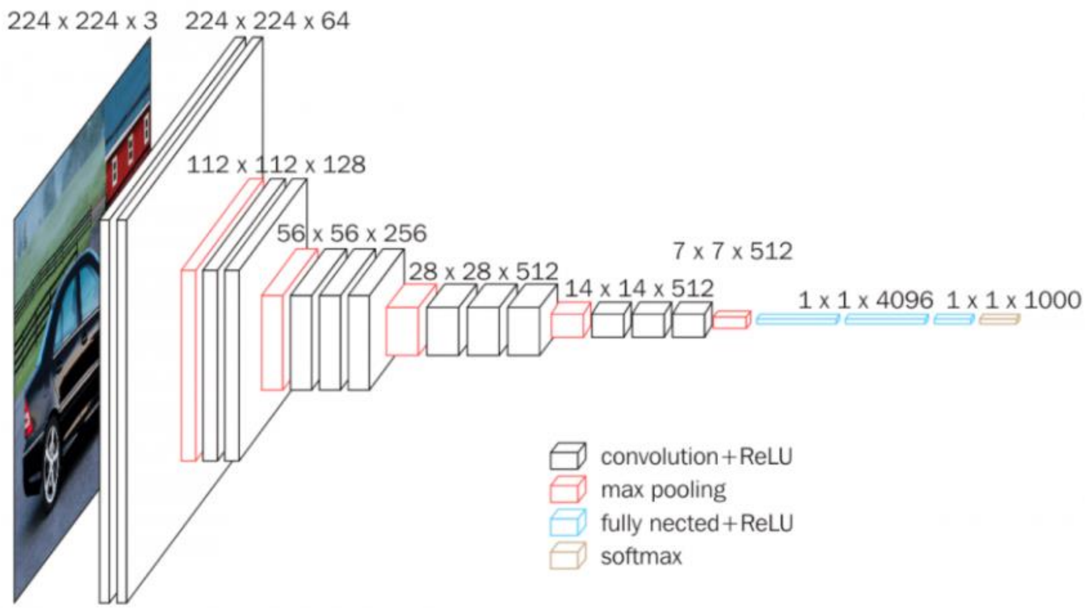
AI for Video Data Processing 3:
R-CNN for Object Detection

Outline

1. R-CNN
2. Fast R-CNN
3. Faster R-CNN
4. Faster R-CNN with FPN
5. Mask R-CNN
6. RetinaNet

1. From CNN to R-CNN

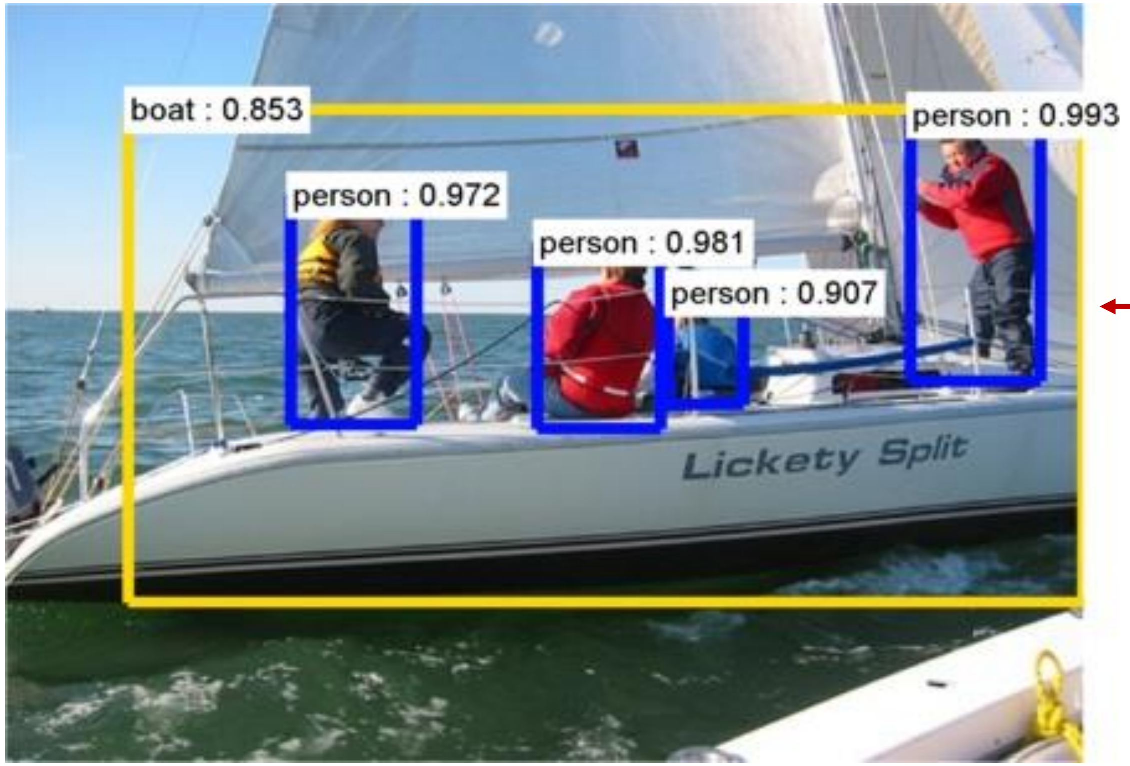
Original CNNs are designed for Image Classification:
LeNet, AlexNet, VGG, ResNet, DenseNet, ...



https://www.jeremyjordan.me/semantic-segmentation/

1. From CNN to R-CNN

If we want to detect objects in an image, then …



What?

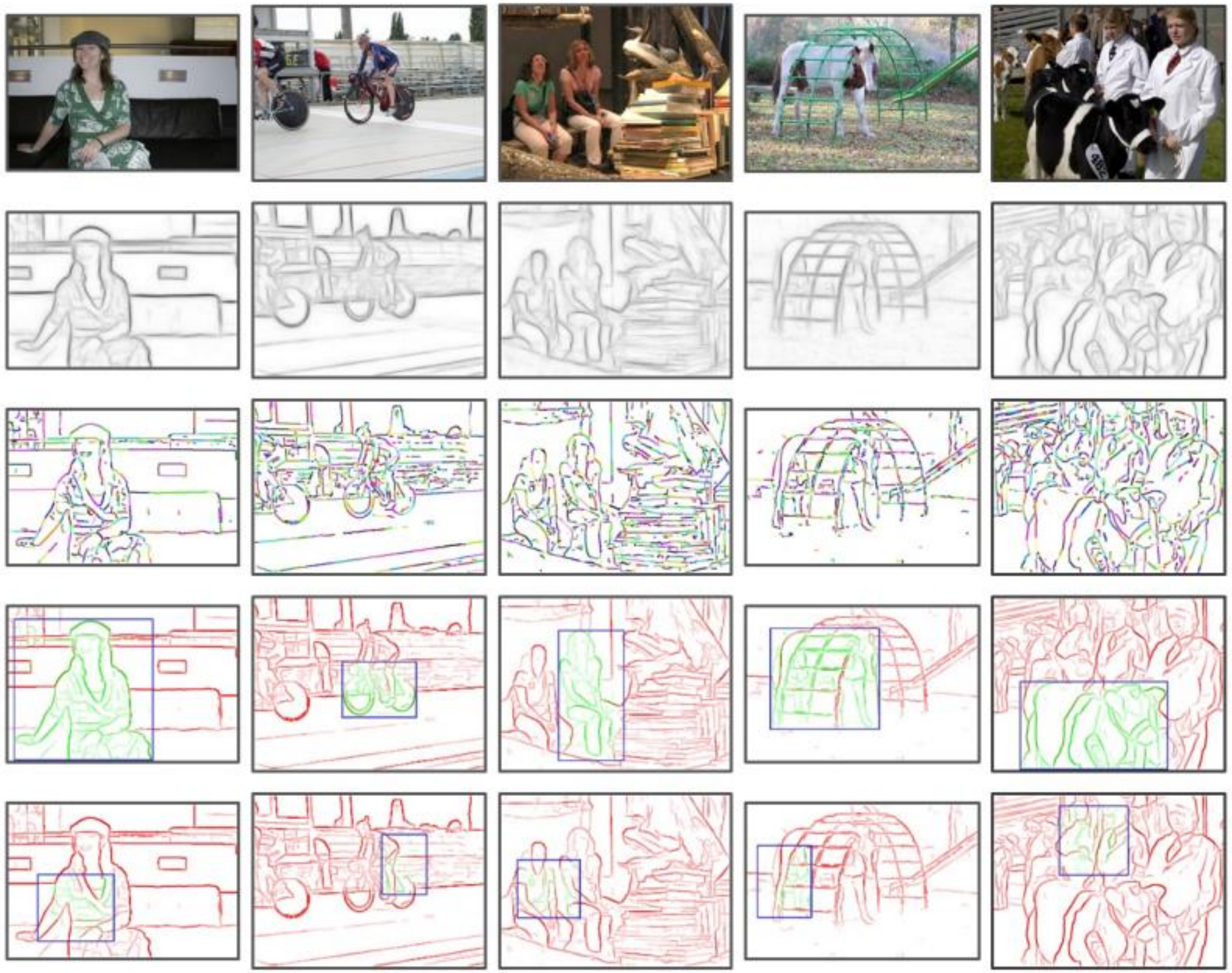
Where?

Object detection with bounding boxes

1. Object Proposal Algorithm in CV

Zitnick, C. Lawrence, and Piotr Dollár. "Edge boxes: Locating object proposals from edges." In *European Conference on Computer Vision*, pp. 391-405. Springer, Cham, 2014.

For example: 2k object proposals for one image

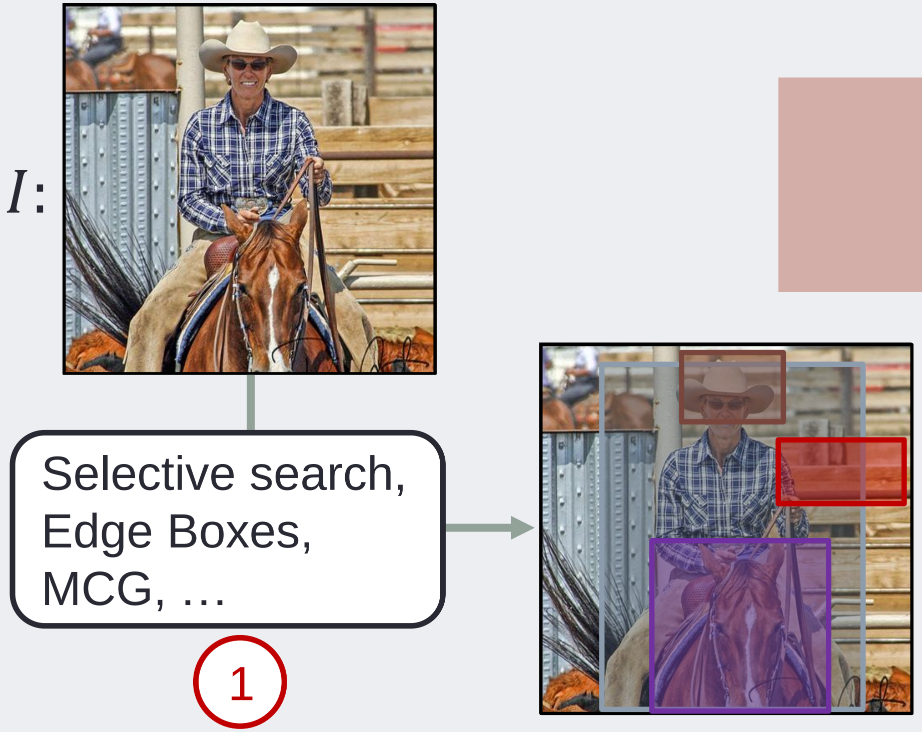


Girshick, Donahue, Darrell, Malik. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. CVPR 2014.

1.R-CNN (Region-based Convolutional Neural Net)

Per-image computation

Per-region computation

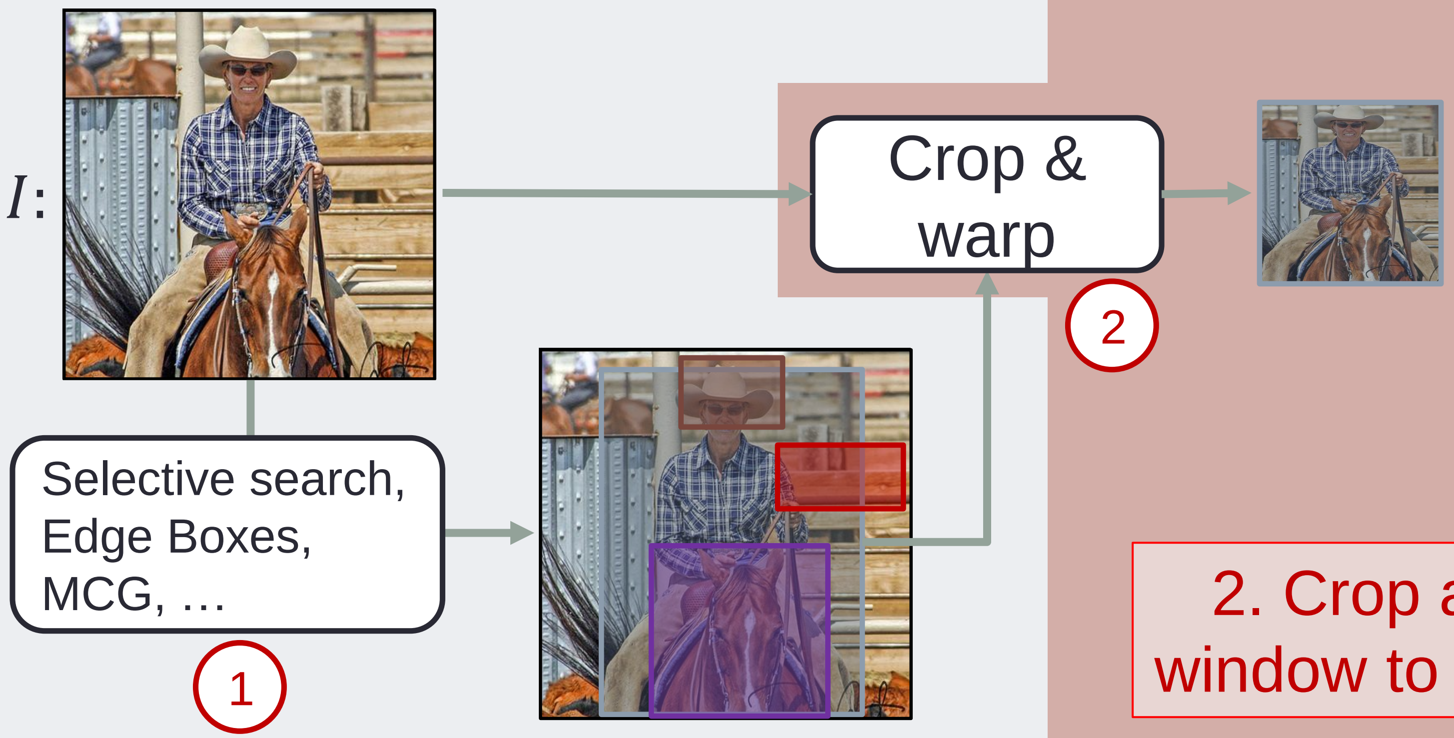


1. Use an off-the-shelf *Region of Interest* (RoI) proposal algorithm (~2k proposals per image)

1. R-CNN

Per-image computation

Per-region computation for each $r_i \in r(I)$

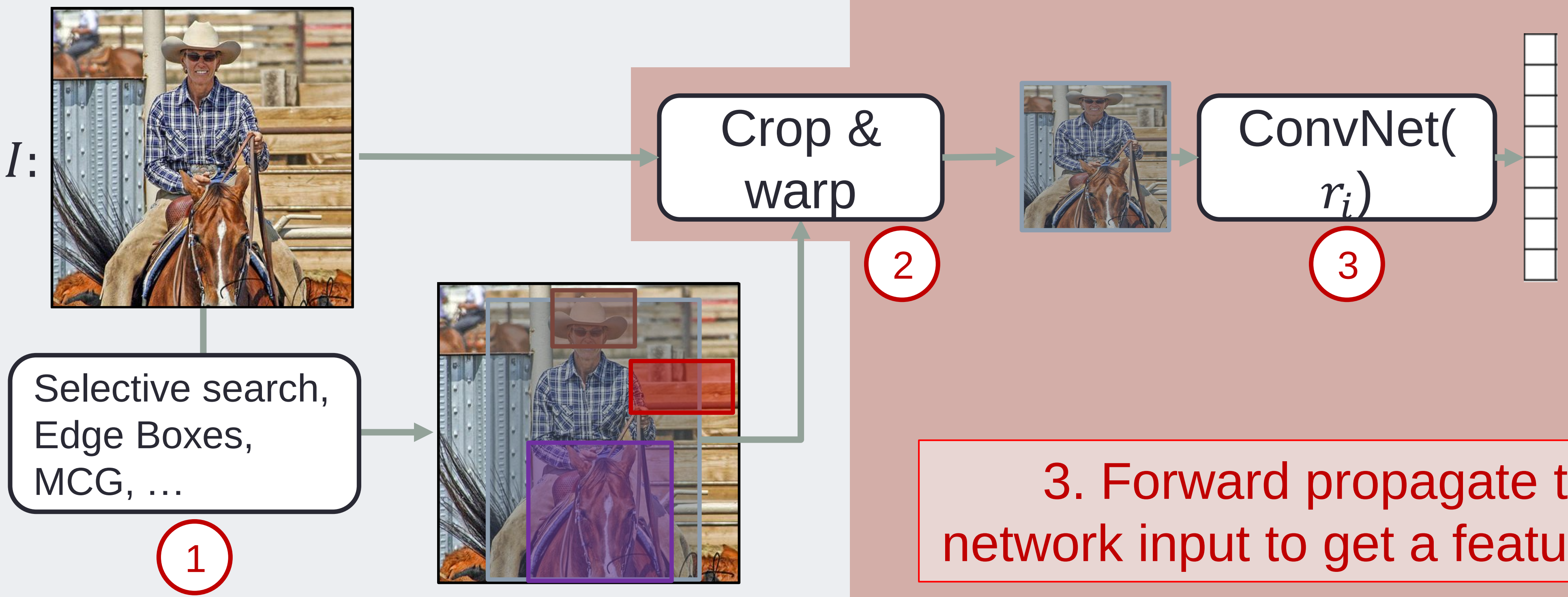


2. Crop and warp each proposal image window to obtain a fixed-size network input

1. R-CNN

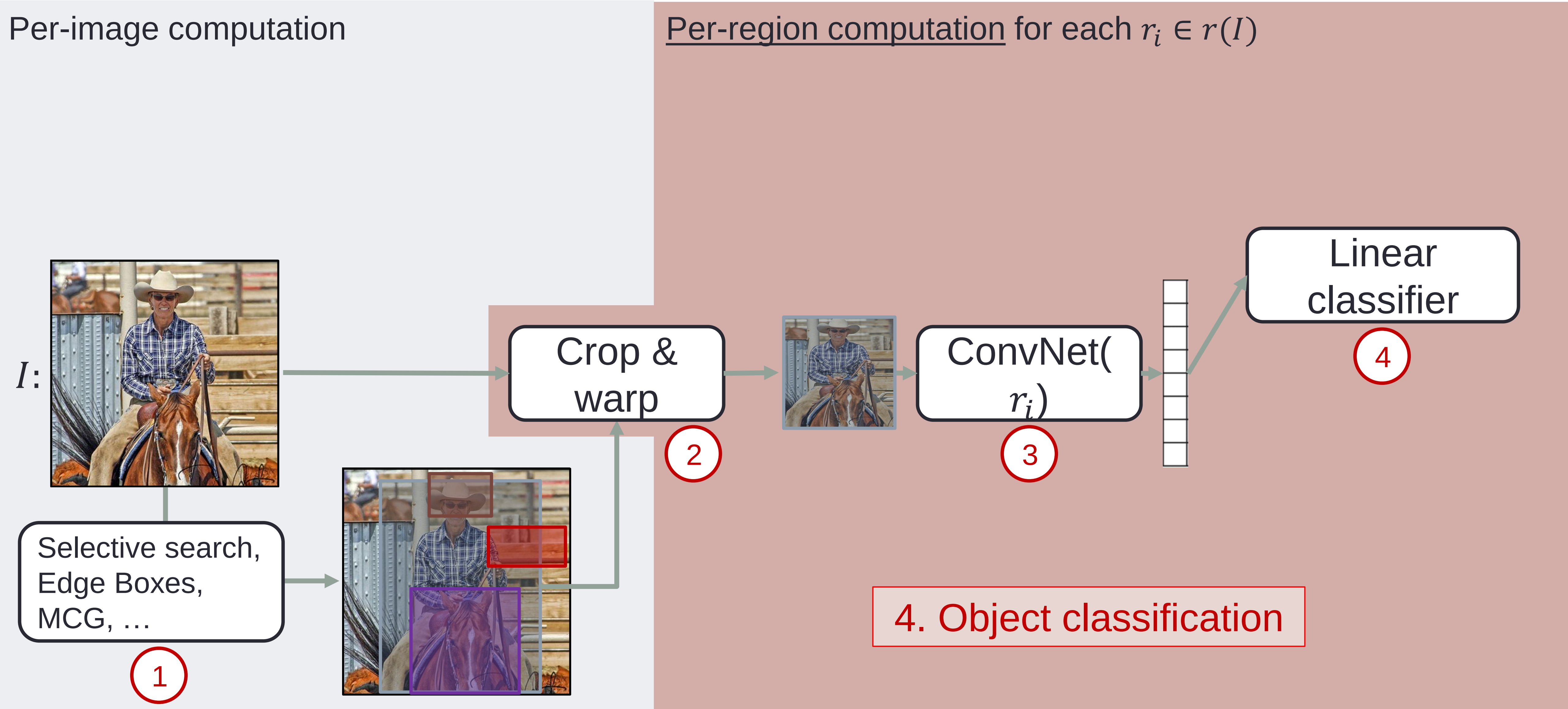
Per-image computation

Per-region computation for each $r_i \in r(I)$

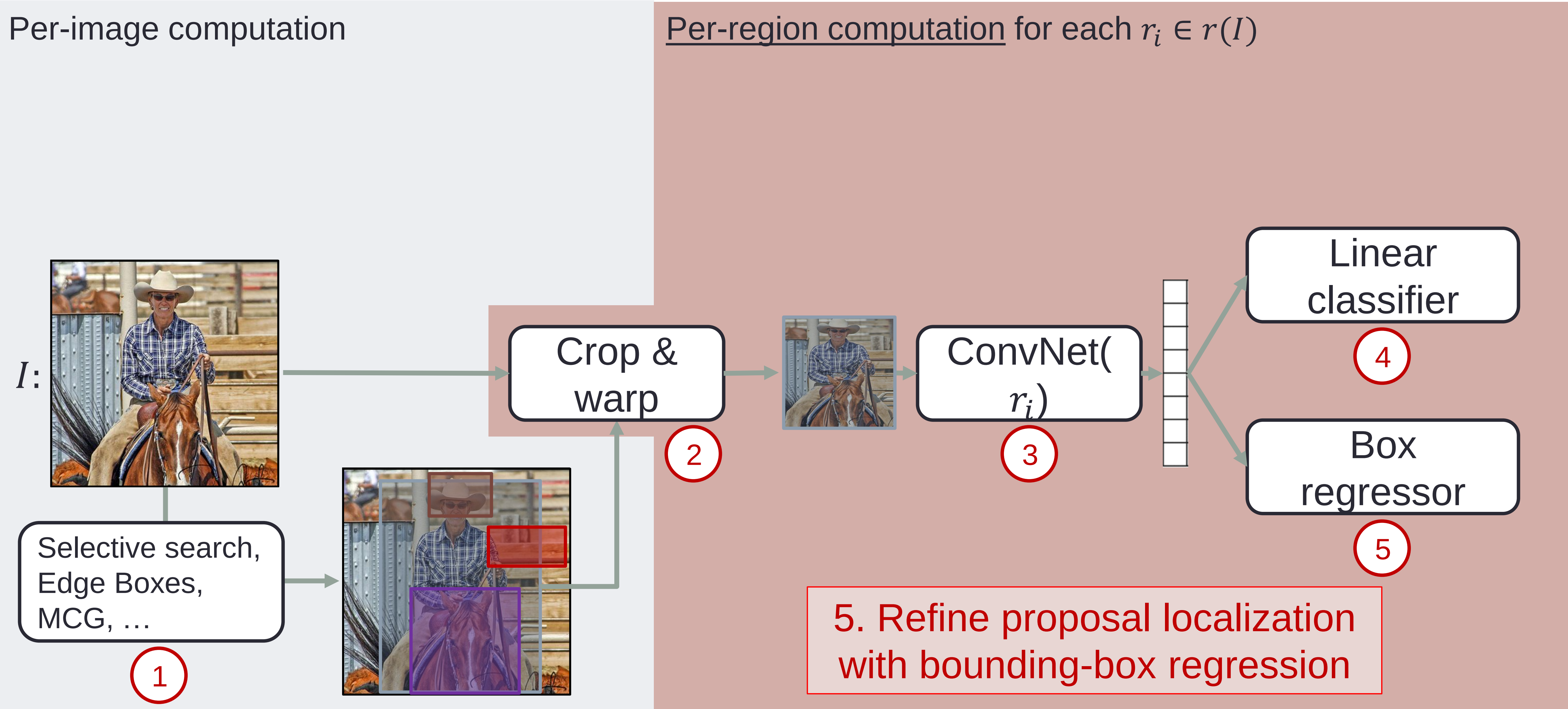


3. Forward propagate the fixed-size network input to get a feature representation

1. R-CNN


Per-image computation
Per-region computation for each $r_i \in r(I)$
I:
Selective search, Edge Boxes, MCG, …
1
Crop & warp
2
ConvNet(r_i)
3
Linear classifier
4
4. Object classification

