Deep Learning Applications

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Acknowledgements:
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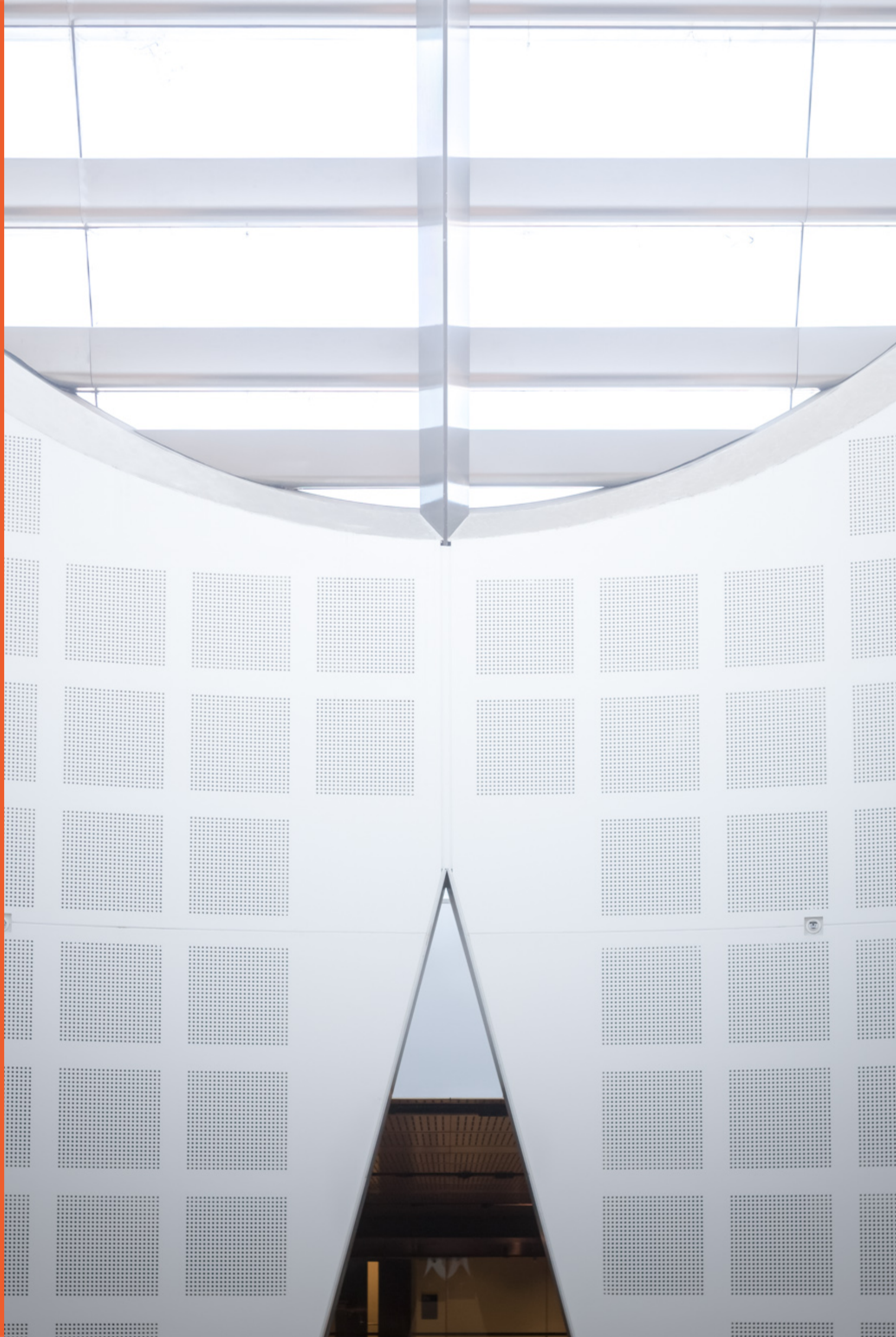
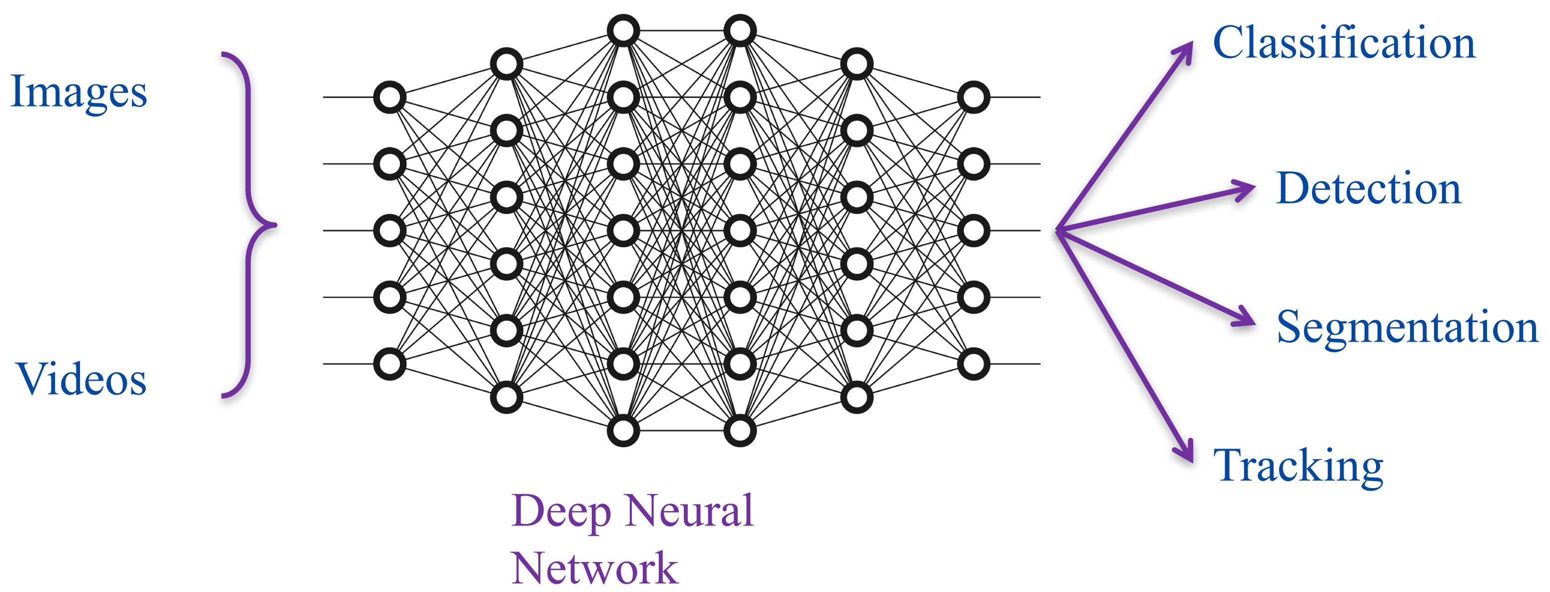


Quick Review

Applications

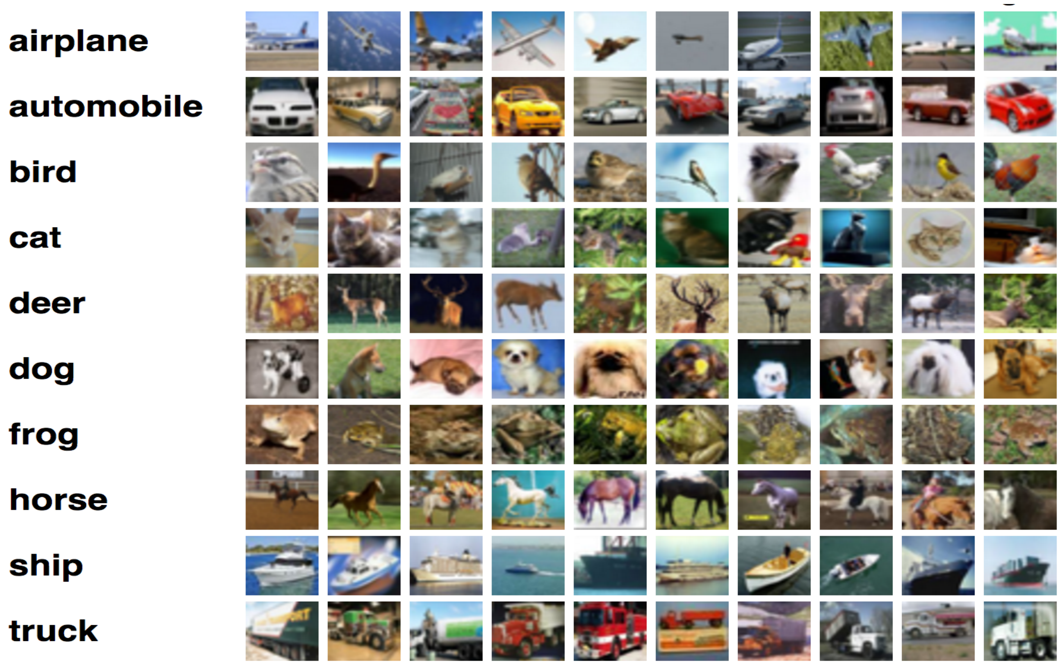
Introducing Deep Learning for Computer Vision

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.



