Computer Vision

Designing, Visualizing and Understanding Deep Neural Networks

CS 182/282A

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10/04/2022

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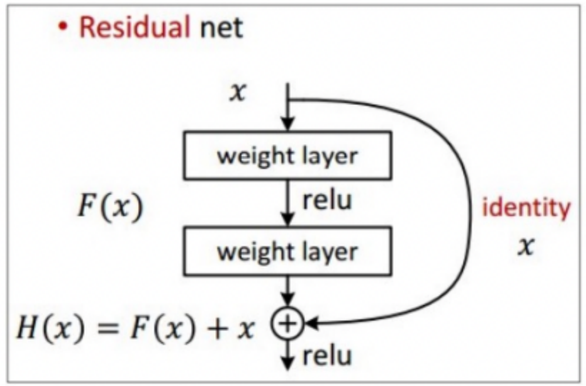
UC Berkeley

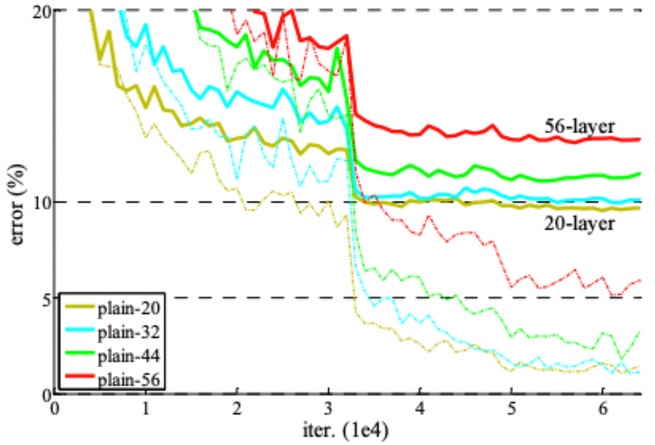
CNNs : Training, Debugging, Understanding

Review : Skip Connections & ResNets



$$\frac{dH}{dx} = \frac{dF}{dx} + \mathbf{I}$$

regulate ill-conditioned gradients

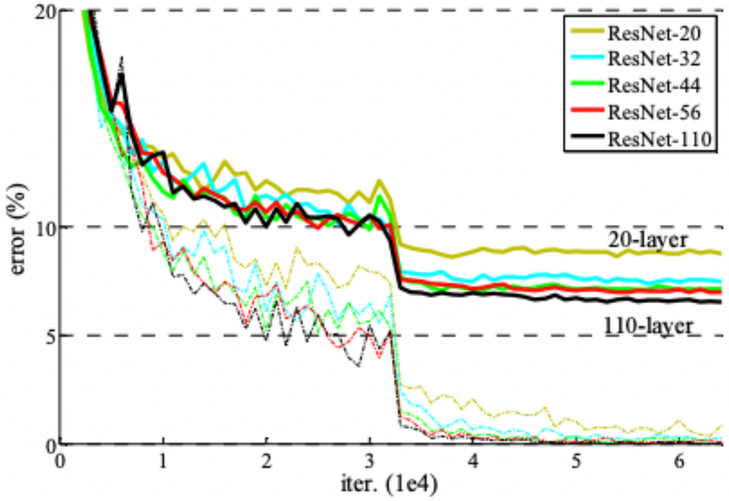


Training plain-CNN without skip-connections, deeper networks doesn't optimize to better error%.

Pseudocode

```
def resnetBlockV1(x):
    op = nn.Sequential(
                    Conv2D,
                    BatchNorm2D,
                    ReLU,
                    Conv2D,
                    BatchNorm2D)

    out = x+op(x)
    return ReLU(out)
```



CNNs w/ skip connections improves trainability of deeper models, by improving gradient flow.

He et al. "**Deep Residual Learning for Image Recognition**" 2015

Training : How fast?

Natural followup question:

Well, what are challenges in speeding up model training?

→optimization challenges:

× use same learning rate schedule

✓ *linearly scale LR*

→increasing batch size :

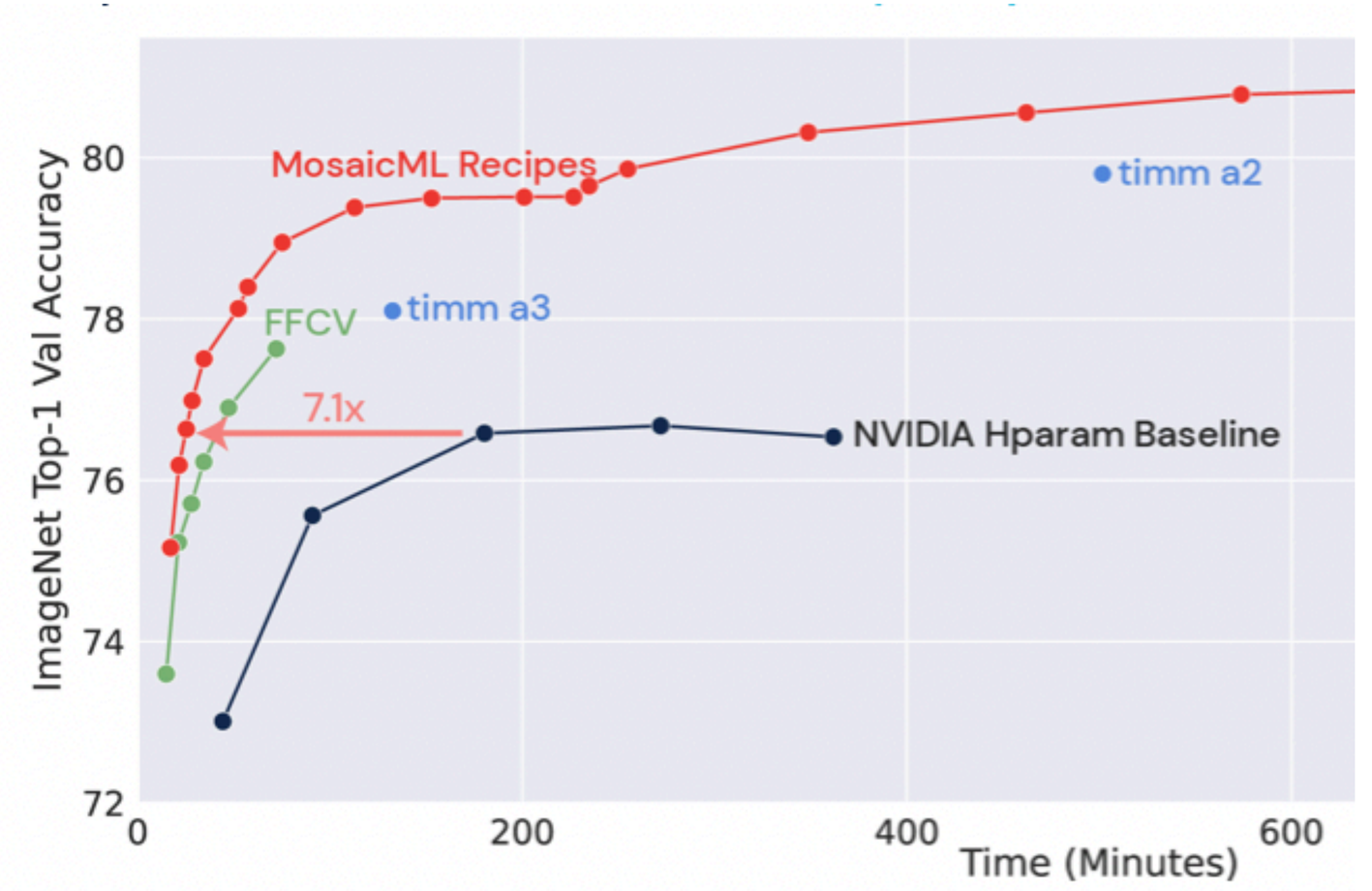
× activations don't fit memory

✓ *distributed dataparallel training*

→ data augmentation :

× overfitting to train-set fast, does not necessarily improve generalization

✓ *regularize with data-augmentations*

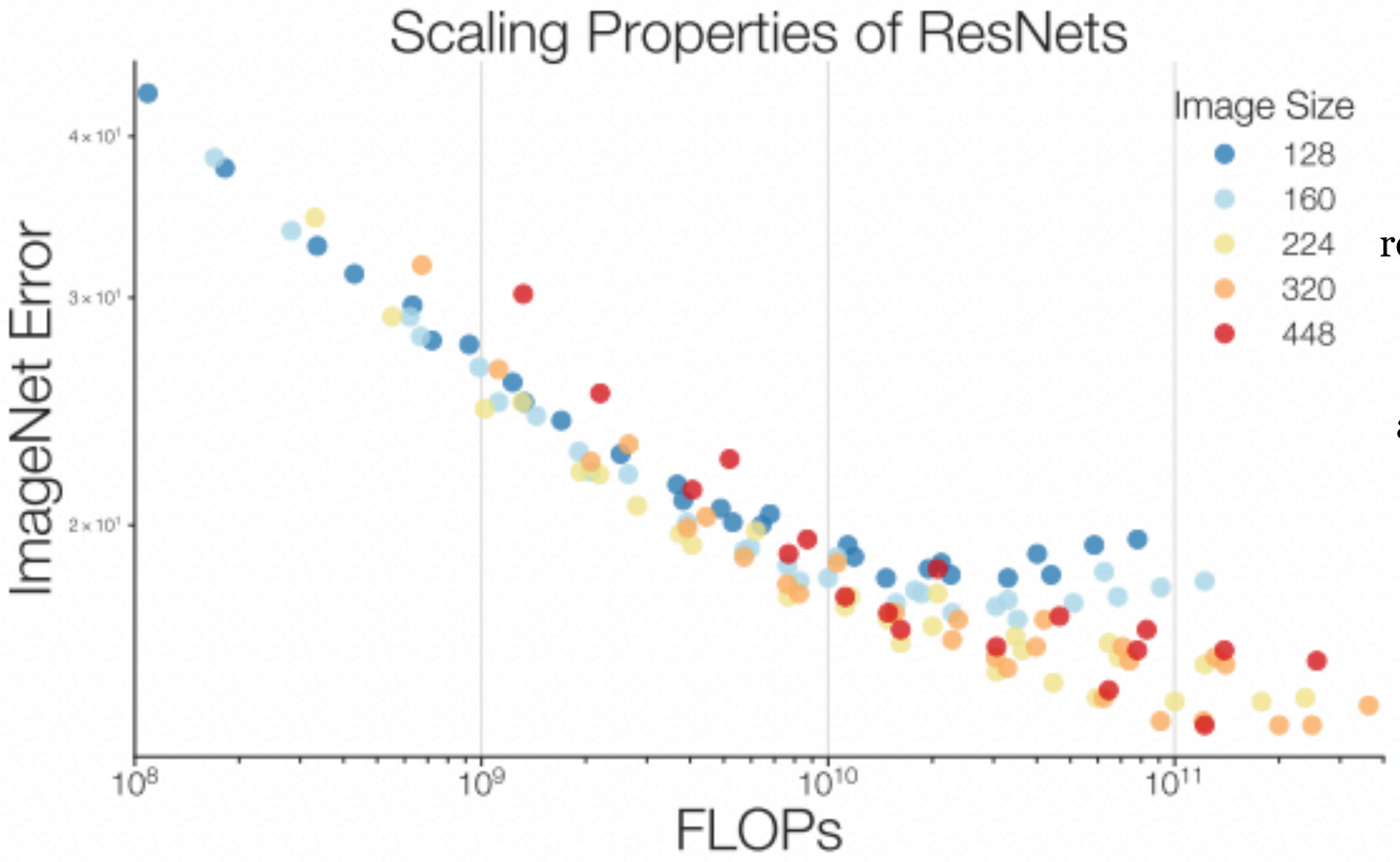


Training Resnet-50 models on Imagenet [1.2M samples] with 8A100 GPUs, typically requires around <20min to achieve > 75.2% test-set accuracy. More details at https://github.com/mosaicml/benchmarks/

Goyal et al. "**Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour**" 2017

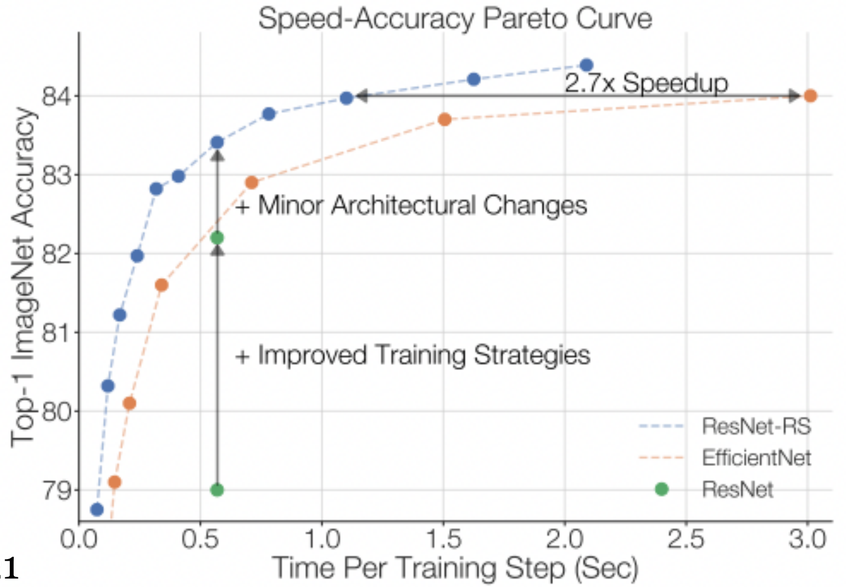
ResNet50 recipes : https://github.com/mosaicml/benchmarks/

Revisiting ResNet training across scale



For a given network architecture (ResNet), the error approximately scales as a power law with FLOPs (linear fit on the log-log curve). Scaling includes width-multipliers, depth and image resolutions.

