Lecture 7 - Even more about ConvNets

DD2424

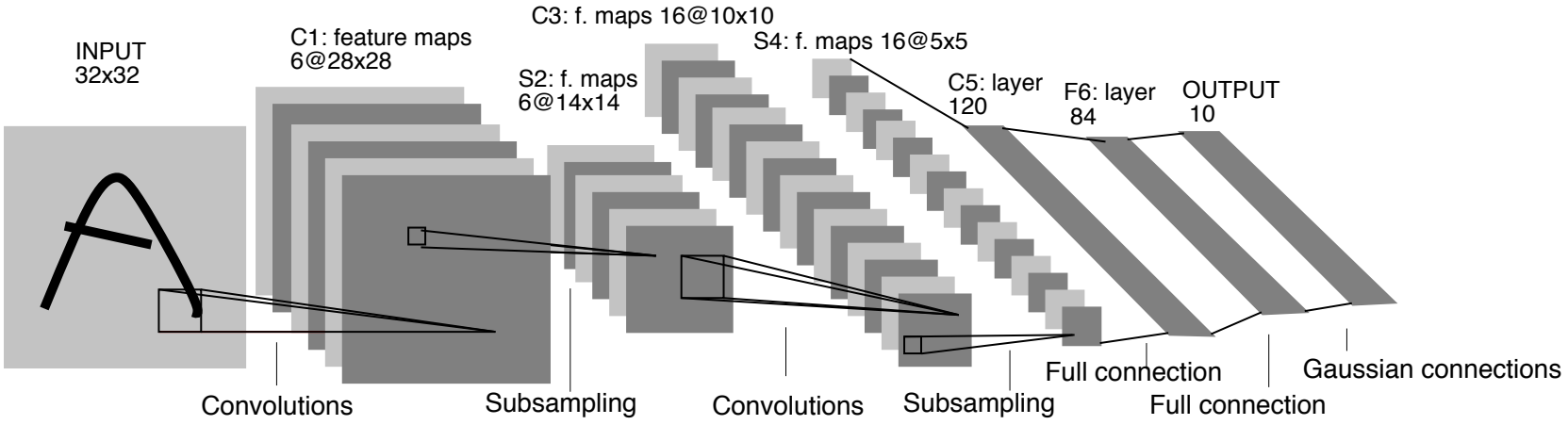
April 2, 2019

Overview of today's lecture

- More on Modern ConvNet architectures
- Practicalities of training & designing ConvNets
  - Stacking convolutional filters.
  - Data augmentation.
  - Batch Normalization for convolutional layers.
  - Transfer learning.
- ConvNets for Semantic segmentation
  - Transposed convolutions

Architecture of Modern ConvNets

LeNet-5 [LeCun et al., 1998]



- Conv filters are 5×5, applied at stride 1
- Pooling layers are 2×2, applied at stride 2
- Architecture is

  [CONV-POOL-TANH-CONV-POOL-TANH-FC-TANH-FC-TANH-FC]

AlexNet [Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

Output size	**Layer type**	**Details**
$227 \times 227 \times 3$	Input	
$55 \times 55 \times 96$	Conv	96 filters, size 11×11 at stride 4, pad 0
$27 \times 27 \times 96$	Max Pool	3×3 regions at stride 2
$27 \times 27 \times 96$	Norm	Normalization layer
$27 \times 27 \times 256$	Conv	256 filters, size 5×5 at stride 1, pad 2
$13 \times 13 \times 256$	Max Pool	3×3 regions at stride 2
$13 \times 13 \times 256$	Norm	Normalization layer
$13 \times 13 \times 384$	Conv	384 filters, size 3×3 at stride 1, pad 1
$13 \times 13 \times 384$	Conv	384 filters, size 3×3 at stride 1, pad 1
$13 \times 13 \times 256$	Conv	256 filters, size 3×3 at stride 1, pad 1
$6 \times 6 \times 256$	Max Pool	3×3 regions at stride 2
4096	Fully connected	4096 neurons
4096	Fully connected	4096 neurons
1000	Fully connected	1000 neurons (class scores)

VGGNet [Simonyan and Zisserman, 2014]

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB imag)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

The 6 different architecures of VGG Net. Configuration D produced the best results

- Only filters of size 3×3 in the convolutional layers, stride 1 and pad 1.
- Relatively sparse use of **Max Pooling** with region size 2×2 and stride 2.
- **Improved ILSVRC Performance** top 5 error:

  2013 best 11.2% $\rightarrow$ 7.3% (VGGNet ensemble)

VGGNet architecture [Simonyan and Zisserman, 2014]

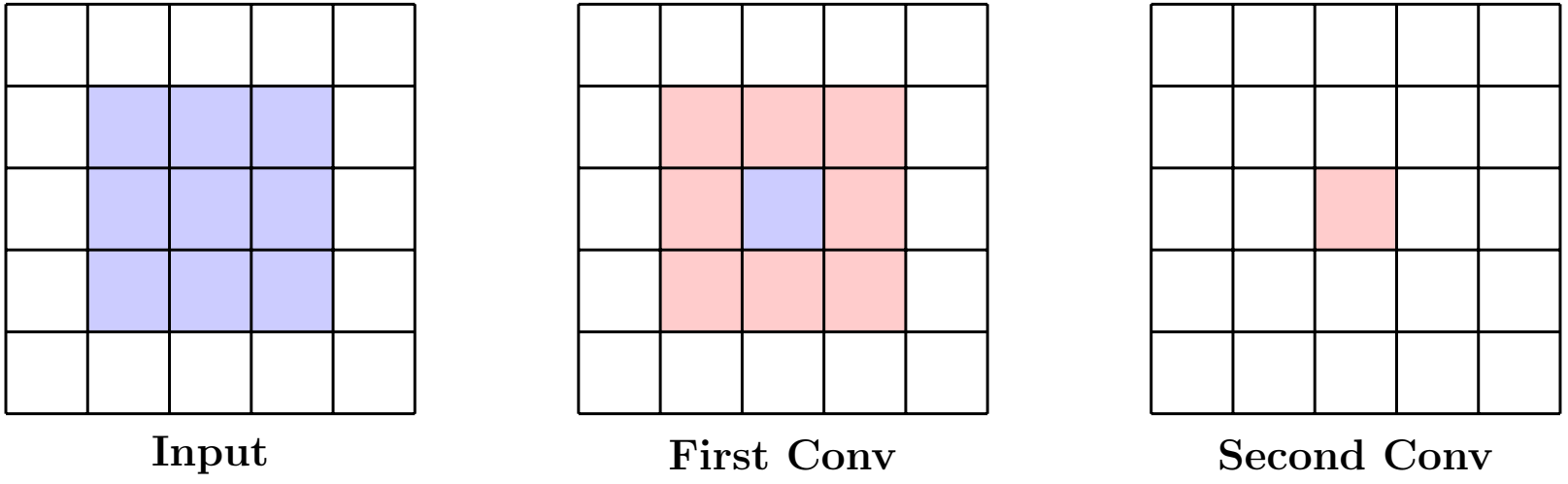
Output size	Layer type	Memory	# parameters
$224 \times 224 \times 3$	Input	224*224*3 = 150K	0
$224 \times 224 \times 64$	Conv	224*224*64 = 3.2M	1,728 = (3*3*3)*64
$224 \times 224 \times 64$	Conv	224*224*64 = 3.2M	36,864 = (3*3*64)*64
$112 \times 112 \times 64$	Max Pool	112*112*64 = 800K	0
$112 \times 112 \times 128$	Conv	112*112*128 = 1.6M	73,728 = (3*3*64)*128
$112 \times 112 \times 128$	Conv	112*112*128 = 1.6M	147,456 = (3*3*128)*128
$56 \times 56 \times 128$	Max Pool	56*56*128 = 400K	0
$56 \times 56 \times 256$	Conv	56*56*256 = 800K	294,912 = (3*3*128)*256
$56 \times 56 \times 256$	Conv	56*56*256 = 800K	589,824 = (3*3*256)*256
$56 \times 56 \times 256$	Conv	56*56*256 = 800K	589,824 = (3*3*256)*256
$28 \times 28 \times 256$	Max Pool	28*28*256 = 200K	0
$28 \times 28 \times 512$	Conv	28*28*512 = 400K	1,179,648 = (3*3*256)*512
$28 \times 28 \times 512$	Conv	28*28*512 = 400K	2,359,296 = (3*3*512)*512
$28 \times 28 \times 512$	Conv	28*28*512 = 400K	2,359,296 = (3*3*512)*512
$14 \times 14 \times 512$	Max Pool	14*14*512 = 100K	0
$14 \times 14 \times 512$	Conv	14*14*512 = 100K	2,359,296 = (3*3*512)*512
$14 \times 14 \times 512$	Conv	14*14*512 = 100K	2,359,296 = (3*3*512)*512
$14 \times 14 \times 512$	Conv	14*14*512 = 100K	2,359,296 = (3*3*512)*512
$7 \times 7 \times 512$	Max Pool	7*7*512 = 25K	0
$1 \times 1 \times 4096$	Fully connected	4096	102,760,448 = 7*7*512*4096
$1 \times 1 \times 4096$	Fully connected	4096	16,777,216 = 4096*4096
$1 \times 1 \times 1000$	Fully connected	1000	4,096,000 = 4096*1000

- Most memory is in early convolutional layers.
- Most parameters in the early fully connected layers.

Why use smaller filters?

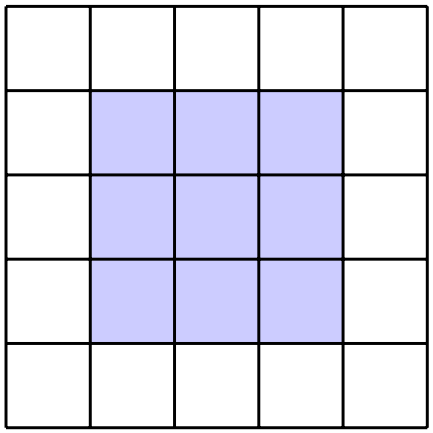
The power of small filters

- Have two consecutive 3×3 conv layers with stride 1.
- Each response *sees* 3×3 region in previous activation map.

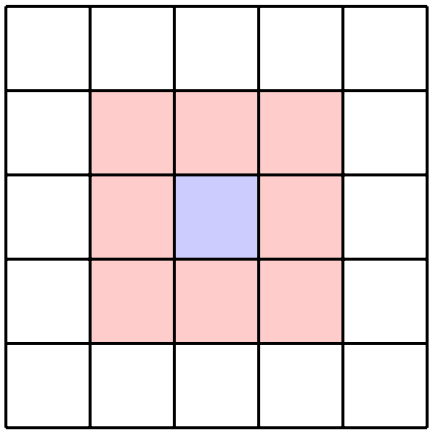


The power of small filters

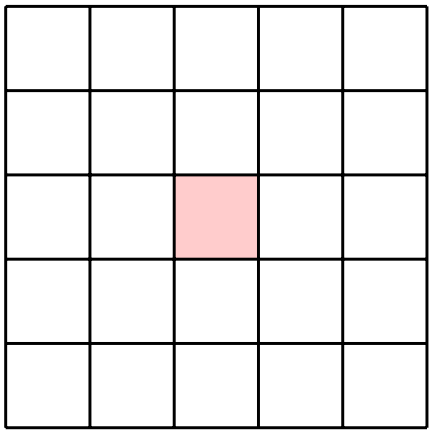
- How big of a region in the input does a response in the second conv layer see?
- **Answer**: 5×5



Input



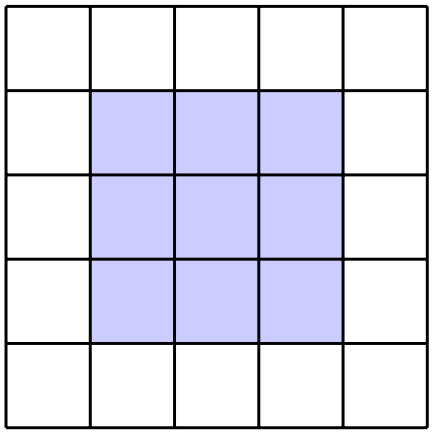
First Conv



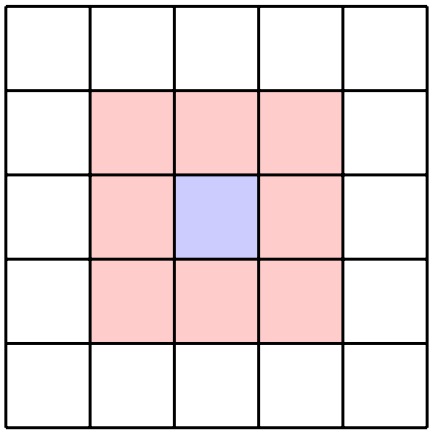
Second Conv

The power of small filters

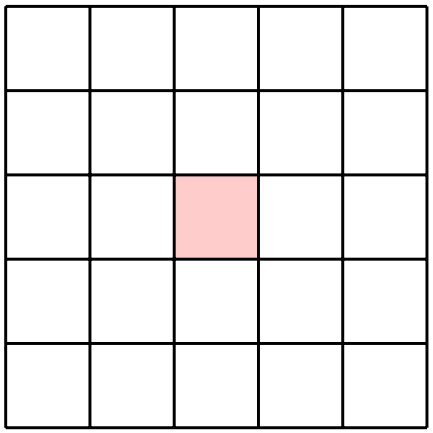
- How big of a region in the input does a response in the second conv layer see?
- **Answer**: 5×5



Input



First Conv



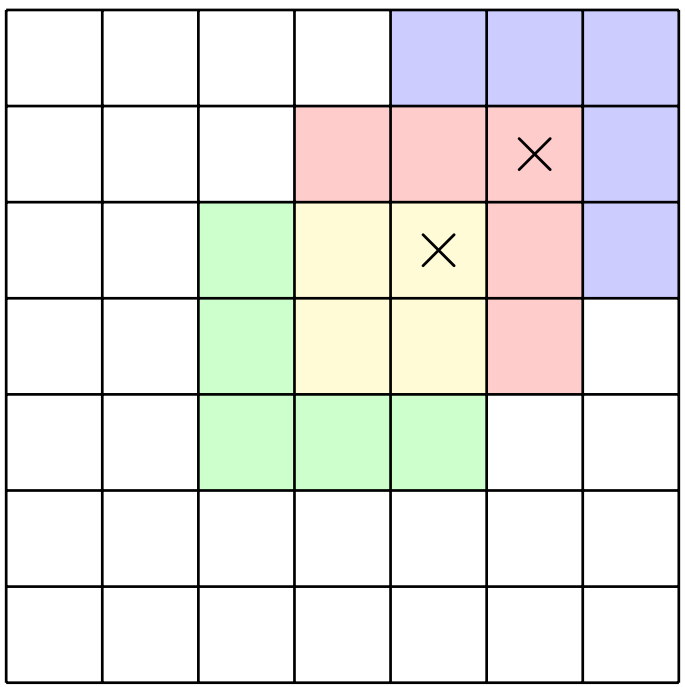
Second Conv

The power of small filters

- We stack three 3×3 conv layers.
- How big is the region in the input layer does that a response in the third layer sees?

The power of small filters

- We stack three 3×3 conv layers.
- How big is the region in the input layer does that a response in the third layer sees?
- **Answer**: 7×7
- Three stacked 3×3 convolutions give similar representational powers as a single 7×7 convolution.



The power of small filters

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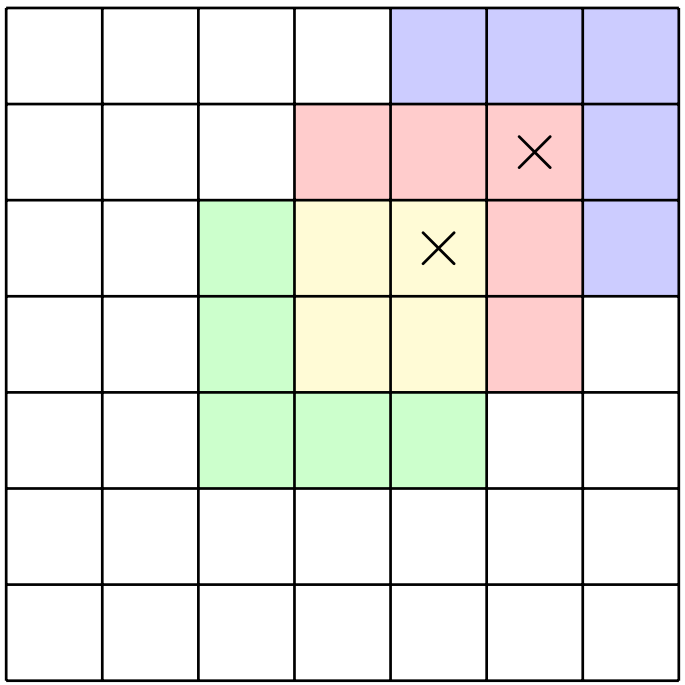


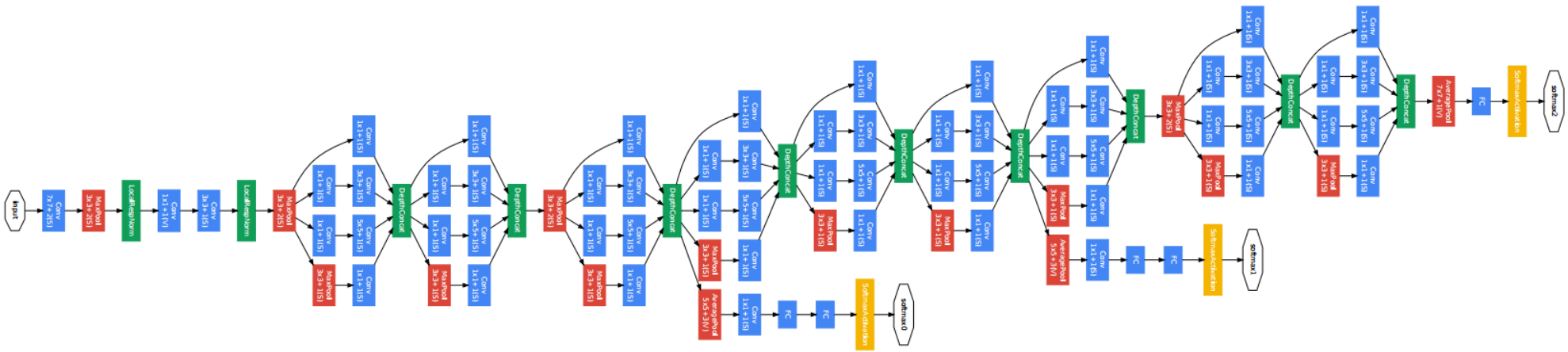
The power of small filters

- Suppose input is $W \times H \times D$ and use D filters to preserve the depth (stride $= 1$, zero-padding to preserve W, H).
- **Option 1** Apply one layer of D filters of size 7×7
- **Option 2** Apply three layers of D filters of size 3×3
- After both options the activations are calculated from the same sized regions in the input image.
- Overview of options:

Option	# of layers	size of filters	# of parameters	# of $\times$'s & $+$'s
1	1	7×7	$D(7 * 7 * D) = 49D^2$	$49WHD^2$
2	3	3×3	$3D(3 * 3 * D) = 27D^2$	$27WHD^2$

- Option 2 requires fewer parameters, less computational effort and applies more non-linearity.

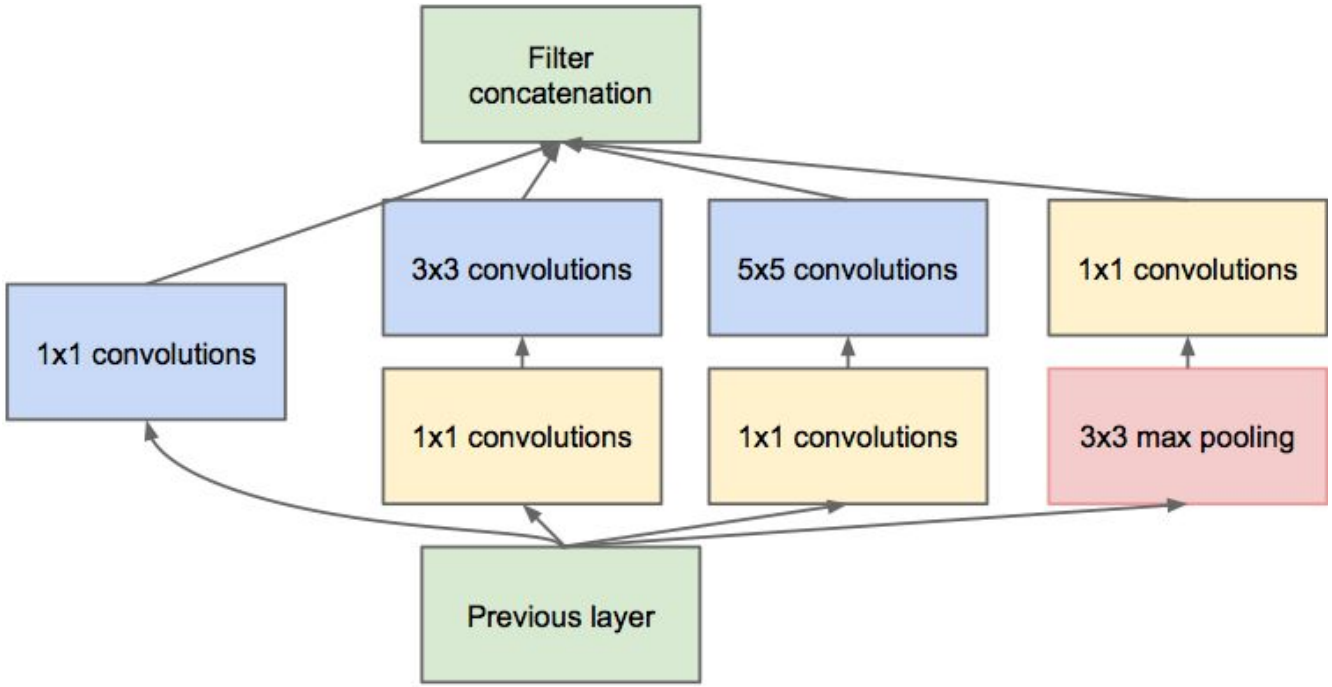
GoogLeNet [Szegedy et al., 2014]



- Convolution layer
- Pooling layer
- SoftMax layer

ILSVRC 2014 winner (6.7% top 5 error)

GoogLeNet: Inception Module



Use $1 \times 1 \times D$ filters to reduce the depth of the response volume before applying the larger more computationally expensive filters.

Back to the power of small filters

- Why stop at 3×3 filters?
- Why not try 1×1 filters?

