Introduction to Data Science
Final Project

Topic :
RCNN-Family

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R-CNN

1. Region Proposals (selective search)
2. Feature Extractor (AlexNet)
3. Detector (SVM classifier, bbox regressor)

Region Proposals (selective search)

Image from Jasper RR Uijlings [1]

Region Proposals (selective search)

Algorithm 1: Hierarchical Grouping Algorithm

Input: (colour) image
Output: Set of object location hypotheses L

Obtain initial regions $R = \{r_1, \cdots, r_n\}$ using [13]
Initialise similarity set $S = \emptyset$
foreach *Neighbouring region pair* (r_i, r_j) **do**
    Calculate similarity $s(r_i, r_j)$
    $S = S \cup s(r_i, r_j)$

while $S \neq \emptyset$ **do**
    Get highest similarity $s(r_i, r_j) = \max(S)$
    Merge corresponding regions $r_t = r_i \cup r_j$
    Remove similarities regarding $r_i : S = S \setminus s(r_i, r_*)$
    Remove similarities regarding $r_j : S = S \setminus s(r_*, r_j)$
    Calculate similarity set S_t between r_t and its neighbours
    $S = S \cup S_t$
    $R = R \cup r_t$

Extract object location boxes L from all regions in R

Selective search 演算法流程

Feature Extractor (AlexNet)

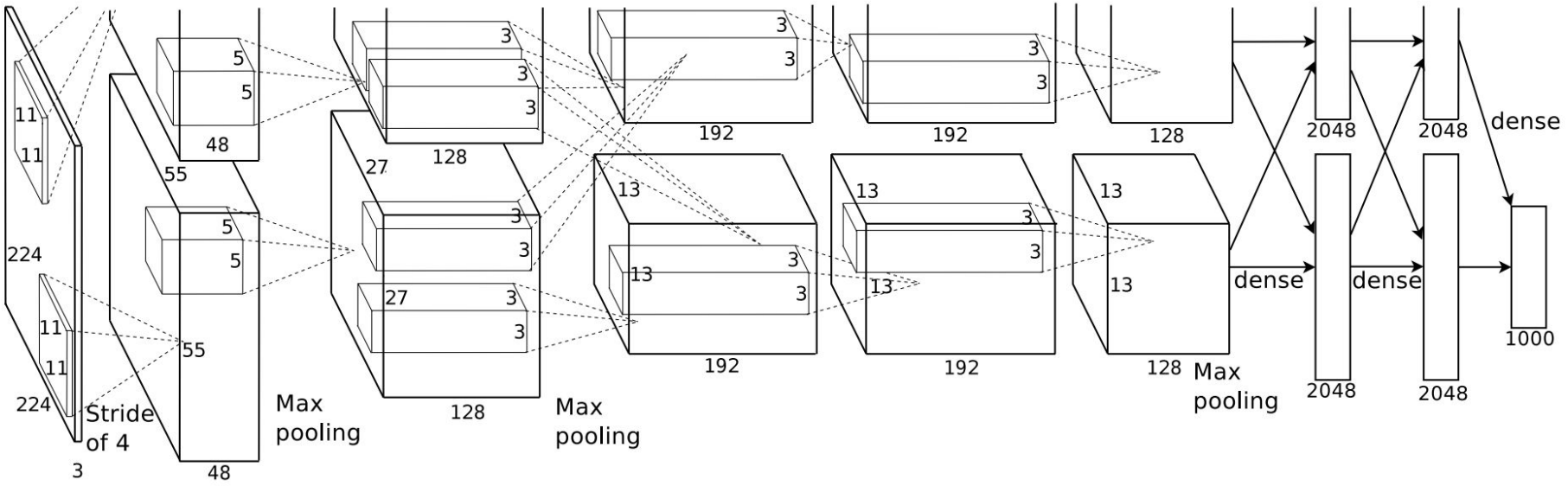
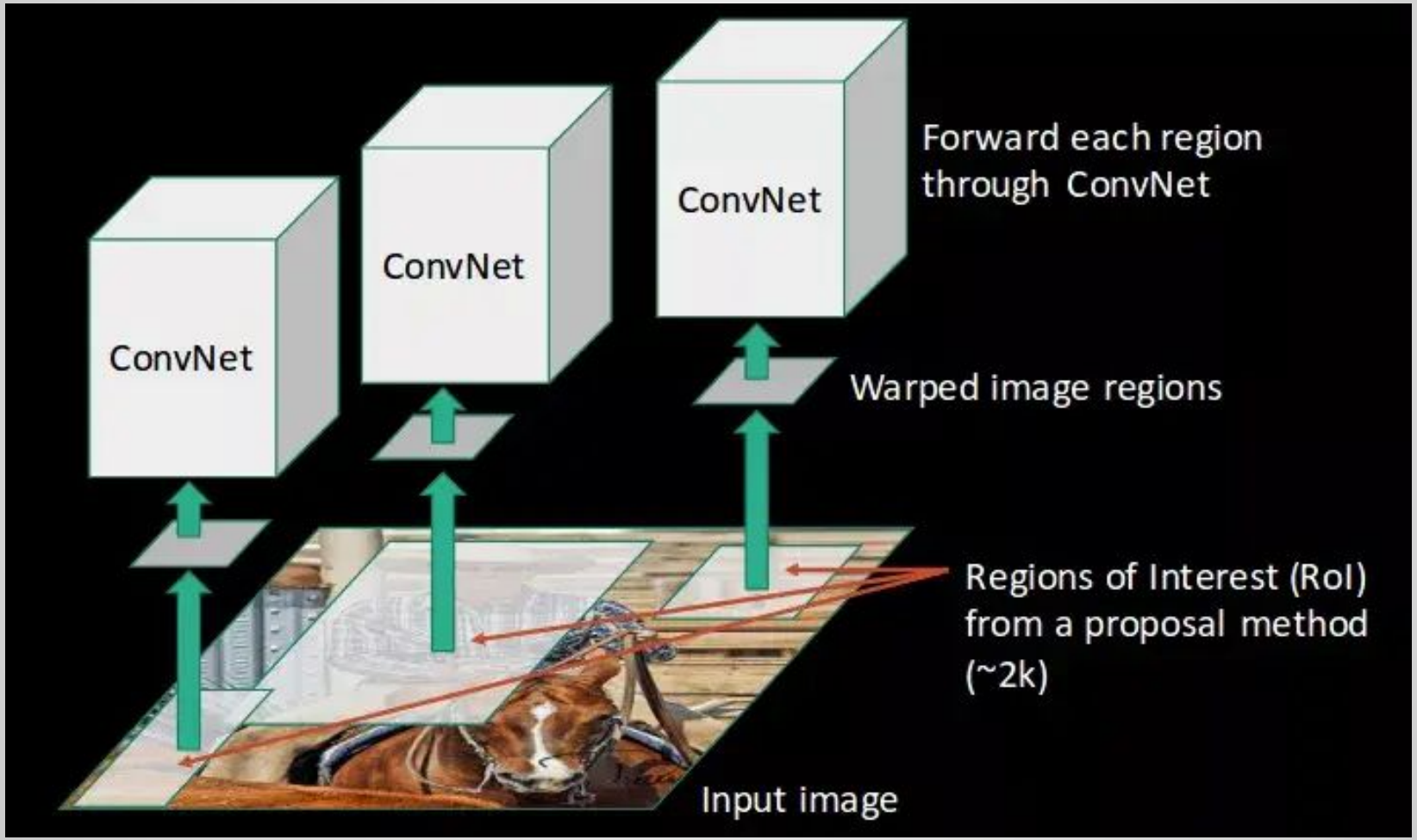


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.

