Dive into Deep Learning in 1 Day

1 Basics · **2 Convnets** · 3 Computation · 4 Sequences

AMLC 2019

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amlc-d2l.corp.amazon.com

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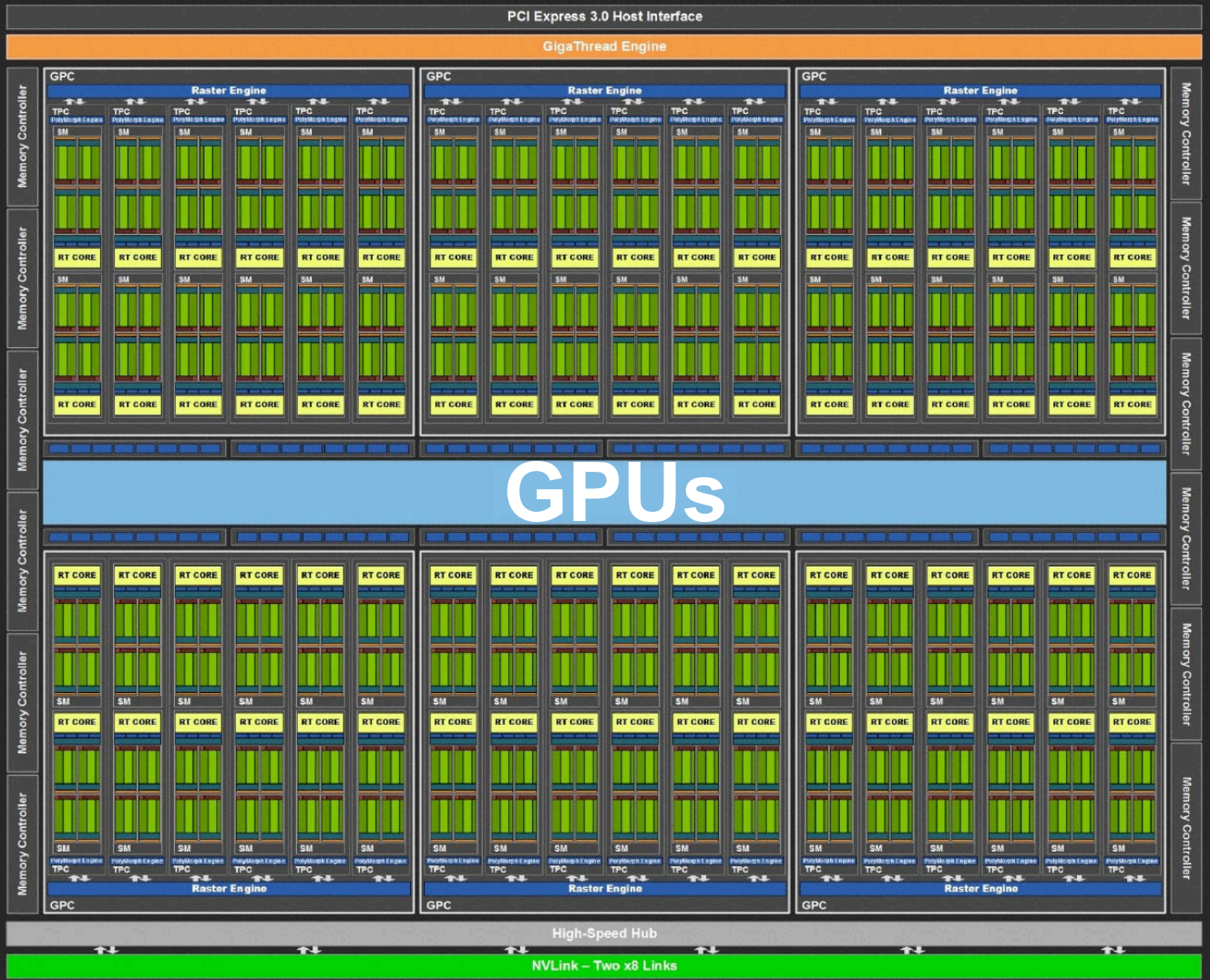
Outline

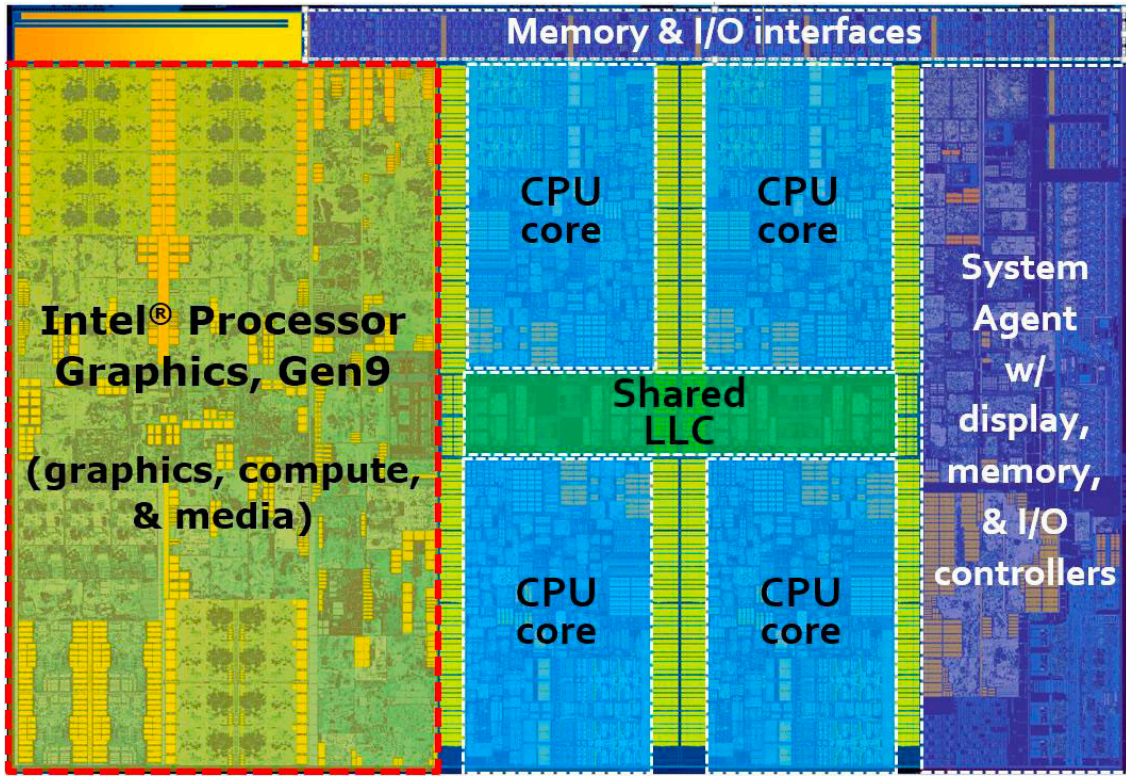
- GPUs
- Convolutions
- Pooling, Padding and Stride
- Convolutional Neural Networks (LeNet)
- Deep ConvNets (AlexNet)
- Networks using Blocks (VGG)
- Residual Neural Networks (ResNet)



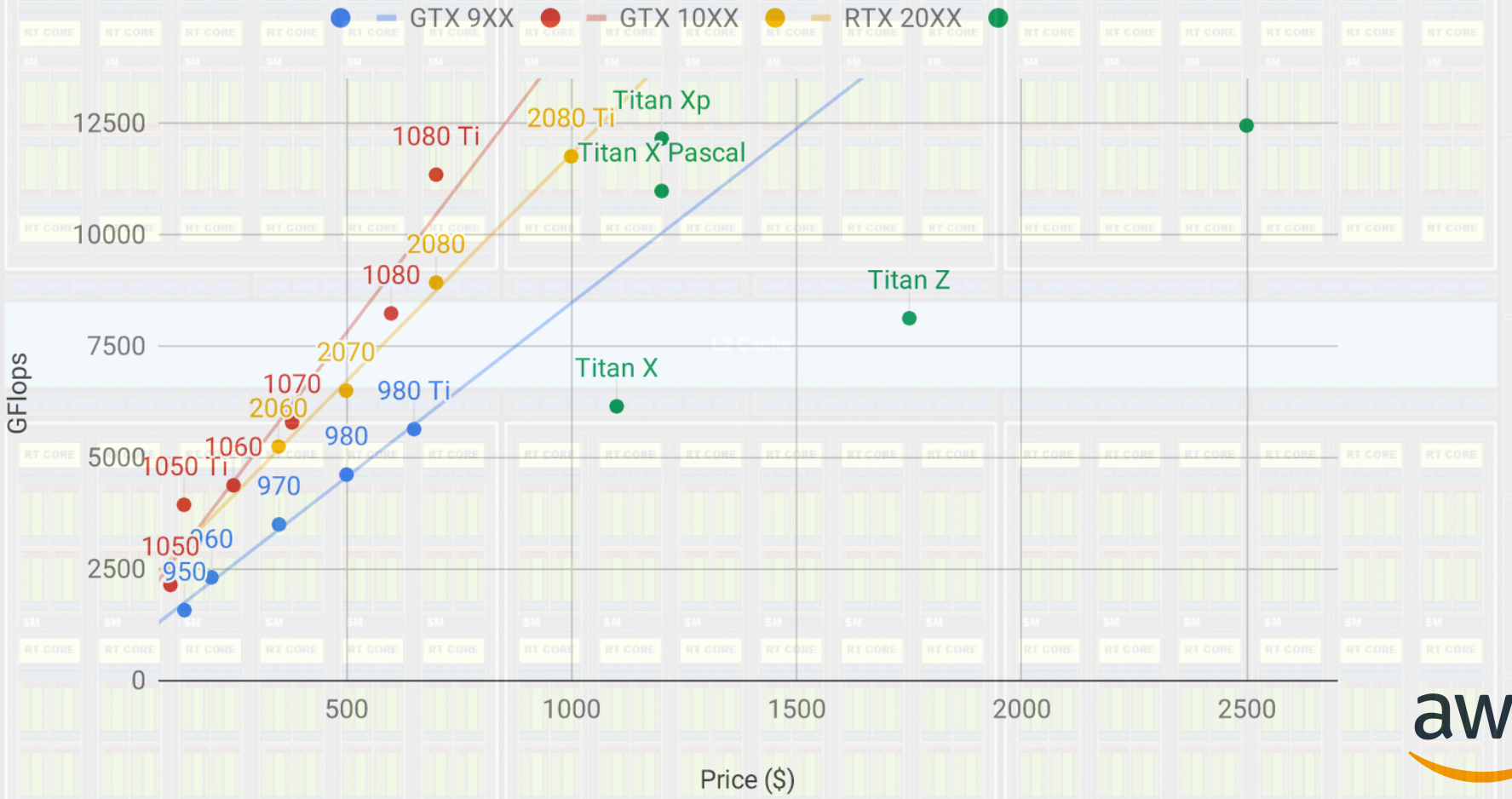
NVIDIA Turing TU102

Intel i7-6700K

- 4 Physical cores
- Per core
  - 64KB L1 cache
  - 256KB L2 cache
- Shared 8MB L3 cache
- 30 GB/s to RAM

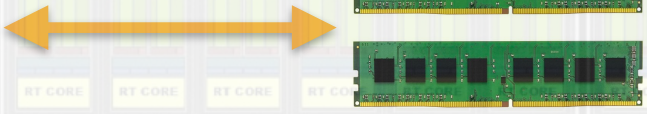


GPU performance



Highend Gaming / DeepLearning PC

Intel i7
0.15 TFLOPS



DDR4
32 GB

Nvidia Titan RTX
12 TFLOPS (130TF for FP16 TensorCores)
24 GB

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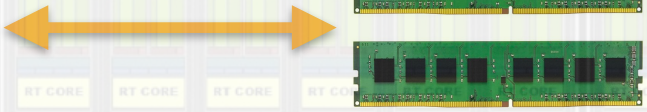
Highend Gaming / DeepLearning PC

Intel i7
0.15 TFLOPS



DDR4
32 GB

```
ctx = npx.cpu()
```

```
x.copyto(ctx)
```

Nvidia Titan RTX
12 TFLOPS (130TF for FP16 TensorCores)
24 GB

```
ctx = npx.gpu(0)
```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GPU Notebook


From fully connected
to convolutions

Classifying Dogs and Cats in Images

- Use a good camera
- RGB image has 36M elements
- The model size of a single hidden layer MLP with a 100 hidden size is 3.6 Billion parameters
- Exceeds the population of dogs and cats on earth (900M dogs + 600M cats)

Dual

12MP

wide-angle and telephoto cameras

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Flashback - Network with one hidden layer

Output layer

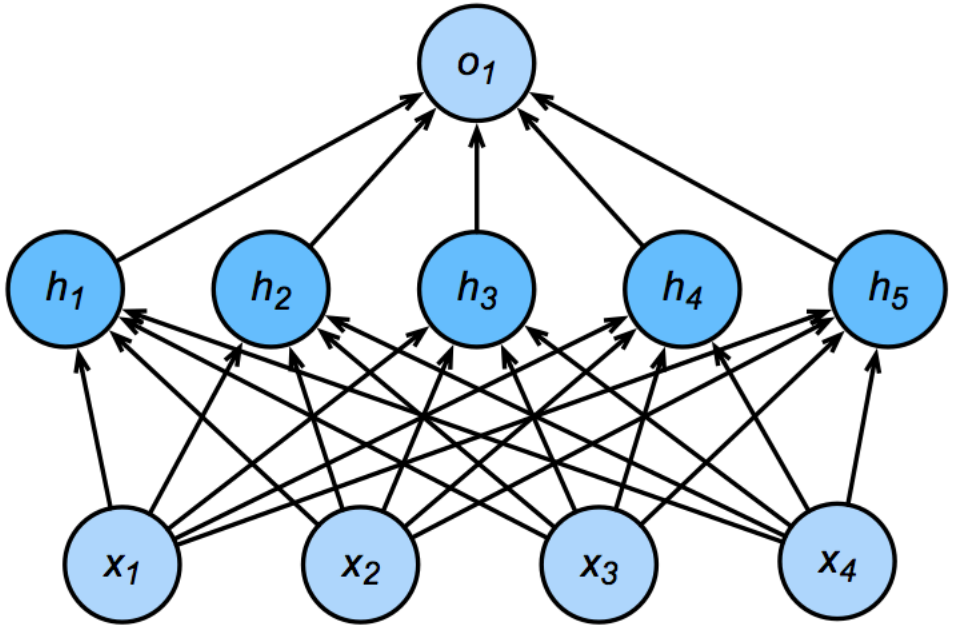
100 neurons

Hidden layer

3.6B parameters = 14GB

36M features

Input layer



$$\mathbf{h} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$$

Where is Waldo?

Two Principles

- Translation Invariance
- Locality

Rethinking Dense Layers

- Reshape inputs and output into matrix (width, height)
- Reshape weights into 4-D tensors (h,w) to (h',w')

$$h_{i,j} = \sum_{k,l} w_{i,j,k,l} x_{k,l} = \sum_{a,b} v_{i,j,a,b} x_{i+a,j+b}$$

V is re-indexes W such as that

$$v_{i,j,a,b} = w_{i,j,i+a,j+b}$$

Idea #1 - Translation Invariance

$$h_{i,j} = \sum_{a,b} v_{i,j,a,b} x_{i+a,j+b}$$

- A shift in *x* also leads to a shift in *h*
- *v* should not depend on *(i,j)*. Fix via $v_{i,j,a,b} = v_{a,b}$

$$h_{i,j} = \sum_{a,b} v_{a,b} x_{i+a,j+b}$$

That's a ~~2-D convolution~~
cross-correlation

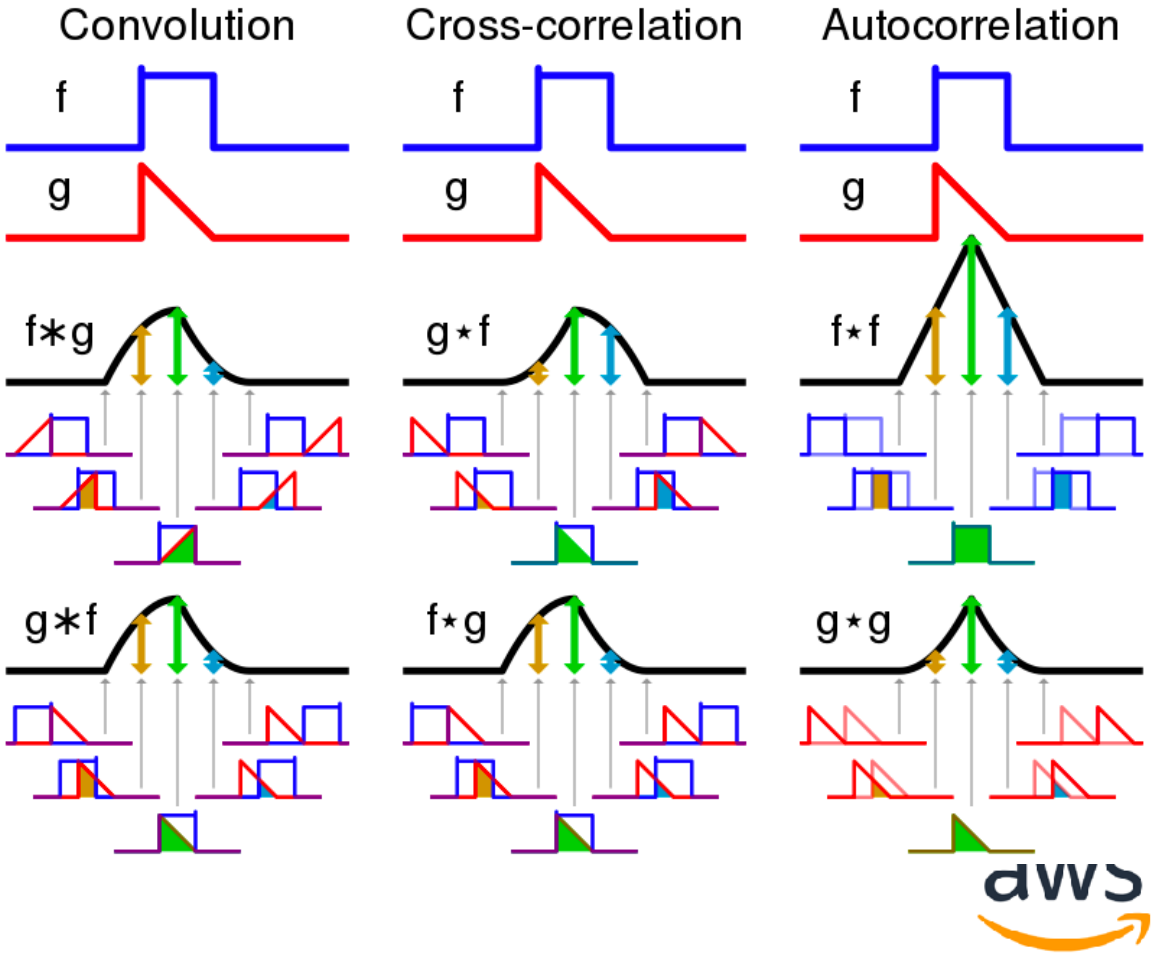
Idea #2 - Locality

$$h_{i,j} = \sum_{a,b} v_{a,b} x_{i+a,j+b}$$

- We shouldn't look very far from x(i,j) in order to assess what's going on at h(i,j)
- Outside range $|a|, |b| > \Delta$ parameters vanish $v_{a,b} = 0$

$$h_{i,j} = \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} v_{a,b} x_{i+a,j+b}$$

