



Deep Learning

Convolutional Neural Network

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https://github.com/safayani/deep_learning_course



Computer Vision Problems

Image Classification



→ Cat? (0/1)

64x64
Object detection



Neural Style Transfer

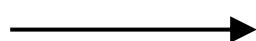


Content Style



Generated image

Deep Learning on large images



Cat? (0/1)

$$64 \times 64 \times 3 = 12288$$

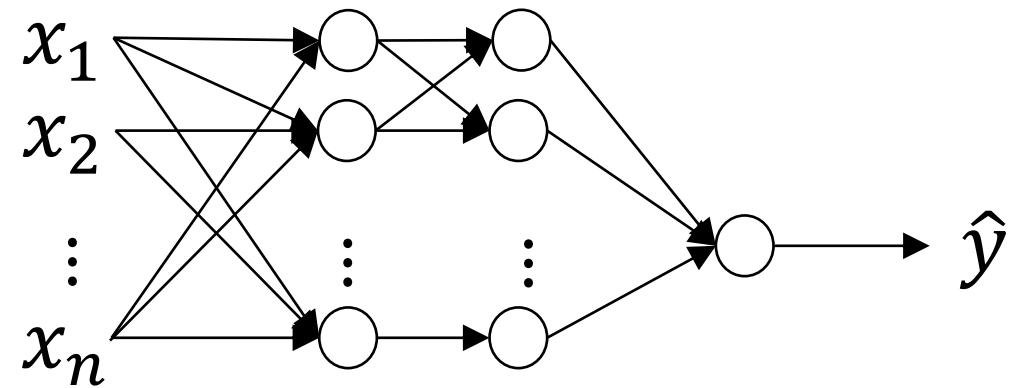


$$1000 \times 1000 \times 3 = 3m$$

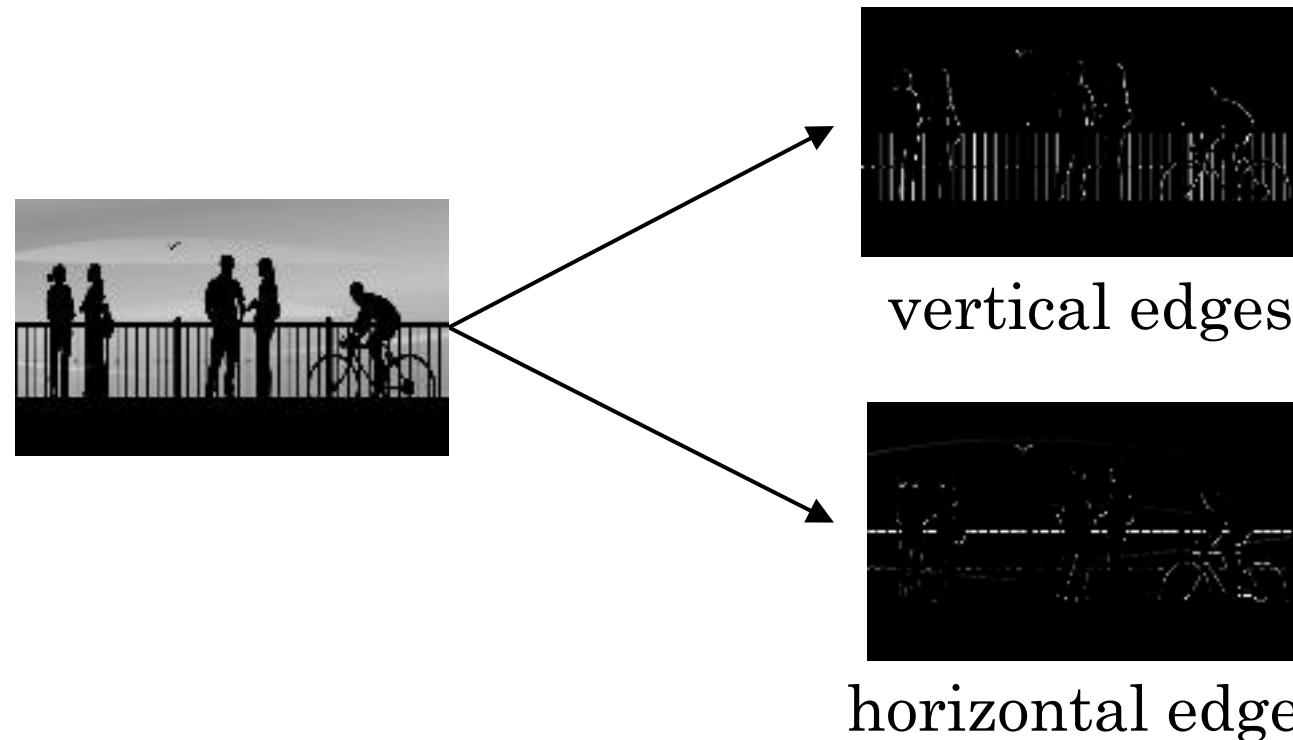
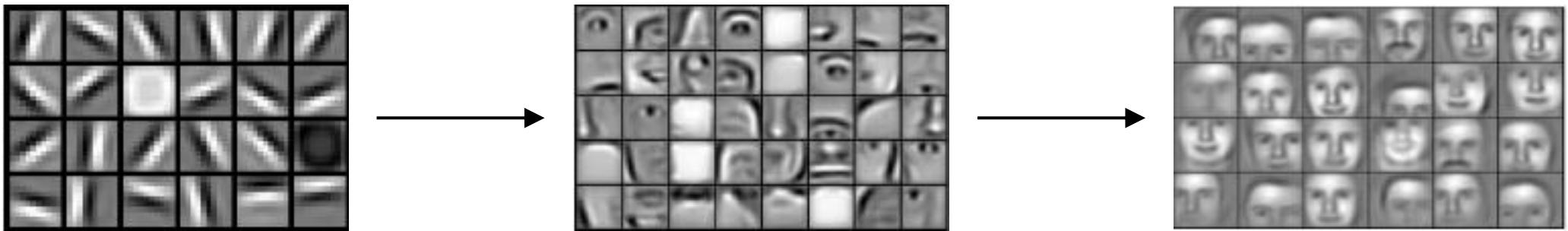
$$n=3m$$

$$n^1 = 1000$$

$$W_{(1000,3m)}^1$$



Edge detection



Vertical edge detection

3 ¹	0 ⁰	1 ⁻¹	2 ⁻¹	7 ⁻⁰	4 ⁻¹
1 ¹	5 ⁰	8 ⁻¹	9 ⁻¹	3 ⁻⁰	1 ⁻¹
2 ¹	7 ⁰	2 ⁻¹	5 ⁻¹	1 ⁻⁰	3 ⁻¹
0 ¹	1 ⁰	3 ⁻¹	1 ⁻¹	7 ⁻⁰	8 ⁻¹
4	2	1	6	2	8
2	4	5	2	3	9

*

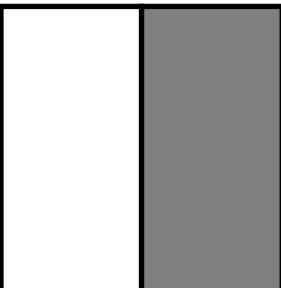
1	0	-1
1	0	-1
1	0	-1

=

-5	-4	0	8
-10	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

Vertical edge detection

$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0
$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0
$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0
$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0
$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0
$10^{\frac{1}{2}}$	10^0	$10^{-\frac{1}{2}}$	0	0	0

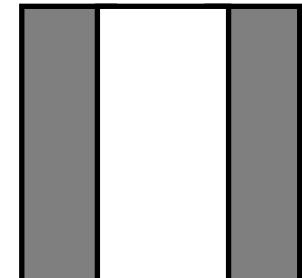


*

1	0	-1
1	0	-1
1	0	-1

*

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



Vertical edge detection examples

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1



=

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

*

1	0	-1
1	0	-1
1	0	-1



=

0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0



Vertical and Horizontal Edge Detection

1	0	-1
1	0	-1
1	0	-1

Vertical

1	1	1
0	0	0
-1	-1	-1

Horizontal

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

*

1	1	1
0	0	0
-1	-1	-1

=

0	0	0	0
30	10	-10	-30
30	10	-10	-30
0	0	0	0

Learning to detect edges

1	0	-1
1	0	-1
1	0	-1

1	0	-1
2	0	-2
1	0	-1

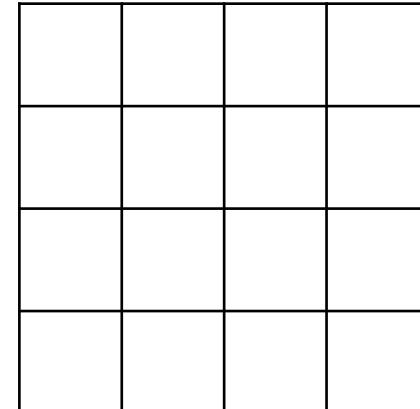
3	0	-1
10	0	-10
3	0	-3

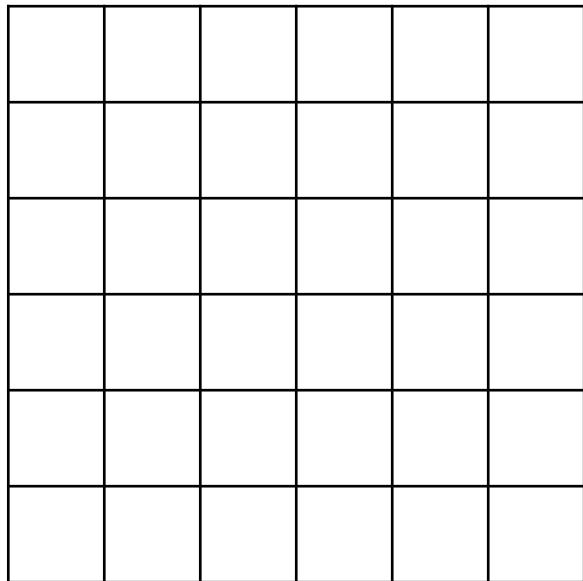
Sobel filter

Schass filter

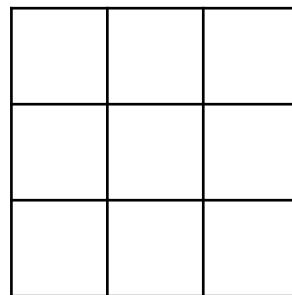
3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

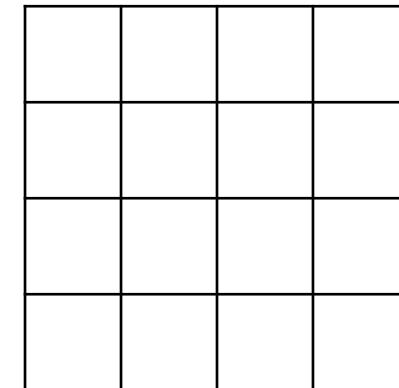


 $n \times n$ 6×6

*

 $f \times f$ 3×3

=

 $n - f + 1 \times n - f + 1$ 4×4

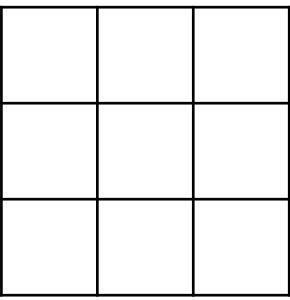
Padding

0	0	0	0	0	0	0	0
0							0
0							0
0							0
0							0
0							0
0							0
0	0	0	0	0	0	0	0

$$n + 2p \times n + 2p$$

$$6 + 2 \times 6 + 2$$

*



$$f \times f$$

=

$$n + 2p - f + 1 \times n + 2p - f + 1$$

$$3 \times 3$$

$$6 \times 6$$

Valid and Same convolutions

“Valid”:

$$n \times n$$

$$f \times f$$

$$n - f + 1 \times n - f + 1$$

“Same”: Pad so that output size is the same as the input size.

$$n + 2p - f + 1 = n$$

$$p = \frac{f - 1}{2}$$

Strided convolution

2	3	3	4	7	3	4	4	6	3	2	4	9	4
6	1	6	0	9	1	8	0	7	1	4	0	3	2
3	-3	4	4	8	-3	3	4	8	-3	9	4	7	4
7	1	8	0	3	1	6	0	6	1	3	0	4	2
4	-3	2	4	1	-3	8	4	3	-3	4	4	6	4
3	1	2	0	4	1	1	0	9	1	8	0	3	2
0	-1	1	0	3	-1	9	0	2	-1	1	0	4	3

*

3	4	4
1	0	2
-1	0	3

=

91	100	83
69	91	127
44	72	74

$$\left\lfloor \frac{n-f}{s} + 1 \right\rfloor$$

×

$$\left\lfloor \frac{n-f}{s} + 1 \right\rfloor$$

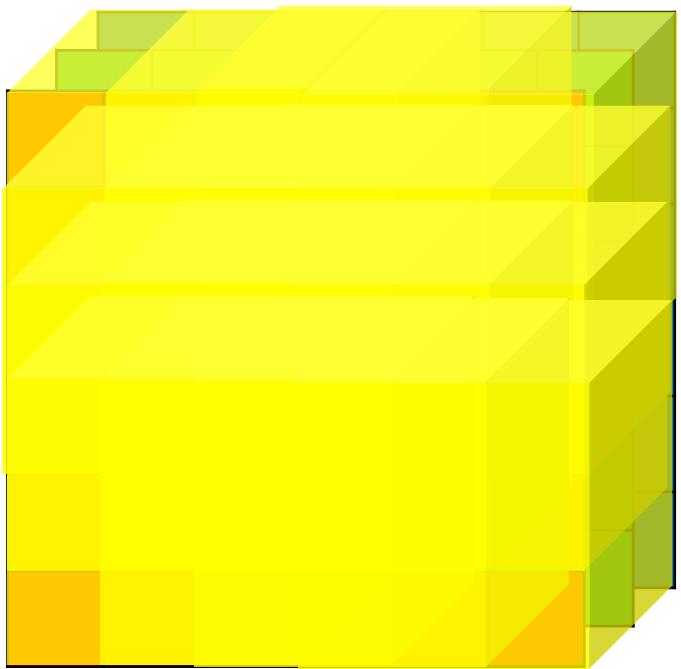
Summary of convolutions

$n \times n$ image $f \times f$ filter

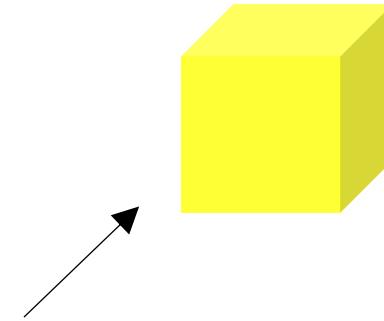
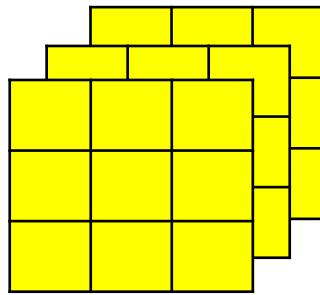
padding p stride s

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \quad \times \quad \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

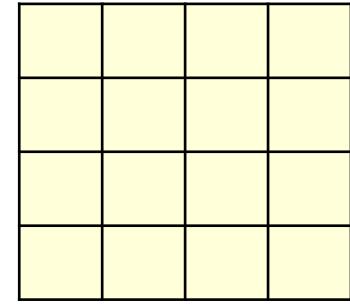
Convolutions on RGB image



*

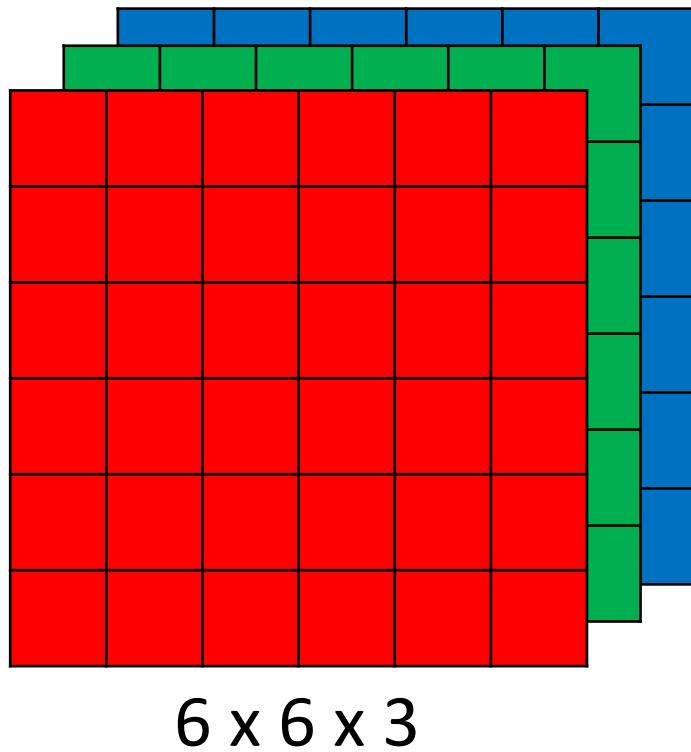


=



4×4

Multiple filters

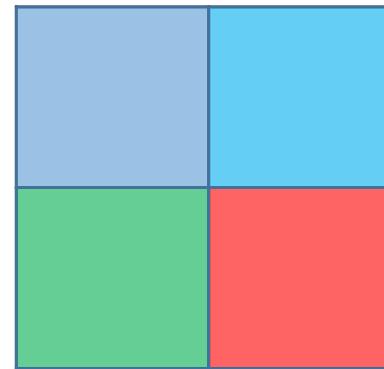


$$\begin{matrix} * & \begin{matrix} \text{3} \times \text{3} \times \text{3} \\ \text{3} \times \text{3} \times \text{3} \end{matrix} & = & \begin{matrix} \text{4} \times \text{4} \\ \text{4} \times \text{4} \end{matrix} \\ & \begin{matrix} \text{3} \times \text{3} \times \text{3} \\ \text{3} \times \text{3} \times \text{3} \end{matrix} & = & \begin{matrix} \text{4} \times \text{4} \\ \text{4} \times \text{4} \times \text{2} \end{matrix} \end{matrix}$$

The diagram illustrates the convolution process. It shows two sets of 3x3x3 kernel filters (yellow) being applied to the input tensor. The result of the first application is a 4x4 output tensor (light yellow). The result of applying both kernels is a 4x4x2 output tensor (light yellow).

Pooling layer: Max pooling

1	3	2	1
2	9	1	1
1	3	2	3
5	6	1	2



Pooling layer: Max pooling

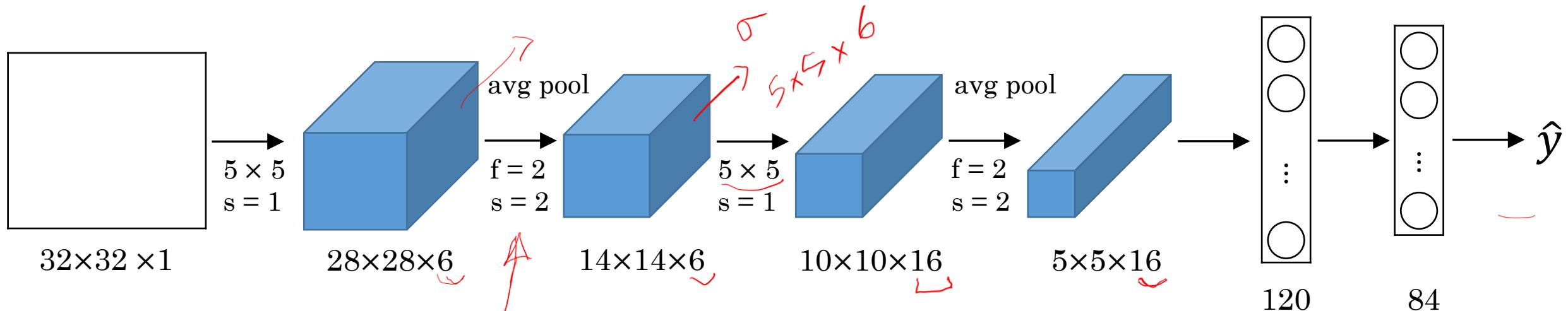
1	3	2	1	3
2	9		1	5
1				2
8	3		1	0
5	6	1	2	9

Pooling layer: Average pooling

1	3	2	1
2	9	1	1
1	4	2	3
5	6	1	2



LeNet - 5

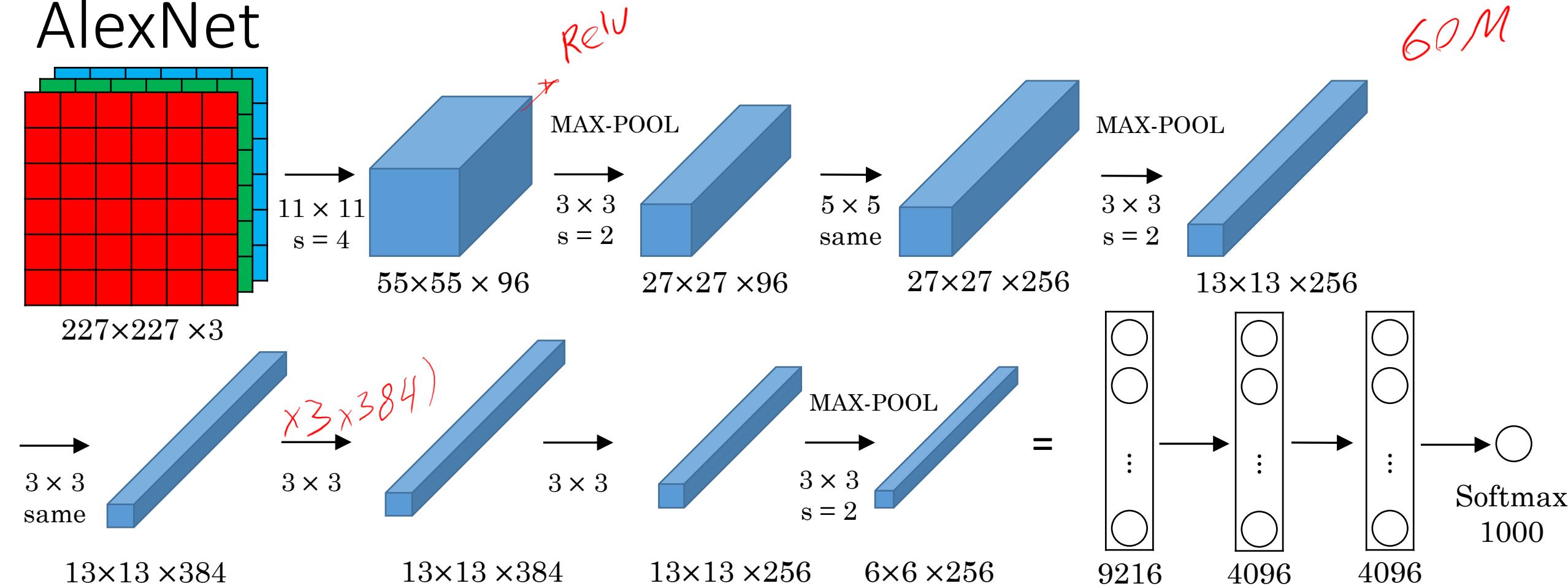


	0	1	2	3	4	...	15
1	x		x		x		x
2	x		x		x		x
3		x		x		x	x
4		x			x		x
5		x				x	
6			x				

Neural network example

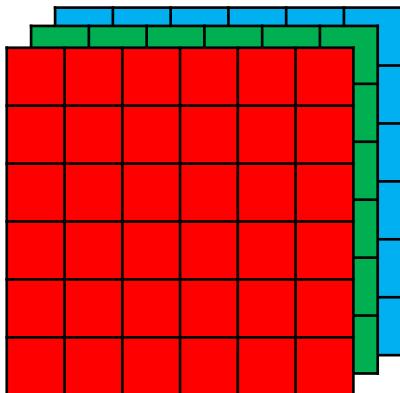
	Activation shape	Activation Size	# parameters
Input:	(32,32,3)	3,072	0
			$(5 \times 5 \times 3 + 1) \times 8$
$x=2$ $y=2$	↙		
$x=2$ $y=2$			$(5 \times 5 \times 8 + 1) \times 16$
			$5 \times 5 \times 16 \times 120 + 120$
			$120 \times 84 + 84$
			$84 \times 10 + 10$

AlexNet

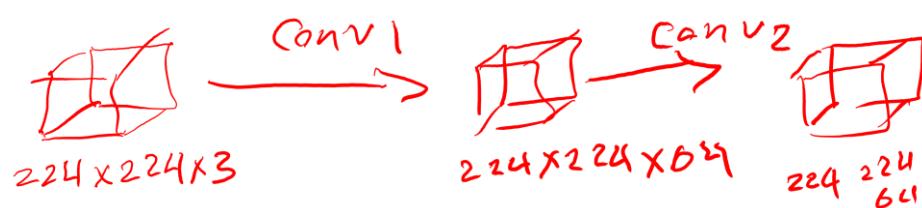


VGG - 16 ^{VGG-19}

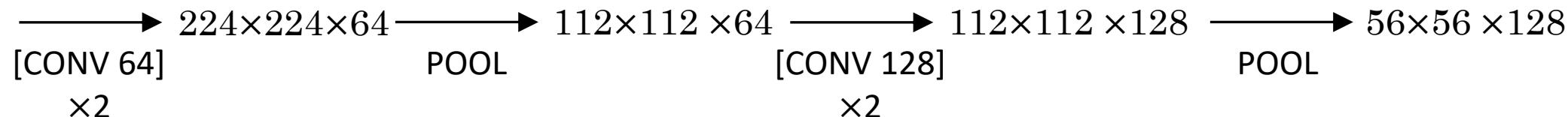
CONV = 3×3 filter, $s = 1$, same



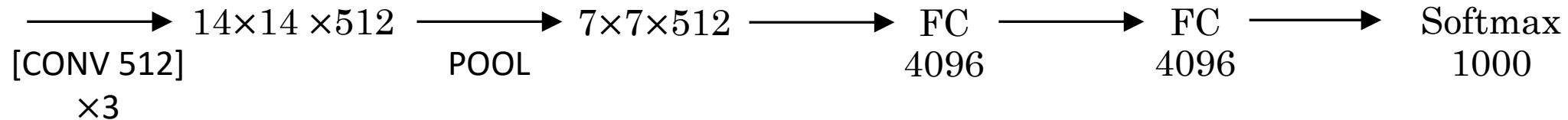
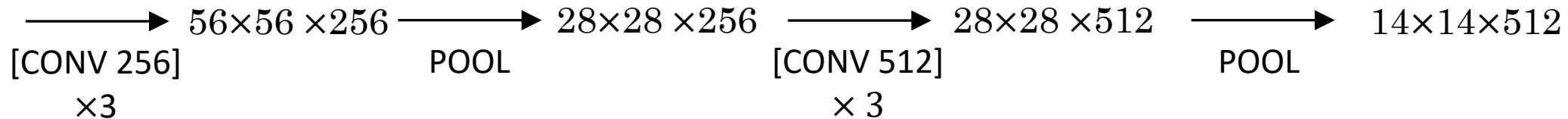
MAX-POOL = 2×2 , $s = 2$



$224 \times 224 \times 3$



138M



ResNet

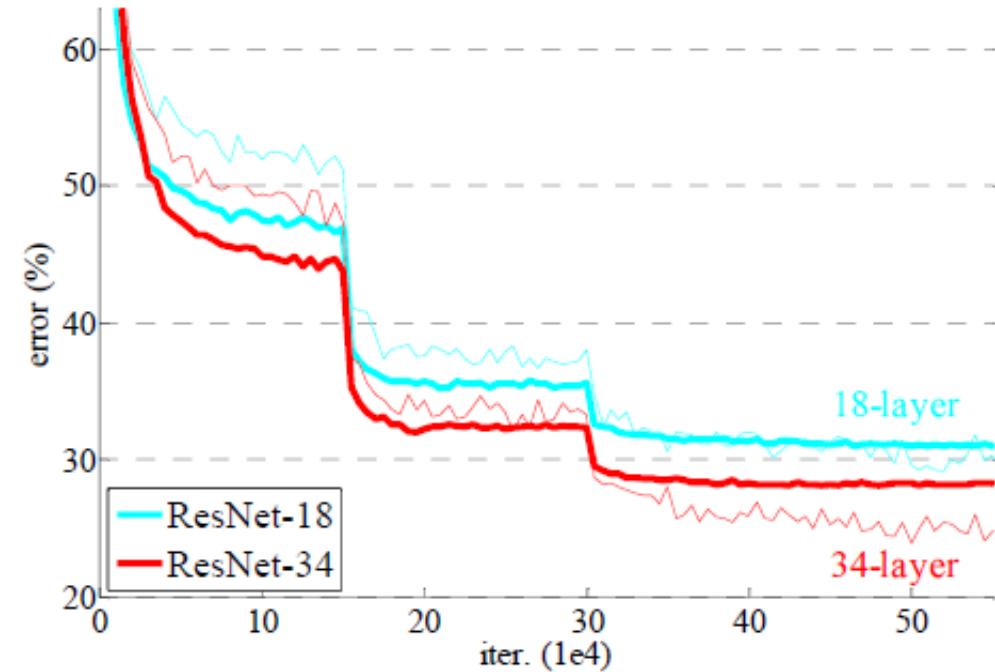
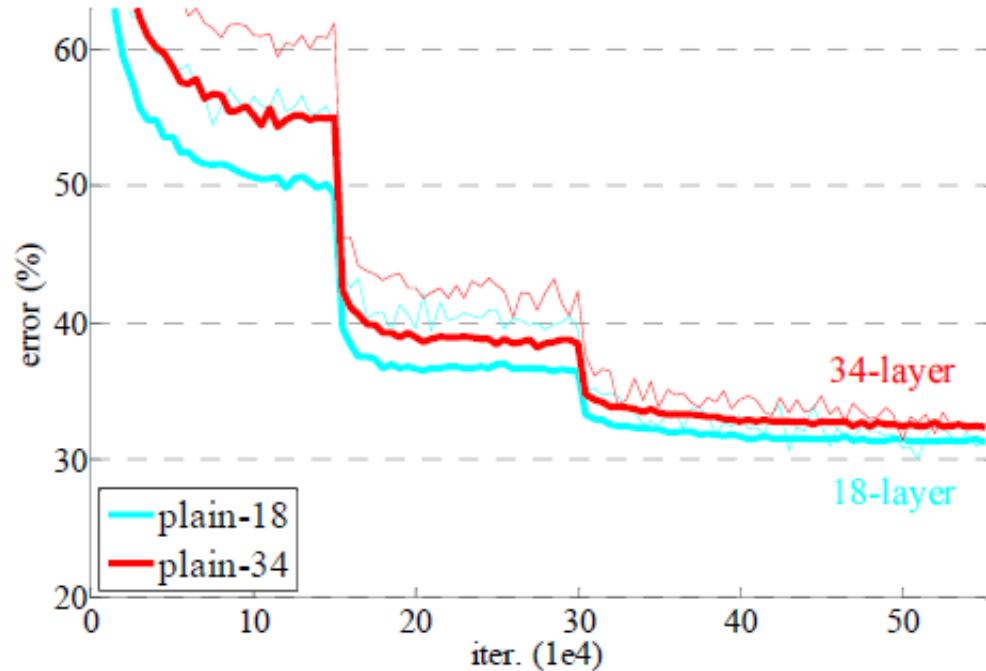
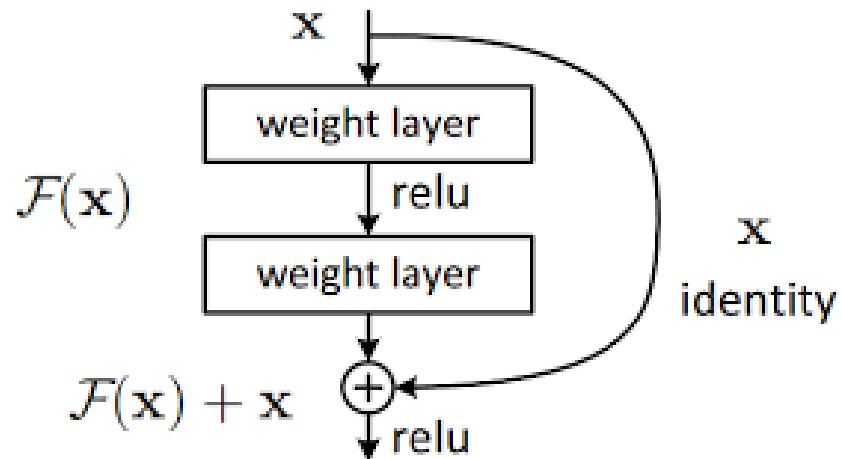


Figure 4. Training on ImageNet. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts.

