Convolutional Neural Networks

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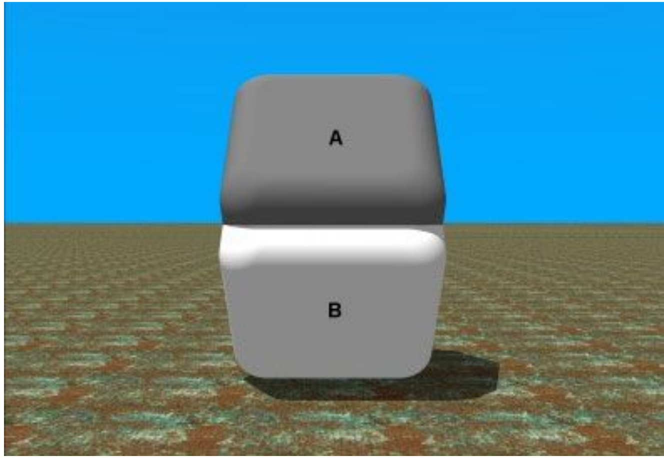
Deep Networks for Image Recognition

- 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

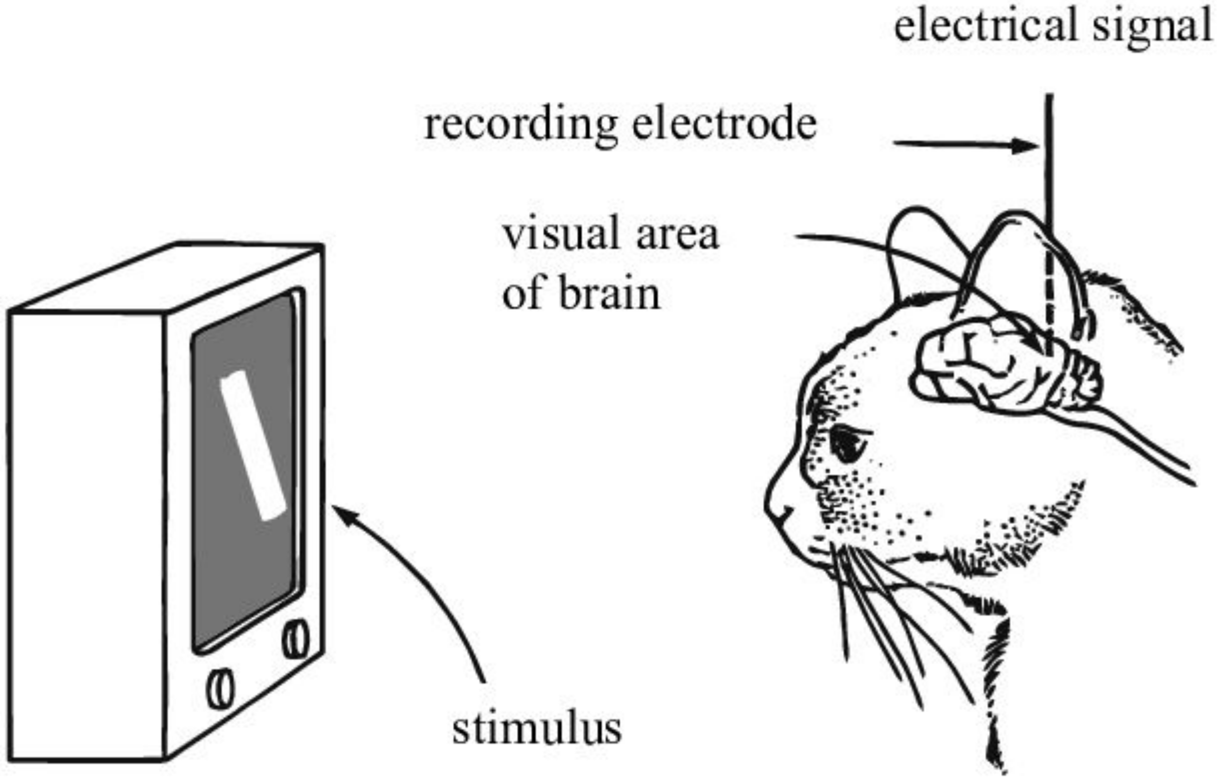
http://brainden.com/color-illusions.htm

