Week 7: Detection and instance segmentation

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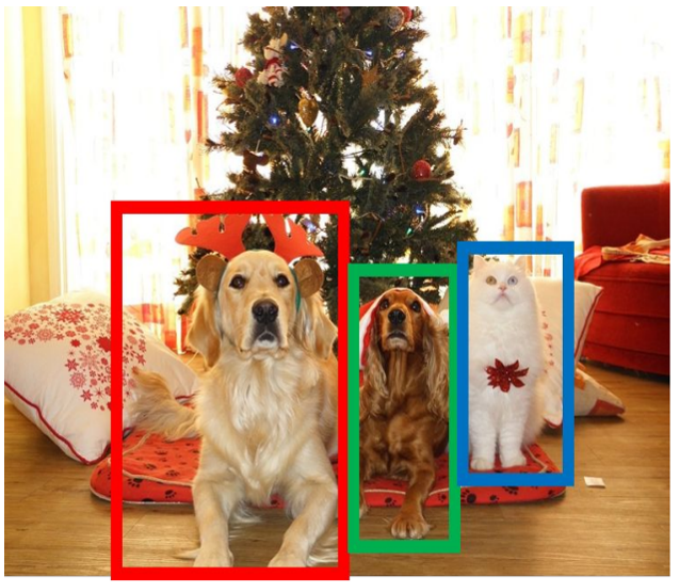
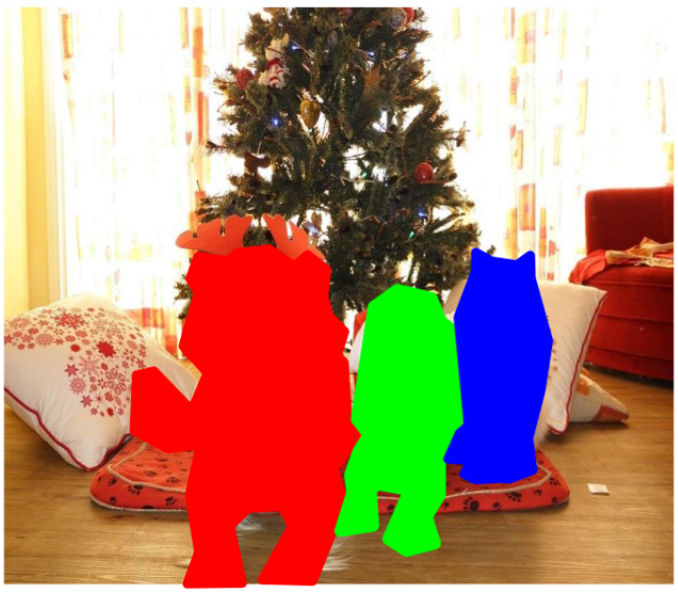
Object detection vs. instance segmentation

- Object (instance) detection: classify and localize object instances with bounding boxes
- Instance segmentation: semantically segment each instance
- Applications: self-driving, surveillance, medical image analysis



DOG, DOG, CAT



DOG, DOG, CAT

Figure from Stanford CS231n 2017 lecture 11

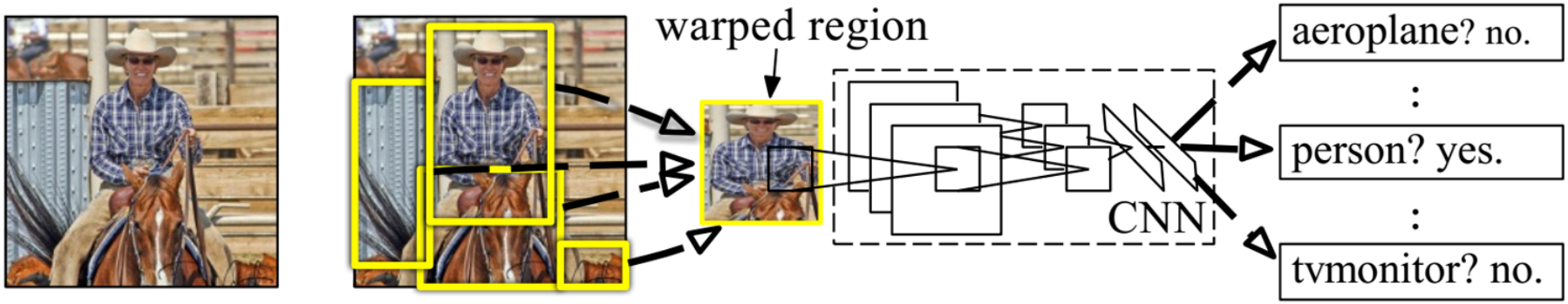
Two-stage approach

1^{st} stage: propose candidate object bounding boxes

2^{nd} stage: classify and fine-tune bounding-boxes

Region-based CNN (R-CNN) for object detection

- Use CNN or CNN+SVM classifier for each proposal region
- Fine-tune bounding box location and size with regression
  $\triangle (x, y, w, h) = regressor(initial\ box)$
- Number of model output: $C + 4$ (for each box proposal)



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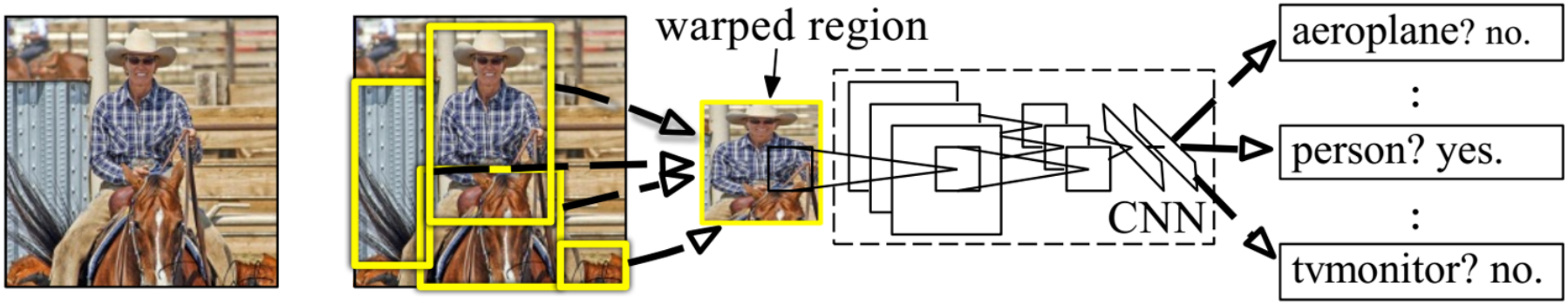

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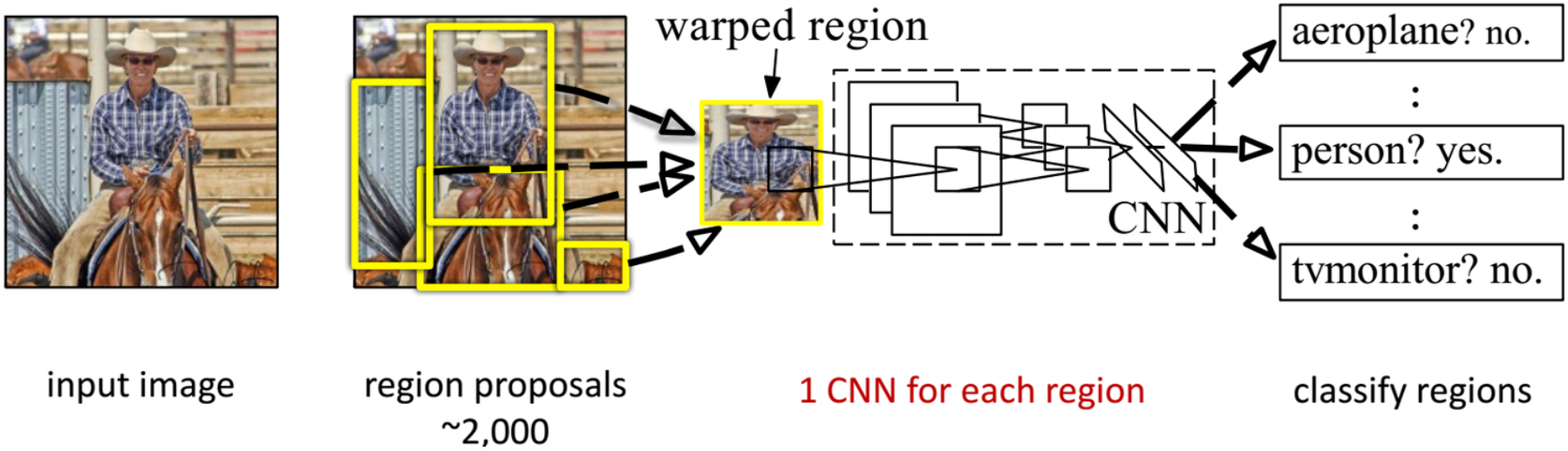

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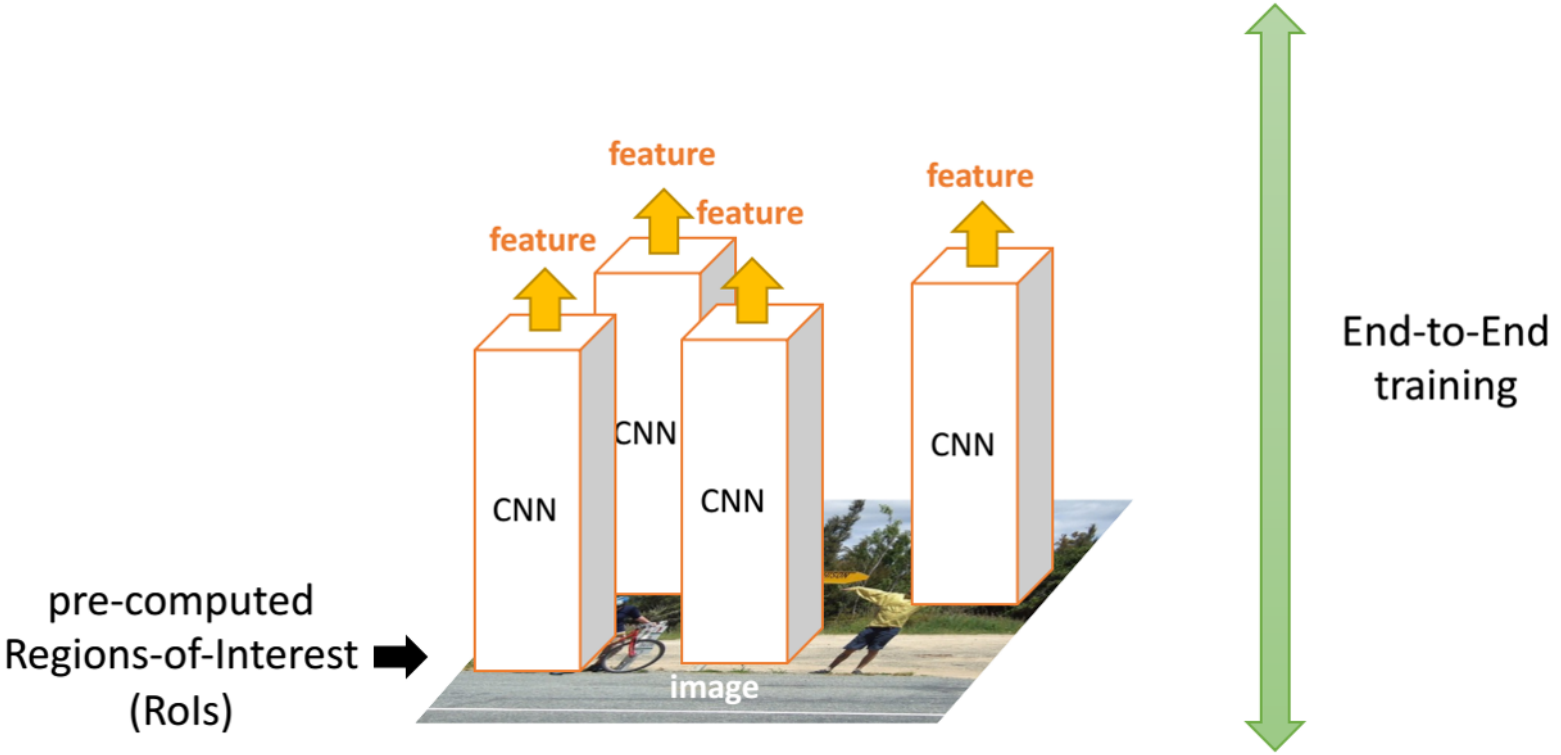
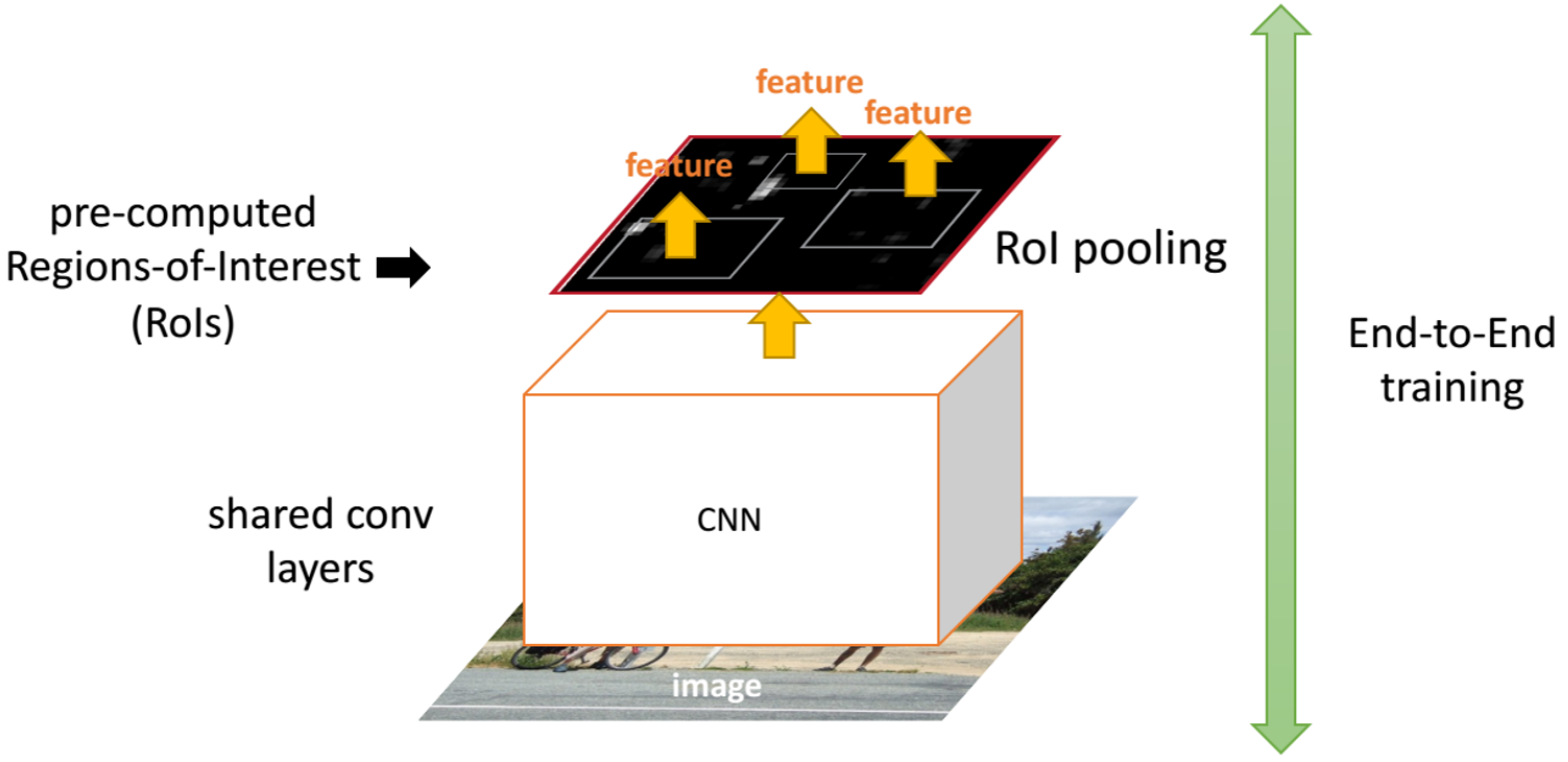
R-CNN (cont')

