MULTIPLE LABELS

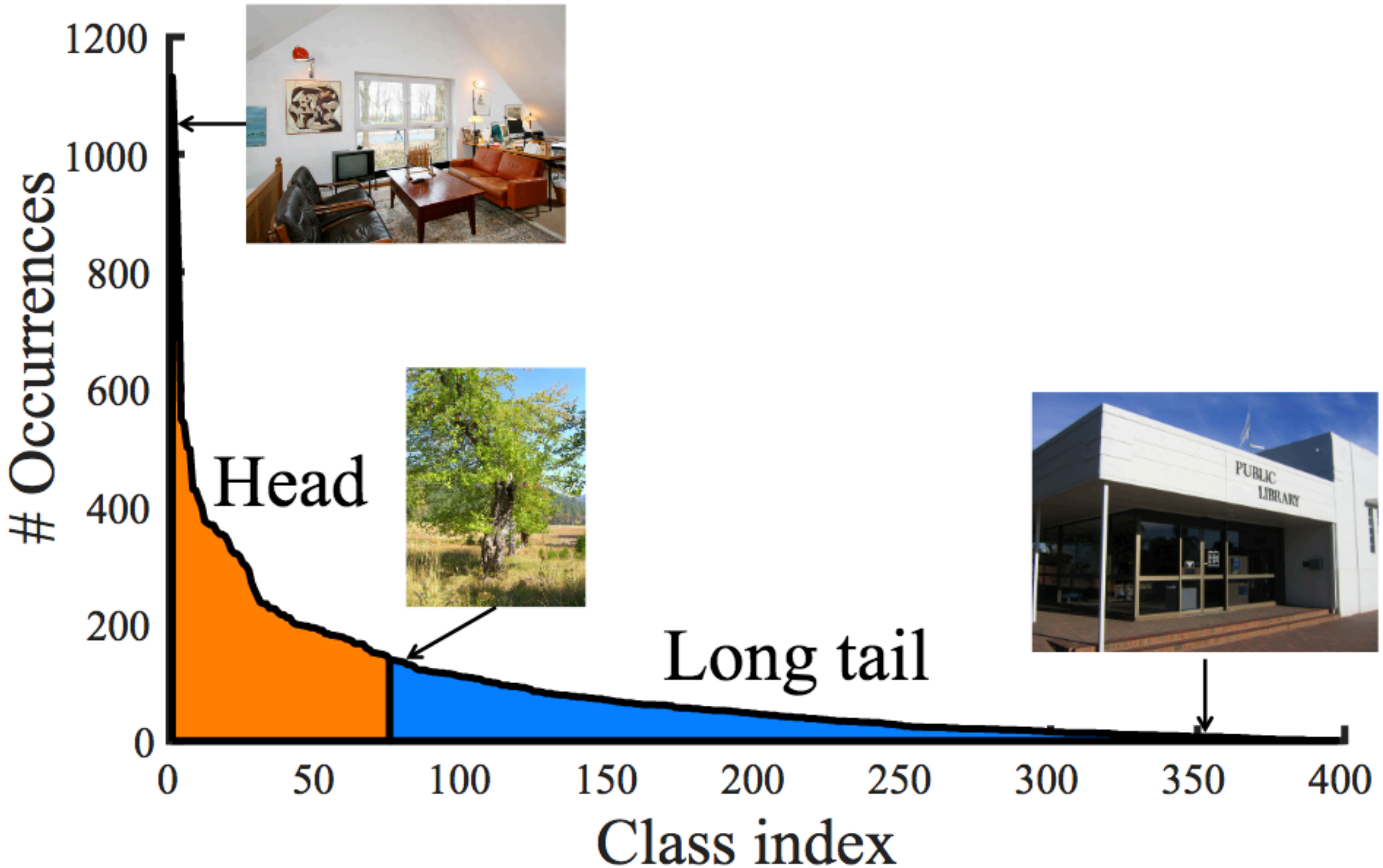
Deep Learning for Computer Vision

Arthur Douillard

Preambule:

Imbalance Learning

Long-tailed distributions



[Wang et al. NeurIPS 2017]

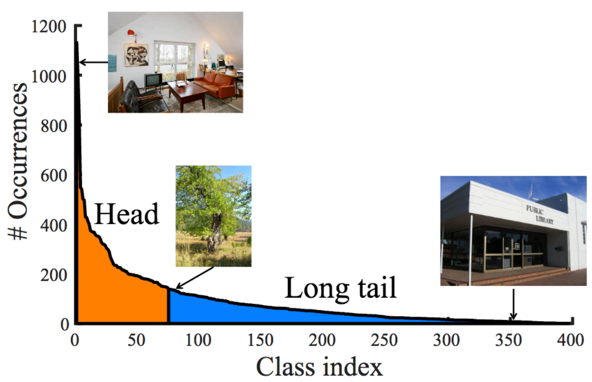
Common Solution to Imbalanced Learning

- **Oversample** minority classes
    - Works better than undersampling majority classes

- **Class weight** to give more/less importance in the loss to minority/majority classes
    - Before averaging all losses in a batch, multiply each loss by the weight associated to the class ground-truth

- **Sample weight** is like class weight but per sample
    - Example: hard mining

- **Metric Learning** learns a metric not actual classes
    - More on it in the next course!



Multi-labels

Multi-Labels Classification

<u>Classification</u>

"cat"

[0, 0, 0, 0, …, 1, 0, …, 0]

Softmax activation

<u>Multi-Labels Classification</u>

{*"cat"*, *"dog"*}

[0, 0, 1, 0, …, 1, 0, …, 0]

Sigmoid activation

Sparse & Imbalanced

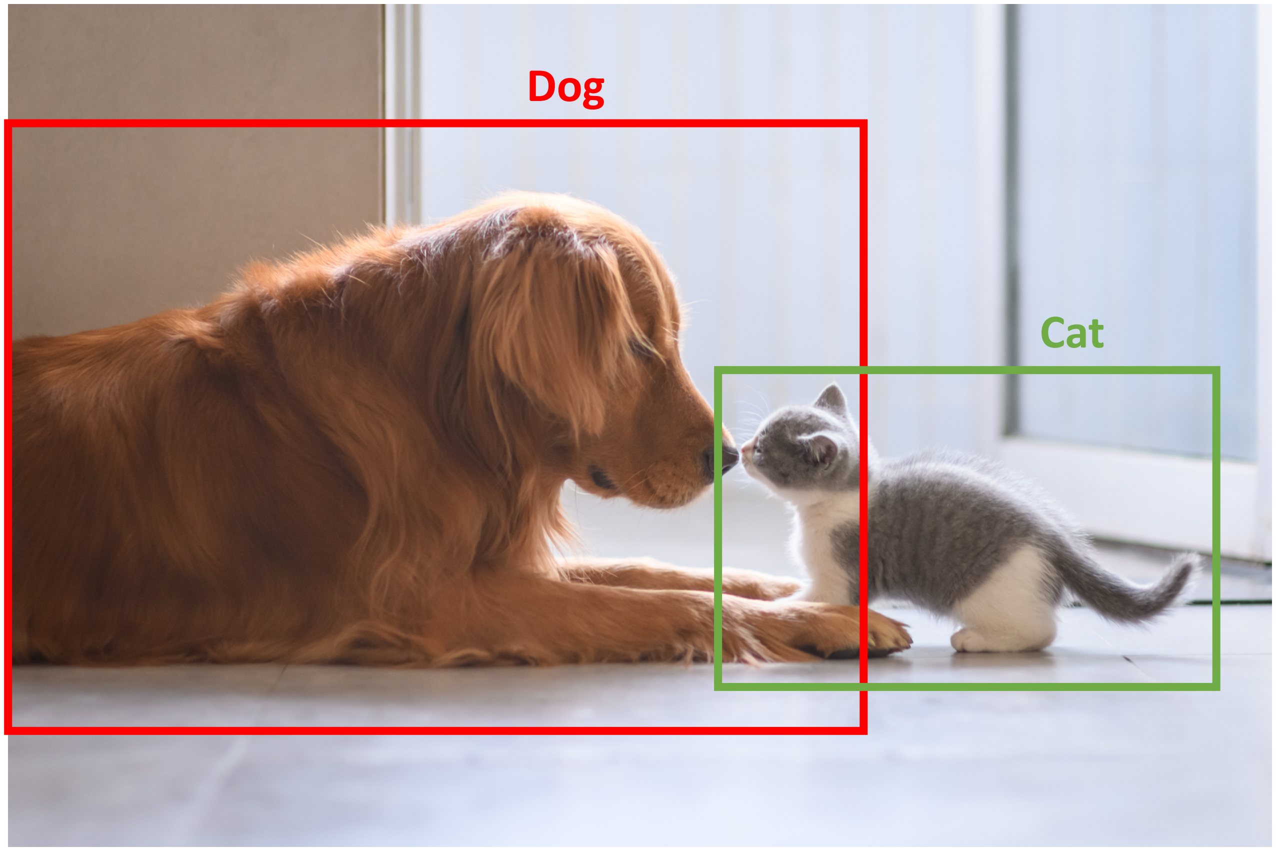
1,000 clothing attributes

Some are very common others not → class weights can be useful

[DeepFashion, Liu et al. CVPR 2016]