	Improvements	Top-1	Δ
	ResNet-200	79.0	—
training methods	+ Cosine LR Decay	79.3	**+0.3**
	+ Increase training epochs	78.8 †	-0.5
regularization methods	+ EMA of weights	79.1	**+0.3**
	+ Label Smoothing	80.4	**+1.3**
	+ Stochastic Depth	80.6	**+0.2**
	+ RandAugment	81.0	**+0.4**
	+ Dropout on FC	80.7 ‡	-0.3
architecture methods	+ Decrease weight decay	82.2	**+1.5**
	+ Squeeze-and-Excitation	82.9	**+0.7**
	+ ResNet-D	83.4	**+0.5**



Bello et al. "**Revisiting ResNets: Improved Training and Scaling Strategies**" 2021

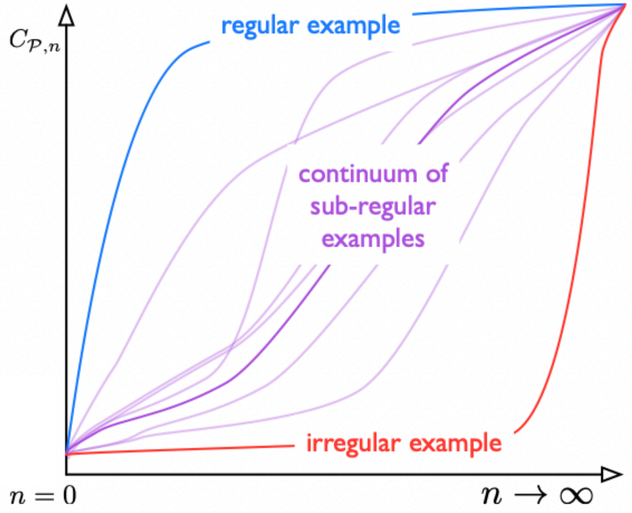
What do CNNs learn? An instance-level view

Intuition : "Easy" samples should be learned faster

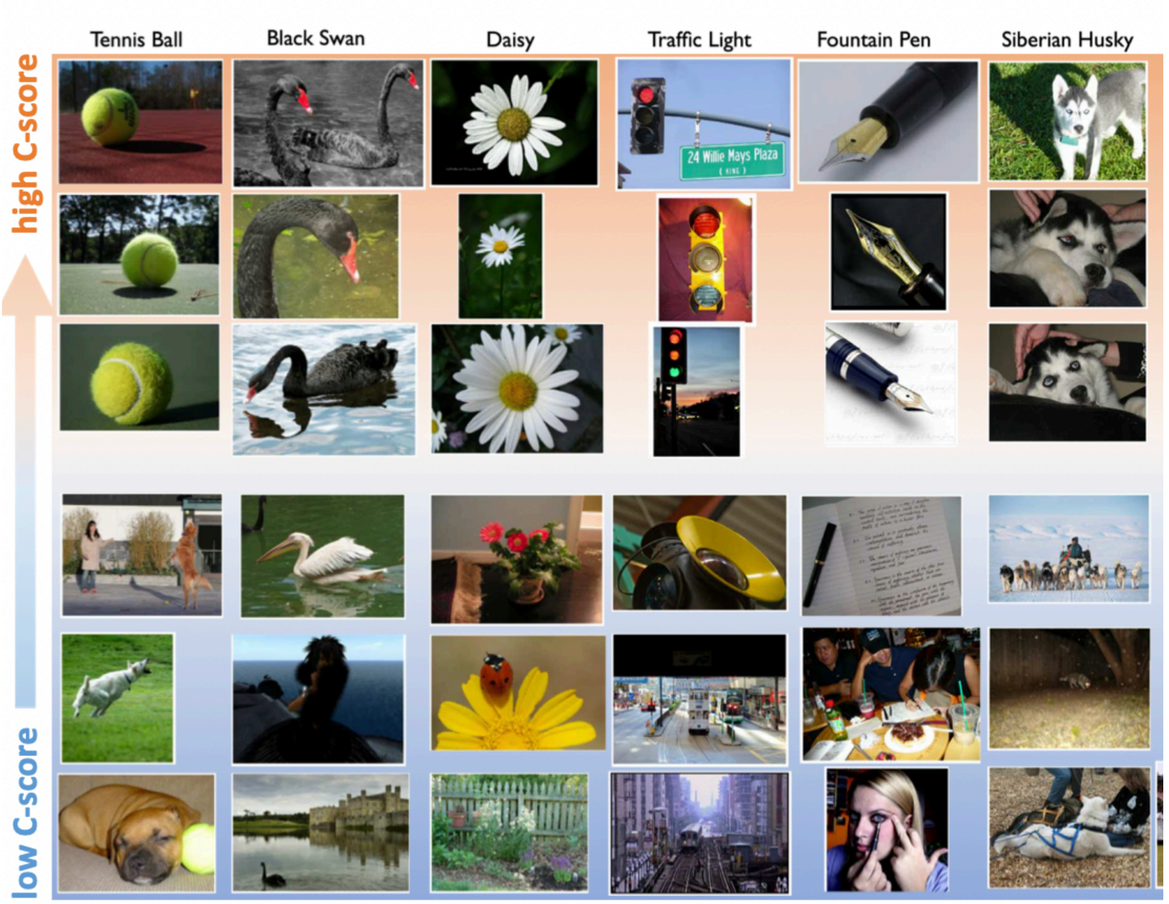
How to characterize *example-difficulty*?
Consider dataset $\mathscr{D} \sim_n P$ where we take n iid-samples, define the consistency-profile for an instance (x, y) as

$$C_{\mathrm{P},n}(x,y) = \mathbb{E}_{\mathscr{D}\sim_n \mathrm{P}}\left[\mathbb{P}\left(f(x;\mathscr{D}\backslash\{(x,y)\}) = y\right)\right]$$

Regularities and exceptions in a binary chairs vs non-chairs problem



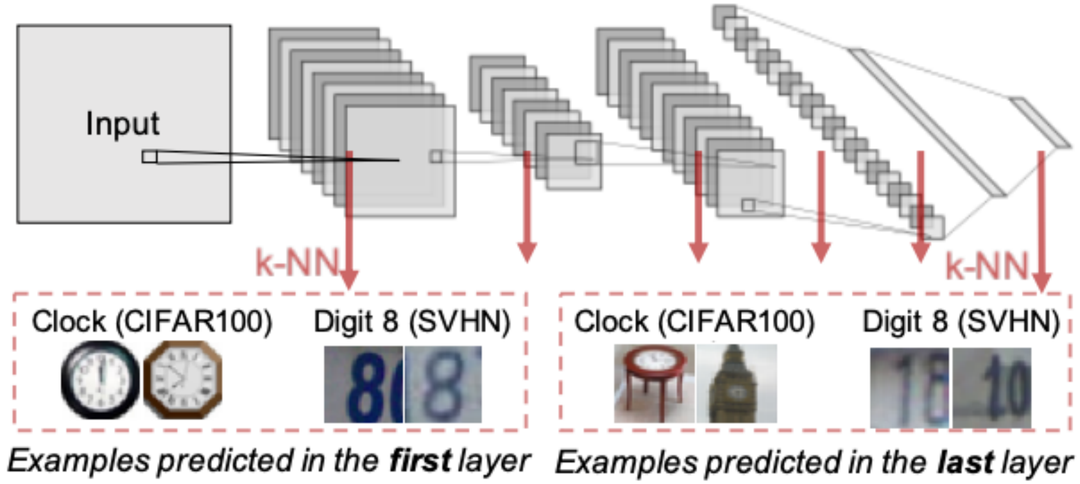
Consistency profiles across samples.



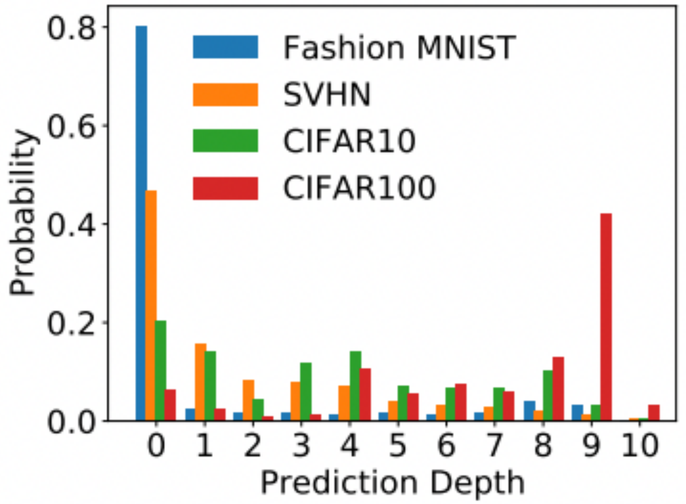
On the ImageNet dataset, instances are ordered by estimates of C-score, from regularities **(high C-score)** to exceptions **(low C-score).**

Jiang et al. "**Characterizing Structural Regularities of Labeled Data in Overparameterized Models**" 2020

Example Difficulty & Depth-Complexity



For representations at intermediate layer, we look at the predictions of k-NN classifier.

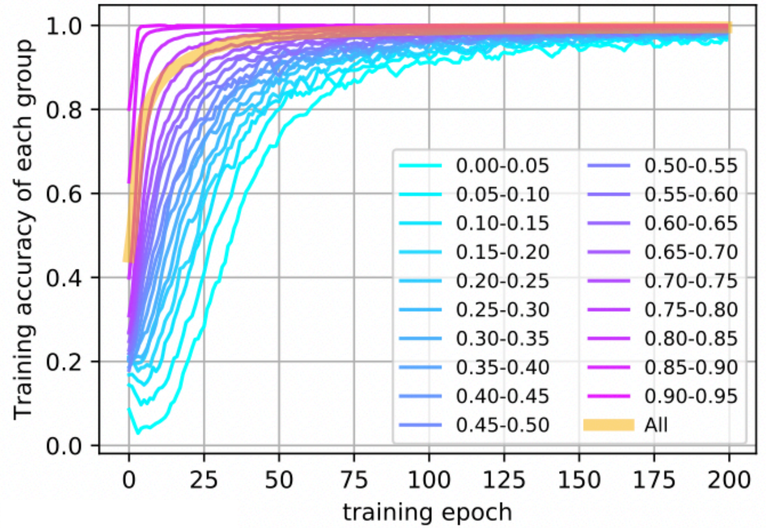


Prediction depth across samples on benchmarking vision datasets.

$$\text{prediction\_depth}(x, f_\theta) = \arg\min_{l \in L} f(x, \theta_l) = f(x, \theta_{>l})$$

Some takeaways

1. Prediction depth is a good proxy for example difficulty.
2. "Easier" examples are learned "first", both in terms of optimization (earlier epochs) and model (earlier layers).
3. Estimating example difficulty allows us to early-exit, saving compute at inference!

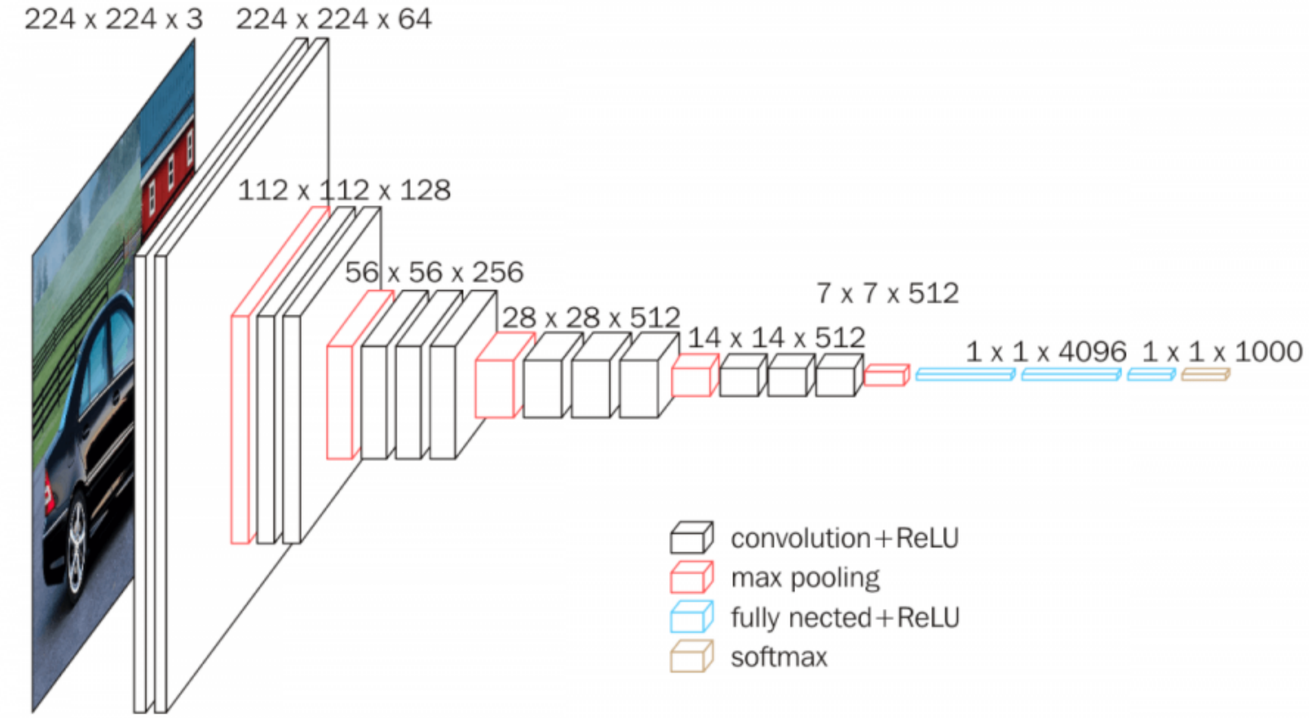


C-score correlates with *learning-speed*

Baldock et al. "**Deep Learning Through the Lens of Example Difficulty**" 2021

Beyond Image Classification

So far …



convolutional networks: map **image** to **output value**

e.g., semantic category (“bicycle”)

Dense Prediction with Convolutions

→ Images are rich-source of information about the environment.

In practice:

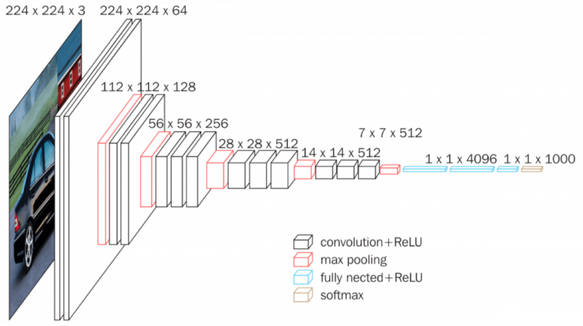
→ identify all distinct objects in a scene (multi-output)

→ find object position beyond labels

→ from 2D to 3D (e.g. depth estimation from images)

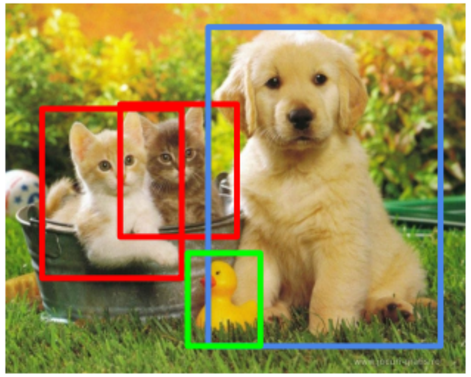
https://github.com/facebookresearch/detectron2

Standard computer vision tasks

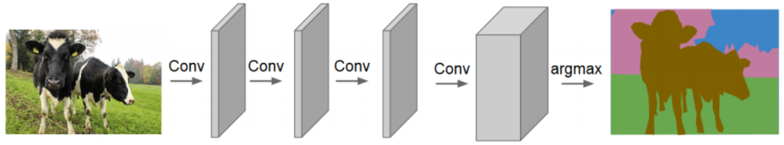


object classification

object localization



object detection



semantic segmentation

Object Localization

The Problem Setup

Previously : $\mathcal{D} = \{x_i, y_i\}$

image **label** l_i

Now : $\mathcal{D} = \{x_i, y_i\}$

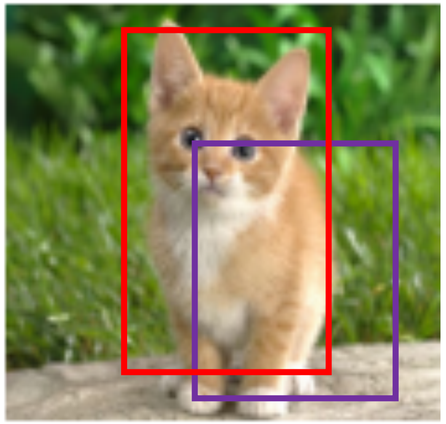
image $(l_i, x_i, y_i, w_i, h_i)$

convolutional networks: map **image** to **output value**

e.g., label, object location, BoundingBox

Measuring localization accuracy

learned model



(x, y, w h)

predicted bounding box

"cat" : 0.64

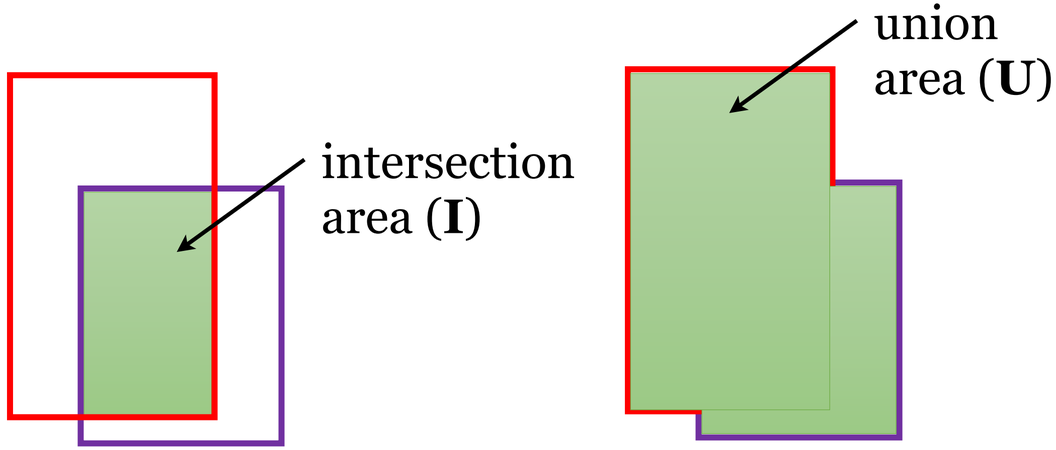
prediction score (e.g. probability)

Did we get it right?