Residual Networks(ResNets)

- Residual Block



$$z^{[1]} = w^{[1]}x + b^{[1]}$$

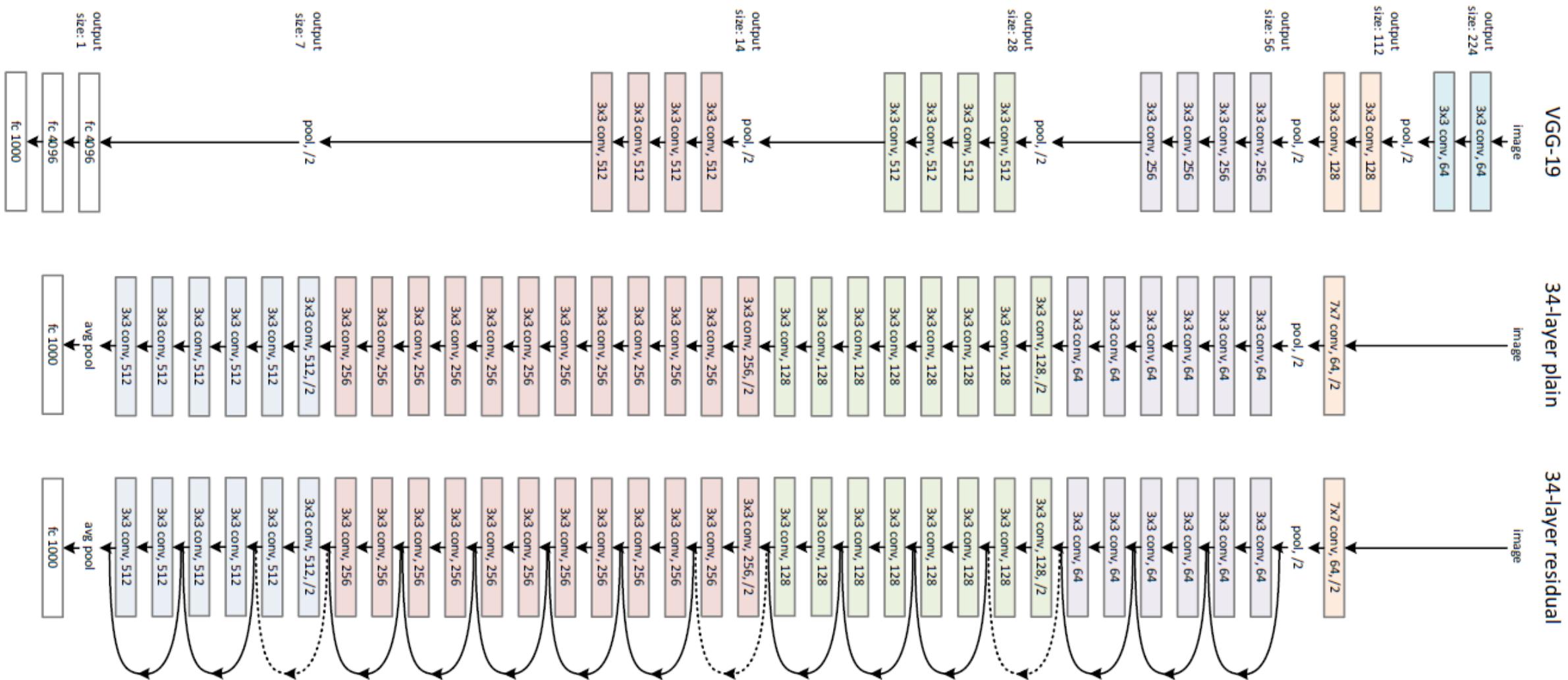
$$a^{[1]} = g(z^{[1]})$$

$$z^{[2]} = w^{[2]}a^{[1]} + b^{[2]}$$

$$a^{[2]} = g(z^{[2]} + x)$$

$$a^{[2]} = g(z^{[2]} + w_s x)$$

ResNet



ResNet

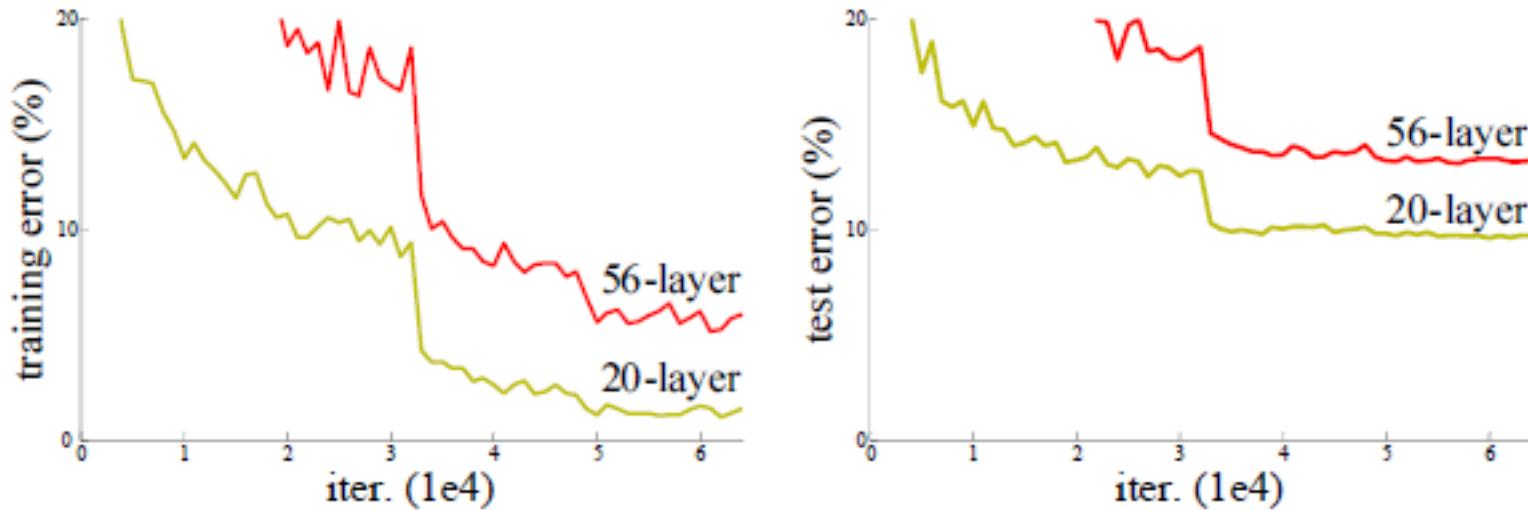
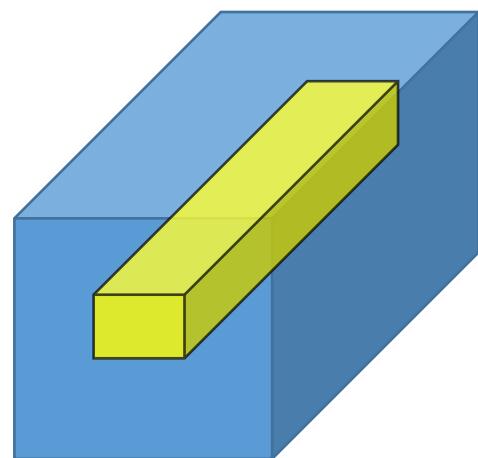


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

Why does a 1×1 convolution do?

1	2	3	6	5	8
3	5	5	1	3	4
2	1	3	4	9	3
4	7	8	5	7	9
1	5	3	7	4	8
5	4	9	8	3	5

6×6



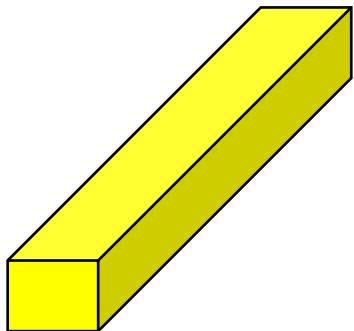
$6 \times 6 \times 192$

*

2

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*

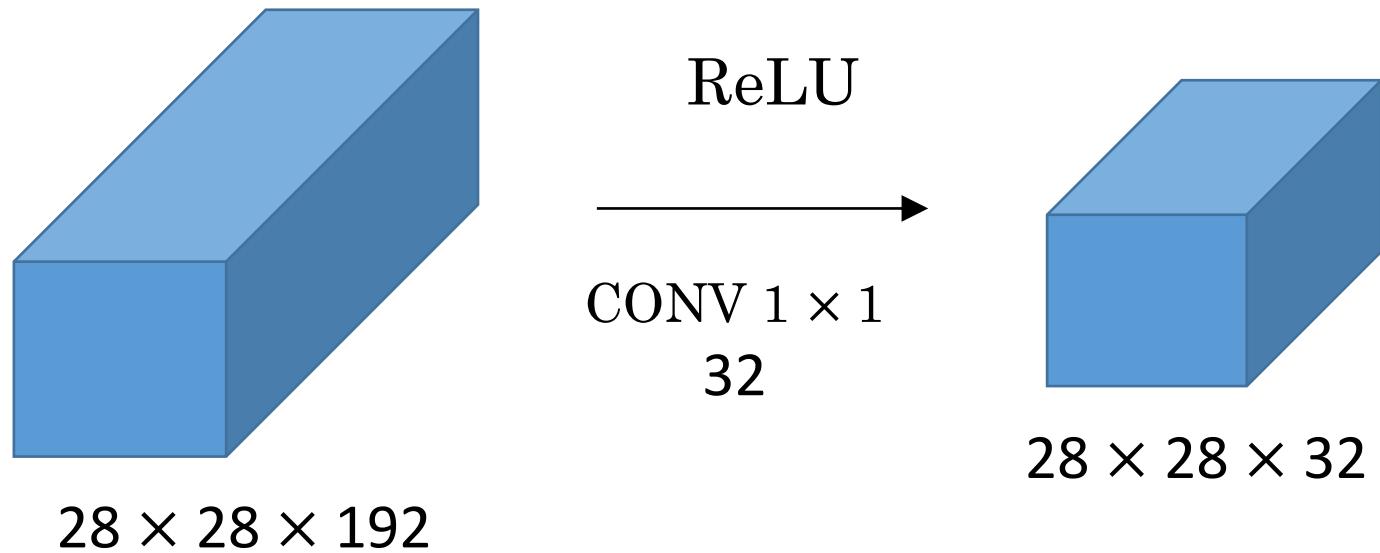


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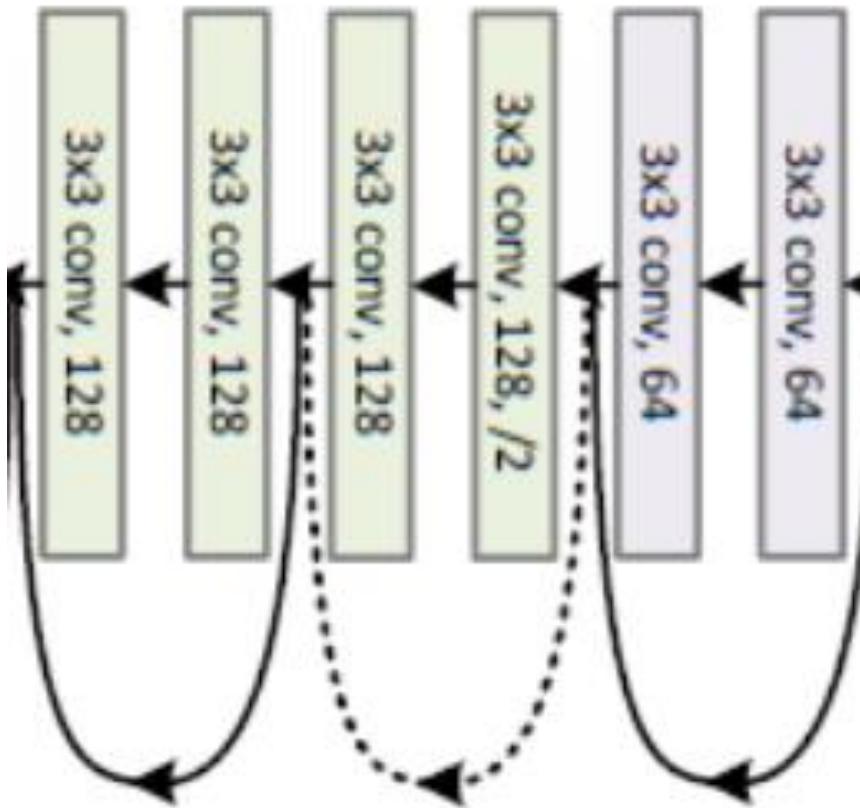
$1 \times 1 \times 192$

$6 \times 6 \times \# \text{ filters}$

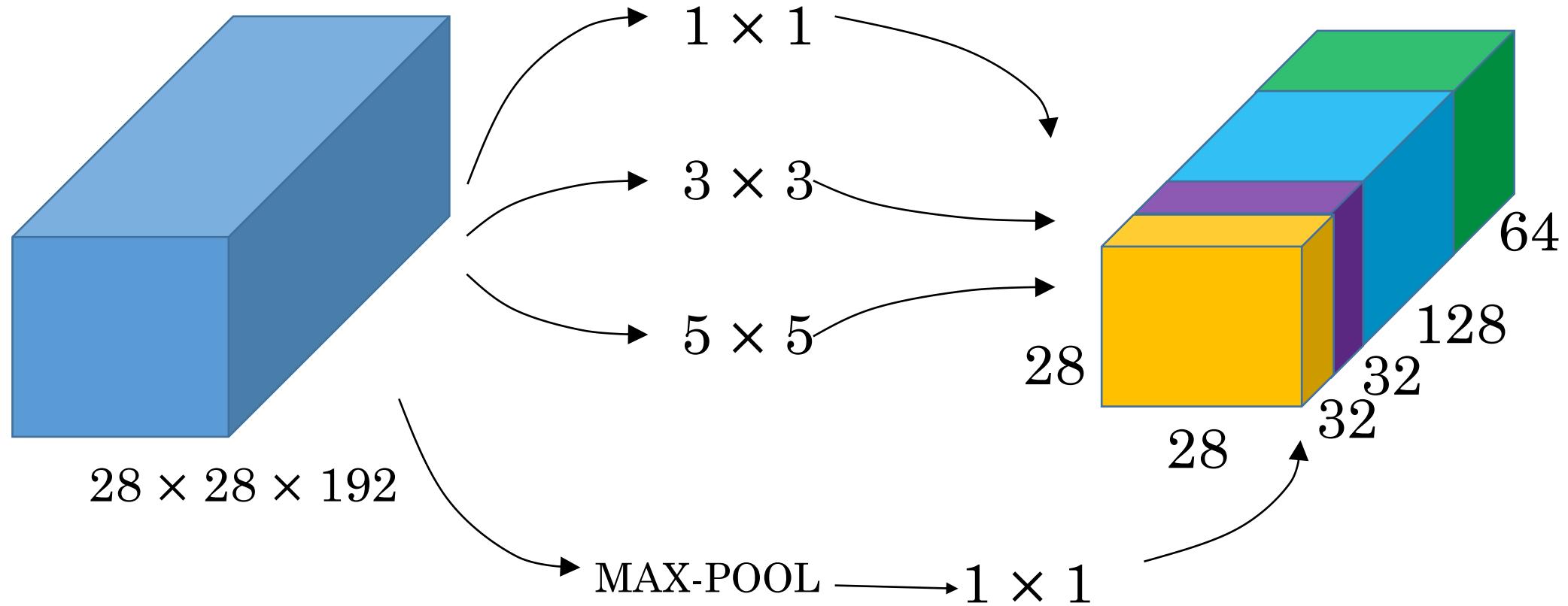
Using 1×1 convolutions



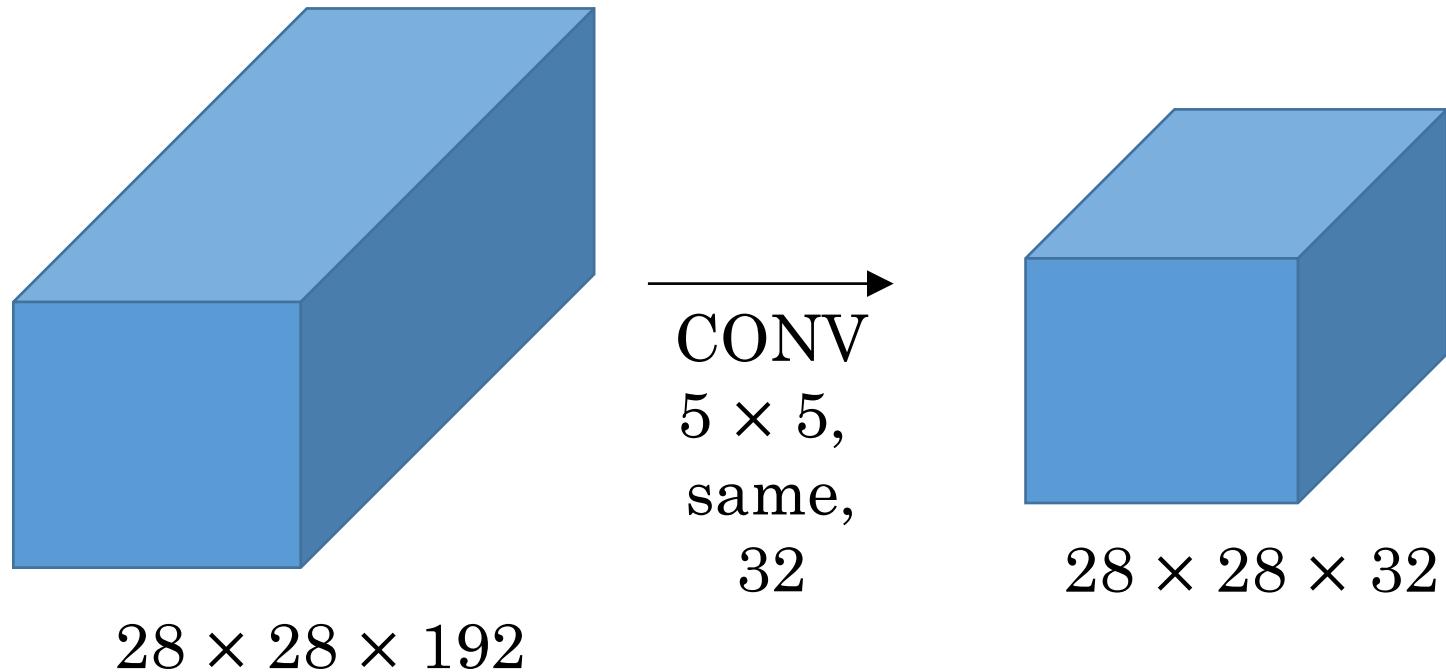
Resnet



Motivation for inception network

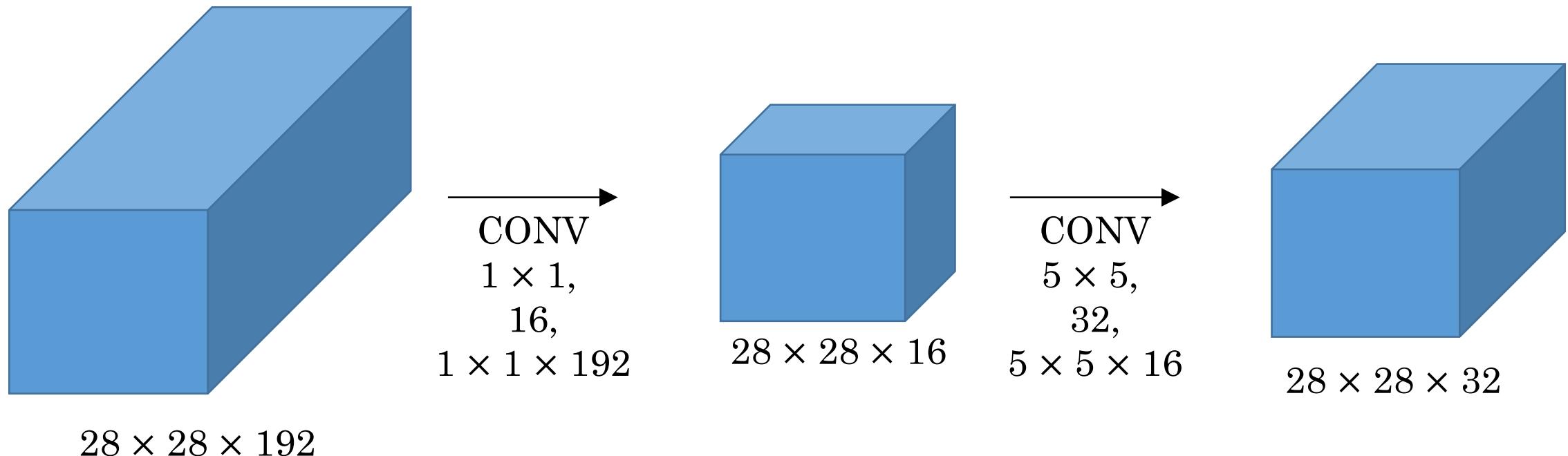


The problem of computational cost



$$28 \times 28 \times 32 \times 5 \times 5 \times 192 = 120m$$

Using 1×1 convolution

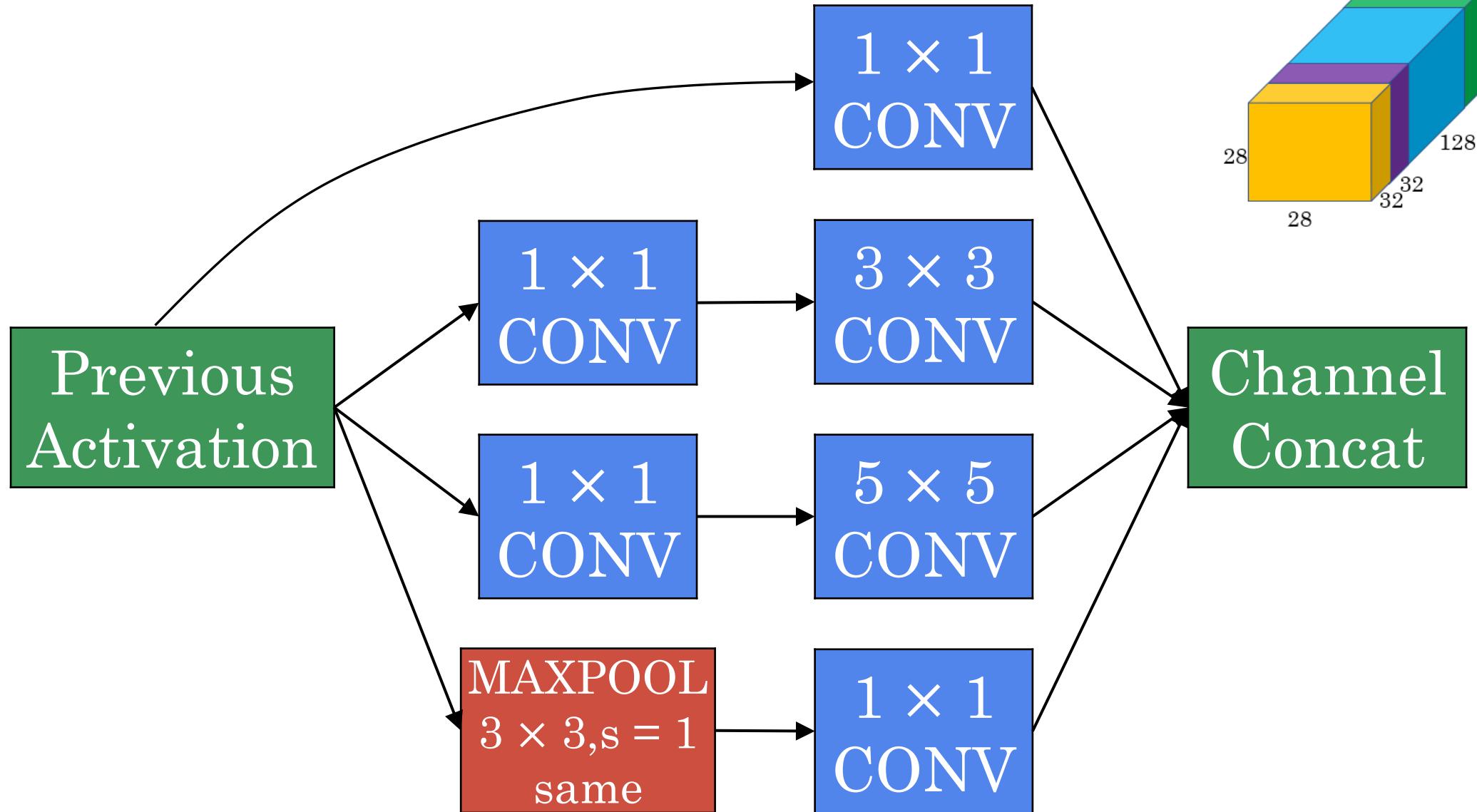


$$28 \times 28 \times 16 \times 192 = 2.4m$$

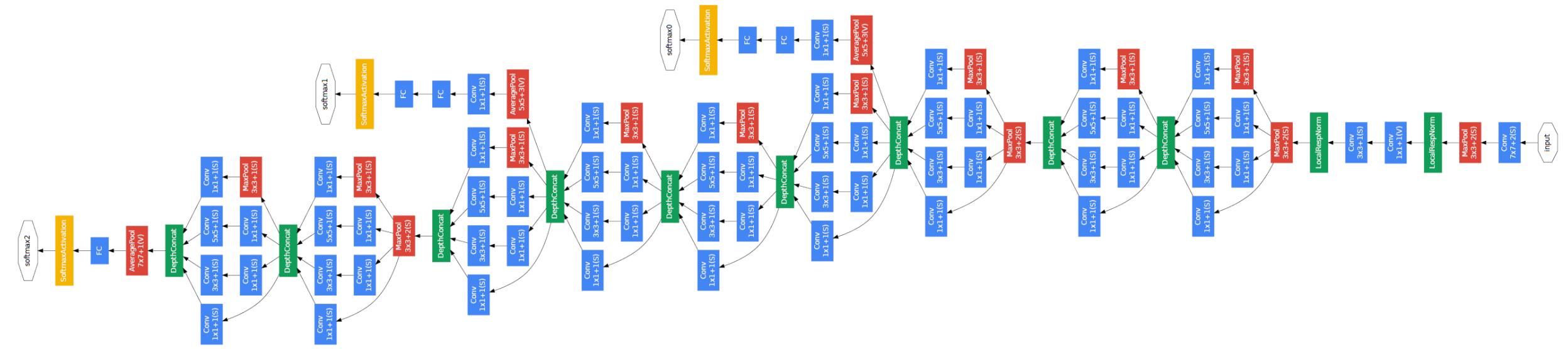
$$28 \times 28 \times 32 \times 5 \times 5 \times 16 = 10m$$

$$\text{Total computational cost} = 10m + 2.4m = 12.4m$$

Inception module



GoogLeNet



[Szegedy et al. 2014. Going deeper with convolutions]

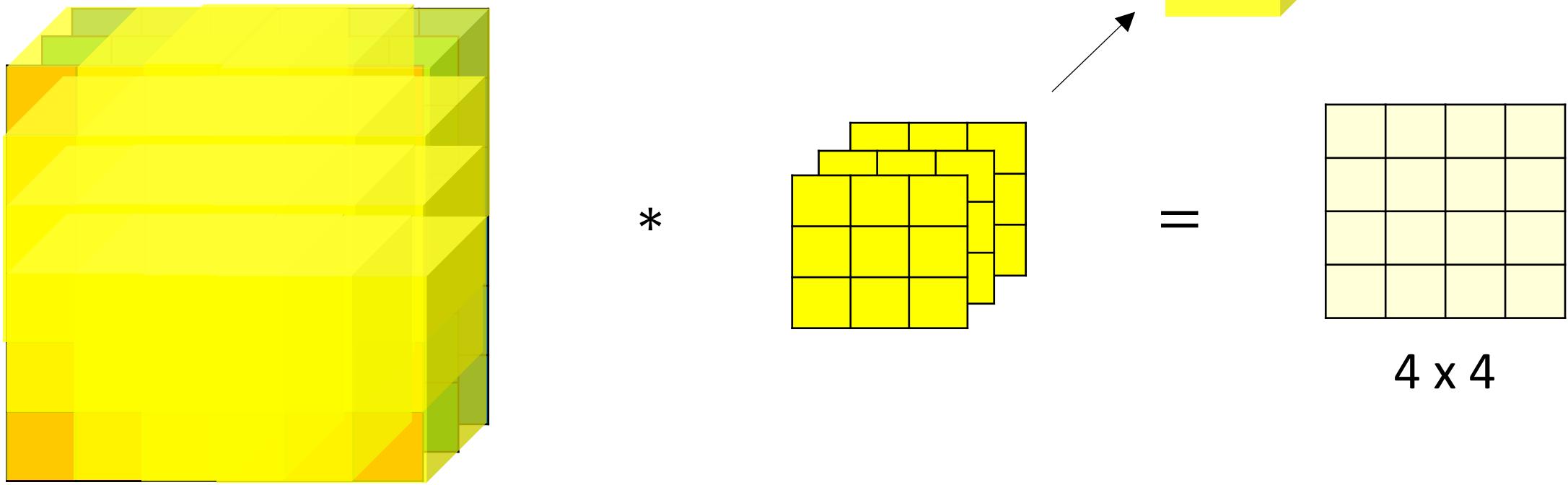
Motivation for MobileNets

- Low computational cost at deployment
- Useful for mobile and embedded vision applications
- Key idea: Normal vs. depthwise-separable convolutions

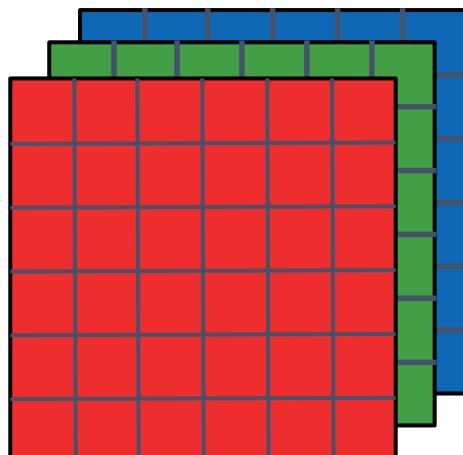


[Howard et al. 2017, MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications]

