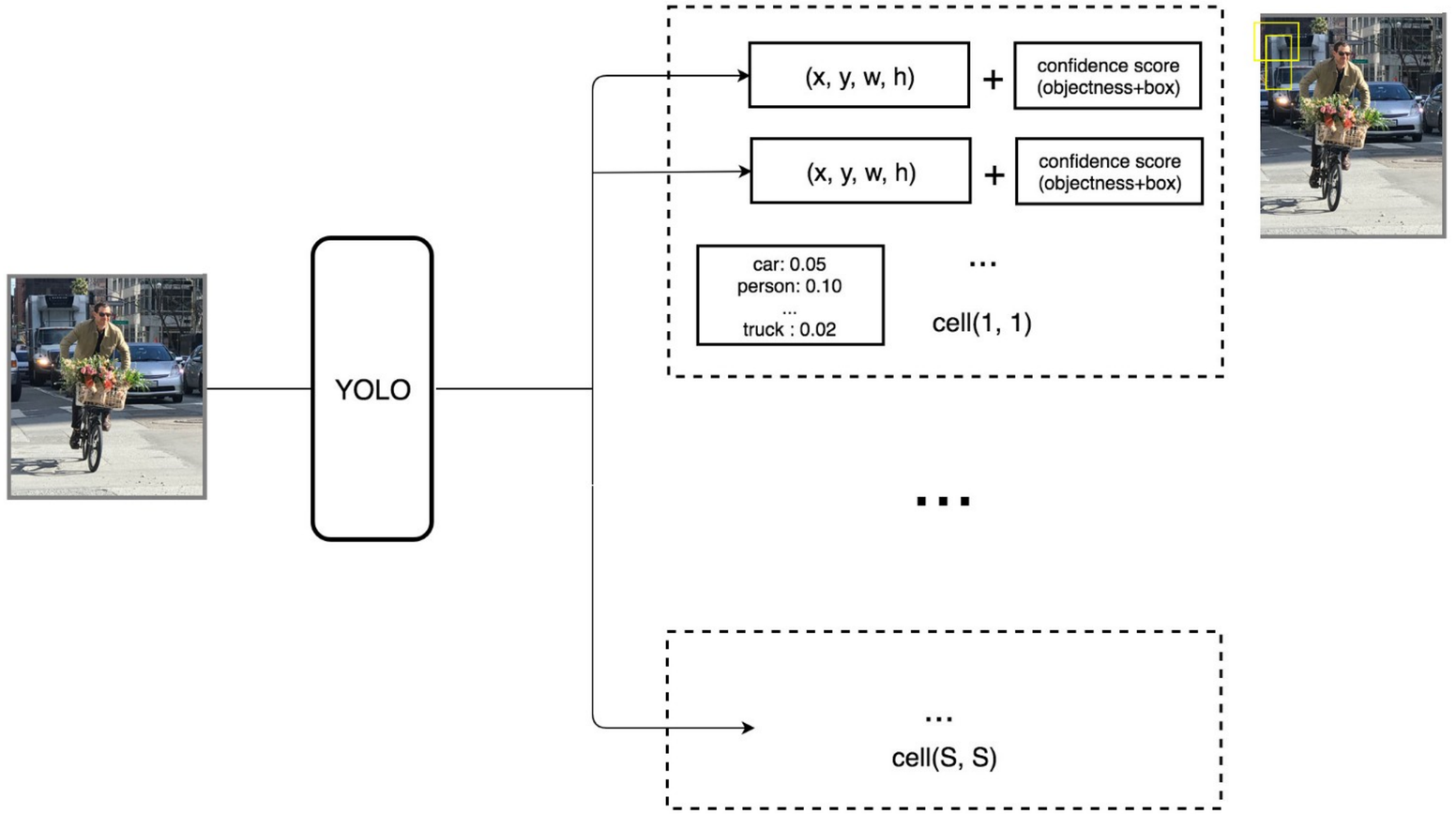
- We will suppose here that each grid cell proposes 2 bounding boxes.



Source: https://medium.com/@jonathan_hui/real-time-object-detection-with-yolo-yolov2-28b1b93e2088

YOLO (You Only Look Once)