- Region proposals are pre-computed for each image
- Same CNN is applied multiple times, once for each proposal
- So, slow inference



Fast R-CNN

- Region proposals are extracted from feature maps
- CNN is applied only once for all proposals
- So, fast inference
- Note: classifier and regression applied multiple times



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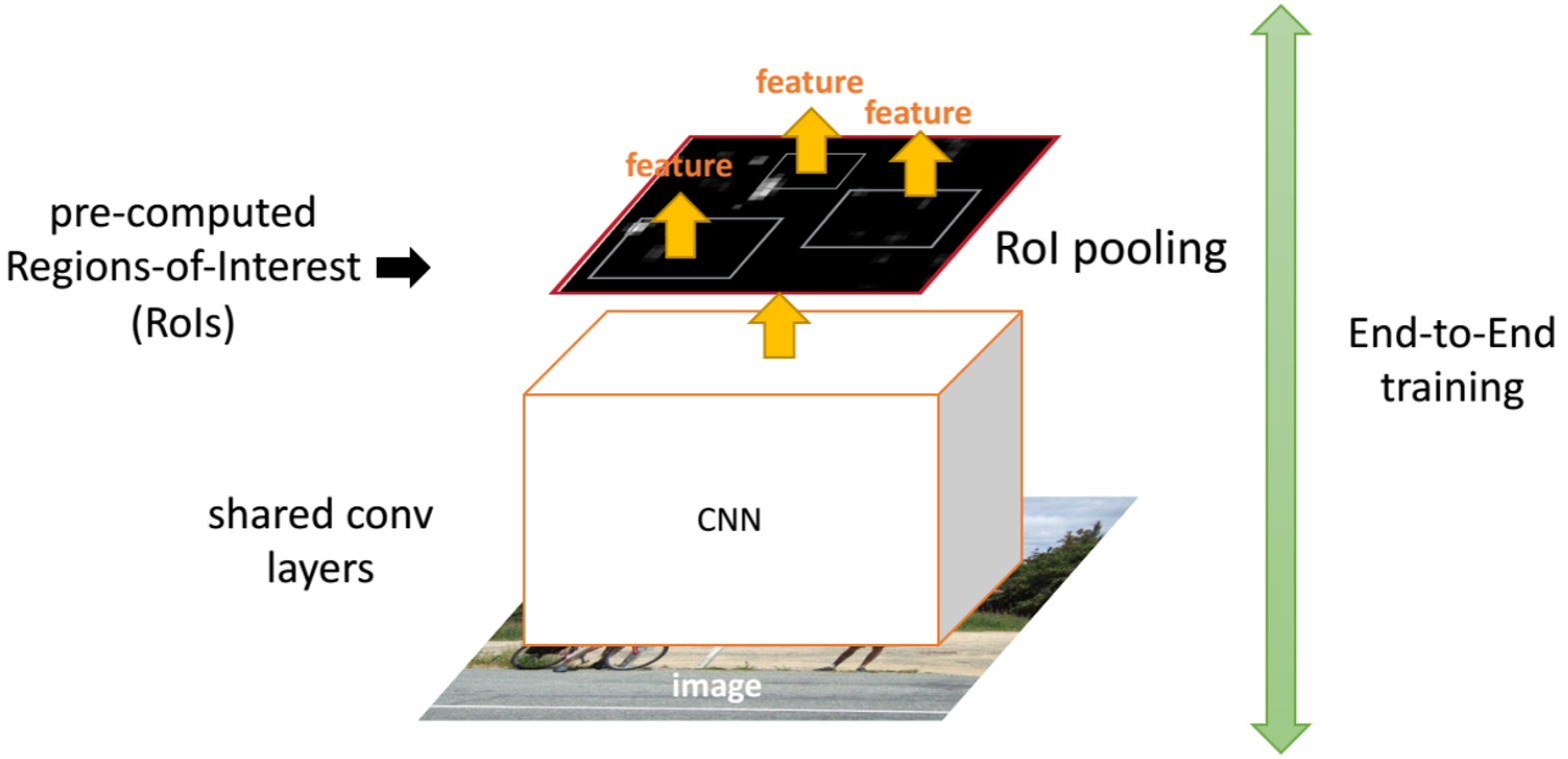
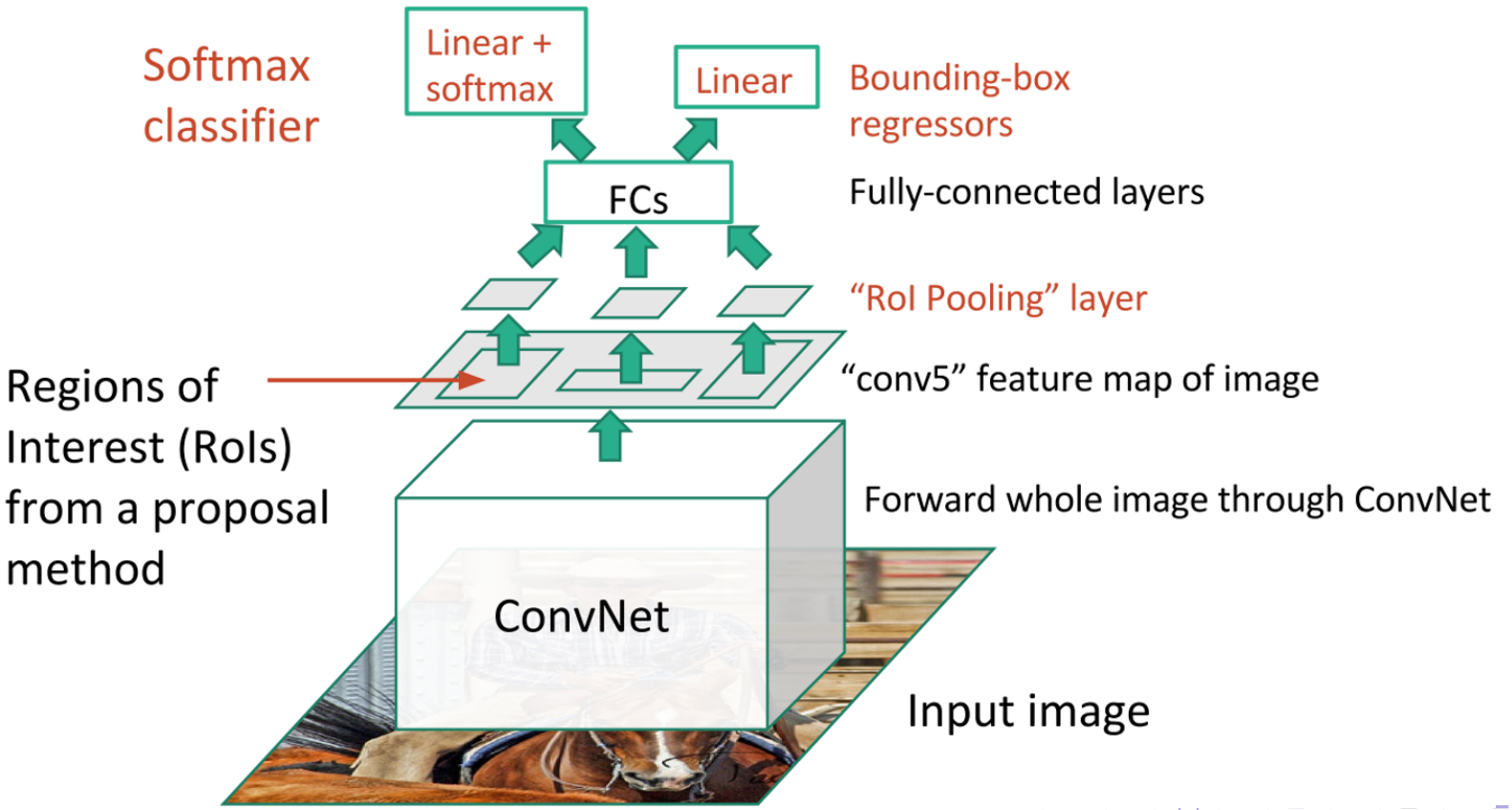
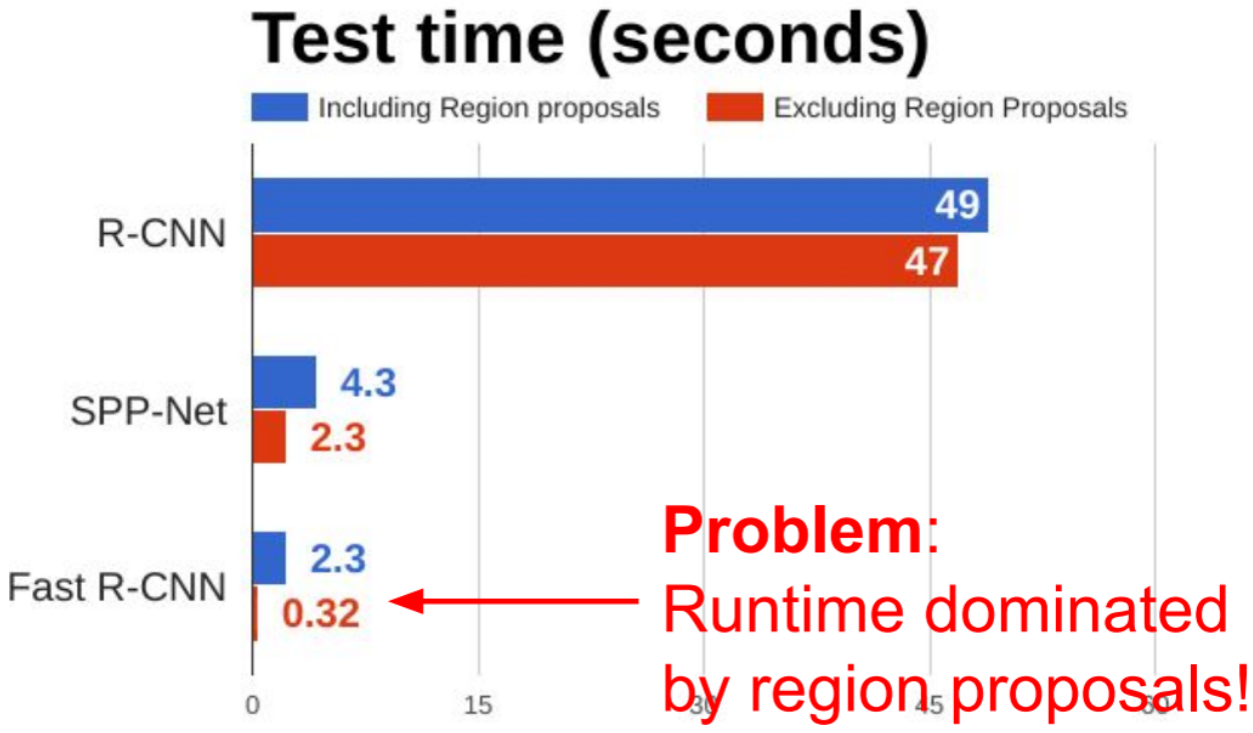


Fast R-CNN (cont')

- RoI pooling layer: pool each RoI to a pre-fixed $S \times S$ region
- Every RoI pooling output is connected to FC layers for classification and bounding box offset prediction
- Training loss $L = L_{cls} + L_{box}$

