Lecture 10
Convolutional and Deep Neural Networks

EE-UY 4563/EL-GY 9123: INTRODUCTION TO MACHINE LEARNING

PROF. SUNDEEP RANGAN WITH MODIFICATION BY YAO WANG

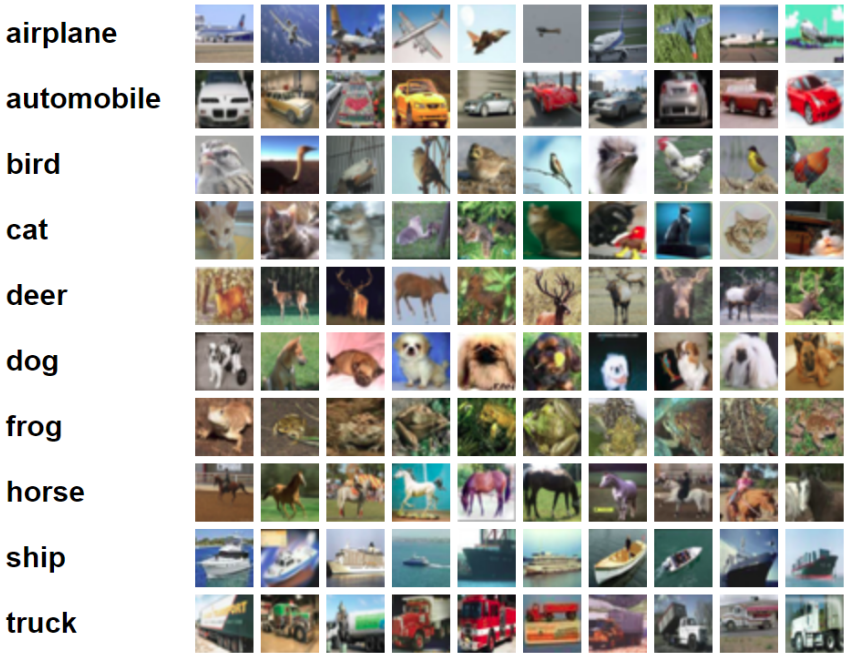
Outline

- Motivation: ImageNet Large-Scale Visual Recognition Challenge (ILSVR)
- Deep Networks and Feature Hierarchies
- 2D convolutions
- Convolutional neural networks
- Creating and visualizing convolutional layers in Keras
- Backpropagation training in CNNs
- Exploring VGG16: A state-of-the-art deep network

Large-Scale Image Classification

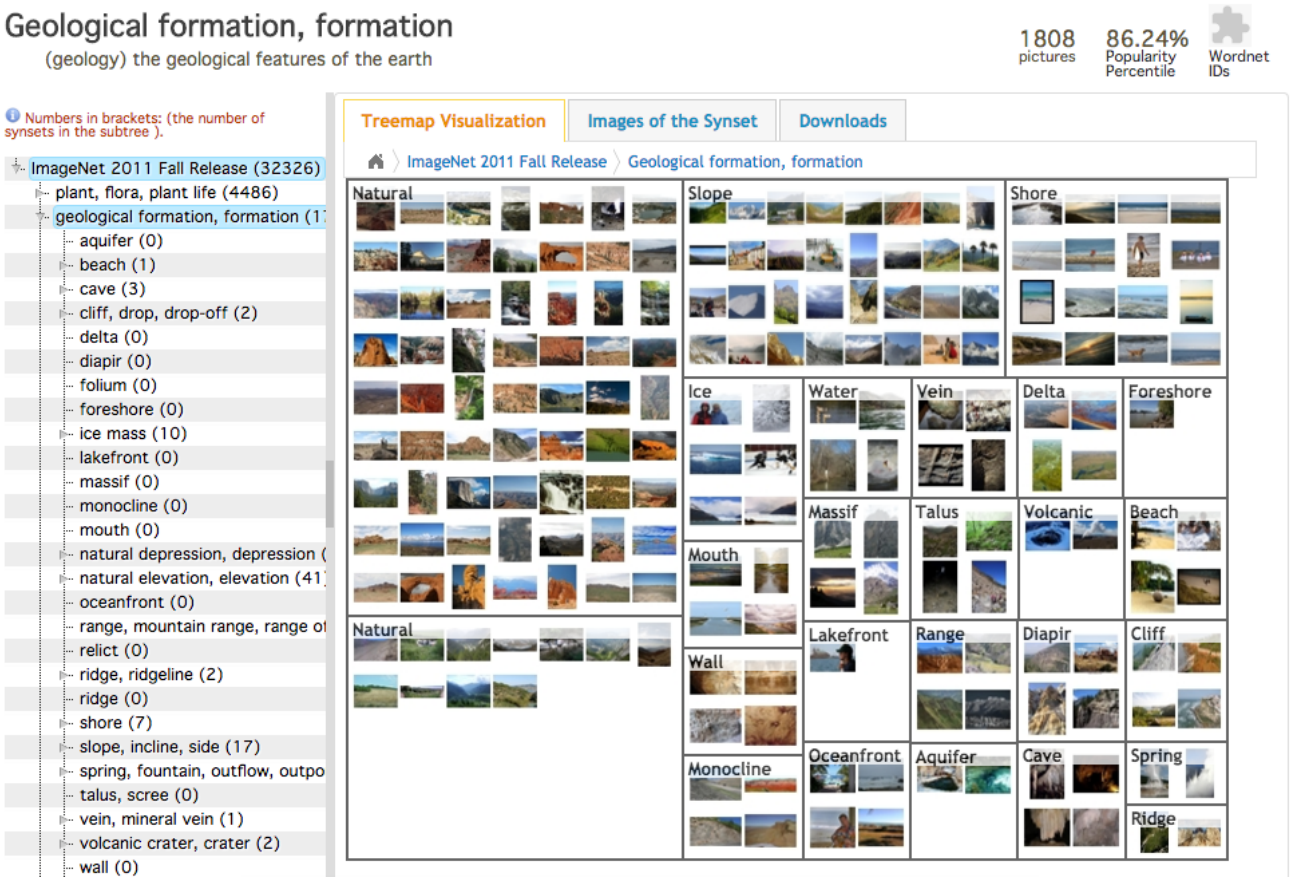
- Pre-2009, many image recognition systems worked on relatively small datasets
  - MNIST: 10 digits
  - CIFAR 10 (right)
  - CIFAR 100
  - …
- Small number of classes (10-100)
- Low resolution (eg. 32 x 32 x 3)
- Performance saturated
  - Difficult to make significant advancements

https://www.cs.toronto.edu/~kriz/cifar.html



ImageNet (2009)

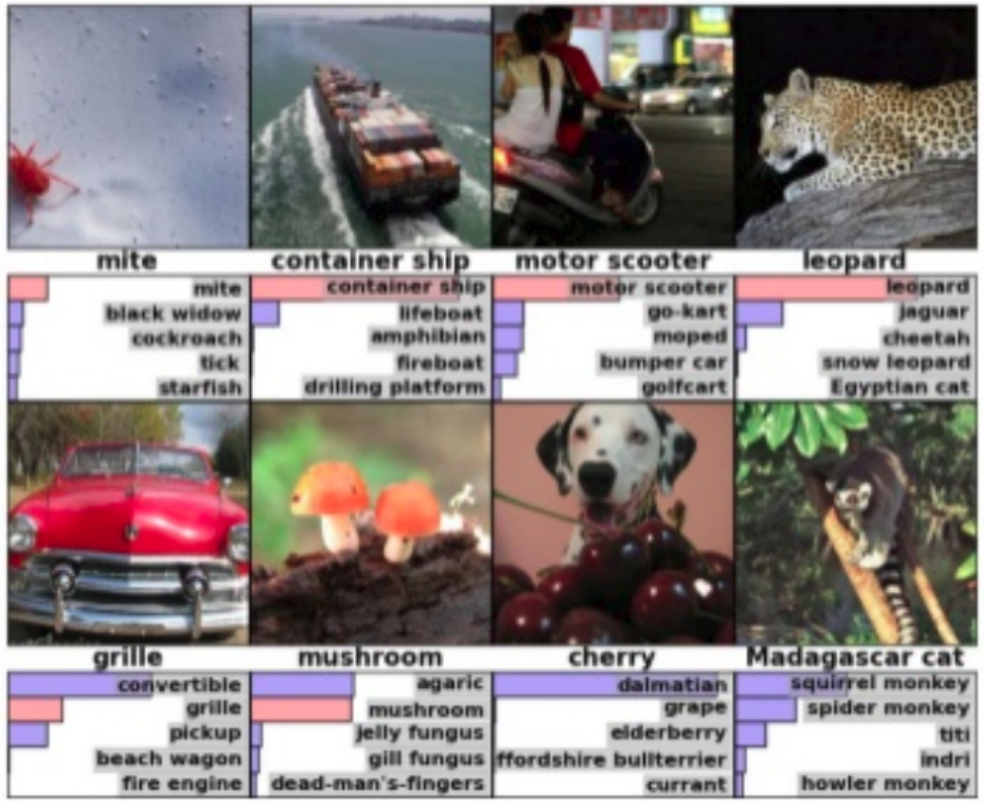
- Better algorithms need better data
- Build a large-scale image dataset
- 2009 CVPR paper:
  - 3.2 million images
  - Annotated by mechanical turk
  - Much larger scale than any previous
- Hierarchical categories



Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009, June). Imagenet: A large-scale hierarchical image database. In *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on* (pp. 248-255). IEEE.

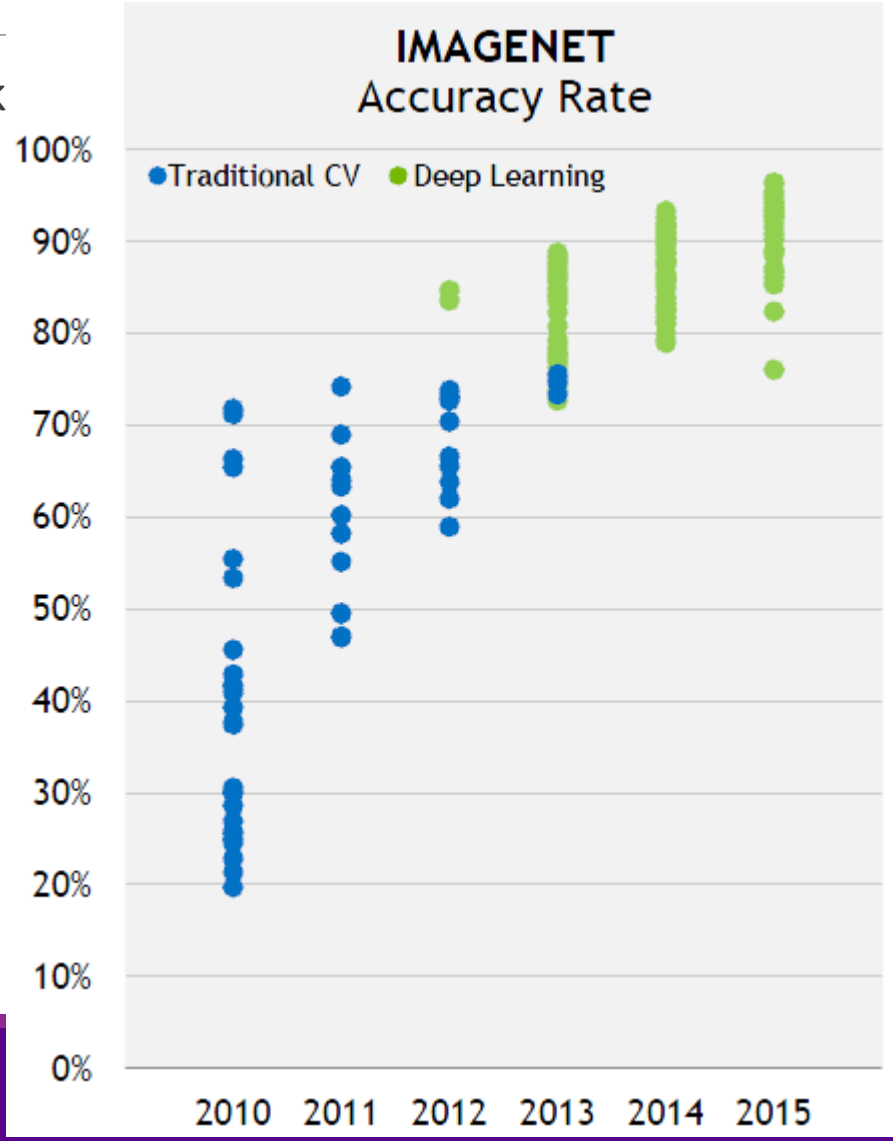
ILSVRC

- ImageNet Large-Scale Visual Recognition Challenge
- First year of competition in 2010
- Many developers tried their algorithms
- Many challenges:
  - Objects in variety of positions, lighting
  - Occlusions
  - Fine-grained categories
    (e.g. African elephants vs. Indian elephants)
  - …



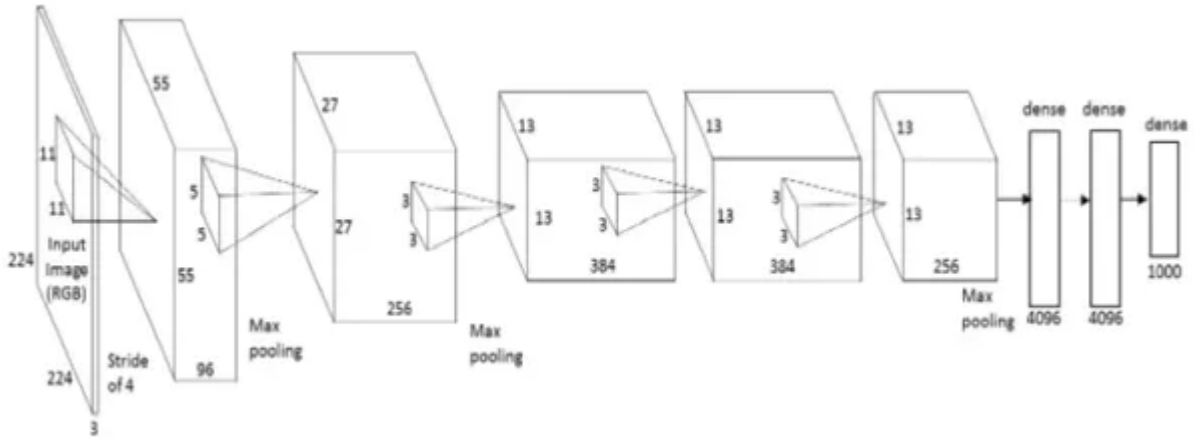
Deep Networks Enter 2012

- 2012: Stunning breakthrough by the first deep network
- "AlexNet" from U Toronto
- Easily won ILSVRC competition
  - Top-5 error rate: 15.3%, second place: 25.6%
- Soon, all competitive methods are deep networks



