BOSTON UNIVERSITY

Deep Learning for Data Science DS 542

Lecture 10
Convolutional Networks

Slides originally by Thomas Gardos.
Images from [Understanding Deep Learning] unless otherwise cited.

Challenges Processing Images, Audio, Text, Video…

- Much bigger inputs?
- Variable size inputs?
- But some obvious structure to leverage?

Bigger Inputs

Original image size:

2560x1707x3=

13,109,760 values

Original image: kpmb.com

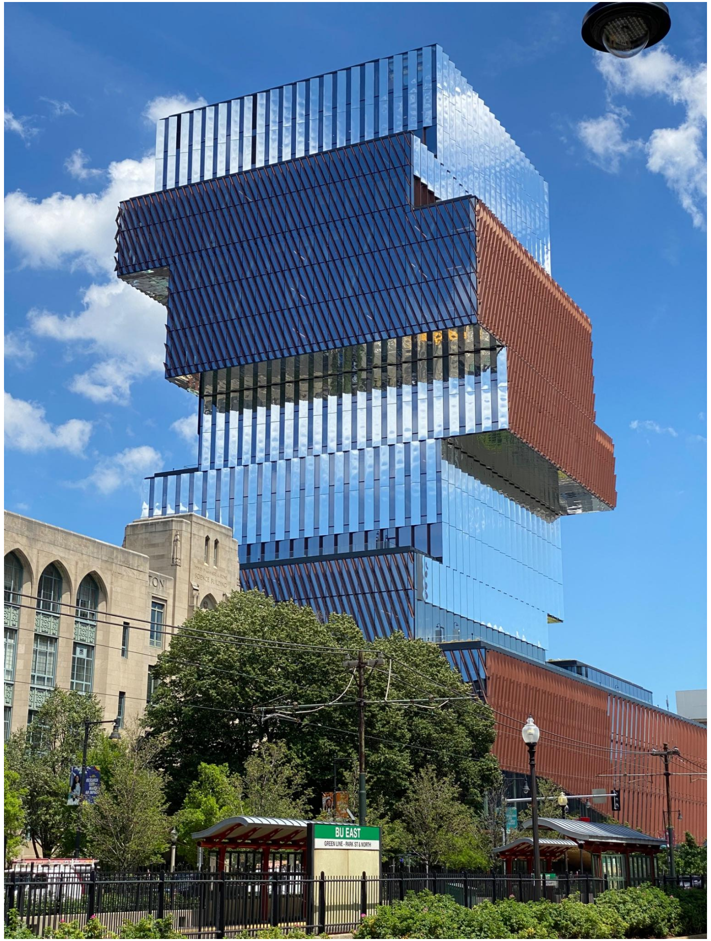
Variable Size

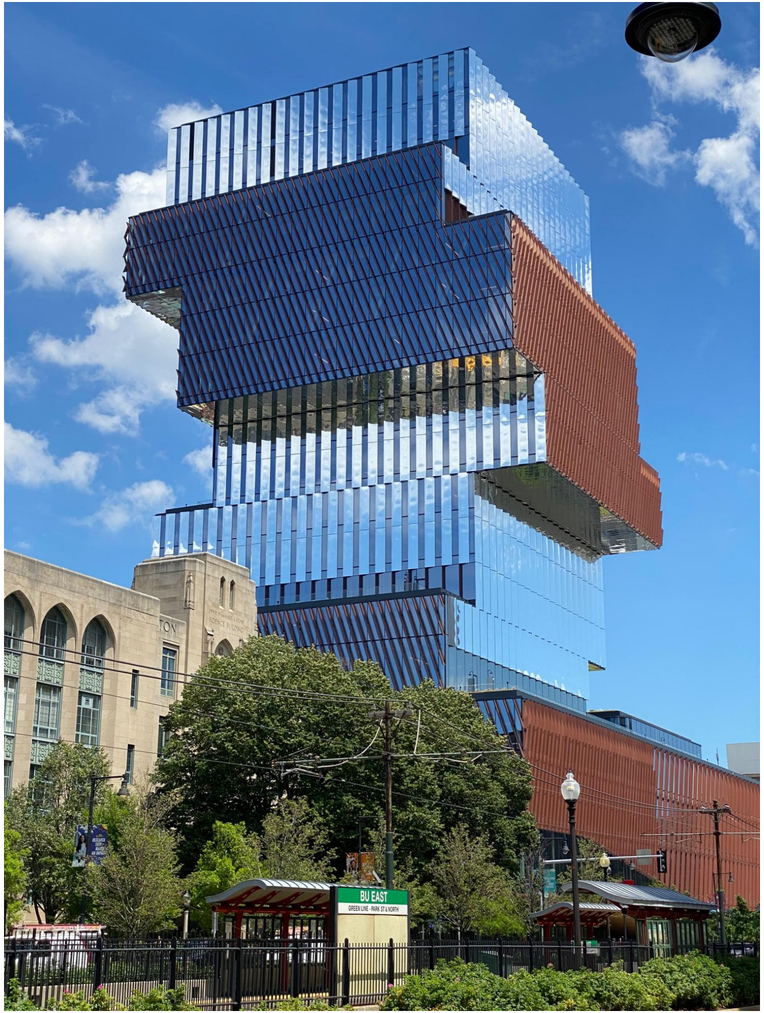
Original size: 3024x4032x3=

36,578,304 values

Vs previous 2560x1707x3

(not even same ratio)





Structure

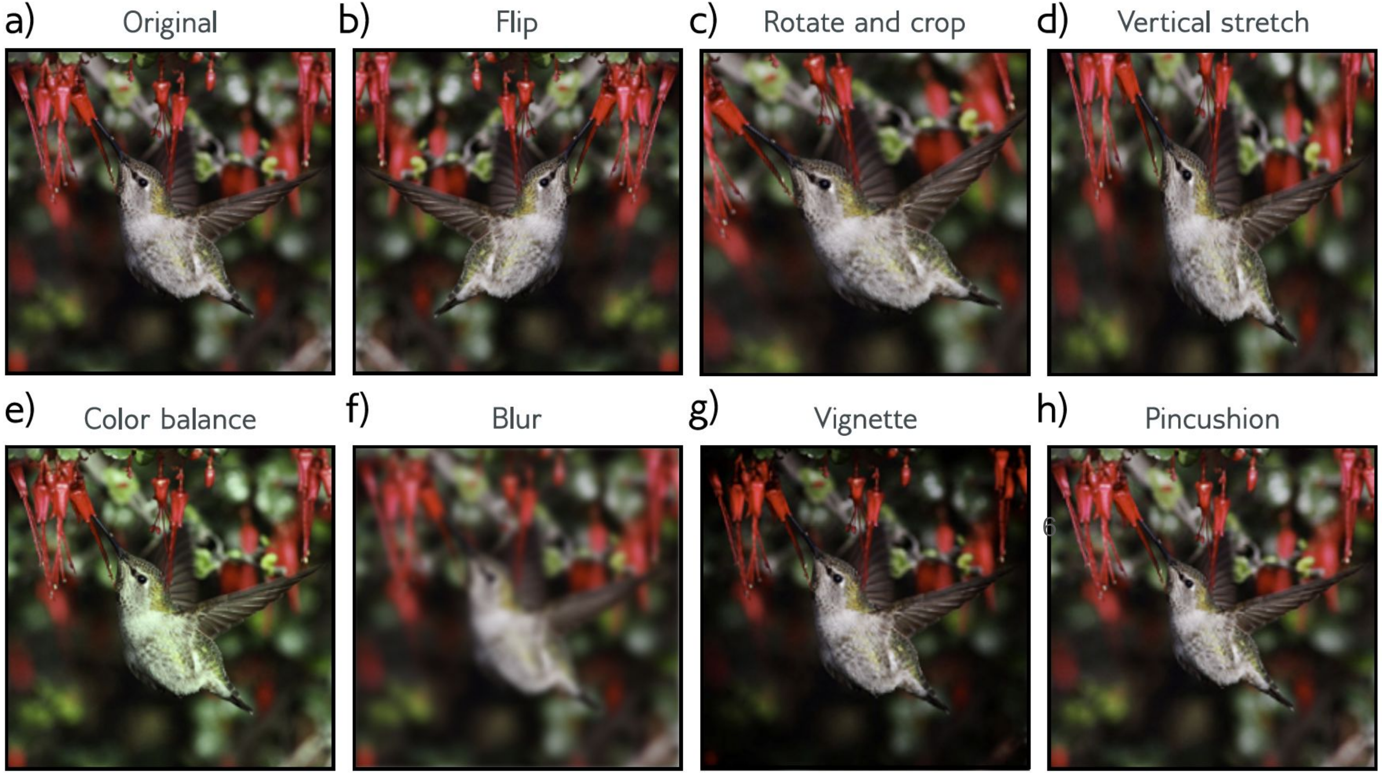
←Original

3024x4032x3

Shrunk ⅛ →

378x504x3

Data augmentation (from last time)



Convolutional networks

Our first useful approach to these problems with large but structured inputs.

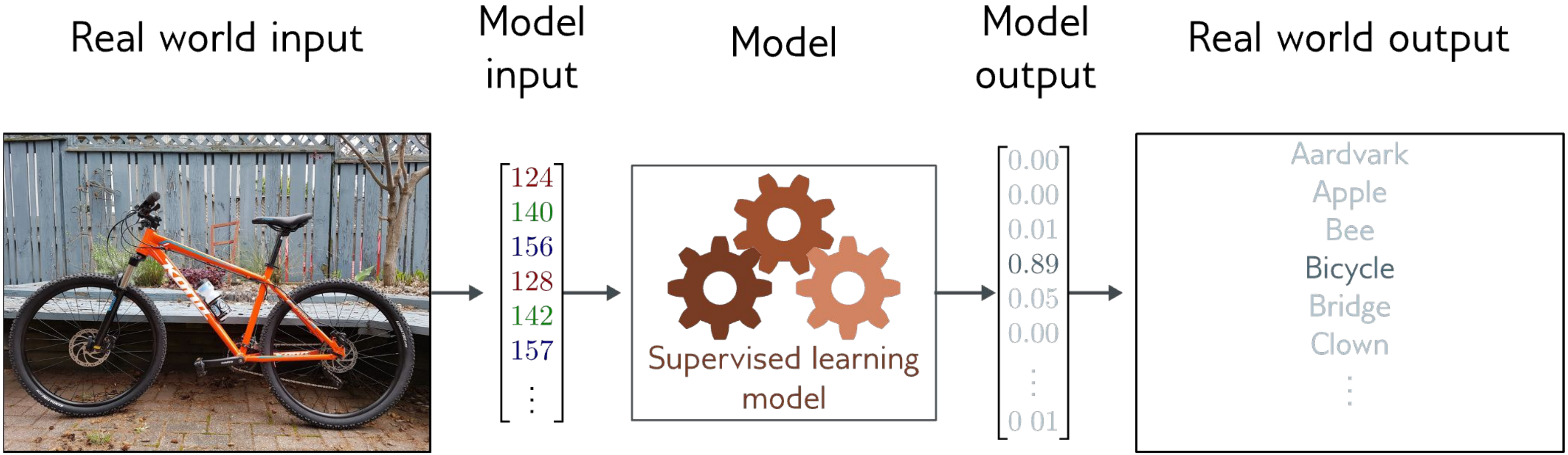
- Much bigger inputs? ✅
- Variable size inputs? ❌ but often can rescale as workaround
- But some obvious structure to leverage? ✅

Spoiler: recognizing structure helps learn with bigger inputs.

Convolutional networks

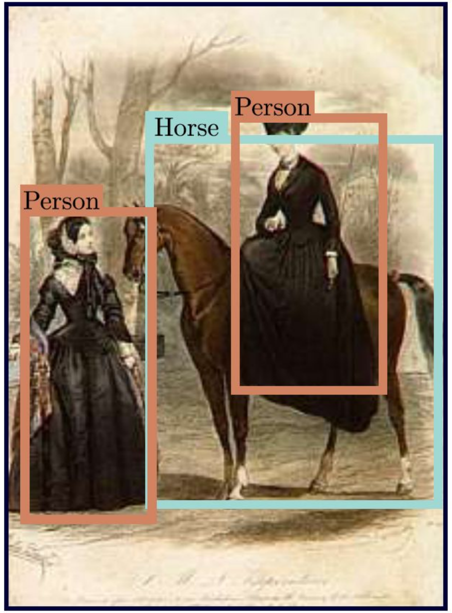
- Networks for images
- Invariance and equivariance
- 1D convolution
- Convolutional layers
- Channels
- Receptive fields
- Convolutional network for MNIST 1D

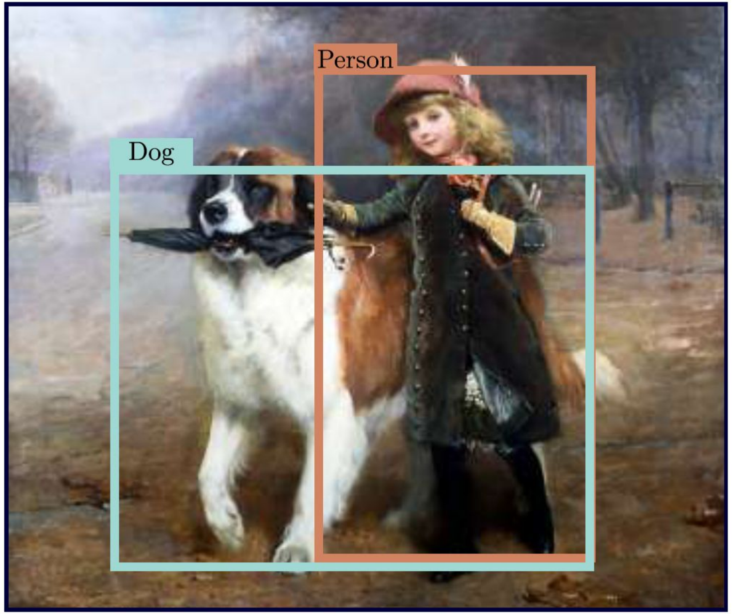
Image classification



- Multiclass classification problem (discrete classes, >2 possible classes)
- Convolutional network

Object detection





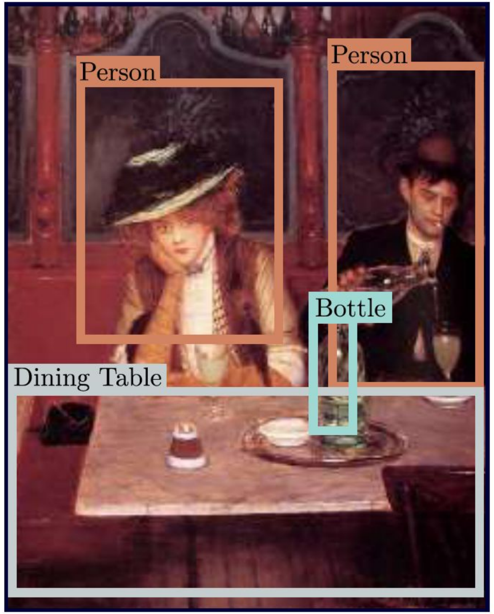
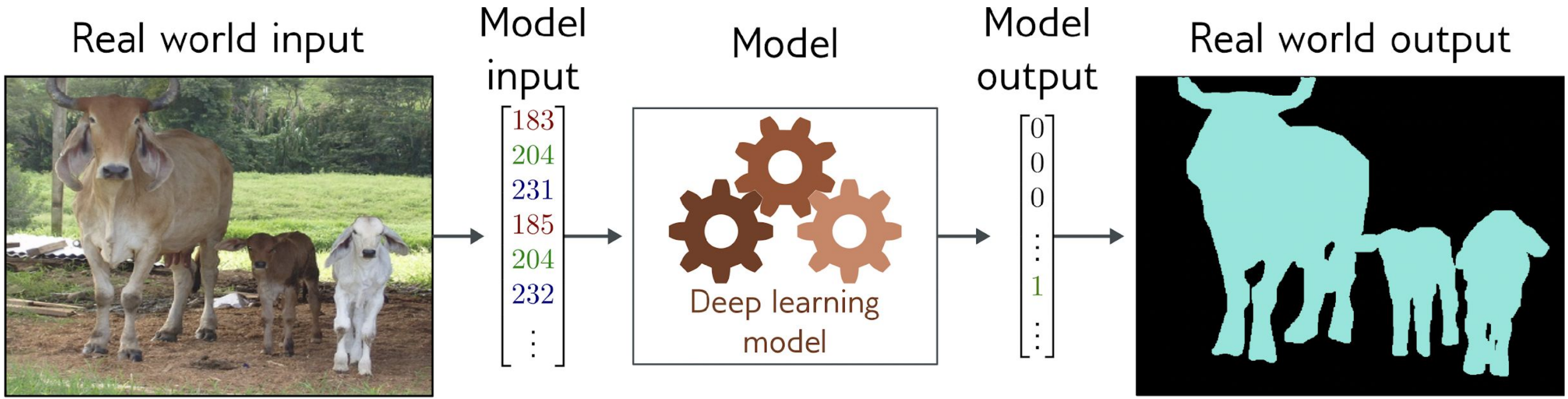


Image segmentation



- Multivariate binary classification problem (many outputs, two discrete classes)
- Convolutional encoder-decoder network

Networks for images

Problems with fully-connected networks

1. Size
   - 224x224 RGB image = 150,528 dimensions
   - Hidden layers generally larger than inputs
   - One hidden layer = 150,520x150,528 weights -- 22 billion
2. Nearby pixels statistically related
   - But could permute pixels and relearn and get same results with FC
3. Should be stable under transformations
   - Don’t want to re-learn appearance at different parts of image

Networks for images

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2. Nearby pixels statistically related
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3. Should be stable under transformations
   - Don’t want to re-learn appearance at different parts of image

Opportunities for regularization?