Intersection over Union (IoU)
Different datasets have different protocols, but one reasonable one is: correct if IoU > 0.5

If also ouputting class label (usually the case) : correct if IoU > 0.5 and class is correct

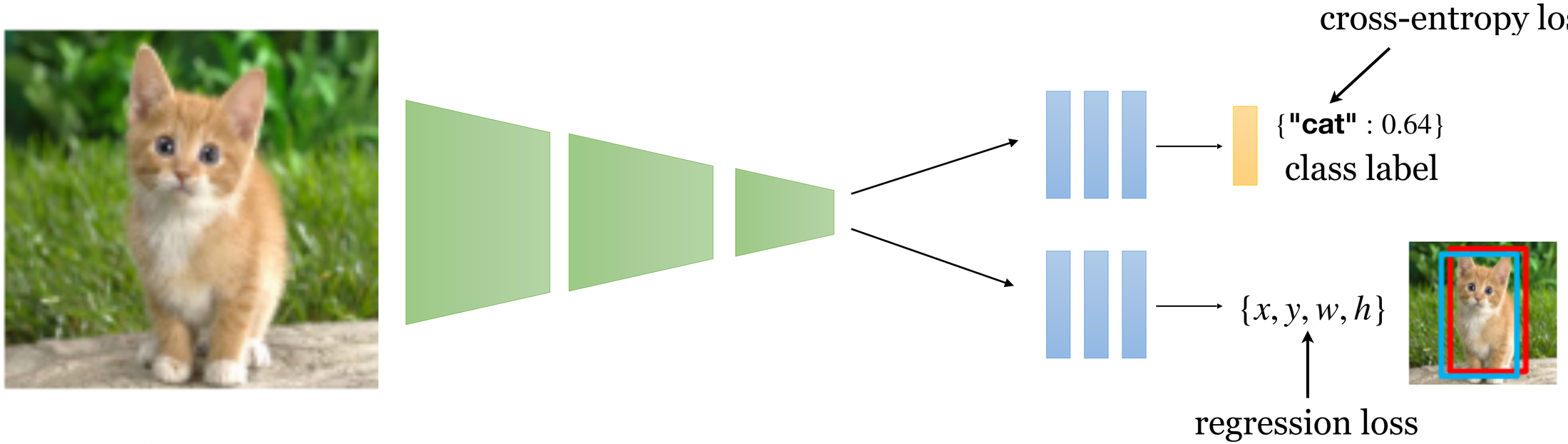
Note : Not the loss function ! Metric for evaluation model quality



IoU = I/U

Object Localization as Regression

$$\mathcal{D} = \{(x_i, y_i)\} \quad y_i = (\ell_i, x_i, y_i, w_i, h_i)$$

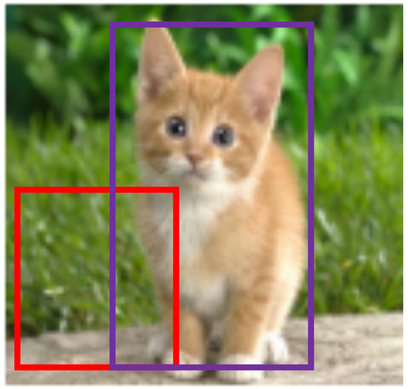


→ simple design

→ train either jointly (multi-task, more on this later), or use pretrained classification model, then train regression head

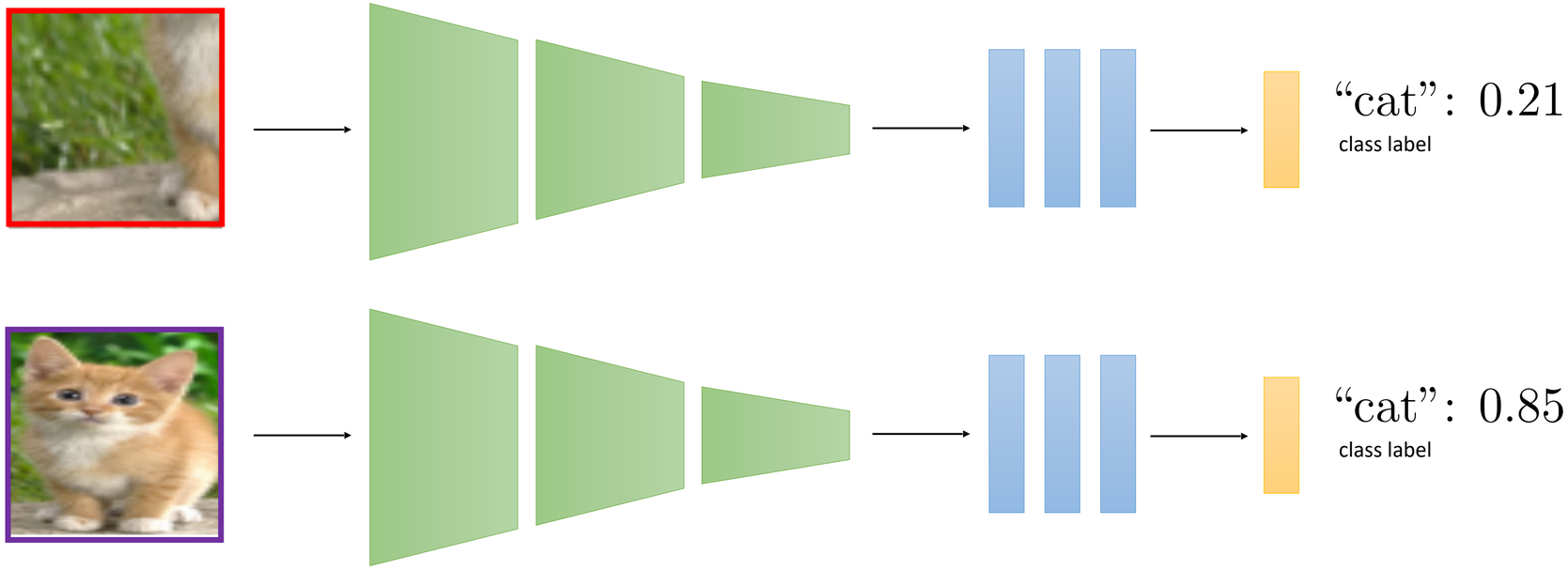
→ Not usually the standard approach, we're not using structure of the problem.

Sliding Windows



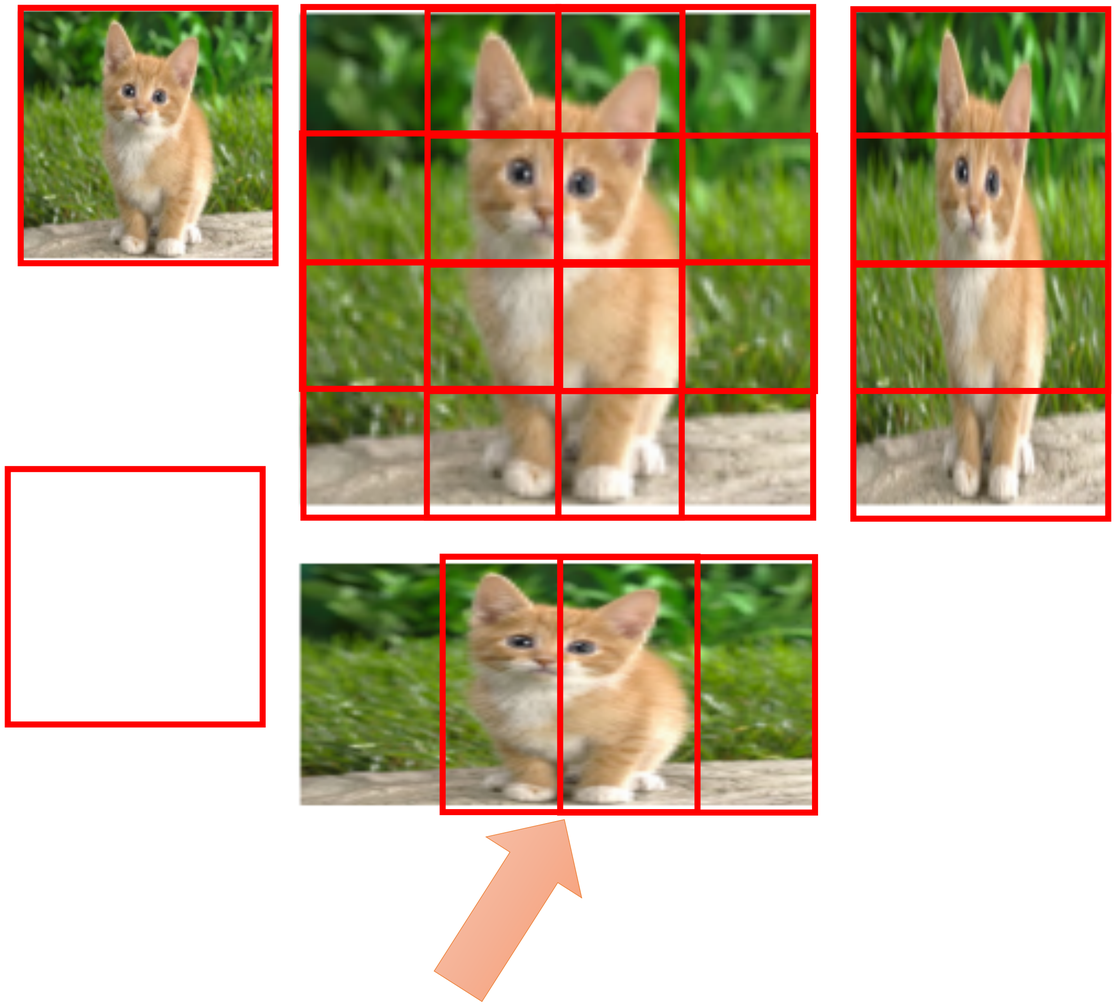
$$\mathcal{D} = \{(x_i, y_i)\} \;\; y_i = (\ell_i, x_i, y_i, w_i, h_i)$$

What if we classify **every** patch in the image?



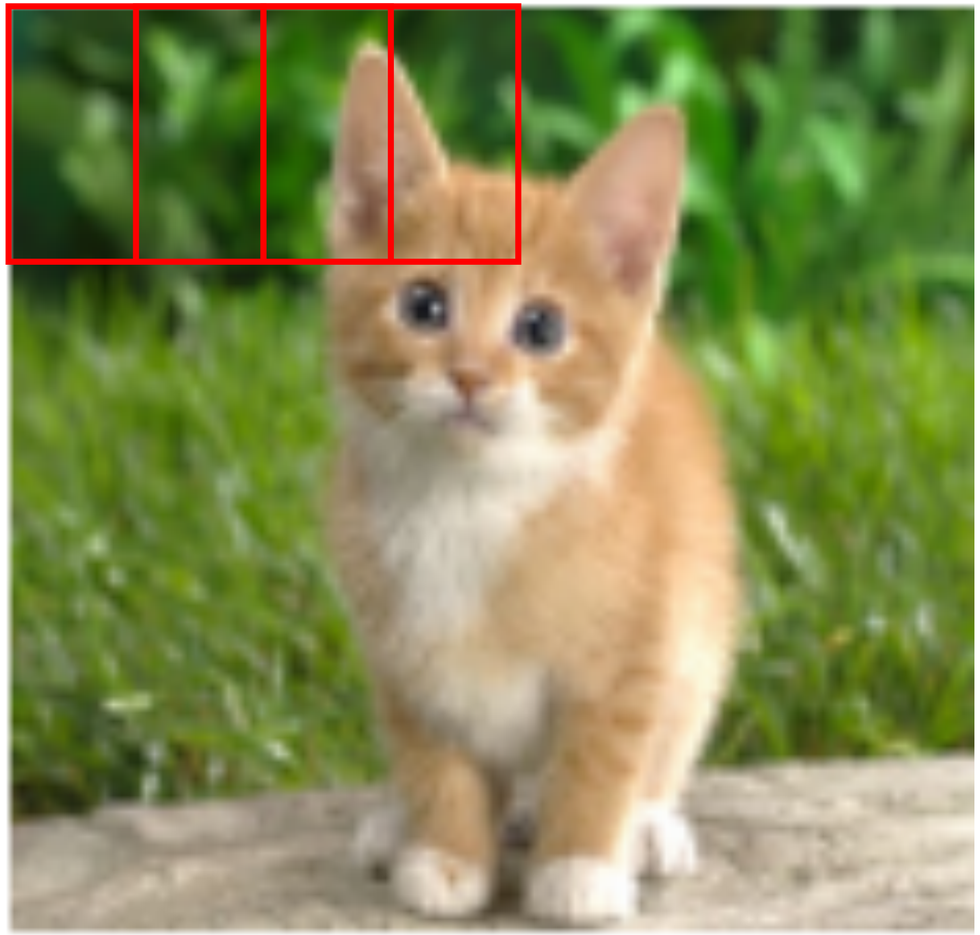
Sliding Windows

$\mathcal{D} = \{(x_i, y_i)\}$ $y_i = (\ell_i, x_i, y_i, w_i, h_i)$

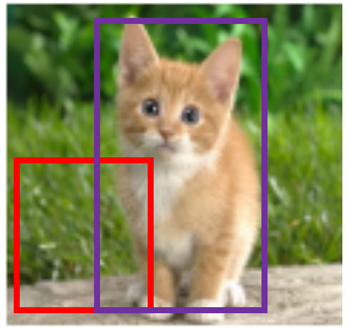


could just take the box with the **highest** class probability

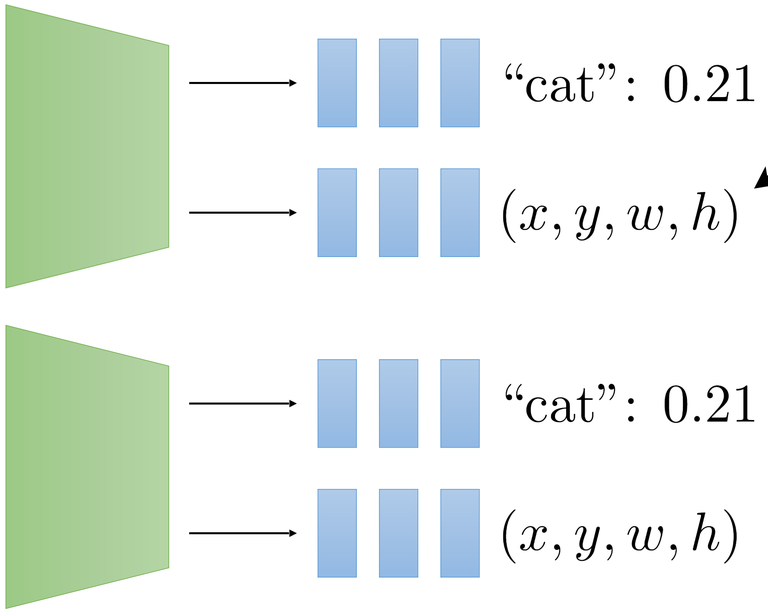
more generally: **non-maximal suppression**



