Convolutional Neural Networks

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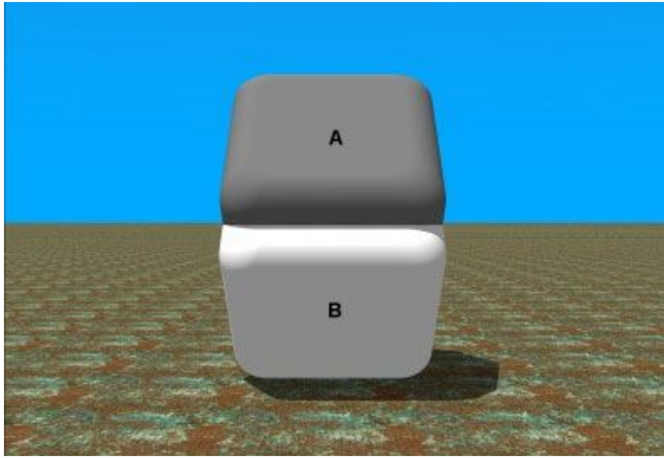
Deep Networks for Image Recognition

- Images are composed of large numbers of pixels
- A particular pixel value can vary a lot:
  - Color, illumination
- Objects can vary a lot
  - Size, orientation, perspective

Individual pixels are irrelevant…

it is the groups of pixels that matter



