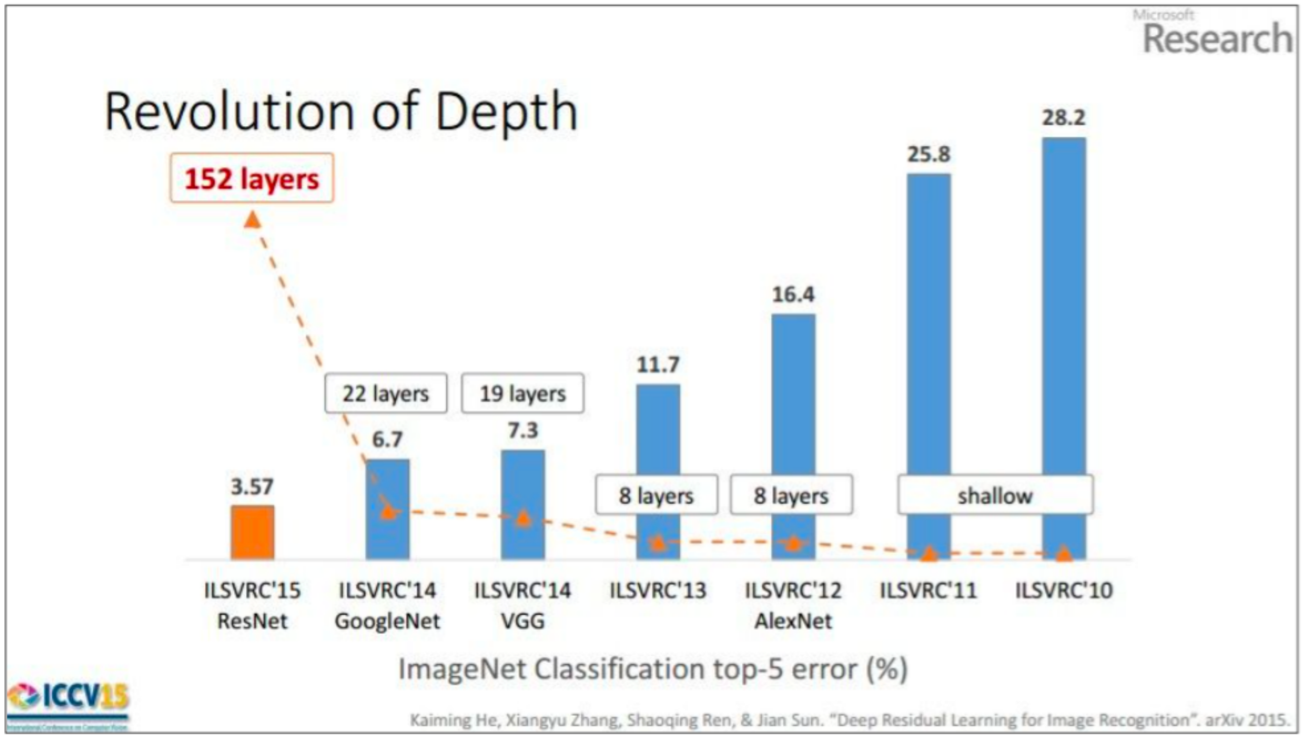
# TTIC 31230, Fundamentals of Deep Learning

David McAllester, Winter 2020

## Convolutional Neural Networks (CNNs)

## Imagenet Classification

1000 kinds of objects.