Back to the power of small filters

- Why not try 1×1 filters?

$$W \times H \times D$$

$$\Downarrow \text{ Apply } \frac{D}{2} \ 1 \times 1 \text{ conv filters}$$

$$W \times H \times \frac{D}{2}$$

1. Use *bottleneck* 1×1 conv filters to reduce the depth dimensionality.

Back to the power of small filters

- Why not try 1×1 filters?

$$W \times H \times D$$

$$\Downarrow \text{ Apply } \frac{D}{2} \; 1 \times 1 \text{ conv filters}$$

$$W \times H \times \frac{D}{2}$$

$$\Downarrow \text{ Apply } \frac{D}{2} \; 3 \times 3 \text{ conv filters}$$

$$W \times H \times \frac{D}{2}$$

1. Use *bottleneck* 1×1 conv filters to reduce the depth dimensionality.
2. Apply 3×3 conv filters at the reduced depth.

Back to the power of small filters

- Why not try 1×1 filters?

$$W \times H \times D$$

$$\Downarrow \text{ Apply } \frac{D}{2} \; 1 \times 1 \text{ conv filters}$$

$$W \times H \times \frac{D}{2}$$

$$\Downarrow \text{ Apply } \frac{D}{2} \; 3 \times 3 \text{ conv filters}$$

$$W \times H \times \frac{D}{2}$$

$$\Downarrow \text{ Apply } D \; 1 \times 1 \text{ conv filters}$$

$$W \times H \times D$$

1. Use *bottleneck* 1×1 conv filters to reduce the depth dimensionality.
2. Apply 3×3 conv filters at the reduced depth.
3. Restore original depth dimension with another D 1×1 conv filters.

Back to the power of small filters

- Why not try 1×1 filters?

$W \times H \times D$

$\Downarrow$ Apply $\frac{D}{2}$ 1×1 conv filters

$W \times H \times \frac{D}{2}$

$\Downarrow$ Apply $\frac{D}{2}$ 3×3 conv filters

$W \times H \times \frac{D}{2}$

$\Downarrow$ Apply D 1×1 conv filters

$W \times H \times D$

Bottleneck sandwich

$W \times H \times D$

$\Downarrow$ Apply D 3×3 conv filters

$W \times H \times D$

Single 3×3 conv filter

Back to the power of small filters

- Why not try 1×1 filters?

$W \times H \times D$

$\Downarrow$ Apply $\frac{D}{2}$ 1×1 conv filters

$W \times H \times \frac{D}{2}$

$\Downarrow$ Apply $\frac{D}{2}$ 3×3 conv filters

$W \times H \times \frac{D}{2}$

$\Downarrow$ Apply D 1×1 conv filters

$W \times H \times D$

$3.25D^2$ parameters

$W \times H \times D$

$\Downarrow$ Apply D 3×3 conv filters

$W \times H \times D$

$9D^2$ parameters

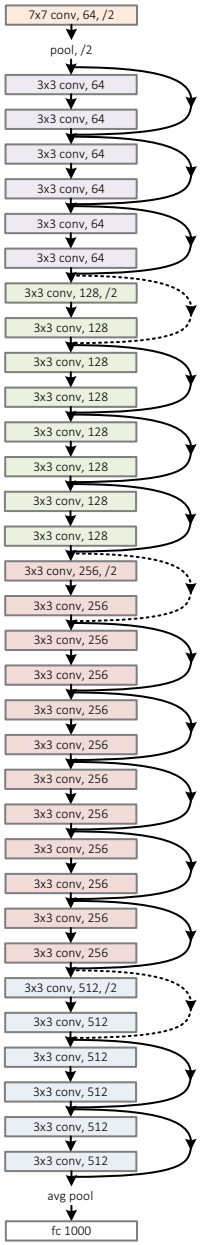
More non-linearity, fewer params, less computations

GoogLeNet: architecture

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

- Only 5 million params! (Only one FC layer $\Longrightarrow$ far fewer parameters)
- Compared to AlexNet:
  - 12× less params
  - 2× more compute
  - Performance on ILSVRC: 6.67% (vs. 16.4%)

ResNet [He et al., 2015]



- ILSVRC 2015 winner (3.6% top 5 error)
- 2-3 weeks of training on 8 GPU machine
- At runtime: faster than a VGGNet! (even though it has 8× more layers)

← "shallow" version of winning entry.

Next slides from:

Deep Residual Networks, Deep Learning Gets Way Deeper by Kaiming He, ICML 2016 tutorial.

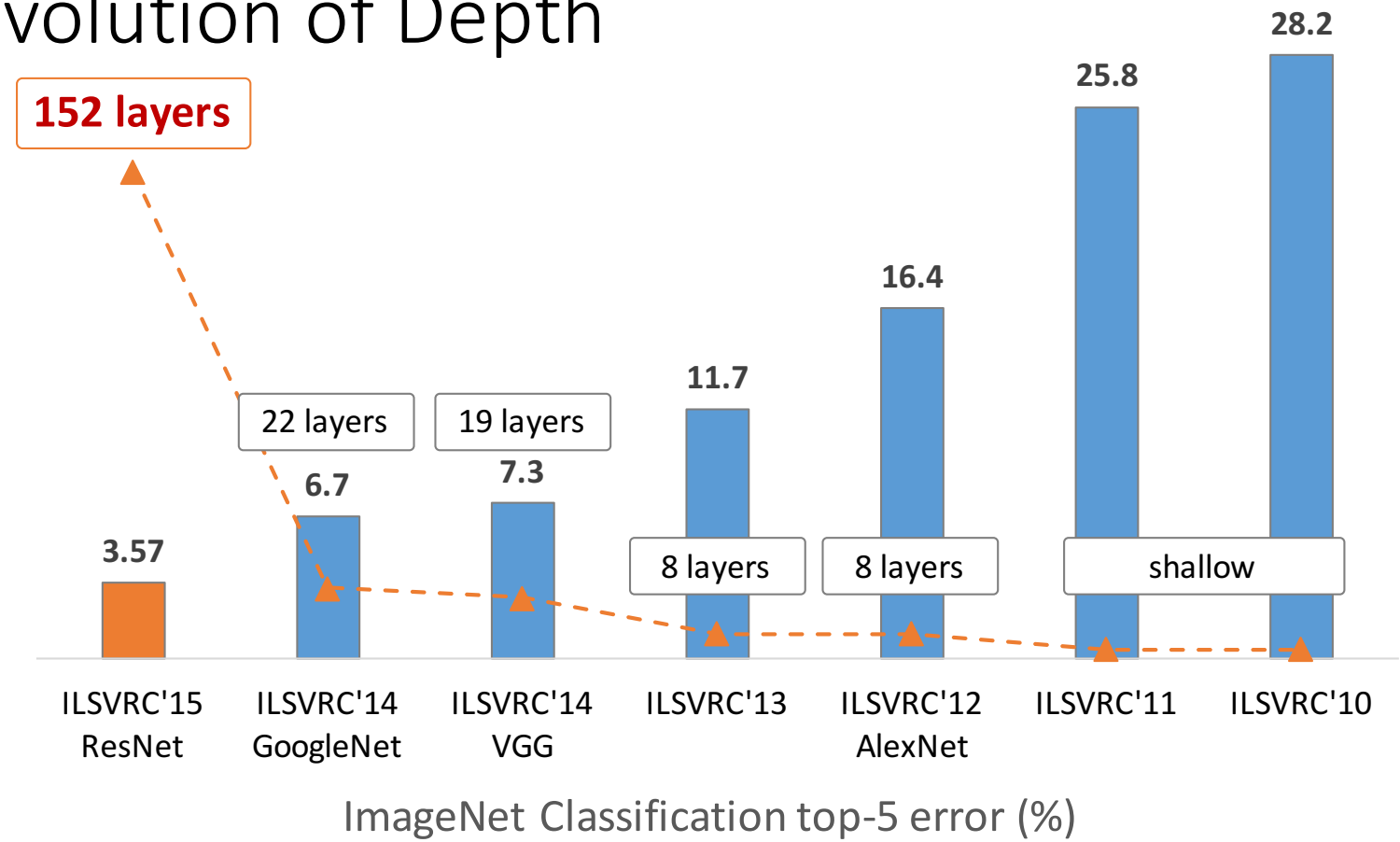
ResNets @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: "*Ultra-deep*" 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

*improvements are relative numbers

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

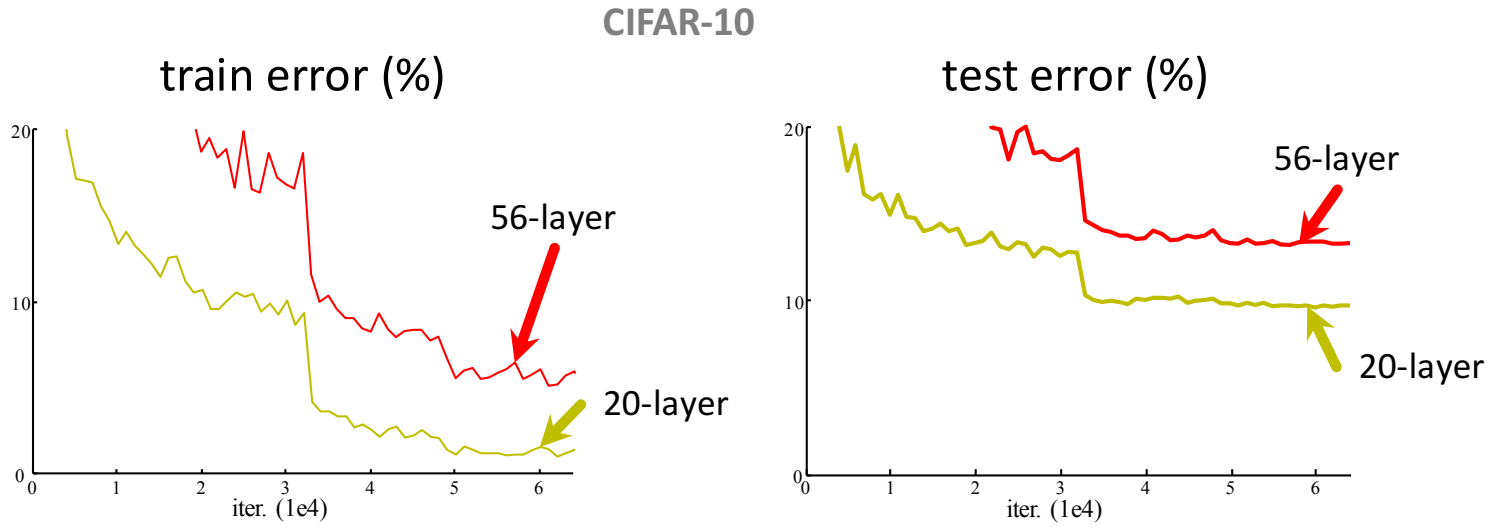
ResNet Motivation [He et al., 2015]

Going Deeper requires

- Care with initialization ✓
- Batch Normalization ✓

Is learning better networks as simple as stacking more layers?

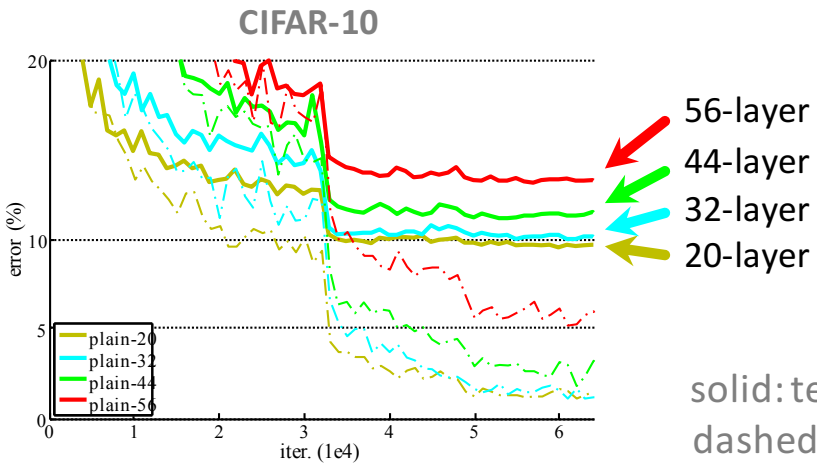
Simply stacking layers?

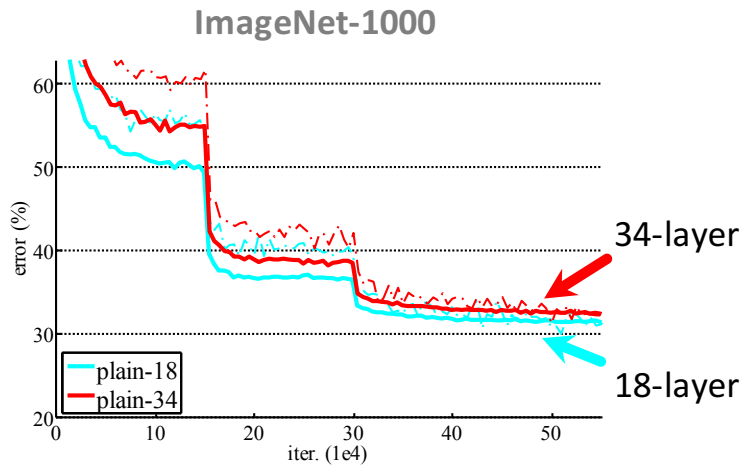


- *Plain* nets: stacking 3x3 conv layers…
- 56-layer net has **higher training error** and test error than 20-layer net

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Simply stacking layers?

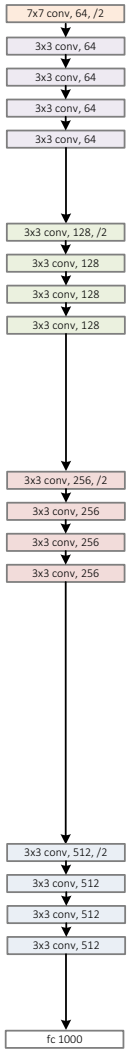


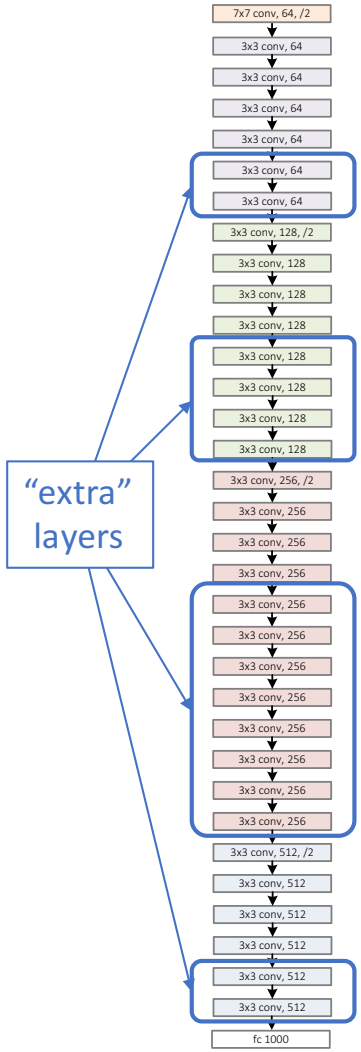


- "Overly deep" plain nets have **higher training error**
- A general phenomenon, observed in many datasets

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

a shallower model (18 layers)





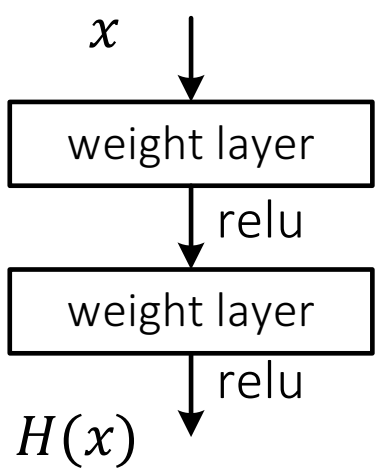
a deeper counterpart (34 layers)

- Richer solution space
- A deeper model should not have **higher training error**
- A solution *by construction*:
  - original layers: copied from a learned shallower model
  - extra layers: set as identity
  - at least the same training error
- Optimization difficulties: solvers cannot find the solution when going deeper…

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Deep Residual Learning

- Plaint net



any two stacked layers

$H(x)$ is any desired mapping,

hope the 2 weight layers fit $H(x)$

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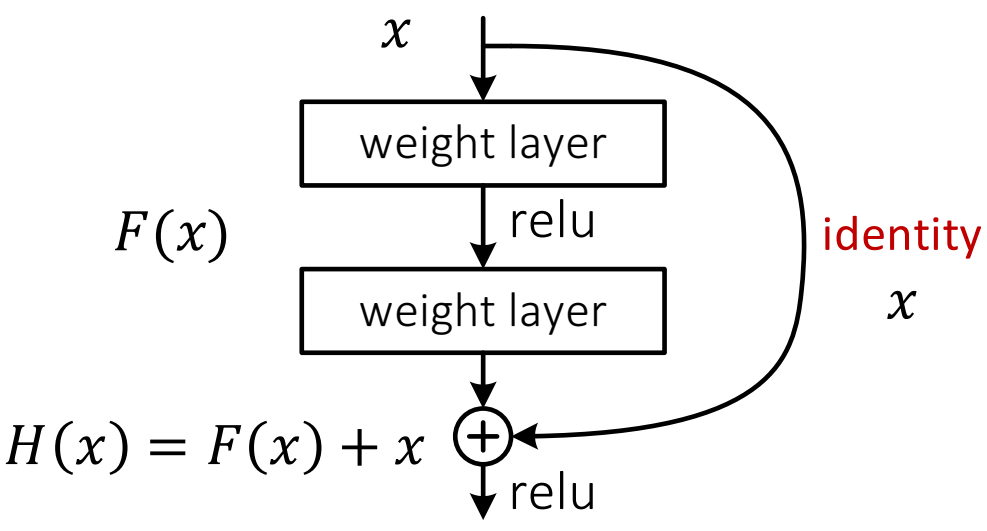
Deep Residual Learning

- Residual net



$H(x)$ is any desired mapping,

~~hope the 2 weight layers fit $H(x)$~~

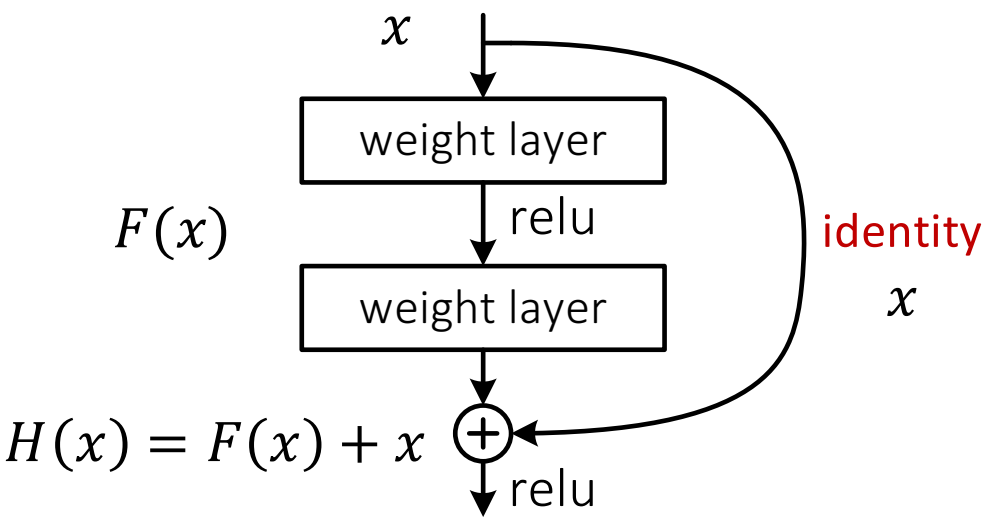
hope the 2 weight layers fit $F(x)$

let $H(x) = F(x) + x$

Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Deep Residual Learning

- $F(x)$ is a residual mapping w.r.t. identity



- If identity were optimal, easy to set weights as 0
- If optimal mapping is closer to identity, easier to find small fluctuations

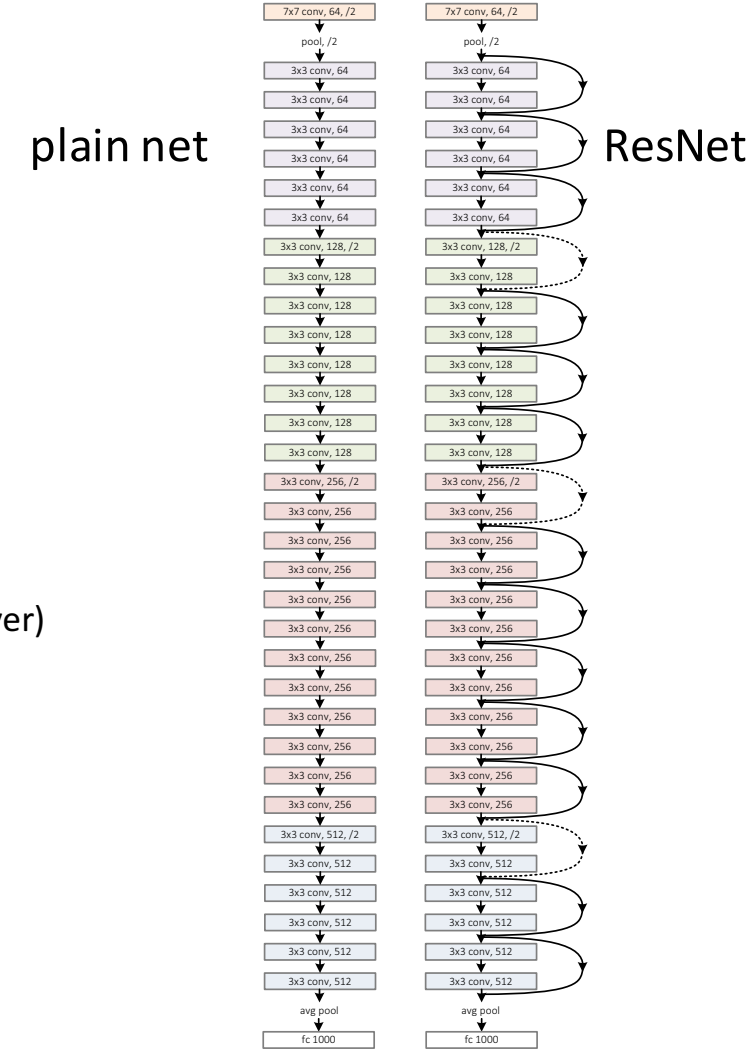
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Network “Design”

- Keep it simple

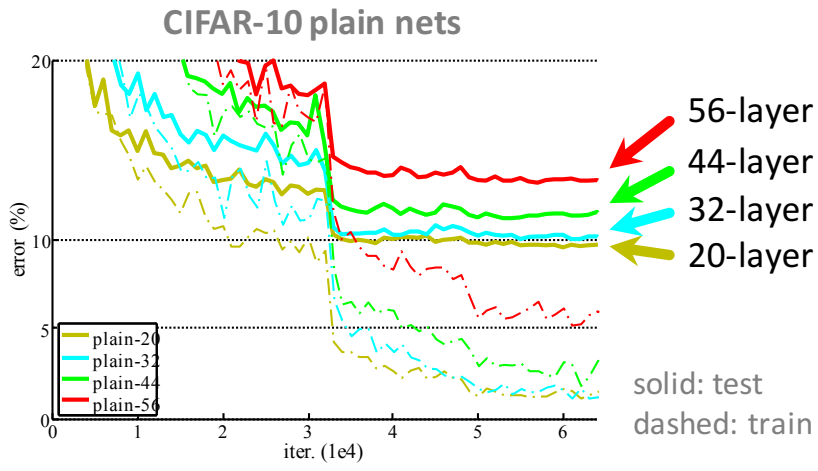
- Our basic design (VGG-style)
  - all 3x3 conv (almost)
  - spatial size /2 => # filters x2 (~same complexity per layer)
  - Simple design; just deep!

