

Kernel size, stride, dilation all work as you would expect

### How many parameters?

• If there are  $C_i$  input channels and kernel size K x K

$$\boldsymbol{\omega} \in \mathbb{R}^{C_i \times K \times K}$$



• If there are  $C_i$  input channels and  $C_o$  output channels

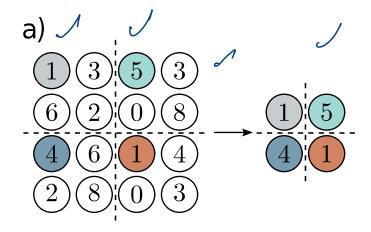
$$\boldsymbol{\omega} \in \mathbb{R}^{C_i \times C_o \times K \times K}$$



### Convolution #2

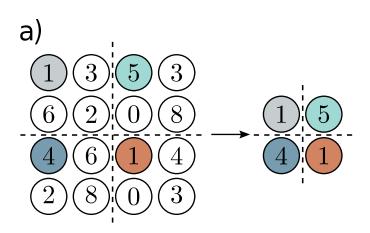
- 2D Convolution
- Downsampling and upsampling, 1x1 convolution
- Image classification
- Object detection
- Semantic segmentation
- Residual networks
- U-Nets and hourglass networks

# Downsampling

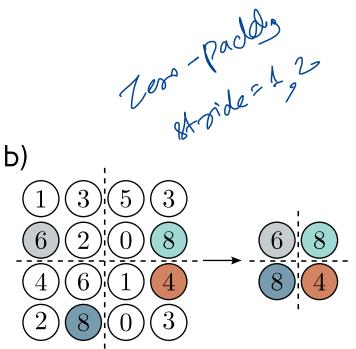


Sample every other position (equivalent to stride two)

### Downsampling



Sample every other position (equivalent to stride two)



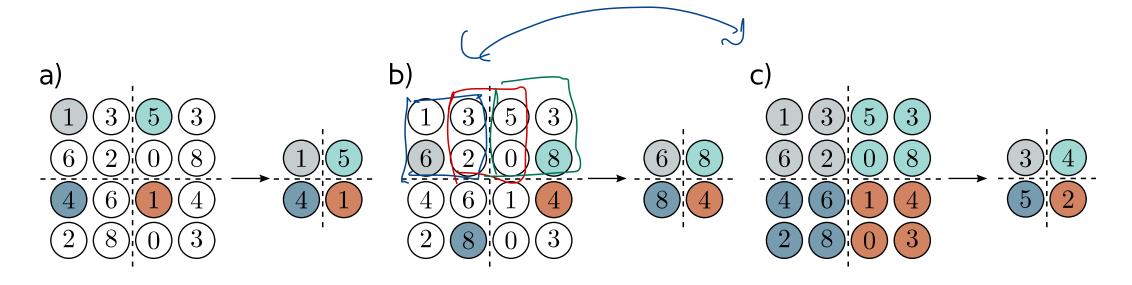
Wight 2x2 Storide = 2

Size Max pooling

(partial invariance to translation)

7.5 2.70 21

### Downsampling

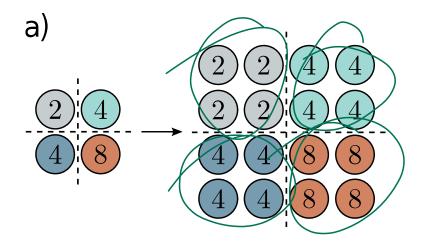


Sample every other position (equivalent to stride two)

Max pooling (partial invariance to translation)