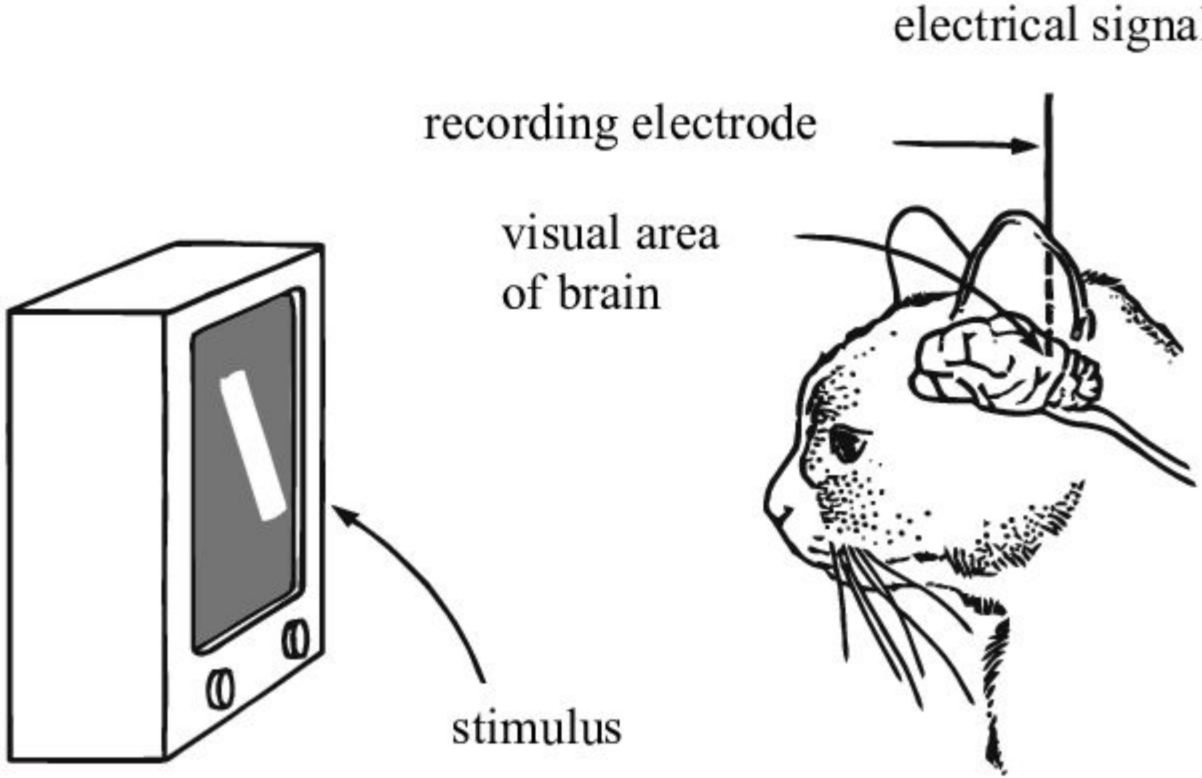
http://brainden.com/color-illusions.htm

Deep Networks for Image Recognition

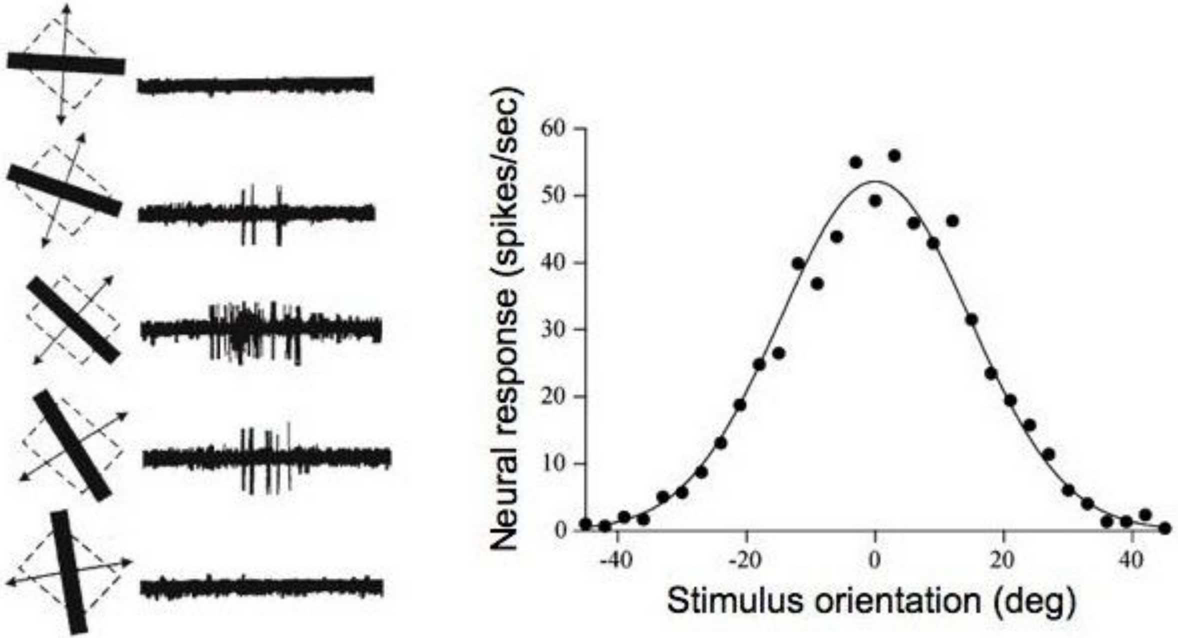
- 1920 (columns) x 1020 (rows) x 3 (channels = RGB) is almost 6 million inputs
- If the next dense layer has 1000 units, then we would have 6 billion parameters!

Need lots of examples and lots of training time. How do we get beyond this?

Hubel and Wiesel (1968)

