Deep Learning Applications

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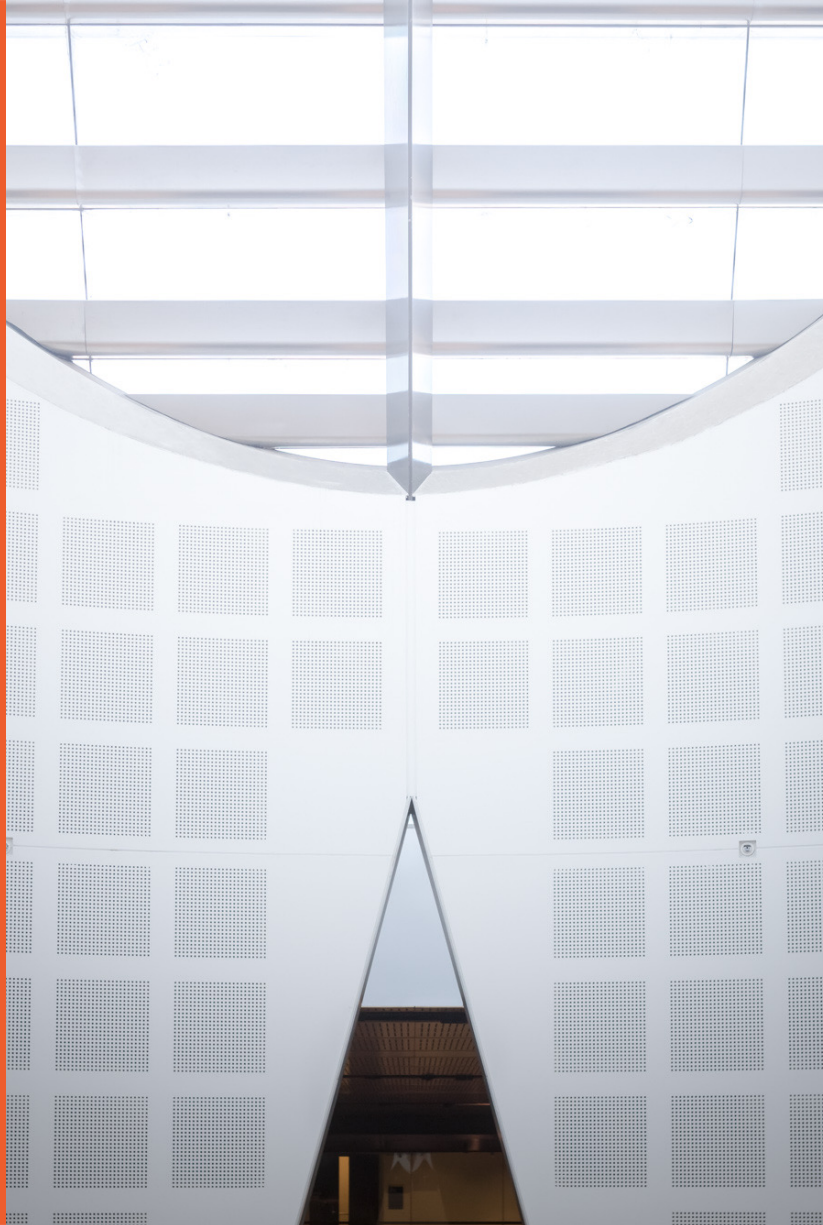
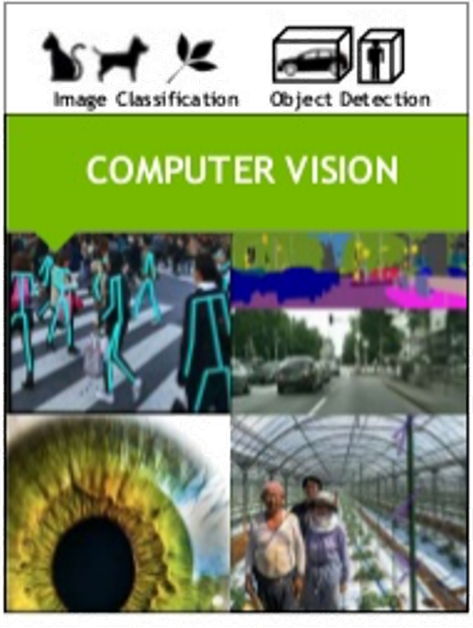
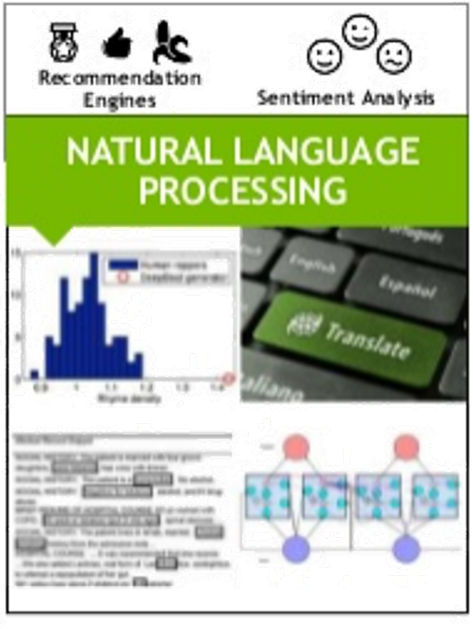


Applications

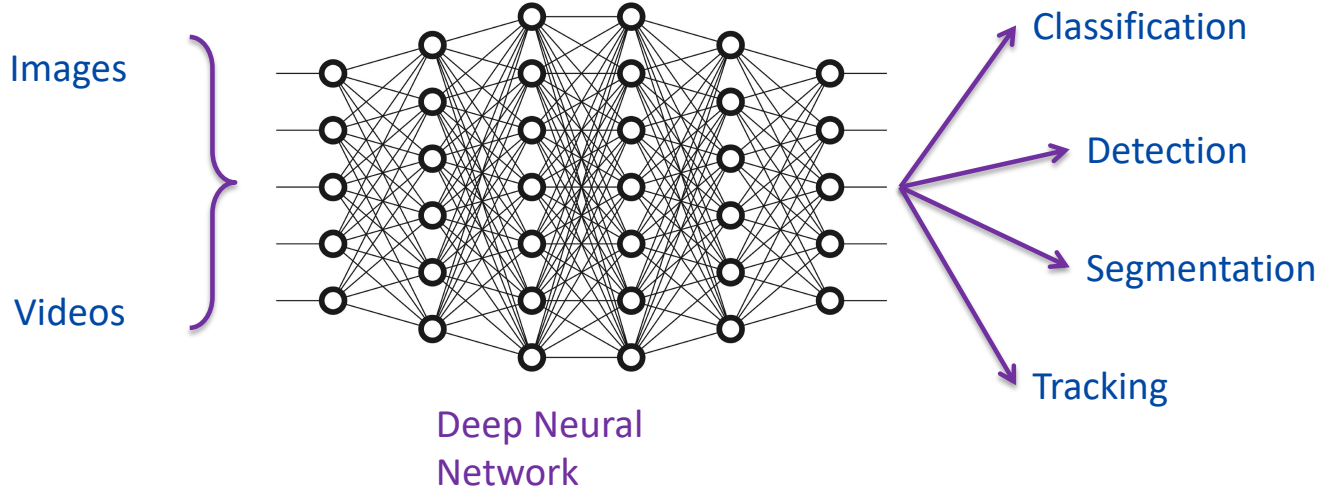




Introducing Deep Learning for Computer Vision

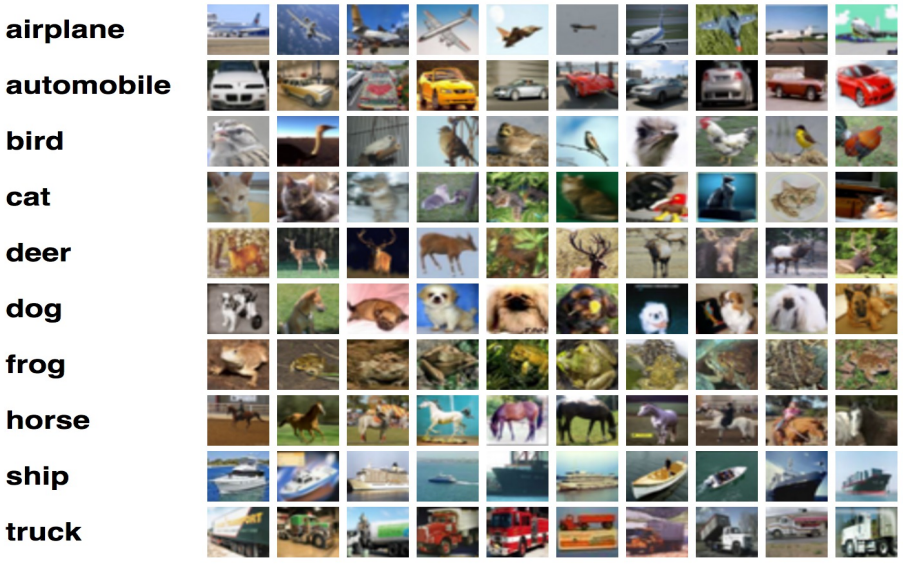
Deep convolutional neural network (DCNN) is the key concept for introducing deep learning to the development of computer vision. By imitating the biological nervous systems, deep neural networks can provide unprecedented ability to interpret complicated data patterns and thus effectively tackle various computer vision tasks.

extract feature representation



Classification

Goal: Assign a label to an input image based on a fixed set of categories.