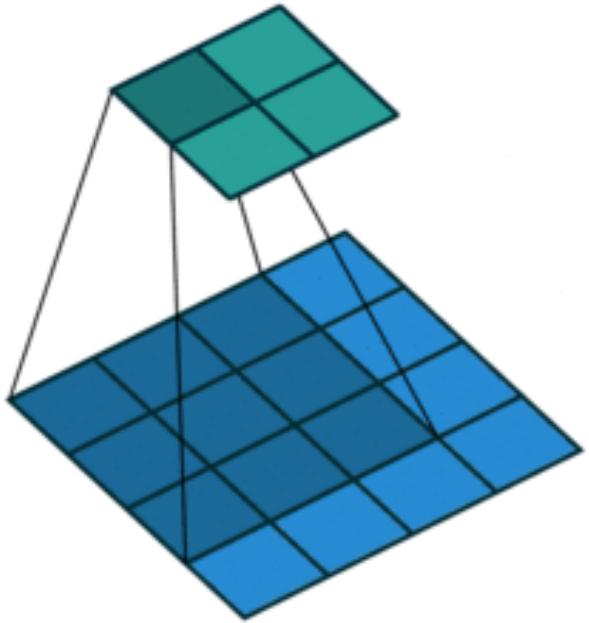
Convolution



2-D Cross Correlation

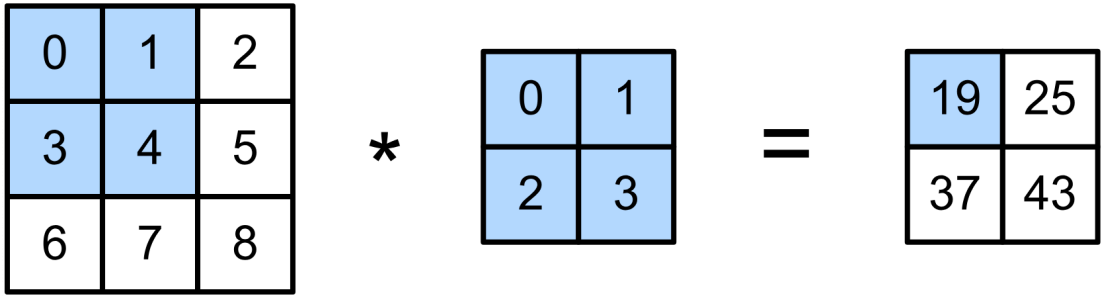
Input			*	Kernel		=	Output	
0	1	2		0	1		19	25
3	4	5		2	3		37	43
6	7	8						

$$0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,$$
$$1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,$$
$$3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,$$
$$4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.$$



(vdumoulin@ Github)

2-D Convolution Layer



- $\mathbf{X}$: $n_h \times n_w$ input matrix
- $\mathbf{W}$: $k_h \times k_w$ kernel matrix
- b: scalar bias
- $\mathbf{Y}$: $(n_h - k_h + 1) \times (n_w - k_w + 1)$ output matrix

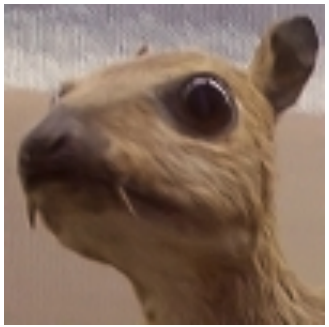
$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + b$$

- **W** and *b* are learnable parameters

Examples

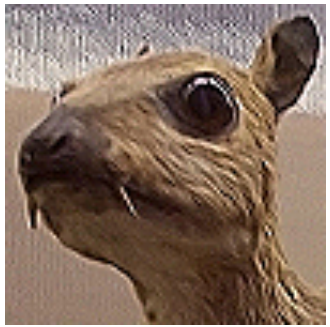
$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Edge Detection



(wikipedia)

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



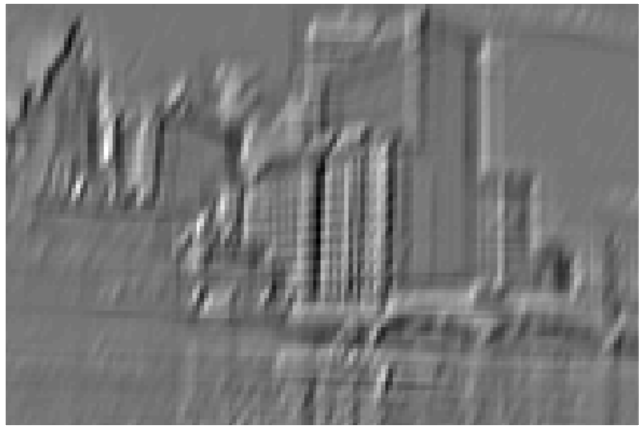
Sharpen

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

Gaussian Blur

Examples

(Rob Fergus)



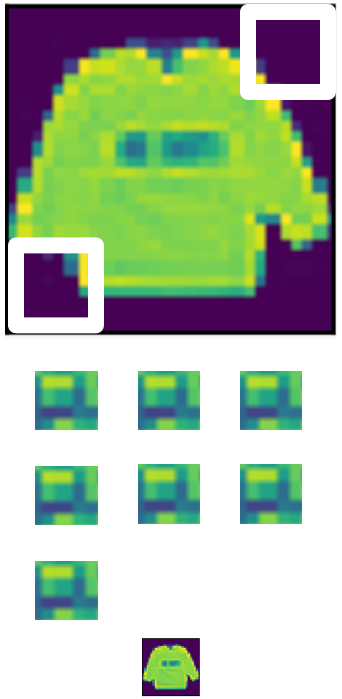
Convolutions Notebook


Padding and Stride

Padding

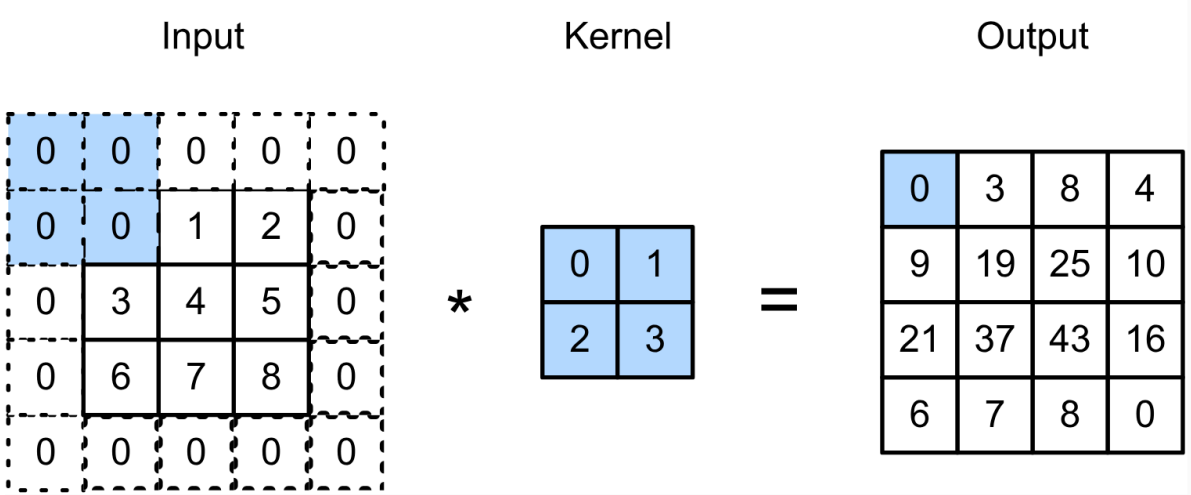
- Given a 32 x 32 input image
- Apply convolutional layer with 5 x 5 kernel
  - 28 x 28 output with 1 layer
  - 4 x 4 output with 7 layers
- Shape decreases faster with larger kernels
  - Shape reduces from $n_h \times n_w$ to

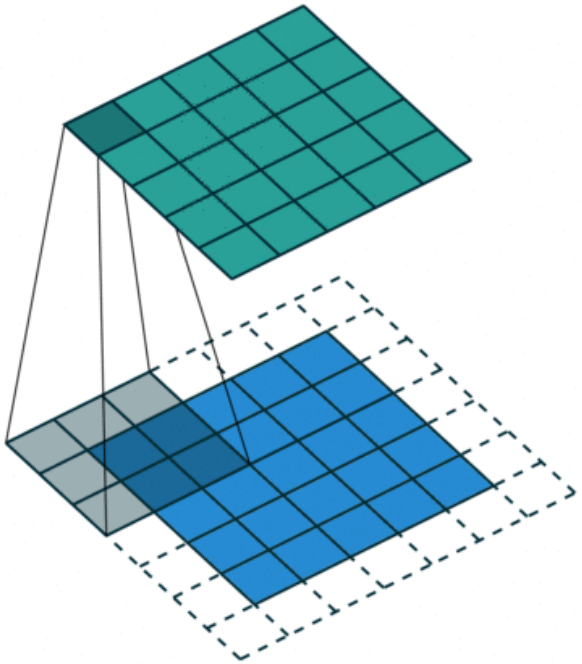
$$(n_h - k_h + 1) \times (n_w - k_w + 1)$$



Padding

Padding adds rows/columns around input





$$0 \times 0 + 0 \times 1 + 0 \times 2 + 0 \times 3 = 0$$

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Padding

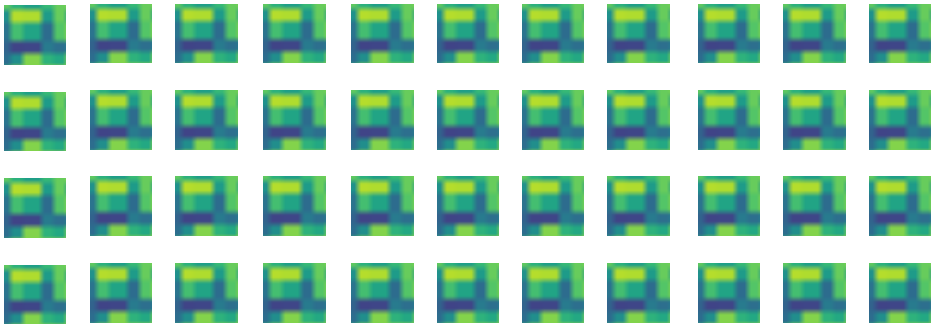
- Padding p_h rows and p_w columns, output shape will be

$$(n_h - k_h + p_h + 1) \times (n_w - k_w + p_w + 1)$$

- A common choice is $p_h = k_h - 1$ and $p_w = k_w - 1$
  - Odd k_h : pad $p_h/2$ on both sides
  - Even k_h : pad $\lceil p_h/2 \rceil$ on top, $\lfloor p_h/2 \rfloor$ on bottom

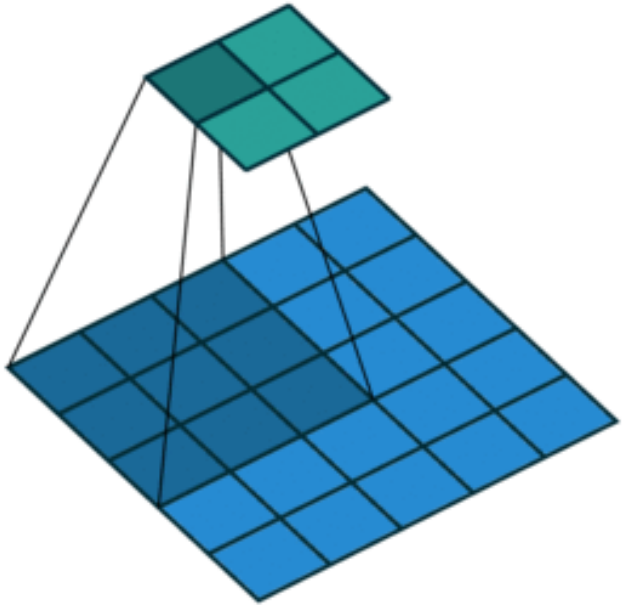
Stride

- Padding reduces shape linearly with #layers
  - Given a 224 x 224 input with a 5 x 5 kernel, needs 44 layers to reduce the shape to 4 x 4
  - Requires a large amount of computation

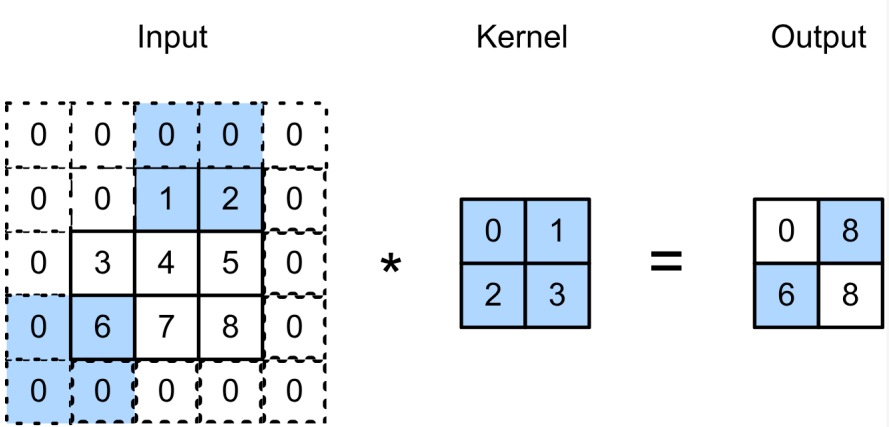


Stride

- Stride is the #rows/#columns per slide



Strides of 3 and 2 for height and width



$$0 \times 0 + 0 \times 1 + 1 \times 2 + 2 \times 3 = 8$$
$$0 \times 0 + 6 \times 1 + 0 \times 2 + 0 \times 3 = 6$$

Stride

- Given stride s_h for the height and stride s_w for the width, the output shape is