Normal Convolution

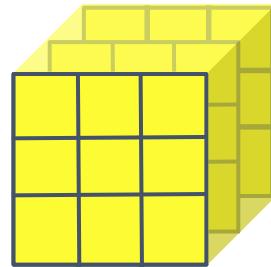


Normal Convolution



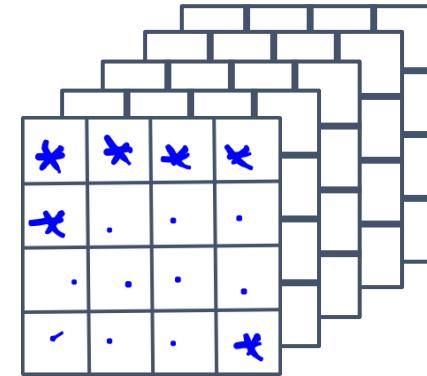
6 x 6 x 3

*



3 x 3 x 3

=



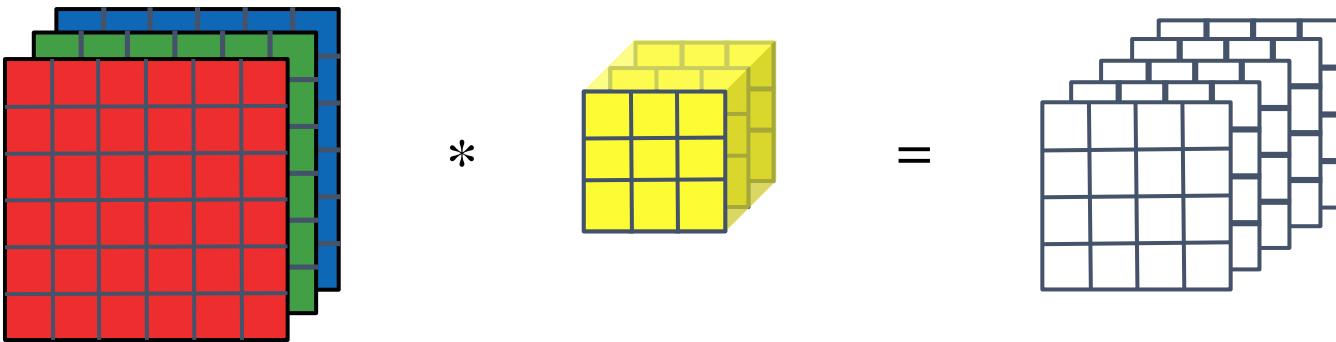
4 * 4 * 5

Computational cost = #filter params x # filter positions x # of filters

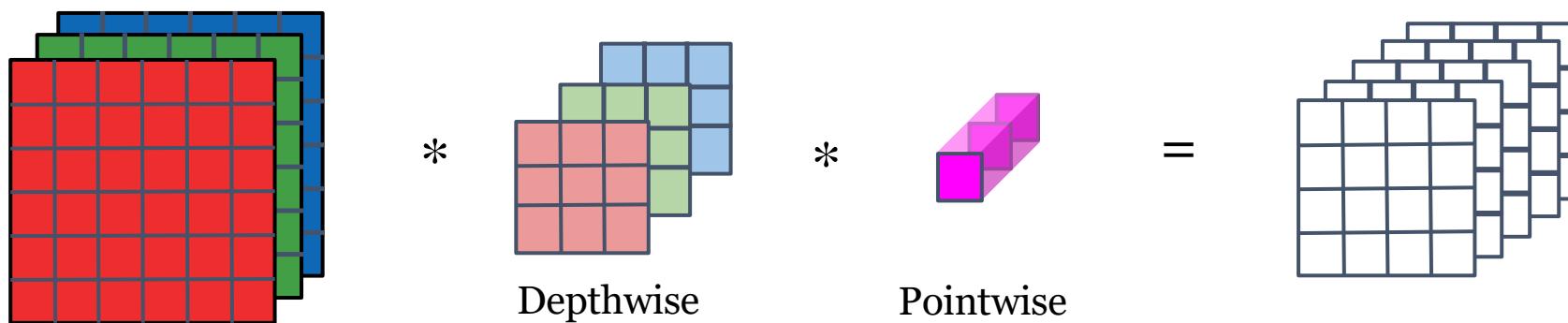
$$2160 = 3 * 3 * 3 * 4 * 4 * 5$$

Depthwise Separable Convolution

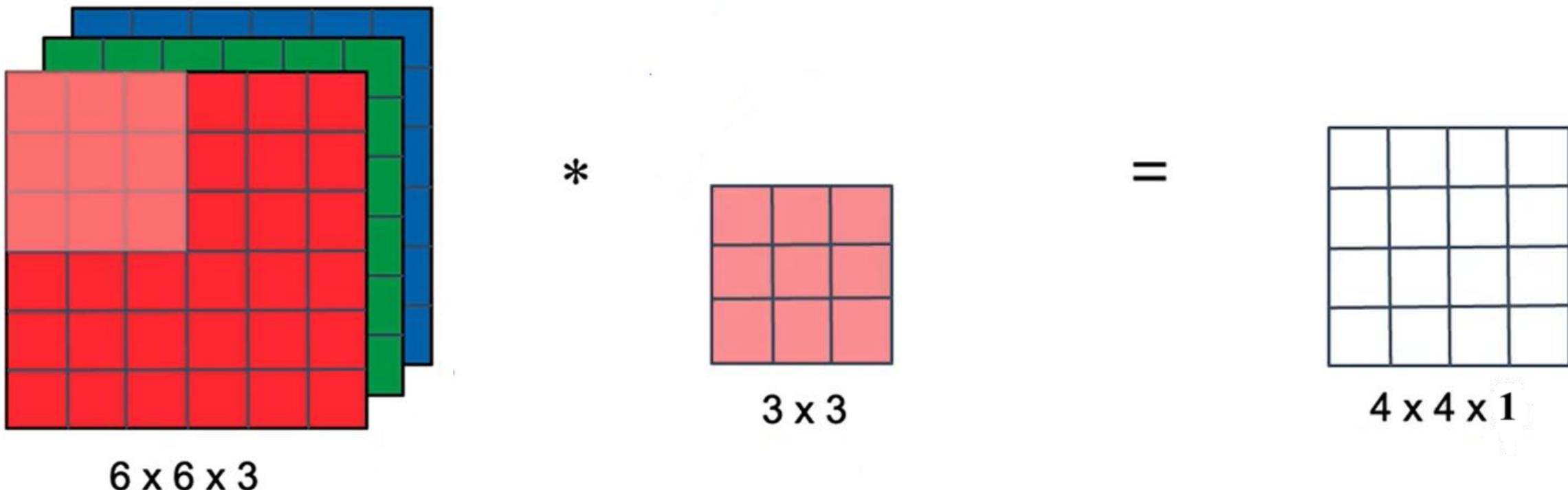
Normal Convolution



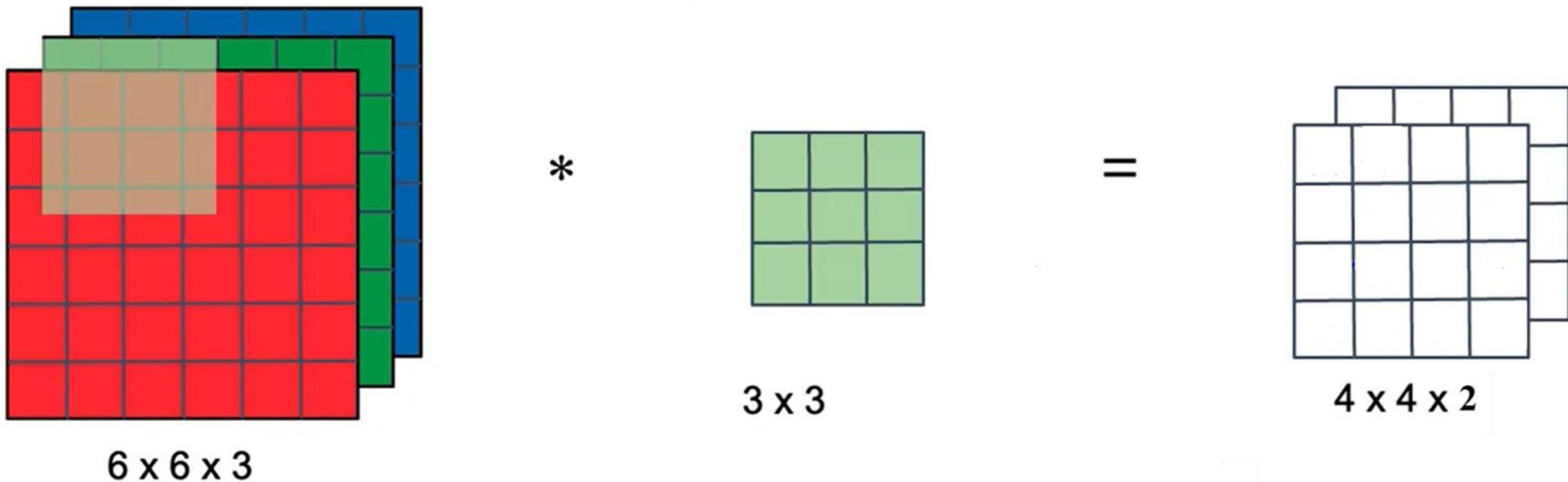
Depthwise Separable Convolution



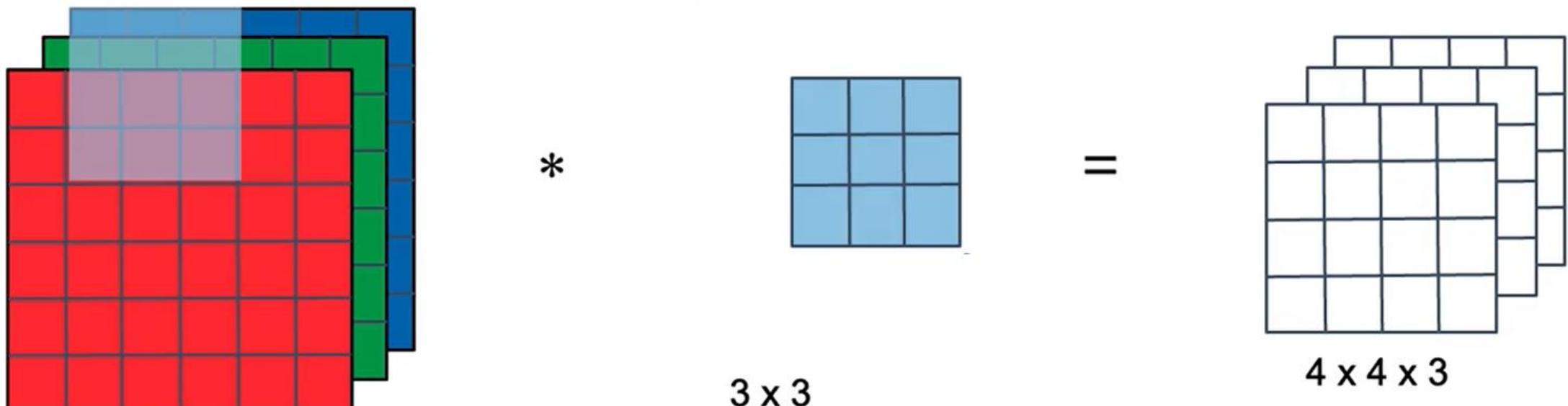
Depthwise Convolution



Depthwise Convolution



Depthwise Convolution

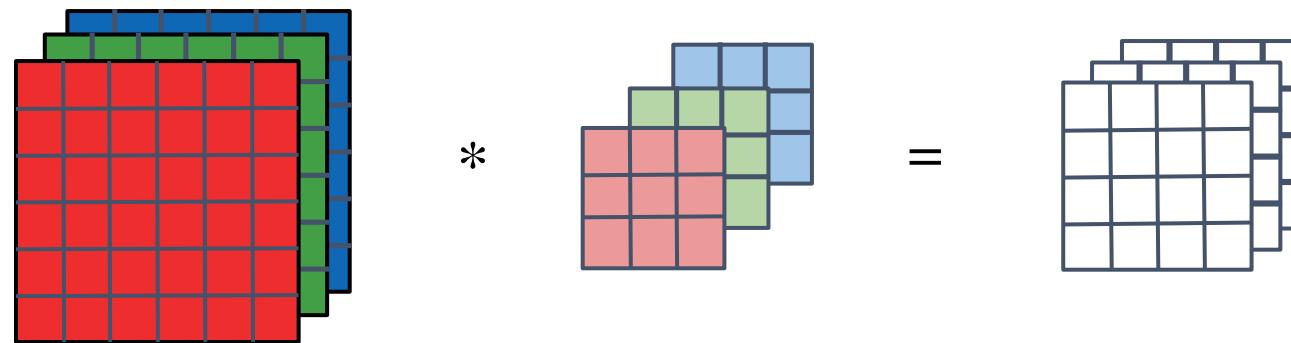


Computational cost = #filter params \times # filter positions \times # of filters

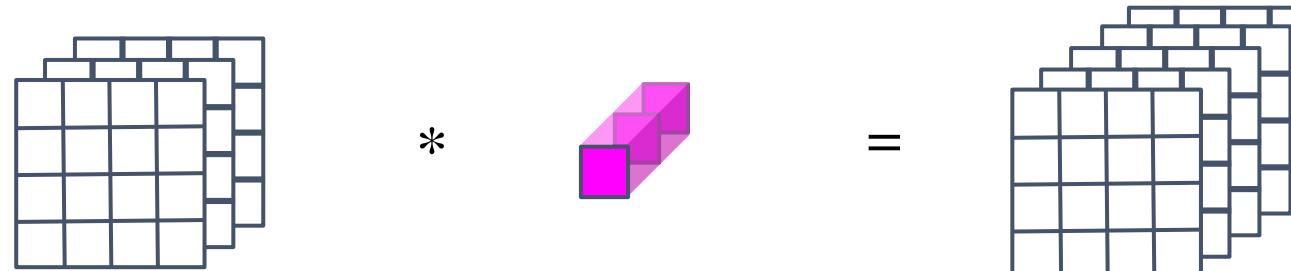
$$432 = 3 * 3 * 4 * 4 * 3$$

Depthwise Separable Convolution

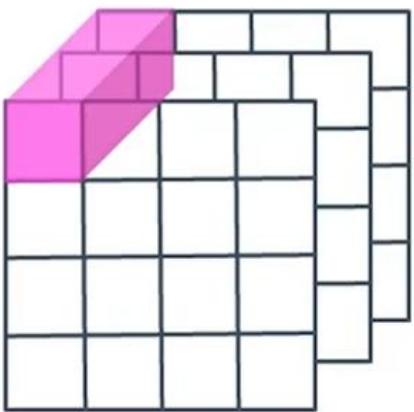
Depthwise Convolution



Pointwise Convolution

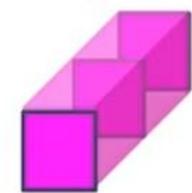


Pointwise Convolution



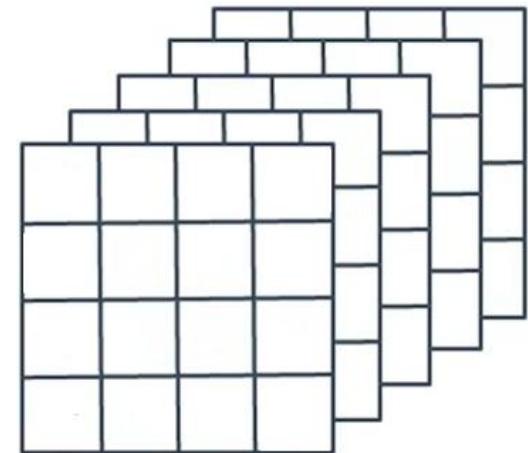
$4 \times 4 \times 3$

*



$1 \times 1 \times 3$

=



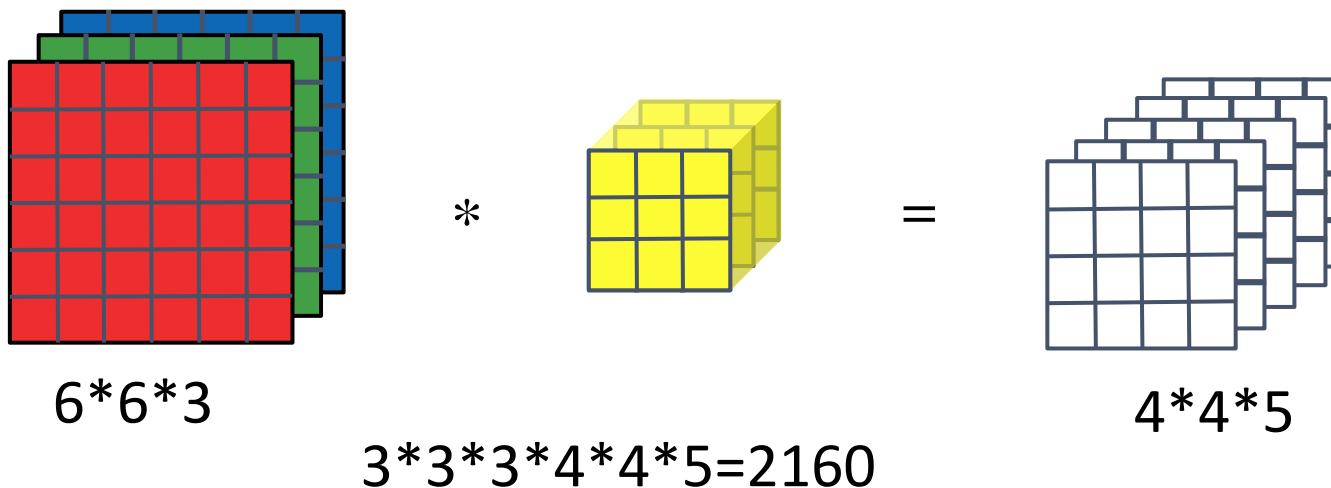
$4 \times 4 \times 5$

Computational cost = #filter params \times # filter positions \times # of filters

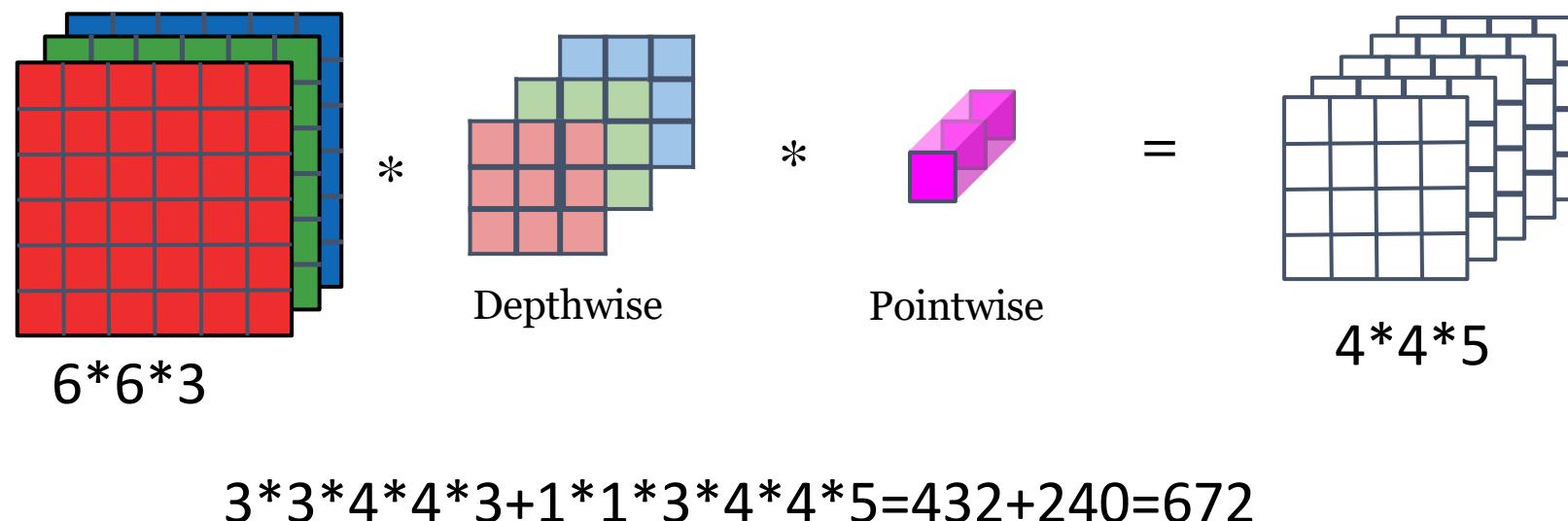
$$240 = 1 * 1 * 3 * 4 * 4 * 5$$

Depthwise Separable Convolution

Normal Convolution



Depthwise Separable
Convolution



Cost Summary

Cost of normal convolution

$$3*3*3*4*4*5=2160$$

Cost of depthwise separable convolution

$$3*3*4*4*3+1*1*3*4*4*5=432+240=672$$

$$\frac{672}{2160} = 0.31$$

n_c : #output channel

n'_c : #input channel

$filter_{size}=f^2$

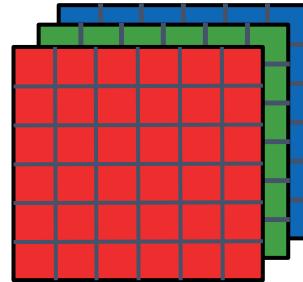
$$\frac{output_{size} * n'_c * f^2 + output_{size} * n_c * n'_c}{output_{size} * n_c * f^2 * n'_c} = \frac{1}{n_c} + \frac{1}{f^2} \sim \frac{1}{512} + \frac{1}{9} \sim \frac{1}{9}$$

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5 \times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

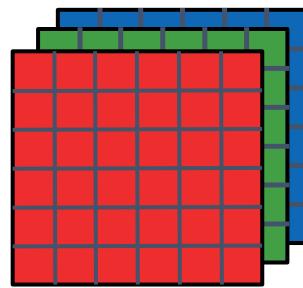
MobileNet-V2

MobileNet v1



13 times

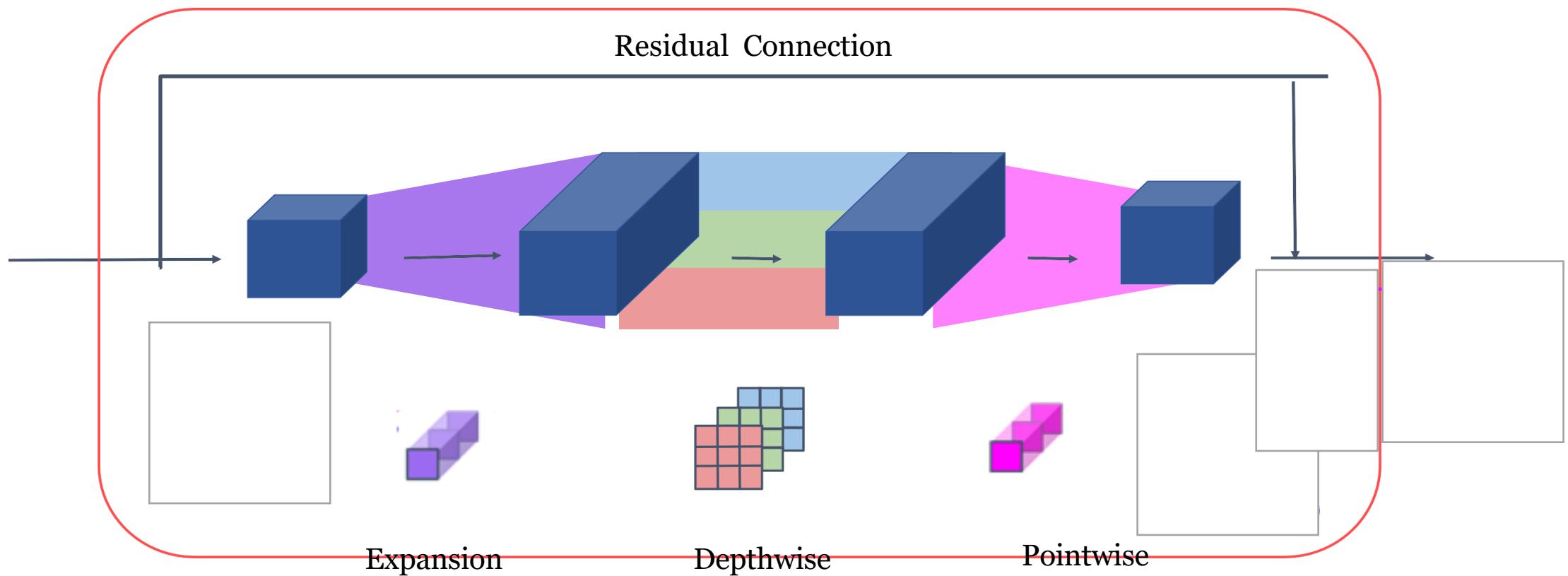
MobileNet v2



17 times

[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

MobileNet v2 Bottleneck



[Sandler et al. 2019, MobileNetV2: Inverted Residuals and Linear Bottlenecks]

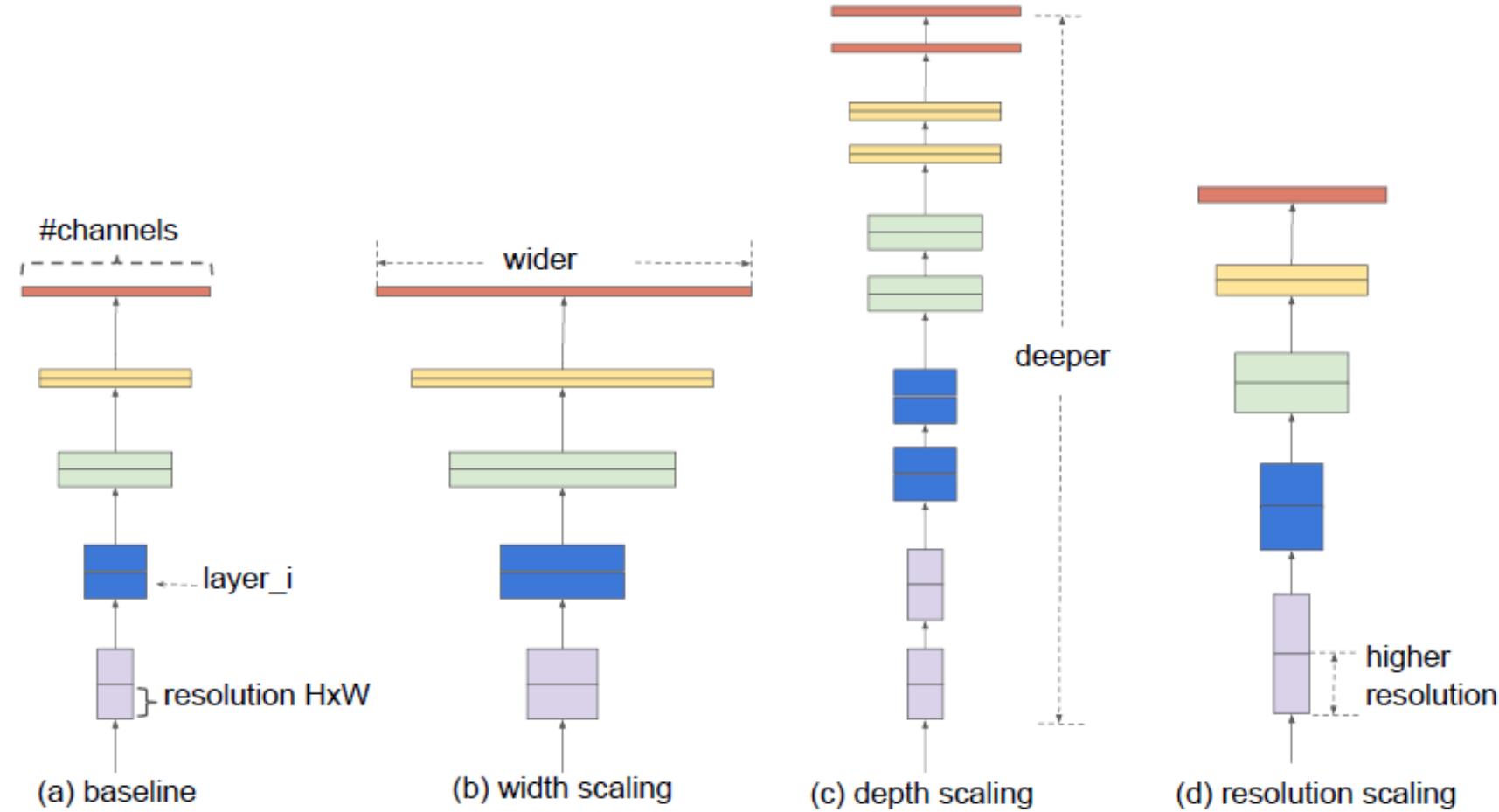
Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s= s , ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table 1: *Bottleneck residual block* transforming from k to k' channels, with stride s , and expansion factor t .

Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	-

Table 2: MobileNetV2 : Each line describes a sequence of 1 or more identical (modulo stride) layers, repeated n times. All layers in the same sequence have the same number c of output channels. The first layer of each sequence has a stride s and all others use stride 1. All spatial convolutions use 3×3 kernels. The expansion factor t is always applied to the input size as described in Table 1.

EfficientNet



[Tan and Le, 2019, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks]

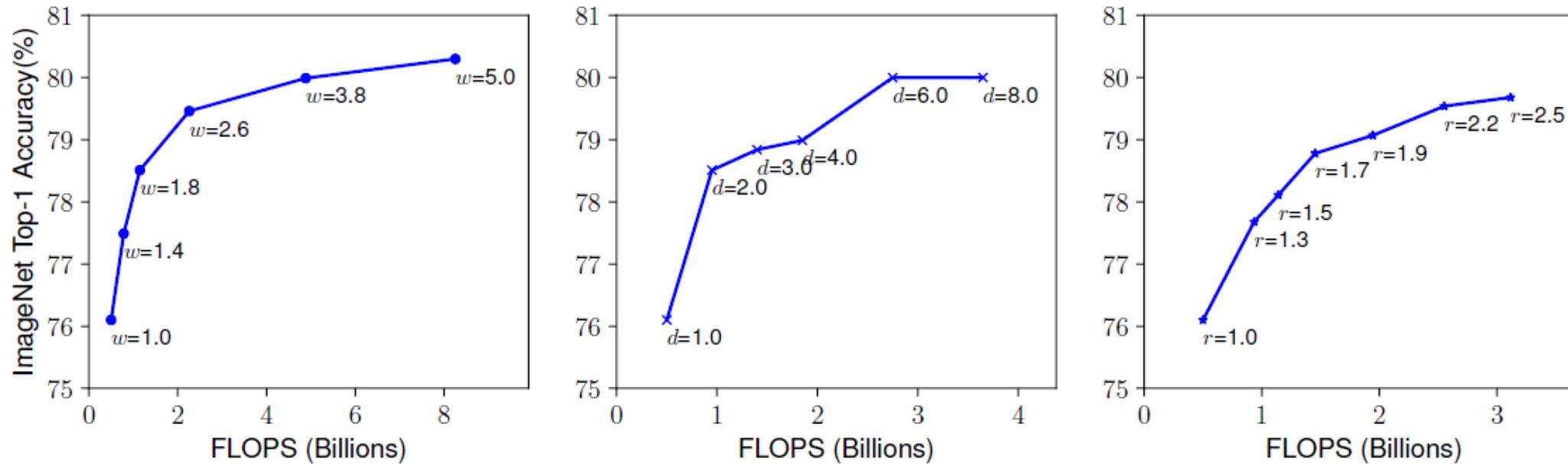


Figure 3. Scaling Up a Baseline Model with Different Network Width (w), Depth (d), and Resolution (r) Coefficients. Bigger networks with larger width, depth, or resolution tend to achieve higher accuracy, but the accuracy gain quickly saturates after reaching 80%, demonstrating the limitation of single dimension scaling. Baseline network is described in Table 1.

- **Observation 1 –** Scaling up any dimension of network width, depth, or resolution improves accuracy, but the accuracy gain diminishes for bigger models.

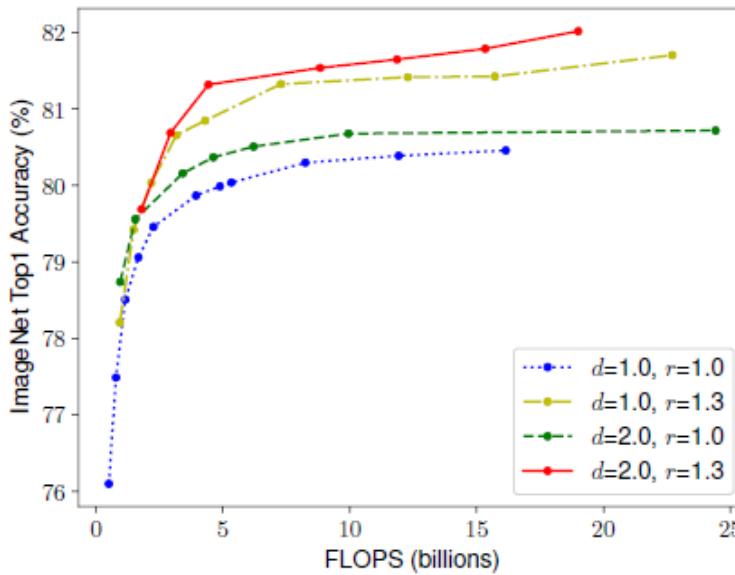


Figure 4. Scaling Network Width for Different Baseline Networks. Each dot in a line denotes a model with different width coefficient (w). All baseline networks are from Table 1. The first baseline network ($d=1.0, r=1.0$) has 18 convolutional layers with resolution 224x224, while the last baseline ($d=2.0, r=1.3$) has 36 layers with resolution 299x299.

- If we only scale network width w without changing depth ($d=1.0$) and resolution ($r=1.0$), the accuracy saturates quickly. With deeper ($d=2.0$) and higher resolution ($r=1.3$), width scaling achieves much better accuracy under the same FLOPS cost.
- **Observation 2** – In order to pursue better accuracy and efficiency, it is critical to balance all dimensions of network width, depth, and resolution during ConvNet scaling.

EfficientNet

Starting from the baseline EfficientNet-B0, we apply our compound scaling method to scale it up with two steps:

- STEP 1: we first fix $\phi = 1$, assuming twice more resources available, and do a small grid search of α, β, γ based on Equation 2 and 3. In particular, we find the best values for EfficientNet-B0 are $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$, under constraint of $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$.
- STEP 2: we then fix α, β, γ as constants and scale up baseline network with different ϕ using Equation 3, to obtain EfficientNet-B1 to B7 (Details in Table 2).

for any new ϕ , the total FLOPS will approximately increase by 2^ϕ .

$$\begin{aligned} & \max_{d,w,r} \text{Accuracy}(\mathcal{N}(d, w, r)) \\ \text{s.t. } & \mathcal{N}(d, w, r) = \bigodot_{i=1 \dots s} \hat{\mathcal{F}}_i^{d \cdot \hat{L}_i}(X_{\langle r \cdot \hat{H}_i, r \cdot \hat{W}_i, w \cdot \hat{C}_i \rangle}) \\ & \text{Memory}(\mathcal{N}) \leq \text{target_memory} \\ & \text{FLOPS}(\mathcal{N}) \leq \text{target_flops} \end{aligned} \tag{2}$$

$$\begin{aligned} \text{depth: } & d = \alpha^\phi \\ \text{width: } & w = \beta^\phi \\ \text{resolution: } & r = \gamma^\phi \\ \text{s.t. } & \alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \\ & \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \end{aligned} \tag{3}$$

[Tan and Le, 2019, EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks]

Input	Operator	Output
$h \times w \times k$	1x1 conv2d , ReLU6	$h \times w \times (tk)$
$h \times w \times tk$	3x3 dwise s=s, ReLU6	$\frac{h}{s} \times \frac{w}{s} \times (tk)$
$\frac{h}{s} \times \frac{w}{s} \times tk$	linear 1x1 conv2d	$\frac{h}{s} \times \frac{w}{s} \times k'$

Table 1: *Bottleneck residual block* transforming from k to k' channels, with stride s , and expansion factor t .

Table 1. EfficientNet-B0 baseline network – Each row describes a stage i with \hat{L}_i layers, with input resolution $\langle \hat{H}_i, \hat{W}_i \rangle$ and output channels \hat{C}_i . Notations are adopted from equation 2.

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{H}_i \times \hat{W}_i$	#Channels \hat{C}_i	#Layers \hat{L}_i
1	Conv3x3	224×224	32	1
2	MBConv1, k3x3	112×112	16	1
3	MBConv6, k3x3	112×112	24	2
4	MBConv6, k5x5	56×56	40	2
5	MBConv6, k3x3	28×28	80	3
6	MBConv6, k5x5	14×14	112	3
7	MBConv6, k5x5	14×14	192	4
8	MBConv6, k3x3	7×7	320	1
9	Conv1x1 & Pooling & FC	7×7	1280	1

Table 2. EfficientNet Performance Results on ImageNet (Russakovsky et al., 2015). All EfficientNet models are scaled from our baseline EfficientNet-B0 using different compound coefficient ϕ in Equation 3. ConvNets with similar top-1/top-5 accuracy are grouped together for efficiency comparison. Our scaled EfficientNet models consistently reduce parameters and FLOPS by an order of magnitude (up to 8.4x parameter reduction and up to 16x FLOPS reduction) than existing ConvNets.

Model	Top-1 Acc.	Top-5 Acc.	#Params	Ratio-to-EfficientNet	#FLOPs	Ratio-to-EfficientNet
EfficientNet-B0	77.1%	93.3%	5.3M	1x	0.39B	1x
ResNet-50 (He et al., 2016)	76.0%	93.0%	26M	4.9x	4.1B	11x
DenseNet-169 (Huang et al., 2017)	76.2%	93.2%	14M	2.6x	3.5B	8.9x
EfficientNet-B1	79.1%	94.4%	7.8M	1x	0.70B	1x
ResNet-152 (He et al., 2016)	77.8%	93.8%	60M	7.6x	11B	16x
DenseNet-264 (Huang et al., 2017)	77.9%	93.9%	34M	4.3x	6.0B	8.6x
Inception-v3 (Szegedy et al., 2016)	78.8%	94.4%	24M	3.0x	5.7B	8.1x
Xception (Chollet, 2017)	79.0%	94.5%	23M	3.0x	8.4B	12x
EfficientNet-B2	80.1%	94.9%	9.2M	1x	1.0B	1x
Inception-v4 (Szegedy et al., 2017)	80.0%	95.0%	48M	5.2x	13B	13x
Inception-resnet-v2 (Szegedy et al., 2017)	80.1%	95.1%	56M	6.1x	13B	13x
EfficientNet-B3	81.6%	95.7%	12M	1x	1.8B	1x
ResNeXt-101 (Xie et al., 2017)	80.9%	95.6%	84M	7.0x	32B	18x
PolyNet (Zhang et al., 2017)	81.3%	95.8%	92M	7.7x	35B	19x
EfficientNet-B4	82.9%	96.4%	19M	1x	4.2B	1x
SENet (Hu et al., 2018)	82.7%	96.2%	146M	7.7x	42B	10x
NASNet-A (Zoph et al., 2018)	82.7%	96.2%	89M	4.7x	24B	5.7x
AmoebaNet-A (Real et al., 2019)	82.8%	96.1%	87M	4.6x	23B	5.5x
PNASNet (Liu et al., 2018)	82.9%	96.2%	86M	4.5x	23B	6.0x
EfficientNet-B5	83.6%	96.7%	30M	1x	9.9B	1x
AmoebaNet-C (Cubuk et al., 2019)	83.5%	96.5%	155M	5.2x	41B	4.1x
EfficientNet-B6	84.0%	96.8%	43M	1x	19B	1x
EfficientNet-B7	84.3%	97.0%	66M	1x	37B	1x
GPipe (Huang et al., 2018)	84.3%	97.0%	557M	8.4x	-	-

We omit ensemble and multi-crop models (Hu et al., 2018), or models pretrained on 3.5B Instagram images (Mahajan et al., 2018).

