Deep Learning Basics

Lecture 6: Computer Vision Applications (Semantic Segmentation and Detection)

최성준 (고려대학교 인공지능학과)

Semantic Segmentation

Semantic Segmentation

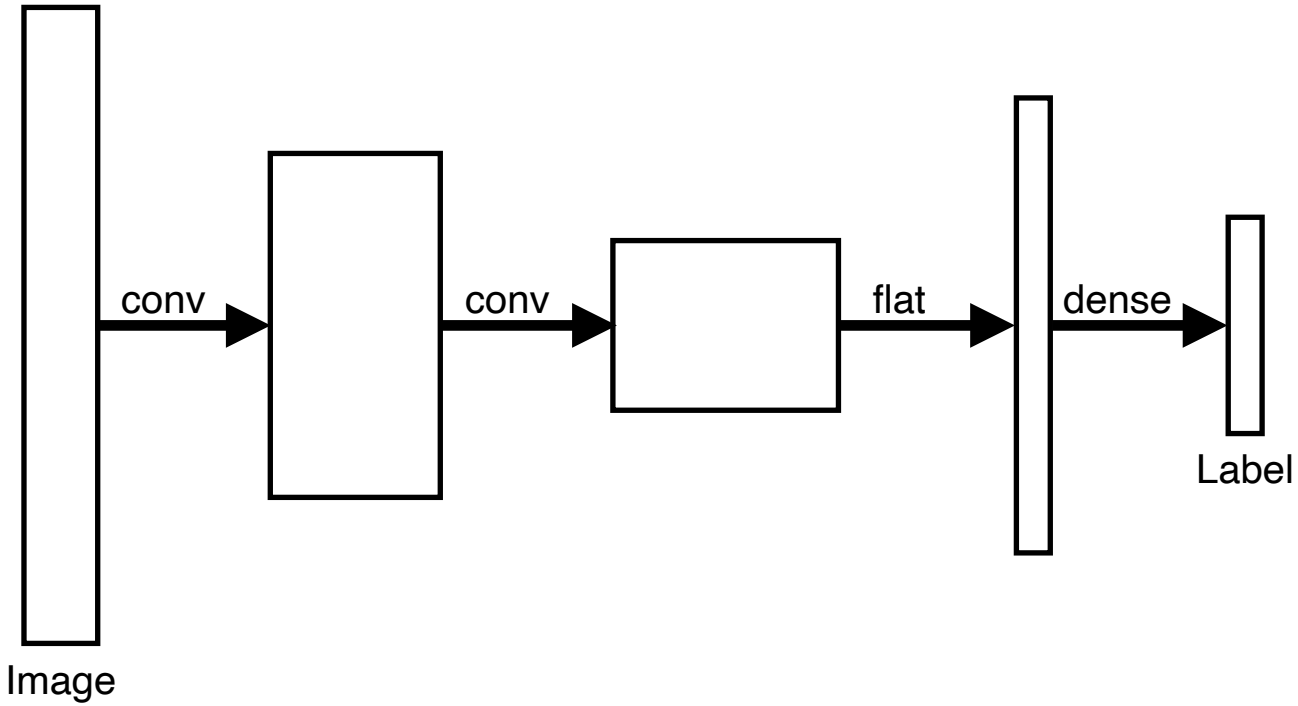
predict

Person
Bicycle
Background

Semantic Segmentation

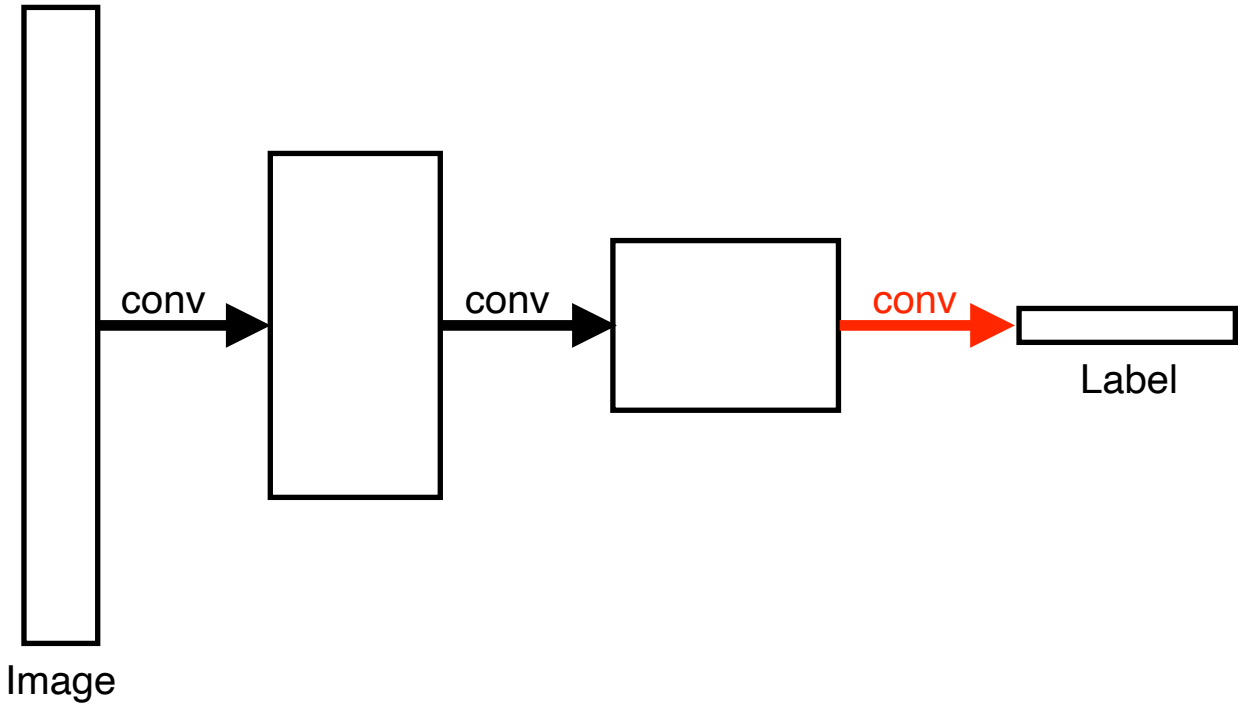
https://youtu.be/ATlcEDSPWXY

Fully Convolutional Network



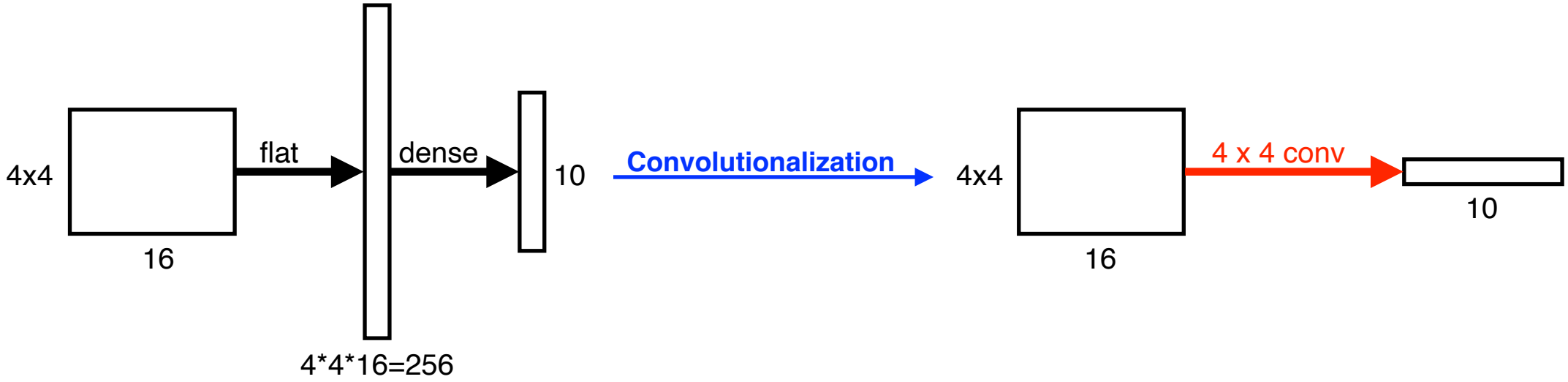
- This is how an ordinary CNN looks like.