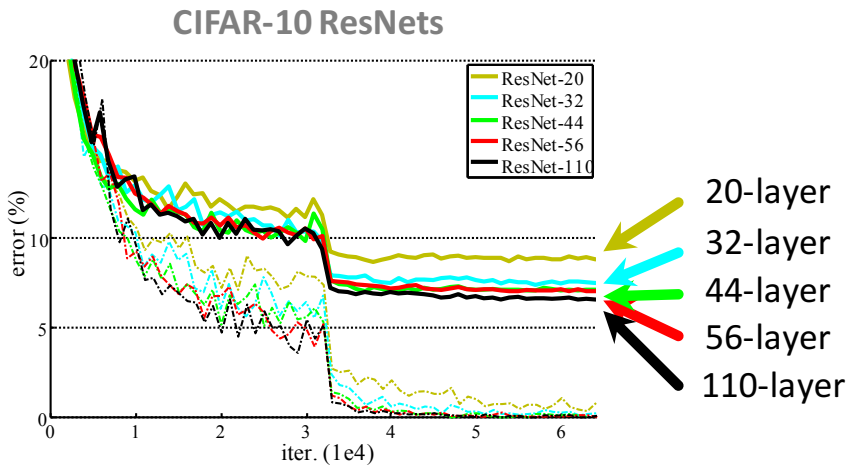
- Other remarks:
  - no hidden fc
  - no dropout



Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. “Deep Residual Learning for Image Recognition”. CVPR 2016.

CIFAR-10 experiments



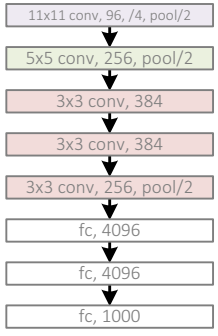


- Deep ResNets can be trained without difficulties
- Deeper ResNets have **lower training error**, and also lower test error

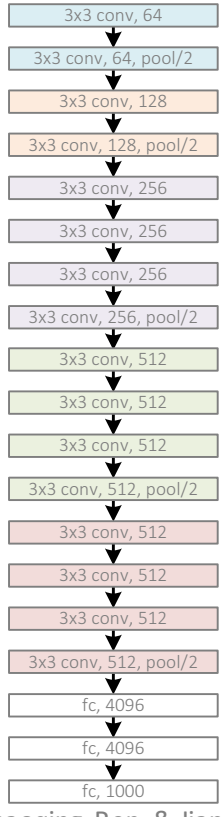
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)

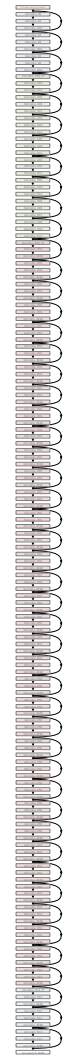
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)

VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

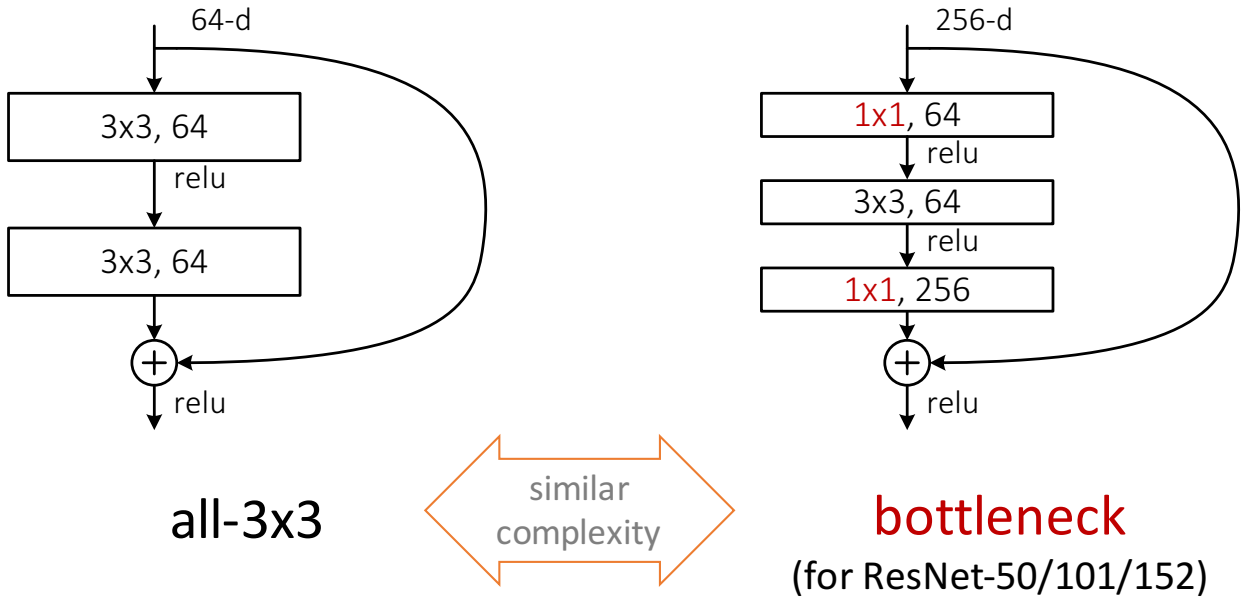


Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

- Batch Normalization after every CONV layer.
- Xavier/2 initialization from He et al.
- SGD + Momentum (0.9).
- Learning rate: 0.1, divided by 10 when validation error plateaus.
- Mini-batch size 256.
- Weight decay of 1e-5.
- No dropout used.

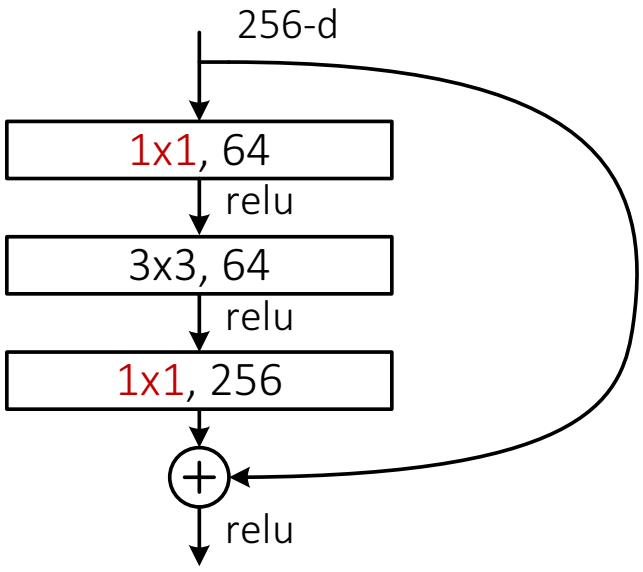
ImageNet experiments

- A practical design of going deeper

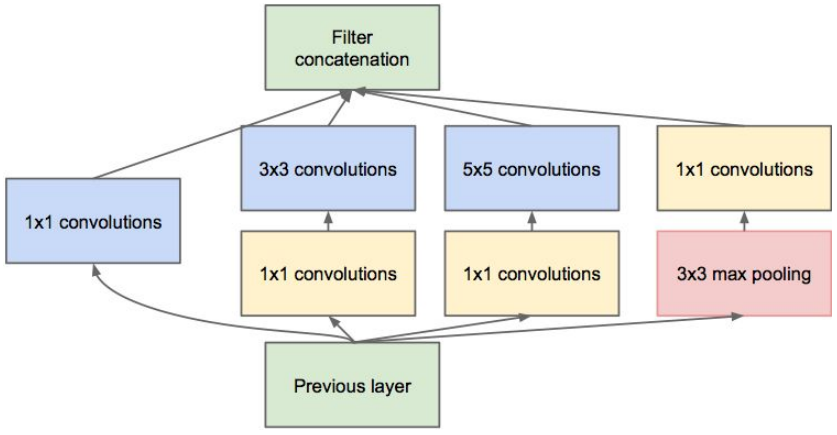


Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". CVPR 2016.

Same trick as used in GoogLeNet

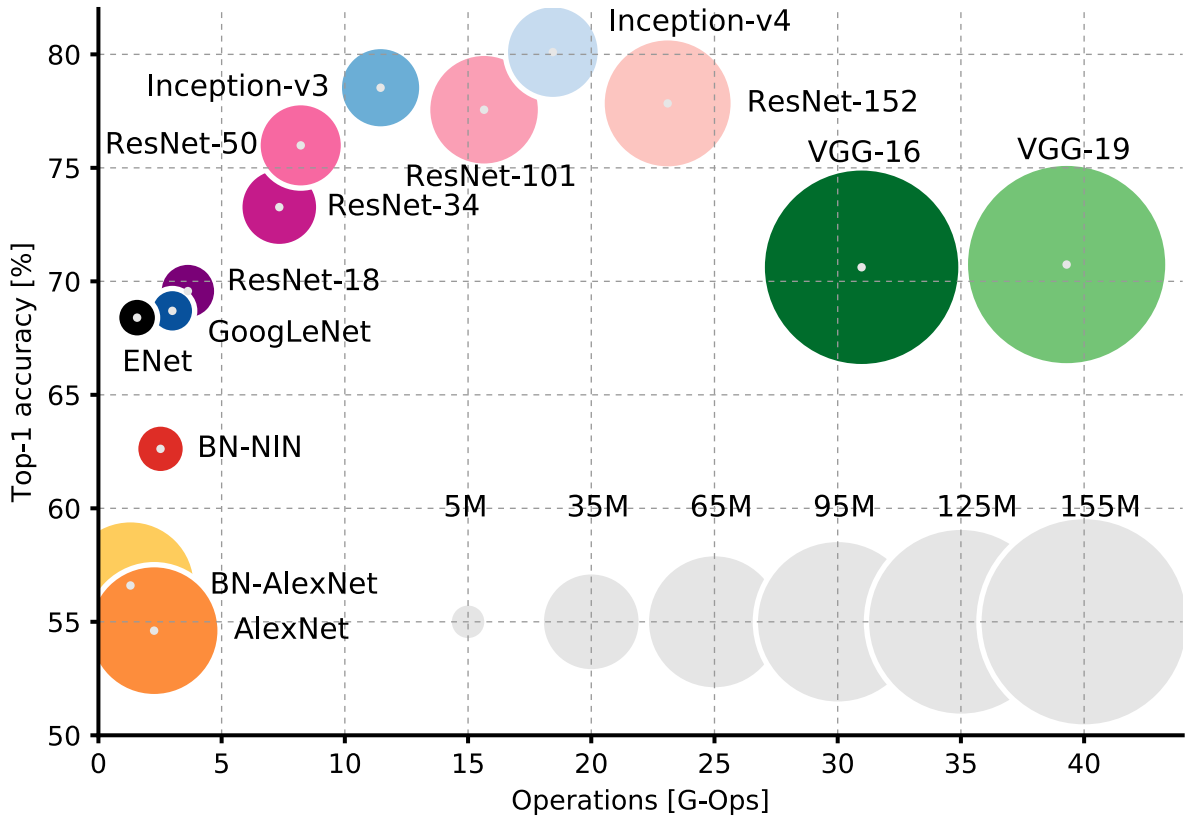


ResNet



GoogLeNet

Accuracy on ImageNet Vs network size



- Top-1 one-crop accuracy Vs amount of operations required for a single forward pass.
- The size of the blobs is proportional to the number of network parameters.

Fig: **An Analysis of Deep Neural Network Models for Practical Applications** by Canziani, Culurciello & Paszke.

Summary: ConvNet Architectures

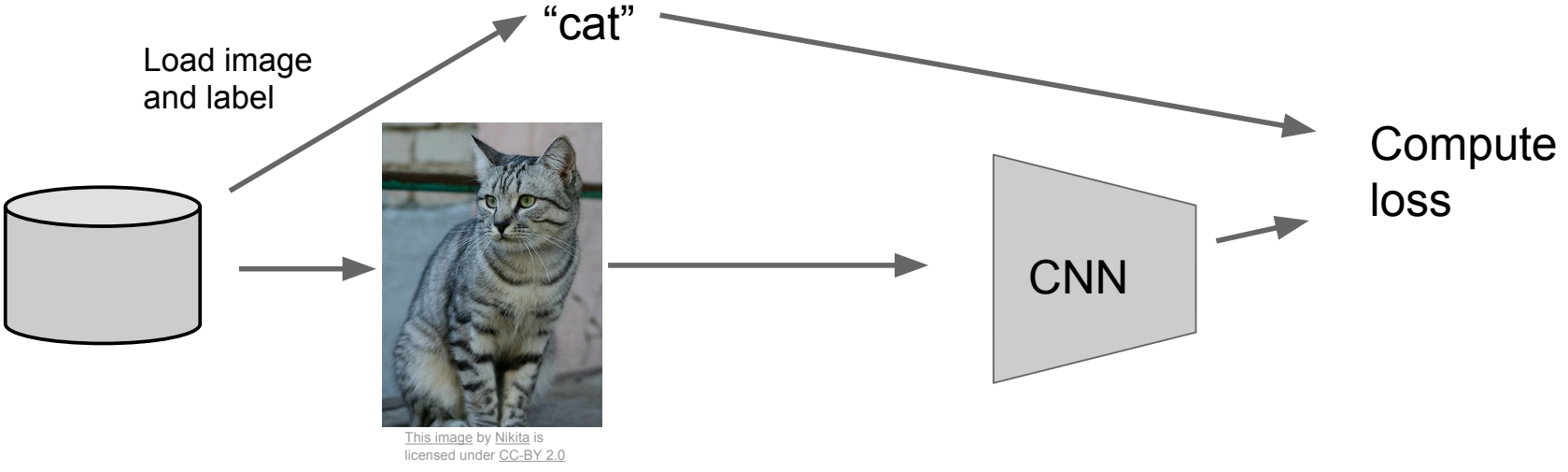
- VGG, GoogLeNet, ResNet all in wide use, available in model zoos.
- ResNet current best default.
- Research focused on design of layer / skip connections and improving gradient flow
- More recent trend towards examining necessity of depth vs. width and residual connections.

Practicalities of training ConvNets

- Data augmentation.
- Batch Normalization for convolutional layers
- Transfer learning.

Data Augmentation - regularization strategy to avoid over-fitting

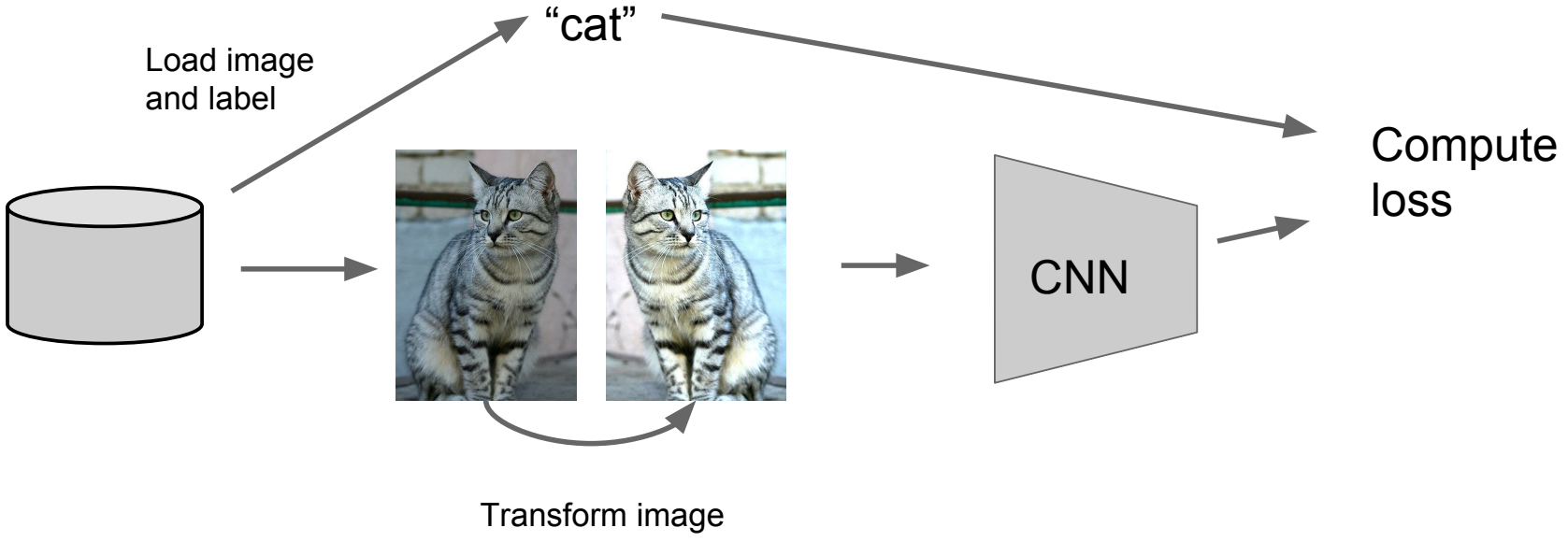
Straightforward approach to training examples



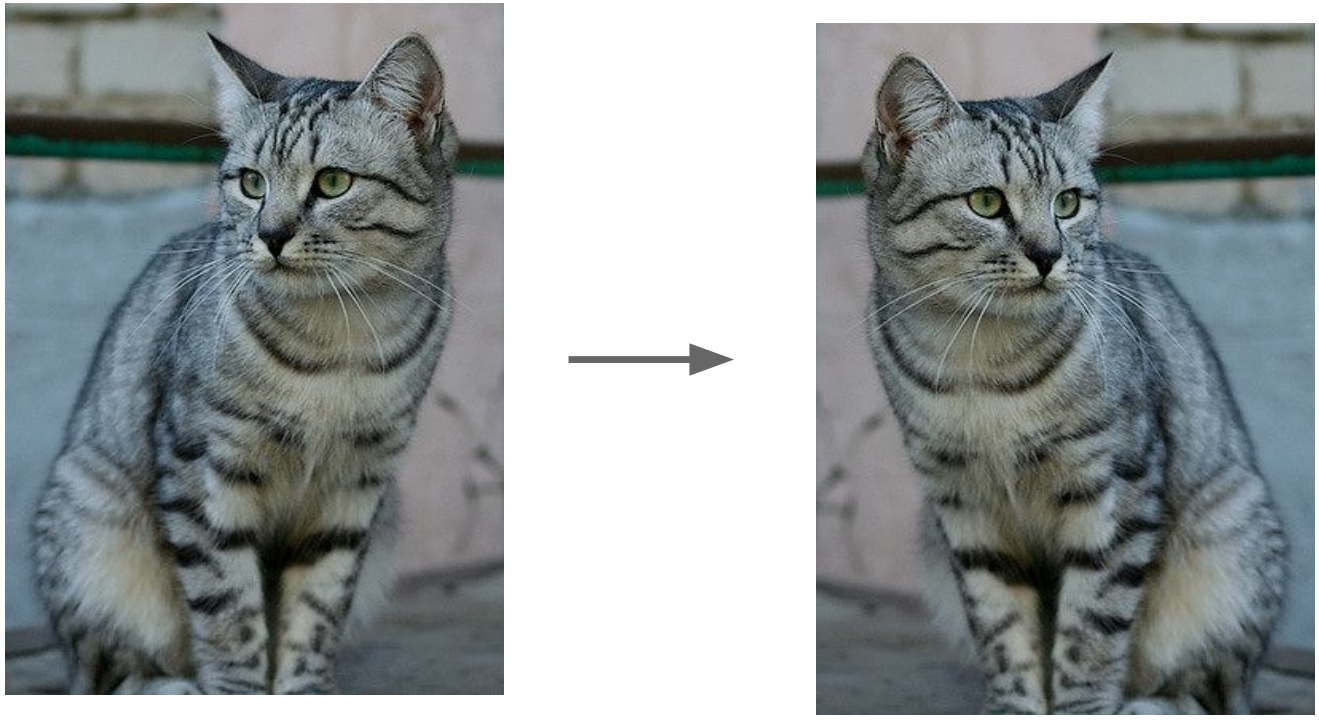
Have n labelled training examples $\implies$ have n training examples.

Data augmentation

- Encounter a training example *transform* it.
- If have n labelled training examples $\implies$ potentially infinite training examples.