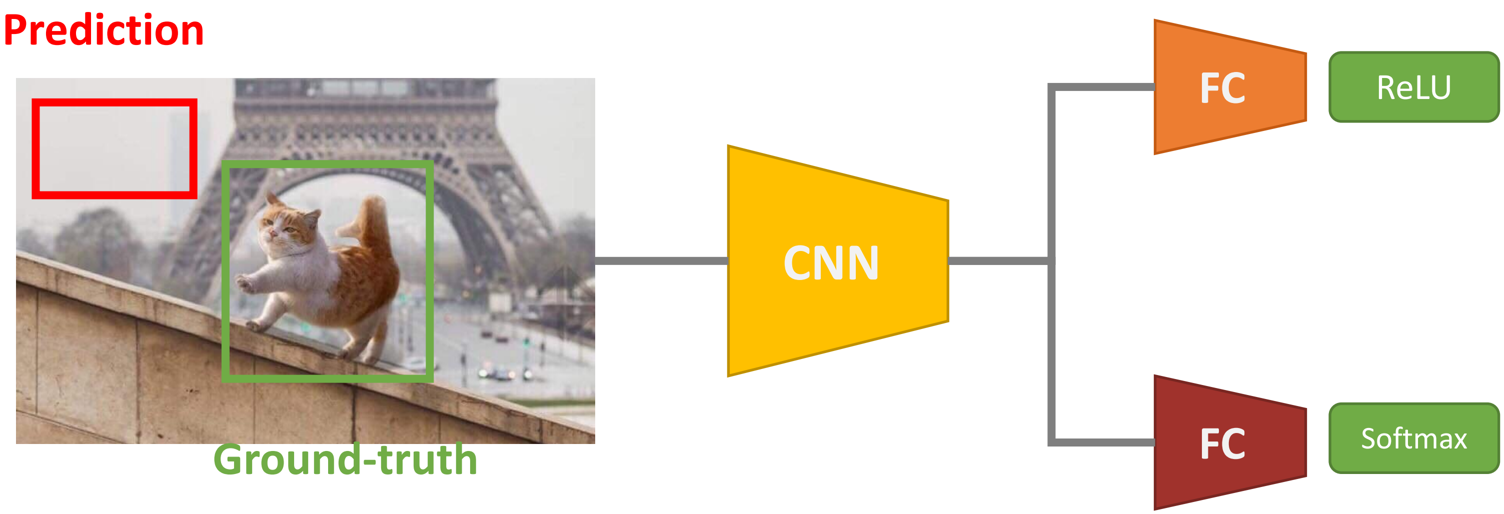
Object Detection

Object Detection



Bounding boxes around the object: (x, y, w, h)
Class prediction: c

Localizing a single class

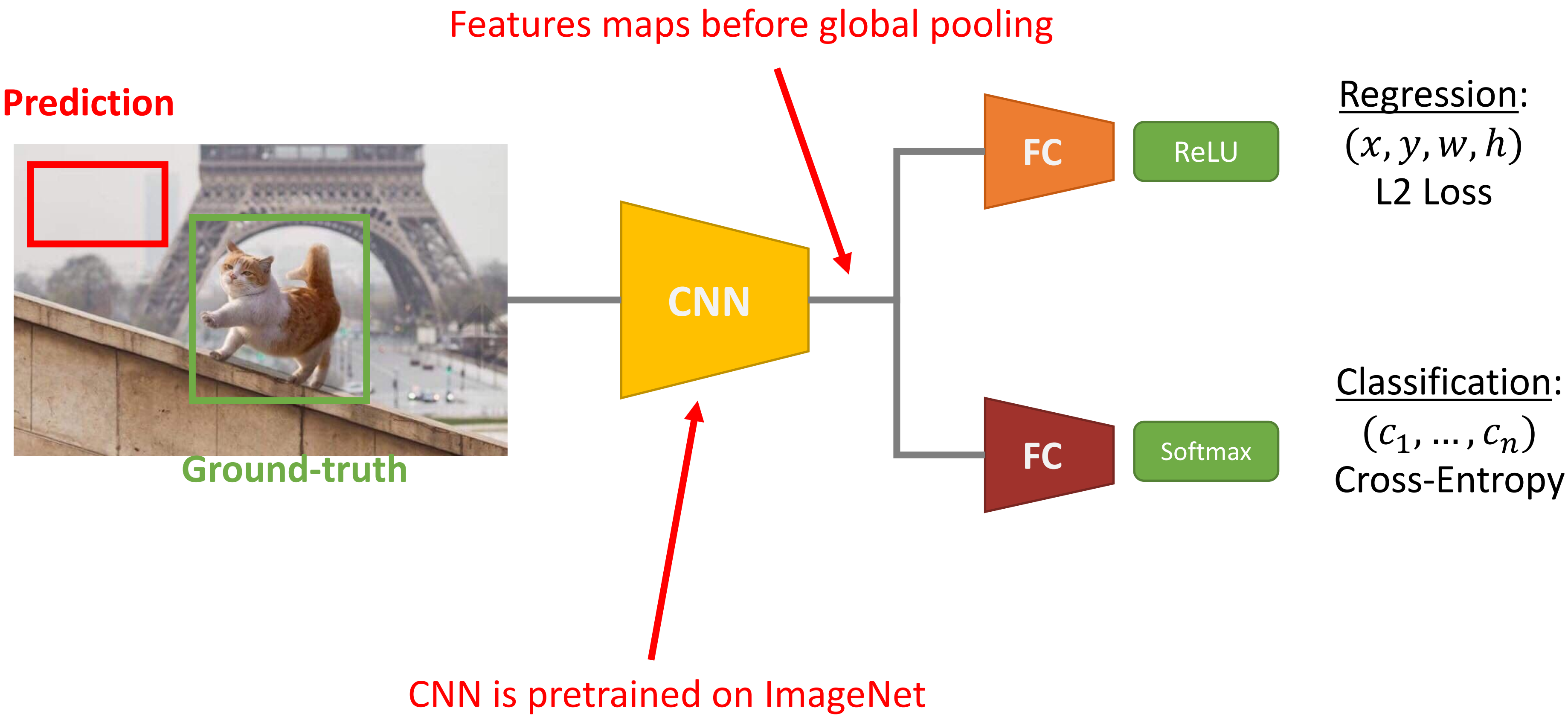


Regression:
(x, y, w, h)
L2 Loss

Classification:
$(c_1, \ldots, c_n)$
Cross-Entropy

Naive model!

Localizing a single class



Naive model!

Localizing multiple classes

Two tasks:

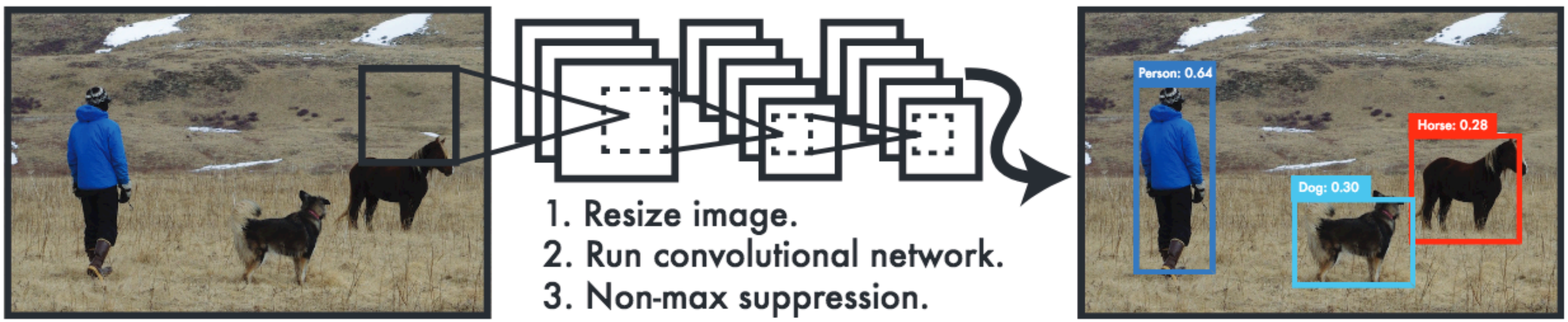
1. Find the **regions of interest** (RoIs) of the image
2. Classify them as either a known class $(c_1, c_2, \ldots, c_n)$ or **background** class

Two families:

- **Two-Stage**: first determine which regions may contains an object (1), then classify the said object (2)
  → Fast R-CNN, Faster R-CNN, Mask R-CNN, etc.

- **Single-Stage**: solve the two tasks together
  → SSD, Yolo, RetinaNet, etc.

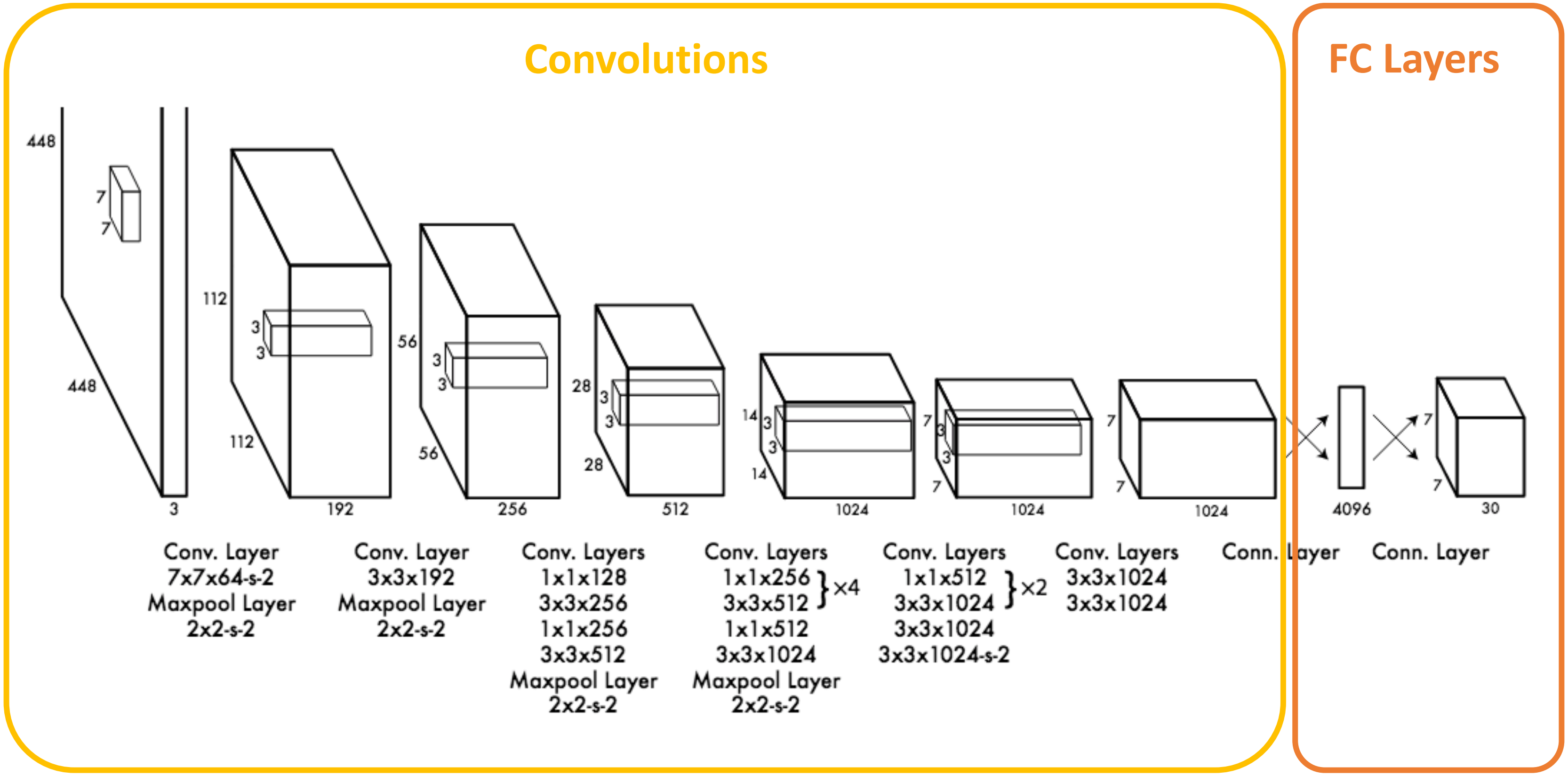
Single Stage: Yolo: You Only Look Once



1. Resize image to 448x448
2. Extract features with DarkNet and apply object detection procedure
3. Non-max suppression to remove overlapping predictions

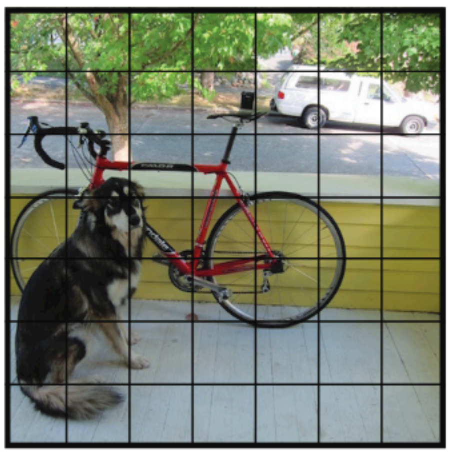
[Redmon et al. CVPR 2016]

Single Stage: Yolo: You Only Look Once



The interesting part is in the **FC layers**

Single Stage: Yolo: You Only Look Once



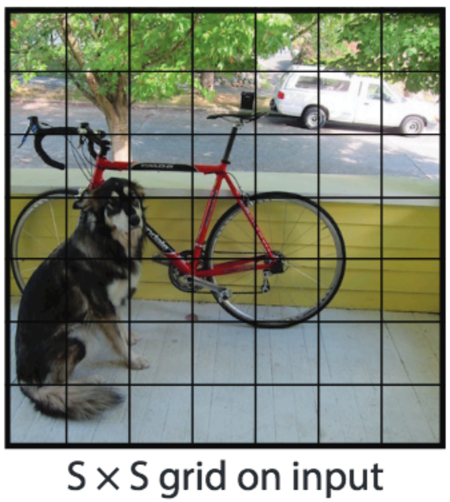
Define hardcoded cells

Define hardcoded cells.

The model will predict multiple attributes for all these cells.

Single Stage: Yolo: You Only Look Once

B boxes per cell, and the regression head predicts how to deform them to best fit the object

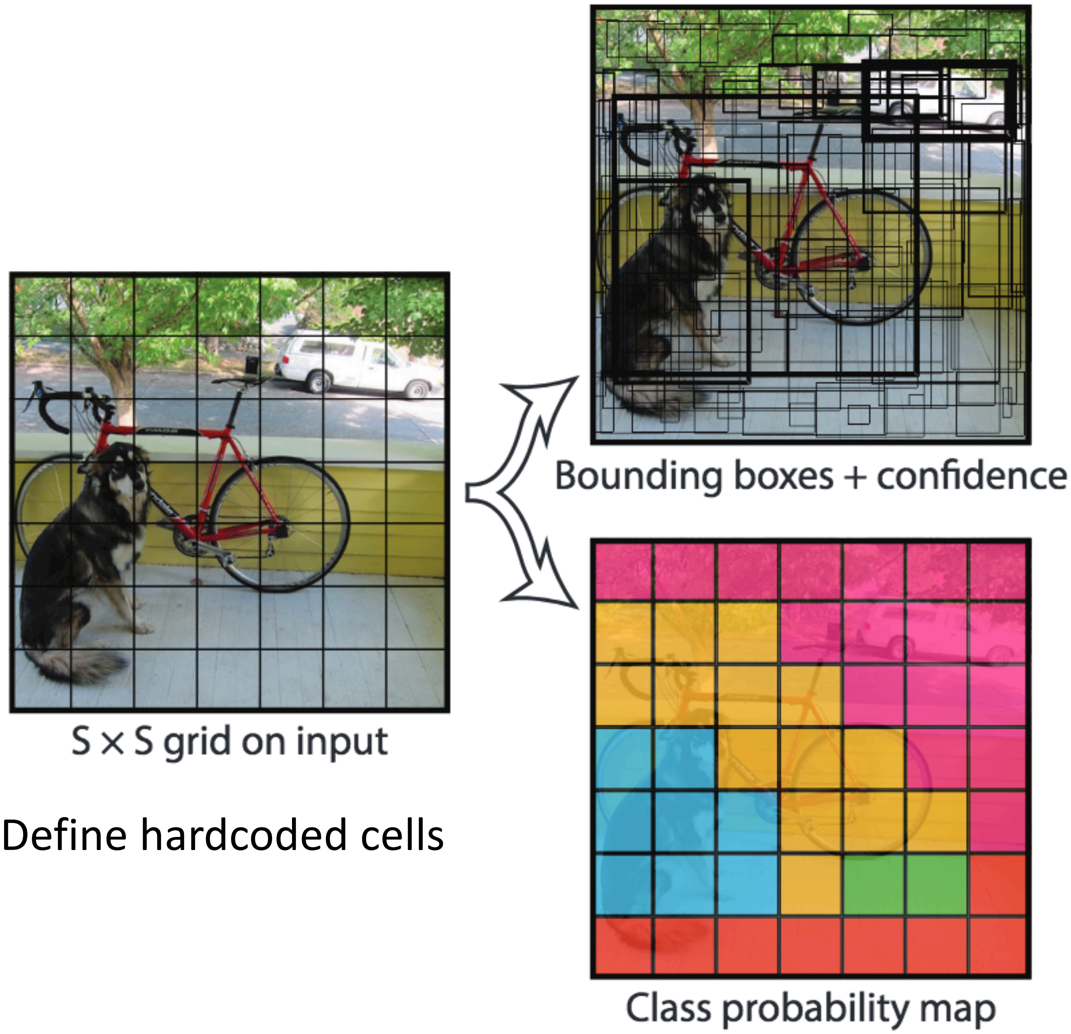


Define hardcoded cells

Each bounding box has 5 values:

- x, y: the **center of the box** relative to the cell center
- w, h: the **width and height** of the box, so it can be deformed to better fit an object
- c: the **confidence** that there is an object in that box

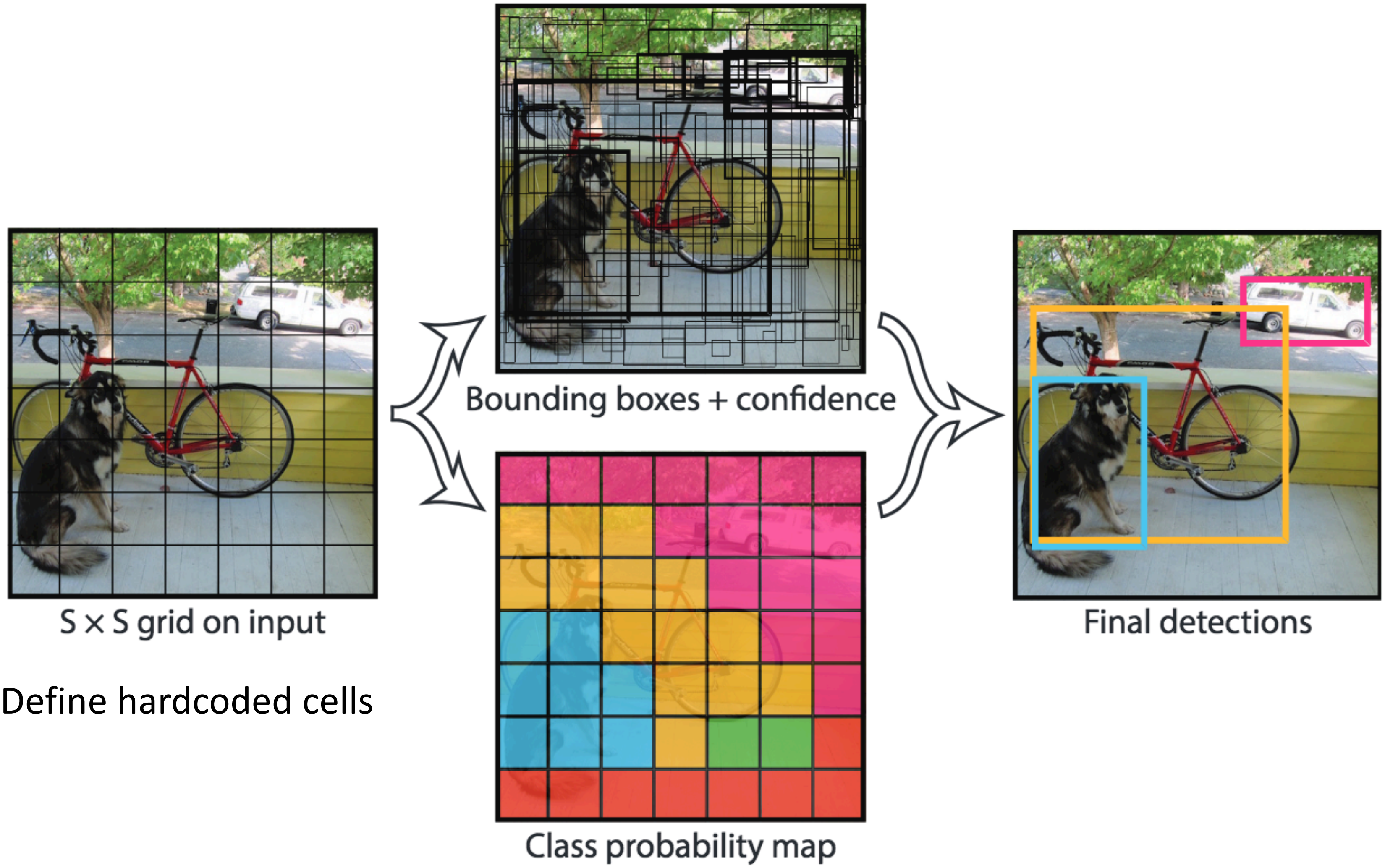
Single Stage: Yolo: You Only Look Once



Define hardcoded cells

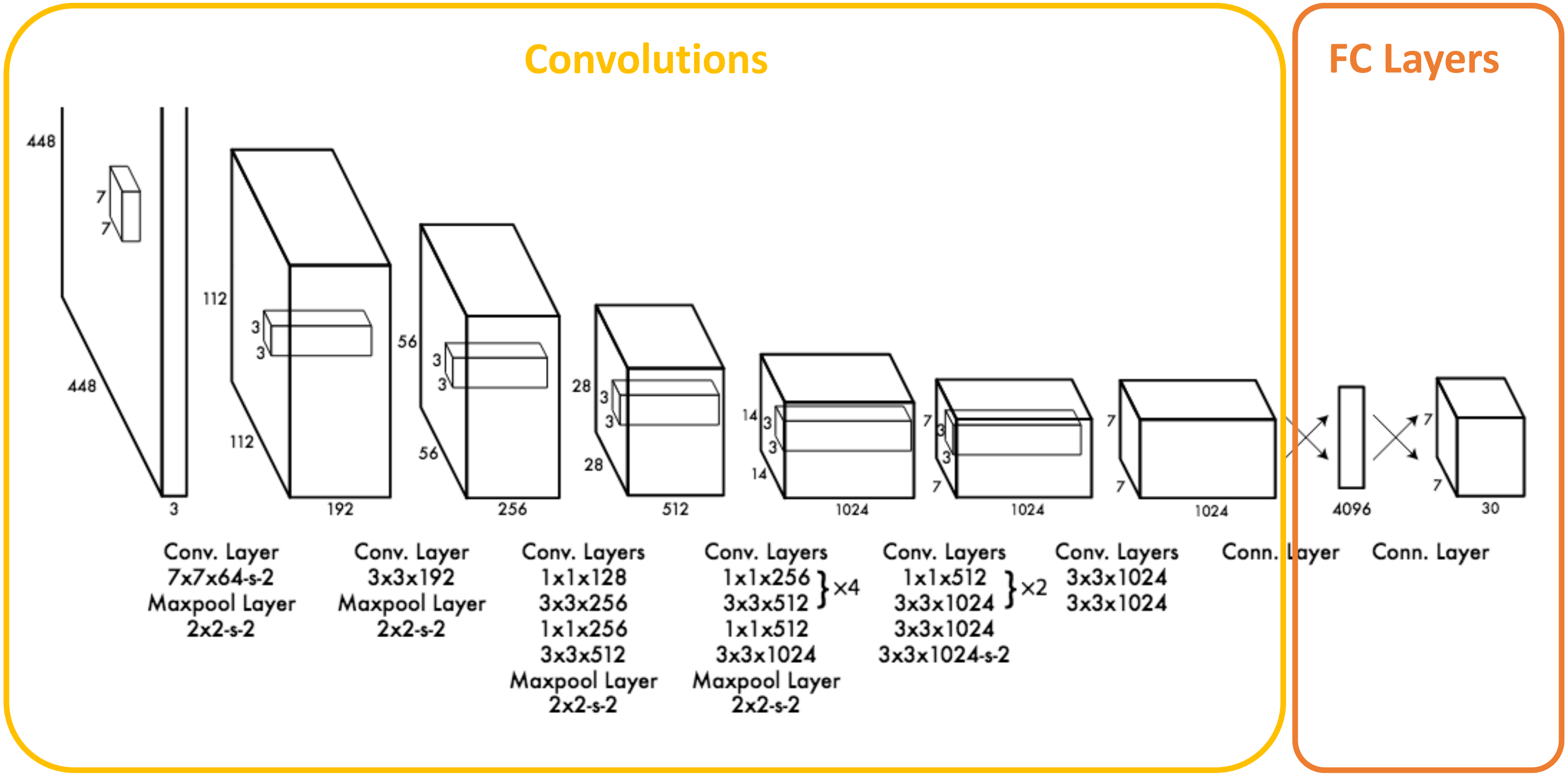
Each cell (not each box!) has an associated class

Single Stage: Yolo: You Only Look Once



Define hardcoded cells

Single Stage: Yolo: You Only Look Once



Last layer predict a vector of size 1470:

$$1470 = 7 \times 7 \times (2 \times 5 + 20) = S \times S \times (B \times 5 + C)$$

S : number of cells per side

B : number of bounding boxes per cell

C : number of classes (including background class)

Single Stage: Yolo: You Only Look Once

$$\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right]$$

Center the box towards the ground-truth (GT) center

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

Match the GT box shape (width and height)

$$+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2$$

Increase object confidence if GT object is actually present

$$+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2$$

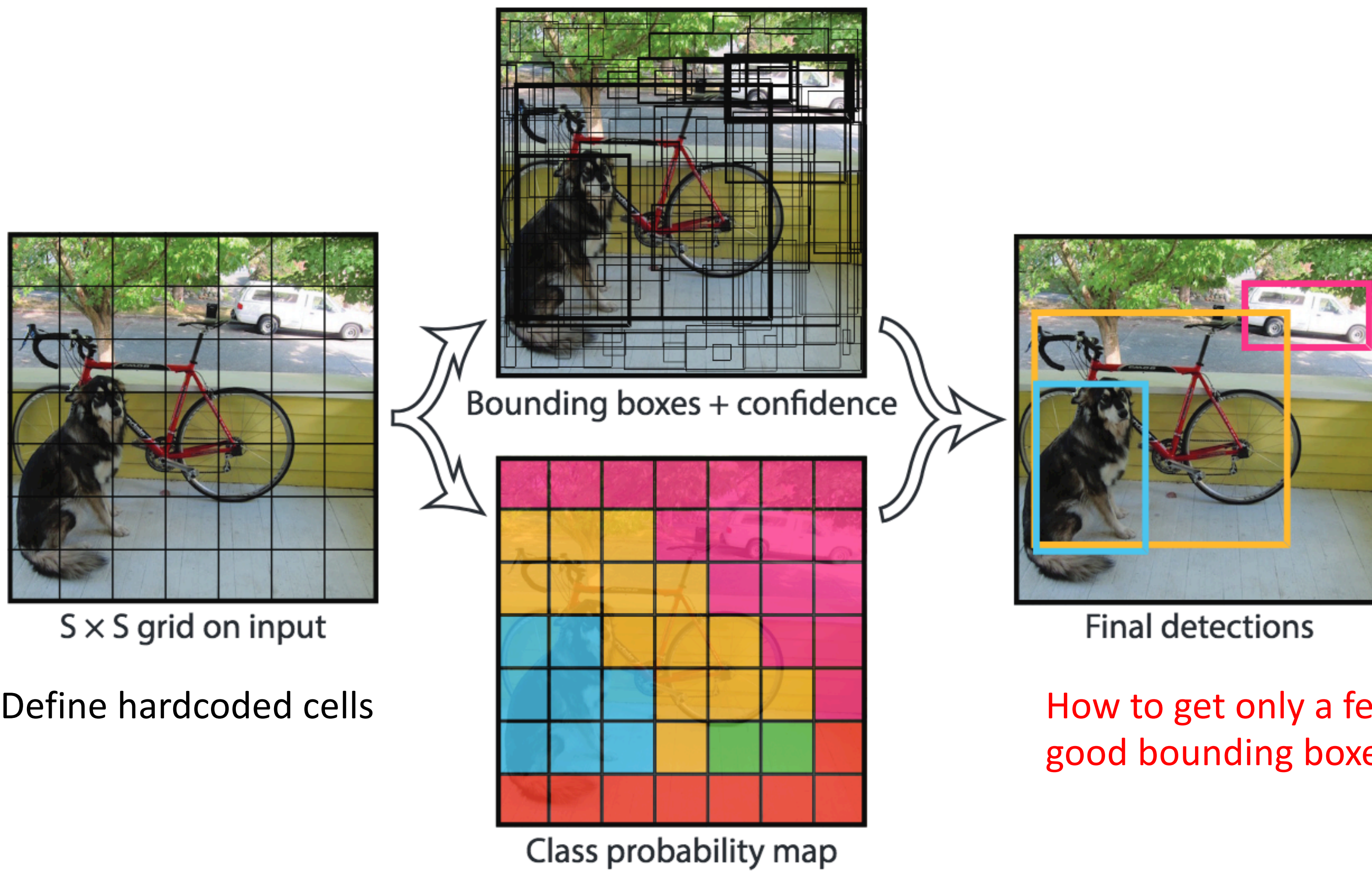
Decrease object confidence if GT object is actually not present

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

Increase correct class prediction if GT object is actually present

S : number of cells per side
B : number of bounding boxes per cell
C : number of classes (including background class)