Fully Convolutional Network



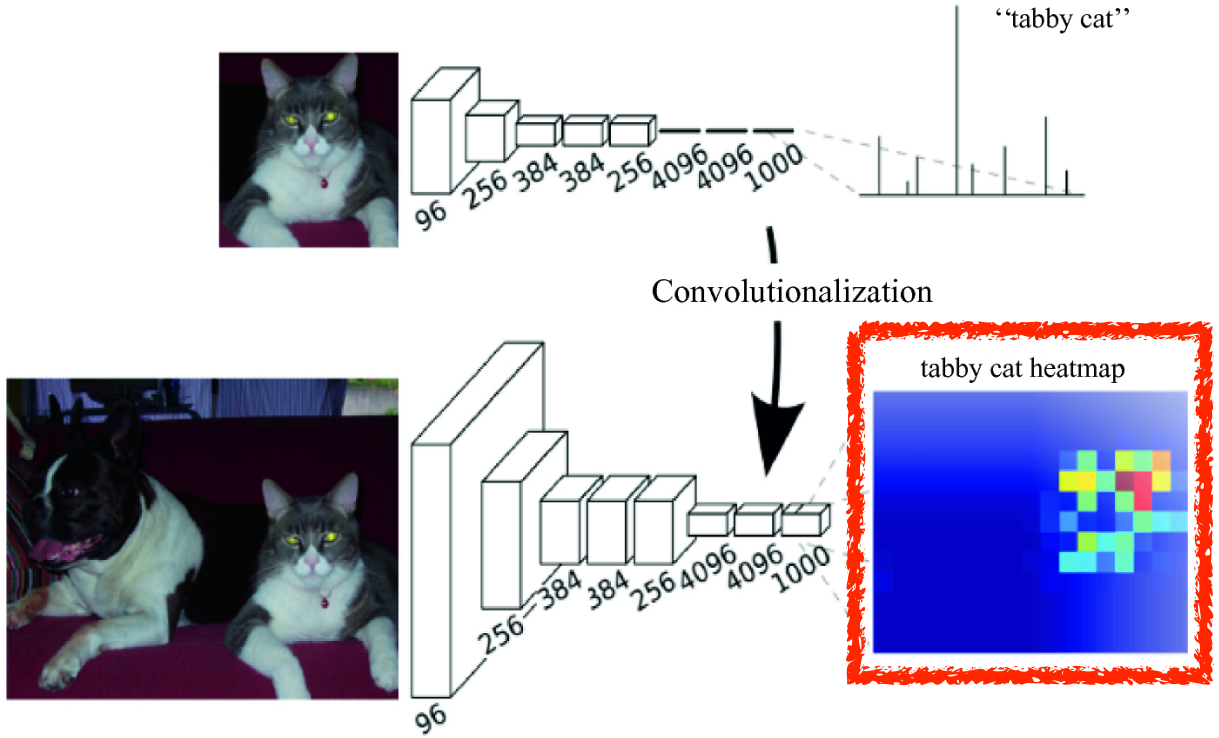
- This is a **fully convolutional** network.

Fully Convolutional Network



- # of parameters
  - Left: $4 \times 4 \times 16 \times 10 = 2{,}560$
  - **Right**: $4 \times 4 \times 16 \times 10 = 2{,}560$
- This process is called **convolutionalization**.

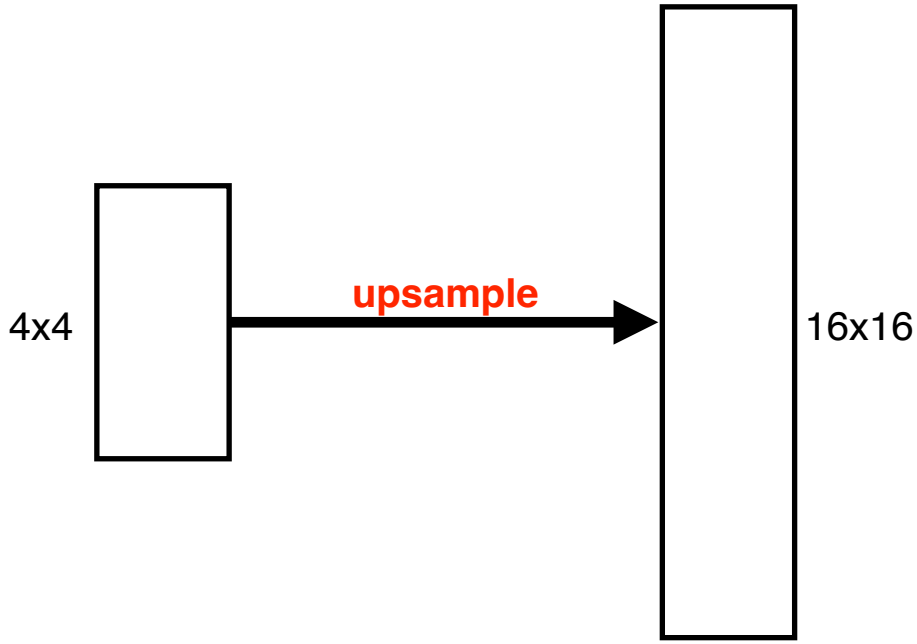
Fully Convolutional Network



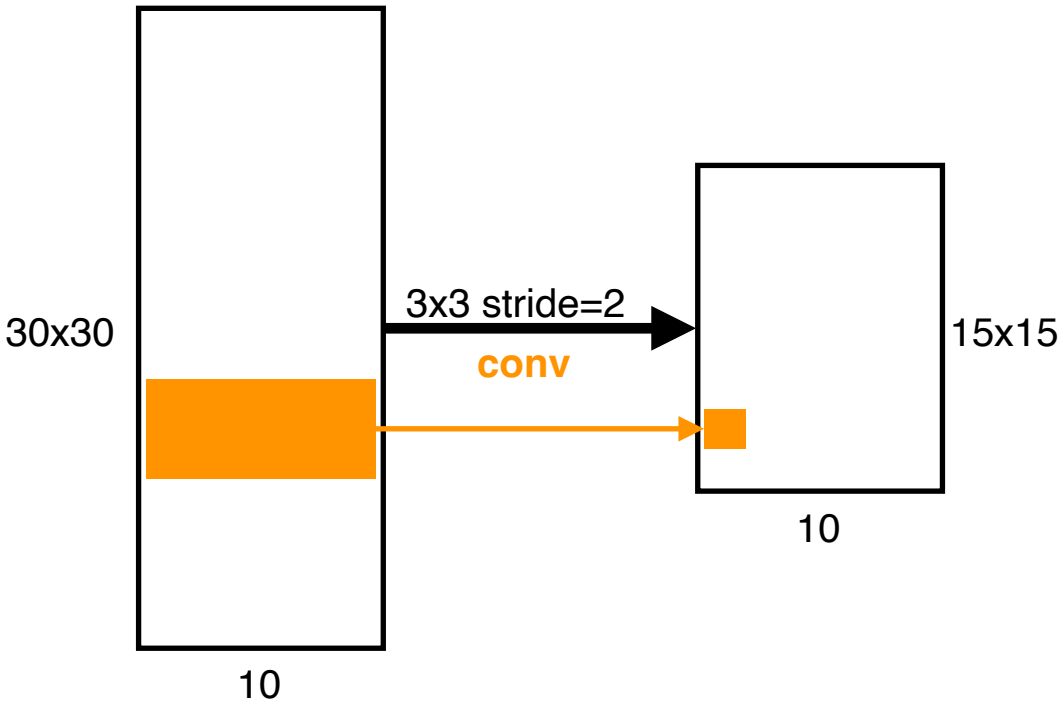
- Transforming fully connected layers into convolution layers enables a classification net to output a heap map.

Fully Convolutional Network

- While FCN can run with inputs of any size, the output dimensions are typically reduced by subsampling.
- So we need a way to connect the coarse output to the dense pixels.