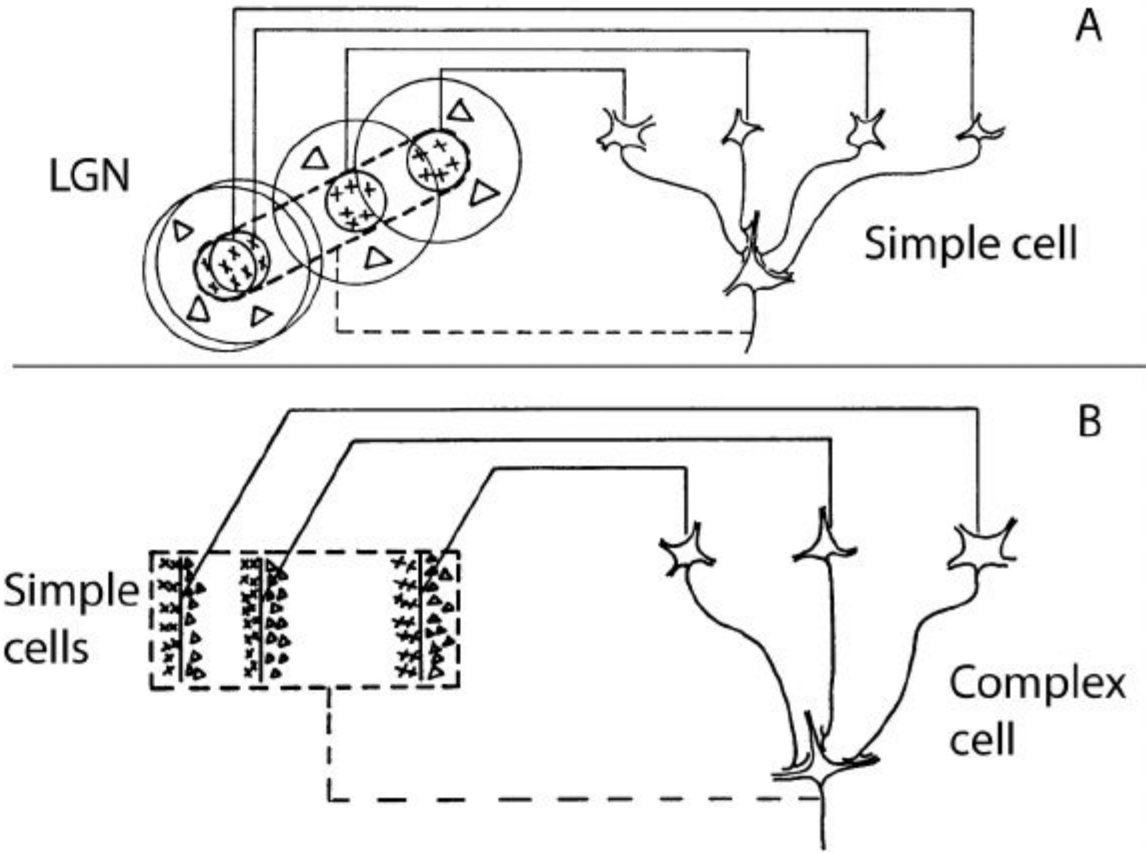


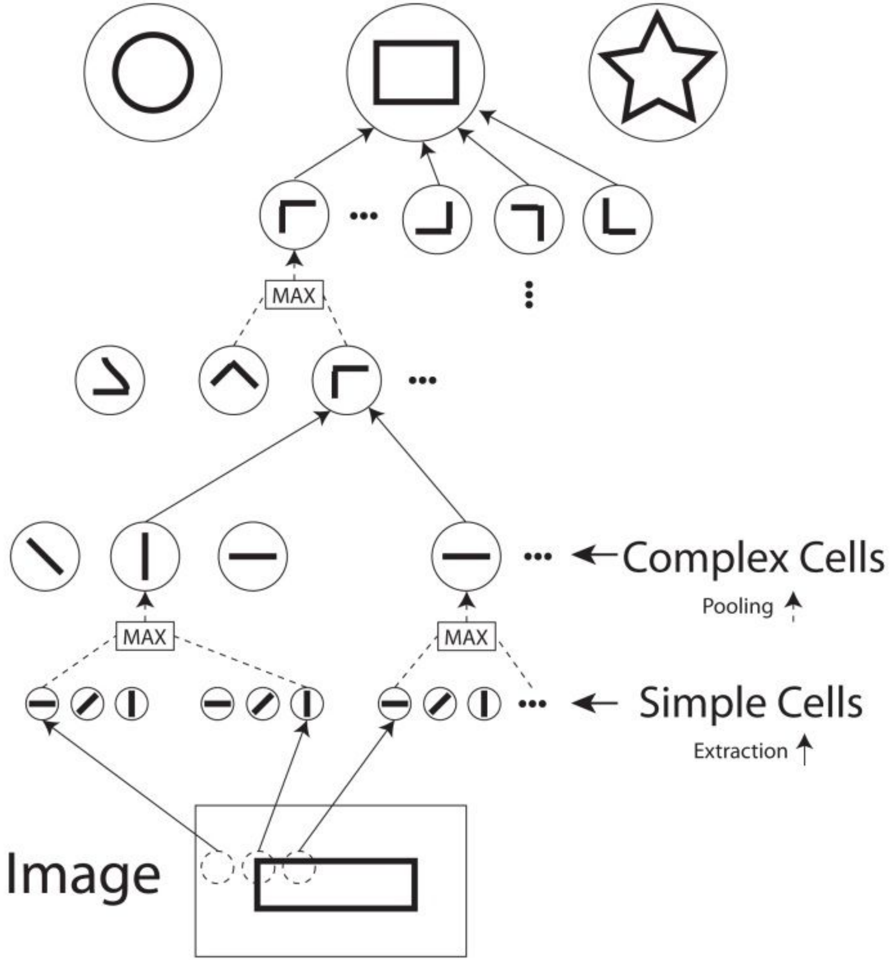
Orientation Sensitivity



Hubel & Wiesel, 1968

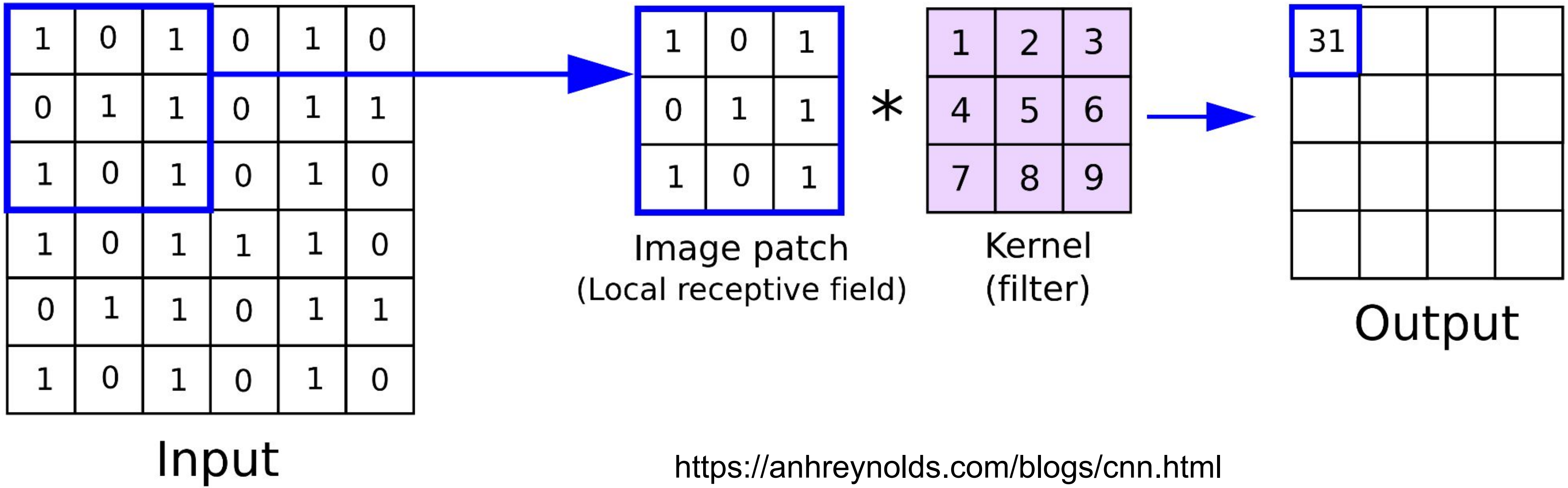
Complex Features Formed from Simple Ones





https://www.intechopen.com/books/visual-cortex-current-status-and-perspectives/models-of-information-processing-in-the-visual-cortex

