Artificial Intelligence and Machine learning course

Deep Learning lesson n.3

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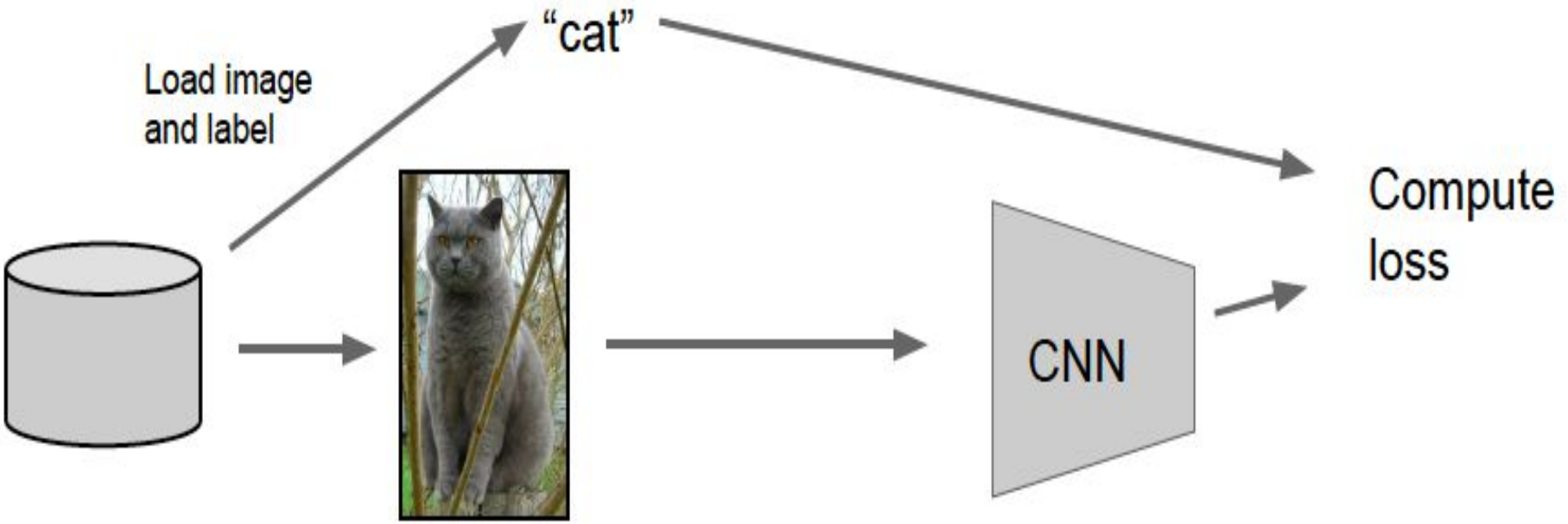
Today

Working with CNNs in practice:

- Making the most of your data
  - Data augmentation
  - Transfer learning
- All about convolutions:
  - How to arrange them
  - How to compute them fast
- "Implementation details"
  - GPU / CPU, bottlenecks, distributed training

Data Augmentation

Data Augmentation



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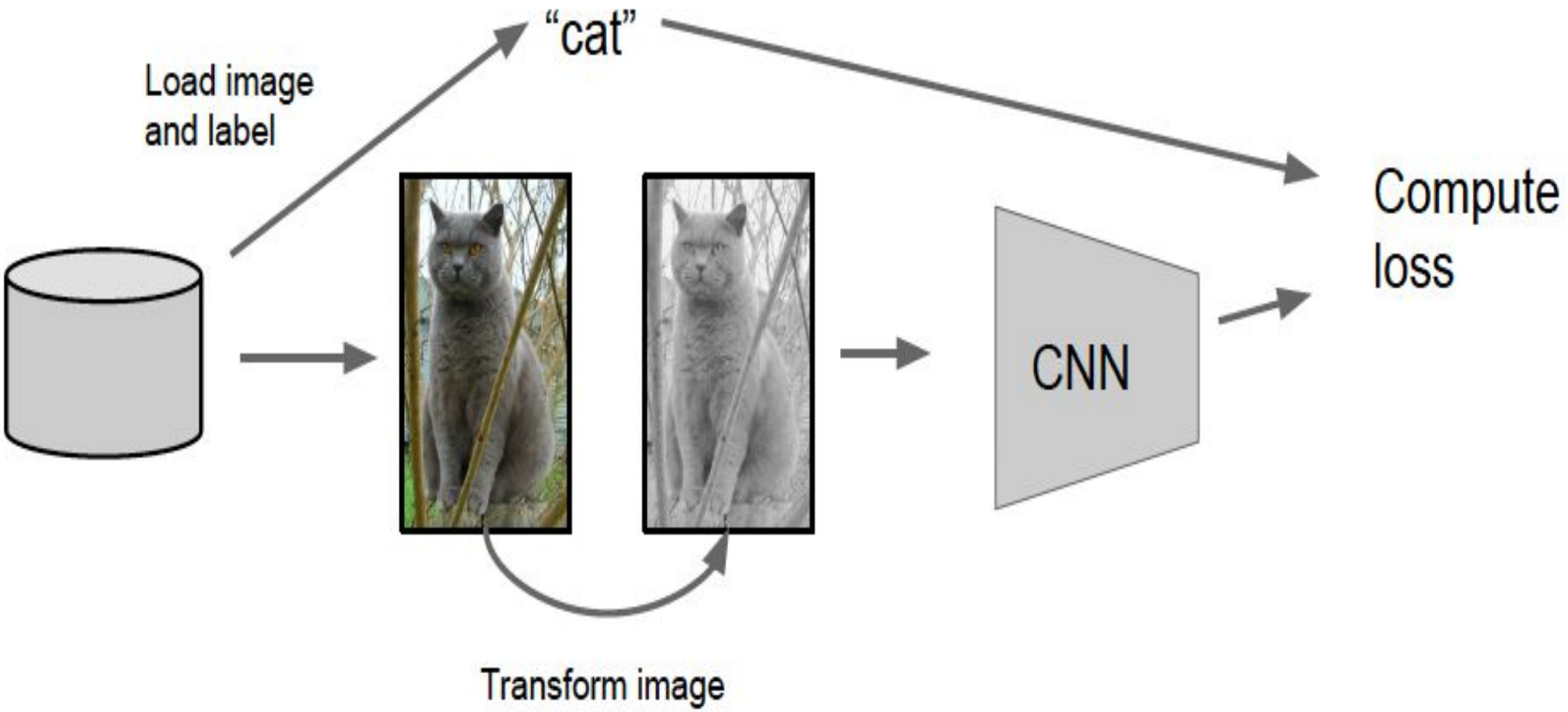
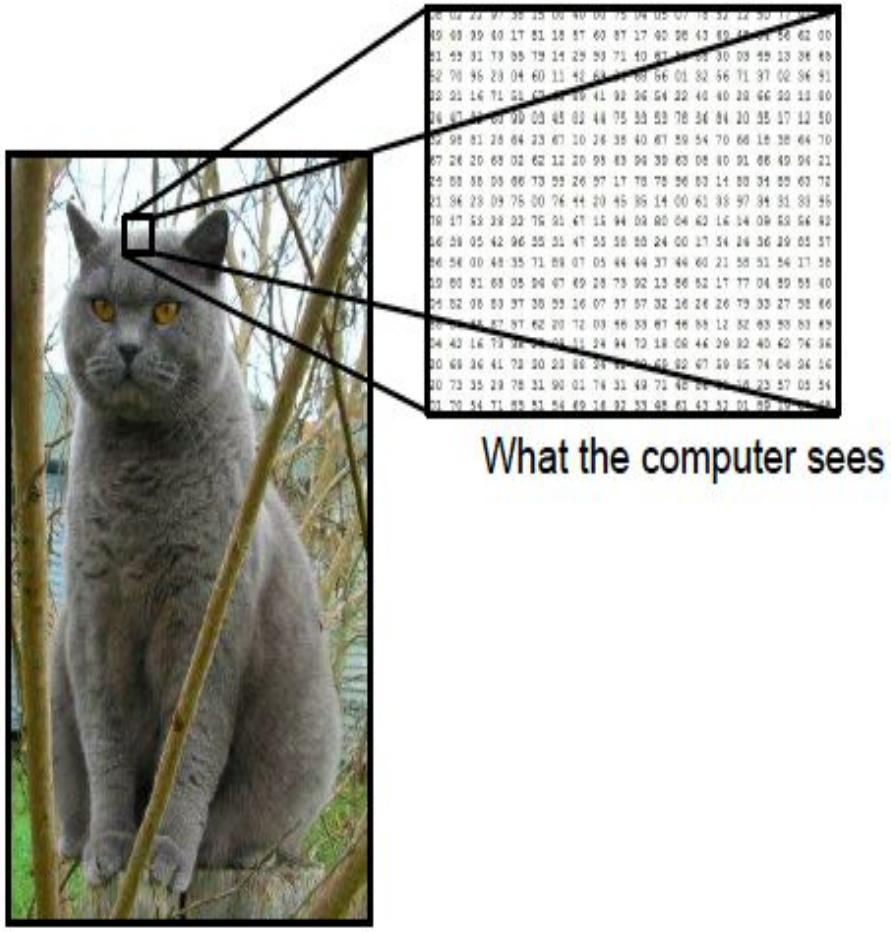


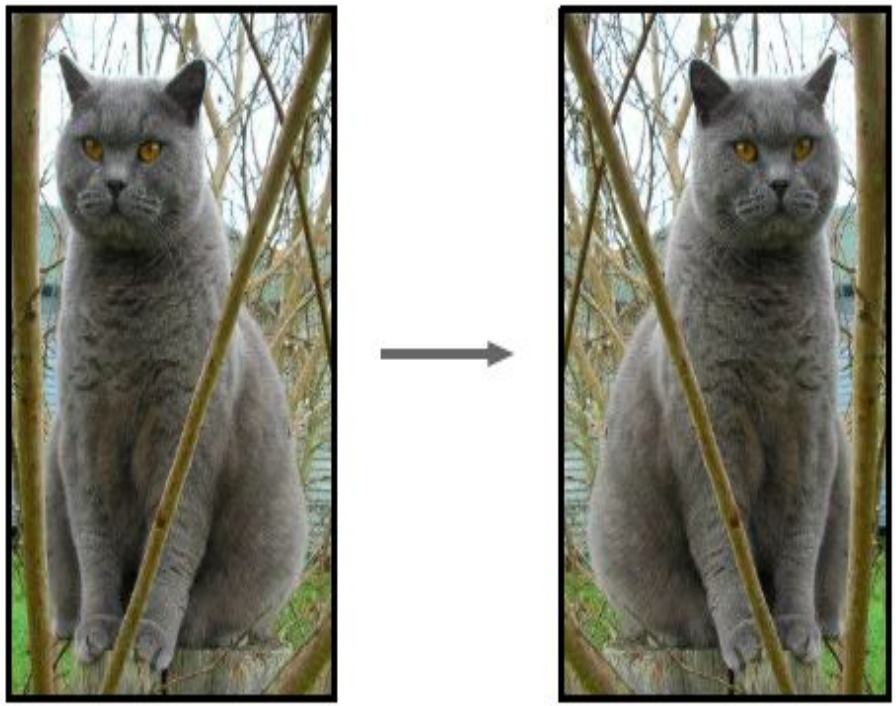
Data Augmentation

- Change the pixels without changing the label
- Train on transformed data
- VERY widely used



Data Augmentation

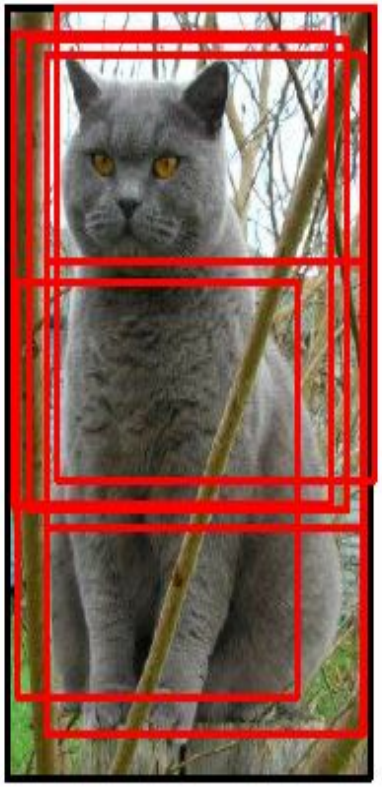
1. Horizontal flips



Data Augmentation

2. Random crops/scales

Training: sample random crops / scales



Data Augmentation

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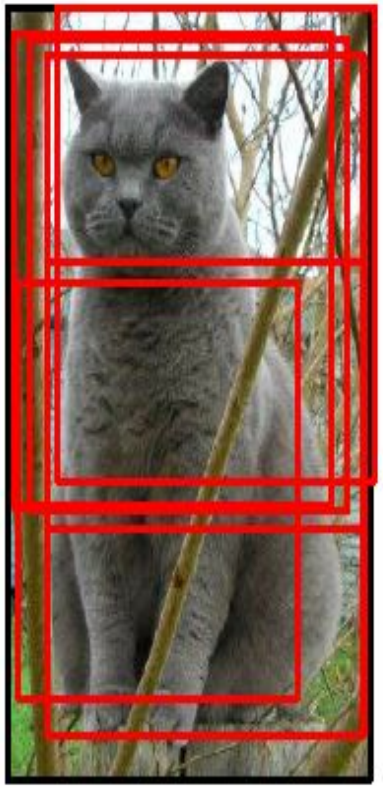
Training: sample random crops / scales

ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short side = L
3. Sample random 224 x 224 patch



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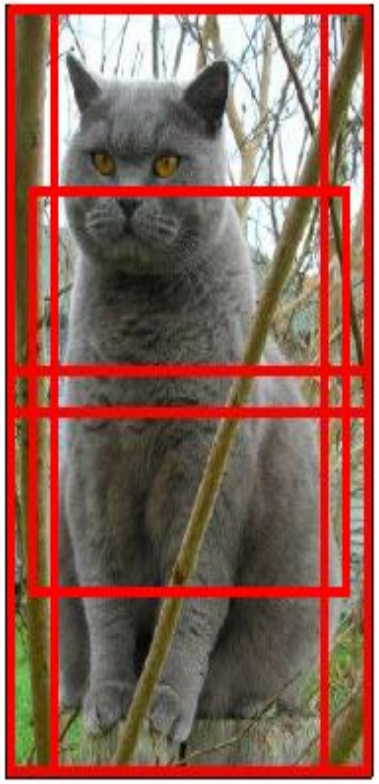
Testing: average a fixed set of crops



