Computer Vision with Convolutional Neural Networks

COnvolution, LeNet, AlexNet, VGGNet, GoogleNet, Resnet, DenseNet, R-CNN, Fast R-CNN, YOLO, FCN, VQA LSTM CNN, Adversarial images

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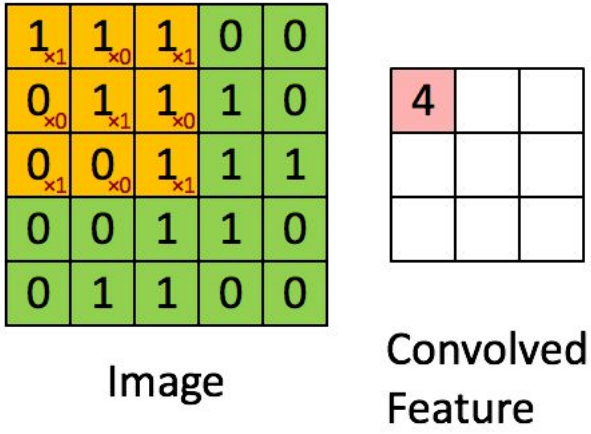
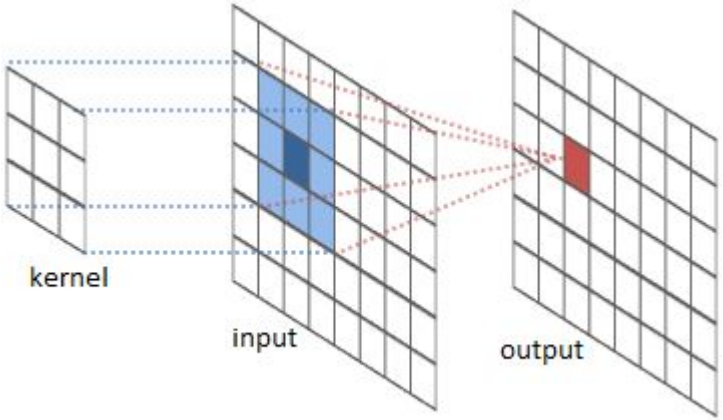
Sept 17, 2018

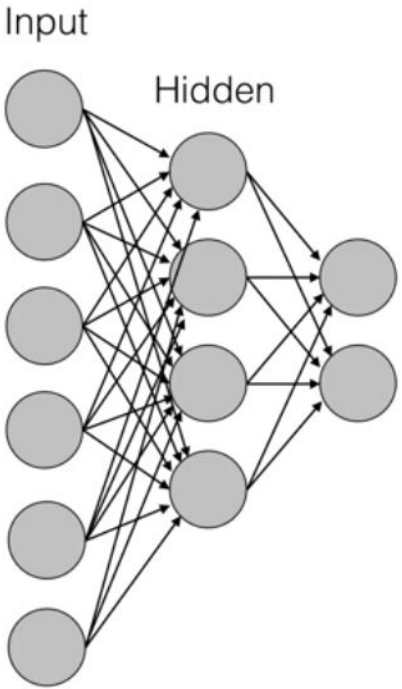
Online version link (with animations)

Convolution

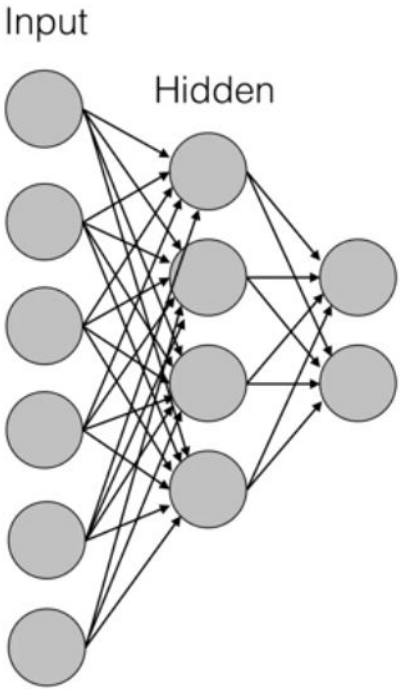




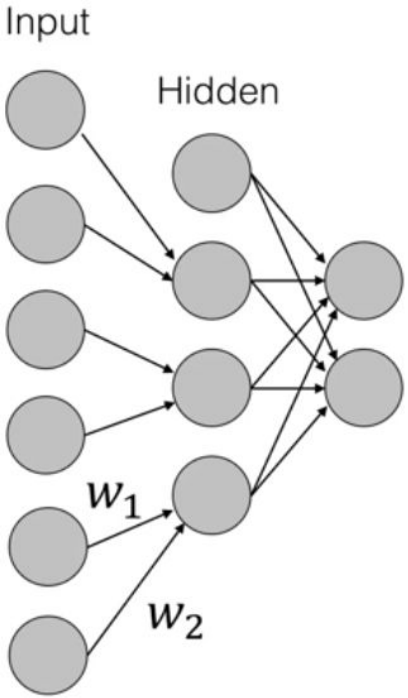
Convolution in Neural Networks



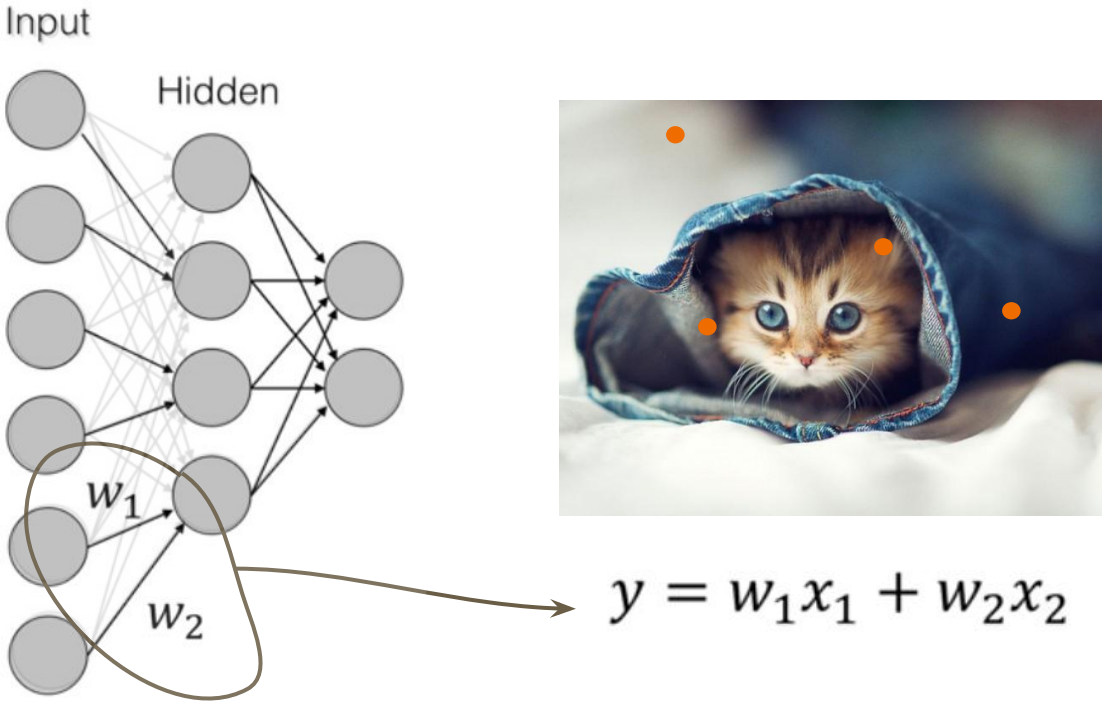
Convolution in Neural Networks



Convolution in Neural Networks

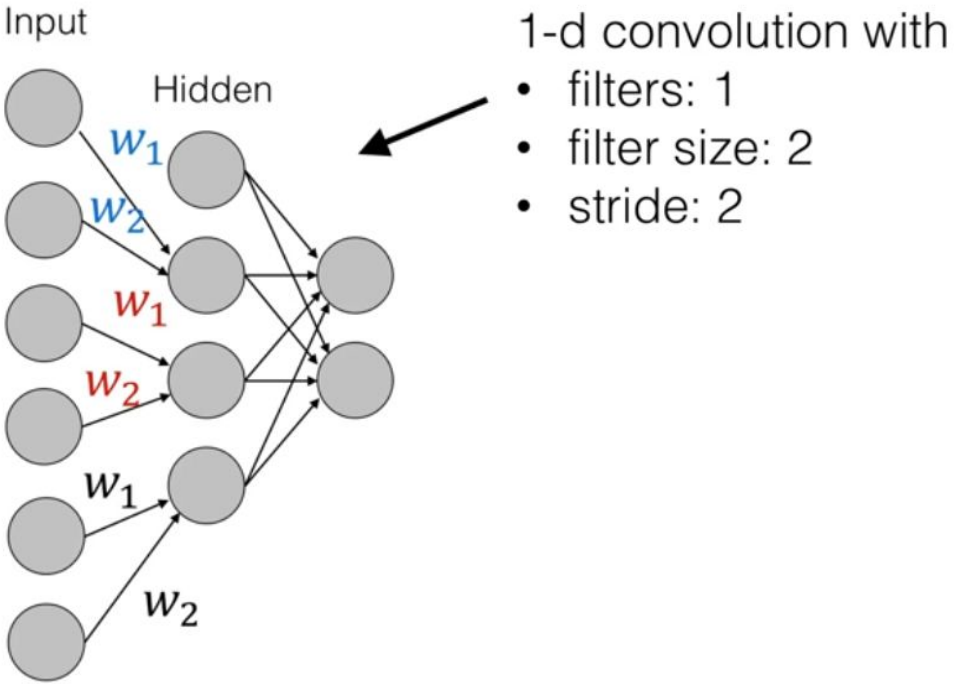


Convolution in Neural Networks



$$y = w_1 x_1 + w_2 x_2$$

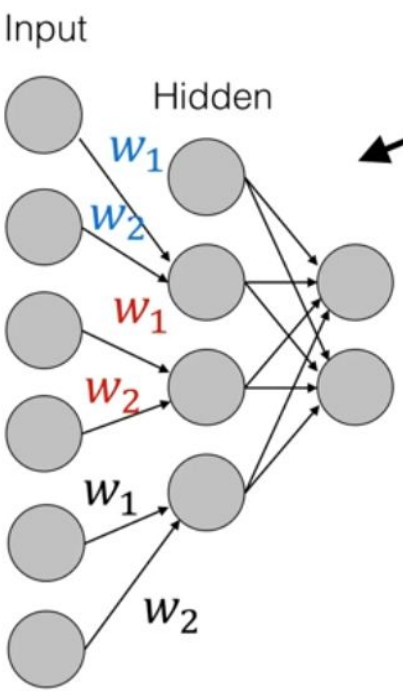
Stride 1-D



1-d convolution with

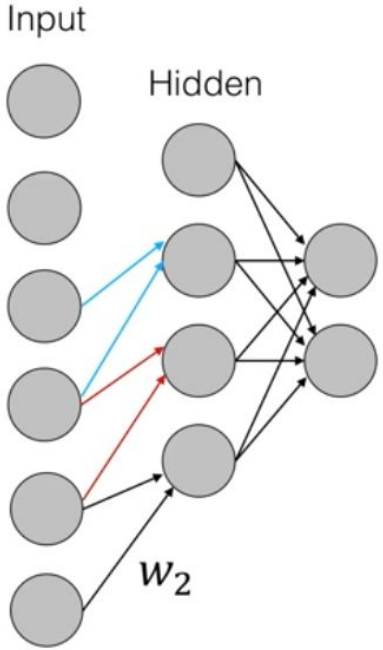
- filters: 1
- filter size: 2
- stride: 2

Stride 1-D

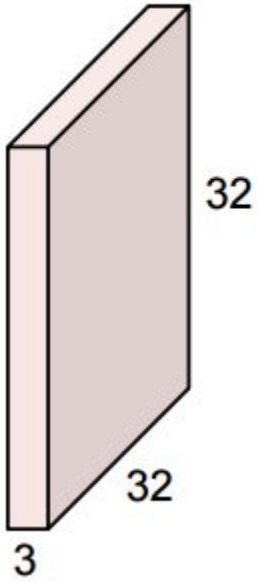


1-d convolution with
- filters: 1
- filter size: 2
- stride: 2

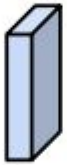
1-d convolution with
- filters: 1
- filter size: 2
- stride: **1**



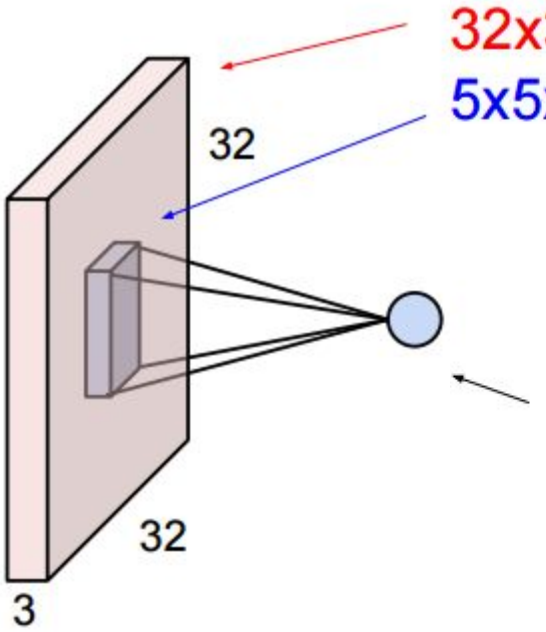
32x32x3 image



5x5x3 filter

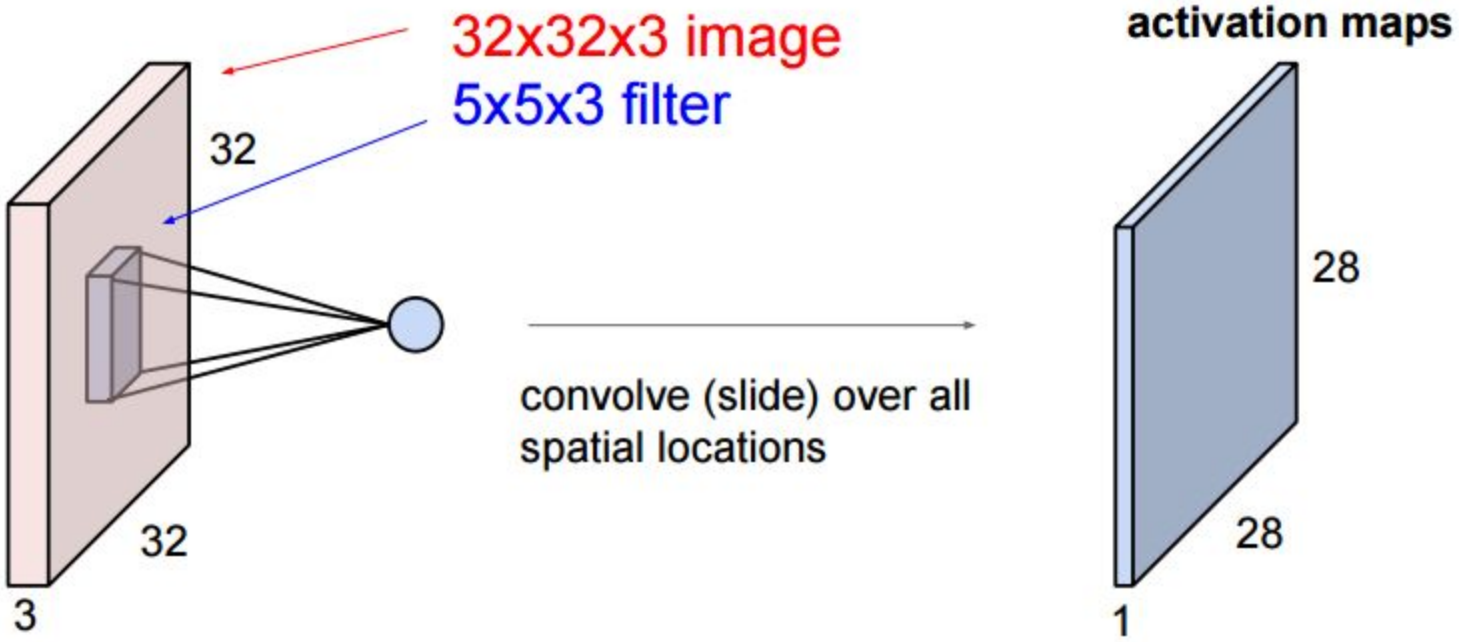


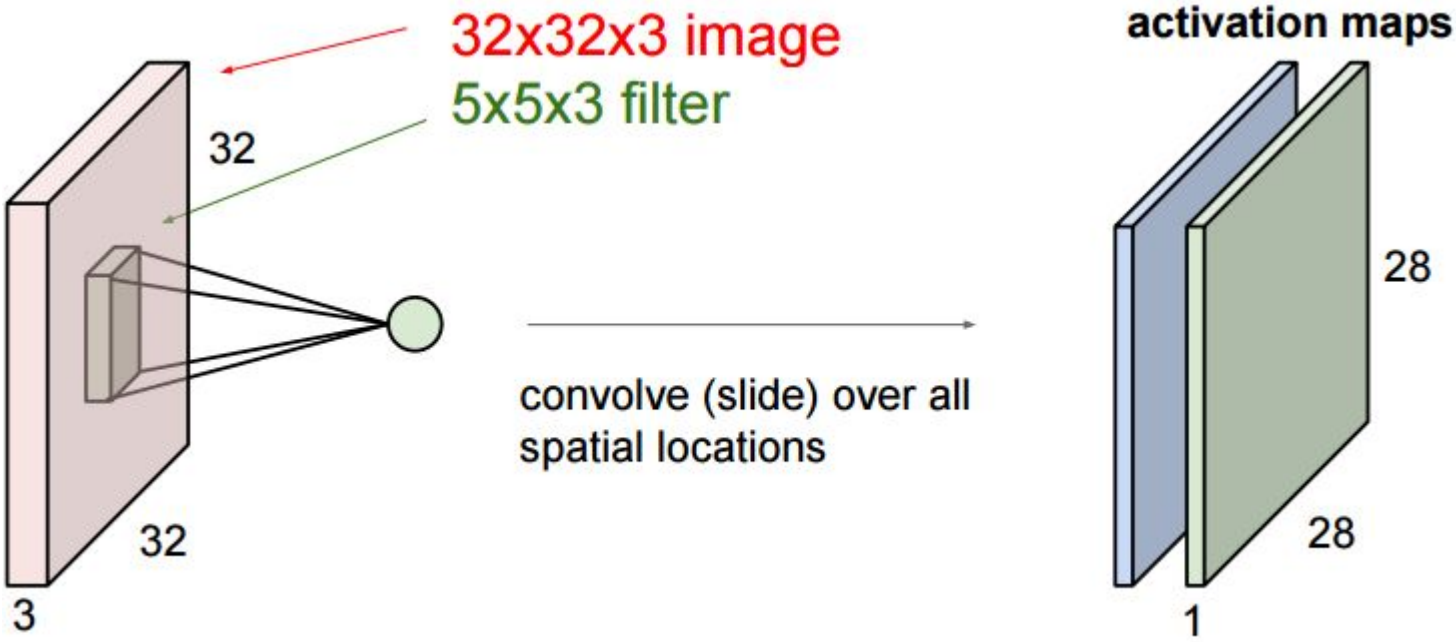
Convolve the filter with the image
i.e. “slide over the image spatially,
computing dot products”



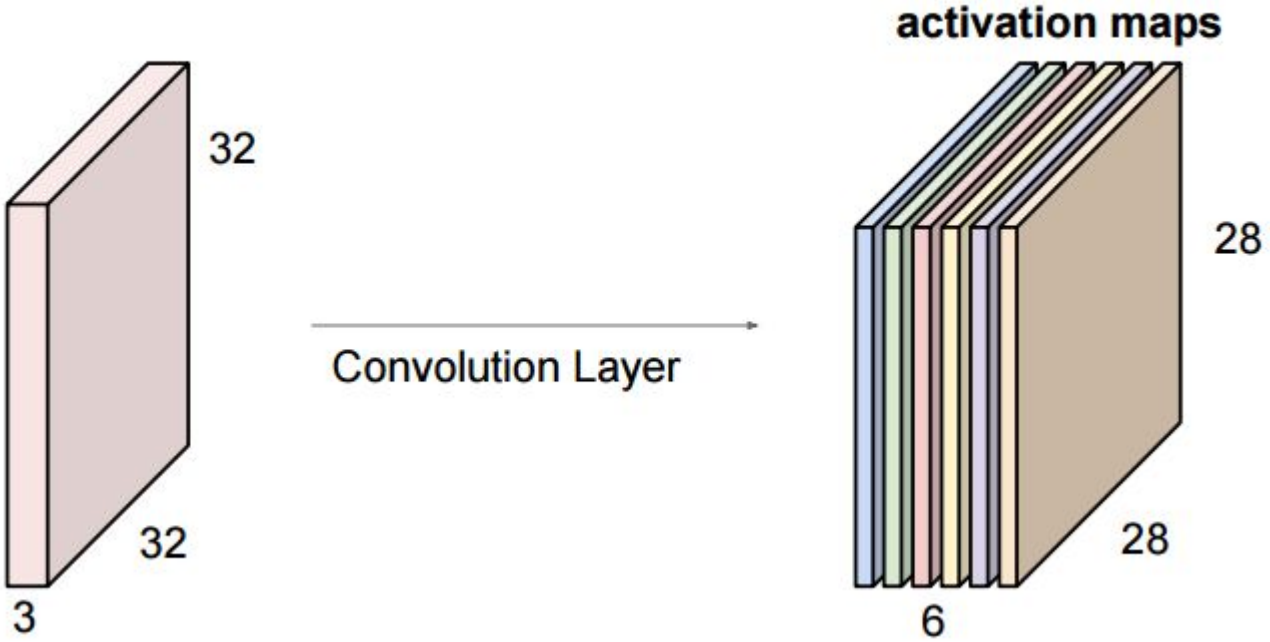
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

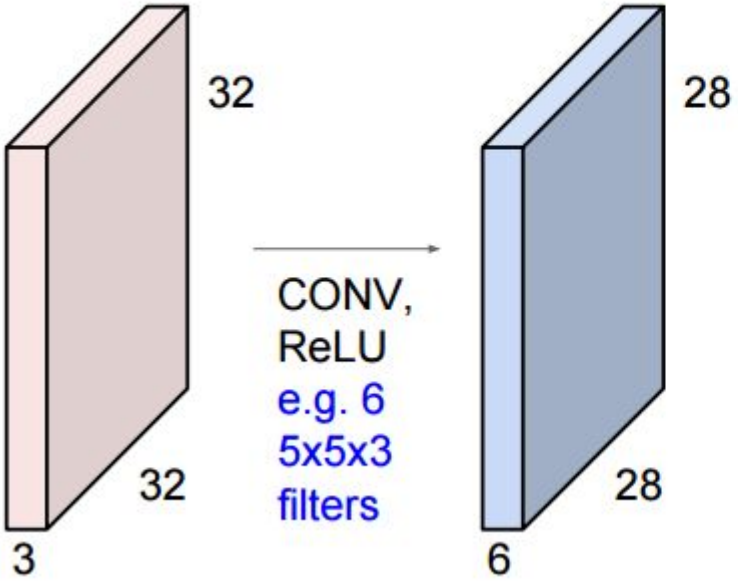

32x32x3 image
5x5x3 filter
32
32
3
convolve (slide) over all
spatial locations
activation maps
28
28
1


32x32x3 image
5x5x3 filter
32
32
3
convolve (slide) over all
spatial locations
activation maps
28
28
1