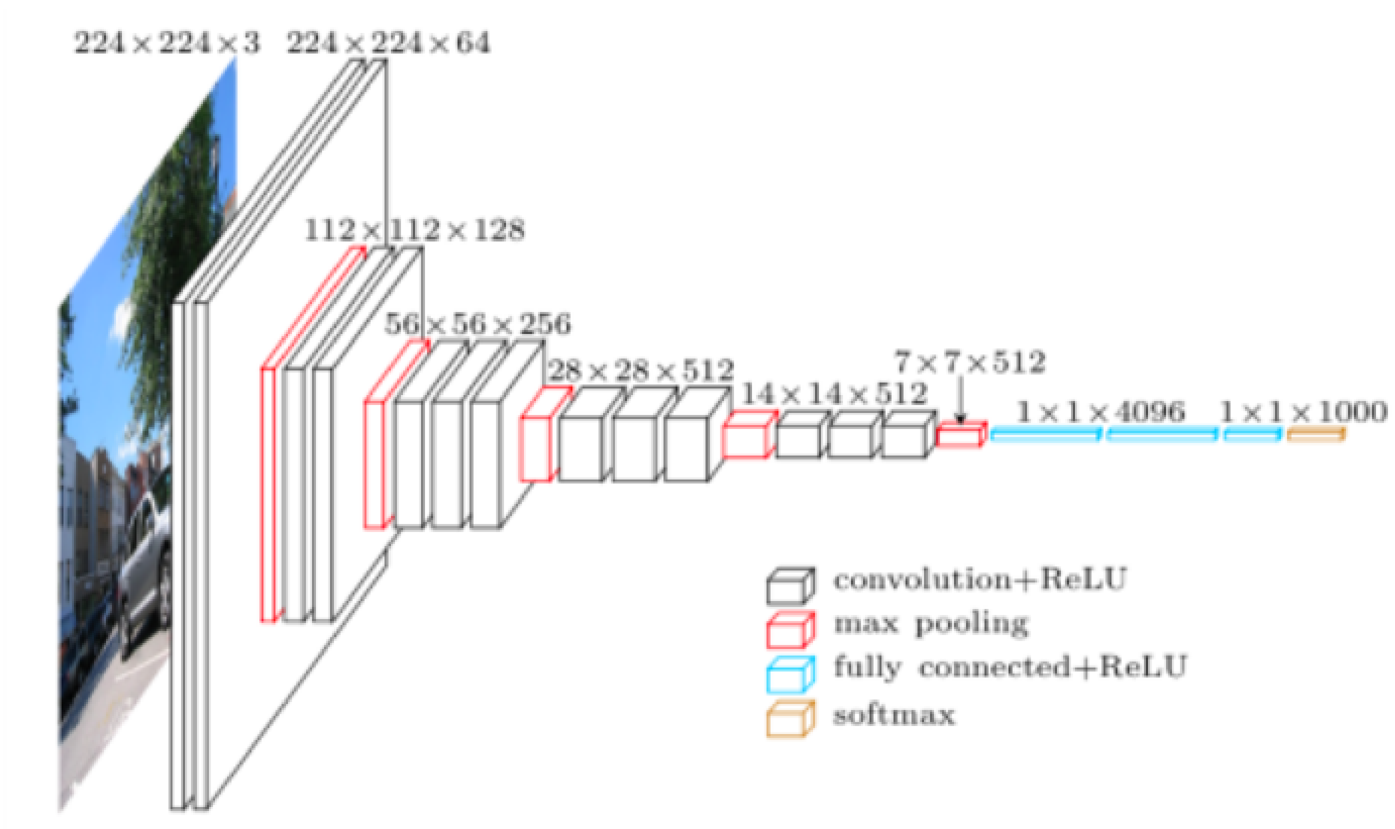
(slide from Kaiming He's recent presentation)

2016 is 3.0%, is 2017 2.25%

SOTA as of January 2020 is 1.3%

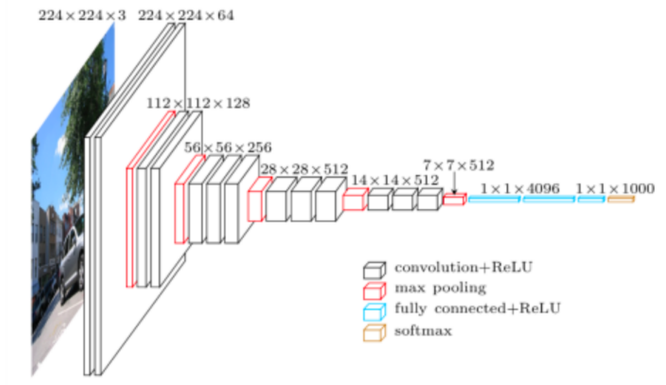
## What is a CNN?

## VGG, Zisserman, 2014



Davi Frossard

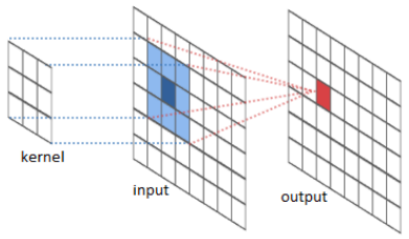
## A Convolution Layer



Each box is a tensor $L_\ell[b,x,y,i]$

For a convolution layer, each $L_{\ell+1}[b,x,y,j]$ is the output of a single linear threshold unit computed from $L_\ell[b,x,y,i]$.

## A Convolution Layer



$W[\Delta x, \Delta y, i, j]$ $\qquad$ $L_\ell[b, x, y, i]$ $\qquad$ $L_{\ell+1}[b, x, y, j]$

River Trail Documentation

$$L_{\ell+1}[b, x, y, j]$$

$$= \sigma\left(\left(\sum_{\Delta x, \Delta y, i} W[\Delta x, \Delta y, i, j]\; L_\ell[b, x + \Delta x, y + \Delta y, i]\right) - B[j]\right)$$

## Many “Neurons” (Linear Threshold Units)

Each $L_{\ell+1}[b,x,y,j]$ is the output of a single linear threshold unit.

$$L_{\ell+1}[b,x,y,j]$$

$$= \sigma\left(\left(\sum_{\Delta x,\Delta y,i} W[\Delta x,\Delta y,i,j]\; L_\ell[b,x+\Delta x,y+\Delta y,i]\right) - B[j]\right)$$

## 2D CNN in PyTorch

conv2d(**input, weight, bias, stride, padding, dilation, groups**)

**input** tensor (minibatch,in-channels,iH,iW)

**weight** filters (out-channels, in-channels/groups, in-channels,kH,kW)

**bias** tensor (out-channels) . Default: None

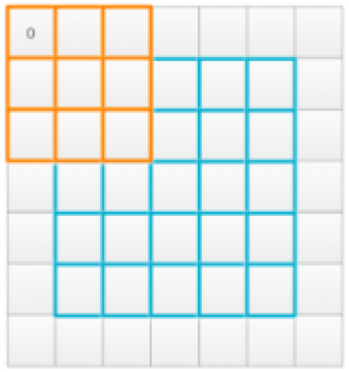
**stride** Single number or (sH, sW). Default: 1

**padding** Single number or (padH, padW). Default: 0

**dilation** Single number or (dH, dW). Default: 1

**groups** split input into groups. Default: 1

## Padding



Jonathan Hui

If we pad the input with zeros then the input and output can have the same spatial dimensions.