Alex Net

- Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, University of Toronto, 2012
- Key idea: Build a very deep neural network
- 60 million parameters, 650000 neurons
- 5 conv layers + 3 FC layers
- Final is 1000-way softmax



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- ❑ Deep Networks and Feature Hierarchies
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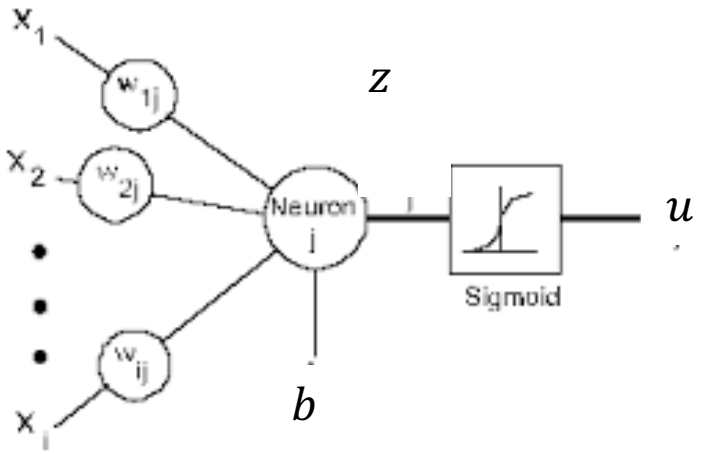
- ❑ Exploring VGG16: A state-of-the-art deep network

Neural Network Units

- Why do deep networks work?
- Recap: Neural networks composed of basic units:
  - z = one linear output (in a hidden or output layer)
  - $\boldsymbol{x} = (x_1, \ldots, x_N)$ = input to the layer
  - $\boldsymbol{w}$ = weight vector
  - b = bias

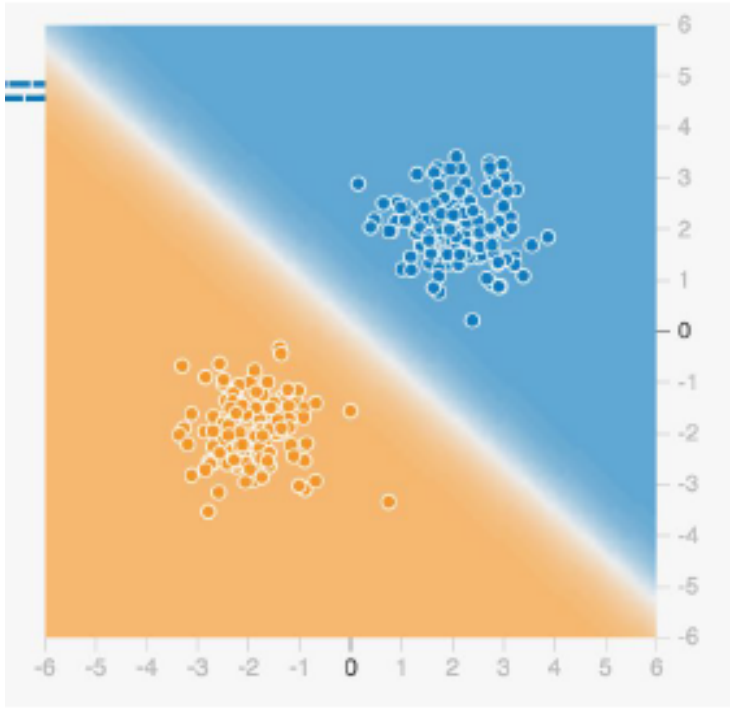


Linear Feature

- Suppose activation is a hard threshold:

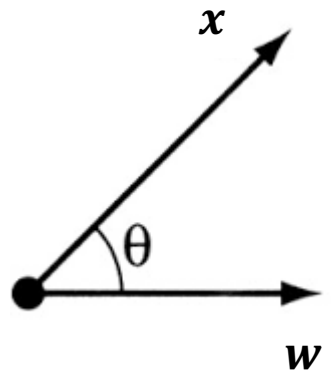
$$g_{act}(z) = \begin{cases} 1 & z > 0 \\ 0 & z < 0 \end{cases}$$

- Then, hidden unit divides input space into two half spaces
- Linearly separated
- Each unit can learn a linear feature $z_m = \boldsymbol{w}_m^T \boldsymbol{x} + b_m$
  - Classifies its input by being in a half space
- Shape of the feature defined by weight $\boldsymbol{w_m}$



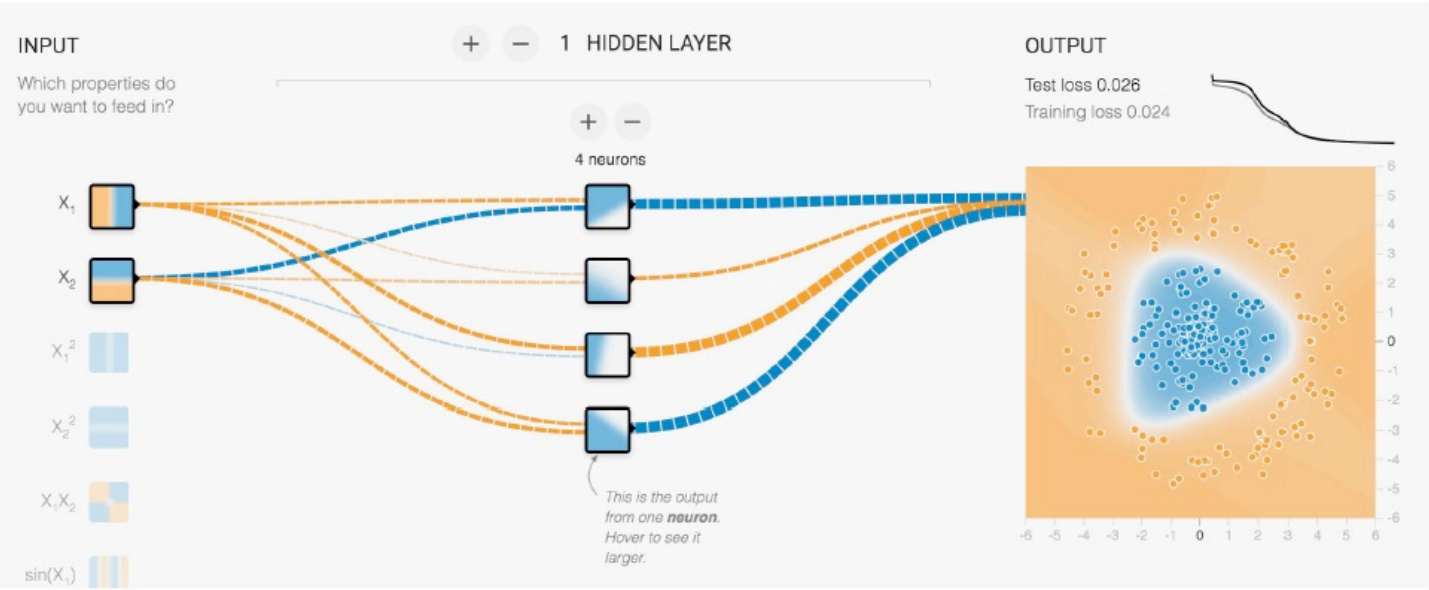
Tuning to a Feature

- Each unit will output a large value when z is large.
- When is z large?
- Recall: $z = \boldsymbol{w}^T \boldsymbol{x} + b = \|\boldsymbol{w}\| \|\boldsymbol{x}\| \cos\theta + b$
- Conclusion: z is maximized when $\theta = 0 \Rightarrow \boldsymbol{x} = \alpha \boldsymbol{w}$
  - $\boldsymbol{x}$ should be aligned with $\boldsymbol{w}$
- Say that unit is tuned to feature $\boldsymbol{w}$



- The weight for a unit describes one desirable "pattern" in the previous layer output

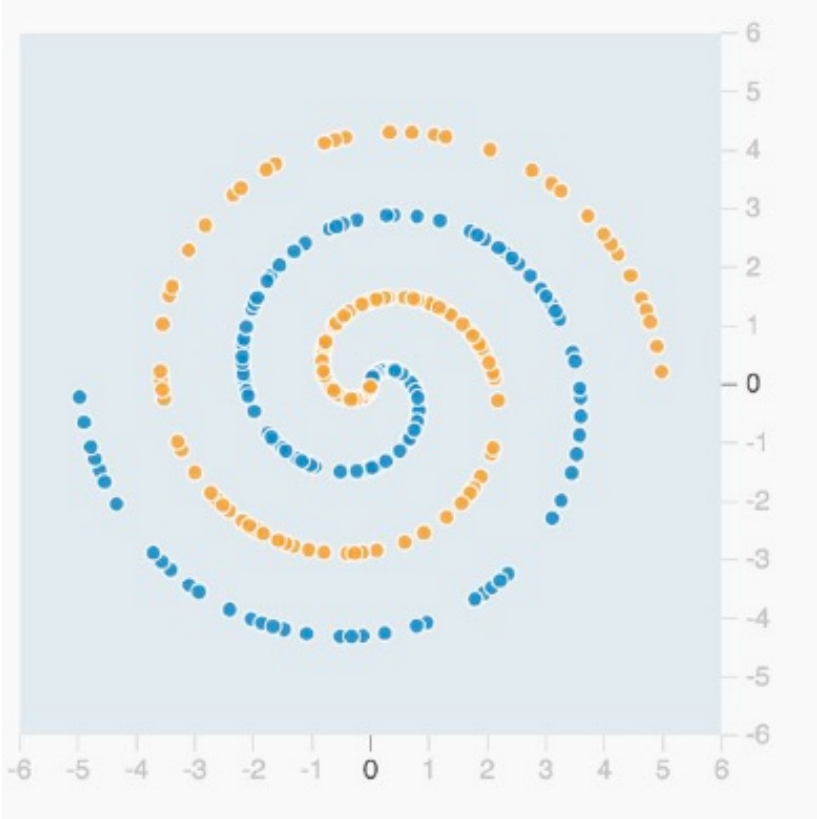
Classifying a Nonlinear Region



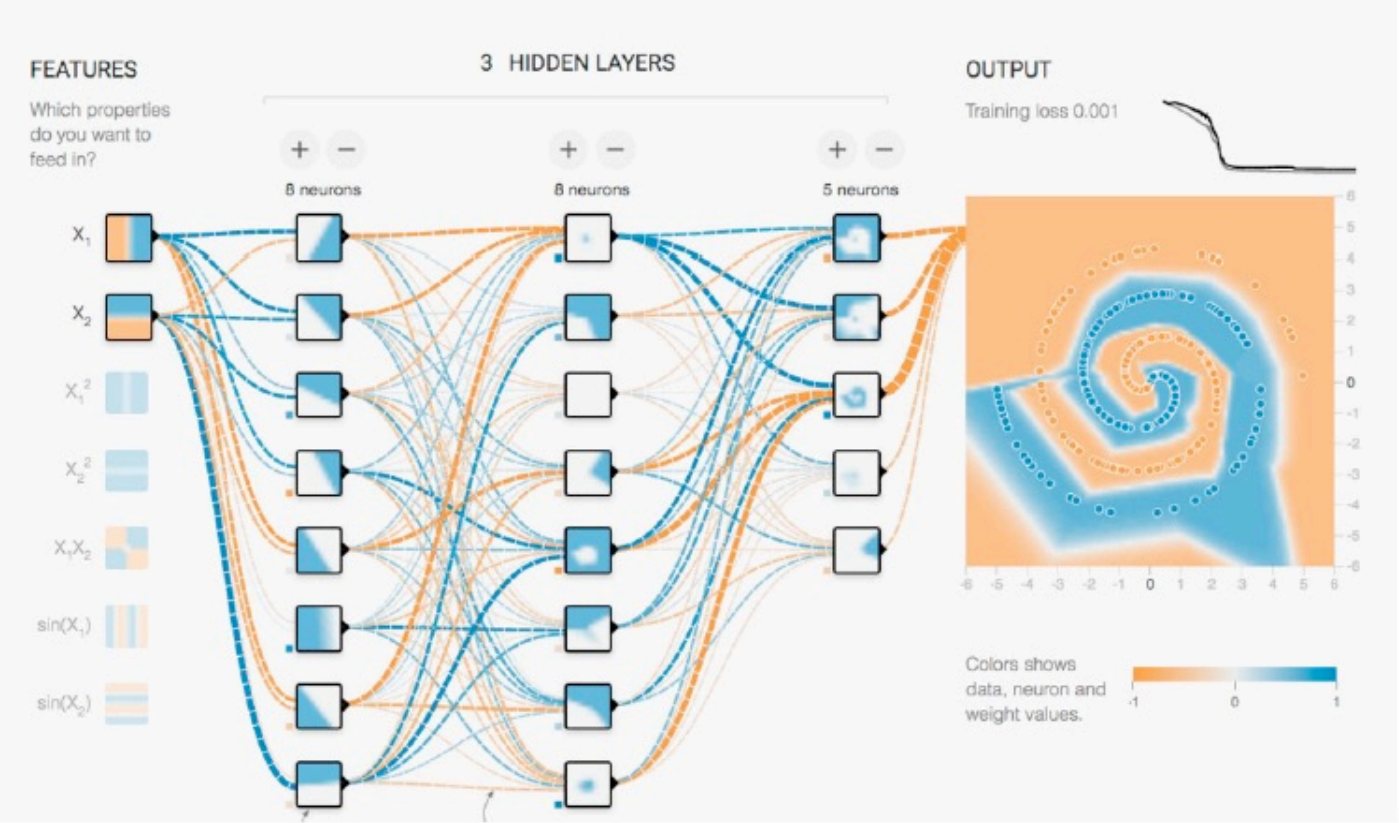
- Nonlinear regions
- Build from linear regions
- Picture to left:
  - Output of Tensorboard
  - Tool in TensorFlow
  - Provided for visualizing neural nets

From Kaz Sato, “Google Cloud Platform Empowers TensorFlow and Machine Learning”

What about a More Complicated Region?