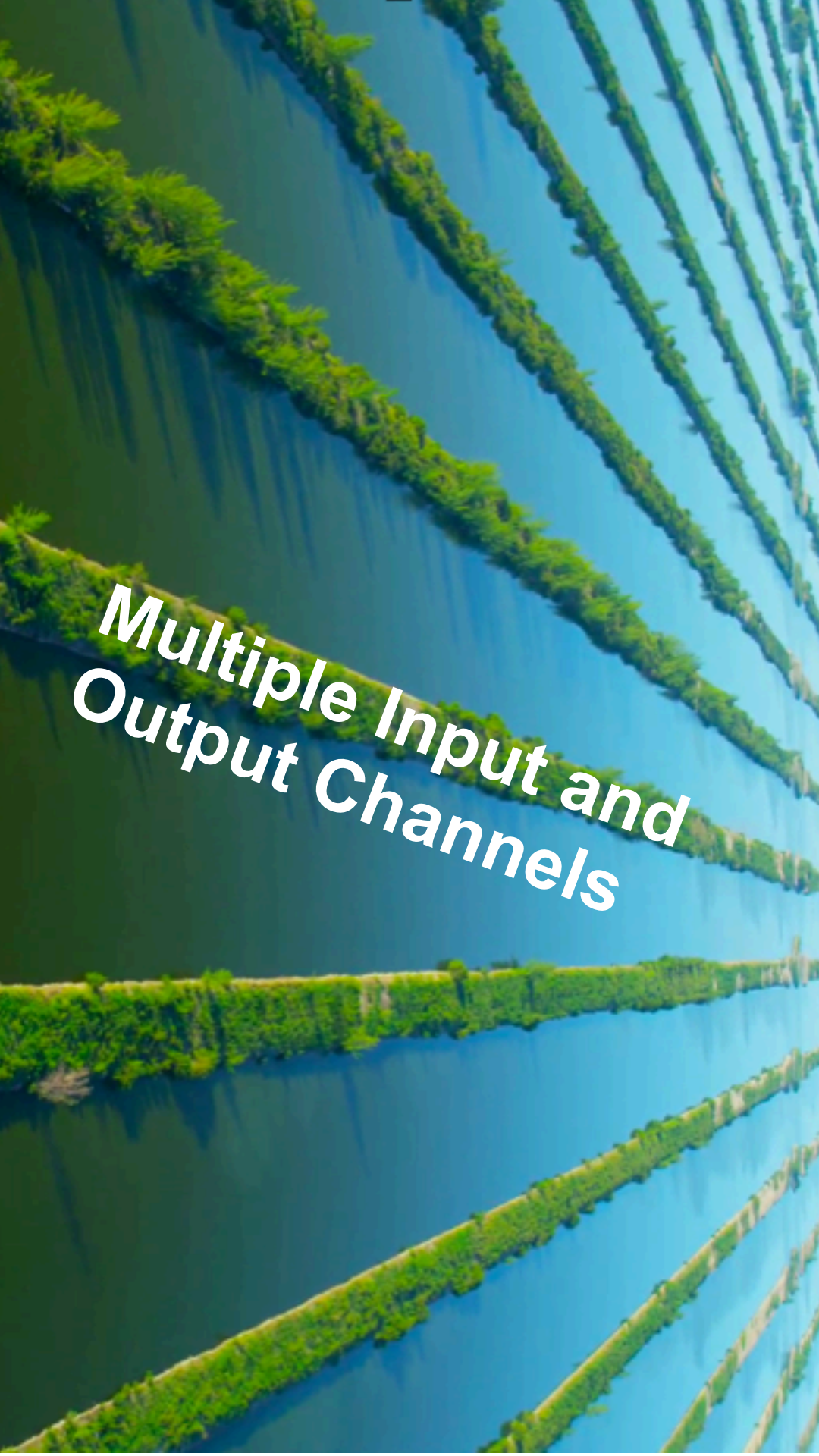
$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

- With $p_h = k_h - 1$ and $p_w = k_w - 1$

$$\lfloor (n_h + s_h - 1)/s_h \rfloor \times \lfloor (n_w + s_w - 1)/s_w \rfloor$$

- If input height/width are divisible by strides

$$(n_h/s_h) \times (n_w/s_w)$$


Multiple Input and
Output Channels

Multiple Input Channels

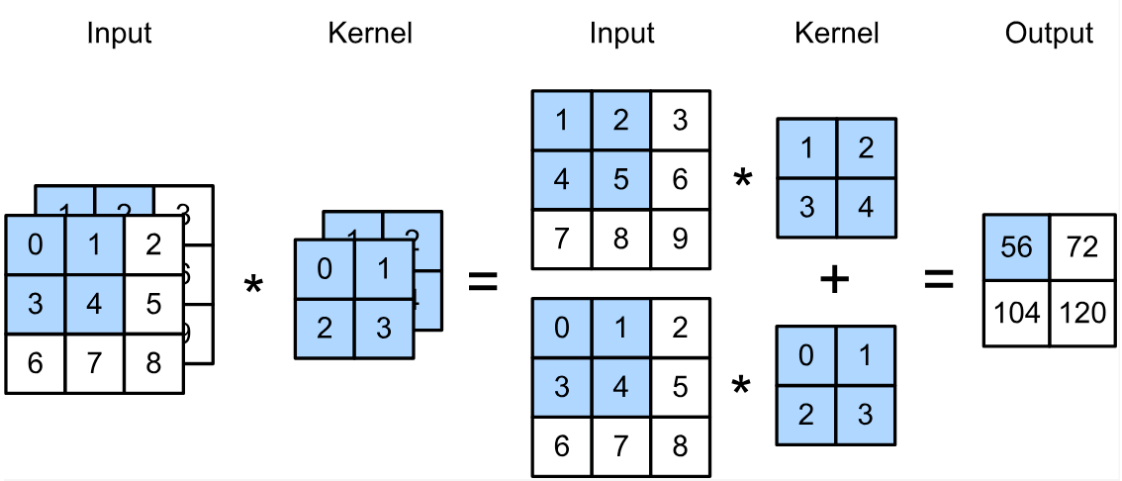
- Color image may have three RGB channels
- Converting to grayscale loses information

Multiple Input Channels

- Color image may have three RGB channels
- Converting to grayscale loses information

Multiple Input Channels

- Have a kernel for each channel, and then sum results over channels



$$(1 \times 1 + 2 \times 2 + 4 \times 3 + 5 \times 4) + (0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3) = 56$$

Multiple Input Channels

- $\mathbf{X} : c_i \times n_h \times n_w$ input
- $\mathbf{W} : c_i \times k_h \times k_w$ kernel
- $\mathbf{Y} : m_h \times m_w$ output

$$\mathbf{Y} = \sum_{i=0}^{c_i} \mathbf{X}_{i,:,:} \star \mathbf{W}_{i,:,:}$$

Multiple Output Channels

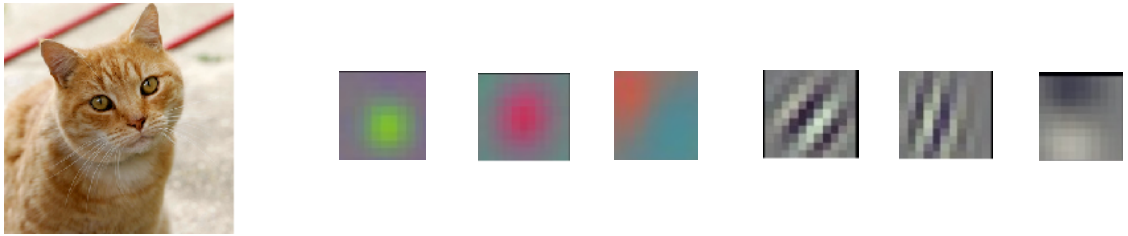
- No matter how many inputs channels, so far we always get single output channel
- We can have multiple 3-D kernels, each one generates a output channel
- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:}$$

for $i = 1, \ldots, c_o$

Multiple Input/Output Channels

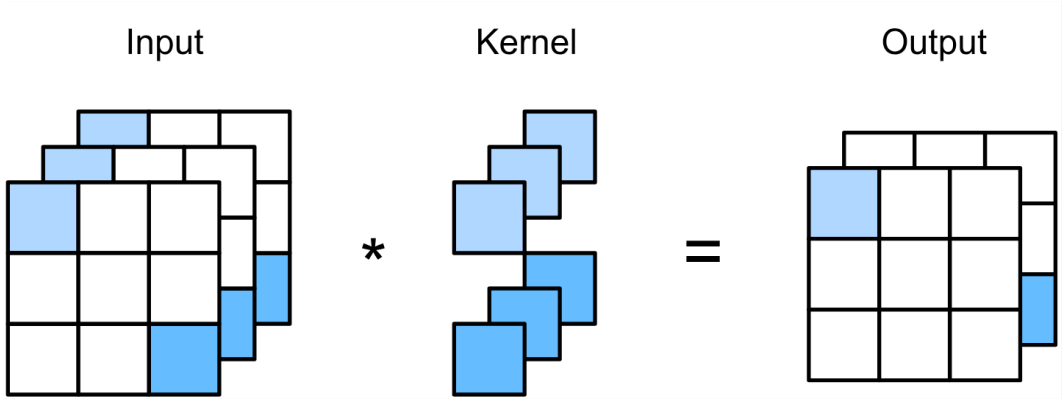
- Each output channel may recognize a particular pattern



- Input channels kernels recognize and combines patterns in inputs

1 x 1 Convolutional Layer

$k_h = k_w = 1$ is a popular choice. It doesn't recognize spatial patterns, but fuse channels.



Equal to a dense layer with $n_h n_w \times c_i$ input and $c_o \times c_i$ weight.

2-D Convolution Layer Summary

- Input $\mathbf{X} : c_i \times n_h \times n_w$
- Kernel $\mathbf{W} : c_o \times c_i \times k_h \times k_w$
- Bias $\mathbf{B} : c_o \times c_i$
- Output $\mathbf{Y} : c_o \times m_h \times m_w$

$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + \mathbf{B}$$

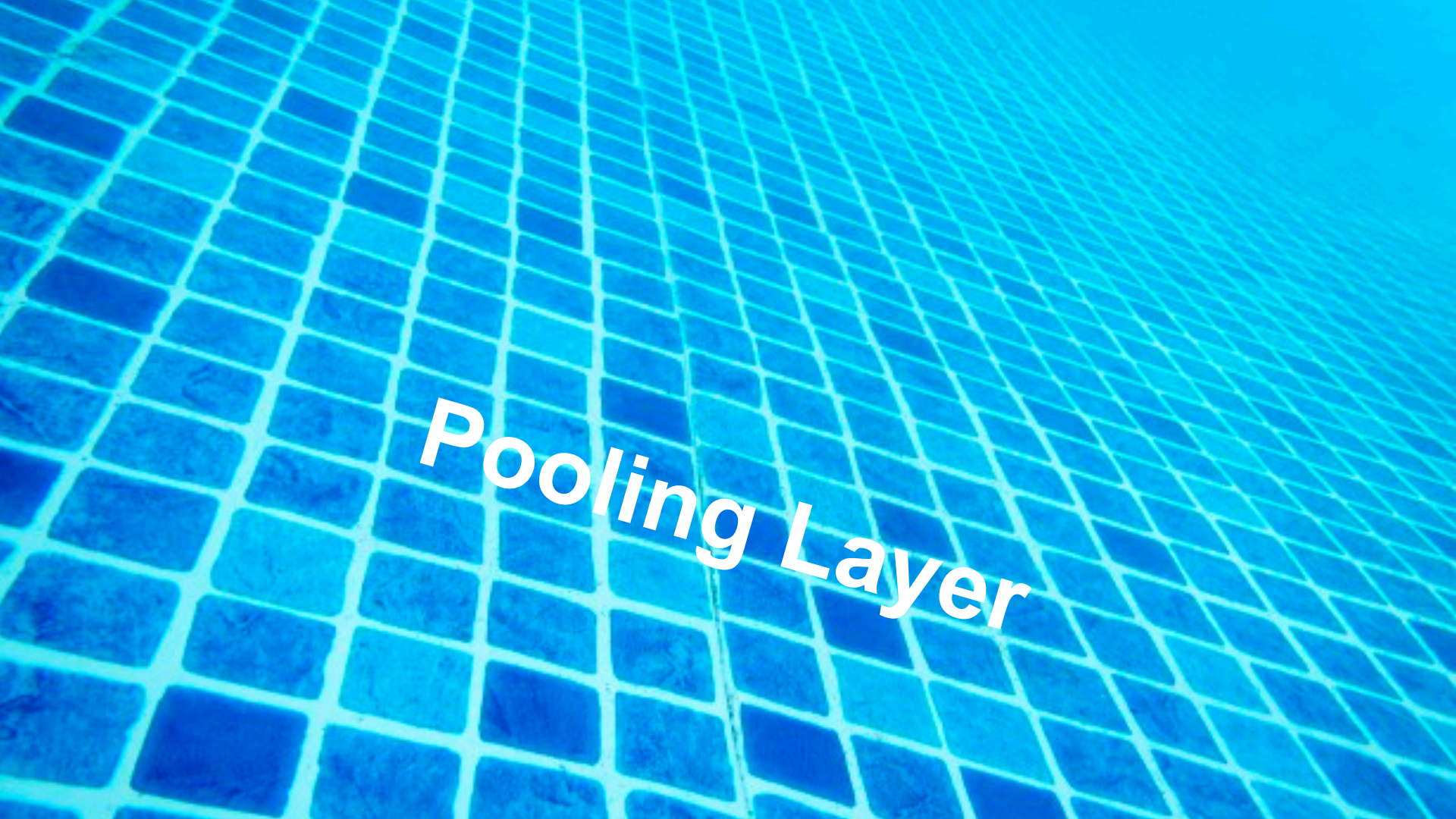
- Complexity (number of floating point operations FLOP)

$$c_i = c_o = 100$$
$$k_h = h_w = 5$$
$$m_h = m_w = 64$$

$$O(c_i c_o k_h k_w m_h m_w)$$

1GFLOP

- 10 layers, 1M examples: 10PF
  (CPU: 0.15 TF = 18h, GPU: 12 TF = 14min)


Pooling Layer

Pooling

- Convolution is sensitive to position
  - Detect vertical edges

0 output with 1 pixel shift

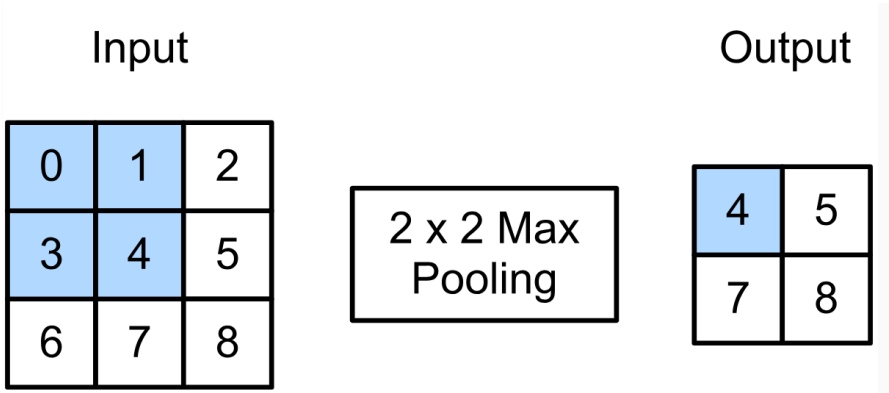
```
X  [[1. 1. 0. 0. 0.
    [1. 1. 0. 0. 0.
    [1. 1. 0. 0. 0.
    [1. 1. 0. 0. 0.

Y  [[ 0.  1.  0.  0.
    [ 0.  1.  0.  0.
    [ 0.  1.  0.  0.
    [ 0.  1.  0.  0.
```

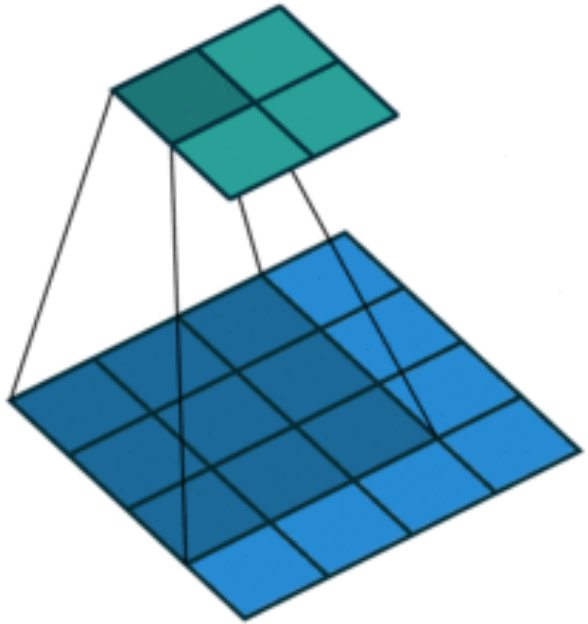
- We need some degree of invariance to translation
  - Lighting, object positions, scales, appearance vary among images

2-D Max Pooling

- Returns the maximal value in the sliding window



$$\max(0,1,3,4) = 4$$



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2-D Max Pooling

- Returns the maximal value in the sliding window

Vertical edge detection

```
[[1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
```

Conv output

```
[[ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
```

2 x 2 max pooling

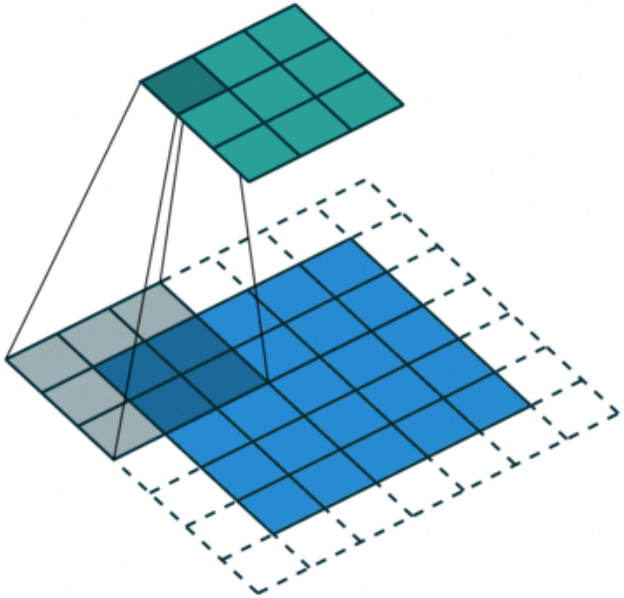
```
[[ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
```

Tolerant to 1 pixel shift

Padding, Stride, and Multiple Channels

- Pooling layers have similar padding and stride as convolutional layers
- No learnable parameters
- Apply pooling for each input channel to obtain the corresponding output channel