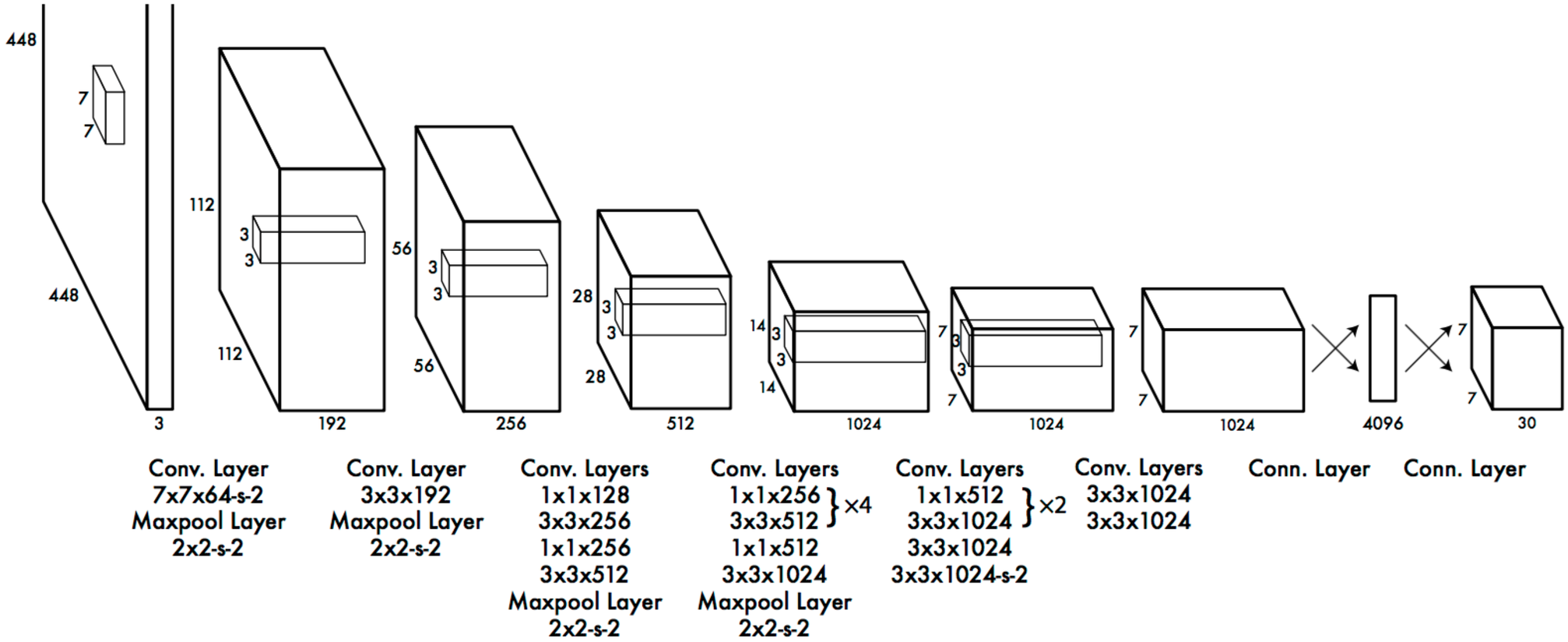
- Each grid cell predicts a probability for each of the 20 classes, and two bounding boxes (4 coordinates and a confidence score per bounding box).
- This makes C + B * 5 = 30 values to predict for each cell.



Source: https://medium.com/@jonathan_hui/real-time-object-detection-with-yolo-yolov2-28b1b93e2088

YOLO : CNN architecture

- YOLO uses a CNN with 24 convolutional layers and 4 max-pooling layers to obtain a 7x7 grid.
- The last convolution layer outputs a tensor with shape (7, 7, 1024). The tensor is then flattened and passed through 2 fully connected layers.
- The output is a tensor of shape (7, 7, 30), i.e. 7x7 grid cells, 20 classes and 2 boundary box predictions per cell.

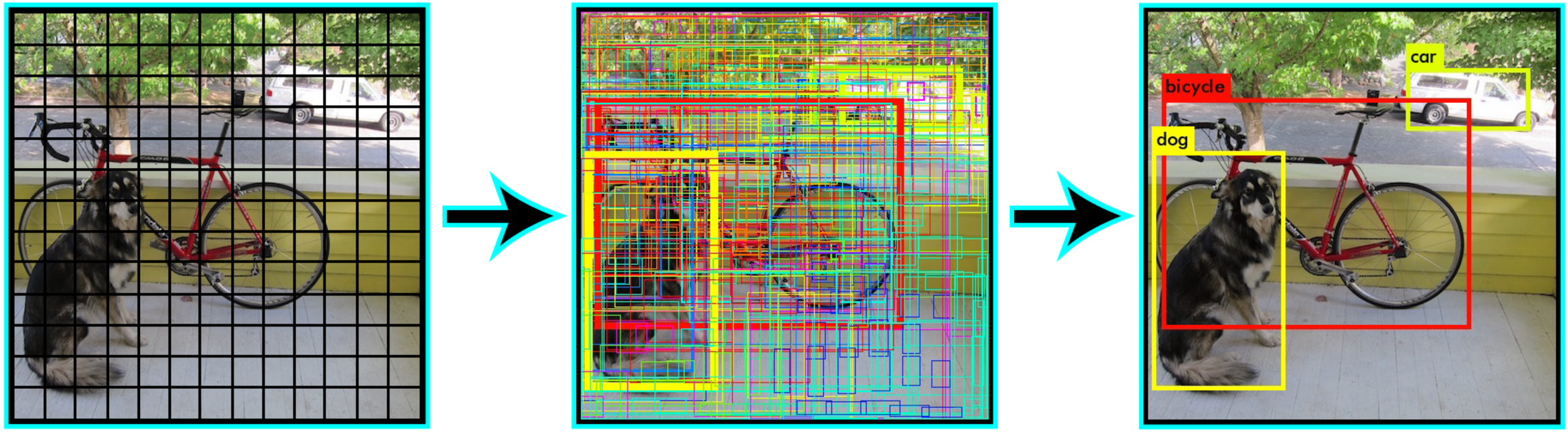


YOLO : confidence score

- The 7x7 grid cells predict 2 bounding boxes each: maximum of 98 bounding boxes on the whole image.
- Only the bounding boxes with the **highest class confidence score** are kept.