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

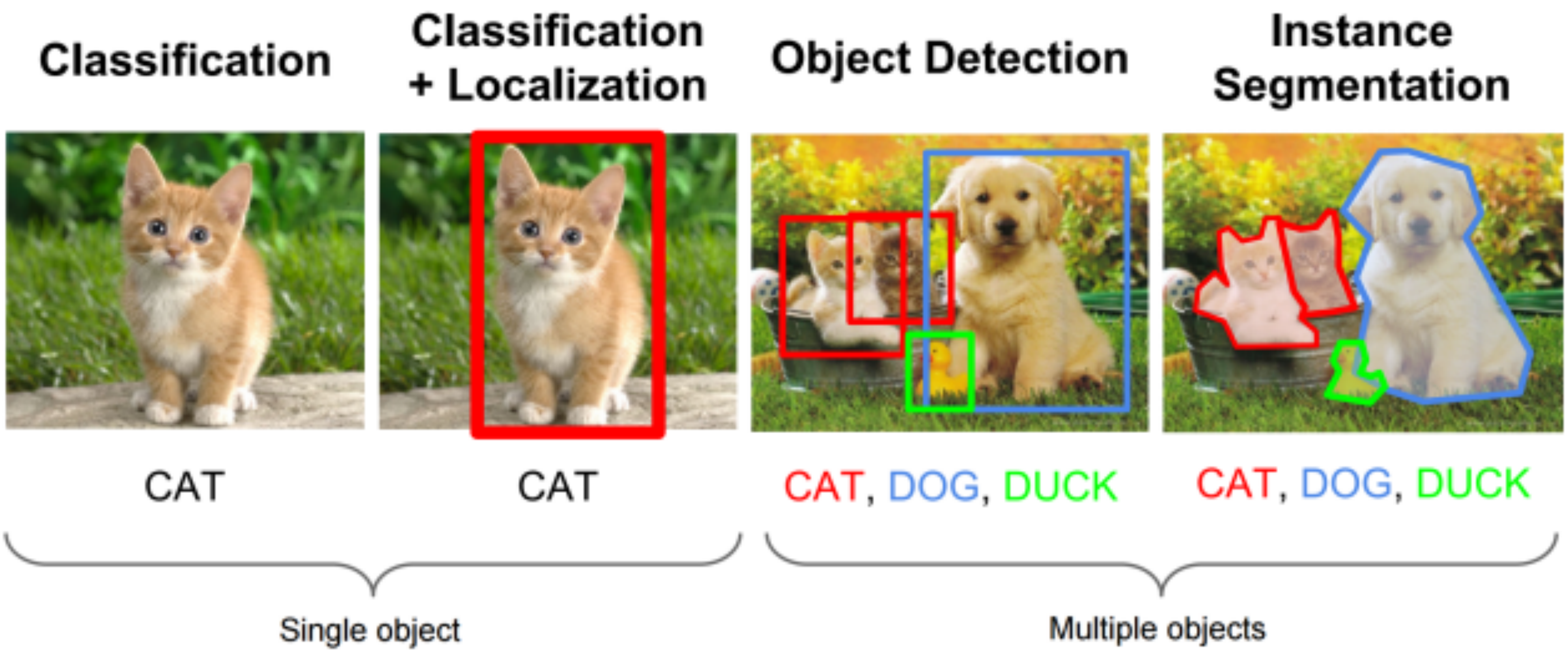
Deep Learning-based Classification

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

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

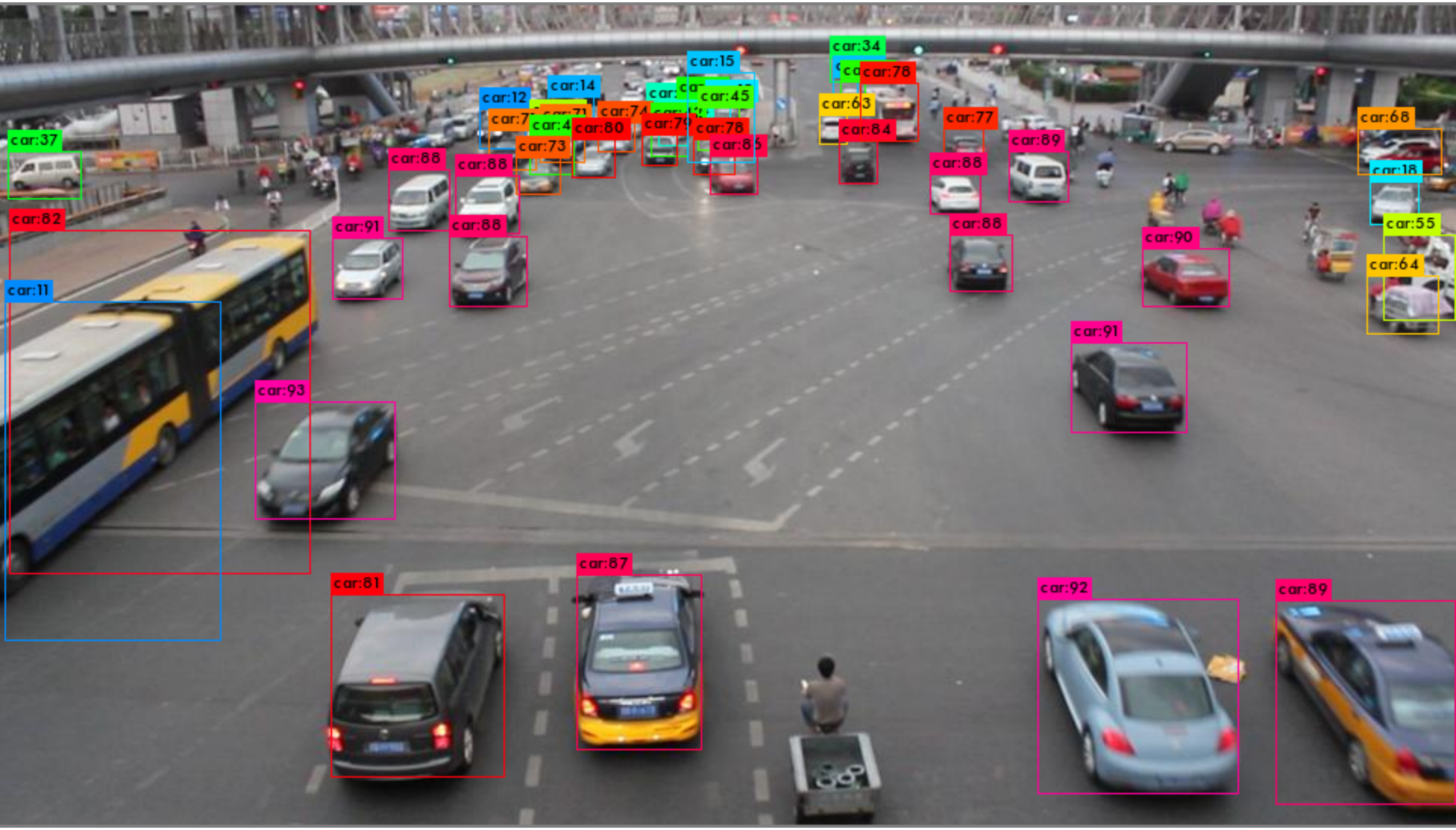
where y is the predicted class label and f represents a series of operations parameterized based on W for processing the input image.

Computer Vision Tasks

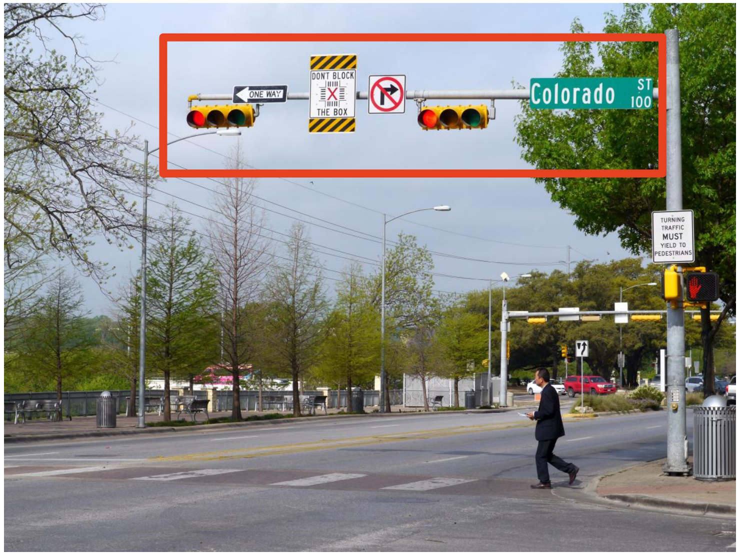


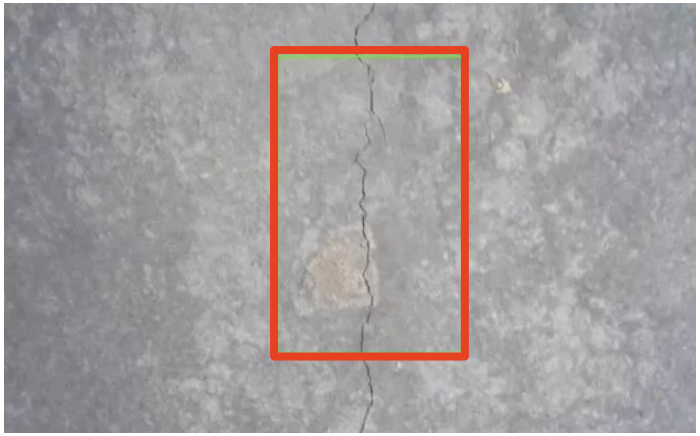
Pedestrian Detection

Car Detection



Other Applications





Localize objects with regression

Input: image

Neural Net

Output:
Box coordinates
(4 numbers)

Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

Only one object,
simpler than detection

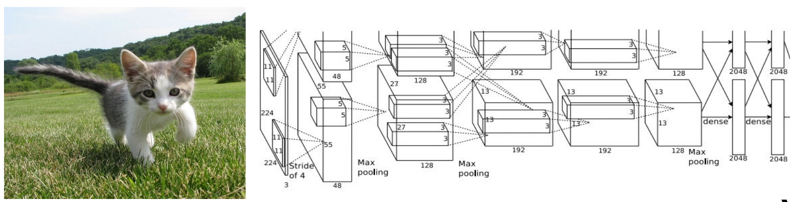
Classification with Localization

Correct label:
Cat

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Softmax Loss

Fully Connected:
4096 to 1000



This image is CC0 public domain

Vector: 4096

Multitask Loss

+ → **Loss**

Fully Connected:
4096 to 4

Box Coordinates
(x, y, w, h)

L2 Loss

Correct box:
(x', y', w', h')

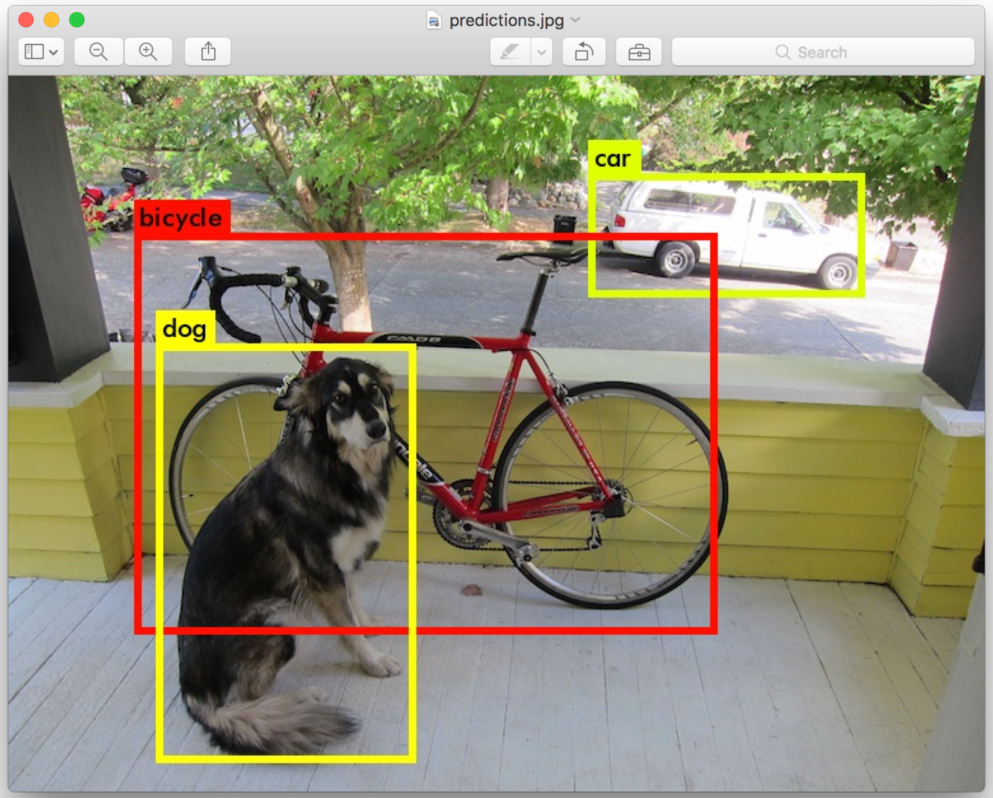
Treat localization as a regression problem!

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

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

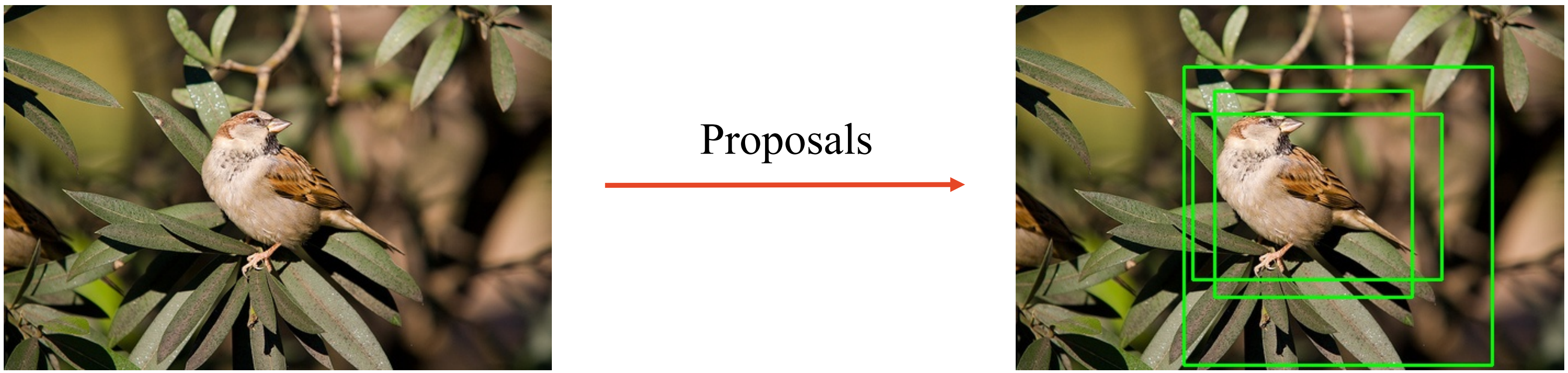
Detection

Goal: Detect semantic objects of certain classes in images.