Credit To: https://medium.com/@tifa2up/image-classification-using-deep-neural-networks-a-beginner-friendly-approach-using-tensorflow-94b0a090ccd4

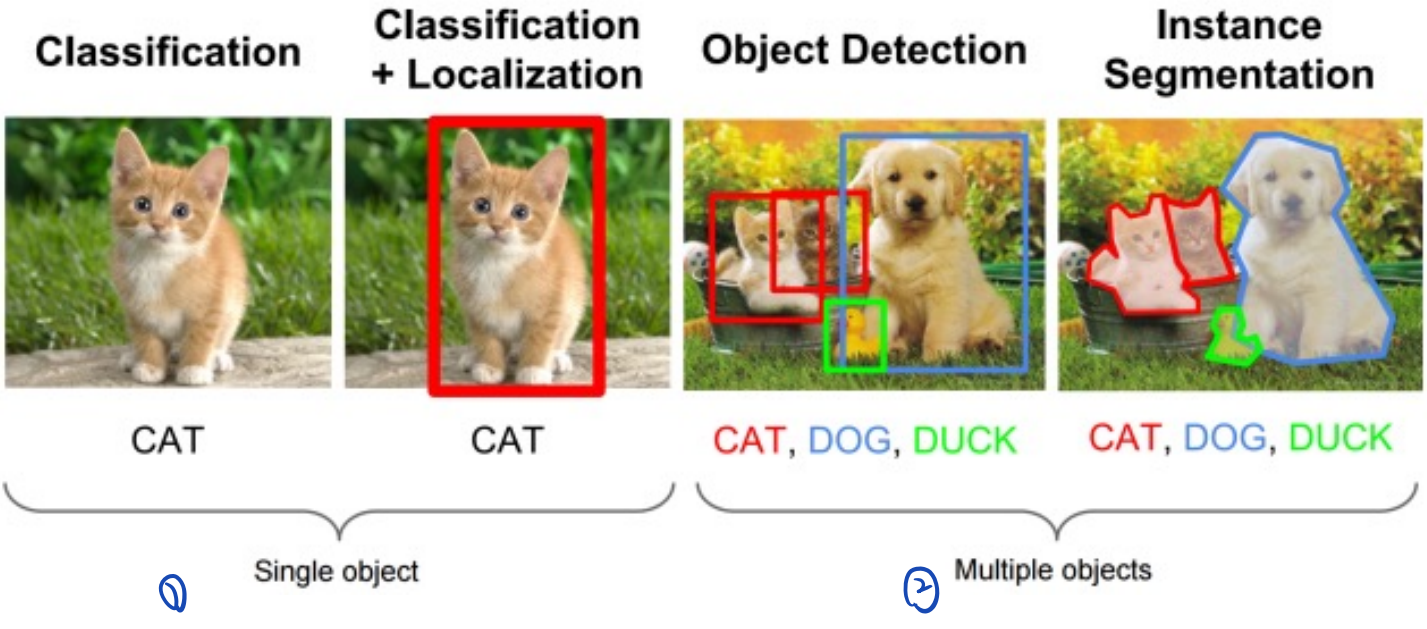
Deep Learning-based Classification

Suppose W is the parameter set of a deep neural network. Given an input image I, classification can be tackled by:

$$y = f(W, I)$$

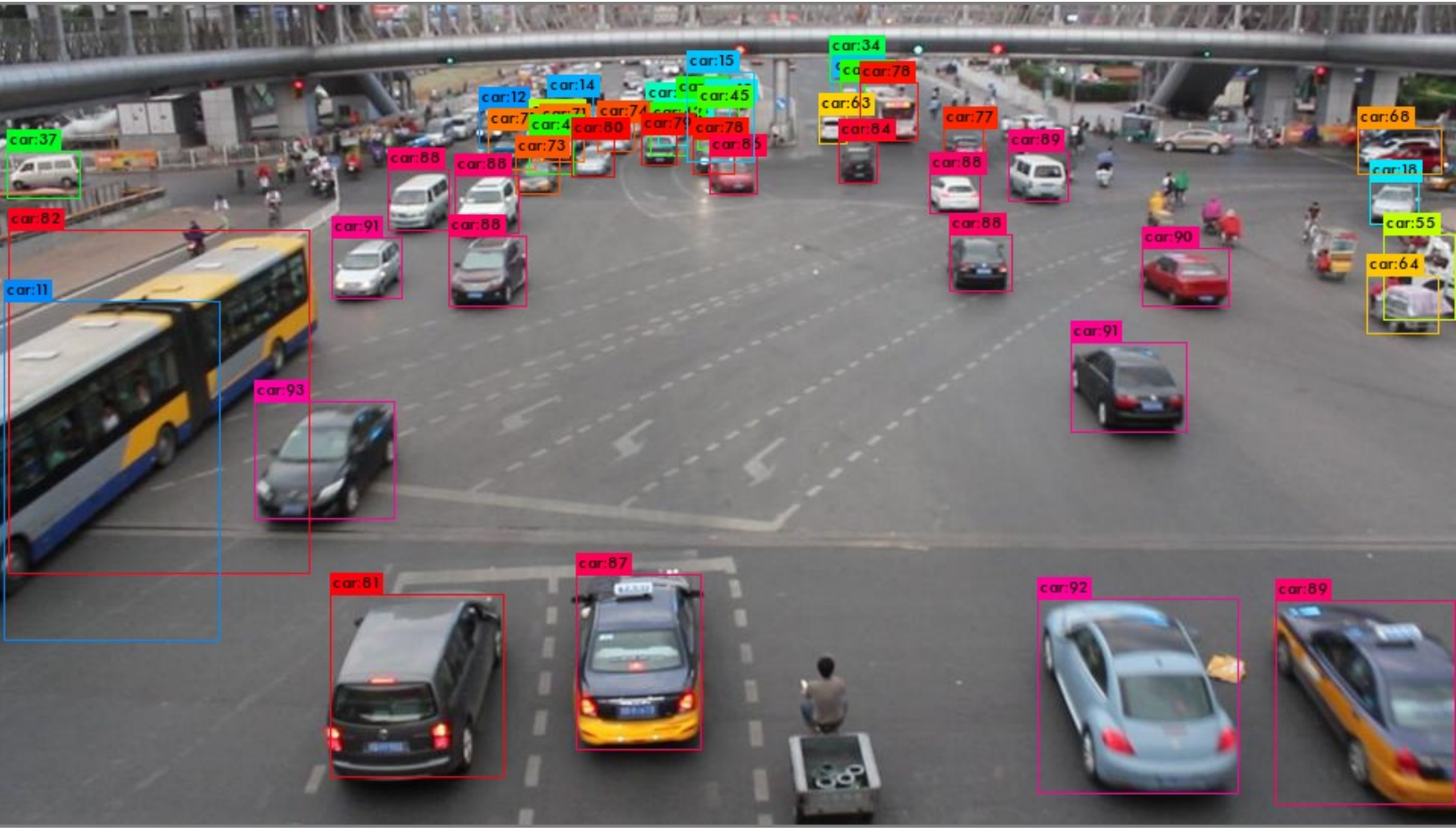
where y is the predicted class label and f represents a series of operations parameterized based on W for processing the input image.

Computer Vision Tasks

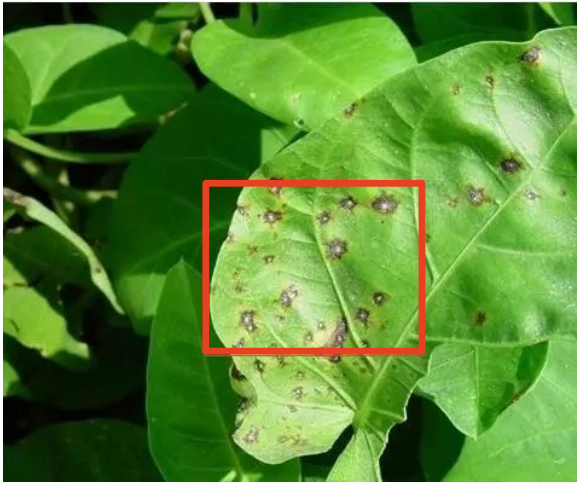


Pedestrian Detection

Car Detection



Other Applications



Localize objects with regression

Input: image

Only one object,
simpler than detection

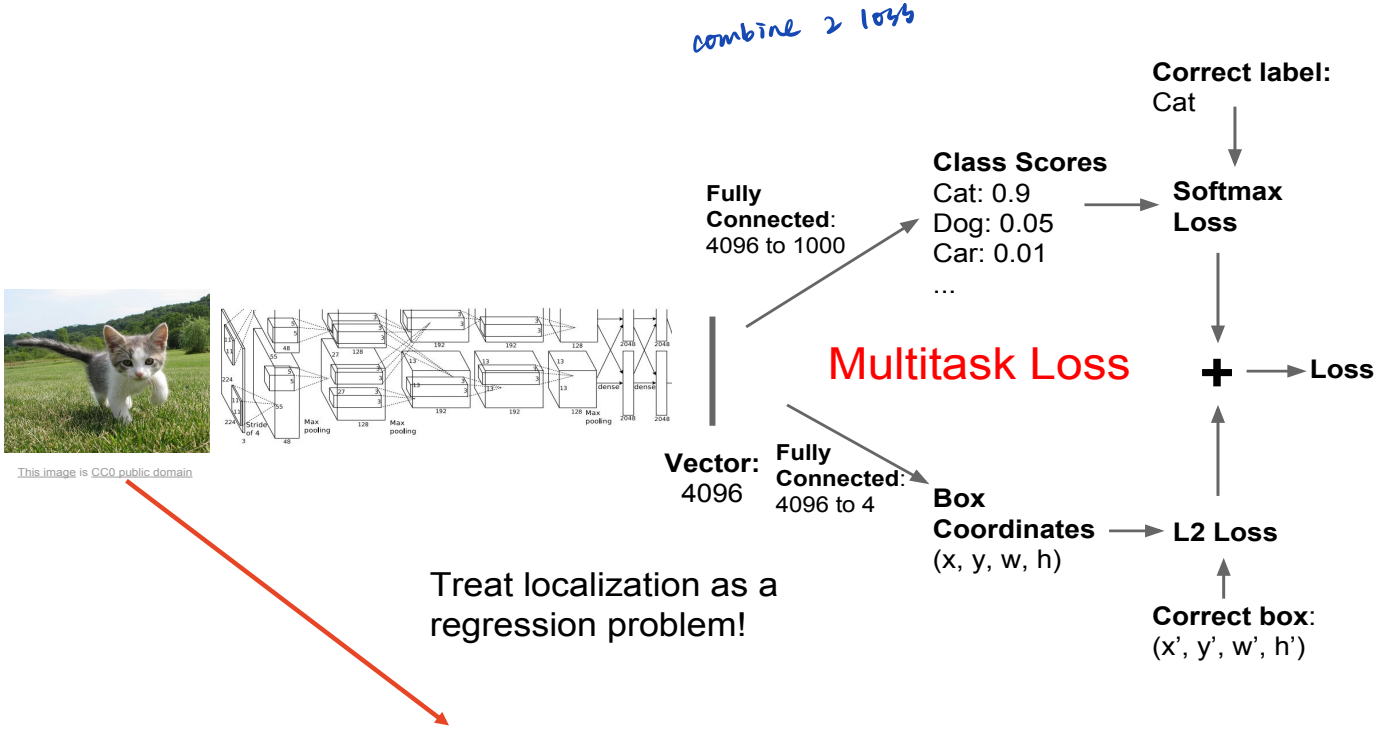
Neural Net

Output:
Box coordinates
(4 numbers)

Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

Classification with Localization



It is assumed that there is only one object in an input image.

Credit To: FeiFei Li's deep learning lecture ppt.