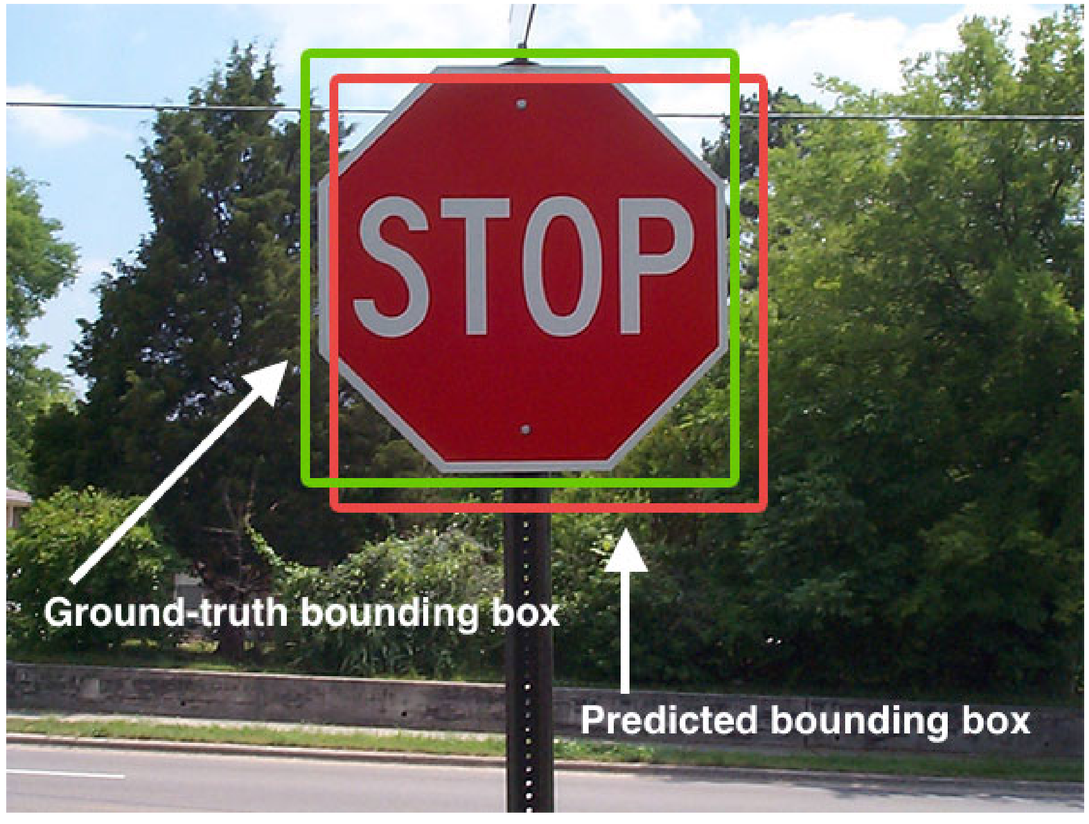
$$\text{class confidence score} = \text{box confidence score} * \text{class probability}$$

- In practice, the class confidence score should be above 0.25 to be retained.



YOLO : Intersection over Union (IoU)

- To ensure specialization, only one bounding box per grid cell should be responsible for detecting an object.
- During learning, we select the bounding box with the biggest overlap with the object.
- This can be measured by the **Intersection over the Union** (IoU).



$$IoU = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

Source: https://www.pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/

YOLO : loss functions

- The output of the network is a 7x7x30 tensor, representing for each cell:
  - the probability that an object of a given class is present.
  - the position of two bounding boxes.
  - the confidence that the proposed bounding boxes correspond to a real object (the IoU).
- We are going to combine three different loss functions:

1. The **categorization loss**: each cell should predict the correct class.
2. The **localization loss**: error between the predicted boundary box and the ground truth for each object.
3. The **confidence loss**: do the predicted bounding boxes correspond to real objects?

YOLO : classification loss

- The classification loss is the **mse** between:
  - $\hat{p}_i(c)$: the one-hot encoded class c of the object present under each cell i, and
  - $p_i(c)$: the predicted class probabilities of cell i.

$$\mathcal{L}_{\text{classification}}(\theta) = \sum_{i=0}^{S^2} 1_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2$$

where 1_i^{obj} is 1 when there actually is an object behind the cell i, 0 otherwise (background).

- They could also have used the cross-entropy loss, but the output layer is not a softmax layer.
- Using mse is also more compatible with the other losses.

YOLO : localization loss

- For all bounding boxes matching a real object, we want to minimize the **mse** between:
  - $(\hat{x}_i, \hat{y}_i, \hat{w}_i, \hat{h}_i)$: the coordinates of the ground truth bounding box, and
  - (x_i, y_i, w_i, h_i): the coordinates of the predicted bounding box.

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

where 1_{ij}^{obj} is 1 when the bounding box j of cell i “matches” with an object (IoU).

- The root square of the width and height of the bounding boxes is used.
- This allows to penalize more the errors on small boxes than on big boxes.