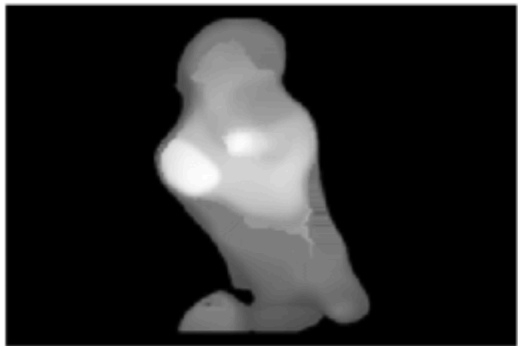
#output channels = #input channels



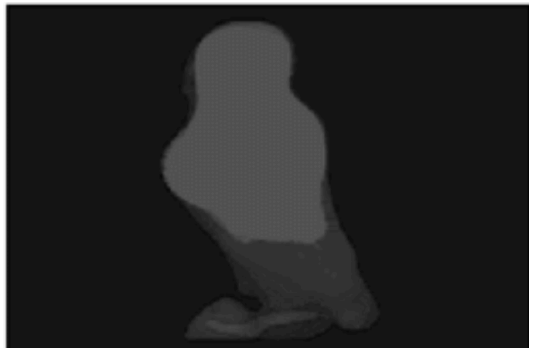
Average Pooling

- Max pooling: the strongest pattern signal in a window
- Average pooling: replace max with mean in max pooling
    - The average signal strength in a window

Max pooling

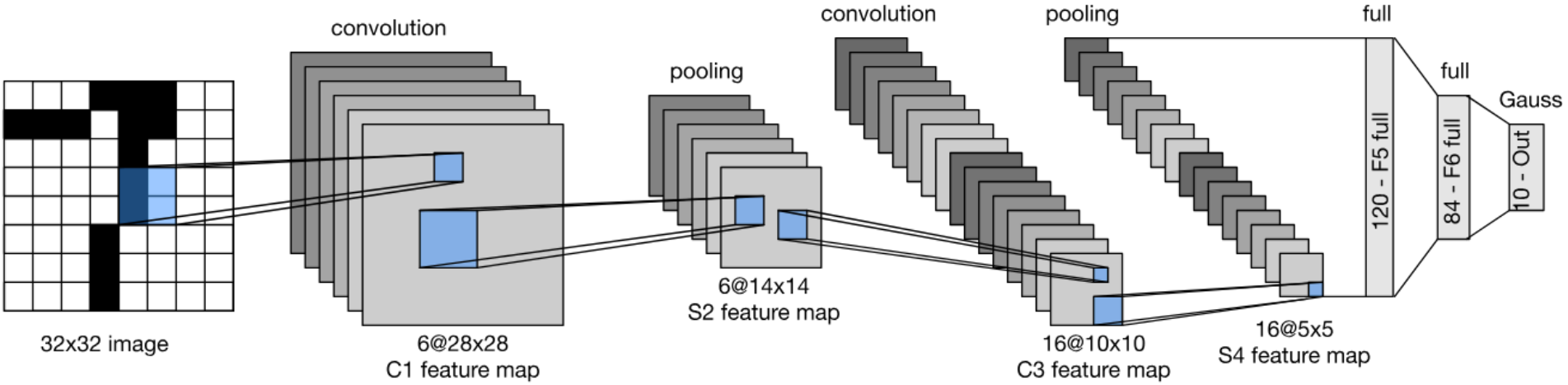


Average pooling

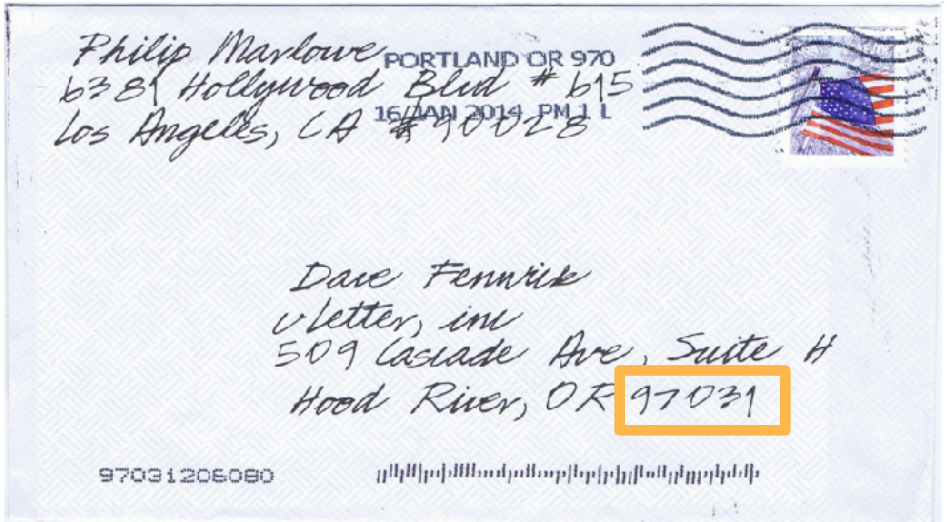


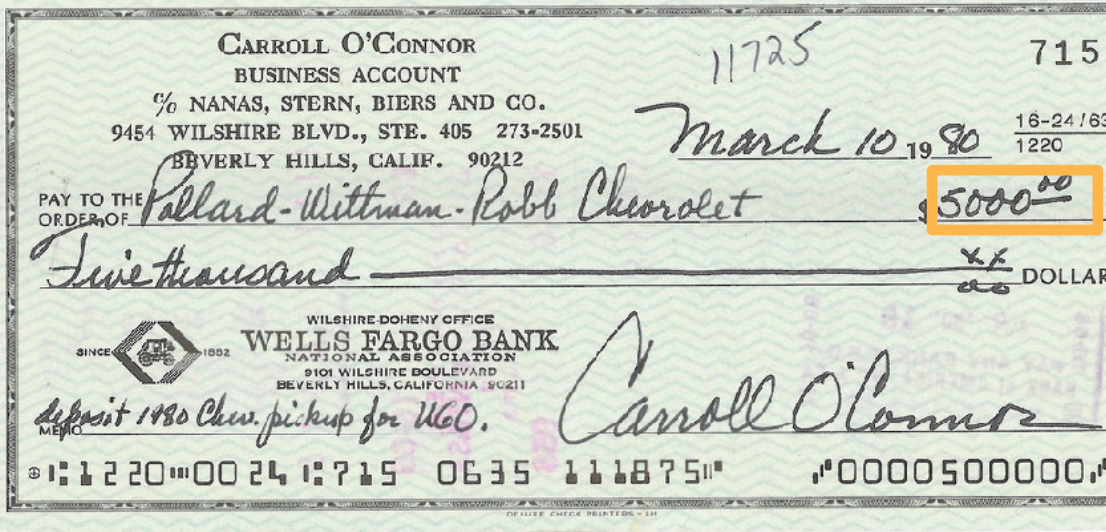
Pooling Notebook

LeNet


convolution
pooling
convolution
pooling
full
full
Gauss
120 - F5 full
84 - F6 full
10 - Out
32x32 image
6@28x28
C1 feature map
6@14x14
S2 feature map
16@10x10
C3 feature map
16@5x5
S4 feature map

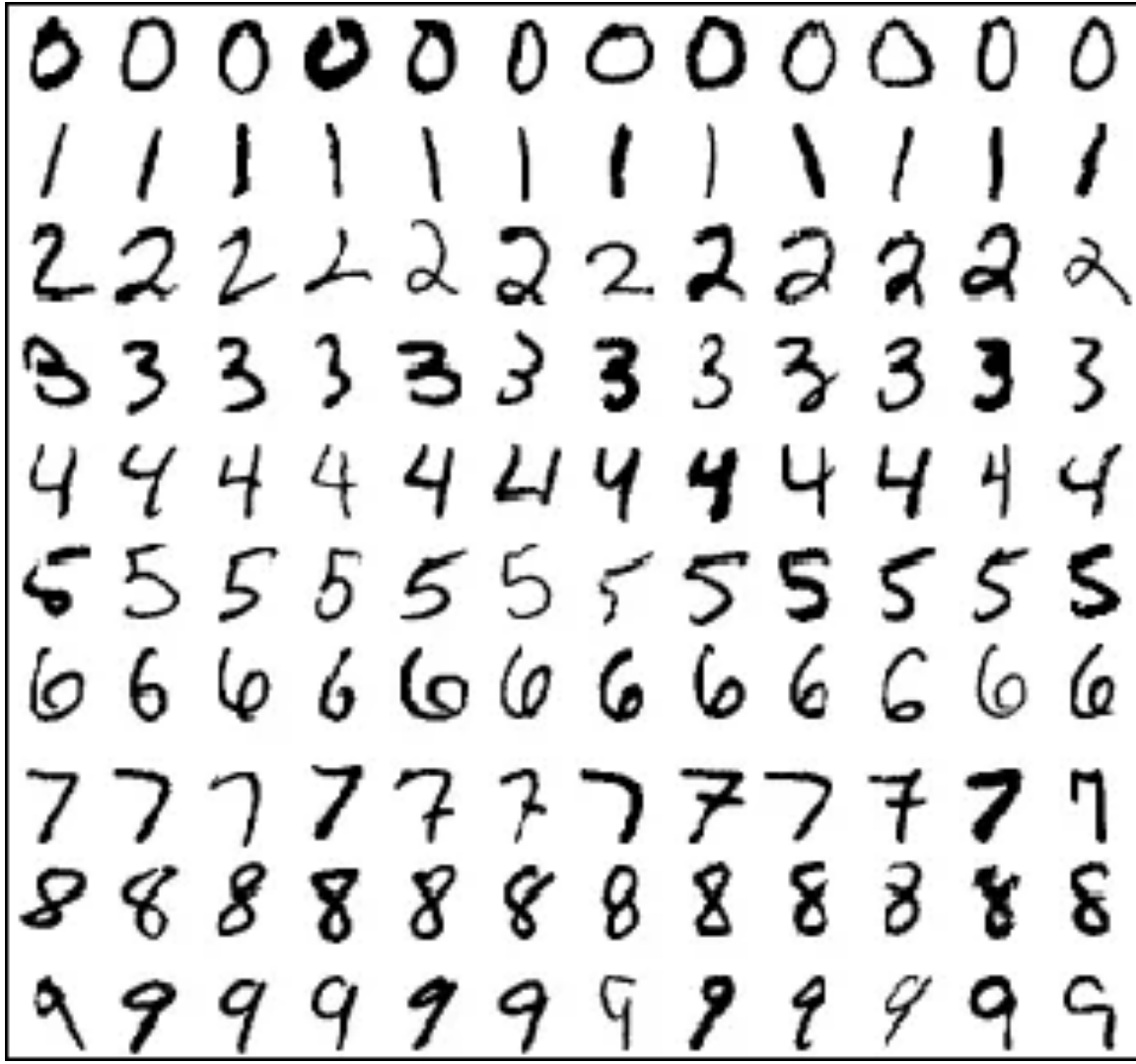
Handwritten Digit Recognition





MNIST

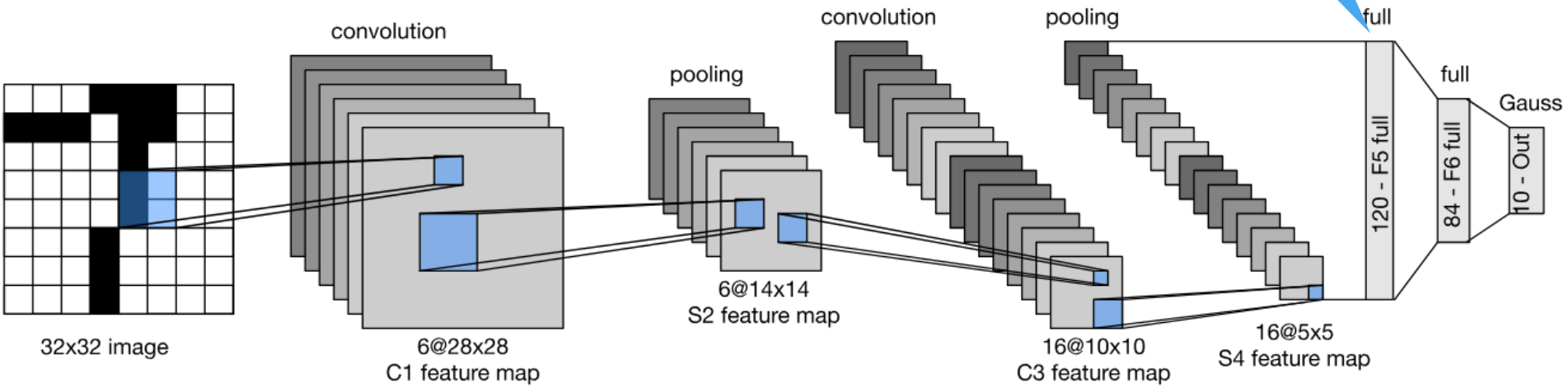
- Centered and scaled
- 50,000 training data
- 10,000 test data
- 28 x 28 images
- 10 classes



Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition

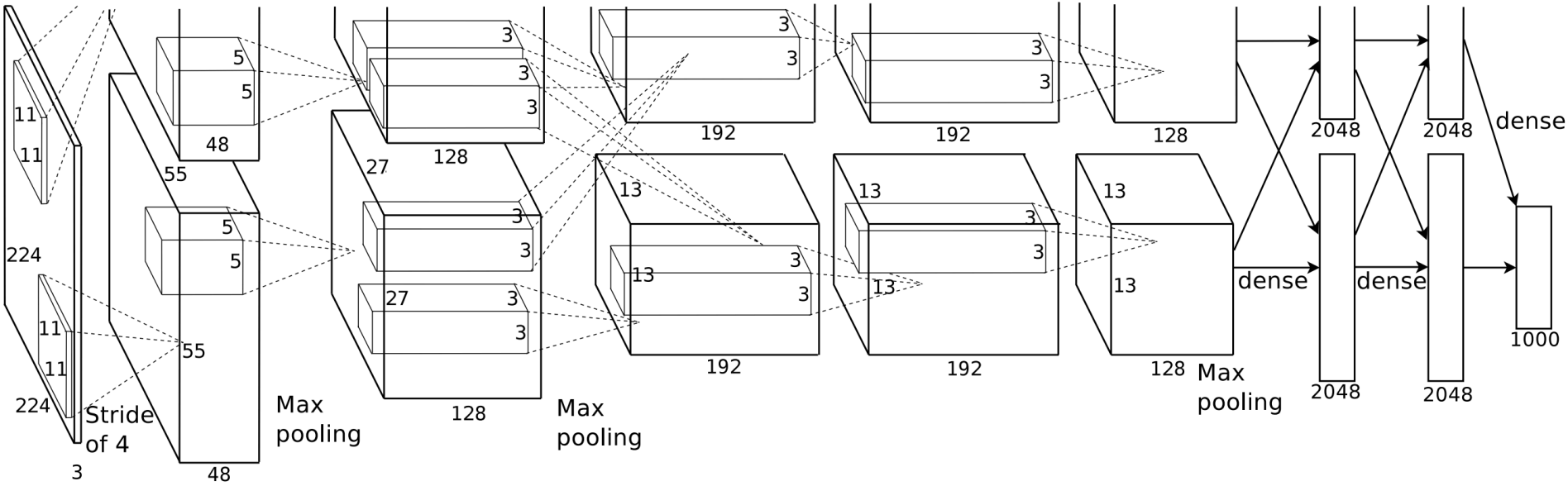
aws

Expensive if we have many outputs



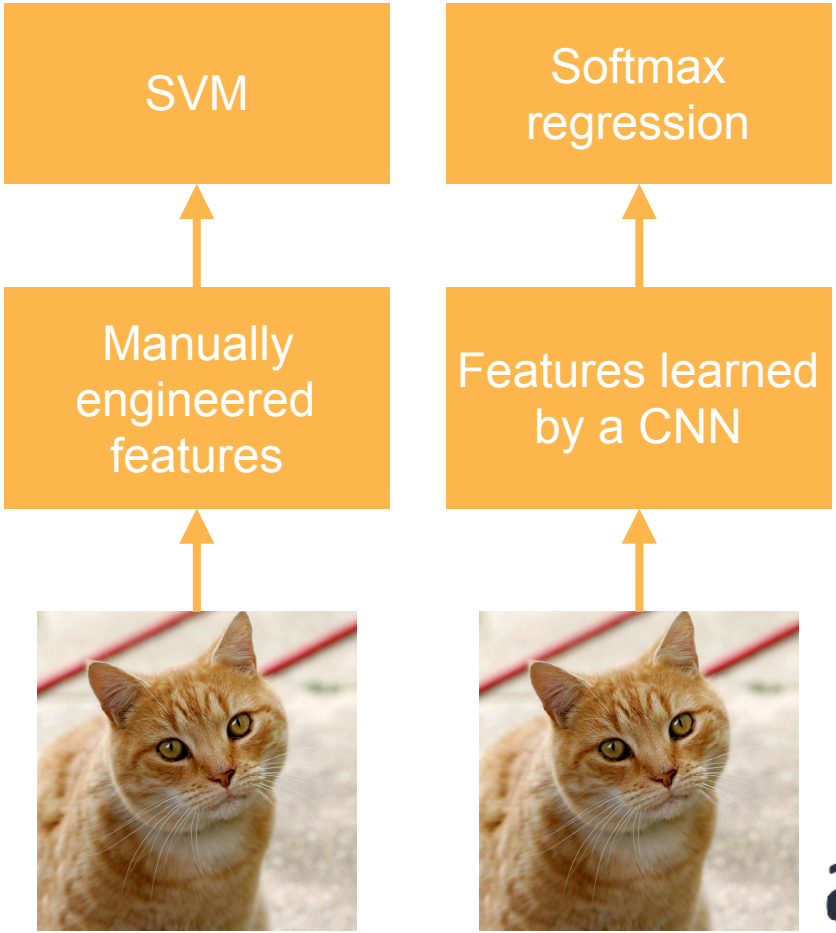
LeNet Notebook

AlexNet

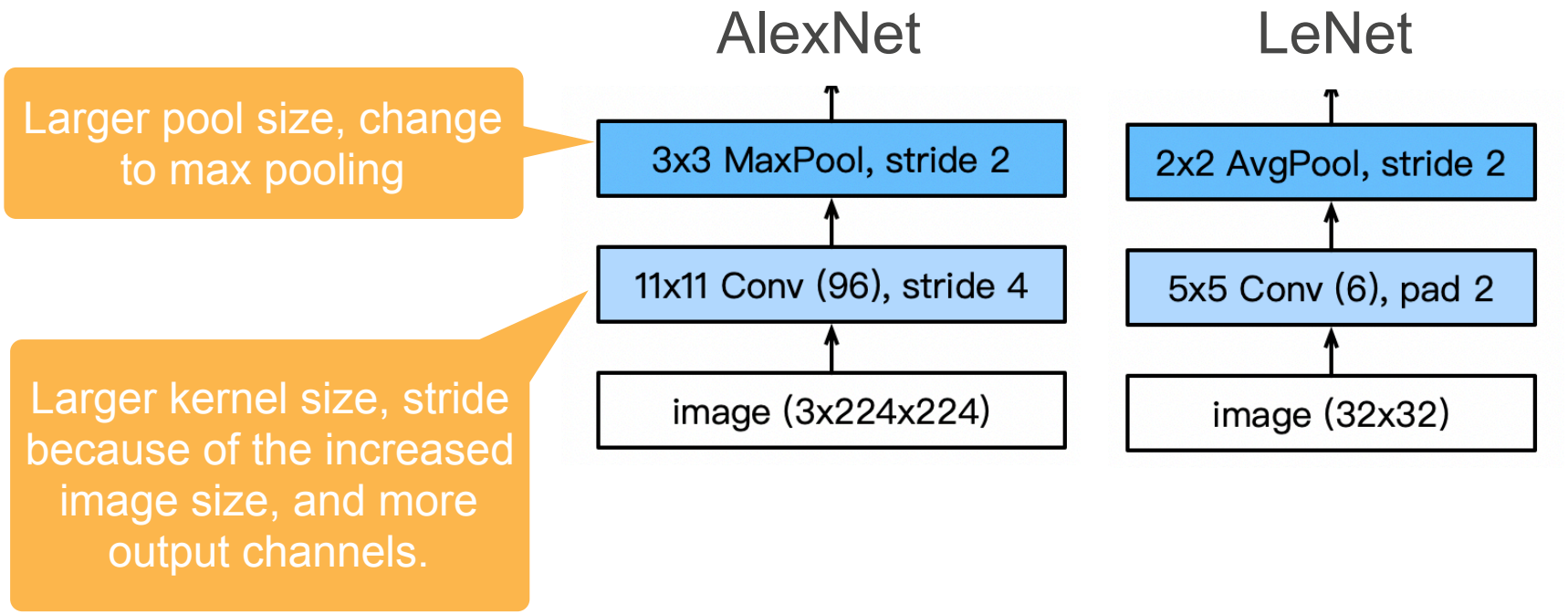

11
11
224
224
3
Stride
of 4
5
5
48
55
48
55
5
5
Max
pooling
3
3
3
128
27
128
27
3
3
3
Max
pooling
3
3
192
13
13
3
3
3
192
3
3
13
13
192
3
3
13
13
128
Max
pooling
dense
dense
2048
2048
2048
2048
dense
1000

AlexNet

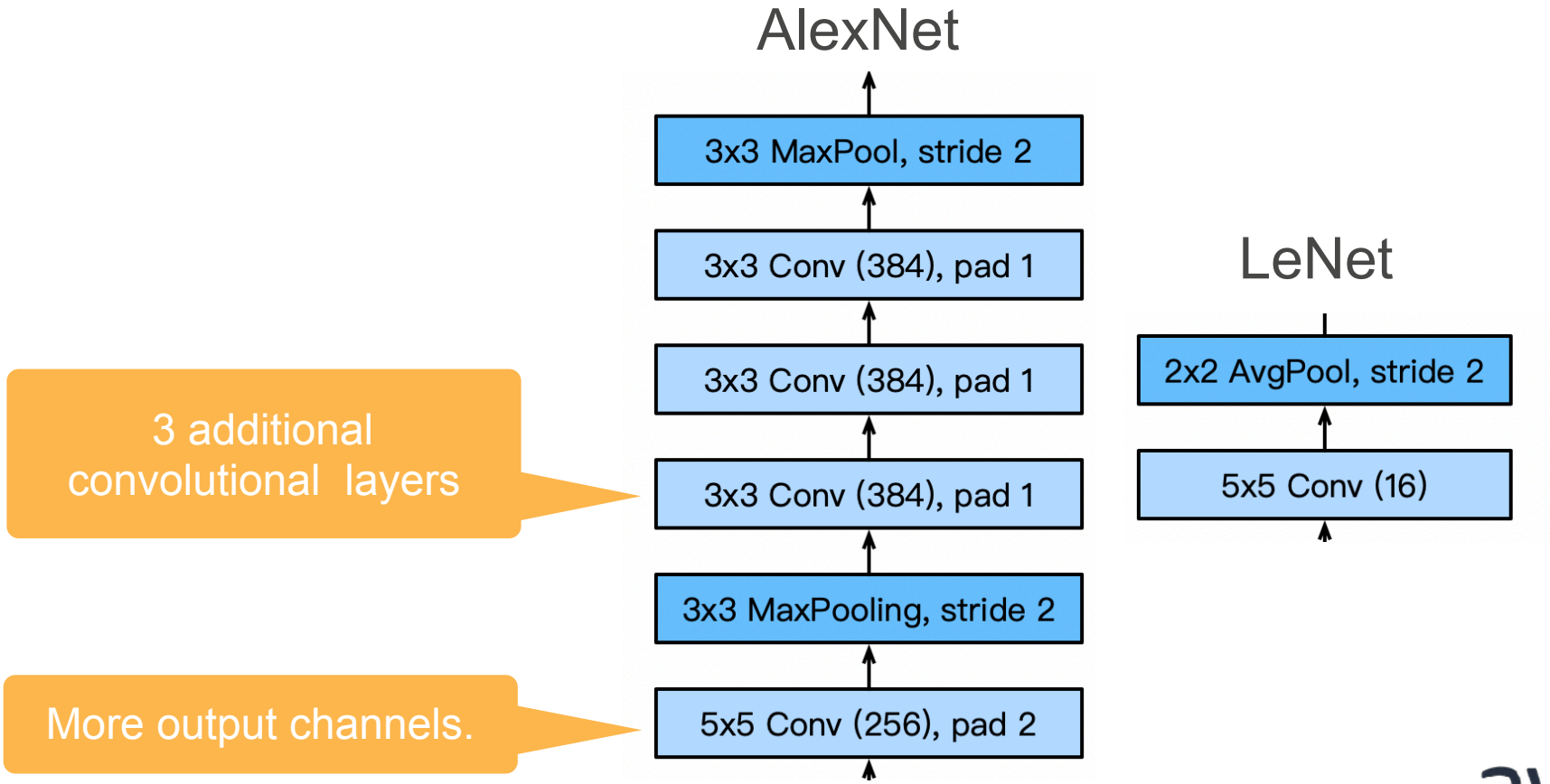
- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Key modifications
  - Dropout (regularization)
  - ReLu (training)
  - MaxPooling
- Paradigm shift for computer vision



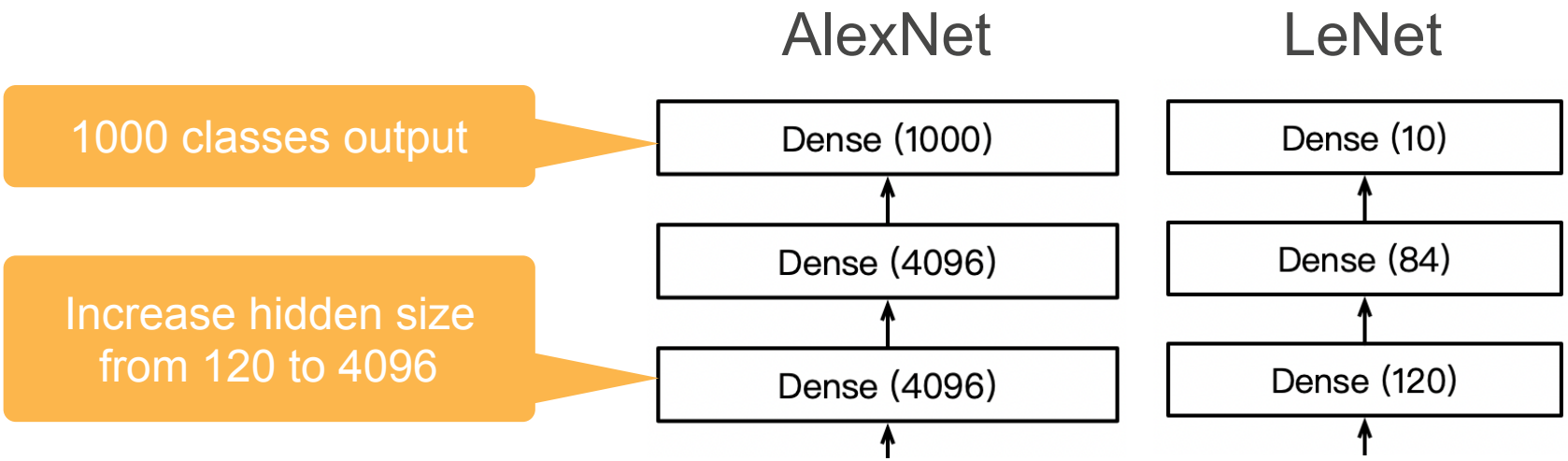
AlexNet Architecture



AlexNet Architecture

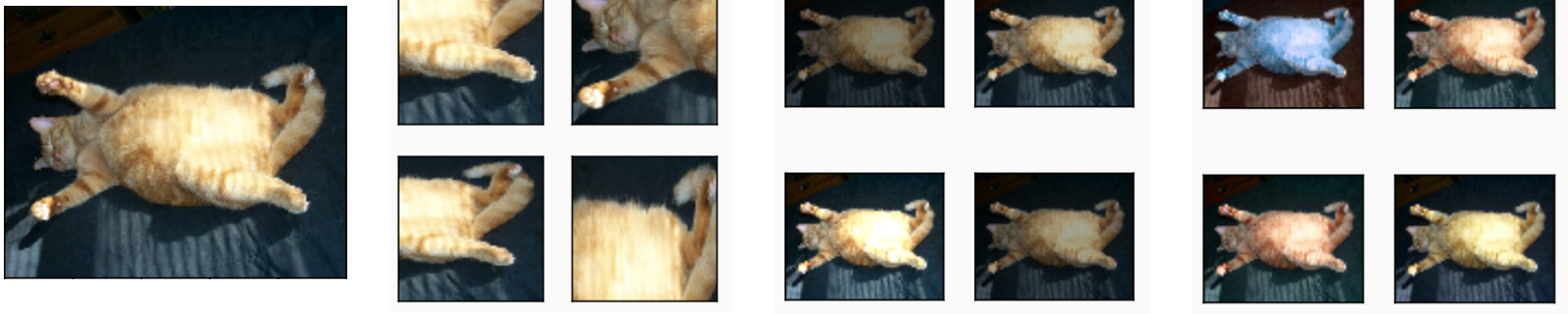


AlexNet Architecture



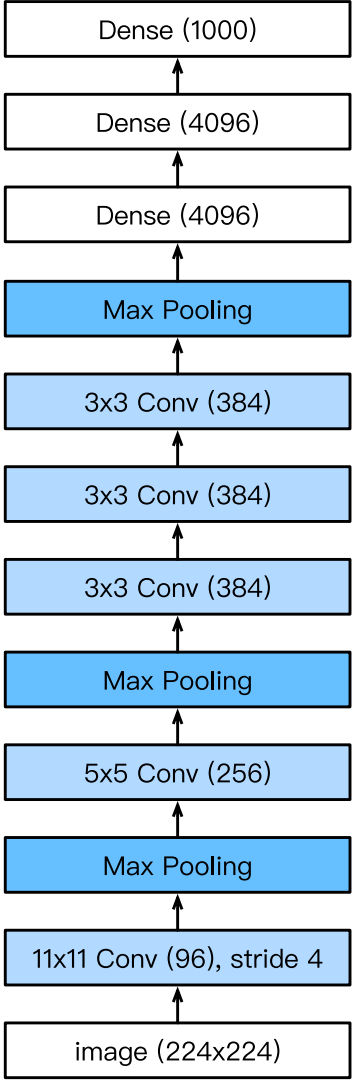
More Tricks

- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Add a dropout layer after two hidden dense layers (better robustness / regularization)
- Data augmentation



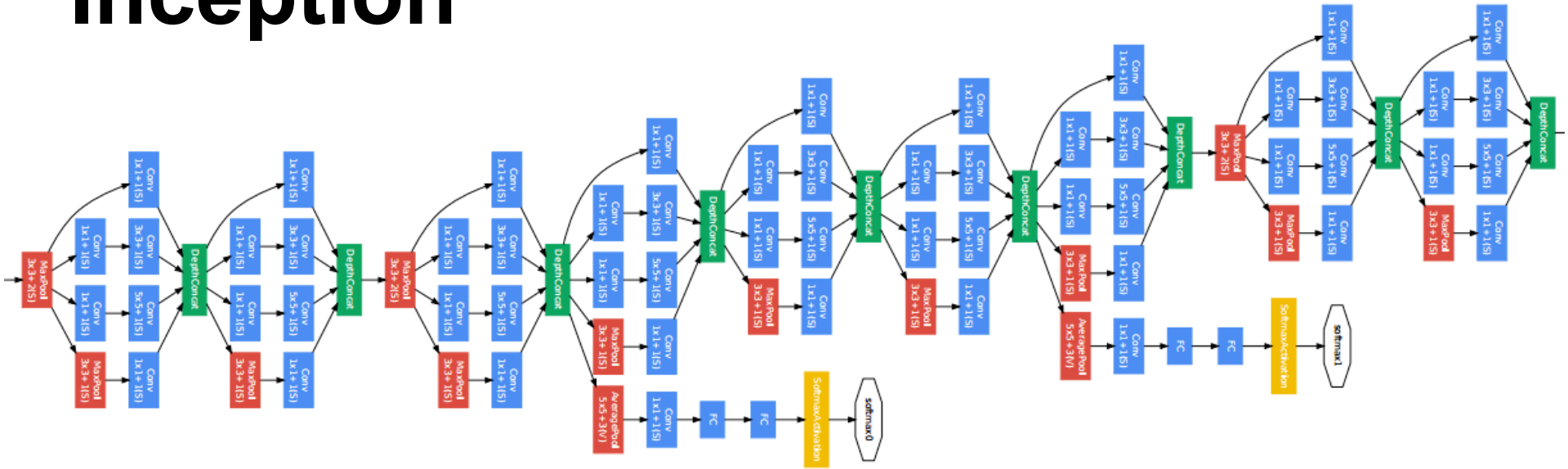
Complexity

	#parameters		FLOP	
	AlexNet	LeNet	AlexNet	LeNet
Conv1	35K	150	101M	1.2M
Conv2	614K	2.4K	415M	2.4M
Conv3-5	3M		445M	
Dense1	26M	0.48M	26M	0.48M
Dense2	16M	0.1M	16M	0.1M
Total	46M	0.6M	1G	4M
Increase	11x	1x	250x	1x



AlexNet Notebook

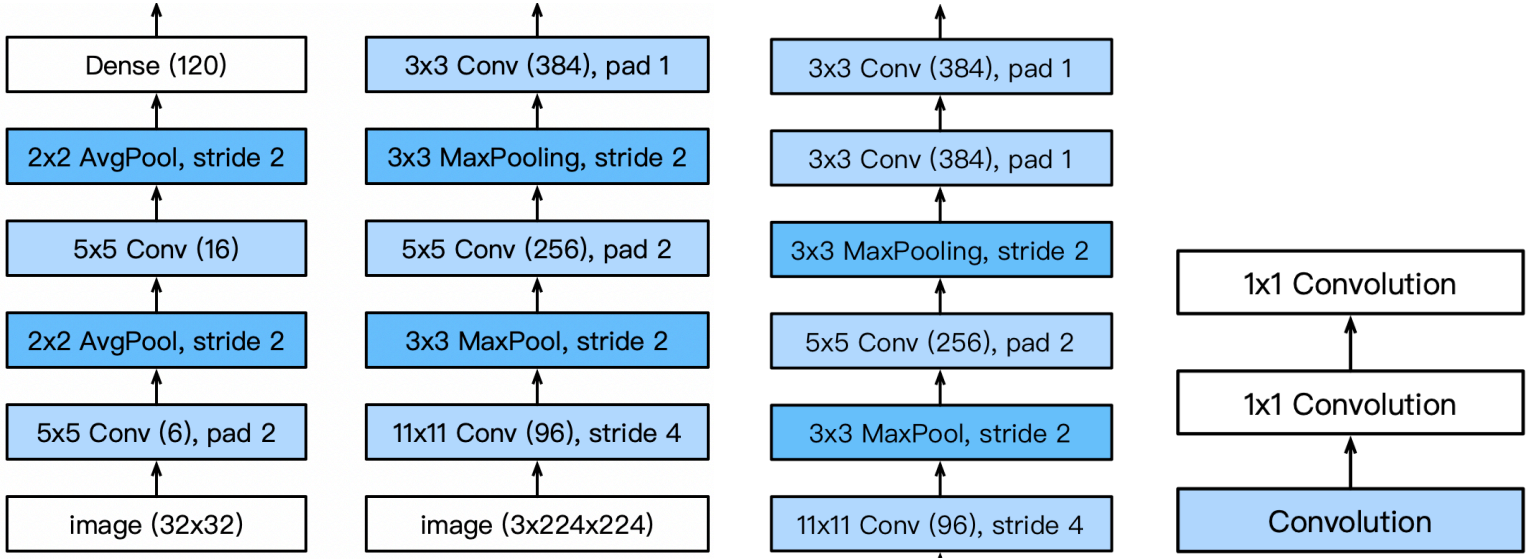
Inception


MaxPool 3x3+ 2(S)
Conv 1x1+ 1(S)
Conv 3x3+ 1(S)
Conv 5x5+ 1(S)
DepthConcat
FC
SoftmaxActivation
softmax0
softmax1