Convolutional networks

- Parameters only look at local image patches
- Share parameters across image

Convolutional networks

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- 1D convolution
- Convolutional layers
- Channels
- Receptive fields
- Convolutional network for MNIST 1D

Invariance

A function f[x] is invariant to a transformation t[] if:

$$\mathbf{f}\left[\mathbf{t}\left[\mathbf{x}\right]\right] = \mathbf{f}[\mathbf{x}]$$

i.e., the function output is the same even after the transformation is applied.

Invariance example

e.g., Image classification

- Image has been translated, but we want our classifier to give the same result

Equivariance

- A function f[x] is equivariant to a transformation t[] if:

$$\mathbf{f}\left[\mathbf{t}[\mathbf{x}]\right] = \mathbf{t}\left[\mathbf{f}[\mathbf{x}]\right]$$

i.e., the output is transformed in the same way as the input

Equivariance example

e.g., Image segmentation

- Image has been translated and we want segmentation to translate with it

Convolutional networks

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Convolution* in 1D

- Input vector **x:**

$$\mathbf{x} = [x_1, x_2, \ldots, x_I]$$

- Output is weighted sum of neighbors:

- Convolutional kernel or filter:

$$z_i = \omega_1 x_{i-1} + \omega_2 x_i + \omega_3 x_{i+1}$$

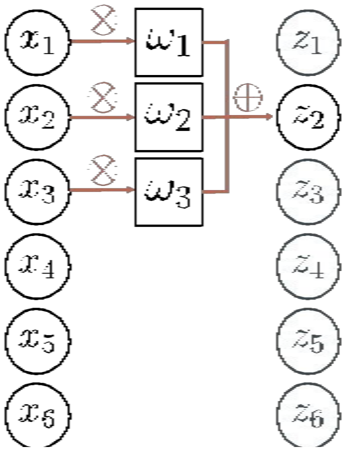
$$\boldsymbol{\omega} = [\omega_1, \omega_2, \omega_3]^T$$

Kernel size = 3

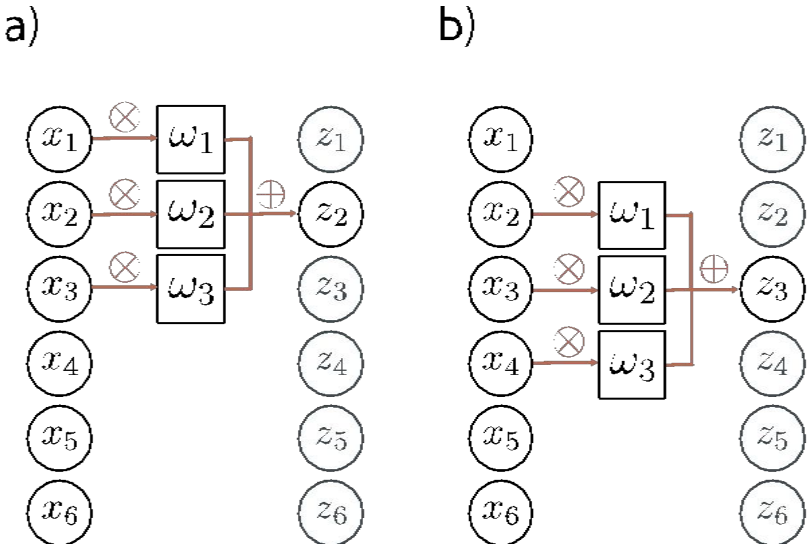
* Not really technically convolution

Convolution with kernel size 3

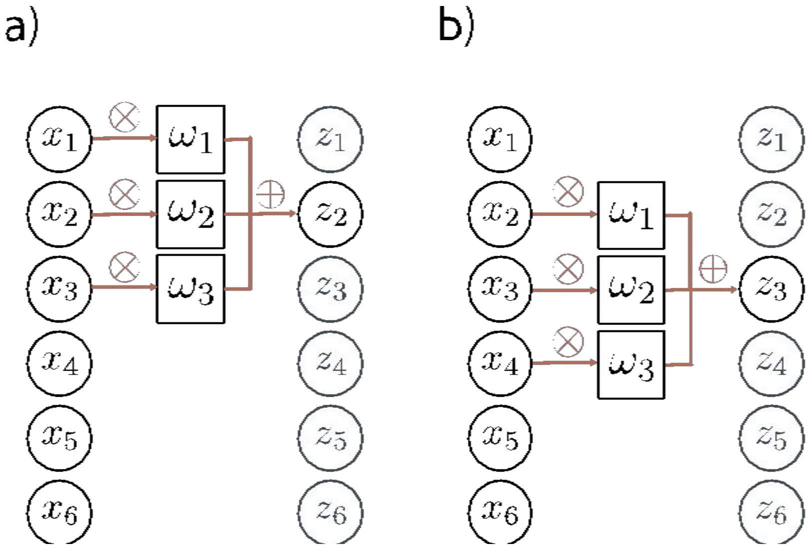
a)



Convolution with kernel size 3

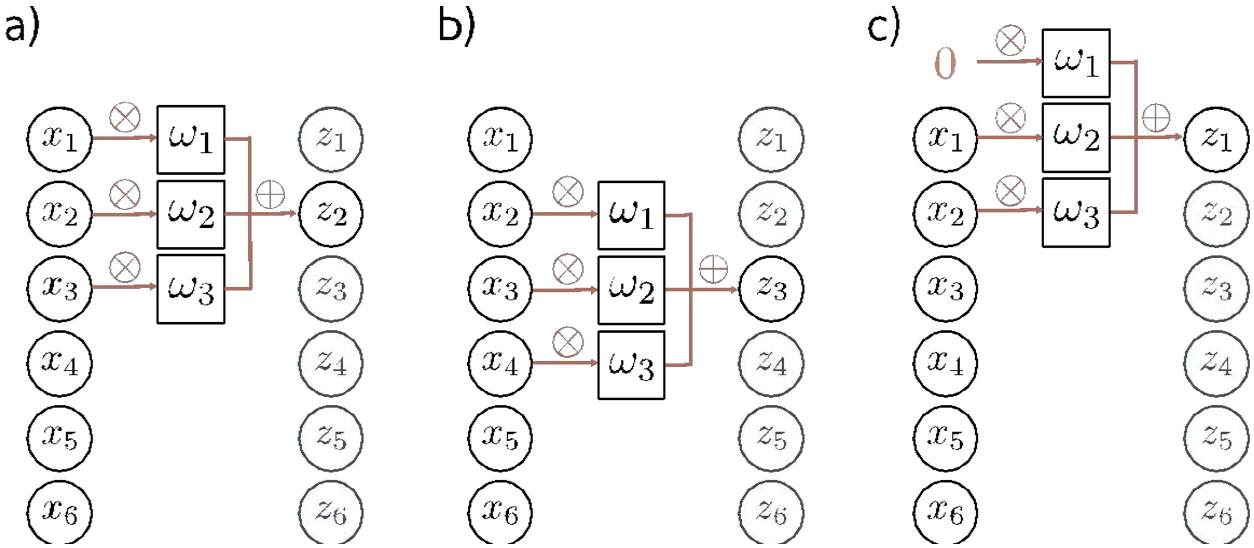


Convolution with kernel size 3



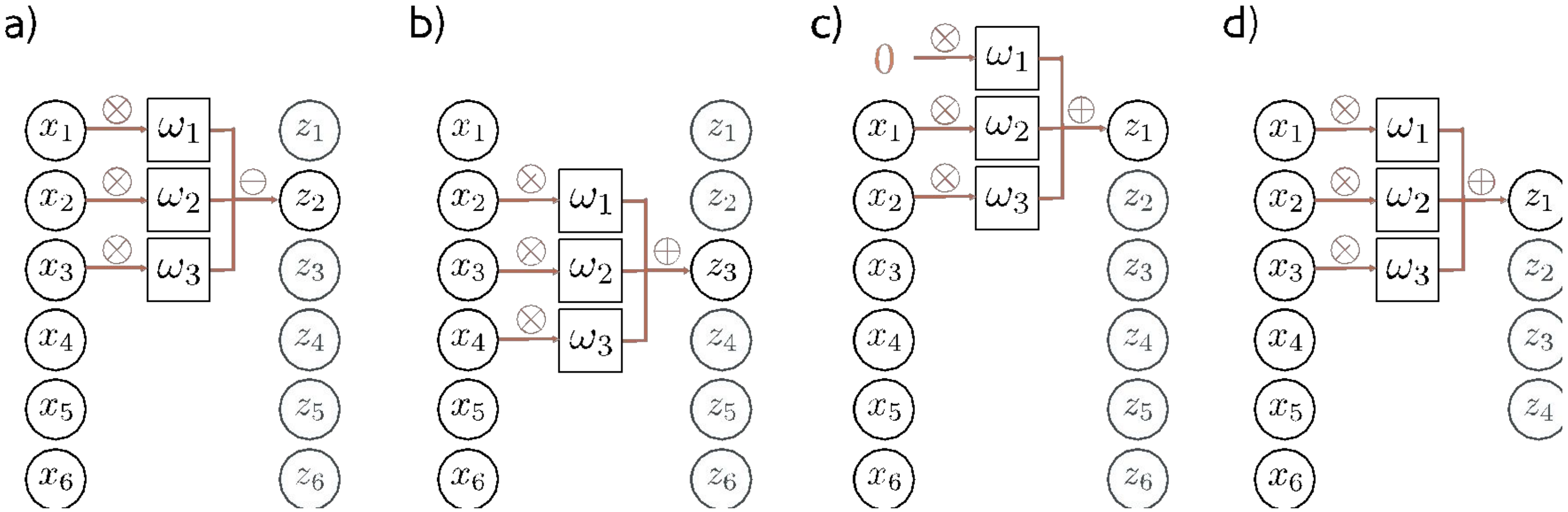
Equivariant to translation of input $\mathbf{f}[\mathbf{t}[\mathbf{x}]] = \mathbf{t}[\mathbf{f}[\mathbf{x}]]$

Zero padding



Treat positions that are beyond end of the input as zero.

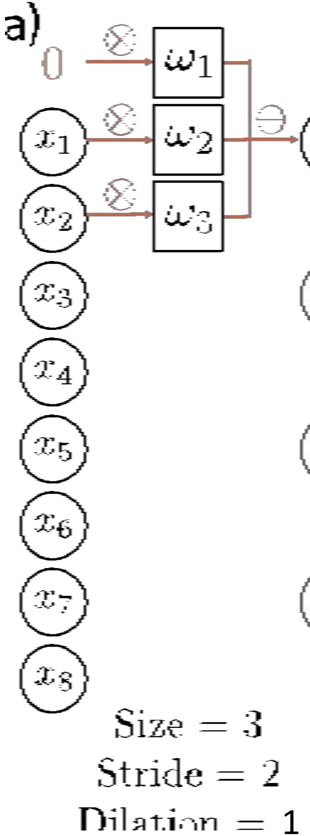
“Valid” convolutions

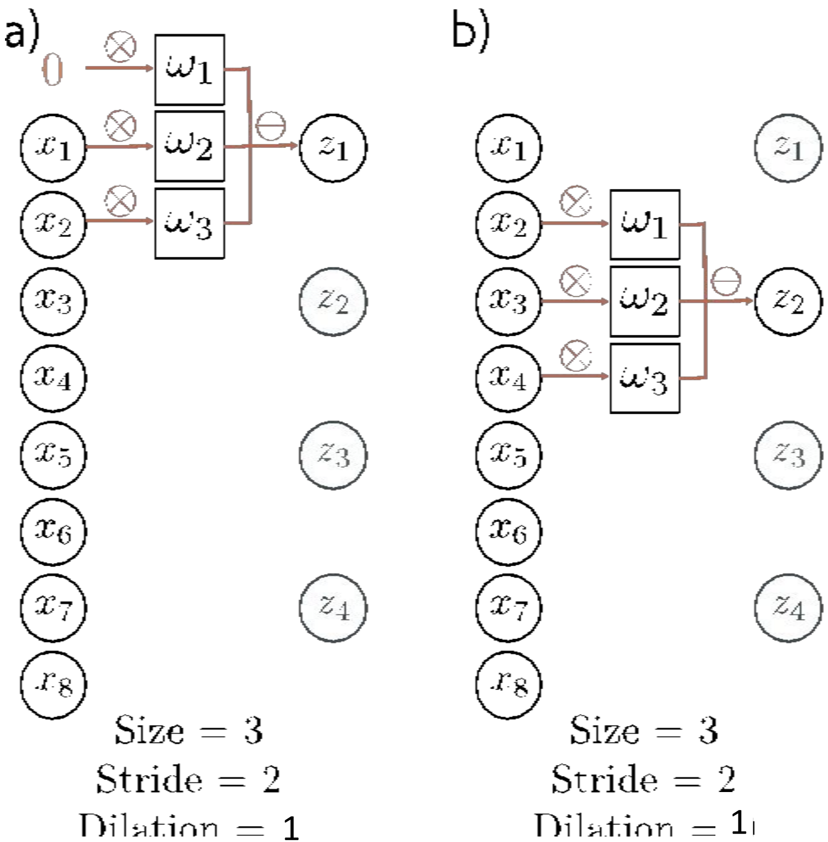


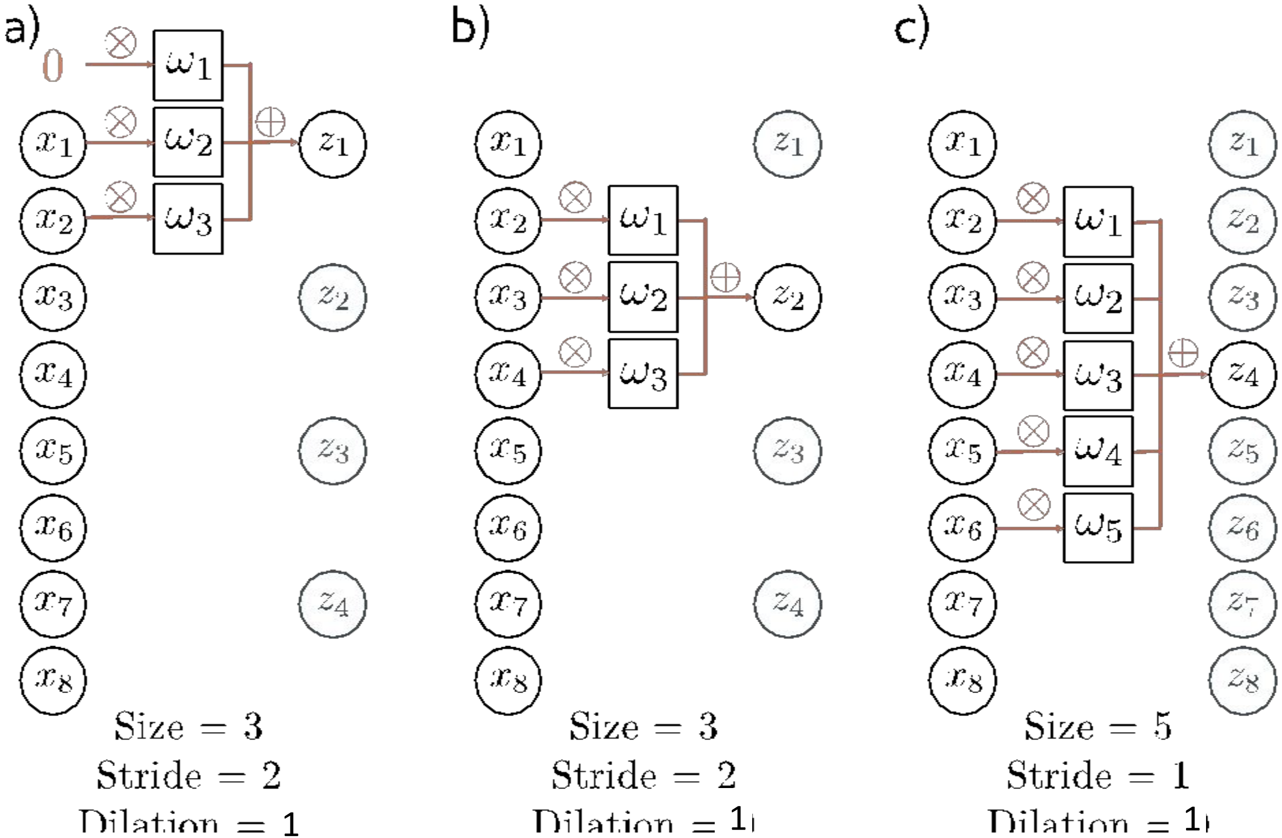
Only process positions where kernel falls in image (smaller output).