1. R-CNN


Per-image computation
Per-region computation for each $r_i \in r(I)$
I:
Selective search,
Edge Boxes,
MCG, …
1
Crop &
warp
2
ConvNet(r_i)
3
Linear
classifier
4
Box
regressor
5
5. Refine proposal localization
with bounding-box regression

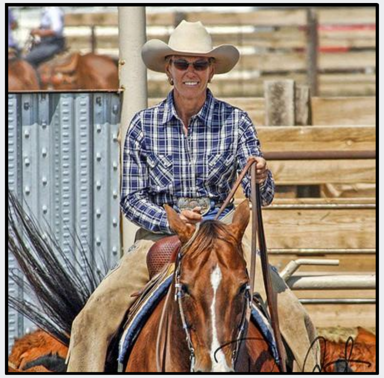
1. From R-CNN to Generalized R-CNN Framework

1. Generalized R-CNN Framework

Per-image computation

Per-region computation for each $r_i \in r(I)$

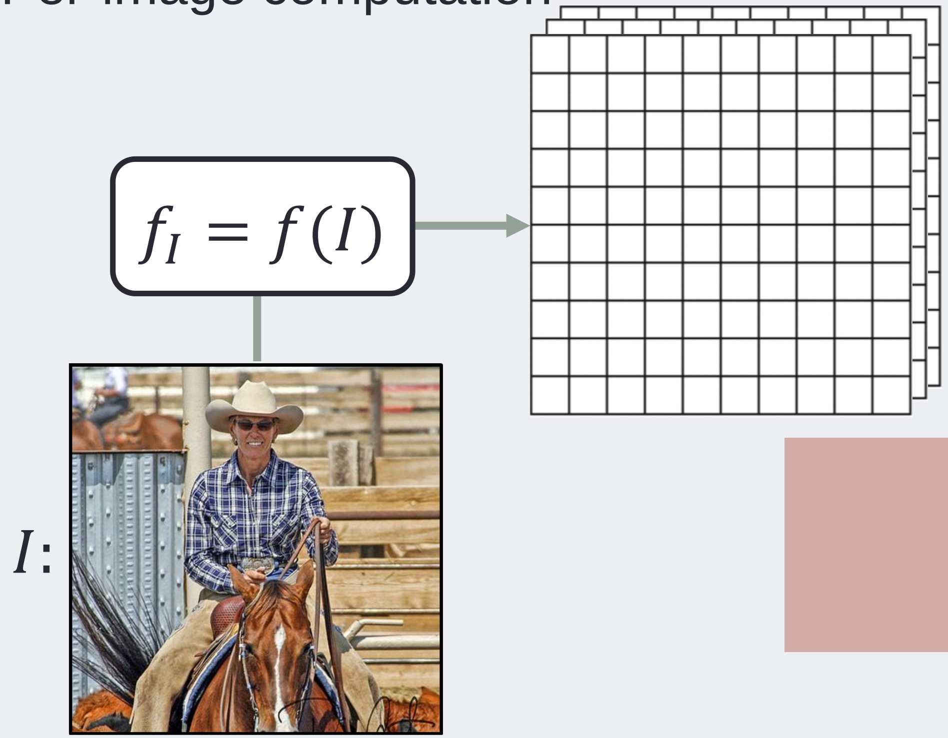
I:



Input image
per-image operations | per-region operations

1. Generalized R-CNN Framework

Per-image computation

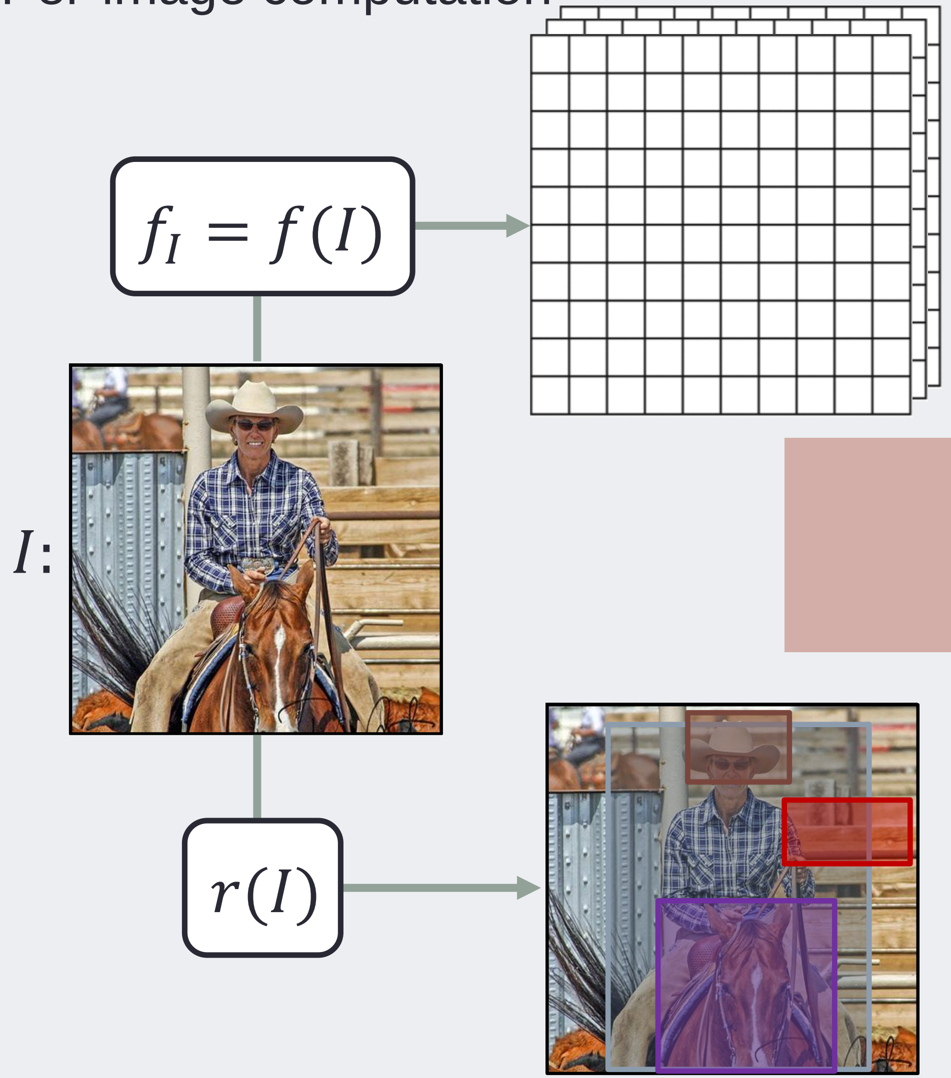


Per-region computation for each $r_i \in r(I)$

Transformation of the input image
into a featurized representation

1. Generalized R-CNN Framework

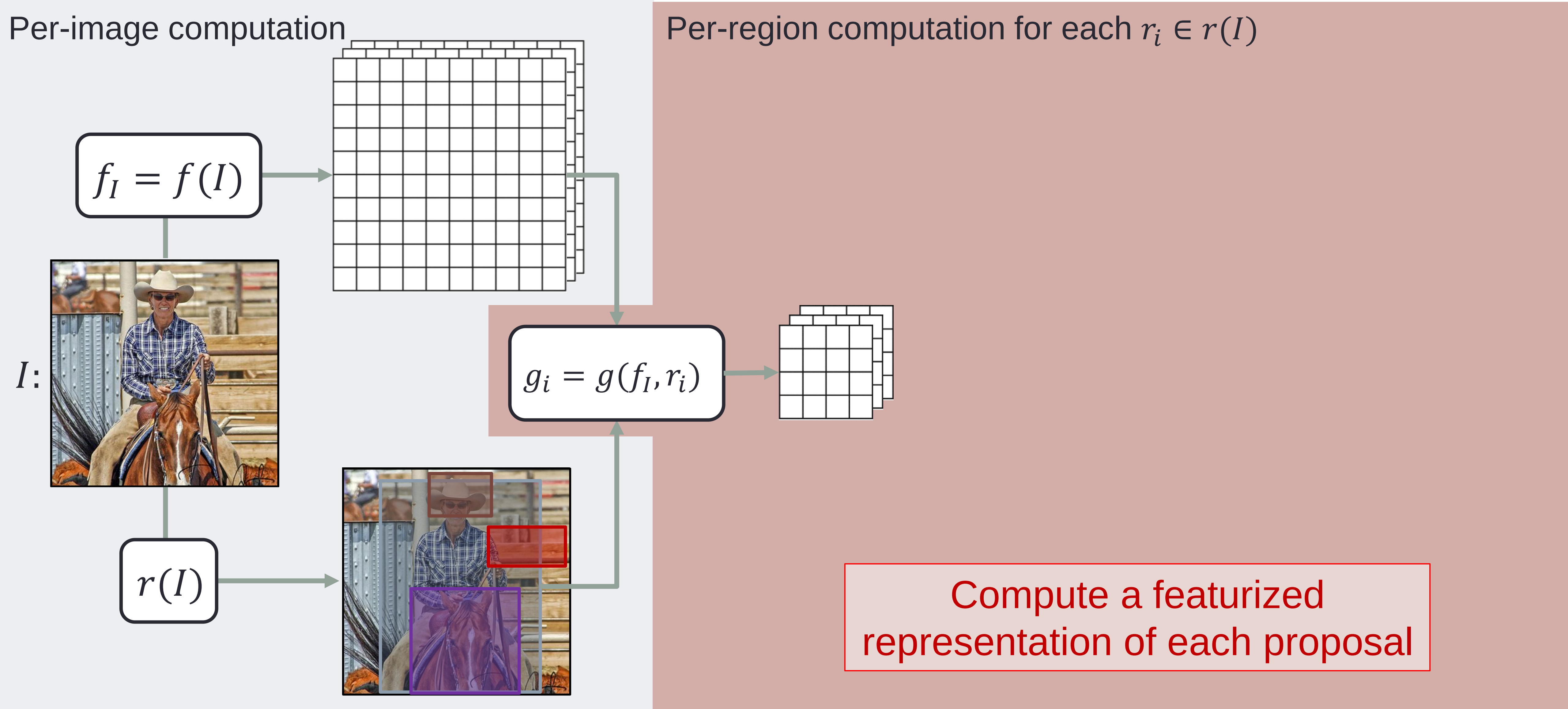
Per-image computation



Per-region computation for each $r_i \in r(I)$

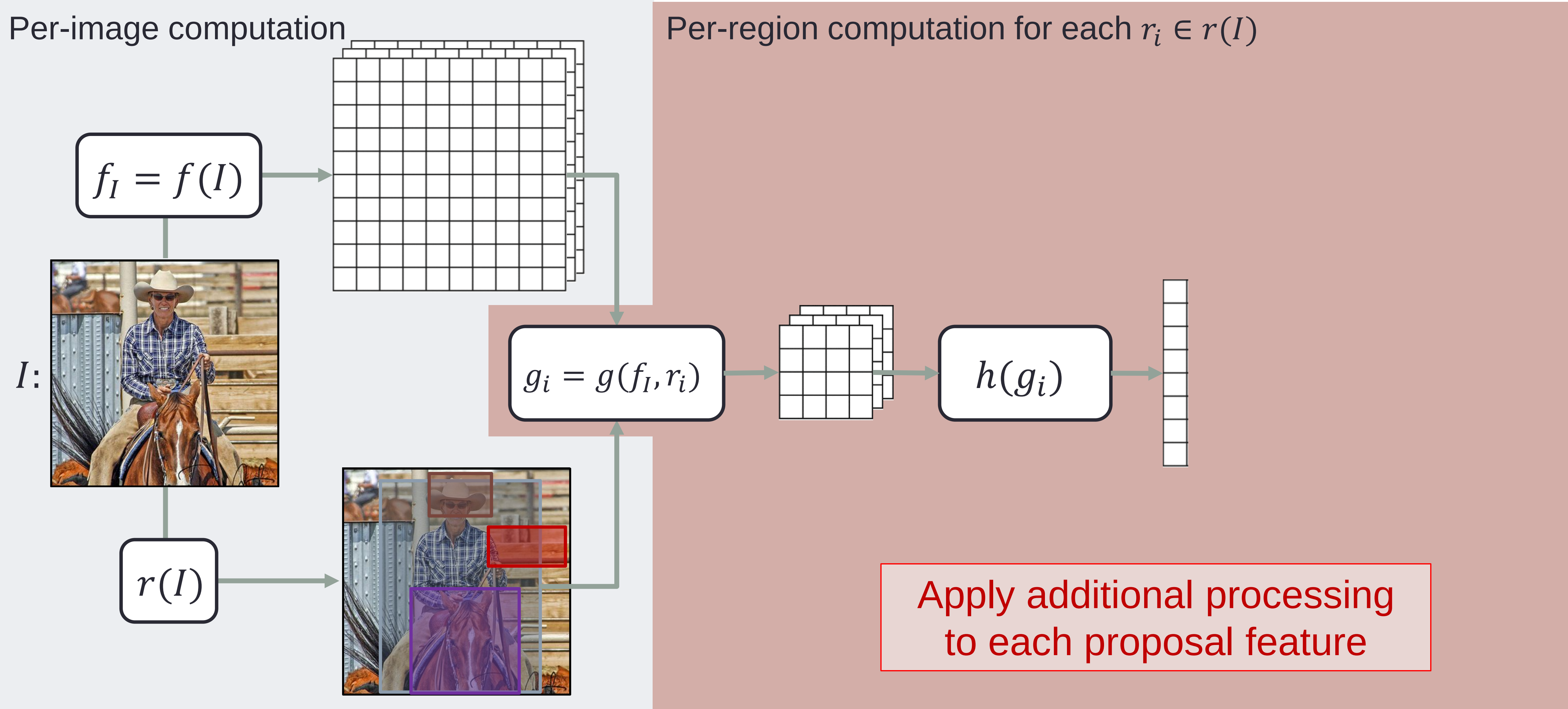
Region of Interest proposals computed for the image

1. Generalized R-CNN Framework



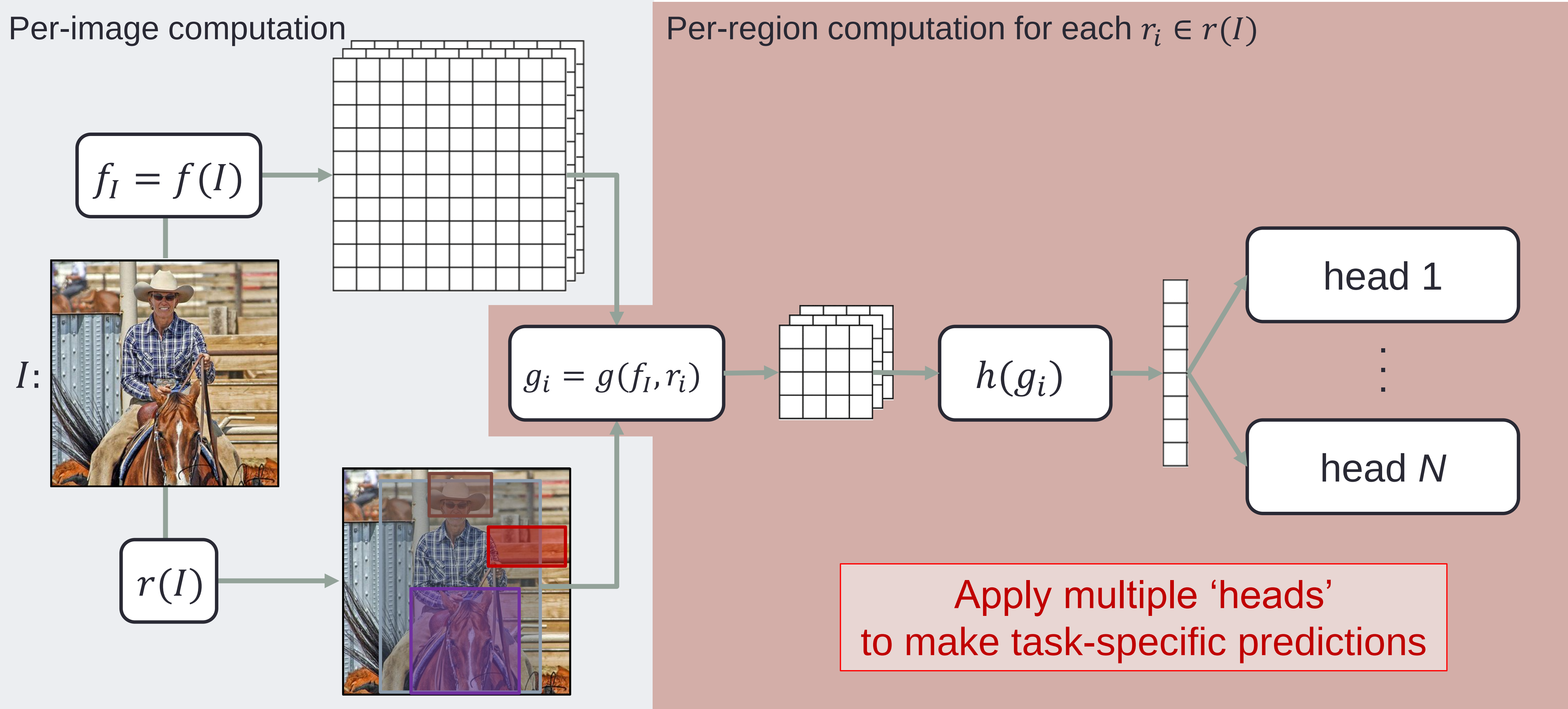
Compute a featurized representation of each proposal

1. Generalized R-CNN Framework



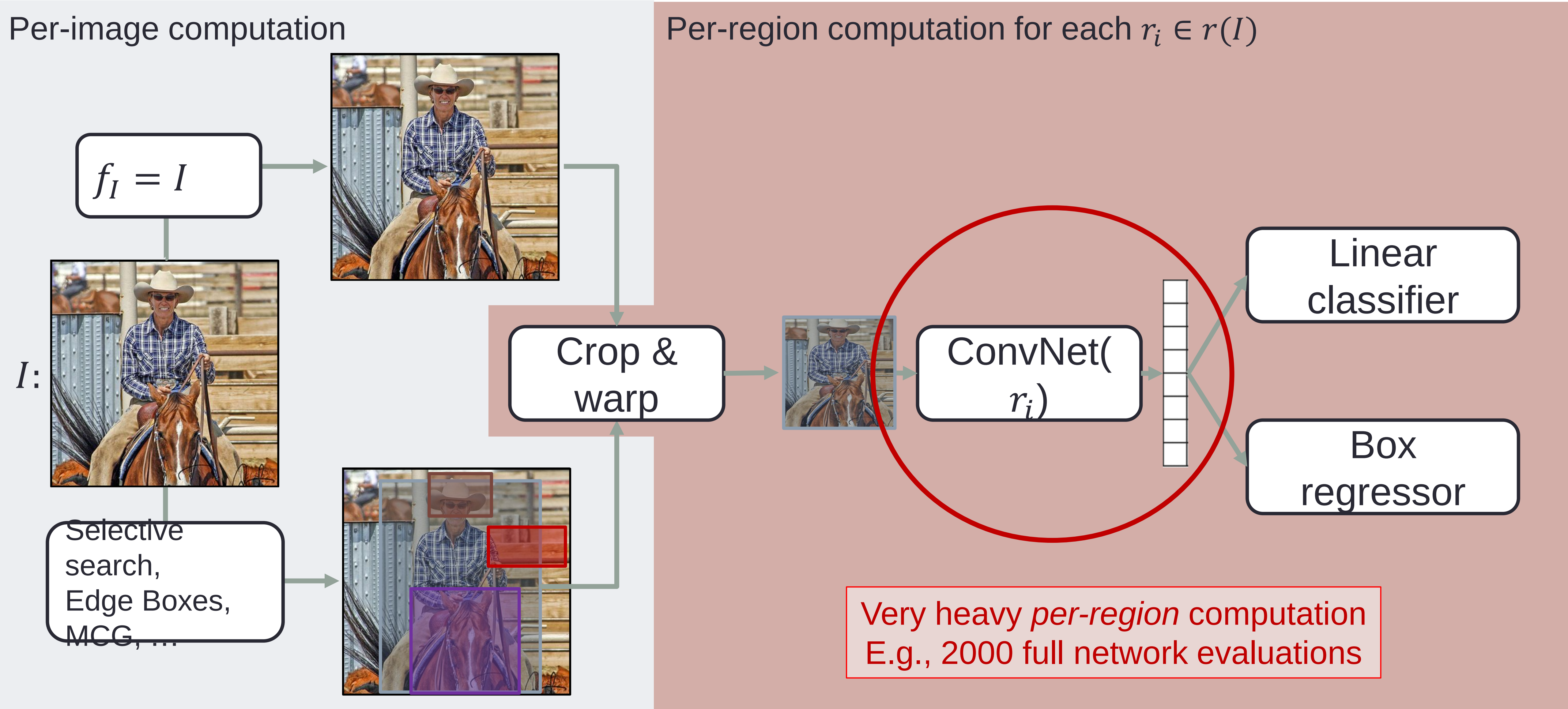
Apply additional processing to each proposal feature

1. Generalized R-CNN Framework



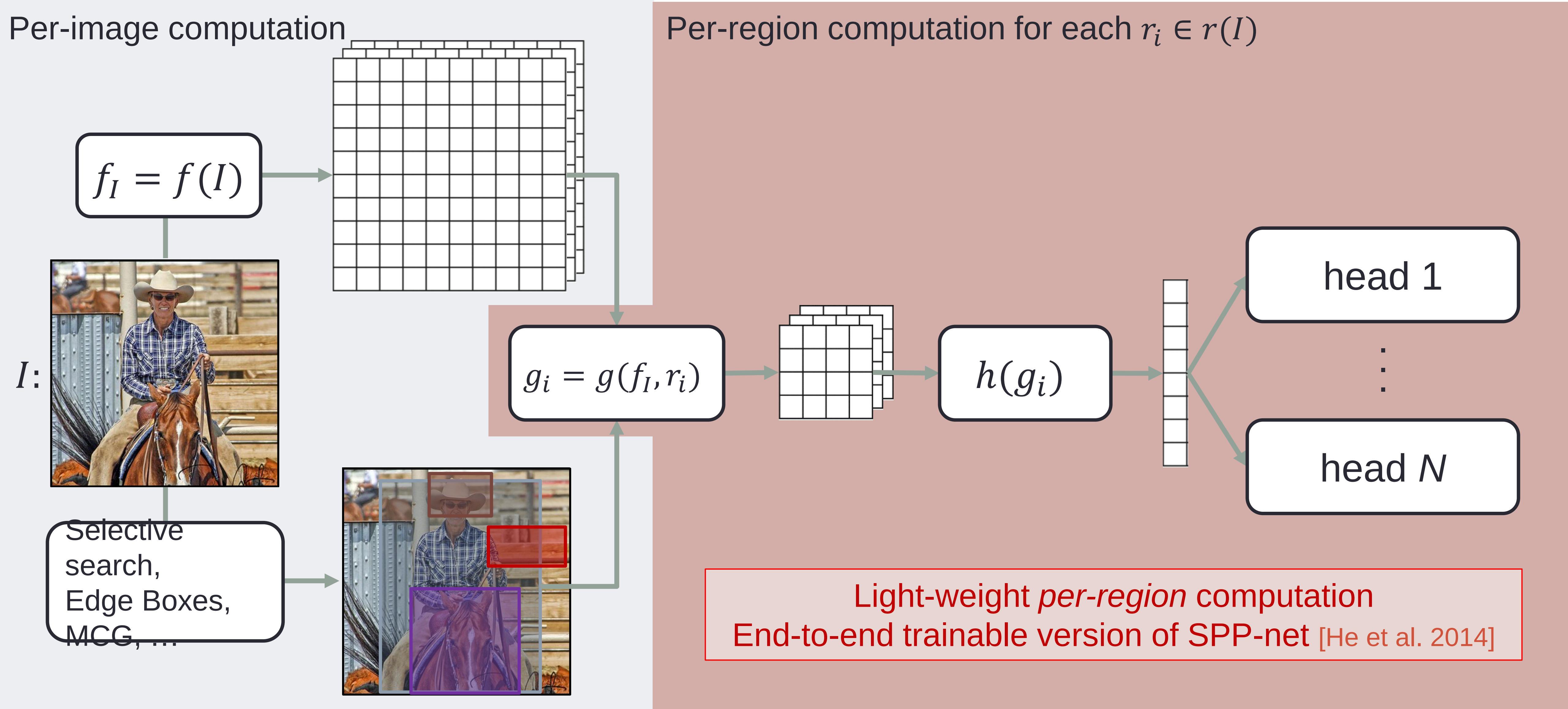
2. Fast R-CNN

"Slow" R-CNN


Per-image computation
Per-region computation for each $r_i \in r(I)$
$f_I = I$
I:
Selective search, Edge Boxes, MCG, ...
Crop & warp
ConvNet(r_i)
Linear classifier
Box regressor
Very heavy *per-region* computation
E.g., 2000 full network evaluations

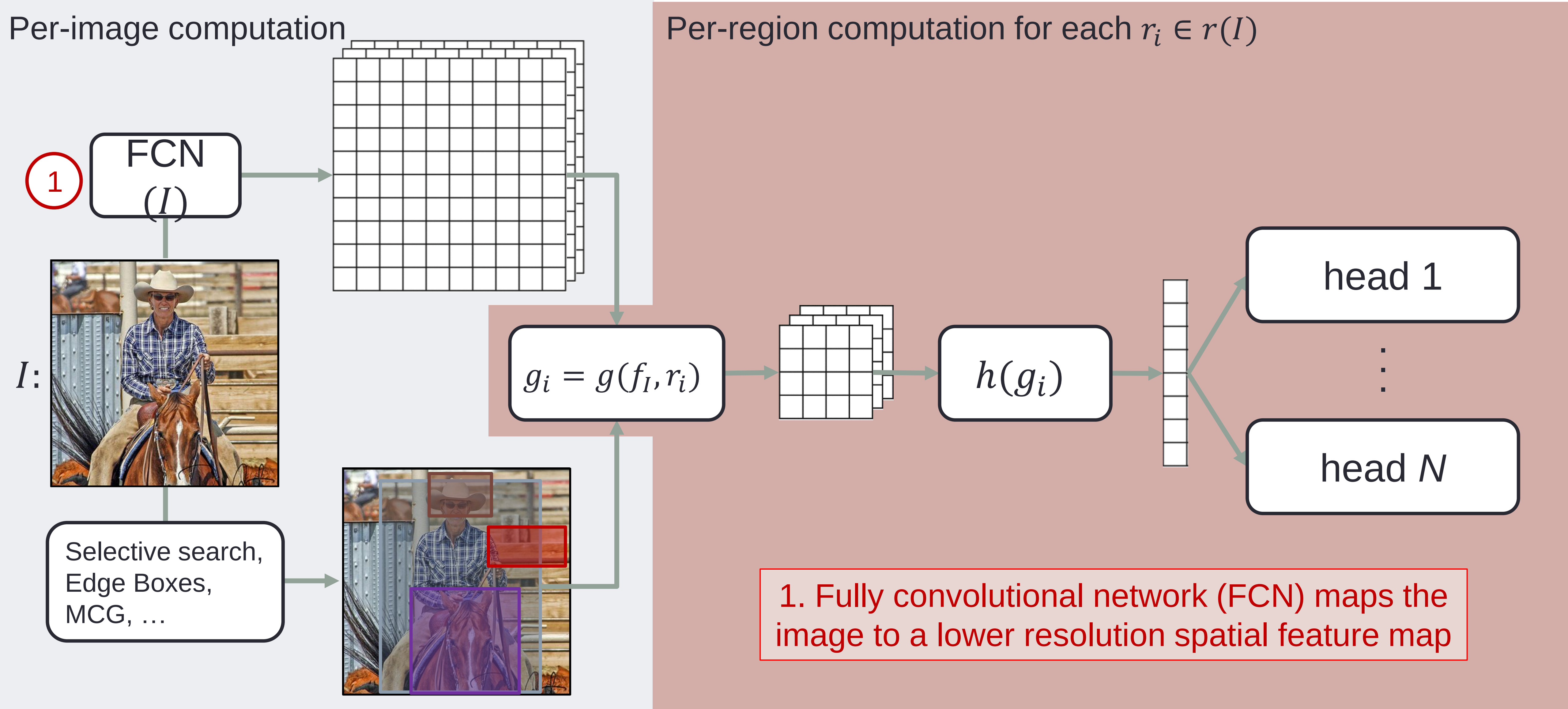
Girshick. Fast R-CNN. ICCV 2015.