Convolution

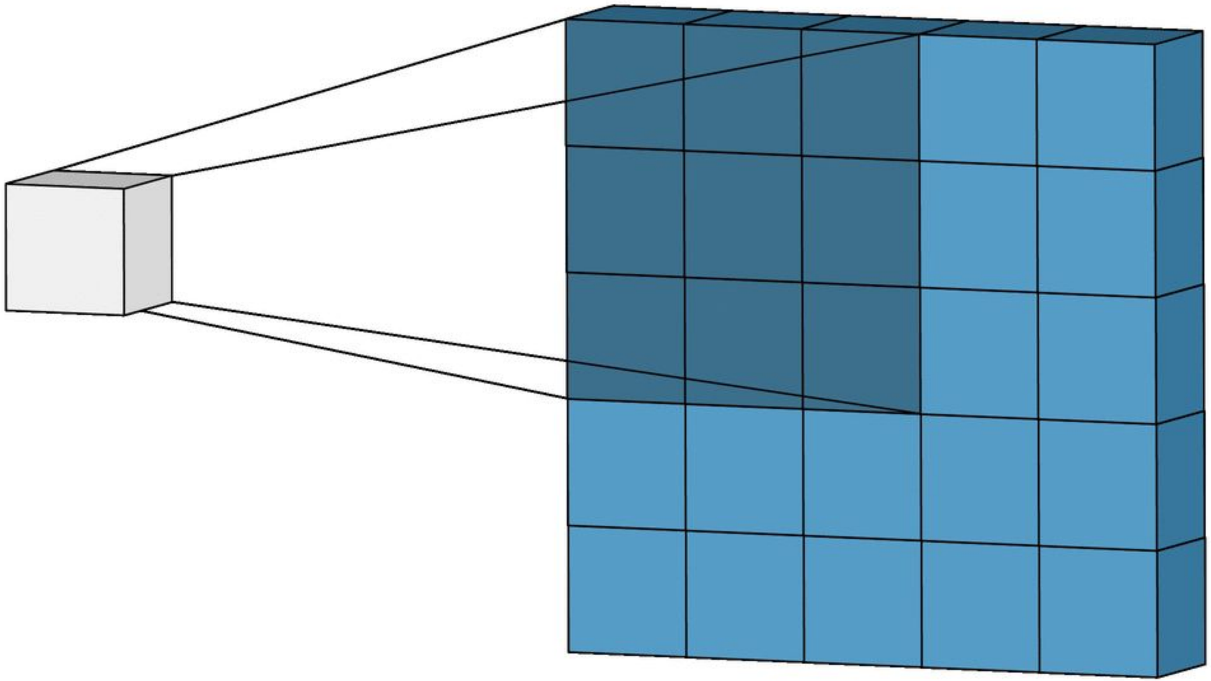


https://anhreynolds.com/blogs/cnn.html

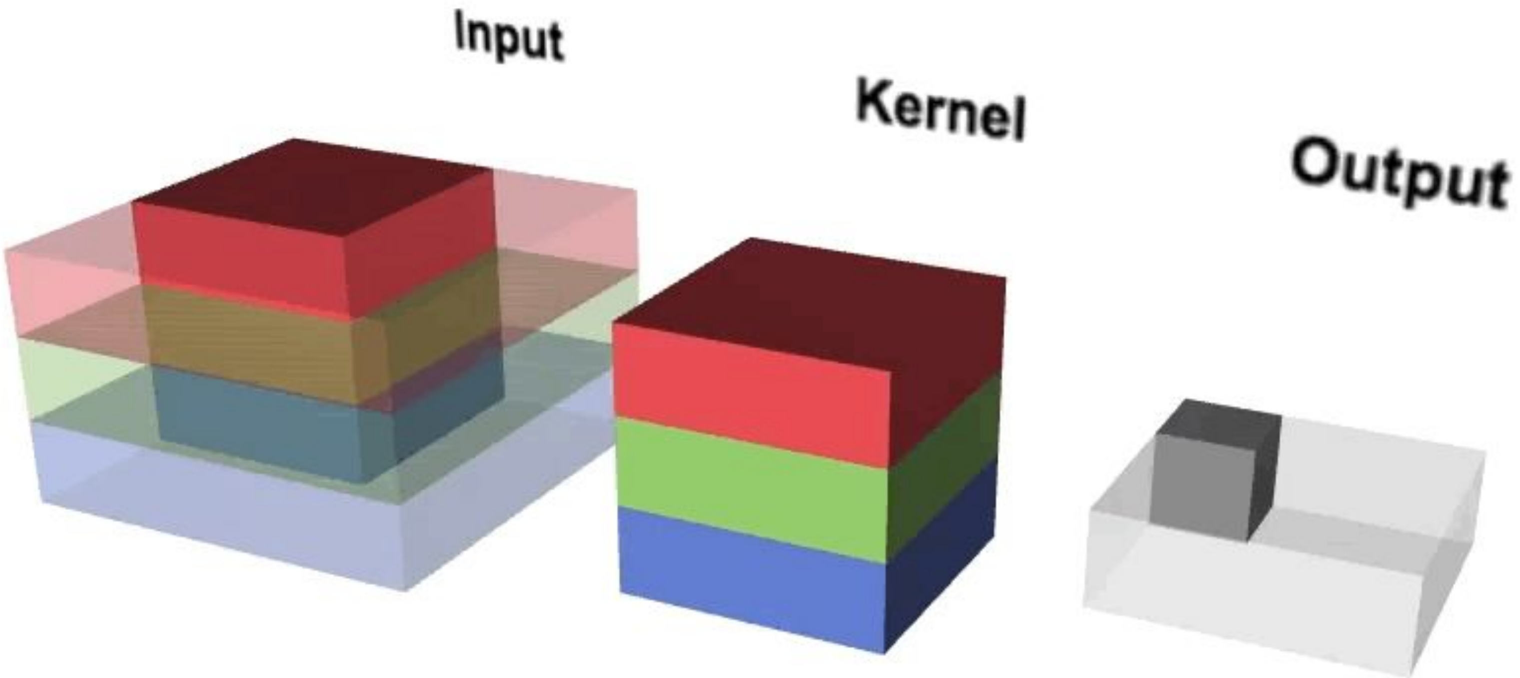
Convolution: Edge Detector

$$\begin{bmatrix} 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \\ 10 & 10 & 10 & 10 & 0 & 0 & 0 & 0 \end{bmatrix} * \underbrace{\begin{bmatrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{bmatrix}}_{\text{Vertical}} = \begin{bmatrix} 0 & 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 30 & 30 & 0 & 0 \\ 0 & 0 & 30 & 30 & 0 & 0 \end{bmatrix}$$