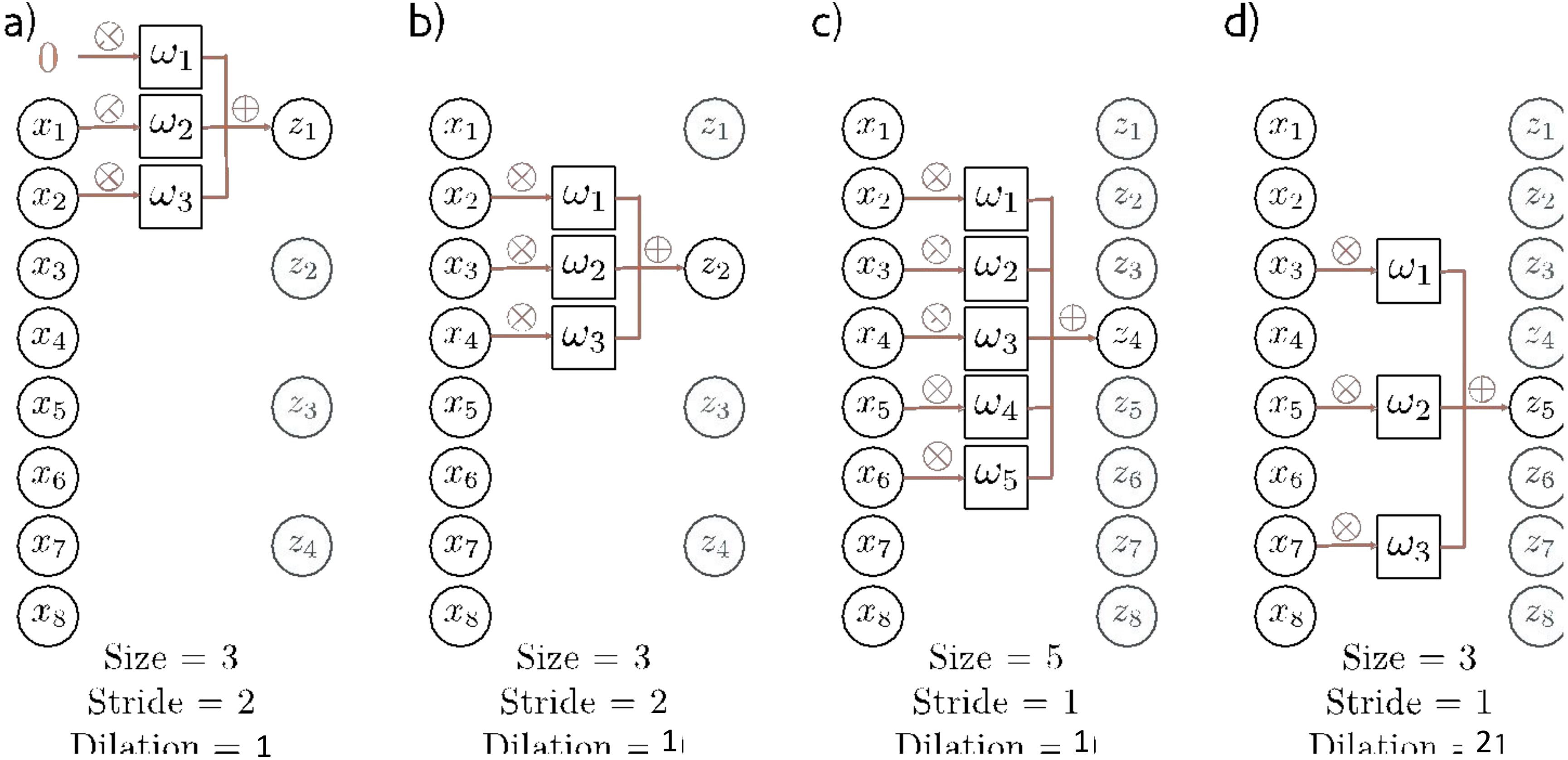
Stride, kernel size, and dilation

- Stride = shift by k positions for each output
    - Decreases size of output relative to input
- Kernel size = weight a different number of inputs for each output
    - Combine information from a larger area
    - But kernel size 5 uses 5 parameters
- Dilated or atrous convolutions = intersperse kernel values with zeros
    - Combine information from a larger area
    - Fewer parameters


a)
0
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
ω_1
ω_2
ω_3
z_1
z_2
z_3
z_4
Size = 3
Stride = 2
Dilation = 1


a)
b)
0
ω_1
ω_2
ω_3
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
z_1
z_2
z_3
z_4
Size = 3
Stride = 2
Dilation = 1
Size = 3
Stride = 2
Dilation = 1


a)
0
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
ω_1
ω_2
ω_3
z_1
z_2
z_3
z_4
Size = 3
Stride = 2
Dilation = 1
b)
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
ω_1
ω_2
ω_3
z_1
z_2
z_3
z_4
Size = 3
Stride = 2
Dilation = 1
c)
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
ω_1
ω_2
ω_3
ω_4
ω_5
z_1
z_2
z_3
z_4
z_5
z_6
z_7
z_8
Size = 5
Stride = 1
Dilation = 1



a)
0
ω_1
ω_2
ω_3
x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8
z_1 z_2 z_3 z_4
Size = 3
Stride = 2
Dilation = 1
b)
ω_1
ω_2
ω_3
x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8
z_1 z_2 z_3 z_4
Size = 3
Stride = 2
Dilation = 1
c)
ω_1
ω_2
ω_3
ω_4
ω_5
x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8
z_1 z_2 z_3 z_4 z_5 z_6 z_7 z_8
Size = 5
Stride = 1
Dilation = 1
d)
ω_1
ω_2
ω_3
x_1 x_2 x_3 x_4 x_5 x_6 x_7 x_8
z_1 z_2 z_3 z_4 z_5 z_6 z_7 z_8
Size = 3
Stride = 1
Dilation = 2

Convolutional networks

- Networks for images
- Invariance and equivariance
- 1D convolution
- Convolutional layers
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Convolutional layer

$$\begin{aligned} h_i &= \mathrm{a}\left[\beta + \omega_1 x_{i-1} + \omega_2 x_i + \omega_3 x_{i+1}\right] \\ &= \mathrm{a}\left[\beta + \sum_{j=1}^{3} \omega_j x_{i+j-2}\right] \end{aligned}$$

Special case of fully-connected network

Convolutional network:

$$
\begin{aligned}
h_i &= \mathrm{a}\left[\beta + \omega_1 x_{i-1} + \omega_2 x_i + \omega_3 x_{i+1}\right] \\
&= \mathrm{a}\left[\beta + \sum_{j=1}^{3} \omega_j x_{i+j-2}\right]
\end{aligned}
$$

Fully connected network:

$$
h_i = \mathrm{a}\left[\beta_i + \sum_{j=1}^{D} \omega_{ij} x_j\right]
$$

Special case of fully-connected network

Convolutional network:

$$
\begin{aligned}
h_i &= \mathrm{a}\left[\beta + \omega_1 x_{i-1} + \omega_2 x_i + \omega_3 x_{i+1}\right] \\
&= \mathrm{a}\left[\beta + \sum_{j=1}^{3} \omega_j x_{i+j-2}\right]
\end{aligned}
$$

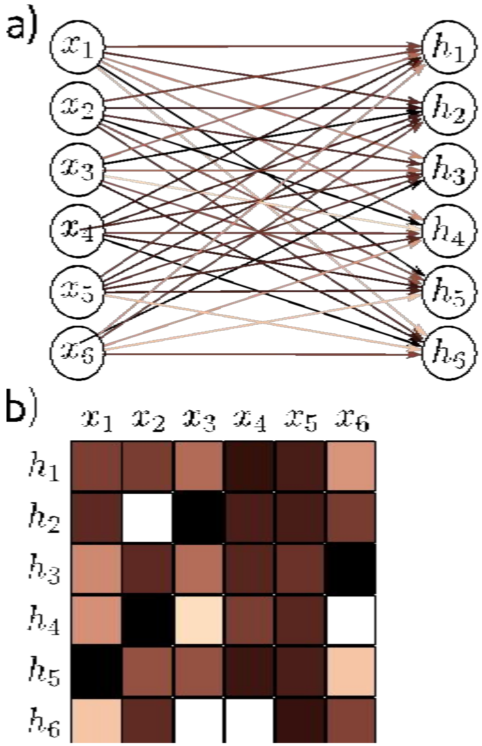
3 weights, 1 bias

Fully connected network:

D^2 weights, D biases

$$
h_i = \mathrm{a}\left[\beta_i + \sum_{j=1}^{D} \omega_{ij} x_j\right]
$$

Special case of fully-connected network

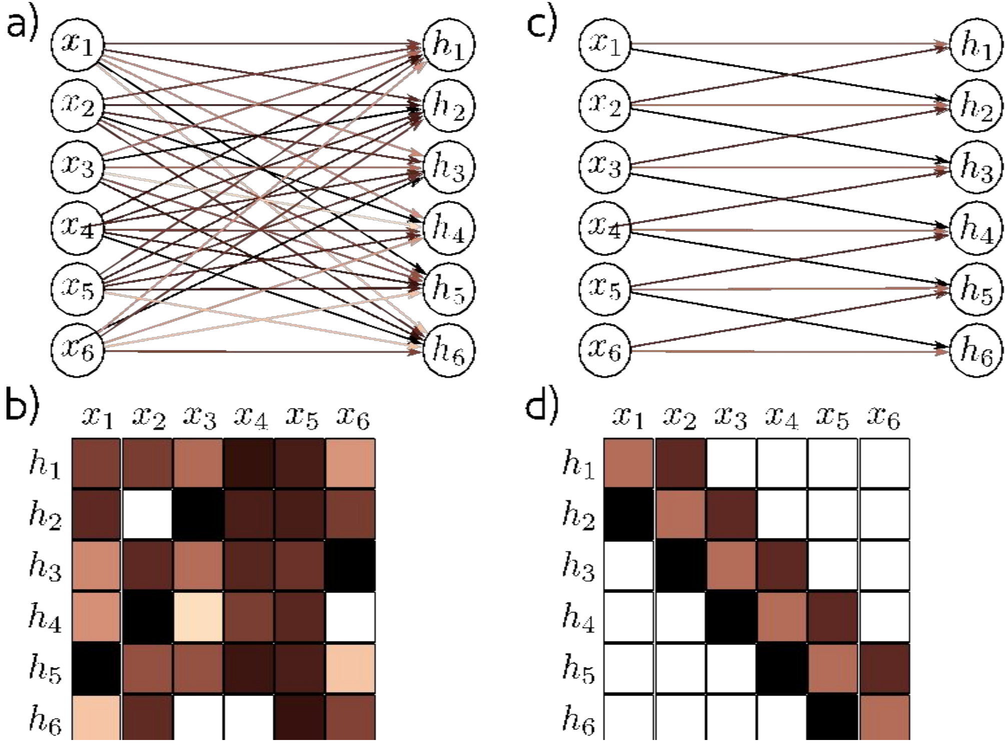


Weight Matrix

Fully connected network

Bias is implied

Special case of fully-connected network



Weight Matrices

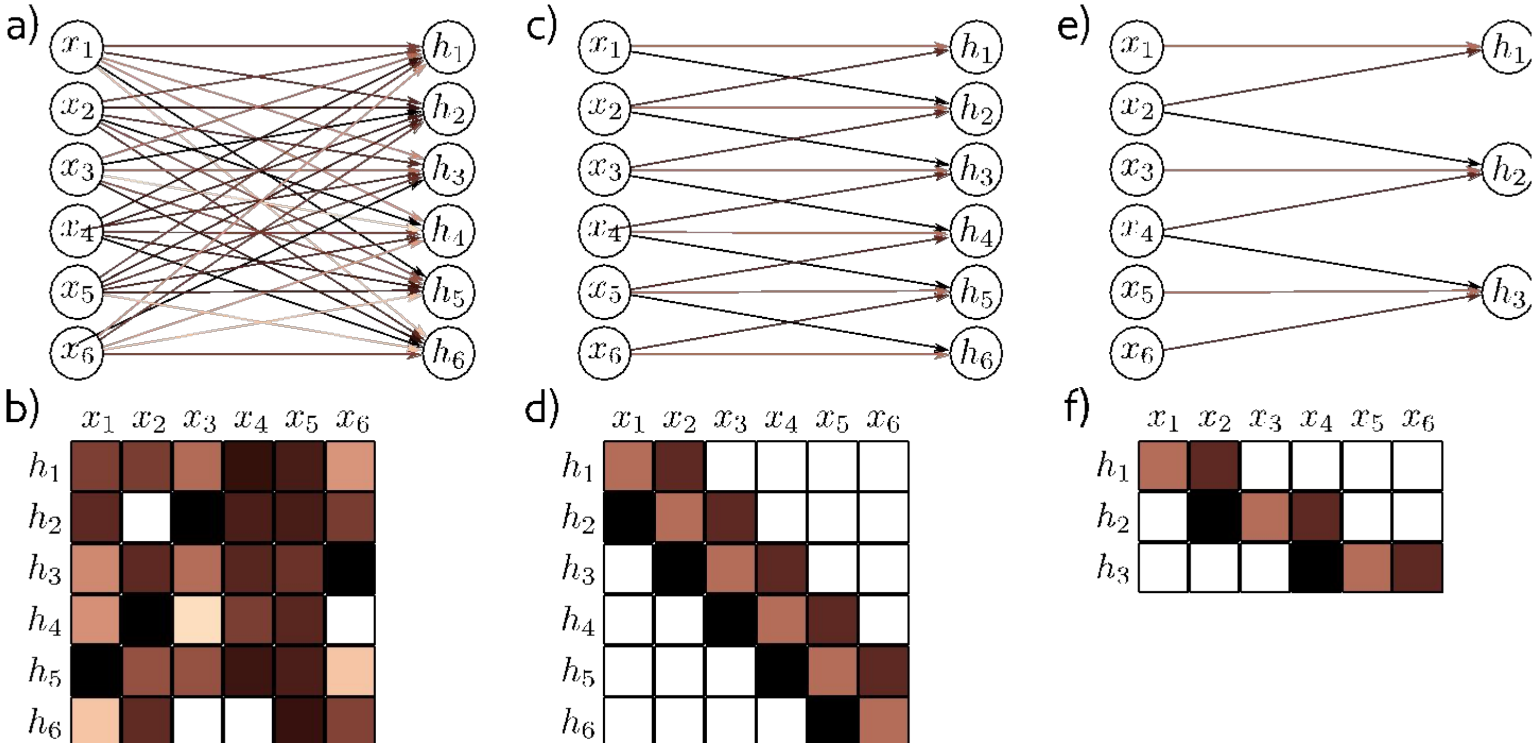
Fully connected network

Convolution, kernel 3, stride 1, dilation 1

Bias is implied

Special case of fully-connected network

Bias is implied



Weight Matrices

Fully connected network

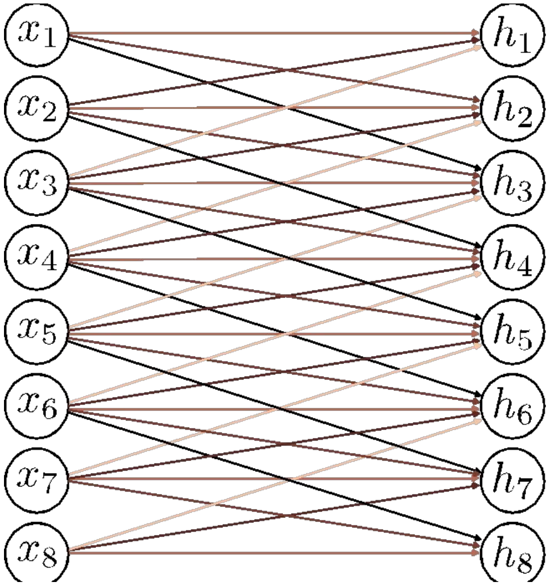
Convolution, size 3, stride 1, dilation 1, zero padding

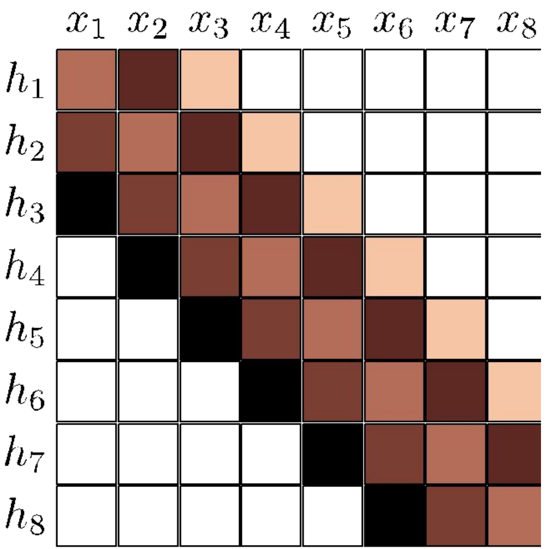
Convolution, size 3, stride 2, dilation 1, zero padding

Question 1

Bias is implied

- Kernel size?
- Stride?
- Dilation?
- Zero padding / valid?

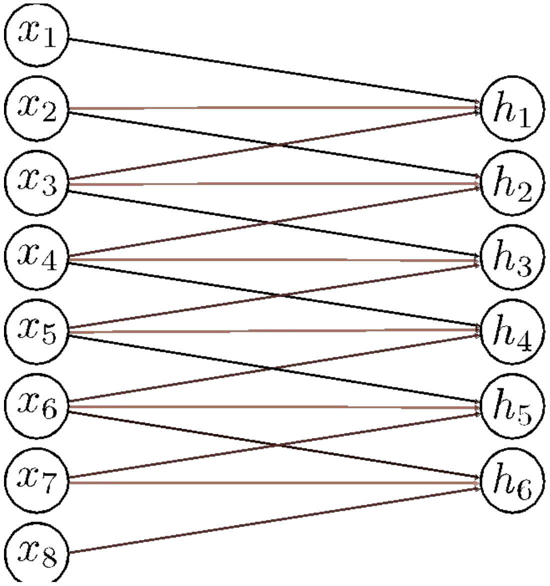


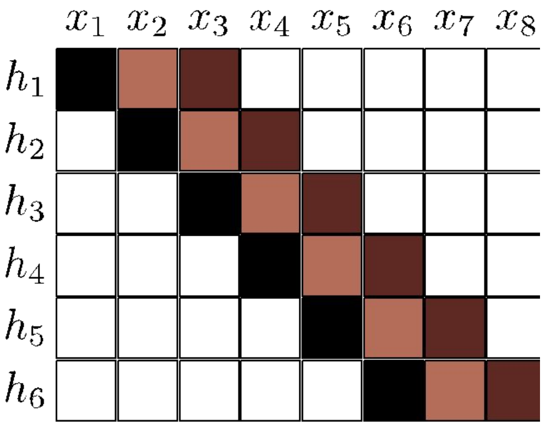


Question 2

Bias is implied

- Kernel size?
- Stride?
- Dilation?
- Zero padding / valid?