Deep Networks for Image Recognition

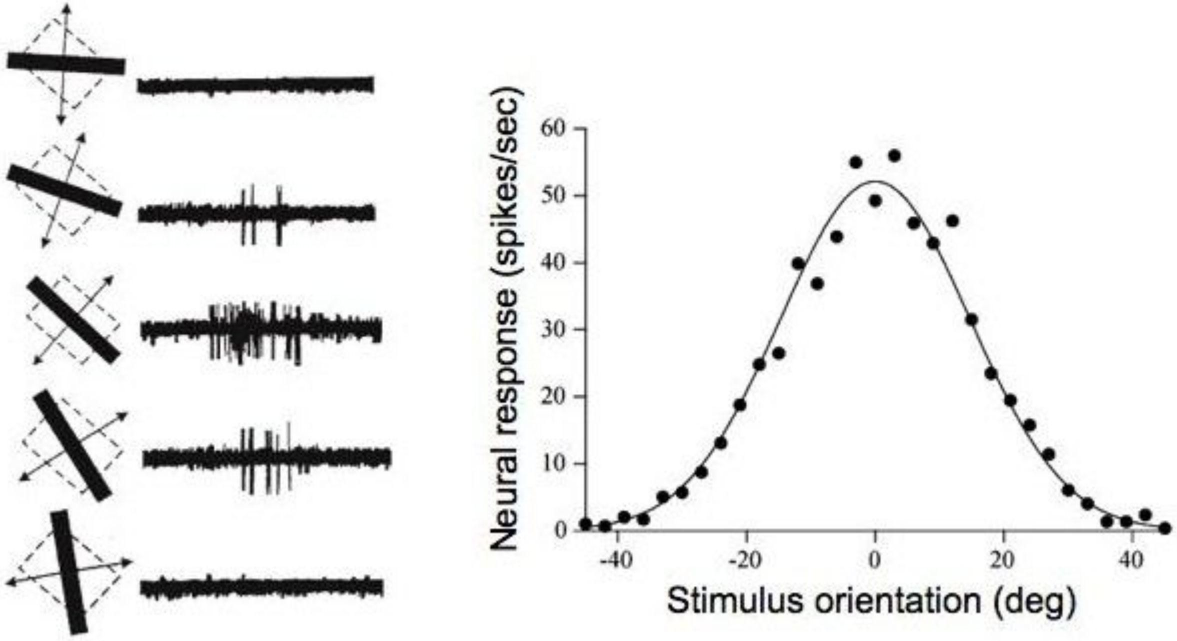
- 1920 (columns) x 1020 (rows) x 3 (channels = RGB) is almost 6 million inputs
- If the next dense layer has 1000 units, then we would have 6 billion parameters!

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

Hubel and Wiesel (1968)