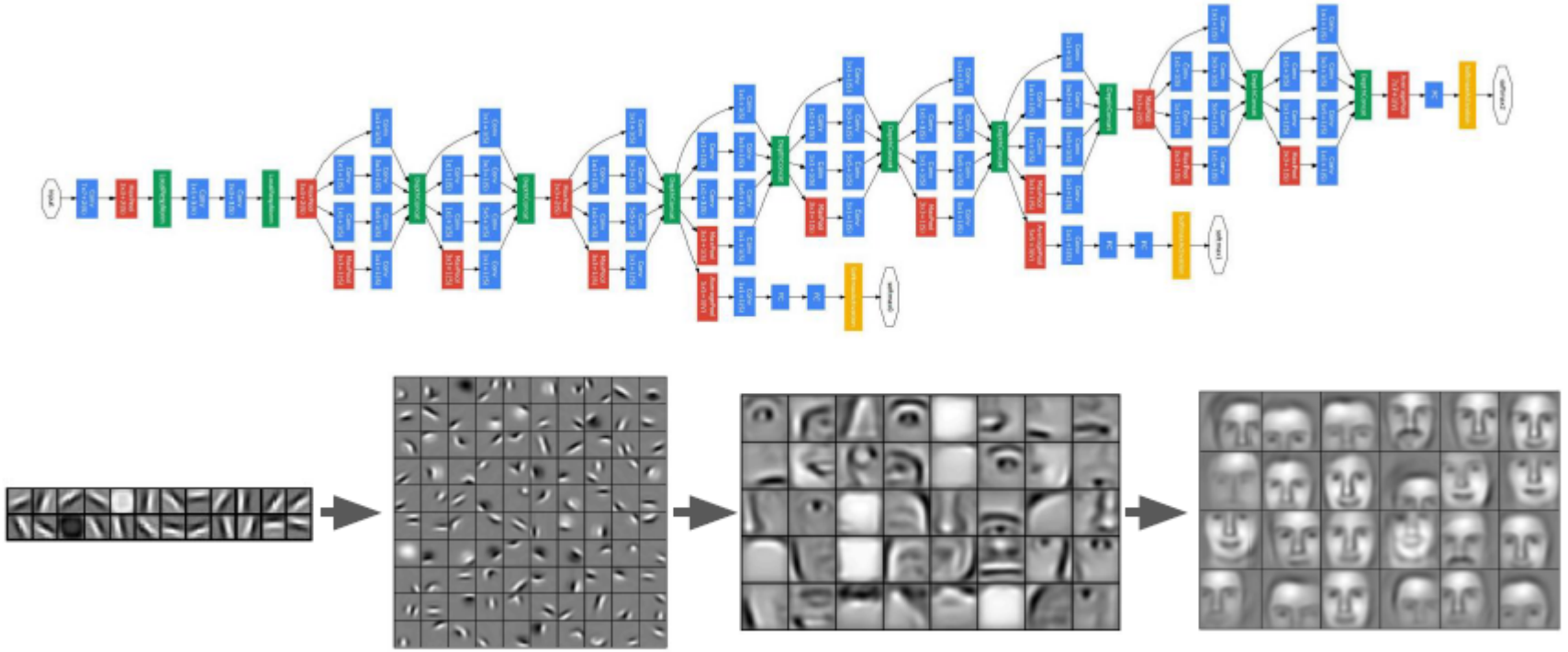
Use Multiple Layers



- More hidden layers
- Hierarchies of features
- Generate very complex shapes

Can you Classify This?

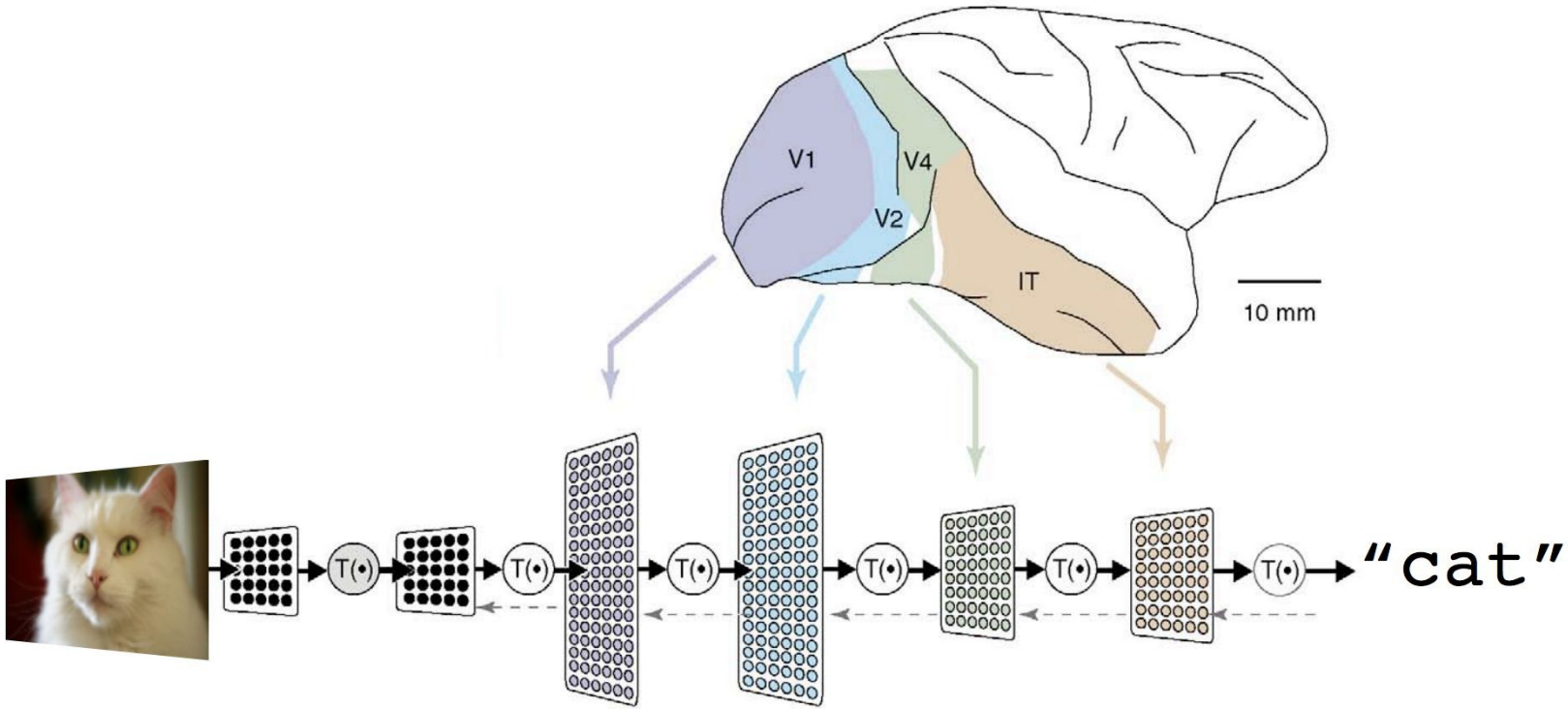
Build a Deep Neural Network



From: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations, Honglak Lee et al.

Biological Inspiration

- Processing in the brain uses multi-layer processing



History and Why Now?

- Early works:
  - Using multiple layers dates to 1965 (Ivakhenko and Lapa)
  - Convolutional networks with pooling (Fukushima, 1979)
  - Back-propagation with a CNN on MNIST (LeCun, 1993)
- But, larger networks were a challenge:
  - Vanishing gradient
  - Lack of data, over-fitting
  - Computational power
- AlexNet:
  - ReLU and dropout

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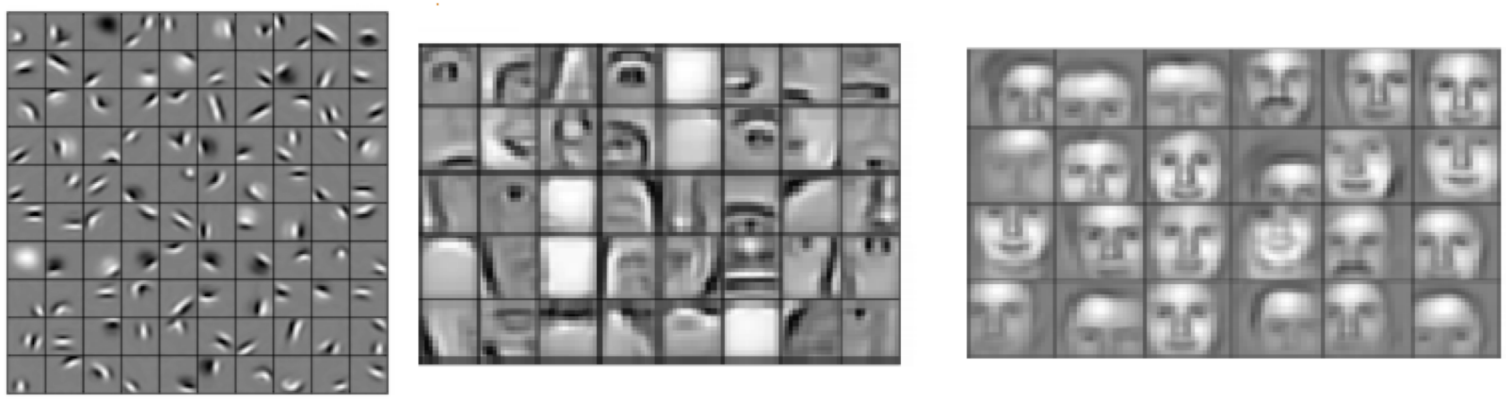
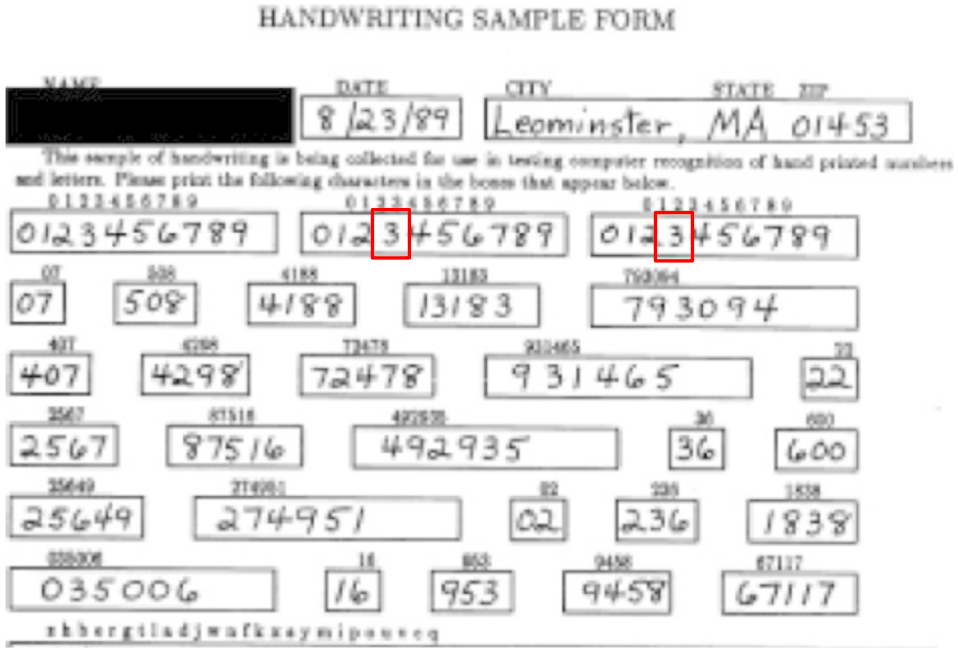
Local Features

- Early layers in deep neural networks often find local features
- Small patterns in larger image
  - Examples: Small lines, curves, edges
- Build more complex classification from the local features



Local Features

- How do we find local features?
- A localization problem.
- Example: Find the digit “3” in the form



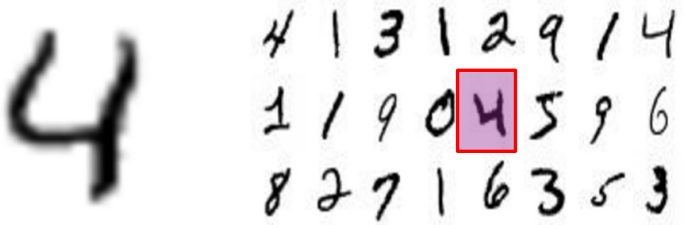
Localization via a Sliding Window

- Simple idea: Find local feature by sliding window
- Large image: X $N_1 \times N_2$ (e.g. 512 x 512)
- Small filter: W $K_1 \times K_2$ (e.g. 8 x 8)
- At each offset (i, j) compute:

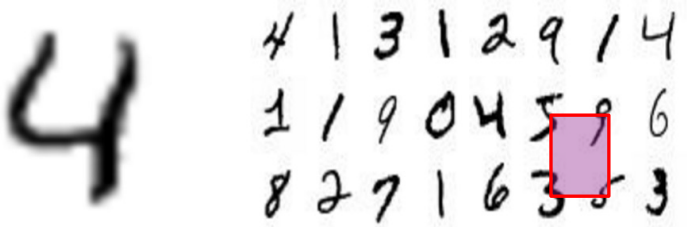
$$Z[i,j] = \sum_{k_1=0}^{K_1-1} \sum_{k_2=0}^{K_2-1} W[k_1, k_2] X[i+k_1, j+k_2]$$

  - Correlation of W with image box starting at (i, j)
  - $Z[i, j]$ is large if feature is present around (i, j)

Filter $\boldsymbol{W}$ Image $\boldsymbol{X}$ $Z[i,j]$



High



Low

Convolution in 1D

- Sliding window is similar to convolution (will make connection precise below)
- Given two signals:
  - x, length N
  - w, length K
- Convolution is:

$$z[n] = \sum_{k=0}^{K-1} w[k]x[n-k]$$

  - Typically zero pad for samples outside boundary
  - Output length is $M = N + K - 1$
- Write $z = w * x$

1D Convolution Example

- Example $x = [1,2,3,4], \quad w = [1,2]$
- Number outputs = 4+2-1=5
- Computations:

$$z[0] = w[0]x[0] = (1)(1) = 1$$
$$z[1] = w[0]x[1] + w[1]x[0] = 2 + 2 = 4$$
$$z[2] = w[0]x[2] + w[1]x[1] = 3 + 4 = 7$$
$$z[3] = w[0]x[3] + w[1]x[2] = 4 + 6 = 10$$
$$z[4] = w[1]x[3] = 8$$