Data Augmentation

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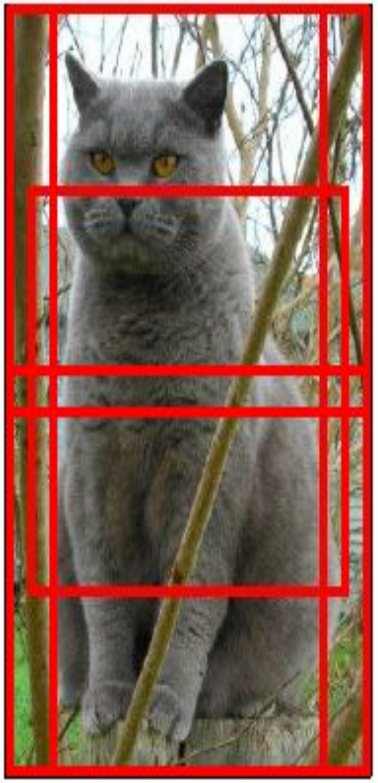

Training: sample random crops / scales

ResNet:

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3. Sample random 224 x 224 patch

Testing: average a fixed set of crops

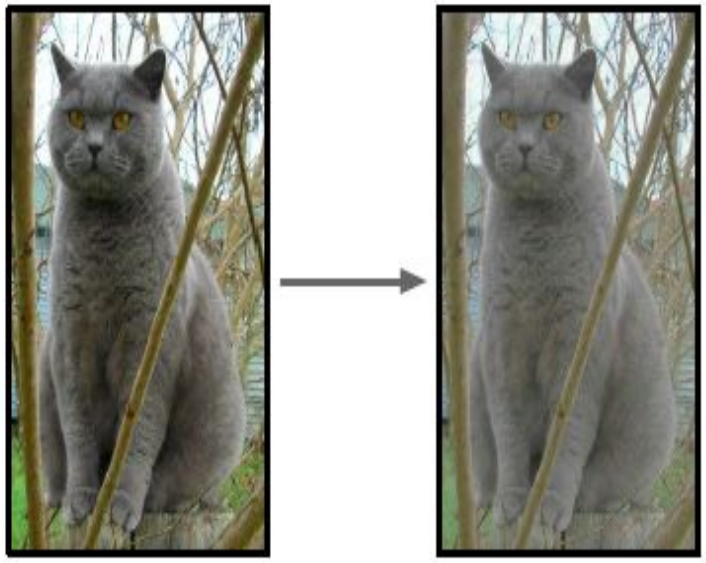
ResNet:

1. Resize image at 5 scales: {224, 256, 384, 480, 640}
2. For each size, use 10 224 x 224 crops: 4 corners + center, + flips

Data Augmentation

3. Color jitter

Simple:
Randomly jitter contrast



Data Augmentation

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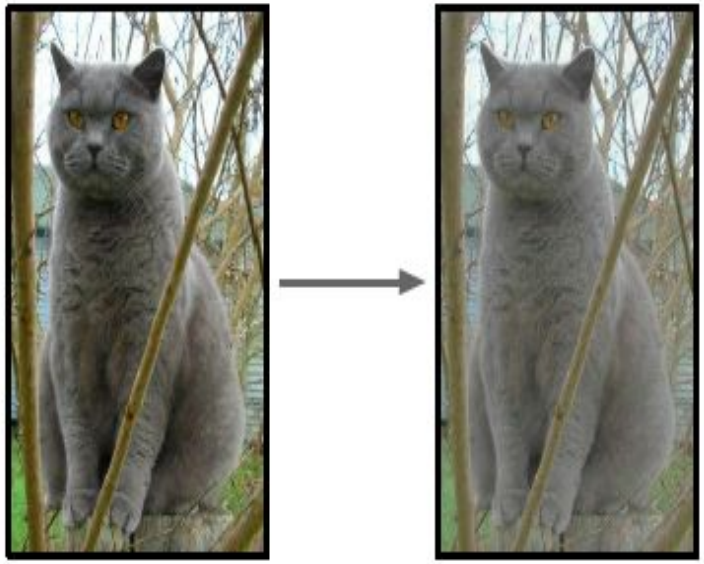


Complex:

1. Apply PCA to all [R, G, B] pixels in training set
2. Sample a "color offset" along principal component directions
3. Add offset to all pixels of a training image

(As seen in *[Krizhevsky et al. 2012]*, ResNet, etc)

Data Augmentation

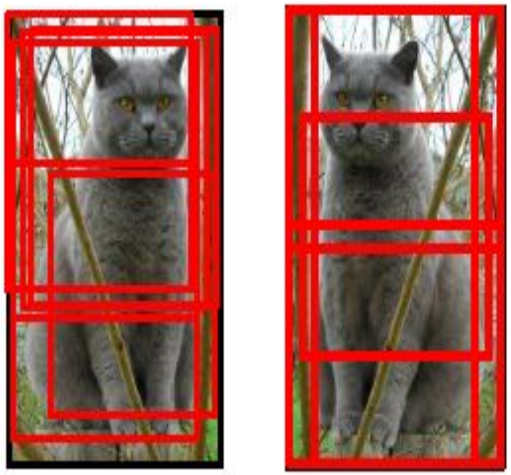
4. Get creative!

Random mix/combinations of :

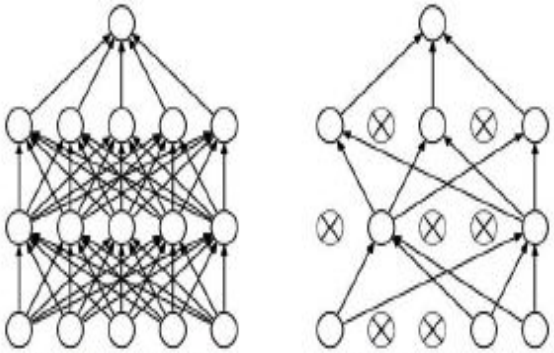
- translation
- rotation
- stretching
- shearing,
- lens distortions, … (go crazy)

A general theme:

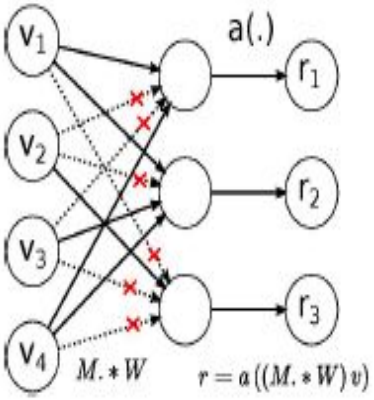
1. **Training**: Add random noise
2. **Testing**: Marginalize over the noise



Data Augmentation



Dropout



DropConnect

Batch normalization, Model ensembles

Data Augmentation: Takeaway

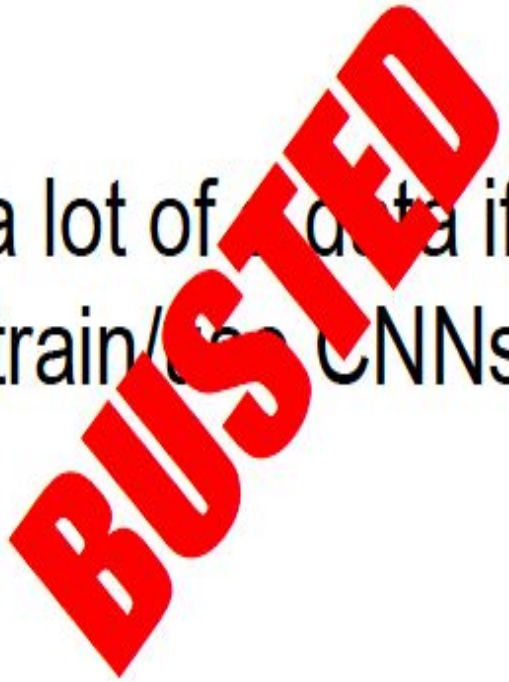
- Simple to implement, use it
- Especially useful for small datasets
- Fits into framework of noise / marginalization

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

Transfer Learning

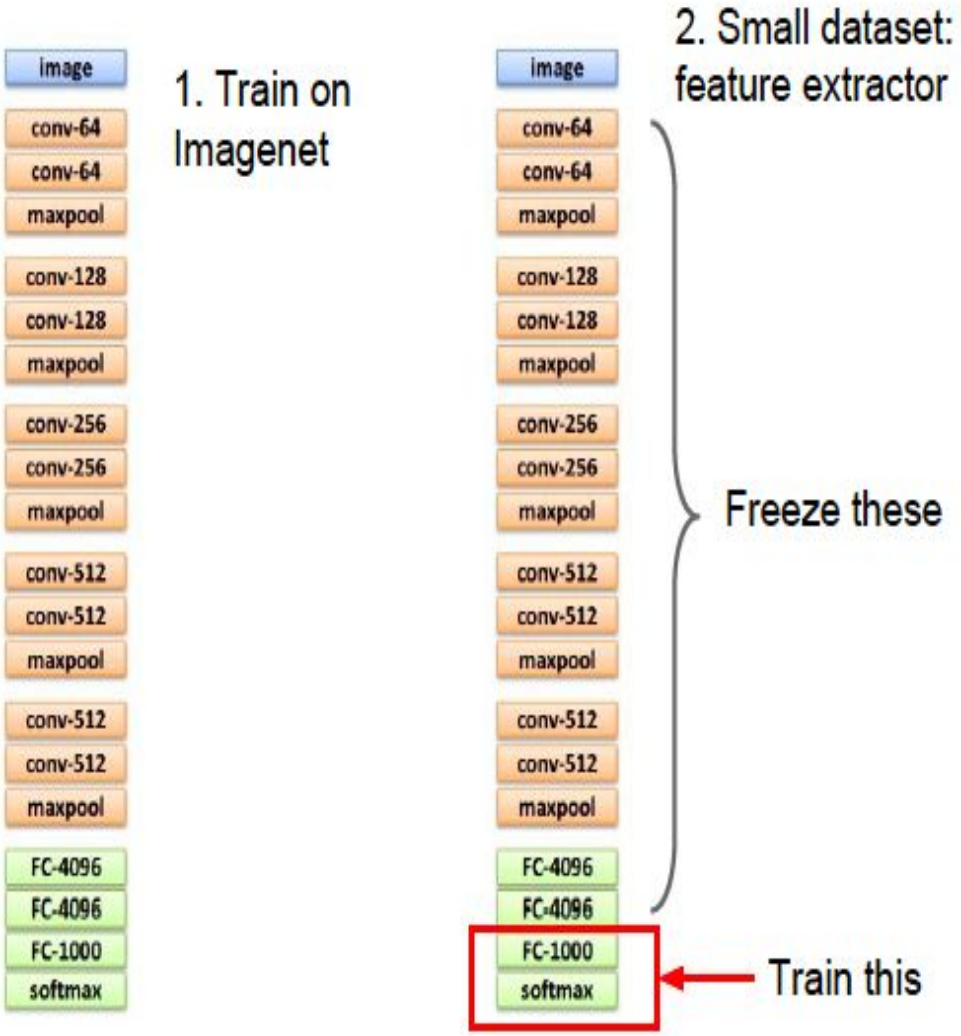
"You need a lot of data if you want to train/use CNNs"