## Zero Padding in NumPy

In NumPy we can add a zero padding of width p to an image as follows:

```
padded = np.zeros(W + 2*p,  H + 2*p)

padded[p:W+p, p:H+p] = x
```

## Padding

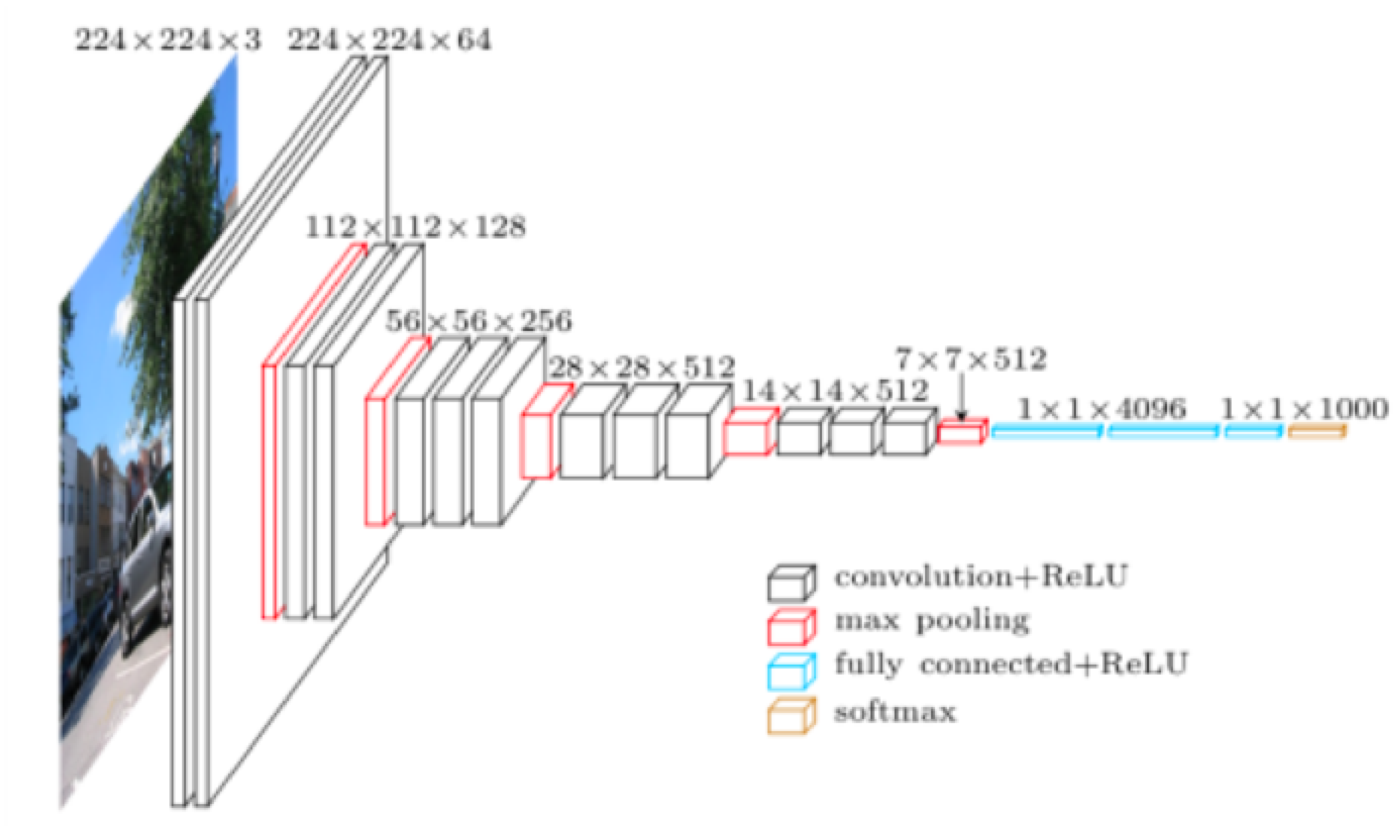
$$L'_\ell = \mathrm{Padd}(L_\ell,\ p)$$

$$L_{\ell+1}[b,x,y,j] =$$

$$\sigma\left(\left(\textstyle\sum_{\Delta x,\Delta y,i}\ W[\Delta x,\Delta y,i,j]\ L'_\ell[b,x+\Delta x,y+\Delta y,i]\right) - B[j]\right)$$

If the input is padded but the output is not padded then $\Delta x$ and $\Delta y$ are non-negative.