Horizontal Flip

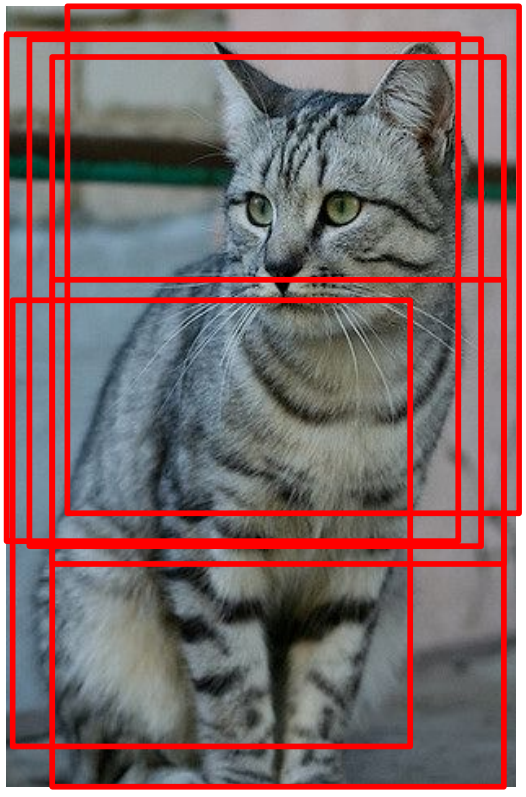


Random crops and scales

During training: Sample random crops / scales

Example for ResNet:

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

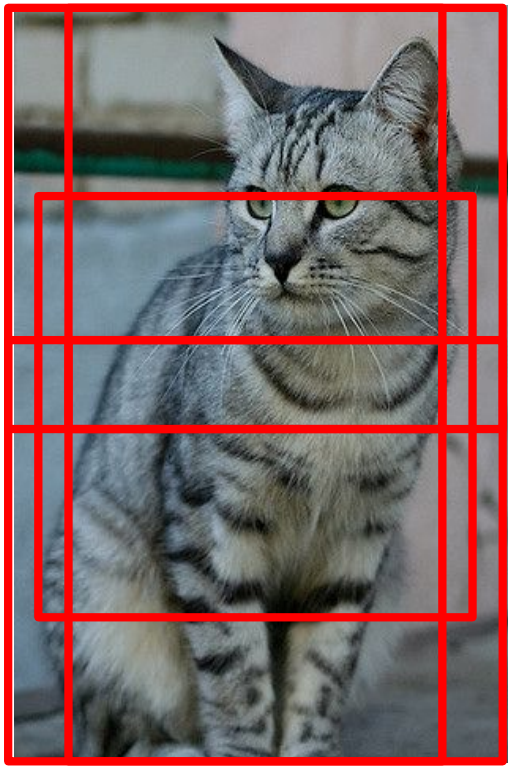


Random crops and scales

At testing time: Average a fixed set of crops

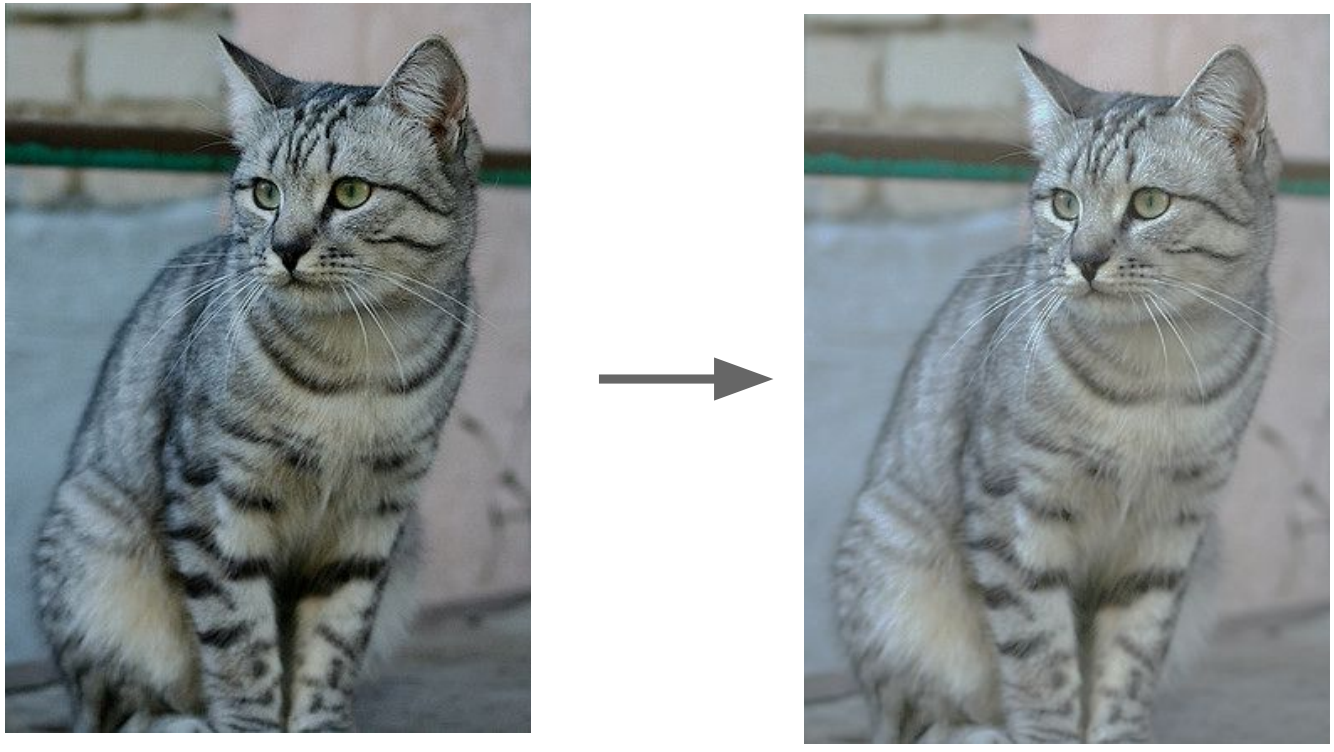
Example for ResNet:

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



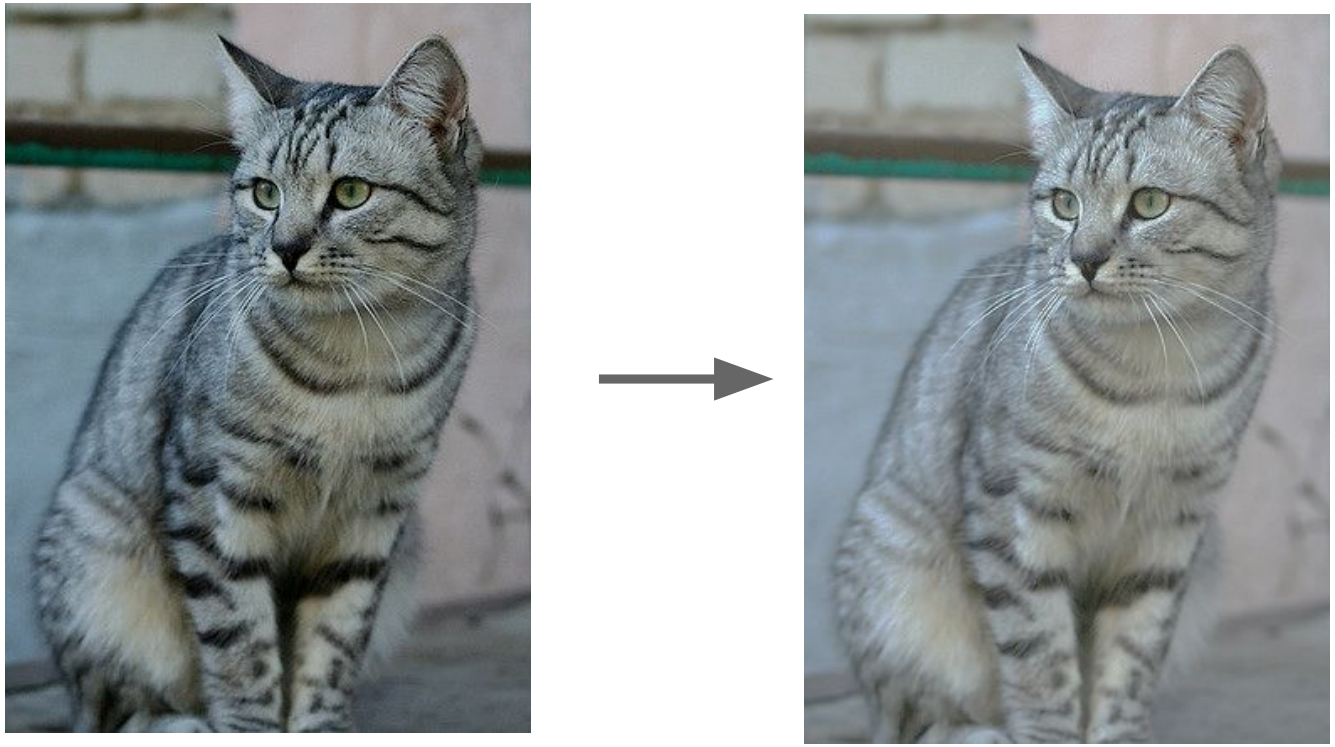
Colour Jitter - simple version

- Randomize contrast and brightness



Colour Jitter - more complex

1. Apply PCA to all (r, g, b) pixels in training set.
2. Sample a "*colour offset*" along the principal component directions.
3. Add offset to all pixels of a training image.



Types of data augmentation

Only limited by your imagination and computational resources

Random mix/combinations of

- translation
- rotation
- stretching
- shearing,
- lens distortions,
- ...

Batch Normalization: Help with gradient flow + regularization

Batch Normalization for Convolutional Layers

Option 1: Perform batch norm. as in a fully connected layer.

- Let $\mathcal{B} = \{\mathbf{X}_1, \ldots, \mathbf{X}_n\}$ be the mini-batch of data.
- Each $\mathbf{X} \in \mathcal{B}$ has the form $\mathbf{X} = \{X_1, \ldots, X_D\}$ where X_i is $W \times H$
- Compute the mean 3D array $\mathbf{M}$ ($W \times H \times D$) for the batch:

$$\mathbf{M} = \frac{1}{n} \sum_{\mathbf{X} \in \mathcal{B}} \mathbf{X}$$

- Compute the 3D array $\mathbf{V}$ ($W \times H \times D$) of variances for the batch:

$$\mathbf{V} = \frac{1}{n} \sum_{\mathbf{X} \in \mathcal{B}} (\mathbf{X} - \mathbf{M}) \odot (\mathbf{X} - \mathbf{M}) \quad \leftarrow \odot \text{ denotes element-wise mult.}$$

- for each $\mathbf{X} \in \mathcal{B}$ set

$$\hat{X}_{k,ij} = \frac{X_{k,ij} - M_{k,ij}}{\sqrt{V_{k,ij}}} \text{ for } k = 1, \ldots, D,\ i = 1, \ldots, W,\ j = 1, \ldots, H$$

Batch Normalization for Convolutional Layers

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$$\mathbf{V} = \frac{1}{n} \sum_{\mathbf{X} \in \mathcal{B}} (\mathbf{X} - \mathbf{M}) \odot (\mathbf{X} - \mathbf{M}) \quad \leftarrow \odot \text{ denotes element-wise mult.}$$

- for each $\mathbf{X} \in \mathcal{B}$ set

$$\hat{X}_{k,ij} = \frac{X_{k,ij} - M_{k,ij}}{\sqrt{V_{k,ij}}} \text{ for } k = 1, \ldots, D,\ i = 1, \ldots, W,\ j = 1, \ldots, H$$

Does this make much sense? **No**. Have a separate mean and variance for each spatial location $\Rightarrow\Leftarrow$.

Batch Normalization for Convolutional Layers

Option 2: Compute means and variances per filter.

- Let $\mathcal{B} = \{\mathbf{X}_1, \ldots, \mathbf{X}_n\}$ be the mini-batch of data.
- Each $\mathbf{X} \in \mathcal{B}$ has the form $\mathbf{X} = \{X_1, \ldots, X_D\}$ where X_i is $W \times H$
- Compute the mean vector $\mathbf{m}$ $(D \times 1)$ for the batch:

$$m_k = \frac{1}{nWH} \sum_{\mathbf{X} \in \mathcal{B}} \sum_{i=1}^{W} \sum_{j=1}^{H} X_{k,ij} \text{ for } k = 1, \ldots, D$$

- Compute the vector $\mathbf{v}$ $(D \times 1)$ of variances for the batch:

$$v_k = \frac{1}{nWH} \sum_{\mathbf{X} \in \mathcal{B}} \sum_{i=1}^{W} \sum_{j=1}^{H} (X_{k,ij} - m_k)^2 \text{ for } k = 1, \ldots, D$$

- for each $\mathbf{X} \in \mathcal{B}$ set

$$\hat{X}_k = \frac{X_k - m_k}{\sqrt{v_k}} \text{ for } k = 1, \ldots, D$$

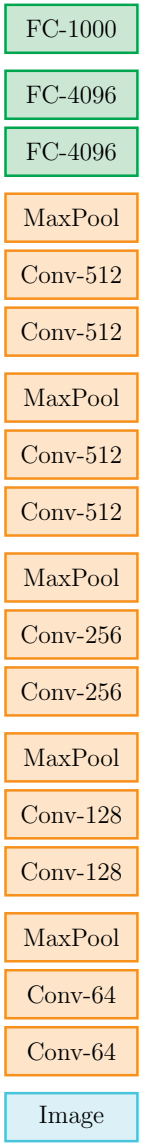
Transfer Learning

"*You need a lot of labelled data if you want to train/use ConvNets*"

Transfer Learning

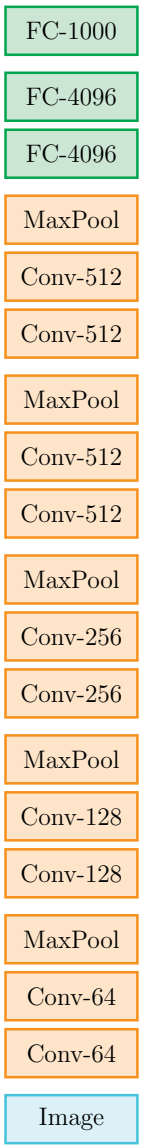
"*You need a lot of labelled data if you want to train/use ConvNets*"

1. Train on ImageNet

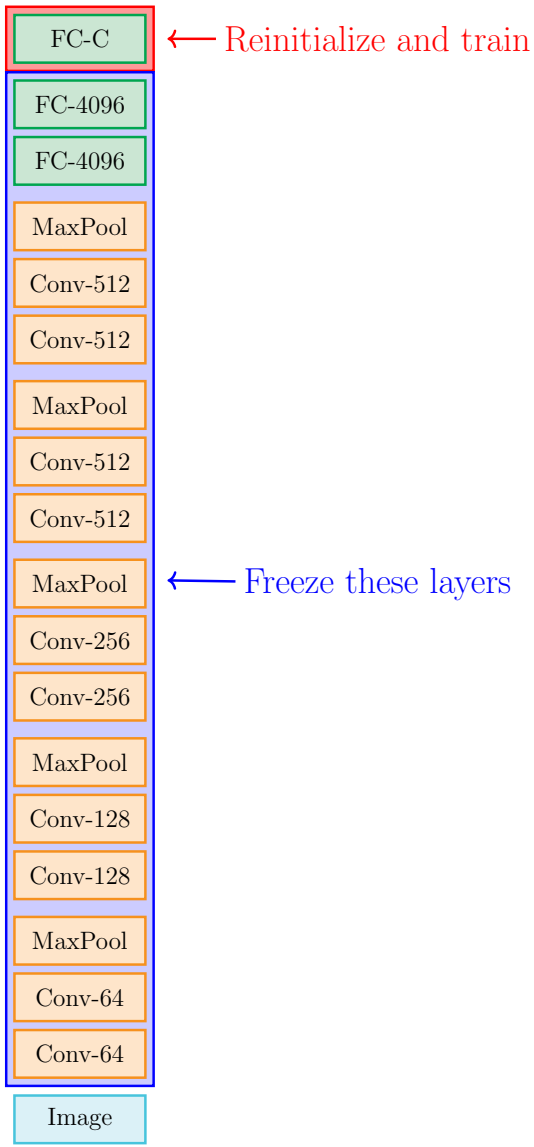


Transfer Learning with ConvNets

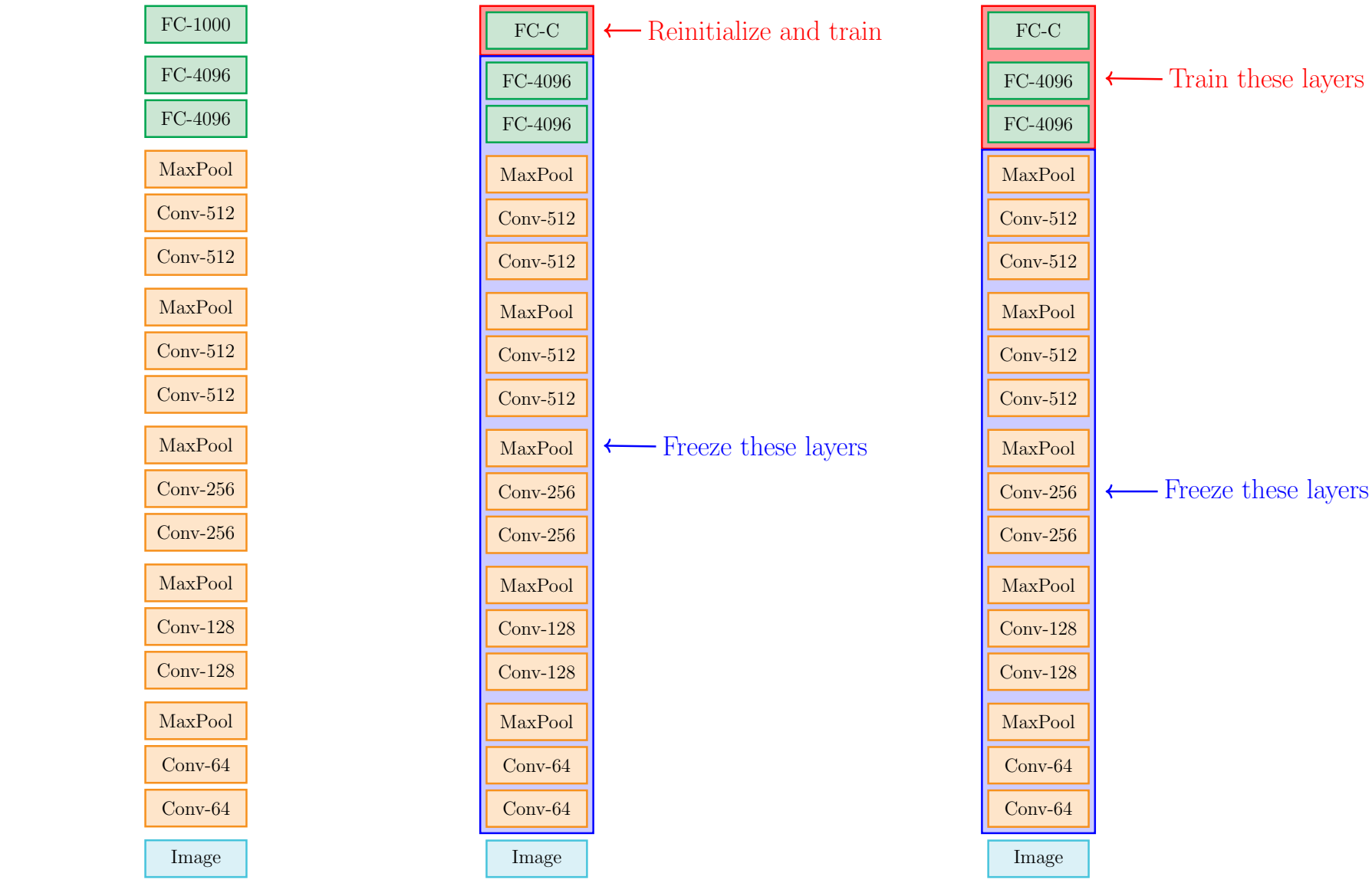
1. Train on ImageNet



2. Small dataset (C classes)

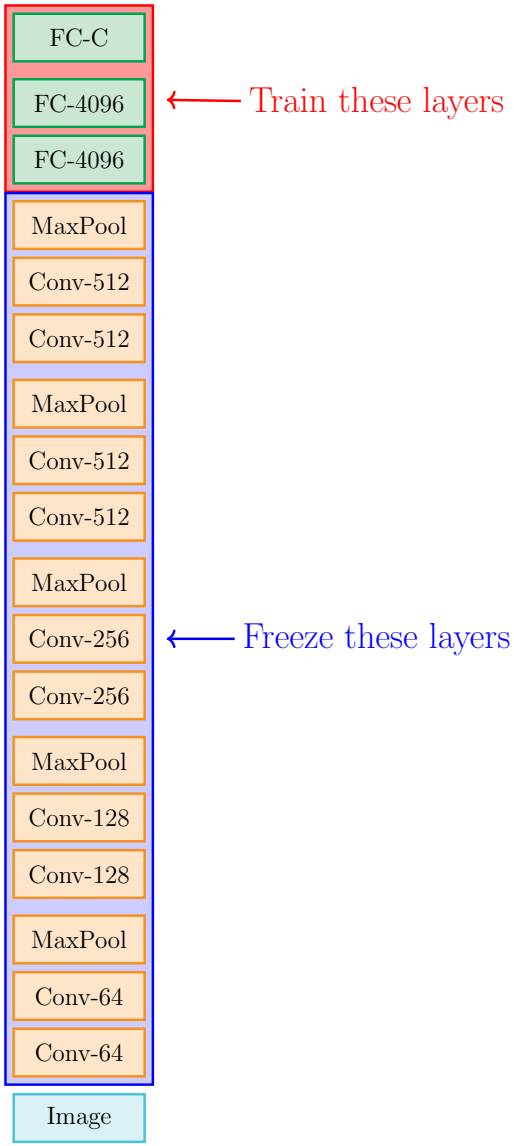


Transfer Learning with ConvNets



Transfer Learning with ConvNets

Bigger dataset



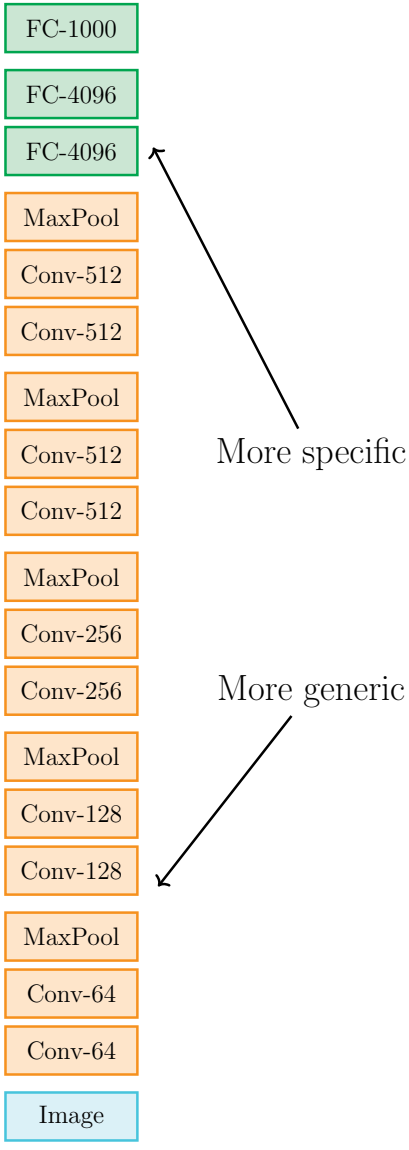
- With bigger dataset, train more layers.
- Lower learning rate when finetuning; 1/10 of original learning rate is good starting point.