- Can be computed via flip and shift method

Properties of Convolution

- Linearity
- Delta function:

$$x_k * \delta_k = x_k, \qquad \delta_k = \begin{cases} 1 & k = 0 \\ 0 & k \neq 0 \end{cases}$$

- Commutative: $x_k * y_k = y_k * x_k$
- Shifting: Shift input by $L \Rightarrow$ Output shifted by L

$$z_k = x_k * y_k \Rightarrow z_{k-L} = x_{k-L} * y_k$$

- Many more: See a signals & systems class

Convolution in 2D

- Easily extends to higher dimensions
- Given two images:
  - x, size $N_1 \times N_2$
  - w, size $K_1 \times K_2$
- Convolution in 2D is:

$$z[n_1, n_2] = \sum_{k_2=0}^{K_2-1} \sum_{k_1=0}^{K_2-1} w[k_1, k_2] x[n_1 - k_1, n_2 - k_2]$$

  - Output size is $M_1 \times M_2, M_1 = N_1 + K_1 - 1, M_2 = N_2 + K_2 - 1$
- Write $z = w * x$

Convolution and Matched Filter

- Recall, we want the sliding correlation:

$$Z[i,j] = \sum_{k_1=0}^{K_1-1} \sum_{k_2=0}^{K_2-1} W[k_1,k_2] X[i+k_1, j+k_2]$$

- Given kernel W, define the matched filter: $\widetilde{W}[k_1,k_2] = W[K_1-k_1-1, K_2-k_2-1]$
  - Flip horizontally and vertically
- Then,

$$Z[i,j] = (\widetilde{W} * X)[i,j]$$

- Conclusion: Sliding correlation with $W[k_1,k_2]$= Convolution with $\widetilde{W}[k_1,k_2]$

Terminology

- In signal processing and math, convolution includes flipping:

$$z[n_1, n_2] = \sum_{k_2=0}^{K_2-1} \sum_{k_1=0}^{K_2-1} w[k_1, k_2] x[n_1 - k_1, n_2 - k_2]$$

  - For this class, we will call this convolution with reversal

- But, in many neural network packages (including Keras), convolution does not include flipping:

$$z[n_1, n_2] = \sum_{k_2=0}^{K_2-1} \sum_{k_1=0}^{K_2-1} w[k_1, k_2] x[n_1 + k_1, n_2 + k_2]$$

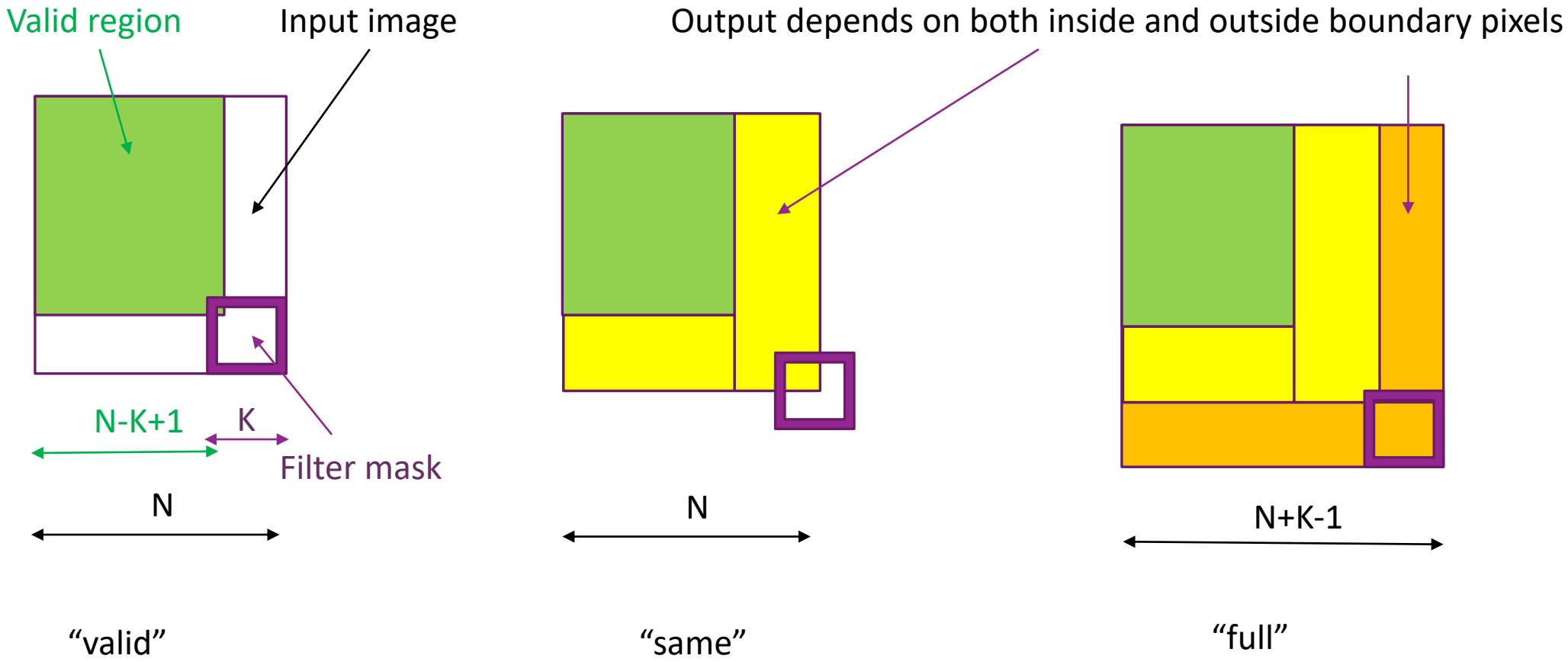
  - Will call this convolution without reversal (= correlation)

Boundary Conditions

- Suppose inputs are
  - x, size $N_1 \times N_2$, w: size $K_1 \times K_2$, $K_1 \leq N_1, K_2 \leq N_2$
  - $z = x * w$ (without reversal)

$$z[n_1, n_2] = \sum_{k_2=0}^{K_2-1} \sum_{k_1=0}^{K_2-1} w[k_1, k_2] x[n_1 + k_1, n_2 + k_2]$$

- Different ways to define outputs
- Valid mode: $0 \leq n_1 < N_1 - K_1 + 1,\ 0 \leq n_2 < N_2 - K_2 + 1$
  - Requires no zero padding
- Same mode: Output size $N_1 \times N_2$
  - Usually use zero padding for neural networks
- Full mode: Output size $(N_1 + K_1 - 1) \times (N_2 + K_2 - 1)$
  - Not used often in neural networks



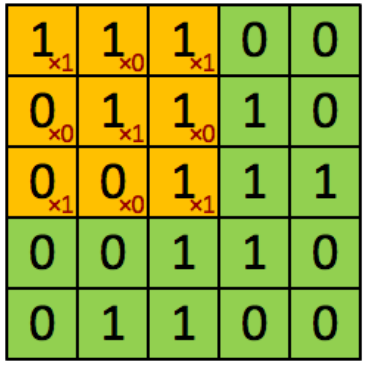
Note that with convolution with reversal, the boundary effect will be observed at the top and left sides (see demo_conv)

Convolution 2D Example

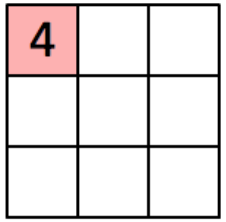
- Kernel

$$W = \widetilde{W} = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

- Compute convolution in valid region
- Partially compute in class
- Finish on your own



Image



Convolved Feature

https://stats.stackexchange.com/questions/199702/1d-convolution-in-neural-networks

Example Convolution in Python

- Load an image
- Use skimage package
  - Many routines for image processing
- Also need scipy signal package

```
import scipy.signal
import skimage.data
```

- Convolution:

```
scipy.signal.convolve2d(im, G, mode='valid')
```

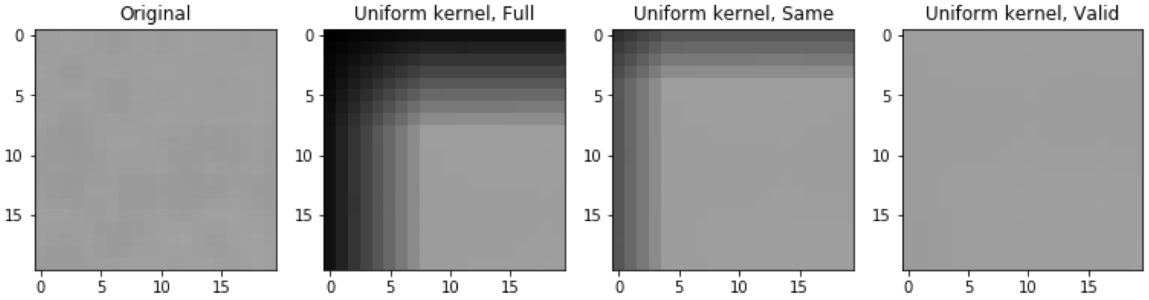
```
im = skimage.data.camera()
disp_image(im)
```

Using convolution for averaging with different boundary options


```
kx = 9
ky = 9
sig = 3
G_unif = np.ones((kx,ky))/(kx*ky)
im_unif_full = scipy.signal.convolve2d(im, G_unif, mode='full')
im_unif_same = scipy.signal.convolve2d(im, G_unif, mode='same')
im_unif_valid = scipy.signal.convolve2d(im, G_unif, mode='valid')
```

```
1 print("Input shape = " + str(im.shape))
2 print("Output shape (Full) = " + str(im_unif_full.shape))
3 print("Output shape (Same) = " + str(im_unif_same.shape))
4 print("Output shape (valid) = " + str(im_unif_valid.shape))
```

```
Input shape = (512, 512)
Output shape (Full) = (520, 520)
Output shape (Same) = (512, 512)
Output shape (valid) = (504, 504)
```




```
# Plot the original image and the three outputs at the top left corner
plt.figure(figsize=(13,13))
plt.subplot(1,4,1)
plt.imshow(im[0:20,0:20], vmin=0, vmax=255, cmap='gray')
plt.title('Original')
plt.subplot(1,4,2)
plt.imshow(im_unif_full[0:20,0:20], vmin=0, vmax=255, cmap='gray')
plt.title('Uniform kernel, Full')
plt.subplot(1,4,3)
plt.imshow(im_unif_same[0:20,0:20], vmin=0, vmax=255, cmap='gray')
plt.title('Uniform kernel, Same')
plt.subplot(1,4,4)
plt.imshow(im_unif_valid[0:20,0:20], vmin=0, vmax=255, cmap='gray')
plt.title('Uniform kernel, Valid')
```

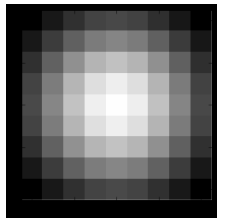
Averaging with different window sizes

Averaging vs. Gaussian Filtering for Noise Removal

- Gaussian filter: Using standard deviation (σ)

  to control the amount of blurring

  Window size K>= $2\sigma + 1$



9x9 Gaussian blur kernel

Gradient filter (edge detection)

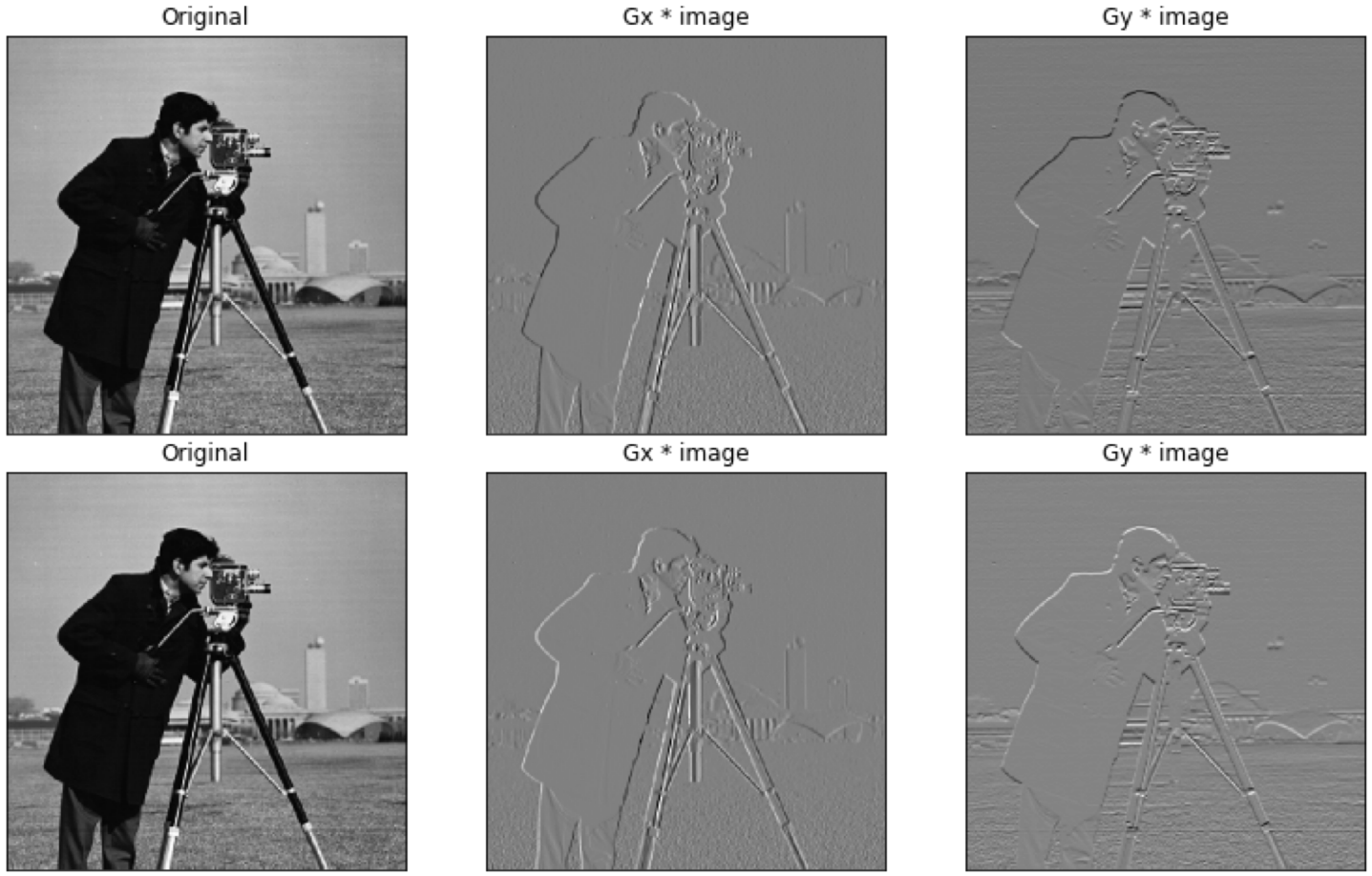
- Sobel filters:

$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, \qquad G_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

- Define $Z_x = G_x * X, \;\; Z_y = G_y * X$ (without reversal)

- Called gradient filters since:
  - $Z_x[i,j] = Z_y[i,j] = 0$ in areas where image is constant
  - $Z_x[i,j] =$ large positive on strong decrease in x-direction = vertical edge from white to black
  - $Z_x[i,j] =$ large negative on strong increase in x-direction = vertical edge from black to white
  - $Z_y[i,j]$ is similarly sensitive to horizontal edges

Computing gradients using Sobel filter



Conv. with reverval (using original filter)

```
Gx = np.array([[1,0,-1],[2,0,-2],[1,0,-1]])  # Gradi
Gy = np.array([[1,2,1],[0,0,0],[-1,-2,-1]])  # Gradi
```

```
# Perform the convolutions
imx = scipy.signal.convolve2d(im, Gx, mode='valid')
imy = scipy.signal.convolve2d(im, Gy, mode='valid')
```

```
Input shape = (512, 512)
Output shape = (510, 510)
```

Conv. without reversal (first flipping the filter)

```
Gxflip = np.fliplr(np.flipud(Gx))
Gyflip = np.fliplr(np.flipud(Gy))

imx = scipy.signal.convolve2d(im, Gxflip, mode='valid')
imy = scipy.signal.convolve2d(im, Gyflip, mode='valid')
```

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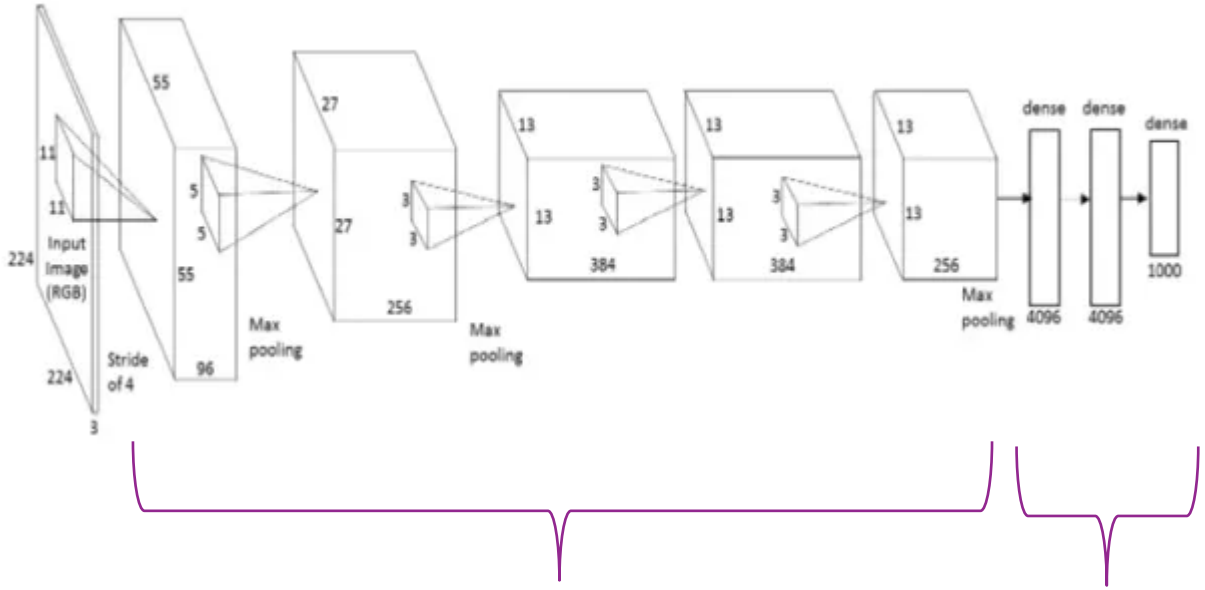
- Exploring VGG16: A state-of-the-art deep network

Classic CNN Structure



- Alex Net example
- Each convolutional layer has:
  - 2D convolution
  - Activation (eg. ReLU)
  - Pooling or sub-sampling

Convolutional layers

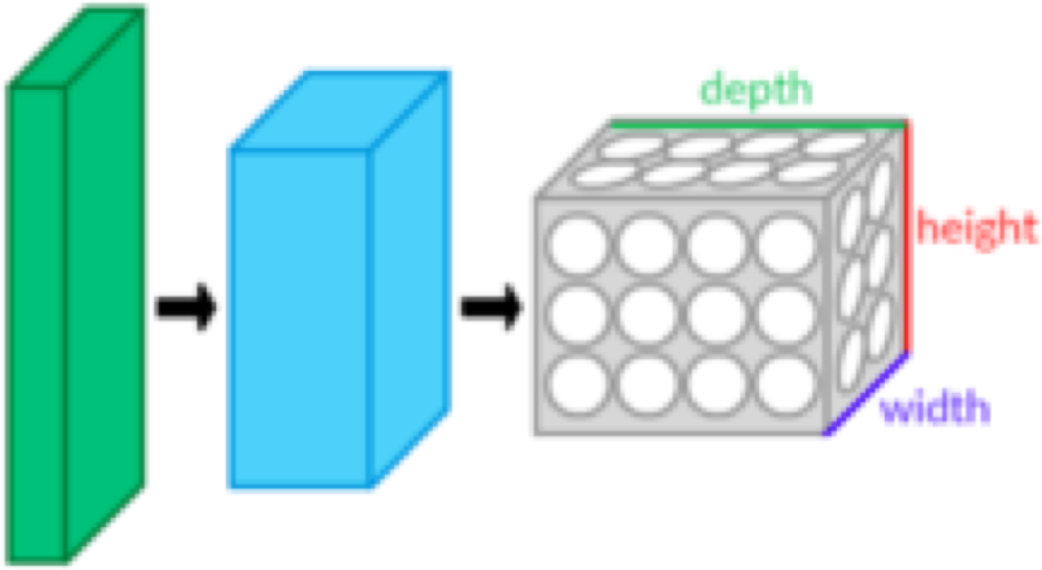
2D convolution with Activation and pooling / sub-sampling

Fully connected layers

Matrix multiplication & activation

Convolutional Inputs & Outputs

- Inputs and outputs are images with multiple channels
  - Number of channels also called the depth
- Can be described as tensors
- Input tensor, X shape (N_1, N_2, N_{in})
  - $N_1, N_2 =$ input image size
  - N_{in} = number of input channels
- Output tensor, Z shape (M_1, M_2, N_{out})
  - $M_1, M_2 =$ output image size
  - N_{out} = number of output channels



Convolutions with Multiple Channels

- Weight and bias:
  - W: Weight tensor, size $(K_1, K_2, N_{in}, N_{out})$
  - b: Bias vector, size N_{out}
- Convolutions performed over space and added over channels

$$Z[i_1, i_2, m] = \sum_{k_1=0}^{K_1-1} \sum_{k_2=0}^{K_2-1} \sum_{n=0}^{N_{in}-1} W[k_1, k_2, n, m] X[i_1 + k_1, i_2 + k_2, n] + b[m]$$

- For each output channel m, input channel n
  - Computes 2D convolution with $W[:, :, n, m]$ (2D filters of size $K_1 \times K_2$)
  - Sums results over n
  - Different 2D filter for each input channel and output channel pair

Activation and Sub-Sampling

- Convolution typically followed by activation and pooling
- Activation, typically ReLU
  - Zeros out negative values
- Sub-sampling
  - Downsample output after activation
  - Different methods (striding, sub-sampling or max-pooling)
  - Output combines local features from adjacent regions
  - Creates more complex features over wider areas
- Details for sub-sampling not covered in this class
  - See web for more info

Convolution vs Fully Connected

- Convolution exploits translational invariance
  - Same features is scanned over whole image
- Greatly reduces number of parameters
  - Nin input channels of size M1xN1, Nout output channels with size M2xN2
  - Fully connected network: Nin*Nout*M1*N1*M2*N2+Nout*M2*N2
  - Convolutional network with K1xK2 filter: Nin*Nout*K1*K2+Nout
- Example: Consider first layer in LeNet
  - 32 x 32 image (1 channel) to 6 channels using 5 x 5 filters
  - Creates 6 x 28 x 28 outputs (keeping only the valid region)
  - Fully connected would require 32 x 32 x 6 x 28 x 28 + 6 x 28 x 28 = 4.9 million parameters!
  - Convolutional layer requires only 6 x 5 x 5 + 6 = 156 parameters
  - Reserve fully connected layers for last few layers (for non-image output such as classification).

Outline

- ❑ Motivation: ImageNet Large-Scale Visual Recognition Challenge (ILSVR)
- ❑ Deep Networks and Feature Hierarchies
- ❑ 2D convolutions
- ❑ Convolutional neural networks
- ❑ Creating and visualizing convolutional layers in Keras
- ❑ Backpropagation training in CNNs
- ❑ Exploring VGG16: A state-of-the-art deep network

Creating Convolutional Layers in Keras

- Done easily with Conv2d
  - Specify input_shape (if first layer), kernel size and number of output channels

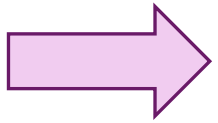
- To illustrate:
  - We create a network with a single convolutional layer
  - Set the weights and biases (normally these would be learned)
  - Run input through the layer (using the predict command)
  - Look at the output

```
# Create network
K.clear_session()
model = Sequential()
model.add(Conv2D(input_shape=input_shape,filters=nchan_out,
                 kernel_size=kernel_size,name='conv2d'))
```

Example 1: Gradients of a BW image

- Create simple convolutional layer
- Input: BW image, $N_{in} = 1$ input channel
- Two output channels: x- and y-gradient, $N_{out} = 2$

$*$ $G_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$, $G_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$



Input.
One channel
Shape = (512,512,1)

Filters
Two gradient

Create a Layer in Keras

```
K.clear_session()
model = Sequential()
kernel_size = Gx.shape
nchan_out = 2
model.add(Conv2D(input_shape=input_shape,filters=nchan_out,
                 kernel_size=kernel_size,name='conv2d'))
```

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 510, 510, 2)       20
=================================================================
Total params: 20
Trainable params: 20
Non-trainable params: 0
_________________________________________________________________
```

- Create a single layer model
- Use the Conv2D layer
- Specify
  - Kernel size
  - Number of output channels
  - Input shape
- Why do we have 20 parameters?

Set the Weights

```
layer = model.get_layer('conv2d')
W, b = layer.get_weights()
print("W shape = " + str(W.shape))
print("b shape = " + str(b.shape))
```

```
W shape = (3, 3, 1, 2)
b shape = (2,)
```

- Read the weights and the shapes

```
W[:,:,0,0] = Gx
W[:,:,0,1] = Gy
b = np.zeros(nchan_out)
layer.set_weights((W,b))
```

- Set the weights to the two filters
- Normally, these would be trained

```
x = im.reshape(batch_shape)
y = model.predict(x)
```

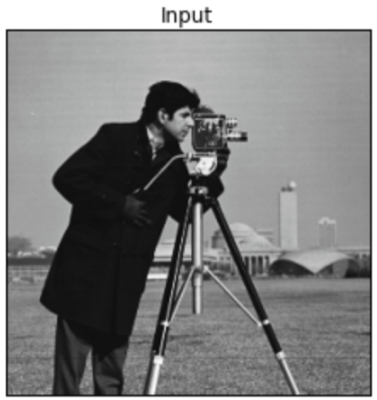
- Run the input through the network

Perform Convolution in Keras

- Create input x
  - Need to reshape
- Use predict command to compute output
- Generates two output channels y

```
x = im.reshape(batch_shape)
y = model.predict(x)
```

Input x

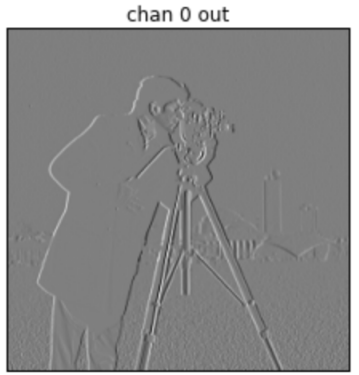


*

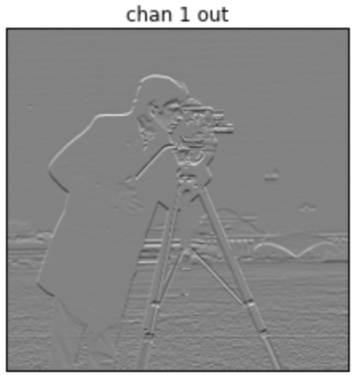
Filters

Two gradients

y[:,:,0]



y[:,:,1]

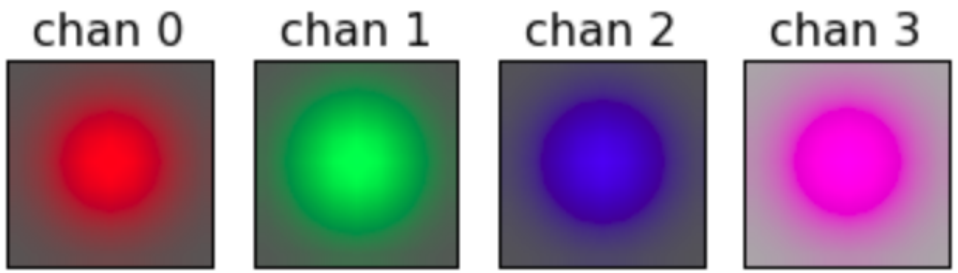


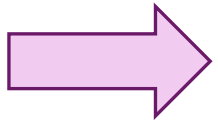
Example 2: Color Input

- Input: Single color input
  - $N_{in} = 3$ input channels
  - Input size per sample = 368 x 487 x 3
- Output: Filter with four different color filters
  - Each kernel is 9 x 9
  - $N_{out} = 4$ output channels

```
Image shape is (368, 487, 3)
```

*





Create the Layer in Keras

```
# Dimensions
nchan_out = 4
kernel_size = (9,9)

# Create network
K.clear_session()
model = Sequential()
model.add(Conv2D(input_shape=input_shape,filters=nchan_out,
                 kernel_size=kernel_size,name='conv2d'))
```

- Model with single layer
- Input shape = (368, 488,3)

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 360, 479, 4)       976
=================================================================
Total params: 976
Trainable params: 976
Non-trainable params: 0
_________________________________________________________________
```

- Output shape = (360,479,4)
- What the number of parameters is 976?