COCO DATASET FORMAT

```
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        "iscrowd": 0,
        "segmentation": [[164.81, 417.51, 164.81, 41
        "image_id": 242287,
        "area": 42061.80340000001,
        "bbox": [19.23, 383.18, 314.5, 244.46]
    },
    {
        "id": 1409619,
```
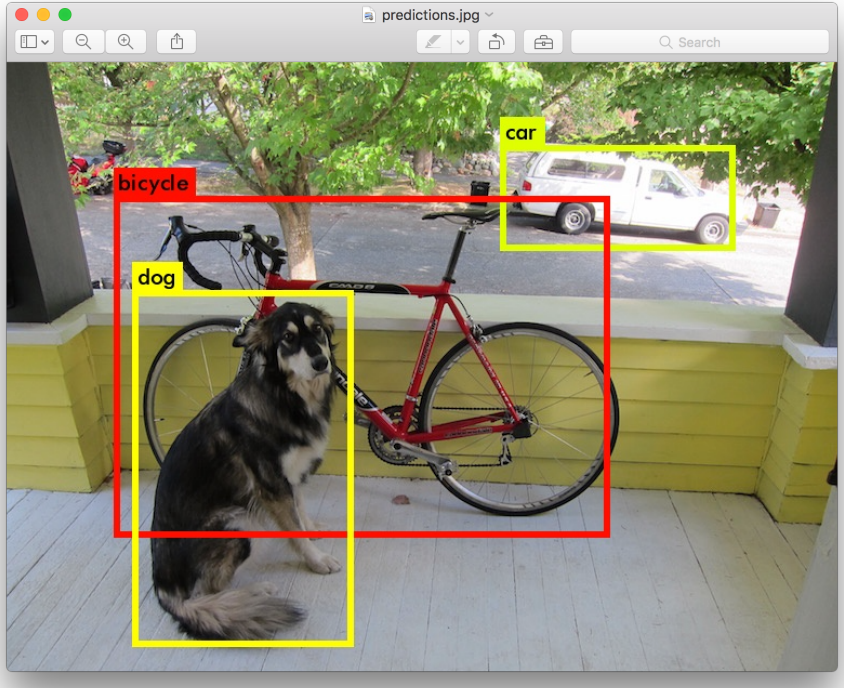

weight height

top left corner, w, h.

Detection

Goal: Detect semantic objects of certain classes in images.



- Region CNN
- SPPNet
- Fast RCNN
- Faster RCNN
- Mask R-CNN

Typical architecture

Proposals

1.Region proposal: Given an input image, find all possible places where objects can be located. The output of this stage should be a list of bounding boxes of likely positions of objects. These are often called region proposals or regions of interest.

candidates

2.Final classification: for every region proposal from the previous stage, decide whether it belongs to one of the target classes or to the background. Here we could use a deep convolutional network.

Deep Learning-based Detection

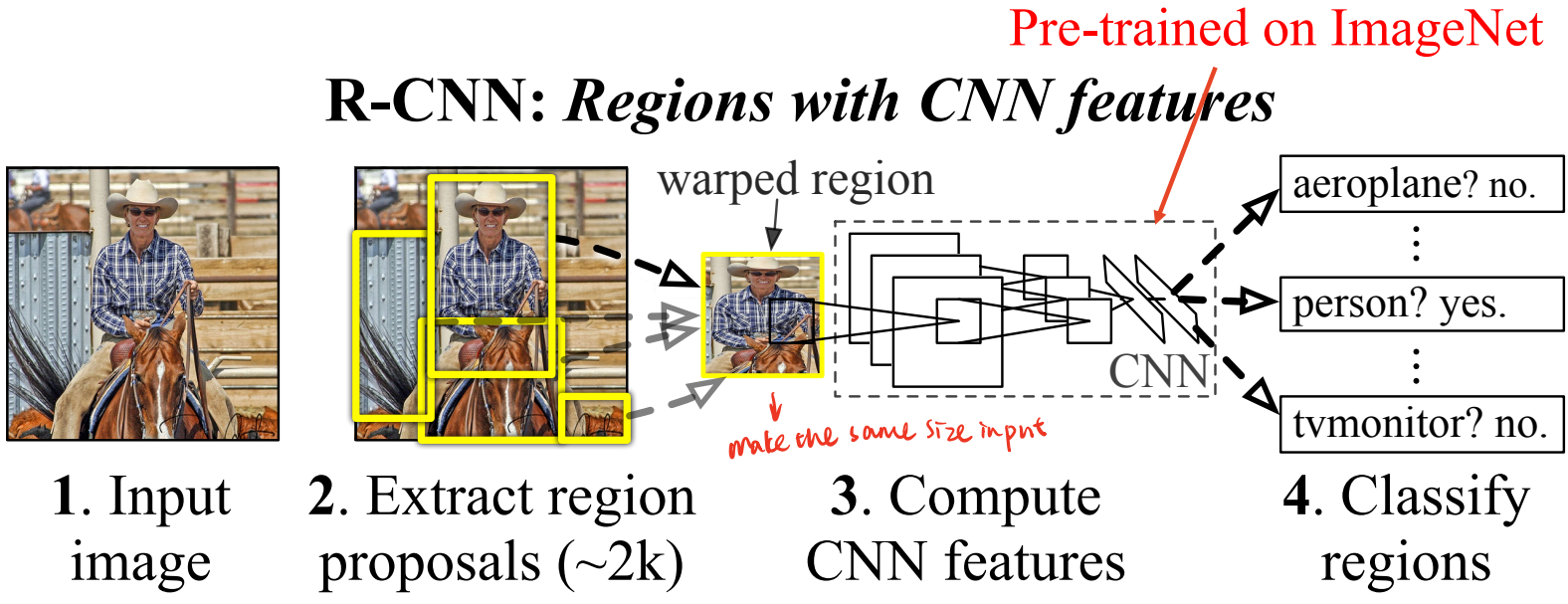
Given a deep neural network parameterized by W, the goal of object detection is to predict a set of bounding boxes that may contain objects together as well as the objects' categories.

$$\{y_i, (x_1, y_1, x_2, y_2)_i\} = f(W, I)$$

where y_i is the predicted class label and $(x_1, y_1, x_2, y_2)_i$ describes the four coordinates (i.e. the top-left coordinate and the bottom-right coordinate) of the estimated bounding box for the i-th result.

Region CNN (R-CNN)

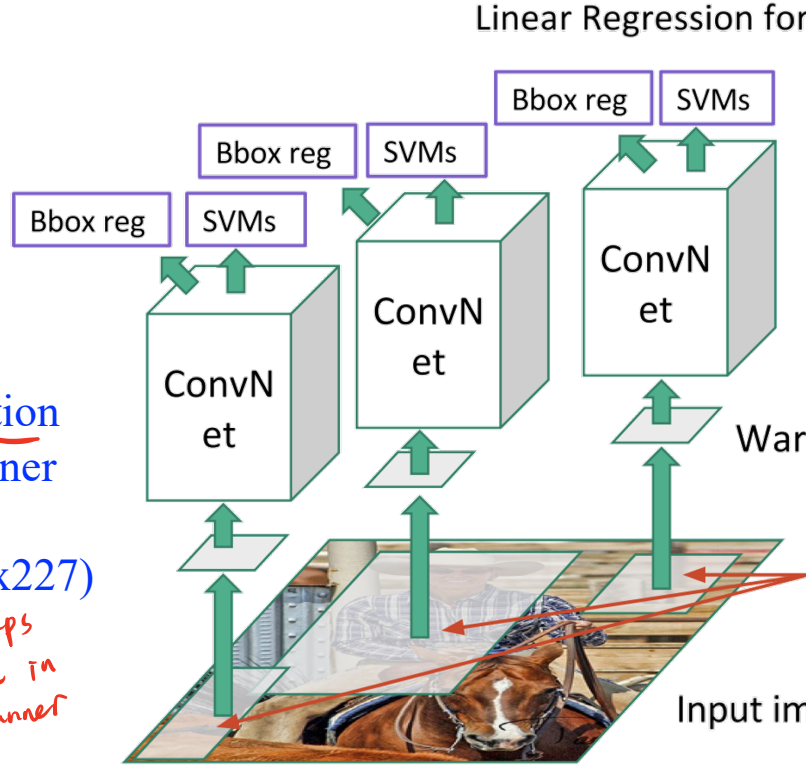
Object detection → image classification



Object Detection to Image Classification

[Girshick14] R. Girshick, J. Donahue, S. Guadarrama, T. Darrell, J. Malik: **Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation**, CVPR 2014

Region CNN (R-CNN)



overlap region

- Duplication of calculation
- Not in end-to-end manner
- Slow
- Fixed image size (227x227)

region CNN in different steps
→ cannot be optimize in end-to-end manner

*Selective Search

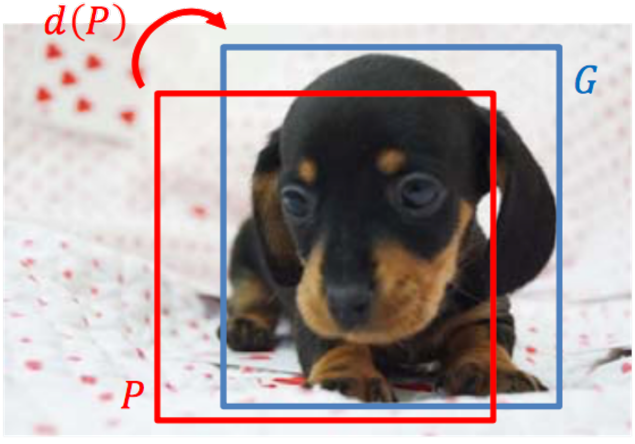
- Motivation
  - Sliding window approach is not feasible for object detection with convolutional neural networks.
  - We need a more faster method to identify object candidates.
- Finding object proposals
  - Greedy hierarchical superpixel segmentation
  - Diversification of superpixel construction and merge
    - Using a variety of color spaces
    - Using different similarity measures
    - Varying staring regions

[Uijlings13] J. R. R. Uijlings, K. E. A. van de Sande, T. Gevers, A. W. M. Smeulders: **Selective Search for Object Recognition**. IJCV 2013

*Bounding Box Regression

- Learning a transformation of bounding box
  - Region proposal: $P = (P_x, P_y, P_w, P_h)$
  - Ground-truth: $G = (G_x, G_y, G_w, G_h)$
  - Transformation: $d(P) = (t_x, t_y, t_w, t_h)$

Transformation
P → G.