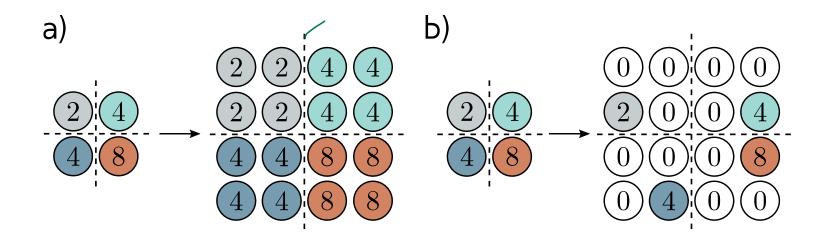
Mean pooling

# Upsampling



Duplicate

# Upsampling

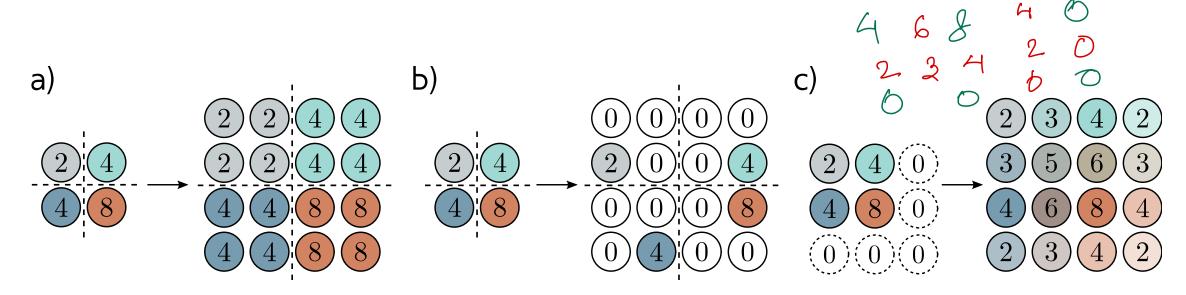


**Duplicate** 

Max-upsampling

Max-unpools

# Upsampling



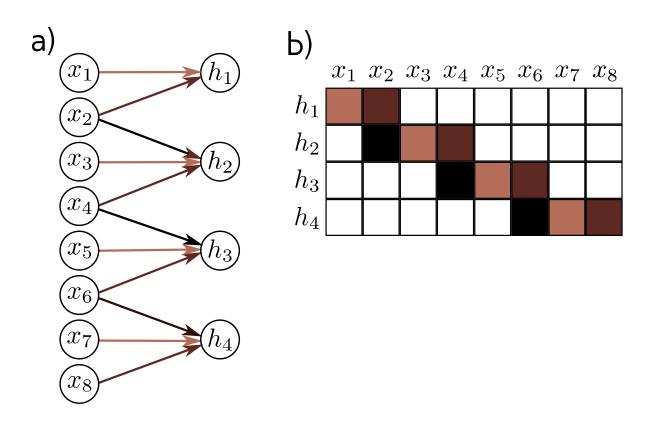
**Duplicate** 

Max-upsampling

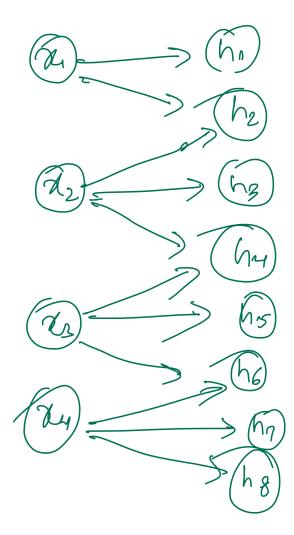
Bilinear interpolation

#### In-Network upsampling: "Max Unpooling" **Max Pooling** Max Unpooling Remember which element was max! Use positions from peoling layer 0 0 2 3 2. 0 0 0 6 5 3 5 4 0 0 0 0 2 8 Rest of the network 3 0 0 4 3 8 Output: 4 x 4 Input: 4 x 4 Output: 2 x 2 servatic segmentation Corresponding pairs of downsampling and upsampling layers c lass"