<u>Single Stage</u>: Yolo: You Only Look Once

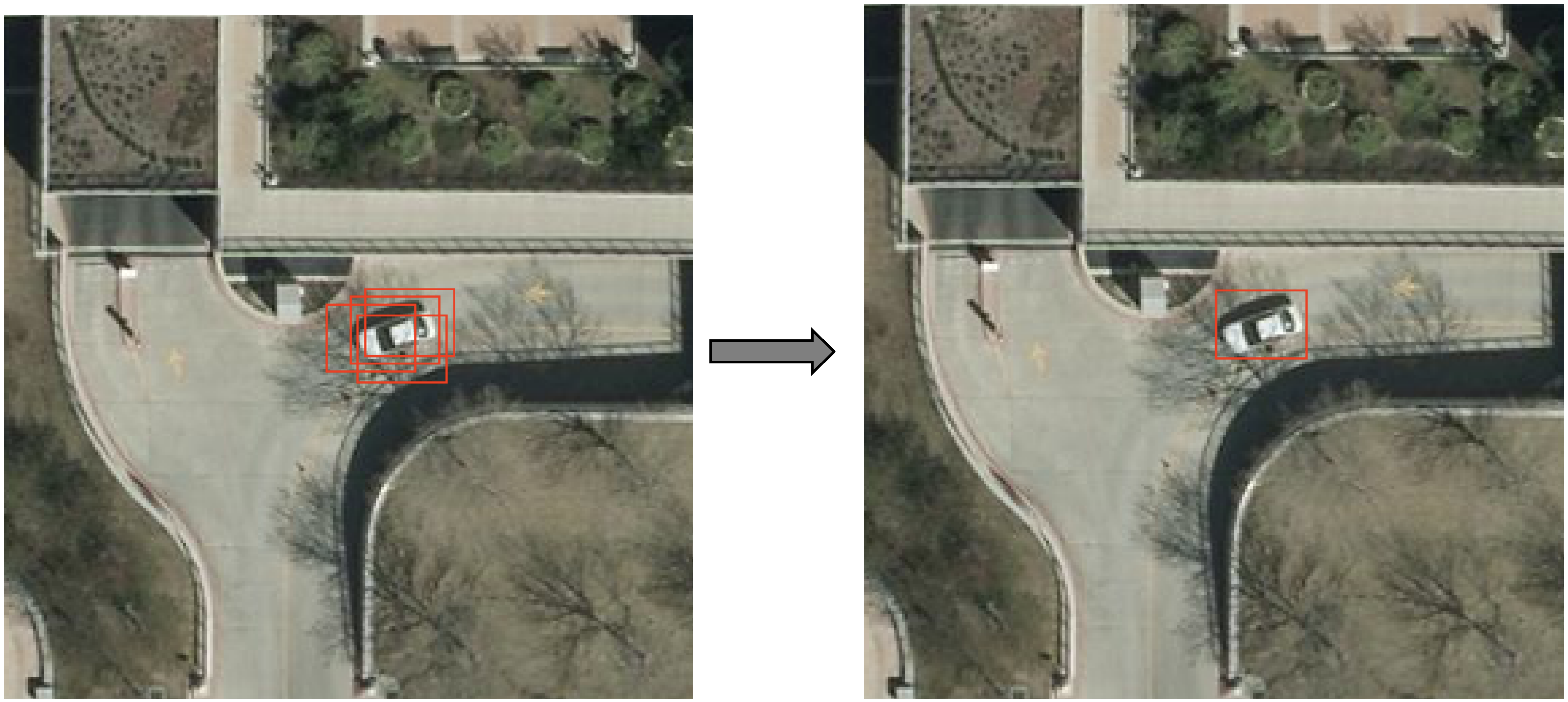


Define hardcoded cells

How to get only a few good bounding boxes?

Background + NMS

1. Remove all bounding boxes associated to the class “*background*”
2. Then apply **Non-Max Suppression** (NMS)

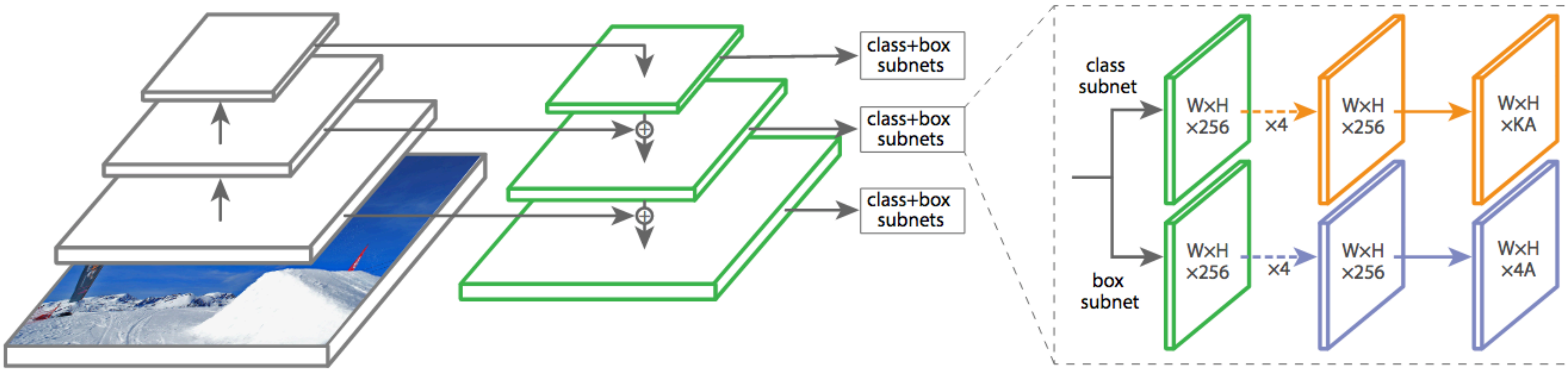


Among all overlapping bounding boxes, keep the most confident one.

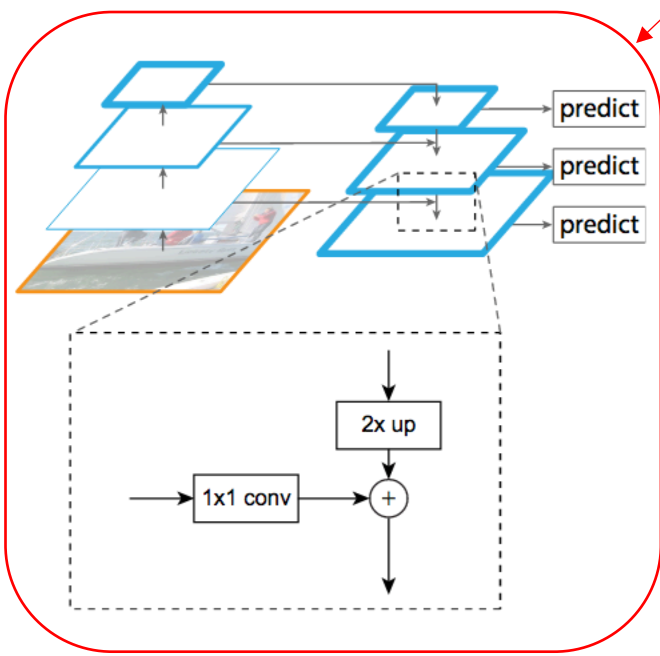
Non differentiable post-processing done in inference!

[Douillard et al. Nato challenge 2018]

Single-Stage: RetinaNet



(a) ResNet (b) feature pyramid net (c) class subnet (top) (d) box subnet (bottom)



Fully Convolutional Architecture (FCN)

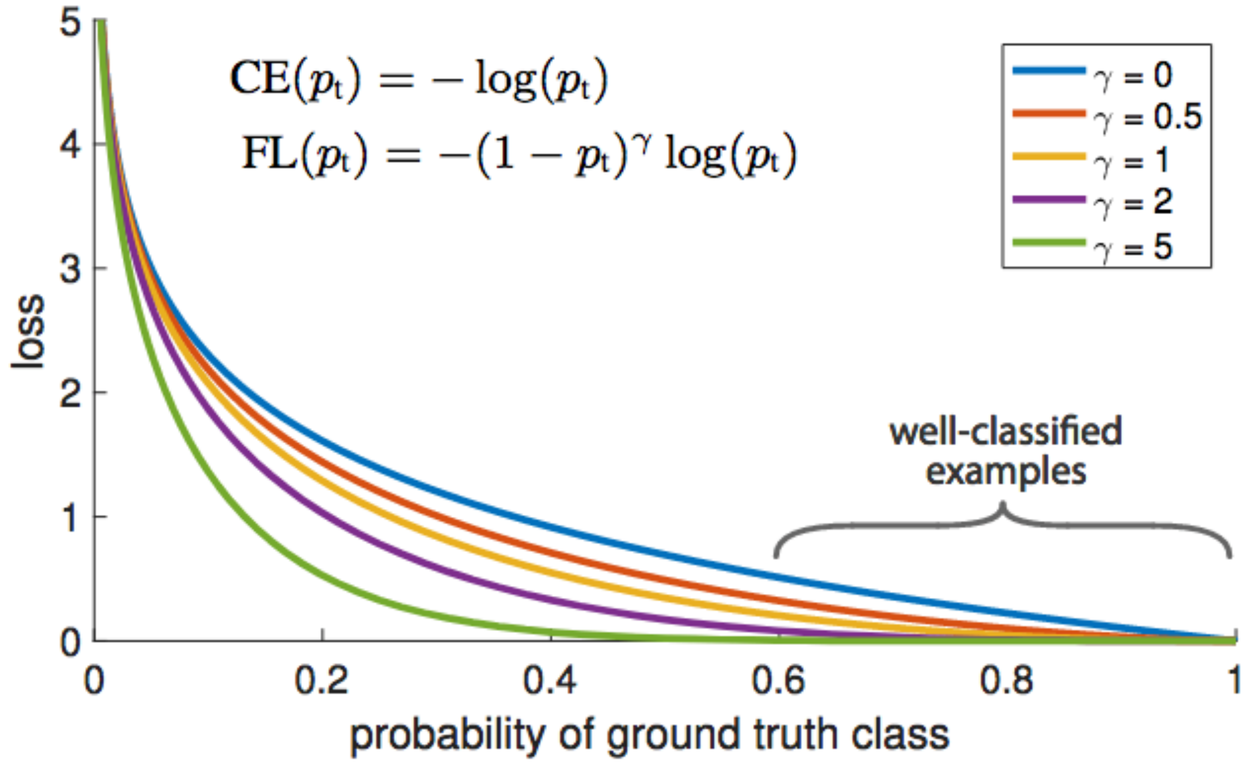
[Lin et al. ICCV 2019]

Single-Stage: RetinaNet's Focal Loss

$$\mathrm{FL}(p_t) = -\alpha_t (1 - p_t)^\gamma \log(p_t)$$

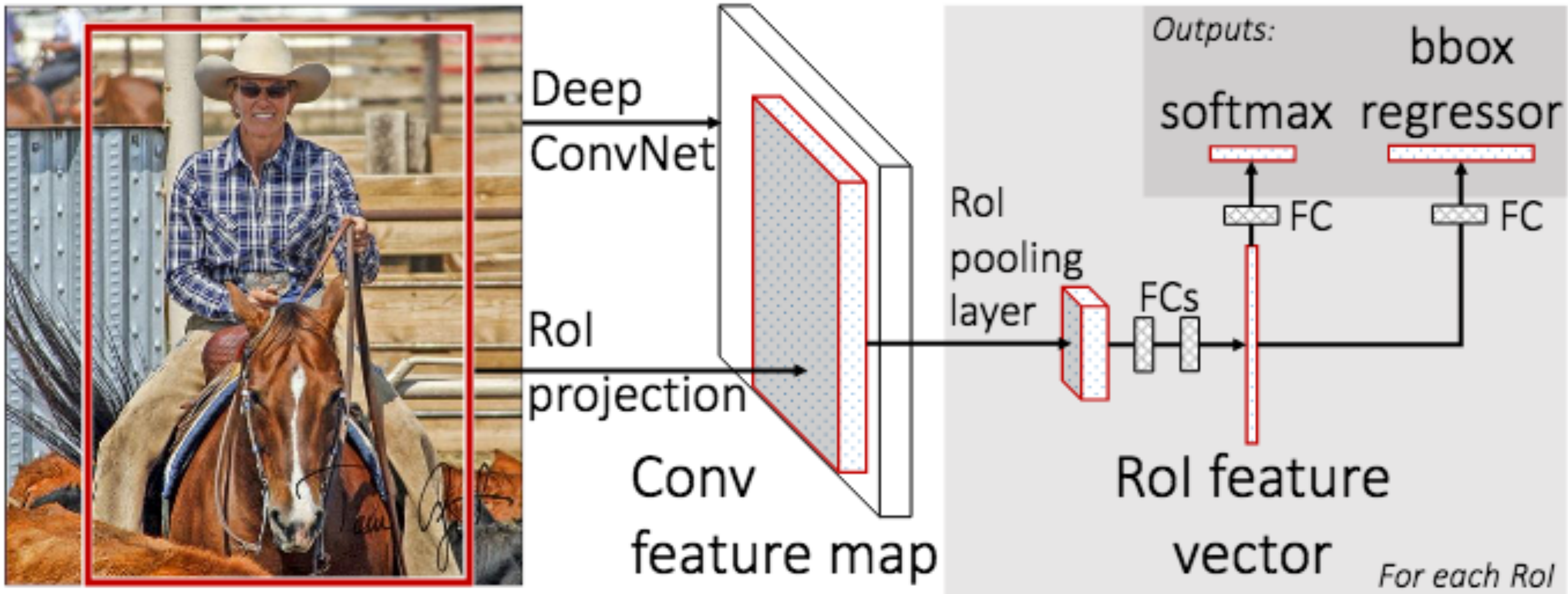
Single-stage models have a huge imbalance with many potential RoIs that are **background**.

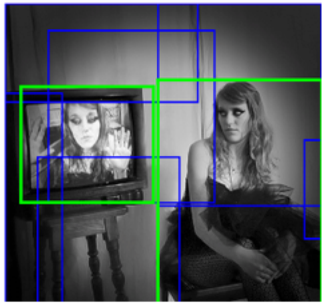
Focal loss reduces the loss if the correct class is predicted with too much confidence.