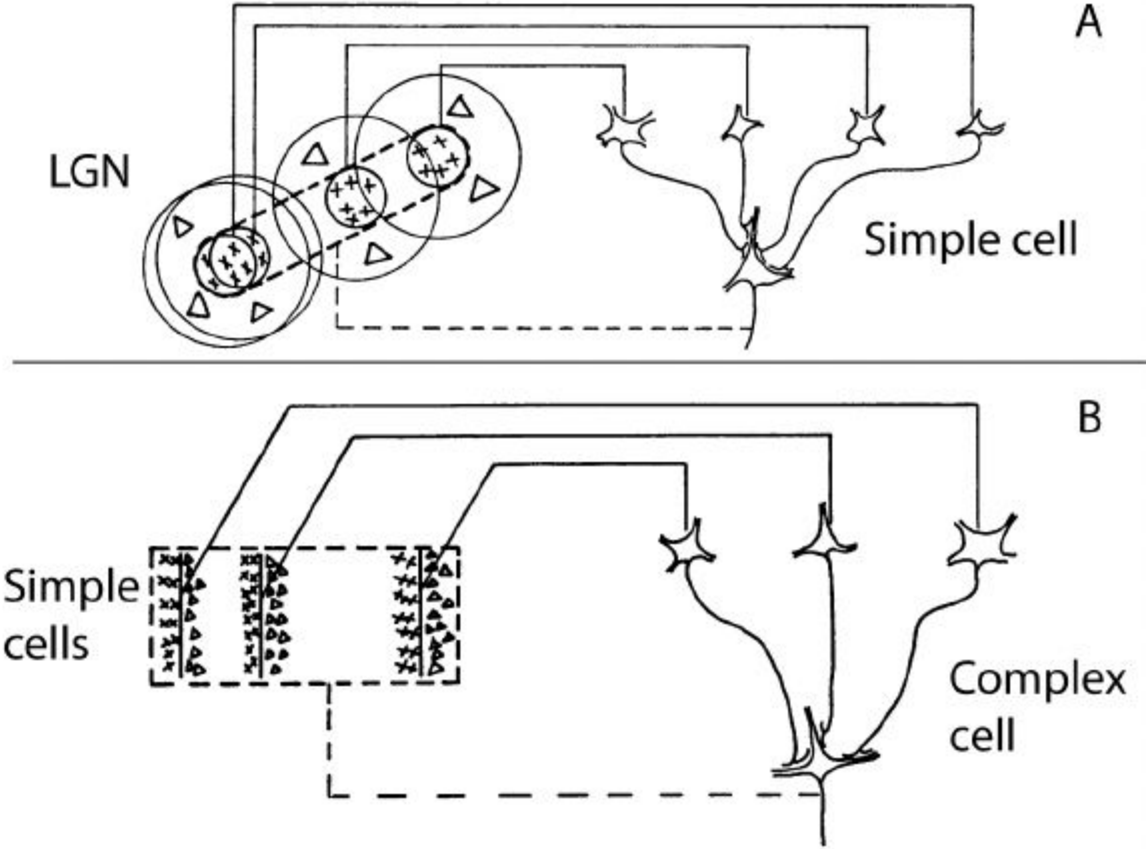


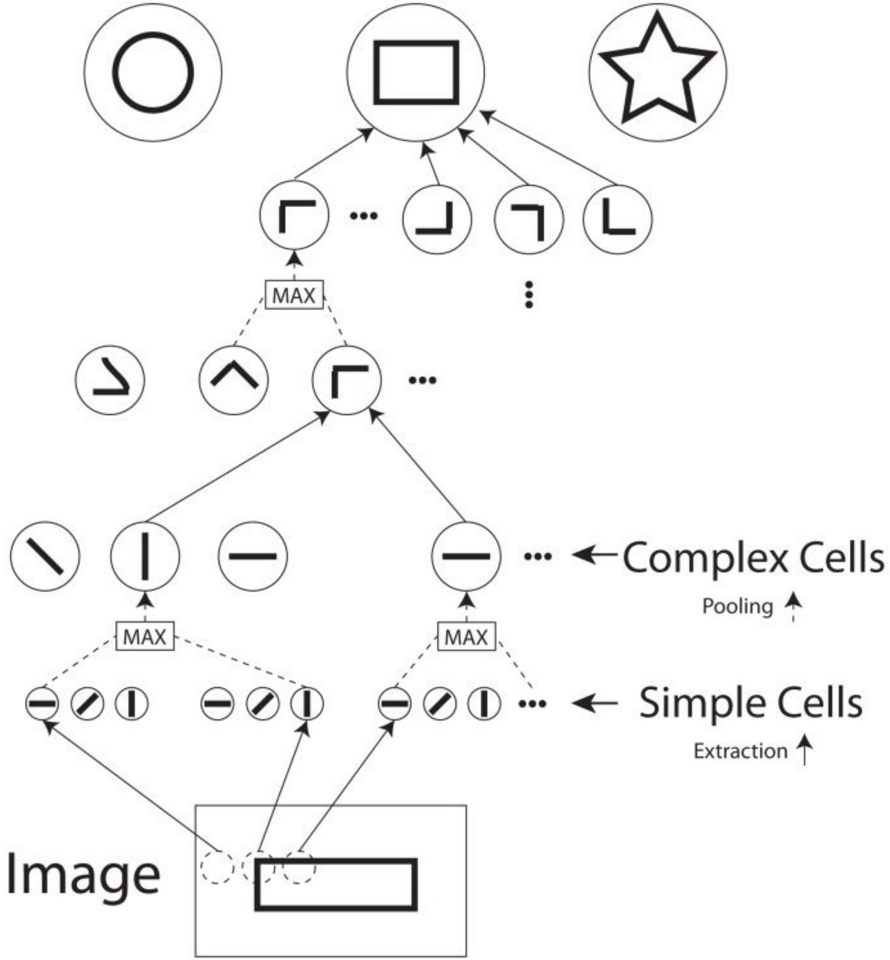
Orientation Sensitivity



