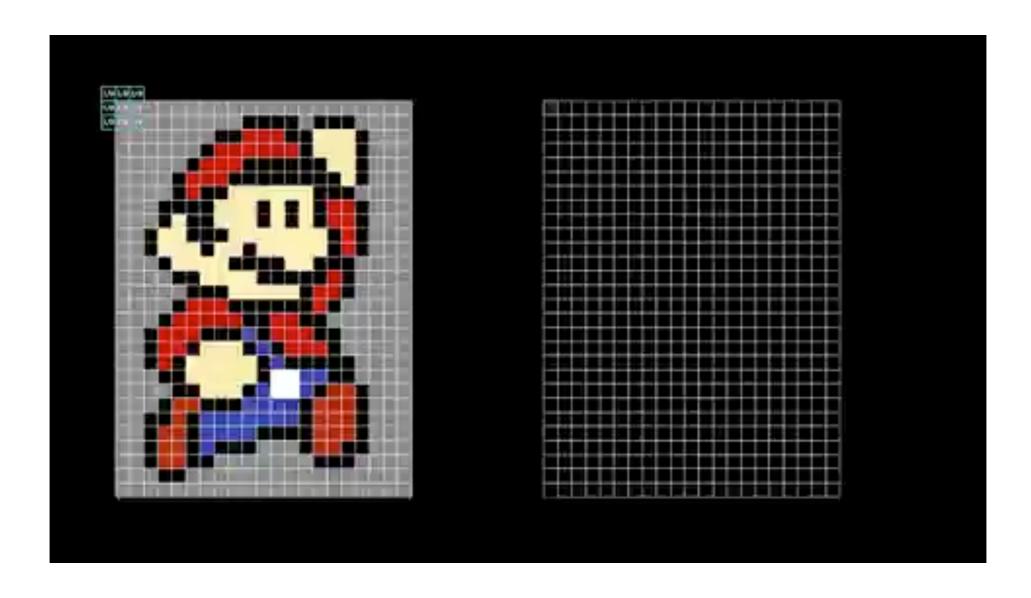
#### Convolutional neural networks

Romain Tavenard (Université de Rennes)

# Convolution in practice

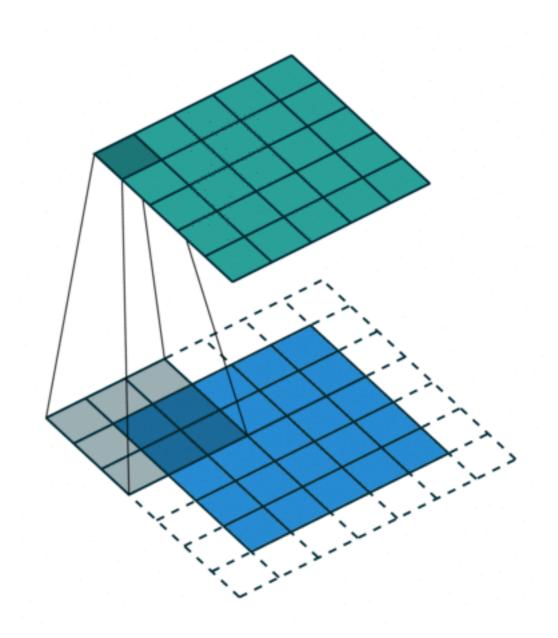


Source: Grant Sanderson, Twitter <a href="https://twitter.com/3blue1brown/status/1303489896519139328?s=20">https://twitter.com/3blue1brown/status/1303489896519139328?s=20</a>

# The convolution operator



- 2D convolution
  - Blue: input image
  - Gray: convolution kernel
  - Cyan: activation map
- Convolution operation =
  Dot product between
  - convolution kernel (aka filter)
  - subpart of the input



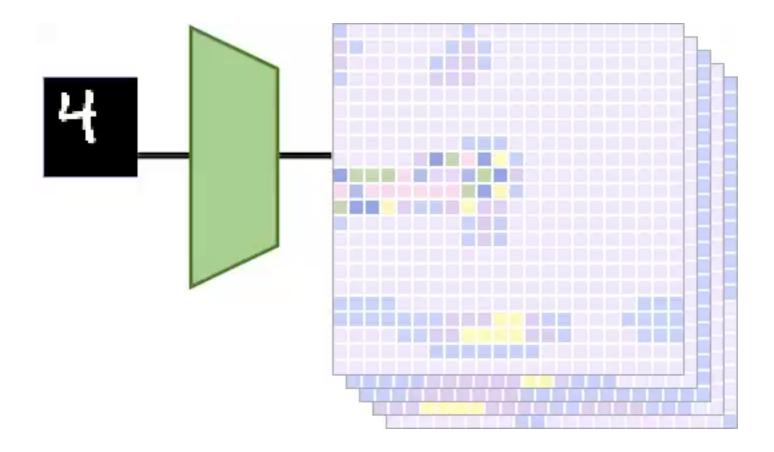




- A convolution layer is made of
  - convolution kernels
  - biases (1 per kernel)
  - an activation function