2. Generalized R-CNN → Fast R-CNN



Girshick. Fast R-CNN. ICCV 2015.

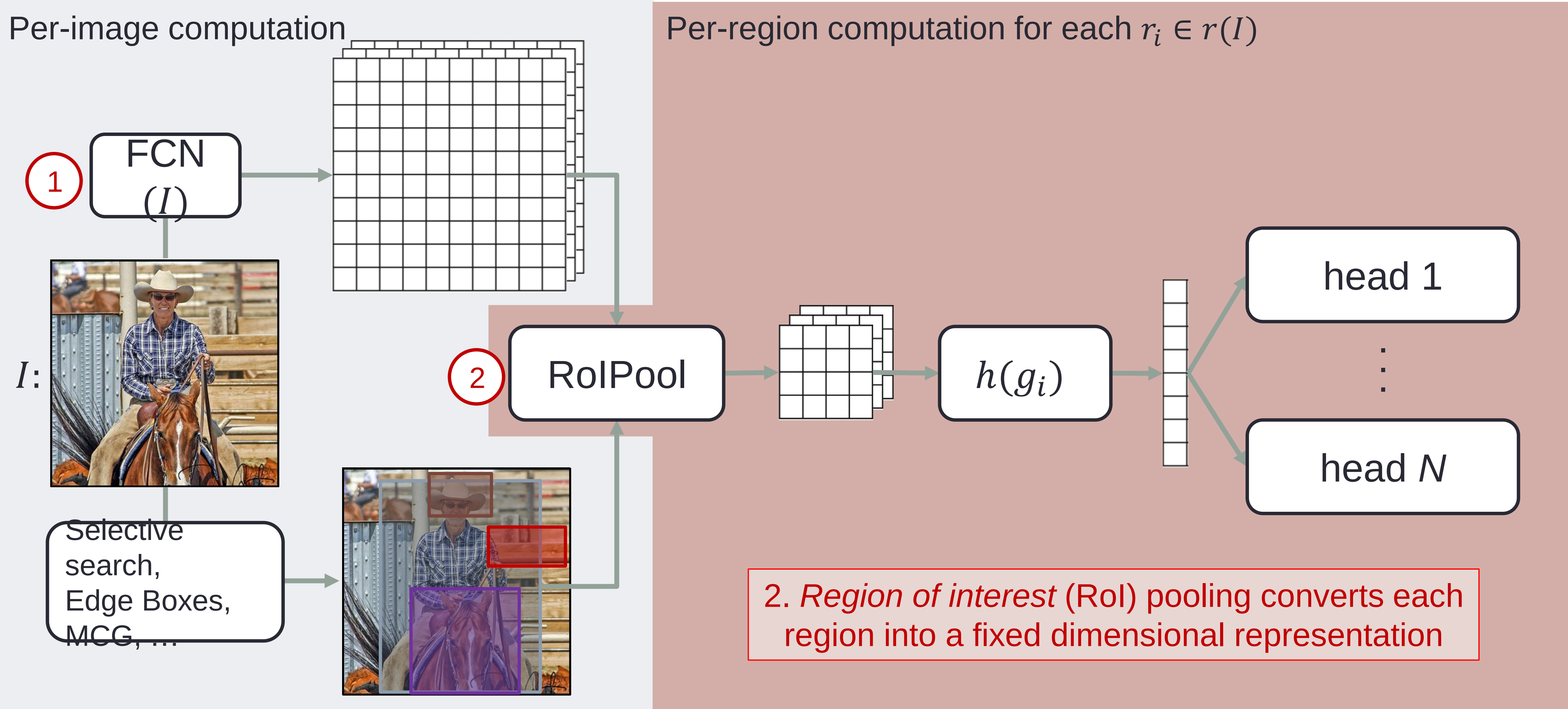
2. Generalized R-CNN → Fast R-CNN



1. Fully convolutional network (FCN) maps the image to a lower resolution spatial feature map

Girshick. Fast R-CNN. ICCV 2015.

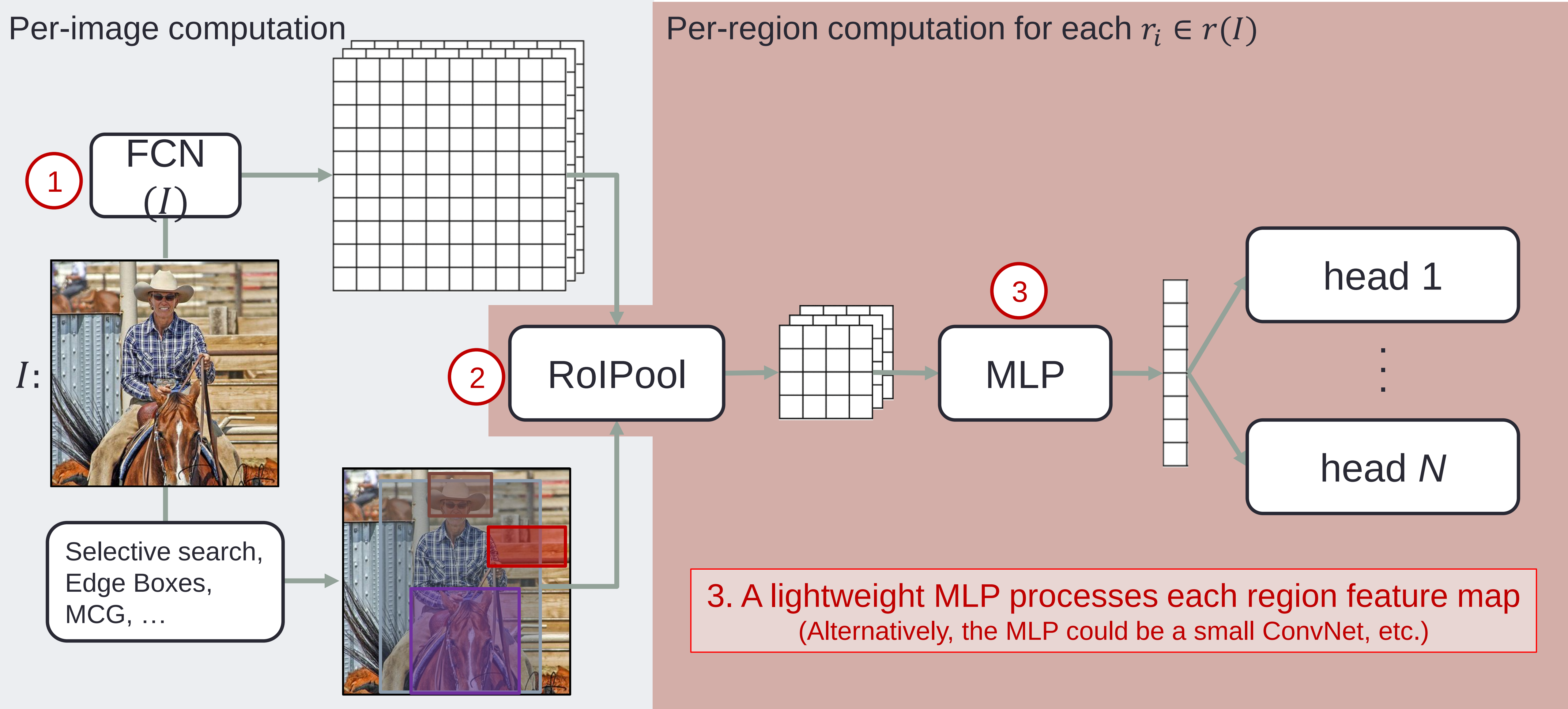
2. Generalized R-CNN → Fast R-CNN



2. *Region of interest* (RoI) pooling converts each region into a fixed dimensional representation

Girshick. Fast R-CNN. ICCV 2015.

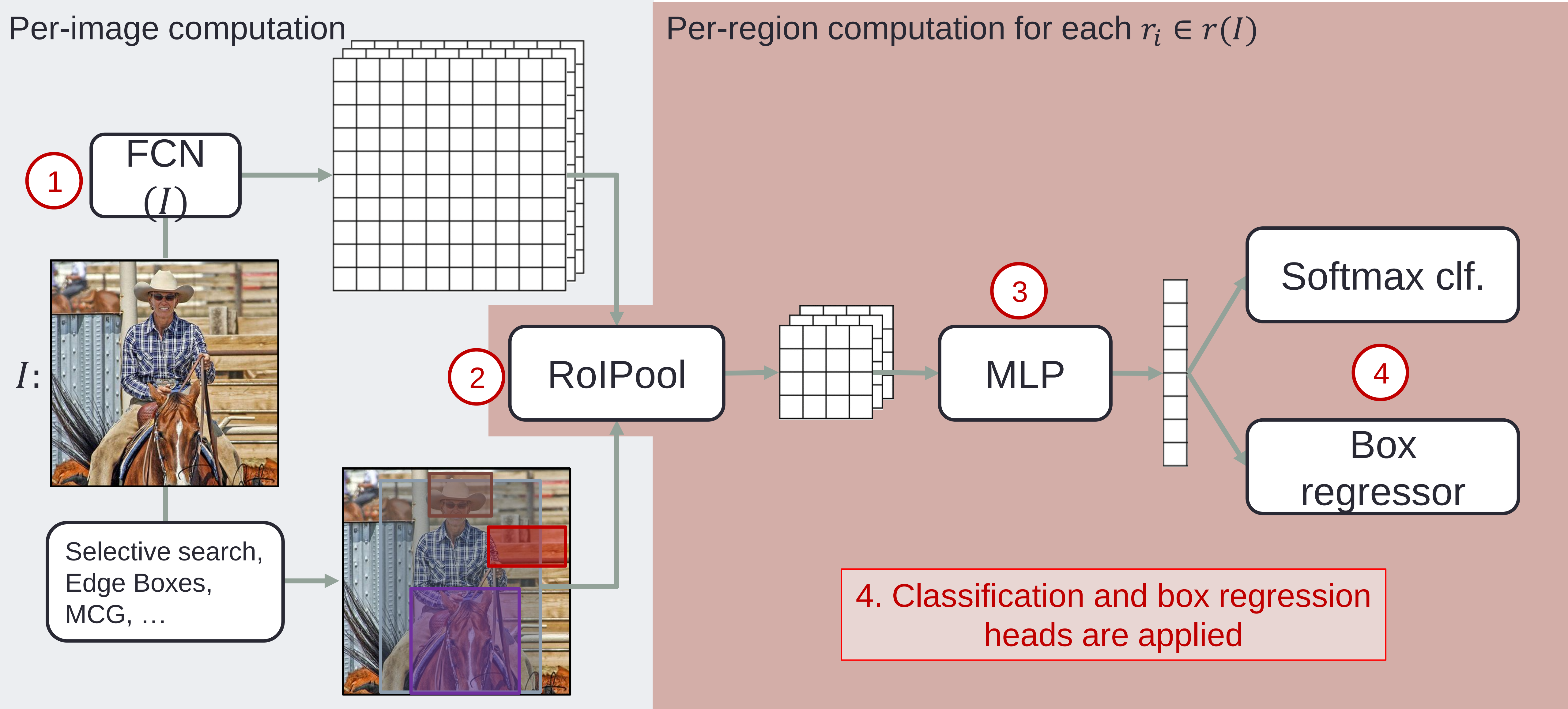
2. Generalized R-CNN → Fast R-CNN



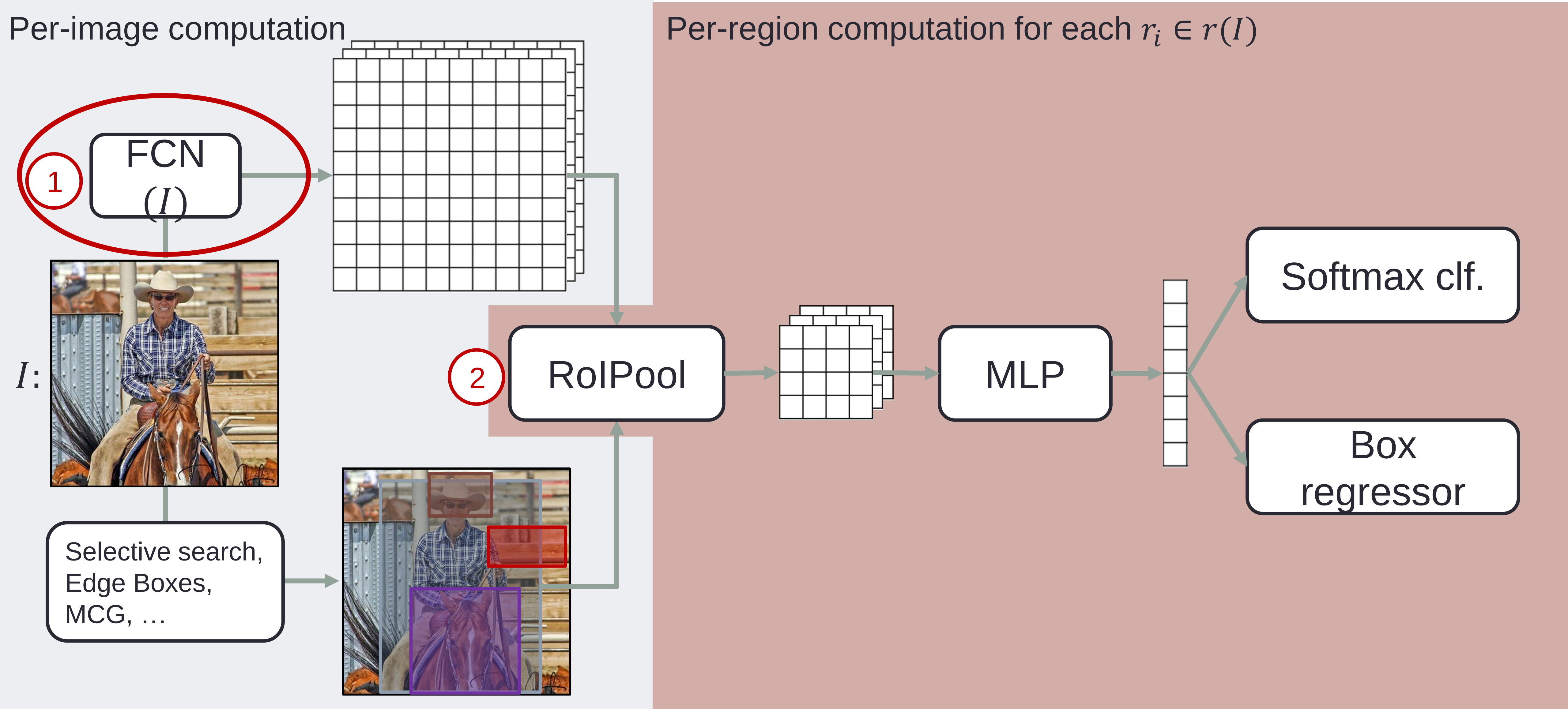
3. A lightweight MLP processes each region feature map
(Alternatively, the MLP could be a small ConvNet, etc.)

Girshick. Fast R-CNN. ICCV 2015.

2. Generalized R-CNN → Fast R-CNN



2. Fast R-CNN


Per-image computation
Per-region computation for each $r_i \in r(I)$
1
FCN (I)
I:
Selective search, Edge Boxes, MCG, …
2
RoIPool
MLP
Softmax clf.
Box regressor

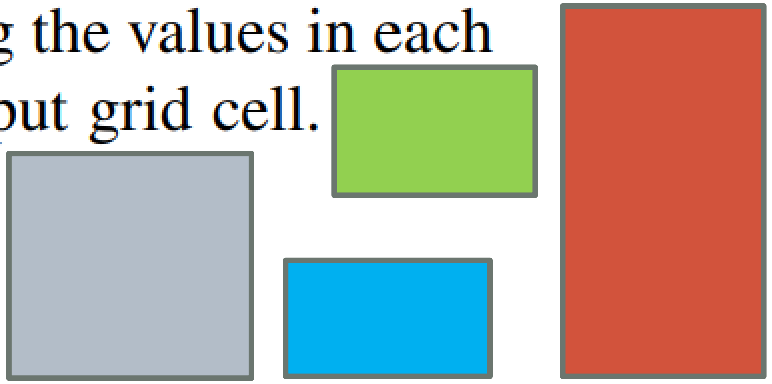
2. Fast R-CNN-RoI Pooling

2 RoIPool

2. Fast R-CNN-RoI Pooling

Transform arbitrary size proposal into a fixed-dimensional representation (e.g., H=7 x W=7)

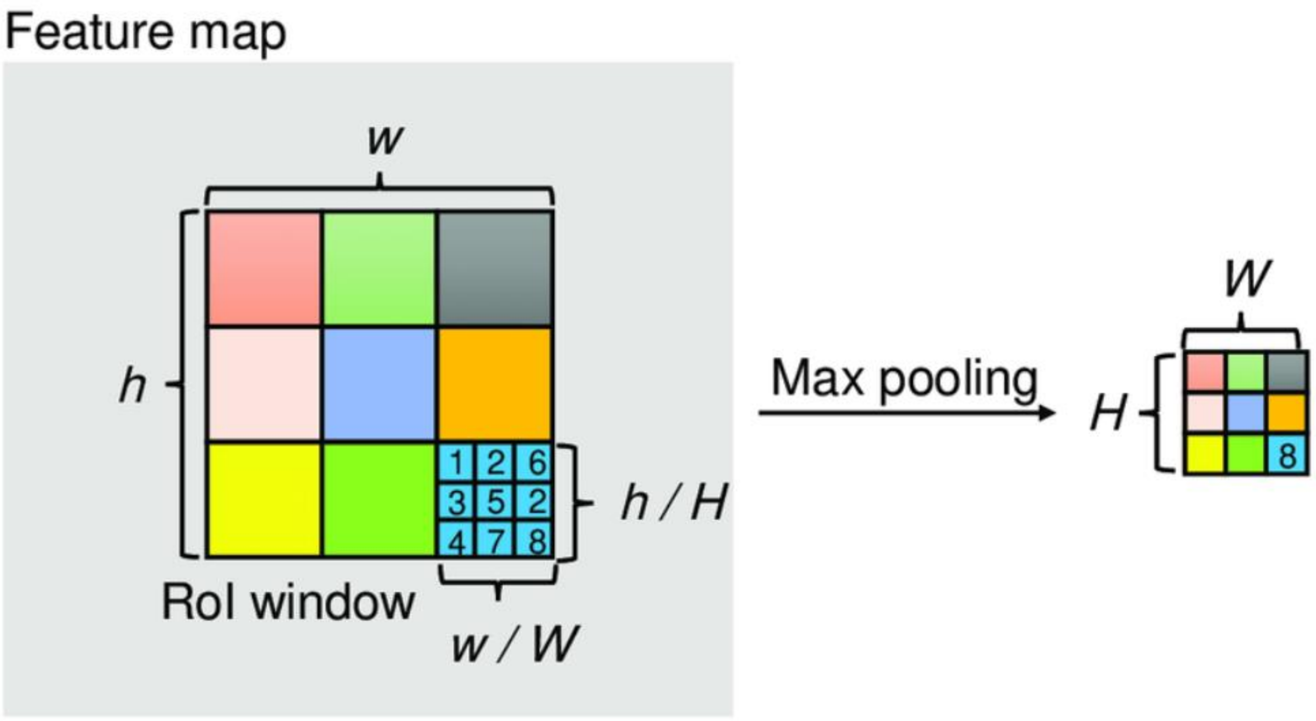
RoI max pooling works by dividing the $h \times w$ RoI window into an $H \times W$ grid of sub-windows of approximate size $h/H \times w/W$ and then max-pooling the values in each sub-window into the corresponding output grid cell.



Girshick. Fast R-CNN. ICCV 2015.