Hubel & Wiesel, 1968

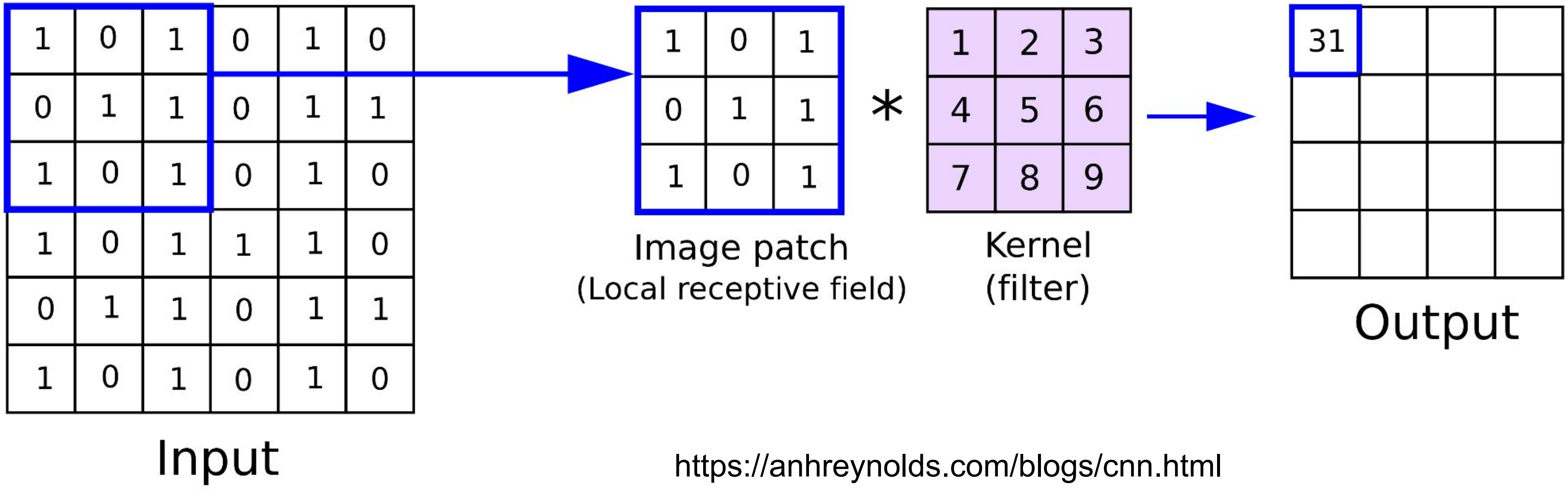
Complex Features Formed from Simple Ones