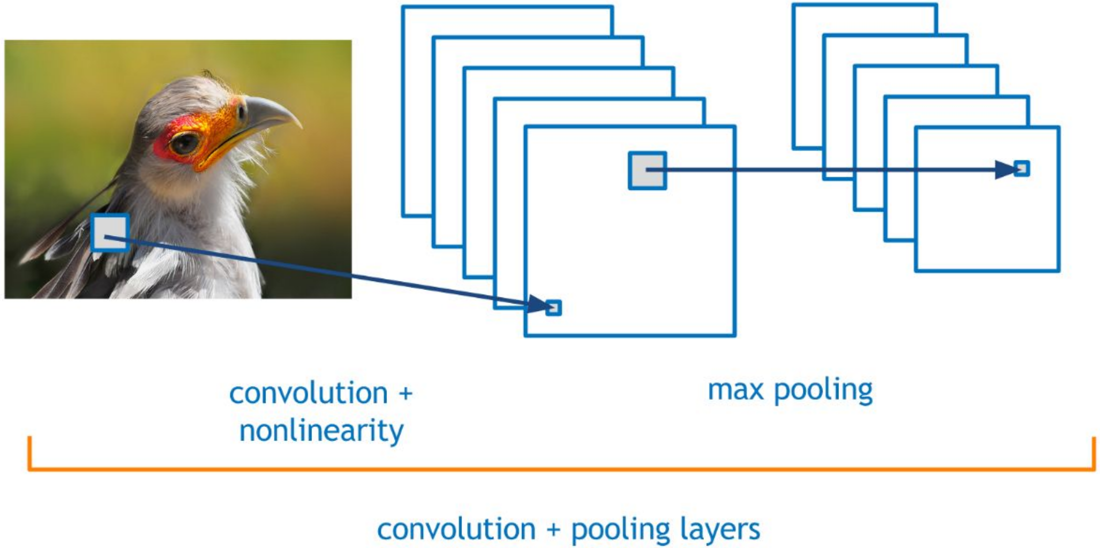
https://anhreynolds.com/blogs/cnn.html



https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1


Input
Kernel
Output

Local Operators



wp.flickr.net

Operator Types

- Convolution: Feature detection - recognize some pattern over a small grid of inputs
  - At a given layer, have many different patterns that we are looking for in parallel
- Max Pooling: does there exist some pattern within a small grid of inputs?
- Scaling: Allows simple feature detection and pooling to apply at multiple visual scales

Local Operators

- Multiple stacked modules consisting of:
    - Pattern recognition (convolution),
    - Pooling (max)
    - Scaling (striding)
- With each module, our representation becomes more and more abstract
    - Ultimately: feathers, eyes, beaks …
    - All have specific visual patterns, though there may be many variations of each

Local Operators

Typical module:

- Reduce spatial dimensions by half
- Increase number of features by factor of 2
- In total: number of variables drops by a factor of 2

Module structure:

- (r,c,f) -C-> (r,c,f) -C-> … -C-> (r,c,f) -C-> (r,c,2f) -P->(r/2, c/2,2f)

Beyond the Primitives

How should the primitives be combined to form more of a semantic representation (dog, cat, grandma, etc.)?

- After computing the primitives in the first layers of our deep network, employ dense layers to allow for arbitrary combinations of the primitives