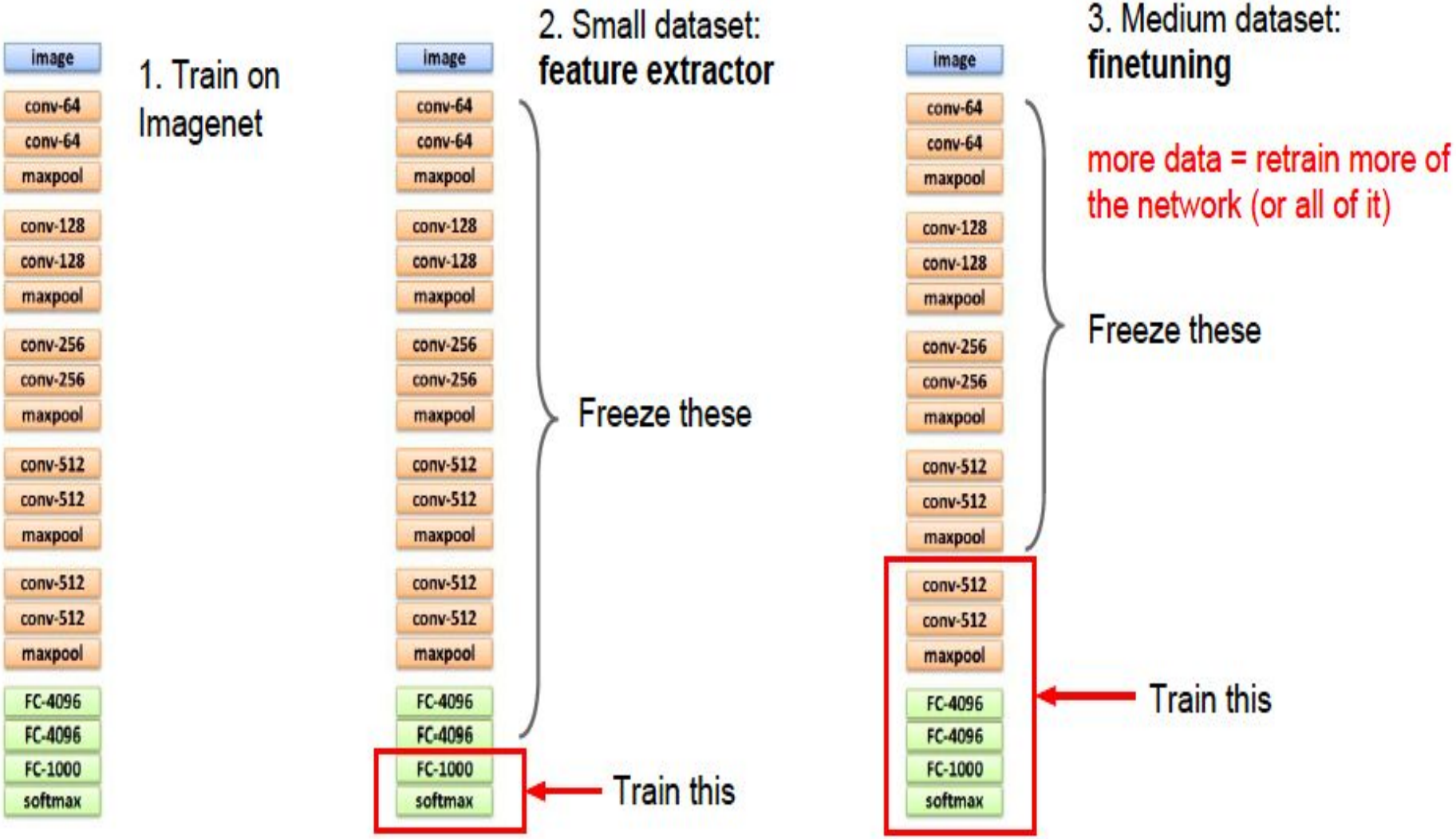
Transfer Learning with CNNs

1. Train on Imagenet

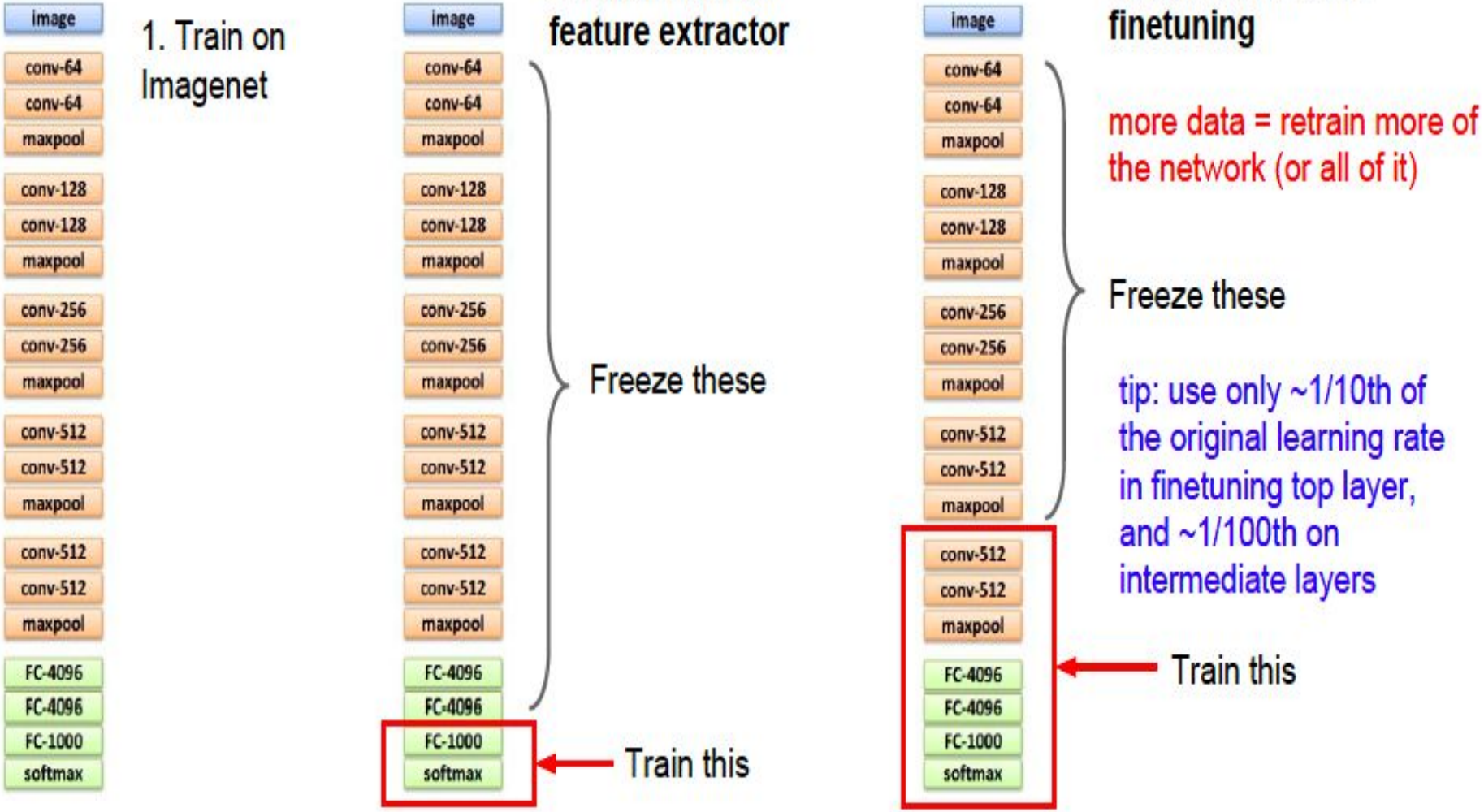
Transfer Learning with CNNs



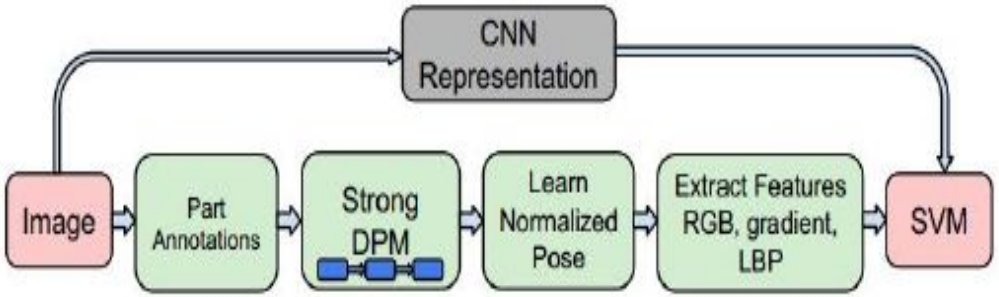
Transfer Learning with CNNs



Transfer Learning with CNNs

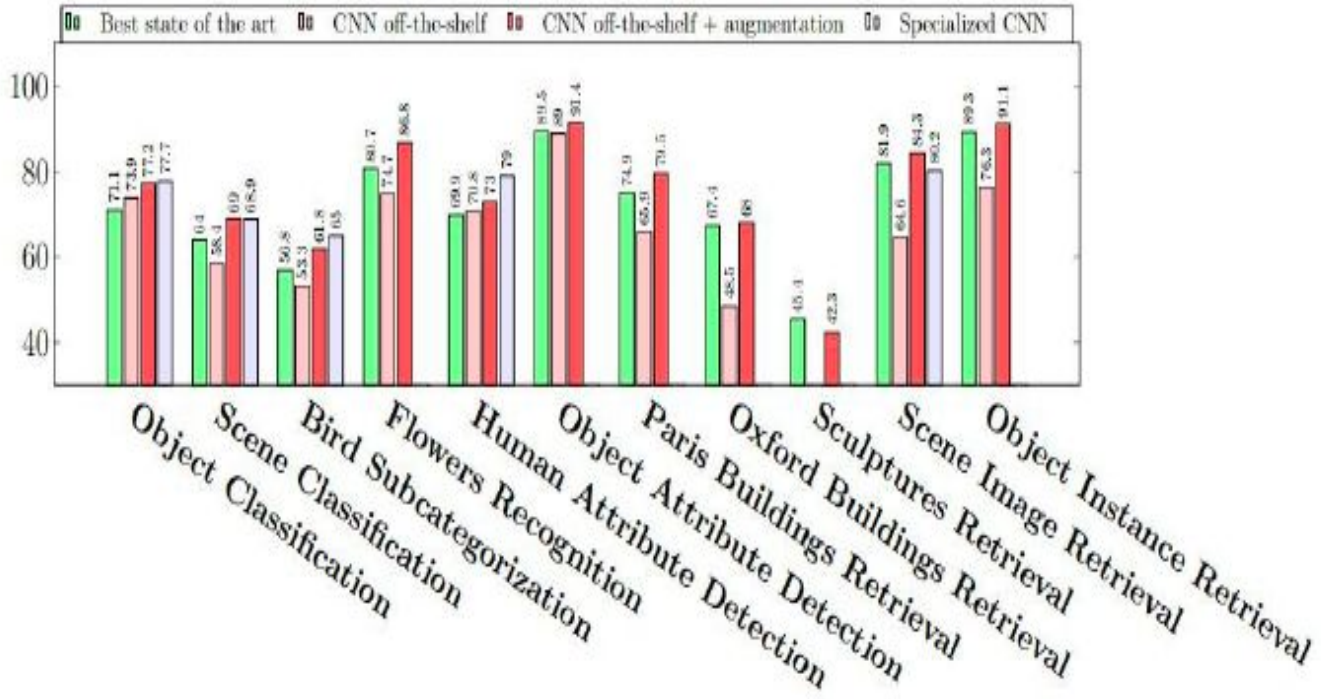


CNN Features off-the-shelf: an Astounding Baseline for Recognition [Razavian et al, 2014]



DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition [Donahue, Jia*, et al., 2013]*

	$DeCAF_6$	$DeCAF_7$
LogReg	**40.94 ± 0.3**	40.84 ± 0.3
SVM	39.36 ± 0.3	40.66 ± 0.3
Xiao et al. (2010)	38.0	



	very similar dataset	very different dataset
very little data	?	?
quite a lot of data	?	?

	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	?
quite a lot of data	Finetune a few layers	?

	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

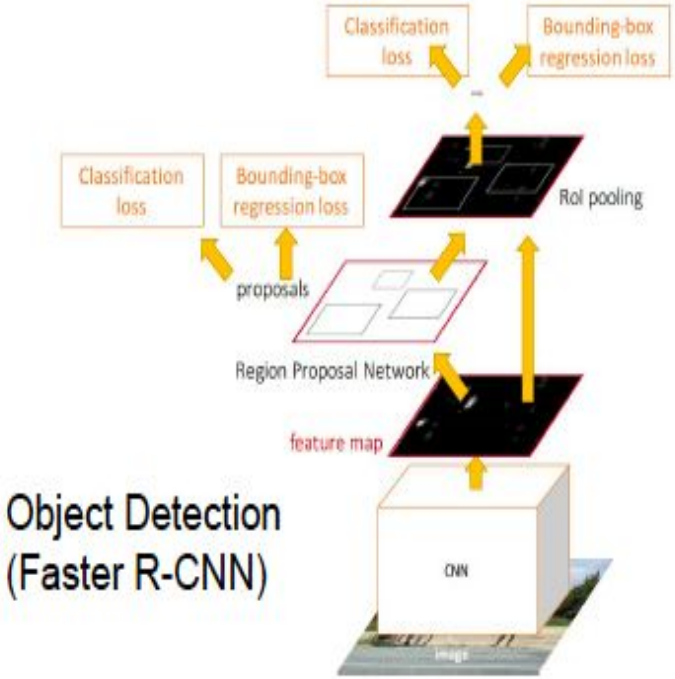
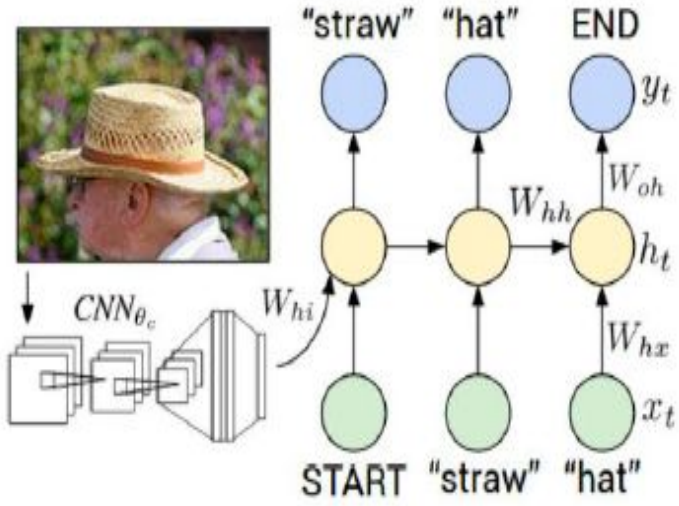


Image Captioning: CNN + RNN



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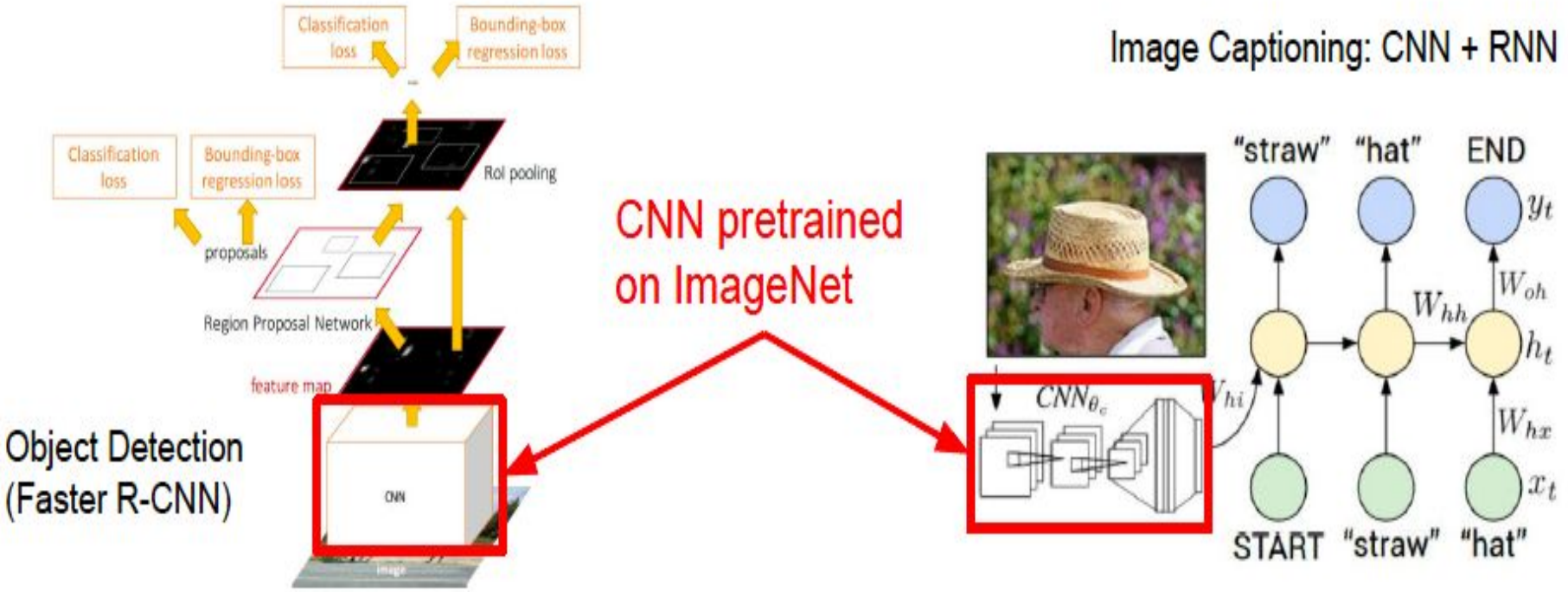