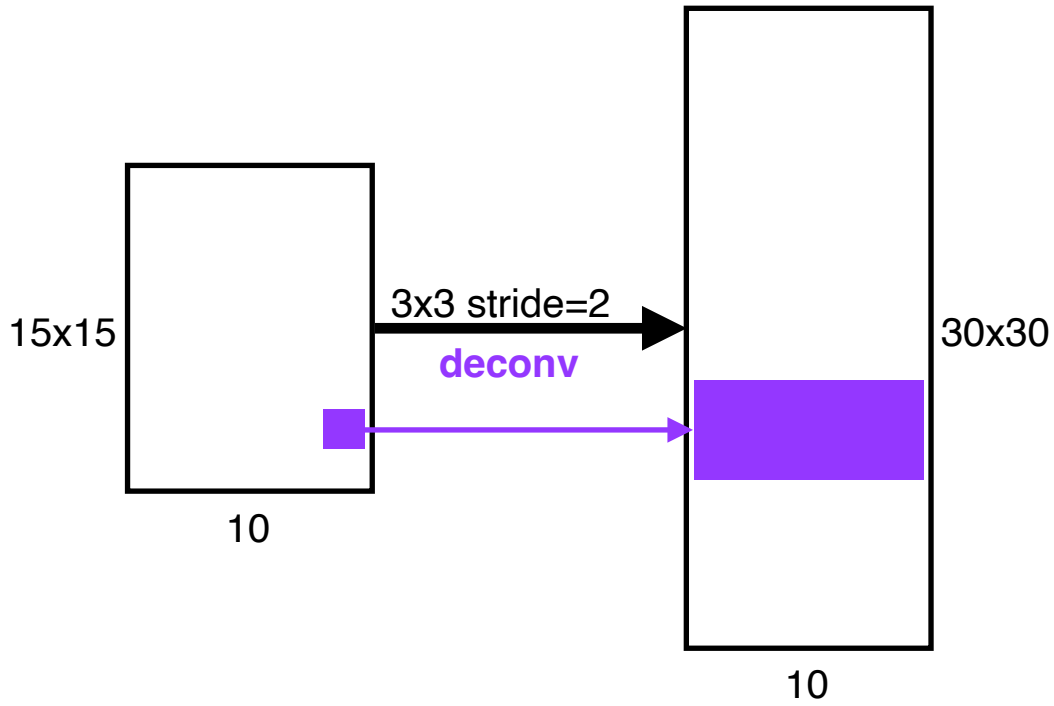


Deconvolution (conv transpose)



Convolution

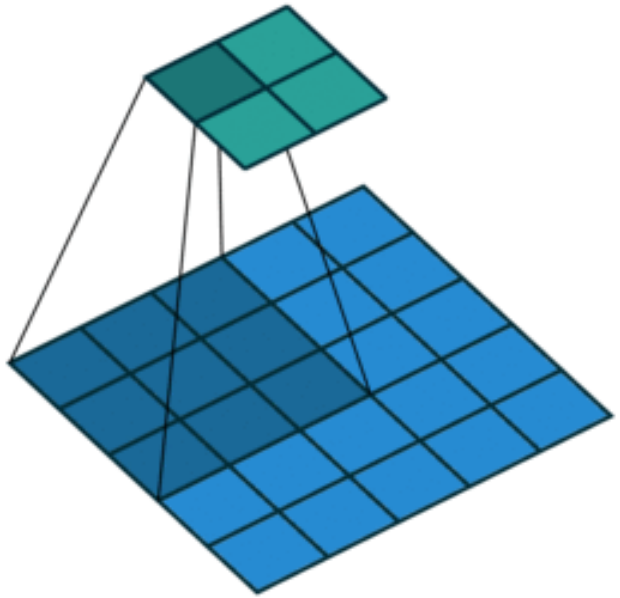
#param: 3*3*10*10



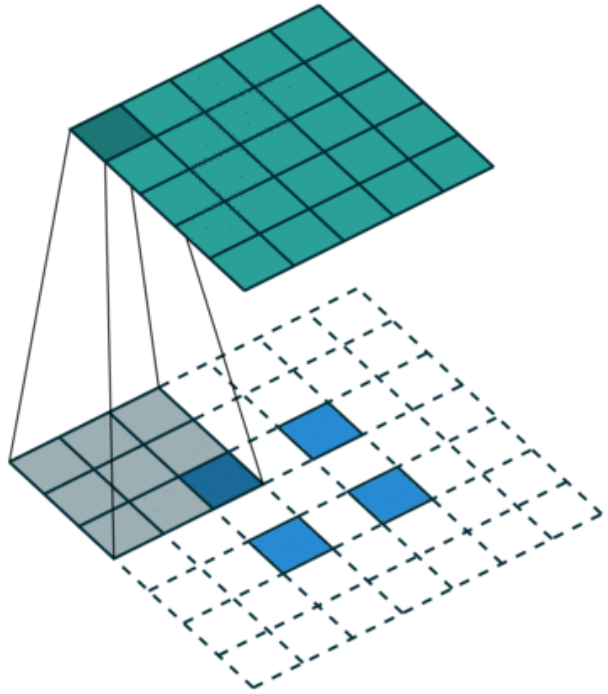
Deconvolution

#param: 3*3*10*10

Deconvolution (conv transpose)