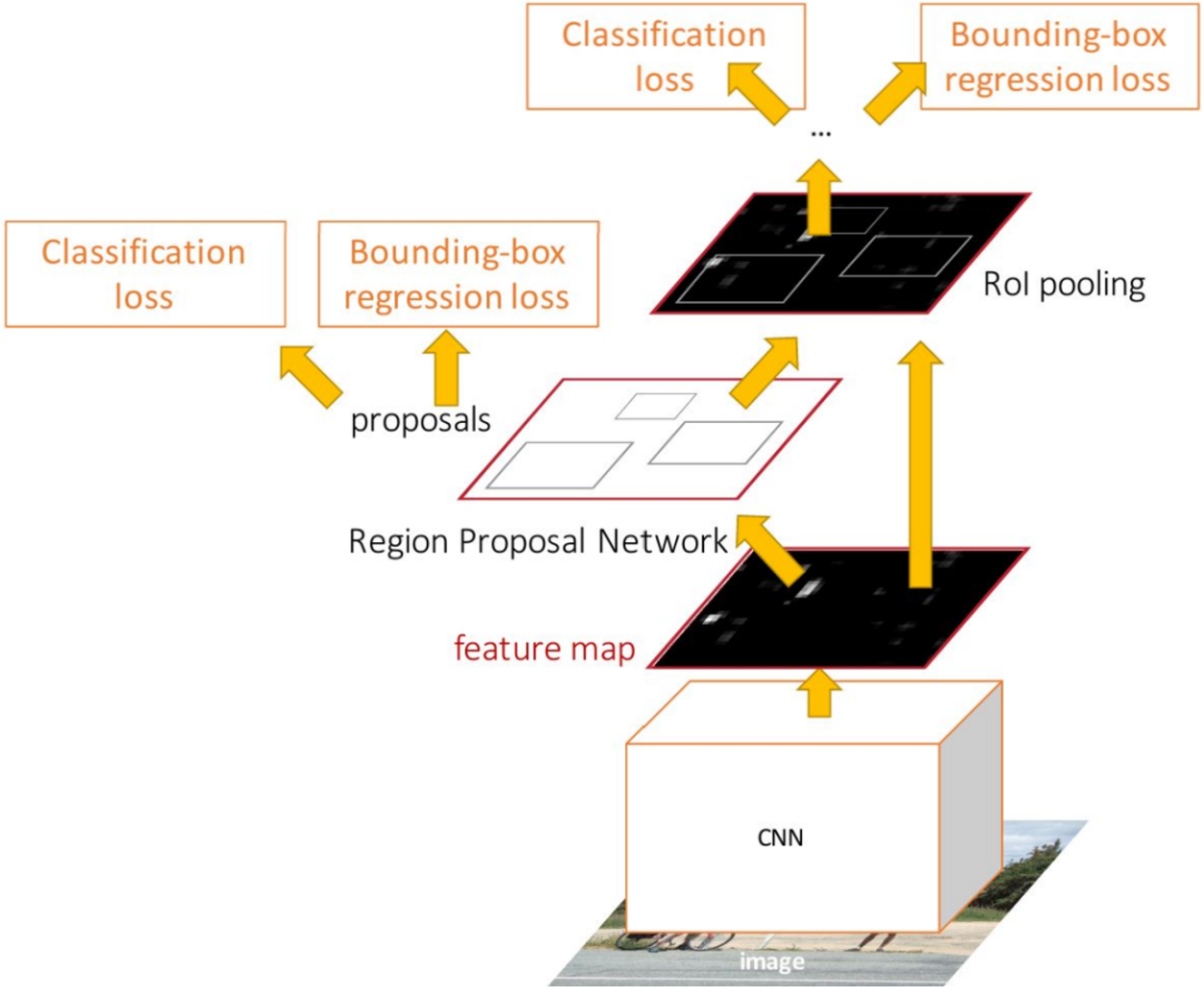


Fast R-CNN (cont')



Faster R-CNN: make CNN do proposals

- Region Proposal Network (RPN) predicts proposals
- Jointly train 4 losses; fast inference (5fps)

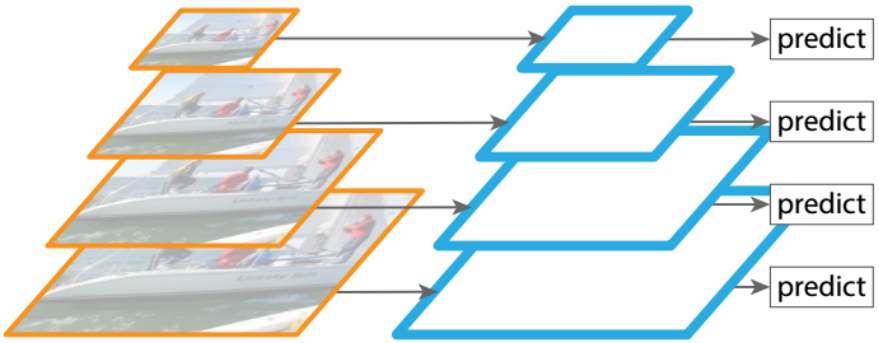


Not only faster ...

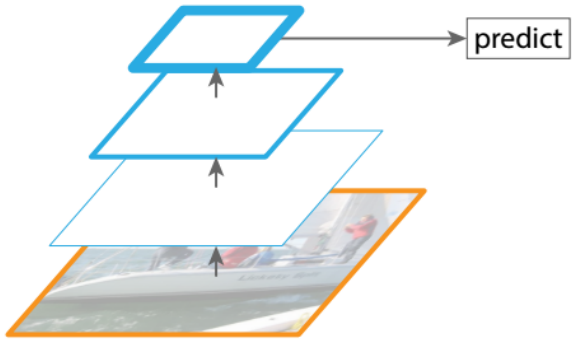
We also need more accurate detections!

Feature pyramid network (FPN) for object detection

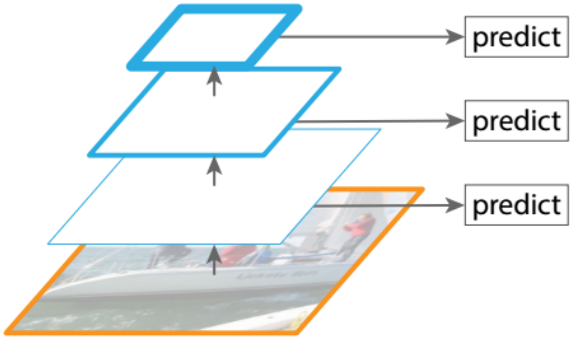
- All recent recognition and detection challenge winners use multi-scale testing on featurized image pyramids (fig. a). Key observation: features at all levels are *semantically strong*!
- However, expensive computation during prediction



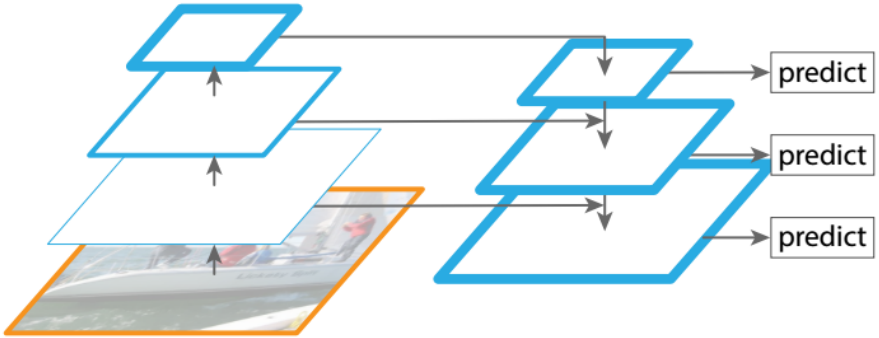
(a) Featurized image pyramid



(b) Single feature map



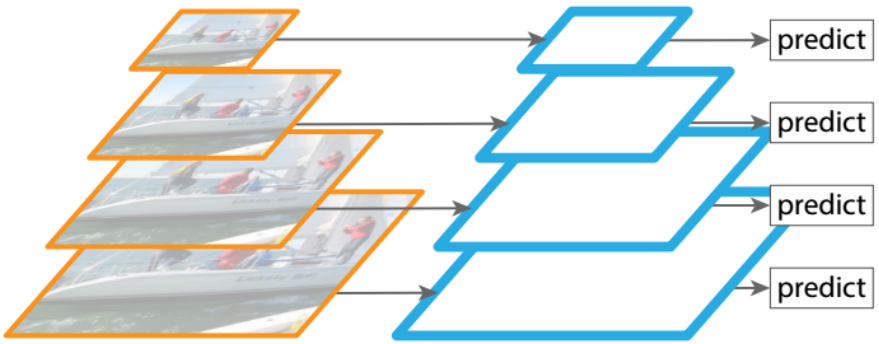
(c) Pyramidal feature hierarchy



(d) Feature Pyramid Network

Feature pyramid network (FPN) for object detection

- Recently, use single scale features for faster detection (fig. b)
- High-resolution feature maps have low-level features (fig. c)



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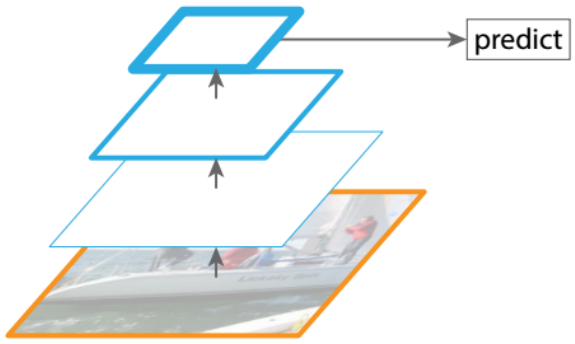
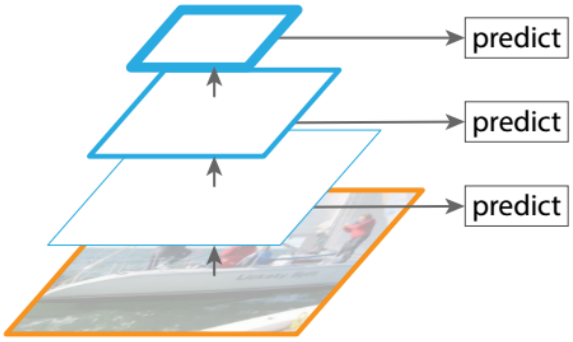


(b) Single feature map



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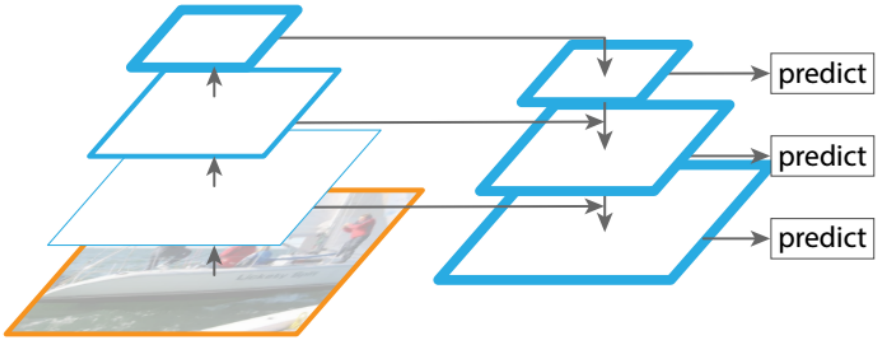
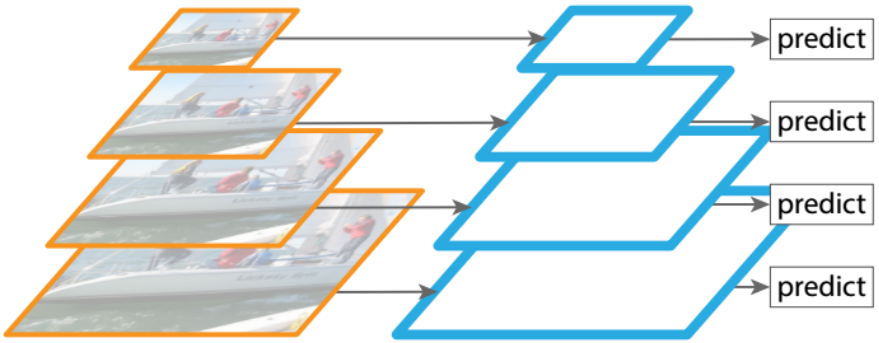


(d) Feature Pyramid Network

Feature pyramid network (FPN) for object detection

- Feature pyramid network (fig. d): rich semantics at all levels



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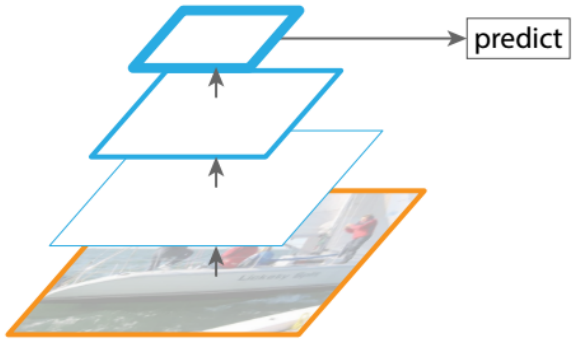

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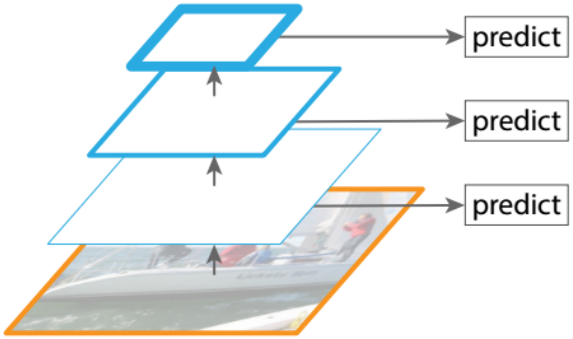

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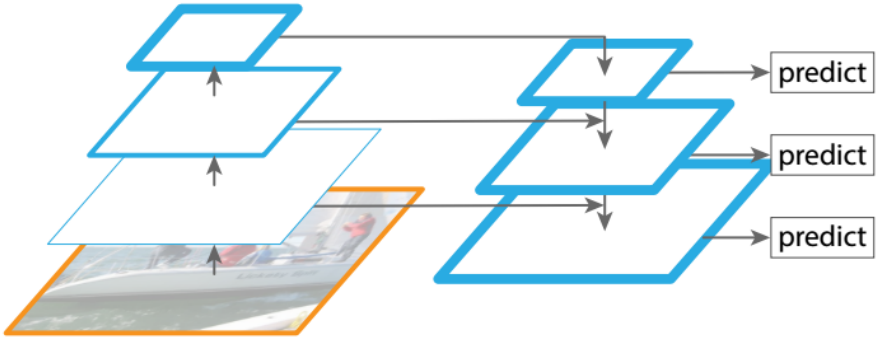
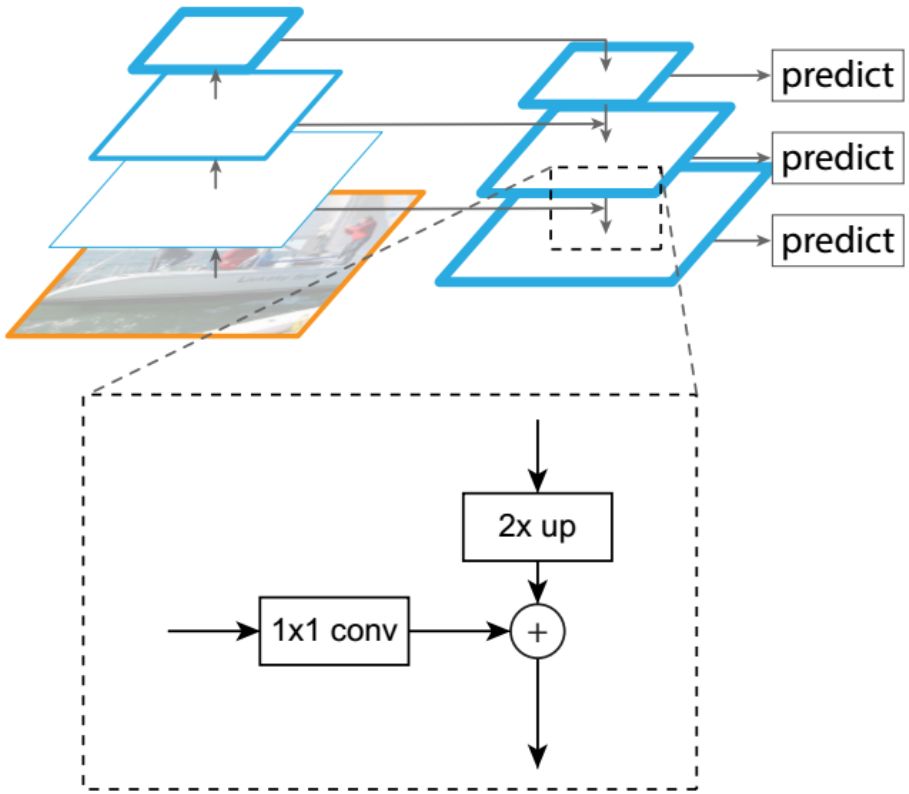