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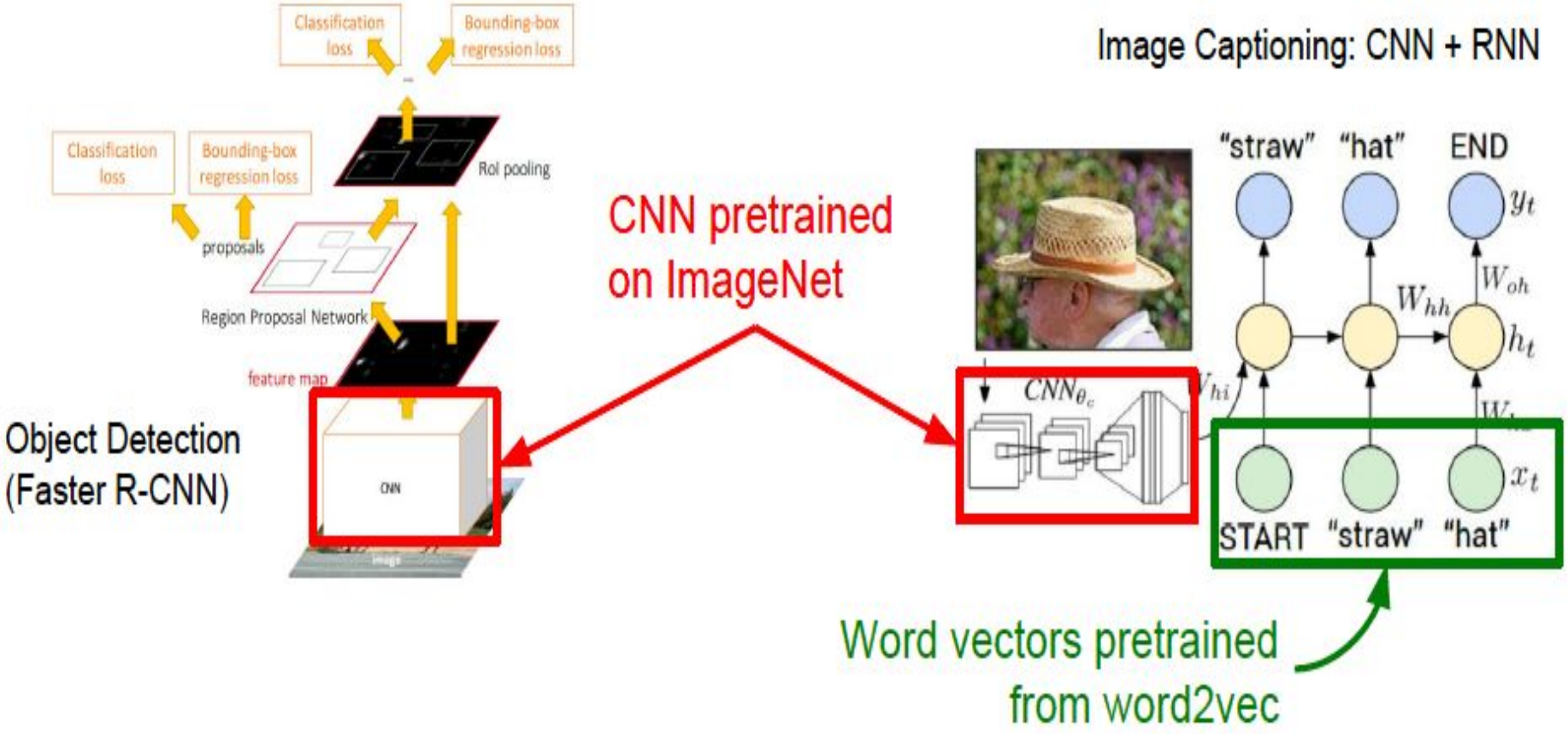


Takeaway for your projects/beyond:

Have some dataset of interest but it has < ~1M images?

1. Find a very large dataset that has similar data, train a big ConvNet there.
2. Transfer learn to your dataset

Caffe ConvNet library has a **"Model Zoo"** of pretrained models:
https://github.com/BVLC/caffe/wiki/Model-Zoo

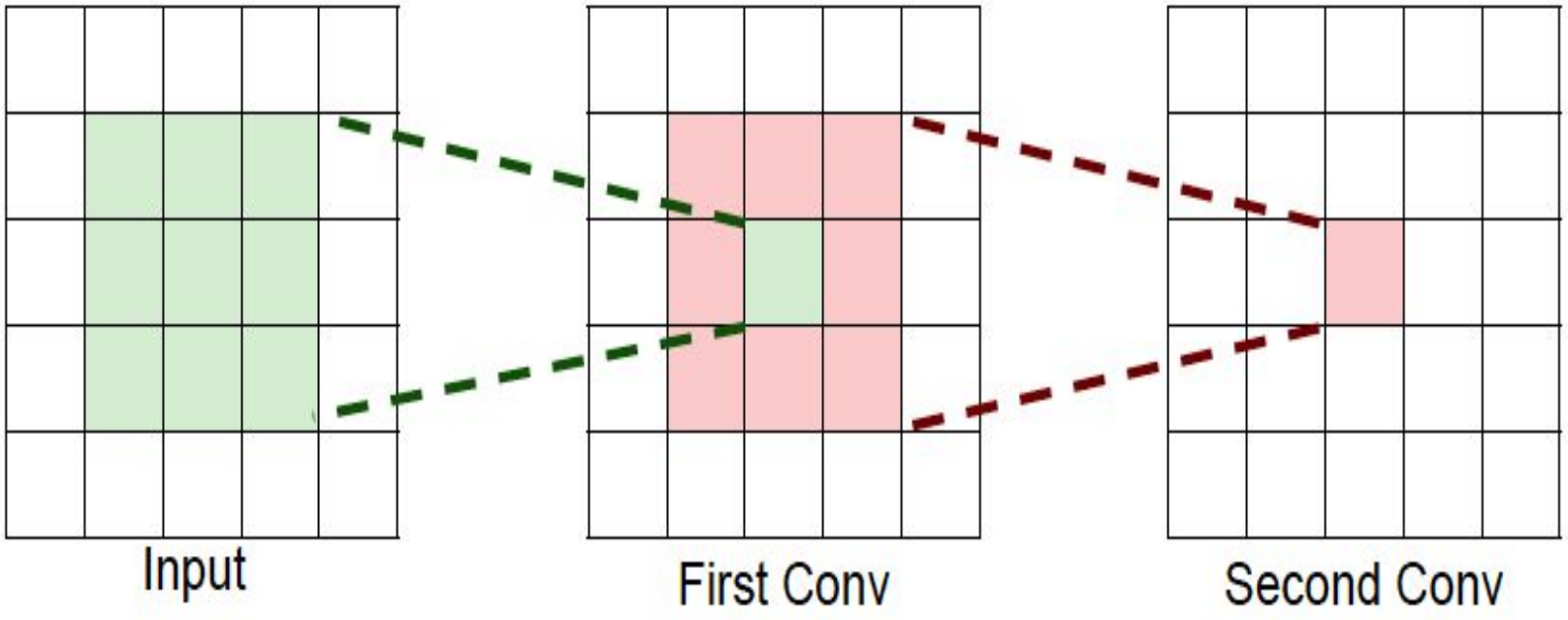
All About Convolutions

All About Convolutions

Part I: How to stack them

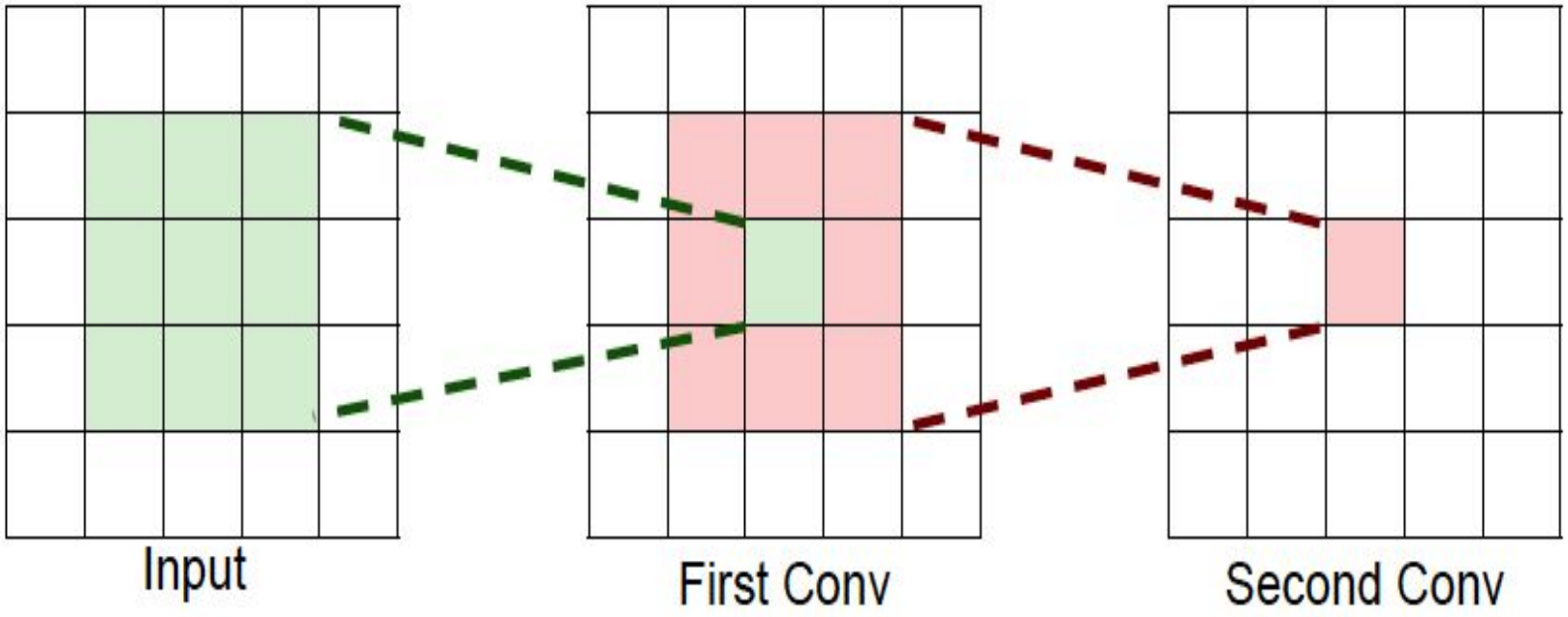
The power of small filters

Suppose we stack two 3x3 conv layers (stride 1)
Each neuron sees 3x3 region of previous activation map



The power of small filters

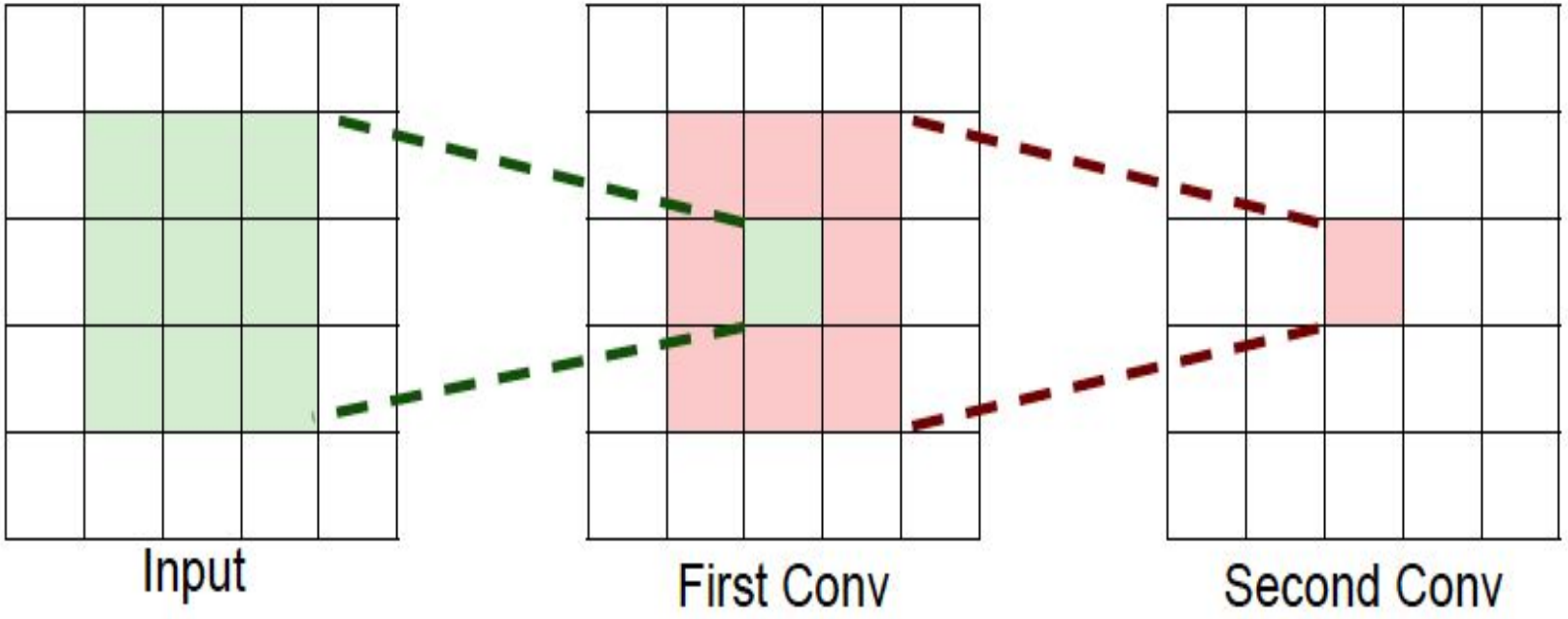
Question: How big of a region in the input does a neuron on the second conv layer see?



The power of small filters

Question: How big of a region in the input does a neuron on the second conv layer see?

Answer: 5 x 5



The power of small filters

Question: If we stack **three** 3x3 conv layers, how big of an input region does a neuron in the third layer see?