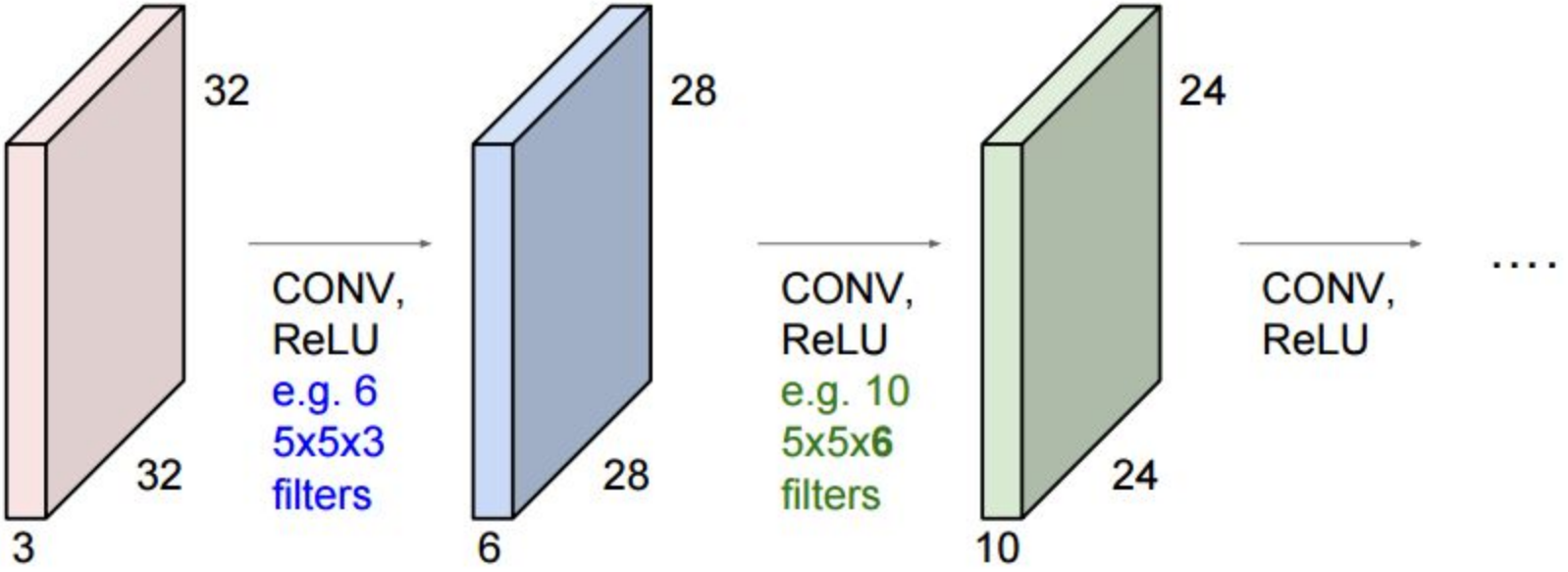
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



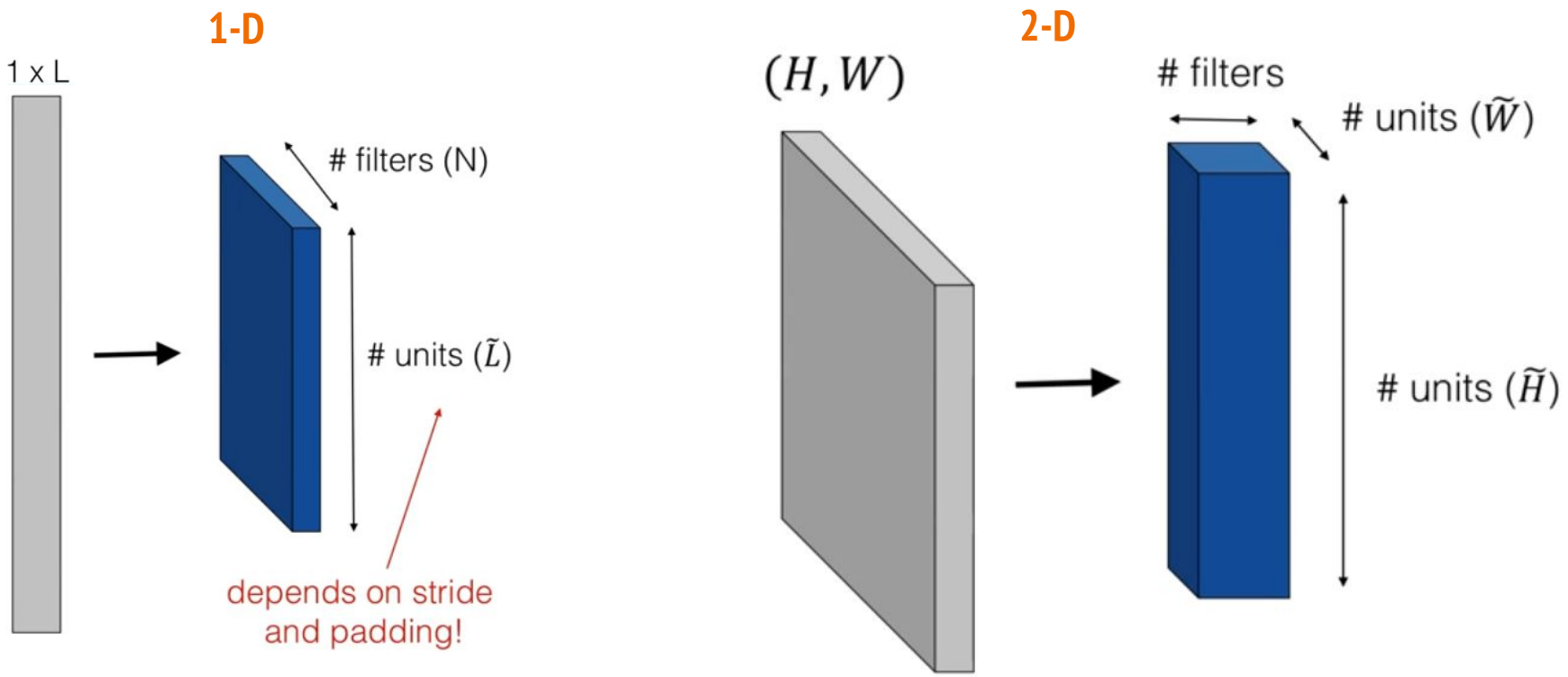
Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions

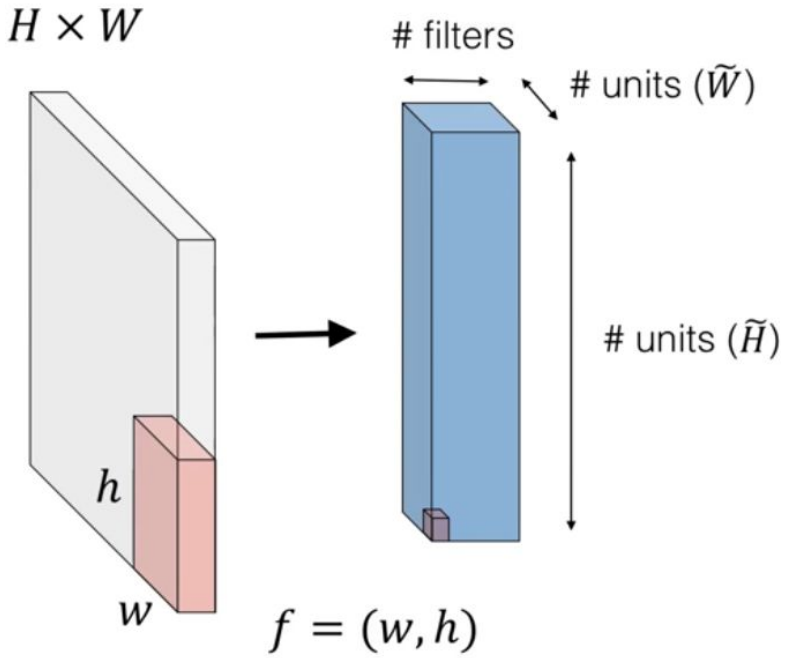


Features / Filters



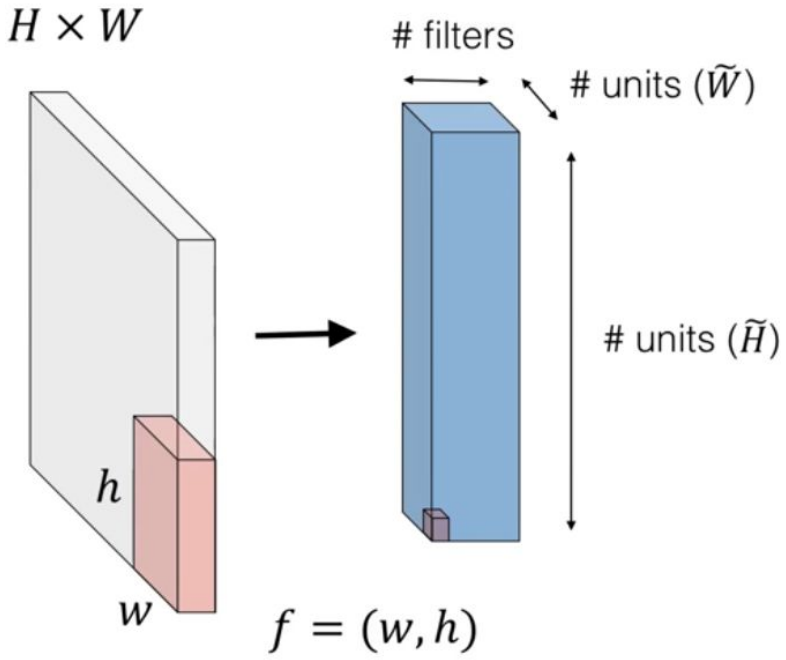
Features / Filters

2-D

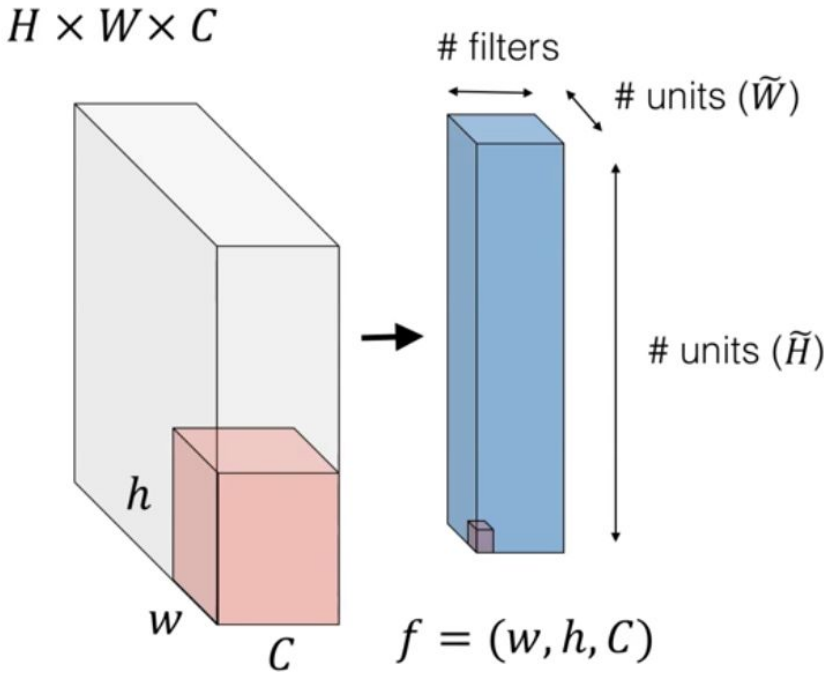


Features / Filters

2-D

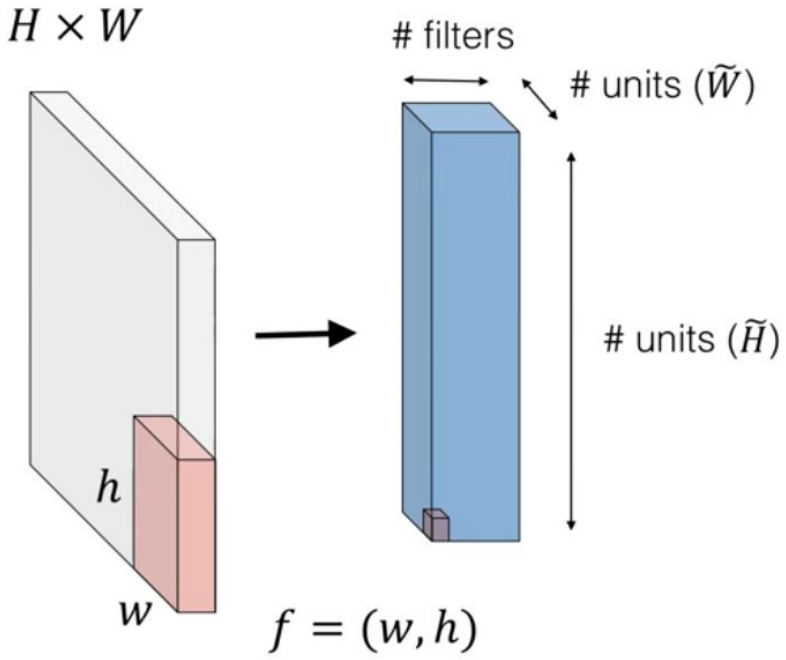


3-D

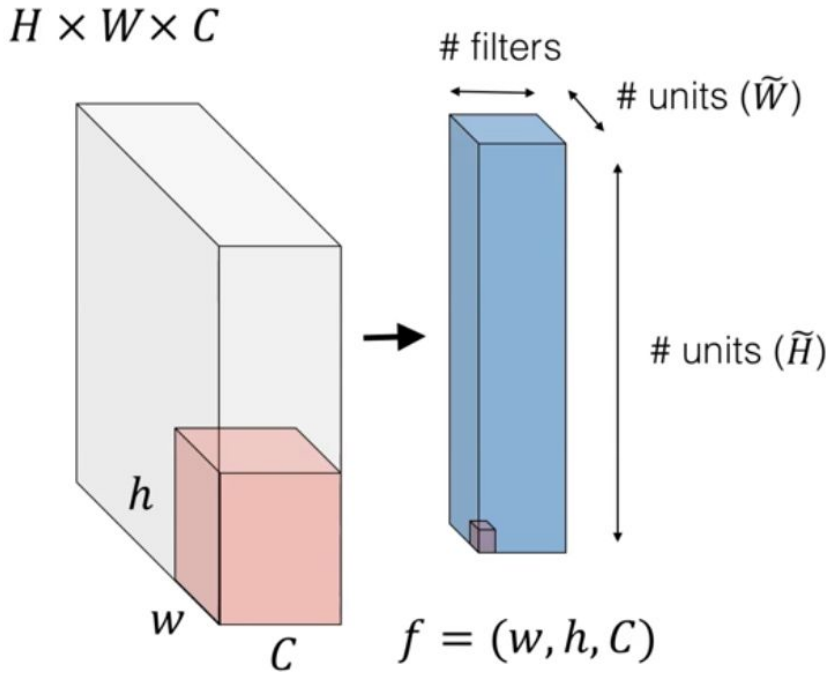


Features / Filters

2-D

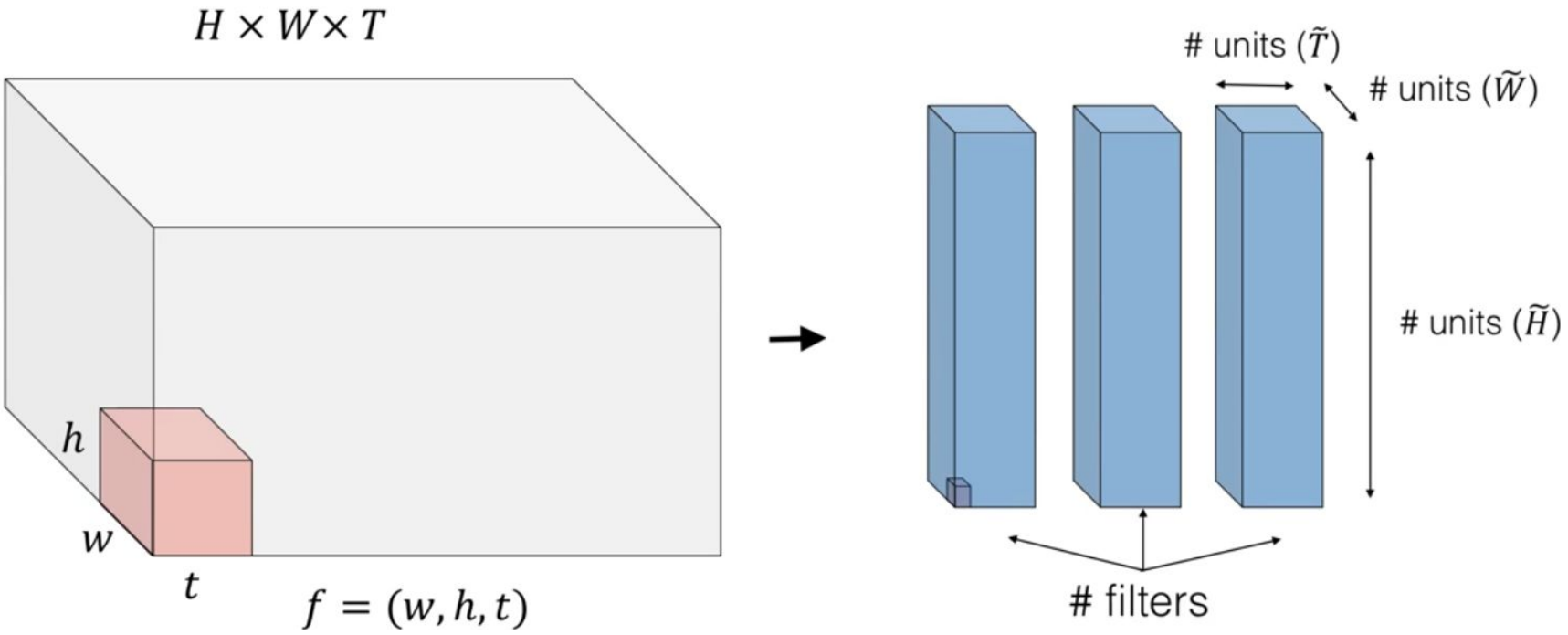


~~3-D~~ 2-D Multichannel

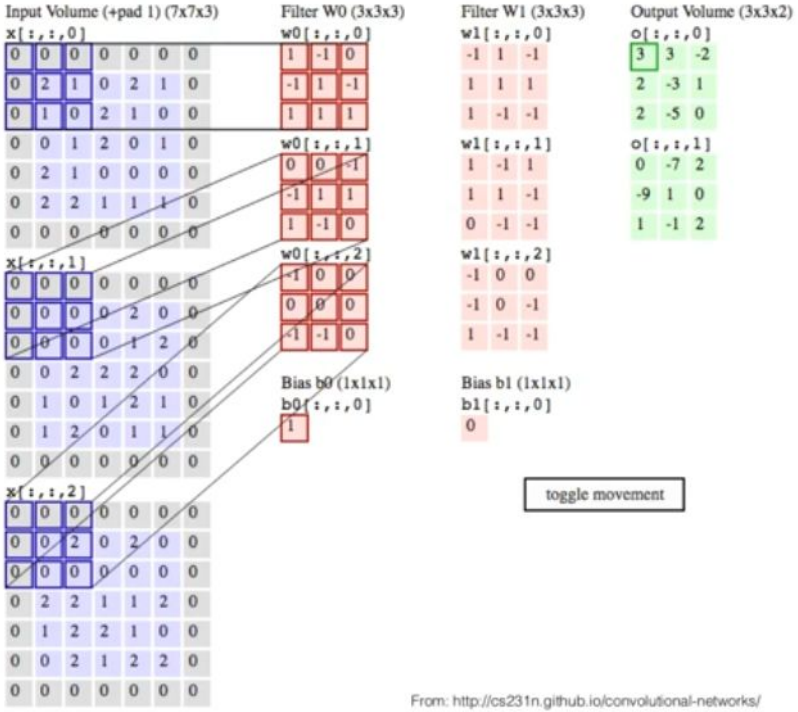


Features / Filters

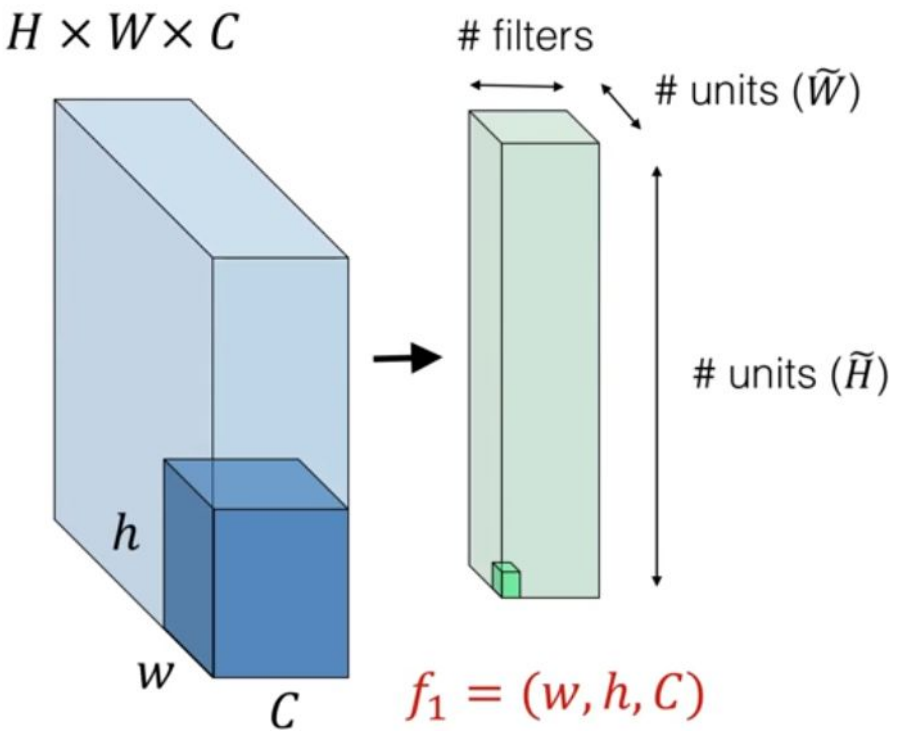
3-D



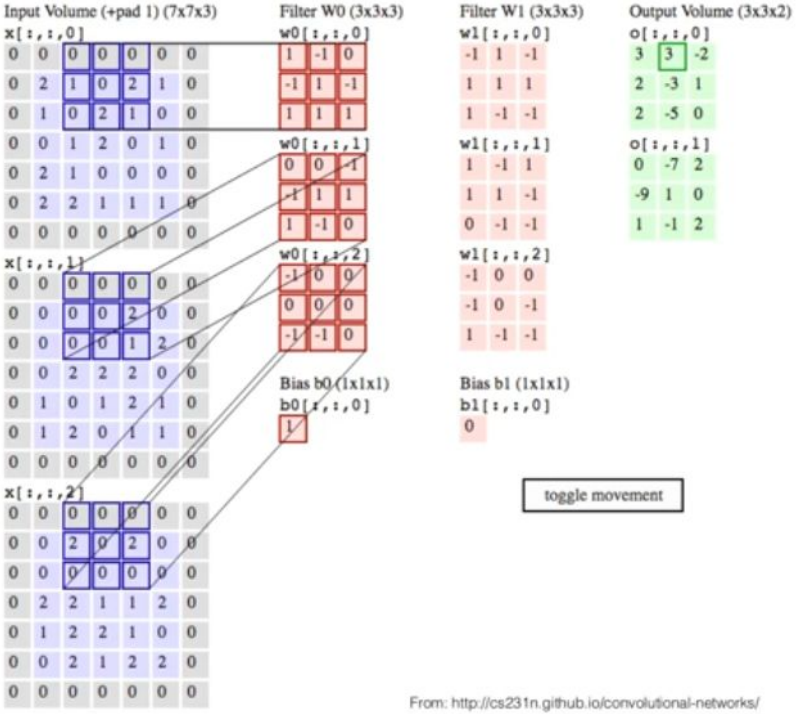
2-D Convolution



From: http://cs231n.github.io/convolutional-networks/



2-D Convolution



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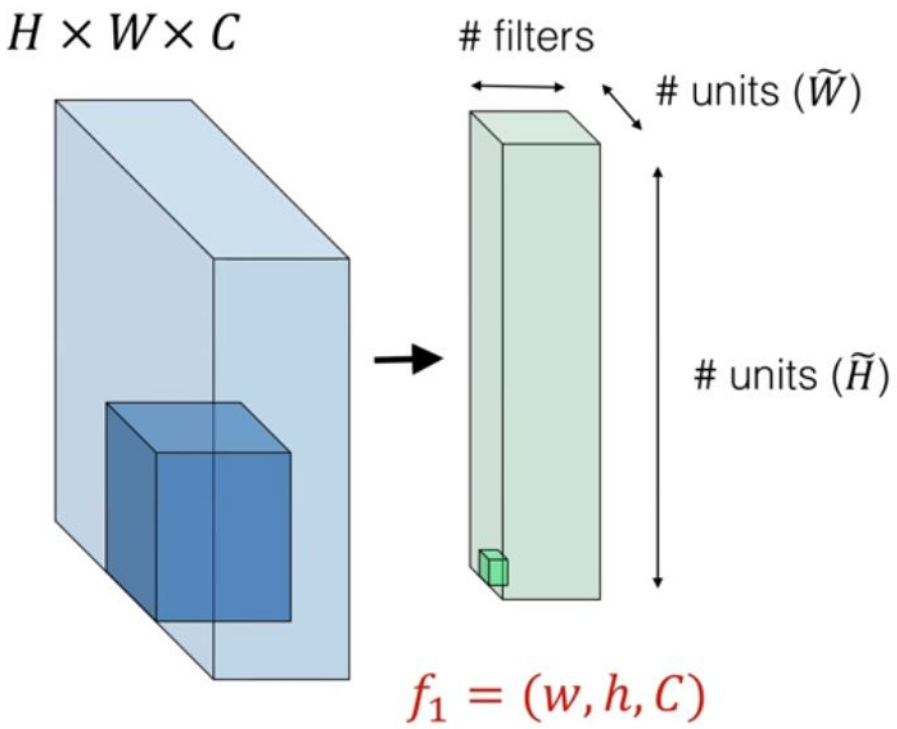
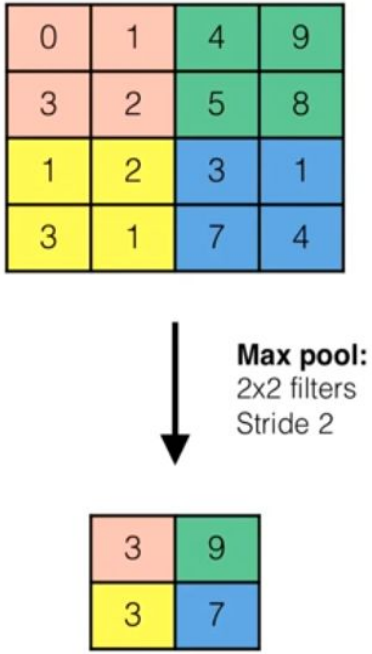
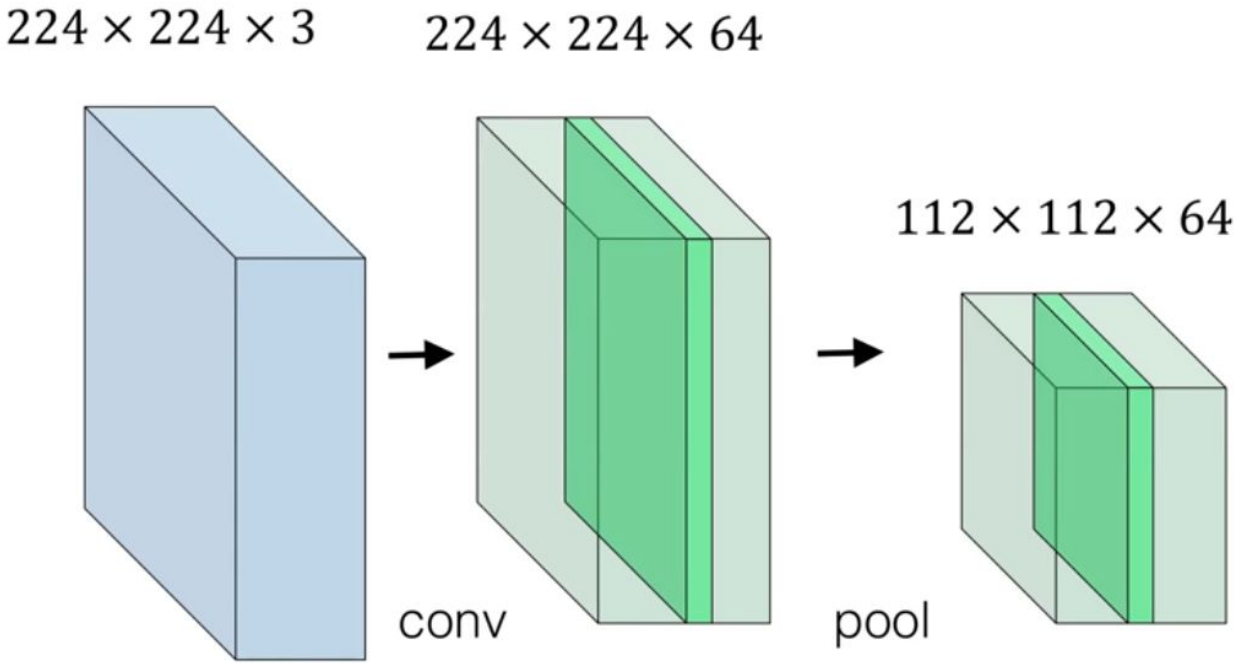


Pooling

1-D

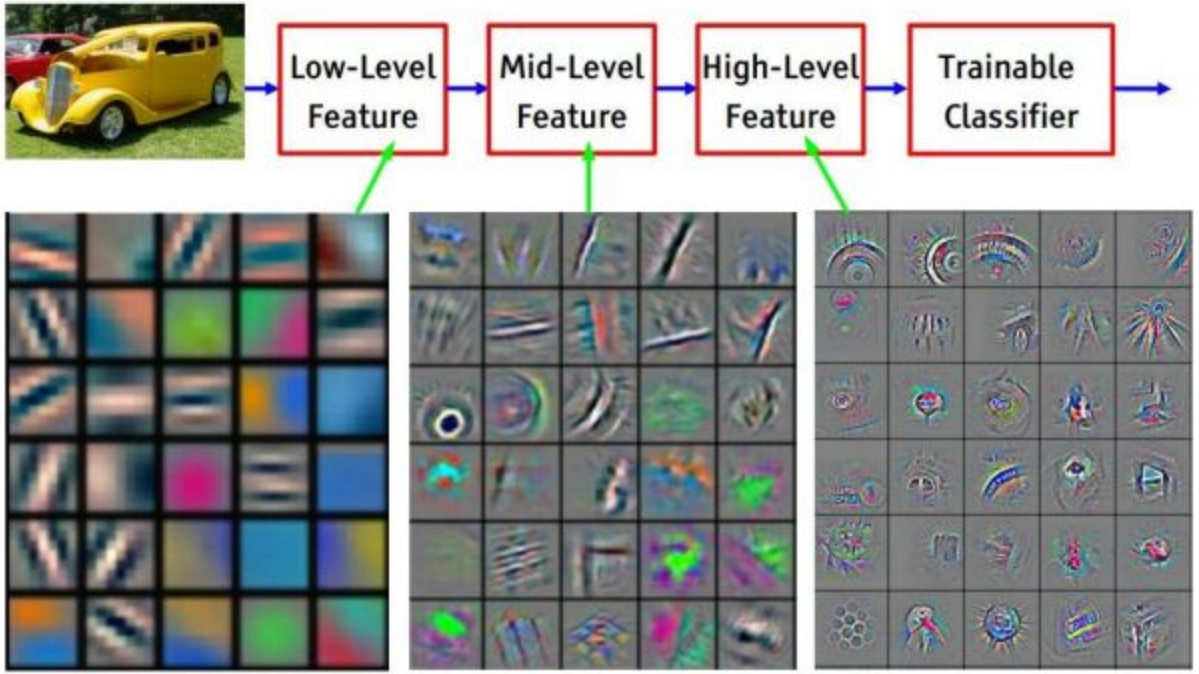


2-D



Inside Convolutional Neural Network

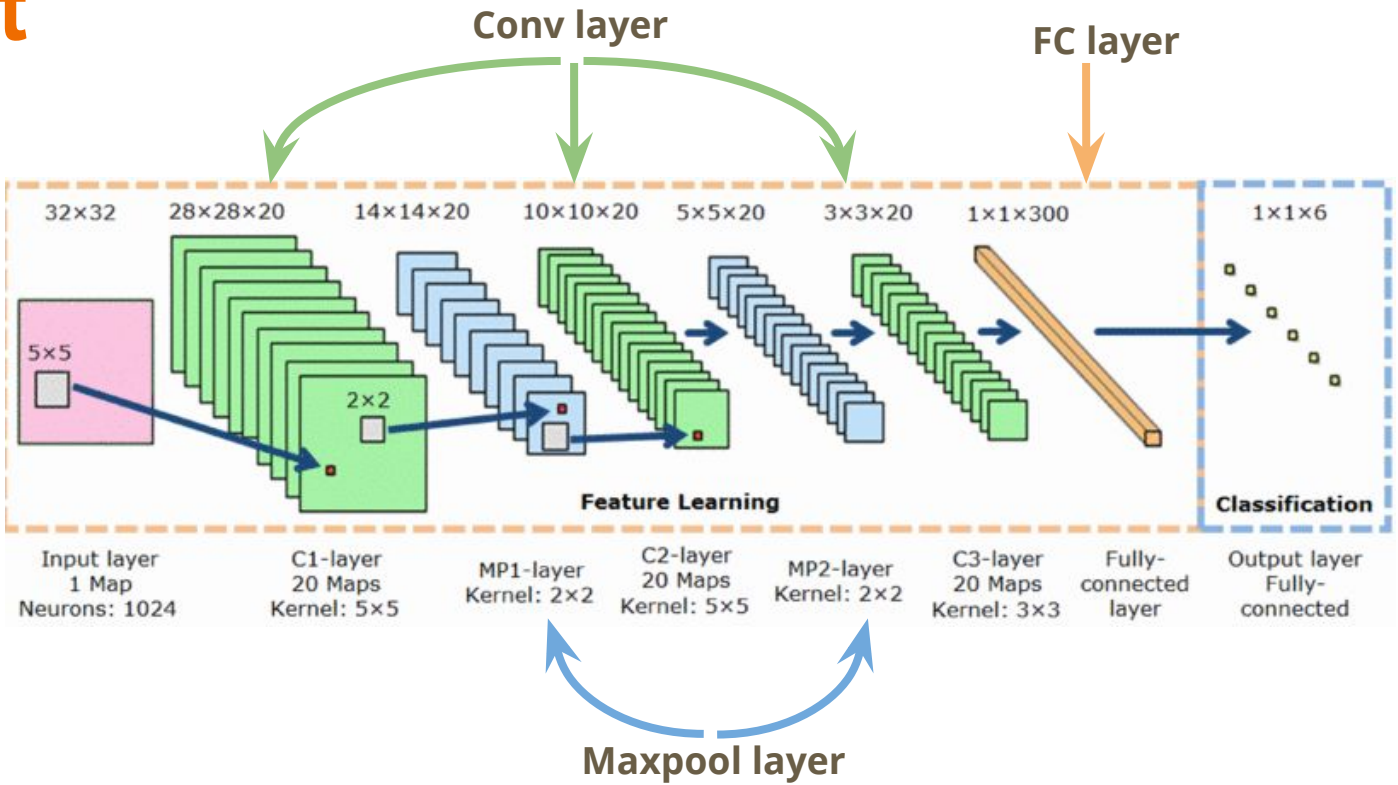
Inside Convolutional Neural Network



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]


conv1 p1 n1 conv2 p2 n2 conv3 conv4 conv5 p5 fc6 fc7 fc8 prob
fwd conv5_151 | Back: deconv (from conv5_151, disp raw) | Boost: 0/1

LeNet



*Original LeNet-5 has two FCL at the end, and filter sizes are slightly different

AlexNet (2012 Winner)

Architecture:

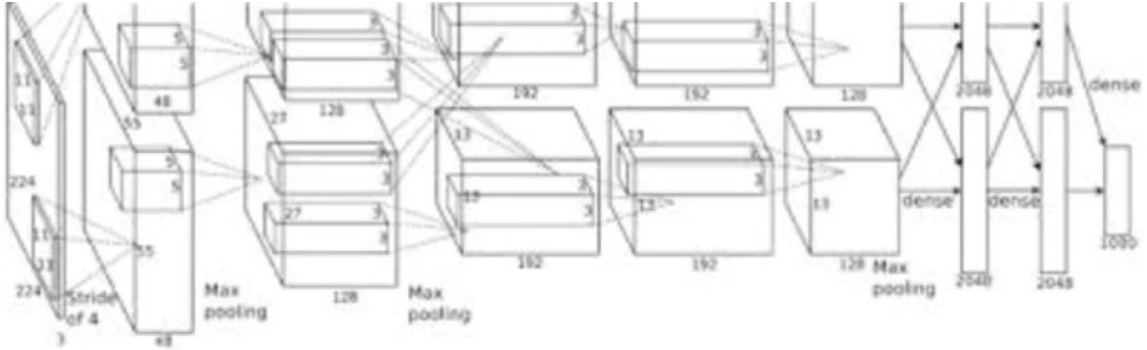
[227x227x3] INPUT

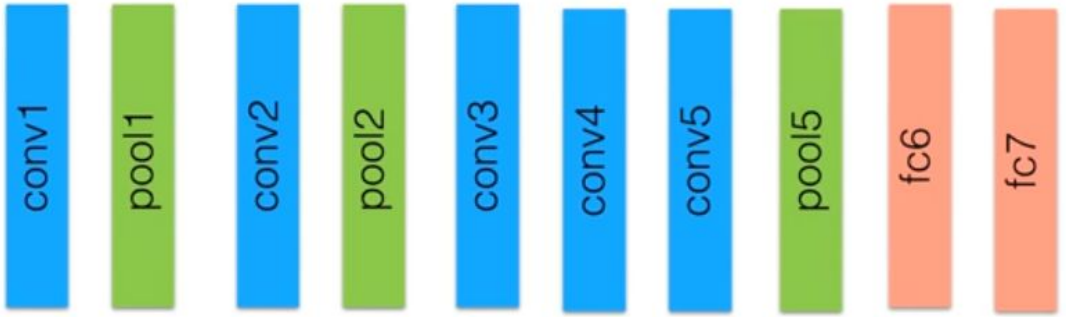
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer

[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer

[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2 [4096]

FC6: 4096 neurons [4096]
FC7: 4096 neurons [1000]
FC8: 1000 neurons (class scores)



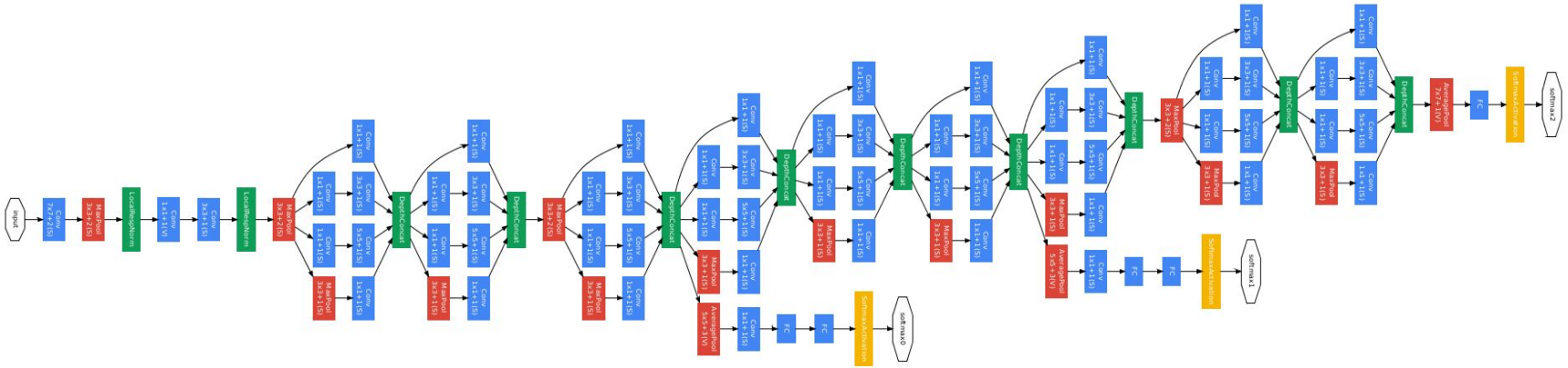


VGG Net

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

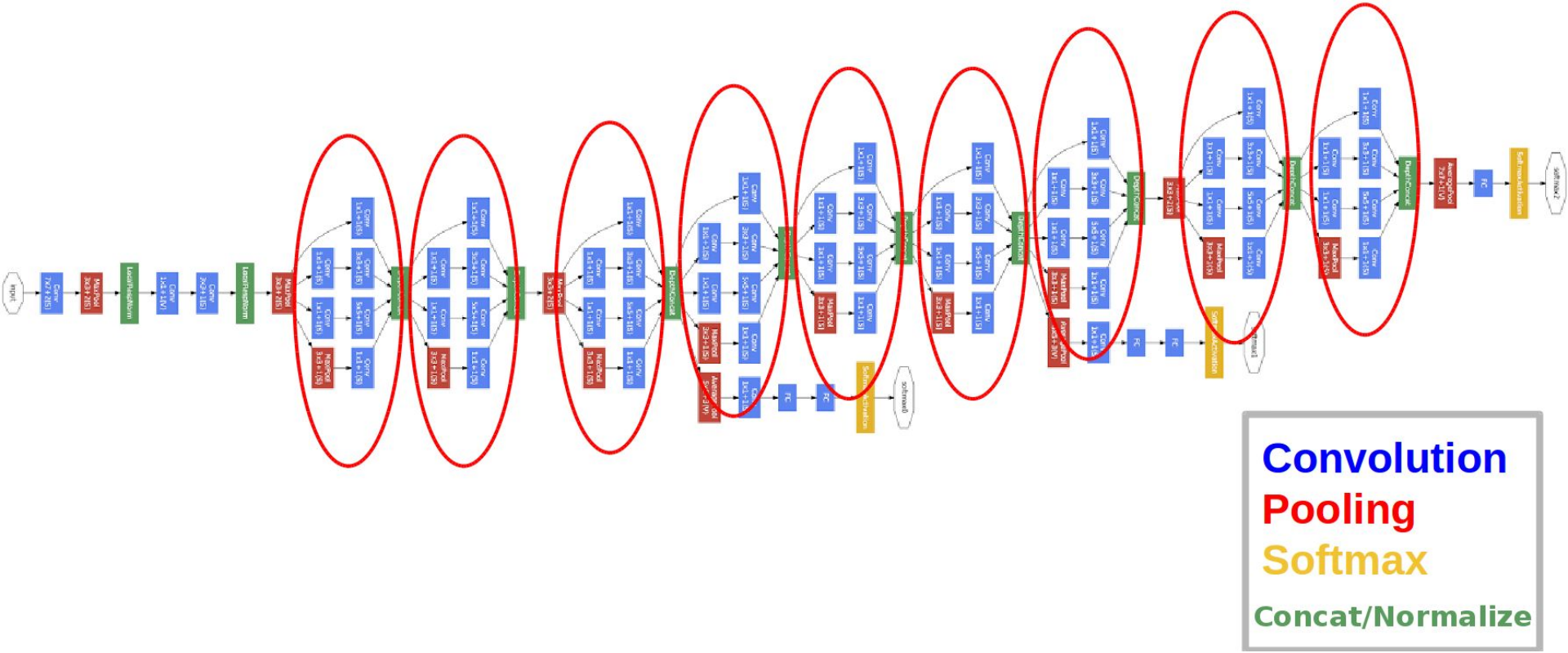
ConvNet Configuration		
B	C	D
13 weight layers	16 weight layers	16 weight layers
put (224 × 224 RGB image)		
conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64
maxpool		
conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128
maxpool		
conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**
maxpool		
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**
maxpool		
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**
maxpool		
FC-4096		
FC-4096		
FC-1000		
soft-max		

GoogLeNet (2014 winner)

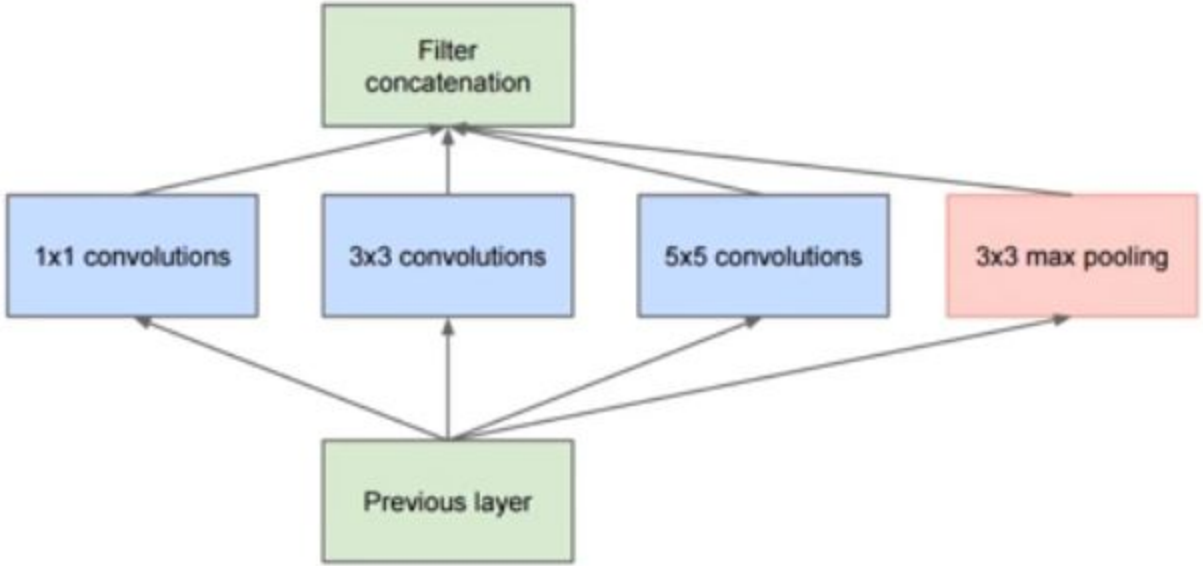


Peasant’s network vs Google’s

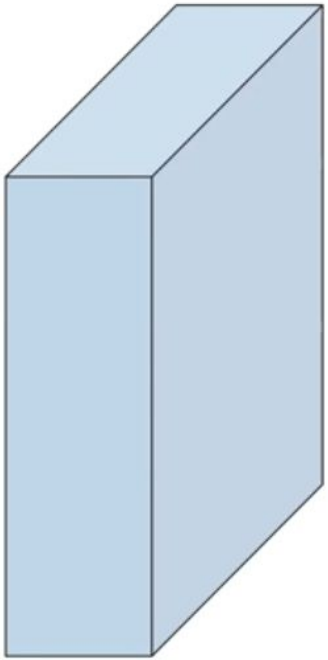
GoogLeNet (2014 winner)



Inception


Filter concatenation
1x1 convolutions
3x3 convolutions
5x5 convolutions
3x3 max pooling
Previous layer

Inception

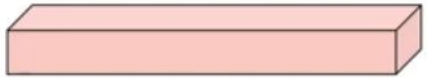


1 x 1?