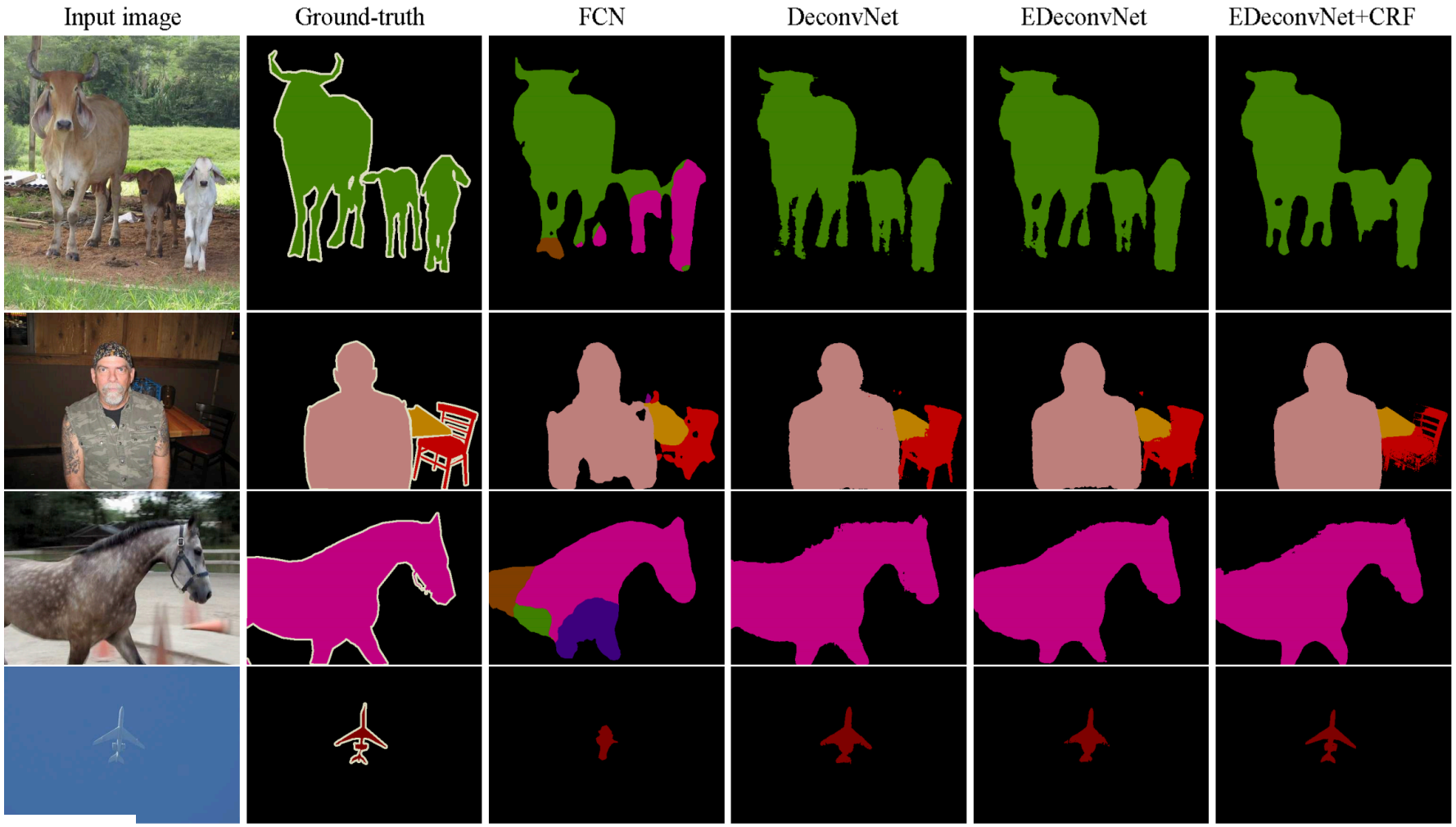


Convolution



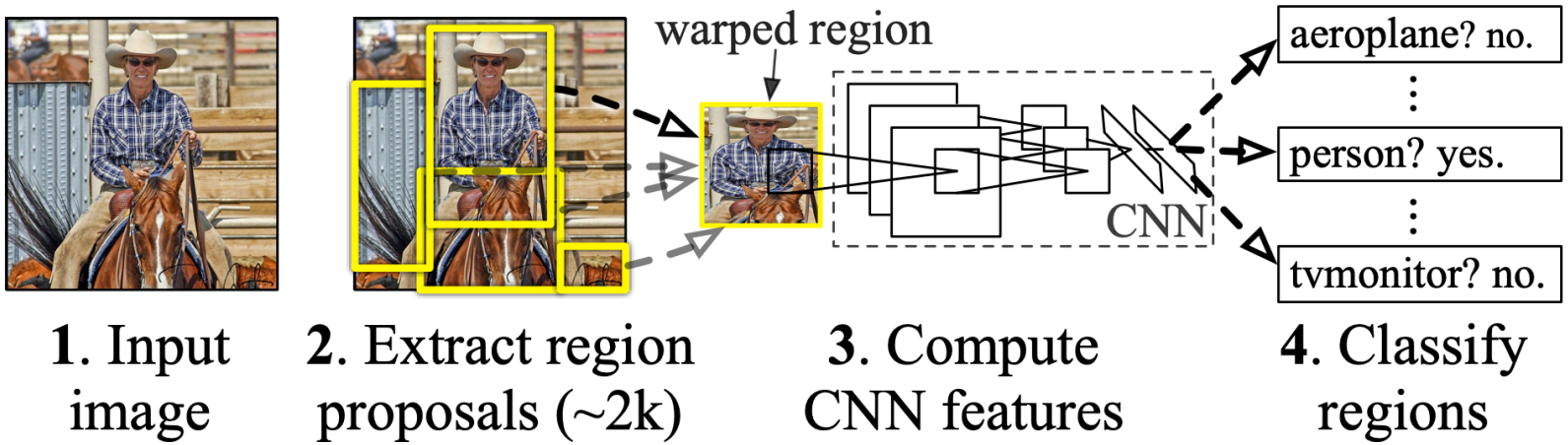
Deconvolution

Results



Detection

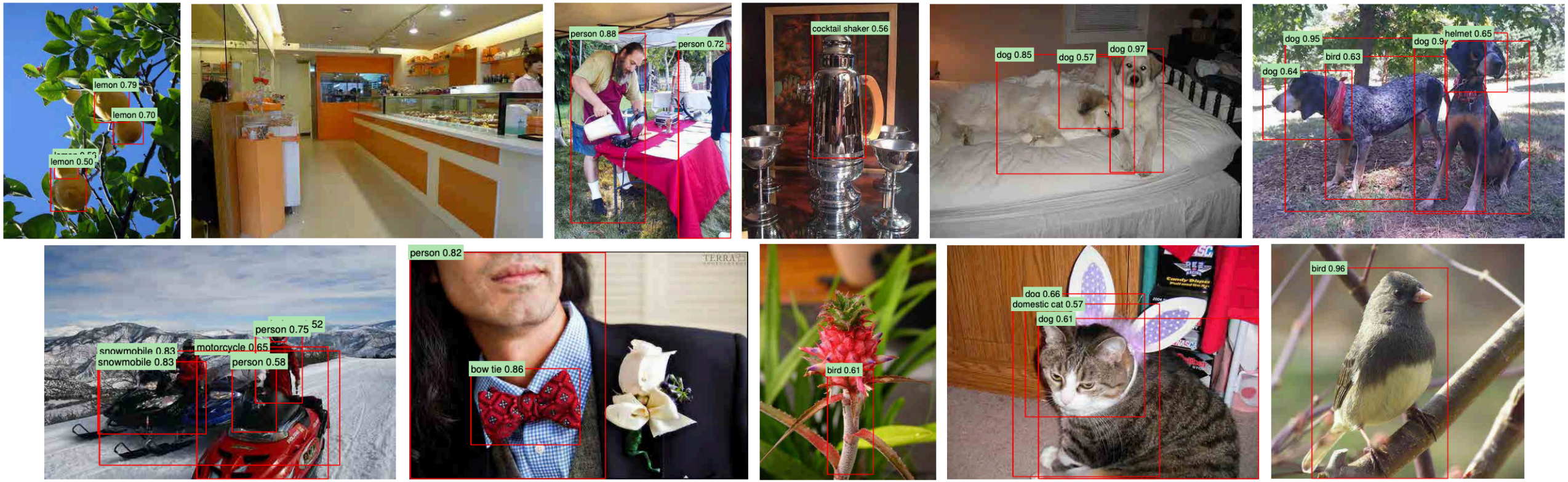
R-CNN



- R-CNN (1) takes an input image, (2) extracts around 2,000 region proposals (using Selective search), (3) compute features for each proposal (using AlexNet), and then (4) classifies with linear SVMs.