Feature Extractor (AlexNet)

1. Replacing Sigmoid with ReLU in LeNet
2. Replacing Avg Pooling with Max Pooling
3. Use Dropout in sixth and seventh to replace Fully Connected NN

Feature Extractor (AlexNet)



Detector (SVM classifier, Bbox regressor)

1. SVM classifier -> classification
2. Bbox regressor -> regression

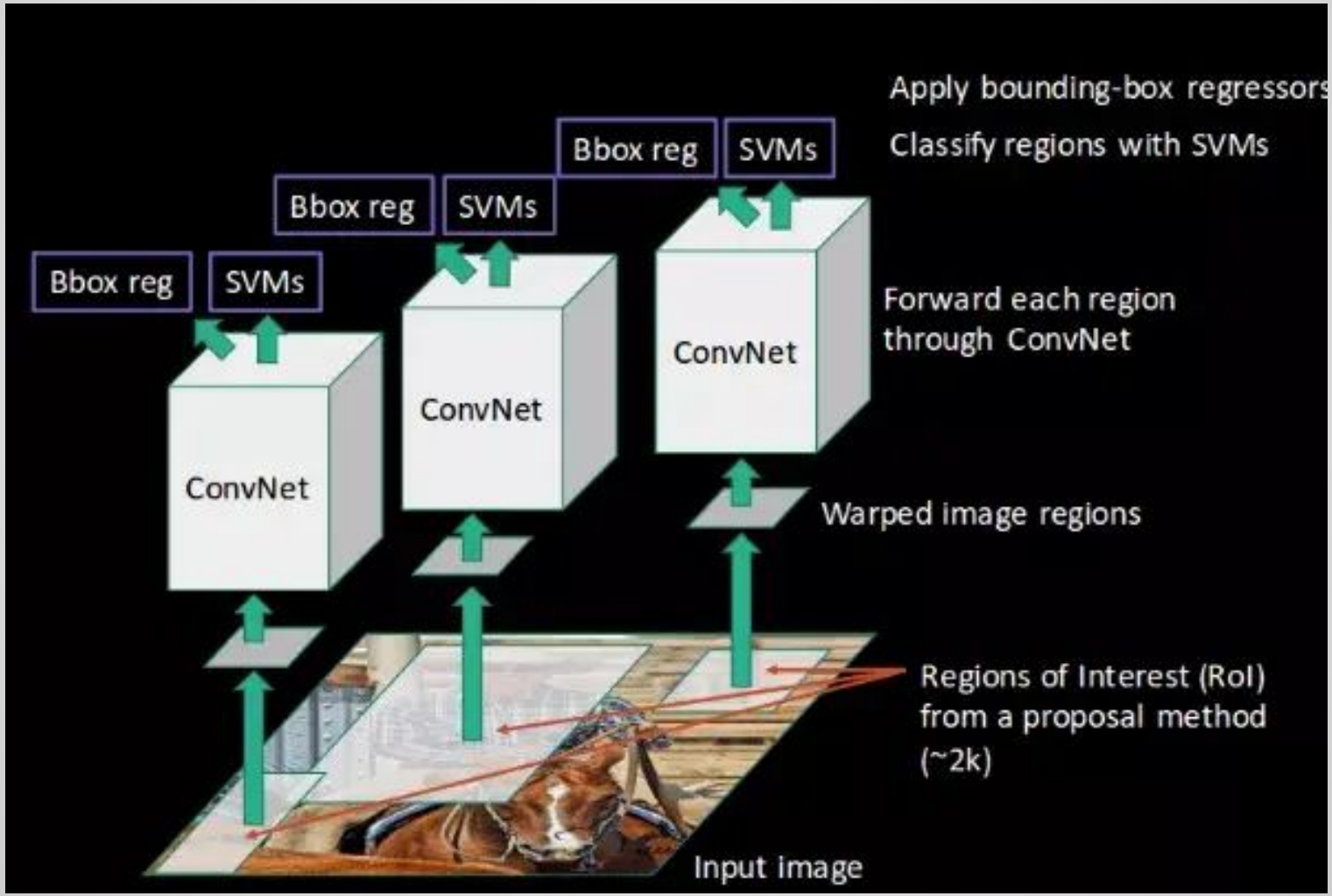
Detector (SVM classifier, Bbox regressor)

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

$$t_x = (G_x - P_x)/P_w$$
$$t_y = (G_y - P_y)/P_h$$
$$t_w = \log(G_w/P_w)$$
$$t_h = \log(G_h/P_h).$$

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^{\mathrm{T}} \boldsymbol{\phi}_5(P^i))^2 + \lambda \|\hat{\mathbf{w}}_\star\|^2$$

Detector (SVM classifier, Bbox regressor)