## Reducing Spatial Dimention



## Strides

We can move the filter by a "stride" $s$ for each spatial step.

$$L_{\ell+1}[b, x, y, j] =$$

$$\sigma\left(\left(\sum_{\Delta x, \Delta y, i} W[\Delta x, \Delta y, i, j] L_\ell[b, s*x + \Delta x, s*y + \Delta y, i]\right) - B[j]\right)$$

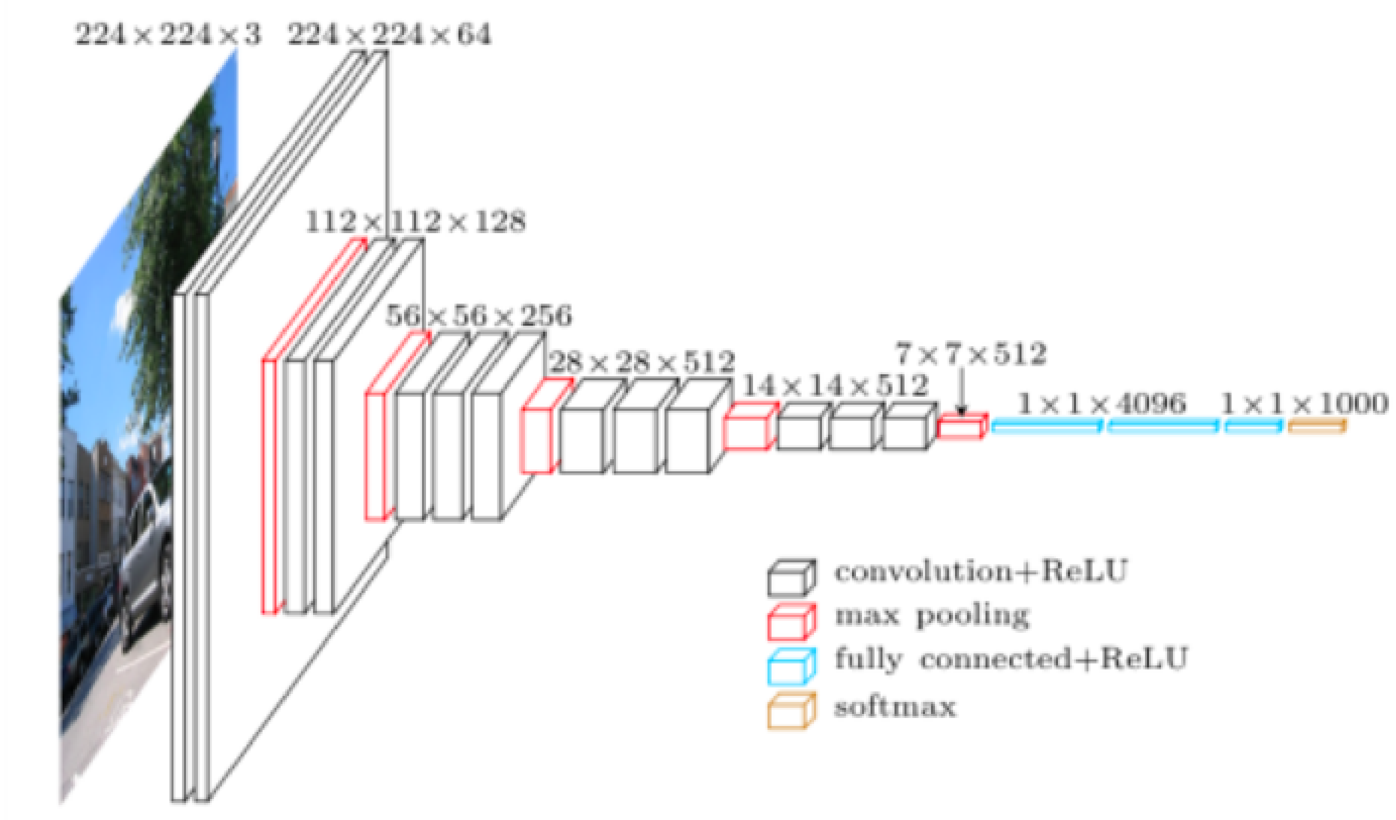
For strides greater than 1 the spatial dimention is reduced.

## Max Pooling

$$L_{\ell+1}[b, x, y, i] = \max_{\Delta x, \Delta y} L_\ell[b, s * x + \Delta x,\ s * y + \Delta y,\ i]$$

This is typically done with a stride greater than one so that the image dimension is reduced.

## Fully Connected (FC) Layers



## Fully Connected (FC) Layers

We reshape $L_\ell[b,x,y,i]$ to $L_\ell[b,i']$ and then

$$L_{\ell+1}[b,j] = \sigma\left(\left(\sum_{i'} W[j,i']\; L_\ell[b,i']\right) - B[j]\right)$$

## Image to Column (Im2C)

Reduce convolution to matrix multiplication

more space but faster.

$$\tilde{L}_{\ell+1}[b, x, y, j]$$

$$= \left( \sum_{\Delta x, \Delta y, i} W[\Delta x, \Delta y, i, j] * L_\ell[b, x + \Delta x,\ y + \Delta y,\ i] \right) + B[j]$$

We make a bigger tensor $\tilde{L}$ with two additional indeces.

$$\tilde{L}_\ell[b, x, y, \Delta x, \Delta y, i] = L_\ell[b, x + \Delta x, y + \Delta y, i]$$