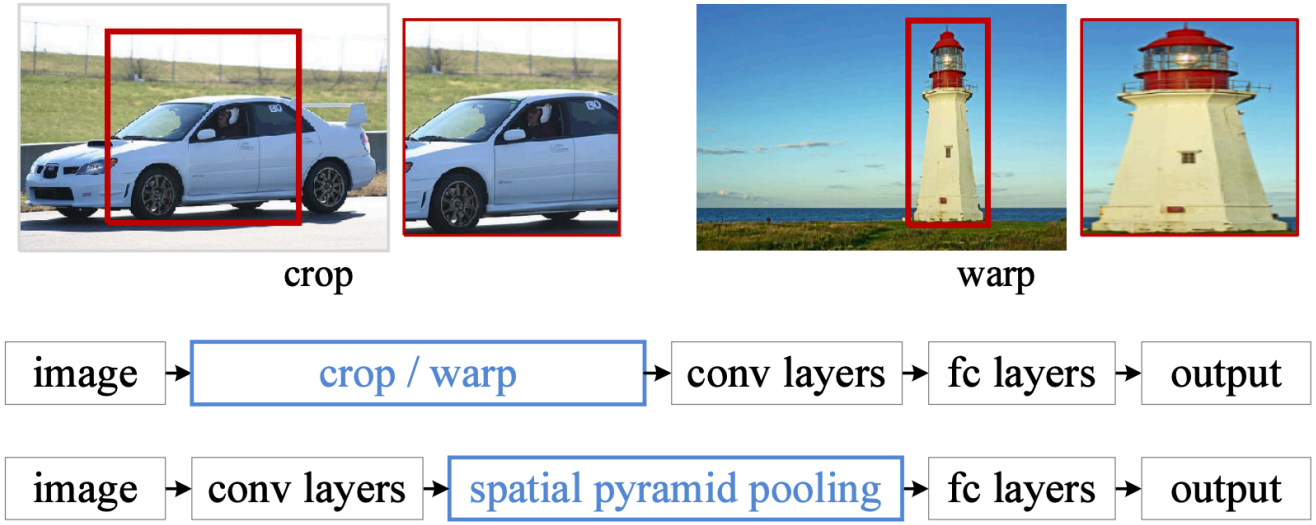
https://arxiv.org/pdf/1311.2524

R-CNN



https://arxiv.org/pdf/1311.2524

SPPNet

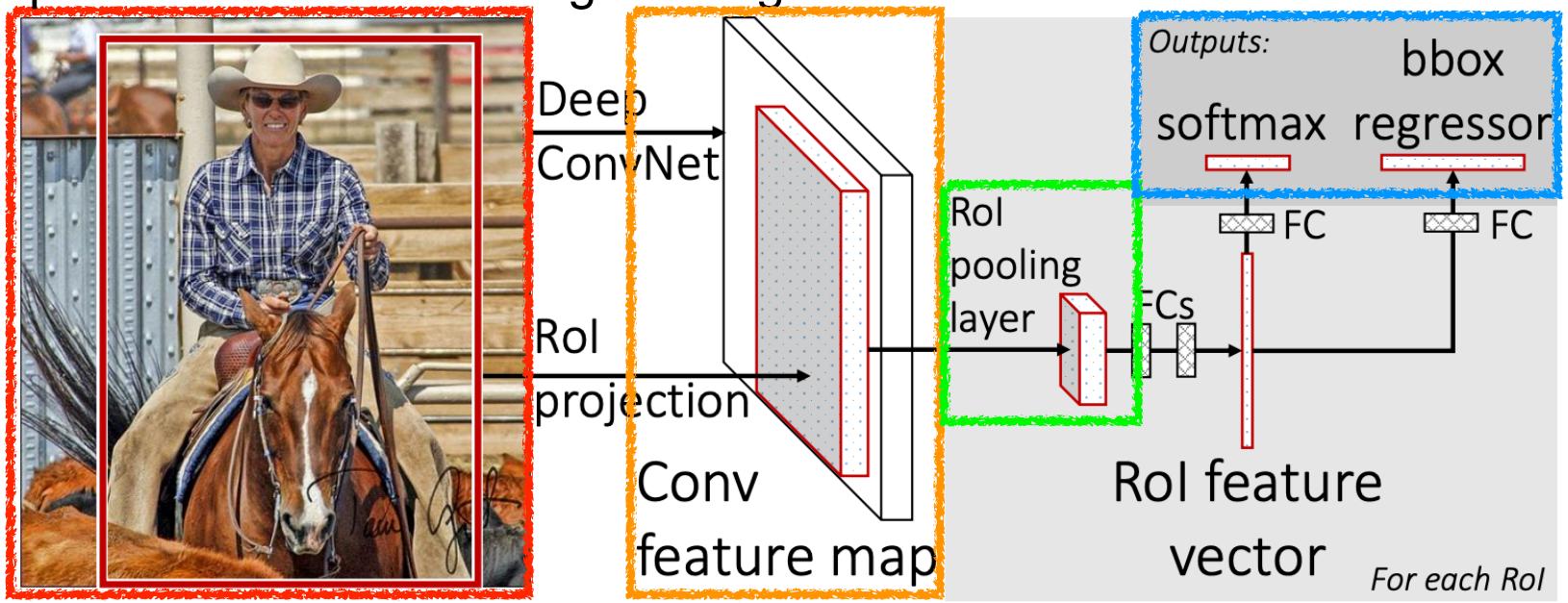


- In R-CNN, the number of crop/warp is usually over 2,000 meaning that CNN must run more than 2,000 times (59s/image on CPU).
- However, in SPPNet, CNN runs once.

https://arxiv.org/abs/1406.4729

Fast R-CNN

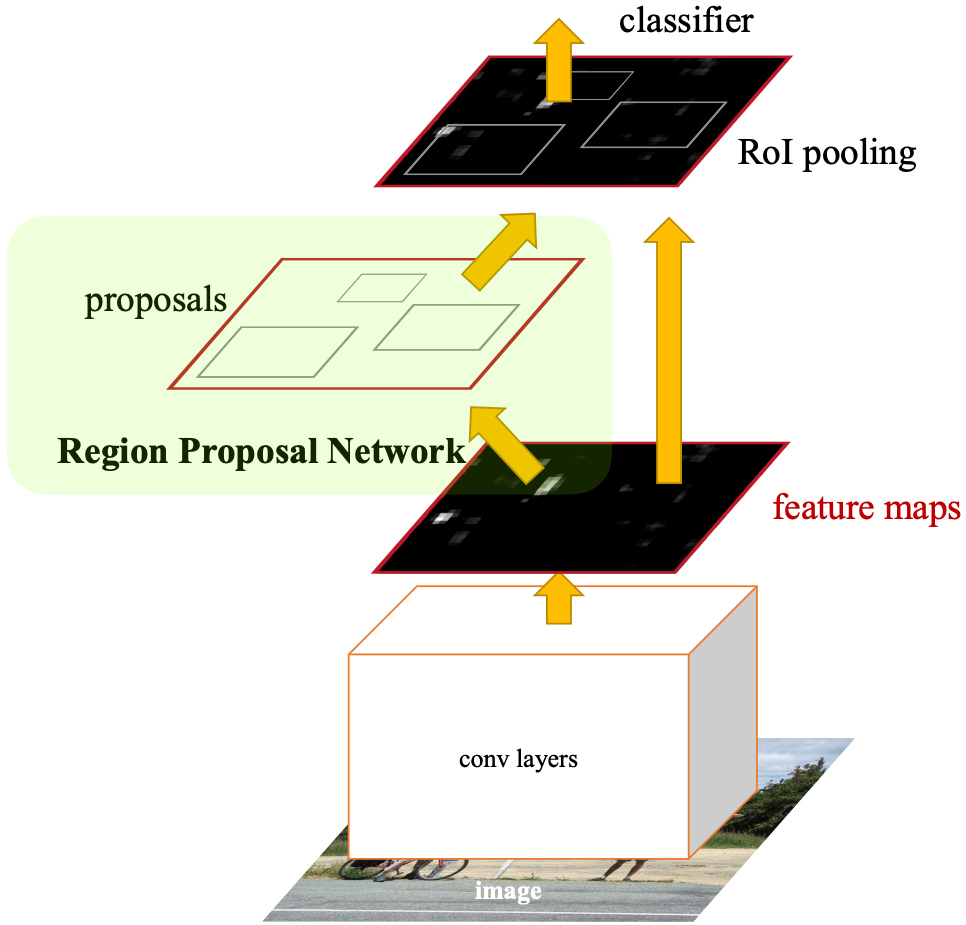
1. Takes an input and a set of bounding boxes.
2. Generated convolutional feature map
3. For each region, get a fixed length feature from ROI pooling
4. Two outputs: class and bounding-box regressor.



https://arxiv.org/abs/1504.08083

Faster R-CNN

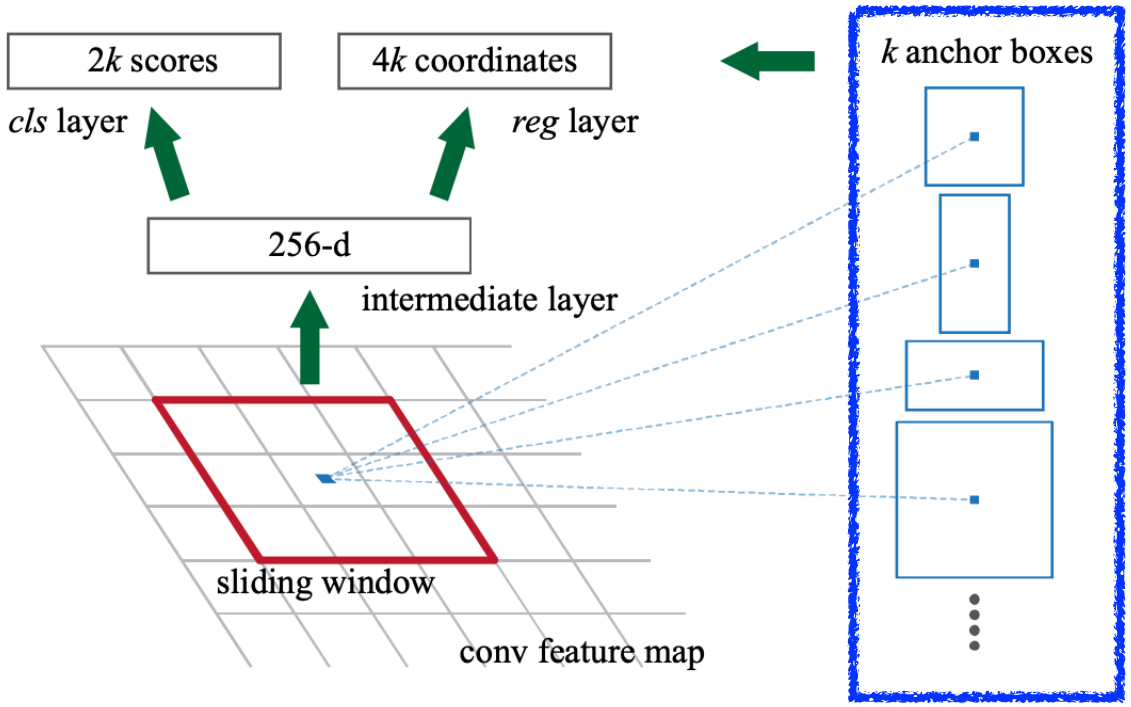
This part is new!