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

Typical architecture



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.

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.

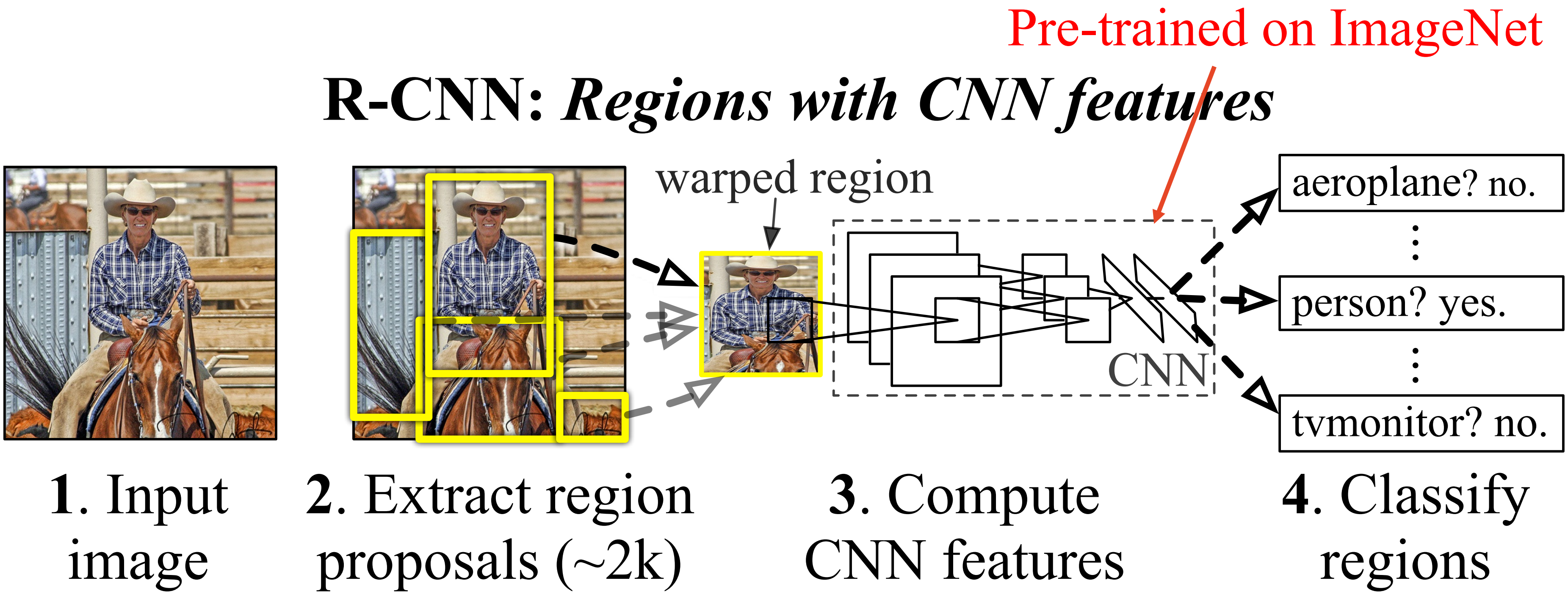
Deep Learning-based Detection

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)

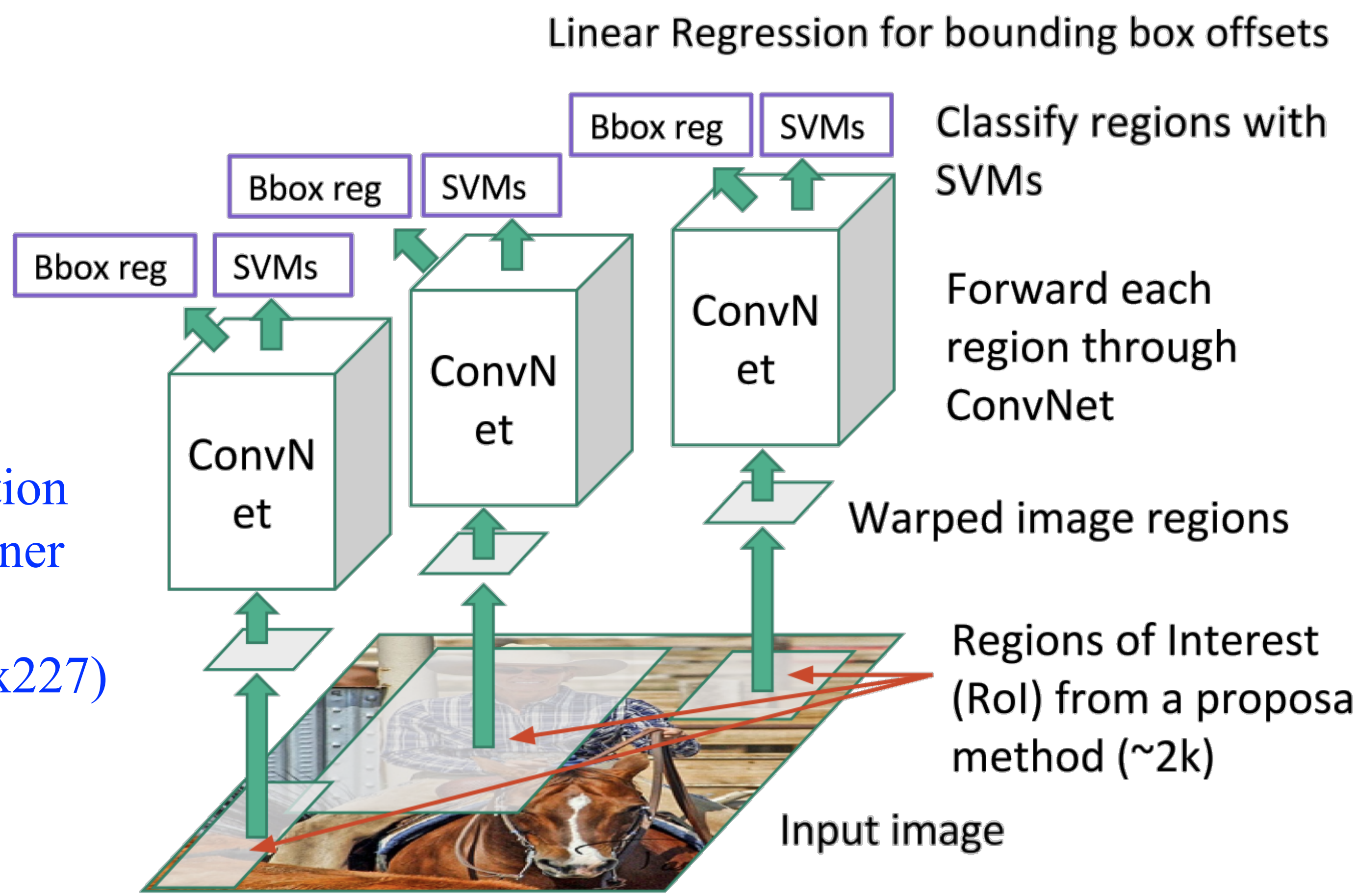


Object Detection to Image Classification

[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)

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



Credit To: towardsdatascience.com

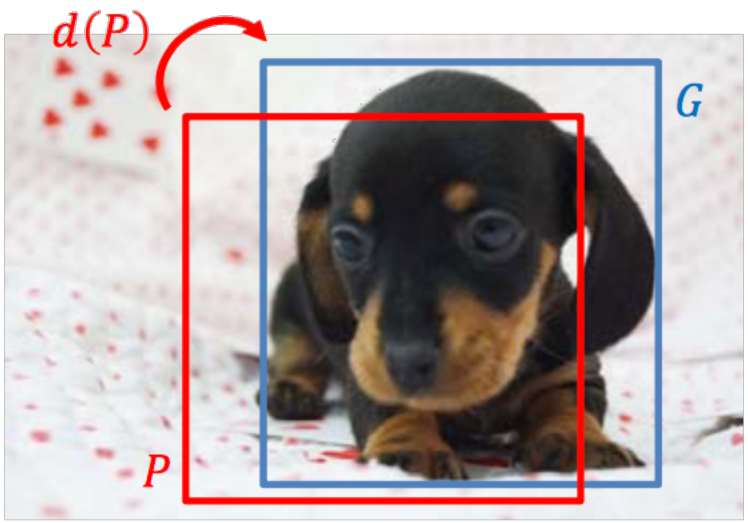
*Selective Search

- 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: $P = (P_w, P_h, P_w, P_h)$
  - Ground-truth: $G = \left(G_x, G_y, G_w, G_h\right)$
  - Transformation: $d(P) = (t_x, t_y, t_w, t_h)$



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

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

CNN pool5 feature

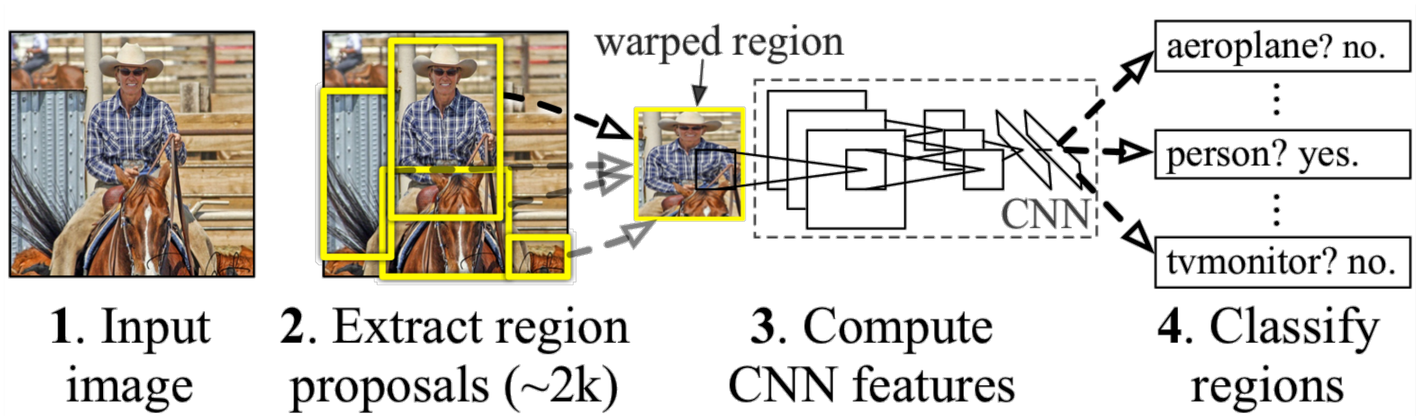
$$\mathbf{w}_i^* = \underset{\mathbf{w}_i}{\operatorname{argmin}} \sum_{k=1}^{N} \left(t_i^k - \mathbf{w}_i^{\mathrm{T}} \phi_5(P^k)\right)^2 + \lambda \|\mathbf{w}_i\|^2$$

Fast R-CNN

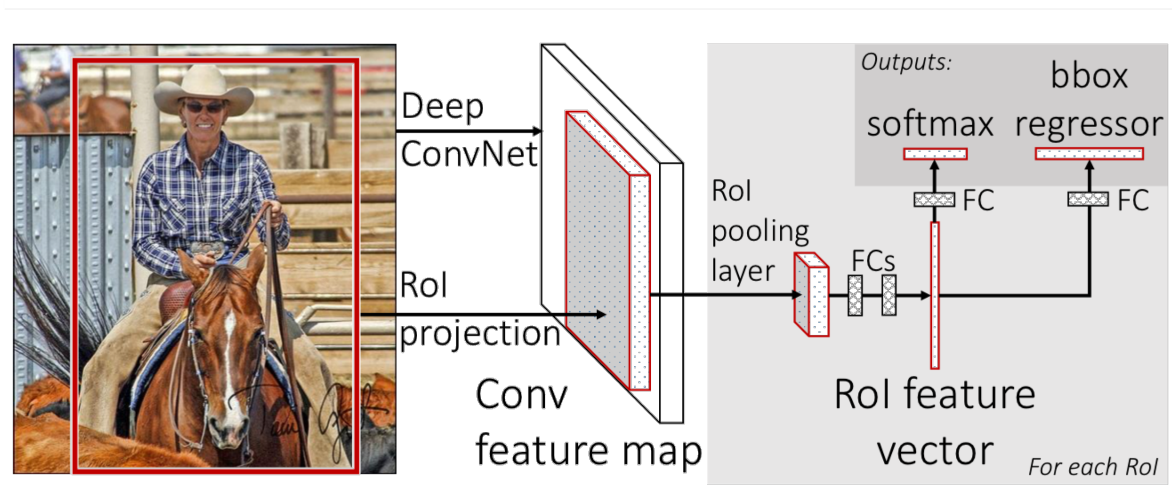
Drawback of R-CNN and the modification:

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

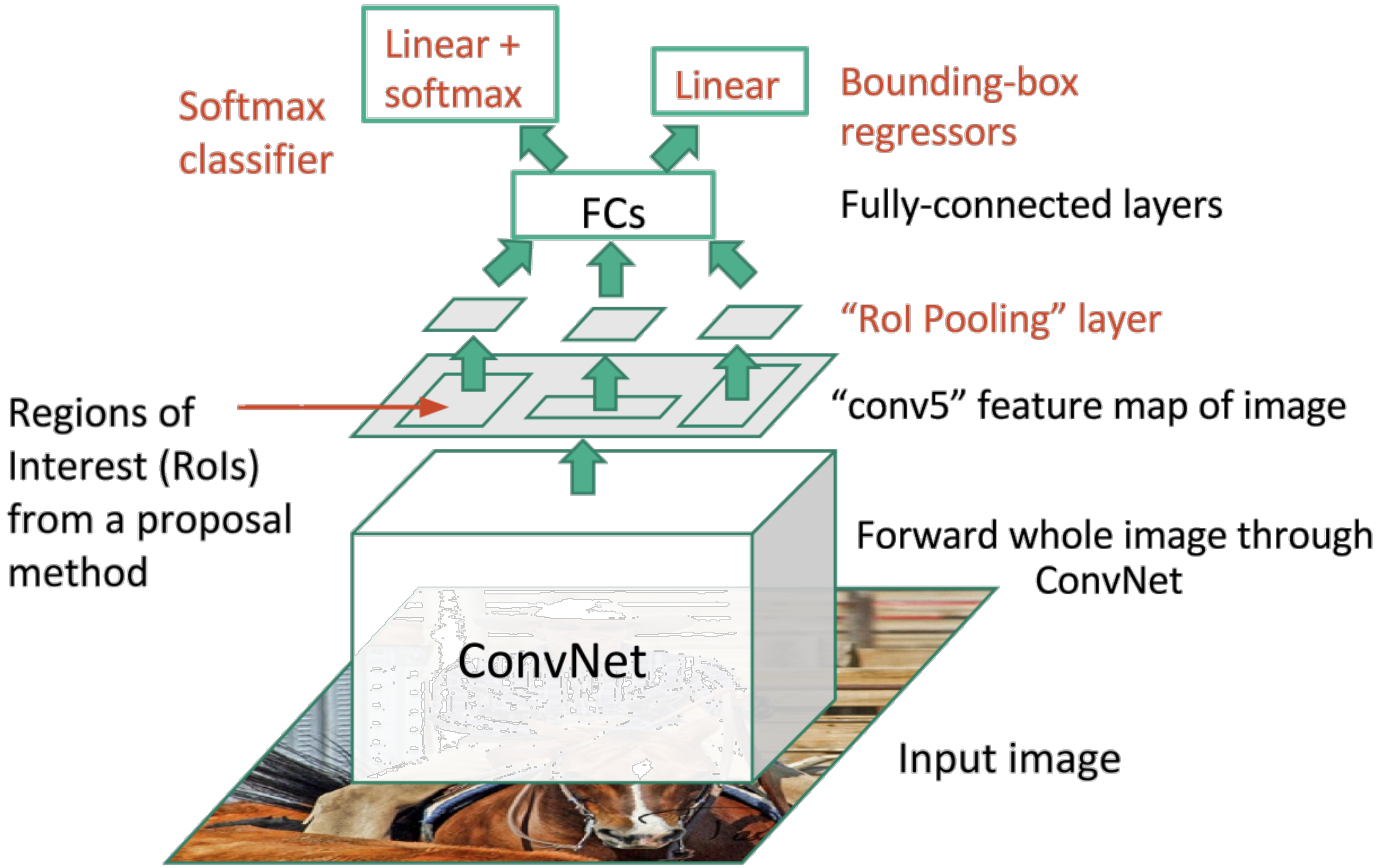
R-CNN



Fast R-CNN

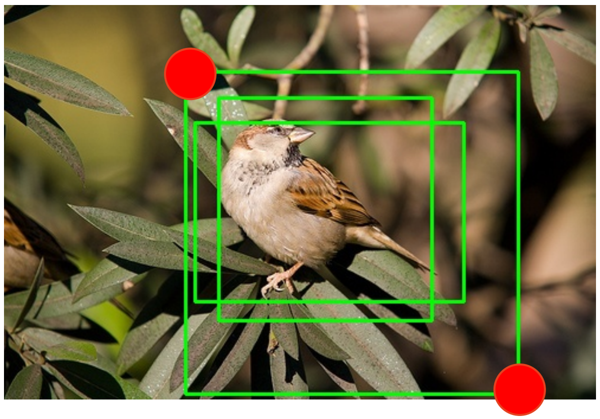


Fast R-CNN


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

Region of Interest Pooling

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

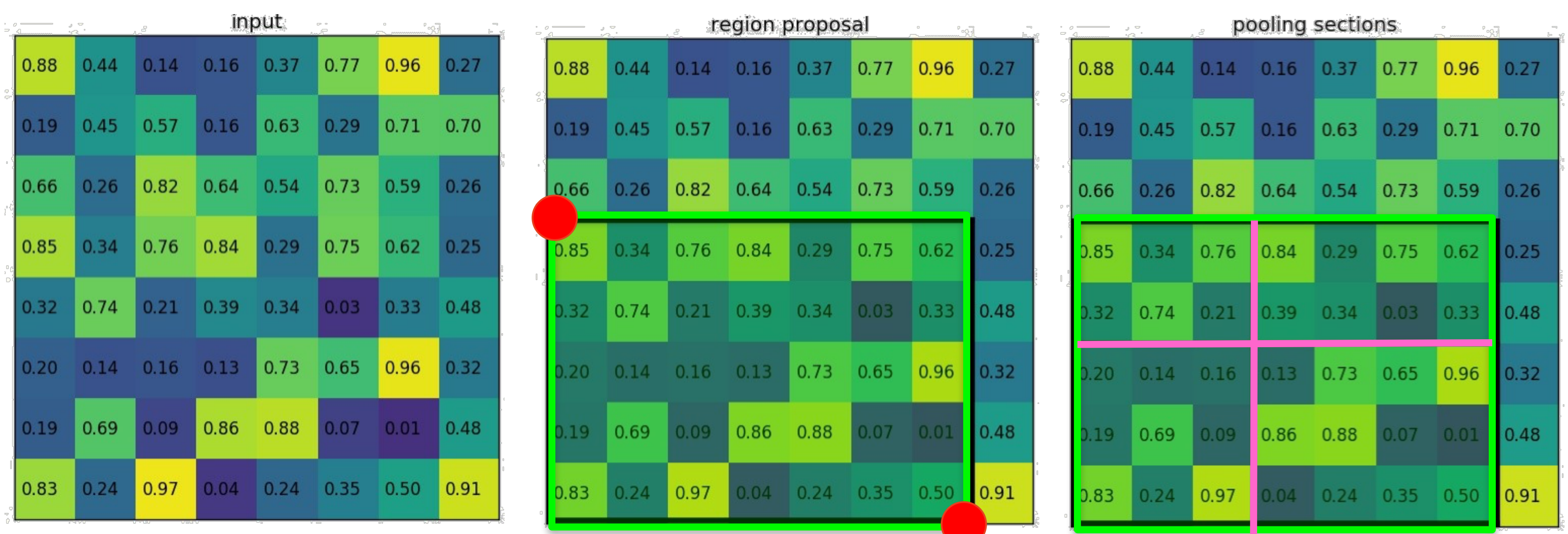


Input to ROI pooling layer:

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

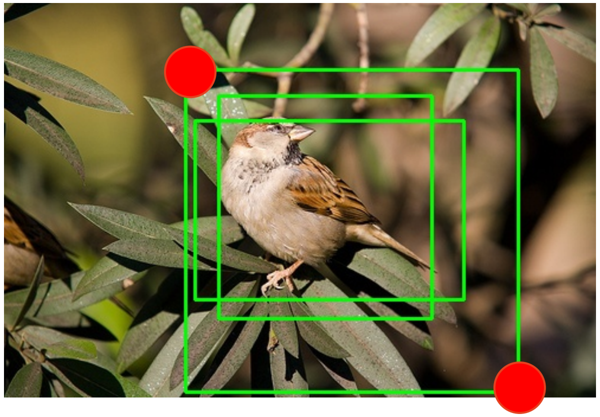
a region proposal

8×8 feature map → 2×2 output



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

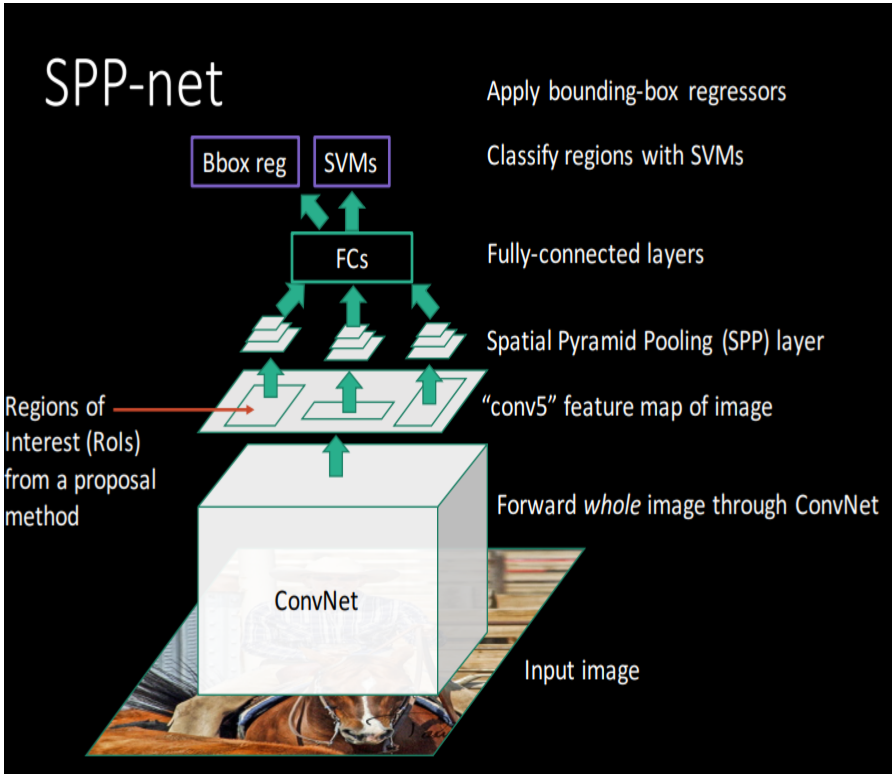
8×8 feature map $\xrightarrow{\text{a region proposal}}$ 2×2 output