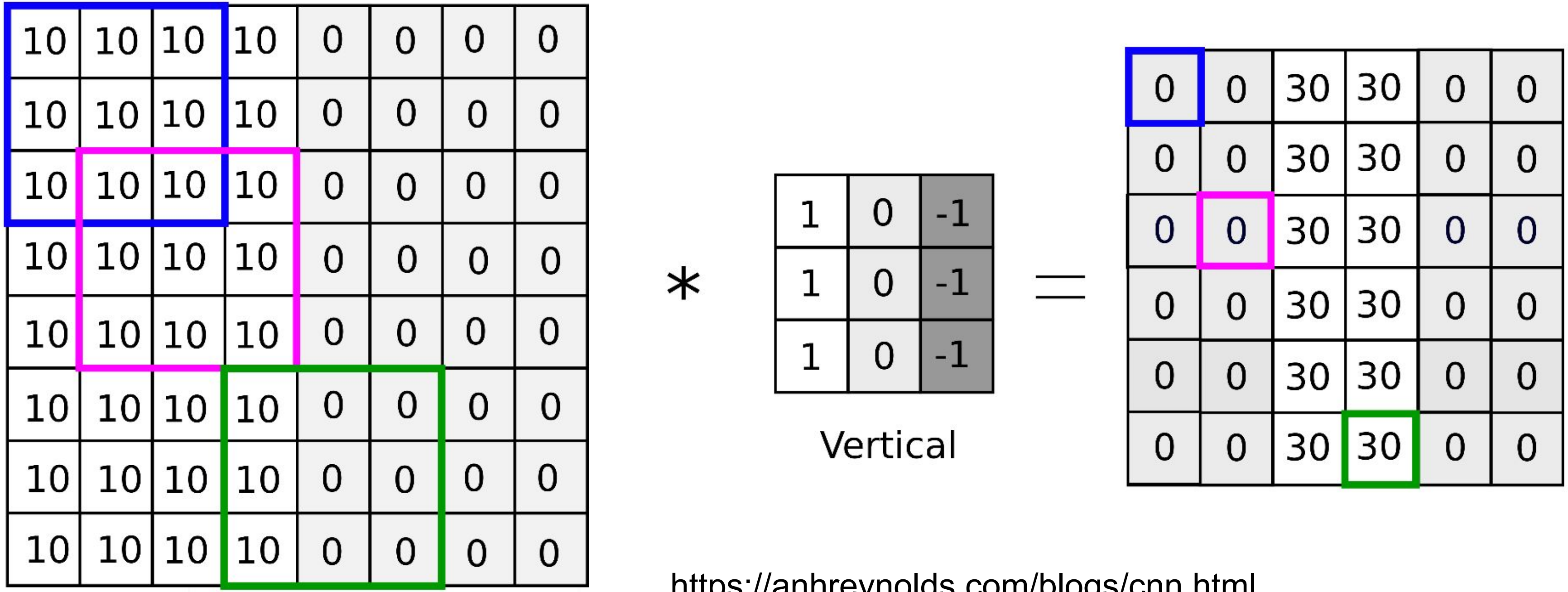
https://www.intechopen.com/books/visual-cortex-current-status-and-perspectives/models-of-information-processing-in-the-visual-cortex