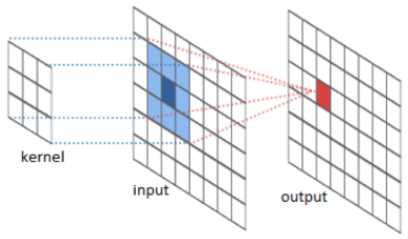
## Image to Column (Im2C)

$$
\begin{aligned}
&\tilde{L}_{\ell+1}[b,x,y,j] \\
&= \left(\sum_{\Delta x,\Delta y,i} W[\Delta x,\Delta y,i,j] * L_\ell[b,x+\Delta x,\ y+\Delta y,\ i]\right) + B[j] \\
&= \left(\sum_{\Delta x,\Delta y,i} \tilde{L}_\ell[b,x,y,\Delta x,\Delta y,i] * W[\Delta x,\Delta y,i,j]\right) + B[j] \\
&= \left(\sum_{(\Delta x,\Delta y,i)} \tilde{L}_\ell[(b,x,y),(\Delta x,\Delta y,i)] * W[(\Delta x,\Delta y,i),j]\right) + B[j]
\end{aligned}
$$

## Dilation

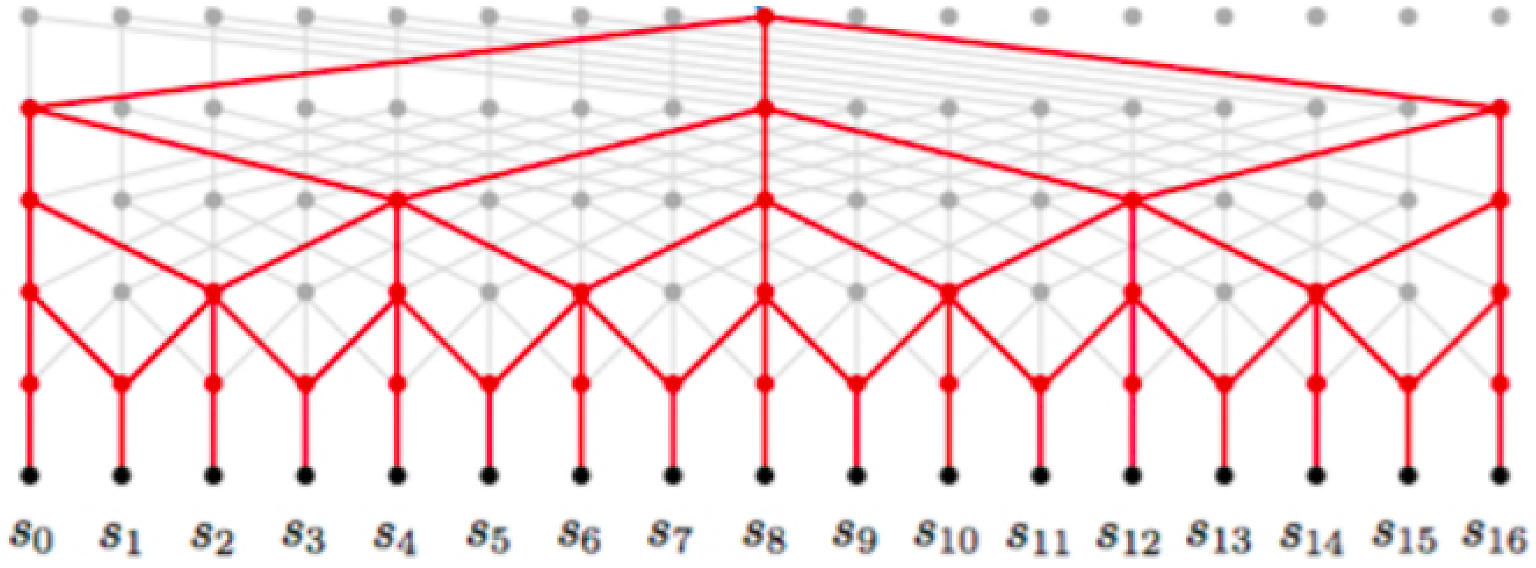
A CNN for image classification typically reduces an $N \times N$ image to a single feature vector.

Dilation is a trick for treating the whole CNN as a "filter" that can be passed over an $M \times M$ image with $M > N$.



An output tensor with full spatial dimension can be useful in, for example, image segmentation.

## Dilation



$s_0$ $s_1$ $s_2$ $s_3$ $s_4$ $s_5$ $s_6$ $s_7$ $s_8$ $s_9$ $s_{10}$ $s_{11}$ $s_{12}$ $s_{13}$ $s_{14}$ $s_{15}$ $s_{16}$

This is called a “fully convolutional” CNN.

## Dilation

To implement a fully convolutional CNN we can "dilate" the filters by a dilation parameter $d$.

$$\tilde{L}_{\ell+1}[b,x,y,j] = W[\Delta x, \Delta y, i, j] L_\ell[b, x + d * \Delta x, y + d * \Delta y, i] + B[j]$$

## Hypercolumns

An alternative to dilation and fully convolutional networks is hypercolumns.

$$L_{\ell+1}[b,x,y] = L_1[b,x,y];\cdots;L_n[b,x/W_\ell,y/W_\ell];\cdots;L_N[b]$$

where x;y denotes the concatenation of vectors $x$ and $y$.