Picking the best convolution …

1x1 | 3x3 | 5x5 | Max pooling | Multiple 1x1

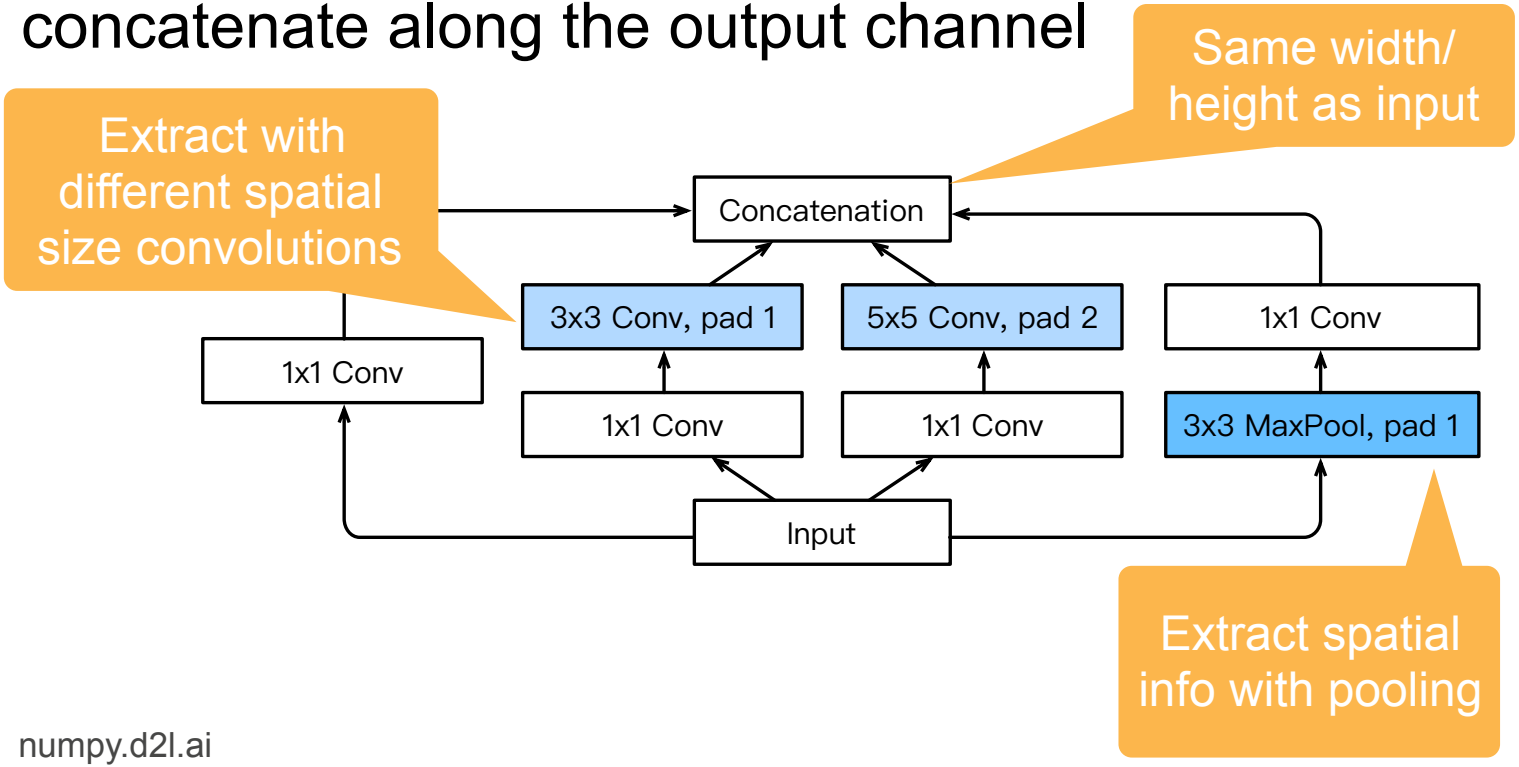
LeNet | AlexNet | VGG | NiN



Why choose? Just pick them all.

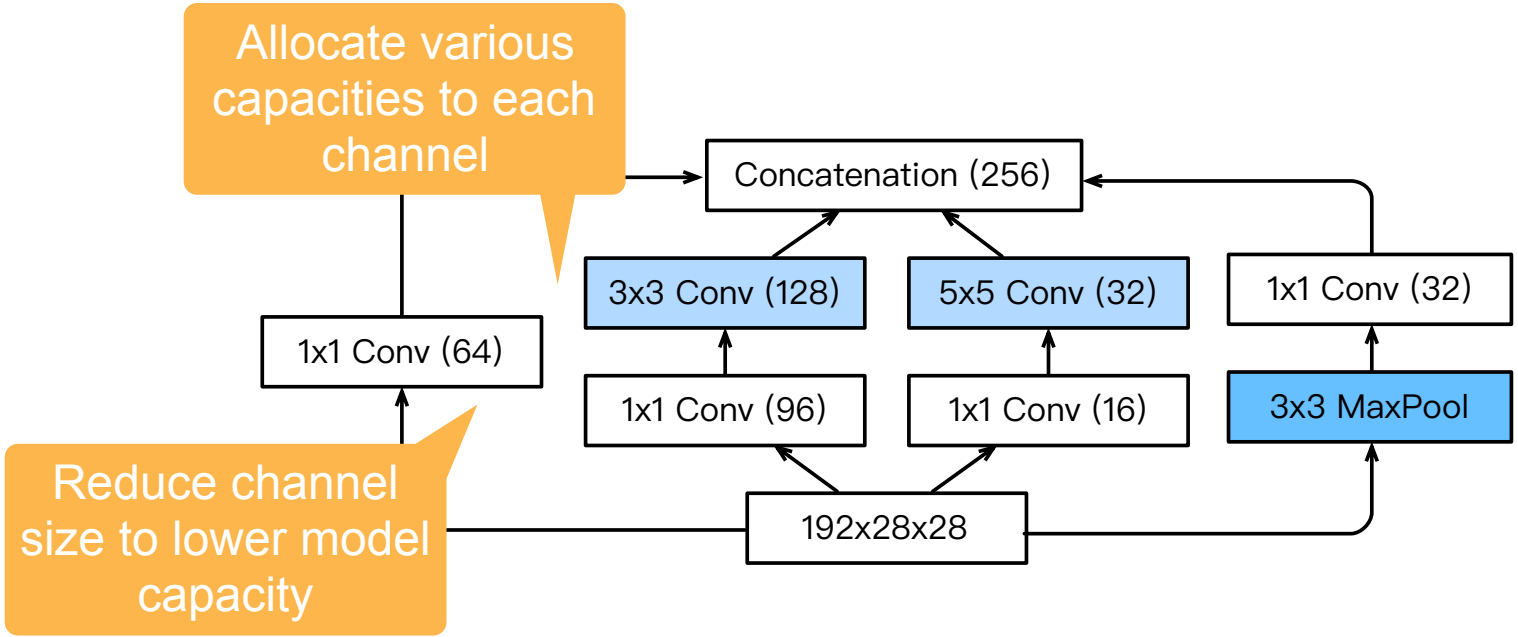
Inception Blocks

4 paths extract information from different aspects, then concatenate along the output channel



Inception Blocks

The first inception block with channel sizes specified

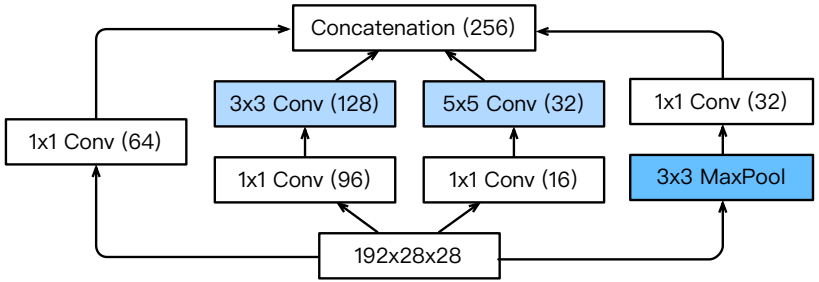


Inception Blocks

Inception blocks have fewer parameters and less computation complexity than a single 3x3 or 5x5 convolutional layer

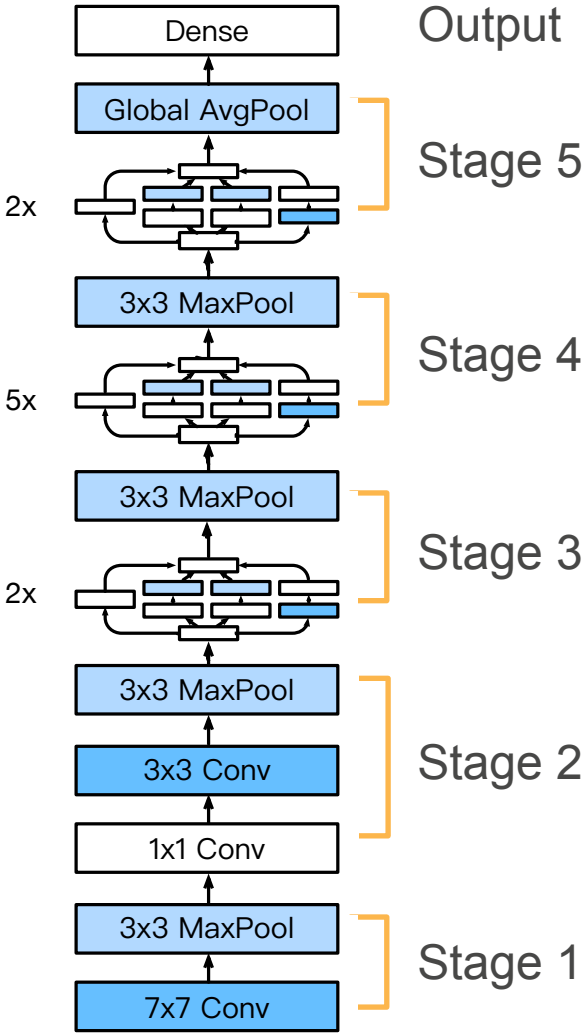
- Mix of different functions (powerful function class)
- Memory and compute efficiency (good generalization)

	#parameters	FLOPS
Inception	0.16 M	128 M
3x3 Conv	0.44 M	346 M
5x5 Conv	1.22 M	963 M



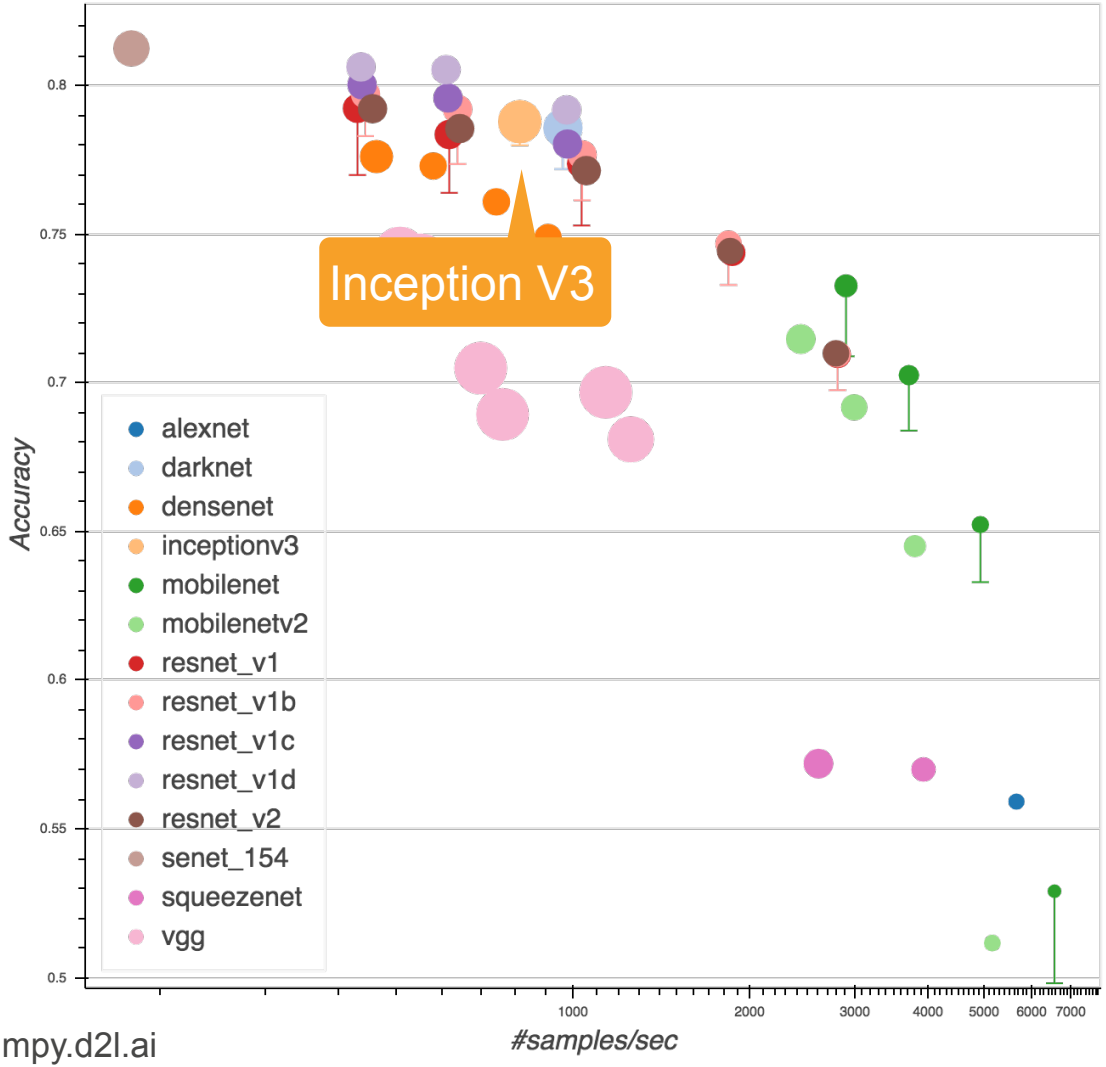
GoogLeNet

- 5 stages with 9 inceptions blocks



The many flavors of Inception Networks

- Inception-BN (v2) - Add batch normalization
- Inception-V3 - Modified the inception block
  - Replace 5x5 by multiple 3x3 convolutions
  - Replace 5x5 by 1x7 and 7x1 convolutions
  - Replace 3x3 by 1x3 and 3x1 convolutions
  - Generally deeper stack
- Inception-V4 - Add residual connections (more later)



GluonCV Model Zoo

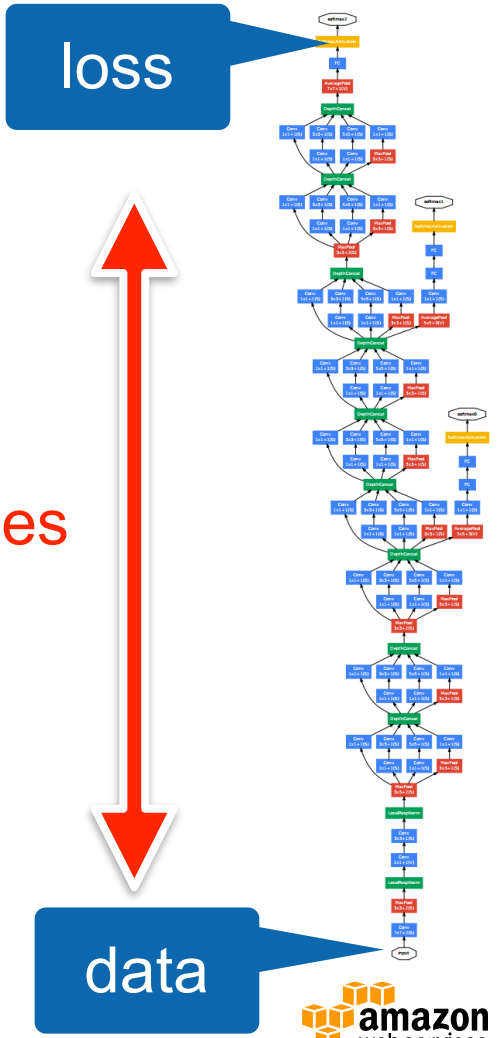
https://gluon-cv.mxnet.io/model_zoo/classification.html

aws


SMALL BATCH NORM
• PACIFICA, CALIFORNIA •
Batch # 22716-06
Hand Made All Natural
BLACKBERRY JAM

Batch Normalization

- Loss occurs at last layer
  - Last layers learn quickly
- Data is inserted at bottom layer
  - Bottom layers change - **everything** changes
  - Last layers need to relearn many times
  - Slow convergence
- This is like covariate shift
  Can we avoid changing last layers while learning first layers?