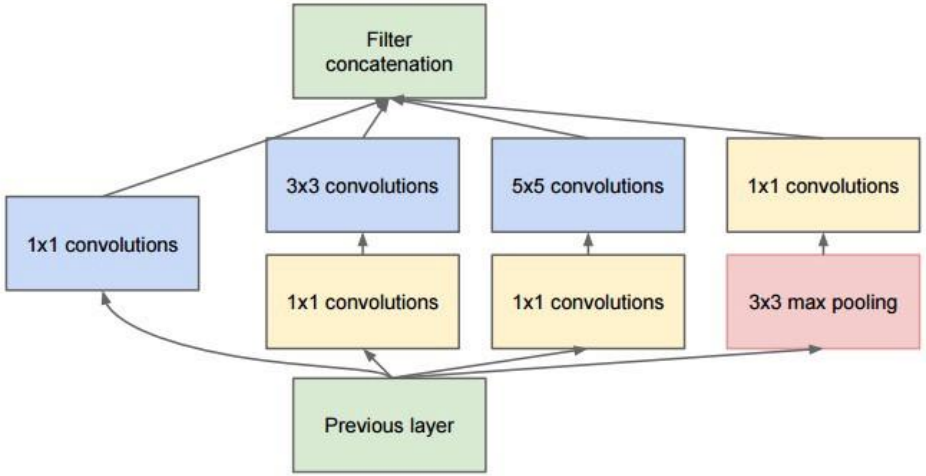
3 x 3?

5 x 5?

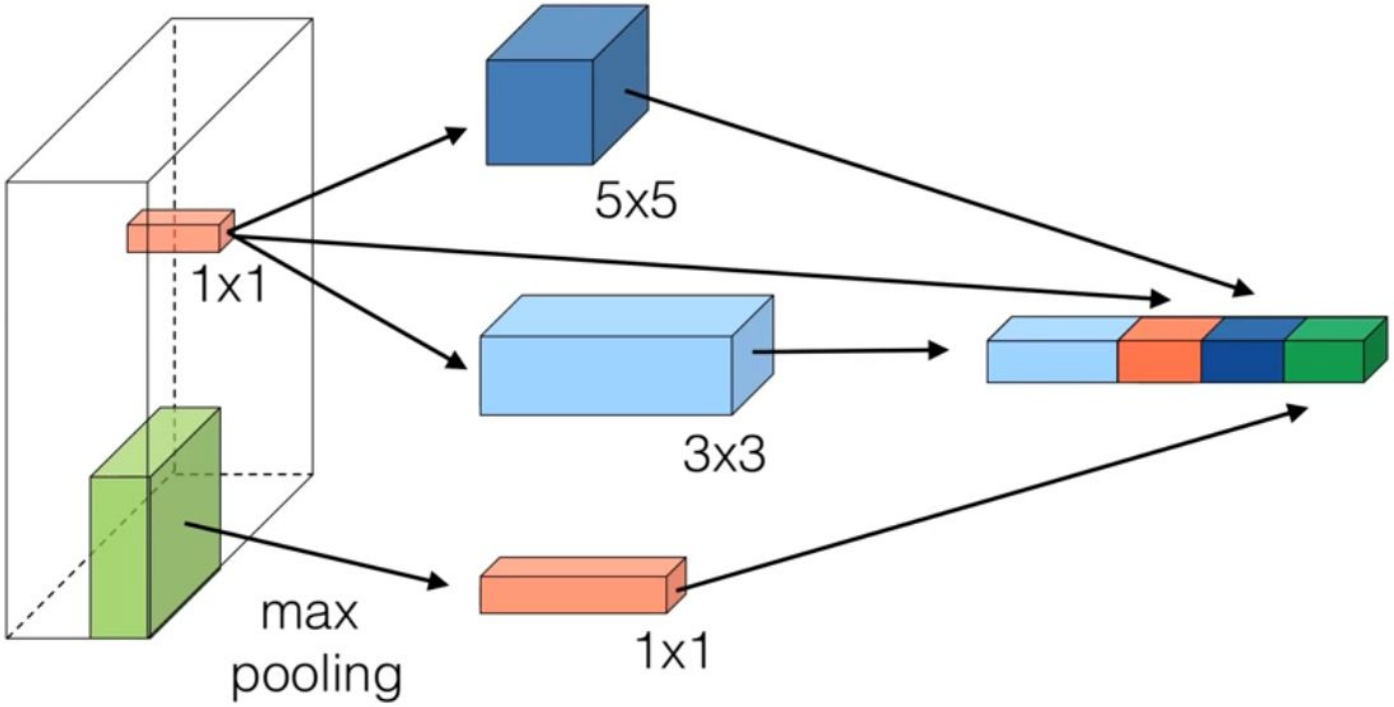
Pooling?



Inception


Filter concatenation
3x3 convolutions
5x5 convolutions
1x1 convolutions
1x1 convolutions
1x1 convolutions
1x1 convolutions
3x3 max pooling
Previous layer

Inception



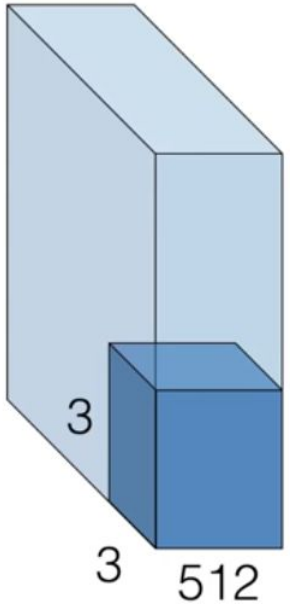
Inception

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M

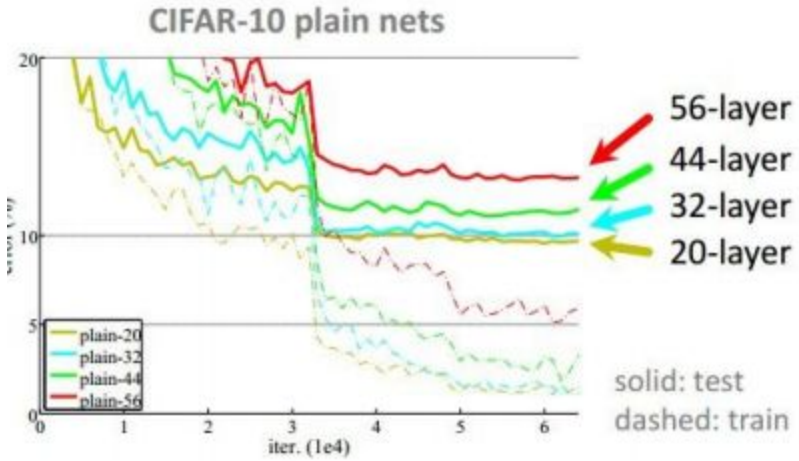
If we used (3 x 3, 512) convolution:

(3 x 3 x 512 x 512) parameters = 2.359 million parameters

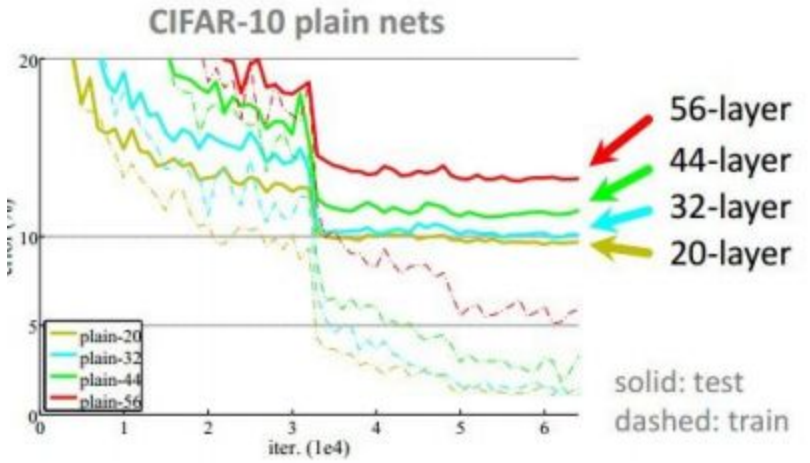
Inception module: 437K parameters

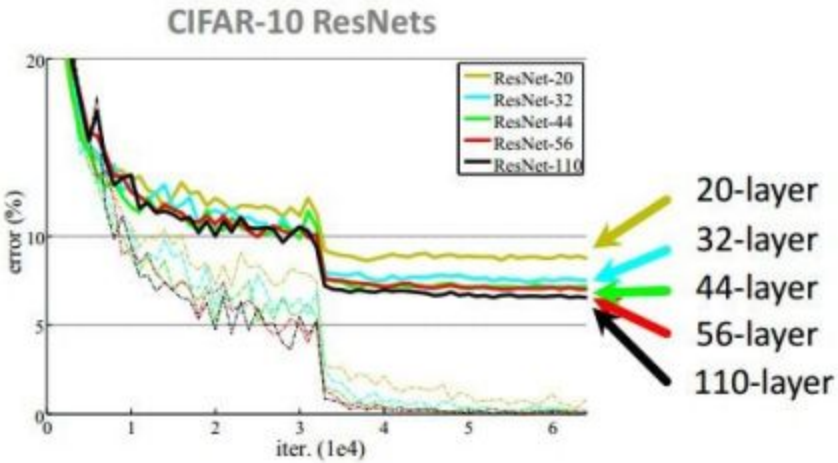


Going Deeper

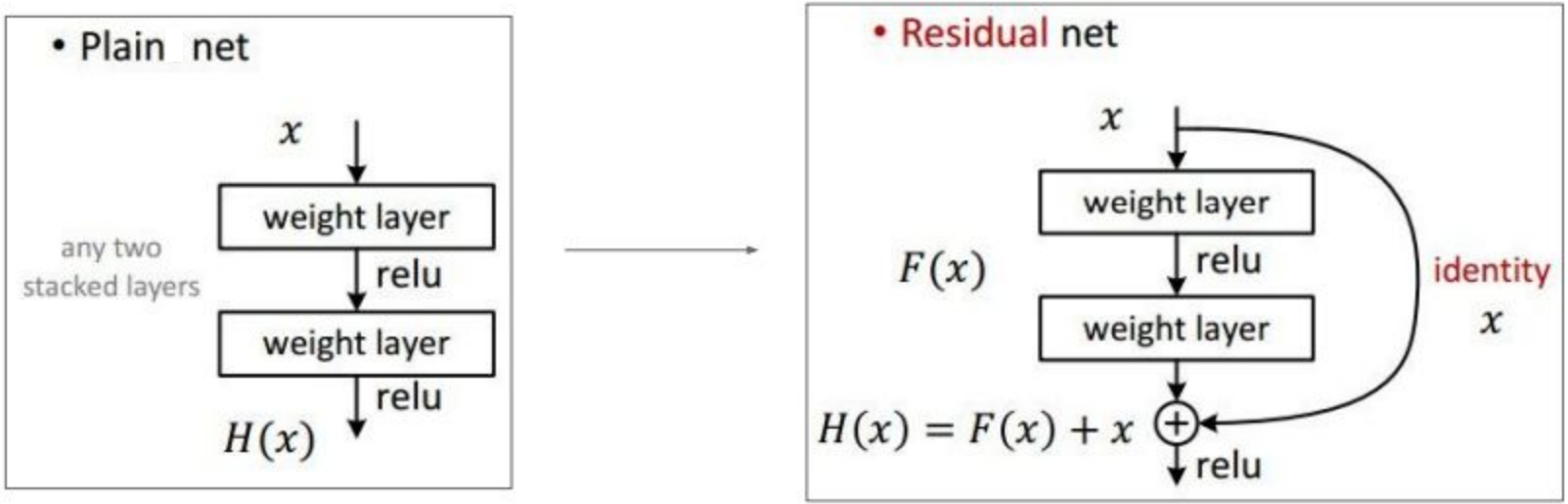


Going Deeper





Resnet (2015 winner)

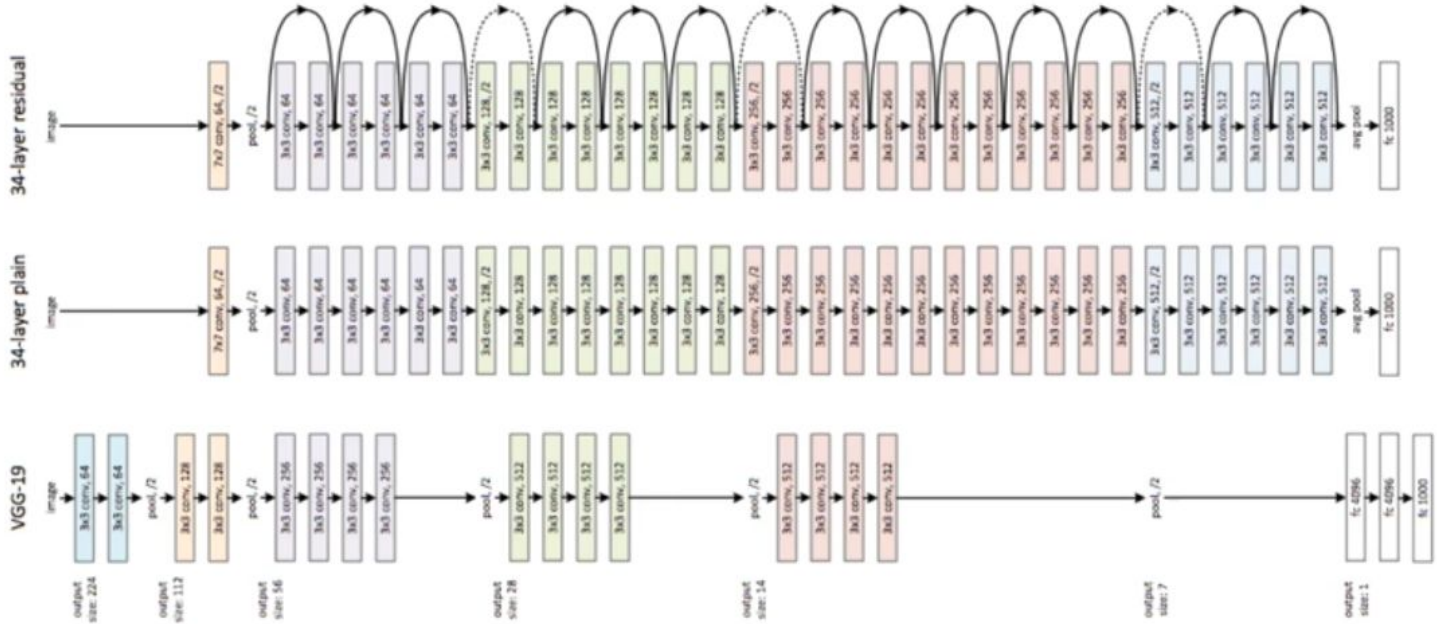


Resnet - comparison with other nets

34-residual

34-plain

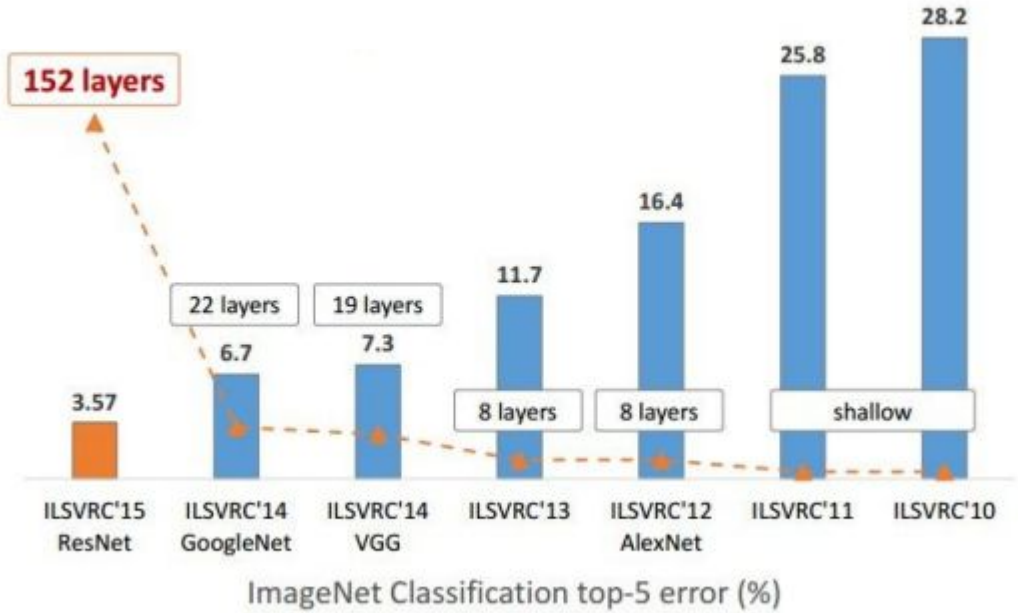
VGG



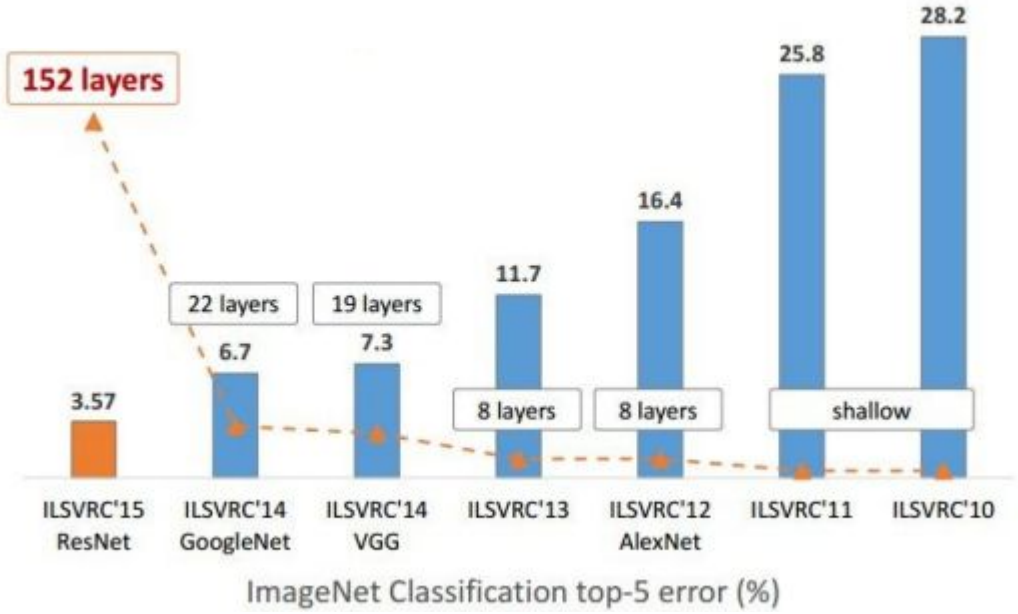
Resnet - Number of layer comparison

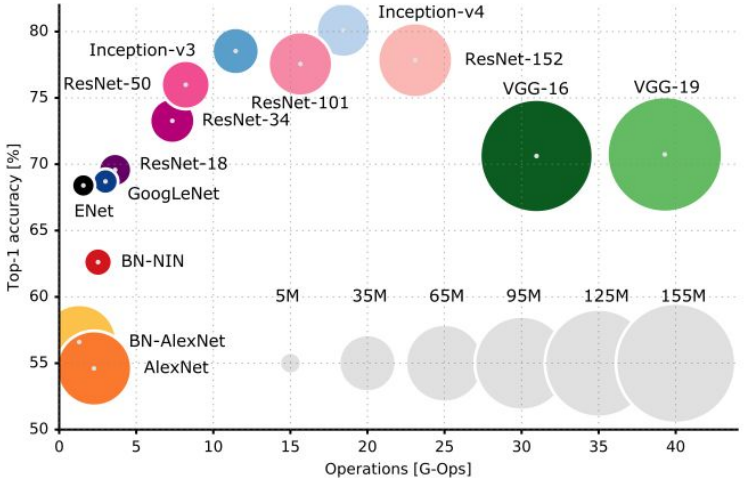
layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Depth - The Stigma

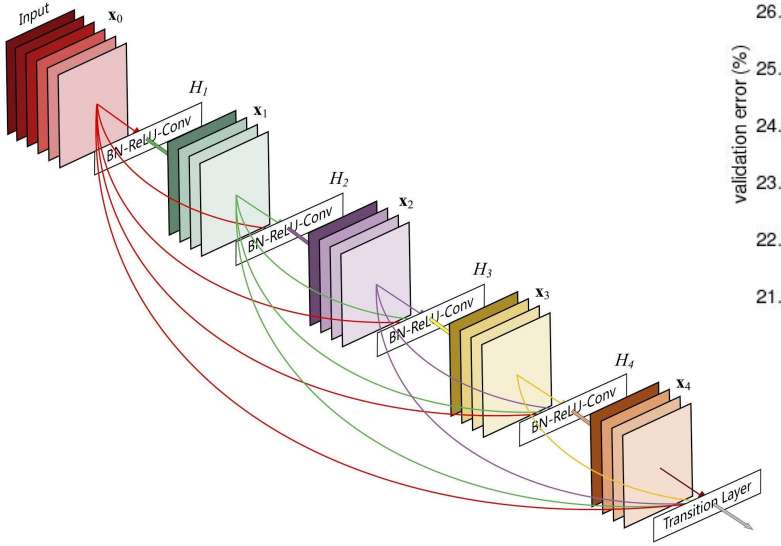


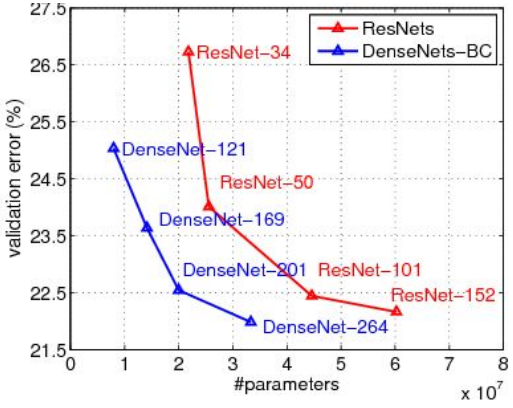
Depth - The Stigma

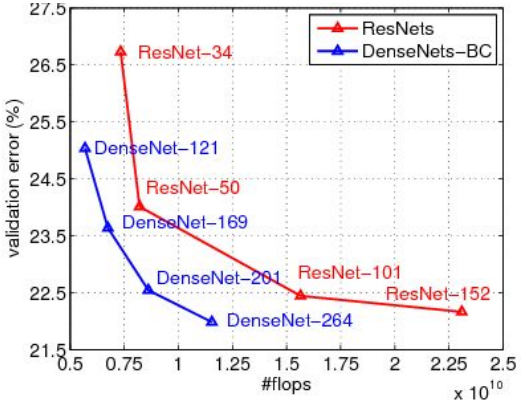




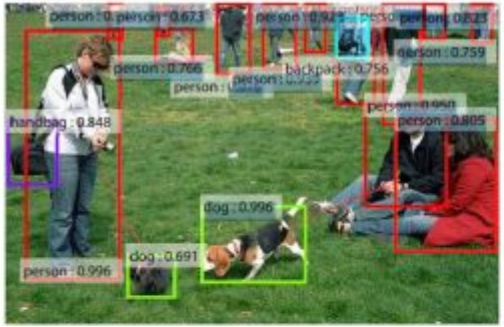
DenseNet

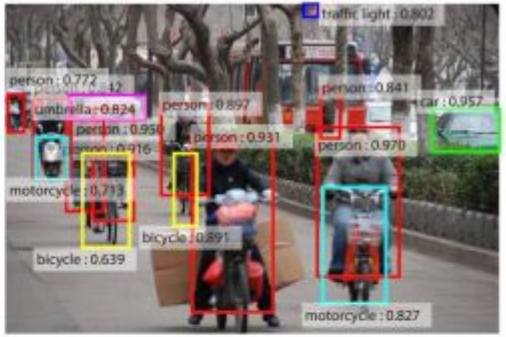

Input
$\mathbf{x}_0$
H_1
$\mathbf{x}_1$
BN-ReLU-Conv
H_2
$\mathbf{x}_2$
BN-ReLU-Conv
H_3
$\mathbf{x}_3$
BN-ReLU-Conv
H_4
$\mathbf{x}_4$
BN-ReLU-Conv
Transition Layer


ResNets
DenseNets–BC
ResNet–34
DenseNet–121
ResNet–50
DenseNet–169
DenseNet–201
ResNet–101
ResNet–152
DenseNet–264
validation error (%)
#parameters
x 10^7


ResNets
DenseNets–BC
ResNet–34
DenseNet–121
ResNet–50
DenseNet–169
DenseNet–201
ResNet–101
ResNet–152
DenseNet–264
validation error (%)
#flops
x 10^10