$$\hat{G}_x = P_w d_x(P) + P_x$$
$$\hat{G}_y = P_h d_y(P) + P_y$$
$$\hat{G}_w = P_w \exp\big(d_w(P)\big)$$
$$\hat{G}_h = P_h \exp\big(d_h(P)\big)$$

$$d_i(P) = \boldsymbol{w}_i^{\mathrm{T}} \phi_5(P)$$

CNN pool5 feature

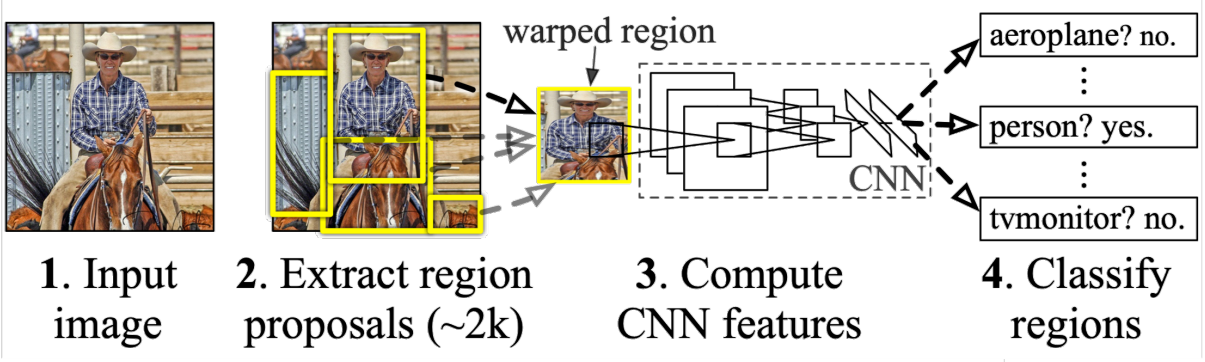
$$\boldsymbol{w}_i^* = \underset{\boldsymbol{w}_i}{\operatorname{argmin}} \sum_{k=1}^{N} \left(t_i^k - \boldsymbol{w}_i^{\mathrm{T}} \phi_5\big(P^k\big)\right)^2 + \lambda \|\boldsymbol{w}_i\|^2$$

Fast R-CNN

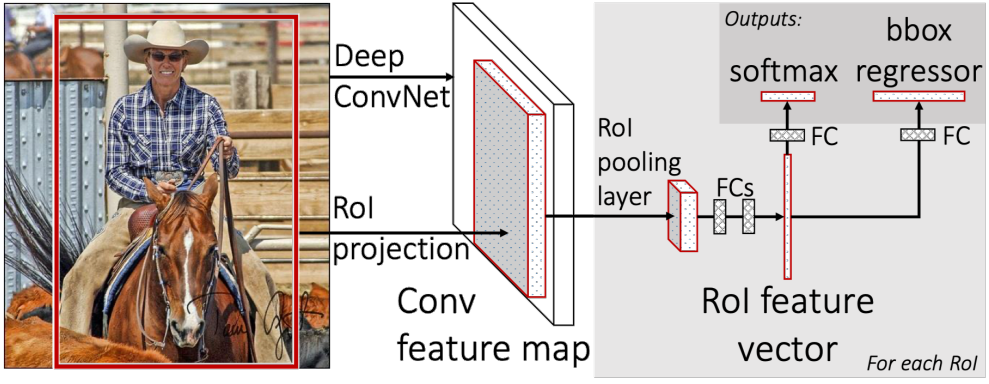
Drawback of R-CNN and the modification:

1. Multi-stage training. → End-to-end joint training.
2. Expensive in space and time. → Convolutional layer sharing.
3. Test-time detection is slow. → Single scale testing

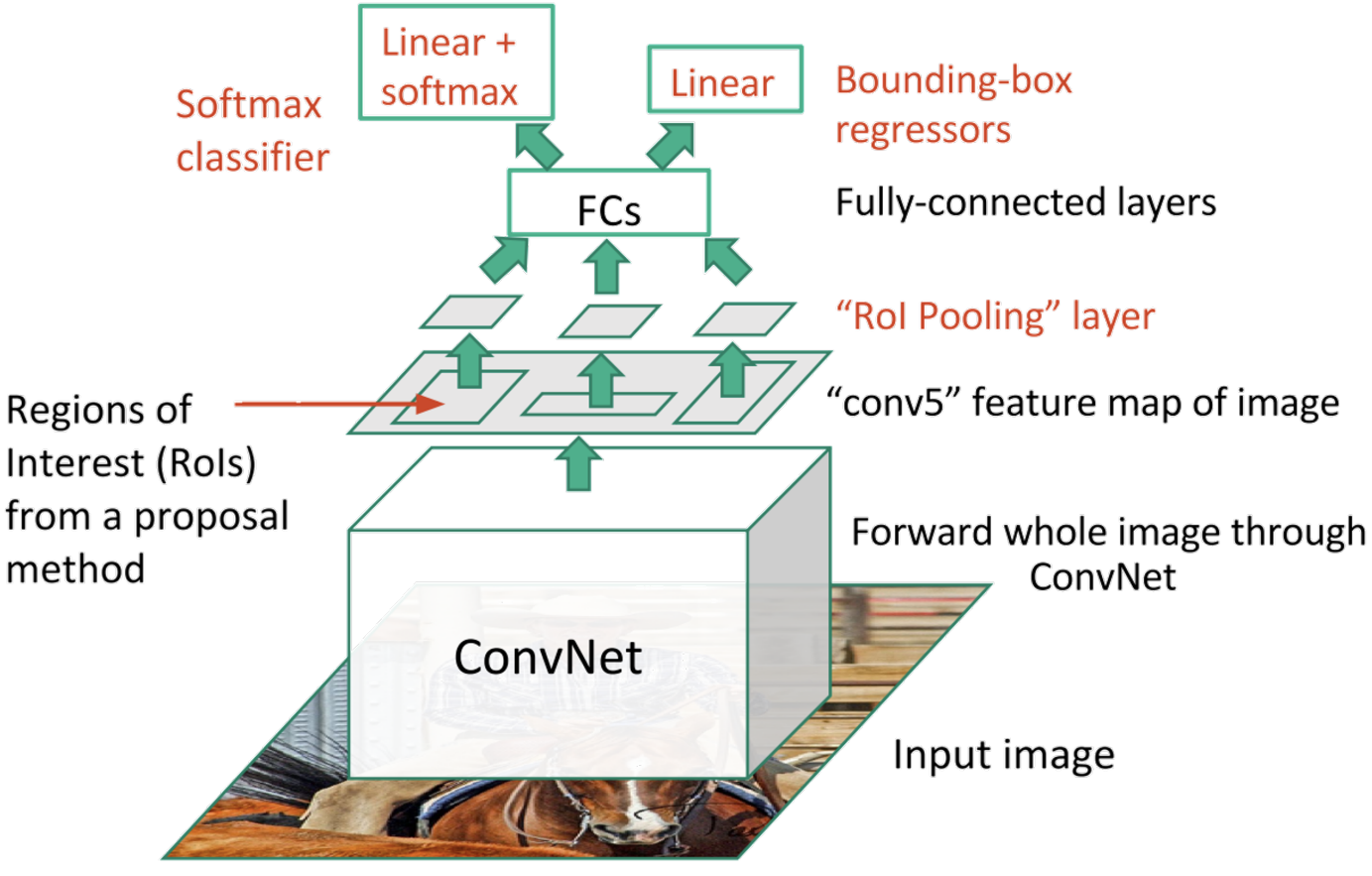
R-CNN



Fast R-CNN

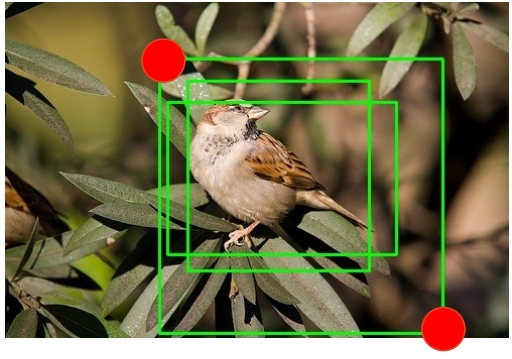


Fast R-CNN


Linear + softmax
Linear
Softmax classifier
Bounding-box regressors
FCs
Fully-connected layers
"RoI Pooling" layer
Regions of Interest (RoIs) from a proposal method
"conv5" feature map of image
Forward whole image through ConvNet
ConvNet
Input image

Region of Interest Pooling

A type of max-pooling. The output always has the same size.



Input to ROI pooling layer:

1. A fixed-size feature map
2. A list of regions of interest

0.85	0.84
0.97	0.96

a region proposal

8 × 8 feature map → 2 × 2 output

2×2 pooling

input

0.88	0.44	0.14	0.16	0.37	0.77	0.96	0.27
0.19	0.45	0.57	0.16	0.63	0.29	0.71	0.70
0.66	0.26	0.82	0.64	0.54	0.73	0.59	0.26
0.85	0.34	0.76	0.84	0.29	0.75	0.62	0.25
0.32	0.74	0.21	0.39	0.34	0.03	0.33	0.48
0.20	0.14	0.16	0.13	0.73	0.65	0.96	0.32
0.19	0.69	0.09	0.86	0.88	0.07	0.01	0.48
0.83	0.24	0.97	0.04	0.24	0.35	0.50	0.91

region proposal

0.88	0.44	0.14	0.16	0.37	0.77	0.96	0.27
0.19	0.45	0.57	0.16	0.63	0.29	0.71	0.70
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0.83	0.24	0.97	0.04	0.24	0.35	0.50	0.91

pooling sections

0.88	0.44	0.14	0.16	0.37	0.77	0.96	0.27
0.19	0.45	0.57	0.16	0.63	0.29	0.71	0.70
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Region of Interest Pooling

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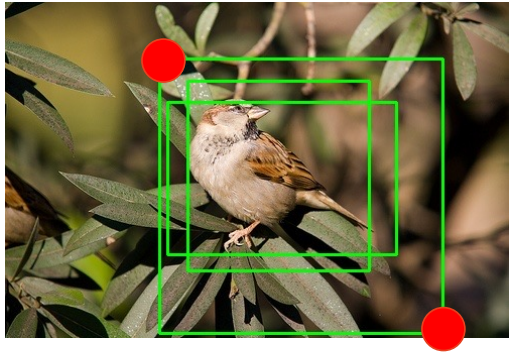

Input to ROI pooling layer:

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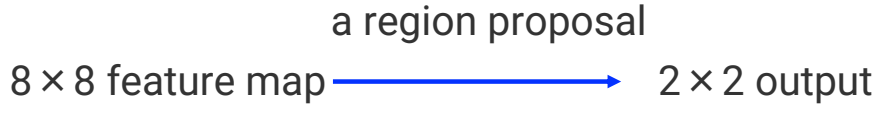
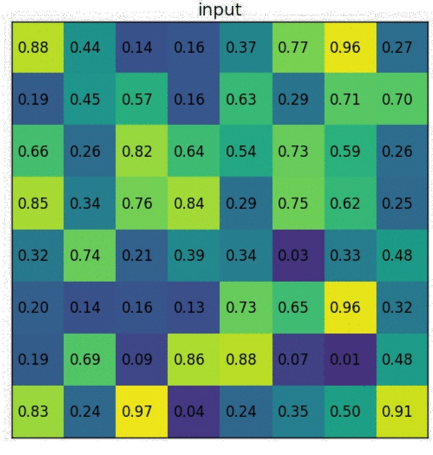




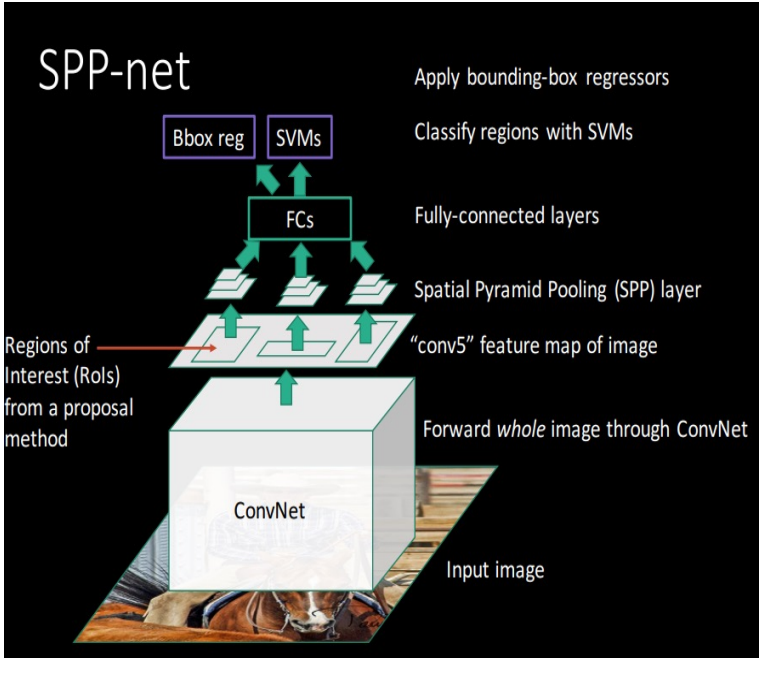
- Used for object detection tasks
- Reuse the feature map from CNNs
- Speed up both train and test time
- Train detection model in an end-to-end manner

extract feature only once

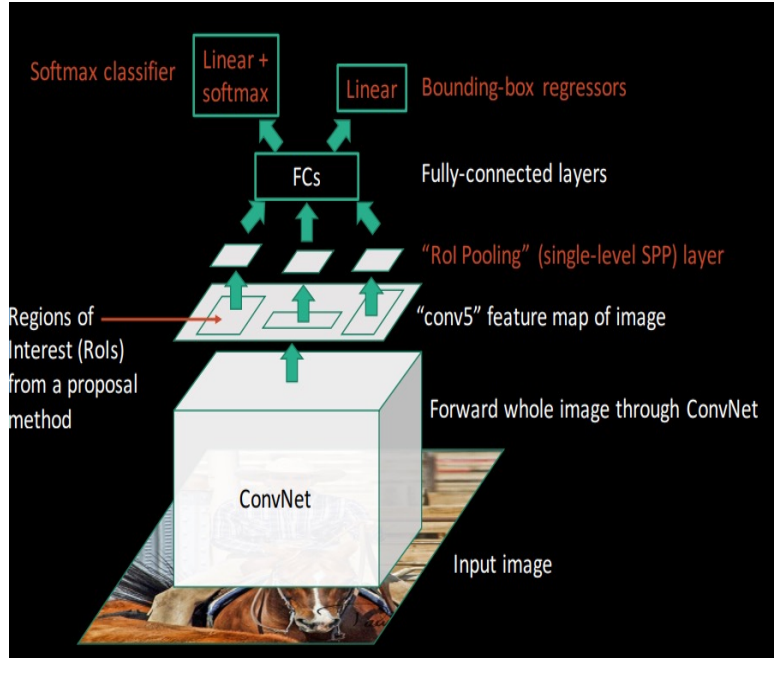
Fast R-CNN

more than one extraction layer

single layer SPP



VS

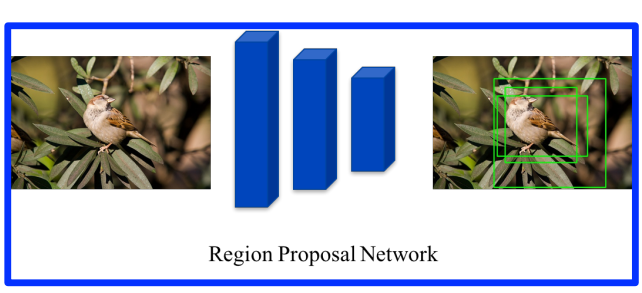


Credit To: http://www.robots.ox.ac.uk/~tvg/publications/talks/fast-rcnn-slides.pdf

Faster R-CNN

RoI stage hasn't been included in the end-to-end manner
⇒ replace with RPN

Replace the slow selective search algorithm with a fast neural net - region proposal network (RPN).