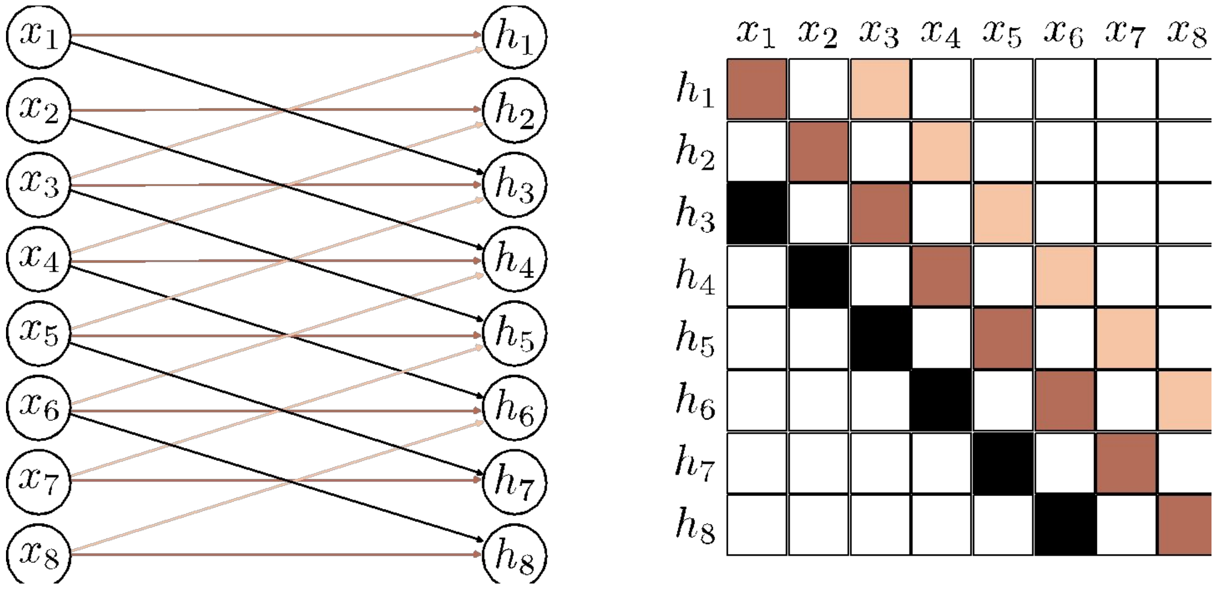




Question 3

Bias is implied

- Kernel size?
- Stride?
- Dilation?
- Zero padding / valid?



Convolutional networks

- Networks for images
- Invariance and equivariance
- 1D convolution
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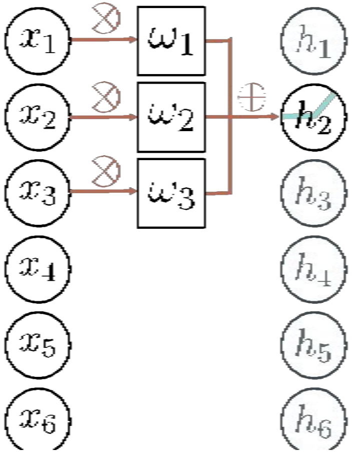
Channels

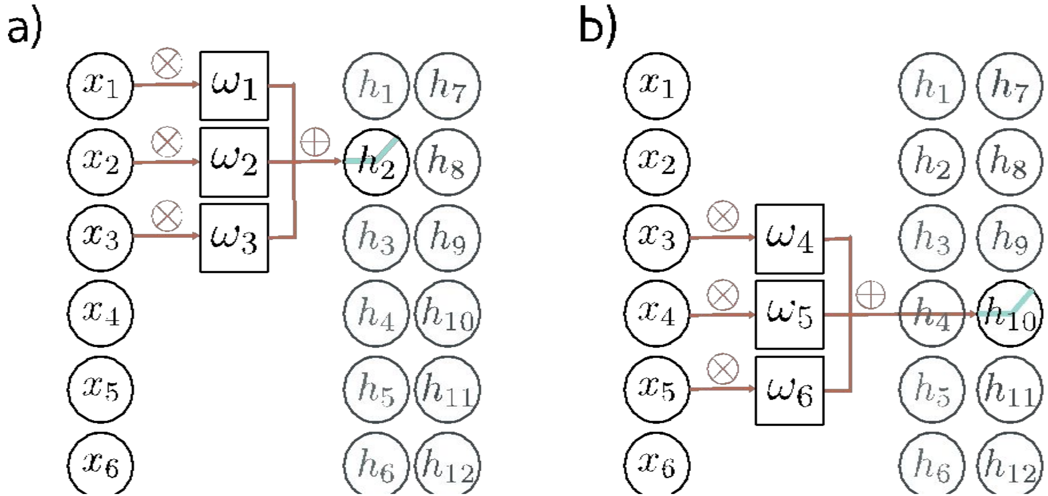
- The convolutional operation averages together the inputs
- Plus passes through ReLU function
- Result is loss of information
- Solution:
  - apply several convolutions and stack them in channels
  - Sometimes also called feature maps
  - Similar motivations to having multiple units in a hidden layer

Two output channels, one input channel

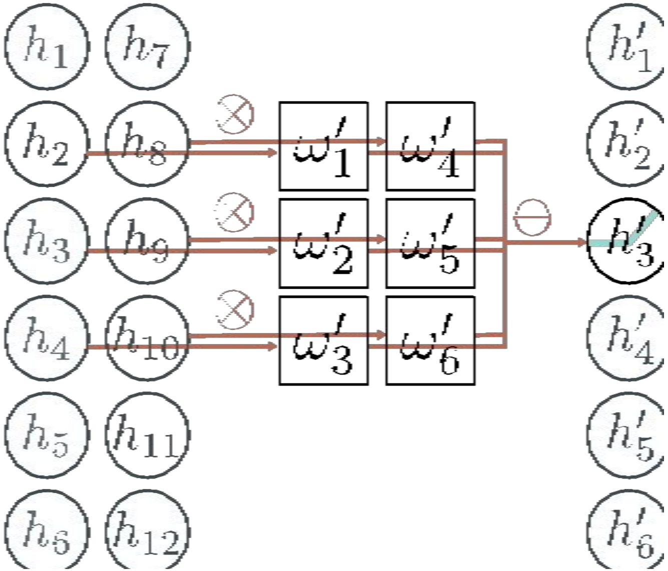
a)



Two output channels, one input channel



Two input channels, one output channel



How many parameters?

- If there are C_i input channels and kernel size K

$$\boldsymbol{\Omega} \in \mathbb{R}^{C_i \times K} \qquad \boldsymbol{\beta} \in \mathbb{R}$$

- If there are C_i input channels and C_o output channels

$$\boldsymbol{\Omega} \in \mathbb{R}^{C_i \times C_o \times K} \qquad \boldsymbol{\beta} \in \mathbb{R}^{C_o}$$

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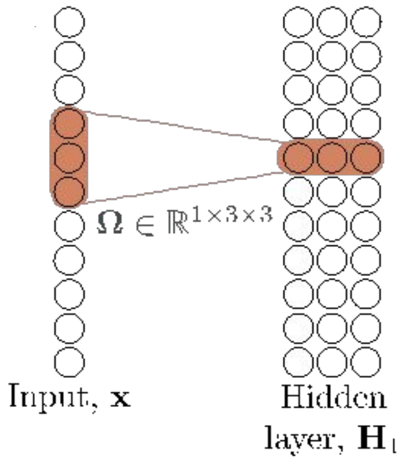
Receptive fields

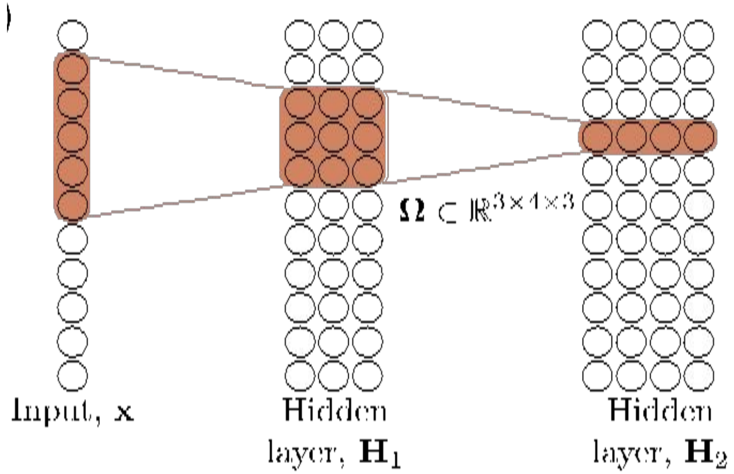
$\mathbb{R}^{C_i \times C_o \times K}$



Receptive fields

$\mathbb{R}^{C_i \times C_o \times K}$

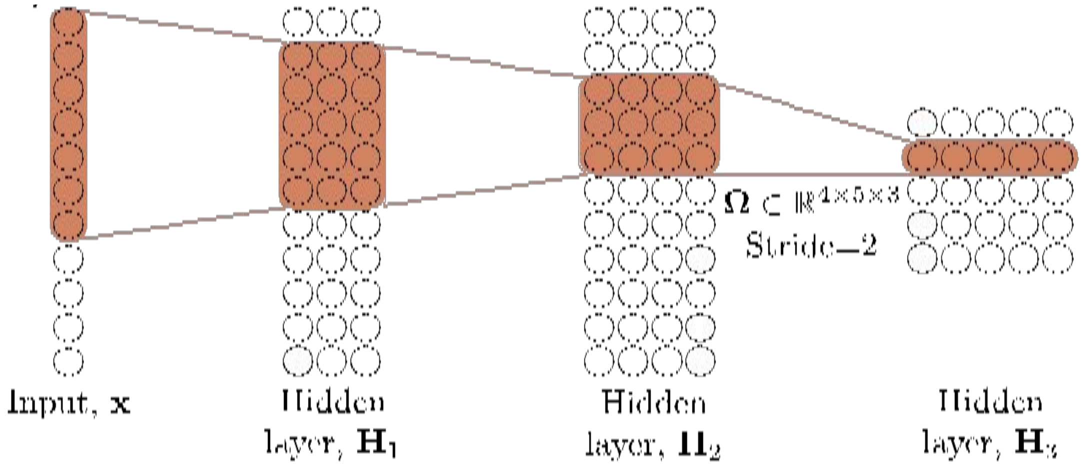
$$[\omega_1, \omega_2, \omega_3] \otimes [\omega_1, \omega_2, \omega_3] = [\omega_1, \omega_2, \omega_3, \omega_4, \omega_5]$$



Receptive fields

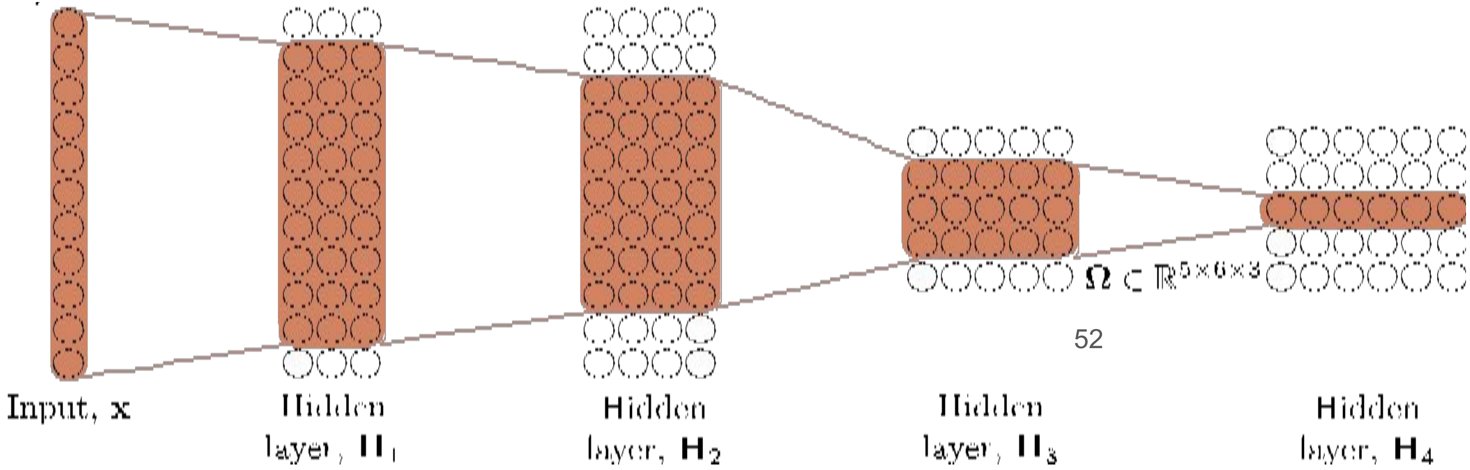
$$\mathbb{R}^{C_i \times C_o \times K}$$

$$[\omega_1, \omega_2, \omega_3, \omega_4, \omega_5] \otimes [\omega_1, \omega_2, \omega_3] = [\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6, \omega_7]$$



Receptive fields

$$\mathbb{R}^{C_i \times C_o \times K}$$



Convolutional networks

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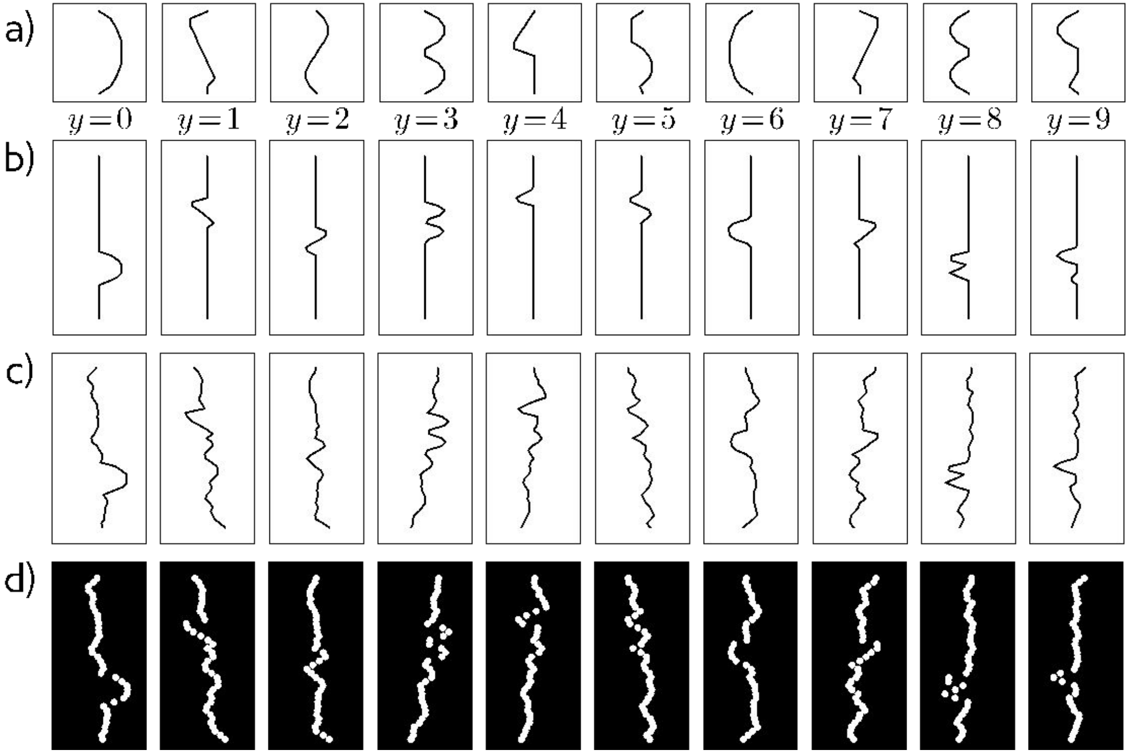
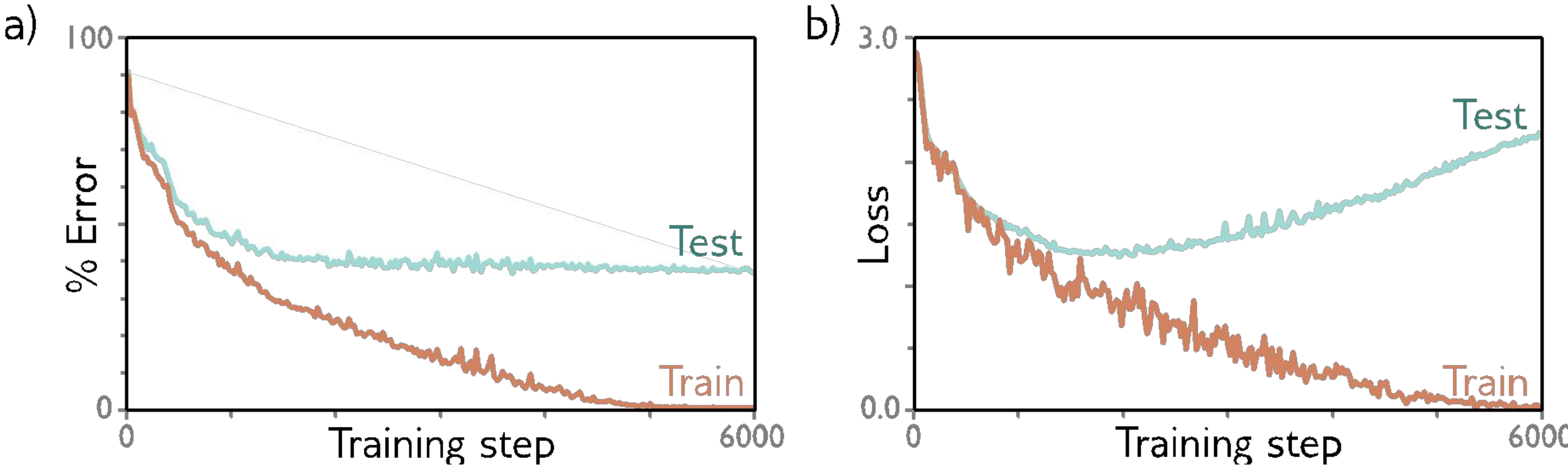
MNIST 1D Dataset