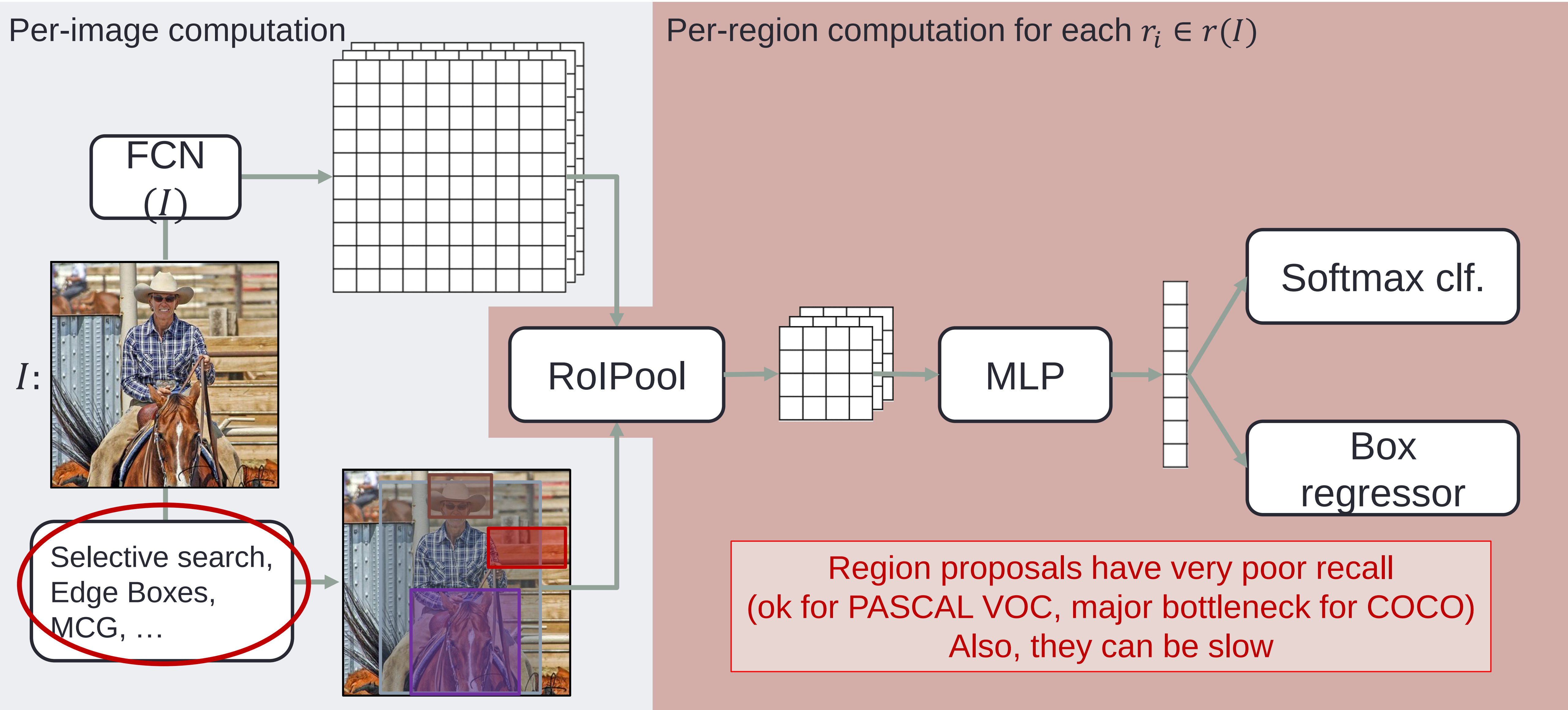
2. Fast R-CNN-RoI Pooling

Transform arbitrary size proposal into a fixed-dimensional representation (e.g., H=7 x W=7)



https://www.researchgate.net/figure/Illustration-of-the-RoI-pooling-operation_fig4_333521857

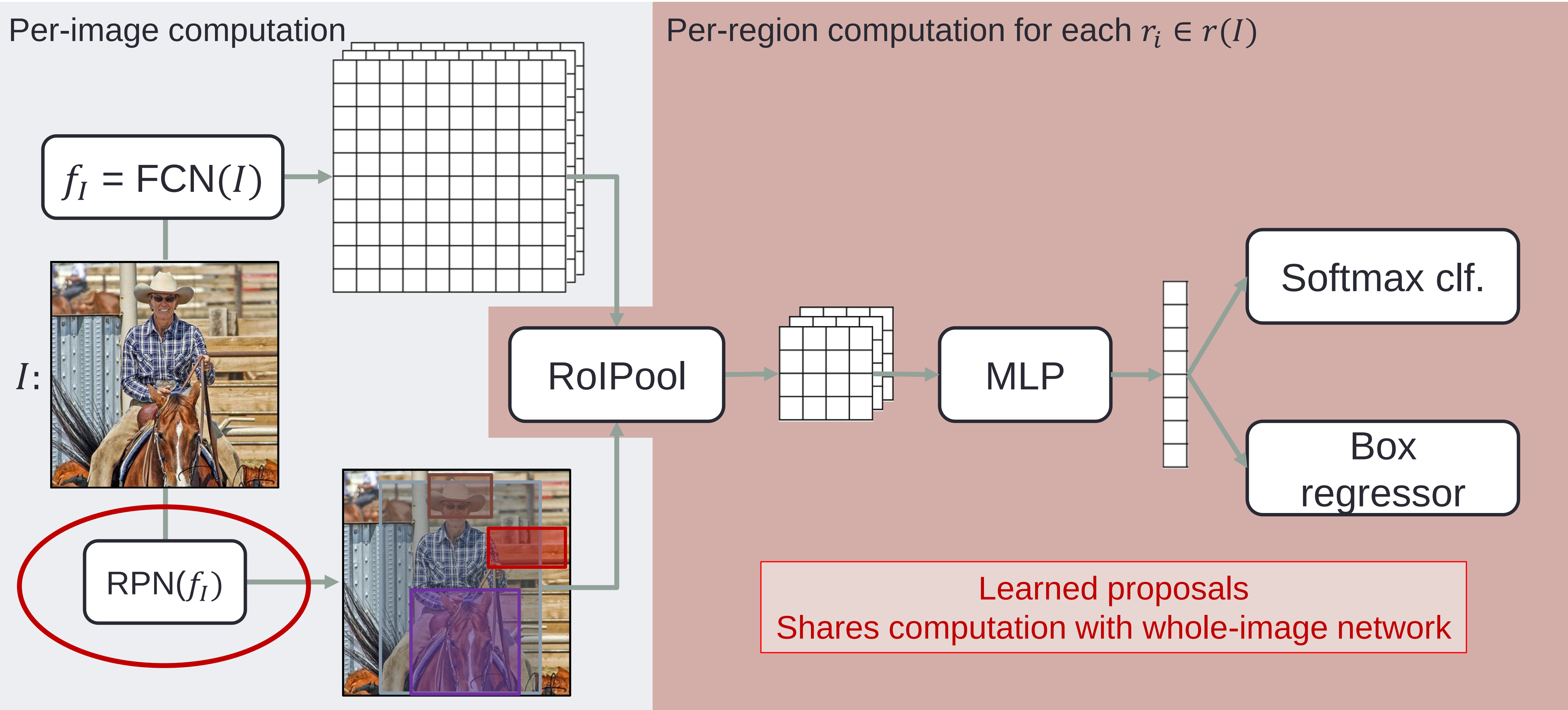
2. The Problem with Fast R-CNN



Region proposals have very poor recall
(ok for PASCAL VOC, major bottleneck for COCO)
Also, they can be slow

Ren, He, Girshick, Sun. Faster R-CNN: Towards Real-Time Object Detection. NIPS 2015.

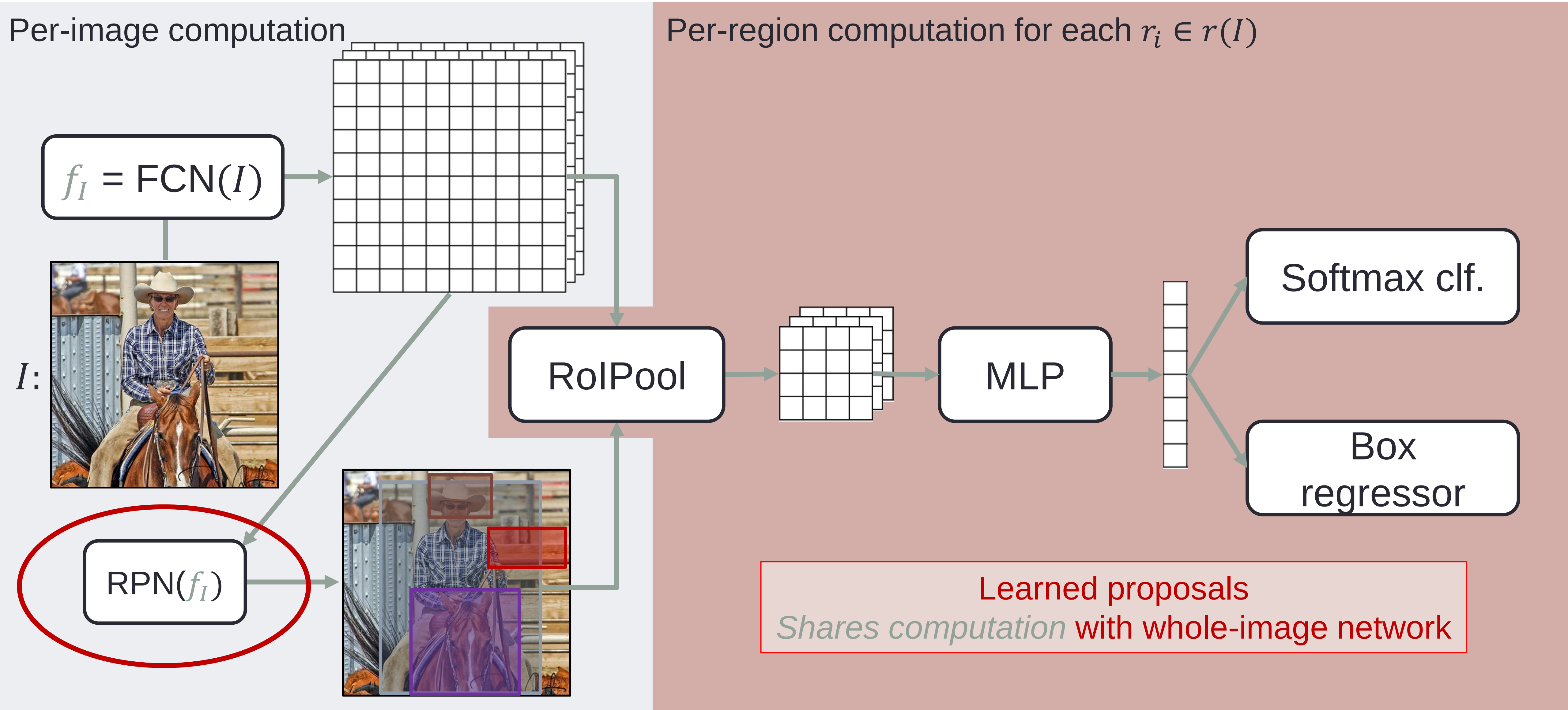
2. Faster R-CNN



Learned proposals
Shares computation with whole-image network

Ren, He, Girshick, Sun. Faster R-CNN: Towards Real-Time Object Detection. NIPS 2015.

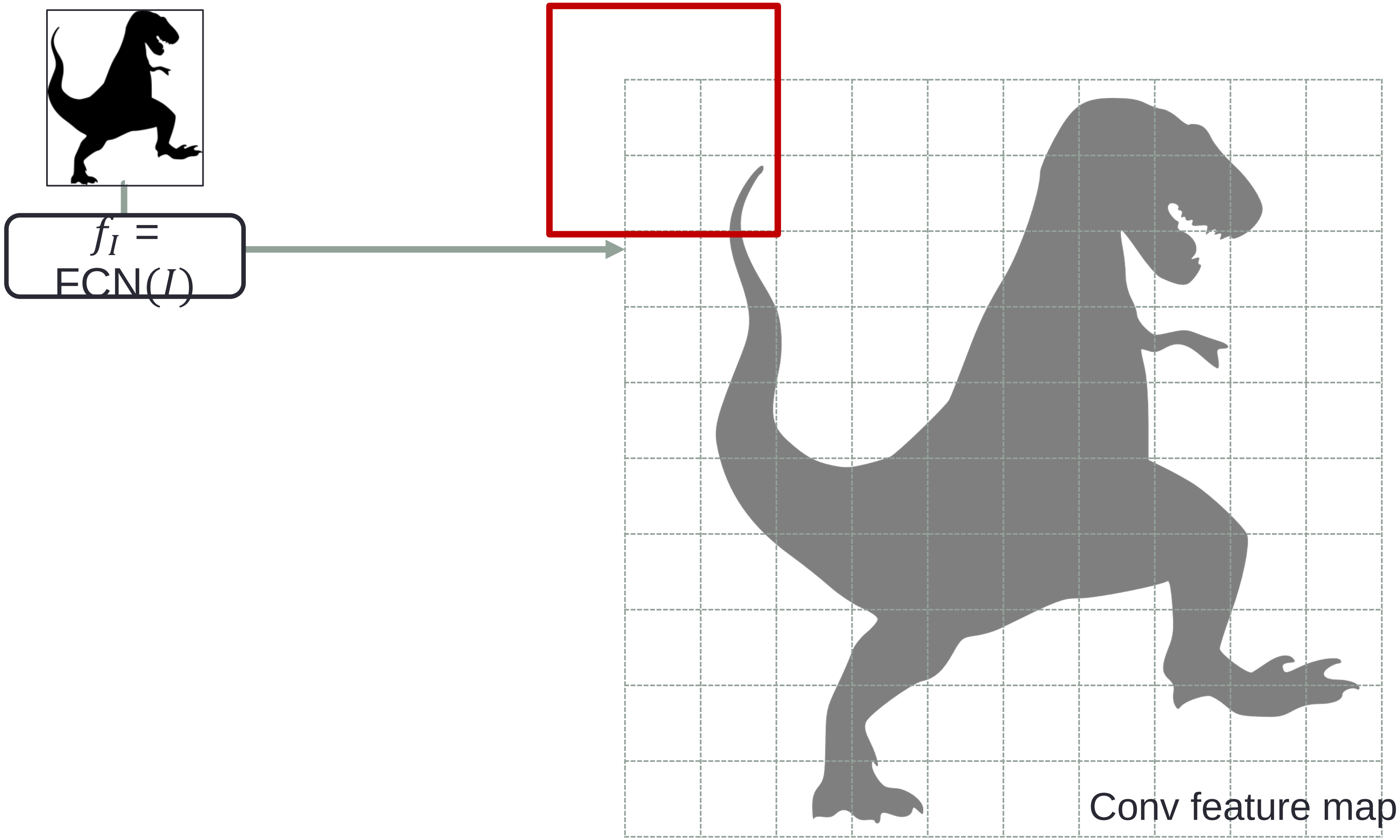
3. Faster R-CNN



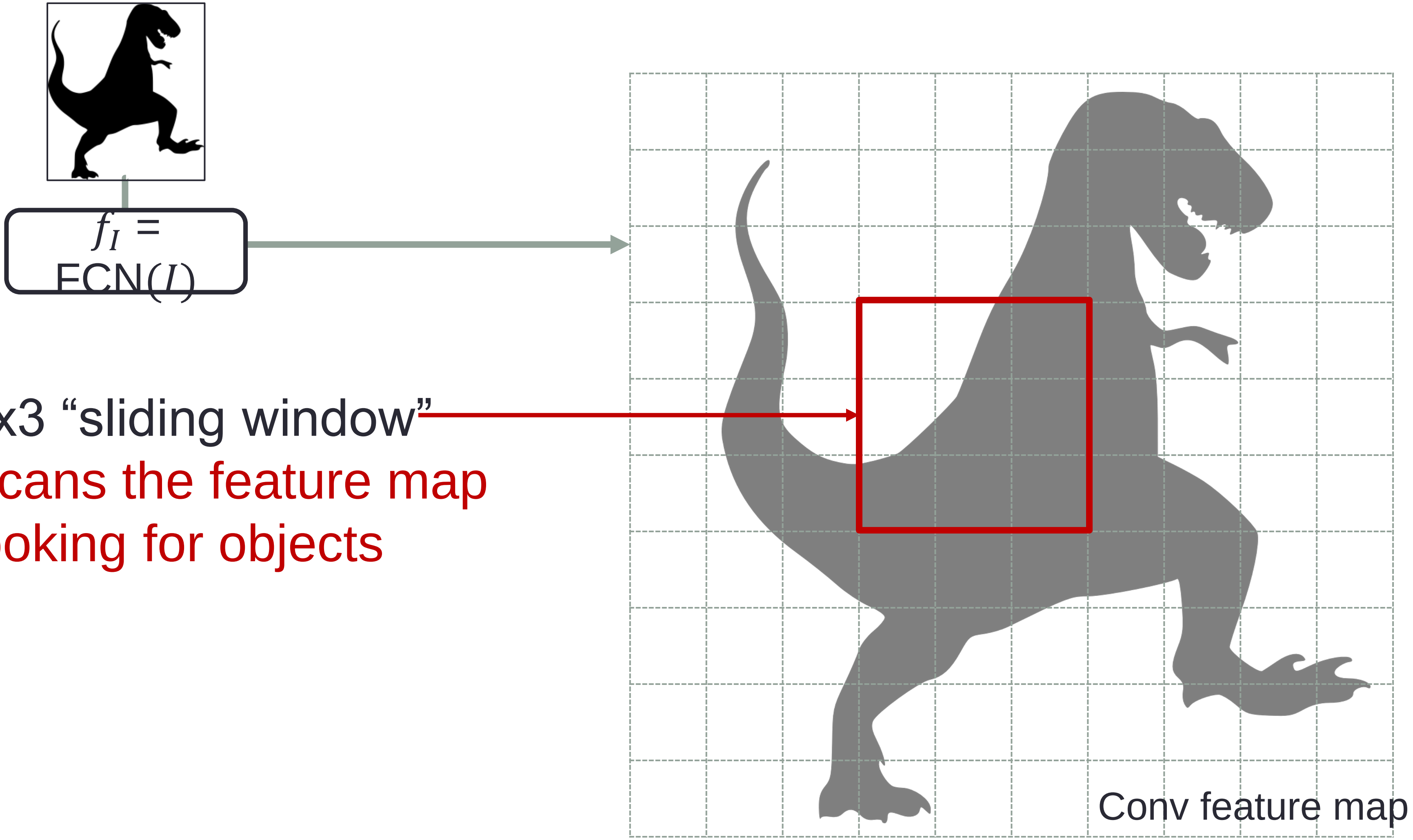
Learned proposals

Shares computation with whole-image network

3. RPN: Region Proposal Network



3. RPN: Region Proposal Network

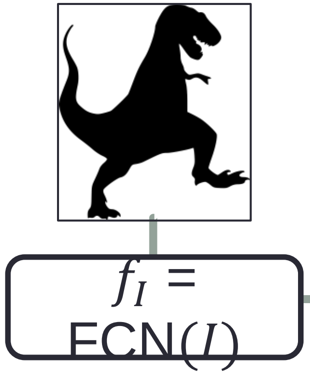


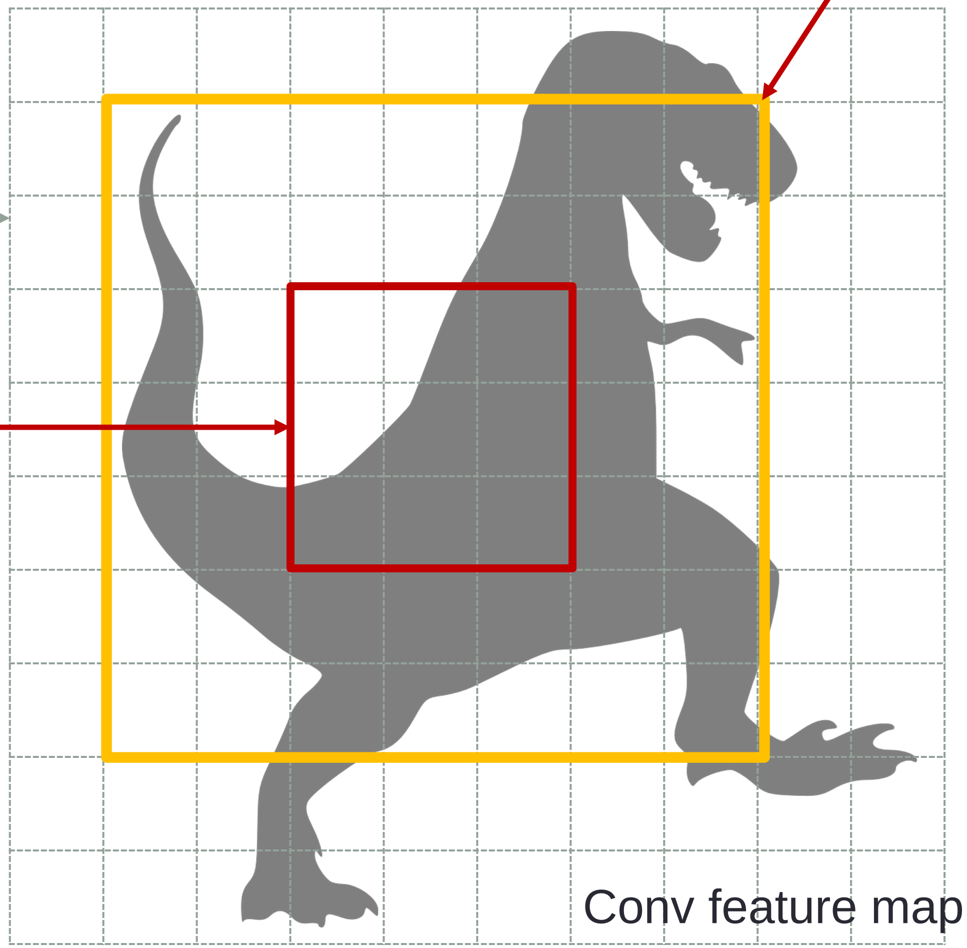
3x3 "sliding window"

Scans the feature map looking for objects

3. RPN: Anchor Box

Anchor box: predictions are w.r.t. this box, *not the 3x3 sliding window*



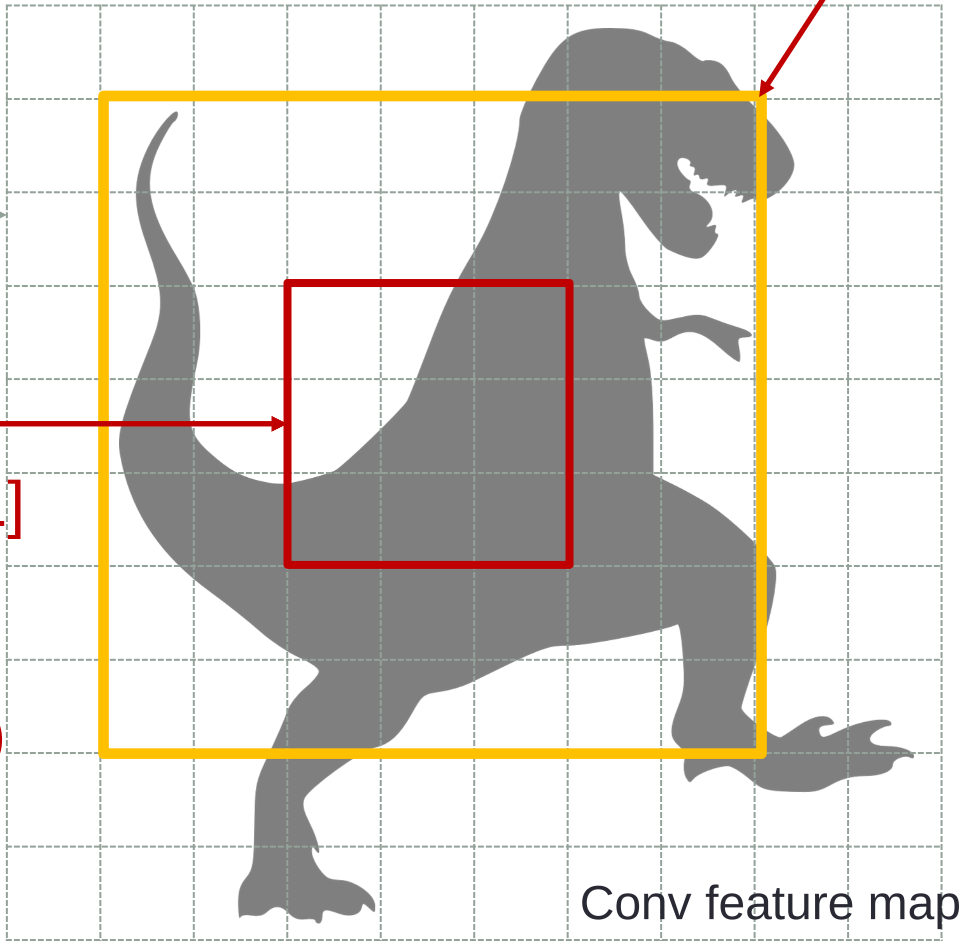


3x3 "sliding window"

Scans the feature map looking for objects

3. RPN: Anchor Box

f_I = FCN(I)



Anchor box: predictions are w.r.t. this box, *not the 3x3 sliding window*

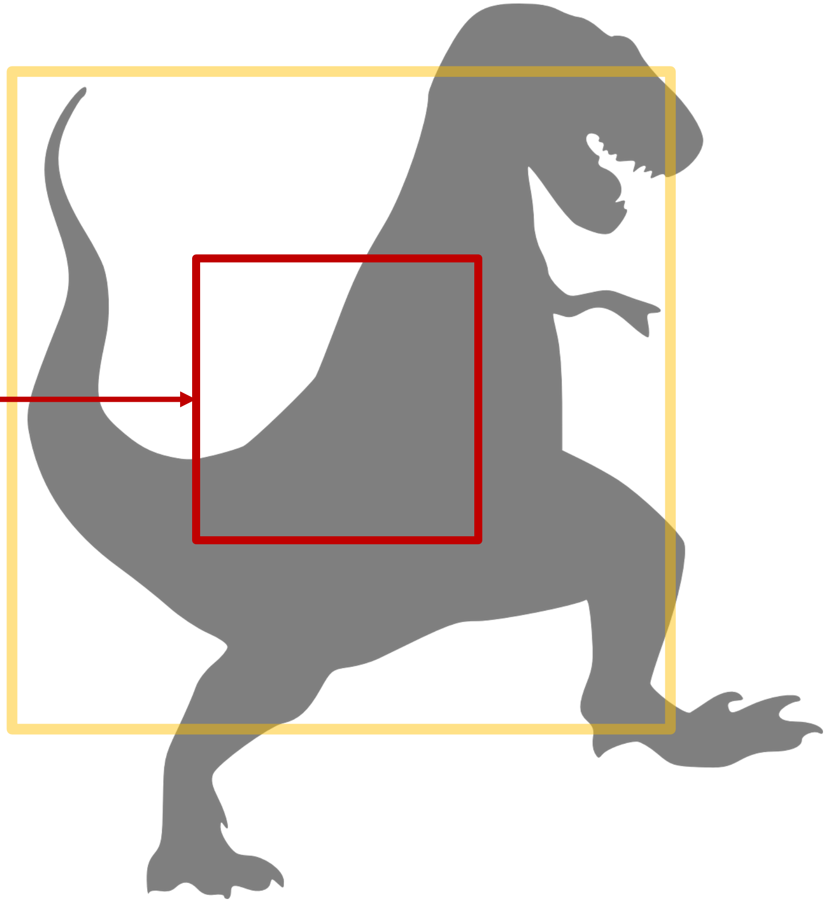
3x3 “sliding window”

- Objectness classifier [0, 1]
- Box regressor predicting (dx, dy, dh, dw)

3. RPN: Prediction (on object)

Objectness score

P(object) = 0.94



3x3 “sliding window”