Transfer Learning with ConvNets References

- Donahue et al., *DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition*, ICML 2014

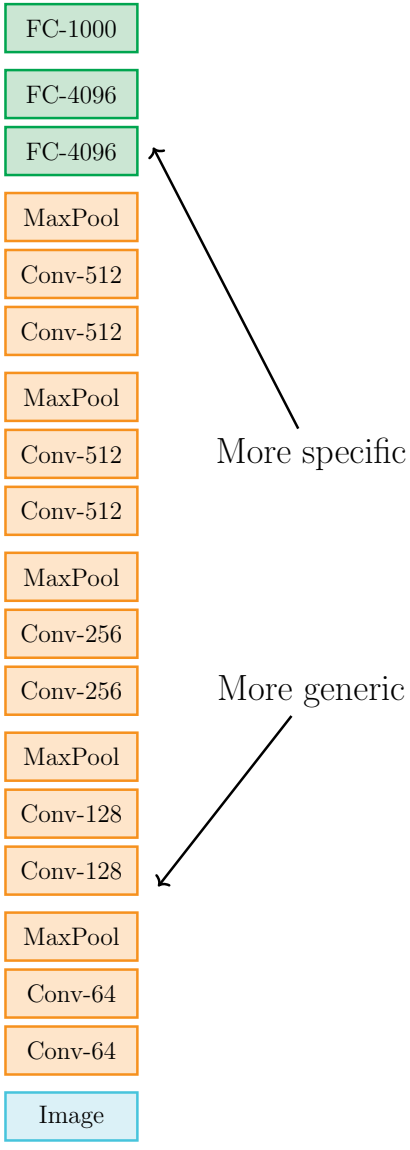
- Razavian et al., *CNN Features Off-the-Shelf: An Astounding Baseline for Recognition*, CVPR Workshops 2014

Transfer Learning with ConvNets



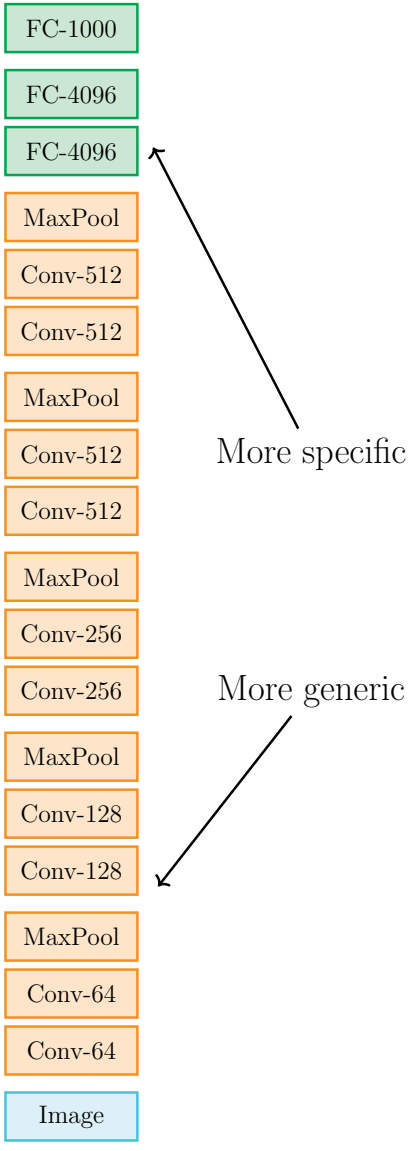
	Your new dataset	
Amount of data	**very similar**	**very different**
very little	?	?
quite a lot	?	?

Transfer Learning with ConvNets



	Your new dataset	
Amount of data	**very similar**	**very different**
very little	Use linear classifier on top layer.	?
quite a lot	Finetune a few layers	?

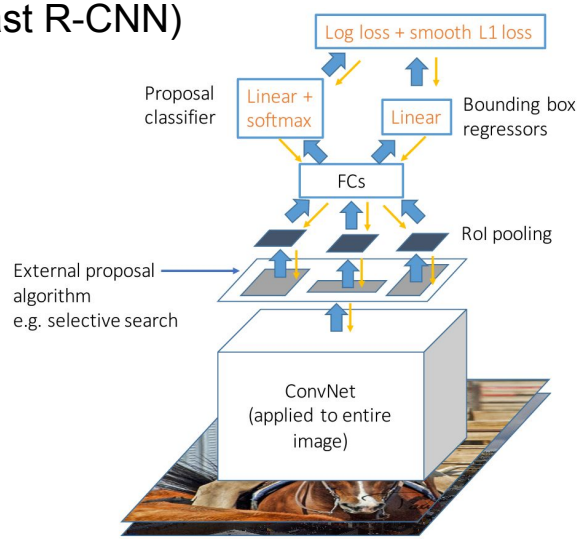
Transfer Learning with ConvNets



	Your new dataset	
Amount of data	**very similar**	**very different**
very little	Use linear classifier on top layer.	Oh dear! Try linear classifier from different stages.
quite a lot	Finetune a few layers	Finetune a larger number of layers

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

Object Detection
(Fast R-CNN)



Girshick, "Fast R-CNN", ICCV 2015
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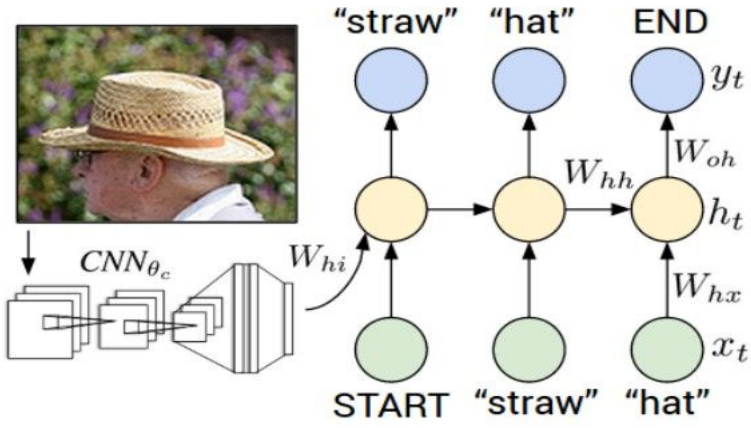
Image Captioning: CNN + RNN



Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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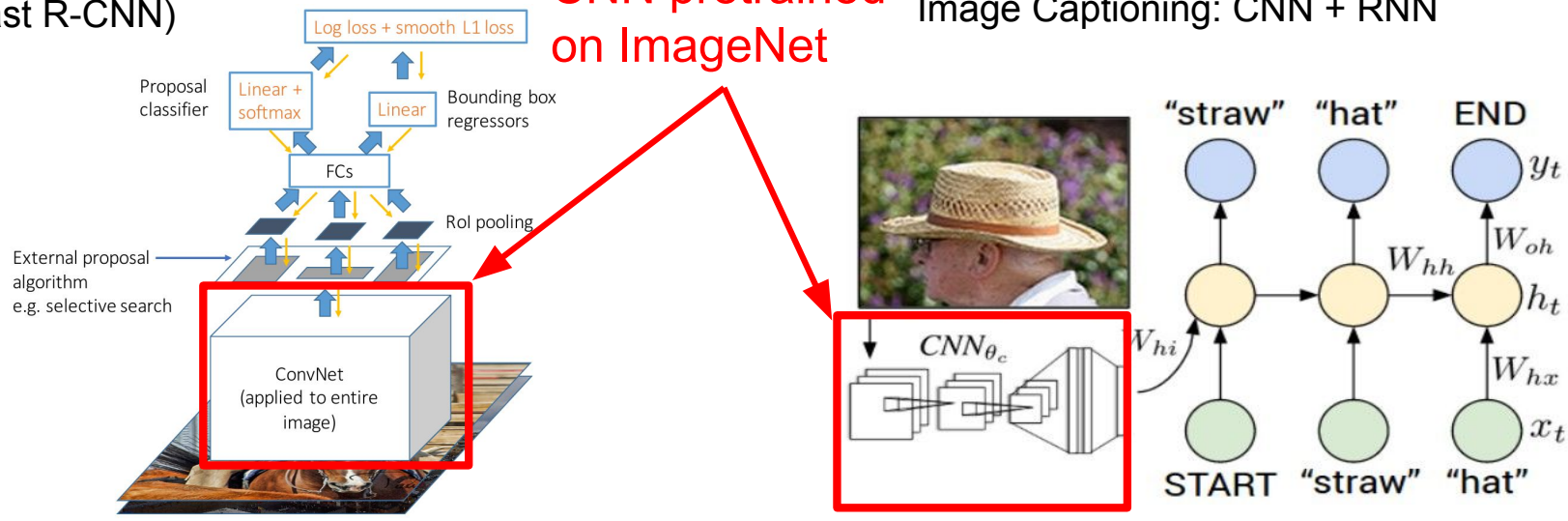
Transfer learning with CNNs is pervasive…
(it's the norm, not an exception)

Object Detection
(Fast R-CNN)

CNN pretrained
on ImageNet

Image Captioning: CNN + RNN



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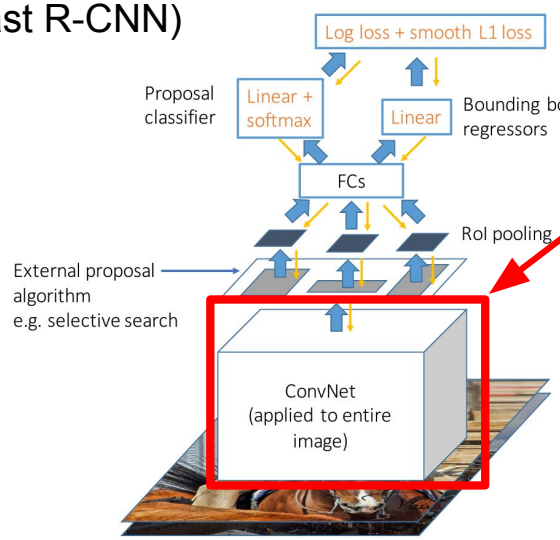
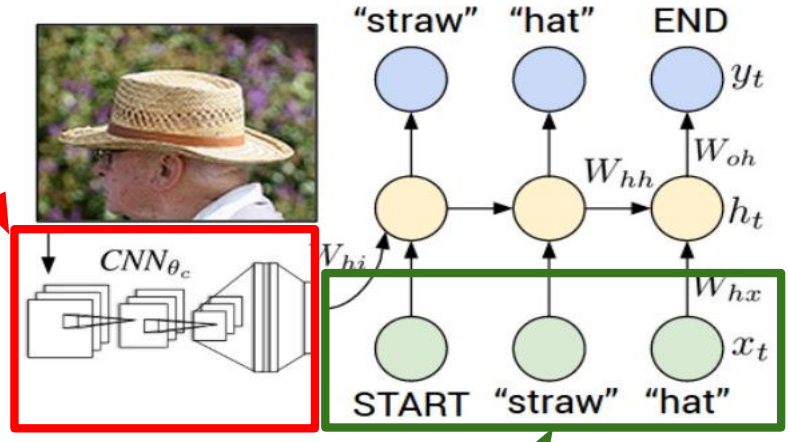


CNN pretrained on ImageNet

Image Captioning: CNN + RNN



Word vectors pretrained with word2vec

Girshick, "Fast R-CNN", ICCV 2015
Figure copyright Ross Girshick, 2015. Reproduced with permission.

Karpathy and Fei-Fei, "Deep Visual-Semantic Alignments for Generating Image Descriptions", CVPR 2015
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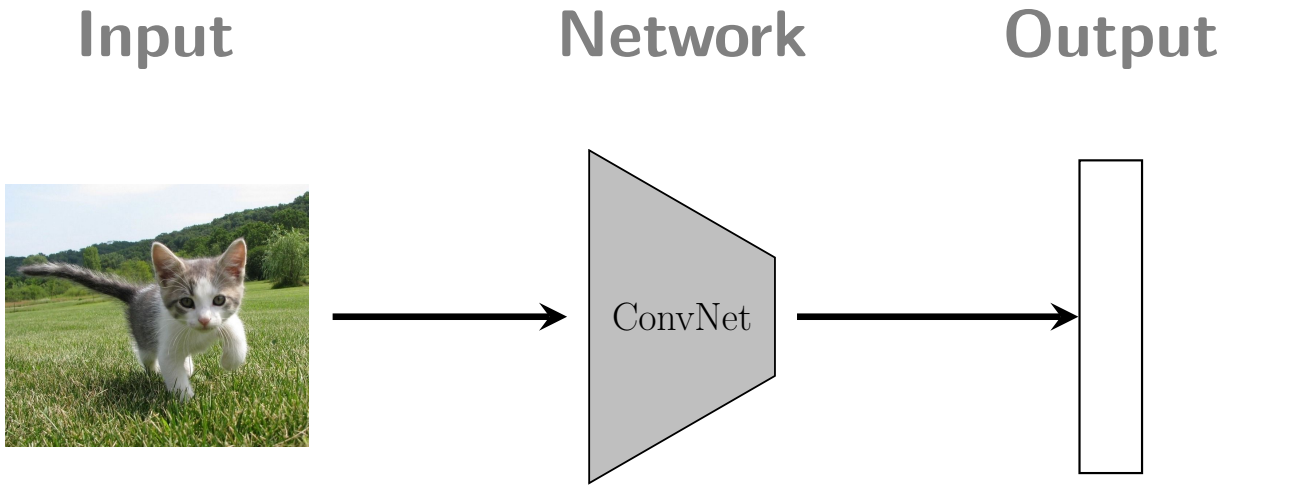
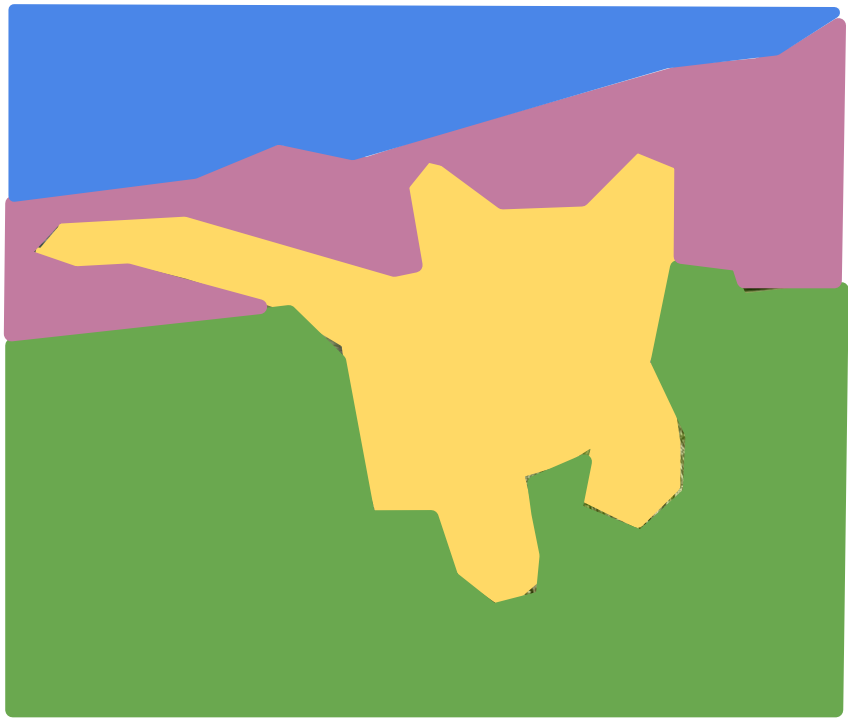
Can we use ConvNets to solve other Computer Vision tasks??

So far: Image Classification



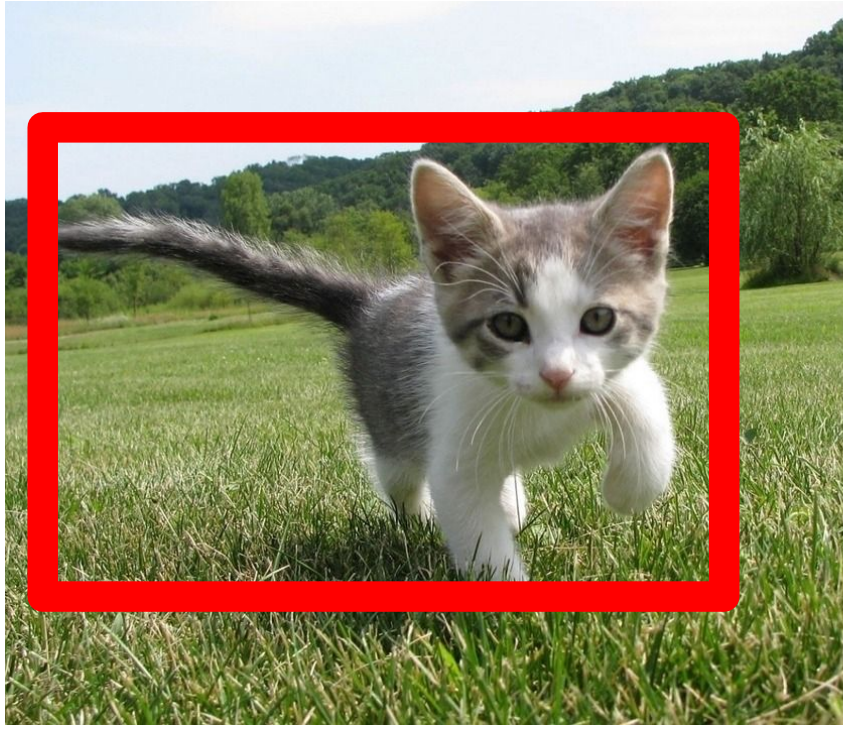
Semantic Segmentation



Grass, **Cat**, **Tree**, **Sky**

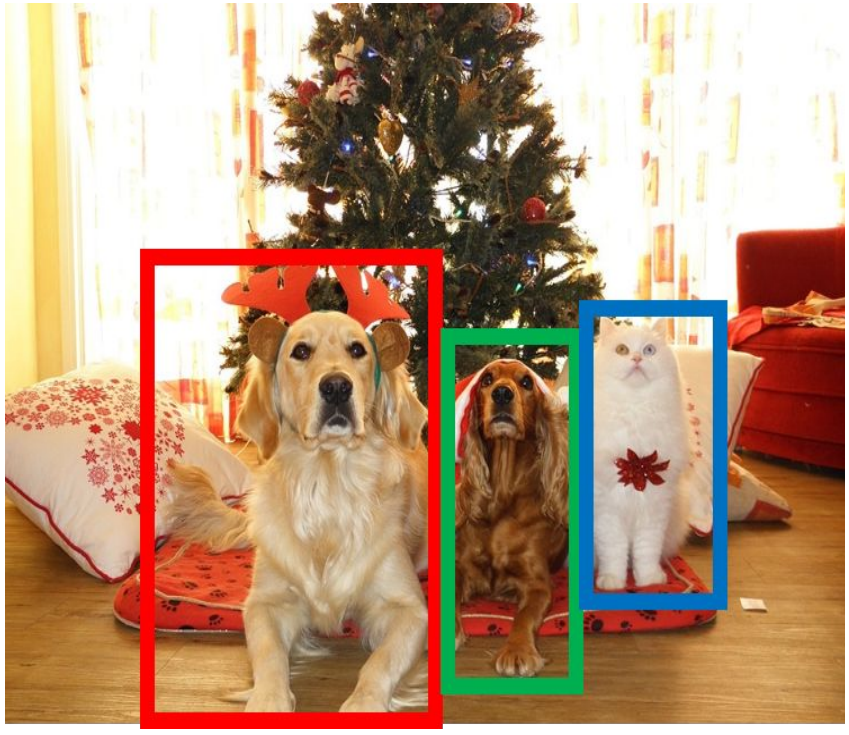
Predict a label for each pixel in the image.

Classification & Localization



Classify object in the image and where it is.

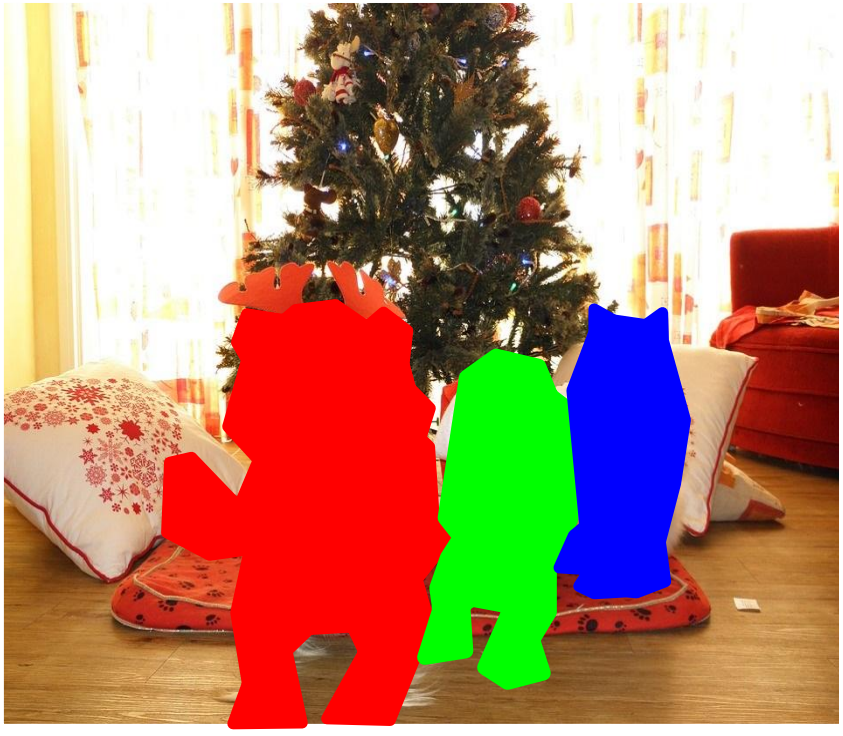
Object Detection



Dog, **Dog**, **Cat**

Classify objects and detect where they are.

Instance Segmentation



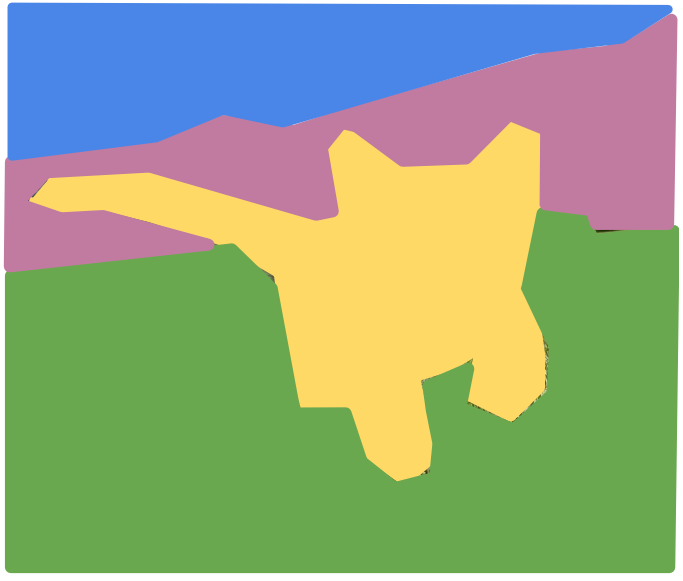
Dog, Dog, Cat

Identify the pixels belonging to each detected object.

Focus on Semantic Segmentation

Input

Output

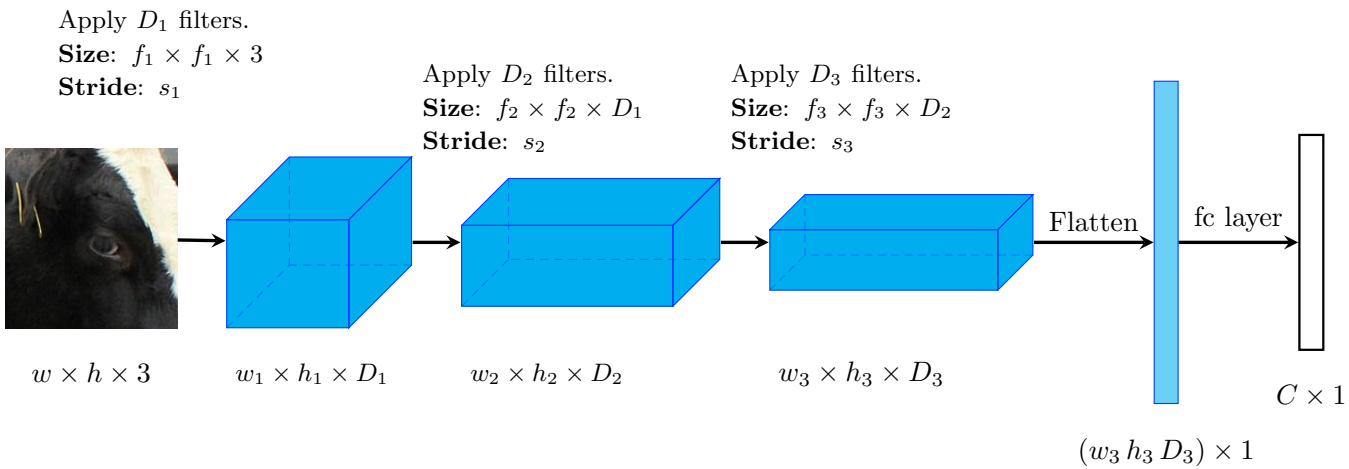


Grass, **Cat**, **Tree**, **Sky**

- Predict a label for each pixel in the image.
- Don't differentiate instances, only care about pixels.