Table 3. Scaling Up MobileNets and ResNet.

Model	FLOPS	Top-1 Acc.
Baseline MobileNetV1 (Howard et al., 2017)	0.6B	70.6%
Scale MobileNetV1 by width ($w=2$)	2.2B	74.2%
Scale MobileNetV1 by resolution ($r=2$)	2.2B	72.7%
compound scale ($d=1.4$, $w=1.2$, $r=1.3$)	2.3B	75.6%
Baseline MobileNetV2 (Sandler et al., 2018)	0.3B	72.0%
Scale MobileNetV2 by depth ($d=4$)	1.2B	76.8%
Scale MobileNetV2 by width ($w=2$)	1.1B	76.4%
Scale MobileNetV2 by resolution ($r=2$)	1.2B	74.8%
MobileNetV2 compound scale	1.3B	77.4%
Baseline ResNet-50 (He et al., 2016)	4.1B	76.0%
Scale ResNet-50 by depth ($d=4$)	16.2B	78.1%
Scale ResNet-50 by width ($w=2$)	14.7B	77.7%
Scale ResNet-50 by resolution ($r=2$)	16.4B	77.5%
ResNet-50 compound scale	16.7B	78.8%

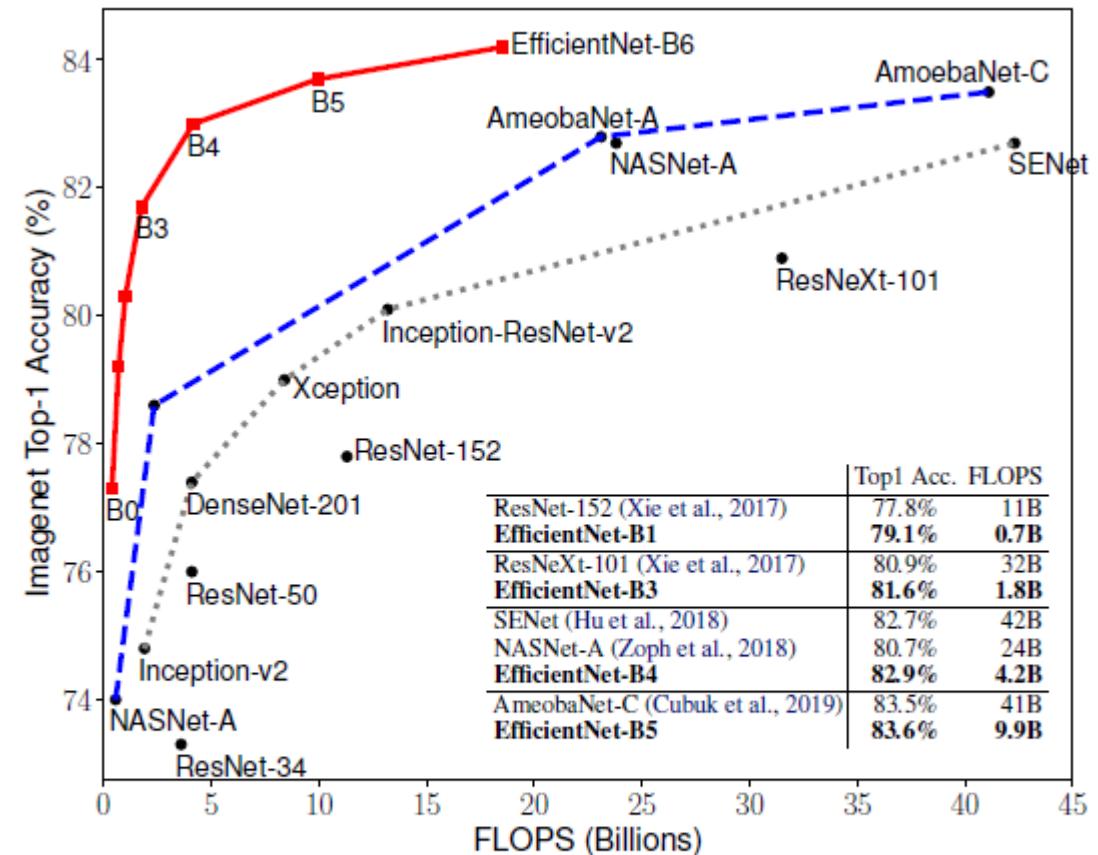


Figure 5. FLOPS vs. ImageNet Accuracy – Similar to Figure 1 except it compares FLOPS rather than model size.

Common augmentation method

Mirroring



Random Cropping



Rotation
Shearing
Local warping

...

Color shifting



+20,-20,+20



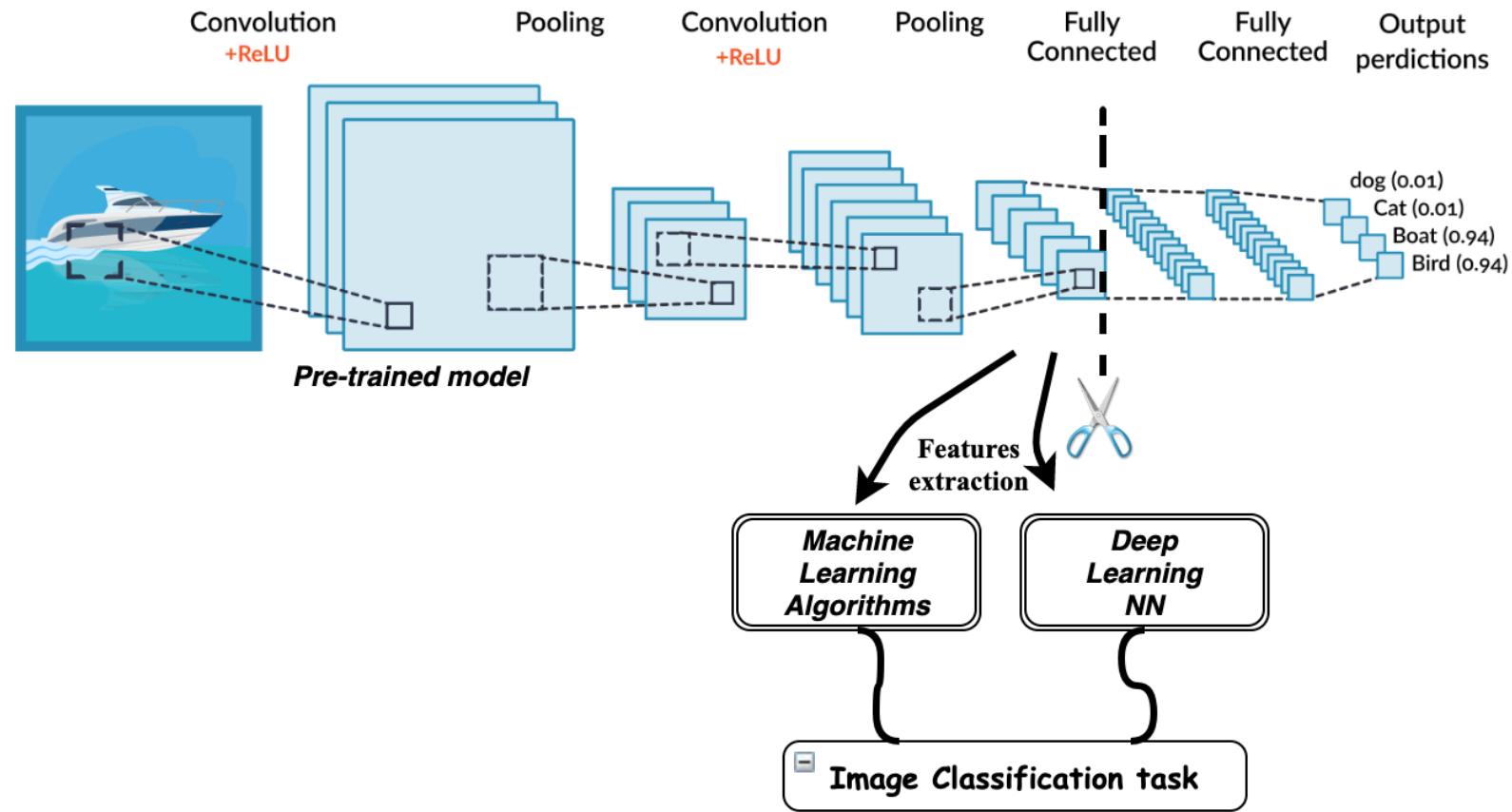
-20,+20,+20



+5.0,+50



Transfer Learning

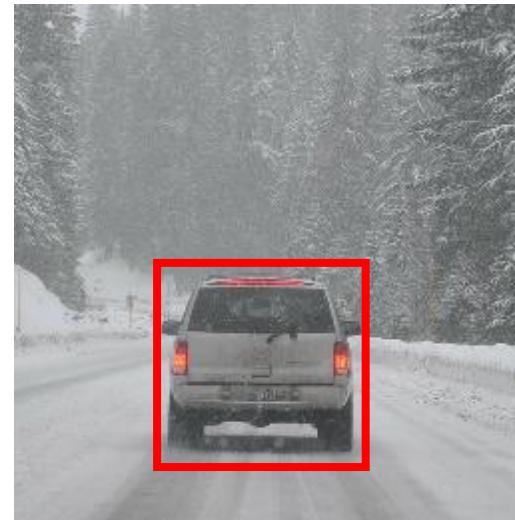


What are localization and detection?

Image classification



Classification with
localization

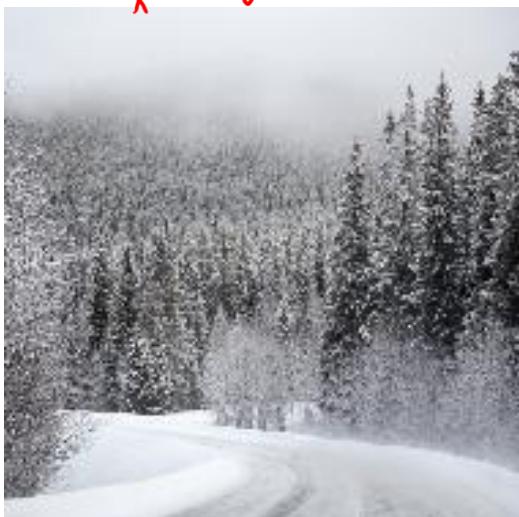
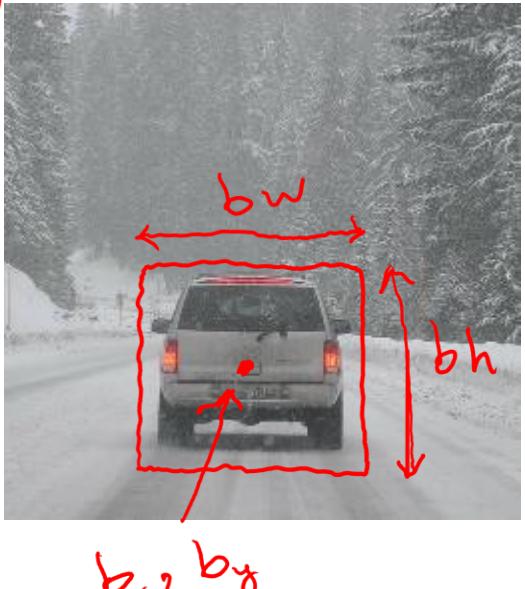


Detection

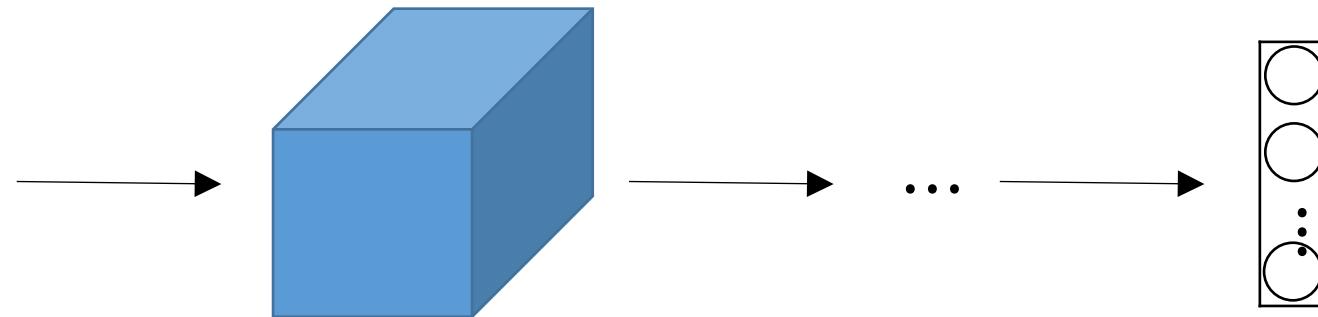


Classification with localization

(..)



(1,1)

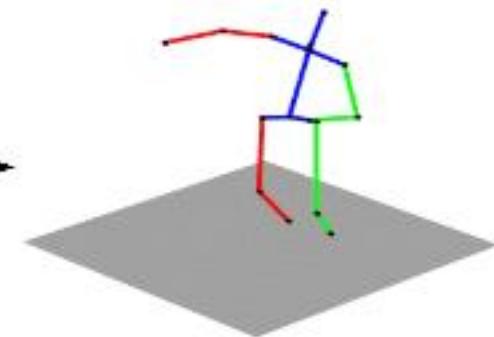
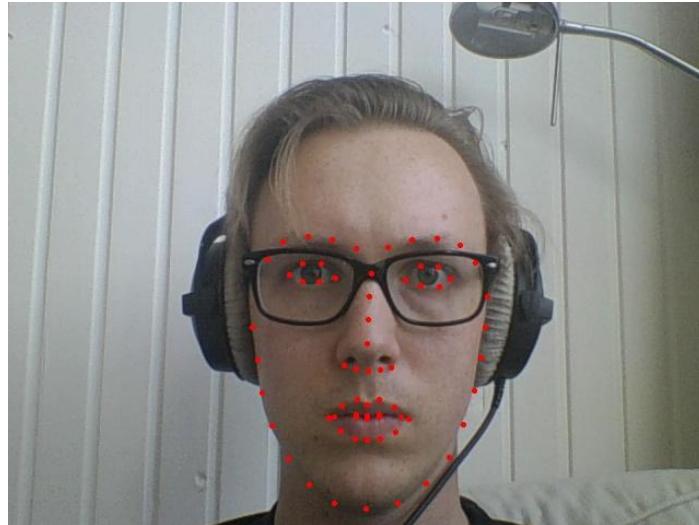


$$\begin{array}{ll} b_x = 0.5 & b_h = 0.3 \\ b_y = 0.7 & b_w = 0.4 \end{array}$$

- 1 - pedestrian
- 2 - car
- 3 - motorcycle
- 4 - background

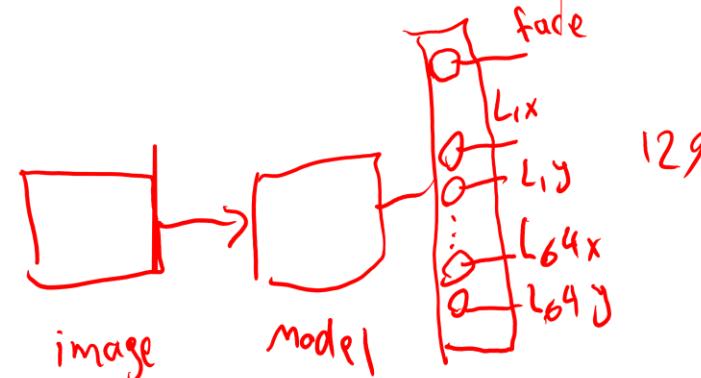


Landmark detection



b_x, b_y, b_h, b_w

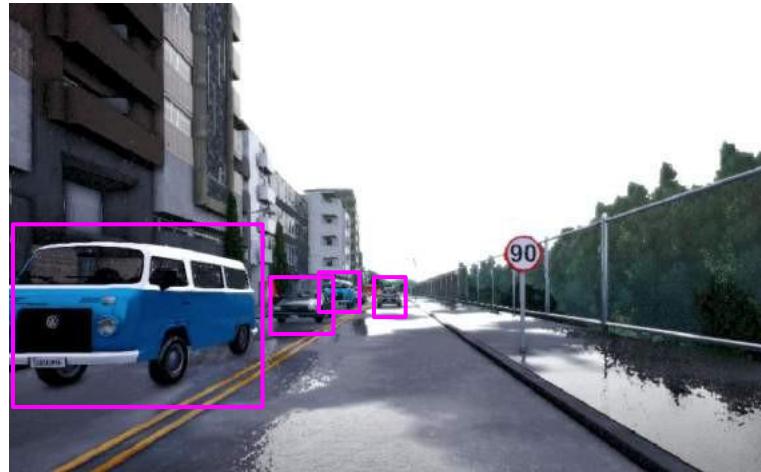
L_{1x}, L_{1y}
 L_{2x}, L_{2y}
 \vdots
 L_{64x}, L_{64y}



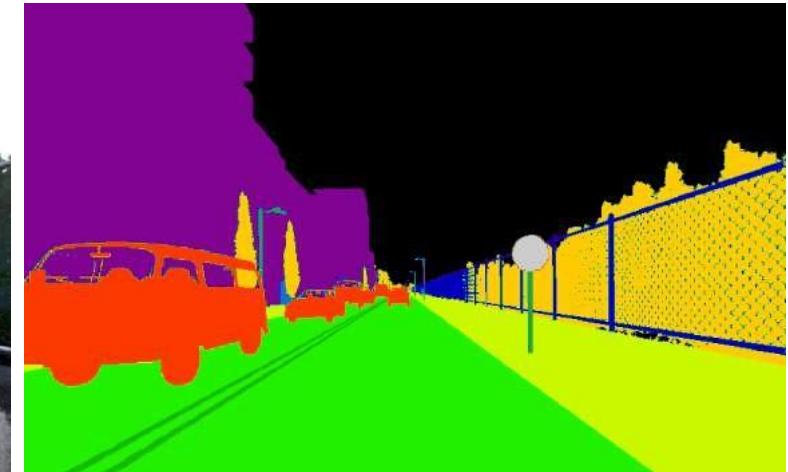
Object Detection vs. Semantic Segmentation



Input image

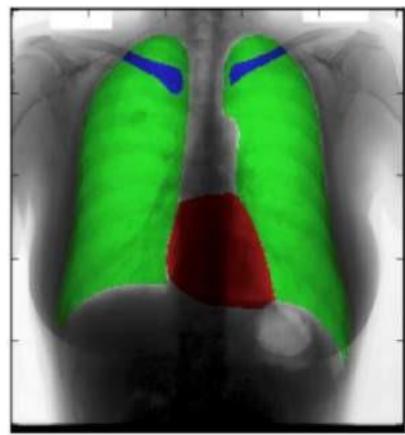


Object Detection

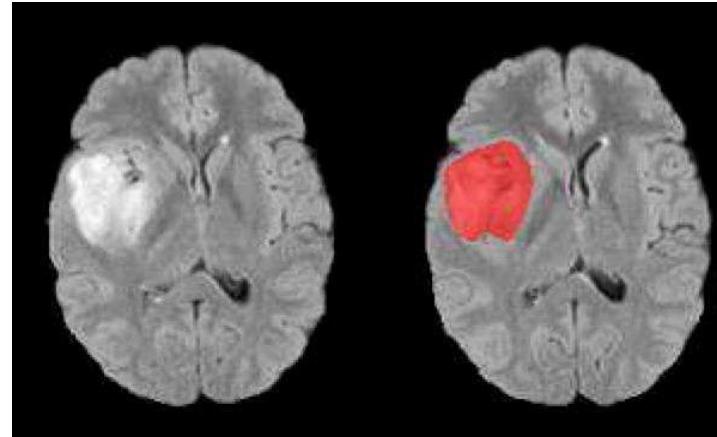


Semantic Segmentation

Motivation for U-Net



Chest X-Ray

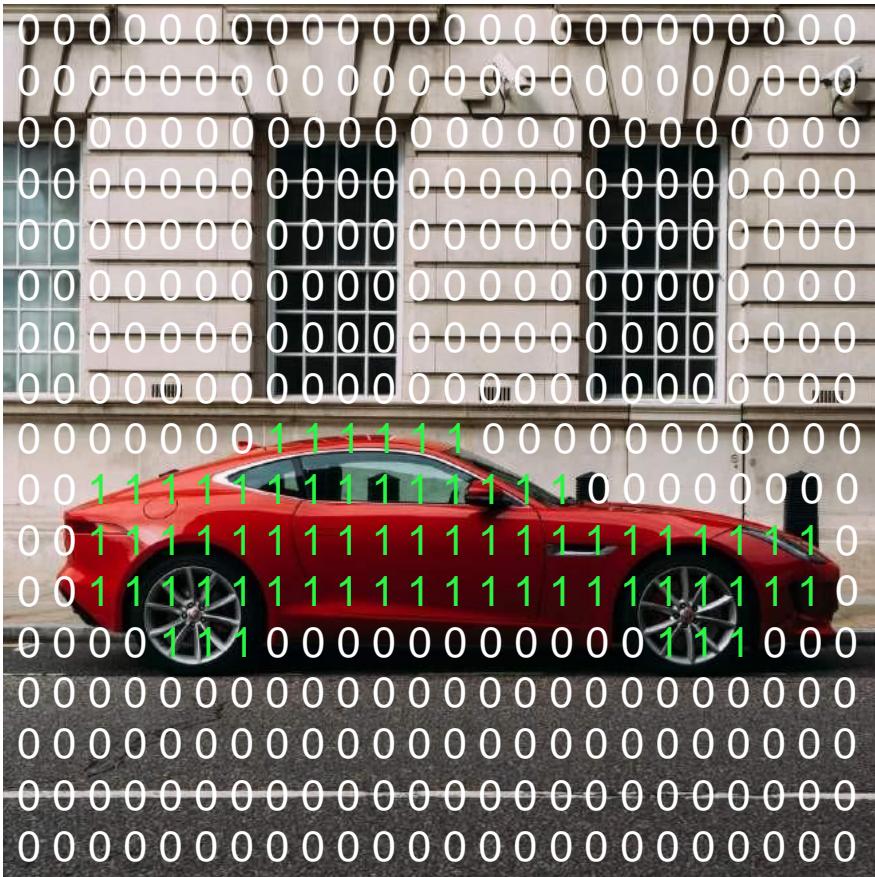


Brain MRI

[Novikov et al., 2017, Fully Convolutional Architectures for Multi-Class Segmentation in Chest Radiographs]

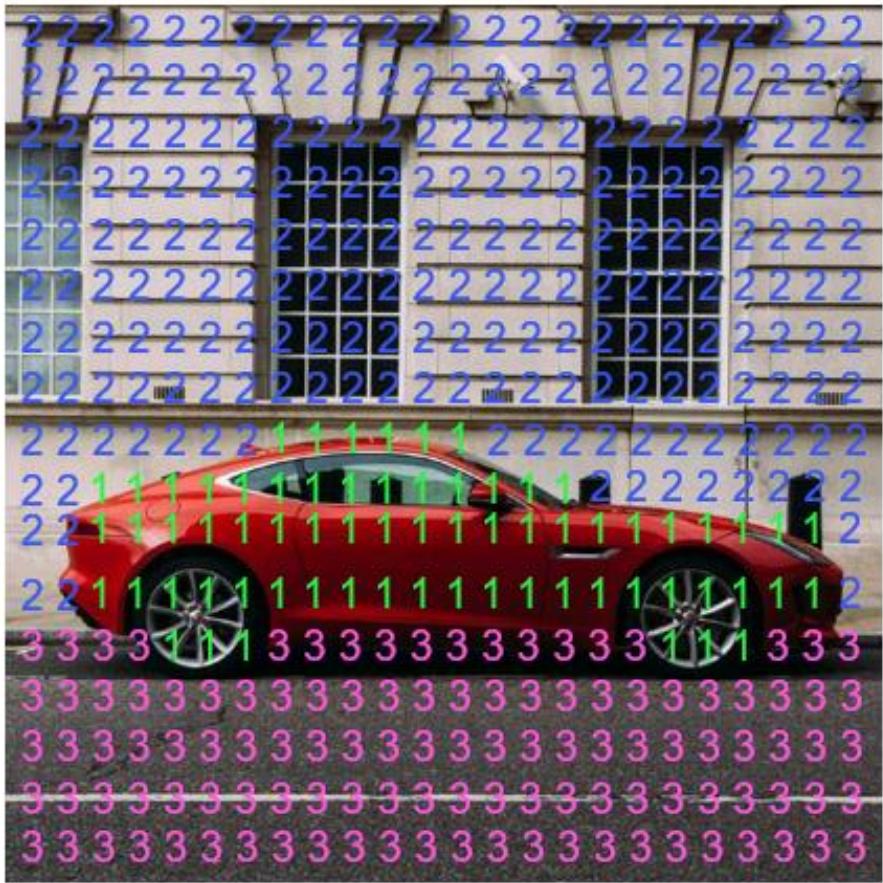
[Dong et al., 2017, Automatic Brain Tumor Detection and Segmentation Using U-Net Based Fully Convolutional Networks]