Fast R-CNN

Region Proposal Network

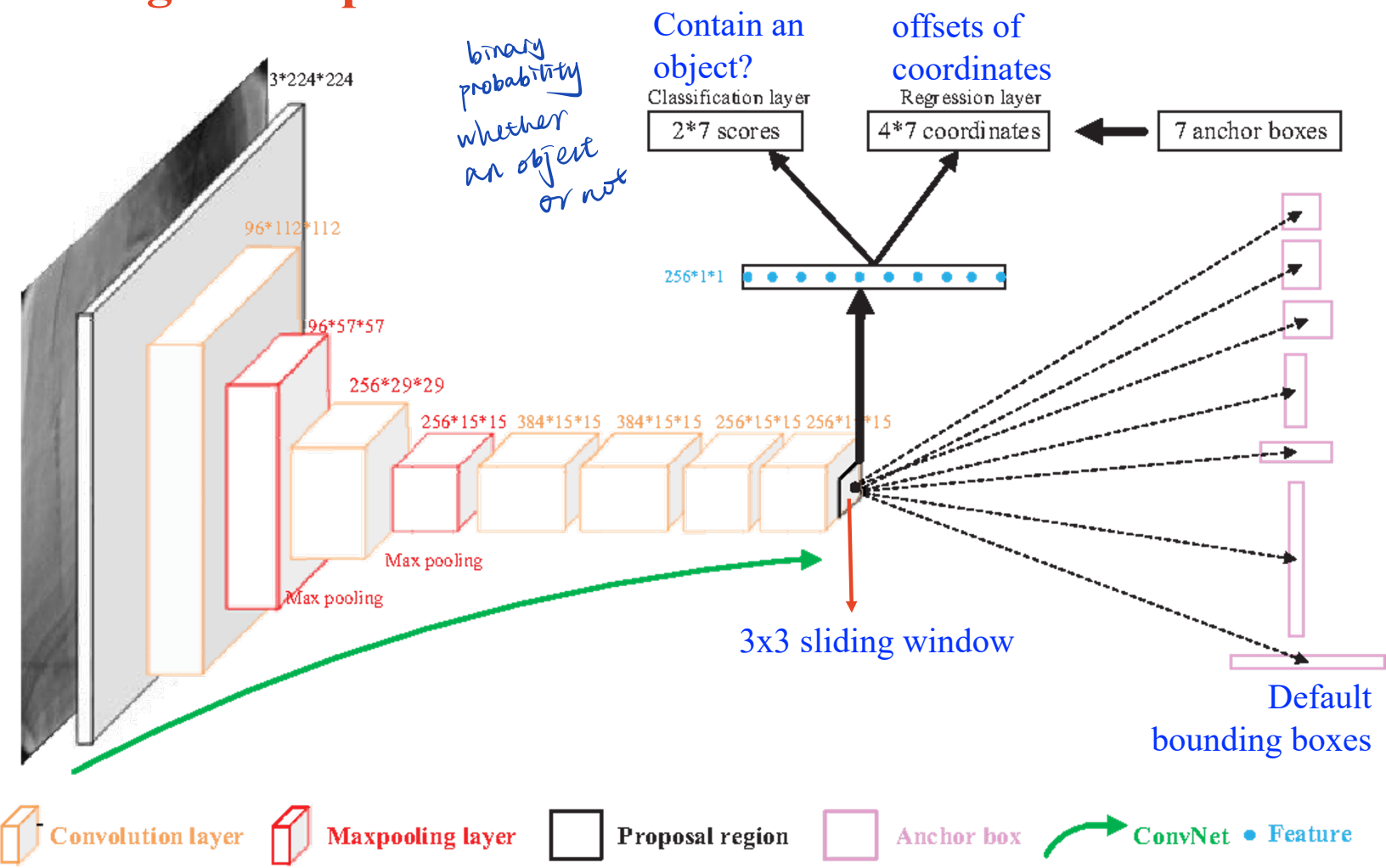
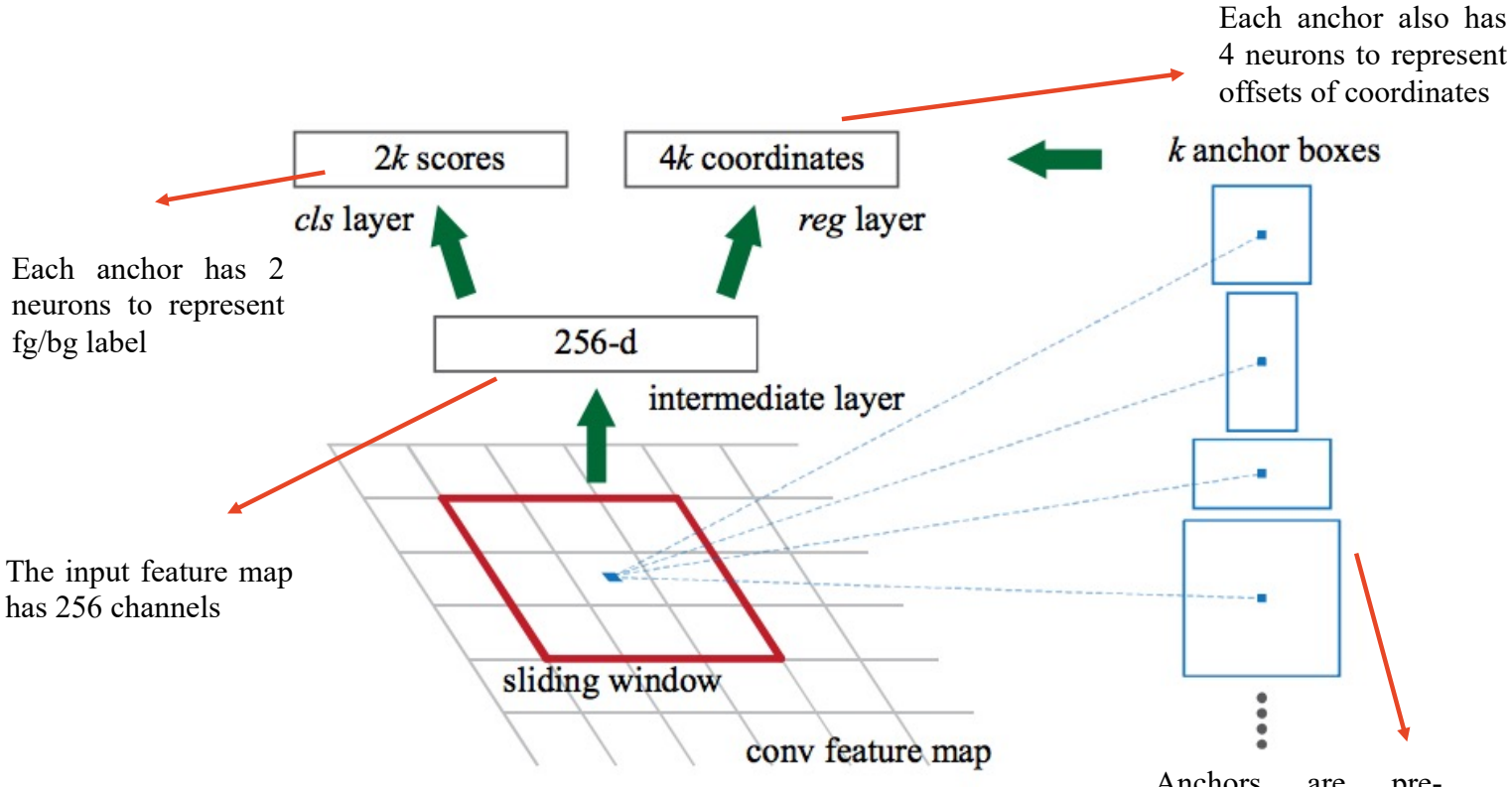
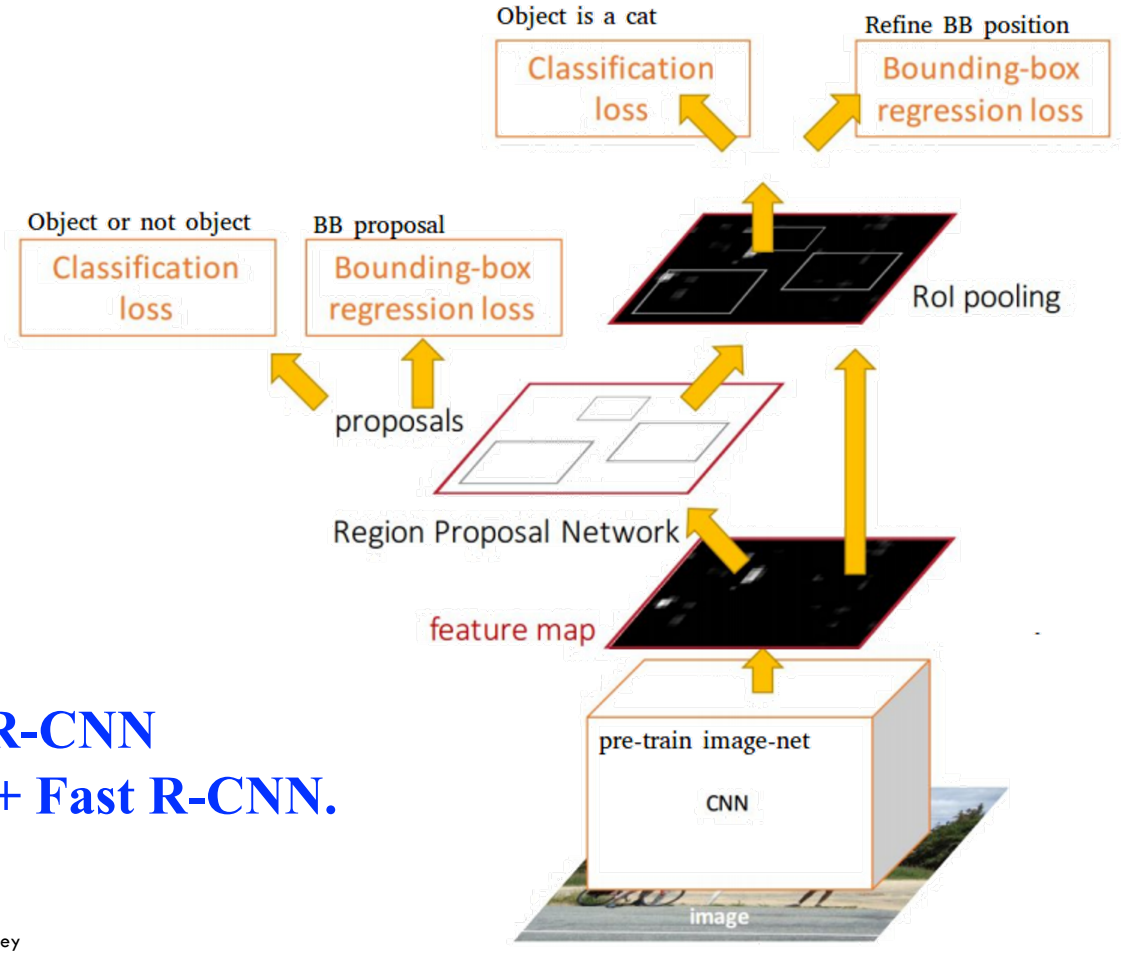


Image Credit to [Li Wang et al. 2017]