A practical approach : OverFeat



$\mathcal{D} = \{(x_i, y_i)\}$ $\quad$ $y_i = (\ell_i, x_i, y_i, w_i, h_i)$

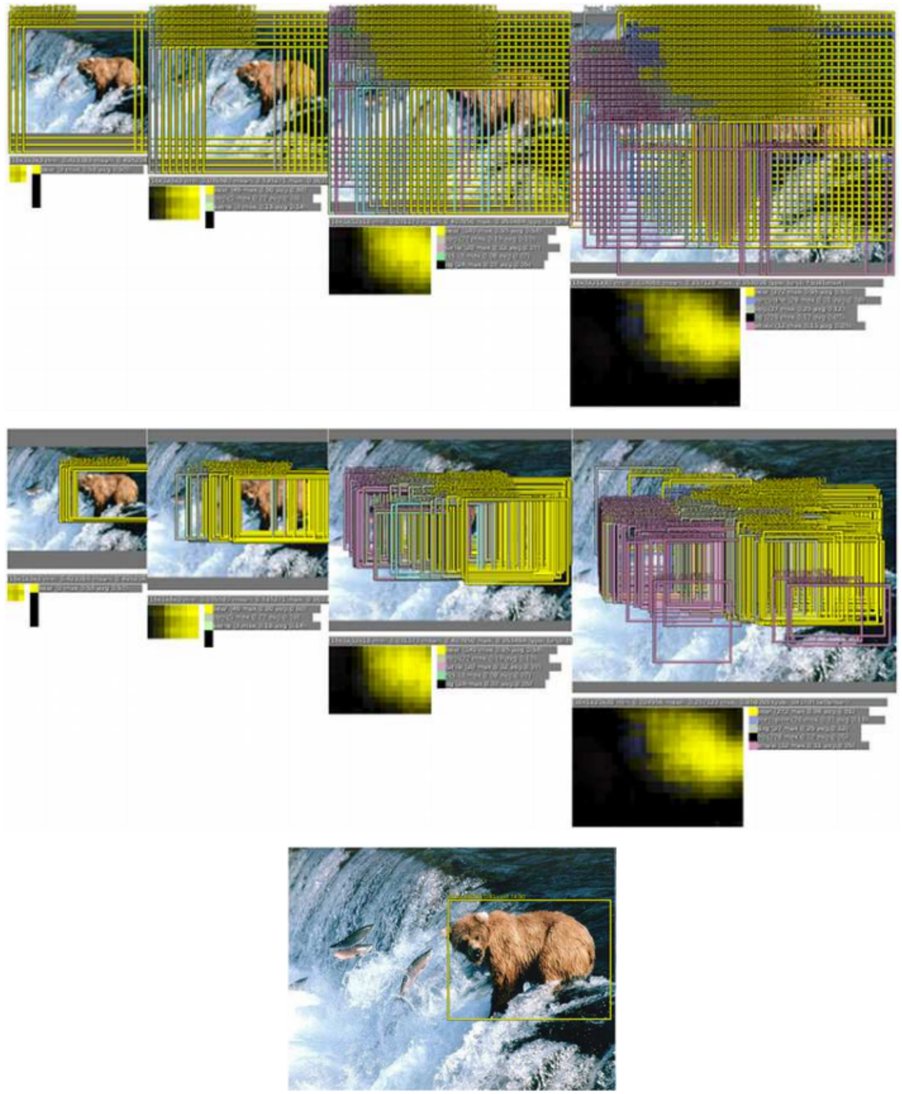


provides a little "correction" to sliding window

- Pretrain on **just** classification
- Train regression head on top of classification features
- Pass over different regions at different scales
- "Average" together the boxes to get a single answer

Sermanet et al. "**OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.**" 2013

Sliding windows & reusing calculations



Sliding window **classification** outputs at each scale/position (yellow = bear)

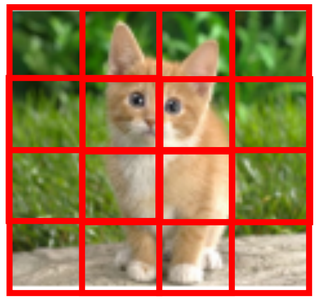
Predicted box x, y, w, h at each scale/ position (yellow = bear)

Final combined bounding box prediction (yellow = bear)

Sermanet et al. “**OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.**” 2013

Sliding windows & reusing calculations

Problem: sliding window is very expensive! (36 windows = 36x the compute cost)

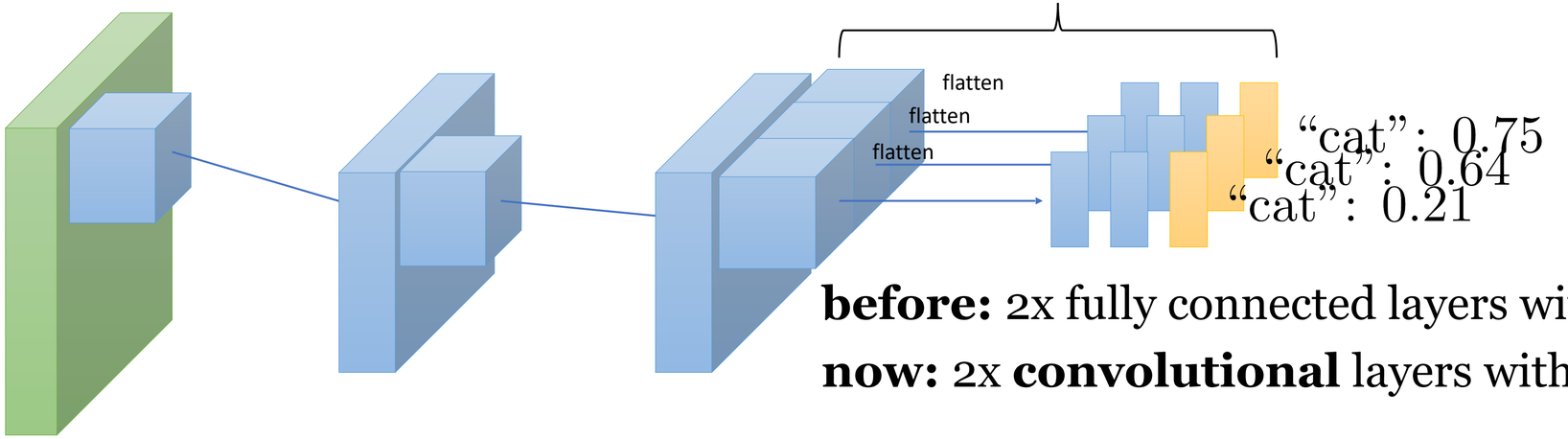


This looks **a lot** like convolution…

Can we just **reuse** calculations across windows?

“Convolutional classification”

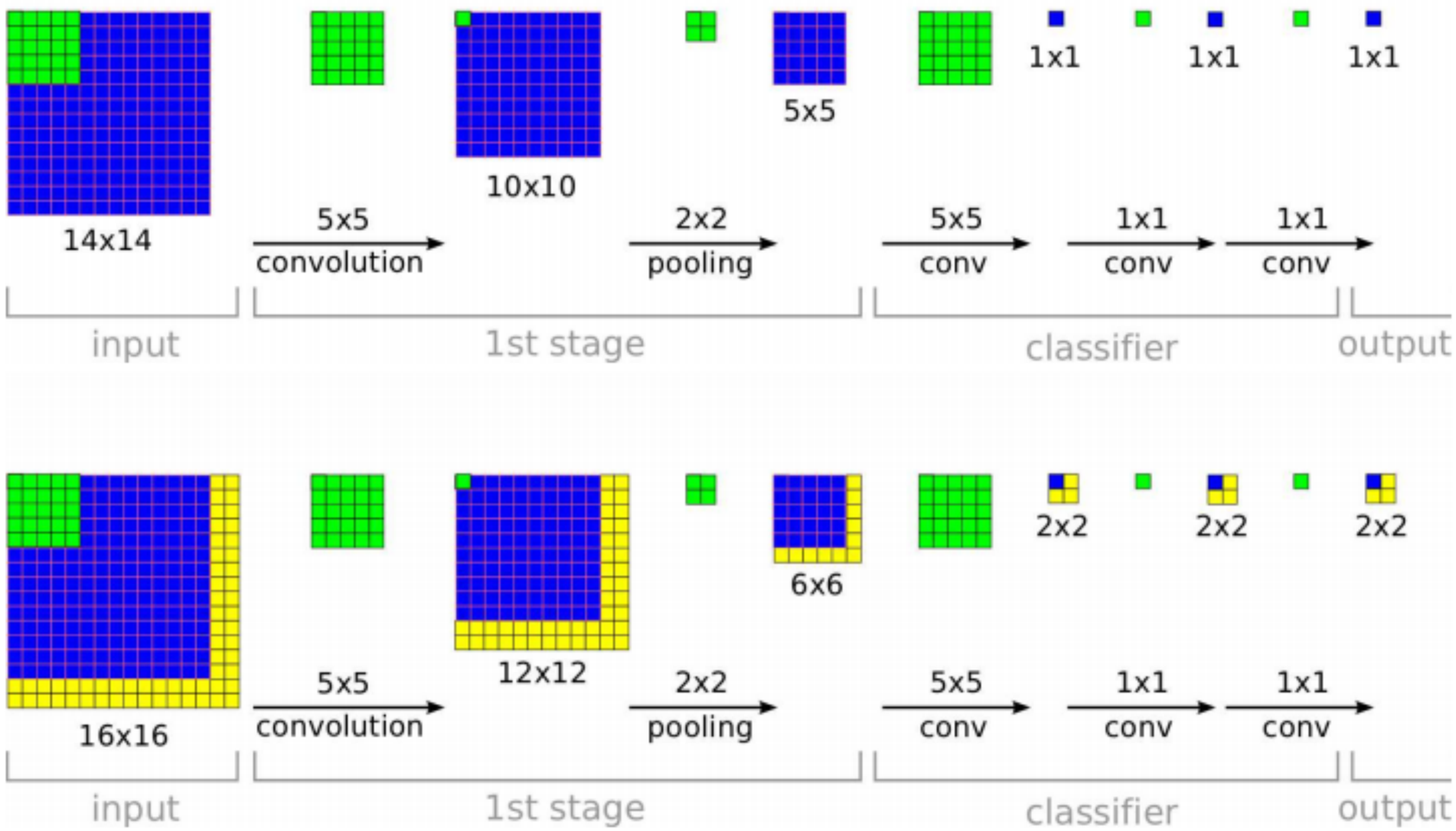
these are just convolutional layers!



before: 2x fully connected layers with 4096 units

now: 2x **convolutional** layers with 1 x 1 x 4096 filters

Sliding windows and reusing computation



This kind of calculation reuse is extremely powerful for localization problems with conv nets

We'll see variants of this idea in every method we'll cover today!

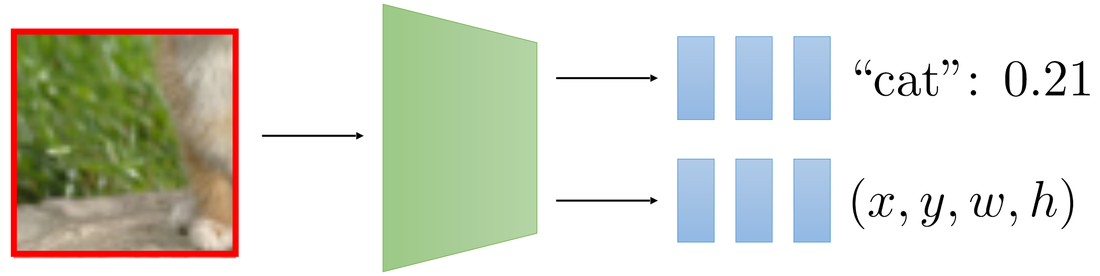
Sermanet et al. "**OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.**" 2013

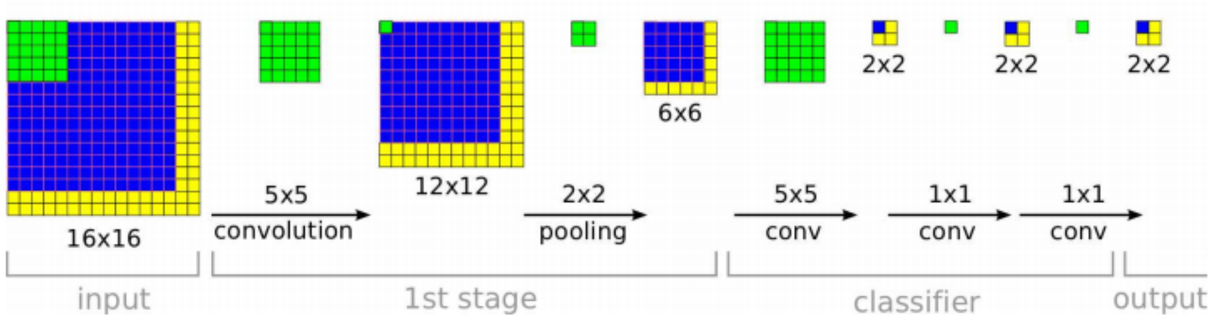
Summary

Building Block : Conv Net that outputs class and bounding box coordinates

Evaluate this network at multiple scales and for many different crops, each one producing a probability and bounding box

Implement the sliding window as just another convolution, with 1x1 convolutions for the classiifer/regressor at the end to save on computation



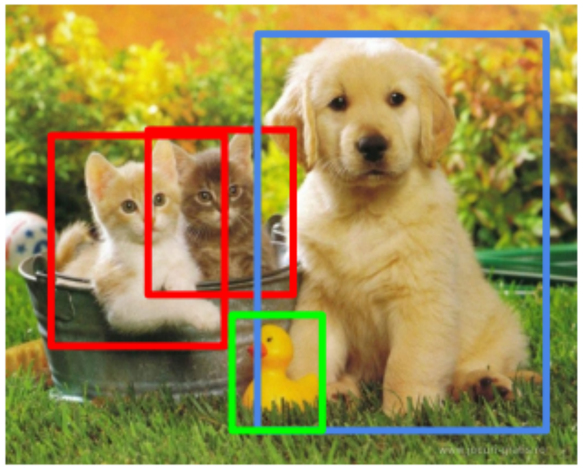


Object Detection

The Problem Setup

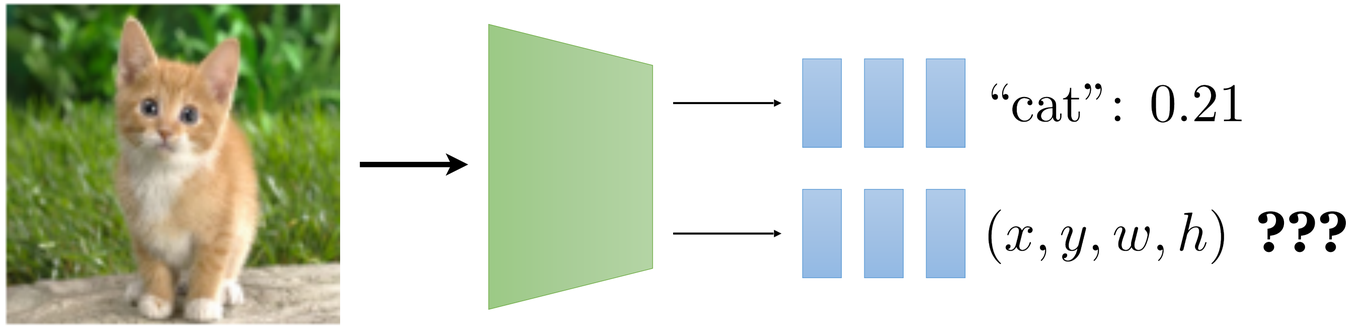
Before

Now



$$(x_i, c_{i,1}, x_{i,1}, y_{i,1}, w_{i,1}, h_{i,1}, c_{i,2}, x_{i,2}, y_{i,2}, w_{i,2}, h_{i,2}, \ldots, c_{i,n_i}, x_{i,n_i}, y_{i,n_i}, w_{i,n_i}, h_{i,n_i})$$

number of objects n_i different for each image x_i!