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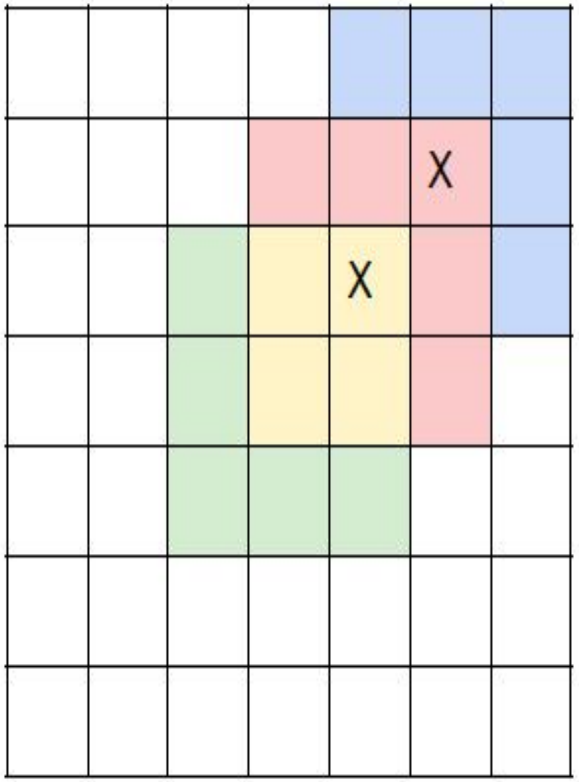
Answer: 7 x 7



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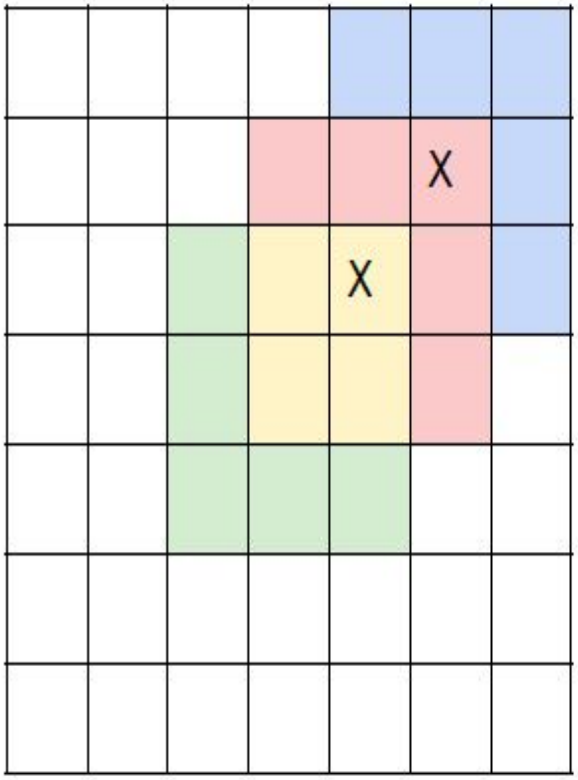

Three 3 x 3 conv gives similar representational power as a single 7 x 7 convolution

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Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

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one CONV with 7 x 7 filters

Number of weights:

three CONV with 3 x 3 filters

Number of weights:

The power of small filters

Suppose input is H x W x C and we use convolutions with C filters to preserve depth (stride 1, padding to preserve H, W)

one CONV with 7 x 7 filters

Number of weights:
= C x (7 x 7 x C) = **49 C^2**

three CONV with 3 x 3 filters

Number of weights:
= 3 x C x (3 x 3 x C) = **27 C^2**

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Fewer parameters, more nonlinearity = GOOD

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Number of multiply-adds:
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Number of multiply-adds:
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three CONV with 3 x 3 filters

Number of weights:
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Number of multiply-adds:
= **27 HWC^2**

Less compute, more nonlinearity = GOOD

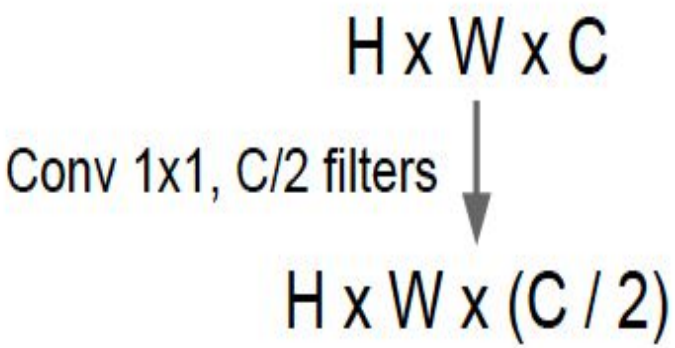
5 minutes break

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?



1. "bottleneck" 1 x 1 conv to reduce dimension

The power of small filters

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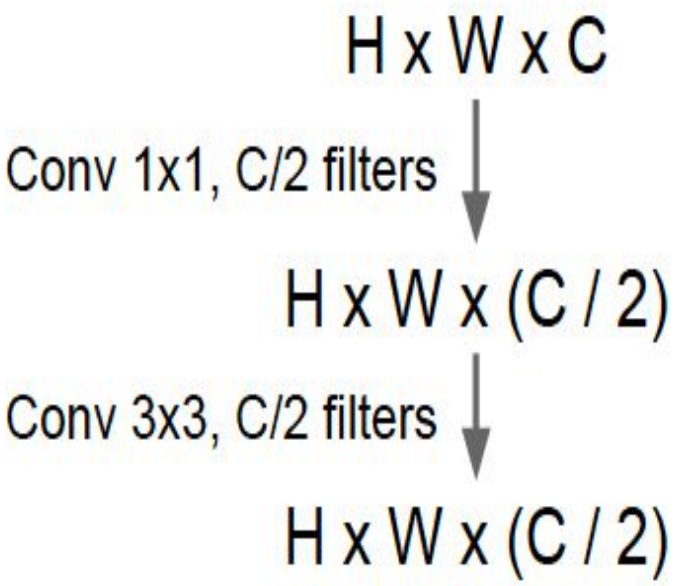

1. "bottleneck" 1 x 1 conv to reduce dimension
2. 3 x 3 conv at reduced dimension

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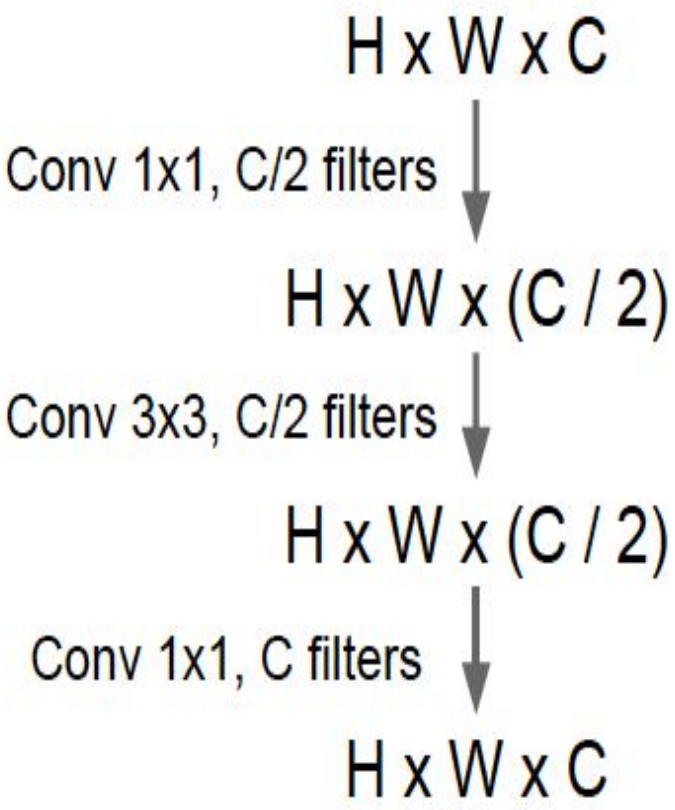
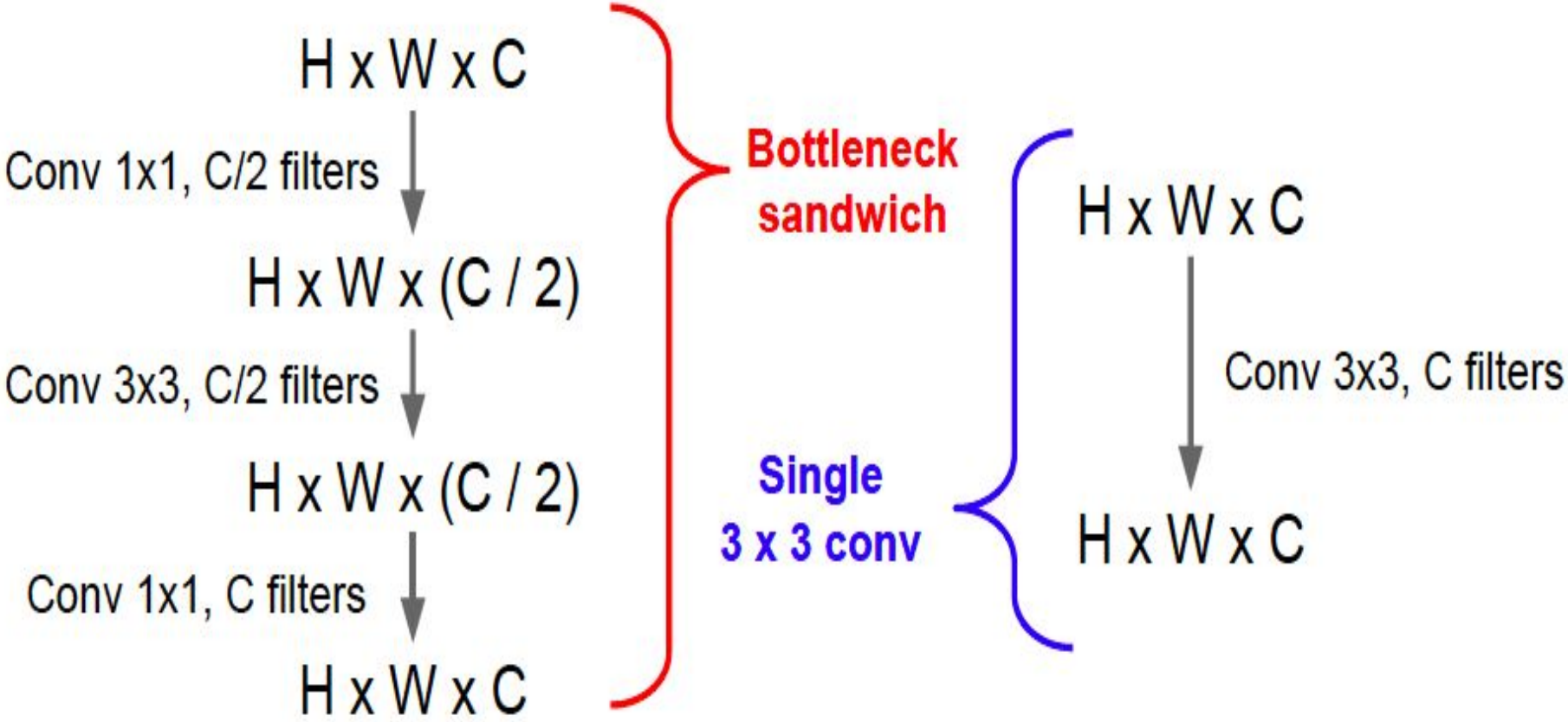


1. "bottleneck" 1 x 1 conv to reduce dimension
2. 3 x 3 conv at reduced dimension
3. Restore dimension with another 1 x 1 conv

[Seen in Lin et al, "Network in Network", GoogLeNet, ResNet]

The power of small filters

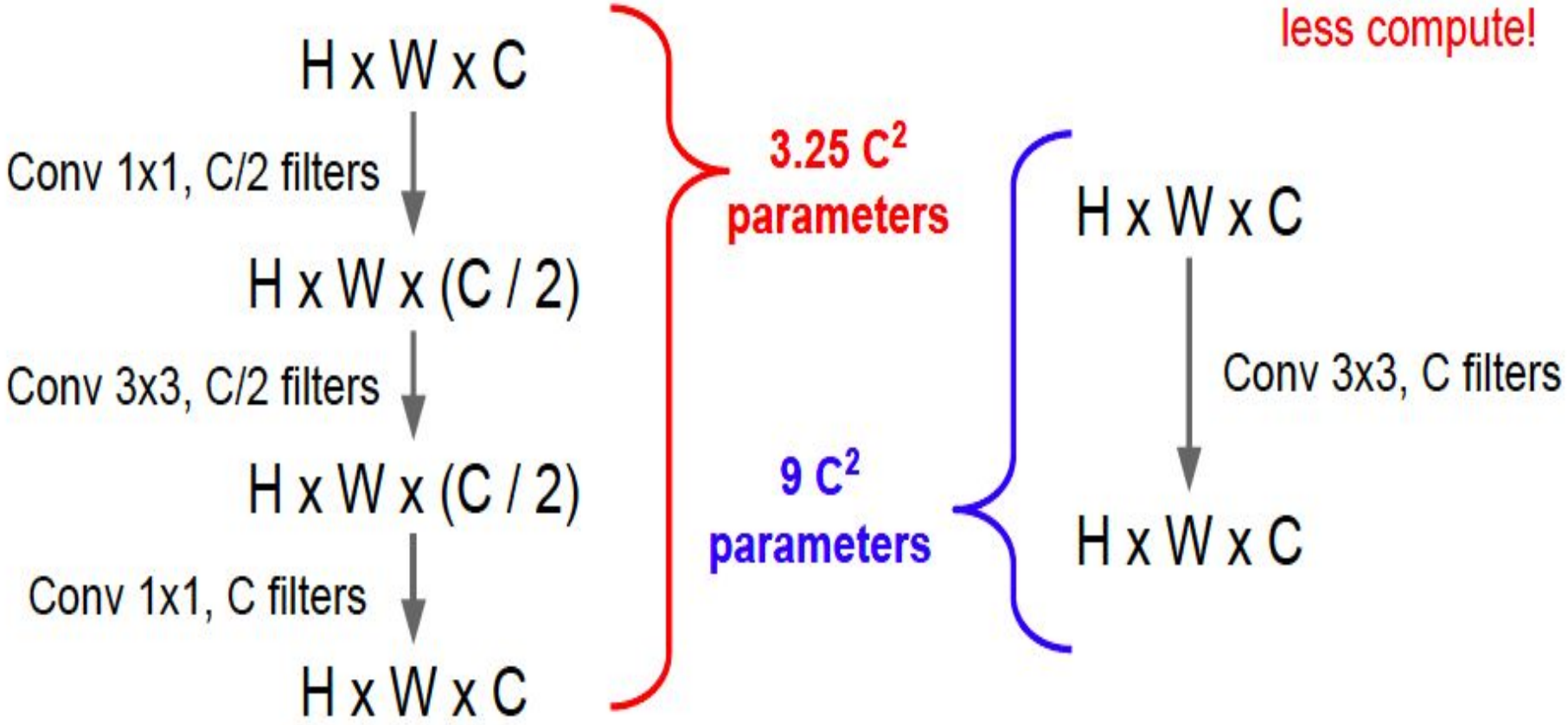
Why stop at 3 x 3 filters? Why not try 1 x 1?



The power of small filters

Why stop at 3 x 3 filters? Why not try 1 x 1?