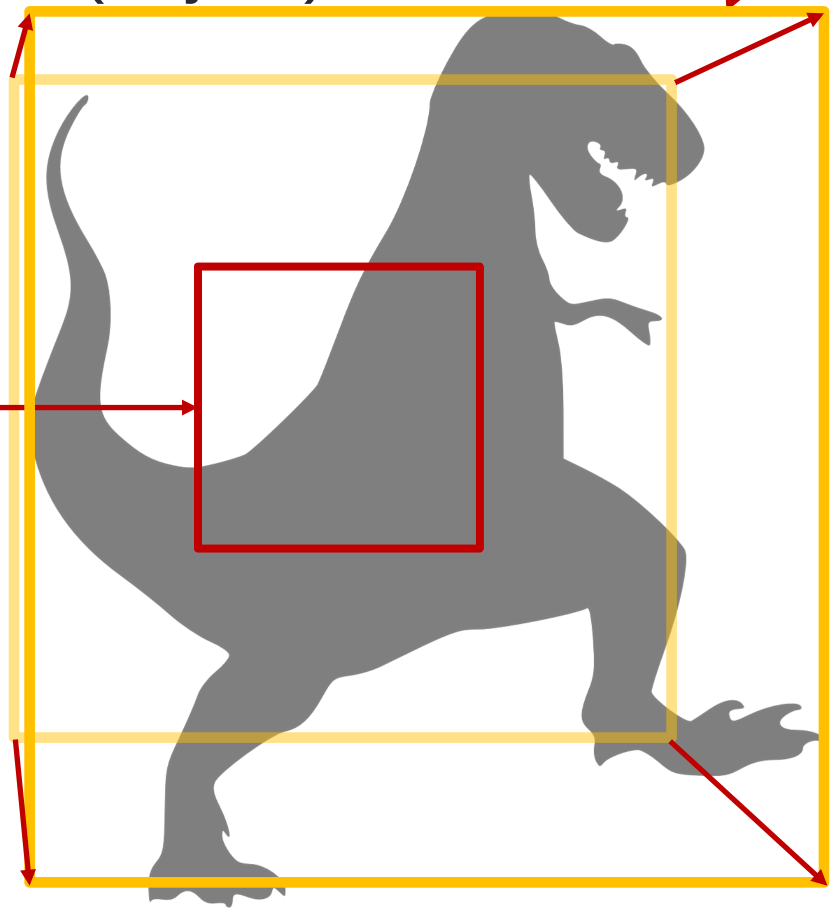
- Objectness classifier [0, 1]

- Box regressor
  predicting (dx, dy, dh, dw)

3. RPN: Prediction (on object)

Anchor box: transformed by box regressor

P(object) = 0.94



3x3 "sliding window"

- ➢ Objectness classifier [0, 1]
- ➢ Box regressor predicting (dx, dy, dh, dw)

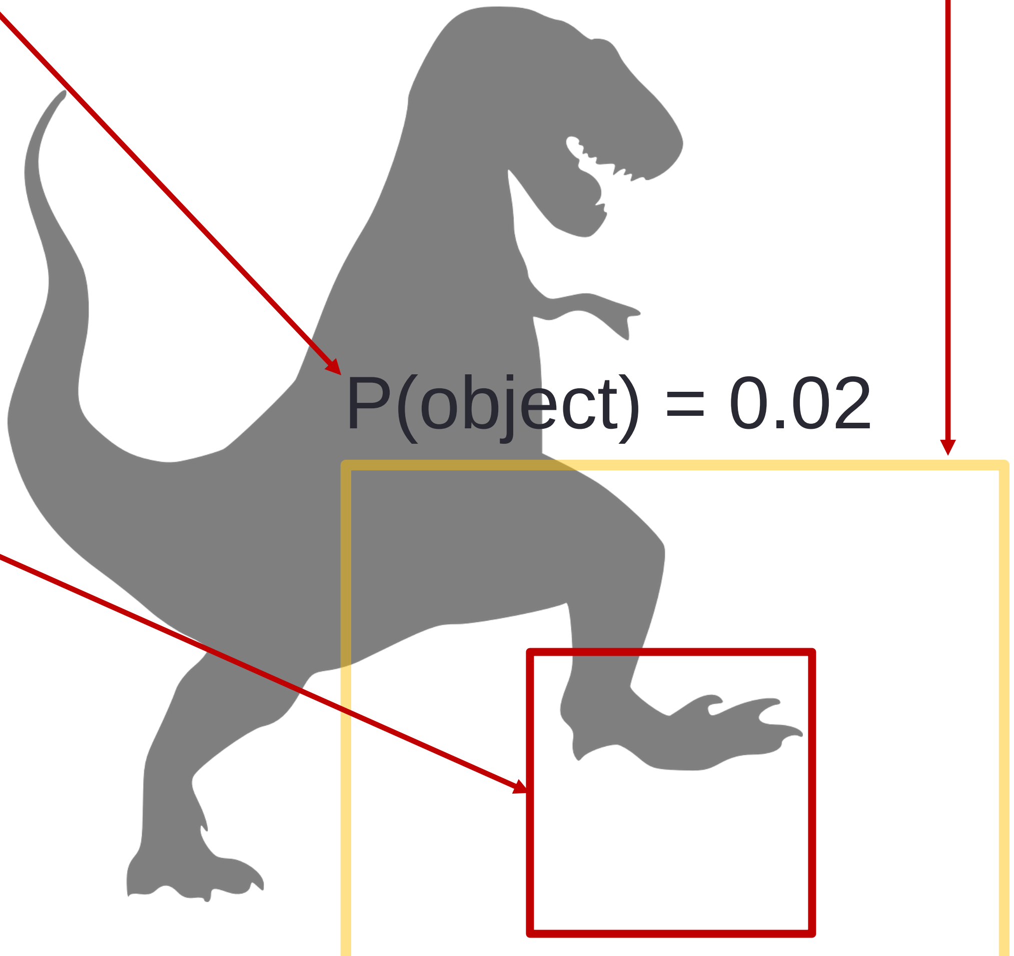
3. RPN: Prediction (off object)

Anchor box: transformed by box regressor

Objectness score

3x3 “sliding window”

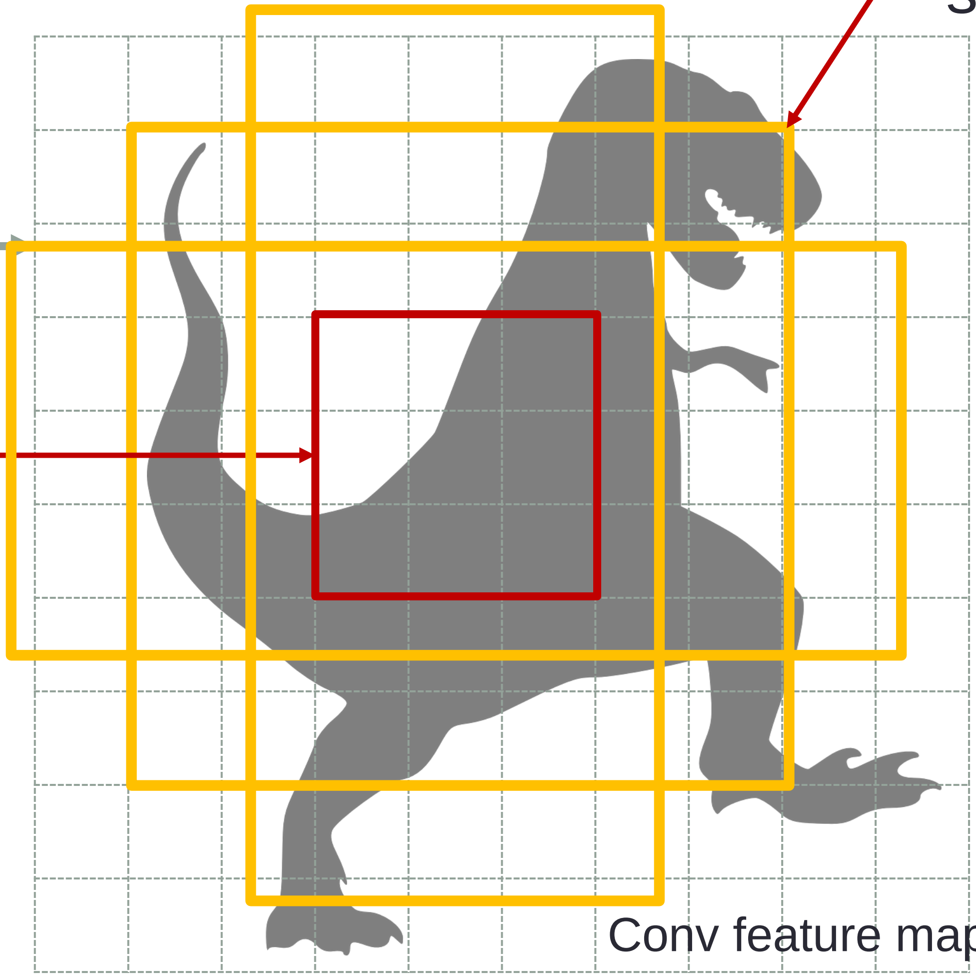
- Objectness classifier
- Box regressor predicting (dx, dy, dh, dw)



3. RPN: Multiple Anchors

Anchor boxes: *K* anchors per location with different scales and aspect ratios

$f_I = \mathrm{FCN}(I)$

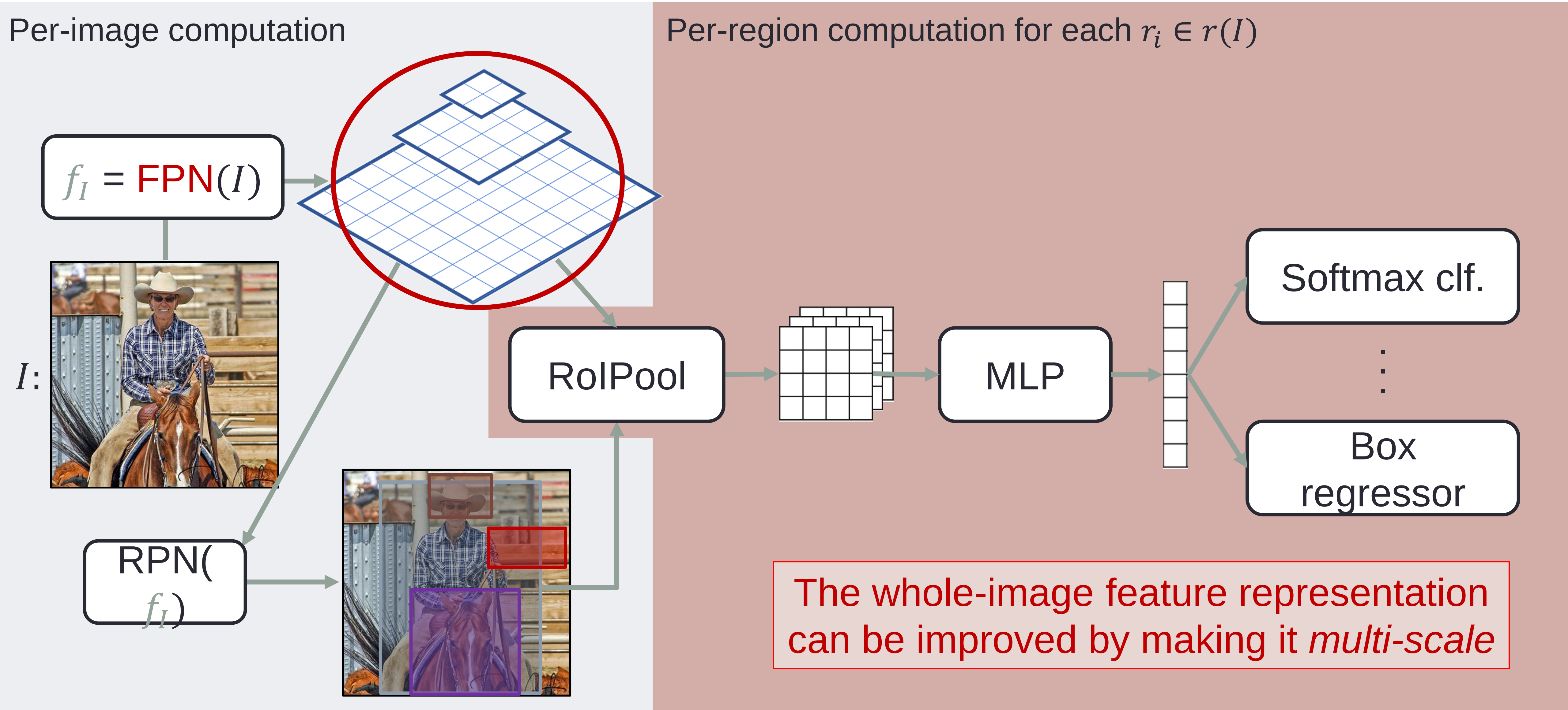


3x3 “sliding window”

- *K* objectness classifiers
- *K* box regressors

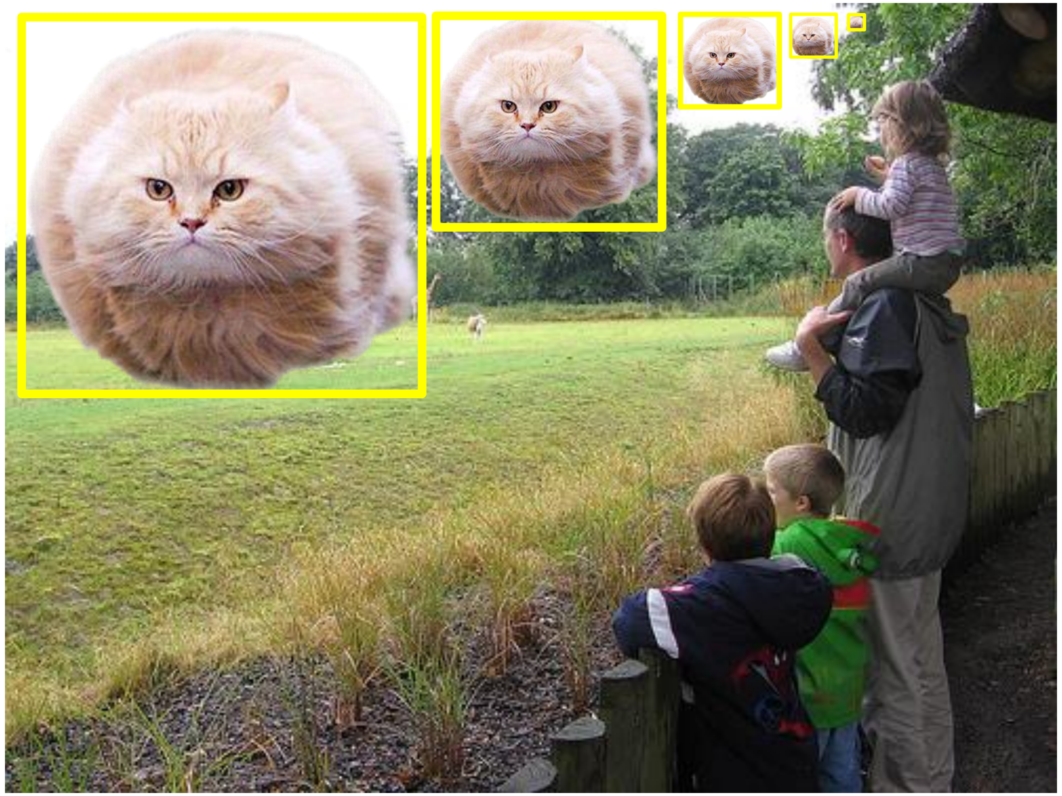
Lin et al. Feature Pyramid Networks for Object Detection. CVPR 2017.

4. Faster R-CNN with a Feature Pyramid Network



The whole-image feature representation can be improved by making it *multi-scale*

4. FPN: Improving Scale Invariance and Equivariance



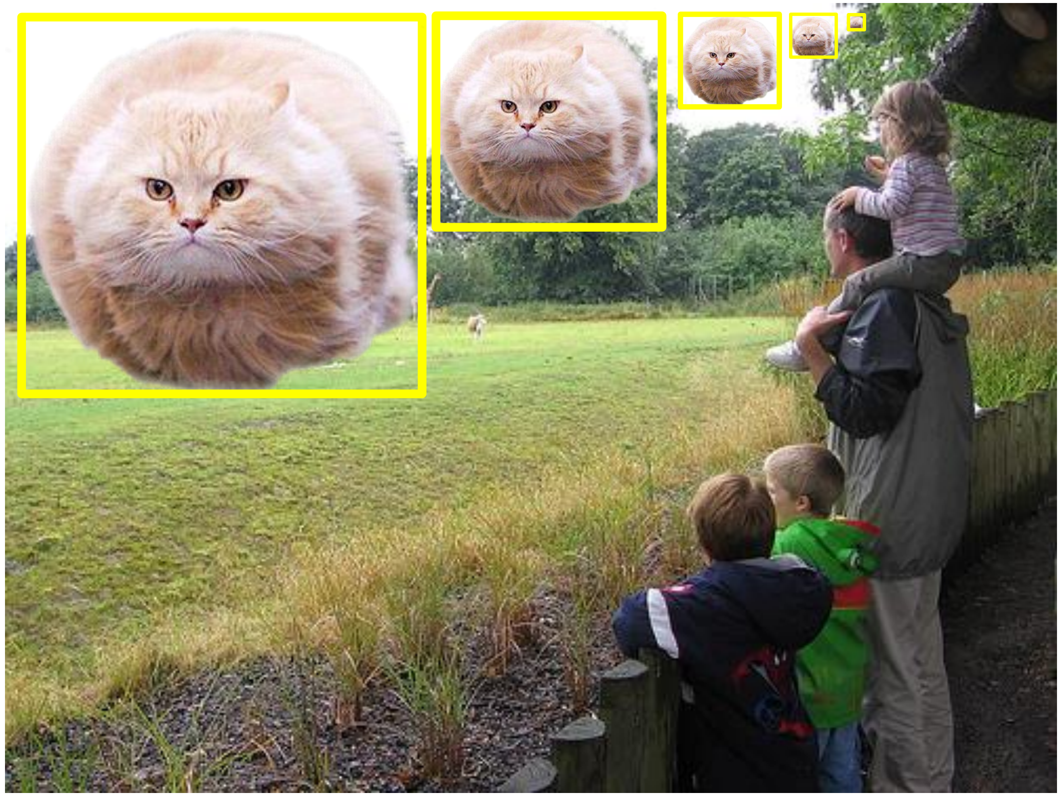
Detectors need to

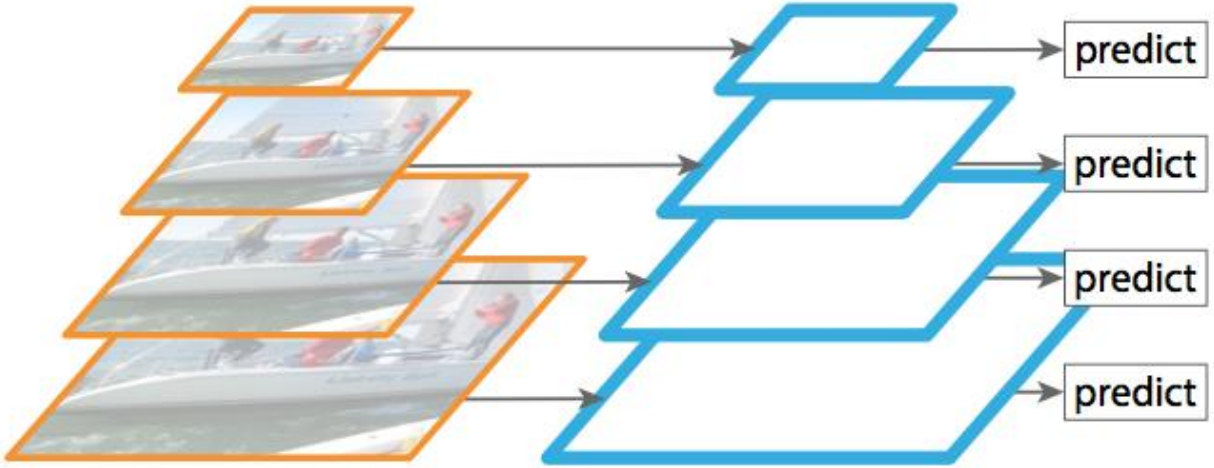
1. classify and
2. localize

objects over a wide range of scales

FPN improves this ability

Strategy 1: Image Pyramid



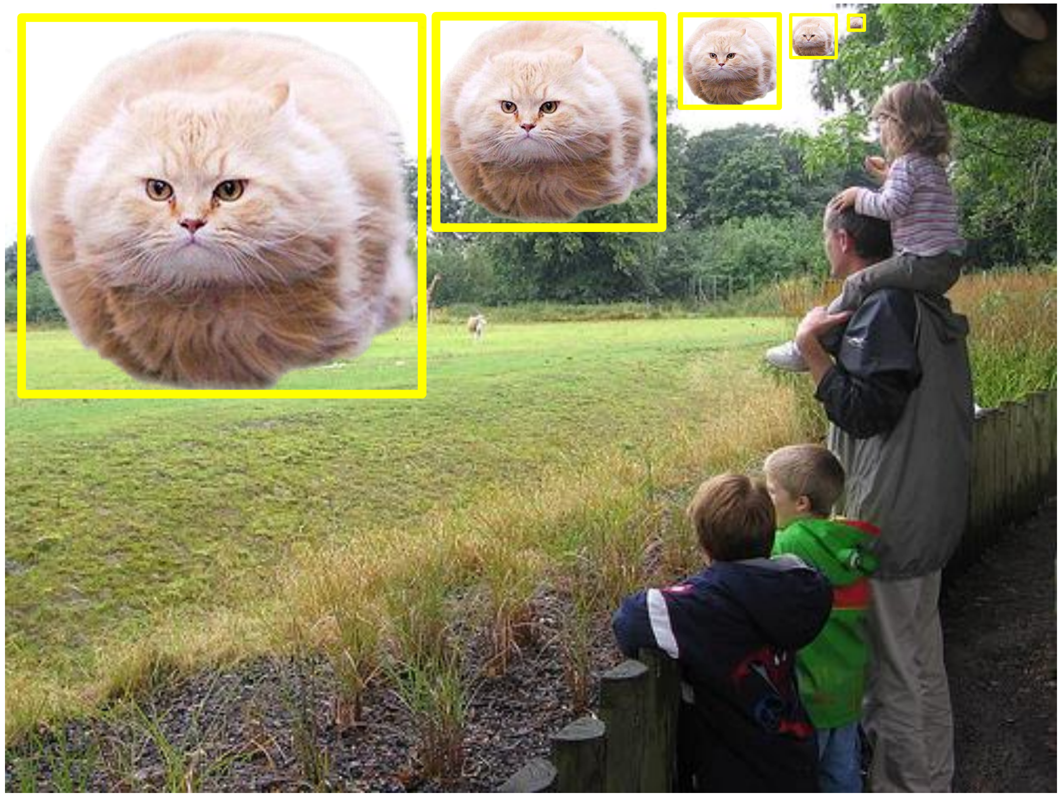


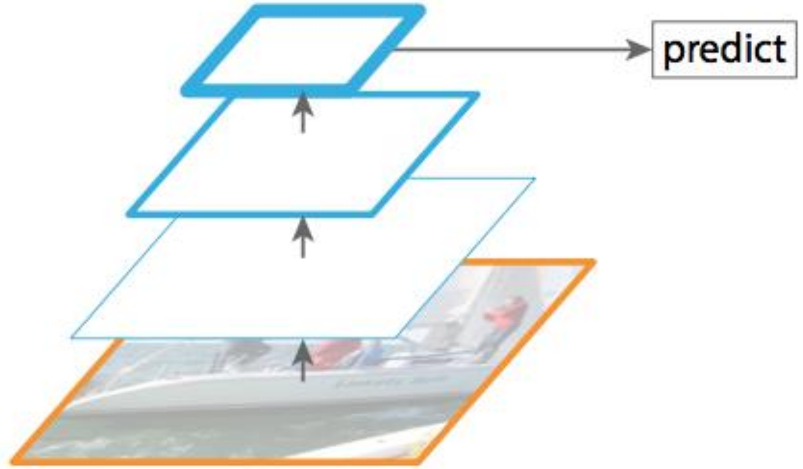
(a) Featurized image pyramid

Standard solution – *slow!*

(E.g., Viola & Jones, HOG, DPM, SPP-net, multi-scale Fast R-CNN, …)

Strategy 2: Multi-scale Features (Single-scale Map)



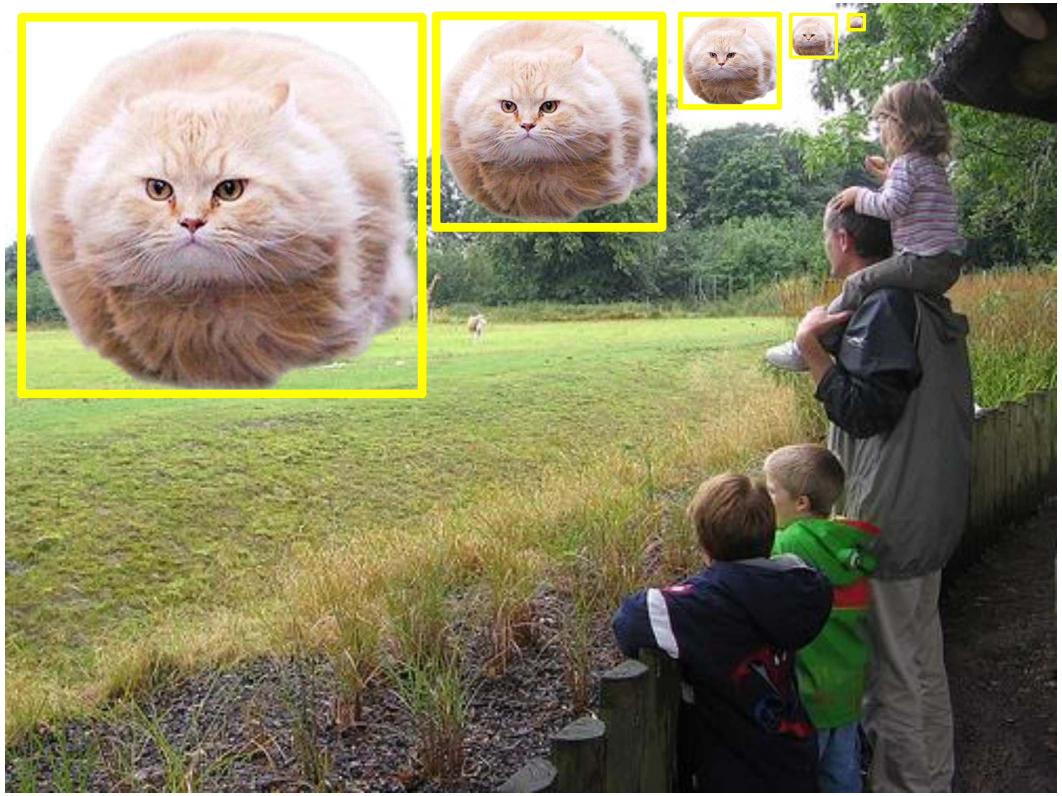


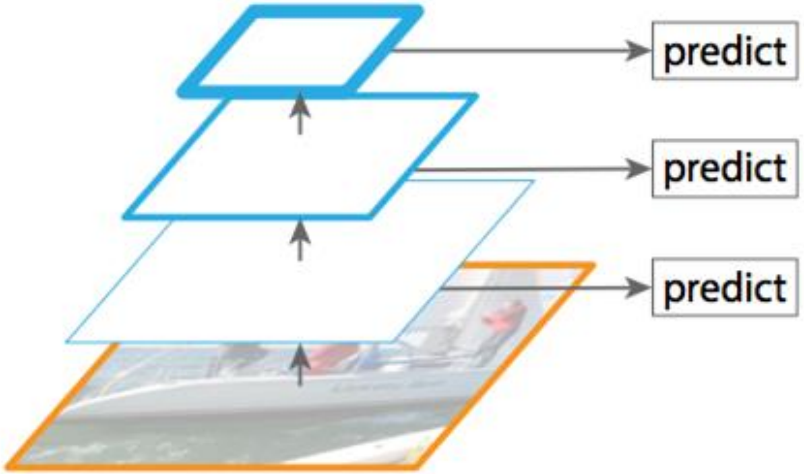
(b) Single feature map

Leave it all to the features – *fast, suboptimal*

(E.g., Fast/er R-CNN, YOLO, …)