Per-pixel class labels



- 1. Car
- 0. Not Car

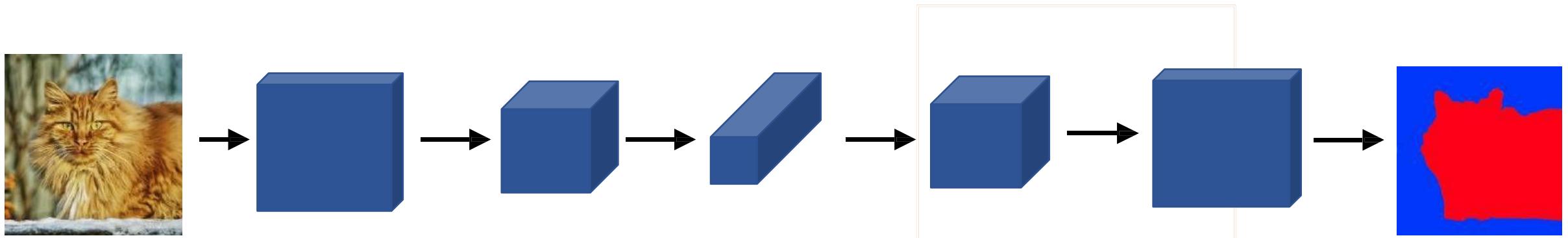
Per pixel class label



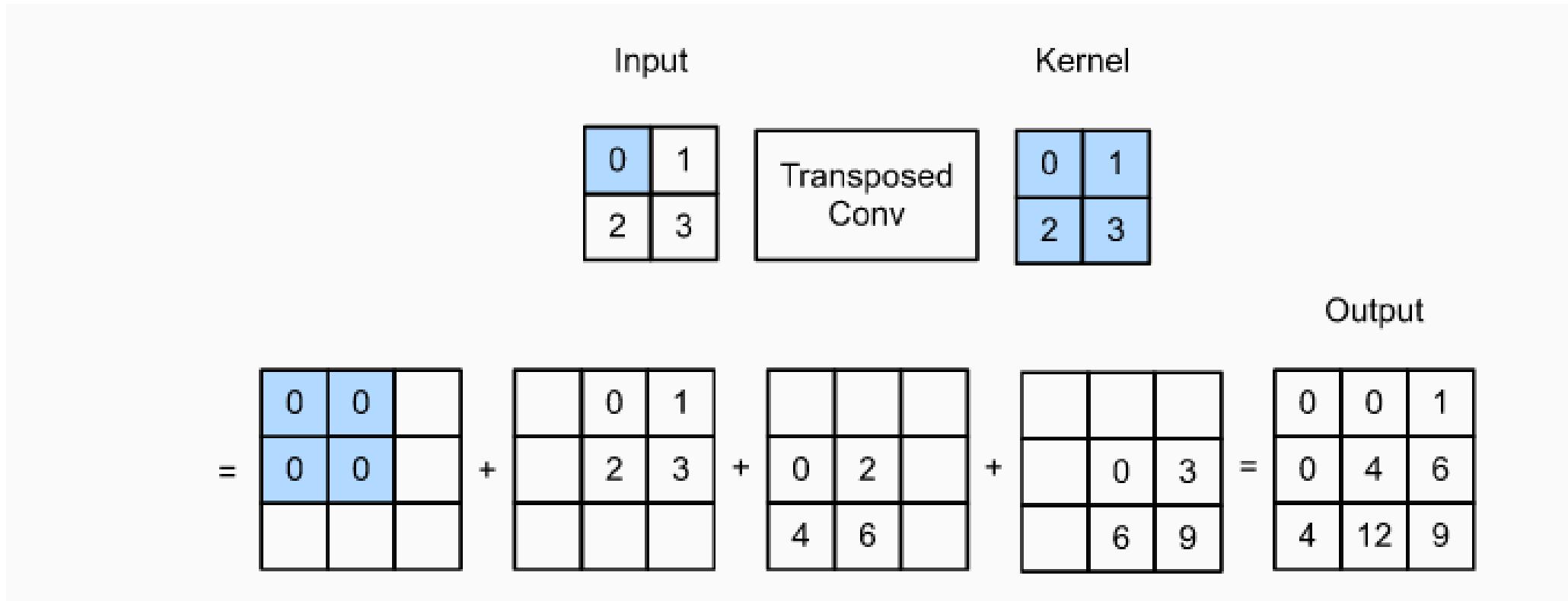
1. Car
 2. Building
 3. Road

Segmentation Map

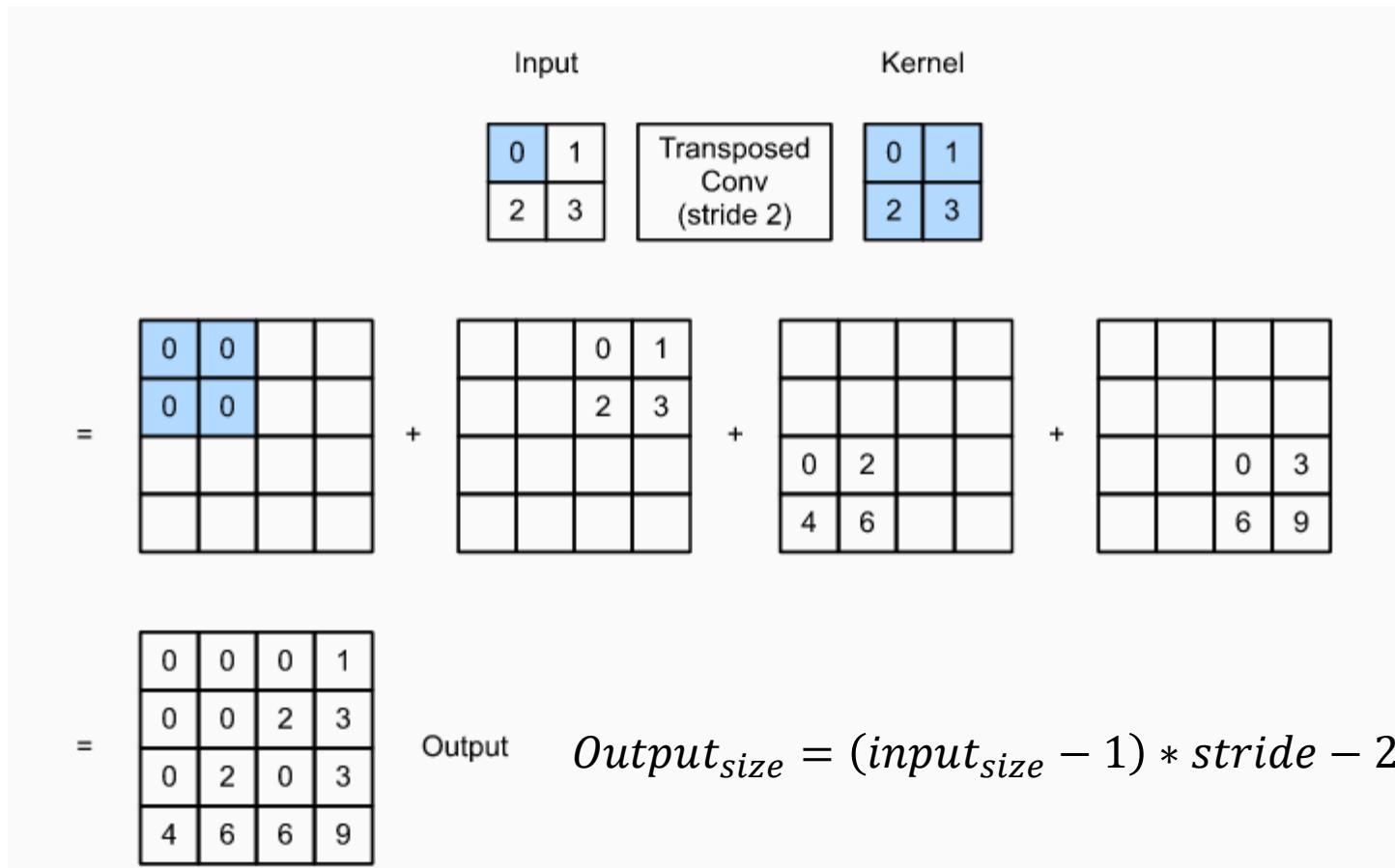
Deep Learning for Semantic Segmentation



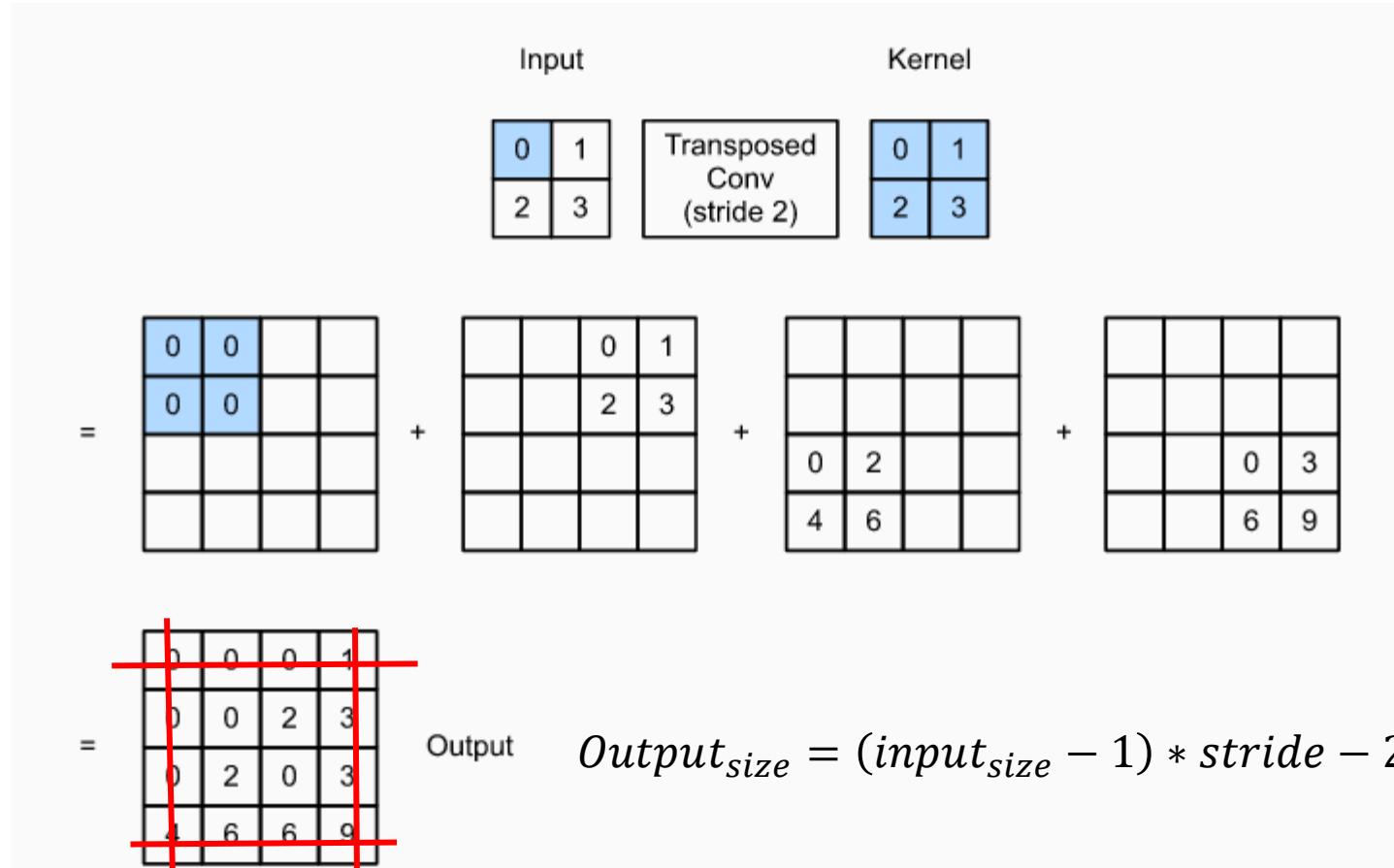
Transpose Convolution



Transpose Convolution with stride

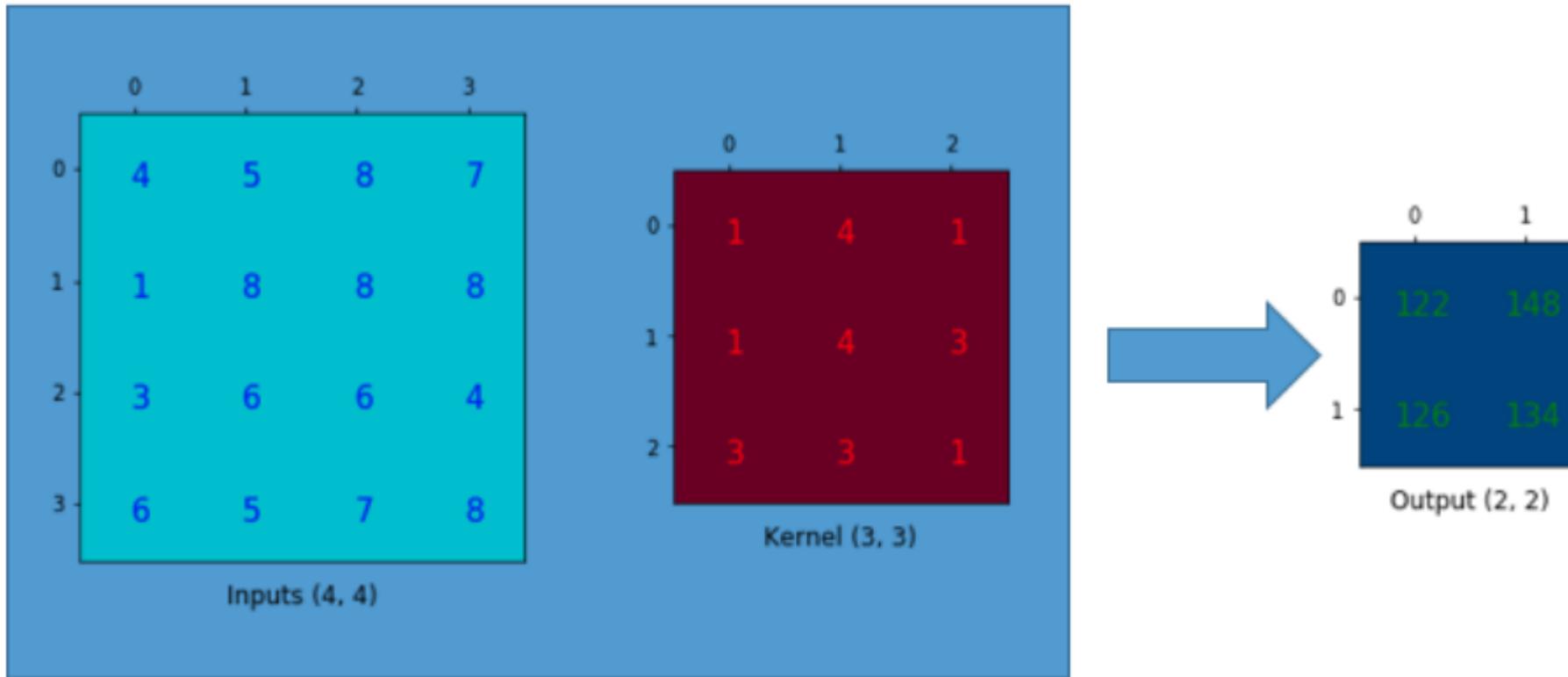


Transpose Convolution with stride and padding



Stride=2
Padding=1

Why transpose convolution?



<https://towardsdatascience.com/up-sampling-with-transposed-convolution-9ae4f2df52d0>

A diagram illustrating a matrix operation. On the left, a 3x3 matrix is shown with values 1, 4, 1; 1, 4, 3; and 3, 3, 1. A blue curved arrow points from the bottom-right cell (1) to a separate 2x2 matrix on the right, which contains 122, 148 in the top row and 126, 134 in the bottom row. Below the 3x3 matrix is a 4x4 matrix with values 4, 5, 8, 7; 1, 8, 8, 8; 3, 6, 6, 4; and 6, 5, 7, 8.

1	4	1
1	4	3
3	3	1

122	148
126	134

4	5	8	7
1	8	8	8
3	6	6	4
6	5	7	8

A diagram illustrating a matrix operation. On the left, a 3x3 matrix is shown with values 1, 4, 1; 1, 4, 3; and 3, 3, 1. A blue curved arrow points from the bottom-right cell (1) to a separate 2x2 matrix on the right, which contains 122, 148 in the top row and 126, 134 in the bottom row. Below the 3x3 matrix is a 4x4 matrix with values 4, 5, 8, 7; 1, 8, 8, 8; 3, 6, 6, 4; and 6, 5, 7, 8.

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122	148
126	134

4	5	8	7
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6	5	7	8

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122	148
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A diagram illustrating a matrix operation. On the left, a 3x3 matrix is shown with values 1, 4, 1; 1, 4, 3; and 3, 3, 1. A blue curved arrow points from the bottom-right cell (1) to a separate 2x2 matrix on the right, which contains 122, 148 in the top row and 126, 134 in the bottom row. Below the 3x3 matrix is a 4x4 matrix with values 4, 5, 8, 7; 1, 8, 8, 8; 3, 6, 6, 4; and 6, 5, 7, 8.

1	4	1
1	4	3
3	3	1

122	148
126	134

4	5	8	7
1	8	8	8
3	6	6	4
6	5	7	8

	0	1	2
0	1	4	1
1	1	4	3
2	3	3	1

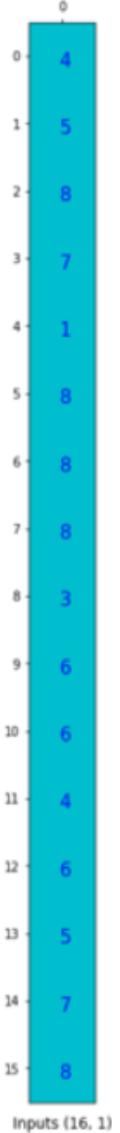
Kernel (3, 3)

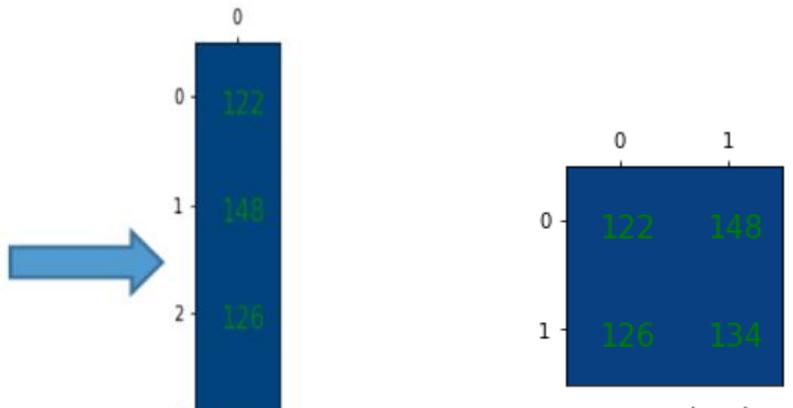
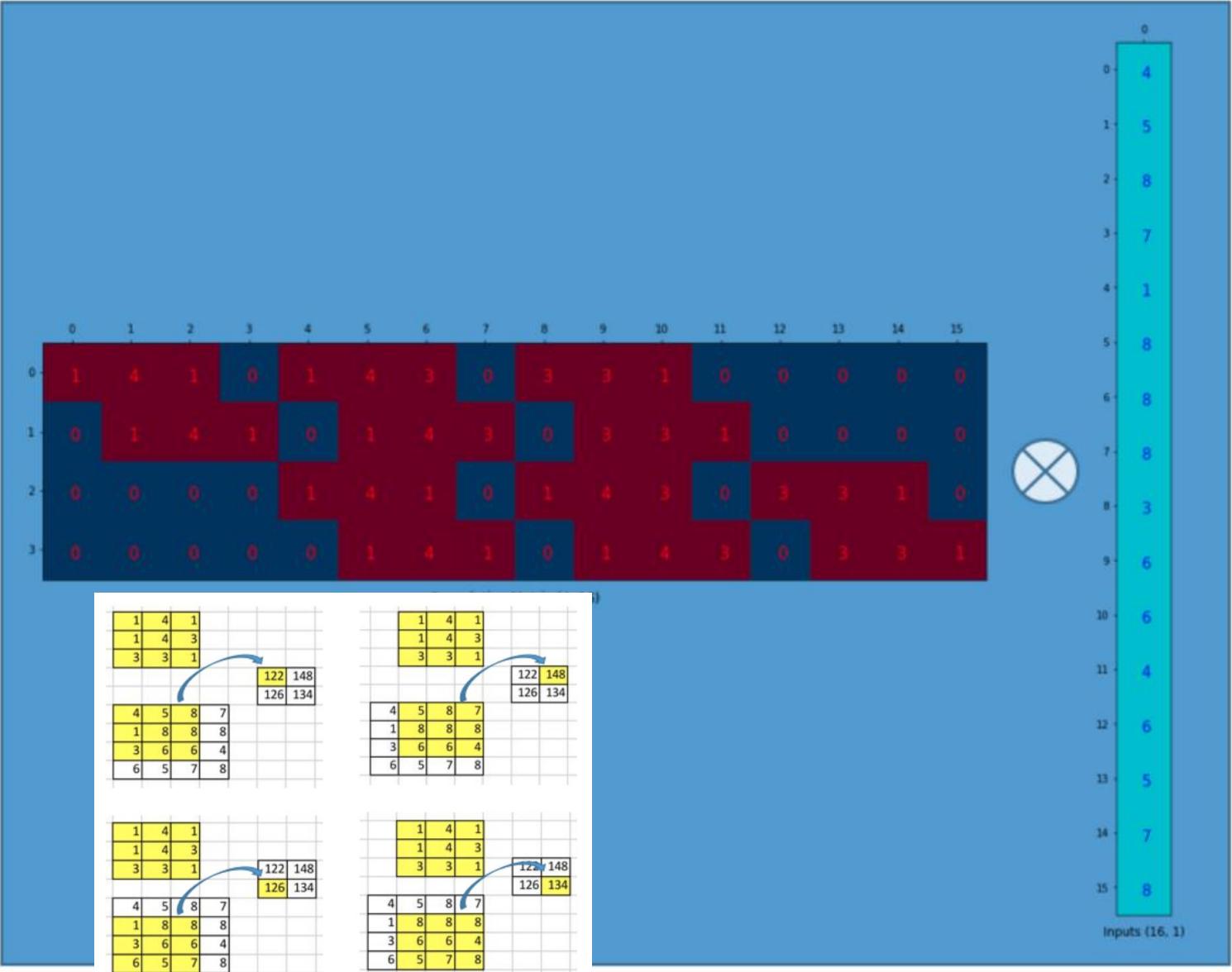
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	1	4	1	0	1	4	3	0	3	3	1	0	0	0	0	0
1	0	1	4	1	0	1	4	3	0	3	3	1	0	0	0	0
2	0	0	0	0	1	4	1	0	1	4	3	0	3	3	1	0
3	0	0	0	0	0	1	4	1	0	1	4	3	0	3	3	1

Convolution Matrix (4, 16)

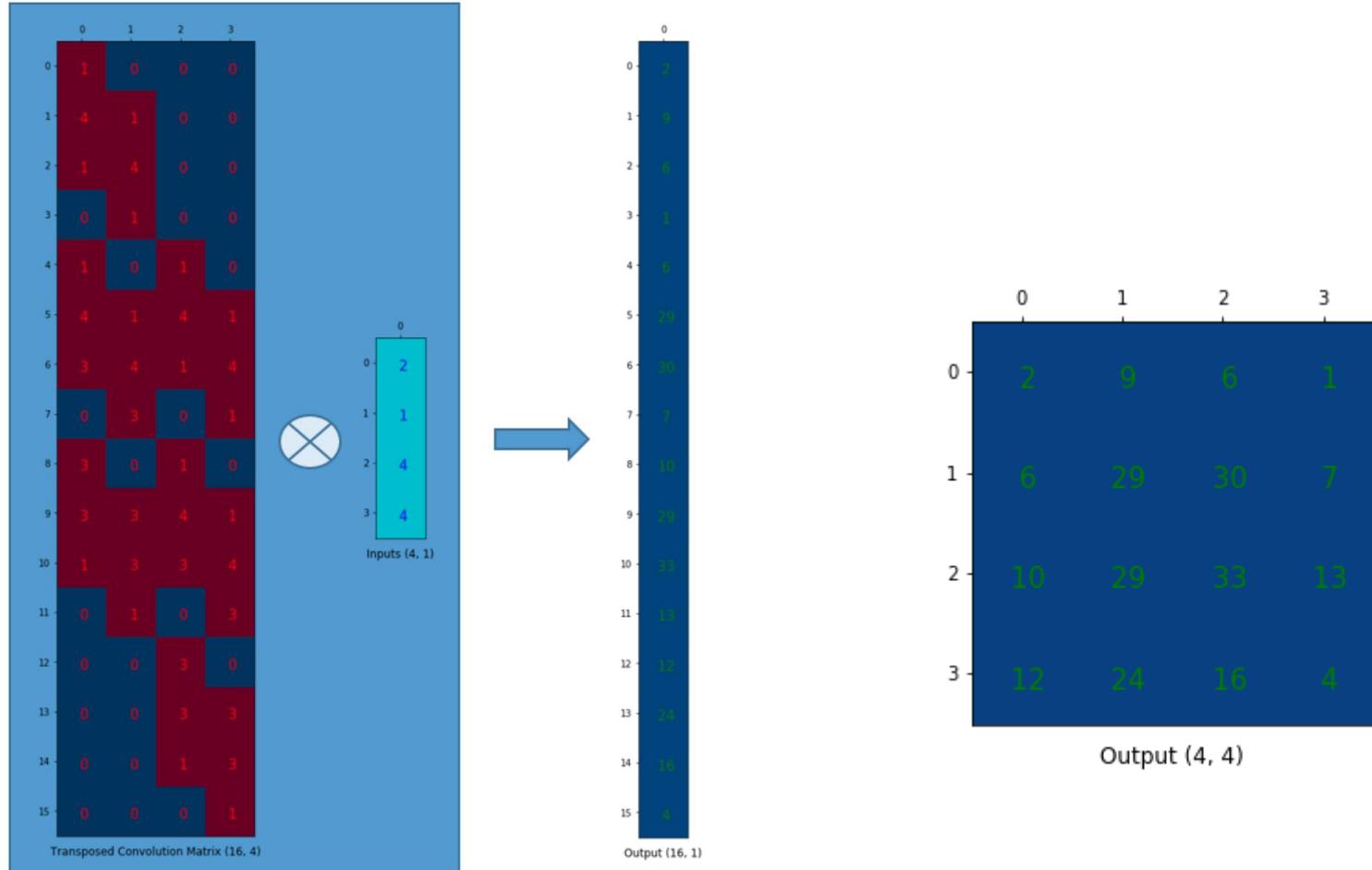
	0	1	2	3
0	4	5	8	7
1	1	8	8	8
2	3	6	6	4
3	6	5	7	8

Inputs (4, 4)

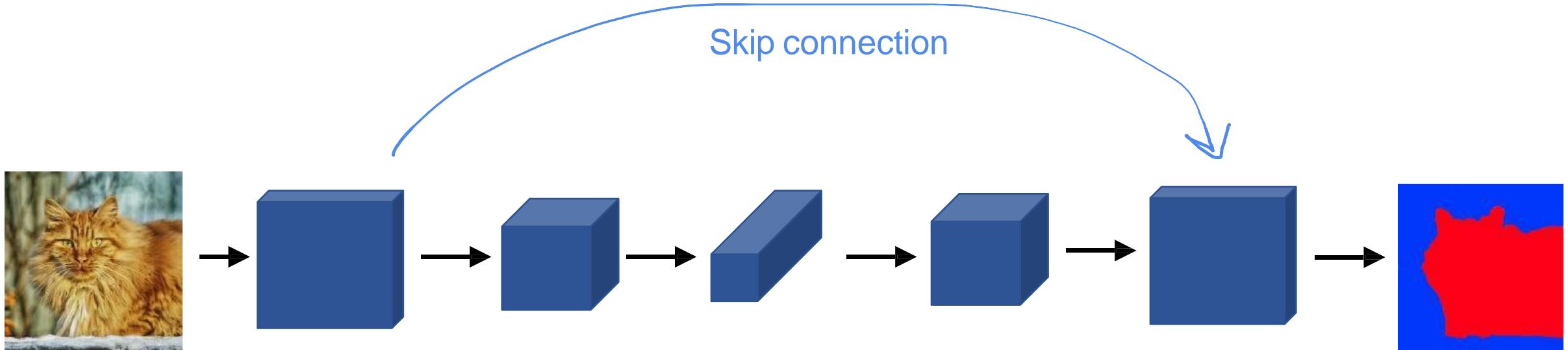




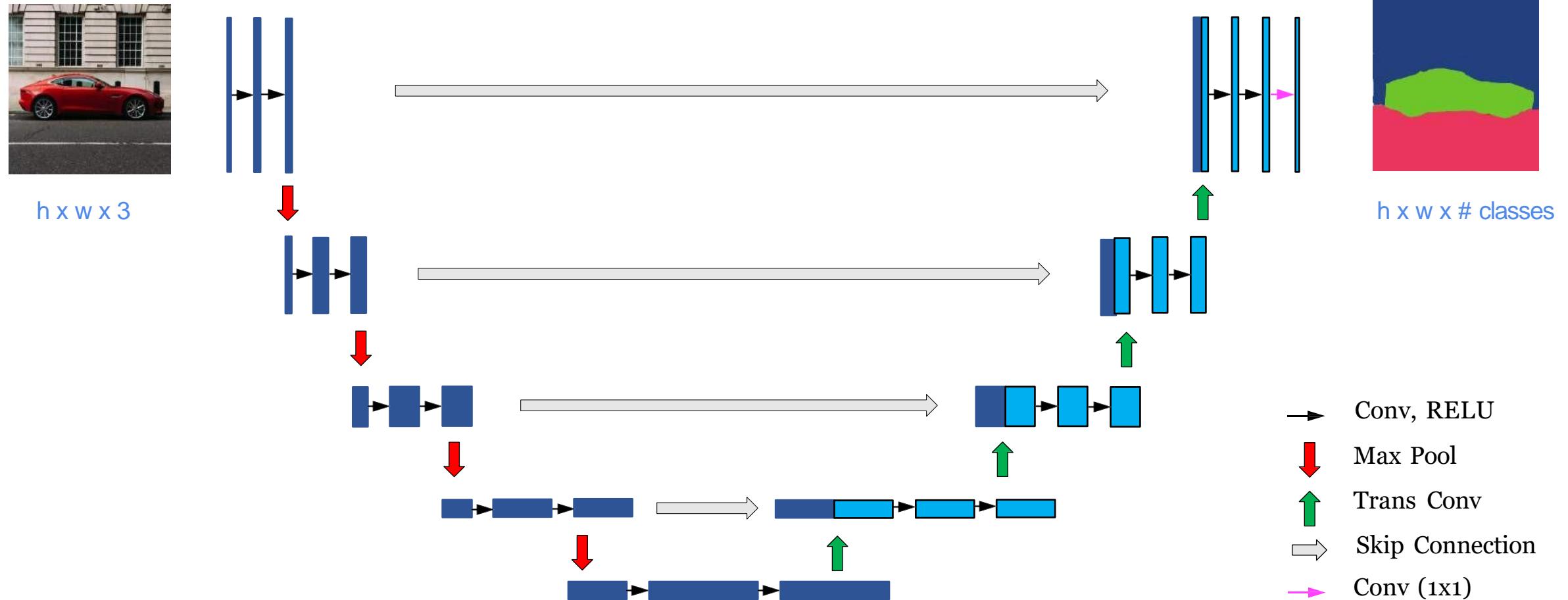
Transposed Convolution Matrix



UNET Motivation



U-Net



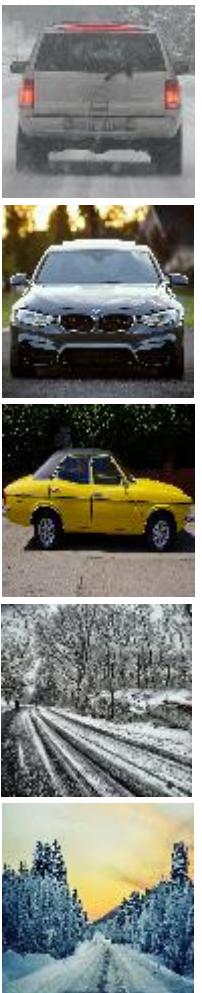
[Ronneberger et al., 2015, U-Net: Convolutional Networks for Biomedical Image Segmentation]

Car detection example

Training set:



x



y

1

1

1

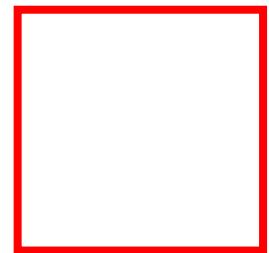
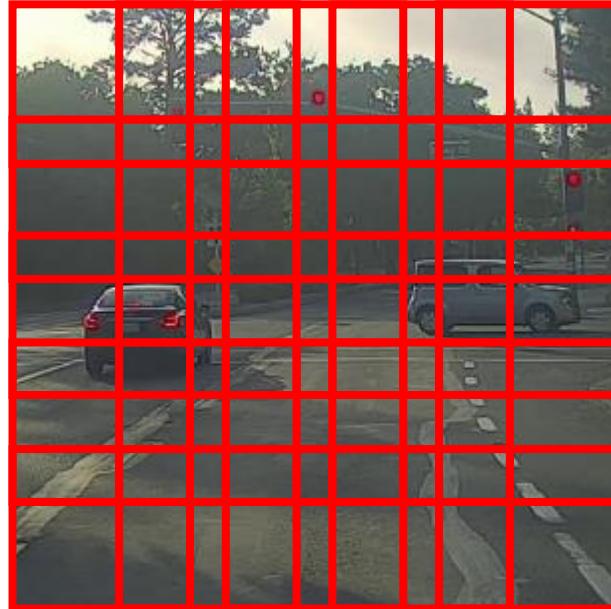
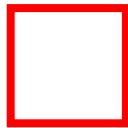
0

0

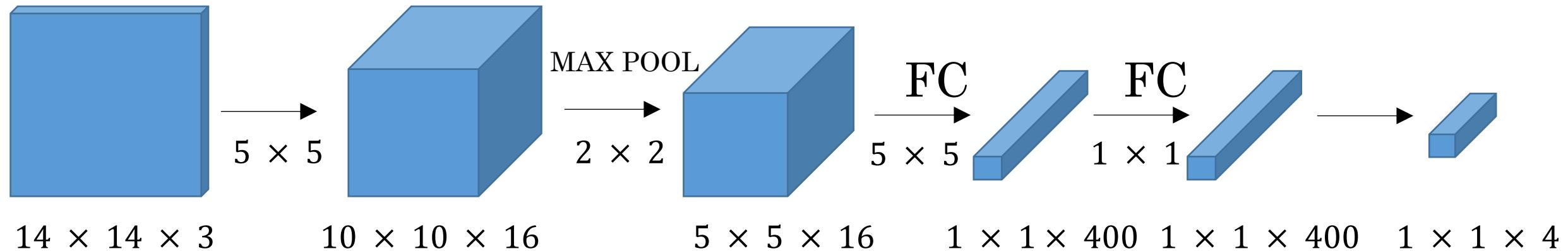
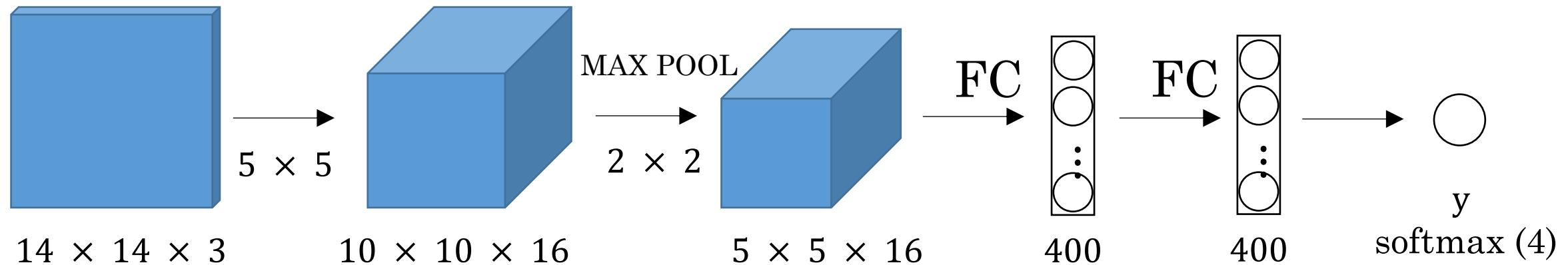


→ ConvNet → y

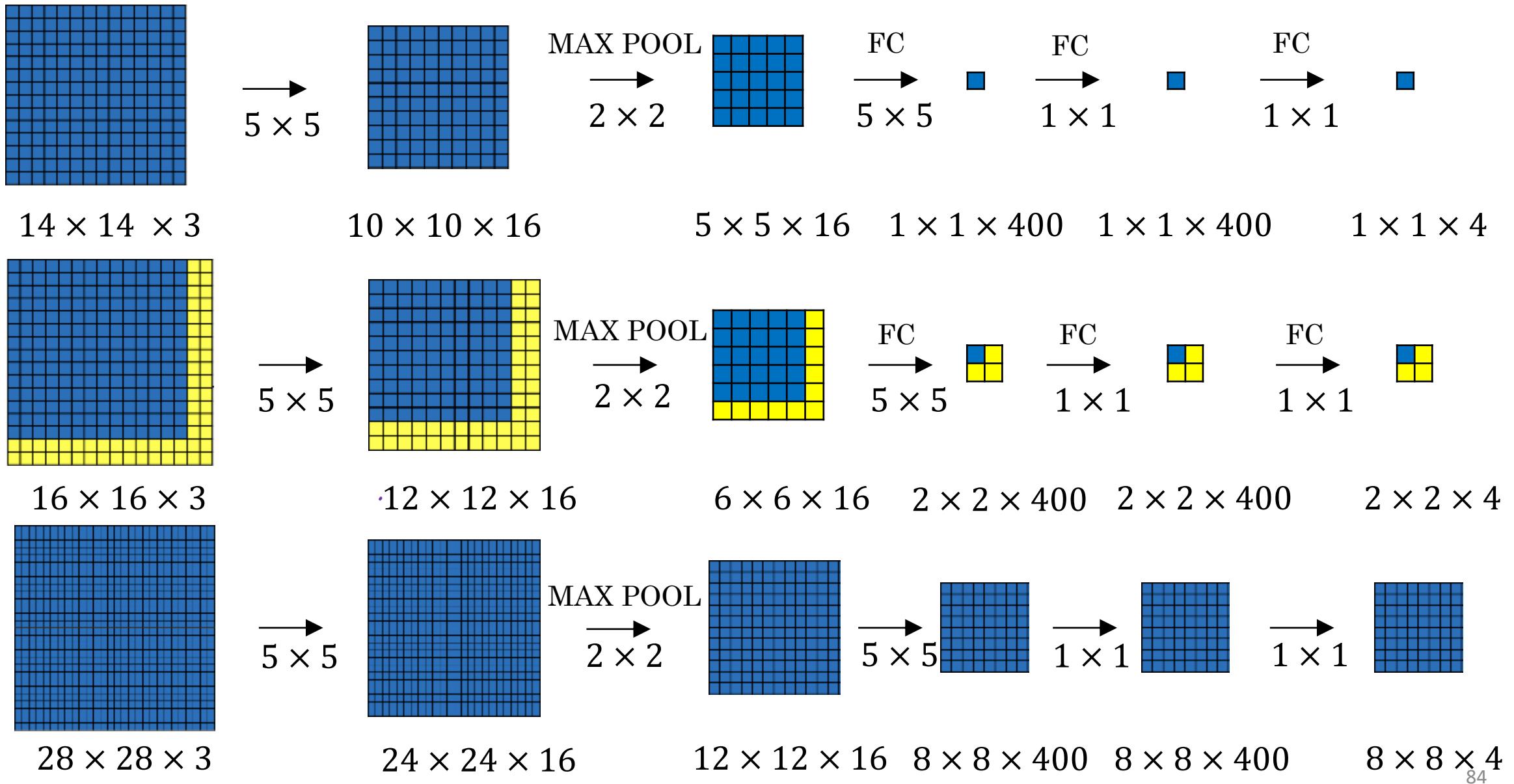
Sliding windows detection



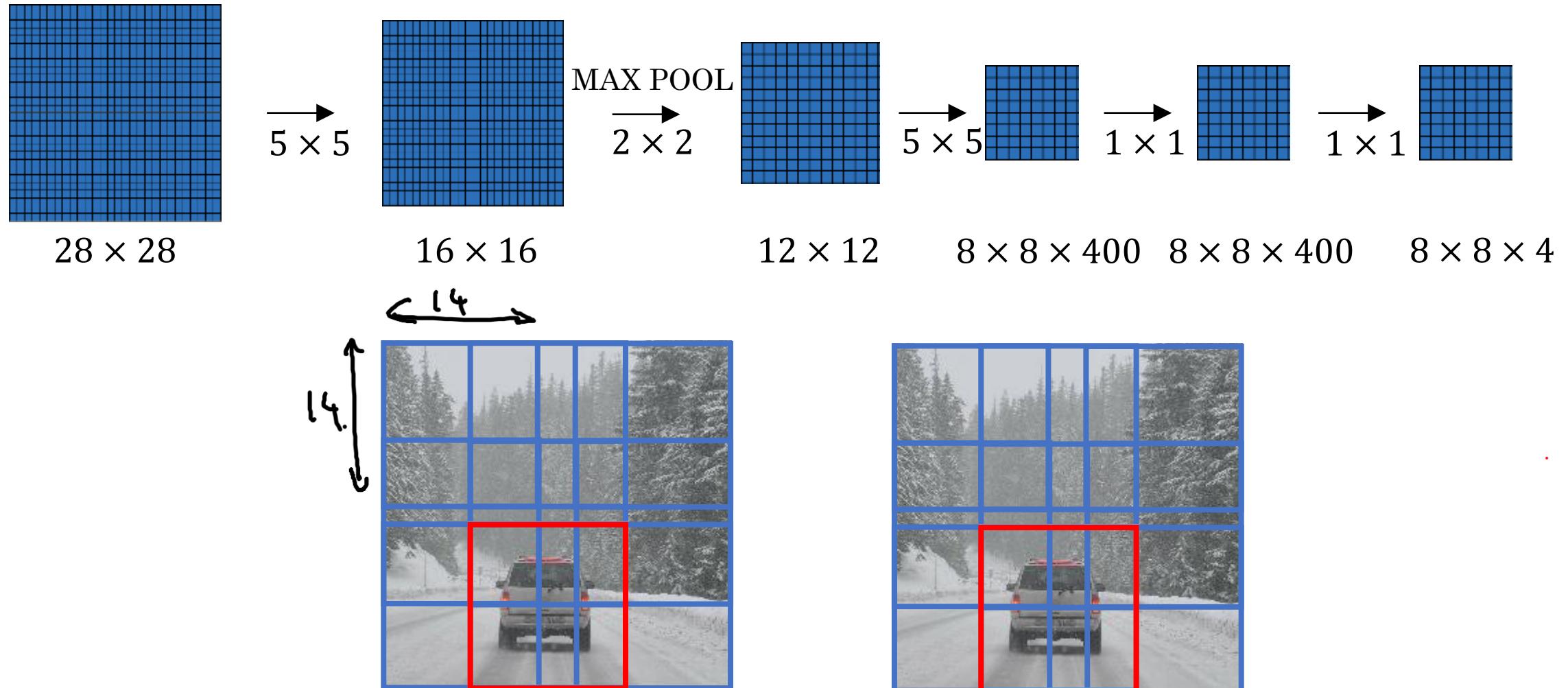
Turning FC layer into convolutional layers