[Lin et al. ICCV 2019]

Two Stages: Fast R-CNN





1. Extract features from pixels with “Deep ConvNet”
2. Generate RoIs from pixels using Selective Search
3. Index the features using the RoIs

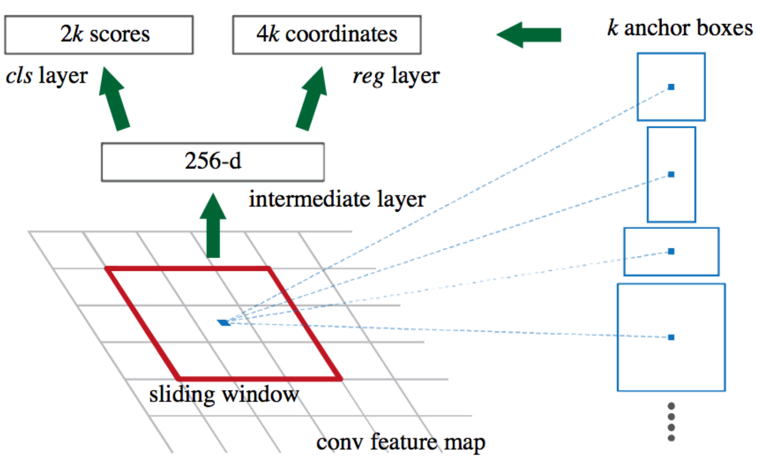
[Girshick ICCV 2015]

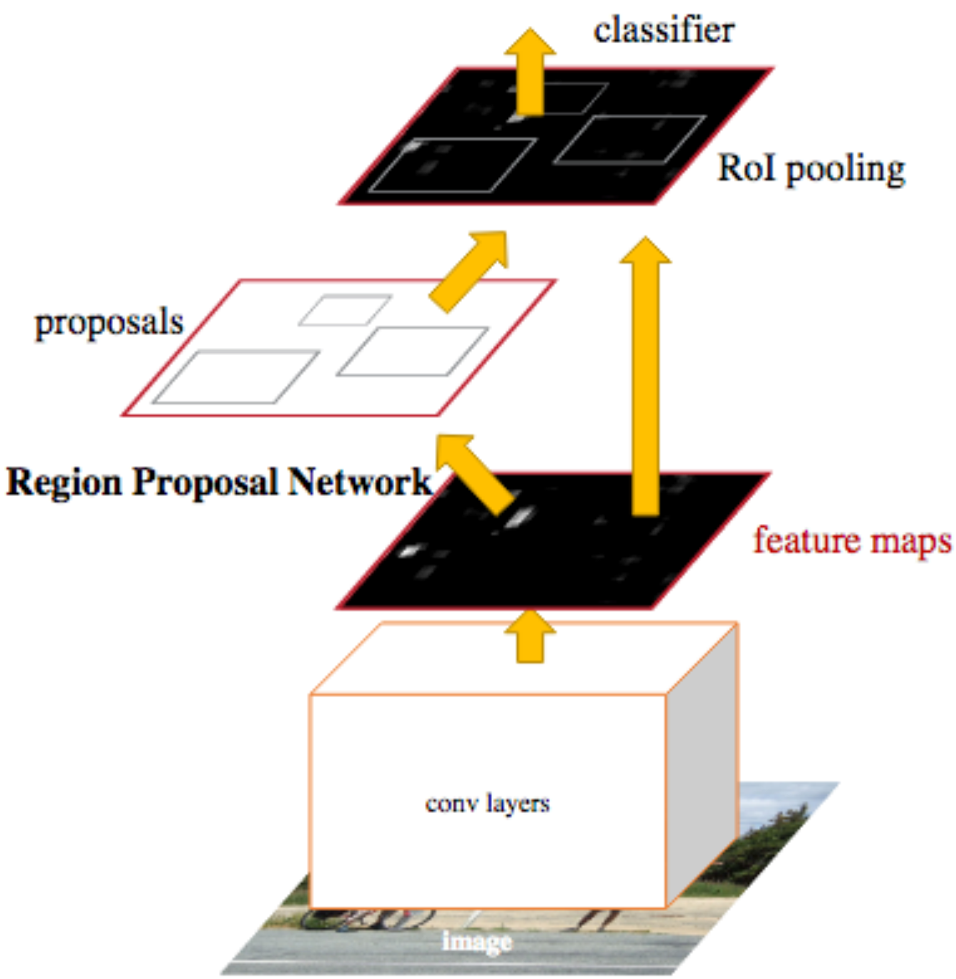
Two Stages: Faster R-CNN

Similar to Fast R-CNN but ditch the selective search for a **Region Proposal Network** (RPN).

Mini-network that slides different anchors and predict a binary classification:

background vs non-background



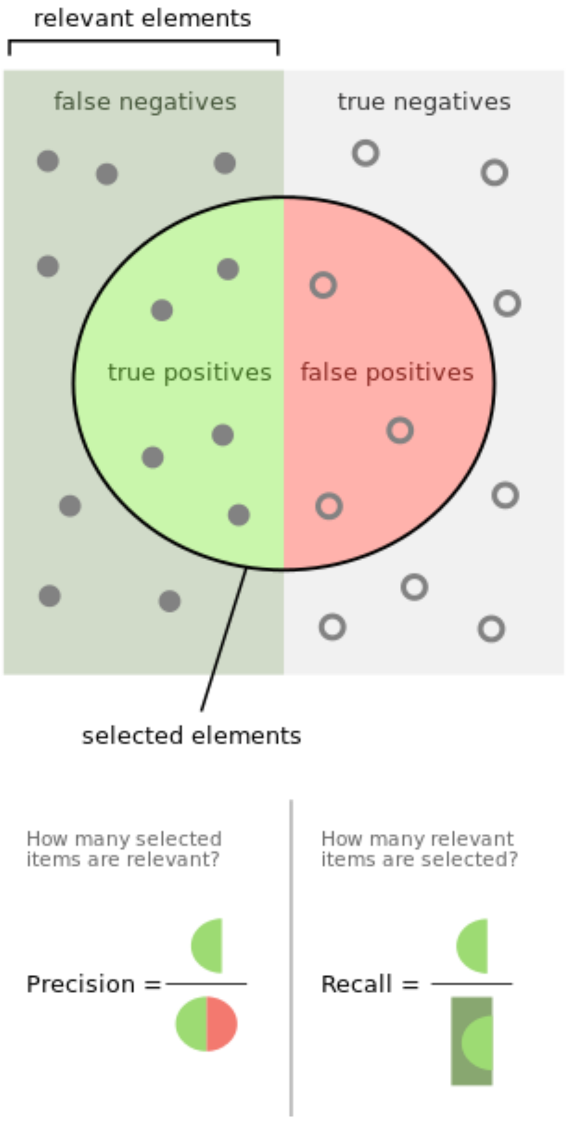


[Ren et al. NeurIPS 2015]

Metric: Precision & Recall

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$



[Wikipedia]

Metric: Intersection over Union

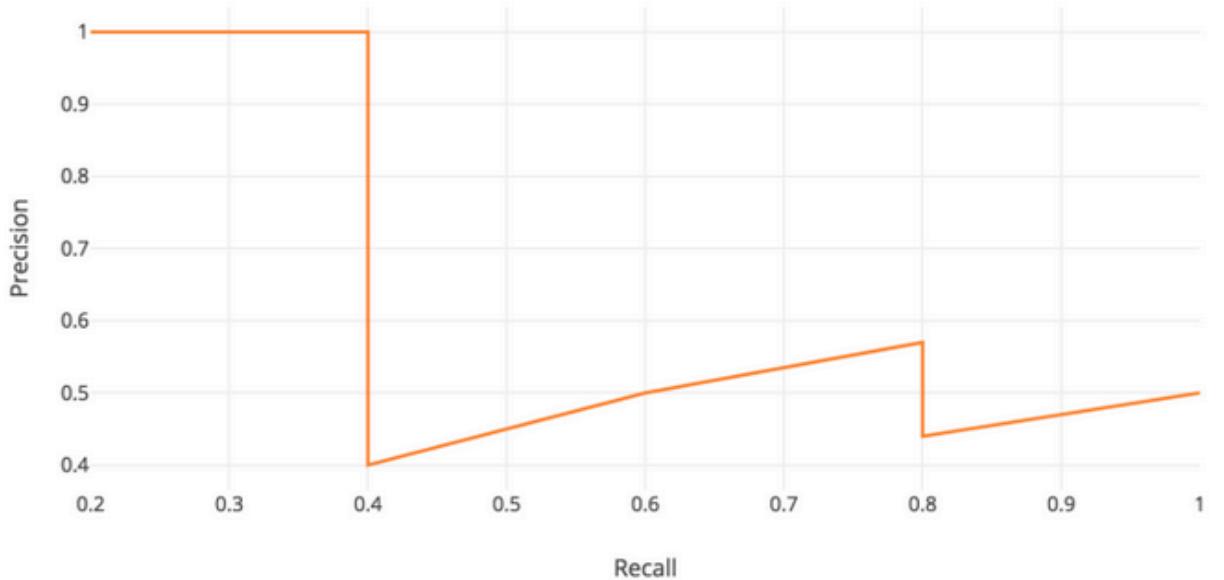
Ground truth

Prediction

$$IoU = \frac{\text{area of overlap}}{\text{area of union}}$$

[Hui's Medium]

Metric: mean Average Precision (mAP)



Precision-recall curve

$$\mathrm{AP} = \int_0^1 p(r)dr$$

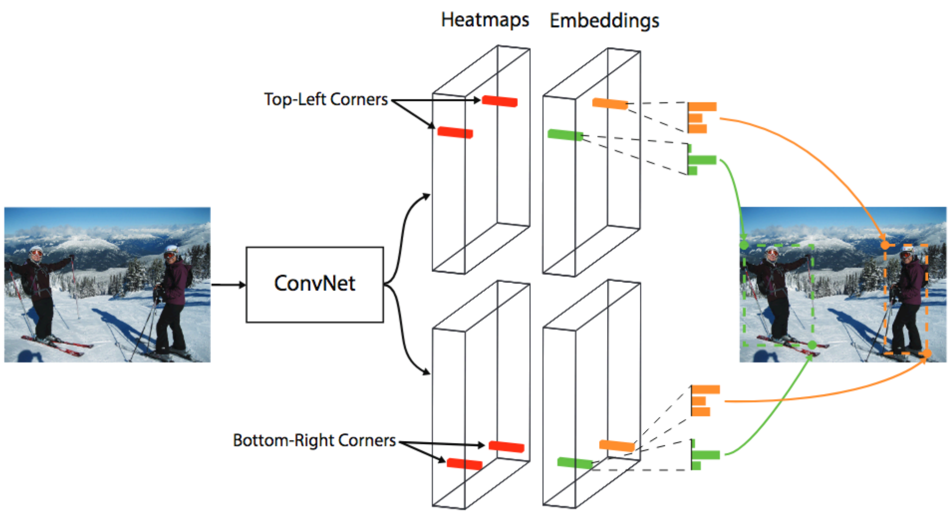
An object is correctly predicted if IoU > 0.5 with ground-truth.

AP is the area under the curve for the graph Recall-Precision.
→ We want a high precision while not missing an object (recall)

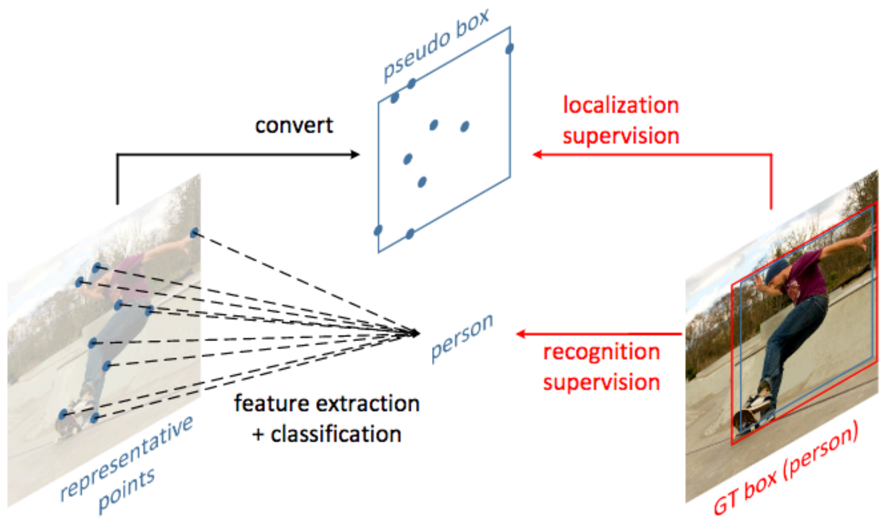
[Hui's Medium]

Beyond anchors

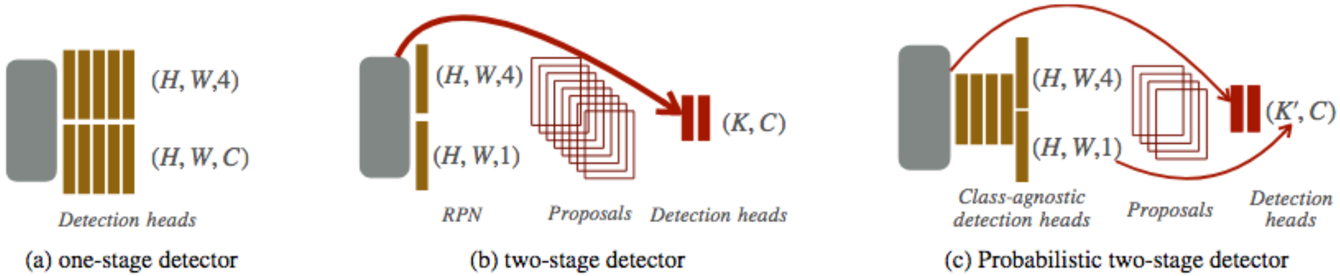
CornerNet, predicting the top-left and bottom-right corners.
[Law et al. ECCV 2018]



