4-4 More Examples

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MobileNet

1. A computationally efficient model, which can be deployed on mobiles
   - It is based on “a timely fasion on a computationally limited platform”
   - It uses “depth-wise separable convolutions”

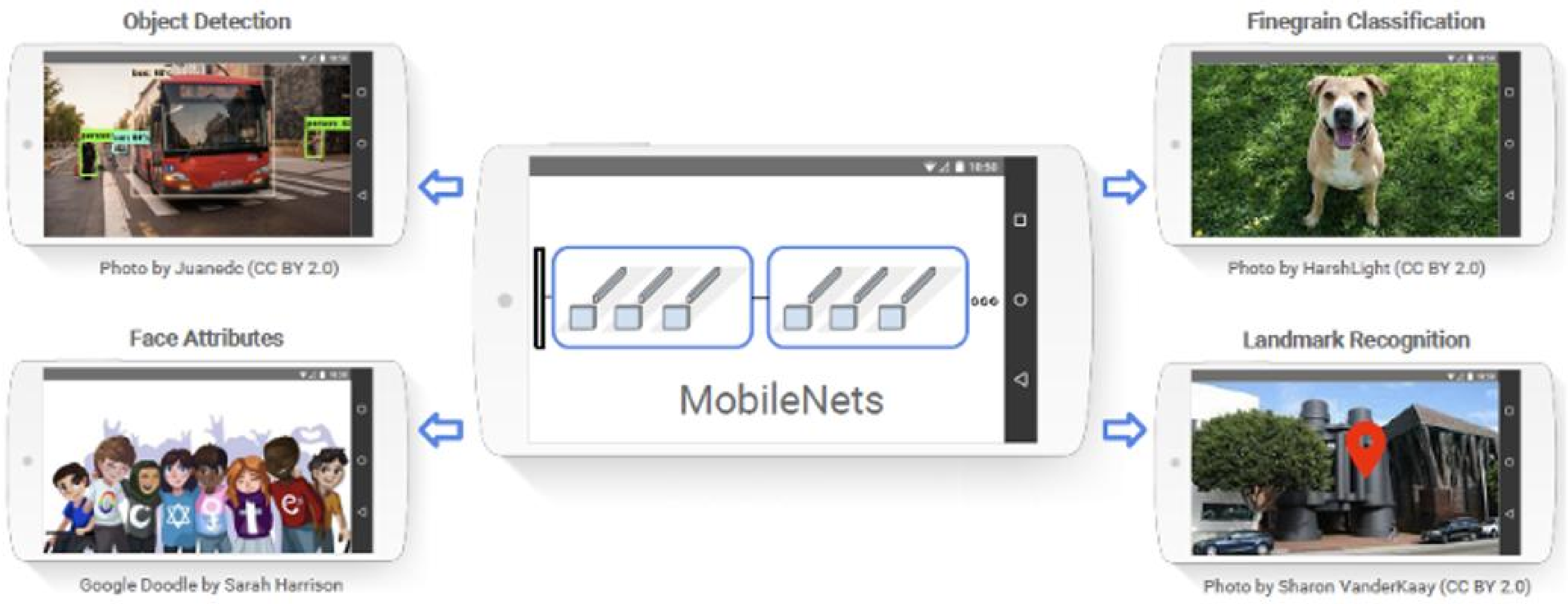
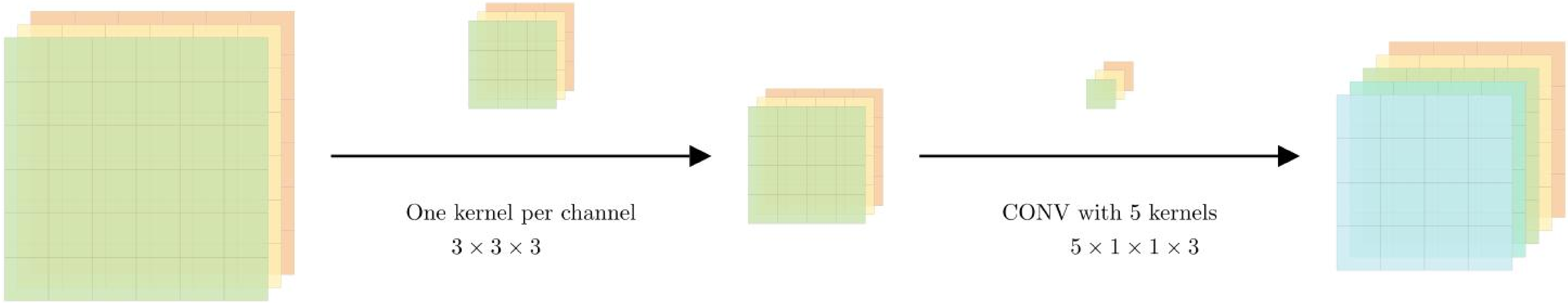


Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

[Howard, A.G., Zhu, M., Chen, B. et al., (2017) MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications]

Motivating example



Input $\mathbb{R}^{6\times6\times3}$

Output $\mathbb{R}^{4\times4\times5}$

1. There are only $3 \times 3 \times 3 + 3 \times 5$=42 parameters for this layer

YOLO

1. Up to now, we only consider classification tasks
2. Object detection is also an important task in practice
3. Next, we focus on classification as well as location detection

YOLO

[https://www.superannotate.com/blog/yolo-object-detection]

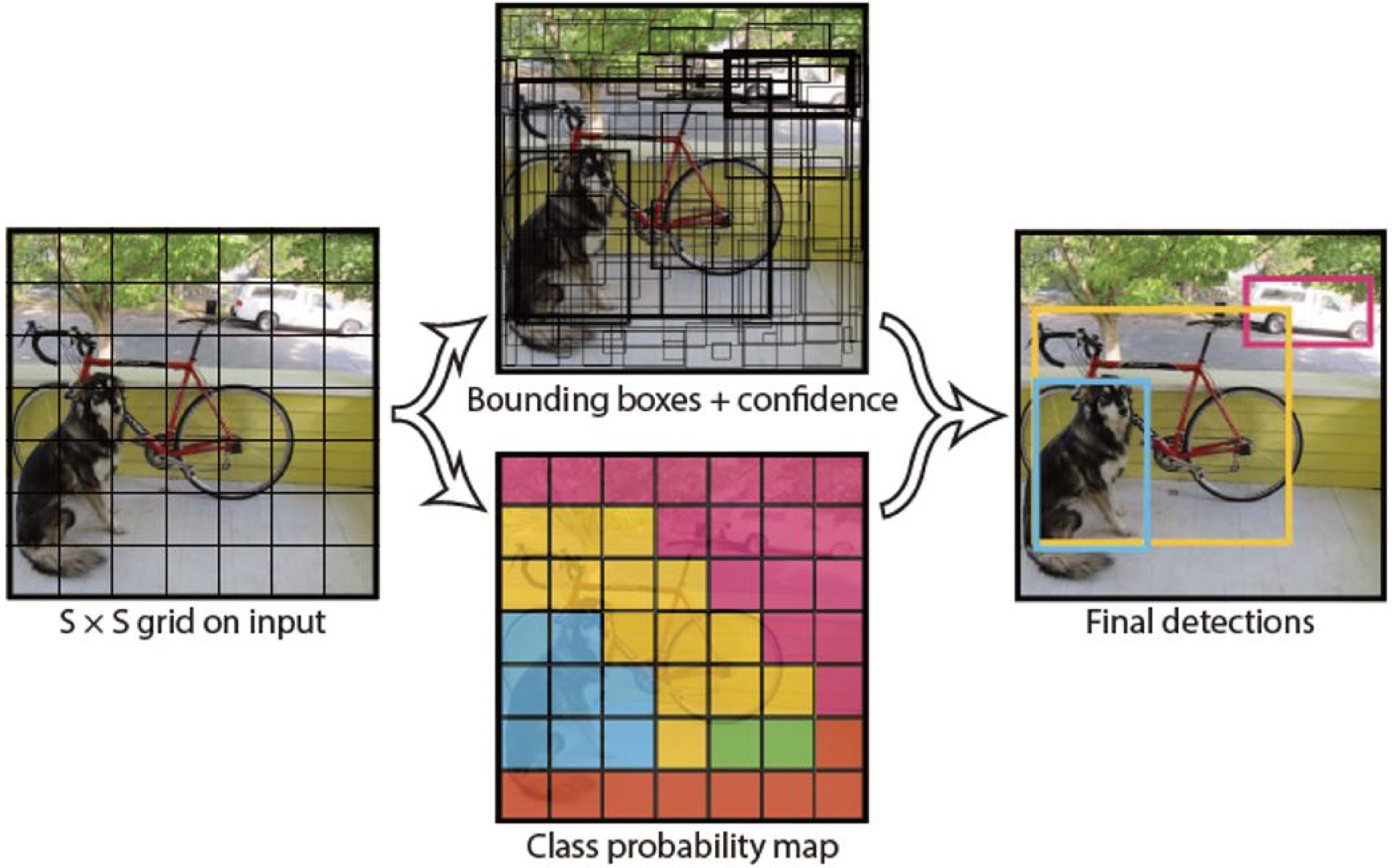
YOLO

1. We are interested in classifying C classes and identifying locations
2. YOLO (You Only Look Once) provides a good solution
3. We only focus on YOLO v1 (Redmon et al., 2016)
4. See https://www.bilibili.com/video/BV1JT411j7MR?p=2 for more details