(d) Feature Pyramid Network

Figures here and in the next two slides from Lin, Dollar, Girshick, He, Hariharan, Belongie, 'Feature pyramid network for object detection', CVPR, 2017

FPN

- Top-down path: upsample spatially coarser but semantically stronger from higher levels; embed semantics into lower levels
- All levels use shared classifiers/regressors
- Each RoI is assigned to one level for object detection
- Only use a single-scale input image



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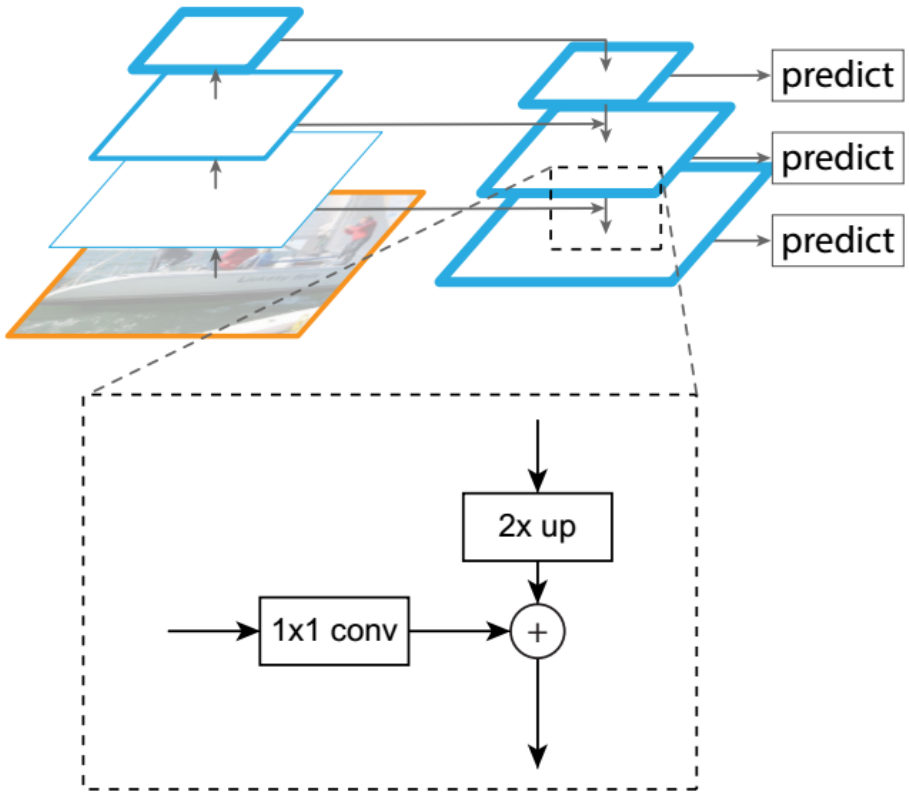


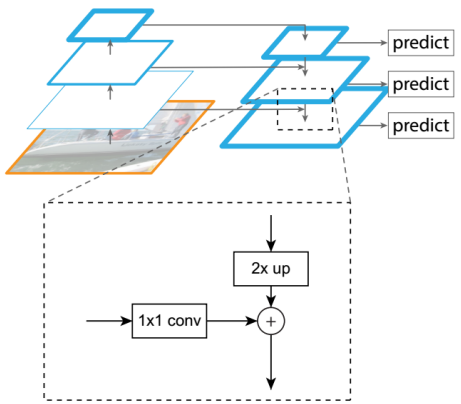
FPN (cont')

FPN is a network architecture

- Independent of backbone networks like ResNet
- Can be used for Region Proposal Network, Fast R-CNN

FPN vs. FCN in head architecture

- FCN head is connected to last upsampled conv layer and fully convolutoinal
- FPN head is connected to each upsampled layer and ends with either fully connected layers for classification/regression or with fully convolutional layer for segmentation



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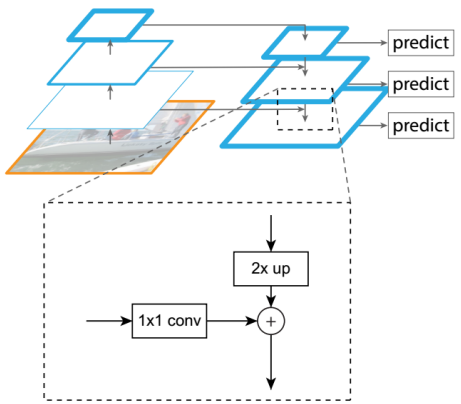


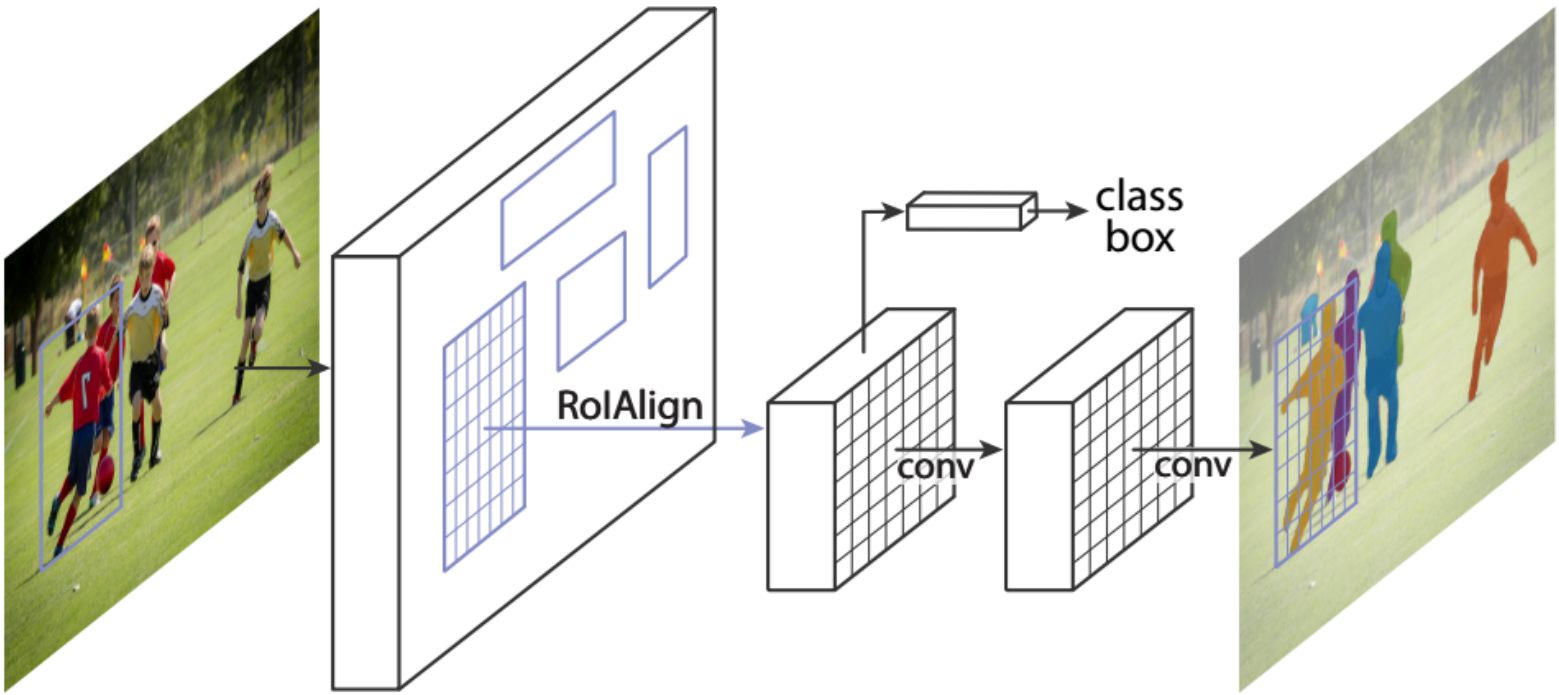
So far ...

Seen object detections and semantic segmentation!

Combine them for instance segmentation!

Mask R-CNN

- Extends Faster R-CNN by adding a sub-network (FCN) branch to predict segmentation masks on each RoI
- Mask R-CNN = Faster R-CNN + FCN
- Segmentation mask output: K (i.e., # classes) channels



Figures here and in the next three slides from He, Gkioxari, Dollar, Girschick, 'Mask R-CNN', ICCV 2017

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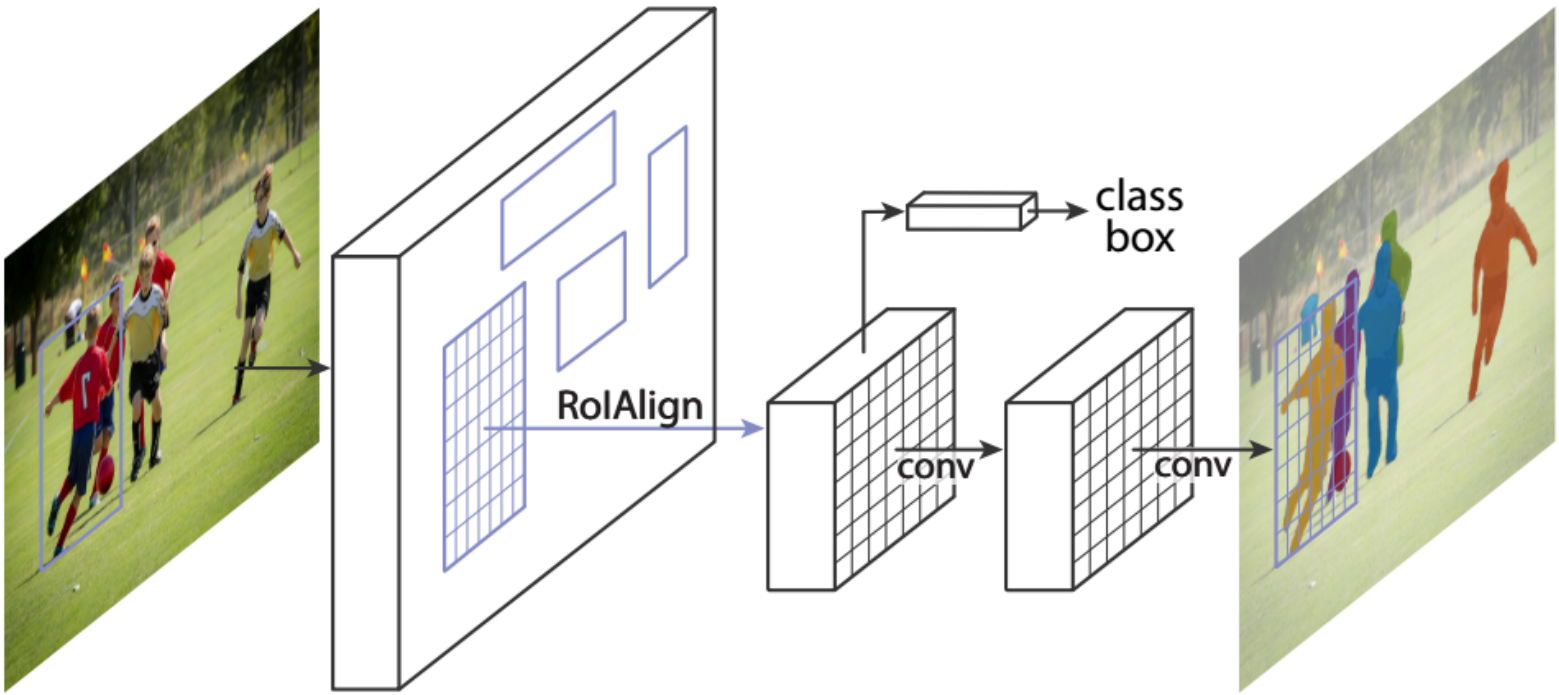

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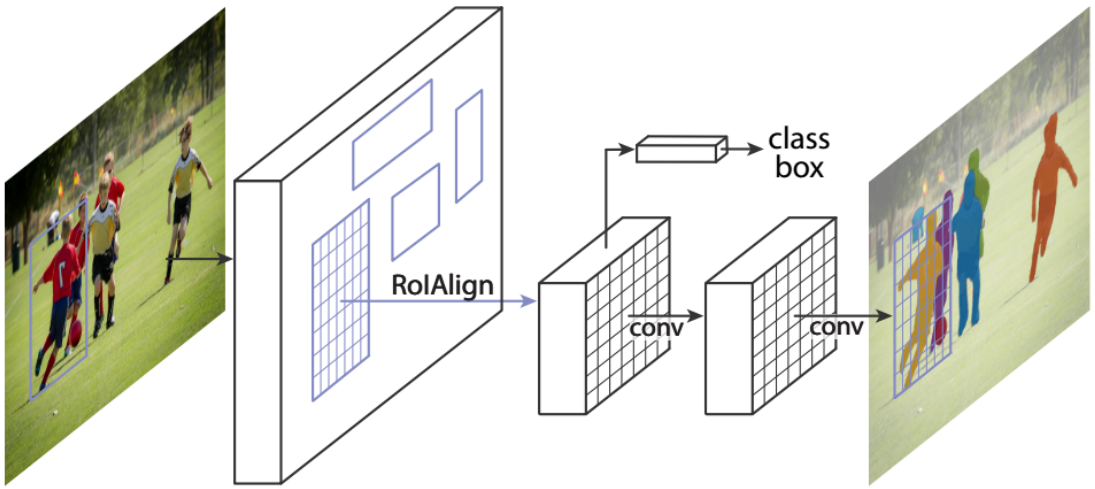
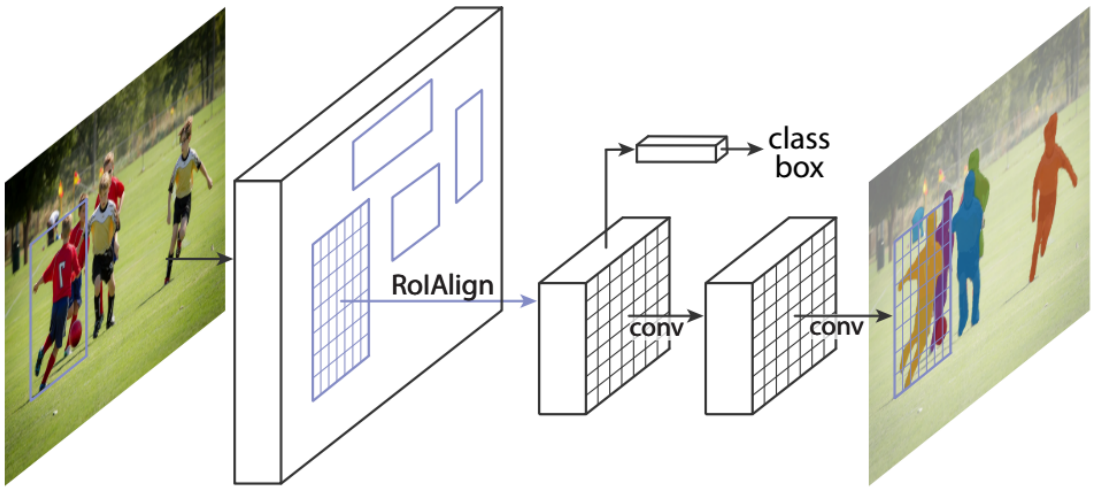
Mask R-CNN

- Training loss $L = L_{cls} + L_{box} + L_{mask}$



Mask R-CNN

- Training loss $L = L_{cls} + L_{box} + L_{mask}$
- Novelty 1: decouple segmentation and classification tasks, i.e., generate masks for every class without competition among classes (or: per-pixel binary categorization).
  Other FCNs: perform per-pixel multi-class categorization!