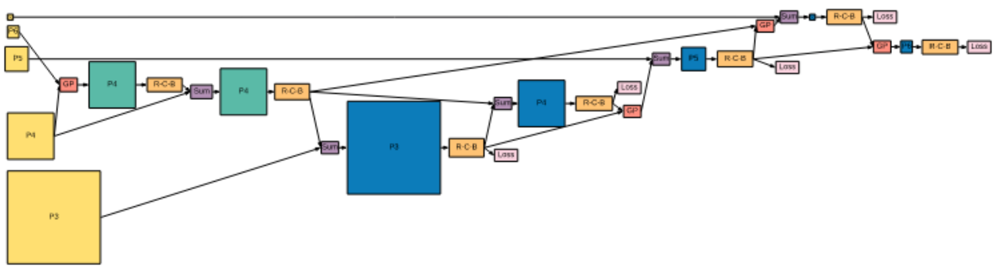
RepPoints, predicting points that bound an object.
[Yang et al. ICCV 2019]



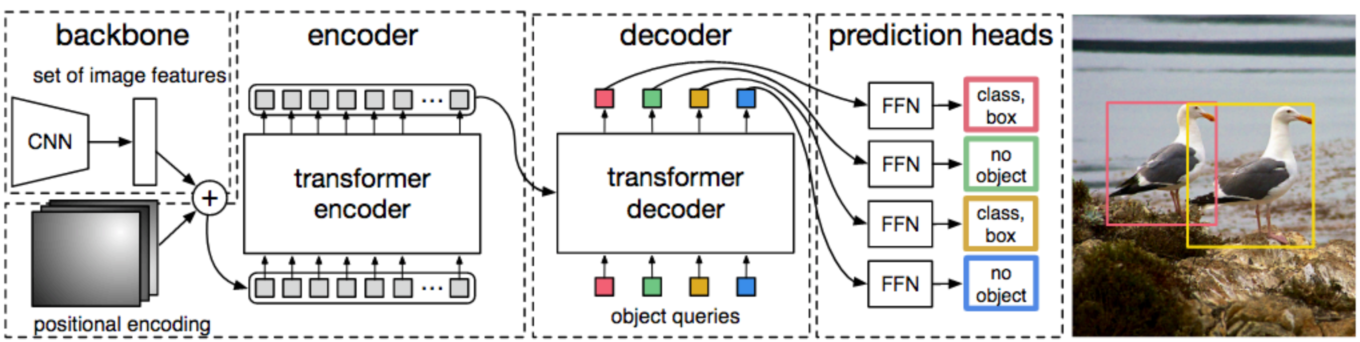
State of the Art



Combining RPN prediction with final class prediction:[CenterNet2, Zhou et al. arXiv 2021]



NAS-FPN + Aggressive copy-pasted based augmentation: [Ghiasi et al. CVPR 2021]



Transformers-based to produce a **set** of boxes: [Carion et al. ECCV 2020]

Segmentation

Semantic Segmentation

Each pixel has a class

[kharshit.github.io]

Instance Segmentation

Each pixel has a foreground class and an instance

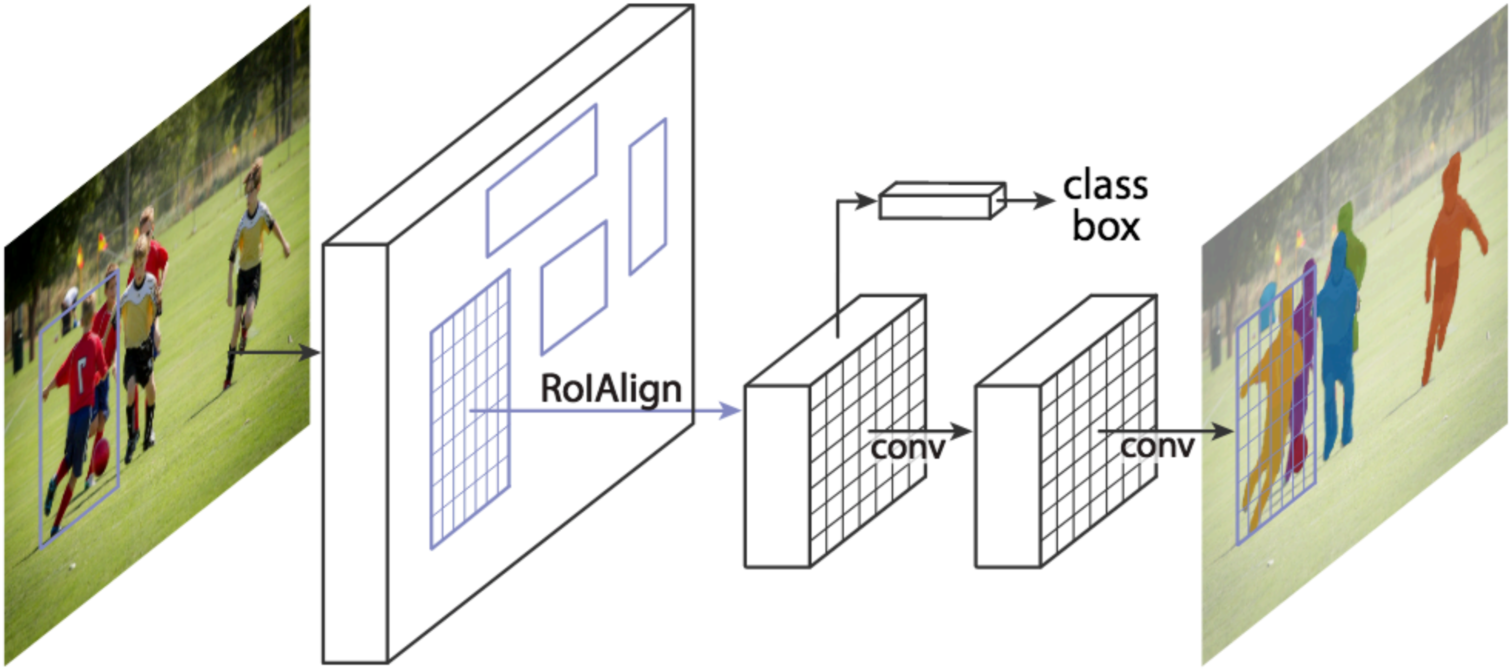
[kharshit.github.io]

Panoptic Segmentation

Semantic + Instance Segmentation

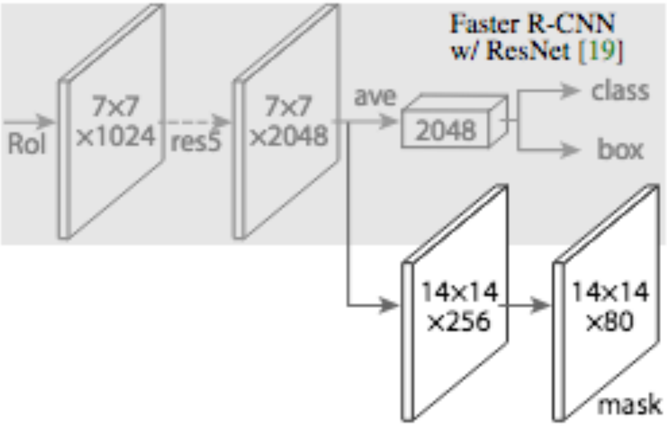
[kharshit.github.io]

Instance Segmentation: Mask R-CNN



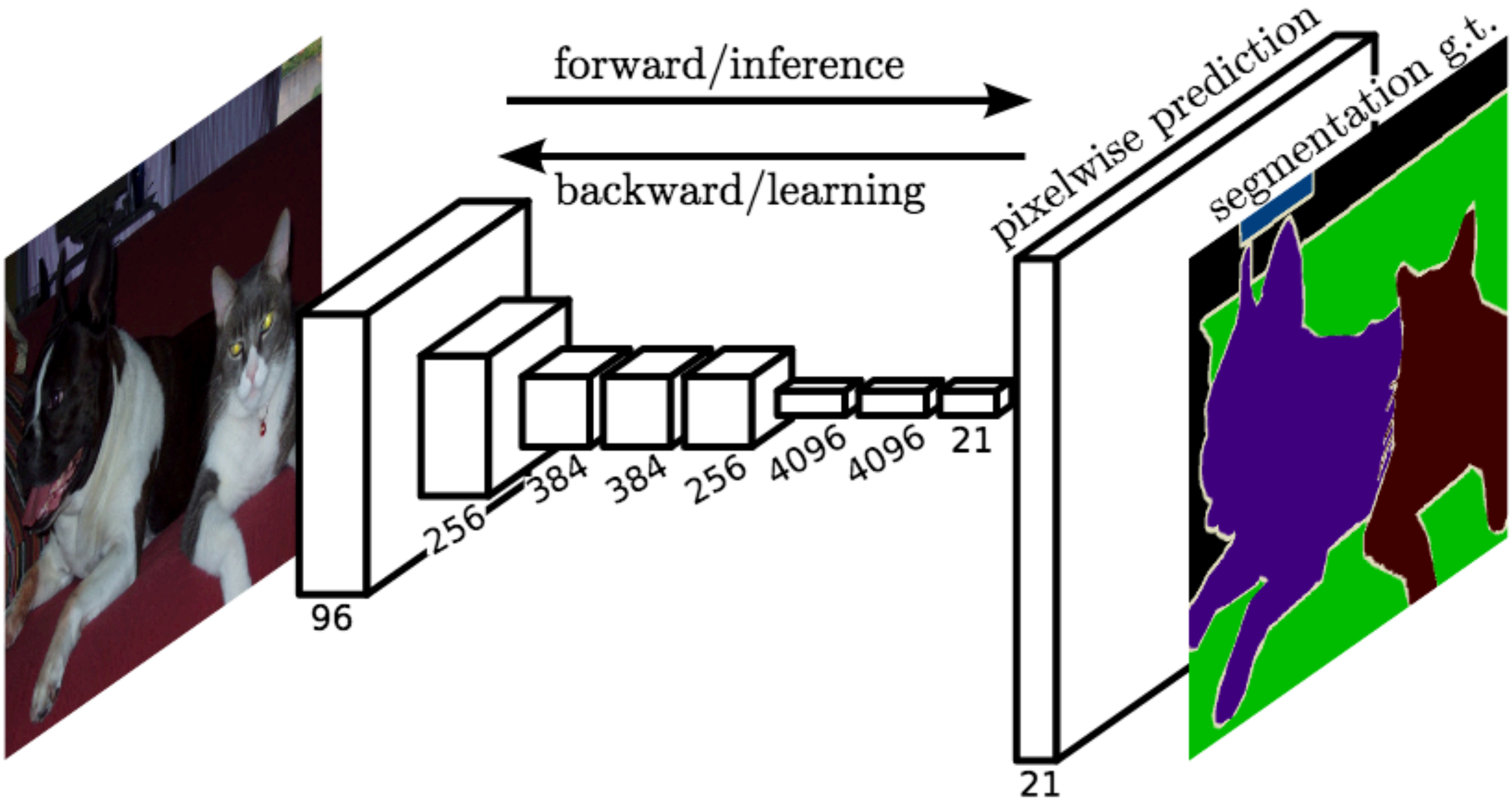
Extend Faster R-CNN with a new branch made only of convolutions.

The branch predict a class per pixels per box.



[He et al. ICCV 2017]

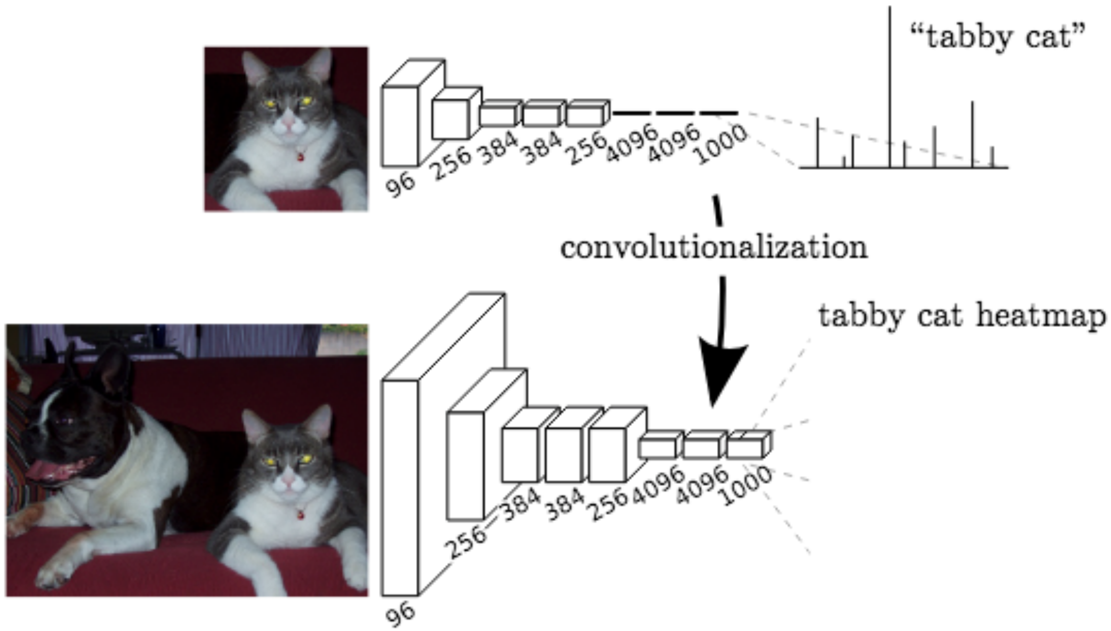
Semantic Segmentation: Fully Convolutional Network



Predict 21 classes per features/logits pixels, upscale the prediction to image size and classify per pixel with cross-entropy.