YOLO v1

1. Partition the image into $S \times S$ grid cells
2. Form B bounding boxes for each grid cell
3. For each grid cell, use IoU to select one "representative" bounding box
4. Minimize a specific cost function
5. Use non-max supression algorithm to finalize the boundary

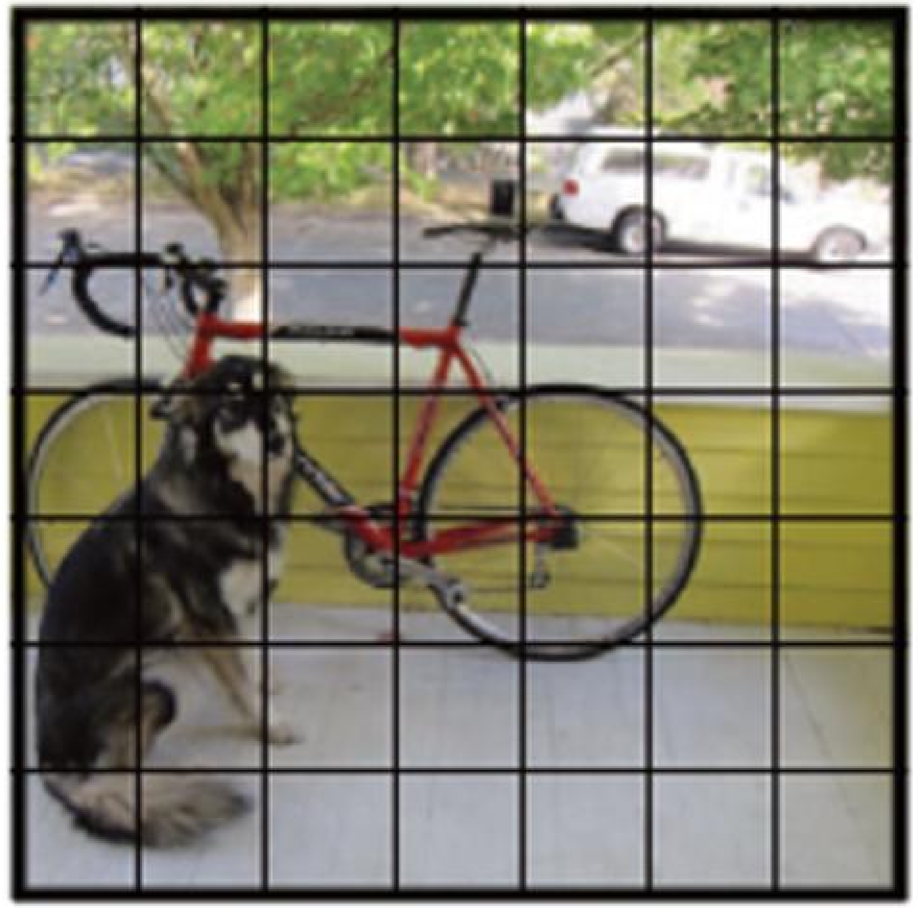
YOLO v1



[Redmon, J., Divvala, S., Girshick, R., Farhadi, A. (2016), You Only Look Once: Unified, Real-Time Object Detection, CVPR, 779–788]

YOLO v1

1. Partition the image into $S \times S$ grid cells



S × S grid on input

YOLO v1

1. For each grid cell, consider two candidate bounding boxes
   - Only one bounding box is representative for the object, and IoU is used to select it
   - Each bounding box is represented by five elements
     - ▷ x, y: Center of the box relative to the bounds of that grid cell
     - ▷ w, h: width and height of the box relative to the whole image
     - ▷ $confidence$: confidence score that the box contains an object and how accurate it thinks the box is that it predicts.