input

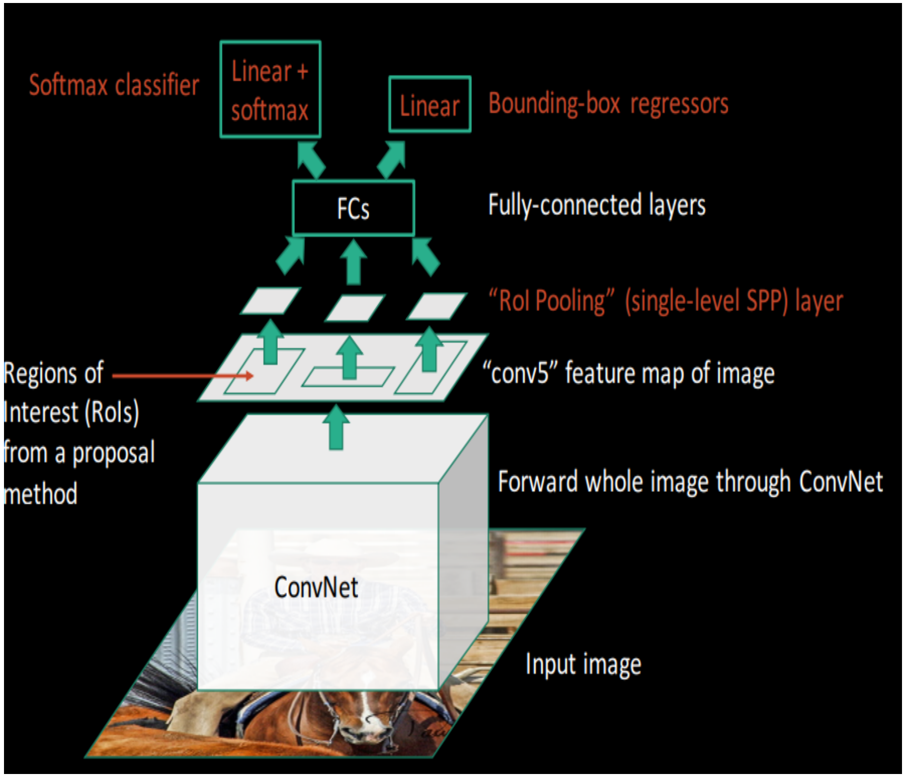
0.88	0.44	0.14	0.16	0.37	0.77	0.96	0.27
0.19	0.45	0.57	0.16	0.63	0.29	0.71	0.70
0.66	0.26	0.82	0.64	0.54	0.73	0.59	0.26
0.85	0.34	0.76	0.84	0.29	0.75	0.62	0.25
0.32	0.74	0.21	0.39	0.34	0.03	0.33	0.48
0.20	0.14	0.16	0.13	0.73	0.65	0.96	0.32
0.19	0.69	0.09	0.86	0.88	0.07	0.01	0.48
0.83	0.24	0.97	0.04	0.24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

- 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

Fast R-CNN



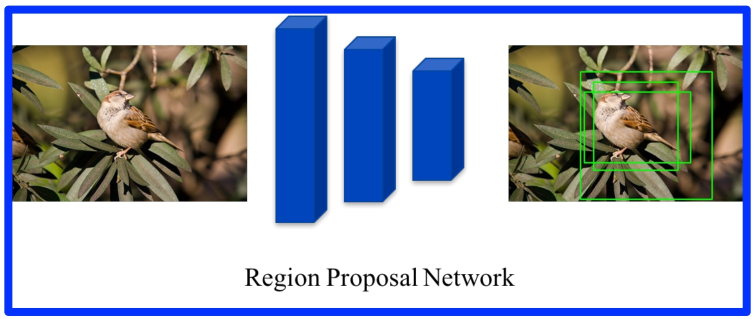
VS

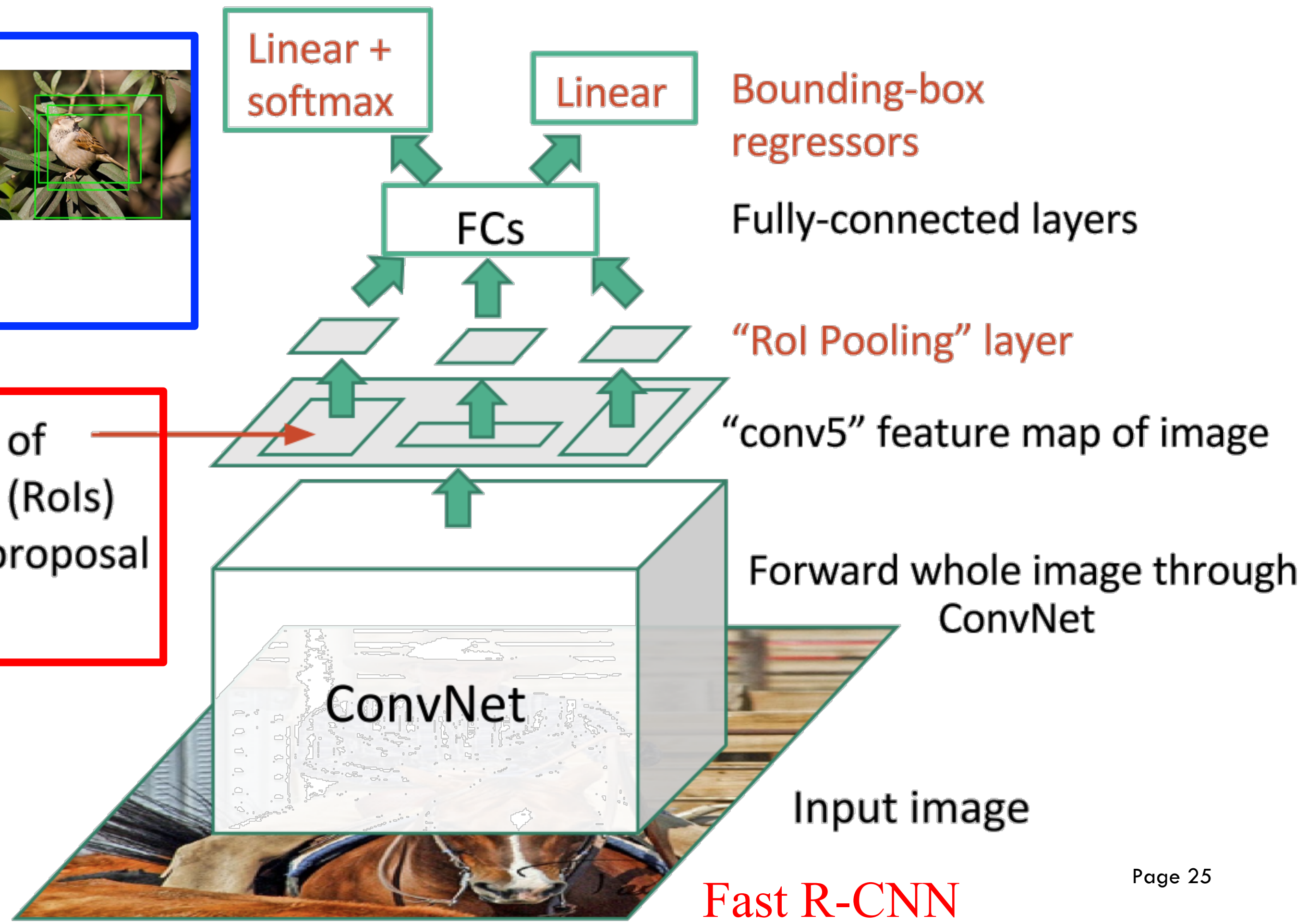


Credit To: http://www.robots.ox.ac.uk/~tvg/publications/talks/fast-rcnn-slides.pdf

Faster R-CNN

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





Fast R-CNN

Region Proposal Network

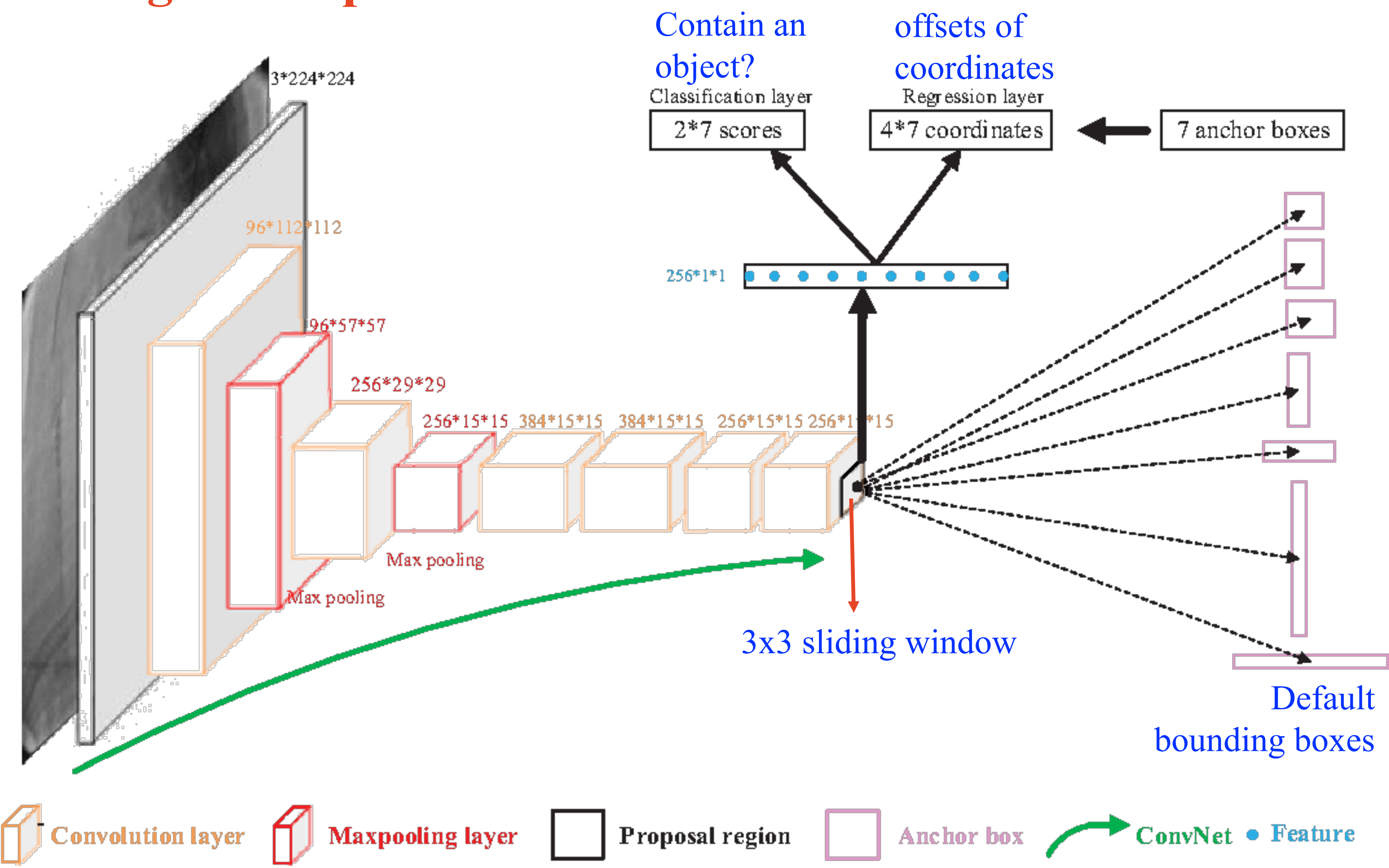
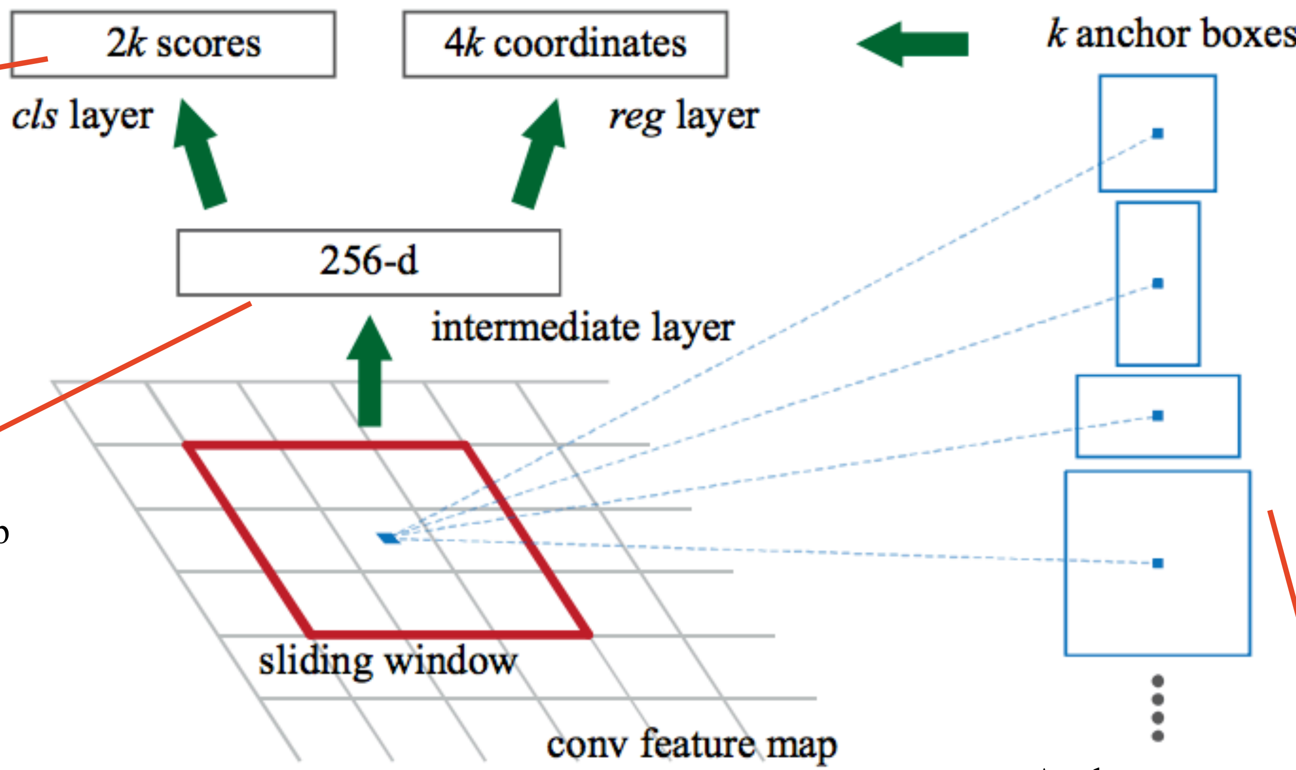