## Grouping

$$L_{\ell+1}[b,x,y] = L^{1}_{\ell+1}[b,x,y]; \cdots ; L^{G}_{\ell+1}[b,x,y]$$

$$\tilde{L}^{g}_{\ell+1}[b,x,y,j] = \left(\sum_{\Delta x,\Delta y,i} W^{g}[\Delta x,\Delta y,i,j] * L_{\ell}[b,x+\Delta x,\ y+\Delta y,\ i]\right.$$

For a fixed number of features $j$ in the total output $L_{\ell+1}[b,x,y,j]$ using $G$ groups reduces the number of weight parameters by a factor of $G$.

## 2D CNN in PyTorch

conv2d(**input, weight, bias, stride, padding, dilation, groups**)

**input** tensor (minibatch,in-channels,iH,iW)

**weight** filters (out-channels, in-channels/groups, in-channels,kH,kW)

**bias** tensor (out-channels) . Default: None

**stride** Single number or (sH, sW). Default: 1

**padding** Single number or (padH, padW). Default: 0

**dilation** Single number or (dH, dW). Default: 1

**groups** split input into groups. Default: 1

## Modern Trends

Modern Convolutions use 3X3 filters. This is faster and has fewer parameters. Expressive power is preserved by increasing depth with many stride 1 layers.

Max pooling and dilation seem to have disappeared.

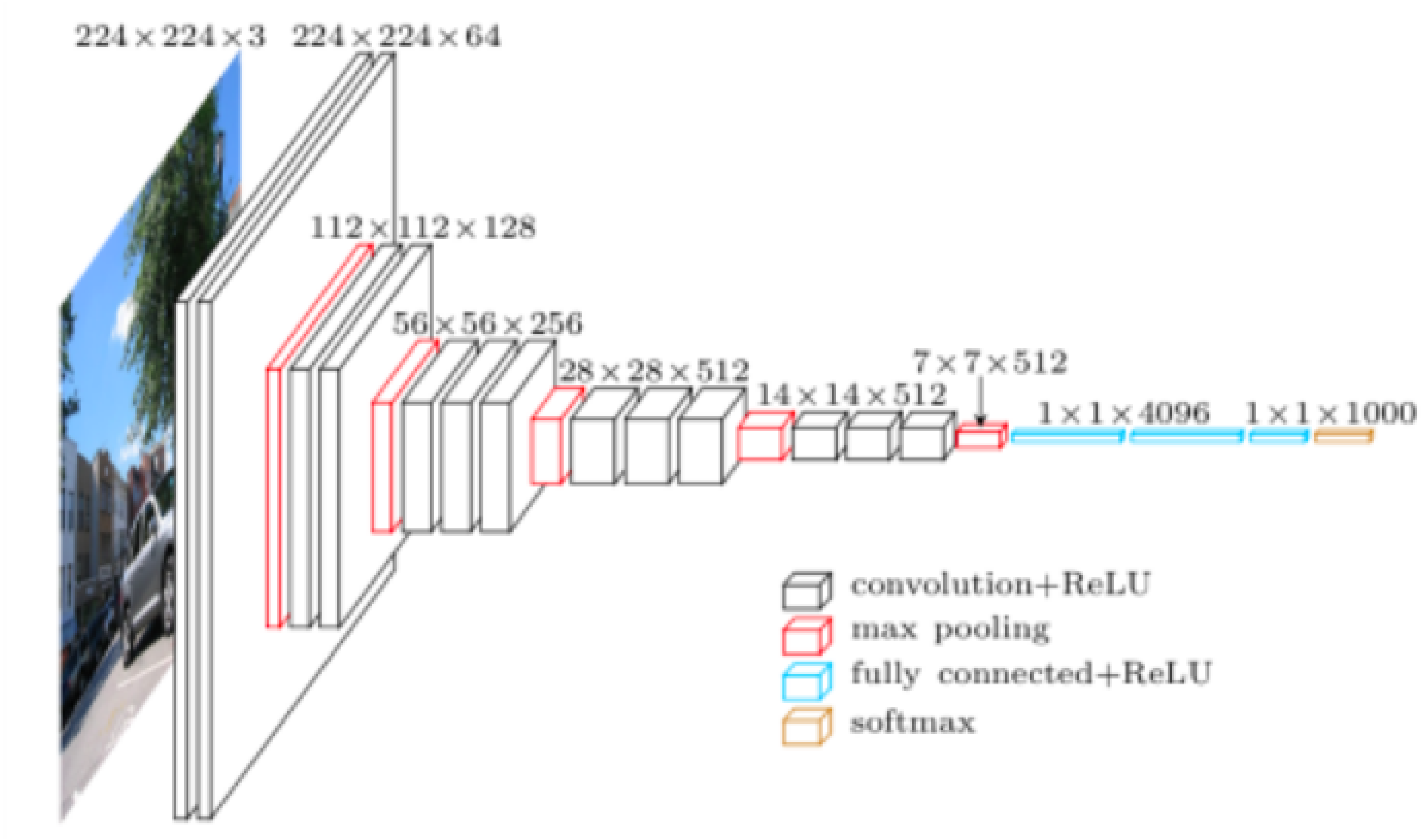
Resnet and resnet-like architectures are now dominant (next lecture).