YOLO : confidence loss

- Finally, we need to learn the confidence score of each bounding box, by minimizing the **mse** between:
  - C_i: the predicted confidence score of cell i, and
  - $\hat{C}_i$: the IoU between the ground truth bounding box and the predicted one.

$$\mathcal{L}_{\text{confidence}}(\theta) = \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} (C_{ij} - \hat{C}_{ij})^2 + \lambda^{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{noobj}} (C_{ij} - \hat{C}_{ij})^2$$

- Two cases are considered:
  1. There was a real object at that location ($1_{ij}^{\text{obj}} = 1$): the confidences should be updated fully.
  2. There was no real object ($1_{ij}^{\text{noobj}} = 1$): the confidences should only be moderately updated ($\lambda^{\text{noobj}} = 0.5$)
- This is to deal with **class imbalance**: there are much more cells on the background than on real objects.

YOLO : loss function

- Put together, the loss function to minimize is:

$$\mathcal{L}(\theta) = \mathcal{L}_{\text{classification}}(\theta) + \lambda_{\text{coord}}\, \mathcal{L}_{\text{localization}}(\theta) + \mathcal{L}_{\text{confidence}}(\theta) \tag{1}$$

$$= \sum_{i=0}^{S^2} 1_i^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \tag{2}$$

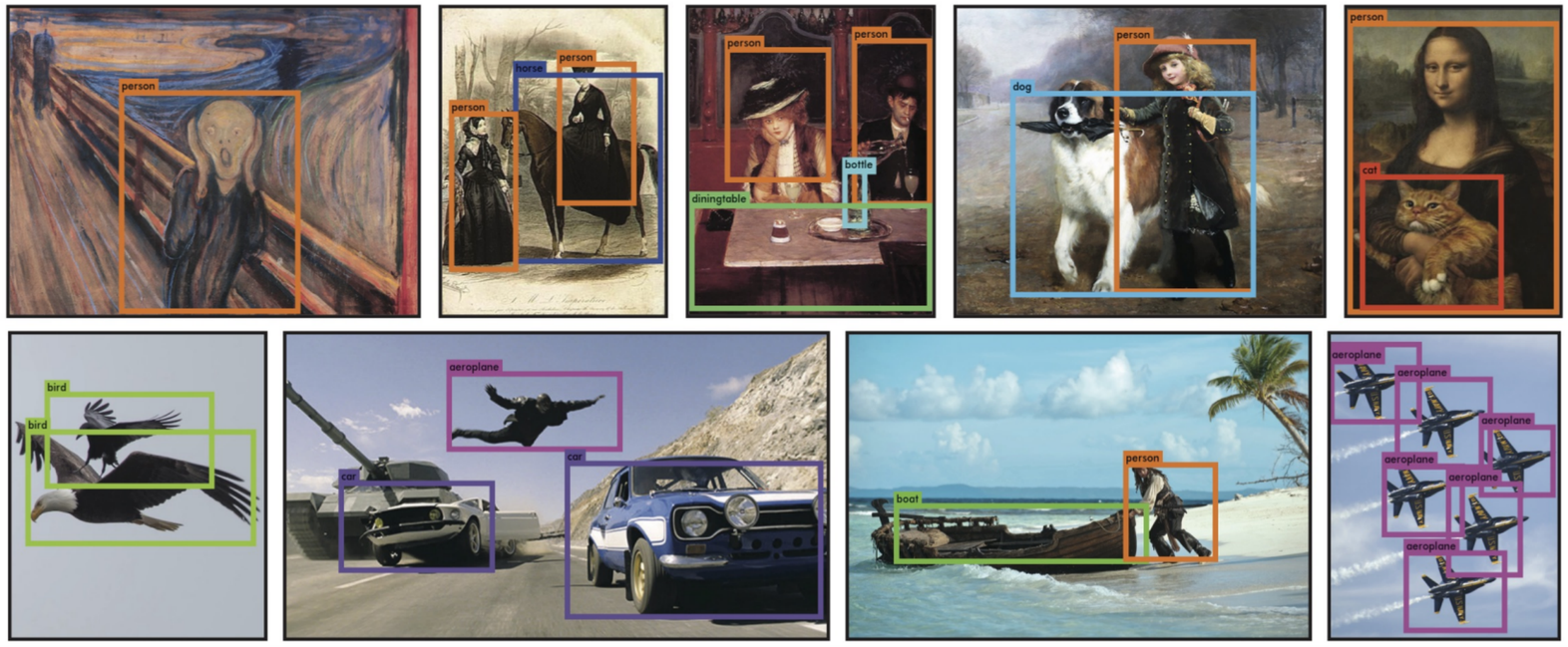
$$+ \lambda_{\text{coord}} \sum^{S^2} \sum^{B} 1_{ij}^{\text{obj}} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] \tag{3}$$

$$+ \lambda_{\text{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} [(\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2] \tag{4}$$

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{obj}} (C_{ij} - \hat{C}_{ij})^2 \tag{5}$$