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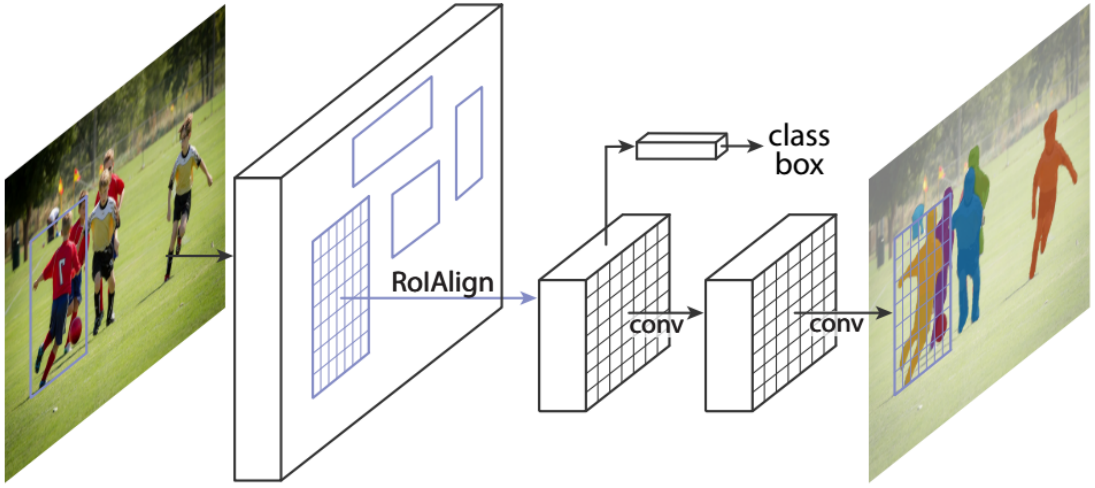
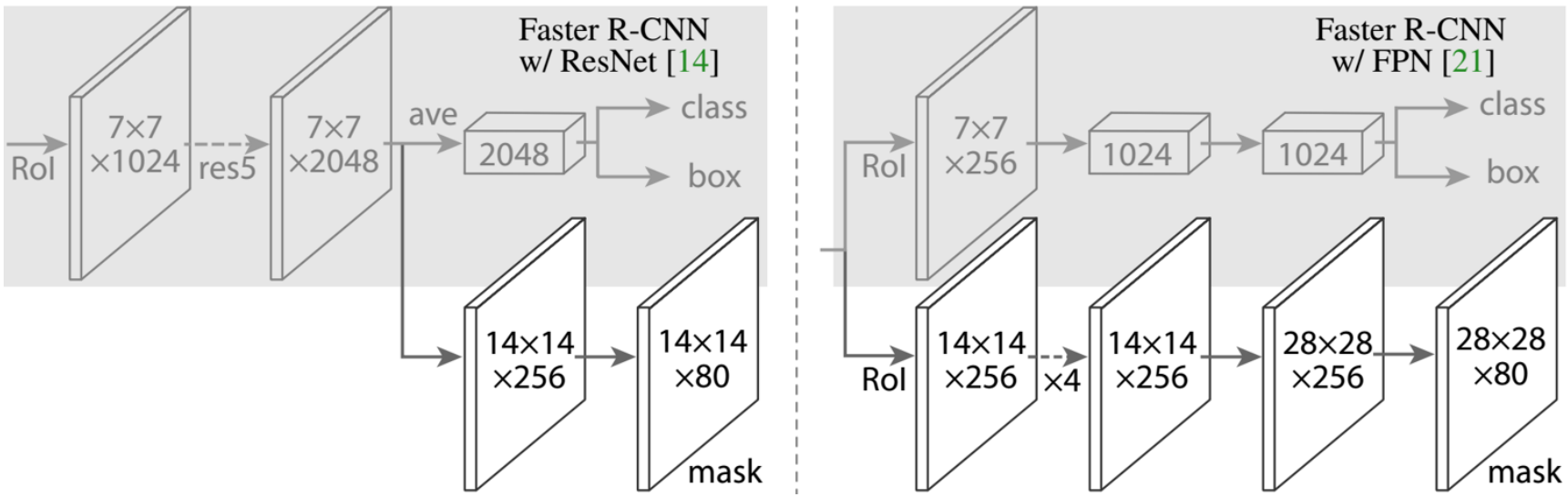
- Novelty 1: decouple segmentation and classification tasks, i.e., generate masks for every class without competition among classes (or: per-pixel binary categorization).
  Other FCNs: perform per-pixel multi-class categorization!
- Novelty 2: RoIAlign - avoid quantization of RoI locations and bins during RoIPool, e.g., use $x/16$ instead of $\lfloor x/16 \rfloor$



Mask R-CNN

Network architectures: backbone + head

- backbone: first four conv blocks of ResNet or FPN
- head architecture, e.g.,



Mask R-CNN: result

- Outperform COCO challenge 2016 winners in bounding-box object detection, instance segmentation, etc.
- Still fast: 5 fps

One-stage approach

Above are two-stage models!

In comparison, one-stage models:

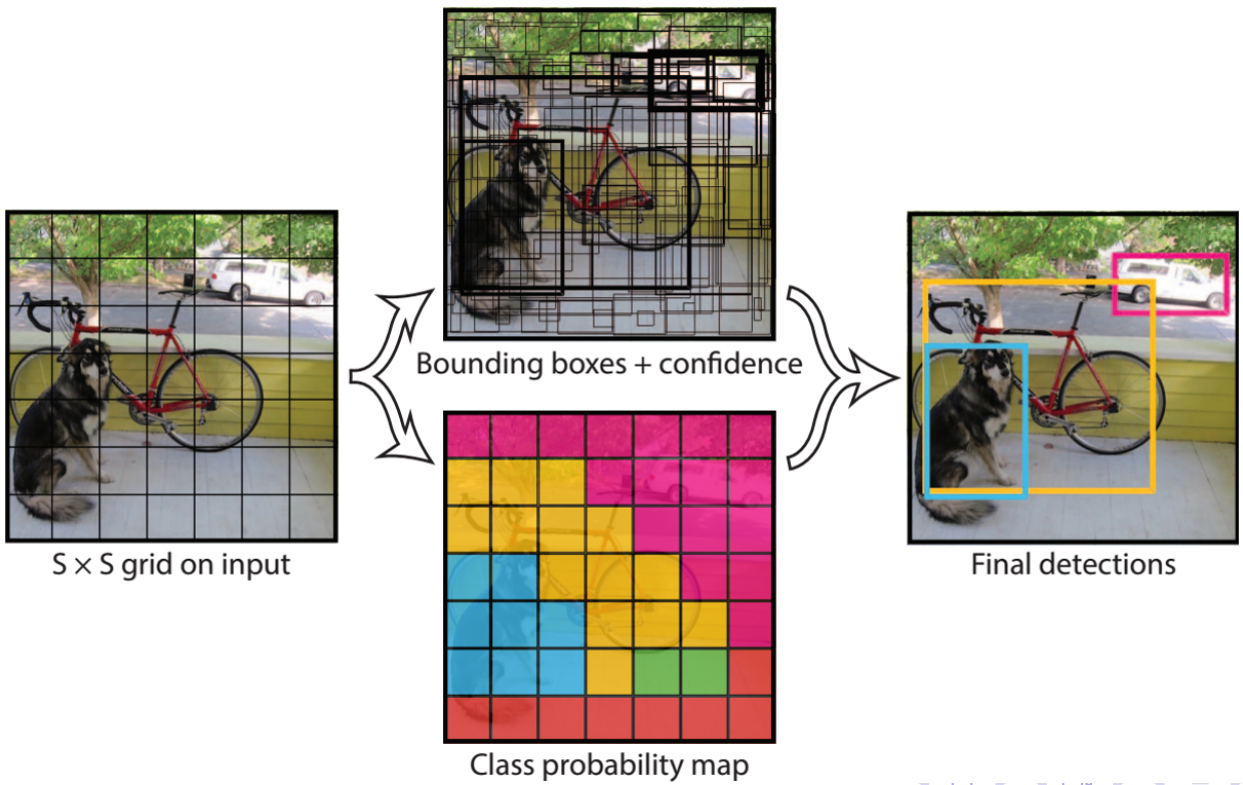
No need region proposal stage!

Simultaneously predict boxes and class probabilities!

Fast (real-time), but lower detection accuracy!

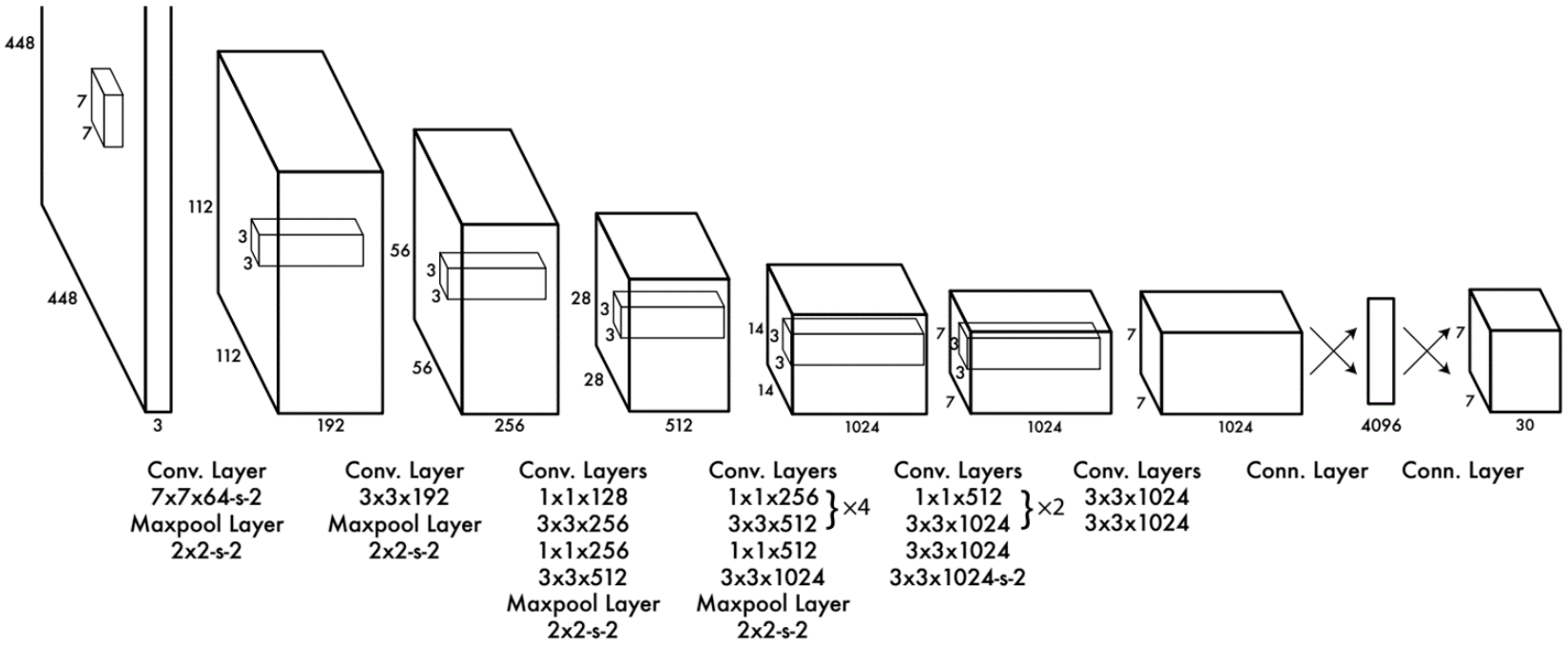
YOLO: You Only Look Once

- Divide input image into an $S \times S$ grid
- If the centre of an object falls into a grid cell, that grid cell is responsible for detecting that object.
- Each cell: predicts B boxes & confidences, C class probabilities (Confidence: IoU between predicted and ground-truth boxes)