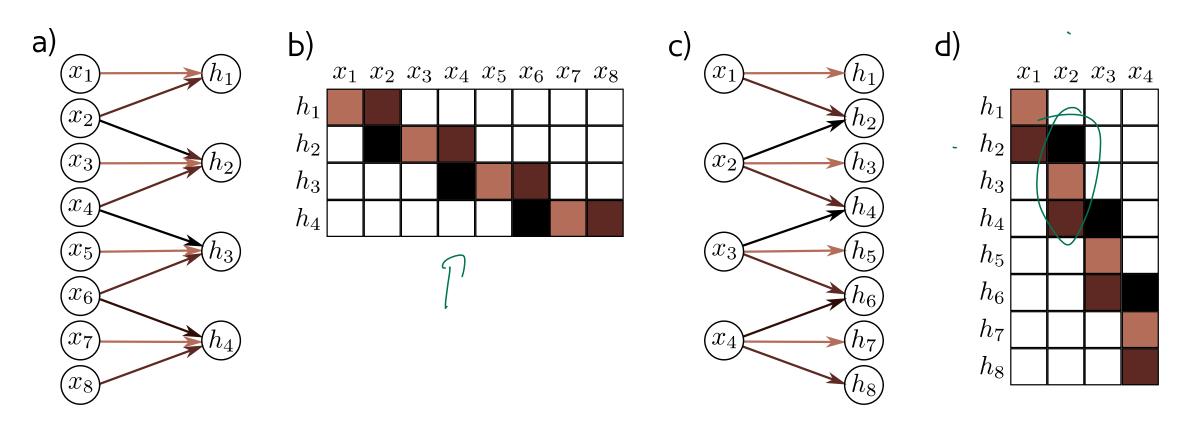
# Transposed convolutions



Kernel size 3, Stride 2 convolution



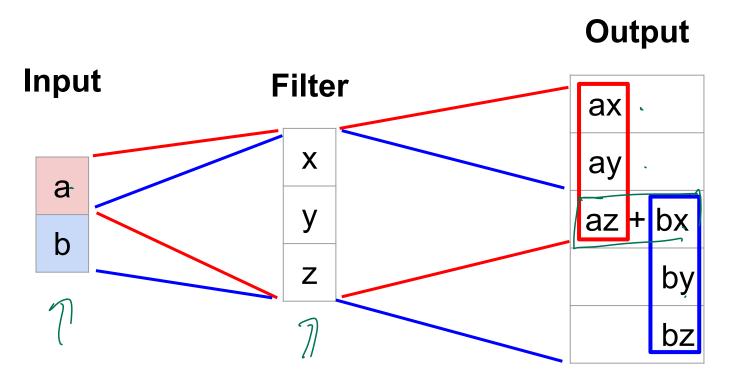
# Transposed convolutions



Kernel size 3, Stride 2 convolution

Transposed convolution

#### Learnable Upsampling: 1D Example



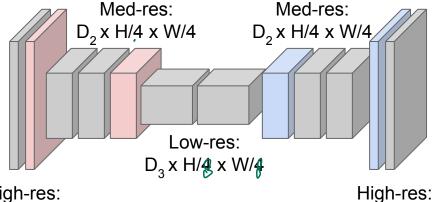
Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

### Semantic Segmentation Idea: Fully Convolutional

**Downsampling**: Pooling, strided convolution



Input: 3 x H x W Design network as a bunch of convolutional layers, with downsampling and upsampling inside the network!



High-res: D<sub>1</sub> x H/2 x W/2 **Upsampling**:

Unpooling or strided transposed convolution

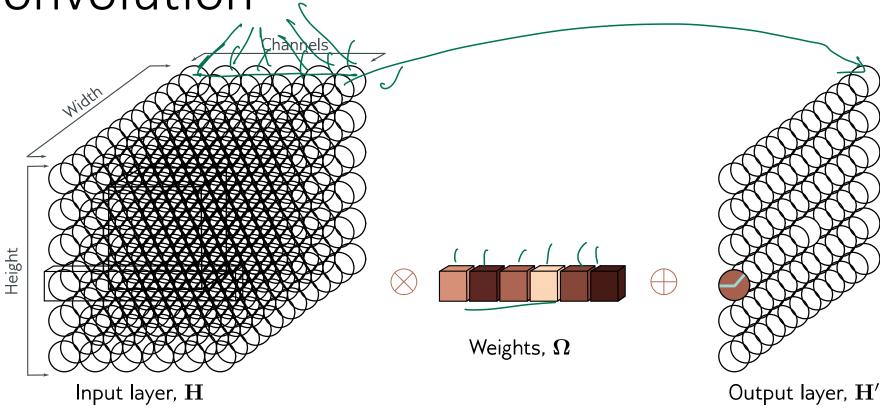


Predictions: H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015 Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