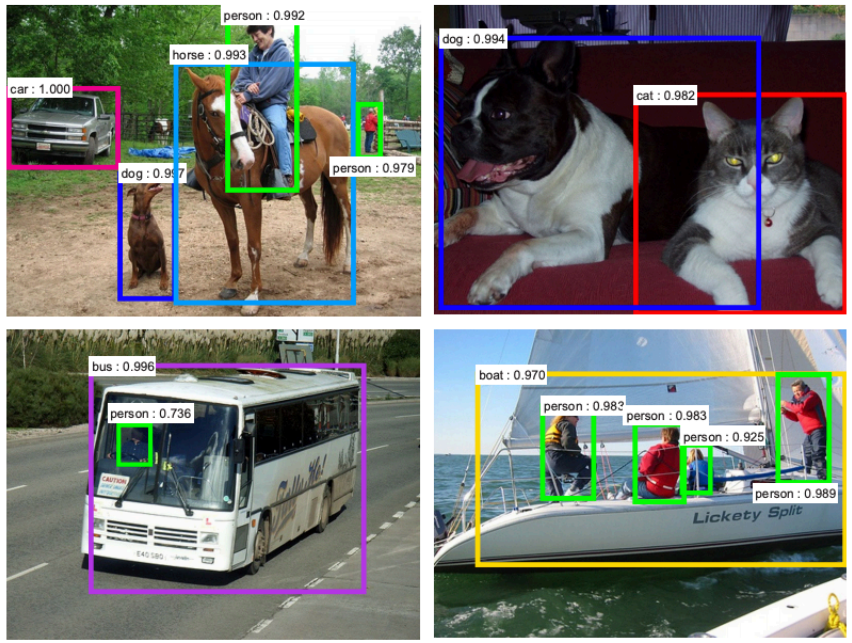


- Faster R-CNN = **Region Proposal Network** + Fast R-CNN

https://arxiv.org/abs/1506.01497

Region Proposal Network

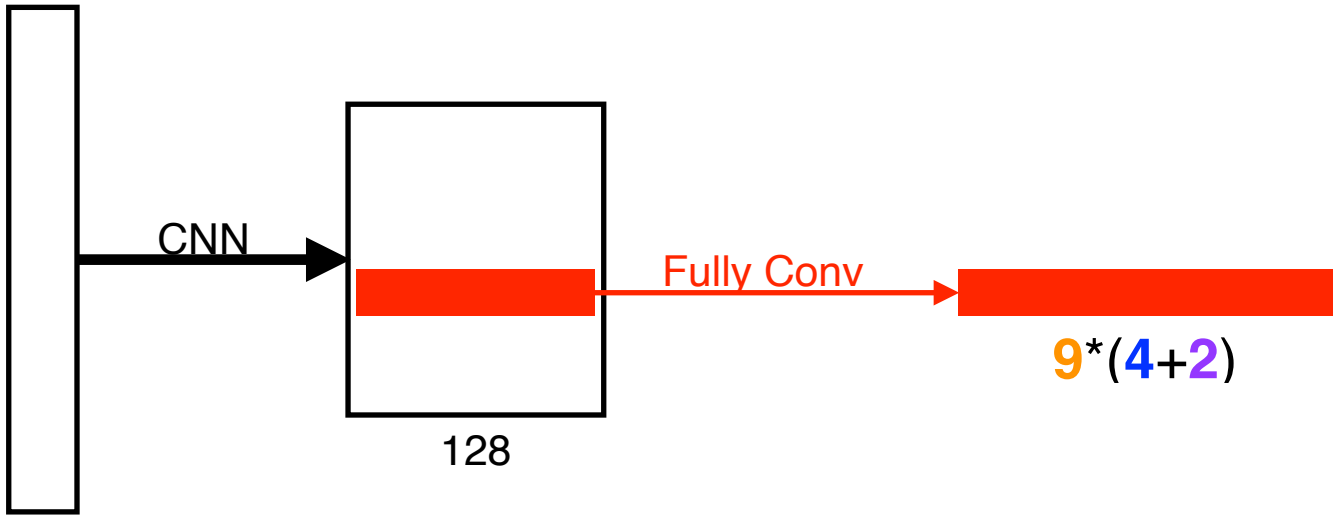




Anchor boxes: detection boxes with predefined sizes.

https://arxiv.org/abs/1506.01497

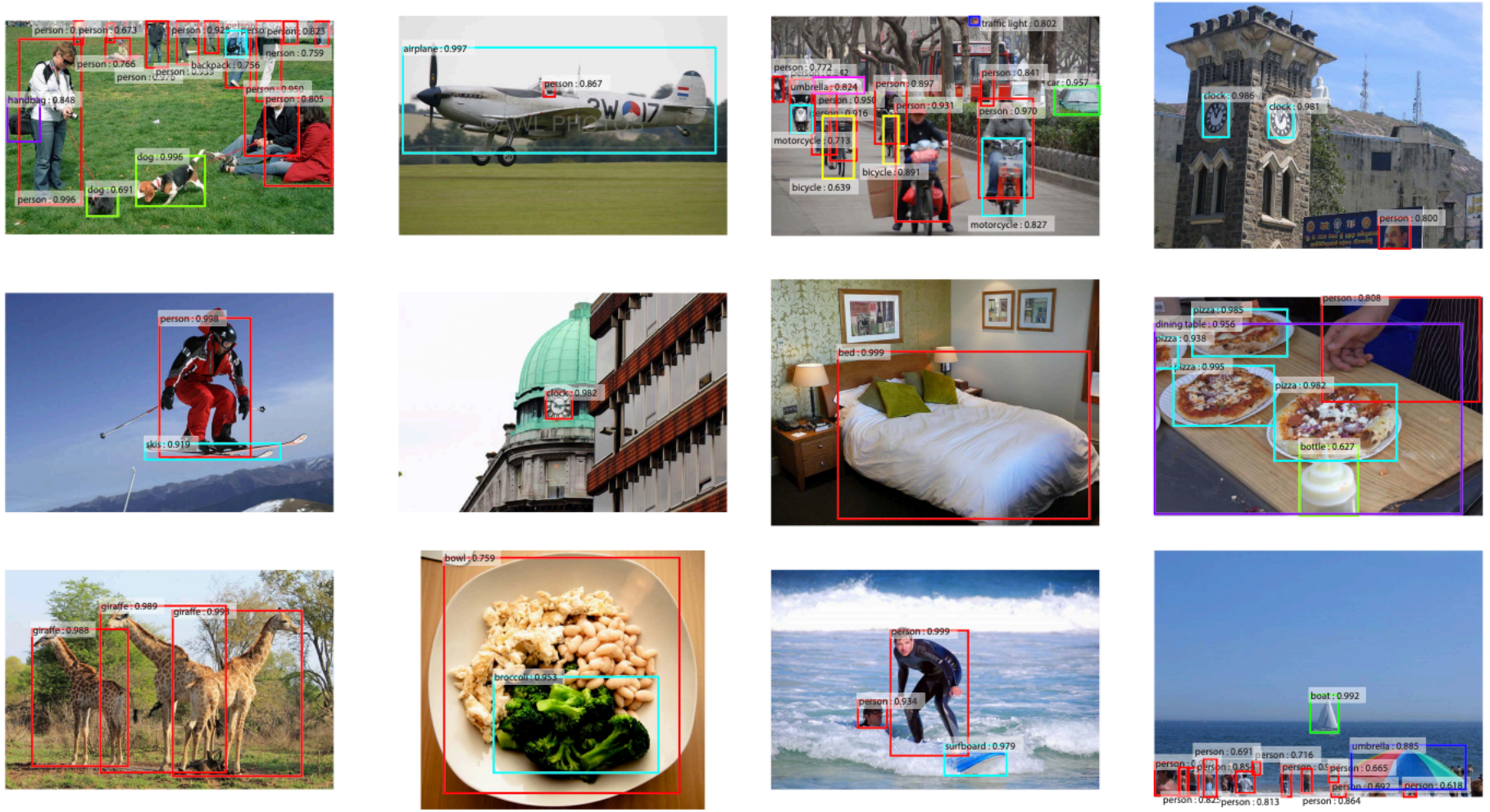
Region Proposal Network



- **9**: Three different region sizes (128, 256, 512) with three different ratios (1:1, 1:2, 2:1)
- **4**: four bounding box regression parameters
- **2**: box classification (whether to use it or not)