YOLO: You Only Look Once

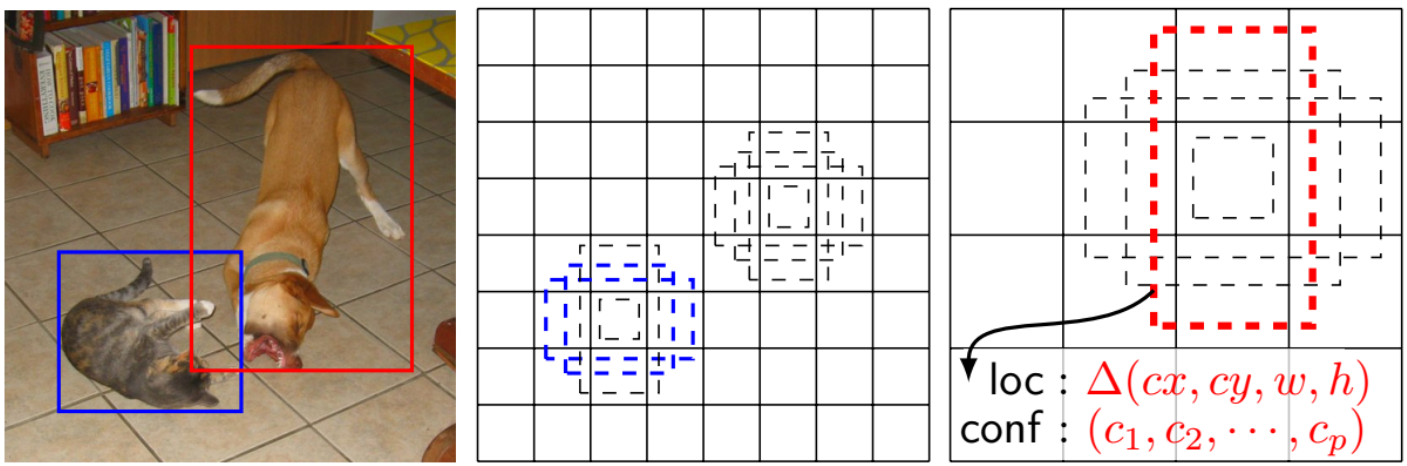
- FC layer: use features from entire image to predict each box
- Output of network: $S \times S \times (B * 5 + C)$, e.g., $B = 2$, $C = 20$
- Non-maximal suppression to fix multiple nearby detections
- Inference: 45fps; cannot detect small objects in groups



Figures here and in the previous slide from Redmon, Divvala, Girshick, Farhadi, 'You only look once: unified, real-time object detection', CVPR, 2016

SSD: single shot multibox detector

- Use multiple layers of feature maps
- B (4 or 6) default boxes generated at each location per layer
- Dashed blue & red: positive boxes (good match with objects)
- $\triangle\ (cx, cy, w, h)$: predicted offset (from red box) by network to well match ground-truth box
- $(c_1, c_2, \ldots, c_p)$: predicted class probabilities for red box
- Minimize loss $L = L_{cls} + L_{box}$

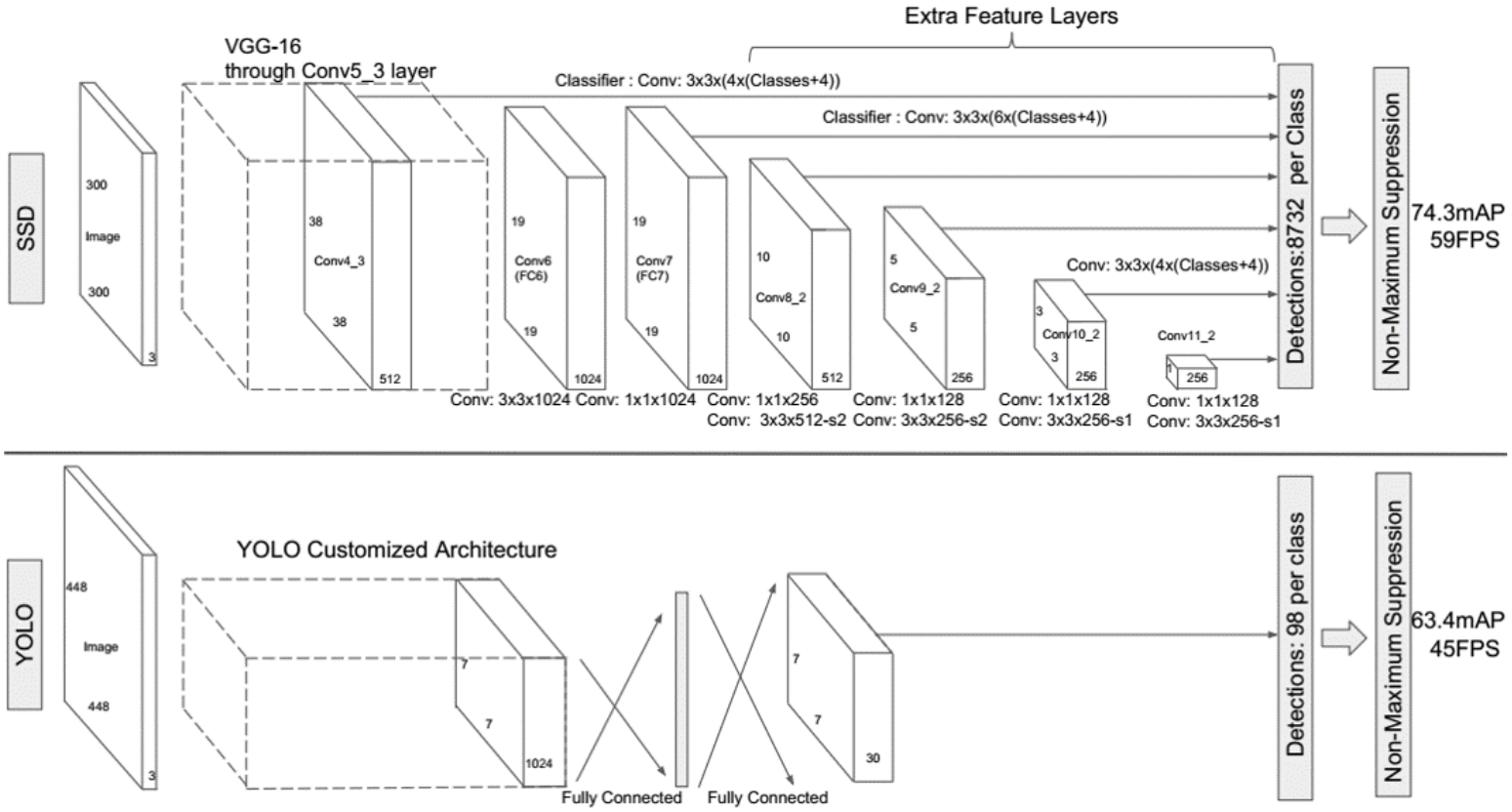


(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

Figures here and in next slide from Liu et al., 'SSD: single shot multibox detector', ECCV, 2016

SSD: single shot multibox detector

- Train different predictors (with small filters) for different aspect ratio detection per layer
- For a $S \times S$ feature map: $S \times S \times B \times (C + 4)$ outputs
- Inference: faster: ~ 60fps; more accurate than YOLO



Why one-stage models have lower accuracy?

One-stage models: faster, but *lower* accuracy.

Why?

They densely sample locations, scales, aspect ratios.

So: extreme foreground-background class imbalance during training!

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Why?

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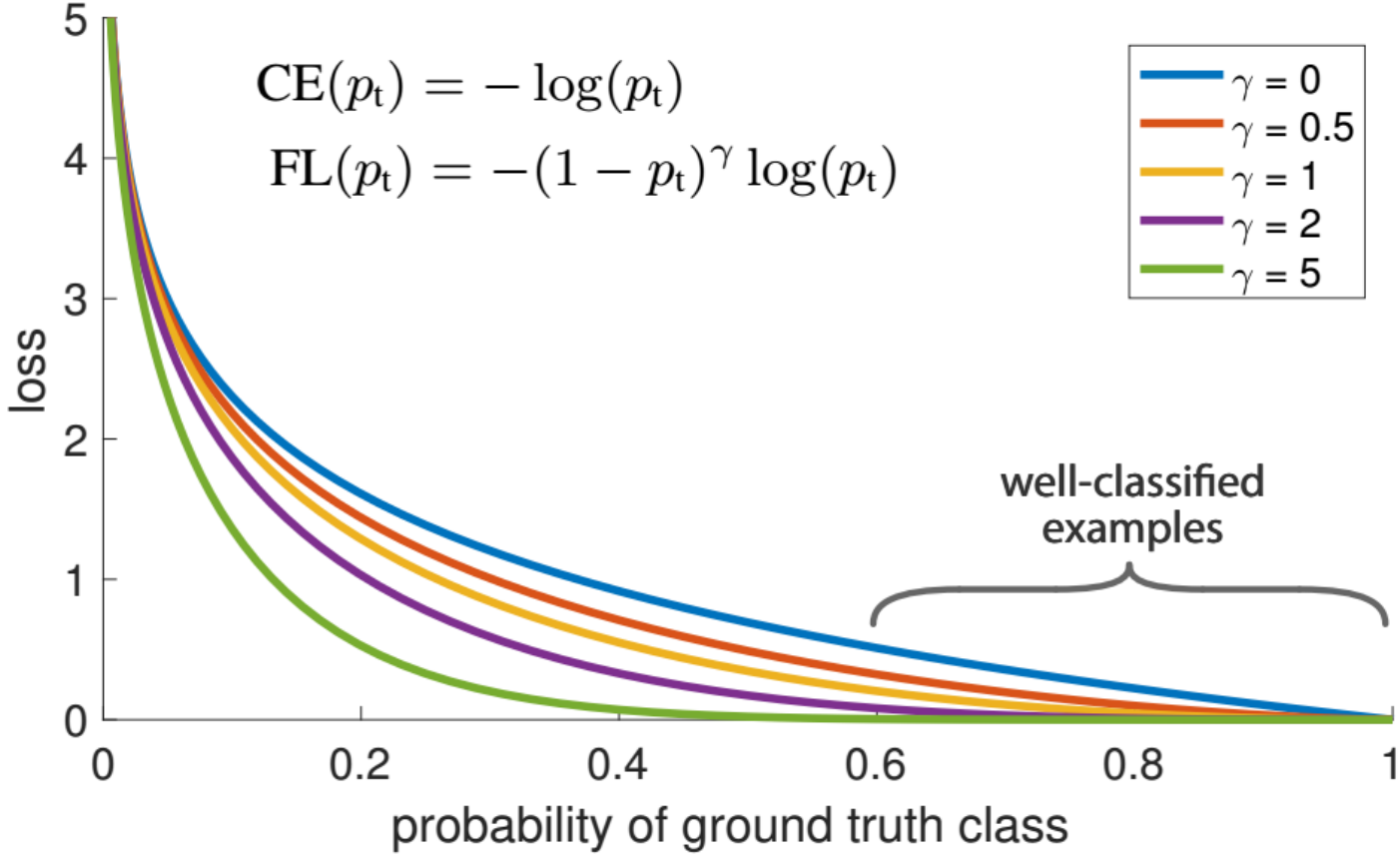
So: extreme foreground-background class imbalance during training!

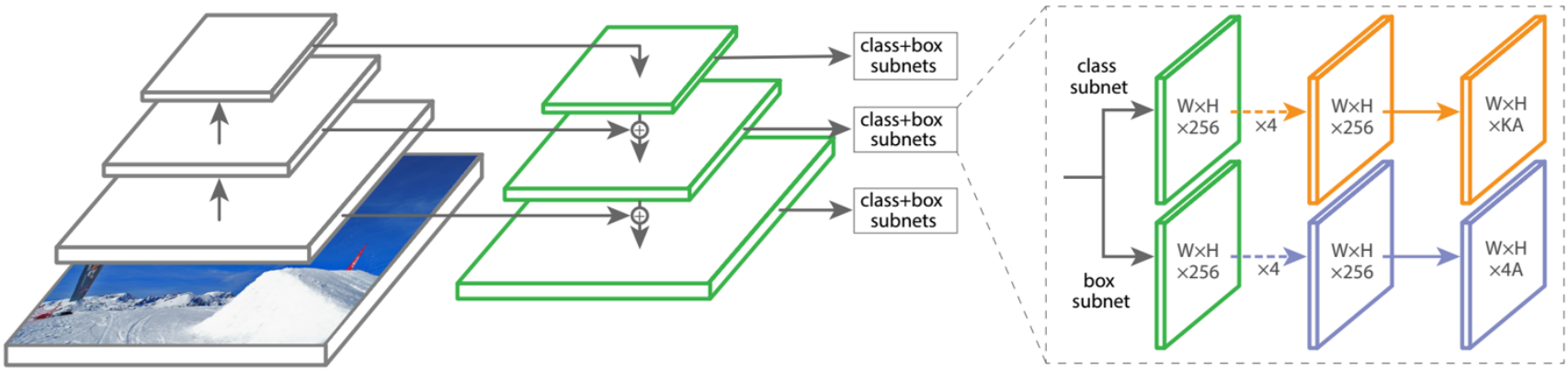
Solution: focal loss

- Focal loss down-weights the loss for well-classified examples
- It automatically focuses on hard examples during training
- CE: cross-entropy loss; FC: focal loss; p_t: model prediction



RetinaNet

- RetinaNet: ResNet+FPN+2 FCNs
- *One-stage* model for object detection
- Parameters of two subnets shared across all levels
- Focal loss for classification subnet
- Merge detections across levels, non-maximum suppression
- Achieve state-of-the-art results when trained with focal loss
- A: number of default ('anchor') boxes at each location



Figures here and in previous slide from Lin, Goyal, Girshick, He, Dollar, 'Focal loss for dense object detection', ICCV, 2017

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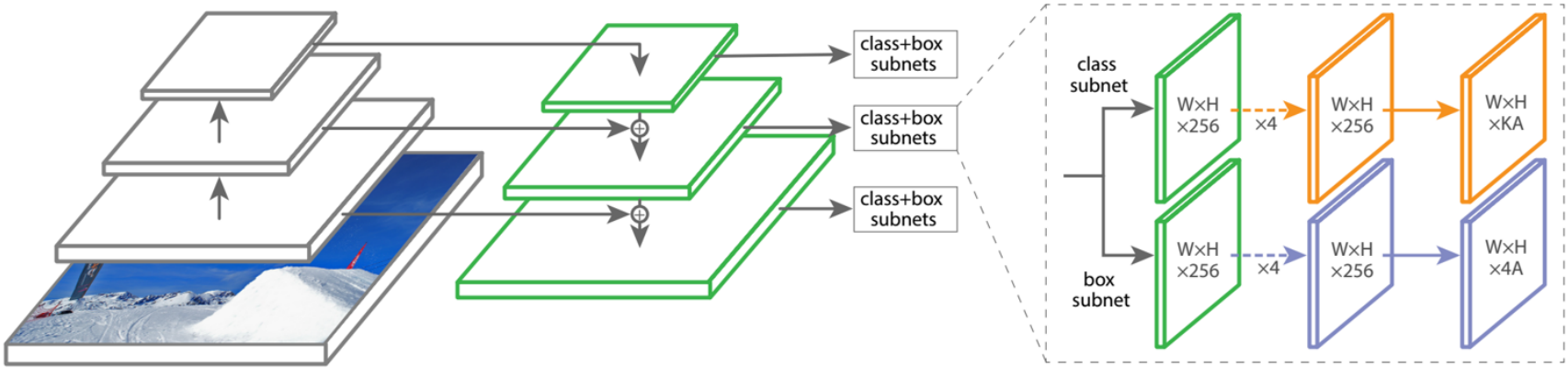