[Long et al. CVPR 2015]

Semantic Segmentation: Fully Convolutional Network



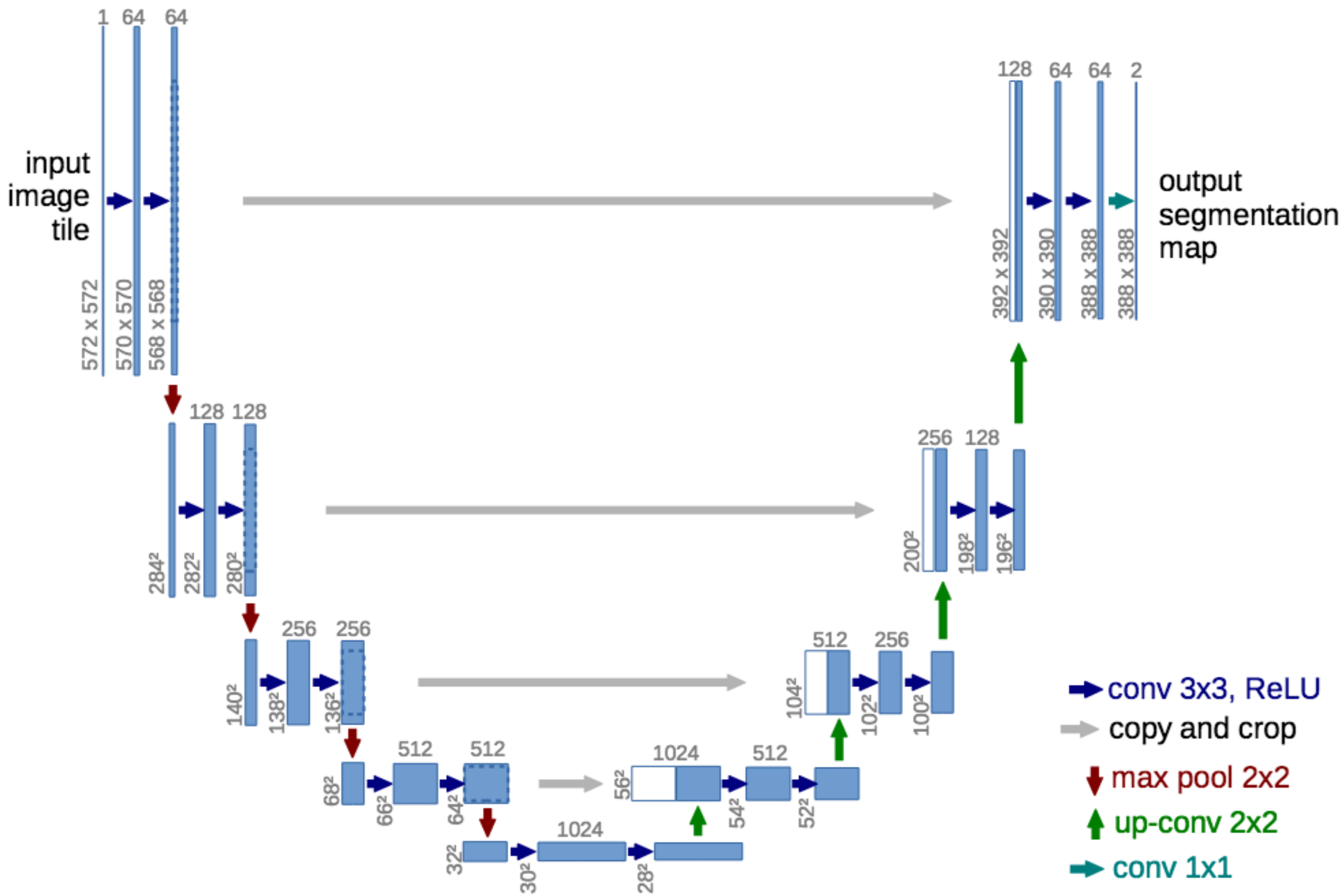
Init the network with model pretrained on ImageNet.

And convert the last FCs layers into 1x1 convolutions… while keeping weights!

FC weight: $C_i \times C_o$
Conv weight: $C_i \times C_o \times k \times k$

[Long et al. CVPR 2015]

Semantic Segmentation: U-Net

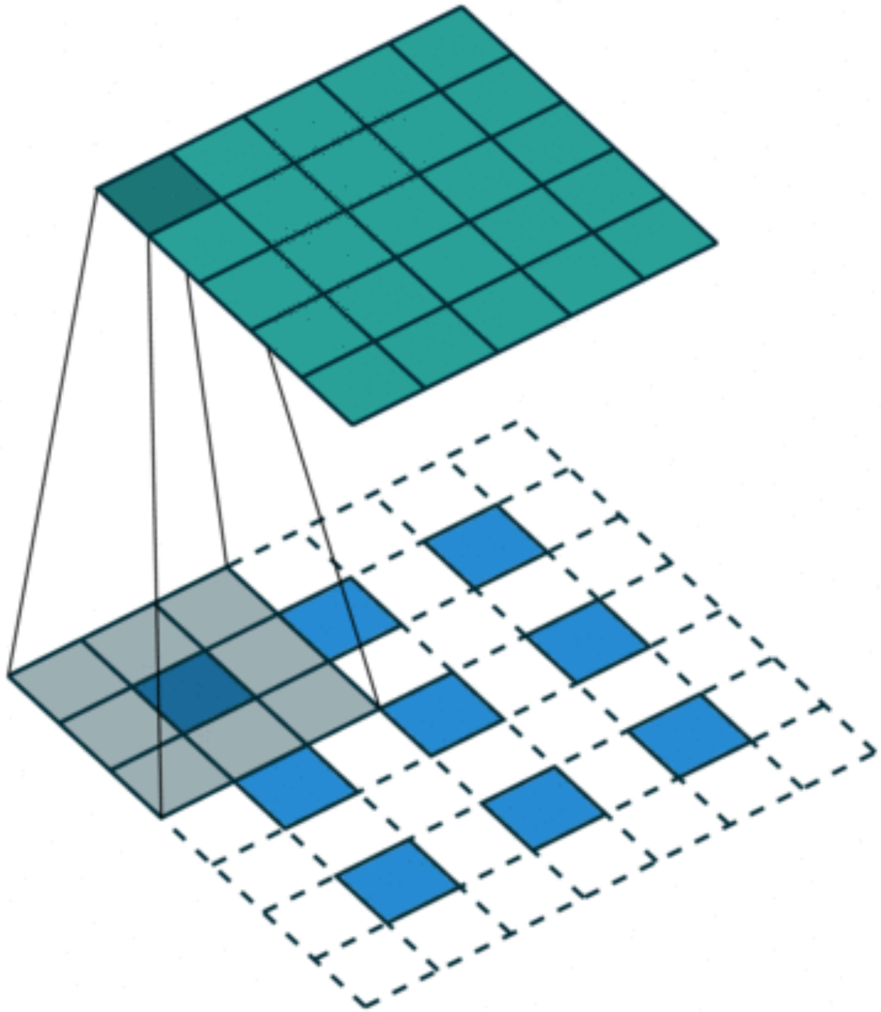


Upsample the small features maps with **transposed convolution**

[Ronnerberger et al. MICCAI 2015]

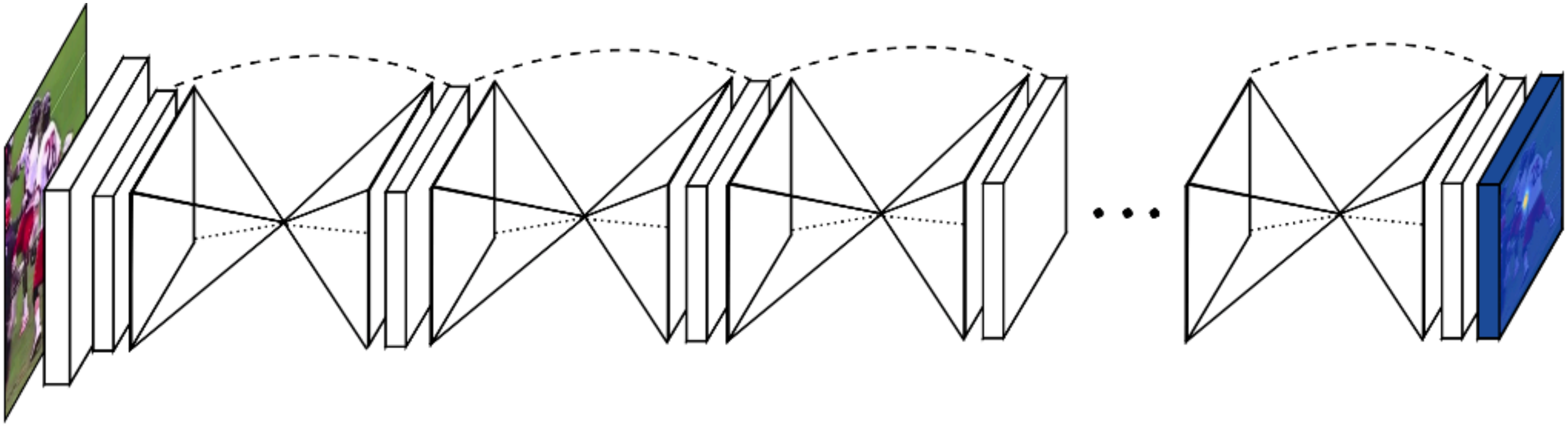
Transposed Convolution

Add padding inside the input features.



[vdumoulin's github]

Semantic Segmentation: Hourglass Network



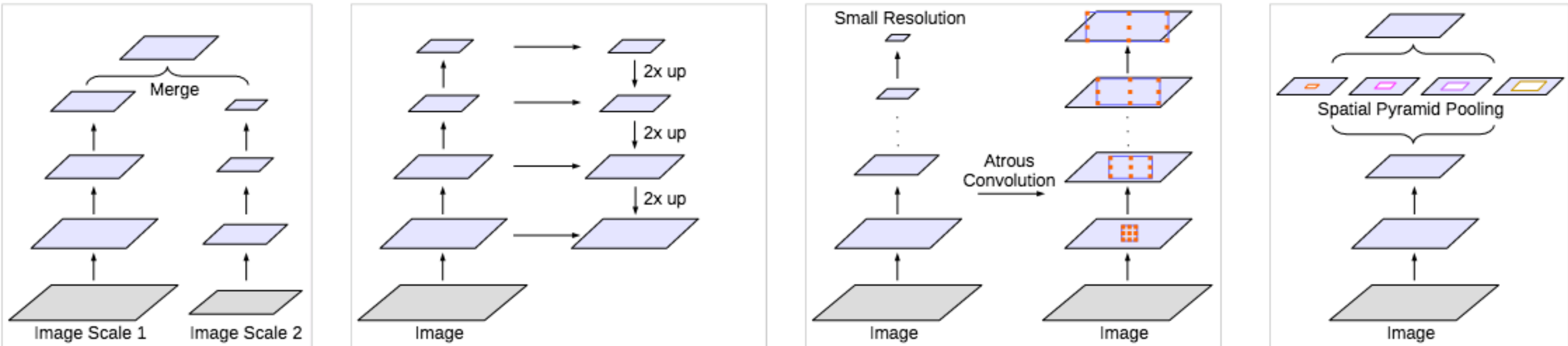
Stack of Hourglass, which are similar to U-Net

Each hourglass is trained to predict the final segmentation map.

The N+1 hourglass refines the results of the N hourglass, as in boosting.