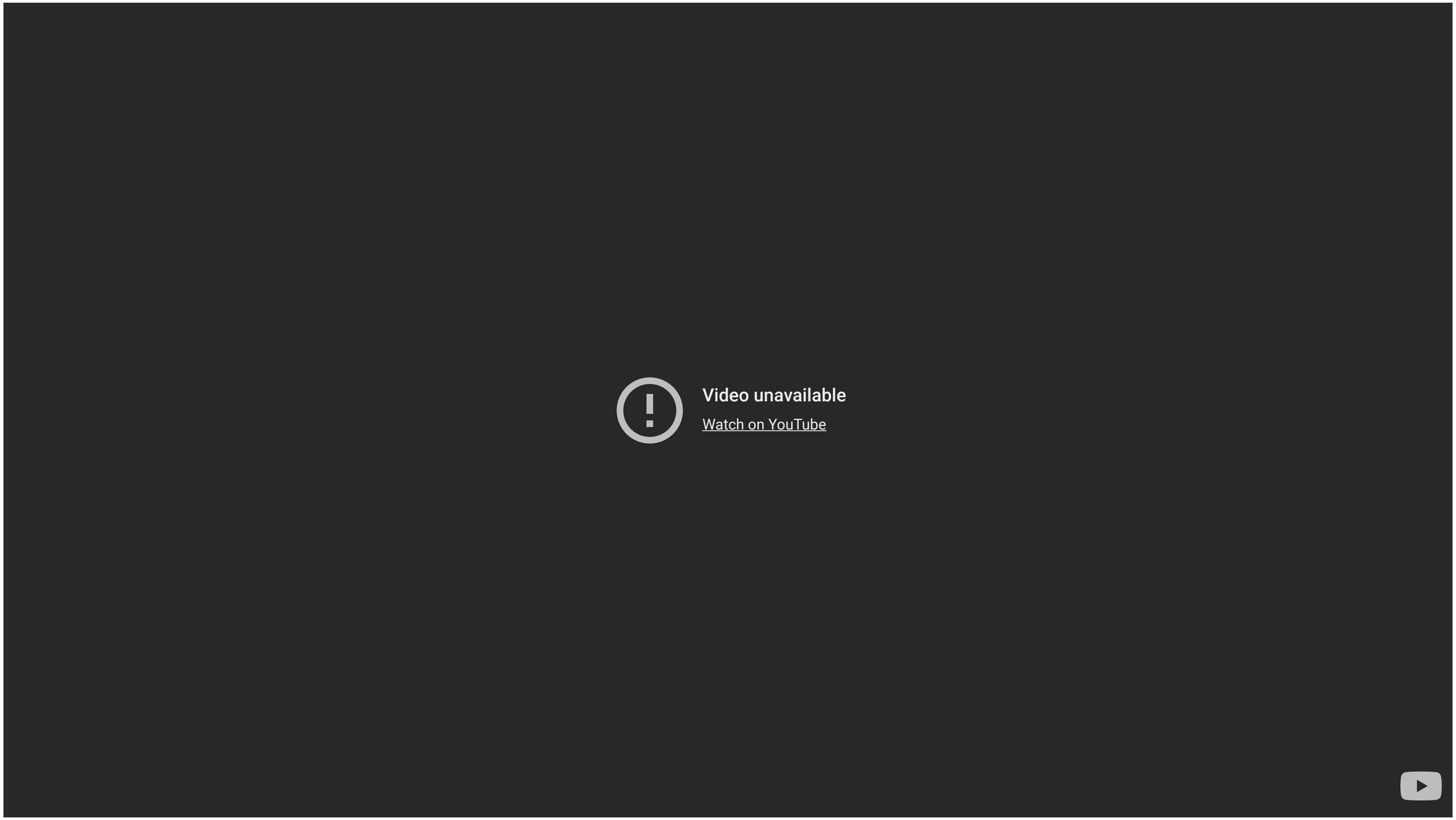
$$+ \lambda^{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} 1_{ij}^{\text{noobj}} (C_{ij} - \hat{C}_{ij})^2 \tag{6}$$