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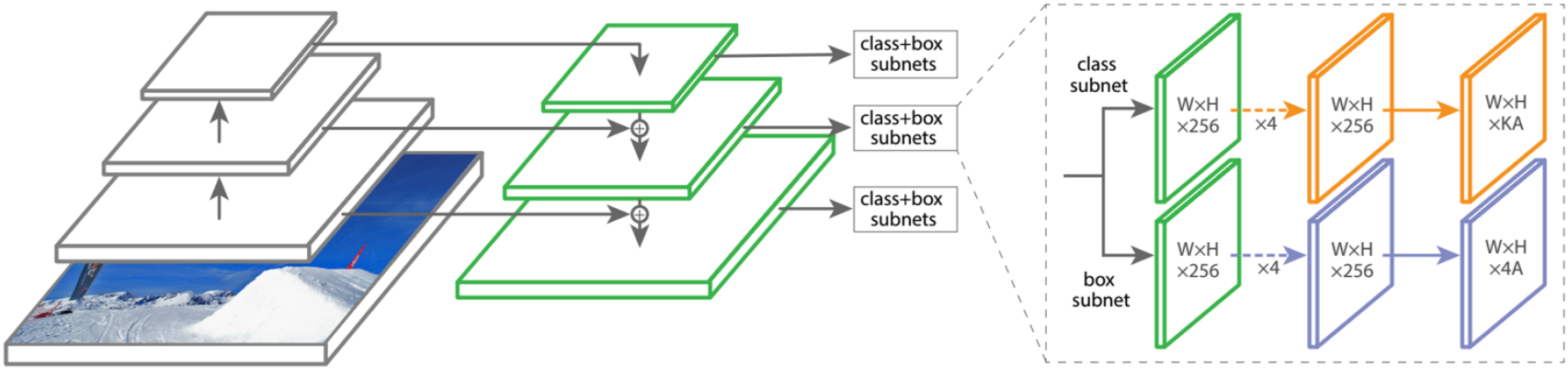

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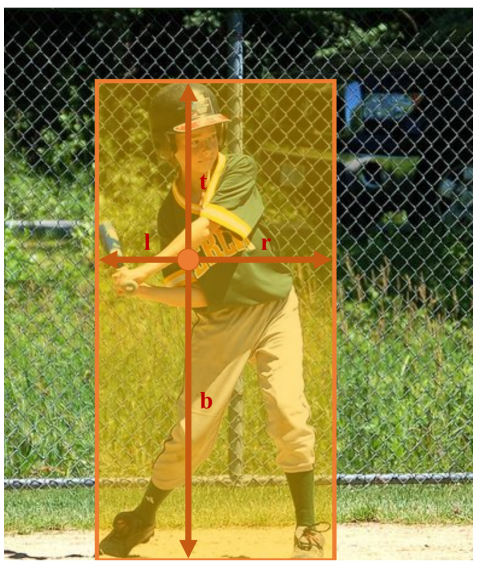
FCOS: fully convolutional one-stage object detection

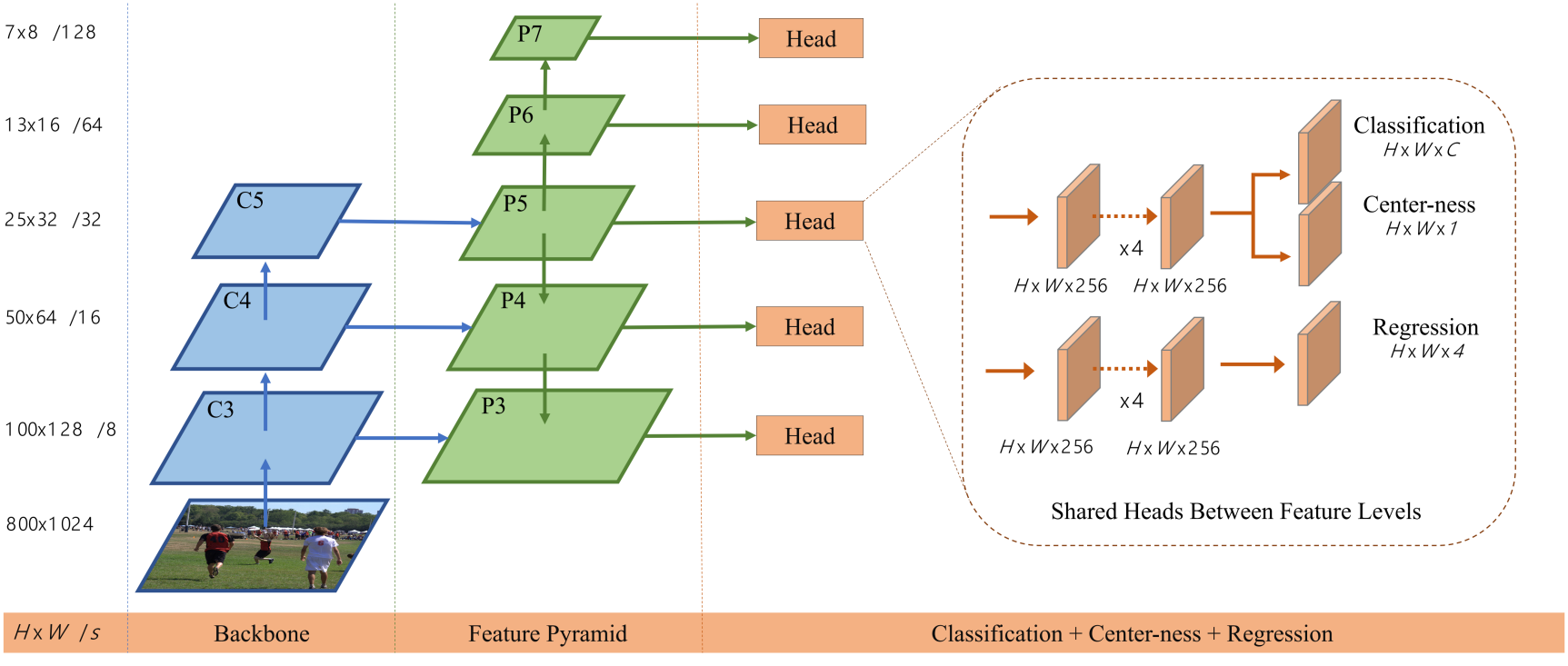
- Bounding box free: avoid hyper-parameters (size, aspect ratio)
- Predict distances from *each* foreground pixel to 4 boundaries (left, top, right, bottom) of the object



Figures here and in next slide from Tian, Shen, Che, He, 'FCOS: fully convolutional one-stage object detection', arXiv, 2019

FCOS (cont')

- Architecture similar to RetinaNet; loss different
- Different levels of feature maps for objects of different sizes
- *One-stage* model for object detection

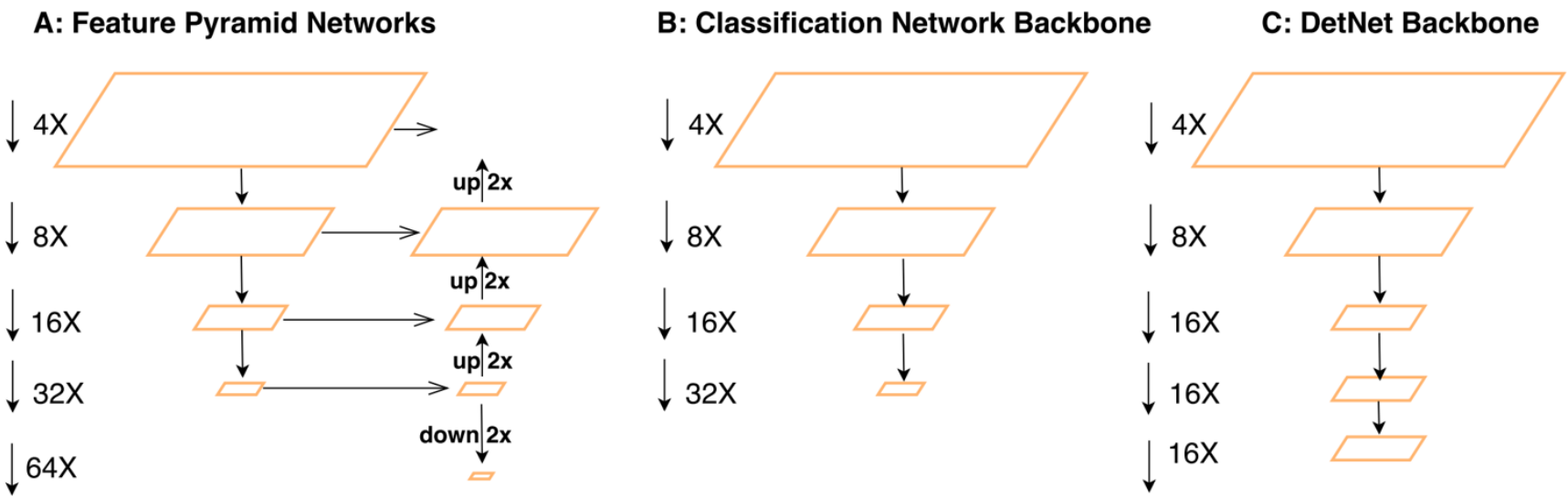


Issue for both one-stage and two-stage models

Above *detection* models depend on network pretrained on ImageNet for *classification* task

DetNet: a backbone network for object detection

- Large stride (downsampling) is harmful for localization (fig. B)
- Large stride causes missing of small objects (fig. B)
- Shallower layers have low semantic information (fig. B)
- Even in FPN, context cues of small objects also miss (fig. A)



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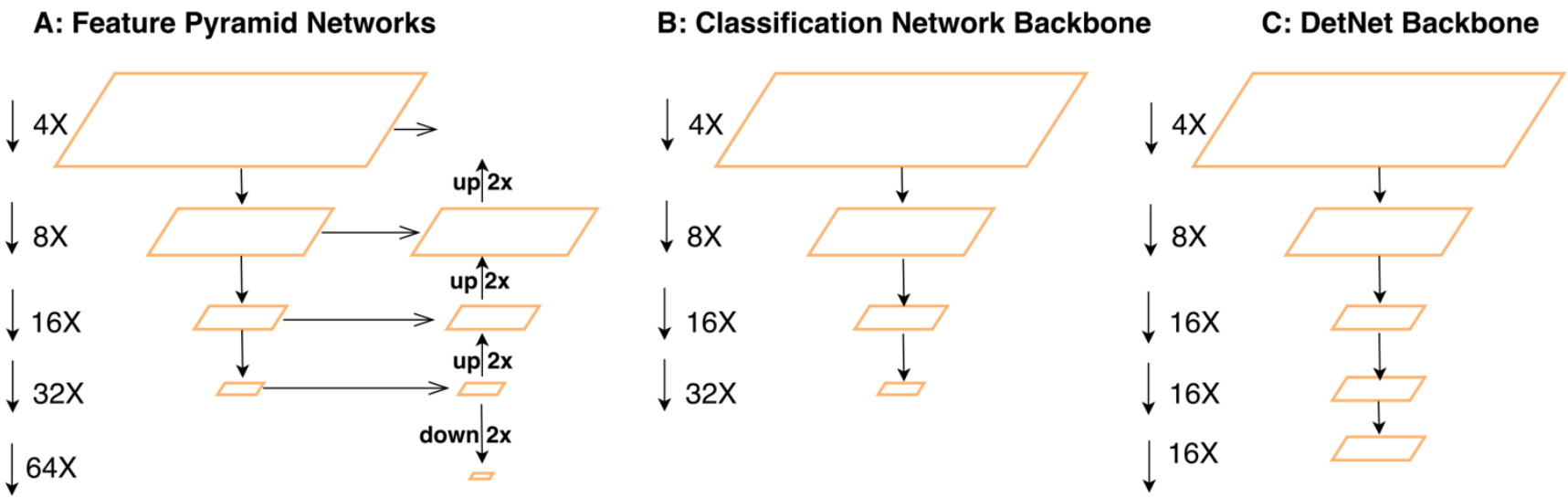

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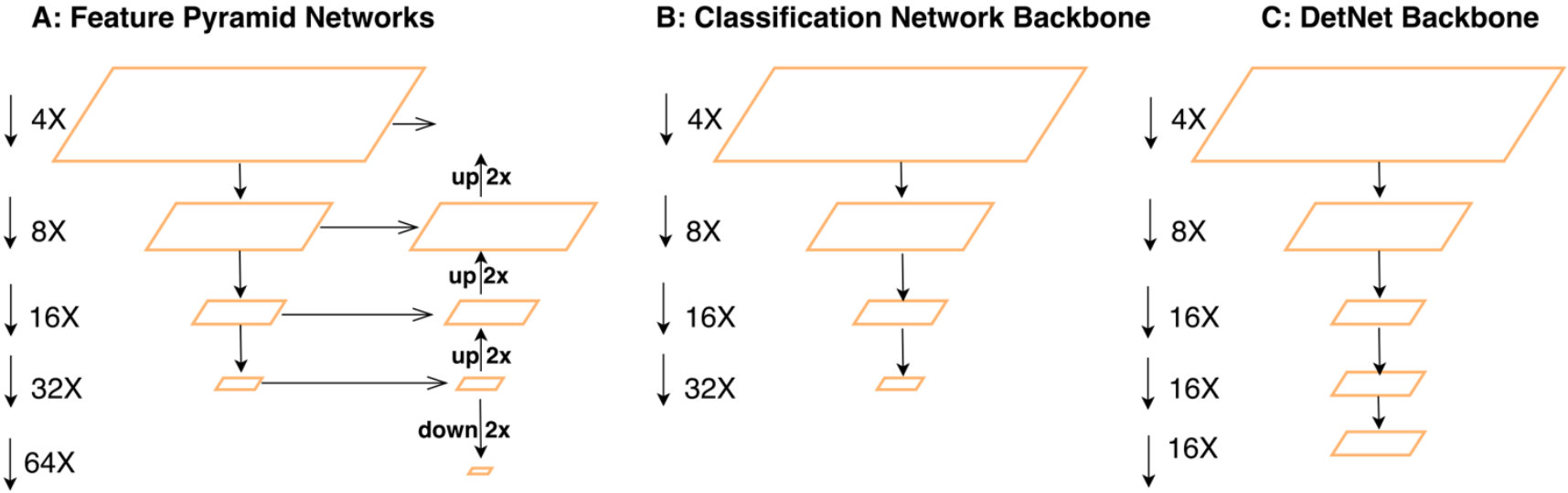