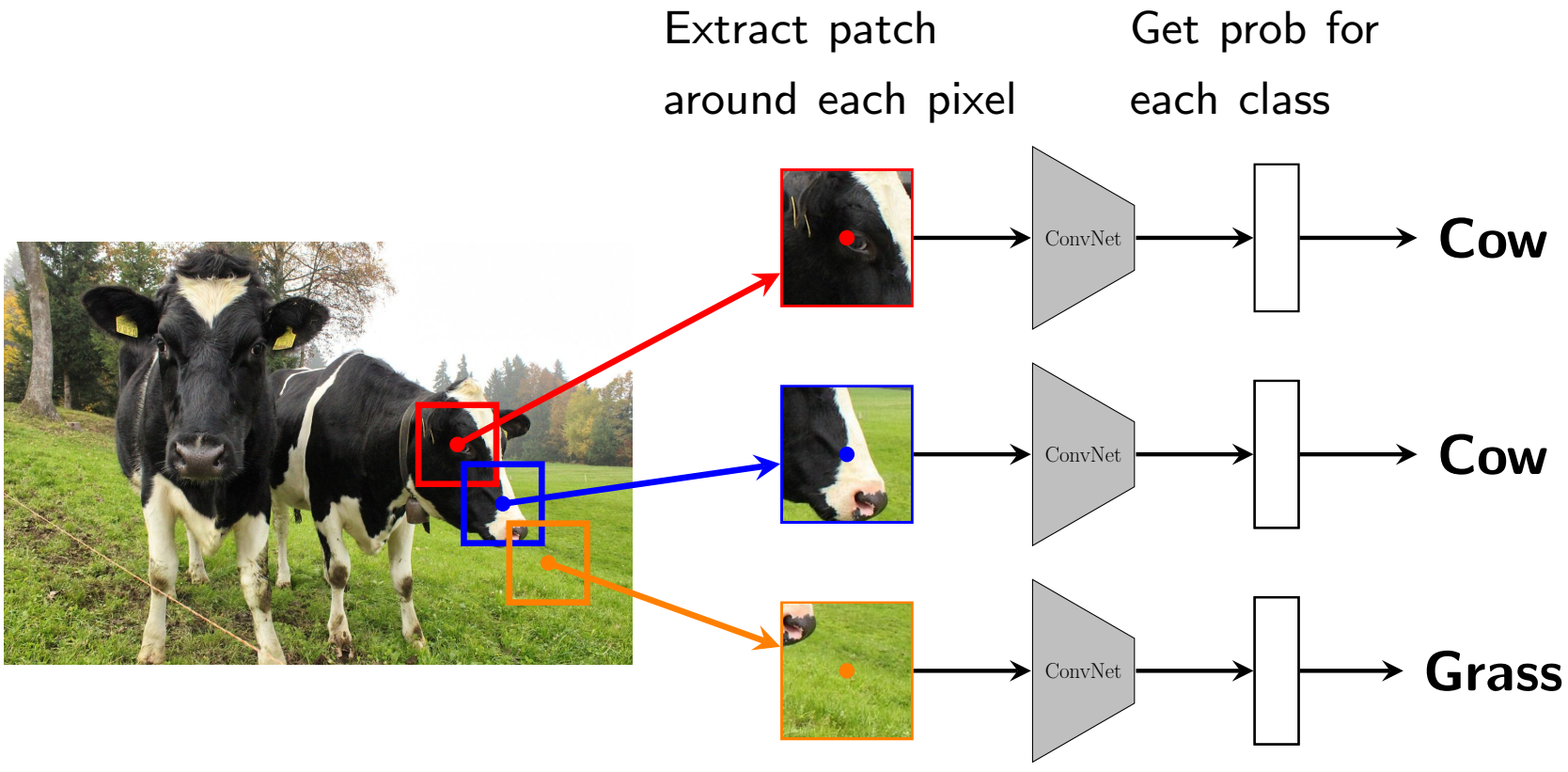
Sliding Window Approach to Semantic Segmentation

Assume have a classification network

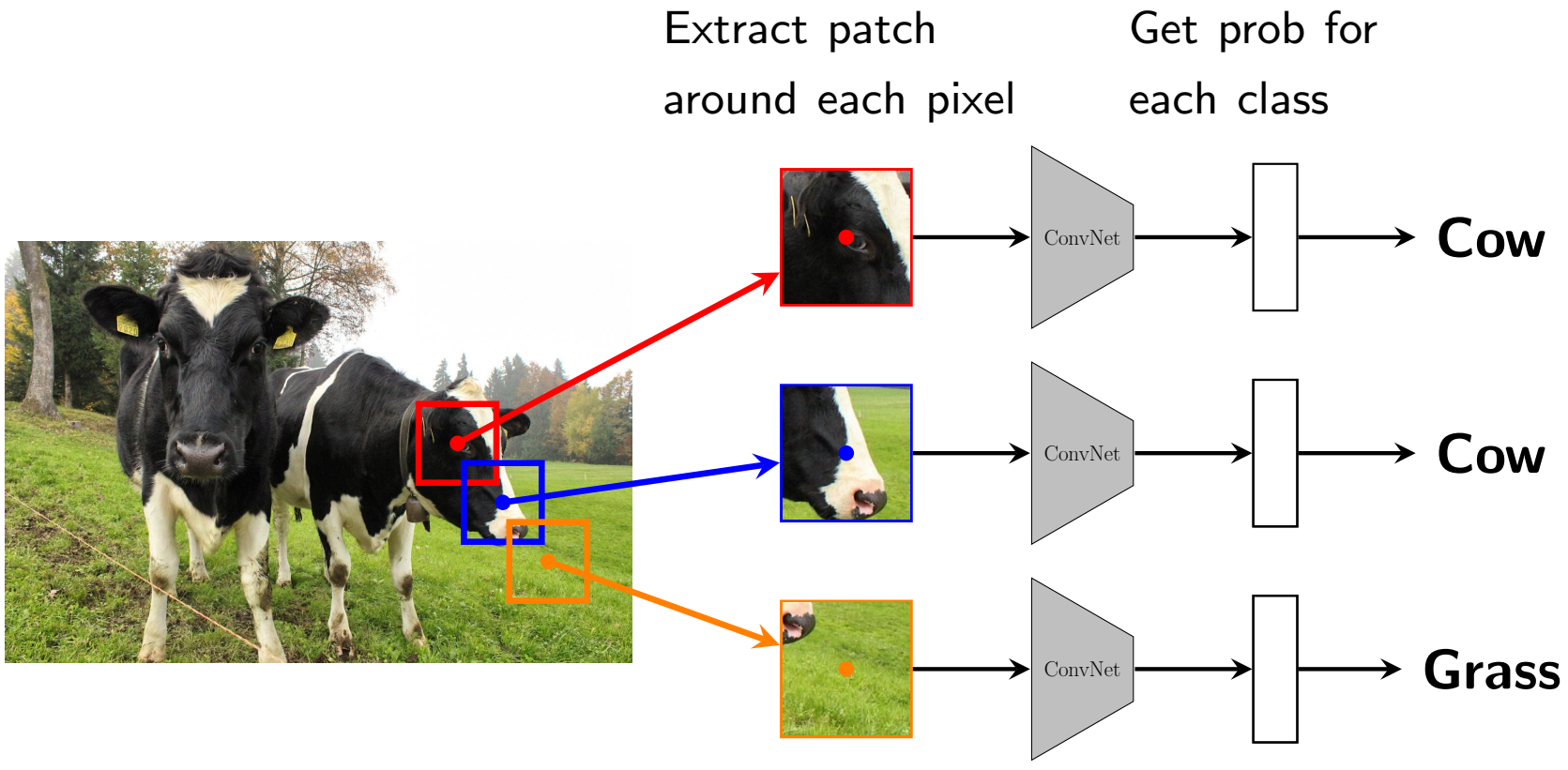


- Have a network with convolutional layers and one fully connected layer.
- Network only works for input images of size $w \times h \times 3$ because of fully-connected layer.

Sliding Window Approach to Semantic Segmentation

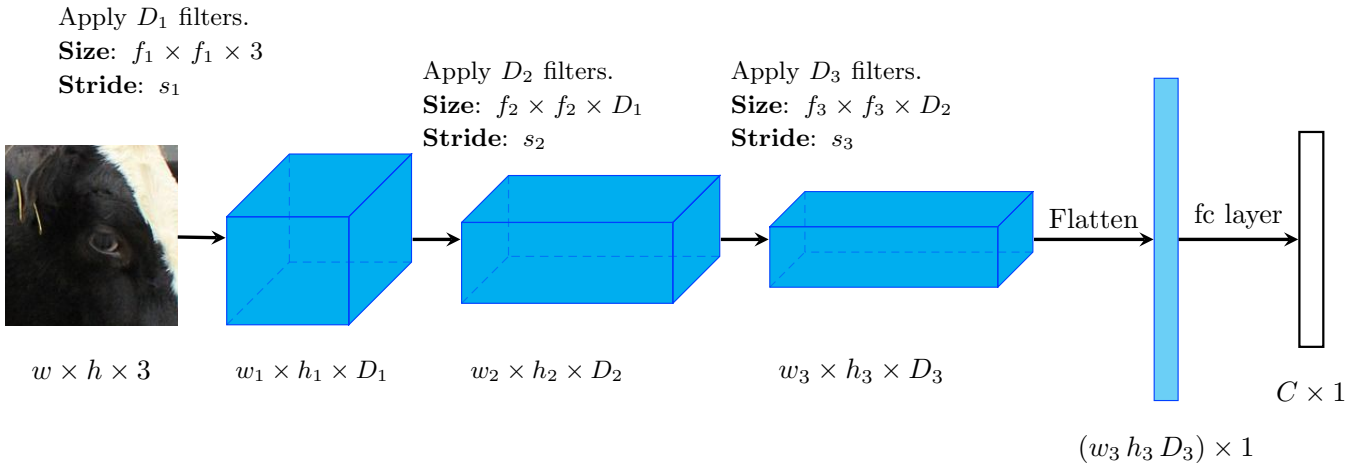


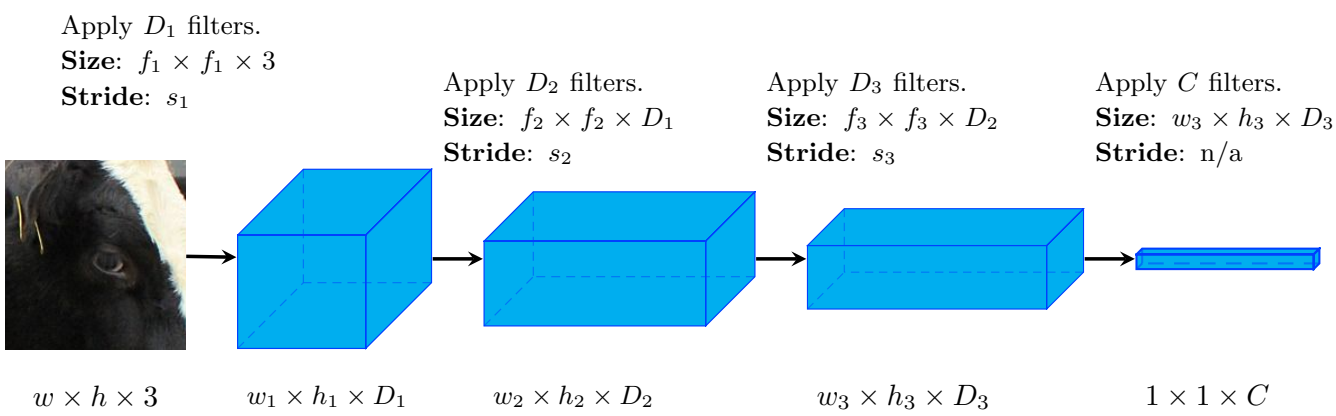
Sliding Window Approach to Semantic Segmentation



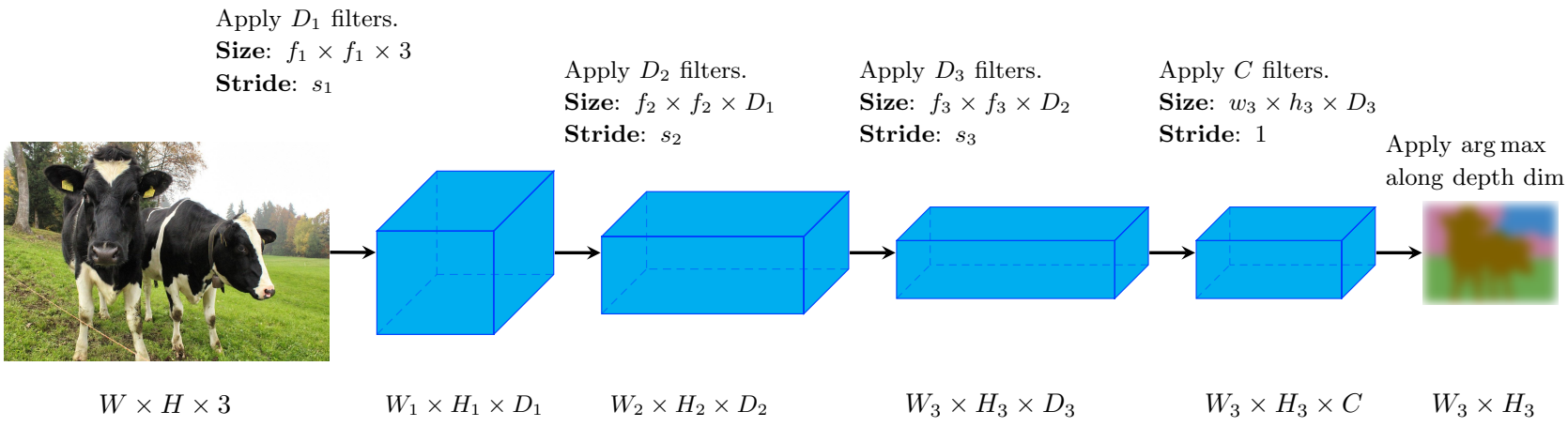
Problem: Very inefficient! Recomputing the same features multiple times between overlapping patches.

Idea: Replace fully connected layer with convolutional layer



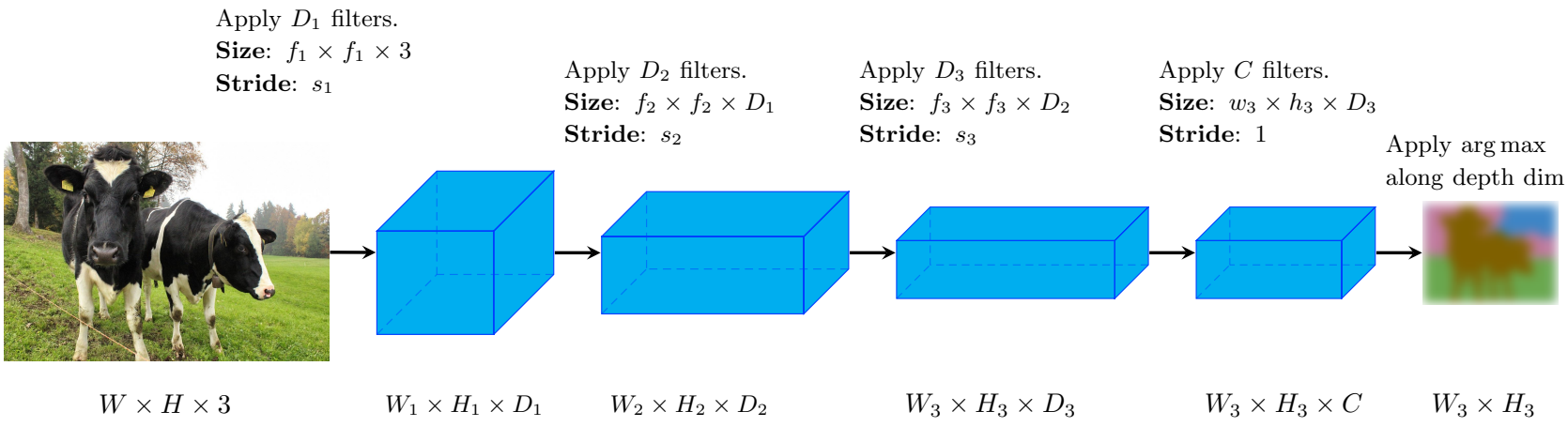


Replace fully connected layer with convolutional layer



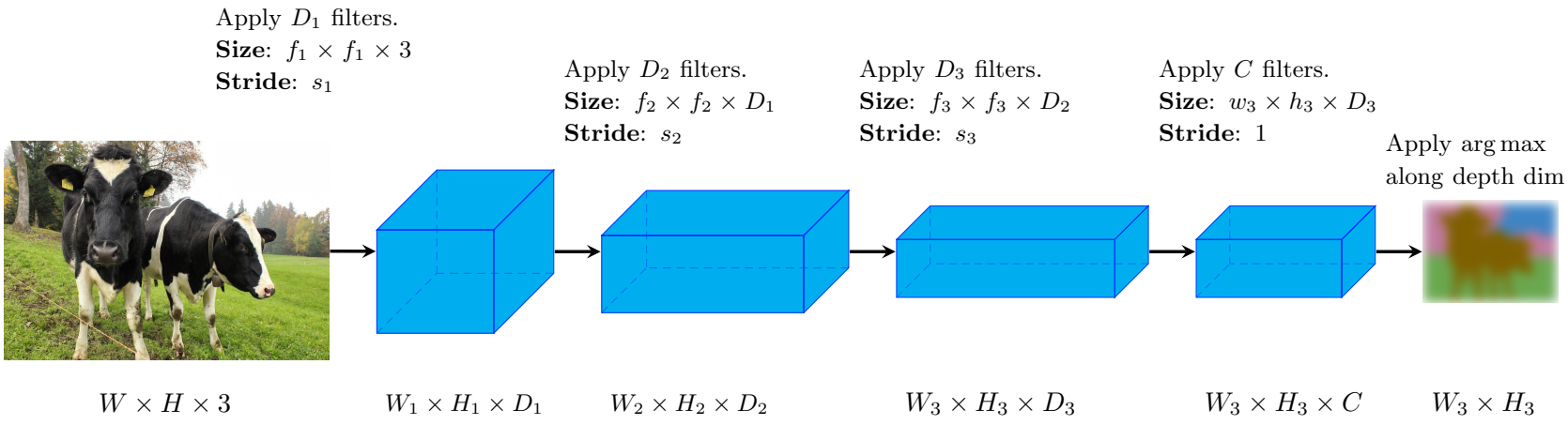
- Can now input any sized image into the network and get C predictions at multiple locations...
- **Problem**: Only have predictions for a subset of the original pixels!

Replace fully connected layer with convolutional layer

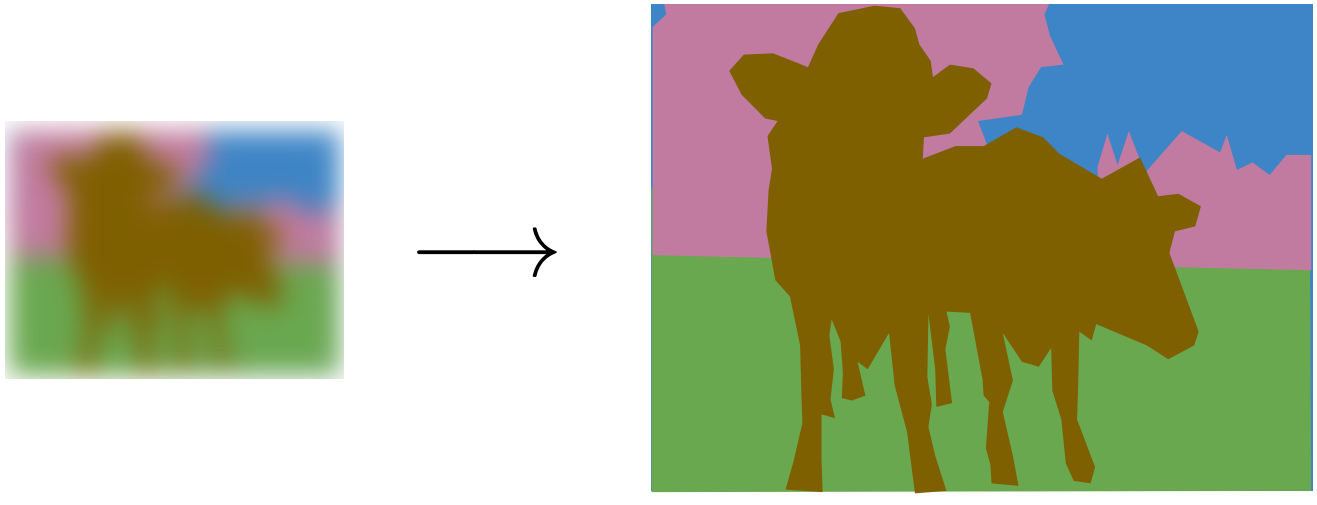


- Can now input any sized image into the network and get C predictions at multiple locations...
- **Problem**: Only have predictions for a subset of the original pixels!