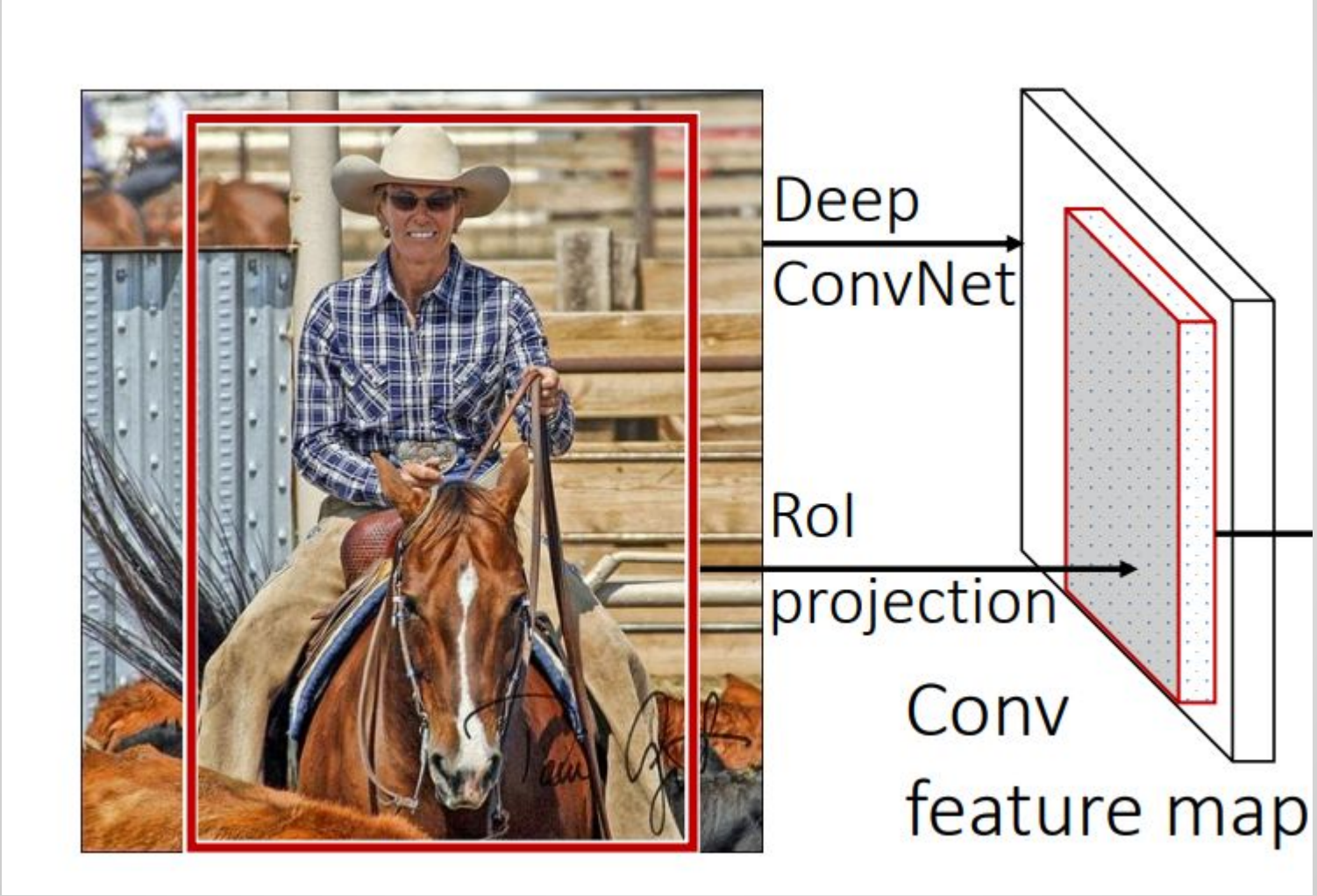
Shortcoming

1. Need large memory to store feature vector of proposal
2. Many times convolution training
3. 47 seconds per detection

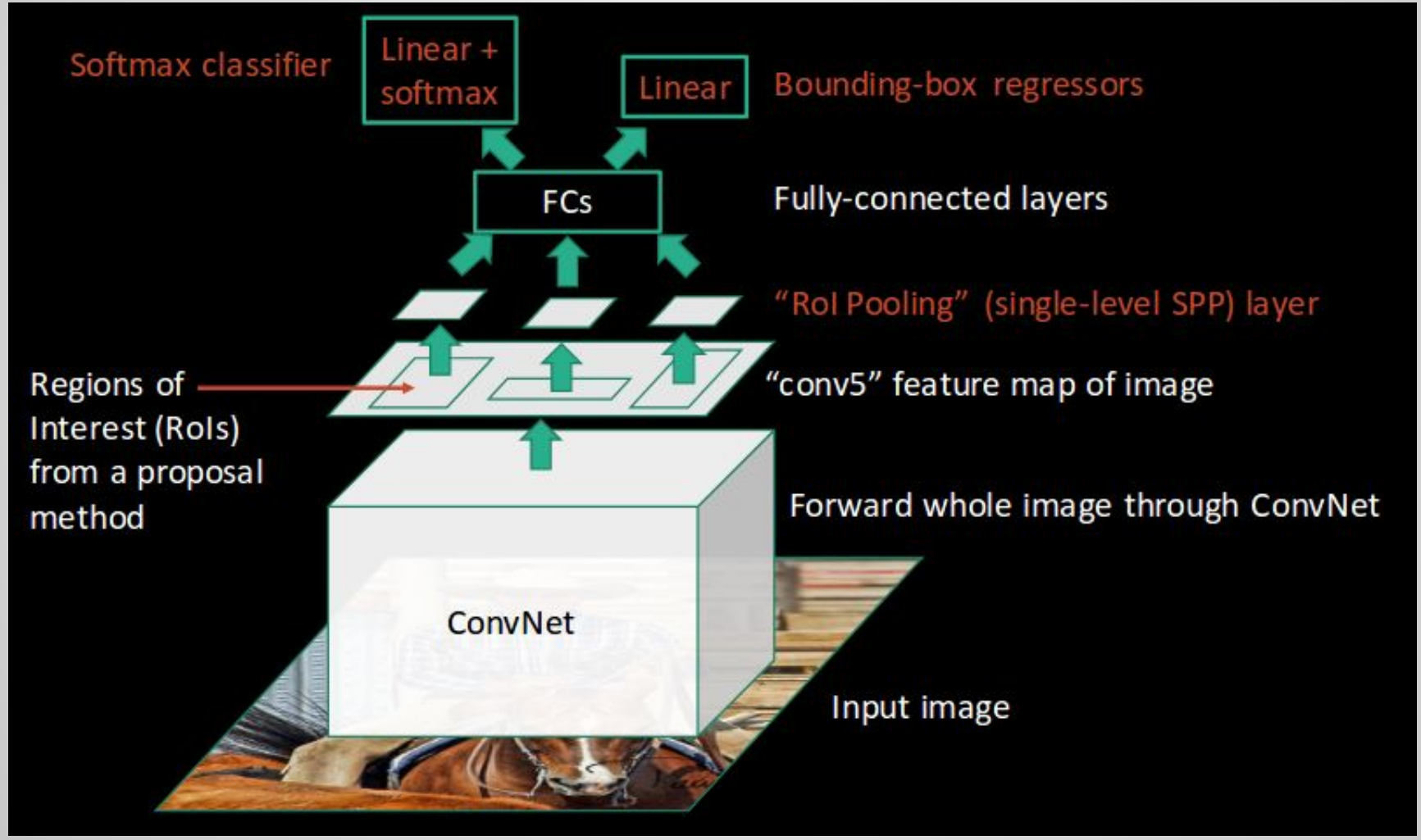
Fast R-CNN

1. Pass the entire image through convolution to generate a feature map.
2. Utilize ROI pooling layer to standardize dimensions.
3. Replace SVM with softmax for classification in the neural network.

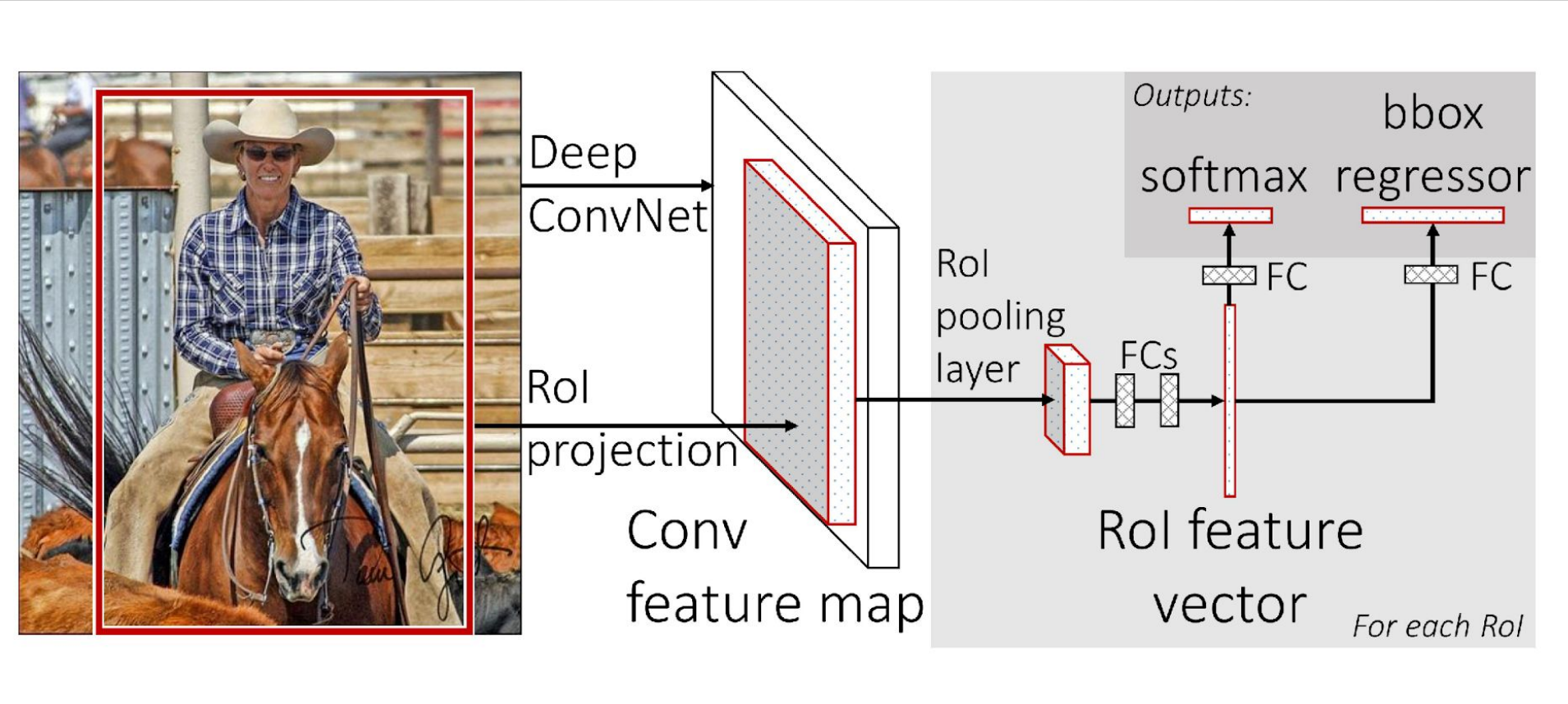
Region of Interest (selective search)



Region Proposals (selective search)