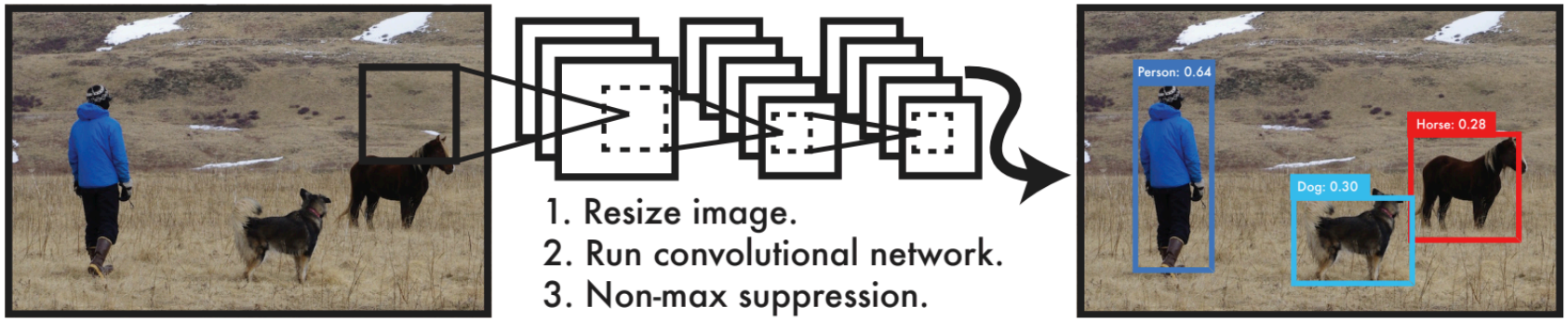
https://arxiv.org/abs/1506.01497

Faster R-CNN



https://arxiv.org/abs/1506.01497

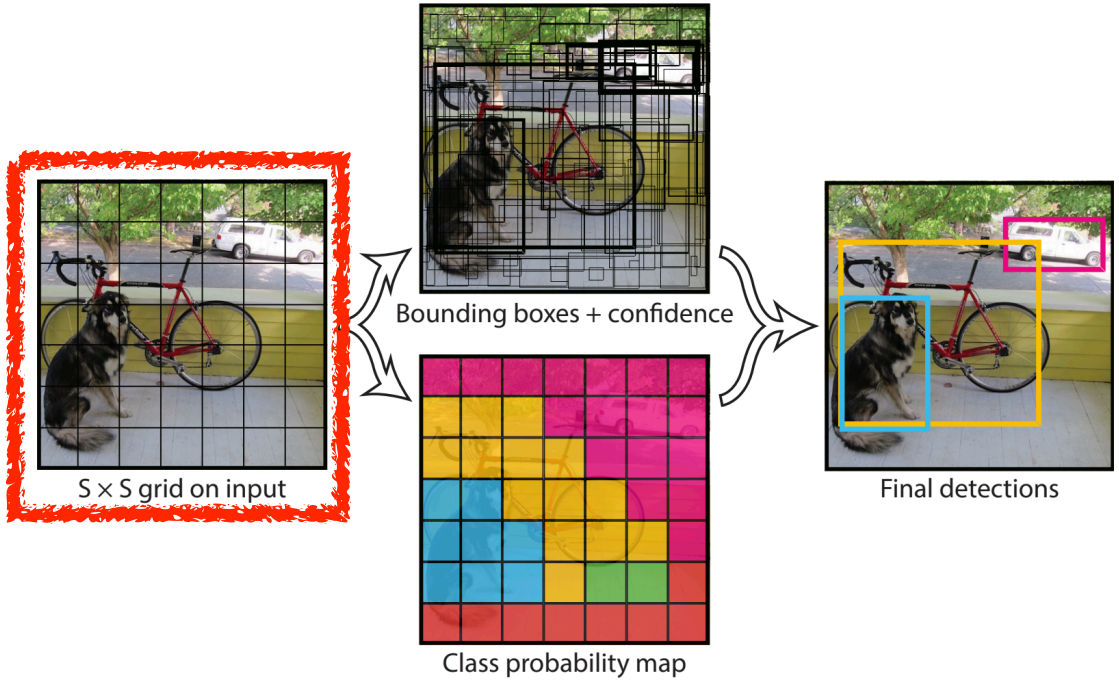
YOLO



- YOLO (v1) is an extremely fast object detection algorithm.
  - baseline: 45fps / smaller version: 155fps
- It **simultaneously** predicts multiple bounding boxes and class probabilities.
  - No explicit bounding box sampling (compared with Faster R-CNN)

https://arxiv.org/abs/1506.02640

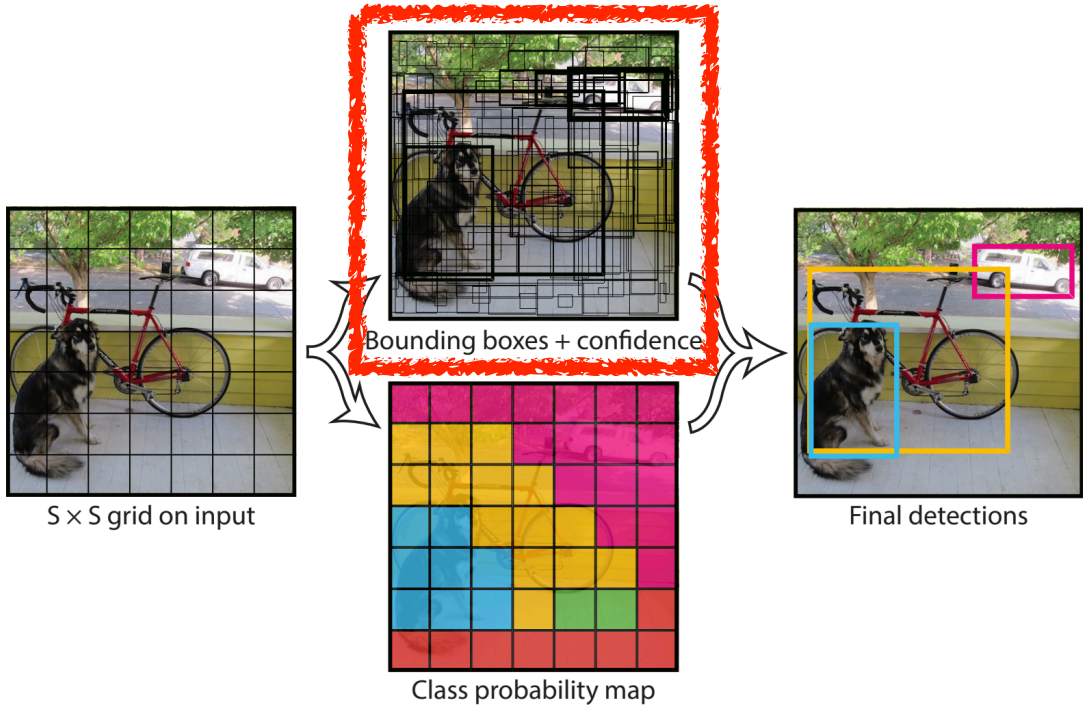
YOLO



- Given an image, **YOLO** divides it into SxS grid.
  - If the center of an object falls into the grid cell, that grid cell is responsible for detection.