MNIST-1D results for fully-connected network



Fully connected network

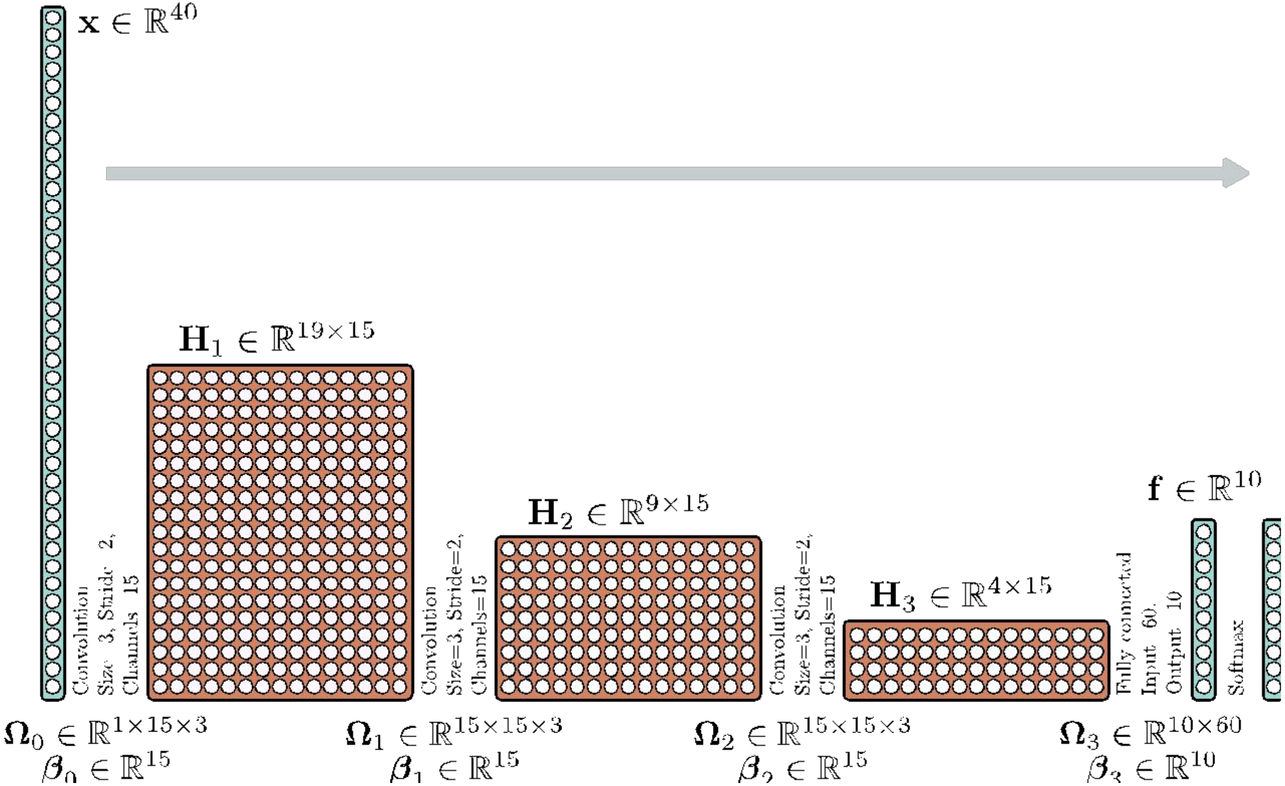
- Exactly same number of layers and hidden units
- All fully-connected layers
- Total parameters = 150,185

Convolutional network

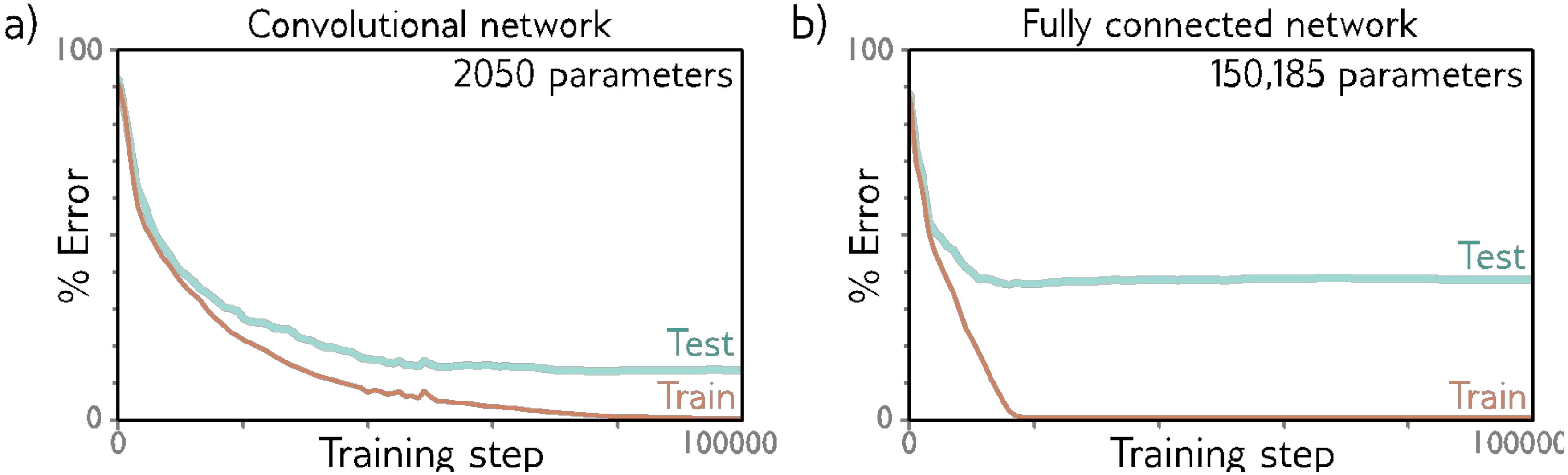
- Four hidden layers
- Three convolutional layers
- One fully-connected layer
- Softmax at end
- Total parameters = 2050
- Trained for 100,000 steps with SGD, LR = 0.01, batch size 100

```
==========================================================================================
Layer (type:depth-idx)                   Output Shape              Param #
==========================================================================================
Sequential                               [100, 10]                 --
├─Conv1d: 1-1                            [100, 15, 19]             60
├─ReLU: 1-2                              [100, 15, 19]             --
├─Conv1d: 1-3                            [100, 15, 9]              690
├─ReLU: 1-4                              [100, 15, 9]              --
├─Conv1d: 1-5                            [100, 15, 4]              690
├─ReLU: 1-6                              [100, 15, 4]              --
├─Flatten: 1-7                           [100, 60]                 --
├─Linear: 1-8                            [100, 10]                 610
==========================================================================================
Total params: 2,050
Trainable params: 2,050
Non-trainable params: 0
Total mult-adds (Units.MEGABYTES): 1.07
==========================================================================================
Input size (MB): 0.02
Forward/backward pass size (MB): 0.39
Params size (MB): 0.01
Estimated Total Size (MB): 0.42
==========================================================================================
```

MNIST-1D convolutional network



Performance



Why?

- Better inductive bias
- Forced the network to process each location similarly
- Shares information across locations
- Search through a smaller family of input/output mappings, all of which are plausible

2D Convolution

Convolution #2

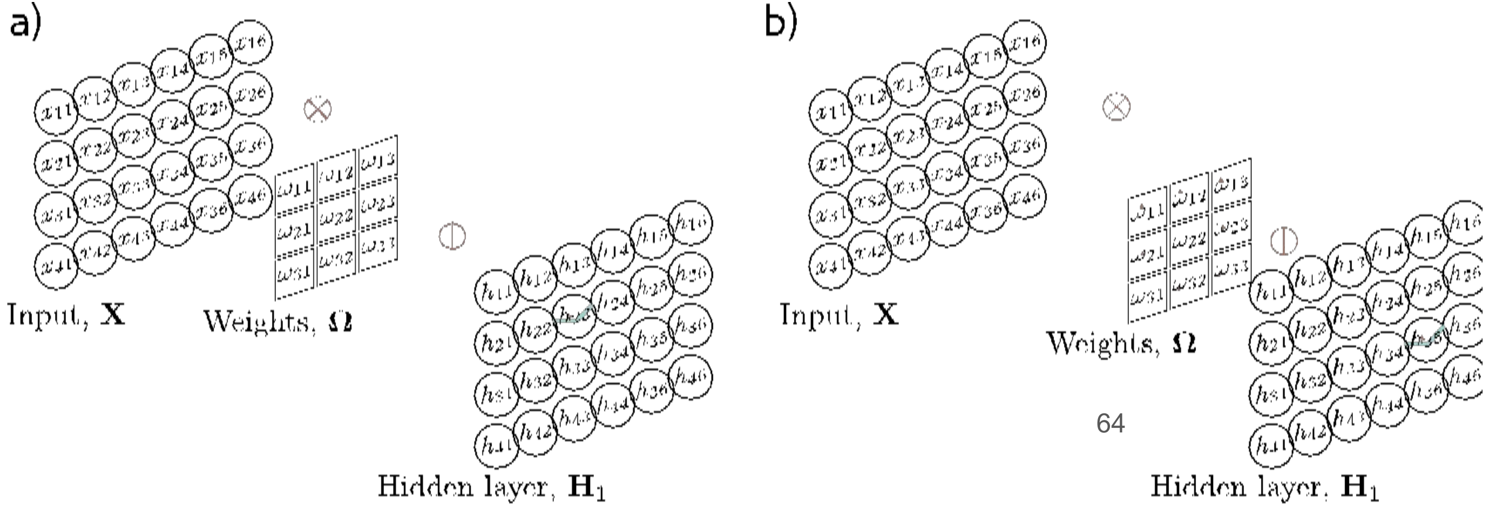
- 2D Convolution
- Downsampling and upsampling, 1x1 convolution
- Image classification
- Object detection
- Semantic segmentation
- Residual networks
- U-Nets and hourglass networks

2D Convolution

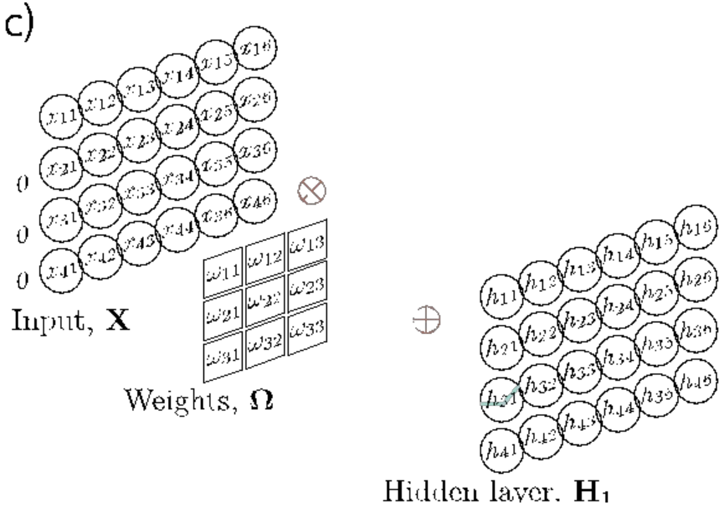
- Convolution in 2D
  - Weighted sum over a K x K region
  - K x K weights
- Build into a convolutional layer by adding bias and passing through activation function

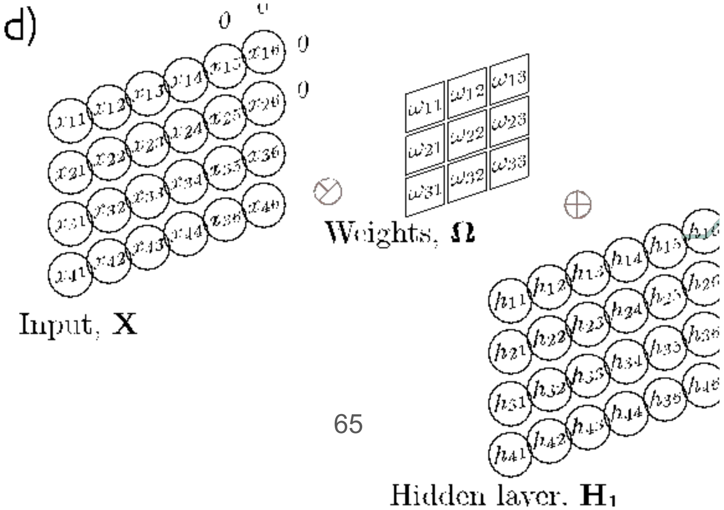
$$h_{i,j} = \mathrm{a}\left[\beta + \sum_{m=1}^{3}\sum_{n=1}^{3}\omega_{m,n}x_{i+m-2,j+n-2}\right]$$

2D Convolution

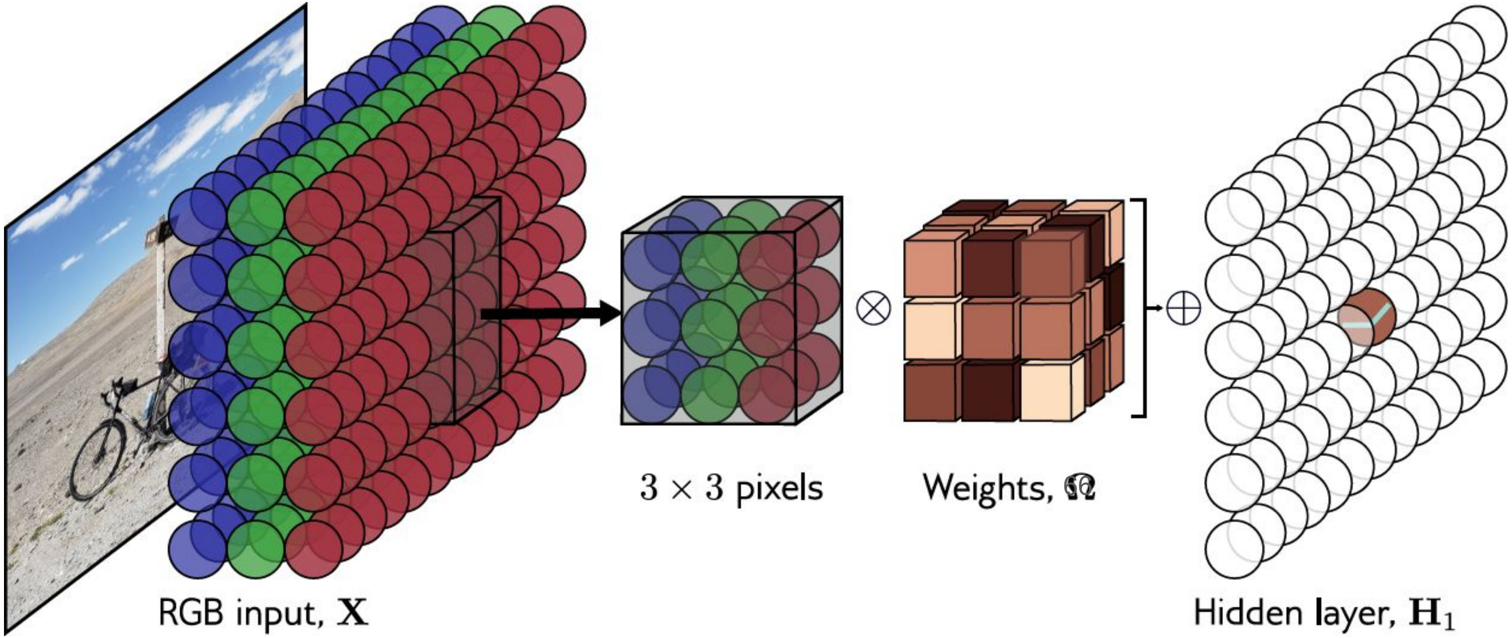


2D Convolution with Zero Padding





Channels in 2D convolution



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

How many parameters?