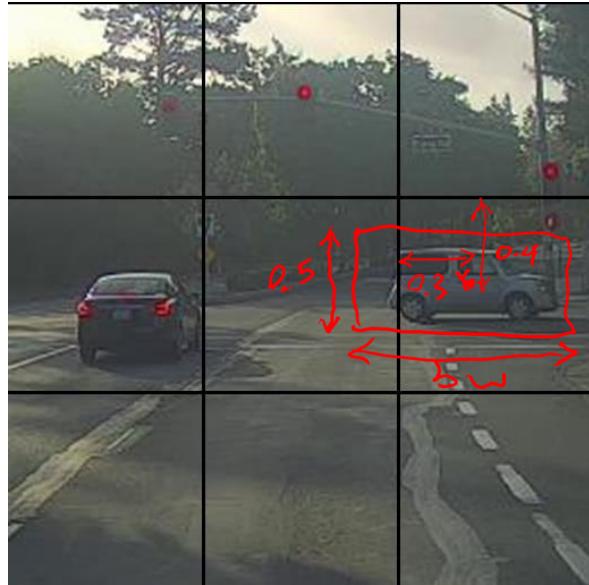
Convolution implementation of sliding windows



Convolution implementation of sliding windows

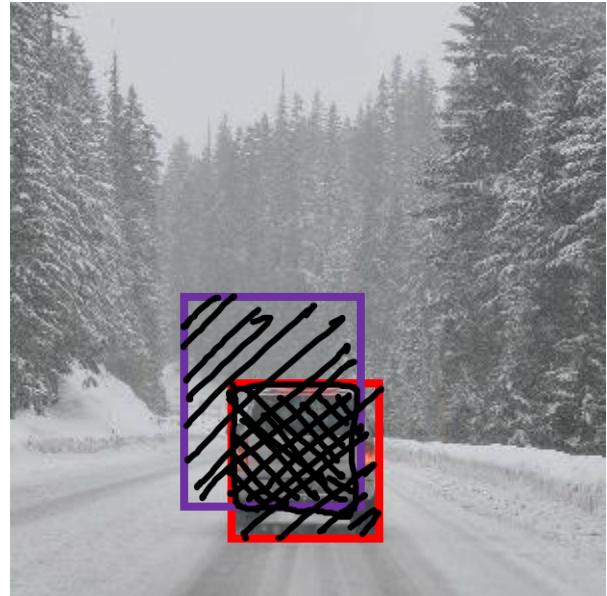


Specify the bounding boxes



$$y = \begin{bmatrix} 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix} \quad \begin{aligned} b_x &= 0.3 \\ b_y &= 0.4 \\ b_h &= 0.5 \\ b_w &= 1.1 \end{aligned}$$

Evaluating object localization



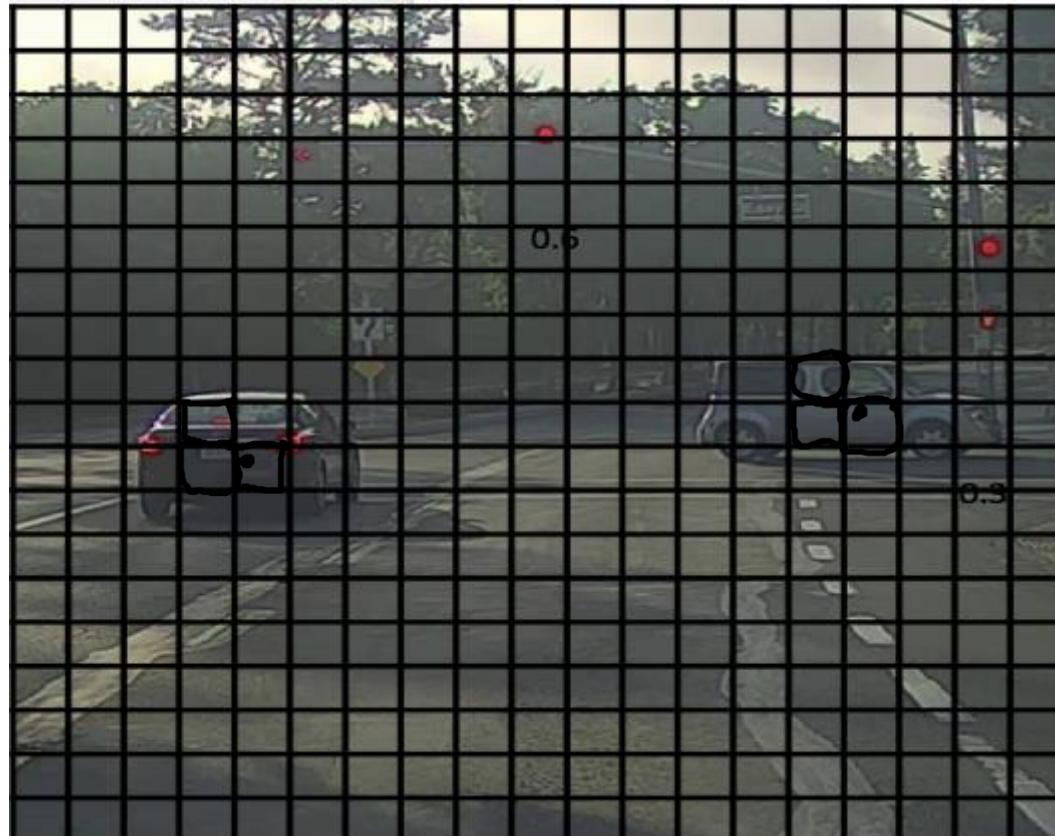
Intersection over Union (IoU)

$$= \frac{\text{Size of intersection}}{\text{Size of union}}$$

“Correct” if $\text{IoU} \geq 0.5$

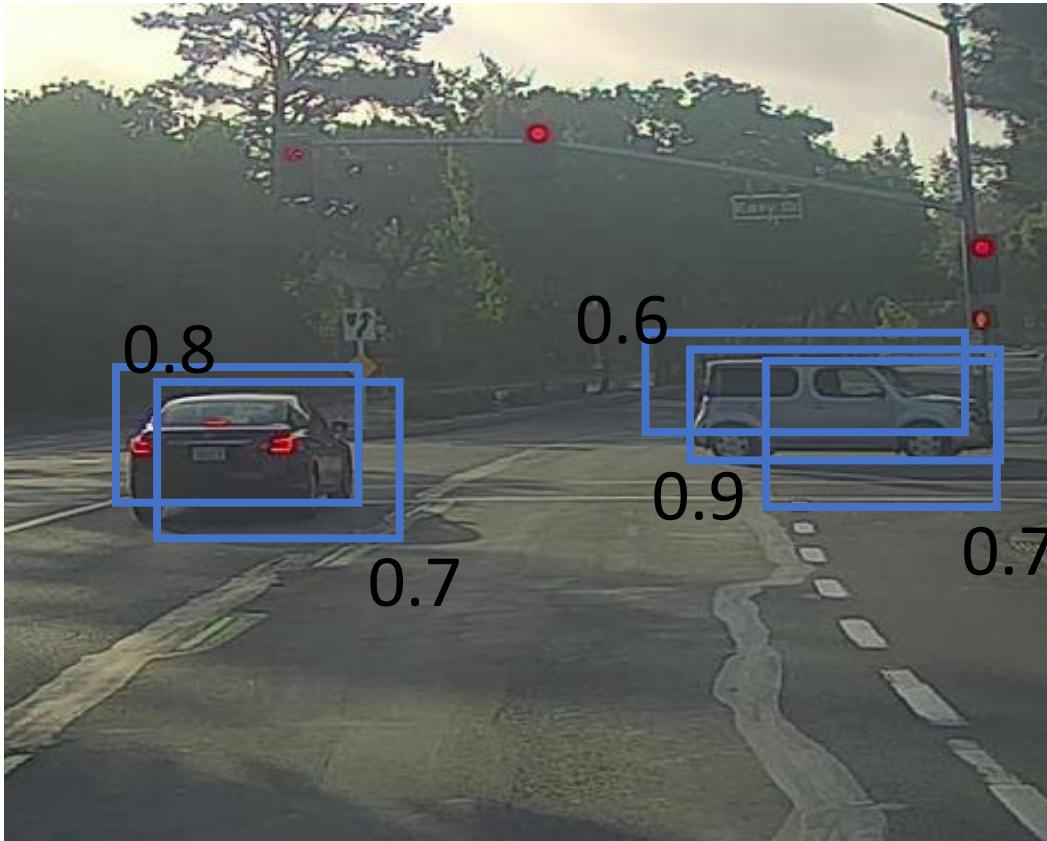
More generally, IoU is a measure of the overlap between two bounding boxes.

Non-max suppression example

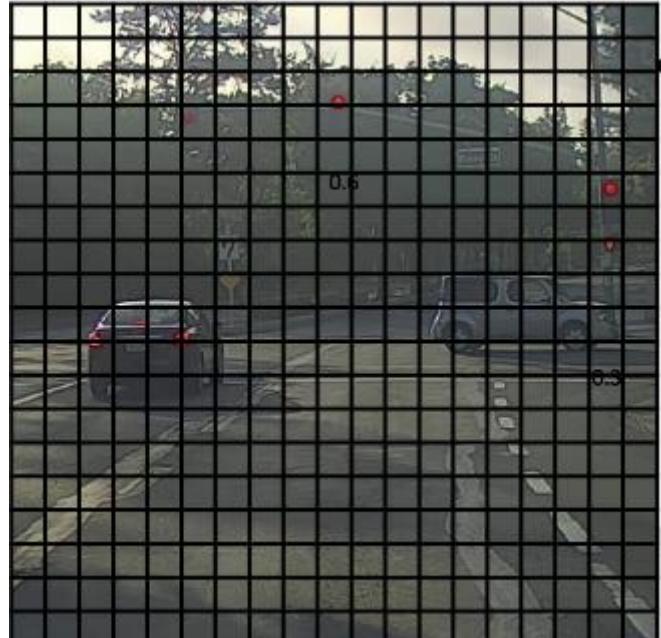


19×19

Non-max suppression example



Non-max suppression algorithm



19× 19

Each output prediction is:

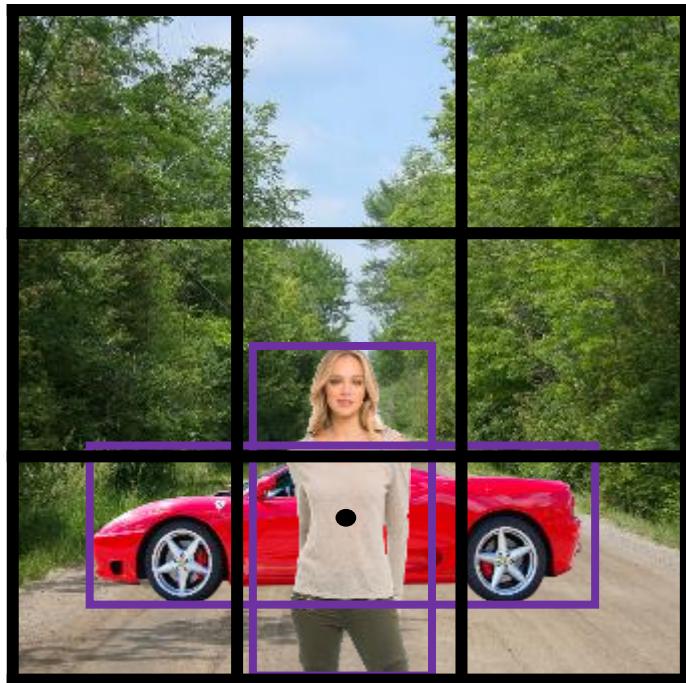
$$\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \end{bmatrix}$$

Discard all boxes with $p_c \leq 0.6$

While there are any remaining boxes:

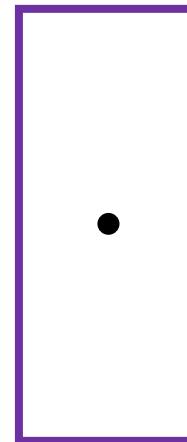
- Pick the box with the largest p_c
Output that as a prediction.
- Discard any remaining box with
 $\text{IoU} \geq 0.5$ with the box output
in the previous step

Overlapping objects:

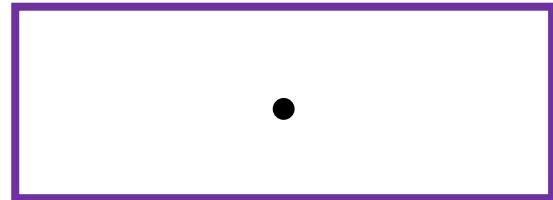


$$\mathbf{y} = \begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Anchor box 1:



Anchor box 2:



Anchor box algorithm

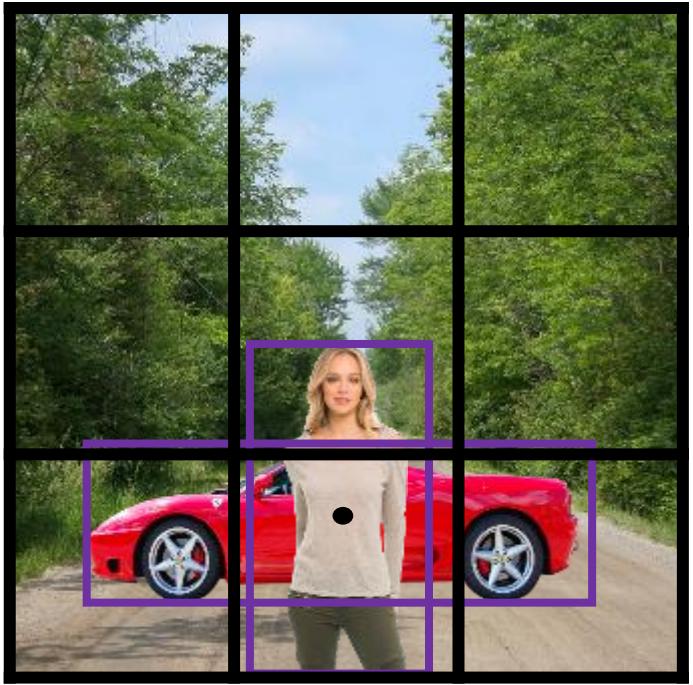
Previously:

Each object in training image is assigned to grid cell that contains that object's midpoint.

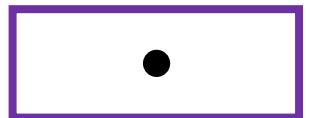
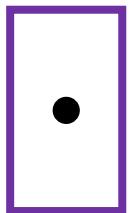
With two anchor boxes:

Each object in training image is assigned to grid cell that contains object's midpoint and anchor box for the grid cell with highest IoU.

Anchor box example



Anchor box 1: Anchor box 2:

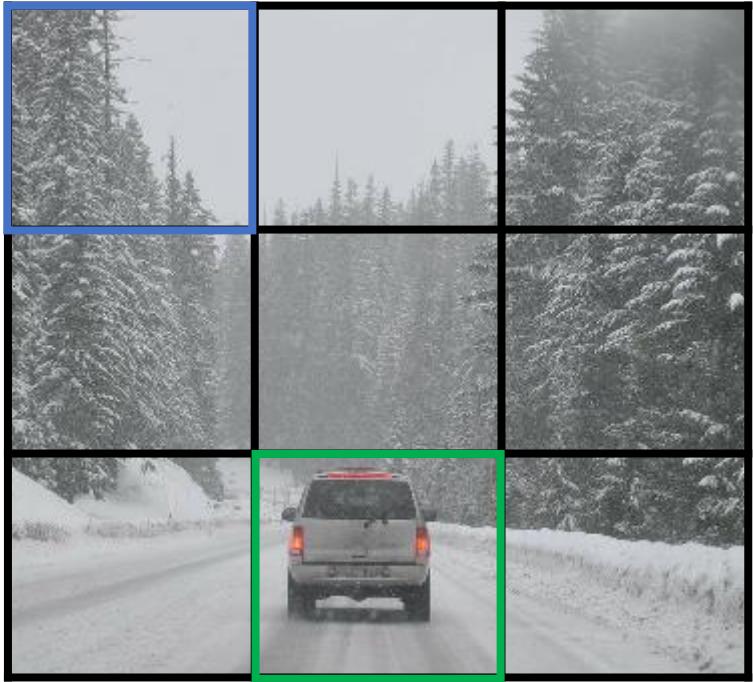


$y =$

$$\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix}$$

Please note: In the original
yolo paper, only one class set
is assigned to a cell

Training



y is $3 \times 3 \times 2 \times 8$

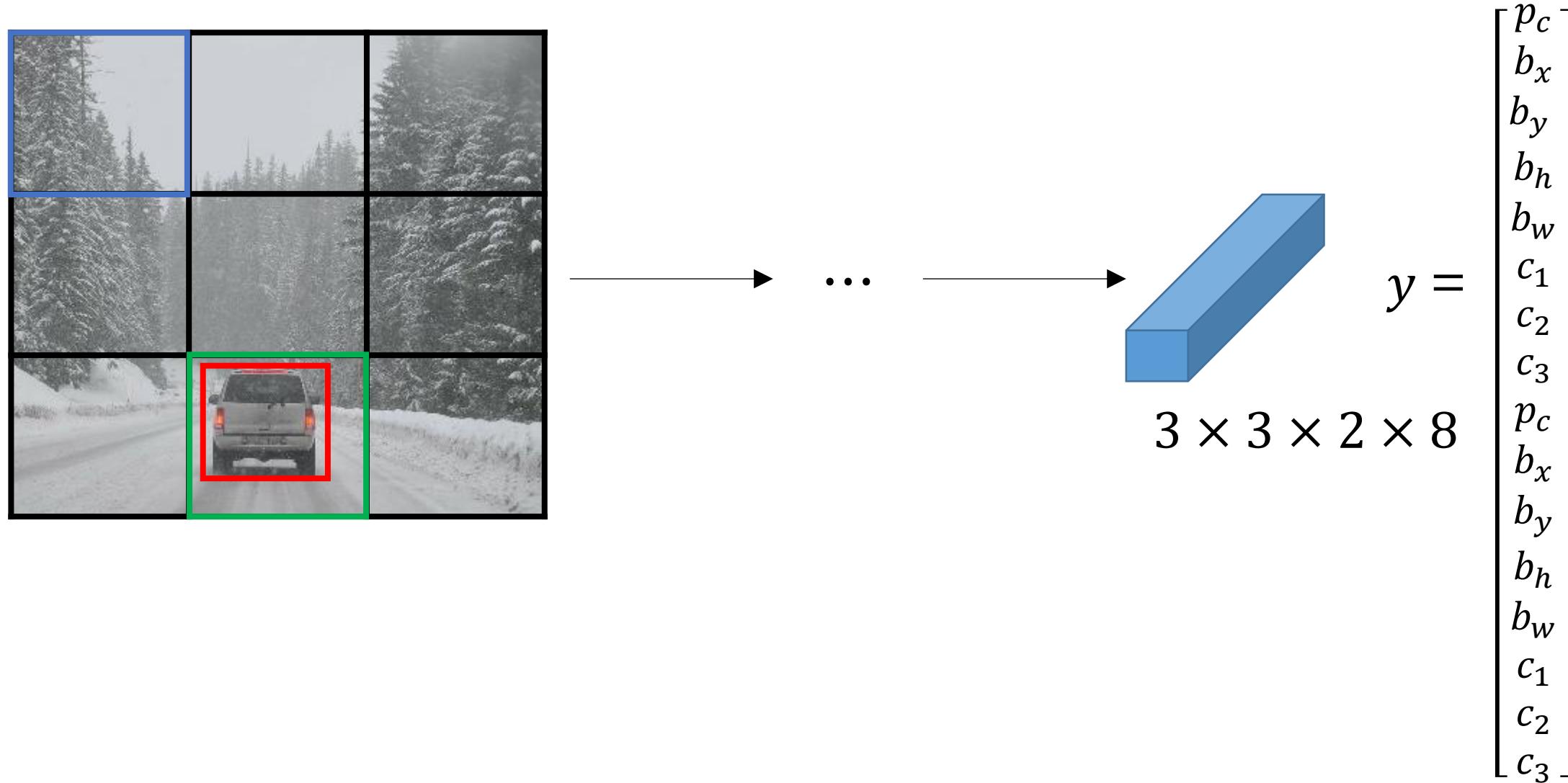
- 1 - pedestrian
- 2 - car
- 3 - motorcycle

$y =$

$$\begin{bmatrix} p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \\ p_c \\ b_x \\ b_y \\ b_h \\ b_w \\ c_1 \\ c_2 \\ c_3 \end{bmatrix} \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \end{bmatrix} \begin{bmatrix} 0 \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ ? \\ 1 \\ b_x \\ b_y \\ b_h \\ b_w \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

[Redmon et al., 2015, You Only Look Once: Unified real-time object detection]

Making predictions

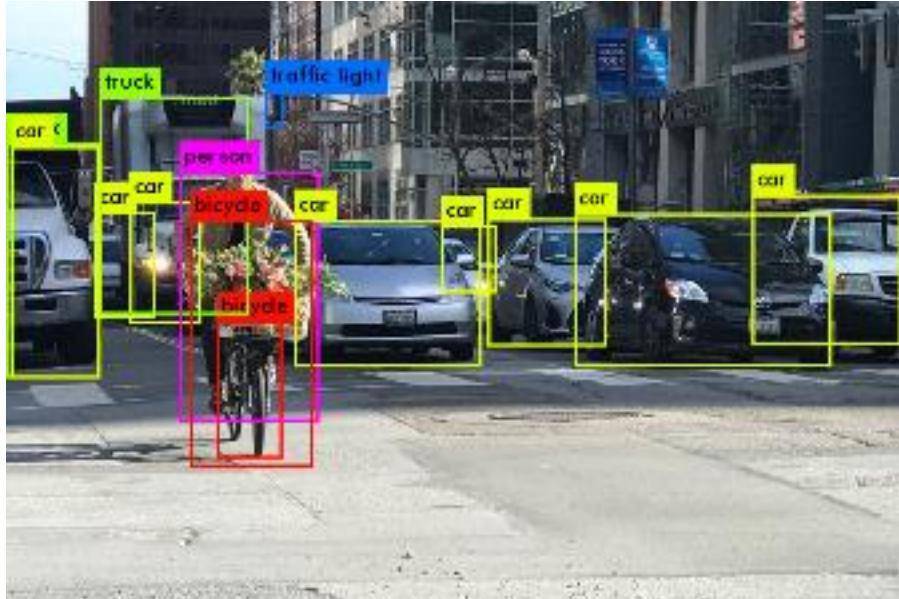


Yolo loss function

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

- 1_i^{obj} is 1 when there is an object (precisely, object's center) in cell i and 0 elsewhere. $\lambda_{coord} = 5$
 - 1_{ij}^{obj} is 1 if the j th predictor has the highest IoU with the ground truth "is responsible", else it is 0. $\lambda_{noobj} = 0.5$
- 1_{ij}^{noobj} is 1 when there is no object in the cell i and j th predictor has confidence more than the threshold

Outputting the non-max suppressed outputs



- For each grid call, get 2 predicted bounding boxes.
- Get rid of low probability predictions.
- For each class (pedestrian, car, motorcycle) use non-max suppression to generate final predictions.

Face verification vs. face recognition

Verification

- Input image, name/ID
- Output whether the input image is that of the claimed person

Recognition

- Has a database of K persons
- Get an input image
- Output ID if the image is any of the K persons (or “not recognized”)

One-shot learning

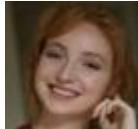


Learning from one example to recognize the person again

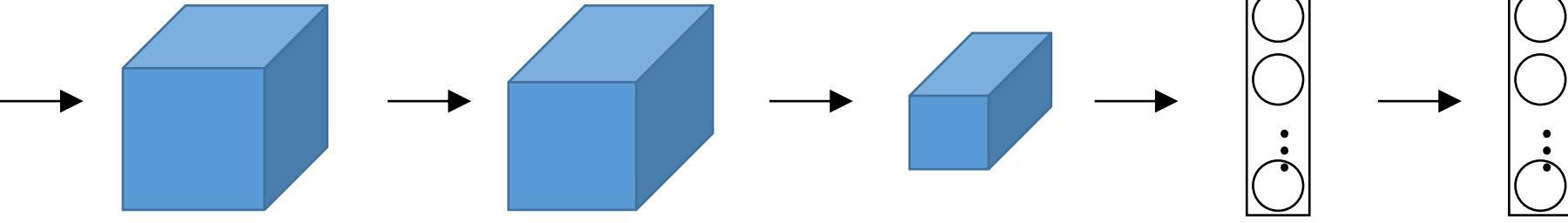
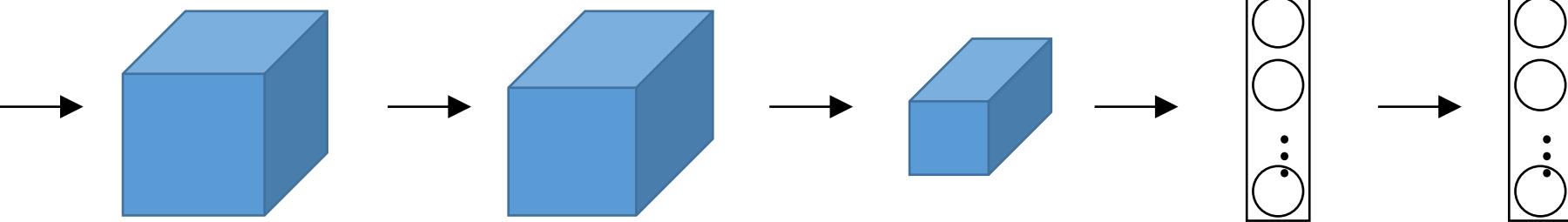
Learning a “similarity” function

$d(\text{img1}, \text{img2}) = \text{degree of difference between images}$

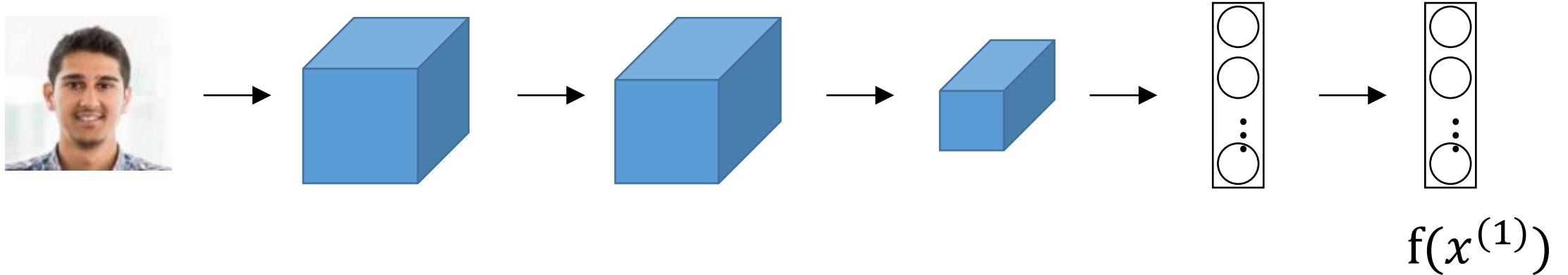
If $d(\text{img1}, \text{img2}) \leq \tau$ same
 $> \tau$ different



Siamese network

 $x^{(1)}$  $x^{(2)}$

Goal of learning



Parameters of NN define an encoding $f(x^{(i)})$

Learn parameters so that:

If $x^{(i)}, x^{(j)}$ are the same person, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is small.

If $x^{(i)}, x^{(j)}$ are different persons, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is large.

Contrastive loss

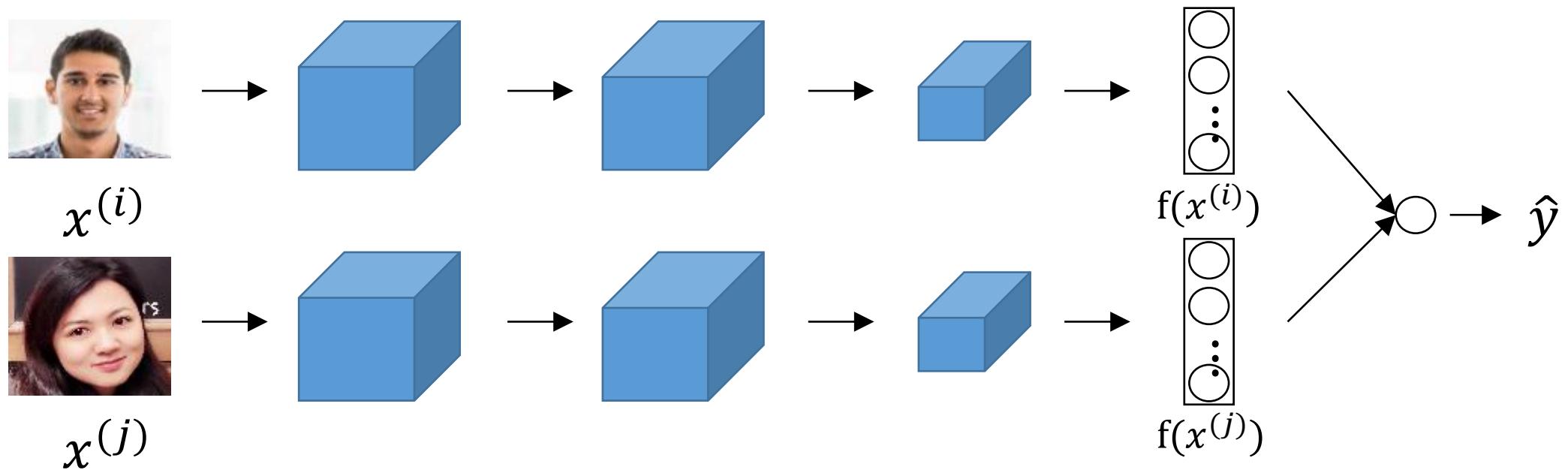
If $x^{(i)}, x^{(j)}$ are the same person, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is small.

If $x^{(i)}, x^{(j)}$ are different persons, $\|f(x^{(i)}) - f(x^{(j)})\|^2$ is large.

$$(Y) \boxed{(D_W)^2} + (1 - Y) \boxed{\{max(0, m - D_W)\}^2}$$

Y is 0 for dissimilar pairs and 1 for similar pairs.

Learning the similarity function



$$d(f_1, f_2) = \sum_i \alpha_i |f_1[i] - f_2[i]|$$

$$\chi^2(f_1, f_2) = \sum_i w_i (f_1[i] - f_2[i])^2 / (f_1[i] + f_2[i])$$

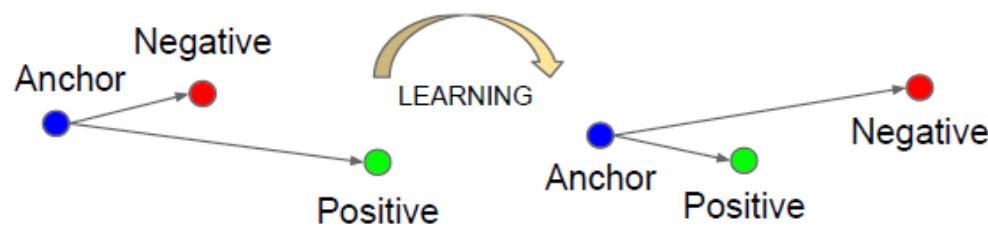
Face verification supervised learning

x	y
	 1
	 0
	 0
	 1

Triplet loss



Anchor Positive



Anchor Negative

$$\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2$$

$$\sum_i^N \left[\|f(x_i^a) - f(x_i^p)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \right]_+$$

Choosing the triplets A,P,N

During training, if A,P,N are chosen randomly,
 $d(A, P) + \alpha \leq d(A, N)$ is easily satisfied.

Choose triplets that're “hard” to train on.