- Useful because
  - reduces #parameters
  - encodes translation equivariance (translation in the input induces translation in the output, cf. next slide)

#### Convolution and translation

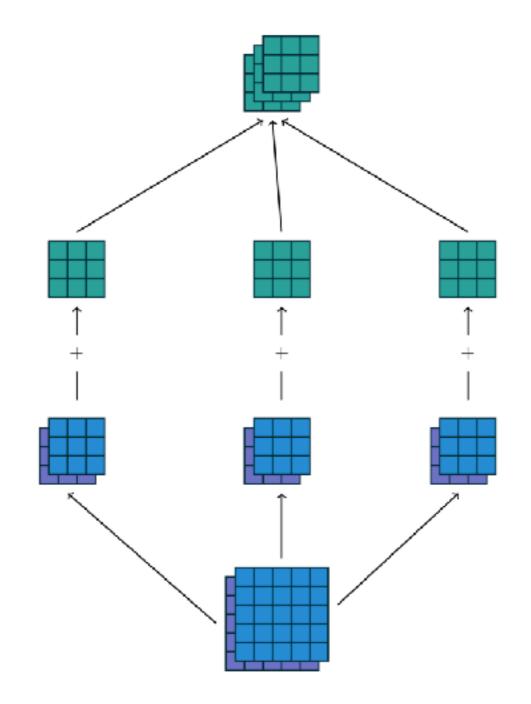


Source: Christian Wolf, Twitter <a href="https://twitter.com/chriswolfvision/status/1313059518574718977?s=20">https://twitter.com/chriswolfvision/status/1313059518574718977?s=20</a>

# Convolutional layers in NN (2/2)



- Multiple input channel case
  - sum the response over all channels
- Multiple kernel case
  - each kernel leads to one output channel

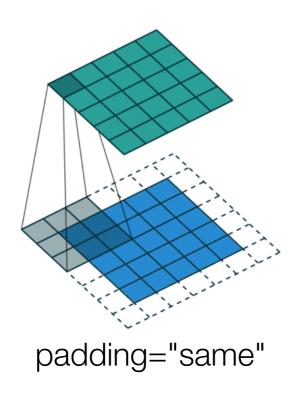


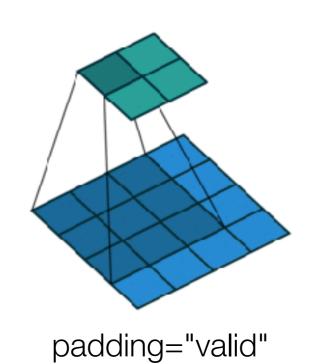
2 input channels, 3 kernels

# Convolutional layers in NN: hyper parameters

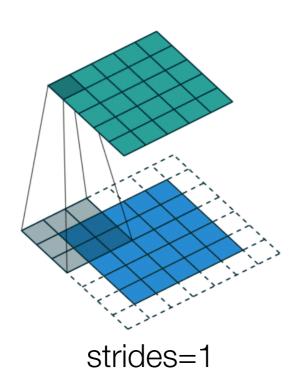


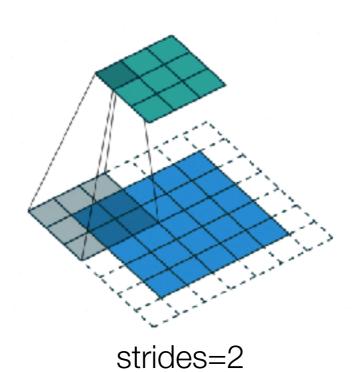
Padding





Strides





# Pooling (aka subsampling) layers in NN



- Max pooling / Average pooling
- Hyper-parameters
  - pool size
  - strides (use None in keras)
  - padding (use "valid" in keras)