YOLO : Training on PASCAL VOC

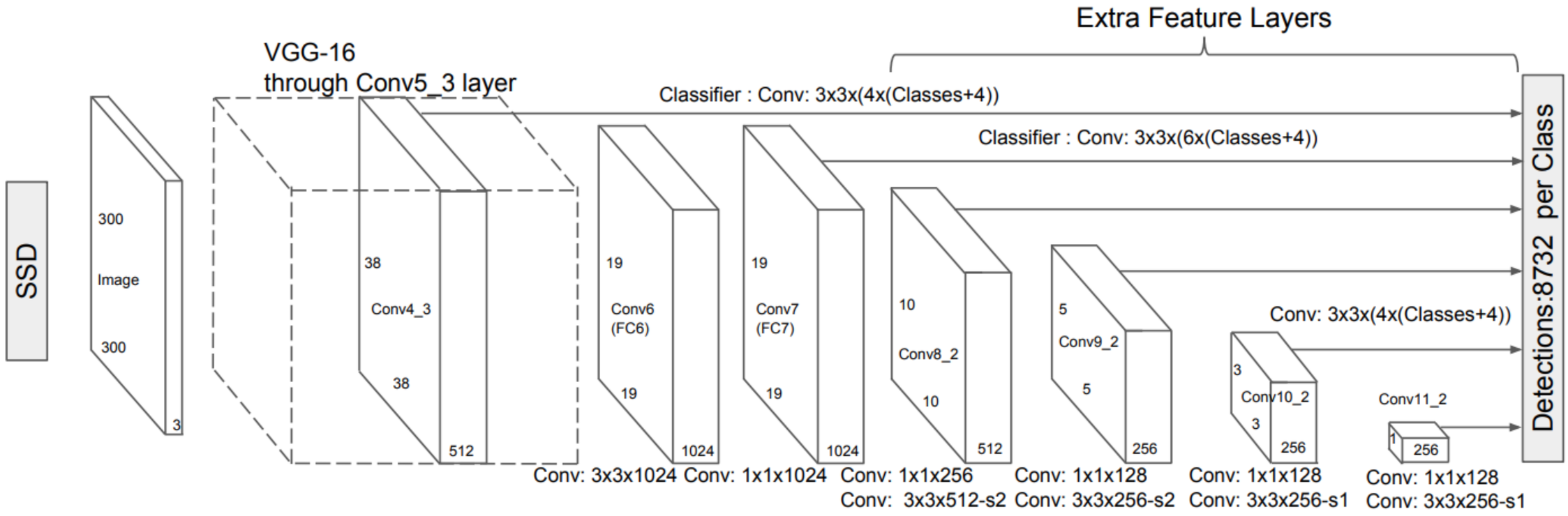


	VOC 2007	Picasso		People-Art
	AP	AP	Best F_1	AP
YOLO	**59.2**	**53.3**	**0.590**	**45**
R-CNN	54.2	10.4	0.226	26
DPM	43.2	37.8	0.458	32
Poselets [2]	36.5	17.8	0.271	
D&T [4]	-	1.9	0.051	

- YOLO was trained on PASCAL VOC (natural images) but generalizes well to other datasets (paintings…).
- Runs real-time (60 fps) on a NVIDIA Titan X.
- Faster and more accurate versions of YOLO have been developed: YOLO9000, YOLOv3, YOLOv4, YOLOv5…


Video unavailable
Watch on YouTube

SSD: Single-Shot Detector

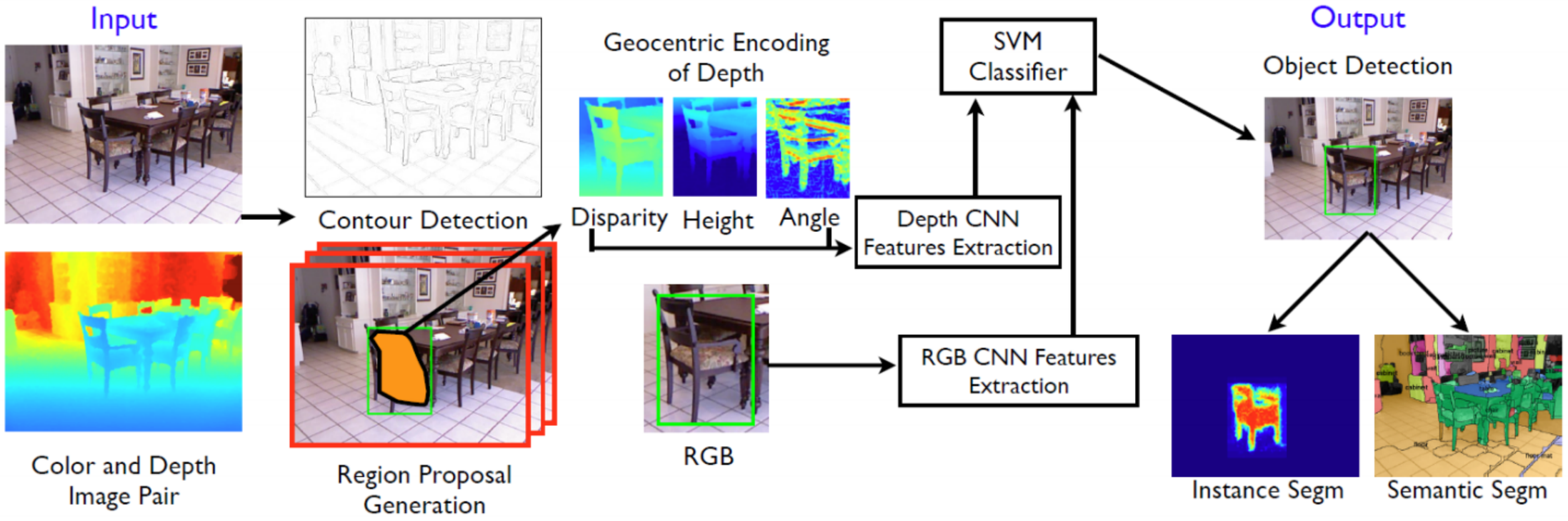


- The idea of SSD is similar to YOLO, but:
  - faster
  - more accurate
  - not limited to 98 objects per scene
  - multi-scale
- Contrary to YOLO, all convolutional layers are used to predict a bounding box, not just the final tensor.
  - Skip connections.
- This allows to detect boxes at multiple scales (pyramid).