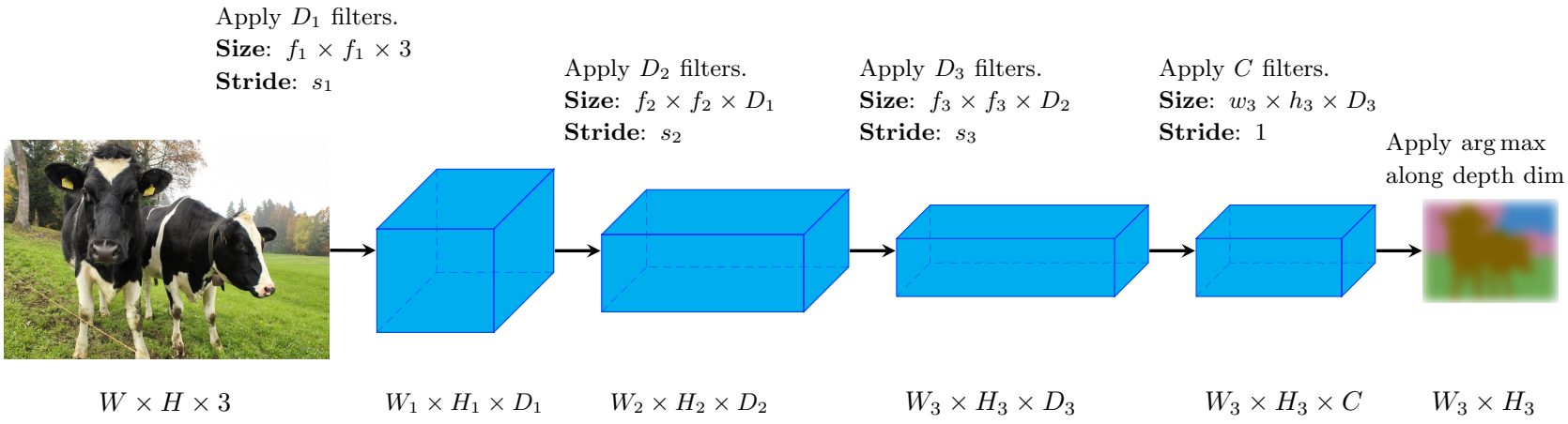
How can we get a high-resolution segmentation map?



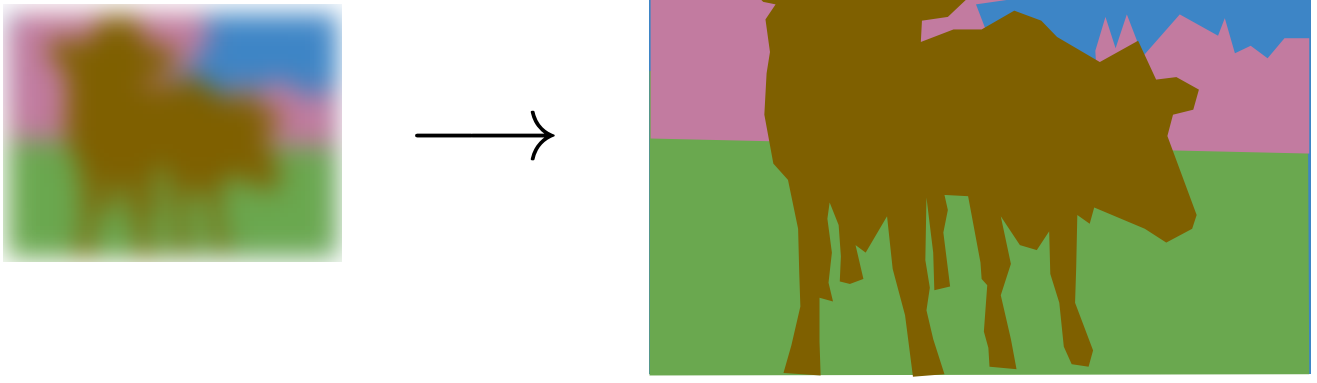
Is there some magic interpolation?



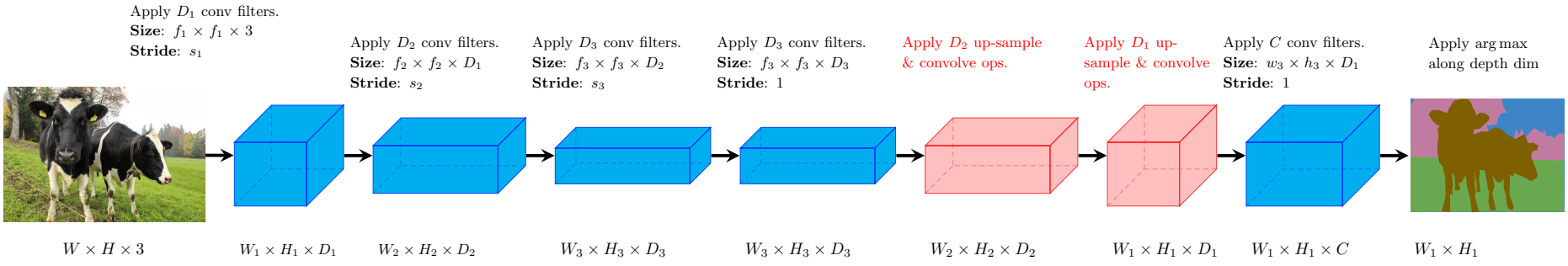
How can we get a high-resolution segmentation map?



Is there some magic interpolation? Nearest neighbour, bilinear, etc. interpolation is probably not going to do the job!

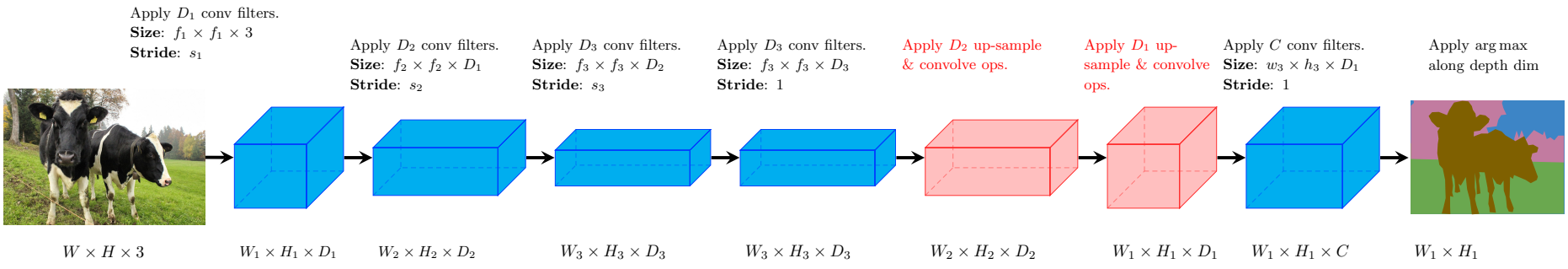


Idea: Learn how to up-sampling within the network



What is the up-sampling combined with convolution operation?

Idea: Learn how to up-sampling within the network



What is the up-sampling combined with convolution operation?

Transposed convolution

Learnable Upsampling: Transposed Convolution

Introduce this concept via our simple example

Simple Example

- Have an input image X of size 4×4.
- Have a filter F of size 3×3.
- Set the stride $s = 1$ and zero-padding $P = 0$.
- Convolve X by F gives a response map of size 2×2

$$S = X * F$$

- Each entry of S can be written as

$$S_{lm} = \sum_{i=1}^{3} \sum_{j=1}^{3} X_{l+i-1,m+j-1} F_{ij}$$

Can write convolution as a matrix multiplication

Write this convolution as a matrix multiplication involving $\text{vec}(X)$

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} \\ X_{21} & X_{22} & X_{23} & X_{24} \\ X_{31} & X_{32} & X_{33} & X_{34} \\ X_{41} & X_{42} & X_{43} & X_{44} \end{pmatrix} * \begin{pmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{pmatrix}$$

Solution:

$$\begin{pmatrix} S_{11} \\ S_{12} \\ S_{21} \\ S_{22} \end{pmatrix} = \underbrace{\begin{pmatrix} \overbrace{F_{11} & F_{12} & F_{13} & 0}^{\text{row 1 of } X} & \overbrace{F_{21} & F_{22} & F_{23} & 0}^{\text{row 2 of } X} & \overbrace{F_{31} & F_{32} & F_{33} & 0}^{\text{row 3 of } X} & \overbrace{0 & 0 & 0 & 0}^{\text{row 4 of } X} \\ 0 & F_{11} & F_{12} & F_{13} & 0 & F_{21} & F_{22} & F_{23} & 0 & F_{31} & F_{32} & F_{33} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & F_{11} & F_{12} & F_{13} & 0 & F_{21} & F_{22} & F_{23} & 0 & F_{31} & F_{32} & F_{33} & 0 \\ 0 & 0 & 0 & 0 & 0 & F_{11} & F_{12} & F_{13} & 0 & F_{21} & F_{22} & F_{23} & 0 & F_{31} & F_{32} & F_{33} \end{pmatrix}}_{M_F^{\text{filter}}} \text{vec}(X)$$

Thus

$$\text{vec}(S) = M_F^{\text{filter}} \, \text{vec}(X)$$

where M_F^{filter} is 4×16.

Transposed Convolution defined by F, stride 1, zero-pad 0

- Given a response map, $\tilde{S}$, of size 2×2.
- **Transposed convolution** of $\tilde{S}$ by F is given by

$$(M_F^{\text{filter}})^T \ \text{vec}(\tilde{S})$$

- Let $\tilde{\mathbf{s}} = \text{vec}(\tilde{S})$ and

$$\tilde{\mathbf{x}} = (M_F^{\text{filter}})^T \ \tilde{\mathbf{s}}$$

- What is the size of $\tilde{\mathbf{x}}$?
- What does $\tilde{X}$ correspond to if $\text{vec}(\tilde{X}) = \tilde{\mathbf{x}}$?

Answers

Have:

$$\tilde{\mathbf{x}} = \left(M_F^{\text{filter}}\right)^T \tilde{\mathbf{s}}$$

- **Q1**: M_F^{filter} is $4 \times 16 \implies \left(M_F^{\text{filter}}\right)^T$ is $16 \times 4 \implies \tilde{\mathbf{x}}$ is 16×1
- **Q2**:

$$\text{vec}(\tilde{X}) = \begin{pmatrix} F_{11} & 0 & 0 & 0 \\ F_{12} & F_{11} & 0 & 0 \\ F_{13} & F_{12} & 0 & 0 \\ 0 & F_{13} & 0 & 0 \\ F_{21} & 0 & F_{11} & 0 \\ F_{22} & F_{21} & F_{12} & F_{11} \\ F_{23} & F_{22} & F_{13} & F_{12} \\ 0 & F_{23} & 0 & F_{13} \\ F_{31} & 0 & F_{21} & 0 \\ F_{32} & F_{31} & F_{22} & F_{21} \\ F_{33} & F_{32} & F_{23} & F_{22} \\ 0 & F_{33} & 0 & F_{23} \\ 0 & 0 & F_{31} & 0 \\ 0 & 0 & F_{32} & F_{31} \\ 0 & 0 & F_{33} & F_{32} \\ 0 & 0 & 0 & F_{33} \end{pmatrix} \text{vec}(\tilde{S}) \implies \tilde{X} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \tilde{S}_{11} & \tilde{S}_{12} & 0 \\ 0 & 0 & \tilde{S}_{21} & \tilde{S}_{21} & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} * \begin{pmatrix} F_{33} & F_{32} & F_{31} \\ F_{23} & F_{22} & F_{21} \\ F_{13} & F_{12} & F_{11} \end{pmatrix}$$

- Therefore **transposed convolution** of $\tilde{S}$ by a filter F applied with zero-padding 0 and stride 1 is:

$$\tilde{X} = \tilde{S}_{\text{zero-pad}} * F_{\text{rot180}}$$

where the zero-padding of $\tilde{S}$ is $3 - 1 = 2$.

Transposed Convolution defined by F, stride 2, zero-pad 0?

- Define M_F^{filter} by applying a filter F of size 2×2 with stride 2 and no zero-padding.

$$S = \begin{pmatrix} X_{11} & X_{12} & X_{13} & X_{14} \\ X_{21} & X_{22} & X_{23} & X_{24} \\ X_{31} & X_{32} & X_{33} & X_{34} \\ X_{41} & X_{42} & X_{43} & X_{44} \end{pmatrix} * \begin{pmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{pmatrix}$$

- Then S has size 2×2 and M_F^{filter} is

$$\begin{pmatrix} F_{11} & F_{12} & 0 & 0 & F_{21} & F_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & F_{11} & F_{12} & 0 & 0 & F_{21} & F_{22} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & F_{11} & F_{12} & 0 & 0 & F_{21} & F_{22} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & F_{11} & F_{12} & 0 & 0 & F_{21} & F_{22} \end{pmatrix}$$

- Apply transposed convolution operator to $(M_F^{\text{filter}})^T$ to the 2×2 array $\tilde{S}$.

- Then do we get the same relationship as before? that is

$$\text{vec}(\tilde{X}) = \left(M_F^{\text{filter}}\right)^T \text{vec}(\tilde{S}) \implies \tilde{X} = \tilde{S}_{\text{zero-pad}} * F_{\text{rot180}}$$

Transposed Convolution defined by F, stride 2, zero-pad 0?

- Not quite instead we get:

$$\text{vec}(\tilde{X}) = \begin{pmatrix} F_{11} & 0 & 0 & 0 \\ F_{12} & 0 & 0 & 0 \\ 0 & F_{11} & 0 & 0 \\ 0 & F_{12} & 0 & 0 \\ F_{21} & 0 & 0 & 0 \\ F_{22} & 0 & 0 & 0 \\ 0 & F_{21} & 0 & 0 \\ 0 & F_{22} & 0 & 0 \\ 0 & 0 & F_{11} & 0 \\ 0 & 0 & F_{12} & 0 \\ 0 & 0 & 0 & F_{11} \\ 0 & 0 & 0 & F_{12} \\ 0 & 0 & F_{21} & 0 \\ 0 & 0 & F_{22} & 0 \\ 0 & 0 & 0 & F_{21} \\ 0 & 0 & 0 & F_{22} \end{pmatrix} \text{vec}(\tilde{S}) \implies \tilde{X} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & \tilde{S}_{11} & 0 & \tilde{S}_{12} & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & \tilde{S}_{21} & 0 & \tilde{S}_{21} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} * \begin{pmatrix} F_{22} & F_{21} \\ F_{12} & F_{11} \end{pmatrix}$$

- Zero-pad $\tilde{S}$ with $P = 2 - 1 = 1$ and zeros are inserted between the entries of $\tilde{S}$.

- Apply the same transformation to F as before $F \to F_{\text{rot180}}$

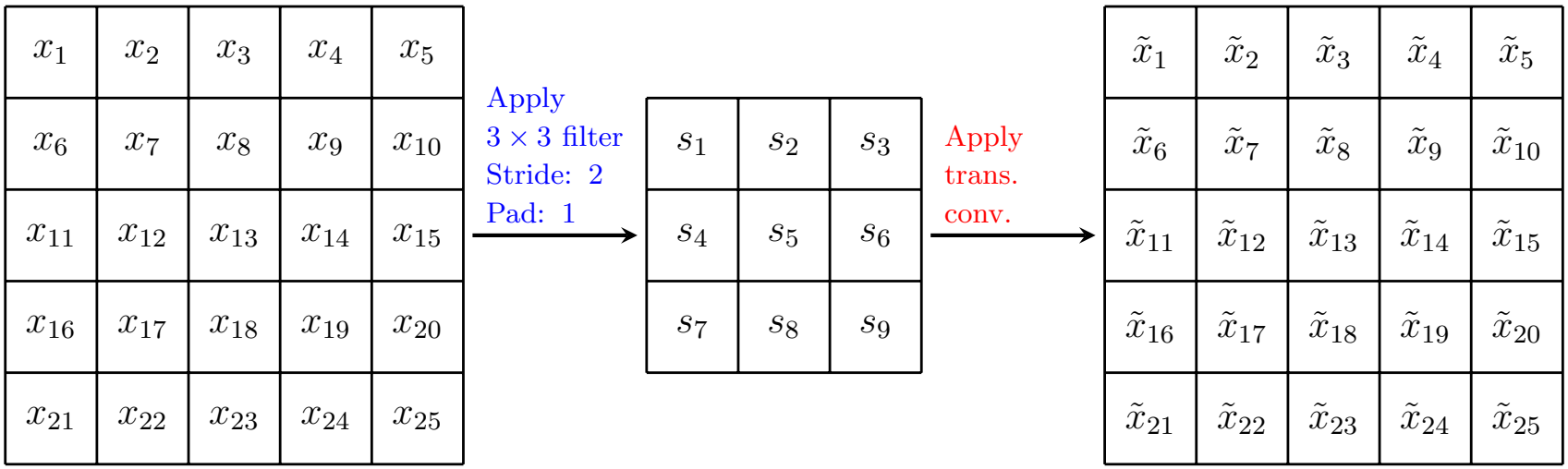
Transposed Convolution defined by F, stride s, zero-pad p?

General case:

- Create M_F^{filter} by applying
  - a convolutional filter of size $f \times f$
  - with stride s and
  - zero-padding p
  - to an input of size $w \times w$
- Then apply $(M_F^{\text{filter}})^T$ to $\tilde{S}$ of size $w' \times w'$ with $w' = (w - f - 2p)/s + 1$ to implement a transposed convolution.
- This transposed convolution is equivalent to applying a convolutional filter
  - of size $f \times f$
  - with stride $s' = 1$ and
  - zero-padding $p' = f - p - 1$

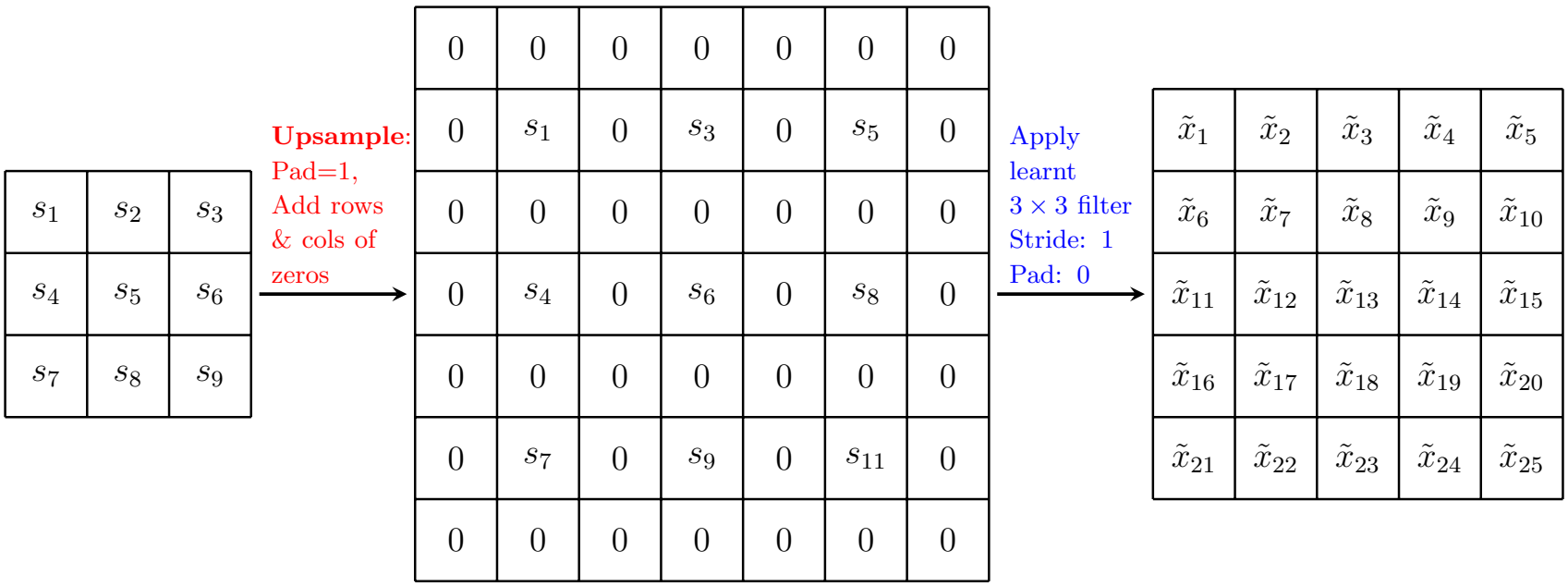
  to the new version of $\tilde{S}$ generated by adding $s - 1$ zeros between each entry in $\tilde{S}$.

Visualization of Transposed Convolution



- Convolve a 5×5 input with a 3×3 filter applied with stride 2 and zero-padding equal to 1.
- Get a 3×3 output.
- Apply a transposed convolution operation to up-sample 3×3 output to 5×5 output. How?

Visualization of Transposed Convolution

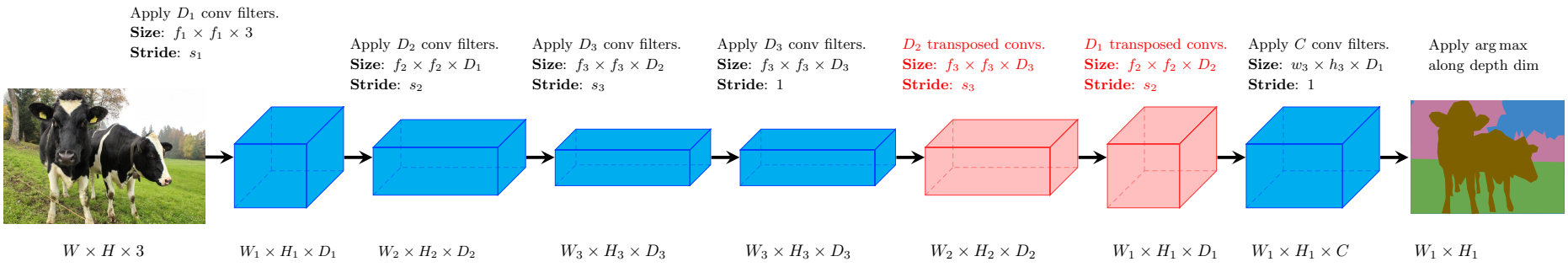


- Up-sample 3×3 output to size 7×7 by
  - Add $s - 1 = 2 - 1 = 1$ rows and columns of zeros between elements of output.
  - Zero-pad with $f - p - 1 = 3 - 1 - 1 = 1$.
- Apply a normal convolution operation to the upsampled output with a filter of size 3×3 with stride 1 and zero-pad 0.

Summary of using Transposed Convolution to up-sample

- Have a 2d array of responses X of size $w' \times h'$.
- The *transposed convolution* is a operator we can use to up-sample $\mathbf{X}$ to a larger spatial size.
- Conceptually you have a filter F of size $f \times f$
  - Insert between each entry of X $s-1$ zeros to get $\mathbf{X}_{\text{tc}}$ - (both between rows and columns).
  - $\mathbf{X}_{\text{tc}} =$ Zero-pad $\mathbf{X}_{\text{tc}}$ with $f-p-1$ zeros.
  - Convolve $\mathbf{X}_{\text{tc}}$ with F with stride 1 and zero-padding 0.
- The choice of s dictates the amount of up-sampling. Should not have $s > f$.

Include transposed convolution in segmentation network



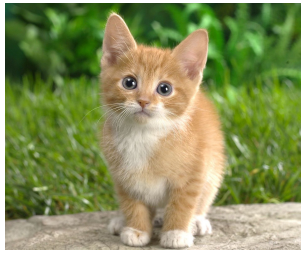
Good blog post on semantic segmentation: An overview of semantic image segmentation.