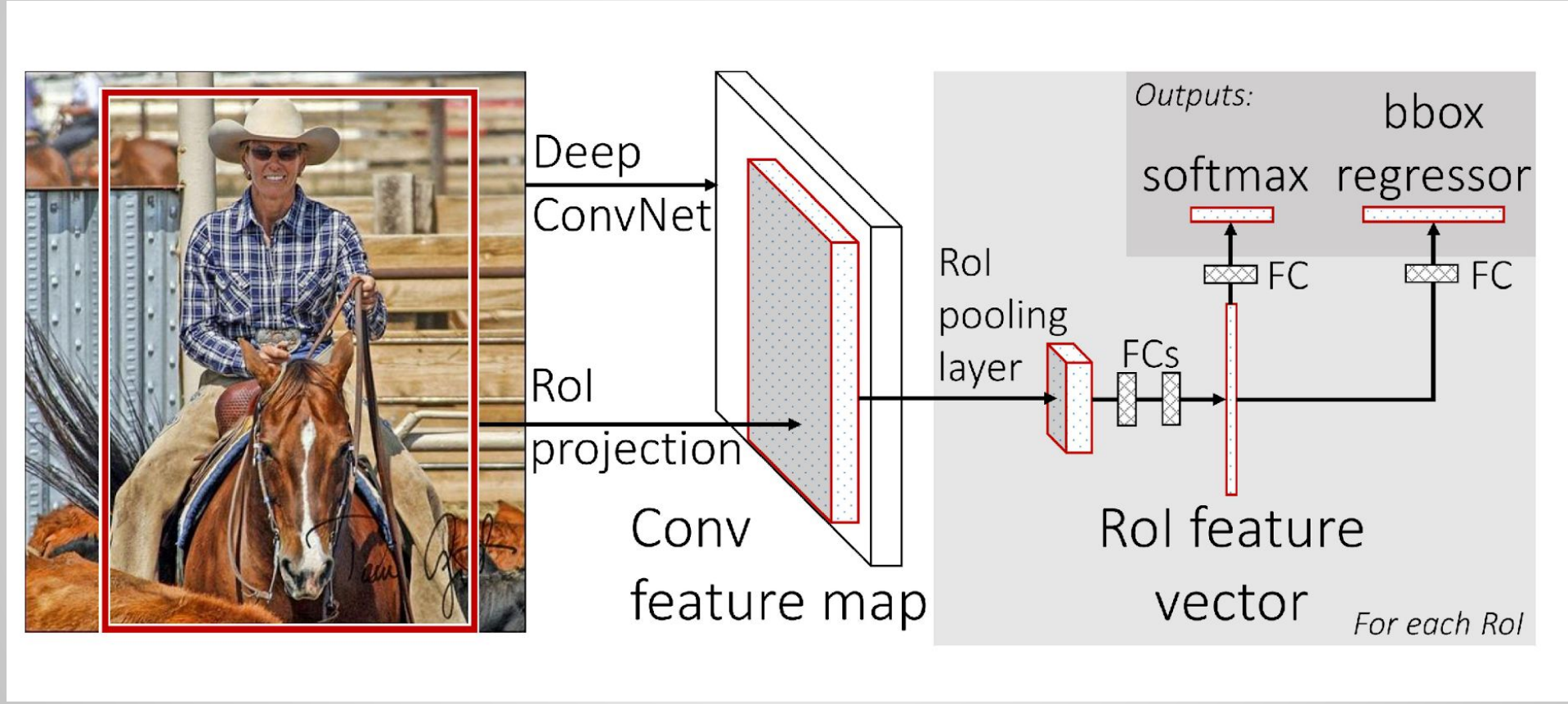


Feature Extractor (VGG net)



ROI Pooling Layer

Detector


Deep
ConvNet
RoI
projection
Conv
feature map
RoI
pooling
layer
FCs
Outputs:
softmax
bbox
regressor
FC
FC
RoI feature
vector
For each RoI

Loss Function

$$L(p, u, t^u, v) = L_{\text{cls}}(p, u) + \lambda[u \geq 1] L_{\text{loc}}(t^u, v), \qquad (1)$$

$$L_{\text{loc}}(t^u, v) = \sum_{i \in \{\text{x,y,w,h}\}} \text{smooth}_{L_1}(t_i^u - v_i), \qquad (2)$$