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

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

Convolution #2

- 2D Convolution
- Downsampling and upsampling, 1x1 convolution
- Image classification
- Object detection
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- Residual networks
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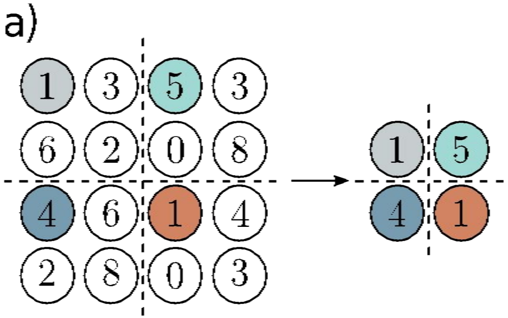
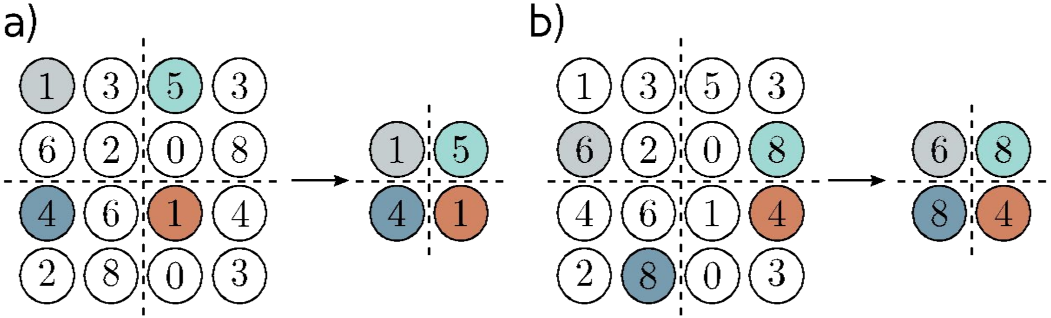
Downsampling



Sample every other position (equivalent to stride two)

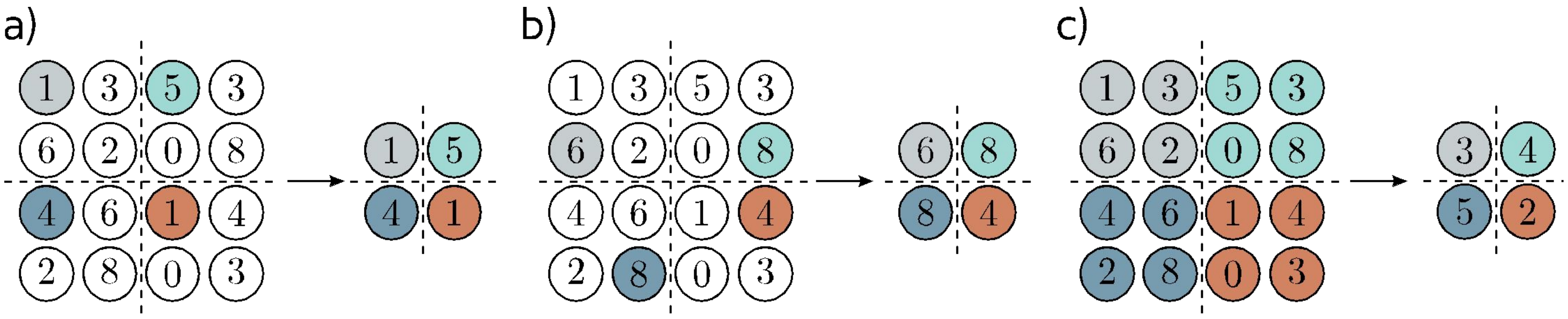
Downsampling



Sample every other position (equivalent to stride two)

Max pooling (partial invariance to translation)

Downsampling



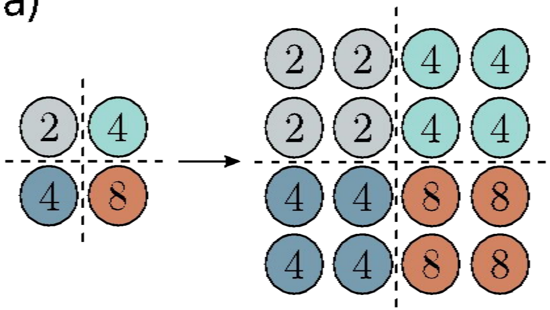
Sample every other position (equivalent to stride two)

Max pooling (partial invariance to translation)

Mean pooling

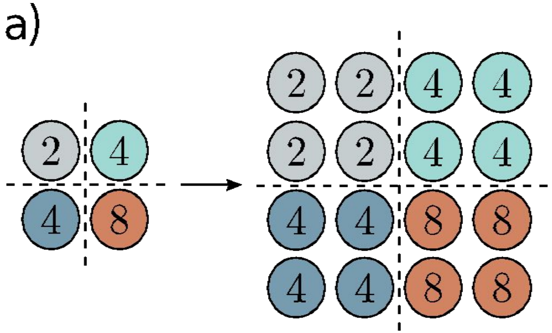
Upsampling

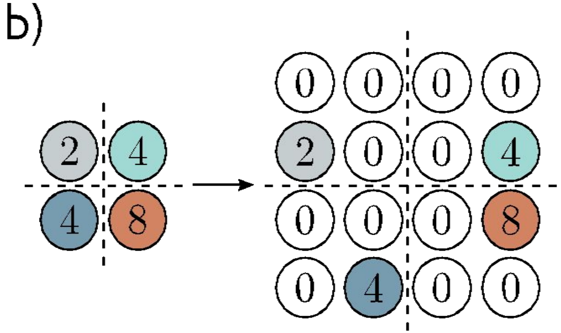
a)



Duplicate

Upsampling

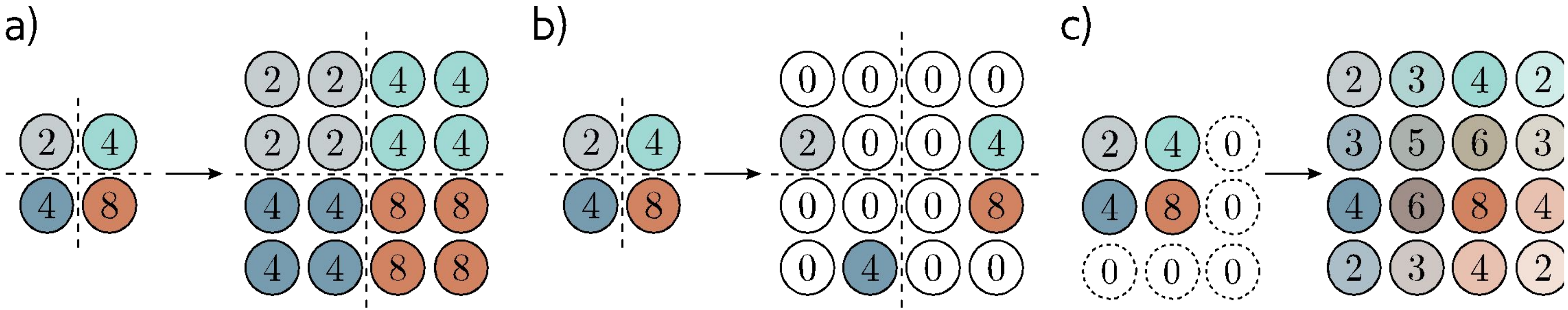




Duplicate

Max-upsampling

Upsampling

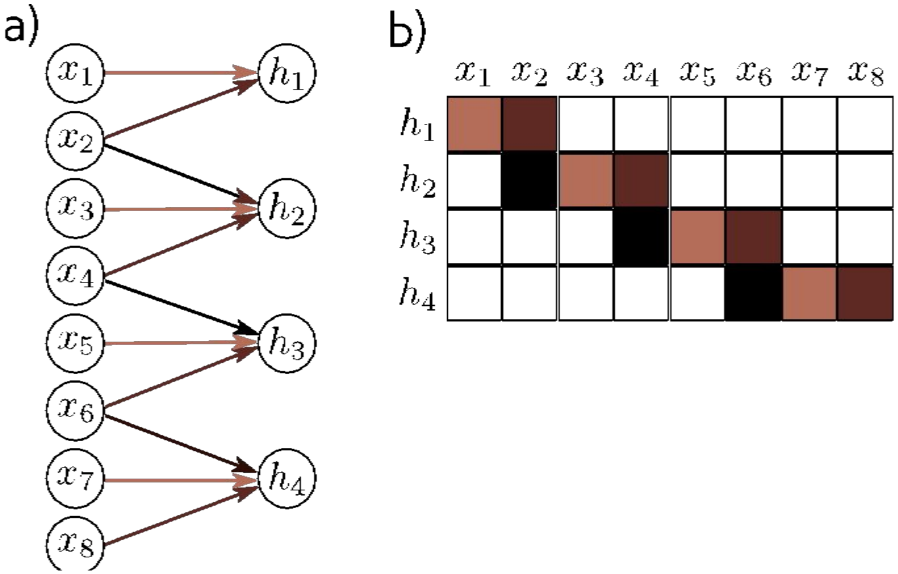


Duplicate

Max-upsampling

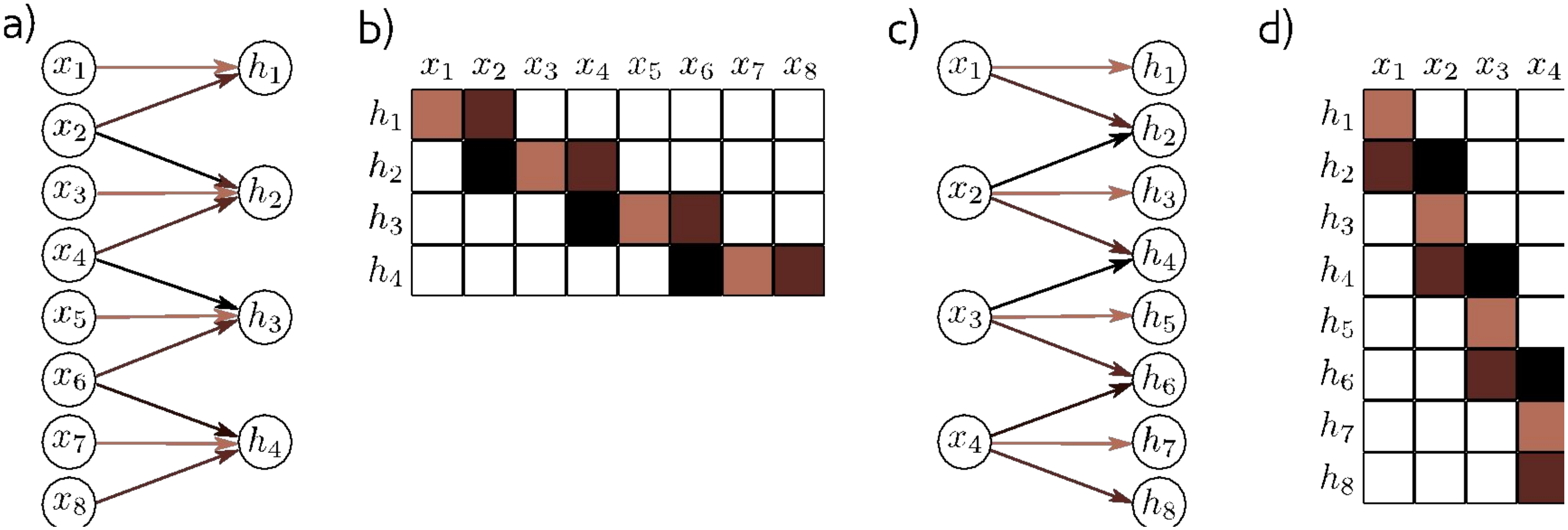
Bilinear interpolation

Transposed convolutions



Kernel size 3, Stride 2
convolution

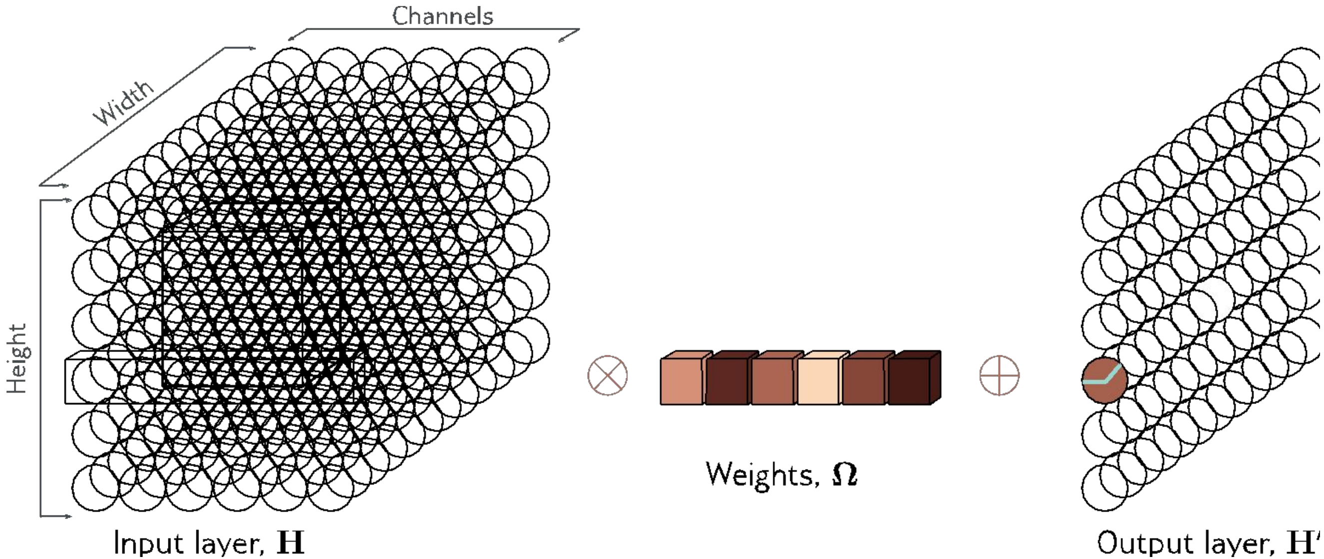
Transposed convolutions



Kernel size 3, Stride 2 convolution

Transposed convolution

1x1 convolution



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

Convolution #2

- 2D Convolution
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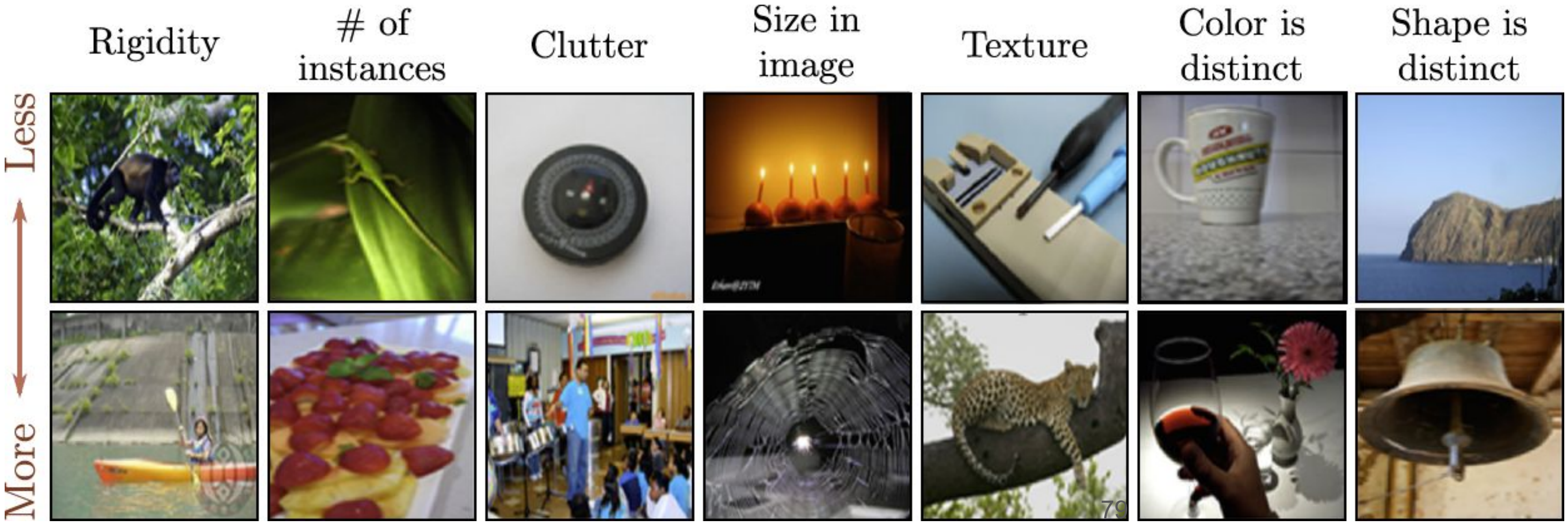
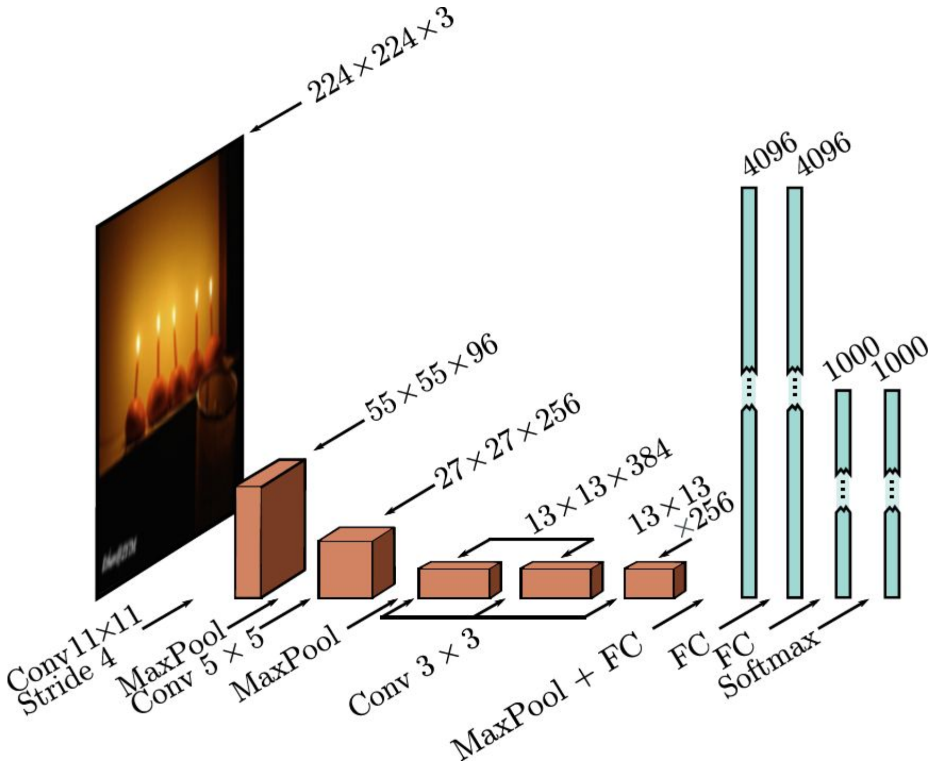
ImageNet database