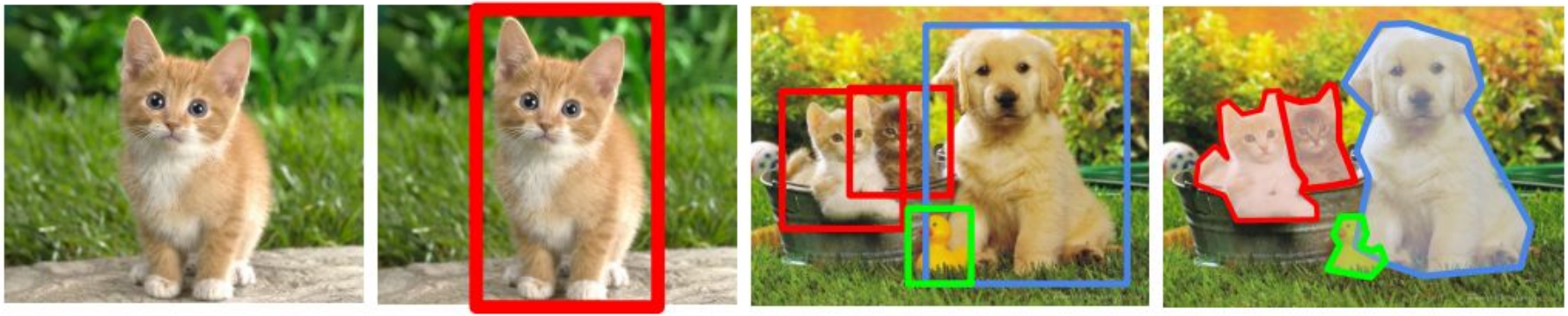
Localization and Detection





Source: cs231n

Classification vs Localization vs Detection vs Segmentation



Source: cs231n

Detection - Fast and Accurate

MobilEye (video)

Nikon S60

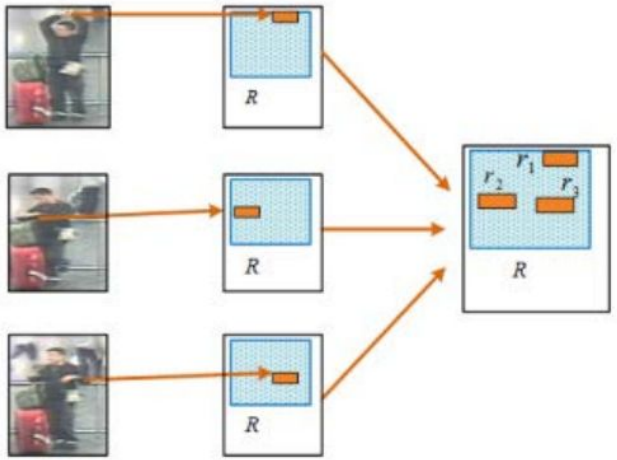
Source: Ross Girshick

Demo

Source: YOLO

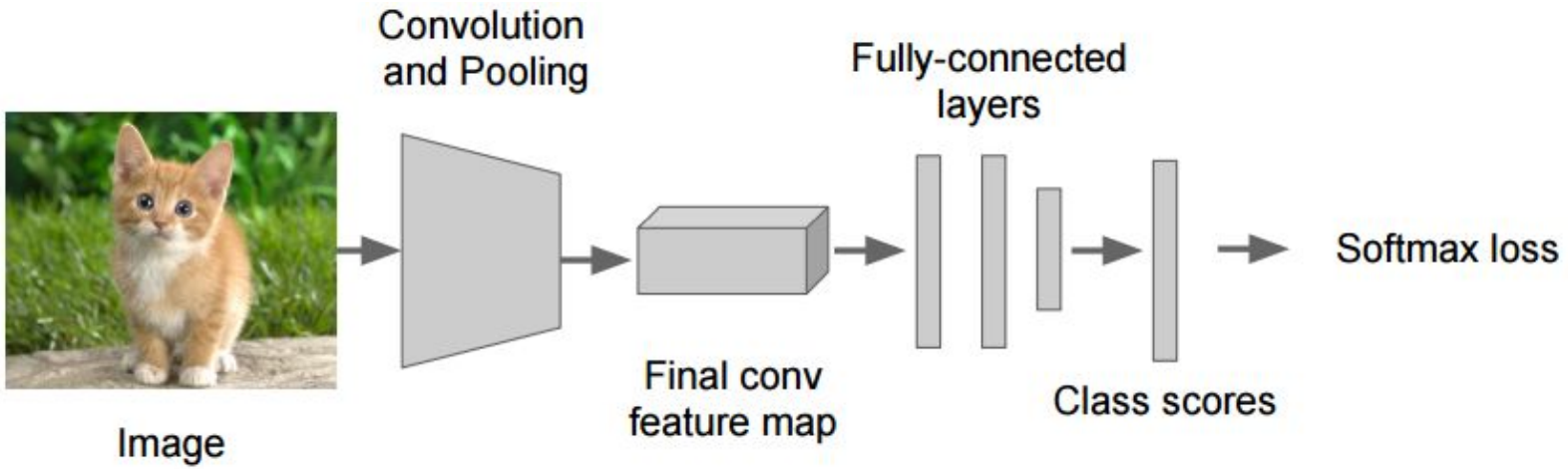
Before deep learning

- Deformable Parts Model
  - low-level features based on HOG, SVM classifier
  - mAP: 33%
- Selective Search
  - Bag-of-words with SIFT features, merge similar segments found by segmentation
  - mAP: 35%
- Regionlets
  - HOG, LBP, Covariance features, relative position of sub-parts
  - mAP: 40%



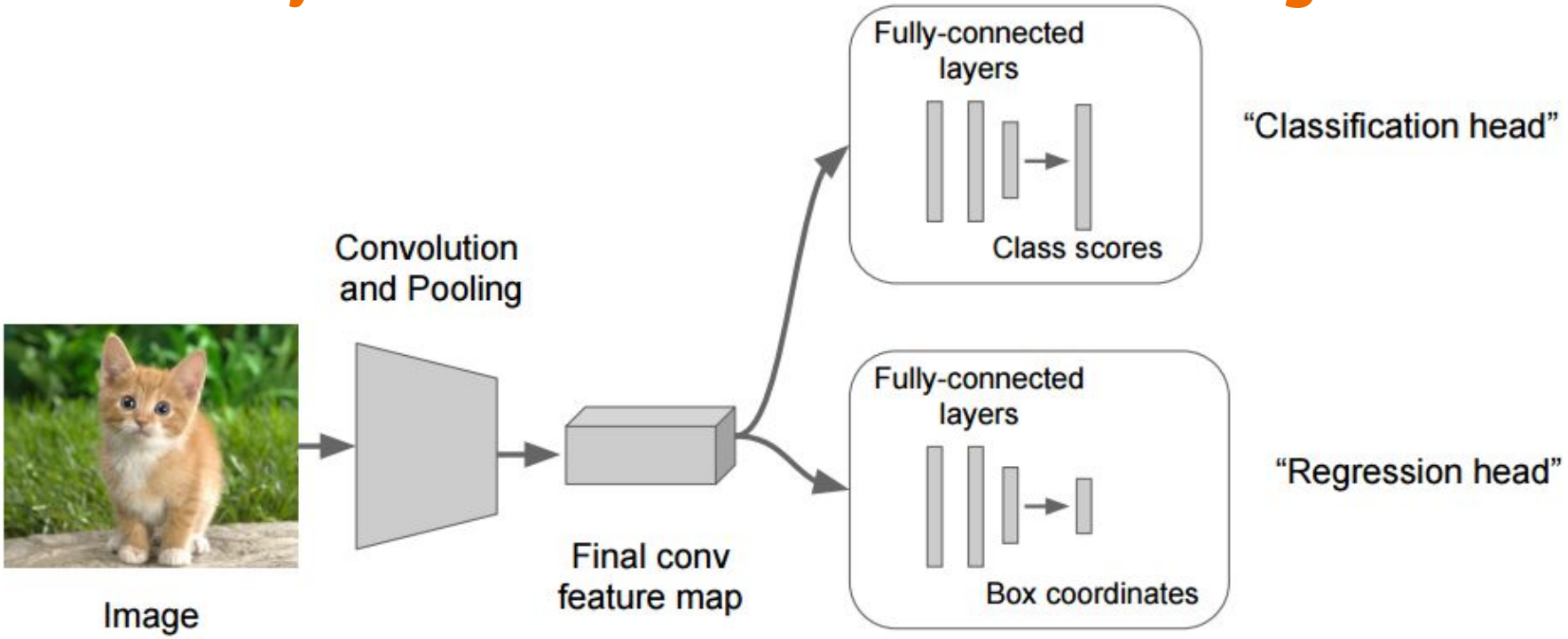
Source: Wang et al

Naive way to use CNN for localization - Regression



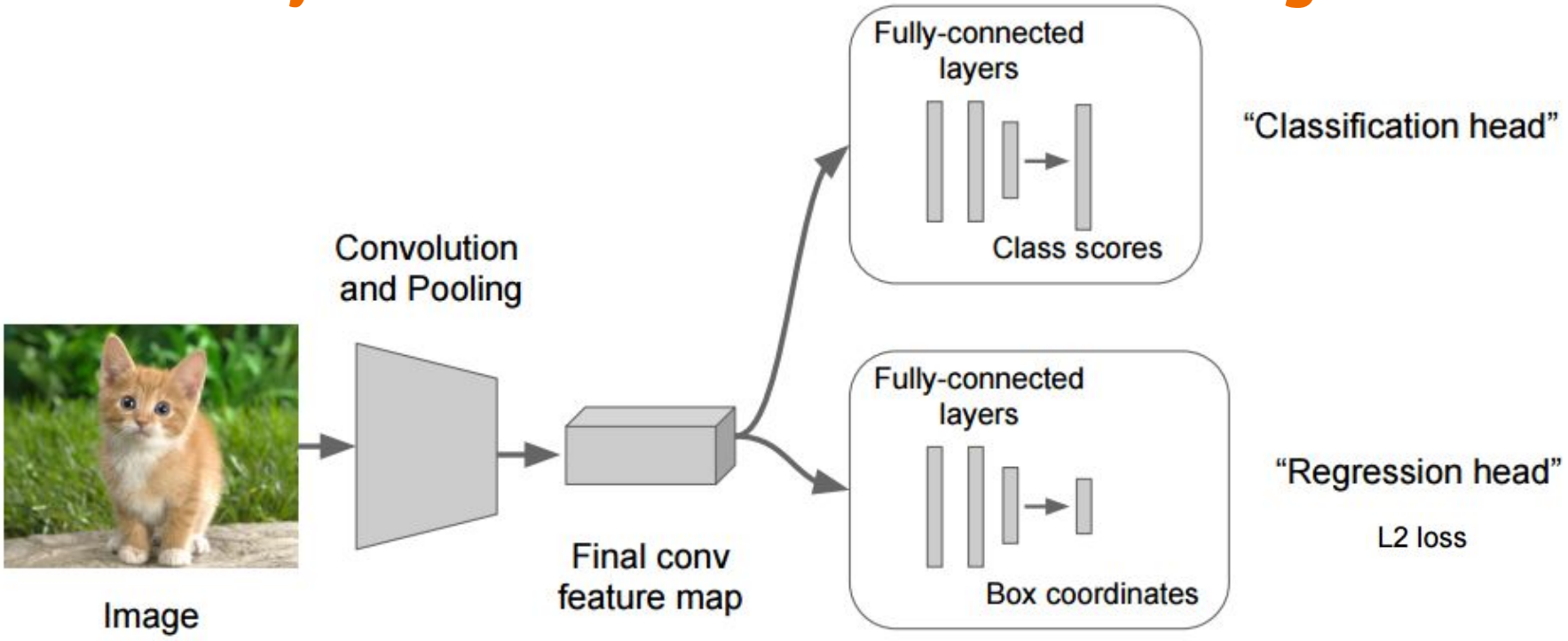
Source: cs231n

Naive way to use CNN for localization - Regression



Source: cs231n

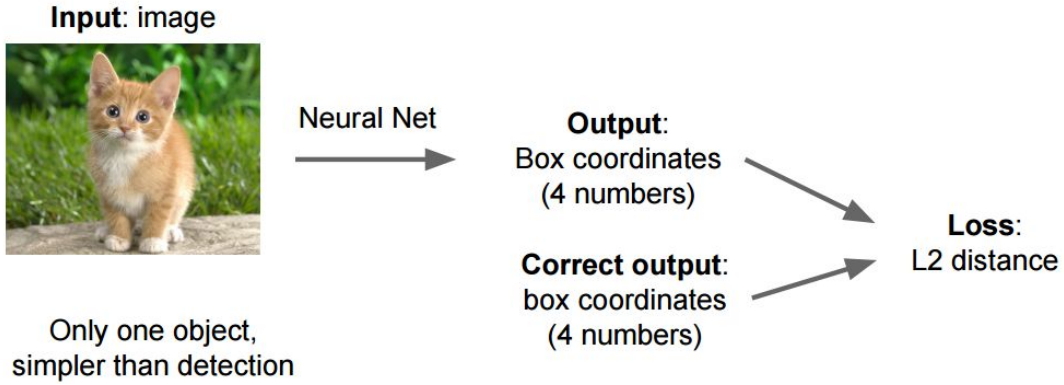
Naive way to use CNN for localization - Regression



Source: cs231n

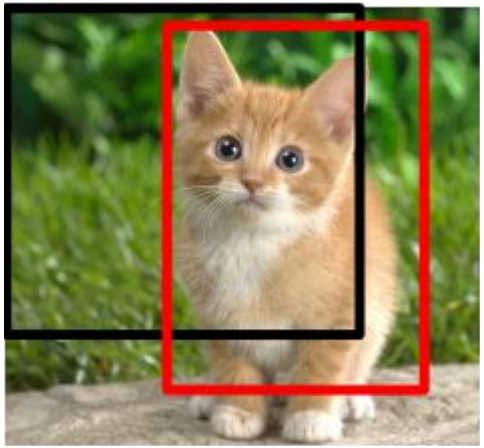
Naive way to use CNN for localization - Regression

- Limited to ‘one’ class per image
- Limited to ‘one’ instance of object per image
- Cannot separate object parts - like ear, head, eyes
- Limited to ‘rectangle’ object boundaries



Source: cs231n

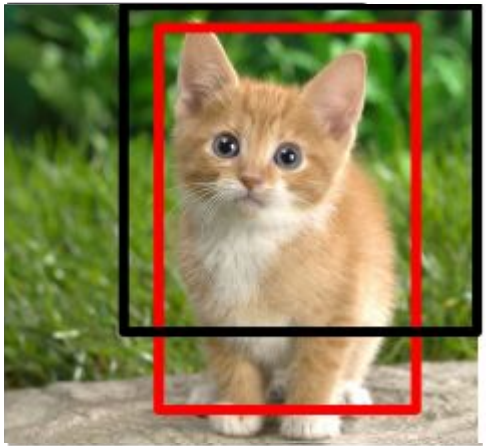
Better way - Sliding window



0.5	

Source: cs231n

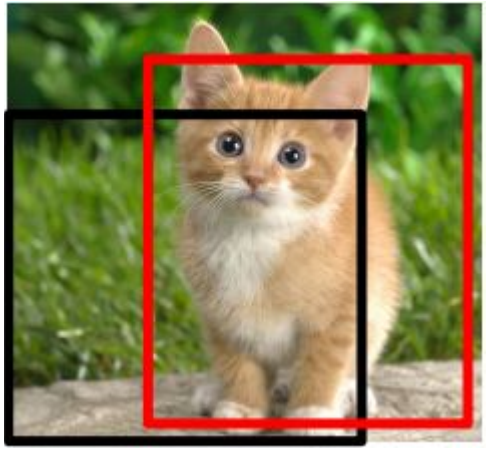
Better way - Sliding window



0.5	0.75

Source: cs231n

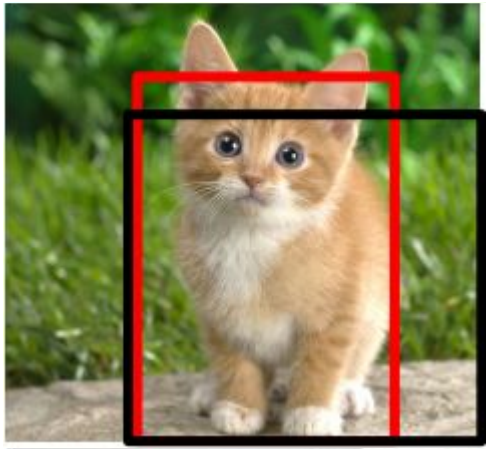
Better way - Sliding window



0.5	0.75
0.6	

Source: cs231n

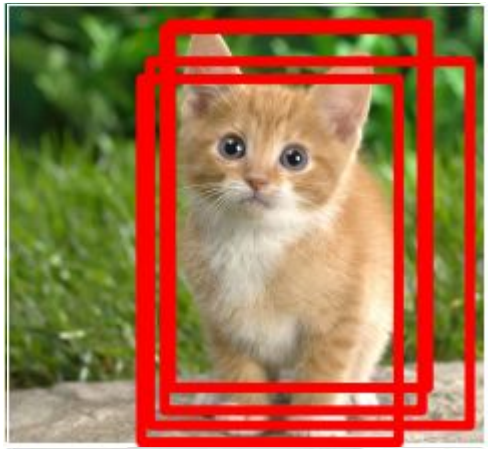
Better way - Sliding window



0.5	0.75
0.6	0.8

Source: cs231n

Better way - Sliding window



0.5	0.75
0.6	**0.8**

Source: cs231n

Imagenet results (Localization)

AlexNet: Localization method not published

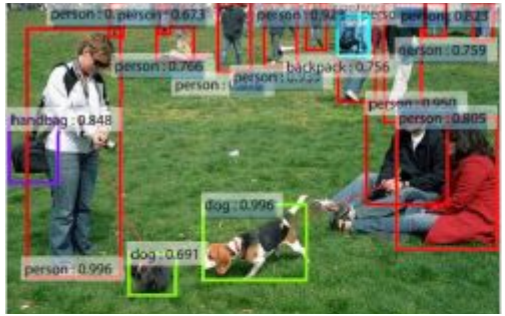
Overfeat: Multiscale convolutional regression with box merging

VGG: Same as Overfeat, but fewer scales and locations; simpler method, gains all due to deeper features

ResNet: Different localization method (RPN) and much deeper features

Can we do detection as regression?

- Four corners for every object, many numbers to regress.
- No idea on how many objects to expect.



Can we do detection as classification?

- How many boxes should we check? All of them?
- At what scale? Some dogs are smaller (or far away)

Can we do detection as regression?

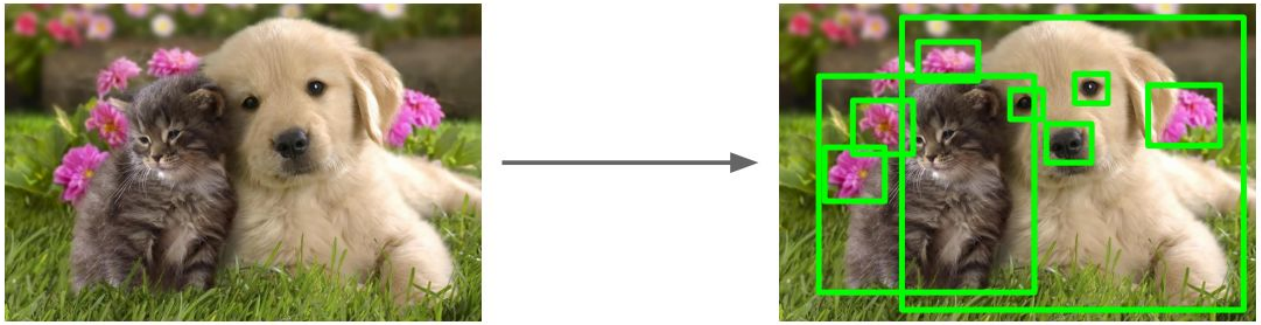
- Four corners for every object, many numbers to regress.
- No idea on how many objects to expect.

Can we do detection as classification?

- How many boxes should we check? All of them?
- At what scale? Some dogs are smaller (or far away)

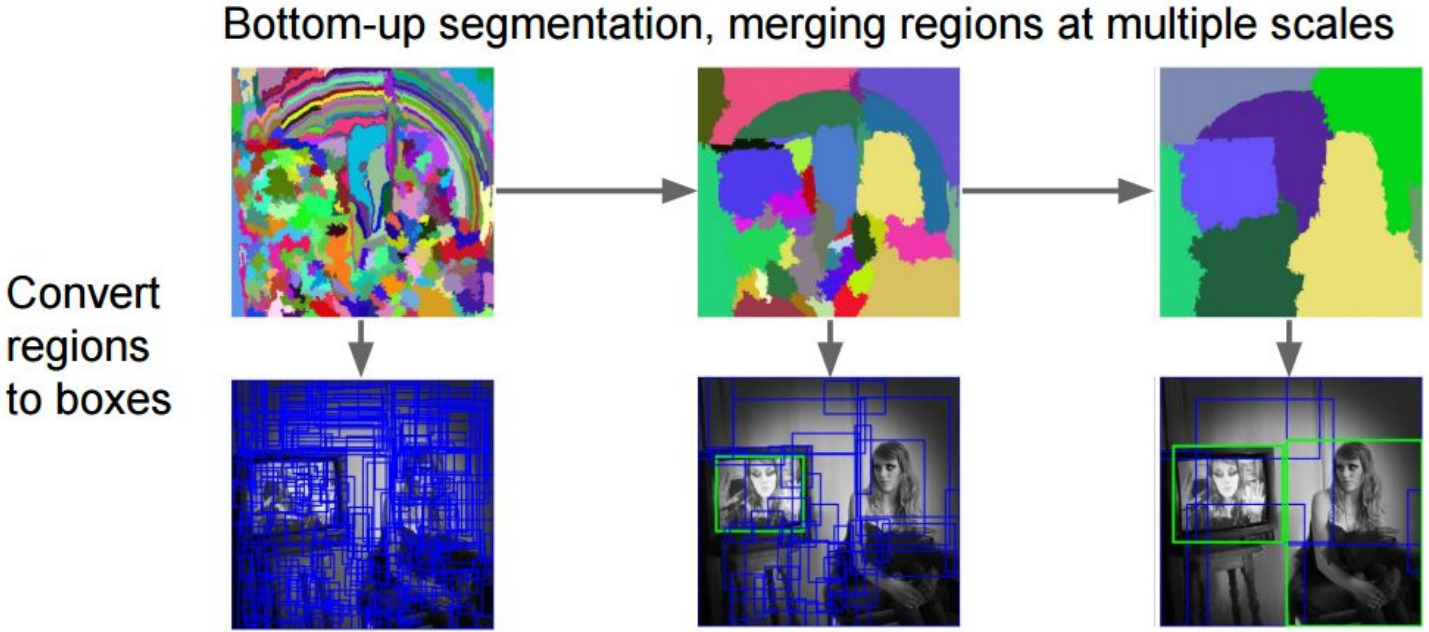
Solution: Only check at few places

Better solution - Region proposals

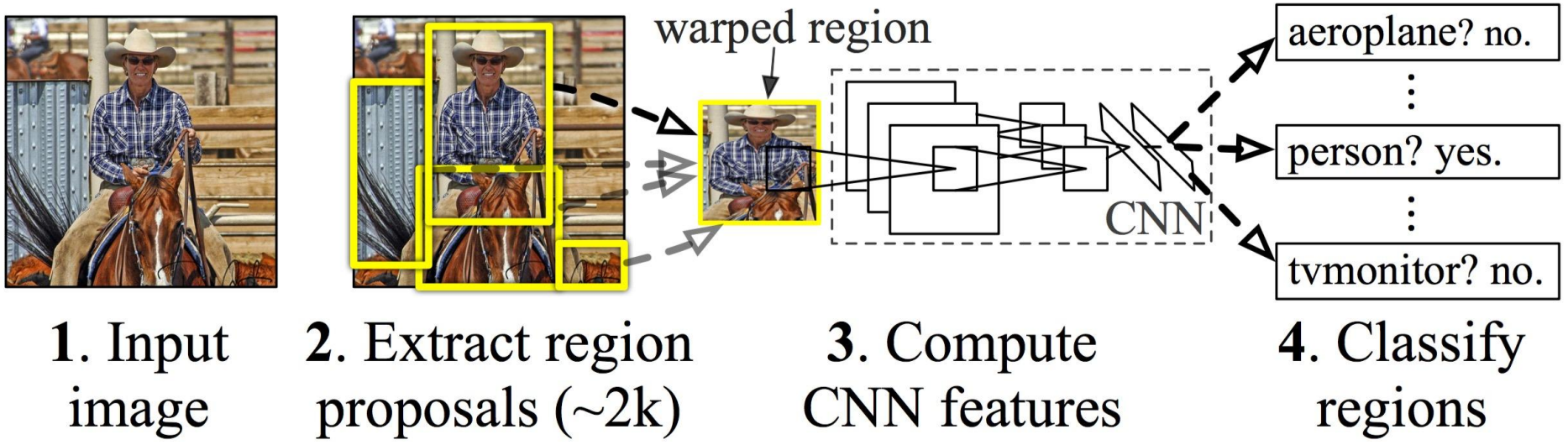


- Find ‘regions-of-interest’ that are likely to contain some objects
- A simple detector which just says there is something of interest and not necessarily about the class
- These region proposals could be just blob of pixels or ‘super-pixels’.
- There are lot of techniques, like BING, CPMC, EdgeBoxes, Geodesic, MCG etc