https://arxiv.org/abs/1506.02640

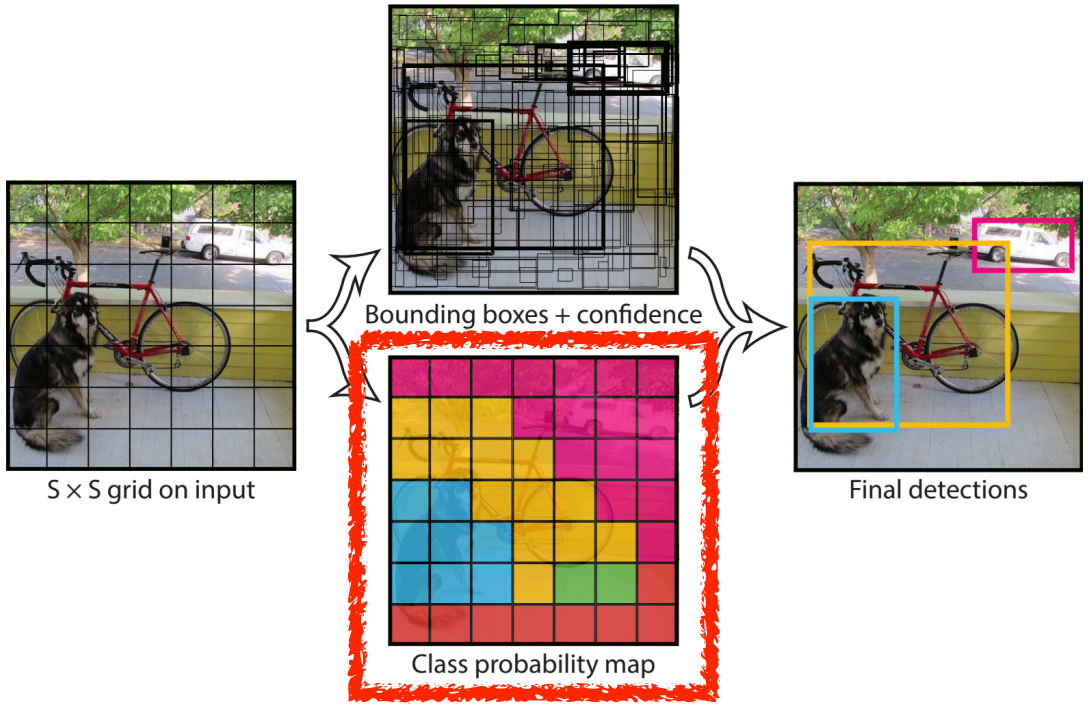
YOLO



- Each cell predicts B bounding boxes (B=5).
  - Each bounding box predicts
    - box refinement (x / y / w / h)
    - confidence (of objectness)

https://arxiv.org/abs/1506.02640

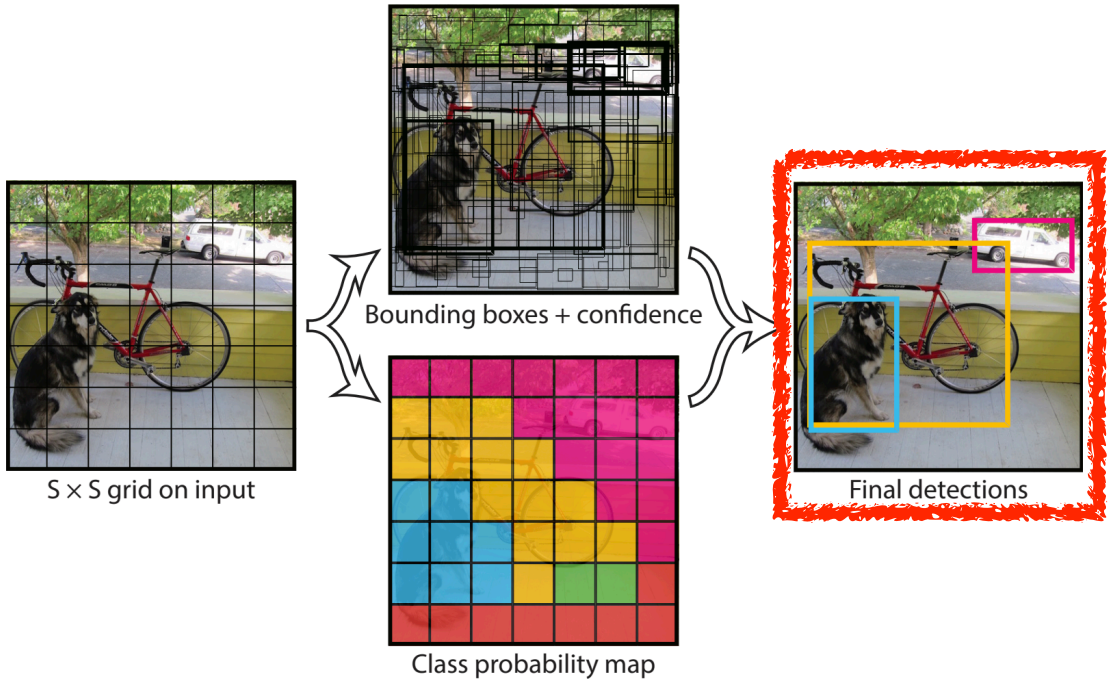
YOLO



- Each cell predicts B bounding boxes (B=5).
  - Each bounding box predicts
    - box refinement (x / y / w / h)
    - confidence (of objectness)
- Each cell predicts C class probabilities.

https://arxiv.org/abs/1506.02640

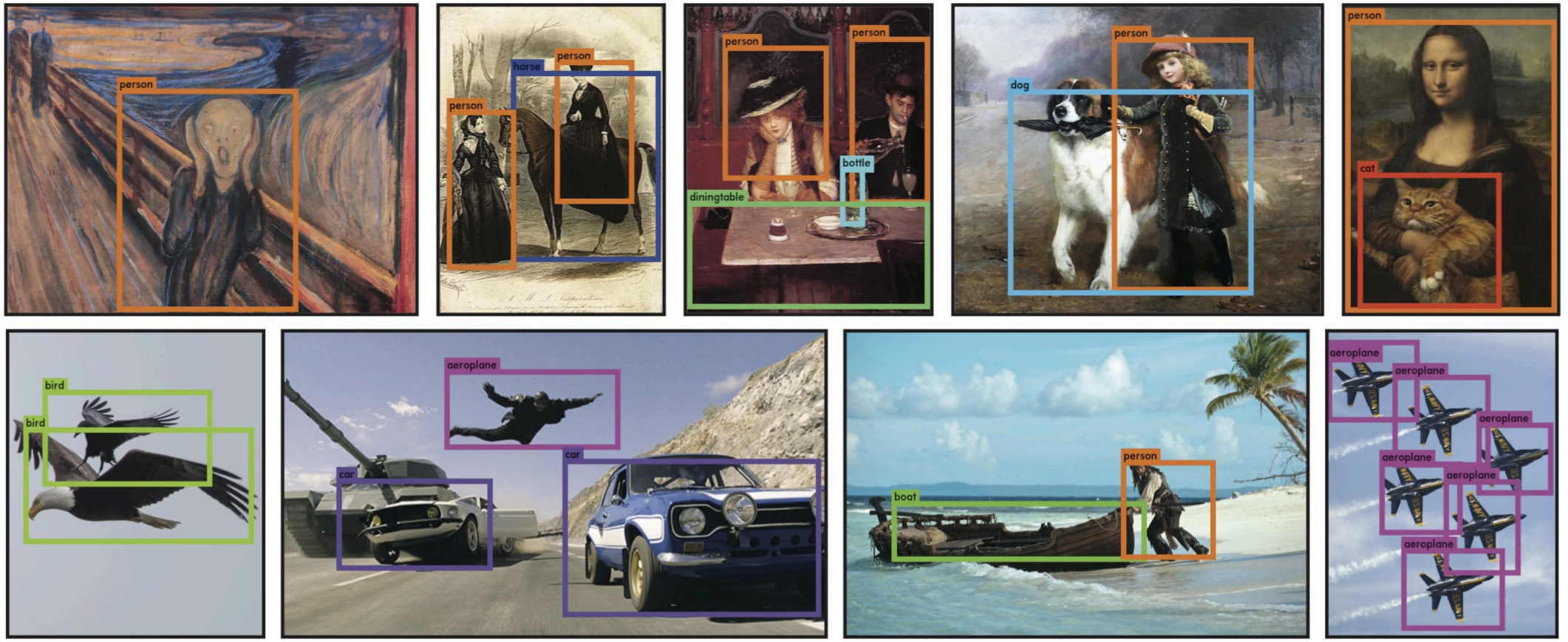
YOLO



- In total, it becomes a tensor with SxSx(B*5+C) size.
  - SxS: Number of cells of the grid
  - B*5: B bounding boxes with offsets (x,y,w,h) and confidence
  - C: Number of classes

https://arxiv.org/abs/1506.02640

YOLO



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Thank you for listening