Convolution

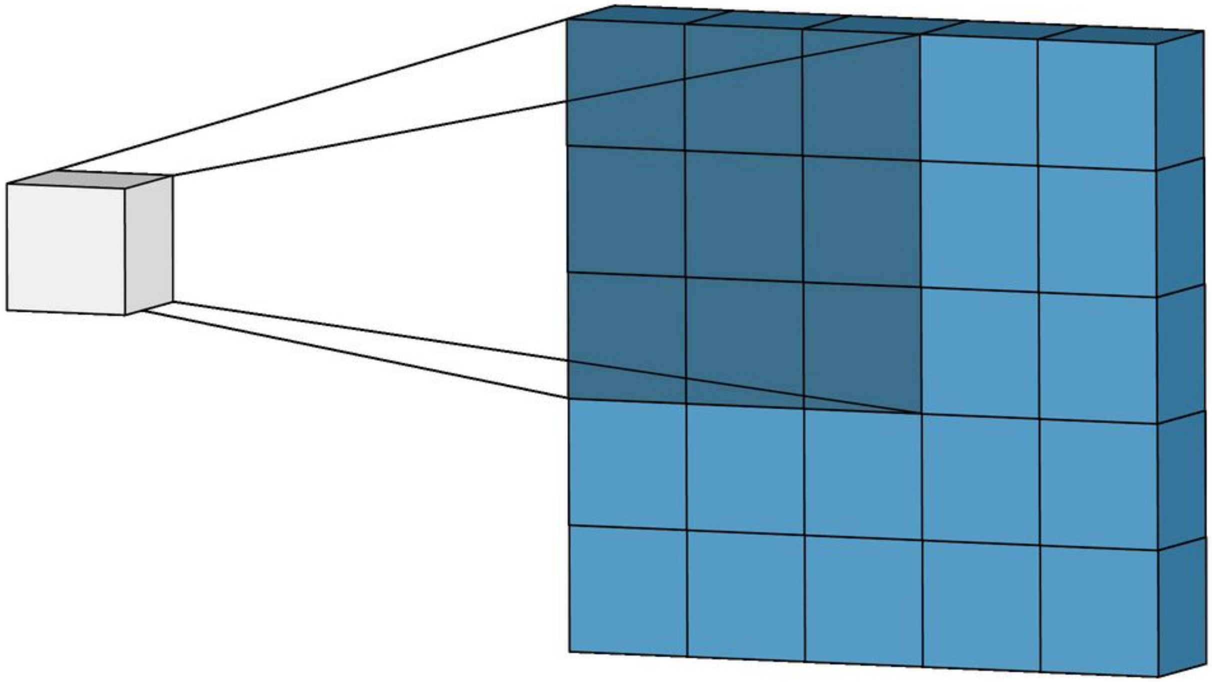


https://anhreynolds.com/blogs/cnn.html

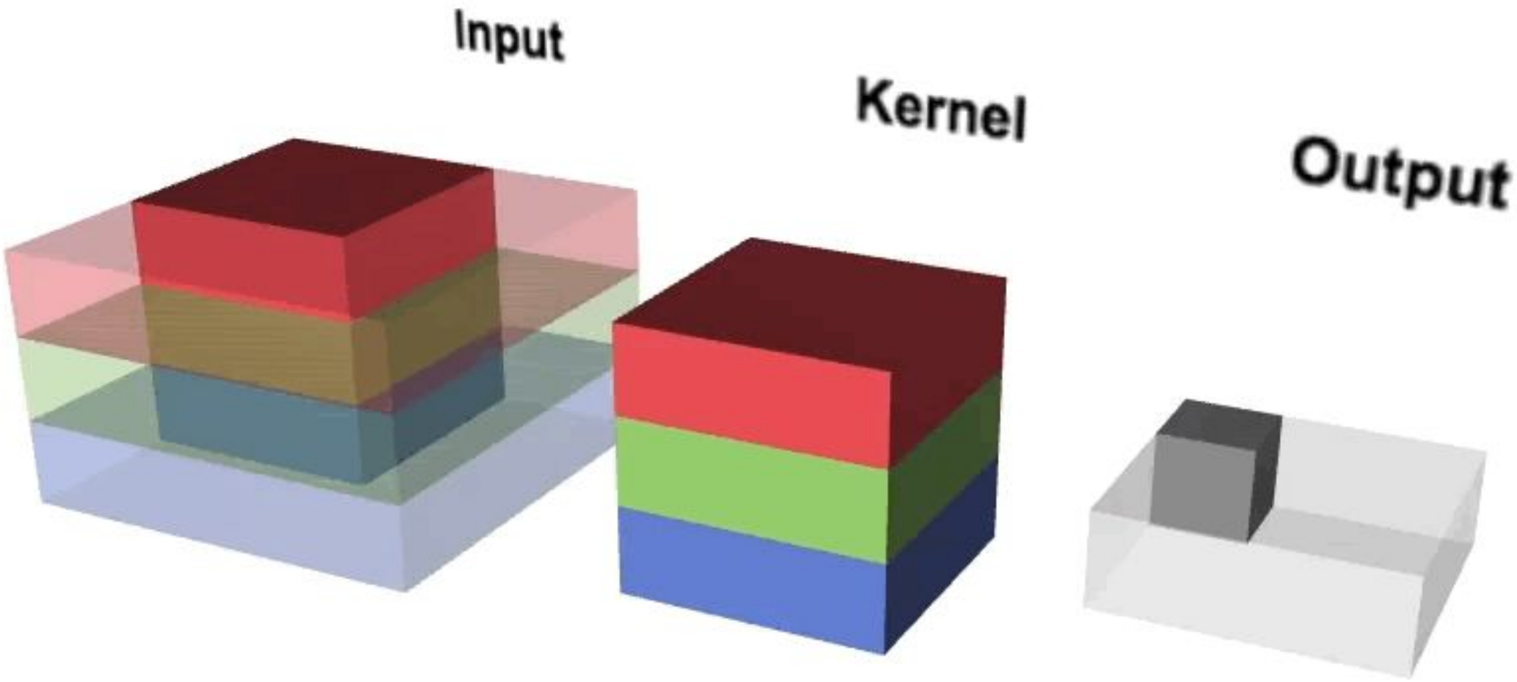
Convolution: Edge Detector



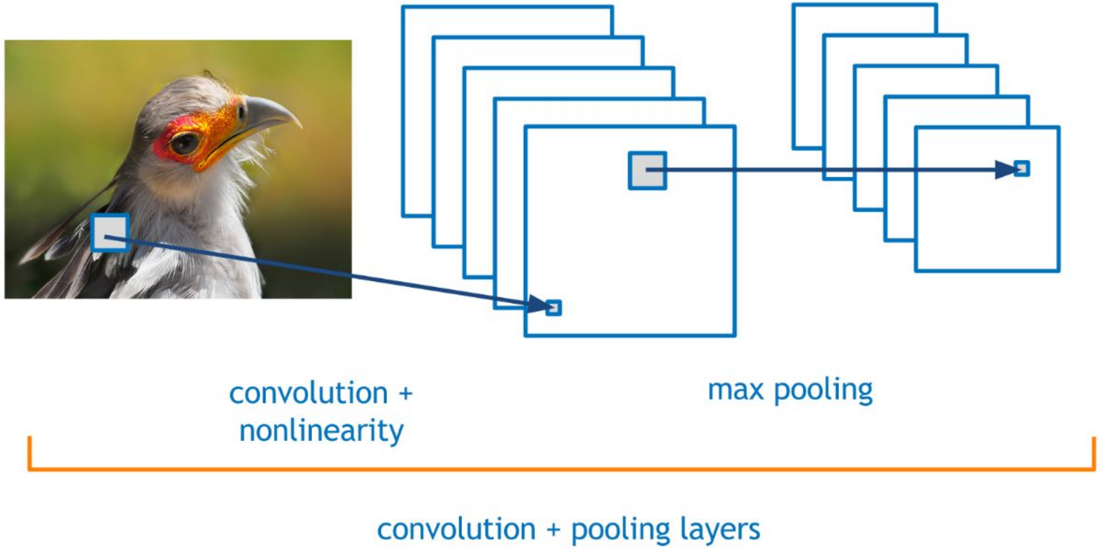
https://anhreynolds.com/blogs/cnn.html



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

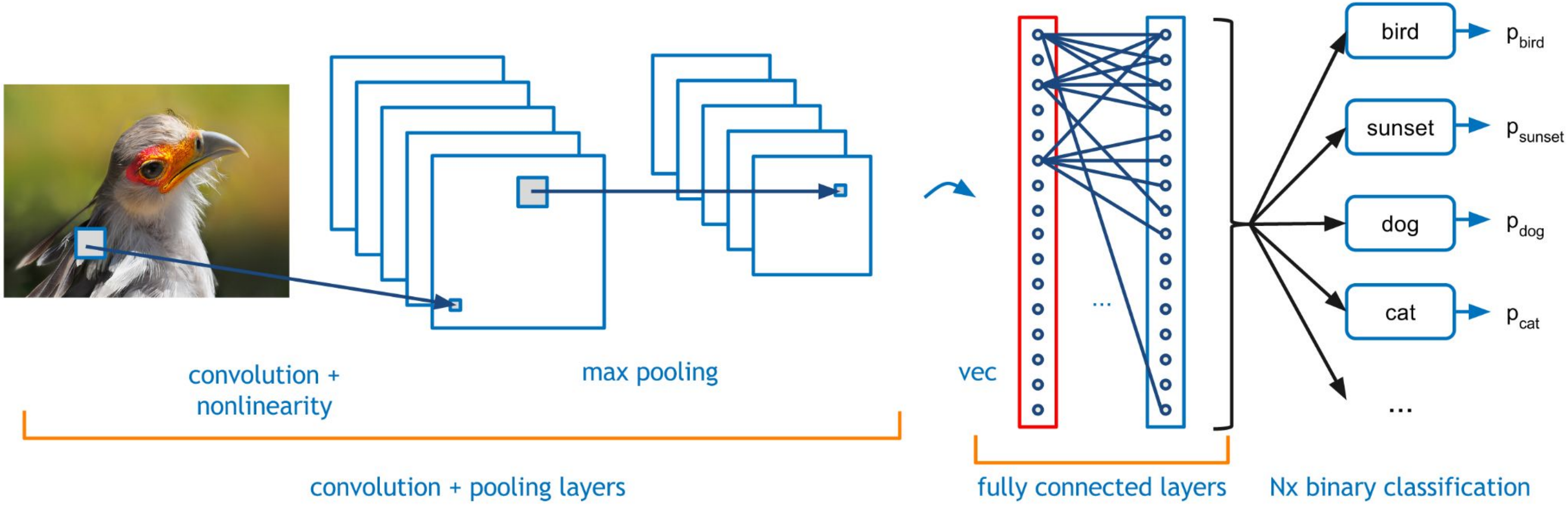
- Multiple stacked modules consisting of pattern recognition (convolution), pooling (max) and scaling (striding)
- With each module, our representation becomes more and more abstract
  - Ultimately: feathers, eyes, beaks …
  - All have specific visual patterns, though there may be many variations of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

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



wp.flickr.net

Applications of CNNs