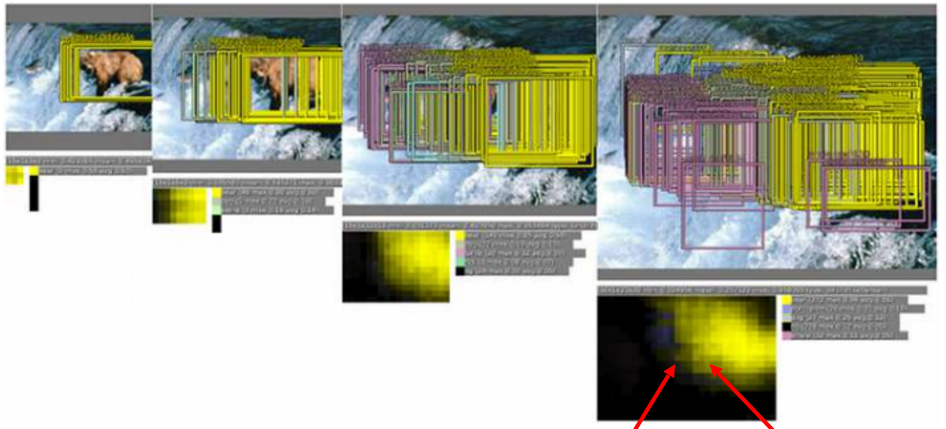
Dense-Prediction : Generating multiple outputs

Sliding window: each window can be a different object

Instead of selecting the window with the highest probability (or merging windows), just output an object in each window above some threshold

Big problem: a high-scoring window probably has **other** high-scoring windows nearby

Non-maximal suppression: (informally) kill off any detections that have other higher-scoring detections of the same class nearby



non-maximal

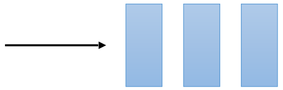
maxim

works great if combined

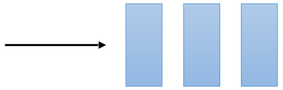
Actually output multiple things: output is a list of bounding boxes

Obvious problem: need to pick number, usually pretty small

not good by itself



$\{$ “cat”: 0.21, “dog”: 0.54 $\}$



$(x_1, y_1, w_1, h_1, x_2, y_2, w_2, h_2)$

Case Study : You Only ~~Live~~ Once [YOLO]

Look

Actually, you look a few times (49 times to be exact…)

different output for each of the 7x7 (49) grid cells (a bit like sliding window)

for each cell, output:

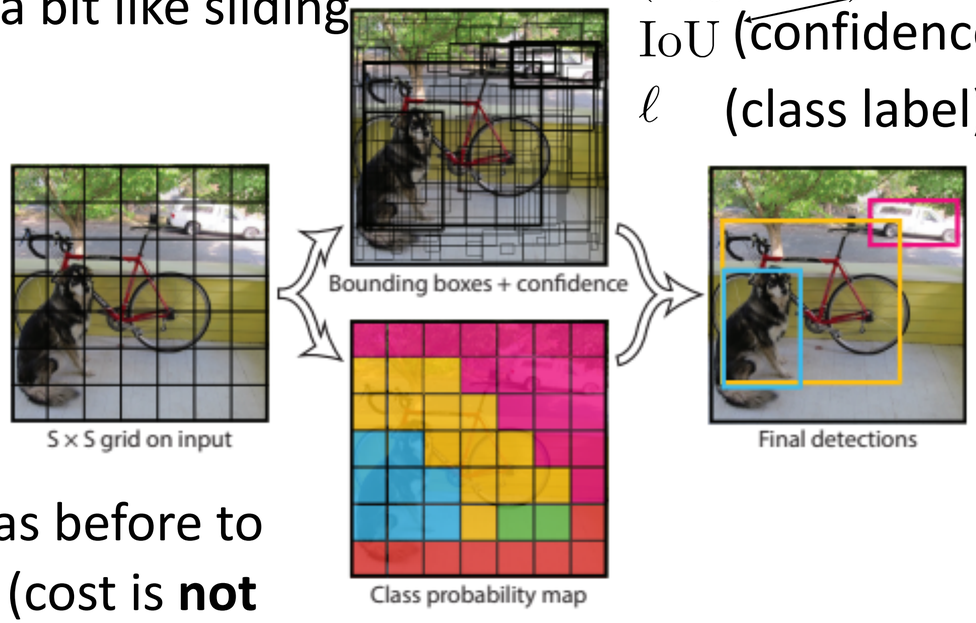
(x, y, w, h)

IoU (confidence)

ℓ (class label)

zero if no object

output B of these



some training details:

need to assign which output is "responsible" for each true object during training

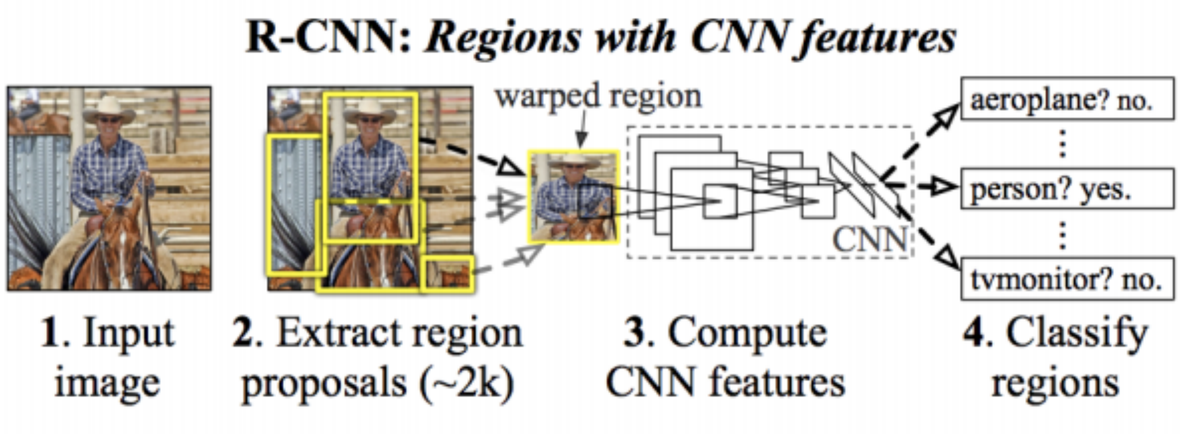
just use the "best-fit" object in that cell (i.e., the one with highest IoU)

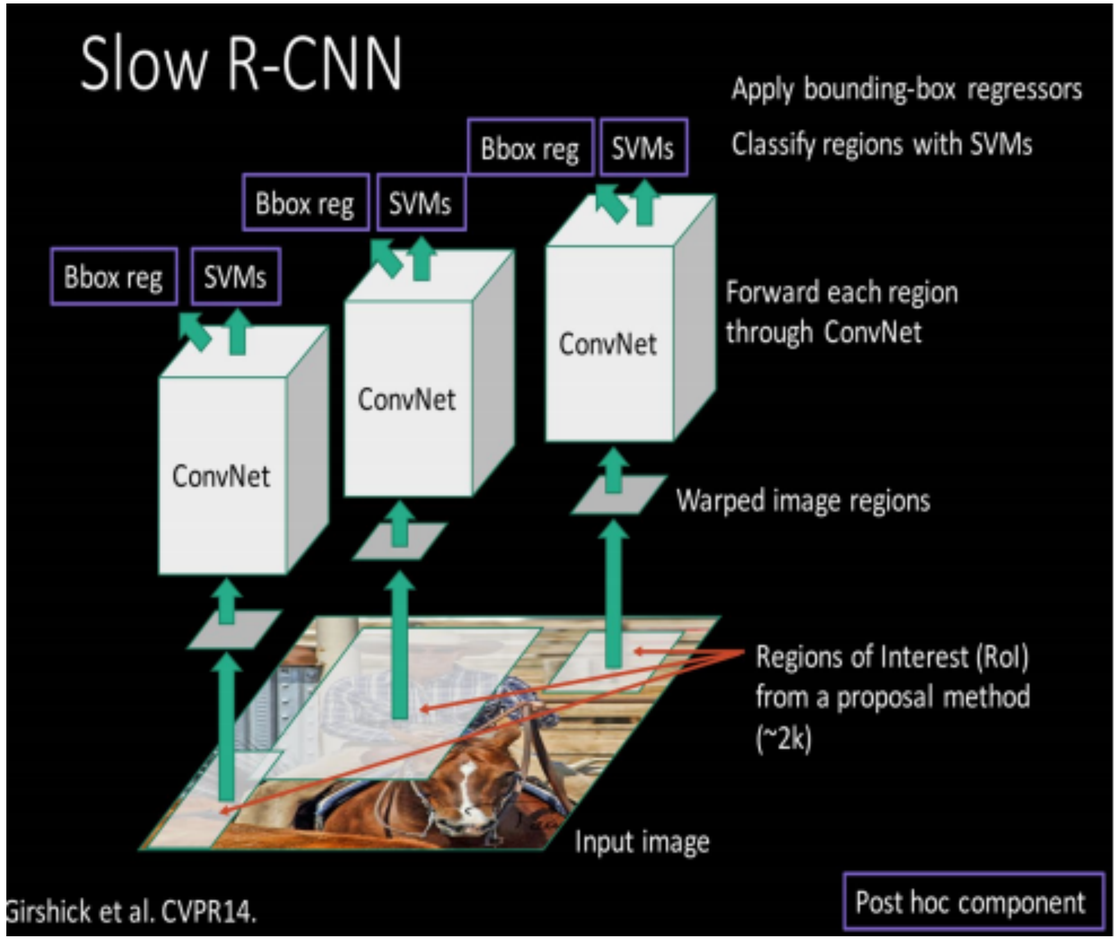
use the same trick as before to reuse computation (cost is **not** 49x higher!)

What if we have too many objects? Well, nothing… we just miss them

Redmon et al. "**You Only Look Once: Unified, Real-Time Object Detection.**" 2015

CNNs + Region proposals





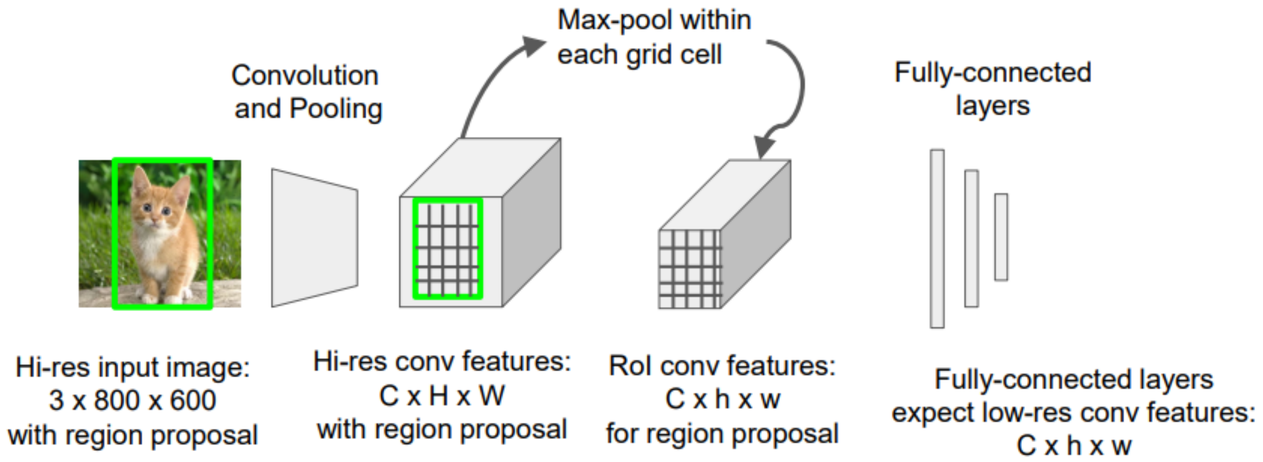
This is really slow

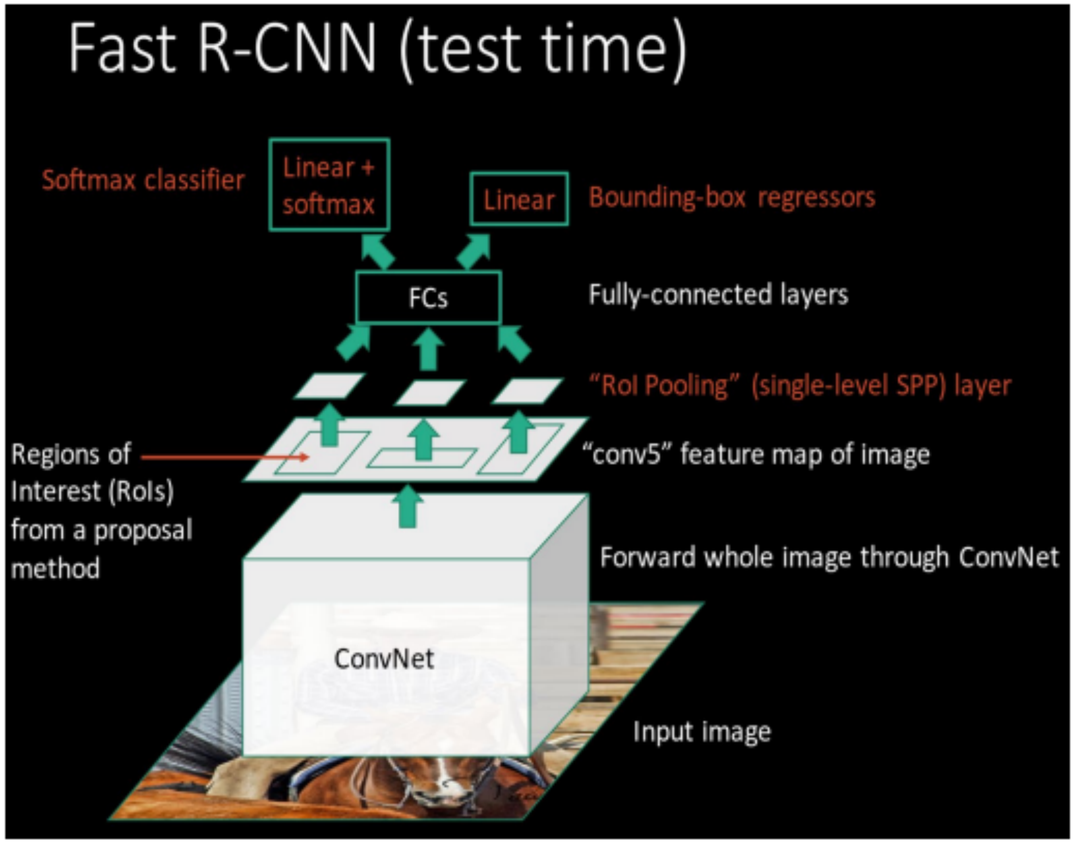
But we already know how to fix this!