Training set using triplet loss

Anchor



Positive



Negative



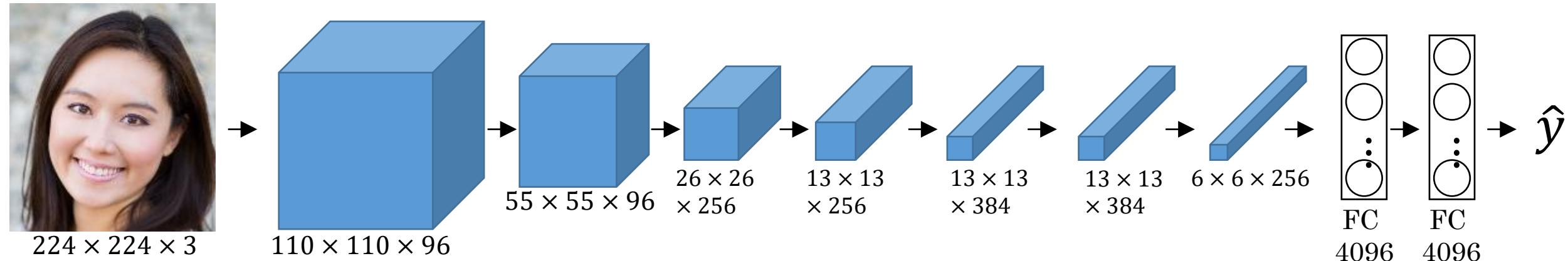
⋮

⋮

⋮



Visualizing what a deep network is learning



Pick a unit in layer 1. Find the nine image patches that maximize the unit's activation.

Repeat for other units.

Visualizing deep layers: Layer 1



Layer 1



Layer 2



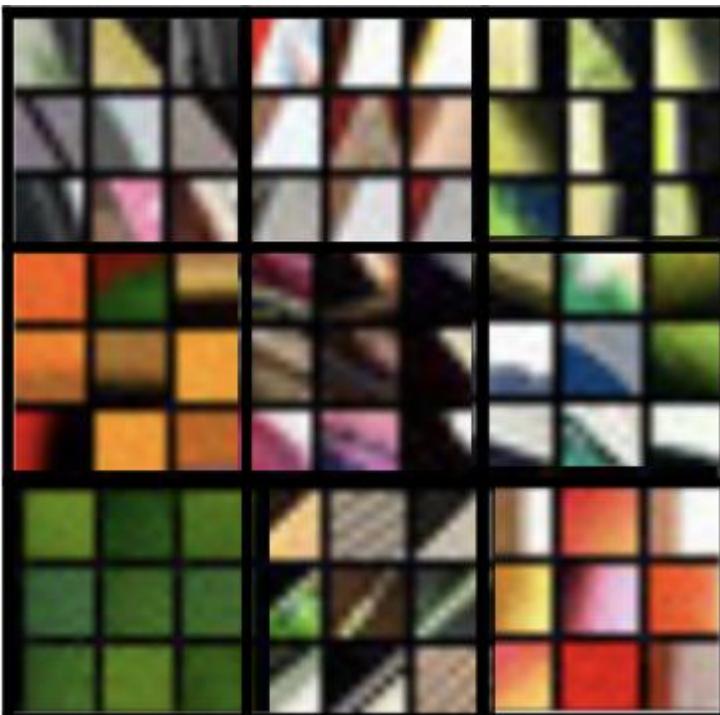
Layer 3



Layer 4



Layer 5



Visualizing deep layers: Layer 2



Layer 1



Layer 2



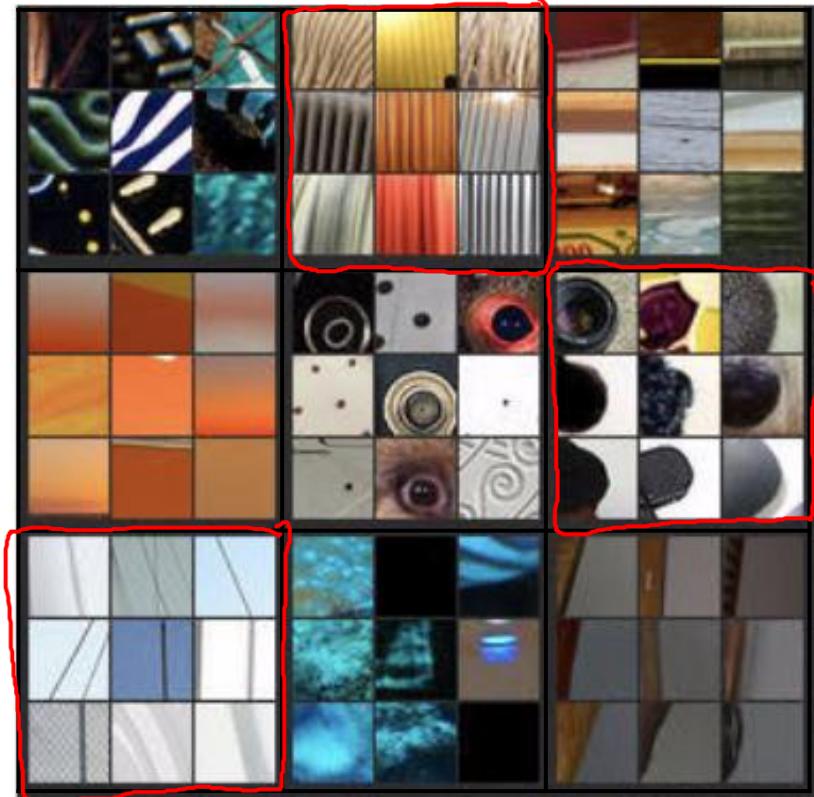
Layer 3



Layer 4



Layer 5



Visualizing deep layers: Layer 3



Layer 1



Layer 2



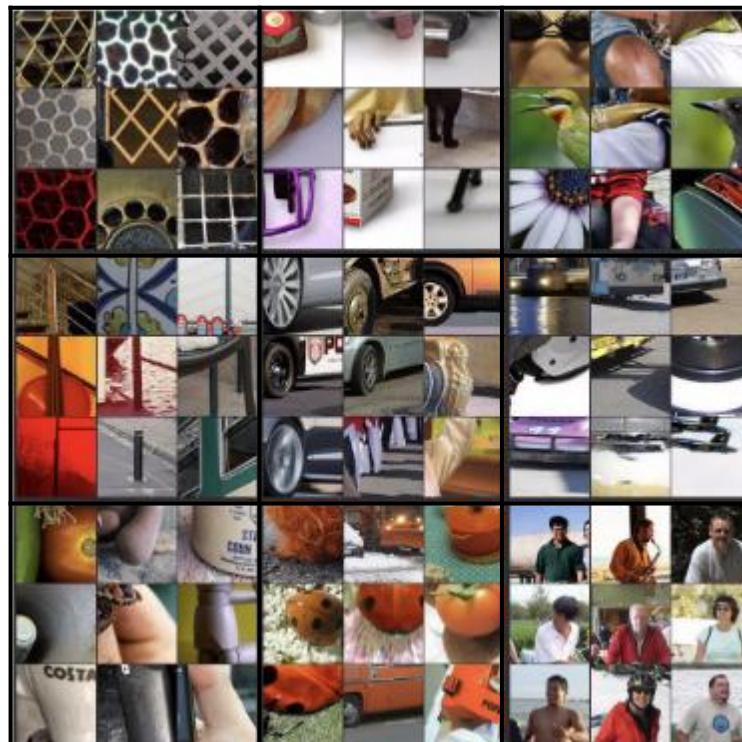
Layer 3



Layer 4



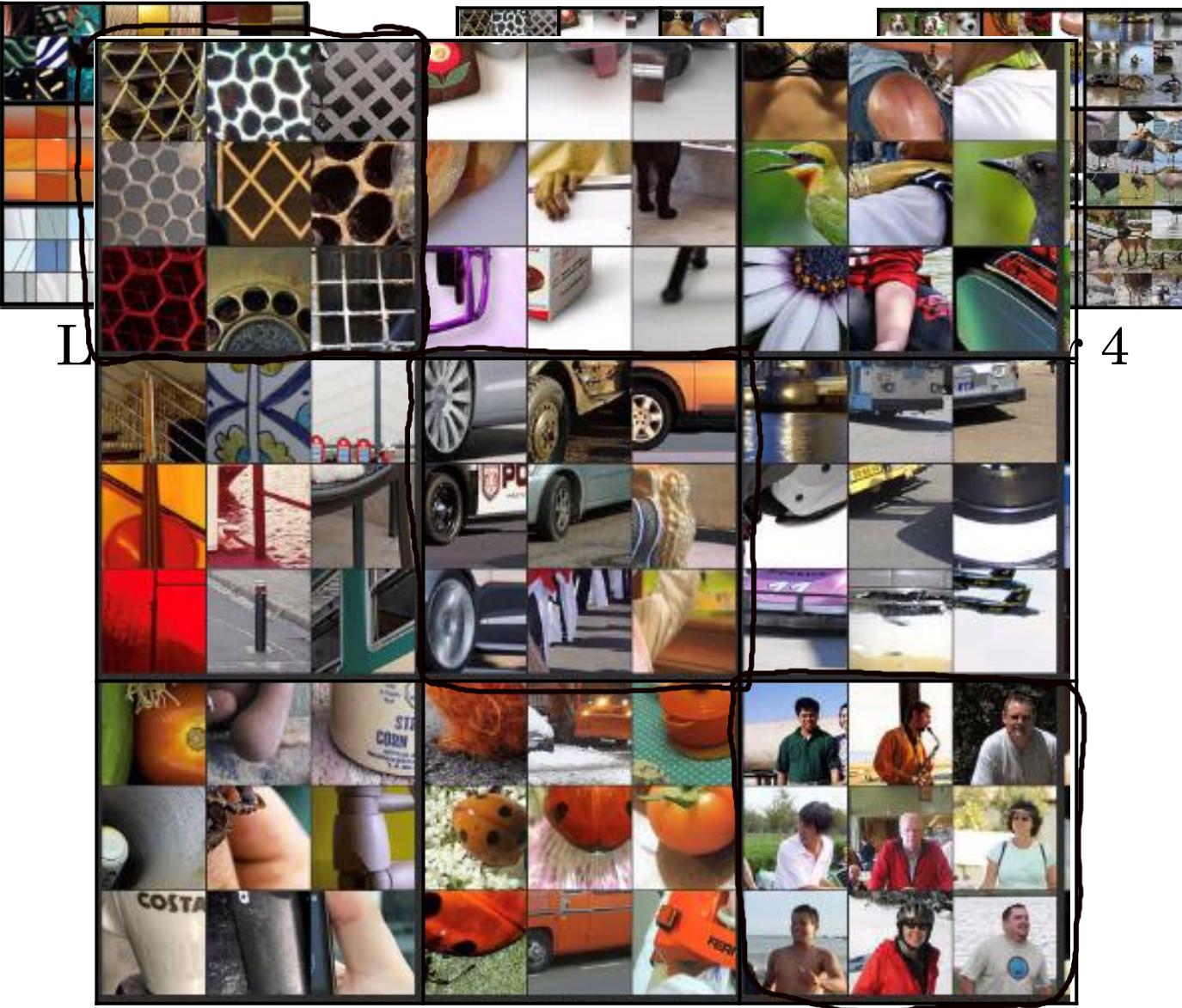
Layer 5



Visualizing deep layers: Layer 3



Layer 1



Layer 3

Layer 4



Layer 5

Visualizing deep layers: Layer 4



Layer 4



Layer 4



Layer 5

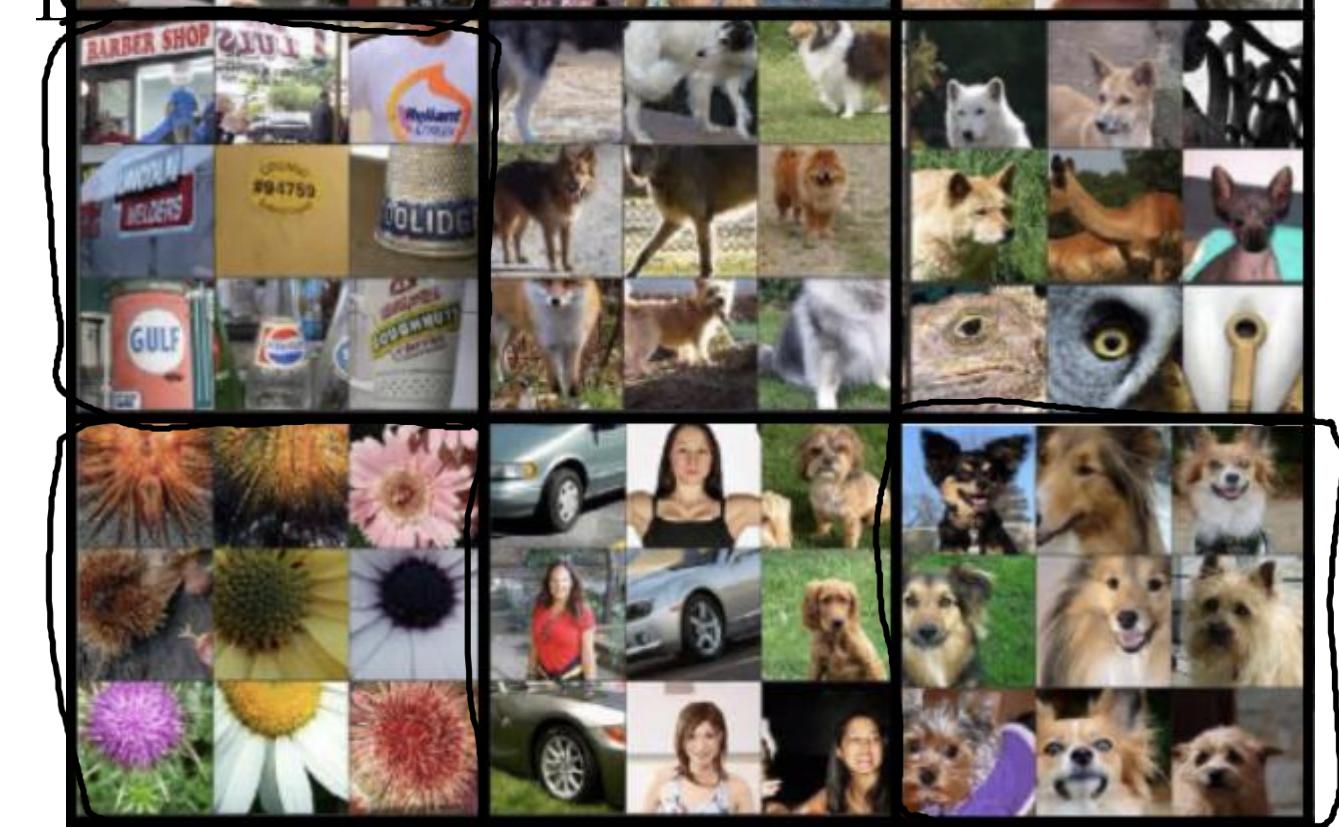
Visualizing deep layers: Layer 5



Layer 1



Layer 5

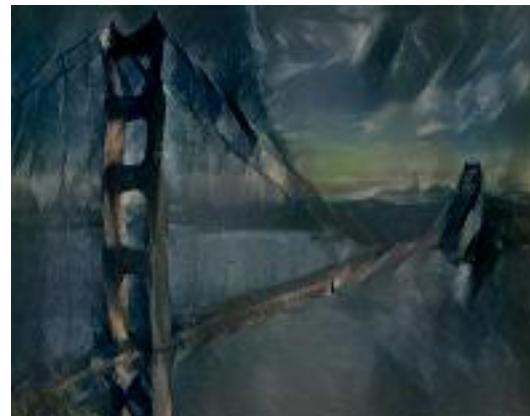


Layer 5

Neural Style Transfer



Content Style



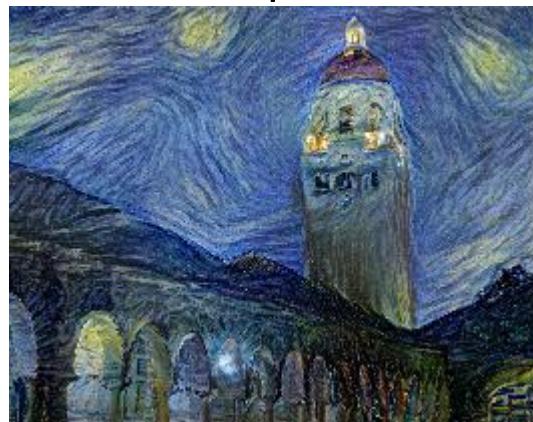
Generated image

Neural style transfer cost function



Content C

Style S

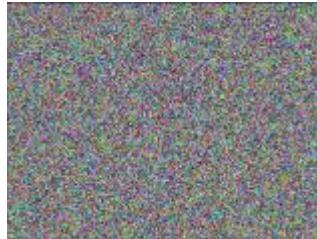


Generated image G

Find the generated image G

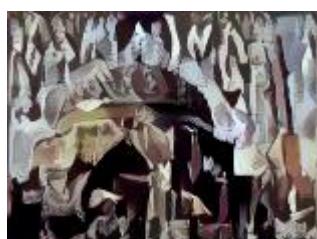
1. Initiate G randomly

G: $100 \times 100 \times 3$



2. Use gradient descent to minimize $J(G)$

$$G = G - \frac{\delta J(G)}{\delta G}$$



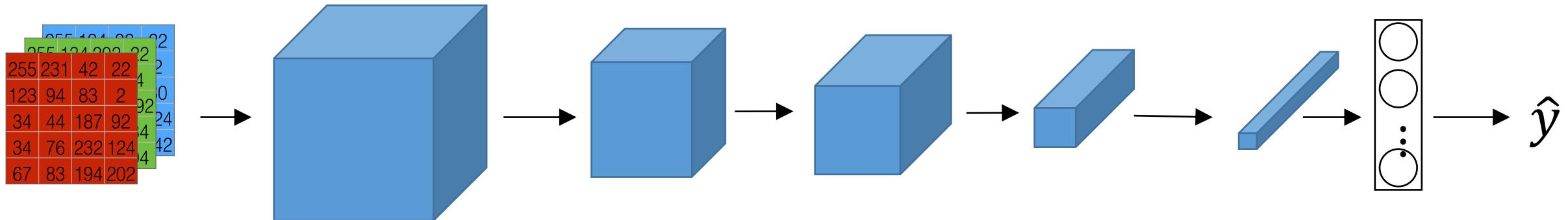
Content cost function

$$J(G) = \alpha J_{content}(C, G) + \beta J_{style}(S, G)$$

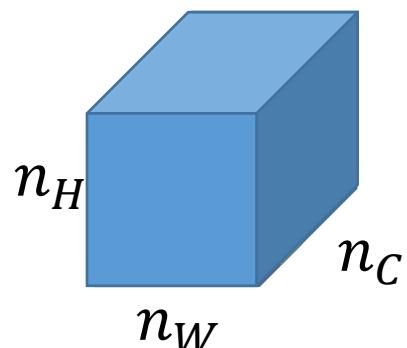
- Say you use hidden layer l to compute content cost.
- Use pre-trained ConvNet. (E.g., VGG network)
- Let $a^{[l](C)}$ and $a^{[l](G)}$ be the activation of layer l on the images
- If $a^{[l](C)}$ and $a^{[l](G)}$ are similar, both images have similar content

$$J_{content}(C, G) = \frac{1}{2} \times (a^{[L][C]} - a^{[L][G]})^2$$

Meaning of the “style” of an image



Say you are using layer l 's activation to measure “style.”
Define style as correlation between activations across channels.



$$\text{Gram}_{KK'}^{[L][G]} = \sum_{i=1}^{nh} \sum_{j=1}^{nw} a_{ijk}^{[L][G]} a_{ijk'}^{[L][G]}$$

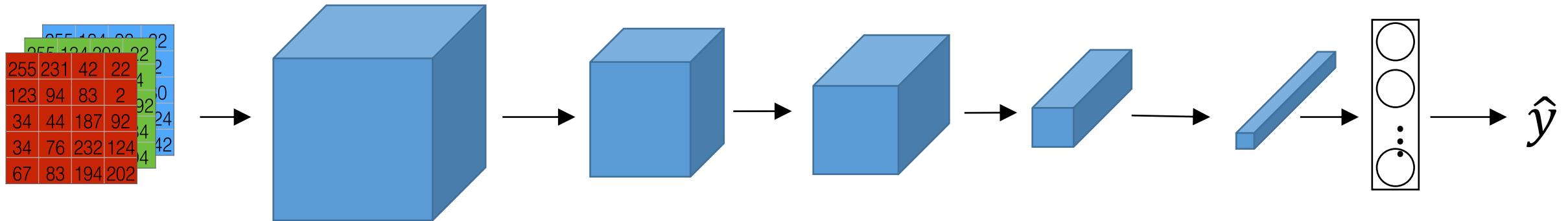
where,

nh = height of gram matrix

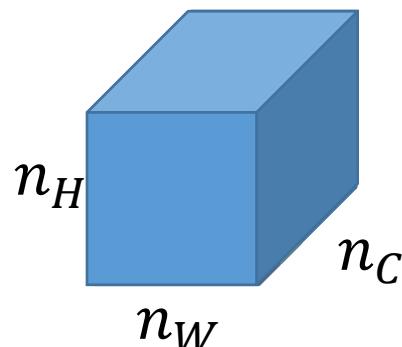
nw = width of gram matrix

n_C = number of channels in gram matrix

Meaning of the “style” of an image



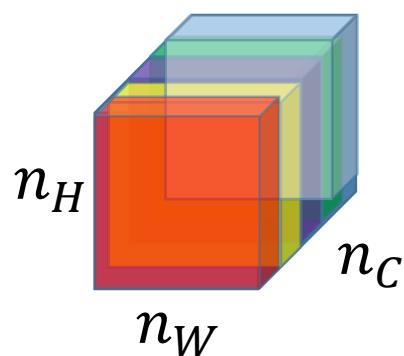
Say you are using layer l 's activation to measure “style.”
Define style as correlation between activations across channels.



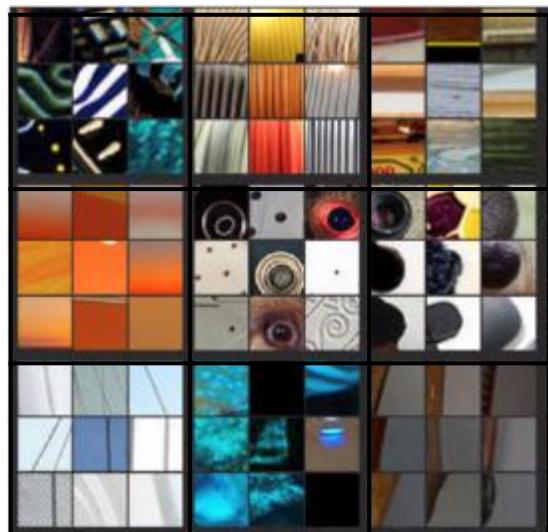
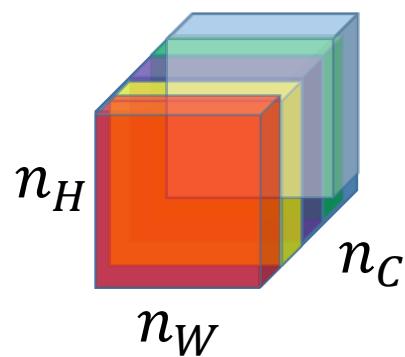
How correlated are the activations
across different channels?

Intuition about style of an image

Style image



Generated Image



$$\text{Gram}_{KK'}^{[L][S]} = \sum_{i=1}^{nh} \sum_{j=1}^{nw} a_{ijk}^{[L][G]} a_{ijk'}^{[L][G]}$$

where,

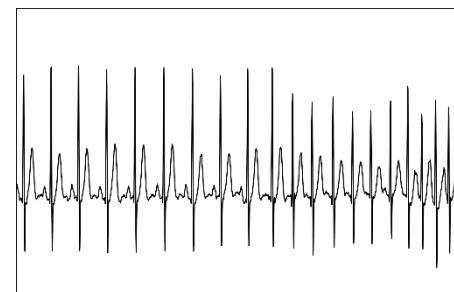
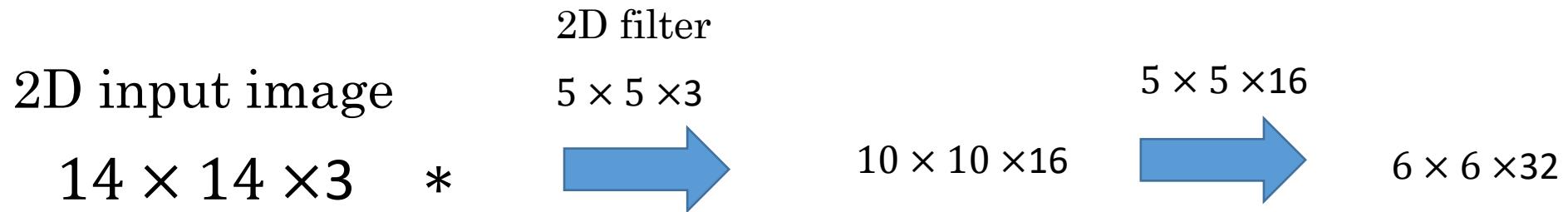
nh = height of gram matrix

nw = width of gram matrix

nc = number of channels in gram matrix

$$J_{\text{style}}(S, G) = \frac{1}{(2 \times nh \times nw \times nc)^2} \times \sum_K \sum_{K'} (\text{Gram}^{[L][S]} - \text{Gram}^{[L][G]})^2$$