Combining Local Operators to Recognize Global Patterns

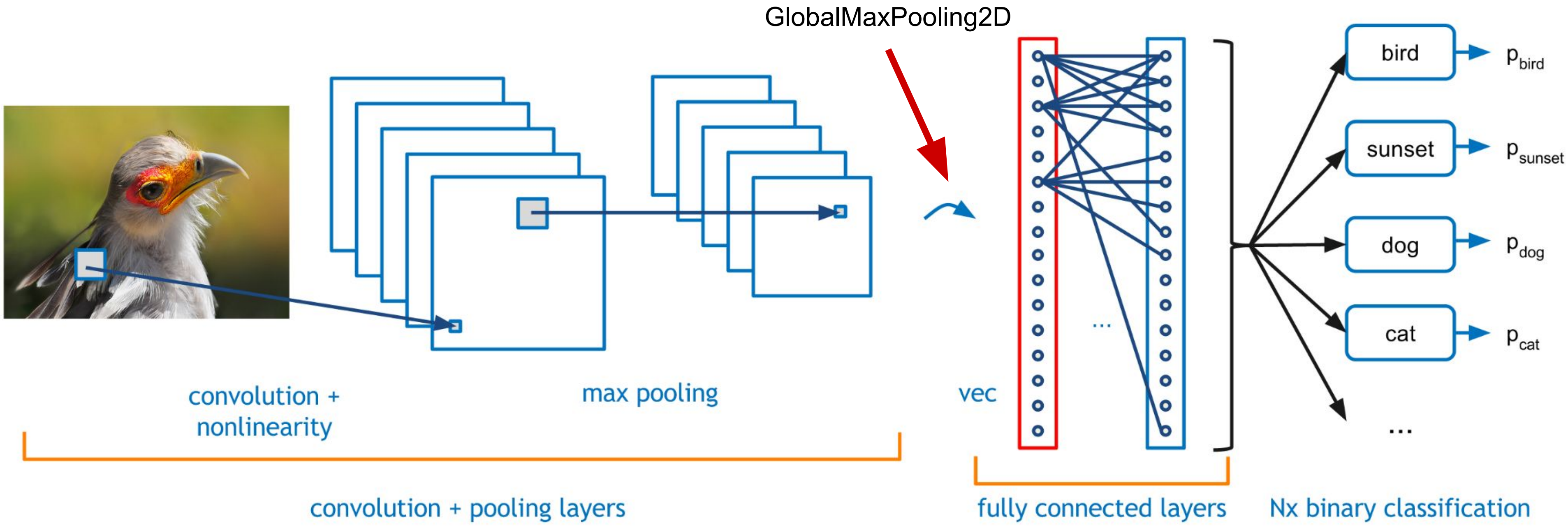


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Image Classification (Exclusive Classes)

Final layer:

- One output per class
- Nonlinearity: softmax
- Unusual nonlinearity:
  - Output i is a function of all of the other net inputs
  - Can interpret the output vector as a probability distribution (all elements are non-negative and they sum to 1)

CNN Details: Convolution

```
from keras.layers import Convolution2D
######

model = Sequential()

model.add(InputLayer(input_shape=(image_size[0],
                                        image_size[1],
                                        nchannels), name='input'))

# Input shape: (rows, cols, chans)

model.add(Convolution2D(filters=10,
                              kernel_size=3,               # Implies (3,3)
                              strides=1,
                              padding='valid',
                              use_bias=True,
                              name='C0',
                              activation='elu'))

# Output shape: (rows-2, cols-2, 10)
```

Convolution2D

Convolution2d other key properties:

- kernel_initializer
- bias_initializer
- kernel_regularizer
- bias_regularizer
- activity_regularizer

Pooling

```
from keras.layers import MaxPooling2D

######

# Input shape: (rows, cols, chans)

model.add(MaxPooling2D(pool_size=2,             # Implicit: (2,2)
                       strides=2,               # Also (2,2)
                       padding='same',
                       name='MP0'))

# Output shape: (rows//2, cols//2, chans)
```

Global Max Pooling

```
from keras.layers import GlobalMaxPooling2D

######

# Input shape: (rows, cols, chans)

model.add(GlobalMaxPooling2D())

# Output shape: (chans,)
```

Dropout

Drop entire channel at once

- (dropping single elements within a layer does not help)

```
from keras.layers import SpatialDropout2D

######

# Input shape: (rows, cols, chans)

model.add(SpatialDropout2D(p))

# Output shape: (rows, cols, chans)
```

CNN Notes

- 1D, 2D, and 3D versions built into Keras/TF
- Can use BatchNormalization() as usual
    - Applies individually to every element in the

      (rows, cols, chans) Tensor

CNN Modules

Sequence of layers:

- k x Conv2D
- MaxPooling2D
- SpatialDropout2D
- BatchNormalization

CNN for Image Classification

- n x CNN Module
  - Decreasing rows & cols while increasing filters (product should decrease)
- GlobalMaxPooling2D
- m x Dense
  - Decreasing number of hidden units
- Dense(nclasses, activation='softmax')
  - Classes are exclusive

Different N-Class Network Configs

All: N output units

	Exclusive Classes	**Multi-Class (any combination of classes)**
Nonlinearity	softmax	sigmoid
Desired output: binary encoding of class	**One-hot encoding** categorical_crossentropy categorical_accuracy	**Any binary vector** binary_crossentropy binary_accuracy
Desired output: 1 integer (class number)	sparse_categorical_crossentropy sparse_categorical_accuracy	**X**

Applications of CNNs

- Image classification
- Image recoding: deblurring, colorization, semantic segmentation
- Image generation

1D and 3D data are possible, too