# Alexnet

Given $\mathrm{Input}[227, 227, 3]$

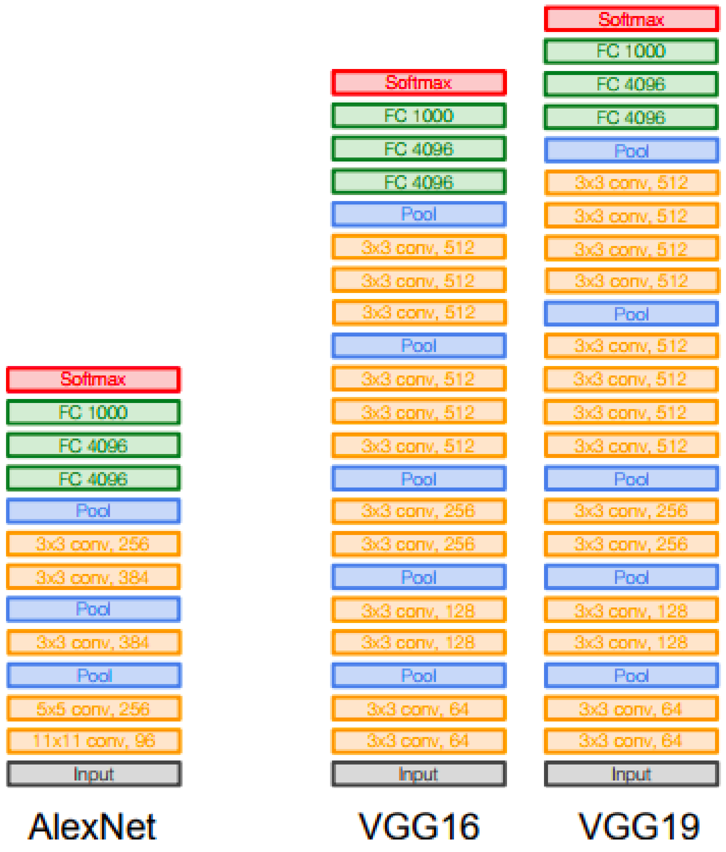
$$\begin{aligned}
L_1[55 \times 55 \times 96] &= \mathrm{ReLU}(\mathrm{CONV}(\mathrm{Input}, \Phi_1, \mathrm{width}\ 11, \mathrm{pad}\ 0, \mathrm{stride}\ 4)) \\
L_2[27 \times 27 \times 96] &= \mathrm{MaxPool}(L_1, \mathrm{width}\ 3, \mathrm{stride}\ 2)) \\
L_3[27 \times 27 \times 256] &= \mathrm{ReLU}(\mathrm{CONV}(L_2, \Phi_3, \mathrm{width}\ 5, \mathrm{pad}\ 2, \mathrm{stride}\ 1)) \\
L_4[13 \times 13 \times 256] &= \mathrm{MaxPool}(L_3, \mathrm{width}\ 3, \mathrm{stride}\ 2)) \\
L_5[13 \times 13 \times 384] &= \mathrm{ReLU}(\mathrm{CONV}(L_4, \Phi_5, \mathrm{width}\ 3, \mathrm{pad}\ 1, \mathrm{stride}\ 1)) \\
L_6[13 \times 13 \times 384] &= \mathrm{ReLU}(\mathrm{CONV}(L_5, \Phi_6, \mathrm{width}\ 3, \mathrm{pad}\ 1, \mathrm{stride}\ 1)) \\
L_7[13 \times 13 \times 256] &= \mathrm{ReLU}(\mathrm{CONV}(L_6, \Phi_7, \mathrm{width}\ 3, \mathrm{pad}\ 1, \mathrm{stride}\ 1)) \\
L_8[6 \times 6 \times 256] &= \mathrm{MaxPool}(L_7, \mathrm{width}\ 3, \mathrm{stride}\ 2)) \\
L_9[4096] &= \mathrm{ReLU}(\mathrm{FC}(L_8, \Phi_9)) \\
L_{10}[4096] &= \mathrm{ReLU}(\mathrm{FC}(L_9, \Phi_{10})) \\
s[1000] &= \mathrm{ReLU}(\mathrm{FC}(L_{10}, \Phi_s)) \ \ \text{class scores}
\end{aligned}$$