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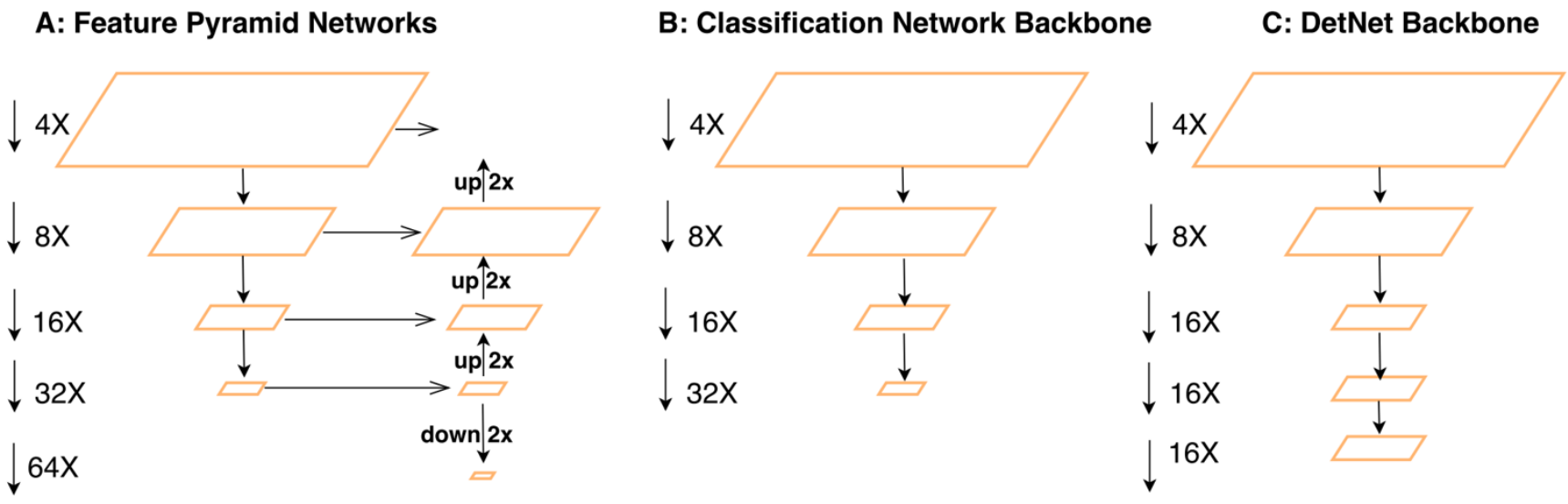
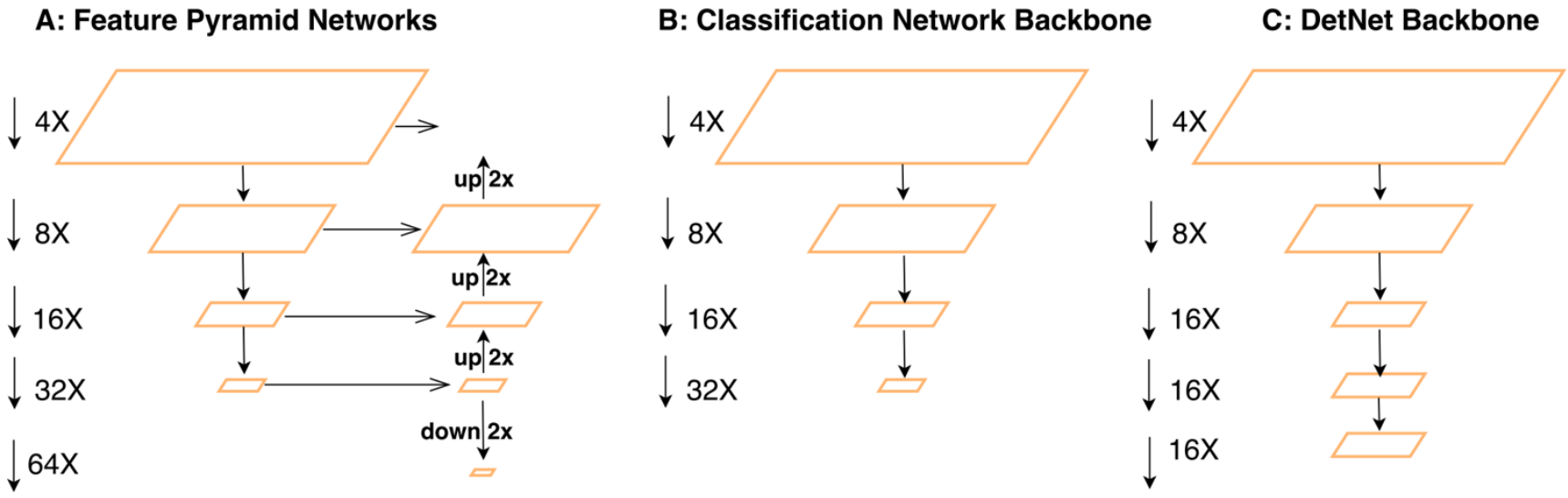
DetNet: a backbone network for object detection

- DetNet: designed directly for object detection and pretrained on ImageNet dataset (fig. C)
- Larger feature map size and also larger receptive field
- Better in locating large objects and detect small objects



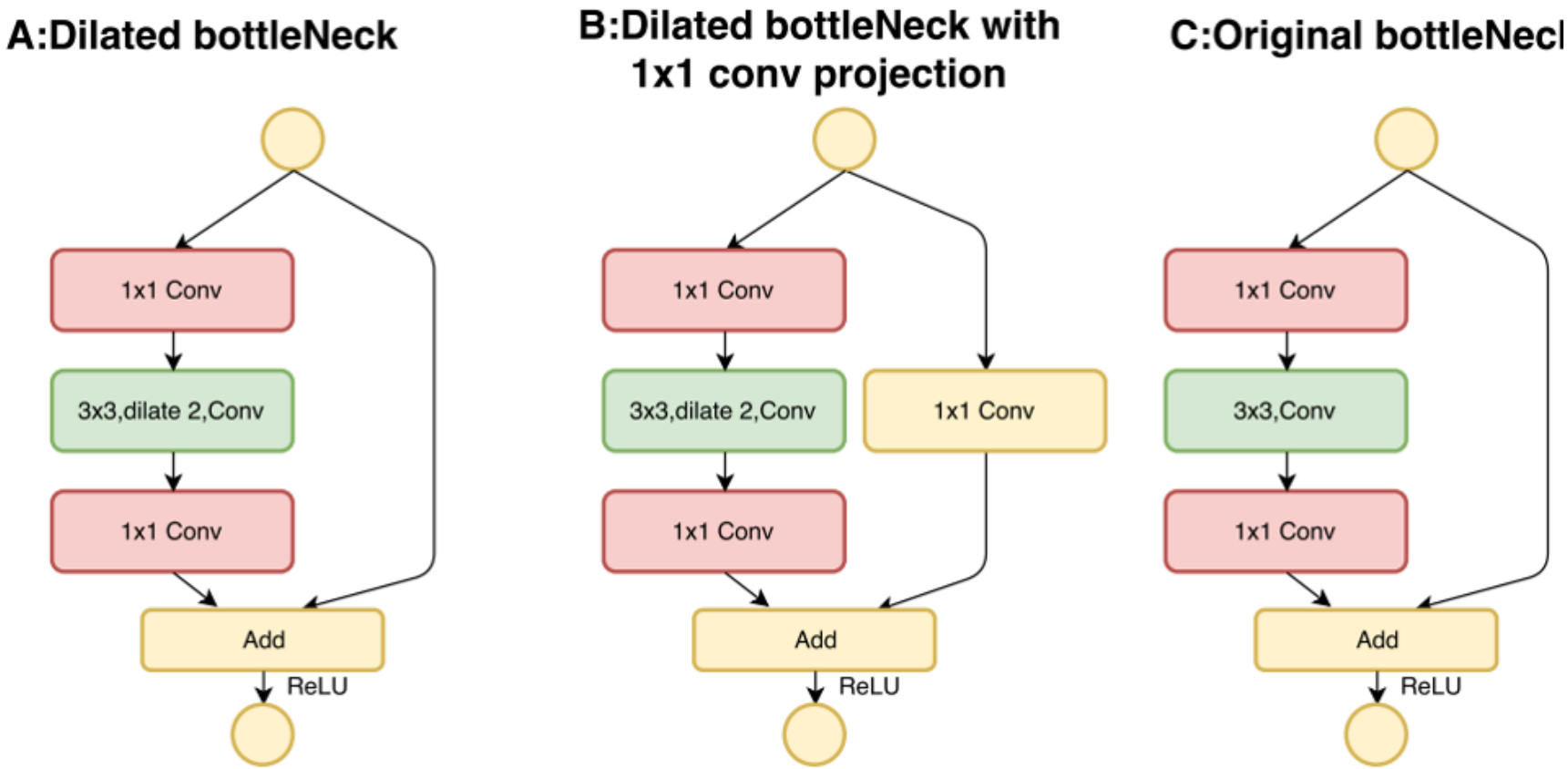
DetNet: a backbone network for object detection

- DetNet: designed directly for object detection and pretrained on ImageNet dataset (fig. C)
- Larger feature map size and also larger receptive field
- Better in locating large objects and detect small objects
- Overall structure like DeepLab, but for different tasks



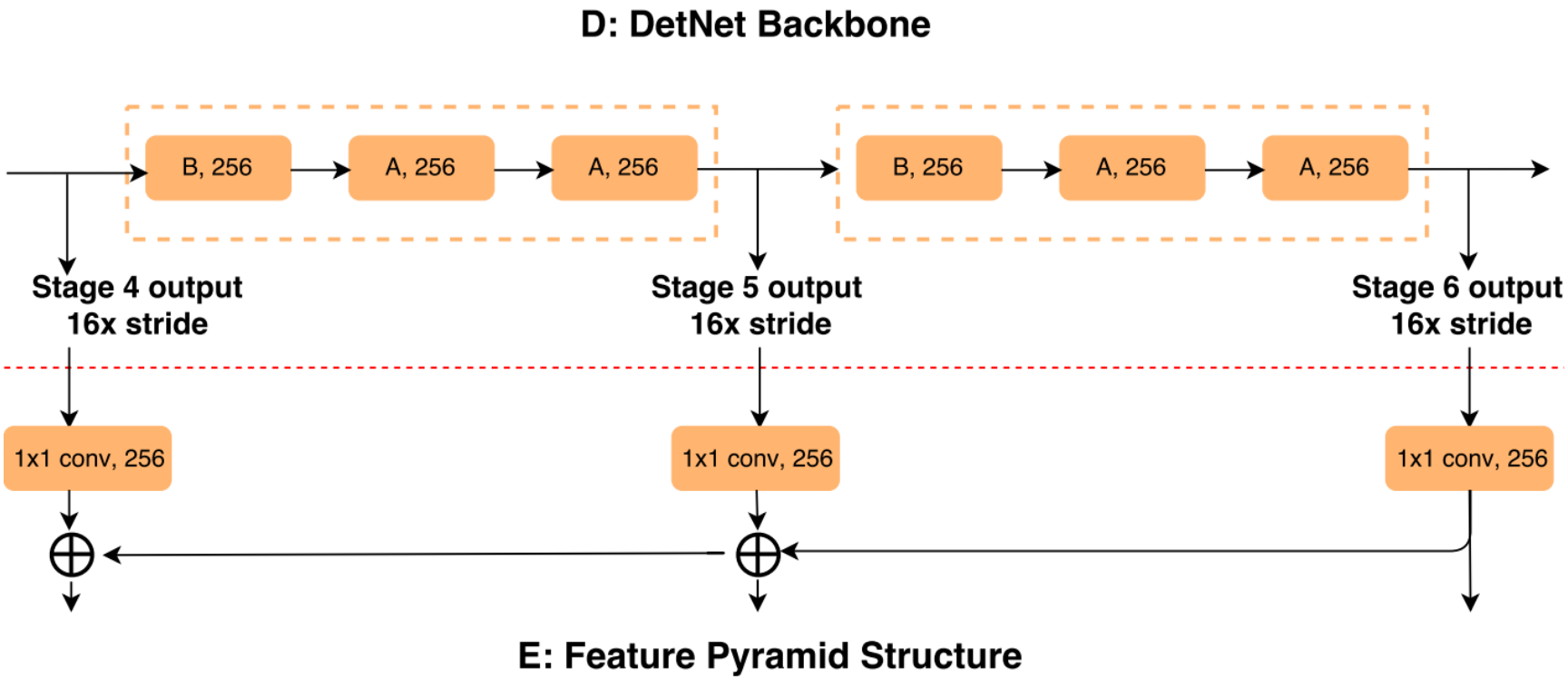
DetNet: a backbone network for object detection

- Novelty: dilated residual unit (A), dilated residual unit with 1×1 convolutional projection (B)
- Dilated convolution enlarges receptive field (as in DeepLab)



DetNet: a backbone network for object detection

- Easy to integrate DetNet with any detector, e.g., FPN
- 1×1 convolution (i.e., type B) helps create a new stage



DetNet with FPN: state-of-the-art result

- Large objects: accurate localization
- Small objects: detected, few missing

Summary

- From R-CNN to Mask R-CNN: faster, more accurate
- One-stage models: real-time, becoming more accurate
- Backbone network designed & pretrained specifically for detection
- Evolved fast! What are next innovations?

Further reading:

- Liu et al., Path aggregation network for instance segmentation, CVPR, 2018
- Hu et al., Learning to segment every thing, CVPR, 2018
- Wang et al., Region proposal by guided anchoring, arXiv, 2019

Comments on 1st assignment

- Be clear, specific, concise
- Both short (<100 words) and long (better 600-800) summary
- Highlight the key innovation in short summary
- Follow points listed on Week 1's last slide
- Say more about limitations and possible improvement
- Describe experiments in words, but concisely
- Just maximally one or two tables/figures/formulae
- If using figure, add figure caption below
- Delete redundant and non-academic information
- Not too many short paragraphs; not too long paragraphs
- Not use bullet points; link paragraphs smoothly
- 'we'/'I' to be replaced by 'the author(s)'/'the method', etc.
- Not select papers from low-rank conferences/journals