Image Credit to [Li Wang et al. 2017]

Region Proposal Network

Each anchor also has 4 neurons to represent offsets of coordinates

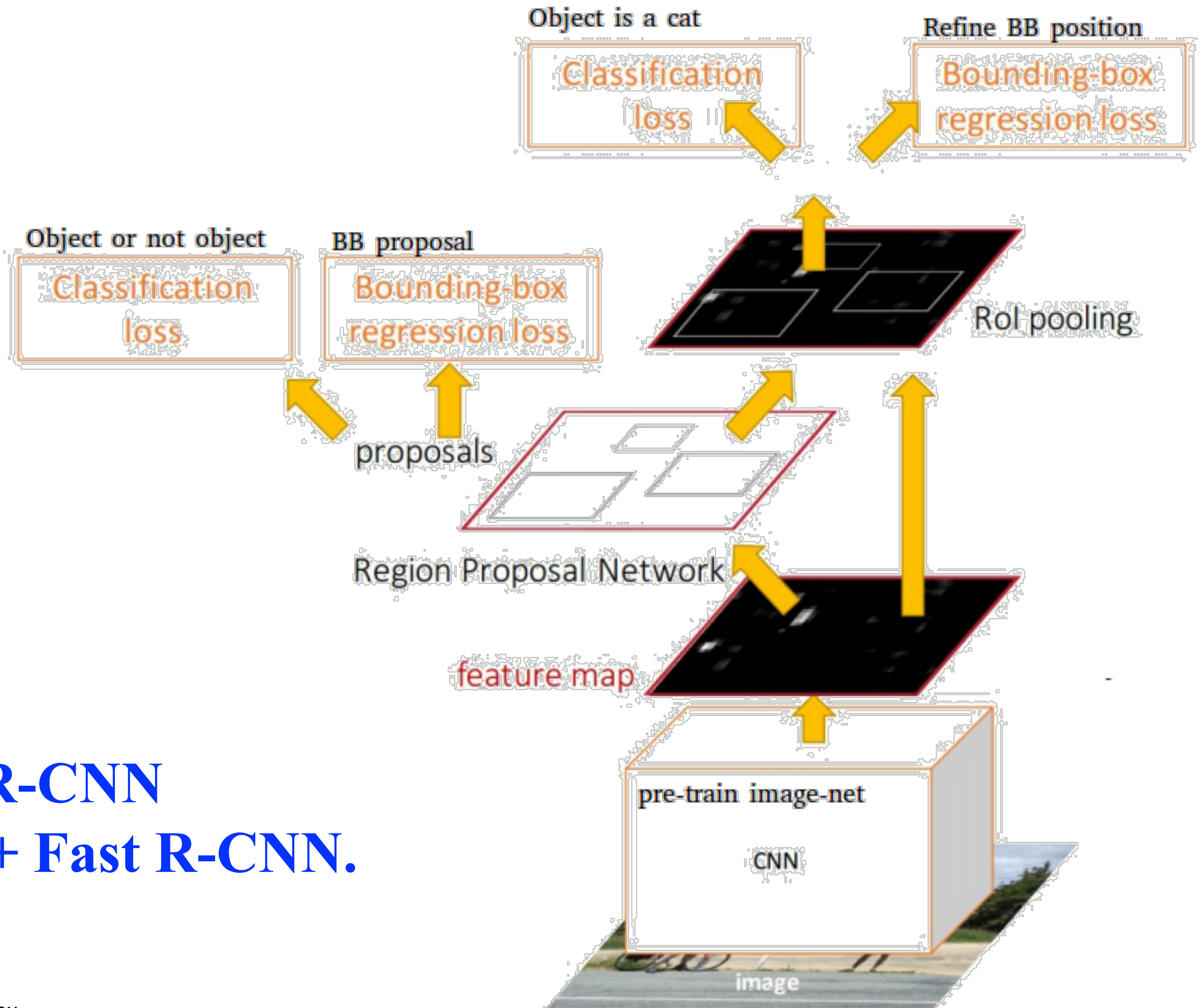


Each anchor has 2 neurons to represent fg/bg label

The input feature map has 256 channels

Anchors are pre-determined boxes whose sizes can be ranged from 32^2 to 512^2 and aspect ratios can be ranged from 0.5 to 2.

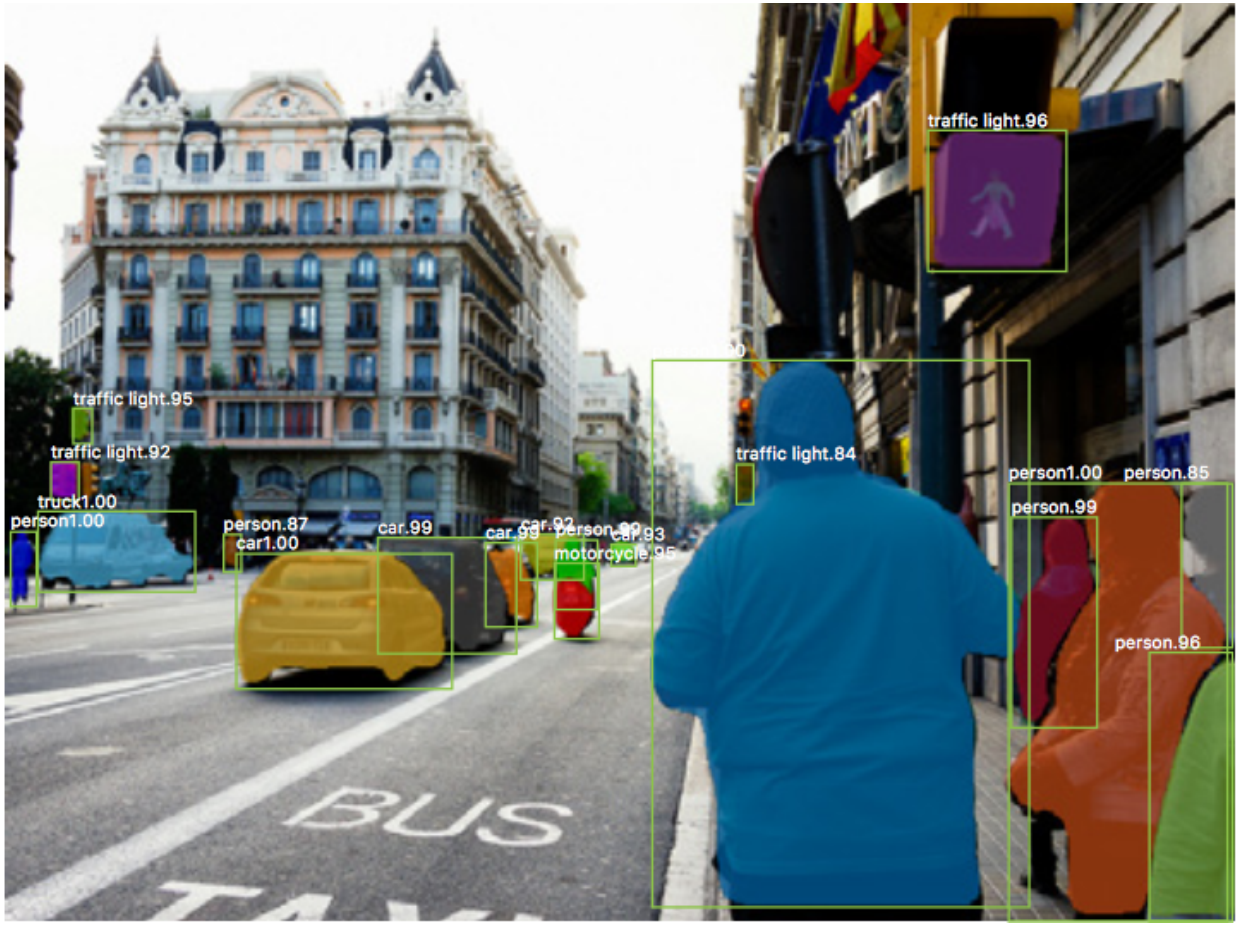
Faster R-CNN



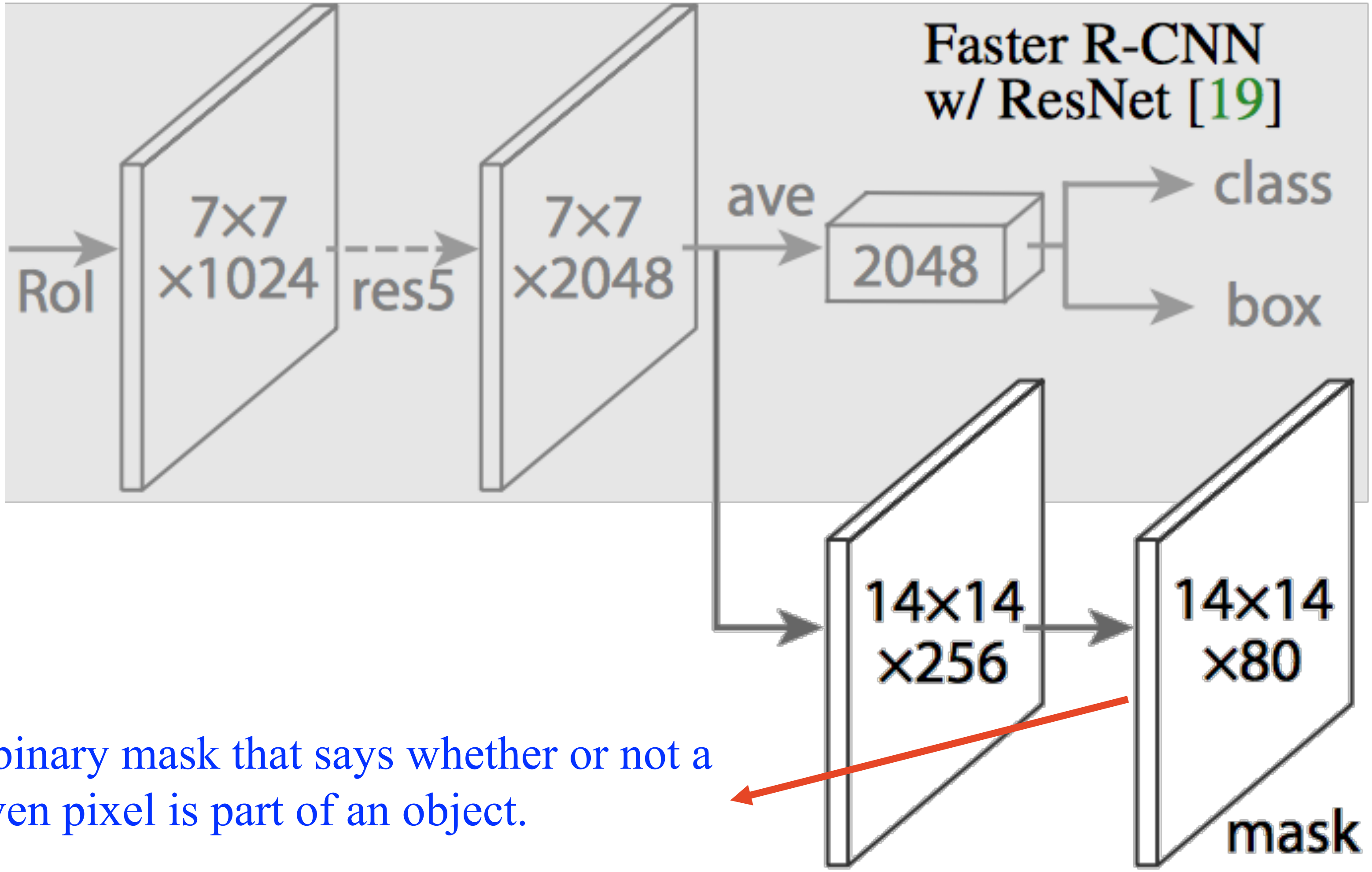
Faster R-CNN
= RPN + Fast R-CNN.