Girschick et al. "**Fast R-CNN.**" 2015

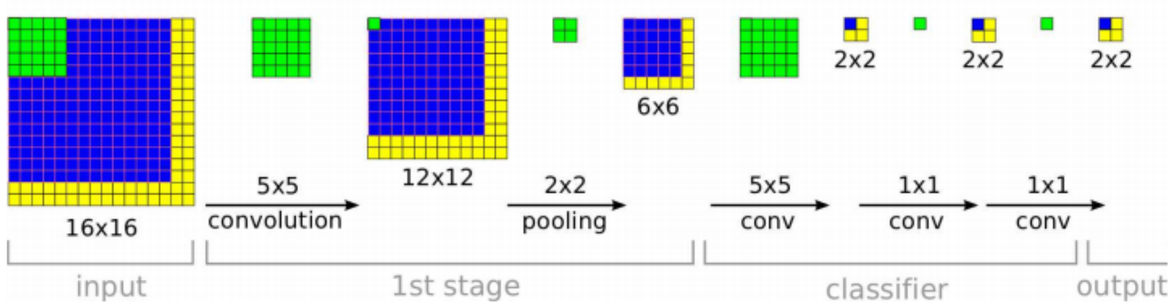
CNNs + Region proposals

A smarter "sliding window": region of interest proposals





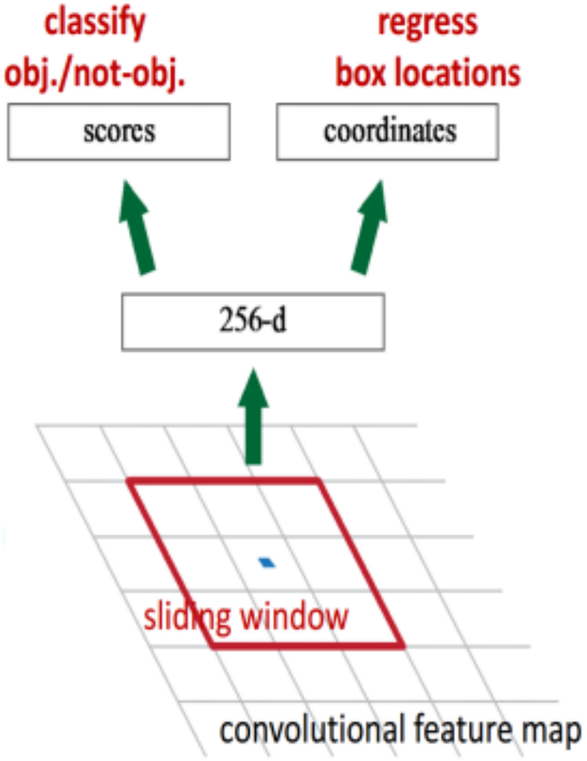
Compare this to evaluating every location:

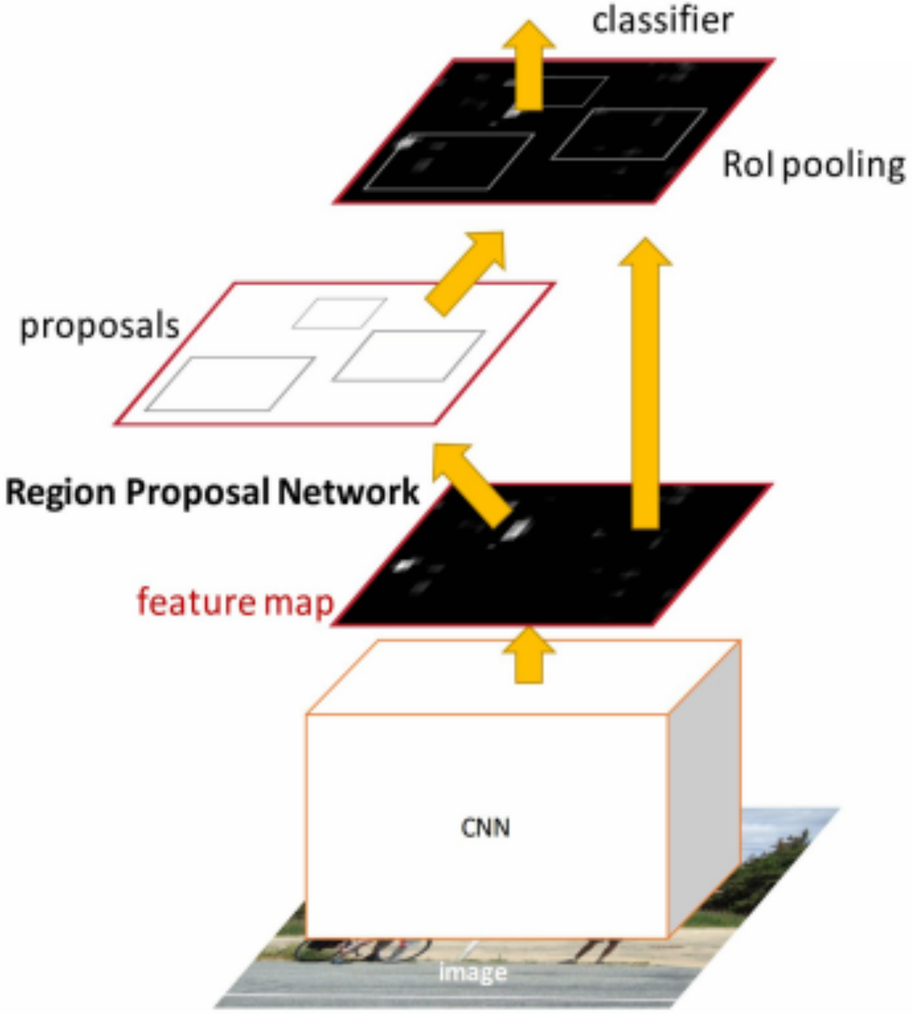


CNNs + Region proposals

How to train region of interest proposals?

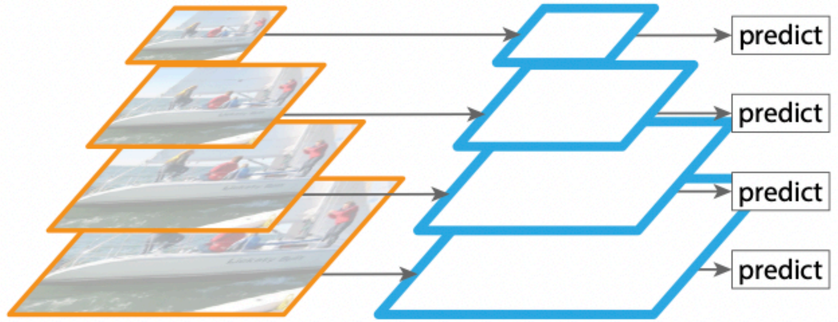
Very similar design to what we saw before (e.g., OverFeat, YOLO), but now for predicting if **any** object is present around that location



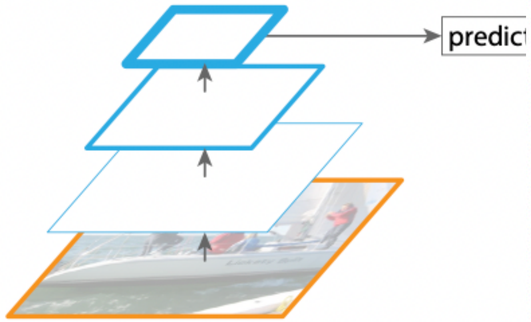


Ren et al. "**Faster R-CNN.**" 2015

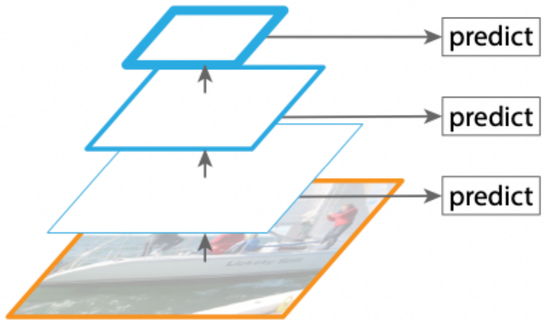
Building Efficient Detectors : Feature Pyramids



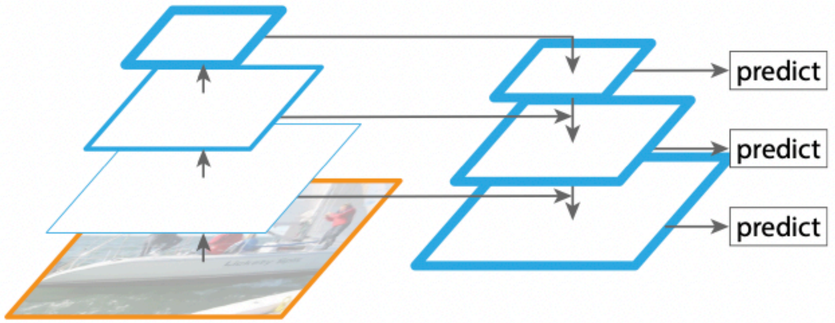
(a) Featurized image pyramid



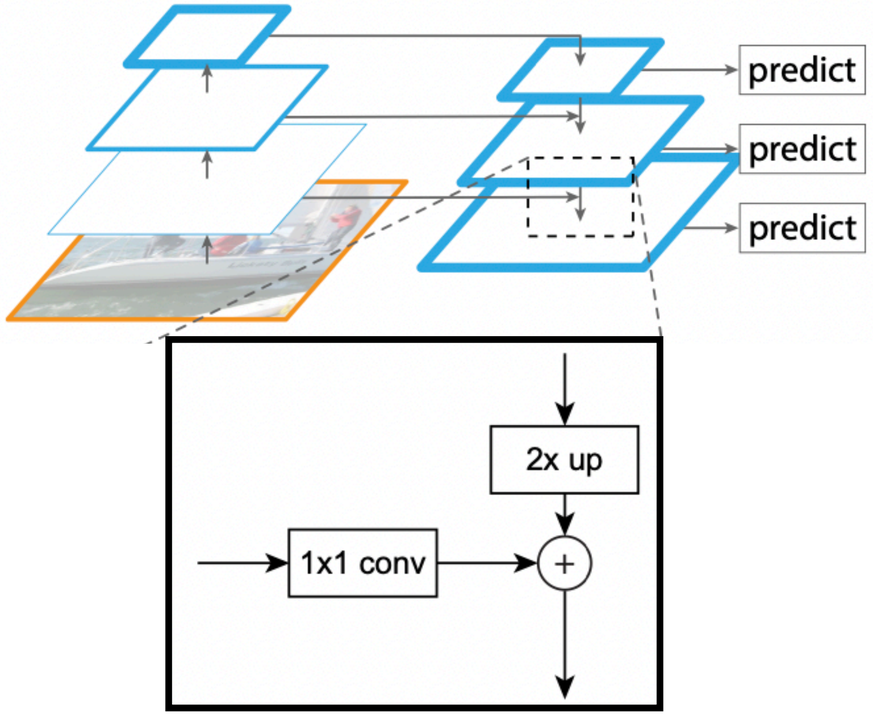
(b) Single feature map



(c) Pyramidal feature hierarchy



(d) Feature Pyramid Network



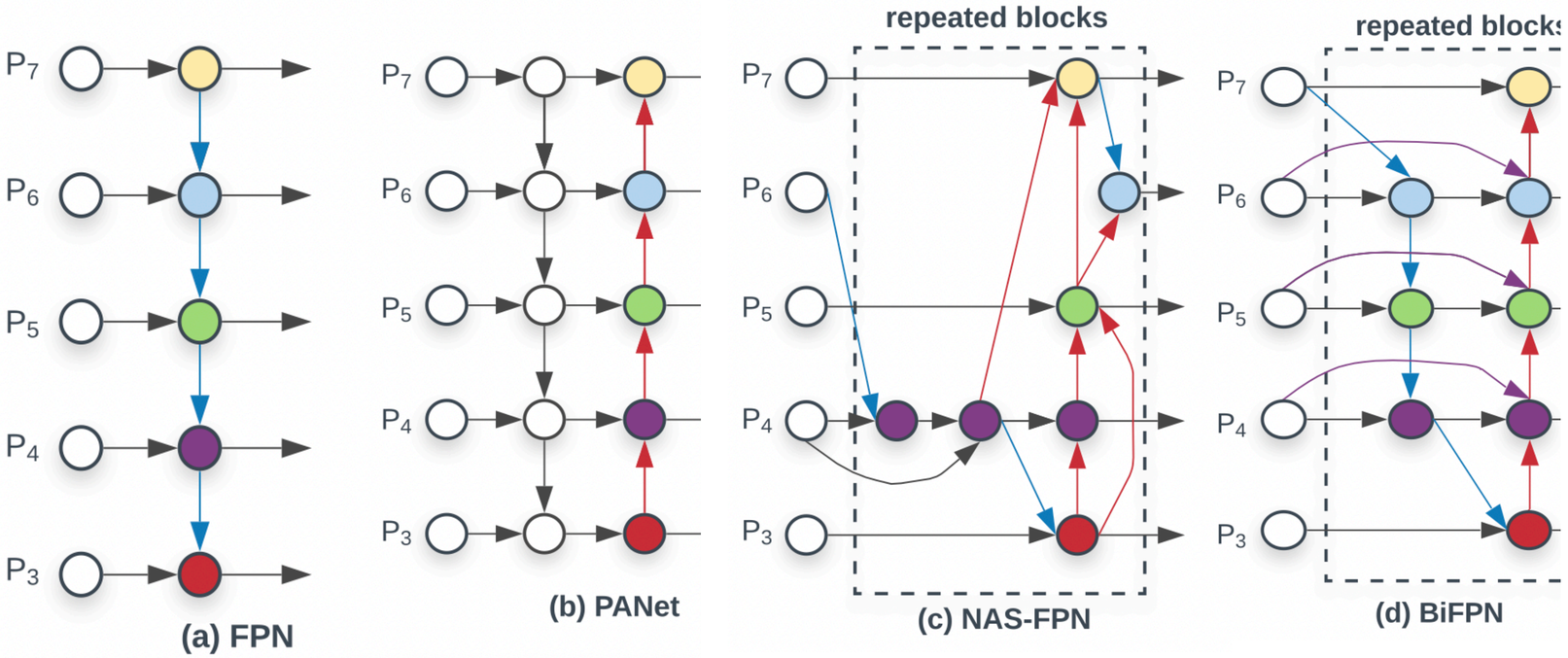
design principles
+ multi-scale features
+ skip-connections
+ single-forward pass

new operator
+ up-sampling convolution

Key Idea : Aggregate information across multiple scales

Lin et al. "**Feature Pyramid Networks for Object Detection**" 2016

Compute Efficient Detection



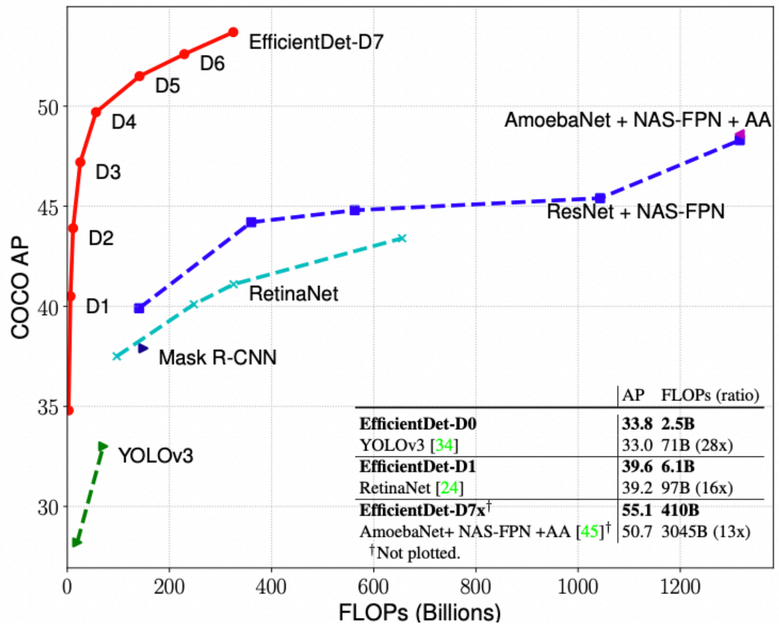


Figure 2: **Feature network design –** (a) FPN [23] introduces a top-down pathway to fuse multi-scale features from level 3 to 7 (P_3 - P_7); (b) PANet [26] adds an additional bottom-up pathway on top of FPN; (c) NAS-FPN [10] use neural architecture search to find an irregular feature network topology and then repeatedly apply the same block; (d) is our BiFPN with better accuracy and efficiency trade-offs.