Set the Weights

```
# Color weights
color_wt = np.array([
    [1,    -0.5, -0.5],   # Sensitive to red
    [-0.5,    1, -0.5],   # Sensitive to green
    [-0.5, -0.5,    1],   # Sensitive to blue
    [ 0.5,   -1,  0.5],   # Sensitive to red-blue mix
])

# Gaussian kernel over space
krow, kcol = kernel_size
G = gauss_kernel(krow,kcol,sig=2)

# Multiply by weigthing color
W = G[:,:,None,None]*color_wt.T[None,None,:,:]
b = np.zeros(b.shape)
layer.set_weights((W,b))
```

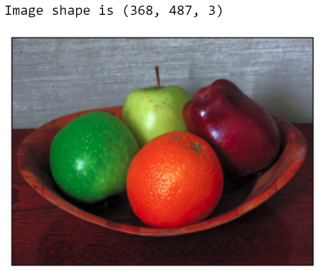
- Consider weight of the form:

$$W[i,j,k,\ell] = G[i,j]C[\ell,k]$$

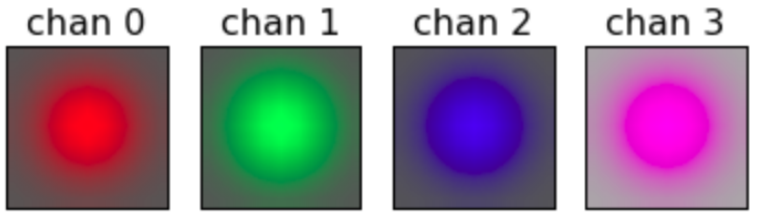
- $G[i,j]$= filter over space
  - Use Gaussian blur
- $C[\ell,k]$ = filter over channel
  - Weighting of color k in output channel ℓ
- Each filter:
  - Average over space and selects color
- Again, normally we would train the weights

Perform Convolution

Input, x
(3 channels)

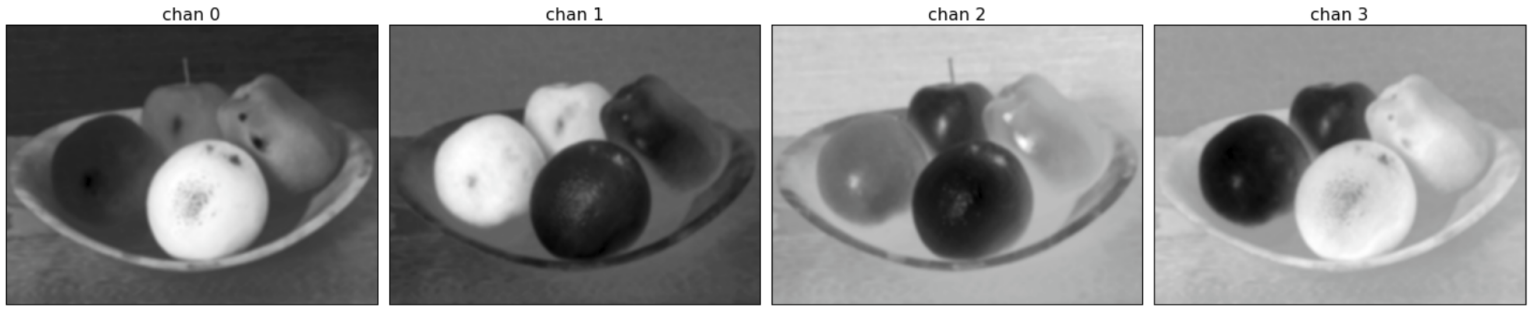


*



Filters, W
(9,9,3,4)

```
y = model.predict(x)
```

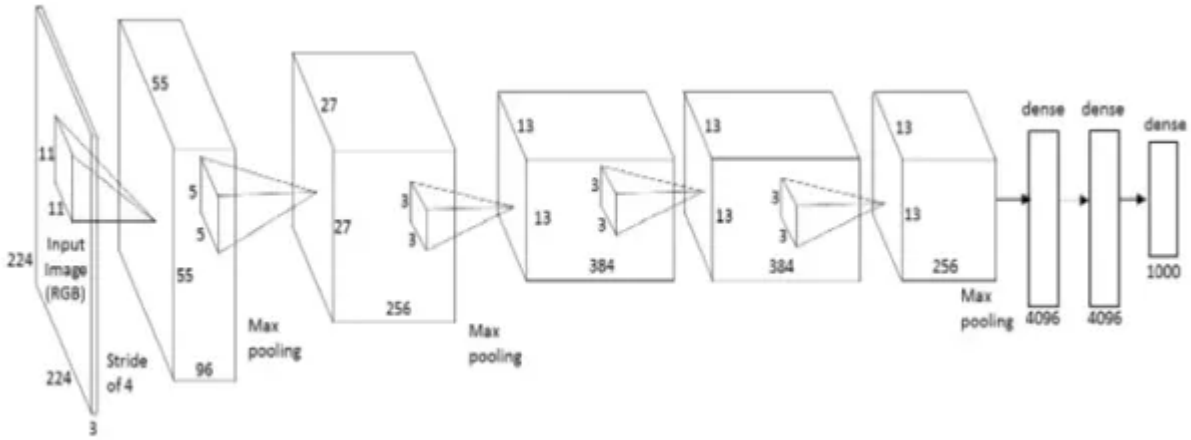


Output y
4 channels

`y[:,:,0]` `y[:,:,1]` `y[:,:,2]` `y[:,:,3]`

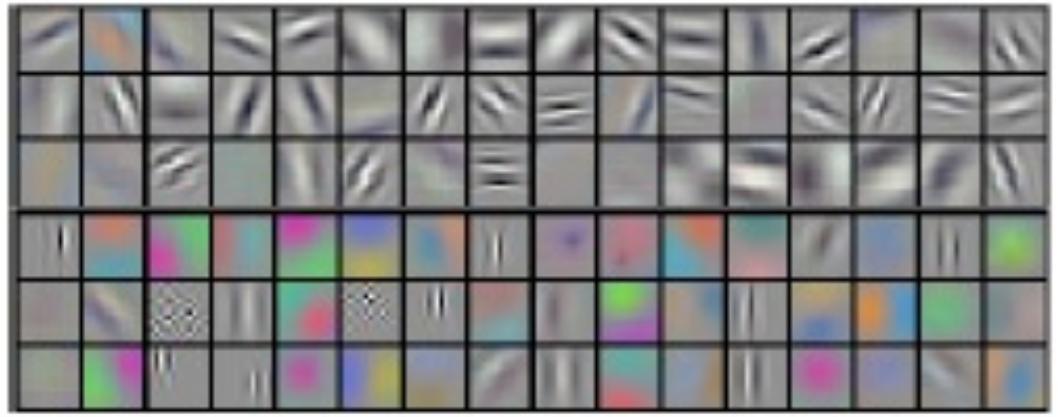
Alex Net

- Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, University of Toronto, 2012
- Key idea: Build a very deep neural network
- 60 million parameters, 650000 neurons
- 5 conv layers + 3 FC layers
- Final is 1000-way softmax
- Use RELU as regularizer
- Use dropout for training
- Top winner in imagenet competition in 2012



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

First layer filter in AlexNet



- AlexNet first layer
  - 96 filters
  - Size 11 x 11 x 3
  - Applied to image of 224 x 224 x 3
- What do these learned features look like?
- Selective to basic low-level features
  - Curves, edges, color transitions, …

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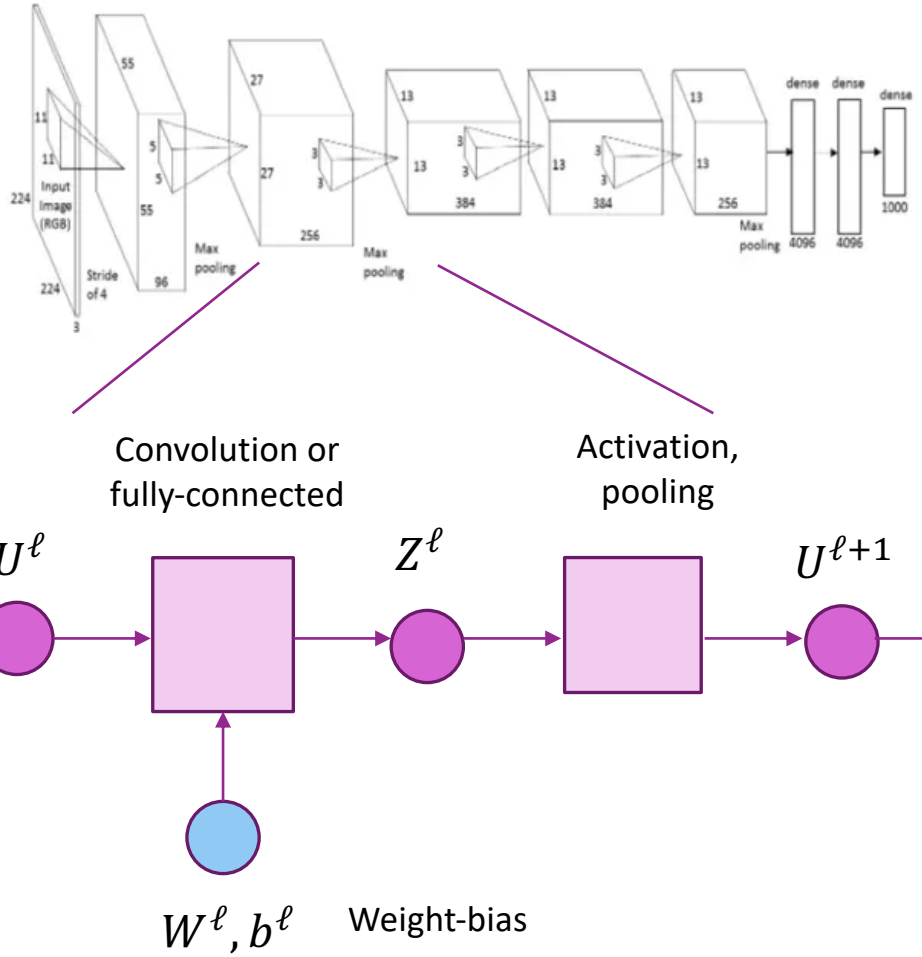
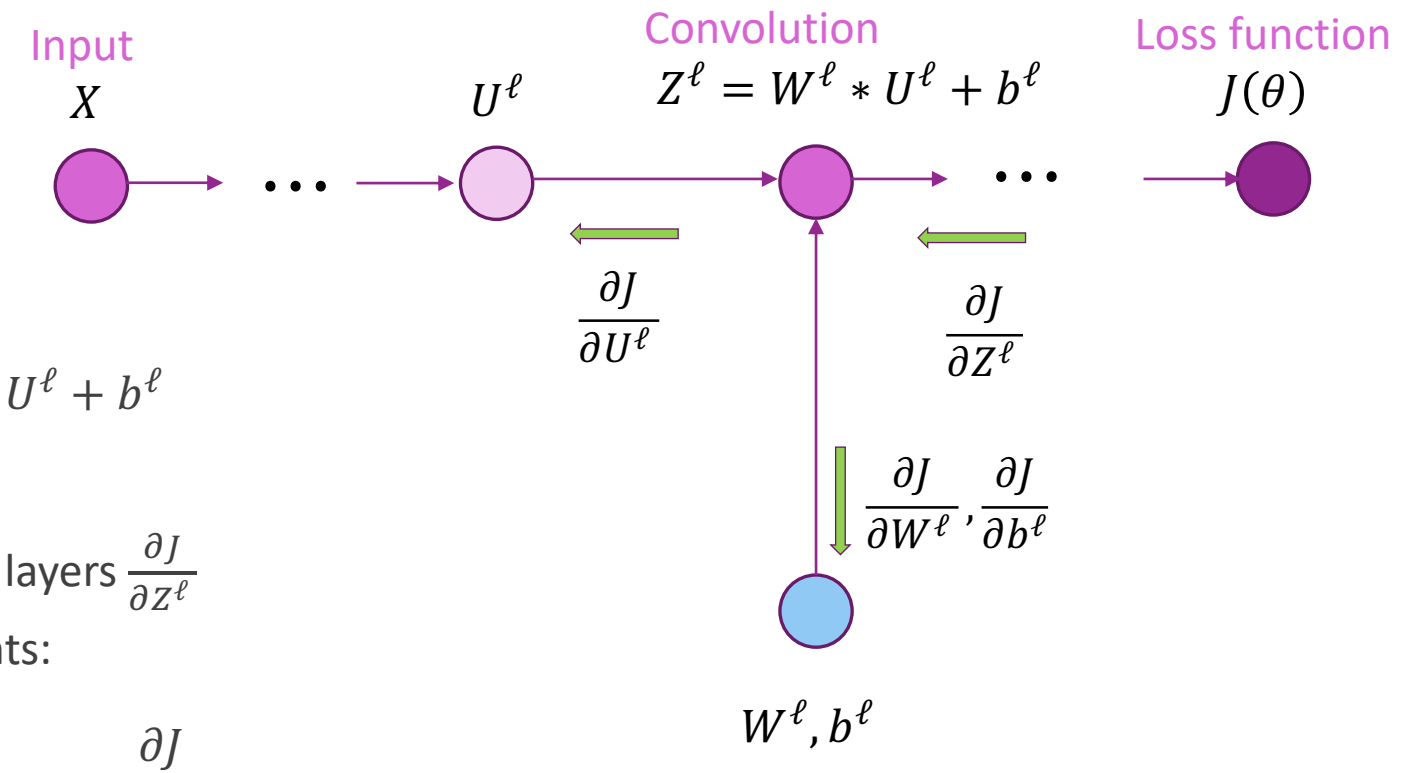
Indexing Multi-Layer Networks