Strategy 3: Naïve In-network Pyramid



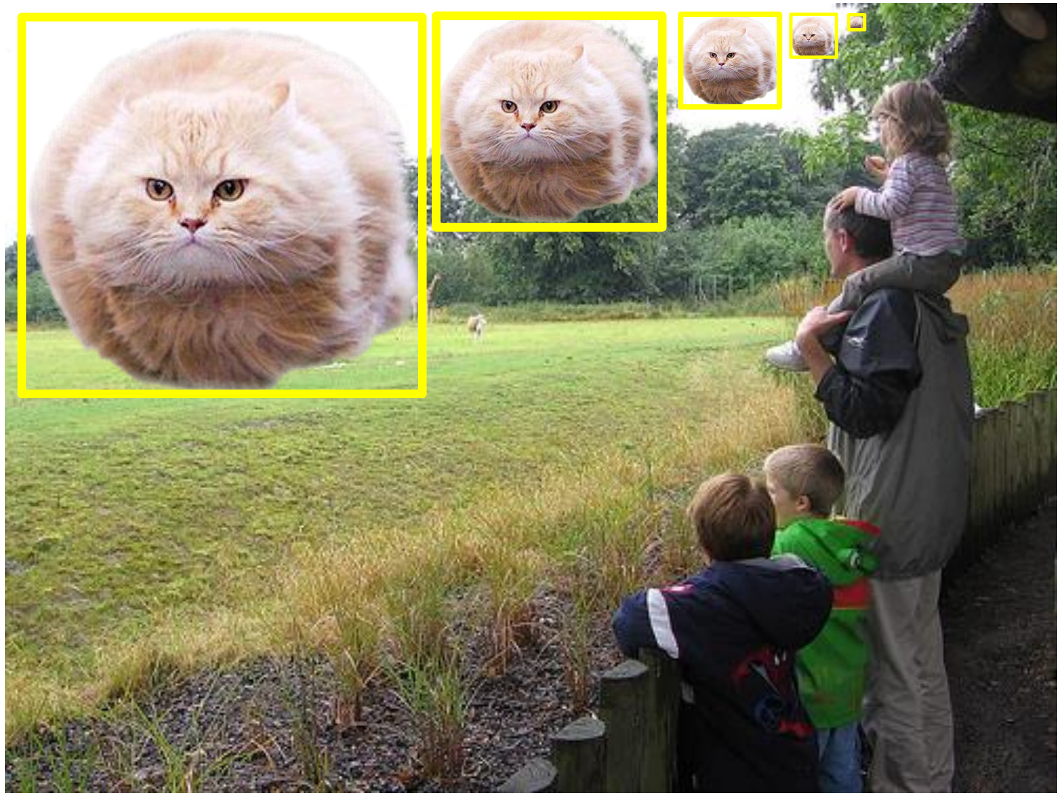


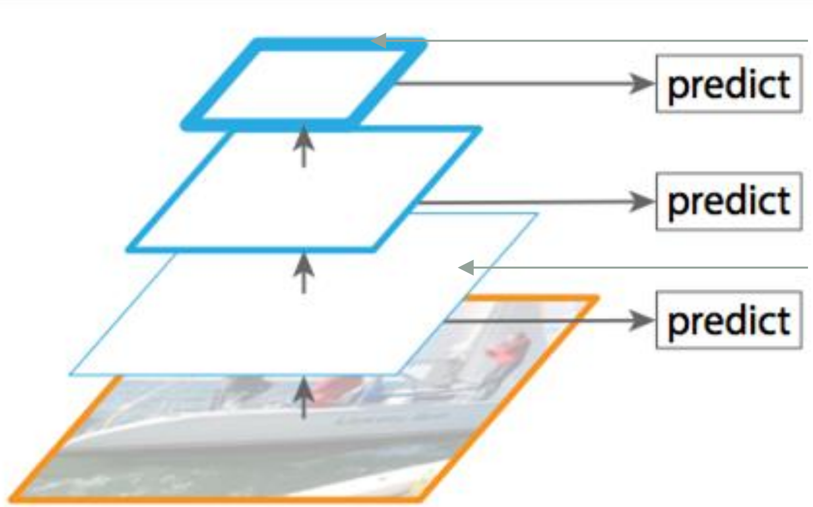
(c) Pyramidal feature hierarchy

Use the internal pyramid – *fast, suboptimal*

(E.g., ≈ SSD, …)

Strategy 3: Naïve In-network Pyramid





(c) Pyramidal feature hierarchy

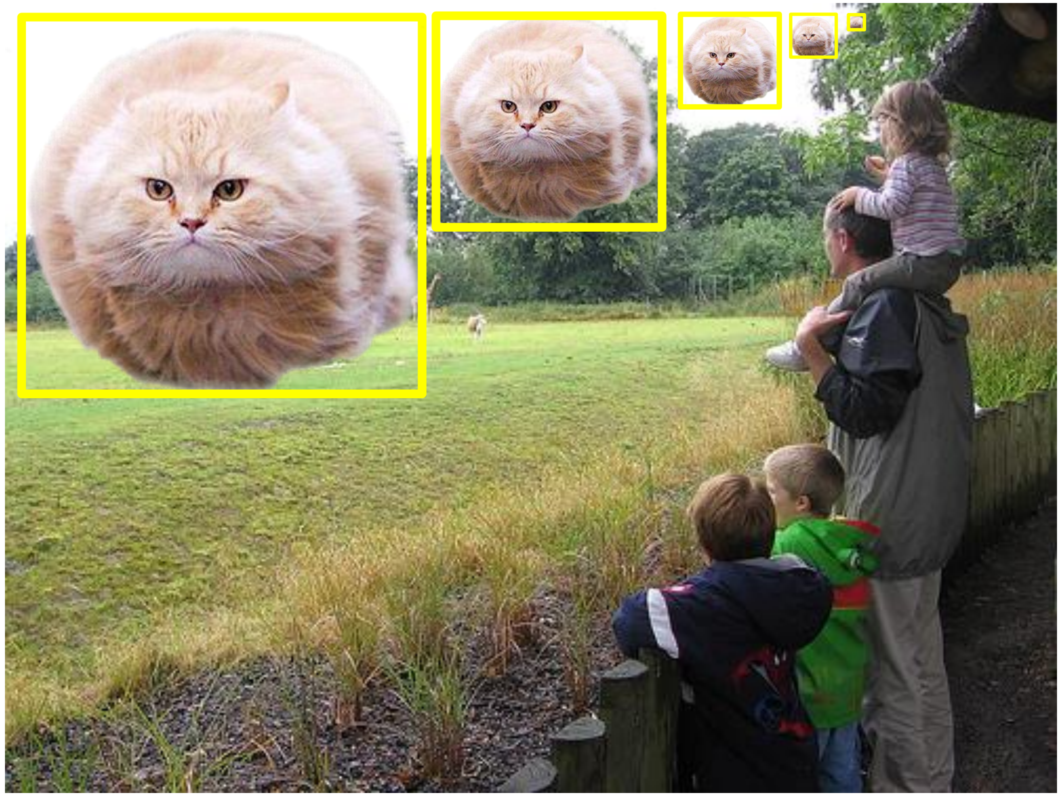
Low resolution,
Strong features

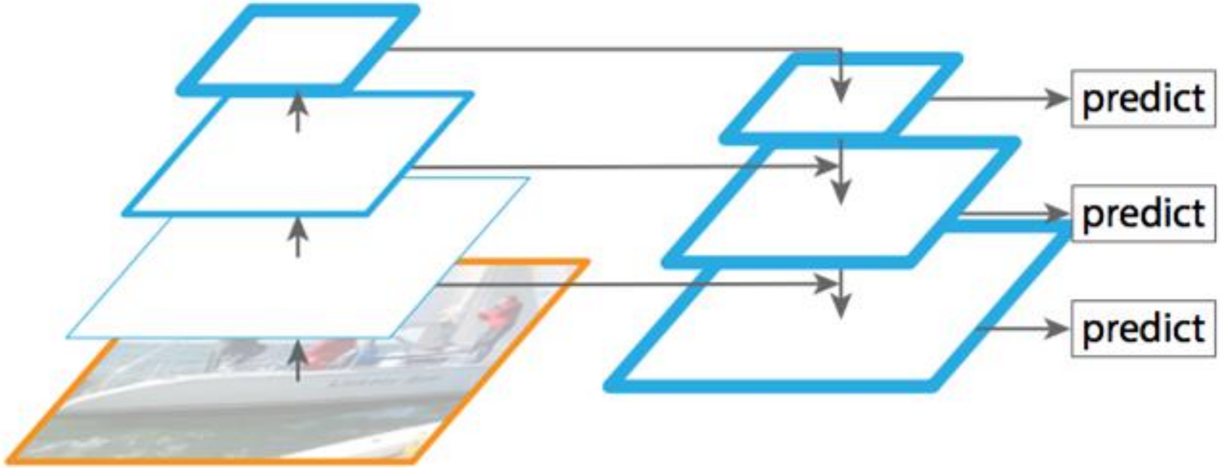
High resolution,
Weak features

Use the internal pyramid – *fast, suboptimal*

(E.g., ≈ SSD, …)

Strategy 4: Feature Pyramid Network



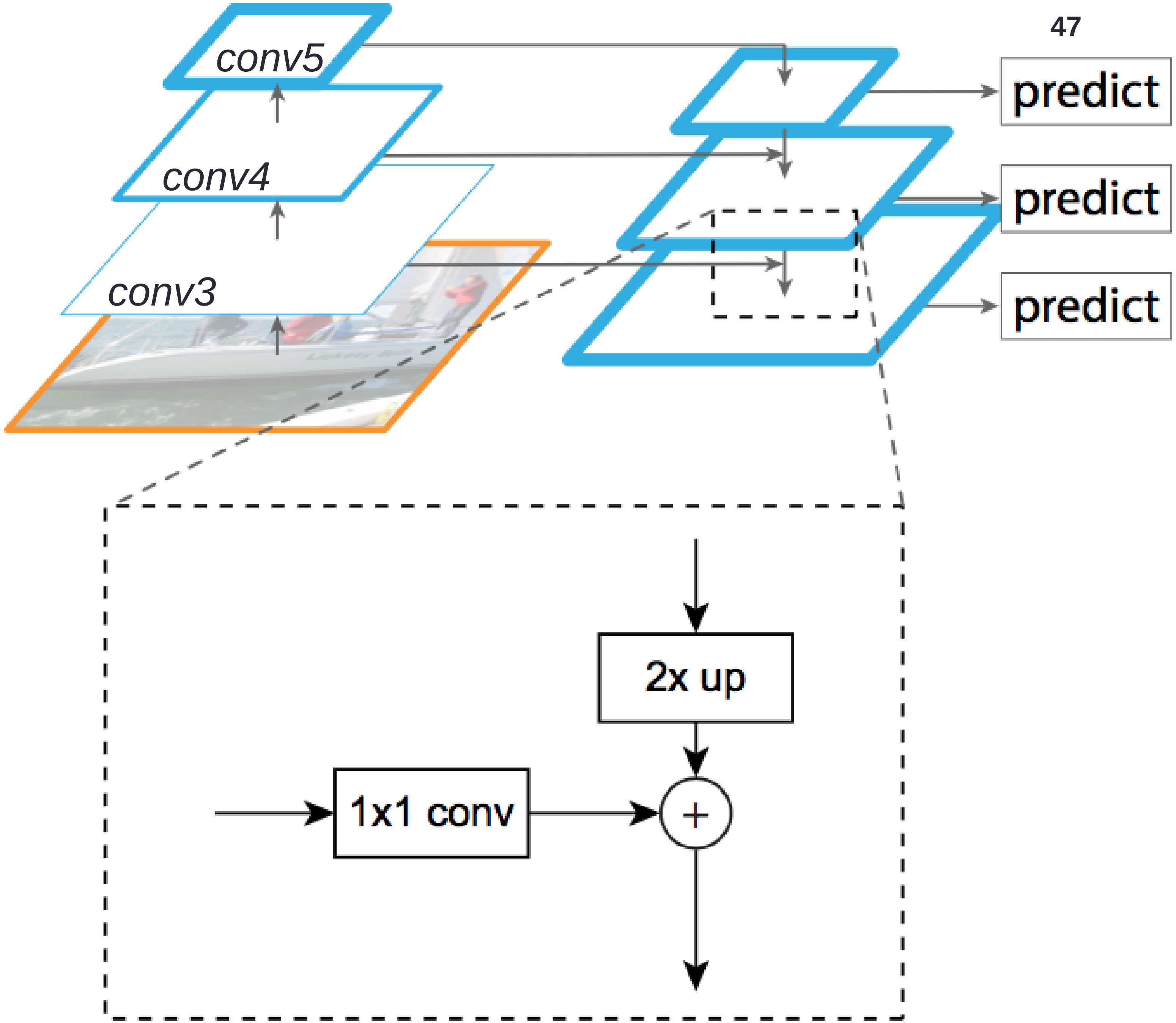


(d) Feature Pyramid Network

Top-down enrichment of high-res features – *fast, less suboptimal*

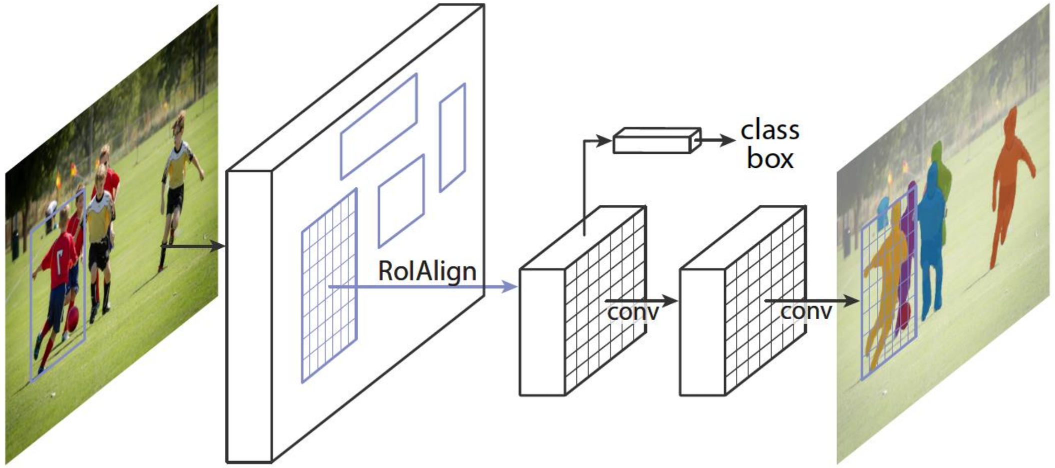
Lin et al. Feature Pyramid Networks for Object Detection. CVPR 2017.

FPN: Light-weight, Top-down Refinement Module

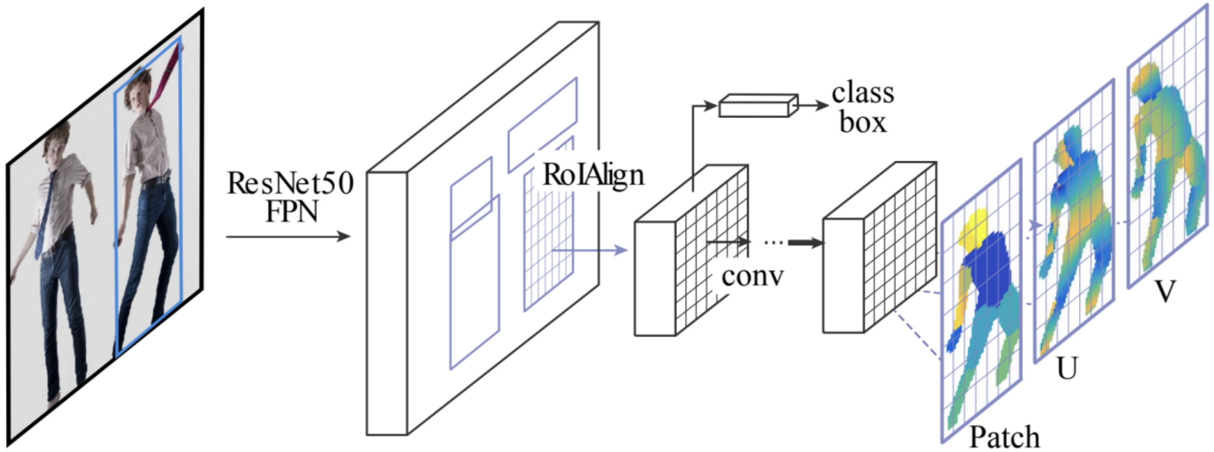


Lin et al. Feature Pyramid Networks for Object Detection. CVPR 2017.

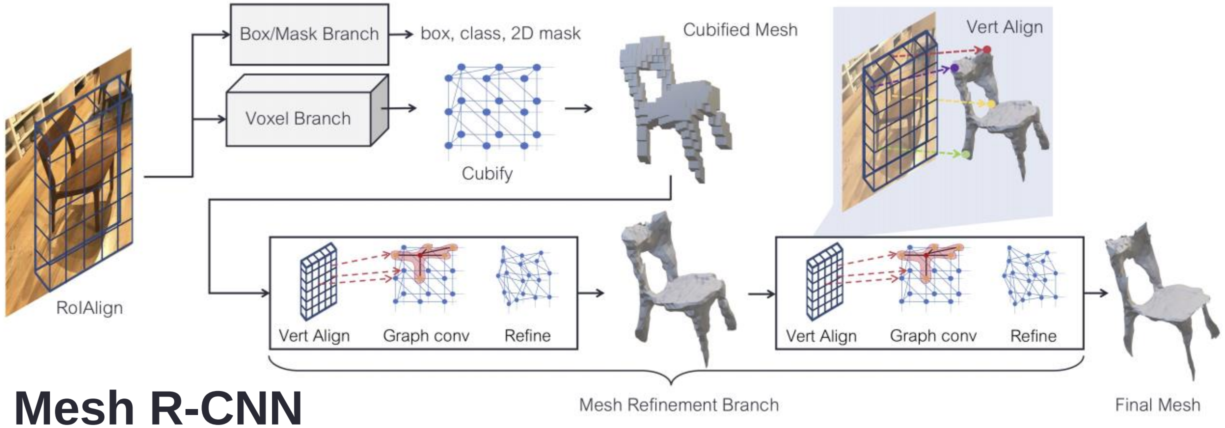
5. Generalized R-CNN: Adding More Heads



Mask R-CNN
[He, Gkioxari, Dollár, Girshick]

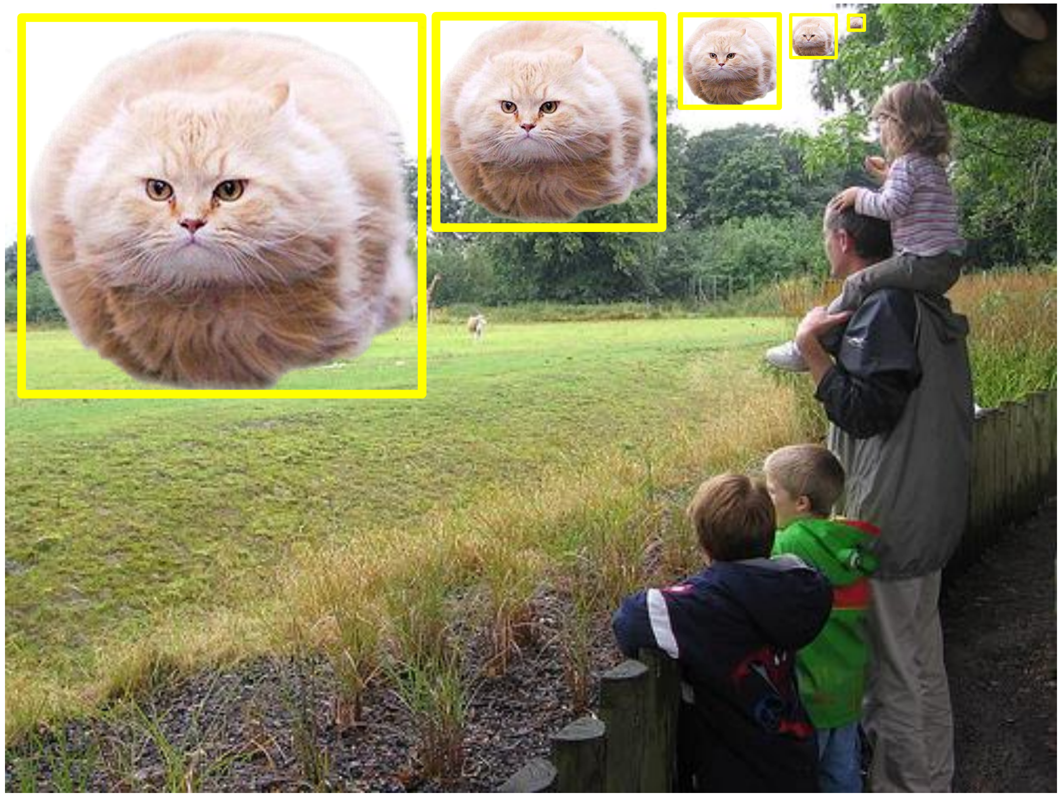


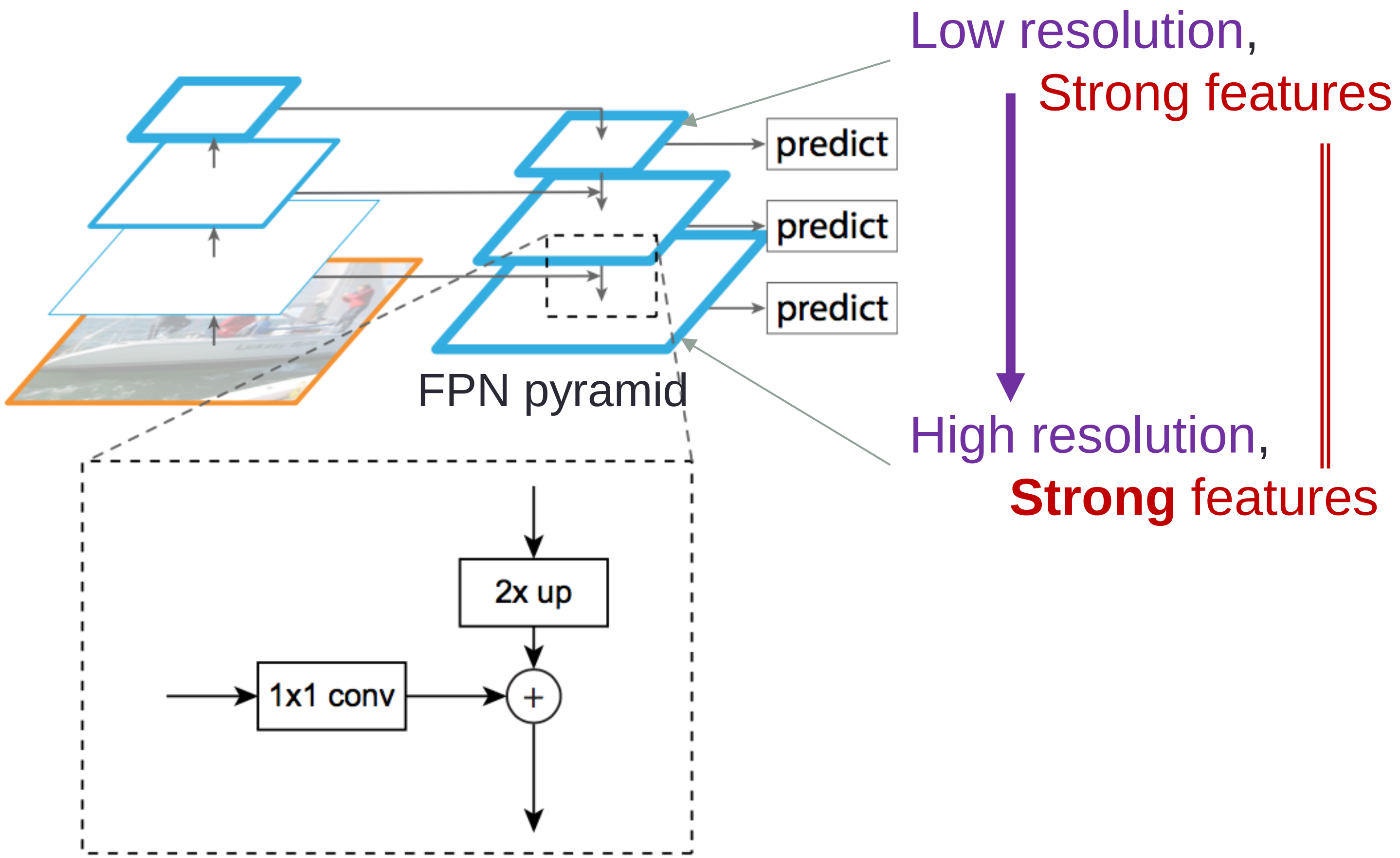
DensePose
[Güler, Neverova, Kokkinos]