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

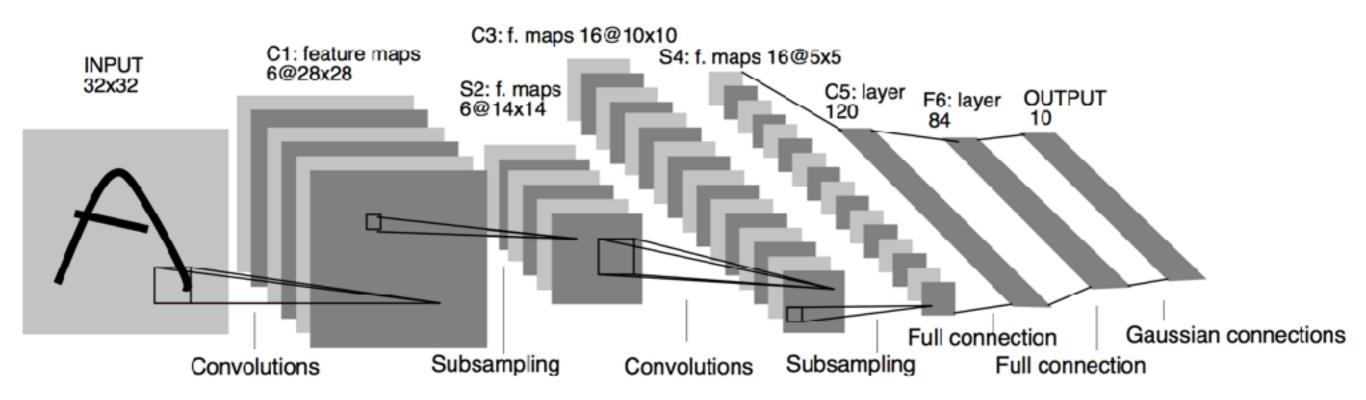
3.0	3.0	3.0
3.0	3.0	3.0
3.0	2.0	3.0

pool\_size=3, strides=1 (not recommended)