D<sub>1</sub> x H/2 x W/2

1x1 convolution

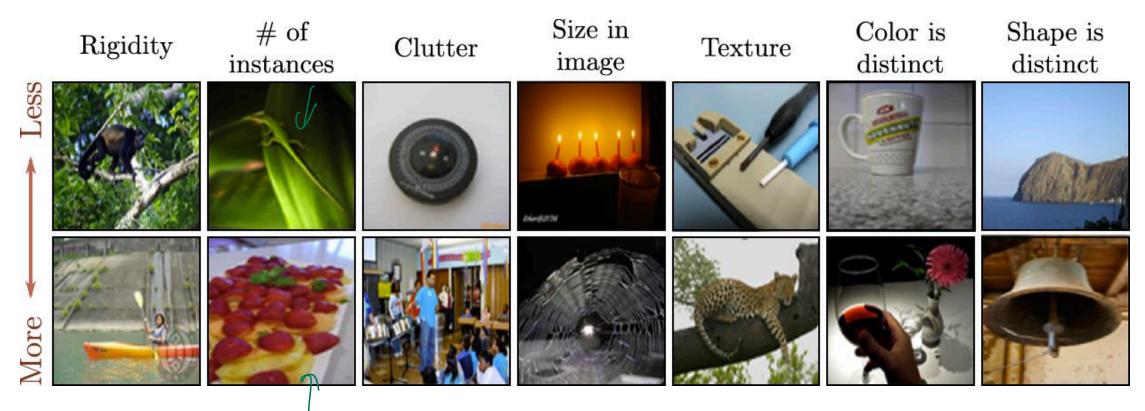


- Mixes channels
- Can change number of channels
- Equivalent to running same fully connected network at each position

### Convolution #2

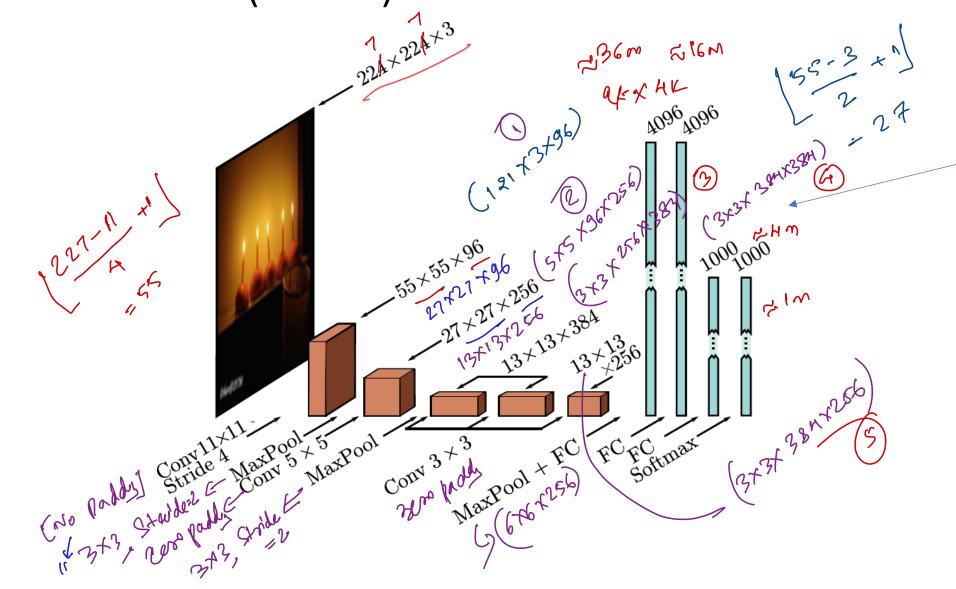
- 2D Convolution
- Downsampling and upsampling, 1x1 convolution
- Image classification
- Object detection
- Semantic segmentation
- Residual networks
- U-Nets and hourglass networks