Convolutions in 2D and 1D



*



1	20	15	3	18	12	4	17
---	----	----	---	----	----	---	----

1	3	10	3	1
---	---	----	---	---

1D input data

14×1

*

1D filter

5×1



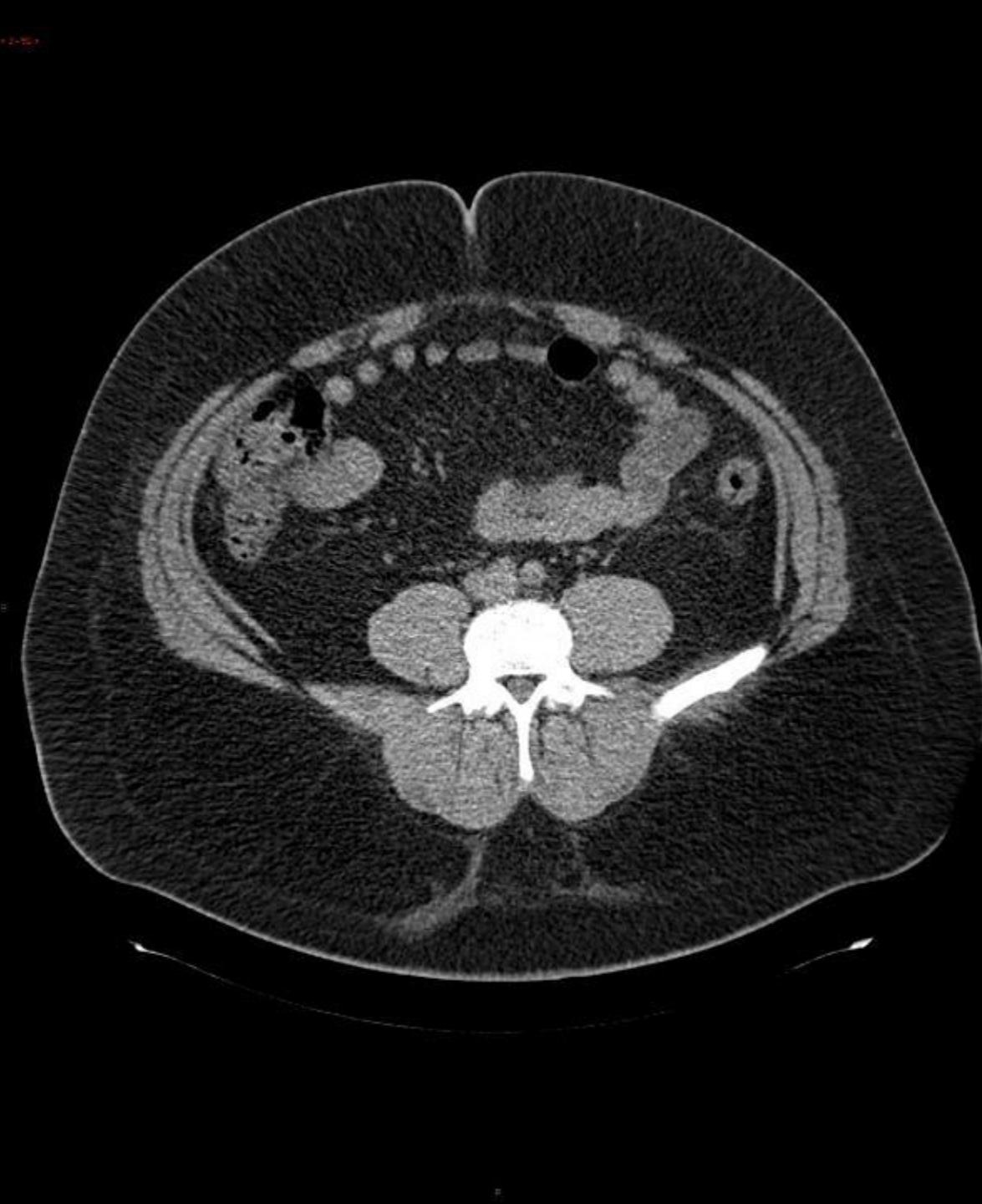
10×16

5×16



6×32

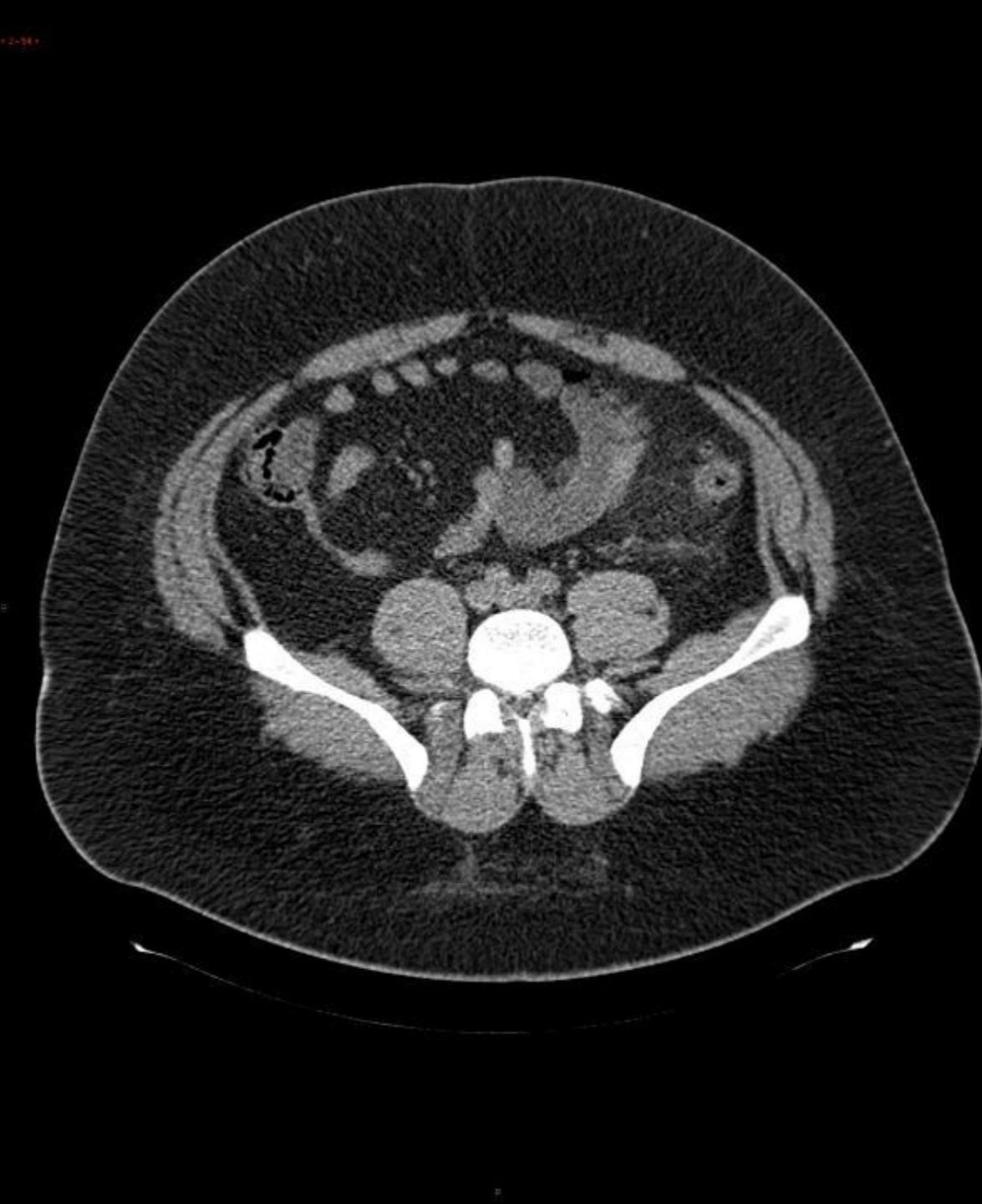
3D data



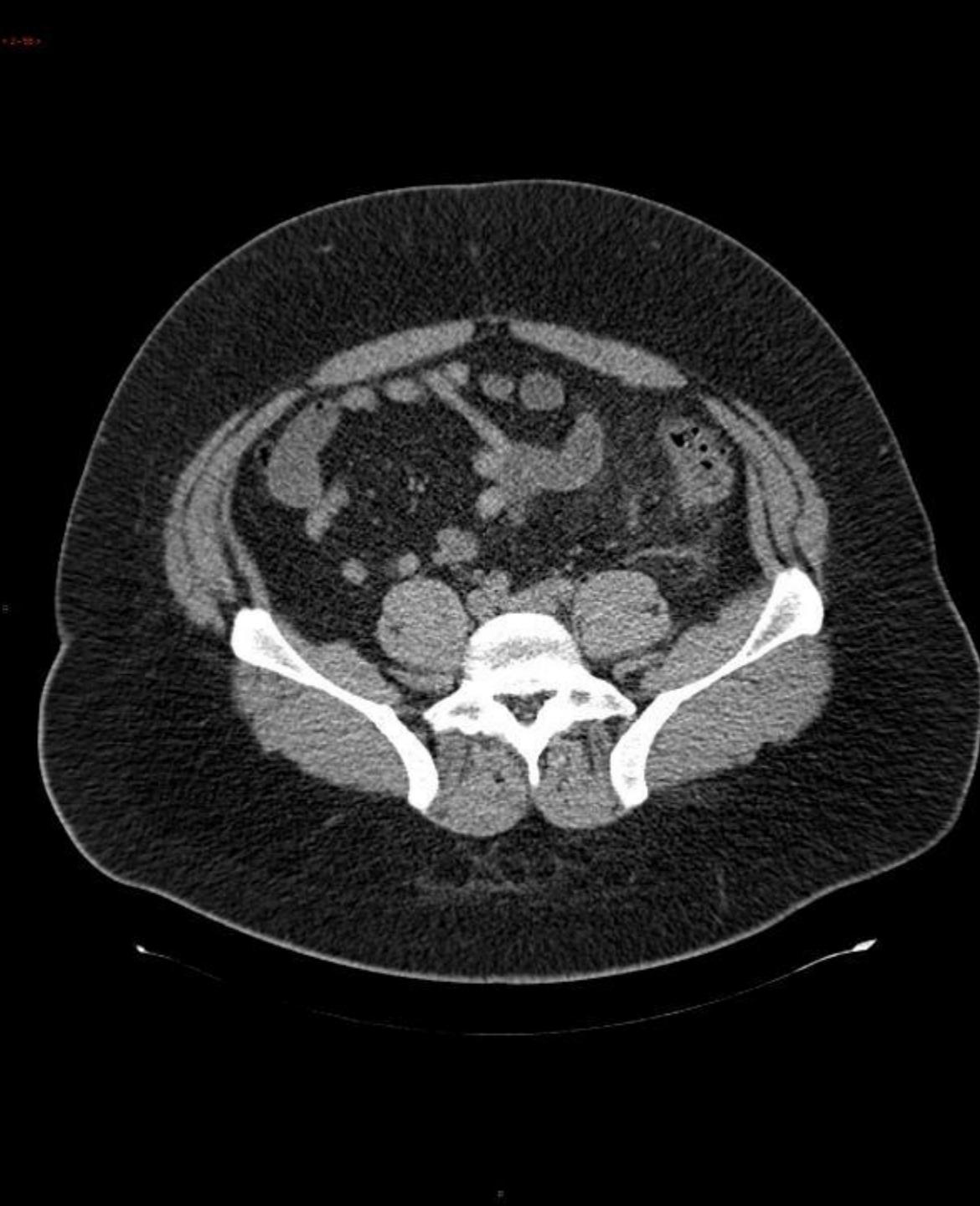
3D data



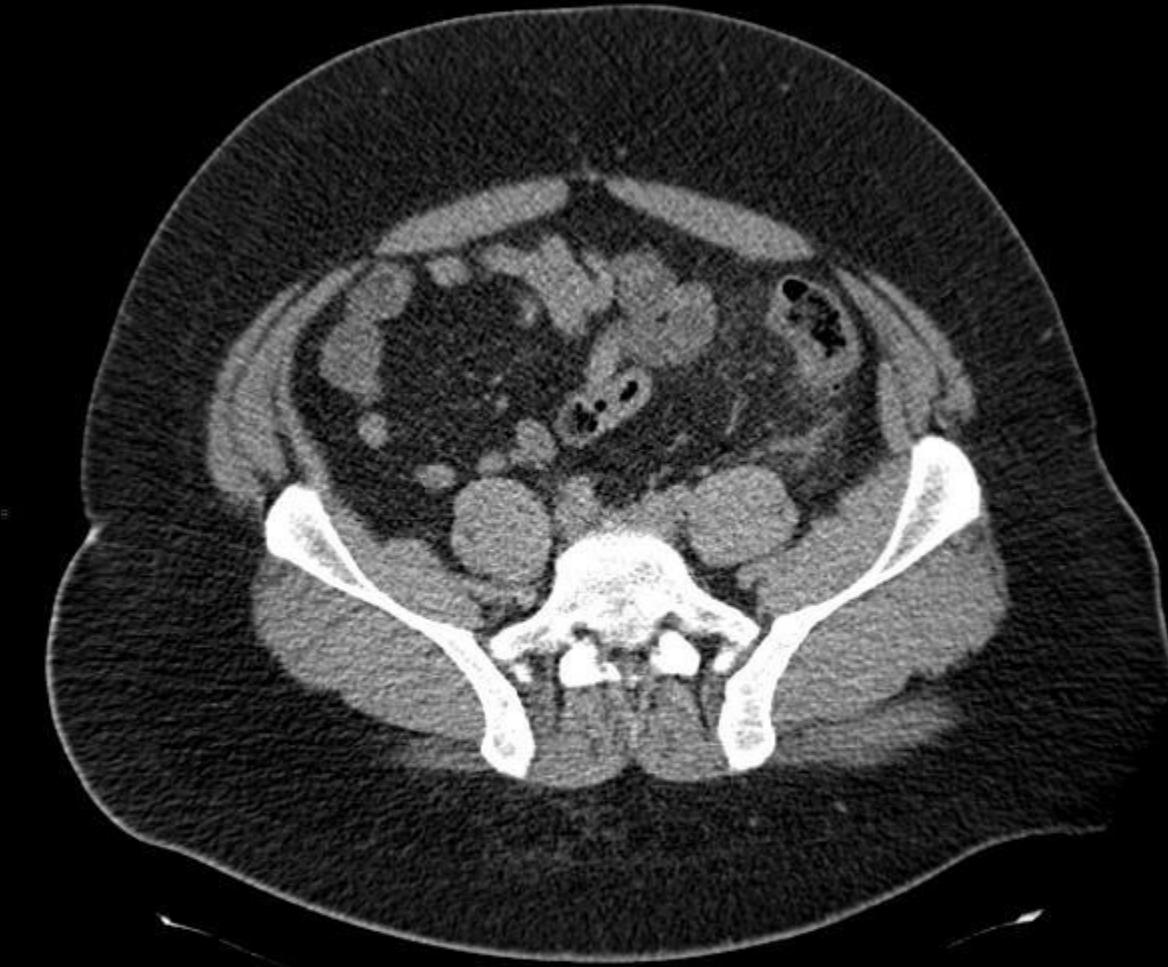
3D data



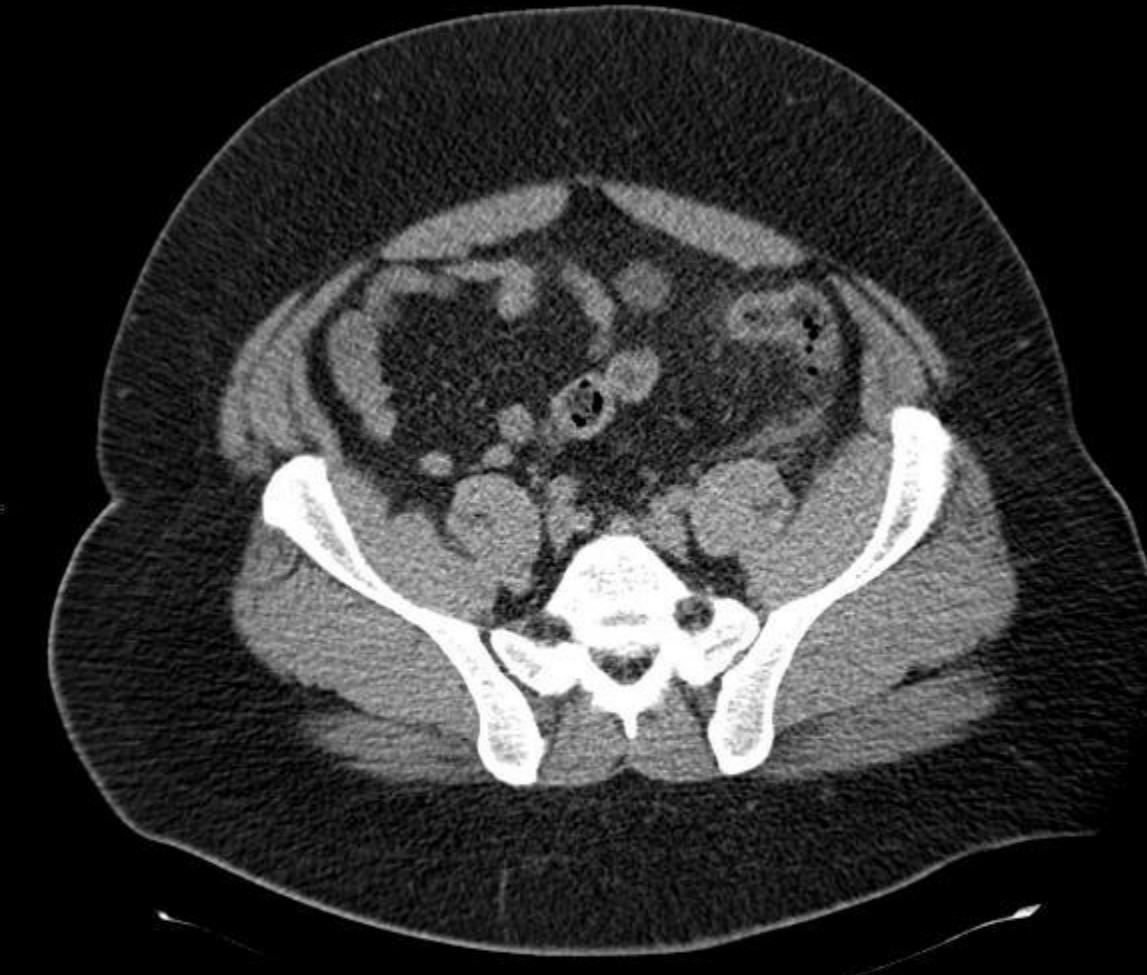
3D data



3D data



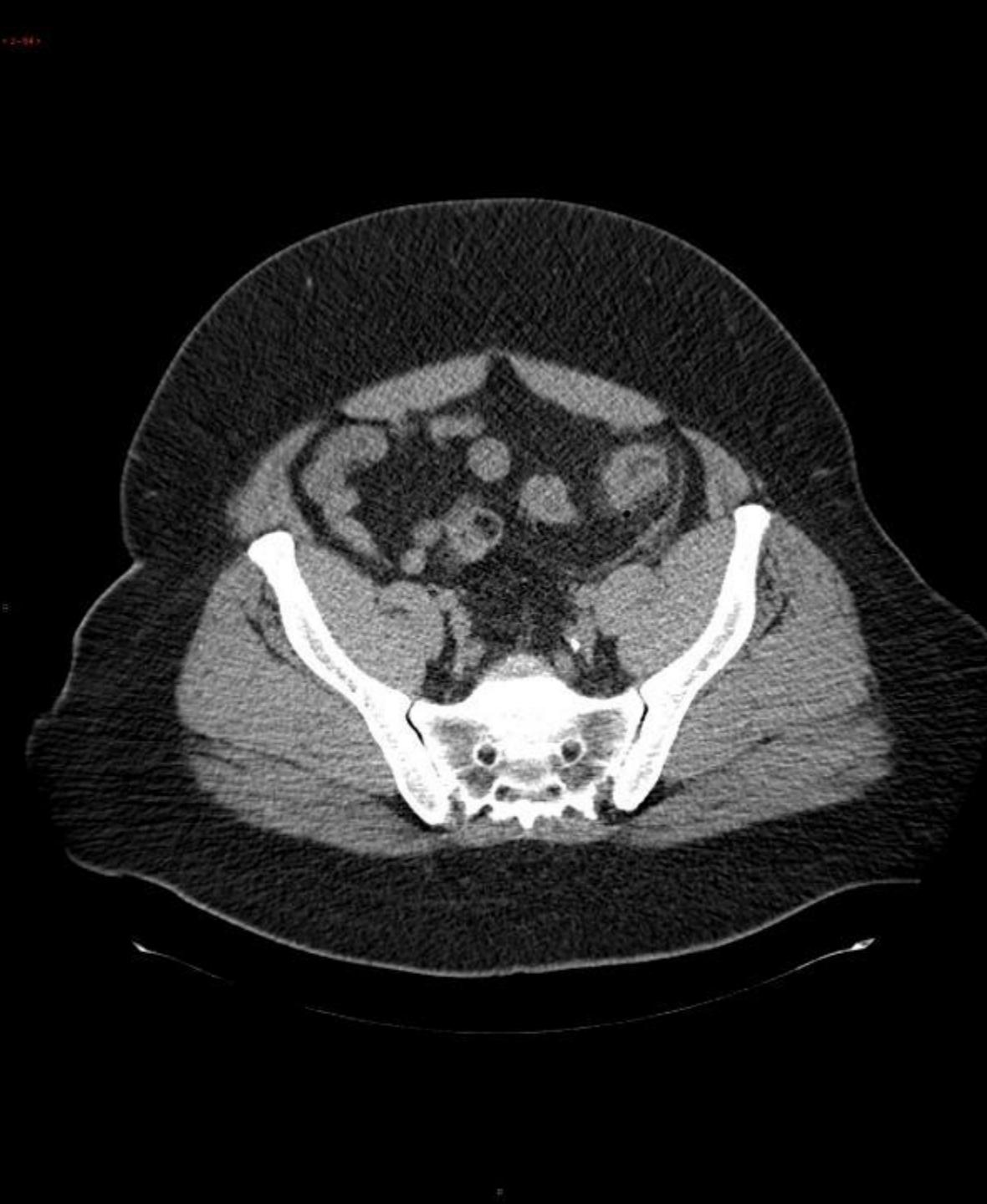
3D data



3D data



3D data



3D data



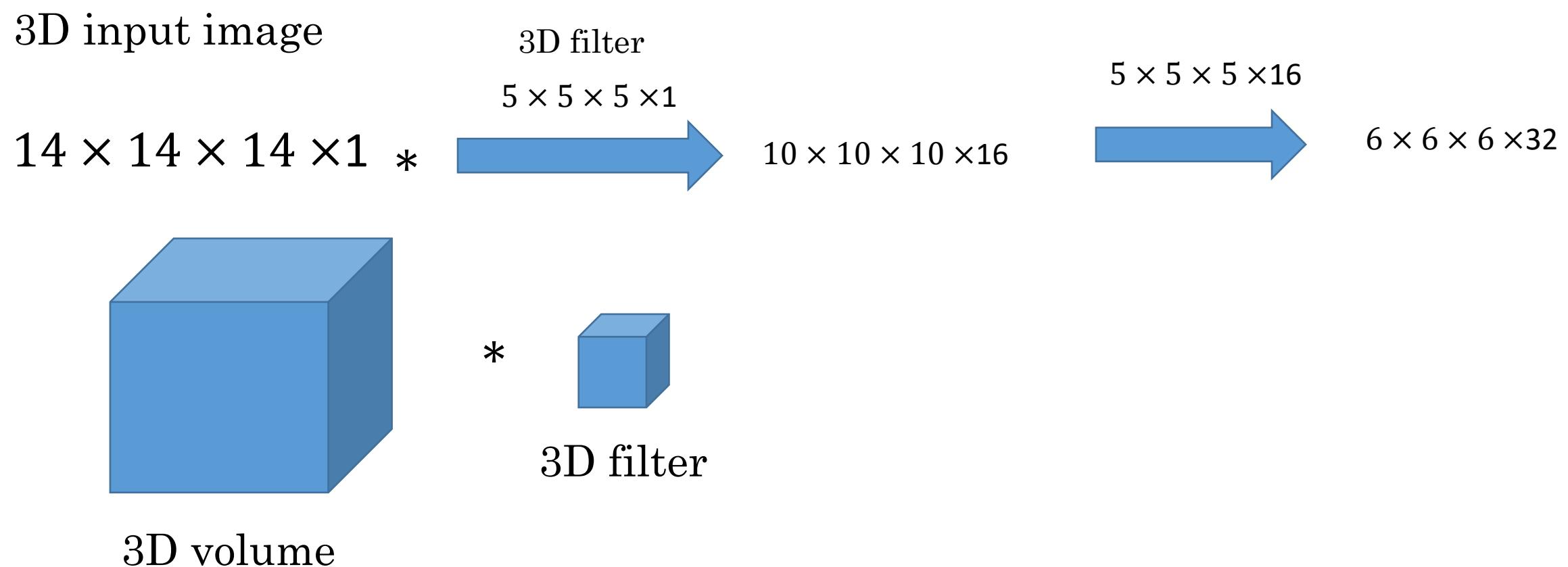
3D data



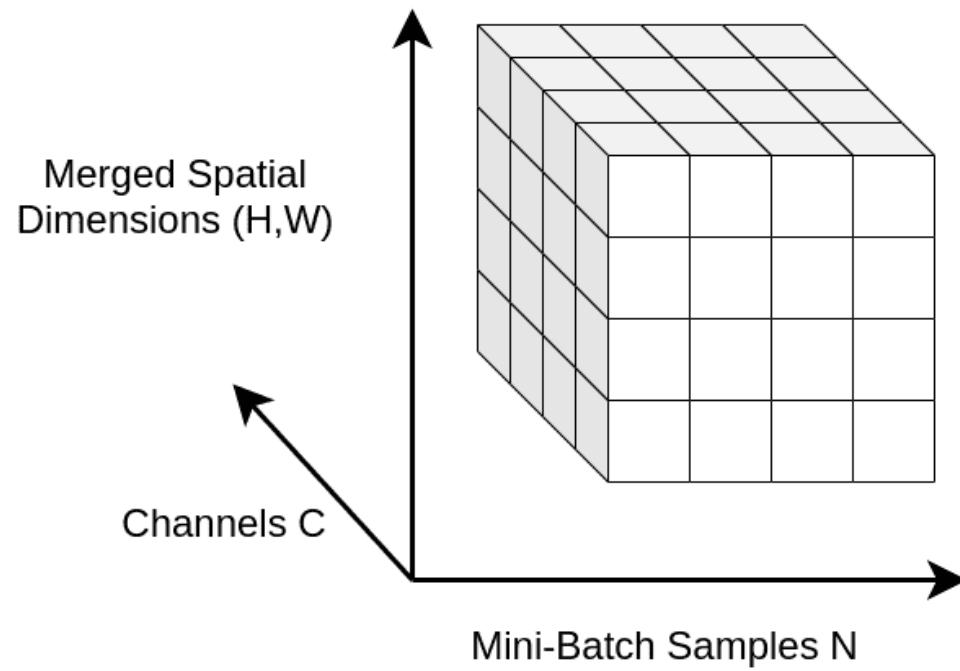
3D data



Convolutions in 3D



Normalization in CNN



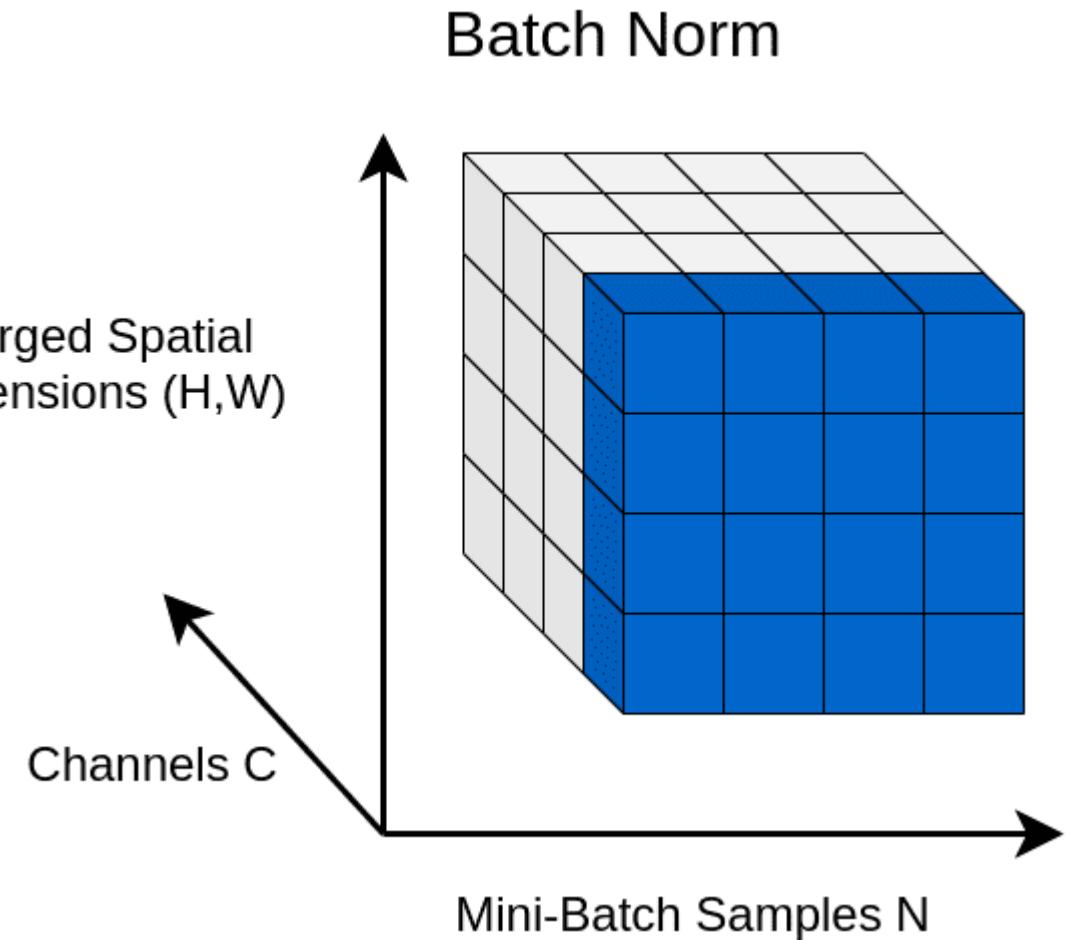
Batch normalization

$$BN(x) = \gamma \left(\frac{x - \mu(x)}{\sigma(x)} \right) + \beta$$

$$\mu_c(x) = \frac{1}{NHW} \sum_{n=1}^N \sum_{h=1}^H \sum_{w=1}^W x_{nchw}$$

$$\sigma_c(x) = \sqrt{\frac{1}{NHW} \sum_{n=1}^N \sum_{h=1}^H \sum_{w=1}^W (x_{nchw} - \mu_c(x))^2}$$

$$\gamma \in R^{Channel} \quad \beta \in R^{Channel}$$



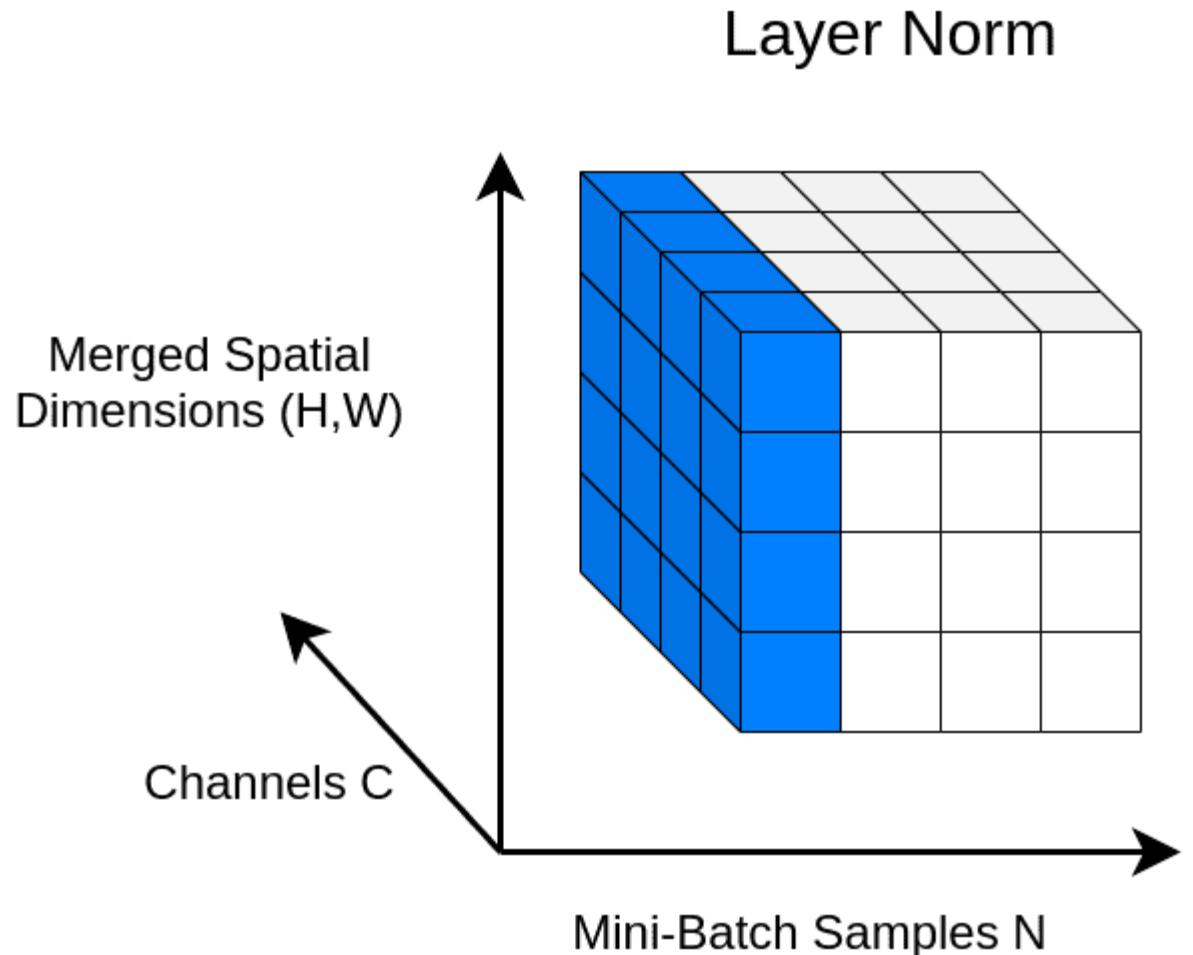
Layer normalization

$$LN(x) = \gamma \left(\frac{x - \mu(x)}{\sigma(x)} \right) + \beta$$

$$\mu_n(x) = \frac{1}{CHW} \sum_{c=1}^C \sum_{h=1}^H \sum_{w=1}^W x_{nchw}$$

$$\sigma_n(x) = \sqrt{\frac{1}{CHW} \sum_{c=1}^C \sum_{h=1}^H \sum_{w=1}^W (x_{nchw} - \mu_n(x))^2}$$

$$\gamma \in R^{Channel} \quad \beta \in R^{Channel}$$



Instance Normalization

$$IN(x) = \gamma \left(\frac{x - \mu(x)}{\sigma(x)} \right) + \beta$$

$$\mu_{nc}(x) = \frac{1}{HW} \sum_{h=1}^H \sum_{w=1}^W x_{chw}$$

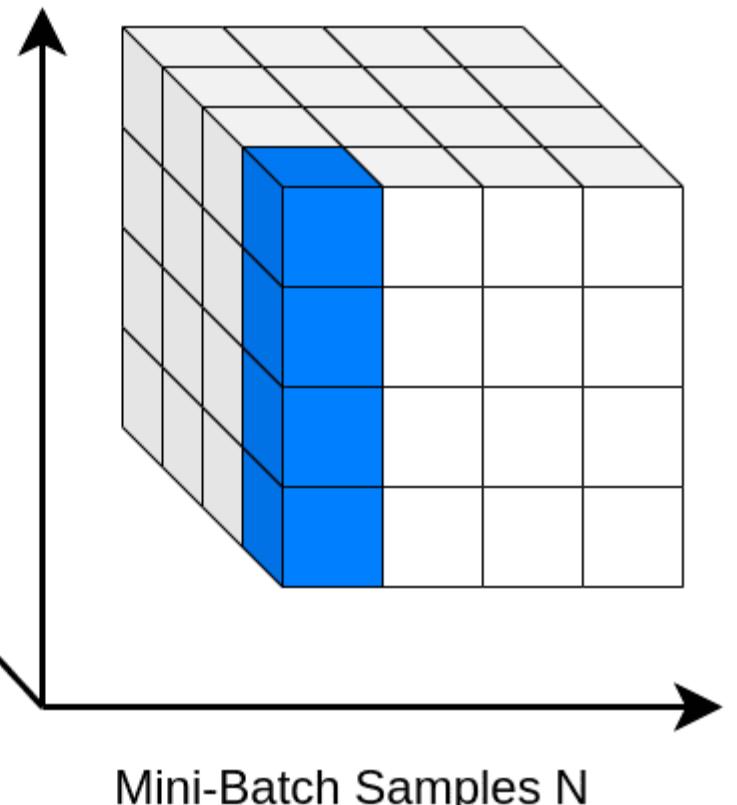
$$\sigma_{nc}(x) = \sqrt{\frac{1}{HW} \sum_{h=1}^H \sum_{w=1}^W (x_{nchw} - \mu_c(x))^2}$$

$$\gamma \in R^{Channel} \quad \beta \in R^{Channel}$$

Merged Spatial Dimensions (H,W)

Channels C

Instance Norm



Group Normalization

$$\mu_i = \frac{1}{m} \sum_{k \in \mathcal{S}_i} x_k, \quad \sigma_i = \sqrt{\frac{1}{m} \sum_{k \in \mathcal{S}_i} (x_k - \mu_i)^2 + \epsilon}$$

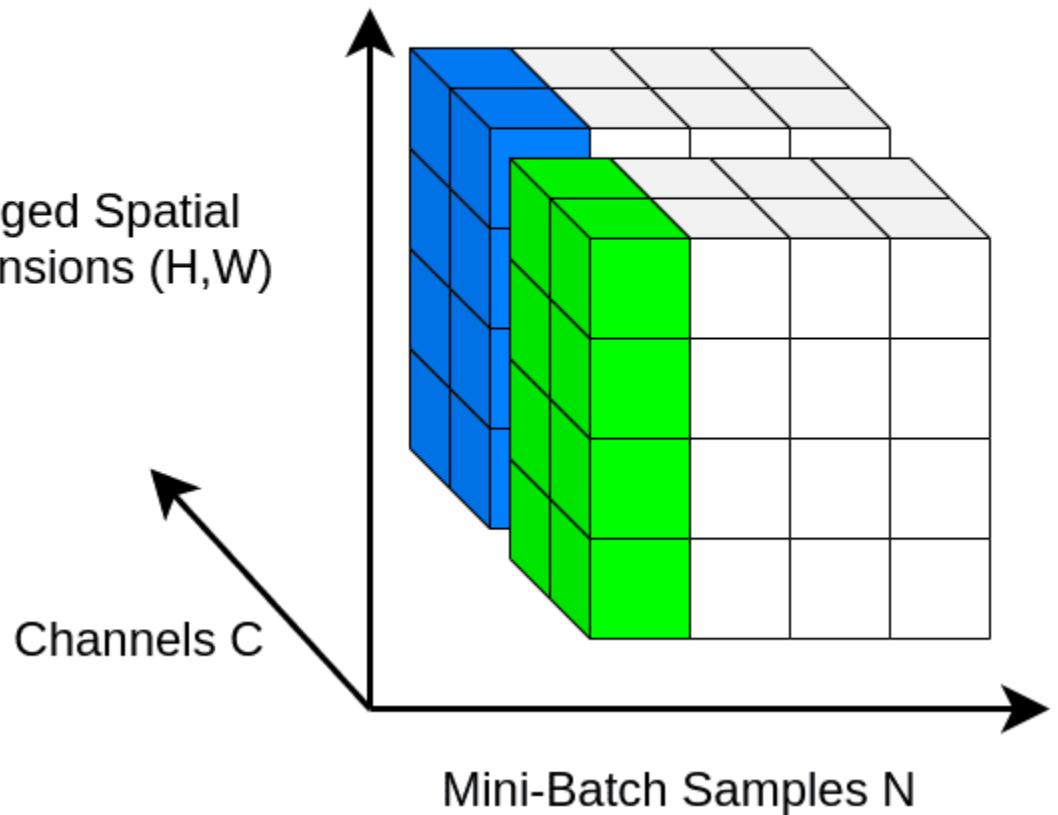
$$\mathcal{S}_i = \left\{ k \mid k_N = i_N, \left\lfloor \frac{k_C}{C/G} \right\rfloor = \left\lfloor \frac{i_C}{C/G} \right\rfloor \right\}$$

$$\hat{x}_i = \frac{1}{\sigma_i} (x_i - \mu_i).$$

$$y_i = \gamma \hat{x}_i + \beta,$$

$$\gamma \in R^{Channel} \quad \beta \in R^{Channel}$$

Group Normalization



Weight standardization

$$\hat{W} = \left[\hat{W}_{i,j} \mid \hat{W}_{i,j} = \frac{W_{i,j} - \mu_{W_i}}{\sigma_{W_i}} \right]$$

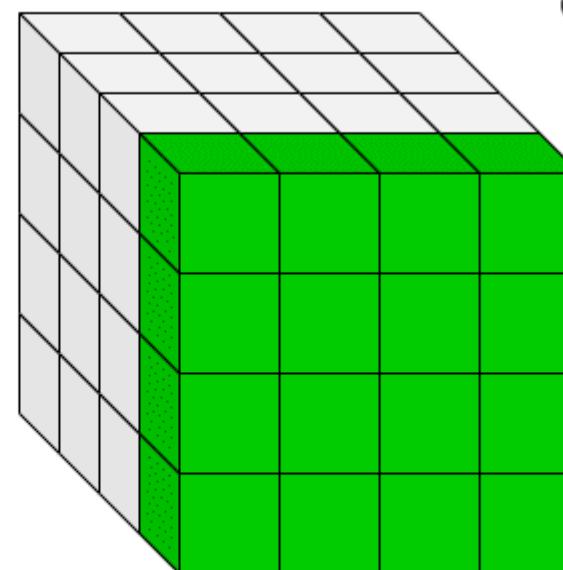
$$y = \hat{W} * x$$

$$\mu_{W_i} = \frac{1}{I} \sum_{j=1}^I W_{i,j}, \quad \sigma_{W_i} = \sqrt{\frac{1}{I} \sum_{i=1}^I (W_{i,j} - \mu_{W_i})^2}$$

Kernel size

Output channels

The 3D weight of a conv layer



Input channels