Region Proposals - Selective Search



Region based CNN (R-CNN)



R-CNN Training

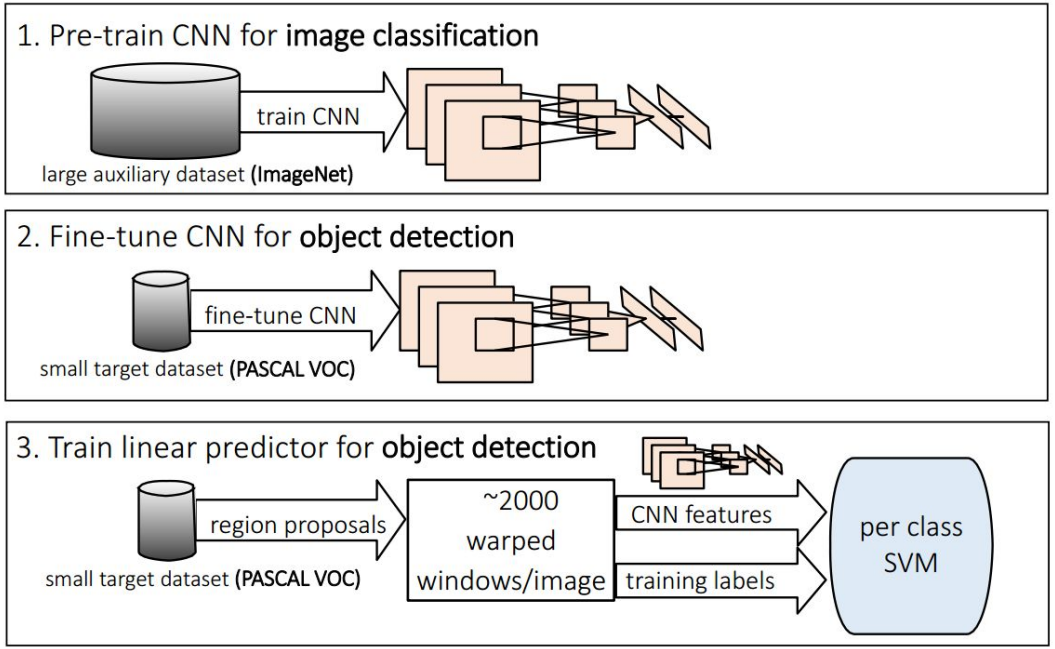
1. [offline] ~~M ←~~ Pre-train a ConvNet for ImageNet classification

2. ~~M' ←~~ Fine-tune M for object detection (softmax classifier + log loss) [add background class]

3. ~~F ←~~ Cache feature vectors to disk using M'

4. Train *post hoc* linear SVMs on F (hinge loss) [binary classifier]

5. Train *post hoc* linear bounding-box regressors on F (squared loss)



Source: E Mercan, R Girshick

R-CNN Results/Analysis

mAP - mean Average Precision
- Average of Average Precision for each class.
- True positive if IoU with ground-truth box > 0.5.
- AP is area under the Precision-Recall curve.

1. Very slow (upto 20 seconds per image on K40 GPU).

2. Needs to run full CNN pass on each proposed region.

3. Not end-to-end training.

4. CNN features are not updated with results of training SVM

5. Better results than any other system

Source: E Mercan

R-CNN Results/Analysis

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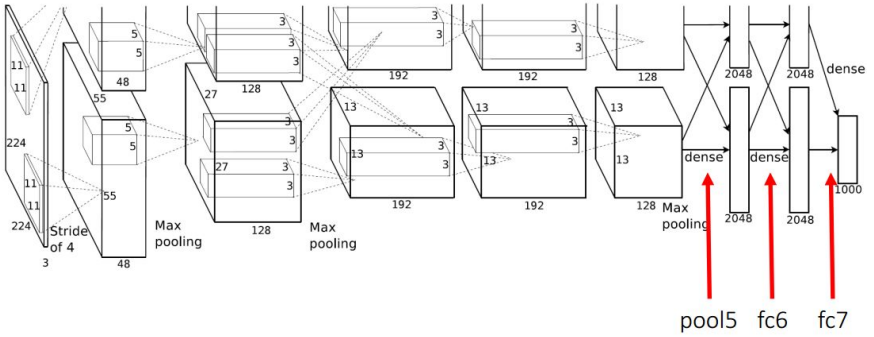
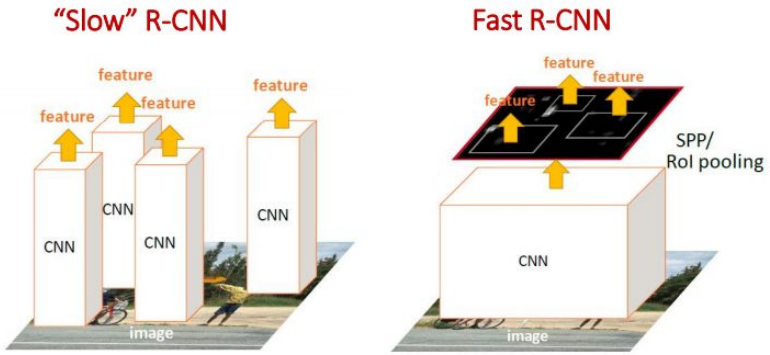
5. Better results than any other system

		VOC 2007	VOC 2010
reference	DPM v5 (Girshick et al. 2011)	33.7%	29.6%
	UVA sel. search (Uijlings et al. 2012)		35.1%
	Regionlets (Wang et al. 2013)	41.7%	39.7%
pre-trained only	R-CNN $pool_5$	44.2%	
	R-CNN fc_6	46.2%	
	R-CNN fc_7	44.7%	
fine-tuned	R-CNN $pool_5$	47.3%	
	R-CNN fc_6	53.1%	
	R-CNN fc_7	54.2%	50.2%%
	R-CNN fc_7 (Bounding Box regression)	**58.5%**	53.7%



Source: E Mercan

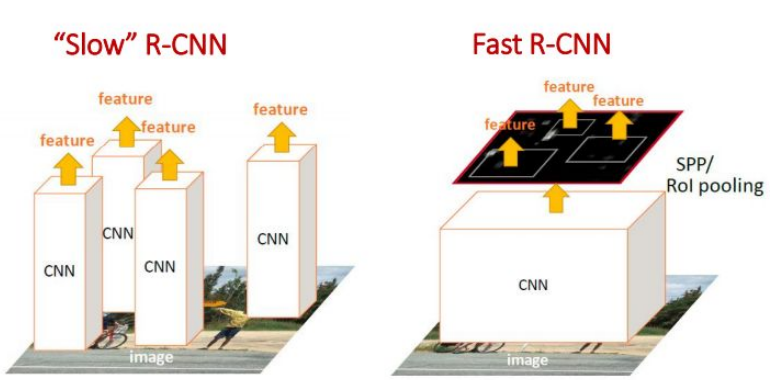
Fast R-CNN

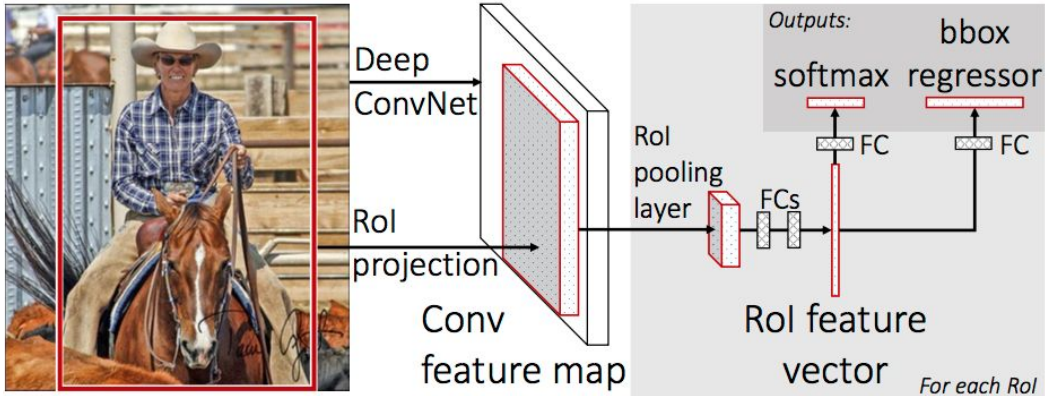


- Share computation of convolutional layers between 'regions of proposal'

Source: Ross Girshick

Fast R-CNN





- Share computation of convolutional layers between 'regions of proposal'
- Train the whole system end-to-end
  - no more post-hoc classifiers
  - No caching features to disk

Source: Ross Girshick, Kaiming He

Fast R-CNN

True box coordinates

Predicted box coordinates

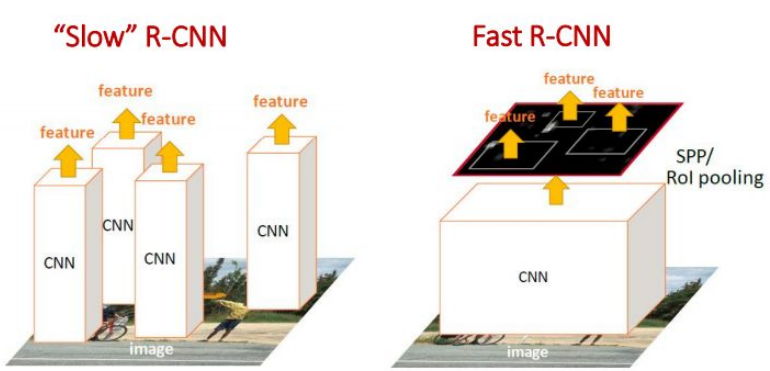
$$L(p, u, t^u, v) = L_{\text{cls}}(p, u) + \lambda[u \geq 1]L_{\text{loc}}(t^u, v)$$

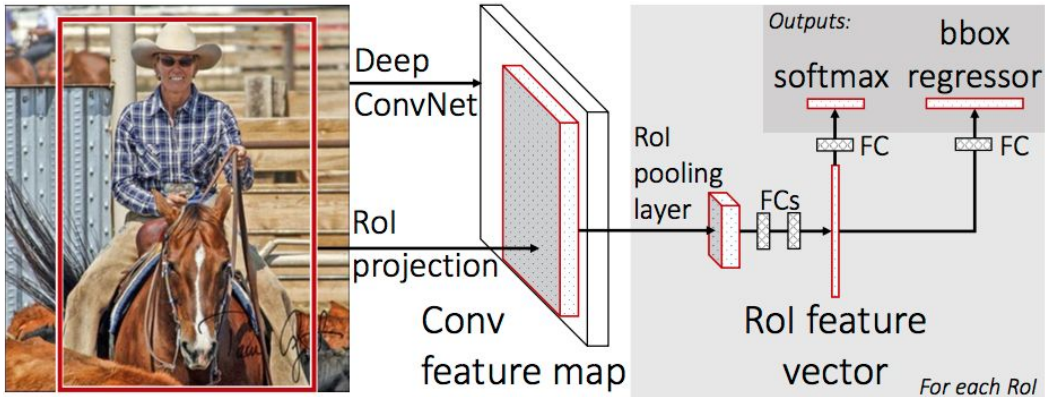
Predicted class scores

True class scores

Log loss

Smooth L1 loss



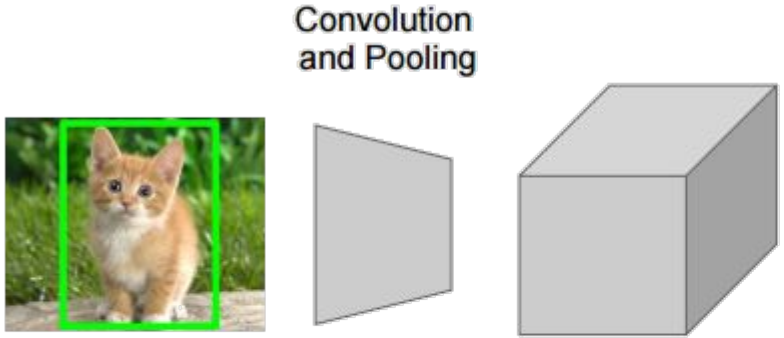


- Share computation of convolutional layers between 'regions of proposal'
- Train the whole system end-to-end
  - no more post-hoc classifiers
  - No caching features to disk

- Positive samples are those with IoU overlap with ground-truth bounding box > 0.5.
- Negative samples are in interval [0.1,0.5)
- 25%/75% ratio of Positive to Negative samples

Source: Ross Girshick, Kaiming He

Fast R-CNN: Region of Interest Pooling

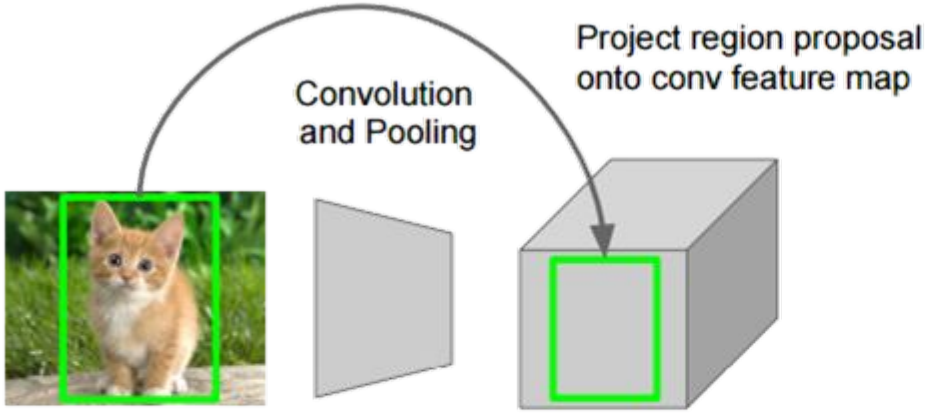


Hi-res input image:
3 x 800 x 600
with region
proposal

Hi-res conv features:
C x H x W
with region proposal

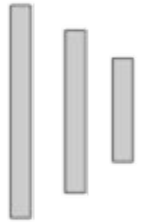
Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling



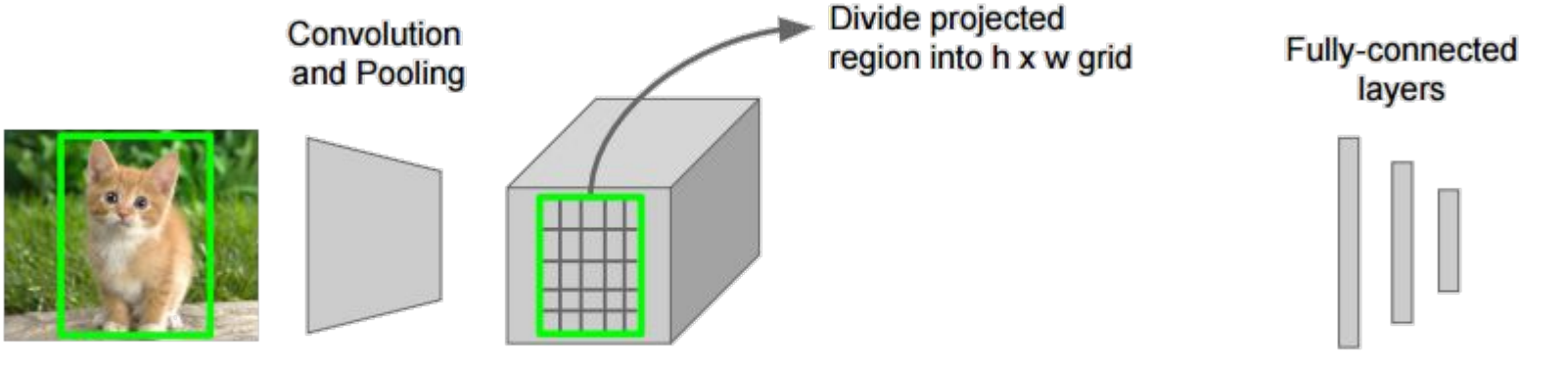
Hi-res input image:
3 x 800 x 600
with region
proposal