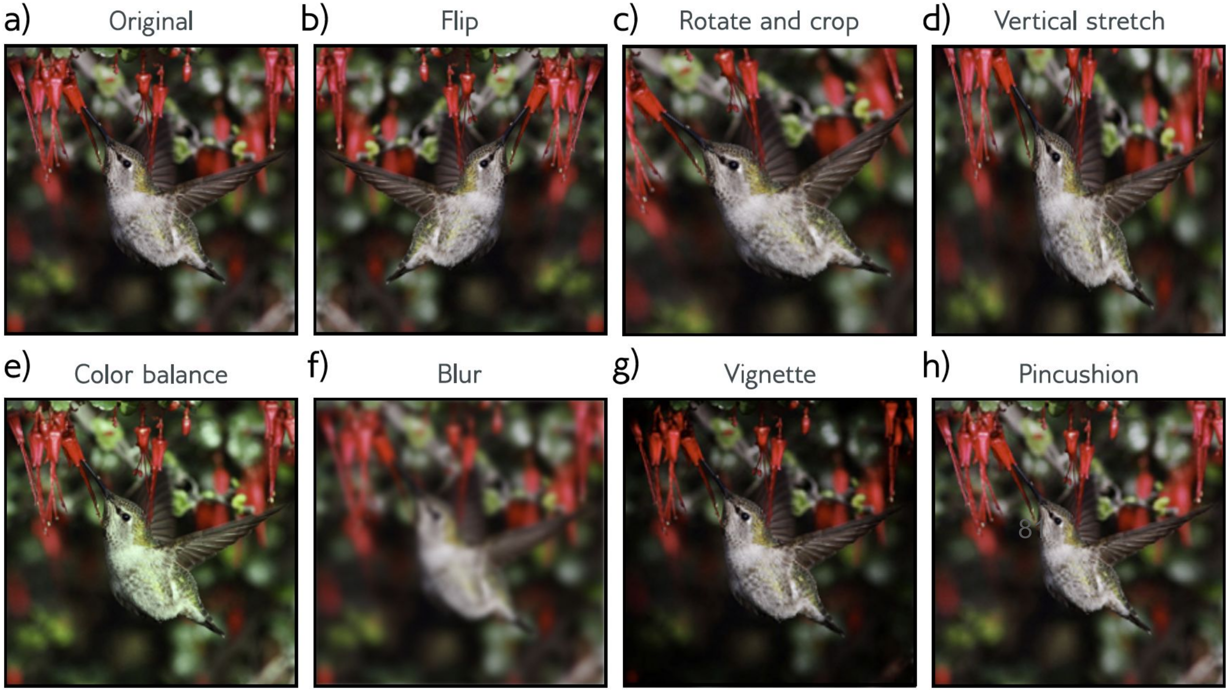
- 224 x 224 images
- 1,281,167 training images, 50,000 validation images, and 100,000 test images
- 1000 classes

AlexNet (2012)



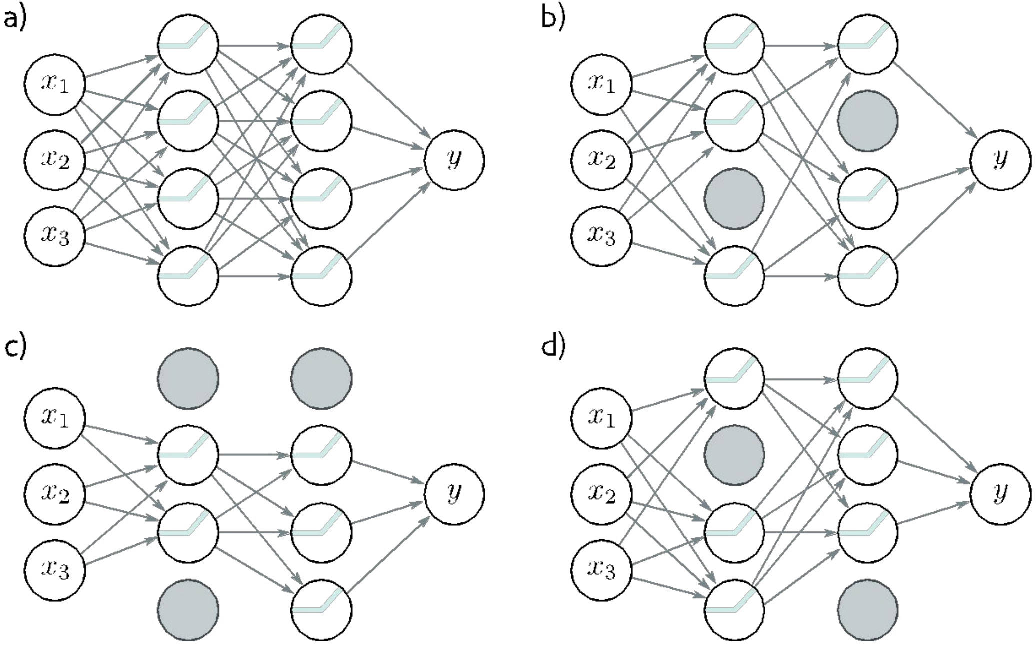
Almost all the 60 million parameters parameters are in fully connected layers

Data augmentation



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

Dropout

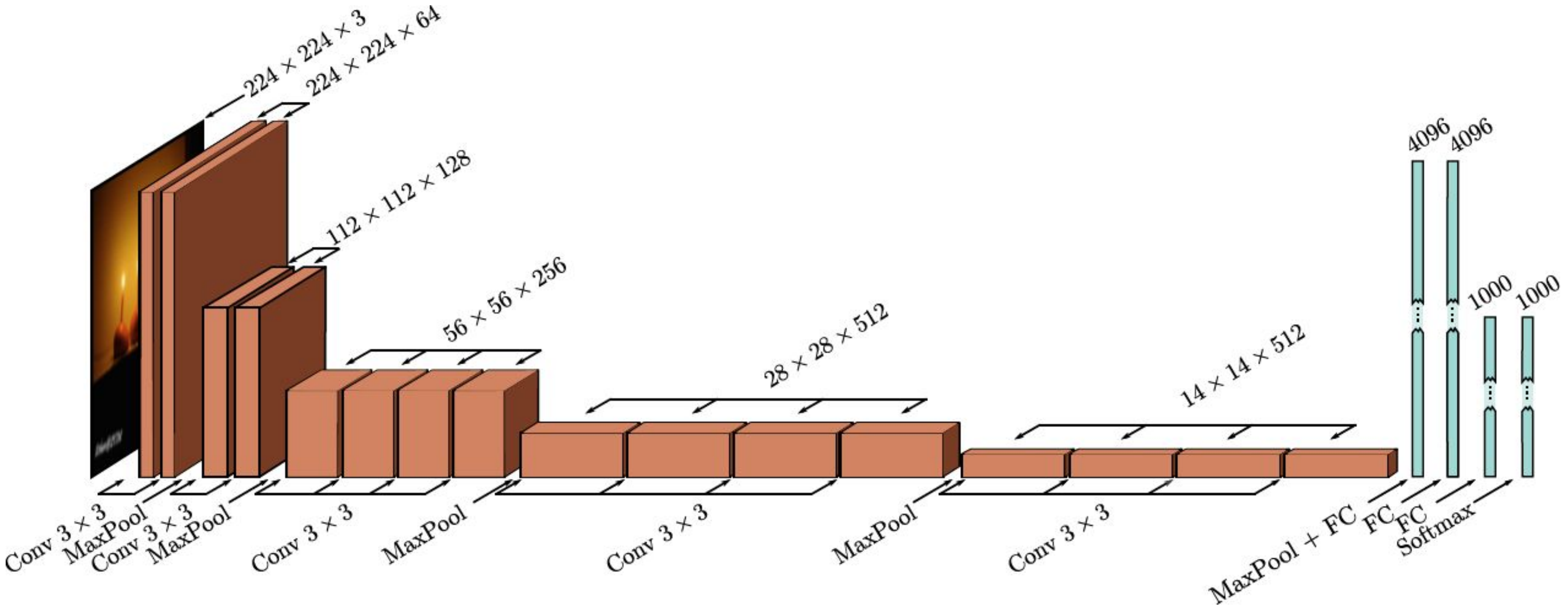


- Dropout was applied in the fully connected layers

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.

VGG (2015)

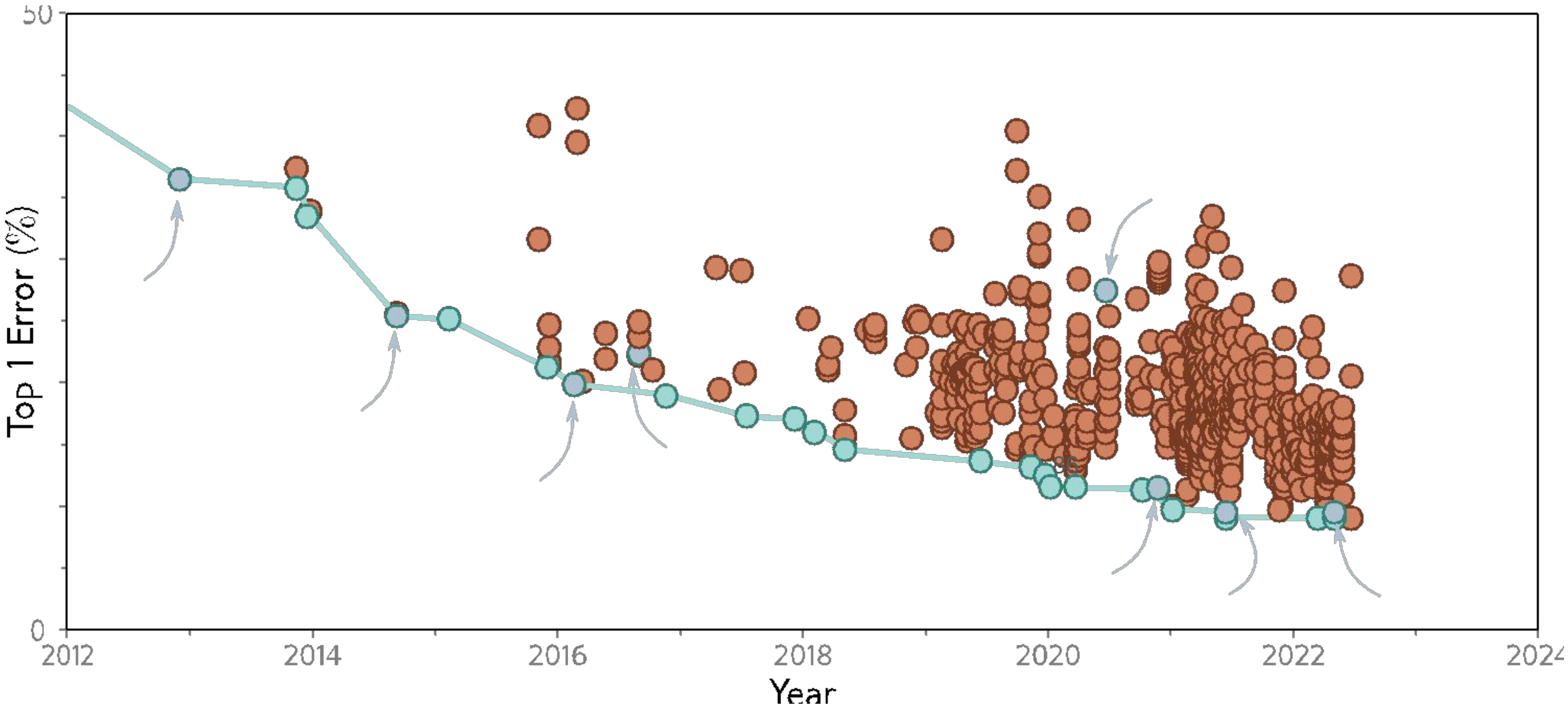


224 × 224 × 3
224 × 224 × 64
112 × 112 × 128
56 × 56 × 256
28 × 28 × 512
14 × 14 × 512
4096
4096
1000
1000
Conv 3 × 3
MaxPool
Conv 3 × 3
MaxPool
Conv 3 × 3
MaxPool
Conv 3 × 3
MaxPool
Conv 3 × 3
MaxPool + FC
FC
FC
Softmax

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
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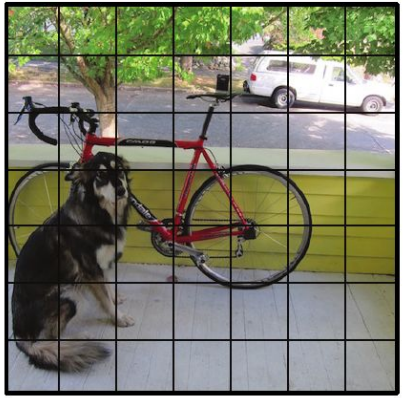
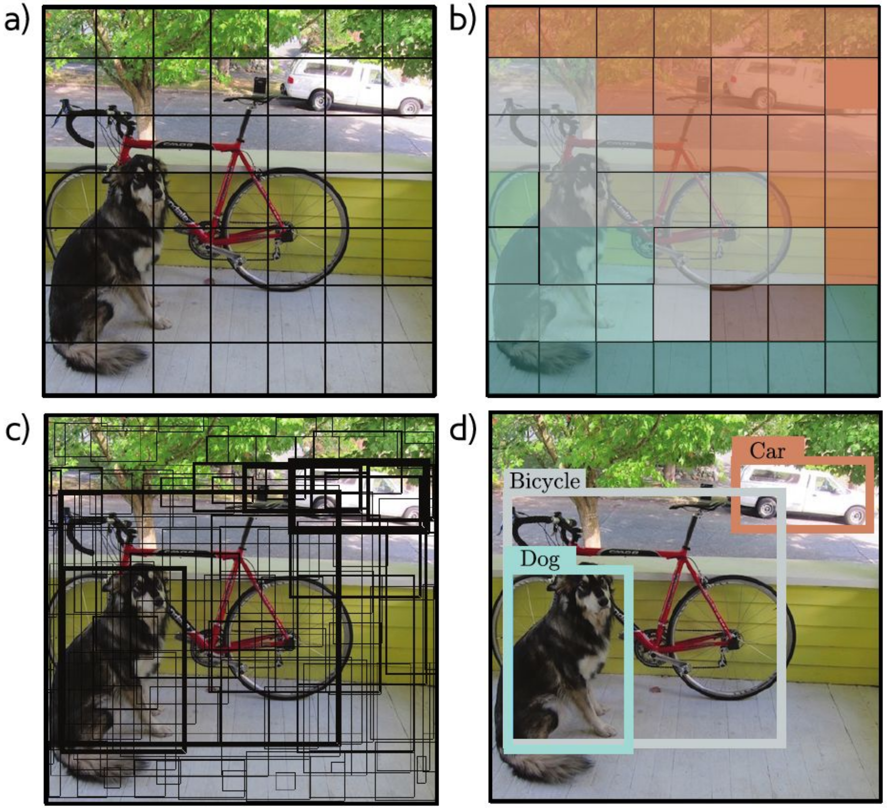
You Only Look Once (YOLO)