## VGG, Zisserman, 2014



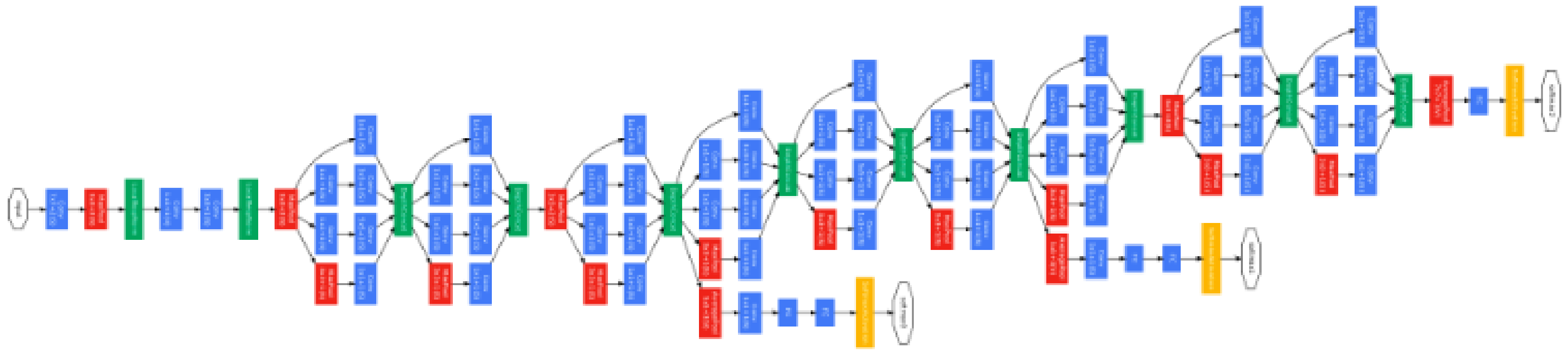
Davi Frossard

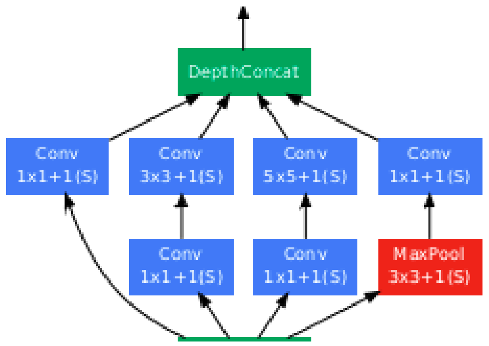
# VGG



Stanford CS231

# Inception, Google, 2014



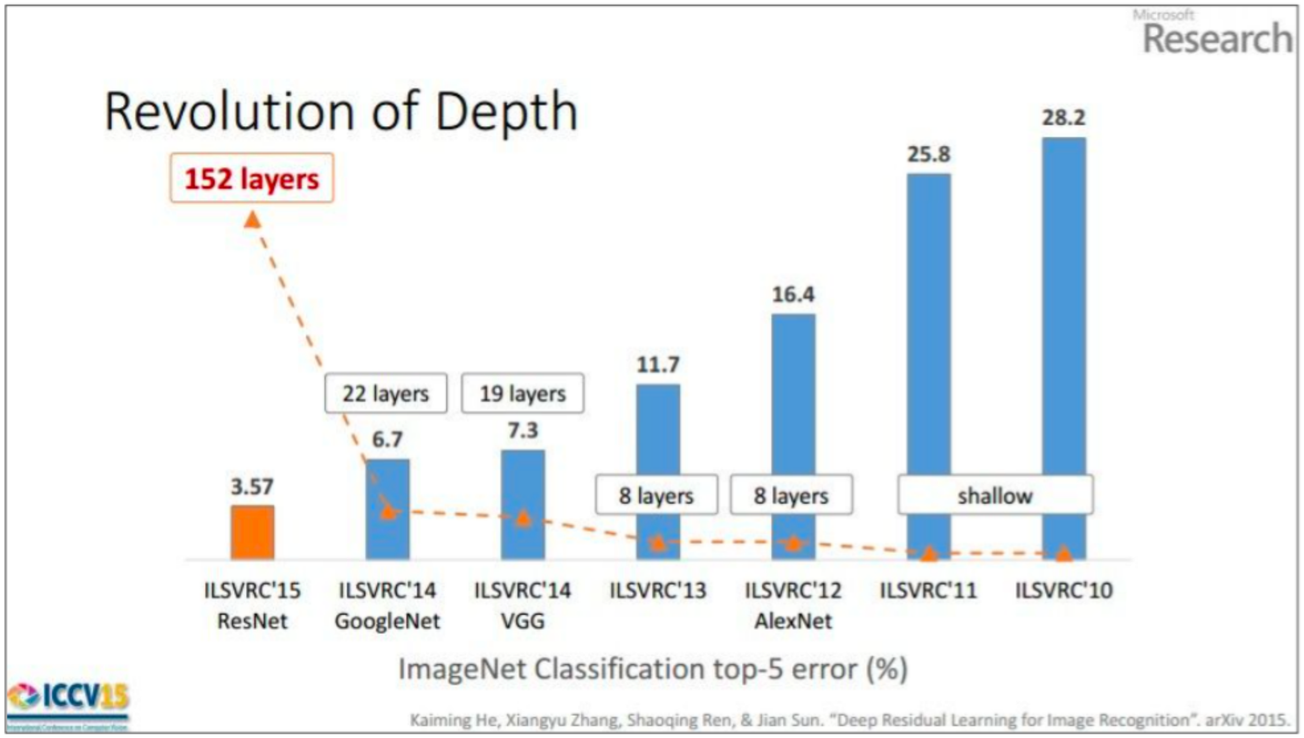


## Models for Image Classification in PyTorch

- AlexNet
- VGG
- ResNet
- SqueezeNet
- DenseNet
- Inception v3
- GoogLeNet
- ShuffleNet v2
- MobileNet v2
- ResNeXt
- Wide ResNet
- MNASNet

## Imagenet Classification

1000 kinds of objects.



(slide from Kaiming He's recent presentation)

2016 is 3.0%, is 2017 2.25%

SOTA as of January 2020 is 1.3%

**END**