# ImageNet database



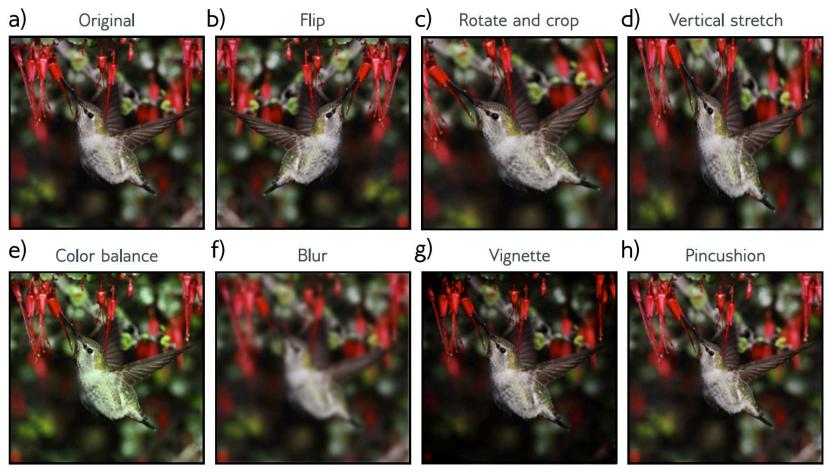
- 224 x 224 images
- 1,281,167 training images, 50,000 validation images, and 100,000 test images
- 1000 classes

# AlexNet (2012)



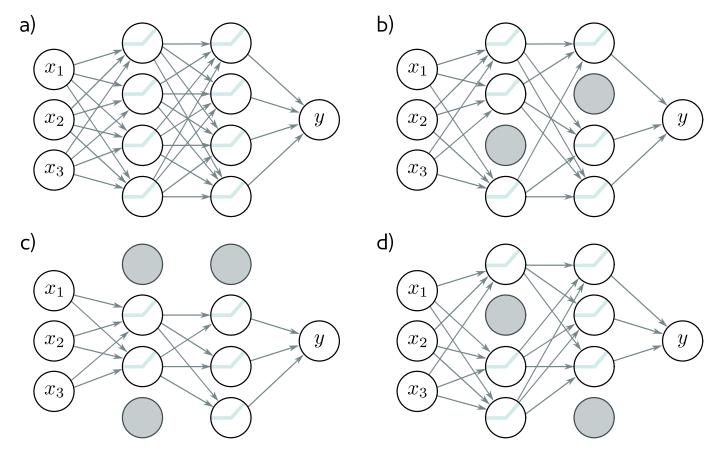
Almost all the 60 million parameters parameters are in fully connected layers

### Data augmentation



• Data augmentation a factor of 2048 using (i) spatial transformations and (ii) modifications of the input intensities.