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.

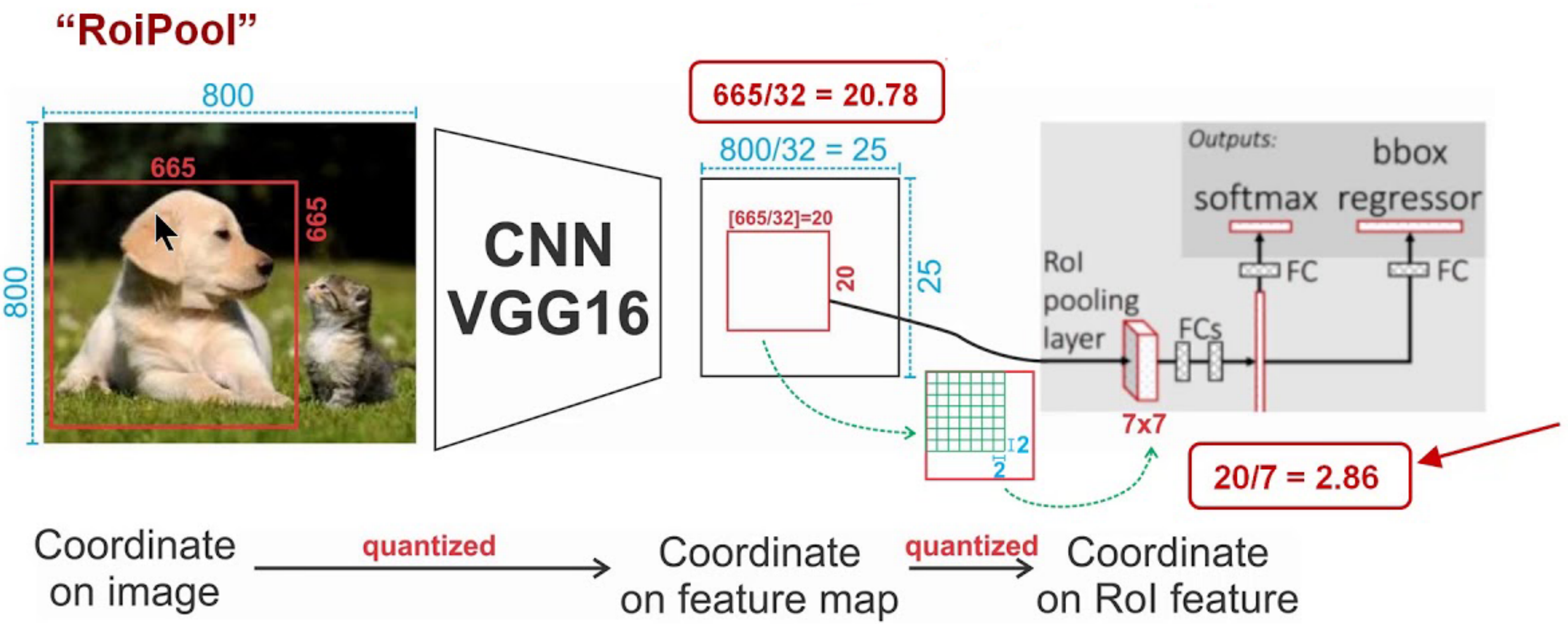
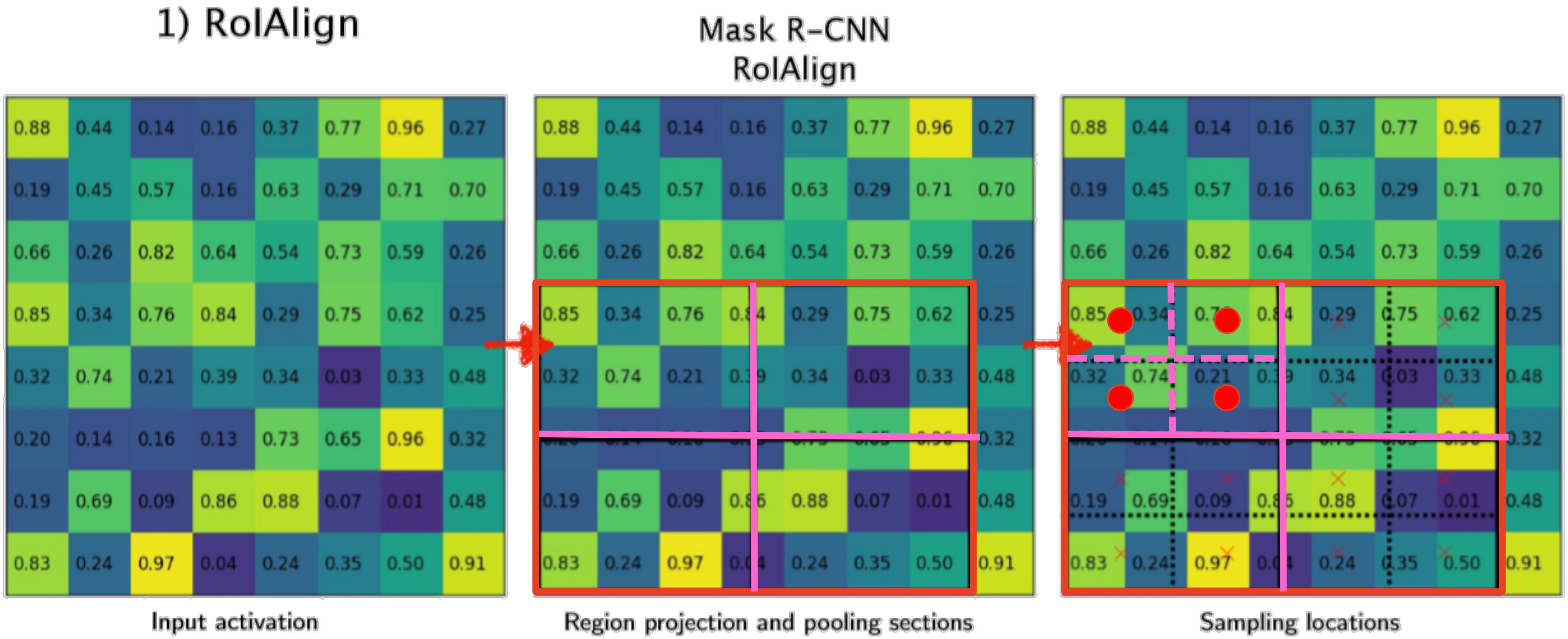
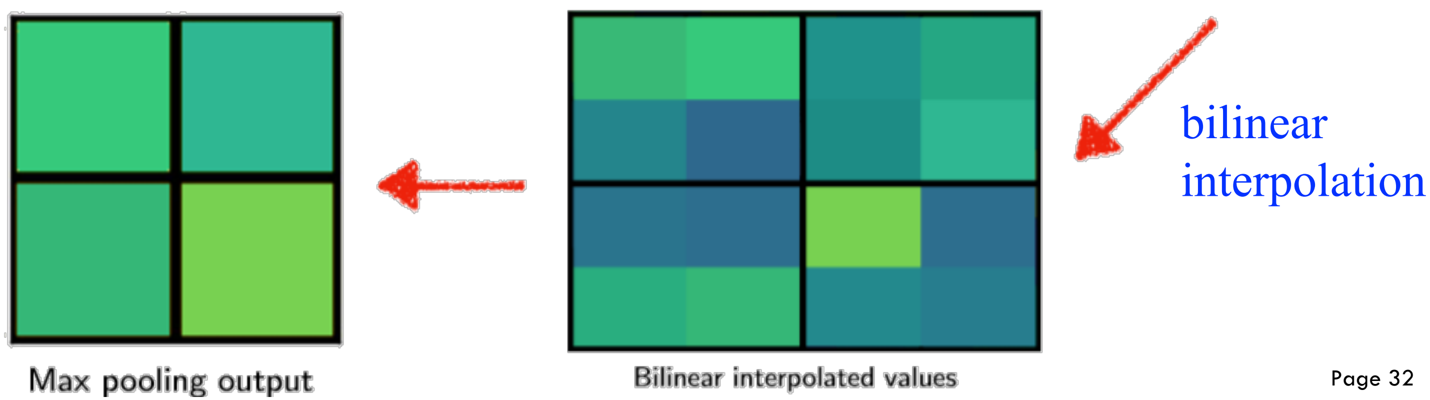


Image credit to Ardian Umam

RoIAlign

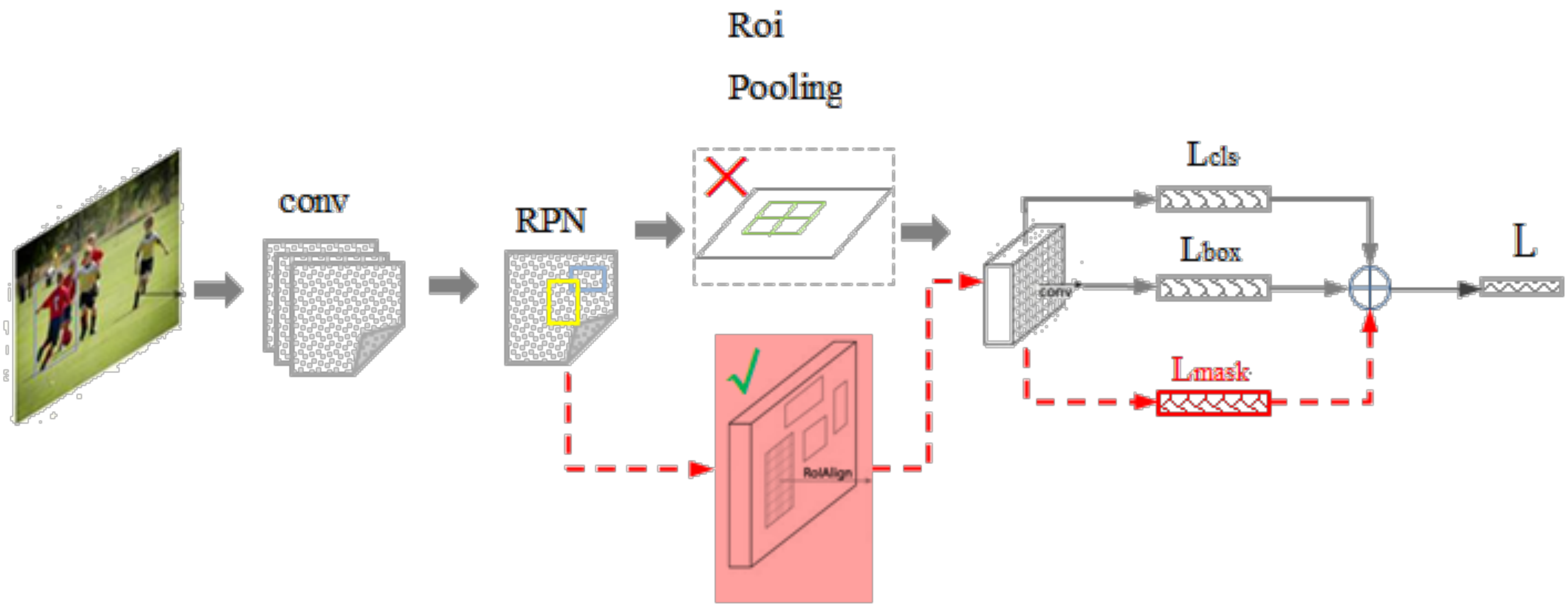




Credit To: https://www.slideshare.net/windmdk/mask-rcnn

RoIAlign

Realigning RoI Pooling to be More Accurate.