Classification + Localization: Task

Classification: C classes
Input: Image
Output: Class label
Evaluation metric: Accuracy

CAT

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union



(x, y, w, h)

Classification + Localization: Do both

Idea #1: Localization as Regression

Input: image

Only one object,
simpler than detection

Neural Net

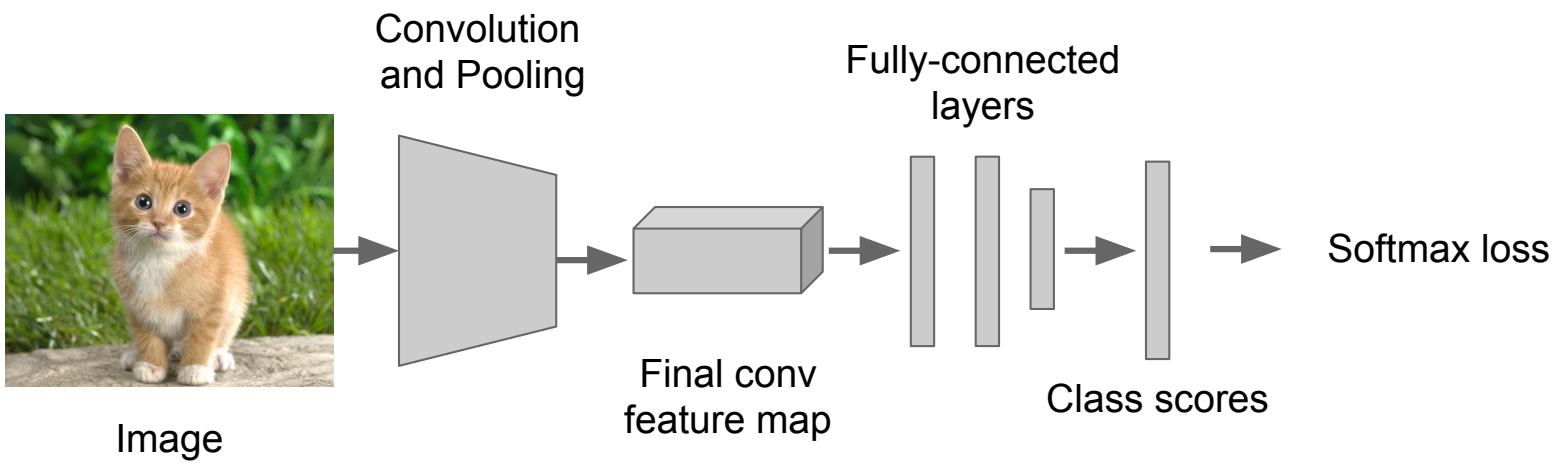
Output:
Box coordinates
(4 numbers)

Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

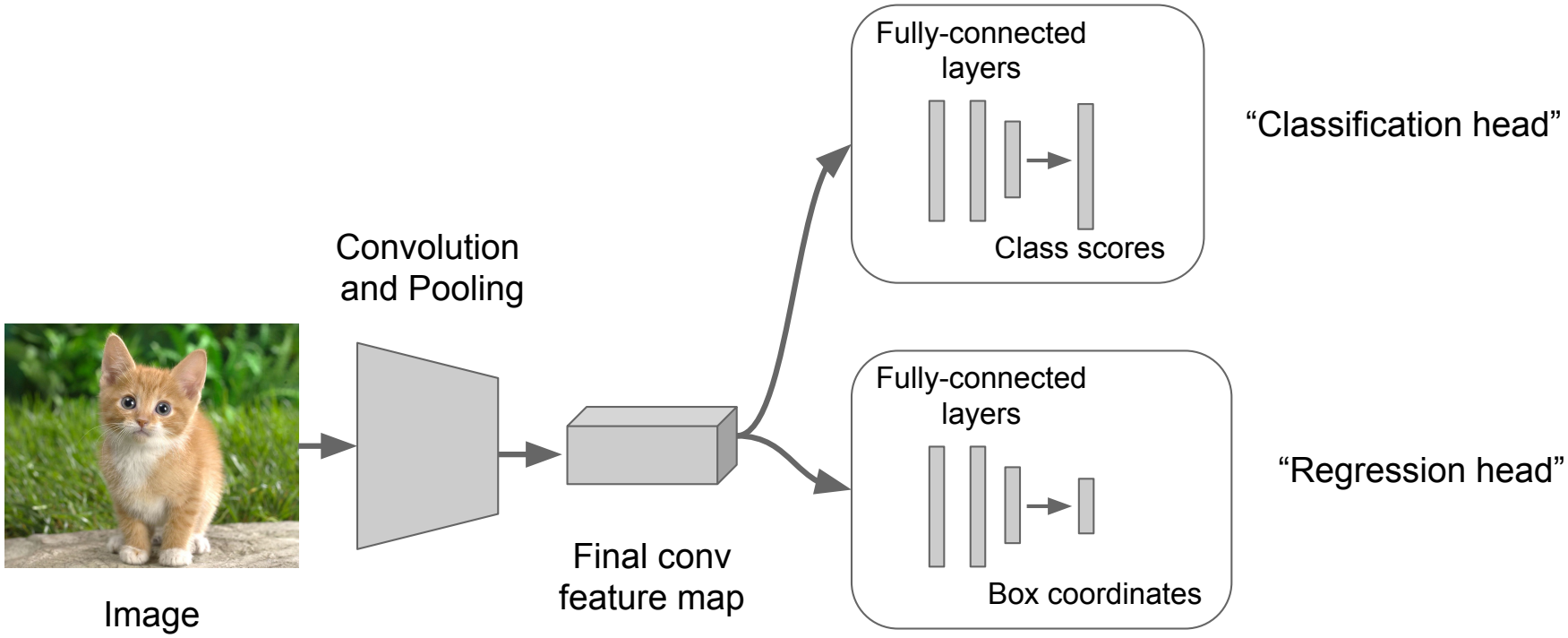
Simple Recipe for Classification + Localization

Step 1: Train (or download) a classification model (AlexNet, VGG, GoogLeNet)



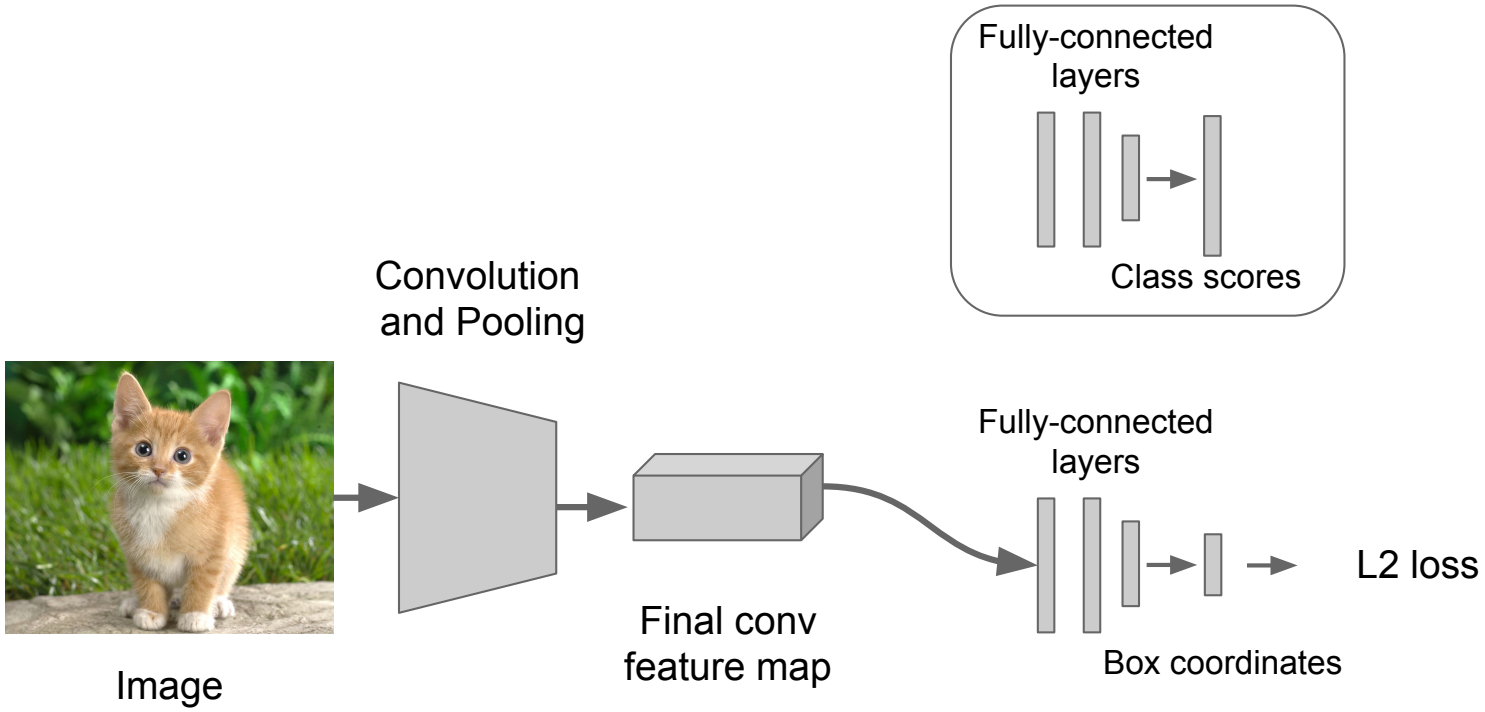
Simple Recipe for Classification + Localization

Step 2: Attach new fully-connected "regression head" to the network



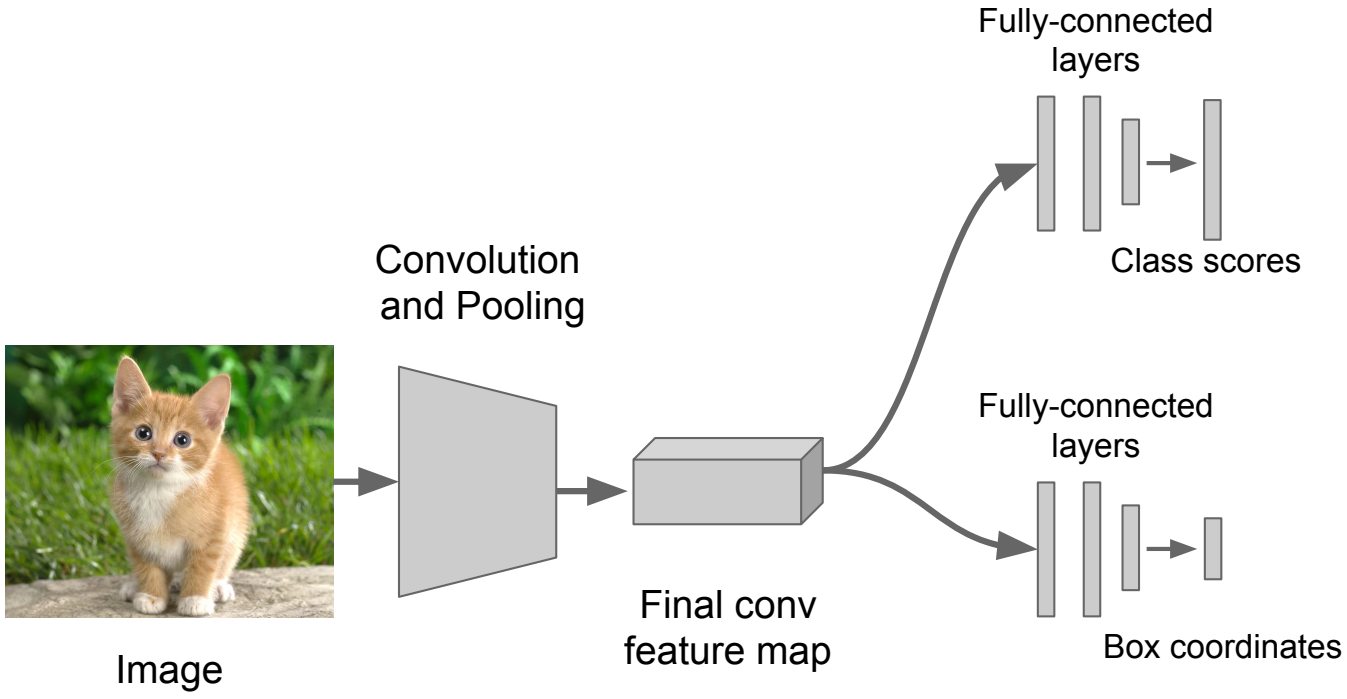
Simple Recipe for Classification + Localization

Step 3: Train the regression head only with SGD and L2 loss



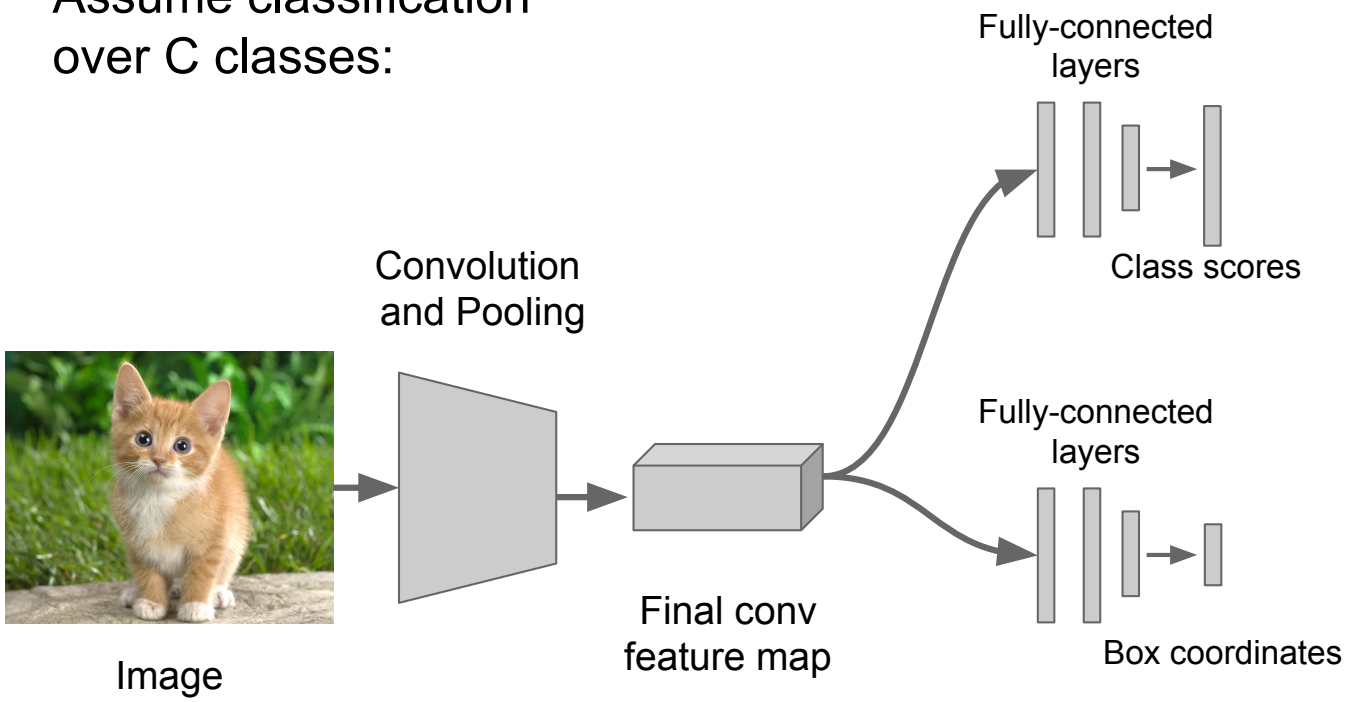
Simple Recipe for Classification + Localization

Step 4: At test time use both heads



Per-class vs class agnostic regression

Assume classification over C classes:

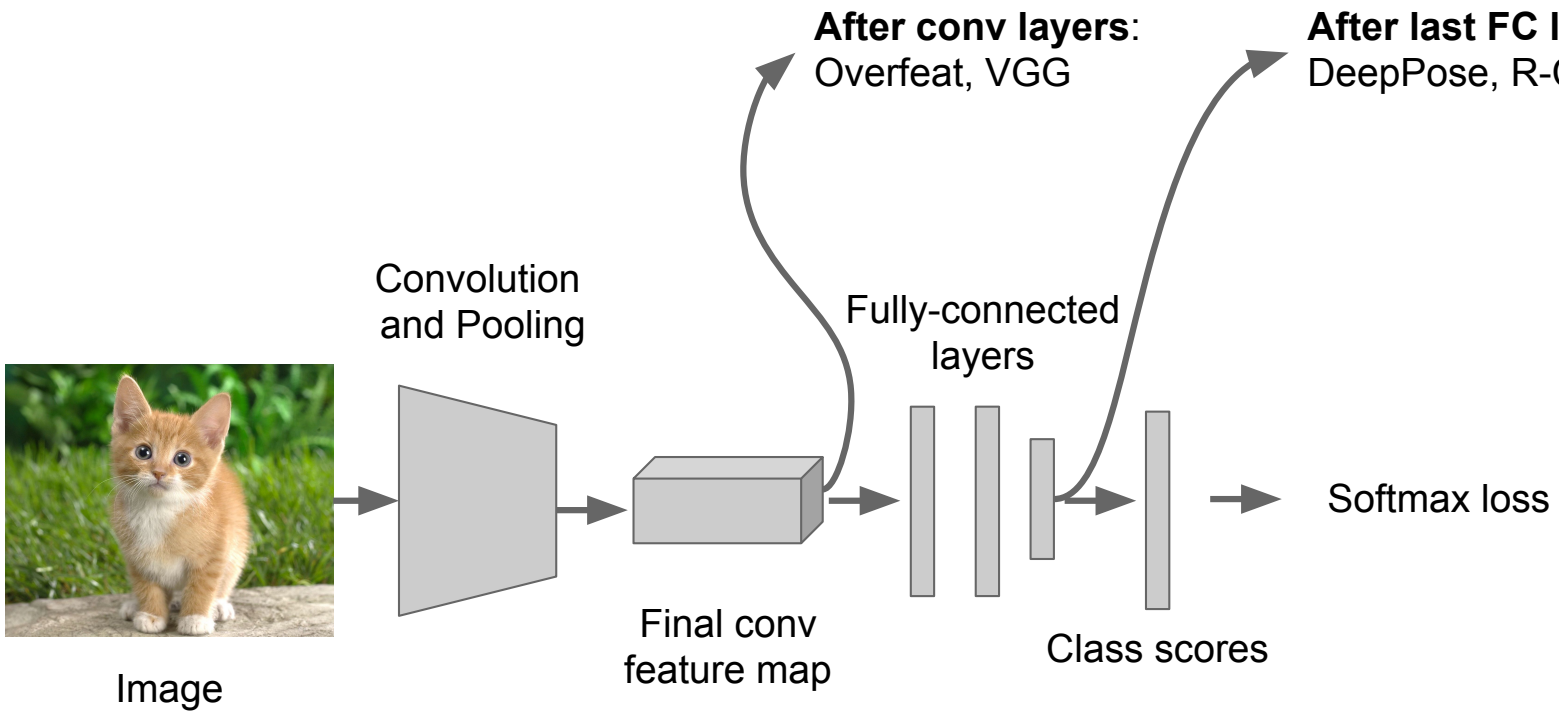


Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)

Class specific:
C x 4 numbers
(one box per class)

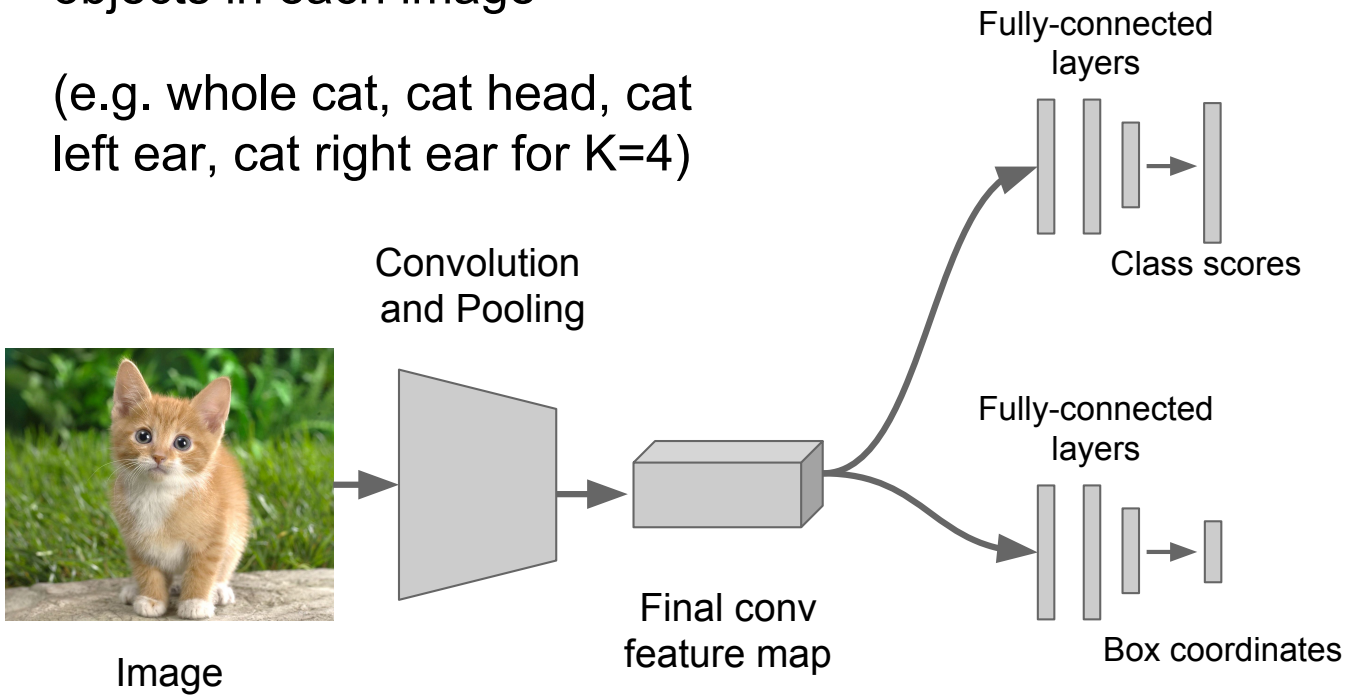
Where to attach the regression head?



Aside: Localizing multiple objects

Want to localize **exactly** K objects in each image

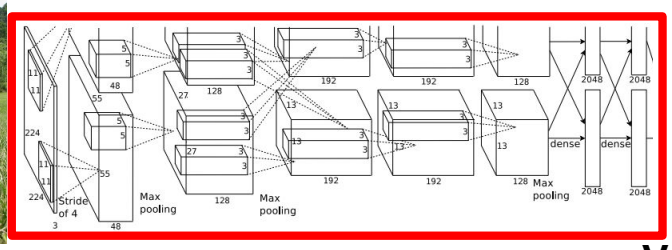
(e.g. whole cat, cat head, cat left ear, cat right ear for K=4)



K x 4 numbers
(one box per object)

Classification + Localization

This image is CC0 public domain



Often pretrained on ImageNet
(Transfer learning)

Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label: Cat

Softmax Loss

Fully Connected: 4096 to 4

Box Coordinates (x, y, w, h)

L2 Loss

Correct box: (x', y', w', h')

+ → **Loss**

Treat localization as a regression problem!