Batch Normalization

- Can we avoid changing last layers while learning first layers?
- Fix mean and variance

$$\mu_B = \frac{1}{|B|}\sum_{i \in B} x_i \text{ and } \sigma_B^2 = \frac{1}{|B|}\sum_{i \in B}(x_i - \mu_B)^2 + \epsilon$$

and adjust it separately

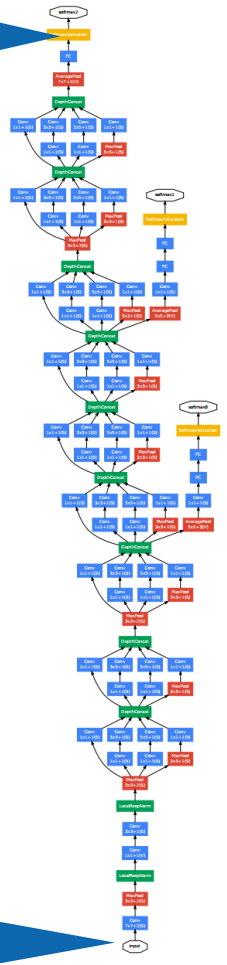
$$x_{i+1} = \gamma \frac{x_i - \mu_B}{\sigma_B} + \beta$$

mean

variance

loss

data



This was the original motivation …

What Batch Norms really do

- Doesn't really reduce covariate shift (Lipton et al., 2018)
- Regularization by noise injection

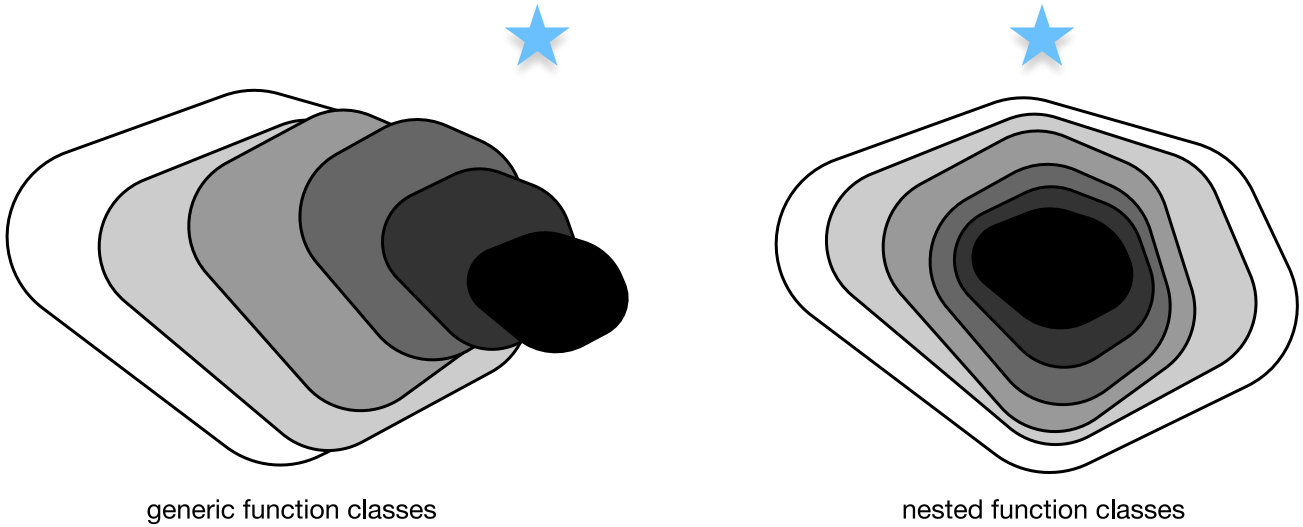
$$x_{i+1} = \gamma \frac{x_i - \hat{\mu}_B}{\hat{\sigma}_B} + \beta$$

Random offset

Random scale

  - Random shift per minibatch
  - Random scale per minibatch
- No need to mix with dropout (both are capacity control)
- Ideal minibatch size of 64 to 256

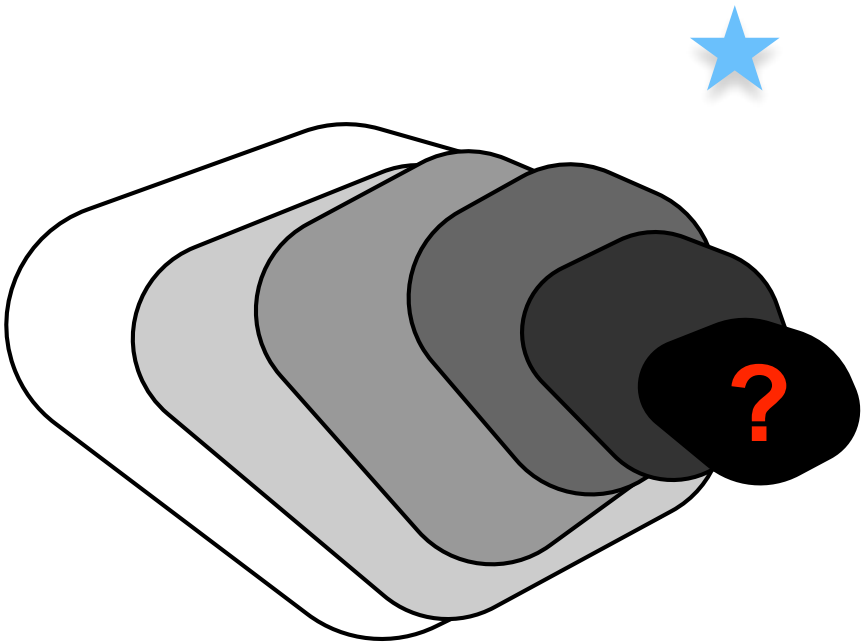
Residual Networks



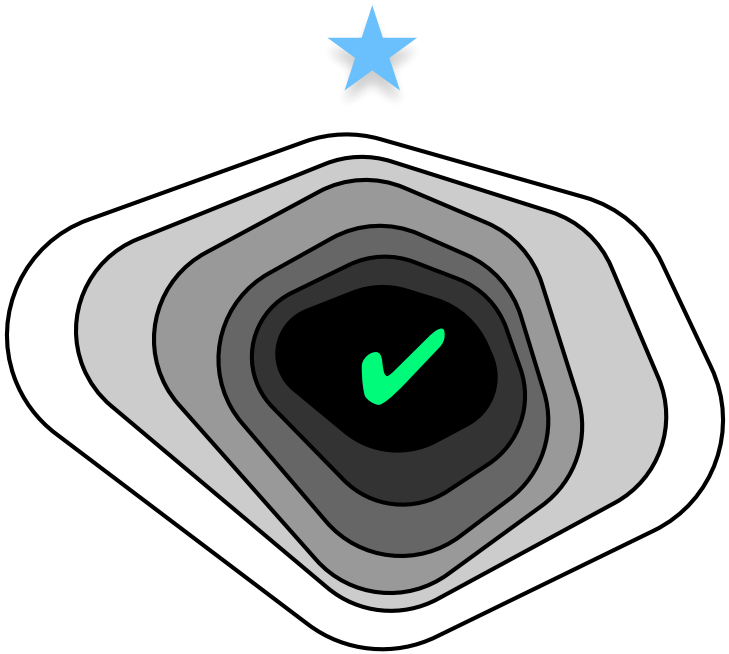
generic function classes

nested function classes

Does adding layers improve accuracy?



generic function classes

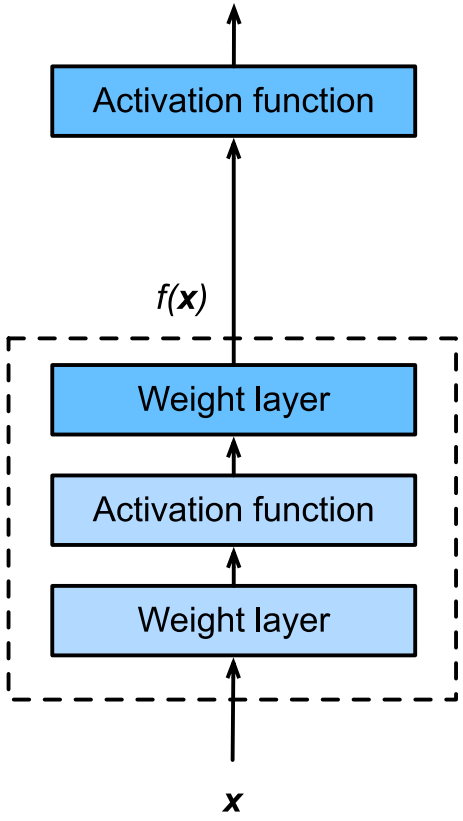


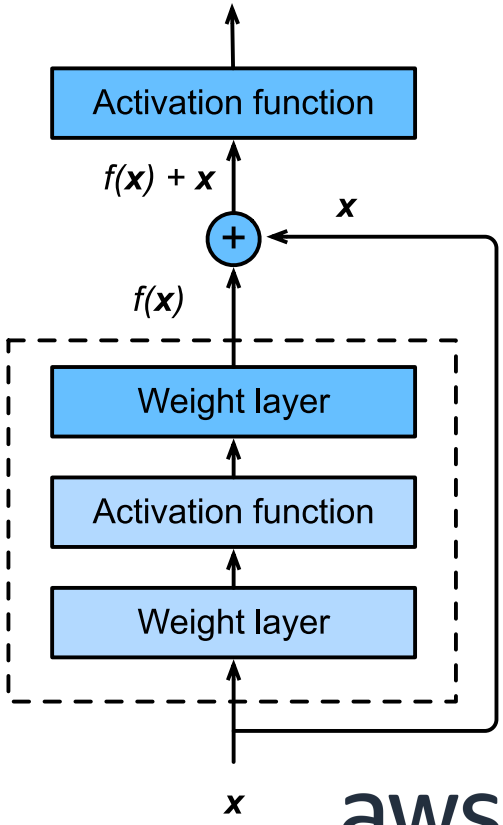
nested function classes

Residual Networks

- Adding a layer **changes** function class
- We want to **add to** the function class
- 'Taylor expansion' style parametrization

$$f(x) = x + g(x)$$

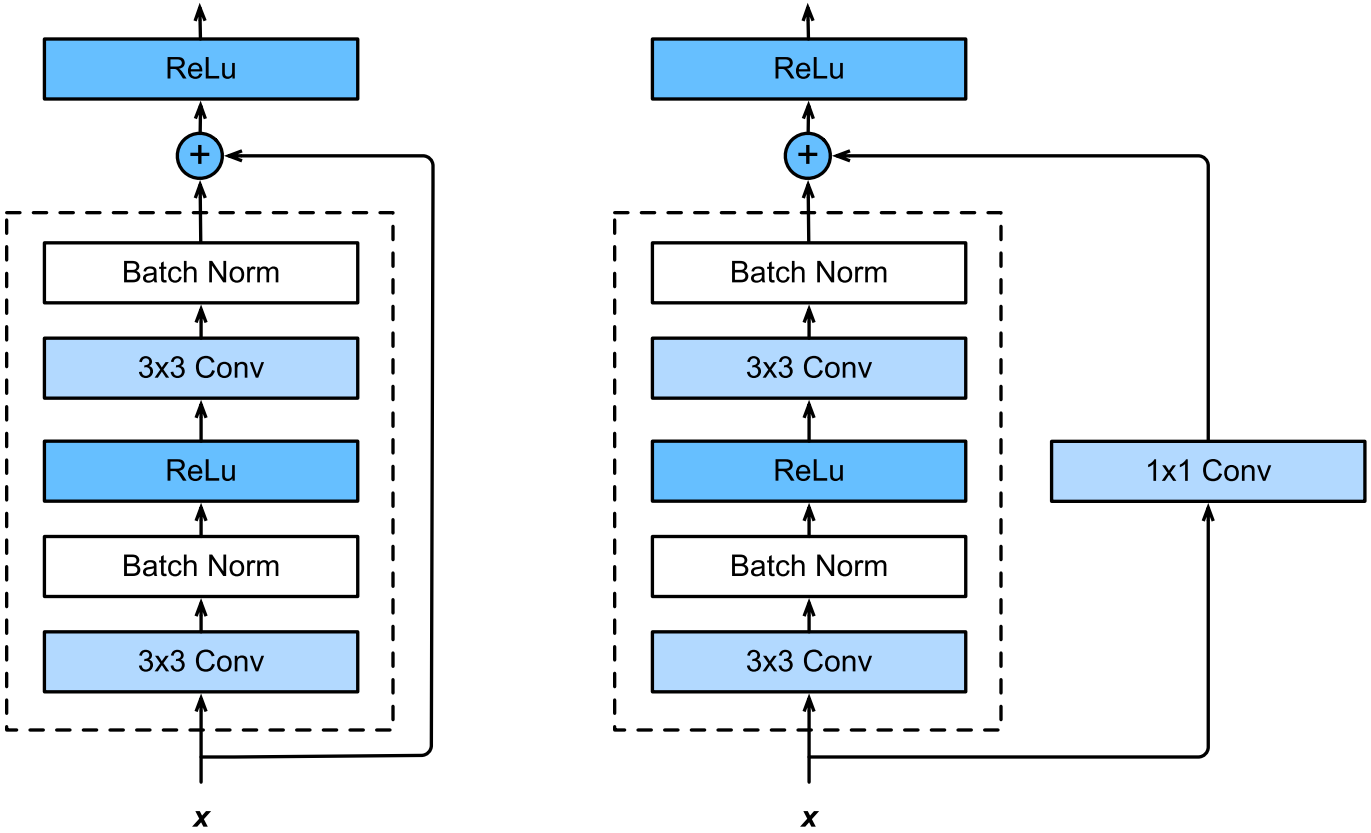




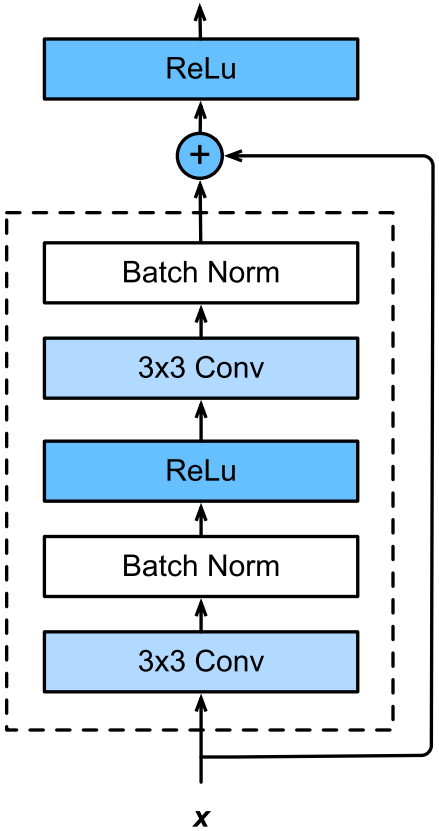
He et al., 2015

aws

ResNet Block in detail

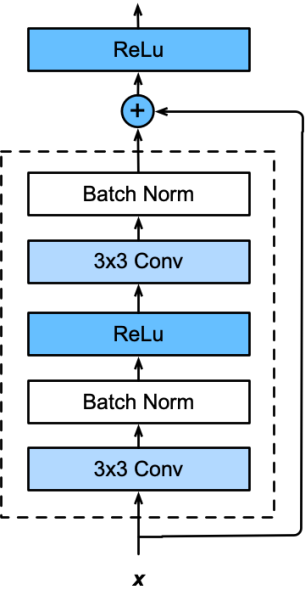


In code

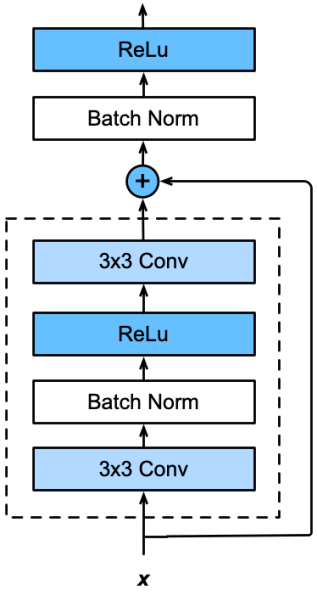



```
def forward(self, X):
  Y = npx.relu(self.bn1(self.conv1(X)))
  Y = self.bn2(self.conv2(Y))
  if self.conv3:
     X = self.conv3(X)
  return npx.relu(Y + X)
```