Tan et al. "**EfficientDet: Scalable and Efficient Object Detection**" 2019

Suggested readings

- Redmon et al. "**You Only Look Once: Unified, Real-Time Object Detection.**" 2015
  - Just regress to different bounding boxes in each cell
  - A few follow-ups (e.g., YOLO v5) that work better

- Girschick et al. "**Fast R-CNN.**" 2015
  - Uses region of interest proposals instead of sliding window/convolution

- Ren et al. "**Faster R-CNN.**" 2015
  - Same as above with a few improvements, like region of interest proposal learning

- Liu et al. **SSD: Single Shot MultiBox Detector**. 2015
  - Directly "classifies" locations with class and bounding box shape

- Lin et al. **Feature Pyramid Networks for Object Detection,** 2016
  - Proposes Feature Pyramid Networks (FPN), aggregating information at multiple scales

- Tan et al. **EfficientDet: Scalable and Efficient Object Detection.** 2019
  - Compute efficient detectors with Bidirectional FPN (BiFPN)

Semantic Segmentation

The Problem Setup

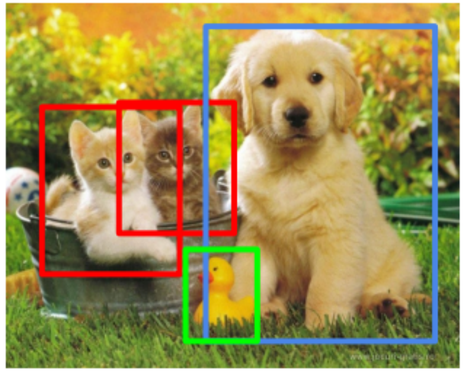
Problem:
K-class classification problem, predicting a label per pixel $y_i \in \mathcal{S} = \{c_1, c_2, \ldots, c_K\}$

Learning a mapping
$f_\theta : \mathbb{R}^{3\times H\times W} \mapsto \mathcal{S}^{H\times W}$

Note that the output should have the same resolution as the input!

Bruteforce baseline
→Never downsample (i.e. zero padding, stride 1, no pooling)
→ Computational cost?

Before



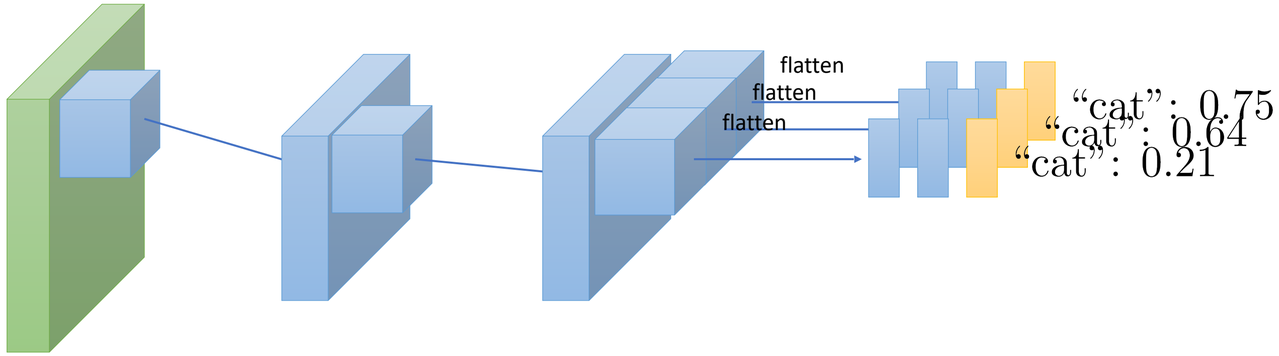
Detect **all objects** in an image

Now

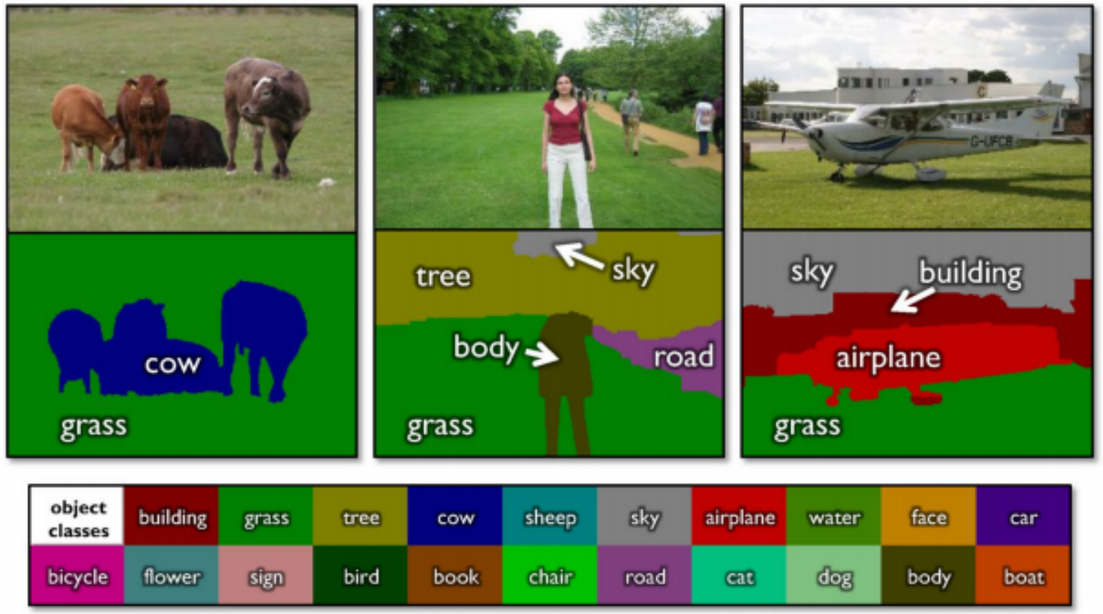
Label **every single pixel** with its class

Actually simpler in some sense:
- No longer variable #outputs
- Every pixel has a label

Learn "per-pixel" classifier



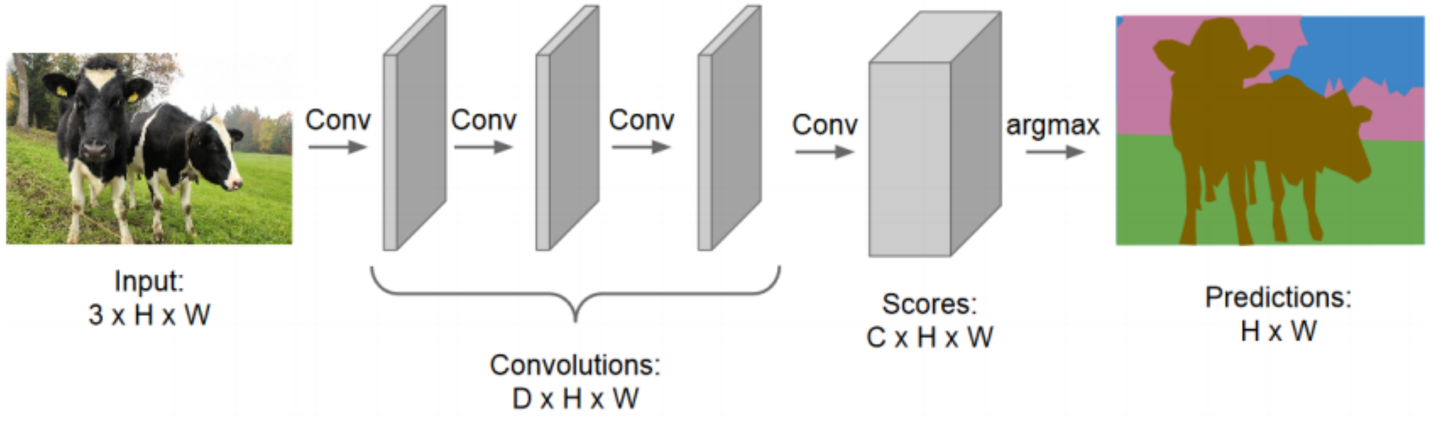
The Problem Setup



Task: Classify every point with a class

Don't worry for now about instances (e.g., we don't distinguish between two adjacent cows, they "look" like a "cow blob". This is okay for now, instance-segmentation deals with different instances)

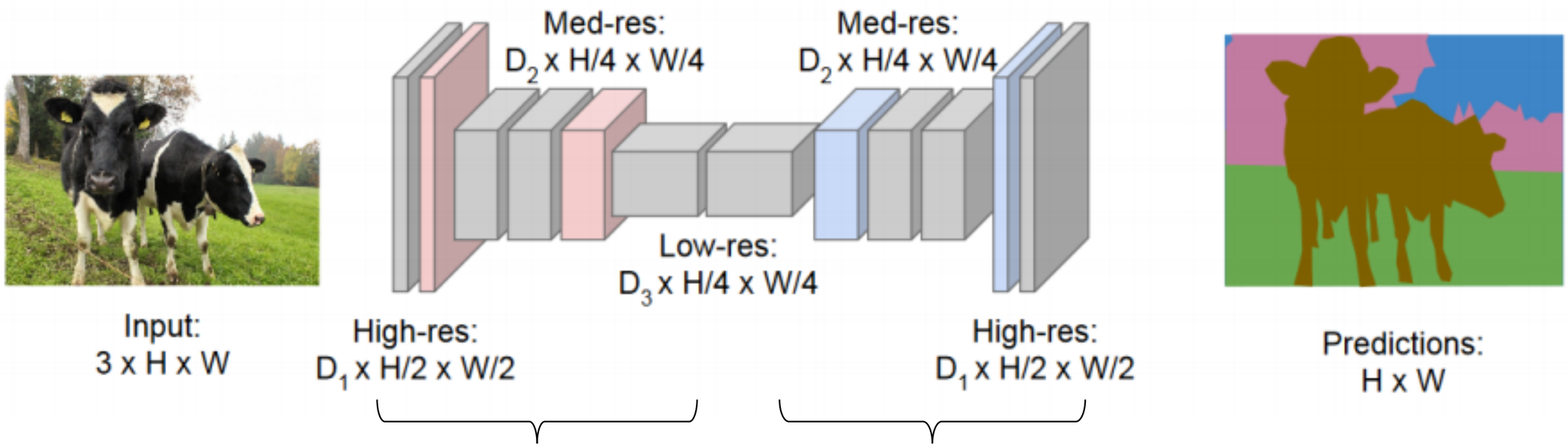
The challenge: Design a network architecture that makes this "per-pixel classification" problem computationally tractable.



Fully Convolutional Networks

Desiderata:
set of operations that preserve resolution at output

Constraints:
effective *receptive field* of convolution filters grows with depth (early layers have local view)



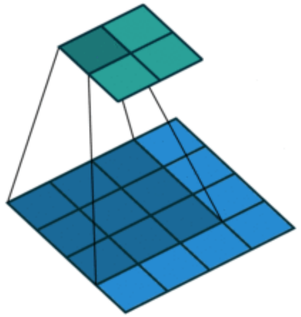
Low-res (but high-depth) processing in the middle integrates context from the entire image

Up-sampling at the end turns these low-res feature vectors into high-res per-pixel predictions

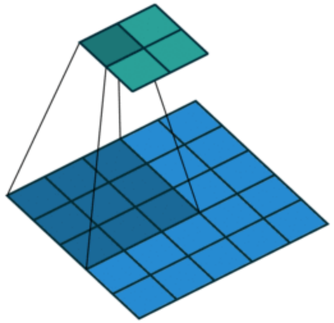
Slide borrowed from Fei-Fei Li, Justin Johnson, Serena Yeung

Conv. Operators : Down/UpSampling

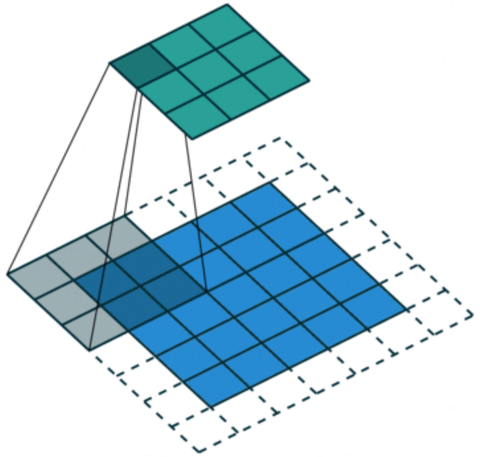
Normal Convolutions:
reduce resolution with stride, padding



no-padding, no-stride

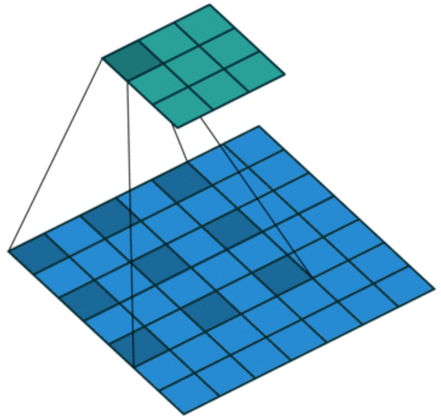


no-padding, stride



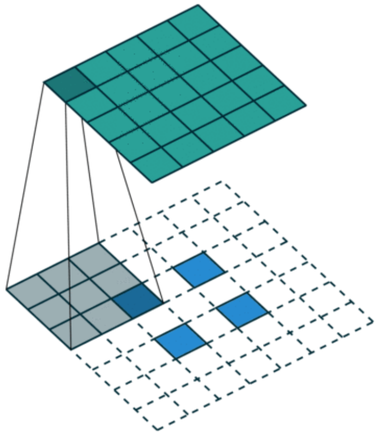
padding+stride

Dilated Convolutions:
Increase *receptive-field* more rapidly



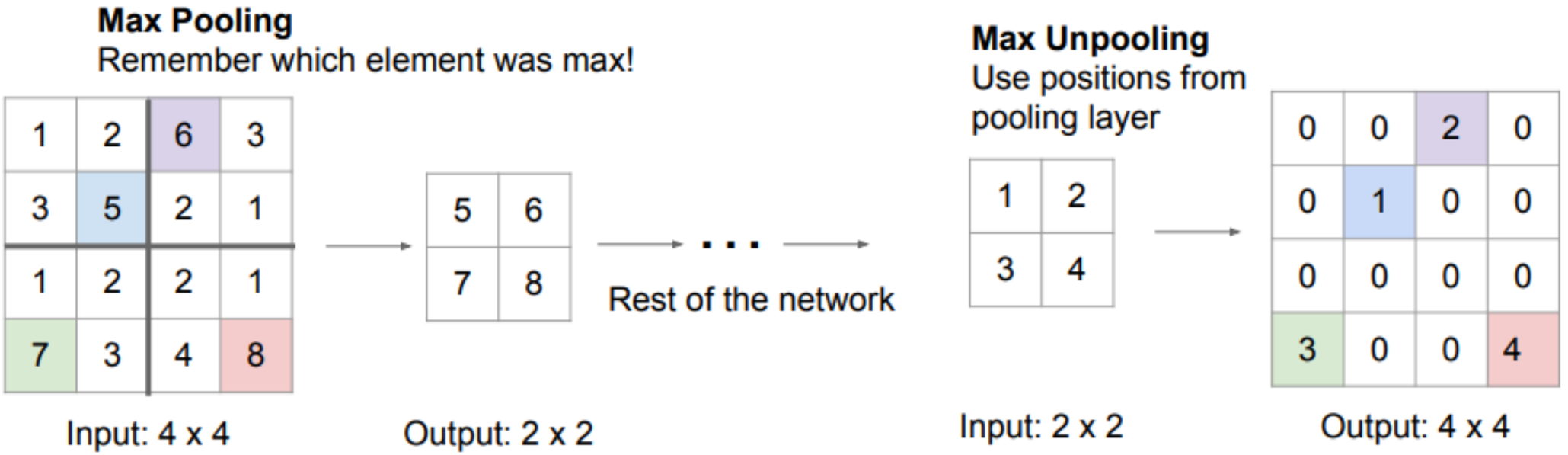
no-padding, no-stride

Transpose Convolutions:
increase resolution with
fractional "stride"