Mask R-CNN

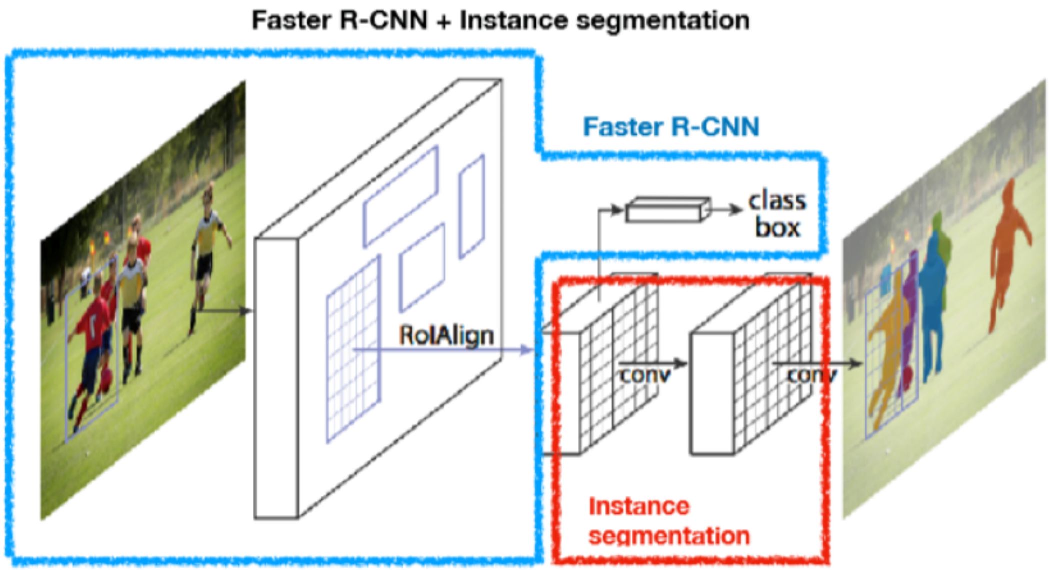
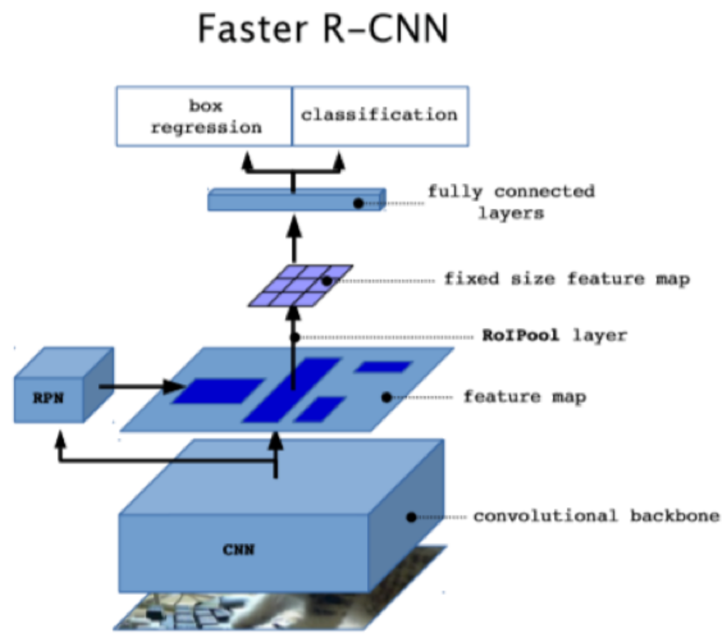


Figure 1. The **Mask R-CNN** framework for instance segmentation.

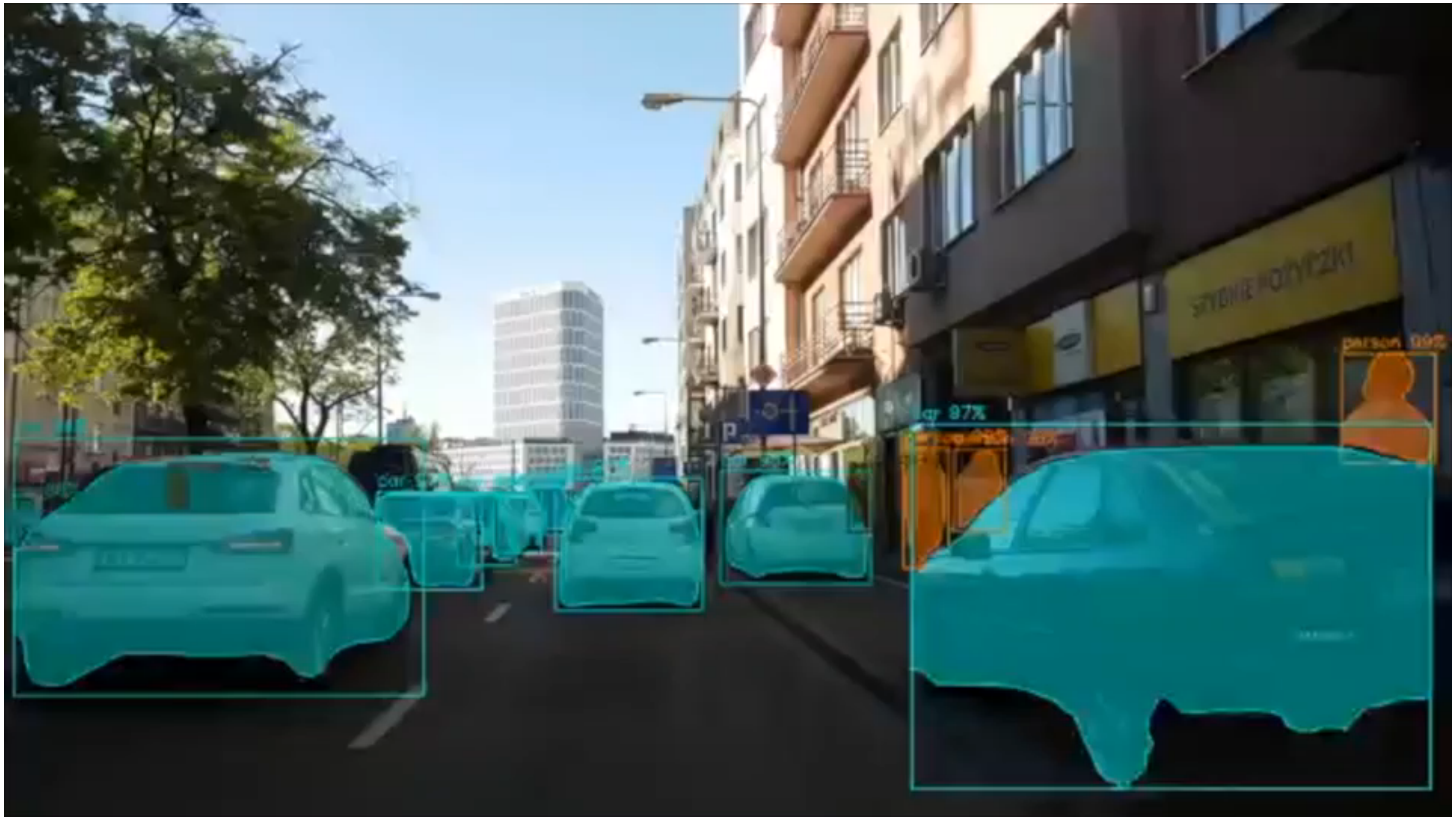


Mask R-CNN
= Instance Segmentation+ Faster R-CNN.

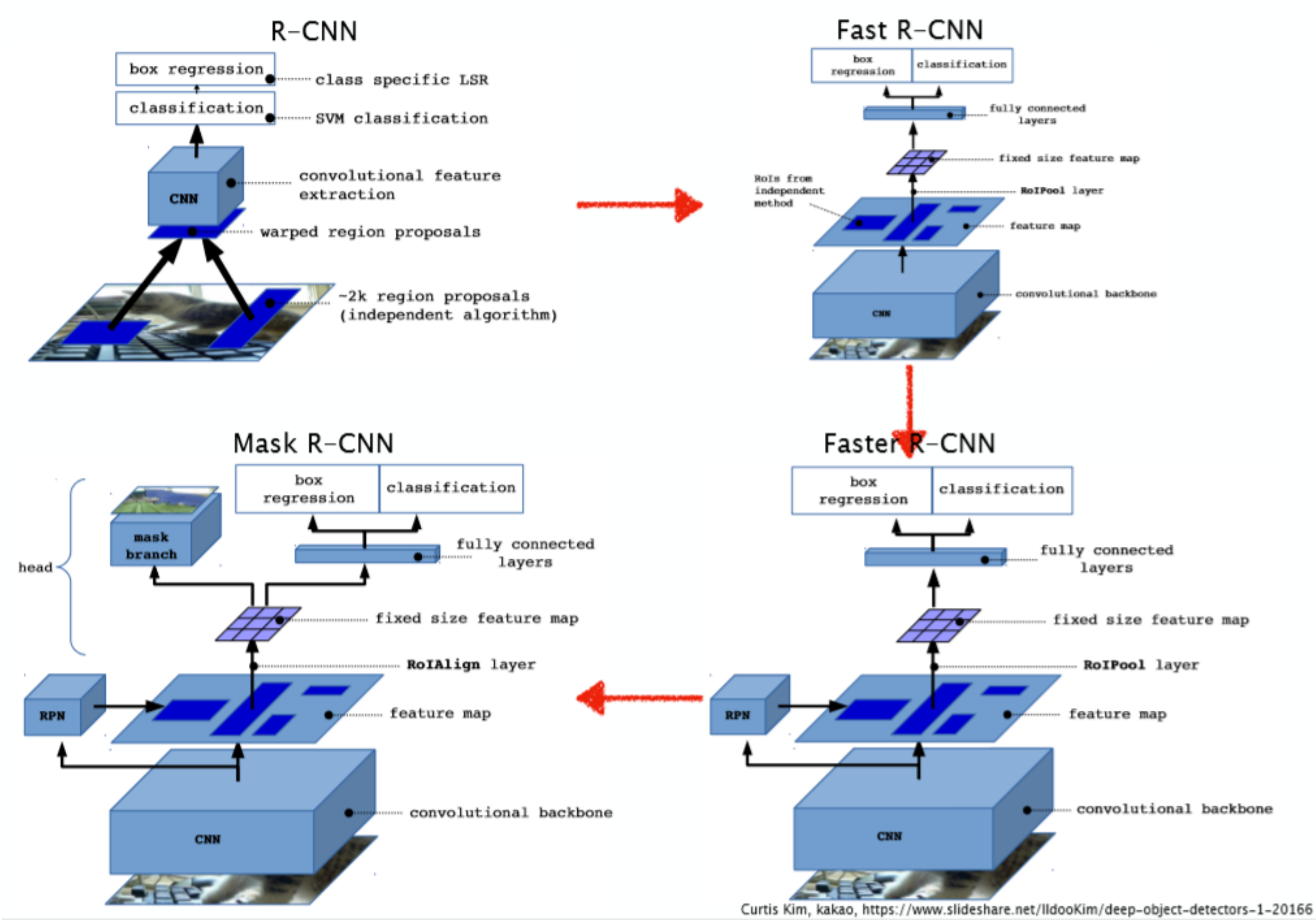
Credit To: https://www.slideshare.net/windmdk/mask-rcnn

Mask R-CNN

Demo



From R-CNN to Mask R-CNN



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