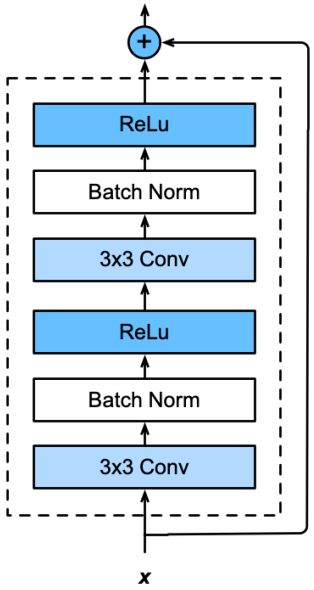
The many flavors of ResNet blocks



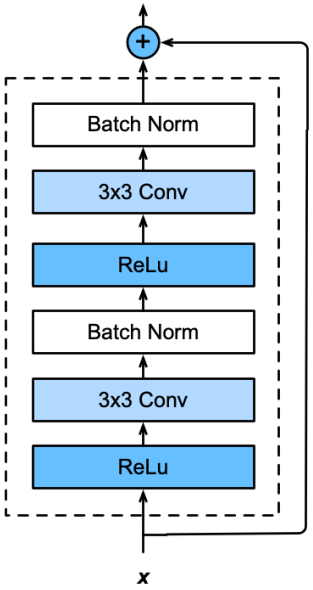
original



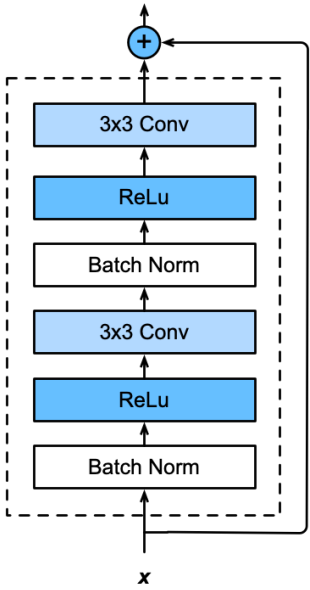
Batch Norm after addition



ReLu last



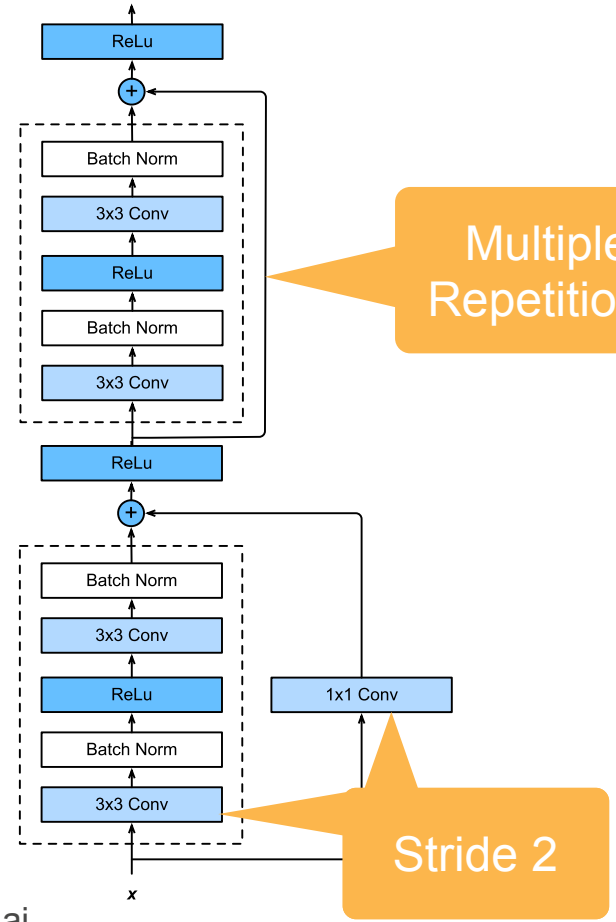
Batch Norm last



Pre-activation

Try every permutation

ResNet Module



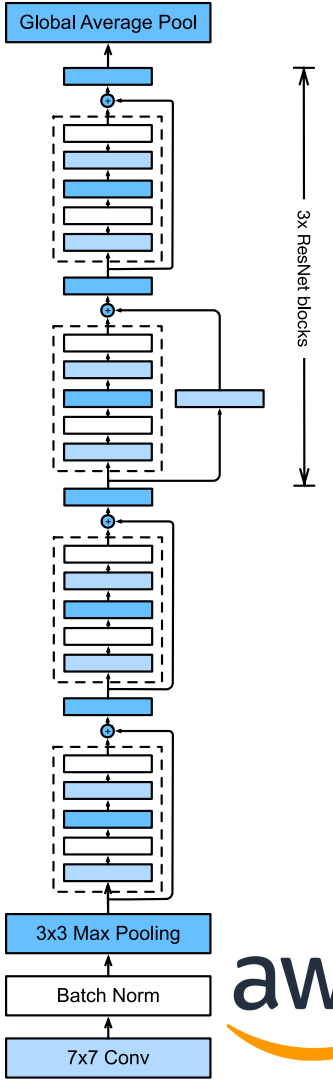
- Downsample per module (stride=2)
- Enforce some nontrivial nonlinearity per module (via 1x1 convolution)
- Stack up in blocks

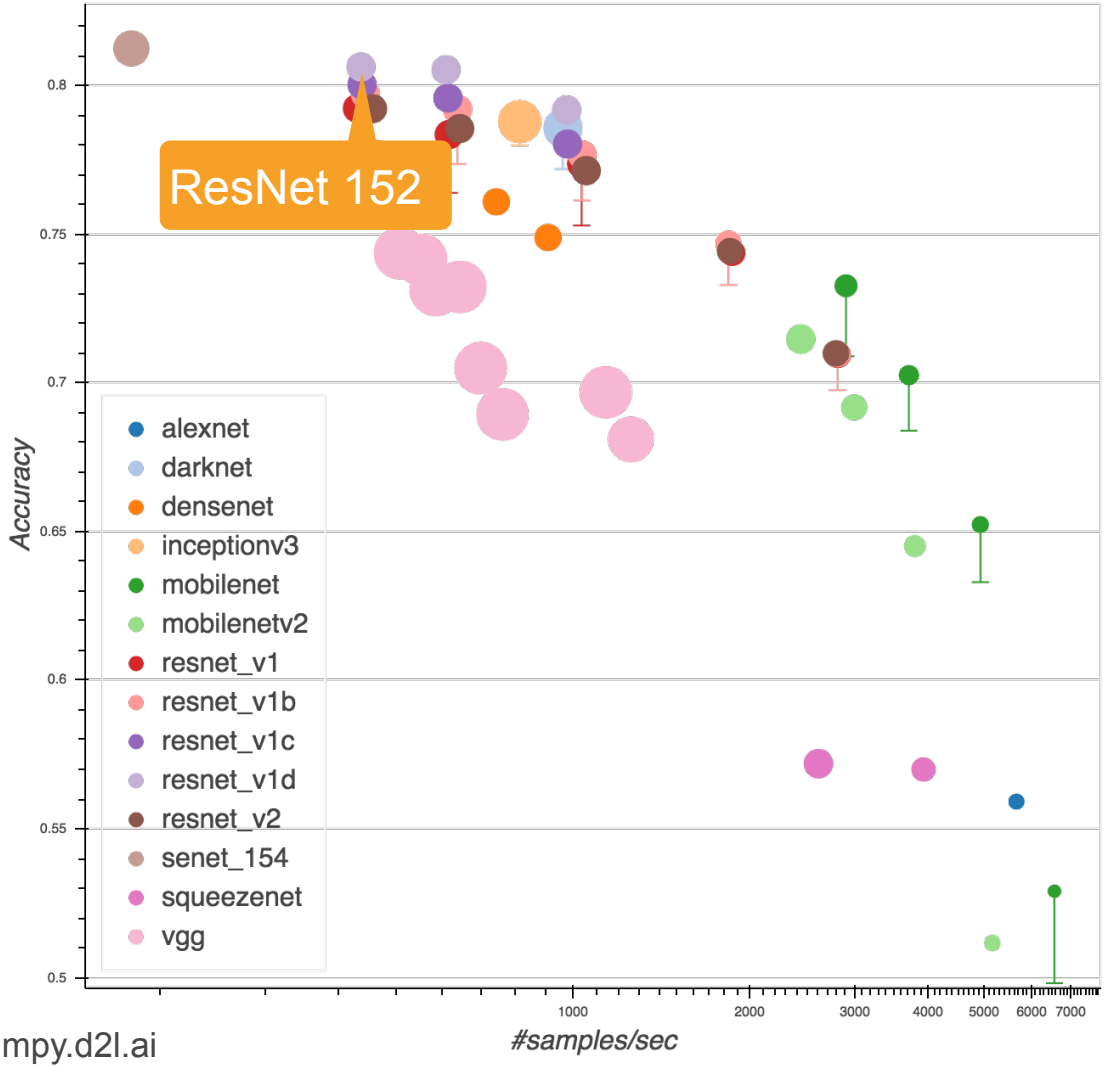
```
blk = nn.Sequential()
for i in range(num_residuals):
   if i == 0 and not first_block:
      blk.add(Residual(num_channels,
         use_1x1conv=True, strides=2))
   else:
      blk.add(Residual(num_channels))
```

Putting it all together

- Same block structure as e.g. VGG or GoogleNet
- Residual connection to add to expressiveness
- Pooling/stride for dimensionality reduction
- Batch Normalization for capacity control

… train it at scale …





GluonCV Model Zoo

https://gluon-cv.mxnet.io/model_zoo/classification.html

aws

Jupyter Notebook

More Ideas

DenseNet (Huang et al., 2016)

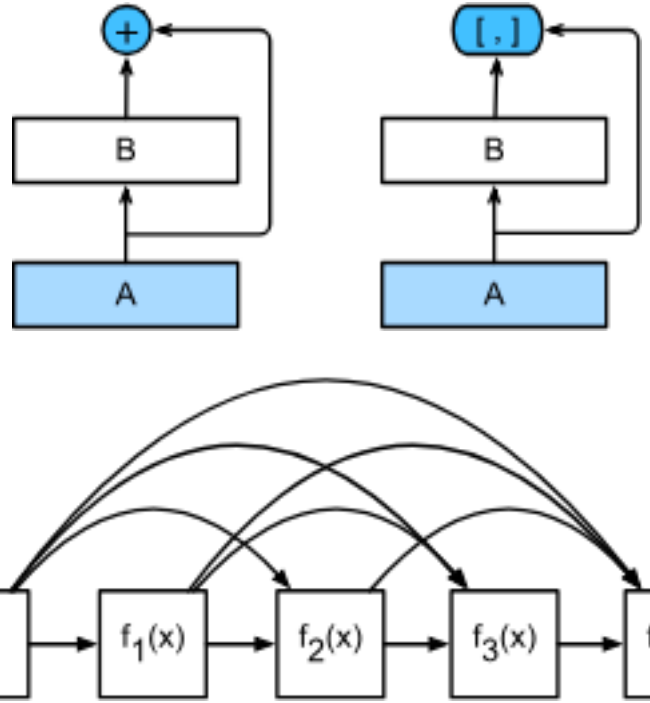
- ResNet combines x and f(x)
- DenseNet uses higher order 'Taylor series' expansion

$$x_{i+1} = [x_i, f_i(x_i)]$$

$$x_1 = x$$

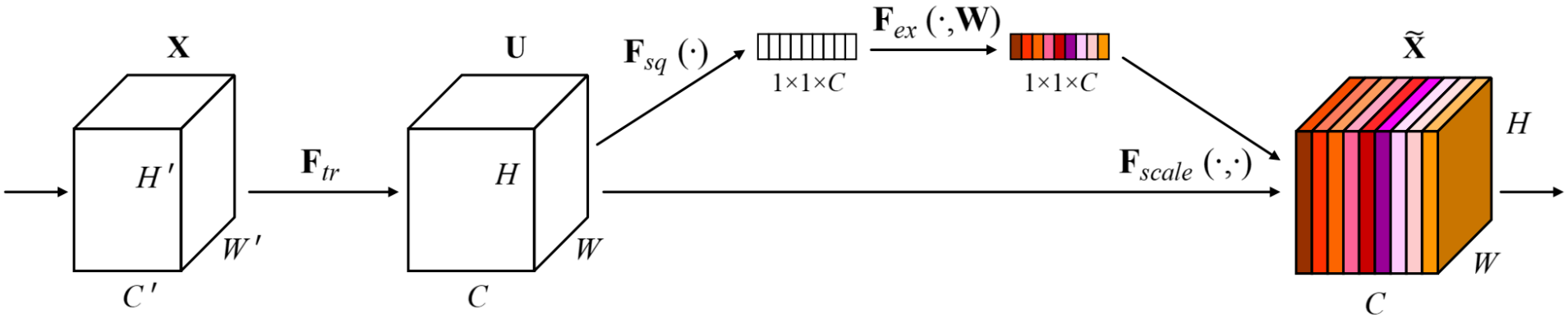
$$x_2 = [x, f_1(x)]$$

$$x_2 = [x, f_1(x), f_2([x, f_1(x)])]$$



- Occasionally need to reduce resolution (transition layer)

Squeeze-Excite Net (Hu et al., 2017)

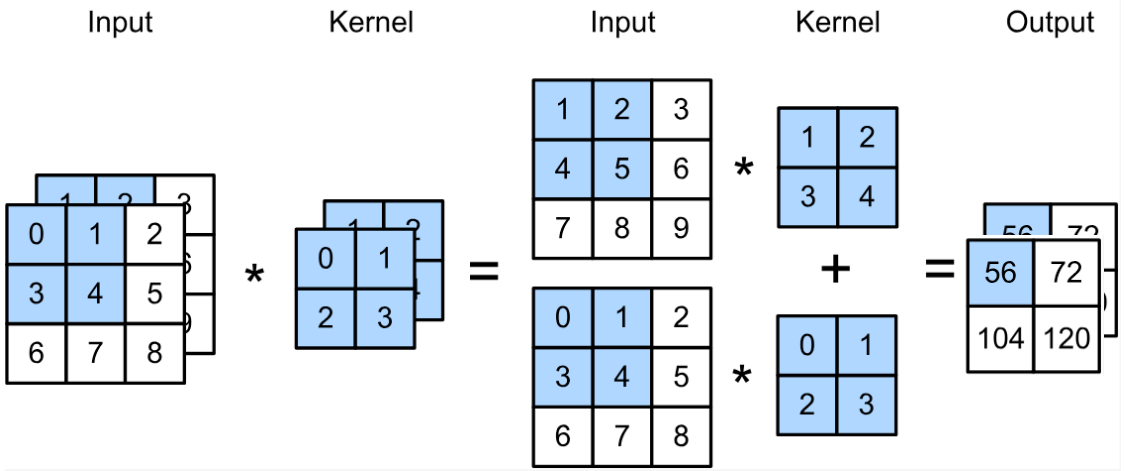


- Learn global weighting function per channel
- Allows for fast information transfer between pixels in different locations of the image

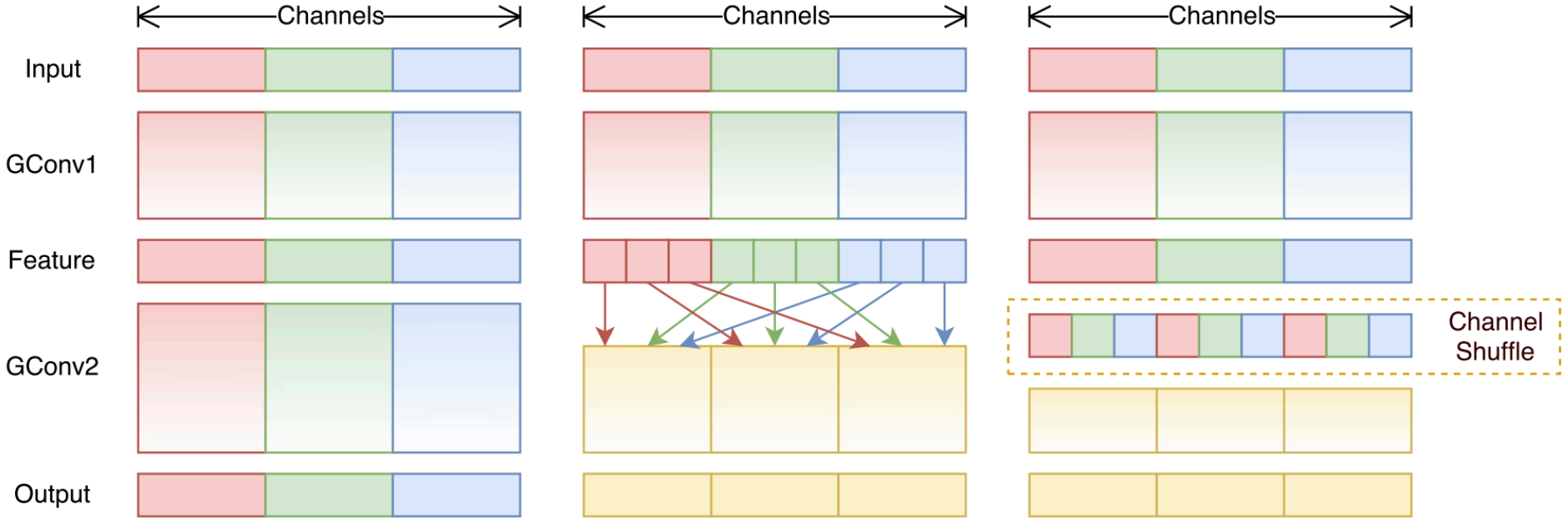
Separable Convolutions - all channels separate

- **Parameters** $k_h \cdot k_w \cdot c_i \cdot c_o$
- **Computation** $m_h \cdot m_w \cdot k_h \cdot k_w \cdot c_i \cdot c_o$
- **Break up channels** to the extreme
  No mixing between channels

$$m_h \cdot m_w \cdot k_h \cdot k_w \cdot c$$



ShuffleNet (Zhang et al., 2018)



- ResNext breaks convolution into channels
- ShuffleNet mixes by grouping (very efficient for mobile)

aws

Outline

- GPUs
- Convolutions
- Pooling, Padding and Stride
- Convolutional Neural Networks (LeNet)
- Deep ConvNets (AlexNet)
- Networks using Blocks (VGG)
- Residual Neural Networks (ResNet)