Mesh R-CNN
[Gkioxari, Malik, Johnson arXiv 2019]

No Compromise on Feature Quality, Still Fast

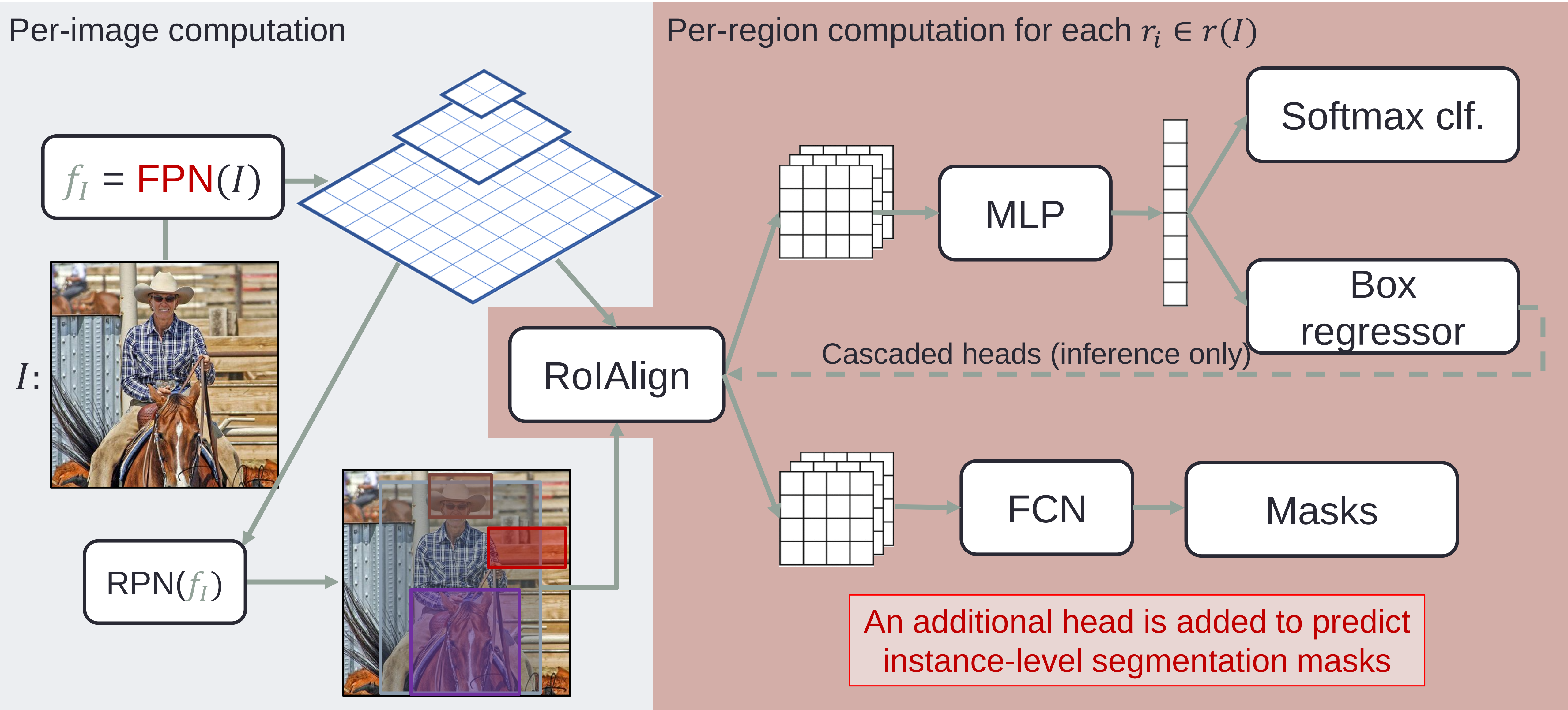




Lin et al. Feature Pyramid Networks for Object Detection. CVPR 2017. See also: Shrivastava’s TDM.

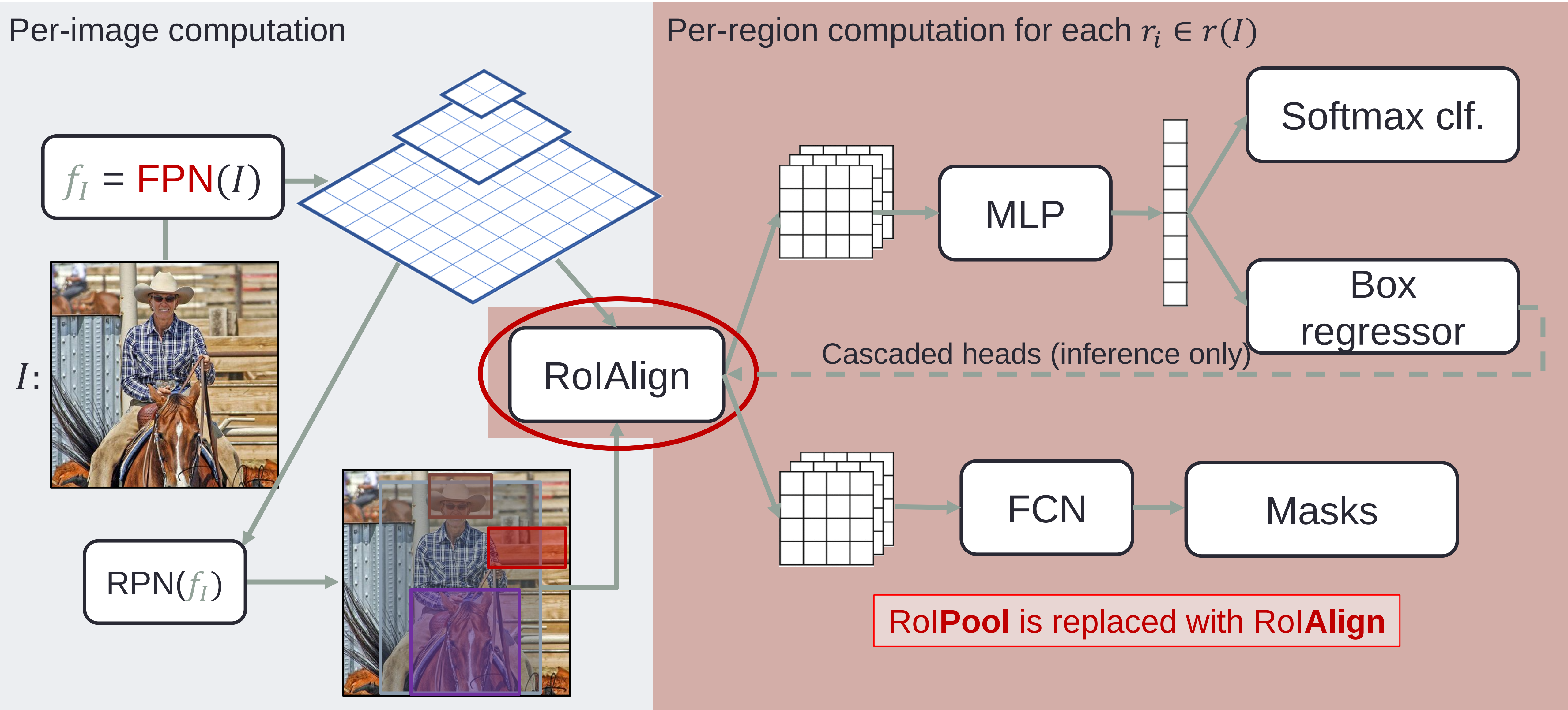
He et al. Mask R-CNN. ICCV 2017.
Best Paper Award

5. Mask R-CNN



He et al. Mask R-CNN. ICCV 2017.
Best Paper Award

5. Mask R-CNN

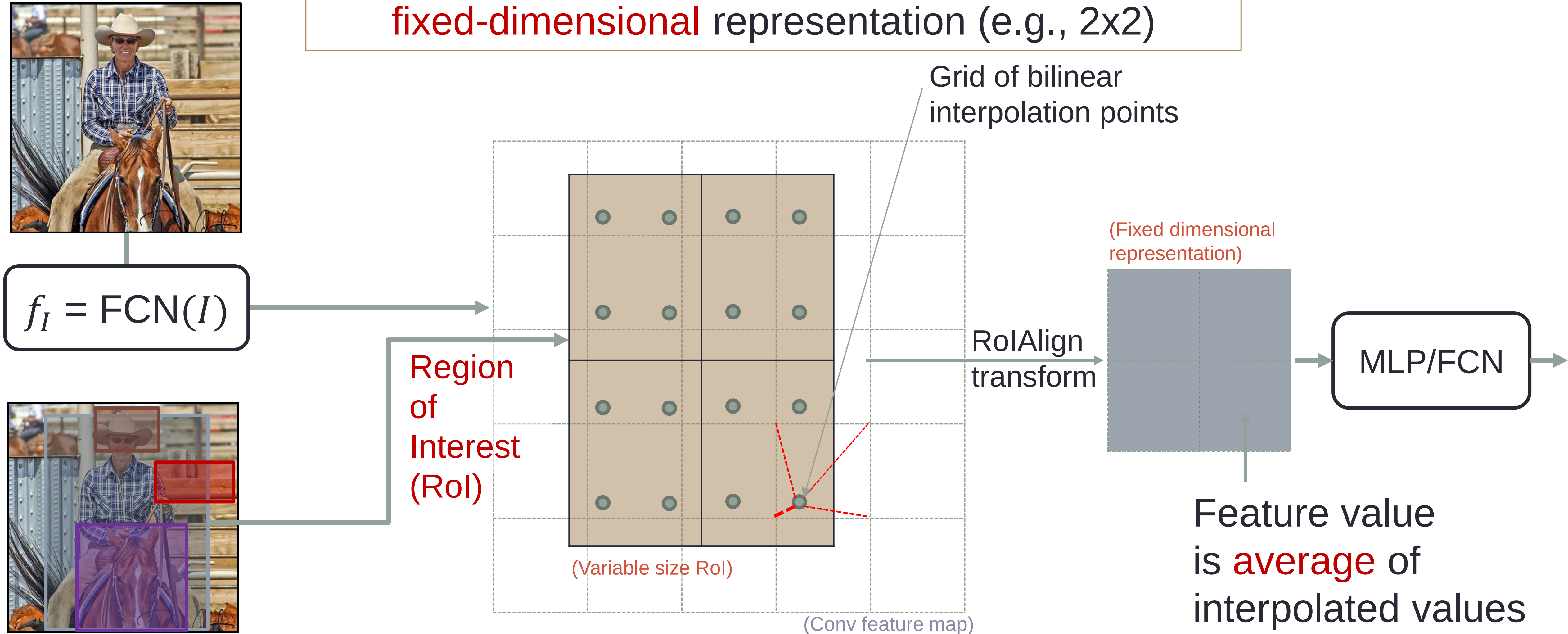


RoI**Pool** is replaced with RoI**Align**

He et al. Mask R-CNN. ICCV 2017.
Best Paper Award

5. RoIAlign Operation (on each Proposal)

Transform arbitrary size proposal into a fixed-dimensional representation (e.g., 2x2)




person1.00
person1.00
person1.00
person1.00
person.98
person.91
person.74
surfboard1.00
surfboard1.00
surfboard.98
surfboard1.00
surfboard1.00


person1.00
person.88
tv.98
tv.84
person1.00
person1.00
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wine glass.99
dining table.95
wine glass1.00
wine glass1.00


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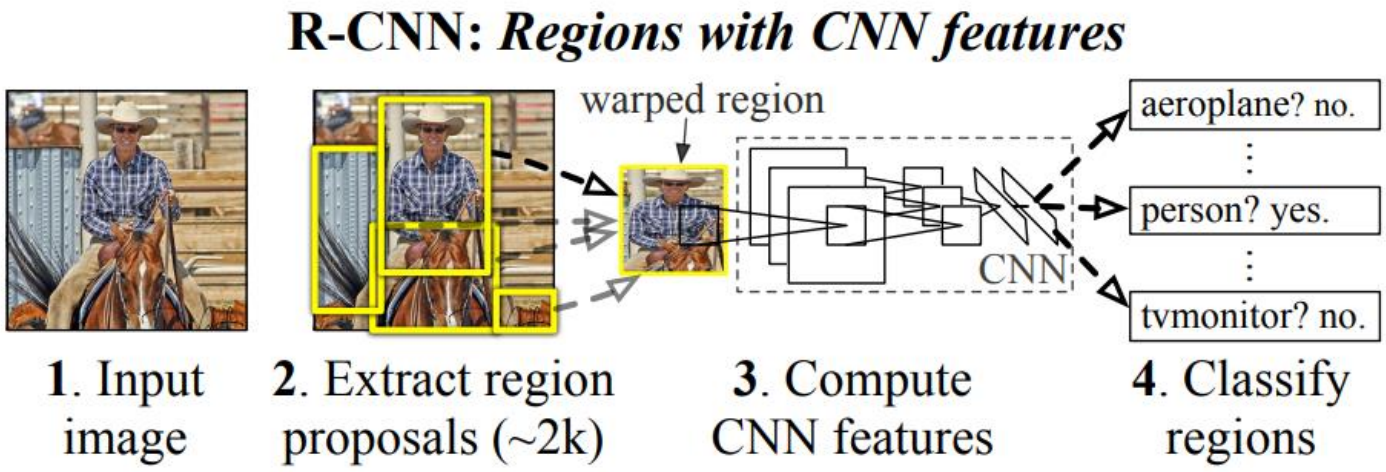
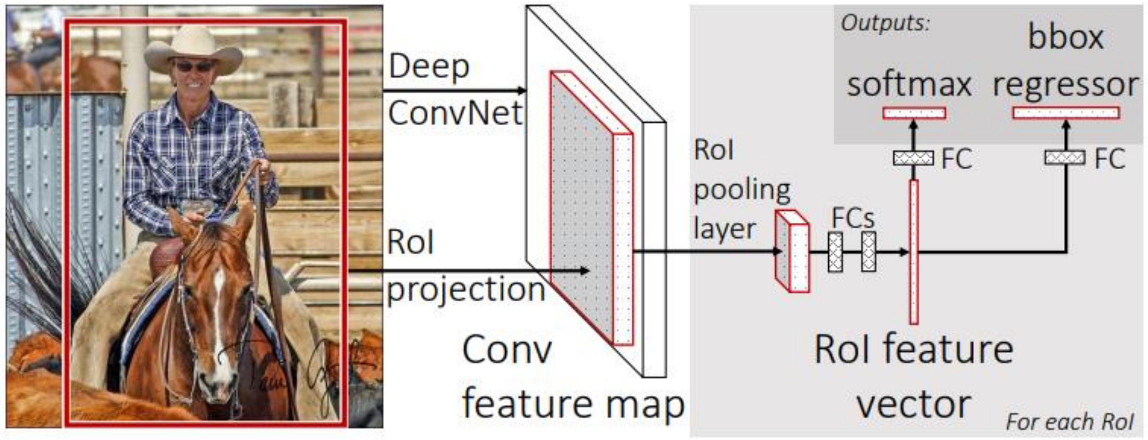
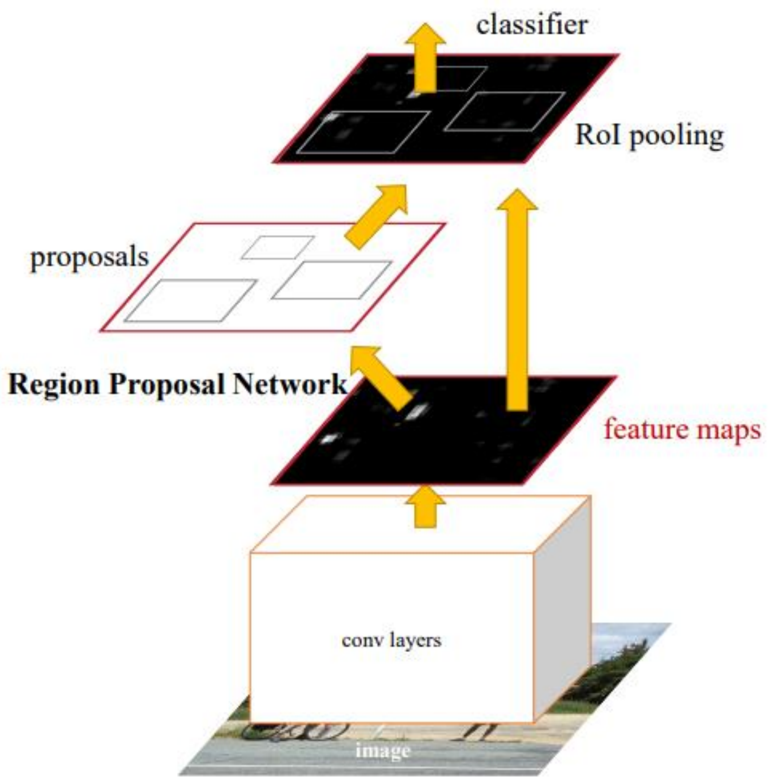
Summary of 1-5







Summary of 1-5

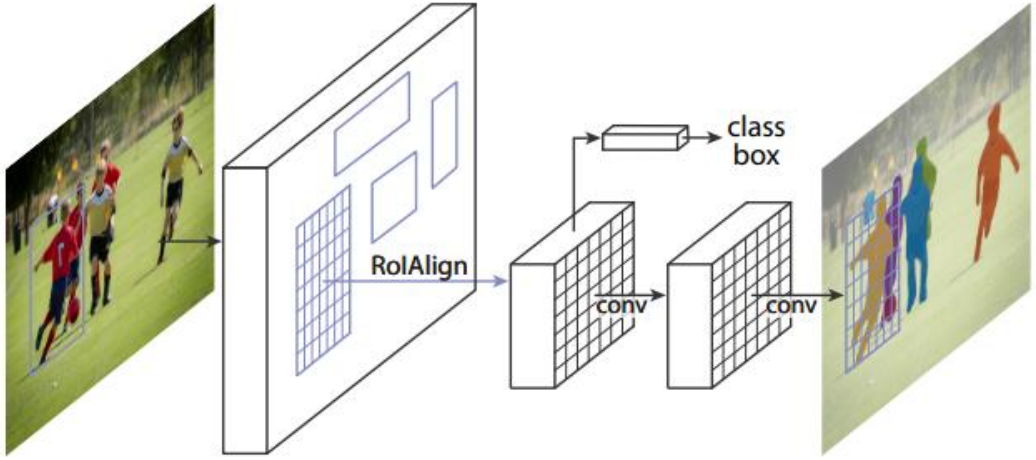
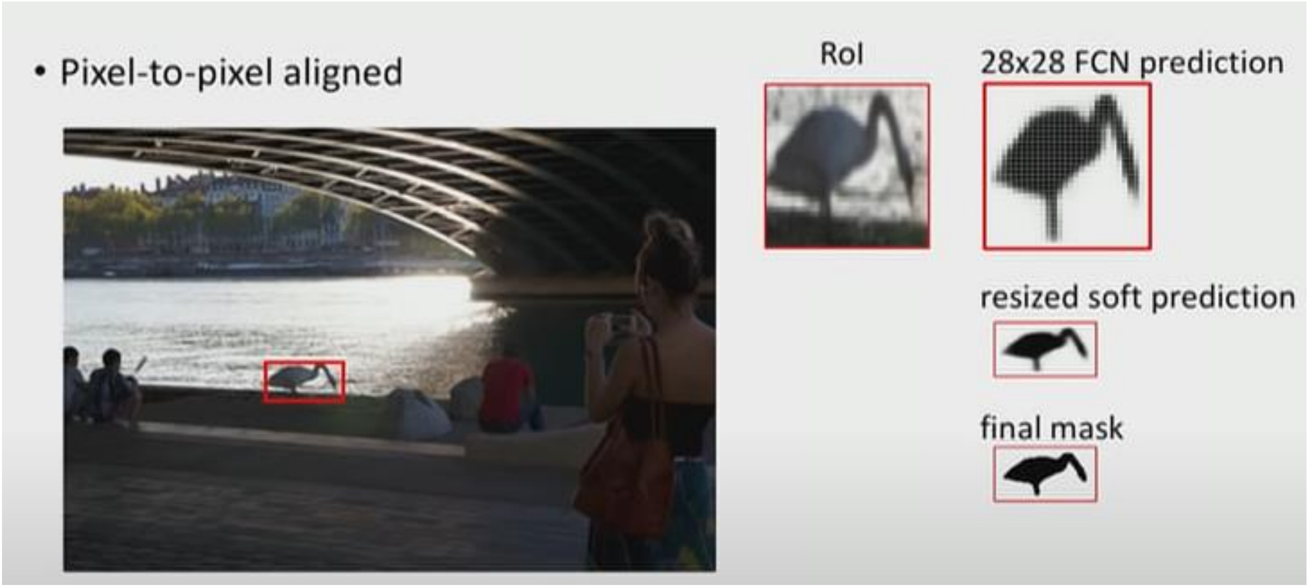
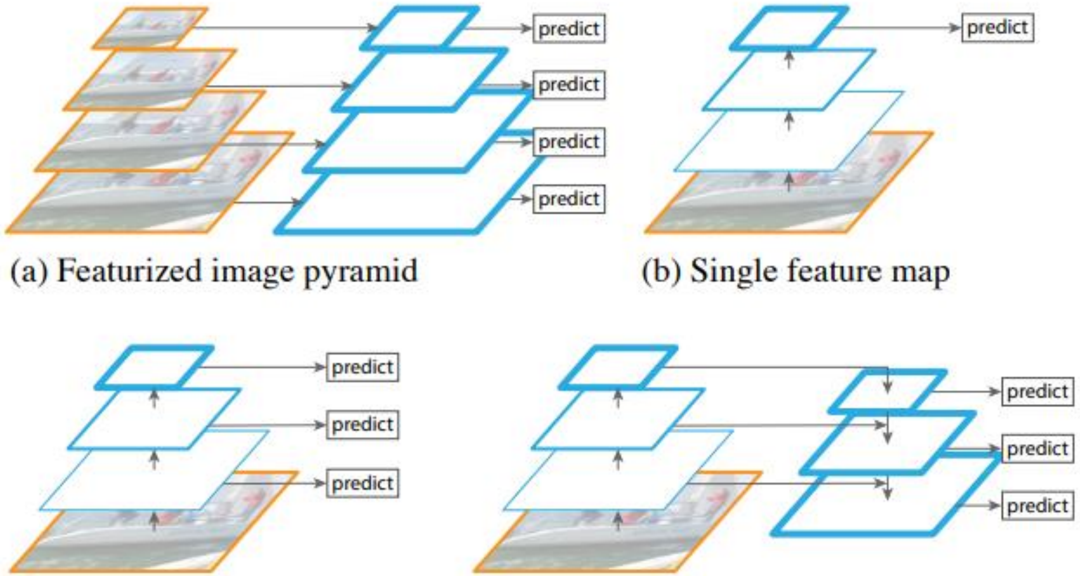


Figure 1. The **Mask R-CNN** framework for instance segmentation.