Region Proposal Network



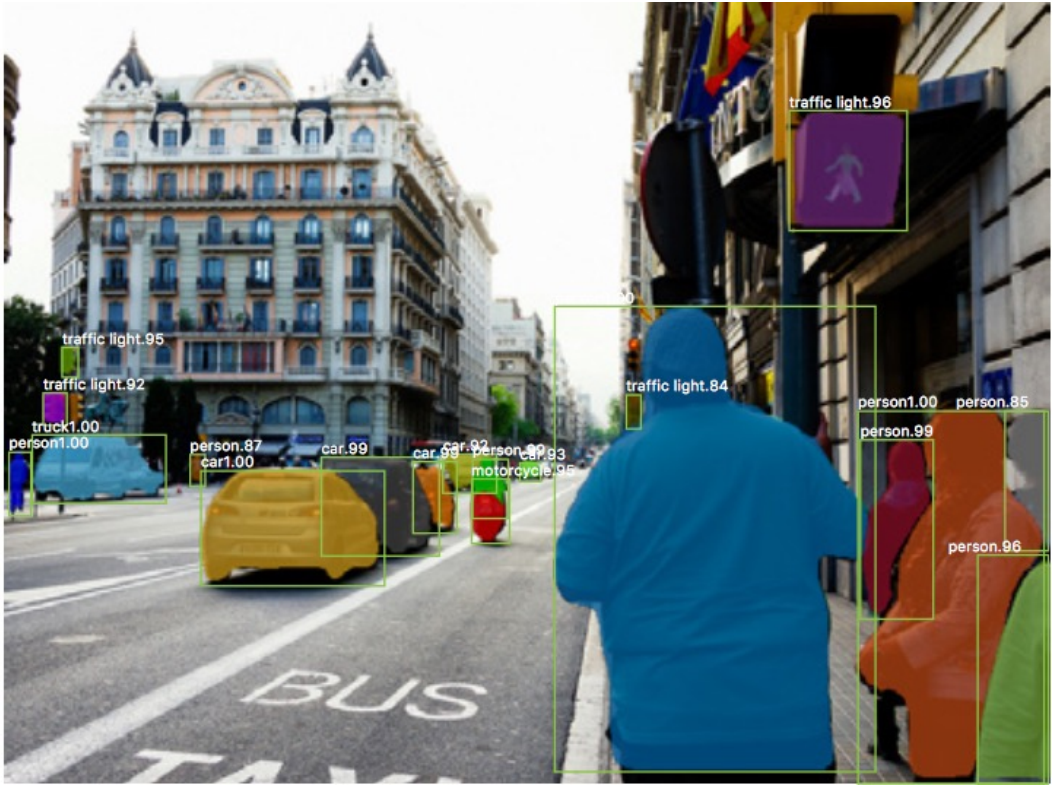
Faster R-CNN



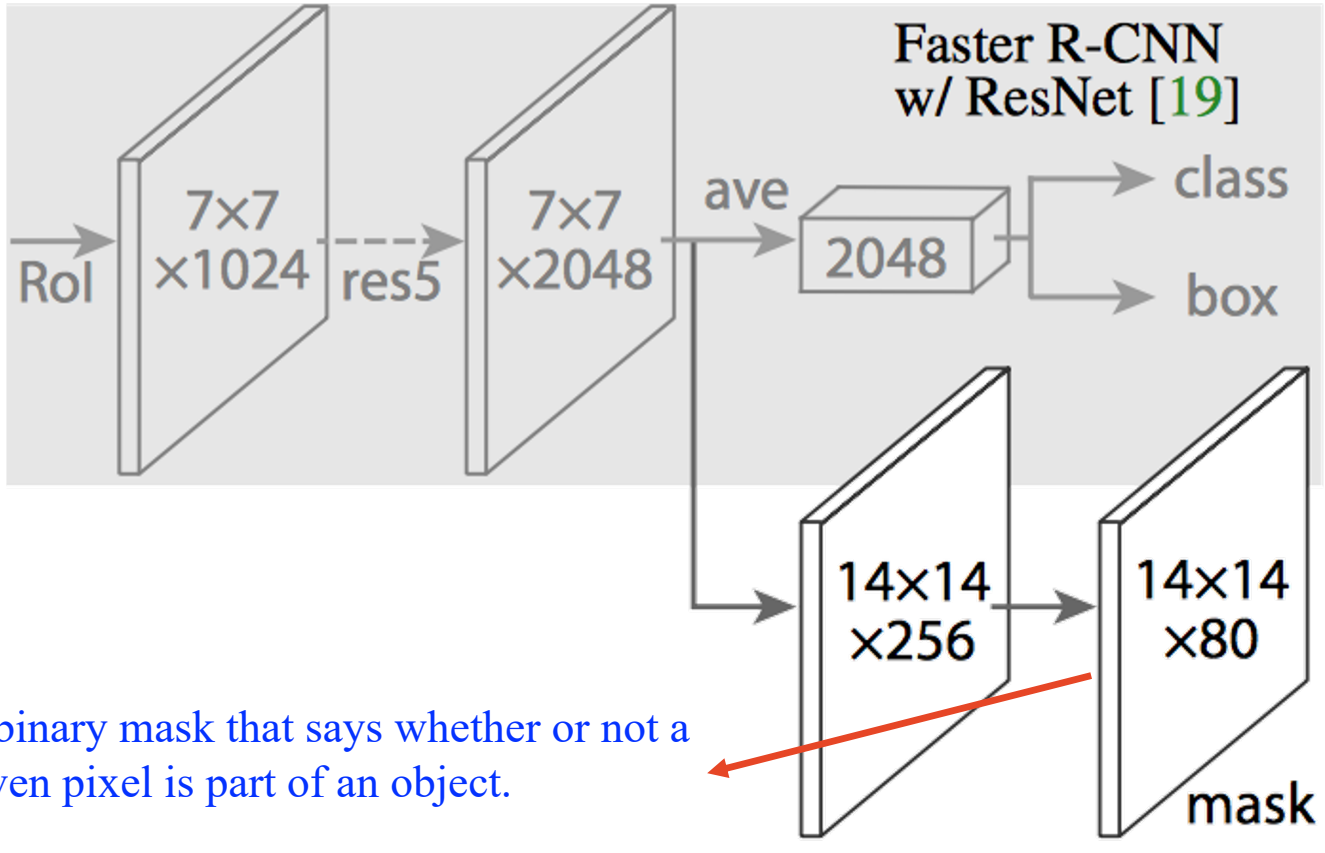
Faster R-CNN
= RPN + Fast R-CNN.

Mask R-CNN

Image instance segmentation is to identify, at a pixel level, what the different objects in a scene are.



Mask R-CNN



A binary mask that says whether or not a given pixel is part of an object.

RoIAlign

Realigning RoI Pooling to be More Accurate.

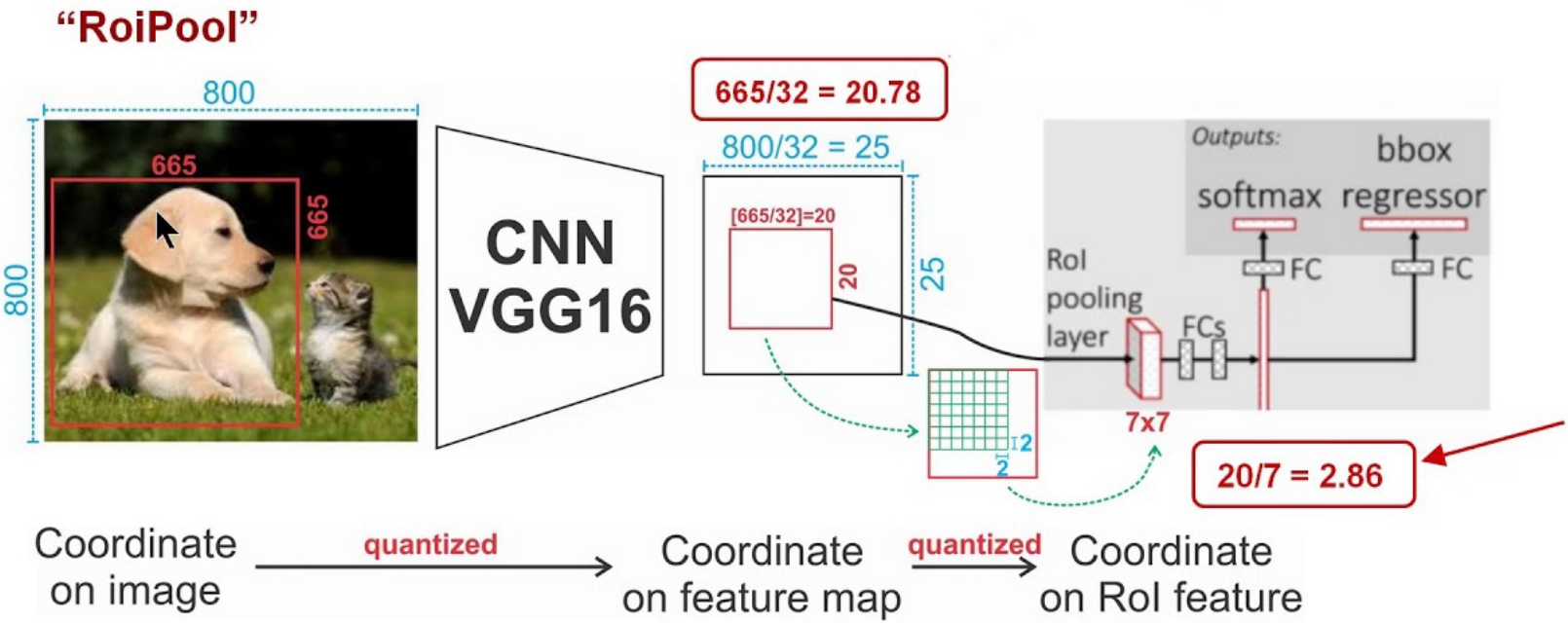


Image credit to Ardian Umam

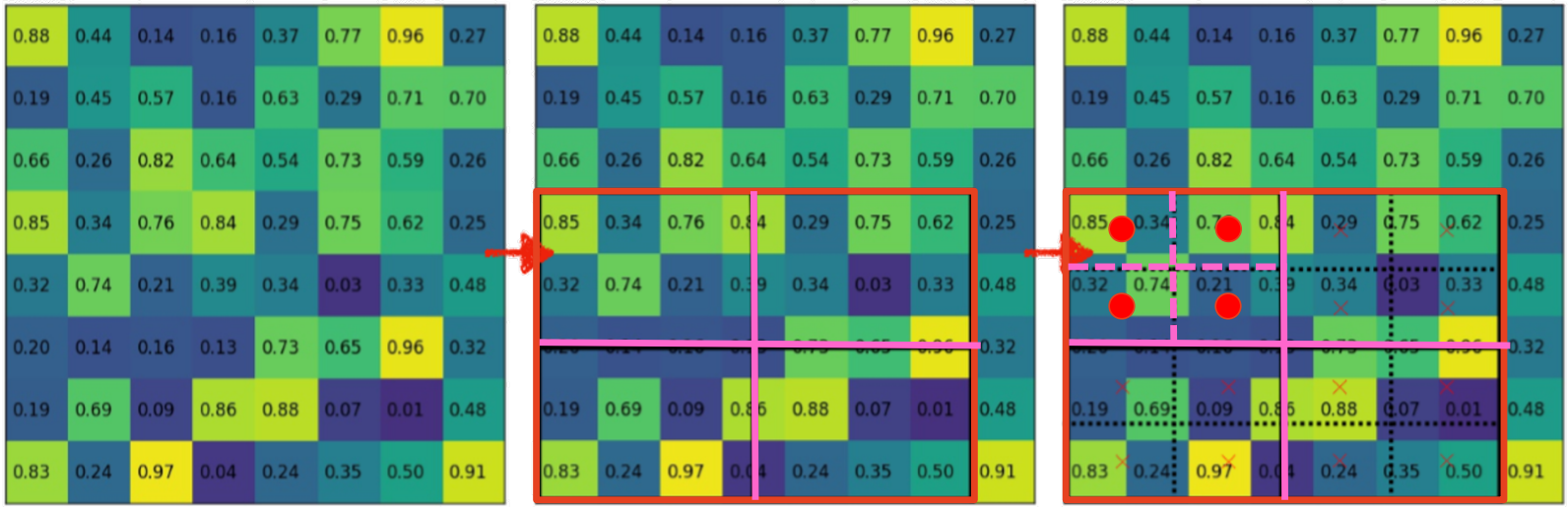
size of box, size of pooling not match

take the correct cordinate

RoIAlign

1) RoIAlign

Mask R-CNN
RoIAlign



Input activation

Region projection and pooling sections

Sampling locations

5x7

2x2.

Max pooling output

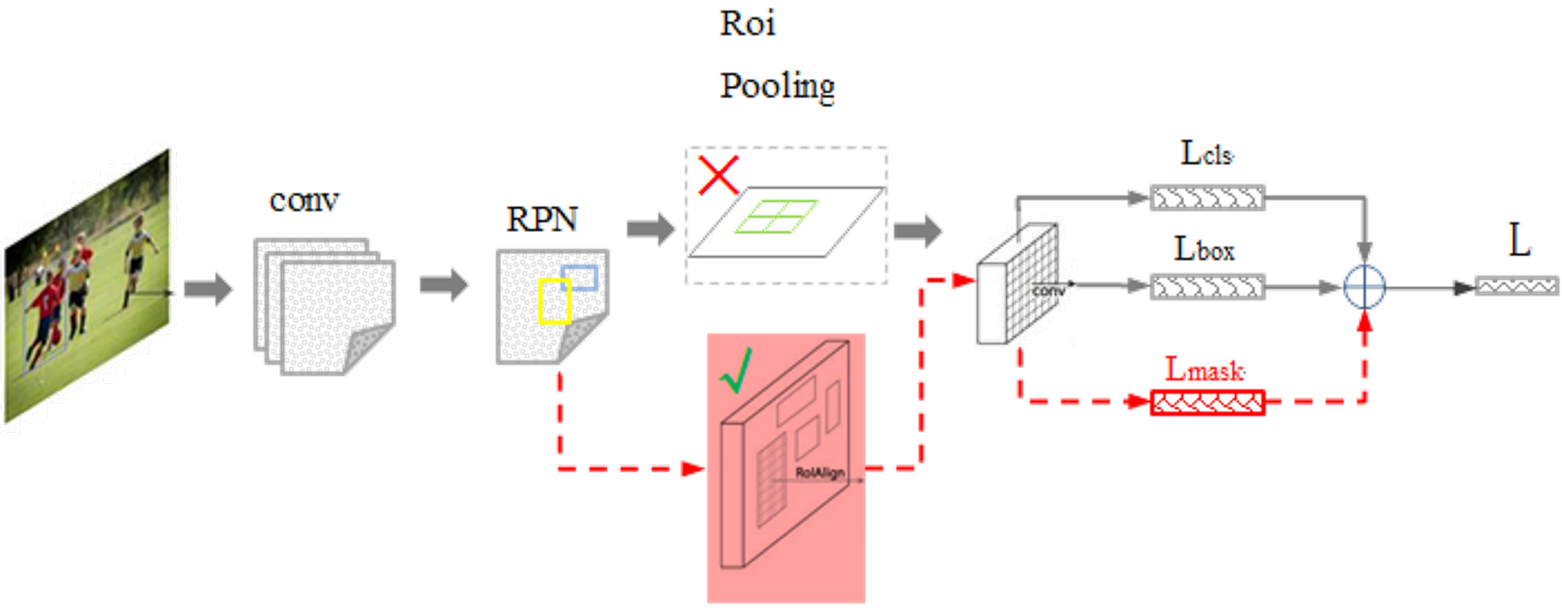
Bilinear interpolated values

bilinear interpolation

Credit To: https://www.slideshare.net/windmdk/mask-rcnn

RoIAlign

Realigning RoI Pooling to be More Accurate.