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

1D and 3D data are possible, too

CNN Details: Convolution

```
from tensorflow.keras.layers import Conv2D
######

model = Sequential()

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

# Input shape: (rows, cols, chans)

model.add(Conv2D(filters=10,
                 kernel_size=3,
                 strides=1,
                 padding='valid',
                 use_bias=True,
                 name='C0',
                 activation='elu'))

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

Convolution2D

Conv2d other key properties:

- kernel_initializer
- bias_initializer
- kernel_regularizer
- bias_regularizer
- activity_regularizer

Pooling

```
from tensorflow.keras.layers import MaxPooling2D

######

# Input shape: (rows, cols, chans)

model.add(MaxPooling2D(pool_size=2,
                          strides=2,
                          padding='same',
                          use_bias=True,
                          name='MP0'))

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

Global Max Pooling

```
from tensorflow.keras.layers import GlobalMaxPooling2D

######

# Input shape: (rows, cols, chans)

model.add(MaxPooling2D())

# Output shape: (chans,)
```

Dropout

Drop entire channel at once

```
from tensorflow.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: 1-hot encoding of class	categorical_crossentropy categorical_accuracy	binary_crossentropy binary_accuracy
Desired output: **1 integer (class number)**	sparse_categorical_crossentropy sparse_categorical_accuracy	**X**