More nonlinearity, fewer params, less compute!



The power of small filters

Still using 3 x 3 filters … can we break it up?

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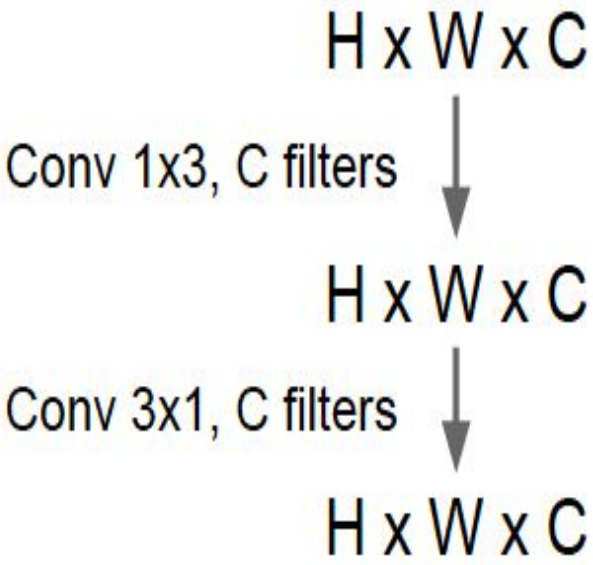

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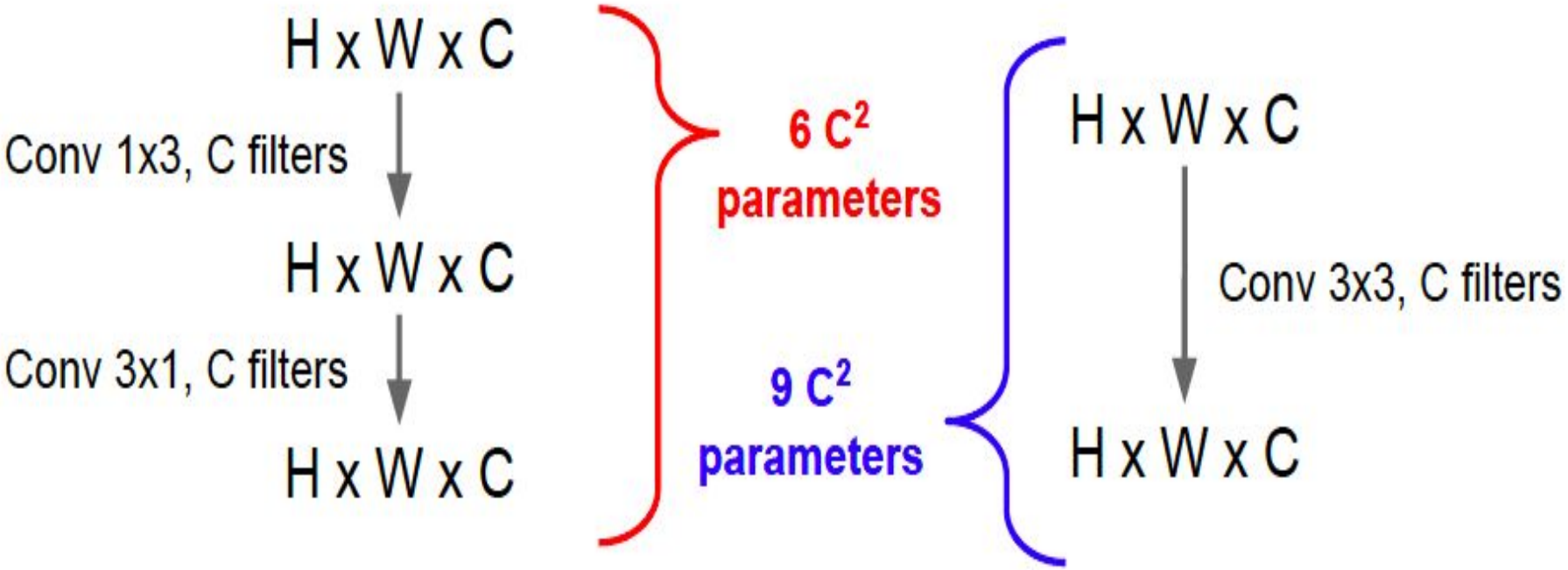
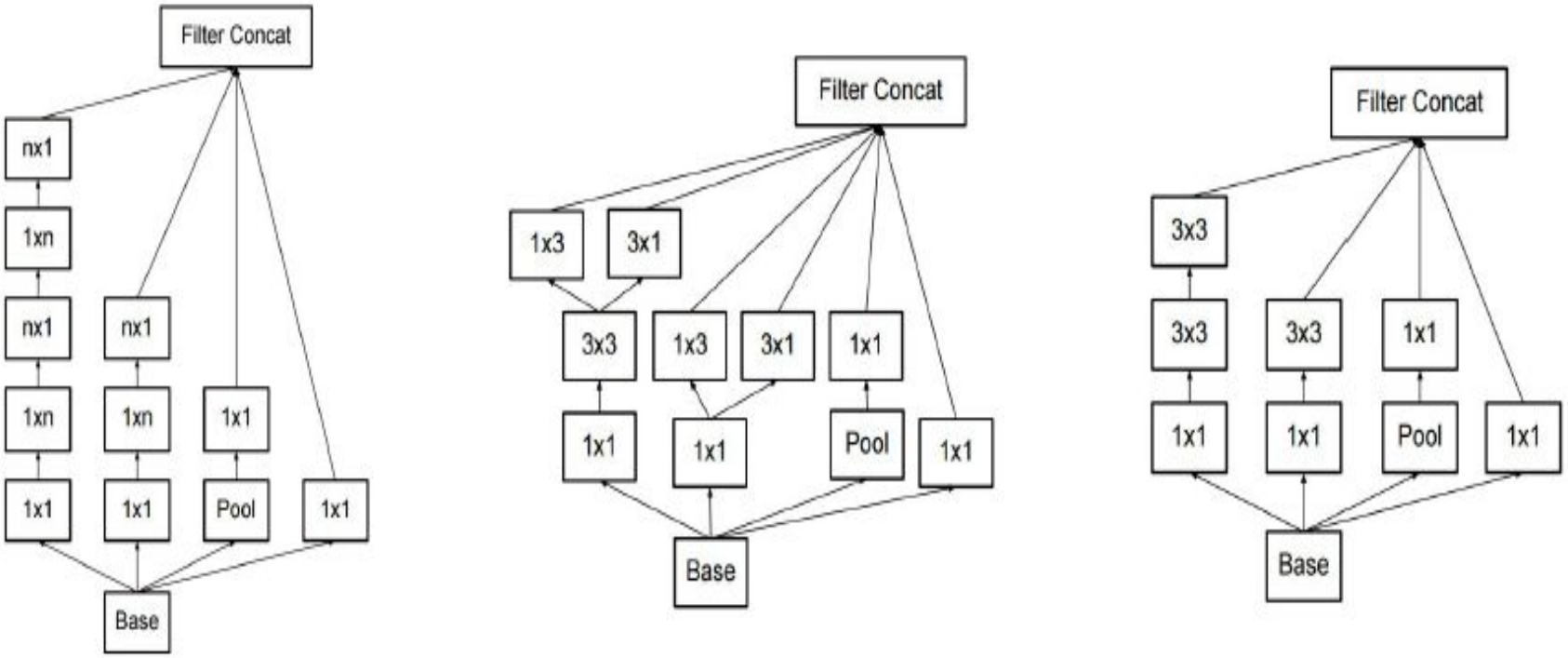


The power of small filters

Latest version of GoogLeNet incorporates all these ideas



Szegedy et al, "Rethinking the Inception Architecture for Computer Vision"

How to stack convolutions: Recap

- Replace large convolutions (5 x 5, 7 x 7) with stacks of 3 x 3 convolutions
- 1 x 1 “bottleneck” convolutions are very efficient
- Can factor N x N convolutions into 1 x N and N x 1
- All of the above give fewer parameters, less compute, more nonlinearity

All About Convolutions

Part II: How to compute them

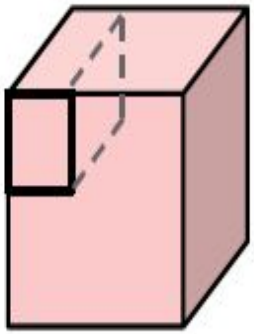
Implementing Convolutions: im2col

There are highly optimized matrix multiplication routines for just about every platform

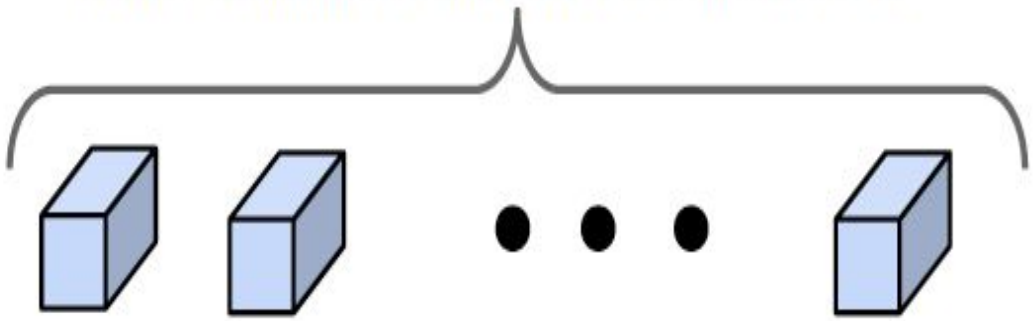
Can we turn convolution into matrix multiplication?

Implementing Convolutions: im2col

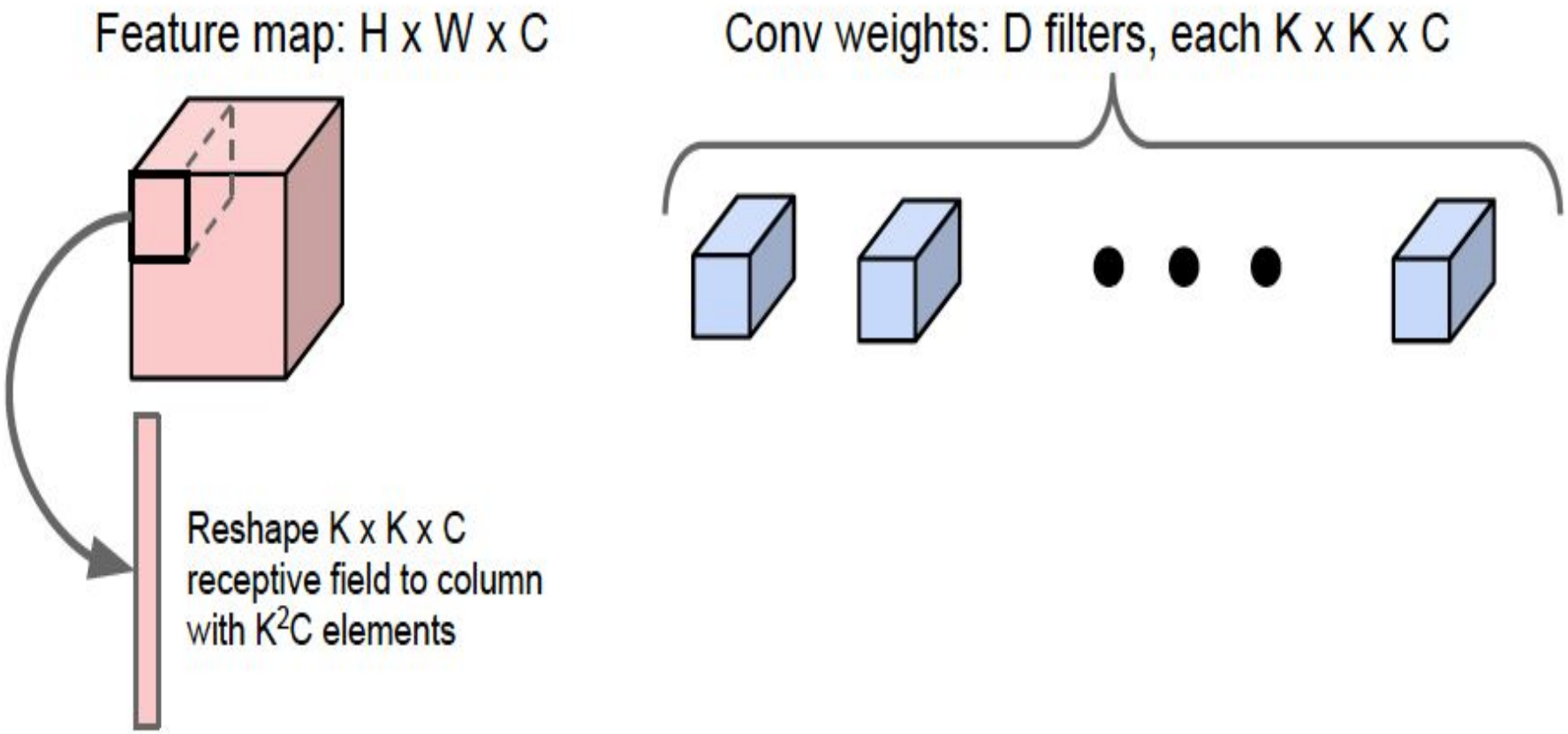
Feature map: H x W x C



Conv weights: D filters, each K x K x C



Implementing Convolutions: im2col



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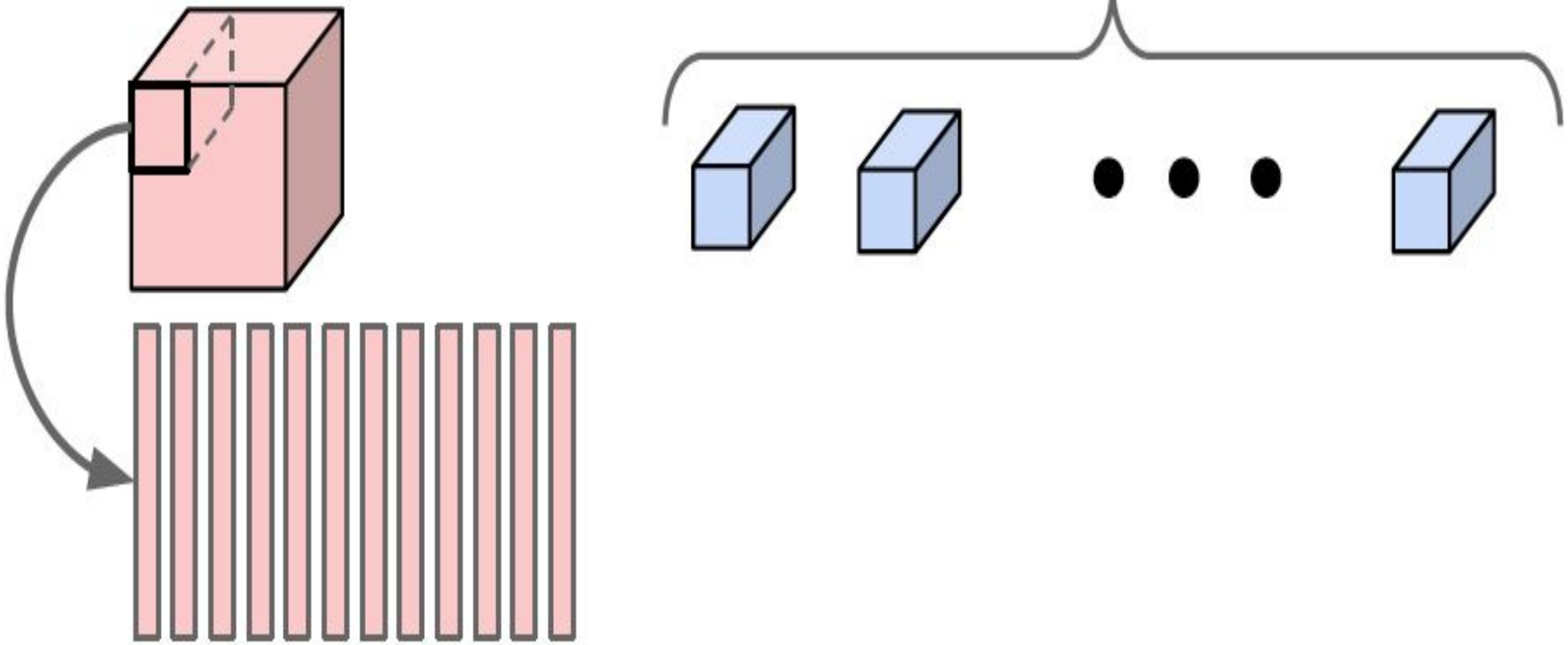