in which

$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases} \qquad (3)$$

Shortcoming

1. 25 times faster, but still too slow
2. Region Proposal bottle neck

Faster R-CNN

1. Use Anchor
2. Replace Selective Search with Region Proposal Network

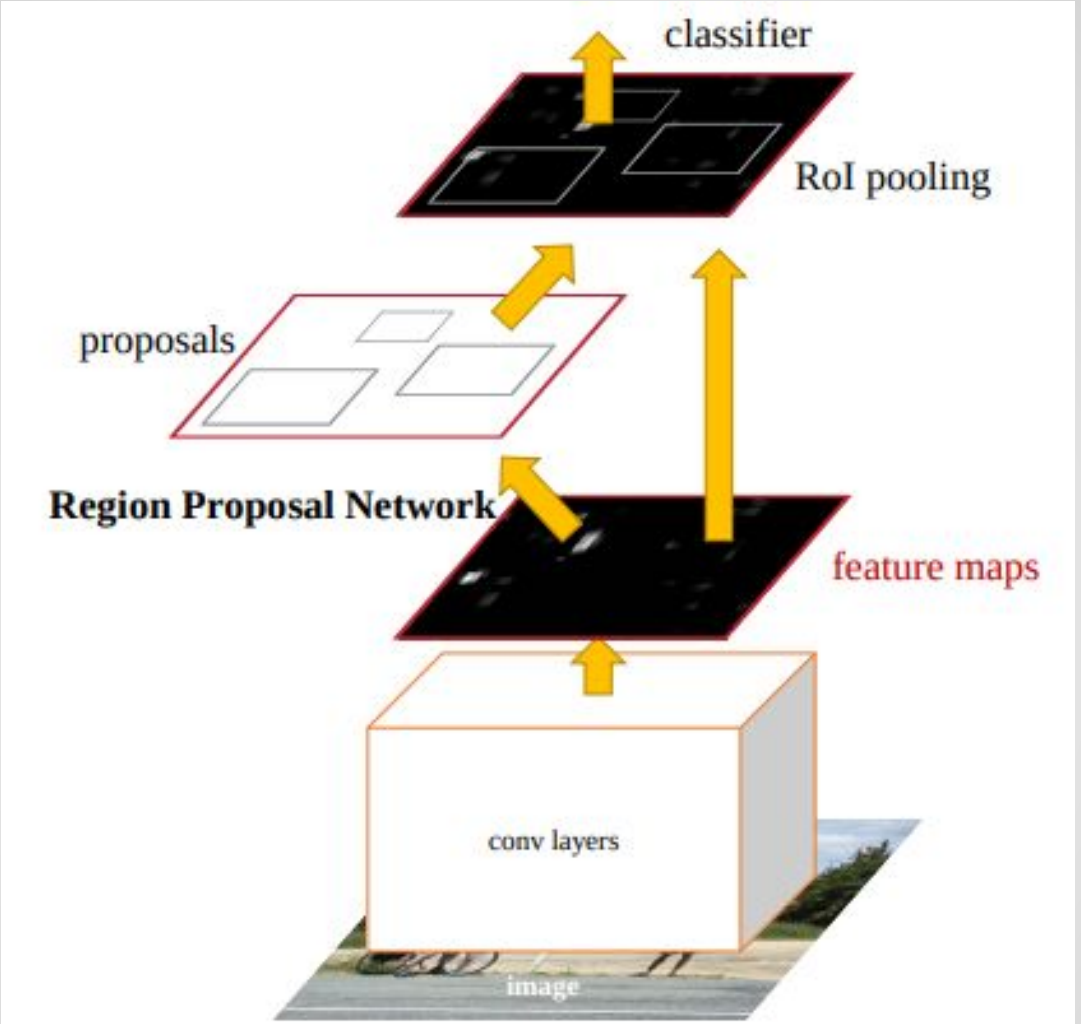
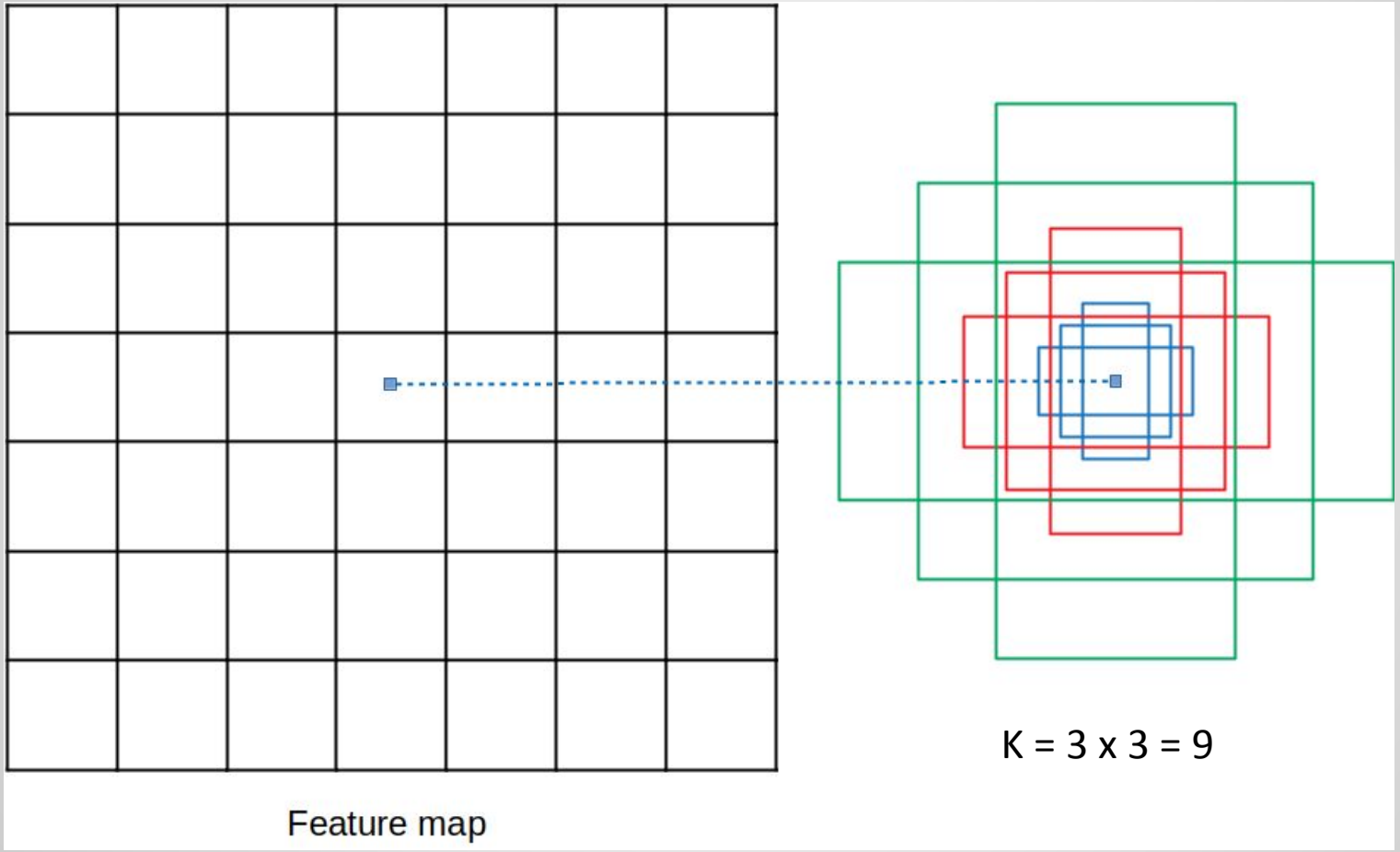
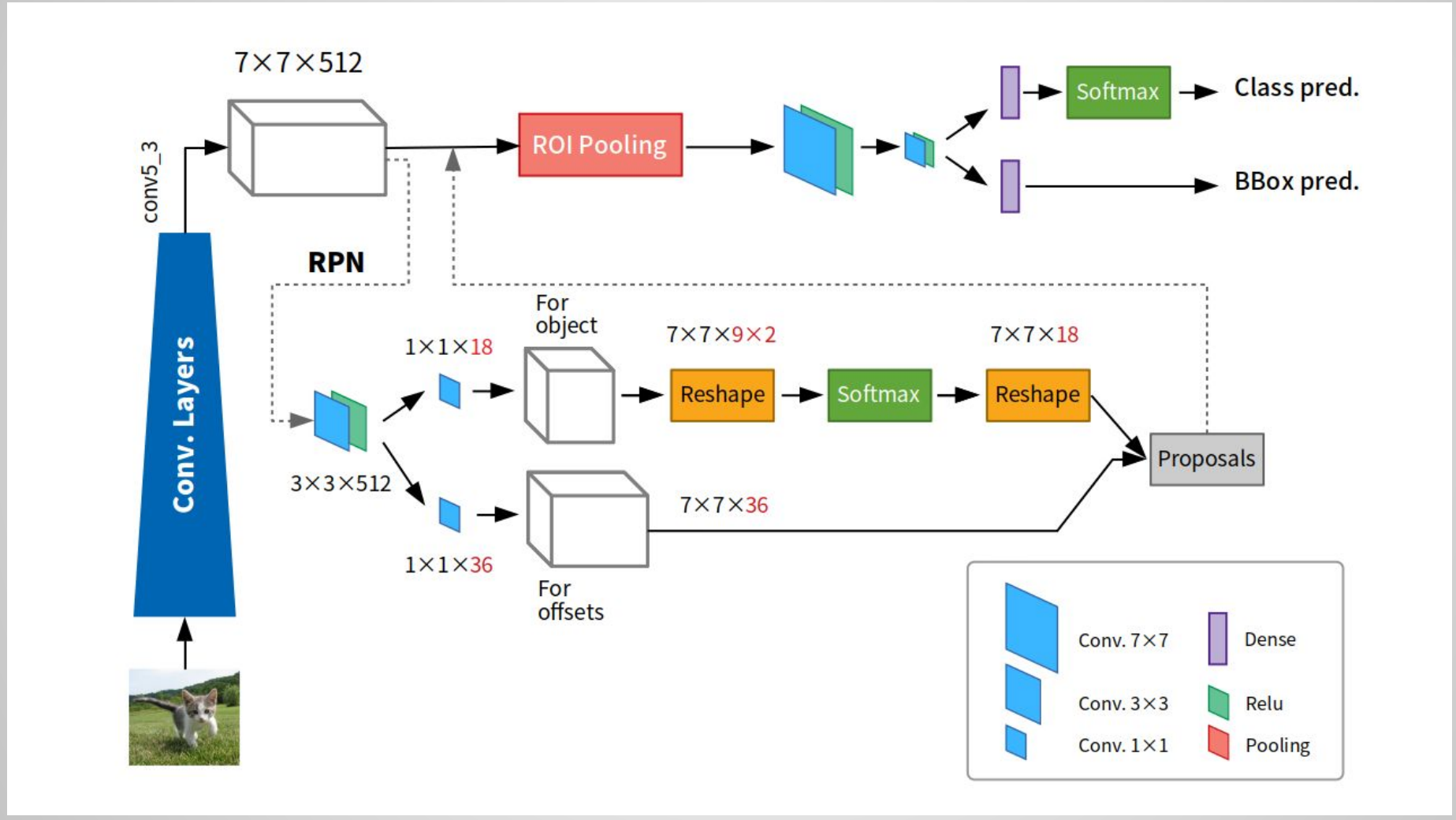


Figure 2: Faster R-CNN is a single, unified network for object detection. The RPN module serves as the 'attention' of this unified network.