Hi-res conv features:
C x H x W
with region proposal

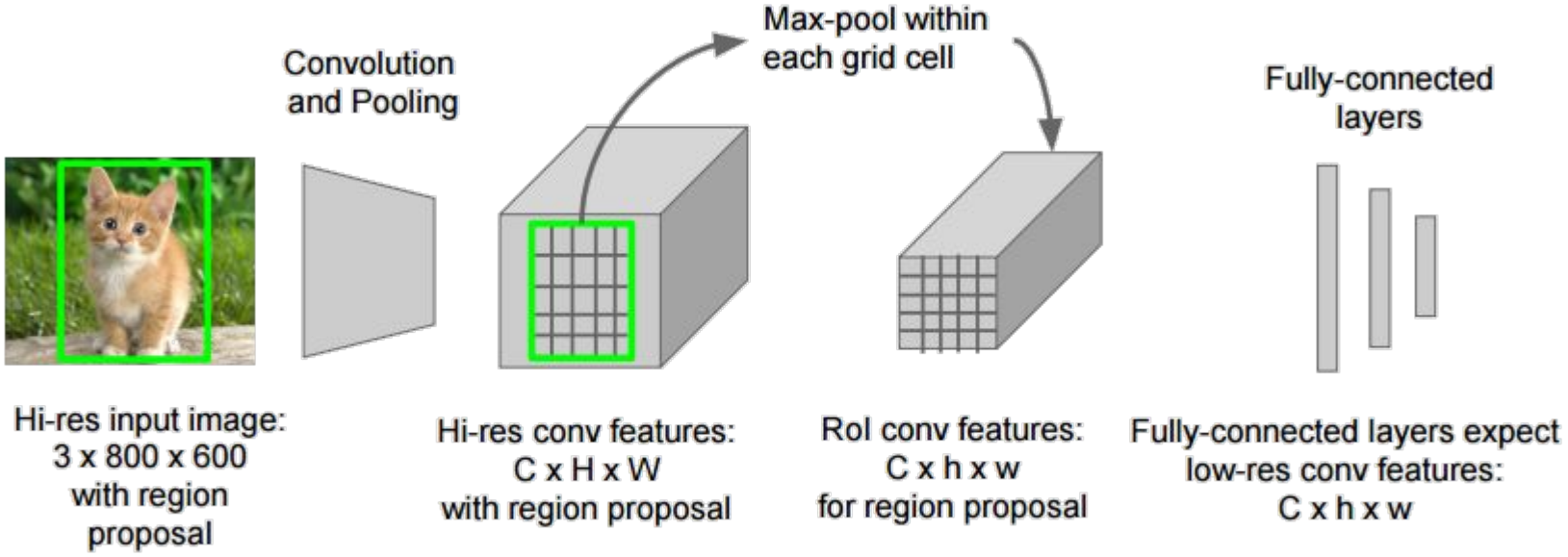


Problem: Fully-connected layers expect low-res conv features: C x h x w

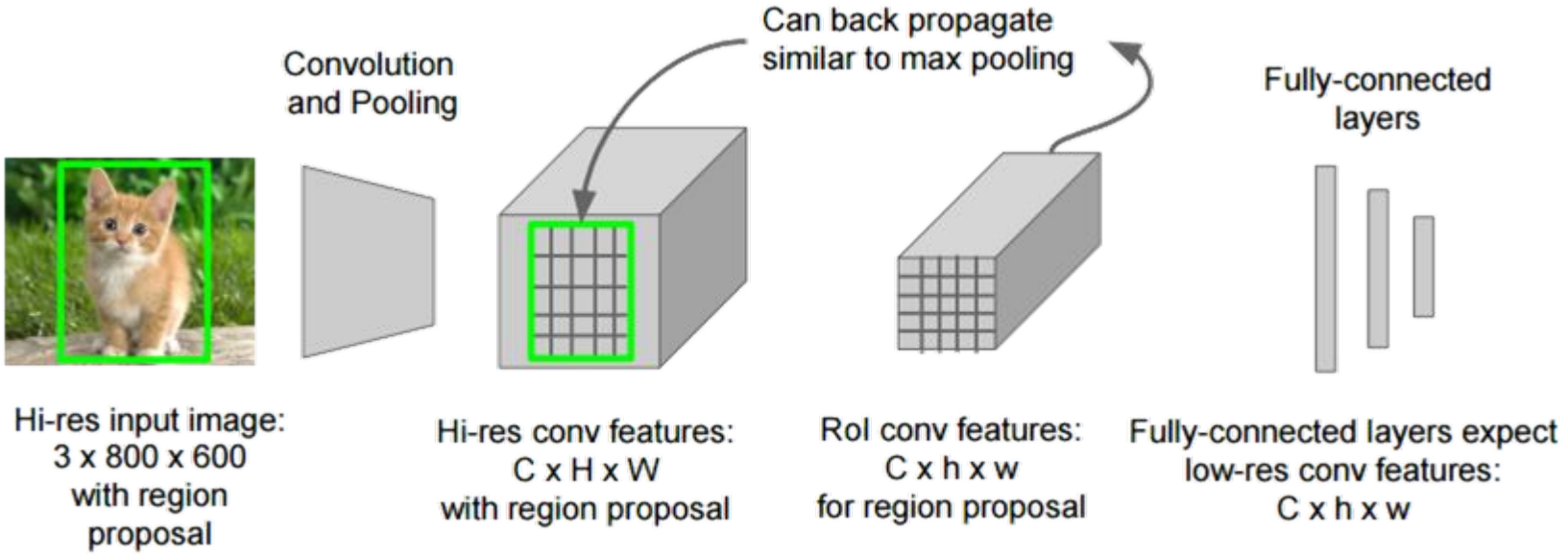
Fast R-CNN: Region of Interest Pooling



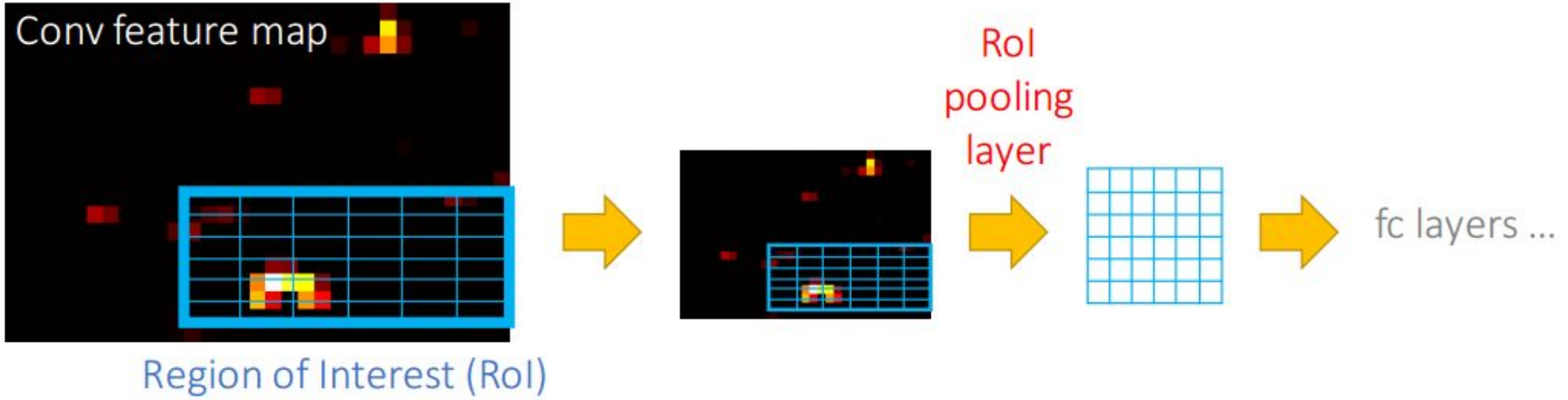
Fast R-CNN: Region of Interest Pooling



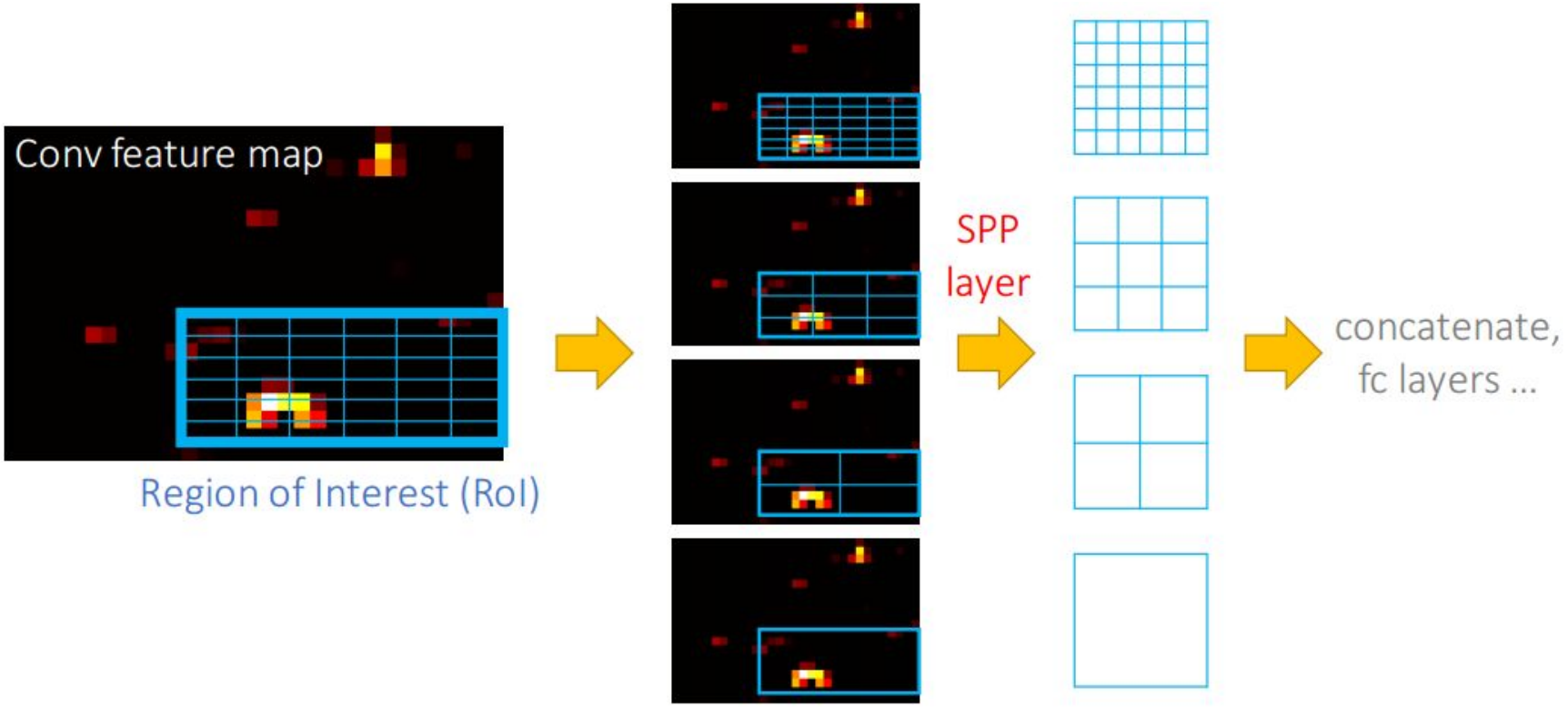
Fast R-CNN: Region of Interest Pooling



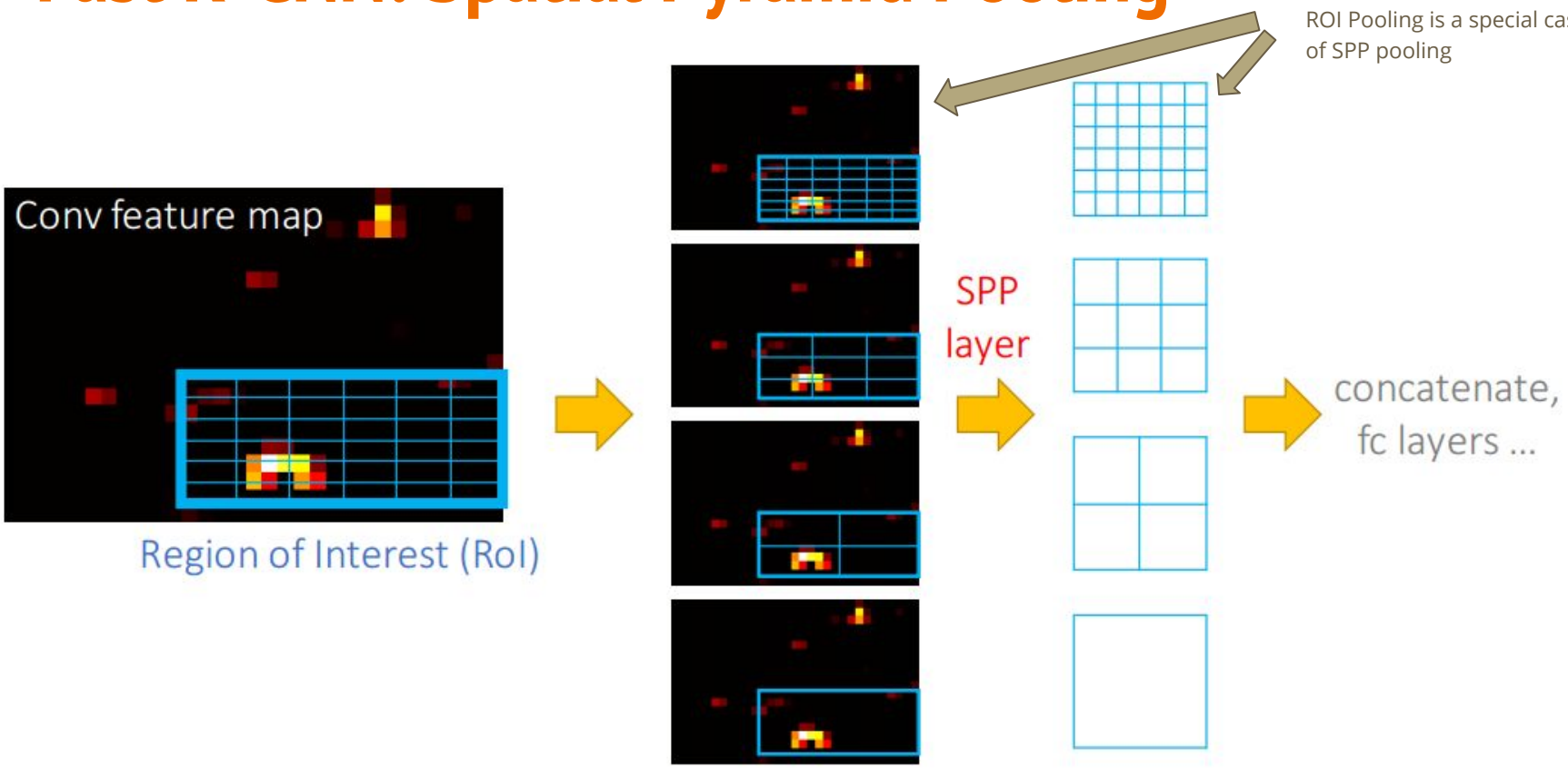
Fast R-CNN: Region of Interest Pooling



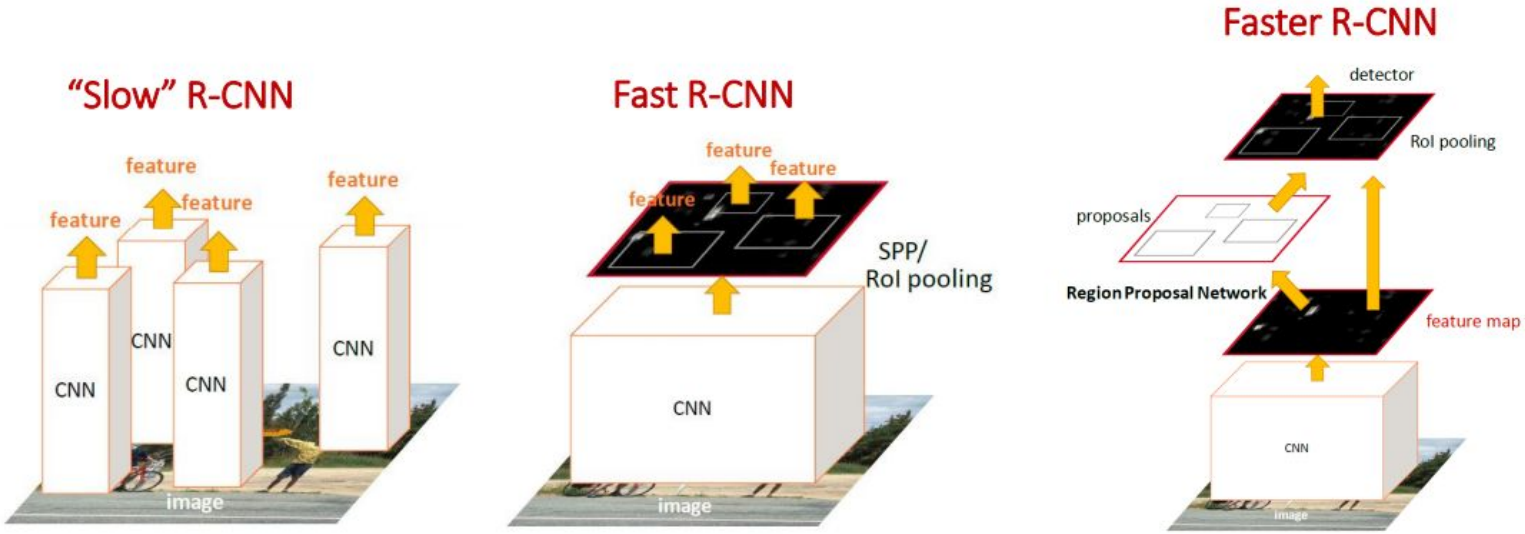
Fast R-CNN: Spatial Pyramid Pooling



Fast R-CNN: Spatial Pyramid Pooling



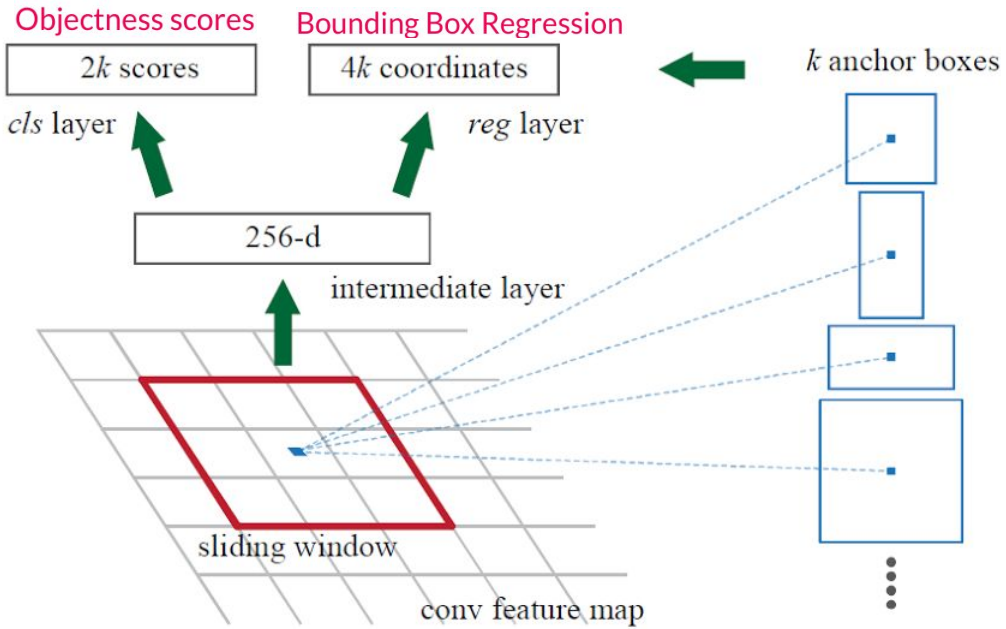
Faster R-CNN



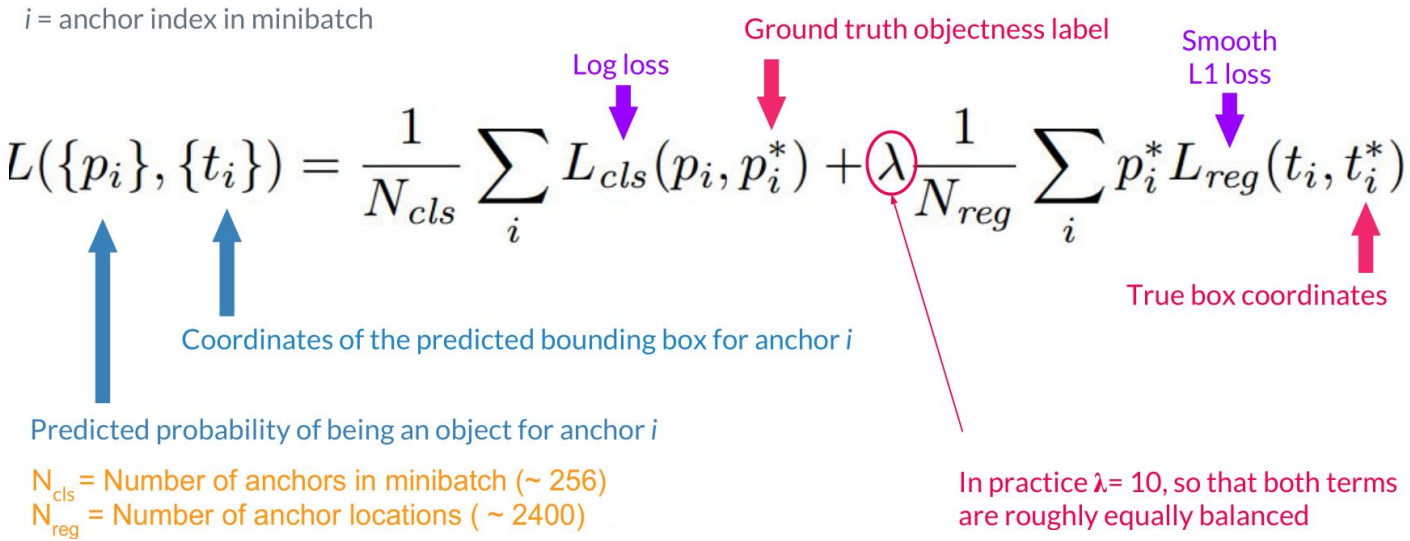
- In R-CNN and Fast R-CNN, bottleneck is 'region proposal' (selective search, CPMC, MCG).
- Replace external proposals with Region Proposal Network (RPN), trained with model directly.
- After RPN use ROI Pooling like Fast R-CNN

Region Proposal Network

- Slide a small window (anchor boxes) on the feature map.
- Have multiple such (k) anchor boxes.
- Build small network for
  - binary classification of object in an anchor. (👍)
  - regression of bounding box (anchor->proposal)
- Position of sliding window provides localization information with reference to the image.
- Binary classification gives probability that each anchor shows an object.
- Regression score gives offset from anchor boxes
- Anchors are selected for different scales and different aspect ratio, generally 3 each, total 9.



Faster R-CNN: RPN



Anchor is labelled positive if:

- anchor is the one with highest IoU overlap with ground truth box
- anchor has IoU overlap with a ground-truth box higher than 0.7

Anchor is labelled negative if IoU lower than 0.3 for all ground-truth boxes.

50%/50% ratio of positive to negative samples

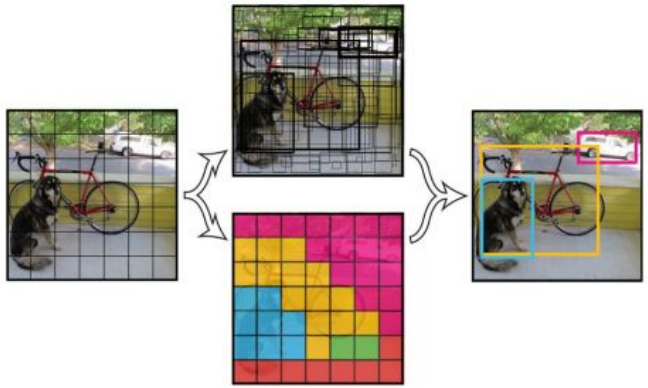
Source: A Salvador

Faster R-CNN: Comparison accuracy/speed

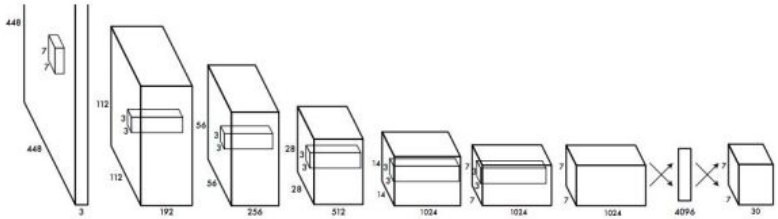
	R-CNN	Fast R-CNN	**Faster R-CNN**
Test time per image	50 seconds	2 seconds	0.2 seconds
Speedup (+proposal)	1x	25x	250x
mAP (VOC 2007)	66.0	66.9	66.9

You Only Look Once (YOLO)

- Divide image into S x S grid
- Within each grid cell predict:
  - B Boxes (4 coordinates + confidence)
  - Class scores: C scores
- Regression from image to 7 x 7 x (5 * B + C) tensor
- Direct prediction using a CNN
- Faster than Faster R-CNN but not as good
- Struggles with small objects and different aspect ratio



Real-Time Detectors	Train	mAP	FPS
100Hz DPM [30]	2007	16.0	100
30Hz DPM [30]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [37]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[27]	2007+2012	73.2	7
Faster R-CNN ZF [27]	2007+2012	62.1	18

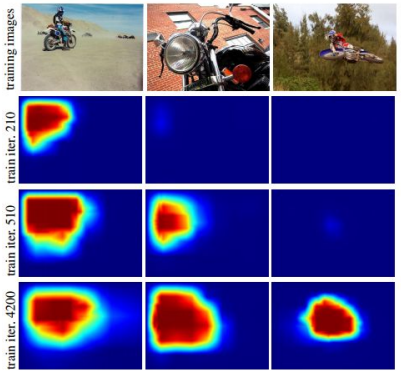


"I remember, when I was reading this paper for the first time, I had a really hard time figuring out what was going on." - Andrew Ng

Can you do this without spatial ground-truth?

Weakly supervised object localization

- If you look at the pixels which give maximum activation for a given class, it is no surprise that pixels corresponding to actual object have higher activation.
- But how do you control of actual object pixels? Remember the ‘tank problem’?
- Also this is not reliable in a cluttered scene containing many objects, and partially occluded objects or cropped objects.
- Oquab et al,
    - removed the Fully Connected layer at the end of a CNN model to prevent losing any more localization information and,
    - Added global max-pooling (GMP) to output layer to find highest scoring object position in the image.



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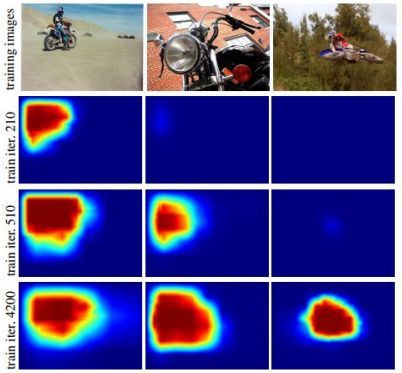
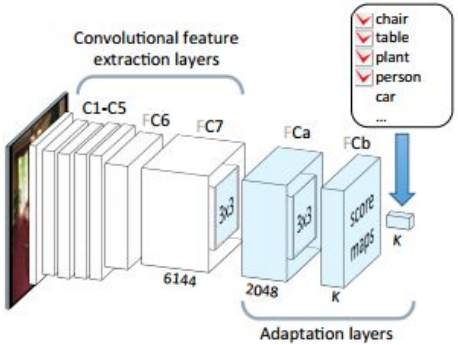
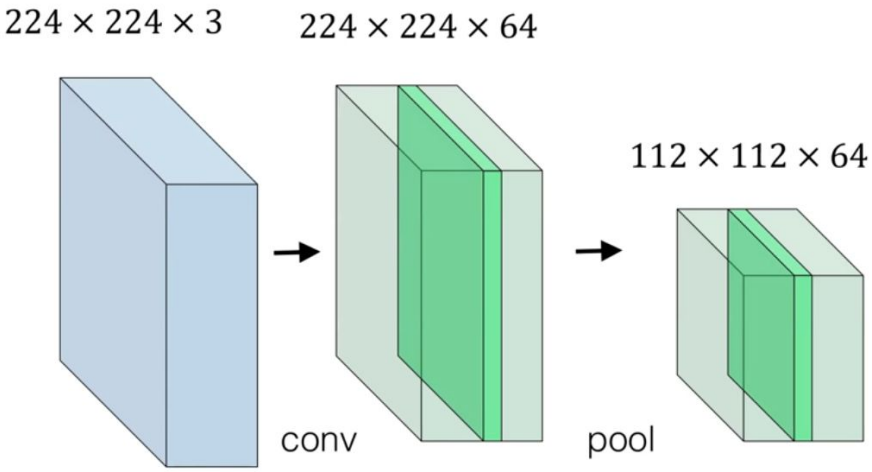
    - Added global max-pooling (GMP) to output layer to find highest scoring object position in the image.
- GMP enforces correspondence between feature maps and categories, and thus they can be interpreted as ‘confidence maps’.
- Best part - it is parameter free.