- Similar to single layer NNs
  - But must keep track of layers
- Consider batch of image inputs:
  - $X[i,j,k,n]$, (sample,row,col,channel)
- Input tensor at layer ℓ:
  - $U^{\ell}[i,j,k,n]$ for convolutional layer
  - $U^{\ell}[i,n]$ for fully connected layer
- Output tensor from linear transform:
  - $Z^{\ell}[i,j,k,n]$ or $Z^{\ell}[i,n]$
- Output tensor after activation / pooling:
  - $U^{\ell+1}[i,j,k,n]$ or $U^{\ell+1}[i,n]$



Back-Propagation in Convolutional Layers



- Convolutional layer in forward path

$$Z^\ell = W^\ell * U^\ell + b^\ell$$

- During back-propagation:
  - Obtain gradient tensor from upstream layers $\frac{\partial J}{\partial Z^\ell}$
  - Need to compute downstream gradients:

$$\frac{\partial J}{\partial W^\ell}, \quad \frac{\partial J}{\partial b^\ell}, \quad \frac{\partial J}{\partial U^\ell}$$

Gradient Details

- Write convolution as:

$$Z[i_1, i_2, m] = \sum_{k_1=0}^{K_1-1} \sum_{k_2=0}^{K_2-1} \sum_{n=0}^{N_{in}-1} W[k_1, k_2, n, m] U[i_1 + k_1, i_2 + k_2, n] + b[m]$$

  - Drop layer index ℓ and sample index i

- In backpropagation, we receive gradient tensor: $\frac{\partial J}{\partial Z[i_1, i_2, m]}$

- First compute gradient wrt weights: $\frac{\partial J}{\partial W[k_1, k_2, n, m]}$

Gradient With Respect to Weights

- Gradient wrt weights:

$$\frac{\partial Z[i_1, i_2, m]}{\partial W[k_1, k_2, n, m]} = U[i_1 + k_1, i_2 + k_2, n]$$

- By chain rule:

$$\frac{\partial J}{\partial W[k_1, k_2, n, m]} = \sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} \frac{\partial Z[i_1, i_2, m]}{\partial W[k_1, k_2, n, m]} \frac{\partial J}{\partial Z[i_1, i_2, m]}$$

$$= \sum_{i_1=1}^{N_1} \sum_{i_2=1}^{N_2} U[i_1 + k_1, i_2 + k_2, n] \frac{\partial J}{\partial Z[i_1, i_2, m]}$$

- Gradient wrt weights can be computed via convolution
  - Convolve input U with gradient tensor $\frac{\partial J}{\partial Z[i_1, i_2, m]}$
- Similar computations for gradients with respect to $\frac{\partial J}{\partial b}$, $\frac{\partial J}{\partial U}$
  - See homework

GPUs

- State-of-the-art networks involve millions of parameters
- Require enormous datasets
- Conventional processors cannot train in reasonable time
- Use Graphics Processor Units
  - Originally for graphics acceleration
  - Now essential for deep learning
- Cannot use the GPU on your laptop
- But, can:
  - Rent GPU instances in cloud (~$0.80 / hour)
  - Purchase GPU workstation (~$2000)

Batch Size	Training Time CPU	Training Time GPU	GPU Speed Up
64 images	64 s	7.5 s	8.5X
128 images	124 s	14.5 s	8.5X
256 images	257 s	28.5 s	9.0X

Speed up on 2012 ImageNet winner using Nvidia Tesla K40
From http://www.nvidia.com/content/events/geoInt2015/LBrown_DL.pdf

Much faster results available today

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Pre-Trained Networks

- State-of-the-art networks take enormous resources to train
  - Millions of parameters
  - Often days of training, clusters of GPUs
  - Extremely expensive
- Pre-trained networks in Keras
  - Load network architecture and weights
  - Models available for many state-of-the-art networks
- Can be used for:
  - Making predictions
  - Building new, powerful networks (see lab)

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.715	0.901	138,357,544	23
VGG19	549 MB	0.727	0.910	143,667,240	26
ResNet50	99 MB	0.759	0.929	25,636,712	168
InceptionV3	92 MB	0.788	0.944	23,851,784	159
InceptionResNetV2	215 MB	0.804	0.953	55,873,736	572
MobileNet	17 MB	0.665	0.871	4,253,864	88

https://keras.io/applications/

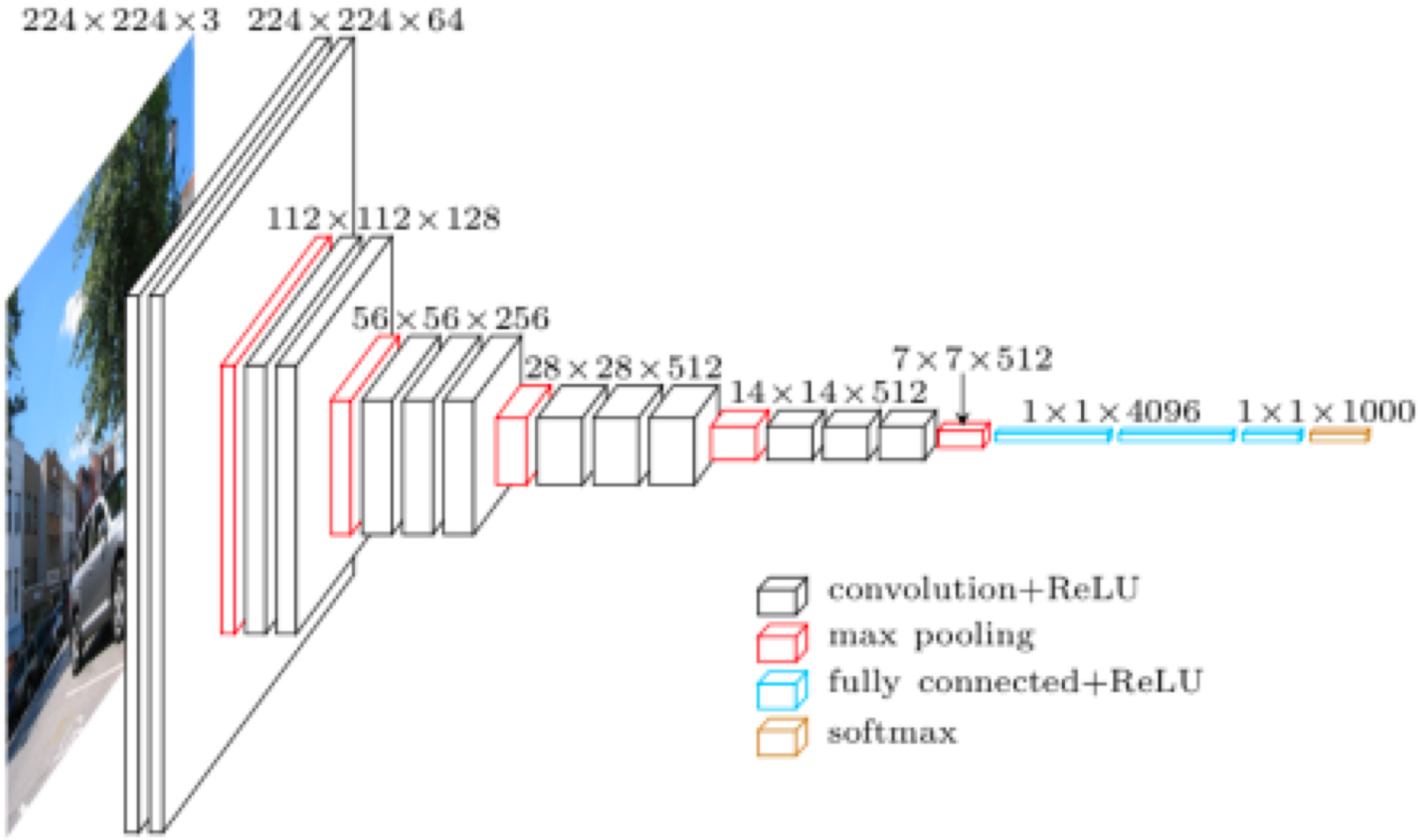
VGG16

- From the Visual Geometry Group
  - Oxford, UK
- Won ImageNet ILSVRC-2014
- Remains a very good network
- Lower lower layers are often used as feature extraction layers for other tasks
- Will load this network today

Model	top-5 classification error on ILSVRC-2012 (%)	
	validation set	test set
16-layer	7.5%	7.4%
19-layer	7.5%	7.3%
model fusion	7.1%	7.0%

http://www.robots.ox.ac.uk/~vgg/research/very_deep/

K. Simonyan, A. Zisserman
Very Deep Convolutional Networks for Large-Scale Image Recognition
arXiv technical report, 2014



https://blog.heuritech.com/2016/02/29/a-brief-report-of-the-heuritech-deep-learning-meetup-5/

Loading the Pre-Trained Network

```
from keras.applications.vgg16 import VGG16
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input, decode_predictions
```

- Load the packages

```
model = VGG16(weights='imagenet')
```

- Create the model
  - Downloads the h5 file
  - First time, may be a while
  - 500 MB file

Display the Network

```
: model.summary()
```

Layer (type)	Output Shape	Param #
input_5 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000

```
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
```

- Very deep: 16 layers (Do not count pooling layers)
- 130 million parameters!

Get Some Test Images

- Get images from the web of some category (e.g. elephants)
- Many possible sources.
  - Example: Flickr API (see Demo in github)
- Re-size / pad images so that they match expected input of VGG16
  - Input shape (224, 224, 3)




Make Predictions

```
x = preprocess_input(x)
```

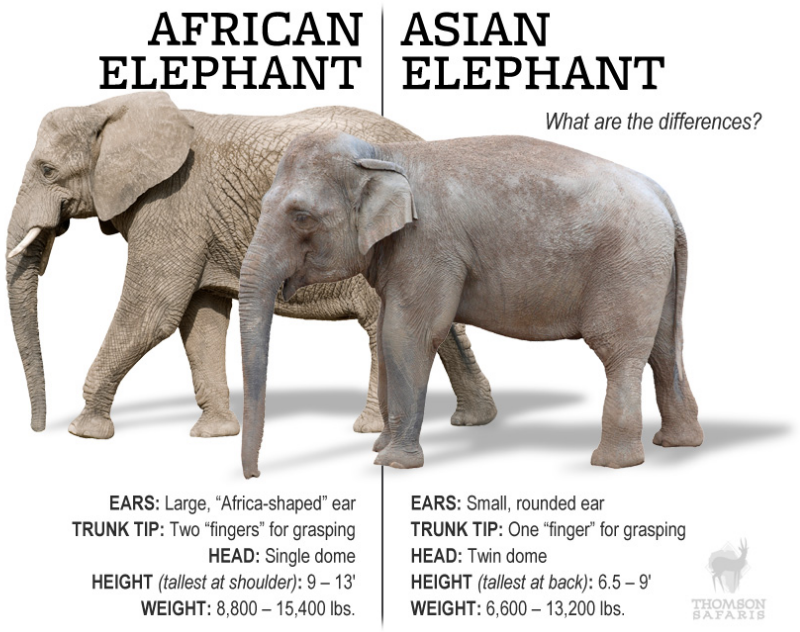
```
preds = model.predict(x)
preds_decoded = decode_predictions(preds, top=3)
```

	class 0	class 1	class 2	prob 0	prob 1	prob 2
0	Indian_elephant	African_elephant	tusker	0.776757	0.196798	0.026314
1	African_elephant	tusker	Indian_elephant	0.514596	0.414825	0.057157
2	tusker	Indian_elephant	African_elephant	0.682218	0.217784	0.099942
3	African_elephant	tusker	Indian_elephant	0.736568	0.228160	0.035263
4	African_elephant	tusker	Indian_elephant	0.409717	0.301944	0.287880
5	water_buffalo	African_elephant	warthog	0.737919	0.129731	0.037343
6	African_elephant	tusker	Indian_elephant	0.745698	0.140428	0.103136
7	Indian_elephant	tusker	African_elephant	0.970890	0.026875	0.002234
8	African_elephant	tusker	Indian_elephant	0.819497	0.108567	0.067853
9	tusker	African_elephant	Indian_elephant	0.499149	0.338156	0.162537

- Pre-process
- Predict
  - Runs input through network
- Decode predictions
  - Creates data structure for outputs

ImageNet Classification can be Hard

- Some categories differences are subtle



	class 0	class 1	class 2	prob 0	prob 1	prob 2
0	Indian_elephant	African_elephant	tusker	0.776757	0.196798	0.026314
1	African_elephant	tusker	Indian_elephant	0.514596	0.414825	0.057157
2	tusker	Indian_elephant	African_elephant	0.682218	0.217784	0.099942
3	African_elephant	tusker	Indian_elephant	0.736568	0.228160	0.035263
4	African_elephant	tusker	Indian_elephant	0.409717	0.301944	0.287880
5	water_buffalo	African_elephant	warthog	0.737919	0.129731	0.037343
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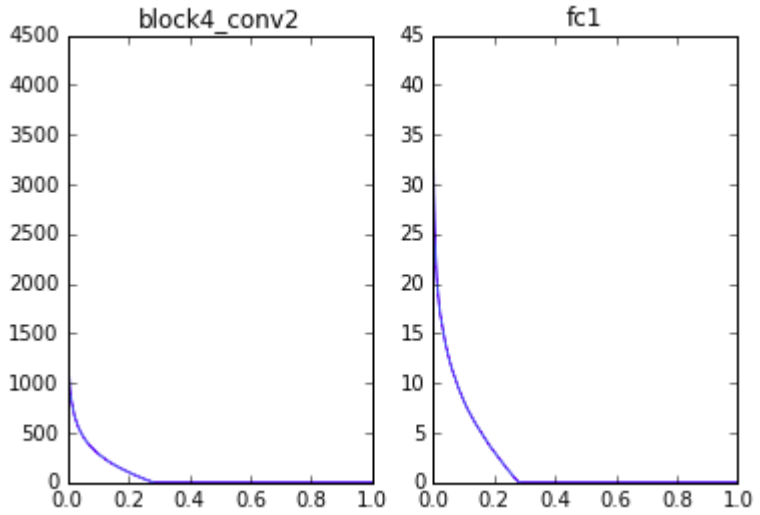
Intermediate Layers

```
from keras.models import Model

# Construct list of layers
layer_names = ['block4_conv2', 'fc1']
out_list = []
for name in layer_names:
    out_list.append(model.get_layer(name).output)

# Create the model with the intermediate layers
model_int = Model(inputs=model.input, outputs=out_list)
```

```
y = model_int.predict(x)
```



- Often need outputs of hidden layers
- Provides "latent" representation of image
  - Can be useful for other tasks
  - See lab
- In Keras, create new model
  - Specify output layers
- Predict with new model to extract hidden outputs
- Hidden layers see high level of sparsity
  - Many coefficients are zero

Output of first few convolution layers

- Output of first convolution layers (first 4 channels) for a given image

First, third, and fourth channels looks like gradient images in different directions

In general, first few layers extract low level features!