Liu et al. (2016) SSD: Single Shot MultiBox Detector. arXiv:1512.02325

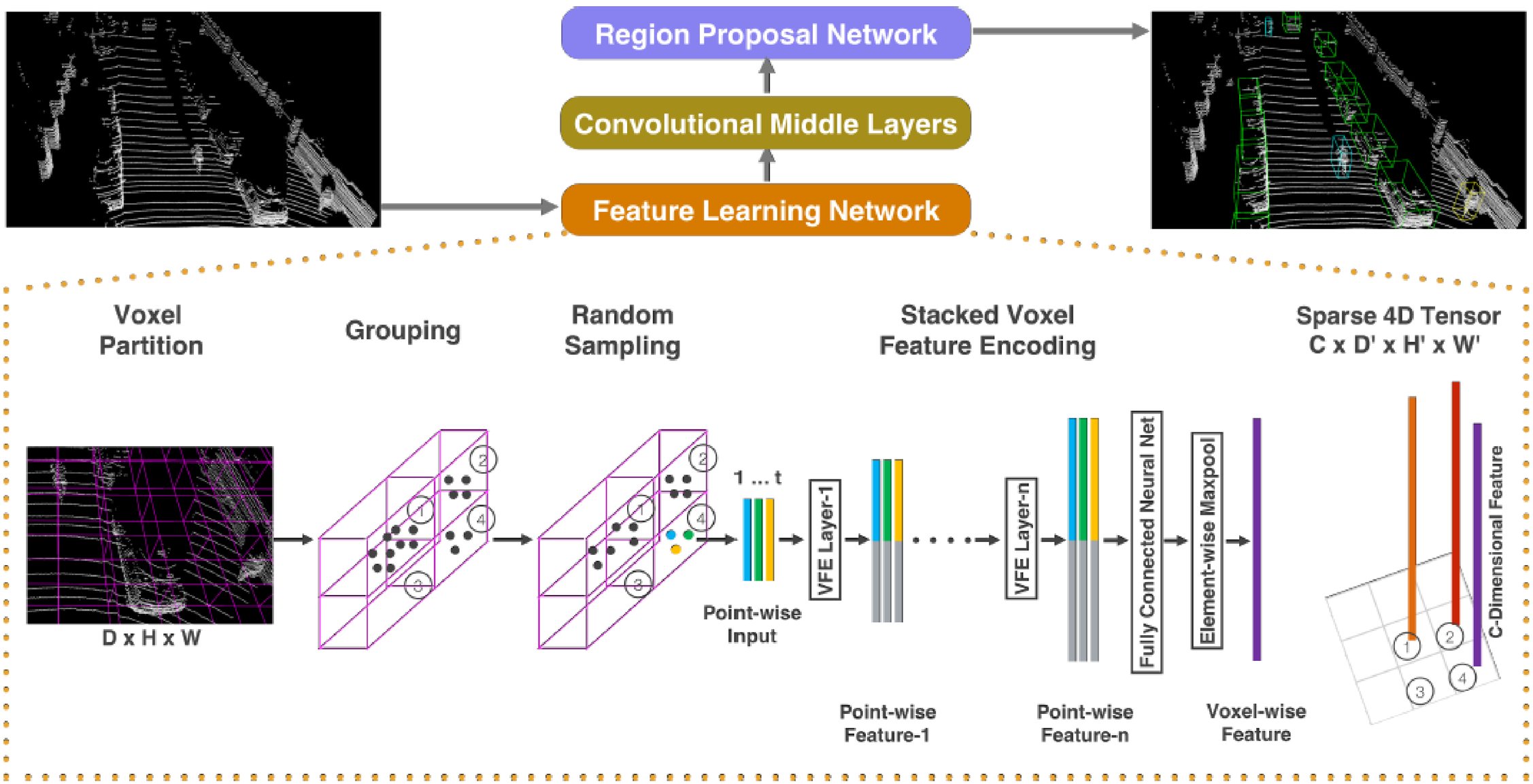
R-CNNs on RGB-D images

- It is also possible to use **depth** information (e.g. from a Kinect) as an additional channel of the R-CNN.
- The depth information provides more information on the structure of the object, allowing to disambiguate certain situations (segmentation).



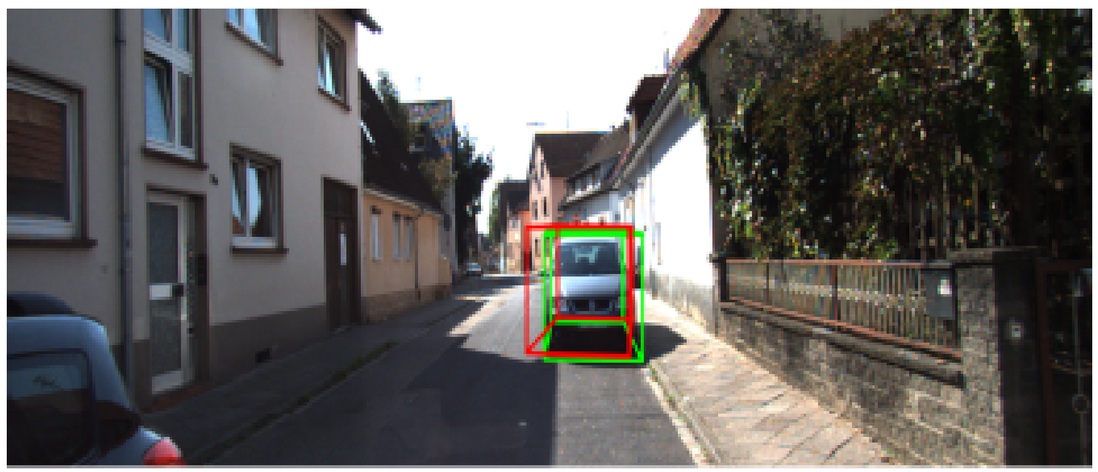
VoxelNet

- Lidar point clouds can also be used for detecting objects, for example **VoxelNet** trained on the KITTI dataset.