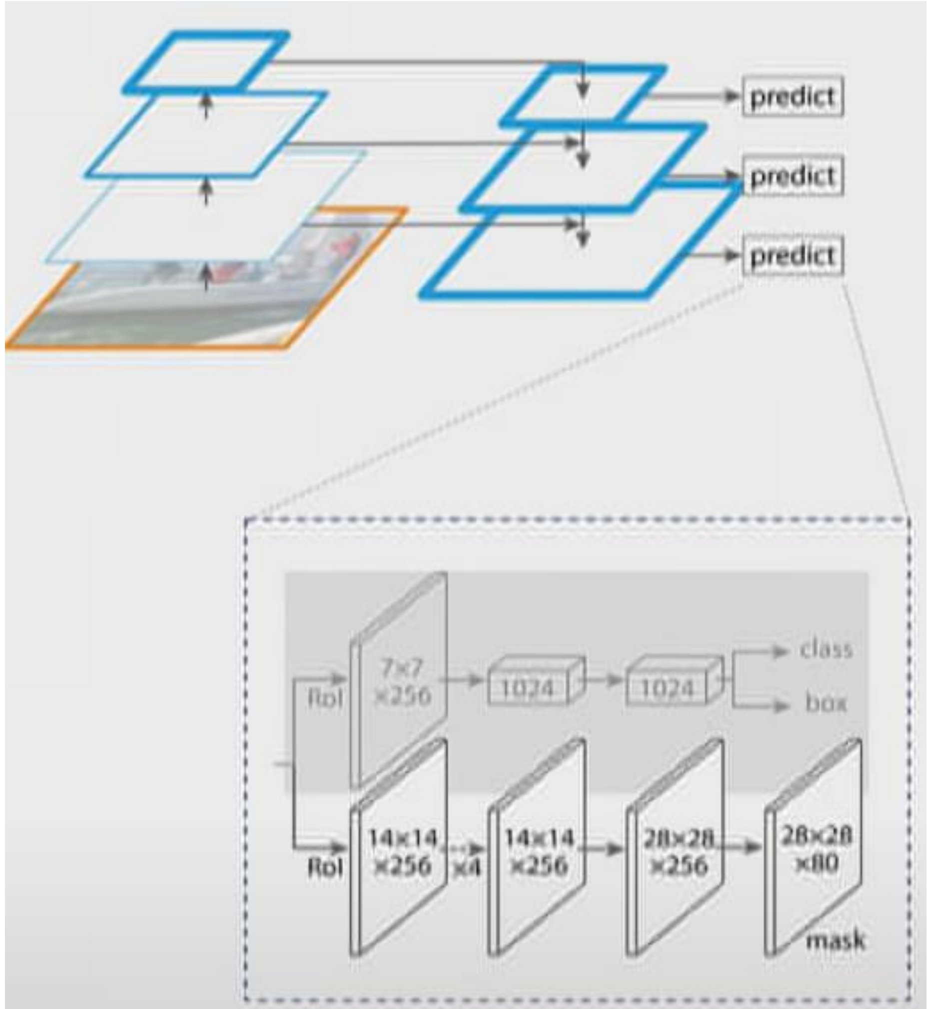


Summary of 1-5



(a) Featurized image pyramid (b) Single feature map

(c) Pyramidal feature hierarchy (d) Feature Pyramid Network

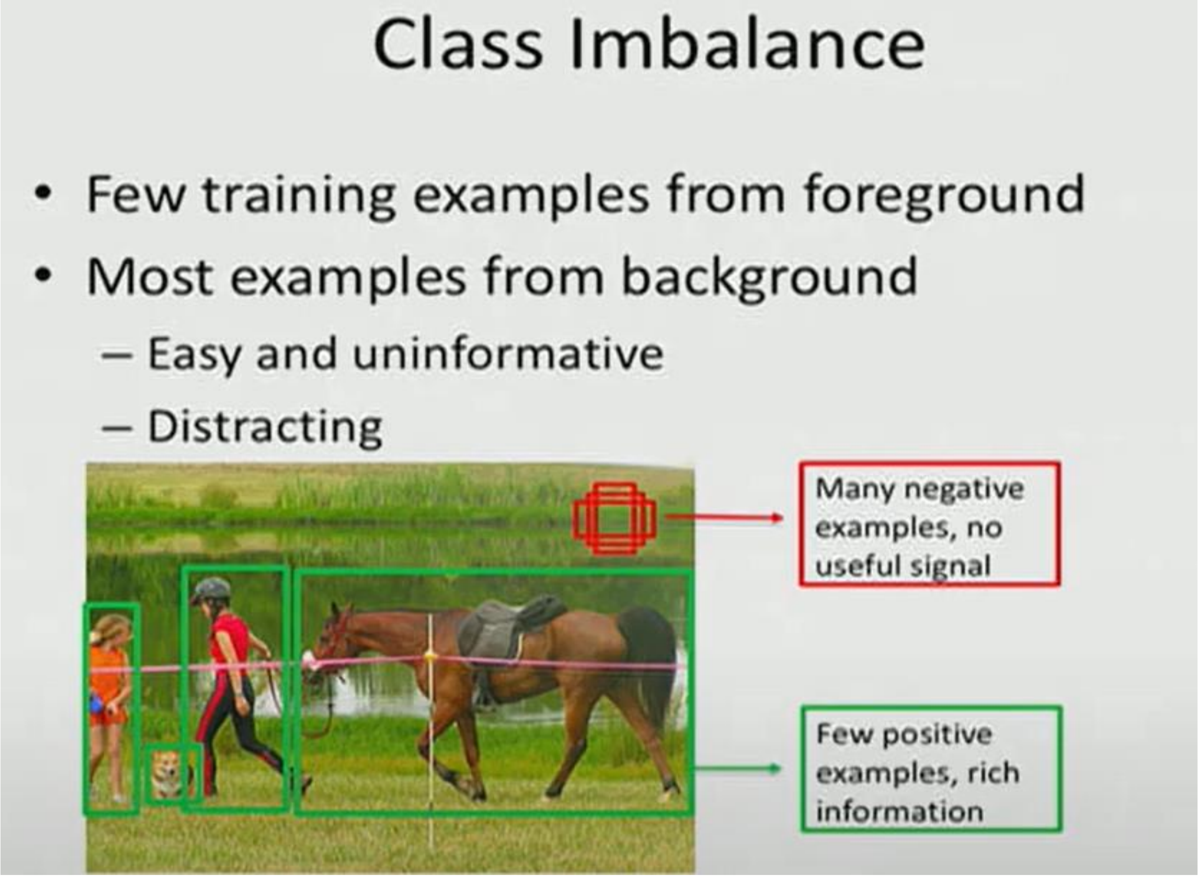


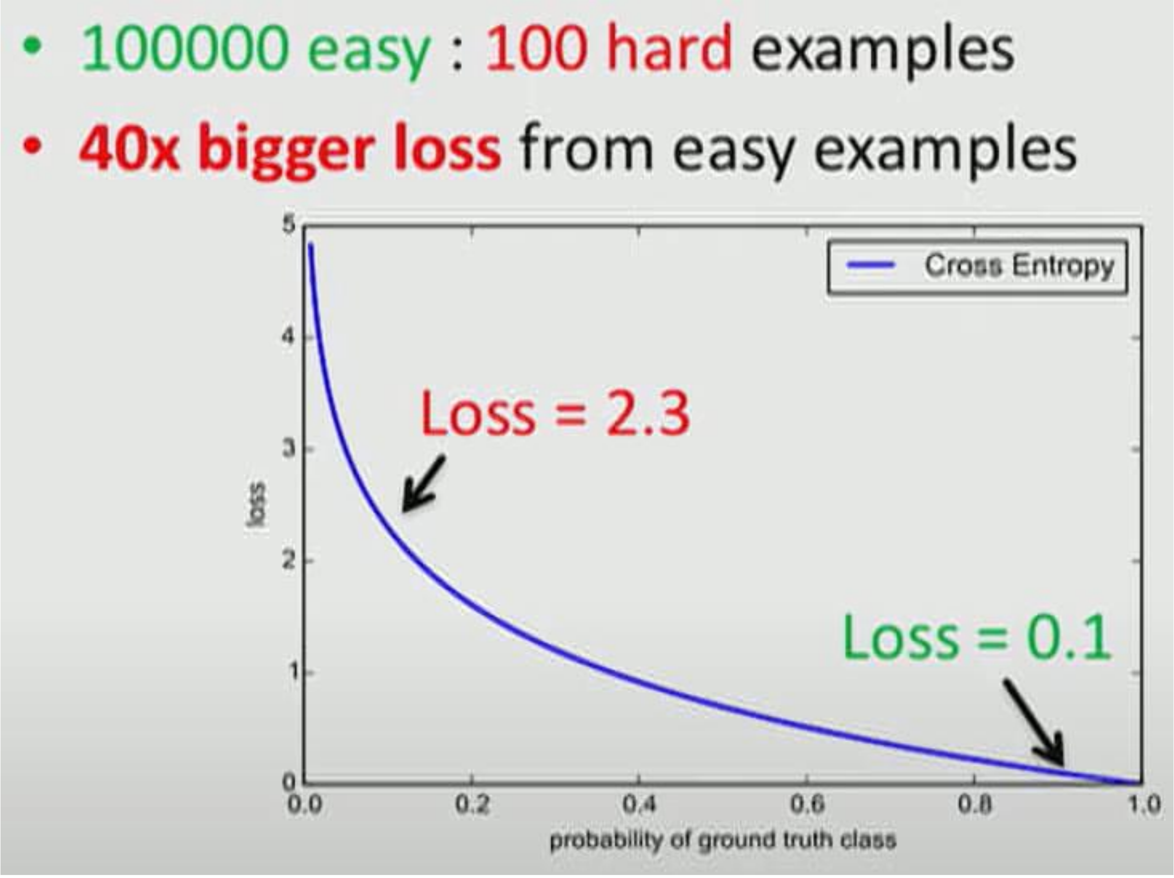
6. RetinaNet

Lin, Tsung-Yi, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. "Focal loss for dense object detection." In *IEEE International Conference on Computer Vision*, pp. 2980-2988. 2017.
Best Student Paper Award

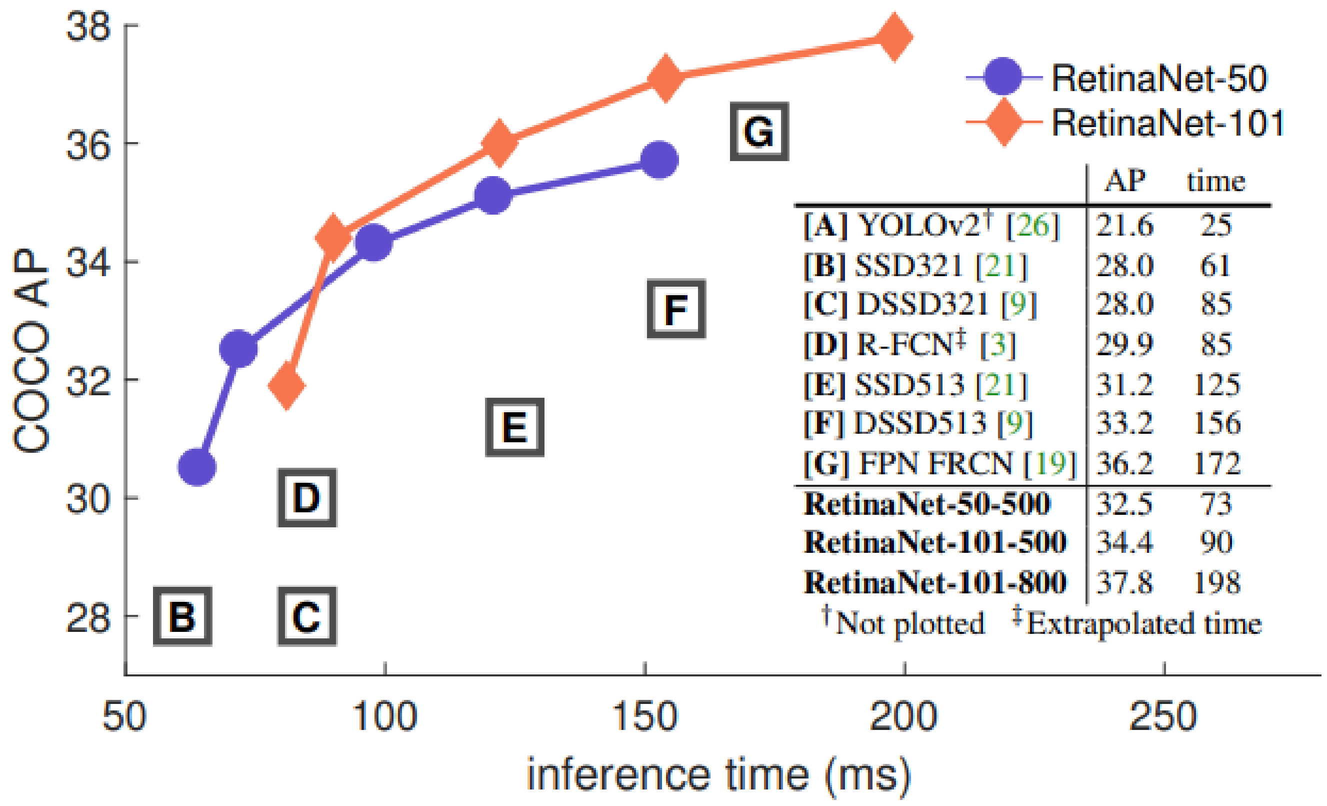
- Identify **class imbalance** is the major issue for training one-stage dense detector
- Propose **Focal Loss** to address class imbalance
- Achieve state-of-the-art **accuracy** and **speed**

6. RetinaNet


Class Imbalance
• Few training examples from foreground
• Most examples from background
– Easy and uninformative
– Distracting
Many negative examples, no useful signal
Few positive examples, rich information


• 100000 easy : 100 hard examples
• 40x bigger loss from easy examples
Cross Entropy
Loss = 2.3
Loss = 0.1
loss
probability of ground truth class
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4
5

6. RetinaNet

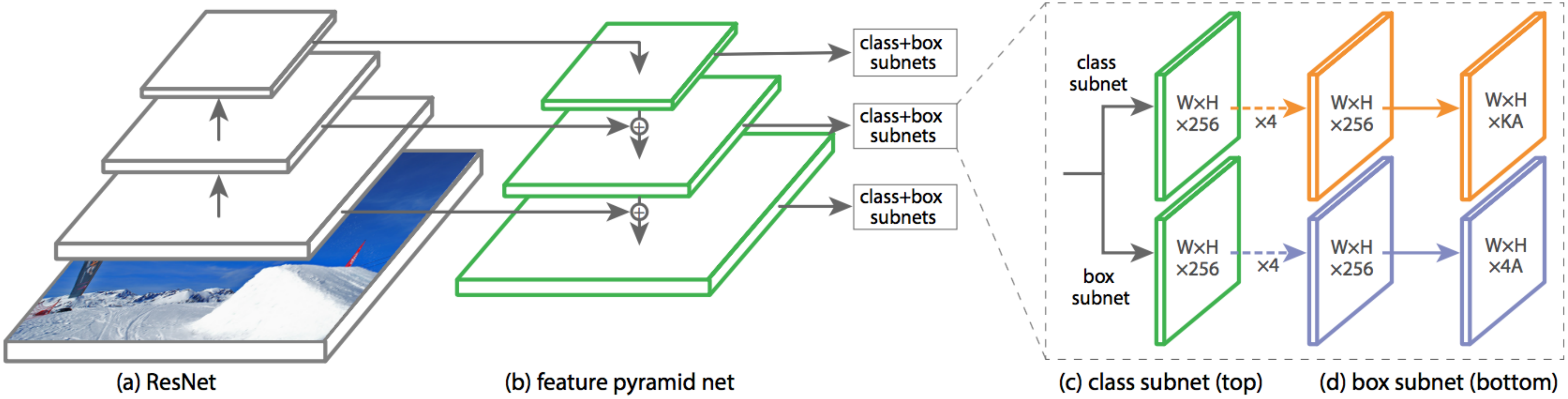


	AP	time
[A] YOLOv2† [26]	21.6	25
[B] SSD321 [21]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [21]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [19]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

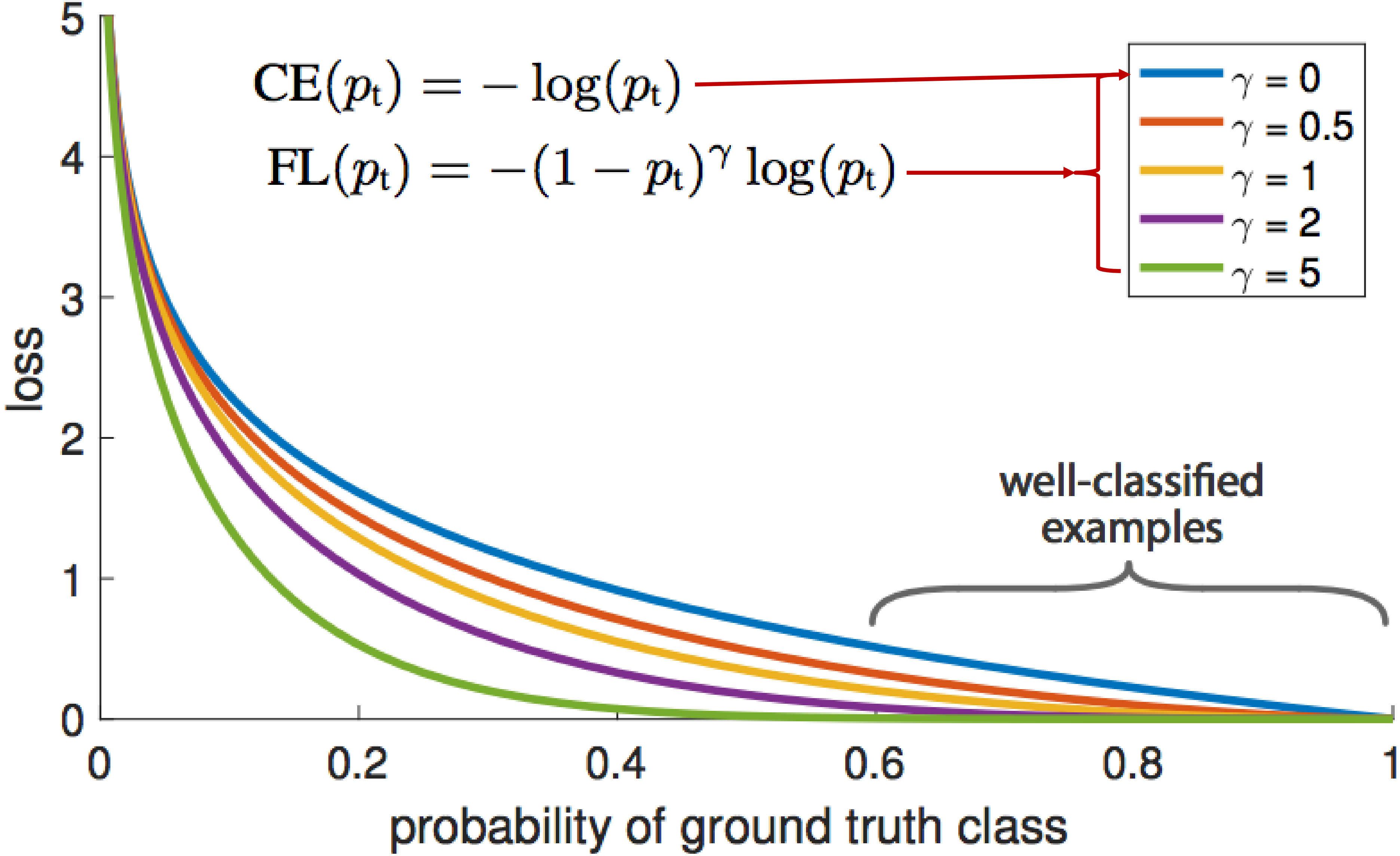
The one-stage RetinaNet detector outperforms all previous one-stage and two-stage detectors

6. RetinaNet Model Description



- Backbone with FPN
- 6 anchors per location (2 scales × 3 aspect ratios)
- 100 – 200k anchor boxes to classify per image → "dense" detection

6. Focal Loss: larger Gamma focuses more on Hard-Example



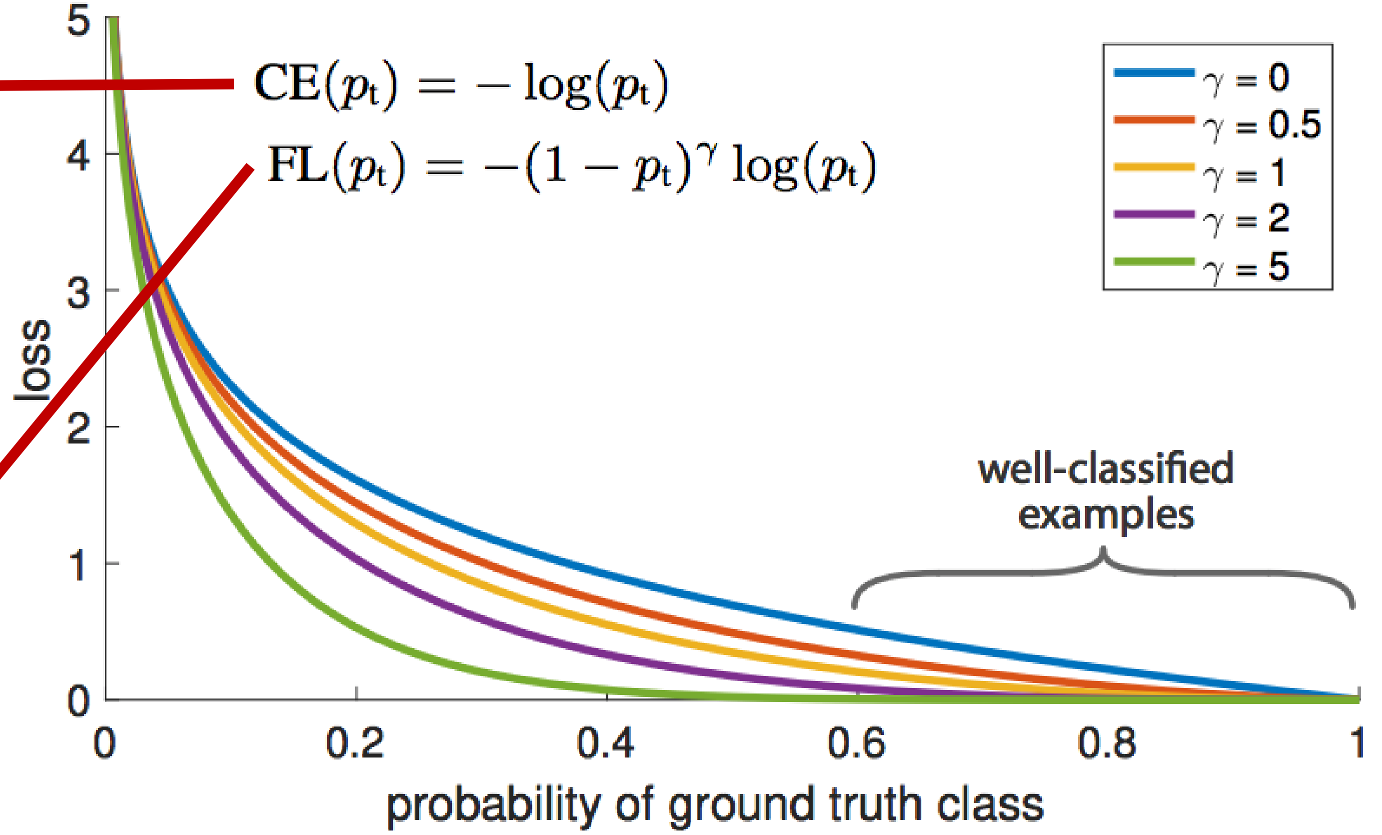
6. Impact of Focal Loss (FL)

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

γ	α	AP	AP_{50}	AP_{75}
0	.75	31.1	49.4	33.0
0.1	.75	31.4	49.9	33.1
0.2	.75	31.9	50.7	33.4
0.5	.50	32.9	51.7	35.2
1.0	.25	33.7	52.0	36.2
2.0	.25	**34.0**	**52.5**	**36.5**
5.0	.25	32.2	49.6	34.8

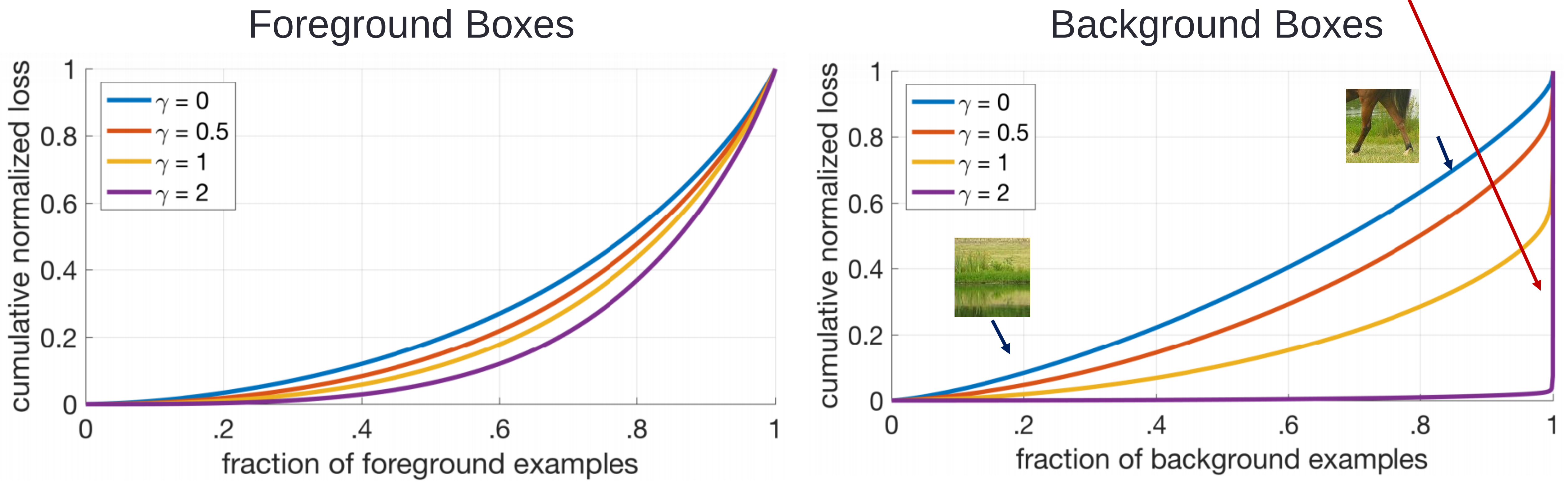
(b) **Varying γ for FL** (w. optimal α)

(ResNet-50-FPN 600px input image)



6. Loss Distribution under Focal Loss

Hard mining behavior



Reference:

1. Dr. Ross Girshick, Facebook AI Research, CVPR 2019 Tutorial on Visual Recognition and Beyond
https://www.dropbox.com/s/rakgo35h6b8p7uv/cvpr2019_tutorial_ross_girshick.pptx?dl=0

2. Dr. Kaiming He, ICCV 2017 Oral Talk for the Mask R-CNN paper.
https://www.youtube.com/watch?v=g7z4mkfRjI4&ab_channel=ComputerVisionFoundationVideos

3. Dr. Tsung-Yi Lin, ICCV 2017 Oral Talk for the Focal Loss paper.
https://www.youtube.com/watch?v=44tlnmmt3h0&ab_channel=ComputerVisionFoundationVideos