Mask R-CNN

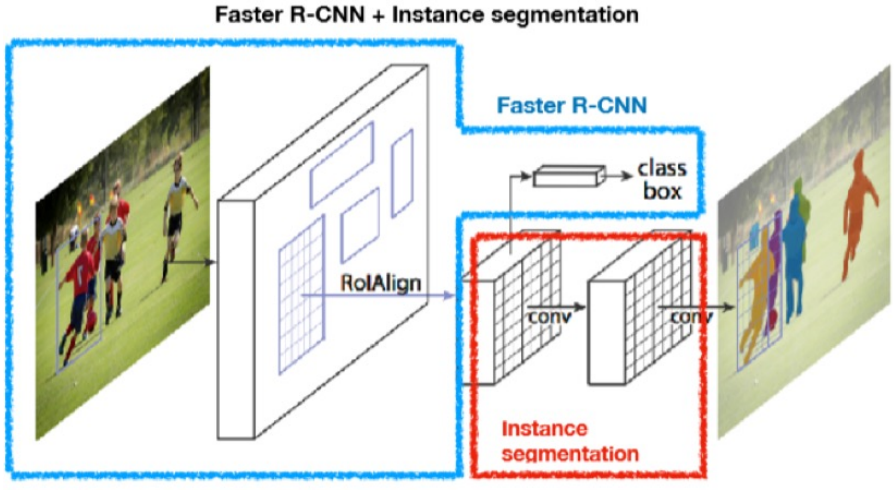
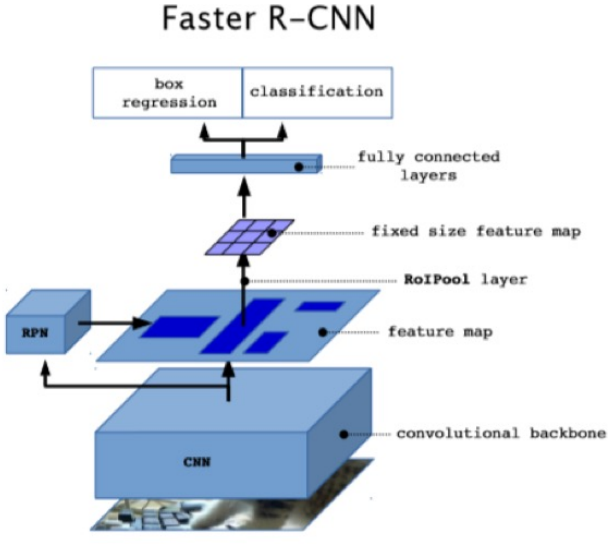


Figure 1. The **Mask R-CNN** framework for instance segmentation.

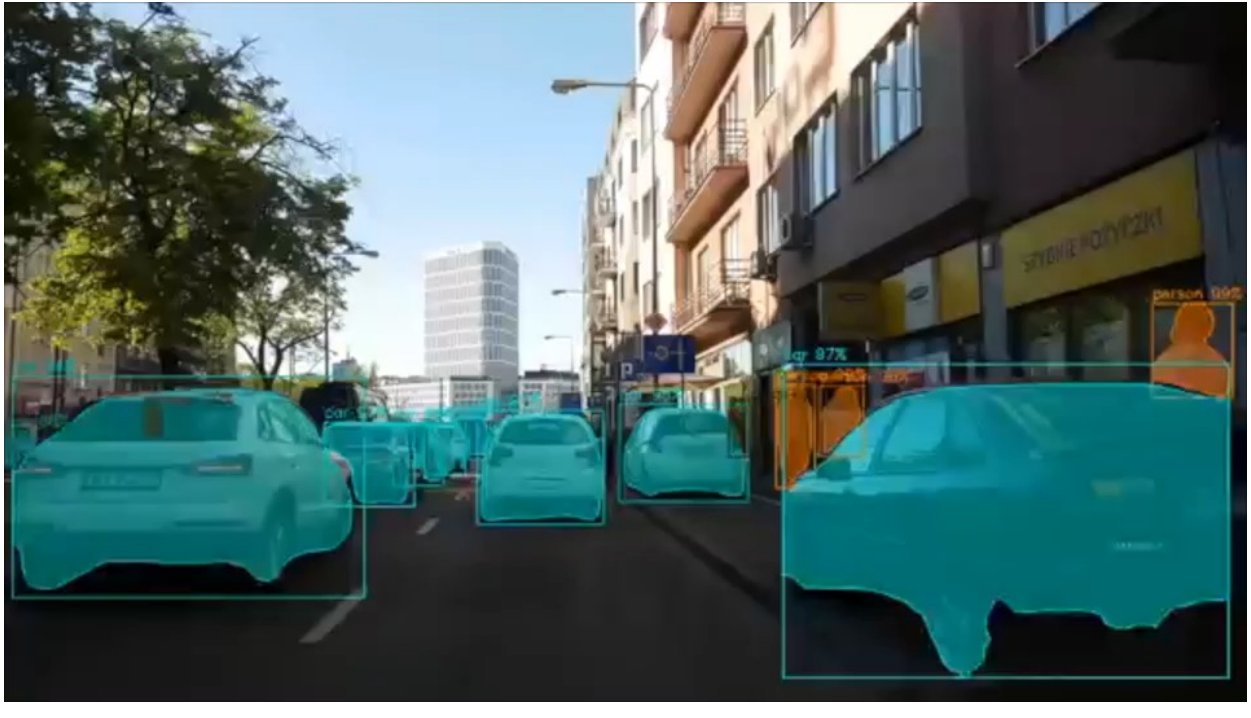


Mask R-CNN
= Instance Segmentation+ Faster R-CNN.

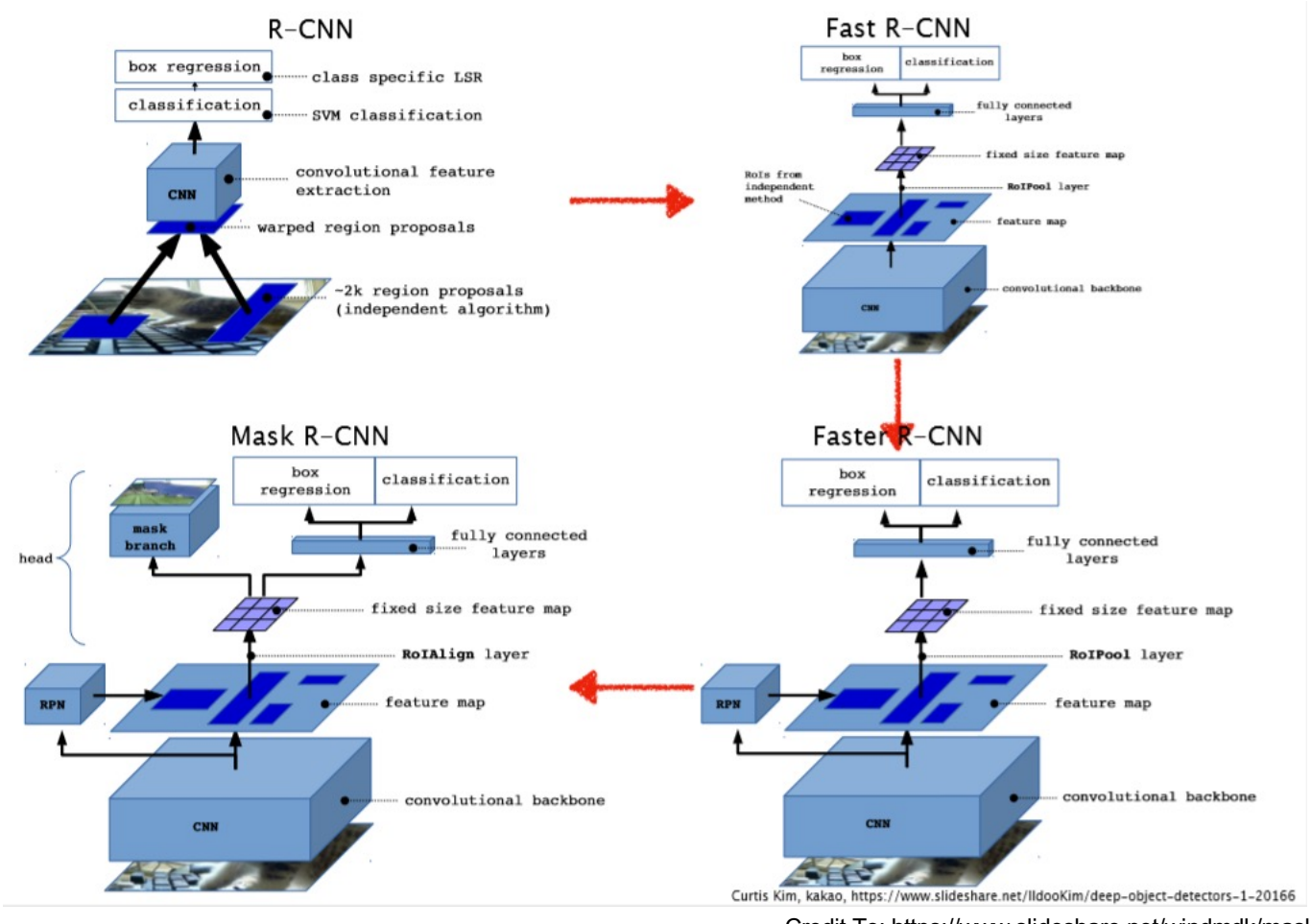
Credit To: https://www.slideshare.net/windmdk/mask-rcnn

Mask R-CNN

Demo



From R-CNN to Mask R-CNN



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