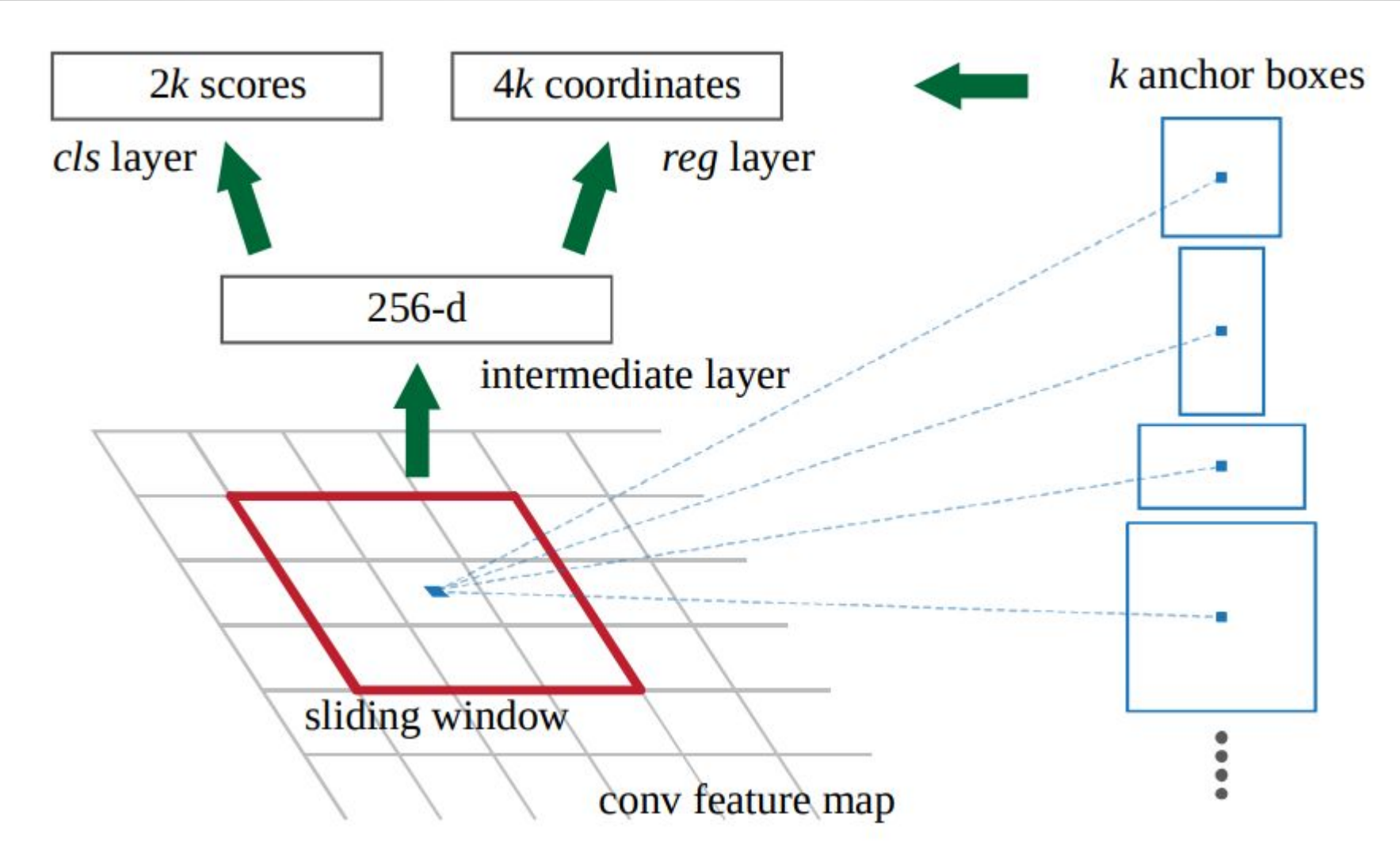
Anchor



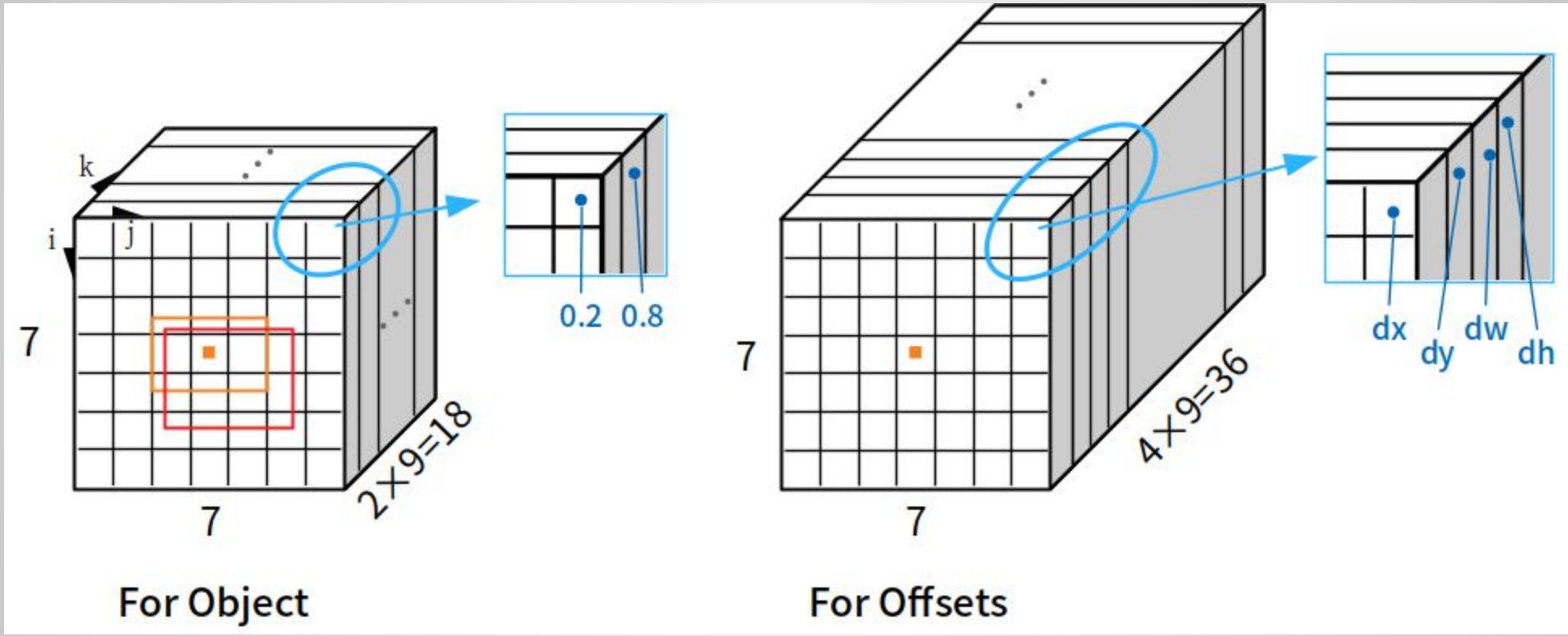
Region Proposal Network (RPN)



Region Proposal Network (RPN)



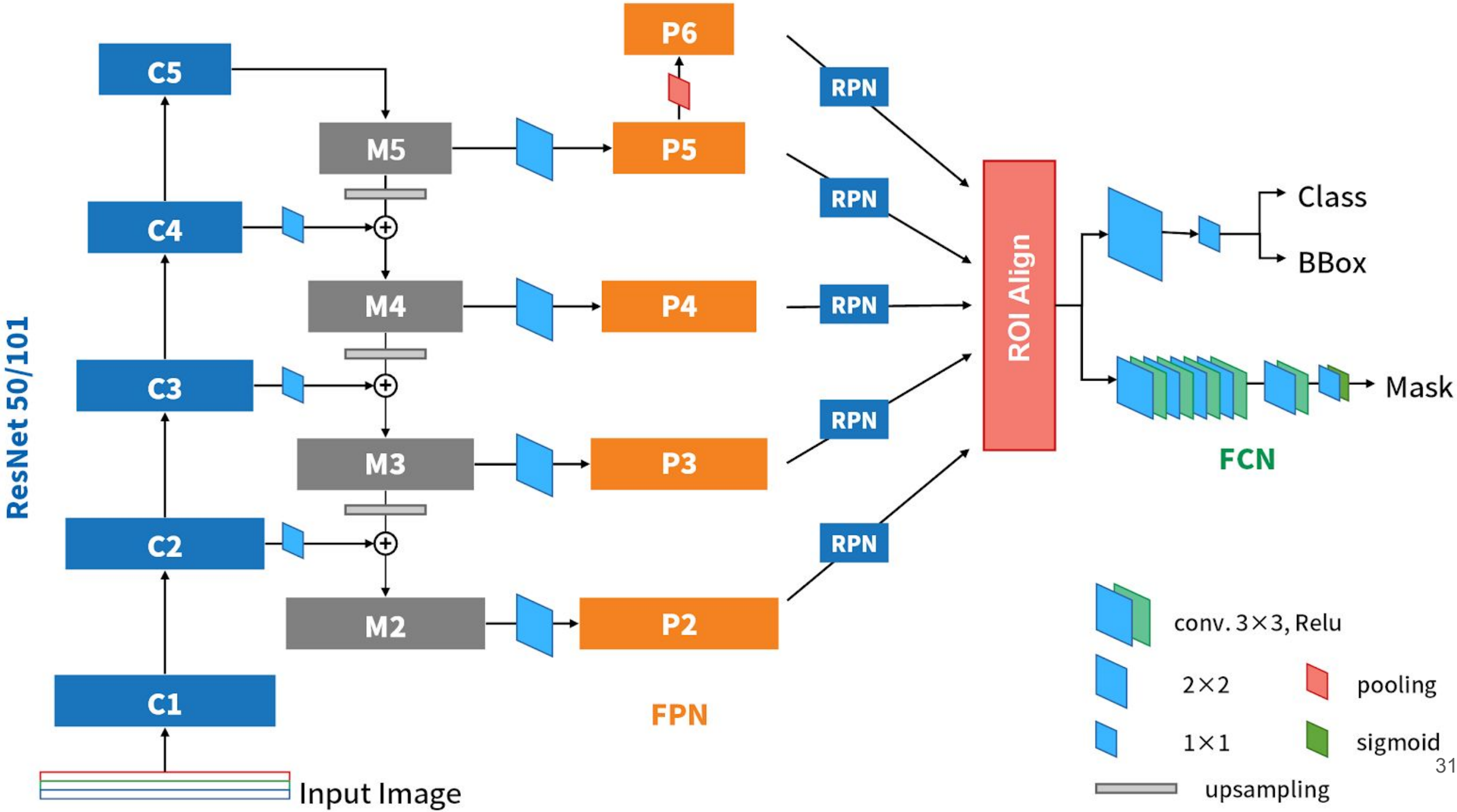
Region Proposal Network (RPN)