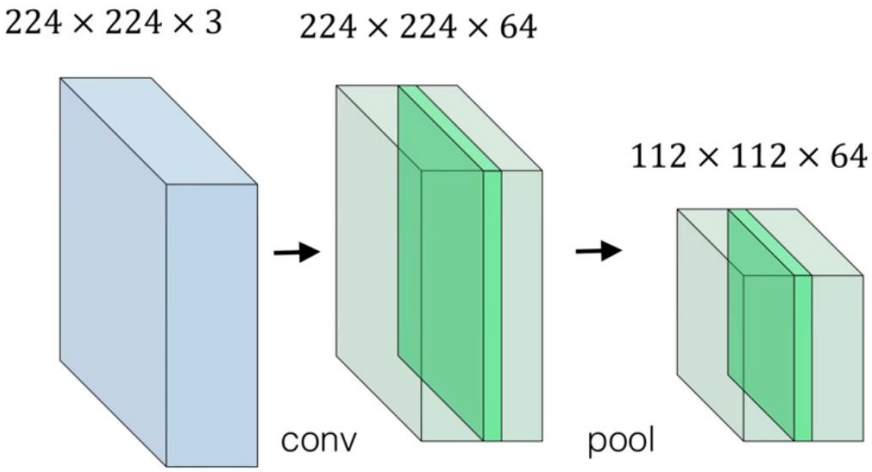


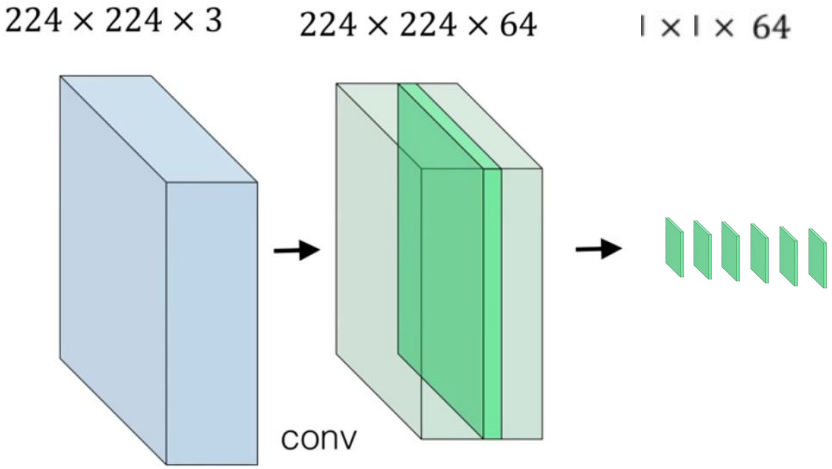


Max Pooling vs Global Max Pooling

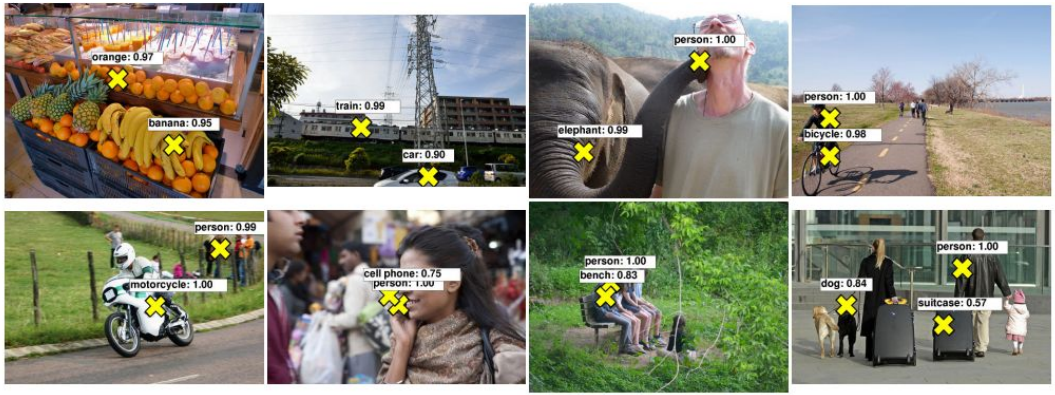


Max Pooling vs Global Max Pooling





Global Max Pooling - Results



Object-level sup.	mAP
A. NUS-SCM [51]	82.2
B. OQUAB [37]	82.8
Image-level sup.	**mAP**
C. Z&F [60]	79.0
D. CHATFIELD [6]	83.2
E. NUS-HCP [56]	84.2
F. FULL IMAGES	78.7
G. WEAK SUP	**86.3**

- Localization is only about finding ‘center’ point, cannot draw bounding box
- Helps improve the classification score
- Masked pooling is where you minimize the object score outside the masked area (requires location GT)

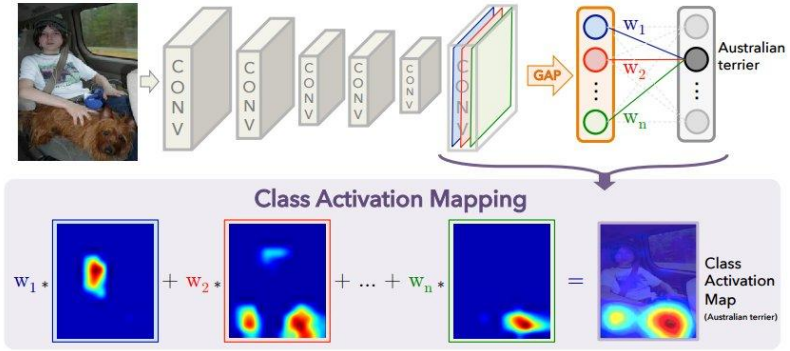
Setup	Classification		Location Prediction	
Dataset	VOC	COCO	VOC	COCO
H. FULL IMAGES	76.0	51.0	-	-
I. MASKED POOL	**82.3**	62.1	72.3	**42.9**
J. WEAK SUP	81.8	**62.8**	74.5	41.2
K. CENTER PRED.	-	-	50.9	19.1
L. RCNN*	79.2	-	**74.8**	-

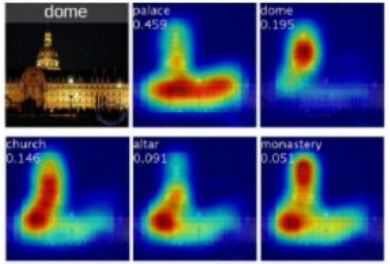
Class activation map

- Replace Global Max Pooling (GMP) with Global Average Pooling (GAP).
- The use of average pooling encourages the network to identify the complete extent of the object
- Intuition behind this is that the loss for average pooling benefits when the network identifies all discriminative regions of an object as compared to max pooling
- Class activation map is when you take the output of GAP and add a ‘fully connected layer’ (without nonlinearity). Use the weights of this layer to weight the activation at unit k, to generate a spatial map.

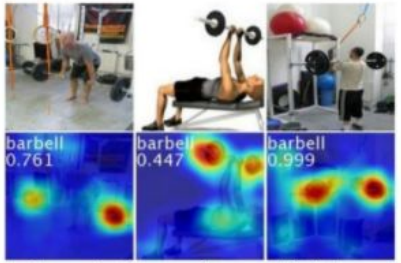
$$M_c(x,y) = \sum_{d \epsilon \mathbf{D}} w_d^c \, f_d(x,y) \quad \text{where } w_d^c \text{ is the learned of class } c \text{ for feature map } d$$

- For training, you maximize the cross entropy between predicted class and true distribution $P(c) = \frac{\exp(\sum_{xy} M_c(x,y))}{\sum_c \exp(\sum_{xy} M_c(x,y))}$
- This means it can “highlight” only one salient class in a given image. Gives more than center but not bounding box.



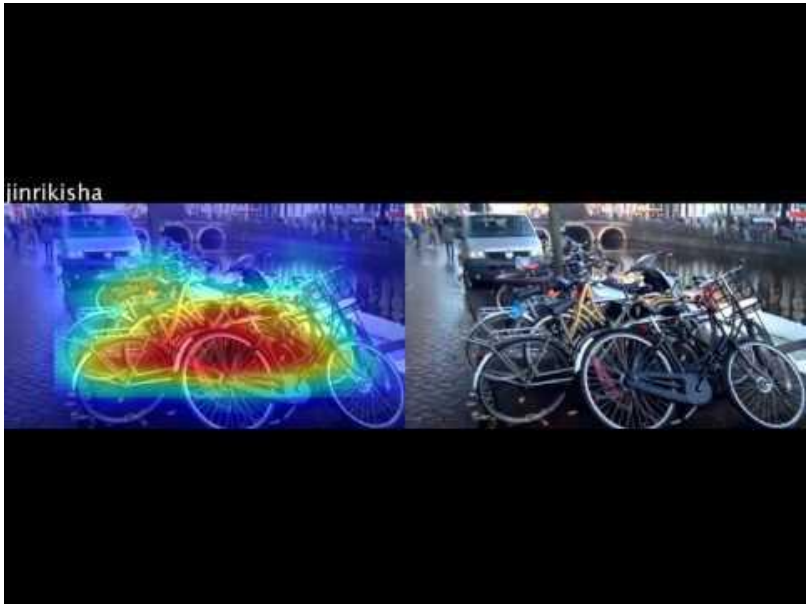


Class activation maps of top 5 predictions

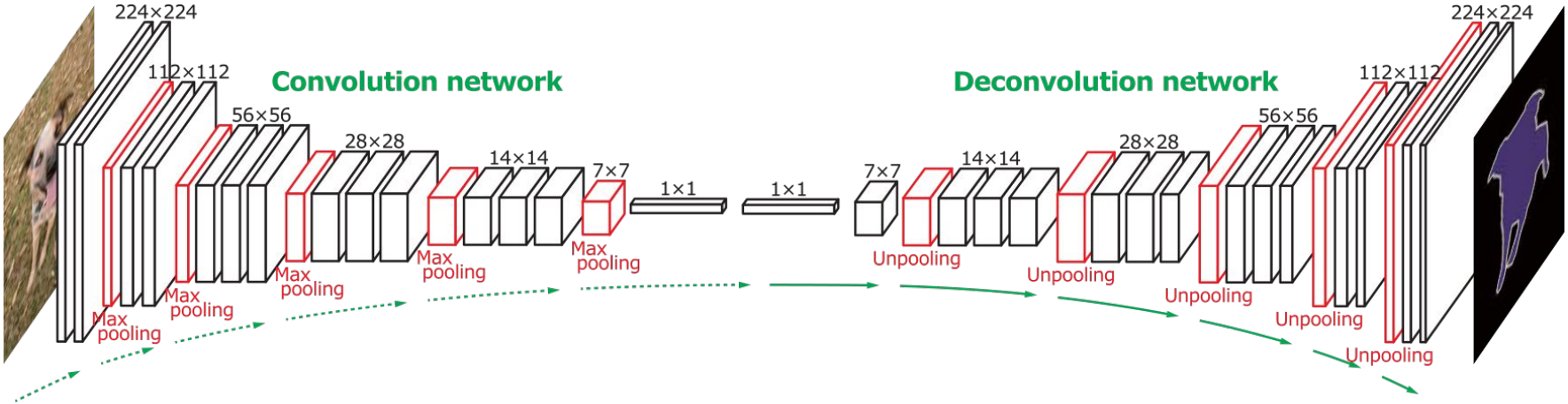


Class activation maps for one object class

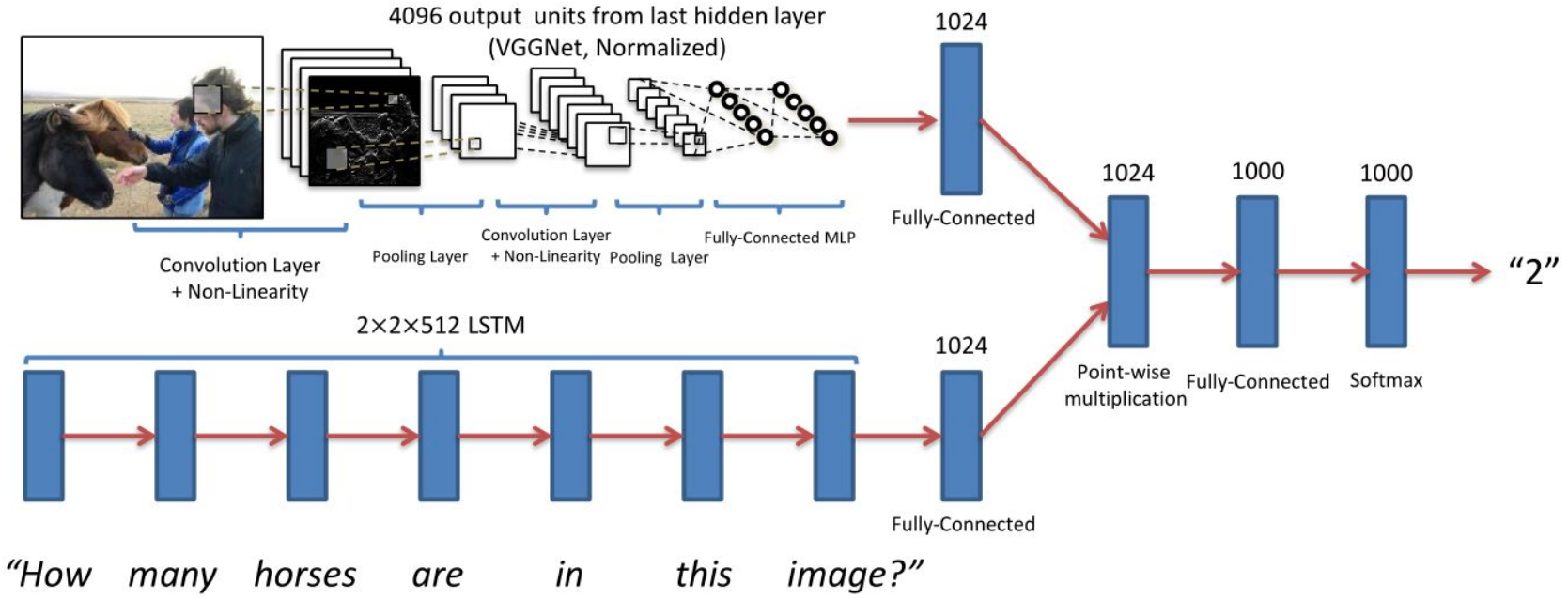
Class activation map



Semantic Segmentation

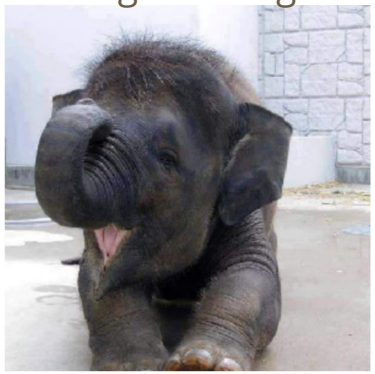


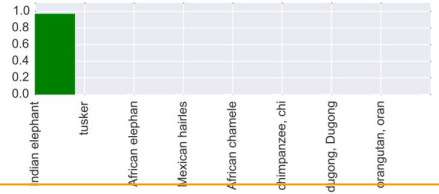
Visual Question Answering



Adversarial Attack

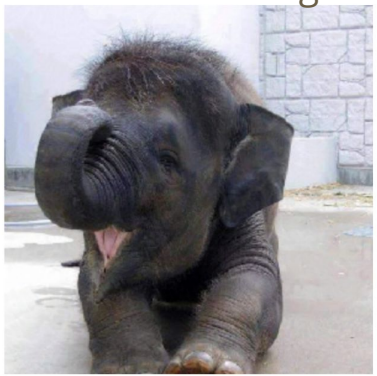
Original Image

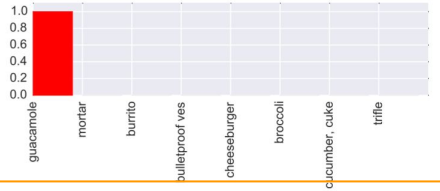




Predicted: Indian Elephant (99.7%)

Adversarial Image

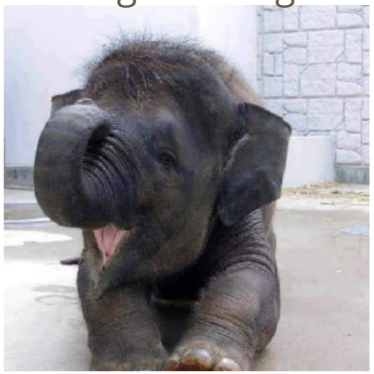


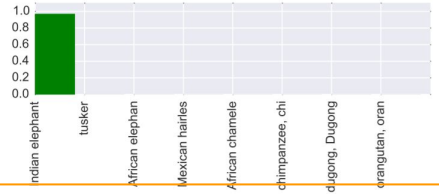


Predicted: Guacamole (99.9%)

Adversarial Attack

Original Image

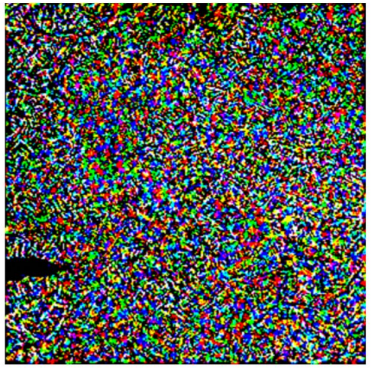


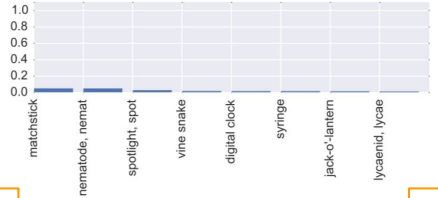


Predicted: Indian Elephant (99.7%)

$+ \epsilon$

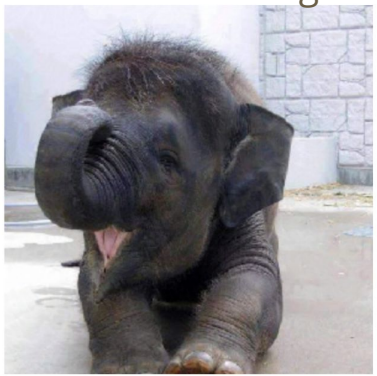
Perturbations

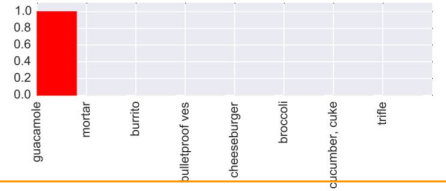




$=$

Adversarial Image



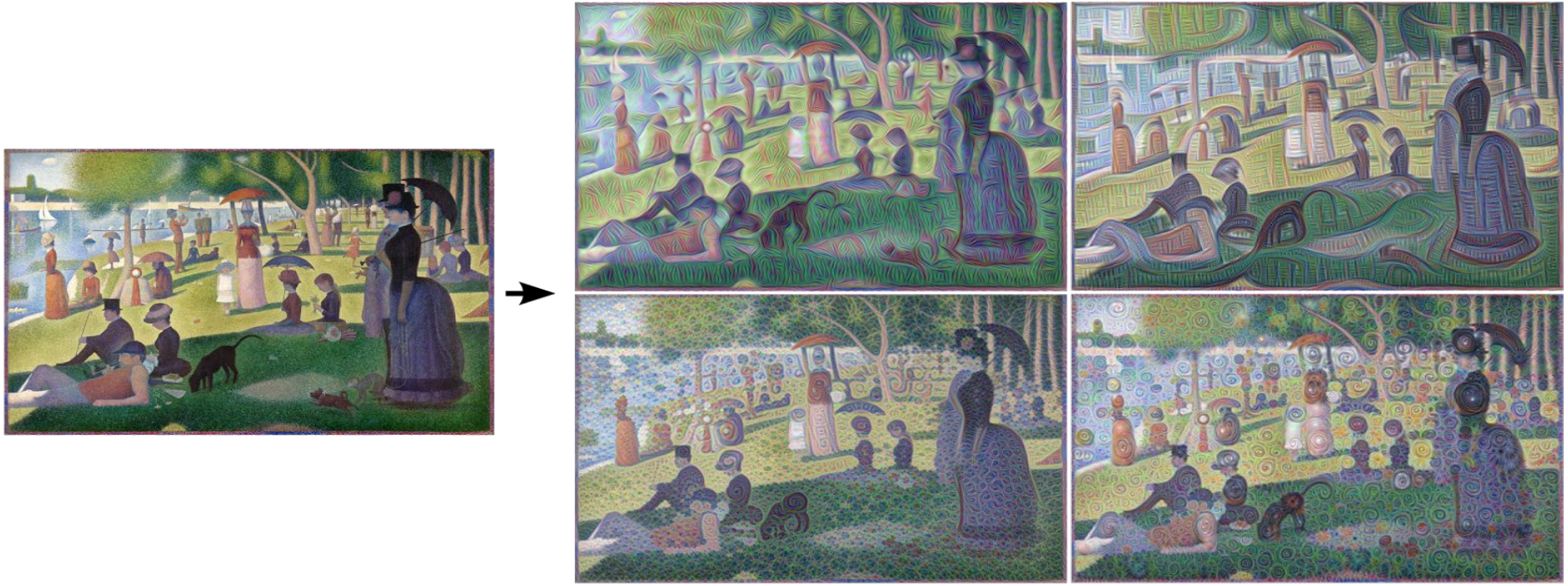


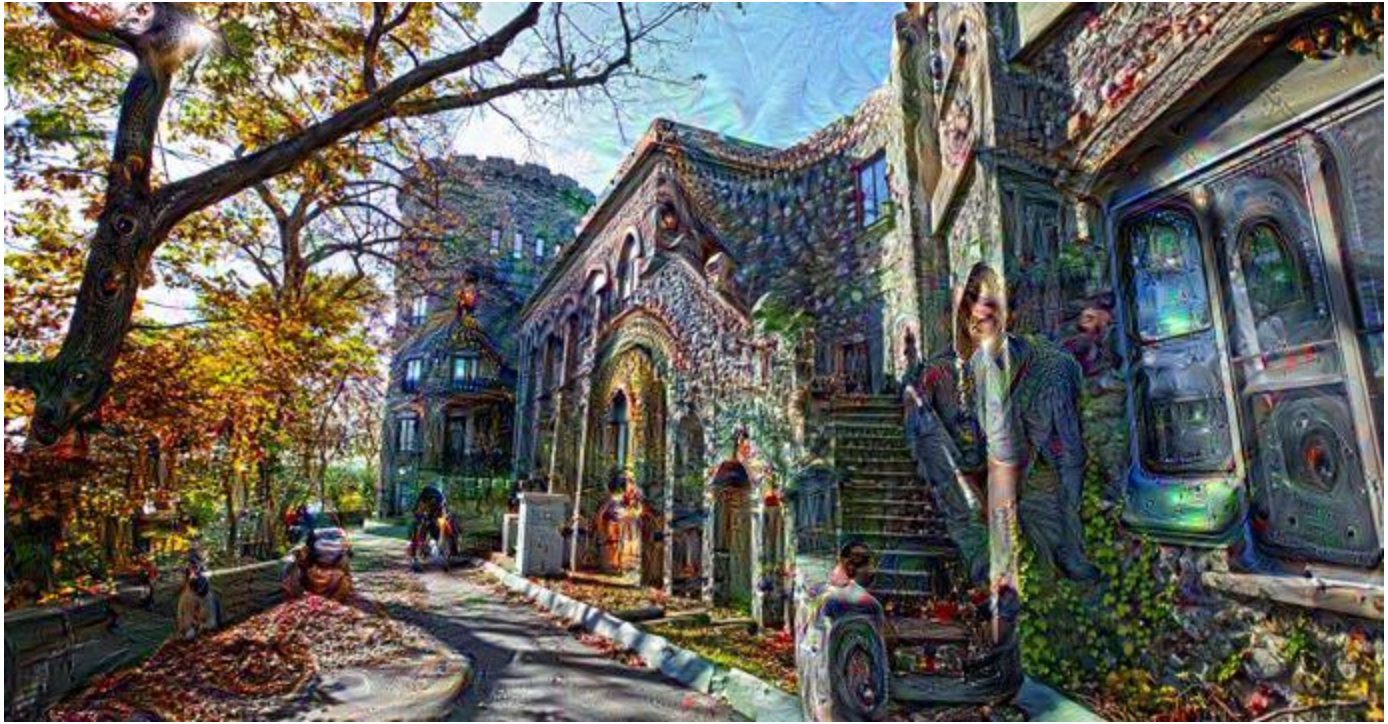
Predicted: Guacamole (99.9%)

- With cleverly designed additive noise the classification of the image can be changed
- It is easy to find noise which makes the classifier predict any given class - Targeted attack

Deep Dream

Inceptionism: Going Deeper into Neural Networks Album





Summary

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like

  [(CONV-RELU)*N-POOL?]*M-(FC-RELU)*K,SOFTMAX

  where N is usually up to ~5, M is large, 0 <= K <= 2.
- but recent advances such as ResNet/GoogLeNet challenge this paradigm

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Credits

1. CS231n Convnets
2. Chris Colah's awesome blog
3. Chris Burger - Style transfer images
4. Convolutional Neural Networks - Nervana Systems
5. DeepVis - Jason Yosinski
6. Fooling CNNs - Anh Nguyen
7. More demos - Yann LeCun

Any questions?

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