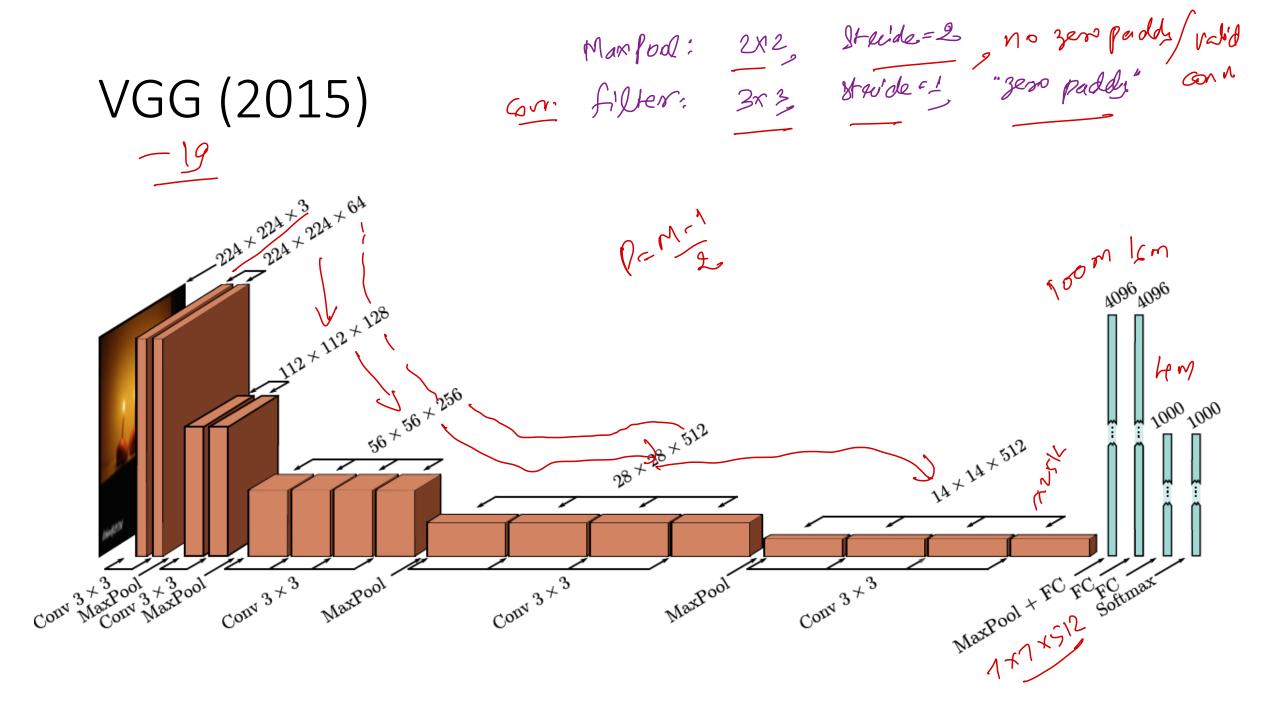
### Dropout



Dropout was applied in the fully connected layers

### Details

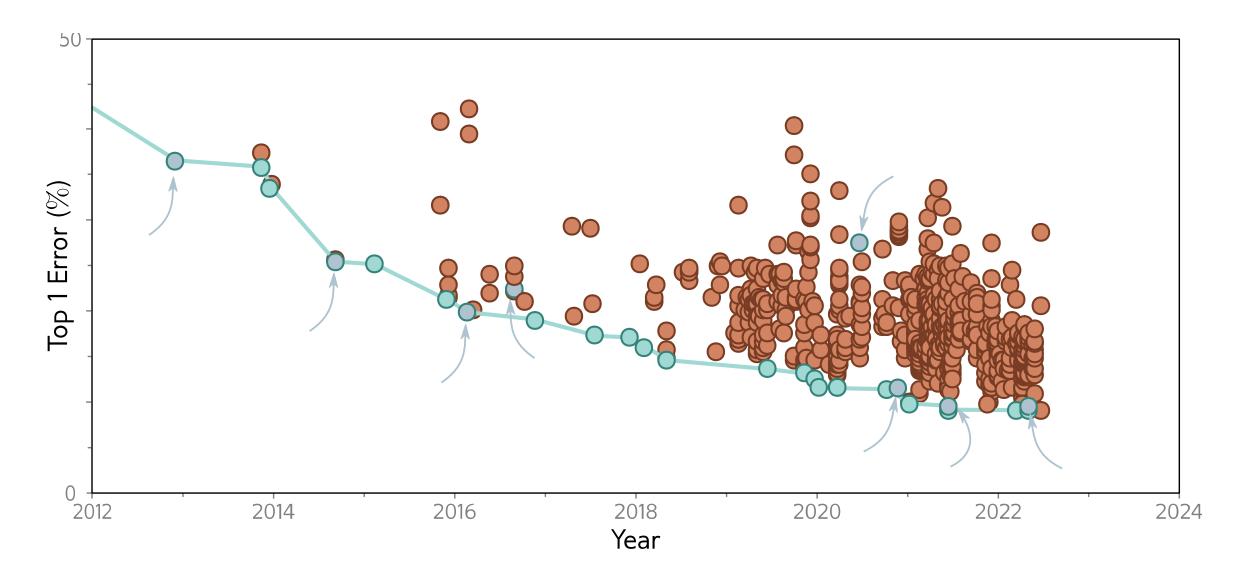
- At test time average results from five different cropped and mirrored versions of the image
- SGD with a momentum coefficient of 0.9 and batch size of 128.
- L2 (weight decay) regularizer used.
- This system achieved a 16.4% top-5 error rate and a 38.1% top-1 error rate.



### Details

- 19 hidden layers
- 144 million parameters
- 6.8% top-5 error rate, 23.7% top-1 error rate

# ImageNet History



### Convolution #2

- 2D Convolution
- Downsampling and upsampling, 1x1 convolution
- Image classification
- Object detection
- Semantic segmentation
- Residual networks
- U-Nets and hourglass networks