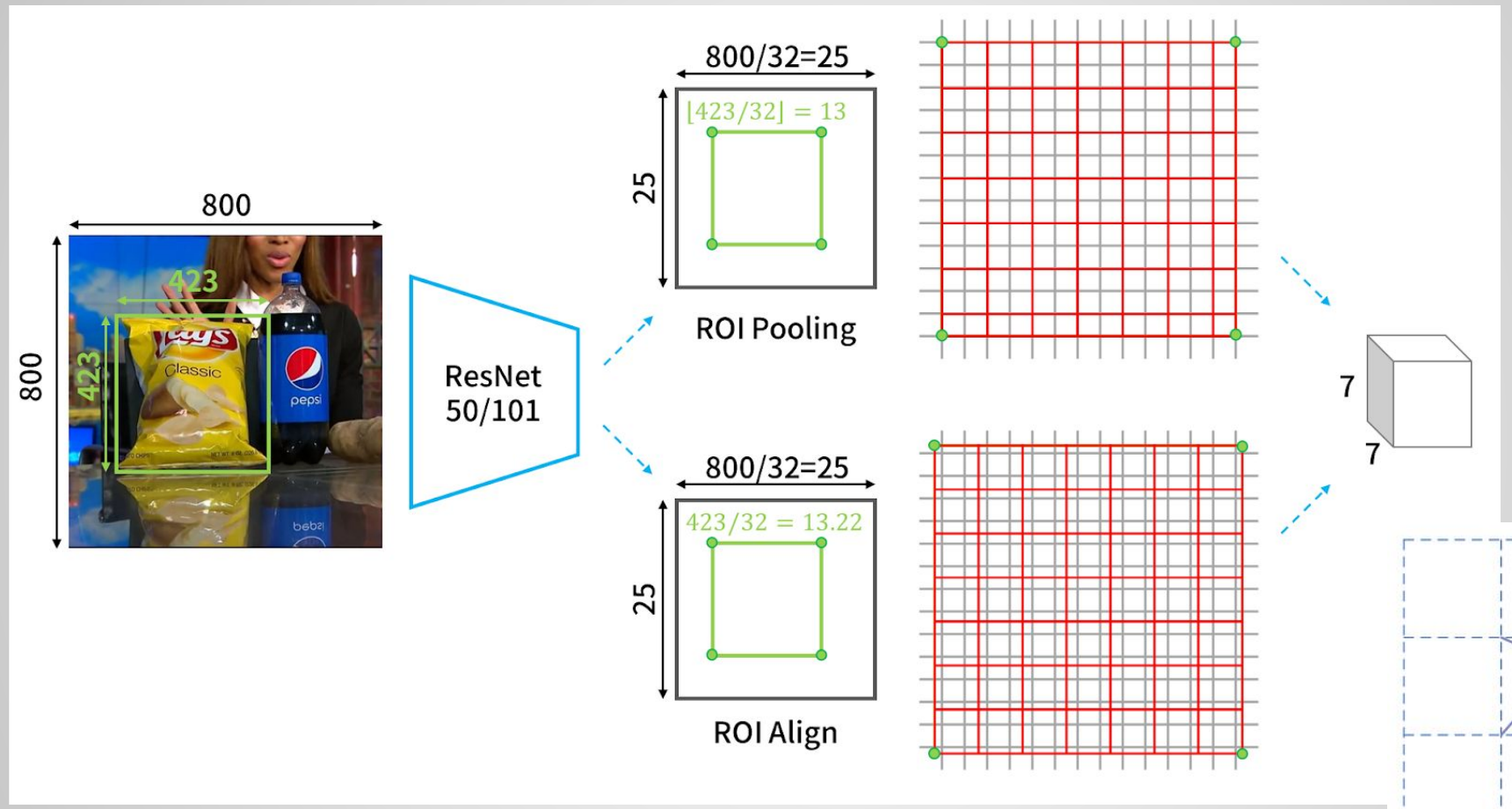
RPN Loss Function

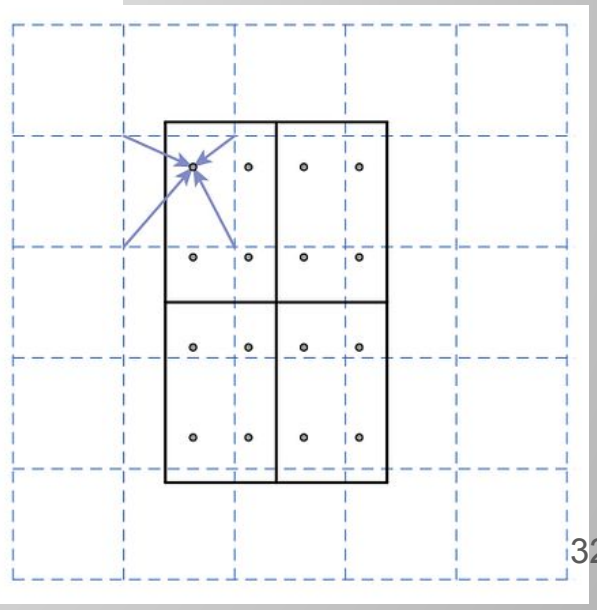
$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*). \quad (1)$$

Mask R-CNN


ResNet 50/101
C5
C4
C3
C2
C1
Input Image
M5
M4
M3
M2
P6
P5
P4
P3
P2
FPN
RPN
RPN
RPN
RPN
RPN
ROI Align
Class
BBox
Mask
FCN
conv. 3×3, Relu
2×2
pooling
1×1
sigmoid
upsampling

ROI Align


800
800
423
423
ResNet
50/101
800/32=25
[423/32] = 13
25
ROI Pooling
800/32=25
423/32 = 13.22
25
ROI Align
7
7