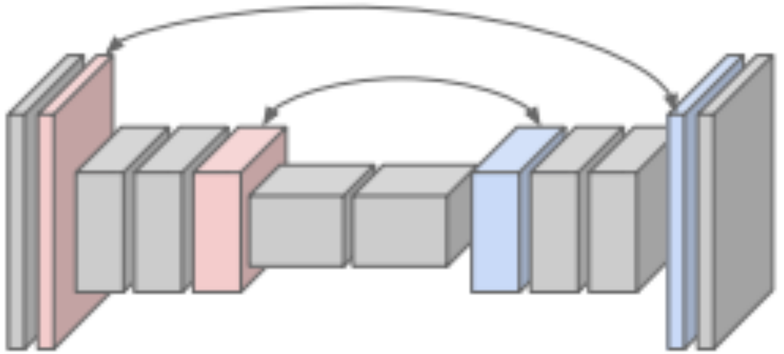


Dumoulin et al. "**https://github.com/vdumoulin/conv_arithmetic**" 2016

Un-pooling

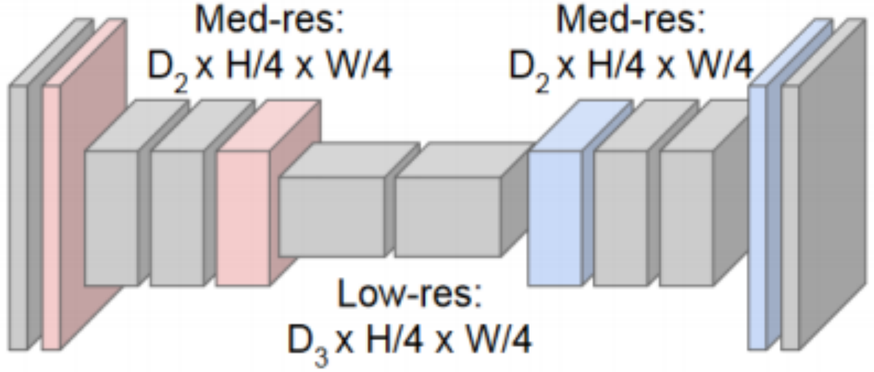


Corresponding pairs of
downsampling & upsampling layers



Bottleneck architecture

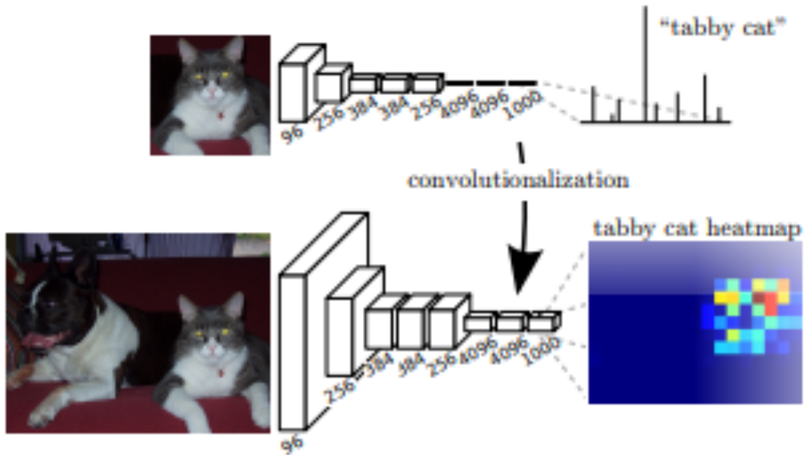
Input:
3 x H x W

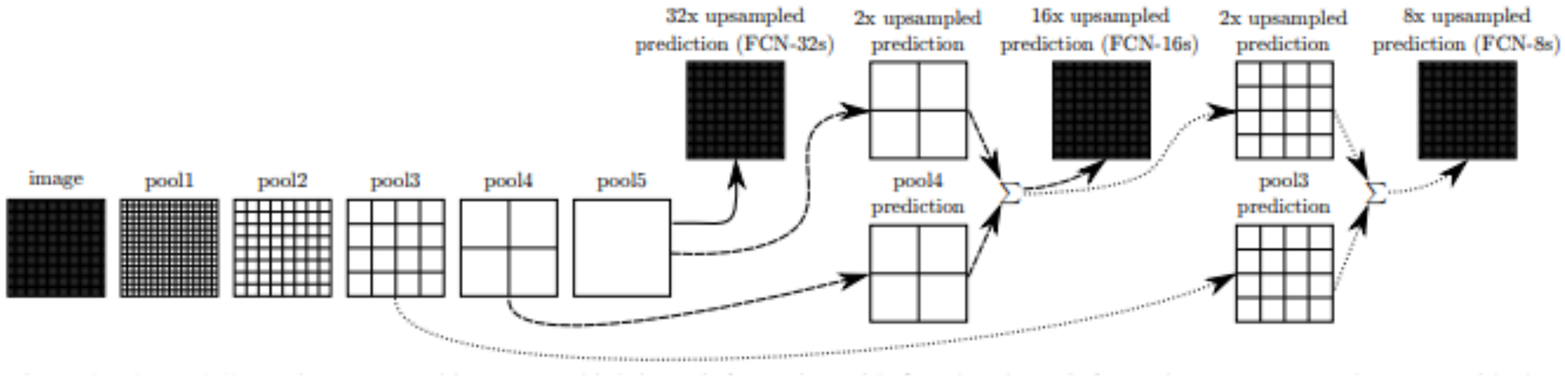


High-res:
D1 x H/2 x W/2

High-res:
D1 x H/2 x W/2

Predictions:
H x W



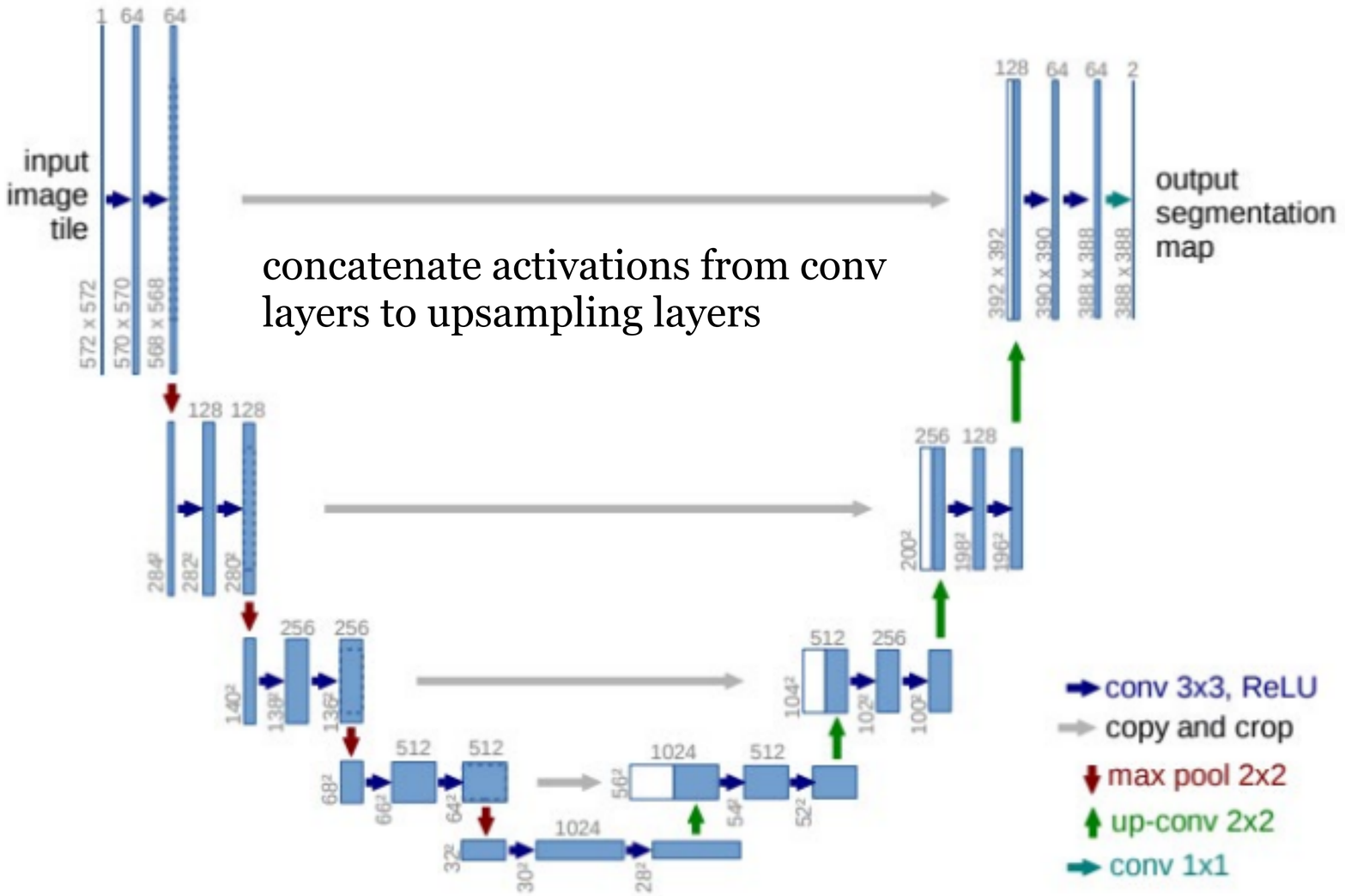


Long et al. "**Fully Convolutional Networks for Semantic Segmentation**." 2014

U-Net Architecture

Problem:
Downsampling loses information, that upsampling cannot recover.

Intuition:
Explicitly append filters from earlier downsampling layer that preserve high-frequency details (such as edges)



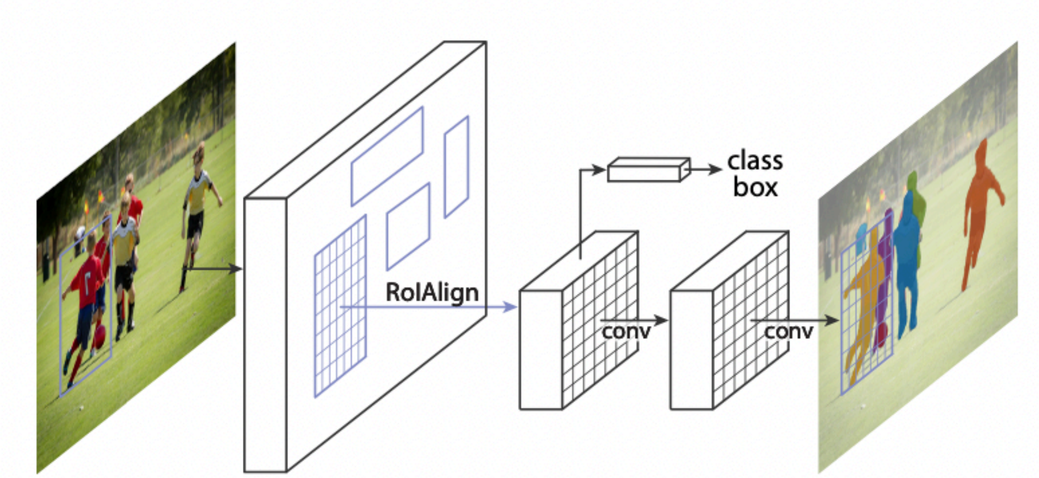
Ronneberger et al. **U-net: Convolutional networks for biomedical image segmentation**. 2015

Instance Segmentation : Mask R-CNN

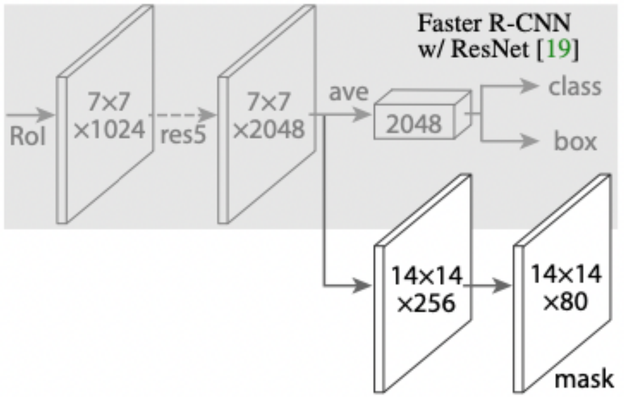
Problem:
Can we use RPNs and RCNNs for instance segmentation?

Intuition:
Alongside the class, bounding box predict a mask per region-proposal.

General principle
Masking (learned or imposed) is very useful way of generating irregular predictions.



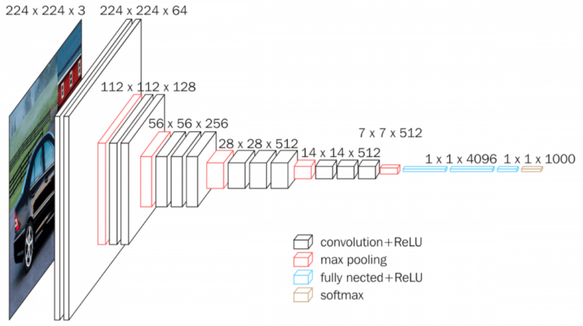
Mask R-CNN framework for instance segmentation



Effectively Mask R-CNN adds another prediction branch to predict instance-specific masks per RoI.

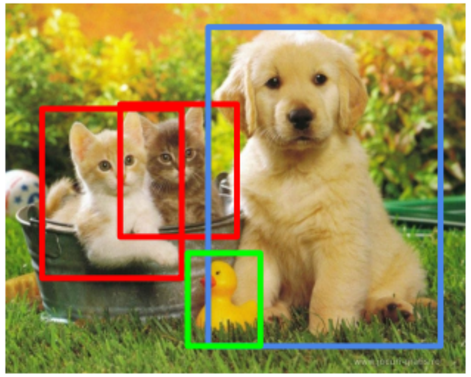
He et al. **Mask R-CNN**. 2017

Standard computer vision tasks

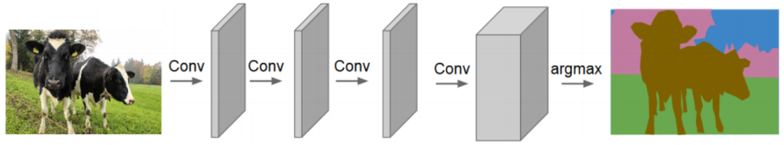


object classification

object localization



object detection



semantic segmentation