[Newell et al. ECCV 2016]

Semantic Segmentation: DeepLab v2-v3



(a) Image Pyramid (b) Encoder-Decoder (c) Deeper w. Atrous Convolution (d) Spatial Pyramid Pooling

Multi-Scale images

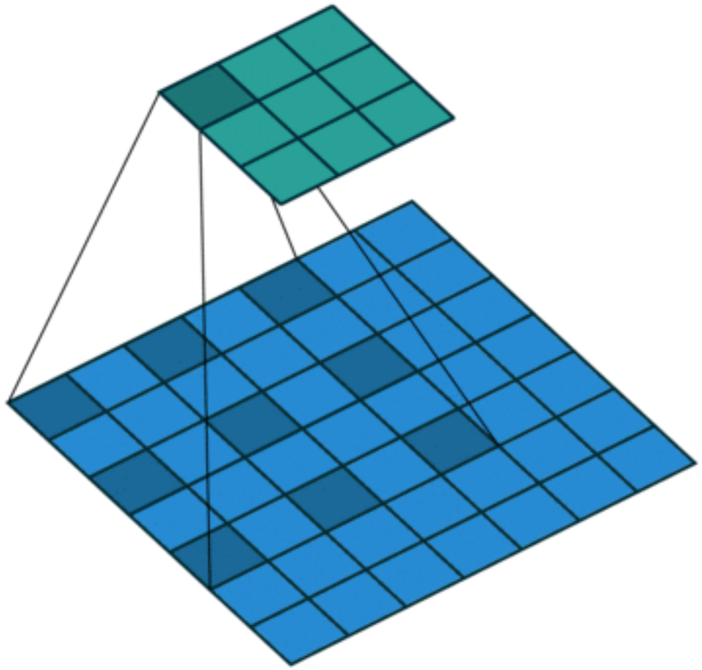
U-Net like architectures

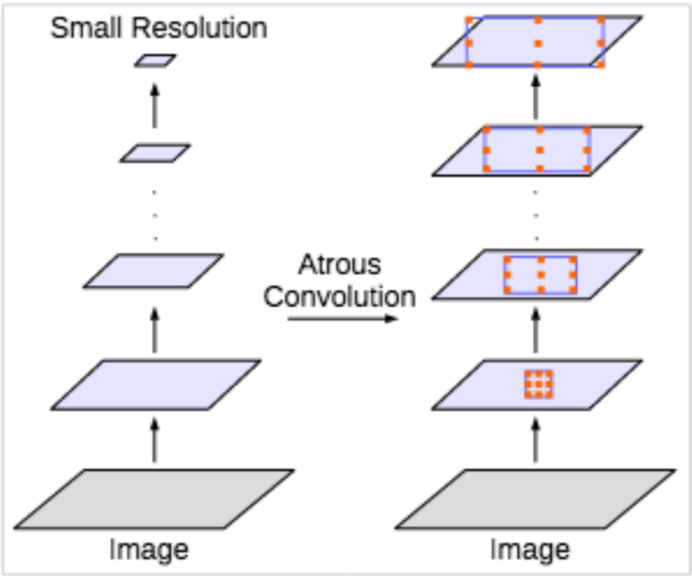
DeepLab v2

DeepLab v3

[DeepLab v2, Chen et al. TPAMI 2016], [DeepLab v3, Chen et al. arXiv 2017]

Semantic Segmentation: DeepLab v2





(c) Deeper w. Atrous Convolution

Dilated (Atrous) convolutions.

Add padding inside kernel

→ **Larger receptive field-of-view**
→ Add also a lot of padding around the input features to keep large resolution

[DeepLab v2, Chen et al. TPAMI 2016], [vdumoulin's github]

Semantic Segmentation: DeepLab v3

Atrous Spatial Pyramid Pooling (ASPP):

→ Combine multiple dilation rate, each seeing a different "scale"

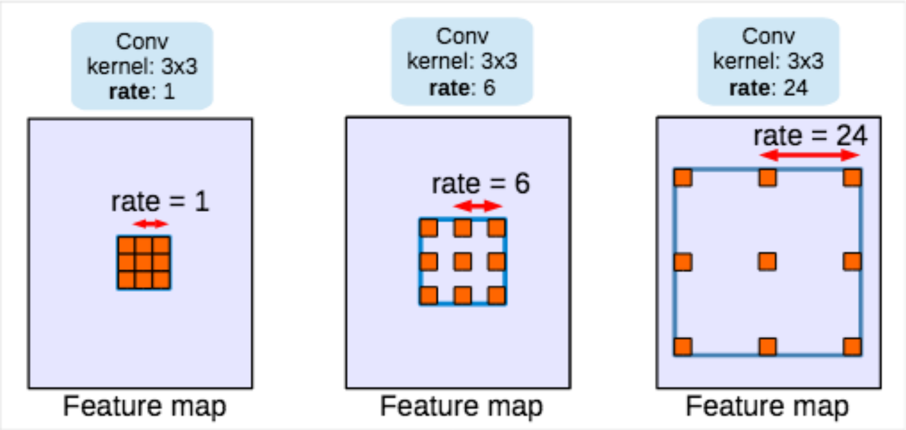
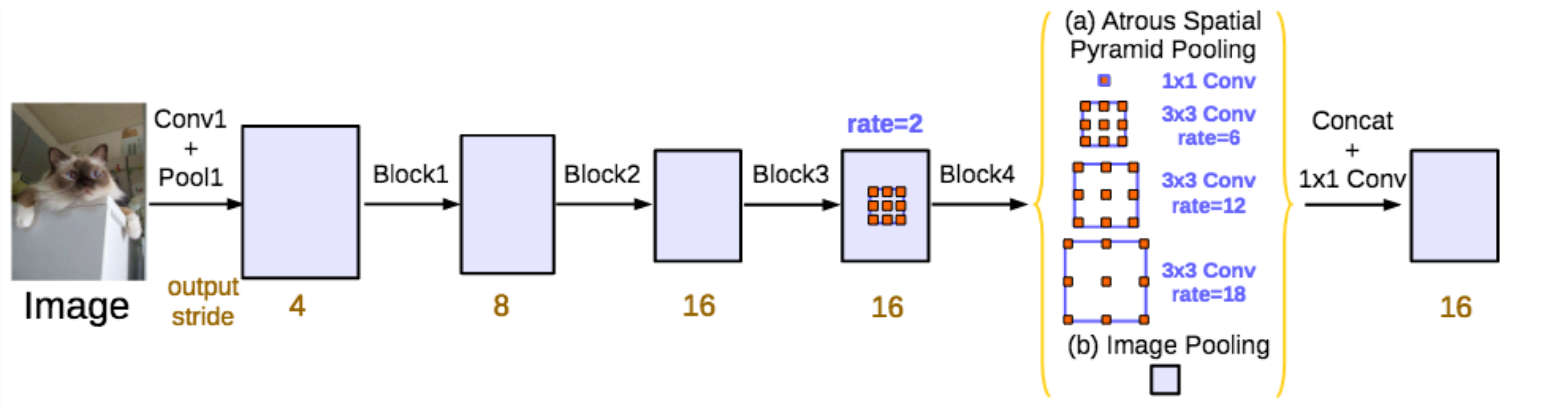


Figure 1. Atrous convolution with kernel size 3 × 3 and different rates. Standard convolution corresponds to atrous convolution with $rate = 1$. Employing large value of atrous rate enlarges the model's field-of-view, enabling object encoding at multiple scales.

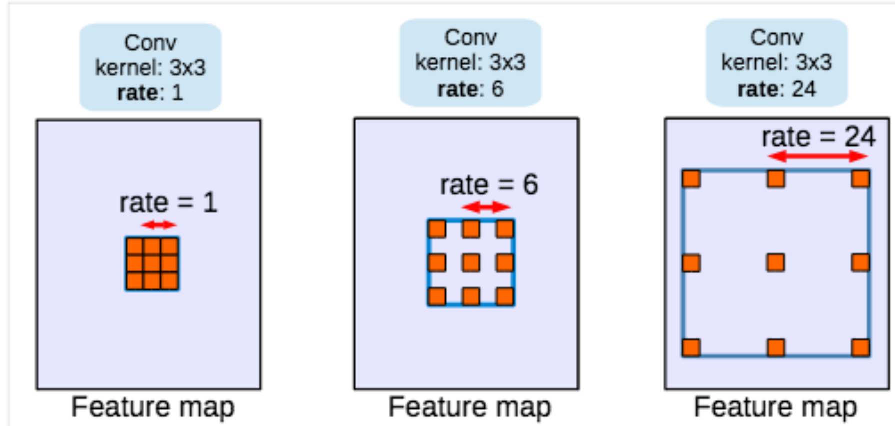


[DeepLab v3, Chen et al. arXiv 2017]

Semantic Segmentation: DeepLab v3

Atrous Spatial Pyramid Pooling (ASPP):

→ Combine multiple dilation rate, each seeing a different "scale"



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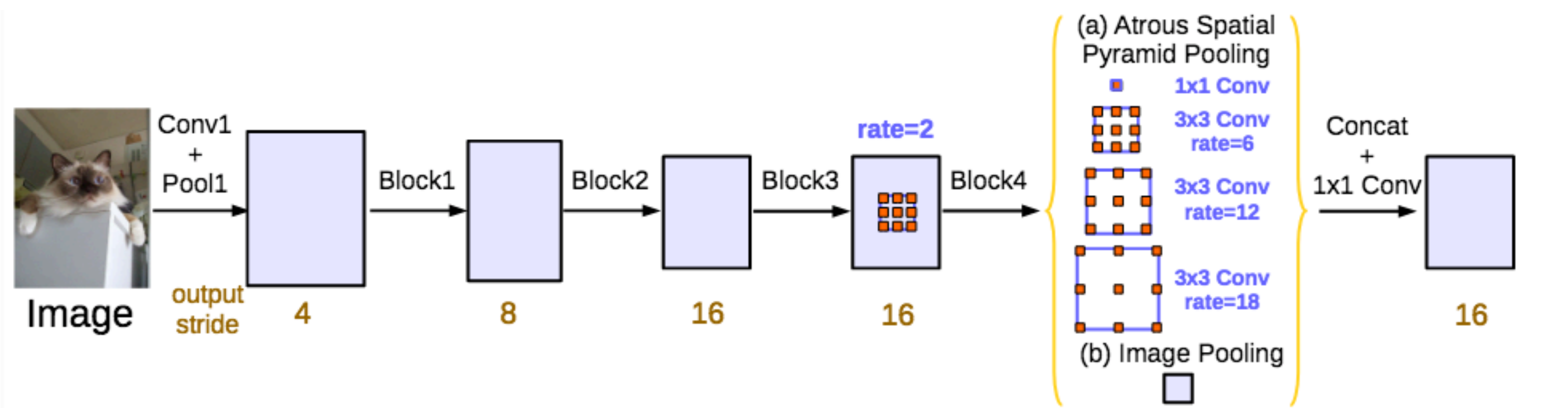


[DeepLab v3, Chen et al. arXiv 2017]

Two key ideas for segmentation

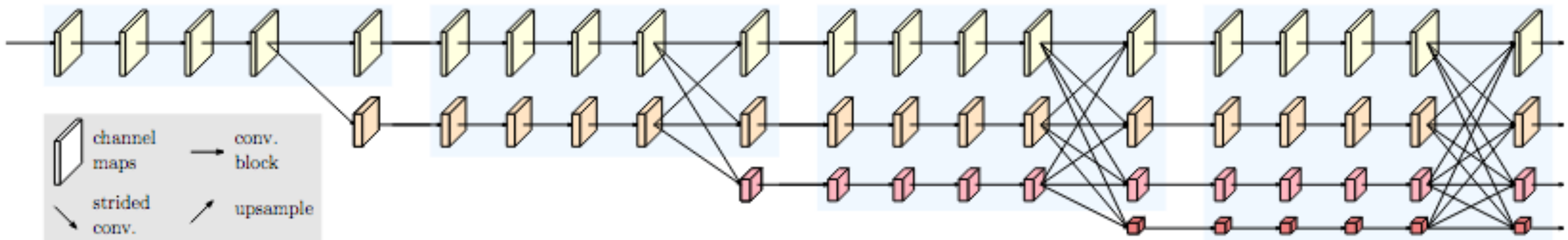
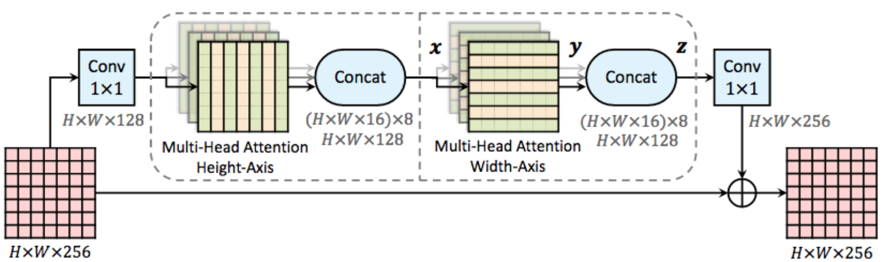
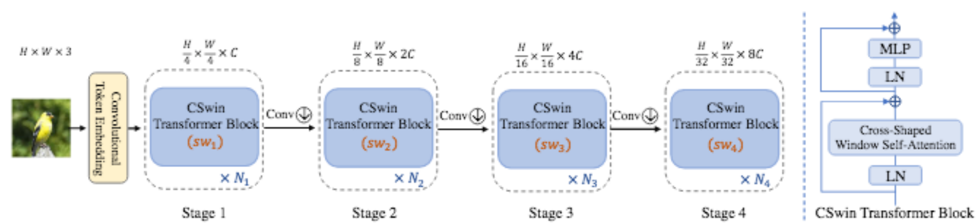


Figure 1. A simple example of a high-resolution network. There are four stages. The 1st stage consists of high-resolution convolutions. The 2nd (3rd, 4th) stage repeats two-resolution (three-resolution, four-resolution) blocks. The detail is given in Section 3.

Multi-scale/resolution is very important to detect all kinds of object. [Sun et al. CVPR 2019]





Attention to far away pixels is also important. [Wang et al. ECCV 2020]

Thus, transformers will probably be a good choice.
[Dong et al. arXiv 2021]

Given fixed method, two possible improvements

Better backbone:

- Larger, wider, deeper, with all modern tricks (EffNet vs ResNet vs VGG)
- Pretrained on a dataset as large as possible (ImageNet, JFT300M, Instagram1B)

Better augmentation and regularization:

- Many data augmentation are possible (erasing, copy-pasting, etc.)
- Regularization trick may help (which kind of normalization? DropPath? Focal Loss?)

Small break,
then coding session!