YOLO v1

1. IoU is short for "intersection over union"
2. During the training procedure, we observe labels, so we can choose a box with larger IoU for each grid cell
3. This bounding box can be further tuned for the object

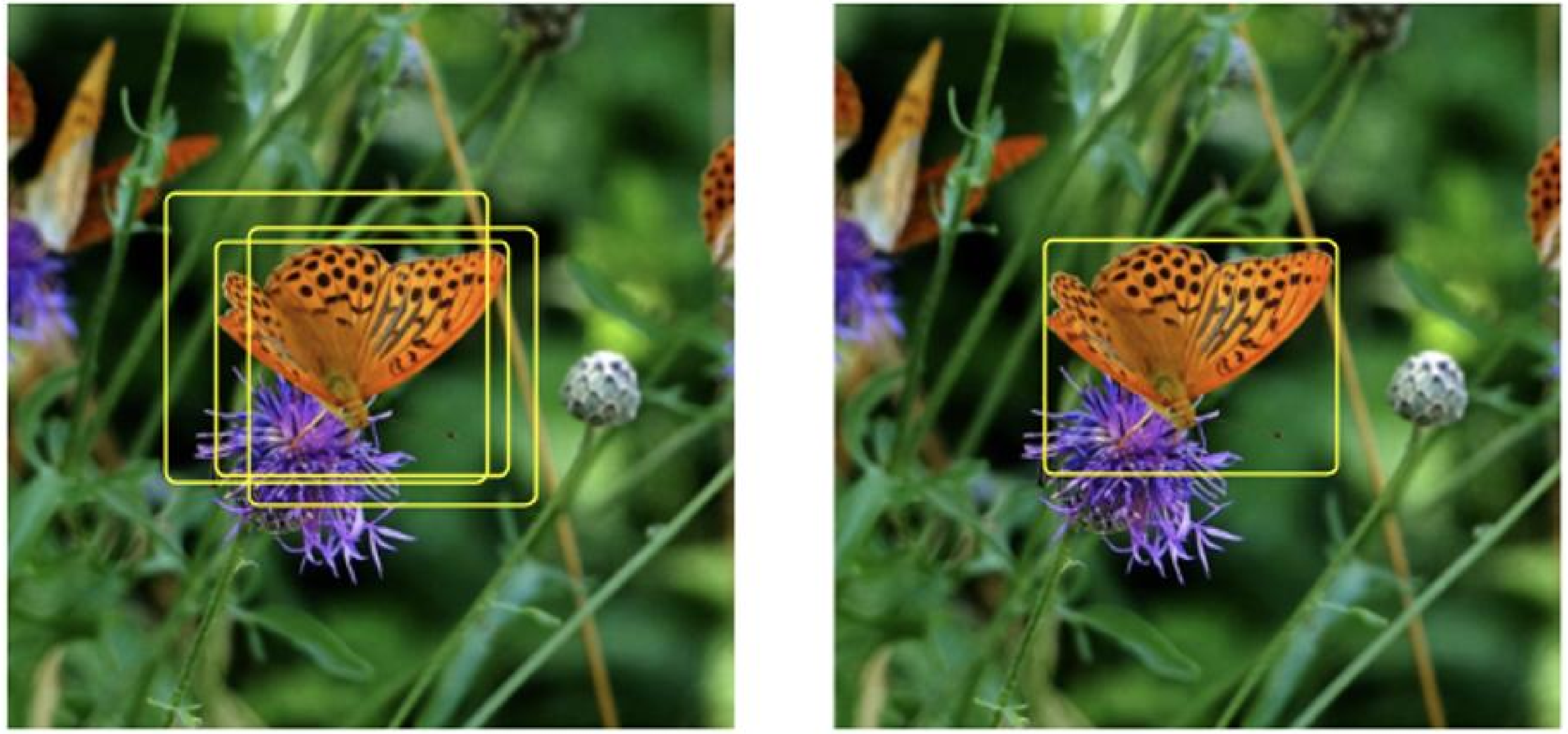
YOLO v1

1. The cost function, with $\lambda_{\text{coord}} = 5$ and $\lambda_{\text{noobj}} = 0.5$ is

$$
\begin{aligned}
&\lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 \right] \\
&+ \lambda_{\textbf{coord}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(\sqrt{w_i} - \sqrt{\hat{w}_i} \right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i} \right)^2 \right] \\
&+ \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \lambda_{\text{noobj}} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(C_i - \hat{C}_i \right)^2 \\
&+ \sum_{i=0}^{S^2} \mathbb{1}_{i}^{\text{obj}} \sum_{c \in \text{classes}} (p_i(c) - \hat{p}_i(c))^2 \qquad (3)
\end{aligned}
$$

YOLO v1

1. For each class, discard all bounding boxes with confidence less than a threshold
2. Among the remaining overlapping ones, only keep the one with the largest confidence, and discard those with IoU larger than a threshold



[https://www.oreilly.com/library/view/practical-machine-learning/9781098102357/ch04.html]