Output of higher layers

- Output of last layer before the flatten layer (first 4 channels)

- These carry “high level semantic information” about object category
- See demo for outputs of other layers

Try It Yourself!

In-Class Excerise

Find any image of your choice and use the pre-trained network to make a prediction.

- Download the image to your directory
- Load it into an image batch
- Predict the class label and decode the predictions

= ?

Regularization: Batch normalization

- In addition to normalize the input data, also normalize the input to each intermediate layer within each batch
- Then rescale the data using two parameters
- Can use a higher learning rate and hence converge faster
- Reduces overfitting: more invariant to intensity shift

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma\widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

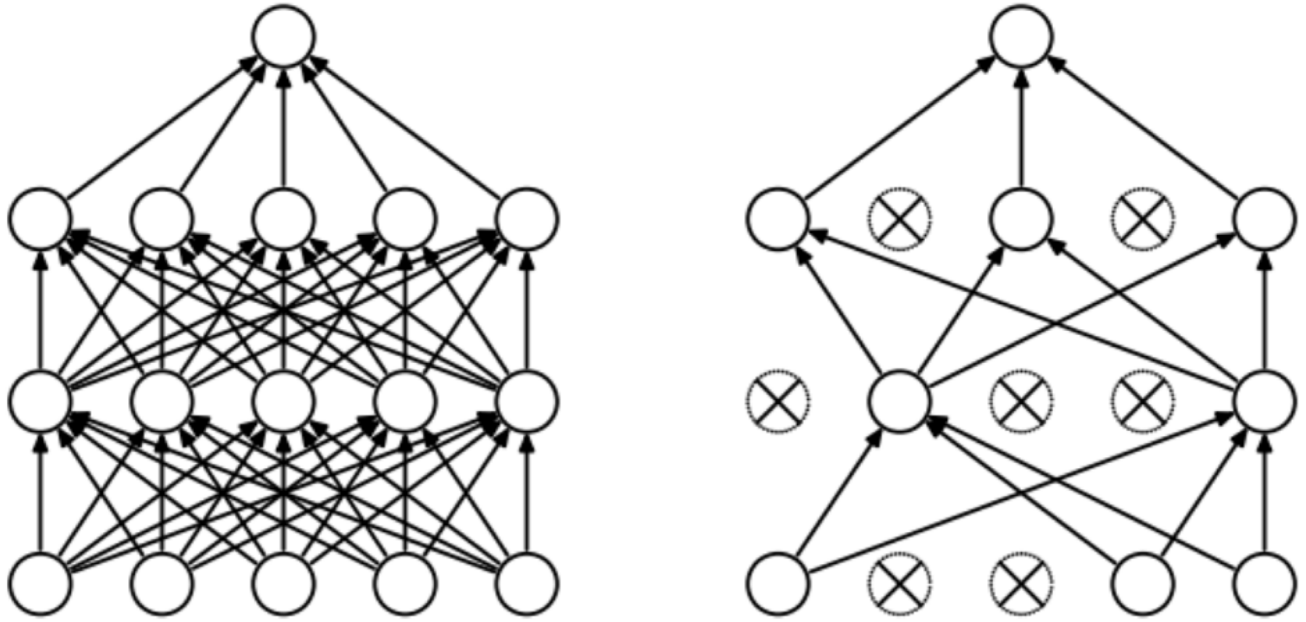
Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

https://www.youtube.com/watch?v=nUUqwaxLnWs
https://towardsdatascience.com/batch-normalization-in-neural-networks-1ac91516821c

Sergey Ioffe, Christian Szegedy: **Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift.**
https://arxiv.org/pdf/1502.03167v3.pdf

Regularization: Dropout

- Drop some percentage of nodes in each layer both in forward and backward pass in each training epoch
- Implemented by setting a certain input elements to this layer to zero
- Dropout forces a neural network to learn more robust features that are useful in conjunction with many different random subsets of the other neurons.
- Reduces overfitting
- Need more epochs to converge but each epoch takes less time



(a) Standard Neural Net (b) After applying dropout.

Srivastava, Nitish, et al. ”Dropout: a simple way to prevent neural networks from overfitting”, JMLR 2014

Data Augmentation

- When the training data are limited, can generate additional samples based on the anticipated diversity in the input data
- Image augmentation: by shifting, scaling, rotating the original training images

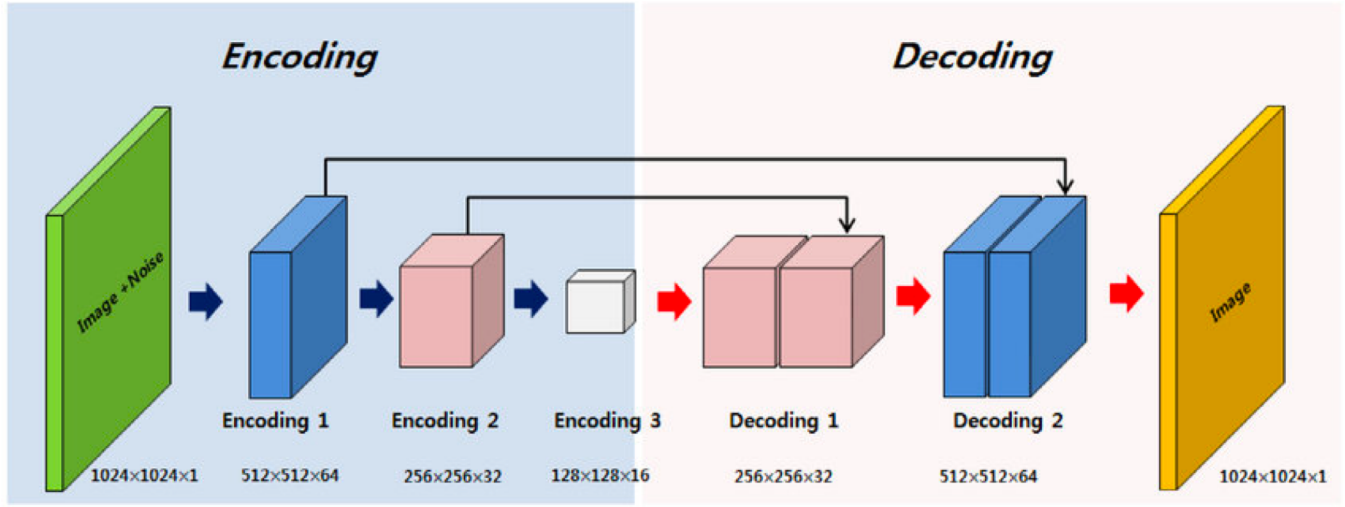
```
from keras.preprocessing.image import ImageDataGenerator
datagen = ImageDataGenerator(
    featurewise_center=False,  # set input mean to 0 over the dataset
    samplewise_center=False,  # set each sample mean to 0
    featurewise_std_normalization=False,  # divide inputs by std of the dataset
    samplewise_std_normalization=False,  # divide each input by its std
    zca_whitening=False,  # apply ZCA whitening
    rotation_range=0,  # randomly rotate images in the range (degrees, 0 to 180)
    width_shift_range=0.1,  # randomly shift images horizontally (fraction of total width)
    height_shift_range=0.1,  # randomly shift images vertically (fraction of total height)
    horizontal_flip=True,  # randomly flip images
    vertical_flip=False)  # randomly flip images
```

Demo: Training a small image classifier

- Train an image classifier using the CIFAR10 data (32x32 color images, 10 classes)
- Two conv layer each followed by max pooling, two dense layer
- Compare different training procedures:
  - Basic: Without batch normalization nor dropout: Stops improving after one epoch
  - +BN: With batch normalization : significant improvement
  - +Dropout: With slightly better performance on validation set
  - +Data Augmentation:
  - Performance limited by the small training set and limited number of epochs used.
- Go through demo

Autoencoder

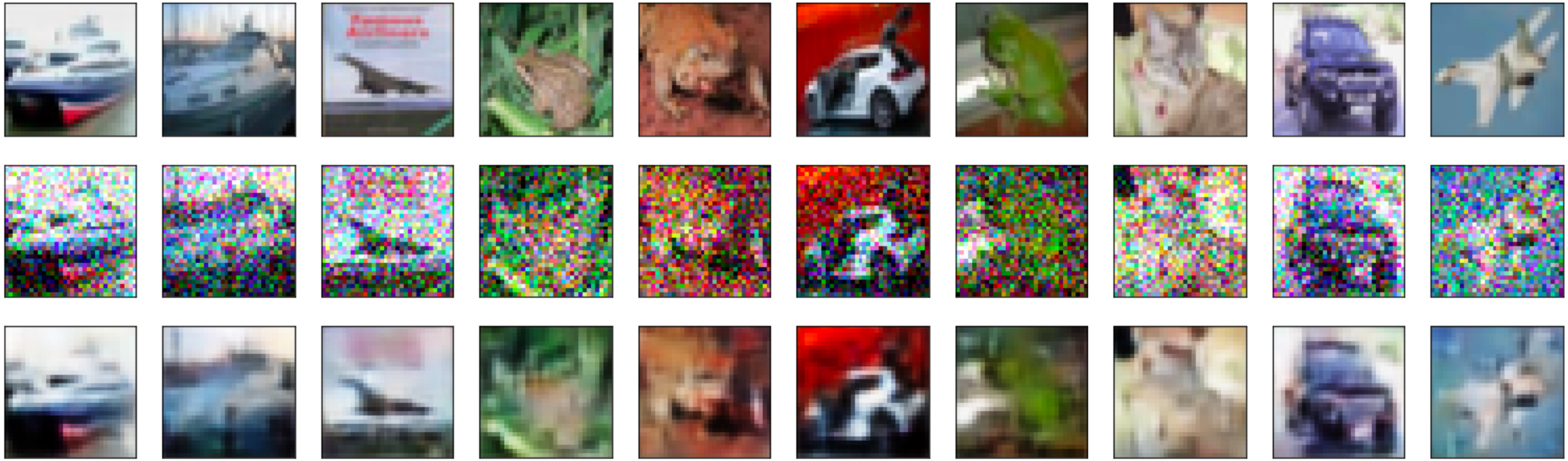
- CNN is not limited for classification!
- When all the layers are convolution, the output can have the same shape as the input (speech->speech, image->image)
- Autoencoder= Encoder+Decoder
- Encoder: image-> features;
- Decoder: features -> image



Symbol	Description	Parameters
➡	Convolution and ReLu activation	Kernel size = 3 × 3 Stride = 2 × 2
➡	Deconvolution and ReLu activation	Kernel size = 3 × 3 Stride = 2 × 2
→	Concatenate	Concatenate Encoding 1, Decoding 2 Concatenate Encoding 2, Decoding 1

Demo: Autoencoder for image denoising

- Using a subset of training samples in the cifar10 dataset
- 2 encoding layers producing 32 (or 16) channels, 3 decoding layers



Other Applications of autoencoders

- Image processing applications:
  - Image compression
  - Image segmentation
  - Saliency detection
- Other applications
  - Unsupervised feature extraction
  - Speech denoising …
  - Language translation
  - …

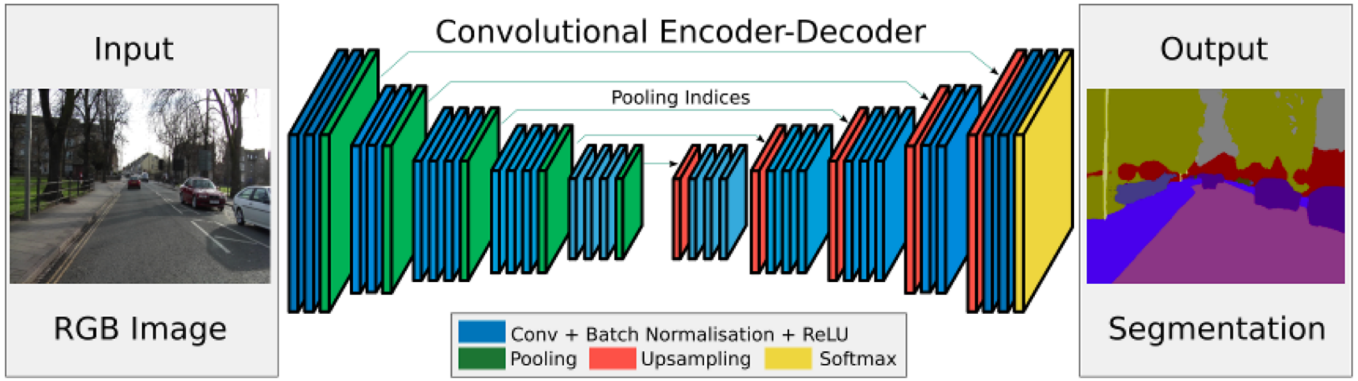


Fig. 2. An illustration of the SegNet architecture. There are no fully connected layers and hence it is only convolutional. A decoder upsamples its input using the transferred pool indices from its encoder to produce a sparse feature map(s). It then performs convolution with a trainable filter bank to densify the feature map. The final decoder output feature maps are fed to a soft-max classifier for pixel-wise classification.

https://github.com/arahusky/Tensorflow-Segmentation

- Autoencoder loss depends on the underlying application
- Using adversarial loss can help to make the output look more like the target output (beyond this class)

Lab: Transfer Learning with a Pre-Trained Deep Neural Network (VGG)

- For image classification or other applications, training from scratch takes tremendous resources
- Instead, can refine the VGG or other well trained networks
- Can use VGG convolutional layers, and retrain only the fully connected layers (possibly some later convolutional layers) for different problems.
- Or can use VGG conv layers as the “initial model” and further refine.
- Lab: load VGG model, and fix all conv. Layers, retrain additional fully connected layers for binary classification, try and compare different training tricks
  - Using Flickr API for downloading images for a given keyword

What you should have learnt?

- ❑ Convolution as local feature matching
- ❑ Convolutional neural networks for feature extraction
- ❑ Backpropagation training in CNNs
- ❑ Creating and visualizing convolutional layers in Keras
- ❑ Exploring VGG16: A state-of-the-art deep network
- ❑ Regularization: batch normalization and dropout
- ❑ Data augmentation
- ❑ Autoencoder for non-classification task
- ❑ Transfer learning