#### Convolutional model zoo

### 1. LeNet [LeCun et al., 1989]

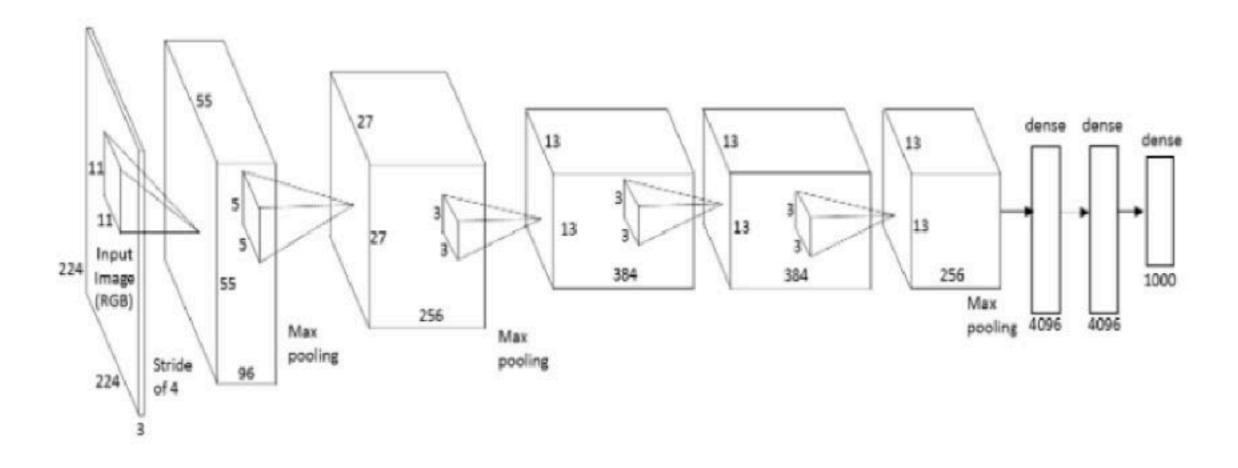
60k parameters



#### Convolutional model zoo

# 2. AlexNet [Krizhevsky et al., 2012]

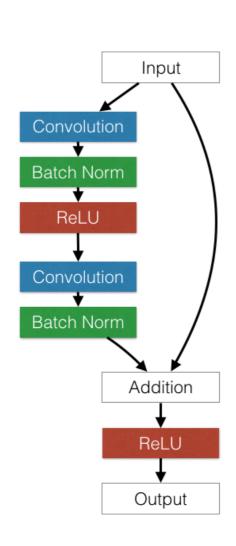
#### 60M parameters

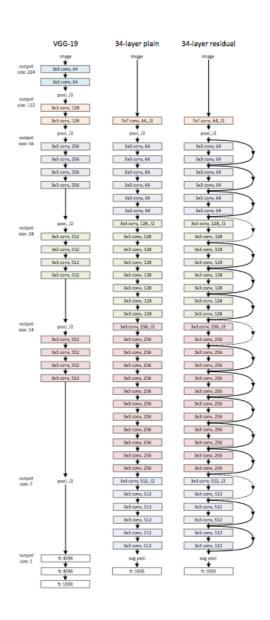


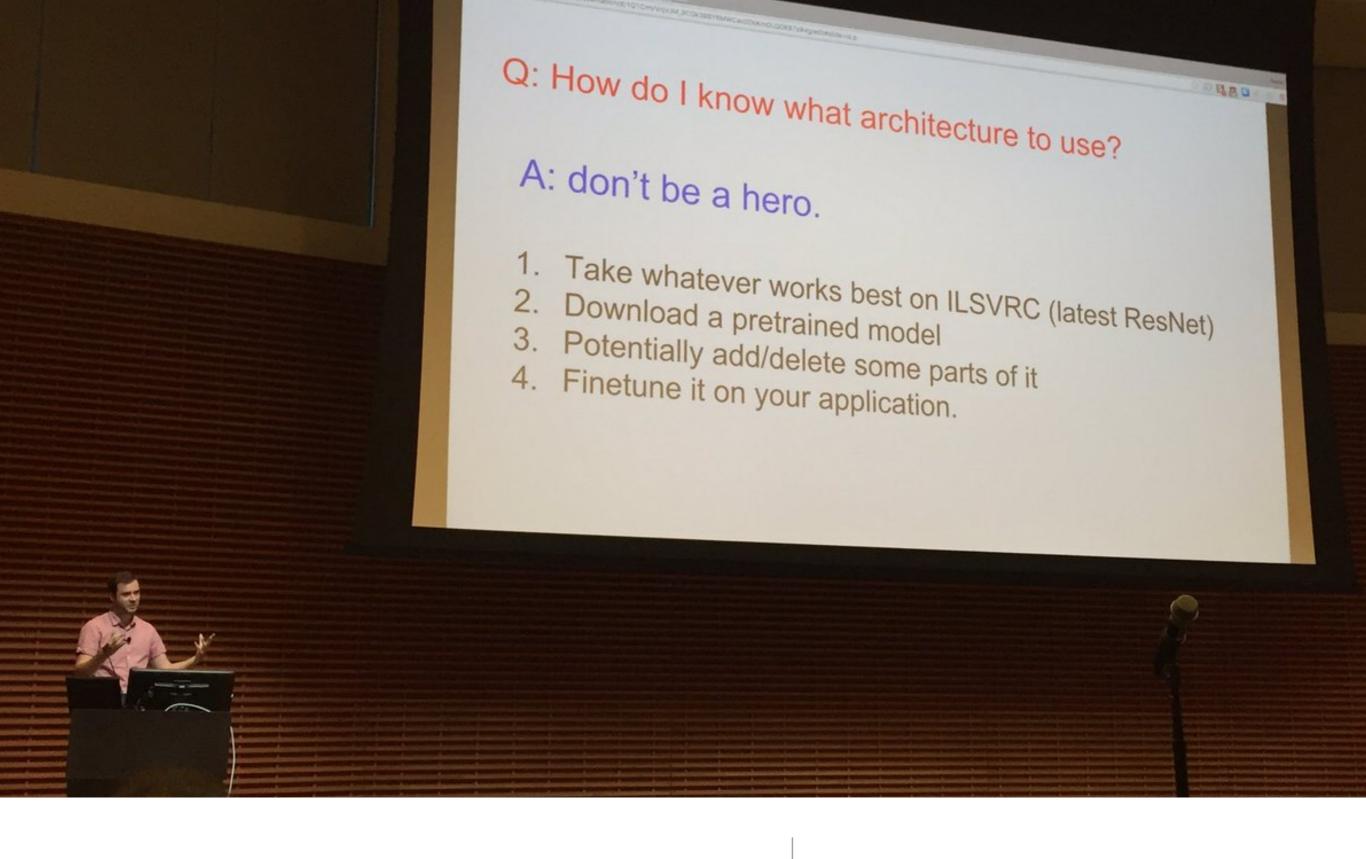
#### Convolutional model zoo

# 3. Residual Networks [He et al., 2016]

- Aims at facing the vanishing gradient effect
- ResNet-110: ~2M parameters







Andrej Karpathy, Deep Learning Summer School, 2016