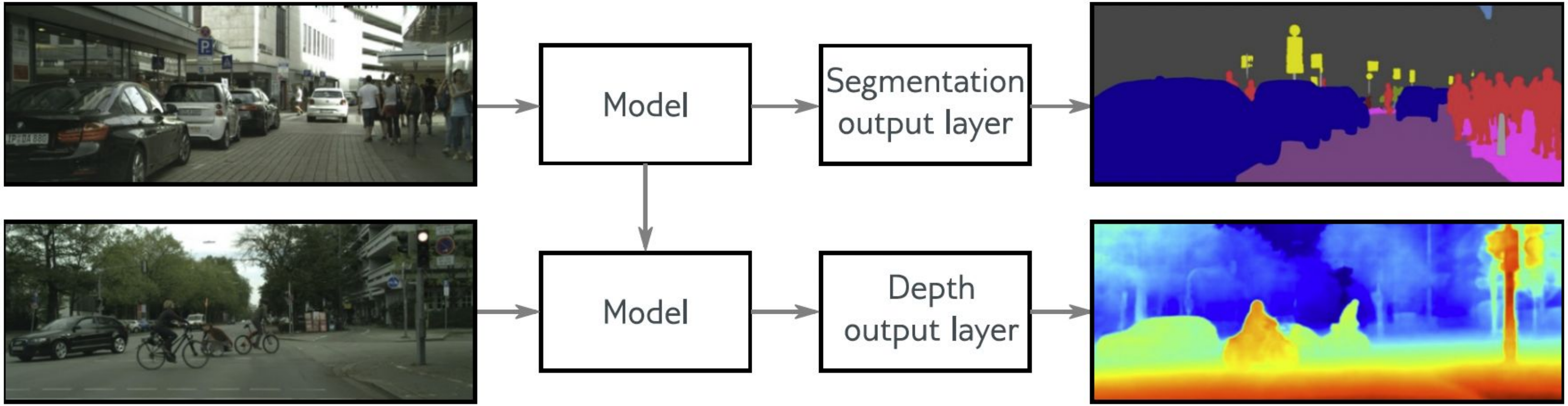


- Network similar to VGG (448x448 input)
- 7×7 grid of locations
- Predict class at each location
- Predict 2 bounding boxes at each location
  - Five parameters –x,y, height, width, and confidence
- Momentum, weight decay, dropout, and data augmentation
- Heuristic at the end to threshold and decide final boxes – (non maximum suppression)

Object detection (YOLO)

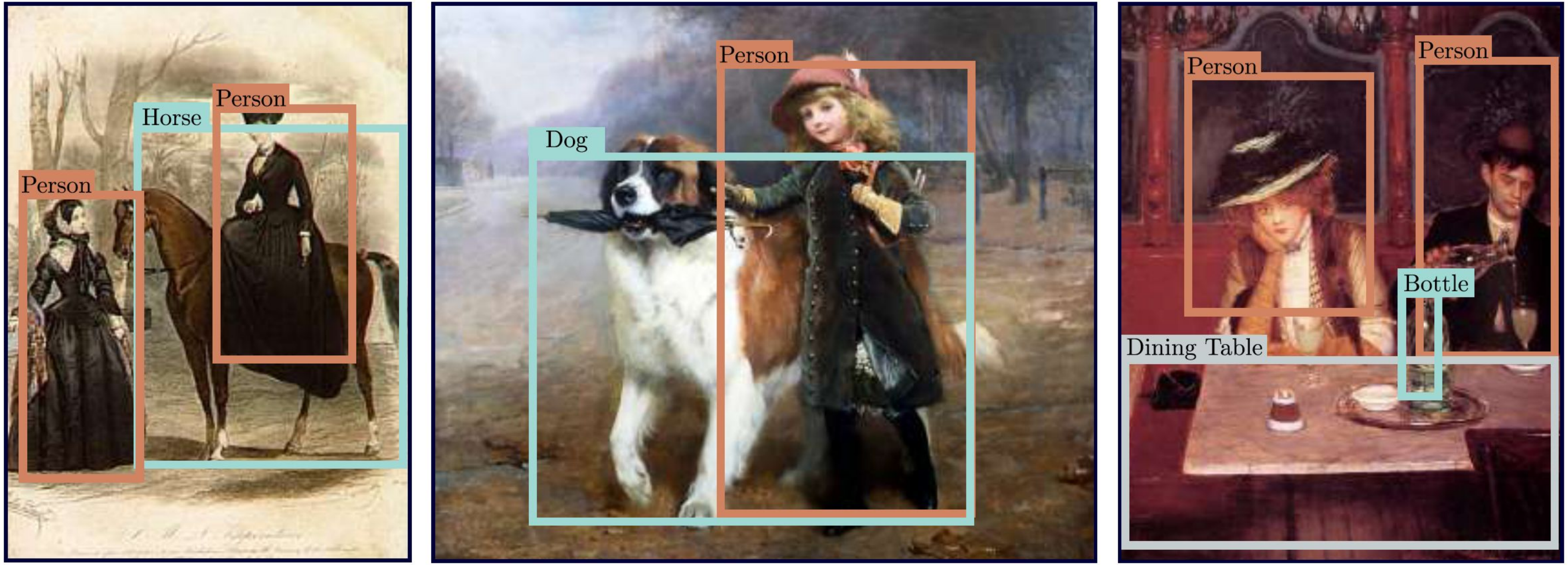


Transfer learning



Transfer learning from ImageNet classification

Results


Person
Horse
Person
Person
Dog
Person
Person
Bottle
Dining Table

Convolution #2

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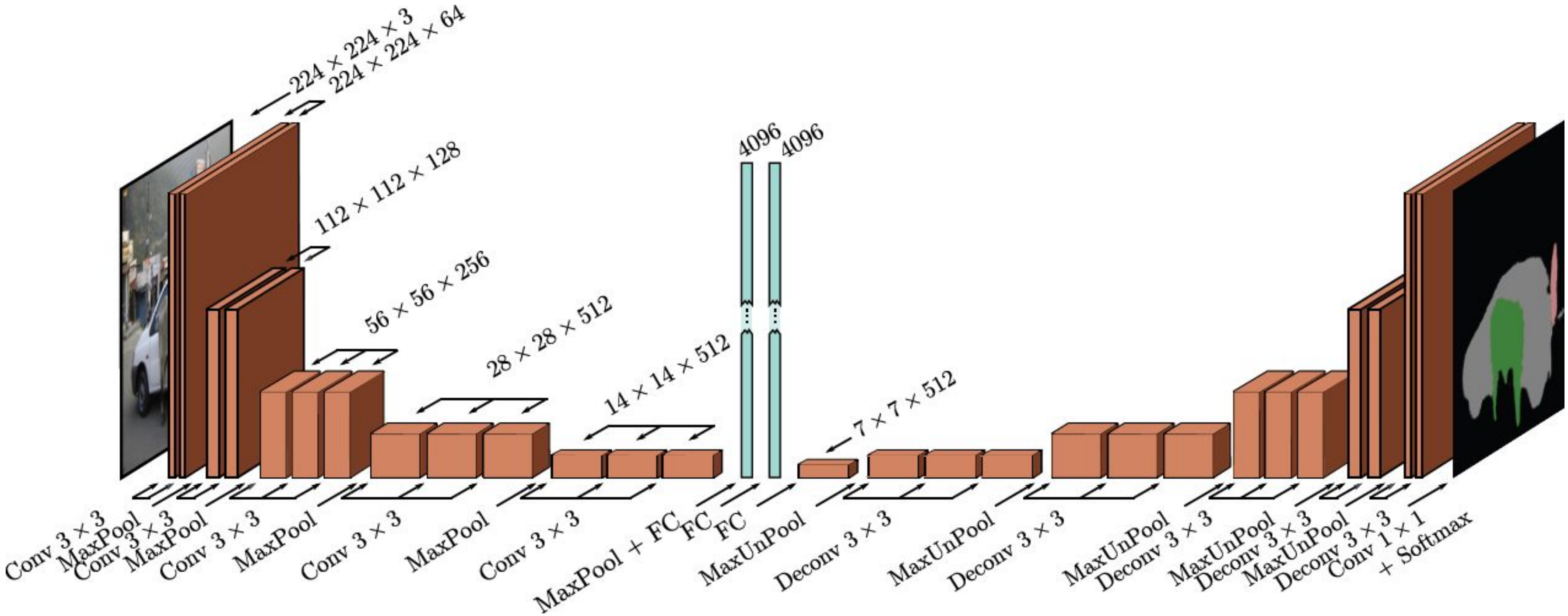
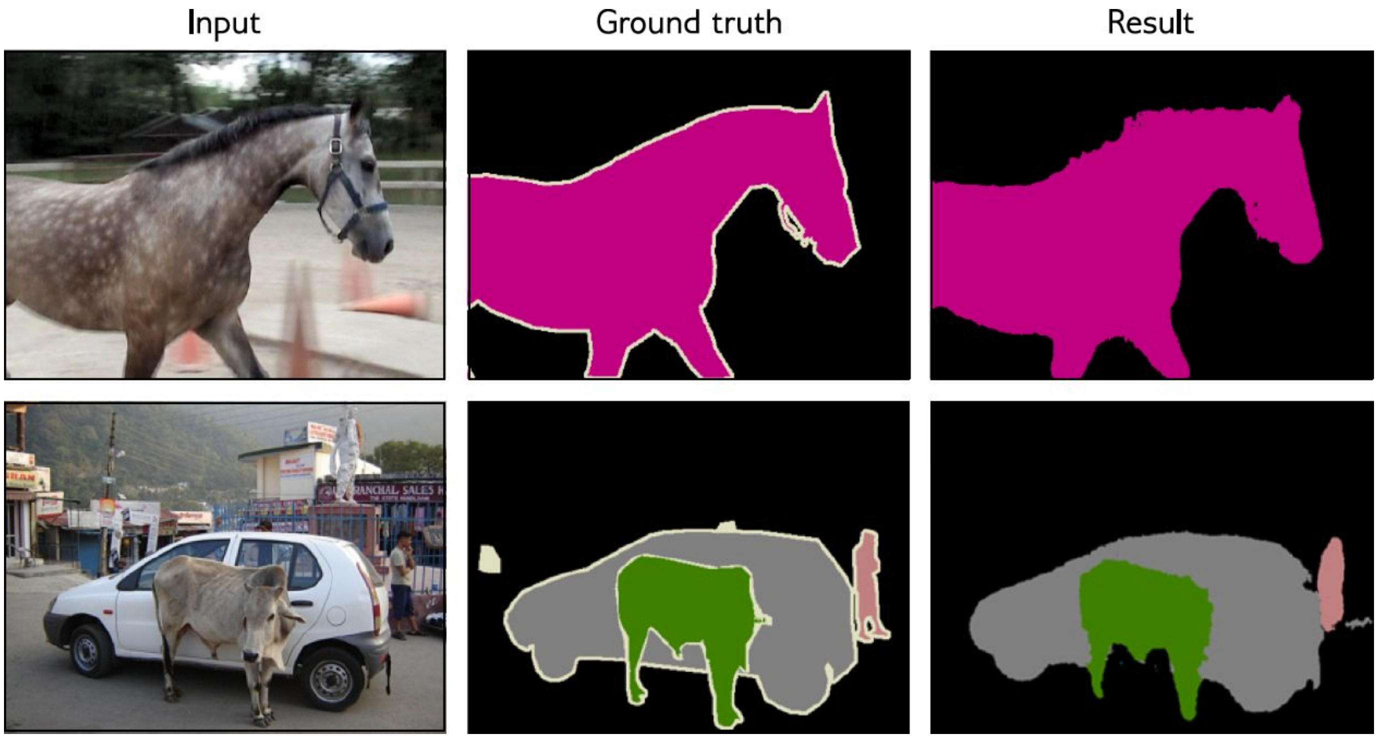
Semantic Segmentation (2015)



Encoder Decoder

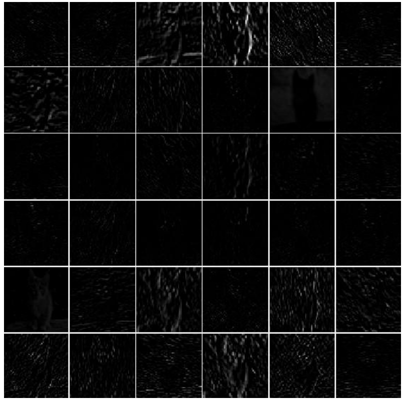
Semantic segmentation results



AlexNet

Cat image input
(not actual image)

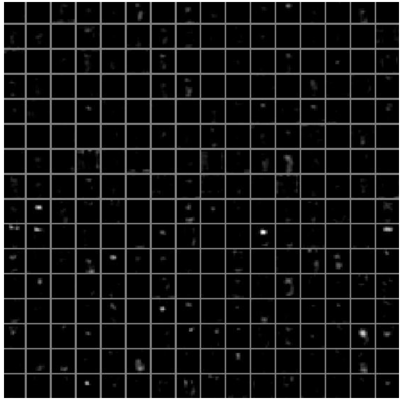
Activations
(feature maps)



1st Layer

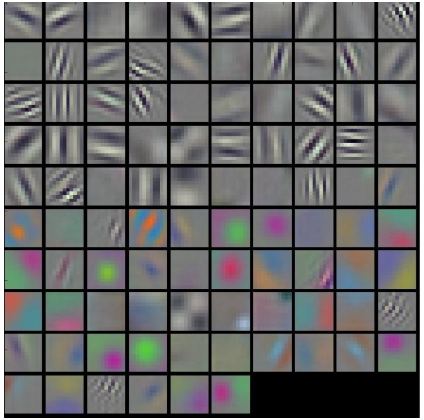
. . .

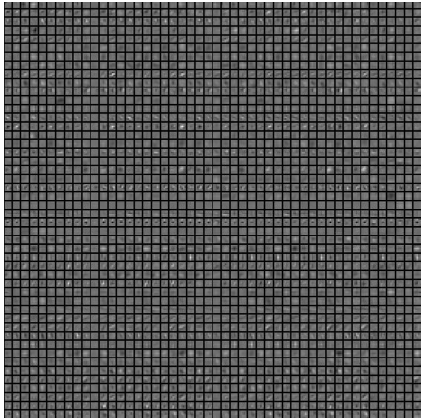
2nd Layer



5th Layer

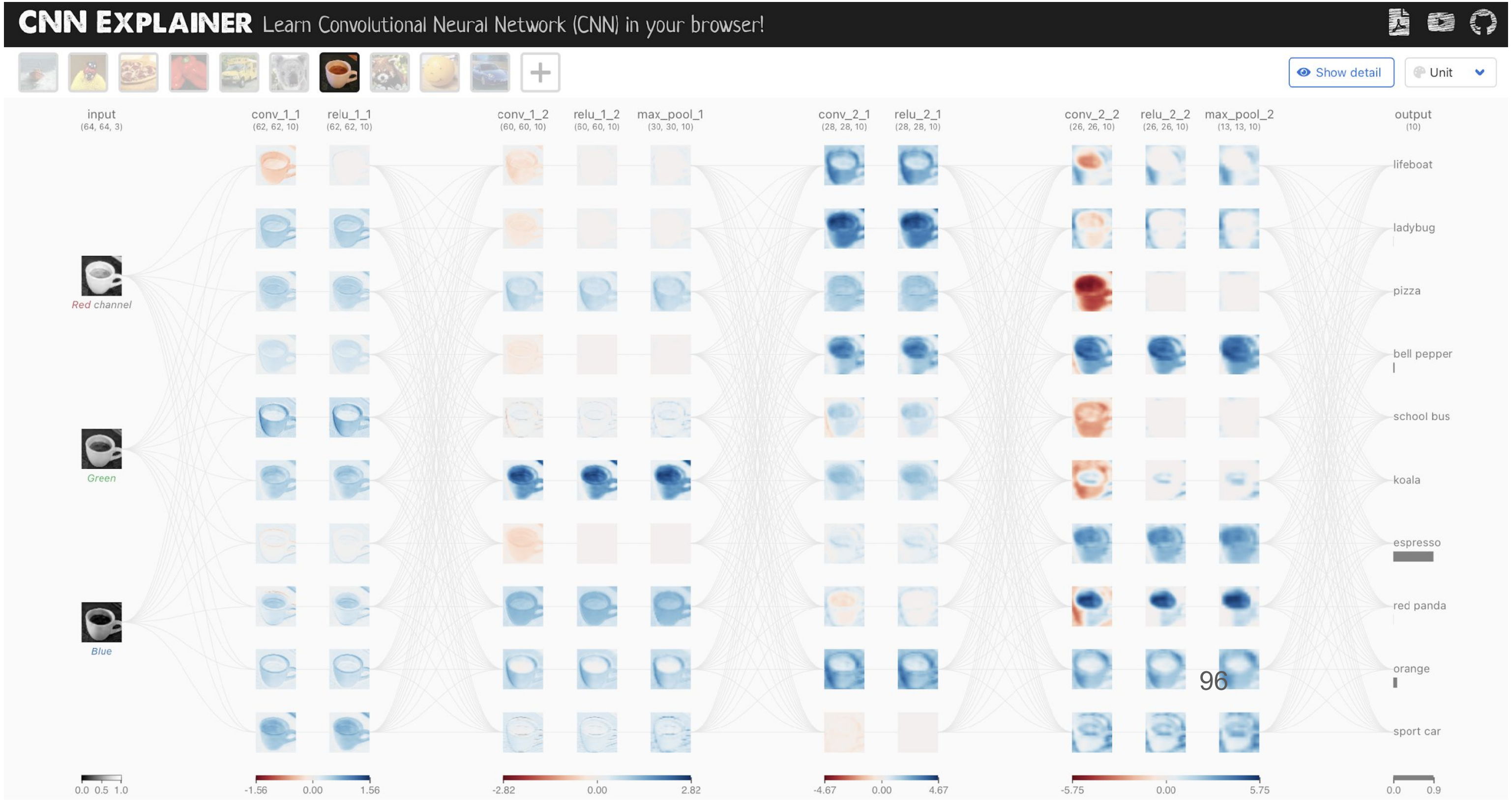
Filter Kernels





. . .

https://cs231n.github.io/understanding-cnn/



https://poloclub.github.io/cnn-explainer/

Other Approaches

After midterm:

- Recurrent neural networks
  - Repeatedly run same network on small chunks to update persistent state.
- Attention / Transformers
  - Run same network on small chunks of input, combined all of them via weighted averages…
  - Originally designed for text, but also state of the art for some vision problems now

My favorite, but not a topic for this course

- Neural fields
  - Big network re-parameterizing inputs as functions with small inputs and outputs

Feedback?