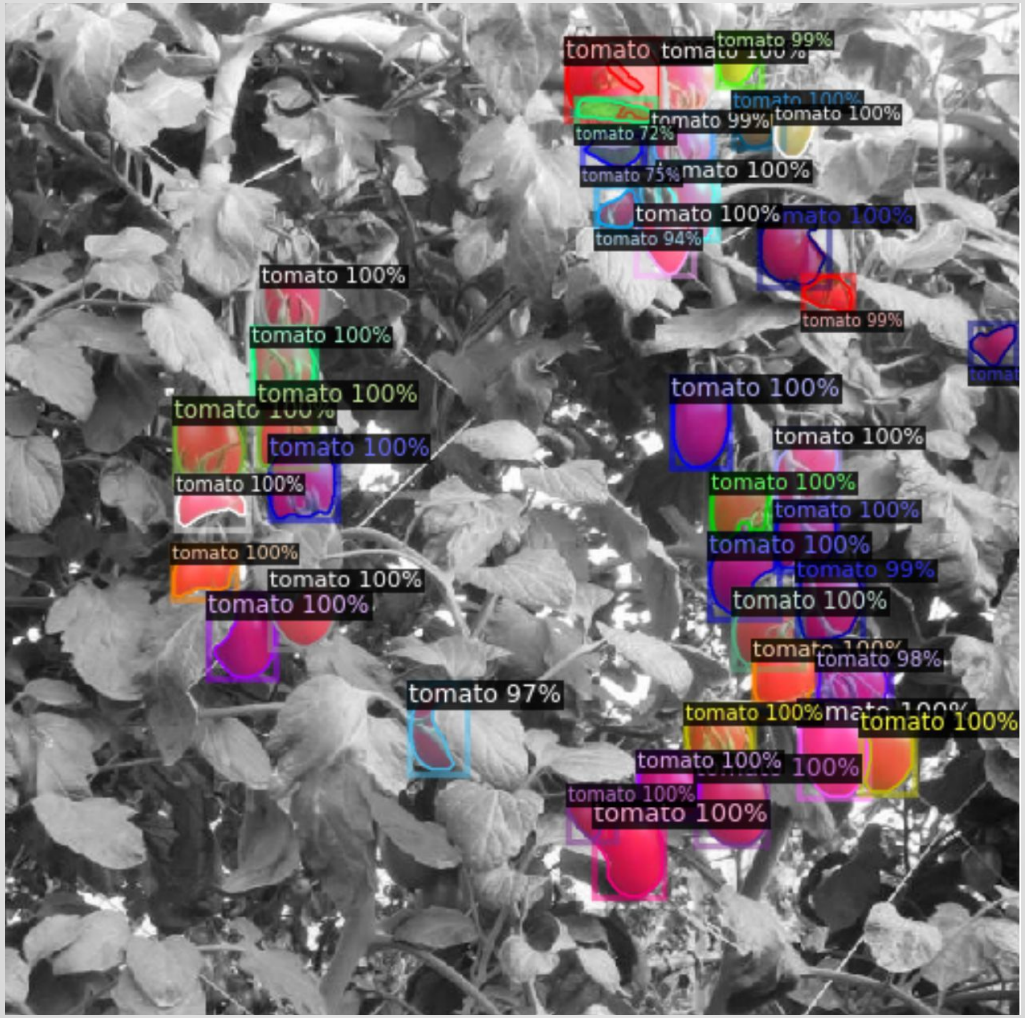


Detection Tomato

Label

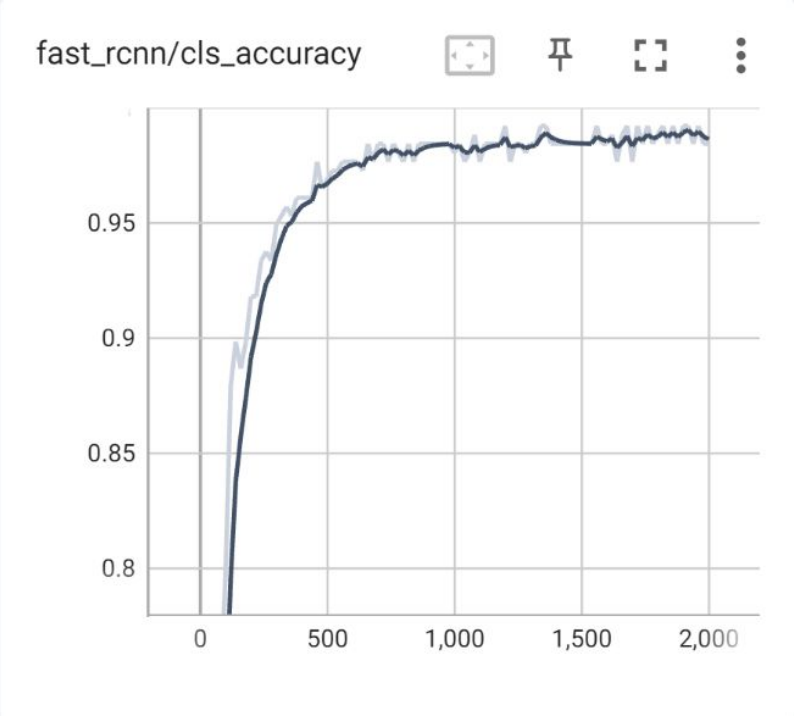
Detection Tomato

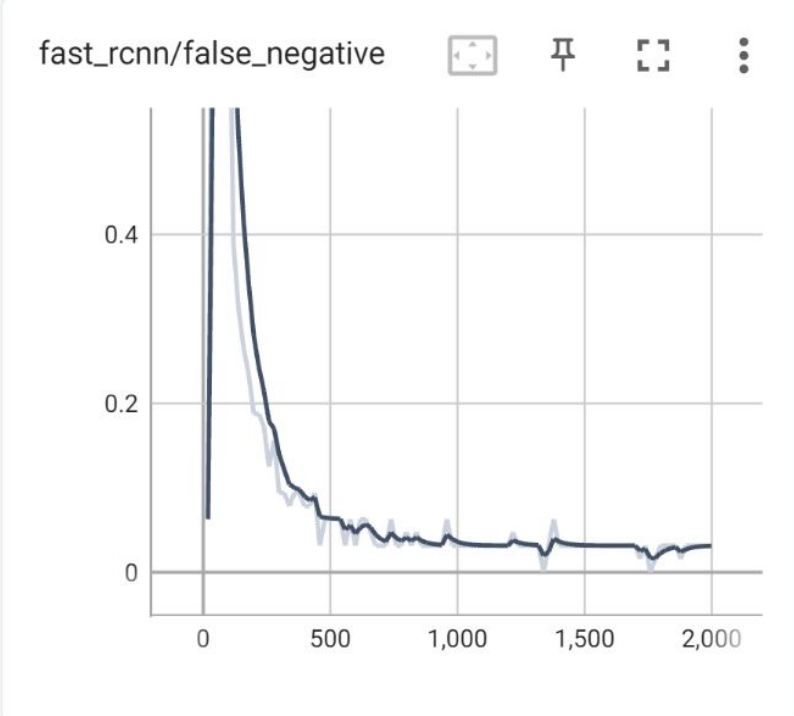
Predict

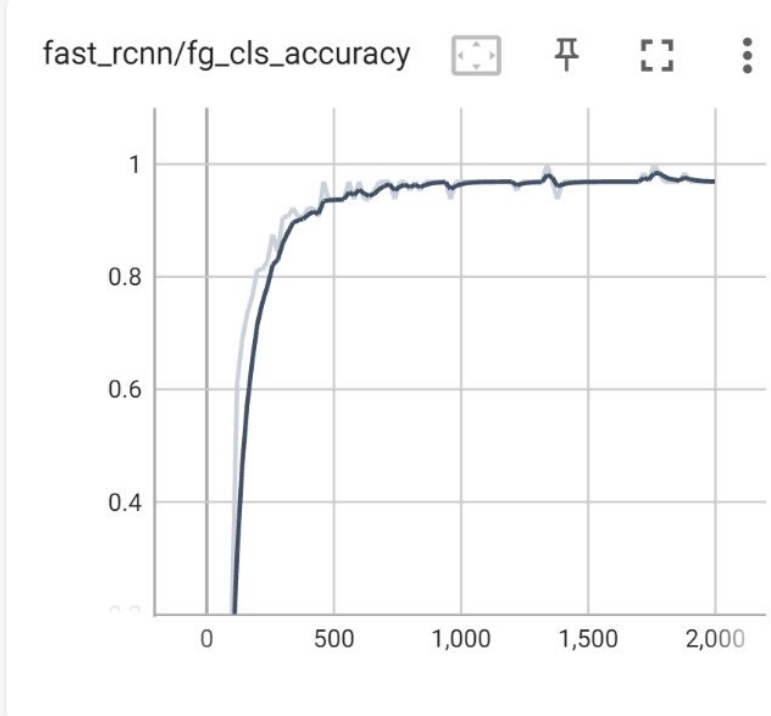


Detection
Tomato

fast_rcnn 3 cards







Code :

https://colab.research.google.com/drive/1uy_55Ziq3U-FBIOlv-v8A2Hy3od4rWyr?usp=sharing

Reference :

https://github.com/facebookresearch/detectron2

https://arxiv.org/abs/1703.06870

For more information about Tomato Detection Demo, ask us in QA time :

https://hackmd.io/@2peEy1j8QSygBgdKIEZpJQ/HkIsfQih2