Repeat for all columns to get $(K^2C) \times N$ matrix
(N receptive field locations)

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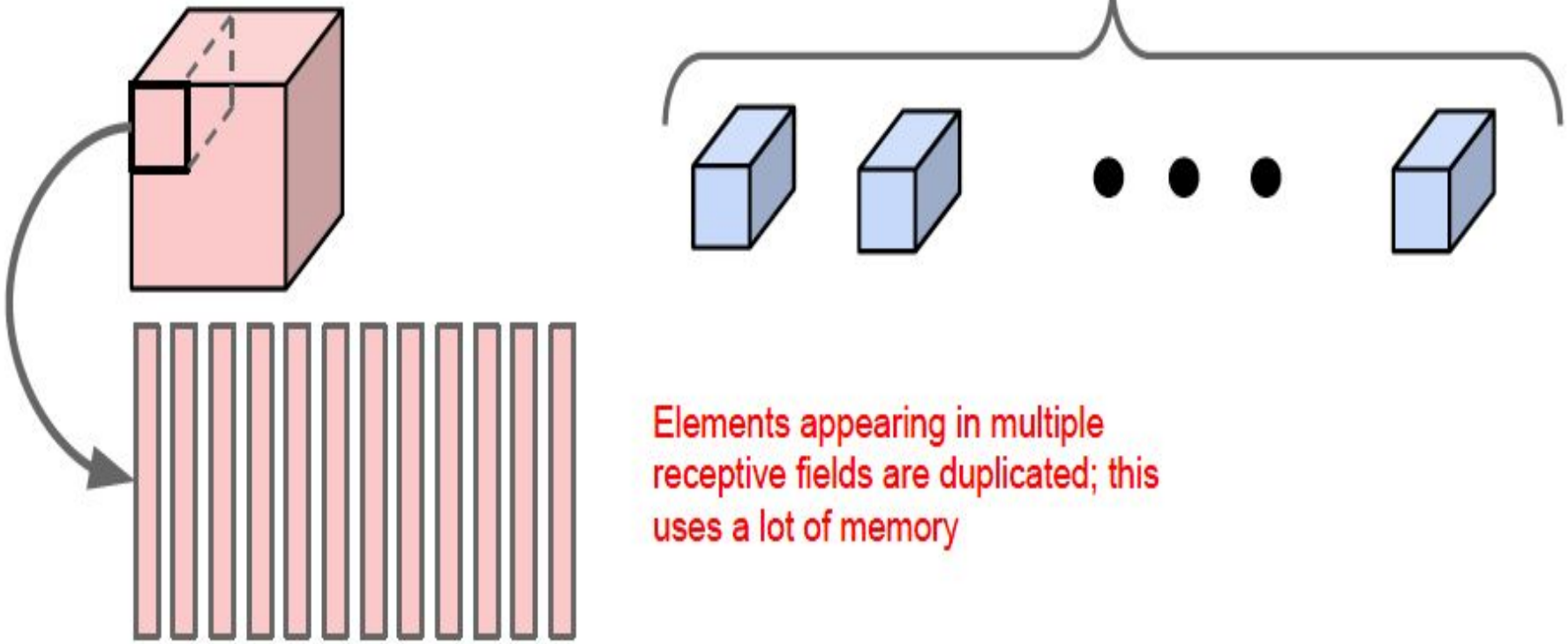
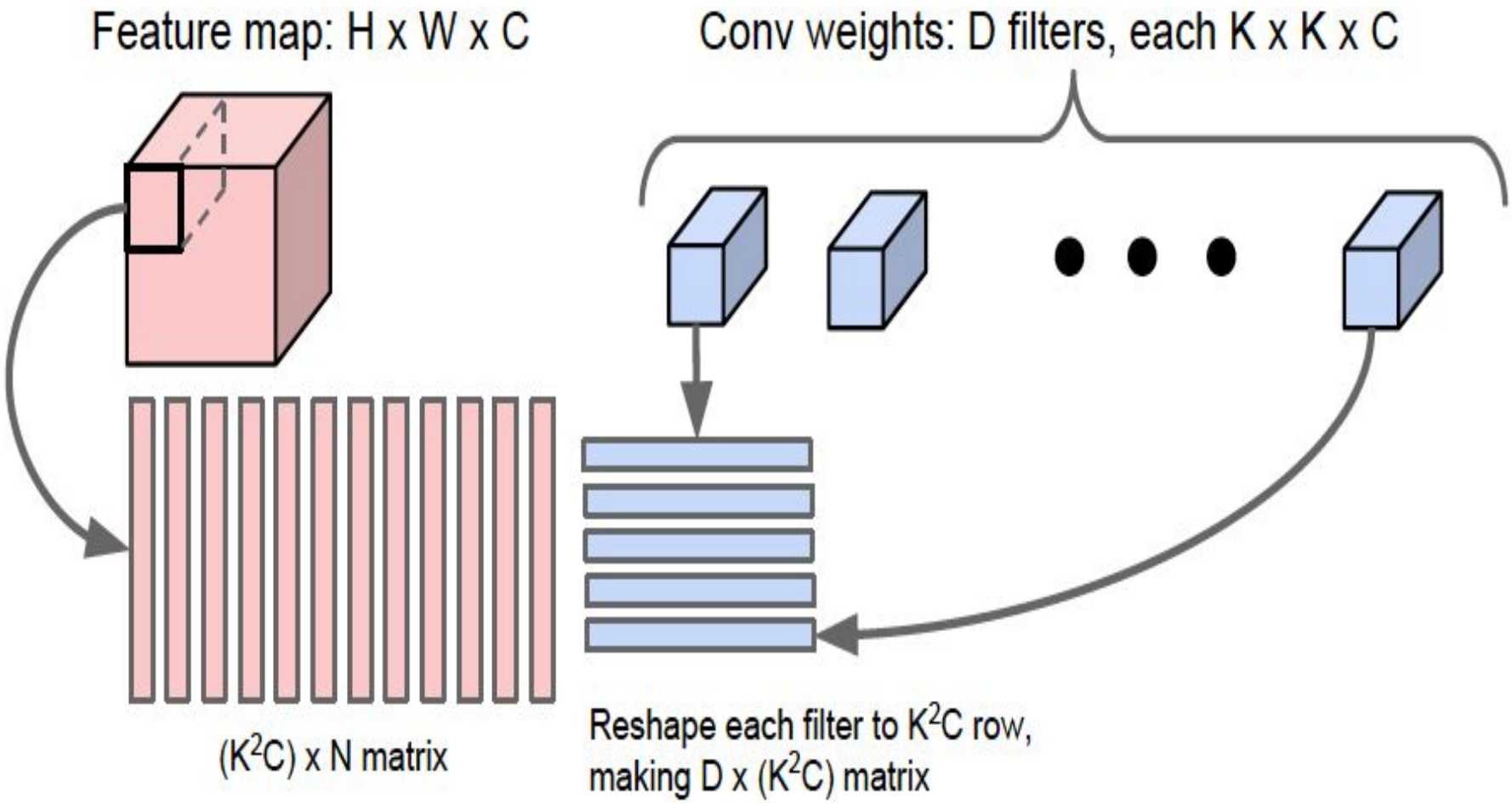


Elements appearing in multiple receptive fields are duplicated; this uses a lot of memory

Repeat for all columns to get $(K^2C) \times N$ matrix
(N receptive field locations)

Implementing Convolutions: im2col



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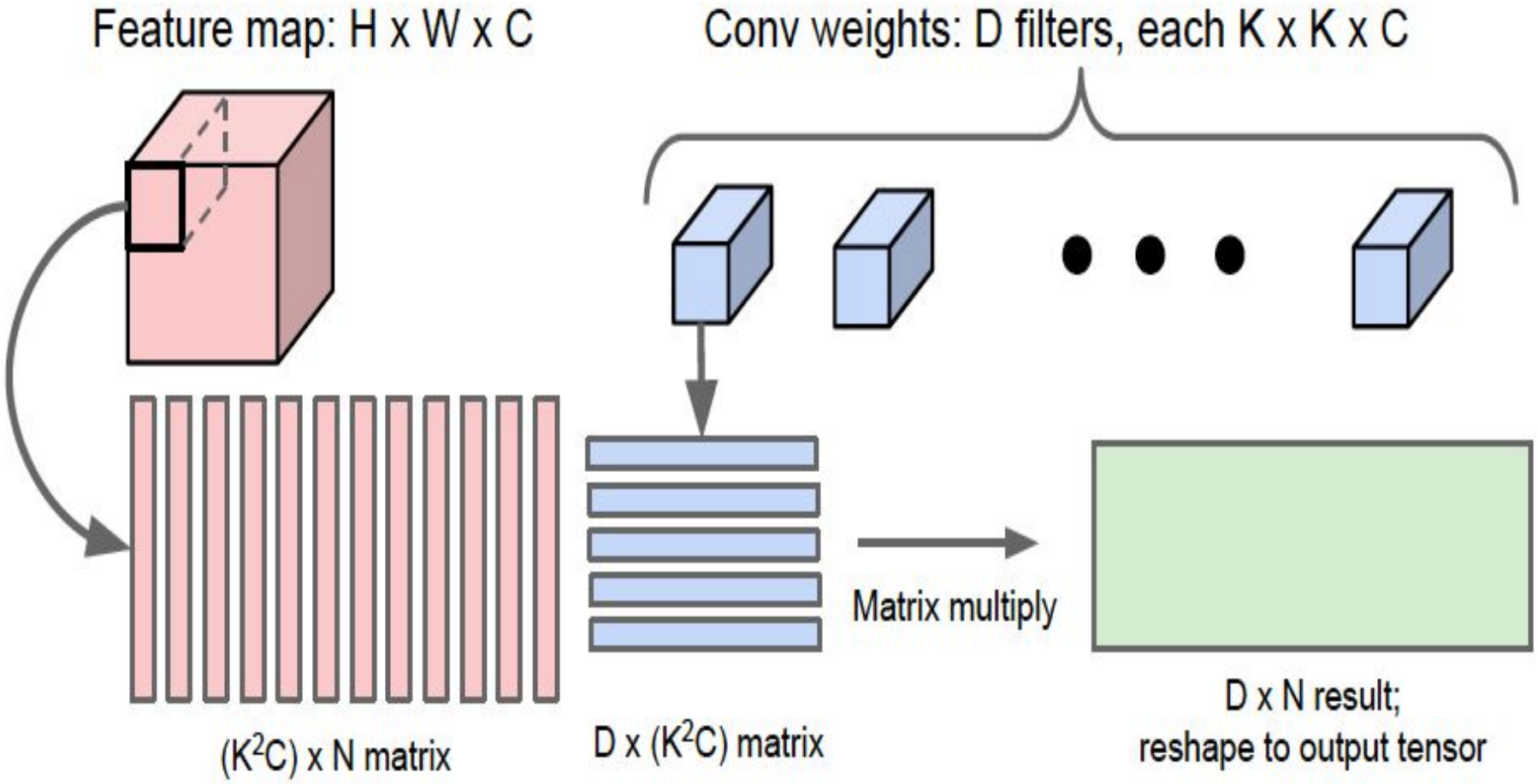


Implementing convolutions: FFT

Convolution Theorem: The convolution of f and g is equal to the elementwise product of their Fourier Transforms:

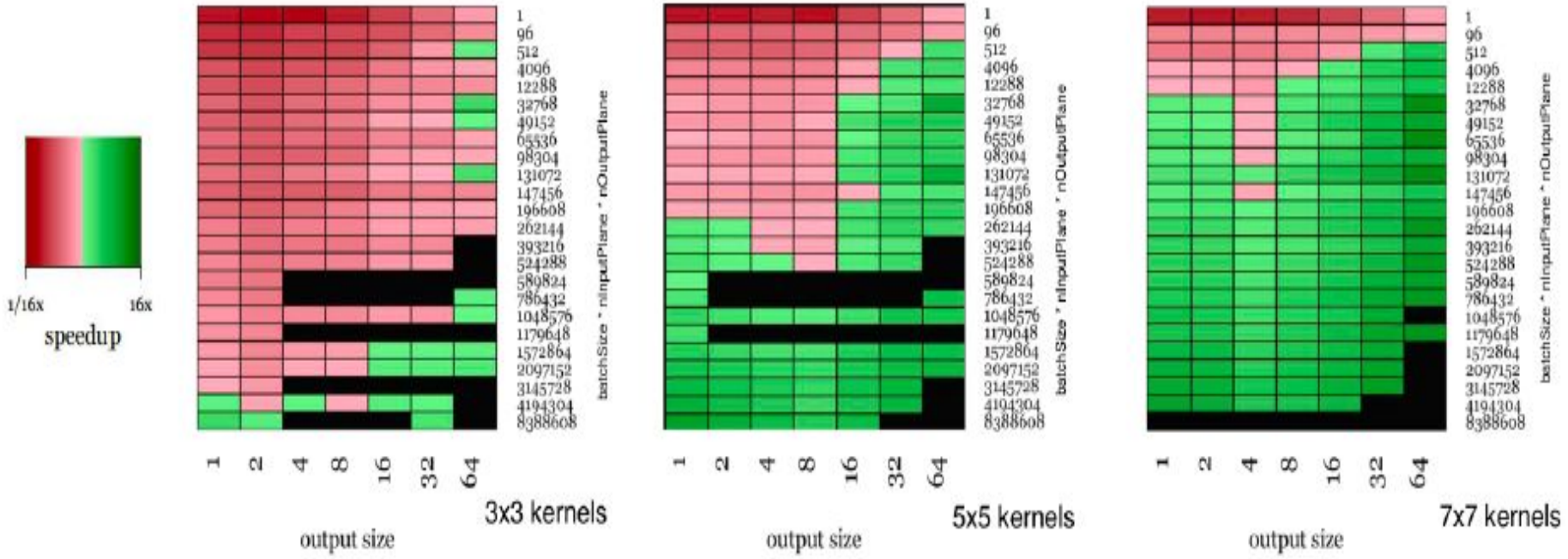
$$\mathcal{F}(f * g) = \mathcal{F}(f) \cdot \mathcal{F}(g)$$

Using the **Fast Fourier Transform**, we can compute the Discrete Fourier transform of an N-dimensional vector in O (N log N) time (also extends to 2D images)

Implementing convolutions: FFT

1. Compute FFT of weights: $F(W)$
2. Compute FFT of image: $F(X)$
3. Compute elementwise product: $F(W) \circ F(X)$
4. Compute inverse FFT: $Y = F^{-1}(F(W) \circ F(X))$

Implementing convolutions: FFT



FFT convolutions get a big speedup for larger filters

Not much speedup for 3x3 filters =(

Vasilache et al, Fast Convolutional Nets With fbfft: A GPU Performance Evaluation

Implementing convolution: "Fast Algorithms"

Naive matrix multiplication: Computing product of two N x N matrices takes $O(N^3)$ operations

Strassen's Algorithm: Use clever arithmetic to reduce complexity to $O(N^{\log_2(7)}) \sim O(N^{2.81})$

$$A = \begin{bmatrix} A_{1,1} & A_{1,2} \\ A_{2,1} & A_{2,2} \end{bmatrix}$$

$$B = \begin{bmatrix} B_{1,1} & B_{1,2} \\ B_{2,1} & B_{2,2} \end{bmatrix}$$

$$C = \begin{bmatrix} C_{1,1} & C_{1,2} \\ C_{2,1} & C_{2,2} \end{bmatrix}$$

$$\begin{aligned}
M_1 &:= (A_{1,1} + A_{2,2})(B_{1,1} + B_{2,2}) \\
M_2 &:= (A_{2,1} + A_{2,2})B_{1,1} \\
M_3 &:= A_{1,1}(B_{1,2} - B_{2,2}) \\
M_4 &:= A_{2,2}(B_{2,1} - B_{1,1}) \\
M_5 &:= (A_{1,1} + A_{1,2})B_{2,2} \\
M_6 &:= (A_{2,1} - A_{1,1})(B_{1,1} + B_{1,2}) \\
M_7 &:= (A_{1,2} - A_{2,2})(B_{2,1} + B_{2,2})
\end{aligned}$$

$$\begin{aligned}
C_{1,1} &= M_1 + M_4 - M_5 + M_7 \\
C_{1,2} &= M_3 + M_5 \\
C_{2,1} &= M_2 + M_4 \\
C_{2,2} &= M_1 - M_2 + M_3 + M_6
\end{aligned}$$

From Wikipedia

Implementing convolution: "Fast Algorithms"

Similar cleverness can be applied to convolutions

Lavin and Gray (2015) work out special cases for 3x3 convolutions:

$$F(2,3) = \begin{bmatrix} d_0 & d_1 & d_2 \\ d_1 & d_2 & d_3 \end{bmatrix} \begin{bmatrix} g_0 \\ g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} m_1 + m_2 + m_3 \\ m_2 - m_3 - m_4 \end{bmatrix}$$

$$m_1 = (d_0 - d_2)g_0 \qquad m_2 = (d_1 + d_2)\frac{g_0 + g_1 + g_2}{2}$$

$$m_4 = (d_1 - d_3)g_2 \qquad m_3 = (d_2 - d_1)\frac{g_0 - g_1 + g_2}{2}$$

$$B^T = \begin{bmatrix} 1 & 0 & -1 & 0 \\ 0 & 1 & 1 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 1 & 0 & -1 \end{bmatrix}$$

$$G = \begin{bmatrix} 1 & 0 & 0 \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -\frac{1}{2} & \frac{1}{2} \\ 0 & 0 & 1 \end{bmatrix}$$

$$A^T = \begin{bmatrix} 1 & 1 & 1 & 0 \\ 0 & 1 & -1 & -1 \end{bmatrix}$$

$$g = \begin{bmatrix} g_0 & g_1 & g_2 \end{bmatrix}^T$$

$$d = \begin{bmatrix} d_0 & d_1 & d_2 & d_3 \end{bmatrix}^T$$

Lavin and Gray, "Fast Algorithms for Convolutional Neural Networks", 2015

Implementing convolution: “Fast Algorithms”

Huge speedups on VGG for small batches:

N	cuDNN		F(2x2,3x3)		Speedup
	msec	TFLOPS	msec	TFLOPS	
1	12.52	3.12	5.55	7.03	2.26X
2	20.36	3.83	9.89	7.89	2.06X
4	104.70	1.49	17.72	8.81	5.91X
8	241.21	1.29	33.11	9.43	7.28X
16	203.09	3.07	65.79	9.49	3.09X
32	237.05	5.27	132.36	9.43	1.79X
64	394.05	6.34	266.48	9.37	1.48X

Table 5. cuDNN versus $F(2 \times 2, 3 \times 3)$ performance on VGG Network E with fp32 data. Throughput is measured in Effective TFLOPS, the ratio of direct algorithm GFLOPs to run time.

N	cuDNN		F(2x2,3x3)		Speedup
	msec	TFLOPS	msec	TFLOPS	
1	14.58	2.68	5.53	7.06	2.64X
2	20.94	3.73	9.83	7.94	2.13X
4	104.19	1.50	17.50	8.92	5.95X
8	241.87	1.29	32.61	9.57	7.42X
16	204.01	3.06	62.93	9.92	3.24X
32	236.13	5.29	123.12	10.14	1.92X
64	395.93	6.31	242.98	10.28	1.63X

Table 6. cuDNN versus $F(2 \times 2, 3 \times 3)$ performance on VGG Network E with fp16 data.

Computing Convolutions: Recap

- im2col: Easy to implement, but big memory overhead
- FFT: Big speedups for small kernels
- “Fast Algorithms” seem promising, not widely used yet

Implementation Details


GEFORCE GTX
CORSAIR
AX1200i

Spot the CPU!

Spot the CPU!

"central processing unit"

Spot the GPU!

"graphics processing unit"

Spot the GPU!

"graphics processing unit"

VS

AMD

VS

AMD

NVIDIA is much more common for deep learning

CPU

Few, fast cores (1 - 16)

Good at sequential processing

GPU

Many, slower cores (thousands)

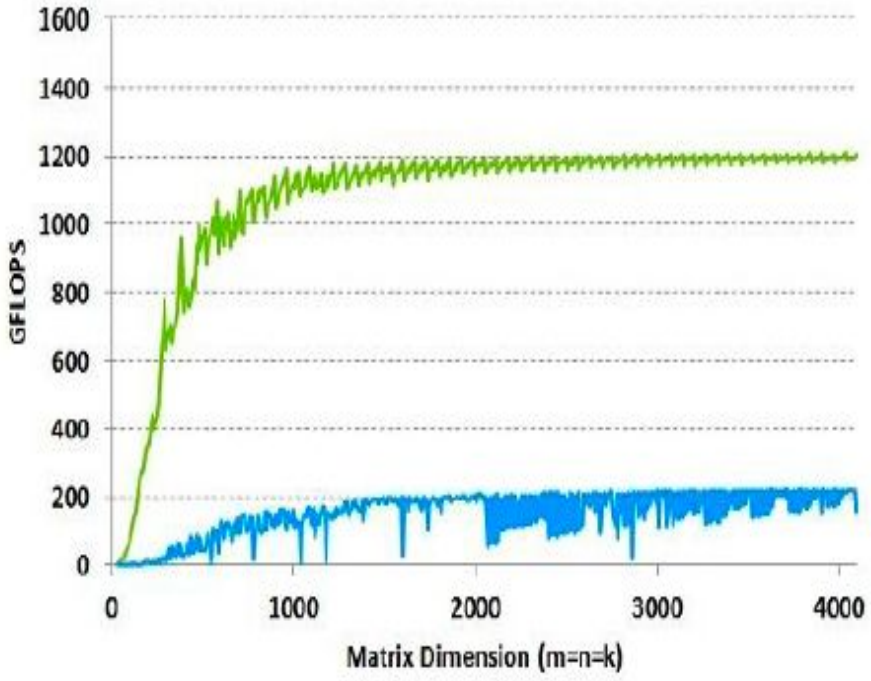
Originally for graphics

Good at parallel computation

GPUs can be programmed

- CUDA (NVIDIA only)
  - Write C code that runs directly on the GPU
  - Higher-level APIs: cuBLAS, cuFFT, cuDNN, etc
- OpenCL
  - Similar to CUDA, but runs on anything
  - Usually slower :(
- Udacity: Intro to Parallel Programming https://www.udacity.com/course/cs344
  - For deep learning just use existing libraries

GPUs are really good at matrix multiplication:



GPU: NVIDA Tesla K40 with cuBLAS

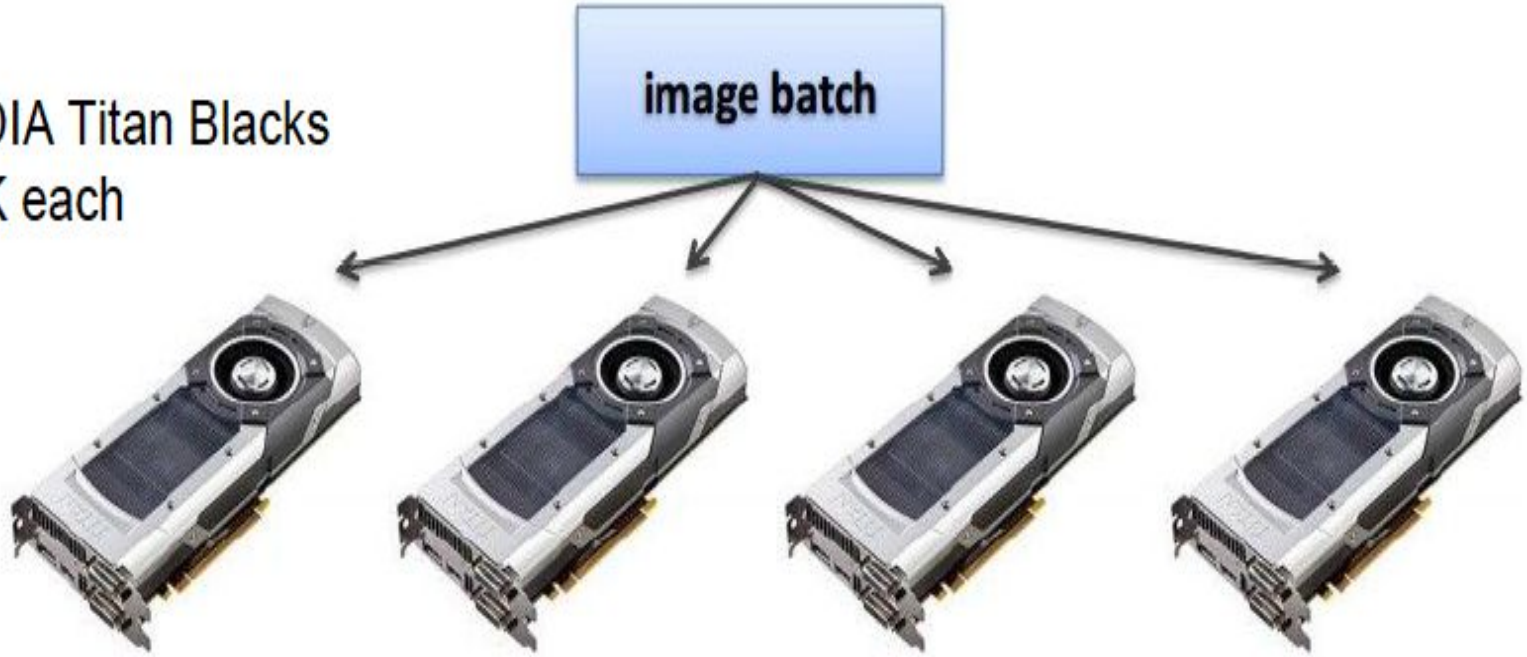
CPU: Intel E5-2697 v2 12 core @ 2.7 Ghz with MKL

Even with GPUs, training can be slow

VGG: ~2-3 weeks training with 4 GPUs

ResNet 101: 2-3 weeks with 4 GPUs

NVIDIA Titan Blacks
~$1K each



ResNet reimplemented in Torch: http://torch.ch/blog/2016/02/04/resnets.html

Bottlenecks

to be aware of

GPU - CPU communication is a bottleneck.

=>

CPU data prefetch+augment thread running

while

GPU performs forward/backward pass

CPU - disk bottleneck

Moving parts lol

Hard disk is slow to read from

=> Pre-processed images stored contiguously in files, read as raw byte stream from SSD disk

GPU memory bottleneck

Titan X: 12 GB <- currently the max
GTX 980 Ti: 6 GB

e.g.
AlexNet: ~3GB needed with batch size 256

Tips & Tricks

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- Don't use ReLU or LeakyReLU's gates before max pooling, instead apply it after to save computation
- Normalize the data! *try* to squeeze into [-1,1] (Pytorch approach)

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- If your input data has a spatial parameter try to go for CNN's end to end (conv layer retain spatiality informations, remember!)
- Modify your models to use 1x1 CNN's layers where it is possible
- Don't even try to train anything without a high end GPU. Well, you can try on some veeeeery small networks ;)

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Deep Learning is the **Neutron Bomb** of Machine Learning, BUT…

Understand the architecture you are using and what you are trying to achieve. Don't mindlessly copy models!

That’s all!