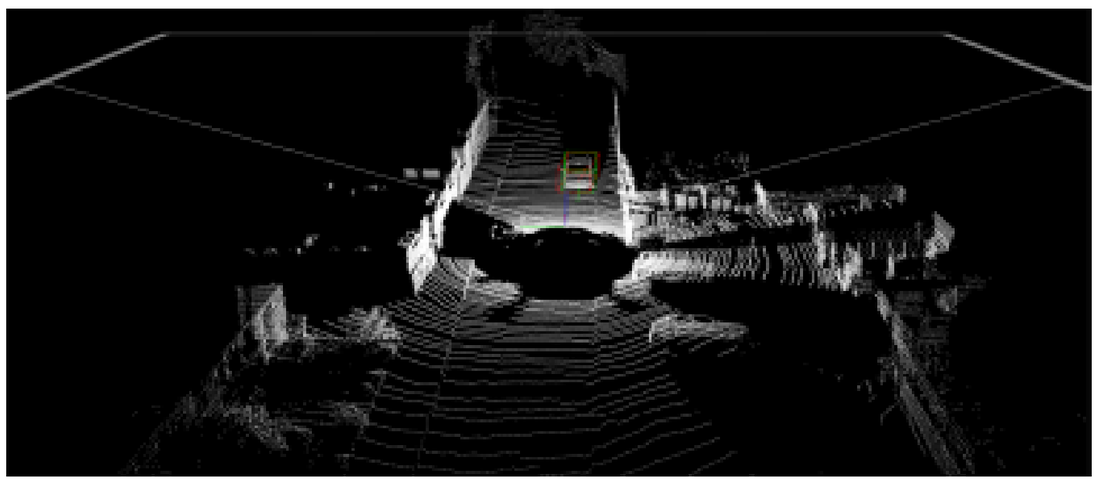


Zhou Y, Tuzel O. (2017). VoxelNet: End-to-End Learning for Point Cloud Based 3D Object Detection. arXiv:171106396

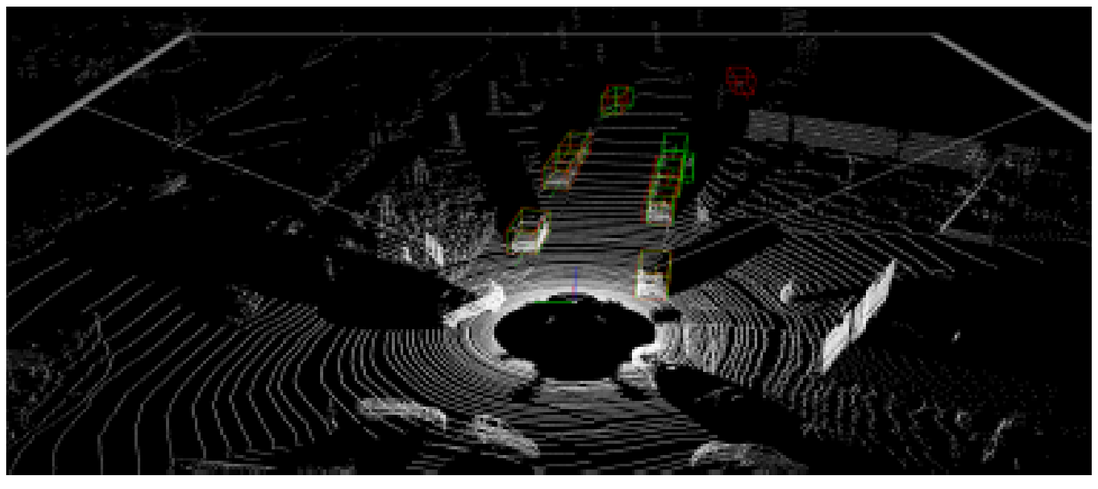
VoxelNet



(a)



(b)



Source: https://medium.com/@SmartLabAI/3d-object-detection-from-lidar-data-with-deep-learning-95f6d400399a

Additional resources on object detection

- https://medium.com/comet-app/review-of-deep-learning-algorithms-for-object-detection-c1f3d437b852
- https://medium.com/@smallfishbigsea/faster-r-cnn-explained-864d4fb7e3f8
- https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e
- https://medium.com/@jonathan_hui/real-time-object-detection-with-yolo-yolov2-28b1b93e2088
- https://medium.com/@jonathan_hui/ssd-object-detection-single-shot-multibox-detector-for-real-time-processing-9bd8deac0e06
- https://towardsdatascience.com/lidar-3d-object-detection-methods-f34cf3227aea